

## Inconsistency and Uncertainty Handling in Lightweight Description Logics

Zied Bouraoui

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# Inconsistency and uncertainty handling in lightweight description logics

## **THÈSE**

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### **Abstract**

This thesis investigates the dynamics of beliefs and uncertainty management in *DL-Lite*, one of the most important lightweight description logics. The first part of the thesis concerns the problem of handling uncertainty in DL-Lite. First, we propose an extension of the main fragments of DL-Lite to deal with the uncertainty associated with axioms using a possibility theory framework without additional extra computational costs. We then study the revision of possibilistic DL-Lite bases when a new piece of information is available. Lastly, we propose a min-based assertional merging operator when assertions of ABox are provided by several sources of information having different levels of priority. The second part of the thesis concerns the problem of inconsistency handling in flat and prioritized *DL-Lite* knowledge bases. We first propose how to reason from a flat DL-Lite knowledge base, with a multiple ABox, which can be either issued from multiple information sources or resulted from revising DL-Lite knowledge bases. This is done by introducing the notions of modifiers and inference strategies. The combination of modifiers plus inference strategies can be mapped out in order to provide a principled and exhaustive list of techniques for inconsistency management. We then give an approach based on selecting multiple repairs using a cardinality-based criterion, and we identified suitable strategies for handling inconsistency in the prioritized case. Lastly, we perform a comparative analysis, followed by experimental studies, of the proposed inconsistency handling techniques. A tool for representing and reasoning in possibilistic *DL-Lite* framework is implemented.

### Résumé

Cette thèse étudie la dynamique des croyances et la gestion de l'incertitude dans DL-Lite, une des plus importantes familles des logiques de description légères. La première partie de la thèse porte sur la gestion de l'incertitude dans DL-Lite. En premier lieu, nous avons proposé une extension des principaux fragments de DL-Lite pour faire face à l'incertitude associée aux axiomes en utilisant le cadre de la théorie des possibilités. Cette extension est réalisée sans engendrer des coûts calculatoires supplémentaires. Nous avons étudié ensuite la révision des bases DL-Lite possibilistes en présence d'une nouvelle information. Enfin, nous avons proposé un opérateur de fusion lorsque les assertions de ABox sont fournies par plusieurs sources d'information ayant différents niveaux de priorité. La deuxième partie de la thèse traite le problème de la gestion d'incohérence dans les bases de connaissances DL-Lite. Nous avons étudié, tout d'abord, comment raisonner à partir d'une base DL-Lite standard avec des ABox multiples en introduisant les notions de modificateurs et de stratégies d'inférence. La combinaison des modificateurs et de stratégies d'inférence fournit une liste exhaustive des principales techniques de gestion de l'incohérence. Nous avons proposé ensuite une approche, basée sur un critère de cardinalité, de sélection des réparations, et nous avons identifié les stratégies appropriées pour la gestion de l'incohérence pour les bases DL-Lite stratifiées. Enfin, nous avons effectué une analyse comparative, suivie par des études expérimentales, des différentes techniques de gestion d'incohérence proposées. Finalement, un outil de représentation et de raisonnement à partir des bases *DL-Lite* possibiliste est réalisé.

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### GENERAL INTRODUCTION

### **Context and motivations**

In the last years, there is a growing use of ontologies in many application areas. Description Logics (DLs for short), mostly based on first order logic, are recognized as powerful formal frameworks for representing and reasoning on ontologies. A DL knowledge base is built upon two distinct components: A terminological base (called *TBox*), representing generic structural knowledge about an application domain, and an assertional base (called *ABox*), containing the assertional facts (*i.e.* individuals or constants) that instantiate the generic knowledge. In the context of Semantic Web, DLs provide the logical basis of the Web Ontology Language (OWL), standardized by the W3C.

In many applications, ontologies are generally very large and some reasoning tasks can be prohibitive. There exist several description languages where the majority of them are intractable (e.g. SHOIQ, SROIQ), in the sense that they do not guarantee a polynomial complexity when reasoning. To this end, several lightweight DLs (e.g. EL [Baader et al., 2005a], DL-Lite [Calvanese et al., 2005]), mainly motivated by applications (like the ones involving large ontological knowledge), have been proposed. In particular, these logics allow a flexible representation of knowledge with a tractable computational complexity of the reasoning process.

DL-Lite [Calvanese et al., 2005] is a family of tractable DLs specifically dedicated to applications that use large volumes of data where query answering is the most important reasoning task. The consistency checking problem and all standard reasoning tasks are polynomial with respect to the size of the assertional base [Calvanese et al., 2007a]. In these logics, an important reasoning task is the one of answering complex queries (especially conjunctive queries) where reasoning complexity is in LogSpace for data complexity (namely, the size of the data) [Artale et al., 2009]. This fact makes DL-Lite especially well-suited for the context of Ontology-Based Data Access (OBDA), which studies how to query a set of data sources using an unified generic (ontological) view. In such settings, the terminological base acts as a schema used to reformulate the queries in order to offer a better access to the set of data stored in several assertional bases [Poggi et al., 2008]. A crucially important problem that arises in the OBDA setting is how to handle efficiently the multiple data sources.

In this context, assertions are often provided by several and potentially conflicting sources having different reliability levels. Moreover, a given source may provide different sets of uncertain assertions with different confidence levels. Gathering such sets of assertions gives a prioritized or a stratified assertional base. This stratification generally results from two situations as pointed out in several research papers (e.g. [Baral et al., 1992; Benferhat et al., 1995; Benferhat et al., 1998b]).

- The first one is when each source provides its set of data without any priority between them, but there exists a *total pre-ordering* between different sources reflecting their *reliability*.
- The other one is when the sources are considered as equally reliable (*i.e.* having the same reliability level), but there exists a preference ranking between the set of provided data according to their *level* of certainty.

The standard *DL-Lite* framework does not offer means of taking advantage of priority or uncertainty in the knowledge. In [Dubois and Prade, 1991a], it is argued that handling priority/uncertainty is in a complete agreement with possibility theory [Dubois and Prade, 1988b]. This latter offers a very natural framework to deal with ordinal, qualitative uncertainty, preferences and priorities. This framework

is particularly appropriate when the uncertainty/priority scale only reflects a priority relation between different pieces of information. Recently, several works have been proposed to deal with probabilistic and non-probabilistic uncertainty [Dubois *et al.*, 2006; Lukasiewicz *et al.*, 2012a] on the one hand and to deal with fuzzy information [Bobillo and Straccia, 2012; Lukasiewicz and Straccia, 2009] on the other hand. A particular attention was given to fuzzy extensions of DLs (*e.g.* [Bobillo *et al.*, 2012; Bobillo *et al.*, 2013; Pan *et al.*, 2007; Straccia, 2006b; Straccia, 2013]). Besides, some works are devoted to possibilistic extensions of description logics (*e.g.* [Dubois *et al.*, 2006; Hollunder, 1995; Qi *et al.*, 2011]) which are basically based on standard reasoning services. This thesis fills this gap and proposes an extension of *DL-Lite* within a possibility theory setting.

In *DL-Lite* and ODBA settings, inconsistency and contradictions are always defined with respect to some assertions that contradict the terminology. Indeed, a *DL-Lite* terminology may be incoherent but never inconsistent. Faced to inconsistency, there are two main attitudes:

- i) The first one consists in *merging* (e.g. [Kotis et al., 2006; Moguillansky and Falappa, 2007]) the knowledge base using some aggregation strategies. Knowledge bases merging or belief merging (e.g. [Bloch et al., 2001; Konieczny and Pino Pérez, 2002]), is a problem largely studied within the propositional logic setting. It focuses on aggregating pieces of information issued from distinct, and may be conflicting or inconsistent, sources in order to obtain a unified point of view by taking advantage of pieces of information provided by each source. Generally in OBDA setting, applying merging techniques on data sources lead to removing some assertions that contradict the terminological base (which may be seen as an integrity constraint) in order to restore consistency. This approach is too cautious since it comes down to throw out an important part of the data which becomes no longer useful when reasoning. In ontology area, there are few works which studied the application of merging techniques proposed within propositional logics to merge DL knowledge bases. The existing works mainly reduce the merging problem to an inconsistency handling one.
- ii) The second attitude consists in accepting and leaving inconsistency while coping with it when performing inference using different inconsistency-tolerant inference strategies. Handling inconsistency is also a problem largely studied within the propositional logic setting [Bertossi et al., 2005b]. Several approaches were proposed to deal with inconsistency in propositional logic knowledge bases. These approaches focus either on restoring consistency (e.g. [Benferhat et al., 1997a]), using paraconsistent logics (e.g. [Hunter, 1998]), analyzing and measuring the inconsistency (e.g. [Hunter and Konieczny, 2005]), employing argumentation framework (e.g. [Besnard and Hunter, 2008]). In the same spirit, several works (e.g. [Oi and Hunter, 2007; Corcho et al., 2009; Ma and Hitzler, 2010; Lukasiewicz et al., 2013]) were proposed to handle inconsistency or incoherency in ontologies (Ontology debugging or repairing). Regarding DL-Lite, in the context of OBDA, existing works (e.g. [Lembo et al., 2010; Bienvenu, 2012; Bienvenu and Rosati, 2013]), basically inspired by the approaches proposed in the database area, tried to deal with inconsistency in *DL-Lite* by proposing and adapting several inconsistency-tolerant inference methods. All the proposed approaches are based on the notion of repair which is closely related to the notion of database repair defined in order to answer queries raised to inconsistent databases. A repair of a database contradicting a set of integrity constraints is a database obtained by applying a minimal set of changes in order to restore consistency. This notion was extended to the DL-Lite setting [Lembo et al., 2010] by defining assertional-based repair for DL-Lite knowledge bases which is simply a maximal assertional subbase consistent with the *TBox*. Clearly, these works are closely related to works on restoring consistency, proposed for handling inconsistency in propositional logic knowledge bases.

In this thesis, we study merging of different data sources linked to the same ontological view, seen as integrity constraints. Besides, we more investigate inconsistency handling for *DL-Lite* in case where the

knowledge base is flat or prioritized.

Another problem addressed in this thesis is the one of ontology dynamics. In fact, description logics have been proposed to represent the static knowledge of a domain of interest. However, knowledge may be non static and may evolve and change from one situation to another in order to take into account and integrate the changes that occur over time. One of the fundamental issues in Web applications is the dynamics of the knowledge base (e.g. [Qi et al., 2006c; Wang et al., 2010; Kharlamov et al., 2013]) which is a problem closely related to the belief revision one (e.g. [Alchourrón et al., 1985; Katsuno and Mendelzon, 1991; Hansson, 1998]). Several approaches were proposed by adapting revision operators proposed within propositional logic setting to description logics ones. There are two main approaches for revision: Model-based approaches (e.g. [Qi and Du, 2009; Wang et al., 2010]) or formula-based approaches (e.g. [Halaschek-wiener et al., 2006; Ribeiro and Wassermann, 2007]). As pointed out in [Calvanese et al., 2010], model-based approaches of revision are in general not appropriate for DL-Lite in the sense that the result of the revision is not expressible in the initial DL-Lite language (before the revision process). In this thesis, we follow a formula-based approach for revising DL-Lite knowledge bases when the ABox is prioritized.

This thesis investigates the dynamics of knowledge and beliefs and uncertainty management in *DL-Lite*, one of the most important lightweight DLs. It contains three main contributions: i) an extension of *DL-Lite* to possibility theory, ii) a proposition for a roadmap for handling inconsistency in flat *DL-Lite* knowledge bases, and iii) an analysis of revision and inconsistency handling in prioritized *DL-Lite* knowledge bases.

### **Contributions**

The first contribution of the thesis concerns the problem of handling uncertainty in *DL-Lite*. In fact, in many contexts, the available information and knowledge may be uncertain or prioritized requiring a framework to manage uncertainty and priorities.

#### Part I

- Possibilistic *DL-Lite*: We investigate an extension of the main fragments of *DL-Lite* to deal with uncertainty associated with objects, concepts or relations using a possibility theory framework. It is particularly useful for handling inconsistent knowledge. We first provide foundations of possibilistic *DL-Lite*, denoted by π-*DL-Lite*, by extending the *DL-Lite*<sub>core</sub> logic, the core fragment of all *DL-Lite* logics, within a possibility theory setting. We present syntax and semantics of π-*DL-Lite*<sub>core</sub>, study the reasoning tasks and show how to compute the inconsistency degree of a π-*DL-Lite*<sub>core</sub> knowledge base. We then extend our possibilistic approach to *DL-Lite*<sub>F</sub> and *DL-Lite*<sub>R</sub>, two important fragments of *DL-Lite* family. Finally, we address the problem of query answering over a π-*DL-Lite* knowledge bases. An important result is that the extension of the expressive power of *DL-Lite* is done without additional extra computational costs. A tool for representing and reasoning in π-*DL-Lite* is implemented.
- Conditioning and merging of possibilistic DL-Lite knowledge bases: We first focus on the use of a minimum-based operator, well known as idempotent conjunctive operator, to combine  $\pi$ -DL-Lite possibility distributions and show that this semantic fusion has a natural syntactic counterpart when dealing with  $\pi$ -DL-Lite knowledge bases. The min-based fusion operator is recommended when distinct sources that provide information are dependent. We then define a merging operator for  $\pi$ -DL-Lite knowledge bases based on conflict resolution. We investigate a min-based assertional merging operator. We study in particular the situation where the sources share the generic

knowledge. We present a syntactic method based on conflict resolution which has a meaningful semantic counterpart when merging possibility distributions. We finally provide an analysis in the light of a new set of postulates dedicated to uncertain *DL-Lite* bases merging.

We also give first results on the revision of possibilistic *DL-Lite* knowledge bases when a new input piece of information, possibly conflicting or uncertain, becomes available. We first study revision at the semantic level consisting in directly conditioning possibility distributions. In particular, we show that such conditioning provides in some situations some counterintuitive results compared with the ones of conditioning directly the knowledge base syntactically. We then study revision at the syntactic level of possibilistic *DL-Lite* knowledge bases.

### Part II

• Inconsistency handling in flat *DL-Lite* knowledge bases: We propose how to reason from a *DL-Lite* knowledge base with a multiple ABox, called an MBox *DL-Lite* knowledge base. An MBox is a multi-set of ABox's which can be either issued from multiple information sources or resulted from revising inconsistent *DL-Lite* knowledge bases. We provide different inference strategies for query answering from MBox *DL-Lite* knowledge bases. We then discuss three main elementary changes or modifiers that can be operated on an MBox: i) Expansion modifiers, ii) Splitting modifiers and iii) Selection-based modifiers. The second part of the chapter uses the concept of MBox to provide a roadmap for handling inconsistent standard *DL-Lite* knowledge bases. We view the problem of repairing an inconsistent *DL-Lite* knowledge base as composed of a composite or a complex modifier on a given MBox followed by an inference-based strategy. Lastly, we show that there are exactly eight major composite modifiers that can be applied on an inconsistent standard *DL-Lite* knowledge base and identify those that produce a single consistent and preferred repair.

### Part III

The question addressed in this part is how to revise *DL-Lite* knowledge bases with a new piece of information, in a prioritized setting. Moreover, as highlighted in fusion problems, there is a need to deal with inconsistent prioritized information. It appears that only few works addressed this problem in the *DL-Lite* setting. So, the third part of the thesis concerns the evolution and inconsistency handling of *DL-Lite* knowledge bases when the assertions in the ABox's are prioritized.

- Assertional-based revision: We investigate "Prioritized Removed Sets Revision" (PRSR) for revising stratified *DL-Lite* knowledge bases when a new sure piece of information, called the input, is added. The strategy of revision is based on inconsistency minimization and consists in determining the smallest subsets of assertions (prioritized removed sets) that should be dropped from the current stratified knowledge base in order to restore consistency and accept the input. We consider different forms of input: A membership assertion, a positive or a negative inclusion axiom. In some situations, the revision process leads to several possible revised knowledge bases where defining a selection function is required to keep the results within *DL-Lite* fragment. Lastly, we show how to use the notion of hitting set in order to compute the PRSR outcome.
- Selecting one preferred repair from prioritized *DL-Lite* knowledge bases: We first review the existing approaches for selecting preferred assertional-based repairs. Then, we focus on suitable strategies for handling inconsistency in *DL-Lite*. We propose, in particular, new approaches based on the selection of one assertional-based repair. These approaches have as a starting point the non-defeated assertional-based repair followed by additional ingredients like the linear-based, cardinality-based, deductive closure, etc. Lastly, we provide a comparative analysis followed by experimental studies of the different studied approaches.

### **Organization of the thesis**

This thesis is organized as follows. We first give in Chapter 1, a refresher on description logics, with a focus on *DL-Lite*. We then give in Chapter 2, an overview about possibility theory, belief change problem in the context of propositional logic and description logics. Chapter 3 presents the extension of *DL-Lite* within a possibility theory setting. Chapter 4 first investigates merging of possibilistic *DL-Lite* and proposes a method based on conflict resolution to aggregate several sets of data linked to the same terminological base. It also gives preliminary results on conditioning in possibilistic *DL-Lite* framework. Chapter 5 provides a non-merging roadmap for inconsistency handling in flat *DL-Lite* knowledge bases. Chapter 6 proposes a lexicographic-based approach for revising stratified *DL-Lite* knowledge bases when a new sure piece of information becomes available. Chapter 7 studies inconsistency handling in *DL-Lite* knowledge bases where the assertional base is prioritized. Finally, the thesis contains a conclusion and some future works. We also provide in the appendix additional material for Chapter 5 and a description of our tool developed for representing and reasoning in possibilistic *DL-Lite* framework.

### **Publications achieved in this thesis**

International journal papers

- 1. Salem Benferhat and Zied Bouraoui. Min-based possibilistic *DL-Lite*. In the Journal of Logic and Computation (JLC 2015).
- 2. Salem Benferhat, Zied Bouraoui, Odile Papini, and Eric Würbel. Prioritized Assertional-Based Removed Sets Revision of *DL-Lite* Belief Bases, In the Annals of Mathematics and Artificial Intelligence (Accepted with minor revision).

### International conference papers

- 1. Salem Benferhat, Zied Bouraoui, Karim Tabia. How to select one preferred assertional-based repair from inconsistent and prioritized *DL-Lite* knowledge bases?. In the International Joint Conference on Artificial Intelligence (IJCAI 2015).
- 2. Salem Benferhat, Zied Bouraoui, Odile Papini, and Eric Würbel. A prioritized assertional-based revision for *DL-Lite* knowledge bases. In the European Conference on Logics in Artificial Intelligence (JELIA 2014).
- 3. Salem Benferhat, Zied Bouraoui, Sylvain Lagrue, and Julien Rossit. Min-based assertional merging approach for prioritized *DL-Lite* knowledge bases. In the International Conference on Scalable Uncertainty Management (SUM 2014).
- 4. Salem Benferhat, Zied Bouraoui, Odile Papini, and Eric Würbel. Assertional-based prioritized removed sets revision of *DL-Lite* knowledge bases. In the European Conference on Artificial Intelligence (ECAI 2014).
- 5. Salem Benferhat, Zied Bouraoui, and Karim Tabia. On the revision of prioritized *DL-Lite* knowledge bases. In the International Conference on Scalable Uncertainty Management (SUM 2014).
- 6. Salem Benferhat, Zied Bouraoui, Odile Papini and Eric Würbel. Assertional-based removed set revision of *DL-Lite* belief bases. In the International Symposium on Artificial Intelligence and Mathematics (ISAIM 2014).

- 7. Salem Benferhat and Zied Bouraoui. Possibilistic *DL-Lite*. In International Conference on Scalable Uncertainty Management (SUM 2013).
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### Part I

# **Preliminaries**

# KNOWLEDGE REPRESENTATION AND ONTOLOGIES

### 1.1 Introduction

The efficiency of information and knowledge handling is one of the most crucial challenges in many applications such as medicine, biology, economie, etc. This is due to the fact that the volume of knowledge continuously increases while the structure of this latter becomes more and more complex. In fact, knowledge may be provided by multiple, heterogeneous and often conflicting sources of information. A real need to compactly represent and structure this information is required. Information should be faithfully handled, while avoiding confusions, incoherencies, contradictions or ambiguities between elements representing the domain of interest.

During the two last decades, lines of research from both the database and the artificial intelligence communities have focused on complex knowledge representation formalisms. A particular attention was given to the use of ontologies. An ontology provides an explicit and semantically rich framework for representing knowledge [Mika et al., 2004; Mika and Akkermans, 2004]. Ontologies play a crucial role in sharing resources [Torniai et al., 2008] and reasoning about the modeled domain with the ability of checking contradictions.

There exist various languages supporting ontologies such as fragments of first order logic, conceptual graphs (e.g. [Chein and Mugnier, 2009; Chein and Mugnier, 2014]), UML class diagrams, description logics [Baader et al., 2010], etc. In this thesis, we are interested in the use of description logics, a family of logic-based languages of ontologies, mainly based on first order logics, which allows an efficient encoding and reasoning about the knowledge of a particular domain. Description logics have regained an important place in various domain areas such as the ontology-based data access (e.g. [Pinto et al., 2012; Artale et al., 2013]), information and data integration (e.g. [Meyer et al., 2005]) and the Semantic Web (e.g. [Baader et al., 2005b]) where they provide the foundations of the Web Ontology Language (OWL).

Nowadays, there exist several description logic languages that serve ontologies. As all logical formalisms, each description language is characterized by its expressive power and its reasoning complexity (the complexity of algorithms used for inference). There is a tradeoff between expressiveness and complexity of reasoning. Namely, more the language is expressive, more the computational complexity of reasoning is high [Brachman and Levesque, 1985].

The compromise between expressivity and complexity of reasoning is one of the main concerns in description logics area. Besides, most of the well-known classical description logics are intractable, in the sense that they do not guarantee polynomial complexity when reasoning. In general, these description logics are not designed to face recent applications where new challenges have raised. One can cite for instance, applications that involve large generic knowledge or huge volume of data where reasoning algorithms should scale up.

In recents years, several lines of research led to the introduction of lightweight description logics. These logics offer a nice compromise between the expressiveness and the tractability of the basic reasoning tasks. In this thesis, we focus on prominent members of the *DL-Lite* family that underly the *OWL2-QL* 

profile, especially dedicated for applications that use large amounts of data.

The rest of this chapter is organized as follows: Section 1.2 introduces the notion of ontology and recalls the main languages that support ontologies. Section 1.3 overviews main concepts of description logics. Section 1.4 presents the *DL-Lite* family. Section 1.5 concludes this chapter.

### 1.2 Ontology languages

The term ontology has its origin in philosophy and refers to the study of existence and being. In knowledge representation and reasoning, a branch of artificial intelligence, the term ontology refers to a representation framework that explicitly describes a formal conceptualization of a domain of interest [Hitzler et al., 2009]. An ontology specifies elements of a particular domain and describes relations and constraints holding over them. This latter is given by two distinct levels:

**An intensional level**: It describes a set of elements and specifies how to structure them using a set of rules called axioms.

**Extensional level**: It represents basic objects of the different elements given in the intensional level.

An ontology is supported by a language used to structure a domain of interest. In general, a language used to express an intensional level is usually built upon the following elements:

- **Concept**: Also called class, entity type or frame, it is used to denote a collection of objects (*e.g.* the concept "Mother" denotes the set of mothers of a particular domain).
- **Relationship**: Also called association, relationship, role or object property, it is used to express an association among concepts (*e.g.*, "hasChild" is defined on "Mother" and "Person").
- **Property**: Also called attribute, feature, slot, data property, it is used to qualify an element of the ontology (*i.e.* a concept or a relationship). A property can be either atomic (*e.g.* integer, real, string, etc) or structured (*e.g.* set, list, etc).
- **Axiom**: Also called assertion, it is a logical formula used to express constraints or rules that must be satisfied by the elements specified at the extensional level (*e.g.* Subsumption axiom: "Male" is a "Person", disjointness axiom: "Female" is not a "Male", etc).

A language used to encode an extensional level usually includes:

- **Instances**: An instance represents an individual or an object that belongs to a concept (*e.g.* Paul is an instance of Person).
- Facts: A fact represents a relationship holding between instances (e.g. HasChild(Marie,Paul)).

Note that in the rest of the thesis, we do not make difference between facts and instances. In the following, we present a classification of main ontology languages.

• Graph-based languages: Family of languages based on graphs to represent ontologies such: UML class diagrams, semantic networks [Sowa, 1987], conceptual graphs [Chein and Mugnier, 2009], etc.

- Frame-based languages: Family of languages based on the frame approach [Gruber, 1995]. The most known languages based on frames are OKBC<sup>1</sup> (Open Knowledge Base Connectivity), KM<sup>2</sup> (Knowledge Machine).
- Logic-based languages: It is a family of languages based on logics to represent ontologies such as first order logic (e.g. KIF<sup>3</sup>, CycL<sup>4</sup>), Description Logics [Baader et al., 2010], Existential Rule (e.g. [Calì et al., 2012; Mugnier and Thomazo, 2014]), F-logic [Kifer and Lausen, 1989], etc.

In this thesis, we are interested in logic-based languages, and in particular, the use of description logics as ontology languages. To obtain a semantically rich representation of a domain of interest, one can formalize the intensional level and the extensional level as a theory and then use this latter to perform reasoning tasks.

Semantic Web has been conceived as an extension of the World Wide Web that allows computers to intelligently search, combine, and process Web contents based on the meaning that this content has to humans [Hitzler et al., 2009; Shadbolt et al., 2006]. As for today, the most prominent standard technologies, recommended by the W3C<sup>5</sup>, for Semantic Web are based on ontologies. Description logics provide the foundations of the Web Ontology Language, one of the most important markup ontology languages recommended for the Semantic Web. In the following, we recall the widely used markup ontology languages:

- Resource Description Framework (RDF) <sup>6</sup>: It is a standard used for data interchange on the Web.
   RDF has features that assist data merging even if the underlying schemas differ. Moreover, RDF specifically supports the evolution of schemas over time without requiring the modification of the data which are based on it.
- RDF Schema (RDFS)<sup>7</sup>: It is a semantic extension of RDF that provides a data-modelling vocabulary for RDF data.
- Ontology Web Language (OWL)<sup>8</sup>: It is an ontology language for the Semantic Web based on description logics.

According to [W3C, 2008], a concrete syntax is needed in order to store *OWL2* ontologies and to exchange them among tools and applications. The primary exchange syntax for *OWL2* is the *RDF/XML* language, which is compatible with the *XML* serializations of *RDF* documents, and it is the syntax that must be supported by all *OWL2* tools. There are also other concrete syntaxes that may also be used, for instance the Manchester syntax (largely used in ontology editing tools) and the functional syntax (used to specify the structure of the ontology language). Finally, two alternative semantics for *OWL* are proposed: the direct semantics (*OWL2-DL*) which is based on a description logic called *SROIQ* and the RDF-based semantics (*OWL2-Full*). To develop applications that manipulate ontologies, the most commonly used tools are:

• *Protégé-OWL API* <sup>9</sup>: The Protege-OWL API is an open-source Java library for the OWL and RDF(S). The API provides classes and methods to load and save OWL files, to query and ma-

```
Inttp://www.ai.sri.com/~okbc/
2nttp://www.cs.utexas.edu/users/mfkb/RKF/km.html
3nttp://www.ksl.stanford.edu/knowledge-sharing/kif/
4nttp://www.cyc.com/documentation/syntax-cycl
5nttp://www.w3.org
6nttp://www.w3.org/RDF/
7nttp://www.w3.org/TR/rdf-schema/
8nttp://www.w3.org/standards/techs/owl
9nttp://protegewiki.stanford.edu/wikiProtegeOWL_API_Programmers_Guide
```

nipulate OWL data models, and to perform reasoning based on description logic algorithms. Furthermore, the API is optimized for the implementation of graphical user interfaces. Protégé-OWL API is built on top of OWL API.

- *OWL API* <sup>10</sup>: It is a Java API and reference implementation for creating, manipulating and serializing OWL ontologies. The OWL API includes the following components: An API for OWL2 and an efficient in-memory reference implementation and parsers and writers for OWL in several formats, *e.g.* RDF/XML, OWL/XML parser, functional syntax of OWL, etc. Finally, it provides a reasoner interface that is supported by many description logics reasoners.
- *Jena API* <sup>11</sup>: Jena is an open source framework for Java. It provides an API to extract data from and write to RDF graphs. The graphs are represented as an abstract "model". A model can be sourced with data from files, databases, URLs or a combination of these.

In recent years, there is a large use of ontologies in various application areas where new challenges emerged. These challenges mainly consist in equipping ontologies with new reasoning capabilities (*e.g.* evolution, merging, inconsistency handling, etc) or additional expressivity (*e.g.* uncertainty management) in order to face new requirements. In the following, we present some current lines of research on ontology formalisms:

- 1. Ontology matching (*e.g.* [Euzenat and Shvaiko, 2013; Shvaiko and Euzenat, 2013]): Given two heterogeneous ontologies, matching consists in producing an unified ontology associated with mappings that explicit the different correspondences between the vocabularies used in the input ontologies.
- 2. Ontology translation (e.g. [Dou et al., 2005; Gruber, 1993; Dou et al., 2011]): Consists in equivalently translating an ontology, (i.e. axioms and/or vocabulary) expressed using a language  $\mathcal{L}_1$ , into an ontology using another representation language  $\mathcal{L}_2$ .
- 3. Ontology integration (e.g. [Meyer et al., 2005; Hou et al., 2005]): Given a set of ontologies that represent knowledge about a similar domain, integration consists in combining these ontologies in order to obtain more knowledge by unifying the domain.
- 4. Ontology modularity (e.g. [Grau et al., 2008; Grau et al., 2009]): It consists in extracting the smallest independent subsets of an ontology, called modules, with the aim to reusing them later in other applications.
- 5. Ontology evolution (e.g. [Noy et al., 2006; Plessers et al., 2007]): It consists in modifying an ontology according to a set of change operations that may concern the knowledge about the domain or the structure of the ontology.
- 6. Ontology merging (e.g. [Moguillansky and Falappa, 2007; Kotis et al., 2006; Noy and Musen, 2000]): Given two ontologies that represent knowledge on the same domain, merging consists in producing a single ontology that represents a global point of view.
- 7. Ontology debugging (e.g. [Kalyanpur et al., 2005; Corcho et al., 2009]): It includes i) ontology diagnosis which consists in restoring the coherency of the intensional level of an ontology (e.g. [Peñaloza and Sertkaya, 2010; Ludwig and Peñaloza, 2014]) and ii) ontology repairing which consists in restoring consistency of the ontology (e.g. [Lembo et al., 2010; Bienvenu, 2012]).

<sup>10</sup>http://owlapi.sourceforge.net

<sup>11</sup>https://jena.apache.org

- 8. Ontology uncertainty management <sup>12</sup> (*e.g.* [Lukasiewicz and Straccia, 2008; Lukasiewicz *et al.*, 2012a; Bobillo *et al.*, 2013]): This consists in dealing with imprecision/uncertainty that can be attached to the elements of the vocabulary (*e.g.* concepts reflecting imprecise terms) or axioms (*e.g.* uncertainty attached to an axiom).
- 9. Ontology peer-to-peer systems (e.g. [Adjiman et al., 2006]): It consists in offering access to the information maintained by a set of peers linked to each other.
- 10. Ontology-based Data Access (e.g. [Pinto et al., 2012; Artale et al., 2013]): This consists in uniforming access to independent sets of data sources using an unified ontological view to which the data sources are linked.

This thesis focuses on some ontology challenges given above, namely ontology evolution, merging, debugging (especially inconsistency handling within Ontology-Based Data Access setting) and uncertainty management management in ontologies. Note that these tasks are closely related to existing works done on belief revision, belief merging, uncertainty and inconsistency handling within the propositional logic setting. Chapter 2 gives an overview of these topics.

As said before, we use description logics as ontology language, with a focus on *DL-Lite*, a family of lightweight description logics especially tailored for Ontology-Based Data Access. Before introducing description logics and *DL-Lite*, we first recall basic concepts of propositional logic and first order logic, needed to follow this thesis, and we fixe some notations.

### 1.3 Logic-based languages

The aim of logic in artificial intelligence is to develop languages to formally represent knowledge of a domain and make them available for reasoning [Huth and Ryan, 2004]. A formal language, denoted by  $\mathcal{L}$ , is equipped with a syntax, allowing a logical expression of formulas attached to a formal semantics telling the right meaning of these formulas. In general, the semantics of a language specifies how one can reason on the knowledge encoded syntactically through formulas.

### 1.3.1 Propositional logic

Propositional logic is one of the simplest languages for knowledge representation and reasoning. It is used in many applications to express statements to which one assigns a truth value (*i.e.* true or false) according to the possible world. This section recalls the syntax and the semantics of propositional logic. For more details, see for example [Garriga, 2013].

**Syntax.** The propositional logic vocabulary  $\mathcal{V}$  is given in terms of propositional variables, called also propositions or atoms and denoted by tiny letters (a, b, ...). A propositional variable is a boolean variable that one can assign either true or false as truth value. The language  $\mathcal{L}$  of propositional logic is built over a set of propositional variables, boolean constants: True  $(\top)$  and False  $(\bot)$ , a set of logical connectors composed of: negation  $(\neg)$ , conjunction  $(\land)$ , disjunction  $(\lor)$ , implication  $(\rightarrow)$  and equivalence  $(\leftrightarrow)$ .

**Definition 1.1.** Given a propositional language  $\mathcal{L}$ , the elements of  $\mathcal{L}$  are called propositional formulas (or well-formed formulas) and expressed in the following way:

•  $\perp$  and  $\top$  are formulas,

<sup>12</sup>http://www.w3.org/2005/Incubator/urw3/XGR-urw3-20080331/

- if  $p \in \mathcal{V}$ , then p is a formula.
- if  $\phi$  is a formula, then  $\neg \phi$  is a formula (Negation).
- if  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \wedge \phi_2)$  is a formula. (Conjunction)
- if  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \vee \phi_2)$  is a formula. (Disjunction)
- if  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \to \phi_2)$  is a formula. (Implication)
- if  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \leftrightarrow \phi_2)$  is a formula (Equivalence)

Propositional formulas are built using formulas given above. A literal l is either a propositional variable, called a positive literal, or its negation, called a negative literal. A clause is a finite disjunction of literals (in particular the constant  $\top$ , when the set of literals is empty) and a term is a finite conjunction of literals (in particular the constant  $\bot$ , when the set of literals is empty). A propositional formula  $\phi$  is said to be in a Conjunctive Normal Form (CNF) if it is formed by a conjunction of clauses. A propositional formula  $\phi$  is said to be in a Disjunctive Normal Form (DNF) if it is constituted by a disjunction of terms.

**Semantics.** The semantics of propositional logic is given in terms of interpretations.

**Definition 1.2.** An interpretation, denoted by I, is a mapping that assigns to each propositional variable p of a formula a truth value, true or false, denoted by  $p^I$ . Given an interpretation I, the propositional formulas are interpreted as follows:

- $\top^I = true \text{ and } \bot^I = false.$
- $(\neg \phi)^I = true \text{ if } (\phi)^I = \text{false, and } (\neg \phi)^I = false \text{ otherwise.}$
- $(\phi_1 \wedge \phi_2)^I = true$  if  $(\phi_1)^I = true$  and  $(\phi_2)^I = true$  and  $(\phi_1 \wedge \phi_2)^I = false$  otherwise.
- $(\phi_1 \vee \phi_2)^I = true$  if  $(\phi_1)^I = true$  or  $(\phi_2)^I = true$  and  $(\phi_1 \vee \phi_2)^I = false$  otherwise.
- $(\phi_1 \to \phi_2)^I = true$  if  $(\phi_1)^I = false$  or  $(\phi_2)^I = true$ , and  $(\phi_1 \to \phi_2)^I = false$  otherwise.

Let I be an interpretation (an instantiation of all propositional variables) and  $\phi$  be a propositional formula. We say that I is a model of  $\phi$  or I satisfies  $\phi$ , denoted by  $I \models \phi$  if and only if  $(\phi)^I = true$ , otherwise, we say that I falsifies  $\phi$  or I is a counter-model of  $\phi$  and it is denoted by  $I \not\models \phi$ .  $\phi$  is said to be valid (*i.e.* a tautology) if it does not admit any counter-model. Otherwise, it is said to be invalid. A contradiction is a formula that does not admit any model.

Up to now, we presented the knowledge representation aspect in propositional logic. We now introduce the reasoning aspect which consists in deriving implicit knowledge from the ones explicitly represented. The principle of logical deduction represents the central element of reasoning in all logics. Logical deduction in propositional logic can be defined as follows:

**Definition 1.3** (Logical deduction). Given two formulas  $\phi_1$  and  $\phi_2$ . We say that  $\phi_2$  is entailed by  $\phi_1$ , denoted  $\phi_1 \models \phi_2$ , if for every interpretation I that is model of  $\phi_1$ , I is also a model of  $\phi_2$ .

The truth table is a sure way to check the validity of a logical deduction (all reasoning tasks in general). However, it is not practically possible, since one should, in the worst case, enumerate  $2^n$  interpretations to find a model, where n is the number of propositional variables present in the considered formulas. To this end, logical deduction can be done syntactically using the well-known refutation theorem, which states that  $\phi_2$  is a logical consequence of  $\phi_1$  if and only if  $\phi_1 \wedge \neg \phi_2$  is unsatisfiable. Finally, note that the complexity of satisfiability problem of a set of propositional formulas is NP-complete [Cook, 1971].

### 1.3.2 First order logic

This section gives a brief refresher on the syntax of First Order Logic (FOL for short), also called predicate logic. For more details on FOL, the readers can refer to [Fitting, 1990; Huth and Ryan, 2004] for examples.

The first order logic vocabulary V is built upon disjoint and finite sets  $N_C$ ,  $N_F$ ,  $N_P$  and  $N_V$  where  $N_C$  is a set of constant symbols (also called individuals),  $N_F$  is a set of function symbols,  $N_P$  is a set of predicate symbols (or simply predicates) and  $N_V$  is a set of variable names. Each function or predicate symbol is associated with a natural number, called arity.

**Definition 1.4** (First-order terms). Given a first-order vocabulary  $\mathcal{V} = (N_C, N_F, N_P, N_V)$ , the set of terms is defined such that:

- if  $x \in N_V$ , then x is a term.
- if  $a \in N_C$ , then a is a term.
- Let f be an n-ary function and  $t_1, t_2, ..., t_n$  be terms, then  $f(t_1, t_2, ..., t_n)$  is a term. Note that a 0-ary function is called a constant.

The terms are used also as arguments for predicates to form atomic formulas.

**Definition 1.5** (First order atom). Let  $\mathcal{V} = (N_C, N_F, N_P, N_V)$  be a first-order vocabulary. Let f be an n-ary predicate and  $t_1, t_2, ..., t_n$  be terms. Then an expression of the form  $P(t_1, t_2, ..., t_n)$  is said to be an atom. In first order logic with equalities, expressions of the form  $t_1 = t_2$  or  $t_1 \neq t_2$  where  $t_1$  and  $t_2$  are terms, are also called atoms.

The language  $\mathcal{L}$  of a FOL is built over a set of atoms, a set of logical connectors  $(\neg, \land, \lor, \rightarrow)$  and (+) as in propositional logic, the symbols  $(\top)$  and (+) that correspond to 0-ary predicates, the universal quantifier  $(\forall)$  and the existential quantifier  $(\exists)$ .

**Definition 1.6** (First order formulas). Given a first-order language  $\mathcal{L}$ , the elements of  $\mathcal{L}$  are called first-order formulas and they are formed as follows:

- $\perp$  and  $\top$  are formulas,
- Each atom is a formula. (Atomic formula)
- If  $\phi$  is a formula, then  $(\neg \phi)$  is a formula. (Negation)
- If  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \wedge \phi_2)$  is a formula. (Conjunction)
- If  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \vee \phi_2)$  is a formula. (Disjunction)
- If  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \to \phi_2)$  is a formula. (Implication)
- If  $\phi_1$  and  $\phi_2$  are formulas, then  $(\phi_1 \leftrightarrow \phi_2)$  is a formula. (Equivalence)
- If x is a variable and  $\phi$  is a formula, then  $(\forall x. \phi)$  is a formula. (Universal quantification)
- If x is a variable and  $\phi$  is a formula, then  $(\exists x.\phi)$  is a formula. (Existential quantification)
- Let '=' be a binary predicate symbol, the formulas =(x,y) and  $\neg=(x,y)$  are called equalities and they are simply denoted by x=y and  $x\neg y$ . (Equalities)

Note that the quantifiers have higher priority over all other connectors which have the same priorities as in propositional logic. A 0-ary predicate is called a proposition. Indeed, propositional logic is a fragment of first-order logic where predicates are restricted to 0-ary predicates and without using quantifications.

**Definition 1.7** (Subformulas). Let  $\phi$  be a first-order formula. The subformulas of  $\phi$  are  $\phi$  itself and all immediate subformulas of  $\phi$ .

- Atomic formulas  $\top$  and  $\bot$  have no immediate subformulas.
- The only immediate subformula of  $\neg \phi$  is  $\phi$ . The immediate subformulas of  $\phi_1 \lor \phi_2$  or  $\phi_1 \land \phi_2$  or  $\phi_1 \rightarrow \phi_2$  or  $\phi_1 \leftrightarrow \phi_2$  are  $\phi_1$  and  $\phi_2$ . The only immediate subformula of  $\forall x.\phi$  or  $\exists x.\phi$  is  $\phi$ .

**Definition 1.8** (Scope, bound variable and free variable). Let  $\phi$  be a formula, Q a quantifier, and  $Qx.\varphi$  a subformula of  $\phi$ . Then Qx is called a quantifier for x. Its scope in  $\varphi$  is the subformula  $\varphi$  except subformulas of  $\varphi$  that begin with a quantifier for the same variable x.

Each occurrence of the variable x in the scope of Qx is said to be *bound* in  $\phi$  by Qx. Each occurrence of x that is not in the scope of any quantifier for x is a *free* occurrence of x in  $\phi$ .

Namely, x is bound if it is not contained in any subformula  $Qx.\varphi$  of  $\phi$ . A formula is said to be a closed formula if it contains only bound occurrences of variables. Otherwise, it is said to be an open formula. A ground term is a term containing no variable. A ground formula is a formula containing no variable.

### 1.3.3 Description logics

Description logics (DLs for short) are a family of formalisms designed to represent knowledge of a particular domain, and subsequently, reason by deriving new knowledge. DLs were introduced as decidable subsets of FOL, having a precise model-theoretic semantics [Baader et al., 2010]. A DL language only uses unary and binary predicates, called respectively concepts and roles. To represent generic knowledge (i.e. intensional level), DLs restrict forms of logical formulas (called axioms), using only concepts and role inclusions. To represent the extensional level, DLs use ground facts expressed in term of membership assertions on concepts or roles. Interestingly enough, DLs provide a good compromise between expressive power and computational complexity. Throughout this section, we present basic concepts of DLs.

A DL knowledge base is built upon a description vocabulary  $\mathcal V$  consisting of atomic concepts which correspond to unary predicates to denote sets of individuals, and atomic roles, which correspond to binary predicates, to denote binary relations among individuals.

**Definition 1.9** (DL vocabulary). A DL description vocabulary V is a triple  $(N_C, N_R, N_I)$  of pairwise disjoint sets of atomic concept names, denoted by  $N_C$ , atomic role names, denoted by  $N_R$  and individual names, denoted by  $N_I$ .

**Example 1.1.** For example, the atomic concept "Mother" represents the set of all mothers in a particular domain. The atomic role "marriedTo" represents the set of all married couples in a particular domain. The individuals "Marie" and "Paul" represent constants in a particular domain.

### **Syntax**

A description language  $\mathcal{L}$  is characterized by a set of constructs used to form complex concepts and roles from atomic ones. It is used to structure a domain of interest through a set of logical formulas, called

axioms. Each description language allows different sets of constructs. We start with one of the most basic description languages, called  $\mathcal{ALC}$  (Attributive Language with Complement), which is an extension of the  $\mathcal{AL}$  language that constitutes the foundation framework of many other DLs. The  $\mathcal{ALC}$  allows the use of conjunction, disjunction, negation, universal quantification and existential quantification to form complex concepts and roles as presented in Table 1.1:

Constructor	Designation	
Т	Top concept	
	Bottom concept	
A	Atomic concept	
$\neg C$	Negation	
$C \sqcap D$	Conjunction	
$C \sqcup D$	Disjonction	
$\exists R.C$	Existential quantification	
$\forall R.C$	Universal quantification	

Table 1.1: Constructors of the ALC logic where C and D are concepts and R is a role.

Note that  $\exists R$  and  $\forall R$  can be used as an abbreviation of  $\exists R. \top$  and  $\forall R. \top$  and any atomic concept  $A \in N_C$  is also a concept.

**Example 1.2.** Let the following atomic concepts "Male", "Female" and "Person" be three atomic concepts and let "hasChild" be an atomic role. Using  $\mathcal{ALC}$  language, one can express the following complex concepts:

- $Person \sqcap \neg Parent$ : Persons who are not parents.
- $Female \sqcap Person$ : Female persons.
- $(Male \sqcap Person) \sqcap \exists hasChild.Person$ : Male persons who have at least a child.
- $Person \sqcap \forall hasChild. \neg Female$ : Persons who do not have a Female as child.

A DL knowledge base, denoted by  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  contains two distinct components: A terminological base, called TBox and denoted by  $\mathcal{T}$ , that describes the generic knowledge about the domain, and an assertional base, called ABox and denoted by  $\mathcal{A}$ , that contains the assertional facts (*i.e.* individuals or constants) that instantiate the terminological knowledge. Namely, the TBox encodes the intensional level and the ABox stores the extensional level of an ontology.

**Definition 1.10** (DL axioms). Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be an  $\mathcal{ALC}$  knowledge base. Then:

- The TBox contains a set of terminological axioms of the form:
  - $C \sqsubseteq D$ : C is a subconcept of D.
  - $C \equiv D$ : C is equivalent to D (namely,  $C \sqsubseteq D$  and  $D \sqsubseteq C$ ).
- The ABox contains a set of assertion axioms of the form:

- C(a): a is an instance of C.
- R(a,b): a and b are related by R.

where C and D are concepts, R is a role and a and b are individuals.

**Example 1.3.** Consider the following set of atomic concepts  $N_C = \{Person, Female, Male\}$  and the following set of atomic roles  $N_R = \{hasChild\}$ . In the following, we give an example of an  $\mathcal{ALC}$  TBox:

$$Woman \equiv Person \sqcap Female$$

$$Male \sqsubseteq \neg Female$$

$$Man \equiv Person \sqcap \neg Women$$

$$Mother \equiv Woman \sqcap \exists hasChild.Person$$

$$Father \equiv Man \sqcap \exists hasChild.Person$$

$$Parent \equiv Father \sqcup Mother$$

$$ParentWithoutDaughter \equiv Parent \sqcap \forall haschild. \neg Woman$$

In the following, we give an example of ABox:

$$Person(Paul)$$
  $Person(Marie)$   $Male(Bob)$   $Female(Marie)$   $hasChild(Marie, Paul)$   $hasChild(Bob, Alice)$ 

### **Semantics**

The semantics of ALC is in the spirit of first order logic semantics and it is given in terms of interpretations.

**Definition 1.11** (DL interpretation). An interpretation  $\mathcal{I}=(\Delta^{\mathcal{I}}, \mathcal{I})$  consists of a non-empty domain, denoted by  $\Delta^{\mathcal{I}}$ , and an interpretation function, denoted by  $\mathcal{I}$ , defined from  $N_I$  to  $\Delta^{\mathcal{I}}$ . The function  $\mathcal{I}$  associates with each individual a an element  $a^{\mathcal{I}}$  of  $\Delta^{\mathcal{I}}$ , to each atomic concept A a subset  $A^{\mathcal{I}}$  of  $\Delta^{\mathcal{I}}$  and to each atomic role R a binary relation  $R^{\mathcal{I}}$  over  $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$ . Furthermore, the interpretation function  $\mathcal{I}$  is extended in a straightforward way for  $\mathcal{ALC}$  concepts and roles as follows:

$$A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$$

$$R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$$

$$(\neg C)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$$

$$(C \cap D)^{\mathcal{I}} = C^{\mathcal{I}} \cap D^{\mathcal{I}}$$

$$(C \cup D)^{\mathcal{I}} = C^{\mathcal{I}} \cup D^{\mathcal{I}}$$

$$(\exists R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} | \exists y \in \Delta^{\mathcal{I}} \text{ such that } (x, y) \in R^{\mathcal{I}} \text{ and } y \in C^{\mathcal{I}} \}$$

$$(\forall R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} | \text{ if } (x, y) \in R^{\mathcal{I}} \text{ then } y \in C^{\mathcal{I}} \}$$

**Example 1.4.** Let us continue Example 1.3. Assume that  $\Delta^{\mathcal{I}} = \{Marie, Paul, Bob, Alice, Titi\}$ . One

can consider the following interpretation:

```
(Person)^{\mathcal{I}} = \{Paul, Marie, Bob, Alice\}
(Female)^{\mathcal{I}} = \{Marie, Alice, Titi\}
(Male)^{\mathcal{I}} = \{Bob, Paul\}
(hasChild)^{\mathcal{I}} = \{(Marie, Paul), (Bob, Alice)\}
(Woman)^{\mathcal{I}} = \{Marie, Alice\}
(Man)^{\mathcal{I}} = \{Bob, Paul\}
(Mother)^{\mathcal{I}} = \{Marie\}
(Father)^{\mathcal{I}} = \{Bob\}
(ParentWithoutDaughter)^{\mathcal{I}} = \{Marie\}
(Parent)^{\mathcal{I}} = \{Marie, Bob\}
```

An interpretation  $\mathcal{I}$  is said to satisfy a knowledge base  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  if and only if  $\mathcal{I}$  satisfies every axiom in  $\mathcal{T}$  and every axiom in  $\mathcal{A}$ . Such interpretation is said to be a model of  $\mathcal{K}$ .

**Definition 1.12.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be an  $\mathcal{ALC}$  DL knowledge base. The satisfiability of axioms of  $\mathcal{K}$  with respect to an interpretation  $\mathcal{I}$  is defined as follows:

- $\mathcal{I} \models C \sqsubseteq D$  if and only if  $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ .
- $\mathcal{I} \models C \equiv D$  if and only if  $C^{\mathcal{I}} = D^{\mathcal{I}}$ .
- $\mathcal{I} \models C(a)$  if and only if  $a^{\mathcal{I}} \in C^{\mathcal{I}}$ .
- $\mathcal{I} \models R(a,b)$  if and only if  $(a^{\mathcal{I}},b^{\mathcal{I}}) \in R^{\mathcal{I}}$ .

**Example 1.5.** From Example 1.4, one can check that  $\mathcal{I}$  is a model of the knowledge bases of Example 1.3

### Basic reasoning tasks

Reasoning is a fundamental issue in DLs. It allows to derive implicit knowledge from the one explicitly represented in the knowledge base. The main standard reasoning services over a DL knowledge base are:

- Concept satisfiability: A concept C is said to be satisfiable (or consistent), with respect to a TBox  $\mathcal{T}$ , if there exists an interpretation  $\mathcal{I}$  that is a model of  $\mathcal{T}$  such that  $C^{\mathcal{I}} \neq \emptyset$ .
- Subsumption checking: A concept C is said to be subsumed by another concept D with respect to a TBox  $\mathcal{T}$ , denoted by  $\mathcal{T} \models C \sqsubseteq D$ , if for each interpretation  $\mathcal{I}$  such that  $\mathcal{I} \models \mathcal{T}$ ,  $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$  holds.
- Classification: Given a TBox  $\mathcal{T}$ , classification consists in computing all pairs of concepts (C, D) such that  $\mathcal{T} \models C \sqsubseteq D$ .
- Knowledge base satisfiability or consistency: An ABox  $\mathcal{A}$  is said to be consistent with respect to a TBox  $\mathcal{T}$ , if there exists an interpretation  $\mathcal{I}$  such that  $\mathcal{I} \models \mathcal{T}$  and  $\mathcal{I} \models \mathcal{A}$ .
- Instance checking: An individual a (resp. a and b) is said to be an instance of C (resp. are related by a role R) with respect to a knowledge base  $K = \langle \mathcal{T}, \mathcal{A} \rangle$ , denoted by  $K \models C(a)$  (resp.  $K \models R(a,b)$ ), if for each interpretation  $\mathcal{I}$  such that  $\mathcal{I} \models \mathcal{T}$  and  $\mathcal{I} \models \mathcal{A}$ , we have  $a^{\mathcal{I}} \in C^{\mathcal{I}}$  (resp.  $(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$ ).

	Description	Syntax	Semantics
$\mathcal{R}_+$	Transitive role	(traR)	$(a^{\mathcal{I}},b^{\mathcal{I}}){\in}R^{\mathcal{I}} \text{ and } (b^{\mathcal{I}},c^{\mathcal{I}}){\in}R^{\mathcal{I}} \text{ implies } (a^{\mathcal{I}},c^{\mathcal{I}}) \in R^{\mathcal{I}}$
$\mathcal{H}$	Role hierarchies	$R \sqsubseteq S$	$R^{\mathcal{I}} \subseteq S^{\mathcal{I}}$
$\mathcal{I}$	Inverse roles	$R^-$	$\{(b,a) (a,b)\in R^{\mathcal{I}}\}$
$\mathcal{F}$	Functional roles	(functR)	$(a^{\mathcal{I}},b^{\mathcal{I}})\in R^{\mathcal{I}}$ and there is no $c^{\mathcal{I}}\neq b^{\mathcal{I}}$ s.t $(a^{\mathcal{I}},c^{\mathcal{I}})\in R^{\mathcal{I}}$
O	Nominals	$\{a_1,, a_n\}$	$\{a_1^{\mathcal{I}},,a_n^{\mathcal{I}}\}$
0	Role composition	$R \circ S$	$\{(a^{\mathcal{I}},c^{\mathcal{I}}) \exists b{\in}\Delta^{\mathcal{I}} \text{ s.t } (a^{\mathcal{I}},b^{\mathcal{I}}){\in}R^{\mathcal{I}} \text{ and } (b^{\mathcal{I}},c^{\mathcal{I}}) \in S^{\mathcal{I}}$
	Complex role hierarchies	$R \circ S \sqsubseteq R$	$(R \circ S)^{\mathcal{I}} \subseteq R^{\mathcal{I}}$
$\mathcal{N}$	Number restrictions	$\bowtie nR$	$\left\{a \in \Delta^{\mathcal{I}}   card \left\{b \in \Delta^{\mathcal{I}}   (a, b) \in R^{\mathcal{I}} \right\} \bowtie n \right\}$
Q	Qualified number		
	restrictions	$\bowtie nR.C$	$\left\{a \in \Delta^{\mathcal{I}}   card \left\{b \in \Delta^{\mathcal{I}}   (a, b) \in R^{\mathcal{I}} \land b \in C^{\mathcal{I}} \right\} \bowtie n \right\}$

Table 1.2: DLs constructors where card(X) denotes the cardinality of the set X and  $\bowtie$  denotes  $\leq$  or  $\geq$ .

The knowledge base satisfiability or consistency problem is the main reasoning task in DLs. It allows to check whether the knowledge encoded in the TBox and the ABox is non-contradictory. According to [Horrocks and Patel-Schneider, 2004], all the above reasoning tasks can be reduced from subsumption test to satisfiability test, from instance checking to knowledge base consistency, etc. For instance [Baader et al., 2010]:

- C is unsatisfiable if and only if  $\mathcal{T} \models C \sqsubseteq \bot$ .
- $\mathcal{T} \models C \sqsubseteq D$  if and only if  $C \sqcap \neg D$  is unsatisfiable.
- C is satisfiable if and only if  $\{C(a)\}$  is consistent with respect to  $\mathcal{T}$ .
- $\mathcal{A} \models C(a)$  if and only if  $\mathcal{A} \cup \{\neg C(a)\}$  is inconsistent with respect to  $\mathcal{T}$ .

In general, there exist several approaches of reasoning. The most widely used one is the so called tableau algorithm [Baader et al., 2010]. A tableau algorithm uses the concepts of negation to reduce subsumption to an (un)satisfiability problem. A tableau algorithm verifies whether a knowledge base contains contradictions or not by checking the existence of an interpretation that is a model of the knowledge base by constructing its finite representation, so-called tableau. Such technique decomposes axioms of the knowledge base using a set of consistency-preserving transformation rules (depending on the constructors used in the DL), called completion rules. For each application of a rule, an expression of an axiom is decomposed while preserving the semantics behind it into simple expressions. This decomposition leads to exhibit contradictory elements of the ABox. Therefore, one can check if there exists a model for the given knowledge base.

### **Expressive description logics**

To define a DL language, one first needs to specify the set of concept and role constructors that can be used, and then what types of axioms that can be expressed in the knowledge base. In order to meet the needs of applications that require more expressiveness, the set of constructors in  $\mathcal{ALC}$  was enriched with several constructors. Table 1.2 summarizes the most used ones.

By convention, we use S to denote  $ALCR_+$ , the ALC constructors extended with role transitivity. A DL language is defined by a string of capital letters referring to the used constructors. There exist several DLs where the majority of them underly the ontology Web language OWL. For instance, in its first version OWL1 where OWL-Lite is based on SHIF and OWL-DL is based on SHOIN, and in its second version OWL2 where OWL2-DL is based on SROIQ, etc.

### Computational complexity in description logics

The computational complexity of DLs is well studied in the literature. Given a decision problem, the complexity of DL reasoning tasks is performed around two settings.

- The combined complexity: It considers all the components of the knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  as inputs, namely the size of the problem is equal to  $|\mathcal{K}|$  with  $|\mathcal{K}| = |\mathcal{T}| + |\mathcal{A}|$ .
- The data complexity: It considers the TBox as fixed and only takes as input the size of the ABox |A|.

Table 1.3 summarizes the computational complexity of consistency checking in some important DLs, The complexity results of other DLs including the ones given in Table 1.3, can be found at the following link <sup>13</sup>.

DL familly	Combined Complexity	Data Complexity
ALC	EXPTIME-complete	NP-complete
SHIF	EXPTIME-complete	NP-complete
SHOIN	NEXPTIME-complete	NP-hard
SROIQ	N2EXPTIME-complete	NP-hard

Table 1.3: Computational complexity of consistency checking of some expressive DLs

### **Description logics Reasoners**

There are several implementations of reasoning task algorithms for DLs. These implementations are operated in general around ontology languages and using programming tools presented in Section 1.2. In what follows, we give a description of some well-known reasoners. <sup>14</sup>.

• Pellet <sup>15</sup>: Pellet is an open-source reasoner for *SROIQ* DL with simple datatypes (*i.e. OWL2-DL*) developed in Java. It can be used in command line, OWL API, Jena API, Pellet API or with Protégé. It supports the *OWL2-DL* language and includes some support for the *OWL2* profiles. The main features of Pellet is that it incorporates optimizations for the use of nominals, conjunctive query answering, and incremental reasoning. As a reasoning technique, Pellet uses a tableau-based algorithm.

<sup>13</sup>http://www.cs.man.ac.uk/~ezolin/dl/

<sup>&</sup>lt;sup>14</sup>A complete list of DL reasoners with their description is available at this link: http://www.cs.man.ac.uk/~sattler/reasoners.html

<sup>15</sup>http://clarkparsia.com/pellet

- HermiT <sup>16</sup>: HermiT is an open-source reasoner for *SROIQ* DL with simple datatypes (*i.e. OWL2-DL*) that supports description graphs. In particular, HermiT implements a reasoner based on a novel "hypertableau" calculus which provides much more efficient reasoning than any previously known algorithm. It can be used with OWL API or integrated with Protégé editor.
- FaCT++ <sup>17</sup>: FaCT++ is an open-source reasoner for *SROIQ* DL with simple datatypes (*i.e. OWL2-DL*) implemented in C++. It implements a tableau-based algorithm for general TBoxe's (subsumption, satisfiability, classification) and ABoxe's (query). Now, it is used as one of the default reasoners in the Protégé 4 editor.

From Table 1.3, one can check that the classical DLs are intractable in the sense that there is no efficient (*i.e.* polynomial time) algorithm for checking satisfiability. To this end, several lightweight fragments of DLs that offer a nice tradeoff between expressivity and complexity of reasoning, were introduced. One of these lightweight fragments DLs, is the *DL-Lite* family.

According to the official documentation of W3C three profiles of OWL2 are proposed as sub-languages of the full OWL2 language, to offer important advantages in particular application scenarios. These lightweight logics are the  $\mathcal{EL}$  family [Baader et~al., 2005a] (underpinning OWL2-EL), the DL-Lite family [Calvanese et~al., 2007a; Artale et~al., 2009] (underpinning OWL2-QL), and the DL Programs [Grosof et~al., 2003] (underpinning OWL2-RL).

In this thesis, we are interested in the *DL-Lite* family of description logics. *DL-Lite* is well suitable for ontology-based data access setting.

### 1.4 The *DL-Lite* family

In recent years, a lot of attention was given to *DL-Lite*, a family of lightweight DLs specifically designed for applications using huge volumes of data such as Web applications where query answering is the most important reasoning task [Calvanese *et al.*, 2007a]. In particular, *DL-Lite* guarantees an efficient computational complexity of the reasoning process. In fact, the idea behind the reasoning (consistency checking and query answering) in *DL-Lite* is based on the so-called FOL-reducibility property. This latter permits to considerably reduce reasoning tasks to the evaluation of FOL queries over the set of assertions (*i.e.* data). The efficiency of reasoning in *DL-Lite* is ensured thanks to the use of relational database techniques.

### 1.4.1 The *DL-Lite* family and *OWL2-QL*

The knowledge representation format considered in this thesis is the one of DL-Lite language. We mainly consider three tractable members of the DL-Lite family. Namely, the DL-Lite $_{core}$  which is the core fragment of all DL-Lite logics, DL-Lite $_F$  and DL-Lite $_R$  which underlies the OWL2-QL profile. For the sake of simplicity and when there is no ambiguity, through this section (and this thesis, in general), we use DL-Lite to refer to these three fragments.

**Syntax** The starting points are  $N_C$ ,  $N_R$  and  $N_I$ , three pairwise disjoint sets of atomic concepts, atomic roles and individuals. The *DL-Lite* language uses three unary connectors: "¬", "∃" and "¬" and a binary connector " $\sqsubseteq$ " to define complex concepts and roles and inclusions between concepts and roles. Let  $A \in N_C$ ,  $P \in N_R$ , basic concepts (resp. roles) B (resp. R) and complex concepts (resp. roles) R0 (resp. R1) are defined in R2-Lite as follows:

<sup>16</sup>http://hermit-reasoner.com

<sup>17</sup>http://owl.cs.manchester.ac.uk/tools/fact/

where  $P^-$  represents the inverse of P.

A *DL-Lite* knowledge base is a pair  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$ . The *DL-Lite*<sub>core</sub> TBox is constituted by a finite set of inclusion axioms between concepts of the form

$$B \sqsubseteq C$$
.

In the original conference paper [Calvanese *et al.*, 2005], DL- $Lite_{core}$  does not use negation of roles. In the journal paper [Calvanese *et al.*, 2007a], negation appears in DL-Lite. Here, we follow description of DL-Lite used in the journal paper [Calvanese *et al.*, 2007a].

The ABox contains a finite set of membership assertions (or facts) on atomic concepts and on atomic roles respectively of the form

$$A(a)$$
 and  $P(a,b)$ 

where  $A \in N_C$ ,  $P \in N_R$  and  $a, b \in N_I$ .

The DL- $Lite_F$  language extends DL- $Lite_{core}$  with the ability of specifying functionality on roles or on their inverses of the form:

The DL- $Lite_R$  language extends DL- $Lite_{core}$  with the ability of specifying in the TBox inclusion axioms between roles of the form:

$$R \sqsubseteq E$$
.

Note that *DL-Lite* language does not allow the use of the conjunctive and the disjunctive operators. However, one can easily add conjunctions (*resp.* disjunctions) in the right-hand side (*resp.* left-hand side) of inclusion axioms. Indeed, as we will see it later, the conjunction of the form  $B \sqsubseteq C_1 \sqcap C_2$  is equivalent to the pair of inclusion axioms  $B \sqsubseteq C_1$  and  $B \sqsubseteq C_2$ , while the disjunction of the form  $B_1 \sqcup B_2 \sqsubseteq C$  is equivalent to the pair of inclusion assertions  $B_1 \sqsubseteq C$  and  $B_2 \sqsubseteq C$ .

Any *DL-Lite* knowledge base can be equivalently written as a FOL knowledge base. Table 1.4 summarizes all possible expression of axiom in *DL-Lite* and their translation from to FOL formulas. For the ABox assertions, one can easily check that they are equivalent to ground atoms in FOL setting (see Section 1.3.2).

DL-Lite axiom	FOL formula	DL-Lite axiom	FOL formula
$A_1 \sqsubseteq A_2$	$\forall x. A_1(x) \to A_2(x)$	$A_1 \sqsubseteq \neg A_2$	$\forall x. A_1(x) \to \neg A_2(x)$
$A \sqsubseteq \exists P$	$\forall x. A(x) \rightarrow \exists y. P(x,y)$	$A \sqsubseteq \neg \exists P$	$\forall x. A(x) \rightarrow \neg \exists y. P(x,y)$
$A \sqsubseteq \exists P^-$	$\forall x. A(x) \rightarrow \exists y. P(y, x)$	$A \sqsubseteq \neg \exists P^-$	$\forall x. A(x) \rightarrow \neg \exists y. P(y, x)$
$\exists P \sqsubseteq A$	$\forall x. \exists y P(x,y) \to A(x)$	$\exists P \sqsubseteq \neg A$	$\forall x. \exists y P(x,y) \to \neg A(x)$
$\exists P^- \sqsubseteq A$	$\forall x. \exists y P(y,x) \to A(x)$	$\exists P^- \sqsubseteq \neg A$	$\forall x. \exists y P(y, x) \to \neg A(x)$
$\exists P_1 \sqsubseteq \exists P_2$	$\forall x. \exists y P_1(x,y) \to \exists z(x,z)$	$\exists P_1 \sqsubseteq \neg \exists P_2$	$\forall x. \exists y P_1(x,y) \to \neg \exists z(x,z)$
$\exists P_1 \sqsubseteq \exists P_2^-$	$\forall x. \exists y P_1(x,y) \to \exists z(z,x)$	$\exists P_1 \sqsubseteq \neg \exists P_2^-$	$\forall x. \exists y P_1(x,y) \to \neg \exists z(z,x)$
$\exists P_1^- \sqsubseteq \exists P_2$	$\forall x. \exists y P_1(y,x) \to \exists z(x,z)$	$\exists P_1^- \sqsubseteq \neg \exists P_2$	$\forall x. \exists y P_1(y, x) \to \neg \exists z(x, z)$
$\exists P_1^- \sqsubseteq \exists P_2^-$	$\forall x. \exists y P_1(y,x) \to \exists z(z,x)$	$\exists P_1^- \sqsubseteq \neg \exists P_2^-$	$\forall x. \exists y P_1(y, x) \to \neg \exists z(z, x)$
$P_1 \sqsubseteq P_2$	$\forall x, y. P_1(x, y) \to P_2(x, y)$	$P_1 \sqsubseteq \neg P_2$	$\forall x, y. P_1(x, y) \rightarrow \neg P_2(x, y)$
$P_1^- \sqsubseteq P_2^-$	$\forall x, y. P_1(x, y) \to P_2(x, y)$	$P_1^- \sqsubseteq \neg P_2^-$	$\forall x, y. P_1(x, y) \rightarrow \neg P_2(x, y)$
$P_1 \sqsubseteq P_2^-$	$\forall x, y. P_1(x, y) \to P_2(y, x)$	$P_1 \sqsubseteq \neg P_2^-$	$\forall x, y. P_1(x, y) \rightarrow \neg P_2(y, x)$
$P_1^- \sqsubseteq P_2$	$\forall x, y. P_1(x, y) \to P_2(y, x)$	$P_1^- \sqsubseteq \neg P_2$	$\forall x, y. P_1(x, y) \to \neg P_2(y, x)$
(functP)	$\forall x, y, z. P(x, y) \land P(x, z) \rightarrow y = z$	$(funct P^-)$	$\forall x, y, z. P(y, x) \land P(z, x) \rightarrow y = z$

Table 1.4: The equivalence of the *DL-Lite* axioms in FOL.

**Example 1.6.** Let *Teacher* and *Student* be two atomic concepts and *TeachesTo* and *HasSupervisor* be two atomic roles. In the following, we give an example of DL- $Lite_{core}$  TBox:

 $Teacher \sqsubseteq \neg Student$   $Teacher \sqsubseteq \exists Teaches To$   $\exists Teaches To^- \sqsubseteq Student$   $Student \sqsubseteq \exists Has Supervisor$   $\exists Has Supervisor^- \sqsubseteq Teacher$ 

To obtain a DL- $Lite_R$  TBox, one can extend the above DL- $Lite_{core}$  TBox with the following axiom:

 $HasSupervisor^- \sqsubseteq TeachesTo$ 

To obtain a DL- $Lite_F$  TBox, one can extend the DL- $Lite_{core}$  TBox with the following axiom:

(funct Has Supervisor)

Finally, a *DL-Lite* ABox can be expressed as follows:

Student(Paul) HasSupervisor(Paul, Alice) TeachesTo(Alice, Bob)

**Semantics** The semantics is given in terms of interpretations where as usual an interpretation  $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$  consists of a non-empty domain  $\Delta^{\mathcal{I}}$  and an interpretation function  $\cdot^{\mathcal{I}}$  that assigns each  $a \in N_I$  to an element  $a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$ , each  $A \in N_C$  to a subset  $A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$  and each  $P \in N_R$  to  $P^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$ .

Furthermore, the interpretation function  $.^{\mathcal{I}}$  is extended in a straightforward way for  $DL\text{-}Lite_{core}$  concepts and roles as follows:

$$(P^{-})^{\mathcal{I}} = \{(y, x) \in \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}} | (x, y) \in P^{\mathcal{I}} \}$$

$$(\exists R)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} | \exists y \in \Delta^{\mathcal{I}} such that (x, y) \in R^{\mathcal{I}} \}$$

$$(\neg B)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus B^{\mathcal{I}}$$

$$(\neg R)^{\mathcal{I}} = \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}} \setminus R^{\mathcal{I}}$$

An interpretation  $\mathcal{I}$  is said to be a model of a concept (resp. role) inclusion axiom, denoted by  $\mathcal{I} \models B \sqsubseteq C$  (resp.  $\mathcal{I} \models R \sqsubseteq E$ ), if and only if  $B^{\mathcal{I}} \subseteq C^{\mathcal{I}}$  (resp.  $R^{\mathcal{I}} \subseteq E^{\mathcal{I}}$ ). Similarly, we say that an interpretation  $\mathcal{I}$  is a model of a membership assertion A(a) (resp. P(a,b)), denoted by  $\mathcal{I} \models A(a)$  (resp.  $\mathcal{I} \models P(a,b)$ ), if and only if  $a^{\mathcal{I}} \in A^{\mathcal{I}}$  (resp.  $(a^{\mathcal{I}},b^{\mathcal{I}}) \in P^{\mathcal{I}}$ ).

Regarding  $DL\text{-}Lite_F$ , we say that an interpretation  $\mathcal{I}$  is a model of an axiom  $(funct\,R)$  if and only if  $R^{\mathcal{I}}$  is a function, i.e., if  $(c,c')\in R^{\mathcal{I}}$  and  $(c,c'')\in R^{\mathcal{I}}$  implies c'=c''. Notice that we only consider DL-Lite with unique name assumption.

Note that the interpretation function  $.^{\mathcal{I}}$  is extended for  $\square$  and  $\sqcup$  constructors respectively as follows:  $(C_1 \sqcap C_2)^{\mathcal{I}} = C_1^{\mathcal{I}} \cap C_2^{\mathcal{I}}$  and  $(C_1 \sqcup C_2)^{\mathcal{I}} = C_1^{\mathcal{I}} \cup C_2^{\mathcal{I}}$ .

An interpretation  $\mathcal{I}$  is said to satisfy a knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  if and only if  $\mathcal{I}$  satisfies every axiom in  $\mathcal{T}$  and every axiom in  $\mathcal{A}$ . Such interpretation is said to be a model of  $\mathcal{K}$ .

**Incoherence and inconsistency** Two kinds of inconsistency can be distinguished in DL-based knowledge bases: *incoherence* and *inconsistency* [Baader *et al.*, 2010]. The former is considered as a kind of inconsistency in the TBox, *i.e.* the terminological part of a knowledge base. The latter is the standard notion of inconsistency of knowledge bases. A knowledge base is said to be inconsistent if and only if it does not admit any model and it is said to be incoherent if there exists at least a non-satisfiable concept (*i.e.* no individual can belong to the concept). More formally:

**Definition 1.13.** A *DL-Lite* terminological base  $\mathcal{T}$  is said to be incoherent if there exists a concept C such that for each interpretation  $\mathcal{I}$  which is a model of  $\mathcal{T}$ , we have  $C^{\mathcal{I}} = \emptyset$ .

**Example 1.7.** An example of incoherent TBox is the one composed of the two inclusion axioms  $\mathcal{T} = \{B_1 \sqsubseteq B_2, B_1 \sqsubseteq \neg B_2\}$ . One can easily check that for all models  $\mathcal{I}$  of  $\mathcal{T}$  we have  $B_1^{\mathcal{I}} = \emptyset$ .

In a propositional setting the counterpart of incoherence is a so-called potential inconsistency, as defined for instance in [Nonfjall and Larsen, 1992].

The concept of knowledge base inconsistency is defined by:

**Definition 1.14.** A *DL-Lite* knowledge base  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  is said to be inconsistent if it does not admit any model.

**FOL-reducibility** An important property, called FOL-reducibility, has been established in [Calvanese *et al.*, 2007a] for consistency checking and query answering in *DL-Lite*. This property reduces reasoning tasks in *DL-Lite* knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  to the evaluation over the ABox of FOL queries obtained from  $\mathcal{T}$ . Clearly, such a property separates the TBox and the ABox when reasoning. Namely, the reasoning tasks are done in two steps: The first one consists in producing FOL queries using axioms of the TBox. The second step consists in evaluating the obtained queries over the ABox that can be stored in a relational database, and thus, one can use SQL engines.

It is important to note that for other DL-Lite members that allow more expressivity (presented in Section 1.4.2) than DL- $Lite_{core}$ , DL- $Lite_F$  and DL- $Lite_R$ , the FOL-reducibility property is not always guaranteed [Artale *et al.*, 2009].

Consistency checking in *DL-Lite* In *DL-Lite* a TBox  $\mathcal{T} = \{\mathcal{T}_p, \mathcal{T}_n\}$  can be viewed as composed of a set of positive inclusion axioms (denoted  $\mathcal{T}_p$ ) and a set of negative inclusion axioms (denoted  $\mathcal{T}_n$ ). A positive inclusion axiom (PI) is of the form  $B_1 \sqsubseteq B_2$  and a negative inclusion axiom (NI) is of the form  $B_1 \sqsubseteq \neg B_2$ . Intuitively  $\mathcal{T}_p$  specifies inclusion dependencies, while  $\mathcal{T}_n$  defines integrity constraints.

The DL-Lite logics, and in particular DL-Lite $_{core}$ , DL-Lite $_F$  and DL-Lite $_R$ , enjoy the canonical model property [Calvanese et al., 2007a]. This property states that given a consistent DL-Lite knowledge base K, one can construct a single model  $\mathcal{I}_c$  of K so that any other model  $\mathcal{I}$  of K can be obtained from  $\mathcal{I}_c$ . This model is called canonical model and defined through the notion of Chase [Abiteboul et al., 1995]. Using the notion of canonical interpretation, it was shown that a knowledge base that only contains PIs in its ABox is always consistent [Calvanese et al., 2007a]. Inconsistency is caused by NI axioms. Note that in query answering, the canonical interpretation allows to find the correct answers of queries.

**DL-Lite** deductive closure The negative closure of  $\mathcal{T}$ , denoted by  $cln(\mathcal{T})$ , performs interaction between positive and negative axioms. It represents the propagation of the negative axioms using both positive axioms and negative axioms in the TBox. For  $DL\text{-}Lite_{core}$ , the  $cln(\mathcal{T})$  is obtained using the following rules repeatedly until reaching a fixed point (see [Calvanese *et al.*, 2007a] for more details):

- 1. All negative axioms in  $\mathcal{T}$  are in  $cln(\mathcal{T})$ .
- 2. If  $B_1 \sqsubseteq B_2$  is in  $\mathcal{T}$  and  $B_2 \sqsubseteq \neg B_3$  is in  $cln(\mathcal{T})$ , then  $B_1 \sqsubseteq \neg B_3$  is in  $cln(\mathcal{T})$ .
- 3. If  $B_1 \sqsubseteq B_2$  is in  $\mathcal{T}$  and  $B_3 \sqsubseteq \neg B_2$  is in  $cln(\mathcal{T})$ , then  $B_1 \sqsubseteq \neg B_3$  is in  $cln(\mathcal{T})$ .

For the DL- $Lite_R$  and DL- $Lite_F$  logics, we need the following additional rules:

- 4. All functionality axioms in T are also in  $cln(\mathcal{T})$ .
- 5. If  $R_1 \sqsubseteq R_2$  is in  $\mathcal{T}$  and  $\exists R_2 \sqsubseteq \neg B$  or  $B \sqsubseteq \neg \exists R_2$  is in  $cln(\mathcal{T})$ , then  $\exists R_1 \sqsubseteq \neg B$  is in  $cln(\mathcal{T})$ ;
- 6. If  $R_1 \sqsubseteq R_2$  is in  $\mathcal{T}$  and  $\exists R_2^- \sqsubseteq \neg B$  or  $B \sqsubseteq \neg \exists R_2^-$  is in  $cln(\mathcal{T})$ , then  $\exists R_1^- \sqsubseteq \neg B$  is in  $cln(\mathcal{T})$ ;
- 7. If  $R_1 \sqsubseteq R_2$  is in  $\mathcal{T}$  and  $R_2 \sqsubseteq \neg R_3$  or  $R_3 \sqsubseteq \neg R_2$  is in  $cln(\mathcal{T})$ , then  $R_1 \sqsubseteq \neg R_3$  is in  $cln(\mathcal{T})$ ;
- 8. (a) in the case where T is a DL-Lite<sub>R</sub> TBox, if one of the axioms ∃R ⊆ ¬∃R, ∃R⁻ ⊆ ¬∃R⁻ or R ⊆ ¬R is in cln(T), then all these three axioms are in cln(T).
  (b) in the case where T is a DL-Lite<sub>F</sub> TBox, if one of the axioms ∃R ⊆ ¬∃R, ∃R⁻ ⊆ ¬∃R⁻ is in cln(T), then both such axioms are in cln(T).

**Example 1.8.** From the DL- $Lite_{core}$  TBox given in Example 1.6, one can derive the following negated closure:

$$Teacher \sqsubseteq \neg Student$$
$$\exists Teaches To^- \sqsubseteq \neg Teacher$$
$$\exists Has Supervisor^- \sqsubseteq \neg Student$$

The negated closure of the DL- $Lite_R$  TBox is constituted by adding the following axioms to the DL- $Lite_{core}$  negated closure:

```
\exists TeachesTo \sqsubseteq \neg Student \\ \exists HasSupervisor \sqsubseteq \neg Teacher
```

The negated closure of the DL- $Lite_F$  TBox is obtaining by adding the following axiom to the DL- $Lite_{core}$  negated closure :

(funct HasSupervisor)

Formally,  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  is consistent if and only if  $\langle cln(\mathcal{T}), \mathcal{A} \rangle$  is consistent [Calvanese *et al.*, 2007a]. In fact, this is a consequence of the property of FOL reducibility. Namely, it has been shown in [Calvanese *et al.*, 2007a] that consistency checking can be reduced to evaluating FOL queries (called Unsat queries) over the ABox which may be considered as a relational database. Table 1.5 summarizes transformations from NI axioms to Unsat queries.

NI axiom	Unsat query	
$A_1 \sqsubseteq \neg A_2$	$\exists x. A_1(x) \land A_2(x)$	
$A \sqsubseteq \neg \exists P \text{ or } \exists P \sqsubseteq \neg A$	$\exists x. A(x) \land \exists y. P(x,y)$	
$A \sqsubseteq \neg \exists P^- \text{ or } \exists P^- \sqsubseteq \neg A$	$\exists x. A(x) \land \exists y. P(y, x)$	
$\exists P_1 \sqsubseteq \neg \exists P_2$	$\exists x. \exists y. P_1(x,y) \land \exists z. P_2(x,z)$	
$\exists P_1 \sqsubseteq \neg \exists P_2^- \text{ or } \exists P_1^- \sqsubseteq \neg \exists P_2$	$\exists x. \exists y. P_1(x,y) \land \exists z. P_2(z,x)$	
$\exists P_1^- \sqsubseteq \neg \exists P_2^-$	$\exists x. \exists y. P_1(y,x) \land \exists z. P_2(z,x)$	
$P_1 \sqsubseteq \neg P_2 \text{ or } P_1^- \sqsubseteq \neg P_2^-$	$\exists x, y. P_1(x, y) \land P_2(x, y)$	
$P_1 \sqsubseteq \neg P_2^- \text{ or } P_1^- \sqsubseteq \neg P_2$	$\exists x, y. P_1(x, y) \land P_2(y, x)$	
(funct P)	$\exists x, y, z. P(x, y) \land P(x, z) \land y \neq z$	
$(funct P^-)$	$\exists x, y, z. P(y, x) \land P(z, x) \land y \neq z$	

Table 1.5: Transformation of the negative inclusion axioms to unsat queries

**Example 1.9.** From Example 1.8, the set of queries associated with the DL- $Lite_{core}$  negated closure is as follows:

```
q_1(x) = \exists x.Teacher(x) \land Student(x)

q_2(x) = \exists x.\exists y.TeachesTo(y,x) \land Professor(x)

q_3(x) = \exists x.\exists y.HasSupervisor(y.x) \land Student(x)
```

For the DL- $Lite_R$  negated closure, we add the following queries:

$$q_4(x) = \exists x. \exists y. TeachesTo(x, y) \land Student(x)$$
  
 $q_5(x) = \exists x. \exists y. HasSupervisor(x, y) \land Teacher(x)$ 

For the DL- $Lite_F$  negated closure, we add the following query:

$$q_4(x) = \exists x, y, z. HasSupervisor(x, y) \land HasSupervisor(x, z) \land y \neq z$$

**Queries and certain answers over** *DL-Lite* An *n*-ary query is an open formula of first-order logic with equality of the form

$$q = \{\vec{x} \mid \phi(\vec{x})\},\$$

where  $\phi(\vec{x})$  is a FOL formula with free variables  $\vec{x} = x_1, ..., x_n$  (called also answer variables) and the arity n of q is the number of its free variables. When n=0, the query is said to be a boolean or ground query. A boolean query of the form  $q=\{\ |\phi\ \}$  is a query that does not involve free variables (i.e. with no answer variables).

Given an interpretation  $\mathcal{I}=(\Delta^{\mathcal{I}}, \mathcal{I})$ , a boolean query is either interpreted as true in  $\mathcal{I}$  if  $[\phi]^I=true$  or false if  $[\phi]^I=false$ . Indeed, the answer to such a query is either "yes" or "no". When n>0, a non-boolean query q is interpreted as the set of tuples of the domain elements, called answer sets with respect to  $\mathcal{I}$ , such that if we substitute  $\vec{x}$  by an answer set  $\vec{a}$  the query q will be evaluated to true in  $\mathcal{I}$ . Namely  $q^{\mathcal{I}}=\{\vec{a}_i\in(\Delta^{\mathcal{I}})^n|[\phi(\vec{a}_i)]^I=true\}$ . An interpretation that evaluates a boolean query (resp. non-boolean query) to true (resp. to a non empty answer set), is said to be a model of that query, written  $I\models q$ .

In *DL-Lite*, the more interesting queries are the class of conjunctive queries and the class of union of conjunctive queries. A Conjunctive Query (CQ) is a query of the form:

$$q = \{\vec{x} \mid \exists \vec{y}.conj(\vec{x}, \vec{y})\},\$$

where  $\vec{x}$  are free variables called distinguished or answer variables,  $\vec{y}$  are existentially quantified variables called non-distinguished or bounded variables, and  $conj(\vec{x}, \vec{y})$  is a conjunction of atoms of the form  $A(t_i)$  or  $P(t_i, t_j)$  and equalities, where the predicates A and P are respectively an atomic concept name and an atomic role name appearing in  $\mathcal{K}$ , and  $t_i$ ,  $t_j$  are terms, i.e constants (individuals) in  $\mathcal{A}$  or variables in  $\vec{x}$  or  $\vec{y}$ . Notice that we call instance query the one consisting of a single atom with no free variable, namely an ABox assertion. A Union of Conjunctive Query (UCQ) denoted by Q is simply an expression of the form:

$$Q = \{\vec{x} \mid \bigvee_{i=i,\dots,n} \exists \vec{y_i}.conj(\vec{x}, \vec{y_i})\}.$$

where each  $conj(\vec{x}, \vec{y_i})$  is a conjunction of atoms and equalities with answer variables  $\vec{x}$  and bound variable  $\vec{y_i}$ . Obviously, the class of UCQ contains the one of conjunctive queries.

Given  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  a *DL-Lite* knowledge base and a CQ q, we write  $\mathcal{K}\models q$  when  $I\models q$  for all models  $\mathcal{I}$  of  $\mathcal{K}$ , otherwise  $\mathcal{K}\not\models q$ . The answer to q over  $\mathcal{K}$ , denoted  $ans(q,\mathcal{K})$ , is the set of tuples of constants appearing in  $\mathcal{K}$  such that  $\forall \vec{a_i} \colon \vec{a_i}^{\mathcal{I}} \in q^{\mathcal{I}}$ , for every model  $\mathcal{I}$  of  $\mathcal{K}$ . Namely  $ans(q,\mathcal{K}) = \{\vec{a_i} \in (\mathcal{K})^n | \mathcal{K} \models q(\vec{a_i})\}$  where  $q(\vec{a_i})$  is the closed formula obtained by replacing the answer variables  $\vec{x}$  in q by an answer set  $\vec{a_i}$ , and  $\mathcal{K}\models q(\vec{a_i})$  means that every model of  $\mathcal{K}$  is also model of  $q(\vec{a_i})$ . This corresponds to the well-known certain answers semantics defined in [Artale *et al.*, 2009; Calvanese *et al.*, 2007a]. Given  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  a *DL-Lite* knowledge base and a CQ q, a certain answer to q over  $\mathcal{K}$  is an answer that holds in all the models satisfying  $\mathcal{K}$ .

It is important to note that CQ answering can be reduced to boolean query answering. Namely, given a CQ q with free variables  $\vec{x} = \{x_1, ..., x_n\}$ , an answer set  $\vec{a} = \{a_1, ..., a_n\}$  is a certain answer for q over  $\mathcal{K}$  if the boolean query  $q(\vec{a})$  obtained by replacing each variable  $x_i$  by  $a_i$  in  $q(\vec{x})$ , evaluates to true for every model of  $\mathcal{K}$ . Lastly, if  $\mathcal{K}$  is inconsistent, then  $ans(q, \mathcal{K})$  is trivially the set of all possible answer sets, denoted  $AllTup(q, \mathcal{K})$ .

**DL-Lite** Reasoner QuOnto <sup>18</sup> is a free reasoner for *DL-Lite* developed in Jave. It implements a query rewriting algorithm for both consistency checking and query answering for unions of conjunctive queries over *DL-Lite* knowledge bases where the ABox is managed using a relational database.

#### 1.4.2 The extended *DL-Lite* family

We now introduce the extended *DL-Lite* family of description logics proposed with the aim of capturing typical conceptual modeling formalisms, such as UML class diagrams and Entity-Relation models, while maintaining good computational properties of standard DL reasoning tasks [Artale *et al.*, 2009]. For more details, see the original paper [Artale *et al.*, 2009].

As usual, let  $N_C$ ,  $N_R$  and  $N_I$  respectively be pairwise disjoint sets of concepts, roles and individuals names. Let  $A \in N_C$ ,  $P \in N_R$  and  $a \in N_I$ . The syntax of the extended family of *DL-Lite* is composed of *DL-Lite* $_{\alpha}^{\beta}$  logics where

```
\alpha = \{core, krom, horn, bool\} and \beta = \{-, \mathcal{H}, \mathcal{F}, \mathcal{N}, \mathcal{HF}, \mathcal{HN}, (\mathcal{HF}), (\mathcal{HN}), (\mathcal{HF})^+, (\mathcal{HN}))^+\}, is defined using the following syntax:
```

with  $z \in \mathbb{N}$ , and  $\top = \neg\bot$ ,  $C_1 \sqcup C_2 = \neg(\neg C_1 \sqcap \neg C_2)$ ,  $\exists R = \exists R. \top = (\geq 1R)$ ,  $\leq zR = \neg(\geq z+1R)$ .  $\mathcal{H}$  denotes role hierarchies (i.e. role inclusion axioms), F denotes functionality (i.e.  $(Funct\ R)$ , and  $\mathcal{N}$  denotes number restriction  $\geq zR$ . The semantics of  $\mathcal{N}$ ,  $\mathcal{H}$  and  $(Funct\ R)$  is given in Table 1.2.

Let  $\mathcal{L}_{\alpha}$  be  $DL\text{-}Lite_{\alpha}$  language where  $\alpha = \{core, krom, horn, bool\}$ . Table 1.6 gives the forms of concept inclusion axioms and assertions that can be allowed in a DL-Lite knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  expressed using  $\mathcal{L}_{\alpha}$ .

	$DL ext{-}Lite_{bool}$	DL-Lite <sub>krom</sub>	DL-Lite <sub>horn</sub>	$DL ext{-}Lite_{core}$
TBox	$C_1 \sqsubseteq C_2$	$B_1 \sqsubseteq B_2, B_1 \sqsubseteq \neg B_2, \neg B_1 \sqsubseteq B_2$	$ \sqcap B_n \sqsubseteq B $	$B_1 \sqsubseteq B_2, B_1 \sqsubseteq \neg B_2$
ABox	$A(a), \neg A(a), P(a,b), \neg P(a,b)$			

Table 1.6: Concept inclusion axioms and assertions in extended *DL-Lite* logics.

There is a tight relationship between the different DL-Lite members. The  $DL\text{-}Lite_{bool}^{HN}$  logic is considered as the supremum (most expressive) of all above logics. The most basic one (least expressive) is the  $DL\text{-}Lite_{core}$  logic (presented in Section 1.4.1). Indeed,  $DL\text{-}Lite_{core}$  is situated in the intersection of  $DL\text{-}Lite_{krom}$  and  $DL\text{-}Lite_{horn}$  since  $B_1 \sqsubseteq \neg B_2$  is equivalent to  $B_1 \sqcap B_2 \sqsubseteq \bot$ . Moreover,  $DL\text{-}Lite_{\alpha}^H$  logics are considered as fragments of  $DL\text{-}Lite_{\alpha}^{HF}$  where these latter are considered as fragments of  $DL\text{-}Lite_{\alpha}^{HN}$  (since from > zR, one can express  $\exists R$  for z=1 and  $(funct\ R)\ (resp.\ (funct\ R^-)\ as <math>\ge 2R\ \sqsubseteq\ \bot$  ( $resp.\ \ge 2R^-\ \sqsubseteq\ \bot$ ) for z=2). Lastly, the TBox's of  $DL\text{-}Lite_{\alpha}^{(HN)}$ ,  $DL\text{-}Lite_{\alpha}^{(HF)^+}$ ,  $DL\text{-}Lite_{\alpha}^{(HF)^+}$  can contain role constraints of the form:

<sup>18</sup>http://www.dis.uniromal.it/~quonto/

- Transitivity (tra(R)):  $\mathcal{I} \models tra(R)$  if and only if  $(x,y) \in R^{\mathcal{I}} \land (y,z) \in R^{\mathcal{I}} \rightarrow (x,z) \in R^{\mathcal{I}}$ .
- Disjointness (dis(R,S)):  $\mathcal{I} \models dis(R_1,S_2)$  if and only if  $R_1^{\mathcal{I}} \cap R_2^{\mathcal{I}} = \emptyset$ .
- Reflexivity (ref(R)):  $\mathcal{I} \models ref(R)$  if and only if  $(x, x) \in R^{\mathcal{I}}$  for all  $x \in \Delta^{\mathcal{I}}$ .
- Irreflexivity (irr(R)):  $\mathcal{I} \models irr(R)$  if and only if  $(x, x) \notin R^{\mathcal{I}}$  for all  $x \in \Delta^{\mathcal{I}}$ .
- Symmetry (sym(R)):  $\mathcal{I} \models sym(R)$  if and only if  $R^{\mathcal{I}} = (R^{-})^{\mathcal{I}}$ .
- Asymmetry (asy(R)):  $\mathcal{I} \models asy(R)$  if and only if  $R^{\mathcal{I}} \cap (R^{-})^{\mathcal{I}} = \emptyset$ .

Table 1.7 summarizes the different members of the extended *DL-Lite* family.

Role	inclusion	Number restriction	Constraints on roles
No	Yes	Trumber restriction	Constraints on Toles
$DL$ -Lite $_{lpha}$	$DL ext{-}Lite^H_lpha$	$\exists R$	No
$DL ext{-}Lite^F_lpha$	$DL ext{-}Lite_lpha^{HF}$	$\exists R/funct$	No
$DL ext{-}Lite^N_lpha$	$DL ext{-}Lite_lpha^{HN}$	$\geq zR$	No
	$DL ext{-}Lite_{lpha}^{(HF)}$	$\exists R.D/funct$ (c)	dis, (a)sym, (ir)ref
	$DL ext{-}Lite_{lpha}^{(HN)}$	$\geq zR.D$ (c)	dis, (a)sym, (ir)ref
	$DL$ -Lit $e_{lpha}^{(HF)^+}$	$\exists R.D/funct$	dis, (a)sym, (ir)ref, tra
	$DL$ -Lite $_{lpha}^{(HN)^+}$	$\geq zR.D$	dis, (a)sym, (ir)ref, tra

Table 1.7: The extended *DL-Lite* family

Note that in Table 1.7, only  $DL\text{-}Lite_{\alpha}^{(HN)^+}$  and  $DL\text{-}Lite_{\alpha}^{(HF)^+}$  allow role transitivity constraint. Moreover  $DL\text{-}Lite_{\alpha}^{(HN)}$  and  $DL\text{-}Lite_{\alpha}^{(HF)}$  are restricted by the following constraints [Artale *et al.*, 2009]:

- $\mathcal{T}$  may contain only positive occurrences of qualified number restrictions  $\geq zR.C$ , where C is a conjunction of concepts allowed in the right-hand side of DL-Lite $_{\alpha}$  concept inclusions.
- if  $\geq zR.C$  occurs in  $\mathcal{T}$ , then  $\mathcal{T}$  does not contain negative occurrences of number restrictions  $\geq z'R$  or  $\geq z'R^-$  with  $z' \geq 2$ ;
- if R has a proper sub-role in  $\mathcal{T}$ , then  $\mathcal{T}$  does not contain negative occurrences of  $\geq zR$  or  $\geq zR^-$  with  $z \geq 2$ .

In fact, the above restrictions limit the interaction between role inclusions and number restrictions in each DL- $Lite_{\alpha}$  TBox in order to reduce the complexity of reasoning and allow the use of the above role constraints which increase the expressive power of the logics but do not affect their computational properties.

Table 1.9 reviews main computational complexity results of the different logics of the *DL-Lite* family. For a more detailed description on *DL-Lite* family, see [Artale *et al.*, 2009].

	Complexity			
Languages	Combined Complexity	Data Complexity		
	Satisfiability	Instance checking	Query Answering	
DL-Lite <sup>[ H]</sup>	NLogSpace	$AC^0$	$AC^0$	
$DL ext{-}Lite_{horn}^{[\  H]}$	P	$AC^0$	$AC^0$	
$DL ext{-}Lite_{krom}^{[\  H]}$	NLogSpace	$AC^0$	coNP	
$DL ext{-}Lite^{[\  H]}_{bool}$	NP	$AC^0$	coNP	
$DL ext{-}Lite_{core}^{[F N (HF) (HN)]}$	NLogSpace	$AC^0$	$AC^0$	
$DL ext{-}Lite_{horn}^{[F N (HF) (HN)]}$	P	$AC^0$	$AC^0$	
$DL ext{-}Lite_{krom}^{[F N (HF) (HN)]}$	NLogSpace	$AC^0$	coNP	
$DL ext{-}Lite_{bool}^{[F N (HF) (HN)]}$	NP	$AC^0$	coNP	
$DL ext{-}Lite_{core/horn}^{HF}$	EXPTIME	P	P	
$DL ext{-}Lite_{krom/bool}^{HF}$	EXPTIME	coNP	coNP	
$DL ext{-}Lite^{HN}_{core/horn}$	EXPTIME	coNP	coNP	
$DL ext{-}Lite^{HN}_{krom/bool}$	EXPTIME	coNP	coNP	

Table 1.8: Complexity of reasoning in *DL-Lite* logics (with unique name assemption)

Note that  $DL\text{-}Lite_{core}^H$  (resp.  $DL\text{-}Lite_{core}^F$ ) language is the  $DL\text{-}Lite_R$  (resp.  $DL\text{-}Lite_F$ ) language presented is section 1.4. The following table summarizes their complexity.

	Complexity			
Languages	Combined Complexity Data Complexity		mplexity	
	Satisfiability	Instance checking	Query Answering	
$DL$ - $Lite_{core}$	NLogSpace	$AC^0$	$AC^0$	
$DL$ - $Lite_R$	NLogSpace	$AC^0$	$AC^0$	
$DL$ - $Lite_F$	NLogSpace	$AC^0$	$AC^0$	

Table 1.9: Complexity of reasoning in DL- $Lite_{core}$ , DL- $Lite_R$  and DL- $Lite_F$ 

Recall that, in this thesis we only consider  $DL\text{-}Lite_{core}$ ,  $DL\text{-}Lite_F$  and  $DL\text{-}Lite_R$  logics. For the sake of simplicity and when there is no ambiguity, we use DL-Lite to refer to these three fragments.

# 1.5 Conclusion

In this chapter, we presented description logics, as decidable fragments of first order logics, that offer a nice logical framework to serve ontologies. We focused on three main members of the *DL-Lite* family

investigated in this thesis: DL- $Lite_{core}$ , DL- $Lite_F$  and DL- $Lite_R$  which underly the OWL2-QL profile especially dedicated for applications using large data.

In real world applications, knowledge and data are usually affected with uncertainty and imprecision. Moreover, knowledge evolves from a situation to another or may be issued from different information sources. As pointed out in Section 1.2, merging, evolution and inconsistency and uncertainty management in ontologies are recognized as challenging problems. Next chapter will focus on these issues and will provide an overview on different techniques and tools proposed in the literature, especially in a propositional logic setting, to handle them.

# BELIEF CHANGE AND UNCERTAINTY MANAGEMENT

#### 2.1 Introduction

Originally ontologies have been proposed to represent the knowledge of a domain of interest [Baader *et al.*, 2010] in a static form. However, in some applications (like Web-based ones), the knowledge may be non static and may evolve and change from one situation to another in order to take into account and integrate the changes that occur over time. This dynamic aspect of ontologies is closely related to the belief revision problem studied within propositional logic frameworks (*e.g.* [Alchourrón *et al.*, 1985; Katsuno and Mendelzon, 1991]). Moreover, in some Web applications, knowledge may come form different and often conflicting sources of information where aggregating them in order to provide a global point of view, is required. Merging different pieces of information is also largely studied within a propositional logic setting (*e.g.* [Bloch *et al.*, 2001; Konieczny and Pino Pérez, 2002]).

In the artificial intelligence community, it is well-known that nonmonotonic reasoning and revision are considered as the two sides of the same coin [Makinson and Gärdenfors, 1989]. In general, revision or merging of different information sources may lead to inconsistency problems where several approaches based on either restoring the consistency of the knowledge base in order to exploit it and perform inferences (e.g. [Benferhat et al., 1997a]), or analyzing inconsistency using different measures (e.g. [Hunter and Konieczny, 2005]), or using argumentation framework (e.g. [Besnard and Hunter, 2008]) to make decisions, were proposed.

Regarding the quality of the information, it can be affected with uncertainty and imprecision. This is due for instance to the reliability of sources that provide them. In general, information qualified as imperfect may be of different forms: incomplete information, heterogeneous information, incommensurable information, imprecise information, uncertain information, etc. Faithfully handling such pieces of information and taking them into account when reasoning is an important issue that arises in many Web applications. Probability theory is the oldest and the most widely used theory for handling uncertain information. This latter is suitable especially within a frequentist setting. Moreover, several non-classical probabilistic and non-probabilistic theories for handling uncertainties and imprecisions have been proposed. The most well-known ones are fuzzy set theory [Zadeh, 1965; Zadeh, 1988], Dempster-Shafer theory of evidence (or belief functions) [Shafer, 1976], the Spohn's ordinal conditional functions [Spohn, 1988], and possibility theory [Zadeh, 1978; Dubois and Prade, 1988b].

Choosing the right and appropriate framework to represent and reason under imperfect information is closely related to the context of the applications. In this thesis, we focus on possibility theory [Dubois and Prade, 1988b] which is a very natural framework to deal with ordinal and qualitative uncertainty. It deals with non-probabilistic information and it is particularly appropriate when the uncertainty scale only reflects a priority relation between different pieces of information. For instance, the choice of possibility theory in our context, can be justified in an Ontology-Based Data Access setting in which as presented in Section 1.2 data may be provided by different sources which can have different levels of priority.

This chapter aims to provide an overview about belief change and uncertainty management from a

propositional logic point of view while giving the related works done in description logics in order to situate our works.

The rest of the chapter is organized as follows: Section 2.2 reviews the notion of uncertainty and imprecision and recalls basic concepts of probability theory and provides a refresher on possibility theory. Section 2.3 recalls the context of merging, revision and uncertainty handling and presents relevant works done in description logics. Section 2.4 concludes this chapter.

# 2.2 Uncertainty management

An information, in a broad sense, refers to any collection of symbols or signs produced either through the observation of natural or artificial phenomena or by cognitive human activity [Dubois and Prade, 2010]. A piece of information, can be of different forms (objective, subjective, quantitative, qualitative, singular, generic, etc) [Dubois and Prade, 2011] and can be affected with different kinds of imperfection (incompleteness, confusion, irrelevance, imprecision, vagueness, etc) which are considered as forms of ignorance [Parsons and Hunter, 1998].

Throughout this section, we use the following notations.

- $\Omega = \{\omega_1, ..., \omega_n\}$ : Denotes the set of the states of the world, called the universe of discourse.
- $\omega_i \in \Omega$ : Denotes a state of the world, called an interpretation or elementary event.
- A, B, ..., E: Capital letters denote subsets of  $\Omega$ . A subset  $A \subseteq \Omega$  is called an event.
- v: Denotes a vector of variables where  $\Omega$  is its domain.

A subset A of  $\Omega$  is considered as a disjunctive set and it is viewed as a proposition that asserts a variable v in A. However, the propositions expressible on  $\Omega$  may be attached with imperfections as said before. In the following, we present pieces of information qualified as incomplete.

**Incomplete information.** A piece of information is said to be incomplete (or partial) in a given context, if it is not sufficient enough to answer a relevant question asked in the same context. For instance, one can consider the following examples:

**Example 2.1.** The following gives examples of incomplete information.

- 1. Consider the following question: "What is exactly the age of Paul?". Let "Paul was born between 1980 and 1984" be an information that one knowns. Such information does not allow to answer the above question.
- 2. Consider the following question: "What is the temperature of the patient?". Let "The temperature of the patient is high" be an information that one has. Such information does not allow to precisely answer the question about the exact temperature.
- 3. Consider the following question: "Does student Paul succeed this year?". Let "The success rate for this year is about 50%" be an information about the known success rate. Such information is not enough to answer the asked question.

From Example 2.1, one can see that the nature of an incomplete information is not the same. Incompleteness can be, in general, imprecision, fuzziness, uncertainty, etc. For more details, see [Parsons and Hunter, 1998; Dubois and Prade, 2011] for example.

Imprecise information Given a proposition that asserts a variable v in  $A \subseteq \Omega$ , a piece of information is said to be imprecise, if it is insufficient to give the current value of the variable v in A. Imprecision is related to the content of the information. Said differently, the number of elements in A, that may correspond to v is greater than 1. Note that v takes only one value from A at a given time, and thus, elements in A are considered as possible values of v and they are mutually exclusive. Let us consider the following example.

**Example 2.2.** From Example 2.1 item 1, the quantity  $v = birthyear(Paul) \in \{1980, 1981, 1982, 1983, 1984\}$  which states that "Paul" was born between 1980 and 1984". This leads to consider that v = 1980 or v = 1981 or v = 1982 or v = 1983 or v = 1984.

**Fuzzy information** A fuzzy piece of information (or gradual linguistic piece of information) is considered as a subtype of imprecision. It represents a proposition asserting a variable v in  $A \subseteq \Omega$  where one can not claim if it is totally true or totally false. Namely, the proposition is not boolean.

**Example 2.3.** From Example 2.1 item 2, the proposition stating that "The temperature of the patient is high" is fuzzy since it does not give the exact value of the temperature. Said differently, we only know that it is "high". Indeed, a temperature equal to 42 looks more credible than a temperature equal to 40 which is itself more credible than a temperature equal to 39. However, saying that "the temperature is equal to 37" is completely false referring to the context of the information that said that the temperature is high. In this case, one would rather say that the temperature of the patient is normal.

In fact, a fuzzy piece of information ranks values in A in terms of their relevance to give the current value of v [Dubois and Prade, 2011]. Note that the meaning of a fuzzy information may be altered using linguistic quantifiers expressing intensity, for instance, consider the proposition "the temperature is very high" or "the temperature is slightly high", etc.

**Uncertain information** A piece of information is said to be uncertain when one can not decide if the information is completely true or completely false (for instance the question asked in item 3 of Example 2.1). Uncertainty is due either to variability (randomness) or lack of information about the real world, and it is in general related to the source providing the information. An uncertain piece of information is attached with a certainty qualifier which can be numerical (*e.g.* a probability) or symbolic (*e.g.* plausible).

**Example 2.4.** Let us consider the following information pieces:

- The probability that the task takes more than one hour is about 0.7.
- It is very possible that it will rain tomorrow.
- It is not absolutely certain that Paul will come to the meeting tomorrow.

Usually, an uncertain piece of information is represented by attaching (using a function f defined over  $\Omega$ ) to each event  $A\subseteq\Omega$  a number f(A) belonging to the unit interval [0,1] which evaluates the likelihood of A with respect to a proposition asserting  $v\in A$ . In other words, f(A) is the confidence of the agent in the truth of  $v\in A$ . Note that, contrary to fuzzy information, the proposition is boolean, namely it only takes true or false. When dealing with uncertainty, the following requirements are needed:

```
1. f(\Omega) = 1 and f(\emptyset) = 0.
```

2.  $\forall A \subseteq \Omega, \forall B \subseteq \Omega : if A \subseteq B then f(A) < f(B)$  (Monotonicity).

- 3.  $\forall A \subseteq \Omega, \forall B \subseteq \Omega : g(A \cap B) \le \min(f(A), f(B)).$
- 4.  $\forall A \subseteq \Omega, \forall B \subseteq \Omega : g(A \cup B) \ge \max(f(A), f(B)).$

**Example 2.5.** From Example 2.1, one can be completely certain that the birth year of Paul is between 1980 and 1984, but less certain that Paul's birth date is in {1980, 1981, 1982}, even less certain that it is in 1981.

A piece of information could be at the same time:

- Precise and certain: "Paul was born is 1983".
- Precise and uncertain: "It is probable that Paul was born in 1984, with a confidence degree of 30%".
- Imprecise and certain: "It is certain that Paul was born between 1982 and 1984".
- Imprecise and uncertain: "It is possible that Paul was born between 1981 and 1984".

Lastly, there are other kinds of imperfect pieces of information such as heterogeneous information (*i.e.* information having different nature or expressed differently), incommensurable information (*i.e.* information expressed over different scales), multiple source information (*i.e.* information provided by different sources), etc.

#### 2.2.1 Probability theory

Probability theory is the oldest and the most widely acknowledged among uncertainty theories. This section recalls basic concepts of probability theory.

#### **Basic notions**

The notion of probability distribution is the central element of probability theory. A probability distribution, denoted by p, is defined over the universe of discourse  $\Omega$  such that  $\forall \omega_i \in \Omega, \, p(\omega_i) \in [0,1]$ . A probability measure  $P: 2^\Omega \to [0,1]$  is a function that assigns to each event  $A \subseteq \Omega$  a degree belonging to the unit interval [0,1]. This degree reflects the chance or the likelihood of the occurrence or the realization of A. A probability measure and probability distribution satisfy the following requirements:

- Positivity:  $\forall A \subseteq \Omega, P(A) \ge 0$ .
- Normalization :  $P(\Omega) = 1$
- Additivity:  $P(A \cup B) = P(A) + P(B)$  (if A and B are disjoint, namely  $A \cap B = \emptyset$ ).

The first axiom states that an event of  $\Omega$  may be (in the worst case) impossible, *i.e.* P(A) = 0. The second states that the universe of discourse  $\Omega$  is certain. Finally, the third axiom states that the probability of the union of two disjoint events is equal to the sum of the probabilities of the two events separately. As consequence of the above requirements, we have:

- $\sum_{i=1}^n p(\omega_i) = 1$ ,
- $P(\emptyset) = 0$
- $P(A) = 1 P(\bar{A})$  (where  $\bar{A}$  is the complementary of A in  $\Omega$ , namely  $\bar{A} = \Omega \setminus A$ )

•  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$  where  $A \in \Omega$  and  $B \in \Omega$ .

Given a probability distribution p defined on  $\Omega$ , one can derive the probability measure of a subset  $A \subseteq \Omega$  as follows:

$$P(A) = \sum_{\omega \in A} p(\omega)$$

Let B be an event of  $\Omega$ . The probability of the realization of an event A can be updated according to the probability of the realization of the event B. Let P(A|B) denote the probability of the event A knowing the event B. The transformation from P(A) to P(A|B) is called probabilistic conditioning and it is computed as follows:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

The following property is called product rule and it is defined by (it is a consequence of the conditioning rule):

$$P(A \cap B) = P(A) * P(B|A) = P(B) * P(A|B)$$

Bayes theorem states that the conditional probability of an event A given B is related to the converse conditional probability of B given A. This permits to compute the probability of B if we know A as follows:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Bayes rule is very useful when performing inference like in classification problems, or learning from statistical data.

# 2.2.2 Possibility theory

Possibility theory, introduced first by Zadeh [Zadeh, 1999] and then developed by Dubois and Prade [Dubois and Prade, 1988b] and many other researchers, is a very natural framework to deal with ordinal and qualitative uncertainty. It deals with non-probabilistic information and it is particularly appropriate when the uncertainty scale only reflects a priority relation between different pieces of information. There are several interpretations of possibility degrees. The most supported ones are as follows [Dubois and Prade, 2011]:

- The feasibility or realizability, for instance "it is possible to repair the old car".
- The plausibility which refers to the degree to which an event can occur, for instance "it is possible that it will snow tomorrow".
- Consistency or compatibility which refers to a logical view of possibility and concerns the available
  information itself, for instance "it is impossible that Paul votes", knowing that "Paul is two years
  old".

#### **Basic concepts**

This section introduces basic concepts of possibility theory. We first recall the notion of possibility distribution.

**Possibility distribution.** A possibility distribution, denoted by  $\pi$ , is a mapping from the universe of discourse  $\Omega$  to a totally ordered scale O. This scale may often be a finite set of integers or the unit interval [0,1] and encodes our knowledge on the real world. In general, it is the interval [0,1] and it could be interpreted in two ways: a numerical interpretation when values have a real sense and an ordinal interpretation when values only reflect a total pre-order between the different states of the world. We further explain these two settings in Section 2.2.2.

The degree  $\pi(\omega)$  is called possibility degree and represents the plausibility or compatibility of  $\omega$  with available knowledge encoded by  $\pi$ . By convention, when  $\pi(\omega)=1$ , we say that  $\omega$  is a totally possible state, and when  $\pi(\omega)=0$ , we say that  $\omega$  is an impossible state. Given two states of the world  $\omega$  and  $\omega'$ , if  $\pi(\omega)>\pi(\omega')$ , we say that  $\omega$  is more preferred than  $\omega'$  or more plausible. Possibility theory can capture the two extreme forms of knowledge, namely:

- 1. Total ignorance when  $\forall \omega \in \Omega, \pi(\omega)=1$ .
- 2. Complete knowledge when  $\exists \omega' \in \Omega, \pi(\omega') = 1$  and  $\forall \omega \in \Omega, \omega' \neq \omega, \pi(\omega) = 0$ .

**Example 2.6.** The following possibility distributions give situations of total certainty, partial ignorance and total ignorance.

$\omega_i$	$\pi(\omega_i)$
$\omega_1$	1
$\omega_2$	0
$\omega_3$	0

$$\begin{array}{c|c} \omega_i & \pi(\omega_i) \\ \hline \omega_1 & 1 \\ \omega_2 & 1 \\ \omega_3 & .5 \\ \hline \end{array}$$

$$\begin{array}{c|cc}
\omega_i & \pi(\omega_i) \\
\omega_1 & 1 \\
\omega_2 & 1 \\
\omega_3 & 1
\end{array}$$

(a) Total certainty

(b) Partial ignorance

(c) Total ignorance

A possibility distribution is said to be normalized if it admits at least one totally possible state, namely  $\exists \omega \in \Omega$  such that  $\pi(\omega) = 1$ . Otherwise the possibility distribution is said to be sub-normalized. In this case, the inconsistency degree of the possibility distribution  $\pi$ , denoted  $Inc(\pi)$ , is defined as follows:

$$Inc(\pi) = 1 - max_{\omega \in \Omega} \{\pi(\omega)\}\$$

The concept of sub-normalization reflects the presence of contradictions in the set of available knowledge encoded by  $\pi$ . Lastly, possibility theory is driven by the principle of minimal specificity that states that any hypothesis not known to be impossible cannot be ruled out [Yager, 1992]. Given two possibility distributions  $\pi$  and  $\pi'$ ,  $\pi$  is said to be more specific than  $\pi'$  if and only if  $\forall \omega \in \Omega$ ,  $\pi(\omega) \leq \pi'(\omega)$ .

**Example 2.7.** Consider the following two possibility distributions:

$\omega_i$	$\pi_1(\omega_i)$
$\omega_1$	1
$\omega_2$	.1
$\omega_3$	0

	i
$\omega_i$	$\pi_2(\omega_i)$
$\omega_1$	1
$\omega_2$	.5
$\omega_3$	.8

One can check that  $\pi_1$  is is more specific than  $\pi_2$ .

**Possibility and Necessity measures.** Possibility theory offers two measures to assess the possibility (or the plausibility) and the necessity (or the certainty) of an event.

**Possibility measure** Given a possibility distribution  $\pi$ , a possibility measure, denoted by  $\Pi$ , of an event  $A \subseteq \Omega$  is defined as follows:

$$\Pi(A) = \max_{\omega \in A} (\pi(\omega))$$

Intuitively,  $\Pi(A)$  evaluates to what extent A is plausible or compatible with the available knowledge expressed by  $\pi$ . We have:

- if  $\Pi(A) = 1$  and  $\Pi(\bar{A}) = 0$ : this means that A is certain.
- if  $\Pi(A) = 1$  and  $0 < \Pi(\bar{A}) < 1$ : this means that A is somewhat certain.
- if  $\Pi(A) = 1$  and  $\Pi(\bar{A}) = 1$ : this means that there is total ignorance about A.
- if  $\Pi(A) > \Pi(B)$ : this meaning that A is more plausible than B.

In the following, we give some properties of  $\Pi$  when the possibility distribution  $\pi$  is normalized.

- $\max(\Pi(A), \Pi(\bar{A})) = 1$ : Meaning that A and  $\bar{A}$  cannot be both somewhat impossible (consequence of the normalization axiom)
- $\Pi(A \cap B) \leq \min(\Pi(A), \Pi(B))$
- $\Pi(A \cup B) = \max(\Pi(A), \Pi(B))$  (Maximitivity axiom)

**Necessity Measure** The necessity measure, denoted by N, of an event  $A \subseteq \Omega$  is the dual of the possibility measure and it is defined follows:

$$N(A) = 1 - \Pi(\bar{A}) = \min_{\omega \notin A} (1 - \pi(\omega))$$

Intuitively, N(A) defines the certainty degree associated to an event A. Namely, it evaluates to what extent A is certainly implied from the available knowledge encoded by  $\pi$ . It is important to note that in a possibility theory setting, in order for an event A to have a certainty degree greater than zero, it must be totally possible. In other words, A must be completely possible before being somewhat certain. This fact ensures that  $N(A) \leq \Pi(A)$ . We have:

- if N(A) = 1 and  $N(\bar{A}) = 0$ : this means that A is certain,
- if  $N(A) \in [0, 1]$  and  $N(\bar{A}) = 0$ : this means that A is somewhat certain,
- if N(A) = 0 and  $N(\bar{A}) = 0$ : this means that there is a total ignorance about A,

The following gives some properties of N when the possibility distribution  $\pi$  is normalized,

- $min(N(A), N(\bar{A})) = 0$ : Meaning that A and  $\bar{A}$  can not be both somewhat certain.
- $N(A \cap B) = \min(N(A), N(B))$
- $N(A \cup B) \ge \max(N(A), N(B))$

**Example 2.8.** Let us consider the following possibility distribution defined over to binary variables X and Y:

$\omega_i$	X	Y	$\pi(XY)$
$\omega_1$	$x_1$	$y_1$	1
$\omega_2$	$x_2$	$y_1$	.8
$\omega_3$	$x_1$	$y_2$	.5
$\omega_4$	$x_2$	$y_2$	.1

One can check that:

- i)  $\Pi(x_1)=1$  and  $N(x_1)=.2$
- ii)  $\Pi(y_1)=1$  and  $N(y_1)=.5$

#### Quantitative and qualitative settings

Contrary to many uncertainty frameworks (like probability theory, belief functions, etc.), possibilities could be expressed either using numeric values or using a ranking relation. These two kinds of interpretations correspond respectively to the quantitative setting (*i.e.* numerical interpretation of possibilities) and the qualitative setting (*i.e.* an ordinal interpretation of the possibility scale) [Dubois and Prade, 1998].

**Quantitative Setting.** The quantitative setting of possibility theory refers to the case where possibility degrees are real numbers in the unit interval [0, 1]. In such setting, possibility degrees have precise signification and must be a priori justified. Indeed, one can check that there are links between possibilities and probabilities. In fact, a degree of possibility can be considered as the upper probability bound [Dubois and Prade, 1992], and a possibility distribution can be viewed as a likelihood function [Dubois et al., 1997] where a possibility measure is also considered as a special case of plausibility function of Dempster-Shafer theory of evidence, etc.

However, in some situations, it remains difficult to assign exact numerical values for possible states of the world. It seems to be more flexible, in this case, to consider that a state  $\omega$  of the world is more plausible than another one  $\omega'$  instead of attaching to each state a numerical value. Hence, the idea to use a ranking relation over possible states of the universe of discourse  $\Omega$ .

Qualitative possibility theory. The possibilistic qualitative setting refers to the case where the possibility distribution is a mapping from a universe of discourse  $\Omega$  to a totally pre-ordered scale that ranks possible states of  $\Omega$ . The idea of ranking the different states of the universe of discourse, was first introduced in [Spohn, 1988] through the so-called Spohn's ordinal conditional functions (OCF), well-known as kappa functions which map states of  $\Omega$  into ordinals belonging to  $[0, +\infty]$ .

The idea behind qualitative settings is that the universe of discourse  $\Omega$  is equipped with a total preorder, denoted by  $\geq_{\pi}$ , which corresponds to a plausibility relation on  $\Omega$  allowing to affirm that a state  $\omega$  is more plausible than another one  $\omega'$ . Given two possible states  $\omega$  and  $\omega'$ , when:

- $\omega =_{\pi} \omega'$ , we say that  $\omega$  is as plausible as  $\omega'$ ,
- $\omega <_{\pi} \omega'$ , we say that  $\omega$  is less plausible than  $\omega'$ ,
- $\omega >_{\pi} \omega'$ , we say that  $\omega$  is more plausible than  $\omega'$ .

The pre-order  $\geq_{\pi}$  leads to induce a well-ordered partition of  $\Omega$ , namely  $\Omega = \{S_1,...,S_n\}$ . In the qualitative setting, the ordinal scale O is of the form:  $O = \{1,\alpha_1,\alpha_2,...,\alpha_n,0\}$  where  $1 > \alpha_1 > \alpha_2 > \ldots > \alpha_n > 0$ . A possibility distribution that maps a universe of discourse  $\Omega$  to a totally ordered scale O, is called qualitative possibility distribution. It is important to note that the possibility scale can be numerical, namely of the form  $O = \{0,0.1,0.3,...,1\}$  where only the order relation between the values is significant, and not the real numerical values.

#### Possibilistic conditioning

Given a possibility distribution  $\pi$ , conditioning comes down to revise the available knowledge encoded in  $\pi$ , when a new piece of information (*i.e.* an evidence) is available [Dubois and Prade, 1988a; Dubois and Prade, 1990]. Conditioning the original possibility distribution  $\pi$  by an event B takes as input  $\pi$  and B and transforms  $\pi$  to a new possibility distribution denoted by  $\pi' = \pi(.|B|)$ . Depending on the framework that we use (qualitative or quantitative), there are two main definitions of conditioning:

**Quantitative setting** In a quantitative setting, the widely used method of conditioning is called product-based conditioning. It uses the Dempster's rule of conditioning of belief functions, specialized to possibility measures which states that the conditional measure  $\pi(.|B)$  by an event B is such that (we assume that  $\Pi(B) > 0$ ):

$$\Pi(A|B) * \Pi(B) = \Pi(A \cap B)$$

Therefore, the impact of the event B on the available knowledge associated with an event A is given as follows (we assume that  $\Pi(B) > 0$ ):

$$\Pi(A|_p B) = \frac{\Pi(A \cap B)}{\Pi(B)}$$

Given a possibility distribution  $\pi$ , the presence of the new evidence B alters  $\pi$ , by first declaring all states outside B as impossible, and then, proportionally changing all the states with respect to B. More formally:

$$\pi(\omega|_p B) = \begin{cases} \frac{\pi(\omega)}{\Pi(B)} & if \ \omega \in B\\ 0 & otherwise \end{cases}$$

It is important to note that there exit other ways for conditioning in the quantitative setting. For more details, see (e.g. [Fonck, 1997; Baets et al., 1999; Bouchon-Meunier et al., 2002]).

**Qualitative setting** Within a qualitative setting, the so-called min-based conditioning is the widely used method for conditioning. This latter is based on the qualitative counterpart of the Bayesian rule [Hisdal, 1978; Dubois and Prade, 1988b] which states that:

$$\Pi(A \cap B) = \min(\Pi(A|B), \Pi(B))$$

The min-based conditioning respects the minimum specificity principle which consists in assigning to the best element of the event B, the highest possibility degree (namely, 1). More formally, the min-based conditioning is performed as follows:

$$\Pi(A|_{m}B) = \begin{cases} 1 & if \Pi(A \cap B) = \Pi(B) \\ \Pi(A \cap B) & if \Pi(A \cap B) < \Pi(B) \end{cases}$$

Therefore, the min-based conditioning defined on all the states of a possibility distribution is given as follows:

$$\pi(\omega|_m B) = \begin{cases} 1 & if \ \pi(\omega) = \Pi(B) \ and \ \omega \in B \\ \pi(\omega) & if \ \pi(\omega) < \Pi(B) \ and \ \omega \in B \\ 0 & otherwise \end{cases}$$

**Example 2.9.** Let  $\pi$  be a possibility distribution over two binary variables X and Y and let  $y_2$  be a new certain piece of information (observed information). One can compute the new possibility distribution  $\pi' = \pi(.|y_2)$ , using the qualitative or quantitative conditioning as follows:

$\overline{X}$	Y	$\pi(XY)$
$\overline{x_1}$	$y_1$	1
$x_2$	$y_1$	.8
$x_1$	$y_2$	.5
$x_2$	$y_2$	.1

X	Y	$\pi(XY _p x_2)$
$x_1$	$y_1$	0
$x_2$	$y_1$	0
$x_1$	$y_2$	1
$x_2$	$y_2$	.2

X	Y	$\pi(XY _m b_2)$
$x_1$	$y_1$	0
$x_2$	$y_1$	0
$x_1$	$y_2$	1
$x_2$	$y_2$	.1

(a) Initial possibility distribution

(b) Quantitative conditioning

(c) Qualitative conditioning

#### Possibilistic logic

Using a possibility theory framework, the knowledge of an agent can be compactly encoded using different ways. One can either use logic-based formalisms (for instance, the ones presented in Section 1.3) which lead to obtain a possibilistic belief (or knowledge) base or a graphical-based formalism which leads to define a possibilistic graph or network (e.g. [Dubois and Prade, 1991b]). In this thesis, we use logic-based formalisms to encode possibilistic knowledge. This section recalls standard possibilistic logic [Dubois et al., 1994], an extension of propositional logic within a possibility theory setting. Next chapter (Chapter 3) is dedicated to the extension of DL-Lite within a possibility theory framework.

**Syntax.** Let  $\mathcal{B}^* = \{\phi_i : i = 1, ..., n\}$  be a propositional knowledge base composed of a finite set (more precisely, a conjunction) of propositional formulas. A possibilistic knowledge base or belief base  $\mathcal{B}$ , consists of a finite set of possibilistic formulas  $(\phi_i, \alpha_i)$  of the form:

$$\mathcal{B} = \{ (\phi_i, \alpha_i) : i = 1, ..., n \}$$

where  $\phi_i$  is a propositional formula and  $\alpha_i$  is its certainty degree, meaning that  $N(\phi_i) > \alpha_i$ . Note that formulas with  $\alpha_i$ 's equal to '0' are not explicitly represented in the knowledge base. Moreover, when all  $\alpha_i$ 's are equal to 1,  $\mathcal{B}$  coincides with a standard propositional knowledge base  $\mathcal{B}^*$ .

**Semantics.** The semantics of a possibilistic knowledge base  $\mathcal{B}$  is given by a possibility distribution, denoted by  $\pi_{\mathcal{B}}$ , defined over the set of propositional interpretations, namely  $\Omega = \{I_1, \ldots, I_n\}$ . The possibility distribution  $\pi_{\mathcal{B}}$  attaches to each interpretation  $I \in \Omega$  a possibility degree reflecting to what extent this latter satisfies<sup>2</sup> formulas of the knowledge base. The possibility degree of an interpretation  $\pi(I)$  depends on the maximum weight of formulas falsified by the interpretation I.

<sup>&</sup>lt;sup>1</sup>Note that throughout this Chapter and this thesis in general, and when there is no ambiguity, we do not make difference between belief base and knowledge base.

<sup>&</sup>lt;sup>2</sup>The satisfaction relation is recalled in Section 1.3.1

$$\forall I \in \Omega, \pi_{\mathcal{B}}(I) = \begin{cases} 1 & \text{if } \forall (\phi_i, \alpha_i) \in \mathcal{B}, I \models \phi_i, \\ 1 - \max\{\alpha_i : (\phi_i, \alpha_i) \in \mathcal{B}, I \not\models \phi_i\} & \text{otherwise} \end{cases}$$

It is important to note that a possibilistic knowledge base is considered as a compact representation of a possibility distributions. Namely, from each possibilistic knowledge base  $\mathcal{B}$ , one can generate its possibility distribution  $\pi_{\mathcal{B}}$ .

By referring to classical logic, when the formulas of the knowledge base are completely certain (namely, having weights equal to 1 in a possibilistic setting), then the knowledge base will contain only models (i.e.  $\pi_{\mathcal{B}}(I)=1$ ) or countermodels ( $\pi_{\mathcal{B}}(I)=0$ ). As a consequence, the consistency of the knowledge base is binary, namely  $\mathcal{B}$  is consistent or inconsistent. This is not the case in possibilistic knowledge bases. As the possibility distribution allows to attribute to the countermodels a degree of compatibility with the available knowledge. In this case, the consistency of an interpretation with respect to the available knowledge is not binary. Therefore, one can associate to a possibilistic knowledge base a degree of inconsistency between 0 and 1.

**Example 2.10.** Let  $\mathcal{B} = \{(a, .6), (a \land b, .1), (c \lor b, .4)\}$  be a possibilistic knowledge base. The joint possibility distribution  $\pi_{\mathcal{B}}$  of  $\mathcal{B}$  is as follows:

I	$\pi_{\mathcal{B}}(I)$
abc	1
$ab\overline{c}$	1
$a\overline{b}$ c	.9
$a\overline{b}\overline{c}$	.6
$\overline{a}bc$	.4
$\overline{a}b\overline{c}$	.4
$\overline{a}\overline{b}\mathbf{c}$	.4
$\overline{a}\overline{b}\overline{c}$	.4

Let  $\mathcal{B} = \{(\phi_i, \alpha_i) : i = 1, ..., n\}$  be a possibilistic knowledge base, the inconsistency degree of  $\mathcal{B}$ , denoted by  $Inc(\mathcal{B})$ , is defined semantically and syntactically as follows:

- Semantically using the induced possibility distribution:  $Inc(\mathcal{B}) = 1 \max_{I \in \Omega}(\pi_B(I))$  where  $\pi_B$  is its possibility distribution.
- Syntactically using the concepts of  $\alpha$ -cut:  $Inc(\mathcal{B}) = \max\{\alpha_i : \mathcal{B}_{\geq \alpha} \text{ is inconsistent}\}$  where  $\mathcal{B}_{\geq \alpha}$ , is called the  $\alpha$ -cut of  $\mathcal{B}$  and it is the subbase of  $\mathcal{B}$  composed by formulas having weights greater than or equal to  $\alpha$ . If  $\mathcal{B}_{\geq 0}$  is consistent then  $Inc(\mathcal{B}) = 0$ .

It was shown in [Dubois et al., 1994] that the computational complexity of computing the inconsistency degree of a possibilistic knowledge base is in  $(log_2(n)*SAT)$  where n is the number of different weights in the knowledge base and SAT is the complexity of the propositional satisfiability problem. Namely, computing inconsistency degrees needs  $log_2(n)$  calls to a SAT solver. Contrary to classical logic, using the notion of inconsistency degree, possibilistic logic allows reasoning from an inconsistent knowledge base.

Let  $\mathcal{B} = \{(\phi_i, \alpha_i) : i = 1, ..., n\}$  be a possibilistic knowledge base, possibilistic entailments are defined semantically as follows:

• A formula is a logical consequence of a possibilistic knowledge base, denoted by  $\pi_{\mathcal{B}} \models \phi_i$  if and only if  $N(\phi_i) > 0$  where  $N(\phi_i)$  is the necessity degree of  $\phi_i$  computed from  $\pi_{\mathcal{B}}$ .

• A formula is a logical consequence of a possibilistic knowledge base with a certainty degree  $\alpha_i$ , denoted by  $\pi_{\mathcal{B}} \models (\phi_i, \alpha_i)$  if and only if  $N(\phi_i) \geq \alpha_i > 0$  where  $N(\phi_i)$  is the necessity degree of  $\phi_i$  computed from  $\pi_{\mathcal{B}}$ .

The above reasoning tasks can be done syntactically as follows:

- A formula  $\phi_i$  is said to be a plausible conclusion of  $\mathcal{B}$ , denoted by  $\mathcal{B} \models_P \phi_i$  if and only if  $\mathcal{B}_{\geq inc(\mathcal{B})} \models_P \phi_i$ .
- A formula  $\phi_i$  is said to be a possibilistic conclusion of  $\mathcal{B}$ , denoted by  $\mathcal{B} \models_{\pi} (\phi_i, \alpha_i)$  if and only if  $\mathcal{B}_{\geq \alpha_i}$  is consistent,  $\mathcal{B}_{\geq \alpha_i} \models \phi_i$  and  $\forall \beta > \alpha_i, \mathcal{B}_{\geq \beta} \not\models \phi_i$ .

Note that the above inferences can be reduced to computing the inconsistency degree of the possibilistic knowledge base. More formally:

- $\mathcal{B} \models_P \phi_i$  if and only if  $Inc(\mathcal{B} \cup \{(\neg \phi_i, 1)\}) > Inc(\mathcal{B})$ .
- $\mathcal{B} \models_{\pi} (\phi_i, \alpha_i)$  if and only if  $Inc(\mathcal{B} \cup \{(\neg \phi_i, 1)\}) > \alpha_i$ .

Another compact representation of possibility distributions is the one of possibilistic networks.

#### Possibilistic networks

Possibilistic networks (e.g. [Fonck, 1994; Gebhardt and Kruse, 1996; Benferhat et al., 2001; Benferhat et al., 2002a]) are frameworks used for representing and reasoning with uncertain information. Comparing with possibilistic logic, possibilistic networks explicit relationships between different variables of the domain while possibilistic logic only ranks formulas according to their certainty level.

A possibilistic network  $\mathcal{G}=\langle G,\Theta\rangle$  is specified by:

- i) A graphical component G consisting of a directed acyclic graph (DAG) where vertices represent the variables and edges represent direct dependence relationships between variables. Each variable  $A_i$  is associated with a domain  $D_i$  containing the values  $a_i$  taken by the variable  $A_i$ .
- ii) A numerical component  $\Theta$  allowing to assess the uncertainty relative to each variable using local possibility tables. The possibilistic component consists in a set of local possibility tables  $\Theta_i = \{\theta_{a_i|u_i}\}$  where  $a_i \in D_i$  and  $u_i$  is an instance of  $U_i$  denoting the parent variables of  $A_i$  in the network  $\mathcal{G}$ .

Note that all the local possibility distributions  $\Theta_i$  must be normalized, namely

$$\forall i = 1..n, \forall u_i \in D_{U_i}, \max_{a_i \in D_i} (\theta_{a_i|u_i}) = 1.$$

**Example 2.11.** Figure 2.1 gives an example of a possibilistic network over four boolean variables A, B, C and D.

The structure of  $\mathcal{G}$  encodes a set of independence relationships  $I_r = \{I_r(A_i, U_i, Y)\}$  where each variable  $A_i$  in the context of its parents  $U_i$  is independent of its non descendants Y. For example, in the network of Figure 2.1, variable C is independent of B and D in the context of A.

In possibilistic networks, the joint possibility distribution is factorized using the possibilistic chain rule:

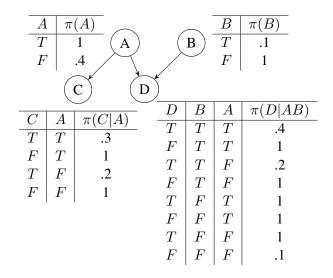


Figure 2.1: Example of a possibilistic network

$$\pi(a_1, a_2, ..., a_n) = \bigotimes_{i=1}^n (\pi(a_i|u_i)).$$

where  $\bigotimes$  is either the product-based or min-based operator.

Lastly, there exists a translation from possibilistic networks to possibilistic knowledge bases [Benferhat *et al.*, 2002a]. For reasoning in possibilistic networks, see [Fonck, 1994; Benamor, 2002; Ayachi *et al.*, 2013] for instance.

#### 2.2.3 Uncertainly management in description logics

Uncertainty reasoning for the World Wide Web has received in recent years a lot of attention <sup>3</sup>. Several approaches are proposed and they are based on the extension of DLs within uncertainty theories. In the following, we recall the main proposed approaches.

#### **Probabilistic description logics**

Probabilistic Description Logics (e.g.[Giugno and Lukasiewicz, 2002; Lukasiewicz, 2002; Lukasiewicz and Straccia, 2008; Lukasiewicz et~al., 2012a]) is an extension of standard DLs with probabilistic terminological axioms and probabilistic assertional facts in order to manage uncertainty. Probabilistic knowledge in probabilistic description logics is modeled using the notion of probabilistic conditional constraints [Lukasiewicz, 1999]. A conditional constraint of the form (A|B)[l,u] is expressed by attaching a belief interval reflecting the lower bound l and the upper bound u of the probability of concluding A given an evidence B where A and B are two concepts. Intuitively, a conditional constraint represents a concept inclusion relation between two concepts A and B of the form  $B \sqsubseteq A$ , with a probability degree between l and u. This permits to model the fact that "generally, if an individual belongs to B, then it belongs to A with a probability lying between l and u". Similarly, for probabilistic assertions, a conditional constraint (A(a)|T)[l,u] is used to express the fact that a is an instance of the concept A with a probability degree that lies between l and u".

<sup>3</sup>http://www.w3.org/2005/Incubator/urw3/XGR-urw3-20080331/

In a probabilistic knowledge base, generic knowledge is encoded in a probabilistic TBox, denoted by PTBox, and assertions are stored in a probabilistic ABox, denoted by PABox. A PTBox PT = (T, P) contains a set of standard DL axioms, *i.e.* a standard TBox  $\mathcal{T}$  (expressed using the used DL language), and a set of conditional constraints P defined over the concepts of the domain. A PABox  $P_o$  is a finite set of conditional constraints defined on probabilistic individuals  $o \in I_p$ . A probabilistic knowledge base is a triple  $PK = (T, P, (P_o)_{o \in I_P})$  relative to  $I_P$ . It is important to note that the set of individuals is partitioned into a set of standard individuals  $I_s$  and a set of probabilistic individuals  $I_p$ .

From a reasoning point of view, consistency checking in a probabilistic knowledge and entailment are based respectively on the notions of consistency and lexicographic entailment proposed in probabilistic default reasoning [Lukasiewicz, 2002].

#### **Fuzzy description logics**

Fuzzy Description Logics (e.g. [Straccia, 1998; Straccia, 2001; Bobillo and Straccia, 2007; Bobillo and Straccia, 2012; Lukasiewicz and Straccia, 2009]) are extensions of DLs within fuzzy sets theory. The aim of such extension is to model fuzziness attached to the elements of the domain. From a syntactic point of view, a fuzzy description logic uses first fuzzy concepts and weighted ABox assertions of the form (A(a), n) where A(a) is an ABox assertion and  $n \in [0, 1]$  is its membership degree to the fuzzy concept A

The semantics of fuzzy DL relies on the fuzzy set semantics [Zadeh, 1965]. Recall that, a fuzzy set S is defined with respect to a set S' by a membership function  $\mu_S: S' \to [0,1]$ , that assigns to each element in S' a membership degree in [0,1]. Within a description logic setting, a fuzzy interpretation is a pair  $\mathcal{I}=(\Delta^{\mathcal{I}},\mathcal{I})$  where  $\Delta^{\mathcal{I}}$  is the domain of the interpretation, defined as in the standard description logic semantics, and  $\mathcal{I}$  is an interpretation function that maps i) each individual as in the standard case, ii) each concept into a membership function  $\Delta^{\mathcal{I}} \to [0,1]$  iii) and each role into membership function  $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}} \to [0,1]$ .

Given an interpretation  $\mathcal{I}$ , a concept A is interpreted as a membership function and  $A^{\mathcal{I}}(a)$  with a an individual (i.e.  $a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$ ) is interpreted as the truth degree of the object a being an element of A under the interpretation  $\mathcal{I}$ . The fuzzy interpretation is extended to DL constructs following a fuzzy semantics aggregation modes.

Lastly, it is important to note that this representation can be handled efficiently using possibility theory. For more details about fuzzy description logics, see [Lukasiewicz and Straccia, 2008].

#### Possibilistic description logics

Possibilistic Description Logics are frameworks introduced to deal with uncertainty and to ensure reasoning under inconsistent knowledge bases. The use of possibility theory to extend DLs has been proposed in [Hollunder, 1995] and discussed in [Dubois *et al.*, 2006]. In [Hollunder, 1995] a possibilistic DL knowledge base was defined syntactically by attaching to every terminological axiom or assertion a necessity degree. However there is no formal foundation of the semantic counterpart of this extension. In addition, only some standard inference services have been defined. From an algorithmic point of view, Hollunder's method [Hollunder, 1995] is based on an instantiation of possibilistic entailment with a classical inference algorithm for DLs.

In [Qi et al., 2007b; Qi et al., 2007a], the authors go one step further in the definition of possibilistic DL. A possibilistic DL knowledge base has been defined syntactically by equipping every axiom with a confidence degree to encode its certainty. This confidence degree is simply the necessity value of an axiom and it reflects to what extent this latter can be considered as certain (priority, importance, etc) with respect to the available knowledge. These degrees are then used to determine the inconsistency degree

of a knowledge base and to ensure inference services. From a computational point of view, an algorithm to compute inconsistency degrees and possibilistic inference services has been provided. In general, it has been shown [Qi et al., 2007b; Qi et al., 2007a] that checking the consistency degree and several inference services can be done with classical DLs reasoning services through consistent sub-sets of the Possibilistic DL knowledge base. Clearly, computing inconsistency degrees comes down to perform a dichotomie search among the certainty scale while calling a standard DL reasoner is closely related to the method proposed in [Dubois et al., 1994] for computing inconsistency degrees of a possibilistic propositional knowledge base.

An implementation of a reasoner called "DL-Poss", has been provided in [Qi et al., 2010a] (see also [Qi et al., 2011] for a discussion on Possibilistic DLs). Finally, another method has been introduced in [Couchariere et al., 2008a; Qi et al., 2008b; Zhu et al., 2013] for checking the inconsistency of a possibilistic DL base as a direct extension of the tableau algorithm [Baader et al., 2010].

In Chapter 3, we more discuss these works and we follow another direction to extend *DL-Lite* within a possibility theory setting. The main feature of this extension is that it is done by slightly modifying the reasoning method proposed in standard *DL-Lite* by propagating the uncertainty degrees associated with formulas in the knowledge base. Compared to the existing works, this extension allows to equip *DL-Lite* with many other reasoning capabilities like merging (Chapter 4), inconsistency handling (Chapter 7) when the assertional base is prioritized.

# 2.3 Belief change

As pointed out in Section 1.2, there are several lines of research that aim to equip ontologies with additional reasoning abilities (in addition to classical ones). In this thesis, we consider the problem of ontology evolution, ontology merging and ontology repairing, with a focus on the context of Ontology-Based Data Access. These problems are respectively closely related to belief revision, belief merging an inconsistency handling in a propositional logic setting. This section gives a brief overview on these topics.

#### 2.3.1 Belief revision

Originally, description logics have been introduced to represent the static aspects of a domain of interest [Baader *et al.*, 2010]. However, for some applications, knowledge may not be static and evolves from a situation to another in order to cope with changes that occur over time. Such dynamic aspects have been recognized as important problems (*e.g.* [Qi *et al.*, 2006c; Calvanese *et al.*, 2010; Wang *et al.*, 2010; Kharlamov *et al.*, 2013]) and often concern the situation where new information should be taken into account requiring to modify the old one while ensuring the consistency of the result. Such problem is well-known as belief revision.

#### Belief revision problem in a propositional logic setting

Belief revision has been defined as knowledge change and was characterized for instance by the well-known AGM postulates [Alchourrón *et al.*, 1985]. These postulates are based on the following three main ideas:

1. The principle of priority 4 which states that the priority between beliefs is given to the new pieces

<sup>&</sup>lt;sup>4</sup>Note that the notion of priority here refers to the fact that the new information is more reliable than the old one while in a prioritized setting two pieces of information may have different priority levels reflecting their plausibility with respect to to available knowledge. Indeed, the priority of the new information refers to the dynamic aspect while in a static context, one can

of information,

- 2. The principle of *consistency* which states that the result of the revision operation must be a consistent set of beliefs, and
- 3. The principle of *minimal* change which states that as less as possible initial beliefs should be changed in the revision operation.

Belief revision has been largely considered in the literature when knowledge bases are encoded using a propositional language. In a propositional logic setting, the AGM postulates were equivalently presented in [Katsuno and Mendelzon, 1991]. Given a knowledge base and a new information expressed respectively using two propositional formulas  $\phi$  and  $\varphi$  and a revision operator, denoted by  $\circ$ , then  $\phi \circ \varphi$  should satisfy the following postulates, well-known as KM postulates [Katsuno and Mendelzon, 1991]:

- **(R1)**  $\phi \circ \varphi$  implies  $\varphi$
- **(R2)** if  $\phi \wedge \varphi$  is satisfiable, then  $\phi \circ \varphi \equiv \varphi \wedge \phi$
- **(R3)** if  $\varphi$  is satisfiable, then  $\phi \circ \varphi$  is satisfiable
- **(R4)** if  $\phi_1 \equiv \phi_2$  and  $\varphi_1 \equiv \varphi_2$ , then  $\phi_1 \circ \varphi_1 \equiv \phi_2 \circ \varphi_2$ .
- **(R5)**  $(\phi \circ \varphi) \wedge \psi$  implies  $\phi \circ (\varphi \wedge \psi)$
- **(R6)** if  $(\phi \circ \varphi) \wedge \psi$  is satisfiable, then  $\phi \circ (\varphi \wedge \psi)$  implies  $(\phi \circ \varphi) \wedge \psi$  (where  $\psi$  is a propositional formula).

Intuitively, postulate (R1) states that the models of the revised formula with the new information  $\varphi$  are also models of  $\varphi$ , or simply the new information should be entailed from the result of revision. (R2) says that if the new information is consistent with the initial one, then the result of revision of  $\varphi$  with  $\varphi$  is made by their intersection. (R3) indicates that the result of revision is satisfiable if the new information is satisfiable. (R4) expresses the syntax independence of the revision operator. (R5) and (R6) together ensure closeness, *i.e.* the minimal change principle.

It is important to note that the KM postulates are equivalent to AGM postulates [Katsuno and Mendelzon, 1991] in a propositional logic setting. Moreover, a representation theorem, based on the notion of *syncretic assignment* was proposed. Recall that a *faithful assignment* is a function that defines a total preorder  $\leq_{\phi}$  over the set of interpretations that represents the formula  $\phi$ . Let  $mod(\phi)$  be the set of models of  $\phi$ , the pre-order  $\leq_{\phi}$  associated to  $\phi$  is a *faithful assignment* if and only if:

- if  $I \in mod(\phi)$  and  $I' \in mod(\phi)$ , then  $I =_{\phi} I'$ ,
- if  $I \in mod(\phi)$  and  $I' \notin mod(\phi)$ , then  $I <_{\phi} I'$ ,
- if  $\phi \equiv \varphi$ , then  $\leq_{\phi} = \leq_{\varphi}$ .

A revision operator satisfies postulates (R1)-(R6) if there exist a *faithful assignment* that associates to  $\phi$  a total pre-order  $\leq_{\phi}$  such that:

$$mod(\phi \circ \varphi) = \min(mod(\varphi), \leq_{\phi})$$

Note that there exists other representation theorems used to define revision operators in addition of the representation theorem based on *faithful assignment*. Based on these works, several belief revision approaches are proposed. One can classify these approaches in two main classes:

have different pieces of information with different priority/uncertainty levels.

**Semantics approaches**: well-known as model-based approaches, they are based on the interpretations of the formulas such as Grove's approach based on spheres [Grove, 1988], revision operators based on distance between interpretations (*e.g.* [Borgida, 1985; Dalal, 1988; Satoh, 1988]), etc.

**Syntactic approaches**: well-known as formula-based approaches, they are based on formulas such as semi-revision [Hansson, 1997], selective revision [Fermé and Hansson, 1999], removed set revision [Papini, 1992; Würbel *et al.*, 2000], etc.

Note that AGM postulates were defined for revising belief sets, i.e deductively closed sets of formulas, possibly infinite. Besides, an axiomatic characterization for revising belief bases, namely finite set of formulas was given in [Fuhrmann, 1997; Hansson, 1998].

There is an extended approach of revision, called iterative revision [Lehmann, 1995; Darwiche and Pearl, 1997] that permits revision of a knowledge base with a sequence of pieces of information, namely  $(\varphi_1,...\varphi_n)$  where as usual each piece of information  $\varphi_i$  has the priority over the set of initial beliefs and  $\varphi_j$  is more preferred than  $\varphi_i$  for 1 < i < j < n. A logical characterization of iterative revision was given by Darwiche and Pearl in [Darwiche and Pearl, 1997]. There are several operators for iterative revision such as: revision proposed by Boutilier [Boutilier, 1993], possibilistic revision [Benferhat *et al.*, 2002c], revision approach based on polynomials [Benferhat *et al.*, 2002b], etc.

#### **Revision within description logic settings**

Recently, several works have been proposed for revising DLs knowledge bases. In [Flouris *et al.*, 2004; Flouris *et al.*, 2005] an adaptation of the AGM postulates was discussed in order to generalize it to DLs. The authors in [Qi *et al.*, 2006c] focused on revising a finite representation of belief sets. They used a semantic reformulation of AGM postulates, done by Katsuno and Mendelzon [Katsuno and Mendelzon, 1991], to extend it to DLs knowledge bases. Recently, several works were proposed to define revision operators for description logics. In [Halaschek-wiener *et al.*, 2006; Ribeiro and Wassermann, 2007; Qi *et al.*, 2008a] an extension of kernel-based revision and semi-revision operators to DLs frameworks has been proposed. It is closely related to the one proposed by [Hansson, 1997] in a propositional logic setting. In [Qi and Yang, 2008; Qi and Du, 2009; Wang *et al.*, 2010], model-based approaches for revising DLs have also been proposed.

However, as pointed out in [Calvanese *et al.*, 2010] model-based approaches of revision are not expressible in *DL-Lite* in the sense that the result of revision is not expressible in the language in which the initial knowledge base is expressed. Moreover, most of the approaches are restricted to the revision of the TBox [Qi and Du, 2009; Zhuang *et al.*, 2014] or the ABox (*e.g.* [Liu *et al.*, 2006; Gao *et al.*, 2012]) but not both. Regarding *DL-Lite* knowledge bases, few works have been proposed for the revision problem. In [Calvanese *et al.*, 2010; Kharlamov and Zheleznyakov, 2011], a formula-based approach for revising *DL-Lite* knowledge bases has been presented. Two algorithms have been proposed: one for revising the TBox, and the other for revising the ABox. Another operator for ABox revision in *DL-Lite* based on graph structure has been introduced in [Gao *et al.*, 2012]. In this work, the new information is restricted to ABox assertions. In [Zhuang *et al.*, 2014] a revision approach based on propositional logic reduction was proposed to revise a TBox.

In Chapter 6, we investigate a formula-based approach for revising *DL-Lite* with either a TBox axiom or an ABox assertion. We consider the case of a *DL-Lite* knowledge base where the ABox is prioritized. In such setting, a new TBox axiom can only expand (enrich) generic knowledge while revision process comes down to throw out some assertional facts in order to restore consistency.

#### 2.3.2 Belief merging

Knowledge bases merging or belief merging (e.g. [Bloch et al., 2001; Everaere et al., 2010]; Everaere et al., 2012]) is an important problem addressed in many application areas such as multi-agent systems, distributed databases, etc. It focuses on aggregating pieces of information issued from distinct, and may be/potentially conflicting or inconsistent, sources of information. It leads to a global point of view of the considered problems by taking advantage of pieces of information provided by each source. Merging pieces of information requires to use some fusion operators that permit to combine them while respecting different constraints between sources. In the literature, several fusion operators have been proposed which depend on the nature and the representation of knowledge such as merging propositional knowledge bases (e.g. [Konieczny and Pino Pérez, 2002]), prioritized knowledge bases (e.g. [Delgrande et al., 2006]) or weighted logical knowledge bases (e.g. [Benferhat et al., 1993a]).

The next two sections introduce merging in the framework of propositional logic and possibilistic logic.

#### Merging within a propositional logic setting

In propositional logic frameworks, a belief base denoted by  $K_i$ , is constituted by a finite set of propositional formulas. Let us use  $\mathcal{E} = \{K_i, ..., K_n\}$  to denote a multi-set, called belief profile, to represent the belief bases to be merged. Assume that each belief base is consistent. Merging multiple consistent belief bases may lead to conflicts between bases. Hence, the aggregation process requires to perform suitable merging operators.

Let us use  $\triangle$  to denote a merging operator and  $\triangle(\mathcal{E})$  to denote the result of this merging which is equal to a propositional formula (*i.e.* a knowledge base). In some cases, a merging operator is submitted to integrity constraints, denoted by  $\rho$ , generally expressed by a set of propositional formulas. Hence, a merging operation with integrity constraints, denoted by  $\triangle_{\rho}(\mathcal{E})$ , must retain the integrity constraints explicitly represented in the merging result and not simply implicitly consistent with the merging result. A logical characterization of integrity constraints merging operators has been proposed in [Konieczny and Pino Pérez, 2002] through a set of rational postulates extended for the one proposed for belief revision. We recall rational postulates proposed to characterize the ideal behavior of a fusion operator.

- (IC0)  $\triangle_{\rho}(\mathcal{E}) \models \rho$
- **(IC1)** If  $\rho$  is consistent, then  $\triangle_{\rho}(\mathcal{E})$  is consistent.
- (IC2) If  $\bigwedge_{K \in \mathcal{E}} K$  is consistent with  $\rho$ , then  $\triangle_{\rho}(\mathcal{E}) = \bigwedge_{K \in \mathcal{E}} K \wedge \rho$
- (IC3) If  $\mathcal{E}_1 \equiv \mathcal{E}_2$  and  $\rho_1 \equiv \rho_2$ , then  $\triangle_{\rho_1}(\mathcal{E}_1) \equiv \triangle_{\rho_2}(\mathcal{E}_2)$
- (IC4) If  $K \models \rho$  and  $K' \models \rho$ , then  $\triangle_{\rho}(\{K, K'\}) \land K$  is consistent if and only if  $\triangle_{\rho}(\{K, K'\}) \land K'$  is consistent.
- (IC5)  $\triangle_{\rho}(\mathcal{E}_1) \wedge \triangle_{\rho}(\mathcal{E}_2) \models \triangle_{\rho}(\mathcal{E}_1 \sqcup \mathcal{E}_2)$
- (IC6) If  $\triangle_{\rho}(\mathcal{E}_1) \wedge \triangle_{\rho}(\mathcal{E}_2)$  is consistent, then  $\triangle_{\rho}(\mathcal{E}_1 \sqcup \mathcal{E}_2) \models \triangle_{\rho}(\mathcal{E}_1) \wedge \triangle_{\rho}(\mathcal{E}_2)$
- (IC7)  $\triangle_{\rho_1}(\mathcal{E}) \wedge \rho_2 \models \triangle_{\rho_1 \wedge \rho_2}(\mathcal{E})$
- (IC8) if  $\triangle_{\rho_1}(\mathcal{E}) \wedge \rho_2$  is consistent, then  $\triangle_{\rho_1 \wedge \rho_2}(\mathcal{E}) \models \triangle_{\rho_1}(\mathcal{E}) \wedge \rho_2$

Intuitively, these postulates seek for a set of propositional formulas that represents the fusion result in the most faithful way to merge belief bases while respecting the integrity constraints. Indeed, the first

postulate (**IC0**) states that the fusion result must satisfy the integrity constraints. (**IC1**) ensures that if the set of integrity constraints is consistent then the fusion result must also be consistent. (**IC2**) means that whenever is possible, the fusion result is simply the conjunction of the merged beliefs bases and the integrity constraint. (**IC3**) simply refers to the syntax-irrelevancy principle and it states that if two belief profiles are equivalent and that two integrity constraint sets are logically equivalent then the resulting belief base of each belief profile are logically equivalent. (**IC4**) assures that when merging a pair of belief bases then the merging operator must not give any preference to one of them. (**IC5**) and (**IC6**) together affirm that if possible one can find two subgroups of sources which are in agreement on at least one interpretation, then the fusion result is exactly the interpretations on which the two groups are in agreement. Finally, (**IC7**) and (**IC8**) are introduced to preserve the notion of closeness (early presented in KM postulates [Katsuno and Mendelzon, 1991] through the postulates R5 and R6).

In [Konieczny and Pino Pérez, 2002] merging operators were classified in two major subclasses, namely majority merging operators and arbitration merging operators. Formally, the family of majority merging operators is logically characterized by the following postulate:

(**Maj**) 
$$\exists n \in \mathbb{N} \text{ such that } \triangle_{\rho} (\mathcal{E}_1 \bigsqcup \mathcal{E}_2^n) \models \triangle_{\rho} (\mathcal{E}_2)$$

This postulate affirms that if a particular set of beliefs is repeated quite enough in the whole set of belief profile then this particular set of beliefs must prevail in the fusion result. Hence, it is obvious that majority operators behavior is sensitive to redundancy.

Contrary to majority merging operators that take into account the opinion of the majority about a situation, arbitration merging operators try to better satisfy opinions as many opinions as possibles among integrity constraints [Konieczny and Pino Pérez, 2002]. Namely, if a set of preferred opinions among a set of integrity constraints  $\rho_1$  for a belief base K corresponds to the preferred opinions among the set of integrity constraints  $\rho_2$  of another base K' and if the opinions that belong to a set of integrity constraints but not to the other are equally preferred for the whole groups ( $\{K, K'\}$ ), then the subset of preferred opinions among the disjunction of integrity constraints will coincide with the preferred opinions of each base among their respective integrity constraints. Formally, the arbitration merging operators are logically characterized by the following postulate:

$$(\mathbf{Arb}) \begin{array}{l} \triangle_{\rho_{1}}\left(K_{1}\right) \equiv \triangle_{\rho_{2}}\left(K_{2}\right) \\ \triangle_{\rho_{1} \leftrightarrow \neg \rho_{2}}\left(\left\{K_{1}, K_{2}\right\}\right)\left(\rho_{1} \leftrightarrow \neg \rho_{2}\right) \\ \rho_{1} \nvDash \rho_{2} \\ \rho_{2} \nvDash \rho_{1} \end{array} \right\} \Rightarrow \triangle_{\rho_{1} \vee \rho_{2}}\left(\left\{K_{1}, K_{2}\right\}\right) \equiv \triangle_{\rho_{1}}\left(K_{1}\right)$$

Now, according to rational postulates **IC0-IC8**, an integrity constraint merging operator is logically defined by a representation theorem according to the notion of *syncretic assignment* [Konieczny and Pino Pérez, 2002]. The *syncretic assignment* tries to build up a pre-order on interpretations and it is defined as an extension *faithful assignment* defined for belief revision [Katsuno and Mendelzon, 1991]. Note that a *majority syncretic assignment* and *arbitration syncretic assignment* are also defined by adding some conditions to those of *syncretic assignment*.

According to the notion of *syncretic assignment*, the representation theorem for integrity constraint merging operators states that the result of merging the belief sets with the merging operator  $\triangle_{\rho}$  is simply represented by the pre-order  $\leq_{\mathcal{E}}$  on the interpretations that consist in computing minimal interpretations to the pre-order associated to the belief bases to be merged. Namely, an integrity constraint merging operator satisfies postulates (IC1)-(IC8) if and only if there exists a *syncretic assignment* that associates to  $\mathcal{E}$  a total pre-order  $\leq_{\mathcal{E}}$  such that:

$$mod(\triangle_{\rho}(\mathcal{E})) = \min(mod(\rho), \leq_{\mathcal{E}})$$

Generally, pieces of information provided by each source are represented, on one hand, syntacticly using a propositional set of formulas, and on the other hand, semantically through a set of interpretations. Thus, as for belief revision approaches, one can identify two categories of merging operators.

**Semantic merging operators** well-known as model-based merging operators, they are parametrized by a distance and an aggregation function. Merging process consists first in ranking interpretations using some distance measures, then combining them using an aggregation function to generally obtain a unique ordering on interpretations for all sources of information. There are several model-based operators: The *Sum* merging operator which is considered as majority merging operator and satisfies the postulate (**IC0**)-(**IC8**), the *Max* merging operator which is considered as an approximation of arbitration merging operator, the *GMax* operator [Konieczny and Pino Pérez, 2002], the DA<sup>2</sup> operators which are based on a distance (D) and two aggregation function (A<sup>2</sup>), the disjunctive operators [Everaere *et al.*, 2010], etc.

Syntactic merging operators well-known as formula-based merging operators, they consist to merge formulas of each belief base to obtain a unique consistent belief base that represents all sources of information. The fusion result which must be a consistent set of formulas depends on the syntactic representation of the merged belief bases. This family of merging operators tries to find from the union of merged belief bases, the consistent and maximal subsets of formulas. Note that the maximality criterion here is in the sense of set inclusion (it can also be defined in terms of cardinality). Formally, let us use  $MaxCons(K, \rho)$  to denote the collection of the maximal consistent subsets from  $K \cup \rho$  which necessarily satisfies the integrity constraints  $\rho$ . Namely, a maximal consistent subset  $M \in MaxCons(K, \rho)$  satisfies the following requirements: i)  $M \subseteq K \cup \rho$ , ii)  $\rho \in M$ , and iii) if  $M \subset M' \subseteq \{K \cup \rho\}$  then M' is inconsistent.

Let  $MaxCons(\mathcal{E},c) = MacCons(\bigcup_{K_i \in \mathcal{E}} K_i, \rho)$ . When the maximality criterion is in the sense of cardinality criterion, we will use  $MaxCons_{card}(\mathcal{E},\rho)$  as notation. One can define the combination operators as follows: Let  $\mathcal{E}$  be a belief set an  $\rho$  be an integrity constraint:

$$\begin{split} \triangle_{\rho}^{C_1}\left(\mathcal{E}\right) &= \bigvee MaxCons\left(\mathcal{E},\rho\right) \\ \triangle_{\rho}^{C_3}\left(\mathcal{E}\right) &= \bigvee \{M: M \in MaxCons\left(\mathcal{E}, \top\right) \text{ and } M \cup \{\rho\} \text{ is consistent}\} \\ \triangle_{\rho}^{C_4}\left(\mathcal{E}\right) &= \bigvee MaxCons_{card}\left(\mathcal{E},\rho\right) \\ \triangle_{\rho}^{C_5}\left(\mathcal{E}\right) &= \bigvee \{M \cup \{\rho\}: M \in MaxCons\left(\mathcal{E}, \top\right) \text{ and } M \cup \{\rho\} \text{ is consistent}\} \text{ if this set is not empty, otherwise } \rho. \end{split}$$

As pointed out in [Konieczny and Pino Pérez, 2002], the combination operators are rather similar to the techniques dedicated to inconsistency-tolerant reasoning from an inconsistent belief bases, than merging operators. Hence, combination operators do not exploit the repartition of the information between sources. Besides, they generally lose the original information provided by merged information sources. To overcome this inconvenient behavior of combination operators, one can define selection functions in the same way as the belief revision. Those selection functions try to select from the whole maximal consistent sets a group in order to attenuate as much possible the fusion result produced by combination operators.

# Merging in a possibilistic logic setting

In a possibility theory framework, several fusion operators (e.g. [Dubois et al., 1992; Benferhat et al., 1997b; Benferhat and Kaci, 2003]) have been proposed for merging pieces of information issued from different and potentially conflicting or inconsistent sources. In general, the possibilistic fusion process first consists in combining a set of possibility distributions that encode the information in order to obtain

a unique possibility distribution that represents the global point of view of the available information, and then, it provides for each fusion operator used to combine possibility distributions its syntactic counterpart when merging possibilistic knowledge bases.

Let  $\mathcal{E} = \{\mathcal{B}_1, ..., \mathcal{B}_n\}$  be n possibilistic knowledge bases to be merged where each of them is associated to a possibility distribution, denoted by  $\pi_i$ . Let  $V(I) = \langle \pi_1(I), ..., \pi_n(I) \rangle$  be a vector that groups for each interpretation all possibility degree  $\pi_i(I)$ . When aggregating possibility distributions, two main properties are required:

- If  $\forall i, \pi_i(I) = 1$  then  $\pi_{\odot} = 1$  and,
- If  $\forall i, \pi_i(I') \leq \pi_i(I)$  then  $\pi_{\odot}(I') \leq \pi_{\odot}(I)$ .

The first property is called consistency property and it states that if the different sources agree that nothing prevents I to be the real world, then the fusion result must confirm the total possibility of I. Intuitively, this property ensures the consistency of the fusion result if the union of the merged belief bases is consistent. The second property is called monotonicity property and it affirms that if all information sources are agree that an interpretation I is at least as preferred as another interpretation I', then the fusion result must conserve this preference.

According to the properties presented above, a possibilistic merging approach first introduces a semantic merging operator to combine possibility distributions, represented by V(I), to obtain a unique possibility distribution, denoted by  $\pi_{\odot}$ . Then it provides the syntactic counterpart for this operator used to combine possibility distributions for merging possibilistic knowledge bases and obtain a unique base, denoted by  $\mathcal{B}_{\odot}^{5}$  such that  $\pi_{\mathcal{B}_{\odot}} = \pi_{\odot}$ .

The basic aggregation modes proposed for possibilistic merging are the conjunction and the disjunction modes.

Conjunctive operators When all the information sources are considered as equally and fully reliable, then one can exploit the complementarity between the difference sources. Namely, when the available information is inconsistent from one source to another. Thus all values that are considered as impossible by one source but possible by the others are rejected. A conjunctive merging operator, denoted by  $\oplus$  is defined as follows:

$$\forall a \in [0,1], \oplus(a,1) = \oplus(1,a) = a$$

The result of the syntactic counterpart of conjunctive merging operator is a possibilistic knowledge base obtained as follows:

$$\mathcal{B}_{\oplus} = \mathcal{B}_1 \cup \mathcal{B}_2 \cup \{(\varphi_i \vee \phi_i, 1 - \oplus (1 - a_i, 1 - b_i))\}\$$

In this case, possibilistic fusion preserves all the available information when the union of merged sources is consistent.

Now, when the information sources are considered as dependent, one can see the redundancy as a way of strengthening or confirmation. Whereas when the information sources are assumed to be independent, the redundancy may be ignored. Indeed, the conjunctive aggregation modes may be adapted to these two kinds of situations. In the first case (dependent information sources) the conjunctive aggregation modes are called idempotent aggregation operators and they satisfy the following property:

<sup>&</sup>lt;sup>5</sup>For the sake of simplicity and to respect notations proposed in the original papers on possibilistic merging, we used  $\mathcal{B}_{\odot}$  instead of  $\triangle_{\odot}$ .

$$\forall a \in [0,1], \oplus(a,a) = a$$

It is obvious that idempotent operators ignore redundancy. Namely, if two different sources provide the same possibility distribution, then the result of their aggregation is simply the same possibility distribution. As an example of idempotent conjunctive operator, the well-known minimum (Min) operator defined as follows:

$$\pi_{min}(I) = min(\pi_1(I), ..., \pi_n(I))$$

As syntactic counterpart associated to  $\pi_{min}(I)$ , we have the following possibilistic knowledge base:

$$\mathcal{B}_{\oplus} = \mathcal{B}_1 \cup \mathcal{B}_2$$

In [Benferhat *et al.*, 2000], it was shown that, in some conditions, that the conjunctive operator may be considered as a majority merging operator. Formally, there exists n such that  $(\mathcal{B}_1 \oplus \mathcal{B}_2^n) \models \mathcal{B}_2$  where  $\mathcal{B}_2^n$  is the aggregation of  $\mathcal{B}_2$  with  $\oplus$  for n iterations.

**Disjunctive operators** When the different sources are conflicting and having the same reliability, it seems to be unsafe to privilege one source to another. Namely, if the union of two distinct knowledge bases  $\mathcal{B}_1$  and  $\mathcal{B}_2$  is inconsistent, then the fusion result should neither imply  $\mathcal{B}_1$  nor  $\mathcal{B}_2$ . Such situation requires to use a disjunctive operator, denoted by  $\otimes$ , and defined as follows:

$$\forall a \in [0,1], \otimes (a,1) = \otimes (1,a) = 1$$

As syntactic counterpart, one can associate to  $\otimes$  the following possibilistic knowledge base:

$$\mathcal{B}_{\otimes} = \{ (\varphi_i \vee \phi_i, 1 - \oplus (1 - a_i, 1 - b_i)) \}$$

According to [Benferhat *et al.*, 2000], a disjunctive operator may lead to a situation of total ignorance. To this end, another class of disjunctive operators, called regular operators was introduced. This class satisfies the following condition.

$$\forall a \neq 1, \forall b \neq 1, \otimes (a, b) \neq 1$$

Intuitively, if the different sources consider an information as somewhat certain, then when aggregating them this information must be also somewhat certain. Clearly, in the presence of inconsistency the fusion result recovers the common set between belief bases. Formally, a regular disjunctive operator is as follows:

$$\mathcal{B}_{\oplus}^* = \mathcal{B}_1^* \vee \mathcal{B}_2^*$$

where  $\mathcal{B}_i^*$  is the standard knowledge bases associated to  $\mathcal{B}$  by ignoring all the weights in  $\mathcal{B}$ .

Finally, note that the disjunctive regular operators are not appropriate when the sources are assumed to be consistent since these operators promote less informative beliefs.

**Ontology merging** Regarding ontology merging, there are few approaches on belief merging for description logics in the spirit of standard belief merging. However, the existing approaches (*e.g.* [Noy and Musen, 2000; Kotis *et al.*, 2006; Moguillansky and Falappa, 2007]) are mainly based on techniques proposed in ontology debugging which is closely related to inconsistency handling in propositional logic. Moreover, there is to the best of our knowledge no approach for merging prioritized DLs knowledge bases.

#### 2.3.3 Inconsistency handling

In the artificial intelligence community, it is well-known that nonmonotonic reasoning and revision are considered as the two sides of the same coin [Makinson and Gärdenfors, 1989]. In general, revision or merging of different information sources may lead to inconsistency problems. Several approaches were proposed to deal with inconsistency in flat propositional logic knowledge bases (by a flat propositional logic knowledge base, we mean a base where all the formulas have the same priority) and prioritized knowledge bases. This is generally done through the definition of many suitable notions for consequence relations. There exist several attitudes when faced to inconsistency. In what follows, we recall the main approaches of inconsistency handling:

**Restoring consistency** Consists in getting rid of inconsistency by first computing the set of maximal or not maximally consistent subsets that restore consistency of the initial base, then using them to perform inference. Let K be an inconsistent knowledge base. Inference relation comes down first to compute maximally consistent subsates of K. A maximally consistent subset, denoted by K, is defined as follows:

- $K' \subseteq K$
- K' is consistent
- if  $K' \subset K'' \subseteq K$ , then K'' is inconsistent

Let MC(K) denote the set of maximally consistent subsets of K. Many inference strategies are proposed to select bases from MC(K) in order to perform inference. The well-known inconsistency-tolerant inference relations are: the universal inference [Rescher and Manor, 1970], existential inference [Rescher and Manor, 1970], argued inference [Benferhat  $et\ al.$ , 1993b; Amgoud, 2005; Amgoud and Prade, 2009], cardinality-based inference [Benferhat  $et\ al.$ , 1997a], safe inference [Benferhat  $et\ al.$ , 1992]. An extension of these inference strategies is proposed when the knowledge base is layered or stratified (i.e. the formulas are attached with priorities) [Brewka, 1989; Benferhat  $et\ al.$ , 1998a]. In (e.g. [Lang and Marquis, 2002; Lang and Marquis, 2010; Konieczny  $et\ al.$ , 2005]) another approach, based on the notion of variable forgetting, is proposed.

**Paraconsistent logics** This consists in accepting inconsistency while coping with it by weakening inference relations. This can be done either by weakening logical connectors (see for instance [Besnard and Hunter, 1995; Hunter, 1998; Dubois *et al.*, 2003] for more details) or localizing inconsistency using, for instance, richer semantics (*e.g.* the multi-valued-semantics) (see for instance [Konieczny and Marquis, 2002; Konieczny *et al.*, 2008] for more details).

Inconsistency analysis: A standard knowledge base is either considered as completely consistent or completely inconsistent. In case of inconsistency, one cannot deduce meaningful conclusions. As mentioned in Section 2.2.2, one way for reasoning is to use the subset of formulas induced from the inconsistency degree to do reasoning. In the same way, many inconsistency approaches were proposed for analysising and measuring the inconsistency of a knowledge base in order to make inference (for more details, see [Hunter and Konieczny, 2005; Hunter and Konieczny, 2010; Grant and Hunter, 2011; Grant and Hunter, 2013] for example).

**Argumentation framework**: Argumentation frameworks [Besnard and Hunter, 2008] offers a good way to reason and make decision from conflicting pieces of information. Given a set of conflicting information, argumentation helps to identify pros and cons argument for a particular conclusion [Amgoud and Cayrol, 2002; Hunter and Konieczny, 2005; Bertossi *et al.*, 2005b].

Ontology debugging In the context of ontologies, several approaches are proposed to handle inconsistency. As explained above, there are works that dealt with inconsistency by: i) restoring consistency (e.g. [Kalyanpur et al., 2005; Flouris et al., 2006a; Lam et al., 2008; Corcho et al., 2009]); ii) using paraconsistent semantics (e.g. [Ma et al., 2011; Zhou et al., 2012]); and iii) measuring inconsistency (e.g. [Qi and Hunter, 2007; Ma and Hitzler, 2010]); and using argumentation (e.g. [Zhang and Lin, 2013; Croitoru and Vesic, 2013])

A crucially important problem that arises in Ontology-Based Data Access is how to manage inconsistency; otherwise the knowledge base is meaningless and useless. In such setting, inconsistency is defined with respect to some assertions that contradict the terminology. Typically, a *TBox* is usually verified and validated while the assertions can be provided in large quantities by various and unreliable sources and may contradict the *TBox*. Moreover, it is often too expensive to manually check and validate all the assertions. This is why it is very important in OBDA to reason in the presence of inconsistency. This consists in accepting and keeping the inconsistencies in the knowledge base while coping with them when performing inference (*i.e.* while answering queries).

Regarding *DL-Lite*, and especially within OBDA setting, existing works [Giacomo *et al.*, 2007; Lembo *et al.*, 2010; Bienvenu, 2012; Bienvenu and Rosati, 2013], basically inspired by the approaches proposed in the database area, tried to deal with inconsistency in *DL-Lite* by proposing and adapting several inconsistency-tolerant inference methods. All the proposed approaches are based on the notion of repair (restoring consistency) which is closely related to the notion of database repair defined in order to answer queries raised to inconsistent databases. A repair of a database contradicting a set of integrity constraints is a database obtained by applying a minimal set of changes in order to restore consistency. This notion of repair was extended to the *DL-Lite* setting by defining assertional-based repair for *DL-Lite* knowledge bases which is simply a maximal assertional subbase consistent with the terminology. In the *DL-Lite* framework, the notion of assertional-based reparation is in the sprit of maximal consistent subsets defined in propositional logic. Clearly an assertional-based reparation is a maximal assertional subbase of the *ABox* that is consistent with the *TBox*.

In this thesis, we are interested in repairing or restoring consistency for *DL-Lite* knowledge bases. Many inference strategies will be discussed in Chapter 5, within an OBDA setting, and in Chapter 7 when the ABox is prioritized.

# 2.4 Conclusion

In the first part of this chapter, we recalled the basic concepts of possibility theory which offers a natural way to deal with ordinal and qualitative uncertainty. We then reviewed the main extensions of description logics to handle uncertainty/imprecision when specifying ontologies. The second part of this chapter introduced the belief change problem (merging and revision) and the different techniques for handling inconsistency in propositional logic settings while recalling relevant related works done in the description logics area. The rest of this thesis investigates these issues within *DL-Lite* frameworks, especially when the knowledge base is prioritized. To this end, we need to extend the *DL-Lite* languages to support uncertainty or priority between axioms that represent a domain of interest. Next chapter studies this extension using a possibility theory setting.

# PART II

# On the possibilistic extension of *DL-Lite*

# MIN-BASED POSSIBILISTIC DL-Lite

#### 3.1 Introduction

Nowadays, in real world applications, knowledge is usually affected with uncertainty and imprecision. Recently, several works have been proposed to deal with probabilistic and non-probabilistic uncertainty [Dubois *et al.*, 2006; Lukasiewicz *et al.*, 2012a] on the one hand and to deal with fuzzy information [Bobillo and Straccia, 2012; Lukasiewicz and Straccia, 2009] on the other hand. A particular attention was given to fuzzy extensions of DLs (*e.g.* [Bobillo *et al.*, 2012; Bobillo *et al.*, 2013; Pan *et al.*, 2007; Straccia, 2006b; Straccia, 2013]. Besides, some works are devoted to possibilistic extensions of DLs (*e.g.* [Dubois *et al.*, 2006; Hollunder, 1995; Qi *et al.*, 2011]) which are basically based on standard reasoning services.

This chapter concerns the development of uncertainty-based DL-Lite using possibility theory. We focus on main fragments of DL-Lite. Namely DL-Lite $_{core}$  which is the simplest DL-Lite language, DL-Lite $_F$  and DL-Lite $_R$  which underlie the OWL2-QL language. Indeed, we first develop our study on the extension of DL-Lite $_{core}$  within a possibility theory setting. The restriction to DL-Lite $_{core}$  is mainly motivated by the clarity and lightness of the language on which we can easily show how the extension of DL-Lite to the possibility theory can be achieved. We then extend our approach to richer DL-Lite languages such as DL-Lite $_F$  or DL-Lite $_R$ .

An important question addressed in this chapter is: "can one extend the expressive power of *DL-Lite*, to deal with possibilistic uncertain information, without increasing the computational cost?" This chapter provides a positive answer to this question.

Note first that some existing extensions of possibilistic DLs [Qi et al., 2007b; Qi et al., 2007a] may need some extra computational costs (although their inference process is still in P). For instance, in some existing approaches (e.g. [Qi et al., 2007b; Qi et al., 2007a]), computing inconsistency degrees comes down to achieve  $log_2(n)$  calls where n is the size of the uncertainty scale  $^1$ ) to the inconsistency checking in standard (without uncertainty) DLs. This method, based on a dichotomy search, is closely related to the method proposed in [Dubois et al., 1994] for computing inconsistency degrees of a possibilistic propositional knowledge base (see Section 2.2.2).

This chapter departs from several approaches for computing the inconsistency degrees of a knowledge base and follows another direction to achieve reasoning tasks in possibilistic *DL-Lite*. The idea is to slightly modify the algorithm for checking the inconsistency of a knowledge base used in standard *DL-Lite* by propagating the uncertainty degrees associated with axioms. The uncertainty propagation does not generate any extra computational cost.

Note that a tool for representing and reasoning in possibilistic *DL-Lite* framework is implemented. A description of this tool is provided in the appendix A.

The rest of this chapter is organized as follows: Section 3.2 rephrases the possibility theory framework over DL-Lite interpretations. Section 3.3 discusses the possibilistic extension of DL- $Lite_{core}$ , denoted  $\pi$ -DL- $Lite_{core}$ , where we present its syntax and its semantics. Section 3.4 introduces the so-called  $\pi$ -negated closure of a  $\pi$ -DL- $Lite_{core}$  knowledge base. Section 3.5 gives a method to compute

<sup>&</sup>lt;sup>1</sup>number of levels in the used scale

the inconsistency degree of a  $\pi$ -DL- $Lite_{core}$  knowledge base using query evaluations. Section 3.6 extends possibilitic DL- $Lite_{core}$  to DL- $Lite_F$  and DL- $Lite_R$ , two important fragments of DL-Lite family. Section 3.7 studies different standard possibilistic inferences. Section 3.8 addresses the problem of query answering within  $\pi$ -DL-Lite framework. Section 3.9 deals with related works and Section 3.10 concludes the chapter.

# 3.2 Possibility distribution over *DL-Lite* interpretations

In this section, we rephrase the semantics of possibility theory over *DL-Lite* interpretations. Let  $\mathcal{L}$  be a finite *DL-Lite* description language as defined in Section 1.4,  $\Omega$  be a universe of discourse (here represented by a set of *DL-Lite* interpretations) and  $\mathcal{I} = (\Delta^{\mathcal{I}}, \mathcal{I}) \in \Omega$  be a *DL-Lite* interpretation.

# 3.2.1 Possibility distribution

In the context of possibilistic *DL-Lite*, a possibility distribution is a mapping, denoted by  $\pi$ , from the universe of discourse  $\Omega$  to the unit interval [0,1]. It assigns to each interpretation  $\mathcal{I} \in \Omega$  a possibility degree  $\pi(\mathcal{I}) \in [0,1]$  that represents its compatibility or consistency degree with respect to the set of available knowledge. When  $\pi(\mathcal{I}) = 1$ , we say that  $\mathcal{I}$  is totally possible and it is fully consistent with the set of available knowledge. When  $\pi(\mathcal{I}) = 0$ , we say that  $\mathcal{I}$  is impossible and it is fully inconsistent with the set of available knowledge. Two special cases exist:

- 1. Total ignorance when  $\forall \mathcal{I} \in \Omega, \pi(\mathcal{I}) = 1$ .
- 2. Complete knowledge when  $\exists \mathcal{I}' \in \Omega, \pi(\mathcal{I}') = 1$  and  $\forall \mathcal{I} \in \Omega, \mathcal{I}' \neq \mathcal{I}, \pi(\mathcal{I}) = 0$ .

A possibility distribution  $\pi$  is said normalized if there exists at least one totally possible interpretation, namely  $\exists \mathcal{I} \in \Omega$  such that  $\pi(\mathcal{I}) = 1$ , otherwise, we say that  $\pi$  is sub-normalized. The concept of normalization reflects the presence of conflicts in the set of available information. For two interpretations  $\mathcal{I}$  and  $\mathcal{I}'$ , we say that  $\mathcal{I}$  is more consistent or more compatible than I' (with respect to the available knowledge) if  $\pi(\mathcal{I}) > \pi(\mathcal{I}')$ .

#### 3.2.2 Possibility and necessity measures

Let us consider M to be a subset of  $\Omega$ . Let  $\overline{M}$  be the complementary of M, namely  $\overline{M} = \Omega \setminus M$ . In a standard possibility theory, given a possibility distribution  $\pi$ , one can define two measures from  $2^{\Omega}$  to the interval [0,1] which discriminate between the plausibility and the certainty regarding the subset M. These two measures are:

**Possibility measure** A possibility measure, denoted by  $\Pi$ , is a function that assigns to each  $M \subseteq \Omega$  a degree between [0,1]. Given a possibility distribution  $\pi$ ,  $\Pi(M)$  is defined as:

$$\Pi(M) = \sup \{ \pi(\mathcal{I}) : \mathcal{I} \in M \}.$$

 $\Pi(M)$  evaluates to what extent the subset M is compatible with the available knowledge encoded by the possibility distribution  $\pi$ . When  $\Pi(M)$ =1, we say that M is totally possible if  $\Pi(\overline{M})=0$  and M is somewhat possible if  $\Pi(\overline{M})\in ]0,1[$ . When  $\Pi(M)$ =1 and  $\Pi(\overline{M})$ =1, we say that there is a total ignorance about M. A possibility measure  $\Pi$  satisfies the following properties for normalized possibility distributions:

$$\forall M \subseteq \Omega, \forall L \subseteq \Omega, \Pi(M \cup L) = max(\Pi(M), \Pi(L)),$$

and

$$\forall M \subseteq \Omega, \forall L \subseteq \Omega, \Pi(M \cap L) \leq min(\Pi(M), \Pi(L)).$$

**Necessity measure** A necessity measure, denoted by N, is a function dual to  $\Pi$ . It is defined from  $\Pi$  as follows:

$$N(M) = 1 - \Pi(\overline{M}).$$

N(M) evaluates to what extent M is certainty entailed from available knowledge encoded by  $\pi$ . When N(M)=1, we say that M is certain. When  $N(M) \in ]0,1[$ , we say that  $\varphi$  is somewhat certain. When N(M)=0 and  $N(\overline{M})=0$ , we say that there is a total ignorance about M.

A necessity measure N satisfies the following properties for normalized possibility distributions:

$$\forall M \subseteq \Omega, \forall L \subseteq \Omega, N(M \cap L) = min(N(M), N(L)),$$

and

$$\forall M \subseteq \Omega, \forall L \subseteq \Omega, N(M \cup L) \ge max(N(M), N(L)).$$

Remark 3.1. Clearly not all subsets of  $\Omega$ , the universe of discourse defined over a set of interpretations, represent axioms of a *DL-Lite* language. Namely, if M is a subset of  $\Omega$ , then it may happen that there is no  $\phi$ , an axiom of a *DL-Lite* language, such that  $M = [\phi]$  where  $[\phi]$  denotes the models of  $\phi$ . This is due to the fact that *DL-Lite* is not a very expressive language. For instance, assume that our vocabulary is composed of one concept A and two individuals  $a_1$  and  $a_2$ . Assume that we have two interpretations  $\mathcal{I}_1 = (\Delta^{\mathcal{I}} = \{a_1, a_2\}, \mathcal{I}_1)$  and  $\mathcal{I}_2 = (\Delta^{\mathcal{I}} = \{a_1, a_2\}, \mathcal{I}_2)$  such that  $A^{\mathcal{I}_1} = \{a_1\}$  and  $A^{\mathcal{I}_2} = \{a_2\}$ . Clearly,  $\{\mathcal{I}_1, \mathcal{I}_2\}$  does not correspond to any axiom of our *DL-Lite* language, since  $\{\mathcal{I}_1, \mathcal{I}_2\}$  intuitively encodes the formula  $A(a_1) \vee A(a_2)$ , while the disjunction operator between two assertions is not allowed in the *DL-Lite* language.

In the following, possibility and necessity measures are assumed to be only defined over a *DL-Lite* language. If  $\phi$  is an axiom of the *DL-Lite* language, we use  $[\phi]$  to denote the set of models of  $\phi$ , we define its associated possibility measure and its associated necessity measure respectively as follows:

$$\Pi([\phi]) = \sup_{\mathcal{I} \in \Omega} \{ \pi(\mathcal{I}) : \mathcal{I} \models \phi \},\$$

and

$$N([\phi]) = 1 - \sup_{I \in \Omega} \{ \pi(\mathcal{I}) : \mathcal{I} \not\models \phi \}.$$

where  $\mathcal{I} \not\models \phi$  means that  $\mathcal{I}$  is not a model of  $\phi$ .

Remark 3.2. In standard propositional possibilistic logic, the necessity measure is the dual of the possibility measure and it is defined by  $N([\psi]) = 1 - \Pi([\neg \psi])$  where  $\psi$  is a propositional formula and  $[\psi]$  is its associated propositional models (see Section 2.2.2). In possibilistic *DL-Lite*, the necessity measure cannot be defined as the dual of the possibility measure because the negation of a *DL-Lite* axiom is not allowed (except if  $\phi$  denotes basic facts, i.e membership assertions of the form A(a) or P(a,b)).

# **3.3** Possibilistic DL- $Lite_{core}$

In this section, we provide a possibilistic extension of  $DL\text{-}Lite_{core}$ , denoted by  $\pi\text{-}DL\text{-}Lite_{core}$ . We first present the syntax of  $\pi\text{-}DL\text{-}Lite_{core}$ . We then show how to generate the possibility distribution associated with a  $\pi\text{-}DL\text{-}Lite_{core}$  knowledge base. The section also contains some properties of  $\pi\text{-}DL\text{-}Lite_{core}$ .

#### 3.3.1 Syntax of $\pi$ -DL-Lite<sub>core</sub>

Let us consider  $\mathcal{L}_{core}$  a  $DL\text{-}Lite_{core}$  description language recalled in Section 1.4. A  $\pi\text{-}DL\text{-}Lite_{core}$  knowledge base is defined as follows:

**Definition 3.1.** A  $\pi$ -DL- $Lite_{core}$  knowledge base  $\mathcal{K} = \{ \langle \phi_i, \alpha_i \rangle : 1, ..., n \}$  is a finite set of possibilistic axioms of the form  $\langle \phi, \alpha \rangle$  where  $\phi$  is an axiom expressed in  $\mathcal{L}_{core}$  language and  $\alpha \in ]0,1]$  is the necessity (i.e. certainty) degree of  $\phi$ .

Only somewhat certain information (namely  $\alpha>0$ ) is explicitly represented in a  $\pi$ -DL-Lite knowledge base. A weighted axiom  $\langle \phi, \alpha \rangle$  means that the certainty degree of  $\phi$  is at least equal to  $\alpha$ . The higher the degree  $\alpha$  the more certain is the axiom or the fact. The degree  $\alpha$  can be associated either with an inclusion assertion between concepts (TBox), or with a membership assertion (ABox). A  $\pi$ -DL-Lite knowledge base  $\mathcal K$  will also be represented by a couple  $\mathcal K$ = $\langle \mathcal T, \mathcal A \rangle$  where both elements in  $\mathcal T$  and  $\mathcal A$  are at least somewhat certain. Note that in the definition of possibilistic-DL knowledge base proposed by Hollunder in [Hollunder, 1995], a possibilistic axiom is attached with a possibility value or a necessity value. Here, we only represent certainty using necessity values.

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Note that, if we consider \forall \alpha_i, \alpha_i = 1 then we represent a classical DL-Lite knowledge base: \mathcal{K}^* = \{\phi_i : \langle \phi_i, \alpha_i \rangle \in \mathcal{K} \}.
```

**Example 3.1.** Let Loyal, Discount, NeedBased, Impulse and Wandering be five atomic concepts that represent different types of customers. Let FidelityService be an atomic concept that represents fidelity service to be accorded to loyal customers. Let satisfiedBy be an atomic role that represents whether a loyal customer is satisfied by a fidelity service. We consider the following  $\pi$ -DL-Lite knowledge base where we use an ordinal uncertainty scale  $\{0, \gamma_1, ..., \gamma_n, 1\}$  with  $0 < \gamma_1 < \gamma_2 < ... < \gamma_n < 1$  and its possibilistic TBox  $\mathcal T$  contains the following axioms:

```
 \langle Discount \sqsubseteq Loyal, \gamma_6 \rangle \qquad \langle Impulse \sqsubseteq Discount, \gamma_3 \rangle 
 \langle NeedBased \sqsubseteq \neg Loyal, \gamma_2 \rangle \qquad \langle NeedBased \sqsubseteq Discount, \gamma_8 \rangle 
 \langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle \qquad \langle Wandering \sqsubseteq Impulse, \gamma_5 \rangle 
 \langle \exists satisfiedBy \vdash \sqsubseteq FidelityService, 1 \rangle \qquad \langle \exists satisfiedBy \sqsubseteq Loyal, 1 \rangle
```

and its possibilistic ABox A contains the following axioms:

```
\langle Wandering(John), \gamma_4 \rangle \qquad \langle Loyal(Mary), \gamma_1 \rangle \\ \langle NeedBased(John), \gamma_9 \rangle \qquad \langle satisfiedBy(John, Gifts), \gamma_{11} \rangle
```

This running example will be used in the rest of the chapter.

In a  $\pi$ -DL-Lite knowledge base, the necessity degree attached with an axiom reflects its confidence and evaluates to what extent this axiom is considered as certain. For instance in Example 3.1, the axiom  $\langle Discount \sqsubseteq Loyal, \gamma_6 \rangle$  states that "a Discount customer may be a Loyal customer with a certainty degree equal or greater than  $\gamma_6$ ". The degree 1 is used to represent fully certain pieces of information.

${\mathcal I}$	. I	$\pi_{\mathcal{K}}$
	$Loyal = \{John, Mary\}, Discount = \{\}$	
$\mathcal{I}_1$	$Impulse=\{\}, NeedBased=\{John\}, Wandering=\{John\},$	$1$ - $\gamma_8$
	$FidelityService = \{Gifts\}, satisfiedBy = \{(John, Gifts)\}$	
$\mathcal{I}_2$	$Loyal = \{John, Mary\}, Discount = \{John\}$	
	$Impulse = \{\}, NeedBased = \{John\}, Wandering = \{\}$	$1$ - $\gamma_4$
	$FidelityService = \{Gifts\}, satisfiedBy = \{(John, Gifts)\}$	
$\mathcal{I}_3$	$Loyal = \{John, Mary\}, Discount = \{John\}$	
	$Impulse=\{John\}, NeedBased=\{John\}, Wandering=\{John\}$	$1-\gamma_{10}$
	$FidelityService = \{Gifts\}, satisfiedBy = \{(John, Gifts)\}$	

Table 3.1: Example of a possibility distribution  $\pi_{\mathcal{K}}$  computed using Definition 3.2.

#### 3.3.2 From a $\pi$ -DL-Lite<sub>core</sub> knowledge base to a $\pi$ -DL-Lite<sub>core</sub> possibility distribution

The semantics of  $\pi$ -DL- $Lite_{core}$  is given by a possibility distribution, denoted by  $\pi_{\mathcal{K}}$ , defined over the set of all interpretations  $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$  of a DL-Lite language  $\mathcal{L}_{core}$  (see Section 3.2). As in standard possibilistic logic [Dubois *et al.*, 1994], given a  $\pi$ -DL- $Lite_{core}$  knowledge base  $\mathcal{K}$ , the possibility distribution induced by  $\mathcal{K}$  is defined as follows:

**Definition 3.2.** For every  $\mathcal{I} \in \Omega$ ,

$$\pi_{\mathcal{K}}(\mathcal{I}) = \begin{cases} 1 & if \ \forall \langle \phi_i, \alpha_i \rangle \in \mathcal{K}, \mathcal{I} \models \phi_i \\ 1 - max\{\alpha_i : \langle \phi_i, \alpha_i \rangle \in \mathcal{K}, \mathcal{I} \not\models \phi_i \} \text{ otherwise} \end{cases}$$

where  $\models$  is the satisfaction relation of *DL-Lite* formulas recalled in Section 1.4.  $\langle \phi_i, \alpha_i \rangle \in \mathcal{K}$  means that  $\langle \phi_i, \alpha_i \rangle$  either belongs to the TBox  $\mathcal{T}$  or to the ABox  $\mathcal{A}$  of  $\mathcal{K}$ .

**Example 3.2.** [Example 3.1 continued] Using Definition 3.2, Table 3.1 below gives possibility degree of three interpretations  $\mathcal{I}_1$ ,  $\mathcal{I}_2$  and  $\mathcal{I}_3$ . We assume that  $\Delta^{\mathcal{I}} = \{John, Mary, Gifts\}$  is the same for the three interpretations:

In this example, we can see that the interpretation  $\mathcal{I}_1$  does not satisfy  $\langle Need\text{-}Based\sqsubseteq\neg Loyal,\gamma_2\rangle$ ,  $\langle NeedBased\sqsubseteq Discount,\gamma_8\rangle$  and  $\langle Wandering\sqsubseteq Impulse,\gamma_5\rangle$ . The interpretation  $\mathcal{I}_2$  does not satisfy  $\langle NeedBased\sqsubseteq\neg Loyal,\gamma_2\rangle$  and  $\langle Wandering(John),\gamma_4\rangle$ . The interpretation  $\mathcal{I}_3$  does not satisfy  $\langle NeedBased\sqsubseteq\neg Loyal,\gamma_2\rangle$  and  $\langle Impulse\sqsubseteq\neg NeedBased,\gamma_{10}\rangle$ . Hence, none of these interpretations is a model of  $\mathcal{K}$ .

A  $\pi$ -DL-Lite<sub>core</sub> knowledge base  $\mathcal{K}$  is said to be consistent if its associated possibility distribution  $\pi_{\mathcal{K}}$  is normalized, namely there exists an interpretation  $\mathcal{I}$  such that  $\pi_{\mathcal{K}}(\mathcal{I})=1$ . Otherwise,  $\mathcal{K}$  is said to be inconsistent and its inconsistency degree is defined semantically as follows:

**Definition 3.3.** The inconsistency degree of a  $\pi$ -DL- $Lite_{core}$  knowledge base  $\mathcal{K}$ , denoted by  $Inc(\mathcal{K})$ , is semantically defined as follows:

$$Inc(\mathcal{K}) = 1 - \max_{\mathcal{I} \in \Omega} \{ \pi_{\mathcal{K}}(\mathcal{I}) \}.$$

If  $Inc(\mathcal{K})=1$  then  $\mathcal{K}$  is fully inconsistent and if  $Inc(\mathcal{K})=0$  then it is simply said to be consistent. One can easily check that  $Inc(\mathcal{K})=1-\Pi([\top])$ , where  $\Pi$  is the possibility measure defined in Section 3.2 and  $\top$  is a tautology.

**Example 3.3.** [Example 3.2 continued] One can check that the inconsistency degree of  $\mathcal{K}$  according to  $\pi_{\mathcal{K}}$  is:  $Inc(\mathcal{K})=1-\max_{\mathcal{I}\in\Omega}\{\pi_{\mathcal{K}}(\mathcal{I})\}=\gamma_4$ , and hence  $\mathcal{K}$  is inconsistent (in fact, there is no way to find an interpretation that satisfies  $\mathcal{K}$  with a degree greater than  $\gamma_4$ ).

The inconsistency degree allows to define different inference processes as follows:

**Definition 3.4** (Flat inference). Let  $\mathcal{K}$  be a  $\pi$ -DL- $Lite_{core}$  knowledge base,  $\pi_{\mathcal{K}}$  be the possibility distribution associated with  $\mathcal{K}$  and  $\phi$  be a DL-Lite axiom.  $\mathcal{K} \models_{\pi} \phi$  if and only if  $N_{\pi}(\phi) > Inc(\mathcal{K})$  where  $N_{\pi}$  is the necessity measure induced by  $\pi_{\mathcal{K}}$ .

Here, what is important is just to know whether the conclusion is plausible or not.

The following definition extends Definition 3.4, by requiring that a conclusion should be entailed with some degree.

**Definition 3.5** (Weighted inference). Let  $\mathcal{K}$  be a  $\pi$ -DL- $Lite_{core}$  knowledge base,  $\pi_{\mathcal{K}}$  be the possibility distribution associated with  $\mathcal{K}$  and  $\phi$  be a DL-Lite axiom.  $\mathcal{K} \models_{\pi} (\phi, \alpha)$  if and only if  $N_{\pi}(\phi) = \alpha > Inc(\mathcal{K})$  where  $N_{\pi}$  is the necessity measure induced by  $\pi_{\mathcal{K}}$ .

A method based on inconsistency computation for implementing inferences of Definitions 3.4 and Definition 3.5 is given in Section 3.7. Besides, the two kinds of inference detailed in this chapter are:

- Flat entailment, from which one is only interested to know whether an axiom is entailed or not from a possibilistic *DL-Lite* knowledge base,
- Weighted entailment, where given a weight  $\alpha$ , one is interested whether an axiom can be inferred with this specified degree.

Now if one is interested to compute the maximal degree of entailment of an axiom, we can use dichotomic search. The dichotomic search is applied over the set of all degrees used in the knowledge base (in both weighed TBox and weighted ABox).

Remark 3.3. In a propositional possibilistic logic setting, each possibilistic knowledge base induces a unique joint possibility distribution and each possibility distribution can be represented by a possibilistic knowledge base. Although each  $\pi$ -DL-Lite knowledge base induces a unique joint possibility distribution, the converse does not always hold.

Consider again the example where we only have one concept A and two individuals  $a_1$  and  $a_2$ . Consider four interpretations  $\mathcal{I}_1$ ,  $\mathcal{I}_2$ ,  $\mathcal{I}_3$  and  $\mathcal{I}_4$  having the same domain  $\Delta^{\mathcal{I}} = \{a_1, a_2\}$  where  $(A)^{\mathcal{I}_1} = \{a_1\}$ ,  $(A)^{\mathcal{I}_2} = \{a_2\}$ ,  $(A)^{\mathcal{I}_3} = \{a_1, a_2\}$  and  $(A)^{\mathcal{I}_4} = \emptyset$ . Assume that  $\pi(\mathcal{I}_1) = \pi(\mathcal{I}_2) = 1$  and  $\pi(\mathcal{I}_3) = \pi(\mathcal{I}_4) = .5$ . One can check that there is no  $\pi$ -DL-Lite knowledge base such that  $\pi_{\mathcal{K}} = \pi$ . This remark has no incidence on the results of this chapter. It simply points out some differences between standard propositional possibilistic logic and possibilistic DL-Lite $_{core}$ .

# 3.3.3 Logical properties of $\pi$ -DL-Lite<sub>core</sub>

In the following, we present some properties of  $\pi$ -DL- $Lite_{core}$ . These properties simply show that one can add conjunctions (*resp.* disjunctions) in the right side (*resp.* left side) of weighted inclusion axioms. Such results already hold in standard DL- $Lite_{core}$  [Calvanese *et al.*, 2007a] and in standard possibilistic logic [Dubois *et al.*, 1994]. For the sake of clarity, we rephrase them for possibilistic  $\pi$ -DL- $Lite_{core}$ .

Proposition 3.1 shows that a complex inclusion axiom of the form  $\langle B_1 \sqsubseteq C_1 \sqcap C_2, \alpha \rangle$  can be splitted into two elementary inclusion axioms that can be added to the  $\pi$ -DL-Lite<sub>core</sub> knowledge base without modifying its possibility distribution.

**Proposition 3.1.** Let  $K = \{ \langle B \sqsubseteq C_1 \sqcap C_2, \alpha \rangle, \mathcal{A} \}$  and  $K' = \{ \langle B \sqsubseteq C_1, \alpha \rangle, \langle B \sqsubseteq C_2, \alpha \rangle, \mathcal{A} \}$  be two  $\pi$ -DL-Lite<sub>core</sub> knowledge bases. Then K and K' induce the same possibility distribution, namely  $\forall \mathcal{I} \in \Omega, \pi_{K}(\mathcal{I}) = \pi_{K'}(\mathcal{I}).$ 

Proof of Proposition 3.1. The proof is immediate. Let  $\mathcal{I} = (\Delta^{\mathcal{I}}, \mathcal{I})$  be an interpretation. Assume that  $\mathcal{I} \models \langle B \sqsubseteq C_1 \sqcap C_2, \alpha \rangle$ . By definition of the satisfaction relation, this means that  $(B)^{\mathcal{I}} \subseteq ((C_1)^{\mathcal{I}} \cap (C_2)^{\mathcal{I}})$ . Hence  $(B)^{\mathcal{I}} \subseteq (C_1)^{\mathcal{I}}$  and  $(B)^{\mathcal{I}} \subseteq (C_2)^{\mathcal{I}}$ , which means that  $\mathcal{I} \models \langle B \sqsubseteq C_1, \alpha \rangle$  and  $\mathcal{I} \models \langle B \sqsubseteq C_2, \alpha \rangle$ . Therefore  $\pi_{\mathcal{K}}(\mathcal{I}) = \pi_{\mathcal{K}'}(\mathcal{I})$ .

Conversely, assume that  $\mathcal{I} \models \langle B \sqsubseteq C_1, \alpha \rangle$  and  $\mathcal{I} \models \langle B \sqsubseteq C_2, \alpha \rangle$ . By definition of the satisfaction relation, this again means that  $(B)^{\mathcal{I}} \subseteq (C_1)^{\mathcal{I}}$  and  $(B)^{\mathcal{I}} \subseteq (C_2)^{\mathcal{I}}$ . Hence  $(B)^{\mathcal{I}} \subseteq ((C_1)^{\mathcal{I}} \cap (C_2)^{\mathcal{I}})$  which means that  $\mathcal{I} \models \langle B \sqsubseteq C_1 \sqcap C_2, \alpha \rangle$ . Therefore  $\pi_{\mathcal{K}}(\mathcal{I}) = \pi_{\mathcal{K}'}(\mathcal{I})$ .

The other cases, where  $\mathcal{I} \not\models (B \sqsubseteq C_1 \sqcap C_2, \alpha)$  or  $\mathcal{I} \not\models (B \sqsubseteq C_1, \alpha)$  and  $\mathcal{I} \not\models (B \sqsubseteq C_2, \alpha)$  follow similarly.

Proposition 3.2 shows that a complex inclusion axiom of the form  $(B_1 \sqcup B_2 \sqsubseteq C, \alpha)$  can be splitted into two elementary inclusion axioms that can be added to a  $\pi$ -DL-Lite<sub>core</sub> knowledge base without modifying its possibility distribution.

**Proposition 3.2.** Let  $K = \{\langle B_1 \sqcup B_2 \sqsubseteq C, \alpha \rangle, A\}$  and  $K' = \{\langle B_1 \sqsubseteq C, \alpha \rangle, \langle B_2 \sqsubseteq C, \alpha \rangle\}, A\}$  be two  $\pi$ -DL-Lite<sub>core</sub> knowledge bases. Then K and K' induce the same possibility distribution, namely  $\forall \mathcal{I} \in \Omega, \pi_{K}(\mathcal{I}) = \pi_{K'}(\mathcal{I}).$ 

*Proof of Proposition 3.2.* The proof of Proposition 3.2 is similar to the one of Proposition 3.1.  $\Box$ 

# 3.4 Possibilistic negated closure in $\pi$ -DL-Lite<sub>core</sub>

The aim of this section is to define the so-called  $\pi$ -negated closure of a  $\pi$ -DL-Lite<sub>core</sub> knowledge base. This notion is crucial for characterizing the concepts of consistency and inference from a  $\pi$ -DL-Lite<sub>core</sub> knowledge base.

#### 3.4.1 Rules used to obtain $\pi$ -negated closure

A possibilistic  $\pi$ -DL- $Lite_{core}$  TBox  $\mathcal{T} = \{\mathcal{T}_p, \mathcal{T}_n\}$  can be viewed as composed of positive inclusion axioms of the form  $\langle B_1 \sqsubseteq B_2, \alpha \rangle$  and negative inclusion axioms of the form  $\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle$ . The possibilistic negated closure, denoted by  $\pi$ - $neg(\mathcal{T})$ , will contain all the possibilistic negated axioms of the form  $\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle$  that can be derived from  $\mathcal{T}$ . Roughly speaking, the set  $\pi$ - $neg(\mathcal{T})$  is obtained by applying a set of three rules that extend the ones defined in standard DL- $Lite_{core}$  when axioms are weighted with certainty degrees.

At the beginning  $\pi$ -neg( $\mathcal{T}$ ), is set to an empty set.

**Rule 3.1.** Let  $\mathcal{T} = \{\mathcal{T}_p, \mathcal{T}_n\}$  then add all negated axioms of  $\mathcal{T}$  to  $\pi$ -neg( $\mathcal{T}$ ).

**Example 3.4.** [Example 3.1 continued] Using Rule 3.1, we add  $\langle NeedBased \sqsubseteq \neg Loyal, \gamma_2 \rangle$  and  $\langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle$  to  $\pi$ -neg( $\mathcal{T}$ ).

The first rule states that negative axioms that are explicitly stated in  $\mathcal{K}$  are trivially entailed from  $\mathcal{K}$ , and hence can be added to  $\pi$ -neg( $\mathcal{T}$ ).

**Rule 3.2.** If  $\langle B_1 \sqsubseteq B_2, \alpha_1 \rangle \in \mathcal{T}$  and  $\langle B_2 \sqsubseteq \neg B_3, \alpha_2 \rangle \in \pi$ -neg( $\mathcal{T}$ ) then add  $\langle B_1 \sqsubseteq \neg B_3, min(\alpha_1, \alpha_2) \rangle$  to  $\pi$ -neg( $\mathcal{T}$ ).

The second rule expresses transitivity relation induced by the inclusion assertion relation.

```
Rule 3.3. If \langle B_1 \sqsubseteq B_2, \alpha_1 \rangle \in \mathcal{T} and \langle B_3 \sqsubseteq \neg B_2, \alpha_2 \rangle \in \pi-neg(\mathcal{T}) then add \langle B_1 \sqsubseteq \neg B_3, min(\alpha_1, \alpha_2) \rangle to \pi-neg(\mathcal{T}).
```

*Remark* 3.4. Note that instead of Rule 3.3 one can define the following rule:

```
If \langle B_1 \sqsubseteq \neg B_2, \alpha \rangle \in \pi-neg(\mathcal{T}) then add \langle B_2 \sqsubseteq \neg B_1, \alpha \rangle \in \pi-neg(\mathcal{T}) and then re-use Rule 3.2.
```

As we will see in Proposition 3.3, these rules (Rules 3.1-3.3) are enough for  $\pi$ -DL- $Lite_{core}$ . In particular, these rules will be useful to equivalently define an efficient inference using directly  $\pi$ - $neg(\mathcal{T})$ . As it will be shown later, the minimum operation used in the rules for propagating certainty degrees is justified by the fact that the joint possibility distribution will not be affected if the derived inclusion relations are added to the knowledge base. Lastly, when the degrees  $\alpha_i$ 's are equal to 1, then  $\pi$ - $neg(\mathcal{T})$  simply collapses with the standard negated closure defined for standard DL- $Lite_{core}$  knowledge bases. In fact,  $\pi$ - $neg(\mathcal{T})$  extends standard DL- $Lite_{core}$  when one only deals with fully certain pieces of information.

**Example 3.5.** [Example 3.1 continued] Using  $\pi$ -neg( $\mathcal{T}$ ) of Example 3.4, Rules 3.2-3.3 allow to derive the following negative axioms:

- $\langle Discount \sqsubseteq Loyal, \gamma_6 \rangle$  and  $\langle NeedBased \sqsubseteq \neg Loyal, \gamma_2 \rangle$  lead to adding  $\langle Discount \sqsubseteq \neg NeedBased, \gamma_2 \rangle$  to  $\pi$ -neg( $\mathcal{T}$ ).
- $\langle Impulse \sqsubseteq Discount, \gamma_3 \rangle$  and  $\langle Discount \sqsubseteq \neg NeedBased, \gamma_2 \rangle$  lead to adding  $\langle Impulse \sqsubseteq \neg NeedBased, \gamma_2 \rangle$  to  $\pi$ -neg( $\mathcal{T}$ ).
- $\langle NeedBased \sqsubseteq Discount, \gamma_8 \rangle$  and  $\langle Discount \sqsubseteq \neg NeedBased, \gamma_2 \rangle$ , lead to adding  $\langle NeedBased \sqsubseteq \neg NeedBased, \gamma_2 \rangle$  to  $\pi$ -neg( $\mathcal{T}$ ).

Next lemma deals with redundancy and simply states that an axiom does not need to appear several times in a knowledge base. It is enough to keep the one having the highest degree.

**Lemma 3.1.** Let  $K = \langle T, A \rangle$  be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base. Let  $B_1 \sqsubseteq B_2$  (or  $B_1 \sqsubseteq \neg B_2$ ) be a TBox axiom and X be an ABox assertion.

- 1. Assume that  $\langle B_1 \sqsubseteq B_2, \alpha_1 \rangle$  and  $\langle B_1 \sqsubseteq B_2, \alpha_2 \rangle$  belong to  $\mathcal{T}$ . Then  $\mathcal{K}$  and  $\mathcal{K}' = \langle \mathcal{T}', \mathcal{A} \rangle$  where  $\mathcal{T}' = (\mathcal{T} \setminus \{\langle B_1 \sqsubseteq B_2, \alpha_1 \rangle, \langle B_1 \sqsubseteq B_2, \alpha_2 \rangle\}) \cup \{\langle B_1 \sqsubseteq B_2, max(\alpha_1, \alpha_2) \rangle\}$  are equivalent in the sense that for all  $\mathcal{I} \in \Omega$ ,  $\pi_{\mathcal{K}}(\mathcal{I}) = \pi_{\mathcal{K}'}(\mathcal{I})$ .
- 2. Similarly, assume that  $\langle X, \alpha_1 \rangle$  and  $\langle X, \alpha_2 \rangle$  belong to  $\mathcal{A}$ . Then  $\mathcal{K}$  and  $\mathcal{K}' = \langle \mathcal{T}, \mathcal{A}' \rangle$  where  $\mathcal{A}' = (\mathcal{A} \setminus \{\langle X, \alpha_1 \rangle, \langle X, \alpha_2 \rangle\}) \cup \{\langle X, max(\alpha_1, \alpha_2) \rangle\}$  are equivalent in the sense that for all  $\mathcal{I} \in \Omega$ ,  $\pi_{\mathcal{K}}(\mathcal{I}) = \pi_{\mathcal{K}'}(I)$ .

*Proof of Lemma 3.1.* The proof of the lemma immediately follows from the definition of the possibility distribution associated with a  $\pi$ -DL- $Lite_{core}$  knowledge base.

**Example 3.6.** [Example continued] In the  $\pi$ -neg( $\mathcal{T}$ ) of Examples 3.4 and 3.5, we observe that we derive both  $\langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle$  and  $\langle Impulse \sqsubseteq \neg NeedBased, \gamma_{2} \rangle$ . Using Lemma 3.1, we only keep  $\langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle$  in  $\pi$ -neg( $\mathcal{T}$ ).

**Example 3.7.** [Example continued] We now give the  $\pi$ - $neg(\mathcal{T})$  of the Example 3.1 using Rules 3.1-3.3 and Lemma 3.1:

```
 \langle NeedBased \sqsubseteq \neg Loyal, \gamma_2 \rangle \qquad \langle NeedBased \sqsubseteq \neg NeedBased, \gamma_2 \rangle \\ \langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle \qquad \langle Wandering \sqsubseteq \neg NeedBased, \gamma_5 \rangle \\ \langle Discount \sqsubseteq \neg NeedBased, \gamma_2 \rangle \qquad \langle \exists satisfiedBy \sqsubseteq \neg NeedBased, \gamma_2 \rangle
```

# 3.4.2 Properties of $\pi$ -negated closure

This subsection gives some properties of the  $\pi$ -negated closure of a  $\pi$ -DL-Lite<sub>core</sub>. Given  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  a  $\pi$ -DL-Lite<sub>core</sub> knowledge base, we define the  $\alpha$ -cut of  $\mathcal{K}$  (resp.  $\mathcal{T}$  and  $\mathcal{A}$ ), denoted by  $\mathcal{K}_{\geq \alpha}$  (resp.  $\mathcal{T}_{\geq \alpha}$  and  $\mathcal{A}_{\geq \alpha}$ ), the subbase of  $\mathcal{K}$  (resp.  $\mathcal{T}$  and  $\mathcal{A}$ ) composed of axioms having weights  $\alpha_i$  that are at least equal to  $\alpha$  and the strict  $\alpha$ -cut of  $\mathcal{K}$  (resp.  $\mathcal{T}$  and  $\mathcal{A}$ ), denoted by  $\mathcal{K}_{>\alpha}$  (resp.  $\mathcal{T}_{>\alpha}$ ,  $\mathcal{A}_{>\alpha}$ ), as a subbase of  $\mathcal{K}$  (resp.  $\mathcal{T}$  and  $\mathcal{A}$ ) composed of axioms having weights  $\alpha_i$  strictly greater than  $\alpha$ .

**Lemma 3.2.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base. Let  $\alpha_1$  and  $\alpha_2$  be two degrees in [0,1] such that  $\alpha_1 > \alpha_2$ . Then:

$$\pi$$
-neg( $\mathcal{T}_{>\alpha_1}$ ) $\subseteq \pi$ -neg( $\mathcal{T}_{>\alpha_2}$ )

*Proof of Lemma 3.2.* The proof is immediate. Indeed, to obtain  $\pi$ - $neg(\mathcal{T}_{\geq \alpha_2})$ , one may apply Rules 3.1-3.3 to all axioms of  $\mathcal{T}_{\geq \alpha_2}$  and implicitly  $\mathcal{T}_{\geq \alpha_1}$ , since  $\mathcal{T}_{\geq \alpha_1} \subseteq \mathcal{T}_{\geq \alpha_2}$ . This leads to trivially obtain  $\pi$ - $neg(\mathcal{T}_{\geq \alpha_1})$  by re-applying again Rules 3.1-3.3 on remaining weighted axioms of  $\mathcal{T}_{\geq \alpha_1}$ .

The following lemma states that deriving negative axioms with weights greater or equal to  $\alpha$  can be equivalently done either by deriving all weighted negative axioms then select those having a weight greater or equal to  $\alpha$ , or select initial axioms from  $\mathcal K$  having a weight greater or equal to  $\alpha$  then apply the negative closure of this subbase of  $\mathcal K$ .

**Lemma 3.3.** Let K be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base. Let  $\pi$ -neg( $\mathcal{T}$ ) be the possibilistic negative closure of K. Then:

$$\pi$$
-neg( $\mathcal{T}$ )> $\alpha$ = $\pi$ -neg( $\mathcal{T}$ > $\alpha$ )

*Proof of Lemma 3.3.* The proof of this lemma can be obtained by first noticing that to compute  $\pi$ - $neg(\mathcal{T})$  one may start with only axioms having a weigh greater or equal to  $\alpha$ . This leads to  $\pi$ - $neg(\mathcal{T}_{\geq \alpha})$ . Now, applying Rules 3.1-3.3 to axioms with weights strictly less than  $\alpha$  leads to derive negative axioms with weights also less than  $\alpha$ . Hence, they will not belong to  $\pi$ - $neg(\mathcal{T})_{>\alpha}$ .

Proposition 3.3 states that adding all negative axioms of  $\pi$ - $neg(\mathcal{T})$  to  $\mathcal{T}$  does not change the induced possibility distribution.

**Proposition 3.3.** Let  $\mathcal{T} = \{\mathcal{T}_p, \mathcal{T}_n\}$  and  $\pi\text{-}neg(\mathcal{T})$  be the negated closure of  $\mathcal{T}$  obtained using Rules (3.1-3.3). Then  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  and its  $\mathcal{K}' = \langle \mathcal{T} \cup \pi - neg(\mathcal{T}), \mathcal{A} \rangle$  induce the same possibility distribution, namely  $\forall \mathcal{I} \in \Omega : \pi_{\mathcal{K}}(\mathcal{I}) = \pi_{\mathcal{K}'}(I)$ .

Proof of Proposition 3.3. It is sufficient to show that one application of Rule 3.2 (or Rule 3.3) does not modify the possibility distribution. It is enough then to repeat the application of Rule 3.2 (or Rule 3.3) on the obtained and derived negative inclusion axioms. Assume that  $\langle B_1 \sqsubseteq B_2, \alpha_1 \rangle \in \mathcal{T}$  and  $\langle B_2 \sqsubseteq \neg B_3, \alpha_2 \rangle \in \mathcal{T}$ . Let us show that the result of applying Rule 3.2, which leads to add  $\langle B_1 \sqsubseteq \neg B_3, \min(\alpha_1, \alpha_2) \rangle$  does not modify the possibility distribution. Namely,  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  and  $\mathcal{K}' = \langle \mathcal{T} \cup \{\langle B_1 \sqsubseteq \neg B_3, \min(\alpha_1, \alpha_2) \}, \mathcal{A} \rangle$  are equivalent. Let  $\mathcal{I} = (\Delta^{\mathcal{I}}, \mathcal{I})$  be an interpretation. We consider three cases:

1.  $\mathcal{I} \models B_1 \sqsubseteq B_2$  and  $\mathcal{I} \models B_2 \sqsubseteq \neg B_3$ . By definition of the satisfaction relation, this means that:  $(B_1)^{\mathcal{I}} \subseteq (B_2)^{\mathcal{I}}$  and  $(B_2)^{\mathcal{I}} \subseteq (\neg B_3)^{\mathcal{I}}$ . Hence,  $(B_1)^{\mathcal{I}} \subseteq (\neg B_3)^{\mathcal{I}}$ , which means that  $\mathcal{I} \models B_1 \sqsubseteq \neg B_3$ . Therefore  $\pi_{\mathcal{K}}(\mathcal{I}) = \pi_{\mathcal{K}'}(\mathcal{I})$ .

2.  $\mathcal{I} \models B_1 \sqsubseteq B_2$  and  $\mathcal{I} \models B_2 \sqsubseteq \neg B_3$  (the other case, where  $\mathcal{I} \not\models B_1 \sqsubseteq B_2$  and  $\mathcal{I} \models B_2 \sqsubseteq \neg B_3$ , follows similarly). Let  $\mathcal{K}'' = \mathcal{K} \setminus \{ \langle B_1 \sqsubseteq B_2, \alpha_1 \rangle, \langle B_2 \sqsubseteq \neg B_3, \alpha_2 \rangle \}$ . We have:

$$\pi_{\mathcal{K}}(\mathcal{I}) = \min(\pi_{\mathcal{K}''}(\mathcal{I}), 1 - \alpha_2)$$

$$= \min(\pi_{\mathcal{K}''}(\mathcal{I}), 1 - \alpha_2, 1 - \min(\alpha_1, \alpha_2))$$

$$= \pi_{\mathcal{K}'}(\mathcal{I})$$

3.  $\mathcal{I} \not\models B_1 \sqsubseteq B_2$  and  $\mathcal{I} \not\models B_2 \sqsubseteq \neg B_3$ . Again let  $\mathcal{K}'' = \mathcal{K} \setminus \{\langle B_1 \sqsubseteq B_2, \alpha_1 \rangle, \langle B_2 \sqsubseteq \neg B_3, \alpha_2 \rangle\}$ . We have

$$\pi_{\mathcal{K}}(\mathcal{I}) = \min(\pi_{\mathcal{K}''}(\mathcal{I}), 1 - \alpha_1, 1 - \alpha_2)$$
  
= 
$$\min(\pi_{\mathcal{K}''}(\mathcal{I}), 1 - \alpha_1, 1 - \alpha_2, 1 - \min(\alpha_1 \alpha_2))$$
  
= 
$$\pi_{\mathcal{K}'}(\mathcal{I}).$$

# 3.5 Checking inconsistency degrees

In this section, we show how to compute the inconsistency degree of a  $\pi$ -DL- $Lite_{core}$  knowledge base using query evaluations.

# 3.5.1 Additional properties of $\pi$ -neg( $\mathcal{T}$ )

In the previous section (Section 3.4), we showed that adding  $\pi$ - $neg(\mathcal{T})$  to  $\mathcal{T}$  does not modify the joint possibility distribution (Proposition 3.3). This subsection shows that computing the inconsistency degree of  $\mathcal{K}=\langle \mathcal{T},\mathcal{A}\rangle$  comes down to compute the inconsistency degree of  $\mathcal{K}'=\langle \pi$ - $neg(\mathcal{T}),\mathcal{A}\rangle$ .

We first introduce the two following technical lemmas.

**Lemma 3.4.** Let K be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base. Let  $K^*$  be the standard DL-Lite<sub>core</sub> knowledge base obtained from K by ignoring the weights associated with axioms of K. Let  $cln(\mathcal{T}^*)$  be the negated closure (NI-closure) defined in [Calvanese et al., 2007a]. Then:

$$cln(\mathcal{T}^*) = \{B_1 \sqsubseteq \neg B_2 : \langle B_1 \sqsubseteq \neg B_2, \alpha \rangle \in \pi\text{-}neg(\mathcal{T})\}$$

This lemma states that our definition of  $\pi$ -neg( $\mathcal{T}$ ) recovers the one used in standard DL- $Lite_{core}$ . Namely, we derive the same set of negative axioms as in standard DL- $Lite_{core}$  knowledge base. However, in our approach the negative axioms are attached with certainty degrees.

*Proof of Lemma 3.4.* The proof of Lemma 3.4 follows from the fact that removing weights from Rules 3.1-3.3 gives exactly the same rules used in [Calvanese *et al.*, 2007a] for deriving the negated closure, denoted by  $cln(\mathcal{T})$ , of a standard DL- $Lite_{core}$  knowledge base  $\mathcal{B} = \langle \mathcal{T}, \mathcal{A} \rangle$ .

**Lemma 3.5.** Let K be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base. Then

$$cln(\mathcal{T}^*_{>\alpha}) = \{B_1 \sqsubseteq \neg B_2 : \langle B_1 \sqsubseteq \neg B_2, \beta \rangle \in \pi\text{-}neg(\mathcal{T}) \text{ and } \beta \geq \alpha \}$$

Lemma 3.5 is in the spirit of Lemma 3.4. It states that the negative closure of a subbase of K can be recovered from  $\pi$ -neg(T).

**Proposition 3.4.** Let  $K = \langle T, A \rangle$  and let  $K' = \langle \pi \text{-}neg(T), A \rangle$  Then:

$$Inc(\mathcal{K}) = Inc(\mathcal{K}')$$

Proof of Proposition 3.4. Recall that in standard DL-Lite, a DL-Lite<sub>core</sub> knowledge base  $\mathcal{K}_s = \langle \mathcal{T}_s, \mathcal{A}_s \rangle$  is inconsistent if and only if the knowledge base  $\langle cln(\mathcal{T}_s), \mathcal{A}_s \rangle$  is inconsistent, where  $cln(\mathcal{T}_s)$  is the negative closure of  $\mathcal{K}_s$  defined in [Calvanese et al., 2007a] (see Section 1.4).

Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL- $Lite_{core}$  knowledge base. Now assume that  $Inc(\mathcal{K}) = \alpha$ . This means that  $\mathcal{K}_{>\alpha}$  is consistent and  $\mathcal{K}_{>\alpha}$  is inconsistent. This also means that (using the above lemmas):

$$\langle cln(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$$
 is consistent,

and

$$\langle cln(\mathcal{T}, \mathcal{A}) \rangle_{\alpha}$$
 is inconsistent.

Now, using Lemma 3.5, this also means that:

$$\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$$
 is consistent

while

$$\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$$
 is inconsistent,

which means that the inconsistency degree of  $\mathcal{K}' = \langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle$  is equal to  $\alpha$ . The converse follows in a similar way.

Proposition 3.4 is important since it provides a way to compute the inconsistency degree of a  $\pi$ -DL- $Lite_{core}$  knowledge base. Indeed, computing the inconsistency degree of  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  is reduced to computing the inconsistency degree of  $\mathcal{K}' = \langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle$ .

### 3.5.2 Computing inconsistency degrees in $\pi$ -DL-Lite<sub>core</sub>

We now provide a characterization of the inconsistency degree of a  $\pi$ -DL- $Lite_{core}$  knowledge base by only focusing on  $\langle \pi$ - $neg(\mathcal{T}), \mathcal{A} \rangle$ . First recall that the ABox only contains positive membership assertions (facts). Hence, the ABox alone is always consistent. Similarly, the TBox  $\pi$ - $neg(\mathcal{T})$  alone (namely, when ABox= $\emptyset$ ) is also consistent. Indeed, it is easy to define an interpretation  $\mathcal{I}$  which is a model of  $\pi$ - $neg(\mathcal{T})$ . For each  $\langle B_i \sqsubseteq \neg B_j, \alpha \rangle \in \pi$ - $neg(\mathcal{T})$ , we let  $(B_i)^{\mathcal{I}} = \emptyset$  if  $B_i$  is a concept and  $(R)^{\mathcal{I}} = \emptyset$  if  $B_i$  is of the form  $\exists R$  or  $\exists R^-$  and R is a role.  $\mathcal{I}$  is then trivially a model of  $\pi$ - $neg(\mathcal{T})$ . Hence, pieces responsible of inconsistency should involve both elements from  $\pi$ - $neg(\mathcal{T})$  and  $\mathcal{A}$ .

We now introduce the concept of a conflict and to what extent its elements are conflicting.

**Definition 3.6.** A conflict C of  $\langle \pi - neg(T), A \rangle$  is a subbase of  $\langle \pi - neg(T), A \rangle$  of the form

$$\{\langle B_1 \sqsubseteq \neg B_2, \alpha_1 \rangle, \langle X, \alpha_2 \rangle, \langle Y, \alpha_3 \rangle\}$$

such that:

- $\langle B_1 \sqsubseteq \neg B_2, \alpha_1 \rangle \in \pi \text{-}neg(\mathcal{T}).$
- $\langle X, \alpha_2 \rangle \in \mathcal{A}$  and  $\langle Y, \alpha_3 \rangle \in \mathcal{A}$  with X and Y are such that there exist two individuals a and b where:

$$X = \begin{cases} A(a) & \text{if } B_1 \text{ is a basic concept A,} \\ P(a,b) & \text{if } B_1 \text{ is of the form } \exists P \text{ and } P \text{ is a role,} \\ P(b,a) & \text{if } B_1 \text{ is of the form } \exists P^- \text{ and } P \text{ is a role.} \end{cases}$$

```
Y = \begin{cases} A(a) & \text{if } B_2 \text{ is a basic concept A}, \\ P(a,b) & \text{if } B_2 \text{ is of the form } \exists P \text{ and } P \text{ is a role}, \\ P(b,a) & \text{if } B_2 \text{ is of the form } \exists P^- \text{ and } P \text{ is a role}. \end{cases}
```

Besides, an inconsistency problem is always defined with respect to some ABox assertions and a TBox axiom, since a TBox may be incoherent but never inconsistent. Before introducing the property of conflict in  $\pi$ -DL-Lite<sub>core</sub>, let us first remind the Calvanese *et al.* result [Calvanese *et al.*, 2010].

**Lemma 3.6.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a DL-Lite knowledge base. If K is inconsistent, then there exists a subset  $A_0 \subseteq A$  with at most two elements, such that  $\mathcal{T} \cup A_0$  is inconsistent.

The following lemma relates the concept of conflict given in Definition 3.6 with a standard definition of conflicts.

**Lemma 3.7.** C is a conflict of  $\langle \pi\text{-}neg(\mathcal{T}), \mathcal{A} \rangle$  (using Definition 3.6) if and only if it is a minimal inconsistent subset of  $\langle \pi\text{-}neg(\mathcal{T}), \mathcal{A} \rangle$ .

*Proof of Lemma 3.7.* Assume that C is a conflict in the sense of Definition 3.6. By definition, C is inconsistent.

- Let us show that  $\mathcal C$  is minimal. Indeed, let  $\mathcal C = \{\langle B_1 \sqsubseteq \neg B_2, \alpha_1 \rangle, \langle X, \alpha_2 \rangle, \langle Y, \alpha_3 \rangle\}$ . First note that if  $B_1 = B_2$  (hence X = Y and  $\alpha_2 = \alpha_3$ ) then clearly  $\{\langle B_1 \sqsubseteq \neg B_1, \alpha_1 \rangle\}$  and  $\langle X, \alpha_2 \rangle$  are individually consistent. More generally, when  $B_1 \neq B_2$ , we have  $\mathcal C \setminus \{\langle B_1 \sqsubseteq \neg B_1, \alpha_1 \rangle\}$  is consistent since it is only composed of assertional facts. Similarly,  $\mathcal C \setminus \{\langle X, \alpha_2 \rangle\}$  (resp.  $\mathcal C \setminus \{\langle Y, \alpha_2 \rangle\}$ ) is also consistent. Indeed if  $X = B_1(a)$  (the other cases where X = P(a, b) or X = P(b, a) follow similarly), then it is enough to define a model  $\mathcal I$  in which  $(B_1)^{\mathcal I} = \{a\}$  and  $(B_2)^{\mathcal I} = \emptyset$ .
- Now let us show the converse. Namely, assume that  $\mathcal{C}$  is a minimal inconsistent subset of  $\langle \pi neg(\mathcal{T}), \mathcal{A} \rangle$ . Since  $\pi neg(\mathcal{T})$  and  $\mathcal{A}$  taken alone are consistent, then  $\mathcal{C}$  necessarily contains at least an element of  $\pi neg(\mathcal{T})$  and at least an element from  $\mathcal{A}$ . Besides, from Lemma 3.6, there exists at most two elements from  $\mathcal{A}$  in  $\mathcal{C}$ . If there exists exactly one element  $\langle X, \alpha_2 \rangle$  from  $\mathcal{A} \in \mathcal{C}$ , then there exists necessarily one negative axiom  $\langle B_1 \sqsubseteq \neg B_1, \alpha_1 \rangle$  in  $\pi neg(\mathcal{T})$  which is inconsistent with  $\langle X, \alpha_2 \rangle$ . This is a particular case of Definition 3.6 where  $B_1 = B_2$ , X = Y and  $\alpha_2 = \alpha_3$ . Now, if there are two elements  $\langle X, \alpha_2 \rangle$  and  $\langle Y, \alpha_3 \rangle$  from  $\mathcal{A}$  in  $\mathcal{C}$  then necessarily there exists again one axiom  $\langle B_1 \sqsubseteq \neg B_2, \alpha_1 \rangle$  from  $\mathcal{T}$  (otherwise  $\mathcal{C}$  will not be minimal). We get again the characterization of conflicts given in Definition 3.6.

A conflict is clearly an inconsistent subset of information. It is minimal (up to a particular case where  $B_1 = B_2$ ). Indeed, removing any element of a conflict restores consistency. A particular case is when  $B_1 \sqsubseteq \neg B_1$  belongs to  $\pi$ -neg( $\mathcal{T}$ ). This corresponds to the situation of an unsatisfiable concept. Namely, there is no way to find an individual that belongs to  $B_1$ . In this case, a conflict is only composed of two elements. A conflict hence involves one negative axiom from  $\pi$ -neg( $\mathcal{T}$ ) and one or two membership assertions.

**Example 3.8.** [Example continued] Using Definition 3.6, from  $\pi$ - $neg(\mathcal{T})$  of Example 3.7 and the ABox of Example 3.1, we have the following conflicts:

•  $C_1 = \{\langle NeedBased \sqsubseteq \neg NeedBased, \gamma_2 \rangle, \langle NeedBased(John), \gamma_9 \rangle \}$  (conflict composed only of two elements).

- $C_2 = \{ \langle Wandering \sqsubseteq \neg NeedBased, \gamma_5 \rangle, \langle NeedBased(John), \gamma_9 \rangle, \langle Wandering(John), \gamma_4 \rangle \}$
- $C_3 = \{ \langle \exists satisfiedBy \sqsubseteq \neg NeedBased, \gamma_2 \rangle, \langle satisfiedBy(John, Gifts), \gamma_{11} \rangle, \langle NeedBased(John), \gamma_9 \rangle \}.$

The following definition introduces the concepts of the degree of a conflict.

**Definition 3.7.** Let  $\mathcal{C}$  be a conflict. We define the degree of conflict, denoted by  $Deq(\mathcal{C})$ , as:

$$Deg(\mathcal{C}) = min(\alpha_1, \alpha_2, \alpha_3),$$

where  $(B_1 \sqsubseteq \neg B_2, \alpha_1) \in \mathcal{C}, (X, \alpha_2) \in \mathcal{C}$  and  $(Y, \alpha_3) \in \mathcal{C}$ , and X, Y are defined in Definition 3.6.

**Example 3.9.** [Example continued] From Example 3.8, the degree of the conflict  $C_1$  is  $Deg(C_1) = (\gamma_2, \gamma_9) = \gamma_2$ , the degree of the conflict  $C_2$  is  $Deg(C_2) = min(\gamma_5, \gamma_4, \gamma_9) = \gamma_4$  and the degree of the conflict  $C_3$  is  $Deg(C_3) = min(\gamma_2, \gamma_{11}, \gamma_9) = \gamma_2$ .

We are now ready to give a characterization of  $Inc(\mathcal{K})$  using conflicts and their degrees:

**Proposition 3.5.** Let  $K = \langle T, A \rangle$  be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base and  $\pi$ -neg(T) be its negated closure. Then:

$$Inc(\mathcal{K}) = Inc(\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle)$$
  
=  $max\{Deg(\mathcal{C}) : \mathcal{C} \text{ is a conflict of } \langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle\}$ 

*Proof of Proposition 3.5.* Assume that  $Inc(\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle) = \alpha$ . This means that:

$$\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$$
 is consistent

but

$$\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{\geq \alpha}$$
 is inconsistent

This also means that there exists a conflict  $C \in \langle \pi\text{-}neg(\mathcal{T}), \mathcal{A} \rangle_{\geq \alpha}$ . Indeed, to build a conflict C from the inconsistent knowledge base  $\langle \pi\text{-}neg(\mathcal{T}), \mathcal{A} \rangle_{\geq \alpha}$ , it is enough to proceed iteratively by removing one element at once until reaching minimal inconsistency. More precisely,

- i) we first let  $\mathcal{C} = \langle \pi \text{-}neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$ ,
- ii) if there exists  $x \in \mathcal{C}$  such that  $\mathcal{C} \setminus \{x\}$  is inconsistent, then  $\mathcal{C} = \mathcal{C} \setminus \{x\}$ ,
- iii) repeat step (ii) until there is no x such that  $\mathcal{C} \setminus \{x\}$  is inconsistent.  $\mathcal{C}$  is then a conflict.

Besides,  $Deg(\mathcal{C}) = \alpha$ . Otherwise  $\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$  would be inconsistent. Now, the fact that  $\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$  is consistent means that there is no conflict  $\mathcal{C}$  that belongs to  $\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$ . Hence,  $max\{Deg(\mathcal{C}) : \mathcal{C} \text{ is a conflict of } \langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle\} = \alpha$ .

The converse is also straightforward. Indeed, let  $max\{Deg(\mathcal{C}): \mathcal{C} \text{ is a conflict of } \langle \pi-neg(\mathcal{T}), \mathcal{A} \rangle\} = \alpha$ . This means that  $\langle \pi-neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$  is consistent. Otherwise there exists a conflict  $\mathcal{C} \in \langle \pi-neg(\mathcal{T}), \mathcal{A} \rangle_{>\alpha}$  with  $Deg(\mathcal{C}) > \alpha$  (which is impossible).

This also means that  $\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle_{\geq \alpha}$  is inconsistent. Therefore, by definition,  $Inc(\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle) = \alpha$ .

**Example 3.10.** [Example continued] From Example 3.9, one can easily check that  $Inc(\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle) = \gamma_4$ .

Proposition 3.5 is important since it provides a natural way to compute  $Inc(\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle)$ . A contradiction is present when the same individual belongs to two concepts that compose a negated axiom (i.e. an axiom of  $\pi$ -neg( $\mathcal{T}$ )). The idea in computing the inconsistency degree is to evaluate over  $\mathcal{A}$  suitable weighted queries expressed from  $\pi$ -neg( $\mathcal{T}$ ) to exhibit whether the ABox  $\mathcal{A}$  contains or not contradictions and to compute the inconsistency degree.

The first idea in the algorithm is to first remove the redundancies from both the TBox and ABox. Then we compute for each  $\pi$ -negated axiom  $\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle$  in  $\pi$ -negated pairs of instances from the ABox  $\mathcal A$  that contradict this  $\pi$ -negated axiom. To this end, we will use FOL-reducibility property of standard *DL-Lite* (see Section 1.4). It consists in evaluating FOL queries over  $\mathcal A$  stored in a database using for instance an SQL engine in order to detect contradictions. Note that for an efficient evaluation of queries, we remove the redundancies from that ABox. This does not affect the results according to Lemma 3.1.

We will first need to use some standard notations.  $\psi$  denotes a translation function that takes as argument a possibilistic negative axiom  $\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle$  and produces a weighted FOL query of the form  $\langle q, \alpha \rangle$ . Note that the semantics of q is similar to the one used in standard DL-Lite. Here we simply use the notation  $\langle q, \alpha \rangle$  in order to take into account the weight  $\alpha$  when computing inconsistency degree. The notation  $\sigma_i$  used below simply represents the degree attached to an assertion  $A(x_i)$  in the ABox.

**Definition 3.8.**  $\psi$  is a function that transforms all axioms in  $\pi$ -neg( $\mathcal{T}$ ) to a weighted query  $\langle q, \alpha \rangle$ :

$$\psi(\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle) = \langle (x, \sigma_1, \sigma_2).\lambda_1(x, \sigma_1) \wedge \lambda_2(x, \sigma_2), \alpha \rangle$$

with  $\lambda_i$  is a translation function from axioms in  $\pi$ -neg( $\mathcal{T}$ ) to FOL formulas, defined as follows:

- $\lambda_i(x,\sigma_i)=A_i(x,\sigma_i)$  if  $B_i=A_i$ ,
- $\lambda_i(x,\sigma_i) = \exists y.P_i(x,y,\sigma_i) \text{ if } B_i = \exists P_i,$
- $\lambda_i(x,\sigma_i) = \exists y.P_i(y,x,\sigma_i) \text{ if } B_i = \exists P_i^-,$

where  $\sigma_i$  is the degree to which  $A_i(x)$  (resp.  $P_i(x,y)$ ,  $P_i(y,x)$ ) holds in the ABox.

Intuitively, if  $\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle$  belongs to  $\pi$ -neg( $\mathcal{T}$ ), then a query associated with  $B_1 \sqsubseteq \neg B_2$  is simply denoted by  $\psi(\langle B_1 \sqsubseteq \neg B_2, \alpha \rangle)$  and it means return all pairs of assertions  $\{\langle X, \sigma_1 \rangle, \langle Y, \sigma_2 \rangle\}$  that are present in the ABox and conflict with  $B_1 \sqsubseteq \neg B_2$  where X and Y are given in Definition 3.6. In fact,  $\psi$  can be viewed as a simple rewriting of the concept of conflict presented in Definition 3.6.

**Example 3.11.** [Example continued] From Example 3.7, recall that we have  $\pi$ - $neg(\mathcal{T})$ . Using  $\psi$  defined in Definition 3.8 on  $\langle NeedBased \sqsubseteq \neg Loyal, \gamma_2 \rangle$ , we obtain  $\langle (x, \sigma_1, \sigma_2). \ NeedBased(x, \sigma_1) \land Loyal(x, \sigma_2), \gamma_2 \rangle$ . Applying  $\psi$  on all axioms in  $\pi$ - $neg(\mathcal{T})$  gives the following queries:

- $(q_1) \langle (x, \sigma_1, \sigma_2).NeedBased(x, \sigma_1) \wedge Loyal(x, \sigma_2), \gamma_2 \rangle$
- $(q_2) \langle (x, \sigma_1, \sigma_2).Impulse(x, \sigma_1) \wedge NeedBased(x, \sigma_2), \gamma_{10} \rangle$
- $(q_3) \langle (x, \sigma_1, \sigma_2).Discount(x, \sigma_1) \wedge NeedBased(x, \sigma_2), \gamma_2 \rangle$
- $(q_4) \langle (x, \sigma_1, \sigma_2).NeedBased(x, \sigma_1) \wedge NeedBased(x, \sigma_2), \gamma_2 \rangle$
- $(q_5) \langle (x, \sigma_1, \sigma_2).Wandering(x, \sigma_1) \wedge NeedBased(x, \sigma_2), \gamma_5 \rangle$
- $(q_6) \langle (x, \sigma_1, \sigma_2). \exists y.satisfiedBy(x, y, \sigma_1) \land NeedBased(x, \sigma_2), \gamma_2 \rangle$ .

One query is associated with each negated query of  $\pi$ -neg( $\mathcal{T}$ ). For instance  $\langle (x, \sigma_1, \sigma_2).NeedBased(x, \sigma_1) \wedge Loyal(x, \sigma_2), \gamma_2 \rangle$ , means compute all pair of membership assertions  $NeedBased(x, \sigma_1)$  and  $Loyal(x, \sigma_2)$  that belong to  $\mathcal{A}$ . If  $\mathcal{A}$  is implemented using a relational database, this can be easily computed using an SQL query.

### 3.5.3 An algorithm for computing inconsistency degrees

Now, we provide below an algorithm called Inconsistency, which takes as input a  $\mathcal{K}' = \langle \pi \text{-}neg(\mathcal{T}), \mathcal{A} \rangle$  and computes  $Inc(\mathcal{K}')$ , the inconsistency degree of  $\mathcal{K}'$  (recall that it is equal to  $Inc(\mathcal{K})$ , the inconsistency degree of  $\mathcal{K}$ ). Algorithm 1 implements main definitions and properties presented in this chapter.

```
Input: \mathcal{K}' = \langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle
Output: Inc(\mathcal{K}')
  1: remove redundancies from \pi - neg(\mathcal{T}) and \mathcal{A}
  3: for all (\phi_i, \alpha_i) \in \pi - neg(\mathcal{T}); i = 1..|\pi - neg(\mathcal{T})| do
            if \alpha_i > cont then
 4:
                   (q, \alpha_q) \leftarrow (\psi(\phi_i, \alpha_i))
  5:
                  if Eval(q, A) \neq \emptyset then
  6:
                         \beta \leftarrow min(\alpha_q, max(Eval(q, \mathcal{A})))
  7:
  8:
                         if \beta > cont then
                               cont \leftarrow \beta
      return cont
```

Algorithm 1: Inconsistency

Algorithm 1 has as input the  $\pi$ -negated closure of  $\mathcal{T}$  plus the ABox  $\mathcal{A}$ . It has as output the inconsistency degree of the whole  $\pi$ -DL-Lite knowledge base. The variable cont stores the highest inconsistency degree found during the execution of the algorithm. At the beginning, we assume that  $\mathcal{K}'$  is consistent. This is the meaning of the initialization Step 2: cont=0. Then for each weighted negated axiom (of  $\pi - neg(\mathcal{T})$ ) we look whether the current inconsistency degree can be increased or not. In line 4, if  $\alpha_i \leq cont$  then the inconsistency degree cannot increase. Hence, there is no need to consider conflicts induced by the negated axiom  $(\phi_i, \alpha_i)$ .  $Eval(q, \mathcal{A})$  denotes the evaluation of a weighted query q over  $\mathcal{A}$  obtained by transforming an axiom of  $\pi$ - $neg(\mathcal{T})$  with the function given in Definition 3.8.  $Eval(q, \mathcal{A})$  (uses an SQL engine for instance) returns all possibilistic assertions that contradict the query and their corresponding certainty degrees. Note that if  $\exists P$  (resp.  $\exists P^-$ ) in one of the atoms of the query q, the function  $Eval(q, \mathcal{A})$  returns all first (resp. second) components of the role P that may be grounded for the query. Next, the function  $max(Eval(q, \mathcal{A}))$  is used to return the maximal weight, stored in the variable  $\beta$ , of all pairs of assertions that contradict a query q.

This degree represents the inconsistency level of the ABox  $\mathcal{A}$  and the asked query q and it is calculated as follows: for each pair of assertions  $\langle B_1(a), \alpha_i \rangle$  and  $\langle B_2(a), \alpha_j \rangle$  presented in a query result, we only consider one constant having the lowest certainty degree, i.e.  $(a, min(\alpha_j, \alpha_j))$ . Note that the use of the min operator for propagating and aggregating the certainty degrees comes from the property of the conjunction of necessity valued formulas (see Section 3.2). Recall that dropping only one assertion leads to eliminate a conflict (Definition 3.6). The degree  $\beta$  corresponds the highest one among these degrees. In case of consistency, the "if part" of the algorithm (lines 6-9) is never used, and the algorithm returns the value 0 (namely,  $Inc(\mathcal{K})$ =0). This explains why cont is initialized to 0 (line 2).

**Example 3.12.** [Example continued] From queries of Example 3.11 and the ABox of Example 3.1, we have:  $Eval(q_1, A) = \emptyset$ ,  $Eval(q_2, A) = \emptyset$  and  $Eval(q_3, A) = \emptyset$ . Next, we have  $Eval(q_4, A) \neq \emptyset$  with

 $(q_4):\langle (x,\sigma_1,\sigma_2).NeedBased(x,\sigma_1)\wedge NeedBased(x,\sigma_2),\gamma_2\rangle$  and  $\langle (a,.\gamma_9,\gamma_9)\rangle$  is the query result. Thus  $\beta=\gamma_9$  and  $cont=max(0,min(\gamma_9,\gamma_2))=\gamma_2$ . Continuing with  $q_5$ , we have  $Eval(q_5,\mathcal{A})\neq\emptyset$  where  $\langle (a,.\gamma_4,\gamma_9)\rangle$  is the query result. So,  $\beta=\gamma_4$  and  $cont=max(\gamma_2,min(\gamma_4,\gamma_5))=\gamma_4$ . Lastly, we have  $Eval(q_6,\mathcal{A})\neq\emptyset$  where  $\langle (a,.\gamma_9,\gamma_{11})\rangle$  is the query result. So,  $\beta=\gamma_9$  and  $cont=max(\gamma_4,min(\gamma_2,\gamma_9))=\gamma_4$ .

Therefore, the inconsistency degree of the knowledge base is  $Inc(\mathcal{K}) = \gamma_4$ .

We now provide two propositions that show on one hand that  $\pi$ -DL-Lite extends standard DL-Lite and on the other hand that the computational complexity of Algorithm 1 is the same as the one in standard DL-Lite.

**Proposition 3.6.** Let  $K_s = \langle \mathcal{T}_s, \mathcal{A}_s \rangle$  be a standard DL-Lite knowledge base. Let  $K_\pi = \langle \mathcal{T}_\pi, \mathcal{A}_\pi \rangle$  a  $\pi$ -DL-Lite knowledge base where  $\mathcal{T}_\pi$  (resp.  $\mathcal{A}_\pi$ ) is defined from  $\mathcal{T}_s$  (resp.  $\mathcal{A}_s$ ) by assigning a degree 1 to each axiom of  $\mathcal{T}_s$  (resp.  $\mathcal{A}_s$ ), namely:  $\mathcal{T}_\pi = \{\langle \phi_i, 1 \rangle : \phi_i \in \mathcal{T}_s \}$  and  $\mathcal{A}_\pi = \{\langle \phi_i, 1 \rangle : \phi_i \in \mathcal{A}_s \}$ . Then  $K_s$  is consistent (in the sense of standard DL-Lite) if and only if  $Inc(K_\pi) = 0$  and  $K_s$  is inconsistent if and only if  $Inc(K_\pi) = 1$ .

**Proposition 3.7.** The complexity of Algorithm 1 is the same as the one used in standard DL-Lite ([Calvanese et al., 2007a], section 3.3, Theorem 26).

The complexity of reasoning in *DL-Lite* is recalled in Table 1.7.

*Proof of Proposition 3.7.* To see why proposition 3.7 holds it is enough to see the differences between Algorithm 1 and the one used in ([Calvanese *et al.*, 2007a], section 3.1.3) for standard *DL-Lite*. The first remark, concerns the returned result. In our algorithm, results of queries are weighted while in standard *DL-Lite*, they are not. This does not change the complexity. The difference concerns lines 6-9, where in standard *DL-Lite* algorithm they are replaced by:

- 1: if  $Eval(q, A) \neq \emptyset$  then
- 2: **return** True
- 3: **else**
- 4: **return** False

At first, in case of consistency both algorithms perform the same steps, because the "if part of the algorithm" is never considered. Now in case of inconsistency, the worst case appears when the whole "loop" is used, namely inconsistency appears with the last element of  $\pi$ -neg( $\mathcal{T}$ ). In both cases, let  $\mathcal{A}$  be the result of the evaluation of  $Eval(q_c, \mathcal{A})$ . This needs at least  $\mathcal{O}(|\mathcal{A}|)$  steps. Algorithm 1 (contrary to the algorithm in standard DL-Lite [Calvanese et al., 2007a]) computes also  $max\{\alpha_i: \langle \phi_i, \alpha_i \rangle \in \mathcal{A}\}$  which needs again  $\mathcal{O}(|\mathcal{A}|)$ . Since  $\mathcal{O}(2|\mathcal{A}|) = \mathcal{O}(|\mathcal{A}|)$ , our algorithm has the same complexity as in standard DL-Lite. Hence we increase the expressive power of DL-Lite while keeping the complexity as low as the one of standard DL-Lite.

# **3.6** Possibilistic DL- $Lite_F$ and possibilistic DL- $Lite_R$

In this section, we first briefly show how to extend the possibilistic  $DL\text{-}Lite_{core}$  approach to  $DL\text{-}Lite_R$  and  $DL\text{-}Lite_F$ , two other important fragments of DL-Lite family. These extensions, denoted by  $\pi\text{-}DL\text{-}Lite_R$  and  $\pi\text{-}DL\text{-}Lite_F$ , follow the same steps as  $\pi\text{-}DL\text{-}Lite_{core}$ .

We first give rules to obtain the negated closure of  $\pi$ -DL- $Lite_R$  and  $\pi$ -DL- $Lite_F$  knowledge bases. These rules extend the ones proposed in Section 3.4 to obtain the negated closure of  $\pi$ -DL- $Lite_{core}$ . We then generalize inconsistency degree checking process for  $\pi$ -DL- $Lite_R$  and  $\pi$ -DL- $Lite_F$  knowledge bases.

Considering  $\mathcal{L}_R$  (resp.  $\mathcal{L}_F$ ) a  $DL\text{-}Lite_R$  (resp.  $DL\text{-}Lite_F$ ) description language, a  $\pi\text{-}DL\text{-}Lite_R$  (resp.  $\pi\text{-}DL\text{-}Lite_F$ ) knowledge base  $\mathcal{K} = \{\langle \phi_i, \alpha_i \rangle : 1, ..., n\}$  is a finite set of possibilistic axioms of the form  $(\phi, \alpha)$  where  $\phi$  is an axiom expressed in  $\mathcal{L}_R$  (resp.  $\mathcal{L}_F$ ) and  $\alpha \in ]0,1]$  is the certainty degree of  $\phi$ . As in  $\pi\text{-}DL\text{-}Lite_{core}$ , the semantics of  $\pi\text{-}DL\text{-}Lite_R$  (resp.  $\pi\text{-}DL\text{-}Lite_F$ ) is given by a possibility distribution, denoted by  $\pi_{\mathcal{K}}$ , defined over the set of all interpretations  $\mathcal{I}=(\Delta^{\mathcal{I}}, \mathcal{I})$  of a  $DL\text{-}Lite_R$  (resp.  $DL\text{-}Lite_F$ ) language  $\mathcal{L}_R$  (resp.  $\mathcal{L}_F$ ). This possibility distribution is computed using again Definition 3.2.

# 3.6.1 $\pi$ -DL-Lite<sub>F</sub> negated closure

Recall that the DL- $Lite_F$  extends DL- $Lite_{core}$  with the ability of specifying functionality on roles or on their inverses of the form:

Let us start by defining the negated closure of a  $\pi$ -DL- $Lite_F$  knowledge base. The following rules are added to rules 3.1-3.3 (Section 5.1) to show how to obtain this negated closure of  $\pi$ -DL- $Lite_F$  knowledge base.

**Rule 3.4.** If  $\langle (funct R), \alpha \rangle \in \mathcal{T}$  then add  $\langle (funct R), \alpha \rangle$  to  $\pi$ -neg $(\mathcal{T})$ .

**Rule 3.5.** If  $\langle \exists R \sqsubseteq \neg \exists R, \alpha \rangle \in \pi\text{-neg}(\mathcal{T})$  then add  $\langle \exists R^- \sqsubseteq \neg \exists R^-, \alpha \rangle$  to  $\pi\text{-neg}(\mathcal{T})$ .

**Rule 3.6.** If 
$$\langle \exists R^- \sqsubseteq \neg \exists R^-, \alpha \rangle \in \pi\text{-}neg(\mathcal{T})$$
 then add  $\langle \exists R \sqsubseteq \neg \exists R, \alpha \rangle$  to  $\pi\text{-}neg(\mathcal{T})$ .

Once the  $\pi$ -DL- $Lite_F$  negated closure computed, calculating the inconsistency degree of the knowledge base comes down to compute the maximal degree of potential conflicts. A conflict  $\mathcal{C}$  in  $\mathcal{K}$  is an inconsistent subset of  $\mathcal{K}$ , such that no one of subsets of  $\mathcal{C}$  is consistent. By adding functionality on roles, new forms of conflict are present in addition to conflicts defined for a  $\pi$ -DL- $Lite_{core}$  knowledge base (Definition 3.6). These new conflicts are of the form:

$$\{ \langle (funct \, P), \alpha_1 \rangle, \langle P(a,b), \alpha_2 \rangle, \langle P(a,c), \alpha_3 \rangle \}, \text{ with } b \text{ different from } c. \\ \{ \langle (funct \, P^-), \alpha_1 \rangle, \langle P(b,a), \alpha_2 \rangle, \langle P(c,a), \alpha_3 \rangle \}, \text{ with } b \text{ different from } c.$$

As said in Section 3.5, the main idea of computing the inconsistency degree is to evaluate over the ABox queries obtained from the  $\pi$ -negated closure in order to determine the maximal degree of conflicting elements. To obtain queries from a  $\pi$ -DL-Lite<sub>F</sub> knowledge base, we extend Definition 3.8 as follows:

$$\psi(\langle (funct \, P), \alpha \rangle) = \langle (x, \sigma_1, \sigma_2). \exists y. \exists z. P(x, y, \sigma_1) \land P(x, z, \sigma_2) \land y \neq z, \alpha \rangle$$

$$\psi(\langle (funct P^-), \alpha \rangle) = \langle (x, \sigma_1, \sigma_2). \exists y. \exists z. P(y, x, \sigma_1) \land P(z, x, \sigma_2) \land y \neq z, \alpha \rangle$$

Where  $\sigma_i$  is the degree to which R(x, y) and R(x, z) hold in the ABox.

**Example 3.13.** [Example continued] Let us extend the TBox of Example 3.1 with the following axiom  $\langle (funct \, Satis fied \, By), \gamma_{14}) \rangle$  and the ABox with the following axiom  $\langle Satis fied \, By(john, discount), \gamma_{15}) \rangle$ . One can check that  $\{\langle (funct \, Satis fied \, By), \gamma_{14}) \rangle, \langle Satis fied \, By(john, discount), \gamma_{15}) \rangle, \langle Satis fied \, By(john, gifts), \gamma_{11}) \rangle \}$  is a conflict set.

# 3.6.2 $\pi$ -DL-Lite<sub>R</sub> negated closure

The DL- $Lite_R$  extends DL- $Lite_{core}$  with the ability of specifying inclusion axioms between roles of the form:

$$R \sqsubseteq E$$

We now show how to obtain the negated closure of a  $\pi$ -DL- $Lite_R$  knowledge base. In addition to Rules 3.1-3.3 proposed in section 3.5 for  $\pi$ -DL- $Lite_{core}$  knowledge bases, the following rules should be added for  $\pi$ -DL- $Lite_R$ .

**Rule 3.7.** If  $\langle R_1 \sqsubseteq R_2, \alpha_1 \rangle \in \mathcal{T}$  and  $\langle \exists R_2 \sqsubseteq \neg B, \alpha_2 \rangle \in \pi\text{-neg}(\mathcal{T})$  or  $\langle B \sqsubseteq \neg \exists R_2, \alpha_2 \rangle \in \pi\text{-neg}(\mathcal{T})$  then add  $\langle \exists R_1 \sqsubseteq \neg B, \min(\alpha_1, \alpha_2) \rangle$  to  $\pi\text{-neg}(\mathcal{T})$ .

**Rule 3.8.** If  $\langle R_1 \sqsubseteq R_2, \alpha_1 \rangle \in \mathcal{T}$  and  $\langle \exists R_2^- \sqsubseteq \neg B, \alpha_2 \rangle \in \pi\text{-neg}(\mathcal{T})$  or  $\langle B \sqsubseteq \neg \exists R_2^-, \alpha_2 \rangle \in \pi\text{-neg}(\mathcal{T})$  then add  $\langle \exists R_1^- \sqsubseteq \neg B, \min(\alpha_1, \alpha_2) \rangle$  to  $\pi\text{-neg}(\mathcal{T})$ .

**Rule 3.9.** If  $\langle R_1 \sqsubseteq R_2, \alpha_1 \rangle \in \mathcal{T}$  and  $\langle R_2 \sqsubseteq \neg R_3, \alpha_2 \rangle \in \pi$ -neg( $\mathcal{T}$ ) or  $\langle R_3 \sqsubseteq \neg R_2, \alpha_2 \rangle \in \pi$ -neg( $\mathcal{T}$ ) then add  $\langle R_1 \sqsubseteq \neg R_3, min(\alpha_1, \alpha_2) \rangle$  to  $\pi$ -neg( $\mathcal{T}$ ).

**Rule 3.10.** if  $\langle R \sqsubseteq \neg R, \alpha \rangle \in \pi\text{-}neg(\mathcal{T})$  or  $\langle \exists R \sqsubseteq \neg \exists R, \alpha \rangle \in \pi\text{-}neg(\mathcal{T})$  or  $\langle \exists R^- \sqsubseteq \neg \exists R^-, \alpha \rangle \in \pi\text{-}neg(\mathcal{T})$  then add  $\langle R \sqsubseteq \neg R, \alpha \rangle$  and  $\langle \exists R \sqsubseteq \neg \exists R, \alpha \rangle$  and  $\langle \exists R^- \sqsubseteq \neg \exists R^-, \alpha \rangle$  to  $\pi\text{-}neg(\mathcal{T})$ .

Given this set of rules and syntax of a  $\pi$ -DL- $Lite_R$  knowledge base, a new form of conflicts may be generated. Namely,

$$\{\langle R_1 \sqsubseteq \neg R_2, \alpha_1 \rangle, \langle R_1(a,b), \alpha_2 \rangle, \langle R_2(a,b), \alpha_3 \rangle\}$$

To this end, Definition 3.8 needs to be extended in order to obtain weighted queries used to exhibit contradictions in the ABox and compute the inconsistency degree of a  $\pi$ -DL- $Lite_R$  knowledge base as follows:

$$\psi(\langle R_1 \sqsubseteq \neg R_2, \alpha \rangle) = \langle (x, y, \sigma_1, \sigma_2) . \nu_1(x, y, \sigma_1) \wedge \nu_2(x, y, \sigma_2), \alpha \rangle$$

with

- $\nu_i(x, y, \sigma_i) = P_i(x, y, \sigma_i)$  if  $R_i = P_i$
- $\nu_i(x, y, \sigma_i) = P_i(y, x, \sigma_i)$  if  $R_i = P_i^-$

Where  $\sigma_i$  is the degree to which R(x, y) holds in the ABox.

**Example 3.14.** [Examples 3.1 and 3.7 continued] Let us extend the TBox with the following axiom  $\langle AppropriateFor^- \sqsubseteq SatisfiedBy, \gamma_{14} \rangle \rangle$  and the ABox with the following axiom  $\langle AppropriateFor(Gifts, John), \gamma_{15} \rangle \rangle$ . Using rule 3.7, one can generate the following negated axiom:  $\langle AppropriateFor^- \sqsubseteq \neg NeedBased, \gamma_{14} \rangle$ . One can check that  $\{\langle AppropriateFor^- \sqsubseteq \neg NeedBased, \gamma_{14} \rangle, \langle AppropriateFor (Gifts, John), \gamma_{15} \rangle \rangle$ ,  $\langle Neadbased(John, \gamma_9) \rangle \}$  is a conflict.

# 3.7 Basic inferences in $\pi$ -DL- $Lite_{core}$

In this section, we present standard  $DL\text{-}Lite_{core}$  inference services (*i.e.* subsumption and instance checking) within a possibility theory setting. We show how to compute possibilistic inferences given in Definition 3.4 and Definition 3.5 when  $\phi$  is either a membership assertion (*i.e.* a fact) or a subsumption relation (*i.e.* a TBox axiom).

In  $\pi$ -DL- $Lite_{core}$ , we define two different kinds of inference services, namely flat subsumption (resp. instance checking) and weighted subsumption (resp. instance checking). The main difference between flat subsumption (resp. instance checking) and weighted subsumption (resp. instance checking) is that in the first case, we only check whether the subsumption (resp. instance checking) holds whatever is the degree, while in the second case, the subsumption (resp. instance checking) should be satisfied to a maximal degree.

In what follows, we detail these two types of inferences and we start by studying flat inference.

**Proposition 3.8** (Flat subsumption). Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base (such that Inc(K) < 1),  $C_1$  and  $C_2$  be two general concepts, X be an atomic concept not appearing in  $\mathcal{T}$  and x be a constant not appearing in  $\mathcal{A}$ . Then,  $K \models C_1 \sqsubseteq C_2$  if and only if the knowledge base  $K_1 = \langle \mathcal{T}_1, \mathcal{A}_1 \rangle$  is inconsistent to some degree  $(\exists \alpha > 0$  such that  $Inc(K_1) = \alpha$ ) where

$$\mathcal{T}_1 = \mathcal{T}_{>Inc(\mathcal{K})} \cup \{\langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle\} \text{ and } \mathcal{A}_1 = \{\langle X(x), 1 \rangle\}$$

*Proof of Proposition 3.8.* Let us assume that  $\mathcal{K} \models C_1 \sqsubseteq C_2$ . By Definition 3.4, this means that:

$$N(C_1 \sqsubseteq C_2) > Inc(\mathcal{K}).$$

By definition of necessity measures, this leads to:

$$N(C_1 \sqsubseteq C_2) = 1 - \max_{\mathcal{I} \in \Omega} \{ \pi(\mathcal{I}) : \mathcal{I} \not\models C_1 \sqsubseteq C_2 \} > Inc(\mathcal{K})$$
$$= \max_{\mathcal{I} \in \Omega} \{ \pi(\mathcal{I}) : \mathcal{I} \not\models C_1 \sqsubseteq C_2 \} < 1 - Inc(\mathcal{K}).$$

which means that:

$$\forall \mathcal{I} \in \Omega \text{ such that } \mathcal{I} \not\models C_1 \sqsubseteq C_2, \text{ we have } \pi(\mathcal{I}) < 1 - Inc(\mathcal{K}).$$
 (1)

Besides, it is easy to show that:

$$\mathcal{I} \not\models \mathcal{T}_{>Inc(\mathcal{K})}$$
 if and only if  $\pi(\mathcal{I}) = 1 - Inc(\mathcal{K})$ . (2)

From (1) and (2), we conclude that:

$$\forall \mathcal{I} \in \Omega \text{ such that } \mathcal{I} \models \mathcal{T}_{>Inc(\mathcal{K})}, \text{ we have } \mathcal{I} \models C_1 \sqsubseteq C_2.$$
 (3)

From (3), it is impossible to satisfy  $\mathcal{T}_{>Inc(\mathcal{K})}$  and formulas  $\{X \sqsubseteq C_1, X \sqsubseteq \neg C_2, X(x)\}$  (since models of  $\mathcal{T}_{>Inc(\mathcal{K})}$  satisfy  $C_1 \sqsubseteq C_2$ ) which means that  $\mathcal{K}_1$  is inconsistent.

Conversely, let us assume that  $K_1 = \langle \mathcal{T}_1, \mathcal{A}_1 \rangle$  is inconsistent. Then, there exists an  $\alpha > 0$  such that  $Inc(\mathcal{K}_1) = \alpha$ . This means that:

 $\mathcal{K}_{1>\alpha}$  is inconsistent,

and

 $\mathcal{K}_{1>\alpha}$  is consistent.

Besides, it is easy to see that:

$$\mathcal{K}_{1>\alpha} \models_{\pi} \{ \langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle \}.$$
 (4)

This means that:

$$\mathcal{K}_{1>\alpha} \not\models C_1 \sqsubseteq C_2$$
 (5)

From (4) and (5), one can easily show that there exists an interpretation  $\mathcal{I}$  such that:

$$\pi(\mathcal{I}) < 1 - \alpha$$
 and  $\mathcal{I} \not\models C_1 \sqsubseteq C_2$ .

Since all axioms of  $K_1$  have weights greater than Inc(K) then:

$$\pi(\mathcal{I}) < 1 - \alpha < 1 - Inc(\mathcal{K})$$
 (6)

So, from (6), we have  $N(C_1 \sqsubseteq C_2) > Inc(\mathcal{K})$ . Therefore by Definition 3.4,  $\mathcal{K} \models_{\pi} C_1 \sqsubseteq C_2$ .

**Example 3.15.** [Example continued] Let us check if  $\mathcal{K}\models NeedBased \sqsubseteq Loyal$ . From Example 3.12, we have  $Inc(\mathcal{K})=\gamma_4$  then  $\mathcal{T}_{>\gamma_4}$  is as follows:

```
\langle Discount \sqsubseteq Loyal, \gamma_6 \rangle \qquad \langle NeedBased \sqsubseteq Discount, \gamma_8 \rangle \\ \langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle \qquad \langle Wandering \sqsubseteq Impulse, \gamma_5 \rangle \\ \langle \exists satisfiedBy \vdash \sqsubseteq FidelityMethod, 1 \rangle \qquad \langle \exists satisfiedBy \sqsubseteq Loyal, 1 \rangle
```

By adding the intermediary concept X, the knowledge base  $\mathcal{K}_1 = \langle \mathcal{T}_1, \mathcal{A}_1 \rangle$  is as follow:

$$\mathcal{T}_1 = \mathcal{T}_{> \gamma_4} \cup \{\langle X \sqsubseteq NeedBased, 1 \rangle, \langle X \sqsubseteq \neg Loyal, 1 \rangle\} \text{ and } \mathcal{A}_1 = \{\langle X(x), 1 \rangle\}$$

Computing now  $\pi$ -neg( $\mathcal{T}_1$ ), we obtain the following negative inclusion axioms:

```
 \langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle \qquad \langle NeedBased \sqsubseteq \neg X, \gamma_{6} \rangle 
 \langle Wandering \sqsubseteq \neg NeedBased, \gamma_{5} \rangle \qquad \langle X \sqsubseteq \neg X, \gamma_{6} \rangle 
 \langle X \sqsubseteq \neg Loyal, 1 \rangle \qquad \langle \exists satisfiedBy \sqsubseteq \neg X, 1 \rangle 
 \langle Discount \sqsubseteq \neg X, \gamma_{6} \rangle
```

One can easily check that  $X \sqsubseteq \neg X$  conflicts with X(x). Then, we conclude that  $\mathcal{K}_1$  is inconsistent. Therefore  $\mathcal{K} \models NeedBased \sqsubseteq Loyal$ .

**Proposition 3.9** (Flat instance checking). Let K be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base (such that Inc(K) < 1), C be a concept, X be an atomic concept not appearing in T and x be a constant appearing in A. Then,  $K \models C(x)$  if and only if the knowledge base  $K_1 = \langle T_1, A_1 \rangle$  is inconsistent to some degree where

$$\mathcal{T}_1 = \mathcal{T}_{>Inc(\mathcal{K})} \cup \{\langle X \sqsubseteq \neg C, 1 \rangle\} \text{ and } \mathcal{A}_1 = \mathcal{A}_{>Inc(\mathcal{K})} \cup \{\langle X(x), 1 \rangle\}$$

*Proof of Proposition 3.9.* The proof is basically the same as the one of Proposition 3.8.  $\Box$ 

**Example 3.16.** [Example continued] Let us check if  $\mathcal{K}\models Loyal(John)$ . Consider the TBox  $\mathcal{T}_{>\gamma_4}$  of Example 3.15 and the following ABox  $\mathcal{A}_{>\gamma_4}$  where  $Inc(\mathcal{K})=\gamma_4$ :

$$\langle NeedBased(John), \gamma_9 \rangle$$
  $\langle satisfiedBy(John, Gifts), \gamma_{11} \rangle$ 

By adding the intermediary concept X,  $\mathcal{K}_1 = \langle \mathcal{T}_1, \mathcal{A}_1 \rangle$  is as follow:

$$\mathcal{T}_1 = \mathcal{T}_{>\gamma_4} \cup \{\langle X \sqsubseteq \neg Loyal, 1 \rangle\} \quad and \quad \mathcal{A}_1 = \mathcal{A}_{>\gamma_4} \cup \{\langle X(John), 1 \rangle\}$$

Computing now  $\pi$ -neg( $\mathcal{T}_1$ ), we obtain the following negative inclusion axioms:

$$\langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle \qquad \langle Discount \sqsubseteq \neg X, \gamma_{6} \rangle$$

$$\langle Wandering \sqsubseteq \neg NeedBased, \gamma_{5} \rangle \qquad \langle NeedBased \sqsubseteq \neg X, \gamma_{6} \rangle$$

$$\langle X \sqsubseteq \neg Loyal, 1 \rangle \qquad \langle \exists satisfiedBy \sqsubseteq \neg X, 1 \rangle$$

One can easily check that  $\langle NeedBased \sqsubseteq \neg X, \gamma_6 \rangle$  conflicts with  $\langle X(John), 1 \rangle$  and  $\langle NeedBased(John), \gamma_9 \rangle$  and  $\langle \exists satisfiedBy \sqsubseteq \neg X, 1 \rangle$  conflict with  $\langle X(John), 1 \rangle$  and  $\langle satisfiedBy(John, Gifts), \gamma_{11} \rangle$ . Then, we conclude that  $\mathcal{K}_1$  is inconsistent. Therefore  $\mathcal{K} \models Loyal(John)$ .

As we can see, flat inference is done in a similar way than inference in standard DL- $Lite_{core}$  and it permits to cope with inconsistency. However, the second type of inference (i.e. weighted inference) is stronger than flat inference and it deals with uncertainty by determining to what extent an inference task can be done from a  $\pi$ -DL- $Lite_{core}$  knowledge base.

**Proposition 3.10** (Weighted subsumption). Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base,  $C_1$  and  $C_2$  be two general concepts, X be an atomic concept not appearing in  $\mathcal{T}$ , and x be a constant not appearing in  $\mathcal{A}$ . Then,  $K \models_{\pi} \langle C_1 \sqsubseteq C_2, \alpha \rangle$  if and only if the  $Inc(K_1) = \alpha > Inc(K)$  where  $K_1 = \langle \mathcal{T}_1, \mathcal{A}_1 \rangle$  with

$$\mathcal{T}_1 = \mathcal{T}_{>\alpha} \cup \{\langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle\} \quad and \quad \mathcal{A}_1 = \{\langle X(x), 1 \rangle\}$$

*Proof of Proposition 3.10.* The proof of Proposition 3.10 is similar to the one of Proposition 3.8. Let us assume that  $\mathcal{K} \models_{\pi} \langle C_1 \sqsubseteq C_2, \alpha \rangle$ . From Definition 3.5, we have

$$N(C_1 \sqsubseteq C_2) = \alpha > Inc(\mathcal{K})$$

By definition of necessity measure, this leads to:

$$N(C_1 \sqsubseteq C_2) = 1 - \max_{\mathcal{I} \in \Omega} \{ \pi(\mathcal{I}) : \mathcal{I} \not\models C_1 \sqsubseteq C_2 \} = \alpha > Inc(\mathcal{K}),$$
  
=  $\max_{\mathcal{I} \in \Omega} \{ \pi(\mathcal{I}) : \mathcal{I} \not\models C_1 \sqsubseteq C_2 \} = 1 - \alpha < 1 - Inc(\mathcal{K}).$ 

which means that:

$$\forall \mathcal{I} \in \Omega$$
 such that  $\mathcal{I} \not\models C_1 \sqsubseteq C_2$ , we have  $\pi_{\mathcal{K}}(\mathcal{I}) \leq 1 - \alpha < 1 - Inc(\mathcal{K})$  (1)

Note that  $\alpha > Inc(\mathcal{K})$ . This means that  $\mathcal{T}_{\geq \alpha}$  is consistent, and

$$\forall \mathcal{I}' \in \Omega \text{ such that } \mathcal{I}' \models \mathcal{T}_{\geq \alpha}, \text{ we have } \pi_{\mathcal{K}}(\mathcal{I}') \leq 1 - \alpha$$
 (2)

From (1) and (2), we conclude that:

$$\forall \mathcal{I}' \in \Omega \text{ such that } \mathcal{I}' \models \mathcal{T}_{\geq \alpha}, \text{ it implies } \mathcal{I}' \models_{\pi} \langle C_1 \sqsubseteq C_2, \alpha \rangle \text{ and } \mathcal{I}' \not\models_{\pi} \{ \langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle \}.$$

This also means that  $\mathcal{K}_1$  is inconsistent. Hence  $Inc(\mathcal{K}_1) \geq \alpha > Inc(\mathcal{K})$ . Since  $\mathcal{T}_{\geq \alpha} \cup \{\langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle\}$  is inconsistent. Then  $Inc(\mathcal{K}_1) = \max_{\mathcal{I} \in \Omega} \{\pi_{\mathcal{K}}(\mathcal{I})\} \leq 1 - \alpha$  (since all formulas of  $\mathcal{K}_1$  have a weight greater than  $\alpha$ ).

Let us now show that  $Inc(\mathcal{K}_1) = \alpha$ . It is enough to show that:

$$\mathcal{T}_{>\alpha} \cup \{\langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle\}$$
 is consistent

Assume that it is inconsistent. This means that  $\forall \mathcal{I} \in \Omega$ , if  $\mathcal{I} \models \mathcal{T}_{>\alpha}$  then  $\mathcal{I} \not\models \{X \sqsubseteq C_1, X \sqsubseteq \neg C_2, X(x)\}$  and  $\mathcal{I} \models C_1 \sqsubseteq C_2$ . Recall that  $\mathcal{T}_{>\alpha}$  is consistent. This means that  $\max\{\mathcal{I}': \mathcal{I}' \not\models C_1 \sqsubseteq C_2\} < 1 - \alpha$  which contradicts  $N(C_1 \sqsubseteq C_2) = \alpha$ . Hence  $\mathcal{K}_{1>\alpha}$  is consistent. Therefore  $Inc(\mathcal{K}_1) = \alpha > Inc(\mathcal{K})$ .

Conversely, let us assume that  $K_1$  is inconsistent and  $Inc(K_1) = \alpha > Inc(K)$ . This means that:

$$\mathcal{K}_{1>\alpha}$$
 is consistent, (3)

and

$$\mathcal{K}_{1\geq\alpha}$$
 is inconsistent. (4)

From (3) we have:

$$\mathcal{K}_{1>\alpha} \models_{\pi} \{ \langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle \}$$

Since trivially  $\{\langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle\} \subseteq \mathcal{K}_{1>\alpha}$ 

This means that:

$$\mathcal{K}_{1>\alpha} \not\models_{\pi} \langle C_1 \sqsubseteq C_2, \alpha \rangle$$
 (5)

From (4), we have

$$\mathcal{T}_{\geq \alpha} \cup \{\langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle\}$$
 is inconsistent.

Since  $Inc(\mathcal{K}_1) \ge \alpha > Inc(\mathcal{K})$ , this means that  $\mathcal{T}_{\ge \alpha}$  is consistent and

$$\forall \mathcal{I}'$$
 such that  $\mathcal{I}' \models \mathcal{T}_{>\alpha}$ , we have  $\pi_{\mathcal{K}}(\mathcal{I}') \leq 1 - \alpha$  (6)

$$\forall \mathcal{I}'$$
 such that  $\mathcal{I}' \models \mathcal{T}_{\geq \alpha}$  implies  $\mathcal{I} \models_{\pi} \langle C_1 \sqsubseteq C_2, \alpha \rangle$  but  $\mathcal{I}' \not\models_{\pi} \{ \langle X \sqsubseteq C_1, 1 \rangle, \langle X \sqsubseteq \neg C_2, 1 \rangle, \langle X(x), 1 \rangle \}$  (7)

From (5), (6) and (7), one can show that there exists an interpretation  $\mathcal{I}$  such that:

$$\pi(\mathcal{I}) \leq 1 - \alpha$$
 and  $\mathcal{I} \not\models C_1 \sqsubseteq C_2$ . (8)

From (8), we conclude that  $N(C_1 \sqsubseteq C_2) = \alpha$ . Therefore by Definition 3.5,  $\mathcal{K} \models_{\pi} \langle C_1 \sqsubseteq C_2, \alpha \rangle$ .

**Example 3.17.** [Example continued] From Example 3.15, one can easily check that  $Inc(\mathcal{K}_1) = \gamma_6$  then  $\mathcal{K} \models_{\pi} \langle NeedBased \sqsubseteq Loyal, \gamma_6 \rangle$ .

**Proposition 3.11** (Weighted instance checking). Let K be a  $\pi$ -DL-Lite<sub>core</sub> knowledge base, C be a concept, X be an atomic concept not appearing in T and x be a constant not appearing in A. Then,  $K \models_{\pi} \langle C(x), \alpha \rangle$  if and only if  $Inc(K_1) = \alpha > Inc(K)$  where  $K_1 = \langle T_1, A_1 \rangle$  with

$$\mathcal{T}_1 = \mathcal{T}_{>\alpha} \cup \{\langle X \sqsubseteq \neg C, 1 \rangle\} \quad and \quad \mathcal{A}_1 = \mathcal{A}_{>\alpha} \cup \{\langle X(x), 1 \rangle\}$$

*Proof of 3.11*. The same proof as the proof of Proposition 3.10.

**Example 3.18.** [Example continued] From Example 3.16, one can easily check that  $Inc(\mathcal{K}_1) = \gamma_6$  then  $\mathcal{K} \models_{\pi} \langle Loyal(John), \gamma_6 \rangle$ .

Hence from Proposition 3.8-3.11, we deduce that flat subsumption (*resp.* instance checking) and weighted subsumption (*resp.* instance checking) can be obtained using Algorithm 1 presented above. The above results show that the complexity of flat subsumption (*resp.* instance checking) and weighted subsumption (*resp.* instance checking) in  $\pi$ -DL-Lite is the same as the one used in standard DL-Lite.

# 3.8 Query answering in possibilistic DL-Lite

In this section, we briefly address the problem of query answering within  $\pi$ -DL-Lite framework. The problem of standard query answering is closely related to the ontology-based data access problem which takes a set of assertions (*i.e.* an ABox), an ontology (*i.e.* a TBox) and a conjunctive query q and aims to find if there exists an answer or find all the answers to q over the set of data. In such a setting, an ontology acts as a schema used to enrich the query. The problem of query answering within DL-Lite setting has been mainly studied in [Calvanese *et al.*, 2007a]. Query answering process comes down first to the reformulation of the query q over the TBox in order to enrich it while eliminating all the redundancies and then evaluate the new obtained queries over the ABox.

We now briefly present query answering process over the  $\pi$ -DL-Lite setting. This procedure follows similar steps as in [Calvanese *et al.*, 2007a; Straccia, 2006a; Straccia, 2012]. It consists in:

- 1. Query reformulation: given a query q over  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  a  $\pi$ -DL-Lite knowledge base, we first use the positive axioms of  $\mathcal{T}_{>Inc(\mathcal{K})}$  to enrich the query q. This leads at each possible application of a positive axiom to obtain a new query q'. The resulting set of queries is then used under the ABox (stored as a database). Let us denote by  $Q = ref(q, \mathcal{T}_{>Inc(\mathcal{K})})$  the set of queries obtained by reformulating q over  $\mathcal{T}_{>Inc(\mathcal{K})}$ .
- 2. Query evaluation: given  $ref(q, \mathcal{T}_{>Inc(\mathcal{K})})$ , we first evaluate over  $\mathcal{A}_{>Inc(\mathcal{K})}$  each q' in  $ref(q, \mathcal{T}_{>Inc(\mathcal{K})})$  while taking the most certain answers. Let us denote by  $ans_{\pi}(\mathcal{K}, q)$  the certain answers of the query q over  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  a  $\pi$ -DL-Lite knowledge base.

In DL-Lite, the evaluation of a Conjunctive Query (CQ) uses the notion of FOL-reducibility and it is based on a method that separates the TBox and the ABox. Namely, we use positive axioms of the TBox for reformulating a CQ on the Union of Conjunctive Query (UCQ) to be evaluated over the ABox (may be represented by a relational database). Given a CQ q, we recall the query reformulation algorithm PerfectRef proposed in [Calvanese *et al.*, 2007a] that reformulates q taking into account only positive axioms of a  $\pi$ -DL-Lite TBox  $\mathcal T$  having weights strictly greater than the inconsistency degree.

```
Input: \mathcal{T}_{>\alpha} where \alpha = Inc(\mathcal{K}) and q a CQ
Output: Q query reformulation
  1: Q_1 \leftarrow \{q\} // set of queries
 2: repeat
 3:
           Q_2 \leftarrow Q_1
 4:
           for all q \in Q_2 do
                for all g in q do
 5:
                     for all PI_i \in \mathcal{T}_{>\alpha} do
 6:
                          if PI is applicable to g then
 7:
                                Q_1 \leftarrow Q_1 \cup \{q \left[ g / gr(g, PI) \right] \}
 8:
 9:
           for all g_1, g_2 in q do
10:
                if g_1 and g_2 unify then
                     Q_1 \leftarrow Q_1 \cup \{\tau \left[reduce(q, g_1, g_2)\right]\}
11:
12: until Q_2 \leftarrow Q_1 return (Q_2)
```

Algorithm 2:  $PerfectRef(q, \mathcal{T}_{>\alpha})$ 

In this algorithm, gr(g,PI) denotes the result of applying a positive axiom to an atom of the query. Let use the symbol "\_" to denote non-distinguished non-shared variables (i.e. appeared only once in the query), the function gr(g,PI) is described as follows: A positive axiom is applicable to a factual concept A(x), if the positive inclusion has the concept A in its right-hand side. Similarly a positive inclusion is applicable to a factual relation  $P(x_1,x_2)$ , if either (i)  $x_1=$  and  $\exists P$  is in its right-hand side, or (ii)  $x_2=$  and  $\exists P$  is in its right-hand side, (iii) positive inclusion is a role inclusion and on in its right-hand side is P or P-.

Furthermore q [g/gr(g,PI)] denotes the CQ obtained from q by replacing the atom g with a new atom gr(g,PI). In addition reduce is a function that takes as input a CQ q and two atoms  $g_1$  and  $g_2$  and returns a CQ q' obtained by applying to q the most general unifier between  $g_1$  and  $g_2$ . Finally  $\tau$  is a function that takes as input a CQ q and returns a new CQ obtained by replacing each occurrence of an unbound variable in q with the symbol "\_". Note that gr(g,PI), q [g/gr(g,PI)],  $\tau$  and reduce are the same used in [Calvanese et al., 2007a]. For more details see [Calvanese et al., 2007a].

**Example 3.19.** [Examples 3.1 continued] Let us consider the following TBox with  $\mathcal{T}_{>Inc(\mathcal{K})}$ .

```
 \langle Discount \sqsubseteq Loyal, \gamma_6 \rangle \qquad \qquad \langle NeedBased \sqsubseteq Discount, \gamma_8 \rangle \\ \langle Impulse \sqsubseteq \neg NeedBased, \gamma_{10} \rangle \qquad \langle Wandering \sqsubseteq Impulse, \gamma_5 \rangle \\ \langle \exists satisfiedBy \sqsubseteq EridelityService, 1 \rangle \qquad \langle \exists satisfiedBy \sqsubseteq Loyal, 1 \rangle \\ \text{Let us consider the following conjunctive query } q:
```

```
q(x) \leftarrow \exists y.satisfiedBy(x,y) \land FidelityService(y)
```

At the first execution of algorithm  $PerfectRef(q, \mathcal{T}_{>\alpha})$ ) the following query is added in  $Q_1$ :

```
q_1(x) \leftarrow \exists y.satisfiedBy(x,y) \land satisfiedBy(-,y)
```

since  $\exists satisfiedBy^- \sqsubseteq FidelityService$  is applicable to the atom FidelityService(y). Now, one can see that the two atoms of the added query unify, then the algorithm inserts the following query:

$$q_2(x) \leftarrow satisfiedBy(x, \_)$$

The above two queries and the original one are returned by the algorithm as the set of queries obtained by reformulating q over  $\mathcal{T}_{>Inc(\mathcal{K})}$ .

We now explain the main ideas behind query answering in  $\pi$ -DL-Lite framework. Let  $q(\vec{x}) \leftarrow \exists \vec{y}.conj(\vec{x},\vec{y})$  be a conjunctive query with answer variable  $\vec{x} = x_1,...,x_n$  and arity n. Given an interpretation  $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$ , recall that in standard DL-Lite,  $q^{\mathcal{I}}$  is interpreted as a set of tuples  $\vec{a} \in (\Delta)^n$  that belong to the domain of interpretation such that if we substitute  $\vec{x}$  by the constants  $\vec{a}$  the query q will be evaluated as true under  $\mathcal{I}$ .

In the spirit of instance checking (presented in Section 3.7), when certainty degrees are available over the set of constants in  $\mathcal{A}$ , query answering process comes down to search the most certain answers for the query q and to compute to what extent the answer of this query holds. As mentioned at the beginning of this section, the first step of query answering is the query reformulation. This step leads to obtain a set of queries where the union of the answer sets of these queries will be the answer to the original query. Before given the way to deal with  $Q = ref(q, \mathcal{T}_{>Inc(\mathcal{K})})$  the set of queries obtained by reformulating q over  $\mathcal{T}_{>Inc(\mathcal{K})}$ , let us first show how to deal with CQ over  $\pi$ -DL-Lite setting in order to take into account the weights attached to assertions in the ABox.

Let  $\mathcal{I}=(\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$  be a DL-Lite interpretation and  $q(\vec{x}) \leftarrow \exists \vec{y}.conj(\vec{x}, \vec{y})$  be a CQ. Let us first consider the case where the query does not involve existential variables, namely q is of the form  $q(\vec{x}) \leftarrow \bigwedge A_i(\vec{x})$  where  $A_i$  are atoms. Let  $\vec{a} \in (\Delta^{\mathcal{I}})^n$  be a tuple of constants considered as a possible substitution of the conjunction between atoms under  $\mathcal{I}$ . Within  $\pi$ -DL-Lite setting, the certainty degree of  $\vec{a}$  is the minimum weight (i.e. min) of certainty degrees of constants  $a_i \in \vec{a}$ . Recall that within standard possibilistic logic, given  $\phi$  and  $\varphi$  two formulas, we have  $N(\phi \wedge \varphi) = min(N(\phi), N(\varphi))$ .

**Example 3.20.** Consider the following ABox:  $\langle A(a), \alpha_1 \rangle$ ,  $\langle B(a), \alpha_2 \rangle$ ,  $\langle A(b), \alpha_3 \rangle$  and  $\langle B(b), \alpha_4 \rangle$  with  $\alpha_i \in ]0,1]$  and the query  $q(x) \leftarrow A(x) \land B(x)$ . The answer set to the query q consists of  $\langle a, min(\alpha_1, \alpha_2) \rangle$  and  $\langle b, min(\alpha_3, \alpha_4) \rangle$ .

Let us consider now the case where the query contains existential quantifications. Suppose that we have a query that contains only one atom with an existential variable y (i.e.  $q(x) \leftarrow \exists y. P(x,y)$ ). Then for each fixed constant a that may substitute x a free variable, there may exist several possible constants c that may substitute y where each one is attached with a certainty degree. In that case, the certainty degree of the answer is the maximal degree (i.e. max) for each valid join on y. Recall that within standard possibilistic logic, given  $\phi$  and  $\varphi$  two formulas, we have  $N(\phi \lor \varphi) \ge max(N(\phi), N(\varphi))$ .

**Example 3.21.** Let us consider the following ABox:  $\langle P(a,b_1), \alpha_1 \rangle$ ,  $\langle P(a,b_2), \alpha_2 \rangle$ ,  $\langle P(b_1,c_1), \alpha_3 \rangle$ ,  $\langle P(b_1,c_2), \alpha_4 \rangle$ ,  $\langle P(b_2,c_1), \alpha_5 \rangle$ ,  $\langle P(b_2,c_2), \alpha_6 \rangle$  with  $\alpha_i \in ]0,1]$  and the query  $q(x) \leftarrow \exists y. P(x,y)$ . The answer set of this query consists of  $\langle a, max(\alpha_1,\alpha_2) \rangle$ ,  $\langle b_1, max(\alpha_3,\alpha_4) \rangle$  and  $\langle b_2, max(\alpha_5,\alpha_6) \rangle$ .

Now the certainty degree of a general conjunctive query  $q(\vec{x}) \leftarrow \exists \vec{y}.conj(\vec{x}, \vec{y})$  is simply computed by first considering for each valid join on y the certainty degree of the conjunction of possible substitution using the min to aggregate their values, and then considering the maximal degree for each valid join having the same constants as answer.

**Example 3.22.** Let us consider the ABox of Example 3.21 and the query  $q(x_1, x_2) \leftarrow \exists y$ .  $P(x_1, y) \land P(y, x_2)$ . The possible joins and their certainty degrees are:

```
\langle a, b_1, c_1, min(\alpha_1, \alpha_3) \rangle, \langle a, b_1, c_2, min(\alpha_1, \alpha_4) \rangle, \langle a, b_2, c_1, min(\alpha_2, \alpha_5) \rangle and \langle a, b_2, c_2, min(\alpha_2, \alpha_6) \rangle. Then the answer set consists of
```

```
Then the answer set consists of \langle a, c1, max(min(\alpha_1, \alpha_3), min(\alpha_2, \alpha_5)) \rangle and \langle a, c2, max(min(\alpha_1, \alpha_4), min(\alpha_2, \alpha_6)) \rangle.
```

Let us denote by  $\langle \vec{a}, \alpha \rangle$  an answer of a query q with  $\vec{a}$  is a tuple of constants occurring in  $\mathcal{A}_{>inc(\mathcal{K})}$  and  $\alpha$  is the least certainty degree in which all atoms occurring in the query q grounded by  $\vec{a}$  having

weights at least greater or equal to  $\alpha$  are necessarily true. Namely, we say that  $\mathcal{K}_{>inc(\mathcal{K})}$  entails a tuple  $\vec{a}$  for a query q to a degree  $\alpha$ , denoted  $\mathcal{K}_{>inc(\mathcal{K})}\models \langle q(\vec{a}),\alpha\rangle$  if and only if  $\forall \mathcal{I},q^I(\vec{a})\geq \alpha$ .

For a given conjunctive query, it may correspond several tuples  $\langle \vec{a}_i, \alpha_i \rangle$  as answer sets. So, a more interesting thing is to find the maximal entailment degree of a query. Given q a conjunctive query, this maximal entailment degree of q is as follows:

$$\alpha = max\{\alpha_i | \mathcal{K}_{>inc(\mathcal{K})} \models \langle q(\vec{a}_i), \alpha_i \rangle \}.$$

**Example 3.23.** [Example 3.1 continued] Let us consider now the following ABox obtained from  $\mathcal{A}_{>Inc(\mathcal{K})}$  and some new assertions:

```
 \langle NeedBased(Mary), \gamma_8 \rangle \qquad \langle satisfiedBy(John, Gifts1), \gamma_{10} \rangle \\ \langle NeedBased(John), \gamma_9 \rangle \qquad \langle satisfiedBy(John, Gifts2), \gamma_6 \rangle \\ \langle NeedBased(Paul), 1 \rangle \qquad \langle satisfiedBy(Mary, Gifts3), \gamma_{11} \rangle \\ \langle NeedBased(Bob), \gamma_{12} \rangle \qquad \langle satisfiedBy(Mary, Gifts1), \gamma_5 \rangle
```

Let us consider the following query q:

$$q(x) \leftarrow \exists y. NeedBased(x) \land satisfiedBy(x, y)$$

According to the above ABox, we have two tuples as the answer set of the query  $q: \langle John, max(min(\gamma_9, \gamma_{10}), min(\gamma_9, \gamma_6)) \rangle$  and  $\langle Mary, max(min(\gamma_8, \gamma_{11}), min(\gamma_8, \gamma_5)) \rangle$  where  $\mathcal{K}_{>inc(\mathcal{K})} \models \langle q(John), \gamma_9 \rangle$  and  $\mathcal{K}_{>inc(\mathcal{K})} \models \langle q(Mary), \gamma_8 \rangle$ . One can easily check that the maximal entailment degree of q is  $\gamma_9$ .

Now given  $Q=ref(q,\mathcal{T}_{>Inc(\mathcal{K})})$  the set of queries obtained by reformulating q over  $\mathcal{T}_{>Inc(\mathcal{K})}$ , we view Q as a disjunction of queries. Let us denote by  $ans_{\pi}(\mathcal{K},q)$  the answer set of the query q formed by considering the union of all answer sets of each  $q_i \in Q$ . As said above, for each query  $q_i \in Q$ , there may correspond a set of tuples  $\langle \vec{a}_i, \alpha_i \rangle$  as answer set where the maximal degree of the  $\alpha_i$ 's corresponds the maximal entailment degree of  $q_i$ . Indeed, the entailment degree of  $q_i$  is the highest degree among the entailment degrees of all  $q_i$ 's found by query reformulation since within possibilistic logic, given  $\phi$  and  $\varphi$  two formulas, we have  $N(\phi \lor \varphi) \ge max(N(\phi), N(\varphi))$ .

**Example 3.24.** [Example 3.23 continued] Let us consider the following query q:

$$q(x) \leftarrow Loyal(x)$$

By applying  $PerfectRef(q, \mathcal{T}_{>\alpha})$  algorithm, the set  $ref(q, \mathcal{T}_{>Inc(\mathcal{K})})$  will contain in addition of the original query the following ones:

```
q_1(x) \leftarrow Discount(x) \text{ and } q_2(x) \leftarrow NeadBased(x)
```

Let us consider now the following ABox:

```
 \begin{array}{ll} \langle Loyal(Mary), \gamma_7 \rangle & \langle Discount(Bob), \gamma_6 \rangle \\ \langle Loyal(John), \gamma_9 \rangle & \langle NeedBased(Eric), \gamma_5 \rangle \\ \langle NeedBased(Paul), \gamma_{13} \rangle & \langle Discount(Elise), \gamma_{10} \rangle \end{array}
```

According to the above ABox and the set of queries  $ref(q, \mathcal{T}_{>Inc(\mathcal{K})})$ , the answer set  $ans(\mathcal{K}, q)$  of the query q is  $\langle John, \gamma_9 \rangle$ ,  $\langle Mary, \gamma_7 \rangle$ ,  $\langle Paul, \gamma_{13} \rangle$ ,  $\langle Bob, \gamma_6 \rangle$ ,  $\langle Eric, \gamma_5 \rangle$ ,  $\langle Elise, \gamma_{10} \rangle$ . The entailment degree of q is equal to  $\gamma_{13}$ .

When the assertional facts in the ABox are attached with weights, an answer to a query is a set of tuples that satisfy with a certain degree the asked query. In that case, one may consider a new reasoning task.

It consists first in ranking answers according to their certainty degrees and then selecting the relevant ones. This task is closely related to the top-k ranking query answering approach introduced in [Straccia, 2006b; Straccia, 2006a; Straccia, 2012] within fuzzy DL-Lite logics. The top-k query answering permits to order the results according to their attached degrees and then chose the top-k relevant results. More formally, given  $\mathcal{K}=\langle T,A\rangle$  a  $\pi$ -DL-Lite knowledge base and  $Q=ref(q,\mathcal{T}_{>Inc(\mathcal{K})})$  the set of queries obtained by reformulating q over  $\mathcal{T}_{>Inc(\mathcal{K})}$ , we search for the top-k ranked tuples of the answer set of q, denoted  $ans_k(\mathcal{K},q)=Top_k\{\langle \vec{a},\alpha\rangle|q_i\in Q \text{ and } \mathcal{A}_{>Inc(\mathcal{K})}\models (q_i(c),\alpha)\}$ . To compute the set  $ans_k(\mathcal{K},q)$ , one can calculate first the answer set  $ans_\pi(\mathcal{K},q)$  by considering the union of all answer sets of query reformulation, and then order  $ans_\pi(\mathcal{K},q)$  in descending order with respect to degrees of tuples and then selecting the top-k relevant tuples.

**Example 3.25.** [Example continued] From the answer set  $ans(\mathcal{K}, q)$  of Example 3.24, the top-4 relevant results for  $q(x) \leftarrow Loyal(x)$  are:  $\langle Paul, \gamma_{13} \rangle$ ,  $\langle Elise, \gamma_{10} \rangle$ ,  $\langle John, \gamma_{9} \rangle$ ,  $\langle Mary, \gamma_{7} \rangle$ .

# 3.9 Discussions and related works

There are few works devoted to the possibilistic extension of description logics (DLs). The original work on this topic has been introduced in [Hollunder, 1995] where a possiblistic DL knowledge base is only syntactically defined as a set of terminological (*resp.* assertion) axioms attached with possibility or necessity degrees. In [Hollunder, 1995], the author is only interested in basic inference tasks such as instance checking and subsumption problem and extends them with respect to possibilistic entailments. These inference services allow to check whether an axiom is inferred or not from a possibilistic DL knowledge base and the degree of possibility or the necessity of its entailment. From an algorithmic point of view, Hollunder's [Hollunder, 1995] method uses classical inference algorithm for DLs to check inferences. In our definition of a possibilistic *DL-Lite* knowledge base, we only represent certainty degrees using necessity values. This is in agreement with standard propositional logic, and has a meaningful counterpart when generating possibility distributions.

In [Qi et al., 2011; Qi et al., 2007b; Qi et al., 2007a], the authors first provided the syntax and semantics of possibilistic DLs knowledge bases and then they define inference process. In this chapter, the syntax and semantic of  $\pi$ -DL-Lite knowledge bases is given in a similar way as in [Qi et al., 2011].

Given K a possibilistic DL knowledge base, in [Qi et al., 2011; Qi et al., 2007b; Qi et al., 2007a] an  $\alpha$ -cut approach is used to compute the inconsistency degree of K. Namely, the inconsistency degree of K is the maximum weight of axioms making the  $\alpha$ -cut of K by this weight inconsistent and the strict  $\alpha$ -cut of K by this same weight consistent. Using such approach, the algorithm proposed in [Qi et al., 2011; Qi et al., 2007b; Qi et al., 2007a] operates a binary search to find this weight and this comes down to achieve a number of calls, at most  $log_2(n) + 1$ , where n is the size of the different uncertainty scale appearing in the knowledge base, to a standard DLs (without uncertainty) inconsistency checking algorithm. This definition is in the spirit of standard possibilistic logic [Dubois et al., 1994]. In [Calvanese et al., 2007a] checking inconsistency of a standard DL-Lite knowledge base can be done in a polynomial time with respect to combined complexity k (the size of the whole knowledge base). Knowing that the size n of certainty scales is at least equal to the size of the knowledge base k, it is important to note that although the  $\alpha$ -cut algorithm [Qi et al., 2011; Qi et al., 2007b; Qi et al., 2007a] requires an extra cost (at least  $log_2(n)$  calls to a standard DL inconsistency check algorithm in order to compute inconsistency degree). However, this still can be achieved in polynomial time.

Other lines of approaches have been proposed to compute the inconsistency degrees of possibilistic DLs knowledge bases, such as the works of [Couchariere et al., 2008a; Couchariere et al., 2008b; Qi et al., 2008b; Zhu et al., 2013]. These approaches are based on the extension of a Tableau algorithm within possibilistic logic setting. As shown in [Couchariere et al., 2008a; Qi et al., 2008b; Zhu et al., 2013],

such extension does not require any extra computational cost. However, these approaches are not defined within *DL-Lite* languages.

In [Zhou et al., 2009], the authors give a method to measure the inconsistency of a *DL-Lite* knowledge base based on the three-valued semantics. The proposed algorithm calculates the number of axioms that fall into the third truth value (denoting contradictory information) and can be achieved in polynomial time. This clearly departs from our approach.

In our work, computing inconsistency degree is done by a direct extension of the main standard consistency check algorithm presented in [Calvanese et al., 2007a] of a standard DL-Lite knowledge base. This represents a new way to compute the inconsistency degree of a possibilistic DL-Lite knowledge base that departs from the existing works. There is no exiting work that extends rules for the defined negated closure in a possibility theory framework. Our approach comes down to first defining the notion of negated closure when each axiom in the knowledge base is equipped with a certainty degree. This negated closure is then transformed to weighted queries performed over the set of individuals in order to compute the inconsistency degree. The inconsistency degree associated with a query and a given tuple of individuals (provided as an answer for the query) is the maximum weight among all the certainty degrees of the query and this tuple. The computational complexity associated to this procedure does not require any extra cost comparing with the one of consistency checking algorithm of classical DL-Lite knowledge bases.

# 3.10 Conclusion

In this chapter, we proposed a possibilistic extension of DL-Lite. We first introduced the syntax and the semantics of such extension. We provided properties of  $\pi$ -DL-Lite and showed how to compute the inconsistency degree of  $\pi$ -DL-Lite knowledge base having a complexity identical to the one used in standard DL-Lite. This is done by defining  $\pi$ -DL-Lite negative closure that extends the one of standard DL-Lite. Then, we gave a method to check the consistency for  $\pi$ -DL-Lite. Finally, we discussed inference problems. In particular, we distinguished different inference tasks depending whether we use flat inferences or weighted inferences. Results of this chapter are important since they extend DL-Lite languages to deal with priorities (between TBox axioms or ABox axioms) or uncertainty degrees without increasing the computational complexity.

In several situations, pieces of information are provided with uncertainty which can simply represent reliability of the distinct sources. Next chapter addresses the problem of fusion of multiple data sources linked to the same terminology in the case where the sources have different levels of priorities.

# MIN-BASED CONDITIONING AND MERGING APPROACH OF *DL-Lite* KNOWLEDGE BASES

# 4.1 Introduction

In several situations, pieces of information are provided with uncertainty which can represent reliability of the distinct sources. Possibility theory is a very natural framework to deal with such pieces of information. In the framework of possibility theory, several approaches for merging possibilistic logic bases have been proposed (*e.g.* [Benferhat *et al.*, 1999; Benferhat *et al.*, 2000; Benferhat *et al.*, 1993a; Qi *et al.*, 2010b]). However there is no work that deals with the problem of merging possibilistic DLs knowledge bases by introducing convenient fusion operators although the impact of possibilistic DLs on ontology merging has been introduced in [Oi *et al.*, 2011].

In the first part of this chapter, we study merging within possibilistic DL-Lite framework. We first focus on the use of minimum-based (min-based) operator, well known as idempotent conjunctive operator presented in Section 2.3.2, for merging possibilistic DL-Lite knowledge bases. We then place ourselves in the context of Ontology-based Data Access (OBDA) setting, in which a TBox is used to reformulate posed queries to offer a better access to the set of data encoded in the ABox [Poggi et al., 2008]. We go one step further in the definition of merging operators for  $\pi$ -DL-Lite knowledge bases by investigating the aggregation of assertional bases (ABox) which are linked to the same TBox. Two important results of this study are:

- Our merging approach based on conflict resolution can be extended to define other merging operators, and
- The computational complexity of min-based assertional fusion outcome is polynomial.

Another important reasoning task in possibilistic setting is the one of conditioning possibilistic knowledge bases [Benferhat *et al.*, 2002c]. Unfortunately, there is to the best of our knowledge no approach for conditioning possibilistic DLs or DL-Lite when a new uncertain information is available. This chapter fills this gap and gives a first result of possibilistic DL-Lite conditioning.

The rest of this chapter is organized as follows: Section 4.2 first introduces merging of  $\pi$ -DL-Lite possibility distributions using a min-based operator and then discusses the syntactic counterpart when merging  $\pi$ -DL-Lite knowledge bases. In Section 4.3, we first introduce a syntactic merging operator, namely a min-based assertional operator based on conflict resolution. We show that such a merging operator gives a more satisfactory result compared with the one proposed in Section 4.2. We then study merging at a semantic level, and we show that our operator has a natural counterpart when combining several possibility distributions. Lastly, we rephrase the set of postulates proposed in [Konieczny and Pino Pérez, 2002] to characterize the logical behavior of belief bases merging operators and we provide a postulates-based logical analysis of the min-based assertional operator in the light of this new set of

postulates dedicated to the uncertain *DL-Lite* framework. Section 4.4 presents first result on possibilistic *DL-Lite* conditioning and Section 4.5 concludes the chapter.

# 4.2 Min-based merging of $\pi$ -DL-Lite knowledge bases

This section first introduces merging of  $\pi$ -DL-Lite possibility distributions using a min-based operator and then discusses the syntactic counterpart of the proposed operator when merging  $\pi$ -DL-Lite knowledge bases.

**Example 4.1.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base where  $\mathcal{T}=\{(T \sqsubseteq \neg S, .8), (\exists F \sqsubseteq T, .6), (\exists F^- \sqsubseteq S, .5)\}$  and  $\mathcal{A}=\{(F(b,c),1)\}$ . The possibility distribution  $\pi_{\mathcal{K}}$  associated to  $\mathcal{K}$  is computed using Definition 3.2 as follows where  $\Delta^{\mathcal{I}}=\{b,c\}$ :

$\mathcal{I}$	$\mathcal{I}$	$\pi_1$
$\mathcal{I}_1$	$S = \{b, c\}, T = \{b\}, F = \{(b, c)\}$	.2
$\mathcal{I}_2$	$S = \{b, c\}, T = \{\}, F = \{(b, c)\}$	.4
$\mathcal{I}_3$	$S = \{c\}, T = \{b\}, F = \{(b, c)\}$	1

Table 4.1: Example of a possibility distribution induced from a  $\pi$ -DL-Lite knowledge base

One can observe that  $\pi_{\mathcal{K}}(\mathcal{I}_3)=1$  meaning that  $\pi_{\mathcal{K}}$  is normalized, and thus,  $\mathcal{K}$  is consistent.

# **4.2.1** Merging of $\pi$ -DL-Lite possibility distributions

In a possibility theory framework, several fusion operators (e.g. [Dubois et al., 1992; Benferhat et al., 1997b; Benferhat and Kaci, 2003]) have been proposed for merging pieces of information issued from different and potentially conflicting or inconsistent sources. These fusion operators lead to combine multiple possibility distributions that encode sources of information to obtain a unique possibility distribution that represent the global point of view of available information. Moreover, a syntactic counterpart for each fusion operator used to combine possibility distributions has been introduced to merge possibilistic knowledge bases.

When the distinct sources that provide possibility distributions are dependent, then the recommended fusion operator is the min-based operator well-known as idempotent conjunctive operator. The aim of this section is to study semantic merging of  $\pi$ -DL-Lite possibility distributions using min-based operator. The syntactic counterpart of this combination will be presented in Section 4.2.2. Let us assume that  $\pi_1, ..., \pi_n$  are possibility distributions provided by n sources of information that share the same domain of interpretations (namely  $\Delta_1^{\mathcal{I}} = ... = \Delta_n^{\mathcal{I}}$ ), and that all possibility distributions use the same scale to represent uncertainty.

**Definition 4.1.** A min-based operator or idempotent conjunctive operator, denoted by  $\oplus$ , is a mapping from  $\forall \mathcal{I} \in \Omega, \nu(I) = (\pi_1(\mathcal{I}), ..., \pi_n(\mathcal{I}))$  a vectors of possibility values to an interval [0,1] defined as follows:

$$\pi_{\oplus}(\mathcal{I}) = \min_{\mathcal{I} \in \Omega}(\nu(\mathcal{I}))$$

According to Definition 4.1, the min-based operator ignores redundancy. Since, if all the sources provide the same possibility distribution then the result of fusion using  $\oplus$  is the same possibility distribution.

**Proposition 4.1.** The min-based operator satisfies the characteristic properties:

- If  $\forall \mathcal{I} \in \Omega : \pi_i(\mathcal{I}) = 1$  then  $\pi_{\oplus}(\mathcal{I}) = 1$ .
- If  $\forall \mathcal{I}', \forall \mathcal{I} \in \Omega : \pi_i(\mathcal{I}) \geq \pi_i(\mathcal{I}')$  then  $\pi_{\oplus}(\mathcal{I}) \geq \pi_{\oplus}(\mathcal{I}')$ .

**Example 4.2.** Let us continue example 4.1. Let  $\pi_2$  be the possibility distribution that encodes pieces of information of  $\mathcal{K}_2$  a  $\pi$ -DL-Lite knowledge base. Assume that  $\Delta^{\mathcal{I}} = \{b, c\}$ :

$\mathcal{I}$	·	$\pi_2$
$\mathcal{I}_1$	$S = \{b, c\}, T = \{b\}, P = \{b\}$	1
$\mathcal{I}_2$	$S = \{b, c\}, T = \{\}, P = \{\}$	1
$\mathcal{I}_3$	$S = \{c\}, T = \{b\}, P = \{\}$	.1

Using Definition 4.1, we present the following possibility distribution  $\pi_{\oplus}$  as the result of merging  $\pi_1$  (Example 4.1) and  $\pi_2$ .

$\mathcal{I}$	$\mathcal{I}$	$\pi_{\oplus}$
$\mathcal{I}_1$	$S = \{b, c\}, T = \{b\}, P = \{b\}, F = \{(b, c)\}$	.2
$\mathcal{I}_2$	$S = \{b, c\}, T = \{\}, P = \{\}, F = \{(b, c)\}$	.4
$\mathcal{I}_3$	$S = \{c\}, T = \{b\}, P = \{\}, F = \{(b, c)\}$	.1

One can easily check that merging two  $\pi$ -DL-Lite normalized possibility distributions may lead to a sub-normalized possibility distribution. This is the case with our example (Example 4.2).

Now, we focus on the normalization problem when the use of min-based operator  $\oplus$  provides a subnormalized possibility distribution. Let us consider:

$$h(\pi_{\oplus}) = \max_{\mathcal{I} \in \Omega} \{ \pi_{\oplus}(\mathcal{I}) \}$$

a function that computes to what extent there exists at least one interpretation which is confirmed by all sources. Considering  $\pi_{N\oplus}$  the normalized possibility distribution of  $\pi_{\oplus}$ ,  $\pi_{N\oplus}$  must respect the following conditions.

**Proposition 4.2.**  $\forall \mathcal{I}', \forall \mathcal{I} \in \Omega$ , the minimal requirements for  $\pi_{N\oplus}$  are:

- $\exists \mathcal{I}, \pi_{N \oplus}(\mathcal{I}) = 1.$
- If  $\pi_{\oplus}(\mathcal{I}) > \pi_{\oplus}(\mathcal{I}')$  then  $\pi_{N\oplus}(\mathcal{I}) > \pi_{N\oplus}(\mathcal{I}')$ .
- If  $\pi_{\oplus}(\mathcal{I})$  is normalized then  $\pi_{\oplus}(\mathcal{I}) = \pi_{N\oplus}(\mathcal{I})$ .

The first condition states that  $\pi_{N\oplus}$  must be normalized (there exists at least one interpretation such that  $\pi_{N\oplus}(\mathcal{I})=1$ ). The second condition entails that only interpretations having possibility degrees equal to  $h(\pi_{\oplus})$  can receive value 1 in the normalization process. Assuming these following requirements for  $\pi_{N\oplus}$  (Proposition 4.2), we consider the following definition of normalization.

**Definition 4.2.** For every  $\mathcal{I} \in \Omega$  and  $h(\pi_{\oplus}) > 0$ 

$$\pi_{N\oplus}(\mathcal{I}) = \begin{cases} 1 & if \ \pi_{\oplus}(\mathcal{I}) = h(\pi_{\oplus}) \\ \pi_{\oplus}(\mathcal{I}) & otherwise \end{cases}$$

**Example 4.3.** [Example 4.2 continued] Using Definition 4.2, we present the following normalized possibility distribution  $\pi_{N\oplus}$  from  $\pi_{\oplus}$ .

$\mathcal{I}$	$\overset{\mathcal{I}}{\cdot}$	$\pi_{N_\oplus}$
$\mathcal{I}_1$	$S = \{b, c\}, T = \{b\}, P = \{b\}, F = \{(b, c)\}$	.2
$\mathcal{I}_2$	$S = \{b, c\}, T = \{\}, P = \{\}, F = \{(b, c)\}$	1
$\mathcal{I}_3$	$S = \{c\}, T = \{b\}, P = \{\}, F = \{(b, c)\}$	.1

### **4.2.2** Syntactical merging of $\pi$ -DL-Lite knowledge bases

Let us consider  $\mathcal{K}_1,...,\mathcal{K}_n$  a set of  $\pi$ -DL-Lite knowledge bases where each  $\mathcal{K}_i$  represents the knowledge of a single source of information or agent and  $\pi_1,...,\pi_n$  is a set of n possibility distributions associated with  $\mathcal{K}_1,...,\mathcal{K}_n$ . Namely each  $\pi$ -DL-Lite knowledge base  $\mathcal{K}_i$  is associated with a possibility distribution  $\pi_i$  which is its semantical counterpart. In the previous section, we have presented merging of possibility distributions using min-based operator. In this section, we give a syntactical counterpart of merging n  $\pi$ -DL-Lite knowledge bases  $\mathcal{K}_1,...,\mathcal{K}_n$  provided by n different sources.

Let us consider  $S_1, ..., S_n$  be the signatures of  $K_1, ..., K_n$ . A signature S is the set of concept names, role names and individual names used in K. We assume that all  $K_i$ 's share the same signature. Namely if a concept name (*resp.* role name, individual name) A appears in  $S_1$  and  $S_2$  then A is assumed to be the same.

Now, we look to identify syntacticly the min-based operator  $\oplus$  on the  $\mathcal{K}_i$ 's which correspond to the min-based operator  $\oplus$  on the  $\pi_i$ 's reviewed in the Section 4.2.1 . More formally, given  $(\pi_1,...,\pi_n)$  possibility distributions associated with  $(\mathcal{K}_1,...,\mathcal{K}_n)$   $\pi$ -DL-Lite knowledge bases, then for the min-based operator  $\oplus$  applied to  $(\pi_1,...,\pi_n)$ , we look for a  $\pi$ -DL-Lite knowledge base  $\mathcal{K}_\oplus$  constructed from  $(\mathcal{K}_1,...,\mathcal{K}_n)$  such that  $\pi_\oplus = \pi_{\mathcal{K}_\oplus}$ .

**Definition 4.3.** The syntactic counterpart of the min-based operator  $\oplus$  for  $\pi$ -DL-Lite knowledge bases is defined as follow where  $(\phi_i, \alpha_i) \in \mathcal{K}_1$  and  $(\varphi_i, \beta_i) \in \mathcal{K}_2$ :

$$\mathcal{K}_{\oplus} = \mathcal{K}_1 \cup \mathcal{K}_2$$

**Example 4.4.** Let  $\mathcal{K}_2 = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base where  $\mathcal{T} = \{(P \sqsubseteq S, .7), (P \sqsubseteq T, .9)\}$  and  $\mathcal{A} = \{(S(b), .9)\}$ . The possibility distribution  $\pi_2$  associated to  $\mathcal{K}_2$  is presented in Example 4.2.

Now, using Definition 4.3, we present the following  $\pi$ -DL-Lite knowledge base  $\mathcal{K}_{\oplus}$  as result of merging  $\mathcal{K}_1$  (Example 4.1) and  $\mathcal{K}_2$ :  $\mathcal{T}_{\oplus} = \{(T \sqsubseteq \neg S, .8), (P \sqsubseteq S, .7), (P \sqsubseteq T, .9), (\exists F \sqsubseteq T, .6), (\exists F^- \sqsubseteq S, .5)\}$   $\mathcal{A}_{\oplus} = \{(S(b), .9), (F(b, c), 1)\}$ . The semantic counterpart of  $\mathcal{K}_{\oplus}$  is reported in Example 4.2 through the possibility distribution  $\pi_{\oplus}$ .

Remark 4.1. In *DL-Lite* literature, it is often assumed that TBox are consistent (admit a model). This makes sense when one has one source of information. However, when we deal with multiple sources such assumption is questionable. In particular, it may happen that, one can cheek that there is no ABox  $\mathcal{A}$  such that  $\mathcal{T}_{\oplus} \cup \mathcal{A}$  is consistent.

In general, merging two  $\pi$ -DL-Lite consistent knowledge bases may lead to an inconsistent knowledge base. This is the case with our example (Example 4.4) where  $\mathcal{K}_1$  (Example 4.1) and  $\mathcal{K}_2$  (Example 4.4) are consistent but their merging is inconsistent. Hence, we study the normalization problem at the syntactical level when the use of min-based operator  $\oplus$  provides an inconsistent  $\pi$ -DL-Lite knowledge base.

Let  $\mathcal{K}_{\oplus}$  be a  $\pi$ -DL-Lite knowledge base associated with  $\pi_{\oplus}$ , a sub-normalized possibility distribution where  $h(\pi_{\oplus}) = \max_{\mathcal{I} \in \Omega} \{\pi_{\oplus}(\mathcal{I})\}$ . Then the normalization rule can be defined as follows where  $\mathcal{K}_{N\oplus}$  denotes the normalized  $\pi$ -DL-Lite knowledge base:

**Proposition 4.3.** The possibility distribution, where

$$\mathcal{I} \in \Omega: \pi_{N\oplus}(\mathcal{I}) = \begin{cases} 1 & if \ \pi_{\oplus}(\mathcal{I}) = h(\pi_{\oplus}) \\ \pi_{\oplus}(\mathcal{I}) & otherwise \end{cases}$$

is associated with:

$$\mathcal{K}_{N\oplus} = \{(\phi_i, \alpha_i) | (\phi_i, \alpha_i) \in \mathcal{K}_{\oplus} \text{ and } \alpha_i > 1 - h(\pi_{\oplus}) \}$$

According to Definition 4.3, the normalization does not modify the certainty degrees of  $\pi$ -DL-Lite knowledge base encoded by  $\pi_{\oplus}$ . It just permits to ignore the presence of contradictions (or conflicts) and maintains all the axioms of  $\mathcal{K}_{\oplus}$  whose certainty degrees are higher than the inconsistency degree of  $\mathcal{K}_{\oplus}$ .

**Example 4.5.** Using Definition 4.3, we give the normalized  $\pi$ -DL-Lite knowledge base  $\mathcal{K}_{N\oplus}$  associated to the normalized possibility distribution  $\pi_{N\oplus}$ :  $\mathcal{T}_{\oplus} = \{(T \sqsubseteq \neg S, .8), (P \sqsubseteq S, .7), (P \sqsubseteq T, .9)\}$   $\mathcal{A}_{\oplus} = \{(S(b), .95), F(b, c), 1\}$ .

In this example, it is easy to see that  $\mathcal{K}_{N\oplus}$  is consistent and this is confirmed through  $\pi_{N\oplus}$  where the interpretation  $\mathcal{I}_1$  is a model of  $\mathcal{K}_{N\oplus}$ .

It is important to note that the normalization process allows to find an inconsistency degree identical to the one computed using an algorithmic approach proposed in Section 3.5 to compute the inconsistency degree of a  $\pi$ -DL-Lite knowledge base.

# 4.3 Min-based assertional merging approach for $\pi$ -DL-Lite knowledge bases

This section introduces a syntactic merging operator, namely a min-based assertional operator based on conflict resolution. We show that such a merging operator gives a more satisfactory result compared with the one proposed in the previous Section 4.2 and has a natural semantic counterpart.

### **4.3.1** Syntactic merging of $\pi$ -DL-Lite assertional bases

Let us consider  $A_1,...,A_n$  a set of assertional bases (ABox) where each  $A_i$  represents assertional facts provided by a single source of information. We assume that we have a well-formed and coherent terminological base (TBox) T where each  $A_i$  is consistent with T.

In this section, we study syntactic merging of n assertional bases  $\mathcal{A}_1,...,\mathcal{A}_n$  that are linked to the same TBox  $\mathcal{T}$ . We cast available information within the  $\pi$ -DL-Lite framework. For the sake of simplicity, we omit the weights notation attached to the TBox axioms considered as the ones having the highest certainty level, namely, an axiom in  $\mathcal{T}$  is of the form  $(\varphi,1)$ . We only represent explicitly weights attached to  $\mathcal{A}_i$  assertions. An assertion f in  $\mathcal{A}_i$  is of the form  $f=(\varphi,\alpha)$  where  $\alpha\in[0,1]$ . Note that copies of the same assertions  $\varphi$  are allowed in several  $\mathcal{A}_i$  and they are considered as different in the sense of priorities or certainty and not in terms of interpretations since we use the *Unique Name Assumption*.

Let us consider  $S_1, ..., S_n$  be the signatures of  $A_1, ..., A_n$  and  $\mathcal{T}$ . Recall that a signature S of a knowledge base  $\mathcal{K}$  is the set of concept names, role names and individual names used in  $\mathcal{K}$ . We assume that all  $A_i$ 's and  $\mathcal{T}$  share the same signature. We look to identify a syntactical merging operator on the  $A_i$ 's with respect to a TBox  $\mathcal{T}$  which will be semantically meaningful. Merging at semantic level will be presented in Section 4.3.2.

**Example 4.6.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base where  $\mathcal{T} = \{(A \sqsubseteq B, 1), (B \sqsubseteq \neg C, .9)\}$  and  $\mathcal{A} = \{(A(a), .6), (C(b).5)\}$ . The possibility distribution  $\pi_{\mathcal{K}}$  associated to  $\mathcal{K}$  is computed using Definition 3.2 as follows where  $\Delta^{\mathcal{I}} = \{a, b\}$ :

I	. I	$\pi_{\mathcal{K}}$
$I_1$	$A=\{a\},B=\{\},C=\{b\}$	0
$I_2$	$A=\{a\},B=\{a\},C=\{b\}$	1
$I_3$	$A={},B={},C={}a,b{}$	.4
$I_4$	$A=\{a,b\},B=\{a,b\},C=\{\}$	.5

Table 4.2: Example of a possibility distribution induced from a  $\pi$ -DL-Lite KB

One can observe that  $\pi_{\mathcal{K}}(I_2)=1$ , meaning that  $\pi_{\mathcal{K}}$  is normalized, and thus,  $\mathcal{K}$  is consistent.

## Merging using the classical min-based operator

To show properties of our assertional-based merging operator, we first perform merging of  $\mathcal{A}_1,...,\mathcal{A}_n$  a with respect to  $\mathcal{T}$  using the classical min-based merging operator proposed in Section 4.2 to aggregate  $\pi$ -DL-Lite knowledge bases. The min-based merging operator, denoted by  $\oplus$  considers the union of all ABox. Namely:  $\mathcal{A}_{\oplus}$ = $\mathcal{A}_1 \cup \mathcal{A}_2 \cup ... \cup \mathcal{A}_n$ . The following definition gives the formal logical representation of the normalized knowledge base.

**Definition 4.4.** Let  $\mathcal{T}$  be a TBox and  $\mathcal{A}_{\oplus}$  be the aggregation of  $\mathcal{A}_1, ... \mathcal{A}_n$ , n ABox using classical min-based operator. Let  $x=Inc(\langle \mathcal{T}, \mathcal{A}_{\oplus} \rangle)$ . Then, the normalized knowledge base, denoted,  $\mathcal{K}_{N\oplus}$  is such that:

$$\mathcal{K}_{N\oplus}=\langle \mathcal{T}, \{(\varphi,\alpha): (\varphi,\alpha)\in \mathcal{A}_{\oplus} \ and \ \alpha>x\}\rangle$$

**Example 4.6** continued] Let us continue with the TBox  $\mathcal{T}=\{A \sqsubseteq B, B \sqsubseteq \neg C\}$  presented in Example 4.6 while assuming that the certainty degree of each axioms is set to 1. Let us consider the following set of ABox to be linked to  $\mathcal{T}$ :

```
 \begin{split} &\mathcal{A}_1 \!\!=\!\! \{ (A(a),.6), (C(b),.5) \}, \\ &\mathcal{A}_2 \!\!=\!\! \{ (C(a),.4), (B(b),.8), (A(b),.7) \} \text{ and } \\ &\mathcal{A}_3 \!\!=\!\! \{ (A(b),.2), (A(c),.5), (B(c),.4) \}. \end{split} \\ &\text{We have } &\mathcal{A}_{\oplus} \!\!=\!\! \{ (A(a),.6), (C(b),.5), (C(a),.4), (B(b),.8), (A(b),.7), (A(b),.2), (A(c),.5), (B(c),.4) \} \\ &\text{where } &Inc(\langle \mathcal{T}, \mathcal{A}_{\oplus} \rangle) = .5. \text{ Then } &\mathcal{K}_{N \oplus} \!\!=\!\! \mathcal{T} \cup \{ (A(a),.6), (B(b),.8), (A(b),.7) \}. \end{split}
```

According to Definition 4.4, merging operation does not modify the certainty degrees of the  $\pi$ -DL-Lite knowledge base. It just permits to ignore the presence of contradictions (or conflicts) and maintain all the assertions of  $\mathcal{A}_{\oplus}$  whose certainty degrees are higher than the inconsistency degree of  $\langle \mathcal{T}, \mathcal{A}_{\oplus} \rangle$ . It is clear that the formal expression of the normalized  $\pi$ -DL-Lite knowledge base  $\mathcal{K}_{\oplus}$  given in Definition 4.4 provides a consistent knowledge base. However, this result is not very satisfactory, since many assertions in  $\mathcal{A}_1,...,\mathcal{A}_n$ , which are not involved in any conflict are thrown out.

**Example 4.8.** [Example 4.7 continued] One can see that the assertions (A(c), .5) and (B(c), .4) are not involved in any conflict, but they are not integrated in the merging result.

To this end, we investigate a new approach to merge assertional bases based on conflict detection.

### Min-based assertional merging using conflict resolution

Let  $\mathcal{K}=\langle \mathcal{T},\mathcal{A}\rangle$  be a  $\pi$ -DL-Lite knowledge base. In Section 3.5, it was shown that computing the inconsistency degree of  $\mathcal{K}$  comes down to compute the one of  $\langle \pi - neg(\mathcal{T}), \mathcal{A} \rangle$  where  $\pi$ -neg( $\mathcal{T}$ ) is the negated closure of  $\mathcal{T}$ . Indeed, computing inconsistency degree of  $\mathcal{K}$  consists in calculating the maximal weight attached to minimal inconsistent subsets involved in inconsistency (i.e. Definition 3.6). Within a DL-Lite setting, the inconsistency problem is always defined with respect to some ABox, since a TBox may be incoherent but never inconsistent. Recall that in this chapter, we assume that  $\mathcal{T}$  is coherent. So, from the definition of minimal inconsistent subsets, we define the notion of ABox conflict as a minimal inconsistent subset of assertions. More formally:

**Definition 4.5.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be an inconsistent  $\pi$ -DL-Lite knowledge base where axioms in  $\mathcal{T}$  are set to 1. A subbase  $\mathcal{C} \subseteq \mathcal{A}$  is said to be an assertional conflict set of  $\mathcal{K}$  if and only if

- $Inc(\langle \mathcal{T}, \mathcal{C} \rangle) > 0$  and
- $\forall f \in \mathcal{C}, Inc(\langle \mathcal{T}, \mathcal{C} \{f\} \rangle) = 0$

It is clear that in Definition 4.5, removing any assertion  $\varphi$  from  $\mathcal{C}$  restores the consistency of  $\langle \mathcal{T}, \mathcal{C} \rangle$ . Recall that when the TBox is coherent, a conflict involves exactly two assertions.

**Example 4.9.** [Example 4.7 continued] Let us consider  $\mathcal{T}$  and  $\mathcal{A}_{\oplus}$  from the above example. The  $\pi$ - $neg(\mathcal{T})=\{A\sqsubseteq\neg C, B\sqsubseteq\neg C\}$ . One can compute the following conflict sets:

```
 \begin{array}{l} \mathcal{C}_1 = \{(A(a),.6),(C(a),.4)\},\\ \mathcal{C}_2 = \{(C(b),.5),(B(b),.8)\},\\ \mathcal{C}_3 = \{(C(b),.5),(A(b),.7)\} \text{ and }\\ \mathcal{C}_4 = \{(C(b),.5),(A(b),.2)\}. \end{array}
```

Let us assume that  $A_1,...,A_n$  are assertional bases provided by n sources of information to be linked to the same TBox  $\mathcal{T}$  and they use the same scale to represent uncertainty. Let denote by  $f=(\varphi,\alpha)$  an assertion or a fact in  $A_i$ , we define the notion of conflict vector as follows:

**Definition 4.6.** Let  $\mathcal{T}$  be a TBox and  $\mathcal{A}_1,...,\mathcal{A}_n$  be a set of ABox provided by n distinct sources of information to be linked to  $\mathcal{T}$ . Then  $\forall f \in \mathcal{A}_i$  we define a conflict vector associated with,

$$\forall i \in \{1,..,n\}, \forall f = (\varphi,\alpha) \in \mathcal{A}_i, \mathcal{V}(f) = \langle \nu_1, \nu_2, ..., \nu_n \rangle$$

such that:

$$\forall j = 1..n : \mathcal{V}_j(f) = \begin{cases} 1 & if \langle \mathcal{T}, \{(\varphi, 1) \cup \mathcal{A}_i\} \rangle \text{ is consistent} \\ Inc(\langle \mathcal{T}, \{(\varphi, 1) \cup \mathcal{A}_i\} \rangle) \text{ otherwise} \end{cases}$$

Where  $V_i$  represents the  $i^{th}$  component of the vector V.

Intuitively, for each assertion provided by an information source we built upon a vector that represents to what extend this latter contradicts the other ones provided by other source. To this end, we add first the assertion with a highest prescribed level in each source and then we compute the inconsistency degree of this one. It is obvious that the conflict vector of a non conflicting assertion is equal to  $\mathcal{V}(f) = \langle 1, 1, ..., 1 \rangle$ . However assertions that are involved in conflict will have at least a  $\nu_i$  strictly less than 1.

**Example 4.10** (Example continued). One can obtain the following conflict vectors:

$$\mathcal{V}((A(a),.6)) = \langle 1,.6,1 \rangle,$$

$$\mathcal{V}((A(b),.7)) = \langle .5,1,1 \rangle,$$

```
 \begin{array}{l} \mathcal{V}((A(b),.2)) = \langle .5,1,1 \rangle, \\ \mathcal{V}((A(c),.5)) = \langle 1,1,1 \rangle, \\ \mathcal{V}((B(b),.8)) = \langle .5,1,1 \rangle, \\ \mathcal{V}((B(c),.4)) = \langle 1,1,1 \rangle, \\ \mathcal{V}((C(a),.4)) = \langle .4,1,1 \rangle \text{ and } \\ \nu((C(b),.5)) = \langle 1,.2,.8 \rangle \\ \end{array}
```

From now on, we give the way to aggregate assertional bases using conflict vectors attached to each assertion. Let denote by  $\Sigma$  the set of conflict vectors, we define the min-based assertional merging operators, denoted by  $\Lambda$  as follows:

**Definition 4.7.** Let  $\mathcal{T}$  be a TBox and  $\mathcal{A}_1, \mathcal{A}_2, ..., \mathcal{A}_n$  be a set of ABox provided by n sources to be linked to  $\mathcal{T}$ . Let  $\Sigma$  be the collection of conflict vectors associated to each assertion on  $\mathcal{A}_i$ . Then the min-based assertional merging operator, denoted by  $\Lambda$ , is defined on  $\Sigma$  as follows:

$$\forall \mathcal{V}(f) \in \Sigma : \Lambda(f) = min\{\nu_i(f)\}$$

Let us denote by  $\Sigma_{\Lambda}$ , the vector resulting by min aggregation of conflict vectors.

**Example 4.11** (Example continued).  $\Sigma_{\Lambda}$  contains the following elements:

```
\Lambda((A(a), .6)) = .6,

\Lambda((A(b), .7)) = .5,

\Lambda((A(b), .2)) = .5,

\Lambda((A(c), .5)) = 1,

\Lambda((B(b), .8)) = .5,

\Lambda((B(c), .4)) = 1,

\Lambda((C(a), .4)) = .4 and

\Lambda((C(b), .5)) = .2.
```

According to conflict vectors, one can associate to the set of assertions a new pre-order by attaching to each of them a new weight (i.e.  $\forall (\varphi, \alpha) \in \mathcal{A}_i : (\varphi, \alpha) = (\varphi, \Lambda(f))$ ). According to this new pre-order, we define the knowledge base resulting from the fusion operation as follows.

**Definition 4.8.** Let  $\mathcal{T}$  be a TBox and  $\mathcal{A}_1,...,\mathcal{A}_n$  be a set of n ABox to be linked to  $\mathcal{T}$ . Let  $\mathcal{A}_{\Lambda} = \{(\varphi,\Lambda(f)): f = (\varphi,\alpha) \in \mathcal{A}_i \text{ and } \Lambda(f) \in \Sigma_{\Lambda}\}$ . Let  $x=Inc(\langle \mathcal{T},\mathcal{A}_{\Lambda} \rangle)$ . Then the resulting knowledge base  $\mathcal{K}_{\Lambda}$  is such that:

$$\mathcal{K}_{\Lambda} = \langle \mathcal{T}, \{ (\varphi, \alpha) : (\varphi, \alpha) \in \mathcal{A}_{\Lambda} \ and \ \alpha > x \} \rangle$$

Example 4.12 (Example continued). One can obtain:

```
\mathcal{A}_{\Lambda} = \{ (A(a), .6), (A(b), .5), (A(b), .5), (A(c), 1), (B(b), .5), (B(c), 1), (C(a), .4), (C(b), .2) \} where Inc(\langle \mathcal{T}, \mathcal{A}_{\Lambda} \rangle = .4.
Then \mathcal{K}_{\Lambda} = \mathcal{T} \cup \{ (A(a), .6), (A(b), .5), (A(b), .5), (A(c), 1), (B(b), .5), (B(c), 1) \}.
```

According to Definition 4.8, it is clear that method based on conflict vectors is more productive than the classical definition of the *min*-based merging operator proposed in Definition 4.4. Note that this approach can easily propose others aggregation modes such as product-based merging or sum-based merging.

The definition of this merging operator is based on a notion of conflict measure between sources of information. However, one can observe that original weights attached to assertions are lost. Regarding for instance assertion B(c), it is provided by only one source where its initial weight was .4. This means that

B(c) is not a totally reliable information. In the new knowledge base its weight is raised to 1. This can be justified by the fact that such assertion is not involved in any conflict. However when we proceed to an iteration process this approach may be not very useful. To overcome such limitation while preserving the same productivity of the fusion result, we propose the following definition.

**Definition 4.9.** Let  $\mathcal{T}$  be a TBox and  $\mathcal{A}_1, ..., \mathcal{A}_n$  be a set of n ABox to be linked to  $\mathcal{T}$ . Let  $\mathcal{A}_{\Lambda} = \{(\varphi, \Lambda(f)) : (\varphi, \alpha) \in \mathcal{A}_i\}$ . Let  $x = Inc(\langle \mathcal{T}, \mathcal{A}_{\Lambda} \rangle)$ . Then the resulting knowledge base  $\mathcal{K}'_{\Lambda}$  is such that:

$$\mathcal{K}'_{\Lambda} = \langle \mathcal{T}, \{ f = (\varphi, \alpha) \in \mathcal{A}_i : i \in \{1, ..., n\}, (\varphi, \Lambda(f)) \in \mathcal{A}_{\Lambda} \text{ and } \Lambda(f) > x \} \rangle$$

# 4.3.2 Semantic counterpart

Let us consider  $\mathcal{A}_1,...,\mathcal{A}_n$  a set of ABox's where each  $\mathcal{A}_i$  represents data of a single source of information. We assume that we have a well-formed and coherent TBox  $\mathcal{T}$  where each  $\mathcal{A}_i$  is consistent with the  $\mathcal{T}$ . Let  $\pi_1,...,\pi_n$  be the set of possibility distributions associated with  $\mathcal{K}_1,...,\mathcal{K}_n$  where each  $\mathcal{K}_i = \langle \mathcal{T}, \mathcal{A}_i \rangle$ . Namely each  $\pi$ -DL-Lite knowledge base  $\mathcal{K}_i$  is associated with a possibility distribution  $\pi_i$  which is its semantic counterpart.

In this section, we investigate fusion of weighted  $\pi$ -DL-Lite assertional bases at semantic level. We show that such merging operation is the natural semantic counterpart of the  $\Lambda$  merging operators (presented in 4.3.1) used to merge  $\pi$ -DL-Lite ABox  $A_1$ ,..., $A_n$  with respect to a  $\mathcal{T}$ .

More formally, given  $(\pi_1,...,\pi_n)$  possibility distributions associated with  $(\mathcal{K}_1,...,\mathcal{K}_n)$   $\pi$ -DL-Lite knowledge bases, then for the proposed operator  $\Lambda$  applied to aggregate  $\mathcal{A}_1,...,\mathcal{A}_n$  with respect to  $\mathcal{T}$ , we look for a  $\pi$ -DL-Lite possibility distribution  $\pi_{\Lambda}$  constructed from the aggregation of  $(\pi_1,...,\pi_n)$  with the semantic counterpart of  $\Lambda$  that corresponds to the possibility distribution  $\pi_{\mathcal{K}_{\Lambda}}$  induced from  $\mathcal{K}_{\Lambda}$ . Namely  $\pi_{\Lambda}$ = $\pi_{\mathcal{K}_{\Lambda}}$ .

As usual, assume that  $\pi_1,...,\pi_n$  share the same domain of interpretations (namely  $\Delta_1^{\mathcal{I}}=...=\Delta_n^{\mathcal{I}}$ ), and that all possibility distributions use the same scale to represents uncertainty. The following definition introduces the semantic definition of conflict vectors.

**Definition 4.10.** Let  $\mathcal{A}_1,...,\mathcal{A}_n$  be a set of ABox and  $\pi_1,...,\pi_n$  be a the set of possibility distributions induced from  $\mathcal{K}_1,...,\mathcal{K}_n$  where each  $\mathcal{K}_i=\langle \mathcal{T},\mathcal{A}_i\rangle$ . Then  $\forall f\in\mathcal{A}_i$  with  $f=(\varphi,\alpha)$ , we define semantically a conflict vector, denoted by  $\mathcal{V}(f)$ , as follows:

$$\mathcal{V}(f) = \langle \Pi_{\pi_1}(\varphi), \Pi_{\pi_2}(\varphi), ..., \Pi_{\pi_n}(\varphi) \rangle$$

where  $\forall i=1..n:\Pi_{\pi_i}(f)$  denotes the possibility measure of  $\varphi$  induced from the possibility distribution  $\pi_i$ 

Intuitively, a conflict vector associated to any ABox assertion represents to what extent this latter is compatible with available knowledge provided by each source.

**Example 4.13.** [Examples continued] Assuming that  $\Delta^{\mathcal{I}} = \{a, b, c\}$ , let us consider the following possibility distributions  $\pi_1$ ,  $\pi_2$  and  $\pi_3$  to be merged. Note that we only have considered interpretations that are models of  $\mathcal{T}$ .

$\mathcal{I}$	$\mathcal{I}$	$\pi_1$	$\pi_2$	$\pi_3$
$\mathcal{I}_1$	$A = \{a\}, B = \{a\}, C = \{b, c\}$	1	.2	.5
$\mathcal{I}_2$	$A = \{b\}, B = \{b\}, C = \{a, c\}$	.4	1	.5
$\mathcal{I}_3$	$A = \{c\}, B = \{c\}, C = \{a, b\}$	.4	.2	.8
$\mathcal{I}_4$	$A = \{a, b\}, B = \{a, b\}, C = \{c\}$	.5	.6	.5
$\mathcal{I}_5$	$A = \{a, c\}, B = \{a, c\}, C = \{b\}$	1	.2	.8
$\mathcal{I}_6$	$A = \{b, c\}, B = \{b, c\}, C = \{a\}$	.4	1	1
$\mathcal{I}_7$	$A = \{a, b, c\}, B = \{a, b, c\}, C = \{\}$	.5	.6	1
$\mathcal{I}_8$	$A = \{\}, B = \{\}, C = \{a, b, c\}$	.4	.2	.5

Table 4.3: Possibility distributions induced from three knowledge bases

One can compute the following conflict vectors for each assertion:

 $\mathcal{V}(A(a)) = \langle max(1, .5, 1, 1), max(.2, .6, .2, .6), max(.5, .6, .8, 1) \rangle = \langle 1, .6, 1 \rangle,$ 

 $V(A(b)) = \langle max(.4, .5, .5, 5), max(1, .6, .1, .6), max(.5, .5, 1, 1) \rangle = \langle .5, 1, 1 \rangle,$ 

 $V(A(c)) = \langle max(.4, 1, .4, .5), max(.2, .2, 1, .6), max(.8, .8, 1, 1) \rangle = \langle 1, 1, 1 \rangle,$ 

 $\mathcal{V}(B(b)) = \langle .5, 1, 1 \rangle$ ,  $\mathcal{V}(B(c)) = \langle 1, 1, 1 \rangle$ ,  $\mathcal{V}(C(a)) = \langle .4, 1, 1 \rangle$  and  $\mathcal{V}(C(b)) = \langle 1, .2, .8 \rangle$  which are equal to the ones computed syntactically in Example 4.10.

Let us denote by  $\Sigma$  the collection of conflict vectors associated to each assertion of  $A_i$ . Next definition introduces min-based assertional merging operator, denoted  $\Lambda$ , on the conflict vectors of  $\Sigma$ .

**Definition 4.11.** Let  $\mathcal{A}_1,...,\mathcal{A}_n$  be a set of ABox and  $\pi_1,...,\pi_n$  be a the set of possibility distributions induced from  $\mathcal{K}_1,...,\mathcal{K}_n$  where each  $\mathcal{K}_i=\langle \mathcal{T},\mathcal{A}_i\rangle$ . Let  $\Sigma$  be the collection of conflict vectors associated to each assertion on  $\mathcal{A}_i$  computed using Definition 4.10. Then the min-based assertional merging operator, denoted by  $\Lambda$ , is defined on  $\Sigma$  as follows:  $\forall \mathcal{V}(f) \in \Sigma: \mathcal{V}(f) = \langle \Pi_{\pi_1}(\varphi), \Pi_{\pi_2}(\varphi), ..., \Pi_{\pi_n}(\varphi) \rangle$ ,

$$\Lambda(f) = min\{\nu_i(f) \in \mathcal{V}(f)\}$$

Let us denote by  $\Sigma_{\Lambda}$ , the vector resulting by min-based aggregation of conflict vectors.

**Example 4.14.** [Example continued] One can compute the set  $\Sigma_{\Lambda}$  as follow:  $\Lambda((A(a), .6)) = .6$ ,  $\Lambda((A(b), .7)) = .5$ ,  $\Lambda((A(b), .2)) = .5$ ,  $\Lambda((A(c), .5)) = 1$ ,  $\Lambda((B(b), .8)) = .5$ ,  $\Lambda((B(c), .4)) = 1$ ,  $\Lambda((C(a), .4)) = .4$  and  $\Lambda((C(b), .5)) = .2$ .

From Definition 4.11, one can associate to each assertion a new weight that represents its compatibility with other assertions provided by the other sources.

**Definition 4.12.** Let  $A_1,...,A_n$  be a set of ABox and  $\pi_1,...,\pi_n$  be a the set of possibility distributions induced from  $K_1,...,K_n$  where each  $K_i = \langle \mathcal{T}, A_i \rangle$ . Then the possibility distribution  $\pi_{\Lambda}$  as follows:

$$\forall I \in \Omega : \pi_{\Lambda}(I) = \begin{cases} 1 & if \ \forall \ (\varphi, \alpha) \in \mathcal{A}_i, I \models \varphi \\ 1 - max\{\Lambda((\varphi, \alpha)) : (\varphi, \alpha) \in \mathcal{A}_i, and \ I \not\models \varphi\} \ otherwise \end{cases}$$

where  $\Lambda(\varphi_i)$  is the compatibility measure of  $\varphi_i$  computed using definition 4.11

**Example 4.15** (Example continued). We have (A(c), .1), (B(c), 1), (A(a), .6), (A(b), .5), (B(b), .5), (C(a), .4), (C(a), .2). Then:

$\mathcal{I}$	$\mathcal{I}_1$	$\mathcal{I}_2$	$\mathcal{I}_3$	$\mathcal{I}_4$	$\mathcal{I}_5$	$\mathcal{I}_6$	$\mathcal{I}_7$	$\mathcal{I}_8$
$\pi_{\Lambda}$	0	0	.4	0	.5	.4	.6	0

Table 4.4: Possibility distribution resulting from assertional min-based merging.

One can check that merging normalized possibility distributions may lead to a sub-normalized possibility distribution. This is the case with our example. Indeed, we focus on the normalization problem when the use of min-based assertional operators min provides a subnormal possibility distribution.

**Definition 4.13.** Let us consider:  $h(\pi_{\Lambda}) = \max_{I \in \Omega} \{\pi_{\Lambda}(I)\}$ . Then for every  $\mathcal{I} \in \Omega$  and  $h(\pi_{\Lambda}) > 0$ ,

$$\pi_{N\Lambda}(I) = \begin{cases} 1 & if \ \pi_{\Lambda}(I) = h(\pi_{\Lambda}) \\ \pi_{\Lambda}(I) & otherwise \end{cases}$$

**Example 4.16** (continued). From previous Example, we have:

$\mathcal{I}$	$\mathcal{I}_1$	$\mathcal{I}_2$	$\mathcal{I}_3$	$\mathcal{I}_4$	$\mathcal{I}_5$	$\mathcal{I}_6$	$\mathcal{I}_7$	$\mathcal{I}_8$
$\pi_{\Lambda}$	0	0	.4	0	.5	.4	.6	0
$\pi_{N\Lambda}$	0	0	.4	0	.5	.4	1	0

Table 4.5: Normalized possibility distribution resulting from assertional min-based merging

The following proposition states the equivalence between the semantic and syntactic approaches.

**Proposition 4.4.** Let  $A_1,...,A_n$  be a set of ABox and  $\pi_1,...,\pi_n$  be a the set of possibility distributions induced from  $K_1,...,K_n$  where each  $K_i = \langle \mathcal{T}, \mathcal{A}_i \rangle$ . Then the possibility distribution

$$\pi_{N\Lambda}(I) = \begin{cases} 1 & if \ \pi_{\Lambda}(I) = h(\pi_{\Lambda}) \\ \pi_{\Lambda}(I) & otherwise \end{cases}$$

is associated with

$$\mathcal{K}_{\Lambda} = \langle \mathcal{T}, \{ (\varphi, \Lambda(f)) : (\varphi, \Lambda(f)) \in \mathcal{A}_{\Lambda} \ and \ \Lambda(f) > x \} \rangle$$

### 4.3.3 Logical properties

Let us use  $E = \{\mathcal{K}_1, ..., \mathcal{K}_n\}$  to denote a multi-set, called belief profile, that represents the knowledge bases to be merged (where each  $\mathcal{K}_i$  is associated with a possibility distribution  $\pi_i$ ). Let us use  $\triangle$  to denote a merging operator. This merging operator can be parametrized by an integrity constraint, being a konwledge base  $\mathcal{K}$ , and  $\Delta_{\mathcal{K}}(E)$  denotes the result of the merging operator under this constraint  $\mathcal{K}$ . A logical characterization of integrity constraint merging operators has been proposed in [Konieczny and Pino Pérez, 2002] through a set of rational postulates extended from the ones proposed for belief revision [Katsuno and Mendelzon, 1991]. The following postulates rephrase the ones proposed in [Konieczny and Pino Pérez, 2002] within *DL-Lite* framework.

$$(\mathbf{M}_{\mathbf{0}}^{\pi}) \triangle_{\mathcal{K}}(E) \models \mathcal{K}$$

 $(\mathbf{M}_{\mathbf{1}}^{\pi})$  if  $\mathcal{K}$  is consistent, then  $\triangle_{\mathcal{K}}(E)$  is consistent

$$(\mathbf{M}_{\mathbf{2}}^{\pi})$$
 if  $\mathcal{K} \cup \bigcup_{\mathcal{K}_i \in E} \mathcal{K}_i$  is consistent, then  $\triangle_{\mathcal{K}}(E) = \mathcal{K} \cup \bigcup_{\mathcal{K}_i \in E} \mathcal{K}_i$ 

$$(\mathbf{M}_3^{\pi})$$
 if  $E_1 \approx E_2$  and  $\mathcal{K}_1 \equiv \mathcal{K}_2$ , then  $\triangle_{\mathcal{K}_1}(E_1) \equiv \triangle_{\mathcal{K}_2}(E_2)$ .

 $(\mathbf{M}_{\mathbf{4}}^{\pi})$  if  $\mathcal{K}_1 \models \mathcal{K}$  and  $\mathcal{K}_2 \models \mathcal{K}$ , then  $\triangle_{\mathcal{K}}(\mathcal{K}_1 \cup \mathcal{K}_2)$  is consistent implies that  $\triangle_{\mathcal{K}}(\mathcal{K}_1 \cup \mathcal{K}_2) \cup \mathcal{K}_2$  is consistent

$$(\mathbf{M}_{\mathbf{5}}^{\pi}) \triangle_{\mathcal{K}}(E_1) \cup \triangle_{\mathcal{K}}(E_2) \models \triangle_{\mathcal{K}}(E_1 \uplus E_2)$$

$$(\mathbf{M}_{\mathbf{6}}^{\pi})$$
 if  $\triangle_{\mathcal{K}}(E_1) \cup \triangle_{\mathcal{K}}(E_2)$  is consistent, then  $\triangle_{\mathcal{K}}(E_1 \uplus E_2) \models \triangle_{\mathcal{K}}(E_1) \cup \triangle_{\mathcal{K}}(E_2)$ 

$$(\mathbf{M}_{7}^{\pi}) \ \triangle_{\mathcal{K}}(E) \cup \mathcal{K}' \models \triangle_{\mathcal{K} \cup \mathcal{K}'}(E)$$

$$(\mathbf{M}_{\mathbf{8}}^{\pi})$$
 if  $\triangle_{\mathcal{K}}(E) \cup \mathcal{K}'$  is consistent, then  $\triangle_{\mathcal{K} \cup \mathcal{K}'}(E) \models \triangle_{\mathcal{K}}(E) \cup \mathcal{K}'$ 

$$(\mathbf{M}_{\mathbf{mai}}^{\pi}) \exists n \triangle_{\mathcal{K}}(E_1 \uplus E_2^n) \models \triangle_{\mathcal{K}}(E_2)$$

$$(\mathbf{M}_{\mathbf{I}}^{\pi}) \ \forall n \ \triangle_{\mathcal{K}}(E_1 \uplus E_2^n) \equiv \triangle_{\mathcal{K}}(E_1 \uplus E_2)$$

With:

- 1.  $\mathcal{K}_1 \models \mathcal{K}_2$  if and only if  $\arg \max_I \pi_{\mathcal{K}_1}(I) \subseteq \arg \max_I \pi_{\mathcal{K}_2}(I)$
- 2.  $\mathcal{K}_1 \equiv \mathcal{K}_2$  if and only if  $\mathcal{K}_1 \models \mathcal{K}_2$  and  $\mathcal{K}_2 \models \mathcal{K}_1$
- 3.  $E_1 \approx E_2$  if and only if there exists a bijection g from  $E_1$  to  $E_2$  such that  $\forall \mathcal{K} \in E_1 : \pi_{\mathcal{K}} = \pi_{g(\mathcal{K})}$
- 4. ⊎ is the union of multisets [Knuth, 1998]

5. 
$$E^n = \underbrace{E \uplus ... \uplus E}_{n \text{ times}}$$

Note that in the special case where we only consider only one TBox  $\mathcal{T}_1$  for E, these postulates are equivalent with the ones proposed in [Qi et al., 2006b], by considering the revision of  $\mathcal{T}_1$  by the shared TBox  $\mathcal{T}$ . Hence, our postulates extend (with very few adaptations) the notion of Revision of [Qi et al., 2006b].

For the assertional-based merging operator considered in the present chapter, the integrity constraint is  $\mathcal{K}=\langle \mathcal{T},\emptyset \rangle$  where  $\mathcal{T}$  is the set of TBox axioms of each  $\mathcal{K}_i \in E$  and  $\mathcal{K}_i = \langle \mathcal{T}, \mathcal{A}_i \rangle$ .

Finally, one can check that the min-based assertional merging operators satisfies  $(\mathbf{M}_0^\pi)$ ,  $(\mathbf{M}_1^\pi)$ ,  $(\mathbf{M}_2^\pi)$ ,  $(\mathbf{M}_3^\pi)$ ,  $(\mathbf{M}_5^\pi)$ ,  $(\mathbf{M}_6^\pi)$ ,  $(\mathbf{M}_7^\pi)$ ,  $(\mathbf{M}_8^\pi)$ ,  $(\mathbf{M}_1^\pi)$  and falsifies  $(\mathbf{M}_4^\pi)$ ,  $(\mathbf{M}_{\mathbf{maj}}^\pi)$ .

# 4.4 Conditioning of possibilistic *DL-Lite* knowledge bases: Preliminary results

In this section, we first study conditioning of  $\pi$ -DL-Lite knowledge bases semantically by conditioning the possibility distribution associated to DL-Lite interpretations by the new information. We start by adapting the standard conditioning proposed in the possibilistic setting to the  $\pi$ -DL-Lite setting. We show in particular that conditioning the possibility distribution within DL-Lite differs from the one proposed by [Benferhat  $et\ al.$ , 2002c] within the standard possibilistic setting in the sense that a direct adaptation of conditioning to  $\pi$ -DL-Lite framework is not satisfactory. Roughly speaking, according to the interaction between the new information and the knowledge base, we identify situations where conditioning in DL-Lite differs from the one of the standard possibilistic setting. To this end, we study revision at syntactic level of  $\pi$ -DL-Lite knowledge bases. We propose two other definitions that generalize and refine the classical one.

# 4.4.1 Conditioning of *DL-Lite* possibility distributions

Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base where  $\pi_{\mathcal{K}}$  is its joint possibility distribution computed according to Definition 3.2. For the sake of simplicity, we assume that  $\mathcal{K}$  is consistent (namely  $\pi_{\mathcal{K}}$  is normalized).

**Example 4.17.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base where  $\mathcal{T}=\{(A \sqsubseteq B, A)\}$  and  $\mathcal{A}=\{(A(a), .5), (C(a), .7)\}$ ). One can compute  $\pi_{\mathcal{K}}$  the possibility distribution induced from  $\mathcal{K}$  using Definition 3.2.

$\mathcal{I}$	$\mathcal{I}$	$\pi_{\mathcal{K}}$
$\mathcal{I}_1$	$A = \{\}, B = \{\}, C = \{\}$	.3
$\mathcal{I}_2$	$A = \{a\}, B = \{\}, C = \{\}$	.3
$\mathcal{I}_3$	$A = \{\}, B = \{a\}, C = \{\}$	.3
$\mathcal{I}_4$	$A = \{\}, B = \{\}, C = \{a\}$	.5
$\mathcal{I}_5$	$A = \{a\}, B = \{a\}, C = \{\}$	.3
$\mathcal{I}_6$	$A = \{a\}, B = \{\}, C = \{a\}$	.6
$\mathcal{I}_7$	$A = \{\}, B = \{a\}, C = \{a\}$	.5
$\mathcal{I}_8$	$A = \{a\}, B = \{a\}, C = \{a\}$	1

Table 4.6: Example of a possibility distribution  $\pi_{\mathcal{K}}$  computed using Definition 3.2.

One can observe that  $\pi_{\mathcal{K}}(\mathcal{I}_8)=1$  meaning that the knowledge base is consistent. Note that we have chosen a simple example in order to enumerate all interpretations. This will be helpful to illustrate the conditioning of a  $\pi$ -DL-Lite possibility distribution.

Let us denote by  $(\varphi, \mu)$  the new information to be accepted. Within the  $\pi$ -DL-Lite setting,  $\varphi$  may be an assertion of the form A(a) or P(a,b), a positive inclusion axiom of the form  $B_1 \sqsubseteq B_2$  or a negative inclusion axiom of the form  $B_1 \sqsubseteq B_2$  and  $\mu \in ]0,1]$ . The new input can be a totally reliable information (i.e.  $\mu=1$ ) or uncertain (i.e.  $0<\mu<1$ ). In  $\pi$ -DL-Lite, conditioning comes down to add the new information with its prescribed level of certainty while ensuring the consistency of the results.

In the following, we investigate conditioning at the semantic level. It consists in conditioning the original possibility distribution  $\pi_{\mathcal{K}}$  by the new information  $(\varphi, \mu)$ . This operation takes as input a possibility distribution  $\pi_{\mathcal{K}}$  and the new information  $(\varphi, \mu)$  and transforms  $\pi_{\mathcal{K}}$  to a revised possibility distribution  $\pi'=\pi_{\mathcal{K}}(.|(\varphi,\mu))$ . Here, the input  $(\varphi,\mu)$  is considered as a constraint that must be satisfied in  $\pi'$ . More precisely, the revised distribution is such that  $\Pi'(\varphi)=1$  (recall that in the possibilistic setting, in order for an event  $\varphi$  to have a certainty degree greater than zero, it must be totally possible, hence  $\Pi'(\varphi)=1$ , see Section 2.2.2) and  $N'(\varphi)\geq\mu$  meaning that the axiom  $\varphi$  is certain at least to the degree  $\mu$ . Here  $\Pi'$  (resp. N') is the possibility (resp. necessity) measure induced by the revised possibility distribution  $\pi'$ .

### Logical properties

In [Benferhat *et al.*, 2002c], conditioning in the possibilistic logic setting is characterized with the following properties rephrased in our framework. A revised possibility distribution  $\pi'$  is considered eligible for revising the initial distribution  $\pi_{\mathcal{K}}$  with the new input  $(\varphi, \mu)$  if it satisfies the following properties.

- (A1)  $\max_{I \in \Omega} (\pi'(\mathcal{I})) = 1$ .
- (A2)  $\Pi'(\varphi)=1$  and  $N'(\varphi)\geq \mu$ .
- (A3)  $\forall \mathcal{I}_1 \not\models \varphi, \mathcal{I}_2 \not\models \varphi$ , if  $\pi_{\mathcal{K}}(\mathcal{I}_1) < \pi_{\mathcal{K}}(\mathcal{I}_2)$  then  $\pi'(\mathcal{I}_1) < \pi'(\mathcal{I}_2)$ .

(A4) 
$$\forall I_1 \models \varphi, \mathcal{I}_2 \models \varphi$$
, if  $\pi_{\mathcal{K}}(\mathcal{I}_1) \leq \pi_{\mathcal{K}}(\mathcal{I}_2)$  then  $\pi'(\mathcal{I}_1) \leq \pi'(\mathcal{I}_2)$ .

(A5) If 
$$N_{\mathcal{K}}(\varphi) > 0$$
 then  $\forall \mathcal{I} \models \varphi : \pi_{\mathcal{K}}(\mathcal{I}) = \pi'(\mathcal{I})$ 

(A6) If 
$$\pi_{\mathcal{K}}(\mathcal{I})=0$$
 then  $\pi'(\mathcal{I})=0$ .

Property A1 ensures the consistency of the revised possibility distribution by guaranteeing a normalized distribution  $\pi'$ . A2 guarantees that the added information should be inferred from the revised distribution  $\pi'$  with a weight at least equal to its prescribed priority level. A3 ensures that the relative order between the interpretations that falsify  $\varphi$  is preserved. A4 states that the new possibility distribution  $\pi'$  should preserve the previous pre-order between interpretations which are models of  $\varphi$ . A5 means that the conditioning process does not affect models of  $\varphi$  when  $\varphi$  is a priori fully accepted. A6 states that every impossible interpretation remains impossible after conditioning. In order to satisfy properties A3 and A4, it is clear that the conditioning operation should condition both the interpretations satisfying  $\varphi$ and those falsifying  $\varphi$ .

According to properties A1-A6, two different types of possibility distribution conditioning when  $\Pi(\varphi) > 0$  are proposed in [Dubois and Prade, 1988a], namely in an ordinal setting and in a quantitative setting. These conditionings are extended to the case where the new input is uncertain in [Dubois and Prade, 1997] and studied in [Benferhat et al., 2011]. In this chapter, we only focus on conditioning in the ordinal setting, well-known as min-based conditioning [Benferhat et al., 2002c].

Belief conditioning (or revision) with uncertain information was studied in many works and its close relation to Jeffrey's rule [Jeffrey, 1965] (generalizing probability theory's conditioning) is pointed out. In [Benferhat et al., 2002c] the possibilistic counterpart was given for belief revision with uncertain inputs when dealing with belief bases encoded in possibilistic logics (e.g. [Dubois et al., 1994]) The authors show that the conditioning process comes down syntactically to adding the new information with a prescribed level of certainty while maintaining the consistency of the resulting base and semantically to conditioning the possibility distribution representing the current epistemic state in order to add the new input.

#### Min-based $\pi$ -DL-Lite possibility distribution conditioning

In order to define conditioning of possibility distribution  $\pi_{\mathcal{K}}$ , let us first recall that in standard propositional possibilistic logic, the necessity measure is the dual of the possibility measure and it is defined by  $N(\phi)=1-\Pi(\neg\phi)$  where  $\phi$  is a propositional formula. In possibilistic DL-Lite, a necessity measure cannot be defined as the dual of the possibility measure because the negation of an axiom in *DL-Lite* is not allowed (see Section 3.2).

The following definition rephrases conditioning within the possibilistic *DL-Lite* setting.

**Definition 4.14.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_{\mathcal{K}}$  be its joint possibility distribution. Let  $(\varphi,\mu)$  be a new information. The min-based conditioning is extended to the  $\pi$ -DL-Lite setting as follows:

• 
$$\forall \mathcal{I} \models \varphi, \pi_{\mathcal{K}}(.|_{m}(\varphi, \mu)) = \begin{cases} 1 & if \ \pi_{\mathcal{K}}(\mathcal{I}) = \Pi(\varphi) \\ \pi(\mathcal{I}) & otherwise \end{cases}$$

• 
$$\forall \mathcal{I} \models \varphi, \pi_{\mathcal{K}}(.|_{m}(\varphi, \mu)) = \begin{cases} 1 & if \ \pi_{\mathcal{K}}(\mathcal{I}) = \Pi(\varphi) \\ \pi(\mathcal{I}) & otherwise \end{cases}$$
  
•  $\forall \mathcal{I} \not\models \varphi, \pi_{\mathcal{K}}(.|_{m}(\varphi, \mu)) = \begin{cases} 1 - \mu & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \\ 1 - \mu & if \ \pi_{\mathcal{K}}(\mathcal{I}) > 1 - \mu \\ \pi(\mathcal{I}) & otherwise \end{cases}$ 

According to Definition 4.14, accepting the input consists in raising the degree of the most plausible model of  $\varphi$  to 1. This allows to deal only with axioms that are consistent with the input. For the countermodels, it is clear that the most plausible is set to 1- $\mu$  and all the interpretations that are more compatible than 1- $\mu$  should be shifted down to 1- $\mu$ .

**Proposition 4.5.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_K$  be its joint possibility possibility distribution. Let  $(\varphi, \mu)$  be a new information. Then  $\pi' = \pi_K(.|(\varphi, \mu))$  computed using Definition 4.14 satisfies postulates (A1)-(A6).

**Example 4.18.** Let us consider  $\pi_{\mathcal{K}}$  presented in Example 4.17. Assume that we have in this example separately two cases of new information pieces to be accepted. The first one is  $(B \sqsubseteq \neg C, .9)$  and the second one is  $(B \sqsubseteq \neg C, .2)$ . Using Definition 4.14, the min-based revised possibility distribution  $\pi' = \pi_{\mathcal{K}}(\mathcal{I}|_m(B \sqsubseteq \neg C, .9))$  (resp.  $\pi' = \pi_{\mathcal{K}}(\mathcal{I}|_m(B \sqsubseteq \neg C, .2))$ ) is as follows:

$\mathcal{I}$	$\mathcal{I}$	$\pi_{\mathcal{K}}$	$\pi_{\mathcal{K}}(\mathcal{I} _{m}(B \sqsubseteq \neg C,.9))$	$\pi_{\mathcal{K}}(\mathcal{I} _{m}(B\sqsubseteq \neg C,.2))$
$\mathcal{I}_1$	$A = \{\}, B = \{\}, C = \{\}$	.3	.3	.3
$\mathcal{I}_2$	$A = \{a\}, B = \{\}, C = \{\}$	.3	.3	.3
$\mathcal{I}_3$	$A = \{\}, B = \{a\}, C = \{\}$	.3	.3	.3
$\mathcal{I}_4$	$A = \{\}, B = \{\}, C = \{a\}$	.5	.5	.5
$\mathcal{I}_5$	$A = \{a\}, B = \{a\}, C = \{\}$	.3	.3	.3
$\mathcal{I}_6$	$A = \{a\}, B = \{\}, C = \{a\}$	.6	1	1
$\mathcal{I}_7$	$A = \{\}, B = \{a\}, C = \{a\}$	.5	.1	.5
$\mathcal{I}_8$	$A = \{a\}, B = \{a\}, C = \{a\}$	1	.1	.8

Table 4.7: Example of possibility distribution revisied by two information pieces.

In this example, the first scenario is revising  $\pi_{\mathcal{K}}$  associated to  $\mathcal{K}$  with the input  $(B \sqsubseteq \neg C, .9)$ . Given that in  $\pi_{\mathcal{K}}$ , we have a priori  $\Pi(B \sqsubseteq \neg C)$ =.6 (hence it's necessity is 0) then the new input requires to be satisfied to increase the necessity of the axiom  $B \sqsubseteq \neg C$  until .9.

In the second scenario, the necessity of the axiom  $B \sqsubseteq \neg C$  has to be shifted down to .2. One can observe in  $\pi_{\mathcal{K}}$  that the interpretations  $\{\mathcal{I}_1, \mathcal{I}_2, \mathcal{I}_3, \mathcal{I}_4, \mathcal{I}_5, \mathcal{I}_6\} \models B \sqsubseteq \neg C$  where  $\Pi(B \sqsubseteq \neg C) = .6$  while  $\{\mathcal{I}_7, \mathcal{I}_8\} \not\models B \sqsubseteq \neg C$  where  $\max\{\pi(\mathcal{I}) : \mathcal{I} \not\models B \sqsubseteq \neg C\} = 1$ .

Definition 4.14 is a direct adaptation of conditioning in possibilistic logic [Dubois and Prade, 1988a] to  $\pi$ -DL-Lite framework. As it will be shown in the following example, conditioning of Definition 4.14 is not satisfactory as it provides somehow counterintuitive results. More precisely, conditioning of Definition 4.14 works when the new information is inconsistent with the knowledge base or it is a priori inferred with a weight less than its prescribed level  $\mu$ . Hence conditioning here consists in simply adding the new information to the old knowledge (it is a kind of knowledge expansion). However, conditioning of Definition 4.14 does not work properly when the input is a priori inferred with a weight greater than its prescribed level  $\mu$ . The following example illustrates this situation.

**Example 4.19.** Assume that we have a  $\pi$ -DL-Lite knowledge base  $\mathcal{K}$  where the TBox  $\mathcal{T}=\{(A\sqsubseteq B, .4), (B\sqsubseteq C, .7)\}$  and the ABox  $\mathcal{A}=\{(A(a), .3)\}$ . One can easily check that we have a priori  $\mathcal{K}\models_{\pi}(A\sqsubseteq C, .4)$  (indeed, as it is shown in Table 4.8, the axiom  $A\sqsubseteq C$  has a necessity degree of .4 in the possibility distribution  $\pi_{\mathcal{K}}$  associated to  $\mathcal{K}$ ). Now assume the two following situations: In the first one, the information piece to be accepted by  $\mathcal{K}$  is  $(A\sqsubseteq C, .9)$  while in the second situation  $\mathcal{K}$  is revised with  $(A\sqsubseteq C, .2)$ . Let  $\pi_{\mathcal{K}}$  be the possibility distribution associated with  $\mathcal{K}$  and Let  $\pi'=\pi_{\mathcal{K}}(\mathcal{I}|_m(A\sqsubseteq C, .9))$  (resp.  $\pi''=\pi_{\mathcal{K}}(\mathcal{I}|_m(A\sqsubseteq C, .2))$ ) the conditioned min-based possibility distribution using Definition 4.14.

$\mathcal{I}$	$\mathcal{I}$	$\pi_{\mathcal{K}}$	$\pi' = \pi_{\mathcal{K}}(\mathcal{I} _m(A \sqsubseteq C,.9))$	$\pi''=\pi_{\mathcal{K}}(\mathcal{I} _m(A\sqsubseteq C,.2))$
$\mathcal{I}_1$	$A=\{\}, B=\{a\}, C=\{\}$	.3	.3	.3
$\mathcal{I}_2$	$A=\{a\}, B=\{\}, C=\{a\}$	.6	.6	.6
$\mathcal{I}_3$	$A=\{\}, B=\{\}, C=\{\}$	.7	.7	.7
$\mathcal{I}_4$	$A=\{\}, B=\{\}, C=\{a\}$	.7	.7	.7
$\mathcal{I}_5$	$A=\{\}, B=\{a\}, C=\{a\}$	.7	.7	.7
$\mathcal{I}_6$	$A=\{a\}, B=\{a\}, C=\{a\}$	1	1	1
$\mathcal{I}_7$	$A=\{a\}, B=\{\}, C=\{\}$	.6	.1	.8
$\mathcal{I}_8$	$A=\{a\},B=\{a\},C=\{\}$	.3	.1	.3

Table 4.8: Second example of possibility distribution conditioning by two information pieces.

The interpretations  $\{\mathcal{I}_1, \mathcal{I}_2, \mathcal{I}_3, \mathcal{I}_4, \mathcal{I}_5, \mathcal{I}_6\}$  satisfy the input axiom  $A \sqsubseteq C$  and we have a priori  $\Pi(A \sqsubseteq C) = 1$  and  $\Pi_n(A \sqsubseteq C) = .6$ . The possibility degrees of the interpretations  $\{\mathcal{I}_7, \mathcal{I}_8\}$  are set to (1-.9)=.1 in order to ensure that  $N'(A \sqsubseteq C)=.9$ . It is easy to check that properties (A1)-(A6) are satisfied by the distribution  $\pi'$  computed according to Definition 4.14. However when the input is  $(A \sqsubseteq C, .2)$ , there is a problem regarding the possibility degree associated to  $\mathcal{I}_2$  in  $\pi''$ . Indeed, we have  $A \sqsubseteq C$  is implied by the fact  $A \sqsubseteq B$  and  $B \sqsubseteq C$ . Hence, in order to have a necessity degree of  $A \sqsubseteq C$  of .2 then one has to shift down at least the necessity degree of the axiom  $A \sqsubseteq B$  down to .2 as it has a lower priority than  $B \sqsubseteq C$ . However, if the necessity of  $A \sqsubseteq B$  is shifted down to .2 then the corresponding  $\pi_K$  after this modification will not be equivalent to the one given in Table 4.8. For instance, the interpretation  $\mathcal{I}_2$  will be associated with a degree of .8 instead of .6 currently. Clearly revision with conditioning of Definition cannot fully capture syntactic revision detailed in the following section.

It is important to note that in the *DL-Lite* framework, it is not guaranteed that any set of interpretations represents a *DL-Lite* axiom (see Section 3.2).

In the next section, we analyze revision at syntactic level. We then provide a definition of conditioning possibility distributions that refines Definition 4.14.

#### 4.4.2 Syntactic revision

In this section, we study revision with the new information  $(\varphi, \mu)$  at the syntactic level. Revision here consists in obtaining from a  $\pi$ -DL-Lite knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  associated to a possibility distribution  $\pi_{\mathcal{K}}$  and an uncertain input information  $(\varphi, \mu)$ , a new  $\pi$ -DL-Lite knowledge base  $\mathcal{K}' = \langle \mathcal{T}', \mathcal{A}' \rangle$ . As in possibilistic logic, in  $\pi$ -DL-Lite, revision comes down to add the new information with its prescribed level of certainty while ensuring the consistency of the revision results.

As mentioned is the previous section a simple adaptation of conditioning in possibilistic logic to  $\pi$ -DL-Lite framework is not very satisfactory. So, we identify cases where  $\mathcal{K}' = \langle \mathcal{T}', \mathcal{A}' \rangle$  is associated to possibility  $\pi_{\mathcal{K}'}$  such that:

$$\forall \mathcal{I} \in \Omega, \pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_m(\varphi, \mu))$$

where  $\pi_{\mathcal{K}'}$  is the possibility distribution obtained from conditioning  $\pi_{\mathcal{K}}$  by  $(\varphi, \mu)$  using minimum-based conditioning of Definition 4.14.

As illustrated in Example 4.19, Definition 4.14 doesn't provide good results and in particular when the  $(\varphi, \mu)$  is inferred from the knowledge base with a weight greater than its prescribed one. Indeed, according the logical form of  $\mathcal{K}'$ , we propose an new definition of minimum-based conditioning that refine Definition 4.14.

When adding the new information to the knowledge base, several situations may be encountered, namely when the input is consistent or inconsistent with the the original knowledge. The following two subsections analyse these situations where they give formal representation of the revised knowledge base and re-define minimum-based conditioning in order to  $\pi_{K'}$  from  $\pi_{K}$ .

#### The input $(\varphi,\mu)$ is inconsistent with the knowledge base

We address here the situation where the new information  $(\varphi,\mu)$  is inconsistent with the knowledge base  $\mathcal{K}$ , namely  $\Pi_{\mathcal{K}}(\varphi) < 1$  (recall that in possibility theory, if  $\Pi(\varphi) < 1$  then  $N(\varphi) = 0$ ). There are two situations to be considered. The first one is when  $(\varphi,\mu)$  is implicitly inhibited by higher priority TBox or ABox axioms that contradict it. The second one is when  $(\varphi,\mu)$  is not inhibited by higher priority axioms that contradict it. For these two cases, the construction of the augmented  $\pi$ -DL-Lite knowledge base  $\mathcal{K}'$  is performed according to the following steps:

- 1. Add the input  $\varphi$  to the knowledge base  $\mathcal{K}$  with the highest prescribed level (i.e.  $\mu$ =1).
- 2. Compute the inconsistency degree  $\beta = Inc(\mathcal{K}_1)$  with  $\mathcal{K}_1 = \mathcal{K} \cup \{(\varphi, 1)\}$ .
- 3. Drop every axiom in  $\mathcal{K}_1$  having a priority less than or equal to the inconsistency degree  $\beta$ . Let  $\mathcal{K}_2$  the obtained consistent knowledge base.
- 4. Add  $\varphi$  with its prescribed level  $\mu$  to  $\mathcal{K}_2$ . Let  $\mathcal{K}' = \mathcal{K}_2 \cup \{(\varphi, \mu)\}$ .

These steps ensure the consistency of the resulting knowledge base after adding the input  $(\varphi,\mu)$  with its prescribed level. The following proposition relates the resulting knowledge base  $\mathcal{K}'$  with the possibility distribution  $\pi_{\mathcal{K}'}$  associated to  $\mathcal{K}'$  with the results of conditioning at the semantic level using Definition 4.14. namely  $\pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_m(\varphi,\mu))$  using min-based conditioning defined in Definition 4.14.

**Proposition 4.6.** Let  $K = \langle T, A \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_K$  be its joint possibility distribution. Let  $(\varphi, \mu)$  be the added uncertain input information and  $\beta = Inc(K_1)$  where  $K_1 = K \cup \{(\varphi, 1)\}$ . Let  $K' = \langle T', A' \rangle$  such that  $K' = \{(\varphi, \mu)\} \cup \{(\varphi, \alpha) : (\varphi, \alpha) \in K \text{ and } \alpha > \beta\}$  and let  $\pi_{K'}$  be the possibility distribution associated to K'. Then.

$$\forall I \in \Omega, \pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_{m}(\varphi, \mu)),$$

where  $\pi_{\mathcal{K}}(\mathcal{I}|_m(\varphi,\mu))$  denotes the revised possibility distribution  $\pi_{\mathcal{K}}$  computed using min-based conditioning defined in Definition 4.14.

Example 4.20 (examples 4.17 and 4.18 continued). We have  $\mathcal{T} = \{(A \sqsubseteq B, 4)\}$  and  $\mathcal{A} = \{(A(a), .5), (C(a), .7)\}$ ). Let us first assume a new input  $(B \sqsubseteq \neg C, .9)$  and then another input  $(B \sqsubseteq \neg C, .2)$ . One can easily check that  $Inc(\mathcal{K} \cup \{(B \sqsubseteq \neg C, 1)\} = .4$ . So,  $(B \sqsubseteq \neg C, .2)$  (resp.  $(B \sqsubseteq \neg C, .9)$ ) is inhibited (resp. not inhibited) by higher priority axioms that contradict it. For the first case, it is easy to check that  $\mathcal{K}' = \{(B \sqsubseteq \neg C, .2), (A(a), .5), (C(a), .7)\}$  is such that  $\pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_m(B \sqsubseteq \neg C, .2))$  presented in Example 4.18. For the second case however,  $\mathcal{K}' = \{(B \sqsubseteq \neg C, .9), (A(a), .5), (C(a), .7)\}$ ) such that  $\pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_m(B \sqsubseteq \neg C, .9))$  presented in Example 4.18.

#### The input $(\varphi,\mu)$ is consistent with the knowledge base

When the input  $(\varphi,\mu)$  is consistent with the knowledge base  $\mathcal{K}$  (namely  $\Pi(\varphi)=1$ ), two situations are to be considered:

1. The first one is when  $(\varphi, \mu)$  is a priori inferred from the knowledge base  $\mathcal{K}$ , namely  $\mathcal{K} \models_{\pi} \phi$ .

2. The second one is when  $(\varphi, \mu)$  cannot be inferred from  $\mathcal{K}$ , namely  $\mathcal{K} \not\models_{\pi} \phi$ . Here, revision is performed with a simple expansion of  $\mathcal{K}$  with the input  $(\varphi, \mu)$ , namely  $\mathcal{K}' = \mathcal{K} \cup (\varphi, \mu)$ .

Let us first discuss the situation where the input  $(\varphi, \mu)$  is a priori inferred from the knowledge base  $\mathcal{K}$ . In this situation, two scenarios can hold depending on the a priori necessity measure of  $\varphi$  (denoted  $N(\varphi)=\nu$ ), and its prescribed posterior necessity  $N'(\varphi)=\mu$ . Namely:

- 1. When  $\nu \le \mu$  meaning that the new information is inferred with a certainty degree  $\nu$  less than its prescribed one  $\mu$ . Note that this situation is similar to the case of revising with a certain input (namely case where  $\mu$ =1).
- 2. When  $\nu > \mu$  meaning that the new information is inferred with a certainty degree  $\nu$  that is greater than its prescribed one  $\mu$ .

In the  $\pi$ -DL-Lite framework, two different kinds of inference services are given, namely flat subsumption (resp. instance checking) and weighted subsumption (resp. instance checking) (see Section 3.7). To determine to what extent the input  $(\varphi)$  is inferred from the knowledge base, namely  $\mathcal{K}\models_{\pi}(\varphi,\nu)$  with  $\nu\geq\mu$  or  $\nu<\mu$ , we first add to  $\mathcal{K}$  the assumption that  $\varphi$  is false encoded by the following statements:  $\{(Y\sqsubseteq C_1,1),(Y\sqsubseteq \neg C_2,1),(Y(y),1)\}$  if  $\varphi=C_1\sqsubseteq C_2$  and  $\{(Y\sqsubseteq \neg C_1,1),(Y(a),1)\}$  if  $\varphi=C_1(a)$  where Y (resp. y) is a new concept (resp. individual) not appearing in  $\mathcal{K}$ . Then we compute the inconsistency degree of the augmented knowledge base. This inconsistency degree corresponds to  $\nu$ . Namely  $\mathcal{K}\models_{\pi}(\varphi,\nu)$  if and only if  $Inc(\mathcal{K}_1)=\nu$  where  $\mathcal{K}_1=\langle \mathcal{T}_1,\mathcal{A}_1\rangle$  with  $\mathcal{T}_1=\mathcal{T}\cup\{(Y\sqsubseteq C_1,1),(Y\sqsubseteq \neg C_2,1)\}$  and  $\mathcal{A}_1=\{(Y(y),1)\}$  or  $\mathcal{T}_1=\mathcal{T}\cup\{(Y\sqsubseteq \neg C_1,1)\}$  and  $\mathcal{A}_1=\mathcal{A}\cup\{(Y(a),1)\}$ .

Now, the construction of the augmented  $\pi$ -DL-Lite knowledge base K' is performed using the following steps:

- 1. Add the assumption that  $\varphi$  is false to  $\mathcal{K}$  with the highest prescribed level (i.e.  $\mu = 1$ ).
- 2. Compute the inconsistency degree of the augmented knowledge base (i.e.  $Inc(\mathcal{K}_1)=\nu$ ).
- 3. If  $\mu \ge \nu$ , then the revision outcome is  $\mathcal{K}' = \mathcal{K} \cup \{(\varphi, \mu)\}$ .
- 4. if  $(\mu < \nu)$  two solutions can be proposed.
  - (a) The first one is to shift down the weights of axioms in K which are between  $\mu$  and  $\nu$  to  $\mu$ .
  - (b) The second solution is to compute first the set  $\mathcal{X} \subseteq \mathcal{K}$  of axioms in  $\mathcal{K}$  that imply  $\varphi$ . Then we shift down the weights of axioms in  $\mathcal{X}$  which are between  $\mu$  and  $\nu$  to  $\mu$ .

These steps ensure inferring the new input  $\varphi$  from the resulting knowledge base  $\mathcal{K}'$  with its prescribed level  $\mu$ . Following these steps, it is clear that the revision process does not change the initial weights attached to axioms of  $\mathcal{K}$  if  $\mathcal{K}\models_{\pi}(\varphi,\nu)$  with  $\nu\leq\mu$ . However it changes the initial weights attached to some axioms responsible or not for inferring  $\varphi$  from  $\mathcal{K}$  with the weight  $\mu$  when  $\nu>\mu$ . According to the Example 4.19 presented in the previous section, conditioning proposed by Definition 4.14 is counterintuitive when  $(\mu<\nu)$ . To this end, we fit Definition 4.14 before giving the formal representation of  $\mathcal{K}'$ .

#### **Semantic counterpart**

Let us start with the case where  $\nu > \mu$ . The following definition gives a min-based conditioning of  $\pi$ -DL-Lite possibility distribution generalizing Definition 4.14.

**Definition 4.15.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_{\mathcal{K}}$  be its joint possibility possibility distribution. Let  $(\varphi,\mu)$  be the new information. The min-based conditioning is extended to the  $\pi$ -DL-Lite setting as follows:

• 
$$\forall \mathcal{I} \models \varphi, \pi_{\mathcal{K}}(.|_{m}(\varphi, \mu)) = \begin{cases} 1 & if \ \pi_{\mathcal{K}}(\mathcal{I}) = \Pi(\varphi) \\ 1 - \mu & if \ \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \leq \pi_{\mathcal{K}}(\mathcal{I}) \leq 1 - \mu \\ \pi(\mathcal{I}) & otherwise \end{cases}$$

• 
$$\forall \mathcal{I} \not\models \varphi, \pi_{\mathcal{K}}(.|_{m}(\varphi,\mu)) = \begin{cases} 1-\mu & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \ or \ \pi_{\mathcal{K}}(\mathcal{I}) > 1-\mu \\ \pi(\mathcal{I}) & otherwise \end{cases}$$

According to Definition 4.15, accepting the input consists in raising the degree of the most plausible model of  $\varphi$  to 1. Moreover when  $N(\varphi) \geq \mu$ , some models of  $\varphi$  will all be set to  $1 - \mu$ . For the countermodels, the most plausible is set to  $1 - \mu$  and all interpretations that are more compatible than  $1 - \mu$  should be shifted down to  $1 - \mu$ . Moreover, when  $N(\varphi) = \nu > \mu$  the interpretations that falsify less priority axioms inferring  $\varphi$  will be revised.

**Proposition 4.7.** Let  $K = \langle T, A \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_K$  be its joint possibility possibility distribution. Let  $(\varphi, \mu)$  be the new information. If  $\Pi(\varphi) < 1$ , Then  $\pi' = \pi_K(.|(\varphi, \mu))$  computed using Definition 4.15 satisfies postulates (A1), (A2), (A3), (A4), (A6).

The following proposition relates the resulting knowledge base  $\mathcal{K}'$  with the possibility distribution  $\pi_{\mathcal{K}'}$  associated to  $\mathcal{K}'$  with the results of conditioning at the semantic level using Definition 4.15

**Proposition 4.8.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_K$  be its joint possibility distribution. Let  $(\varphi, \mu)$  be the added uncertain input information and  $\nu = Inc(K_1)$  where  $K_1$  is the augmented knowledge base by the assumption that  $\varphi$  is false. Then the revised  $\pi$ -DL-Lite knowledge base  $K' = \langle \mathcal{T}', \mathcal{A}' \rangle$  such that:

$$\mathcal{K}' = \{(\varphi, \mu)\} \cup \{(\phi, \alpha) : (\phi, \alpha) \in \mathcal{K} \ and \ \alpha > \nu\} \cup \{(\phi, \alpha) : (\phi, \alpha) \in \mathcal{K} \ and \ \alpha < \mu\} \cup \{(\phi, \mu) : (\phi, \alpha) \in \mathcal{K} \ and \ \alpha < \mu\} \cup \{(\phi, \mu) : (\phi, \alpha) \in \mathcal{K} \ and \ \alpha < \mu\}$$

The possibility distribution  $\pi_{\mathcal{K}'}$  associated to  $\mathcal{K}'$  is such that:

$$\forall I \in \Omega, \pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_{m}(\varphi, \mu)),$$

where  $\pi_{\mathcal{K}}(\mathcal{I}|_m(\varphi,\mu))$  denotes the revised possibility distribution of  $\pi_{\mathcal{K}}$  using the min-based conditioning of Definition 4.15.

Proposition 4.8 leads to shift down the weights of axioms in K which are between  $\mu$  and  $\nu$  to  $\mu$ . However, one can improve the result with a minimal change consisting in revising only the weights of some axioms responsible of implying the new information.

**Example 4.21** (Examples 4.19 continued). We have  $\mathcal{T} = \{(A \sqsubseteq B, .4), (B \sqsubseteq C, .7)\}$  and  $\mathcal{A} = \{(A(a), .3)\}$ . Let us consider  $(A \sqsubseteq C, .9)$  and  $(A \sqsubseteq C, .2)$ . One can easily check that  $Inc(\mathcal{K}_1) = .4$  where  $\mathcal{K}_1 = \langle \mathcal{T} \cup \{(Y \sqsubseteq A, 1), (Y \sqsubseteq \neg C, 1)\}, \{(Y(y), 1)\}\rangle$ . So  $\mathcal{K} \models_{\pi} (A \sqsubseteq C, .4)$ . When the input is  $(A \sqsubseteq C, .9)$ , then  $\mathcal{K}' = \{(A \sqsubseteq B, .4), (B \sqsubseteq C, .7), (A \sqsubseteq C, .9), (A(a), .3)\}$  such that  $\pi_{\mathcal{K}'}(\mathcal{I}) = \pi_{\mathcal{K}}(\mathcal{I}|_{m}(A \sqsubseteq C, .2))$  presented in Example 4.19. Now, when the input is  $(A \sqsubseteq C, .2)$ , then  $\mathcal{K}' = \{(A \sqsubseteq B, .2), (B \sqsubseteq C, .7), (A \sqsubseteq C, .2), (A(a), .2)\}$  such that  $\pi_{\mathcal{K}'}(\mathcal{I}) = \pi_{\mathcal{K}}(\mathcal{I}|_{m}(A \sqsubseteq C, .2))$  presented in Example 4.19 becomes as follows:

$\mathcal{I}$	$\mathcal{I}$	$\pi_{\mathcal{K}}$	$\pi' = \pi_{\mathcal{K}}(\mathcal{I} _m(A \sqsubseteq C,.9))$	$\pi'' = \pi_{\mathcal{K}}(\mathcal{I} _m(A \sqsubseteq C,.2))$
$\mathcal{I}_1$	$A=\{\}, B=\{a\}, C=\{\}$	.3	.3	.3
$\mathcal{I}_2$	$A=\{a\}, B=\{\}, C=\{a\}$	.6	.6	.8
$\mathcal{I}_3$	$A=\{\}, B=\{\}, C=\{\}$	.7	.7	.8
$\mathcal{I}_4$	$A=\{\}, B=\{\}, C=\{a\}$	.7	.7	.8
$\mathcal{I}_5$	$A=\{\}, B=\{a\}, C=\{a\}$	.7	.7	.8
$\mathcal{I}_6$	$A=\{a\}, B=\{a\}, C=\{a\}$	1	1	1
$\mathcal{I}_7$	$A=\{a\}, B=\{\}, C=\{\}$	.6	.1	.8
$\mathcal{I}_8$	$A=\{a\},B=\{a\},C=\{\}$	.3	.1	.3

Table 4.9: Example of possibility distribution revision by two information pieces using Definition 4.15

Given the set  $\mathcal{X} \subseteq \mathcal{K}$  of axioms in  $\mathcal{K}$  that infer  $\varphi$ , we distinguish semantically four sets of interpretations when the new information  $\varphi$  is satisfied:

- 1. Interpretations that are models of  $\mathcal{X}$  and  $\mathcal{K}$ - $\mathcal{X}$ ,
- 2. Interpretations that are models of  $\mathcal{X}$  but are not models of  $\mathcal{K}$ - $\mathcal{X}$ ,
- 3. Interpretations that are models of  $\mathcal{K}$ - $\mathcal{X}$  but are not models of  $\mathcal{X}$  and
- 4. Interpretations that are neither models of  $\mathcal{K}$ - $\mathcal{X}$  nor  $\mathcal{X}$ .

The following definition provides another min-based conditioning of  $\pi$ -DL-Lite possibility distribution that also adapts Definition 4.14.

**Definition 4.16.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_{\mathcal{K}}$  be its joint possibility possibility distribution. Let  $(\varphi, \mu)$  be the new information. Let  $\mathcal{X} \subseteq \mathcal{K}$  be the set of axioms inferring  $\varphi$ . Let

$$\mu' = max\{\alpha : (\phi, \alpha) \in \mathcal{K} - \mathcal{X} \text{ and } \mathcal{I} \not\models \phi\}.$$

In an ordinal setting, we define the min-based conditioning as follows:

• 
$$\forall \mathcal{I} \models (\varphi \cup \mathcal{X}), \pi(.|_{m}(\varphi,\mu)) = \begin{cases} 1 & if \pi(\mathcal{I}) = \Pi(\varphi) \\ \pi(\mathcal{I}) & otherwise \end{cases}$$

$$\bullet \ \forall I \models \varphi \cup (\mathcal{K} - \mathcal{X}), \mathcal{I} \not\models \mathcal{X}, \pi(.|_{m}(\varphi, \mu)) = \begin{cases} 1 - \mu & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \\ \pi(\mathcal{I}) & otherwise \end{cases}$$

• 
$$\forall I \models \varphi, I \not\models \mathcal{X}, I \not\models \mathcal{K} - \mathcal{X}, \pi(.|_{m}(\varphi, \mu)) = \begin{cases} 1 - \mu & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \ and \ 1 - \mu' \geq 1 - \mu \\ 1 - \mu' & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \ and \ 1 - \mu' \leq 1 - \mu \\ \pi(\mathcal{I}) & otherwise \end{cases}$$
•  $\forall I \not\models \varphi, \pi(.|_{m}(\varphi, \mu)) = \begin{cases} 1 - \mu & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \\ 1 - \mu & if \ \pi(\mathcal{I}) > 1 - \mu \\ \pi(\mathcal{I}) & otherwise \end{cases}$ 

• 
$$\forall I \not\models \varphi, \pi(.|_{m}(\varphi, \mu)) = \begin{cases} 1-\mu & if \ \pi(\mathcal{I}) = \max\{\pi(\mathcal{I}) : \mathcal{I} \not\models \varphi\} \\ 1-\mu & if \ \pi(\mathcal{I}) > 1-\mu \\ \pi(\mathcal{I}) & otherwise \end{cases}$$

**Proposition 4.9.** Let  $K = \langle T, A \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_K$  be its joint possibility possibility distribution. Let  $(\varphi, \mu)$  be the new information. If  $\Pi(\varphi) < 1$ . Then  $\pi' = \pi_K(.|(\varphi, \mu))$  computed using Definition 4.16 satisfies postulates (A1),(A2),(A3) and (A6).

The following proposition relates the resulting knowledge base  $\mathcal{K}'$  with the possibility distribution  $\pi_{\mathcal{K}'}$  associated to  $\mathcal{K}'$  with the results of conditioning at the semantic level using Definition 4.16.

**Proposition 4.10.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a  $\pi$ -DL-Lite knowledge base and  $\pi_K$  be its joint possibility distribution. Let  $(\varphi, \mu)$  be the added uncertain input information and  $\nu = Inc(K_1)$  where  $K_1$  is the augmented knowledge base by the assumption that  $\varphi$  is false. Then the revised  $\pi$ -DL-Lite knowledge base  $K' = \langle \mathcal{T}', \mathcal{A}' \rangle$  such that

$$\mathcal{K}' = \{(\varphi, \mu)\} \cup \{\mathcal{K} - \mathcal{X}\} \cup \{(\phi, \alpha) : (\phi, \alpha) \in \mathcal{X} \ and \ \alpha > \nu\} \cup \{(\phi, \mu) : (\phi, \nu) \in \mathcal{X} \ and \ \nu = \alpha\}$$

*The possibility distribution*  $\pi_{\mathcal{K}'}$  *associated to*  $\mathcal{K}'$  *is such that:* 

$$\forall I \in \Omega, \pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_{m}(\varphi, \mu)),$$

where  $\pi_{\mathcal{K}}(\mathcal{I}|_m(\varphi,\mu))$  denotes the revised possibility distribution of  $\pi_{\mathcal{K}}$  using the min-based conditioning defined in Definition 4.16.

**Example 4.22** (Examples 4.19 continued). When the input is  $(A \sqsubseteq C, .9)$ , then  $\mathcal{K}' = \{(A \sqsubseteq B, .4), (B \sqsubseteq C, .7), (A \sqsubseteq C, .9), (A(a), .3)\}$  such that  $\pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_m(A \sqsubseteq C, .9))$  presented in Example 4.19. Now, when the input is  $(A \sqsubseteq C, .2)$ , then  $\mathcal{K}' = \{(A \sqsubseteq B, .2), (B \sqsubseteq C, .7), (A \sqsubseteq C, .9), (A(a), .3)\}$  such that  $\pi_{\mathcal{K}'}(I) = \pi_{\mathcal{K}}(\mathcal{I}|_m(A \sqsubseteq C, .2))$  becomes as follows:

$\mathcal{I}$	$\mathcal{I}$	$\pi_{\mathcal{K}}$	$\pi' = \pi_{\mathcal{K}}(\mathcal{I} _{m}(A \sqsubseteq C,.9))$	$\pi''=\pi_{\mathcal{K}}(\mathcal{I} _m(A\sqsubseteq C,.2))$
$\mathcal{I}_1$	$A=\{\}, B=\{a\}, C=\{\}$	.3	.3	.3
$\mathcal{I}_2$	$A=\{a\}, B=\{\}, C=\{a\}$	.6	.6	.8
$\mathcal{I}_3$	$A=\{\}, B=\{\}, C=\{\}$	.7	.7	.7
$\mathcal{I}_4$	$A=\{\}, B=\{\}, C=\{a\}$	.7	.7	.7
$\mathcal{I}_5$	$A=\{\}, B=\{a\}, C=\{a\}$	.7	.7	.7
$\mathcal{I}_6$	$A=\{a\}, B=\{a\}, C=\{a\}$	1	1	1
$\mathcal{I}_7$	$A=\{a\}, B=\{\}, C=\{\}$	.6	.1	.8
$\mathcal{I}_8$	$A=\{a\},B=\{a\},C=\{\}$	.3	.1	.3

Table 4.10: Example of possibility distribution revision by two information pieces using Definition 4.16

Let us now discuss the case where  $\mu \ge \nu$ . It is similar to the revision by a totally reliable information (i.e.  $\mu$ =1). In this case, it is natural that all the interpretations that are models of  $\varphi$  must be preserved and all the interpretations that falsify  $\varphi$  must be set as impossible (the necessity degree of the input equals 0). In this case the conditioning operation follows from Definitions 4.15 and 4.16. Moreover conditioning according Definitions 4.15 and 4.16 agrees with Definition 4.14. Finally when  $(\varphi, \mu)$  cannot be inferred from  $\mathcal{K}$ , this means that the revision process is performed simply with an expansion of  $\mathcal{K}$  with the input. In such situation, conditioning follows trivially according to Definitions 4.15 and 4.16 and coincides with Definition 4.14. It is similar to the case where the input is inconsistent with  $\mathcal{K}$ . Clearly,  $Inc(\mathcal{K} \cup (\varphi, \mu))$ =0.

#### **Discussions**

According to the new definition, conditioning of  $\pi$ -DL-Lite possibility distribution with  $(\varphi, \mu)$  establishes a new pre-order between counter-models and models of  $\varphi$ . This new ranking depends on the a priori necessity measure of  $\varphi$ , and the prescribed posterior necessity measure of  $\varphi$ . Roughly speaking, if  $N(\varphi) \leq \mu$  then with a min-based conditioning every interpretation that falsifies  $\varphi$  and that is more compatible than 1- $\mu$  is shifted down to 1- $\mu$ . This means that some a priori pre-order on these interpretations will be lost. Moreover, the fact that within  $\pi$ -DL-Lite framework, the necessity measure is not the dual of the possibility measure, some a priori pre-order on interpretations which are models of  $\varphi$  will also be lost. This is a consequence of shifting down to 1- $\mu$  some more compatible counter-models of  $\varphi$  when  $N(\varphi) \leq \mu$ . Regarding the computational complexity of the syntactic revision, it is obvious that it is polynomial since computing the inconsistency degree of a  $\pi$ -DL-Lite knowledge base is polynomial using the algorithm proposed in Section 3.5.

To compute the revision outcome, we need one step further when  $(\varphi, \mu)$  is inferred from the knowledge base. Namely, we need to compute the set of axioms responsible for deducing the input. The computational complexity of this subset is also polynomial. This step is in the spirit of computing the  $\pi$ -negated closure of a  $\pi$ -DL-Lite knowledge base. Clearly, computing this subset X comes down by adding every axiom involved in computing the  $\pi$ -neg $(\mathcal{T}_1)$  starting only from the negative inclusion axiom added from the assumption that  $\varphi$  is false. This is for obtained TBox axioms. Obtaining ABox assertions comes down to detect all assertions in the original ABox that contradict negative inclusion in  $\mathcal{X}$ .

#### 4.5 Conclusion

In this chapter, we first investigated merging of uncertain DL-Lite knowledge bases by adapting the min-based idempotent conjunctive operator. We then proposed a new min-based operator for merging multiple sources ABoxe's sharing the same terminology in the context of  $\pi$ -DL-Lite. We propose a syntactic version of this operator and its semantic counterpart. This operator turns out to be more productive than the classical one, without increasing the complexity of the merging process. In particular, it picks any piece of information that is not in contradiction with the other bases: it is not affected by the drowning effect. We finally provide an analysis in the light of a new set of postulates dedicated to uncertain DL-Lite merging.

This chapter addressed also conditioning of  $\pi$ -DL-Lite knowledge bases when a new piece of information  $(\varphi, \mu)$ , possibly conflicting or uncertain, becomes available. We first studied revision at the semantic level by adapting conditioning of possibility distributions proposed within the possibilistic setting. We have shown that such conditioning may provide some counterintuitive results. We then investigated revision at the syntactic level of  $\pi$ -DL-Lite knowledge bases. Finally, we proposed two other definitions of  $\pi$ -DL-Lite possibility distribution s conditioning that generalize the first one.

From the works on merging, it seems that our merging approach based on conflict resolution is closely related to handling inconsistency approaches. In fact, among the crucial issues when merging is how to deal with conflicting information. This has led us to orientate our works towards inconsistency management. Unfortunately, even in the flat case, (when there is no priority between sources), only few works addressed this problem. To this end, the second part concerns the problem of inconsistency handling in flat *DL-Lite* knowledge bases.

#### PART III

## Inconsistency handling in flat *DL-Lite* knowledge bases

# NON-MERGE INCONSISTENCY MANAGEMENT ROADMAP IN FLAT *DL-Lite*KNOWLEDGE BASES

#### 5.1 Introduction

In this chapter, we place ourselves in the context of handling an inconsistent set of pieces of information. As a case of study, we consider the setting of flat Ontology Based Data Access (OBDA) that studies how to query a set of independent data sources using an unified ontological view. A specific research challenge within the OBDA setting addresses the case when the data sources put together are inconsistent. Existing works (e.g. [Lembo and Ruzzi, 2007; Lembo et al., 2010; Bienvenu and Rosati, 2013; Rosati, 2014]) have focused on the study of different inference strategies (called semantics) based on productivity criteria (how two semantics relate to each other based on their answer sets) and computational complexity. In these studies, closely related to works on consistent query answering from inconsistent databases (e.g. [Chomicki, 2007; Bertossi, 2011]), there is a lack of studies on how existing inference strategies can be placed within the space of possible inference strategies.

This chapter produces a *roadmap of different inconsistency management techniques* from a *DL-Lite* knowledge base with a multiple ABox, called an MBox *DL-Lite* knowledge base. An MBox is a multi-set of ABox's which can be issued from multiple information sources (as per the OBDA view) but could also, for instance, be resulted from revising inconsistent *DL-Lite* knowledge bases.

We build upon the state of the art and:

- 1. Introduce, discuss and provide properties for three main elementary changes or modifiers that can be operated on an MBox, namely expansion modifiers, splitting modifiers and selection-based modifiers.
- 2. Provide and study different inference strategies for query answering from MBox *DL-Lite* knowledge bases.
- 3. Show how the combination of modifiers and inference strategies provides a natural general setting that extends existing consistent query answering OBDA techniques.
- 4. Provide a study of productivity results for modifier plus inference strategies combinations.

Based on the above notions, an additional and important contribution in this chapter is providing a generalized view for handling inconsistent standard *DL-Lite* knowledge bases. The important points of this roadmap lay in its principled nature and completeness. Within this setting, the particular problem of repairing an inconsistent *DL-Lite* knowledge base can be seen as made out of a (1) composite or a complex modifier on a given MBox followed by (2) an inference-based strategy. We show that there are exactly eight major composite modifiers that can be applied on an inconsistent *DL-Lite* knowledge base and identify those that produce a single consistent and preferred repair.

The rest is organized as follows: Section 5.2 first defines the concept of *DL-Lite* knowledge bases with multiple ABox, and then introduces three elementary modifiers that, applied on MBox, define new modifiers. Section 5.3 presents several inference-based strategies that can be applied on an MBox *DL-Lite* knowledge base. Section 5.4 investigates the problem of repairing an inconsistent *DL-Lite* knowledge base, which is considered as composed of a composite modifier applied on a given MBox followed by an inference-based strategy. Section 5.5 studies the productivity and gives a complexity analysis of the different inconsistency-tolerant inferences. Section 5.6 discusses the different results. Section 5.7 concludes the chapter. Finally, additional propositions and counterexamples can be found in the appendix B.

#### 5.2 Reasoning from MBox knowledge bases

This section proposes how to reason from a *DL-Lite* knowledge base with a multiple ABox, called an MBox *DL-Lite* knowledge base. We discuss three main elementary changes or modifiers on an MBox. We provide different ways to compose them in order to obtain a composite modifier and propose inference strategies for querying MBox *DL-Lite* knowledge bases.

#### **5.2.1** MBox: Multiple ABox

We first introduce the concept of *DL-Lite* knowledge bases with multiple ABox, called MBox *DL-Lite* knowledge bases.

**Definition 5.1.** A *DL-Lite* knowledge base with an MBox, called MBox *DL-Lite* knowledge base, is of the form  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  where  $\mathcal{T}$  is a standard *DL-Lite* TBox and  $\mathcal{M} = \{\mathcal{A}_1, \dots, \mathcal{A}_n\}$  is a multi-set of facts, called MBox, where each  $\mathcal{A}_i$  is a standard *DL-Lite* ABox.

In the above definition, there is no additional assumption regarding the consistency of each  $\langle \mathcal{T}, \mathcal{A}_i \rangle$ . However, in general,  $\langle \mathcal{T}, \mathcal{A}_i \rangle$ 's are often assumed to be consistent while  $(\mathcal{T}, \bigcup_{\mathcal{A}_i \in \mathcal{M}} \mathcal{A}_i)$  is unlikely to be consistent. An MBox may be viewed as a convenient way to represent a multiple-sources of information, where each ABox  $\mathcal{A}_i$  is assumed to be provided by a distinct source. An MBox may also be the result of revising an inconsistent standard *DL-Lite* knowledge base. In this case, each element of the MBox reflects a possible repair of the inconsistent *DL-Lite* knowledge base. This view of an MBox will be assumed in large in Section 5.4.

In the rest of the chapter, an MBox *DL-Lite* knowledge base  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \{\mathcal{A}_1, ..., \mathcal{A}_n\} \rangle$  is said to be consistent if each  $\langle \mathcal{T}, \mathcal{A}_i \rangle$  is individually consistent. A standard knowledge base will be indifferently represented by  $\langle \mathcal{T}, \mathcal{A} \rangle$  or by an MBox knowledge base  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{\mathcal{A}\} \rangle$  with only a single ABox in  $\mathcal{M}$ .

**Example 5.1.** Let  $\mathcal{T} = \{C \sqsubseteq B\}$  be a *DL-Lite* TBox. Let  $\mathcal{M} = \{\{C(a), B(a)\}, \{B(c), B(a)\}\}$  and  $\mathcal{M}' = \{\{C(a), B(a), B(c)\}\}$  be two MBox's. Then  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  is a *DL-Lite* knowledge base with an MBox containing a set of ABox and  $\mathcal{K}'_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M}' \rangle$  is a *DL-Lite* knowledge base with an MBox that is only composed with one single ABox.  $\mathcal{K}'_{\mathcal{M}}$  encodes a standard *DL-Lite* knowledge base.

#### **5.2.2** Elementary modifiers on MBox

We now introduce elementary modifiers that, applied on MBox, define new modifiers.

#### **Expansion modifiers**

The first considered modifier operators concern expansion of ABox's. It consists in adding to each ABox  $A_i$  some assertions. One natural way to define an expansion modifier on MBox is to use the notion of a deductive closure of DL-Lite knowledge bases. There are different definitions of deductive closures in DL-Lite (e.g. [Lembo et al., 2010]). Here, we propose the one that is appropriate for the context of inconsistency handling.

Note that the use of deductive closure of an ABox fully makes sense in DL languages, while for instance in propositional logic the closure of an inconsistent knowledge base trivially leads to produce the whole language. We denote by  $\circ_{cl}(\mathcal{M})$  the expansion modifier on MBox  $\mathcal{M}$ , defined as:

Let us denote by  $\circ_{cl}(\mathcal{M})$  the deductive closure operator of an MBox  $\mathcal{M}$ , defined as follows:

**Definition 5.2.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be an MBox *DL-Lite* knowledge base. Let  $\mathcal{T}_p$  be the set of all positive inclusion axioms of  $\mathcal{T}^1$ ,  $D_I$  be the set of all individuals in all ABox's;  $D_C$  and  $D_R$  be the set of concepts respectively roles in  $\mathcal{K}_{\mathcal{M}}$ .

• Standard *DL-Lite*: the deductive closure of a given ABox  $A_i$  with respect to T is defined as:

$$Cl_{\mathcal{T}}(\mathcal{A}_i) = \{B(a) : \langle \mathcal{T}_p, \mathcal{A}_i \rangle \models B(a), B \in D_C, a \in D_I \}$$

$$\cup$$

$$\{R(a,b) : \langle \mathcal{T}_p, \mathcal{A}_i \rangle \models R(a,b), R \in D_R, a \in D_I, b \in D_I \}$$

• *DL-Lite* with an MBox: the deductive closure of  $\mathcal{M}$  is defined as:

$$\circ_{cl}(\mathcal{M}) = \{Cl(\mathcal{A}_i) : \mathcal{A}_i \in \mathcal{M}\}$$

The expansion modifier  $\circ_{cl}(\mathcal{M})$  takes as input an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$  and produces as output an MBox  $\circ_{cl}(\mathcal{M})$  obtained by replacing each  $\mathcal{A}_i \in \mathcal{M}$  by its deductive closure.

**Example 5.2.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base where  $\mathcal{T} = \{\exists P \sqsubseteq B, A \sqsubseteq B, A \sqsubseteq \neg C\}$  and  $\mathcal{M} = \{\{A(a), P(c, b)\}, \{C(d)\}\}$ . Using Definition 5.2, the deductive closure of  $\mathcal{M}$  is :  $\circ_{cl}(\mathcal{M}) = \{\{A(a), B(a), P(c, b), B(c)\}, \{C(d)\}\}$ .

The deductive closure represents one natural way to define an expansion of an MBox. Another natural way to define an expansion is to add to each  $A_i \in \mathcal{M}$  the set of common assertions that can be derived from each  $\langle \mathcal{T}, A_i \rangle$ .

$$\mathcal{A}_{i} = \mathcal{A}_{i} \cup \{B(a) : \forall \mathcal{A}_{j} \in \mathcal{M}, \langle \mathcal{T}_{p}, \mathcal{A}_{j} \rangle \models B(a), a \in \mathbb{D}_{I}, B \in \mathbb{D}_{C}\} \cup \{R(a,b) : \forall \mathcal{A}_{j} \in \mathcal{M}, \langle \mathcal{T}_{p}, \mathcal{A}_{j} \rangle \models R(a,b), R \in \mathbb{D}_{R}, a \in \mathbb{D}_{I}, b \in \mathbb{D}_{I}\}$$

Where  $\mathbb{D}_C$  (resp.  $\mathbb{D}_R$ ,  $\mathbb{D}_I$ ) is the set of all concepts (resp. roles, individuals) used in  $\mathcal{M}$ .

In the rest of the chapter, by an expansion modifier, we refer to the use of deductive closure modifier  $\circ_{cl}$  given in Definition 5.2.

#### **Splitting modifiers**

The second class of modifiers is called splitting modifiers. The idea is to replace some  $A_i$  of an MBox by one or several of their subsets. This typically happens when some  $A_i$  is inconsistent with respect to

<sup>&</sup>lt;sup>1</sup>Positive inclusion axioms are of the form  $B_1 \sqsubseteq B_2$ .

 $\mathcal{T}$ . Then it may be reasonable to replace each  $\mathcal{A}_i$  by some of its consistent subsets. Here, we choose as a splitting modifier the widely used inclusion-based maximally consistent subsets, defined by:

**Definition 5.3.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a standard *DL-Lite* knowledge base.  $\mathcal{R} \subseteq \mathcal{A}$  is an inclusion-based maximally consistent subset of  $\mathcal{A}$  with respect to  $\mathcal{T}$  if and only if:

- 1.  $\langle \mathcal{T}, \mathcal{R} \rangle$  is consistent,
- 2. if  $\mathcal{R} \neq \mathcal{A}$  then  $\forall \mathcal{R}' : \mathcal{R} \subsetneq \mathcal{R}', \langle \mathcal{T}, \mathcal{R}' \rangle$  is inconsistent.

According to Definition 5.3, adding any fact f from  $\mathcal{A} \setminus \mathcal{R}$  to  $\mathcal{R}$  entails the inconsistency of  $\langle \mathcal{T}, \mathcal{R} \cup \{f\} \rangle$ . Note that if  $\mathcal{K}$  is consistent, then  $\mathcal{K}$  admits a unique maximally consistent subset which is  $\mathcal{R} = \mathcal{A}$ . The splitting modifier on a single ABox  $\mathcal{A}$ , denoted indifferently by  $\circ_{incl}(\mathcal{A})$  or  $\circ_{incl}(\{\mathcal{A}\})$ , is the set of all maximally inclusion-based consistent subsets of  $\mathcal{A}$  with respect to  $\mathcal{T}$ .

Definition 5.3 is extended to MBox as follows:

**Definition 5.4.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be an MBox *DL-Lite* knowledge base. An inclusion-based modifier on  $\mathcal{M}$ , denoted  $\circ_{incl}(\mathcal{M})$ , is defined by:

$$\circ_{incl}(\mathcal{M}) = \bigcup_{\mathcal{A}_i \in \mathcal{M}} \{X : X \in \circ_{incl}(\mathcal{A}_i)\}$$

Namely,  $\circ_{incl}(\mathcal{M})$  consists in replacing each inconsistent  $\mathcal{A}_i$  of  $\mathcal{M}$  by its maximally consistent subbases.

**Example 5.3.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base where  $\mathcal{T} = \{C \subseteq \neg B\}$  and  $\mathcal{M} = \{\{B(a), C(a), B(b)\}, \{C(e), B(e)\}\}$ .

Using Definition 5.4,  $\circ_{incl}(\mathcal{M}) = \{\{B(a), B(b)\}, \{C(a), B(b)\}, \{C(e)\}, \{B(e)\}\}$ .

#### **Selection-based modifiers**

The last elementary modifiers considered in this chapter are selection-based modifiers which consist in considering only some subsets of  $\mathcal{M}$  to make inferences for instance. An example of a selection modifier simply consists in keeping only ABox's issued from the most reliable sources and getting rid those that are not enough reliable. Another natural way to define such a selection function is to only keep the largest ABox's. This selection function, adopted in this chapter, is called cardinality-based selection, denoted by  $\circ_{card}(\mathcal{M})$  and is defined as follows:

**Definition 5.5.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be an MBox *DL-Lite* knowledge base. A cardinality-based selection on MBox  $\mathcal{M}$  is an MBox, denoted  $\circ_{card}(\mathcal{M})$ , defined by:

$$\circ_{card}(\mathcal{A}) = \{A_i : \mathcal{A}_i \in \mathcal{M} \text{ such that } \nexists \mathcal{A}_j \in \mathcal{M}, |\mathcal{A}_j| > |\mathcal{A}_i| \}.$$

Namely,  $\circ_{card}(\mathcal{M})$  selects among the ABox's in  $\mathcal{M}$  the ones with maximal assertion number.

**Example 5.4.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base where  $\mathcal{T} = \{\exists P \sqsubseteq B, B \sqsubseteq \neg C\}$  and  $\mathcal{M} = \{A_1 = \{P(c,b),B(a)\}, A_2 = \{C(a),B(b),\}, A_3 = \{B(c)\}\}$ . One can check that  $\circ_{card}(\mathcal{M}) = \{\{P(c,b),B(a)\},\{C(a),B(b)\}\}$ . Indeed,  $|\mathcal{A}_1| = |\mathcal{A}_2| = 2$ , while  $|\mathcal{A}_3| = 1$ . Hence, only  $\mathcal{A}_1$  and  $\mathcal{A}_2$  are kept.

#### 5.2.3 Composite modifiers on MBox

In the above section, we presented three main elementary modifiers<sup>2</sup> that operate on an MBox. These modifiers can be combined and composed to define composite modifiers.

The following lemma first shows that the elementary modifiers  $\circ_{cl}$ ,  $\circ_{incl}$  and  $\circ_{card}$  are idempotent. Besides, it also shows that expansion and splitting modifiers only need to be applied once. These properties considerably reduce the number of combinations that can be done on elementary modifiers.

**Lemma 5.1.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be an MBox DL-Lite knowledge base.

- 1. Let  $\circ_{cl}$ ,  $\circ_{incl}$ ,  $\circ_{card}$  be the three elementary modifiers on MBox presented in Section 5.2.2. Then:
  - (a)  $\circ_{incl}(\circ_{incl}(\mathcal{M})) = \circ_{incl}(\mathcal{M})$
  - (b)  $\circ_{card}(\circ_{card}(\mathcal{M})) = \circ_{card}(\mathcal{M})$ , and
  - (c)  $\circ_{cl}(\circ_{cl}(\mathcal{M})) = \circ_{cl}(\mathcal{M}).$
- 2. Let  $\circ_d$  be a composite modifier (i.e. a combination of elementary modifiers). Then:
  - (a)  $\circ_{cl}(\circ_d(\circ_{cl}(\mathcal{M}))) = \circ_d(\circ_{cl}(\mathcal{M}))$ , and
  - (b)  $\circ_{incl}(\circ_d(\circ_{incl}(\mathcal{M}))) = \circ_d(\circ_{incl}(\mathcal{M})).$

*Proof of Lemma 5.1.* The proof of the item (1.a) follows from the facts that:

- $\forall A_i \in \circ_{incl}(\mathcal{M}), \langle \mathcal{T}, A_i \rangle$  is consistent,
- if  $\langle \mathcal{T}, \mathcal{A}_i \rangle$  is consistent, then  $\circ_{incl}(\mathcal{A}_i) = \{\mathcal{A}_i\}$ .

The proof of the item (1.b) follows from the facts that:

- $\forall A_i \in \circ_{card}(\mathcal{M}), \forall A_j \in \circ_{card}(\mathcal{M}), \text{ we have } |A_i| = |A_j|$
- if  $\forall A_i \in \circ_{card}(\mathcal{M}), \forall A_j \in \circ_{card}(\mathcal{M}), |A_i| = |A_j| \text{ then } \circ_{card}(\mathcal{M}) = \mathcal{M}.$

For item (1.c), it is enough to show that for a given  $\mathcal{A} \in \mathcal{M}, \circ_{cl}(\circ_{cl}(\mathcal{A})) = \circ_{cl}(\mathcal{A})$ . From the definition of  $\circ_{cl}$ , clearly we have  $\circ_{cl}(\mathcal{A}) \subseteq \circ_{cl}(\circ_{cl}(\mathcal{A}))$ . Now assume that  $f \in \circ_{cl}(\circ_{cl}(\mathcal{A}))$  but  $f \notin \circ_{cl}(\mathcal{A})$ . Let  $B_f \subseteq \circ_{cl}(\mathcal{A})$  be the subset that allows to derive f, namely  $\langle \mathcal{T}_p, B_f \rangle \models f$ . Now for each element x of  $B_f$ , we have  $\langle \mathcal{T}_p, \mathcal{A} \rangle \models x$ . Then clearly,  $\langle \mathcal{T}_p, \mathcal{A} \rangle \models f$ .

Regarding item (2.a), if  $\circ_d$  is an elementary modifier then it can be either  $\circ_{cl}$ ,  $\circ_{card}$ , or  $\circ_{incl}$ . If  $\circ_d = \circ_{cl}$  then the result holds thanks to item (1.c). If  $\circ_d = \circ_{card}$  then the selected elements from  $\circ_{card}(\circ_{cl}(\mathcal{M}))$  are closed set of assertions since  $\circ_{card}$  only discards some elements of  $\circ_{cl}(\mathcal{M})$  but does not change the content of remaining elements. Lastly, let us consider the case where  $\circ_d = \circ_{incl}$ . Again  $\forall \mathcal{A}' \in \circ_{incl}(\circ_{cl}(\mathcal{M})), \mathcal{A}' = \circ_{cl}(\mathcal{A}')$ . Let us recall that  $\mathcal{A}'$  is maximally consistent subset of  $\mathcal{A} \in \circ_{cl}(\mathcal{M})$ , with  $\mathcal{A} = \circ_{cl}(\mathcal{A})$ . If  $\mathcal{A}' \neq \circ_{cl}(\mathcal{A})$  this means that  $\exists f \in \circ_{cl}(\mathcal{A}')$  (hence  $f \in \mathcal{A}$ ) such that  $f \notin \mathcal{A}'$  despite the fact that  $\langle \mathcal{T}, \mathcal{A}' \rangle \models f$ . This is impossible since  $\mathcal{A}'$  should be a maximal consistent subbase of  $\mathcal{A}$ . Since each  $\circ_d \in \{\circ_{cl}, \circ_{card}, \circ_{incl}\}$  applied on closed ABox preserves the closeness property, then clearly a composite modifier also preserves this closeness property.

The proof of item (2.b) follows immediately from the fact that

•  $\forall A_i \in \circ_{incl}(\mathcal{M}), \langle \mathcal{T}, A_i \rangle$  is consistent,

<sup>&</sup>lt;sup>2</sup>One can add other elementary modifiers as a concatenate modifier or a merging modifier (using different strategies). This will lead to obtaining other composite modifiers which are not considered in this chapter and are left to future works

- if  $\mathcal{M}$  is consistent, then  $\forall \circ_d \in \{\circ_{cl}, \circ_{card}, \circ_{incl}\}$  gives a consistent subbase, and
- $\circ_{incl}(\mathcal{M}) = \mathcal{M}$  if  $\mathcal{M}$  is consistent.

Figure 5.1 presents the set of all possible composite modifiers that can be applied on MBox. The starting point is an MBox *DL-Lite* knowledge base  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$ .

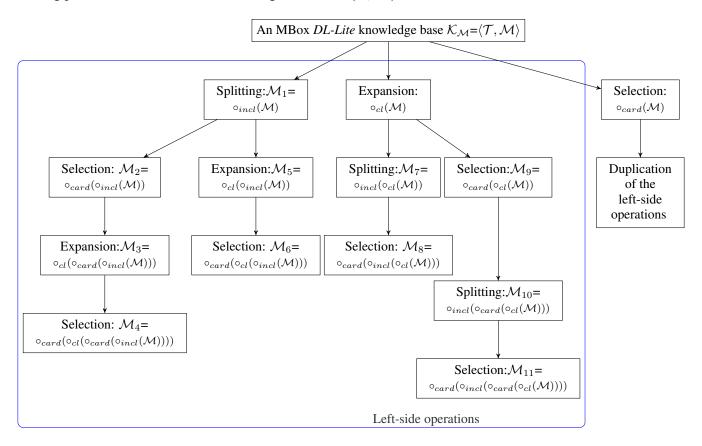


Figure 5.1: Composite modifiers on MBox

At the beginning, one can either use expansion modifier  $(\circ_{cl}(\mathcal{M}))$ , selection modifier  $(\circ_{card}(\mathcal{M}))$  or a splitting modifier  $(\circ_{incl}(\circ_{cl}(\mathcal{M})))$ . Expansion can only be followed either by a splitting modifier  $(\circ_{incl}(\circ_{cl}(\mathcal{M})))$  or by a selection modifier  $(\circ_{card}(\circ_{cl}(\mathcal{M})))$ . From the splitting operation one can only make selection  $(\circ_{card}(\circ_{incl}(\circ_{cl}(\mathcal{M}))))$  thanks to Lemma 5.1. From the selection operation one can only make splitting operation  $(\circ_{incl}(\circ_{card}(\circ_{cl}(\mathcal{M}))))$  thanks to Lemma 5.1. This splitting operation allows again the reuse of a selection operation  $(\circ_{card}(\circ_{incl}(\circ_{card}(\circ_{cl}(\mathcal{M})))))$ .

From the MBox  $\circ_{incl}(\circ_{cl}(\mathcal{M}))$  only a selection can be applied, thanks to Lemma 5.1, where  $\circ_{incl}(\mathcal{M})$  and  $\circ_{cl}(\mathcal{M})$  only needs to be applied once. Similarly, if one starts with a splitting operation followed by a selection operation, then only an expansion can be applied (thanks to Lemma 5.1 where  $\circ_{incl}(\mathcal{M})$  needs only to applied). From  $\circ_{cl}(\circ_{card}(\circ_{incl}(\mathcal{M})))$  only a selection can be applied, since again from Lemma 5.1,  $\circ_{incl}(\mathcal{M})$  and  $\circ_{cl}(\mathcal{M})$  needs only to be applied once. If one starts by a splitting modifier followed by an expansion, then only a selection needs to be applied. If one starts with a selection operation, then one can either apply an expansion or a splitting operation, and thus, we duplicate the same operations presented in the left-side box of the figure.

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Note that if one starts with an MBox *DL-Lite* knowledge base that only contains one ABox, then there is no need to add a selection child to the root. Similarly for such singleton MBox, applying an expansion modifier followed by a selection modifier leads to same results as if one start with an expansion modifier followed by a splitting modifier  $(\mathcal{M}_9 = \circ_{cl}(\mathcal{M}))$ . Hence we have  $\mathcal{M}_{10} = \mathcal{M}_7$  and  $\mathcal{M}_{11} = \mathcal{M}_8$ . The case where the starting point is a singleton MBox will be discussed in Section 5.4.

#### 5.3 Inference-based strategies from MBox

This section addresses the issue of query answering from MBox *DL-Lite* knowledge bases. It presents several inference-based strategies that can be applied on an MBox *DL-Lite* knowledge base. An inference-based strategy takes as input an MBox  $\mathcal{M}$ , a TBox  $\mathcal{T}$  (i.e. an ontology) and a query and aims to find if there exists an answer for such a query over the set of ABox's of the MBox *DL-Lite* knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{M} \rangle$ .

Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M}$ . The following subsections provide main inference-based strategies that can be applied on  $\mathcal{K}_{\mathcal{M}}$ .

#### 5.3.1 Universal inference

The universal inference-based strategy states that a conclusion is valid if and only if it can be obtained (in a standard way) from every ABox  $A_i$  of a given MBox M. More precisely,

**Definition 5.6.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$ . A query q is said to be a universal consequence of  $\mathcal{K}_{\mathcal{M}}$ , denoted by  $\mathcal{K}_{\mathcal{M}} \models_{\forall} q$ , if and only if  $\forall \mathcal{A}_i \in \mathcal{M}, \langle \mathcal{T}, \mathcal{A}_i \rangle \models_q 3$ .

**Example 5.5.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base where  $\mathcal{T} = \{D \sqsubseteq B, C \sqsubseteq B, D \sqsubseteq \neg C\}$  and  $\mathcal{M} = \{\{D(a), C(b)\}, \{C(a)\}\}$ . One can check that  $\mathcal{K}_{\mathcal{M}} \models_{\forall} B(a)$ , since

- $\langle \mathcal{T}, \{D(a), C(b)\} \rangle \models B(a)$ , and
- $\langle \mathcal{T}, \{C(a)\} \rangle \models B(a)$ .

The universal inference is a standard way to derive conclusions from different sources. It is also known as a skeptical inference, used for instance in default reasoning [Reiter, 1987], where one only accepts conclusions derived from each extension of a default theory.

In Definition 5.6, q in general represents a first order formula. Now, when we deal with *DL-Lite* framework, q may (and often) represents a conjunctive query.

When q is a boolean query, then q holds universally from an MBox DL-Lite knowledge base  $\mathcal{K}_{\mathcal{M}}$  if and only if q holds in each standard DL-Lite knowledge base  $\mathcal{K}_i = \langle \mathcal{T}, \mathcal{A}_i \rangle$ , with  $\mathcal{A}_i \in \mathcal{M}$ .

If q is a general conjunctive query of the form

$$q(x_1,\ldots,x_n) \leftarrow (x_1,\ldots,x_n) : \exists y_1,\ldots,y_l.B_1 \wedge \ldots \wedge B_m$$

then  $q(a_1,...,a_n)$  universally follows from an MBox *DL-Lite* knowledge base  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  if  $q(a_1,...,a_n)$  follows from each standard *DL-Lite* knowledge base  $\mathcal{K}_i = \langle \mathcal{T}, \mathcal{A}_i \rangle$  with  $\mathcal{A}_i \in \mathcal{M}$ , where  $(a_1,...,a_n)$  is an instance of the distinguished variables  $(x_1,...,x_n)$ .

<sup>&</sup>lt;sup>3</sup> ⊨ is the inference relation from a standard *DL-Lite* knowledge base presented in Section 1.4

Said differently, using the universal consequence relation, answers to a query q from an MBox DL-Lite knowledge base  $\mathcal{K}_{\mathcal{M}}$  is defined as the intersection of answers to q obtained from each standard DL-Lite  $\mathcal{K}_i$  of  $\mathcal{K}_{\mathcal{M}}$ .

**Example 5.6.** Let  $\mathcal{K}=\langle \mathcal{T},\mathcal{M}\rangle$  be a DL-Lite knowledge base where  $\mathcal{T}=\{\exists S\sqsubseteq B,\exists S^-\sqsubseteq C,S\sqsubseteq \neg H,\exists H\sqsubseteq B,\exists H^-\sqsubseteq D\}, \text{ and } \mathcal{M}=\{\mathcal{A}_1,\mathcal{A}_2,\mathcal{A}_3\} \text{ where } \mathcal{A}_1=\{S(a,c),H(c,b),S(b,f),H(f,k)\}, \mathcal{A}_2=\{S(a,d),H(d,b),S(b,t)\} \text{ and } \mathcal{A}_3=\{S(a,e),H(g,b),S(b,y)\}$ 

Let us illustrate universal inferences over the different forms of queries: instance query (or instance checking), atomic ground queries, boolean queries, general conjunctive queries and first order formulas.

- 1. Let  $q \leftarrow B(a)$  be an instance query. One can check that  $\mathcal{K}_{\mathcal{M}} \models_{\forall} B(a)$ , since B(a) holds respectively from  $A_1$ ,  $A_2$ , and  $A_3$  using  $\mathcal{T}$ .
- 2. Let  $q \leftarrow B(b) \land D(b)$  be an atomic ground query. One can check that  $\mathcal{K}_{\mathcal{M}} \models_{\forall} q$ .
- 3. Let  $q \leftarrow \exists z. D(b) \land S(b, z)$  be a boolean query with existential variables. One can verify that  $\mathcal{K}_{\mathcal{M}} \models_{\forall} q$ .
- 4. Let  $q(x_1, x_2) \leftarrow (x_1, x_2) \exists y. S(x_1, y) \land H(y, x_2)$  be a conjunctive query. The answer sets that can be computed from each ABox in  $\mathcal{M}$  are :

```
Using A_1: \{ \langle a, b \rangle, \langle b, k \rangle \}
Using A_2: \{ \langle a, b \rangle \}
Using A_3: \{ \langle a, b \rangle \}
```

The certain answers to q that universally hold from  $\mathcal{K}_{\mathcal{M}}$  are:  $\{\langle a, b \rangle\}$ .

5. Let  $q \leftarrow C(c) \lor C(d) \lor C(e)$  be a first order query. One can verify that  $\mathcal{K}_{\mathcal{M}} \models_{\forall} q$ .

#### **5.3.2** Existential inference

The existential inference-based strategy is an inference strategy that only checks if a conclusion holds from at least one ABox of a given MBox. More formally,

**Definition 5.7.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$ . A query q is said to be an existential consequence of  $\mathcal{K}_{\mathcal{M}}$ , denoted by  $\mathcal{K}_{\mathcal{M}} \models_{\exists} q$ , if and only if  $\exists \mathcal{A}_i \in \mathcal{M}, \langle \mathcal{T}, \mathcal{A}_i \rangle \models q$ .

The existential inference, called also credulous inference, is a very adventurous inference relation. It only makes sense in some decision problems when one is only looking for a possible solution of a set of constraints or preferences. It is often considered as undesirable when  $\mathcal{K}_{\mathcal{M}}$  represents available knowledge base on some problem. The existential consequence relation is so adventurous that it may lead to an inconsistent set of conclusions (with respect to  $\mathcal{T}$ ).

**Example 5.7.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* where  $\mathcal{T} = \{C \sqsubseteq B\}$  and  $\mathcal{M} = \{\{C(a), B(a)\}, \{C(b), B(d)\}, \{B(c)\}\}$ . One can check that  $\mathcal{K}_{\mathcal{M}} \models_{\exists} B(b)$ , since  $\langle \mathcal{T}, \{C(b), B(d)\} \rangle \models B(b)$ .

#### **5.3.3** Safe inference

The safe inference-based strategy considers as valid conclusions those that are only derived from facts belonging to the intersection of all ABox's. More formally,

**Definition 5.8.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$ . A query q is said to be a safe consequence of  $\mathcal{K}_{\mathcal{M}}$ , denoted by  $\mathcal{K}_{\mathcal{M}} \models_{\cap} q$ , if and only if  $\langle \mathcal{T}, \bigcap_{\mathcal{A}_i \in \mathcal{M}} \mathcal{A}_i \rangle \models_{q}$ .

Obviously, the safe inference is a very sound and conservative inference relation since it only considers common assertions between the different ABox, to perform inferences.

**Example 5.8.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base where  $\mathcal{T} = \{C \sqsubseteq B\}$  and  $\mathcal{M} = \{\{C(a)\}, \{C(a), B(b)\}, \{C(a), B(c)\}\}$ . We have  $\bigcap_{\mathcal{A}_i \in \mathcal{M}} \mathcal{A}_i = \{C(a)\}$ , and thus,  $\mathcal{K}_{\mathcal{M}} \models_{\cap} B(a)$ , since  $\langle \mathcal{T}, \{C(a)\} \rangle \models B(a)$ .

#### **5.3.4** Other inferences

We now provide additional inference-based strategies called: Majority-based inference, Proportional-based inference and Non-objection inference. These inference relations offer a good compromise between universal or safe inference relations and existential inference relations.

#### **Majority-based inference**

The majority-based inference relation (maj for short) considers a conclusion as valid if it is confirmed by the majority of ABox's. More formally:

**Definition 5.9.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$ . A query q is said to be a majority-based consequence of  $\mathcal{K}_{\mathcal{M}}$ , denoted  $\mathcal{K}_{\mathcal{M}} \models_{maj} q$ , if and only if:

$$\frac{|\mathcal{A}_i: \mathcal{A}_i \in \mathcal{M}, \langle \mathcal{T}, \mathcal{A}_i \rangle \models q|}{|\mathcal{M}|} > 1/2.$$

Definition 5.9 simply states that a query q is a majority-based consequence of  $\mathcal{K}_{\mathcal{M}}$  if and only if it can be deduced from more than the half of ABox's in  $\mathcal{M}$ .

**Example 5.9.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base where  $\mathcal{T} = \{C \sqsubseteq B\}$  and  $\mathcal{M} = \{\{C(a)\}, \{C(a), B(b)\}, \{C(c), B(c)\}\}$ . We have  $\langle \mathcal{T}, \{C(a)\} \rangle \models B(a)$  and  $\langle \mathcal{T}, \{C(a), B(b)\} \rangle \models B(a)$  and  $|\mathcal{M}| = 3$ . Hence  $\mathcal{K}_{\mathcal{M}} \models_{maj} B(a)$ .

#### **Proportional-** $\alpha$ **-based inference**

The Proportional- $\alpha$ -based inference (prop for short) requires that a conclusion is valid if it can be derived from a proportion  $\alpha$  of ABox's of an MBox. More formally:

**Definition 5.10.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$  and  $\alpha \geq 0$ . A query q is said to be a proportional- $\alpha$ -based consequence of  $\mathcal{K}_{\mathcal{M}}$ , denoted  $\mathcal{K}_{\mathcal{M}} \models_{\alpha} q$ , if and only if

$$\frac{|\mathcal{A}_i: \mathcal{A}_i \in \mathcal{M}, \langle \mathcal{T}, \mathcal{A}_i \rangle \models q|}{|\mathcal{M}|} \ge \alpha.$$

Following Definition 5.10, the proportional- $\alpha$ -based inference generalizes the above inference-based strategies as follows:

- if  $\alpha = 1$ , then we recover the universal inference.
- if  $\alpha > 1/2$ , then we recover the majority-based inference.
- if  $\alpha = \epsilon$ , then we recover the existential inference.

Note that, the major difference of Proportional- $\alpha$ -based inference relation is how to fit the parameter  $\alpha$ .

#### Non-objection inference

The non-objection inference or argued inference (obj for short) is an inference strategy where a conclusion q is accepted if it can be obtained using at least one ABox while there is no ABox that implies  $\neg q$ . More formally:

**Definition 5.11.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a *DL-Lite* knowledge base with an MBox  $\mathcal{M} = \{\mathcal{A}_1, ..., \mathcal{A}_n\}$ . A query q is said to be a non-objection consequence relation of  $\mathcal{K}_{\mathcal{M}}$ , denoted by  $\mathcal{K}_{\mathcal{M}} \models_{obj} q$ , if and only if

- 1.  $\exists A_i \in \mathcal{M} : \langle \mathcal{T}, A_i \rangle \models q$ , and
- 2. there exists no  $A_i \in \mathcal{M}$  such that  $\langle \mathcal{T}, A_i \rangle \models \neg q$ .

**Example 5.10.** Let 
$$\mathcal{K} = \langle \mathcal{T}, \mathcal{M} \rangle$$
 be a *DL-Lite* where  $\mathcal{T} = \{C \sqsubseteq \neg B, B \sqsubseteq D\}$  and  $\mathcal{M} = \{\{C(a)\}, \{B(a)\}\}$ . One can check that  $\mathcal{K} \models_{obj} D(a)$ .

One can easily check that, if q is a first order formula then the non-objection inference is more cautious than the existential inference relation but it is more productive than the universal inference relation.

As it is said before, within *DL-Lite* framework, q is often restricted to conjunctive queries. In this case, the second item of Definition 5.11 does not really make sense, since negation is not allowed in the definition of a conjunctive query. Besides, if one restricts inferences to boolean queries, and interprets  $\langle \mathcal{T}, \mathcal{A}_i \rangle \models \neg q$  in definition as  $\langle \mathcal{T}, \mathcal{A}_i \rangle \models q$  does not hold, then the non-objection is simply equivalent to existential inference.

In the rest of the chapter, we will not make reference to non-objection inference, since it comes down to existential inference for boolean query. Of course, one may weaken item 2 of Definition 5.11 for atomic grounded queries of the form  $(\bigwedge_{i=1}^n A_i(a)) \wedge (\bigwedge_{j=1}^m P_j(a,b))$  where  $A_i$  and  $P_j$  are concepts and roles respectively. In item 2, one may replace  $\langle \mathcal{T}, \mathcal{A}_i \rangle \models \neg q$  by  $\langle \mathcal{T}, \mathcal{A}_i \cup q \rangle$  is inconsistent. This weakened form of Definition 5.11 is not considered in the chapter and is left for further research.

Given the limitations of existential, non-objection and proportional-based inferences, in the rest of the chapter, we only focus on universal, safe and majority-based inference.

#### 5.3.5 Comparing inference-based strategies from a fixed MBox

Given a fixed MBox  $\mathcal{M}$ , the following figure summarizes the cautiousness relationships between different inference-based strategies, defined in the above subsections.

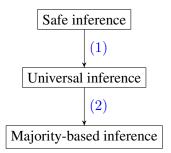


Figure 5.2: Comparison between inference-based strategies

The top of Figure 5.2 corresponds to the most conservative inference relation which is the safe inference relation. The existential inference is the most productive inference. In Figure 5.2,  $X \longrightarrow Y$  means that each conclusion of X is also a conclusion of Y.

**Proposition 5.1** (Figure 5.2). Let  $\mathcal{M}$  be a consistent MBox with respect to a TBox  $\mathcal{T}$ . Let q be a query. Then:

- 1. if  $\langle \mathcal{T}, \mathcal{M} \rangle \models_{\cap} q$  then  $\langle \mathcal{T}, \mathcal{M} \rangle \models_{\forall} q$ .
- 2. if  $\langle \mathcal{T}, \mathcal{M} \rangle \models_{\forall} q \text{ then } \langle \mathcal{T}, \mathcal{M} \rangle \models_{maj} q$ .

*Proof of Proposition 5.1.* Item 1 holds from the fact that  $\forall A_i \in \mathcal{M}$ , we have  $(\bigcap_{A_i \in \mathcal{M}} A_i) \subseteq A_i$ . Items 2 holds due to the fact that universal consequence requires that q follows from all ABox in  $\mathcal{M}$ . Hence, q holds in at least the half of  $A_i$ 's in  $\mathcal{M}$ .

**Example 5.11** (Counter-examples of Proposition 5.1). The following gives counter-examples for items 1-3 of Proposition 5.1.

- 1. Let  $\mathcal{T} = \{D \sqsubseteq B, C \sqsubseteq B, D \sqsubseteq \neg C\}$  and  $\mathcal{M} = \{\{D(a), C(b)\}, \{C(a)\}\}$ . Let  $q \leftarrow B(a)$ . We have  $\langle \mathcal{T}, \mathcal{M} \rangle \models_{\forall} B(a)$  but  $\langle \mathcal{T}, \mathcal{M} \rangle \not\models_{\cap} B(a)$ .
- 2. Let  $\mathcal{T} = \{D \subseteq B\}$  and  $\mathcal{M} = \{\{D(a)\}, \{D(a), B(b)\}, \{D(c), B(c)\}\}$ . Let  $q \leftarrow B(a)$ . We have  $\langle \mathcal{T}, \mathcal{M} \rangle \models_{maj} B(a)$  but  $\langle \mathcal{T}, \mathcal{M} \rangle \not\models_{\forall} B(a)$ , since  $\langle \mathcal{T}, \{D(c), B(c)\} \rangle$  does not allow to entail B(a).

The following lemma gives cautiousness relations between different inference strategies from two MBox's where one MBox is included (or equal) in the other. This lemma and the next one will be helpful for next sections.

**Lemma 5.2.** Let  $\mathcal{M}_1$  and  $\mathcal{M}_2$  be two consistent MBox with respect to a TBox  $\mathcal{T}$  s.t  $\mathcal{M}_1 \subseteq \mathcal{M}_2$  (namely,  $\forall \mathcal{A}_i \in \mathcal{M}_1$ , we have  $\mathcal{A}_i \in \mathcal{M}_2$ ). Let q be a query. Then:

- 1. If  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\forall} q \text{ then } \langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\forall} q$ .
- 2. If  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\cap} q \text{ then } \langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\cap} q$ .
- 3. The majority-based inference from  $\mathcal{M}_1$  is incomparable with the one obtained from  $\mathcal{M}_2$ .

*Proof of Lemma 5.2.* The proof is immediate. For item 1, if q holds in all  $\mathcal{A}_i$  of  $\mathcal{M}_2$  then trivially it holds in all  $\mathcal{A}_j$  of  $\mathcal{M}_1$  (since  $\mathcal{M}_1 \subseteq \mathcal{M}_2$ ). Item 2 holds due to the fact that  $\mathcal{M}_1 \subseteq \mathcal{M}_2$  implies that  $\bigcap_{\mathcal{A}_i \in \mathcal{M}_2} \mathcal{A}_i \subseteq \bigcap_{\mathcal{A}_i \in \mathcal{M}_1} \mathcal{A}_j$ .

**Example 5.12** (Counter-examples of Lemma 5.2). The converse of Items 1 and 2 does not hold. As it is shown by the following counter-example (we also provides the counter-example of item 3). Let  $\mathcal{T} = \emptyset$ ,  $\mathcal{M}_1 = \{B(a)\}$  and  $\mathcal{M}_2 = \{\{B(a)\}, \{B(c)\}, \{B(c)\}\}$ . First, note that  $\mathcal{M}_1 \subseteq \mathcal{M}_2$ . Clearly  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\forall} B(a)$  (resp.  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\cap} B(a)$ ) holds, while  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\forall} B(a)$  (resp.  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\cap} B(a)$ ) does not hold.

Regarding majority-based inference, one can check that  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} B(a)$  holds while  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{maj} B(a)$  does not hold. And  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{maj} B(c)$  holds while  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} B(c)$  does not hold.

The following inference relations hold between an MBox  $\mathcal{M}$  and its expansion  $\circ_{cl}(\mathcal{M})$ .

**Lemma 5.3.** Let  $\mathcal{M}_1$  and  $\mathcal{M}_2$  be two consistent MBox with respect to  $\mathcal{T}$ . Let  $\mathcal{M}_2$  be the closure of  $\mathcal{M}_1$ , namely  $\mathcal{M}_2 = \{Cl(\mathcal{A}_i): \mathcal{A}_i \in \mathcal{M}_1\}$ . Let q be a query. Then:

1. 
$$\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\forall} q \text{ if and only if } \langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\forall} q.$$

2. 
$$\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} q \text{ if and only if } \langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{maj} q.$$

3. if 
$$\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\cap} q$$
 then  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\cap} q$ .

*Proof of Lemma 5.3.* The proof is again immediate. Item 1 and 2 follow from the fact that in standard *DL-Lite*, if  $\mathcal{A}$  is a consistent ABox with  $\mathcal{T}$ , then  $\langle \mathcal{T}, \mathcal{A} \rangle \models q$  iff  $\langle \mathcal{T}, Cl_{\mathcal{T}}(\mathcal{A}) \rangle \models q$ . Item 3 follows from the fact that  $\mathcal{A}_i \subseteq Cl(\mathcal{A}_i)$  for each  $\mathcal{A}_i \in \mathcal{M}_1$ . Hence  $\bigcap_{\mathcal{A}_i \in \mathcal{M}_1} \mathcal{A}_i \subseteq \bigcap_{\mathcal{A}_i \in \mathcal{M}_1} Cl(\mathcal{A}_i) = \bigcap_{\mathcal{A}_i \in \mathcal{M}_2} \mathcal{A}_j$ .

#### 5.4 Handling inconsistency=Composite modifiers+inference strategies

As it is said in the introduction, an MBox may be issued from multiple-sources of information or may be resulted from handling inconsistent standard DL-Lite knowledge base K, where each element of the MBox represents a possible repair of K. In the context of multiple-sources of information, it may make sense to merge the ABox's of an MBox, in order to get a single ABox. As it is suggested in the title of this chapter, this work is not oriented towards merging ABox's but rather on the use of MBox as a way to represent and reason about inconsistent DL-Lite knowledge bases. We view the problem of repairing an inconsistent DL-Lite knowledge base as composed of a composite modifier on a given MBox followed by an inference-based strategy.

As it was said before, from Figure 5.1, if one starts with a standard *DL-Lite* knowledge base (*i.e.* a single MBox), there are only eight main composite modifiers useful for handling inconsistency (Lemma 5.4). These composite modifiers are given in Figure 5.1, and summarized in Table 5.1.

MBox	Combination
$\mathcal{M}_1$	$\circ_{\mathcal{M}_1} = \circ_{incl}(\mathcal{M})$
$\mathcal{M}_2$	$\circ_{\mathcal{M}_2} = \circ_{card}(\circ_{incl}(\mathcal{M}))$
$\mathcal{M}_3$	$\circ_{\mathcal{M}_3} = \circ_{cl}(\circ_{card}(\circ_{incl}(\mathcal{M})))$
$\mathcal{M}_4$	$\circ_{\mathcal{M}_4} = \circ_{card}(\circ_{cl}(\circ_{card}(\circ_{incl}(\mathcal{M}))))$
$\mathcal{M}_5$	$\circ_{\mathcal{M}_5} = \circ_{cl}(\circ_{incl}(\mathcal{M}))$
$\mathcal{M}_6$	$\circ_{\mathcal{M}_6} = \circ_{card}(\circ_{cl}(\circ_{incl}(\mathcal{M})))$
$\mathcal{M}_7$	$\circ_{\mathcal{M}_7} = \circ_{incl}(\circ_{cl}(\mathcal{M}))$
$\mathcal{M}_8$	$\circ_{\mathcal{M}_8} = \circ_{card}(\circ_{incl}(\circ_{cl}(\mathcal{M})))$

Table 5.1: Composite modifiers on MBox with  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{\mathcal{A}\} \rangle$ 

**Lemma 5.4.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\{ \circ_{\mathcal{M}_1}, ..., \circ_{\mathcal{M}_8} \}$  be the eight composite modifiers summarized in Table 5.1. Then for each composite modifier  $\circ_d$  (obtained by a finite combination of elementary modifiers  $\circ_{incl}, \circ_{card}, \circ_{cl}$ ), there exists  $\circ_c \in \{ \circ_{\mathcal{M}_1}, ..., \circ_{\mathcal{M}_8} \}$  such that  $\circ_d(\mathcal{M}) = \circ_c(\mathcal{M})$ .

Let us now provide the set inclusion relations between the different MBox's resulting from applying composite modifiers  $\circ_{\mathcal{M}_1},...,\circ_{\mathcal{M}_8}$  on an initial inconsistent *DL-Lite* knowledge base  $\mathcal{K}_{\mathcal{M}}=\langle \mathcal{T},\mathcal{M}=\{\mathcal{A}\}\rangle$ . Figure 5.3 gives different relations between MBox's issued from applying the main composite modifiers:

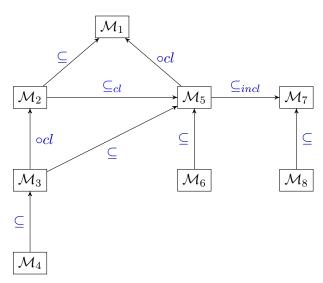


Figure 5.3: Inclusion relations between MBox's where " $X \longrightarrow Y$ " means that the MBox X is included (set inclusion) in Y, " $X \longrightarrow Y$ " means that  $\forall A \in X$ ,  $\exists B \in Y$  s.t  $A \subseteq B$ . " $X \longrightarrow Y$ " means that for each  $A \in X$ ,  $\exists B \in Y$  s.t  $B = \circ_{cl}(A)$  and " $X \longrightarrow_{\circ cl} Y$ " means that  $X = \circ_{cl}(Y)$ .

Let us briefly explain why the relations given in Figure 5.3 hold. First, note that by definition of the elementary modifier  $\circ_{card}$ ,  $\circ_{card}(\mathcal{M}) \subseteq \mathcal{M}$  (since  $\circ_{card}$  is a selection operation), hence the relations:

$$\mathcal{M}_4 \subseteq \mathcal{M}_3$$
,  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ ,  $\mathcal{M}_6 \subseteq \mathcal{M}_5$ , and  $\mathcal{M}_8 \subseteq \mathcal{M}_7$ 

trivially hold.

Similarly, using the definition of the elementary modifier  $\circ_{cl}()$ , we also have:

$$\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$$
 and  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$ .

As consequence of the above relations, we have:

$$\mathcal{M}_3 \subseteq \mathcal{M}_5$$
.

Regarding  $\mathcal{M}_2 \circ cl \mathcal{M}_5$ , we have  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ , hence  $\forall A \in \mathcal{M}_2$ , we also have  $A \in \mathcal{M}_1$ . Recall that  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$ . This means that  $\forall A \in \mathcal{M}_2, \exists B \in \mathcal{M}_5$  such that B = Cl(A).

It remains now to show that  $M_5 \circ clM_7$ . Let  $B \in \circ_{incl}(\{A\})$  and let us show that there exists a set of assertions X such that  $\circ_{cl}(\{B\}) \subseteq X$  and  $X \in \mathcal{M}_7$ . Since  $B \in \circ_{incl}(\{A\})$ , this means by definition that  $B \subseteq A$  and hence  $B \subseteq \circ_{cl}(A)$ . Now, B is consistent, this means that there exists  $R \in \circ_{incl}(\circ_{cl}(A)) = \mathcal{M}_7$  such that  $B \in R$ . From Lemma 5.1, R is a closed set of assertions, then this means that  $Cl(B) \subseteq R$ .

#### 5.5 Comparative studies

We now compare main inference-based strategies (Section 5.3) applied on the eight identified composite modifiers for handling inconsistent standard *DL-Lite* knowledge base. The studies concern productivity relations and computational complexity.

#### 5.5.1 Productivity

This section provides an exhaustive study of productivity results for modifier plus inference strategies combinations.

#### Composite modifiers + universal inference

The following figure summarizes existing cautiousness relations between universal consequence relations ( $\forall$ -entailment) applied on  $\{\mathcal{M}_1,...,\mathcal{M}_2\}$  identified in Section 5.2.3.

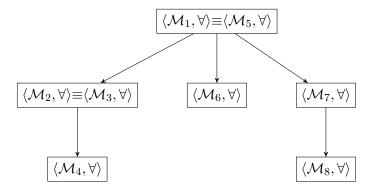


Figure 5.4: Relationships between  $\forall$ -entailment from  $\mathcal{M}_1$ - $\mathcal{M}_8$ 

In Figure 5.4, the arrow  $n1\rightarrow n2$  means that each conclusion that can be derived using n1 is also a conclusion using n2. Proofs of different links and counter-examples of the converse relations are given in the Appendix.

#### **Composite modifiers + safe inference**

Figure 5.5 gives existing cautiousness relations between safe inferences ( $\cap$ -entailment) applied on  $\{\mathcal{M}_1,...,\mathcal{M}_2\}$ .

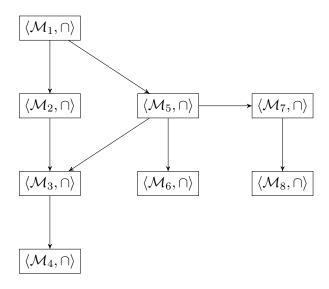


Figure 5.5: Relationships using safe entailment from  $\mathcal{M}_1$ - $\mathcal{M}_8$ 

In Figure 5.5: the bold arrow  $n1 \rightarrow n2$  means that each conclusion that can be derived using n1 is also a conclusion using n2.

#### Composite modifiers + majority-based inference

Figure 5.6 considers the case of majority-based consequence relations.

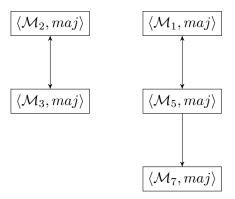


Figure 5.6: Relationships using majority-based inference from  $\mathcal{M}_1\text{-}\mathcal{M}_8$ 

#### Global schema

Figure 5.7 pairwise compares inference-based strategies given in Figure 5.2. Dashed arrow only holds for instance checking.

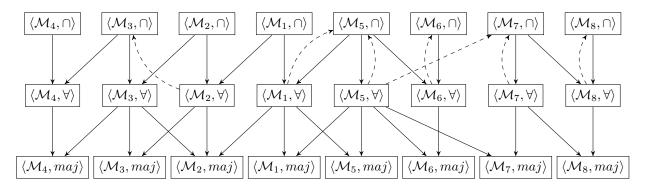


Figure 5.7: Relationships between different inference relations

Lastly, when the initial knowledge base is consistent, then all inference relations collapse with standard inferences, namely:

**Proposition 5.2.** Let  $K = \langle \mathcal{T}, \mathcal{M} \rangle$  be a consistent standard DL-Lite knowledge base. Then:  $\forall s \in \{\forall, maj, \cap\}, \forall \mathcal{M}_i \in \{\mathcal{M}_1, ..., \mathcal{M}_8\}, \langle \mathcal{T}, \mathcal{M}_i \rangle \models_s q \text{ if and only if } \langle \mathcal{T}, \mathcal{M} \rangle \models_q q.$ 

*Proof of Proposition* 5.2. The proof basically follows from three facts:

- 1. when  $\langle \mathcal{T}, \mathcal{M} \rangle$  is consistent then  $\circ_{incl}(\mathcal{M}) = \mathcal{M}$  and  $\circ_{card}(\mathcal{M}) = \mathcal{M}$ ,
- 2.  $\mathcal{M}_1 = \mathcal{M}_2 = \mathcal{M}$  and for i = 3, ..., 8:  $\mathcal{M}_i = \circ_{cl}(\mathcal{M})$ , and
- 3.  $\forall q, \langle \mathcal{T}, \mathcal{M} \rangle \models q \text{ if and only if } \langle \mathcal{T}, \circ_{cl}(\mathcal{M}) \rangle \models q.$

**5.5.2** Complexity analysis

This section discusses computational complexity of inference relations presented in the chapter. We first give the main ideas behind the complexity of inference relation  $\langle \mathcal{M}_2 = \mathcal{L} \circ_{incl}(\mathcal{M}), \forall \rangle$ , and then provide different tables summarizing complexity results of inference relations studied in this chapter.

Let K be an inconsistent knowledge base, we first define the notion of conflict which is a minimal inconsistent subset of A, more formally:

**Definition 5.12.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be an inconsistent *DL-Lite* knowledge base. A conflict set C is a set of membership assertions such that:

- $C \subseteq \mathcal{A}$ ,
- $\langle \mathcal{T}, C \rangle$  is inconsistent,
- $\forall C', C' \subset C, \langle \mathcal{T}, C' \rangle$  is consistent.

We denote by  $\mathcal{C}(\mathcal{A})$  the collection of conflicts in  $\mathcal{K}$ . Since  $\mathcal{K}$  is assumed to be finite, if  $\mathcal{K}$  is inconsistent then  $\mathcal{C}(\mathcal{A}) \neq \emptyset$  is also finite. Moreover, as mentioned in Lemma 3.6 and 3.7 in possibilistic DL-Lite,  $\forall C \in \mathcal{C}(\mathcal{A})$ , it holds that |C|=2. Note that this definition is in the spirit of 4.5 in prioritized case.

Let us now consider a simple case of instance-based checking, namely what is the complexity of the decision problem:

"Does 
$$\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\forall} B(a) \ (resp... \ R(a, b)) \ holds ?$$
"

where  $B \in D_C$  (resp.  $R \in D_R$ ), and  $a \in D_I$ (resp.  $a, b \in D_I$ ).

The complexity analysis can be easily generalized to any conjunctive query q and also to the inference relation  $\langle \mathcal{M}_8, \forall \rangle$ . To reach this aim, we will use complexity results which are known in graph theory regarding the problem of Maximum Independent Sets (MIS). Let us recall k-MIS the following decision problem:

"Given a symmetric graph G, is there an independent set of size (at least) k?"

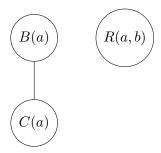
The computational complexity of k-MIS is known to be NP complete. [Garey and Johnson, 1979]. The following gives transformations between graphs and *DL-Lite* knowledge bases.

#### A transformation from an inconsistent DL-Lite knowledge base to G

Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be an inconsistent *DL-Lite* knowledge base. Let  $\mathcal{C}(\mathcal{A})$  be the set of all conflicts in  $\mathcal{A}$ . Recall that when  $\mathcal{T}$  is coherent, then all conflicts of  $\mathcal{C}$  are pairs of  $\mathcal{A}$  and are computed in PTime. We define a graph associated with  $\mathcal{K}$  as follows:

- 1. The set of nodes is simply the set of assertions in A (one assertion = one different node), and
- 2. A non-oriented arc is drawn from f to g if there is  $f \in \mathcal{A}$ ,  $g \in \mathcal{A}$  such that (f,g) is a conflict of  $\langle \mathcal{T}, \mathcal{A} \rangle$ .

**Example 5.13.** Let us consider  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  a *DL-Lite* knowledge base where  $\mathcal{T} = \{B \sqsubseteq \neg C\}$  and  $\mathcal{A} = \{B(a), C(a), R(b, c)\}$ . The graph associated with  $\mathcal{K}$  is :



Then we have the following result:

**Proposition 5.3.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a DL-Lite knowledge base, and G be its associated graph as it is defined above. Let  $\mathcal{R} \subseteq \mathcal{A}$  be a subset of  $\mathcal{A}$  and  $G_R$  be the set of nodes associated to R. Then R is a maximal consistent subset of  $\mathcal{A}$  if and only if  $G_R$  is a maximal independent set of G.

*Proof of Proposition 5.3.* The proof is immediate.

Assume that R is a maximal consistent subbase of  $\mathcal{A}$  but  $G_R$  is not a maximal independent set of G. This means that there exists a node f (namely an assertion of  $\mathcal{A}$ ) such that  $f \notin G_R$  and  $\forall g \in G_R$ , there is no arc between f and g. Said differently, there exists an assertion  $f \in \mathcal{A}$  such that  $f \notin R$  and  $\forall g \in R$ , there is no conflict  $\mathcal{C}$  of the form (f,g). This means that  $R \cup \{g\}$  is consistent and this contradicts the fact that R is a maximally consistent subbase of  $\mathcal{A}$ .

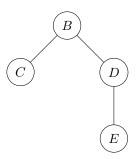
Similarly, assume that  $G_R$  is a maximal independent set of G and let us show that R (the subset of assertions present in  $G_R$ ) is a maximally consistent subset of A. Clearly, R is consistent, since  $\forall f \in \mathcal{R}, \forall g \in R$ , we have  $(f,g) \notin \mathcal{C}$  where  $\mathcal{C}$  is conflict (otherwise, the would be an arc between f and g). R is maximal, since  $\forall h \notin R$  there is an arc between h and a node from  $G_R$ . Hence there is a conflict between h and an element of R, namely  $R \cup \{h\}$  is inconsistent. Hence R is maximal.

#### Let us now give the converse transformation

Let G be a non-oriented graph. The *DL-Lite* knowledge base associated with G is defined as follows:

- 1. We associate to each node e a concept also denoted by e (two different nodes have two distinct associated concepts),
- 2. We use "a" as the unique individual used in A,
- 3. For each non-oriented arc  $e \longrightarrow f$ , we add  $(e \sqsubseteq \neg f)$  to  $\mathcal{T}$ , namely the TBox associated with G is defined by:  $\mathcal{T} = \{e \sqsubseteq \neg f : e \longrightarrow f \text{ is an arc of } G\}$ , and
- 4. The ABox is simply the set of nodes with the same individual "a", namely  $\mathcal{A} = \{e(a) : a \text{ is an individual and } e \text{ is a node of } G\}$ .

#### **Example 5.14.** Let G be the following graph:



Then the *DL-Lite* knowledge base associated with G is :  $\mathcal{T} = \{B \sqsubseteq \neg C, B \sqsubseteq \neg D, D \sqsubseteq \neg E\}$  and  $\mathcal{A} = \{B(a), C(a), D(a), E(a)\}.$ 

The *DL-Lite* knowledge base associated with a graph only involves one individual. It neither contains positive axioms nor relation symbols.

**Proposition 5.4.** Let G be a non-oriented graph, and  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be the DL-Lite knowledge base associated with G, as it is defined above. Then,  $\forall e(a) \in \mathcal{A}, \forall f(a) \in \mathcal{A}, (e(a), f(a)) \in \mathcal{C}$  if and only if there is an non-oriented arc between f and e.

Proof of Proposition 5.4. The proof is immediate. Since there is no relation symbols nor positive axioms, then the negative closure of  $\mathcal{T}$  is simply  $\mathcal{T}$ . Besides, for each  $e \sqsubseteq \neg f$  of  $\mathcal{T}$  (namely, an arc from G by construction), there exists exactly one conflict (e(a), f(a)) from  $\mathcal{A}$  (since there is exactly one individual a).

Using the two above propositions, the following proposition gives the complexity of computing the cardinality of the largest maximal consistent subbase of A.

**Proposition 5.5.** Let  $K = \langle T, A \rangle$  be an inconsistent DL-Lite knowledge base. The complexity of computing the cardinality of the largest maximal consistent subset of K is  $O(\log_2(|A|)*k$ -MIS.

*Proof of Proposition 5.5.* The proof is immediate. It is enough to apply a dichotomy search between 1 and  $|\mathcal{A}|$ , and for each value  $1 \le k \le |\mathcal{A}|$  we call a k-MIS problem.

We are now ready to give the complexity of the decision problem, denoted (\forall -card), namely

$$(\forall - card)$$
 "Does  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\forall} B(a)$  (resp. R(a,b)) hold?"

**Proposition 5.6.** Let  $K = \langle T, A \rangle$  be an inconsistent DL-Lite knowledge base. Assume that  $k_{max}$  is the size of the largest maximal subbase of A. Then  $(\forall -card)$  is NP-complete.

Proof of Proposition 5.6. Recall first that in standard consistent *DL-Lite* knowledge base  $\mathcal{K}_1 = \langle \mathcal{T}_1, \mathcal{A}_1 \rangle$ , checking if  $\mathcal{K}_1 \models B(a)$  comes down to check if  $\langle \mathcal{T} \cup \{D \sqsubseteq \neg B\}, \mathcal{A}_1 \cup \{D(a)\} \rangle$  is consistent, where a is a new individual and D is a new symbol.

Let D be a new concept symbol an a be a new individual. Let  $\mathcal{K}' = \langle \mathcal{T}' = \mathcal{T} \cup \{D \sqsubseteq \neg B\}, \mathcal{A}' = \mathcal{A} \cup \{D(a)\}\rangle$  be a DL-Lite knowledge base. Let G' be the graph associated with  $\mathcal{K}'$ . Then one can check that  $\langle \mathcal{T}, \circ_{cl}(\circ_{incl}(\mathcal{A})) \rangle \not\models_{\forall} B(a)$  iff G' admits a maximal independent set of size  $(k_{max} + 1)$ .

Indeed, assume that G' does not admit a maximal independent set of size  $(k_{max}+1)$ . This means that  $\forall R'$  a maximally consistent subset of  $\mathcal{A}'$  is of size  $k_{max}$ . This means that  $\forall R$  a maximally consistent subset of  $\mathcal{A}$  consistent with D(a) with respect to  $\mathcal{T}$ , hence  $\mathcal{K} \models B(a)$ . Similarly, if G' admits a maximal independent set of size  $(k_{max}+1)$ . This means that  $\exists R'$  a maximally consistent subset of  $\mathcal{A}'$  of size  $(k_{max}+1)$ . Hence, there exists R a maximally consistent subset of  $\mathcal{A}$  with respect to  $\mathcal{T}'$  which is consistent with D(a). Hence  $R \models B(a)$  and therefore  $\mathcal{K} \models_{\forall} B(a)$ .

**Proposition 5.7.** Computing  $\langle \mathcal{M}_2, \cap \rangle$  needs  $|\mathcal{A}|$  calls to a solver of k-MIS problem.

*Proof.* Recall that  $\langle \mathcal{M}_2, \cap \rangle = \bigcap_{A_i \in \mathcal{M}_2} A_i$  where  $\mathcal{M}_2 = \mathcal{L} \circ_{incl}(\mathcal{A})$ .

Hence, one way to compute  $\langle \mathcal{M}_2, \cap \rangle$  is to check whether each instance of  $\mathcal{A}$  is a universal consequence of  $\mathcal{M}_2$ . Following Proposition 5.6, checking whether an instance of  $\mathcal{A}$  follows from  $\langle \mathcal{M}_2, \forall \rangle$  needs exactly one call to a solver of k-MIS problem. Hence, computing  $\langle \mathcal{M}_2, \cap \rangle$  needs  $|\mathcal{A}|$  calls to a solver of k-MIS problem.

Similarly proof can be given for  $\langle \mathcal{M}_8, \cap \rangle$ , where it is enough to replace  $|\mathcal{A}|$  by  $|\circ_{cl}(()\mathcal{A})|$ .

As corollary, we have:

- The proof of NP completeness of  $\langle \mathcal{M}_3, \forall \rangle$  follows immediately from the result of Proposition 5.6 and from the fact that  $\langle \mathcal{M}_2, \forall \rangle$  is equivalent to  $\langle \mathcal{M}_3, \forall \rangle$ .
- Similarly, we have shown that  $\langle \mathcal{M}_1, \forall \rangle$  is equivalent to  $\langle \mathcal{M}_5, \forall \rangle$ . Hence, the proof of the completeness of  $\langle \mathcal{M}_5, \forall \rangle$  follows from the fact that  $\langle \mathcal{M}_1, \forall \rangle$  has been shown to be NP-complete in [Lembo *et al.*, 2010].
- The proof of NP-completeness of  $\langle \mathcal{M}_7, \forall \rangle$  is exactly the same as the one of  $\langle \mathcal{M}_1, \forall \rangle$ . The main difference is rather to start with the initial ABox  $\mathcal{A}$ , one should start with its closure  $\circ_{cl}(\mathcal{A})$ . Note that  $\langle \mathcal{M}_7, \forall \rangle$  is equivalent to CAR-entailment proposed in [Lembo *et al.*, 2010] where it has been shown that this latter is NP-complete.
- The proof of NP-completeness of  $\langle \mathcal{M}_8, \forall \rangle$  is exactly the same as the one of  $\langle \mathcal{M}_2, \forall \rangle$ . The main difference is rather to start with the initial ABox  $\mathcal{A}$ , one should start with its closure  $\circ_{cl}(\mathcal{A})$ .
- The computational complexity of  $\langle \mathcal{M}_4, \forall \rangle$ ,  $\langle \mathcal{M}_6, \forall \rangle$  comes down to enumerate all possible repairs.

We now provide a study of computational complexity of the rest of inference relations.

The majority-based inference  $\langle \mathcal{M}_i, maj \rangle$  for i = 1, ..., 8 are in #P (for more details on #P class of complexity, see [Valiant, 1979]), since it comes down to counting models implying the query.

We now give the complexity of safe inference relations. Note that, once  $\bigcap_{A_i \in \mathcal{M}_j} A_i$  is computed, the query answering has a same complexity as in standard *DL-Lite*.

- The inference relation  $\langle \mathcal{M}_1, \cap \rangle$  (resp.  $\langle \mathcal{M}_7, \cap \rangle$ ) is in PTime, since it comes down to compute conflict set from  $\mathcal{A}$  (resp.  $\circ_{cl}(\mathcal{A})$ ) and throw them out in order to obtain  $\bigcap_{\mathcal{A}_i \in \mathcal{M}_1} \mathcal{A}_i$  (resp.  $\bigcap_{\mathcal{A}_i \in \mathcal{M}_7} \mathcal{A}_i$ ) where the computation of conflict sets in *DL-Lite* is in PTime.
- The computational complexity of computing  $\langle \mathcal{M}_2, \cap \rangle$  (resp.  $\langle \mathcal{M}_8, \cap \rangle$ ) is  $\mathcal{O}(|\mathcal{A}| * k\text{-MIS})$  (resp.  $\mathcal{O}(|\mathcal{C}l(\mathcal{A})| * k\text{-MIS})$ ).

#### 5.6 Related works and discussions

This section first gives related works and then discusses the main inference strategies studied in this chapter.

#### 5.6.1 Related works

Handling inconsistency in ontologies is a very important problem that received a particular attention in recent years either on works on debugging or repairing generic knowledge (*e.g.* [Schlobach and Cornet, 2003; Haase *et al.*, 2005; Peñaloza and Sertkaya, 2010]) or revising ontologies (*e.g.* [Qi and Du, 2009; Wang *et al.*, 2010; Zhuang *et al.*, 2014]).

This present work is rather oriented to inconsistency handling within an OBDA setting. In [Lembo et al., 2010] four inconsistency-tolerant semantics called AR, IAR, CAR and ICAR were proposed. An inconsistency-tolerant semantics corresponds in our work to the combination of an MBox composite modifier followed by an inference-based strategy. It is easy to check that AR, IAR, CAR and ICAR semantics correspond respectively to  $\langle \mathcal{M}_1, \forall \rangle$ ,  $\langle \mathcal{M}_1, \cap \rangle$ ,  $\langle \mathcal{M}_7, \forall \rangle$  and  $\langle \mathcal{M}_7, \cap \rangle$ . It was shown in that CQ answering from AR and CAR is co-NP-complete in data complexity and IQ (instance checking) from CAR is in PTime, but it remains co-NP-complete under AR semantics. Besides both IQ and CQ answering under IAR and ICAR are in PTime for data complexity.

In [Bienvenu, 2012] a new semantics, called ICR, was given as a sound approximation for AR semantics. The ICR semantics corresponds to  $\langle \mathcal{M}_5, \cap \rangle$  in our work.

In [Bienvenu and Rosati, 2013], two parametrized inconsistency-tolerant semantics, called k-support and k-defeater semantics, were studied for DL- $Lite_{horn}$  and DL- $Lite_{core}$  logics where it was shown that instance checking (resp. CQ answering), within DL- $Lite_{core}$  framework, is NLSpace (resp. NP) for both k-support and k-defeater semantics. In a nutshell, a query q is said to be a k-support consequence of an inconsistent DL-Lite knowledge base K, if there exist k consistent subsets  $\{S_1, ..., S_n\}$  of A such that  $\forall S_i, \langle \mathcal{T}, S_i \rangle \models q$  and  $\forall A_i \in \mathcal{M}_1$ , there is at least an  $S_i \subseteq A_i$ . A query is said to be a k-defeater consequence of K, if there does not exists a consistent subset S of S with  $|S| \leq k$  such that S such that S is a minimal support of S (i.e. there is no proper subset of S that support S is inconsistent where S is a minimal support of S (i.e. there is no proper subset of S that support S is a minimal support of S (i.e. there is no proper subset of S that support S is a minimal support of S (i.e. there is no proper subset of S that support S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. there is no proper subset of S is a minimal support of S (i.e. the condition of S is a minimal support of S (i.e. the condition of S is a minimal support of S (i.e. the condition of S is a minimal support of S (i.e. the condition of S (i.e. the condition of S is a minimal support of S (i.e. t

Another family of parametrized semantics, called k-lazy semantics, was proposed in [Lukasiewicz et al., 2012b] within Datalog+/- setting. However, as mentioned in [Bienvenu and Rosati, 2013], these semantics are not a sound approximation of consistent query answering and they don't have good computational properties where CQ answering is co-NP-hard in data complexity for every  $k \ge 1$ .

In [Zhou et al., 2012] a four-valued semantics reasoning approach, was proposed to reason under inconsistent *DL-Lite* knowledge bases. However this approach leads to derive inconsistent conclusion

with respect to generic knowledge.

#### 5.6.2 Majority-based inference within *DL-Lite* framework

In the context of the use of majority-based inference for managing inconsistent set of information, there is one main and major advantage of using *DL-Lite* language rather than expressive DLs or propositional logic: It concerns the consistency of the set of derived conclusions. To illustrate our proposal, let us focus on instance checking problem and let consider  $\langle \mathcal{M}_1, maj \rangle$ . which represents majority-based inference over the set of maximally consistent subset of an inconsistent knowledge base. Then we have:

**Proposition 5.8.** Let  $K = \langle T, A \rangle$  be an inconsistent standard DL-Lite knowledge base. Then

$$Res(\mathcal{K}) = \{A(a) : a \in D_I, A \in D_C, \langle \mathcal{M}_1, Maj \rangle \models A(a)\} \cup \{R(a,b) : a,b \in D_I, R \in D_R, \langle \mathcal{M}_1, Maj \rangle \models R(a,b)\}$$

is consistent with respect to T, where  $D_I$ ,  $D_C$  and  $D_R$  are given in Def.5.3.

Note that, Proposition 5.8 does not hold with general DLs. Assume that we have a DL language where  $'\Box'$  is allowed in the left-side of inclusion axioms. Consider the following knowledge base

$$\mathcal{K} = \langle \mathcal{T} = \{ A \cap B \sqsubseteq \neg C, A \cap C \sqsubseteq \neg B, B \cap C \sqsubseteq \neg A \}, \mathcal{A} = \{ A(a), B(a), C(a) \} \rangle.$$

Clearly,  $\mathcal{K}$  admits three maximally consistent subsets, namely  $\mathcal{M}_1 = \{A_1 = \{A(a), B(a)\}, \mathcal{A}_2 = \{A(a), C(a)\}, \mathcal{A}_3 = \{B(a), C(a)\}\}$ . Clearly  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} A(a), \langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} B(a)$  and  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} C(a)$ , while the set  $\{A(a), B(a), C(a)\}$  is consistent with  $\mathcal{T}$ . A similar example can be provided in a propositional logic setting.

### 5.6.3 Which inference relations are appropriate to deal with inconsistent *DL-Lite* knowledge bases?

Intuitively, an appropriate method is such that:

- i Outputs a single ABox, or a limited set of ABox's,
- ii Produces as many safe conclusions as possible, and
- iii the size of the produced ABox should be polynomial with respect to the initial ABox.

Clearly majority-based and universal inference do not fit item (i) and (iii). If one is interested in keeping inference relations that avoid deriving contestable conclusions, then inference  $\langle \mathcal{M}_7, s \rangle$  and  $\langle \mathcal{M}_8, s \rangle$ , with  $s \in \{\forall, maj, \cap\}$ , should be discarded. Indeed, considering first the closure, may lead to consider as plausible a conclusion with a contestable support. For instance, let  $\mathcal{K} = \langle \{A \sqsubseteq \neg B, A \sqsubseteq C\}, \mathcal{M} = \{A(a), B(a)\} \rangle$ . Clearly,  $\langle \mathcal{T}, \mathcal{M}_7 \rangle \models_s C(a)$  (resp.  $\langle \mathcal{T}, \mathcal{M}_8 \rangle \models_s C(a)$ ). This conclusion C(a) is obtained using A(a), but A(a) is contestable and it is not a conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  (resp.  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ ).

The inclusion-based criterion (namely  $\mathcal{M}_1$ ) followed by universal entailment is widely used in the literature. The cardinality-based criterion may make sense in some applications where counting falsified formulas is important. For instance, consider an ABox encoding facts about women and men (distinguished by the TBox) attending a conference. From the point of view of the output, safe inferences  $\langle \mathcal{M}_i, \cap \rangle$  are appropriate for handling inconsistency in *DL-Lite*. Safe inferences using different  $\mathcal{M}_i$ 's, fit at the requirement (i) and (iii). The inference  $\langle \mathcal{M}_1, \cap \rangle$  is considered as safe since it is equivalent to consider a subbase of the initial ABox obtained by ignoring all conflicting facts, namely:

$$A_r = \bigcap_{A_i \in \mathcal{M}_1} A_i = \{ f : f \in A \text{ and } \nexists \mathcal{C} \in \mathcal{C}(A) \text{ such that } f \in \mathcal{C} \}$$

where  $\mathcal{C}(\mathcal{A})$  is the set of conflicts. The main advantage of this approach is that computing  $\mathcal{A}_r$  is done in linear time. However, the main limitations is that its associated inference relation is very cautious. To get a more productive one and to better fit requirement (ii), one may take the intersection of largest consistent sets from the ABox, namely,  $\mathcal{A}_r = \bigcap_{\mathcal{A}_i \in \mathcal{M}_j} \mathcal{A}_i, j = 2,...,6$ . The advantage of this approach is that the obtained inference relation is productive and its space complexity is  $|D_I| \times |D_C| + |D_I|^2 \times |D_R|$ , in the worst case.

#### 5.7 Conclusion

This chapter considered an MBox as a result of modifying inconsistent standard *DL-Lite* knowledge base. We generalize techniques for non-merge inconsistency management approaches in flat knowledge bases by introducing the notions of (1) modifier and (2) inference strategy. The combination modifiers plus inference strategies can be mapped out in order to provide a principled and exhaustive list of techniques for inconsistency management. We study the productivity and give a complexity analysis for such techniques in the case of flat knowledge bases and show how our work extends the state of the art.

The last part of this thesis concerns dynamics and handling inconsistency in prioritized assertional *DL-Lite* knowledge bases.

#### PART IV

### On the revision of prioritized *DL-Lite* knowledge bases

# PRIORITIZED ASSERTIONAL-BASED REMOVED SETS REVISION OF *DL-Lite* KNOWLEDGE BASES

#### 6.1 Introduction

Dynamics of a DL-based knowledge bases gave rise to increasing interest (e.g. [Qi et al., 2006c; Qi and Du, 2009]) and often concerns the situation where new information should be incorporated while ensuring the consistency of the result. Several works have recently dealt with revising DL-Lite TBox with a terminological information (e.g. [Wang et al., 2010; Calvanese et al., 2010]) or with an assertional information (e.g. [Calvanese et al., 2010; Kharlamov and Zheleznyakov, 2011; Gao et al., 2012]) as input.

Besides, data are often provided by several and potentially conflicting sources. Concatenating them gives a prioritized or a stratified ABox. This stratification generally results from two situations as pointed out in [Benferhat *et al.*, 1995; Benferhat *et al.*, 1998b]. The first one is when each source provides its set of data without any priority between them, but there exists a total pre-ordering between different sources reflecting their reliability. The other one is when the sources are considered as equally reliable (i.e. having the same reliability level), but there exists a preference ranking between the set of provided data according to their level of certainty. The role of priorities in belief revision is very important and it was largely studied in the literature where knowledge bases are encoded in a propositional logic setting (*e.g.* [Benferhat *et al.*, 2002c; Benferhat *et al.*, 2010b]). The notion of priorities in DLs is used in (*e.g.* [Baader and Hollunder, 1995; Qi *et al.*, 2006a; Qi and Pan, 2007]) to deal with default terminologies while assuming that the ABox is completely sure. However, as far as we know, revising prioritized *DL-Lite* knowledge bases has not been addressed so far.

Belief revision has been largely considered in the literature when knowledge bases are encoded using a propositional language. Among these revision approaches the so-called Removed Sets Revision, also known as a cardinality-based approach, has been proposed in [Papini, 1992; Benferhat *et al.*, 1993a] for revising a set of propositional formulas. This approach stems from removing a minimal number of formulas, called removed set, to restore consistency. The minimality in Removed Sets Revision refers to the cardinality criterion and not to the set-inclusion one. This approach has interesting properties: it has not a high computational complexity, it is not too cautious and satisfies all rational AGM postulates when extended to belief sets revision.

This chapter studies Prioritized Removed Sets Revision (PRSR), when knowledge bases are described in DL-Lite logics. One of the motivations in considering PRSR is to take advantage of tractability of DL-Lite for the revision process as well as of rational properties satisfied by PRSR. In particular, we investigate the well-known DL- $Lite_R$  logic which offers a good compromise between expressive power and computational complexity. We consider different forms of input: a membership assertion, a positive inclusion axiom or a negative inclusion axiom, since they lead to different revision problems, different algorithms and different complexity results. A crucially important problem that arises when revising

a *DL-Lite* knowledge base is how to restore consistency. In this chapter restoring consistency leads to ignoring some assertions, namely we give a priority to TBox over ABox. Another important feature when dealing with *DL-Lite* knowledge base is that computing the set of minimal information responsible of inconsistency can be done in polynomial time. Besides minimal assertional sets that cause inconsistency are either singletons or doubletons. This is helpful in defining removed sets necessary to restore consistency in presence of new information.

The rest of this chapter is organized as follows. Section 6.2 studies Prioritized Removed Sets Revision within this framework when priorities between assertional facts are available. Section 6.3 reformulates the well-known Hansson's postulates defined for propositional belief bases revision within a *DL-Lite* setting and gives logical properties of PRSR operators. Section 6.4 provides algorithms for computing prioritized removed sets through the use of hitting sets. Finally, Section 6.5 presents some related works and Section 6.6 concludes the chapter.

#### 6.2 Assertional-based revision of *DL-Lite* knowledge bases

In this section, we investigate the revision of *DL-Lite* knowledge bases in the case where priorities are available between assertions in the ABox. We study different forms of the input: An assertion, a positive inclusion axiom or a negative inclusion axiom. We consider a lexicographical strategy where only smallest subsets of assertions should be dropped from the knowledge base in order to restore its consistency and accept the new piece of information. Note that the choice of dropping information only from the ABox is motivated by the fact that in many applications (such as in ontology-based data access applications) a TBox is often seen as a well-formed and coherent ontology whereas the ABox represents data that are not necessarily reliable and consistent with the ontology. In other words, when the input is a terminological information, the revising process comes down to enrich the ontology while preserving the coherence of the resulting TBox. However, in case of inconsistency, the ABox may be modified in order to take into account the input.

Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent *DL-Lite* knowledge base. Let us denote by N a new consistent information to be accepted. The presence of this new information may lead to inconsistency according to the content of the TBox and the nature of the input information.

Within the DL-Lite language, the new piece of information N may be :

- A membership assertion of the form A(a) or P(a, b),
- A positive inclusion axiom (PI) of the form  $B_1 \sqsubseteq B_2$  or
- A negative inclusion axiom (NI) of the form  $B_1 \sqsubseteq \neg B_2$ .

We assume that the input is consistent with the terminological base (otherwise, the input will be simply ignored. According to [Calvanese et al., 2007a], every DL-Lite knowledge base  $\mathcal K$  with only PIs in its TBox is always satisfiable (consequence of Lemma 7 in [Calvanese et al., 2007a]). Hence, if N is a membership assertion or a PI axiom, there is no inconsistency. However when the TBox  $\mathcal T$  contains NI axioms then N may have an undesirable interaction with  $\mathcal K$  and which leads to an inconsistency.

We use C(A) the collection of conflicts in K as defined in Definition 5.12. Recall that when T is coherent, then  $\forall C \in C(A), |C| = 2$ .

**Example 6.1.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be an inconsistent knowledge base such that  $\mathcal{T} = \{B_1 \sqsubseteq B_2, B_2 \sqsubseteq \neg B_3\}$  and  $\mathcal{A} = \{B_1(a), B_3(a), B_2(b), B_3(b), B_1(c)\}$ . We have  $cln(\mathcal{K}) = \{B_2 \sqsubseteq \neg B_3, B_1 \sqsubseteq \neg B_3\}$ . Then  $\mathcal{C}(\mathcal{A}) = \{\{B_1(a), B_3(a)\}, \{B_2(b), B_3(b)\}\}$ .

#### 6.2.1 Prioritized *DL-Lite* assertional base

We use the notion of a *DL-Lite* prioritized knowledge base, simply denoted by  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$ . We assume that  $\mathcal{T}$  is coherent and not stratified. Namely, all elements of  $\mathcal{T}$  have the same level of importance. On contrast, the ABox is assumed to be stratified, *i.e.* partitioned into n strata,  $\mathcal{A} = \mathcal{A}_1 \cup \cdots \cup \mathcal{A}_n$  such that:

- The strata are pairwise disjoint, namely  $\forall A_i, \forall A_j : A_i \cap A_j = \emptyset$ ,
- The assertions in  $A_i$  have the same level of priority,
- The assertions of  $A_i$  have higher priority than the ones in  $A_j$  where j > i. Hence assertions in  $A_1$  are the most important ones, while assertions in  $A_n$  are the least important ones.

We first define the lexicographic preference relation between subsets of the ABox as follows.

**Definition 6.1.** let X and X' be two subsets of A. X is strictly preferred to X', denoted by  $X <_{lex} X'$ , if and only if, there exists  $i, 1 \le i \le n$  such that:

- $|X \cap \mathcal{A}_i| < |X' \cap \mathcal{A}_i|$ , and
- $\forall j, 1 \leq j < i, |X \cap \mathcal{A}_j| = |X' \cap \mathcal{A}_j|.$

Similarly, X is equally preferred to X', denoted by  $X =_{lex} X'$ , if and only if  $\forall i, 1 \leq i \leq n, |X \cap \mathcal{A}_i| = |X' \cap \mathcal{A}_i|$ . Lastly, X is at least as preferred as X', denoted by  $X \leq_{lex} X'$ , if and only if  $X <_{lex} X'$  or  $X =_{lex} X'$ . The relation  $\leq_{lex}$  is a total pre-order.

**Example 6.2.** Let  $\mathcal{A}$  be a stratified ABox,  $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3$  where  $\mathcal{A}_1 = \{B_1(a)\}, \mathcal{A}_2 = \{B_2(b)\}$  and  $\mathcal{A}_3 = \{B_3(a), B_3(b)\}$ . Let  $X = \{B_3(a), B_3(b)\}$  and  $X' = \{B_3(a), B_2(b)\}$  be two subsets of  $\mathcal{A}$ , we have  $X <_{lex} X'$ .

#### 6.2.2 Prioritized Removed Sets Revision of *DL-Lite* knowledge bases

We now investigate the revision of *DL-Lite* knowledge bases according to the nature of the input information. We consider an approach using a lexicographical strategy well-known as "Prioritized Removed Sets Revision" (PRSR) [Benferhat *et al.*, 2010a] proposed within a propositional logic setting.

Within the *DL-Lite* framework, in order to restore consistency while keeping new information, the Prioritized Removed Sets Revision strategy removes exactly one assertion in each conflict minimizing the minimum number of assertions from  $A_1$ , then the minimum number of assertions in  $A_2$ , and so on. Using lexicographic criterion instead of set inclusion one, will reduce the set of potential conflicts.

Note that taking the stratification of the ABox into account has not been considered before for revising or repairing *DL-Lite* knowledge bases. Next Chapter (Chapter 7) investigates repairing *DL-Lite* knowledge bases when the ABox is layered.

#### Revision by a membership assertion

We first consider the case where N is an ABox assertion which corresponds to the revision by a fact or by an observation. In this case, N is added to a new stratum having the highest and a new priority. However, in order to avoid heavy notations, we simply write  $\mathcal{K} \cup \{N\}$  or  $\langle \mathcal{T}, \mathcal{A} \cup \{N\} \rangle$  where  $\mathcal{A}$  is a prioritized ABox, to denote the fact that N is added to a new and highest priority stratum of  $\mathcal{A}$ .

The following definition introduces the concept of prioritized removed sets.

**Definition 6.2.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent stratified knowledge base and N be a membership assertion. A *prioritized removed set*, denoted by X, is a set of membership assertions such that:

- $X \subseteq \mathcal{A}$ ,
- $\langle \mathcal{T}, (\mathcal{A} \backslash X) \cup \{N\} \rangle$  is consistent,
- $\forall X' \subseteq \mathcal{A}$ , if  $\langle \mathcal{T}, (\mathcal{A} \backslash X') \cup \{N\} \rangle$  is consistent then  $X \leq_{lex} X'$ .

We denote by  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  the set of all prioritized removed sets of  $\mathcal{K} \cup \{N\}$ . If  $\mathcal{K} \cup \{N\}$  is consistent then  $\mathcal{PR}(\mathcal{K} \cup \{N\}) = \{\emptyset\}$ . Besides, if  $\mathcal{K} \cup \{N\}$  is inconsistent then every conflict C of  $\mathcal{K} \cup \{N\}$  contains N. More formally.

**Lemma 6.1.** Let  $K = \langle T, A \rangle$  be a consistent prioritized knowledge base and N be an assertion. If  $K \cup \{N\}$  is inconsistent then  $\forall C \in C(A)$  it holds that  $N \in C$ .

Proof of Lemma 6.1. The proof is immediate. If  $\mathcal{K} \cup \{N\}$  is inconsistent then  $\mathcal{C}(\mathcal{K} \cup \{N\}) \neq \emptyset$ . This means that there exists at least a conflict  $C = (\alpha, \beta) \in \mathcal{C}(\mathcal{K} \cup \{N\})$  (recall that |C| = 2). Let  $\mathcal{C}$  be a conflict of  $\mathcal{K} \cup \{N\}$ . Suppose that  $N \notin \mathcal{C}$ . This means that  $\alpha \in \mathcal{A}$  and  $\beta \in \mathcal{A}$ . This is a contradiction since  $\mathcal{K}$  is assumed to be consistent, namely  $\mathcal{C}(\mathcal{A}) = \emptyset$ .

As consequence, there exists exactly one prioritized removed set. More formally.

**Proposition 6.1.** Let K be a consistent stratified knowledge base and N be a membership assertion. If  $K \cup \{N\}$  is inconsistent then  $|\mathcal{PR}(K \cup \{N\})| = 1$ .

Proof of Proposition 6.1. Suppose that there are two prioritized removed sets X and X' such that  $X \neq X'$ . By Definition 6.2,  $X \subseteq \mathcal{A}$ ,  $X' \subseteq \mathcal{A}$  and  $X =_{lex} X'$ . Since  $(\mathcal{T} \cup \{N\}) \cup (\mathcal{A} \setminus X)$  and  $(\mathcal{T} \cup \{N\}) \cup (\mathcal{A} \setminus X')$  are consistent, we have  $\forall C \in \mathcal{C}(\mathcal{K} \cup \{N\})$  on one hand  $C \cap X \neq \emptyset$  and  $|C \cap X| = 1$  and on the other hand  $C \cap X' \neq \emptyset$  and  $|C \cap X'| = 1$ . Moreover, since N is a single assertion, by Lemma 6.1,  $|C \cap N| = 1$ . Therefore there are three elements in C namely N, one element of X'. Hence, this contradicts Lemma 3.6 that states that  $|C \cap \mathcal{A}| \leq 2$ .

**Definition 6.3.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent stratified knowledge base and N be a membership assertion. The revised knowledge base  $\mathcal{K} \circ_{PRSR} N$  is such that  $\mathcal{K} \circ_{PRSR} N = \langle \mathcal{T}, \mathcal{A} \circ_{PRSR} N \rangle$  where  $\mathcal{A} \circ_{PRSR} N = (\mathcal{A} \backslash X) \cup \{N\}$  with  $X \in \mathcal{PR}(\mathcal{K} \cup \{N\})$ .

**Example 6.3.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent stratified knowledge base such that:

 $\mathcal{T} = \{B_1 \sqsubseteq B_2, B_2 \sqsubseteq \neg B_3, B_3 \sqsubseteq \neg B_4\} \text{ and } \mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3 \text{ where } \mathcal{A}_1 = \{B_1(a)\} \mathcal{A}_2 = \{B_3(b)\}, \text{ and } \mathcal{A}_3 = \{B_4(a)\}.$ 

Let  $N = B_3(a)$  then  $K \cup \{N\}$  is inconsistent. By Definition 5.12,  $C(K \cup \{N\}) = \{\{B_1(a), B_3(a)\}, \{B_3(a), B_4(a)\}\}.$ 

Hence by Definition 6.2,  $\mathcal{PR}(\mathcal{K} \cup \{N\}) = \{\{B_1(a), B_4(a)\}\}$ . Therefore  $\mathcal{A} \circ_{PRSR} N = \{B_3(a), B_3(b)\}$  and  $\mathcal{A} \circ_{PRSR} N = \mathcal{A}'_1 \cup \mathcal{A}'_2 \cup \mathcal{A}'_3$  where  $\mathcal{A}'_1 = \{B_3(a)\}, \mathcal{A}'_2 = \{B_3(b)\}$  and  $\mathcal{A}'_3 = \emptyset$ .

As detailed in Section 6.4 (precisely, subsection 6.4.1) computing the set of conflicts is polynomial. Moreover when the input information is a membership assertion, as stated by Proposition 6.1 and illustrated in the above example, there is only one prioritized removed set. Next subsection investigates the case where the input information is a positive or a negative inclusion axiom.

#### Revision by a positive or a negative axiom

We now consider the case where the input N is a PI axiom or a NI axiom. This new axiom should be added to the TBox and since we gave priority to the TBox over the ABox, the input is kept in the revised knowledge base. In this case,  $K \cup \{N\}$  denotes  $\langle T \cup \{N\}, A \rangle$ . Since T is considered as non prioritized, then  $T \cup \{N\}$  simply denotes a simple addition of N to T.

**Definition 6.4.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent stratified knowledge base and N be a PI or a NI axiom. A prioritized removed set, denoted by X, is a set of assertions such that:

- $X \subseteq \mathcal{A}$ ,
- $\langle \mathcal{T} \cup \{N\}, (\mathcal{A} \backslash X) \rangle$  is consistent and
- $\forall X' \subseteq \mathcal{A}$ , if  $\langle \mathcal{T} \cup \{N\}, (\mathcal{A} \backslash X') \rangle$  is consistent then  $X \leq_{lex} X'$ .

Let us point out that Definition 6.4 is similar to Definition 6.2, except that new information is not added to the ABox but to the TBox. However, the revision process still considers the TBox as a stable knowledge, and hence to restore consistency assertional elements from ABox should be removed. We denote again by  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  the set of prioritized removed sets of  $\mathcal{K} \cup \{N\}$ .

**Example 6.4.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent stratified knowledge base such that

$$\mathcal{T} = \{B_1 \sqsubseteq B_2, B_3 \sqsubseteq \neg B_4\}$$
 and

$$A = A_1 \cup A_2 \cup A_3$$
 where  $A_1 = \{B_1(a)\}, A_2 = \{B_2(b)\}, \text{ and } A_3 = \{B_3(a), B_3(b)\}.$ 

Let 
$$N = B_2 \sqsubseteq \neg B_3$$
 then  $\mathcal{K} \cup \{N\}$  is inconsistent.  $\mathcal{C}(\mathcal{K} \cup \{N\}) = \{\{B_1(a), B_3(a)\}, \{B_2(b), B_3(b)\}\}.$ 

The four possible candidates to be removed are:

$$X_1 = \{B_1(a), B_2(b)\},\$$

$$X_2 = \{B_1(a), B_3(b)\},\$$

$$X_3 = \{B_3(a), B_2(b)\},$$
and

$$X_4 = \{B_3(a), B_3(b)\}.$$

There is only one prioritized removed set  $X_4$  as illustrated in Table 6.1.

$\mathcal{A}_i$	$ X_1 \cap \mathcal{A}_i $	$ X_2 \cap \mathcal{A}_i $	$ X_3 \cap \mathcal{A}_i $	$ X_4 \cap \mathcal{A}_i $
$\mathcal{A}_3$	0	1	1	2
$\mathcal{A}_2$	1	0	1	0
$\mathcal{A}_1$	1	1	0	0

Table 6.1: One prioritized removed set.

If the stratification of A, now is  $A_1 = \{B_1(a), B_3(a)\}$ ,  $A_2 = \{B_2(b)\}$ ,  $A_3 = \{B_3(b)\}$ , then there are two prioritized removed sets  $X_2$  and  $X_4$  as illustrated in Table 6.2.

$\mathcal{A}_i$	$ X_1 \cap \mathcal{A}_i $	$ X_2 \cap \mathcal{A}_i $	$ X_3 \cap \mathcal{A}_i $	$ X_4 \cap \mathcal{A}_i $
$\overline{\mathcal{A}_3}$	0	1	0	1
$\mathcal{A}_2$	1	0	1	0
$\mathcal{A}_1$	1	1	1	1

Table 6.2: Two prioritized removed sets.

We have seen that when the input is a membership assertion then there exists exactly one prioritized removed set. However, when the input information is a NI or a PI axiom there may exist one or several prioritized removed sets, as illustrated in the previous example. The first case to consider, which is also the easiest one, is when each conflict intersects two distinct strata: then, there exists only one prioritized removed set. More formally,

**Proposition 6.2.** If for each  $C \in \mathcal{C}(\mathcal{K} \cup \{N\})$  there exists i and j,  $i \neq j$ , such that  $C \cap \mathcal{A}_i \neq \emptyset$  and  $C \cap \mathcal{A}_i \neq \emptyset$  then  $|\mathcal{PR}(\mathcal{K} \cup \{N\})| = 1$ .

Proof of proposition 6.2. Suppose there are two prioritized removed sets, X and X' and  $X \neq X'$ . By Definition 6.4,  $X \subseteq \mathcal{A}$ ,  $X' \subseteq \mathcal{A}$ , and  $X =_{lex} X'$ . Since  $(\mathcal{T} \cup \{N\}) \cup (\mathcal{A} \setminus X)$  and  $(\mathcal{T} \cup \{N\}) \cup (\mathcal{A} \setminus X')$  are consistent,  $\forall C \in \mathcal{C} (\mathcal{K} \cup \{N\})$  we have  $C \cap X \neq \emptyset$  and  $C \cap X \neq \emptyset$ . If  $|C \cap X| = 2$  (resp.  $|C \cap X'| = 2$ ) then X (resp. X') is not a prioritized removed set, since C is a minimal inconsistent subset with two elements by Lemma 3.6. If  $|C \cap X| = 1$  and  $|C \cap X'| = 1$  two cases hold. If  $|C \cap X| = 1$  since there exists  $|C \cap X| = 1$  and  $|C \cap X| = 1$  and  $|C \cap X| = 1$  and  $|C \cap X| = 1$  then  $|C \cap X| = 1$  and  $|C \cap X'| = 1$  then  $|C \cap X'| = 1$  then |C

This situation holds when each stratum is consistent with  $\mathcal{T} \cup \{N\}$  for example, when the stratification comes from several experts with different degrees of reliability. In this case, as detailed in Section 6.4.2 computing the unique prioritized removed set is polynomial.

There may be several prioritized removed sets as soon as there are conflicts included in a stratum where each conflict may lead to two prioritized removed sets. Namely, let NC be the number of conflicts such that each one is included in a stratum, the number of prioritized removed sets is bounded by  $2^{NC}$ . In such case, each prioritized removed set leads to a possible revised knowledge base:  $\mathcal{K}_i = \langle \mathcal{T} \cup \{N\}, (\mathcal{A} \setminus X_i) \rangle$  with  $X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\})$ .

In *DL-Lite* language it is not possible to find a knowledge base that represents the disjunction of such possible revised knowledge bases. If we want to keep the result of revision in *DL-Lite* one can define a selection function that selects from  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  one or several prioritized removed sets. More formally.

**Definition 6.5.** A selection function f is a mapping from  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  to  $\mathcal{A}$  such that:

- $f(\mathcal{PR}(\mathcal{K} \cup \{N\})) \subseteq \mathcal{A}$
- $\exists X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\})$  such that  $X_i \subseteq f(\mathcal{PR}(\mathcal{K} \cup \{N\}))$
- $f(\mathcal{PR}(\mathcal{K} \cup \{N\})) \subseteq \bigcup_{X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\})} X_i$

The first item in Definition 6.5 simply states that  $f(\mathcal{PR}(\mathcal{K} \cup \{N\}))$  should only contain elements of  $\mathcal{A}$ . This condition guarantees that the result of revision will be within the *DL-Lite* language. The second item states that at least one prioritized removed set should be in  $f(\mathcal{PR}(\mathcal{K} \cup \{N\}))$ . This guarantees that  $\langle \mathcal{T}, \mathcal{A} \setminus f(\mathcal{PR}(\mathcal{K} \cup \{N\})) \rangle$  is consistent. The last item states that only elements from  $\bigcup_{X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\})} X_i$  should be removed and ignored to restore consistency. Hence, elements which are not responsible of conflicts will not be removed.

We now define the revised knowledge base as follows.

**Definition 6.6.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a consistent and stratified knowledge base and N be a PI or a NI axiom. Let f be a selection function, the revised knowledge base  $\mathcal{K} \circ_{PRSR} N$  is such that  $\mathcal{K} \circ_{PRSR} N = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \circ_{PRSR} N \rangle$  where  $\mathcal{A} \circ_{PRSR} N = (\mathcal{A} \setminus f(\mathcal{PR}(\mathcal{K} \cup \{N\})))$ .

In the next subsection, we present some examples of selection functions.

#### **6.2.3** Examples of selection functions

The definition of selection functions can be seen as the application of modifiers (presented in Chapter 5) on an MBox (resulting from the revision process) followed by inference based strategy.

Let us first start with two basic selection functions, denoted simply by  $f_1$  and  $f_2$ . The first selection function  $f_1$  consists in taking all prioritized removed sets. More formally,

$$f_1(\mathcal{PR}(\mathcal{K} \cup \{N\})) = \bigcup_{X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\})} X_i$$

which corresponds to the intersection of all possible revised knowledge bases. In this case  $\mathcal{K} \circ_{PRSR} N = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \circ_{PRSR} N \rangle$  where  $\mathcal{A} \circ_{PRSR} N = \mathcal{A} \setminus f_1(\mathcal{PR}(\mathcal{K} \cup \{N\})) = \cap_{i=1}^n (\mathcal{A} \setminus X_i)$ . This first selection function may be too cautious since it could remove too many assertions and is not in agreement with the minimal change principle.

Another option is to choose a selection function that only picks one prioritized removed set, more formally,

$$f_2(\mathcal{PR}(\mathcal{K} \cup \{N\})) = X_i$$

which corresponds to the choice of only one revised knowledge base. This option is less cautious than the previous one and captures, in some sense, the existence of a possibility for restoring consistency.

**Example 6.5.** Let us consider the knowledge base of Example 4. We have

```
\mathcal{T} = \{B_1 \sqsubseteq B_2, B_3 \sqsubseteq \neg B_4\} \text{ and } \\ \mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3 \text{ where } \mathcal{A}_1 = \{B_1(a), B_3(a)\}, \, \mathcal{A}_2 = \{B_2(b)\} \text{ and } \mathcal{A}_3 = \{B_3(b)\}. \\ \text{Let } N = B_2 \sqsubseteq \neg B_3 \text{ be a new piece of information. We have } \mathcal{K} \cup \{N\} \text{ is inconsistent. The prioritized removed sets are: } X_1 = \{B_1(a), B_3(b)\} \text{ and } X_2 = \{B_3(a), B_3(b)\}. \text{ We have: } f_1(\mathcal{PR}(\mathcal{K} \cup \{N\})) = \{B_1(a), B_3(b), B_3(a)\} \text{ and } f_2(\mathcal{PR}(\mathcal{K} \cup \{N\})) \text{ can be either } \{B_1(a), B_3(b)\} \text{ or } \{B_3(a), B_3(b)\}.
```

The third example of selection function, denoted by  $f_3$ , is strongly related to the notion of universal or skeptical inference that can be defined from  $\mathcal{PR}(\mathcal{K} \cup \{N\})$ . Namely, we first need to define the set of all possible assertions that can be derived from each  $\mathcal{A} \setminus X_i$  with  $X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\})$ .

More precisely, let  $D_C$  be the set of concepts of  $\mathcal{T}$ ,  $D_R$  be the set of roles of  $\mathcal{T}$  and  $D_I$  be the set of individuals of  $\mathcal{A}$ . Then we define the set of universal assertional consequences, denoted  $UAC(\mathcal{K} \cup \{N\})$  as:

$$UAC(\mathcal{K} \cup \{N\}) = \{A(a) : a \in D_I, A \in D_C \text{ and } \\ \forall X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\}), \langle \mathcal{T}, \mathcal{A} \setminus X_i \rangle \models A(a)\} \\ \cup \\ \{R(a,b) : a \in D_I, b \in D_I, R \in D_R \text{ and } \\ \forall X_i \in \mathcal{PR}(\mathcal{K} \cup \{N\}), \langle \mathcal{T}, \mathcal{A} \setminus X_i \rangle \models R(a,b)\}$$

The selection function  $f_3$  is then simply defined by :

$$f_3(\mathcal{PR}(\mathcal{K} \cup \{N\})) = \mathcal{A} \setminus UAC(\mathcal{K} \cup \{N\})$$

**Example 6.6.** Let us consider  $\mathcal{T} = \{A \sqsubseteq B, C \sqsubseteq B\}$  and  $\mathcal{A} = \mathcal{A}_1$  where  $\mathcal{A}_1 = \{B(b), A(a), C(a)\}$ . Let  $N=A \sqsubseteq \neg C$  be a new piece of information. We have  $\mathcal{K} \cup \{N\}$  is inconsistent. The two possible

prioritized removed sets that can be computed are: 
$$X_1 = \{A(a)\}$$
 and  $X_2 = \{C(a)\}$ .  
One can check that  $UAC(\mathcal{K} \cup \{N\}) = \{B(a), B(b)\}$ . Hence  $f_3 = \{A(a), C(a)\}$ .

The last selection function uses the notion of deductive closure using Definition 5.2. Using the notion deductive closure, one can refine the set of prioritized removed sets in which a selection function operates. This new subset, denoted  $\mathcal{CPR}(\mathcal{K} \cup \{N\}, \text{ is made by keeping only prioritized removed sets } X \text{ in } \mathcal{PR}(\mathcal{K} \cup \{N\}, \text{ such that the deductive closure of the set } A \setminus X \text{ is maximal with respect to lexicographical criterion.}$  More formally,

**Definition 6.7.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a *DL-Lite* knowledge base and N be a new information. Let  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  be the set of prioritized removed sets. The set  $\mathcal{CPR}(\mathcal{K} \cup \{N\})$  is composed of prioritized removed sets X from  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  such that  $\nexists Y \in \mathcal{PR}(\mathcal{K} \cup \{N\}), |\circ_{cl}(\mathcal{A} \setminus Y)| \geq |\circ_{cl}(\mathcal{A} \setminus X)|$ .

Then the last selection function, denoted by  $f_4$  and based on the deductive closure, is simply defined by :

$$f_4(\mathcal{PR}(\mathcal{K} \cup \{N\})) = \bigcup_{X_i \in \mathcal{CPR}(\mathcal{K} \cup \{N\})} X_i$$

Clearly,  $\mathcal{CPR}(\mathcal{K} \cup \{N\}) \subseteq \mathcal{PR}(\mathcal{K} \cup \{N\})$  then we have  $f_2(\mathcal{PR}(\mathcal{K} \cup \{N\})) \subseteq f_3(\mathcal{PR}(\mathcal{K} \cup \{N\})) \subseteq f_1(\mathcal{PR}(\mathcal{K} \cup \{N\}))$ .  $f_4(\mathcal{PR}(\mathcal{K} \cup \{N\}))$  offers a good compromise between an arbitrary choice of the prioritized removed set to be ignored from the ABox  $\mathcal{A}$ , and a skeptical choice where all prioritized removed sets are ignored from the ABox.

**Example 6.7.** From Example 6.5, one can check that:

$$\begin{array}{l} \circ_{cl}(\mathcal{A}\setminus X_1)=\{B_3(a),B_2(b)\}, \text{ and } \\ \circ_{cl}(\mathcal{A}\setminus X_2)=\{B_1(a),B_2(a),B_2(b)\}. \\ \text{Then } \mathcal{CPR}(\mathcal{K}\cup\{N\})=\{X_2\}. \end{array}$$

#### **6.2.4** Multiple revision

In the pervious sections, it is assumed that the input information is only composed of a single element: An assertional fact, a positive axiom or a negative axiom. This section briefly discusses the case where the input contains more than one element. This problem is known as multiple revision and has been addressed for instance in [Hansson, 1992; Fuhrmann and Hansson, 1994] in a propositional setting.

Let  $\mathcal{K}=\langle \mathcal{T},\mathcal{A}\rangle$  be a *DL-Lite* prioritized knowledge base. Let us start with the situation where the input, simply denoted again by N, is a set of assertional facts. If  $\langle \mathcal{T}, N \rangle$  is consistent, then our approach can be applied straightforwardly. The definition of prioritized removed set is exactly the same. Definitions 6.2 to 6.7 can be used as it is except that N is a set of assertional facts instead of a single one. The same holds for Lemma 6.1 as well as Propositions 6.1-6.2.

**Example 6.8.** Let us consider  $\mathcal{T} = \{A \sqsubseteq \neg B\}$  and  $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2$  where  $\mathcal{A}_1 = \{A(a), B(c)\}$  and  $\mathcal{A}_2 = \{B(b)\}$ .

Let 
$$N = \{A(b), B(a)\}$$
 where  $\langle \mathcal{T}, N \rangle$  is consistent. Now,  $\langle \mathcal{T}, \mathcal{A} \cup N \rangle$  is inconsistent. There only exists one prioritized removed set:  $X_1 = \{A(a), B(b)\}$  and  $\mathcal{A} \circ_{PRSR} N = \{A(b), B(a), B(c)\}$ .

Now assume that  $\langle \mathcal{T}, N \rangle$  is inconsistent. In this case, if we still consider that  $\mathcal{T}$  as a stable knowledge, then the input cannot be completely accepted. In this case, the prioritized removed set will both contain elements from  $\mathcal{A}$  and also from N, with elements of N being preferred to all elements of  $\mathcal{A}$ . Definition 6.2 needs the following adaptation:

**Definition 6.8.** Let  $K = \langle T, A \rangle$  be a consistent stratified knowledge base and N be a set of membership assertions. A *prioritized removed set*, denoted by X, is a set of membership assertions such that:

- $X \subset \mathcal{A} \cup N$ ,
- $\langle \mathcal{T}, (\mathcal{A} \cup N) \setminus X \rangle$  is consistent,
- $\forall X' \subseteq A \cup N$ , if  $\langle \mathcal{T}, (A \cup N) \setminus X' \rangle$  is consistent then  $X \leq_{lex} X'$ .

Note that  $A \cup N$  is a new prioritized ABox, where elements of N are put in a new important stratum. Namely, let  $A = A_1 \cup \ldots \cup A_n$  be a prioritized ABox. Then  $A \cup N = A'_1 \cup \ldots \cup A'_{n+1}$  where  $A'_1 = N$ , and  $A'_i = A_{i-1}$  for  $i = 1, \ldots, n+1$ .

The remaining definitions are valid, however Lemma 3.6 and Proposition 6.1 do not hold as it is shown the following counter-example.

**Example 6.9.** Let us consider  $\mathcal{T} = \{A \sqsubseteq \neg B\}$  and  $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2$  where  $\mathcal{A}_1 = \{A(a)\}$  and  $\mathcal{A}_2 = \{B(c)\}$ . Let  $N = \{A(b), B(b), B(a)\}$  where  $\langle \mathcal{T}, N \rangle$  is inconsistent. We have  $\langle \mathcal{T}, N \cup \mathcal{A} \rangle$  is also inconsistent. The conflict sets are:  $C_1 = \{A(a), B(a)\}$  and  $C_2 = \{A(b), B(b)\}$ . The two prioritized removed sets are:  $X_1 = \{A(a), A(b)\}$  and  $X_2 = \{A(a), B(b)\}$ .

One can check that there exist more than one prioritized removed set which both contain elements from  $\mathcal{A}$  and N.

When the input N is a set of PI axioms or NI axioms. We assume that  $\mathcal{T} \cup N$  is coherent, since the TBox of the knowledge base is assumed to be stable. Of course  $\langle \mathcal{T} \cup N, \mathcal{A} \rangle$  may be inconsistent. In this case PRSR behaves in the same way as simple revision by a single input. In both cases (set of assertions or axioms), the most noticeable difference is that the number of conflicts may be higher and by consequence the size of prioritized removed sets may be higher.

Lastly, if the input contains both membership assertions and PI axioms or NI axioms, then this comes down to revise the *DL-Lite* prioritized knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  with another knowledge base  $\langle \mathcal{T}', \mathcal{A}' \rangle$ . One way to achieve such revision is to apply PRSR on  $\langle \mathcal{T} \cup \mathcal{T}', \mathcal{A} \cup N \rangle$ .

**Example 6.10.** Let us consider  $\mathcal{T} = \{A \sqsubseteq \neg B\}$  and  $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2$  where  $\mathcal{A}_1 = \{A(a)\}$  and  $\mathcal{A}_2 = \{B(b)\}$ . Let  $N = \{C \sqsubseteq A, C(a), A(b)\}$ . We have  $\langle \mathcal{T} \cup \mathcal{T}', \mathcal{A} \cup N \rangle$  is inconsistent. There exists only one conflict set  $C_1 = \{A(b), B(b)\}$ , and then one prioritized removed set  $X_1 = \{B(b)\}$ .

#### **6.3** Logical properties

In this section we go a step further in the characterization of Prioritized Removed Sets Revision for *DL-Lite* knowledge bases by presenting logical properties of the proposed operator through a set of postulates.

As mentioned in the Introduction, the AGM postulates [Alchourrón et al., 1985] have been formulated to characterize belief revision in a propositional logic setting. Flouris at al. [Flouris et al., 2004; Flouris et al., 2005; Flouris et al., 2006b] have studied which logics are AGM-compliant, that is, DLs where the revision operation satisfies AGM postulates. Indeed, the problem is that AGM postulates are defined for belief sets, i.e deductively closed sets of formulas, possibly infinite. Qi et al. [Qi et al., 2006c] focused on revising a finite representation of belief sets. They used a semantic reformulation of AGM postulates, done by Katsuno and Mendelzon [Katsuno and Mendelzon, 1991], to extend it to DLs knowledge bases. However, as pointed out in [Calvanese et al., 2010] known model-based approaches of revision are not expressible in DL-Lite. AGM postulates are defined for belief sets, however efficient implementation and computational tractability require finite representations. Moreover, cognitive realism stems from finite structures [Hansson, 2008] since infinite structures are cognitively inaccessible. Revision within the framework of DLs, particularly, DL-Lite, requires belief bases, i.e. finite sets of formulas. Postulates have been proposed for characterizing belief bases revision in a propositional logic setting [Fuhrmann, 1997; Hansson, 1998].

In order to give logical properties of PRSR operators, we first rephrase Hansson's postulates within the *DL-Lite* framework. We then analyze to what extent our operators satisfy these postulates.

#### 6.3.1 Hansson's postulates reformulated

Let  $\mathcal{K}$ ,  $\mathcal{K}'$  be DL-Lite knowledge bases, N and M be either membership assertions or a positive or a negative axiom,  $\circ$  be a revision operator.  $\mathcal{K}+N$  denotes the non closing expansion, i.e.  $\mathcal{K}+N=\mathcal{K}\cup\{N\}$ . Let  $\mathcal{K}=\langle\mathcal{T},\mathcal{A}\rangle$  be a knowledge base. When N is a membership assertion  $\mathcal{K}+N=\langle\mathcal{T},\mathcal{A}\cup\{N\}\rangle$  and when N is a positive or a negative axiom  $\mathcal{K}+N=\langle\mathcal{T}\cup\{N\},\mathcal{A}\rangle$ . We rephrase the Hansson's postulates as follows.

Success $N \in \mathcal{K} \circ N$ Inclusion $\mathcal{K} \circ N \subseteq \mathcal{K} + N$ .Consistency $\mathcal{K} \circ N$  is consistent.

Vacuity If  $K \cup \{N\}$  is consistent then  $K \circ N = K + N$ .

*Pre-expansion*  $(K + N) \circ N = K \circ N.$ 

Internal exchange If  $N, M \in \mathcal{K}$  then  $\mathcal{K} \circ N = \mathcal{K} \circ M$ .

Core retainment If  $M \in \mathcal{K}$  and  $M \notin \mathcal{K} \circ N$  then there exists  $\mathcal{K}'$  such that

 $\mathcal{K}' \subseteq \mathcal{K} + N$  and  $\mathcal{K}'$  is consistent but  $\mathcal{K}' \cup \{M\}$  is incon-

-sistent.

Relevance If  $M \in \mathcal{K}$  and  $M \notin \mathcal{K} \circ N$  then there exists  $\mathcal{K}'$  such that

 $\mathcal{K} \circ N \subseteq \mathcal{K}' \subseteq \mathcal{K} + N$ , and  $\mathcal{K}'$  is consistent but  $K' \cup \{M\}$ 

is inconsistent.

Success and Consistency express the basic principles of revision. Inclusion states that the union of the initial knowledge bases is the upper bound of any revision operation. Vacuity says that if the new information is consistent with the knowledge base then the result of revision equals the non closing expansion. Pre-expansion states that expanding first by an assertion does not change the result of revision by the same assertion. Internal exchange says that revising by two different assertions from the knowledge base does not change the result of revision. Core-retainment and Relevance express the intuition that nothing is removed from the original knowledge bases unless its removal in some way contributes to make the result consistent.

#### 6.3.2 Prioritized Removed Sets Revision: logical properties

We now present the logical properties of Prioritized Removed Sets operators.

**Proposition 6.3.** Let K be a consistent stratified DL-Lite knowledge base and N be a membership assertion. The revision operator  $\circ_{PRSR}$  satisfies Success, Inclusion, Consistency, Vacuity, Pre-expansion, Internal exchange, Core retainment and Relevance.

Proof of proposition 6.3. Since N is a membership assertion,  $\mathcal{K} \cup \{N\} = \langle \mathcal{T}, \mathcal{A} \cup \{N\} \rangle$ . By Definition 6.3,  $\mathcal{K} \circ_{PRSR} N = \langle \mathcal{T}, \mathcal{A} \circ_{PRSR} N \rangle$  with  $\mathcal{A} \circ_{PRSR} N = (\mathcal{A} \backslash X) \cup \{N\}$  and the postulates Success, Inclusion, Consistency are satisfied.

*Vacuity*: If  $K \cup \{N\}$  is consistent, then  $PR(K \cup \{N\}) = \emptyset$  and  $A \circ_{PRSR} N = A \cup \{N\}$ , therefore the postulate holds.

*Pre-expansion*:  $(A \cup \{N\}) \circ_{PRSR} N = ((A \cup \{N\}) \setminus X) \cup \{N\} = (A \setminus X) \cup \{N\}$ , therefore the postulate is satisfied.

Internal exchange: If  $N, M \in \mathcal{A}$ ,  $\mathcal{A} \cup \{M\} = \mathcal{A} \cup \{N\} = \mathcal{A}$  and  $\mathcal{PR}(\mathcal{K} \cup \{N\}) = \mathcal{PR}(\mathcal{K} \cup \{M\}) = \emptyset$ , therefore the postulate is satisfied.

Core retainment: The case where  $M \in \mathcal{T}$  is impossible since the  $\circ_{PRSR}$  operator may only modify the ABox. When M is a membership assertion, if  $M \in \mathcal{K}$  and  $M \notin \mathcal{K} \circ_{PRSR} N$  then there exists X such that  $M \in X$  and  $X \in \mathcal{PR}(\mathcal{K} \cup \{N\})$ . Let  $\mathcal{K}' = \langle \mathcal{T}, \mathcal{A} \backslash X \rangle$ , we have  $\mathcal{K}' \subseteq \mathcal{K} \cup \{N\}$  et  $\mathcal{K}'$  is consistent but  $\mathcal{K}' \cup \{M\}$  is inconsistent, therefore the postulate is satisfied.

Relevance: Since the postulate Core retainment is satisfied, and by Proposition 6.1 we have  $|\mathcal{PR}(\mathcal{K} \cup \{N\})| = 1$ , so  $\mathcal{K} \circ_{PRSR} N \subseteq \mathcal{K}'$  and thus the postulate holds.

This proposition states that PRSR with a membership assertion as input satisfies all postulates. The situation is slightly different when N is a PI or a NI axiom.

**Proposition 6.4.** Let K be a consistent stratified DL-Lite knowledge base. If N is a PI or a NI axiom then for any selection function, the revision operator  $\circ_{PRSR}$  satisfies Success, Inclusion, Consistency, Vacuity, Pre-expansion, Internal exchange, Core retainment but does not satisfy Relevance.

Proof of proposition 6.4. Since N is a positive or a negative axiom,  $\mathcal{K} \cup \{N\} = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \rangle$ . By Definition 6.6,  $\mathcal{K} \circ_{PRSR} N = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \circ_{PRSR} N \rangle$  with  $\mathcal{A} \circ_{PRSR} N = (\mathcal{A} \setminus f(\mathcal{R}(\mathcal{K} \cup \{N\})))$  and the postulates Success, Inclusion, Consistency are satisfied.

*Vacuity*: If  $K \cup \{N\}$  is consistent,  $PR(K \cup \{N\}) = \emptyset$  and  $A \circ_{PRSR} N = A$ , therefore the postulate holds.

*Pre-expansion*:  $(\mathcal{K} \cup \{N\}) \circ_{PRSR} N$ ,  $(\langle \mathcal{T} \cup \{N\}, \mathcal{A} \rangle) \circ_{PRSR} N = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \circ_{PRSR} N \rangle$ , therefore the postulate is satisfied.

Internal exchange: If  $N, M \in \mathcal{T}, \mathcal{T} \cup \{M\} = \mathcal{T} \cup \{N\} = \mathcal{T} \text{ and } \mathcal{PR}(\mathcal{K} \cup \{N\}) = \mathcal{PR}(\mathcal{K} \cup \{M\}) = \emptyset$ , therefore the postulate is satisfied.

Core retainment: The case where  $M \in \mathcal{T}$  is impossible since the  $\circ_{PRSR}$  operator may only modify the ABox. When M is a membership assertion, if  $M \in \mathcal{K}$  and  $M \notin \mathcal{K} \circ_{PRSR} N$ , then for any selection function used for defining  $\circ_{PRSR}$ , there exists  $X \in \mathcal{PR}(\mathcal{K} \cup \{N\})$  such that  $M \in X$  and  $X \subseteq f(\mathcal{R}(\mathcal{K} \cup \{N\}))$  by Definition 6.5. Let  $\mathcal{K}' = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \backslash X \rangle$ , we have  $\mathcal{K}' \subseteq \mathcal{K} \cup \{N\}$  and  $\mathcal{K}'$  is consistent but  $\mathcal{K}' \cup \{M\}$  is inconsistent, therefore the postulate is satisfied.

Relevance: Since the postulate Core retainment is satisfied, there exists  $\mathcal{K}' = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \backslash X \rangle$  that is consistent. Since there may exist several prioritized removed sets, let X and X' be two prioritized removed sets such that  $X' \neq X$ , suppose that  $f(\mathcal{PR}(\mathcal{K} \cup \{N\})) = X'$ , we have  $\mathcal{K} \circ_{PRSR} N = \langle \mathcal{T} \cup \{N\}, \mathcal{A} \backslash X' \rangle$  therefore  $\mathcal{K} \circ_{PRSR} N \not\subseteq \mathcal{K}'$ , therefore the postulate Relevance is not satisfied. We now give a counter-example where  $\mathcal{K}$  and  $\mathcal{N}$  come from Example 6.4. Let  $M = B_3(b), X = \{B_3(a), B_3(b)\}$  and  $X' = \{B_1(a), B_3(b)\}$  be two prioritized removed sets, suppose that  $f(\mathcal{PR}(\mathcal{K} \cup \{N\})) = X'$  we have  $\mathcal{A} \circ_{PRSR} N = \{B_3(a), B_2(b)\}$  and  $\mathcal{A} \backslash X = \{B_1(a), B_2(b)\}$ .

In fact, Relevance requires the existence of only one prioritized removed set which is the case where N is a membership assertion. However, when N is a PI or a NI axiom, in general, there may exist several prioritized removed sets.

## 6.4 Computing the revision operation outcome

As stated before, when trying to revise a *DL-Lite* knowledge base by a membership assertion, a PI axiom or a NI axiom, we want to withdraw only ABox assertions in order to restore consistency, *i.e.* prioritized removed sets will only contain elements from the ABox.

From the computational point of view, we have to distinguish several cases depending on the nature of the input N and the content of the knowledge base.

First of all, if the TBox  $\mathcal{T}$  only contains PI axioms, and if the input N is a PI axiom or a membership assertion, no inconsistency can occur, so the revision operation PRSR trivially becomes a simple union. Among the remaining cases, we distinguish two different situations:

- (i) N is a membership assertion: the computation of conflicts and the overall revision algorithm is a very simple task, thanks to Proposition 6.1, and is detailed below.
- (ii) N is a PI axiom or a NI axiom: this is the most complicated case, as several prioritized removed sets may exist. Moreover, we will see that this case has to be splitted into two subcases. Whatever case we consider, we first need to compute the conflicts of  $\mathcal{K} \cup \{N\}$ .

In what follows, we use the following notations:  $\mathcal{K}' = \langle \mathcal{T}', \mathcal{A}' \rangle = \mathcal{K} \cup \{N\}$  where:

- $\mathcal{T}' = \mathcal{T} \cup \{N\}$  and  $\mathcal{A}' = \mathcal{A}$ , if N is a PI or NI axiom, and
- $\mathcal{T}' = \mathcal{T}$  and  $\mathcal{A}' = \mathcal{A} \cup \{N\}$ , if N is an ABox assertion.

#### 6.4.1 Computing the conflicts

This step follows from the algorithm given in [Calvanese *et al.*, 2007a] for checking the consistency of a *DL-Lite* knowledge base. The main difference is that in [Calvanese *et al.*, 2007a] the aim is to check whether a *DL-Lite* knowledge base is consistent or not. Here, we have to perform one step further, as we need to enumerate all assertional pairs involved in conflicts. Hence, we need to adapt the algorithm.

Computing  $\mathcal{C}(\mathcal{K} \cup \{N\})$  first requires to obtain the negative closure  $cln\left(\mathcal{T}'\right)$ , using the rules recalled in the refresher on DL-Lite logic in Section 1.4. We suppose that this is performed by a NEGCLOSURE function. Then the computation of the conflicts proceeds with the evaluation over  $\mathcal{A}'$  of each NI axiom in  $cln\left(\mathcal{T}'\right)$  in order to exhibit whether  $\mathcal{A}'$  contains pairs of assertions that contradict the NI axioms. Intuitively, for each  $X \sqsubseteq \neg Y$  belonging to  $cln\left(\mathcal{T}'\right)$ , the evaluation of  $X \sqsubseteq \neg Y$  over the  $\mathcal{A}'$  simply amounts to return all (X(x),Y(x)) such that X(x) and Y(x) belong to  $\mathcal{A}'$ . Note X(x) (resp. Y(x)) may be a basic concept assertion, or a role assertion of the form R(x,y) if  $X = \exists R$  (resp.  $Y = \exists R$ ) or R(y,x) if  $X = \exists R^-$  (resp.  $Y = \exists R^-$ ). The result of the evaluation of a NI axiom is a collection of sets containing two elements, or one element if N is a membership assertion). Algorithm 3 describes the algorithm of the function COMPUTECONFLICTS, which computes  $\mathcal{C}(\mathcal{K} \cup \{N\})$ .

```
1: function ComputeConflicts(\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle, N)
              \mathcal{K}' = \langle \mathcal{T}', \mathcal{A}' \rangle \leftarrow \mathcal{K} \cup \{N\}
2:
             \mathcal{C}(\mathcal{K}') \leftarrow \emptyset
3:
              cln(\mathcal{T}') \leftarrow \text{NegClosure}(\mathcal{T}')
4:
              for all X \sqsubseteq \neg Y \in cln\left(\mathcal{T}'\right) do
5:
                      for all \{\alpha_t, \alpha_j\} \in \mathcal{A}' do
6:
                              if \langle X \sqsubseteq \neg Y, \{\alpha_t, \alpha_j\} \rangle is inconsistent then
7:
                                      \mathcal{C}(\mathcal{K}') \leftarrow \mathcal{C}(\mathcal{K}') \cup \{\{\alpha_t, \alpha_i\}\}
8:
              Return C(\mathcal{K}')
9:
```

Algorithm 3: COMPUTECONFLICTS( $\mathcal{K}$ )

The set  $\mathcal{C}(\mathcal{K}')$  stores the conflict sets. The first step of the algorithm consists in the computation of the negative closure of  $\mathcal{T}'$ . Then, for each NI axiom  $X \sqsubseteq \neg Y$  of  $cln(\mathcal{T}')$  the algorithm looks for the existence of a contradiction in the ABox. This is done by checking whether  $\langle X \sqsubseteq \neg Y, \{\alpha_t, \alpha_j\} \rangle$  is consistent or not. Note that this step can be performed by a boolean query expressed from  $X \sqsubseteq \neg Y$  to

look whether  $\{\alpha_t, \alpha_j\}$  contradicts the query, or not. If the ABox is consistent with  $X \subseteq \neg Y$ , then the result of the query is an empty set.

It is important to note that if N is a membership assertion, then in each conflict  $\{\alpha_t, \alpha_j\}$  either  $\alpha_t$  or  $\alpha_j$  belongs to  $\mathcal{A}$  (but not both), and that either  $\alpha_t$  or  $\alpha_j$  is equal to N (but not both). This special case is detailed in the next subsection.

#### 6.4.2 Computing the PRSR outcome

Based on the computation of conflict sets, we propose in what follows algorithms for computing the results of revision according to the different cases.

#### Revision by an assertion

When the input N is a membership assertion (namely a fact), then there exists only one prioritized removed set, and the priorities are not involved. The computation of this single prioritized removed set amounts in picking in each conflict the membership assertion which is different from the new information N. One can easily check that every conflict set  $\{\alpha_t, \alpha_j\}$  that contradicts a NI axiom is of the form  $\{x, N\}$  where  $x \in \mathcal{A}$ . This means that there exists exactly one prioritized removed set. Hence, in this case the prioritized removed set computation can be performed in polynomial time: when returning from the call to Compute Conflicts, the only prioritized removed set is  $\bigcup_{c_i \in \mathcal{C}(\mathcal{K} \cup \{N\})} (c_i \setminus \{N\})$ .

Algorithm 4 describes the algorithm of the function COMPUTEPRSR1 as a special case of Algorithm 3. It computes directly the single prioritized removed set when revising by a membership assertion.

```
1: function COMPUTEPRSR1(\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle, N = A(a) or N = R(a,b))
2: R \leftarrow \emptyset
3: cln\left(\mathcal{T}\right) \leftarrow \text{NEGCLOSURE}(\mathcal{T})
4: for all X \sqsubseteq \neg Y \in cln\left(\mathcal{T}\right) do
5: for all \alpha \in \mathcal{A} do
6: if \langle X \sqsubseteq \neg Y, \{\alpha, N\} \rangle is inconsistent then
7: R \leftarrow R \cup \{\alpha\}
8: return R
```

Algorithm 4: COMPUTEPRSR1(K, N)

#### Revision by an axiom

Now, we detail the case where N is a PI or a NI axiom. According to Definition 6.4, the computation of  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  starts with the computation of  $\mathcal{PR}((\mathcal{T} \cup \{N\}) \cup \mathcal{A}_1)$ , followed by the computation of  $\mathcal{PR}((\mathcal{T} \cup \{N\}) \cup (\mathcal{A}_1 \cup \mathcal{A}_2))$ , and so on. A prioritized removed set is formed by picking in each conflict the least priority element. However, according to the form of conflicts, two situations hold, as pointed out in Section 6.2.2. The first one is when *each conflict* involves two elements having different levels of priority. In this case, Proposition 6.2 ensures that there exists only one prioritized removed set. We provide algorithm COMPUTEPRSR2 which computes this single prioritized removed set  $PR \in \mathcal{PR}(\mathcal{K} \cup \{N\})$ .

The algorithm COMPUTEPRSR2 proceeds from a current layer to all the other less preferred layers and selects the assertions that conflict with the ones in the current layer. Here we increment from a layer to another in order to ensure the minimality of the prioritized removed set with respect to lexicographic ordering. Note that this algorithm is based on inconsistency checking and its computational complexity is polynomial.

```
1: function ComputePRSR2 (\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle, N)
 2:
              Res \leftarrow \mathcal{A}_1
              PR \leftarrow \emptyset
 3:
             \mathcal{C} \leftarrow \text{COMPUTECONFLICTS}(\mathcal{K}, N)
 4:
              for i \leftarrow 2, n do
 5:
                     for all \alpha \in \mathcal{A}_i do
 6:
                            if \exists C \in \mathcal{C}, Res \cap C \neq \emptyset and \alpha \in C then
 7:
                                   PR \leftarrow PR \cup \{\alpha\}
 8:
                                   \mathcal{A}_i \leftarrow \mathcal{A}_i \setminus \{\alpha\}
 9:
                     Res \leftarrow Res \cup \mathcal{A}_i
10:
11:
              Return PR
```

Algorithm 5: COMPUTEPRSR2

Now, we detail the second case where there exists at least a conflict involving two elements having the same priority level. In such situation there exists several prioritized removed sets, as pointed out in section 6.2.2. To compute them, we use the hitting set notion [Reiter, 1987] and adapt it to the stratified structure of the knowledge base.

A hitting set is a set which intersects each set in a collection. A minimal hitting set, with respect to set inclusion, is called a kernel. Moreover, kernels which are minimal according to cardinality correspond to the definition of a removed set [Würbel et al., 2000]. The same result holds for *DL-Lite* knowledge bases where the computation of the kernels of  $\mathcal{C}(\mathcal{K} \cup \{N\})$  is performed using Reiter's algorithm [Reiter, 1987], modified in [Wilkerson et al., 1989]. We recall this algorithm.

**Definition 6.9.** A tree T is an HS-tree of  $\mathcal{C}(\mathcal{K} \cup \{N\})$  if and only if it is the smallest tree having the following properties:

- 1. Its root is labeled by an element from  $\mathcal{C}(\mathcal{K} \cup \{N\})$ . If  $\mathcal{C}(\mathcal{K} \cup \{N\})$  is empty, its root is labeled by ' $\sqrt{\phantom{a}}$ '.
- 2. If m is a node from T, let H(m) be the set of branch labels on the path going from the root to T to m. If m is labeled by ' $\sqrt{\ }$ ', it has no successor in T.
- 3. If m is labeled by a set  $C \in \mathcal{C}(\mathcal{K} \cup \{N\})$ , then, for each  $c \in C$ , m has a successor node  $m_c$  in T, joined to m by a branch labeled by c. The label of  $m_c$  is a set  $C' \in \mathcal{C}(\mathcal{K} \cup \{N\})$  such that  $C' \cap H(m_c) = \emptyset$ , if such a set exists. Otherwise,  $m_c$  is labeled by ' $\sqrt{\phantom{m}}$ '.

The kernels correspond to the leaves labeled by  $\sqrt{.}$  For each such node m, H(m) is a kernel of  $\mathcal{C}(\mathcal{K} \cup \{N\})$ . We use the same pruning techniques as in [Wilkerson *et al.*, 1989].

Prioritized removed sets are not necessarily minimal with respect to cardinality, but they are minimal with respect to lexicographic ordering ( $\leq_{lex}$  for short). So, a naive algorithm for computing  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  could be: (i) compute the kernels of  $\mathcal{C}(\mathcal{K} \cup \{N\})$ . (ii) keep only minimal ones with respect to  $\leq_{lex}$ . However, we can improve this algorithm. As we said before, a prioritized removed set is computed from a layer to another. The idea of the enhancement of the algorithm is as follows: Compute conflicts in the first layer, i.e. in  $\langle \mathcal{T} \cup \{N\}, \mathcal{A}_1 \rangle$ . Then, build the hitting set tree on this collection of conflicts. This tree allows for the computation of the kernels of  $\langle \mathcal{T} \cup \{N\}, \mathcal{A}_1 \rangle$ , which are minimal with respect to  $\leq_{lex}$ . From these kernels, we continue the construction of the tree using conflicts in  $\langle \mathcal{T} \cup \{N\}, \{\mathcal{A}_1 \cup \mathcal{A}_2\} \rangle$  if they exist, and so on until reaching a fixed point where no conflict will be generated. Then, the kernels of the final hitting set tree — i.e. those built using the conflicts in  $\langle \mathcal{T} \cup \{N\}, \{\mathcal{A}_1 \cup \mathcal{A}_2 \cup ... \cup \mathcal{A}_n\} \rangle$ 

```
1: function ComputePRSR3 (\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle, N)
               \mathcal{T}' \leftarrow \mathcal{T} \cup \{N\}, \mathcal{K}' = \langle \mathcal{T}', \mathcal{A} \rangle
 2:
               cln\left(\mathcal{T}'\right) \leftarrow \text{NegClosure}(\mathcal{T}')
 3:
               \mathcal{PR}(\mathcal{K}') \leftarrow \emptyset, \mathcal{C} \leftarrow \emptyset, Tree \leftarrow \emptyset, i \leftarrow 1
 4:
               while i \leq n do
  5:
                       for all X \sqsubseteq \neg Y \in cln\left(\mathcal{T}'\right) do
 6:
                               for all (\alpha, \beta) s.t. \alpha \in \mathcal{A}_1, \beta \in \mathcal{A}_1 \cup \ldots \cup \mathcal{A}_i do
 7:
                                       if \langle X \sqsubseteq \neg Y, \{\alpha, \beta\} \rangle is inconsistent then
 8:
                                               \mathcal{C} \leftarrow \mathcal{C} \cup \{\alpha, \beta\}
 9:
                       TREE \leftarrow TREE.ADDFROMLEXKERNEL(HS(C))
10:
                       \mathcal{C} \leftarrow \emptyset,
11:
12:
                       i \leftarrow i + 1
               \mathcal{PR}(\mathcal{K}') \leftarrow \text{LexKernel}(\text{Tree})
13:
               return \mathcal{PR}(\mathcal{K}')
14:
```

Algorithm 6: COMPUTEPRSR3

— which are minimal with respect to  $\leq_{lex}$  are the prioritized removed sets. Algorithm 6 describes the algorithm of the function COMPUTEPRSR3, which computes  $\mathcal{PR}(\mathcal{K} \cup \{N\})$ .

In this algorithm, the function  $HS(\mathcal{C})$  takes as input the conflicts computed in each strata (if they exist) and builds the corresponding hitting sets tree (TREE) using the algorithm presented in [Reiter, 1987; Wilkerson et al., 1989]. From one layer to another, we resume the construction of (TREE) from its current kernels minimal with respect to  $\leq_{lex}$ . Namely, the function ADDFROMLEXKERNEL((HS( $\mathcal{C}$ )) builds the hitting set tree out of a collection of conflicts  $\mathcal{C}$ , starting from the branches of the current TREE which are minimal with respect to  $\leq_{lex}$ . Finally,  $\mathcal{PR}(\mathcal{K} \cup \{N\})$  corresponds to the kernels of TREE obtained using function Lexkernel(Tree) which are minimal with respect to  $\leq_{lex}$ . Note that Computerred is a generalization of Computerred, since when all conflicts involve elements from distinct layers, then the final tree will only contain one prioritized removed set. The following example illustrates this algorithm.

**Example 6.11.** Consider  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$ , with  $\mathcal{T} = \{A \sqsubseteq B, C \sqsubseteq B\}$  and  $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3 \cup \mathcal{A}_4$  where  $\mathcal{A}_1 = \{A(a), D(a)\}, \mathcal{A}_2 = \{C(a), B(b)\}, \mathcal{A}_3 = \{D(b)\}$  and  $\mathcal{A}_4 = \{D(c), C(c)\}$ . We want to revise  $\mathcal{K}$  with  $N = B \sqsubseteq \neg D$ . Then, we have  $cln(\mathcal{T} \cup \{B \sqsubseteq \neg D\}) = \{B \sqsubseteq \neg D, A \sqsubseteq \neg D, C \sqsubseteq \neg D\}$ .

- The set of conflicts obtained from  $\langle cln\left(\mathcal{T}'\right),\mathcal{A}_1\rangle$  is  $\{\{A(a),D(a)\}\}$ . The HS tree built by calling HS( $\{\{A(a),D(a)\}\}$ ) will contain two branches labeled respectively by A(a) and D(a) which are kernels minimal with respect to  $\leq_{lex}$  ( $\leq_{lex}$ -kernel).
- We go on with  $\langle cln\left(\mathcal{T}'\right), \mathcal{A}_1 \cup \mathcal{A}_2 \rangle$  where  $\{C(a), D(a)\}$  is a newly identified conflict. We resume the construction of the tree from its current  $\leq_{lex}$ -kernel branches labeled by A(a) and D(a), and we obtain three HS-tree branches:  $\{A(a), C(a)\}, \{A(a), D(a)\}$  and D(a), where only D(a) is a  $\leq_{lex}$ -kernel.
- Now, we go to the next strata, that is, we use  $\langle cln(\mathcal{T}'), \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3 \rangle$ . This produces a new conflict  $\{B(b), D(b)\}$  and we continue the construction of the Tree from D(a). We potentially obtain  $\{D(a), D(b)\}$  and  $\{D(a), B(b)\}$  as new prioritized removed sets, but only  $\{D(a), D(b)\}$  is a  $\leq_{lex}$  kernel.
- Finally, we identify a new conflict  $\{D(c), C(c)\}$  from  $\langle cln(\mathcal{T}'), \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3 \cup \mathcal{A}_4 \rangle$ . We continue the construction of the tree from the branch labeled by  $\{D(a), D(b)\}$ . We obtain two other

branches labeled respectively by  $\{D(a), D(b), C(c)\}$  and  $\{D(a), D(b), D(c)\}$  which are two  $\leq_{lex}$  kernels. Hence,  $\mathcal{PR}(\mathcal{K} \cup \{N\}) = \{\{D(a), D(b), C(c)\}, \{D(a), D(b), D(c)\}\}.$ 

#### 6.5 Discussions and related works

In [Calvanese et al., 2010], the authors study the problem of knowledge base evolution in DL-Lite. Under the word evolution, they encompass both revision and update operations. Note that the update focuses on the changes of the actual state whereas revision focuses on the integration of new information [Wang et al., 2010]. In this chapter, we focus on revision. The part of the article [Calvanese et al., 2010] dedicated to formula-based approaches is closely related to our work. They define several operators which perform revision of a knowledge base expressed in DL-Lite at a syntactical level. The first difference concerns the form of the input. In our case, new information is a membership assertion, a single PI axiom or NI axiom, that is a single formula. In [Calvanese et al., 2010], the input is a set of formulas. The second difference is that in [Calvanese et al., 2010] they develop two operators whose strategy is to non-derministically choose some maximal consistent subset. The first one, called BoldEvol, starts with the input, and incrementally and non-deterministically adds as many formulas as possible from the closure of the knowledge base. The algorithm for computing such set is polynomial. However, in the case where the input is a set of membership assertions, they give a result similar to our operator. Namely, the result only gives one maximal consistent subset, which corresponds to Proposition 6.1.

The selected maximal subset is a subset of the *consequences* of the knowledge base, which is very different from our point of view. Prioritized Removed Sets Revision relies only on the explicit content of the knowledge base. The resulting knowledge base will not contain formulas which are not present in the original knowledge base. Only working with explicitly given information, we follow Hansson's point of view [Hansson, 2008].

Following this line, extensions of belief bases revision to DLs have been proposed, however these approaches differ from ours in several aspects. Within the general framework of DLs, in [Qi et al., 2008a] the authors extend kernel-based revision [Hansson, 1994] for revising flat terminologies. Our approach is very different since we deal with knowledge bases which are prioritized and expressed in a lightweight DLs. Furthermore, our revision operators do not modify the TBox but revise the prioritized ABox according to a lexicographical strategy.

In [Halaschek-wiener *et al.*, 2006], the authors focus on  $\mathcal{SHOIN}$  DL, they extend kernel revision and semi-revision operators [Hansson, 1997] to  $\mathcal{SHOIN}$  knowledge bases. Moreover, they propose an algorithm for revision stemming from the computation of kernels. This algorithm shares several common points with our algorithm for the computation of prioritized removed sets. What they call justification of the inconsistency is very similar to our notion of conflict. But in their case, the generation of conflicts has a higher computational cost than in our case, as they work with  $\mathcal{SHOIN}$  logic. In order to lower this extra-complexity, they rely on an optimized version of the Pellet consistency checker which uses properties of the  $\mathcal{SHOIN}$  logic, allowing them to define an incremental version of their consistency checking tableau algorithm.

In [Ribeiro and Wassermann, 2007], the authors propose another extension of kernel-based revision and semi-revision operators to DLs, namely external kernel revision and semi-revision with weak success. Again, their logical framework is richer than ours, since they consider SHOIN and SHIF logics in order to capture all the OWL-DL and OWL-Lite languages. Our revision operators can be viewed as restrictions of the operator they define under the name  $kernel\ revision\ without\ negation$ . The restrictions are: (i) our knowledge bases are prioritized and expressed in DL-Lite; (ii) the minimality of the result of the incision function is defined in terms of lexicographic criterion in our case.

Following another idea, the authors in [Qi et al., 2006a] extend weakening-based revision to  $\mathcal{ALC}$  knowledge bases. Instead of removing conflicting assertions, the proposed revision operators weaken terminological axioms or assertions by adding exceptions which drop individuals responsible of the conflicts. Furthermore, this weakening-based revision is generalized to stratified knowledge bases. Our revision operators differ from this approach since our prioritized knowledge bases are expressed in *DL-Lite*. Moreover, the spirit is different since PRSR removes conflicting assertions according to a lexicographical strategy.

#### 6.6 Conclusion

In this chapter, we investigated the problem of revising prioritized *DL-Lite* knowledge bases where the ABox is stratified. We considered several forms of the incorporated information, more precisely, when the input is a membership assertion, a positive or negative inclusion axiom. According to the form of the input we proposed a family of operators, Prioritized Removed Sets (PRSR) operators, stemming from a lexicographical strategy for removing some assertions, namely the prioritized removed sets, in order to restore consistency.

When the input is a membership assertion, the revision process leads to a unique revised knowledge base. However, when the input is a positive or negative inclusion axiom, the revision process may lead to several possible revised knowledge bases. In this case, we defined selection functions in order to keep the result within the *DL-Lite* language and we gave some concrete PRSR operators with examples of selection functions. We studied the logical properties of PRSR operators through Hansson's postulates rephrased within the *DL-Lite* framework. From a computational point of view, we first proposed an algorithm for pinpointing inconsistencies, then according to the nature of the input, we proposed algorithms, some of them using the notion of hitting set, for computing the prioritized removed sets.

Based on the discussion about suitable techniques for inconsistency handling presented in Chapter 5 and the assumption that the ABox is prioritized, next chapter proposes several approaches to select *one* preferred assertional-based repair from inconsistent and prioritized *DL-Lite* knowledge bases.

# HOW TO SELECT ONE PREFERRED ASSERTIONAL-BASED REPAIR FROM INCONSISTENT AND PRIORITIZED DL-Lite KNOWLEDGE BASES?

#### 7.1 Introduction

In Chapter 5, we addressed the problem of inconsistency handling in flat *DL-Lite* knowledge bases. We showed, in particular, that dealing with inconsistency in an Ontology-Based Data Access setting comes down first to compute the assertional-based repairs, and then, perform inference. However, as pointed out in previous chapter (Chapter 6), assertions are often provided by several and potentially conflicting sources having different reliability levels. In the previous chapter, we were interested in analyzing the problem of adding a new piece of information (assertional fact, positive inclusion axiom and negative inclusion axiom) in *DL-Lite* knowledge bases when the assertional base is prioritized. We followed a revision strategy that consists in throwing out some assertional facts to restore consistency. This chapter goes one step further and studies the problem of inconsistency handling in prioritized *DL-Lite* knowledge bases. The main question addressed in this chapter is how to select one preferred assertional-based repair. Selecting only one repair is important since it allows efficient query answering once the preferred repair is computed.

In this context, several works (e.g. [Martinez et al., 2008; Staworko et al., 2012]) studied the notion of priority when querying inconsistent databases. In [Du et al., 2013], a maximal repair with respect to set inclusion was introduced in order to answer queries from an inconsistent SHIQ DL knowledge base. In the DL-Lite area, there is to the best of our knowledge only one work [Bienvenu et al., 2014] dealing with reasoning under inconsistency using the priorities of assertions within the OBDA setting.

In this chapter, we first review the main existing inconsistency-tolerant reasoning methods for prioritized knowledge bases. We provide consequence relations based either i) on the selection of one consistent prioritized assertional base which is in general not maximal or ii) on the choice of several prioritized repairs. It is important to note that some inference relations are specific to *DL-Lite* even if they are inspired by other formalisms, such as propositional logic settings.

This chapter also contains different main strategies for computing repairs that are suitable for the *DL-Lite* setting. As mentioned in Chapter 5, a suitable inconsistency-tolerant relation is a one that outputs a consistent *DL-Lite* knowledge base and produces as many safe conclusions as possible. In particular, it should be at least as productive as taking the intersection of all the repairs. Interestingly enough, many of such consequence relations allow an efficient handling of inconsistency in *DL-Lite* knowledge base.

The rest of this chapter is organized as follows: Section 7.2 reviews existing works for computing preferred repairs. Section 7.3 introduces the notion of prioritized deductive closure and studies the properties of existing approaches with respect to the notion of deductive closure. Section 7.4 investigates new inference strategies based on the selection of one preferred repair. Section 7.5 provides a compara-

tive analysis of the main approaches studied in this chapter. Section 7.6 gives experimental studies and Section 7.7 concludes the chapter.

**Notations:** Let us first summarize in Table 7.1 the different notations of repairs that will be used in the rest of this chapter.

A	D.C.:	C'an'Cast'an
Acronym	Definition	Signification
$\mathit{MAR}(\mathcal{A})$	Definition 5.3	(flat) inclusion-based repairs of ${\cal A}$
$MAR_{card}(\mathcal{A})$	$\circ_{card}(\circ_{incl}(\mathcal{A}))$ (Chapter 5)	(flat) cardinality-based repairs of ${\cal A}$
PAR(A)	Definition 7.1	preferred inclusion-based repair of ${\cal A}$
$\pi(\mathcal{A})$	Definition 7.5	possibilistic-based repair of ${\cal A}$
$\ell(\mathcal{A})$	Definition 7.7	linear-based repair of ${\cal A}$
$pr_{lex}(\mathcal{A})$	Definition 7.3	preferred lexicographic-based repair of ${\cal A}$
$nd(\mathcal{A})$	Definition 7.10	non-defeated reapir of ${\cal A}$
$free(\mathcal{S})$	Definition 7.11	non-conflicting assertions of a subset ${\mathcal S}$ w.r.t a TBox ${\mathcal T}$
$clnd(\mathcal{A})$	Equation 7.2	closed non-defeated repair of ${\cal A}$
$\ell nd(A)$	Algorithm 7	linear-based non-defeated repair of ${\cal A}$
$nd(\mathcal{A})_{card}$	Definition 7.13	cardinality-based non-defeated repair of ${\cal A}$
$consnd(\mathcal{A})_{card}$	Definition 7.14	consistent cardinality-based non-defeated repair of ${\cal A}$
$pind(\mathcal{A})$	Definition 7.15	prioritized inclusion-based non-defeated repair of ${\cal A}$
$pind_{lex}(\mathcal{A})$	Equation 7.5	prioritized lexicographical-based non-defeated repair of ${\cal A}$

Table 7.1: Notations of repairs using in this Chapter.

### 7.2 Existing assertional-based preferred repairs

This section reviews approaches dealing with inconsistent *DL-Lite* knowledge bases that either have been proposed in a DLs setting or have been proposed in a propositional logic setting but need a slight adaptation to be suitable for *DL-Lite*.

A *DL-Lite* knowledge base  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  with a prioritized assertional base is a *DL-Lite* knowledge base where  $\mathcal{A}$  is partitioned into n layers (or strata) of the form

$$\mathcal{A} = \mathcal{S}_1 \cup \ldots \cup \mathcal{S}_n$$

where each layer  $S_i$  contains the set of assertions having the same level of priority i and they are considered as more reliable than the ones present in a layer  $S_j$  when j > i. Within the OBDA setting, we assume that  $\mathcal{T}$  is stable and hence its elements are not questionable in the presence of conflicts. Throughout this chapter and when there is no ambiguity, we simply use "prioritized DL-Lite knowledge base  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$ " to refer to a DL-Lite knowledge base with a prioritized assertional base of the form  $\mathcal{A} = S_1 \cup \ldots \cup S_n$ .

**Example 7.1.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  such that  $\mathcal{T}=\{A \sqsubseteq \neg B\}$  and that assertional facts of  $\mathcal{A}$  come from three distinct sources  $\mathcal{A}=\mathcal{S}_1 \cup \mathcal{S}_2 \cup \mathcal{S}_3$  where  $\mathcal{S}_1=\{B(a),A(b)\}$ ,  $\mathcal{S}_2=\{A(a)\}$  and  $\mathcal{S}_3=\{B(c)\}$ .  $\mathcal{S}_1$  contains the most reliable assertions.

In Example 7.1, it is easy to check that the knowledge base is inconsistent. Coping with inconsistency can be done by first computing the set of repairs, then using them to perform inference. In order to compute the repairs, we use the notion of conflict sets presented in Chapter 5 (Definition 5.12).

#### 7.2.1 Preferred inclusion-based repair

In the flat case<sup>1</sup>, one of the main strategies for handling inconsistency comes down to computing the ABox repairs of an inconsistent DL-Lite knowledge base. A repair is a maximal subbase of the ABox, denoted by MAR, that is consistent with the TBox (Definition 5.3 in Section 5.2).

**Example 7.2.** Consider 
$$\mathcal{T} = \{A \sqsubseteq \neg B\}$$
 and  $\mathcal{A} = \{A(a), B(a), A(b)\}$ . We have  $\mathcal{C}(\mathcal{A}) = \{A(a), B(a)\}$ . The set of  $MAR$  is:  $\mathcal{R}_1 = \{A(a), A(b)\}$  and  $\mathcal{R}_2 = \{B(a), A(b)\}$ .

According to the definition of MAR, adding any assertion f from  $A \setminus \mathcal{R}$  to  $\mathcal{R}$  entails the inconsistency of  $\langle \mathcal{T}, \mathcal{R} \cup \{f\} \rangle$ . Moreover, the maximality in MAR is used in the sense of set inclusion. We denote by MAR(A) the set of MAR of A with respect to  $\mathcal{T}$ . A query is said to be a universal consequence (i.e.  $\langle \mathcal{M}1, \forall \rangle$  given in Chapter 5) if it can be derived from every MAR. The following definition extends the definition of MAR when the DL-Lite ABox is prioritized.

**Definition 7.1.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. A preferred inclusion-based repair  $(PAR) \mathcal{P} = P_1 \cup \ldots \cup P_n$  of  $\mathcal{A}$  is such that there is no a  $MAR \mathcal{P}' = P_1' \cup \ldots \cup P_n'$  of  $\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_n$ , and an integer i where:

- i)  $P_i$  is strictly included in  $P'_i$ , and
- ii)  $\forall j = 1..(i-1), P_j$  is equal to  $P'_j$

This definition of PAR has been largely used in a propositional logic setting (e.g. [Brewka, 1989; Benferhat et al., 1998a]) and has been recently used in a DL-Lite framework [Bienvenu et al., 2014]. A PAR of A is formed by first computing the PAR of A, then enlarging this PAR as much as possible by assertions of A0 while preserving consistency, and so on.

**Example 7.3.** Consider 
$$\mathcal{T} = \{A \subseteq \neg B\}$$
 and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a)\}$  and  $\mathcal{S}_2 = \{B(a), A(b)\}$ .

Priorities reduce the number of MAR as one can see in Example 7.3 in comparison with Example 7.2. Indeed, within a prioritized setting, the notion of PAR operates as a selection function among possible MAR. Following the definition of ABox conflict (Definition 5.12), an important feature in restoring consistency in DL-Lite, when the ABox is layered, is that when there is no conflict in  $\mathcal{A}$  involving two assertions having the same priority level, there exists only one PAR.

**Proposition 7.1.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite. Let C(A) be the set of conflicts in A. Then if  $\forall C = (f, g) \in C(A)$  we have  $f \in S_i$ ,  $g \in S_j$  and  $i \neq j$  then there exits exactly one PAR.

*Proof of Proposition 7.1.* The proof is immediate. In every conflict in A, we throw out only the assertion having the lowest priority level. Therefore there exits only one PAR of A.

<sup>&</sup>lt;sup>1</sup>By a flat knowledge base, we mean a base where all the assertions have the same priority.

When a conflict involves two assertions having the same priority level, restoring consistency leads to several PAR. From now on, PAR(A) denotes the set of PAR of A. The following definition introduces universal inference when A is layered.

**Definition 7.2.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. A query q is said to be a *PAR*-consequence of  $\mathcal{K}$ , denoted  $\mathcal{K} \models_{PAR} q$ , if and only if  $\forall \mathcal{P} \in PAR(\mathcal{A}), \langle \mathcal{T}, \mathcal{P} \rangle \models^2 q$  where  $PAR(\mathcal{A})$  denotes the set of PAR of  $\mathcal{A}$ .

Definition 7.2 states that a query q is a universal consequence if and only if it can be deduced from every preferred inclusion-based repair. Note that the PAR-entailment extends the definition of MAR-entailment (i.e.  $\langle \mathcal{M}_1, \forall \rangle$  proposed in Section 5) when the ABox is prioritized. Besides, it is argued that priorities simplify the computation of PAR, but it remains a hard task since in the flat case the inference is coNP-complete (see Section 5.5.2 on complexity analysis). When a conflict involves two assertions having the same priority level, restoring consistency often leads to several PAR.

#### 7.2.2 Lexicographic preferred-based repair

This subsection rewrites the cardinality-based or lexicographic inference or prioritized removed set repair, defined in Chapter 6, to the context of inconsistency handling. The lexicographic inference has been widely used in the propositional setting (e.g. [Benferhat et al., 1998a]). In fact, one of the major problems of PAR-entailment is the large number of PAR that can be computed from an inconsistent DL-Lite knowledge base. In order to better choose a PAR, one can follow a lexicographic-based approach. We introduce a preferred lexicographic-based repair which is based on the cardinality criterion instead of the set inclusion criterion.

**Definition 7.3.** Let PAR(A) be the set of PAR of A. Then  $\mathcal{L} = L_1 \cup ... \cup L_n$  is said to be a lexicographical preferred-based repair, denoted by  $PAR_{lex}$ , if and only if:

```
i) \forall \mathcal{P} = P_1 \cup \ldots \cup P_n \in PAR(\mathcal{A}): there is no i such that |P_i| > |L_i|,
```

ii) 
$$\forall j < i, |P_j| = |L_j|$$
.

where |X| is the cardinality of the set X.

Clearly, using a lexicographic-based approach comes down to select among the set of repairs in PAR(A) the ones having the maximal number of elements.

**Definition 7.4.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. A query q is said to be Lex-consequence of  $\mathcal{K}$ , denoted by  $\mathcal{K} \models_{\mathcal{L}} q$ , if and only if  $\forall \mathcal{L} \in PAR_{lex}(\mathcal{A}) : \langle \mathcal{T}, \mathcal{L} \rangle \models q$ .

**Example 7.4.** Consider 
$$\mathcal{T} = A \sqsubseteq \neg B, B \sqsubseteq \neg C$$
 and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a), B(a)\}$  and  $\mathcal{S}_2 = \{C(a)\}$ . We have two  $PAR$ :  $\mathcal{P}_1 = \{A(a), C(a)\}$  and  $\mathcal{P}_2 = \{B(a)\}$  and only one  $PAR_{lex}$  which is  $\mathcal{L} = \{A(a), C(a)\}$ .

We propose to review in the two next subsections inconsistency-tolerant inferences based only on selecting one preferred repair.

<sup>&</sup>lt;sup>2</sup> \= denotes the standard entailment used from flat and consistent *DL-Lite* knowledge base [Calvanese *et al.*, 2007a]

#### 7.2.3 Possibilistic-based repair

This section briefly rewrites possibilistic-based approach of Chapter 3 when the knowledge base is stratified.

One of the interesting aspects of possibilistic knowledge bases, and more generally weighted knowledge bases, is the ability of reasoning with partially inconsistent knowledge [Dubois and Prade, 1991a]. As shown in Chapter 3, entailment in possibilistic DL-Lite, an extension of DL-Lite within a possibility theory setting, is based on the selection of one consistent, but not necessarily maximal, subbase of K. This subbase is induced by a level of priority called the inconsistency degree of K. The following definition reformulates the definition of inconsistency degree to fit the case where A is prioritized.

**Definition 7.5.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be an inconsistent prioritized *DL-Lite* knowledge base. The inconsistency degree of  $\mathcal{K}$ , denoted  $Inc(\mathcal{K})$ , is defined as follows:  $Inc(\mathcal{K})=i+1$  if and only if:

- i)  $\langle \mathcal{T}, \mathcal{S}_1 \cup \ldots \cup \mathcal{S}_i \rangle$  is consistent and,
- ii)  $\langle \mathcal{T}, \mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i+1} \rangle$  is inconsistent.

The subbase  $\pi(\mathcal{A})$  is made of the assertions having priority levels that are strictly less than  $Inc(\mathcal{K})$ , namely  $\pi(\mathcal{A}) = \mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{(Inc(\mathcal{K})-1)}$ . If  $\mathcal{K}$  is consistent then we simply let  $\pi(\mathcal{A}) = \mathcal{A}$ . The following definition extends the possibilistic entailment ( $\pi$ -entailment) to the case where  $\mathcal{A}$  is stratified.

**Example 7.5.** Consider  $\mathcal{T} = \{A \sqsubseteq \neg B\}$  and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup \mathcal{S}_3$  where  $\mathcal{S}_1 = \{A(a)\}$ ,  $\mathcal{S}_2 = \{B(a), A(b)\}$  and  $\mathcal{S}_3 = \{B(b)\}$ . One can check that  $\pi(\mathcal{A}) = \{A(a)\}$  since  $\langle \mathcal{T}, \mathcal{S}_1 \rangle$  is consistent, but  $\langle \mathcal{T}, \mathcal{S}_1 \cup \mathcal{S}_2 \rangle$  is inconsistent.

**Definition 7.6.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. A query q is said to be a  $\pi$ -consequence of  $\mathcal{K}$ , denoted  $\mathcal{K} \models_{\pi} q$ , if and only if  $\langle \mathcal{T}, \pi(\mathcal{A}) \rangle \models q$ .

The  $\pi$ -entailment is cautious in the sense that assertions from  $\mathcal{A}\setminus\pi(\mathcal{A})$  that are not involved in any conflict are inhibited because of their low priority levels.

#### 7.2.4 Linear-based repair

One way to recover the inhibited assertions by the possibilistic entailment is to define the linear-based repair from  $\mathcal{A}$ . The following definition introduces the notion of linear subset. Linear entailment has been used in a propositional logic setting in [Nebel, 1994] and has been applied for a DL setting (*e.g.* [Qi *et al.*, 2011]).

**Definition 7.7.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite*. The *linear* assertional-based repair of  $\mathcal{A}$ , denoted  $\ell(\mathcal{A}) = \mathcal{S}_1 \cup \ldots \cup \mathcal{S}_n$ , is obtained as follows:

- i) For  $i = 1 : \ell(S_1) = S_1$  if  $\langle \mathcal{T}, S_1 \rangle$  is consistent. Otherwise  $\ell(S_1) = \emptyset$ .
- ii) For  $i > 1 : \ell(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_i) = \ell(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i-1}) \cup \mathcal{S}_i$  if  $\langle \mathcal{T}, \ell(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i-1}) \cup \mathcal{S}_i \rangle$  is consistent. Otherwise  $\ell(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_i) = \ell(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i-1})$ .

Clearly,  $\ell(A)$  is obtained by discarding a layer  $S_i$  when its facts conflict with the ones involved in the previous layer.

**Definition 7.8.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. A query q is a linear consequence ( $\ell$ -consequence) from  $\mathcal{K}$ , denoted  $\mathcal{K} \models_{\ell} q$ , if and only if  $\langle \mathcal{T}, \ell(\mathcal{A}) \rangle \models q$ .

**Example 7.6.** Let us consider again  $\mathcal{T} = \{A \sqsubseteq \neg B\}$  and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup \mathcal{S}_3$  where  $\mathcal{S}_1 = \{A(a)\}$ ,  $\mathcal{S}_2 = \{B(a), A(b)\}$  and  $\mathcal{S}_3 = \{B(b)\}$ . One can check that  $\ell(\mathcal{A}) = \{A(a), B(b)\}$  since  $\langle \mathcal{T}, \mathcal{S}_1 \rangle$  is consistent,  $\langle \mathcal{T}, \mathcal{S}_1 \cup \mathcal{S}_2 \rangle$  is inconsistent and  $\langle \mathcal{T}, \mathcal{S}_1 \cup \mathcal{S}_3 \rangle$  is consistent.

The subbase  $\ell(A)$  is unique and consistent with  $\mathcal{T}$ . The following proposition gives the complexity of  $\pi$ -entailment and  $\ell$ -entailment which are in P.

**Proposition 7.2.** The computational complexity of  $\pi$ -entailment is in  $\mathcal{O}(cons)$  where cons is the complexity of consistency checking of standard DL-Lite. The complexity of  $\ell$ -entailment is in  $\mathcal{O}(n*cons)$  where n is the number of strata in the knowledge base.

*Proof of Proposition* 7.2. The proof of the complexity of  $\pi$ -entailment can be found in Section 3.5. The proof of the complexity of  $\ell$ -entailment is immediate since to see whether a stratum should be kept or not in the result of restoring consistency, one consistency check is needed.

The  $\ell$ -entailment is more productive than  $\pi$ -entailment as one can see in Example 7.6 in comparison with Example 7.6, but incomparable with *PAR*-entailment and *Lex*-entailment. However from Definitions 7.5 and 7.7, both  $\pi(A)$  and  $\ell(A)$  are not guaranteed to be maximal.

#### 7.3 Sensitivity to the prioritized closure

Before presenting new strategies that only select one preferred repair, we briefly introduce the concept of a prioritized closure and check which among existing approaches is sensitive to the use of the deductive closure.

The inference relations given in the previous section can be either defined on  $\langle \mathcal{T}, \mathcal{A} \rangle$  or on  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$  where  $\circ_{cl}$  denotes the deductive closure of a set of assertions. The following definition extends Definition 5.2 to the prioritized case.

**Definition 7.9.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. Then, we define the prioritized closure of  $\mathcal{A}$  with respect to  $\mathcal{T}$ , simply denoted by  $\circ_{cl}(\mathcal{A})$ , as follows:

$$\circ_{cl}(\mathcal{A}) = \mathcal{S}'_1 \cup \ldots \cup \mathcal{S}'_n$$

where:

$$\mathcal{S}'_1 = \circ_{cl}(\mathcal{S}_i),$$

$$\forall i = 2, ..., n : \mathcal{S}'_i = \circ_{cl}(\mathcal{S}'_1 \cup ... \cup \mathcal{S}'_i) \setminus (\mathcal{S}'_1 \cup ... \cup \mathcal{S}'_{i-1})$$

**Example 7.7.** Consider  $\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq C, C \sqsubseteq \neg D\}$  and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a), D(a)\}$  and  $\mathcal{S}_2 = \{B(b)\}$ . Using Definition 7.9, we have  $\circ_{cl}(\mathcal{A}) = \mathcal{S}'_1 \cup \mathcal{S}'_2$  where  $\mathcal{S}'_1 = \{A(a), B(a), C(a), D(a)\}$  and  $\mathcal{S}'_2 = \{B(b), C(b)\}$ .

An important feature of  $\pi$ -inference and  $\ell$ -inference is that they are insensitive to the deductive closure. This is not the case with *PAR*-entailement or *Lex*-entailment, more precisely:

**Proposition 7.3.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. Then  $\forall q$ :

- $\langle \mathcal{T}, \mathcal{A} \rangle \models_{\pi} q \text{ if and only if } \langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle \models_{\pi} q.$
- $\langle \mathcal{T}, \mathcal{A} \rangle \models_{\ell} q \text{ if and only if } \langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle \models_{\ell} q.$

Proof of Proposition 7.3. Intuitively, both  $\pi$ -inference and  $\ell$ -inference use a consistency checking of the whole stratum to decide whether this stratum should be kept or not for restoring the consistency of the knowledge base. Besides, one can easily check that in standard DL-Lite,  $\langle \mathcal{T}, \mathcal{A} \rangle$  is consistent if and only if  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$  is consistent.

The following proposition shows that preferred inclusion-based inference and lexicographic-based inference are sensitive to the deductive closure.

**Proposition 7.4.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. Then,

- the preferred inclusion-based inference (PAR-entailment) applied to  $\langle \mathcal{T}, \mathcal{A} \rangle$  is incomparable with the one applied to  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$ .
- the lexicographic inference (Lex-entailment) applied to  $\langle \mathcal{T}, \mathcal{A} \rangle$  is incomparable with the one applied to  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$ .

**Example 7.8** (Counterexample for *PAR*-entailment). Let  $\mathcal{T} = \{A \sqsubseteq \neg B, A \sqsubseteq D, D \sqsubseteq \neg E\}$  and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a), B(a)\}$  and  $\mathcal{S}_2 = \{E(a)\}$ . We have  $\mathcal{P}_1 = \{A(a)\}$  and  $\mathcal{P}_2 = \{B(a), E(a)\}$ . Consider now the deductive closure: we have  $\circ_{cl}(\mathcal{S}_1) = \{A(a), B(a), D(a)\}$  and  $\circ_{cl}(\mathcal{S}_1 \cup \mathcal{S}_2) = \{E(a)\}$ . We also have:  $\mathcal{P}_1 = \{A(a), D(a)\}$  and  $\mathcal{P}_2 = \{B(a), D(a)\}$ . One can check that i) D(a) is a *PAR*-entailment of  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$  while it does not follow from  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$ .

**Example 7.9** (Counterexample *Lex*-entailment). Let us consider the following cases:

- i)  $\mathcal{T} = \{A \sqsubseteq \neg B, A \sqsubseteq C\}$  and  $\mathcal{A} = \mathcal{S}_1 = \{A(a), B(a)\}$ . We have  $\langle \mathcal{T}, \mathcal{A} \rangle \not\models_{lex} C(a)$  while  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle \models_{lex} C(a)$ .
- ii)  $\mathcal{T} = \{A \sqsubseteq \neg B, B \sqsubseteq F, F \sqsubseteq \neg A, C \sqsubseteq \neg B\}$  and  $\mathcal{S}_1 = \{A(a), B(a)\}$  and  $\mathcal{S}_2 = \{C(a)\}$ . We only have a lexicographic subbase of  $\langle \mathcal{T}, \mathcal{S}_1 \cup \mathcal{S}_2 \rangle$  which is  $\mathcal{L} = \{A(a), C(a)\}$  hence  $\langle \mathcal{T}, \mathcal{L} \rangle \models_{lex} C(a)$ . Besides  $\circ_{cl}(\mathcal{S}_1) = \{A(a), B(a), F(a)\}$  and  $\circ_{cl}(\mathcal{S}_2) = \{C(a)\}$ . We also have one lexicographic subbase of  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$  which is  $\mathcal{L} = \{B(a), F(a)\}$  hence  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle \not\models_{lex} C(a)$ .

#### 7.4 New strategies for selecting one preferred repair

This section presents new strategies that only select one preferred repair. Selecting only one repair is important since it allows efficient query answering once the preferred repair is computed. These strategies are based on the so-called non-defeated entailment, described in the next section, by adding different criteria: deductive closure, cardinality, consistency and priorities.

#### 7.4.1 Non-defeated repair

One way to get one preferred repair is to iteratively apply, layer per layer, the intersection of maximally assertional-based repairs (*i.e.* MAR). More precisely:

**Definition 7.10.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. We define the non-defeated reapir, denoted by  $nd(\mathcal{A}) = \mathcal{S}'_1 \cup \ldots \cup \mathcal{S}'_n$ , as follows:

$$\forall i = 1, ..., n : \mathcal{S}_i' = \bigcap_{\mathcal{R}_i \in MAR(\mathcal{S}_1 \cup ... \cup \mathcal{S}_i)} \mathcal{R}_i$$
(7.1)

As it will be shown below, the non-defeated entailment corresponds to the definition of non-defeated subbase proposed in [Benferhat *et al.*, 1998a] within a propositional logic setting. However, contrarily to the propositional setting i) the non-defeated repair can be applied on  $\mathcal{A}$  or its deductive closure  $\circ_{cl}(\mathcal{A})$  which leads to two different inference relations, ii) the non-defeated repair is computed in polynomial time in a *DL-Lite* setting while its computation is hard in a propositional logic setting. Let us now rephrase non-defeated repair (Equation 7.1) using the concept of free inference. First, we recall the notion of non-conflicting or free elements.

**Definition 7.11.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be *DL-Lite* knowledge base. An assertion  $f \in \mathcal{A}$  is said to be *free* if and only if  $\forall \mathcal{C} \in \mathcal{C}(\mathcal{A}) : f \notin \mathcal{C}$ .

Intuitively, *free* assertions are those assertions that are not involved in any conflict. Let  $S \in A$  be a set of assertions, we denote by free(S) the set of free assertions in S. The notions of free elements and free-entailment are originally proposed in [Benferhat  $et\ al.$ , 1992] where knowledge bases are encoded in a propositional logic setting. The definition of free-entailment is also equivalent to the MBox  $\mathcal{M}_1$  followed by the safe inference strategy  $i.e.\ \langle \mathcal{M}_1, \cap \rangle$  presented in Section 5.5.

The following proposition shows that the notion of free(A) extended to the prioritized case gives a non-defeated repair.

**Proposition 7.5.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. The non-defeated repair of A, given in Definition 7.10, is equivalent to:

$$nd(\mathcal{A}) = free(\mathcal{S}_1) \cup free(\mathcal{S}_1 \cup \mathcal{S}_2) \cup \ldots \cup free(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_n)$$

where  $\forall i : free(S_1 \cup \ldots \cup S_i)$  denotes the set of free facts in  $(S_1 \cup \ldots \cup S_i)$ .

*Proof.* The proof is immediate since 
$$\forall i : free(S_1 \cup \ldots \cup S_i) = \bigcap_{\mathcal{R} \in MAR(S_1 \cup \ldots \cup S_i)} \mathcal{R}$$
.

The non-defeated repair is an extension of the *free* assertional base when  $\mathcal{A}$  is prioritized. The following definition introduces non-defeated entailment.

**Definition 7.12.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. A query q is a non-defeated consequence (nd-consequence) of  $\mathcal{K}$ , denoted  $\mathcal{K} \models_{\mathsf{nd}} q$ , if and only if  $\langle \mathcal{T}, nd(\mathcal{A}) \rangle \models q$ .

In Definition 7.11, a *free* element is not involved in any conflict. Hence the following proposition holds.

**Proposition 7.6.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. Let nd(A) be its dominant subbase. Then  $\langle T, nd(A) \rangle$  is consistent.

*Proof of Proposition* 7.6. We will use the recurrence to show the proof. Namely, assume that for some i:

$$free(S_1) \cup free(S_1 \cup S_2) \cup \ldots \cup free(S_1 \cup \ldots \cup S_i)$$

is consistent.

This assumption is true for i = 1, since by definition  $free(S_1)$  is consistent. Let us show that the assumption holds for rank (i + 1), namely:

$$free(S_1) \cup free(S_1 \cup S_2) \cup \ldots \cup free(S_1 \cup \ldots \cup S_{i+1})$$

is consistent.

Assume that this is not the case. This means that there exists  $f \in free(\mathcal{S}_1) \cup free(\mathcal{S}_1 \cup \mathcal{S}_2) \cup \ldots \cup free(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_i)$  and  $g \in free(\mathcal{S}_1) \cup free(\mathcal{S}_1 \cup \mathcal{S}_2) \cup \ldots \cup free(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i+1})$  such that (f,g) is conflicting. Since,

$$free(S_1) \cup free(S_1 \cup S_2) \cup \ldots \cup free(S_1 \cup \ldots \cup S_i) \subseteq free(S_1) \cup free(S_1 \cup S_2) \cup \ldots \cup free(S_1 \cup \ldots \cup S_{i+1})$$

this means that  $f \in free(\mathcal{S}_1) \cup free(\mathcal{S}_1 \cup \mathcal{S}_2) \cup \ldots \cup free(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i+1})$  and  $g \in free(\mathcal{S}_1) \cup free(\mathcal{S}_1 \cup \mathcal{S}_2) \cup \ldots \cup free(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i+1})$ . Hence, this is a contradiction, since g cannot belong to  $free(\mathcal{S}_1) \cup free(\mathcal{S}_1 \cup \mathcal{S}_2) \cup \ldots \cup free(\mathcal{S}_1 \cup \ldots \cup \mathcal{S}_{i+1})$ .

**Example 7.10.** Let us consider again 
$$\mathcal{T} = \{A \sqsubseteq \neg B\}$$
 and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup \mathcal{S}_3$  where  $\mathcal{S}_1 = \{A(a)\}$ ,  $\mathcal{S}_2 = \{B(a), A(b)\}$  and  $\mathcal{S}_3 = \{B(b)\}$ . One can check that  $nd(\mathcal{A}) = \{A(a), A(b)\}$ .

The computational complexity of the computation of the *dominant* subbase of A is polynomial.

**Proposition 7.7.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. The complexity of nd-entailment is in P.

*Proof of Proposition 7.7.* The proof follows from the fact that computing free subbase is done in polynomial time. nd-entailment proceeds to a linear number of computations of free subbases.

#### 7.4.2 Adding the deduction closure

The non-defeated inference, when it is defined on  $\mathcal{A}$ , is safe since it only uses elements of  $\mathcal{A}$  which are not involved is conflicts. One way to get a more productive inference is to use  $\circ_{cl}(\mathcal{A})$  instead of  $\mathcal{A}$ . Namely, we define, a closed non-defeated repair, denoted  $clnd(\mathcal{A}) = \mathcal{S}'_1 \cup \ldots \cup \mathcal{S}'_n$ , such that:

$$S_i' = \bigcap_{\mathcal{R} \in MAR(\circ_{cl}(S_1 \cup \dots \cup S_i))} \mathcal{R}$$

$$(7.2)$$

**Example 7.11.** Consider  $\mathcal{T} = \{A \sqsubseteq \neg B, B \sqsubseteq C\}$  and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a)\}$  and  $\mathcal{S}_2 = \{B(a)\}$ . We have  $\mathit{MAR}(\circ_{cl}(\mathcal{S}_1)) = \{A(a)\}$  and  $\mathit{MAR}(\circ_{cl}(\mathcal{S}_1 \cup \mathcal{S}_2)) = \{(A(a), C(a)), (B(a), C(a))\}$ .

Contrarily to  $\pi$ -entailment and  $\ell$ -entailment, the following proposition shows that nd-inference is sensitive to the use of the deductive closure.

**Proposition 7.8.** Let  $K = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized DL-Lite knowledge base. Then  $\forall q$ : if  $\langle \mathcal{T}, \mathcal{A} \rangle \models_{nd} q$  then  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle \models_{nd} q$ . The converse is false.

Proof of Proposition 7.8. For the converse it is enough to consider  $\mathcal{T} = \{E \sqsubseteq \neg B, B \sqsubseteq C, E \sqsubseteq C\}$  and  $\mathcal{A} = \mathcal{S}_1 = \{E(a), B(a)\}$ . We have  $nd(\mathcal{A}) = \emptyset$  and  $nd(\circ_{cl}(\mathcal{A})) = \{C(a)\}$ . Hence C(a) is an nd-consequence of  $\langle \mathcal{T}, \circ_{cl}(\mathcal{A}) \rangle$  but it is not an nd-consequence of  $\langle \mathcal{T}, \mathcal{A} \rangle$ 

#### 7.4.3 Combining linear entailment and non-defeated entailment: Adding consistency

We now present a new way to select a single preferred assertional-based repair. It consists in slightly improving linear entailment, where rather to ignore a full stratum, in case of inconsistency, one can only ignore conflicting elements.

More precisely, the linear-based non-defeated repair, denoted by  $\ell nd(\mathcal{A})$ , is given by the following algorithm:

```
Input: \mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle where \mathcal{A} = \mathcal{S}_1 \cup \ldots \cup \mathcal{S}_n

Output: \ell nd(\mathcal{A})

1: \ell nd(\mathcal{A}) = free(\mathcal{S}_1)

2: for i = 2 to n do

3: if \langle \mathcal{T}, \ell nd(\mathcal{A}) \cup \mathcal{S}_i \rangle is consistent then

4: \ell nd(\mathcal{A}) \leftarrow \ell nd(\mathcal{A}) \cup \mathcal{S}_i

5: else

6: \ell nd(\mathcal{A}) \leftarrow \ell nd(\mathcal{A}) \cup free(\mathcal{S}_i \cup \ell nd(\mathcal{A}))
```

Algorithm 7: linear-based non-defeated repair

**Example 7.12.** Let 
$$\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq \neg C\}$$
 and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup \mathcal{S}_3$  where  $\mathcal{S}_1 = \{A(a)\}$ ,  $\mathcal{S}_2 = \{C(a), C(b)\}$  and  $\mathcal{S}_3 = \{B(b), A(c)\}$ . We have  $\ell nd(\mathcal{A}) = \{A(a), C(b), A(c)\}$ .

Clearly  $\ell nd(\mathcal{A})$  is consistent and it is more productive than  $\pi(\mathcal{A})$  and  $\ell(\mathcal{A})$ , but it remains incomparable with other approaches. Note that  $\ell nd(\mathcal{A}) \cup free(\mathcal{S}_i \cup \ell nd(\mathcal{A})) = \bigcap \{\mathcal{R} : \mathcal{R} \in MAR(\mathcal{S}_i \cup \ell nd(\mathcal{A})) \text{ and } \mathcal{R} \cup \ell nd(\mathcal{A})\}$  is consistent. Hence,  $\ell nd(\mathcal{A})$  extends  $nd(\mathcal{A})$  by only focusing on  $MAR(\mathcal{S}_i \cup \ell nd(\mathcal{A}))$  that are consistent with  $\ell nd(\mathcal{A})$ . The nice feature of  $\ell nd$ -entailment is that the extension of  $\ell$ -entailment and nd-entailment is done without extra computational cost. More precisely, computing  $\ell nd(\mathcal{A})$  is in P.

#### 7.4.4 Introducing cardinality in non-defeated inference

A natural question is whether one can introduce a cardinality criterion, instead of set inclusion criterion, in the definition of non-defeated repair given by Equation 7.1. Namely, we define the cardinality-based non-defeated repair as follows:

**Definition 7.13.** Let  $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$  be a prioritized *DL-Lite* knowledge base. The cardinality-based non-defeated repair, denoted by  $nd(\mathcal{A})_{card} = \mathcal{S}'_1 \cup \ldots \cup \mathcal{S}'_n$ , is defined as follows:

$$\forall i = 1, .., n : \mathcal{S}_i' = \bigcap_{\mathcal{R} \in MAR_{card}(\mathcal{S}_1 \cup ... \cup \mathcal{S}_i)} \mathcal{R}$$

$$(7.3)$$

where  $MAR_{card}(S) = \{ \mathcal{R} : \mathcal{R} \in MAR(S) \text{ and } \nexists \mathcal{R}' \in MAR(S) \text{ such that } |\mathcal{R}'| > |\mathcal{R}| \}.$ 

One main advantage of this approach is that it produces more conclusions then the standard non-defeated inference relation. Namely,  $nd(A) \subseteq nd(A)_{card}$  where nd(A) and  $nd(A)_{card}$  are respectively given by Equations 7.1 and 7.3. The converse is false.

**Proposition 7.9.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. Then

$$nd(\mathcal{A}) \subseteq nd(\mathcal{A})_{card}$$

where nd(A) and  $nd(A)_{card}$  are respectively given by Equations 7.1 and 7.3. The converse is false.

*Proof.* The proof follows from the fact that:

$$\forall i = 1, ..., n : MAR_{card}(S_1 \cup ... \cup S_i) \subseteq MAR(S_1 \cup ... \cup S_i)$$

For the converse, consider the following counter-example.

**Example 7.13** (counter-example). Let 
$$\mathcal{T} = \{A \sqsubseteq \neg B, B \sqsubseteq \neg C\}$$
 and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a), B(a)\}$  and  $\mathcal{S}_2 = \{C(a)\}$ . We have  $nd(\mathcal{A}) = \emptyset$  while  $nd(\mathcal{A})_{card} = \{A(a), C(a)\}$ .

The main limitation of  $nd(A)_{card}$  is that it may be inconsistent with  $\mathcal{T}$  as it is illustrated with the following example.

**Example 7.14.** Consider  $\mathcal{T} = \{A \sqsubseteq \neg B, A \sqsubseteq \neg C\}$  and  $\mathcal{A}=\mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a)\}$  and  $\mathcal{S}_2 = \{B(a), C(a)\}$ . Using Equation 7.3, we have  $\mathcal{S}_1' = \{A(a)\}$  and  $\mathcal{S}_2' = \{B(a), C(a)\}$ . Clearly,  $nd(\mathcal{A})_{card} = \mathcal{S}_1' \cup \mathcal{S}_2'$  contradicts  $\mathcal{T}$ .

One way to overcome such limitation is to only select  $MAR_{card}$  of  $(S_1 \cup ... \cup S_i)$  that are consistent with  $(S'_1 \cup ... \cup S'_{i-1})$ , namely:

**Definition 7.14.** Let  $K = \langle T, A \rangle$  be an prioritized *DL-Lite* knowledge base. We define the consistent cardinality-based non-defeated repair, denoted by  $consnd(A)_{card} = S'_1 \cup \ldots \cup S'_n$  such that:

$$\mathcal{S}_1' = \bigcap_{\mathcal{R} \in \mathit{MAR}_{\mathit{card}}(\mathcal{S}_1)} \mathcal{R}$$

 $\forall i = 2,..,n : \mathcal{S}_i' = \bigcap \{\mathcal{R}: \mathcal{R} \in MAR_{card}(\mathcal{S}_1 \cup ... \cup \mathcal{S}_i) \text{ and } \mathcal{R} \text{ is consistent with } \mathcal{S}_1' \cup ... \cup \mathcal{S}_{i-1}'\}$ 

Clearly, contrarily to  $nd(A)_{card}$ ,  $consnd(A)_{card}$  is always consistent.

**Example 7.15.** Consider the example where  $\mathcal{T} = \{A \sqsubseteq \neg B, A \sqsubseteq \neg C\}$  and  $\mathcal{A} = \mathcal{S}_1 \cup \mathcal{S}_2$  where  $\mathcal{S}_1 = \{A(a)\}$  and  $\mathcal{S}_2 = \{B(a), C(a)\}$ . We have  $\mathcal{S}_1' = \{A(a)\}$  and  $\mathcal{S}_2' = \emptyset$ . Clearly  $consnd(\mathcal{A})_{card}$  is consistent with  $\mathcal{T}$ .

#### 7.4.5 Adding priorities to non-defeated inference

In the definition of *nd*-inference, given by Equation 7.1, a flat notion of *MAR* (maximally inclusion-based repair) has been used. A natural way to extend the *nd*-entailment is to use a prioritized version of *MAR* (*i.e. PAR*), namely:

**Definition 7.15.** Let  $\mathcal{K}=\langle \mathcal{T}, \mathcal{A} \rangle$  be an prioritized *DL-Lite* knowledge base. We define the prioritized inclusion-based non-defeated repair, denoted by  $pind(\mathcal{A}) = \mathcal{S}'_1 \cup \ldots \cup \mathcal{S}'_n$ , as follows:

$$\forall i = 1, ..., n : \mathcal{S}'_i = \bigcap_{\mathcal{P} \in PAR(\mathcal{S}_1 \cup ... \cup \mathcal{S}_i)} \mathcal{P}$$

$$(7.4)$$

The following proposition shows that there is no need to consider all  $S'_i$  for i < n when computing pind(A), namely:

**Proposition 7.10.** Let  $K = \langle T, A \rangle$  be a prioritized DL-Lite knowledge base. Then

$$pind(\mathcal{A}) = \bigcap_{\mathcal{P} \in PAR(\mathcal{S}_1 \cup ... \cup \mathcal{S}_n)} \mathcal{P}.$$

*Proof.* The proof follows from the fact that  $\forall i < n, \forall A \in PAR(S_1 \cup \ldots S_{i+1}), \exists B \in PAR(S_1 \cup \ldots S_i)$  such that  $B \subseteq A$ . Namely, prioritized inclusion-based maximal repairs from  $S_1 \cup \ldots S_{i+1}$  are obtained from prioritized inclusion-based maximal repairs from  $S_1 \cup \ldots S_i$  by adding some elements from  $S_{i+1}$ . Hence, for i < n, we have:

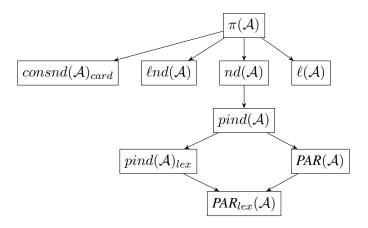


Figure 7.1: Relationships between inferences

$$\bigcap_{B \in \mathit{PAR}(\mathcal{S}_1 \cup \dots \cup \mathcal{S}_i)} B \subseteq \bigcap_{B \in \mathit{PAR}(\mathcal{S}_1 \cup \dots \cup \mathcal{S}_{i+1})} B$$

Therefore:

$$pind(\mathcal{A}) = \bigcap_{B \in PAR(\mathcal{S}_1 \cup ... \cup \mathcal{S}_n)} B$$

Besides, a cardinality-based version of Equation 7.4, denoted by  $pind(A)_{lex} = S_1 \cup ... \cup S_n$ , can be defined as follows:

$$\forall i = 1, ..., n : \mathcal{S}'_i = \bigcap_{\mathcal{L} \in PAR_{lex}(\mathcal{S}_1 \cup ... \cup \mathcal{S}_n)} \mathcal{L}$$

$$(7.5)$$

Lastly, both pind(A) and  $pind(A)_{lex}$  can be defined on  $\circ_{cl}(A)$  instead of A or be defined on closed repairs instead of repairs themselves. This leads to new inferences strategies that only select one preferred subbase.

# 7.5 Comparative analysis

From a computational complexity point of view,  $\pi$ -entailment,  $\ell$ -entailment, nd-entailment and  $\ell nd$ -entailment and the entailments based on their closures, are the most promising ones since both computing the repair and query answering are tractable. For other strategies based on the nd-inference, computing the repairs is a hard task, but it is done ONCE. Answering queries, when the single repair is computed, is efficiently computed since it has the same complexity as in standard DL-Lite.

From productivity, Figure 7.1 summarizes the relationships between main entailments considered in the paper when the ABox is prioritized. Note that for the sake of simplicity, we do not make reference in Figure 7.1 to inferences defined on  $\circ_{cl}(\mathcal{A})$ .

In Figure 7.1,  $n1 \rightarrow n2$  means that each conclusion that can be universally derived from repairs in n1 is also a conclusion using repairs in n2. From Figure 7.1,  $\pi$ -entailment is the most cautious relation. Adding priorities, cardinality and consistency to the definition of nd-entailment allow to provide more productive

inference relations. However  $\ell$ -entailment remains incomparable with the nd-entailment, since layers including non free assertions can be present in  $\ell(\mathcal{A})$ . Moreover,  $\ell nd(\mathcal{A})$  is incomparable with other approaches. Within the prioritized setting,  $nd(\mathcal{A})$  plays the same role with respect to PAR as  $free(\mathcal{A})$  for MAR in the flat case. As a consequence, each nd-consequence of  $\mathcal{A}$  is also a PAR-consequence of  $\mathcal{A}$ . The converse is false. Moreover, it is well-known that each PAR-entailment is also a Lex-entailment and the converse is false, since the Lex-entailment only uses subsets of prioritized repair (PAR).

#### 7.6 Experimental evaluation

In this section, we present an experimental evaluation on the computation of main repairs proposed in this Chapter using some algorithms proposed in Chapter 6.

All the experiments are performed on a MacBook Pro laptop with 2.6GHz Intel Core (i7) processor and 16GB 1600 MHz DDR3 RAM. We considered a TBox containing 100 negative inclusion axioms with a proportion of conflicts at least equal to 1/5 per assertion. This TBox is adapted from the DL- $Lite_R$  university benchmark proposed in [Lutz *et al.*, 2013]. We use the Extended University Data Generator (EUDG)  $^3$  to generate the ABox assertions. Once the ABox is produced, we fit it to our setting using 4 strata until 7 strata. Moreover the computation of conflicts is performed layer per layer. Note that the time used for computing the conflicts is not included in the time used for computing the repairs, since this is done in a polynomial time. Said differently, computing conflicts is negligible with respect to computing repairs.

# conflict	#MAR	time #MAR	#MAR <sub>card</sub>	time #MAR <sub>card</sub>
18	28080	105ms	192	65ms
25	688128	2268ms	256	789ms
37	16815986	206089ms	56	5422ms
75	20160000	272830ms	96	216236ms
105	-	Time-out	2034	8259s

Table 7.2: Number of conflicts, number of MAR, time taken to compute MAR in ms (milliseconds) or s (seconds), number of  $\#MAR_{card}$ , time taken to compute  $\#MAR_{card}$ .

Table 7.2 gives the experimental results of the computation of MAR and  $MAR_{card}$ . One can see that using the cardinality criterion instead of the set inclusion one refines the result and improves the computation time of the repairs. Moreover, an important influential parameter when computing the repairs is the number of occurrences of an assertion in conflicts. Namely, the more an assertion is recurring in conflicts the more the conflict resolution has better chances to be achieved. For instance, in Table 7.2 considering the case of 37 conflicts, by increasing the percentage of occurrences of some assertions in conflicts, we obtain  $23082 \ MAR$  in 136ms instead of 16815986 in 206089ms. In such case, the number of Lex decreases also where we compute only  $24 \ \#MAR_{card}$  having cardinality equal to 14 assertions. Similar results on the effect of the number of occurrences of assertions in conflicts are provided [Pivert and Prade, 2010; Deagustini  $et\ al.$ , 2014].

Now, concerning  $PAR_{lex}$ , we also use the notion of minimal inconsistent subsets where the minimality refers to a lexicographic ordering. Table 7.3 gives the results on the computation of  $PAR_{lex}$  and the main repairs given in this paper. One can first observe that given an ABox  $\mathcal A$  whatever is its size, computing  $\pi$  or  $\ell$  does not need long computation time as needed by inconsistency checking. Regarding now the computation of the non-defeated repair, it depends on the number of conflicts in the ABox. Another

<sup>&</sup>lt;sup>3</sup>available at https://code.google.com/p/combo-obda/

parameter that also influences the results is the number of layers. This can be clearly seen when computing  $\#PAR_{lex}$ . Indeed, the number of  $PAR_{lex}$  decreases as the number of layers increases. Clearly, more the stratification of the ABox is important more the conflicts resolution has better chances to be achieved.

# Conflicts	# Strata	time $\pi$	time $\ell$	time nd	$\#PAR_{lex}$	time $PAR_{lex}$
61	4	4ms	7ms	7ms	16	17ms
01	7	4ms	8ms	6ms	2	11ms
123	4	5ms	8ms	10ms	16	43ms
	7	4ms	8ms	9ms	4	38ms
502	4	5ms	9ms	24ms	2024	1072ms
	7	5ms	8ms	13ms	128	90ms
1562	4	4ms	8ms	129ms	1392	128:47s
	7	5ms	8ms	64ms	232	34:52s

Table 7.3: Number of conflicts, number of strata, time taken to compute  $\pi$ ,  $\ell$ , nd and  $PAR_{lex}$  and number of computed  $PAR_{lex}$ .

#### 7.7 Conclusion

This chapter focuses on how to produce a single preferred repair from a prioritized inconsistent *DL-Lite* knowledge base based on the notion of the non-defeated inference relation. We first reviewed some well-known approaches that select one repair (such as possibilistic repair or linear-based repair) or several repairs (such as preferred inclusion-based repairs or lexicographic-based repairs). Then, we presented different strategies for selecting one preferred repair. These strategies have as starting point the non-defeated repair and mainly add one/several of the four main criteria: priorities, deductive closure, cardinality and consistency.

# **CONCLUSION**

In this thesis, we studied dynamics of beliefs and uncertainty management in DL-Lite. In the first part we investigated the problem of uncertainty handling in DL-Lite. We first proposed an extension of the main fragments of DL-Lite to deal with the uncertainty associated with axioms using a possibility theory framework. We introduced the syntax and the semantics of such extensions. We provided the properties of  $\pi$ -DL-Lite and showed how to compute the inconsistency degree of  $\pi$ -DL-Lite knowledge base using query evaluation obtained by defining the  $\pi$ -DL-Lite negative closure that extends the one of standard DL-Lite. This extension permits to deal with priorities or uncertainty degrees (between DL-Lite axioms) without increasing the computational complexity. A tool for representing and reasoning in possibilistic DL-Lite framework is implemented. We introduced main reasoning tasks in  $\pi$ -DL-Lite and we provided a preliminary result on conditioning  $\pi$ -DL-Lite knowledge bases when a new piece of information is available. Lastly, we proposed a min-based assertional merging operator when the assertions of ABox are provided by several sources of information having different levels of priority. We showed that this operator is more productive than the classical one, without increasing the complexity of the merging process.

In the second part of the thesis, we studied the problem of inconsistency handling in flat *DL-Lite* knowledge bases. We generalized techniques for inconsistency handling in flat knowledge bases by introducing the notions of modifier and inference strategy. We showed that the combination of modifiers and inference strategies provides a principled and exhaustive list of techniques for inconsistency management. We studied the productivity and the computational complexity for the proposed techniques and showed how our work extends the state of the art.

The third part of this thesis was dedicated to the revision and inconsistency handling in prioritized *DL-Lite* knowledge bases where the ABox is stratified. We first investigated the problem of revising by considering different forms of input information, namely when the input is an ABox assertion or a TBox axiom. We proposed syntactic revision operators, called Prioritized Removed Sets (PRSR) operators. These operators follow a lexicographical strategy for removing some assertions, namely the prioritized removed sets, in order to restore consistency. We showed in particular that when the input is an ABox axiom, the revision process leads to a unique revised knowledge base. However, when the input is a TBox axiom, the revision process may lead to several possible revised knowledge bases. In this case, we defined selection functions in order to keep the result within the *DL-Lite* language. We provided the logical properties of PRSR operators using Hansson's postulates rephrased within our framework. Finally, we proposed algorithms to computing the prioritized removed sets where some of them are based on the notion of hitting set.

We studied the problem of inconsistency handling in prioritized *DL-Lite* knowledge bases. We introduced several inconsistency-tolerant inference approaches in *DL-Lite* when the ABox is stratified. We first reviewed some well-known approaches that select one assertional-based repair or several assertional-based repairs, and then, proposed different strategies for selecting a single assertional-based repair. These strategies have as starting point the non- defeated assertional-based repair and mainly adding one/several of four main ingredients: priorities, deductive closure, cardinality and consistency. We showed that these inconsistency-tolerant relations are proper to *DL-Lite* logics and some of them allow tractable handling of inconsistency without additional complexity in comparison to standard *DL-Lite*. We provided complexity results and experimental studies showing the efficiency of the proposed entailments.

#### **Future works**

**Uncertainty management** The inconsistency notion used Chapter 3 is fully in the spirit of the one used in standard *DL-Lite*. In presence of certainty degrees, one may consider other forms of inconsistency that depart from the one used in standard DL-Lite logic. This depends on the uncertainty framework and the knowledge modeling steps may play a crucial role. For instance, if one uses a probability theory framework, and roughly speaking if  $\langle A \sqsubseteq B, \alpha \rangle$  is interpreted as "the conditional probability of an individual to be in B given the fact that he is A is  $\alpha$ , then  $\langle A \sqsubseteq B, .9 \rangle$ and  $\langle A \sqsubseteq \neg B, .1 \rangle$  are closely related. Hence, the way we write uncertain pieces has an important role and the definition of inconsistency degrees should take into account the used uncertainty framework. Note that in a possibility theory setting, an axiom  $\varphi$  and its negated axiom  $\neg \varphi$  are only weakly related since we only have  $min(N(\varphi), N(\neg \varphi)) = 0$ . Besides, in the future, we plan to explore more parsimonious definitions of inconsistency degrees. For instance, in the rules used for defining the  $\pi$ -negated closure of a *DL-Lite* knowledge base we used the minimum operator for propagating certainty degrees. The question is how to use other operators (such that leximin or descrimin [Benferhat et al., 1993a; Dubois et al., 1992] or simply the product operators) that lead to new definitions of inconsistency degrees. The aim is to get more productive relations that only provide safe conclusions and run in a polynomial time.

Another future work is to consider richer extensions of DL-Lite logics such as DL –  $Lite_{R,\sqcap}$  and DL –  $Lite_{F,\sqcap}$  [Calvanese et al., 2006] (DL-Lite $_{horn}^H$  and DL-Lite $_{horn}^F$  presented in Section 1.4.2) that allow conjunction on the left side of a concept inclusion. We are also interested in considering possibilistic DL-Lite with disjunctive ABox as it has been done in databases [Molinaro et al., 2009]. Namely, we plan to enrich DL-languages with the propositional disjunction " $A \vee B$ ". The question is then how to extend the concepts of conflicts, associated with negated axioms, to define inconsistency degrees of possibilistic knowledge bases with disjunctive ABox. This extension is useful when one has to merge multiple sources information, where the union of the TBox (issued from each source) is consistent, but the whole set of information is conflicting.

**Knowledge base fusion** This thesis opens several perspectives regarding the fusion issue. For instance, we focus on a *min* operator for aggregating conflict vectors, in order to preserve possibilistic semantics. Nevertheless, other aggregation operators can be considered (*e.g.* the product operator) or direct comparisons from vectors (*e.g.* G-max based operator). From a postulates point of view, other postulates dedicated to DL knowledge bases could be studied and adapted (*e.g.* arbitration [Konieczny and Pino Pérez, 2002]). Moreover, we plan to investigate other measures of conflicts such as Shapley measure proposed in [Hunter and Konieczny, 2010]. Finally, we will investigate the extension of Removed Sets Fusion [Hué *et al.*, 2008], defined in a propositional setting, to the merging of *DL-Lite* knowledge bases. Another extension is to study merging of uncertain *DL-Lite* knowledge bases in the context where uncertainty scales are incommensurable [Benferhat *et al.*, 2007].

Ontological-based revision vs assertional based revision When revising a prioritized *DL-Lite* knowledge base, we only considered the case where the input is a single assertion or a simple positive or negative axiom. A future work will investigate the case where the input is a set of assertions or a set of axioms. A future work will focus on a deeper study of the computational complexity of the PRSR operators. We plan also to study revision of TBox, when a new axiom (*i.e.* rule) is available. We will study revision in the general case, namely when the revision process comes down to throw out both TBox axioms and ABox assertions to restore consistency.

Regarding inconsistency handling, other modifiers such as merging or concatenating modifiers have to be investigated. Besides, the considered framework may be reapplied easily for other

richer *DL-Lite* logics (or rules-based languages (*e.g.* [Baget *et al.*, 2009; Baget *et al.*, 2011; Calì *et al.*, 2012]) provided that data is separated from generic knowledge.

# Appendix

# APPENDIX OF CHAPTER 3

### Possibilistic *DL-Lite* ontology tool

In this appendix, we present a tool for representing and reasoning in possibilistic *DL-Lite* framework. This tool is developed in JAVA and it implements the inconsistency check algorithm based on query evaluation presented in Chapter 3. In this tool, the ABox is managed using SQL database engine. As ontology language, we use the *OWL-QL* functional syntax extended with the ability to attach weights to axioms. To this end, we developed our proper parser in order to manage weighted axioms. In what follows, we present some screenshots of this tool followed by a explanation about its features.

#### **Ontology representation**

The following figure presents the main interface of the possibilistic *DL-Lite* ontology editor. The main interface is partitioned into two panels: one for specifying the TBox and the other for expressing the ABox.

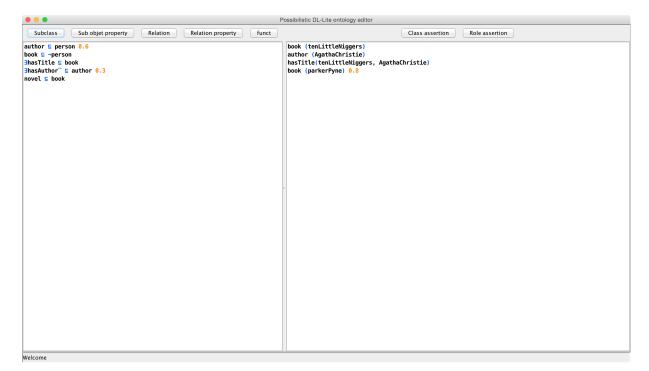


Figure A.1: Main interface

Using the different buttons of the toolbar, one can express either  $\pi$ -DL- $Lite_{core}$ ,  $\pi$ -DL- $Lite_F$  or  $\pi$ -DL- $Lite_R$  axioms. As presented in Figure A.2, one can express either flat axioms (*i.e.* when the weight

associated to the axioms is equal to 1. We do not represent in the interface weights equal to 1 or weighted axioms. Note that when all weights are set to 1, then we represent a standard *DL-Lite* knowledge base.

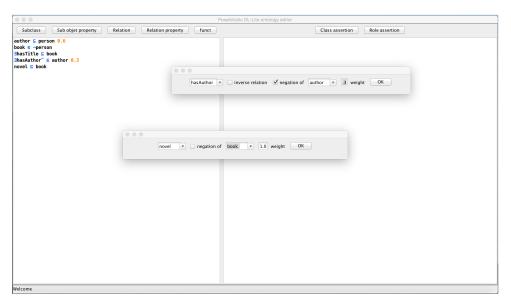


Figure A.2: Example of TBox axioms

Once the TBox is edited, one can export it using extended *OWL-QL* functional syntax as follows:

```
Weighted(SubClassOf(author, person), 0.6)
DisjointClasses(book, person)
ObjectPropertyDomain(hasTitle, book)
Weighted(ObjectPropertyRange(hasAuthor, author), 0.3)
SubClassOf(novel, book)
```

In fact, when developing this tool, we could not use the existing ontology programming tools such Jena, OWL API (see Section 1.2). Hence, we developed our proper parser. Note that when all weights are equal to 1, one can manipulate standard *OWL-QL* functional syntax. Clearly, one can read any standard *OWL-QL* file, edited using a standard ontology editor tool such as Protégé (see Section 1.2) and add different weights. Finally, we adapted such encoding with the aim to add other reasoning capabilities to our tool when dealing with uncertainty or priorities.

Similarly, the ABox is expressed using weighted or flat assertions as presented in Figure A.3. Note that ABox is managed using an SQL-lite<sup>1</sup> engine.

<sup>1</sup>https://www.sqlite.org

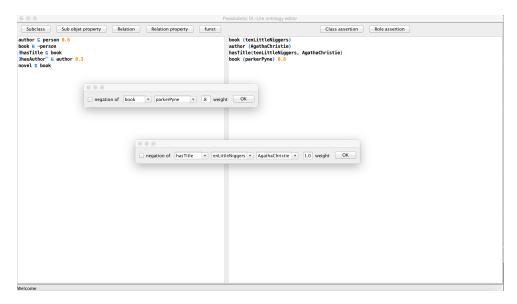


Figure A.3: Example of ABox assertions

#### Reasoning tasks

The current version of the tool implements two main reasoning algorithms. The first reasoning task concerns the detection of modeling errors when specifying the ontology, namely the incoherency of the TBox (see Definition 1.13). An important feature of our tool, compared with existing ones (*i.e.* flat case) is that incoherency detection is done instantly after adding any axiom to the TBox. Once an incoherency is detected and according to the weights of formulas, the editor points out the source of incoherency using "italic style". Figure A.4 gives an example.

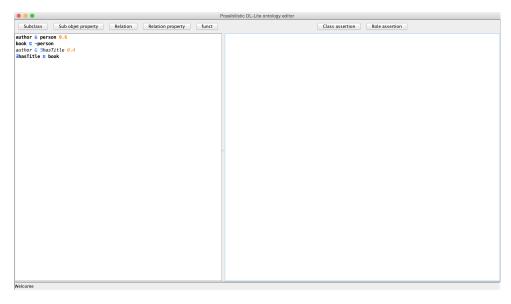


Figure A.4: Incoherency detection

The second main reasoning task is the computation of the inconsistency degree. The tool computes first the negated closure using the rules presented in Section 3.4. As for incoherency checking, the computation of the negated closure is done instantly after adding any axiom. This closure is transformed to

weighted queries performed over the set of individuals in the ABox in order to compute the inconsistency degree. The inconsistency associated with a query and a given tuple of assertions provided as an answer for the query is the maximum weight among all the certainty degrees of the query and this tuple. The maximum among these inconsistency degrees is the inconsistency degree associated with the knowledge base. Figure A.5 shows an example of computation of inconsistency degree. Once the inconsistency degree is computed, all axioms having weights less or equal to this degree are highlighted using "italic style".

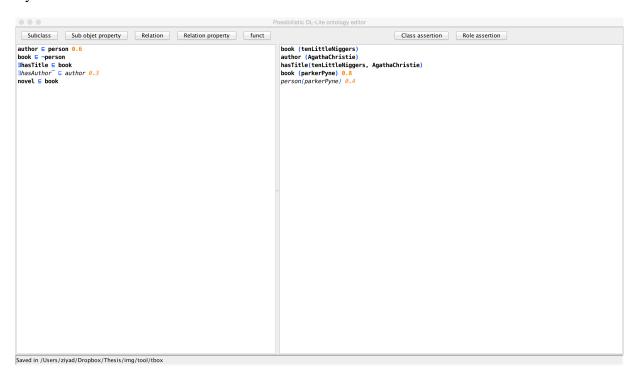


Figure A.5: Inconsistency degree

Lastly, the possibilistic *DL-Lite* tool permits to compute and export ABox conflicts as follows.

```
fconflict (book (pakerpyne), person (pakerpyne))
pconflict ((book (pakerPyne), 0.8), (person (pakerPyne), 0.4)
Note that these conflict sets are used for experimentation in Section 7.6.
```

## APPENDIX OF CHAPTER 5

# Handling inconsistent *DL-Lite* knowledge bases = Composite modifiers+inference strategies

**Proposition B.1** (Figure 5.3). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\{ \mathcal{M}_1, ..., \mathcal{M}_8 \}$  be the eight composite modifiers summarized in Table 5.1. Then:

- 1.  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ .
- 2.  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ .
- 3.  $\mathcal{M}_6 \subseteq \mathcal{M}_5$ .
- 4.  $\mathcal{M}_8 \subseteq \mathcal{M}_7$ .
- 5.  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$ .
- 6.  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$ .
- 7.  $\mathcal{M}_2 \subseteq_{cl} \mathcal{M}_5$ .
- 8.  $\mathcal{M}_3 \subset \mathcal{M}_5$ .
- 9.  $\mathcal{M}_5 \subseteq_{incl} \mathcal{M}_7$ .

*Proof of Proposition B.1.* The proof are as follows:

- Items 1-4 follow from the definition of the elementary modifier  $\circ_{card}$ . Since  $\circ_{card}$  selects subsets of  $\mathcal{M}$  having maximal cardinality. Namely, given  $\mathcal{M}$  an MBox, we have  $\circ_{card}(\mathcal{M}) \subseteq \mathcal{M}$ . Hence relations  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ ,  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ ,  $\mathcal{M}_6 \subseteq \mathcal{M}_5$ , and  $\mathcal{M}_8 \subseteq \mathcal{M}_7$  holds.
- Items 5-6 follow immediately from the definition of the elementary modifier  $\circ_{cl}$ , hence we trivially have  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$  and  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$ .
- Let us show that  $\mathcal{M}_2 \subseteq_{cl} \mathcal{M}_5$ , namely  $\forall A \in \mathcal{M}_2, \exists B \in \mathcal{M}_5$  such that B = Cl(A). The proof is immediate. Recall that  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ , hence  $\forall A \in \mathcal{M}_2$  we also have  $A \in \mathcal{M}_1$ . Recall also that  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$ . This means that  $\forall A \in \mathcal{M}_2, \exists B \in \mathcal{M}_5$  such that B = Cl(A).
- Regarding the proof of Item 8, we have  $\mathcal{M}_2 \subseteq_{cl} \mathcal{M}_5$ . This means that  $\forall A \in \mathcal{M}_2$ , there exists  $B \in \mathcal{M}_5$  such that B = Cl(A). Said differently,  $\forall A \in \mathcal{M}_2$ , we have  $Cl(A) \in \mathcal{M}_5$ . Since  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$ , we conclude that  $\mathcal{M}_3 \subseteq \mathcal{M}_5$ .
- We now show that  $\mathcal{M}_5\subseteq_{incl}\mathcal{M}_7$ . Let  $B\in\circ_{incl}(\{\mathcal{A}\})$  and let us show that there exists a set of assertions X such that  $\circ_{cl}(\{B\})\subseteq X$  and  $X\in\mathcal{M}_7$ . Since  $B\in\circ_{incl}(\{\mathcal{A}\})$ , this means by definition that  $B\subseteq\mathcal{A}$  and hence  $B\subseteq\circ_{cl}(\mathcal{A})$ . Now, B is consistent, this means that there exists  $R\in\circ_{incl}(\circ_{cl}(\mathcal{A}))=\mathcal{M}_7$  such that  $B\subseteq R$ . From Lemma 5.1, R is a closed set of assertions, then this means that  $Cl(B)\subseteq R$ .

**Example B.1** (Counter-examples relations given in Figure 5.3). The converse of relations given in Figure 5.3 does not holds.

П

- 1. The converse of  $\mathcal{M}_2 \subseteq \mathcal{M}_1$  does not hold. Let  $\mathcal{T} = \{B \sqsubseteq C, C \sqsubseteq \neg D\}$  and  $\mathcal{M} = \{\{B(a), C(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{C(a), B(a)\}, \{D(a)\}\}$ , and  $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{\{C(a), B(a)\}\}$ . One can check that  $\mathcal{M}_1 \nsubseteq \mathcal{M}_2$ .
- 2. The converse of  $\mathcal{M}_4 \subseteq \mathcal{M}_3$  does not hold. Let  $\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq \neg C\}$  and  $\mathcal{M} = \{\{A(a), C(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a)\}, \{C(a)\}\},$   $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{\{A(a)\}, \{C(a)\}\},$   $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2) = \{\{A(a), B(a)\}, \{C(a)\}\},$  and  $\mathcal{M}_4 = \circ_{card}(\mathcal{M}_3) = \{\{A(a), B(a)\}\}.$ One can check that  $\mathcal{M}_3 \nsubseteq \mathcal{M}_4$ .
- 3. The converse of  $\mathcal{M}_6 \subseteq \mathcal{M}_5$  does not hold. Let  $\mathcal{T}=\{B \sqsubseteq C, C \sqsubseteq \neg D\}$  and  $\mathcal{M}=\{\{B(a),D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T},\mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1=\circ_{incl}(\mathcal{M})=\{\{B(a)\},\{D(a)\}\},$   $\mathcal{M}_5=\circ_{cl}(\mathcal{M}_1)=\{\{C(a),B(a)\},\{D(a)\}\},$  and  $\mathcal{M}_6=\circ_{card}(\mathcal{M}_5)=\{\{C(a),B(a)\}\}$  One can check that  $\mathcal{M}_5 \nsubseteq \mathcal{M}_6$ .
- 4. The converse of  $\mathcal{M}_8 \subseteq \mathcal{M}_7$  does not hold. Let  $\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq \neg D\}$  and  $\mathcal{M} = \{\{A(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\circ_{cl}(\mathcal{M}) = \{\{A(a), B(a), D(a)\}\}$ ,  $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), B(a)\}, \{D(a)\}\}$ , and  $\mathcal{M}_8 = \circ_{card}(\mathcal{M}_7) = \{\{A(a), B(a)\}\}$ One can check that  $\mathcal{M}_7 \nsubseteq \mathcal{M}_8$ .
- 5. The converse of  $\mathcal{M}_2 \subseteq_{cl} \mathcal{M}_5$  does not hold. Let  $\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq C, C \sqsubseteq \neg D\}$  and  $\mathcal{M} = \{\{A(a), B(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a), B(a)\}, \{D(a)\}\},$   $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a), B(a), C(a)\}, \{D(a)\}\},$  and  $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{\{A(a), B(a)\}\}.$ One can check that  $\mathcal{M}_5 \nsubseteq_{cl} \mathcal{M}_2$ .
- 6. The converse of  $\mathcal{M}_3 \subseteq \mathcal{M}_5$  does not hold. Let  $\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq C, C \sqsubseteq \neg D\}$  and  $\mathcal{M} = \{\{A(a), B(a), D(a)\}\}$ .

```
It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have: \mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a), B(a)\}, \{D(a)\}\}, \mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a), B(a), C(a)\}, \{D(a)\}\}, \mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{\{A(a), B(a)\}\}, and \mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2) = \{\{A(a), B(a), C(a)\}\}. One can check that \mathcal{M}_5 \nsubseteq \mathcal{M}_3.
```

7. The converse of  $\mathcal{M}_5 \subseteq_{incl} \mathcal{M}_7$  does not hold. Let  $\mathcal{T} = \{A \sqsubseteq \neg B, B \sqsubseteq D\}$  and  $\mathcal{M} = \{\{A(a), B(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\circ_{cl}(\mathcal{M}) = \{\{A(a), B(a), D(a)\}\}$ ,  $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), D(a)\}, \{B(a), D(a)\}\}$ ,  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a)\}, \{B(a)\}\}$ , and  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a)\}, \{B(a), D(a)\}\}$ , One can check that  $\mathcal{M}_7 \not\subseteq_{incl} \mathcal{M}_5$ .

**Corollary B.1.** Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\{ \mathcal{M}_1, ..., \mathcal{M}_8 \}$  be the eight composite modifiers summarized in Table 5.1. Then:

```
1. \forall A_i \in \mathcal{M}_3, \exists A_j \in \mathcal{M}_1 such that A_i = Cl(A_j).
```

2. 
$$\forall A_i \in \mathcal{M}_4$$
,  $\exists A_j \in \mathcal{M}_1$  such that  $A_i = Cl(A_j)$ .

3. 
$$\forall A_i \in \mathcal{M}_6$$
,  $\exists A_j \in \mathcal{M}_1$  such that  $A_i = Cl(A_j)$ .

4. 
$$\forall A_i \in \mathcal{M}_1$$
,  $\exists A_j \in \mathcal{M}_7$  such that  $A_i \subseteq A_j$ .

5. 
$$\forall A_i \in \mathcal{M}_1$$
,  $\exists A_j \in \mathcal{M}_8$  such that  $A_i \subseteq A_j$ .

6. 
$$\forall A_i \in \mathcal{M}_4$$
,  $\exists A_j \in \mathcal{M}_2$  such that  $A_i = Cl(A_j)$ .

7. 
$$\forall A_i \in \mathcal{M}_2, \exists A_i \in \mathcal{M}_7 \text{ such that } A_i \subseteq A_i.$$

8. 
$$\forall A_i \in \mathcal{M}_3, \exists A_i \in \mathcal{M}_7 \text{ such that } A_i \subseteq A_i.$$

9. 
$$\forall A_i \in \mathcal{M}_4$$
,  $\exists A_j \in \mathcal{M}_7$  such that  $A_i \subseteq A_j$ .

10. 
$$\forall A_i \in \mathcal{M}_5$$
,  $\exists A_j \in \mathcal{M}_8$  such that  $A_i \subseteq A_j$ .

**Proposition B.2** (Figure 5.3). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\{ \mathcal{M}_1, ..., \mathcal{M}_8 \}$  be the eight composite modifiers summarized in Table 5.1. Then:

- 1.  $\mathcal{M}_6$  and  $\mathcal{M}_8$  are incomparable.
- 2.  $\mathcal{M}_2$  and  $\mathcal{M}_6$  are incomparable.
- 3.  $\mathcal{M}_3$  and  $\mathcal{M}_6$  are incomparable.
- 4.  $\mathcal{M}_4$  and  $\mathcal{M}_6$  are incomparable.
- 5.  $\mathcal{M}_2$  and  $\mathcal{M}_8$  are incomparable.
- 6.  $\mathcal{M}_3$  and  $\mathcal{M}_8$  are incomparable.

7.  $\mathcal{M}_4$  and  $\mathcal{M}_8$  are incomparable.

**Example B.2** (Examples of Proposition B.2). The following examples show incomparability between MBox's

1. The MBox  $\mathcal{M}_6$  and  $\mathcal{M}_8$  are incomparable. Let  $\mathcal{T} = \{B \sqsubseteq \neg C, B \sqsubseteq A, C \sqsubseteq A, A \sqsubseteq \neg D, D \sqsubseteq E, E \sqsubseteq F\}$  and  $\mathcal{M} = \{\{A(a), B(a), C(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{A(a), C(a)\}, \{A(a), B(a)\}, \{D(a)\} \}, \text{ and }$  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{ \{A(a), C(a)\}, \{A(a), B(a)\}, \{D(a), E(a), F(a)\} \}, \text{ and }$  $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{\{D(a), E(a), F(a)\}\},\$  $\circ_{cl}(\mathcal{M}) = \{ \{ A(a), B(a), C(a), D(a), E(a), F(a) \} \},$  $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), C(a), E(a), F(a)\}, \{A(a), B(a), E(a), F(a)\}, \{D(a), E(a), F(a)\}\},\$ and  $\mathcal{M}_8 = \circ_{incl}(\mathcal{M}_7) = \{ \{ A(a), C(a), E(a), F(a) \}, \{ A(a), B(a), E(a), F(a) \} \}$ One can check that  $\mathcal{M}_6$  and  $\mathcal{M}_8$  are incomparable. 2. The MBox  $\mathcal{M}_2$ ,  $\mathcal{M}_3$  and  $\mathcal{M}_4$  are incomparable with  $\mathcal{M}_6$ . Let  $\mathcal{T} = \{ A \sqsubseteq \neg B, C \sqsubseteq A, B \sqsubseteq D, D \sqsubseteq F \}$  and  $\mathcal{M} = \{ \{ A(a), C(a), B(a) \} \}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ A(a), C(a) \}, \{ B(a) \} \},$  $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_2) = \{ \{ A(a), C(a) \} \},$  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{ \{ A(a), C(a) \}, \{ B(a), D(a), F(a) \} \},$  $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{ \{ B(a), D(a), F(a) \} \},\$ One can check that  $\mathcal{M}_2$  is incomparable with  $\mathcal{M}_6$ . We have also  $\mathcal{M}_2 = \mathcal{M}_3 = \mathcal{M}_4 = \{\{A(a), C(a)\}\}\$ , So, we conclude that  $\mathcal{M}_3$  and  $\mathcal{M}_4$  are incomparable with  $\mathcal{M}_6$ . 3. The MBox  $\mathcal{M}_2$ ,  $\mathcal{M}_3$  and  $\mathcal{M}_4$  are incomparable with  $\mathcal{M}_8$ . Let  $\mathcal{T} = \{B \sqsubseteq A, C \sqsubseteq A, A \sqsubseteq \neg D, E \sqsubseteq D, D \sqsubseteq F\}$  and  $\mathcal{M} = \{\{A(a), D(a), E(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ A(a) \}, \{ D(a), E(a) \} \},$  and  $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{D(a), E(a)\}\},$  and  $\mathcal{M}_3 = \mathcal{M}_4 = \{ \{ D(a), E(a), F(a) \} \},$  $\circ_{cl}(\mathcal{M}) = \{ \{ A(a), B(a), C(a), D(a), E(a), F(a) \} \},$ 

### **Comparative studies**

#### Composite modifiers + universal inference

 $\mathcal{M}_8 = \circ_{incl}(\mathcal{M}_7) = \{ \{ A(a), C(a), B(a), F(a) \},$ 

**Proposition B.3** (Figure 5.4). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be a boolean query. Then:

1. q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  iff q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ .

 $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), C(a), B(a), F(a)\}, \{D(a), E(a), F(a)\}\}, \text{ and } \{A(a), C(a), B(a), F(a)\}, \{D(a), E(a), E(a), E(a)\}\}$ 

One can check that  $\mathcal{M}_2$ ,  $\mathcal{M}_3$  and  $\mathcal{M}_4$  are incomparable with  $\mathcal{M}_8$ .

2. q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$  iff q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ .

*Proof.* Item 1 and 2 follow from item 1 of Lemma 5.3 and the facts that  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$  and  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$ .

**Proposition B.4** (Figure 5.4). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be a boolean query. Then:

- 1. If q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  (or  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ ) then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ .
- 2. If q is universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$  (or  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ ) then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ .
- 3. If q is universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  (or  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ ) then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ .
- 4. If q is universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ .
- 5. If q is universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  (or  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ ) then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ .

*Proof.* For Items 1, 2, 3 and 4, we have  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ ,  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ ,  $\mathcal{M}_6 \subseteq \mathcal{M}_5$  and  $\mathcal{M}_8 \subseteq \mathcal{M}_7$ . Then following Item 1 of Lemma 5.2, we have if  $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{\forall} q$  then  $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{\forall} q$ . Similarly for  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ ,  $\mathcal{M}_6 \subseteq \mathcal{M}_5$  and  $\mathcal{M}_8 \subseteq \mathcal{M}_7$ .

Finally, for item 5 recall first that  $\langle \mathcal{M}_5, \forall \rangle \equiv \langle \mathcal{M}_1, \forall \rangle$  and  $\forall A \in \mathcal{M}_5, \exists B \in \mathcal{M}_7$  such that  $A \subseteq B$ . Now let us show that  $\forall B \in \mathcal{M}_7, \exists A \in \mathcal{M}_5$  such that  $A \subseteq B$ . Let  $B \in \mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M}))$ . This means that  $B \subseteq \circ_{cl}(\mathcal{M})$  and B is a maximally consistent subset. Let  $C \in \circ_{incl}(\mathcal{M})$ . This means that  $C \subseteq \mathcal{M} \subseteq \circ_{cl}(\mathcal{M})$ . Since C is also a maximally consistent subset then  $C \subseteq B$ . Now, recall that  $C \subseteq \mathcal{M} \subseteq \circ_{cl}(\mathcal{M})$  is a closed set of assertion, then  $C \subseteq B$ . Therefore we conclude that if a conclusion holds from  $\mathcal{M}_5$ , then it holds from  $\mathcal{M}_7$ .

**Example B.3** (Counter-examples of Proposition B.4 of Figure 5.4). The following counter-examples illustrate the difference between inference relations.

1. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ , but q is not a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$ :

```
Let us consider \mathcal{T} = \{A \subseteq B, B \subseteq \neg C\} and \mathcal{M} = \{\{A(a), B(a), C(a)\}\}.
```

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

$$\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ A(a), B(a) \}, \{ C(a) \} \},$$
 and

 $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{ \{ A(a), B(a) \} \}.$ 

Let  $q \leftarrow A(a)$  be a query. One can check that:

 $\langle \mathcal{M}_2, \forall \rangle \models q \text{ but }$ 

 $\langle \mathcal{M}_1, \forall \rangle \not\models q$ , since  $\langle \mathcal{T}, \{C(a)\} \rangle \not\models q$ .

2. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ , but q is not a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ :

```
Let us consider \mathcal{T} = \{A \sqsubseteq \neg B, A \sqsubseteq F\} and \mathcal{M} = \{\{A(a), B(a)\}\}.
```

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

$$\mathcal{M}_1 = \mathcal{M}_2 = \{\{A(a)\}, \{B(a)\}\},\$$

$$\mathcal{M}_3 = \{\{A(a), F(a)\}, \{B(a)\}\}, \text{ and }$$

$$\mathcal{M}_4 = \{ \{ A(a), F(a) \} \}.$$

Let  $q \leftarrow F(a)$  be a query. One can check that:

$$\langle \mathcal{M}_4, \forall \rangle \models q \text{ but }$$

$$\langle \mathcal{M}_2, \forall \rangle \not\models q$$
, since  $\langle \mathcal{T}, \{B(a)\} \rangle \not\models q$ .

3. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ , but q is not a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ :

```
Let us consider \mathcal{T} = \{B \sqsubseteq C, C \sqsubseteq \neg D\} and \mathcal{M} = \{\{B(a), D(a)\}\}.
 It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have: \mathcal{M}_1 = \{\{B(a)\}, \{D(a)\}\}, \mathcal{M}_5 = \{\{B(a), C(a)\}, \{D(a)\}\},  and \mathcal{M}_6 = \{\{B(a), C(a)\}\}.
 Let q \leftarrow C(a) be a query. One can check that: \langle \mathcal{M}_6, \forall \rangle \models q but \langle \mathcal{M}_5, \forall \rangle \not\models q, since \langle \mathcal{T}, \{D(a)\} \rangle \not\models q
```

4. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ , but q is not a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ :

```
Let us consider \mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq \neg C, C \sqsubseteq D, D \sqsubseteq F\} and \mathcal{M} = \{\{A(a), C(a)\}\}. It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have: \circ_{cl}(\mathcal{M}) = \{A(a), C(a), B(a), D(a), F(a)\}, \mathcal{M}_7 = \{\{A(a), B(a), D(a), F(a)\}, \{C(a), D(a), F(a)\}\}, and \mathcal{M}_8 = \{\{A(a), B(a), D(a), F(a)\}\}. Let q \leftarrow A(a) be a query. One can check that: \langle \mathcal{M}_8, \forall \rangle \models q, but \langle \mathcal{M}_7, \forall \rangle \not\models q, since \langle \mathcal{T}, \{C(a), D(a), F(a)\} \not\models q.
```

5. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ , but q is not a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ :

```
Let \mathcal{T}=\{A \sqsubseteq \neg B, B \sqsubseteq D\} and \mathcal{M}=\{\{A(a), B(a)\}\}. It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have: \mathcal{M}_1=\{\{A(a)\}, \{B(a)\}\},  \circ_{cl}(\mathcal{M})=\{\{A(a), B(a), D(a)\}\},  and \mathcal{M}_7=\{\{A(a), D(a)\}, \{B(a), D(a)\}\}. Let q \leftarrow D(a) be a query. One can check that: \langle \mathcal{M}_7, \forall \rangle \models q but \langle \mathcal{M}_1, \forall \rangle \not\models q, since \langle \mathcal{T}, \{A(a)\} \rangle.
```

**Proposition B.5** (Figure 5.4). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Then:

- 1. The universal inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_7$ .
- 2. The universal inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_8$ .
- 3. The universal inference from  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$ ,  $\mathcal{M}_4$ ) is incomparable with the one obtained from  $\mathcal{M}_6$ .
- 4. The universal inference from  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$ ,  $\mathcal{M}_4$ ) is incomparable with the one obtained from  $\mathcal{M}_7$ .
- 5. The universal inference from  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$ ,  $\mathcal{M}_4$ ) is incomparable with the one obtained from  $\mathcal{M}_8$ .

**Example B.4** (Examples of Figure 5.4). The following examples show incomparability between universal inference.

1. The universal inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_7$ . Let  $\mathcal{T} = \{C \subseteq F, F \subseteq A, A \subseteq \neg B, B \subseteq D\}$  and  $\mathcal{M} = \{\{C(a), B(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ C(a) \}, \{ B(a) \} \}, \text{ and }$  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{ \{ A(a), C(a), F(a) \}, \{ B(a), D(a) \} \}, \text{ and }$  $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{ \{ A(a), C(a), F(a) \} \},\$  $\circ_{cl}(\mathcal{M}) = \{ \{ A(a), C(a), F(a), B(a), D(a) \} \},$  $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{ \{ A(a), C(a), F(a), D(a) \}, \{ D(a), B(a) \} \},$ Let  $q_1 \leftarrow F(a)$  and  $q_2 \leftarrow D(a)$  be two queries. One can check that:  $\langle \mathcal{M}_7, \forall \rangle \models q_2 \text{ but } \langle \mathcal{M}_6, \forall \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_6, \forall \rangle \models q_1 \text{ but } \langle \mathcal{M}_7, \forall \rangle \not\models q_1.$ 2. The universal inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_8$ . Let  $\mathcal{T} = \{B \sqsubseteq \neg C, B \sqsubseteq A, C \sqsubseteq A, A \sqsubseteq \neg D, D \sqsubseteq E, E \sqsubseteq F\}$  and  $\mathcal{M} = \{\{A(a), B(a), C(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ A(a), C(a) \}, \{ A(a), B(a) \}, \{ D(a) \} \},$  and  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{ \{ A(a), C(a) \}, \{ A(a), B(a) \}, \{ D(a), E(a), F(a) \} \}, \text{ and }$  $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{ \{ D(a), E(a), F(a) \} \},\$  $\circ_{cl}(\mathcal{M}) = \{ \{ A(a), B(a), C(a), D(a), E(a), F(a) \} \},$  $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{ \{A(a), C(a), E(a), F(a)\}, \{A(a), B(a), E(a), F(a)\}, \{D(a), E(a), F(a)\} \},$  $\mathcal{M}_8 = \circ_{card}(\mathcal{M}_7) = \{ \{ A(a), C(a), E(a), F(a) \}, \{ A(a), B(a), E(a), F(a) \} \}$ Let  $q_1 \leftarrow D(a)$  and  $q_2 \leftarrow A(a)$  be two queries. One can check that:  $\langle \mathcal{M}_8, \forall \rangle \models q_2 \text{ but } \langle \mathcal{M}_6, \forall \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_6, \forall \rangle \models q_1 \text{ but } \langle \mathcal{M}_8, \forall \rangle \not\models q_1.$ 3. The universal inference from  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$  and  $\mathcal{M}_4$  is incomparable with the one obtained from  $\mathcal{M}_6$ . Let  $\mathcal{T} = \{ A \subseteq \neg B, C \subseteq A, B \subseteq D, D \subseteq F \}$  and  $\mathcal{M} = \{ \{ A(a), C(a), B(a) \} \}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ A(a), C(a) \}, \{ B(a) \} \},$  $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_2) = \{ \{ A(a), C(a) \} \},$  $\mathcal{M}_4 = \{ \{ A(a), C(a) \} \},$  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{ \{ A(a), C(a) \}, \{ B(a), D(a), F(a) \} \},$  $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{\{B(a), D(a), F(a)\}\},\$ Let  $q_1 \leftarrow A(a)$  and  $q_2 \leftarrow B(a)$  be two queries. One can check that:  $\langle \mathcal{M}_2, \forall \rangle \models q_1 \text{ but } \langle \mathcal{M}_6, \forall \rangle \not\models q_1 \text{ while } \langle \mathcal{M}_6, \forall \rangle \models q_2 \text{ but } \langle \mathcal{M}_2, \forall \rangle \not\models q_2.$  Similarly for  $\mathcal{M}_4$ 4. The universal inference from  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$  and  $\mathcal{M}_4$  is incomparable with the one obtained from Let  $\mathcal{T} = \{ A \subseteq \neg B, C \subseteq A, B \subseteq D, D \subseteq F \}$  and  $\mathcal{M} = \{ \{ A(a), C(a), B(a) \} \}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{ A(a), C(a) \}, \{ B(a) \} \},$  $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_2) = \{ \{ A(a), C(a) \} \},$  $\mathcal{M}_4 = \{ \{ A(a), C(a) \} \},\$  $\circ_{cl}(\mathcal{M}) = \{ \{ A(a), C(a), B(a), D(a), F(a) \} \},$ 

 $\langle \mathcal{M}_2, \forall \rangle \models q_1 \text{ but } \langle \mathcal{M}_7, \forall \rangle \not\models q_1 \text{ while } \langle \mathcal{M}_7, \forall \rangle \models q_2 \text{ but } \langle \mathcal{M}_2, \forall \rangle \not\models q_2.$  Similarly for  $\mathcal{M}_4$ .

 $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{ \{ A(a), C(a), D(a), F(a) \}, \{ B(a), D(a), F(a) \} \},$ 

Let  $q_1 \leftarrow A(a)$  and  $q_2 \leftarrow D(a)$  be two queries. One can check that:

5. The universal inference from  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$  and  $\mathcal{M}_4$  is incomparable with the one obtained from  $\mathcal{M}_8$ .

```
Let \mathcal{T}=\{B\sqsubseteq A, C\sqsubseteq A, A\sqsubseteq \neg D, E\sqsubseteq D, D\sqsubseteq F\} and \mathcal{M}=\{\{A(a), D(a), E(a)\}\}.
 It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have: \mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a)\}, \{D(a), E(a)\}\}, and \mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{D(a), E(a)\}\}, and \mathcal{M}_4 = \{\{D(a), E(a), F(a)\}\}, and \mathcal{M}_4 = \{\{D(a), E(a), F(a)\}\}, \mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), C(a), B(a), F(a)\}, \{D(a), E(a), F(a)\}\}, and \mathcal{M}_8 = \circ_{incl}(\mathcal{M}_7) = \{\{A(a), C(a), B(a), F(a)\}, Let q_1 \leftarrow D(a) and q_2 \leftarrow A(a) be two queries. One can check that: \langle \mathcal{M}_2, \forall \rangle \models q_1 but \langle \mathcal{M}_8, \forall \rangle \not\models q_1 while \langle \mathcal{M}_8, \forall \rangle \models q_2 but \langle \mathcal{M}_2, \forall \rangle \not\models q_2. Similarly for \mathcal{M}_4
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#### Composite modifiers+safe inference

**Proposition B.6** (Figure 5.5). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be a boolean query. Then:

- 1. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ .
- 2. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ .
- 3. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ .
- 4. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ .
- 5. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ .
- 6. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ .
- 7. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ .
- 8. If q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ .

#### *Proof.* The proof is as follows:

- 1. For items 1, we have  $\mathcal{M}_2 \subseteq \mathcal{M}_1$ , then following Item 2 of Lemma 5.2, if  $\langle \mathcal{M}_1, \cap \rangle$  implies a query q then  $\langle \mathcal{M}_2, \cap \rangle$  implies it also. The proof follow similarly for Items 4,5, 6 and 8 since  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ ,  $\mathcal{M}_3 \subseteq \mathcal{M}_5$ ,  $\mathcal{M}_6 \subseteq \mathcal{M}_5$ , and  $\mathcal{M}_8 \subseteq \mathcal{M}_7$ .
- 2. For items 2 and 3, we have  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$  and  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$ . Then following Item 3 of Lemma 5.3, if a query holds in  $\langle \mathcal{M}, \cap \rangle$  then it also holds in  $\langle \circ_{cl}(\mathcal{M}), \cap \rangle$ .
- 3. For item 7, we have  $\forall A \in \mathcal{M}_5, \exists B \in \mathcal{M}_7$  such that  $A \subseteq B$ . Let  $A(a) \in \bigcap_{\mathcal{A}_i \in \mathcal{M}_5} \mathcal{A}_i$ . Then one can check that there is no conflict  $\mathcal{C}$  in  $\langle \mathcal{T}, Cl(\mathcal{M}) \rangle$  such that  $A(a) \in \mathcal{C}$ . Indeed, assume that such conflict exists. Then this means that there exists  $B(a) \in Cl(\mathcal{M})$  where  $\langle \mathcal{T}, \{(A(a), B(a)\} \rangle$  is conflicting. Two options:
  - i)  $B(a) \in \mathcal{M}$ . This means that there exists a maximally consistent subset X of  $\mathcal{M}$  with  $B(a) \in X$ . Since B(a) is conflicting with A(a), with respect to  $\mathcal{T}$ . Then A(a) neither belongs to X nor to Cl(X). This contradict the fact that  $A(a) \in \bigcap_{\mathcal{A}_i \in \mathcal{M}_5} \mathcal{A}_i$ .
  - ii)  $B(a) \notin \mathcal{M}$ . Let  $Y \subseteq \mathcal{M}$  such that  $\langle \mathcal{T}, Y \rangle \models B(a)$ . Then clearly  $\langle \mathcal{T}, Y \cup \{A(a)\} \rangle$  is inconsistent. Hence, there exists  $D(a) \in \mathcal{M}$  such that  $\langle \mathcal{T}, \{(D(a), A(a)\} \rangle$  is conflicting and

 $D(a) \in Y$ . This comes down to item (i). Now, since there is no conflict in  $Cl(\mathcal{M})$  containing A(a), then A(a) belong to all maximally consistent subsets of  $Cl(\mathcal{M})$ , hence A(a) belongs to  $\bigcap_{\mathcal{A}_i \in \mathcal{M}_7} \mathcal{A}_j$ . Therefore if a q holds in  $\langle \mathcal{M}_5, \cap \rangle$ , then it holds that  $\langle \mathcal{M}_5, \cap \rangle$ .

**Example B.5** (Counter-examples of Figure 5.5). The following counter-examples illustrate the difference between inference relations given in Figure 5.5.

1. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ , but q is not a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$ :

Let us consider  $\mathcal{T} = \{A \sqsubseteq B, B \sqsubseteq \neg C\}$  and  $\mathcal{M} = \{\{C(a), A(a), B(a)\}\}.$ 

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

```
\mathcal{M}_1 = \{\{C(a)\}\}, \{A(a), B(a)\}\}, and
```

 $\mathcal{M}_2 = \{ \{ A(a), B(a) \} \}.$ 

Let  $q \leftarrow A(a)$  be a query. One can check that:

 $\mathcal{M}_2 \models_{\cap} q$ , since  $\bigcap_{\mathcal{A}_i \in \mathcal{M}_2} \mathcal{A}_i = \{A(a), B(a)\}$  but

 $\mathcal{M}_1 \not\models_{\cap} q$ .

2. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ , but q is not a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$ :

Let us consider  $\mathcal{T} = \{B \sqsubseteq D, B \sqsubseteq \neg C, C \sqsubseteq D\}$  and  $\mathcal{M} = \{\{C(a), B(a)\}\}.$ 

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

$$\mathcal{M}_1 = \{\{C(a)\}, \{B(a)\}\}, \text{ and }$$

$$\mathcal{M}_5 = \{\{B(a), D(a)\}, \{C(a), D(a)\}\}.$$

Let  $q \leftarrow D(a)$  be a query. One can check that :

$$\mathcal{M}_5 \models_{\cap} q \text{ since } \bigcap_{\mathcal{A}_i \in \mathcal{M}_5} \mathcal{A}_i = \{D(a)\}, \text{ but }$$

 $\mathcal{M}_1 \not\models_{\cap} q$ .

3. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ , but q is not a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ :

Let us consider  $\mathcal{T} = \{B \sqsubseteq \neg C, C \sqsubseteq A, B \sqsubseteq A\}$  and  $\mathcal{M} = \{\{C(a), B(a)\}\}.$ 

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

$$\mathcal{M}_1 = \mathcal{M}_2 = \{\{C(a)\}, \{B(a)\}\}$$
,and

$$\mathcal{M}_3 = \{\{C(a), A(a)\}\}, \{B(a), A(a)\}\}.$$

Let  $q \leftarrow A(a)$  be a query. One can check that:

 $\mathcal{M}_3 \models_{\cap} q$ , but

 $\mathcal{M}_2 \not\models_{\cap} q$ .

4. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ , but q is not a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ :

Let us consider  $\mathcal{T} = \{ A \sqsubseteq B, B \sqsubseteq \neg D \}$  and  $\mathcal{M} = \{ \{ A(a), D(a) \} \}$ .

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

$$\mathcal{M}_1 = \mathcal{M}_2 = \{\{A(a)\}, \{D(a)\}\},\$$

$$\mathcal{M}_3 = \{ \{ A(a), B(a) \}, \{ D(a) \} \},$$
 and

$$\mathcal{M}_4 = \{ \{ A(a), B(a) \} \}.$$

Let  $q \leftarrow A(a)$  be a query. One can check that

 $\mathcal{M}_4 \models_{\cap} q$  but

```
\mathcal{M}_3 \not\models_{\cap} q.
```

5. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ , but q is not a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ : Let us consider  $\mathcal{T} = \{A \subseteq B, B \subseteq \neg D\}$  and  $\mathcal{M} = \{\{A(a), D(a), B(a)\}\}.$ 

```
It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
\mathcal{M}_1 = \{ \{ A(a), B(a) \}, \{ D(a) \} \},\
\mathcal{M}_2 = \mathcal{M}_3 = \{\{A(a), B(a)\}\}, \text{ and }
\mathcal{M}_5 = \{\{A(a), B(a)\}, \{D(a)\}\}.
Let q \leftarrow A(a) be a query. One can check that
\mathcal{M}_3 \models_{\cap} q but
\mathcal{M}_5 \not\models_{\cap} q.
```

6. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ , but q is not a safe conclusion of  $\mathcal{M}_5$ :

```
Let us consider \mathcal{T}=\{B\subseteq C, C\subseteq \neg D\} and \mathcal{M}=\{\{B(a),D(a)\}\}.
```

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:

```
\mathcal{M}_1 = \{\{B(a)\}, \{D(a)\}\},\
\mathcal{M}_5 = \{\{B(a), C(a)\}, \{D(a)\}\}, \text{ and }
\mathcal{M}_6 = \{ \{ B(a), C(a) \} \}.
Let q \leftarrow B(a) be a query. One can check that
\mathcal{M}_6 \models_{\cap} q but
\mathcal{M}_5 \not\models_{\cap} q.
```

7. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ , but q is not a safe conclusion of  $\mathcal{M}_5$ :

```
Let \mathcal{T} = \{ A \sqsubseteq \neg B, B \sqsubseteq D \} and \mathcal{M} = \{ \{ A(a), B(a) \} \}.
It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
\mathcal{M}_1 = \{\{A(a)\}, \{B(a)\}\},\
\mathcal{M}_5 = \{\{A(a)\}, \{B(a), D(a)\}\},\
\circ_{cl}(\mathcal{M}) = \{ \{ A(a), B(a), D(a) \} \}, \text{ and }
\mathcal{M}_7 = \{ \{ A(a), D(a) \}, \{ B(a), D(a) \} \}.
Let q \leftarrow D(a) be a query. One can deduce that:
\mathcal{M}_7 \models_{\cap} q but
\mathcal{M}_5 \not\models_{\cap} q.
```

8. There exists a *DL-Lite* knowledge base, and a boolean query q such that q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ , but q is not a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ :

```
Let us consider \mathcal{T} = \{ A \subseteq B, B \subseteq \neg C, C \subseteq D \} and \mathcal{M} = \{ \{ A(a), C(a) \} \}.
It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
\circ_{cl}(\mathcal{M}) = \{A(a), C(a), B(a), D(a)\},\
\mathcal{M}_7 = \{ \{ A(a), B(a), D(a) \}, \{ C(a), D(a) \} \}, \text{ and }
```

$$\mathcal{M}_8 = \{ \{ A(a), B(a), D(a) \} \}.$$

Let  $q \leftarrow A(a)$  be a boolean query. One can deduce that:

```
\mathcal{M}_8 \models_{\cap} q, but
\mathcal{M}_7 \not\models_{\cap} q.
```

**Proposition B.7** (Figure 5.5). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be a boolean query. Then:

- 1. The safe inference from  $\mathcal{M}_2$  is incomparable with the one obtained from  $\mathcal{M}_6$ .
- 2. The safe inference from  $\mathcal{M}_3$  is incomparable with the one obtained from  $\mathcal{M}_6$ .
- 3. The safe inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_7$ .
- 4. The safe inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_8$ .
- 5. The safe inference from  $\mathcal{M}_2$  is incomparable with the one obtained from  $\mathcal{M}_5$ .

**Example B.6** (Examples of Figure 5.5). The following examples show incomparability between MBox's

```
1. The safe inference from \mathcal{M}_6 is incomparable with the one obtained from \mathcal{M}_7. Let \mathcal{T} = \{C \sqsubseteq F, F \sqsubseteq A, A \sqsubseteq \neg B, B \sqsubseteq D\} and \mathcal{M} = \{\{C(a), B(a)\}\}. It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have: \mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{C(a)\}, \{B(a)\}\}, \text{ and } \mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a), C(a), F(a)\}, \{B(a), D(a)\}\}, \text{ and } \mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{\{A(a), C(a), F(a)\}\}, \circ_{cl}(\mathcal{M}) = \{\{A(a), C(a), F(a), B(a), D(a)\}\}, \mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), C(a), F(a), D(a)\}, \{D(a), B(a)\}\}, \text{ Let } q_1 \leftarrow F(a) \text{ and } q_2 \leftarrow D(a) \text{ be two queries. One can check that: } \langle \mathcal{M}_7, \cap \rangle \models q_2 \text{ but } \langle \mathcal{M}_6, \cap \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_6, \cap \rangle \models q_1 \text{ but } \langle \mathcal{M}_7, \cap \rangle \not\models q_1.
```

2. The safe inference from  $\mathcal{M}_6$  is incomparable with the one obtained from  $\mathcal{M}_8$ . Let  $\mathcal{T} = \{B \sqsubseteq \neg C, B \sqsubseteq A, C \sqsubseteq A, A \sqsubseteq \neg D, D \sqsubseteq E, E \sqsubseteq F\}$  and  $\mathcal{M} = \{\{A(a), B(a), C(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a), C(a)\}, \{A(a), B(a)\}, \{D(a)\}\},$   $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a), C(a)\}, \{A(a), B(a)\}, \{D(a), E(a), F(a)\}\},$   $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{\{D(a), E(a), F(a)\}\},$   $\circ_{cl}(\mathcal{M}) = \{\{A(a), B(a), C(a), D(a), E(a), F(a)\}\},$   $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), C(a), E(a), F(a)\}, \{A(a), B(a), E(a), F(a)\}, \{D(a), E(a), F(a)\}\},$ and  $\mathcal{M}_8 = \circ_{incl}(\mathcal{M}_7) = \{\{A(a), C(a), E(a), F(a)\}, \{A(a), B(a), E(a), F(a)\}\}$ Let  $q_1 \leftarrow D(a)$  and  $q_2 \leftarrow A(a)$  be two queries. One can check that:  $\langle \mathcal{M}_8, \cap \rangle \models q_2$  but  $\langle \mathcal{M}_6, \cap \rangle \not\models q_2$  while  $\langle \mathcal{M}_6, \cap \rangle \models q_1$  but  $\langle \mathcal{M}_8, \cap \rangle \not\models q_1$ .

3. The safe inference from  $\mathcal{M}_2$  is incomparable with the one obtained from  $\mathcal{M}_6$ . Let  $\mathcal{T} = \{A \sqsubseteq \neg B, C \sqsubseteq A, B \sqsubseteq D, D \sqsubseteq F\}$  and  $\mathcal{M} = \{\{A(a), C(a), B(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a), C(a)\}, \{B(a)\}\},$   $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_2) = \{\{A(a), C(a)\}, \{B(a), D(a), F(a)\}\},$   $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a), C(a)\}, \{B(a), D(a), F(a)\}\},$   $\mathcal{M}_6 = \circ_{card}(\mathcal{M}_5) = \{\{B(a), D(a), F(a)\}\},$  Let  $q_1 \leftarrow A(a)$  and  $q_2 \leftarrow B(a)$  be two queries. One can check that:  $\langle \mathcal{M}_2, \cap \rangle \models q_1$  but  $\langle \mathcal{M}_6, \cap \rangle \not\models q_1$  while  $\langle \mathcal{M}_6, \cap \rangle \models q_2$  but  $\langle \mathcal{M}_2, \cap \rangle \not\models q_2$ .

4. The safe inference from  $\mathcal{M}_2$  is incomparable with the one obtained from  $\mathcal{M}_5$ . Let  $\mathcal{T}=\{A\sqsubseteq B, C\sqsubseteq B, A\sqsubseteq \neg C, D\sqsubseteq C\}$  and  $\mathcal{M}=\{\{A(a), C(a), D(a)\}\}$ . It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\mathcal{M}_1 = \circ_{incl}(\mathcal{M})=\{\{A(a)\}, \{C(a), D(a)\}\},$   $\mathcal{M}_2 = \circ_{card}(\mathcal{M}_1)=\{\{C(a), D(a)\}\},$  and  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)=\{\{A(a), B(a)\}, \{B(a), D(a), C(a)\}\},$  Let  $q_1 \leftarrow D(a)$  and  $q_2 \leftarrow B(a)$  be two queries. One can check that:  $\langle \mathcal{M}_2, \cap \rangle \models q_1$  but  $\langle \mathcal{M}_5, \cap \rangle \not\models q_1$  while  $\langle \mathcal{M}_5, \cap \rangle \models q_2$  but  $\langle \mathcal{M}_2, \cap \rangle \not\models q_2$ .

#### Composite modifiers+majority-based inference

**Proposition B.8** (Figure 5.6). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be a boolean query. Then:

- $\langle \mathcal{T}, \mathcal{M}_1 \rangle \models_{maj} q \text{ iff } \langle \mathcal{T}, \mathcal{M}_5 \rangle \models_{maj} q.$
- $\langle \mathcal{T}, \mathcal{M}_2 \rangle \models_{maj} q \text{ iff } \langle \mathcal{T}, \mathcal{M}_3 \rangle \models_{maj} q.$
- If  $\langle \mathcal{T}, \mathcal{M}_5 \rangle \models_{maj} q \text{ then } \langle \mathcal{T}, \mathcal{M}_7 \rangle \models_{maj} q$ .

*Proof.* The proof of items 1 and 2 follow immediately from the proof of item 2 of Lemma 5.3, since  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1)$  and  $\mathcal{M}_2 = \circ_{cl}(\mathcal{M}_3)$ . For Item 3, we have  $\forall \mathcal{A}_i \in \mathcal{M}_5, \exists \mathcal{A}_j \in \mathcal{M}_7$  such that  $\mathcal{A}_i \subseteq \mathcal{A}_j$ . From proof of item 5 of proposition B.4, we have  $\forall \mathcal{A}_j \in \mathcal{M}_7, \exists \mathcal{A}_i \in \mathcal{M}_5$  such that  $\mathcal{A}_i \subseteq \mathcal{A}_j$ . We conclude that if a majority-based conclusion holds from  $\mathcal{M}_5$ , it holds also from  $\mathcal{M}_7$ . The converse does not hold.

**Example B.7** (Counter-examples of Figure 5.6). The following counter-examples illustrate the difference between inference relations given in Figure 5.6.

1. There exists a DL-Lite knowledge base, and a query q such that q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ , but q is not a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ :

Let  $\mathcal{T} = \{A \sqsubseteq \neg B, B \sqsubseteq D\}$  and  $\mathcal{M} = \{\{A(a), B(a)\}\}$ .

It is easy to check that  $\langle \mathcal{T}, \mathcal{M} \rangle$  is inconsistent. We have:  $\circ_{cl}(\mathcal{M}) = \{\{A(a), B(a), D(a)\}\},$   $\mathcal{M}_7 = \circ_{incl}(\circ_{cl}(\mathcal{M})) = \{\{A(a), D(a)\}, \{B(a), D(a)\}\},$   $\mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{\{A(a)\}, \{B(a)\}\},$  and  $\mathcal{M}_5 = \circ_{cl}(\mathcal{M}_1) = \{\{A(a)\}, \{B(a), D(a)\}\},$ Let  $q \leftarrow D(a)$  be a query. One can check that:  $\langle \mathcal{M}_7, maj \rangle \models q$  but  $\langle \mathcal{M}_5, maj \rangle \not\models q$ 

**Proposition B.9** (Figure 5.6). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be a boolean query. Then:

- The majority-based inference from  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  is incomparable with the one obtained from  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ .
- The majority-based inference from  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$  is incomparable with the one obtained from  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ .
- The majority-based inference from  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  is incomparable with the one obtained from  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ .
- The majority-based inference from  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  is incomparable with the one obtained from  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ .

**Example B.8** (Examples of Figure 5.6). The following examples show incomparability between majority-based inferences.

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1. The majority-based inference from \langle \mathcal{T}, \mathcal{M}_1 \rangle is incomparable with the one obtained from \langle \mathcal{T}, \mathcal{M}_2 \rangle.
              Let \mathcal{T}=\{B \subseteq \neg C, B \subseteq A, C \subseteq A, A \subseteq \neg D, D \subseteq E, E \subseteq F\} and \mathcal{M}=\{\{A(a), B(a), A \subseteq a\}\}
             C(a), D(a), E(a), F(a)}.
             It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
              \mathcal{M}_1 = \circ_{incl}(\mathcal{M}) = \{ \{A(a), C(a)\}, \{A(a), B(a)\}, \{D(a), E(a), F(a)\} \}, and
              \mathcal{M}_2 = \circ_{card}(\mathcal{M}_1) = \{\{D(a), E(a), F(a)\}\}
             Let q_1 \leftarrow D(a) and q_2 \leftarrow A(a) be two queries. One can check that:
              \langle \mathcal{M}_1, maj \rangle \models q_2 \text{ but } \langle \mathcal{M}_2, maj \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_2, maj \rangle \models q_1 \text{ but } \langle \mathcal{M}_1, maj \rangle \not\models q_1.
2. The majority-based inference from \langle \mathcal{T}, \mathcal{M}_3 \rangle is incomparable with the one obtained from \langle \mathcal{T}, \mathcal{M}_4 \rangle.
             Let \mathcal{T} = \{B \sqsubseteq \neg C, B \sqsubseteq A, C \sqsubseteq A, A \sqsubseteq \neg D, F \sqsubseteq D, D \sqsubseteq E\} and \mathcal{M} = \{\{A(a), B(a), C(a), F(a), F(a
              D(a)}.
             It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
              \mathcal{M}_1 = \mathcal{M}_2 = \{ \{ A(a), C(a) \}, \{ A(a), B(a) \}, \{ D(a), F(a) \} \},
              \mathcal{M}_3 = \{ \{ A(a), C(a) \}, \{ A(a), B(a) \}, \{ D(a), F(a), E(a) \} \},
              \mathcal{M}_4 = \{\{D(a), E(a), F(a)\}\}
             Let q_1 \leftarrow D(a) and q_2 \leftarrow A(a) be two queries. One can check that:
              \langle \mathcal{M}_3, maj \rangle \models q_2 \text{ but } \langle \mathcal{M}_4, maj \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_4, maj \rangle \models q_1 \text{ but } \langle \mathcal{M}_3, maj \rangle \not\models q_1.
3. The majority-based inference from \langle \mathcal{T}, \mathcal{M}_5 \rangle is incomparable with the one obtained from \langle \mathcal{T}, \mathcal{M}_6 \rangle.
             Let \mathcal{T} = \{B \sqsubseteq \neg C, B \sqsubseteq A, C \sqsubseteq A, A \sqsubseteq \neg D, F \sqsubseteq D, D \sqsubseteq E\} and \mathcal{M} = \{\{A(a), B(a), C(a), F(a), F(a
              D(a), E(a)}.
             It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
              \mathcal{M}_1 = \mathcal{M}_5 = \{ \{ A(a), C(a) \}, \{ A(a), B(a) \}, \{ D(a), F(a), E(a) \} \},
              \mathcal{M}_6 = \{\{D(a), E(a), F(a)\}\}
             Let q_1 \leftarrow D(a) and q_2 \leftarrow A(a) be two queries. One can check that:
              \langle \mathcal{M}_5, maj \rangle \models q_2 \text{ but } \langle \mathcal{M}_6, maj \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_6, maj \rangle \models q_1 \text{ but } \langle \mathcal{M}_5, maj \rangle \not\models q_1.
4. The majority-based inference from \langle \mathcal{T}, \mathcal{M}_7 \rangle is incomparable with the one obtained from \langle \mathcal{T}, \mathcal{M}_8 \rangle.
             Let \mathcal{T}=\{B\subseteq \neg C, B\subseteq A, C\subseteq A, A\subseteq \neg D, F\subseteq D, E\subseteq D\} and \mathcal{M}=\{\{A(a), F(a), E(a), E
              B(a), C(a)}.
             It is easy to check that \langle \mathcal{T}, \mathcal{M} \rangle is inconsistent. We have:
              \circ_{cl}(\mathcal{M}) = \{ \{ A(a), C(a), B(a), D(a), F(a), E(a) \} \},
              \mathcal{M}_7 = \{\{D(a), E(a), F(a)\}, \{A(a), B(a)\}, \{A(a), C(a)\}\},and
              \mathcal{M}_8 = \{\{D(a), E(a), F(a)\}\},and
             Let q_1 \leftarrow D(a) and q_2 \leftarrow A(a) be two queries. One can check that:
              \langle \mathcal{M}_7, maj \rangle \models q_2 \text{ but } \langle \mathcal{M}_8, maj \rangle \not\models q_2 \text{ while } \langle \mathcal{M}_8, maj \rangle \models q_1 \text{ but } \langle \mathcal{M}_7, maj \rangle \not\models q_1.
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#### Global schema

**Proposition B.10** (Figure 5.7). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be boolean query. Then  $\forall \mathcal{M}_i \in \{ \mathcal{M}_1, ..., \mathcal{M}_8 \}$ :

- 1. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_i \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_i \rangle$ .
- 2. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_i \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_i \rangle$ .

*Proof.* The proof of item 1 (*resp.* item 2) follows immediately from the proof of Item 1 (*resp.* item 2) of Proposition 5.1.

**Proposition B.11** (Figure 5.7). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be boolean query. Then  $\forall \mathcal{M}_i \in \{ \mathcal{M}_1, ..., \mathcal{M}_8 \}$ :

- 1. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ .
- 2. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ .
- 3. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ .
- 4. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$ .
- 5. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ .
- 6. if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  then q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ .

*Proof.* The proof of item 1 follows from the facts that i) each safe conclusion of  $\mathcal{M}_3$  is a universal conclusion of  $\mathcal{M}_3$  and ii)  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ . The proof of items 3, 5 and 6 follow similarly. Regarding item 2 (*resp.* Item 4), it holds due the fact that  $(\mathcal{M}_2, \forall) \equiv (\mathcal{M}_3, \forall)$  (*resp.*  $(\mathcal{M}_1, \forall) \equiv (\mathcal{M}_5, \forall)$ ). So if a conclusion holds from  $(\mathcal{M}_1, \cap)$  (*resp.*  $(\mathcal{M}_2, \cap)$ ), then it holds from  $(\mathcal{M}_5, \forall)$  (*resp.*  $(\mathcal{M}_3, \forall)$ ).

**Proposition B.12** (Figure 5.7). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1,...,\mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be boolean query. Then:

- 1. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_4 \rangle$ .
- 2. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ .
- 3. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ .
- 4. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$ .
- 5. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ .
- 6. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$ .
- 7. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ .
- 8. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ .
- 9. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  then q is a majority-based conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ .

*Proof.* Item 1 holds due to the facts that i) the universal inference from  $\mathcal{M}_3$  considers as valid a conclusion q iff q follows from each  $\mathcal{A}_i \in \mathcal{M}_3$  and ii) since  $\mathcal{M}_4 \subseteq \mathcal{M}_3$ , then q is a majority-based conclusion of  $\mathcal{M}_4$ . Item 4, 7 and 9 follow similarly. Items 2 and 3 follow immediately from the facts that  $\mathcal{M}_3 = \circ_{cl}(\mathcal{M}_2)$  and  $(\mathcal{M}_2, \forall) \equiv (\mathcal{M}_3, \forall)$ . Then if a conclusion q is a universal conclusion of  $\mathcal{M}_2$  (resp.  $\mathcal{M}_3$ ) then it is a majority-based conclusion of  $\mathcal{M}_3$  (resp.  $\mathcal{M}_2$ ). Items 5 and 6 follow similarly. Item 8 holds from the fact that a universal conclusion of  $\mathcal{M}_5$  is a universal conclusion of  $\mathcal{M}_7$ , and thus, it is a majority-based conclusion of  $\mathcal{M}_7$ .

**Proposition B.13** (Figure 5.7). Let  $\mathcal{K}_{\mathcal{M}} = \langle \mathcal{T}, \mathcal{M} = \{ \mathcal{A} \} \rangle$  be an inconsistent DL-Lite knowledge base. Let  $\mathcal{M}_1, ..., \mathcal{M}_8$  be the eight MBox's given in Table 5.1. Let q be instance query. Then:

- 1. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_2 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_3 \rangle$ .
- 2. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_1 \rangle$  then q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ .

- 3. q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  iff q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ .
- 4. q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$  iff q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_6 \rangle$ .
- 5. q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$  iff q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ .
- 6. q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$  iff q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_8 \rangle$ .
- 7. if q is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  iff q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_7 \rangle$ .

*Proof.* The proof of Item 1 follows from the facts: i)  $\mathcal{M}_2 \subseteq_{cl} \mathcal{M}_3$ , ii) the set of universal conclusions of  $\mathcal{M}_2$   $UC_{\mathcal{M}_2} = \{B(a) : a \in D_I, B \in D_C \text{ and } \forall \mathcal{A}_i \in \mathcal{M}_2, \langle \mathcal{T}, \mathcal{A}_i \rangle \models B(a)\} \cup \{R(a,b) : a \in D_I, b \in D_I, R \in D_R \text{ and } \forall \mathcal{A}_i \in \mathcal{M}_2, \langle \mathcal{T}, \mathcal{A}_i \rangle \models R(a,b)\}$ , and iii) according to the definition of deductive closure modifier  $UC_{\mathcal{M}_2} = \bigcap_{\mathcal{A}_i \in \mathcal{M}_3} \mathcal{A}_j$ . The proof of item 2 and 7 follow similarly.

For item 3, we have fromProposition 5.1, if q is a safe conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$  then it is a universal conclusion of  $\langle \mathcal{T}, \mathcal{M}_5 \rangle$ . Now, let  $UC_{\mathcal{M}_5} = \{B(a) : a \in D_I, B \in D_C \text{ and } \forall \mathcal{A}_i \in \mathcal{M}_5, \langle \mathcal{T}, \mathcal{A}_i \rangle \models B(a)\} \cup \{R(a,b) : a \in D_I, b \in D_I, R \in D_R \text{ and } \forall \mathcal{A}_i \in \mathcal{M}_5, \langle \mathcal{T}, \mathcal{A}_i \rangle \models R(a,b)\}$  be the set of universal conclusions of  $\mathcal{M}_5$ . We have  $\mathcal{M}_5 = \circ_{cl}(\circ_{incl}(\mathcal{M}))$ , then according to the definition of deductive closure modifier, one can check that  $UC_{\mathcal{M}_5} = \bigcap_{A_i \in \mathcal{M}_5} \mathcal{A}_j$ . The same proof holds for items 4,5 and 6.

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