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Run-Time knowledge model enrichment in SWoT

A step toward ambient services selection relevancy

Gérald Rocher[1,2], Jean-Yves Tigli[1,2], Stéphane Lavirotte[1,2], Rahma Daikhi[3]
(1) Université Nice Sophia Antipolis, Polytech'Nice Sophia
(2) Centre National de la Recherche Scientifique, Laboratoire I3S, CNRS UMR 7271
Sophia Antipolis, France
(3) ESPRIT University, Tunis, Tunisia
Gerald.Rocher@unice.fr, Jean-Yves.Tigli@unice.fr, Stephane.Lavirotte@unice.fr

***Abstract*—Semantic web technologies are gaining momentum in the WoT (Web of Things) community for its ability to manage the increasing semantic heterogeneity between devices (Semantic Web of Things, SWoT) in ambient environments. However, most of the approaches rely on ad-hoc and static knowledge models (ontologies) designed for specific domains and applications. While it is a solution for handling the semantic heterogeneity issue, it offers no perspective in term of ontology evolution over time. We study in this paper several approaches allowing: (1) to handle the semantic heterogeneity issue; (2) to capitalize the knowledge contributions throughout the life of the system allowing it to potentially better assist people in their environment over time. One approach is validated on two real use-cases.**

Keywords—Semantic web of things (SWoT); Knowledge modeling; Knowledge capitalization, Ambient services selection.

I. Introduction

During the last decade, achievements in computer hardware miniaturization and power consumption reduction have enabled the multiplication of connected *devices* integrated in everyday life physical *objects* (chair, table, lamp, etc…) and physical environments (house, building, vehicle, etc…). These devices implement *resources* interacting with objects (actuator) and/or gathering data (sensor) about themselves, the objects or the environment [1]. Access to these resources is achieved through *services* exposing their interfaces and allowing communication with the digital world.

Widely deployed in so called ambient environments [2], these devices are selected by applications that make them work in concert to assist users in diverse domains (healthcare, smart houses, etc…). This cooperation requires a strong interoperability between devices, firstly achieved by allowing them to communicate. Although work on communication protocols (IoT, Internet of Things) tries to provide a solution to the technological heterogeneity issue, it is still challenging due to the large number of initiatives [3] in this field. Among all the possible solutions, web services based approach (WoT, Web of Things) is now widely accepted [4]. From this hypothesis, we can now focus on the heterogeneity issue but from a semantic standpoint. Indeed, devices and services are now enriched with semantic annotations used to qualify it (SWoT, Semantic Web of Things) and increase the relevancy of the selected ones (Fig. 1).

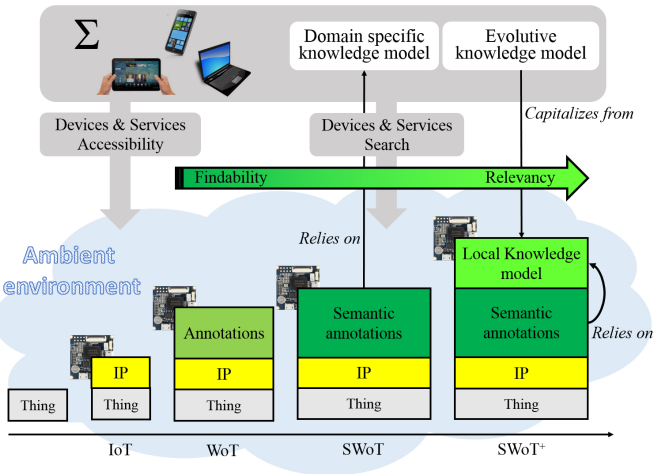

Fig. 1. From IoT to SWoT+

In most of the current work, annotations rely on a static and *ad-hoc* knowledge model (ontology) structuring all the concepts and relationships for a specific domain targeting specific applications (smart homes, smart cities, building automation, healthcare, etc…).

However, while this approach is a solution for handling the semantic heterogeneity issue, it offers no perspective in term of ontology evolution. Thus, extending the scope of use of the information to multiple applicative domains implies to develop a comprehensive ontology from heterogeneous ontologies which is unlikely to happen in the SWoT context where domains to cover are countless. In addition, most of the existing domain ontologies doesn't follow the semantic web best practices[1], limiting, *de facto*, the reusability of their information outside their initial scope [5].

Some projects acknowledged the fact that multiple heterogeneous ontologies management is needed in the case of systems targeting a wide range of applicative domains. For example, in the context of ambient intelligent environments

[1] www.w3.org/2014/02/wot/papers/gyrard-2.pdf

(AIEs), ATRACO project authors [6] envision that a comprehensive, agreed and validated ontology is unlikely to happen, and that, more realistically, device manufacturers will independently develop their own ontologies.

For example, considering an environment with a recent DVD player embedding a local ontology which partially models the knowledge about the video formats it is able to play (i.e. MPEG-2). The query "What are the available appliances able to play MPEG-1?" will return no answer. Considering now a newly discovered DVD player embedding a local ontology which models that MPEG-2 format is backwards-compatible with MPEG-1 format, the previous query will now return the two appliances. By not capitalizing the contribution of this new knowledge, the same query will again return no answer if the second DVD player local ontology is not reachable anymore.

Our contribution relies on a knowledge architecture managing the semantic heterogeneity issue but also permitting to capitalize the knowledge contributions throughout the life of the system.

Firstly in section II, we describe the main semantic web technologies used in SWoT domain to model and manage the knowledge. Then, from this model, we study elements that can be leveraged to enrich the knowledge throughout the life of the system. From this study we propose in section III a dynamic knowledge management model for SWoT. In section IV we study several ontology-based knowledge management approaches and classify them according to two criteria: (1) their capacity at managing the semantic heterogeneity, (2) their faculty at permitting the knowledge model enrichment over time. Two case-studies are detailed in section V and implemented on our experimentation platform to get associated results discussed in section VI. In section VII we present some related works and, finally, we conclude in section VIII by summarizing the results and introducing the future work.

II. Conceptual Foundations

A. Semantic web concepts

At this point, it seems appropriate to first discuss the several knowledge description model used in the semantic web domain and applied to the SWoT domain.

1) Ontology

The knowledge about the environment and the devices is formally and explicitly described using *ontologies*, hierarchically structuring the concepts (in the SWoT context, OWL (Web Ontology Language) is the main language used for that purpose).

The main elements composing an ontology are:

a) ***Classes*** (or concepts) and sub-classes hierarchically organized according to a taxonomy (i.e. Device, Service, Display, Speaker, etc…),

b) ***Properties*** allowing to define ***facts*** or ***relations*** between classes. There are mainly two property types:
   i. Object property that defines a relationship between two instances of a class or between classes,
   ii. Data types properties as a relation between a literal value and a class instance.

c) ***Class instances*** (class individual) which may take the characteristics defined by the properties.

2) Vocabulary

The differences between "ontology" and "vocabulary" is subtle[1]: While an ontology formally and strictly describes the concepts and relations of a given domain, a vocabulary enumerates terms without a strict formalism (context-less) allowing them to be shared and used by several domains.

3) Knowledge base

An ontology can be seen as a meta-system for a knowledge base (KB) describing the knowledge representation it contains. KB includes facts and individuals of all the defined concepts from which a reasoning engine is used to derive implicit knowledge from explicit knowledge. Knowledge in KB is structured at two description levels, *ABox* and *TBox*, respectively defining *assertions* on the instances and individuals, and the general concepts terminologies from which an inference engine is able to deduce implicit knowledge (either from native OWL inference rules or more expressive SWRL rules (Semantic Web Rule Language)).

B. Three knowledge enrichment levels

From the ontology and knowledge base previously described, we denote three main elements: (1) property, (2) instance (*ABox*) and (3) concepts (*TBox*) that can independently modify or enrich the knowledge.

1) The property level

Devices placed in the environment, worn by users or embedded in everyday life objects publish properties values gathered from sensors representing the users, the environment or the objects physical states (temperature, location, battery

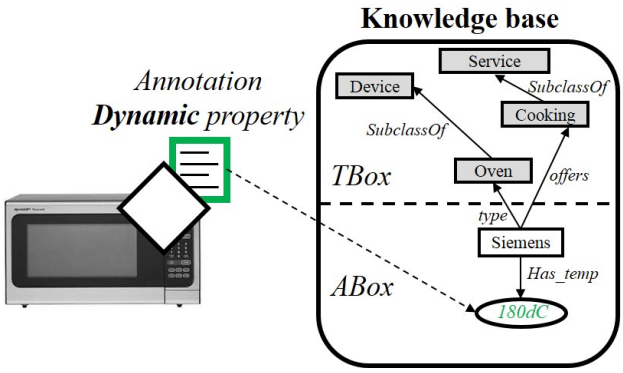

Fig. 2. Knowledge enrichment : the property level

level, etc…). For instance, in Fig. 2, the annotation brings the oven's temperature property value. The KB oven's

[1] http://www.w3.org/standards/semanticweb/ontology

temperature property is updated as the oven temperature value increase or decrease. It allows queries such as:

"*What is the current temperature of the oven?*"

This level relies on an existing knowledge model (i.e. the data type property) and do not allow it to be enriched.

2) The instance level

In a closed environment all devices are known. Therefore, all device instances can be populated in the KB (static ABox) at design time. However, in ambient environments, devices are not known *a priori* and unpredictably appear or disappear in the environment (Fig. 3). A device discovery mechanism is necessary [7][8][9][10], allowing to keep the KB up to date with the instances of the devices as they appear or disappear in the environment (*knowledge base population*).

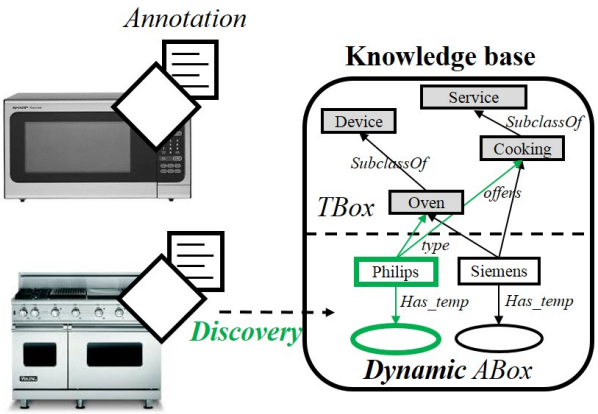

Fig. 3. Knowledge enrichment : the instance level

At each instant, the KB content is a snapshot of the devices available in the environment permitting queries like:

"*What are currently the domestic appliances present in the kitchen?*"

This level again relies on an existing knowledge model (i.e. the concept whose instance is the type) and do not allow it to be enriched.

1) The terminological level

Properties and instances associated concepts are all defined from classes and relations between classes in the ontologies and the knowledge base (*TBox*). Those concepts and relations are necessary for the machine to understand the meaning of all the instances and the properties in the knowledge base, and possibly infer new implicit knowledge. In general, an ontology is bounded to a particular application domain limiting the expressivity of the requests to the defined classes and relations. When dealing with real world environments and devices like it is the case in ambient environments, it is unlikely that an ontology defining all the world concepts and relations can be available. It is therefore necessary to enrich on the fly the ontology content with new concepts and relations (*knowledge base extension*). This additional knowledge could be either brought by the users [9], or from the devices' annotations as they appear in the environment allowing to enrich the ontology throughout the life of the system.

It allows to add more expressivity to the queries. For instance, an initial query like:

"*What are the domestic appliances available allowing to cook?*"

corresponding to the Fig. 3 would return two devices (both ovens being linked to the concept "Cooking"). If one of the device adds the new concept "Grill" (Fig. 4), the initial query can be refined with:

"*What are the domestic appliances available to grill?*"

returning only one result. Note that along with additional concepts and relations, inference rules can also be added as well to refine the knowledge by inferring new relations or adding new properties.

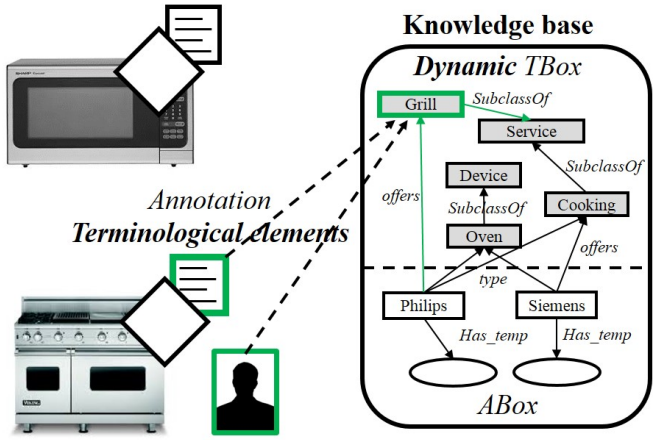

Fig. 4. Knowledge enrichment : the terminological level

III. KNOWLEDGE MANAGEMENT MODEL FOR SWOT

A knowledge management model is presented in Fig. 5 leveraging the aforementioned three knowledge enrichment levels. In order to allow the system knowledge model to be enriched throughout the life of the system, the terminological elements, brought by users or the devices semantic annotations, have to be made *persistent* in the KB. Thus, when a device disappears from the environment, only the associated instance and properties are removed from the KB.

IV. KNOWLEDGE MODEL MANAGEMENT APPROACHES

The terminological knowledge enrichment level is the only one allowing the ontology to be enriched throughout the life of the system. Based on this, and in the SWoT context, we depict hereafter some ontology management approaches and classify them according to two criteria: (1) their capacity at managing the semantic heterogeneity, (2) their faculty at permitting the knowledge enrichment over time.

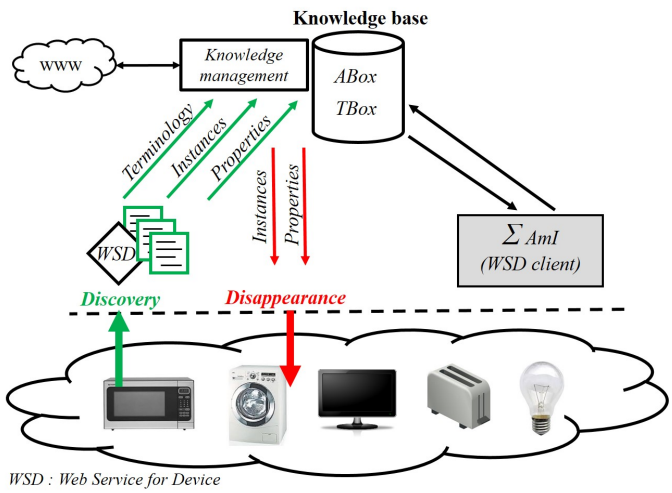

Fig. 5. Knowledge management model for SWoT

1) Fragmented ontology approach

With this approach, devices semantic annotations bring *fragments* of a *comprehensive* domain ontology. The system knowledge grows as devices are discovered over time and contains only the necessary knowledge making it suitable for resource constrained systems. The knowledge enrichment is bounded to the content of the domain ontology the fragments are extracted from, limiting *de facto* the knowledge enrichment capability but it does not suffer from the problem of semantic heterogeneity. Nevertheless, in the context of SWoT, an accepted and validated comprehensive ontology describing the whole world's concepts and relations is unlikely to happen [11], limiting this approach to specific applications.

2) Multiple local ontologies approach

With this approach, each device locally defines and embeds its own domain ontology. In the context of SWoT, although good at supporting knowledge enrichment, the lack of a common vocabulary leads the necessity of implementing ontologies alignment mechanisms (at the first stage of ontology matching [15] and mapping [14]) in order to smooth the semantic heterogeneity. This limits the scaling capability [16] of this approach due to the potential incoherency of the resulting ontology [13]. The lack of a common vocabulary may also lead to degrade new knowledge inference, the vocabulary being the basic building blocks used by the inference engines. Finally, the alignment process computation time may dramatically increase the overall system response time and consequently degrade the user experience as the knowledge grows over time.

3) Multiple local ontology with linked data approach

As in the previous approach, each device locally defines and embeds its own domain ontology. But, concepts and relations definitions can be linked to other concepts described either in other local ontologies (`owl:sameAs` or `owl:equivalentClass`) or defined "somewhere" on the web (dereferenced URI)[12]. This approach is good at managing the semantic heterogeneity and, while it cannot completely make the economy of an alignment engine, it allows reducing its inaccuracies. For that reason, it is the one from which we expect the best results (Fig. 6). In addition, linked data usage can: (1) ensure up to date information over time (for example, dereferenced URI can point to the manufacturer devices knowledge repository returning the latest device description revision as an RDF sub-graph) and then (2) can help alleviating the metadata content.

From this short study, we can classify the several approaches based on their capacity at managing the semantic heterogeneity and their faculty at permitting the knowledge enrichment over time (Fig. 6).

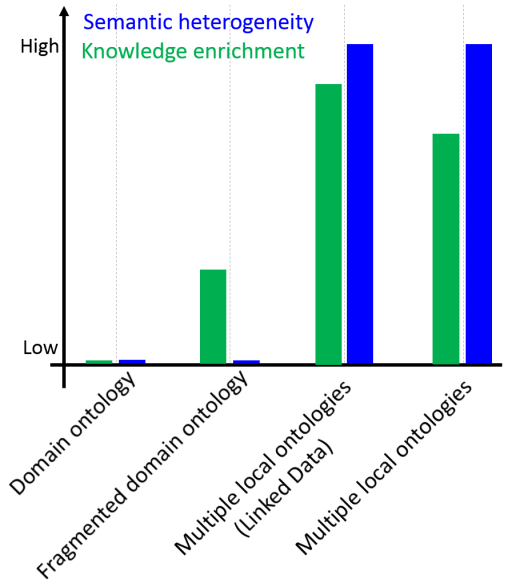

Fig. 6. Knowledge model management approaches expected performances

V. Case Studies

We consider the two following case-studies for our experiments.

A. Use-case#1 : A new environment exploration

We consider in this first use-case (Fig. 7) the possible moves of an elderly person in her macroscopic environment. 99% of the time, this person is either located at home (yellow circle) or run errands (blue circle). While the person remains inside this cycle (pink cycle), no new device are discovered in her environment and the system knowledge remains stable but potentially incomplete. Then, exceptionally, this person has to visit a friend (green circle). Once in her friend's environment, new devices are discovered contributing at enriching the system knowledge and potentially incrementing the initial incomplete knowledge. Back to the traditional move cycle, the newly added knowledge may leads the system to better assist the person.

B. Use-case#2 : Search for energy-efficient devices

In this case study the system searches for energy-efficient appliances for playing a music track. The environment initially

comprises the following appliances: an Android tablet and a hi-fi system installed in the living room.

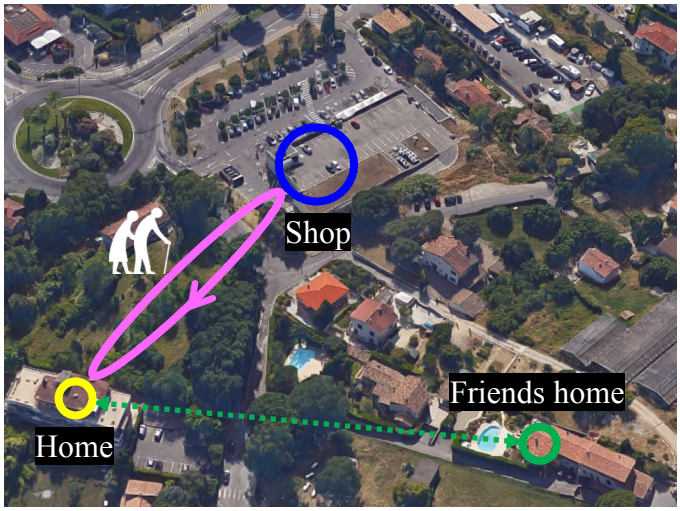

Fig. 7. : Elderly person displacements scheme

These appliances embed devices allowing them to be monitored and controlled by the system. Devices provide semantic annotations describing: (1) the appliance power consumption (as a data property), (2) some terminological concepts about their domains. The problem occurring in the context of searching for energy-efficient devices instances from the available knowledge is that using the appliance power consumption property and an arbitrary trigger may lead to inaccurately discriminate the devices…

Let's consider now that the inhabitant install a new electric meter in the environment. This electric meter brings new knowledge about the energy classification for home appliances that can be based, for instance, on the European Union energy label[1]. This new knowledge is brought in the form of SWRL rules defined in the device annotations and enriches the KB upon device discovery. The reasoning engine then infers, for each device instance in the KB, a new property defining the European Union energy label from the initial power consumption property. It permits to more efficiently search for device instances based on a parameter making sense in the domain of the energy consumption.

VI. Evaluations and Results

The previously described scenario has been tested using the CONTINUUM platform[2] enhanced thanks to the contribution presented in this paper. WComp middleware [17], for service composition by assembling light components, is at the heart of this platform. It implements the SLCA model (Lightweight Service Component Architecture) [7] where the application is formed with an assembly of software components based on the LCA model (Lightweight Component Architecture) and services communicating using events. A functional interface giving access to the functional services is exported. This platform is based on UPnP (Universal Plug and Play). Like DPWS (Device Profile for Web Services), this protocol allows to dynamically manage devices (discovery and disappearance) and registration to the proposed services. This platform is coupled with Conquer knowledge base [18] built on top of Jena API. This knowledge base has been encapsulated in a web service for device (Universal Plug and Play, UPnP) and enhanced with Pellet reasoning engine [19] able to infer on SWRL rules and some real time ontology metrics monitoring capabilities. Using the aforementioned platform, composite web services have been created for each device, exposing an interface allowing the knowledge base to retrieve the semantic annotations upon device discovery. The annotations are written following the RDF/XML format.

A. *Use-case#1 : A new environment exploration*

1) *Dataset selection*

To the best of our knowledge, there is currently no dataset

Location	Device	Classes	Axioms	Degradation
Home	Boiler	100	453	0%
Home	Clock	13	69	43.44%
Home	Computer	24	124	0%
Home	Cooker	48	109	73.28%
Home	DeepFreezer	48	105	76.87%
Home	DishWasher	38	110	75.22%
Home	Fan	24	124	0%
Home	Oven	109	489	0%
Home	Printer	24	124	0%
Shop	CoffeeMaker	24	124	0%
Shop	Computer	13	58	53.22%
Shop	DeepFreezer	100	454	0%
Shop	Entertainment	11	30	75.80%
Shop	Fan	2	4	96.77%
Shop	Fridge	44	73	85.45%
Shop	Printer	11	49	60.48%
Friend	**Clock**	24	122	0%
Friend	Computer	2	4	96.77%
Friend	**Cooker**	88	408	0%
Friend	**DishWasher**	97	444	0%
Friend	Entertainment	24	124	0%
Friend	Fridge	109	502	0%
Friend	Oven	26	67	86.29
Friend	WashingMachine	110	490	0%

TABLE I. Each device, through semantic annotations brings a local ontology describing its domain (potentially incomplete)

available on the web applicable to validate the proposed approach. Instead, most of the works are relying on a comprehensive ontology at a basis to describe all the knowledge for a given domain. Since ontology engineering is a time consuming task necessitating expertise to ensure knowledge modeling coherency, we have used DogOnt ontology [20] rev 3.2.11 describing 926 concepts and containing 9383 axioms. This ontology is general enough to be used in a wide range of domains. The dataset is then created by fragmenting the ontology into sub-ontologies defining and structuring all the knowledge necessary to fully

[1]http://en.wikipedia.org/wiki/European_Union_energy_label

[2]Project for service continuity in ubiquitous and mobile computing - French national research agency - ANR-08-VERS-0005.

describe some devices. Then, from each sub-ontology, are generated a set of degraded sub-ontologies (see Table 1) containing a subset of the device complete knowledge. Using this approach has permitted to elaborate a comprehensive electrical appliances dataset used to get reproducible measures while keeping the control on the fragmentation and degradation rates. From multiple local ontologies approaches standpoint, this experimental dataset assumes that linked data and alignment engine perfectly smooth the semantic heterogeneity appearing when dealing with ontologies independently developed.

2) Results

Results are exhibited in the Fig. 8. After having discovered all devices in the usual environment of the elderly person (1), the system knowledge (blue curve) remains flat as long as the person does not come out of this environment (2). The person visits her friend and new devices are discovered in this new environment (3). The newly added knowledge is made persistent in the system when the person is back to home (4). New knowledge has been added on the clock, the cooker and the dishwasher appliances (Table 1). This leads the system to potentially improve the relevancy of devices to be used in concert and then better assist the elderly person in her everyday life.

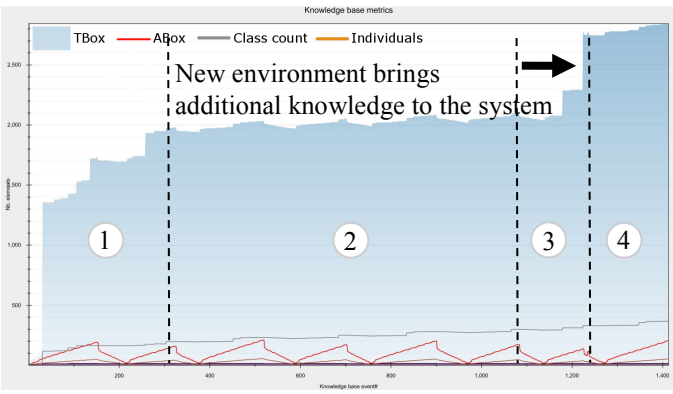

Fig. 8. : Use-case execution results

B. *Use-case#2 : Search for energy-efficient devices*

1) Dataset selection

For this use-case, we have developed simple heterogeneous ontologies describing the concepts for a Hi-fi system and an Android tablet along with a power consumption property (Fig. 9 and Fig. 10).

The electric meter ontology defines SWRL rules allowing to classify the devices based on their power consumption. For instance, the following rule infers that devices with a power consumption property value in between 1W and 10W are classified in category "A":

```
Device(?d), integer[>= 1 , <= 10](?c),
has_power_consumption(?d, ?c) ->
has_consumption_category(?d, "A")
```

1) Results

Following the use-case described in section V.B, two devices are first added in the environment: (1) an Android tablet with 8W power consumption, (2) a Hi-fi sound player with 28W power consumption. Those devices are then discovered and

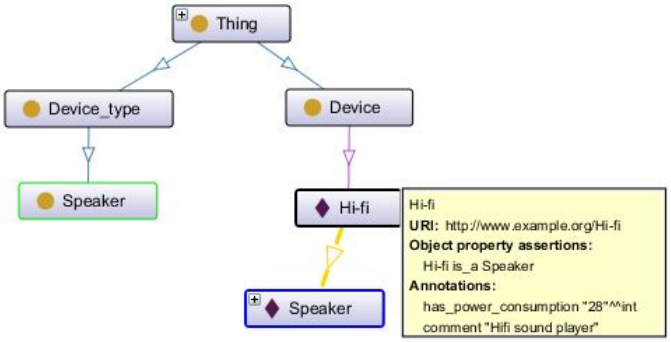

Fig. 9. : Hi-fi device ontology

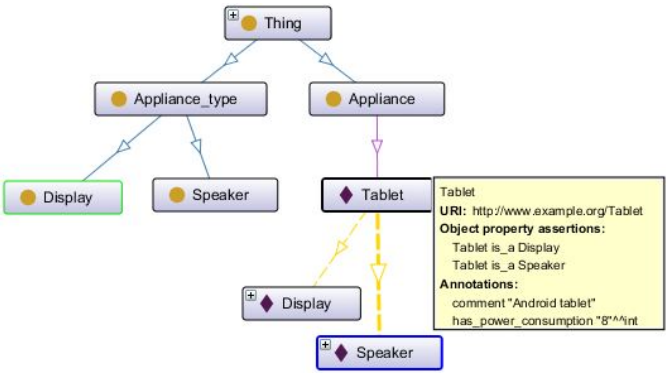

Fig. 10. : Tablet device ontology

their semantic annotations are used to enrich the KB. The alignment engine links "`Appliance*`" and "`Device*`" concepts together (`owl:equivalentClass`). We consider that only the Android tablet is relevant to play a music track with the lower power consumption. At this point, a query is executed to retrieve "Speaker" type devices with a power consumption lower than 30 watts (arbitrary chosen value):

```
SELECT ?d ?c
WHERE
{
?d rdf:type core:Device .
?d core:is_a core:Speaker .
?d core:has_power_consumption ?consumption .
?d rdfs:comment ?c .
FILTER (?consumption < 30)
}
```

With the previous query, both devices are returned:

```
?device = Tablet
?comment = "Android tablet"
?device = Hi-fi
?comment = "Hifi sound player"
```

An electric counter device is added bringing new knowledge about the energy classification for home appliances that can be based, for instance, on the European Union energy label. This new knowledge is added in the form of SWRL rules. A new query can be executed to show up the inference engine execution results (inferring the property "has_consumption_category"):

```
SELECT  ?c ?p ?j
WHERE
{
?i core:has_power_consumption ?p .
?i rdfs:comment ?c .
?i core:has_consumption_category ?j
}
```

The newly created property allows to classify the devices power consumption under term and values making sense in the power consumption domain:

```
?c = "Hifi sound player"
?p = "28"^^xsd:int
?j = "C"
?c = "Android tablet"
?p = "8"^^xsd:int
?j = "A"
```

We are now able to slightly modify the previous query into a more relevant one exploiting the newly added property:

```
SELECT ?d ?c ?category
WHERE
{
?d rdf:type core:Device .
?d core:is a core:Speaker .
?d core:has consumption category ?category .
?d rdfs:comment ?c .
FILTER (?category = "A"^^xsd:string)
}
```

Thanks to the added knowledge, the most relevant device is now the only one selected:

```
?d = Tablet
?c = "Android tablet"
?category = "A"
```

VII. Related works

Several projects aimed at using semantic annotations to leverage semantic web technologies providing the system a formal knowledge understanding of the devices along with querying and reasoning techniques. However, most of the approaches relies on specific and static knowledge models to qualify the devices.

In [21] authors have defined layered ontologies defining a common ontology from which semantic annotations can be defined and deployed on devices. The authors highlight the need for a standardization committee and the need, for the manufacturers to develop their device ontologies based on the defined vocabulary. As it is a good solution from an interoperability standpoint, it doesn't allow the ontology evolution and, in SWoT context, it is unlikely that such a standardization could occur. Many other projects relies on *ad-hoc* ontologies specific to domain like smart offices [24], smart homes [25], ambient assisted living [26], sensors [27],[28] , smart cities [29], etc…

Some projects make use of heterogeneous ontologies. For example, in the context of ambient intelligent environments (AIEs), ATRACO project [6] is built around agents exchanging data between each other. This project is still based on an upper ontology but allows software agents to independently and locally describe and rely on their own ontology. While an ontology alignment engine is developed to cope with the semantic heterogeneity issue at run time, it still offers no perspective for the upper ontology to capitalize the contribution of agents' local ontologies over time.

In [22] authors expose some challenges relative to SWoT domain. One of the identified challenges, is the ability, for the smart products, to be able to learn new emergent knowledge. But authors have been focused on emergent knowledge brought from user's interactions and feedbacks (user's preference learning) or from wiki pages, not from devices knowledge contributions. In [23] authors address the problem of gathering knowledge in order to improve user's interactions with smart products. They propose to use semantic annotations to enrich smart products workflows aimed at defining tasks and participants in several contexts. Authors highlight the problem of the domain ontologies shipped with smart products that have to be enriched over time with the knowledge about user's environment and interests. They consider possible changes at the ontology level (ontology extension) and the instance level (ontology population). The instance level described here corresponds to the knowledge base level. While the authors motivate the need of such knowledge evolution, no automatic mechanism is proposed for the enrichment other than manual.

VIII. Conclusion and perspectives

Semantic web technologies are gaining interest in the WoT (Web of Things) community for their ability to manage the increasing semantic heterogeneity between devices. Thus, by qualifying the devices with semantic annotations relying on a knowledge model, the systems have now the ability to understand and reason about it.

While most of the approaches rely on specific and static knowledge models to qualify the devices, we presented in this paper, the assessment and the design of a knowledge model management approach aimed at: (1) handling devices semantic heterogeneity and, (2) by capitalizing the knowledge contributions throughout the life of the system, at allowing the system knowledge to be enriched over time permitting to better assist people in their environment. This approach can then be integrated in a services composition mechanism [30] in order to improve the selected services relevancy.

However, as the knowledge increases, it is unlikely that the knowledge base content can indefinitely increase. As devices are embedded in everyday life objects, and considering their low available computational resources, limitations may occur in space (system memory limitation) and time (query processing time). A tradeoff will have to be found in between

handling the semantic heterogeneity, the intrinsic system capabilities (CPU, memory) and the user experience (query processing time). Also, care will have to be taken on the data validity over time (obsolescence management).

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