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Knowledge Based Decision Support Systems: A Survey on Technologies and Application Domains

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Abstract. Knowledge-Based Decision Support Systems (KBDSS) have evolved greatly over the last few decades. The key technologies underpinning the development of KBDSS can be classified into two categories: technologies for knowledge modelling and representation, and the technologies for reasoning and inference. This paper provides a review on the recent advances in the two types of technologies, as well as the main application domains of KBDSS. Based on the examination of literature, future research directions are recommended for the development of KBDSS in general and in particular to support group decision making.

Keywords: DSS, KBDSS, Intelligent DSS, knowledge modelling and representation, reasoning and inference, application domains.

1 Introduction

Decision support Systems (DSS) are developed to support decision makers in their semi-structured tasks and appeared in the 70's. The first architecture proposed by [1] was composed by: (1) A model base management system; (2) A data base management system; (3) A human-computer interface.

In order to develop systems the most usable possible, in the 1990s, DSSs were enriched by techniques rooted in Artificial Intelligence, particularly the introduction of a knowledge base into the architecture previously described, so as to give the system the capacity for reasoning. This approach is an Expert Systems type approach, for which the modes of reasoning and the problem to be solved are modeled first and then used on a machine by way of inference engines. This approach leads to develop Intelligent DSS or also called Knowledge Based DSS.

According to [2] the components of a DSS can usually be classified into five distinct parts:

- A database management system and the associated database: which stores, organizes, sorts and returns the data relevant for a particular context of decision making;
- A model base management system and the associated model base: which has a similar role to the database management system, except that it organizes, sorts and stores the organization's quantitative models;

- The inference engine and the knowledge base: which performs the tasks relating to recognition of problems and generation of final or intermediary solutions, along with functions relating to the management of the process of problem solving;
- A user interface: which is a key element in the functions of the overall system;
- A user: who forms an integral part of the process of problem solving.

Thus, in the architecture of these systems, we see the emergence of a technological part drawn from Artificial Intelligence, integrating knowledge modeling into the problem to be solved. The advantage to this architecture lies in the emphasis placed on reasoning in the taking of the decision, and supported by tools such as knowledge-based systems.

The idea of this work is to study the evolution of Knowledge Based DSS (KBDSS) in recent years on several criteria. We studied 29 papers in order to define what are the most used: technologies for knowledge modelling; technologies for reasoning as well as what are the principal application domains. The methodology used to select the papers include four key steps: (1) An initial search was conducted with “ISI Web of Science”. Keywords used for the initial search were “knowledge base”, “reasoning” and “decision support system” and we refined the search by selecting the Science Technology and Social Science in order to eliminate results from arts and humanities. The search is further refined by restricting to the period of 1990-2013. We believe that 1990 is an appropriate starting point for research in KBDSS. We used the “knowledge base”, “reasoning” and “decision support system”, because they have been used as keywords in most cited articles on the subject and to obtain the most complete results possible. (2) Then, on the basis of a thematic analysis of the abstracts of the selected papers, we eliminated those which did not address “knowledge base” or “reasoning” in relation to decision support systems. We also did a cursory reading of the articles we eliminated to be sure that they were out of scope of our literature review. (3) We added five papers that were not included in ISI searching results from two well known journals in DSS area: International Journal of Decision Support Systems Technology, and Journal of Decision Systems. (4) We complemented our selection adding three books widely cited in DSS field. The final selection includes 29 references as analyzed in this literature review.

This paper is organized as follows. After this introduction, in a second part we draw a survey of technologies used for first knowledge modeling and second reasoning. In the third part, we present the main application domains for which KBDSS are successfully designed. The fourth part is devoted to finding the relationships among the used technologies, the application domains. These relationships are then used in order to present some recommendations for KBDSS design. In the last section we propose a conclusion.

2 Survey on Technologies

In order to analyze these papers, we define several criteria. We firstly distinguish two criteria based on the used technologies, which are the used technology for knowledge modelling and then used technologies for reasoning implementation.

2.1 Technologies for Knowledge Modelling

We firstly must distinguish the technologies used for knowledge modelling. We distinguish two kinds of knowledge representations: **clustering** and **ontology**.

The clustering techniques consists in dividing the knowledge in different classes or knowledge classification. Similar rules are represented in the same cluster and distinct clusters of rules are formed using representatives. Several papers use this kind of techniques [3], [4], [5]. These authors assume that time is gaining when dealing with large knowledge base. We noticed from these authors that the future direction can be asked in the following question: When a cluster is formed of several rules, a couple of them will be fully relevant to the question, most of them are only partially relevant, how to increase the relevance?

The ontology modelling technique consists in capturing consensual knowledge, i.e. not personal view of the target phenomenon but one accepted by a group; ontology is not just about presenting information to humans but also processing the information and reason about it. Some works have been conducted on ontology engineering process for which the following steps are proposed: feasibility study, kick-off, refinement, evaluation, maintenance. From the following authors [6], [7], [8], [9] several perspectives have been drawn along the following two axes: a. Clear understanding of how to build ontologies in a systematic way and b. Building fuzzy rules into ontology.

The two main knowledge representations consist in clustering and ontologies. Nevertheless, the considered knowledge can divide three kinds or levels: a. **contextual knowledge**; b. **content knowledge** and c. **unstructured knowledge**.

About contextual knowledge, [10] proposed a review paper in which the context of knowledge is seen through the DSS environment, such as clinical setting, knowledge states of the patients and physicians, and emotions; case-based reasoning suited for capturing contextual knowledge.

From the content knowledge we saw two sub-levels of knowledge: a. medical knowledge; b. organizational knowledge. For the medical knowledge, this kind of implementations have been studied in several works and medicine is the main application domain of KBDSS (for this point see section III.a.). On the other hand ([9] proposed a model of organizational knowledge in the K4Care project.

[11] proposed to develop a model for unstructured knowledge based on narratives documents for which Knowledge resided in client's records and stories.

Some other authors propose to exploit this knowledge through data mining techniques in order to elicit knowledge from explicit data sources [6] or to discovery new knowledge [3]. In order to achieve this objective this paper presents several techniques of learning methods for example lazy learning based on explanation-based learning and that does not cover all the space of known examples and eager learning.

All these modelling technologies are then used by inference engine in order to produce new pieces of knowledge or solutions to a problem. We propose in the next section a classification of reasoning or inference technology based on the same 29 papers.

2.2 Technologies for Reasoning

We distinguish five reasoning or inference technologies: Rule-based reasoning (**RBR**), Case-based reasoning (**CBR**), Narrative-based reasoning (**NBR**), Ontology-based reasoning (**OBR**) and Genetic Algorithms (**GA**).

About the Rule-based reasoning technology, several kinds of rules modelling are used: Traditional RBR; Logical Elements Rule Method for assessing and formalizing clinical rules; Rule verification to ensure high quality of guidelines encoded in KBDSS in the form of rules: redundancy, inconsistency, circularity, incompleteness. This technology is predominant and is used in the following systems implementation [3], [4], [5], [12], [13], [14], [15], [16]. From these papers the following future directions of implementation are drawn to Belief RBR (vagueness, incompleteness, non-linear relationships) and fuzzy rule-based.

The Case-based reasoning technology relies on past and similar cases to find solutions to new problems; it is a kind of implementation of a sort of automatic ranking of past lessons and making available best practice cases. Five steps are distinguished in the process of Case-based reasoning: interpretation, retrieval, reuse, revise, retain. The following authors have implemented KBDSS based on CBR [6], [17]. The following trends are drawn for CBR: extensive application of ontologies to improve the use of the domain from past experiences and diminish impasse situations.

[11] proposes a Narrative-based reasoning KBDSS. This system deals with unstructured narrative information. The objective is to share experience and lessons learned for decision making through stories and narratives. For this system an NBR algorithm comprises three key modules: key concept extraction, similarity analysis, and association analysis. For this implementation the author proposes as future work to measure the similarity among the key concepts in order to have a more precise determination on the similarity analysis and association analysis.

([8] and ([9] propose to implement the reasoning technology for KBDSS through Ontology (Ontology-based technology). Knowledge is implemented through ontology navigation. The K4Care project provides a Case Profile Ontology from a formal representation of all the healthcare concepts and relationships and constraints between concepts, related to the care of chronically ill patients. This project then implements a medical DSS reasoning loop. These authors precise that future ontology will include restrictions on the interactions among intervention plans with the purpose of extending the DSS with mechanisms to compare treatments.

[13] proposes a KBDSS based on Genetic algorithm. He implemented a co-evolutionary genetic algorithm for detecting gamma ray signals: 5 layer hierarchy – input layer, condition layer, rule layer, consequence layer, output layer are distinguished.

Independent of the used implementation technologies, KBDSS are developed for several kinds of application domains. These application domains are described in the following section.

3 Survey on Application Domains of KBDSS

Based on the 29 papers reviewed, the application domains of the KBDSS can be classified into four main areas: medicine, manufacturing, environmental management and others. The applications in medicine are predominant.

3.1 Medicine

The application of knowledge-based systems in Medicine started in early 1970s. Since then, KBDSS has been extensively explored to support decision making in all aspects of medicine because of the fact that medical conditions are highly diverse, fast changing and sometimes unpredictable. This section presents the recent advancements of KBDSS in medicine decision making to support medical tasks, including clinical, management (treatment) and follow-up, in particular,

- clinical diagnosis to improve the accuracy of analysis of conditions and adaption of evidence-based standard intervention plans to the conditions [3], [7], [8], [15], [12], [18];
- clinical pathways to standardize medical activities and thereby improve healthcare quality ([5];
- clinical risk assessment to help reduce medical errors and patient safety incidents and thus reduce the healthcare service costs caused by patient safety incidents [14];
- medication review to improve medication usage, leading to reductions in drug-related problems and potentially savings on healthcare system costs [19];
- home care assistance to support the management of complex distributed healthcare systems ([9];
- mental healthcare for offering timely and quality services so as to maintain the health of the community [11]; and
- finally, it is worth noting that a guest editorial provides a good overview of KBDSS application to health sciences ([10], [17].

3.2 Manufacturing Production Scheduling and Process Optimization

A second main domain that KBDSS has been widely explored is manufacturing including process design and optimization, production planning and scheduling, supply chain and logistics. Manufacturing industry requires support from KBDSS because of a number of reasons: (1) The central role and importance of the manufacturing activities in the value chain. Manufacturing holds the key to delivering high quality products and services to customers on time and with cost competitiveness. Customers will not be willing to pay if there are no products and services to satisfy their requirements. (2) The need for knowledge support from experts and professionals. Manufacturing practices have been existed for hundreds of years which have built up rich experience and best practices in the form of declarative knowledge or procedural knowledge. Sharing, reusing and learning from the vast amount of knowledge developed over time are crucial for continuous improvement of business performance. (3) The high complexity of manufacturing decision situations, including not only the products and the supply chains but also the materials and the market. To make a good manufacturing decision will require knowledge support from the whole value chain, i.e. to bring knowledge from the upstream chain originating about the raw materials and the downstream chain reaching out to final customers and market. Plenty of research has investigated capturing and structuring manufacturing knowledge for business process and reasoning mechanisms for knowledge based

systems in the area. An earlier review on intelligent manufacturing systems can be found in [20]. Recent development on a knowledge-based multi-role decision support system for process optimization in steel making classified manufacturing knowledge in three distinguished categories: public knowledge, rule sets and boundary values [16].

3.3 Environmental Management

The use of knowledge based systems has been proven to be a suitable approach to supporting decision making in environmental systems, especially in the management of water and waste water. Water pollution is an important issue in urban and industry-dominated basins. This section looks at a specific type of environmental issue through waste water systems. The complexity of an urban waste water system lies in the fact that it consists of a number of inter-connected parties such as industries, households, the sewer system, the waste treatment plant and the river. Capturing the huge amount of data and information from the various sources and providing knowledge that can be shared between the various parties has been a challenge for adopting KBDSS in water management practices. Recent research highlighted the importance of using knowledge-based approaches in waste water management decision support systems, in terms of knowledge about the processes, possibilities of improvement and innovation to be effectively revealed, pooled and distributed among all parties involved in the process of industrial wastewater discharges [6], [21].

3.4 Others

Some other applications of KBDSS are scattered around various interesting domains, for example in detecting gamma ray signals in the universe [13] and road safety with the application to car driving [22].

4 Relationships among Application Domains and Used Technologies

The previous sections looked at the used technologies in KBDSS and their application domains separately. This section presents the relationships between different technologies and that between the technologies and application domains. Recommendations on developing future KBDSS are subsequently provided.

4.1 Relationships

As discussed in section 2, there are two main types of technologies in relation to KBDSS: technologies for knowledge modelling and representation, and technologies for reasoning and inference. Main application domains of KBDSS are discussed in section 3. The relationships among the technologies and applications are illustrated in Figure 1. This Figure is generated based on the elicitation of internal relationships existing between different elements (such as clustering and ontology) within each

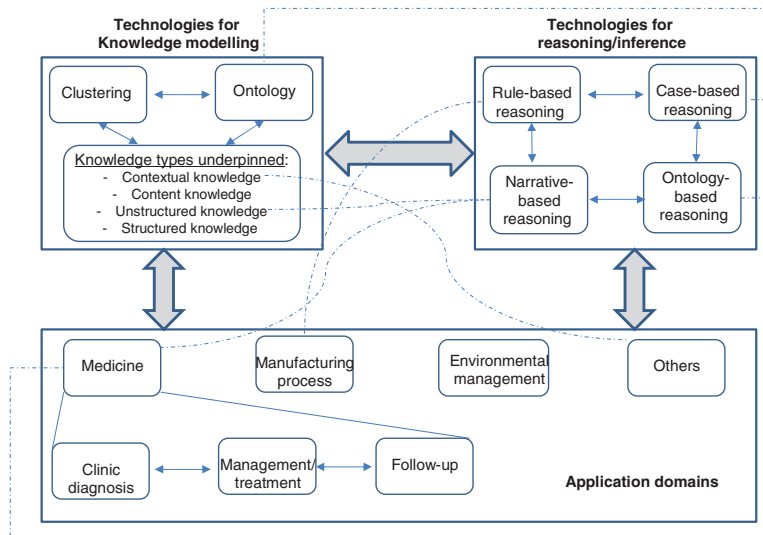


Fig. 1. Relationships among technologies and applications

component (such as modelling technologies) and the external relationships between the three components (i.e. modelling technologies, reasoning technologies and applications).

As shown in the Figure 1, the three blocks in the relationship chart are technologies for knowledge modelling, technologies for reasoning and inference, and the application domains. Three types of relationships can be elicited. Type I relationships are the internal links between elements within the same block and represented by thin solid arrows. For example, links between clustering and ontology, as well as the links between different clinic diagnosis, treatment plan and follow up decisions [5]. Type II relationship are external links between different blocks, such as links between modelling and reasoning technologies. These types of relationships are represented by solid block arrows. For a KBDSS to properly function in any domain areas, it has to be created using appropriate both knowledge modelling and reasoning technologies [8], [9]. Type III relationships are cross links among elements in different blocks which are represented by dashed thin lines. For example, the links from ontology technology through ontology-based reasoning to medical application domain demonstrate that specific knowledge representation technology such as ontology needs particular reasoning mechanism and fits particularly well in medical application, because of the nature of medical decision situation with high variety, high dynamics and unpredictability [8]. Understanding the different types of relationships within, between and across different blocks will help us to justify and choose the right technologies for the development of knowledge base and reasoning mechanisms for the right application domain. Please note that not all links are illustrated in the Figure to keep the Figure clean enough to be legible.

4.2 Recommendations

Based on the examination of the KBDSS technologies and application domains, certain challenges and trends have been observed for future research directions from two perspectives: KBDSS development in general and in particular to support group decision making.

Challenges and recommendations for future KBDSS development in general:

- Even though ontology has been well researched as a means of capturing knowledge and modelling knowledge structure, building a moderately sized ontology in a KBDSS is still a time consuming task. One challenge lies in the acquisition of domain-specific terminology and relationships from a conceptual model. To meet the challenge, ontology learning is emerging to discover ontological knowledge from various forms of data automatically or semi-automatically [23]. Key elements of ontology learning include information extraction, ontology discovery and ontology organization. It is hoped that the advancement of relevant technologies such as cluster analysis may shed lights on identifying the relationships between terms applicable to the domain knowledge. Ontology learning is certainly in its infancy and requires more research in the future in order to support the creation of better KBDSS.
- Even individual reasoning technologies such as rule-based reasoning, case-based reasoning, narrative-based reasoning and ontology-based reasoning have matured and been tested in real-world applications, there is a trend that a combination of different technologies need to be investigated in order to remedy the limitations of a single technology. For example, a commonly accepted limitation of rule-based reasoning is its scalability, i.e. when the total number of rules in the knowledge base increases, the time needed to infer also considerably increases [4]. However, this drawback can be rectified by a combination use of rule-based reasoning together with clustering technology, i.e. by clustering similar rules to form distinct clusters of rules, the time needed for inference can be greatly reduced. Apart from the speed, accuracy has been an important issue to most reasoning technologies. Future research should spend more effort in verifying knowledge [24], for example the rules in the knowledge base should be validated by experts. The need for the knowledge verification becomes even more critical in clinical KBDSS since a single piece of incorrect or inaccurate knowledge could result in a dangerous or wrong recommendation in turn could cause harm or safety issue to patients [12]. A third challenge for reasoning technologies is how to incorporate the uncertainty of knowledge in KBDSS. Recent research has shown that by integrating existing rule-based reasoning or case-based reasoning with fuzzy logic and artificial networks can enhance the reasoning performance in terms of uncertainty [5], which should remain as a hot topic for future research. Finally, because of the intrinsic nature of incompleteness of knowledge, neither domain knowledge nor contextual knowledge is static or complete, as knowledge itself evolves all the time and we would never have complete knowledge of a decision problem or solution at a time. In parallel, reasoning technologies to infer new knowledge based on exiting knowledge captured in the knowledge base should address this issue of evolution [13].

- In terms of application domain, there is plenty of opportunity to explore KBDSS in new industries and sectors other than the domains reviewed in this paper. Inside the medicine domain, future research needs to better address the integration of knowledge from various healthcare stakeholders such as doctors, nurses, patients, carers and the community, so that more coherent healthcare services can be provided across various activities including clinic diagnosis, treatment, home care, community support, and follow up actions [10]. In the manufacturing domain, knowledge about customer and markets, product design and production, as well as maintenance and end-of-life treatment should be integrated in the knowledge base, and the KBDSS should enable the smooth flow of knowledge across the supply chain to foster the emerging knowledge chain management technologies [25].

Recommendations for the development of KBDSS in group decision making:

Decision makers have to work together in group decision making context, therefore a group decision support system (GDSS) emphasizes on both the use of communications and collaborations as well as decision models [24]. KBDSS supporting group decision making has to address knowledge sharing between the group decision makers. It has been well acknowledged that the difficulty of knowledge sharing lies with the sharing of tacit knowledge, especially when decision makers come from very different background and confusing terms (such as business intelligence, enterprise information portal, communities, groupware, knowledge management and knowledge network) are being used simultaneously. When plenty of knowledge-based intangibles (including people's abilities, professional knack, trade secrets, routines – unwritten rules of individual and collective behavior patterns) are floating around the group, but the contextual knowledge is not well defined, it would cause great cognitive burden to decision makers [26]. To address the above issues, existing research has investigated and proposed solutions to the development of interactive learning environment to encourage knowledge transfer across disciplines, use of overlapping teams and joint learning. Further research is needed to develop typologies that can facilitate more effective sharing of tacit knowledge by integrating core elements including trust and care, leadership charisma, knowledge culture, concept ba and social network analysis [27]. By developing the typology and adopting it into KBDSS, the right communication and collaboration infrastructure will be provided to support knowledge flow in group decision making. So far, there is very little research published to address the knowledge modelling and reasoning mechanisms that are particularly suited to foster communication and collaboration to support group decision making, even though some knowledge artefacts as tools have been developed for collaborative user-driven design [28]. Plenty of opportunities exist for future research in integrating mature knowledge modelling and reasoning technologies into functioning KBDSS that can support group decision making scenario, especially in real world decision practices such as in medicine, manufacturing, environmental management and other real decision cases. As a first step, we suggest that new knowledge modelling and reasoning technologies that aim to support group decision making should seriously consider more coherent methodologies such as knowledge chain management and multi-stakeholder approaches.

5 Conclusions

This review paper focuses on the recent development on relevant technologies and application domains of knowledge-based decision support systems (KBDSS). It complements a number of recent survey papers in the literature which were focused on specific, related areas, such as the integration of knowledge based-systems and DSS [29] ontology engineering [23], and contextual knowledge in medical CBR systems [10]. However, this paper brings together knowledge modelling technologies, reasoning and inference technologies together with applications domains, by eliciting the links across different technologies and application domains. Therefore, this paper extends the review to a much broader picture and provides a synergistic view of KBDSS with more complex composition. Recommendations for future research are provided for the development of future KBDSS in general and in particular to support group decision making.

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