Ontology-based multi-agent system to support business users and management

Dejan Lavbič, Olegas Vasilecas and Rok Rupnik

Abstract

For some decision processes a significant added value is achieved when enterprises' internal Data Warehouse (DW) can be integrated and combined with external data gained from web sites of competitors and other relevant Web sources. In this paper we discuss the agent-based integration approach using ontologies (DSS-MAS). In this approach data from internal DW and external sources are scanned by coordinated group of agents, while semantically integrated and relevant data is reported to business users according to business rules. After data from internal DW, Web sources and business rules are acquired, agents using these data and rules can infer new knowledge and therefore facilitate decision making process. Knowledge represented in enterprises' ontologies is acquired from business users without extensive technical knowledge using user friendly user interface based on constraints and predefined templates. The approach presented in the paper was verified using the case study from the domain of mobile communications with the emphasis on supply and demand of mobile phones.

Keywords

Decision support, agent, multi-agent system, ontology, data warehouse, information retrieval, business rules, business process management

1   Introduction

There is a growing recognition in the business community about the importance of knowledge as a critical resource for enterprises. The purpose of knowledge management is to help enterprises create, derive, share and use knowledge more effectively to achieve better decisions, to increase of competitiveness and to decrease the number of errors. In order to run business effectively an enterprise needs more and more information about competitors, partners, customers, and also employees as well as information about market conditions, future trends, government policies and much more. There are several products and technologies available on the market that support advanced Business Process Management (BPM) (Trkman et al., 2007) and advanced decision support. Enterprises expect these applications to support wide range of functionalities - analysing customer profiles, building and analysing business strategies, developing customer-specific products, carrying out targeted marketing and predicting sales trends. Amount of documents in the Web, enterprise data repositories, and public document management systems with documents are rapidly growing. This huge amount of data is managed in some extent, but knowledge workers, managers, and executives still have to spend much of their working time reading dozens of various types of electronic documents spread over several sources in process of making decisions. There is just too much information to digest in a daily life. The tremendous amount of documents that is still growing has far exceeded the human ability for comprehension without intelligent tools. Different applications within information systems (IS) that support wide range of functionalities need to be integrated in order to provide the appropriate level of information support. One of

the prominent approaches for IS integration is the use of ontologies and Multi-Agent Systems (Fuentes et al., 2006; Soo et al., 2006; Dzemydiene and Tankeleviciene, 2009).

The approach presented in this paper is targeted towards using ontologies for several tasks, where emphasis is on using business rules (BR) approach for interoperability between business user and IS. By introduction of BR approach business users do not have to be fully familiar with the technology to manipulate the common understanding of a problem domain in a form of ontology and therefore enabling agents to execute defined analyses models. The use of ontologies in Multi-Agent System (MAS) environment enables agents to share a common set of concepts about contexts, user profiles, products and other domain elements while interacting with each other. Agents can exploit the existing reasoning mechanisms to infer derived contexts from known contexts, to make decisions and to adapt to the environment, current status, and personal setting of the user. The purpose of this paper is to present the approach of integration of several information resources for Decision Support in Enterprises using agent-oriented approach based on ontologies. The goal of our research is to minimize the gap between business users and agents as special type of application systems that perform tasks in their behalf. The intention was to apply BR approach for ontology manipulation in MAS. Ontology used in our Multi-Agent System for Decision Support in Enterprises (DSS-MAS) was divided into task and domain ontologies while business users were enabled to manipulate them directly in a user friendly environment without requirement of detailed technical knowledge.

The remainder of this paper is structured as follows. First we present some background in the following section 2 with emphasis on agents, ontologies and related work with clear definition of the problem and solution proposal. Next, in section 3, we introduce our case study of integrated Multi-Agent environment from the domain of mobile communications with emphasis on architecture and the roles of agents and ontologies. The case study is focused in one of the mobile operators and furthermore oriented to supply and demand of mobile phones. After presentation of system architecture and decomposition of ontology of every agent from DSS-MAS will be presented in detail. Details of case study implementation will be given in section 4. Finally the last section 5 presents conclusions.

2   Some background on decision support, multi-agent systems and ontologies

Decision support systems (DSS) have evolved significantly and there have been many influences from technological and organizational developments (Shim et al., 2002). DSS once utilized more limited database, modelling, and user interface functionality, but technological innovations enabled more powerful DSS functionality. DSS once supported individual decision makers, but later DSS technologies are applied to workgroups or teams, especially virtual teams. The advent of the Web has enabled inter-organizational DSS and has given rise to numerous new applications of existing technology as well as many new decision support technologies themselves. Internet facilitates access to data, information and knowledge sources, but at the same time, it threatens to cognitively overload the decision makers. Authors in (Vahidov and Kersten, 2004) claim that internet technologies require a new type of decision support that provides tighter integration and higher degree of direct interaction with the problem domain. Based on that they propose a generic architecture for dynamic and highly complex electronic environments where DSS's should be situated in the problem domain. Chen et al. (2001) conducted an interesting research about integrated interactive environment for knowledge discovery from heterogeneous data resources. Their work is grounded on acquiring, collecting, and extracting relevant information from multiple data sources, and then forming meaningful knowledge patterns. The proposed system employs common DW and OLAP[1] techniques to form integrated data repository and generate database queries over large data collections from various distinct data resources.

Multi-Agent Systems (MAS) offer a new dimension for cooperation and coordination in an enterprise. The MAS paradigm provides a suitable architecture for a design and implementation of integrated IS, especially DSS. With agent-based technology a support for complex IS development is introduced by natural decomposition, abstraction and flexibility of management for organisational structure changes (Kishore et al.,

---

[1]OnLine Analytical Processing (OLAP)

2006). The MAS consists of a collection of autonomous agents that have their own goals and actions and can interact and collaborate through communication means. In a MAS environment, agents work collectively to solve specific enterprises' problems. MAS provide an effective platform for coordination and cooperation among multiple functional units in an enterprise. The research on agents and MAS has been on the rise over the last two decades. The stream of research on IS and enterprise integration (Lei et al., 2002; Kang and Han, 2003; Tewari et al., 2003) makes the MAS paradigm appropriate platform for integrative decision support within IS. Similarities between the agent in the MAS paradigm and the human actor in business organisations in terms of their characteristics and coordination lead us to a conceptualisation where agents in MAS are used to represent actors in human organizations. Several approaches (Tewari et al., 2003; Rivest et al., 2005; Kishore et al., 2006; Soo et al., 2006) deal with agent support for integration and decision support. Research in (Kishore et al., 2006) has shown that MAS paradigm provides an excellent approach for modelling and implementing integrated business IS. Authors within that research proposed a conceptual framework for MAS based integrative business IS. Some promising results were also found in (Soo et al., 2006), where authors propose a cooperative MAS platform to support the invention process based on the patent document analysis. The platform allows the invention process to be carried out through the cooperation and coordination among software agents delegated by the various domain experts in the complex industrial R&D environment.

Today, semantic technologies based on **ontologies** and inference are considered as a promising means towards the development of the Semantic Web (Davies et al., 2006). In the field of Computer Science and Information Technology (IT) in general ontology has become popular as a paradigm for knowledge representation in Artificial Intelligence (AI), by providing a methodology for easier development of interoperable and reusable knowledge bases (KB). The most popular definition, from an AI perspective, is given in (Gruber, 1993) as follows: "An ontology is an explicit specification of a conceptualization", where a conceptualization is abstracted view of the world that we wish to represent for some purpose. Ontologies can be considered as conceptual schemata, intended to represent knowledge in the most formal and reusable way possible. Formal ontologies are represented in logical formalisms, such as OWL, which allow automatic inferencing over them. An important role of ontologies is to serve as schemata or intelligent views over information resources. Thus they can be used for indexing, querying, and reference purposes over non-ontological datasets and systems, such as databases, document and catalogue management systems. Because ontological languages have a formal semantics, ontologies allow a wider interpretation of data that is inference of facts which are not explicitly stated. In this way, they can improve the interoperability of the conceptualization behind them, their coverage of arbitrary datasets. Ontology can formally be defined as specific sort of knowledge base and can be characterized as comprising a 4-tuple (Davies et al., 2006)

$$O = \langle C, R, I, A \rangle \tag{1}$$

Where C is set of classes representing *concepts* we wish to reason about in the given domain (`Offer`, `Finding`, `Phone`, `Customer`, etc.). R is set of *relations* holding between those classes (`Message hasRecipient Actor`). I is a set of *instances*, where each instance can be an instance of one or more classes and can be linked to other instances by relations (`Nokia is A PhoneBrand; Finding309 hasValue 11,23`). A is a set of *axioms* (`If a new customer buys is A Nokia E72, promotional discount of 10% should be offered`). It is widely recommended that knowledge bases, containing concrete data (instance data or ABox) are always encoded with respect to ontologies, which encapsulate a general conceptual model of some domain knowledge, thus allowing easier sharing and reuse of KBs. Typically, ontologies designed to serve as schema for KBs do not contain instance definitions, but there is no formal restriction in this direction. Drawing the borderline between the ontology (i.e. the conceptual and consensual part of the knowledge) and the rest of the data, represented in the same formal language, is not always trivial task. In our approach we include instances as part of ontologies because instances we define are a matter of conceptualization and consensus and are not only descriptions, crafted for some purpose.

Related work on using ontologies in information systems for decision support is extensive. Regarding the domain of DW and OLAP analyses research has dealt with Document Warehousing (Tseng and Chou, 2006) where extensive semantic information about the documents is available but still not fully employed as in traditional DW. The use of ontologies was found useful as a common interpretation basis for data and metadata. Furthermore research has extended to Web DW (Marotta et al., 2002) with the emphasis on

managing the volatile and dynamic nature of Web sources. Utilization of ontologies is also addressed in Information Retrieval (IR) where it has been used for fuzzy tagging of data from the Web (Buche et al., 2006; Macias and Castells, 2007), query construction tool in semi-automatic ontology mapping (Suomela and Kekalainen, 2006) and semantic based retrieval of information from the World Wide Web (Shan et al., 2003; Garces et al., 2006). Use of ontologies in Data Mining (DM) has also been considered in (Bernaras et al., 1996; Zhou et al., 2002; Singh et al., 2003; Cao et al., 2004) where ontology was used for representation of context awareness and handling semantics inconsistencies. Ontologies have been widely used for data, application and information integration in the context of domain knowledge representation (Qiu, 2006). Jovanović and Gašević (2005) concludes that the need for knowledge sharing and interoperable KBs exists and the key element for achieving interoperability are domain ontologies. In that approach XSLT[2] transformation is used to enable knowledge interoperability. Authors in (Vasilecas and Bugaite, 2006) use ontologies for ontology based IS development and they address the problem of automation of information processing rules. There are also other approaches (Fuentes et al., 2006; Orgun and Vu, 2006; Clark and McCabe, 2007) that use ontologies as knowledge representation mechanisms. Authors in (Clark and McCabe, 2007) use a formal ontology as a constraining framework for the belief store of a rational agent. The static beliefs of the agent are the axioms of the ontology, while dynamic beliefs are the descriptions of the individuals that are instances of the ontology classes. Another work presented in (Fuentes et al., 2006) also uses heterogeneous domain ontology for location based IS in a MAS framework with the emphasis on context-aware MAS. They propose a global ontology to let agents work with heterogeneous domains using a wireless network and the intention is to provide customization about different environment services based on user location and profile.

2.1 Problem and proposal for solution

The review of related work presented in this section pointed out that modern DSS's changed quite substantially especially with the advent of the Web and availability of extensive information in online repositories. For managing complexity and integration issues with decision support many approaches relied on MAS paradigm and used ontologies as knowledge representation mechanism. The existing approaches mainly focused on either supporting existing business processes or improving decision support at some level of detail or integration of several structured resources to achieve better decision support. To our knowledge none of the approaches addressed the problem of enriching data from internal data sources with unstructured data found on internet. The interactivity of reviewed solutions is also limited; meaning that business users are usually limited to small set of parameters they can define to alter default behaviour of the system. These user requirements are usually entered directly into the system and no abstraction layers are provided as in business rules management systems (BRMS) to enable users without technical skills to manipulate the content.

This paper introduces a novel approach in integration of unstructured information found in the Web with information available in several internal data sources (e.g. database, DW, ERP[3], etc.). The MAS paradigm with agents was used for implementation purposes, mainly because related work pointed out that it is a very appropriate solution for integration of business IS. One of the reasons to choose agents is also modelling notion where business users and agents are modelled in a very similar manner. Problem of interaction between human actors and computer programs is also addressed by introduction of ontologies as knowledge representation mechanism. The approach presented in this paper is targeted towards using ontologies for several tasks, where emphasis is on using BR approach to ensure interoperability between business user and IS. Ontology is used not only for every agent to represent the interpretation of a problem domain but also for communication between agents and business users. The use of ontologies in MAS enables agents to share a common set of facts used in user profiles, product descriptions and other domain elements, while interacting with each other. With exploiting reasoning mechanisms new findings can be derived from initially known facts and improve the KB by extending it with new knowledge. To simplify this communication template system based on BR was introduced to enable manipulation of knowledge within the system by users with less technical skills and to control behaviour of individual agent. The approach will be further explained in the following section. The case study presented in this paper is from the domain of mobile telecommunications.

---

[2]XSLT (XSL Transformations) is a declarative, XML-based language used for the transformation of XML documents into other XML documents

[3]Enterprise Resource Planning (ERP)

It is presented in detail (with the impact it has on improving decision support within enterprise) in section 4. In the domain of mobile communications that was used for case study we had to define several tasks in DSS-MAS, needed for decision support - OLAP analyses, DM, IR, context and profile definition, notification, etc.

3 DSS-MAS

3.1 DSS-MAS architecture

DSS-MAS that we propose in this paper is introduced in Figure 1. The case study presented in this paper is from the domain of mobile telecommunications and is based on business environment and information resources from one of the mobile operators. DSS-MAS is situated in the environment of several existing systems, like Data Mining Decision Support System (DMDSS), or DW and various resources available outside of an enterprise on the World Wide Web. Global goal that agents in DSS-MAS should achieve is to support decision making process while using existing systems for business analysis and employing information from environment where enterprise resides. To support this goal DSS-MAS includes several agent roles that are as following: **Data Mining Agent (DMA)**, **OLAP Agent (OLAPA)**, **Information Retrieval Agent (IRA)**, **Knowledge Discovery Agent (KDA)**, **Notifying Agent (NA)** and **Mobile Agent (MA)**. The agents in DSS-MAS have both reactive and proactive characteristics. Reactive are mainly due to responding to the environment according to the model defined in the KB they use. Proactive are due to their ability to learn from the environment and change the initially defined KB to for example improve performance. Ontologies are used as a main interconnection object for domain knowledge representation, agent-to-agent communication and most important for agent-to-business user communication. An important element of an environment is the World Wide Web, where agents acquire information for the purpose of decision making. Retrieved information is saved in a KB and available for further employment for DM and DW analyses. All information gathered from internal and external sources is considered by KDA, where inference over several task ontologies used by individual agents (DMA, OLAPA, IRA, etc.) is performed. Moreover the sub goal of DSS-MAS is delivering of the right information at the right time and to the right users. The system needs to be context aware and to consider the relevant features of the business, i.e. context information such as time, location, and user preferences (Liao et al., 2005). Business users in DSS-MAS are able to employ agents to perform tasks on their behalf. For example, managers in enterprises have to request reports from their systems - OLAP or from transactional databases, and managers have to review reports every appointed period of time (day, week, month, etc.). This task of information acquisition is predecessor for decision making and is more or less straightforward - business user sends a request for analyses and reviews the content according to some Key Performance Indicators (KPI). KPI is simply a measure of performance and is commonly used in enterprises to evaluate how successful they are. In DSS-MAS tasks like this are automated and user participation is reduced as much as possible. An initial analysis model (e.g. OLAP or DM) has to be captured in the ontology by business users, while execution and optimisation is left for agents. Business users first define initial parameters for analyses to be performed, while agents perform these analyses and recommend improvements. When some action is required from business user, he is notified and has the ability to act or change rules of agent's execution.

To enable these functionalities we introduce ontologies as a mediation mechanism for knowledge exchange between actors (agents and business users) that cooperate in DSS-MAS. The following section will present the structure and organization of ontologies we have used for the case study.

3.2 The role of ontology

According to Guarino (1998), ontology can be structured into different sub-ontologies - upper ontology, domain ontology, task ontology and the application ontology. Following similar guidelines we have defined upper ontology named **Common ontology** and combined domain and task ontologies in **Notifying ontology**, **Information retrieval ontology**, **Data Mining and Warehousing ontology** (see Figure 2). The
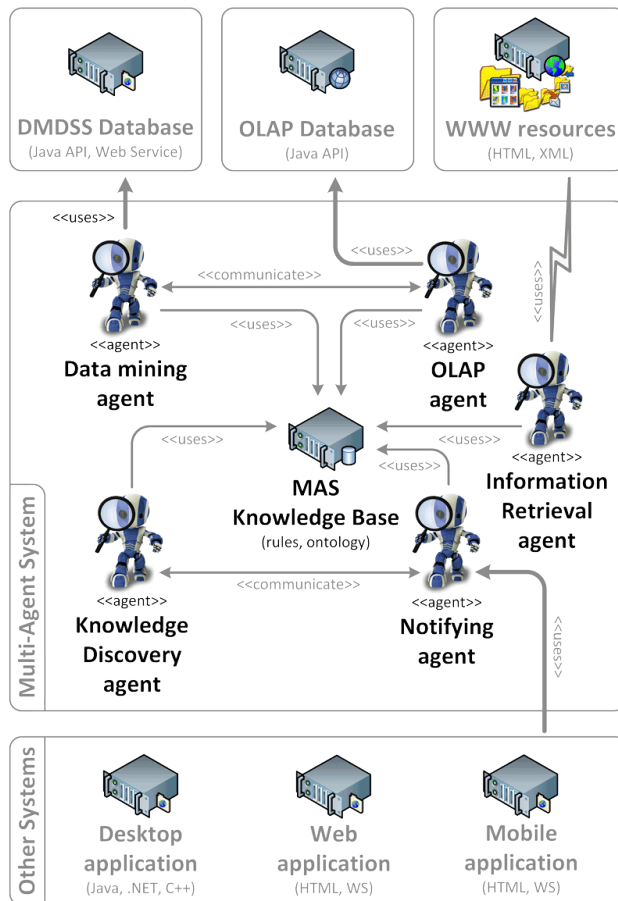
Figure 1: Architecture of MAS used for Decision Support in Enterprises

proposed clustering of ontologies is based on the common understanding of the problem domain being defined in Common ontology. Every agent has its own interpretation of a KB, which is a specialization of a Common ontology with detail definition of knowledge required by individual agent. Common ontology is limited to abstract concepts and it covers reusable dimensions, which are primarily used by KDA. Task ontologies specify concepts of notification, IR, DM and DW. Mobile communications in our case is the domain of all task ontologies and the emphasis is on supply and demand of mobile phones. As already mentioned, we have used the knowledge management approach in our research where every agent has knowledge about its own problem domain. In this case whenever new facts about the common knowledge are discovered, which might be of interest for other agents, they are updated to the common ontology.

The role of ontology in our approach is therefore twofold:

- knowledge representation mechanism used by agents and
- common understanding of problem domain used for communication between business users and agents by utilizing business rules manipulation with introduced templates (see section 4.2).

Figure 2 shows an excerpt from intersection of several ontologies used in our case study. This part of ontology clearly defines the common elements being used for communication between agents and business users (domain specific elements such as phones, new phones and customers, all described with domain specific characteristics). A part of OLAP elements needed for conducting OLAP analyses is also presented. Ontology also presents notification with taxonomy of various warning levels and business users classification by organizational unit and decision making level.

3.3 The role of agents

Our case study uses domain of mobile telecommunications as a platform where we focus on the sales of mobile phones and their accessories. Manipulation with internal data storage is handled by two types of agents - OLAPA and DMA. They both have distinct tasks but still share common goal – periodically or on demand autonomously execute analyses models. Business users at first define these models and describe them with all required parameters (e.g. search for anomalies in sales of Nokia phones in last month period). The information about the execution is stored in the ontology (based on business user preferences) or is requested by another agent of the system. Business user preferences in this context define the execution parameters about the analysis, for example the period at which the analysis is performed (e.g. perform analysis every other day at 13:00). OLAPA has on firsthand straightforward task of performing OLAP analyses on behalf of an agent or a business user and reporting its findings back to the requesting entity and all other entities that should be informed, according to the business policy. Nevertheless OLAPA does much more - after each execution it prepares the report for business user based on findings – movements and KPIs. If certain finding is substantially different from finding obtained in previous case further analysis is performed to discover the reason of change by drilling down (more detailed) or up (less detailed) the hierarchies and levels.

The knowledge is acquired in ontology. Business users can change the behaviour of agents by changing the ontology using graphical user interface. This interface incorporates all logical restrictions defined in ontology and does not allow users to enter unacceptable values and the most important is that it does not require technical knowledge from users. Previous our experiences have shown that business users have great difficulties especially with setting the parameters required to run DM and DW analyses models. So, user interface really has to be friendly and intuitive. In our approach this issue was solved by introducing the architecture depicted in Figure 3 and using templates as further discussed in section 4.

Nowadays Web-based information retrieval systems are widely distributed and deeply analysed from different points of view. The main objective of all such systems is to help users to retrieve information they really need (obviously as quickly as it is possible) (Garces et al., 2006). While the techniques regarding DW, multi-dimensional models, OLAP, or even ad-hoc reports have served enterprises well, they do not completely address the full scope of existing problems. It is believed that, for the business intelligence (BI) of an enterprise, only about 20% of information can be extracted from formatted data stored in relational databases (Tseng and Chou, 2006). The remaining 80% of information is hidden in unstructured or semi-structured documents. This is because the most prevalent medium for expressing information and knowledge is text.
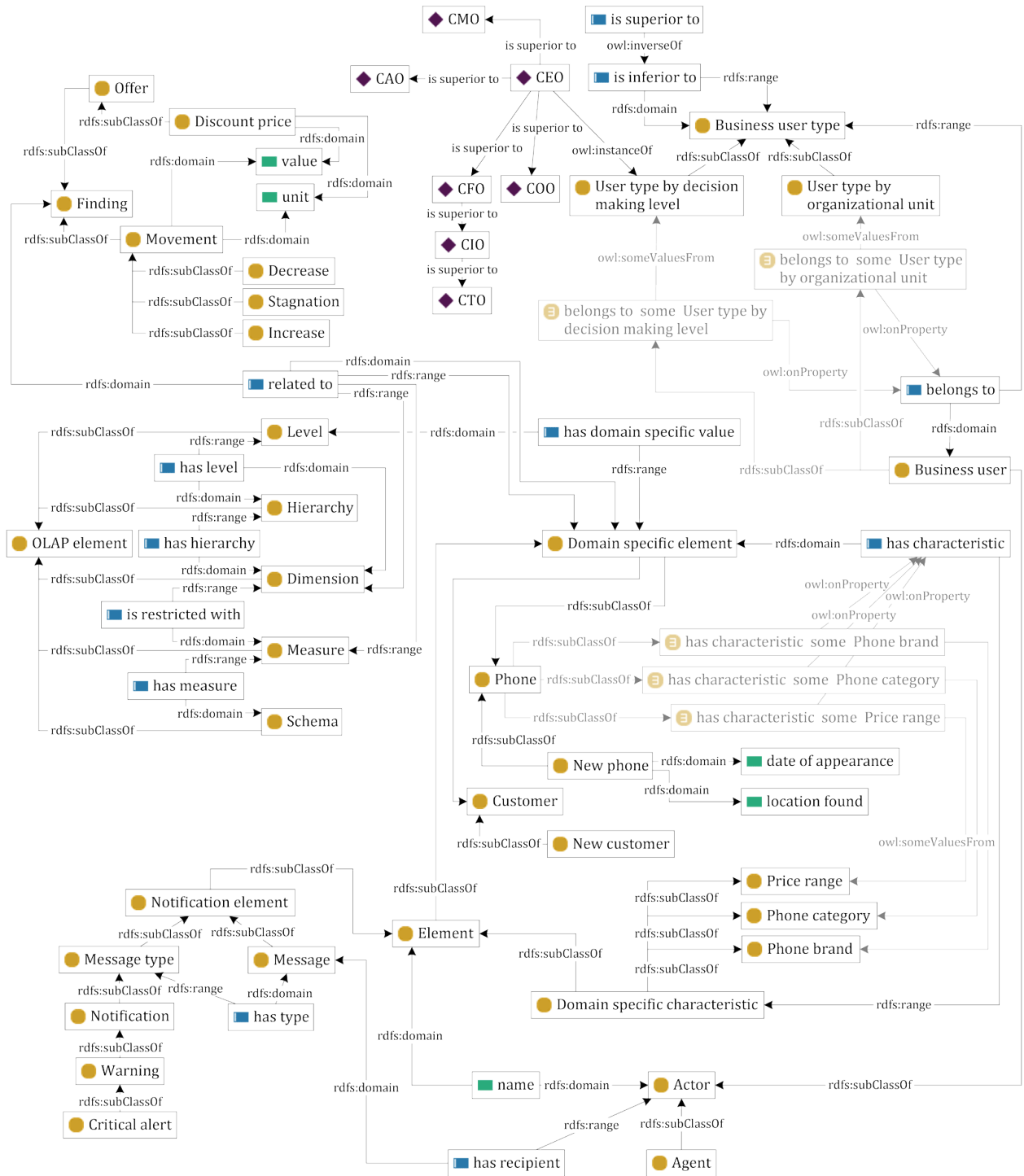
Figure 2: Excerpt from intersection of several ontologies used in our case study
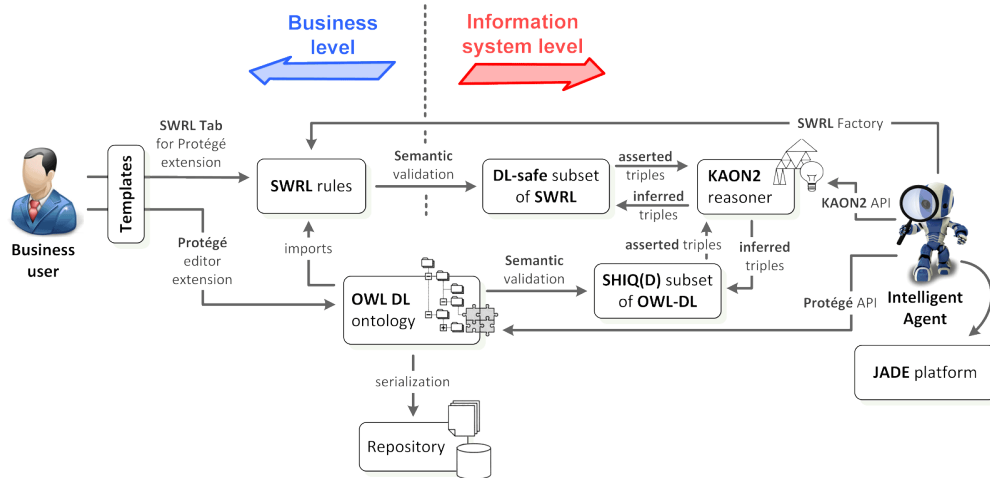
Figure 3: Prototype of selected case study

For instance, market survey reports, project status reports, meeting records, customer complaints, e-mails, patent application sheets, and advertisements of competitors now are all recorded in documents. For that reason in DSS-MAS we introduced IRA for retrieval of data mainly from the World Wide Web. The tasks that IRA performs in presented case study can be grouped into three categories:

- identification of new online shops,
- analysis of mobile phones presented online and
- extending Data Warehouse with information found online.

First two tasks are concerned about the supply of mobile phones at various online shops worldwide. Identification of new online shops is conducted with web crawling and the use of several existing services on the Internet, such as Google, Google Product Search and Bing. Not only these internet resources are managed through ontology, but also rules for text extraction are defined as rules which make all domain knowledge available in IR ontology and not encoded in agent itself. More details about implementation of DSS-MAS case study can be found in section 4. Furthermore every shop found online is analysed to identify unique patterns for searching phones. Search patterns include guidelines for agents performing search at various web pages. They are based on XQuery[4] and regular expressions. To search for phones at Google Products Search, the following URL search pattern `http://www.google.com/products?q=((\w+\s*)+)` is used, accompanied with additional information for web scrapping of required information (e.g. price, availability etc.). Using these search patterns IRA is searching through online shops and determines phones with their market prices and stores this information into IR ontology to be available for further knowledge inference by KDA. Information of found phones is used to determine new market trends, enable price comparison between competitors, facilitate possible inclusion in enterprise's sales program, etc. One of the tasks that IRA also performs is extending DW with information found online. While business users perform OLAP analyses, they deal with only internal information about the business, but in process of decision making other resources also have to be examined, e.g. news about the suppliers and competitors, opinions about certain products and organisations, etc. IRA therefore scans the DW dimension data (through hierarchies and levels) from DW dimensional schema and uses this information for searching several internet resources (news archives, forums, stock changes, Google trends, etc.). When users review OLAP reports these data from the Internet is also displayed according to their restrictions in dimensions. For example, when business users are making decision whether to increase support to Nokia or Sony Ericsson phones it only has reports about sales of selected brand names from their market program. Using our approach the user is provided with additional data that is found online and what will make decision better founded. By this integration of internal and external information users have integrated data source available that they can query from single location.

---

[4]XQuery is a query language that is designed to query collections of structured and semi-structured data

KDA is an important element of DSS-MAS since it consolidates all findings from IR, DM and DW and furthermore delivers derived findings to NA. To employ inference capabilities over several ontologies the enterprises' BR are essential. While business concepts are captured in ontology, these concepts further have to be restricted to define specific meaning. Generally BR are prepared by business users and also some parts of BR in enterprises tend to change frequently; therefore we introduced architecture for BR management (see Figure 3 and further discussion in section 4). Findings of KDA are presented as instances of `Domain-specific-element` and `Findings` classes (see ontology in Figure 2).

As it can be seen from Figure 1 NA represents an interface to DSS-MAS for all external applications and business users. The main role of NA is the information dissemination by simply delivering the right information at the right time to the right users. While in vast majority of today's applications users have to request the information using so called "pull model" in our approach we implemented the "push model", where information is proactively delivered by agents to the user without a specific request. This is achieved by making system context aware and considering the relevant features of the business, i.e. context information such as time, location, position in the organisational hierarchy, etc.

All knowledge about notification is defined in Notifying ontology, where every user has his own context defined and the position within organisation across two dimensions - organisational unit (e.g. Marketing, Sales, Human resources, etc.) and decision making level (e.g. Chief Executive Officer (CEO), Chief Information Officer (CIO), Chief Financial Officer (CFO), Chief Marketing Officer (CMO), Chief Analytics Officer (CAO), etc.). According to that position rules for delivery of several message types are defined. These message types range from Notification to Warning and Critical alert. Each message also addresses the domain of specific organisational unit, e.g. when a new mobile phone is found online at competitor's website, CMO and CAO have to be notified. Organisational structure, as part of Notifying ontology, also defines that both CMO and CAO are inferior to CEO therefore he is also notified, but only in a case of a Critical alert. According to the business user profile, notification can be sent using several technologies from Windows Alert, e-mail, Really Simple Syndication (RSS), Short Message Service (SMS), etc. These notification types are also ordered by priority for each business user and according to this type the content is also adapted.

Mobile agent is an example of an application that can reside on a mobile device (e.g. Personal Digital Assistant (PDA), mobile phone, etc.) and uses resources of DSS-MAS through NA. The typical use case includes sending mobile agent across network to DSS-MAS, where all needed information according to owner context is collected and then the mobile agent is returned back to originating location on a mobile device and presents the collected data to business user. When the process of acquiring data is in progress, business user does not have to be connected to the network, he can just wait offline until mobile agent is ready to return with the findings.

In the following section details about the case study implementation will be presented with technologies used, templates for business rules acquisition and presentation of one specific scenario from case study.

4 Case study implementation and discussion

4.1 Technology

The selected language for ontology presentation is OWL DL (Russomanno and Kothari, 2004), since it offers the highest level of semantic expressiveness for selected case study and is one of the most widely used and standardised ontology language nowadays that has extensive support in different ontology manipulation tools. Besides OWL logical restrictions, Semantic Web Rule Language (SWRL) rules were also used due to its human readable syntax and support for business rules oriented approach to knowledge management (Horrocks et al., 2005). SWRL rules are stored as OWL individuals and are described by OWL classes contained in the SWRL ontology. The use of SWRL enables storing schema, individuals and rules in a single component, which makes management much easier. SWRL rule form in a combination with templates that is introduced in the following subsection b is very suitable for knowledge formalization by business users that do not have extensive technical knowledge.

The ontology manipulation interface for business users is based on Protégé Ontology Editor and Knowledge Acquisition System (Stanford Medical Informatics, 2006a) and SWRL Tab (Stanford Medical Informatics, 2006b) for Protégé. It enables entering OWL individuals and SWRL rules where a step further is made towards using templates for entering information (see Figure 3). At the execution level KAON2 inference engine is used to enable inference capabilities. Due to limitation of $SHIQ(D)$ subset of OWL-DL and DL-safe subset of SWRL language, before inference is conducted, semantic validation takes place to ensure that all preconditions are met. We selected FIPA[5] compliant MAS platform JADE[6] in DSS-MAS because it offers broad range of functionalities and is most widely used platform. This is due to very good support and availability of agent framework, where a lot of common agents' tasks are already implemented (i.e. agent communication at the syntax level, agent management, migration of agents, etc.). For Mobile Agent implementation an add-on JADE-LEAP[7] was used to support the mobility of agents.

4.2 Mediation with BR templates

Using templates with ontology, business logic is excluded from the actual software code whereas the majority of data for templates is acquired from ontology axioms and natural language descriptions in ontology, while other templates are prepared by users with technical knowledge. The main goal of using mediation with BR templates is to enable acquiring knowledge from actual knowledge holders i.e. business users and enable transformation of this high-level knowledge into information system level, where this data together with concepts from business vocabulary can be directly used for inference purposes and bring added value without any further programming by technically educated users.

When acquiring new knowledge into the system from business users, the process always starts with focusing on concepts of business vocabulary that are persisted in a form of ontology. Users can freely traverse through this information space, select concepts and further manipulate all related information within the selected context. Altering and adding new information is all time limited to formal definition of concepts that is defined in ontology. For easier manipulation business user is aided with template and business vocabulary, so BR building process is simplified as it will be presented in detail in the following section.

Example 4.1 presents a BR template that is used for definition of aggregation of findings or domain specific elements. The user interface that is available is directly linked to ontology, where constraints on classes, properties and individuals are considered in realtime. This approach allows to minimize the risk of entering wrong constraints. The DSS-MAS system supports entering of new statements in several forms from simple IF-THEN form to decision table or decision tree.

Example 4.1 (BR template for general finding definition)**.**

> **IF**
>> Condition $= \{\exists x : x \in$ **Domain specific element** $\cup$ **Finding**$\} \wedge |$Condition$| \geq 1$
>
> **THEN**
>> Result $= \{\exists y : y \in$ **Finding**$\} \wedge |$Result$| \geq 1$

The following Example 4.2 represents a BR that states: `If there exist two consequent increases of sold phones of the same phone brand and a new phone of this phone brand was found online within last 2 weeks, then offer a promotion discount of 10% on this new phone to all new customers.`

---

[5]Foundation for Intelligent Physical Agents (FIPA)

[6]Java Agent DEvelopment Framework (JADE)

[7]Java Agent Development Environment-Lightweight Extensible Agent Platform (JADE-LEAP)

Example 4.2 (Example of a rule, developed by using template)**.**

> **IF**
>> First finding is **Increase (Finding)** which {
>>> is **related to** <u>first amount sold</u> which is **Measure (OLAP element)** AND
>>> is **related to** <u>first date</u> which is **Dimension (OLAP element)** AND
>>> is **related to** <u>first phone</u> which is **Phone (Domain specific element)** which {
>>>> has **characteristic** <u>brand</u> which is **Phone brand (Domain specific characteristic)**
>>> }
>> } AND
>> Second finding is **Increase (Finding)** which {
>>> is **related to** <u>second amount sold</u> which is **Measure (OLAP element)** AND
>>> is **related to** <u>second date</u> which is **Dimension (OLAP element)** which {
>>>> is *greater than* <u>first date</u>
>>> } AND
>>> is **related to** <u>second phone</u> which is **Phone (Domain specific element)** which {
>>>> has **characteristic** <u>brand</u> which is **Phone brand (Domain specific characteristic)**
>>> }
>> } AND
>> Found phone is **New phone (Domain specific element)** which {
>>> has **characteristic** <u>brand</u> which is **Phone brand (Domain specific element)** AND
>>> has **date of appearance** <u>found date</u> which is **Dimension (OLAP element)** which {
>>>> is *greater than now - 14 days*
>>> }
>> } AND
>> New customer is **New customer (Domain specific element)**
> **THEN**
>> Promotion discount is **Discount price (Finding)** which {
>> is **related to** <u>new customer</u> AND
>> is **related to** <u>found phone</u> AND
>> has **value** "10" AND
>> has **unit** "%"
> }

When constraint presented in Example 4.2 is transformed to execution form at information system level, standardized SWRL and OWL languages are used to enable reusability (see Figure 4). By this transformation a rule is produced that can be directly used in the inference engine to produce results in a form of inferred triples that are presented to the user.

4.3 Case study

One of the most common cases of using DSS-MAS system is combing information found online with BI reports (DW, DM, IR, etc.) developed on internal data in enterprise DW. Figure 5 presents one of this scenario.

Scenario presented at Figure 5 is triggered by results of IRA activity, when three new mobile phones: `Apple iPhone 3GS`, `Nokia E72` and `Sony Ericsson Xperia 1` are found by IRA at online mobile shops. According
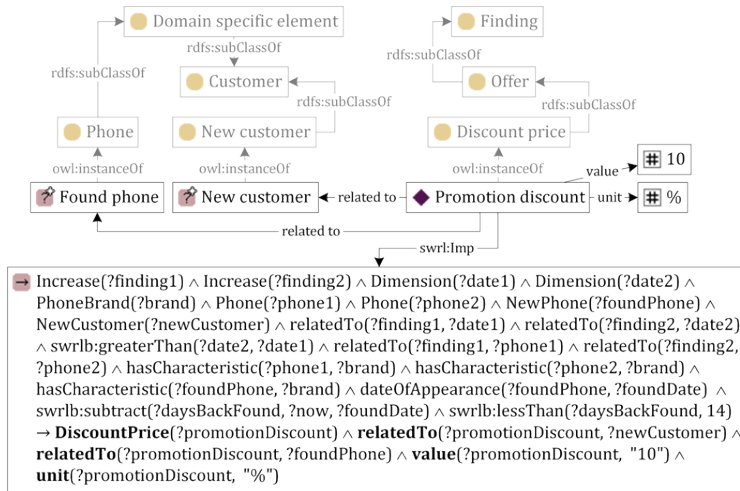
Figure 4: Constraint presented in ontology in SWRL and OWL syntax

to the execution policy from Common ontology, OLAPA is notified with a request to rebuild all DW reports where brands of identified phones can be found in dimension elements. After running OLAP on Sales schema with constrains of Nokia brand in Phone dimension and last year in Date dimension OLAPA creates a report as depicted in Example 4.3.

Example 4.3 (Business Intelligence findings)**.**

[**Phone**] by brand [**Nokia**], by date [**Q1, 2010**] → [**Amount sold**], [**risen by 11, 23%**]

[**Phone**] by brand [**Nokia**], by date [**Last month**] → [**Amount sold**], [**risen by 5, 87%**]

At the information system level the first finding is represented as an excerpt from ontology and is depicted in Figure 6.

The fields that appear in the report are all instances of **Domain specific element**, **OLAP element** and **Finding** from ontology (see Figure 2). After these findings have been asserted, KDA will be executed to derive new knowledge. Based on these new facts represented at Example 4.3 and enterprise business rules (see Example 4.2), the KDA produced results represented in Example 4.4, by using inference engine knowledge is asserted in ontology.

Example 4.4 (Derived finding)**.**

[**New customer**] , [Nokia E72] → [**Promotion discount**], [10%]

After consolidation of all new findings KDA sends message to NA with request to forward notifications to appropriate users. The result of triggered activity of NA is the list of business users that have to be notified about this event. The list shows that in this case CMO and CEO have to be notified whereas their context has to be considered. According to CMO's preferences an e-mail is sent with the following content presented in Example 4.5.

Example 4.5 (Report of findings with explanation)**.**

FACTS

New [**Phone**][**Nokia E72**] is available on the market.

[**Amount sold**] of [**Phone**] by brand [**Nokia**] and by date [**Q1, 2010**] have [**risen by 11, 23%**]

and by date [**last month**] have [**risen by 5, 87%**].

CONCLUSION

[**Phone**][**Nokia E72**] should be offered to [**new customer**] and offered at [**promotion discount**] of [**10%**].
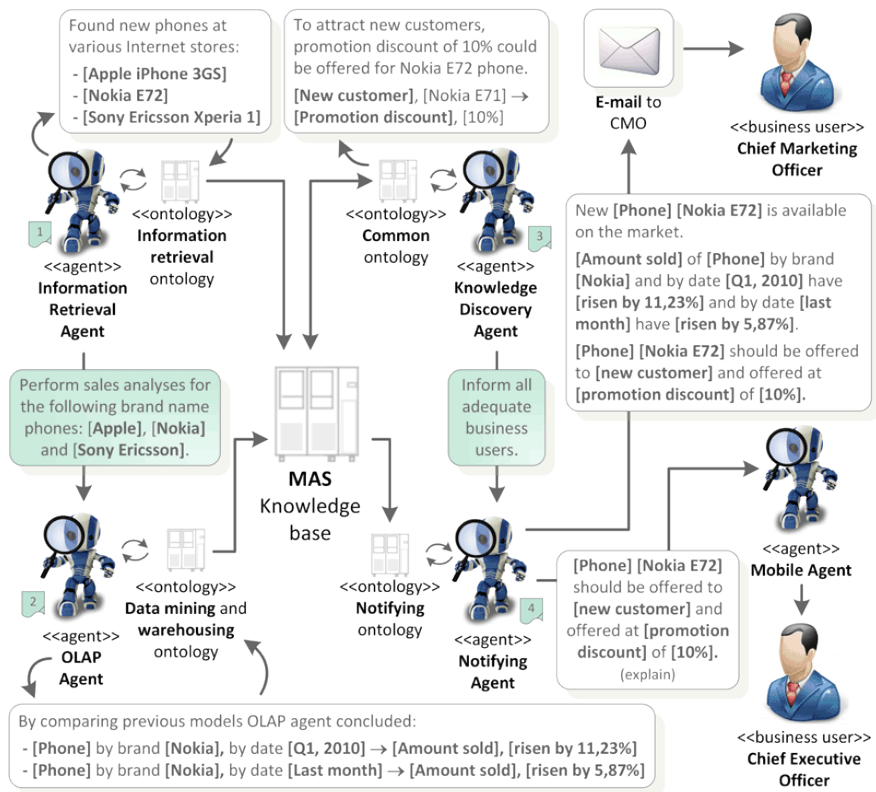
13

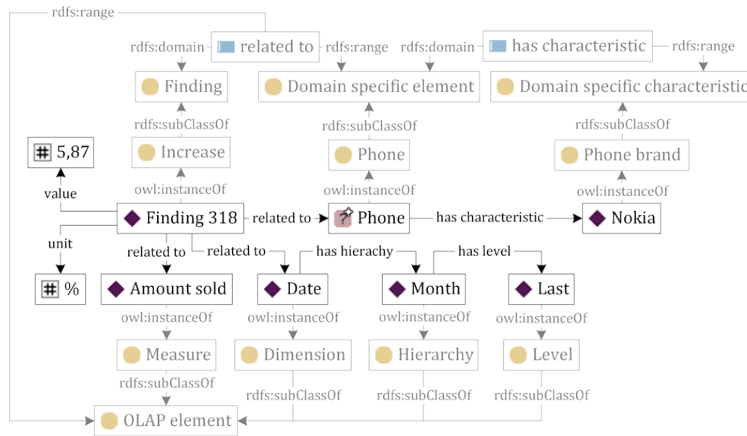Figure 5: Case study of using DSS-MAS in mobile phone domain

Figure 6: Example of representing the finding in ontology

The CEO uses a Mobile Agent on his mobile device and is also notified by a truncated message with new finding, while explanation is available upon request.

5   Conclusion

In this paper we have discussed DSS-MAS where internal and external data is integrated using agent-oriented approach and ontologies as a common understanding of a problem domain and for communication between business users and agents. Agents were used due to their mentalistic notions for modelling, similarities between the agent in the MAS paradigm and the human actor in business organisations, and also possibilities for the use of ontologies as means of agents' internal knowledge base representation. The external information from the Web was integrated by IRA agent with the data in organisation's DW and after applying BR new knowledge was derived by employing agents' inference capabilities. Tasks like information retrieval from competitors, creating and reviewing OLAP reports are autonomously performed by agents, while business users have control over their execution through manipulation of knowledge base. The research also has emphasized agent-to-business user communication, trying to minimize that gap. This was accomplished by introducing different views on ontologies for business user and agent. While agents deal with formal description of business concepts, logical constraints and rules, business user has a simplified view of formal description of knowledge. User is able to manipulate with ontology through templates, where little technical knowledge is required. The mediation mechanism transforms these business level concepts into formal specification at the level of information system.

Presented approach was verified and implemented using a case study from the domain of mobile telecommunications, where the aim was to provide the knowledge worker an intelligent analysis platform that enhances decision making process. The application domain was reduced to its sub domain dedicated for supply and analysis of demand of mobile phones in one of the mobile operators. DW system is constructed from several heterogeneous data sources where majority of those sources are internal to the enterprise. Our approach added information found on the Web (i.e. competitors' offers, stock rates, etc.) to these internal data sources and improved the decision support process within the enterprise. The proposed approach also addressed business users and their communication with the system which was simplified by using templates to define some business requirements that were transformed into analyses models (OLAP, DW, etc.), automatically performed by agents which reported results back to users in charge. The case study presented in the paper was implemented in Java and using mainly open source technologies.

References

Bernaras, A., Laresgoiti, I., and Corera, J. (1996). Building and reusing ontologies for electrical network applications. In *European Conference on Artificial Intelligence (ECAI '96)*.

Buche, P., Dibie-Barthelemy, J., Haemmerle, O., and Hignette, G. (2006). Fuzzy semantic tagging and flexible querying of XML documents extracted from the Web. *Journal of Intelligent Information Systems*, 26(1):25–40.

Cao, L. B., Chao, L., Dan, L., and Li, L. (2004). Ontology services-based information integration in mining telecom business intelligence. *Pricai 2004: Trends in Artificial Intelligence, Proceedings*, 3157:85–94.

Chen, M., Zhu, Q. M., and Chen, Z. X. (2001). An integrated interactive environment for knowledge discovery from heterogeneous data resources. *Information and Software Technology*, 43(8):487–496.

Clark, K. L. and McCabe, F. G. (2007). Ontology schema for an agent belief store. *International Journal of Human-Computer Studies*, 65(7):640–658.

Davies, J., Studer, R., and Warren, P. (2006). *Semantic Web technologies - trends and research in ontology-based systems.* John Wiley & Sons, Chichester, England.

Dzemydiene, D. and Tankeleviciene, L. (2009). Multi-layered knowledge-based architecture of the adaptable distance learning system. *Technological and Economic development of Economy*, 15(2):229–244.

Fuentes, V., Carbo, J., and Molina, J. M. (2006). Heterogeneous domain ontology for location based information system in a multi-agent framework. *Intelligent Data Engineering and Automated Learning - Ideal 2006, Proceedings*, 4224:1199–1206.

Garces, P. J., Olivas, J. A., and Romero, F. P. (2006). Concept-matching IR systems versus word-matching information retrieval systems: Considering fuzzy interrelations for indexing Web pages. *Journal of the American Society for Information Science and Technology*, 57(4):564–576.

Gruber, T. R. (1993). A Translation Approach to Portable Ontology Specifications. *Knowledge Acquisition*, 5(2):199–220.

Guarino, N. (1998). Formal Ontology and Information Systems. In *FOIS'98*, pages 3–15. IOS Press.

Horrocks, I., Patel-Schneider, P. F., Bechhofer, S., and Tsarkov, D. (2005). OWL rules: A proposal and prototype implementation. *Journal of Web Semantics*, 3(1):23–40.

Jovanović, J. and Gašević, D. (2005). Achieving knowledge interoperability: An XML/XSLT approach. *Expert Systems with Applications*, 29(3):535–553.

Kang, N. and Han, S. (2003). Agent-based e-marketplace system for more fair and efficient transaction. *Decision Support Systems*, 34(2):157–165.

Kishore, R., Zhang, H., and Ramesh, R. (2006). Enterprise integration using the agent paradigm: foundations of multi-agent-based integrative business information systems. *Decision Support Systems*, 42(1):48–78.

Lei, Y., Motta, E., and Dominque, J. (2002). IIPS: An Intelligent information presentation system. In *7th International Conference on Intelligent User Interfaces*.

Liao, L. J., Xu, K. Q., and Liao, S. S. Y. (2005). Constructing intelligent and open mobile commerce using a semantic web approach. *Journal of Information Science*, 31(5):407–419.

Macias, J. A. and Castells, P. (2007). Providing end-user facilities to simplify ontology-driven web application authoring. *Interacting with Computers*, 19(4):563–585.

Marotta, A., Motz, R., and Ruggia, R. (2002). Managing source schema evolution in Web Warehouses. *journal of the Brazilian Computer Society*, 8(2):20–31.

Orgun, B. and Vu, J. (2006). HL7 ontology and mobile agents for interoperability in heterogeneous medical information systems. *Computers in Biology and Medicine*, 36(7-8):817–836.

Qiu, R. G. (2006). Towards ontology-driven knowledge synthesis for heterogeneous information systems. *Journal of Intelligent Manufacturing*, 17(1):99–109.

Rivest, S., Bedard, Y., Proulx, M. J., Nadeau, M., Hubert, F., and Pastor, J. (2005). SOLAP technology: Merging business intelligence with geospatial technology for interactive spatio-temporal exploration and analysis of data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 60(1):17–33.

Russomanno, D. J. and Kothari, C. R. (2004). Expressing inter-link constraints in OWL knowledge bases. *Expert Systems*, 21(4):217–228.

Shan, F., Jun, M., Chao, T., and Xu, L. D. (2003). A programmable agent for knowledge discovery on the web. *Expert Systems*, 20(2):79–85.

Shim, J. P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R., and Carlsson, C. (2002). Past, present, and future of decision support technology. *Decision Support Systems*, 33(2):111–126.

Singh, S., Vajirkar, P., and Lee, Y. (2003). Context-based data mining using ontologies. *Conceptual Modeling - ER 2003, Proceedings, Lecture Notes in Computer Science*, 2813:405–418.

Soo, V. W., Lin, S. Y., Yang, S. Y., Lin, S. N., and Cheng, S. L. (2006). A cooperative multi-agent platform for invention based on patent document analysis and ontology. *Expert Systems with Applications*, 31(4):766–775.

Stanford Medical Informatics (2006a). Protégé.

Stanford Medical Informatics (2006b). SWRLTab.

Suomela, S. and Kekalainen, J. (2006). User evaluation of ontology as query construction tool. *Information Retrieval*, 9(4):455–475.

Tewari, G., Youll, J., and Maes, P. (2003). Personalized location-based brokering using an agent-based intermediary architecture. *Decision Support Systems*, 34(2):127–137.

Trkman, P., Štemberger, M. I., Jaklič, J., and Groznik, A. (2007). Process approach to supply chain integration. *Supply chain management - An International journal*, 12(2):116–128.

Tseng, F. S. C. and Chou, A. Y. H. (2006). The concept of document warehousing for multi-dimensional modeling of textual-based business intelligence. *Decision Support Systems*, 42(2):727–744.

Vahidov, R. and Kersten, G. E. (2004). Decision station: situating decision support systems. *Decision Support Systems*, 38(2):283–303.

Vasilecas, O. and Bugaite, D. (2006). Ontology-based information systems development: The problem of automation of information processing rules. In *Advances in Information Systems, Proceedings*, volume 4243 of *Lecture Notes in Computer Science*, pages 187–196.

Zhou, L., Booker, Q. E., and Zhang, D. (2002). ROD - Toward Rapid Ontology Development for Underdeveloped Domains. In *35th Hawaii International Conference on System Sciences*, pages 957–965.

<!– Global site tag (gtag.js) - Google Analytics –> <script async src="https://www.googletagmanager.com/gtag/js?id=UA-1413695-13"></script> <script> window.dataLayer = window.dataLayer || []; function gtag()dataLayer.push(arguments); gtag('js', new Date());

gtag('config', 'UA-1413695-13'); </script>