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Towards Ontology-Driven Approach for Data Warehouse Analysis

Case study : Healthcare domain

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***Abstract*—Understanding, reusing, and maintaining data warehouse resources is a key challenge for data warehouse users. Data warehouses resources are shared by different groups of users. The information interpretation is subjective and depends on user knowledge. Thus, a resource, like a data cube, is interpreted differently from a user to another. Unfortunately, misinterpreting data could induce serious problems and conflicts. To guarantee homogenous interpretation of data warehouse resources additional information are necessary. To tackle these challenges we propose to use ontologies to help the users in the exploitation of data warehouses. In the healthcare domain, this paper proposes an ontology-driven approach to support users to exploit data warehouse. Data warehouse dimensions and facts are semantically enriched by their equivalent domain concepts and related to final resources provided by this data warehouse.**

Keywords- data warehouse; ontology; decision information systems; decision making; healthcare institution management

I. INTRODUCTION

Several surveys proved that big companies need efficient Decision Support Systems (DSS) and seek to expand the number of users over their DSS. To that aim, researchers found that companies need to have flexible decision tools, especially with, users' requirements and domain resources. A DSS is a collection of many tools or applications; we call them in this paper resources; that enable users to analyze, to query and to visualize a huge volume of data. In general, those data are stored in a data warehouse, and a set of Business Intelligence (BI) tools dedicated for data treatment and helping users (directors, managers, analysts, etc.) to make decisions.

Data Warehouse (DW) is the center of the DSS. DW is « a subject oriented, nonvolatile, integrated, time variant collection of data in support of management's decisions» [1]. In this paper we only consider resources provided by a data warehouse in a decision support system. To facilitate the task of DW analysis and treatment, a subset of the DW is created, it is called data mart. A data mart is oriented to a specific business need or a particular user requirement. Most of the times, data mart are organized in a multidimensional structure [2]. Data are represented like a point in a multidimensional space, visualized like a data cube [3], giving to users the possibility to synthetize and analyze data from three (or higher) dimensional array of values and various granularity levels. To manipulate data provided by the DW, end-users could use On Line Analytical Processing (OLAP) technics, classic technics or even dashboards.

Taking user requirements into account is very important for the success or the failure of the DW [4], especially when users belong to different domains. The exploitation level of DW, as well as the preliminary conception level, is mainly based and adapted to user requirements [5]. Most research works devoted for DW focus on the approach design [6], [7], [8]. Even if these approaches are relevant to design the DW, it is important that users understand the semantic around the information he analyses and have a visibility about other resources that could help them to make efficient analysis.

The goal of this research is to design an ontology that relates DW structure, resources and domain concepts in particular we address two main research queries:

- What are the competencies queries that our ontology takes in consideration?
- What are the concepts that compose the ontology to help decision makers in their analysis to understand indicators provided from a data warehouse?

This research is supported by the public hospitals of Marseille; Assistance Publique Hôpitaux de Marseille (APHM), and concerns a DSS based on a DW related to a healthcare domain specific to financial program based on the Program of Medicalization of Information Systems (PMSI) common to all French healthcare institutions.

This paper presents a new ontology-driven approach for DW personalization to resolute the semantic problematic related to the heterogeneous domains. We applied our approach in healthcare management domain.

The paper is organized as follow. Section II presents ontology and data warehouses needed background and related works. Section III presents a case study from the healthcare domain and competencies questions that give an idea about the possible scenarios to help users in their analysis. Section IV presents the ontology-driven approach that we propose with its ontology, and section V presents the ontology-driven framework that uses this ontology to support the user to exploit the DW. Finally, we conclude giving some details on future works.

II. Ontology and Data Warehouse

In this section we first review the basic concepts involved in the representation of ontologies, as well as some related works about ontologies in data warehouse and personalization of the data warehouse domains.

A. Ontologies

Ontology is an explicit specification of shared conceptualization [9]. Different ontologies are proposed to define ontologies. W3C consortium recommends Ontology Web Language (OWL) to define ontologies; they define it as a language for the specification of ontologies. This language is based on the description Logic (DL) [10], it gives the opportunity to reason and represent structured knowledge. The DL language represents knowledge with concepts and roles. The concepts described as a set of individuals (instances) and roles describing a binary relation between individuals.

A knowledge base is represented with an ABOX (assertion box) and a TBOX (terminological box). An ABOX represent extensional knowledge (instances), TBOX describes the intentional knowledge of the domain as axioms.

We present the ontology with 4-uplet <C, P, ClassPropt, ClassAssoc> that concerns the TBOX.

Our ontology describes concepts to relate domain, resources and data warehouse structure. We consider:

- C represents the classes of the ontological model
- P represents the properties of the ontological model. P is partitioned into :
  - P_{value} : represents the characteristics properties
  - P_{fct} : represents domain dependent properties
- ClassPropt : C -> 2P relates each class to its property
- ClassAssoc : C -> (Opr, Expr (C)) is an expression that associate to each class an operator (inclusion or exclusion) and an expression to other classes.

B. Ontology and data warehouse

In the literature researches have already explored the ontology-based data warehouses field. In the ontology-based data warehouses field researches are basically about the multidimensional schema design, representation and its summarizability.

Prat, Akoka and Comyn-Wattiau [11], Prat, Megdiche, and Akoka [14] represent a multidimensional model with an OWL-DL ontology model, based on description logic [13], and define the transformation rules from the multidimensional level into OWL-DL ontologies.

Niemi and Niinimäki [15] provide an RDF model of an OLAP cube, they focus on the relationship between measure and dimension attributes and its effect on summarizability. They define the concept of measure-dimension consistency and they show how to conclude it from OLAP ontology. The OLAP ontology is constructed with semantic web technologies and is basically used to help users for OLAP cube construction and querying. Nebot, Berlanga, Pérez, Aramburu, Pedersen [16] propose a framework for designing semantic data warehouses. They propose the Semantic Data Warehouse to be a repository of ontologies and semantically annotated data resources and propose an ontology-driven framework to design multidimensional analysis models for Semantic Data Warehouses.

In our research, we will use the transformation rules proposed by Prat, Akoka and Comyn-Wattiau [11] to generate the OWL ontology of the DW model. The ontology-based technics give us semantic explanation and personalization opportunities based on the relation between concepts in the ontology.

C. Persnnalization and data warehouse

The personalization in the data warehouse field is important because users need efficient resources adequate to his analysis need to help him in decision making. In the personalization of the data warehouse field we can distinguish three main goals:

- *Customizing data sources schema* [17], [18] adapting the data structures to a specific needs of users
- *Customizing queries visualization* [19], or representation [20]
- *Recommendation of OLAP queries* [21, 22] to assist in the exploration of the ED. We also find various works such as [23], [24], [25], [17], [21], [26].

All these personalization techniques are not based on ontologies. One of these works, Jerbi, Ravat, Teste, Zurfluh [27], add semantic by annotation to the DW schema but this technic is not based on ontologies. In our research we use ontology, also, to personalize users need.

Our research work is an ontology-driven approach to help users to analyze resources provided by a DW. Our approach helps users to retrieve, understand and analyze multidimensional resources e.g files (PDF, Excel, etc.), OLAP queries, etc.

III. Case Study

In this section we present a case study and competencies questions from the healthcare domain specifically applied in the Program of Medicalization of Information Systems (PMSI). This case study is a good example that represents heterogeneous users that share the same DW.

In the French healthcare management system the PMSI has a central place. PMSI is a French adoption for the concept of Professor R. Fetter (Yale university, United States of America) to finance hospitals. The PMSI specifies the cost of sojourn based on diagnosis related groups that classifies the hospitalization of patients in homogeneous and coherent medico-economic groups. Several countries like United States of America and England use this concept.

In the healthcare domain users belong to the medical domain (doctors, pharmacists, biologists, etc.) whereas others don't (financial affaire managers, computer scientists, human resources, etc.). We should note that our approach is not limited to the healthcare domain. It could be applied in other business contexts where users are from different domains. This is, in general, the case of big institutions.

In this context we consider a DW related to PMSI defined by its conceptual model illustrated in Fig. 1. This DW conceptual model is composed of a fact table, dimensions, hierarchies, and measures:

- FACT table = {Activity_PMSI: Sojourn of patients}
- Dimensions = {Date, Structure, Age, Exit_Mode, International_classification_of_desieases, Diagnosis_related_groups }
- Measures = {Number of patient, …}

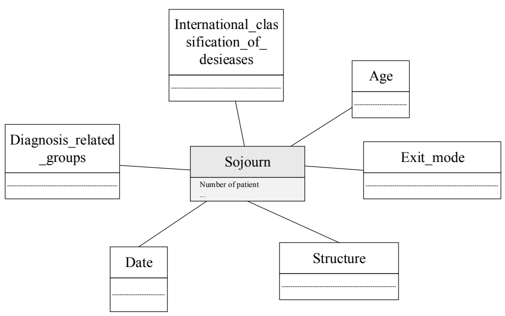

Figure 1. PMSI activity data warehouse conceptual model.

We take an example of a pivot table "Fig. 2" based on (for ethics reason we have taken fictive data):

- DIMENSION Structure
- DIMENSION Diagnosis_related_groups
- MEASURE number of patients

Periode : From january to mars

			Pôle 1	Pôle 2	Pôle 3	Total
DRG	MDC	TYPE DRG TITLE	288	318	519	1125
1	01	SURG CRANIOTOMY AGE >17 W CC	253	26	311	590
2	01	SURG CRANIOTOMY AGE >17 W/O CC	274	520	335	1129
3	01	SURG CRANIOTOMY AGE 0-17	225	319	212	756
4	01	SURG NO LONGER VALID	325	215	122	662
5	01	SURG NO LONGER VALID	125	138	118	381
		Total	1490	1536	1617	4643

Figure 2. PMSI pivot table.

In this research work we take into consideration resources based on DW sources and that represent data in a multidimensional table (defined by of measure, an operations on the measure, two or three dimensions, and a filter). In this context we noticed many difficulties:

Semantic lack

Users don't interpret the results in the same way. They need information about:

- Data warehouse concepts: dimensions definition, measures calculation methods and their sources
- Requirements expression heterogeneity: users don't belong to the same domain. They don't express their need with the same terms. For example: number of sojourn could be expressed as number of venue

Analysis needs

Most of the times, users need to analyze many resources to take a decision. In big institutions the big number of resources makes this task complicated. To facilitate this task, users need a global vision about the existing analysis axes. Thus, users need to have a global vision about the DW structure to visualize the possibilities or existing resources that could help him to take a decision.

These difficulties lead us to propose a new semantic approach that structure the concepts related to the DW based on ontologies.

Competencies questions

We can define different scenarios in order to support user to exploit the DW using the ontology.

Scenario 1:

Entry: DW concept.

Output:

1. *Related DW concept*
   Measures analysis: What are the different measures related to an analysis axe? What is the different analysis axes related to a measure?
   Dimensions (Analysis axes): What are the measures that could be analyzed over a dimension?
2. *Resources concept: What are the existing resources to analyze a measure?*
3. *Domain concepts: What are the existing measures to analyze a domain concept?*

Scenario 2:

Entry: Resources concept.

Output:

1. *DW structure concepts: Which is the data warehouse (data mart) that provides a resource?*
2. *Domain concepts: What are the existing resources to analyze a domain concept?*

Scenario 3:

Entry: Domain concept.

Output:

1. *DW structure: Which is the data warehouse (data mart) related to this domain concept?*
2. *Resources concept: What are the resources to analyze a domain concept?*

Those scenarios could be treated by using ontology based technologies to visualize and obtain semantic to facilitate the DW analysis.

In the context of other application scenarios these requirements should be equivalent, so from our point of view, they can be considered as basic requirements to an ontology-driven approach. Our contribution presented in the introduction of this paper is aimed at covering these requirements.

IV. ONTOLOGY-DRIVEN APPROACH FOR DATA WAREHOUSE ANALYSIS

In this section we describe the architecture of our approach, and then we present the ontology architecture and the demarche to follow to create the ontology knowledge database.

Our approach focuses on two key requirements to address the research problem:

- It represents ontology architecture to describe knowledge about decision support system,
- It provides an ontology-driven approach to help users in their analysis.

A. Approach architecture

Our functional architecture "Fig 3" is based on a knowledge database and an ontology driven framework.

The knowledge database is composed of three inter-related aspects necessary to help users in the analysis process, in order:

- **Data warehouse structure**: the multidimensional model associated to the DW organizes data into facts and dimension. Facts represent the subject of analysis and dimensions represent the axis of analysis. Fact table is the center of the multidimensional model. It stores elementary indicators, called measures. Dimensions can form hierarchies, structured in different granularity levels.
- **Resources structure**: resources are provided by the DW. Resources regroup information necessary for the analysis. To understand a component information about the indicator are needed like: calculation method, unit of measure, calculation period, date of creation, date of update, date of validity, objective, definition and the relation with the data mart.
- **Domain concepts structure**: presents concepts of the domain and the relation between them. A decision is based on one or many indicators. In the analysis processes the user check the information's that he already knows. However, most of the times user needs additional indicators to make his analysis. The domain description provides the information about the relation between domain concepts.

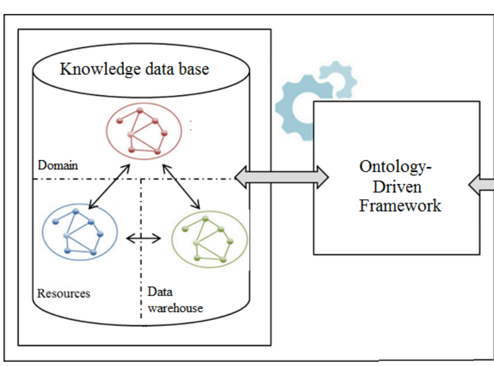

Figure 3. Approach architecture.

The framework system that we propose is based on an ontology interrelating three aspects (domain, DW and resources) to help users in the analysis task.

B. Ontology architecture

We formalize our ontology by the triple < O_{DW}, O_D, *Map*> where:

- O_D is the domain ontology which provides a schema about the domain,
- O_{DW} is a DW schema which describes the resources (DSS components) related to the data warehouse,
- Map is the mapping between O_{DW} and O_D, which establish the connection between domain concepts and the DSS components.

This ontology can be used for many purposes with ontology-based software. In the first hand, to give a vision about the relation between DW, resources and domain concepts, in the other hand, to propose for users other related resources to accomplish his analysis, based on the relation of the three concepts the resources, the data warehouse concepts and the domain concepts. "Fig. 4" presents the ontology architecture meta-model to implement the knowledge base of the framework.

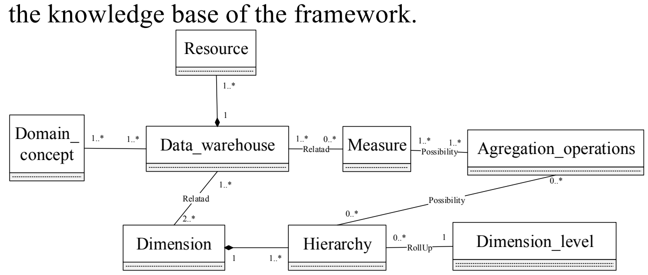

Figure 4. Ontology meta-model.

This ontology meta-model "Fig 4" represents the concepts related to the DW. Each DW is composed of zero or many measures and related to two or many dimensions. Hierarchies are composed of one or many dimensions. It is possible to effectuate operations on measures and aggregation according to the dimensions levels.

The proposed ontology model has been designed as follow to give high expressiveness about data warehouse components and to show the relation between DW concepts, resources (DSS components) and domain concepts.

C. Ontology connection

To create the knowledge database we create the ontology by following steps, the method to create the ontology is developed in section V, in order:

1. Define domain ontology or use an existing domain ontology,
2. Generate the DW structure ontology based on the transformation rules proposed in the work of Prat, Akoka, Comyn-Wattiau [11],
3. Associate the DW structure to the domain ontology, this step could be accomplished in several methods, for example :

- Administrator relates DW concepts to the domain concepts
- Automatically alignment of the DW structure ontology with the existing domain ontology

4. Associate to the DW concepts existing resources Ontology architecture.

The next section is completely devoted to describing the ontology-driven framework to create and visualize the ontology based on the ontology driven approach that we propose.

V. ONTOLOGY-DRIVEN FRAMEWORK

In this section we present a framework based on our ontology. We implemented an ontology based on healthcare domain. Thus, this semantic structure helps users to discover and retrieve resources related to their domain and their first need.

To test our method we chose to implement OWL ontology with Protégé editor [13], and then we use OntoGraph plugin to interrogate and visualize ontology.

A. *Methods*

To create our OWL ontology we use “Protégé” platform:

1. Create three classes DW, Domain, and Resources
2. Export existing domain ontology or create new domain ontology. These ontology concepts be a subset of the domain class
3. Export DW conceptual model ontology. To pass from the DW conceptual model to OWL we applied the transformations rules proposed by [14]. Data warehouse concepts is a subset of the DW class
4. Relate the DW concepts to domain concepts. This task can be automatic by using existing ontology mapping tools; in this work we not consider this option. To relate DW concepts to domain concepts ontology administrator refers to each data warehouse concept the equivalent, opposite, etc. concept in the domain ontology. For example, the DW dimension “Diagnosis_Related_Groups” is related to “DRG” class of the domain ontology
5. Relate the resources provided by the data warehouse to their corresponding concepts. For example, the resource named “PMSI_activity” allows user to analyze the PMSI activity per month and per medical unit. So, this resource are related to DW subclasses dimensions month and medical units

B. *Visualization*

We consider the example of the DW presented in the healthcare domain. We propose an ontology-driven framework.

Input: is a need expressed with a term or a group of terms.

Output: are concepts related to this need, about resources concepts, domain concepts, and DW structure concepts.

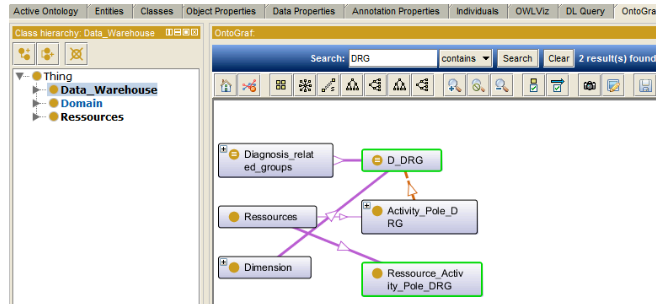

Figure 5. Example, retrieve ‘DRG’ concept from the ontology.

Thus, the user expresses his need with one or more keywords for example DRG.

- Domain concept: DRG is equivalent to “diagnosis related groups”,
- DW concept: DRG is a dimension.

So as “Fig. 5” shows the resulting visualization of the ontology and the existing concepts that contains DRG, equivalent and related concepts using the OntoGraph plugin.

The approach that we proposed facilitates the retrieve and the comprehension of resources for users. But, to automate the creation and the interconnection of ontology concepts based on our approach is a complex task. As a consequence, this process deserves more attention in the future work in order to automate it as much as possible.

VI. CONCLUSION AND FUTUR WORK

The Data Warehouse (DW) resources are shared by users from heterogeneous domains. Those resources could be interpreted differently from a user to another. Consequently, semantic about those resources is necessary to guarantee the coherence of the analysis. Ontologies are effective solutions to add semantic to concepts. They facilitate the management of data, clarify and give a sense to ambiguous concepts.

Different solutions are offered to manage and query these data. In this paper we have implemented an ontology to support users to exploit a DW. This ontology has been implemented with Protégé, interrogated and visualized with the OntoGraph plugin.

The study of concepts from healthcare domain confirms the need of semantic to help users in the analysis of resources provided by DW. One of the main characteristic of our proposed ontology architecture is that it provides a connection between domain concepts, DW structure and DW resources, this connection provide semantic information about resources and help users to choose other resources that can help him in his analysis. This personalization task is based on resources related to connected domain concept in the ontology.

Furthermore, the main asset of our proposition is that it combines ontology and data warehouse to add semantic to resources analysis.

We should note that our approach is not restricted to the healthcare domain it could be applied for any domain for the retrieval of DW resources.

This work leads to many other tasks. In future work, tasks that should be considered (i) test the integrity of the ontology when adding new concepts (like new resources), (ii) extension of this approach to add other type of resources and data source provided from decision support system but not related to the data warehouse, (iii) automation of the ontology creation and interconnection as much as possible, (iv) validate our approach in a larger context.

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