Database Marketing Intelligence Supported by Ontologies

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Abstract: - Marketing departments handles with a great volume of data which are normally task or marketing activity dependent. This requires the use of certain, and perhaps unique, specific knowledge background and framework. This article aims to introduce an almost unexplored research at marketing field: the ontological approach to the Database Marketing process. We propose a framework supported by ontologies and knowledge extraction from databases techniques. Therefore this paper has two purposes: to integrate the ontological approach into Database Marketing and to create a domain ontology, a knowledge base that will enhance the entire process at both levels, marketing and knowledge extraction techniques. In order to structure and systematize the marketing concepts, Action Research methodology has been applied. At the end of this research the ontologies will be used to pre-generalize the Database Marketing knowledge through a knowledge base.

Key-Words: - Ontologies, Database Marketing, Knowledge Extraction Process, Action Research

1 Introduction

Technology has provided marketers with huge amounts of data and artificial intelligence researchers with high level processing rate machines. At the marketing practice we note that marketing databases are used normally in an organizational secret and closed purpose, which limits the knowledge for reuse and sharing. Database Marketing (DBM) is a database oriented process that explores database information in order to support marketing activities and/or decisions. The Knowledge Discovery in Databases (KDD) process is well established among scientific community as a three phase process: data preparation, data mining and deployment/evaluation. The KDD has been successfully applied in various domains particularly in the marketing field. Nevertheless previous well established concepts and scientific dominance regarding each one of these methods, it seems to have a lack of knowledge concerning its application amongst different requirements and conditions.

Available literature describe a DBM project as comprised of a sequence of phases and highlight the particular tasks and their corresponding activities to be performed during each one of the phases. It seems that the large number of tasks and activities, often presented in a checklist manner, are cumbersome to implement and may explain why all the recommended tasks are not always formally implemented. Additionally, there is often little guidance provided towards how to implement a particular task [27]. These issues seem to be especially dominant in case of more complex analytical objectives at marketing activity understanding phase which is the foundational phase of any DBM project.

In computer science, ontologies provide a shared understanding of knowledge about a particular

domain [16]. At the best of our knowledge the number of contributions to the construction of marketing ontologies is very low. However, they are starting to come to light through some marketing or computer research centers [9] [15] [4] [38] [21].
This research is part of a larger project to build and develop a DBM Ontology (DBMO). The DBMO should cover a semantic description of processes supporting DBM, comprising classified marketing objectives and activities, knowledge extractions methods, objectives and tasks.
Our proposed research context focuses DBM as the intersection of two others disciplines (knowledge extraction techniques and marketing). Here, we introduce ontologies as a support to the knowledge structure and integration of both. In the context of knowledge sharing, the term ontology means a specification of a conceptualization. That is, an ontology is a description of the concepts and relationships that can exist for single technological applications or as a reference in a decision support system, and can be designed for the purpose of enabling knowledge sharing and reuse [16] [18] [37].
One of the promising interests of marketing ontologies is their use for guiding the process of knowledge extraction in DBM projects. A tool that gradually accumulates knowledge from the previous domain developed processes is appropriate due its iterative nature. Researchers often rework their data in order to optimize further interactions [30]. Integrating this knowledge with ontology extends the ontology usefulness.
With this work we intend to capture main DBM process steps and elements providing the foundations to propose a general DBMO framework architecture. This work stems the practical phase of the DBMO construction focusing the DBM related knowledge and the DBM process. To achieve this, we have used the Action Research methodology to structure and systematize: marketing concepts, data oriented tasks, modeling and evaluation. Also we focus the knowledge base creation.
We are proposing the initial conceptual structure to the domain ontology as an integral part of a global marketing system. According to some researchers our ontology can be classified as an application ontology [32], serving our main global project.
The framework serves to highlight the dependencies amongst the various tasks of the DBM process and proposes how and when each task may use the ontology. An illustrative example of a relationship marketing database from a multinational distribution company is used to exemplify the proposed framework.

This paper is organized as follows: we start with an introduction to DBM and ontologies. Then the Action Research approach is outlined. Research questions and research findings are presented in the two subsequent sections. Discussion and conclusions are presented in the closing sections

2 Database Marketing

The DBM activity has changed significantly over the last several years. In the past, database marketers applied business rules to target customers directly. Examples include targeting customers solely on their product gap on on marketer's intuition. The current approach, which has widespread use, relies on predictive response models to target customers for offers. These models accurately estimate the probability that a customer will respond to a specific offer and can significantly increase the response rate to a product offering. The old model of "*design-build-sell*" (a product-oriented view), is being replaced by "*sell-build-redesign*" (a customer-oriented view). The traditional process of mass marketing is being challenged by the new approach of one-to-one marketing[28].
DBM departments face several types of business constraints. Typically there are:

- restrictions on the minimum and maximum number of product offers that can be made in a campaign;
- requirements on minimum expected profit from product offers;
- limits on channel capacity;
- limits on funding available for the campaign;
- customer specific 'do not solicit' and credit risk limiting rules; and
- campaign return-on-investment hurdle rates that must be met.

Recently, some DM methodologies and applications have been developed to explore the practices and planning methods of sales and marketing management between customers and sellers in the market [5].
In this work, DBM is referred as the use of database technology for supporting marketing activities, while marketing DB it is referred to the database system it self. Currently there are three different levels of DBM in order to better organize these concepts [11] [22]:

- *Direct Marketing*: Organizations manage lists and conduct basic promotion performance analyses;
- *Customer Relationship Marketing*: Companies apply a more sophisticated,

tailored approach and technological tools to manage their relationship with customers;

- *Customer-centric Relationship Management*: Customer information drives business decisions for the entire enterprise, thus allowing the retailer to dialogue directly with individual customers and ensure by this way, loyal relationship.

DBM has been defined has the establishment of a customers and prospects DB with which it is possible to the organization to communicate with them in a personalized way [34]. Others consider DBM as a medium to use consumer information with the objective of incrementing marketing activities efficacy and efficiency [29]. Finally, it is possible to define DBM as the usage of customer information which benefits both them and to the organization [26].
These definitions emphasize DB technologies as a support to the marketing activities and establish as DBM definition, a set of processes based in marketing DBs exploring and analyzing them looking for new insights [23] [24].

2.1 Data Mining vs. Database Marketing

Data Mining, more formally known as Knowledge Discovery in Databases (KDD), refers to the nontrivial extraction of implicit, previously unknown and potentially useful information from data in databases [12] [13]. While DM and KDD are frequently treated as synonyms, DM is actually part of the knowledge discovery process [19].
In short, DM aims at building models from data. There are many available algorithms; each with specific characteristics. The major DM activities are [13]:

- *Predictive modeling*: mapping a set of "input" values (independent variables) to an "output" value (dependent variables). This kind of models takes two forms depending on the type of the output, as follows:
    - *Classification* - learning a function that associates with each data object one of a finite number of pre-defined classes (e.g., customer profile);
    - *Regression* - learning a function that maps each data object to a continuous value (e.g., amount spent);
- *Descriptive modeling*: discovering groups or categories of data objects that share similarities and help in describing the data space (e.g., customer segments);
- *Dependency modeling*: learning a model that describes significant associations or dependencies among features (e.g., contents of subscription orders, market baskets);
- *Change and deviation detection/modeling:* Detecting the most significant deviations from previous measurements/behaviour or norms (e.g., fraud detection).

The selection of DM activities depends directly from the marketing objectives initially defined.
As DBM is characterized by marketing strategies based on the great volume of information available in large customer DBs, it is possible to point out the following areas as major candidates for the application of KDD for knowledge based marketing [11]:

- Customer Acquisition;
- Cross- and Up-selling;
- Product Development;
- Churn Prediction;
- Fraud Detection;
- Market-basket Analysis;
- Risk Assessment;
- Prediction/Forecasting.

3 Ontologies foundations

Ontologies are nowadays one of the most popular knowledge representation techniques. They have been proposed since the 18th century and they have been developed and deployed for sharable and reusable models. Those intended to meet information modelling and knowledge management and reuse.
Ontologies aim to capture consensual knowledge in a generic way, and that they may be reused and shared across software applications and by groups of people. They are usually built cooperatively by different groups of people in different locations [14].
Ontology is an agreed vocabulary that provides a set of well-founded constructs to build meaningful higher level knowledge for specifying the semantics of terminology systems in a well defined and unambiguous manner [6][25]. Ontologies can be used to assist in communication between humans, to achieve interoperability and communication among software systems, and to improve the design and the quality of software systems [33].

3.1. Main concepts

When ontologies are formalized in any kind of logic representation, they can also support inference mechanisms [20]. For a given collection of facts, these mechanisms can be used to derive new facts or check for consistency. Such computational aids are clearly useful for knowledge management, especially when dealing with complex and heterogeneous knowledge problems or with large amounts of knowledge.

Ontologies use a formal domain or knowledge representation, agreed by consensus and shared by an entire community.

Ontology is a description of conceptual knowledge organized in a computer-based representation [17] [3]. According to the artificial intelligence literature, the most commonly quoted definition for ontology is "a formal, explicit specification of a shared conceptualization" [16]. A conceptualization, as it refers to an abstract model of one thing that describes the semantics of the data. An explicit specification means that the concepts and relationships in the abstract model are given explicit names (terms) and definitions (specification of the meaning of the concept or relation) that can be communicated amongst people and across application systems. Let explore some of the above terms:

- Formal - how the meaning specification is encoded in a language whose formal properties are well understood — in practice, this usually means logic-based languages that have emerged from the knowledge representation community within the field of Artificial Intelligence;
- Shared - means that the main purpose of an ontology is generally to be used and reused across different applications and communities.

An ontology specifies at a higher level the classes of concepts that are relevant to the application domain and the classes of relations that exist between these classes. The ontology captures the intrinsic conceptual structure of a domain. For any given domain, its ontology forms the heart of the knowledge representation. Very shortly we describe here what entities are found in an ontology language. These entities are mainly:

- *Classes* or concepts are the main entities of an ontology. They are interpreted as a set of individuals in the domain., e.g., data or algorithms. To each class it is possible to assign sub-classes, like dataType, or dataValueType for the class Data;
- *Instances or objects* are interpreted as particular individual of a domain, e.g, age it is an instance of the sub-class Demographics;
- *Relations* are the ideal notion of a relation independently to why it applies (e.g., the name relation in itself), they are interpreted as a subset of the products of the domain.
- *Properties* are the relations precisely applied to a class (e.g., the gender of an individual); property instances are the relations applied to precise objects (the name of this individual)
- *Datatypes* are a particular part of the domain which specifies values (as opposed to individuals), values do not have identities.

Ontologies use a formal domain or knowledge representation agreed by consensus and shared by the entire community [17]. There exist several ways to represent such ontologies and many languages have been defined to represent them. There is a wide range from first-order logic (e.g., OWL or RDF) to frame-based languages implemented in ontology management systems (e.g., Protégé or Ontolingua).

3.2. The use of ontologies in marketing

A successful knowledge management system enhances the way how people work together, enables knowledge workers and partners to share information easily so they can build on each other's ideas and work effectively [7].

Ontologies use a formal domain or knowledge representation, agreed by consensus and shared by an entire community. Ontologies roles in DBM have particular significance in a cross research (both marketing and extraction techniques knowledge is needed) area focus. Indeed, ontologies can play an important role describing, in a semantic form, all concepts and techniques around the process. Moreover, with such description it will also be possible, to introduce metrics to compare and therefore select and suggest the best approaches and methods to a new project.

Ontologies are also like a conceptual schema in database systems. A conceptual schema provides a logical description of shared data, allowing application programs and databases to interoperate without having to share data structures. While a conceptual schema defines relations on data, an ontology defines terms with which is possible to represent knowledge (models). Also, ontology defines the vocabulary used to compose complex expressions such as those used to describe resource constraints or resource complex characteristics. Here, the main reason why vocabulary is the focus of ontological commitments [16]. We point as the main contribute of such ontology at DBM domain the following:

i. to enable consistent implementation and interoperation of all methods, tasks and algorithms based on a marketing knowledge background vocabulary;
ii. to play the role of a domain ontology that encompasses the core the DBM process and therefore can be used extensively by any practitioner or researcher;
iii. to generate DBMO forms, based on the ontological knowledge base.

4. DBMO

Starting from a stable DBM concepts structure, in order to design and improve overall DBM perspective (illustrated in Figure 2) we focus the process attaining a semantic description of used procedures and methods. As a result of this research, we will have a general framework that will conduct the knowledge extraction process and knowledge base creation.

The choice of action research was based on two main reasons. Firstly, due the low number of scientific research works that have been conducted to support the DBM process on intelligent structures like ontologies, the process by which this may be completed is unclear. Secondly, ontologies can play an important role in the knowledge development as long as they register past knowledge for future reuse (Figure 1). Thus exploratory research was required and action research provides this capability better than many other alternatives [10].

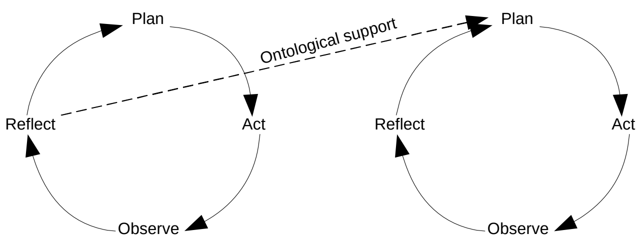

Figure 1 – Action Research Methodology.

Action Research approach develops in a four step framework (Figure 1): first formulate (plan), test (act), deploy (observe) and evaluate (reflect). In this work we introduce a connection element between each interaction: ontological support. Also, action research may be developed at two simultaneous theoretical and practical levels and using two working focus groups:

- Practice over a real relationship marketing program database; and
- Literature oriented field research (an expert panel explored scientific literature and achieved a set of possible tracks to each of one of research focus).

Also in conjunction with the focus groups, convergent work may be required to further test and refine the aimed theoretical framework. Convergent work involves as example, to transpose from reviewed literature approaches or suggestions to practical domain. Each interaction is then registered in terms of the type of data, the data analysis algorithm used and the results achieved with it, for example. Convergent work involves also the conduction of a series of in-depth working groups in order to explore others insights that were not previously registered. It only ends when no new information remains uncovered or unregistered.

Supported by a previous research work throughout the marketing knowledge we have used a symbolic model [2] for representing knowledge and a tree structure (Figure 2). Here we intended to distinguish between different knowledge levels structure tree.

At this research point we had proceed with action research methodology towards the following statements:

i. Principal data information type identification in marketing database;
ii. Main DBM steps from marketing data to customer knowledge;
iii. DBM process' matrix: Knowledge base elements identification and creation.

5 Findings

The research project was done with a group of database marketing practitioners. Our preliminary findings are summarized in Table 1 and discussed next.

5.1. Principal marketing data information type

At this point we identified three main data types used in DBM projects: personal, market and trigger data. In personal type we have identified others related sub-types:

- Psychographics - personal data that can easily be changed, e.g., monthly income or professional occupation;
- Demographics - physical and personal data that is almost definitive and hardly ever changes, e.g, gender, race or birth date;

Transactional - consumer based information regarding its commercial activity, e.g.,

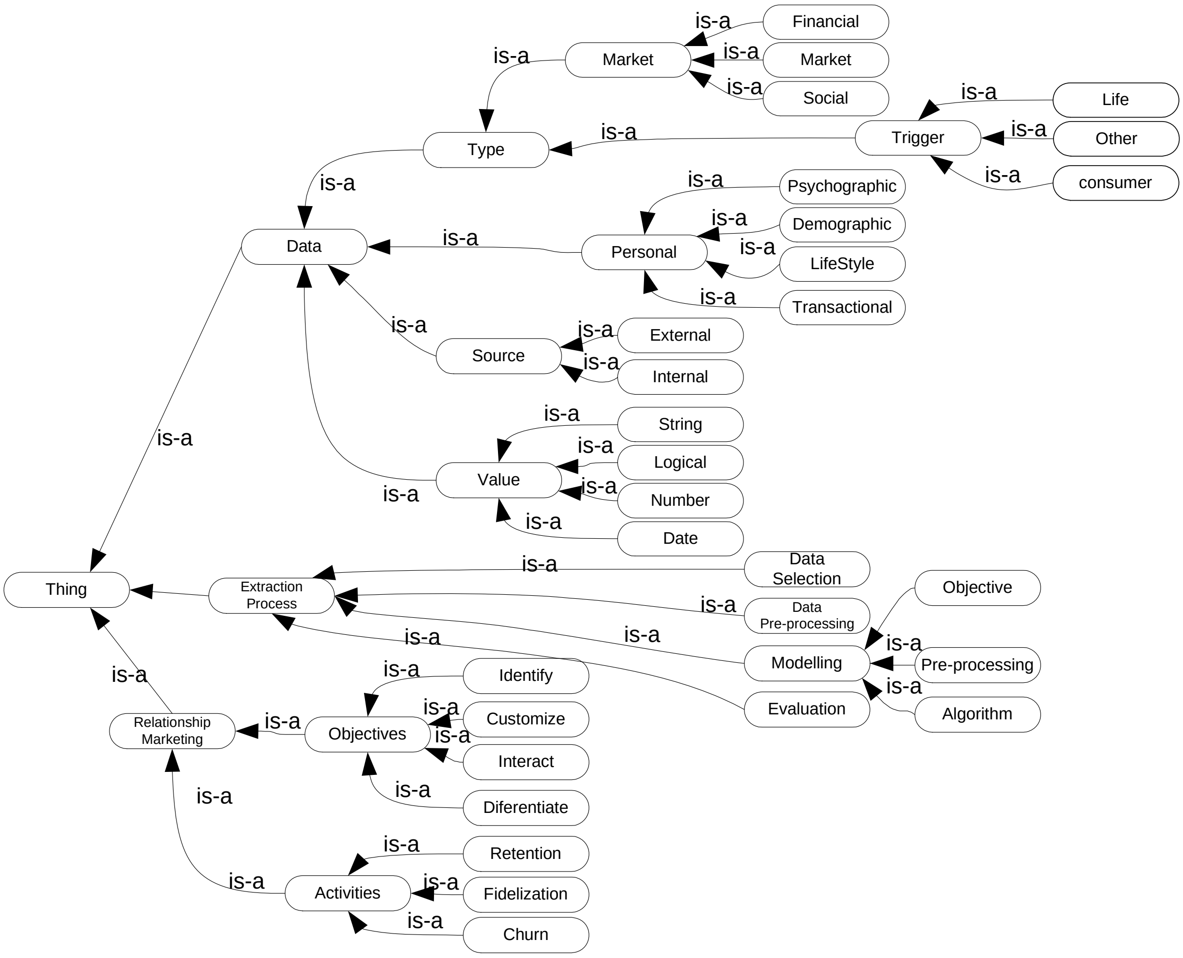

Figure 2 – Extract of the Current Database Marketing Ontology.

- monthly consumption or number transactions/month;
- Life style or behavioral - consumer or social related information, e.g, hobbies or car type.

Regarding market information we have also identified, some others sub-types:

- Environmental market data - Financial (e.g., inflation tax rate);
- Market (e.g., market or product share);
- Social (e.g., national birth or death).

Trigger events are data related to special events that induces important changes at consumer behavior:

- Consumer (e.g., married status change or children number);
- Life related (e.g., new car or house);
- Others (e.g., accident or prison).

Although these data type classification our research has also concluded that almost every DBM practitioners extensively uses as much as possible available data.

5.2. Main DBM process' phases

Here we focus the entire process that goes from data to the expected extracted knowledge. Our findings have founded six main DBM steps:

- Marketing objectives definition and activity selection;
- Data selection;
- Data preparation;
- Data pre-processing;
- Modeling and Model evaluation.

Regarding post DBM process, we have also considered:

- Business deployment and evaluation that focuses model novelty and usefulness at business level.

5.3. DBM process' matrix

At this stage our research focused on a matrix that explicitly correlates marketing objective and related activities with knowledge extraction detailed description. Here we had identified the knowledge base main variables (Figure 3):

- *Input* (marketing objectives, activities and data selected);
- *Task* (data selection, data pre-processing and modeling);
- *Outputs* (modeling and deployment).

Such variables form the ontological layer that will led the entire DBM process (physical layer) through an analytical method:

```
Knowledge Base:{
Results={DBMimodels[{input}{tasks}]}
}
```

5.4. A general framework

Our research allows to the definition of three main components of the DBM process (Figure 3): input, tasks and outputs. Moreover, our research made possible to illustrate a general perspective of how the system works. We have considered a two layer architecture approach:

- *Physical layer* - which holds the process development tasks, namely data handling (selection, preparation, pre-processing and transformation) and modeling;
- *Ontological layer* - may act like a guide to the data analyst and as a reference to the expert marketer. The knowledge base contains the data loaded, the tasks and the methods taken. Moreover, the results obtained at a business perspective are also evaluated and registered. Each record set refers to a complete DBM process developed. The knowledge base may be used to support the decision whenever each phase of DBM process starts.

This architecture as shown in Figure 3 has the aptitude to register knowledge throughout knowledge base entries and actively suggest the best approach to each DBM process phase.

The proposed architecture (Figure 3) has a main function to support and conduct the DBM process throughout the data to expected knowledge (physical layer). In addition, this architecture has the ability to register each DBM process, providing a structure for later use: knowledge share and reuse objectives (using some ontological tools like OWL or RDF).

Table 1 – Action research findings.

Research issue	Findings about the research issues
Principal marketing database data type information	From some literature review and supported by previous work done we found four main marketing data types: - Psychographics; - Demographics; - Life style; - Transactional.
Main DBM steps	Based on both practice and literature review we considered the following steps as a stable DBM process framework: - Marketing objectives definition and activity selection; - Data selection; - Data preparation; - Data pre-processing; - Modelling; - Model evaluation; - Business deployment and evaluation.
DBM process' matrix	<table><tr><td></td><td>Marketing Objectives | Activities</td></tr><tr><td>Knowledge Extraction cases</td><td>Description record set: { Data set Data selection Data pre-processing Data Preparation Algorithm used Technical evaluation Business evaluation }</td></tr></table>

Our proposal is based in a double domain articulation maps objects (steps) and attributes from the dataset and instances of the knowledge base. Thus, formalized knowledge within the knowledge base can be used for database marketing process guidance.

The efficiency of the interaction among marketing objectives, marketing databases and knowledge extraction process is mainly based on the instantiation process in the knowledge base. This process is dependent on the DBM practice history recorded. Furthermore, this process is dependent on data integration issues and has to be controlled by the domain expert, who has to choose the most accurate and valid information related to each case. In this way, the domain expert is in charge of instantiating the right classes and attributes instantiations in the knowledge base.

In practice, information with a DBM project "complete history" is stored in the knowledge base during the instantiation process by adding a property to created instance e.g., case *n*, where *n* represents *nth* the sequential order of registered cases. It should be stressed that each new instance of a knowledge index is computed. This index is calculated according to the data used, its quality and the algorithm results performed with evaluations methods. Therefore, the suggestions from knowledge base would be based on this ranking index.

A synergy between decision support systems and knowledge management is possible [1]. Ontologies can play an important role in this area, integrating both previous and proceeding to the decision. Here we use the knowledge base. Ontological layer is the main core of the system positioned at the middle between physical and operational layers. Whenever a new DBM process starts, it both suggests and registers as follows:

- Registering task is developed according to a relational database structure schema previously defined. Relevant information is registered within those tables with specific rules. Those tables form the knowledge base, which has the ability to organize and systematize DBM process information. Has also the capability to use, compute and provide information in an actionable way to the user needs;
- Suggestion task is performed using previous information saved in the knowledge base. Ontology has the capability to query the knowledge table with previous user loaded information;
- Regarding each data set used we have registered all data tasks performed, like data cleaning, data transformation or data reduction;
- Related to the modeling phase, it was created a record table which besides algorithms was performed but also which data from loaded data set was used.

The model deployment is performed on two counts: analytical and business perspective. Analytical deployment focuses the algorithm performance. Business perspective regards its practical application, that is, there are models with high accuracy but with low interest (e.g., a rule like all women's buys female products) and others with low rating but with high impact regarding their business vale (e.g., customers with less than 50 years, two children, married, high level occupation,…, has 50% probability to buy your product).

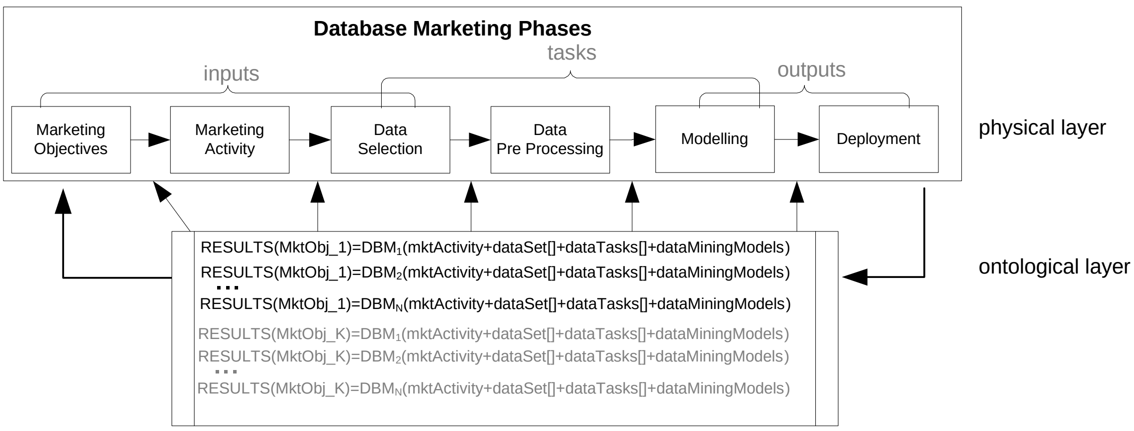

Figure 3 - Database Marketing Ontology, general framework.

6 Experiments

Ending the action research, a practical and functional analysis was made towards a possible conceptual semantic map. Turning our action research to analytic generalization, we can build a theoretical framework [36]. Linked to extant literature that shows how the DBM process is developed, how associated marketing knowledge can be structured and which knowledge discovery approaches may be used.

Following the proposed architecture we have collected a large relationship marketing program database from a distribution multinational company. Our database contains at an individual level different kinds of marketing information, as demographics, psychographics, life style and transactional. Also, some external data is presented as an example market or financial information.

We have processed the data using WEKA [35], a free data mining software and we have found different results according to different data and algorithms used.

Through this experimental work we have extracted complex information from database and organized at individual perspective.

To classify how successful is a DBM project is very subjective. Nevertheless, within the developed approach we can perform, register and implement some analytical procedures that will conduct to some DBM evaluation.

To evaluate resulting models we used two approaches: analytical and business. Former we evaluated the models through AUC (area under curve) and confusion matrix or principal components analysis. Business approach was taken whenever we wanted to understand how much valuable was the resulting information. Besides, regarding used data in each model we also evaluated its quality focusing its completeness, outliers and missing values

All information regarding each developed DBM project has been registered in a knowledge base which has information like as follows:

```
{
marketing objectives;
marketing activity;
data used [
      {demographics},
      {psychographics},
      {life style},
      { transactional}
      ];
data quality [
      {outliers},
      {missing values},
      …]
data procedures [
      {selection},
      {preparation},
      {pre-processing}
      ]
algorithms used [
      {clusterers},
      {classifiers},
      {neural Networks},
      {genetic Algorithms},
      {statisticalTechniques}
      …]
model evaluation method [
      {auc},
      {pcc}
      …]
business deployment [
      {ROI},
      {successfullyTargeted},…]
}
```

6.1.Knowledge base instantiation

At this point we illustrate an object selection e.g., the best fit algorithm, leading to a data selection and therefore a data-preprocessing tasks. This scenario illustrates the selection of algorithms based on the description of similar cases within data mining sub-class and to the specific case of *customer profile* objective.

Reasoning mechanisms had been applied to instances to classify registered cases in the knowledge base (Table 2) according to their individual properties and characteristics, like, *marketingObjectives* and *RelationshipMarketingActivity* under which the case was developed, types of data used (e.g., demographic, psychographic, transactional, or life style) and the resulting model accuracy (*knowledgeBaseIndex*). This allows to detect and to select a set of instances sharing the same or the maximum attributes, as a set of instances belonging to a similar database marketing problem (algorithm_β and algorithm_γ). Therefore, according to the *knowledgeBaseIndex*, that will be selected the individual case as a guide.

Table 2 - Knowledge base instantiation example.

$$a\lg orithm\_\alpha \equiv case\exists hasMarketingObjective(\ni has\,RelatioshipMarketingActivity(\neg customer\,Profile))$$
$$a\lg orithm\_\beta \equiv case\exists hasMarketingObjective(\ni has\,RelationshipMarketingActivity(customer\,Profile))$$
$$\longrightarrow \exists hasData(\ni (Demographic(item_1, item_2 ... item_n)) \wedge \exists hasData(\ni (Psychographic(item_1, item_2 ... item_k))$$
$$\longrightarrow knowledgeBaseIndex(customer\,Profile)$$
$$a\lg orithm\_\gamma \equiv case\exists hasMarketingObjective(\ni has\,RelatioshipMarketingActivity(customer\,Profile)$$
$$\longrightarrow \exists hasData(\ni (Demographic(item_1, item_2 ... item_n)) \wedge \exists hasData(\ni (Psychographic(item_1, item_2 ... item_k)) \wedge \exists hasData(\ni (Psychographic(item_1, item_2 ... item_k))$$
$$\longrightarrow knowledgeBaseIndex(customer\,Profile)$$

7 Discussion and Conclusions

The extent, degree and simplicity of communication enabled by the ontology makes it a synergistic component of DBM strategy. An ontological DBM approach solution appears to be promising for both marketers and computer scientists.

One of the most important issues of DBM ontology is its use to guide the process of knowledge extraction from marketing databases. This idea seems to be much more realistic now that semantic web advances have given rise to common standards and technologies for expressing and sharing ontologies [8] [31]. In this way DBM can take advantage of domain knowledge embedded in DBMO:

i. At the marketing activity definition, ontology can suggest a set of options according available resources, e.g., based on data completeness or heterogeneity;
ii. On DBM objectives, ontology may suggest or select the most appropriate approaches to deal with the available data;
iii. During the data preparation step, DBMO can facilitate the integration of heterogeneous data and guide the selection of the relevant data;
iv. At the modeling phase (e.g., data mining), domain knowledge allows the specification of constrains for guiding data mining algorithms selection by, e.g., narrowing the search space;
v. Reasoning operations through knowledge base instantiation, e.g., algorithm selection, according to some previous data mining objectives;
vi. Optimization, through knowledge updating.

The results of this research have implications for both theory and practice. The first practical results relate the possible feedback between different DBM projects through a table containing all used resources registered. It will be possible to implement, through ontologies, a knowledge base with suggestion or work profile capability. That knowledge base, according to the previous registered experiments, will be also capable to suggest to each marketing objective which marketing activities, data to be selected and also tasks to be performed should be chosen. Another implication relates to the benefits of a global view of marketing databases role in marketing objectives: it is possible to fill them with appropriate data.

Our model further emphasizes the importance of the marketing knowledge to be structured in order to enable resources reuse or even to achieve synergies in marketing activities development. Thus, managers and marketers should be aware of this issue, because there is a loop through which performance of DBM process can effectively be improved.

The research findings and contributions have several implications for the theory about ontologies and DBM, as well as the use of Action Research methodology. This research provides new insights into DBM theory in two ways:

- First, this research appears to provide the initial global investigation about the intersection of ontologies and DBM in organizations, and how it may be achieved. Thus, this research contributed to the theory-deficient area of the integration of ontologies and DBM;
- Second, there is too few literature dedicated to marketing ontologies and thus this research appears to be one of the first academic investigations of this phenomenon.

The impact of such ontology is the future initiation to a shared DBM knowledge platform that will provide a trusted base among marketers, DBM practitioners and artificial intelligence researchers. Indeed, this research identifies a number of areas requiring further research, namely the marketing knowledge tree and therefore marketing ontology.

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