Enhanced Association Rules over Ontology Resources

Eya Ben Ahmed[1], Faiez Gargouri[2]
[1]High Institute of Management of Tunis
University of Tunis, Tunis
[2]High Institute of Computer and Multimedia of Sfax
University of Sfax, Sfax, Tunisia

Abstract: *Data mining has emerged to address the problem of drawing interesting knowledge from data. Among the most used data mining techniques, we concentrate on association rules which lead to the derivation of useful associations and correlations within data. In parallel, the advance of the ontology which is one of the most important concepts in knowledge representation has speedily altered the way of information structuring and sharing. Recently, the area of coupling association rules and ontology has been a focus for several researchers. In this paper, we aim to extract enhanced association rules over ontological resource. Thus, we introduce a new approach ECARD for an enhanced association rules derivation. Indeed, two main categories of knowledge are drawn, namely transitive and causal association rules. The encouraging carried out experimental results show the usefulness of our approach.*

Keywords: Ontologies , Data Mining, Association Rules, Transitive Association Rules, Causal Association Rules, Compound Association Rules

Received: 10 September 2014, Revised 20 October 2014, Accepted 29 October 2014

1. Introduction

In recent years, the exceptional growth in the amount of data was a key factor towards a significant effort within the knowledge discovery in databases process. In this respect, to guarantee an efficient knowledge management, many researches advocate the extraction of frequent patterns.

One of the most important patterns in data mining is to discover association rules from a database. An association rule expresses a correlation between sets of items in a series of transactions [1]. Indeed, such rules are derived from sets of itemsets that occur jointly at least according to given frequency i.e., support. In addition, the association rule is an "*IF antecedent THEN consequent*" rule that promises, with a definite probability i.e., confidence threshold which whenever the antecedent occurs, the consequent will happen. These pattern classes are generated using the Apriori algorithm [2]. Considering a fixed confidence value, the setting of the support threshold will determine the extracted patterns. Such knowledge is very useful in making better decisions [3] and may be drawn from several data sources such as databases, data warehouses,…etc.

In parallel, ontologies are becoming more common and extensively used. According to Gruber [4], ontology is a conceptualization of a specification. Such a conceptualization consists in a corpse of formally represented knowledge, i.e., the objects, the concepts, and the relationships that hold among them in a domain of interest. A conceptualization is a simplified sight of the world that we want to describe to achieve a given goal.

This concept of ontology is increasingly employed to offer a shared understanding of an interest domain aiming to improve communication among humans and computers.

In fact, it is applied to define the semantics of a field through depicting conceptual models [4]. It plays a significant role in offering a generally agreed comprehension of a domain. It is intended to sum up the semantics of such a definite field. Because of that, ontology has become crucial tool for information representation and processing at the semantic level. Facing the semantic wealth of ontologies and the significance of data mining techniques, especially association rules, such coupling of them, allows, on the one hand, the semantic knowledge extraction, on the other hand, it may permit the domain knowledge evaluation through comparing such a derived knowledge to the expert prerequisites.

To the best of our knowledge few works address the coupling of ontology and association rules issue. We may distinguish two main pools, namely: (i) *Ontology as a tool for association rules mining approaches* and (ii) *Ontology as a goal for association rules mining approaches*.

Whatever is the category, any proposal may only draw at the outside two classes of relations namely, associations and compositions. However, more elaborated categories of association rules are sometimes needed to make a better decision. Thus, the originality of our proposal is the consideration of, in addition to the membership relationship, new enhanced categories such as causality fact between ontological concepts, i.e. a given concept generates another concept or transitivity concept which expresses that a given concept engenders a particular concept. Simultaneously, the latter also produces the first one. The main thrust of this paper is to introduce a new approach for mining more enhanced association rules from ontological resources.

The paper is organized as follows. We scrutinize association rules mining approaches over ontologies in Section2. Section 3 studies our contribution. Finally¸ the paper is completed by a conclusion section summarizing some open issues.

2. Association Rules Mining Using Ontologies

Several approaches dedicated to mining association rules from ontologies have been proposed in the literature. According to related sources, we can distinguish two main trends, as depicted in figure 1, namely: (i) *Ontology as a tool for association rules mining approaches* and (ii) *Ontology as a goal for association rules mining approaches*.

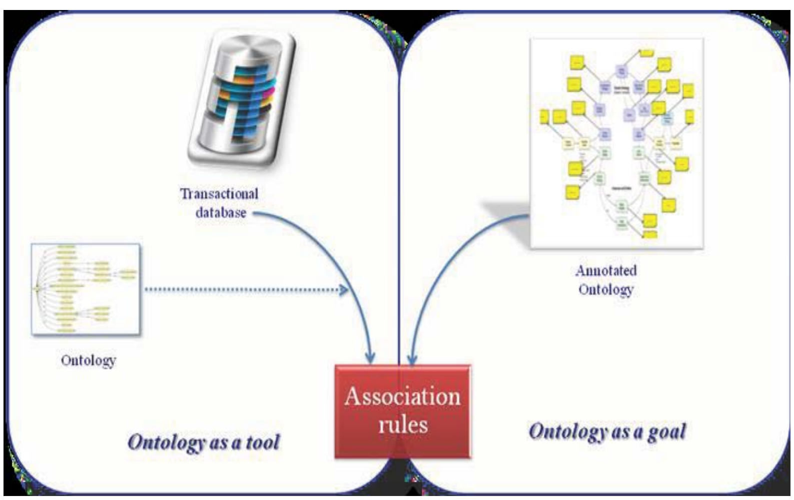

Figure 1. Ontology-based association rules trends

2.1 Ontology as a tool for association rules mining approaches

It is noteworthy that such trend of approaches considers the ontology as a tool to assist the mining process.

2.1.1 Tseng et al proposal

Tseng et al. address the association rules mining using ontological knowledge covering classification and composition relations [16]. For example, for the purchased item "*Sony VAIO*", "*PC*" and "*Desktop*" are its generalizations, while "60 GB

Segate” and “512 MB RAM” are its components. Then, two algorithms AROC and AROS are introduced. Thus, these methods derive associations that can boost distinct hierarchical levels between relations in used ontology.

New transactions are regularly added to the database, and the ontology of items likewise evolves [17]. Thus, the discovery of interesting association rules is an iterative process which requires to repeatedly adjust the support and the confidence thresholds. In this perspective, an algorithm called MIFO is introduced for incremental maintenance of frequent discovered patterns taking into account the evolution of several factors, namely the updated data, the evolved ontology, and quality metrics changing, i.e., support and confidence.

2.1.2 Wu et al. contribution

Wu et *al*. proposed an ontology-based framework for multidimensional association rules mining in order to assist decision-makers in accurate queries formulation with reduced system resources consumption [18, 19]. Such use of ontology is motivated by the limits of hierarchical attributes representation in modeling star data warehouse schema without any exploitable semantics. Indeed, several ontologies are used such as queries history ontology, schema ontology, schema constraints ontology and domain ontology. Its main idea is when any user launches a query, the system checks the used syntax using the history ontology. Then, it checks its semantics using schema constraints ontology. Finally, the search engine undertakes for the useful knowledge extraction.

Based on these different ontologies, the mining platform closely guide the extraction process of association rules for deriving effective and useful results consistent with the expectations of the user. The authors demonstrated an intelligent assistance system during their derivation targeted knowledge.

2.2. Ontology as a goal for association rules mining approaches

Under this category, we classify the approach of Manda et *al.* [11]. It is obvious that Gene Ontology (GO) has become an internationally recognized standard representing the function, process and neighborhoods genes. The richness of GO annotations is a valuable source of implicit knowledge between these data as illustrated in figure 2.

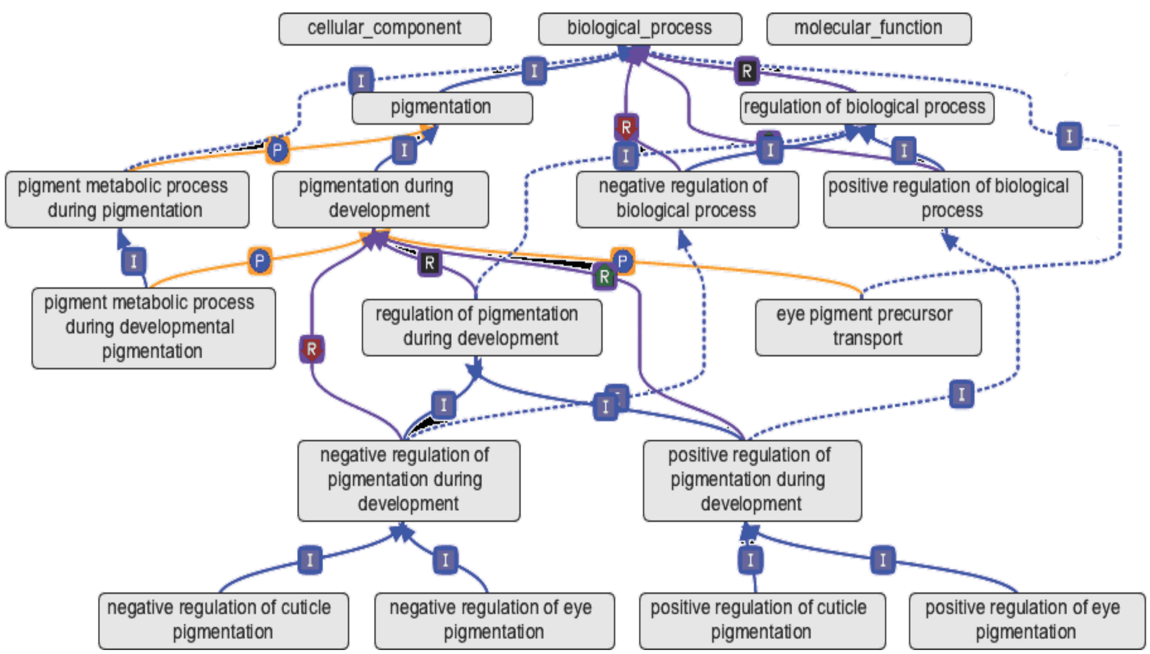

Figure 2. Gene Ontology

Manda et *al*. introduce a new method for association rules mining from sub-ontologies in several levels of abstraction. Indeed, they propose a generalization procedure called bottom-up Cross-Ontology Data Mining-Level by Level taking into account the structure and semantics of GO. Such a strategy generates generalized transactions from the annotated data and derives association rules inter-ontologies at several abstraction levels. GO annotations in form of transactions are usually established at several levels in the GO hierarchy. GO is parsed and loaded into tables of relational databases.

Initially, the T Level is the set of transactions where the level is the depth of the deepest annotation throughout the operation. The Apriori algorithm is applied to the initial set of transactions to generate a set of rules. All the same rules under ontology will be pruned. Rules biologically interesting discovered reveal unexpected knowledge about the co-occurrence of GO terms.

2.3. Discussion

The comparison between these approaches seems crucial. We rely on eight criteria classified into two categories such as: (*i*) class of ontology; (*ii*) ontological relations; *(iii*) constraint-based association rules; (*iv*) incremental aspect ; (*v*) quality measures ; (*vi*) levels; (*vii*) application domain and (*viii*) conducting experimental evaluation.

Table 1 shows a comparison between the different strategies of ontology-based association rules based on these criteria. From the ontological perspective, Tseng et *al*., Wu et *al*., and Manda et *al*., used domain ontologies. In addition, Tseng et *al*. and Wu et *al*., consider classification and composition ontological relations. However, Manda et *al*. integrate more complex relations.

From the mining side, the majority of these approaches use a constraint-based mining of association rules while Wu et *al*. neglect the constraint criteria on association rules derivation. Besides, except the work of Tseng et *al*.[17] all the rest of proposals ignore the incremental aspect on extracting knowledge. Moreover, the quality metrics of generated patterns are exclusively redefined by Tseng et *al*. [17]. With respect to the hierarchies of classes, the hierarchical association rules [14] are the most common class of derived patterns.

In respect to the validation feature, only Manda et *al.*, consider a specific application domain for experiments. Moreover, only Wu et al., discard the experimental evaluation of their study.

At the sight of this comparative analysis, we can infer that extracted association rules classes are generally limited. In this paper, we deal with mining association rules from ontology as a goal issue where more complex relations than composition or generalization are required to urge performed analysis. To do this, a new strategy is proposed to derive enhanced association rules from ontological resources which is the main subject of the next section.

		Ontology					**Association rules**								**Validation**			
		Class of ontology		*Ontological relations*			*Constraints*		*Incremental aspect*		*Quality measures*		*Levels*		*Application domain*		*Experimental evaluation*	
		Domain	Application	Classification	Composition	other relations	Without constraints	With constraints	Static	Incremental	Classic support & confidence	Adapted support & confidence	Uni-level	Multi-levels	specific	general	Yes	No
Ontology as a tool	Tseng et al., [16]	X		X	X		X		X		X			X		X	X	
	Tseng et al. [17]	X		X	X		X			X		X		X		X	X	
	Wu et al., 2011 [18, 19]	X		X	X			X	X		X			X		X		X
Ontology as a goal	Manda et al, 2012 [11]	X		X	X	X	X		X		X			X	X		X	

Table 1. Comparative table of ontology-based association rules mining

3. New Approach For Enhanced Association Rules Extraction From Ontology

This section describes our new enhanced association rules extraction.

3.1 Basic concepts

In the sequel, we introduce the basic concepts that will be of use in the remainder.

Definition 1. (Ontological Formal context)
An ontological formal context is a tuple $OFC = (F, A)$ with F is the set of factors of our ontology, namely its concepts C and relations R and A the set of associations.

Example 1
An illustrative example of an ontological formal context is sketched by table 2.

Definition 2. (Ontological item)
Let C be the set of concepts $C = \{C_1 ,...,C_n \}$. An Ontological item ± is an item belonging to one of the concepts C_i.

Example 2
An example of an ontological item is Transmembrane protein 14C.

Definition 3. (Ontological itemset)
An ontological itemset I defined on $C =\{C_{i\,1},...,D_{i\,m}\}$ is a non empty set of ontological items $I = \{\alpha_i ,...,\alpha_p \}$ with $\forall j \in [1, p]$, α_j is an ontological itemset defined on C.

Example 3
A typical example of ontological itemset is I = [Transmembrane protein 14C , mitochondrion].

Definition 4 (Ontological rule)
An ontological rule r is an annotated implication of the form $X => Y$, where $X \subset I$, $Y \subset I$, and $X \cap Y =ø$ and the implication is expressed using one of existing relations R. We distinguish three classes of ontological rules in this context.

Example 4
Transmembrane protein 14C => mitochondrion is an example of ontological rule.

Definition 5 (Transitive ontological rule)
A transitive ontological rule r is an implication of the form $X <=> Y$ with $Y => X$ and $X=> Y$ where $X \subset$ I, $Y \subset$ I, $X \cap Y =ø$, and the related implication is expressed using one of transitive existing relations R.

Example 5
Transmembrane protein 14C <=> mitochondrion may be extracted as a transitive rule if only if Transmembrane protein 14C => mitochondrion and mitochondrion => Transmembrane protein 14C are valid rules.

Definition 6 (Compound ontological rule)
A compound ontological rule r is an implication of the form $X => Y$ with X a component of Y and $X \subset I$, $Y \subset I$, $X \cap Y = ø$, and the related implication is expressed using one of compound existing relations R.

Example 6
An example of drawn compound rule is metal ion binding => GO_REF:0000004 when metal ion binding is a compound of the database GO_REF:0000004.

Definition 7 (Causal ontological rule)
A causal ontological rule r is an implication of the form $X => Y$ with X a cause of $Y=> X$ and $X \subset I$, $X \subset I$, $X \cap Y = ø$, and the related implication is expressed using one of causal existing relations R.

Example 7
A typical example of causal ontological rule is Golgi membrane => SP_SL:SL-0134 stressing that the GO term name Golgi membrane is caused by SP_SL:SL-0134.

3.2. ECARD EnhanCed Association Rules Derivation Proposal

Starting from an ontology, we propose three-step process for enhanced association rules derivation (*c. f* figure 3):

- ***Preprocessing***: building the formal context;
- ***Processing*** : extraction of enhanced association rules;
- ***Postprocessing***: pruning of uninteresting derived rules or redundant ones.

In what follows, these steps are detailed.

		Factors F					
		Concepts C				Relations R	
	N°	A	B	C	D	Caused-by	Is-a
Associations	1	1	1	0	0	1	0
	2	0	1	1	0	0	1

Table 2. Ontological formal context

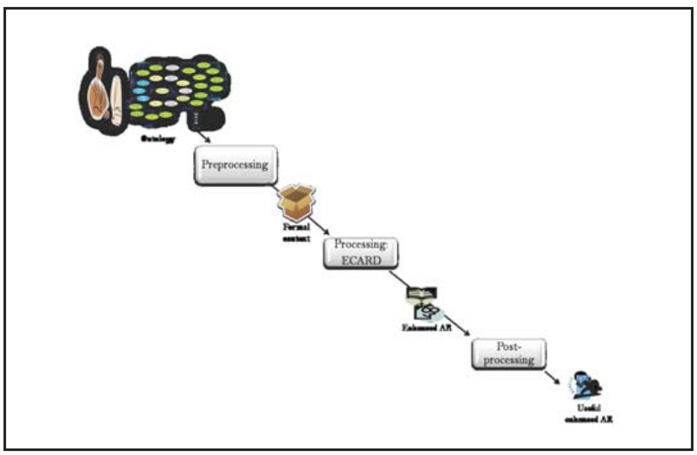

Figure 3. ECARD architecture

ECARD outputs the list of enhanced association rules. In fact, our iterative process, operates in three steps:

3.2.1 Preprocessing

We build the context analysis from our ontology arrayed in the matrix form. Such a step is performed using two tasks: (i) extraction of stored concepts and their related relations; (ii) storage of such extracted items in a matrix. The latter matrix assigns each concept to its related relations. The presence of a relation between two concepts is represented using a row in the matrix and corresponding concepts and relations are described using 1. All the rest of attributes are denoted by 0 in this row. Figure 4 presents an example of our preprocessing step.

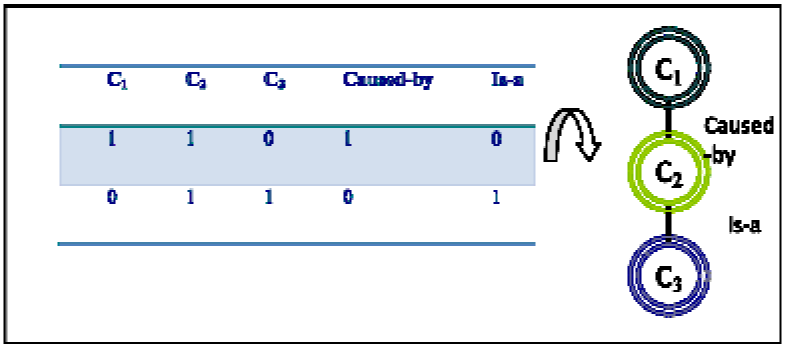

Figure 4. ECARD preprocessing step

3.2.2 Processing

The used notations are depicted by table 3 and its pseudo-code is illustrated by the algorithm in the following. First, we follow a rising level wise search for ontological i-itemsets in the ontological formal context with the level (i) draws the number of items in the set. For each level (i), we generate the set of nonempty candidates being as a conjunction of ontological itemsets. Only frequent itemsets are retained according to the minimum support threshold. Based on retained itemsets, three trends of ontological relations are derived in respect to their corresponding ontological relations : (i) set of transitive rules, (ii) set of compound rules and (iii) set of causal rules.

Notation	Description
OFC	Ontological formal context
Nconcepts	Number of concepts
J (resp.F)	Set of candidates (resp. Frequent)
Minsupp	Minimum support threshold
count(J)	Support of ontological itemset J
r	Generated rule
relations	Set of ontological relations
oi	Ontological relation i
Rtransition	Set of the transitive rules
Rcomposition	Set of the compound rules
Rcausality	Set of the causal rules
R	Set of the generated rules

Table 3. List of used notations

3.2.3 Postprocessing

A huge number of association rules are drawn from our ontological context. However, only some of the rules extracted are of real interest. Most of the rules are superfluous, redundant, or evident. Thus, we propose to prune such redundant and uninteresting rules.

4 . Experimental study

In this section, we detail our performed experiments on ontological resources. We implemented our proposal with Java language. Experiments were carried out on a Pentium IV PC with a CPU clock rate of 3.06 Ghz and a main memory of 2GB.

4. 1 Dataset description

We have performed a series of experiments with real dataset, derived from agbase, a public dataset available from http://agbase.msstate.edu/Education/Workshop_Materials/Datasets_for_Functional_Modeling.htm. Indeed, AgBase offers

```
Algorithm ECARD : EnhanCed Association Rules Derivation from ontological data
Data: C, Nconcepts, Nrelations, Relations
Result: R: Enhanced rules
begin
    F1 = Find 1-itemsets in OFC;
    // CandidateGeneration
    for (k = 2; k = Nconcepts ; k++ ) do
        Jk = CandidatGeneration(Jk-1 );
        Foreach J ⊆ Ck do
        count(J)=0
            Foreach tuplet t ∈ OFC do
            If J ⊆ t.items then
                count(J)=count(J)+ 1
            If count(J) ≥ min_support then
                F =F += J
  //ruleGeneration
  R = ∅, Rtransition= ∅, Rcomposition = ∅, Rcausality = ∅
  Foreach J in Frequent
     Foreach o in Relation
        Foreach rule r: A1,…,Am-1 → Am\J = {A1,…,Am}
            If oi = is - a then
                Rtransition = Rtransition += r
                    If ai = element - of then
                        Rcomposition = Rcomposition += r
                            If ai = caused- by then
                                Rcausality = Rcausality + = r
R = Rtransition U Rcomposition U Rcausality
End
```

resources to assist modeling of functional genomics data and structural and functional annotation of agriculturally important animal, plant, microbe and parasite genomes. Several associated databases of functional genomics data are provided. Moreover, wide-ranging training resources are also available at the AgBase website [20].

4. 2 Experimental findings

Through the carried out experiments, we have a threefold aim. First, we stress on the assessment of the scalability-related criteria. Second, we focus on evaluating the performance of our proposal. Finally, we concentrate on estimating the relevance of generated patterns.

4.2.1 Scalability assessment

Our first experiment was performed to assess the scalability of our proposal with respect to the number of generated patterns and the runtime. Figure 5 shows the scalability of our proposal over the dataset size in terms of extracted patterns. However, the figure 6 plots the results of this experiment in terms of runtime. In fact, for a dataset size equal to 20, the number of extracted association rules is 8655. Hence, the needed runtime is 30 s. Increasingly, when the dataset size is equal to 60, the number of derived patterns is 30466 and 62 s are required to perform this mining task.

As it can be seen, ECARD's execution time almost grows linearly with the size of the dataset as well as its number of derived patterns. Indeed, when the dataset size increases, the number of extracted patterns will also grows up inducing to raise the needed runtime.

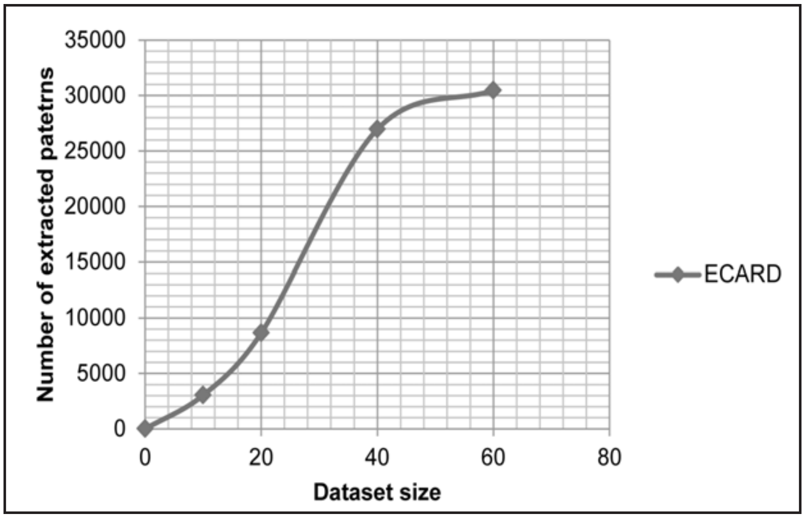

Figure 5. Number of extracted patterns obtained by ECARD over our dataset

4.2.2 Performance evaluation

The number of attributes ranges from 3 to 13. According to figure 7, the required runtime for mining association rules with four attributes is 29.3 s. Such a value highly increases to become 62 s for 13 attributes. The running time increases for each newly added attribute.

As the number of incorporated attributes raises and the dataset becomes larger, there could be many frequent patterns which lead to increasing the runtime.

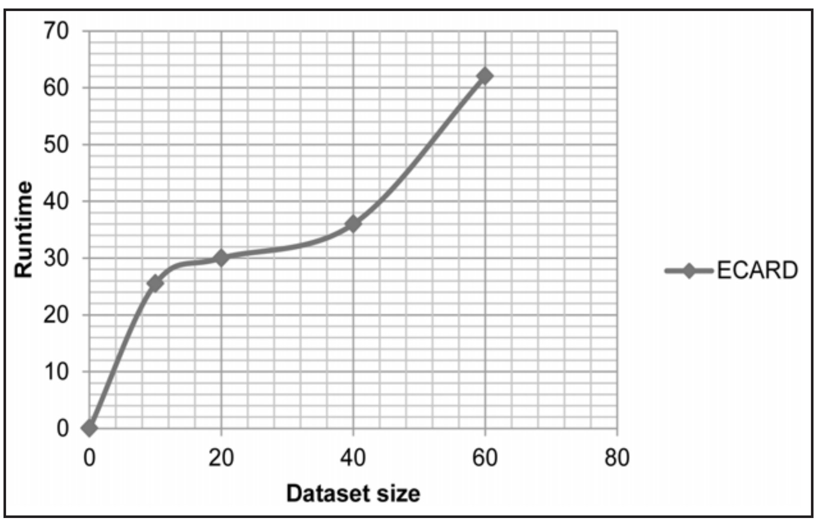

Figure 6. Required runtime for enhanced association rules generation using ECARD over our dataset

4.2.3 Relevance evaluation

In order to evaluate the relevance of our proposal, three categories of derived patterns are analyzed. Figure 8 plots the compound generated association rules. However, Figure 9 illustrates the causal class. As to figure 10, it represents the transitive patterns. For 13 attributes, the number of extracted association rules is allocated as follows 1430 patterns are compound, 11940 are causal and 17094 are transitive. We notice that the same dataset produces transitive, compound and causal knowledge. Such transitive and causal association rules are judged so useful according to the domain expert.

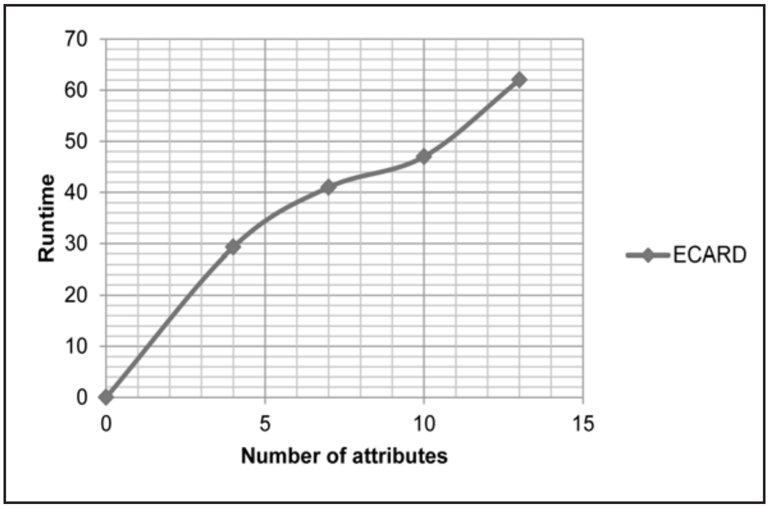

Figure 7. Performance analysis of ECARD

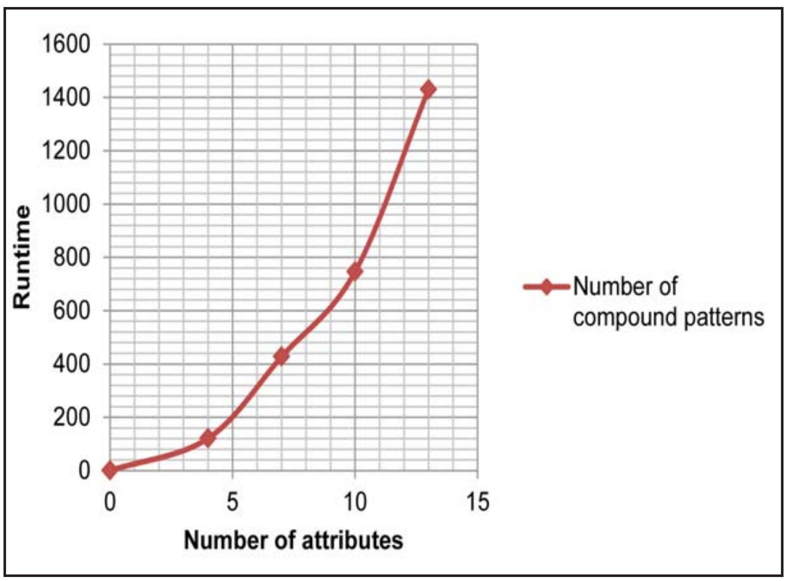

Figure 8. Number of generated compound patterns using ECARD

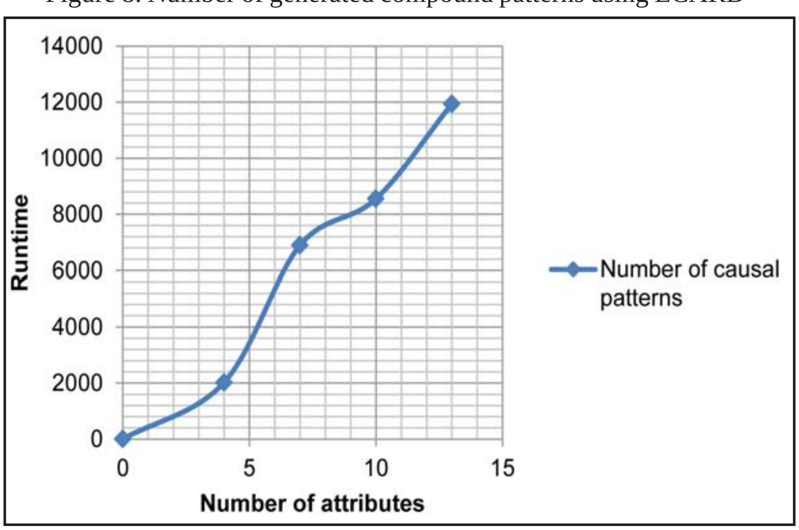

Figure 9. Number of generated causal patterns using ECARD

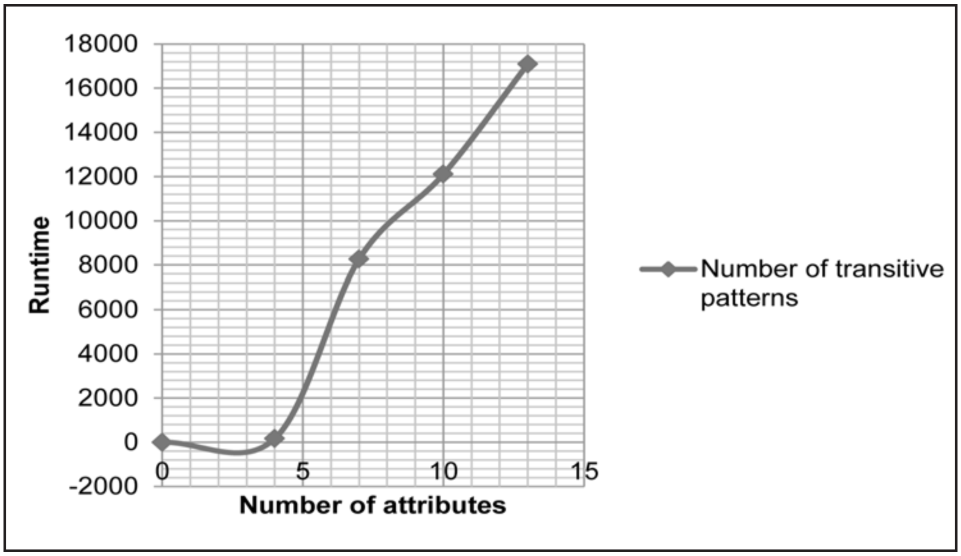

Figure 10. Number of extracted transitive patterns using ECARD

Knowing that a main challenge of existing data mining techniques applied to ontologies is to bring more useful and meaningful knowledge from ontological resource, the main benefit of our proposal is to derive enhanced knowledge classified into three main trends: (i) transitive association rules; (ii) compound association rules and (iii) causal patterns.

5. Conclusion

In this paper, we first draw an overview of ontology-based association rules mining. Current approaches were confronted according to several comparative criteria. Such analytical study allows us to sketch some limitations of mined association rules from ontologies. Thus, we proposed a novel approach for enhanced association rules extraction over ontological resources. Three main trends of extracted patterns are introduced, namely compound, transitive and causal association rules.

Other avenues for future work mainly address the following issues. As shown in figure 11, the ontology-based pattern mining can be categorized with respect to the types of data and involved ontology, through the following criteria:

(i). Kinds of data and features to be extracted: several types of knowledge may be derived such as sequential patterns [15], expressing a sequence of ordered actions or rare patterns [10] describing infrequent associations or contrast association rules [12] which may be used to check the inconsistencies that may exist between a corpus and reference ontology for example;

(ii). Categories of used ontologies : different categories of ontologies can be employed:

a) *Core ontology*: it defines the generic concepts required to understand the other concepts [7], from which generic association rules may be drawn.

b) *Domain ontology*: models a particular domain through defining a set of vocabularies and concepts that describe the target world [5].

Concrete association rules may be derived based on domain ontology.

c) *Task ontology* [13]: tends to conceptualize specific tasks in the systems, such as planning, design or simulation tasks.

Using such trend of ontology, active rules in form of Event Condition Action (ECA) can be extracted [8].

d) *Application ontology*: offers a terminological structure to suit the requirements of an explicit activity.

(iii). ***Specific application domains***: Various categories of application data incorporate spatial data, temporal data, spatiotemporal data and multimedia data. This range can lead to radically varied patterns extraction. For example, from spatial ontology, respectively temporal one, we can extract spatial association rules [9] respectively temporal [6].

(iv). ***Data analysis practices***: ontology-based frequent pattern mining commonly operates as an intermediate stage for enhanced data comprehension.

For instance, it can be employed as a feature extraction step for classification in pattern-based classification or pattern-based clustering. Likewise, pattern analysis can also be employed in recommender systems, which suggest information items.

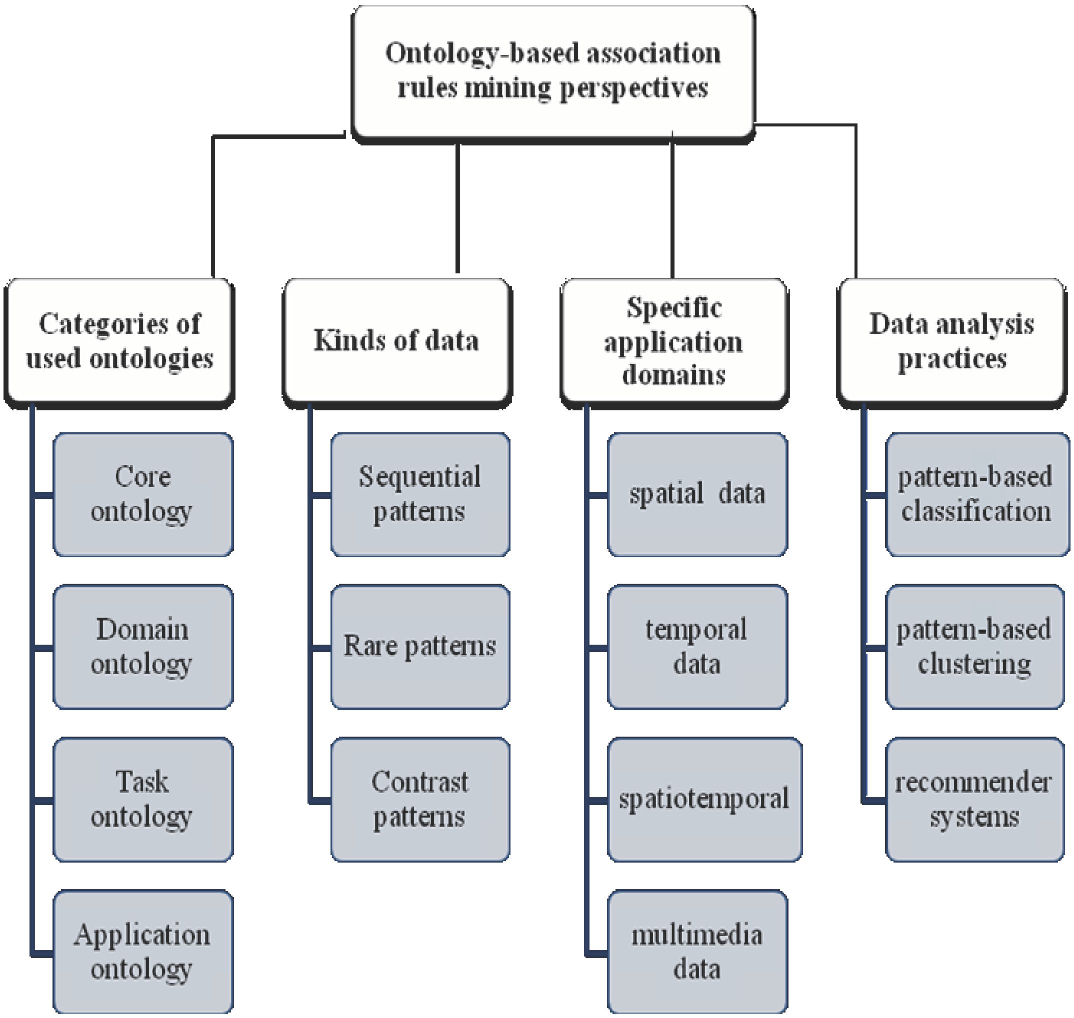

Figure 11. Ontology-based association rules perspectives

References

[1] Agrawal, R., Imielinski, T., Swami, A. (1993). Mining association rules between sets of items in large databases. *In:* Proc. of the ACM SIGMOD Conference on Management of Data, p. 207-216, Washington, D.C., May.

[2] Agrawal, R., Srikant, R. (1994). Fast algorithms for mining association rules. *In*: Proc. of the VLDB Conference, Santiago, Chile, September 1994. Expanded version available as IBM Research Report, RJ 9839, June.

[3] Fayyad, U., Piatesky-Shapiro, G., Smith, P (1996). From data mining to knowledge discovery in databases. *AI Mag* 17 (3) 37-54.

[4] Gruber, T. (1993). A Translation Approach to Portable Ontology Specifications, *Knowledge Acquisition* 5 (2)199-221. Elsevier, Amsterdam.

[5] Jean, S., Dehainsala, H., Nguyen Xuan, D., Pierra, G., Bellatreche, L., Aït-Ameur, Y (2007). OntoDB: It is Time to Embed your Domain Ontology in your Database, *In*: Proceedings of the 12th International Conference on Database Systems for Advanced Applications (DASFAA'07) , volume 4443 of Lecture Notes in Computer Science, p. 1119- 1122.

[6] Juan, M., Ale, G., Rossi, H. (2000). An approach to discovering temporal association rules. *In*: Proc. of the 2000 ACM Symposium on Applied Computing, Villa Olmo, Via Cantoni 1, 22100 Como, Italy, p. 294–30.

[7] Kassel, G. (2009). Vers une ontologie formelle des artefacts, IC 2009 : Actes des 20 Journées Francophones d'Ingénierie des Connaissances, Hammamet, Tunisia, May 25-29.

[8] Klaus, R., Dittrich, R., Gatziu, S., Geppert, A (1995). The Active Database Management System Manifesto: A Rulebase of ADBMS Features. Rules in Database Systems, volume 985 of Lecture Notes in Computer Science, Springer, p. 3-20.

[9] Koperski, K., Han, J. (1995). Discovery of spatial association rules in geographic information databases, Advances in Spatial Databases Lecture Notes in Computer Science Volume 951, p. 47-66.

[10] Liu, B., Hsu, W., Ma, Y.(1999). Mining Association Rules with Multiple Minimum Supports. SIGKDD Explorations ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-99), San Diego, CA, USA.

[11] Manda, P., McCarthy F., Bridges, F, S (2013). Interestingness measures and strategies for mining multi-ontology multi-level association rules from gene ontology annotations for the discovery of new GO relationships. *J Biomed Inform*.

[12] Minaei-Bidgoli, B., Tan, P., Punch, W. (2004). Mining interesting contrast rules for a web-based educational system, *In:* International conference on machine learning applications, Los Angeles, California, p.1–8.

[13] Mizoguchi, R., Kozaki, K. , Sano,T. , Kitamura, Y. (2000). Construction and Deployment of a Plant Ontology, *In:* The 12th International Conference, EKAW2000, p. 113-128.

[14] Srikant, R., Agrawal, R. (1995). Mining generalized association rules. *In*: Proc. of the 21st International Conference on Very Large Databases. Zurich, Switzerland, p. 407- 419.

[15] Srikant, R. Agrawal, R. (1996). Mining sequential patterns: generalizations and performance improvements. In: Proceeding of the 5th international conference on extending database technology (EDBT'96), Avignon, France, p. 3–17.

[16] Tseng, M., Lin, W., Jeng, R. (2007). Mining Association Rules with Ontological Information, *In*: Second International Conference on Innovative Computing, Information and Control, 2007(ICICI '07)

[17] Tseng, M., Lin, W., Jeng, R. (2007). Incrememtal Maintenance of Ontology-Exploiting Association Rules, *In:* International Conference on Machine Learning and Cybernetics, p. 2280 – 2285.

[18] Wu, C., Lin, W., Wu, C. (2007). Ontology-Assisted Query Formulation in Multidimensional Association Rule Mining, IEEE International Conference on Granular Computing, 2007. (GRC 2007)

[19] Wu, C.Lin, W. Jiang,C. Wu,C. (2011). Toward intelligent data warehouse mining: An ontology-integrated approach for multi-dimensional association mining. *Expert Syst. Appl*. 38 (9) 11011-11023.

[20] McCarthy, FM., Gresham, CR., Buza, TJ., Chouvarine, P., Pillai, LR., Kumar, R,, Ozkan, S., Wang, H., Manda, P,, Arick, T.T, Bridges, SM., Burgess, SC. (2010). AgBase: supporting functional modeling in agricultural organisms.Nucleic Acids Res. 2010 Nov 12.