Using Association Rules for Ontology Enrichment

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Abstract

An ontology is a formal description of knowledge as a set of concepts within a domain and the relationships that hold between them. At the same time, data mining techniques are used to discover hidden structures in large databases. In particular, Association Rules are used to discover implicative trends among items in a transactional database. In this context, we propose to develop a method to enrich existing ontologies with the identification of new semantic relationships between concepts in order to have a better coverage of domain knowledge. The enrichment process is realized by association rules discovered by applying the Apriori algorithm. We demonstrate the applicability of this method using an existing ontology.

Keywords

Apriori, Association Rules, Data Mining, knowledge, Ontology, Ontology Enrichment.

1. Introduction

ONTOLOGY, a branch of artificial intelligence, is a formal representation of concepts in a particular domain and the relationships amongst those concepts. In more simplified words, Ontology is the knowledge representation of a domain of interest [1]. Ontologies are regularly subject to updates and changes. The realization of these updates is a costly and tedious task because it mobilizes one or more experts in the field to identify and classify new vocabulary elements in the ontology.

In order to speed up the process of evolution and enrichment, fairly recent research has focused on the implementation of semi-automatic and automatic ontology enrichment techniques. The majority of the approaches cited in the literature, often based on statistical or linguistic tools, have focused on adding new concepts and / or existing relationships between them.

Ontologies can be joined with data mining. Data Mining techniques are used to discover non-trivial, implicit, unknown, potentially useful and understandable models from a large set of data. The idea of data mining is to extract hidden knowledge from a bunch of available data. Various forms of knowledge can be learned from data: they can be in the form of rules, models, regularities, concepts, etc... There are several techniques for extracting knowledge: Association rules, Decision trees, Neural networks, Clustering, etc...

The Association Rules (AR) technique is a practical means widely used in the field of knowledge searches, and which has been the subject of several researches to improve its implementation. The main advantage of the association rules lies in its clarity and simplicity of implementation.

In this article, we propose a new approach for enriching an existing ontology by the use of association rules using the Apriori algorithm applied to a database.

The remainder of this paper is organized as follows: in the next section, we present an overview of related approaches to our field of research. In section 3, we present the steps of the development of our approach. Finally, we conclude the article with a conclusion and an overview of the work in progress.

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2. Related work

The use of ontologies with the integration of association rules has undergone a major evolution with the aim of choosing the right techniques to extract and benefit from useful knowledge while facilitating the use and processing of the information obtained. In this section, we will present some approaches that use association rules and ontologies to solve different problems. We divided our research into four trends of research areas (See Table 1):

1. Association rules guided by ontologies and rule schemas.
2. Evaluation of association rules based on ontologies.
3. Classification of association rules based on ontologies.
4. Association rules for enriching of ontologies.

Table 1

Summary of related work

Source	Objective	Results	Issue	Trend of approach
[2]	Pruning; Compliance research; Research for interesting AR	Ontology & Rule schemas	Application of operators for the comparison between AR and rule schemas	**Association rules guided by ontologies and rule schemas**
[3]	Search for useful AR; Reduced cost and execution time	Ontology & Rule schemas	Filtering of useful attributes and concepts. Generation of useful AR	
[4]	Evaluation of AR	Evaluated AR	Semantic distance calculation based on ontology and user interest.	**Evaluation of association rules based on ontologies**
[5]	Evaluation of AR	Evaluated AR	Extraction of AR; Creation of significant partitions in AR	
[6]	Evaluation of AR	Evaluated AR Medical ontology	Discovery of RA. Elimination of unnecessary AR	
[7]	Evaluation and improvement of AR	Ontology	Extraction of multi-level AR. Define the constraints. Filter the instances	
[8]	Ranking of AR	Ontology	Calculation of the conceptual distance based on an ontology	**Classification of association rules based on ontologies**
[9]	Ranking of AR	Ontology	Calculate the classification of ARs based on the context of items in the ontology	
[10]	Ranking of AR	Ontology	Calculation of the Semantic distance based on an ontology	
[12]	Conceptual and relational enrichment of existing mammography ontology	Updated Ontology	Establish new ARs; Ontology enrichment	**Association rules for enriching of ontologies**
[13]	Enrichment of ontology by the minimum generic base of AR	Updated Ontology	Development of the generic AR database; Enrichment of ontology	
[14]	Enrichment of ontology by sequential patterns	Updated Ontology	Extraction of sequential patterns; Enrichment of ontology	

2.1. The first trend: Association rules guided by ontologies and rule schemas

There are a few works that use association rules guided by ontologies and rules schema. Among these works, we find:

In this thesis [2], the author proposes to model the user's knowledge using a formalism similar to that of association rules, called Rule Schemas. These define, the user's expectations regarding the association rules produced. For the modeling of domain knowledge, the author proposes to use a domain ontology. A "rule schema" allows to express knowledge on the form of the sought rules. It allows to combine the constraints on the attributes with the concepts described in the ontology in order to select only the interesting association rules.

The thesis [3] presents the representation of knowledge by ontologies and rule schemas in the same way as that proposed in the previous approach with a considerable improvement of the Data Mining processing process. The contribution of this approach is to introduce from the start the filtering of useful attributes and concepts and the generation only of useful association rules, based on rule schemas previously chosen by the expert in the field.

2.2. The second trend: Evaluation of association rules based on ontologies

Many works use ontologies for the evaluation of association rules. Among these works, we cite:

In [4], the authors propose a new approach for the evaluation of association rules. This approach is based on two components: the domain ontology, used for calculating the semantic distance between two items, and the preferences of the user modeling his points of view in relation to the domain. This approach assesses the relevance of pairs of items. Therefore, the semantic distance indicating how close two items are semantically, each type of relationship being weighted differently and the expert's knowledge represent the two components used to guide the process during the selection phase of item sets.

In [5] the authors proposed to create significant partitions in all of the extracted association rules. The approach is based on the combination of knowledge from an ontology with the objective measure of reliability.

In the article [6], the authors present a new method for discovering association rules using an ontology to solve the problems expressed. They present data mining based on ontology on a medical database containing clinical data on patients. The proposed ontology-based data mining algorithm makes rules more intuitive, attractive, and understandable, eliminates waste and unnecessary rules, and, as a minor result, dramatically reduces the execution time of the Apriori algorithm.

The authors of [7] propose an integrated framework for the extraction of multilevel association rules based on constraints using an ontology. The system makes it possible to define a set of constraints specific to a domain by using the ontology to filter the instances used in the process of exploring association rules. This method can improve the quality of the rules of the associations extracted in terms of relevance and comprehensibility. The main advantages of this framework can be summarized in terms of scalability and flexibility.

2.3. The third trend: classification of association rules based on ontologies

Other works use ontologies for the classification of association rules. Among these works, we cite:

In [8], the authors propose a new approach for classifying association rules according to their conceptual distance, which has been defined on the basis of ontological distance. The proposed classification algorithm helps the user to identify interesting association rules, in particular expected and unexpected rules. This algorithm uses a fuzzy light ontology to calculate the distance between the antecedent and the consequence of the rules on which the classification is based. More the conceptual distance is large, more the rule presents a high interest.

In [9], the authors propose an approach for classifying association rules using the SWETO ontology (Semantic Web Technology Evaluation Ontology). The user has a Web user interface through which he can enter the two entities in which he wishes to find associations, he can also customize his classification criteria by specifying other criteria such as "Favor rare or common associations", "Favor popular or unpopular associations" and "Favor short or long associations", the associations are stored in an Oracle database.

The authors of [10] propose a measure of interest based on an ontology to encode the usefulness of a rule in order to be able to select and classify rules according to their importance using the Apriori algorithm. The proposed approach is based on the semantic calculation of the similarity between two items i1, i2 using on the measure of [11] which is based on the location of the concepts as well as their common ancestor in the ontological hierarchy.

2.4. The fourth trend: Association rules for enriching of ontologies

Several works use association rules for the enrichment of ontologies. Among these works, we cite:

The author of [12] presents a process of enriching of an existing mammography ontology. This process focuses on conceptual and relational enrichment. Conceptual enrichment is based on the introduction of new concepts. For relational enrichment, the proposed method is based on the extraction of associations between the terms of a domain database.

The principle of this article [13] is based on the deployment of a Minimum Generic Base of association rules (MGB) between terms containing only associations between non-redundant terms, in order to enrich an ontology existing domain and lead to a conceptual network. This network integrates two types of knowledge, namely: semantic knowledge from the initial ontology and implicit knowledge from the generic MGB base, illustrated by the association rules between terms. This ontology enrichment approach is proposed to apply it to real data relating to dystonia disease.

The authors of [14] propose to set up a system using sequential patterns in order to extract the candidate terms for enrichment, and to correlate them to the ontological structure.

For more details on the research work in this section see the article [15].

It appears that the fourth group corresponds to our approach (Association rules for enriching of ontologies) but with other techniques mentioned above. Our approach is the first research that uses Apriori algorithm for ontology enrichment.

3. Proposed approach

The proposed approach consists in using the association rules for the enrichment of an existing ontology, by applying the Apriori algorithm. Our approach goes through the following steps (see Fig .1):

1. Collect and assemble the information in a Database;
2. Application of the apriori algorithm [16] on the Database in order to extract the association rules;
3. Enrichment of the ontology by new concepts using the ARs extracted from the previous step.

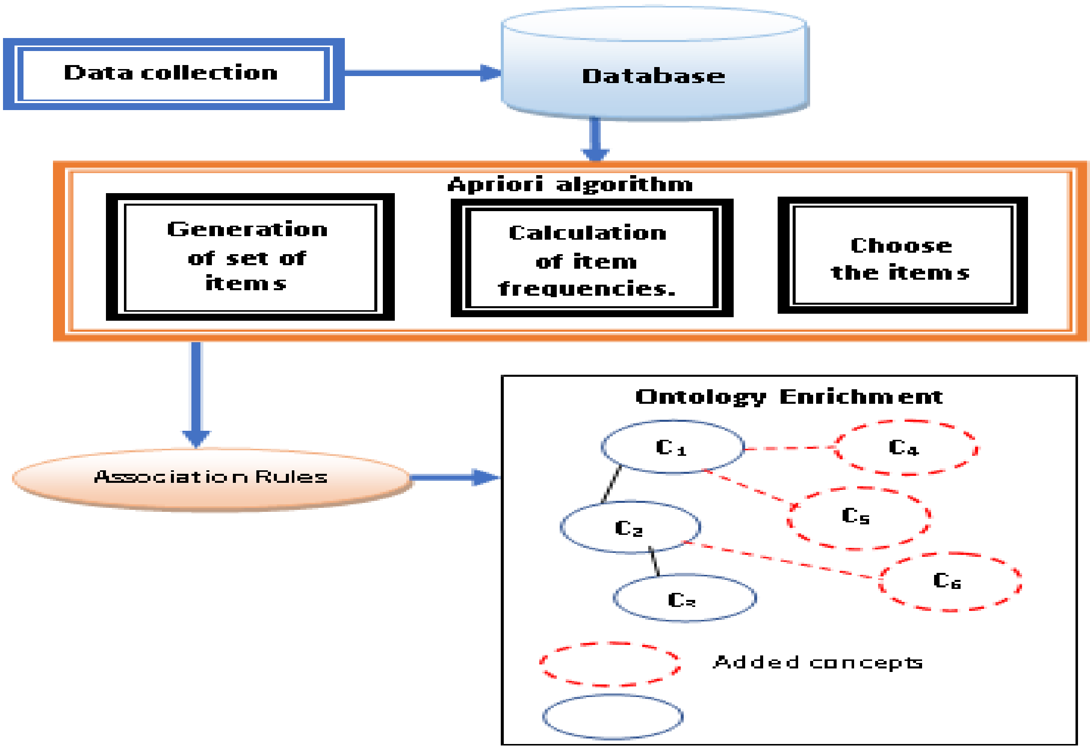


Figure 1: Steps of our approach

3.1. Collect and assemble the information in a Database

3.1.1- “Vêtements” ontology

For the ontology, we used an existing ontology called "Vêtements ontology" which contains the different types of clothes in a store (see Fig 2). This ontology is characterized by a well-structured and fairly compact hierarchy. It contains 104 classes linked by subsumption links and properties.

3.1.2. Save the results in a database

After collecting the data, we must save the results in a database to apply the Apriori algorithm on this database. The database consists of a set of transactions T described through a set of attributes (items) I. We consider that T = {T1, T2,…, Tn} is the set of n transactions, and I = {I1, I2, ..., Im} is the set of m attributes.

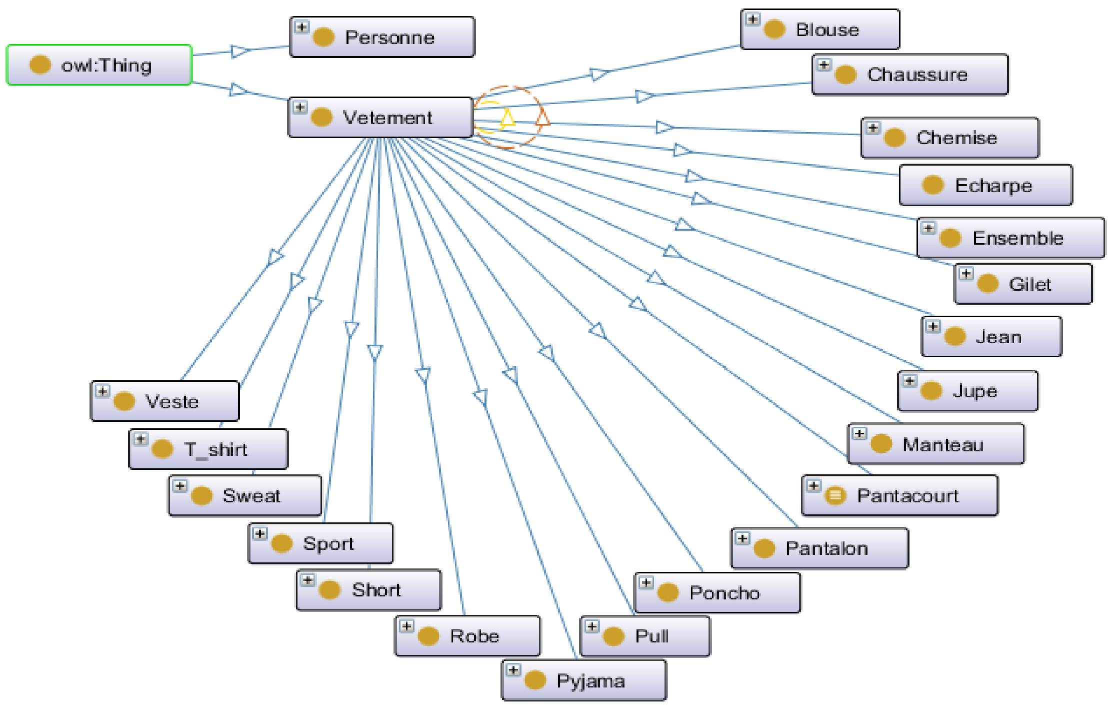


Figure 2: “Vêtements” Ontology.

3.2. Apriori algorithm

Association rules help uncover correlations between pages. Deriving association rules from data was first formulated and is called the "market basket problem" [17]. Given a set of elements and a large collection of transactions that are set (baskets) of elements, one can find relationships between the confinements of various elements within these baskets. In addition to the supermarket scenario, other examples of using association rules are users visiting WWW pages, in which the structure and its contents can be optimized.

The strength of the association will be measured by:

A. Support: The support of a rule is defined by:

The number of transactions containing X and Y items / Total number of transactions.

B. Confidence: The confidence of a rule is defined by:

The number of transactions containing X and Y items / Number of transactions containing X product.

3.2.1. Justification for using apriori algorithm

The Apriori algorithm is one of the most basic and popular algorithms for association rules mining. Agrawal and Srikant proposed the Apriori algorithm in 1994 et al [16]. Until now, this algorithm is the most used and developed by the researcher [18]. Because of the simple process of this algorithm, the advantage of this algorithm is more comfortable to learn, understand, and implemented; this is the reason this algorithm is called the most basic algorithm for association rules Apriori operates on databases containing transactions (for example collection of objects brought by customers, or details of website traffic) [19].

The Apriori algorithm (see Fig. 3) is the most supervised and important algorithm for retrieving frequent itemsets. It goes through the following steps:

- Generating a set of items;
- Frequency of item sets calculation;
- Keeping item sets with minimal support: frequent itemsets;
- Generating and keeping only the rules with minimal trust.

```
L1 = {large 1-itemsets};
for ( k = 2; Lk−1 ≠ ∅; k++ ) do begin
   Ck = apriori-gen(Lk−1);  // New candidates
   forall transactions t ∈ D do begin
      Ct = subset(Ck, t);  // Candidates contained in t
      forall candidates c ∈ Ct do
         c.count++;
   end
   Lk = {c ∈ Ck | c.count ≥ minsup}
end
Answer = ⋃k Lk;
```

Figure 3: Apriori Algorithm [16]

Note that the Ck data (and Lk) is a set of records containing two fields:

- “itemset” this field contains the subset of items;
- “count” this field contains the frequency of this set in the transaction database.

3.2.2- Results of the application of the apriori algorithm on the Database

After collecting the information in a given database and extracting the sequential patterns. We apply the apriori algorithm on these patterns. Table 2 shows the transaction data.

Table 2:

Representation of transaction data

	Robe_longue	Pull	T_shirt	Ballerines	Salopette	Chaussette	Pyjama	baskets	Pantoufle	Jean_slim	Manteau	Echarpe
T1	1	0	0	1	0	0	0	0	0	0	0	0
T2	0	1	0	0	0	0	0	0	0	1	0	0
T3	0	0	1	0	1	0	0	0	0	0	0	0
T4	0	0	0	0	0	1	0	1	0	0	0	0
T5	0	0	0	0	0	0	1	0	1	0	0	0
T6	0	0	0	0	0	0	0	0	0	0	1	1
T7	1	0	0	1	0	0	0	0	0	0	0	0
T8	1	0	0	1	0	0	0	0	0	0	0	0
T9	0	0	0	0	0	0	0	0	0	0	1	1
T10	0	0	0	0	0	1	0	1	0	0	0	0
T11	0	0	0	0	0	1	0	1	0	0	0	0
T12	0	0	0	0	0	0	1	0	1	0	0	0

The following tables (Table 3, Table 4, Table 5 and Table 6) represent rules support and confidence for levels 1, 2, 3 and 12 respectively.

Table 3:

The Support and Confidence of Level 1 rules

Rule	Level	Support	Confidence
Robe_longue → pull	1	0	0
Robe_longue → T_shirt	1	0	0
Robe_longue →ballerine	1	0.25	1
Robe_longue → salopettes	1	0	0
Robe_longue → chaussette	1	0	0
Robe_longue → pyjama	1	0	0
Robe_longue → baskets	1	0	0
Robe_longue → pantoufle	1	0	0
Robe_longue → jean_slim	1	0	0
Robe_longue → manteaux	1	0	0
Robe_longue → écharpe	1	0	0

Table 4:

The Support and Confidence of Level 2 rules

Rule	Level	Support	Confidence
Pull → Robe_longue	2	0	0
Pull → T_shirt	2	0	0
Pull → ballerine	2	0	0
Pull → salopette	2	0	0
Pull → chaussette	2	0	0
Pull → pyjama	2	0	0
Pull → baskets	2	0	0
Pull → pantoufle	2	0	0
Pull → jean_slim	2	0.083	1
Pull → manteau	2	0	0
Pull → écharpe	2	0	0

Table 5:

The Support and Confidence of Level 3 rules

Rule	Level	Support	Confidence
T_Shirt → pull	3	0	0
T_Shirt→Robe_longue	3	0	0
T_Shirt → ballerine	3	0	0
T_Shirt → salopettes	3	0.083	1
T_Shirt → chaussette	3	0	0
T_Shirt → pyjama	3	0	0
T_Shirt → baskets	3	0	0
T_Shirt → pantoufle	3	0	0
T_Shirt → jean_slim	3	0	0
T_Shirt → manteau	3	0	0
T_Shirt → écharpe	3	0	0

Table 6:

The Support and Confidence of Level 12 rules

Rule	Level	Support	Confidence
Echarpe→Robe_longue	12	0	0
Echarpe → T_shirt	12	0	0
Echarpe → ballerine	12	0	0
Echarpe → salopette	12	0	0
Echarpe → chaussette	12	0	0
Echarpe → pyjama	12	0	0
Echarpe → baskets	12	0	0
Echarpe → pantoufle	12	0	0
Echarpe → jean_slim	12	0	0
Echarpe → manteau	12	0.16	1
Echarpe → pull	12	0	0

3.3. Ontology Enrichment

The process of enriching an ontology can be divided into two stages: A phase of research of new concepts and a phase of placement of these concepts.

3.3.1. Research of new concepts

The determined AR: X → Y try to bring together, in a certain way, the candidate concepts X, Y in ontology through association → without naming the relationships. For example, if a rule defines an implication between two concepts "Robe" and "Ballerines" (Dress, Ballerinas) whose support and confidence are respectively higher than the Min_Sup and Min_Conf thresholds, then these two concepts will be associated in the ontology. The transaction table is independent of the ontology, therefore it is possible to find terms that are absent in the ontology.

3.3.2. Placement of new concepts

This step consists in placing the candidate concepts while preserving the coherence of the pre-established concepts in the initial ontology. The addition of these concepts is not random. This allows not to add conceptual redundancies.

4. Implementation

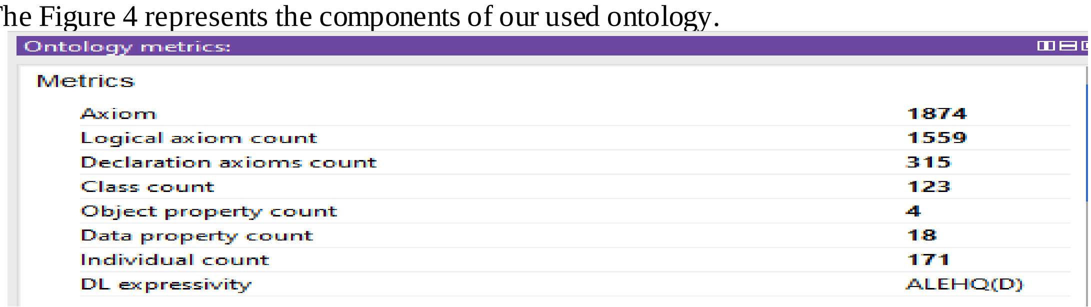
To automate the process of our approach, we have produced a software in Java language, which exploits the SQL transaction database. For the implementation of the different datasets used for enriching the ontology, we opted the following development tools:

- NetBeans[2] which is an open-source development environment used by programmers to write, compile, debug and deploy programs.
- JENA[3] is an open source working environment in Java, for building semantic web applications. JENA allows you to manipulate RDF, RDFS, OWL and SPARQL documents.
- Microsoft SQL Server Management Studio[4] is a visual database design tool that integrates SQL development, administration, database design, creation and maintenance in a transparent environment for the database system.

Protégé tool[5] is an open-source platform that provides a suite of tools for building knowledge bases and ontologies. Its graphical interface allowing to easily define classes and organize them in class / subclass hierarchy.

4.1. "Vêtement" Ontology

The Figure 4 represents the components of our used ontology.


Ontology metrics:

Metrics

Axiom	1874
Logical axiom count	1559
Declaration axioms count	315
Class count	123
Object property count	4
Data property count	18
Individual count	171
DL expressivity	ALEHQ(D)

Figure 4: The components of "Vêtements" Ontology

[2] https://netbeans.apache.org/download/index.html
[3] https://jena.apache.org/
[4] https://docs.microsoft.com/en-us/sql/ssms/download-sql-server-management-studio-ssms?view=sql-server-ver15
[5] https://protege.stanford.edu/

The ontology "Vêtements" consists of 104 classes (see fig 5 and fig 6) illustrated below, they are found in the tab "Class" which is intended for the creation of classes and allows you to manage a tree of classes.

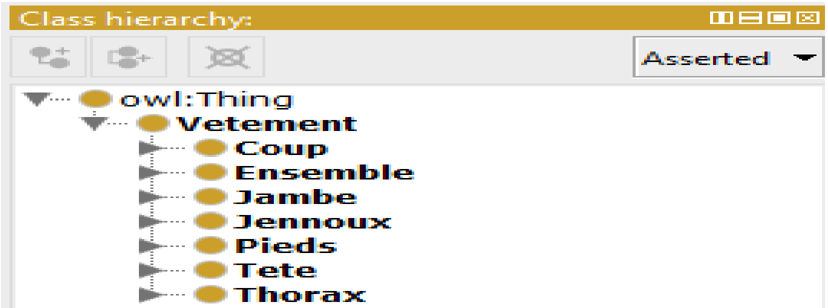


Figure 5: The general classes of "Vêtements" Ontology

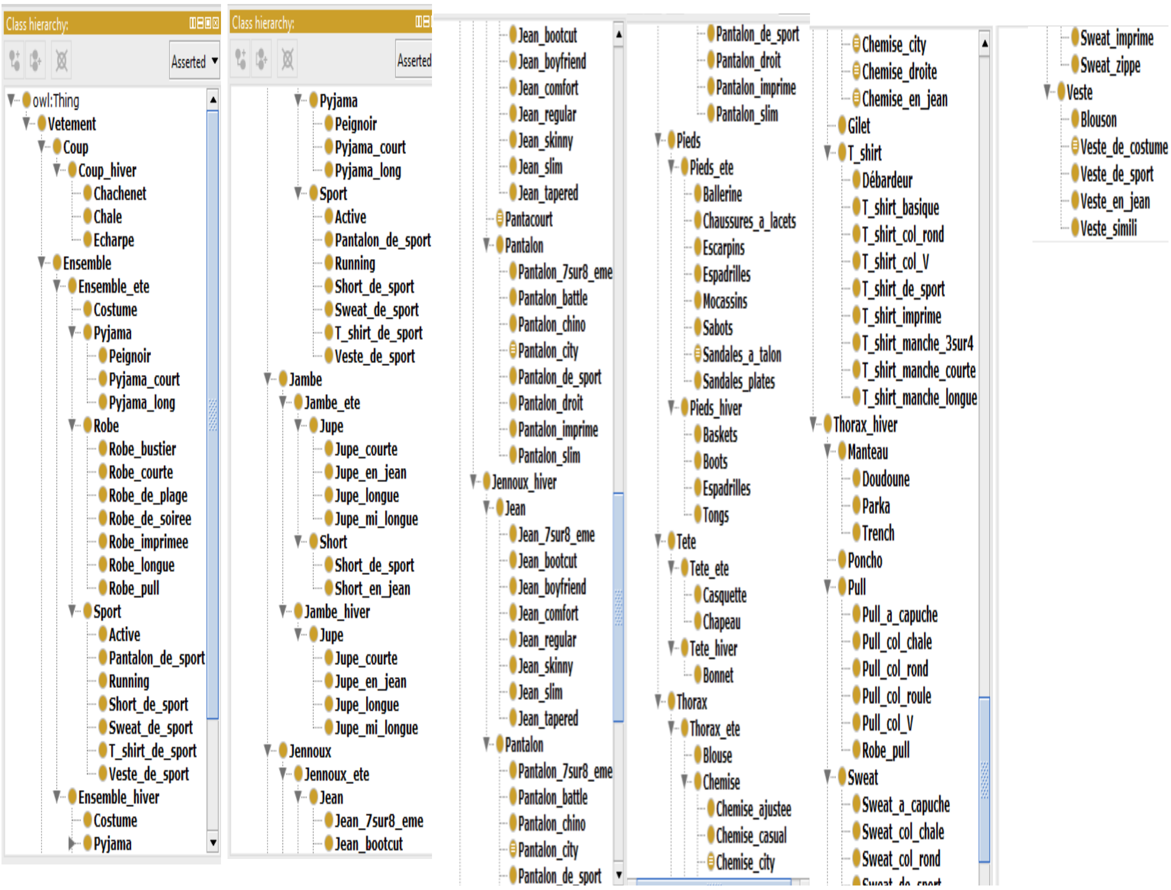


Figure 6: General hierarchy of "Vêtements ontology"

The ontology consists of a few properties, they are found in the 'Data properties' tab (see fig 7).

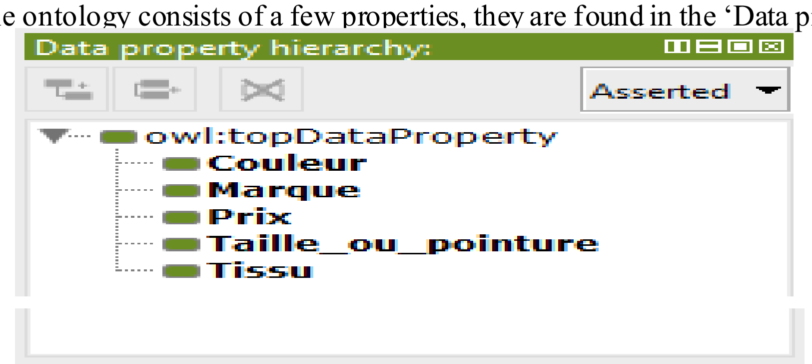


Figure 7: Properties of our ontology

The ontology consists of a few relationships (see fig 8), they are found in the 'Object properties' tab.

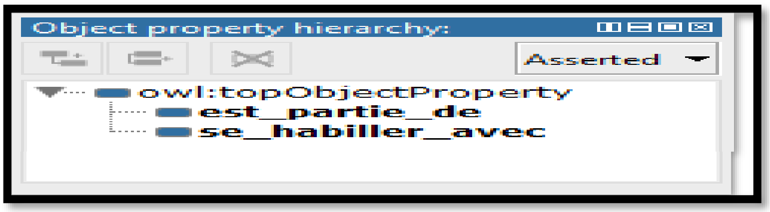


Figure 8: A part of relationships of our ontology

The ontology contains instances (see fig 9), they are found in the "Individuals" tab.

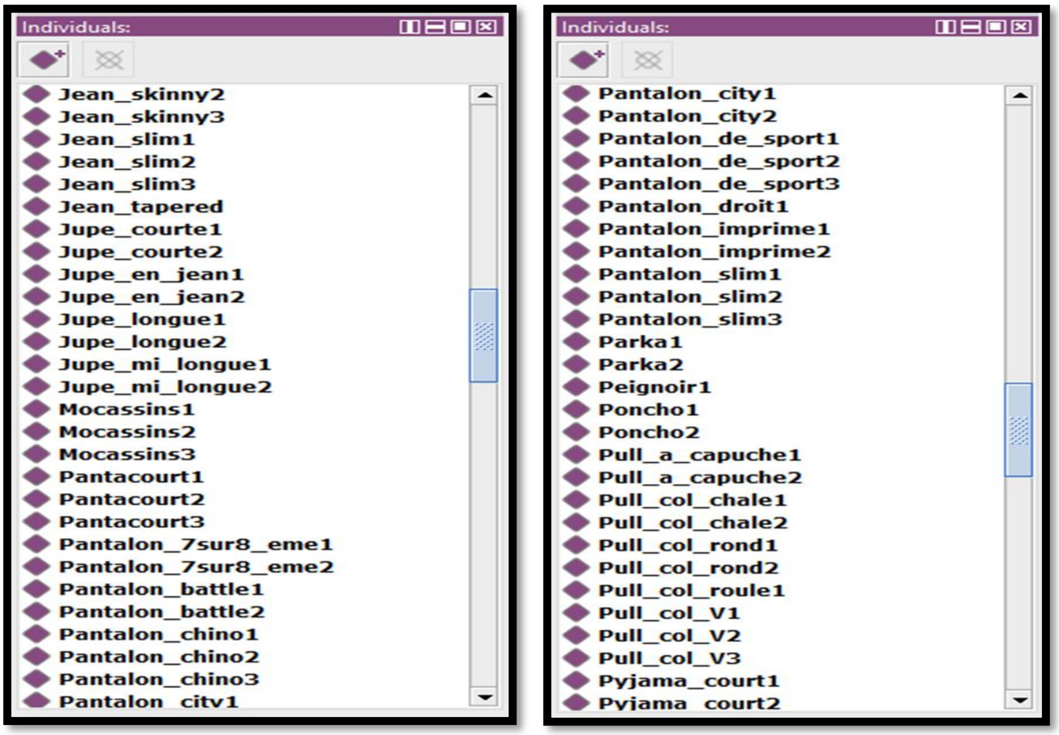


Figure 9: A part of ontology instances

4.2. Connection of Protege with NetBeans by Jena

To establish the connection between Protégé and Netbeans, you must first load all the library (.jar file) and define the general ontology link (found in the ontology) with the following instruction:

Public static final String uri_Ontologie= "http://www.owl-ontologies.com/Vetement.owl";

And the local path of ontology by the following instruction: final String CheminOwl= "D:\\Ontology\\vetement.owl"; Then create a list (ArrayList) to load the tree ontology (jTree) and display it by the following instruction:

jTree_Ontologie.setEnabled(true);

4.3. Creation of the database in Microsoft SQL server

The first step is to create a new database (fig 10) like the following figure:

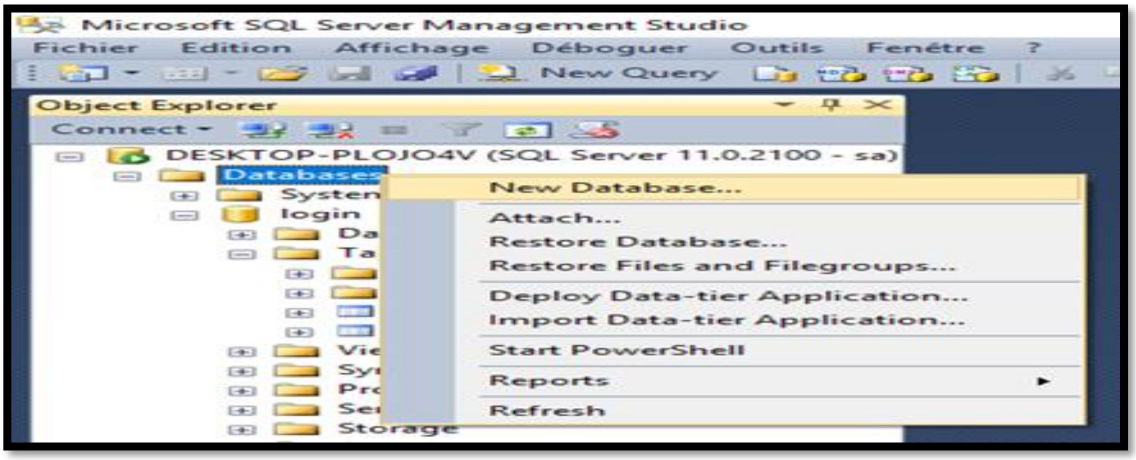


Figure 10: Creation of a new database

Then right click on the "table" node and choose "new table" (fig 11), after naming it we right click on the table and choose "Edit Top 200 Rows".

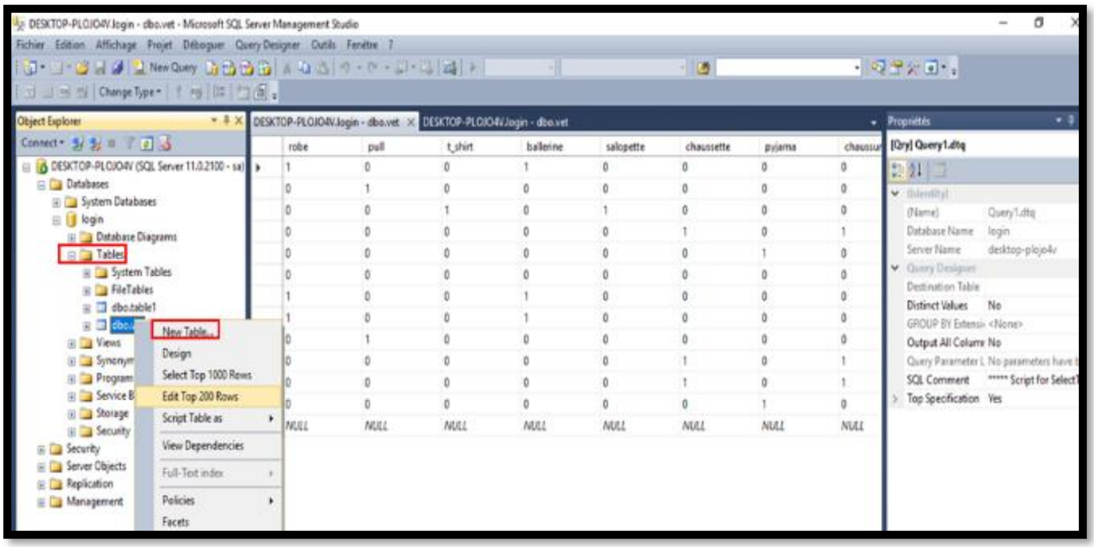


Figure 11: Creation of a new table.

4.4. Connection of Microsoft SQL server with Netbeans

Once the database is created, the connection is made by the following instructions:

Class.forName("com.microsoft.sqlserver.jdbc.SQLServerDriver");
String url ="jdbc:sqlserver://localhost:1433;
databaseName=login; user=sa; password=0000";
Connection con= DriverManager.getConnection(url);

4.5. Development of the interface under NetBeans

For the development of our application, we chose the JAVA language for many reasons:

Java is such a fast language and can be used for a heavy application (online games, image processing software, video encoding, etc.).

- Java is organized, it contains well designed and well distributed classes.
- Java is free.
- Java is portable.
- It is compatible with the JENA API, which allows us to manipulate, browse and model OWL documents.

The figure (Figure 12) below shows the main interface of our application « OnERA Acces ».

Figure 12: Main interface "OnERA Access".

The figure (fig 13) below presents the application processing space.

Figure 13: Processing area of the "OnERA Processing" application.

Step 1. Loading the table and adding a garment

To load the table found in Microsoft SQL Server containing the list of clothes on which the apriori algorithm is applied, just click on the "Display the list" button. And to add a new garment, just click on the body part in the drawing and choose the type of season (Summer or winter) then enter the name of this garment, finally click OK.

The figure (Figure 14) below shows these treatments

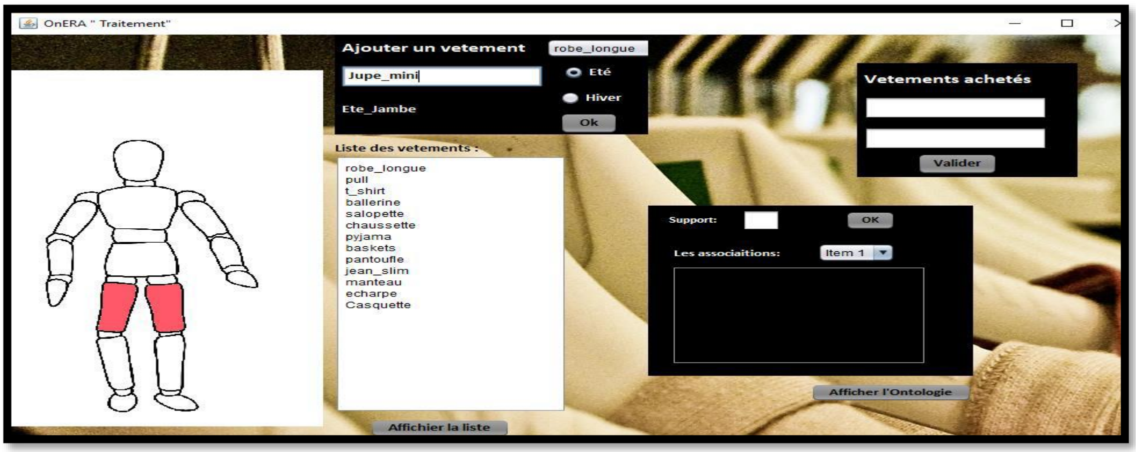


Figure 14: Loading the table and adding a garment

Step 2. Recording a purchase

To register a purchase, choose the two items of clothes from the list and click on Validate. These two clothes will be registered with the value '1' in the database.

The figure (Figure 15) below presents this treatment.

Figure 15: Recording a purchase

Step 3. Application of the APRIORI algorithm

To extract the association rules, enter the Min support, and click OK (Figure 16).

Figure 16: Application of the APRIORI algorithm and extraction of RAs

Step 4. Loading the "Vêtements" ontology

To display the ontology just click on the button "display the ontology" then on "Load the ontology" (figure 17).

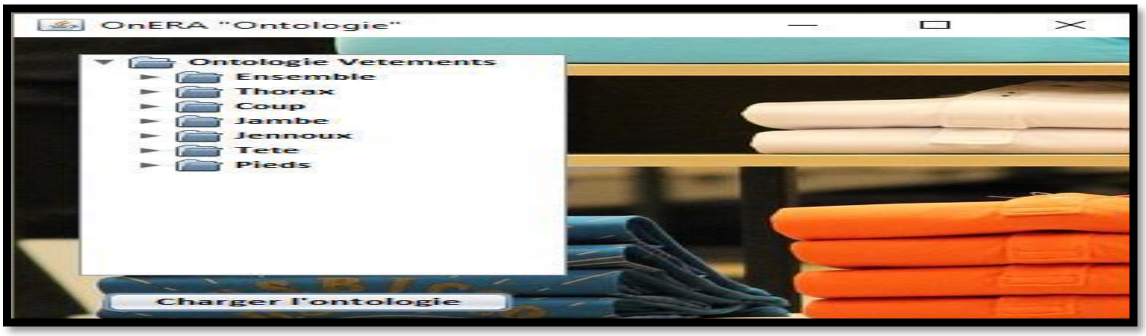


Figure 17: Loading the "Vêtements" ontology

Step 5. Enrichment result in the Protege tool

After the application of the APRIORI algorithm, new concepts will be added (figure 18).

Figure 18: Enrichment result in the Protege tool.

5. Conclusion

In this paper, we have attempted to demonstrate the potential impact of association rules on ontology enrichment. The algorithm applied on a database that we used for the extraction of RA is the APRIORI algorithm. This algorithm has allowed us to enrich the ontology, by adding new concepts. We used an existing domain ontology that represents the knowledge found in a clothing store. Once the application of the APRIORI algorithm is validated, the obtained results enrich our ontology. After using our approach, we can say that our approach allows for giving accurate results and facilitates the enrichment of ontologies.

When implementing our approach, we used the basic Apriori algorithm to find the association rules. However, many algorithms are proposed for this research. The choice of algorithm depends on the context studied. An improvement can be added to our work. We can also extend our work to other functional areas (finance, maintenance, logistics, etc.) to extract the knowledge hidden in the data history.

6. References

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