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ENRICHING DOMAIN ONTOLOGIES WITH KNOWLEDGE-BASED SEMANTICS

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ABSTRACT. Both association rules and ontologies are domain-based knowledge. However, the first is unexpected discovered knowledge from databases, while the second is *a priori* knowledge. In this paper, based on a generic meta-schema as common referential and theoretical foundation, we show how a set of computed and pruned association rules can be useful for enriching a domain ontology. To this end, the meta-schema is scanned with the itemsets appearing in each association rule. Then, according to the formal links between the concepts or the attributes involved, a semantic-based check constraint is built. As a result, the ontology and the database are continuously tuned with new semantics.

1. Introduction. Both association rules (AR) and ontologies are domain-based knowledge. However, while ontologies are *a priori* background knowledge, AR are unexpectedly implicative and interesting tendencies discovered in databases [1]. On the other hand, ontology learning is concerned with knowledge acquisition [2]. Moreover, the creation and maintenance of ontologies helped in the emergence of many tools [3]. Thus, AR which are knowledge obtained by the Knowledge Discovery from Databases (KDD) can be evaluated and interpreted as new semantic-based knowledge in the

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ACM Computing Classification System (1998): D.2.1, H.2.8, K.6.1.
Key words: association rules, relational database, ontology, UML.

development process of the underlying domain ontology. Indeed, following [4], we emphasize that a rule constraint may represent a predicate that specifies, e.g., a relationship, an instantiation of variables, or a SQL aggregate function.

In brief, without loss of generality, the posed problem is to put the AR-based semantics into the ontologies, for enriching repositories' contents of both data and ontologies schemas. According to [5], ontologies have been introduced to semantic data mining for three purposes, namely:

1. to bridge the semantic gap;
2. to provide data mining algorithms with *a priori* knowledge;
3. to formalize the representation of the data mining flow.

However, in fact most works focus on improving the data mining tasks [6, 7, 8, 9], especially the pre-processing, e.g., [10], and post-processing tasks, e.g., [11, 12, 13]. These approaches are amply reviewed in [14, 15, 16]. Association rules also helped for ontology-based classification of web pages [17], and for ontologies mapping [18]. Among the works showing the wide use of AR, we can cite [19], where association rules are mined using an ontological knowledge base as mining source. Various attempts to combine ML techniques and ontologies, semantically annotated data or both are studied in [20].

To the best of our knowledge, only [21] and [22] have dealt with the problem concerning the enrichment of ontologies by association rules.

However, data and domain ontology are not linked in a semantic point of view, namely not in an adequate manner. Moreover, it is unclear how the ontology was built. Indeed, we claim that, for permanently improving the semantics of the sources, business-data and ontologies must be tuned simultaneously. Fortunately, a meta-schema that links data and ontologies from the upper external level downwards to the storage level, namely the Knowledge-based semantic meta-model (KBSM) [23] sustains such task, because of its main feature as an abstract structure independent of the domain. It suffices to exploit the knowledge-based semantics gained from a set of computed AR. Additionally, our approach contributes to reduce the search space for further mining tasks because of the availability of prior knowledge [5], which already resides in the KBSM. Moreover, the KBSM can stand as a referential for ontology learning because it contains the same concepts as defined in [24] for the ontology learning layer cake.

Accordingly, we emphasize that our concern in this work encompasses the first purpose. Such our challenge is motivated by the lack of semantic in both the data and the ontologies' schemas whose we propose the strengthening by reusing a set of discovered AR.

Running example: Let V.CATEGORY= 'JAYA' ⇒ V.FGERM ∈ [90, 98] be a discovered association rule, where V is the concept abstracting all varieties of cereal seed, and FGERM the attribute describing the faculty of germination of all plants, i.e., the current cultivations of cereal seed or of some already certified cereal seeds of the same category.

The semantics of the above rule states that if V.CATEGORY= 'JAYA' then V.FGERM ∈ [90, 98], meaning that, for all cereal seeds of the same category, the attribute FGERM is constrained to take its values in the closed interval [90, 98].

Hence, we say that such rule is a constraint-based semantic rule. In other words, this kind of rule is applicable for adding semantics, permitting to enhance the ontology-based knowledge and constraining data by the same time. Next, the database designers create a domain of values, to be implemented with a CHECK constraint, if both the schemas of data and of the ontology are under construction or to update the schemas if already created.

The remaining of the paper is organized as follows. In **Section 2** we expose the basic notions of the association rules and the ontologies. **Section 3** presents the related work. **Section 4**, where we expose the foundations of our proposal, comprises four subsections. In Subsection 4.1., we recall the different types of constraints for explicating the hidden semantics, namely the notion of semantic-based constraint. Subsection 4.2 points out how association rules are usable as semantics. In Subsection 4.3, we recall the notion of conceptualization and on this basis give the core materials of our proposal. Subsection 4.4 presents our algorithm, the rule drive semantic-based algorithm (RDSB-A). **Section 5** concludes the paper and gives an insight of our future work.

2. Basic notions. Association rules (AR) and ontologies both are domain-based knowledge. Yet, while ontologies are *a priori* background knowledge, AR are unexpected implicative and interesting tendencies discovered in databases [1].

2.1. Association rules. AR are obtained by the task of data mining of the KDD's process. Traditionally, the algorithms of extraction of an association's rules were applied to the transactions of the basket data where a transaction T is described by its identifier TID and a set I of items [25]. More formally, given $I = \{i_1, i_2, ..., i_m\}$ and $D = \{T_1, T_2, ..., T_n\}$, with $T_i \subseteq I$, an association rule is an implication of the form $X \Rightarrow Y$ where $X \subset I$, $Y \subset I$, and $X \cap Y = \varnothing$ [25].

These rules are computed based on the traditional measures of support and confidence, with the well-known Algorithm Apriori [25]. However, a various panel of qualitative measures such as the Piatetsky-Shapiro measure, the Laverage measure, the Centered confidence measure, the Factor of certitude measure have been used for association rules extraction [26]. Besides, several algorithms for association rules mining (ARM) are proposed in the literature, and a survey of these ARM is given in [27]. Thus, given their increasing interest, AR are applied in the emerging nowadays' technologies; e.g., in the Big Data area [28] and in various computing environments [29].

Accordingly, we emphasized that in the present work:

- the mining sources are databases and ontologies;
- qualitative measures are the support and the confidence as defined in [25, 26, 27];
- the computed AR are used for enriching the semantics of both the data and the ontologies' schemas, based on a semantics conceptualization.

Moreover, the qualitative measure of confidence we used for the computation of the rules equals 100%, hence with a factor of certitude [26] totally fulfilled.

On this basis, a transaction is a tuple or an individual; items are attributes of the relations that describe real world, and rules are in the form $\langle A_{i1} = v1 \wedge A_{i2} = v_2 \wedge \ldots \wedge A_{ik} = v_k \Rightarrow A_{i0} \in E \rangle$, where A_{i0} is the predicted attribute and E is an interval or a set of values. As an example, the rule $\langle$V.CATEGORY='JAYA' $\wedge$ V.PS='AVERAGE' $\Rightarrow$ V.FGERM $\in$ [90, 98]$\rangle$ means that if the category of the cereal is JAYA and its specific purity is AVERAGE then the value of the germinal faculty is in the interval [90, 98].

2.2. Ontologies. The term "ontology" in the computer and information science literature appeared for the first time in 1967 [30]. Further, several definitions on what is the notion of ontology have been proposed. According to [31], these include three main definitions, we call informal definitions, since no formal definition exists [32]:

1. "An ontology is an explicit specification of a conceptualization";
2. "An ontology is a formal specification of a shared conceptualization";
3. "An ontology is a formal, explicit specification of a shared conceptualization".

Notice that the third definition is a fusion of the first two.

In addition, following [30], we emphasize that the sense of the term "ontology" varies depending on whether it is used by the information systems', or artificial intelligence's and semantic web's communities. For example, the semantic web's community uses the third definition above, namely understood as an artifact designed for a specific purpose and represented in a specific language, whereas in information systems the term ontology is defined as "a system of categories", independently of language [30]. Thus, following [30], we defined an ontology as "a formalization of the universe of the discourse as an organized structure, and constrained by a set of axioms, according to the knowledge domain" [23]. More precisely, we advocate an ontology as a 6-tuple set, formalized as $O^D = \{\Sigma, \tau_{\leq}, A, \Omega, \rho, \varphi\}$ where:

- Σ is a set of concepts $\{C_1, ..., C_n\}$ belonging to the underlying knowledge domain and assigned with the subsumption (partial order) relation $\tau_{\leq}(C_i, C_j)$ which models the Is-A relationship, i.e. the generalisation property;
- A is a set of attributes of the universe of discourse, describing of the concepts in Σ ;
- Ω is a set of unary and binary relations;
- ρ is a relation over Ω assigning to each $R_i \in \Omega$ a domain ρ_{dom}: $R_i \to \Sigma\times\Sigma$ and a range ρ_{range}: $R_i \to \Sigma\times\Omega$;
- φ is a set of axioms and rules that Σ and Ω must hold.

We emphasize that our research work applies to the agricultural domain, specially the rice seed certification. Thus, based on our above definition, we give an insight of the domain ontology as a "system of categories" through the following example.

Example: Let Σ = {Maintainer, Rice seed, Cereal seed, Corn seed, Plot land, Rice crop, Farm land, Research station, Seed Variety, Cultivation, Contractual, Private Seed Operator}

The semantic UML data models at Fig. 1 and Fig. 2 illustrate the domain ontology, and the data as well.

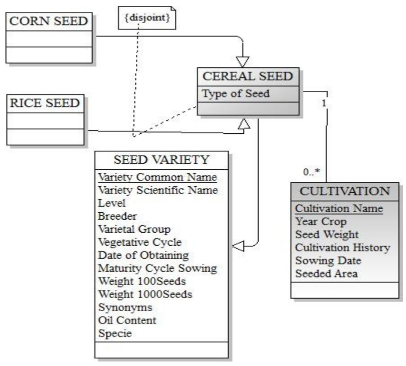

Fig. 1. Ontology-Business data subschema: cultivated cereal seeds

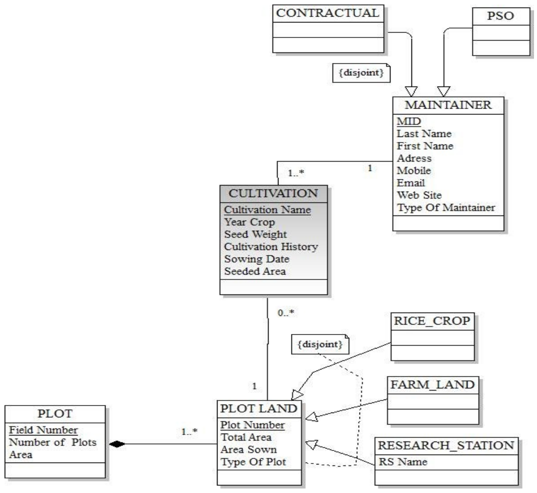

Fig. 2. Ontology-Business data subschema: cultivated cereal seeds, plots and maintainers

Each concept $C_i \in \Sigma$ is represented with a UML class. In addition, according to our definition of the ontology, e.g.:

- $\tau_{\leq}$(CEREAL_SEED, RICE_SEED), $\tau_{\leq}$(PLOT_LAND, RICE_CROP), as abstracted at Fig. 1 with the *IsA* relationship, namely the generalization abstraction, also called subsumption relationship when talking on ontologies;
- Some instances of CEREAL_SEED may hold, e.g., the rule given in our running example and which is an element of φ that also includes all disjunction rules, e.g., a maintainer is either a contractual, or a private seed operator (PSO) as shown in Fig. 2.

Notice that attributes describe the concepts (classes), and that operations and roles are not represented in the above figures.

3. Related work. As emphasized above, to the best of our knowledge, the reuse of AR for ontology-based semantics enrichment have only been studied in [21, 22]. In [21], the work was focused on ontology enrichment, as a pattern discovery problem by exploiting the ML methods in the aim to extend existing ontologies with formal rules and to suggest knew knowledge axioms. Each pattern is a Horn-like clause of the form of B→H called "relational association rule". Given C_i and R_i, respectively the concept and role names of the ontological knowledge base, the discovered rules are in the form:

$$C_1(x) \wedge R_1(x, y) \wedge \ldots \wedge C_n(z) \wedge R_l(z, a) \rightarrow R_k(y, z) \quad (1)$$

$$C_1(x) \wedge R_1(x, y) \wedge \ldots \wedge C_n(z) \wedge R_l(z, a) \rightarrow C_h(y) \quad (2)$$

In our case, knowing the type of plot lands, their state, and the varieties of rice, for each variety of seed of rice an ontologist can deduce the plot land on which it is/must be sowed. Such kind of knowledge can be expressed as following:

$$\text{Plot}(x) \wedge \text{Variety}(y) \wedge \text{hasState}(x, s) \rightarrow \text{sowOn}(x, y) \quad (3)$$

The main difference between the work presented in [21] and ours, sustained by the KBSM, resides in the manner by which data and ontologies have been linked, and processed. Indeed, based on the KBSM [23], any domain ontology schema is mergeable with its canonical database schema. As an advantage, because of the logical link of their meta-schemas, which allows their storage in a single database catalog, the ontology enriches the database semantics and conversely, according to the considered knowledge domain. As illustration, in the example above, the instances of the roles, *hasState* and *sowOn*, and these of the ontology-based concepts, *Plot* and *Variety*, can be stored in a unique database catalog in distinct schemas. Thus, having a set of association rules computed over a given database state, these rules can be applied as new semantics over the schemas. Moreover, any rule of the type (3) can be expressed through a Select-Project-Join (SPJ) query using SQL. Finally, no transformation under the form of (1) and (2) of the computed association rules is necessary. Association rule-based ontology enrichment is also discussed in [22]. However, unlike ours, the ontology and the database are separated, and it is not clear how their schemas are built. Moreover, based on the KBSM [23], itemsets' mapping to the ontology's concepts is not necessary. In brief, one of the main advantages of our approach is the use of a single algorithm for building semantic-based rules.

4. Associations rules as semantics for domain ontologies. When describing databases schemas, according to the considered real world, and the users' points of view, the designers add constraints e.g., the well-known functional dependencies allowing schemas normalization, primary keys and referential constraints definition. Additionally, for data consistency, business-based and knowledge-based constraints are also added to the schemas. For example, a seed breeder have a yearly agreement, the rice gardens and the research stations are plots of land for rice seed reproduction.

4.1. Constraints vs. semantics. According to Curé [33], an AR (X→Y) expresses a functional dependency or a conditional functional dependency between the sets of attributes X and Y. Since functional dependencies are constraints over data, carrying, by the same time, some semantics, we advocate that AR, simultaneously, stand as constraints and semantic rules for both the data's and the ontology's schemas. Yet, five types of constraints have been distinguished [34]:

1. Knowledge-based constraints,
2. Data constraints,
3. Dimension constraints,
4. Rules constraints, and
5. Interestingness-based constraints.

The first type of constraints is used to extract some type of knowledge. From our point of view, the three other types of constraints are business-based constraints. Thus, we distinguish the functional constraints that serve to handle schemata consistency, the business-based constraints for data and knowledge filtering and/or for the classification, and the knowledge-based constraints, i.e. the constraints that carry semantics, e.g. a triggering for a taxonomic relationship tuning. In this order, we claim that AR can be viewed and exploited as meta-rules. Indeed, each assertion belonging to a body X is a relation of the type $R_i(x, y)$ we will write, from now on, $R_i(A_i, v)$ where A_i is an attribute and v a literal; precisely, in our case, v is a numeric.

Accordingly, for each AR, we compute a conversion by performing a cross-scan between the KBSM and the set of rules. As example, given the rule ⟨V.CATEGORY= 'JAYA' ∧ V.PS='AVERAGE' ⇒ V.FGERM ∈ [90, 98]⟩ , thanks to the taxonomic hierarchy, the discovered knowledge is applied to each category of cereal seed no matter the type of the plot of land where it has been sowed (See rule (3)). Furthermore, the disjunction property suffices to determine the plot of land where the seed has been produced through a SELECT DISTINCT SQL query.

Moreover, nowadays-advanced databases systems such as PostgreSQL allow the use of triggering for the propagation of involved updates, ensuring the tuning of the schemas by the same time, e.g. with a rule of the type given in the running example.

4.2. Association rules as semantics. A domain ontology relates to the database of a given Information System, and conversely. Such database contains the minimal canonical ontology [23] of the considered domain, namely the subset of N-ary relations ($N \geq 2$) of its schema which allow the building of the domain ontology's schema. On the other hand, the database's repository stands as the mining source of association rules computing. Hence, computed AR, namely rules of type (3), are usable for the enrichment of the given domain by exploiting the semantics carried by the AR. However, multiplicities cannot be expressed by Horn-like clauses, but nonetheless useful for knowledge retrieval. Fortunately, a well-conceptualized model captures more semantics, by significantly improving the knowledge-based semantics, such as multiplicities.

Now, in the previous sections, we already established that the computed AR are of the form R_i (A_i, v), where A_i is an attribute and v a literal. This means that R_i represents a role name, and that A_i belongs either to a concept or to a relationship between several concepts we respectively name *CConcept* and *Rel* in our meta-model, as shown in Fig. 3. Such conceptualization takes into account both axioms, namely the relations R_i (x, y) and R_i (A_i, v), which are the core components of the ontology and of the association rules, as well. More precisely, if $A_i \in$Rel, then A_i is either a key or a part of key; hence the rule to which it belongs does not bring any new knowledge. In the other case, the concept at which it relates is checked by using the item name as search value through the underlying Attribute table. Next, the rule applies for either adding a default value constraint or a set of values domain constraint. If the concept is involved in a role where the relationship is a taxonomy, the constraint is propagated to all subsumed concepts, thanks to the generalization feature through the subsumption relation $\tau_{\leq}$.

4.3. Semantics conceptualization. A conceptualization is an abstract, simplified view of the world that one wish to represent for some purpose [35]. However, we emphasize that the term "conceptualization" is also to be understood as a process, namely the process of conceptual modeling, which produces semantic data models, called conceptualization or simply conceptual models. Such a process involves identification, analysis, and description of the types of entities (classes), the relationships between these classes, and their behaviors according to the constraints upon the underlying domain of the real world they describe or specify. Hence, a semantic conceptual model is an abstraction of the universe of discourse. Without loss of generality, the activity of modeling needs a semantic data model, e.g., ER/EER, or a modeling language such as the UML standard.

In this work, we used UML as modeling and description language since its expression power is more suitable for our approach, and we limit ourselves on the conceptual models known as UML class diagrams that are based on four main abstractions principles, namely classification, aggregation, composition, and generalization. The main advantage of the conceptual modeling is to produce models supplied with semantics within the business-data that are sharable across several domains of knowledge such as the ontologies.

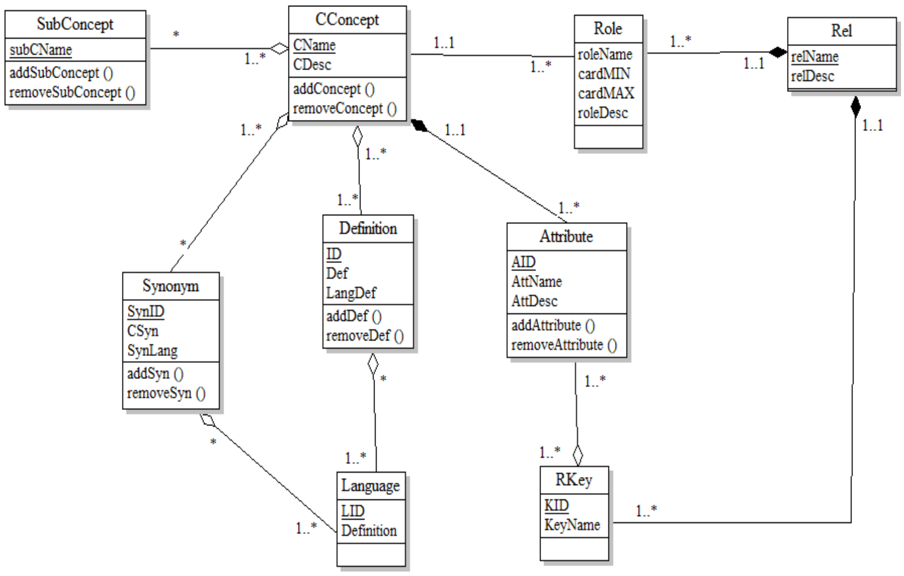

Fig. 3. The KBSM for Semantics conceptualization.

To apply the discovered rules, we scan tables CConcept and Rel with the help of a semantic-based algorithm, which allows the computation and or the scan of a set of AR, already represented and stored.

To this end, our first material is the discovered AR computed by an Apriori-like algorithm launched upon a relational table of certified rice seed. These AR are stored by the mining algorithm in a formatted text file ending with the dot symbol (.), where each line contains a rule of the form $\langle A_{i1} = v_1 \wedge A_{i2} = v_2 \wedge \ldots \wedge A_{ik} = vk \Rightarrow A_{i0} \in E \rangle$ [36]. In this work, the computed AR are stored in a relational table.

Our second material is the KBSM (Fig. 3), which is the basis of our rules-driven semantic-based algorithm (RDSB-A), enhanced by the semantic data model of Fig. 4.

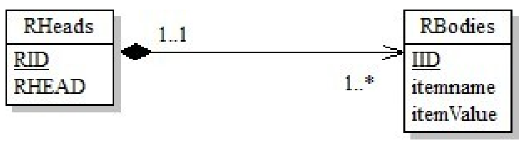

Fig. 4. Rules-driven semantic data model

Accordingly, we expose the RDSB-A Algorithm in the following section.

4.4. A rules-driven semantic-based algorithm. According to Rules's driven semantic data model of Fig. 2, tables 1 and 2 give an insight of the data processed by the RDSB-A Algorithm, with five rules computed from a relational view of four columns. The RHEADS table column represents the predict attribute, namely the germination faculty, we abbreviate FGERM.

RDSB-A Algorithm
Input: RHeads //Rules heads table
RBodies //Rules bodies table
Output: // Outputs are actions in either the database or the meta-schemas.
Begin
For each r in RHeads **do**
Select * Count(rid) as nbItems From RBody Where RBodies.rid= RHeads.rid
If nbItems=1 **Then**
If RBodies (1).name ∉ Rel **Then**
item ← RBodies (1).name
Search (CConcept, item)
Alter table CConcept Add constraint CC check (RBodies (1).value= RHeads (1).value)
End if
End if
If nbItems > 1 **Then**
While not eof (RBodies) **do**
If RBodies (1).name ∉ Rel **Then**
item ← RBodies (1).name
Search (CConcept, item)
//concept containing the item
AddItem (item, t_cons, RBodies (1), RHeads (1))
End if
End while
Alter table CConcept Add <t_cons>
End if
End For Each
End.

Table 1. RHEADS data table

№	RID	RHEADS
1	1	[90, 95]
2	2	[90, 93]
3	3	[90, 93]
4	4	[92, 98]
5	5	[92, 95]

Table 2. RBODIES data table

№	RID	ITEMID	ITEMNAME	ITEMVALUE
1	1	1	variety	jaya
2	2	2	category	base
3	3	1	variety	jaya
4	3	2	category	base
5	4	3	puriy	average
6	5	1	variety	jaya
7	5	3	purity	average

For each rule head in Table 1, we process the data of Table 2 for building a semantic check constraint. For example, from rule 5, we built the semantic check constraint: CHECK (variety = 'jaya' AND purity = 'average' AND fgerm> 92 AND fgerm < 95).

Finally, the proposed approach can easily help to manage data and knowledge, in the context of a decision-making environment. Thereby, let us consider the problem of handling missing-values, assuming completion by imputation with the mean-value. Thus, in the absence of known value, the semantic check constraint implemented thanks to rule 5 above allows us to fix the mean value of the predicted range [92, 95] as a default value for the germination purity. Indeed, the lack of abstract representation of the knowledge requires the collaboration of domain experts for the construction of the ontology from existing databases or conversely. In addition, not all data currently stored in databases is processed, nor all attributes appear in queries.

5. Conclusion. In this paper, we highlighted the relevance of the reuse of a set of already computed association rules for the enrichment of the underlying domain ontology, and of the database, as well. Actually, more than a simple taxonomy, the ontology includes a set of constraints semantic-based on the concepts of the domain. Thus, the main interest of this contribution is the proposed RDSB-A Algorithm through which we described the feasibility of schemas tuning upon an expressive conceptualization for associations rules reusability as semantics. Finally, we emphasize that the proposed generic meta-schema as common referential, we called semantics conceptualization and the RDSB-A Algorithm, constitute the theoretical foundations of this work, and as well, for ontology learning because it contains the same concepts as those defined for the well-known ontology learning layer cake.

The next step is to demonstrate the applicability of the algorithm by its implementation in the aim to show experimental results after the use of the set of rules over the data augmented with semantic abstractions in the underlying database catalog.

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