An Ontolgy-Based Approach for Learning Annotations Reuse

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ABSTRACT: *In this paper, we present an approach to adapt and reuse learning annotations and contexts by describing the process to capitalization and reuse of learning annotations and associated learning contexts. This is to provide to the actor, an appropriate learning which is reviewed or validated previously by others, with similar learning contexts. The modeling and the formalization of learning annotations and learning contexts will allow to define functions for their comparison and their evaluations, in order to reuse them. We propose our method for of measuring similarities allowing to provide learning annotations dedicated to a given and well-defined pedagogical goal. An alignment between the two types of ontology, respectively that of the annotation and that of the context will provide us with a learning based on annotations according to the current context which requires a pertinent criterion of similarity between the learning contexts and the learning annotations.*

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1. Introduction

Our objective consists in building a learning system based on learning annotations according to various learning contexts which shall adapt to the maximum to the needs of various actors.

Through our suggested approach, we first capitalize our interest on a learning based on annotations according to a given goal and a certain learning context. Thus, a well-determined learning is provided to the actor. In fact, the reuse of learning requires its modeling [1]. Several models are suggested in the literature so as to present the object of annotation by explicating the aspects of annotation which meet the needs of the user. These models represent various aspects of annotation namely the semantics, the context of creation, the episodic aspect such as Tazi's [2] but this model does not take into consideration personal knowledge of the annotator. The Memonote which will be used by the teacher as a reminder. None of the previous models is dedicated to all the actors at the same time. Moreover, these models are dedicated to the creation and the activity of annotation rather than to the learning activity based on annotations.

Our interest for proposing a learning based on annotation memory requires a generic and exhaustive annotation model which covers all the models of annotation for different learning system (which can be used by our actors) and which will take into consideration the learning activities dedicated to all the actors at the same time as it is a capitalization and sharing annotations memory that we suggest.

In fact, Our system adapts its content to the current context of the actor taking into account the static and the dynamic aspects of the context [3]. It provide the pedagogical content to actors according to the current learning context.

In our work, a learning context, [4, covers the contextual properties that we covers contextual properties that we classify physical making an application context sensitive (computing context, environment context), the contextual properties which represent the actor's learning (user's context, tasks-activity context) as well as the properties linked to the reuse of learning (context of reuse and context of evaluation).

Accordingly, we then present the key steps for reusing annotations and contexts learning. We combine ontological engineering (modeling, ontology alignment, similarity measurement…) and context-awareness techniques in our approach to reuse.

This paper is organized as follows. The first section presents briefly our "*an ontology-based architecture for reusing and learning through context-aware annotations memory*" OARLCAM. The second section exposes our approach and process for reuse of annotations and contexts learning through dscribing the mainly steps defined. In the third, we present our method of measuring similarities on which is based our approach for reuse.

2. Our Architecture Oarlcam

This architecture OARLCAM assures the reuse, the adaptability and the interoperability between our framework and the various tools used by the various actors, whom can use it as an external memory.

Our architecture (figure 1) includes three subsystems: i) the subsystem of contextualization, containing the modules of context capture, context handling, context server, context presentation and a context top level ontology of training ii) and the learning subsystem, containing the modules of learning objects management, learning objects composer and follow-up of the training; and iii) the annotation subsystem, containing the annotation module, the annotations' manager, the annotations' adapter, the annotation top level ontology, the annotations' presentation module and the annotations warehouse, for later re-uses.

This modular architecture is based on a context-awaret techniques coupled to some ontological engineering in order to build a learning annotations memory, unified by an annotation top level ontology and a context top level ontology for an appropriate learning for all actors. In the next section, we details the approach of reuse supported and applied in our framework OARLCAM.

3. Approach for the Reuse of Learning Annotations Based on Ontology Alignment

Our approach of learning annotation reuse lies essentially on a similarity between the two ontologies of context and annotation respectively to the subsystems of context and annotation. This has for objective to check the annotations which are adequate to the current learning context taking into consideration all the contextual properties which describe it. Our approach of reuse is concerned with the levels of reuse 1) the reuse of stored annotations to take advantage of the included knowledge, benefit from experiences feedback of different actors and consequently, improve the learning quality always according to a pedagogical objective and a current context; 2) the reuse of learning contexts stored in the context server within similar learning contexts by other actors 3) the reuse of the same learning context by the same actor through the planning of further users. Description of our approach of reuse.

3.1 Description of our approach of reuse

Our approach of reuse can be described by a four-step cycle namely: the search for similar contexts, the process of adaptation, the memorization and the evaluation (experience feedback). An actor shall start by defining the request, that is to define his pedagogical goal, his pedagogical activity which correspond to the goal facet and that of the activity-tasks of our context ontology [5]. Our system will apply the approach of reuse in order to provide the actor with a learning adapted to the learning context. We will then illustrate each step through the following figure (figure 2).

Our reuse approach for an annotation memory is thus summarized in the following four steps :

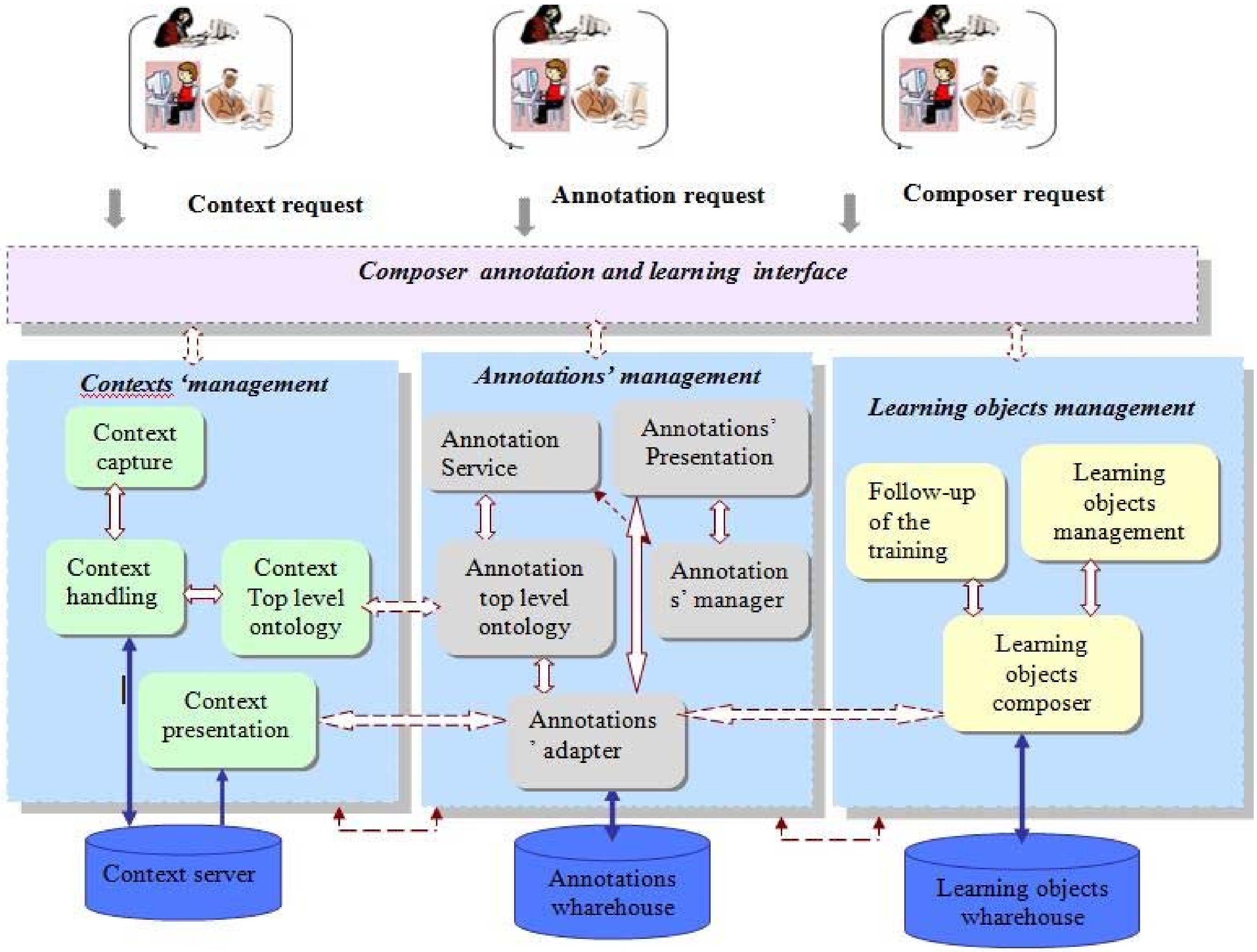

Figure 1. Our approach OARLCAM

1) The search for a similar context

To meet the actor's needs for a learning adapted to his learning context X, we will start by searching, in the context server, for a learning context similar to the context X, if it is the case, we will enrich this context instance with the current computing contextual properties such as the date, the location, etc., then we present it directly to our actor, at the end of the session, the actor shall evaluate the provided learning, our system memorizes this learning context in the context server (implementation of the useful data). If we don't find from the beginning a similar learning context, we will go to the adaptation process in order to extract out a learning adapted to our actor.

2) The Adaptation

This step is primordial for adapting the learning annotations to the current context through the alignment of two ontologies of annotation and context. This alignment shall allow to check the annotations which correspond to the same properties of the current learning context (pedagogical goal, pedagogical activity…). We will adopt then an approach of measurement of semantic and structural similarities which are expressed by a better learning quality. Owing to this alignment, the checked out annotations will be enriched by the contextual data detected by the system context capture. Indeed, it is a learning based on context-aware annotation memory.

3) The Memorization

Once we provided the actor with a learning adapted to his learning context as well as to his pedagogical goal, the learning-context instance is stored in the context server for further use within similar contexts by other actors or by the same actor.

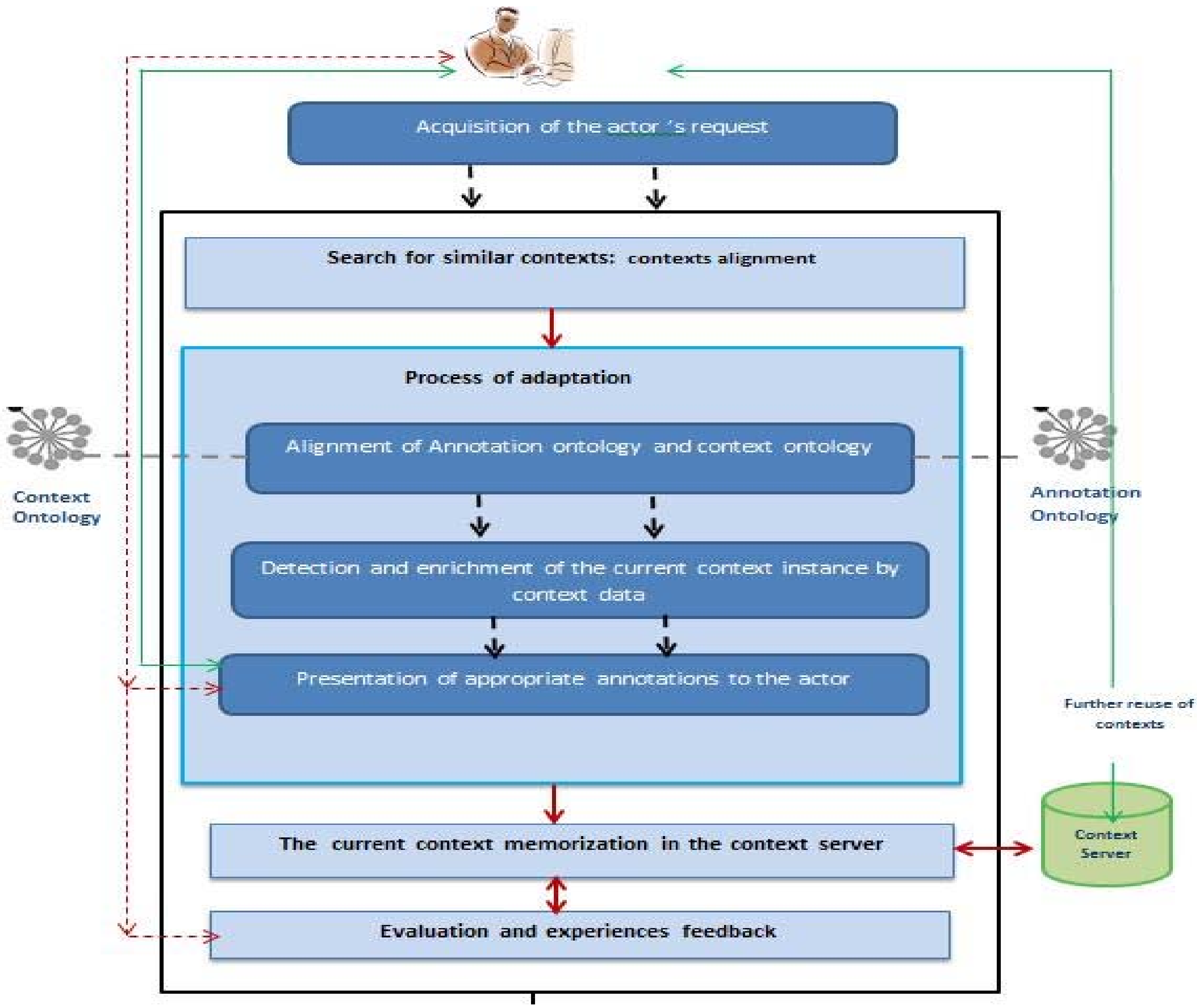

Figure 2. Approach for the reuse of learning annotations

4) The Evaluation and the Experience Feedback

The result/evaluation characteristic defines the level of pertinence of a learning session by our system. It is a criterion which shall be taken into account during the stage of reuse of previous learning contexts. In fact, the reuse lies on one hand on the learner's judgments concerning the pertinence of the quality of learning proposed also by other actors such as the time span which separates successive uses. During his learning, our actor then evaluates the pertinence of his current learning context.

This approach to reuse is actually based on interactions between different ontologies making explicit learning by context-aware annotation memory. The following figure illustrates this interaction (figure 3).

In consequence, this approach lies on a similarity between the annotation ontology and the context ontology in order to check the adequate annotations for a given learning context. We will, then, use our own algorithm of similarity measurement which shall be presented in the following section.

3.2 Illustrative scenario

When reviewing its course of databases, a learner X, in fact, needs the remarks, comments, explanations, improvements. In general explanatory annotations, analytical, prescriptive are essential to an understanding of its course. In some cases, these different annotations can also result from a negotiation with the teacher to provide such additional exercises and satisfactory progress and learning.

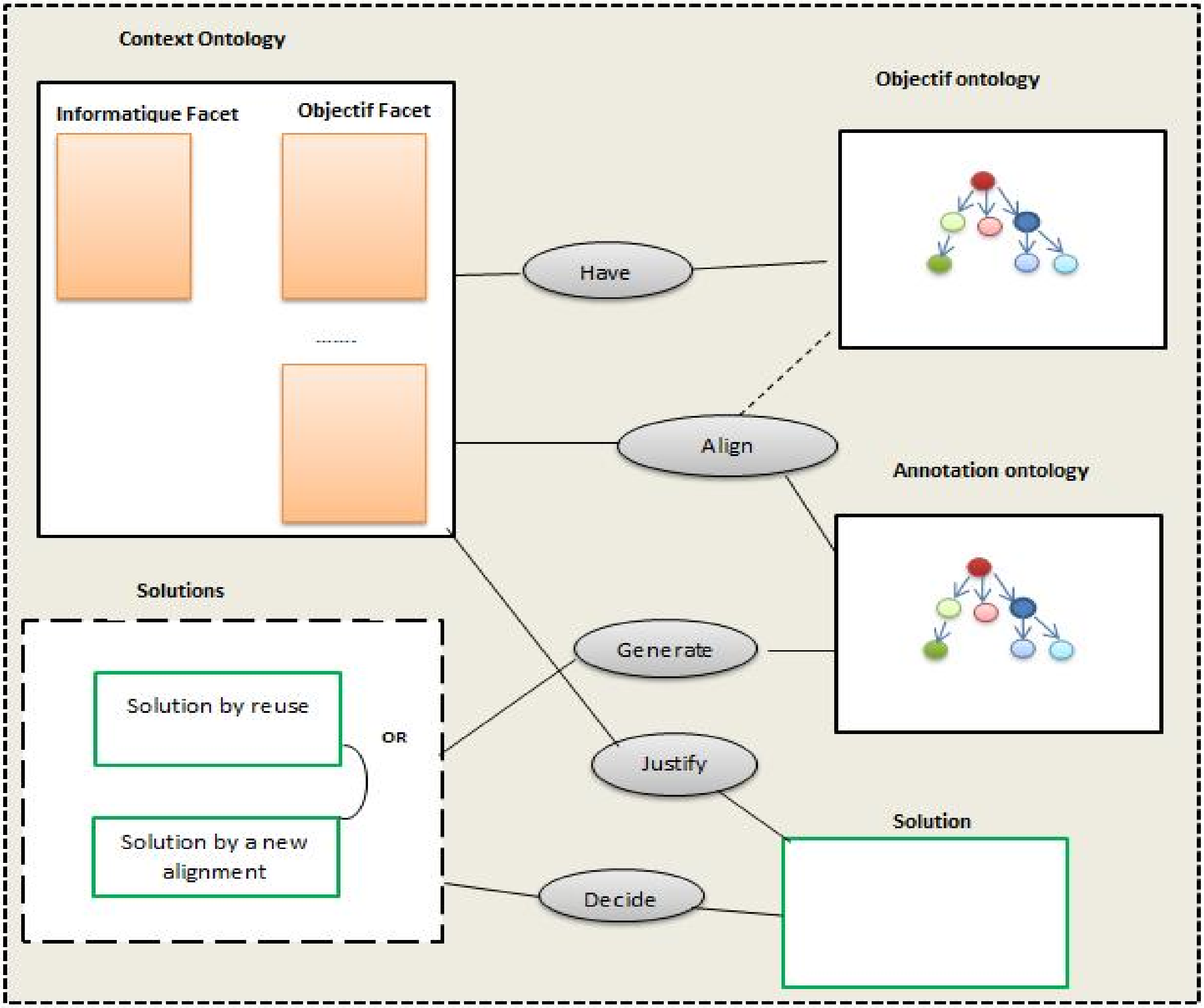

Figure 3. Conceptual graphic of learning reuse

The learner will then connect to our system for a pedagogical purpose = understand the database course. He expresses his request to the system in order to be provided with all the explanatory annotations related to the course. Our system detect the learning context proprieties (learning objective, type of activity, level of learning, course or pedagogical object…) of this learner and starts to search for a similar learning context in the context server. If it finds a similar learning context, it is added to the current contextual data (date, location, hour…) then presents the relevant learning annotations to the learner. Once the learning session is over, the learner shall have the ability to express his level of satisfaction for the learning provided by our system. (satisfied, unsatisfied, fairly satisfied, well satisfied). This evaluation will help us later on to evaluate the learner's training and have an idea about the amount of achievement of our pedagogical objectives by the corresponding learner. This could be useful for us to reassess the most valid and satisfactory learning contexts in the system. The amount of achievement of a goal can be expressed in the form of a percentage which is defined by a tangible figure restrained between 0 and 1.

Unless the system finds a learning context similar to the learner's current context, the adaptation process is triggered in order to extract the adequate annotations out of the annotations memory, a alignment is then performed between the context generic ontology and the annotation generic ontology so as to recover the annotations corresponding to the same instances of the current learning context. Then, the system adds up the adequate annotations to the current contextual proprieties and presents the learning based of annotations to the learner.

Our system supports all the actors together at the same time (teacher, learner, tutor, and co-author) in order to represent, share and capitalize their knowledge included in the annotations (annotation memory) of the e-learning field. The capitalization of learning contexts which would be exploited later on by other actors. In our approach, we rely on the techniques of alignment and similarity measurement for the adaptation of the learning annotations to a given learning context.

In the next section, we describe our method of similarity measurements between the context ontology and the annotations ontology on one hand, and the various instances of context ontology for further reuses of the learning context on the other hand.

4. Measurements of Similarity

Several similarity measurements are suggested in the alignment process [6].

4.1 The Terminology method

Compares the entity labels. It is divided into purely-syntactic methods and those using a lexic. The syntactic method performs the correspondence through the measurements of strings dissimilarity. Whereas the lexical approach performs the correspondence through the lexical relationships (synonymy, hyponymy, Etc.);

4.2 The internal structure comparison method

Compares the entity internal structures (interval, value, attributes cardinality, etc.

4.3 The external structure comparison method

Compares the entity relationships with others. It is divided into entity comparison methods within their taxonomies and external structure comparison methods by taking into account the cycles;

4.4 The instances comparison method

Compares the set of other entities winch are attached to it (instances of classes);

4.5 The semantic method

The semantic method: compares the interpretations [8] (or more exactly models) of entities.

In our learning approach based on annotation memories, our interest is to search for a semantic similarity between the context ontology and the annotation ontology in order to offer the adequate annotations for the current learning context of the current actor. This has for objective to provide a learning adapted to the current context. Therefore, it is indispensable to find semantic and structural similarities between the concepts explicating the learning context (learning field, pedagogical goal, pedagogical activity, type of activity, actor's profile…)

In the case of further reuse, the measurement of similarities is performed between various instances of memorized learning contexts.

4.5.1 Our Method of similarity measurements

We calculate the global similarity with performing two successive steps. The first step allows to calculate the semantic similarity. The second one the structural similarity for each pair of the concepts of both ontologies by exploiting the contiguity structure. We suggest then two functions in order to calculate respectively the structural similarity and the semantic similarity.

1) Measure of semantic similarities

We intend to use the Jaro-Winkler functions as they give good results of similarity according to the comparative study of Cohne [6]. The SimSEM function allows calculating the semantic similarities of the pairs of concepts C1 and C2 respectively of both ontologies O1 and O2 by adopting the following steps:

- For each concept C1 and C2, go through the concepts of O2 so that the category of C1 = C2,
- Calculate the semantic similarity according to the Jaro-Winkler [] function,
- Store the semantic similarity (SimSEM) in the vector VSS.

2) Measure of Structural Similarities

The structural techniques exploit the ontology structure to be compared, often represented in graphics. The comparison of similarities between two concepts of both ontologies can be based on the position of the concepts in their hierarchies. These techniques are based on the following hypothesis : "(H) – *if two entities of two ontologies are identical, their nearby entities will be the same in a certain way* " [9] and [10]. We suggest calculating the structural similarity between the entities of two ontologies by reference to the works of Albohaaany [11]. We calculate then the structural similarity by exploiting the semantic similarity of the pair of concepts to match as well as the contiguous structure by adopting the following steps :

• If the contiguity of a concept c1 noted V(c1) is similar to the contiguity of the concept c2 noted V(c2) then c1 and c2 are similar in a certain way,

• We affect the set of contiguity of c1 (V(c1)) in a vector of contiguity VV(c1),

• We affect the set of contiguity of c2 (V(c2)) in a vector of contiguity VV(c2),

• The position of V(c1) in relation to c1 shall be similar to V(c2) of c2, then we suggest to calculate the structural similarity of the pair (C1, V1) and (C2, V2) so as to get Simst (C1, V1) in order to determine the position of V(c1) in relation to C1 and respectively V(c2) in relation to C2.

• Fctcalculsim is the measurement function of structural similarity that we use.

• We calculate the structural similarity SimST: SimST = fctcalculsim (VV(c1), VV(c2), SimSM).

3) Calculation of global similarity

We quantify the semantic similarity and the structural similarity in order to obtain the global similarity [9]. Our aim is to align the ontology of the learning context and the ontology of annotation in order to provide the adequate learning for the current learning context. We seek a global similarity in order to optimize the learning quality as well as our annotation memory. The calculation of the similarity could be also used between the context of ontologies in the case of reusing the same learning context or searching for similar contexts in the context server, etc.

Algorithm: Similarities
INPUT:
1) $CO1$ and $CO2$: Context Ontology 1 and Context Ontology 2
2) V_{SS}: Semantic vector of similarities 110
3) V_{SSt}: structural vector of similarities
4) Sim_{St}: Weight of structural similarities
5) Sim_S: Weight of semantic similarities
OUTPUT: V_{SG}: global (Semantic and structural) vector of Similarities
Begin
/* go to each concept of context ontology 1 */
For each ($CCO1$ ε $CO1$) **do** /* go to each concept of context ontology 2 */
For each ($CCO2$ ε $CO2$) **do**
If $CCO1$.type == $CCO2$..type **then**
/*Extract semantic similarities between $CCO1$ and CCO2 of V_{SS}*/
Sim_S = EXTRACTSIM (V_{SS}, $CCO1$, $CCO2$)
/*Extract structural simiraties de $CCO1$et $CCO2$ of V_{SSt} */
Sim_{St} = EXTRActSIM (V_{SSt}, $CCO1$, $CCO2$)
/*calculate global similarity*/
$Sim_G = Sim_S + Sim_{St}$
/* Add CCO1, CCO2 and Sim_G in V_{SG}*/
Add (($CCO1$, $CCO2$, Sim_G), VSG)
Return (V_{SG})
END
.

5. Conclusion and Future Works

In this paper, we have describing our process of reuse of two levels for the annotation as a first level and then for the learning contexts as a second level, that is to say the manner in which this knowledge will be exploited in order to generate automatically a learning relatively adapted to a given pedagogical goal in a current context, in addition to the reuse of these contexts later. The reuse and capitalization in our approach are based on ontology alignment; we present thus our method of semantic, structural and global similarity measurements.

Several perspectives are possible, for this work. In Particular, We Aim to experiment and evaluate our method of calculation Similarities by adding improvements especially in terms of measurement functions that can give us better results. We can also create our appropriate function by improving what is available.

In addition, future research will enhance and complement our approach. An interesting perspective is to add to our method a new measures specific to the internal semantic of the ontology.

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