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Towards an Automatic Approach for Ontology Mapping In a Distributed eLearning System

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Abstract : Several existing e-Learning systems use ontologies for describing, organizing and sharing the eLearning resources. However, the increasing number of ontologies causes problems like searching resources from several sources (Ontologies). This problem is undertaken by a process which defines rules to relate relevant parts of different ontologies, called "Ontology Mapping". The present paper describes a methodology for automatic mapping of ontologies, basing our approach on a mathematical model called Information Flow Model and denoted IF Model.

Key words: Automatic Approach, Context, eLearning, Information Flow Model, Mapping, Intentional Ontologies.

INTRODUCTION

In distributed environment, systems exchange information and services in order to achieve global tasks. eLarning is a distributed system, where teachers and learner need to search, obtain, share and exchange information. E-learning is "the delivery of educational content via electronic media" [1]. The U.S. Distance Learning Association defines distance learning as the "acquisition of knowledge and skills through mediated information and instruction, encompassing all technologies and other forms of learning at a distance."

The majority of existing e-learning websites are based on the first generation of learning management systems (LMS) such as blackboard, WebCT, Moodle. The eLearning resources in these systems are not machine understandable, therefore their management is not total. According to Hatem, Ramadn and Neagu [2] the reason for this problem is that these systems are created for human and machine readability but not for computer understandability.

Recent works propose '*Ontologies'* as a great potential in higher education. They are a good mean for the description, the sharing and the reusing of information among distributed eLarning systems. However, the increasing number of ontologies causes other problem, it becomes necessary to provide mapping between these ontologies in order to perform the interoperability in the eLearning system.

Recent advances have spurred the development of some techniques using ontologies in order to achieve interoperability between systems. In [3], the authors proposed an approach which is mainly built on the IF-Map method to map ontologies in the domain of computer science departments from five UK universities. Other approach is MAFRA (MApping FRAmework for distributed ontologies). It supports the interactive, incremental and dynamic ontology mapping process [4]. RDFT is a mapping meta-ontology for mapping XML DTDs to/and RDF schemas targeted towards business integration task, where each enterprise is represented as a Web service specified in WSDL language. C-OWL (Context-OWL) is another approach on ontology mapping, which is a language that extends the ontology language OWL both syntactically and semantically in order to allow for the representation of contextual ontologies. The different cited works propose semi automatic mappings to reach the interoperability.

Thus, it is necessary to develop automatic techniques for mapping ontologies. Our approach shares the idea in [3], which uses of IF Model to solve semantics coordination of ontologies in distributed systems. We propose a methodology which allows an automatic mapping between distributed ontologies, basing on IF [5]. Following what R.Kent said in [6] "Information Flow is the logical design of distributed systems, provides a general theory of regularity that applies to the distributed information inherent in both the natural world of biological and physical systems".

The present paper is divided into five sections. In the first one, we present the current eLearning issues in research. The second section describes the Intentional Ontology part. In the third section, we present the appropriate part of IF model which serves to automatize the mapping between ontologies. The fourth section presents our automatic approach for the mapping of Intentional ontologies. Finally a summary with future research is included in the fifth section.

CURRENT ELEARNING ISSUES

During the last few years, a new learning has appeared, It is the eLearning. This term is defined by the Collins dictionary as a learning that takes place by means of computers and the Internet. For Tastle , eLearning is "the delivery of educational content via electronic media" [1] , learning contents are based on a smallest digital reproducible and addressable resources called Learning object (LO) stored in various Knowledge Base of Learning Management Systems[7]. Teacher, Student and Administrator are the principal actors during the E-learning process. They communicate and exchange learning resources through Web board any time and at any place.

Since the introduction of e-learning, a massive amount of e-learning resources have spread among the distributed

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eLearning Systems. However, these resources are not machine understandable, therefore the information retrieval is manual search and leads to the problem of information overload. As a result, there will be inaccuracies in obtained information. These problems present two major issues in eLearning research.

TABLE 1: CONTEXT-GOAL PAIRS OF TO

Learner Activity	Corresponding Context Goal pair
Login (C0, g0)	*C0=[Lr: Learner, U: Username, P: Password* *g0 = login(Lr)*
Select subject(C1, g1)	*C1=[S: Subject T:Title, A: Author, g0* *g1 = select(S)*
Search chapter (C2,g2)	*C2=[C: Chapter, g1* *g2 = search(C)*
Download content (C3,g3)	*C3=[CC : Content of chapter, A: Author, F: Format, D: Domain, D : Date of creation* *G3 = download(CC,A)*

TABLE 2: CONTEXT-GOAL PAIRS OF TO

Teacher Activity	Corresponding Context Goal pair
Login (C0, g0)	*C0=[Tr: Teacher, U: Username, P: Password* *g0 = login(Tr)*
Add title(C1, g1)	*C1=[T: Title, A: Author, g0* *g1 = add(T)*
Add subject (C2,g2)	*C2=[S: Subject, g0, g1* *g2 = add(S)*
Select subject (C3,g3)	*C3=[S: Subject, g2* *g3 = select(S)*
Add content of chapter(C4,g4)	*C4=[CC : Content of chapter, A: Author, F: Format, D: Domain, D : Date of creation ,g3* *g4 = add(CC,A)*
Add chapter (C5,g5)	*C5=[C: Chapter, g1, g4,* *g5 = add(C)*
Deliver pedagogical content (C6,g6)	*C6=[PC: Pedagogical Content, g5* *g6 = add(C)*

On one side, the description and the organization of e-Learning resources need new opportunities to be developed. Recent works propose 'Ontologies' as a great potential in higher education. They are a good mean for the description, the sharing and the reusing of information among distributed eLearning systems. In the other side, the proliferation of ontologies in distributed elearning Systems causes another issue, it becomes necessary to provide mapping between these ontologies in order to perform the interoperability in the eLearning system. Thus, there is a need to propose and to develop automatic techniques for mapping ontologies. [8],[9],[10].

INTENTIONAL ONTOLOGIES

Ontologies promise a shared and common understanding of some domain that can be communicated and interoperate across people and computers. Ontologies find applicability in many domains of application, in system engineering, knowledge management, eLearning systems. Ontology is generally seen as a formal explicit specification of a shared conceptualization [11], [12], which is a description of the concepts and relationships between them.

In our approach, ontologies describe the distributed eLearning system. As said in section 2, the different actors in the eLearning process are: Teacher, Learner and Administrator. These actors have to communicate and execute collaborative tasks, for example, the teacher add a chapter, the learner consult this chapter, the administrator has to give an account to the learner in order to login and obtain the chapter. In our work, these activities/tasks are represented by intentional ontologies. To present these ontologies we need some preliminary notions.

Preliminaries

Context Notion: The concept of *context* is used in many disciplines such as computer science (mainly Artificial Intelligence and distributed computing), cognitive science, linguistics, philosophy, psychology, or in application areas such as medicine or law. McCarthy defines context as a generalization of a collection of hypotheses. According to Brézillon, the context is always relative to something: the context of an object, the context of an action, the context of interaction: "what constrains something without intervening in it explicitly." [13].

For this purpose, the notion of context is important in understanding the world. In [14], a context is expressed by a recording of dependent types. This recording is a sequence of fields in which labels li correspond to certain types Ti. We use a simplified version of this approach which is based on higher-order logic, while our work takes place in a FOL (First Order Logic). Contexts are modeled by tuples, knowledge structure integrating entities extracted from a domain ontology, constraints and proposals. Inspired by this idea, we formalize contexts distinguishing two categories:

Type-Context: a type of context C is a set of object types {T1, T2, .. Tm}describing entities, properties and/or constraints. We formalize C by the following tuple:

C =[$l1$: $T1$ $l2$: $T2$ … lm : Tm

for example, C = [T :Title F : Format, A : Author, D : Date of creation / edition

Context-Goal pair: In our case study, the activities of different actors (Teacher, Learner, Administrator) are expressed by the notion of goal. A goal is defined by the result of an action associated to a particular context, called the context of the action. When is a type of context, we speak about "type of Goal" and when it is an instance (token) of context, the goal is associated instance goal.

For example, we define the following Context-Goal pairs according to the teacher and learner activities when teacher prepares to deliver a pedagogical content, he adds subjects, chapters, exams. These contents will be searched and downloaded by the learner (see **Table 1** and **Table 2**).

Relations between Context-Goal pairs: We distinguish two types of relationships Causal dependence and Subsumption dependence.

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Causal dependence

Definition1. Contextual inclusion
Let (C, γ) and (C ', γ') two pairs of type contexts and goals (resp. tokens), γ is a type of goal representing the result of a given action on C. If C 'contains γ, then we say that γ is included in C' and wrote $\gamma \subseteq C'$.

The validity of the Context-goal pair (C ', γ') depends on the completion of the goal γ. In other words, we say that the pair (C, γ) "causes" the occurrence of (C ', γ').

Definition 2. *Causal* dependence

A pair Context-Goal $(Cl, \gamma m)i(k)$ of level i in system k is on causal relationship with the pair $(Cl+1, \gamma m+1)i(k)$ in the same level and the same system if $\gamma m\ i(k) \subseteq Cl+1$, we note :

$(Cl , \gamma m)i(k) \leq (Cl+1, \gamma m+1)i(k)$

Subsumption dependence

Definition 3. Subsumption of Context-Goal pairs
A pair Context-goal (Cq, γ r) i +1 (k) of level i +1 in system k subsumes a plan (Cl, γm) i(k), ..., (Cl+p, γ m+p) i(k) at level i of the same system if the achievement of (γr)i+1(k) depends on the achievement of all the goals of the sequence types (γ m, ..., γ m+p) i (k). We note (Cl, γ m) i(k). . . (Cl+p, γm+p) i (k) $\langle$ (Cq, γr) i +1 (k)

As a result, the concepts of our intentional ontologies are Context-Goal pairs and the relationships are the causal and subsumption dependence. In our approach, we define the intentional ontology by a tuple *:* O = (CG ,$\leq$,$\langle$), where CG is a set of Context-Goal pairs

Initially, we propose, two ontologies: Teacher Ontology (TO), Learner Ontolgy (LO) (see fig1 and fig2)

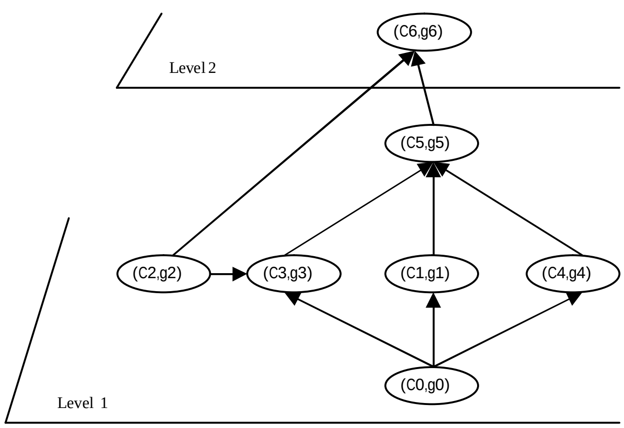

Fig 1: TO Teacher Ontology

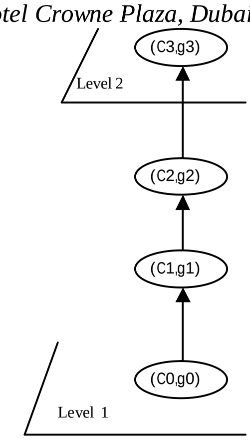

Fig 1: LO Learner Ontology

I. IF MODEL

The IF-based Model IF theory describes how information can flow through channels to convey new information under first order logic. Each local component is described by a an IF Classification. This last is a very simple mathematical structure. As it is defined in [5], it consists of a set of objects to be classified, called tokens and a set of objects used to classify the tokens. Classifications are linked by applications called Infomorphisms. Infomorphisms provide a way to move information back and forth between systems. In our approach, the utility of infomorphisms is not to link classifications of the same system, but to link those of a distributed system, because we need to map between distributed service ontologies.

The information flow in a distributed system is expressed in terms of an IF theory of this system, that is a set of laws describing the system. These laws are expressed by a set of types. The theory is specified by a set of sequents, so by a set of types and the relation between them (|-). The overall “Classification” and “IF theory” constitute what is called a local logic. That is, this system has its own logic expressed by its types. Information Channel is the key for modeling information flow in distributed systems. It is the main step in the process of mapping.The IF theory, in information channel, describes how the different types from different classifications are logically related to each other.

Definition 4:”Classification”: A classification A is a triple < tok(A), typ(A), |=A>, which consists of:

1. a set tok(A) of objects to be classified known as the instances or particulars of A that carry information,
2. a set typ(A) of objects used to classify the instances, the types of A,
3. a binary classification relation |=A between tok(A) and typ(A) that tells one which tokens are classified as being of which types. Classifications are related through infomorphisms.

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Definition 5:"Infomorphism": Let A and B be IF classifications. An infomorphism f = < f^, f˅ >: A ⇔ B is a contravariant pair of functions f^ : typ(A) → typ(B) and f˅ : tok(B) → tok(A) which satisfies the fundamental property:

f∨ (b) |=A α iff b |=B f∧(α) for each α∈ typ(A) and b ∈ tok(b)

TABLE 3 : CLASSIFICATION C1

|=C1	(C0, g0)	(C1, g1)	(C2, g2)	(C3, g3)
g0	1	1	1	1
g1	0	1	1	1
g2	0	0	1	1
g3	0	0	0	1
g4	0	0	0	0
g5	0	0	0	0
	(C4, g4)	(C5, g5)	(C6, g6)	(C4, g4)
g0	1	1	1	1
g1	1	1	1	1
g2	1	1	1	1
g3	1	1	1	1
g4	1	1	1	1
g5	0	1	1	0

TABLE 4 : CLASSIFICATION C'1

|=C'1	*(C0, g0)*	*(C1, g1)*	*(C2, g2)*	*(C3, g3)*
g0	*1*	*1*	*1*	*1*
g1	*0*	*1*	*1*	*1*
g2	*0*	*0*	*1*	*1*

Definition 6: "IF Theory"

An IF theory T is a pair < typ(T), |-T> where typ(T) is a set of types and |-T , a binary relation between subsets of typ(T).

Let A be a classification. A token a ∈tok(A) satisfies the constraint Γ|-Δ where (Γ,Δ) are subsets of typ(A), if a is of some types in Δ whenever a is of every type in Γ. If every token of A is constrained by (Γ;Δ), we have obviously < Γ|-A Δ > and < typ(A), |-A> is the theory generated by A.

Definition 7: "Local Logic": A local logic L = < tok(L),typ(L), |=L, |-L,NL > consists of a regular IF theory th(L) =<typ(L), |-L>, an IF classification cla(L) =<tok(L),typ(L), |=L> and a subset NL ⊆ tok(L) of normal tokens which satisfy all the constraints of th(L). A token a ∈ tok(L) is constrained by th(L). Given a constraint (Γ,Δ) of th(L), whenever a is of all types in Γ, then a is of some type in Δ. An IF logic L is sound if NL = tok(L). In summary, each component of a distributed system is described with a sound logic integrating a classification and its associated theory L =<tok(L),typ(L), |=L>, |-L>

Once local structures have been defined, they must be linked in a way that allows information to flow between components. This is achieved with logic infomorphisms as follows.

Definition 8: "Logic Infomorphism": Given two sound logics L and L′, a logic infomorphism L ⇔ L′ consists of a contravariant pair of functions f =< f∧, f∨ > with

f∧ : typ(L) →typ(L′) and f∨ : tok(L′) →tok(L) such as:

1. f is the classification infomorphism f : cla(L) ⇔cla(L′)
2. for all (Γ,Δ) ⊆ th(L), Γ|-L Δ is a constraint of th(L) iff f∧[Γ] |-L′ f∨ [Δ] is a constraint of th(L′).

Definition 9: "IF Channel": An IF channel consists of two classifications A1 and A2 connected through a core classification C by means of two infomorphisms f1 and f2. Since local logics are inclusive concepts combining the concepts of classification and theory, they capture a more general knowledge than single classifications. Therefore there is a need to consider distributed IF logics of IF channels.

Definition 12: Given a binary channel C = {f1 : A1 ⇔ C, f2 : A2 ⇔ C} with a logic L on the core classification C, the distributed logic DLogC(L) of C generated by L is such as: DLogC(L) = F−1[L]

MAPPING PROCESS

According to the example exposed in section 2, relating TO and LO means that the achievement of g1 in LO depends on the achievement of others from TO. In the following, we refer TO by System S1, and LO by S2. Using IF model, the process of mapping may be summarized into three main steps:

1. Identification of possible classifications in system *S*1 (Teacher), *S*2 (Learner) according to their ontologies.
2. Generation of their possible theories;
3. Construction of the channel. This step has sub steps:

(a) Identification of the kernel classification C;
(b) Generation of local logic for C;
(c) Identification of the distributed logic within the sum of classifications.

Identification of classifications in system S1 (Teacher) and in system S2 (Learner) according to their ontologies: We have one classification by system C1 for S1 and C'1 for S2 (see table 3 and table 4)

Generation of possible theories;

For the classification C1 in S1, we have

|-C1 (C6,g6)
(C0,g0) |-C1 (C1,g1), (C3,g3), (C4,g4)
(C1,g1), (C3,g3), (C4,g4) |-C1 (C5,g5)

For the classification C'1 in S2, we have

|-C'1 (C3,g3)
(C0,g0) |-C1 (C1,g1)
(C1,g1) |-C1 (C2,g2),

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Construction of the channel: It is the central aspect in the process of mapping. In our example, the need, to map between ontologies, occurs when the learner searches for a subject in order to download content, thus we speak about pair (C1, g1) in system S2. To connect this pair with another of the other system we need to define a new classification which plays the role of a reference in order to compare the types of the distributed classifications.

TABLE 5 : CLASSIFICATION A

|=A	*g1*
a	0
b	*1*

In our case, we compare the types of *C*1 with those of *C'1*, which gives rise to an infomorphisms connecting A with C1 and C'1. $I^{(1)} : A \Leftrightarrow C1^{\perp}$ and $I^{(1)} : A \Leftrightarrow C'1^{\perp}$

Applying the property of infomorphisms, we have with *C*1:

$I^{(1)\vee}((C0,g0)) = b$
$I^{(1)\vee}((C1,g1)) = a$
$I^{(1)\vee}((C2,g2)) = b$
$I^{(1)\vee}((C3,g3)) = a$
$I^{(1)\vee}((C4,g4)) = a$
$I^{(1)\vee}((C5,g5)) = a$

We have with *C*'1: $I^{(1)\wedge}(g1) = g1$

Identification of the IF logic on the core of the Information Channel and the Distributed IF logic

The mapping allows the generation of the desired channel between *C1*(*S*1) and *C2*(*S*2). A core classification C is built with a couple of infomorphisms: I'(1) : C ⇔C1 and I'(1) : C ⇔C'1

The core classification C allows to connect tokens of different classifications through the information channel. The types of C are the elements of the disjoint union of types from *C1*(*S*1) and *C'1*(*S*2) . The tokens of C are the cartesian product of tokens in *C1* and tokens in *C'1*.

The IF theory of C is built from the union of types. The theory expresses how the types of *C*1 are related logically to the types of *C'*. According to our example, we are interested to the goal g1 which has (C1,g1) as a type in *C*1. The IF theory relates (C1,g1) with (C0, g0) and (C2,g2) in C1 classification. As a result the constraints in the IF theory are the following: (C0,g0) |- (C1,g1) and (C2,g2) |- (C1,g1)

The IF logic being defined by a classification and an IF theory gives us constraints in terms of sequent, we obtain the sequents : $((C0,g0)^{(S1)}, (C1,g1)^{(S2)})$,$((C2,g2)^{(S1)}, (C1,g1)^{(S2)})$ relating Context-Goal pairs of the two systems. According to the initial constraints, the second sequent matches all condition. From this point, the mapping of the two ontologies is based on a sound logic and on mathematic model.

CONCLUSION AND FUTURE WORK

In this paper, we have presented a formal method for the mapping of distributed ontologies in a sound and automatic manner, based on the IF model. We have demonstrated that the IF model is adequate to produce a sound logic between distributed systems which are considered with an intentional structure (the intentional ontology).

Currently, we are interesting to develop intentional ontologies for the activities of teachers and learners in computer science domain. Testing our methodology will be the next work.

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