Fuzzy Ontology Evolution: Classification of a New Individual

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***Abstract*—Ontologies help to conceive the real world with its semantic constraints. But this world has several uncertainties and imperfections that we cannot conceive using traditional ontologies. In our work, we are mainly interested in the imprecise knowledge representation problem. We believe that the most appropriate way is to use fuzzy logic in order to build ontologies called "Fuzzy ontologies". Even if there are several researches revolve around handling imprecise knowledge, however, there are still some issues to be further studied; one of them is the evolution problem which is still a tedious field. In this paper, and as a first step in the problem of fuzzy ontology evolution, we are interested in the classification of new individuals; for this reason, we use the classificatory reasoning mechanism to enable the classification of new individuals in a fuzzy hierarchy.**

***Index Terms*—Fuzzy logic, Fuzzy ontology, Classification reasoning, Individual classification.**

I INTRODUCTION

Ontologies represent a key focus of research for many applications in knowledge engineering, especially the Semantic Web project. They help to conceive the real world with its semantic constraints [16]. But this world has several uncertainties and imperfections that we cannot conceive using traditional ontologies. The formal representation of ontologies is generally based on the classical descriptions logic which shows its limits for all facts that are not expressed with "true" or "false" values.

Several fuzzy approaches have been proposed in order to simplify the possibilities of imprecise knowledge representation by assigning weights to different links. For example, we say that "the patient has a moderately high fever" rather than "the patient has or does not have a fever". In our work, we are mainly interested in the imprecise knowledge representation problem. We believe that the most appropriate way is to build ontologies called "Fuzzy ontologies". Imprecise knowledge representation is not our unique problem, since the real word is very dynamic; we are also interested in how to evolve these representations. So it will be very interesting to represent these knowledge using fuzzy ontologies as conceptual model and guarantee there evolutions.

In the literature we can find several researches revolve around imprecise knowledge, however, there are still some issues to be further studied; one of them is the evolution problem which is still a tedious field. Authors in [17] assured that a coherent process of ontology evolution is still rarely discussed, a reconstruction process is preferred to evolution one since the creation of ontologies, especially from large text corpus, is a well understood problem [2, 13].

Ontology evolution deals with the problem of incorporating new information in an existing ontology such as new individuals; in this paper, and as a first step in the problem of fuzzy ontology evolution, we are interested in the classification of new individuals in a fuzzy ontology. Classification is the main reasoning mechanism associated with the class-instance representation model. It is a process that, from a structured knowledge base and a new object, finds the proper location of the new object in the knowledge base.

The remainder of this paper is organized as follows. Section 2 provides an overview of the ontology evolution field. In Section 3, we discuss the problem of imprecise knowledge representation and how to use fuzzy logic and fuzzy set theory to take into account the representation of imprecise knowledge and then we try to define the concept of fuzzy ontology. In section 4, we present our proposed classification algorithm in which an individual is connected to his more specific concepts in a fuzzy hierarchy. Finally Section 5 concludes the paper and suggests some future work

II ONTOLOGY EVOLUTION

Ontology is a specification of a shared conceptualization of a domain [9], a change may be appeared in the domain knowledge, or for some need, a change may be caused by the conceptualization or even by the specification of the ontology. Changes in the specification refer to changes in the representation language [7]; this type of change is dealt with in the field of ontology translation (which is out of scope of this paper, for more details the reader is referred at [8]). Since there is no static domain and no perfect conceptualization, changes in the domain or its conceptualization are very common. An ontology evolution is the process of modifying ontology in response to a certain change in the domain or its conceptualization [6].

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Introducing new information to one part of the ontology can induce inconsistencies in other parts of the same ontology, the identification and resolution of any inconsistencies that may arise as a result of a change is one of the most important tasks to be performed during ontology evolution process [14], for that reason we can say that ontology evolution is the process of modifying an ontology while maintaining its validity and consistence.

Ontology evolution is mainly of two types: Ontology Population and Ontology Enrichment [11]. Ontology Population refers to the fact when the new information is the adding of new individuals for already existing concepts in the ontology. Ontology Enrichment refers to the fact when the new information is the changing of the ontology structure, for example adding (deleting) new concepts or properties. Then ontology is enriched by the structure change and populated by the new individuals. Figure 1 is a graphical illustration of these two types of ontology evolution.

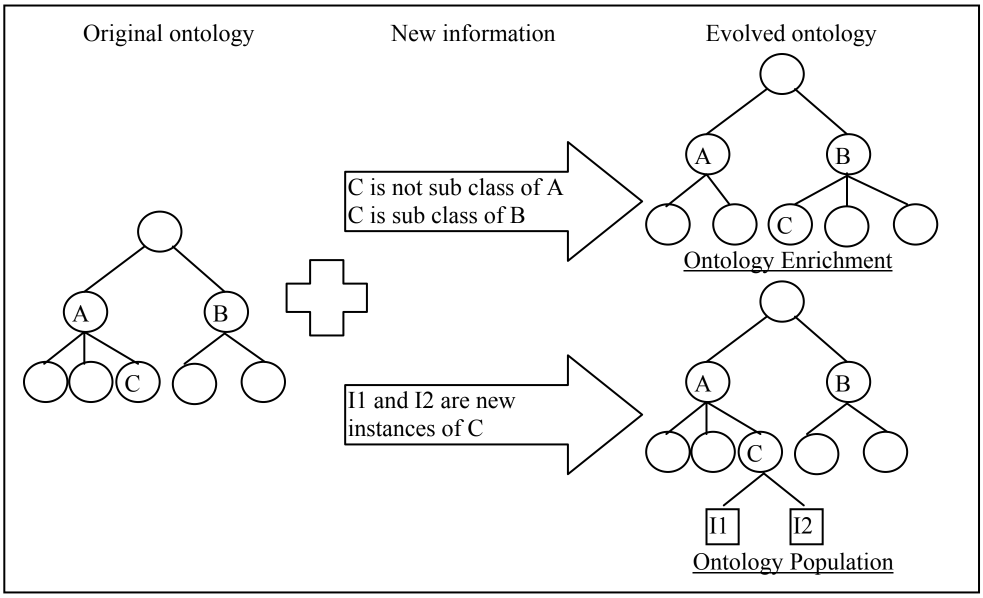

Fig 1: Ontology enrichment and population.

The process of evolution accepts as input a consistent[1] ontology and a set of new information, after a series of phases, the process generates as result a new consistent version of the same ontology. Maedche et al. identified six phases of the ontology evolution process [18]:

Change capturing: In this phase, changes to be applied are identified.

Change representation: the identified changes are formally represented by a finite sequence of elementary changes [2] for example Add (Delete) Concept/ Instance_Of/ Axiom… this decomposition is not always desirable as this might cause a set of unnecessary changes if each change is applied alone. To avoid these needless changes, it should be possible to represent changes in a highest level using the so called composite changes[3] that represent a group of elementary changes applied together for example Merge concepts, Move properties...

Semantics of change: The resulting effects of the required changes are identified in this phase and if there are problems caused by these changes, they will be also identified and resolved in order to guarantee the consistency of the ontology at the end of the process.

Change implementation: When the changes are approved by the user, they will be physically applied to the ontology.

Change propagation: after the modification of the ontology, it will be necessary to propagate the changes to all dependent applications.

Change validation: this phase allows reviewing the changes and possibly undoing them, if desired.

III HANDLING IMPRECISE KNOWLEDGE

The human being reasoning is often based on fuzzy knowledge. To solve everyday problems, he uses knowledge he doubts their validity (uncertain) or poorly expressed due to the complexity of the problem (imprecise). Despite this, it is often possible to solve these complex problems without needing to model them. According to [1], it is often useful to model the behavior of a human operator with the system rather than modeling the system itself. It is also preferable to describe this system with global quantifiers rather than using precise numerical values. Fuzzy logic was introduced as an extension of Boolean logic [19], this logic is not to be precise in the statements, but instead to respond to vague proposals, that requiring some degree of uncertainty.

[1] A consistent state of an ontology is defined in [18] as the state in which all constraints, which are defined on the structure and content of an ontology are satisfied. An example of the structural constraints is the need to define the domain and the range for each relation in the ontology. Content constraints are related to the axioms in the ontology

[2] In the same reference, authors have identified 17 elementary changes.

[3] Always in the same reference, authors have identified 12 composite changes.

III.1 Fuzzy Set Theory and Fuzzy Logic

Fuzzy logic is designed to solve the problem of the representation of uncertain and imprecise knowledge. It allows the characterization of elements in a "gradual" way. It was introduced by LA Zadeh in the late 60s as an extension of Boolean logic [19]. In classical set theory, two situations can be considered: Elements either belong to a set or not. The classical set theory does not take into account several situations frequently encountered in our daily life: It will be very difficult to say its hot today because heat is a progressive concept. If for a temperature of 25 °, we say it's hot, is it not hot with a temperature of 24.8 °?

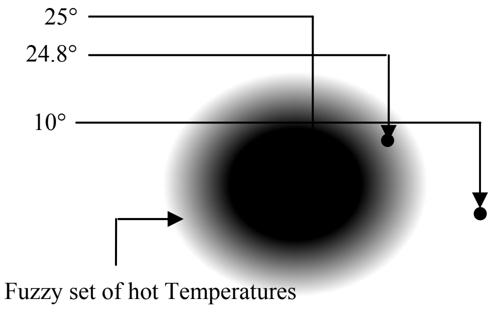

Fig 2: Fuzzy set and partial membership

This example shows that 25° belongs completely to the fuzzy set, so it's a hot temperature; 24.8° belongs partly to the fuzzy set, so this is a moderately hot temperature. When 10°, it does not belong to the fuzzy set, therefore it is not a hot temperature.

Definition: membership function: let X be a set of elements, a fuzzy subset A of X is defined by a function called *membership function* μ_A (x) or simply A(x) which take any value from the real interval [0, 1]. A membership function A(x) is characterized by the following mapping:

$$A(x): x \rightarrow [0, 1], \forall x \in A$$

An element belongs to a fuzzy set to some degree; this is in fact the value taken by the membership function of the fuzzy set at the considered point. As in the classical case, 0 means no-membership and 1 full membership, but now a value between 0 and 1 represents the extent to which x can be considered as an element of A. Membership degrees are calculated based on some specific functions (see Figure 3), we present here the most frequently used:

- *Crisp function:*

$$C(x; a, b) = \begin{cases} 1 & \text{if } a \le x \le b \\ 0 & \text{otherwise} \end{cases}$$

- *Trapezoidal function*:

$$T(x; a, b, c, d) = \begin{cases} (x - a)/(b - a) & \text{if } x \in [a, b] \\ 1 & \text{if } x \in [b, c] \\ (d - x)/(d - c) & \text{if } x \in [c, d] \\ 0 & \text{otherwise} \end{cases}$$

- *Right shoulder function:*

$$R(x; a, b) = \begin{cases} 0 & \text{if } x < a \\ (x - a)/(b - a) & \text{if } x \in [a, b] \\ 1 & \text{if } x > b \end{cases}$$

Fuzzy set theory is designed to take into account this kind of situations, where elements can belong to a defined fuzzy set with a certain degree. In [1] fuzzy set theory is defined as a theory based on the notion of partial membership. Each element is partially or gradually belongs to the defined fuzzy sets. The contours of each fuzzy set (see Figure 2) are not "net", but "fuzzy" or "gradual".

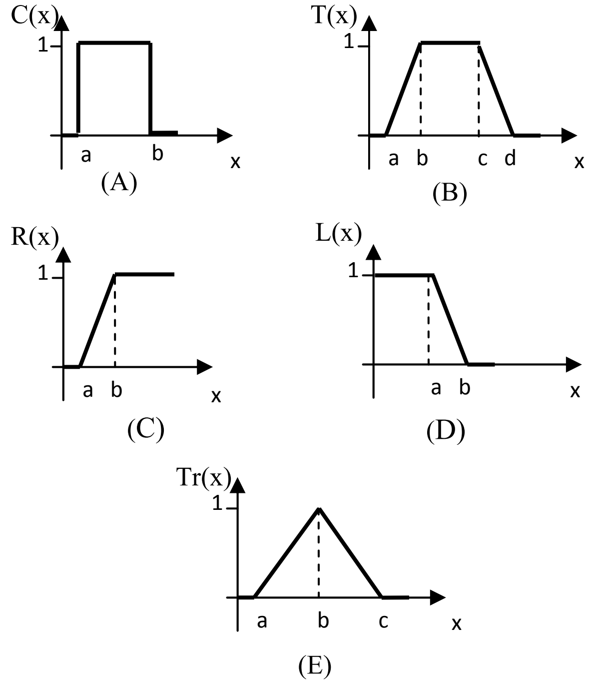

Fig 3: Crisp Function (A), Trapezoïdal Function (B), Right shoulder Function (C), Left shoulder Function (D), Triangular Function (E)

- *Left shoulder function:*

$$L(x; a, b) = \begin{cases} 1 & \text{if } x < a \\ (b - x)/(b - a) & \text{if } x \in [a, b] \\ 0 & \text{if } x > b \end{cases}$$

- *Triangular function:*

$$Tr(x; a, b, c) = \begin{cases} (x - a)/(b - a) & \text{if } x \in [a, b[\\ 1 & \text{if } x = b \\ (c - x)/(c - b) & \text{if } x \in]b, c] \\ 0 & \text{otherwise} \end{cases}$$

III.2 Fuzzy Ontology

Several definitions have been given to describe the term "ontology" [10, 20, and 15]. This diversity of definitions provides different viewpoints but especially complementary, they all revolve around the same goal: design the real world with its semantic constraints. When it comes to conceive imprecise or imperfect knowledge, this will be the role of *fuzzy ontologies* : building of these ontologies is based on fuzzy logic.

Fuzzy ontology consists of two types of components: crisp components (crisp concepts and roles, instances and axioms) and fuzzy components (fuzzy concepts and roles) this components are used to represent the vagueness and imperfection of the real world knowledge [3].

Crisp concepts: if a concept can have a clear and complete definition in which there is no fuzzy properties, this is a crisp concept like car, person, male…

Crisp roles: a crisp role represents the presence or absence of association between the instances of two crisp concepts such as "People *live* in houses", or tow fuzzy concepts like" Rich-People *Drive* Fast-Cars".

Fuzzy concepts: fuzzy concept is described as a concept defined on the basis of a particular value of a linguistic variable relative to the universe of discourse [12]. These linguistic variables represent the fuzzy properties of the concept (age, size, color degradation ...) so that we can represent the uncertainty of fuzzy concepts [3]. Each linguistic variable takes its values in a set of linguistic terms, consider the variable "Size" for example, we can define the following terms: "Small, Average, Tall…" which may become fuzzy concepts: "Small-person, Average-person, Tall-person …"

Fuzzy roles: fuzzy roles are the generalization of crisp roles in which we can allow various degrees of association between instances of crisp concepts such as "Hotels are *close to* the airport", or fuzzy concepts like "Small-People *appears to be* young".

Instances: The membership of an instance to a crisp concept is complete, in the case of fuzzy concept, the instance belongs partly to the concept, and its membership degree is determined by the value taken by the membership function of the instance to the fuzzy concept (modeled as a fuzzy set).

Taking the example of the fuzzy concept "Average-person", the membership degrees of its instances are determined by the values taken by its membership function, which is Trapezoidal type (see Figure 4).

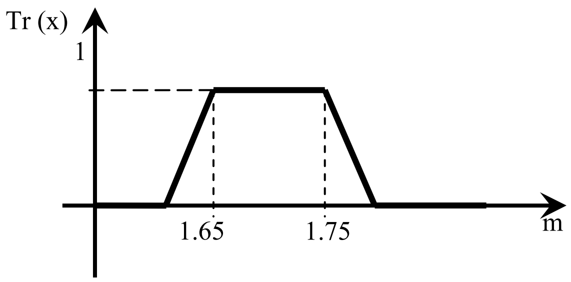

Fig 4: Membership function of the fuzzy concept "Average-person"

The membership degrees to this fuzzy concept are calculated using the following formulas:

$$T(x)=\begin{cases}(1.65 - x)/(1.65 - 1.60) & \text{if } x \in [1.60, 1.65[\\ 1 & \text{if } x \in [1.65, 1.75] \\ (x - 1.75)/(1.80 - 1.75) & \text{if } x \in]1.75, 1.80] \\ 0 & \text{otherwise}\end{cases}$$

Axioms: concept or role assertion axioms can be tainted with uncertainty as we have said; the membership of an instance to a fuzzy concept is partial. Same for the ontology hierarchy: sometimes, we cannot say that a concept is subsumed by another; this cannot be so sure. Axioms are also used to express the formulas of the membership functions [12] (given previously).

IV FUZZY ONTOLOGY EVOLUTION: CLASSIFICATION OF A NEW INDIVIDUAL

In this section we will present a classification algorithm of a new individual. This algorithm starts with an individual which we have a total or partial knowledge (some attributes may not be valued) and a hierarchy graph of the fuzzy ontology. The goal of this algorithm is to find the most specialized concepts to which the individual belongs by bringing him down as low as possible in the concept hierarchy.

Our algorithm is based on the multi-viewpoint classification algorithm of TROPS model presented in [4, 5], in our work, we are not interested in the multi-view point representation model, but how to find the appropriate place of the new individual in an imprecise knowledge hierarchy.

The classification algorithm is based on a loop; the new individual begins in an initial stable state and at each step of the loop, the ontology changes from one stable state to another stable state closer to the purpose which is the attachment of the new individual to his more specialized concepts.

The classification algorithm consists of five procedures: Obtaining-Information, Initial-State-Construction, Matching, Marks-Propagation and Choosing-Next-Concept.

```
Obtaining-Information
Initial-State-Construction
While not (finished) do
    Matching
    Marks-Propagation
    Choosing-Next-Concept
End while
```

IV.1 Obtaining Information

Before launching the classification, the user must provide some information of the new individual; this information is a set of pairs (attribute, value). The algorithm accepts the "unknown" value, which means that the attribute is not valued. Thus the algorithm can classify incomplete instances.

IV.2 Initial State Construction

This procedure consists in creating from the initial information about the individual a stable state by attaching this individual to its membership concepts (this information comes from the user), if the user has no such information, the individual is attached to the concept root of the hierarchy. Once the initial state constructed, the classification is to repeat the loop of the three procedures Matching, Marks-Propagation and Choosing-Next-Concept.

IV.3 Matching

The matching procedure checks the membership of the individual to the current concept. In what follows, we present two types of membership functions: membership function with two values and membership function with three values:

IV.3.1 Membership Function with Two Values

Membership function with two values (Boolean membership function) is used in Boolean logic (classical), it takes its values from the universe of discourse and returns the value *"True"* if the instance belongs to the class, and the value *" false"* otherwise. For example, taking the integer class "pair", its membership function can be described as follows:

$$Pair\ (x) = \begin{cases} True & if\ x\ mod\ 2 = 0 \\ False & if\ x\ mod\ 2 \neq 0 \end{cases}$$

The membership function with two values is well suited for the consideration of complete and precise knowledge for which we can say with certainty that they belong to a particular class or not, which is not the case in our knowledge base, for that reason, we present the membership function with three values

IV.3.2 Membership Function with Three Values

In a fuzzy ontology, we manage imprecise and incomplete knowledge. The scope of the membership function is increased here to accept the value "possible." The function returns the value "possible" for an incomplete instance if the knowledge we have of this instance does not allow affirming or denying its membership to the class. This is the principle of fuzzy logic using a multi valued membership (several membership degrees). A membership function with three values can be described as follows:

$$C(x) = \begin{cases} sure & if\ x \in C \\ impossible & if\ x \notin C \\ possible & otherwise \end{cases}$$

In our Matching procedure, we use the membership function with three values. The comparison between an individual and a concept can give three different results:

- *Sure* if the individual belongs to the concept.
- *Impossible* if the individual is in contradiction with the concept.
- *Possible* if it is not in contradiction with the concept, but missing information to be sure of its membership.

Based on this function, the purpose of the matching procedure is to mark the current concept by one of the three marks: "sure", "possible" or "impossible":

- A concept *C* is marked *"sure"* for the individual *A* (*A* belongs to *C)* if for each attribute of *C* the value of this attribute in *A* satisfies the constraints of *C* (interval, domain, etc...). So, this membership can be determined only if *A* is complete and satisfies the constraints of *C*.
- A concept *C* is marked *"impossible"* for the individual *A* (*A* do not belongs to *C*), when the value of an attribute of *A* does not satisfy the constraints set for this attribute in *C*, here we do not take into account the incompleteness of the individual *A*.
- If *A* has no value for some attributes defined in *C*, and if the valued attributes of *A* are not in contradiction with *C*, we say that the concept *C* is *possible* for the individual *A* (the membership of *A* to the concept *C* cannot be determined because it is missing information).

The marks allocation is based on the satisfaction of the attributes constraints in the concept, if it is a fuzzy attribute; the Matching procedure first begins to calculate the membership degree of the individual to the fuzzy concept based on the attribute value:

If membership degree >0 **then** constraint satisfied

If membership degree ≤0 **then** constraint not satisfied

The user can define another constraint satisfaction threshold; in case he needs to be more sure of the individual membership to the concept, for example, he can define the 0.3 threshold instead of 0:

If membership degree < 0.3 **then** constraint not satisfied

IV.4 Marks-Propagation

The purpose of this procedure is to minimizing the number of concepts to be tested by propagating marks to some concepts based on certain rules:

1- If a class is marked "impossible", all its sub-classes will be marked "impossible".
2- If a class is marked "sure", all its super-classes will be marked "sure".
3- If the current class C is marked "sure" (impossible), ∀D, D≡C (synonym), D will be marked "sure" (impossible).
4- If the current class C is marked "sure" (impossible), ∀D, D ≡ ⌉ C (opposite), D will be marked "impossible" (sure).

IV.5 Choosing-Next-Concept

After the marks propagation, the classification algorithm chooses a new concept to the membership test. Unlike the classification algorithm of TROPS model, our algorithm is not based on the hypothesis of the exclusiveness of sisters classes.[4]

In our conceptualization, fuzzy concepts are modeled as fuzzy sets [3]. The strength of fuzzy logic in knowledge representation comes from the intersection between the fuzzy sets, thus an element can belong to several fuzzy sets with different membership degrees. Therefore, individual can belong to several concepts at the same level of the hierarchy.

Considering the following conceptualization, in which we define two fuzzy concepts as follows:

Medium-size-person: a person with a size between 1.60 and 1.80 m.

Tall–Person: a person with a height exceeding 1.75 m.

And an individual with a height of 1.77 m, he will belong to both concepts "Average–Person and Tall–Person" with two different membership degrees related to the concepts membership functions.

For this reason, our classification algorithm tests all the concepts of the current level before bringing the individual down in the hierarchy.

[4] In the TROPS model, sisters classes describe mutually exclusive sets. Thus, if an instance belongs to one of these classes, it cannot belong to any other class

IV.6 Stopping the Algorithm

The classification algorithm may terminate for one of the following reasons:

1- The matching is complete, and there are no more concepts to be tested:
   - Because the goal is reached and the individual is classified the lowest possible in the hierarchy.
   - Or because he does not belong to the hierarchy and he is not classified.

2- The user wants to stop the classification.

V CONCLUSION

In this paper, we have proposed an algorithm for reasoning with imprecise ontological knowledge. As a first step in the problem of fuzzy ontology evolution, we have proposed this algorithm in order to classify new individuals in such ontology. The underlying key of our algorithm is that it allows the classification of incomplete instances in a fuzzy ontology. The reasoning mechanism that we have used is the individual classification; this reasoning mechanism takes into account the characteristics of the conceptualization of fuzzy ontology: knowledge uncertainty and incompleteness.

As future work, we intend to validate and test the proposed algorithm in an application domain. We would like also to test it in a concept hierarch based on fuzzy subsumption.

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