Representation of Context-Dependent Relevance Relations with Fuzzy Ontologies

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Abstract. Information overload is a common problem in current Information and Knowledge Based Systems. The Web, being the largest public available information source, is particularly affected by this issue, so several approaches to deal with it are being developed by Semantic Web researchers. Most of them are based on using context knowledge to delimit which information is significant to a user, such as the CDR ontology design pattern, our previous contribution to handle relevance depending on context in OWL ontologies. In this work, we extend this proposal with fuzzy Description Logics formalisms in order to represent vague knowledge about context and application-specific facts, and to manage the degree of importance of a relevance relation. A main advantage of our proposal is that current (non-fuzzy) standards and inference engines can be used.

1 Introduction

Anyone who has been staring at his computer screen –INSPEC database, Google Scholar and ScienceDirect on the web browser, in addition to Zotero with selected papers and a couple of seven hundred pages pdf files with the last ESWC proceedings–, hastening to find the right reference to complete a submission one hour before the deadline, has an idea of what information overload is. This state is more precisely defined in Information Systems [1], where information overload is described as the situation when a user is provided with more data than he or she can digest, either because filtering it manually would take too much time or simply because interesting facts cannot be told from useless, resulting in unproductive decision processes and knowledge management failure.

Warding off this situation is one of the purposes of Semantic Web technologies. Agents in the Semantic Web use metadata to locate, discover and integrate different information sources, which will drive eventually to provide users with a considerable amount of data. Clearly, semantic agents must implement mechanisms that reduce the amount of information delivered to users, in such a way that they supply just the just amount of data to them –these which users are *really* interested in–, in order to avoid information overload. That means that, when retrieving information to support users, only those segments of ontologies which are relevant or significant with respect to the current task should be considered. This is known as selective activation of knowledge.

Hence it is necessary to represent which pieces of the available information are relevant to carry out a task. In that regard, what is important depends on (i) which is the problem to be solved, and (ii) other factors, somehow extrinsic, as user environment, preferences, previous actions. etc. All these elements make up, in a wide sense, the context of use of the system. In Semantic Web systems, where knowledge is represented using ontologies, this context can be as well represented using an ontology.

In a previous work, we developed an ontology design pattern to represent in OWL this notion of relevance dependent on context [2]. The so-called Context-Domain Relevance (CDR, read as *cider*) pattern defines a set of rules to build a new OWL ontology where context descriptions and knowledge directly related to the application domain are connected through qualified relations. In that paper, we present a simple use case where this kind of ontologies are very useful. We suppose a doctor who is attending to an unconscious person with a bleeding wound out of the hospital. In order to carry out a proper treatment, it is very valuable for the doctor to know certain facts about the clinical history of the patient which should be taken into account according to the current patient situation –specifically if he has been previously diagnosed of blood borne diseases or adverse reactions to anesthetic drugs administration–, but not every register recorded in the Hospital Information System (HIS). The relevance or CDR ontology represents the connections among context descriptions (the patient situation) and domain knowledge (the registers of the clinical database), making possible to infer the latter given the former with the attached algorithm.

The relevance ontology resulting from applying the CDR pattern has two main lacks. First of them, definitions of complex context concepts (respectively for definitions of complex domain concepts) are crisp, which results in having a context description either included or not in another context description. As a result, it is not possible to represent directly vague contexts, e.g. "the patient is slightly unconscious", and partial similarity between contexts, e.g. "anaphylaxis is quite similar to sepsis". On the other hand, the relevance ontology only allows the developer to associate which concrete information is interesting in a scenario, but it does not measure how important this connection is, which is convenient in some applications. Recalling the example of our doctor, it can be realized that electronic registers about previous adverse drug events are more important in this case and should be presented firstly to the doctor: avoiding an anaphylactic shock is a major priority and medical protocols prevent the doctor from being in contact with patients' blood. Ranking the relevance relations would allow system responses to be ordered by precedence and a threshold to be fixed in order to retrieve only the top k most relevant domains.

In this paper, we propose an extension of the CDR design pattern to deal with vague contexts and domains and to quantify relevance relations. Our approach relies on Fuzzy Description Logics (fuzzy DLs), a logical formalism proposed in the literature which combines Fuzzy Logic theory and classical Description Logics in order to define a sound framework to represent and reason with imprecise and vague knowledge in ontologies.

The contributions of this paper are the following. Firstly, we reassess the original definition of the CDR pattern and, as a novelty, we demonstrate that the reasoning procedure is complete. Secondly, as the main contribution, we formulate an extension of the pattern which results in a fuzzy ontology. This extension allows imprecise context and domain descriptions to be represented and relevance relations to be weighted. Though the fuzzy CDR ontology is not OWL compliant, previous results can be applied to reduce it to a crisp representation in order to use existing inference engines [3, 4].

The paper is structured as follows. Section 2 recalls the CDR design pattern from [2] and completeness and complexity of the reasoning algorithm are discussed. Section 3, the core of the paper, defines the fuzzy extension of the pattern, describes the reasoning process, and proves its utility with an example. Section 4 describes some notable approaches in four areas related to this work: ontology design patterns, contextualization of ontologies, ranking of interest in ontologies, and fuzzy DLs. Finally, in Section 5 we summarize the results of this work and point out some directions for future research.

2 Representation of context-dependent relevance relations

2.1 Basics on DLs

We will use in this paper DLs notation, which can be directly translated to XML-based OWL syntax. An introduction to DLs is provided next; further details can be found in [5].

The signature (or vocabulary) of a description logic contains the symbols used in it. Formally, the signature is the disjoint union $\mathrm{S} = R \uplus C \uplus I$, being $R = \{R_A\}$ the set of atomic roles (or properties), $C = \{C_A\}$ the set of atomic concepts (or classes), and $I = \{a, b, \ldots\}$ the set of individuals (or instances). From these atomic elements in S, new complex roles (noted $\mathsf{Rol}(\mathrm{S}) = \{R_i\}$), concepts ($\mathsf{Con}(\mathrm{S}) = \{C_i\}$), and axioms ($\mathsf{Ax}(\mathrm{S}) = \{O_i\}$) can be composed (subscripts will not be used when disambiguation is not needed). By extension, the signature $\mathrm{S}(O)$ of an axiom (respectively for roles and concepts) is the set of atomic elements of S which are included in O. Several logics are distinguished in DLs depending on the constructors allowed to create new complex expressions; each one is named using capital letters which denote the valid operators. Generally, having more constructors in a logic means that it is more expressive and, consequently, the computational complexity of reasoning processes is higher.

A DL ontology is a triple $\mathcal{K} = \langle \mathcal{T}, \mathcal{R}, \mathcal{A} \rangle$, where $\mathcal{T}$ (the TBox) contains axioms about concepts, $\mathcal{R}$ (the RBox) axioms about roles, and $\mathcal{A}$ (the ABox) axioms about individuals. The signature of an ontology $\mathrm{S}(\mathcal{K})$ is the union of all the signatures $\mathrm{S}(O)$ of the axioms in $\mathcal{K}$. The set of concepts (resp. roles) defined in an ontology is noted $\mathsf{Con}(\mathcal{K})$ (resp. $\mathsf{Rol}(\mathcal{K})$). Hereafter, we will use the basic DL $\mathcal{ALC}$ unless otherwise indicated.

A TBox $\mathcal{T}$ consists of a finite set of general concept inclusion (GCI) axioms of the form $C_1 \sqsubseteq C_2$, which means that concept C_1 is more specific than C_2, i.e. C_2 subsumes C_1. A concept definition $C_1 \equiv C_2$ (C_1 and C_2 are equivalent) is an abbreviation of the pair of axioms $C_1 \sqsubseteq C_2$ and $C_2 \sqsubseteq C_1$. Concept expressions for C_1 and C_2 can be derived inductively from atomic primitives using concept constructors. Table 1 shows the constructors allowed for concepts and roles in $\mathcal{ALC}$. In more complex DLs, a RBox $\mathcal{R}$ consists of a finite set of role axioms stating role properties such as inclusion, transitivity, etc. However, in $\mathcal{ALC}$ the RBox is assumed to be empty and complex role expressions cannot be used in concept and instance axioms. An ABox $\mathcal{A}$ consists of a finite set of axioms about individuals. These axioms describe an individual with respect to a concept ($a : C$, which means that a is an instance of C) or a pair of individuals with respect to a role ($(a, b) : R$, which means that (a, b) is an instance of R).

Table 1. Syntax and semantics of complex concepts and roles in $\mathcal{ALC}$.

Constructor	Syntax	Semantics
(atomic concept)	A	$A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$
(top concept)	$\top$	$\Delta^{\mathcal{I}}$
(bottom concept)	$\bot$	$\emptyset$
(concept conjunction)	$C_1 \sqcap C_2$	$C_1^{\mathcal{I}} \cap C_2^{\mathcal{I}}$
(concept disjunction)	$C_1 \sqcup C_2$	$C_1^{\mathcal{I}} \cup C_2^{\mathcal{I}}$
(concept negation)	$\neg C$	$\Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
(universal quantification)	$\forall R.C$	$\{x : \forall y, (x, y) \notin R^{\mathcal{I}} \text{ or } y \in C^{\mathcal{I}}\}$
(existential quantification)	$\exists R.C$	$\{x : \exists y, (x, y) \in R^{\mathcal{I}} \text{ and } y \in C^{\mathcal{I}}\}$
(atomic role)	R_A	$R_A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$

An interpretation $\mathcal{I}$ of an ontology $\mathcal{K}$ is a pair $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$ where $\Delta^{\mathcal{I}}$, the domain of the interpretation, is a non-empty set, and $\cdot^{\mathcal{I}}$ is a function which maps every individual a onto an element $a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$, each concept in $\mathcal{K}$ with a subset of $\Delta^{\mathcal{I}}$, and each role in $\mathcal{K}$ with a subset of $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$. This interpretation is conveniently extended for complex concepts.

An $\mathcal{ALC}$ interpretation $\mathcal{I}$ is a model of:

- $a : C$ iff $a^{\mathcal{I}} \in C^{\mathcal{I}}$,
- $(a, b) : R$ iff $(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$,
- $C_1 \sqsubseteq C_2$ iff $C_1^{\mathcal{I}} \subseteq C_2^{\mathcal{I}}$,
- a KB $\mathcal{K} = \langle \mathcal{T}, \mathcal{R}, \mathcal{A} \rangle$ iff it satisfies each element in $\mathcal{T}$, $\mathcal{R}$ and $\mathcal{A}$.

One of the main reasoning tasks in DLs is subsumption checking: C_2 subsumes C_1 w.r.t. $\mathcal{K}$ (noted as $\mathcal{K} \models C_1 \sqsubseteq C_2$) iff $C_1^{\mathcal{I}} \subseteq C_2^{\mathcal{I}}$ is verified for every model $\mathcal{I}$ of $\mathcal{K}$. Classifying an ontology $\mathcal{K}$ consists of computing for each pair of concepts $C_1, C_2 \in \mathsf{Con}(\mathcal{K})$ if $\mathcal{K} \models C_1 \sqsubseteq C_2$.

2.2 Formulation of the CDR design pattern

The CDR design pattern defines constructively how to develop a new ontology –the relevance or CDR ontology– built upon the domain-specific and the context vocabulary sub-models.

The domain sub-ontology $\mathcal{K}^D$ contains the knowledge required to solve the concrete problem that the system is facing. We will use the notation D_j ("complex domain") to name concept expressions built using elements in $\mathcal{K}^D$ (and ontology constructs); that is, $\mathrm{S}(D_j) \subseteq \mathrm{S}(\mathcal{K}^D)$. The context ontology $\mathcal{K}^C$ contains the knowledge required to express the circumstances or the surroundings under which the domain knowledge will be used; it can be seen as a formal vocabulary to describe these situations. We will use the notation C_i ("complex context") to name concept expressions defined using elements of $\mathcal{K}^C$ (and ontology constructs); that is, $\mathrm{S}(C_i) \subseteq \mathrm{S}(\mathcal{K}^C)$.

Note that D_j and C_i are not part of the domain and the context ontology.

Actually, they are defined in the CDR ontology ($\mathcal{K}^R$), which is a new ontology where C_i, D_j, and *links* between them are defined. These links, named *profiles*, state that the domain-specific knowledge D_j ought to be considered in situation C_i. A profile concept is a new concept representing a profile-connection, and is defined with existential restrictions on the complex context and the complex domain that it links (via properties R_1 and R_2). Then, the relevance ontology $\mathcal{K}^R$ contains new classes (the so called "profiles") which relate complex contexts C_i and complex domains D_j through quantified roles:

Definition 1. *Let $\mathcal{K}^D$ and $\mathcal{K}^C$ be, respectively, the domain and the context sub-ontologies, C_i a complex context such that $\mathrm{S}(C_i) \subseteq \mathrm{S}(\mathcal{K}^C)$ and D_j a complex domain such that $\mathrm{S}(D_j) \subseteq \mathrm{S}(\mathcal{K}^D)$. The relevance ontology or CDR ontology which relates the set of pairs $\{(C_i, D_j)\}$ (i.e. states that D_j is interesting when C_i happens) is a consistent ontology $\mathcal{K}^R = \langle \mathcal{T}^R, \mathcal{R}^R, \mathcal{A}^R \rangle$ where $\mathcal{T}^R$ includes definitions for the concepts $P_\top, C_\top, D_\top, C_i, D_j, P_{i,j}$, and satisfies:*

1. *$P_\top$, $C_\top$, $D_\top$ are the superclasses Profile, Context and Domain:*
   – $P_{i,j} \sqsubseteq P_\top$, $C_i \sqsubseteq C_\top$, $D_j \sqsubseteq D_\top$
2. *R_1 is the (new) bridge property linking profiles and complex contexts:*
   – $P_\top \sqsubseteq \forall R_1.C_\top$
3. *R_2 is the (new) bridge property linking profiles and complex domains:*
   – $P_\top \sqsubseteq \forall R_2.D_\top$
4. *$P_{i,j}$ is the profile linking the named context C_i and the named domain D_j:*
   – $P_{i,j} \equiv \exists R_1.C_i \sqcap \exists R_2.D_j$

Notice that none of C_i and D_j are part of the domain and the context sub-models, respectively, but they are defined in the new ontology $\mathcal{K}^R$. Therefore, $\mathrm{S}(\mathcal{K}^C) \cup \mathrm{S}(\mathcal{K}^D) \subseteq \mathrm{S}(\mathcal{K}^R)$, i.e. $\mathcal{K}^R$ must import the axioms stated in $\mathcal{K}^C$ and $\mathcal{K}^D$ to preserve the semantics of C_i and D_j.

Proposition 1. *Let $\mathcal{K}^R$ be a CDR ontology, C_i and $C_{i'}$ complex contexts defined in $\mathcal{T}^R$, and D_j and $D_{j'}$ complex domains defined in $\mathcal{T}^R$. The ontology $\mathcal{K}^R$ satisfies the property: $C_i \sqsubseteq C_{i'} \wedge D_j \sqsubseteq D_{j'} \Rightarrow P_{i,j} \sqsubseteq P_{i',j'}$*

This proposition reflects the intuition that if a context and a domain are connected through a profile, more general (i.e. subsuming) contexts and domains will be connected through a more general profile.

Proof. The proof is immediate from the forth condition in Definition 1. □

In general, the reciprocal is not true. This formulation allows a consistent relevance ontology to be created with $P_{i,j} \sqsubseteq P_{i',j'}$, but $C_i \not\sqsubseteq C_{i'}$ and/or $D_j \not\sqsubseteq D_{j'}$.

The main reasoning task involving a relevance ontology consists on finding all the concepts in the domain ontology which are worth to be considered in a given context, that is, the domains that are associated through profiles with a complex context expressed using the context vocabulary.

Definition 2. *Given the ontologies $\mathcal{K}^R$, $\mathcal{K}^D$ and $\mathcal{K}^C$ (with their respective signatures $\mathrm{S}\left(\mathcal{K}^R\right), \mathrm{S}\left(\mathcal{K}^D\right), \mathrm{S}\left(\mathcal{K}^C\right)$) and a complex context E ($\mathrm{S}(E) \subseteq \mathrm{S}\left(\mathcal{K}^C\right)$), the restricted domain of the scenario E w.r.t. $\mathcal{K}^R$, noted as $\mathcal{D}\left(E, \mathcal{K}^R\right)$, consists of the concepts I in $\mathcal{K}^D$ such as:*

$$\mathcal{D}\left(E, \mathcal{K}^R\right) = \left\{I \mid I \in \mathsf{Con}(\mathcal{K}^D) \wedge (E \sqsubseteq C_n) \wedge (P_{n,m} \sqsubseteq P_\top) \wedge (I \sqsubseteq D_m)\right\}$$

Algorithm 1. *$\mathcal{D}\left(E, \mathcal{K}^R\right)$ can be computed in practice as follows:*

1. $\{C_n\} = \{C_n \sqsubseteq C_\top \mid E \sqsubseteq C_n\}$
2. $\{P_{k,l}\} = \{P_{k,l} \sqsubseteq P_\top \mid (P_{k,l} \sqsubseteq \exists R_1.C_k) \wedge (C_n \equiv C_k)\}$
3. $\{D_m\} = \{D_m \sqsubseteq D_\top \mid (P_{k,l} \sqsubseteq \exists R_2.D_l) \wedge (D_m \equiv D_l)\}$
4. $\mathcal{D}\left(E, \mathcal{K}^R\right) = \left\{I \in \mathsf{Con}(\mathcal{K}^D) \mid I \sqsubseteq D_m\right\}$

The final output of the algorithm to the user is the set of simple domain concepts of $\mathcal{K}^D$ which are relevant to the query context E. Due to length restrictions, we refer the reader to our previous work in [2] for an example on the use of the crisp pattern and the algorithm, and to Section 3.3 for an example of the fuzzy counterparts.

Proposition 2. *Algorithm 1 is complete, i.e. it finds all the concepts I related with E through profiles.*

Proof. From the expressions in the steps 1-4 of Algorithm 1, it can be trivially realized that every $P_{k,l}$ subsuming the (hypothetical) profile $P_{E,I}$ linking E and I is retrieved. By definition, $E \sqsubseteq C_n \sqsubseteq C_k$ $\forall n, k$ and $I \sqsubseteq D_m \sqsubseteq D_l$ $\forall m, l$. Recalling Proposition 1, we get directly that $P_{E,I} \sqsubseteq P_{n,m} \sqsubseteq P_{k,l}$. □

The computational complexity of Algorithm 1 is asymptotically bounded by ontology classification, which depends on the expressivity of $\mathcal{K}^R$. Since profile declarations (from Definition 1) are included in $\mathcal{ALC}$, $\mathcal{K}^R$ complexity is conditioned by complexity of C_i and D_j expressions and, subsequently, by complexity of $\mathcal{K}^C$ and $\mathcal{K}^D$ ontologies. In the simplest case, that is $\mathcal{K}^R$, $\mathcal{K}^C$ and $\mathcal{K}^D$ are in $\mathcal{ALC}$ (with general TBoxes), concept satisfiability in $\mathcal{K}^R$ is ExpTime-complete [6]. This complexity might be reduced by restricting the allowed constructors for the complex context and domain expressions.

3 A fuzzy extension of the CDR pattern

3.1 Basics on fuzzy DLs

Fuzzy Sets theory and Fuzzy Logic are aimed at managing imprecise and vague knowledge [7]. Fuzzy DLs extend DLs by letting concepts to denote fuzzy sets of individuals and roles to denote fuzzy binary relations [8]. The notion of interpretation is extended to the fuzzy case, in such a way that an individual of the domain may belong to a concept with some degree in $[0,1]$ (analogously for a pair of individuals and a role). The semantics of the constructors used to build non atomic concepts and roles are conveniently extended; e.g. the semantics of the concept conjunction are given by a t-norm function. Axioms are also extended to the fuzzy case, holding to a degree; e.g. given two fuzzy concepts, a terminological axiom may be asserted to define a fuzzy inclusion relation between them.

In a fuzzy DL we can define, for instance, $TomFavouriteGroups$ as the set of bands that Tom (from MySpace) likes, with *radiohead* completely belonging to it (degree equals to 1), while *the_cardigans* may also belong but with less degree (equals to 0.7). Similarly, two individuals can be partially related through a role: *radiohead isSimilarTo the_cardigans* with degree 0.6. Other axioms may be as well fuzzified, e.g. GCIs: $AcidJazz$ is a subset of $Funk$ with degree 0.7; then, an $AcidJazz$-lover (an individual with membership degree equal to 1) can be inferred to be interested in $Funk$ to some extent (degree equal to 0.7).

In [4], a fuzzy extension of $\mathcal{SHOIN}$ –the DL underlying OWL– is precisely described. The syntax and the semantics of the constructors and the axioms of this $f\mathcal{SHOIN}$ are extensively discussed along that paper. The most interesting contribution of that work is the definition and the implementation of a transformation process that reduces reasoning with a fuzzy ontology to reasoning with an equivalent crisp ontology. According to this result, it is possible to reuse current inference engines, so no new reasoners need to be developed. This work is completed in [3], where a similar description and reduction for a fuzzy extension of $\mathcal{SROIQ}$ –the DL underlying OWL 1.1, the most likely successor of the current standard– is developed.

As mentioned in Section 2.2, in the crisp case, the new profile classes of the relevance ontology are $\mathcal{ALC}$ concepts, whereas no special restrictions are considered for C_i and D_j –at the most, they are expected to be in $\mathcal{SHOIN}(\mathcal{D})$. Consequently, in this fuzzy extension we will consider $f\mathcal{ALC}$ to define the new fuzzy profiles; additionally, more complex fuzzy DLs for C_i and D_j expressions may be contemplated, for instance these $f\mathcal{SHOIN}$ and $f\mathcal{SROIQ}$. Next, the fuzzy DL $f\mathcal{ALC}$ is reviewed.

Let $\rhd = \{\geq, >\}$, $\lhd = \{\leq, <\}$, and $\alpha \in [0,1]$. A $f\mathcal{ALC}$ TBox consists of *fuzzy GCIs*, which constrain the truth value of a GCI, i.e. they are expressions of the form $\langle C \sqsubseteq_{\rhd\alpha} D\rangle$. A $f\mathcal{ALC}$ RBox is empty. A $f\mathcal{ALC}$ ABox consists of a finite set of *fuzzy assertions*. A fuzzy assertion can be an expression of the form $\langle a : C \rhd \alpha\rangle$, $\langle a : C \lhd \alpha\rangle$ or $\langle (a,b) : R \rhd \alpha\rangle$. Note that negative GCIs or negative role membership axioms are not allowed.

A $f\mathcal{ALC}$ interpretation maps every individual a onto an element $a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$, every concept C onto a function $C^{\mathcal{I}} : \Delta^{\mathcal{I}} \rightarrow [0,1]$, and every role R onto a function $R^{\mathcal{I}} : \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}} \rightarrow [0,1]$. For a t-norm $\otimes$, a t-conorm $\oplus$, a negation function $\ominus$ and an implication function $\Rightarrow$, Table 2 summarizes the syntax and the semantics of the interpretation of concept, roles and axioms. We will use Gödel implication for GCIs: $\alpha \Rightarrow \beta = \{1, \text{ if } \alpha \leq \beta \mid\mid \beta, \text{ if } \alpha > \beta\}$; and Zadeh family of functions for the remaining operators: t-norm $\alpha \otimes \beta = \min\{\alpha, \beta\}$, t-conorm $\alpha \oplus \beta = \max\{\alpha, \beta\}$, Łukasiewicz negation $\ominus\alpha = 1 - \alpha$.

Table 2. Syntax and semantics of complex concepts and roles in $f\mathcal{ALC}$.

Constructor	**Syntax**	**Semantics**
(top concept)	$\top$	1
(bottom concept)	$\perp$	0
(atomic concept)	C_A	$C_A^{\mathcal{I}}(x)$
(concept conjunction)	$C \sqcap D$	$C^{\mathcal{I}}(x) \otimes D^{\mathcal{I}}(x)$
(concept disjunction)	$C \sqcup D$	$C^{\mathcal{I}}(x) \oplus D^{\mathcal{I}}(x)$
(concept negation)	$\neg C$	$\ominus C^{\mathcal{I}}(x)$
(universal quantification)	$\forall R.C$	$\inf_{y \in \Delta^{\mathcal{I}}}\{R^{\mathcal{I}}(x,y) \Rightarrow C^{\mathcal{I}}(y)\}$
(existential quantification)	$\exists R.C$	$\sup_{y \in \Delta^{\mathcal{I}}}\{R^{\mathcal{I}}(x,y) \otimes C^{\mathcal{I}}(y)\}$
(atomic role)	R_A	$R_A^{\mathcal{I}}(x,y)$

A fuzzy interpretation $\mathcal{I}$ satisfies (is a model of):

- $\langle a : C \triangleright \alpha \rangle$ iff $C^{\mathcal{I}}(a^{\mathcal{I}}) \triangleright \alpha$,
- $\langle a : C \triangleleft \alpha \rangle$ iff $C^{\mathcal{I}}(a^{\mathcal{I}}) \triangleleft \alpha$,
- $\langle (a,b) : R \triangleright \alpha \rangle$ iff $R^{\mathcal{I}}(a^{\mathcal{I}}, b^{\mathcal{I}}) \triangleright \alpha$,
- $\langle C \sqsubseteq_{\triangleright \alpha} D \rangle$ iff $\inf_{x \in \Delta^{\mathcal{I}}}\{C^{\mathcal{I}}(x) \Rightarrow D^{\mathcal{I}}(x)\} \triangleright \alpha$,
- a fKB $f\mathcal{K} = \langle \mathcal{T}, \mathcal{R}, \mathcal{A} \rangle$ iff it satisfies each element in $\mathcal{T}$, $\mathcal{R}$ and $\mathcal{A}$.

We assume that there are not fuzzy axioms of the form $\tau \geq 0$, $\tau \leq 1$ (which are tautologies), $\tau > 1$ and $\tau < 0$ (which are obvious inconsistencies).

An axiom τ is a *logical consequence* of a knowledge base $\mathcal{K}$, denoted $\mathcal{K} \models \tau$ iff every model of $\mathcal{K}$ satisfies τ. The greatest lower bound (glb) of a fuzzy axiom τ is defined as the $\sup\{\alpha : \mathcal{K} \models \langle \tau \geq \alpha \rangle\}$.

3.2 Formulation of the fuzzy design pattern fCDR

The fuzzy CDR ontology extends the original proposal by letting contexts, domains and profiles to be defined using fuzzy GCIs. Thus, complex context and domain concepts can be stated to be partially similar using fuzzy GCIs, whereas the degree of subsumption in a profile definition represents the importance value of the connection between the involved context and domain.

Definition 3. *Let $\mathcal{K}^D$ and $\mathcal{K}^C$ be, respectively, the domain and the context subontologies, C_i a complex context such as $\mathrm{S}(C_i) \subseteq \mathrm{S}(\mathcal{K}^C)$ and D_j a complex domain such as $S(D_j) \subseteq S(\mathcal{K}^D)$. The fuzzy relevance ontology which relates the set of pairs $\{(C_i,\ D_j)\}$ with degree $\alpha_{i,j}$ (i.e. states that D_j is interesting with rank $\alpha_{i,j}$ when C_i happens) is a consistent fuzzy ontology $f\mathcal{K}^R = \langle \mathcal{T}^R, \mathcal{R}^R, \mathcal{A}^R \rangle$ where $\mathcal{T}^R$ includes (non-exclusively) definitions for the fuzzy concepts $P_\top, C_\top, D_\top, C_i, D_j, P_{i,j}$, and satisfies:*

1. *$P_\top, C_\top, D_\top$ are the superclasses Profile, Context and Domain:*
   - $P_{i,j} \sqsubseteq_{\geq 1} P_\top,\ C_i \sqsubseteq_{\geq 1} C_\top,\ D_j \sqsubseteq_{\geq 1} D_\top$
2. *R_1 is the (fuzzy) bridge property linking profiles and complex contexts:*
   - $P_\top \sqsubseteq_{\geq 1} \forall R_1.C_\top$
3. *R_2 is the (fuzzy) bridge property linking profiles and complex domains:*
   - $P_\top \sqsubseteq_{\geq 1} \forall R_2.D_\top$
4. *$P_{i,j}$ is the (fuzzy) profile which links the named context C_i and the named context D_j:*
   - $P_{i,j} \sqsubseteq_{\geq \alpha_{i,j}} \exists R_1.C_i \sqcap \exists R_2.D_j$

It is interesting to note that the context ontology $\mathcal{K}^C$ and the domain ontology $\mathcal{K}^D$ may be fuzzy or not. However, both C_i and D_j are fuzzy concepts defined with fuzzy GCIs. The example in Section 3.3 shows a fuzzy relevance ontology built upon two crisp ontologies $\mathcal{K}^C$ and $\mathcal{K}^D$.

By extension of the crisp case, the domain restricted by a context w.r.t. a fuzzy relevance ontology contains all the (fuzzy or crisp) concepts of the domain sub-ontology which are relevant in a given (fuzzy) context and the degree of interest. It is formally defined as a set of pairs (domain concept, degree), where "domain concepts" are the domains relevant to the context of the query (i.e. related through profiles) and "degree" is a number computed on $\alpha_{i,j}$ values.

Definition 4. *Given the ontologies $f\mathcal{K}^R$, $\mathcal{K}^D$ y $\mathcal{K}^C$ (with their respective signatures $\mathrm{S}\left(f\mathcal{K}^R\right), \mathrm{S}\left(\mathcal{K}^D\right), \mathrm{S}\left(\mathcal{K}^C\right)$) and a complex context E (($\mathrm{S}(E) \subseteq \mathrm{S}\left(\mathcal{K}^C\right)$), the ranked restricted domain of the scenario E w.r.t. $f\mathcal{K}^R$, noted as $\mathcal{D}\left(E, f\mathcal{K}^R\right)$, consists of the pairs $(I, \alpha_{i,j})$ such as:*

- $I \in \mathsf{Con}(\mathcal{K}^D) \wedge (E \sqsubseteq_{>0} C_n) \wedge (P_{n,m} \sqsubseteq_{>0} \exists R_1.C_n \sqcap \exists R_2.D_m) \wedge (I \sqsubseteq_{>0} D_m)$
- $\alpha_{i,j} = \mathsf{glb}(E \sqsubseteq C_n) \otimes \mathsf{glb}(P_{n,m} \sqsubseteq \exists R_1.C_n \sqcap \exists R_2.D_m) \otimes \mathsf{glb}(I \sqsubseteq D_m)$

The algorithm to calculate the ranked restricted domain of a scenario is a fuzzy extension of Algorithm 1.

Algorithm 2. *$\mathcal{D}\left(E, f\mathcal{K}^R\right)$ can be computed in practice as follows:*

1. *Get the complex contexts subsuming the query context (and their degree):* $Z_1 = \{(C_n, \beta_n) \mid\ (E \sqsubseteq_{>0} C_n) \wedge (\beta_n = \mathsf{glb}(E \sqsubseteq C_n))\}$
2. *Get the profiles which involve the retrieved contexts (and their degree):* $Z_2 = \{(C_k, P_{k,l}, \beta_k) \mid\ (P_{k,l} \sqsubseteq_{>0} \exists R_1.C_k) \wedge (\beta_k = \mathsf{glb}(P_{k,l} \sqsubseteq \exists R_1.C_k)) \wedge (C_k \equiv C_n^{[Z_1]})\}$

3. *Get the complex domains involved by the retrieved profiles (and their degree):*
   $Z_3 = \{(P_{k,l}, D_l, \beta_l) \mid (P_{k,l}^{[Z_2]} \sqsubseteq_{>0} \exists R_2.D_l) \wedge (\beta_l = \mathsf{glb}(P_{k,l} \sqsubseteq \exists R_2.D_l))\}$
4. *Combine the partial degrees of the retrieved profiles using a $\otimes$:*
   $Z_4 = \{(C_k, D_l, \beta_{k,l}) \mid ((C_k, P_{k,l}, \beta_k) \in Z_2) \wedge ((P_{k,l}, D_l, \beta_l) \in Z_3) \wedge (\beta_{k,l} = \beta_k \otimes \beta_l)\}$
5. *Aggregate all the degrees which a domain has been retrieved with using a $\oplus$:*
   $Z_5 = \{(D_m, \beta_m) \mid (\beta_m = \bigoplus_{(C_k,D_m,\beta_{k,l}) \in Z_4} (\beta_{k,l} \otimes \beta_n))\}$
6. *Get the $I \in \mathsf{Con}(\mathcal{K}^D)$ more specific than the retrieved complex domains (and their degree):*
   $\mathcal{D}(E, f\mathcal{K}^R) = \{(I, \alpha_{i,j}) \mid (I \sqsubseteq D_m) \wedge (\alpha_{i,j} = \beta_m \otimes \mathsf{glb}(I \sqsubseteq D_m^{[Z_5]}))\}$

   (for simplicity, we assume that $C_n, C_k \sqsubseteq C_\top, P_{k,l} \sqsubseteq P_\top, D_m, D_l \sqsubseteq D_\top$)

The output of the algorithm is a set of pairs containing all the $I \sqsubseteq D_m$ and their degree of importance. A concept I can be retrieved with more than a degree through different profiles, so these values should be conveniently aggregated, using a t-conorm $\oplus$, in order to provide the user with an only final relevance value. Therefore, the final output of the algorithm to the user will be a set of pairs (simple domain concept, degree) which are the concepts of the domain relevant to the context of the query.

Proposition 3. *Algorithm 2 is complete, i.e. it finds all the concepts I related with E through profiles and the degree of this connection.*

Proof. From the expressions of Algorithm 2, it can be realized that the retrieved $P_{k,l}, C_n, D_m$ are the same as in the crisp case. The only difference with the previous algorithm is the computation of β values.

Therefore, based on proof of Algorithm 1 and Definition 4, we have just to prove that $\beta_{k,l} = \beta_k \otimes \beta_l$ is equal to $\mathsf{glb}(P_{k,l} \sqsubseteq \exists R_1.C_k \sqcap \exists R_2.D_l)$, the degree of the relevance relation between C_k (a superclass of E) and D_l (a superclass of I).

Using the properties of fuzzy sets, we know that $(A \Rightarrow B \otimes C) \geq \alpha$ implies $(A \Rightarrow B) \geq \alpha$ and $(A \Rightarrow C) \geq \alpha$, for some t-norm and its residuum-based implication (for example, for *min* t-norm and Gödel implication). Applying this expression to our GCI, $P_{k,l} \sqsubseteq_{\geq \beta_{k,l}} \exists R_1.C_k \sqcap \exists R_2.D_l \Rightarrow P_{k,l} \sqsubseteq_{\geq \gamma_1} \exists R_1.C_k (\gamma_1 \geq \beta_{k,l})$ and $P_{k,l} \sqsubseteq_{\geq \gamma_2} \exists R_2.D_l (\gamma_2 \geq \beta_{k,l})$. From Algorithm 2, we have the glb*s* β_k and β_l. Since they are the greatest lower bounds, $\beta_k \geq \gamma_1 \geq \beta_{k,l}$ and $\beta_l \geq \gamma_2 \geq \beta_{k,l}$. Consequently, $\beta_k \geq \beta_{k,l} \Rightarrow \beta_{k,l} \leq \beta_k \otimes \beta'$, for any β', and $\beta_l \geq \beta_{k,l} \Rightarrow \alpha_{k,l} \leq \beta_l \otimes \beta''$, for any β''. On the other hand, for *min* t-norm and Gödel implication, $(A \Rightarrow B) \geq \alpha_1$ and $(A \Rightarrow C) \geq \alpha_2$ imply $(A \Rightarrow B \otimes C) \geq \alpha_1 \otimes \alpha_2$. Applying this expression to the GCIs of Algorithm 2, $P_{k,l} \sqsubseteq_{\geq \beta_k} \exists R_1.C_k$ and $P_{k,l} \sqsubseteq_{\geq \beta_l} \exists R_2.D_l$, we have $P_{k,l} \sqsubseteq_{\geq \beta_k \otimes \beta_l} \exists R_1.C_k \sqcap \exists R_2.D_l$. By definition, $\beta_{k,l} \geq \beta_k \otimes \beta_l$.

Consequently, $\beta_{k,l} \leq \beta_k \otimes \beta_l$ and $\beta_{k,l} \geq \beta_k \otimes \beta_l$, so necessarily $\beta_{k,l} = \beta_k \otimes \beta_l$. □

An upper bound for the computational complexity of the reasoning procedure can be deduced from the works [3, 4], where fuzzy ontologies in $f\mathcal{SHOIN}$

and $f\mathcal{SROIQ}$ have been proved to be reducible to crisp ontologies. These contributions show that the complexity of this reduction for a $f\mathcal{SROIQ}$ ontology with Zadeh operators and Gödel implication for GCIs –the top complexity level considered in this work– is, in general, quadratic (in space) with regard to the number of degrees used in the ontology, and that it can be reduced to lineal if a fixed number of degrees is assumed. Therefore, the complexity of subsumption tests with a fuzzy significance ontology is asymptotically bounded by the complexity of this reduction plus the complexity of the reasoning in the crisp ontology. Under certain conditions (new axioms do not introduce new atomic concepts, new atomic roles, or new degrees of truth), this reduction can be performed only once, so this overhead can be avoided.

Besides subsumption tests, Algorithm 2 also calculates a considerable number of glbs (exactly, one for each retrieved concept in Steps 1-4), needing each of them at most $log(N)$ (being N the number of degrees) additional subsumption tests [9]. In the simplest case, that is, with a $f\mathcal{ALC}$ relevance ontology (consequently, the context and domain submodels are $f\mathcal{ALC}$ ontologies too), a fixed number of fuzzy degrees, and no reduction of the fuzzy ontology is needed, the overall complexity of each step is upper-bounded by $|\mathsf{Con}(f\mathcal{K}^S)| \times log(N)$ times the subsumption test complexity (ExpTime).

3.3 Example

Currently, we are using the CDR design pattern to build a relevance ontology for a medical application [10]. More precisely, we are developing a knowledge base stating which registers from a Hospital Information System (HIS) ought to be checked by a doctor attending to a patient. We are proving the benefits of the crisp and the fuzzy CDR patterns, which fit perfectly to this situation.

In this application, we have clearly separated the context and the domain ontologies, being both of them crisp. The context ontology is a vocabulary to describe clinical situations of the patients. There exist several medical ontologies which can be reused for this purpose; our context ontology is strongly based on the OWL translation of the Galen ontology[1], a well-known and sound terminology intended to be used in the implementation of clinical decision support systems [11]. C_i are fuzzy descriptions of patient states defined with the Galen vocabulary. The domain ontology, in turn, abstracts patients' information stored in the HIS, i.e. electronic registers with previously diagnosed diseases and treatments. This ontology has been developed manually from the specifications of ARCHiiMED [12], the HIS of the University Hospital "San Cecilio" in Granada. D_i are fuzzy descriptions of the information items represented in the HIS, though in this case they have crisp semantics.

The (fuzzy) profiles in the relevance ontology connects (vague) descriptions of patient clinical states and (concrete) descriptions of datasets of the HIS, asserting which registers should we be checked in each situation. The degree of importance of each of these associations is represented by using fuzzy GCIs.

[1] `http://www.co-ode.org/galen/full-galen.owl`

The following fuzzy relevance ontology $f\mathcal{K}^R$ is an excerpt of our test knowledge base. This is indeed an $f\mathcal{SROIQ}$ ontology, so it includes some additional constructors to the $f\mathcal{ALC}$ described in this paper –e.g., number restrictions, used in this example. This fuzzy DL is more extensively studied in [3].

Axioms which extend Galen ontology
$\langle Anaphylaxis \sqsubseteq_{\geq 0.7} Shock\rangle$ $\quad$ $\langle SepticShock \sqsubseteq_{\geq 0.5} Anaphylaxis\rangle$
$\langle Shock \sqcap \geq 1 hasComplication \sqsubseteq_{\geq 0.8} EpinephrineAdministration\rangle$

Definition of complex contexts
$\langle C_1 \sqsubseteq_{\geq 1} \exists hasComplication.Elderly\rangle$ $\quad$ $\langle C_2 \sqsubseteq_{\geq 1} Anaphylaxis\rangle$
$\langle C_3 \sqsubseteq_{\geq 1} EpinephrineAdministration\rangle$

Definition of complex domains
$\langle D_1 \sqsubseteq_{\geq 1} EHRCurrentPrescription\rangle$
$\langle D_2 \sqsubseteq_{\geq 1} EHRCurrentPrescription \sqcup EHRDrugIntollerance\rangle$
$\langle D_3 \sqsubseteq_{\geq 1} EHRAntidepressives\rangle$ $\quad$ $\langle D_3 \sqsubseteq_{\geq 1} D_1\rangle$

Definition of relations (for convenience)
$\langle R_1 \equiv relSymptom\rangle$ $\quad$ $\langle R_2 \equiv relRegister\rangle$

Definition of profiles
$\langle P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_1.C_1 \sqcap \exists R_2.D_1\rangle$ $\quad$ $\langle P_{2,2} \sqsubseteq_{\geq 0.5} \exists R_1.C_2 \sqcap \exists R_2.D_2\rangle$
$\langle P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_1.C_3 \sqcap \exists R_2.D_3\rangle$

Mandatory axioms
$\langle C_1 \sqsubseteq_{\geq 1} C_\top\rangle$, $\langle C_2 \sqsubseteq_{\geq 1} C_\top\rangle$, $\langle D_1 \sqsubseteq_{\geq 1} D_\top\rangle$, $\langle D_2 \sqsubseteq_{\geq 1} C_\top\rangle$, $\langle P_{1,1} \sqsubseteq_{\geq 1} P_\top\rangle$, $\langle P_{2,2} \sqsubseteq_{\geq 1} P_\top\rangle$, $\langle P_\top \sqsubseteq_{\geq 1} \forall R_1.C_\top\rangle$, $\langle P_\top \sqsubseteq_{\geq 1} \forall R_2.D_\top\rangle$

Let us suppose the query context $Anaphylaxis \sqcap \exists hasComplication.Elderly$. Using Algorithm 2, we can retrieve the domains asserted to be interesting in this context, that is, $\mathcal{D}\left(Anaphylaxis \sqcap \exists hasComplication.Elderly, f\mathcal{K}^R\right)$.

– ***Step 1***
$Anaphylaxis \sqcap \exists hasComplication.Elderly \sqsubseteq_{\geq 1} Anaphylaxis \sqsubseteq_{\geq 0.7} Shock$,
$Anaphylaxis \sqcap \exists hasComplication.Elderly \sqsubseteq_{\geq 1} \geq 1 hasComplication$
$\Rightarrow Anaphylaxis \sqcap \exists hasComplication.Elderly \sqsubseteq_{\geq 0.7} Shock \sqcap \geq 1 hasComplication$
$Anaphylaxis \sqcap \exists hasComplication.Elderly \sqsubseteq_{\geq 0.7} Shock \sqcap \geq 1 hasComplication$,
$Shock \sqcap \geq 1 hasComplication \sqsubseteq_{\geq 0.8} EpinephrineAdministration$
$\Rightarrow Anaphylaxis \sqcap \exists hasComplication.Elderly \sqsubseteq_{\geq 0.7} EpinephrineAdministration$
$Z_1 = \{(C_1, 1), (C_2, 1), (C_3, 0.7)\}$

– ***Step 2***
$P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_1.C_1 \sqcap \exists R_2.D_1 \Rightarrow P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_1.C_1$
$P_{2,2} \sqsubseteq_{\geq 0.5} \exists R_1.C_2 \sqcap \exists R_2.D_2 \Rightarrow P_{2,2} \sqsubseteq_{\geq 0.5} \exists R_1.C_2$
$P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_1.C_3 \sqcap \exists R_2.D_3 \Rightarrow P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_1.C_3$
$Z_2 = \{(C_1, P_{1,1}, 0.6), (C_2, P_{2,2}, 0.5), (C_3, P_{3,3}, 0.9)\}$

– ***Step 3***
$P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_1.C_1 \sqcap \exists R_2.D_1 \Rightarrow P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_2.D_1$
$P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_2.D_1 \sqsubseteq_{\geq 1} \exists R_2.D_2 \Rightarrow P_{1,1} \sqsubseteq_{\geq 0.6} \exists R_2.D_2$

$P_{2,2} \sqsubseteq_{\geq 0.5} \exists R_1.C_2 \sqcap \exists R_2.D_2 \Rightarrow P_{2,2} \sqsubseteq_{\geq 0.5} \exists R_2.D_2$
$P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_1.C_3 \sqcap \exists R_2.D_3 \Rightarrow P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_2.D_3$
$P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_2.D_3 \sqsubseteq_{\geq 1} \exists R_2.D_1 \Rightarrow P_{1,1} \sqsubseteq_{\geq 0.9} \exists R_2.D_1$
$P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_2.D_1 \sqsubseteq_{\geq 1} \exists R_2.D_2 \Rightarrow P_{3,3} \sqsubseteq_{\geq 0.9} \exists R_2.D_2$
$Z_3 = \{(P_{1,1}, D_1, 0.6), (P_{1,1}, D_2, 0.6), (P_{2,2}, D_2, 0.5), (P_{3,3}, D_3, 0.9),$
$(P_{3,3}, D_1, 0.9), (P_{3,3}, D_2, 0.9)\}$

- ***Step 4***
  $Z_4 = \{(C_1, D_1, min(0.6, 0.6) = 0.6), (C_1, D_2, min(0.6, 0.6) = 0.6),$
  $(C_2, D_2, min(0.5, 0.5) = 0.5), (C_3, D_1, min(0.9, 0.9) = 0.9),$
  $(C_3, D_2, min(0.9,\ 0.9) = 0.9), (C_3, D_3, min(0.9, 0.9) = 0.9)\}$

- ***Step 5***
  $Z_5 = \{(D_1, max(min(0.6, 1), min(0.9, 0.7)) = 0.7),$
  $(D_2, max(min(0.6, 1), min(0.5, 1), min(0.9, 0.7)) = 0.7), (D_3, min(0.9, 0.7) = 0.7)\}$

- ***Step 6***
  $\mathcal{D}\left(E, f\mathcal{K}^R\right) = \{\ (EHRCurrentPrescription, min(0.7, 1) = 0.7),$
  $(EHRCurrentPrescription, min(0.7, 1) = 0.7),$
  $(EHRAntidepressives, min(0.7, 1) = 0.7),$
  $(EHRDrugIntolerance, min(0.7, 1) = 0.7),$
  $(EHRAntidepressives, min(0.7, 1) = 0.7),$
  $(EHRAntidepressives, min(0.7, 1) = 0.7)\}$

If the outputs of the algorithm are aggregated, the final results provided to the user are $(EHRCurrentPrescription, max(0.7, 0.7) = 0.7)$, $(EHRDrugIntollerance, 0.7)$, $(EHRAntidepressives, max(0.7, 0.7, 0.7) = 0.7)$.

These results mean that the system alerts the doctor to check the patient information about current prescriptions, especially those concerning antidepressive drugs, and past diagnoses about drug intolerance; all the recommendations are equally important with degree 0.7. Moreover, these data could be retrieved automatically from the hospital database, once the patient is identified, and the doctor would know directly this information.

4 Related work

Ontology design patterns are concise guidelines which identify common knowledge representation issues and propose advices to solve them. The work [13] provide a good introduction to the use of design patterns during ontology lifecycle. More recently, other approaches have developed techniques for automatic selection of suitable design patterns [14].

Regarding to representation of relevance, a review of different perspectives about implementation of context-sensitivity is presented in [15]. This work cites the so called context-based selection functions, which are quite similar to our contribution in [2]: these functions retrieve the submodel $K' \subset K$ which is worth considering when performing some task or acting in some environment. The

NeOn project[2] is an on-going initiative which offers a similar solution capable of handling degrees of uncertainty [16]. Nevertheless, to the best of our knowledge, our work is the first attempt to represent and reason with context data and context-dependant information using fuzzy DLs.

More general is the idea of contextualization of ontologies, which concerns models which are satisfiable or not (instead of relevant) depending on some circumstances. C-OWL is an extension to OWL to define mappings between locally-interpreted and globally-valid ontologies [17]. Multi-viewpoint reasoning, in turn, concentrates on the conditional interpretation of a model, i.e. how to reduce an ontology depending on the viewpoint submodel [18].

Several fuzzy DLs can be found in the literature (some examples are enumerated in [19]), including an fuzzy extension of OWL [20]. Fuzzy ontologies are not part of the W3C standards, so new tools would be necessary to be developed. As mentioned, thanks to the results [3, 4], a fuzzy ontology (a fuzzy relevance ontology, in our case) can be reduced to an equivalent crisp one (in OWL or OWL 1.1) and reason with it using existing inference engines (e.g. Pellet).

5 Conclusions and future work

In this work, we have reviewed the formulation of the CDR design pattern, which defines a schema to represent relevance in OWL ontologies and a reasoning algorithm to retrieve the domain information relevant to a concept. As a novelty, this algorithm has been proved formally to be complete.

Based on this approach, this paper concentrates on an extension of the design pattern which allows imprecise context and specific-domain knowledge to be managed –fuzzy concepts, relations and axioms may be used in context and domain expressions–, as well as connections between contexts and domains to have a ranking degree. This extension relies on fuzzy DLs, a formalism that provides a complete and sound framework to manage imprecise and vague knowledge in ontologies. Previous contributions describing procedures to reduce reasoning with fuzzy representations to reasoning with crisp ontologies are remarked in the paper, since they avoid to implement new inference engines.

Pattern use is depicted with an example in the healthcare domain, which corresponds to a real application being developed currently in a research project at the University of Granada. Therefore, the main direction for future work is to test the utility of the pattern in this real application in order to show its feasibility and to improve it, taking into account that the complexity of the reasoning algorithm is quite high. Using the pattern in other domains and comparing it with existing similar approaches will be studied as well. Development of supporting tools is also a remarkable effort which will be faced. In this sense, a tight integration with current and future versions of DeLorean [3] –our shell to reason with fuzzy ontologies– will be very useful, because this would prevent users from having to deal with some concrete details of the fuzzy representation.

[2] `http://www.neon-project.org/`

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