Semantic-Based Resource Retrieval using Non-Standard Inference Services in Description Logics

Simona Colucci[1][3], Stefano Coppi[1], Tommaso Di Noia[1], Eugenio Di Sciascio[1], Francesco M. Donini[2], Agnese Pinto[1] and Azzurra Ragone[1]

[1] Politecnico di Bari, Via Re David, 200, I-70125, Bari, Italy
{s.colucci,s.coppi,t.dinoia,disciascio,a.pinto,a.ragone}@poliba.it
[2] Università della Tuscia, via San Carlo, 32, I-01100, Viterbo, Italy
donini@unitus.it
[3] Knowledge Media Institute, The Open University, MK7 6AA, United Kingdom

Abstract. Retrieval of resources semantically annotated is a problem that is gaining interest as more and more documents and services expose descriptions based on languages developed in the framework of Semantic Web. In a semantic-enabled resource retrieval process, given a request, a ranking of compatible resources should be provided. Obviously having semantically annotated resources, the ranking sholud be based on some semantic-based parameters. Furthermore, the availability of such descriptions makes explanation of rank possible and can provide useful information in order to modify or refine the original request in a principled way. In this work we briefly present results obtained and ongoing activity on these challenging topics.

1 Introduction

Semantic-Based Resource retrieval addresses the problem of finding best matches to a request among available resources, where both the request and the resources are described adopting a shared interpretation of the knowledge domain the resource belongs to. The problem of semantic-based resource retrieval arises in several scenarios. Among them, personnel recruitment and job assignment, dating agencies, but also generic electronic marketplaces, web-services discovery and composition, resource matching in the Grid. All these scenarios share a common purpose: given a request, find among available descriptions those best fulfilling it, or "at worse", when nothing better exists, those that fulfill at least some of the requirements. Exact, or full, matches are usually rare –and may be that is not a user really wants– and the true matchmaking process is aimed at providing one or more best available matches to be explored, thus leveraging further interaction. In this perspective also missing and conflicting information can be taken into account. This can be aimed at better specifying the request, or modifying it, but also *e.g.*, in an e-marketplace at initiating a negotiation/transaction process. We stress this point, as we believe that, as in textual information retrieval and in contrast with classic structured-data retrieval, the notion of relevance is central and must be taken into proper account. Obviously, the notion of resources relevance w.r.t. a request calls for the definition of a ranking function, defining a partial or total order of resources sorted w.r.t. the request, but also determine in a semantic-based way, which are the

missing and/or conflicting information, in order to provide an explanation of results. In recent years Description Logics (DLs) [2] have been investigated by both the academic and industrial world as a formalism for Knowledge Representation. Modeling the information domain trough the formalism of a DL allows one to employ reasoning services provided by DLs to perform a knowledge-based search. Knowledge domain is formalized in ontologies, which resource descriptions refer to. The use of ontologies allows us to store elicited descriptions, so that we can infer information from them while retrieving a resource. The need for a common, shared, ontology is usually the main objection towards logic-based approaches to matchmaking. Nevertheless, it should be considered that even when requests and resources are expressed in heterogeneous forms, integration techniques [6] can be employed to make heterogeneous descriptions comparable.

2 The need for a logic-based approach

We start with a description of approaches to resource retrieval, highlighting limitations of non-logical approaches, then discussing the general Knowledge Representation principles that a logical approach may yield. We refer the reader to [15] for examples and wider argumentation. First of all, we note that using standard relational database techniques to model a resource retrieval framework, there is a need to completely align the attributes of the offered and requested resources descriptions, in order to evaluate a match. If requests and offers are simple names or strings, the only possible match would be identity, resulting in an all-or-nothing approach to the retrieval process. Vague query answering, proposed by [26], was an initial effort to overcome limitations of relational databases, with the aid of weights attributed to several search variables. Vector-based techniques taken by classical Information Retrieval can be used, too, thus reverting the search for a matching request to similarity between weighted vectors of stemmed terms, as proposed in the COINS matchmaker [24] or in LARKS [29]. Such a formalization for resource descriptions makes matches only probabilistic, because descriptions lack of a document structure, causing strange situations to ensue. A further approach structures resource descriptions as set of words. This formalization allows one to evaluate not only identity between sets, but also some interesting set-based relations between descriptions, such as inclusion, partial overlap, cardinality of set difference. Modeling resource descriptions as set of words is anyway too much sensible to the choice of words employed to be successfully used: the fixed terminology misses meaning that relate words. Such a problem can be overcome by giving terms a logical and shared meaning through an ontology [17]. Nevertheless set-based approach have some properties we believe are fundamental in a resource matching and retrieval process. If we are searching for a resource described through a set of words, we are also interested in sets including the one we search, because they completely fulfill the resource to retrieve. Moreover even if there are characteristics of the retrieved resource not elicited in the description of the searched resource, an exact match is still possible because absent information have not to be considered negative. The two statements above may be summarized in the following property:

Property 1. **Open-world descriptions**. The absence of a characteristic in the description of a resource to be retrieved should not be interpreted as a constraint of absence.

Instead it should be considered as a characteristic that could be either refined later or left open if it is irrelevant for the user searching for the resource.

The set-based match evaluation is non-symmetric: if we search for a resource A, whose describing set of words is included in a set characterizing resource B, we may consider B a resource perfectly satisfying the request for A. On the other hand if we use the description of B for the search, A may also satisfy the request only partially, as some of the terms describing B may be not included in the A set. We formalize this behaviour as follows:

Property 2. **Non-symmetric evaluation**. Given two resources $\mathcal{O}$ (for Offer) and $\mathcal{R}$ (for Request), a matchmaking system may give different evaluations depending on whether it is trying to match $\mathcal{O}$ with $\mathcal{R}$, or $\mathcal{R}$ with $\mathcal{O}$ — *i.e.*, depending on who is going to use this evaluation.

From now on we assume that resource descriptions, requested and offered, are expressed in a DL, equipped with a model-theoretic semantics. This approach includes the sets-of-keywords one, since a set of keywords can be considered also as a conjunction of concept names. We also assume that a common ontology is established, as a TBox $\mathcal{T}$ in DL.

3   Semantic-based Resource Retrieval

DL-based systems usually provide two basic reasoning services for $\mathcal{T}$, namely satisfiability and subsumption. They can be defined, informally, as follows:

Concept Satisfiability: Given an ontology $\mathcal{T}$ modeling the domain we are investigating on, and a description $\mathcal{R}$ of a resource referring to the ontology: is the information modeled in the description consistent with the one in the ontology?

Subsumption: Given an ontology $\mathcal{T}$ modeling the domain we are investigating on, and two resources described by expressions –$\mathcal{R}$, $\mathcal{O}$– referring to the information modeled in the ontology: is the information about a resource more general than the one related to the other one?

Both Subsumption and Concept Satisfiability are adequate in all those scenarios where a yes/no answer is enough. For example, given a resource and a request represented respectively by a concept $\mathcal{O}$ and a concept $\mathcal{R}$, using Concept Satisfiability we are able to determine whether they are compatible, *i.e.*, $\mathcal{O}$ models information which is not in conflict with the one modeled by $\mathcal{R}$. This task can be performed checking the satisfiability of the concept $\mathcal{O} \sqcap \mathcal{R}$ with respect to a reference ontology $\mathcal{T}$.

On the other hand Subsumption can be used to verify, for example, if a resource described by $\mathcal{O}$ satisfies a request $\mathcal{R}$. It is easy understandable that if the relation $\mathcal{O} \sqsubseteq \mathcal{R}$ holds, then $\mathcal{O}$ is more specific than $\mathcal{R}$ and contains at least all the requested features.

In [7, 13] Concept Contraction and Concept Abduction , new non-standard inference services for DLs, were introduced and defined. In this subsection we briefly recall their definitions, explaining their rationale and the need for them in resource retrieval.

Concept Contraction Starting with the concepts $\mathcal{O}$ and $\mathcal{R}$, if their conjunction $\mathcal{O} \sqcap \mathcal{R}$ is unsatisfiable in the TBox $\mathcal{T}$ representing the ontology, *i.e.*, they are not compatible with each other, our aim is to retract requirements in $\mathcal{R}$, G (for *Give up*), to obtain a concept K (for *Keep*) such that $K \sqcap \mathcal{O}$ is satisfiable in $\mathcal{T}$.

Definition 1. *Let $\mathcal{L}$ be a DL, $\mathcal{O}$, $\mathcal{R}$, be two concepts in $\mathcal{L}$, and $\mathcal{T}$ be a set of axioms in $\mathcal{L}$, where both $\mathcal{O}$ and $\mathcal{R}$ are satisfiable in $\mathcal{T}$. A* Concept Contraction Problem *(CCP), identified by $\langle \mathcal{L}, \mathcal{R}, \mathcal{O}, \mathcal{T} \rangle$, is finding a pair of concepts $\langle G, K \rangle \in \mathcal{L} \times \mathcal{L}$ such that $\mathcal{T} \models \mathcal{R} \equiv G \sqcap K$, and $\mathcal{T} \models K \sqcap \mathcal{O} \not\equiv \bot$. We call K a* contraction *of $\mathcal{R}$ according to $\mathcal{O}$ and $\mathcal{T}$.*

We note that there is always the trivial solution $\langle G, K \rangle = \langle \mathcal{R}, \top \rangle$ to a CCP. This solution corresponds to the most drastic contraction, that gives up everything of $\mathcal{R}$. In our resource retrieval framework, it models the (infrequent) situation in which, in front of some very appealing resource $\mathcal{O}$, incompatible with the requested one, a user just gives up completely his/her specifications $\mathcal{R}$ in order to meet $\mathcal{O}$. On the other hand, when $\mathcal{O} \sqcap \mathcal{R}$ is satisfiable in $\mathcal{T}$, the "best" possible solution is $\langle \top, \mathcal{R} \rangle$, that is, give up nothing – if possible. Hence, a Concept Contraction problem is an extension of a satisfiable one. Since usually one wants to give up as few things as possible, some minimality in the contraction must be defined [19]. In most cases a pure logic-base approach could be not sufficient to decide between which beliefs to give up and which to keep. There is the need of modeling and defining some extra-logical information to be taken into account. One approach is to give up minimal information [7]. Another one considers some information more important than other and the information that should be retracted is the least important one, that is negotiable and strict constraints are introduced [12].

Concept Abduction If the offered resource $\mathcal{O}$ and the requested one $\mathcal{R}$ are compatible with each other, the partial specifications problem still holds, that is, it could be the case that $\mathcal{O}$ – though compatible – does not imply $\mathcal{R}$. Using DL syntax we write: $\mathcal{R} \sqcap \mathcal{O} \not\equiv \bot$ and $\mathcal{O} \not\sqsubseteq \mathcal{R}$. Then, it is necessary to assess what should be hypothesized (H) in $\mathcal{O}$ in order to completely satisfy $\mathcal{R}$.

Definition 2. *Let $\mathcal{L}$ be a DL, $\mathcal{O}$, $\mathcal{R}$, be two concepts in $\mathcal{L}$, and $\mathcal{T}$ be a set of axioms in $\mathcal{L}$, where both $\mathcal{O}$ and $\mathcal{R}$ are satisfiable in $\mathcal{T}$. A* Concept Abduction Problem *(CAP), identified by $\langle \mathcal{L}, \mathcal{R}, \mathcal{O}, \mathcal{T} \rangle$, is finding a concept $H \in \mathcal{L}$ such that $\mathcal{T} \models \mathcal{O} \sqcap H \sqsubseteq \mathcal{R}$, and moreover $\mathcal{O} \sqcap H$ is satisfiable in $\mathcal{T}$. We call H a* hypothesis *about $\mathcal{O}$ according to $\mathcal{R}$ and $\mathcal{T}$.*

Observe that in the definition, we limit to satisfiable $\mathcal{O}$ and $\mathcal{R}$, since $\mathcal{R}$ unsatisfiable implies that the CAP has no solution at all, while $\mathcal{O}$ unsatisfiable leads to counterintuitive results ($\neg \mathcal{R}$ would be a solution in that case). If $\mathcal{O} \sqsubseteq \mathcal{R}$ then we have $H = \top$ as a solution to the related CAP. Hence, Concept Abduction extends subsumption. On the other hand, if $\mathcal{O} \equiv \top$ then $H \sqsubseteq \mathcal{R}$.

Notice that both Concept Abduction and Concept Contraction can be used for respectively subsumption and satisfiability explanation. For Concept Contraction , having two concepts not compatible with each other, in the solution $\langle G, K \rangle$ to the CCP

$\langle \mathcal{L}, \mathcal{R}, \mathcal{O}, \mathcal{T} \rangle$, G represents "why" $\mathcal{R} \sqcap \mathcal{O}$ are not compatible. For Concept Abduction , having $\mathcal{R}$ and $\mathcal{O}$ such that $\mathcal{O} \not\sqsubseteq \mathcal{R}$, the solution H to the CAP $\langle \mathcal{L}, \mathcal{R}, \mathcal{O}, \mathcal{T} \rangle$ represents "why" the subsumption relation does not hold. H can be interpreted as *what is specified in $\mathcal{R}$ and not in $\mathcal{O}$*.

3.1 Approximate Resource Retrieval – Logic-Based Matchmaking – via Concept Abduction and Concept Contraction

In real scenarios, it is quite rare to determine exactly the resource we are looking for. Often we have to reformulate the request in order to obtain satisfactory results in an approximate search. At this point a question arises: *What* should we change? Some suggestions would be useful.

Both Concept Abduction and Concept Contraction can be used to suggest guidelines on what, given an offered resource $\mathcal{O}$, has to be revised and/or hypothesized to obtain a full match with the request. We now show how the previously introduced services can help in an approximate, semantic-based, search of resources, fully exploiting their structured description. Let us suppose to have request a $\mathcal{R}$, a resource $\mathcal{O}$ and an ontology $\mathcal{T}$ such that $\mathcal{T} \models \mathcal{R} \sqcap \mathcal{O} \not\equiv \bot$, *i.e.*, they are incompatible. In order to gain compatibility, a Concept Contraction is needed so that giving up G in $\mathcal{R}$, the remaining K could be satisfied by $\mathcal{O}$. Now, if $\mathcal{T} \not\models \mathcal{O} \sqsubseteq K$, the solution H_K to the CAP $\langle \mathcal{L}, K, \mathcal{O}, \mathcal{T} \rangle$ represents what is K and is not specified in $\mathcal{O}$.

As the $\mathcal{O}$ obtained is an approximated match of $\mathcal{R}$, then a measure on how good is the approximation is needed. Given more than one appealing resources, which one is the best approximation? How it can be assigned a numerical score to the approximation, based on K,H and G, in order to rank the resources? In the following we present a simple algorithm to provide answers to the raised issues.

Algorithm $retrieve(\mathcal{O}, \mathcal{R}, \mathcal{T}, \mathcal{L})$
input $\mathcal{O}, \mathcal{R}$ concepts in $\mathcal{L}$ such that $\mathcal{T} \models \mathcal{O}$ and $\mathcal{T} \models \mathcal{R}$
output $\langle G, K \rangle$, H *i.e.*, the part in $\mathcal{R}$ that should be retracted G and kept K and the part in $\mathcal{O}$ that should be hypothesized to find a full match between $\mathcal{O}$ and $\mathcal{R}$
begin algorithm
1:     **if** $\mathcal{T} \models \mathcal{R} \sqcap \mathcal{O} \equiv \bot$ **then**
2:         $\langle G, K \rangle = contract(\mathcal{O}, \mathcal{R}, \mathcal{T})$;
3:         $H_K = abduce(\mathcal{O}, K, \mathcal{T})$;
4:         **return** $\langle G, K \rangle, H_K$;
5:     **else**
6:         $H = abduce(\mathcal{O}, \mathcal{R}, \mathcal{T})$;
7:         **return** $\langle \top, \mathcal{R} \rangle, H$;
end algorithm

Notice that $H = abduce(\mathcal{O}, \mathcal{R}, \mathcal{T})$ [rows 3,6] determines a solution H for the CAP $\langle \mathcal{L}, \mathcal{R}, \mathcal{O}, \mathcal{T} \rangle$, while $\langle G, K \rangle = contract(\mathcal{O}, \mathcal{R}, \mathcal{T})$ [row 2] determines a solution $\langle G, K \rangle$ for the CCP $\langle \mathcal{L}, \mathcal{R}, \mathcal{O}, \mathcal{T} \rangle$. The algorithm retrieve returns values useful in a retrieval system where explanation of the results is needed and/or a belief revision process is admitted.

[rows 1-4] Having a requested resource $\mathcal{R}$ and an offered one $\mathcal{O}$, if their descriptions conjunction is not satisfiable w.r.t. the ontology they refer to (i.e., they are not compatible with each other for some concepts in their descriptions), first a contraction on $\mathcal{R}$ is performed in order to regain compatibility [row 2] and then what is to be hypothesizes in $\mathcal{O}$ in order to completely satisfy $\mathcal{R}$ (its contraction) is computed [row 3]. The returned values represent:

$\langle G, K \rangle$: What is to be given up in the request – G – in order to continue the process, or, in other words, why $\mathcal{R}$ is not compatible with $\mathcal{O}$. What is the contracted request K.

H_K : After the contraction of $\mathcal{R}$, the request is represented by K, i.e. the portion of R which is compatible with $\mathcal{O}$. H_K represents what is to be hypothesized in $\mathcal{O}$ in order to completely satisfy K, or, in other words, why $\mathcal{O}$ does not completely satisfy K.

[rows 5-7] If the conjunction of $\mathcal{R}$'s and $\mathcal{O}$'s description is satisfiable w.r.t. the ontology they refer to, then no contraction is needed and only an abductive process is carried out.

The algorithm does not depend on the particular DL adopted. Based on the minimality criteria proposed in [7] the length H of the solution to a CAP for an $\mathcal{ALN}$ DL can be computed as proposed by [15]. Hence, a relevance ranking score can be computed by an utility function defined as $U(G, K, H_K)$.

4 Related work

In [18] and [24] matchmaking was introduced, based on KQML, as an approach whereby potential producers / consumers could provide descriptions of their products/needs to be later unified by a matchmaker engine to identify potential matches. A rule based approach using the Knowledge Interchange Format (KIF) [20] (the SHADE [24] prototype) or a free text comparison (the COINS [24] prototype) were used. Approaches similar to the previous ones were deployed in SIMS [1], which used KQML and LOOM as description language and InfoSleuth [23], which adopted KIF and the deductive database language LDL++. LOOM is also at the basis of the matching algorithm addressed in [21].
In [29] and [27] the LARKS language was proposed, specifically designed for agent advertisement. The matching process is a mixture of classical IR analysis of text and semantic match via Θ-subsumption. Nevertheless, a basic service of a semantic approach, such as inconsistency check, seems unavailable with this type of match. First approaches based on standard inference services offered by DL reasoners were proposed in [16, 22, 31]. In [14, 15] properties that a matchmaker should have in a DL based framework, were described and motivated, and algorithms to classify and rank matches into classes were presented. Matchmaking of web-services, providing a ranking of matches based on the DL-based approach of [14] was presented in [8]. An extension to the approach in [27] was proposed in [25] where two new levels for service profiles matching were introduced. Notice that there the *intersection satisfiable* level was introduced, whose definition is close to the one of *potential matching* proposed in [14], but no measure of similarity among intersection satisfiable concepts was given.

Profile matchmaking based on semantic descriptions was investigated, under different prespectives in [5, 10]. Semantic service discovery in the Bluetooth framework was investigated in [28]. Also here the issue of approximate matches, to be somehow ranked and proposed in the absence of exact matches, was discussed, but as in the previous papers no formal framework was given. Instead a logical formulation should allow to devise correct algorithms to classify and rank resources to simplify retrieval of most promising ones. In [4, 3] web services matchmaking was tackled. An approach was proposed, for a limited set of DLs, based on the Difference operator [30], followed by a set covering operation optimized using hypergraph techniques. In [9] the concept covering problem was extended to expressive DLs and algorithms were proposed for approximate concept covering based on concept abduction.

5 Conclusions

We have presented and motivated new DL-based inference services for semantic-based resource retrieval. Current and future application scenarios of the semantic-based retrieval techniques presented here include: electronic-marketplaces of tangible or intangible goods, skill management systems, mediators for web-service discovery and for grid-based computational resources, dating and personnel recruitment agencies. The increased availability of semantic-endowed descriptions will hence boost the emergence of knowledge-based systems able to take full advantage of these structured descriptions to obtain accurate and efficient retrieval. Currently our approach is fully devised, and algorithms and prototype system have been implemented for an $\mathcal{ALN}$ in the MAMAS framework (http://sisinflab.poliba.it/MAMAS-tng/). The system can be invoked both using DIG 1.1 compliant services and a Natural Language interface [11]. Work is ongoing to extend the approach also to more expressive DLs, while keeping computational complexity still tractable.

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