Mediation Spaces for Similarity-based Semantic Web Services Selection

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ABSTRACT:

Semantic Web Services (SWS) aim at the automated discovery, selection and orchestration of Web services on the basis of comprehensive, machine-interpretable semantic descriptions. The latter are in principle deployed by multiple possible actors (i.e. service providers and service consumers), and thus, a high level of heterogeneity between distinct SWS annotations is expected. Therefore, mediation between concurrent semantic representations of services is a key requirement to fully implement the SWS vision. In particular, we argue that "semantic-level mediation" is necessary to identify semantic similarities across distinct SWS representations. To this end, we first formalized and then implemented a mediation approach based on the so-called "Mediation Spaces" (MS), which enables the implicit representation of semantic similarities among distinct SWS descriptions. As a result, given a specific SWS approach and the proposed MS, a general purpose algorithm has been implemented to empower SWS selection with the automatic computation of semantic similarities between a given SWS request and a set of SWS offers. A prototypical application illustrates our approach and highlights the benefits w.r.t. current mediation approaches.

KEY WORDS:
Web Services, Service Discovery, Semantic Web Services, Semantic Mediation, Conceptual Spaces, Integration, Interoperability.

INTRODUCTION

The increasing availability of a broad variety of Web services (WS) raises the need to automatically discover, select and orchestrate appropriate services for a given need. Current WS search engines or service registries (e.g., UDDI) mainly support simple keyword-based search on Web services based on syntactic descriptions such as WSDL. However, this rather syntactic paradigm does not support precise allocation of Web services partially because of the lack of semantics expressed in utilized service descriptions. *Semantic Web Services (SWS)* (Fensel, Lausen, Polleres, de Bruijn, Stollberg, Roman & Domingue, 2006) aim at addressing this challenge on the basis of comprehensive, machine-interpretable semantic descriptions. Existing SWS frameworks, such as WSMO (WSMO Working Group, 2004) or OWL-S (Joint US/EU ad hoc Agent Markup Language Committee, 2004), enable the description of several WS-related functional (e.g. input and output, pre and post conditions, service choreography and orchestration) and non-functional (e.g. Quality of Service) parameters. However, since Web services usually are provided by distinct and independent parties, the actual WS interfaces as well as their semantic representations are highly heterogeneous. This strongly limits the interoperability and raises the need of mediating between semantic descriptions as well as the actual Web services interfaces. We can particularly identify two levels of mediation: *semantic-level* and *data-level* mediation.

Whereas the former refers to the resolution of heterogeneities between concurrent semantic representations of services – e.g. by aligning distinct SWS representations of services equivalent in functionality – the latter refers to the mediation between mismatches related to the Web service implementations themselves, i.e. related to the structure, value or format of I/O messages. Therefore, semantic-level mediation primarily supports the discovery and selection stage, whereas data-level mediation occurs during service orchestration and invocation.

In this paper, we particularly address *semantic-level mediation* to support the WS selection problem. We argue that semantic-level mediation strongly relies on identifying *semantic similarities* between entities across different SWS ontologies (Qu, Hu & Cheng, 2006; Wu, Ranabahu, Gomadam, Sheth & Miller, 2007). However, semantic similarity is not an implicit notion within existing ontology representations. Moreover, automatic similarity detection as demanded by semantic mediation requires semantic meaningfulness. But the symbolic approach – i.e. describing symbols by using other symbols without a grounding in the real world – of established ontology representations does not fully entail semantic meaningfulness, since meaning requires both the definition of a terminology in terms of a logical structure (using symbols) and grounding of symbols to a conceptual level (Cregan, 2007; Harnad, 1999).

Despite the importance of mediation for widespread dissemination of SWS technologies, related approaches are still limited and underdeveloped (Paolucci, Srinivasan & Sycara, 2004). Current attempts to mediation usually foresee the manual development of rather ad-hoc one-to-one mappings or the application of ontology mapping methodologies, mostly based on identifying (a) linguistic commonalities and/or (b) structural similarities (Choi, Song & Han, 2006; Noy & Musen, 2003). Since manually or semi-automatically defining similarity relationships is costly, current approaches are thus not capable to support SWS selection within highly dynamic scenarios and at Web scale.

In our work, we investigate a similarity-based mediation mechanism in order to overcome the need for manual or semi-automatic formalisations of one-to-one mappings between distinct SWS representations. In this respect, we propose a general purpose mediation approach consisting of (a) a representational approach allowing to implicitly represent similarities and (b) a general-purpose mediator for semantic-level mediation, exploiting similarities as represented through (a). In particular, following the principles of Conceptual Spaces (CS) introduced by Gärdenfors in (Gärdenfors, 2000), we introduce the concept of *Mediation Spaces (MS)* to enable the implicit representation of semantic similarities across heterogeneous SWS representations through grounding of SWS descriptions into vector spaces. We demonstrate that refining heterogeneous SWS descriptions in multiple shared MS supports similarity-based mediation at the semantic-level and implicitly facilitates Web services selection.

The provided general-purpose mediator – implemented as a dedicated mediation Web service – is deployable for any semantic-level mediation scenario, when being used to support effective WS selection together with our proposed representational approach. For demonstration purposes, we currently deployed the designed mediator within an existing SWS framework - IRS-III (Cabral, Domingue, Galizia, Gugliotta, Norton, Tanasescu & Pedrinaci, 2006) – based on WSMO and created a proof-of-concept application.

The remainder of the paper is organized as follows: Section 2 introduces the SWS mediation problem. Section 3 outlines the principles at the basis of our approach; i.e. Mediation Spaces as representational foundation for our approach to mediation while a general-purpose methodology to derive MS representation from arbitrary SWS is proposed in Section 4. In Section 5, we introduce the implementation of a generic mediator and its deployment in a proof-of-concept application in Section 6. Finally, we provide an evaluation of our approach in Section 7 and discuss and conclude our work in Section 8.

SEMANTIC-LEVEL MEDIATION TO SUPPORT WEB SERVICES SELECTION

In this paper, we exclusively address semantic-level mediation, what is perceived to be a fundamental requirement to further exploit SWS approaches on a Web scale. To understand the needs of semantic-level mediation, it is necessary to understand the requirements of the SWS selection task to which semantic-level mediation is supposed to contribute. Therefore, we first report below the abstract definitions of SWS and SWS mediation as used throughout the remainder of the paper, together with background information on current mediation approaches, and then outline our vision on semantic-level mediation at WS selection time.

Semantic Web Services

A SWS description (either the description of the Web service or the description of the service request) is formally represented within a particular ontology that complies with a certain SWS reference model such as OWL-S or WSMO. By applying a common formalisation of an ontology (Ehrig, Sure, 2004) to SWS, we define a populated *service ontology O* – as utilised by a particular SWS representation – as a tuple:

$$O = \{C, I, P, R, A\} \subset SWS$$

With C being a set of *n concepts w*here each concept C_i is described through *l(i) concept properties pc*, i.e.:

$$PC_i = \{(pc_{i1}, pc_{i2}, ..., pc_{l(i)}) \mid pc_{ix} \in C_i\}.$$

I represents all *m instances* where each instance I_{ij} represents a particular instance of a concept C_j and consists of *l(i) instantiated properties pi* instantiating the concept properties of C_j:

$$PI_{ij} = \{(pi_{ij1}, pi_{ij2}, ..., pi_{l(i)}) \mid pi_{ijx} \in I_{ij}\}.$$

Hence, the properties P of an ontology O represent the union of all concept properties PC and instantiated properties PI of O:

$$P = \{(PC_1, PC_2, ..., PC_n) \cup (PI_1, PI_2, ..., PI_m)\}$$

Given these definitions, we would like to point out that properties here exclusively refer to so-called data type properties. In that, we define properties as being distinctive to relations R. The latter describe relations between concepts and instances. In addition, A represents a set of *axioms* which define constraints on the other introduced notions. Since certain parts of a SWS ontology describe certain aspects of the Web service (request), such as its capability *Cap*, interface *If* or non-functional properties *Nfp* (Cimpian, Mocan, Stollberg, 2006), a SWS ontology can be perceived as a conjunction of ontological subsets:

$$Cap \cup If \cup Nfp = O \subset SWS$$

The semantic capability description, as central element of a SWS description, consists of further subsets, describing the assumptions *As*, effects *Ef*, preconditions *Pre* and postconditions *Post* of a Web Service. However, given the lack of a clear distinction between assumption/effect and pre-/postcondition, we prefer the exclusive usage of assumptions/effects:

$$As \cup Ef = Cap \subset O \subset SWS$$

Semantic Web Services mediation

Mediation aims at resolving heterogeneities among distinct SWS representations to support all stages that occur at runtime, namely *discovery*, *selection*, *orchestration* and *invocation*. In contrast to (Cimpian et al., 2006; Paolucci et al., 2004), we classify the mediation problem into (i) *semantic-level* and (ii) *data-level mediation*. The simplified schema below (Figure 1) illustrates the chronological order of different mediation tasks at SWS runtime.

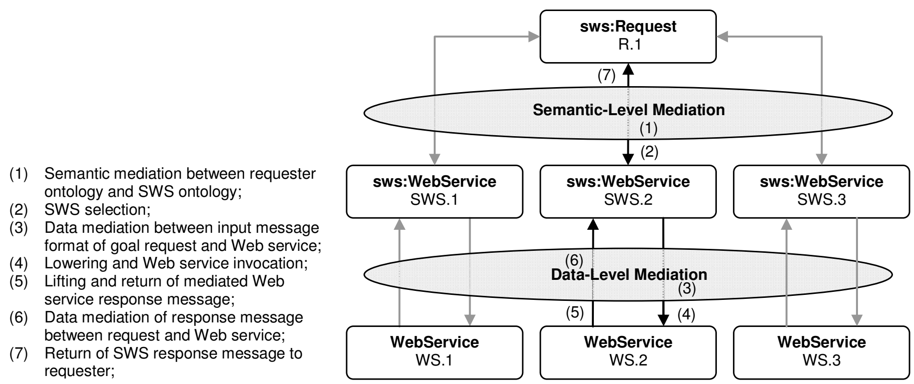


Fig. 1. Semantic-level and data-level mediation as part of SWS discovery, selection, orchestration and invocation.

Several approaches, such as (Bicer, Kilic, Dogac & Laleci, 2005; Bowers & Ludäscher, 2004; Mrissa, Ghedira, Benslimane, Maamar, Rosenberg & Dustdar, 2007; Spencer & Liu, 2004; Wu et al., 2007), aim at addressing the mediation issue partially by dealing either with (i) or (ii). For instance, Bowers & Ludäscher (2004) propose a semantic mediation framework for scientific workflows relying on the notion of semantic type and structural type, defined in a shared ontology. The semantic type gives a meaning to data, and the structural type is the data schema. As in (Spencer & Liu, 2004), their work adapts data with a common semantic type but different structural types. In contrast, Wu et al. (2007) provide an attempt to support similarity detection for mediation within SWS composition by exploiting syntactic similarities between SWS representations. However, it can be stated that all the above mentioned approaches rely on the definition of a priori mappings, the agreement of a shared ontology or the exploitation of semi-automatic ontology mapping approaches. Hence, providing a generic solution to mediation between heterogeneous SWS remains a central challenge.

Semantic-level mediation as a similarity computation problem

At SWS selection stage, in order to identify whether a particular SWS S_1 is potentially relevant for a given request S_2, a SWS broker has to compare the capabilities of S_1 and S_2, i.e. it has to identify whether the following holds true:

$$As_2 \subset As_1 \cup Ef_2 \subset Ef_1$$

However, in order to compare distinct capabilities of available SWS which each utilize a distinct vocabulary, these vocabularies have to be aligned. For instance, to compare whether an assumption expression $As_1 \equiv \neg I_1 \cup I_2$ of one particular SWS_1 is the same as $As_2 \equiv I_3 \cup \neg I_4$ of another SWS_2, where I_i represents a particular instance, matchmaking engines have to perform two steps:

(a) identification of relationships between concepts/instances involved in distinct SWS representations;

(b) evaluation whether the semantics of the SWS expressions match each other.

Whereas current SWS execution environments exclusively focus on (b), SWS discovery also requires semantic-level mediation between different ontologies, as in (a), what can be perceived as a particular instantiation of the *ontology mapping* problem (Wu et al., 2007). The goal is, to establish formal relations between a set of knowledge entities E_1 from an ontology O_1 – used to represent a particular SWS S_1 – with entities E_2 which represent the same or a similar semantic meaning in a distinct ontology O_2 (Choi et al., 2004; Ehrig & Sure, 2004; Pease, Niles & Li, 2002) which is used to represent an additional SWS S_2. The term *set of entities* here refers to the union of all concepts C, instances I, relations R and axioms A defined in a particular SWS ontology. In that, semantic-level mediation strongly relies on identifying *semantic similarities* between entities across different SWS ontologies. Hence, the identification of similarities is a necessary requirement to solve the mediation problem for multiple heterogeneous SWS representations (Qu, Hu, Cheng, 2006; Wu et al., 2007). However, in this respect, the following issues have to be taken into account:

I1 - Symbolic SWS representations lack meaningfulness and are ambiguous: similarity-detection across distinct SWS representations requires semantic expressions rich enough to inherently represent semantic similarity between represented entities. However, the symbolic approach, i.e. describing symbols by using other symbols, without a grounding in the real world, of established SWS representation standards, leads to ambiguity issues and does not fully entail semantic meaningfulness, since meaning requires both the definition of a terminology in terms of a logical structure (using symbols) and grounding of symbols to a conceptual level (Cregan, 2007; Harnad, 1999).

I2 - Lack of automated similarity-detection methodologies: Describing the complex notion of specific SWS capabilities in all their facets is a costly task and may never reach semantic completeness due to *I1*. While capability representations across distinct SWS representations – even those representing the same real-world entities – hardly equal another, semantic similarity is not an implicit notion within SWS representations. But manually or semi-automatically defining similarity relationships is costly. Moreover, such relationships are hard to maintain in the longer term.

Given the lack of inherent similarity representation, current approaches to ontology mapping could be applied to facilitate SWS mediation. These approaches aim at semi-automatic similarity detection across ontologies mostly based on identifying linguistic and/or structural similarities between entities of distinct ontologies (Choi et al., 2006; Noy & Musen, 2003; Maedche & Staab, 2002). Work following a combination of such approaches in the field of ontology mapping is reported in (Mitra, Noy & Jaiswals, 2005; Giunchiglia, Shvaiko & Yatskevich, 2004; Noy & Musen, 2003; Ehrig & Sure, 2004). However, it can be stated, that such approaches require manual intervention, are costly and error-prone, and hence, similarity-computation remains as central challenge.

In our vision, instead of semi-automatically formalising individual mappings, methodologies to automatically compute or implicitly represent similarities across distinct SWS representations are better suited to facilitate SWS mediation.

Similarity-computation based on Conceptual Spaces

Conceptual Spaces (CS), introduced by Gärdenfors (Gärdenfors, 2000; Gärdenfors, 2004), follow a theory of describing entities in terms of their perceptual characteristics similar to natural human cognition in order to avoid the symbol grounding issue. CS consider the representation of concepts as multidimensional geometrical vector spaces which are defined through a set of quality dimensions. Instances are supposed to be represented as vectors, i.e. particular points in a space CS. For instance, a particular color may be defined as point described by vectors measuring the quality dimensions hue, saturation, and brightness. Gärdenfors distinguishes between dimensions and domains - being sets of integral dimensions (Gärdenfors, 2004). Describing instances as points within vector spaces where each vector follows a specific metric enables the automatic calculation of their semantic similarity by means of distance metrics such as the Euclidean, Taxicab or Manhattan distance (Krause, 1987) or the Minkowsky Metric (Suppes & Krantz, 1989). Hence, in contrast to the costly formalisation of such knowledge through symbolic representations, semantic similarity is implicit information carried within a CS representation what is perceived as the major contribution of the CS theory. However, although CS aim at solving SW-related issues such as the symbol grounding problem, several issues still have to be taken into account:

I3 - Lack of representational facilities to base knowledge models on CS;

I4 - Lack of expressiveness to represent arbitrary relations;

I5 - Undefinable scope of particular dimensions;

I6 - Reliance on quantifiable measurements, even for qualitative characteristics.

With respect to *I3*, CS do not provide any representational mechanism enabling the application of CS for knowledge representation in order to solve the aforementioned issues *I1* and *I2* (Section 2). Moreover, the CS theory does not provide any notion to represent any arbitrary relations (*I4*) (Schwering, 2005), such as *part-of* relations which usually are represented within ontologies. In this regard, it is even more obstructive that the scope of a dimension is not definable (*I5*), i.e. a dimension always applies to the entire CS (Schwering, 2005). Nevertheless, similarity computation as major contribution of CS particularly requires the description of concepts through quantifiable metrics (*I6*), even in cases of rather qualitative characteristics.

MEDIATION SPACES

To overcome the issues I1-I6 introduced in the previous sections, we propose a mediation approach which utilises a novel representation mechanism which extends the expressiveness of SWS representations with implicit similarity information. In particular, we claim that basing service models on either SWS or CS is not sufficient and propose a representational approach which grounds a SWS representation into so-called *Mediation Spaces (MS).* MS are inspired by

CS and enable the implicit representation of semantic similarities across heterogeneous SWS representations provided by distinct agents. MS propose the representation of concepts which are used as part of SWS descriptions as CS defined through sets of quality dimensions. Instances as part of SWS descriptions are represented as vectors (members) in a MS where similarity between two vectors is indicated by their spatial distance. Hence, refining heterogeneous SWS descriptions into multiple shared MS supports similarity based mediation at the semantic-level and consequently facilitates SWS selection.

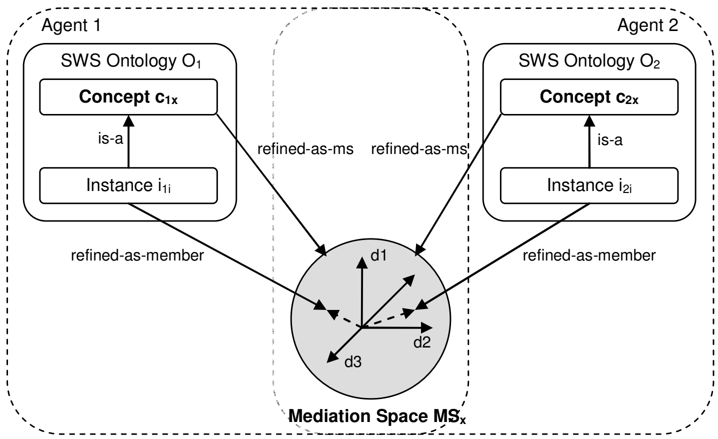


Fig. 2. Representing heterogeneous SWS representations through shared Mediation Spaces.

Whereas CS allow the representation of semantic similarity as a notion implicit to a constructed knowledge model, it can be argued, that representing an entire SWS through a coherent MS might not be feasible, particularly when attempting to maintain the meaningfulness of the spatial distance as a similarity measure. Therefore, we claim that MS are a particularly promising model when being applied to individual concepts – as part of SWS descriptions – instead of representing an entire SWS ontology in a single MS. In that, we would like to highlight that we consider the representation of a set of *n* concepts *C* of a SWS ontology *O* through a set of *n* MS (Figure 2). Hence, instances of concepts are represented as members (i.e. vectors) in the respective MS. While still taking advantage from implicit similarity information within a MS, our hybrid approach – combining SWS descriptions with multiple MS – allows to overcome CS-related issues, such as the lack of expressivity for arbitrary relations, by maintaining the advantages of ontology-based SWS representations. Please note that our approach relies on the agreement on a common set of MS for a given set of distinct SWS ontologies, instead of a common agreement on the used ontologies/vocabularies themselves. Thus, whereas in the latter case two agents have to agree on a common ontology at the concept and instance level, our approach requires just agreement at the schema level, since instance similarity becomes an implicit notion. Moreover, we assume that the agreement on ontologies at the schema level (Figure 2) becomes an increasingly widespread case, due to, on the one hand, increasing use of upper-level ontologies such as DOLCE[1], SUMO[2] or OpenCyc[3] which support a certain degree of commonality between distinct ontologies. On the other hand, SWS ontologies often are provided within closed environments, for instance, virtual organisations, where a common agreement to a certain extent is ensured. In such cases, the derivation of a set of common MS is particularly applicable and straightforward.

1 http://www.loa-cnr.it/DOLCE.html
2 http://www.ontologyportal.org/
3 http://www.opencyc.org/

In order to refine and represent SWS descriptions within a MS, we formalised the MS model into an ontology, currently being represented through OCML (Motta, 1998). The ontology enables the instantiation of a set of MS to represent a given set of concepts as part of SWS descriptions. Referring to (Raubal, 2004), we formalise a MS as a vector space defined through quality dimensions d_i of *MS*. Each dimension is associated with a certain metric scale, e.g. ratio, interval or ordinal scale. To reflect the impact of a specific quality dimension on the entire MS, we consider a prominence value *p* for each dimension (Raubal, 2004). Therefore, a MS is defined by

$$MS^n = \{(p_1 d_1, p_2 d_2, ..., p_n d_n) | d_i \in MS, p_i \in \Re\}.$$

However, usage context, purpose and domain of a particular MS strongly influence the ranking of its quality dimensions. This clearly supports our position of describing distinct MS explicitly for individual concepts. Please note that we enable dimensions to be detailed further in terms of subspaces. Hence, a dimension within one MS may be defined through another MS by using further dimensions. In such a case, the particular quality dimension d_j is described by a set of further quality dimensions. In this way, a MS may be composed of several subspaces and consequently, the description granularity can be refined gradually. Furthermore, dimensions may be correlated. Information about correlation is expressed through axioms related to a specific quality dimension instance.

A member *M* – representing a particular instance – of the MS is described through a set of valued dimension vectors v_i:

$$M^n = \{(v_1, v_2, ..., v_n) | v_i \in M\}$$

With respect to (Dietze, Gugliotta & Domingue, 2008b), we define the semantic similarity between two members of a space as a function of the Euclidean distance between the points representing each of the members. However, we would like to point out that different distance metrics could be considered, dependent on the nature and purpose of the MS. Given a MS definition *MS* and two members *V* and *U*, defined by vectors $v_0, v_1, \ldots, v_n$ and $u_1, u_2, \ldots, u_n$ within *MS*, the distance between *V* and *U* can be calculated as:

$$dist(u,v) = \sqrt{\sum_{i=1}^{n} p_i ((\frac{u_i - \bar{u}}{s_u}) - (\frac{v_i - \bar{v}}{s_v}))^2}$$

where $\bar{u}$ is the mean of a dataset *U* and s_u is the standard deviation from *U*. The formula above already considers the so-called Z-transformation or standardization which facilitates the standardization of distinct measurement scales utilised by different quality dimensions in order to enable the calculation of distances in a multi-dimensional and multi-metric space.

INTRODUCING MEDIATION SPACES IN THE SWS LIFE CYCLE

Following our vision, the provisioning of SWS representations is a highly heterogeneous and distributed procedure that is accomplished autonomously by distinct agents. In particular, we distinguish two groups of involved agents:

(C1) *distributed SWS providers and consumers*

(C2) *centralised SWS maintainers*.

The existence of C2 is implied by the broker-based nature of SWS technologies. Specifically, the overall procedure of providing SWS following our approach is based on the following steps:

S1. Provisioning of a central SWS runtime environment (C2).

S2. Provisioning of SWS representations S^n (C1).

S3. Providing appropriate MS_i/members for each distinct real-world entity represented within an available SWS ontology O.

S3.1. Representing concept properties pc_{ij} of C_i as dimensions d_{ij} of MS_i (C2).

S3.2. Assignment of metrics to each quality dimension d_{ij} (C2).

S3.3. Assignment of prominence values p_{ij} to each quality dimension d_{ij} (C2).

S3.4. Representing all instances I_{ik} of C_i as members in MS_i (C1).

Figure 3 below depicts the 4 steps of the S3 phase introduced above.

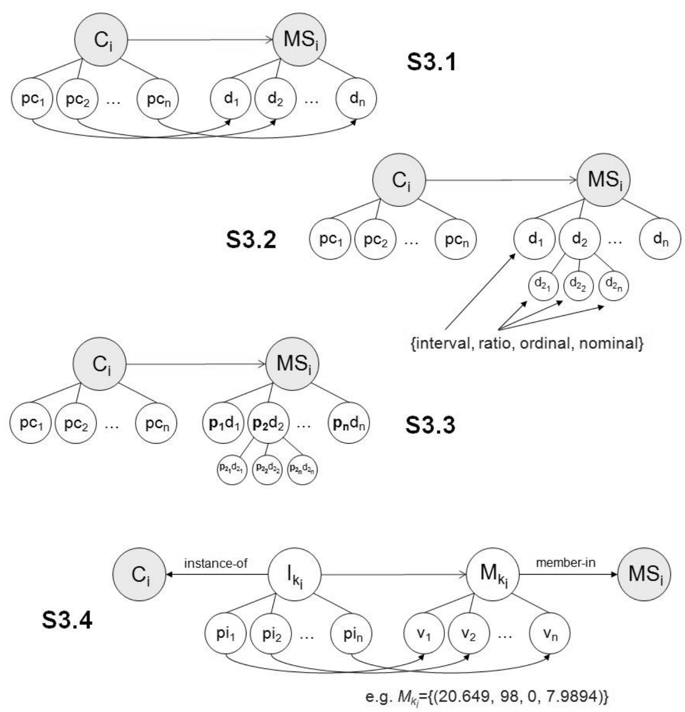


Fig. 3. Procedure to refine concepts/instances of a SWS ontology as MS/members.

Whereas *S1* and *S2* are foreseen within the SWS vision in general, *S3* represents an additional activity aiming at providing the representational facilities required to realise our mediation approach. This activity can be formalised as follows.

We are able to simply instantiate a specific MS by applying a transformation function

$$trans : C_i \Rightarrow MS_i$$

which is aimed at instantiating all elements of a MS, such as dimensions and prominence values *(S3.1 – S3.3*). *S3.1* aims at representing each concept property pc_{ij} of C_i as a particular dimension instance d_{ij} together with a corresponding prominence p_{ij} of a resulting space MS_i:

$$trans: \{(pc_{i1},...,pc_{in}) | pc_{ij} \in PC_i\} \Rightarrow \{(p_{i1}d_{i1},...,p_{in}d_{in}) | d_{ij} \in MS_i, p_{ij} \in \Re\}$$

Please note that we particularly distinguish between data type properties and relations. While the latter represent relations between concepts, these are not represented as dimensions since such dimensions would refer to a range of concepts (instances) instead of quantified metrics, as required by *S3.2*. Alternatively, relations could be refined by means of subspaces, i.e. the concept C_p representing the range of a dimension resulting from the transformation of a relation could be refined as a subspace MS_p in MS_i by applying the transformation function *trans* to C_p. However, in the case of relations, we propose to maintain the relationships represented within the original ontology *O* without representing these within the resulting MS_i. In that, the complexity of MS_i is reduced to enable the maintainability of the spatial distance as appropriate similarity measure. The assignment of metric scales to dimensions (*S3.2*) which naturally are described using quantitative measurements, such as size or weight, is rather straightforward. In such cases, interval scale or ratio scale, could be used, whereas otherwise, a nominal scale might be required. Since different dimensions might each have distinct impact on the entire space MS_i, *S3.3* is aimed at assigning a prominence value p_{ij} to each dimension d_{ij}. Prominence values should be chosen from a predefined value range, such as 0...1. However, since the assignment of prominences to quality dimensions is of major importance for the expressiveness of the similarity measure within a space, most probably this step requires incremental ex-post re-adjustments until a sufficient definition of a MS is achieved. With respect to *S3.4*, one has to represent all instances I_{ik} of a concept C_i as member instances in the created space MS_i:

$$trans : I_{ik} \Rightarrow M_{ik}$$

This is achieved by transforming all instantiated properties pi_{ikl} of I_{ik} as valued vectors in MS_i.

$$trans: \{(pi_{ik1},..., pi_{ikn}) | pi_{ikl} \in PI_{ik}\} \Rightarrow \{(v_{ik1},...,v_{ikn}) | v_{ikl} \in M_{ik}\}$$

Hence, given a particular MS, representing instances as members becomes just a matter of assigning specific measurements to the dimensions of the MS. In order to represent all concepts C_i of a given SWS ontology *O*, the transformation function consisting of the steps *S3.1-S3.4* has to be repeated iteratively for all C_i which are element of *O*. The accomplishment of the proposed procedure results in a set of MS instances which each refine a particular concept together with a set of member instances which each refine a particular instance. We would like to point out that applying the aforementioned procedure requires an additional effort compared with the preliminary development of a symbolic ontology. Assuming an effort e_c required to create all concepts C_i of an ontology *O* and an effort e_i to create all corresponding instances I_j, we estimate equivalent efforts e_{cs} to additionally create all corresponding CS_i and e_m to represent members M_j. This rough estimation has been proven within previous work (Dietze, Gugliotta & Domingue, 2008a; Dietze, Gugliotta & Domingue, 2008b). Moreover, we would like to point out that *S3.1* and *S3.2* might possibly be automated to a certain extent.

In addition, we would like to highlight that certain steps of the procedure are performed by a centralised SWS maintainer (C2) – such as the provisioning of the SWS environment (*S1*) and the representation of concepts involved in SWS descriptions as MS (*S3.1 – S3.3*) – whereas others are accomplished by distributed Web service providers (C1) – such as the provisioning of SWS descriptions (*S2*) and the representation of instances as members following the defined MS (*S3.4*). In that, this methodology takes into account the fact that Web services as well as their semantic annotations usually are provided by distributed and independent actors.

COMPUTING SERVICE SIMILARITY

To facilitate our MS-based approach, we provided a general-purpose mediator – implemented as a particular mediation service – which in fact is composed of two standard Web services (MWS.1, MWS.2). Given the ontological refinement of SWS descriptions into MS as introduced above, the mediation service is reusable and can be deployed to solve all sorts of semantic-level mediation scenarios.

At runtime, the first MWS.1 is invoked. Its inputs are a particular SWS_i (e.g. a service request description), named *base,* and the SWS descriptions of all x available services that are potentially relevant for the base*:*

$$in\,(MWS.1) = SWS_i \cup \{SWS_1, SWS_2, ..., SWS_x\}$$

Each SWS contains a set of concepts $C=\{c_1..c_m\}$ and instances $I=\{i_1..i_n\}$. Exchange of such ontological descriptions through SOAP is enabled by using an XML-serialisation as exchange format. MWS.1 first identifies all members $M(SWS_i)$ – in the form of valued vectors $\{v_1..v_n\}$ – refining the instance i_l of the base as proposed in the previous sections. In addition, for each concept c within the base the corresponding mediation space representations $MS=\{MS_1..MS_m\}$ are retrieved. Similarly, for each SWS_j related to the base, members $M(SWS_j)$ – which refine capabilities of SWS_j and are represented in one of the mediation spaces $MS_1..MS_m$, – are retrieved. In that, the output of MWS.1 represents also the input of MWS.2 and can be described as follows:

$$out\,(MWS.1) = in(MWS.2) = MS \cup M\,(SWS_i) \cup \{M\,(SWS_1), M\,(SWS_2), ..., M\,(SWS_x)\}$$

MWS.2 aims at computing the semantic similarities between the capability descriptions of SWS_i and the x associated SWS_j. In order to do so, MWS.2 is provided with the retrieved ontological descriptions, namely all members $M(SWS_i)$ and $M(SWS_j)$ and the respective space definitions *MS*. Based on the ontological descriptions of the input, for each member v_l within $M(SWS_i)$, MWS.2 computes the Euclidean distances to any member of all $M(SWS_j)$ which is represented in the same space MS_j as v_l. In case one set of members $M(SWS_j)$ contains several members in the same MS – e.g. SWS_j targets several instances of the same kind – the algorithm just considers the closest distance since the closest match determines the appropriateness for a given goal. For example, if one SWS supports several different locations, just the one which is closest to the one required by SWS_i determines the appropriateness.

Consequently, mediation service MWS.2 computes a set of x sets of distances $Dist(SWS_i)=\{Dist(SWS_i,SWS_1), Dist(SWS_i,SWS_2) .. Dist(SWS_i,SWS_x)\}$ where each $Dist(SWS_i,SWS_j)$ contains a set of distances $\{dist_1..dist_n\}$ where any $dist_i$ represents the distance between one particular member v_i of SWS_i and one member refining one instance of the capabilities of SWS_j. Hence, the overall similarity between the base SWS_i and any SWS_j could be defined as being reciprocal to the mean value of the individual distances between all instances of their respective capability descriptions and hence, is calculated as follows:

$$Sim(SWS_i, SWS_j) = \left(\overline{Dist(SWS_i, SWS_j)}\right)^{-1} = \left(\frac{\sum_{k=1}^{n}(dist_k)}{n}\right)^{-1}$$

The final output of the composed mediator is a set of *x* similarity values – computed as described above – which each indicates the similarity between the base SWS_i and one of the *x* target SWS:

$$out(SWS.1.2) = \{Sim(SWS_{i,} SWS_1), Sim(SWS_{i,} SWS_2), .., Sim(SWS_i, SWS_x)\}$$

As a result, the most similar SWS_j, i.e. the closest associated SWS, can be invoked. In order to ensure a certain degree of overlap between the actual request and the invoked functionality, we also defined a *threshold similarity value T* which determines the similarity threshold for any potential invocation.

EVALUATION

In this section we propose an initial prototype implementing our approach and describe findings from its evaluation.

Implementing a prototypical application based on MS

Even though our approach could be applied to any kind of SWS reference model, we adopted WSMO (WSMO Working Group, 2004) to implement a proof-of-concept prototype. The conceptual model of WSMO defines the following four main entities:

- *Domain Ontologies* provide the foundation for describing domains semantically. They are used by the three other WSMO elements. WSMO domain ontologies not only support Web service related knowledge representation but semantic knowledge representation in general.

- *Goals* define the tasks that a service requester expects a Web service to fulfill. In this sense they express the requester's intention.

- *Web service* descriptions represent the functional behavior of an existing deployed Web service. The description also outlines how Web services communicate (*choreography*) and how they are composed (*orchestration*).

- *Mediators* handle data and process interoperability issues that arise when handling heterogeneous systems.

Moreover, we make use of IRS-III (Cabral et al., 2006), a WSMO-compliant reasoner and SWS broker environment. In particular, we deployed the mediation Web services introduced in the previous section as WSMO mediator and introduced its invocation as part of the service discovery mechanism in IRS-III.

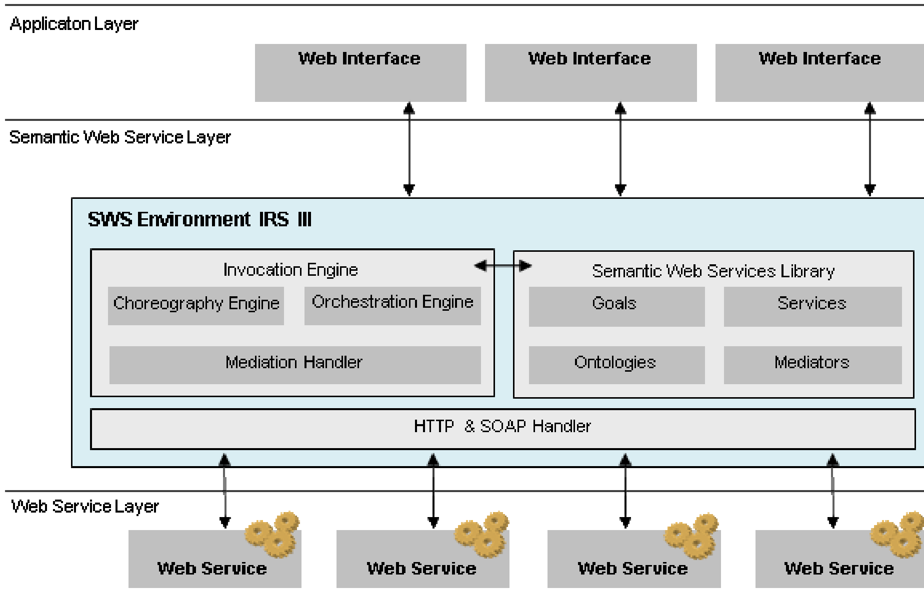


Fig. 4. Semantic-level mediation facilitated through a general-purpose WSMO mediator.

Figure 4 shows the overall architecture of our IRS-III based framework. IRS-III serves as central implementation of a Semantic Web Services Layer and serves requests from external applications (*Application Layer*) by discovering and orchestrating distributed Web services (*Web Service Layer*). Please note that we extended the IRS-III environment by integrating our MS-based mediation and service selection approach. In particular, the MS-based representations of individual SWS are inherent part of the *Semantic Web Services Library*. In addition, the execution of our mediation service introduced in the previous section is being dealt with by the *Mediation Handler* component and was integrated as implicit part of the IRS-III discovery mechanism.

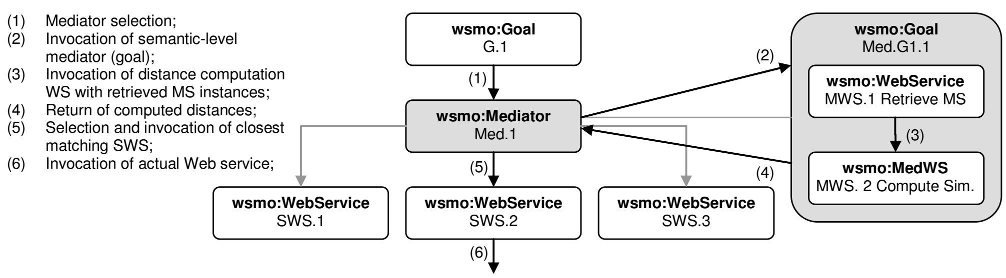


Fig. 5. Semantic-level mediation facilitated through a general-purpose WSMO mediator.

For example, Figure 5 illustrates the functionality of our mediator being deployed to mediate between a goal request and several WSMO SWS. In this example scenario, the WSMO mediator (*Med.1*) mediates between a given goal *G.1* and a set of 3 potentially relevant Web services (*SWS.1, SWS.2, SWS.3*). According to WSMO specifications, *Med.1* is associated with a distinct goal (*G.1.1*) that, in our case, is achieved by the orchestration of MWS.1 and MWS.2. In this example, similarity-based mediation is applied during SWS selection.

The general schemas depicted in Figures 4 and 5 has been also actualised within an initial proof-of-concept prototype application which mediates between different weather forecast Web services.

Here, SWS_1, SWS_2 and SWS_3 provide weather forecast information for different locations. Each service has distinct constraints, and thus distinct SWS descriptions. In detail, SWS_1 is able to provide forecasts for France and Spain while SWS_2 and SWS_3 are providing forecasts for the United Kingdom. All services show different Quality of Service (QoS) parameters. Three distinct service ontologies – O_1, O_2, and O_3 – together with a SWS request ontology O_4 had been created, each defining the capability of the respective service by using distinct vocabularies. For example, SWS_2 considers concepts representing the notions of location and QoS together with corresponding instances (see also Table 1):

$$\{(country, QoS), (UK, QoS2)\} \subset O_2 \subset SWS_2$$

By applying the representational approach proposed in Section 3, each concept of the involved heterogeneous SWS representations had been refined as a shared MS, while instances – defining the capabilities of available SWS and SWS requests - were defined as members. No explicit relations were formalised across ontologies. Instead, similarities between instances are computed by means of distance calculation in the shared MS.

For example, a simplified space (*MS_1: Location Space* in Figure 6) was utilized to refine geographical notions (e.g. country) by using two dimensions indicating the geospatial position of the location:

$$\{(p_1 l_1, p_2 l_2)\} = \{(latitude, longitude)\} = MS_1$$

The two dimensions latitude and longitude are equally ranked, and hence, a prominence value of 1 has been applied to each dimension. Note that each of the depicted concepts and instances, such as O_2*:UK* and O_3*:UK*, are distinct and independent from each other, and thus might show heterogeneities, such as distinct labels, for instance *United Kingdom* and *Great Britain*. In the case of O_2*:UK* and O_3*:UK,* these two instances are refined by two distinct members:

$$L_1(SWS_2) = \{(v_1 = 55.378051, v_2 = -3.435973) | v_i \in MS_1\}$$

and

$$L_1(SWS_3) = \{(v_1 = 55.378048, v_2 = -3.435963) | v_i \in MS_1\}.$$

Each member has been defined by different individuals applying similar, but non-equivalent geodata.

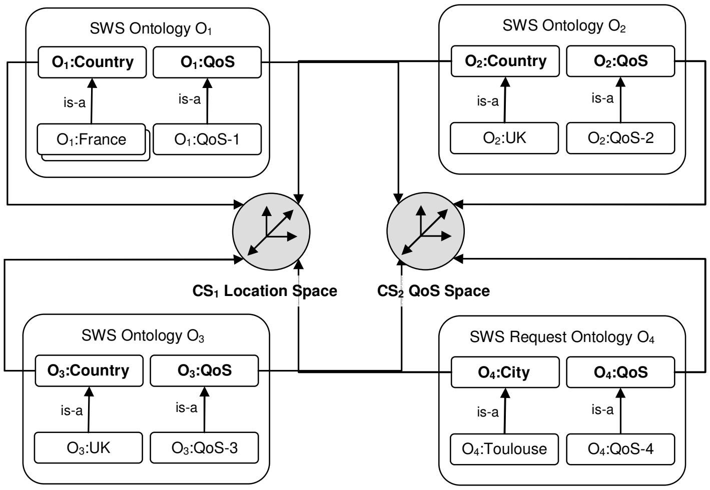


Fig. 6. Grounding assumptions of distinct weather forecast SWS to common MS.

In addition, a second space (*MS_2: QoS Space* in Figure 6) aimed at representing QoS has been defined by three dimensions – latency (in ms), throughput (number of Web services), availability (in %):

$$\{(p_1 r_1, p_2 r_2, p_3 r_3)\} = \{(latency, throughput, availability)\} = MS_2$$

In that, assumptions of available SWS had been described independently in terms of simple conjunctions of instances which were individually refined in shared MS as shown in Table 1.

Table 1. Assumptions of involved SWS and SWS requests described in terms of vectors in MS_1 and MS_2.

	Assumption $Ass_{SWSi}=(L_{1SWSi}\cup L_{2SWSi}\cup..\cup L_{nSWSi})\cup(Q_{1SWSi}\cup Q_{2SWSi}\cup..\cup Q_{mSWSi})$	
	Members L_i in MS_1 (locations)	Members C_j in MS_2 (QoS)
SWS_1	$L_{1(SWS1)}$={(46.227644, 2.213755)} $L_{2(SWS1)}$={(40.463667, -3.74922)}	$Q_{1(SWS1)}$={(155, 2, 91)}
SWS_2	$L_{1(SWS2)}$={(55.378051, -3.435973)}	$Q_{1(SWS2)}$={(15, 50, 98)}
SWS_3	$L_{1(SWS3)}$={(55.378048, -3.435963)}	$Q_{1(SWS3)}$={(78, 5, 95)}
SWS_4	$L_{1(SWS4}$={(55.378048, -3.435963)}	$Q_{1(SWS4)}$={(0,100,100)}

Potential service consumers define a request as a WSMO goal (e.g. SWS_4 in Figure 5) together with the set of input parameters and the underlying assumptions. Analogous to the SWS descriptions, instances used to define the goal assumptions are grounded to members in the corresponding MS. As shown in Table 1, the request SWS_4 assumes a SWS which provides weather forecast for the location UK ($L_1(SWS_4)$) and ideal QoS ($Q_1(SWS_4)$) demanding zero latency but high throughput and availability. Though no exact SWS matches these criteria, at runtime similarities are calculated between SWS_4 and the related SWS (SWS_1, SWS_2, SWS_3) through the mediation services implementing the formula introduced in the previous section. This led to the calculation of the following similarity values:

Table 2. Automatically computed similarities between SWS request SWS_4 and available SWS.

	Similarities
SWS_1	0.010290349
SWS_2	0.038284954
SWS_3	0.016257476

Given these similarities, our mediation service automatically selects the most similar SWS (SWS_2) and triggers its invocation, potentially leading to further data-level mediation tasks.

Evaluation

As one major contribution of our work, we facilitate a rather fuzzy, similarity-based selection of Web services as opposed to the strict matchmaking approaches facilitated by current SWS matchmaking environments. In that, our approach also enables the discovery of services which are annotated with distinct and heterogeneous SWS ontologies. However, to evaluate also the applicability of our approach, initial proof-of-concept prototype applications were provided (Dietze et al., 2008a; Dietze et al., 2008b) which apply the hybrid representational approach proposed in this paper to enable similarity-based matchmaking between distinct representations of SWS capabilities.

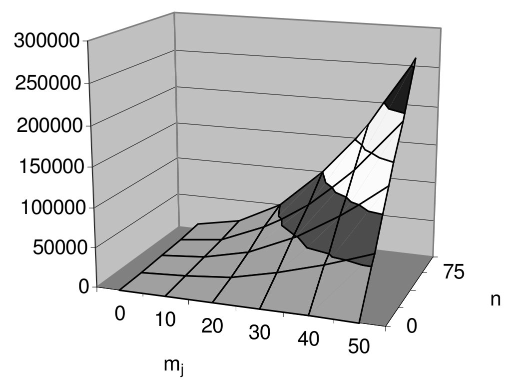
There, an environment as described in Figure 2 was established by enabling a SWS provider (Agent 1) to refine symbolic SWS capability descriptions through MS. In that, by following the approach proposed here, concept instances as part of SWS capability descriptions had been individually represented within MS-based representations. On the other hand, heterogeneous user requests (Agent 2) are dynamically represented as members in the same MS. Instead of (semi-automatically) mapping distinct SWS ontologies utilized by both agents, similarities are computed as proposed above by automatically calculating overall similarity values based on Euclidean distances between a set of MS members.

In order to further evaluate the contribution of our approach, in the following, we provide an attempt to compare the required number of similarity computations – i.e. the required SWS alignment activities - following our approach on the one hand, and following traditional ontological SWS representations on the other. Please note that the authors are aware that providing representations following our two-fold approach requires additional effort to provide the representations enabling to benefit from the contributions discussed here.

Given two SWS ontologies O_1 and O_2 - which consist of n concepts C_j (C_k) with m_j instances I_j (I_k) each - concept similarity is implicitly defined through concept refinement in the equivalent MS as depicted in Figure 2; i.e. two concepts agreeing on the same MS representation necessarily are similar, if not equivalent. In this case, instance similarity is simply computable by means of the spatial distance and thus the required effort is *null*. However, if a MS-based representation as shown in Figure 2 is not provided already, beforehand the ontological schema needs to be mapped in order to be able to agree on a common MS for each concept. In this case, creating the requirements for this case from a set of distinct ontologies, would require n^2 similarity comparisons (mapping activities), with n being the number of concepts within each O_1 and O_2. In contrast, following ontology alignment or manual mapping approaches would require additional comparisons to map instances, in order to fully enable mapping between both ontologies; i.e.:

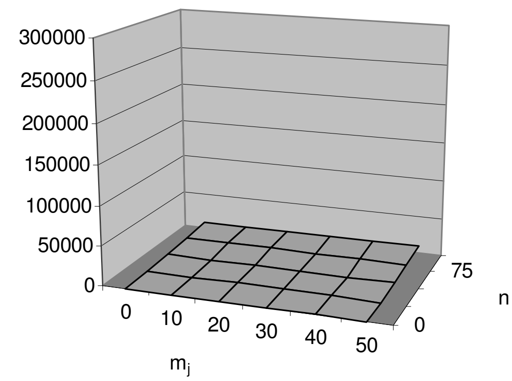
$$x(I(O_1), I(O_2)) = n^2 + \sum_{j=1}^{n} (m_j)^2$$

Figure 7 depicts the expected number of similarity comparisons for the traditional mediation approach (a) and our proposed solution (b). Since in the case of our proposed solution instance similarity is an implicit notion, the respective number of similarity comparisons following our approach is not dependent on the number of involved instances. As shown in Figure 6, the proposed solution significantly reduces the amount of required similarity comparisons, which increase with a growing number of instances m_j when following traditional manual or semi-automatic mediation approaches. Even though an additional effort is required to apply our representational model, this reduction is perceived to be the major contribution of the proposed solution.



m_j	n: 0	25	50	75	100
0	0	225	2500	5625	10000
10	0	2725	7500	13125	20000
20	0	10225	22500	35625	50000
30	0	22725	47500	73125	100000
40	0	40225	82500	125625	170000
50	0	62725	127500	193125	260000

(a)



m_j	n: 0	25	50	75	100
0	0	225	2500	5625	10000
10	0	225	2500	5625	10000
20	0	225	2500	5625	10000
30	0	225	2500	5625	10000
40	0	225	2500	5625	10000
50	0	225	2500	5625	10000

(b)

Fig. 7. Required similarity comparisons to map between two SWS ontologies O_1 and O_2 dependent on number of concepts *n* and number of instances m_j.

Within previous works (Dietze et al., 2008a; Dietze et al., 2008b), the authors already illustrated the applicability of distance metrics in a CS as similarity measure. Consequently, adopting our approach enabled similarity detection across heterogeneous SWS ontologies instead of manually aligning individual instances. It is apparent that an initial effort has to be made to represent heterogeneous concepts in common MS and to represent instances as corresponding vectors. However, once these representations are available, similarity becomes an implicit notion and does not require manual or (semi-) automatic alignments.

DISCUSSION AND CONCLUSIONS

In order to facilitate SWS interoperability we proposed a semantic mediation approach based on two contributions: (a) a hybrid representation using a combination of symbolic SWS representations and concept groundings in multiple MS and (b) a general-purpose mediation service enabling to compute similarities between distinct SWS representations. MS, being inspired by CS, follow the vector space theory and enable the representation of instances as vectors to facilitate the automatic computation of similarities between SWS by means of spatial distances between distinct vectors. A dedicated MS formalisation enables the instantiation of a corresponding MS (member) for each individual concept (instance) of any arbitrary SWS ontology.

The introduced two-fold representational approach supports implicit representation of similarities between instances across heterogeneous SWS, and consequently, provides a means to facilitate Web service interoperability. In fact, given the set of SWS representations conceptually grounded into MS, our general-purpose mediation Web service is able to compute their similarities in order to identify the best possible match. Furthermore, our approach is supported by a formal method on how to derive MS representations for individual concepts of any arbitrary SWS representations. To evaluate our approach, we deployed a prototypical application based on WSMO in a weather forecast scenario.

The proposed approach has the potential to significantly reduce the effort required to mediate between distinct heterogeneous SWS and the extent to which distinct parties have to share their conceptualisations. Whereas traditional mediation methodologies rely on either manual formalisation of one-to-one mappings or mechanisms to semi-automatically detect similarities at the schema and the instance level, our approach supports automatic similarity-computation between instances though requiring a common agreement on a shared MS. However, even for the case of heterogeneous MS, traditional semi-automatic mapping methodologies could be applied to initially align distinct MS. In addition, incomplete similarities are computable between partially overlapping MS. Given the nature of our approach – aiming at mediating between sets of concepts/instances which are used to annotate particular SWS – we argue that our solution is particularly applicable to SWS frameworks which are based on rather light-weight service semantics such as WSMO-Lite (Vitvar, Kopecký, Viskova & Fensel, 2008), SAWSDL[4] or OWL-S (Joint US/EU ad hoc Agent Markup Language Committee, 2004). Moreover, by representing SWS through measured vectors which are independent from the underlying representation language, we believe that our approach also has the potential to bridge between concurrent SWS reference models and modeling languages.

However, the authors are aware that our approach requires a considerable amount of additional effort to establish MS-based representations. Future work will investigate the scalability of our approach, as well as its reusability in distinct and more complex application domains. Moreover, while overcoming issues related to symbolic Semantic Web-based annotations, and CS-based approaches, further issues remain. For example, whereas defining instances, i.e. vectors, within a given MS appears to be a straightforward process of assigning specific quantitative values to quality dimensions, the definition of the MS itself is not trivial and dependent on individual perspectives and subjective appraisals. In addition, whereas semantics of instances are grounded to metrics within a MS, the quality dimensions themselves are subject to ones interpretation what might lead to ambiguity issues. Nevertheless, distance calculation relies on the fact that resources are described in equivalent geometrical spaces. However, particularly with respect to the latter, traditional ontology and schema matching methods could be applied to align heterogeneous spaces. In addition, we would like to point out that the increasing usage of upper level ontologies, such as DOLCE or SUMO, and the progressive reuse of ontologies, particularly in loosely coupled organisational environments, leads to an increased sharing of (SWS) formalisations, particularly at the schema level. As a result, our proposed hybrid representational model and

[4] http://www.w3.org/2002/ws/sawsdl/

mediation approach becomes increasingly applicable by further enabling similarity-computation at the instance-level towards the vision of interoperable Web services.

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[5] http://notube.tv

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