Towards Context-aware Semantic Web Service Discovery through Conceptual Situation Spaces

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ABSTRACT

Context-awareness is highly desired across several application domains. *Semantic Web Services (SWS)* enable the automatic discovery of distributed Web services based on comprehensive semantic representations. However, although SWS technology supports the automatic allocation of resources for a given well-defined task, it does not entail the discovery of appropriate SWS representations for a given situational context. Whereas tasks are highly dependent on the situational context in which they occur, SWS technology does not explicitly encourage the representation of domain situations. Moreover, describing the complex notion of a specific situation in all its facets is a costly task and may never reach semantic completeness. Particularly, following the symbolic SWS approach leads to ambiguity issues and does not entail semantic meaningfulness. Apart from that, not any real-world situation completely equals another, but has to be matched to a finite set of semantically defined parameter descriptions to enable context-adaptability. To overcome these issues, we propose *Conceptual Situation Spaces (CSS)* which are aligned to established SWS standards. CSS enable the description of situation characteristics as members in geometrical vector spaces following the idea of Conceptual Spaces. Semantic similarity between situations is calculated in terms of their Euclidean distance within a CSS. Extending merely symbolic SWS descriptions with context information on a conceptual level through CSS enables similarity-based matchmaking between real-world situation characteristics and predefined resource representations as part of SWS descriptions. To prove the feasibility, we apply our approach to the domain of E-Learning and provide a proof-of-concept prototype.

Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine Systems - *Human information processing*; H.3.5 [**Information Storage and Retrieval**]: Online Information Services – Web-based Services; H.4 [**Information Systems Applications**]: Miscellaneous.

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General Terms

Design, Experimentation.

Keywords

Semantic Web Services, Context, Conceptual Spaces, WSMO, Matchmaking.

1. INTRODUCTION

Context-aware discovery and invocation of Web services and data sources is highly desired across a wide variety of application domains and subject to intensive research throughout the last decade [4][14][23]. Whereas the *context* is defined as the entire set of surrounding *situation characteristics*, each individual *situation* represents a specific state of the world, and more precisely, a particular state of actual context. A *situation description* defines the context in a particular situation, and is described by a combination of *situation parameters*, each representing a particular situation characteristic. Following this definition, *context-adaptation* can be defined as the ability to adapt to distinct possible situations.

Semantic Web Services (SWS) technology [9] supports the automatic discovery of distributed Web services as well as underlying data for a given task based on comprehensive semantic descriptions. First results of SWS research are available, in terms of reference ontologies – e.g. OWL-S [21] and WSMO [27] – as well as comprehensive frameworks (e.g. DIP project[1] results).

However, whereas SWS technology supports the allocation of appropriate resources based on semantic representations, it does not entail the discovery of appropriate SWS representations for a given situation, i.e. the actual context. Even though tasks, as semantically described through SWS representations, are highly dependent on the situation in which they occur, current SWS technology does not explicitly encourage the representation of domain situations related to task representations. Furthermore, describing the complex notion of a specific situational context in all its facets is a costly task and may never reach semantic completeness. The symbolic approach - describing symbols by using other symbols without a grounding in the real world - of established SWS and Semantic Web representation standards in general, such as RDF [25], OWL [26], OWL-S [21], or WSMO [27] leads to ambiguity issues and does not entail semantic

[1] DIP Project: http://dip.semanticweb.org

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 [2][20]. Moreover, whereas not any situation or situation parameter completely equals another, the number of predefined semantic representations of situations and situation parameters within a SWS description is finite. Consequently, to enable context-adaptive resource discovery, a potential infinite set of (real-world) situation characteristics has to be matched to a finite set of semantically defined situation parameter descriptions. Therefore, fuzzy classification and matchmaking techniques are required to classify a real-world situation based on a limited set of predefined parameter descriptions to support the discovery of the most appropriate SWS representation within a given situation context.

Conceptual Spaces (CS), introduced by Gärdenfors [12][13], follow a theory of describing entities at the conceptual level in terms of their natural characteristics similar to natural human cognition in order to avoid the symbol grounding issue. CS enable representation of objects as vector spaces within a geometrical space which is defined through a set of quality dimensions. For instance, a particular color may be defined as point described by vectors measuring the quality dimensions hue, saturation, and brightness. Describing instances as vector spaces where each vector follows a specific metric enables the automatic calculation of their semantic similarity, in terms of their Euclidean distance, in contrast to the costly representation of such knowledge through symbolic SW representations. Even though several criticisms have to be taken into account when utilizing CS (Section 6) they are considered to be a viable option for knowledge representation.

In this paper, we propose *Conceptual Situation Spaces (CSS)* which utilize CS to represent situational contexts. CSS are mapped to standardized SWS representations to enable first the context-aware discovery of appropriate SWS descriptions and finally the automatic discovery and invocation of appropriate resources - Web services and data - to achieve a given task within a particular situation. Extending merely symbolic SWS descriptions with context information on a conceptual level through CSS enables fuzzy and similarity-based matchmaking between real-world situation characteristics and predefined SWS representations. Whereas similarity between situation parameters, as described within a CSS, is indicated by the Euclidean distance between them, real-world situation parameters are classified along predefined prototypical parameters which are implicit elements of a SWS description. Whereas current SWS technology addresses the issue of allocating resources for a given task, our approach supports the discovery of SWS representations within a given situational context. Consequently, the expressiveness of current SWS standards is extended through CSS in order to enable fuzzy matchmaking mechanisms when allocating resources for a given situation.

To prove the feasibility of our approach a proof-of-concept prototype from the domain of E-Learning is provided which uses CSS to describe learning styles, following the Felder-Silverman Learning Style theory [6], as particular learning situation parameter.

The paper is organized as follows. The following Section 2 provides background information on SWS, whereas Section 3 introduces our approach of Conceptual Situation Spaces which are aligned to current SWS representations. Section 4 illustrates the application of CSS to the E-Learning domain and introduces a Conceptual Learning Situation Space, particularly, a CSS subspace representing learning styles. Utilizing CSS, we introduce our approach to similarity-based classification of a given situation based on distance calculation at runtime in Section 5. Finally, we conclude our work in Section 6 and provide an outlook to future research.

2. SEMANTIC WEB SERVICES AND WSMO

SWS technology aims at the automatic discovery, orchestration and invocation of distributed services for a given user goal on the basis of comprehensive semantic descriptions. SWS are supported through representation standards such as WSMO [9][27] and OWL-S [21].

This section introduces the *Web Service Modelling Ontology* (WSMO), a well established SWS reference ontology and framework. WSMO is currently supported through several software tools and runtime environments, such as the Internet Reasoning Service IRS-III 7 and WSMX [28]. 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.

3. CONCEPTUAL SITUATION SPACES FOR SEMANTIC WEB SERVICES

Our approach is based on describing situational contexts as members within a domain-specific Conceptual Situation Space (CSS) which are incorporated into SWS descriptions.

3.1. Conceptual Situation Spaces

CSS enable the description of a particular context within a particular situation as a member of a dedicated CS. Referring to [13][22], we define a CSS (*css:Conceptual Situation Space* in Figure 1) as a vector space:

$$C^n = \{(c_1, c_2, ..., c_n) | c_i \in C\}$$

with c_i being the quality dimensions *(css:Quality Dimension)* of *C*. Please note, that we do not distinguish between dimensions and domains - being sets of integral dimensions [13] - but enable dimensions to be detailed further in terms of subspaces. Hence, a dimension within one space may be defined through another conceptual space by using further dimensions [22]. In such a case, the particular quality dimension c_j is described by a set of further quality dimensions with

$$c_j = D^n = \{(d_1, d_2, ..., d_n) | d_k \in D\}.$$

In this way, a CSS may be composed of several subspaces and consequently, the description granularity of a specific situation can be refined gradually. To reflect the impact of a specific quality dimension on the entire CSS, a prominence value *p (css:Prominence)* for each dimension could be considered. In this case, a CSS would be defined by

$$C^n = \{(p_1 c_1, p_2 c_2, ..., p_n c_n) | c_i \in C, p_i \in P\}$$

where *P* is the set of real numbers. However, the usage context, purpose and domain of a particular CSS strongly influence the ranking of its quality dimensions. This clearly supports our position of describing distinct CSS explicitly for specific domains only.

Particular members (*css:Member* in Figure 1) in the CSS are described through a set of valued dimension vectors (*css:Valued Dimension Vector*). Moreover, referring to [13] we consider prototypes (*css:Prototypical Member*) within a particular space. Prototypical members enable the classification of any arbitrary member *m* within a particular CSS, by simply calculating the Euclidean distances between *m* and all prototypical members within the same space to identify the closest neighbours of *m*. For instance, given a CS to describe apples based on their shape, taste and colour, a green apple with a strong and fruity taste may be close to a prototypical member representing the typical characteristics of the Granny Smith species. Figure 1 depicts the CSS metamodel.

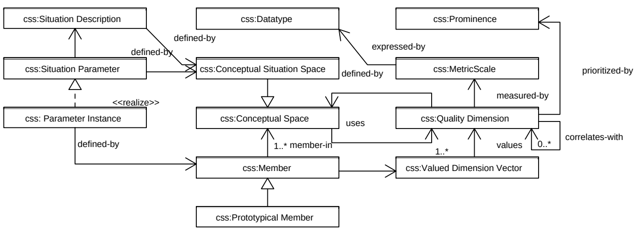

Figure 1. CSS metamodel.

The metamodel introduced above has been formalized into a *Conceptual Situation Space Ontology (CSSO)*, utilizing OCML [19]. In particular, each of the depicted entities is represented as a concept within CSSO whereas associations are reflected as their properties in most cases. The correlation relationship indicates, whether two dimensions are correlated or not. For instance, when describing an apple the quality dimension describing its sugar content may be correlated with the taste dimension. Information about correlation is expressed within the CSSO through axioms related to a specific quality dimension instance. CSSO is aligned to a well-known foundational ontology: the Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE) [11] and, in particular, its module Descriptions and Situations (D&S) [10]. The aspect of gradually refining a CSS through subspaces corresponds to the approach of DOLCE D&S to gradually refine a particular description by using parameters where each parameter can be described by an additional description.

Semantic similarity between two members of a space is perceived as a function of the Euclidean distance between the points representing each of the members. Applying a formalization of CS proposed in [22] to our definition of a CSS, we formalize the Euclidean distance between two members in a CSS as follows. Given a CSS definition *C* and two members represented by two vector sets *V* and *U*, defined by vectors v_0, v_1, …,v_n and u_1, u_2,…,u_n within *C*, the distance between *V* and *U* can be calculated as:

$$|d(u,v)|^2 = \sum_{i=1}^{n} (z(u_i) - z(v_i))^2$$

where $z(u_i)$ is the so-called Z-transformation or standardization [3] from u_i. Z-transformation facilitates the standardization of distinct measurement scales which are utilized by different quality dimensions in order to enable the calculation of distances in a multi-dimensional and multi-metric space. The z-score of a particular observation u_i in a dataset is calculated as follows:

$$z(u_i) = \frac{u_i - \bar{u}}{s_u}$$

where $\bar{u}$ is the mean of a dataset *U* and s_u is the standard deviation from *U*. Considering prominence values p_i for each quality dimension *i*, the Euclidean distance *d(u,v)* indicating the semantic similarity between two members described by vector sets *V* and *U* can be calculated as follows:

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

3.2. Aligning CSS and SWS

Whereas the discovery of distributed Web services for a given user goal is addressed by current SWS technology, such as WSMO, the context-aware selection of a specific SWS goal representation for a given situation is a challenging task to be tackled when developing SWS-driven applications. By providing an alignment of CSS and SWS, we enable the similarity-based classification of a particular situational context or context parameter in order to support fuzzy matchmaking with predefined context-parameters utilized by different SWS goal representations. Therefore, CSS are aligned to WSMO to support the automatic discovery of the most appropriate goal representation for a specific situation. Since both metamodels, WSMO as well as CSS, are represented based on the OCML representation language [19], the alignment was accomplished by defining relations between concepts of both ontologies as depicted in Figure 2.

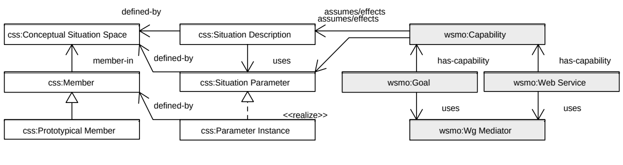

Figure 2. Alignment of CSS and WSMO.

Grey colored concepts in Figure 2 represent concepts of WSMO [27]. A goal description (*wsmo:Goal*) utilizes particular context parameters (*css:Situation Parameters*) to semantically describe its capabilities, i.e. its assumptions, effects, preconditions and postconditions in terms of semantic situation descriptions *(css:Situation Description)*. A WSMO runtime reasoning engine utilizes capability descriptions to identify SWS (*wsmo:Web Service*) which suit a given goal. In contrast, the preliminary selection of the most appropriate goal description for a given situational context is addressed by classification of situation parameters through CSS. For instance, given a set of real-world situation parameters, described as members in a CSS, their semantic similarity with predefined prototypical parameters *(css:Prototypical Member)* is calculated to identify the closest neighbors within the CSS. Given such a classification of a particular real-world situation, a goal representation which assumes matching prototypical parameter instances is selected and achieved through the reasoning engine.

4. A CONCEPTUAL LEARNING SITUATION SPACE

As Gärdenfors states in [13], the prioritization of certain quality dimensions within a CS is highly dependent from the context of the space. For instance, when describing an apple, dimensions may be differently weighted, dependent on whether the apple is subject to visual cognition exclusively or to full sensory perception. Whereas in the first case, dimensions such as color and shape are highly ranked, taste and texture may additionally be important in the latter case.

The same applies to situations which are described within a CSS. Whereas a learning situation may be dependent on quality dimensions such as the learner's competencies or learning objective, a business situation may be more affected by a quality dimension reflecting the costs of a business task. Thus, we assume that a CSS is best to be described for a specific domain context. In this section, we introduce a CSS for the e-Learning domain, a *Conceptual Learning Situation Space*, to illustrate the applicability of our metamodel. The CSS is utilized by several SWS capability descriptions through a common domain ontology, which describes learning situation parameters on a symbolic level which are grounded to a conceptual level through CSS.

4.1. Learning Style as a particular CSS Subspace

As described in [5] a learning situation is defined by parameters such as the technical environment used by a learner, his/her competency profile or the current learning objective. Since each of these parameters apparently is a complex theoretical construct, most of the situation parameters cannot be represented as a single quality dimension within the CSS, but have to be represented as dedicated subspaces which are defined by their very own dimensions (Section 3.1). Therefore, this Section focuses exemplarily on the representation of one parameter through a CSS subspace, which is of particular interest within the E-Learning domain: the learning style of a learner. A learning style is defined as an individual set of skills and preferences on how a person perceives, gathers, and processes learning materials [18]. Whereas each individual has his/her distinct learning style, it affects the learning process 7 and consequently has to be perceived as an important parameter describing a learning situation.

Due to the complex and diverse nature of learning styles, traditional symbolic approaches of the Semantic Web are supposed to fail when describing a specific learning style, since it is nearly impossible to define a specific learning style in a non-ambiguous and comprehensive way by just following a symbolic approach. Moreover, a one-to-one matchmaking between different learning styles is hard to achieve, since fairly not any learning style completely equals another one. Therefore, fuzzy similarity detections, as enabled through CSS, are required.

4.2. A CSS following the Felder-Silverman Learning Style Theory

To describe a learning style, we refer to the Felder-Silverman Learning Style Theory (FSLST) [6] approach to describe learning styles within computer-aided educational environments 7. However, please note that distinct theories can be applied to describe each situation parameter. Following FSLST, a learning style is described by four quality dimensions which are explained in detail in [6]. In short, the Active-Reflective dimension describes whether or not a learner prefers to interact with learning material, whereas the Sensing-Intuitive dimension, describes whether a learner tends to focus on facts and details (Sensing) rather than abstract theories (Intuitive). The Visual-Verbal dimension obviously covers, whether a learner prefers visual rather than verbal learning material, while the Global-Sequential dimension describes, whether a learner tends to learn gradually in small steps (Sequential) rather than following a holistic learning process marked by large learning leaps. Literature shows [8][15][24], that these dimensions can be assumed to be virtually linearly independent, apart from the fact that there seem to be moderate correlations between the Sensing-Intuitive dimension and the Sequential-Global dimension. With regard to the Felder-Silverman theory, we define a CSS L with 4 quality dimensions l_i:

$$L^4 = \{(l_1, l_2, l_3, l_4) | l_i \in L\}$$

Figure 3 depicts the key concepts of the ontology describing L as subspace (*css:FSLST Space*) within the CSS representing the Felder-Silverman Learning Style Theory.

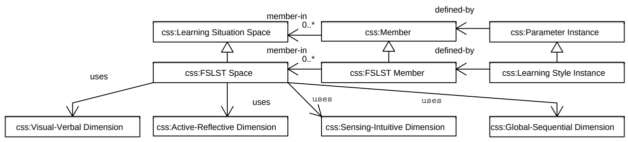

Figure 3. Key concepts representing FSLST as CSS subspace.

Moreover, Figure 3 depicts the alignment of the subspace L (*css:FSLST Space*) with the CSS metamodel. Referring to the learning style, instances representing the learning style (*css:Learning Style Instance*) are defined by particular members (*css:FSLST Member*) within the space L (*css:FSLST Space*), which itself uses 4 quality dimension l_i. The metric scale, datatype, value range and prominence values for each dimension l_i are presented in Table 1:

Table 1. Quality dimensions l_1 – l_4 describing learning styles following FSLST.

	Quality Dimension	Metric Scale	Data-type	Range	Promi-nence
l_1	Active-Reflective	Interval	Integer	-11..+11	1.5
l_2	Sensing-Intuitive	Interval	Integer	-11..+11	1
l_3	Visual-Verbal	Interval	Integer	-11..+11	1.5
l_4	Global-Sequential	Interval	Integer	-11..+11	1

As depicted in Table 1, each quality dimension is ranked on an interval scale with a value range being integers between -11 and +11. This particular measurement scale was defined with respect to an established assessment method, the Index of Learning Styles (ILS) questionnaire defined by Felder and Soloman [7], aimed at identifying and rating the particular learning style of an individual. Utilizing 44 questions within the ILS, each answer is valued by either -1 or 1 indicating a tendency for one of the two extreme values of a particular dimension. Consequently, for instance within the Active-Reflective dimension a vector size below 0 indicates a rather active learning style while otherwise a reflective style can be assumed.

The authors would like to highlight, that prominence values have been assigned which rank the first (l_1) and the third dimension (l_3) higher than the other two, since these have a higher impact with respect to the purpose of the learning situation, which is focused on the aim to deliver appropriate learning material to the learner. Since dimensions l_1 and l_3 are highly critical for the selection process, respectively the adaptation rules which are applied to suit a particular learning style (Section 5), a higher prominence value was assigned. It is obvious, that the assignment of prominence values is a highly subjective process, strongly dependent on the purpose, context and individual preferences. Therefore, future work is aimed at enabling learners to assign rankings of quality dimensions themselves in order to represent their individual priorities regarding the learning context-adaptation and learning resource selection.

4.3. Context-Classification based on Prototypical Situation Parameters

To classify an individual learning style (*css:FSLST Member*), we define prototypical members (*css:FSLST Prototypical Member*) in the FSLST-based vector space *L*. To identify appropriate prototypes, we utilized existing knowledge about typical correlations between the FSLST dimensions, as identified throughout research studies such as [8][24]. In particular, we refer to correlation coefficients which describe dependencies of one particular dimension with each of the other dimensions [24]. For instance, given the fact that a learning style is active in the Active-Reflective dimension, the correlation coefficients with each of the other dimension indicate, that the learner is likely to be sensing, visual and global in the other dimensions. We defined one prototype for each extreme value of each dimension l_i following the indicated correlations in [24]. Moreover, we subsumed prototypes which are equivalently defined by the same prototypical vectors. This resulted in the following 5 prototypical members and their characteristic vectors:

Table 2. Prototypical learning styles defined as prototypical members in the CSS ontology.

Prototype	Act/Ref	Sen/Int	Vis/Ver	Seq/Glo
P1: Active-Visual	**-11**	-11	**-11**	+11
P2: Reflective	**+11**	-11	-11	0
P3: Sensing-Seq.	-11	**-11**	-11	**-11**
P4: Intuitive-Glob.	-11	**+11**	-11	**+11**
P5: Verbal	-11	+11	**+11**	+11

5. FUZZY SWS GOAL DISCOVERY AND ACHIEVEMENT AT RUNTIME

To prove the feasibility of our approach, a proof-of-concept prototype application[2] was provided, which utilizes the CSS metamodel and ontology framework introduced in Sections 3 and 4 to implement a use case from the E-Learning domain.

5.1. Runtime Reasoning Support for CSS and SWS

Analogous to the domain-specificity of SWS domain ontologies, for each domain a specific CSS is derived by applying the CSS metamodel, supported through the *Conceptual Situation Space Ontology (CSSO)*. For instance, to describe situations within the domain of E-Learning, a CSS specific for the domain of E-Learning was provided which is able to represent domain-specific situations described by concepts defined within a particular WSMO domain ontology.

Linking each situation parameter, defined within a WSMO SWS description, to a particular CSS, and defining prototypical instances within each CSS enables the automatic classification of situation parameters in terms of their similarity with a set of prototypical parameters. We would like to highlight, that our approach can be applied not only to WSMO but to other established SWS reference ontologies such as OWL-S [21] in order to extend their expressiveness with comprehensive domain-specific conceptualisations which are grounded to a set of natural quality dimensions. Figure 4 depicts the architecture used to support reasoning on CSS and SWS in distinct domain settings through a Semantic Execution Environment (SEE) which is in our case implemented through IRS-III (Section 2).

[2] The application is utilized within the EU FP6 project LUISA[17].

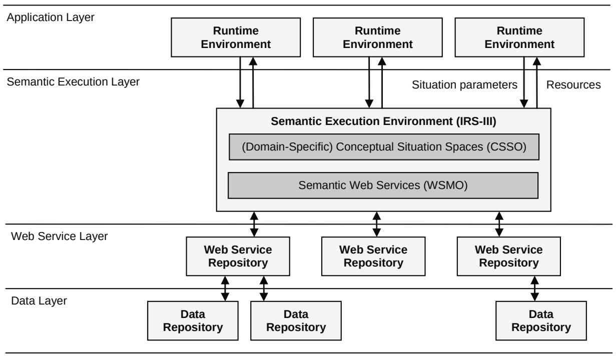

Figure 4. Architecture to support runtime reasoning on CSS and SWS models.

SEE utilizes a semantic representation of the CSS metamodel (CSSO), which is derived for specific domains, and of the SWS metamodel based on WSMO. Both are represented utilizing the OCML representation language [19]. IRS-III dynamically classifies a given situation based on the CSSO and provides resources - represented based on WSMO - which suit a specific runtime situation. Distinct runtime environments can serve as user interfaces to enable users to interact with SEE and to provide knowledge about the current real-world situation. Given a set of real-world situation parameters, their semantic distance to predefined prototypical situation parameters, defined within a domain-specific CSS, is calculated to enable classification of a set of real-world situation parameters. The SEE finally discovers and orchestrates appropriate Web services which show the capabilities to suit the given situation.

5.2. SWS Goal Discovery based on Context Classification

In order to reach situation awareness, the application automatically detects semantic similarity of specific situation parameters with a set of predefined prototypical parameters to enable the allocation of context-appropriate resources through the SEE.

Referring to a CSS subspace *L* described in Section 4.2, given a particular member *U* in *L*, its semantic similarity with each of the prototypical members is indicated by their Euclidean distance. Since we utilize a CSS described by dimensions which each use the same metric scale (ordinal scale), the distance between two members *U* and *V* is calculated disregarding a Z-transformation (Section 3) for each vector:

$$d(u,v) = \sqrt{\sum_{i=1}^{n} p_i (u_i - v_i)^2}$$

The calculation of Euclidean distances using the formula shown above is accomplished by a standard Web service which is exposed as SWS and is invoked through IRS-III at runtime. Given a particular CSS description, a member (representing a specific parameter instance) as well as a set of prototypical member descriptions (representing prototypical parameter instances), the Web service calculates similarities at runtime in order to classify a given situation parameter.

For instance, a particular situation description includes a learner profile indicating a learning style parameter which is defined by a member *U* in the specific CSS subspace to describe learning styles following FSLST (*css:FSLST Space*) with the following vectors:

$$U = \{(u_1 = -5, u_2 = -5, u_3 = -9, u_4 = 3) | u_i \in L\}$$

Learning styles such as the one above, could be assigned to individual learners by utilizing the ILS Questionnaire [7], as assessment method. Calculating the distances between *U* and each of the prototypes described in Table 2 of Section 4.3 led to the following results:

Table 3. Euclidean distances between U and prototypical learning styles.

Prototype	Euclidean Distance
P1: Active-Visual	12.649110640673518
P2: Reflective	20.85665361461421
P3: Sensing-Sequential	17.08800749063506
P4: Intuitive-Global	19.493588689617926
P5: Verbal	31.20897306865447

As depicted in Table 3, the lowest Euclidean distance between *U* and the prototypical learning styles applies to *P1*, indicating a rather active and visual learning style described as in Table 2 of Section 4.3. Figure 5 depicts a screenshot of the user interface of the prototype application presenting a learner profile which shows the several (situation) profile parameters and particularly the learning style of the learner and its distances to prototypes P1 – P5.

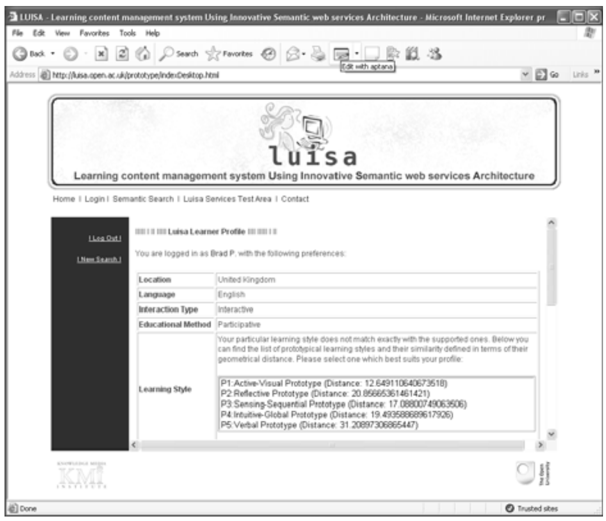

Figure 5. Screenshot of application interface depicting classified learner parameters.

Given the similarities with existing predefined parameters, a user is able to select prototypical parameters which best suit his specific profile. The use of such similarity-based classifications enables the gradual refinement of learning situation description and fuzzy matchmaking between real-world situation parameters, such as *U*, and prototypical parameters such as *P1*.

Classified contexts are utilized to discover the most appropriate SWS goal representation for a given context, by utilizing the alignment of CSS and SWS (Section 3.2). Given a specific situation description, IRS-III first identifies SWS goal representations (*wsmo:Goal*) which suit the given situation and finally selects and orchestrates SWS which are appropriate to suit the given runtime situation. For instance, in the proposed use case, distinct SWS goal representations are available, each retrieving content which addresses a distinct learning style (Figure 6).

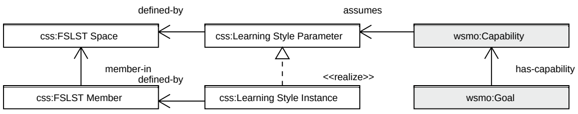

Figure 6. SWS Goals assuming learning styles described as members in a CSS.

Given the similarity-based classification of a set of real-world parameters - e.g. learning styles - a SWS goal representation which assumes matching prototypical parameter instances is selected and achieved through IRS-III (Figure 4, Section 4.1). Finally, IRS-III utilizes the SWS goal capability to identify a SWS which suits the given goal. For instance, given a classified learning style (*css:Learning Style Instance* defined by a *css:FSLST Member*) together with classifications of all further situation parameters, a SWS goal representation which assumes matching prototypical situation parameter instances is selected and achieved at runtime. Consequently, following the alignment of CSS with established SWS frameworks, context-aware SWS applications are enabled which automatically discover not only Web services for a given task but also SWS goal descriptions for a given situation.

6. CONCLUSIONS

In this paper, we proposed an approach to support fuzzy, similarity-based matchmaking between real-world context characteristics and predefined SWS capability descriptions by incorporating semantic context information on a conceptual level into symbolic SWS representations utilizing a novel metamodel for Conceptual Situation Spaces (CSS). By utilizing the CSS and its alignment to SWS technology, the most appropriate resources, whether data or services, for a given situation are identified based on the semantic similarity, calculated in terms of the Euclidean distance, between a given real-world situation and predefined resource descriptions as part of SWS capability representations. Consequently, by aligning CSS to established SWS frameworks, the expressiveness of symbolic SWS standards is extended with context information on a conceptual level to enable fuzzy context-aware discovery of services and resources at runtime. Whereas current SWS frameworks such as WSMO and OWL-S address the allocation of distributed services for a given (semantically) well-described task, the CSS approach particularly addresses the similarity-based discovery of the most appropriate SWS task representation for a given context. To prove the feasibility of our approach, a proof-of-concept prototype application was presented, which applies the CSS metamodel to enable context-adaptive resource discovery in the domain of E-Learning. Whereas the Felder-Silverman Learning Style Theory (FSLST) was exemplarily represented as CSS, the authors would like to highlight that distinct theories could be applied to represent situation parameters. In this paper, FSLST just serves the purpose to illustrate the application of CSS but is not explicitly supported by the authors.

However, although our approach aims at solving Semantic Web (Services)-related issues such as the symbol grounding problem, several criticisms still have to be taken into account when applying CSS. Whereas defining situations, respectively "instances" within a given CSS appears to be a straightforward process of assigning specific values to each quality dimension of a CSS, the definition of the CS itself is not trivial at all and strongly dependent on individual perspectives and subjective appraisals. Whereas the semantics of an object are grounded to metrics in geometrical vector spaces within a CS, the quality dimensions itself are subject to ones perspective and interpretation what may lead to ambiguity issues. With regard to this, the approach of CSS does not appear to fully solve the symbol grounding issue but to shift it from the process of describing instances to the definition of a CSS. This becomes apparent, when defining a CSS for the simple notion of a learning style. Whereas one may define its dimensions to be linearly independent another may argue, that for instance the Active-Reflective dimension and the Sensing-Intuitive dimension are correlated. Moreover, distinct semantic interpretations and conceptual groundings of each dimension may be applied by different individuals. For instance, terms such as "Intuitive" or "Sensing" are not unambiguous in themselves. Apart from that, whereas the size and resolution of a CS is indefinite, defining a reasonable CSS for a specific purpose or domain may become a challenging task. Nevertheless, distance calculation as major contribution of CSS, relies on the fact, that entities are described in the same geometrical space.

Consequently, CS-based approaches such as CSS may be perceived as step forward but do not fully solve the issues related to symbolic Semantic Web (Services)-based knowledge representations. Hence, future work has to deal with the aforementioned issues. For instance, we foresee to enable adjustment of prominence values to quality dimensions of a specific CSS to be accomplished by a user him/herself, in order to most appropriately suit his/her specific priorities and preferences regarding the resource allocation process, since the prioritization of dimensions is a highly individual and subjective process. Besides that, we consider the enrichment of the *CSSO* in order to enable the description of further relevant context parameters based on the CSS metamodel. Nevertheless, further research will be concerned with the application of our approach to further domain-specific situation settings.

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