Fuzzy Context Adaptation through Conceptual Situation Spaces

Stefan Dietze, Alessio Gugliotta, and John Domingue

Abstract.—**Context-adaptive information systems (IS) are highly desired across several application domains and usually rely on matching a particular real-world situation to a finite set of predefined situation parameters. To represent context parameters, semantic and non-semantic representation standards are widely used. However, describing the complex and diverse notion of specific situations is costly and may never reach semantic completeness. Whereas not any situation parameter completely equals another, the number of (predefined) representations of situation parameters is finite. Moreover, following symbolic representation approaches leads to ambiguity issues and does not entail semantic meaningfulness. Consequently, the challenge is to enable fuzzy matchmaking methodologies to match real-world situation characteristics to a finite set of predefined situation descriptions. In this paper, we propose Conceptual Situation Spaces (CSS) which enable the description of situation characteristics as members in geometrical vector spaces following the idea of Conceptual Spaces. Consequently, fuzzy matchmaking is supported by calculating the semantic similarity between the current situation and prototypical situation descriptions in terms of their Euclidean distance within a CSS. Aligning CSS to existing symbolic representation standards, enables the automatic matchmaking between real-world situation characteristics and symbolic parameter representations. To prove the feasibility, we apply our approach to the domain of e-Learning.**

I. INTRODUCTION

CONTEXT-awareness is an highly important feature in information systems (IS) across a wide variety of application domains and subject to intensive research throughout the last decade [3][10][18]. 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 of IS to adapt to distinct possible situations.

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IS usually are build upon the principle of matching a particular real-world situation to a set of predefined situation parameters in order to enable predefined context-adaptation rules to be applied. To represent situation parameters, currently either non-semantic representations, based on XML or relational database models, or more recently, semantic representations - namely ontologies [12] - based on representation languages such as RDF [19] or OWL [21] are used.

However, describing the complex notion of a specific situation 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 representation standards leads to ambiguity issues and does not entail semantic meaningfulness, since meaning requires both the definition of a terminology in terms of a logical structure (using symbols) and grounding of symbols [1][16] to a conceptual level. Furthermore, whereas not any situation and situation parameter completely equals another, the number of (predefined) representations of situations or situation parameters is finite. Consequently, the challenge is to enable fuzzy matchmaking methodologies to match the potentially infinite set of real-world situation characteristics to a finite set of predefined situation and situation parameter descriptions.

Conceptual Spaces (CS), introduced by Gärdenfors [8][9], 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 semantic similarity, in terms of the Euclidean distance between two instances (members), in contrast to the costly representation of such knowledge through symbolic Semantic Web (SW) representations. Even though several criticisms have to be taken into account when utilizing CS (Section IV) they are considered to be a viable option for knowledge representation.

In this paper, we propose *Conceptual Situation Spaces (CSS)*, which enable the conceptual representation of situation characteristics and their mapping to symbolic

SW representations. Utilizing CSS enables a fuzzy, similarity-based matchmaking methodology between real-world situation characteristics and predefined symbolic situation parameters representations. Whereas similarity between situation parameters, as described through CSS, is indicated by the Euclidean distance between them, real-world situation parameters are classified along predefined prototypical parameters, which are implicit elements of SW-based representations.

To prove the feasibility of our approach, we extended previous work in the e-Learning domain [4] by adopting CSS to describe learning styles, following the Felder-Silverman Learning Style theory [5] as particular learning situation parameter.

The paper is organized as follows. Section II introduces Conceptual Situation Spaces. Section III illustrates the application of CSS to the e-Learning domain and introduces a *Conceptual Learning Situation Space (CLSS)* which is utilized within a proof-of-concept prototype application. Finally, we conclude our work in Section V and provide an outlook to future research.

II. CONCEPTUAL SITUATION SPACES

Conceptual Situation Spaces (CSS) enable the description of a particular situation as a member within a dedicated CS. Referring to [9][13][17], we define a CSS as a vector space (*css:Conceptual Space* as depicted in Figure 1):

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

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 [9] - but enable dimensions to be detailed further in terms of subspaces. Thus, a dimension within one space may be defined through an additional subspace by using further dimensions [17]. 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 that, a CSS may be composed of several subspaces and consequently, the description granularity of a specific situation can be refined gradually. Each dimension uses a specific metric (*css:Metric Scale*) whereas its values are described using a specific datatype (*css:Datatype*). To reflect the impact of a specific quality dimension on the entire space, a prominence value *p* (*css:Prominence*) is considered for each dimension. Therefore, a conceptual space is defined by:

$$C^n = \{(p_1c_1, p_2c_2, ..., p_nc_n) | c_i \in C, p_i \in P\}$$

where *P* is the set of real numbers. However, the usage context, respectively the domain, of a particular CSS strongly influences the ranking of its quality dimensions. For instance, within a learning situation the competencies of a particular learner may be more important whereas in a business situation, the costs of a particular task may have a higher impact. This clearly supports our position of describing distinct CSS explicitly for specific domains only.

Members (*css:Member)* in the CSS are described by a set of valued dimension vectors (*css:Valued Dimension Vectors*). Moreover, referring to [9], we consider prototypes which represent specific prototypical members (*css:Prototypical Member*) within a particular space. Prototypical members are utilised to categorize a specific CSS member, in that they enable the classification of any arbitrary member *m* within the same space, by simply calculating the Euclidean distances between *m* and all prototypical members 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:

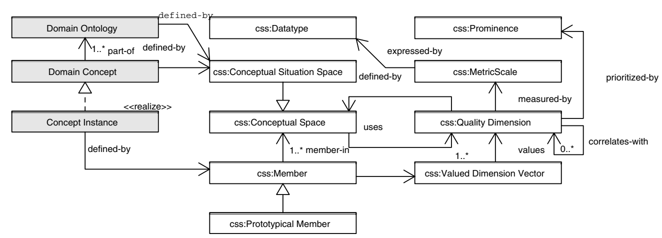

Fig. 1. The CSS metamodel and its relation to generic domain ontology representations.

Even though, the CSS metamodel depicted in Figure 1could be represented by using any kind of knowledge representation language, it currently has been formalized in a *Conceptual Situation Space Ontology (CSSO)* utilizing the OCML knowledge modelling language [15]. In particular, each of the depicted entities is represented as a concept within CSSO whereas associations are reflected as their properties in the most cases. The correlation relationship between two quality dimensions indicates, whether or not two dimensions are correlated. 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.

Figure 1 also depicts the relation between a CSS and symbolic conceptualisations. Given the fact, that CSS can be refined gradually based on subspaces, either a symbolic domain conceptualization (*Domain Ontology*) or a particular domain concept (*Domain Concept*) is defined by a CSS (*css:Conceptual Situation Space*). Instances of concepts are represented as members within a CSS. By creating domain-specific derivations of the CSSO, opportunely aligned to specific domain ontologies, the metamodel can be applied to distinct domains.

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 [17] to our definition of a CSS, the Euclidean distance between two members in a CSS is formalized as follows.

Given a CSS definition *C* and two members within *C* which are represented by two vector sets *V* and *U*, defined by vectors $v_0, v_1, \ldots, v_n$ and $u_1, u_2, \ldots, u_n$ the distance between *V* and *U* can be calculated as:

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

where $z(u_i)$ is the so-called Z-transformation or standardization [2][17] 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 to be 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:

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

III. SPANNING A CONCEPTUAL LEARNING SITUATION SPACE

As Gärdenfors states in [9], the prioritization of certain quality dimensions within a CS is highly dependent from the context and purpose of the space. This applies particularly to situations represented through CSS. Whereas a learning situation may be dependent on quality dimensions such as ones competencies or learning objectives, a business situation context 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.

To prove the feasibility of our approach, we apply CSS to the e-Learning domain and utilize it within a prototype application which is thoroughly described in [4]. The application is aimed at context-aware retrieval of learning resources by using symbolic SW representation standards. In order to enable rather fuzzy situation awareness, we introduce a CSS for the e-Learning domain, a *Conceptual Learning Situation Space (CLSS)*. The CLSS grounds to a conceptual level the symbolic representations of a *Learning Process Ontology* (*LPO)*, which conceptualizes e-Learning domain-specific situations and parameters. Therefore, the fuzzy allocation of context-appropriate resources is supported.

A. Learning Style as a particular CLSS Subspace

As described in [4], 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 II). Therefore, this section focuses exemplarily on the representation of one parameter through a CLSS subspace, which is of particular interest for 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 [14]. Whereas each individual has his/her distinct learning style, it affects the learning process 0 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 SW 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.

B. A CLSS following the Felder-Silverman Learning Style Theory

To describe a learning style, we refer to the Felder-Silverman Learning Style Theory (FSLST) [5] as approach to describe learning styles within computer-aided educational environments 0. 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 [5]. 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 [7][11][19] 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 2 depicts the key concepts of the ontology describing L as subspace (*clss:FSLST Space*) within the CLSS representing the Felder-Silverman Learning Style Theory.

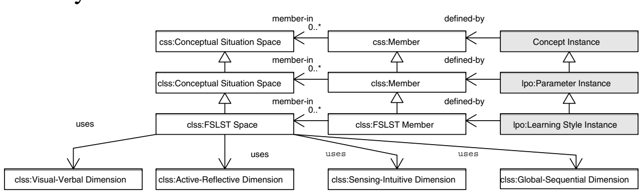

Fig. 2. Key concepts representing the FSLST as CLSS subspace.

Moreover, Figure 2 depicts the alignment of the subspace L (*clss:FSLST Space*) with the CSS metamodel as well as LPO descriptions (grey-colored concepts).

To refer symbolic representations of the LPO to CSS-based representations, a domain-specific derivation of the CSSO has been provided for the e-Learning domain: the *Conceptual Learning Situation Space Ontology (CLSSO).* Referring to the learning style, instances of a parameter representing the learning style within the LPO (*lpo:Learning Style*) are defined by particular members (*clss:FSLST Member*) within the space L (*clss: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 ordinal 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 [6], 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 on the context 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 D), 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.

C. Context Classification based on Prototypes

To classify an individual learning style (*clss:FSLST Member*), we define prototypical members (*clss: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 [7] and [19]. In particular, we refer to correlation coefficients which describe dependencies of one particular dimension with each of the other dimensions

[19]. 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 [19]. 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.

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

D. Fuzzy Context-Adaptation 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), similarities are calculated by a dedicated Web service at runtime in order to classify a given situation parameter. Referring to CLSS subspace *L* (Section B), given a particular member *U* in *L*, its semantic similarity with each of the prototypical members is indicated by their Euclidean distance, calculated by using the formula described in Section II.

For instance, a particular situation description represented through LPO includes a learner profile indicating a learning style parameter which is defined by a member *U* in the specific CLSS subspace to describe learning styles following FSLST (*clss: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 [6], as assessment method. Calculating the distances between *U* and each of the prototypes described in Table 2 of Section C 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 C.

Given the similarities with existing predefined parameters, a user is able to select prototypical parameters that best suit his specific profile. The use of such similarity-based classifications enables the gradual refinement of symbolic learning situation descriptions and finally, fuzzy matchmaking between real-world situation parameters, such as *U*, and prototypical parameters such as *P1*. Given this approach, similarity-based matching between a real-world context and symbolic resource descriptions - for instance described using LPO – is supported.

IV. CONCLUSIONS

In this paper, we proposed an approach to support fuzzy, similarity-based matchmaking between real-world situation parameters and predefined semantic situation descriptions by incorporating semantic context information on a conceptual level into common symbolic SW descriptions utilizing a novel metamodel of Conceptual Situation Spaces. Given the CSS metamodel, the most appropriate resources, whether data or services, for a given situation can be identified based on the semantic similarity, calculated in terms of the Euclidean distance, between a given real-world situation and predefined resource descriptions. To prove the feasibility of our approach, a proof-of-concept prototype application was implemented, 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 applies CS to solve SW-related issues such as the symbol grounding problem, several criticisms still have to be taken into account when applying CSS, and CS in general. Whereas defining objects, respectively situations, within a given CSS appears to be a straightforward process of assigning specific values to each quality dimension, the definition of the CS itself is not trivial at all and is strongly dependent on individual perspectives and subjective appraisals. Whereas the semantics of an object are grounded to metrics in geometrical vector spaces within a CSS, the quality dimensions itself are subject to ones perspective and interpretation what may lead to ambiguity issues. With regard to this, the approach of CS does not appear to completely solve the symbol grounding issue but to shift it from the process of describing instances to the definition of a CS. 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 one 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 CSS is indefinite, defining a reasonable CSS for a specific context might become a challenging task. Nevertheless, distance calculation as major contribution of the CSS approach, relies on the fact, that concepts 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 SW-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 CLSSO in order to enable the representation of further e-Learning situation parameters based on the CSS metamodel. Nevertheless, further research will be concerned with the application of CSS to further domain situations, for instance business process situations.

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