Spatial Groundings for meaningful Symbols

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Abstract. The increasing availability of ontologies raises the need to establish relationships and make inferences across heterogeneous knowledge models. The approach proposed and supported by knowledge representation standards consists in establishing formal symbolic descriptions of a conceptualisation, which, it has been argued, lack grounding and are not expressive enough to allow to identify relations across separate ontologies. Ontology mapping approaches address this issue by exploiting structural or linguistic similarities between symbolic entities, which is costly, error-prone, and in most cases lack cognitive soundness. We argue that knowledge representation paradigms should have a better support for similarity and propose two distinct approaches to achieve it. We first present a representational approach which allows to ground symbolic ontologies by using Conceptual Spaces (CS), allowing for automated computation of similarities between instances across ontologies. An alternative approach is presented, which considers symbolic entities as contextual interpretations of processes in spacetime or Differences. By becoming a process of interpretation, symbols acquire the same status as other processes in the world and can be described (tagged) as well, which allows the bottom-up production of meaning.

1 INTRODUCTION

The widespread use of ontologies as a knowledge engineering device [15] together with the increasing availability of representations of overlapping domains of interest, raises the need to integrate distinct ontologies. This becomes crucial when considering the exploitation of the growing *Semantic Web (SW)* which naturally consists of multiple distributed ontological representations. Following a symbolic representation approach – as done by established representation standards such as RDF-S [29] and OWL [28] – requires the heterogeneity across distinct formalisations to be addressed and relationships between entities across ontologies to be (a) identified and (b) explicitly represented. Hence, formal relations are to be established between a set of knowledge entities E_1 from an ontology O_1 with the corresponding entities E_2 in a distinct ontology O_2 [7][26]. The expression *set of entities* here refers to the union of all concepts C, instances I, relations R and axioms A defined in a particular ontology. In that, the identification and representation of *similarities* [1] between entities across different ontologies, appears to be a necessary requirement to support interoperability between multiple heterogeneous ontologies.

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However, with respect to this goal, several issues have to be taken into account. The symbolic approach proposed by knowledge representation and SW standards – describing symbols by using other symbols – has been criticised for lacking the grounding to a cognitive or perceptual level, what is known as the symbol grounding problem[16]. Without a grounding – i.e. linking symbols to cognition and to the observable reality - heterogeneity across ontologies cannot be handled appropriately [3][20]. Describing all aspects of a specific concept using symbolic representations is a costly task as well as a doubtful one, as the intended meaning of a symbolic concept usually depends on the context of its usage [25].

Due to these issues, in order to address (a), i.e. to identify knowledge entities which represent the same or similar meaning in distinct ontologies, current *ontology mapping* approaches have to exploit similarities at the symbolic level, e.g. based on linguistic or structural similarities across entities [8][13][19][7][26]. But such manual or semi-automatic identification of similarity relationships is also costly and prone to errors. Moreover, since knowledge entities across distinct ontologies usually represent real-world concepts which resemble each other just to a certain extent, representation of the gradual notion of similarity as in (b) is another challenge. Several approaches from the field of *fuzzy logic* aim at the representation of fuzzy and gradual relationships [2][13][23]. These approaches usually rely on the explicit, manual representation of relationships what is a costly and error-prone process as well, and also, tends to capture the subjective viewpoint of one individual.

Therefore, representational frameworks which enable to implicitly describe similarities across ontologies are required to fully facilitate ontology interoperability. Several approaches try to automate the computation of similarities through spatially oriented knowledge representation models. The *Conceptual Spaces (CS)* theory [11] proposes to describe concepts by gradual levels of abstraction starting with elementary sensory features, in order to bridge between the cognitive and the symbolic world. Concepts are represented as multidimensional *Vector Spaces (VS)*, and instances are represented as vectors, i.e. points, in these spaces. *Soft Ontologies (SO)* [17]follow a similar approach by representing a knowledge domain D through a multi-dimensional *ontospace A*. An item I, i.e. an instance, is represented by scaling each dimension to reflect its impact, presence or probability in the case of I. In that, a SO can be perceived as a CS where dimensions are measured exclusively on a ratio-scale. Hence, by relying on measurement-based representation of perceptual features, CS, VS and SO enable the automatic computation of instance similarity by means of distance metrics such as the Euclidean, Taxicab or Manhattan distance [18] or the Minkowsky Metric [24]. However, similarity computation requires the description of concepts through quantifiable metrics, even in case of qualitative characteristics. Moreover, these representation approaches do not provide the

means to represent arbitrary relations [22], such as *part-of* relations, common to symbolic knowledge models. In this regard, it is even more obstructive that the scope of a dimension cannot be defined, i.e. a dimension always applies to the entire CS/SO, for example the colour dimension applies to the whole entity rather than to parts of it [22]. Moreover, it can be argued, that representing an entire knowledge model through a coherent spatial representation, e.g. a CS, might not be feasible, particularly when attempting to maintain the meaningfulness of the spatial distance as a similarity measure.

Another issue with these approaches is that the spaces described are linked to cognitive structures, not to the environment itself. It could be argued that cognition mirrors the environment and that therefore such an approach is grounded. However, this grounding, as in the case of symbols, is only implicit. Moreover, when dimensions of a CS are linked to actual space and time, for example to represent the movement or growth of an entity, actual space and time have to be modeled as explicit conceptual spaces, detached from the environment. A more natural approach would be to consider spacetime as the underlying structure of all entities, and hence, of their conceptual representations, rather than a particular kind of "space".

2 ADDING MEANING TO SYMBOLS THROUGH SPATITEMPORAL GROUNDINGS

Spatiotemporal representations of knowledge are a promising approach to ontology grounding, even considering the previous issues. Indeed, space and time appear to be both cognitive and physical structures. Moreover distances seem the most natural way to represent similarity. We argue that some of the aforementioned issues can be alleviated by applying spatiotemporal structures to individual concepts instead of representing the whole ontology in a single spatial representation. We propose two approaches to achieve this.

2.1 Grounding Ontologies in Conceptual Spaces

A hybrid representational approach – combining symbolic ontologies with corresponding spatial representations – has the potential to enable similarity computation across ontologies. In that, we consider the representation of a set of n concepts C of an ontology O through a set of n spatial representations SR, where SR would be realized e.g. through a representation in a CS as proposed in previous work [5][22]. Figure 1 illustrates the grounding of ontologies in multiple CS as proposed in [5].
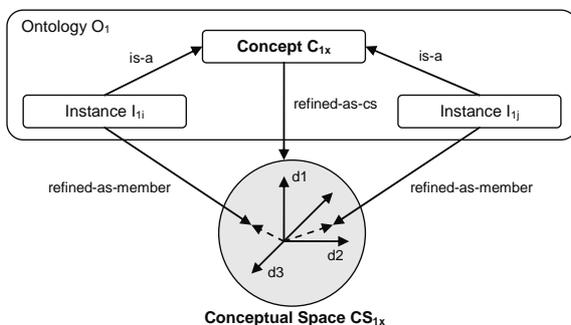

Figure 1. Grounding ontologies in multiple CS.

Note, in order to facilitate this vision, [5] proposes an ontology (CSO) which allows to refine any arbitrary concept as a CS instance while ontology instances are represented as member instances in CSO. After these additional steps, similarity between instances across distinct ontologies is computed by means of their Euclidean distance.

In [4][6] applications are proposed which make use of CSO and the representational approach described here to enable Semantic Web Service (SWS) [9] interoperability. Symbolic representations of the contexts which are either targeted by available SWS or desired by particular service consumers are refined by means of CSO. Based on similarity-computation within CS, the most similar SWS for a given query is being discovered and executed. In that, [4][6] prove the applicability of the proposed representational approach to contribute to the ontology alignment problem and provide detailed case studies from two distinct domains, eLearning and location-based applications.

While still benefiting from implicit similarity information, such a hybrid approach allows maintaining the advantages of ontological knowledge representations. As proposed in [5], spatial representations can be defined in dedicated ontologies. Such a two-fold representational approach allows the implicit representation of similarities between instances across heterogeneous ontologies, and consequently, provides a means to facilitate ontology interoperability. As shown in [4], applying this approach has the potential to reduce the effort required to align distinct heterogeneous ontologies and the extent to which two distinct parties have to share their conceptualisations. Whereas traditional ontology mapping methodologies rely on mechanisms to semi-automatically detect and formally represent similarities at the concept and the instance level, our approach just requires a common agreement at the concept level since similarity information at the instance level is implicitly defined.

2.2 Grounding Ontologies in Processual Spacetime

Another approach to the spatiotemporal grounding of ontologies, introduced in [25][26] and[27], considers reality as a processual continuum structured by spacetime. So-called objects are processes persisting in their form of function and only superficially detached from the larger processual flux. The symbolic approach of naming an element of the world is a process that isolates an entity according to a context. It is the variety of contexts (cultures, languages, purposes, etc.) which produces heterogeneity across ontologies.When isolated from the processual flux, but not yet integrated to a KR paradigm, such as CS or taxonomies, a meaningful entity can be called a *difference*. Differences represent processes and the regions of spacetime that they shape through their activity. They do not require a pre-existing formal conceptualisation, and can therefore appropriately be represented by *tags*. Tags, as everything else, are a part of the processual environment and can also be described, i.e. tagged. We have designed Tagopedia[3] to collect a user's tags and to allow the tag owner as well as other users to *tag the tags* themselves. For example *tank* can be tagged by user *u1* with *fish*, *u2* can tag it with *weapon* and *war*, and *u3* with *container*, and *u4* with *vehicle*. This extension of collaborative

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[3] http://tagopedia.info/

tagging systems has been dubbed *extreme tagging systems*, or ETS. After tagging a tag, the user selects the type of relation between the two tags from a small set. One of the possible relations is *similarity* (e.g. between *tank* and *container* or *vehicle*), another is *copresence* which expresses the fact that two differences (the entities represented by the tags) are often found together in space and time (e.g. *tank*, *weapon* and *war* at the time period when the tagging occurs). Rather than considering the actual shape of a dimension like in CS or having to specify a ratio for characteristics like in SO, the resulting network is arranged according to similarity and frequence relations. A frequentist interpretation of probability provides weights to the graph links: the more often a relation is tagged as similar, the closer the node's meanings are, which shapes the corresponding space. This network can then be consulted in order to map entities from an ontology: the concept *tank* with *wheels* will be associated with *vehicle* from a target ontology even if this concept is not present in the source ontology. Other inferences are possible with this framework. For example, from the fact that *cat* is marked as *copresent* with *house*, one could infer, with the appropriate ontology, that a cat is a kind of pet.

Extreme tagging has been used in [26] to provide an emergent notion of place by linking ETS with Wordnet: tags recognized as geographical entities which were linked to differences recognized as affordances where identified as a geographical place relevant to the query. In [25] an ETS was used to discover relevant services at an appropriate scale. For example (cf. Figure 2), user *u1* is looking for emergency information about a town of interest. Town co-occurs with street in the system's ETS graph but street has not yet been geotagged in the same area. However, it has been linked to the service *s-roads* by user *u2*. This service is geotagged in that region at the appropriate scale and is therefore displayed.
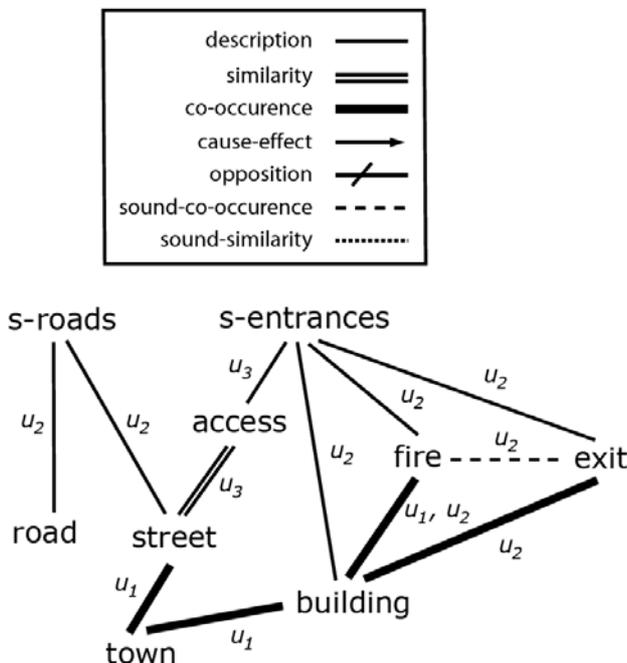

Figure 2. List of associations and ETS graph for service discovery.

In the *Cultures of Legibility* project[4] ETS will be used to present an image of the city defined by places involved in the daily rhythms of the inhabitants. By collecting information about the routines of city dwellers, as well as data regarding their geographical trace and tag based descriptions of the places of interest along these routes, the project aims to provide an image of the city formed by its usage rather than land use categories.

3 CONCLUSION

In this paper we presented two novel approaches which aim at alleviating the lack of of grounding of symbolic ontologies in order to ease the integration of heterogeneous knowledge models.

The first approach proposes a grounding of ontologies in spatial representations – such as CS – and allows for automated computation of similarities of instances across heterogeneous ontologies by means of their spatial distances in the set of shared CS. Hence, it extends symbolic ontologies with grounding to a cognitive level and hence, facilitates similarity computation across ontologies while still taking advantage of the knowledge represented at the symbolic level, such as arbitrary relations between knowledge entities.

The second approach, based on grounding in processual spacetime, offers a bottom-up method to the production of meaning. Similarity is defined by users according to various contexts, which ensures that the result is cognitively sound. Co-occurence ensures a link with the processual environment, and therefore a grounding in reality.

Nevertheless, the contributions stated above come to a certain cost. The first approach (Section 2.1) requires additional effort to establish spatial groundings based on measurements and some issues related with VS-based knowledge representation still remain. For instance, whereas defining instances, i.e. vectors, within a given VS appears to be a straightforward process of assigning specific quantitative values to quality dimensions, the definition of the VS itself is not trivial at all and dependent on individual perspectives and subjective appraisals. The second approach (Section 2.2) leads to issues related to appealing to the "wisdom of crowds" which can be biased or inappropriate for some domains. However, the possibility to restrict the resulting network to the descriptions of members of selected communities can alleviate this. VS-based approaches appear to not fully solve the symbol grounding issue but to shift it from the process of describing instances to the definition of the spatial representation, and the need may occur to align the spaces themselves. Therefore future work on the links of these with actual spatiotemporal processes is needed. Nevertheless, as instance similarity computation becomes an increasingly important challenge, the further investigation of spatial groundings for symbolic representation models seems to us an essential step towards the vision of interoperable ontologies.

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