Semantic Web 0 (0) 1
IOS Press

Foundational Ontologies meet Ontology Matching: A Survey

Daniela Schmidt[1], Giancarlo Guizzardi[2], Adam Pease[3], Cassia Trojahn[4], Renata Vieira[5]
[1] *School of Technology, PUCRS, Brazil*
2 *Free University of Bozen-Bolzano (KRDB/UNIBZ), Italy*
[3] *Articulate Software, USA*
[4]*Institut de Recherche en Informatique de Toulouse France,*
[5]*CIDEHUS, University of Évora, Portugal*

Abstract. Ontology matching is a research area aiming at finding ways to make different ontologies interoperable. Solutions to the problem have been proposed from many disciplines, including databases, natural language processing, and machine learning. The role of foundational ontologies for ontology matching is an important one, it is multifaceted and with room for development. This paper presents an overview of the different tasks involved in ontology matching that consider foundational ontologies. We discuss the weaknesses of existing proposals and highlight the challenges to be addressed in the future.

Keywords: ontology matching, complex alignment, survey, schema matching

1. Introduction

Ontologies can be classified according to their "level of generality", in particular [23]: *(i) foundational ontologies* describe general concepts (e.g., object, event, quality) and relations (e.g., parthood, participation, dependence, causality), which are independent of a particular domain. These ontologies, also named upper or top-level, are sometimes equipped with a rich axiomatic layer; *(ii) domain ontologies* that may also describe the entities related to a particular domain (e.g., biology or aeronautics). The clarity in semantics and a rich formalization of foundational ontologies are important requirements for ontology development improving ontology quality [32, 43] and preventing bad ontology design [26, 59]. These ontologies may also act as semantic bridges supporting interoperability between ontologies [29, 41, 42]. Furthermore, as stated in [2], in the scale of the Linked Open Data, *distinctions such as whether an entity is inherently a class or an individual, or whether it is a physical object or not, are hardly expressed in the data, although they have been largely studied and formalised by foundational ontologies*. Such distinctions are however key aspects in many applications in Artificial Intelligence.

Two approaches for the use of foundational ontologies in the development and integration domain ontologies [60] are (1) a *top-down approach*, the foundational ontology is used as a reference for deriving domain concepts, taking advantage of the knowledge and experience already encoded in it and (2) a *bottom-up approach*, where one usually matches an existing domain ontology to a foundational one. The latter is more challenging since inconsistencies may exist between domain and foundational ontologies and one has to deal with different levels of abstraction and also of formalization in the matching process.

Ontology matching can be seen as the task of generating a set of correspondences (i.e., an alignment) between the entities of different ontologies [13]. Correspondences express relationships between ontology entities, for instance, that an `Author` in one source ontology is equivalent to `Writer` in one target ontology, or that `Writer` in the source is subclass of `Person` in the target. A set of correspondences between two ontologies is called an alignment.

Whereas the area of ontology matching has developed in the last decades, the problem of matching ontologies involving foundational ontologies has seen less development regarding automatic solutions [35, 58]. This is not surprising since matching foundational and domain ontologies is a highly complex task, even when done manually. It requires the deep identification of the semantic context of concepts and, in particular, the identification of subsumption relations. In fact, subsumption and other relations are often neglected by most state-of-the-art matchers.

There is, however, a significant movement regarding foundational ontologies and ontology matching on other grounds. There is a considerable effort for making sense of different foundational ontologies, how they relate to other lexical and semantic data bases, and how they improve the process of matching domain ontologies.

Considering this scenario, this paper reviews the following tasks of ontology matching involving foundational ontologies:

(i) matching of foundational ontologies;

(ii) matching of foundational ontologies to lexicons;

(iii) matching domain ontologies with the help of foundational ontologies; and

(iv) matching foundational ontologies to domain ontologies.

We discuss the main weaknesses of existing approaches and highlight the challenges to be addressed in the the future. We consider that this comprehensive study may set the grounds for advancing domain and foundational ontology matching.

The rest of the paper is organised as follows: §2 introduces the different foundational ontologies. §3-§6 discuss the approaches in the categories (i)-(iv) introduced above. Finally, §7 discusses the open challenges in the field.

2. Foundational ontologies

A foundational ontology is a high-level and domain independent ontology whose concepts (e.g., object, event, quality, disposition) and relations (e.g., parthood, participation, dependence, causality) are intended to be basic and universal to ensure generality and expressiveness for a wide range of domains. It is often characterized as representing commonsense concepts and is limited to concepts which are meta, generic, and philosophical. Diverse foundational ontologies have been developed, influenced by different philosophies and views on the reality. Several comparisons can be found in the literature, as in [33, 41, 60].

Some common criteria for comparing ontologies are artifact representation criteria (dimensions, representation languages, modularity) [41], ontological commitments and subject domain and applications [33].

We introduce the main insights behind each proposal. Their different variants and versions, and the availability of alignments to lexical resources (as WordNet [45]) and ontologies are discussed in the following sections.

- **BFO** [1, 20] [1] (*Basic Formal Ontology*) that adopts a *realistic approach* in terms of the existence in time of entities populating the world. It represents the reality into two disjoint categories of *continuant* (independent and dependent continuants, attributes, and locations) and *occurrent* (processes and temporal regions). It has 34 terms and a similar number of axioms. It is defined in OWL[2] and first-order logic language CLIF[3].
- **DOLCE** [16] (*Descriptive Ontology for Linguistic and Cognitive Engineering*) is an ontology of *particulars* which adopts a *descriptive approach* with a clear cognitive bias, as it aims at capturing the ontological categories underlying natural language and human commonsense. DOLCE is based on a fundamental distinction between *endurant* and *perdurant* entities. *Endurants* represent objects or substances while *perdurants* corresponds to events or processes. The main relation between *endurants* and *perdurants* is that of participation. DOLCE was originally written in the first-order logical language KIF [19] and includes roughly 100 terms and a similar number of axioms. Recent work maintains DOLCE in OWL.
- **Cyc** [24] is a proprietary ontology comprising both an upper-level ontology and a set of domain ontologies in a wide variety of domains. It is meant for the representation of facts, rules, and heuristics to reason about the objects and events of everyday life in the Cyc knowledge base. It involves thousands of "microtheories" with hundreds of thousands of terms and millions of axioms. It comprises OpenCyc is an open source subset of Cyc that is no longer maintained. It is defined in the higher-order CycL language [37].

[1] https://github.com/bfo-ontology/BFO/wiki
[2] https://www.w3.org/OWL/
[3] https://www.iso.org/standard/39175.html

- **GFO** [30][4] (*General Formal Ontology*) considers basic distinctions between individuals. Concrete individuals exist in time or space whereas abstract individuals do not. While an *endurant* is an individual that exists in time, but cannot be described as having temporal parts or phases; a *process*, on the other hand, is extended in time. It is defined in OWL and has 243 terms.
- **PROTON** [68][5] (*PROTo ONtology*) serves as a lightweight foundational ontology organized in four modules. The *top ontology* module, for instance, distinguishes entity types, such as *object* as existing entities (agents, locations, vehicles); *happening* as events and situations; and *abstract* as abstractions that are neither objects, nor happenings. It contains about 500 classes and 150 properties, providing coverage of the general concepts necessary for a wide range of tasks, including semantic annotation, indexing, and retrieval. This ontology is codified in OWL-Lite.
- **SUMO** [48, 53][6] (*Suggested Upper Merged Ontology*) is defined in the higher order logical language of SUO-KIF[7]. It includes dozens of domains ontologies, and contains roughly 20,000 terms and 80,000 logical statements. It has an associated toolset [52], translations to languages used in theorem proving and a complete set of mappings to WordNet[49]
- **UFO** [25, 27][8] (*Unified Foundational Ontology*) has been developed with the intention of providing foundations for Conceptual Modeling. It started as an unification of the GFO and the foundational ontology of universals underlying OntoClean[9]. UFO is divided in three parts representing different aspects of reality: A - endurants (dependent and independent objects and their types), B - perdurants (events and situations), and C - social entities, with notions such as beliefs, desires, intentions, etc. UFO-A has been formalized in First-Order Modal Logics [25, 27, 28] (e.g., the microtheory of endurant universals contains 31 axioms [28]; the microtheory theory dealing with relations contains circa 20 axioms) [14]; UFO-B has been completely formalized in First-Order Logics (185 axioms) with a (partial) translation to $\mathcal{SROIQ}$ [4]. Furthermore, UFO-A has also been used as the foundational for the ontology-driven conceptual modeling language OntoUML [27]. As a foundational for defining the semantics of this language: UFO-A has also been formalized in Alloy, thus, allowing for formal validation of the entire theory via visual simulation [3]; the OntoUML design patterns representing UFO's underlying micro-theories have been formalized in a Single-Push out categorical system in [71].

This list gives an idea of the variety of proposals for a foundational ontology, and it is not exhaustive. There are other top or foundational ontologies such as SOWA's ontology[10], YAMATO [46], GIST [69], KIOTO[11], PSL (Process Specification Language (PSL) [21] or still BORO (Business Objects Reference Ontology) [11].

3. Matching foundational ontologies

As stated in [34], while the purpose of a foundational ontology is to address interoperability among ontologies, the development of different foundational ontologies re-introduces the problem. As briefly discussed in the previous section, these ontologies have been developed directed at different classes of applications, as well as relying on different theoretical assumptions. Early work addressed this problem [20, 63, 67] from different perspectives. While [20] compared specific treatments of fundamental issues (as significant discrepancies related to universals and particulars, qualities, constitution and spatio-temporality) and how similar notions apply differently in BFO and DOLCE, [63] compared the primitive relations (dependence, quality, and constitution) between these ontologies. In [67], an alignment between BFO and DOLCE was established in order to conciliate their respective realistic and cognitive points of view and to integrate medical data. While 100% of BFO categories were aligned to DOLCE, 81% of DOLCE categories were aligned to BFO. More recently, under another perspective, [70] compares BORO and UFO ontologies according to the their metaphysical choices that define their structure and composition. In other words, instead of comparing terms in both ontologies, the authors compare how the two approaches address issues such as *identity* and *dynamic classification*, the

[4] http://www.onto-med.de/ontologies/gfo/
[5] http://ontotext.com/proton
[6] http://www.ontologyportal.org
[7] https://github.com/ontologyportal/sigmakee/blob/master
[8] http://dev.nemo.inf.ufes.br/seon/UFO.html
[9] http://www.ontoclean.org
[10] http://www.jfsowa.com/ontology/toplevel.htm
[11] http://kyoto-project.eu/xmlgroup.iit.cnr.it/kyoto/index.html

treatment of *relationships* (i.e., instances of *relational properties*), as well as the relation between *existence* and *time* in the two approaches. Unlike the case of BFO and DOLCE, which are both tri-dimensionalist (3D) ontologies, while UFO is a 3D ontology, BORO is a Four-dimensionalist (4D) one. The radical difference between these two ontologies, hence, reflect deeper differences in ways of conceiving reality.

Other studies addressed other foundational ontologies. In [34], alignments between BFO, DOLCE and GFO have been established with automatic matching tools and manually, with substantially fewer alignments found by the matching tools. The alignments in the context of the whole ontology revealed a considerable amount of logical inconsistencies.

In [47], the core characterization of mereotopology (a theory of physical parts) of SUMO and DOLCE has been studied, relating their axiomatizations via ontology alignments. This included corrections and additions of axioms to the analyzed theories which eliminate unintended models and characterize missing ones. Finding alignments between DOLCE and SUMO was also addressed in [50], where the SmartDOLCE and SmartSUMO ontologies have been developed on the basis of DOLCE and SUMO. The alignment of the just the taxonomic statements from SUMO to DOLCE involved extracting the upper-level of SUMO and the non-trivial task of aligning the remaining concepts to appropriate DOLCE categories. Aligning foundational ontologies reveals also the problem of matching their different versions. In [61], a method for tracking, explaining and measuring changes between successive versions of BFO1.0, BFO1.1, and BFO2.0 was applied. The aim was to provide a more comprehensive analysis of the changes with respect to the BFOConvert tool[12] which provides an alignment between previous BFO versions, as this resource is limited to allow for a full understanding of the impact of the changes.

Mathematical ontologies [8] within the Common Logic Ontology Repository (COLORE), which are used for the verification of upper ontologies, are applied for the specification of mappings between upper ontologies in [22],. In the same line, [9] shows how to apply techniques for ontology verification to link interpretations among ontologies.

[12]http://ontobull.hegroup.org/bfoconvert (viewed on 25/03/2019)

4. Matching foundational ontologies to lexicons

Several works on equipping lexical resources with foundational ontologies are developed in order to associate a formal semantics to their lexical layer. As stated in [15, 16], while WordNet has been used in numerous works as an ontology, where the hyponym relations between word senses are interpreted as subsumptions relation between concepts, *it is only serviceable as an ontology if some of its links are interpreted according to a formal semantics that tell us something about the world and not just about the language*. In that sense, they have investigated different ontological problems in WordNet (e.g., confusion between concepts and individuals, constraints violations, heterogeneous levels of generality, etc.) [16] and proposed to integrate DOLCE in WordNet, aligning the WordNet top concepts to DOLCE (hyponymy relation aligned to subsumption relations and synsets to concepts). This work has been extended in [17], where a hybrid bottom-up top-down approach to automatically extract association relations from WordNet, and to interpret those associations in terms of a set of conceptual relations in DOLCE has been developed. This resulted in the OntoWordNet resource expressing alignments between WordNet 1.6 version and DOLCE-Lite-Plus. While these works focused mostly on WordNet noun synsets, [65] extended the previous alignments by aligning verbs according to their links to nouns denoting perdurants, transferring the verb to the DOLCE class assigned to the noun that best represents that verb's occurrence. They argue that many NLP applications need to deal with events, actions, states, processes, and other temporal entities that are usually represented by verbs. In that sense, in the context of the OntoWordNet, they have investigated different ontological problems in WordNet (e.g., confusion between concepts and individuals, constraints violations, heterogeneous levels of generality, etc.) [16] provided the WordNet taxonomy with more rigorous semantics via an alignment between WordNet top-level synsets (word senses as groups of synonymous words) and DOLCE. After a meticulous analysis, the WordNet taxonomy was reorganized to meet the OntoClean [?] methodology requirements, and the resulting upper level nouns were then mapped to DOLCE classes representing their highest level categories. This mapping concentrated on the noun database, since most particulars in DOLCE describe categories whose members are denoted by nouns. This work has been further extended [17] in order to extract association relations from WordNet, and to interpret those associations in terms of a set of conceptual relations in DOLCE. This resulted in the OntoWordNet resource expressing in alignments between WordNet 1.6 version and DOLCE-Lite-Plus. Later, this alignment has been updated [18] with a revision of the manual alignments and a different version of DOLCE and WordNet (Table 1). (DOLCE UltraLitePlus), which is a simplified version of DOLCE Lite Plus (called simply DOLCE in the rest of this work), intended to make classes and properties names more intuitive and express axiomatizations in a simpler way, among other features. An additional lightweight oundational ontology, called DOLCE Zero (D0), was also developed and integrated into DULplus, generalizing some of its classes. The OntoWordNet project aims at producing a formal specification of WordNet as an axiomatic theory (an ontology). While these works focused mostly on WordNet noun synsets, [65] extended the previous alignments by aligning verbs according to their links to nouns denoting perdurants, transferring to the verb the DOLCE class assigned to the noun that best represents that verb's occurrence. They argue that many NLP applications need to deal with events, actions, states, and other temporal entities that are usually represented by verbs. The alignment of WordNet to other foundational ontologies as BFO [62], Cyc [55], SUMO [49], and UFO [36] has been also addressed. In [62], a semi-automatic method for aligning WordNet3.0 and BFO2.0 is described. It adopts previous alignments between WordNet and the KYOTO ontology, whose top layer is based on DOLCE. The method involves manually creating a set of alignments between the ontologies and implementing a set of matching rules. The manual creation of the alignments explores diverse existing ones: a) KYOTO and BFO (on the basis of previous alignments between DOLCE to BFO1.0 and BFO1.1 [34, 63, 67], ignoring the axiomatization incompatibilities); b) BFO1.0 and BFO1.1 to BFO2.0 (on the basis of the alignments in [61]); and c) WordNet labels and BFO2.0. The manual alignments have been combined to the results of applying the rules, resulting in 72% correctly assigned BFO types. In [55], the authors report the matching and integration of several background resources and ontologies of varying complexity to the Cyc knowledge base. These resources and ontologies included large pharmaceutical and medical thesauri and large portions of WordNet. For this task, ontologists have been trained with domain experts and interactive clarification dialog-based tools were developed to enable experts to directly match/integrate their ontologies. In [49], SUMO was originally mapped manually to WordNet 1.6 and then manually updated to 3.0 [13]. It is the only complete manual mapping of an ontology to WordNet. Finally, in [36], WordNet has been extended by applying the notion of *semantic types* in order to establish matching rules between the noun synsets of Wordnet and the top-level constructs of the UFO ontology. The proposed rules were validated through an experiment with approximately 5,200 sample correspondences and average accuracy of 93%.

5. Matching domain via foundational ontologies

Foundational ontologies provide a reference for rigorous comparisons of different ontological approaches, and a framework for analysing, harmonizing, matching and integrating existing domain ontologies [50]. In domain ontology matching, in particular, they act as semantic bridges to help the task. Despite the potential gain of exploiting foundational ontologies in domain ontology matching, few works have addressed this alternative, possibility due to the still low coverage of foundational ontologies in domain ontologies. This gain has been quantitatively measured in [42], where a set of algorithms exploiting such semantic bridges are applied. The circumstances of cases where foundational ontologies improve domain ontology matching, with respect to approaches ignoring them, were then studied. The experiments were conducted with SUMO-OWL (a restricted version of SUMO), OpenCyc and DOLCE and demonstrate that overall the alignment via upper ontologies impacts in F-measure positively. Additionally, in [51] a set of alignment patterns based on OntoUML (a conceptual modeling language based on UFO) are applied to a set of alignments generated by matching systems. An analysis of the impact of patterns to avoid common errors was presented.

Very few concrete matching approaches however exploit foundational ontologies. An example is the semi-automatic LOM matcher [39], which applies four methods (1) whole term matching; (2) word constituent matching; (3) synset matching; and (4) type matching. Type matching explores the ontological category of each word constituent for matching using the alignments from WordNet synsets to SUMO. LOM

[13]https://github.com/ontologyportal/sumo/tree/master/WordNetMappings

takes the source terms that are unmatched with the three first methods, collects the set of SUMO terms that their synsets map to, and then compares the SUMO term sets to their counterpart for each term in the target ontology.

From a manually established alignment between biomedical ontologies and BFO, in [64], a matching approach relies on filtering out correspondences at domain level that relate two different kinds of ontology entities. The matching approach is based on a set of similarity measures and the use of foundational ontology as a parameter for better understanding the conceptual nature of terms within the similarity calculation step. Besides the reported improvement in the results obtained, the introduction of foundational ontologies in the alignment process increased the influence of semantic factors in this task, further expanding the universe of information to be explored during the alignment.

6. Matching domain to foundational ontologies

Methodologies for constructing ontologies should not neglect the use of foundational ontologies and should better address it in a *top-down* approach [32]. In the absence of more systematic uses of foundational ontologies within domain ontology development[14], a *bottom-up* approach has to be applied instead.

In fact, many approaches rely on a manual alignment process. In [6], DOLCE has been used to integrate two geoscience knowledge representations, the GeoSciML schema and the SWEET ontology, in order to facilitate cross-domain data integration. The aim was to produce a unified ontology in which the GeoSciML and SWEET representations are aligned to DOLCE and to each other. In that perspective, DOLCE works as a semantic bridge and this approach fits as well the category of domain matching with foundational ontologies. The alignments have been manually established and representation incompatibility issues have been discussed so far. In the same line, in [54] manual alignments have been established between the O&M (Observations and Measurements) ontology and DOLCE, in order to restrict the interpretations of entities in the O&M model and to make explicit the relations between their categories.

DOLCE has been manually aligned to the domain ontology describing services (OWL-S) in [43], in order to address its conceptual ambiguity, poor axiomatization, loose design and narrow scope. They have also developed a core ontology of services to serve as middle level between the foundational and OWL-S, and can be reused to align other Web Service description languages. In [10], several schemata of FactForge, which enables SPARQL query over the LOD cloud, have been aligned to the foundational ontology PROTON in order to provide a unified way to access to the data. The alignments were created by knowledge engineers through a systematic process. Equivalence (e.g., Geonames:Country equivalentClassOf PROTON:Country) and subclass relationships (e.g., DBpedia:OlympicResult subClassOf Proton:Situation) between DBPedia, Geonames and Freebase concepts and PROTON classes have been established. As stated in §5, manual alignments have also been established between biomedical ontologies and BFO, in [64]. In this line, [7] analysed the "compatibility" between an ontology of the biomedical domain (UMLS) and the Cyc Ontology, by manually aligning UMLS to Cyc.

While these proposals mainly generate manual alignments, BLOOMS+ [31] is an early work on automatising the process. It has been used to automatically align PROTON to LOD datasets using as gold standard the alignments provided in [10]. BLOOMS+ first uses Wikipedia to construct a set of category hierarchy trees for each class in the source and target ontologies. It then determines which classes to align using 1) similarity between classes based on their category hierarchy trees; and 2) contextual similarity between these classes to support (or reject) an alignment. BLOOMS+ significantly outperformed existing matchers in the task. SUMO and WordNet were used in a semi-automated process to match the millions of terms in the YAGO[15] taxonomy and create a single large ontology and factbase [12].

In [57] the authors have proposed an automatic approach for matching domain and foundational ontologies that exploits existing alignments between WordNet and foundational ontologies. The matching process is divided in two main steps. The first step identifies the correct synset to a concept and the second one identifies the correspondence of a domain concept to a foundational concept. The approach has been

[14] An exception is OntoUML. By creating a domain or core ontology in OntoUML, the resulting ontology is compliant to UFO

[15] http://yago.r2.enst.fr

evaluated using DOLCE and domain ontologies from the OAEI conference data set[16], with the help of the alignments provided in [17, 49]. This work has been further extended in [58], where two similarity measures for synset disambiguation have been adopted: (1) an adaptation of the Lesk[38] measure and (2) word embeddings[44] similarity. The evaluation has been also extended including DOLCE and SUMO ontologies and their alignments to WordNet and three domain ontologies (SSN[17], CORA[18], and OAEI Conference).

Also [40] uses WordNet as background knowledge, their matching approach combines concept definition enrichment, disambiguation and filtering of candidate correspondences with inconsistency detection. The approach has been used for matching DOLCE+DnS Ultralite and a domain ontolology describing mobile services.

Automatic foundational distinctions of LOD entities (class vs. instance or physical vs. non-physical objects) is done in [2] with two strategies: an (unsupervised) alignment approach and a (supervised) machine learning approach. The alignment approach, in particular, relies on the linking structure of alignments between DBpedia, DOLCE, and lexical linked data, using resources such as BabelNet, YAGO and OntoWordNet. For instance, they use the paths of alignments and taxonomical relations in these resources and automated inferences to classify whether a DBpedia entity is a physical object or not.

7. Discussion

Table 1 summarises the matching approaches involving foundational ontologies described in this paper. Most approaches still rely on manually or semi-automatically established alignments. This task is far from being trivial, even when done manually. This has been recently corroborated in [66], where manually classifying domain entities under foundational ontology classes is reported to be very difficult to do correctly. Manual ontology matching is also an expensive task that may introduce a bias as it represents a point of view expressing the interpretation of the concepts influenced by the background of the expert. As knowledge on foundational ontologies is specialized, it is important that such evaluation considers an overview of different experts in this area. Moreover, while manual alignment on a small set of concepts is feasible, bigger data sets would require extra efforts. The findings in [66] also point out the need for improving the methodological process of manual integration of domain and foundational ontologies, in accord with what has been stated in [32].

Systematically enriching domain ontologies with foundational ones would also promote their use as semantic bridges [42, 64] in the task of matching domain ontologies. Despite the variety of approaches focusing on domain ontologies, few works exploiting foundational ontologies as bridges have been proposed in the literature. While more automation is an obvious requirement in the field, the poor performance of solutions addressing automatically matching different foundational ontologies or with domain ontologies have demonstrated the difficulty of the task, as reported in experiments evaluating current matching tools [34, 56]. Current tools fail on correctly capturing the semantics behind concepts, what requires deeper contextualization on the basis of hierarchies and axioms. In that sense, further context and documentation is required, in particular for domain ontologies, to help identifying the right semantics (e.g, the ontologies from the largely used OAEI Conference dataset have a very poor lexical layer). Besides that, the task requires the identification of other relations than equivalences, such as subsumption and meronym. The latter is largely neglected by current matchers. In particular, the main problem of matching foundational and domain ontologies is that, most matchers typically rely on string-based techniques as an initial estimate of the likelihood that two elements refer to the same real world phenomenon, hence the found correspondences represent equivalences with concepts that are equally or similarly written. However, in many cases, this correspondence is not the case [56]. In fact, when having different levels of abstraction it might be that the matching process is capable of identifying subsumption correspondences rather than equivalence, since the foundational ontologies have concepts at a higher level. Furthermore, while diverse matching approaches rely on external background knowledge, (BabelNet [19], WordNet[20], UMLS[21], etc.), the coverage of foundational ontologies in these resources is still

[16]http://oaei.ontologymatching.org/2017/conference/index.html

[17]https://www.w3.org/TR/vocab-ssn/

[18]IEEE Standard Ontologies for Robotics and Automation," in IEEE Std 1872-2015 , vol., no., pp.1-60, 10 April 2015

[19]https://babelnet.org

[20]https://wordnet.princeton.edu

[21]https://uts.nlm.nih.gov/home.html

	Foundational/lexicon/domain	*Approach*	*Available alignment*
Matching foundational ontologies			
[20]	BFO1.0, DOLCE	Manual comparison	-
[50]	SUMO, DOLCE	Manual alignment	-
[63]	BFO1.0, DOLCE	Manual comparison	-
[67]	BFO1.0, DOLCE	Manual alignment	Set of triples
[34]	BFO1.1, DOLCE-Lite, GFO	Manual, matching tools	List at Romulus[1]
[61]	BFO1.0,1.1,2.0	Semi-automatic (change-tracking)	-
[47]	SUMO, DOLCE-CORE	Manual alignment	FOL alignments
Matching foundational ontologies to lexical resources			
[16, 17]	DOLCE-LitePlus,DOLCE-UltraLite/WordNet1.6	Semi-automatic (NLP, disamb., A-links)	OWL version[2]
[55]	Cyc/WordNet1.6	Semi-automatic (interactive tool, rules)	-
[49]	SUMO/WordNet1.6/3.0	Manual	Textual format
[18]	DOLCEPlusDnS Ultra Lite/WordNet3.0	Semi-automatically (transitive closure)	RDF dataset
[62]	BFO2.0/WordNet3.0	Semi-automatic (matching rules)	-
[65]	DOLCE-LitePlus/WordNet3.0 (verbs)	Semi-automatic (annotation tool, links)	-
[36]	UF0/WordNet3.0	Automatic (SemanticMapper)	-
Matching domain ontologies via foundational ontologies			
[39]	SUMO, Cyc/SENSU	Semi-automatic (LOM matcher)	-
[42]	SUMO-OWL, OpenCyc, DOLCE/ 17 ontologies (agent, bibtex, etc).	Automatic (structural matching)	-
[64]	BFO/GO, INOH Event	Automatic (FOAM+OBOAEA)	-
[51]	UFO/Conference	Manual pattern analysis	-
Matching domain ontologies to foundational ontologies			
[43]	DOLCE/OWL-S	Manual	-
[6]	DOLCE-LitePlus/GeoSciML2.0, SWEET1.1	Manual	UML-syntax
[12]	SUMO, YAGO, WordNet, Wikipedia	Semi-automatic	SUMO axioms
[10]	PROTON/DBPedia, Freebase, Geonames	Manual	-
[31]	PROTON/DBPedia, Freebase, Geonames	Automatic (BLOOMS+)	-
[64]	BFO/GO, INOH Event	Manual	-
[40]	DOLCE Ultralite/Mobile services ontology	Automatic (lexical+reasoning)	-
[57]	DOLCE-LitePlus/OAEI Conference	Automatic (indirect matching)	-
[58]	DOLCE-LitePlus, DOLCE Ultralite, SUM0/Conference, SSN, CORA	Automatic (indirect+embeddings)	Alignment format[3]
[2]	DOLCE-LitePlus, DBPedia	Automatic (machine learning)	-

Table 1

Summary of the approaches on chronological order ([1]http://www.thezfiles.co.za/ROMULUS/ontologyAlignment.html; [2]http://www.ontologydesignpatterns.org/ont/wn/; [3]https://github.com/danielasch/top-match).

low. More recently, the resource Framester[22], exposed as a knowledge graph, addresses this aspect as a hub between several resources such as VerbNet[23], BabelNet, DBpedia[24], and Yago[25].Hence, matchers need to be improved to include more abstract and philosophical semantic relations and semiotic matching, to take advantage of structural features of the ontologies and axioms in order to better compare their formal definitions, and also of background knowledge from external resources, targeting subsumption and other relations. These have to be combined with logical reasoning techniques for guarantee the consistency of the generated alignments. The current approaches have to be thus revised to better deal with the specificities of matching with foundational ontologies. While automatic approaches have been mostly manually evaluated, with few exceptions [10, 58], systematically evaluations of matching systems have been so far dedicated to domain ontologies. Despite the variety of tasks in the OAEI campaigns[26], evaluations involving foundational ontologies have not been addressed. Producing comprehensive evaluation data sets on which matching solutions can be evaluated would foster the development of approaches involving foundational ontologies and support a next generation of semantic matching approaches. With that respect, few of the established alignments generated by the approaches have being publicly made available (Table 1). Furthermore, very few of them adopted a format that can be processed by automatic tools. Only [57] adopts the Align-

[22]https://lipn.univ-paris13.fr/framester/
[23]https://verbs.colorado.edu/verbnet/
[24]https://wiki.dbpedia.org
[25]http://yago.r2.enst.fr

[26]http://oaei.ontologymatching.org/2018/

ment Format[27], the standard *de facto* adopted in the OAEI campaigns.

Another aspect refers to the evolution or the consistency of alignments with respect to the evolution or the different variants of the ontologies. For example, DOLCE and its different variants have been used in diverse proposals, as many efforts have been dedicated to the development of this ontology. DOLCE has been exposed with reduced axiomatization and extensions with generic or domain plugins, such as for DOLCE-Lite [17], DOLCE-Lite-Plus[28] or still DOLCE+DnS Ultralite[29]. Besides their substantial differences in the hierarchical organization and expressiveness, these versions are mostly compatible, what is not the case for other ontologies. For instance, BFO 2.0 represents major updates to BFO not strictly backwards compatible with BFO 1.1 and a manual alignment was required to express their incompatibilities. UFO is also currently being extended by incorporating a new theory of types (including higher-order types), as well as a fuller theory of relationships and events [27]. Despite being, to a large extent, backwards compatible with the original ontology, these are important changes of UFO 2.0. Evolving alignments to cope with the different versions of the ontologies is still an open challenge. While most alignments generated were limited to link a single entity of a source ontology to a single entity of a target ontology, they lack expressiveness to a large extent. In order to better express the relationships between entities from different ontologies, they require rather full fledged axioms, as pointed out in [10, 55]. In the example from [10], the professions are modeled as instances of the class *Profession* in PROTON, and the single entity of DBPedia is matched to an expression in PROTON which restricts the property *hasProfession* to the value of the profession of interest. However, generating complex correspondences is still an open challenge in the ontology matching field in general. Very few foundational ontologies are equipped with lexical layers in languages other than English (e.g., BFO has been enriched with a lexical annotation in Portuguese, SUMO is the exception and is mapped to the 26 languages in Open Multilingual Wordnet [5]). However, with the increasing amount of multilingual data on the Web and the consequent development of ontologies in different languages, foundational ontologies should also be equipped with richer multilingual annotations in order to facilitate the multilingual and cross-lingual ontology matching tasks. The most significant issue in ontology matching is that most ontologies lack definitions of terms in logic, compared to the completeness of natural language definitions in dictionaries. Most of the intended semantics of terms are left to the intuition of humans reading their names. Until richer definitions become the norm, ontology matching, whether manual or automatic, will remain difficult to conduct or evaluate.

[27] http://alignapi.gforge.inria.fr/format.html

[28] http://www.loa.istc.cnr.it/old/ontologies/DLP_397.owl

[29] http://www.ontologydesignpatterns.org/ont/dul/DUL.owl

References

[1] R. Arp, B. Smith, and A. Spear. *Building Ontologies with Basic Formal Ontology*. MIT Press, 2015.

[2] Luigi Asprino, Valerio Basile, Paolo Ciancarini, and Valentina Presutti. Empirical analysis of foundational distinctions in linked open data. *arXiv preprint arXiv:1803.09840*, 2018.

[3] A. Benevides, J. Bourguet, G. Guizzardi, and R. Peñaloza. Representing the UFO-B foundational ontology of events in SROIQ. In *Proc. of the Joint Ontology Workshops*, 2017.

[4] A.B. et al. Benevides. Representing a reference foundational ontology of events in sroiq. *Applied Ontology*, 14(3):293–334, 2019.

[5] F. Bond, C. Fellbaum, S. Hsieh, C. Huang, A. Pease, and P. Vossen. A Multilingual Lexico-Semantic Database and Ontology. In *Towards the Multilingual Semantic Web*, pages 243–258. 2014.

[6] B. Brodaric and F. Probst. Dolce rocks: Integrating geoscience ontologies with dolce. In *Semant. Scient. Know. Integr.*, pages 3–8, 2008.

[7] Anita Burgun and Olivier Bodenreider. Mapping the umls semantic network into general ontologies. In *Proceedings of the AMIA Symposium*, page 81. American Medical Informatics Association, 2001.

[8] Carmen Chui and Michael Grüninger. Mathematical foundations for participation ontologies. In Pawel Garbacz and Oliver Kutz, editors, *Formal Ontology in Information Systems - Proceedings of the Eighth International Conference, FOIS 2014, September, 22-25, 2014, Rio de Janeiro, Brazil*, volume 267 of *Frontiers in Artificial Intelligence and Applications*, pages 105–118. IOS Press, 2014.

[9] Carmen Chui and Michael Grüninger. Merging the DOLCE and PSL upper ontologies. In *KEOD 2014 - Proceedings of the International Conference on Knowledge Engineering and Ontology Development, Rome, Italy, 21-24 October, 2014*, pages 16–26, 2014.

[10] M. Damova, A. Kiryakov, K. Ivanov Simov, and S. Petrov. Mapping the central LOD ontologies to PROTON upper-level ontology. In *Workshop on Ontology Matching*, 2010.

[11] Sergio de Cesare and Chris Partridge. BORO as a Foundation to Enterprise Ontology. *Journal of Information Systems*, 30(2):83–112, 02 2016.

[12] Gerard de Melo, Fabian Suchanek, and Adam Pease. Integrating YAGO into the Suggested Upper Merged Ontology. *Proc. 20th IEEE International Conference on Tools with Artificial Intelligence*, 2008.

[13] Jérôme Euzenat and Pavel Shvaiko. *Ontology Matching, Second Edition*. Springer, 2nd edition, 2013.

[14] C.M. et al. Fonseca. Relations in ontology-driven conceptual modeling. In *International Conference on Conceptual Modeling*, pages 28–42. Springer, 2019.

[15] A Gangemi, N. Guarino, C. Masolo, and A. Oltramari. Restructuring WordNet's Top-Level. *AI Magazine*, 40:235–244, 2002.

[16] A. Gangemi, N. Guarino, C. Masolo, A. Oltramari, and L. Schneider. Sweetening Ontologies with DOLCE. In *13th Conf. on Knowledge Engineering and Knowledge Management*, pages 166–181, 2002.

[17] A. Gangemi, R. Navigli, and P. Velardi. The OntoWordNet Project: Extension and Axiomatization of Conceptual Relations in WordNet. In *On The Move to Meaningful Internet Sys.*, pages 820–838, 2003.

[18] A. Gangemi, A. Nuzzolese, V. Presutti, F. Draicchio, A. Musetti, and P. Ciancarini. Automatic typing of dbpedia entities. In *ISWC 2012*, 2012.

[19] Michael R Genesereth, Richard E Fikes, et al. Knowledge interchange format-version 3.0: Reference manual.

[20] P Grenon. *BFO in a Nutshell: A Bi-categorial Axiomatization of BFO and Comparison with DOLCE*. Leipzig, 2003.

[21] Michael Grüninger and Christopher Menzel. The process specification language (psl) theory and applications. *AI Mag.*, 24(3):63–74, September 2003.

[22] Michael Gruninger, Carmen Chui, and Megan Katsumi. Upper ontologies in colore. In *JOWO*, 2017.

[23] N. Guarino. *Formal Ontology in Information Systems: Proc. of the 1st Conf.* 1998.

[24] V. Guha and D. Lenat. Cyc: A Midterm Report. In *Readings in Knowledge Acquisition and Learning*, pages 839–866, 1993.

[25] G. Guizzardi. *Ontological foundations for structural conceptual models*. PhD thesis, University of Twente, Enschede, The Netherlands, Enschede, 2005.

[26] G. Guizzardi. The role of foundational ontologies for conceptual modeling and domain ontology representation. In *7th DB&IS Conf.*, pages 17–25, 2006.

[27] G. et al. Guizzardi. Towards ontological foundations for conceptual modeling: The unified foundational ontology (ufo) story. *Applied ontology*, 10(3-4):259–271, 2015.

[28] G. Guizzardi. Endurant types in ontology-driven conceptual modeling: Towards ontouml 2.0. In *International Conference on Conceptual Modeling*, pages 136–150, 2018.

[29] Giancarlo Guizzardi. Ontology, ontologies and the "i" of fair. *Data Intelligence*, pages 181–191, 2020.

[30] H. Herre, B. Heller, P. Burek, R. Hoehndorf, F. Loebe, and H. Michalek. General Formal Ontology (GFO): A Foundational Ontology Integrating Objects and Processes. In *Res. Group Ontologies in Medicine*, 2007.

[31] P. Jain, P. Yeh, K. Verma, R. Vasquez, M. Damova, P. Hitzler, and A. Sheth. Contextual Ontology Alignment of LOD with an Upper Ontology: A Case Study with PROTON. In *ESWC*, pages 80–92, 2011.

[32] C. Keet. The use of foundational ontologies in ontology development: An empirical assessment. In *ESWC*, pages 321–335, 2011.

[33] Z. Khan and C. Keet. ONSET: Automated Foundational Ontology Selection and Explanation. In *Proc. of the 18th Intern. Conf. on Knowledge Engineering and Knowledge Management*, pages 237–251, 2012.

[34] Z. Khan and C. Keet. Addressing issues in foundational ontology mediation. In *Proc. of the Inter. Conf. on Knowledge Engineering and Ontology Development*, pages 5–16, 2013.

[35] Z. Khan and C. Keet. Feasibility of Automated Foundational Ontology Interchangeability. In *Proc. of the 19th Conf. on Knowledge Engineering and Knowledge Management*, pages 225–237, 2014.

[36] F. Leao, K. Revoredo, and F. Baiao. Extending WordNet with UFO Foundational Ontology. *Journal of Web Semantics*, 2019.

[37] Douglas B Lenat and Ramanathan V. Guha. The evolution of cycl, the cyc representation language. *ACM SIGART Bulletin*, 2(3):84–87, 1991.

[38] Michael Lesk. Automatic sense disambiguation using machine readable dictionaries: how to tell a pine cone from an ice cream cone. In *Proceedings of the 5th annual international conference on Systems documentation*, pages 24–26, 1986.

[39] J. Li. Lom: A lexicon-based ontology mapping tool. In *Proc. of the PerMIS04*, 2004.

[40] Xiulei Liu, Bo Cheng, Jianxin Liao, Payam Barnaghi, Li Wan, and Jingyu Wang. Omi-dl: an ontology matching framework. *IEEE Transactions on Services Computing*, 9(4):580–593, 2015.

[41] V. Mascardi, V. Cordì, and P. Rosso. A Comparison of Upper Ontologies. In *8th AI*IA/TABOO Workshop on Agents and Industry*, pages 55–64, 2007.

[42] V. Mascardi, A. Locoro, and P. Rosso. Automatic Ontology Matching via Upper Ontologies: A Systematic Evaluation. *IEEE Trans. on Knowl. and Data Eng.*, 22(5):609–623, 2010.

[43] P. Mika, D. Oberle, A. Gangemi, and M. Sabou. Foundations for Service Ontologies: Aligning OWL-S to DOLCE. In *Proc. of the 13th Conf. on World Wide Web*, pages 563–572, 2004.

[44] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

[45] George A Miller. Wordnet: a lexical database for english. *Communications of the ACM*, 38(11):39–41, 1995.

[46] Riichiro Mizoguchi. Yamato: Yet another more advanced top-level ontology. In *Proceedings of the Sixth Australasian Ontology Workshop*, pages 1–16, 2010.

[47] L. Muñoz and M. Grüninger. Verifying and mapping the mereotopology of upper-level ontologies. In *Proc. of the Inter. Conf. on Knowledge Discovery*, pages 31–42, 2016.

[48] I. Niles and A. Pease. Towards a Standard Upper Ontology. In *Conf. on Formal Ontology in Information Systems*, pages 2–9, 2001.

[49] I. Niles and A. Pease. Linking Lexicons and Ontologies: Mapping WordNet to the Suggested Upper Merged Ontology. In *Proc. of the Inter. Conf. on Knowledge Engineering*, pages 412–416, 2003.

[50] D. et al. Oberle. Dolce ergo sumo: On foundational and domain models in the smartweb integrated ontology (swinto). *Web Semantics*, 5(3):156–174, 2007.

[51] N. Padilha, F. Baião, and K. Revoredo. Alignment Patterns based on Unified Foundational Ontology. In *Proc. of the the Brazilian Ontology Research Seminar*, pages 48–59, 2012.

[52] Adam Pease and Christoph Benzmüller. Sigma: An Integrated Development Environment for Logical Theories. *AI Comm.*, 26:9–97, 2013.

[53] Adam Pease. *Ontology: A Practical Guide*. Articulate Software Press, Angwin, CA, 2011.

[54] Florian Probst. Ontological analysis of observations and measurements. In Martin Raubal, Harvey J. Miller, Andrew U. Frank, and Michael F. Goodchild, editors, *Geographic Information Science*, pages 304–320, Berlin, Heidelberg, 2006. Springer Berlin Heidelberg.

[55] S. Reed and D. Lenat. Mapping Ontologies into Cyc. In *Proc. of the Workshop on Ontologies For The Semantic Web*, pages 1–6, 2002.

[56] D. Schmidt, C. Trojahn, and R. Vieira. Analysing Top-level and Domain Ontology Alignments from Matching Systems. In *Workshop on Ontology Matching*, pages 1–12, 2016.

[57] D. Schmidt, R. Basso, C. Trojahn, and R. Vieira. Matching Domain and Top-level Ontologies via OntoWordNet. In *Workshop on Ontology Matching*, pages 1–2, 2017.

[58] D. Schmidt, R. Basso, C. Trojahn, and R. Vieira. Matching domain and top-level ontologies exploring word sense disambiguation and word embedding. In *Emerging Topics in Semantic Tech.*, pages 27–38, 2018.

[59] Stefan SCHULZ. The role of foundational ontologies for preventing bad ontology design. In *Joint Ontology Workshops*, 2018.

[60] S. Semy, M. Pulvermacher, and L. Obrst. Toward the use of an upper ontology for U.S. government and U.S. military domains: An evaluation. Technical report, MTR 04B0000063, The MITRE Corporation, 2004.

[61] S. Seppälä, B. Smith, and W. Ceusters. Applying the realism-based ontology-versioning method for tracking changes in the basic formal ontology. In *Proc. of FOIS*, pages 227–240, 2014.

[62] S. Seppälä. Mapping WordNet to Basic Formal Ontology using the KYOTO ontology. In *Proc. of the Conf. on Biomedical Ontology*, pages 1–2, 2015.

[63] A. Seyed. BFO/DOLCE Primitive Relation Comparison. In *Nature proceedings*, 2009.

[64] V. Silva, M. Campos, J. Silva, and M. Cavalcanti. An Approach for the Alignment of Biomedical Ontologies based on Foundational Ontologies. *Information and Data Management*, 2(3):557–572, 2011.

[65] V. Silva, A. Freitas, and S. Handschuh. Word Tagging with Foundational Ontology Classes: Extending the WordNet-DOLCE Mapping to Verbs. In *Know. Eng. and Know. Man.*, pages 593–605. 2016.

[66] R. Stevens, P. Lord, J. Malone, and N. Matentzoglu. Measuring expert performance at manually classifying domain entities under upper ontology classes. *Journal of Web Semantics*, 2018.

[67] L. Temal, A. Rosier, O. Dameron, and A. Burgun. Mapping BFO and DOLCE. In *Proc. of the World Cong. on Medical Inf.*, pages 1065–1069, 2010.

[68] I. Terziev, A. Kiryakov, and D. Manov. Base Upper-level Ontology (BULO) Guidance. Deliverable 1.8.1, sekt project, 2005.

[69] M Uschold and D McComb. Introduction to gist, 2013.

[70] Michaël Verdonck, Tiago Prince Sales, and Frederik Gailly. A comparative illustration of foundational ontologies: Boro and ufo. In *10th International Conference on Formal Ontology in Information Systems (FOIS 2018)*, volume 2205. CEUR, 2018.

[71] Eduardo Zambon and Giancarlo Guizzardi. Formal definition of a general ontology pattern language using a graph grammar. In *2017 Federated Conference on Computer Science and Information Systems (FedCSIS)*, pages 1–10. IEEE, 2017.