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Challenges Faced by Ontology Matching Techniques: Case Study of the OAEI Datasets

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Abstract: The aim of this study is to review some of the most successful recent techniques in ontology matching and to lay down pending challenges that need to be addressed in this area. Ontologies are essential for the realization of the semantic web, which in turn relies on the ability of systems to identify and exploit relationships that exist between and within ontologies. As ontologies can be used to represent different domains, there is a high need for efficient ontology matching techniques that can allow information to be easily shared between different heterogeneous systems. In this paper, six systems that obtained overall good performance in the Ontology Alignment Evaluation Initiative (OAEI) for the year 2008 and the year 2009 are analyzed based on their underlying techniques, datasets, and matching results. According to the analysis carried out, it is found that although some systems work well for dataset representing a given domain, the same system does not perform well for datasets representing other domains. To assist further research in this area, techniques that work well for particular domains are highlighted and areas for cross-domain ontology matching that still require attention are discussed with recommendations based on lessons learnt from the techniques described.

Key words: Alignment, mapping, ontology alignment evaluation initiative, ontology matching, semantic web, techniques

INTRODUCTION

An ontology is an information artefact that can formally model a domain, using concepts and relations useful for a given purpose and community (Staab and Studer, 2009; Gruber, 1993; Borst, 1997; Studer *et al*., 1998). In general, ontologies solve the problem of data and system interoperability by providing rich semantics to a domain that can be both understood and processed by a computer. Recently, Euzenat and Shvaiko (2007) provided a very detailed explanation for the applications of ontologies and the following three uses for ontologies as summarized by Gruninger and Lee (2002) are excellent illustrations for the potential benefits of ontologies.

- For communication between either humans and computers, or between computers only
- For computational inference
- For reuse (and organization) of knowledge

Consequently, an increasing number of ontologies are being created and it is expected that ontologies will be the backbone for the Semantic Web. However, multiple ontologies created according to the needs of specific communities further bring about the challenge of effectively sharing information between heterogeneous ontologies. This is because in practice, different individuals using different conceptualizations create the situation where ontology mismatches can arise in which systems using different ontologies cannot interoperate (Visser *et al*., 1997). To address this specific problem, several ontology matching techniques have been proposed over the past years. These techniques are intended to find correspondences between ontologies to allow them to interoperate. However, while some techniques proposed are very efficient, others do not perform that well, making it problematic for selecting a proper technique by the Semantic Web community. The Ontology Alignment Evaluation Initiative (OAEI) is a yearly campaign, which has been actively involved in evaluating several of these techniques since 2005. Every year, the campaign provides several ontologies from different domains, for which researchers propose matching techniques that determine correspondences between the ontologies. The techniques are then evaluated on a common basis, providing a suitable framework for identifying successful matching techniques.

This study describes findings related to the techniques used for OAEI 2008 and 2009. The aim of this paper is to identify the most recent successful techniques used in ontology matching as well as the challenges faced by system designers to build ontology based application that require data integration. The materials and methods used for this study are introduced after clarifying the terms ontology matching, mapping and alignment. This is followed by a presentation of the Ontology Alignment Evaluation Initiative and a description of the ontologies used in the evaluation of different matching systems. In addition, six best systems in the OAEI campaign for the year 2008 and 2009 are described and analysed. Each system is compared based on the techniques used, datasets, and matching results obtained. Following which, a summary of observations made is provided and the study is concluded with a review of some potential challenges yet to be addressed in ontology matching as well as some recommendations to meet these challenges.

Defining ontology matching, mapping and alignment: There exist no clear standard for defining the terms matching, mapping, and alignment (Kalfoglou and Schorlemmer, 2003; De Bruijn *et al*., 2003; Choi *et al*., 2006). Therefore, it is common practice for most researchers working on ontologies to define the terms they use in order to maintain consistency in their work. We do not intend to cover all definitions used so far, but report a few in order to show the diversity in the use of the terms matching, mapping, and alignment. Abels *et al*. (2005) for instance, explains that ontology mapping refers to an identification of identical concepts or relations between different ontologies; while ontology alignment, is a process that brings two ontologies into mutual agreement to make them consistent and coherent. Euzenat and Shvaiko (2007), on the other hand, considers ontology matching as the process of finding relationships or correspondences between entities of two or more ontologies and, ontology alignment as the output of the matching process, which consists of a set of correspondences between two or more ontologies. Ontology mapping, in this case is considered as the oriented or directed version of an alignment between the entities of one ontology to at most one entity of another ontology. In contrast, Ehrig and Staab (2004) do not distinguish between mapping and alignment. The authors instead consider both mapping and alignment to mean the same thing as follows:

> Given two ontologies O1 and O2, mapping one ontology onto another means that for each entity (concept C, relation R, or instance I) in ontology O1, we try to find a corresponding entity, which has the same intended meaning, in ontology O2.

Ding and Foo (2002), in addition report that alignment is considered as links established between two ontologies, and ontology mapping is represented as conditional rules, functions, logic, or a set of tables and procedures. Consequently, the meaning for ontology matching, mapping, and alignment remain vague, and so for the present research, it has been decided that the use of these terms should be clarified. To begin with, the definition for ontology matching as used by Euzenat and Shvaiko (2007) is preferred while the terms alignment and mapping are treated as synonyms with similar meaning as used by Ehrig and Staab (2004). In this way, distinction is made between matching as a process, and mapping/alignment as a product of matching systems. Mapping/alignment therefore is considered as a set of relationship established between similar entities from different ontologies.

MATERIALS AND METHODS

The materials selected for this paper are articles reporting matching techniques and performances achieved for the Ontology Alignment Evaluation Initiative (OAEI). The latter initiativeis an annual campaign that invites researchers from all over the globe to submit their ontology matching systems for evaluation on a common framework. Although, the main goal of OAEI is to compare ontology matching systems and their algorithms on a common ground, it also helps in keeping track of the evolution of the field as a centralized location for researchers to publish and obtain information related to ontology matching. Since the aim of this paper is to evaluate the most recent successful techniques, only those articles that reported best performance for the year 2008 and 2009 were considered. The articles were retrieved in November 2010 from the OAEI home page at http://oaei.ontologymatching.org/ and manually analysed during November and December 2010 according to three criteria: underlying technique employed, dataset or ontology techniques was used for, and matching results obtained. By using this method, not only was it possible to determine the techniques that work well for a particular ontology, but it was also possible to identify which techniques do not perform well for other ontologies and the areas that needed further attention of researchers.

Overview of OAEI: The Ontology Alignment Evaluation Initiative was launched in 2005, and since then, varying test cases, with evaluation results have helped identify progress in the field. So every year, the organizers place emphasis on different aspects of ontology matching along with different modalities used for the evaluation process. However, the campaign always comprises three phases as follows: a preparatory phase, in which ontologies to be matched and alignment (if applicable) are provided to researchers; an execution phase, in which participants use their systems to automatically match the ontologies from test cases provided; and finally an evaluation phase, in which the organizers evaluate, and compare the alignments provided by the participants. Typically, precision, recall and F-measures are used to evaluate performance of participating systems. Different modalities

Table 1: Characteristics of test cases for OAEI 2008

Track	Test	Formalism	Relations	Modalities	Language
Benchmark	Benchmark	OWL	0	Open	EN
Expressive	Anatomy	OWL	0	Blind	EN
	FAO	OWL	0	Expert	EN+ES+FR
Directories & Thesauri	Directory	OWL	0	Blind	EN
	Mldirectory	OWL	0	Blind	EN+JP
	Library	SKOS, OWL	Narrow, exact	Blind	EN+DU
	Vlcr	SKOS, OWL	Broad, related Match	Blind	EN+DU
Conference & Consensus	Conference	OWL-DL	=, <=	Blind+ consensual	EN

of the campaign are: open, when a reference alignment is provided to participants; blind, when a reference alignment exists but is not provided to participants; expert, when no reference alignment is present, and an expert assesses alignment quality; and finally consensual, when discussion groups decide on the alignment quality based on a consensus. Since the first campaign, the organizers for OAEI have considerably improved the quality and quantity of ontologies in the form of datasets to be matched by participants. Therefore, results from OAEI 2008 and 2009 make use of a larger dataset than previous years and provide the most recent techniques used in ontology matching.

Ontologies datasets and best matching techniques for OAEI 2008: In 2008, the campaign had four tracks with eight datasets (ontologies), and different evaluation modalities. The data sets were mostly made available in OWL, and a few of them were also available in OWL-DL, and SKOS. Most datasets focused on identifying equivalence relation, and others also included subsumption relation between entities. English was the primary language used in all the datasets, but some of them were in foreign languages such as French, Spanish, Japanese, and Dutch. Table 1 summarizes the characteristics of the dataset used for the OAEI 2008. We describe each dataset further.

The benchmark dataset consists of a reference ontology related to the domain of bibliography, and a set of variations to the reference ontology. Different variations include using synonyms, abstract labels, different structure, suppression of classes, properties etc. According to the OAEI organizers, this dataset is meant to identify areas in which matching algorithm is weak and strong. The anatomy and FAO dataset are real world cases provided for the expressive ontologies track. The anatomy dataset is about finding alignment between the Adult Mouse Anatomy and the National Cancer Institute (NCI) thesaurus about human anatomy; while the FAO dataset consists in finding matches for ontologies related to the fisheries domain developed by the Food and Agricultural Organization of the United Nations. The directories and thesaurus track consists of four datasets as follows: a web directory dataset like open directory, and yahoo; a multi lingual web directory dataset that consists in finding mapping relations between web directories written in different languages; a library dataset which aims at finding mapping between two SKOS thesauri about books; and finally a very large cross lingual resources dataset, which requires matching very large resources such as DBPedia, and WordNet available on the web. The last track is a conference and consensus track in which participants are asked to explore a collection of fifteen ontologies related to conference organization. The aim of this track is to identify debatable correspondences found by systems, which can later be discussed among a group of people. This track also provides opportunity for finding pattern in the mapping strategies used by participating systems. Table 2 shows the participants for the OAEI 2008 campaign along with the corresponding datasets used.

In total, thirteen participants took part in the OAEI 2008 campaign, but only one of them was present in all four tracks. Thus, it is not possible to determine which participant has the best performance over all the datasets provided. Nevertheless, we report here four systems (Lily, SAMBO, RiMOM, and DSSim) that have shown very good performance in the benchmark, anatomy, FAO, directory, and vlcr datasets. We do not include any system from the conference dataset since the OAEI organizers could not report a system with very good results for this particular track.

Lily system: The Lily system (Wang and Xu, 2008), proposed by the Southeast University in China, is determined to have the best performance for the benchmark dataset. The system is said to use a hybrid matching strategy which is able to match both normal and large scale ontologies. Lily makes use of four main functions: (i) a Generic Ontology Matching method (GOM) for matching small size ontologies, (ii) a Large scale Ontology Matching method (LOM) for matching large scale ontologies, (iii) a Semantic Ontology Matching method (SOM) for discovering semantic relations between ontologies, and finally (iv) an ontology mapping debugger to improve alignment results. For discovering semantic matches, Lily makes use of knowledge on the web collected by a search engine.A key feature of Lily is that the system optimizes on finding one-to-one relation between concepts/properties pairs from different

Table 2: Participating systems with corresponding test sets for OAEI 2008

System	Benchmark	Anatomy	FAO	Directory	mldirectory	Library	vlcr	conference
Anchor-Flood	√	√						
AROMA	√	√						
ASMOV	√	√	√	√				
CIDER	√			√				
DSSim	√	√		√	√	√	√	√
GeRoMe	√							
Lily	√	√	√	√	√	√		√
MapPSO	√		√	√	√			
RiMOM	√	√	√	√	√			
SAMBO	√	√	√					
SAMBOdtf	√	√	√					
SPIDER	√							
TaxoMap	√	√		√		√		

ontologies. Therefore, precise description of each entity whether concept or property is a priority. To do so, Lilypreprocesses the ontologies to be matched, and creates subgraphs for each entity with accurate meanings. The developers of Lily refer to these subgraphs as semantic subgraph due to their rich semantic contents. Any similarity matching is then carried on the semantic subgraph. Both text and structure (hierarchy) matching techniques are used in Lily. Typically a Semantic Description Document Matcher will treat small scale ontologies by measuring literal similarities between ontologies, and matching is performed between the literals present in semantic description documents which contain related information for a particular concept or property. In case where literal information is not present, a similarity propagation method is used to determine equivalence. For large scale ontologies, Lily proposes a novel approach that uses negative and positive anchors to predict pairs that are susceptible for further matching calculation. In the debugging phase, Lily can automatically detect imprecise mappings or present the results to users for revision. Lily is seen to perform well in almost all the tracks for the OAEI 2008 campaign. However, the authors remark that using propagation similarity matching technique can be problematic, since as more alignments are discovered, erroneous alignments could propagate. Furthermore the fact that subgraphs have to be determined for each entity in ontologies to be matched raises serious concern for execution performance with increase in ontology size.

SAMBO system: SAMBO (Lambrix *et al*., 2008) is a system proposed from Linkopingsuniversitet of Sweden, and it focuses on biomedical ontologies. In contrast to the common expectation that matching systems should be constructed independent from the domain, the developers for SAMBO tailored their system to exploit the characteristics of biomedical information. Internally, SAMBO consists of two main parts, one which computes alignment suggestions, and another one which interacts with users to refine on final alignments. The alignment suggestion part makes use of several matching algorithms as well as knowledge from sources like an instance corpus, a general dictionary, and a domain thesaurus. The techniques employed by SAMBO include n-gram based similarity measure, edit distance calculation, and the use of Unified Medical Language System (UMLS) Meta-thesaurus, WordNet thesaurus, and life science literature as background knowledge. The algorithms for SAMBO are also specifically designed to process is-a, and part-of hierarchies of an ontology, and this makes it very suitable and efficient for the anatomy dataset. Results obtained from the various techniques in SAMBO are combined, and filtered to be presented to users who either reject or accept the alignments. A conflict checker further makes sure that all alignments presented to users are conflict free. Unfortunately, for the initiative, only the non-interactive part of the system was evaluated, and the developers for SAMBO report that since the non interactive part only provide alignment suggestions to users, the quality of the alignments are not optimized. Furthermore, there is no optimal strategy to select the right matchers, combinations, and filters for the matching process.

RiMOM system: RiMOM (Zhang *et al*., 2008) is a joint venture work between researchers from Tsinghua University, China, and IBM China Research Lab. RiMOM provided the best performance for the Food and Agricultural Organization dataset, and it consists of several matching strategies that can be combined based on the information available in ontologies to be matched. For selecting a matching strategy, RiMOM makes use of three feature factors: (i) Label Similarity Factor (LF), to measure how close two labels are based on their characters, (ii) Structure Similarity Factor (SF), to measure the hierarchical similarity between two ontologies, and (iii) Label Meaning Factor (MF), to evaluate how close two labels are in meaning. Based on the results obtained from the feature factors, the appropriate matching technique is applied by RiMOM. For instance, if a high label similarity factor is obtained, matching methods based on linguistic properties will be invoked. And if a high structural similarity factor is determined, similarity-propagation based strategies with the use of WordNet are used instead. RiMom also allows the manual selection of strategies.Once selected strategies are executed, resulting alignments are combined using linear interpolation method. In the case of high structural similarity, a similarity propagation process is used to refine found alignments. Finally, several heuristics are used to refine final alignments by removing 'unreliable' alignments. Different matching strategies used in RiMOM include edit-distance based strategy, WordNet based strategy, vector-similarity based strategy, path-similarity based strategy, dynamic path- similarity based strategy, Japanese-English path-similarity based strategy, and similarity- propagation based strategies. And, when applied to the OAEI 2008 datasets, RiMOM is found to perform very well both for the benchmark as well as the FAO datasets. However, one difficulty noted by the developers for RiMOM, is that it remains very hardto automatically select an optimum strategy for combining different matching techniques during the matching process.

DSSim system: DSSim (Nagy *et al*., 2008) is a collaborative work between the Open University in UK, and Poznan University of Economics in Poland. DSSim was the only system that provided alignment for the very large cross lingual (vlcr) dataset. According to the authors, large scale ontologies reflect real world cases, and thus a matching system should be scalable. For 2008, the vlcr dataset consisted in finding mappings between WordNet, DBPedia, and GTAA, which is a Dutch thesaurus for audiovisual archives.DSSim makes extensive use of techniques that involve compound nouns comparisons, and abbreviations based on defined language rules. The developers for DSSim state that the compound noun comparison algorithm is based on previous works in fields such as language understanding, question answering, and machine translation from the area of computational linguistic. DSSim also makes use of a multi-agent architecture with each agent verifying a mapping hypothesis. Each mapping provided by an agent is then combined to provide the best mapping solution. Such strategy is well suited for large scale ontologies, whereby the system can split up a large ontology into small fragments for parallel processing by distributed agents. The process involved in DSSimconsists first in fragmenting a large ontology into smaller manageable sizes. Then after parsing, any concept or property to be matched is augmented using WordNet, and syntactically similar concepts and properties are used to create a graph. Then, similarity and semantic measures are used to assess quantitative similarity values between nodes of the graphs created previously, to produce several similarity matrices. Final mappings are generated using Dempster's rule of combination from the matrices obtained. Using this approach, DSSim provides a very efficient method for dealing with large scale ontologies, and it obtained the highest performance for the directory datasets, in which most relation between nodes is modelled as rdfs:subClassOf.

Ontologies datasets and best matching techniques for OAEI 2009: In 2009, the campaign had five tracks with eleven datasets, with similar evaluation modalities as previous years. This year’s data sets were made available in OWL and also in OWL-DL, RDF and SKOS. While most tracks still remained the same as in the previous year, two new tracks which looked at instance matching and subsumption relations were introduced in 2009. English still remained the primary language used in all the datasets, with some datasets provided in foreign languages such as French, Spanish, Japanese, and Dutch.

Table 3 Summarizes the characteristics of the dataset used for the OAEI 2009, followed by a brief description of the changes to this year’s campaign and the new tracks (oriented, and instance matching) introduced.

The benchmark track, similar as in 2008, still consists in matching a reference bibliographic ontology to alternatives of the reference ontology. The expressive ontologies track was modified to accommodate the conference dataset from last year. The FAO dataset has been removed from this track. The anatomy dataset, which consists in matching the Adult Mouse Anatomy to the NCI Human Anatomy Thesaurus, remained unchanged in this track. The directories and thesauri track excluded the multi-lingual directories dataset, and included the fishery dataset from FAO. Web directories were still used as datasets, whereas the library datasets did not consider the National Library of Netherlands collection of books anymore, but instead comprised vocabularies from Library of Congress Subject Heading (LCSH), RAMEAU (heading list used at the French National Library), and SWD (heading list used at the German National Library), all pertaining to the domain of books. The oriented alignment track datasets provide systems with the situation where relations may be more than just equivalence. The dataset was derived from the OAEI 2006 campaign benchmark series, such that subsumption relation exists between different ontologies to be matched. The instance matching track consisted of four datasets, which contained instances extracted from the Web. The focus here is to find alignment based on instances. ARS contains instances from scientific publications, tap dataset cover several topics and structured according to different ontologies, iimb dataset

Table 3: Characteristics of test cases for OAEI 2009

Track	Test	Formalism	Relations	Modalities	Language
Benchmark	Benchmark	OWL	0	Open	EN
Expressive	Anatomy	OWL	0	Blind	EN
	Conference	OWL-DL	=, <=	Blind,Open	EN
Directories &	Fishery (FAO)	OWL	0	Expert	EN+FR+ES
Thesauri	directory	OWL	0	Blind, Open	EN
	Library	SKOS, OWL	Narrow, exact, BroadMatch	Blind	EN+DU+FR
Oriented	benchmarksubs	OWL	=, <, >	Open	EN
Instance	ars	RDF	0	Open	EN
	tap	RDF	0	Open	EN
	iimb	RDF	0	Open	EN
	vlcr	SKOS, OWL	Exact, closeMatch	Blind, expert	DU+EN

Table 4: Participating systems with corresponding test sets for OAEI 2009

System	Benchmark	Anatomy	Conference	Directory	Library	Benchmark-subs	ars	iimb	vlcr
Anchor-Flood	√	√	√	√				√	
AgrMaker	√	√	√						
AMExt			√						
AROMA	√	√	√						
ASMOV	√	√	√	√		√	√	√	
DSSim	√	√	√	√			√	√	√
FBEM							√	√	
GeRoMe	√								
GG2WW	√	√	√	√	√				
Hmatch							√	√	
KOSIMap	√	√	√	√					
Lily	√	√		√					
MapPSO	√								
RiMOM	√	√				√	√	√	
SOBOM	√	√		√					
TaxoMap	√	√		√	√	√			

consists of a reference ontology about actors, sport persons, and business forms, modified according to various criteria, and vlcr datasets remained similar to last year, and consisted in matching the Thesaurus of the Netherlands Institute of Sound and Vision (GTAA), to WordNet and DBPedia. Table 4 further shows the participants for the OAEI 2009 campaign along with the corresponding datasets used. An explanation for each dataset then follows.

A total of sixteen participants took part in the OAEI 2009 campaign, and this time none of them provided results for all datasets. In fact two datasets (Fishery and tap) were not used by any of the participants, and thus was not involved in the evaluation of system performance. Thus, similar to previous years, it remains difficult to identify the overall best system for the OAEI 2009 campaign. In 2009 however, more participants took part in the campaign, and while some systems from 2008 did not participate, new participants such as Agreement Maker, AMExt, FBEM, GG2WW, and KOSIMap made their entry in the evaluation process. Furthermore the performance noted for several of the dataset for this year is very similar to previous year's results.

Lily, for instance, still stands out for its high precision and recall value with the benchmark dataset. SOBOM (Xu *et al*., 2009) results compares closely to that of SAMBO from 2008 for the anatomy dataset. KOSIMap (Reul and Pan, 2009) however outperforms other systems the conference track, for which no systems was found best in 2008. RiMOM, which already proved itself to be very efficient in finding alignment for the FAO dataset in 2008, once again showed itself very effective in the instance matching track. Finally, ASMOV (Jean-Mary *et al*., 2009) outperformed all other systems for both the oriented alignment track, and the directory track. In the next section, we describe both Kosimap and ASMOV so as to obtain a complete overview of the type of system that works best for different datasets provided in the OAEI campaign for 2008 and 2009.

ASMOV system: Similar to RiMOM, ASMOV, developed by INFOTECH Soft and the University of Miami in Florida, makes use of ontology relatedfeatures in its matching strategy. The features for which ASMOV calculates a similarity measure are: lexical elements which makes use of id, label, and comments present in different ontologies; relational structure, which considers ancestor-descendant hierarchy of an ontology; internal structure, which looks at property restrictions for concepts, the types, domains, and ranges for properties, and data values for individuals specified in an ontology; and finally the extension of an ontology, which are basically class and property instances. Each individual similarity measure is then combined using a weighted approach that has been optimized from OAEI 2008 dataset. Here also, as in SAMBO, WordNet and UMLS Methathesaurusis used for calculating lexical similarities. In case a thesaurus is not used, a string matching algorithm determines lexical distance. Other measures calculated for relational, internal, and extensional dimensions are then combined with the lexical distance measure into a similarity matrix. This result is referred to as a pre-alignment, which goes in a semantic checker that verifies for inconsistencies such as multiple mapping, crisscross correspondences, disjointness-subsumption contradiction, etc., using this approach, ASMOV is found to outperform all other systems by obtaining the best F-Score for the directory and oriented alignment dataset. However, as the developers of ASMOV claim, the system is not yet optimized for dealing with large scale ontologies, and so their future work will be to parallelize the algorithm, creating separate threads for execution.

KOSIMap system: KOSIMap (Reul and Pan, 2009) is developed by the VUB STARLab, Vrije Universiteit Brussel, in Brussel, and the University of Aberdeen, in UK. The system obtained very good performance for the conference dataset, and in contrast to other matching systems, it makes use of DL reasoning as matching strategy. A DL reasoner is said to deduce logical consequences about an entity based on asserted axioms that have been specified in a given ontology, and KOSIMap uses DL reasoning to extract background information from ontology entities, as well as to remove incorrect correspondences from any subsequent alignment found. In KOSIMap however, only equivalence relations are considered. But similar to RiMOMand ASMOV, similarity between entities from different ontologies is computed by considering ontology related features. The three features that KOSIMap considers are: lexical description, hierarchical structure, and internal structure (inherited properties, domains and ranges, etc.). Moreover, similar to ASMOV, KOSIMap makes use of a weighted approach to combine the similarity value from all the three features analyzed. The weights are usually set by a user according to the input ontologies, and output requirements. A similarity matrix is then computed from which a maximum similarity score represents potential alignments. These maximum scores are used to select a pre-alignment output, which is further verified for inconsistencies, before the final output. An example of inconsistency occurs when an entity from a source ontology has multiple correspondences to a target ontology, and the DL reasoner does not recognize any equivalence between the matched entities.As implementation note, the developers for KOSIMap claim that property-based similarities are not always useful to extract alignments, and therefore a matching system should have the possibility to automatically select the best strategy for determining an alignment. Furthermore, users are still a major contributing factor to the selection of weights assigned to each similarity measure performed.

RESULTS AND DISCUSSION

Every year, the OAEI campaign proposes several ontologies in different tracks, and test data that need to be matched. It is seen that not all systems participate in every track, such that no system seem appropriate for all types of ontologies. To obtain a better idea of technique suitability for a given dataset, the main characteristics of each dataset and the corresponding techniques that provide the best matching results for OAEI 2008 and 2009 have been summarized in Table 5.

It is clear from Table 5 that there is not a single system that has the best performance for all datasets. As noted by Cruz *et al*. (2007), the matching technique used is highly dependent on the nature, structure and closeness of the ontologies to be matched. In fact, apart from DSSim, no other system was able to participate in all the OAEI tracks. Plausible explanations could be accounted to time limit, dataset complexity, or system suitability for a particular OAEI track. It is also clear that some techniques seem to work best for a particular dataset. Sambo for instance handles part of relations very well, and shows the best performance for the biomedical dataset. Systems like Sambo, RiMOM and DSSim make use of multi-lingual thesauri like WordNet, and technical domain knowledge resource like UMLS, and are therefore suitable for technical or multi-lingual datasets. DSSim also takes a multi-agent architectural approach, and therefore is able to handle large datasets such as the vclr dataset.

In fact, the latter dataset raises issues for the increasing size, and number of ontologies on the web. Current results from the OAEI campaign show that most matching systems are not ready for scalability, and this could hinder the deployment of such systems for web applications. DSSim proposes a multi-agent approach to find alignment over small ontology fragments in parallel, and results obtained are satisfactory. An alternative technique to solve the problem of scalability has been proposed by Doran *et al*. (2009), who suggest that not all ontologies can be matched, and therefore an initial small scale alignment should be able to determine whether further processing will be beneficial for alignment. This certainly does not solve the problem when both ontologies to be matched are large-sized and have full correspondences to each other, but it does provide a working solution for real life applications, especially when large ontologies do not have appropriate correspondences. This approach can thus save time for matching systems to determine apriori whether they should proceed in finding further alignment or not.

Table 5: Summary of dataset attributes and corresponding successful techniques

Dataset	Dataset attributes	Best System	Successful system characteristics
Benchmark (2008)	•Bibliographic domain, •Artificial and real life data, •Several classes, properties, named and anonymous individuals, •Artificial variants to reference ontology.	Lily	•Hybrid matching strategy employed for small and large scale ontologies, •Specializes in 1-1 matching, •Semantically rich subgraphs used, •Uses text, and structure matching technique •Use of Web Knowledge, •Debugger finds imprecision in mapping.
Anatomy (2008)	•Medical domain, •Real life ontology, •Mostly part Of relations, •Annotations and roles specified, •Medical terms used.	SAMBO	•Specializes in is-a, and part of relations, •Use of WordNet and UMLS thesaurus. •Uses text and structure matching technique, •Learning technique employed, •Conflict checker detects alignment errors.
FAO (2008)	•Fishery domain, •Real life data, •simple class structure, •annotations specified, •multi-lingual, •instances may be present, •Mostly class information.	RiMOM	•Feature analysis of ontologies, •Uses text, and structure matching technique •Use of WordNet thesaurus, •Uses Japanese-English path-similarity strategy.
Directory (2008)	•Web directory domain, •Real life data, •Multilingual, •Simple relations such as subclass and see also, •Vague terminologies present, which can contain errors.	DSSim	•Specializes in subclass relations, •Use compound noun comparison, and abbreviations, •Multi-agent architecture, •Use of WordNet •Similarity matrix created from different measures.
Library (2008)	•Bibliography domain •Real life data, •Dutch language, •Contains book description, •Contains preferred labels and notes, •Mostly controlled vocabulary, •Broader and related relations specified, •Poor structural information, •SKOS format.	DSSim	-
Vlcr (2008)	•Lexical domain, •Large real life dataset, •Multilingual, •Contains hyponyms (subclass like) relations, •Contains titles, and abstracts, •Actual documents may be present, •Weak formal structure.	DSSim	-
Conference (2009)	•Conference organization domain, •Artificially created data, •Aim for both equivalence and •subsumption relation.	KOSIMap	•Feature analysis of ontologies •Make use of DL reasoner •Uses text, and structure matching technique •Weighted approach to combine individual measures, •Similarity matrix created from different measures.
Oriented (2009)	•Bibliographic and conference organization domain •Artificially created data, •Ontologies have different granularity level. •Aim for subsumption relation.	ASMOV	•Feature analysis of ontologies •Uses text and structure matching technique Uses class and property instances. •Use of WordNet and UMLS thesaurus •Weighted approach to combine individual measures, •Similarity matrix created from different measures, •Semantic checker resolve inconsistent mapping.
Instance (2009)	•Scientific publication, actors, sport persons, and business firms domain •Instance data only, •No schema data available •Aim is to find similar instance among different dataset •All dataset structured using same schema.	RiMOM	•Use vector-based methods to find similarity between instances.

Furthermore, a common technique observed among most of the systems studied in this study, is that ontology features (structural, lexical, and semantic) are separately computed, and then aggregated to create a matrix of similarity measures to be used to generate alignments. The current trend therefore indicates a move towards a multi-strategy approach where a system can automatically examine different ontology features, and assign appropriate weights to these features for generating the best alignment. In general a framework for selecting the best matching technique could be beneficial as proposed by Alasoud *et al*. (2009).

But even when a multi strategy approach seem to provide very good results as in the case of Lily, ASMOV, and RiMOM, the developers claim that it is very challenging to decide on the best strategy to combine measures from different features. In real life applications, this may imply that ontology matching should be considered as an interactive process, where ontologies and matching systems should be able to communicate about the best strategy to employ. In general an agent architecture could be appropriate, in which information shared between matching system agents and ontology agents may be about the methods agents carry as well as the feature information ontologies carry.

Furthermore, a positive trend observed in the OAEI campaign is that systems are now required to determine different types of relations other than equivalence relation, such as disjointness, named and subsumption relations. However, at the same time, one serious limitation of the campaign is that most matching is done out of context, with no application in mind. Although the rationale behind such choice is plausible for testing system specific techniques, it remains important to apply these techniques to an application context to determine whether users can make use or agree with the mappings. Cañadas *et al*. (2004) already proposed a framework for ontology mapping with the application in mind, and criticized the fact that most matching techniques are treated as independent, when in fact integrated solutions would be beneficial for the problem of ontology matching. In general, most reference alignments used for evaluation have been created by the organizers, and only very few are determined by experts, or discussed within a consensus group.

Current OAEI campaign also focus on automatic techniques only, and although this is a useful requirement for automating systems for the semantic web or similar applications, results so far in the campaign have shown that no systems can reach a 100% accuracy level when determining alignment. Some systems such as Lily, Sambo and KOSIMap still rely on user feedback to determine alignment quality. Thus, user contribution to ontology matching is still a major part of the process. In fact as Conroy *et al*. (2007) mention, fully automatic matching is impossible, and research in ontology matching should be looking into ways to make ontology matching a user friendly task by using techniques such as tagging for concept and relation specification. De Souza and Davis (2004) further add that:

> although they [automated matching systems] have powerful features to support the user in the task of finding the best matching for a given node, there still remains a lot of work that the user must carry out in order to produce a merged ontology.

Hence as Ding and Foo (2002), already concluded in their study, human experts are an essential part of the mapping process. To sum up, current development in ontology matching systems reveals that the characteristics of an ontology are very important for the success of a particular system. Thus, the challenge remains in devising a multi-strategy approach that can run multiple techniques in parallel to exploit lexical, structural, and semantic information from ontologies along with incorporating user needs in order to determine the most accurate alignment.

CONCLUSION

The Ontology Alignment Evaluation Initiative plays a major role in evaluating techniques proposed for ontology matching. Lessons learnt indicate that no unique matching technique can perform well for ontologies across domains. Instead, a particular technique when tailored to a particular ontology, and its underlying characteristics, such as relation types, structure, and background knowledge provides very good performance in determining correspondences between ontologies to be matched. Consequently, this raises concerns for the semantic web, in which heterogeneous ontologies are expected to interoperate. The present study has identified that a possible solution to this problem is to adopt a multi-strategy approach, where an ontology matching systems elects, and combines different techniques so as to obtain successful results. In addition, scalability remains a pressing challenge, for which a multi-agent architecture seems to be more appropriate. Thus, it is recommended that future matching systems should focus on how to combine multiple strategies to obtain better matching performance and at the same time look into ways that can address scalability of the proposed matching systems.

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REFERENCES

Abels, S., L. Haak and A. Hahn, 2005. Identification of common methods used for ontology integration tasks. Proceedings of the First International Workshop on Interoperability of Heterogeneous Information Systems (IHIS '05) Bremen, Germany, November.

Alasoud, A., V. Haarslev and N. Shiri, 2009. An empirical comparison of ontology matching techniques. J. Info. Sci., 35: 379-397.

Borst, W., 1997. Construction of engineering ontologies for knowledge sharing and reuse. Unpublished Manuscript, University of Twente, Netherlands.

Cañadas, G., M. Fernández-López, R. García-García, M. Lama, A. Sánchez-Alberca and C.O.S. Sorzano, 2004. Framework for Automatic Generation of Ontology Mappings. In: Dieste, O. (Ed.), Iberoamerican Conference on Software Engineering Knowledge eIngeniería (JIISIC'04). Madrid, Spain (in Spanish).

Choi, N., I.Y. Song and H. Han, 2006. A survey on ontology mapping. SIGMOD Rec., 35(3): 4-41.

Conroy, C., D.O. Sullivan and D. Lewis, 2007. A 'Tagging' Approach to Ontology Mapping. Ontology Matching Workshop, International Semantic Web Conference (ISWC 2007), Busan, Korea, 11th November, CEUR-WS.

Cruz, I.F., W. Sunna, N. Makar and S. Bathala, 2007. A visual tool for ontology alignment to enable geospatial interoperability. J. Visual Lang. Comput., 18: 230-254.

De Bruijn, J., F. Martin-Recuerda, D. Manov and M. Ehrig, 2003. D4.2.1 state-of-the-art-survey on ontology merging and aligning V1. SEKT Project Deliverable D4.2.1.

De Souza, K.X.S. and J. Davis, 2004. Aligning Ontologies and Evaluating Concept Similarities, In: Meersman, R. and Z. Tari (Eds.), Lecture Notes in Computer Science (LNCS), 3291. Springer-Verlag, Heidelberg, pp: 1012-1029.

Ding, Y. and S. Foo, 2002. Ontology research and development. Part 2-a review of ontology mapping and evolving. J. Inf. Sci., 28: 383-396.

Doran, P., V. Tamma, T. Payne and I. Palmisano, 2009. Dynamic selection of ontological alignments: a space reduction mechanism. Proceedings of the 21st International Joint Conference on Artificial Intelligence. Pasadena, California, USA, July 11-17, pp: 2028-2033.

Ehrig, M. and S. Staab, 2004. Efficiency of ontology mapping approaches. International Workshop on Semantic Intelligent Middleware for the Web and the Grid at ECAI 04, Valencia, Spain, August 2004.

Euzenat, J. and P. Shvaiko, 2007. Ontology Matching. Springer-Verlag Inc., New York.

Gruber, T.R., 1993. A translation approach to portable ontologies. Knowl. Acquis., 5(2): 199-220.

Gruninger, M. and J. Lee, 2002. Ontology Applications and Design. Commun. ACM, 45(2): 39-41.

Jean-Mary, Y.R., E.P. Shironoshita and M.R. Kabuka, 2009. ASMOV: Results for OAEI 2009. Proceedings for the Fourth International Workshop on Ontology Matching, October 25, Chantilly, USA.

Kalfoglou, Y. and M. Schorlemmer, 2003. Ontology mapping: the state of the art. Knowl. Eng. Rev., 18: 1-31.

Lambrix, P., H. Tan and Q. Liu, 2008. SAMBO and SAMBOdtf results for the Ontology Alignment Evaluation Initiative 2008. Proceedings for the Third International Workshop on Ontology Matching, October 26, Karlsruhe, Germany.

Nagy, M., M. Vargas-Vera, P. Stolarski and E. Motta, 2008. DSSim results for OAEI 2008. Proceedings for the Third International Workshop on Ontology Matching, October 26, 2008, Karlsruhe, Germany.

Reul, Q. and J.Z. Pan, 2009. KOSIMap: Ontology alignments results for OAEI 2009. Proceedings for the Fourth International Workshop on Ontology Matching, October 25, Chantilly, USA.

Staab, S. and R. Studer, 2009. Handbook on Ontologies. Springer-Verlag, Berlin.

Studer, R., R. Benjamins and D. Fensel, 1998. Knowledge engineering: Principles and methods. Data Knowl. Eng., 25(1-2): 161-198.

Visser, P.R.S., D.M. Jones, T.J.M. Bench-Capon, and M.J.R. Shave, 1997. An analysis of ontology mismatches: Heterogeneity versus interoperability. AAAI 1997 Spring Symposium on Ontological Engineering, Stanford, USA.

Wang, P. and B. Xu, 2008. Lily: Ontology alignment results for OAEI 2008. Proceedings for the Third International Workshop on Ontology Matching, October 26, 2008, Karlsruhe, Germany.

Xu, P., H. Tao, T. Zang and Y. Wang, 2009. Alignment results for SOBOM for OAEI 2009. Proceedings for the Fourth International Workshop on Ontology Matching, October 25, Chantilly, USA.

Zhang, X., Q. Zhong, J. Li and J. Tang, 2008. RiMOM results for OAEI 2008. Proceedings for the Third International Workshop on Ontology Matching, October 26, Karlsruhe, Germany.