Bima Journal of Science and Technology Vol. 2 No. 1 January, 2018 ISSN25366041

# REVIEW OF ONTOLOGY ALGINMENT SYSTEMS

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## ABSTRACT

Ontologies were developed to describe a given domain in the semantic web. However due to variation in views of developers, ontologies are heterogeneous hence preventing interoperability. Ontology alignment solves this heterogeneity problem by discovering relationships between entities of different ontologies. Various ontology alignment systems have been developed over the years. Different researches have been carried out in an attempt to review this area. However, there is still a need for an up to date review of the ontology alignment systems in order to allow continuous research in the field. In this paper, twelve different ontology alignment systems were reviewed nine were found to be fully automatic while three are semi-automatic. Furthermore most of the systems use a combination of different matching techniques while others use only single matching technique.

**key words**: semantic web, ontology, ontology alignment

## Introduction

The goal of the World Wide Web is to make its content understandable and accessible to both humans and machines. But due to poor structure of the content, the goal is yet to be achieved. The Semantic Web extends the current Web by giving it meaning, classifying and organizing information so that it is not only interpretable by humans but also by machines (Pandey & Dwivedi, 2011). It provides methods and technologies to allow machines to understand the meaning or "semantics" of information on the WWW by using ontologies.

Ontologies describe a given domain by expressing the common terms and relations enabling machines to understand the meaning and reason about data. Ontologies have been developed for different domains by various developers having different perceptions. This leads to semantic heterogeneity. For example, given two ontologies of the same domain, the same entity can be given different names or simply be defined in different ways, or both ontologies may express the same knowledge but in different languages. Such heterogeneity can be solved through ontology mapping or ontology alignment. Ontology mapping is a Formal expression describing a semantic relationship between two (or more) concepts belonging to two (or more) different ontologies while ontology alignment are set of matches between two (or more) ontologies in the same domain or in related domains. These matches are called "Mappings". In summary, Mapping is the process of aligning two ontologies (Amrouch & Mostefai, 2012).

Ontology alignment is the process of discovering maps between entities of different ontologies that describe same domain. An alignment is a set of correspondences between entities belonging to the matched ontologies. Given two ontologies, a correspondence is a 4-Tuple: (id, $e_1$, $e_2$, r), such that: id is an identifier for the given correspondence;

$e_1$ and $e_2$ are entities, e.g., classes and properties of the first and the second ontology, respectively;

r is a relation, e.g., equivalence (=), disjointness (⊥), holding between $e_1$ and $e_2$.

The correspondence id, $e_1$, $e_2$, r asserts that the relation r holds between the ontology entities $e_1$ and $e_2$. Correspondences have some associated *metadata*, such as the correspondence author name (Shvaiko & Euzenet, 2015).

Several ontology alignment systems have been developed over the years using different matching techniques. While many of the systems have been in existence for long and are being improved, others are at a standstill. Different researches have been carried out on the field of ontology alignment, but in other to keep the ball rolling in this area there is need to keep an up to date review. The aim of this paper is to review state of the art alignment systems.

In the second section we provided the general concepts of ontology alignment techniques. Then, we describe in some details the research methodology in the third section. In the forth Section presents sample alignment systems that participated recently in the Ontology Alignment Evaluation Initiative campaign, including their techniques and limitation. Finally, in the fifth section a discussion and conclusion.

**Ontology matching Techniques**

Ontology matching systems apply different matching techniques to calculate similarities between entities from given ontologies. The techniques can be generally classified into two (Shvaico & Euzenat, 2005): In this section we present the three most common similarity measures used in ontology alignment systems and their sub categories with examples

- Element level matching techniques: Techniques under this category perform matching by analyzing entities in isolation, ignoring their relations with other entities. Element level matching techniques are further categorized into String based techniques, Language based techniques, Constraint based techniques, Linguistic Resources, Alignment Reuse, and Upper-level Dolce.
    - String based techniques consider names of entities as strings of characters. The

idea is that, the more similar the strings, the more likely they denote the same concepts. Some examples of string-based techniques which are mostly used in matching systems are (Shvaico & Euzenat, 2005): Edit distance, I-SUB as used in FALCON-AO(Jian et al., 2005), N-gram, Jaccard, Jaro-Winkler as used in ALIN (Silva, Baião, & Revoredo, 2016).

- Language based Techniques consider names of entities as words of a natural language. The techniques involve the following (Shvaico & Euzenat, 2005); Tokenization, Lemmatization, Elimination of stop words as in L-YAM++[(Nasser et. al, 2016)] and SimCat (Khiat et.al, 2016).
- Constraint based Techniques consider internal constraints applied to the definitions of entities such as data types, cardinality of attributes, sub concepts or keys. The similarity of data types or the cardinality of attributes (of entities) determines similarity between the entities. The use constraint technique is applied by LPHOM (Megdiche et.al, 2016).
- Linguistic Resource consider names of entities as words of natural language, thus external resources such as common knowledge or domain specific thesauri are used in order to match words based on linguistic relations (synonyms, hyponyms and so on) between them (Shvaico and Euzenat, 2005). Examlpes of systems using linguistic resource are ALIN (Silva, Baião, & Revoredo, 2016), AML (Daniel, et al 2016), and the extension of FALCON-AO[(Jian et al., 2005),] by (Alhassan B.B, Junaidu S.B, & Obiniyi A.A, January 2015 ).
- Alignment Reuse involves using an external resource which contains alignments of previously matched ontologies (reference alignment). The idea here is that ontologies to be matched may be similar to already matched ones as used in RIMMOM (Shao, Hu, Li et.al, 2016). This can speed up alignment process.
- Upper level formal ontologies are also external resources. Examples of such ontologies include: Suggested Upper Merged Ontology

(SUMO) and Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE).

- Structure-level techniques match entities of given ontologies by analyzing how they appear together in a structure. Structural based techniques can be classified into; Graph-based Techniques, Taxonomy-based techniques, and Model-based techniques.
  - Graph-based Techniques view ontologies as graph-like structures consisting of entities and their interrelationships. Graph algorithms are used to compute similarity between pair of entities by analyzing their positions within the graph. Example of matcher with such intuition is GMO (Graph Matching for Ontologies) (Hu, Jian, Qu, &Wang, 2005).
  - Taxonomy-based techniques align entities using thea graph structure, but only specialization relation i.e. through "is-a" link is considered. The idea behind taxonomic techniques is that is-a links connect terms that are already similar (being a subset or superset of each other). STROMA (Arnold, 2016) is an example of systems that use such technique.
  - Model-based techniques make use of the semantic interpretation of the input ontologies. Major techniques used are the propositional Satisfiability (SAT) description logics reasoning techniques.
- Instance-Based Techniques are considered whenever the schemas to be matched use different terms to describe the same real-world-concept. Instance-based techniques can be used to improve the effectiveness of the schema based approaches. LiLy (Wang & Wang, 2016), AML (Daniel, et al 2016) and RIMMOM(Shao, Hu, Li et.al, 2016).

**Research Method**

In this paper, we reviewed ontology matching techniques i.e the techniques applied by the alignment systems which are basically divided into element level and structure techniques. Next, state of the art ontology alignment systems are reviewed studying the techniques used by each system and their limitations. Most of the reviewed systems are active systems that participated recently in OAEI (Ontology Alignment Evaluation Initiative). The review considered different journal articles and conference proceedings.

### Reviewed Ontology Alignment Systems

**Hertuda** (Hertling, 2012): - is a freely available, simple, fast ontology matching tool. It uses a string matcher and element based matcher that generates only similar matching that are compatible with OWL Lite/DL. It separately does the alignment of classes, data properties and object properties and retrieves among the possible ones reaching certain pre-established thresholds. Despite its simplicity, it outperforms many state-of-the-art ontology matching tools (Oleksiy, 2017).

The approach is only string based working on the element level, so missing labels or comments or replaced terms have a very high effect on the matching algorithm. Another weakness is that a single threshold is set for all matching ontologies irrespective of the size and domain.

**ALIN** (Silva, Baião, & Revoredo, 2016): is an ontology alignment system for large repositories, which involves experts of the domain enhancing the quality of the final alignment. It is based primarily on linguistic matching techniques, using the WordNet as external resource. It uses semantic and structural methods to display a selection of correspondences to the experts based on previous feedback from the experts. ALIN executes six linguist metrics which involves Jaccard, Jaro-Winkler, n-Gram, Wu-Palmer, Jiang-Con and Lin and the result set is the union of results of each metric. A limitation of ALIN is its reliance on an interactive phase and it is also non-robust to user's errors.

**AgreementMakerLight (AML)**

(Daniel, et al 2016): is a free source automated ontology matching system that stems from AgreementMaker which is one of the leading systems in the field of ontology and schema matching since the beginning of its development in 2001(Daniel Faria, et al 2013).AML was initially designed to focus on biomedical ontologies but it is now a general purpose ontology alignment system. It handles large ontology matching problems, it is principally based on lexical matching techniques, also stressing on the use of external resources as background knowledge which are Uberon, DOID, the MeSH, and the WordNet. Microsoft®Translator, translates the names of all classes and properties from the language(s) of the first ontology to the language(s) of the second and vice-versa.

For small ontologies, AML also employs the Multi-Word Matcher, which matches closely related multi-word names that have matching words and/or words with common WordNet synonyms or close hypernyms, and the new Acronym Matcher, which attempts to match acronyms to the corresponding full name.

In 2016 AML was improved to tackle instance matching, using three matching algorithms: HybridStringMatcher, ValueStringMatcher, Value 2 Lexicon Matcher. AgreementMakerLight also carries out Repair by using heuristic repair algorithm to ensure that the final alignment is consistent.

**Lily** (Wang & Wang, 2016) is anontology mapping system that aims to provide high quality 1:1 concept pair or property pair alignments. Lily uses five appropriate matching strategies; *Generic Ontology Matching (GOM)* used for common matching tasks with normal size ontologies, Large scale *Ontology Matching(LOM)* is used for the matching tasks with large size ontologies using the negative anchors and positive anchors to predict the pairs that can be passed in the later matching computing, *Instance Ontology Matching (IOM)*used for instance matching tasks, *Ontology mapping debugging* used to verify and improve the alignment results and *Ontology matching tuning* used to enhance overall performance. In 2016 Lily adopted matching tuning which is not automatic. Lily takes time and consumes high memory which prevents Lily from finishing some challenging tasks. Therefore, needs more optimization to handle large ontologies with limited time and memory, techniques like parallelization should be applied. Also, the matching tuning should be automated ontology matching tuning.

**CroMatcher** (Gulić, Vrdoljak, & Banek, 2016): is an automatic ontology matching system for discovering correspondences between entities of two different ontologies. CroMatcher contains several terminological (n-gram, TF/IDF and cosine similarity) and structural matchers connected through sequential-parallel composition. Before the final alignment, the aggregated correspondence results of the terminological matchers and the aggregated correspondences'results of the structural matchers need to be aggregated using weighted aggregation. Eventually, the method of the final alignment is executed. The advantage is the method iteratively takes the best correspondences between two entities into the final alignment while Consuming time during execution of the structural matchers.

**RIMMOM-2016** (Zhang, Jin, Pan & Li 2016) or **RIMMOM-IM** (Shao, Hu, Li et.al, 2016) is an extended version of RIMMOM(Li , Tang , Li & Luo, 2009)with support for matching instances in an iterative way, which utilizes the aligned instances for matching the remaining instances in each iteration. The extension includes support for cross-lingual instance matching in a supervised or an unsupervised way. TF-IDF is used to compute values of words in each knowledge base. Alignments are generated using supervised method when there is enough reference alignments. The unsupervised method, calculates similarities between two instances on each property, and then aggregate these similarities according to the degree of identifying obtained. Finally, similarity propagation procedure is iteratively run until no more candidate mappings are discovered and the system converges. One of the drawbacks of the system is that it relies heavily on machine translation in cross-lingual matching.

**L-YAM++** (Nasser et. al, 2016)is a fully automatic ontology matching system that extends its base system YAM++( Ngo & Bellahsene, 2016 )with the use of external sources (*BabelNet).*Matching is done using four; *terminological matcher*, a *mapping* *selection module* and, *structural matcher*. The cross-lingual matcher employed relies on the use of related terms and synonyms from Babelnet and the similarity value is estimated using *TF/IDF* similarity measure. LYAM++ is weak in handling large-scale ontology matching scenarios.

**SimCat** (Khiat et.al, 2016) system unlike existing systems that use well-known translators, Sim- Cat employs the Yandex translator and computes the similarities between translated entities based on the categories of the words. The processing steps are; *Segmentation, Translation and Cleaning* where normalized entities are translated using the Yandex translator into English. The similarity between entities is computed using the categories of words. The matcher used is based on an open project named ”Calculate Semantic Similarity” which calculates similarities between sentences by generating list of words from EOWL, then calculates the category of each word using DISCO’s.

semantics. A major drawback of this system is its high computation time especially with large ontologies.

**LPHOM-Linear Program for Holistic Ontology Matching** (Megdiche *et.al*, 2016) is a holistic ontology matching system for matching multiple and pair wise ontologies. Labels of non-English ontologies are translated using Microsoft-translation Java API. The system uses ISUB and 3-gram to compute similarity between tokens, Mongue-Elkan method to compute similarity between entities, *token-based category* (Jaccard), and Lin’s semantic measure (Lin, 1998) are also used. The system requires large amount of memory during processing and does not handle very large ontologies.

**Falcon-AO (Falcon- Aligning Ontologies)**

Falcon-AO (Jian *et al.*, 2005) is a fully automatic ontology alignment system which aims at finding alignments between web ontologies that are expressed in RDFS and OWL format. Falcon-AO uses both structural and string techniques and also considers comment and label information. It has a special method for large ontologies based on divide and conquer approach (Hu& Qu, 2008). An extension of Falcon-AO with an external resource to accommodate semantic matching using WordNet was seen in (Alhassan et.al, 2015).Falcon-AO++ (Jauro et.al, 2014) is also an extension of Falcon-AO with support for interactive contribution of an expert in the matching process. Both extensions have shown significant improvement in alignment results of the system, but the system still supports only one to one mapping and equivalent relation.

**STROMA** (Arnold, 2016):

(**S**eman**T**ic **R**efinement of **O**ntology **MA**ppings) is a mapping enrichment tool that calculates the relation type of correspondences within a given ontology mapping or schema. The process takes place in two steps; ontology matching and mapping enrichment which removes false correspondences, this leads to a better mapping precision. However, such mappings will have a better recall, but a lower precision, which STROMA tries to augment by means of different repair techniques and strong dependency on the initial mapping.

**Table 1:** Summary of origin, automatic, semiautomatic and limitation

| System | Origin | Free or Not | Automatic/ Semi-Automatic | Input | Specific techniques | Relation ship(s) | External Resources | Limitation |
|---|---|---|---|---|---|---|---|---|
| **Hertuda** | Technische Universität Darmstadt in Germany | Free | Automatic | Owl lite/DL | String | Equivalent | | Missing labels or comments or replaced terms have a very high effect on the matching algorithm. |
| **ALIN** | Federal University of the State of Rio de Janeiro,**Brazil** | Free | Semi-Automatic | Ontology | Linguistic,Structural | Equivalent | WordNet | Reliance on an interactive phase and it is also non-robust to user's errors |
| **AML** | **Portugal** and **USA** | Not Free | Automatic | Ontology | String, instance | Equivalent | Uberon, DOID, MeSH, WordNet | |
| **LILY** | Southeast University, Nanjing,**China** | Free | Automatic | Ontology | String,Structural | | | Lily takes time and consumes high memory |
| **CroMatcher** | university of rijeka Croatia | | Automatic | Ontology in OWL | String, Structural,instance | | WordNet,Uberon | Consumes time during execution of the structural matchers |
| **RIMMOM-IM** | Tsinghua University, Beijing,China | | Semi-Automatic | | String, structural, Instance | Equivalent, is-a, inv. is-a | WordNet | Relies heavily on machine translation in cross-lingual matching. |
| **LYAM++** | Universityof Montpellier, France | | Automatic | Ontologies | String, Structural | | BabelNet, Uberon | weak in handling large-scale ontology matching scenarios |
| **SimCat** | **Algeria** | Not free | Automatic | different languages | Categories of words based on an open project's matcher. | - | Yandex translator | high computation time especially with large ontologies |
| **LPHOM** | Institute of Research and Informatics, Toulouse,**France** | free | Automatic | OWL | String | Equivalent | | requires large amount of memory during processing and does not handle very large ontologies. |
| **Falcon-AO** | Southeast University,Nanjing,**China** | Free | Automatic | RDF,OWL | String,Structural | Equal | | Supports only 1 to 1 mapping and equivalent relation. |
| **STROMA** | Leipzig University (2013) | Not free | Automatic | Schema /ontology | Linguistic, structural and instance | equal, is-a, inv. is-a, part-of, has-a, related | linguistic SemRep | High recall, but a lower precision due to mapping repairand strong dependency on the initial mapping |
| **AROMA** | Universite Pierre-Mendes-France | free | Semi-Automatic | OWL | String,Semantic | Equivalence and subsumption | | Requires structural matching technique and parameter tuning to improve precision and recall |

**AROMA** (David, 2011): AROMA is a semi-automatic ontology alignment system that uses a combination of extensional and asymmetric matching approaches to find equivalence and subsumption relations between entities of ontologies, makes use of the association rule paradigm. AROMA efficiently matches ontologies in reasonable time but suffers at the pruning strategy,it is also degraded due to the sub-sumption correspondences it returns. Table1 below represents a summary of the reviewed systems based on input, automatic, semi-automatic, relationship type(s), specific techniques and limitations of the alignment system.

## Discussion

In this paper, we have introduced briefly the idea of semantic web, ontology and ontology alignment. To some extent, different techniques used for ontology matching have been discussed. Various ontology alignment systems have been reviewed considering the techniques applied by each of the systems and areas where improvement is needed. From the research it was observed that some system are hybrid (use a combination of marching techniques) and others use only single matching technique. Other studies were similarly carried out; (Iroju, *et. al*, 2012) conducted a comparative analysis of sixteen ontology alignment systems looking at strategies employed ,ontology structure considered ,output and language supported (Shvaiko ,2013) reviewed seven different ontology alignment systems categorizing them into input language,output alignment, Techniques used,whether or not having a graphical user interface and operation performed,and (Ramar & Gurunathan, 2016) reviewed seven (7) different ontology alignment system focusing on features such as input languages,output, matching technique and user interaction.

## Conclusion

Ontology Alignment is very important in many application domains such as semantic query, artificial intelligence, data integration and data-warehousing. Several methods and systems have been proposed to handle ontology Alignment .In this paper, we have surveyed the techniques and methods adopted by the systems.In conclusion, experts in the field of computing need to keep an up to date research in order to improve the capabilities of ontology alignment technologies and also for the semantic web to achieve its goal.


## Acknowledgement

We appreciate the support and guidance of Dr. Musa A.U of Faculty of Pharmaceutical Science, Ahmadu Bello University Zaria.


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