FCAMap-KG Results for OAEI 2019

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Abstract. In OAEI 2016, we submitted the system FCA-Map for taking advantage of the Formal Concept Analysis (FCA) formalism in aligning large and complex biomedical ontologies. This year, we present a variant called FCAMap-KG, following the rationale of FCA-Map and designed for matching knowledge graphs. Among the 12 matchers participating in the OAEI 2019 Knowledge Graph track, our system ranks the first for instance and property mappings and ranks second for class mappings. As a result, FCAMap-KG has achieved the best overall F-measure for the track. This demonstrates the power of our FCA-based approach in identifying correspondences across different kinds of data and knowledge representation systems.

1 Presentation of the system

In OAEI 2016, we proposed the system FCA-Map [8,9,10] for taking advantage of the Formal Concept Analysis (FCA) formalism in aligning large and complex biomedical ontologies. Further in OAEI 2018, its variant FCAMapX [3] was submitted to largely improve the efficiency of the system. This year, we present a new variant called FCAMap-KG, for exploiting the potential of our FCA-based approach in matching knowledge graphs (KGs).

1.1 State, purpose, general statement

Formal Concept Analysis is a mathematical model for structuring concept hierarchies from clustering individuals [4,7]. In FCA, the domain or problem is described first by a formal context consisting of a set of objects, a set of attributes and their relations. Based on this, a lattice structure can be computed with each node representing a formal concept and edge a subconcept-superconcept relationship. Being a knowledge graph matching system based on FCA, FCAMap-KG follows the rationale of our previous systems FCA-Map and FCAMapX by consecutively constructing lexical and structural formal contexts and extracting mappings across KGs.

Ontologies and KGs are both knowledge representation models sharing RDF graphs as the underlying data structure. Ontologies focus on schematic knowledge and adopt logic-based reasoning to infer implied relations, whereas KGs mainly describe data in RDF triples and train numerical vector representations so as to predict semantic correlations [2]. Ontologies are limited to certain domains with precise knowledge and KGs are much larger in scale where data can be noisy. For both, identifying correspondences between systems is crucial for realizing semantic integration in the Semantic Web. Their distinctive differences, however, make applying ontology matching approaches to KGs a nontrivial endeavor. Particularly in our case, for building formal contexts at the structural level, FCA-Map and FCAMapX mainly use the ontological relationships including taxonomy, partonomy, disjointness, and property axioms among classes. While normally these are not available in KGs, FCAMap-KG turns to RDF triples where two instances are connected by a property. In our FCA-based approach, lexical formal context describes how names share tokens from which lexical mappings are generated. This is effective for both ontology and KG matching tasks as classes, properties and instances are all labeled with preferred names and synonyms.

1.2 Specific techniques used

The steps that FCAMap-KG system implements are presented as follows.

1. **Lexical matching.** For the given two KGs in comparison, the system builds three token-based formal contexts, for classes, properties and instances, respectively. One entity in KG can have multiple names and labels, and every one of them is treated as an object in the formal context; tokens extracted from all the names/labels in two KGs are used as attributes. Note that one object in the formal context can be associated with multiple entities in KGs and at the same time one entity can have multiple entries as objects. In the Galois lattice constructed from token-based formal context [4], lexical mappings are generated when formal concepts contain objects originated from two KGs.
2. **Structural matching.** The system proceeds to construct the structural formal context using lexical mappings obtained so far. KGs tend to have massive instances while properties and classes are much less, and as stated in [6,5], matching instances can be harder than classes and properties. Thus we focus on identifying structural correspondence among instances at this step. For the given two KGs, every instance is used as an object in the formal context. The attributes comes from pairing two RDF triples across KGS whose properties and tail instances have been matched, respectively, at the lexical step. Such a formal context describes how instances share connections to other instances, thus has a potential to reflect the structural similarities across KGs. In the lattice computed, structural mappings are generated when formal concepts contain instances from two KGs.
3. **Mapping filtering.** The OAEI 2019 Knowledge Graph track bases its evaluation on that all mappings are 1:1, i.e., one entity can only have at most one correspondence in the other KG. Due to this, the system employs a filtering process on cases

[4] We implemented the algorithm HERMES [1] for constructing the lattice.

when one entity occurs in multiple mappings identified. Mappings that possess more shared structural attributes and more lexical tokens are selected.

1.3 Adaptations made for the evaluation

Conforming to the evaluation criteria of the Knowledge Graph track this year, the SEALS submission of FCAMap-KG is modified to produce only 1:1 mappings. In general, FCAMap-KG is not restricted this way and can find cases when one entity is matched to multiple entities in another knowledge graph.

1.4 Link to the system and parameters file

The SEALS wrapped version of FCAMap-KG for OAEI 2019 is available at `https://drive.google.com/open?id=1pZ5Hzv8_wfULKYN4Uc_kcmlkPseJ7kQ_`

1.5 Link to the set of provided alignments

The results obtained by FCAMap-KG for OAEI 2019 are available at `https://drive.google.com/open?id=1bS19DDe7nZNC1MlHB8qX-yoACWBWELGR`

2 Results

In this section, we present the evaluation results obtained by running FCAMap-KG on *Knowledge Graph* track under the SEALS client in OAEI 2019 campaign. Although our system was not intended to participate in other tracks, OAEI reported whenever FCAMap-KG could generated an alignment [5]. Therefore, the results for these tracks will also be introduced including *Anatomy*, *Large Biomedical Ontologies*, *Disease and Phenotype*, and *Biodiversity and Ecology*. The evaluation was performed on a virtual machine (VM) with 32GB of RAM and 16 vCPUs (2.4 GHz).

2.1 The OAEI 2019 Knowledge Graph Track

The Knowledge Graph track requires finding alignments at both schema and data level, including class mappings, property mappings and instance mappings. The track consists of a total of five matching tasks among nine isolated knowledge graphs for describing movies, comics, TV and books. We follow the OAEI evaluation criteria in counting positives and negatives based on 1:1 matching and the partialness of gold standard. The overview results of FCAMap-KG are presented in Table 1 where **Size** indicates an average number of mappings obtained. As reported by OAEI [6], among the 12 participants, our system ranks the first in F-measure for instance and property mappings and ranks second for class mappings. As a result, FCAMap-KG has achieved the best overall F-measure for the track.

[5] http://oaei.ontologymatching.org/2019/results/

[6] http://oaei.ontologymatching.org/2019/results/knowledgegraph/index.html

Table 1. Overview results for Knowledge Graph track

Class				Property				Instance				Overall			
Size	Prec.	Rec.	F-m.	Size	Prec.	Rec.	F-m.	Size	Prec.	Rec.	F-m.	Size	Prec.	Rec.	F-m.
18.6	1.00	0.70	0.82	69.0	1.00	0.96	0.98	4530.6	0.90	0.79	0.84	4792.6	0.91	0.79	0.85

The overall performance of FCAMap-KG for each matching task is listed in Table 2, and when breaking down into class, property and instance mappings, the results for each task are shown by Table 3, Table 4, and Table 5, respectively. FCAMap-KG stands out in matching properties by having a 100% precision for four tasks, and according to OAEI, obtains the best F-measure for all five tasks among 12 participants. For instance mappings, the system stays in top three F-measures for all tasks; all the class mappings generated by FCAMap-KG for the track are correct and its F-measure ranks first for two tasks.

Table 2. Overall results for each matching task in Knowledge Graph track

Matching task	Size	Precision	Recall	F-measure
marvel cinematic universe - marvel	2,682	0.84	0.65	0.73
memory alpha - memory beta	13,171	0.92	0.85	0.88
memory alpha - stexpanded	3,174	0.94	0.89	0.91
star wars - swg	2,140	0.90	0.71	0.80
star wars - swtor	2,796	0.93	0.87	0.90

2.2 Other OAEI 2019 Tracks

OAEI reported the performance of our system in tracks other than the Knowledge Graph, and they are *Anatomy*, *Large Biomedical Ontologies*, *Disease and Phenotype*, and *Biodiversity and Ecology*. The results obtained by FCAMap-KG for these tracks are shown in Table 6, 7, 8, and 9, respectively.

– The Anatomy track aims at finding an alignment between the Adult Mouse Anatomy (2744 classes) and a fragment of the NCI Thesaurus (3304 classes) for describing the human anatomy.
– The Large Biomedical Ontologies track consists of identifying mappings among the Foundational Model of Anatomy (FMA), SNOMED CT, and the National Cancer Institute Thesaurus (NCI). These ontologies are of both large-scale and semantic richness, and both whole ontologies and fragments are used.
– The Disease and Phenotype track involves the matching task between the Human Phenotype (HP) Ontology and the Mammalian Phenotype (MP) Ontology, and the

Table 3. Class results for each matching task in Knowledge Graph track

Matching task	Size	Precision	Recall	F-measure
marvel cinematic universe - marvel	8	1.00	1.00	1.00
memory alpha - memory beta	21	1.00	0.29	0.44
memory alpha - stexpanded	24	1.00	0.62	0.76
star wars - swg	12	1.00	0.80	0.89
star wars - swtor	28	1.00	0.80	0.89

Table 4. Property results for each matching task in Knowledge Graph track

Matching task	Size	Precision	Recall	F-measure
marvel cinematic universe - marvel	19	1.00	0.91	0.95
memory alpha - memory beta	93	1.00	0.94	0.97
memory alpha - stexpanded	73	0.98	0.98	0.98
star wars - swg	48	1.00	1.00	1.00
star wars - swtor	112	1.00	0.98	0.99

matching between Human Disease Ontology (DOID) and the Orphanet and Rare Diseases Ontology (ORDO).
- The Biodiversity and Ecology track aims at detecting equivalence between the Environment Ontology (ENVO) and the Semantic Web for Earth and Environment Technology Ontology (SWEET), and between the Plant Trait Ontology (PTO) and the Flora Phenotype Ontology (FLOPO).

Note that unlike FCAMap and FCAMapX specifically for aligning biomedical ontologies, FCAMap-KG targets knowledge graphs where schematic knowledge is generally rare, thus none domain thesauri or external terminologies have been used to facilitate the matching. It is understandable that FCAMap-KG did not perform as well as FCAMap and FCAMapX on life sciences ontologies. Nevertheless, without the support of any domain knowledge, FCAMap-KG ranks first in precision for MA-NCI task among 12 participants, for the two Disease and Phenotype tasks among 8 participants, and for ENVO-SWEET task among 6 participants.

3 General comments

3.1 Comments on the results

This is the third time that we participate in the OAEI campaign with our Formal Concept Analysis based system. Developed targeting knowledge graph matching, FCAMap-KG has achieved a satisfactory result by ranking first in F-measure for overall five KG tasks among 12 participants. For every single task, our system obtains the best F-measure

Table 5. Instance results for each matching task in Knowledge Graph track

Matching task	Size	Precision	Recall	F-measure
marvel cinematic universe - marvel	2,603	0.84	0.65	0.73
memory alpha - memory beta	12,474	0.92	0.85	0.88
memory alpha - stexpanded	3,008	0.94	0.89	0.91
star wars - swg	2,004	0.90	0.70	0.79
star wars - swtor	2,564	0.93	0.86	0.89

Table 6. Results for *Anatomy* track

Matching Task	Size	Precision	Recall	F-measure
MA-NCI	960	0.996	0.631	0.772

for property mappings and remains in top three for instance mappings. Of note, taking advantage of the efficiency mechanism implemented by FCAMapX, FCAMap-KG managed to finish all the KG tasks within given time despite the high computation complexity of FCA formalism per se. Additionally, although unintended, FCAMap-KG is reported in four biomedicine and ecology tracks by OAEI 2019 with a competitive performance in precision.

3.2 Discussions on possible improvements

The very first step of FCAMap-KG is lexical matching whose resultant mappings are used in the subsequent structural matching steps. This means that our system is susceptible to the lexical labeling of entities in knowledge graphs. When the naming is diverse across KGs, as in the case of *marvelcinematicuniverse - marvel*, gold standard mappings like $< marvelcinematicuniverse : Combat\_Enhancers,\ marvel : Adrenaline\_Pills >$ can be missed. For this task, FCAMap-KG's F-measure is 10% to 20% lower than the other four tasks, as listed in Table 2. This indicates the importance of structural matching which is capable of identifying matches not having anything common in names. We are in the process of constructing an iterative framework for using mappings obtained so far to enhance the current loop of matching until no further mappings are found. Such a comprehensive way of incorporating lexical and structural information of classes, properties and instances can take advantage of data and knowledge represented in KGs to the fullest.

As mentioned above, an adjustment made in FCAMap-KG for participating the Knowledge Graph track is to limit the mappings selected to one-to-one. Again, take the task *marvelcinematicuniverse - marvel* for example, where two mappings
$< marvelcinematicuniverse : Zodiac,\ marvel : Zodiac >$ and
$< marvelcinematicuniverse : Zodiac,\ marvel : Zodiac\_Virus >$ are generated by our system and eventually the former is selected whereas the latter is the correct match in gold standard. None whatsoever relevant structural information within the two

Table 7. Results for *Large BioMedical Ontologies* track

Matching Task		Size	Prec.	Rec.	F-m.
FMA-NCI	small fragments	2,508	0.967	0.817	0.886
	whole ontologies	3,765	0.622	0.817	0.706
FMA-SNOMED	small fragments	1,720	0.973	0.222	0.362
	FMA whole w/ SNOMED large fragment	1,863	0.881	0.222	0.355
SNOMED-NCI	small fragments	10,910	0.937	0.555	0.697
	SNOMED large fragment w/ NCI whole	12,813	0.789	0.555	0.652

Table 8. Results for *Disease and Phenotype* track

Matching Task	Size	Precision	Recall	F-measure
HP-MP	734	0.997	0.322	0.487
DOID-ORDO	1,274	0.999	0.443	0.614

KGs makes it difficult to do the right decision. For such cases, external resources shall be exploited, providing necessary knowledge for the domain of interest.

3.3 Comments on the OAEI procedure

With respect to the OAEI procedure, the Knowledge Graph track that our system participated in this year is adequately well designed, with organizers being very supportive in resolving issues arisen in the middle of execution phase. The only difficulty we encountered comes from a dependency on Jena packages on the SEALS platform. The problem got settled successfully in the end, and it might be helpful if participants whose systems include Jena packages can be informed in advance that re-packaging Jena on SEALS platform requires additional declaration of the Global Location Mapper. Overall, we sincerely appreciate the efforts by organizers in establishing the OAEI campaign, and with the prospect of further improving the system, we look forward to be back next year.

4 Conclusions

In this paper, we present a variant of FCA-Map called FCAMap-KG, which is particularly designed for matching knowledge graphs. KGs are normally of large size and focus on describing instance connected with properties rather than schematic knowledge of classes as in domain ontologies. FCAMap-KG's performance in the OAEI 2019 *Knowledge Graph* track, together with its two predecessors, demonstrates the power of our FCA-based approach in detecting correspondences across different kinds of data and knowledge representation systems. With the prevail of knowledge graph research in Semantic Web and knowledge engineering community and in industry, extending our system with comprehensive functions and frameworks shall contribute more to this thriving domain.

Table 9. Results for *Biodiversity and Ecology* track

Matching Task	Size	Precision	Recall	F-measure
FLOPO-PTO	171	0.836	0.601	0.699
ENVO-SWEET	422	0.803	0.518	0.630

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