

# Effect of Enriched Ontology Structures on RDF Embedding-Based Entity Linking

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**Abstract.** RDF embeddings are recently used in Entity Linking systems for disambiguation of candidate entities to match the best mention and entity pairs. In this study, we evaluate the effect of enriched ontology structures for disambiguation task when RDF embeddings are used to identify semantic relatedness between knowledge base concepts. We generate a domain-specific core ontology and put new components upon previous ontology structures. In this way, we obtain four different enriched structures and transform them into RDF embeddings. Then, we observe which enriched structure has more importance to enhance the overall performance of RDF embeddings-based Entity Linking approaches. We select two well-known knowledge-base-agnostic approaches, including AGDISTIS and DoSeR and adapt them into RDF embeddings-based entity disambiguation. Finally, a domain-specific evaluation dataset is generated from Wikipedia to observe the effect of enriched structures on these adapted approaches.

**Keywords:** RDF embeddings · RDF2Vec · HITS · PageRank

## 1 Introduction

Entity Linking systems map mentions of a text with their referent entities in a given knowledge base. These systems involve mention detection and entity disambiguation tasks. After detecting mentions, Entity Linking systems choose the highest ranked entity over all identified candidates for each mention. Ranking of candidate entities is the most critical step of the disambiguation task and independent (local) and collective (global) rankings are two main approaches became prominent in the literature [1]. While independent ranking only considers the relatedness between a candidate entity and a mention, collective ranking approaches focus on the relatedness of candidate entities identified for mentions surrounded by other entities in the referent knowledge base. To compute this relatedness, Milne and Witten [2] propose the semantic relatedness that is one of the primary methods and highly depends on the Wikipedia link structure. Most of the studies such as [3, 4] exploit this measurement in the global coherence based disambiguation task. The main drawback of this measurement is that whether

the background knowledge is not based on the Wikipedia link structure, it is impossible to compute the semantic relatedness of candidate entities.

To avoid the dependency for the Wikipedia link structure, knowledge agnostic approaches have appeared in recent years. Hence we need a knowledge base independent semantic relatedness measure to apply Entity Linking with other knowledge bases than Wikipedia. In recent Entity Linking systems such as AGDISTIS [5] and DoSeR [6] being knowledge agnostic is one of their main focus and they can use any ontology like knowledge bases for Entity Linking. Most recent work DoSeR has achieved higher precision and recall values than AGDISTIS using a transformation Word2Vec [7] model into RDF embeddings to compute semantic similarities. These similarities are leveraged in PageRank algorithm to find out global coherence. Based on successful results of DoSeR, we mainly investigate which joined component of ontology structure has the most impact to the RDF embeddings-based semantic relatedness computation. The different levels of components are added to the core ontology structure and observed which ontology component has more importance than others to increase the performance for knowledge-agnostic Entity Linking approaches depends on RDF embeddings. We adapt HITS algorithm to RDF embeddings in AGDISTIS and PageRank algorithm in DoSeR. Finally, we evaluate them in the entity disambiguation task built from RDF embeddings of domain-specific ontology structures over a domain-specific dataset generated from Wikipedia.

The rest of this paper is organized as follows: In Sect. 2, it gives an overview of related work. In Sect. 3, the selected knowledge agnostic approaches and adaptations of these approaches to RDF embeddings are explained in detail. We present results of the selected approaches on the domain-specific evaluation set in Sect. 4. We conclude our study and highlight the research questions in Sect. 5.

## 2 Related Work

Global coherence approaches for open domain Entity Linking systems such as DBpedia Spotlight [8], Babelfy [9] and WAT [10] have achieved remarkable results in recent years. However, open domain resources are not sharp enough to model domain-specific knowledge bases. Navigli [11] emphasizes the importance of domain specific knowledge bases in Entity Linking task. There are domain specific knowledge bases such as KnowLife [12] and LinkedMDB [13] which can be used in Entity Linking. But these knowledge bases are not depending on a powerful link structure. As a result, knowledge agnostic approaches are one of the directions of this domain-specific Entity Linking because these approaches are independent of the Wikipedia link structure.

The majority of Entity Linking studies mainly depend on Wikipedia link structure in the entity disambiguation step. For instance, TAGME [4] exploits Wikipedia anchor link texts for the mention detection and aims on-the-fly annotation of short texts using agreement approach based on Wikipedia link structure. Also, these approaches focus on global coherence approaches that emphasize the consistency of all mention-entity pairs in the given text. AIDA-light [14]

considers global coherence to disambiguate the entities and exploits YAGO2 [15] and Wikipedia domain hierarchy to annotate “easy tags” first.

In recent years, knowledge agnostic approaches without having a dependency of Wikipedia link structure have become reveal. Further, these approaches can be executed with any knowledge bases. AGDISTIS [5] has a method that is independent of Wikipedia link structure. It uses a Named Entity Recognition tool for detection mentions in the web pages and performs Named Entity Disambiguation into the web-scale. Then, it chooses candidate entities for the detected mentions from surface forms and generates a disambiguation graph for these candidates. The generated disambiguation graph is used in graph-based HITS algorithm to match the best mention-entity pairs in the disambiguation step. RDF embedding-based entity disambiguation approaches achieve remarkable results. One of the prior studies in these approaches is DoSeR [6] and it exploits semantic embeddings generated by given knowledge bases to compute semantic similarities between entities thanks to the personalized PageRank algorithm. In this perspective, this study mainly examines the impact of the semantic embeddings gathered by different ontology structures as explained in the following section.

### 3 Disambiguation Using Enriched Ontology Structures

The enrichment of ontology structure can be defined as adding new ontology elements such as class, property and instances to a given ontology. To obtain the enriched structure, we select an ordinary domain ontology that is independent of DBpedia and Wikipedia link structure to meet the requirement for the knowledge-agnostic environment. Then we add extra categorized components to generate different enriched structures. In this study, Movie Ontology (MO)<sup>1</sup> is selected as the core ontology and categorized components such as financial and locational properties of movies are added to enrich the core ontology. After obtaining different enriched structures, they are transformed into RDF embeddings to disambiguate the best mention-entity pair in Entity Linking task. The main purpose of this study is to observe the impact of these structures in RDF embedding-based Entity Linking approaches.

#### 3.1 Categorization of MO and Quality Metrics

The MO ontology is divided into personal (MO-Per), financial (MO-Fin) and locational (MO-Loc) levels of ontology structures. The selected properties of each ontology structure are enriched by relevant classes, relations and instances from LinkedMDB [13] and DBpedia [16] for the movie domain. MO-Per structure involves enriched director and cast information, whereas MO-Fin structure has enriched budget, distributor and producer properties and MO-Loc has extended location and language properties. After obtaining the core ontology as MO-Per, quality metrics are measured for combinations of financial and locational structures with the core ontology.

<sup>1</sup> <http://www.movieontology.org/>.

To measure ontology quality, OntoQA [17] and OntoMetrics [18] are reviewed in terms of schema, base and knowledge base metrics. Schema metrics focus on the design of the ontology such as attribute, relationship and inheritance richness. Base metrics address the distribution of data on the knowledge base and class categories. Knowledge base metrics deals with class richness, average population and cohesion parameters. As denoted in Table 1, attribute richness (AR) is the average number of attributes for each class and indicates the knowledge density of classes in the given schema. If AR has a higher value, it shows that each class has more comprehensive information.

Relationship richness (RR) describes the diversity of relations in the schema and its score reflects the size of connections between classes. If it has low value, it may have only class-subclass relationships. OntoMetrics [18] explains extra metrics such as axiom, class and relation ratio. Axiom/class ratio (ACR) demonstrates the average numbers of axioms for each class and class/relation ratio (CRR) is the average amount of classes per relationship.

Enriched ontology structures in schema metrics clearly indicate that if an ontology structure is added up categorized elements, it increases measures of schema metrics. MO-Per is selected as the core ontology and is not covered by any other enriched structure, so it has the lowest schema metrics. MO-PerFin is covered by financial features in addition to personal elements. For this reason, RR and CRR values are increased, but AR and ACR values almost remain as the same. MO-PerLoc has greater values than previous structures for all schema metrics and MO-PerFinLoc has the largest covered structure having the highest scores.

**Table 1.** Schema and class metrics for enriched ontology structures.

Schema metrics	MO-Per	MO-PerFin	MO-PerLoc	MO-PerFinLoc
AR	0.054	0.056	0.12	0.248
RR	0.414	0.53	0.642	0.759
ACR	10.865	10.882	11.487	11.98
CRR	0.702	0.785	0.836	0.878

**Table 2.** Base and knowledge base metrics for enriched ontology structures.

Base and KB metrics	MO-Per	MO-PerFin	MO-PerLoc	MO-PerFinLoc
Axioms	891	1062	1287	1521
Class count	82	95	112	127
Properties count	48	65	84	96
Individual count	298	372	468	565
Average population	3.634	3.92	4.185	4.456
Class richness	0.67	0.762	0.834	0.912

In Table 2, Base Metrics comprises axioms, classes and property counts. Axioms are fundamental statements of an ontology and show what is true in a domain. Classes are concepts and involve other classes or individuals. Property counts are the total number of links of classes to individuals or other classes. Individuals are the class instances and describe the actual object of the domain.

Knowledge base metrics is important to measure the effectiveness of the ontology design and observe the number of real-world knowledge representations. The average population is the ratio of individuals per class defined in the given schema. Class richness (CR) states the distribution of instances across classes and is the ratio between classes including instances and the total number of classes. Thus, if a knowledge base contains a high CR value it demonstrates most of the knowledge in the schema is represented by comprehensive data. MO-Per is the core ontology and especially involves classes, properties and individuals from personal features such as director or cast information. Table 2 shows that every combination of categorized structures with MO-Per enlarges the overall metrics in terms of class, property and individual counts. For instance, MO-PerFin is the combination of MO-Per with financial features such as budget and publisher of movies. Therefore, average population and class richness scores are increased after each combination and finally MO-PerFinLoc involves all enriched elements and has the highest scores.

### 3.2 Entity Disambiguation

Entity linking approaches comprise mention detection and entity disambiguation tasks. To detect mentions, we follow mention parsing method of TAGME. This method receives input text and split it into words that are sequenced up to 6 words and queried in the mention dictionary. To build this dictionary, we exploit instances of movie ontology instead of generating mentions from Wikipedia. If a mention of the dictionary is a substring of another mention or any other overlapped strings problem, we use the boundary detection approach of TAGME for overlapped strings. This approach handles two mentions  $m_1, m_2$  and  $m_1$  can be assumed as a substring of  $m_2$  for this condition. If link-probability (lp) of  $m_2$  is greater than  $lp(m_1)$ , then  $m_1$  is removed from the mention dictionary. So,  $lp(m_i)$  is computed as the division of the number of mention  $m_i$  links to the frequency of all occurrences of  $m_i$ .

In this study, we focus on the entity disambiguation task and transform disambiguation methods of AGDISTIS and DoSeR approaches into RDF embedding-based entity relatedness computation to map the best possible mention and entity pair among candidates. In disambiguation step, the entity relatedness measures how candidate entities for each mention are related to each other in the given knowledge base and it is computed with each adapted algorithm from AGDISTIS and DoSeR approaches exploiting the RDF2Vec [19] model. RDF2Vec is an adaptation of Word2Vec model to the RDF embeddings to obtain a neural language model. The main assumption of this model, closer words in texts have high relatedness scores. Instead of using words, RDF embeddings are generated by entities and relations from the given RDF model. Before the neural

language model is trained, RDF model is transformed into the form of RDF embeddings. Consequently, each embedding can be represented as a numerical vector in Latent Feature Space. We use graph walks to transform RDF model into entity-relation sequences. Then, we built Neural Language Model with Skip-gram from generated entity-relation sequences. Ristoski et al. [19] demonstrates that Skip-gram model with negative sampling gives the best performance on computations of relatedness scores. The computation of entity relatedness with Softmax function and has a range between 0 and 1. If the relatedness score of entity pairs are closer to 1, it demonstrates these two entities are more related to each other. Equation 1 denotes the computation of the entity relatedness from the trained model.

$$p(e_0|e_i) = \frac{\exp(v_e 0^T v_{ei})}{\sum_{e=1}^V \exp(v_e'^T v_{ei})} \quad (1)$$

where the entity  $e$  has  $v_e$  as the input vector and  $v_e'$  as the output vector, and  $V$  indicates all entities vocabulary. Iterations and graph depth remain same as optimal values having the best evaluation performance as stated in the RDF2Vec study.

To constitute fair and objective experiments of disambiguation step we detect mentions with the proposed method of TAGME rather than using mention detection steps of AGDISTIS and DoSeR approaches. After obtaining mentions, we transform the similarity function of AGDISTIS into the relatedness function (1) and use HITS algorithm to compute global coherence between entities. The formal model of AGDISTIS aims to find the assignment  $\mu^*$ :

$$\mu^* = \arg_{\mu} \max(p(e_C|e_N)) + \phi(\mu(C, N), K) \quad (2)$$

where  $\phi$  is the coherence function implemented by the HITS algorithm involving an assignment  $\mu(C, N)$  between the matrix of candidate-entity mappings ( $C$ ) and the vector of named entities ( $N$ ) in the given knowledge base ( $K$ ). The similarity function of AGDISTIS is adapted to the entity relatedness method (2) among candidate and named entities.

DoSeR is the last adapted approach and currently adaptable semantic embeddings. Based on semantic embeddings, it applies PageRank algorithm as the global coherence computation to map the best possible mention-entity pair in the entity disambiguation step. For this reason, Entity Transaction Probability (ETP) is computed to identify edge weights between entity nodes in the given knowledge base:

$$ETP(e_u^i, e_v^j) = \frac{\cos(\text{vec}(e_u^i), \text{vec}(e_v^j))}{\sum_{k \in (V \setminus V_i)} \cos(\text{vec}(e_u^i), \text{vec}(k))} \quad (3)$$

where transaction probability is calculated for vectors  $e_u^i$  and  $e_v^j$  as a cosine similarity. ETP measurement indicates edge weights for PageRank algorithm and a transaction possibility from one entity node to another node. In this study, we compute this transaction possibility using Eq. 1 instead of ETP function (3).

## 4 Evaluation

In the evaluation, we serve a domain-specific dataset and compare knowledge agnostic Entity Linking approaches depend on different enriched ontology structures. The main focus of this section is to observe the effect of enriched ontology structures on knowledge-agnostic approaches.

### 4.1 Domain-Specific Evaluation Set

Domain-specific evaluation dataset is generated from Wikipedia articles and is publicly available at the following link<sup>2</sup>. WeDGeM generates automatically an evaluation set for specific domains using Wikipedia categories and DBpedia. Wikipedia category pages and DBpedia taxonomy are used for adjusting domain-specific annotated text generation. Wikipedia disambiguation (Category: Disambiguation) pages are used for adjusting the ambiguity level of the generated texts. This dataset contains many annotated documents represented as NLP Interchange Format(NIF)<sup>3</sup> that is an RDF/OWL-based format providing interoperability between entity annotator tools. Annotated documents include entities for the movie domain and their features such as director, cast and genre. Mentions of the annotated texts are extracted from anchor texts of Wikipedia articles. Each mention is connected to its MO ontology links that are stored as annotated entity list.

English Wikipedia dump<sup>4</sup> is used to generate annotated texts in movie domain. To propose an ambiguous environment, Wikipedia disambiguation pages are used for movies and their properties such as actors, directors and cast. For instance, a sample mention *Wicker Park* has a Wikipedia disambiguation page<sup>5</sup> involving disambiguation pages such as *WickerPark\_(film)*, *WickerPark\_(sound-track)* and *WickerPark\_(ChicagoPark)*. Thanks to these disambiguation pages, we can increase the number of candidate entities for the selected movie domain. The movie evaluation dataset involves 945 annotated texts in English (EN). The number of entities such as movies, directors and starring is 3648 and these are extracted from Wikipedia infoboxes and mapped with referent entities by DBpedia.

To generate an ambiguous evaluation set, the strategy of preparing evaluation test for open domain datasets of Entity Linking task in TAC<sup>6</sup> conference is emulated into the domain specific dataset generation. The generated dataset has entities including their offsets in the annotated text and other entity annotated documents from different domains such as music, books and location to provide a more ambiguous environment for Entity Linking systems. This dataset involves 945 annotated documents and 3648 entities. Whereas Ellis et al. [20]

<sup>2</sup> <https://github.com/einan/WeDGeM>.

<sup>3</sup> <http://persistence.uni-leipzig.org/nlp2rdf/>.

<sup>4</sup> <https://dumps.wikimedia.org/enwiki/20170420/>.

<sup>5</sup> [https://en.wikipedia.org/wiki/Wicker\\_Park](https://en.wikipedia.org/wiki/Wicker_Park).

<sup>6</sup> <http://nlp.cs.rpi.edu/kbp/2016/>.

**Table 3.** Performance of approaches on enriched ontology structures

Ontology structure	AGDISTIS			DoSeR		
	P	R	F1	P	R	F1
MO-Per	0.65	0.463	0.54	0.704	0.47	0.573
MO-PerFin	0.724	0.59	0.65	0.738	0.616	0.672
MO-PerLoc	0.709	0.572	0.633	0.729	0.574	0.642
MO-PerFinLoc	0.781	0.728	0.753	0.819	0.77	0.793

study demonstrates 13% ambiguity and the reference open domain evaluation dataset of [21] study contains 18% ambiguity, the generated dataset has 28.51% ambiguity of entities.

## 4.2 Results

After the preparation of the evaluation set, precision (P), recall (R) and F1 scores are measured for the selected Entity Linking approaches in order to observe the impact of ontology quality on the RDF2Vec model which involves different enriched ontology structures as background knowledge in Table 3.

The evaluation dataset covers 68% of personal, 20% of locational and 12% financial elements in terms of class, property and individual counts. Mo-Per is built by almost personal features but it has also a few fundamental elements in financial and locational components smaller than 5%. MO-PerFin involves 70% personal and 25% financial features whereas MO-PerLoc has 75% personal and 20% locational elements. Both ontology structures involve almost 5% out of enriched elements. The last ontology is MO-PerFinLoc has the most similar coverage as the testbed. In these circumstances, the core ontology MO-Per has the lowest F1 scores for all approaches due to its class, relation and instance count. The coverage of locational features is smaller than financial features and this slightly leads to falling in the overall performance. One of the reasons in this fall is that location names increase the ambiguity between movie names. For example, Wicker Park is a public urban park in Chicago, but it has also a link to the movie as indicated in Wikipedia disambiguation page<sup>7</sup>. In this context, the disambiguation method of DoSeR outperforms AGDISTIS for all ontology structures as denoted in Table 3.

## 5 Conclusion

In this study, Entity Linking approaches based on knowledge-agnostic methods are examined under different enriched ontology structures. Each ontology structure produces RDF embeddings as an input for the RDF2Vec model to evaluate the impact of ontology structure in the Entity Linking task. The evaluation data

<sup>7</sup> [https://en.wikipedia.org/wiki/Wicker\\_Park](https://en.wikipedia.org/wiki/Wicker_Park).

set is gathered from Wikipedia and RDF embeddings for these structures and RDF2Vec model compared with four ontology structures. Hence, the evaluation scores prove that if the ontology has an instance and class rich structure RDF2Vec method can perform better on the domain-specific environment.

The main aim of the proposed study is to observe the effect of enriched features of ontology structures in a small sample set rather than comparing AGDISTIS and DoSeR approaches and exploiting huge amounts of instances. So, instance counts will be increased and different semantic similarity measurements will be inserted into the global coherence computation to improve the overall performance of Entity Linking approaches in the future work. As an another future direction, semantic embedding algorithms are analyzed for different domains besides movie domain. Furthermore, a novel hybrid method will be presented depends on the RDF and document embeddings and compared with knowledge-agnostic Entity Linking systems.

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Metadata and Semantic Research

11th International Conference, MTSR 2017, Tallinn,  
Estonia, November 28 – December 1, 2017,

Proceedings

Garoufallou, E.; Virkus, S.; Siatra, R.; Koutsomiha, D.  
(Eds.)

2017, XXII, 334 p. 72 illus., Softcover

ISBN: 978-3-319-70862-1