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Matching Words and Knowledge Graph Entities with Meta-Embeddings

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Résumé

Word vectors are a key component for matching distinct textual units semantically. However, they are not directly applicable for matching text with structured data, for which graph embeddings exist. In this work, we propose a flexible method in order to map the representation of graph embeddings to word embeddings representation. Thus, we can improve word embeddings with a weighted average with mapped graph embeddings. We evaluate our models on the task of matching natural language questions and SPARQL queries, and significantly improve queries matching accuracy. We also evaluate word meta-embeddings intrinsically and show improvements over previous models.

Mots-clé : Question answering, Knowledge Graphs, Word Embeddings, Graph Embeddings, Meta-Embedding

1 Introduction

Structured data has become ubiquitous, abundant and involved in numerous applications. Knowledge bases like DBpedia, Wikidata, Openyc [FEMR15] provide large and growing structured resources. They contain millions of facts represented as triplets such as (Paris, LOCATED_IN, France). Formal languages such as SPARQL and scalable endpoint architecture allow efficient queries. However, natural language is more convenient for most users. Translating natural language queries into formal language queries (e.g. SPARQL) has been a long standing artificial intelligence task. Table

1 shows an example of a natural language question with associated SPARQL query. But current systems are only successful on restricted versions of this task, e.g. using specific patterns [PHH13, TIDL17].

Since full translation-based systems are not reliable, a useful task would be the matching of related SPARQL requests (either from historical data or from the output of a translation-based system) according to their similarity to a natural language question. In this paper, we tackle the prediction of similarity between natural language questions and SPARQL requests. Word embeddings are a key component in many textual similarity systems and have been used to represent natural language questions. However the components of SPARQL queries are either SPARQL keywords (e.g. SELECT) or Uniform Resource Identifiers (URI) (e.g. http://dbpedia.org/resource/Stanley_Kubrick).

There exists pre-computed URI embeddings, but learning an alignment of the embeddings latent space is needed for similarity computations and relying on task specific manually annotated data is costly. Meta-embeddings could be used in order to solve this problem. A meta-embedding is a representation derived from a set of distinct embeddings (e.g. Word2Vec and GloVe). Yet there exists no meta-embedding method leveraging pretrained knowledge graph embeddings and word embeddings. Such meta embedding could also allow integration of symbolic external knowledge for common sense reasoning or information retrieval.

Our contributions are as follows :

- A meta-embedding method to align word embeddings with graph entities embeddings

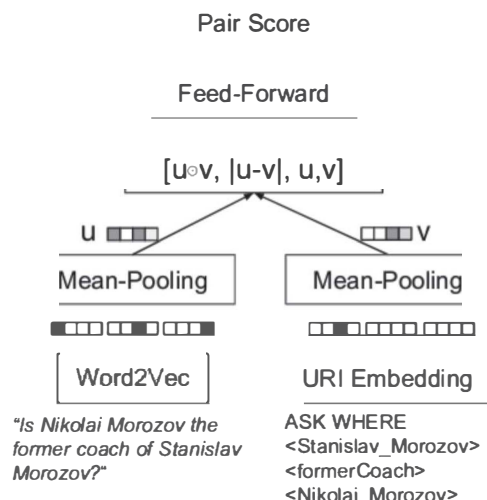


FIGURE 1 – Model architecture for similarity estimation

- Experiment on natural Language/SPARQL query similarity prediction
- Intrinsic evaluation of our meta-embeddings

2 Similarity estimation models

A possible use-case of our method is improvement on similarity prediction between a natural language question and a SPARQL query. In this work, we use a siamese neural network whose architecture is depicted in the figure 1 for such similarity estimation in a supervised setup. We experimented using state of the art [BSA1] models but they did not perform well probably due to the short contexts of queries as opposed to the evaluation datasets used in entity linking literature.

We represent the questions/queries with the average of its symbols (words/URI) embeddings, composed with a matching function (with a concatenation of hadamard product, absolute difference of input vectors) followed by a feed-forward neural network. Average-pooling is a simplistic sequence encoding method but it was shown to be competitive with more complicated architectures [SWW⁺1].

Representing word from natural language questions is straightforward using word embeddings. By contrast, there are several ways to represent DBpedia URI (e.g. http://dbpedia.org/resource/Stanley_Kubrick). For instance text can be derived from the label for the URI (e.g. *Stanley Kubrick*) allowing the use of word

embeddings but disregarding the knowledge from the DBpedia graph.

Pre-computed DBpedia URI embedding [RP16] can also be used. They are embedding computed with the SkipGram algorithm (used in Word2Vec and Code2Vec [1]) with DBpedia¹ graph walks instead of sentences. Such graph walks encode knowledge about entities. For example,

(Stanley_Kubrick,
writer,
A_Clockwork_Orange)

is a possible sub-path containing some useful information about Stanley Kubrick.

RDF2Vec inherits many properties from Word2Vec vectors (e.g. a cosine similarity that reflect relatedness).

In this work, we will compare the use of RDF2Vec and Word2Vec for URI representation, and propose a meta-embedding method to combine them.

3 Proposed Meta-Embedding

Word and graph embedding encode complementary knowledge, but their latent space need to be aligned in order to perform similarity computations. Here, we propose to learn to map the latent space of RDF2Vec to the space of word embeddings.

To do so, we train a feed-forward neural network f_θ in order to predict the word embedding $\text{Word2Vec}(u)$ representation of a given URI u from its URI embedding $\text{RDF2Vec}(u)$. More specifically, we optimize θ in the following loss function :

$$\mathcal{L} = \sum_{u \in \mathcal{V}} \text{MSE}(\text{Word2Vec}(u), f_\theta(\text{RDF2Vec}(u))) \quad (1)$$

\mathcal{V} is the set of training examples, i.e. the set of URIs where a word in a label matches a word vector. When several words are found, we use the average of their embedding. Figure 2 illustrates this approach.

A $f_\theta(\text{RDF2Vec}(u))$ is trained to lie in the same space as $\text{Word2Vec}(u)$, a weighted average of these representations can be also used :

$$\text{Weighted}_\alpha(u) = (1-\alpha)\text{Word2Vec}(u) + \alpha f_\theta(\text{RDF2Vec}(u)) \quad (2)$$

1. (2016-04 version)

question_{NL} How many movie did Stanley Kubrick direct?
 query_{SPARQL} SELECT DISTINCT COUNT(?uri) WHERE
 ?uri <http://dbpedia.org/ontology/director> <http://dbpedia.org/resource/Stanley_Kubrick>

TABLE 1 Sample from *LC-Quad* dataset

URI Representation	Cross-Entropy	Accuracy (%)
one (Majority Class Prediction)	0.6931	90.00
Word2Vec	0.1262	97.1
$g_W(\text{RDF2vec})$	0.2595	95.06
$f_\theta(\text{R2Vec})$	0.2610	90.57
Weighted ($\alpha = 0.075$)	0.1189	97.94

TABLE 2 – Test results of different URI embeddings models; bold value denotes the best results *Weighted* is defined in equation 2

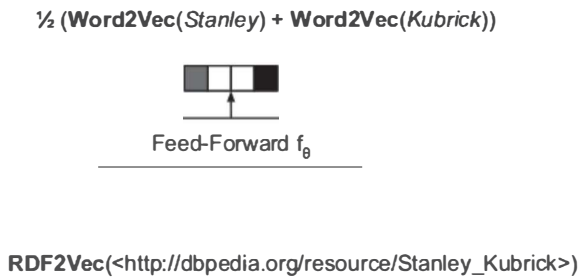


FIGURE 2 – Model architecture for embedding alignment

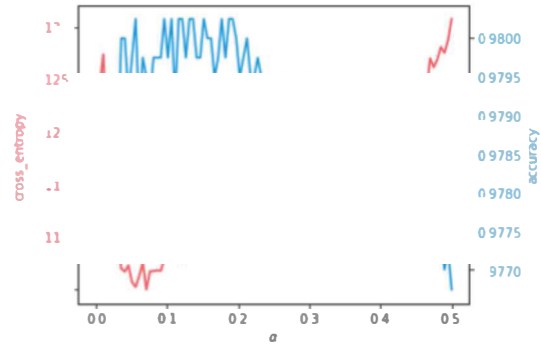


FIGURE 3 – Influence of α on matching prediction validation results

4 Experiments

4.1 Query matching evaluation

We evaluate our model on the LC-QuAD [TMDL17] dataset which is a collection of 5000 natural language questions with associated SPARQL queries. 4000 pairs are used for training and the remaining is used for evaluation. For each example, we generate 9 examples of dissimilar NL/SPARQL queries using random associations of different queries. This process is done on train data and test data separately.

To represent natural language questions, we always use word embeddings from [MGB⁺1] trained on CommonCrawl.

Regarding URI representations we evaluate several embeddings:

$g_W(\text{RDF2Vec})$ is a linear projection of RDF2Vec embedding. The projection W is initialized randomly and

learnt during the matching prediction training.

f_θ is instantiated with a two hidden layer MLP (hidden layer sizes are 200,200) with batch-normalization and ReLU activation. θ is trained on 6.0M URIs, using 1 epoch and using Adam optimizer [KB15] with default parameters, using the loss from equation 1. The parameters are kept fixed in the matching prediction training.

For the matching detection training, 10% of training data is kept aside as validation set in order to determine the best number of epochs (found to be also using Adam optimizer).

We performed cross-validation on the parameter α . Figure 3 shows the influence of α on evaluation metrics. $\alpha = 0$ is the same as only using Word2Vec, and $\alpha = 1$ is equivalent to only using $f_\theta(\text{RDF2Vec})$.

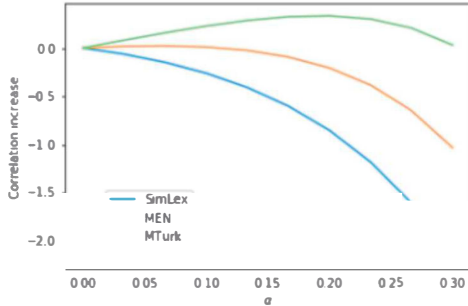


FIGURE 4 – Influence of α on word similarity prediction evaluation using the weighted combination of Word2Vec and $f_{\theta}(\text{RDF2Vec})$. y axis is the pearson correlation improvement over the Word2Vec baseline.

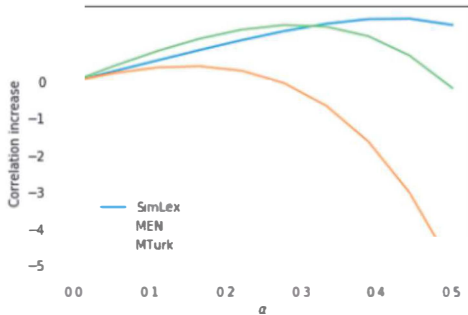


FIGURE 5 – Influence of α on word similarity prediction evaluation using the weighted combination of Word2Vec and $f_{\theta}(\text{WordNet2Vec})$. y axis is the pearson correlation improvement over the Word2Vec baseline.

4.1.1 Query matching results

Table 2 shows the test results of different methods. Since accuracies are high, we also report cross entropy for a more meaningful comparison. Using the word embeddings of label already yields high results. However, when combined with aligned graph embedding with the *Weighted* method the results are significantly better.

4.2 Intrinsic Evaluation

We also evaluate our meta-embedding intrinsically with a standard word similarity prediction evaluation: we use word embeddings to predict cosine similarity between word pairs, and measure the pearson correlation between cosine similarity and human judgments from similarity/relatedness prediction datasets. Sim-

	SimLex	MEN	MTurk
Word2Vec	51.	1.7	73.3
WordNet2Vec	52.4	39.	36.2
CONC	53.6	1.7	73.3
Best Weighted (RDF2Vec)	51.	1.7	73.6
Best Weighted (WordNet2Vec)	53.6	82.1	74.9

TABLE 3 – Pearson correlation between cosine similarity of embeddings and human judgments for several models. We used the best values of α when reporting the score of Weighted models. CONC is a meta-ensembling baseline (concatenation of embeddings).

Lex [HRK15] is a similarity judgement dataset (antonyms should have a low rating) while MEN [BTB14] and MTurk [RAGM11] are relatedness dataset (antonym can have a high rating).

Once again, we use the Weighted meta-embedding model from equation 2. We report the improvement over the Word2Vec baseline according to the value of α . Figure 5 shows the result over various datasets. We also performed the same experiment using WordNet2Vec [BAK⁺17] instead of RDF2Vec. WordNet2Vec is a graph embedding computed using the Wordnet graph consisting of 2.5k relations between words, such as (furniture, is_a, piece_of_furniture)

We used the same experimental setup but performed 2 epochs when optimizing \mathcal{L} . The results of the best Weighted models are reported in table ?? . Our meta-embeddings are competitive with CONC while having lower dimensionality (300 vs 1150).

5 Related Work

Several models exist for meta-embedding [YS16] [JSL17]. However, they use a set of embeddings and return a meta-embedding lying in a new latent space, except [CB17] who shows that meta-embedding can be obtained by simply averaging or concatenating a set of input embeddings.

Retrofitting models [FDJ⁺15,] also improve embeddings by leveraging knowledge graphs, in a different way: they use pre-computed word embeddings and tune word representations so that they fulfill some constraints dictated by the knowledge graph.

The most similar approach to ours is [MLS13] where embeddings in different languages (e.g. french and english) are aligned using a translation matrix learned on a limited size multilingual lexicon.

The specificity of our best model is that it is additive. With proper cross-validation, the weighted version of

our method can ensure better or equal results.

Another line of work deal with Alignment of knowledge from textual data and graph data. It has been explored with joint learning of embeddings from language model and knowledge graph link prediction [ABMiK1]. However, those methods are less flexible, and cannot leverage the high quality word embeddings trained on massive textual datasets without a re-training from scratch.

6 Conclusion

We proposed a simple, flexible meta-embedding method based on word embeddings and labelled graph embedding and reported significant improvement on word representation and SPARQL queries/natural language matching. It can be applied to other graphs such as UMLS [BK^{F+1}] for biomedical LP or social networks graphs [LK14]. Other languages can be used as well. We expect more substantial gains on low resource language where corpus sizes are more limited.

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