MultiKE: A Multi-view Knowledge Graph Embedding Framework for Entity Alignment*

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Abstract. We study the problem of embedding-based entity alignment (EA) between knowledge graphs (KGs), and propose a novel framework that unifies multiple views of entities to learn their embeddings. Experiments on real-world datasets show that this framework largely outperforms the current embedding-based methods.

1 Introduction

Entity alignment (EA) aims to find entities in different knowledge graphs (KGs) referring to the same real-world identity. Conventional methods identify similar entities based on the symbolic features, such as names, textual descriptions and attribute values. Recently, increasing attention has been drawn to leveraging the KG embedding techniques for dealing with this problem, where the key idea is to learn vector representations (called *embeddings*) of KGs and find alignment according to the similarity of the embeddings.

We propose a new EA framework, *MultiKE*, based on multi-view KG embedding. The underlying idea is to divide the various features of KGs into multiple subsets (called *views*), which are complementary to each other (see Figure 1 for example). Thus, entity embeddings can be learnt from each separate view and jointly optimized to improve the alignment performance.

2 Approach

Multi-view KG embedding. Based on the data model of KGs, we define three representative views based on the name, relation and attribute features. First, literals are constituted by sequences of tokens. We embed the name view using the literal embeddings. Second, the relation view characterizes the structure of KGs. We employ TransE to interpret a relation as a translation vector from its head entity to tail entity. Third, for the attribute view, we use a convolutional neural network to extract features from the attributes and values of entities.

Cross-KG training. We propose the cross-KG entity identity inference to capture the alignment information using seed alignment. We also present the cross-KG relation/attribute identity inference to enhance EA.

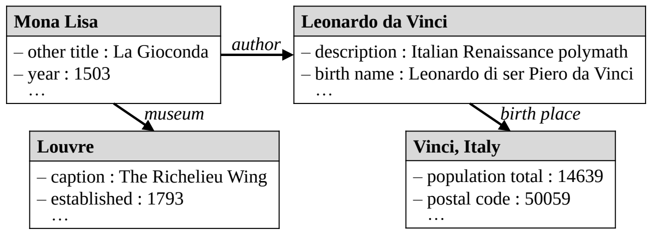

Fig. 1. An example of the multi-view features of four entities in DBpedia. Notations: names (**bold** font), relations (*italic* font) and attributes (regular font).

Table 1. Comparison with existing embedding-based EA methods

Features		Methods	DBP-WD				DBP-YG			
			Hits@1	Hits@10	MR	MRR	Hits@1	Hits@10	MR	MRR
Rel. +	Attributes	JAPE [2]	31.84	58.88	266	0.411	23.57	48.41	189	0.320
	Textual desc.	KDCoE [1]	57.19	69.53	182	0.618	42.71	48.30	137	0.446
	Literals	AttrE [4]	38.96	66.77	142	0.487	23.24	42.70	706	0.300
Multiple views		MultiKE-WVA	90.42	94.59	22	0.921	85.92	94.99	19	0.891
		MultiKE-SSL	91.86	96.26	39	0.935	82.35	93.30	21	0.862
		MultiKE-ITC	91.45	95.19	114	0.928	88.03	95.32	35	0.906

View combinations. Intuitively, general entity embeddings can benefit from multiple view-specific embeddings. We propose weighted view averaging (WVA), shared space learning (SSL) and in-training combination (ITC).

3 Evaluation

We selected two datasets in [3], DBP-WD and DBP-YG, and compared MultiKE with JAPE, KDCoE and AttrE, each of which used one type of extra features as enhancement. Table 1 shows that MultiKE largely outperformed the others.

4 Conclusion

In this paper, we proposed a multi-view KG embedding framework for EA, and our experiments demonstrated its effectiveness. In future work, we will investigate more feasible views (e.g., entity types) and study cross-lingual EA.

References

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