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Attribute-Relationship Joint Embedding for Knowledge Graph Entity Alignment

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***Abstract*—Entity alignment is a key task in performing knowledge graph fusion, aiming to find entity pairs that are formally different but actually the same entity from multi-source knowledge graphs. Most of the current mainstream entity alignment methods focus on the embedding of entity neighborhoods and relationships. As important features of entities, attributes can supplement some more fine-grained information, but existing methods often underutilize them. To address the above problems, a knowledge graph entity alignment method named ARJE (Attribute-Relationship Joint Embedding) is proposed. Firstly, a relation-aware two-layer GAT network utilizes attention mechanism to obtain relation information and aggregates it into entity embedding; Secondly, attribute embedding is calculated based on attribute triples, and different weight is assigned to each attribute; Finally, the obtained relation and attribute information are fused and the entity representation is enhanced in order to achieve a higher entity alignment accuracy rate. Experimental results on three real-world datasets demonstrate that the proposed method ARJE performs better than state-of-the-art methods.**

Keywords-Knowledge graph; Entity alignment; Graph Convolutional Networks

I. INTRODUCTION

Knowledge graphs organize, store, and integrate information in a ternary structure to clearly reveal the deep associations between knowledge[1]-[4].The rapid development of the Internet has driven the establishment of more and more knowledge graphs containing complementary information in various fields, however, they are constructed independently by different organizations and individuals, and the design and construction methods are not uniform due to the different needs, so these knowledge graphs suffer from the problems of heterogeneity and redundancy[5]. A single knowledge graph is often incomplete, and fusion of multi-source knowledge graphs can integrate dispersed knowledge and improve the accuracy and consistency of knowledge, so the fusion of multi-source graphs is necessary. The key to knowledge graph fusion is entity alignment[6]. Through it, multiple knowledge graphs can be integrated to realize multi-source fusion and complementarity.

Embedding-based approaches have become the mainstream methods for entity alignment tasks[7]. Among them, TransE-based[8] model is widely used in entity alignment tasks, which focuses on the structure of the graph. Many excellent methods such as MTransE[9], IPTransE[10], JAPE[11], BootEA[12] and so on are derived from it. However, the structural information of the graph is more limited, and to compensate for the lack of structural information, many approaches utilize GCN[13] to encode the connectivity relation between entities. GCN-Align[14] proposes a new approach for entity alignment based on GCN. RDGCN[15] further introduces relational information by constructing a pairwise relational for embedding learning graph. RNM[16] proposes a new relation-aware neighborhood matching model, and enhances the entity alignment task by iterative alignment.

However, in knowledge graphs, not only relation triples but also attribute triples exist. An entity usually has many attributes associated with it[17]; and equivalent entities usually share the same attributes, so attributes can provide important clues. However, existing research has paid less attention to the attribute information, and most of the approaches focus only on attribute embedding itself, but relying on attribute embedding alone may not be able to adequately capture the complex semantics of entities. Therefore, it is an important challenge to reasonably integrate structural information, relational information, and other features.

To address the issues raised above, this paper proposes an Attribute-Relationship Joint Embedding for Knowledge Graph Entity Alignment Approach with the following three main contributions:

(1) Incorporating the attention mechanism to dynamically capture the information interactions between head and tail entities and obtain a more granular representation of the relation; and further fuse the relation information to enhance the representation capability;

(2) A joint attribute and relation embedding approach is proposed, which integrates attribute embeddings with weights on top of structural embeddings obtained by fusing relation information to enhance entity representation and improve entity alignment accuracy;

(3) The validity of the experiments was verified on three publicly available datasets, and the experimental results show that ARJE outperforms some representative existing methods.

II. PROPOSED MODEL

A. Overall Framework

The overall framework diagram of ARJE model is based on GAT network, the relation information is aggregated into entity embedding; then using GCN, the attribute embedding with weights is constructed based on attribute triples; finally the obtained relationship and attribute information are fused to enhance the entity embedding representation. The overall framework diagram of ARJE model is shown in Figure 1.

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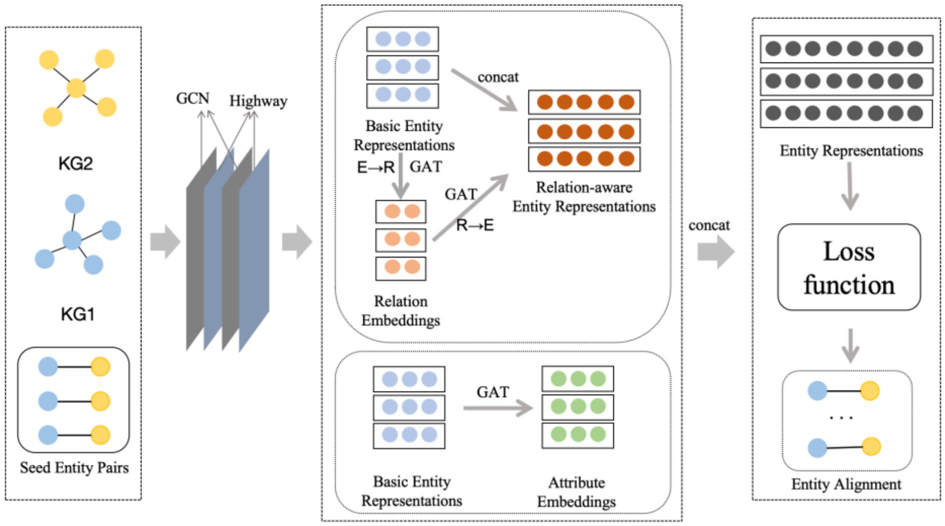

Figure 1 Overall architecture of the proposed model ARJE

B. KG Structure Embedding

To learn basic entity structure embeddings, ARJE uses a two-layer GCN network to encode entity representations. Each GCN layer takes a set of node features as input , the output is obtained by convolutional computation and the node representation is updated. To control the accumulated noise, the highway network[18] is also introduced in the GCN layer, which can effectively control the noise between the GCN cross-layers.

C. Relation Embedding

GCN cannot model relation representations directly, but it can embed entity representations well, therefore, the relation embedding r is obtained by splicing using the average embedding of all head and tail entities connected to it.

The attention score between the head entity e_i and the tail entity e_j are further computed and the embedding representation of the relationship is strengthened by the attention weights:

$$\partial_{ijr} = \mathrm{softmax}(a(\boldsymbol{r}_i \boldsymbol{W}_r \| \boldsymbol{r}_j \boldsymbol{W}_r)) \tag{1}$$

$$\boldsymbol{r}_k = \mathrm{ReLU}(\boldsymbol{W}_h \sum_{\boldsymbol{e}_i \in H_{ri}} \partial_{ijr} \boldsymbol{x}_i + \boldsymbol{W}_t \sum_{\boldsymbol{e}_j \in T_{ri}} \partial_{ijr} \boldsymbol{x}_j + \boldsymbol{W}_r \boldsymbol{r}_i) \tag{2}$$

where r is obtained by the splicing; $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are the head and tail entities, respectively; $\boldsymbol{W}_h$, $\boldsymbol{W}_t$ and $\boldsymbol{W}_r$ are the trainable parameter matrices used for relationship modeling.

Then aggregating the relation information entity embeddings, so entities with neighboring relation can be represented more accurately. The attention formula of the second GAT is as follows:

$$\partial_{ij} = \mathrm{softmax}(a^T \boldsymbol{r}_i) \tag{3}$$

$$\boldsymbol{x}_r = \mathrm{ReLU}(\sum_{\boldsymbol{e}_j \in T_{ri}} \partial_{ij} \boldsymbol{e}_j) \tag{4}$$

Then, by concatenating x_r and initial embedding, a relationship aware entity representation x_e is obtained. Where $\boldsymbol{x}_{int}$ is the initial embedding of an entity that contains entity name information.

$$\boldsymbol{x}_e = [\boldsymbol{x}_{int} \| \boldsymbol{x}_r] \tag{5}$$

D. Attribute Embedding

Attributes account for a large proportion of the real knowledge graph and can provide a lot of useful information for alignment. However, the number of attributes is huge, most of the names are named by English abbreviation or hyphenated naming, and the phenomenon of entity name and attribute name with the same name is common, but the meanings of the two are completely different, it is difficult to obtain embeddings directly. Therefore, referring to the method of relational embedding, we utilize entity embeddings to construct attribute embeddings.

$$\boldsymbol{x}_{ij}^{a} = \frac{\sum_{k \in H_{ai}} \boldsymbol{x}_k}{H_{ai}} \tag{6}$$

Where H_{ai} denotes the set of all entities having attribute i; $\boldsymbol{x}_k$ denotes the embedding representation of the k-th entity in the set of entities H_{ai}.

However, the impact of different attributes on entity alignment is not the same. To more accurately reflect the contribution of different attributes to an entity, attention scores can be calculated to learn the weights between the entity and its related attributes.

$$\partial_{ija} = \frac{\exp(a^T \boldsymbol{x}_{ij}^{a})}{\sum_{n \in T_{ei}} \exp(a^T \boldsymbol{x}_{in}^{a})} \tag{7}$$

To aggregate the feature information of attribute embeddings, the attributes are regarded as the neighbor nodes of the entities, utilize the entity-attribute adjacency matrix to output entity embeddings that aggregate attribute information:

$$\boldsymbol{X}_a^{(l+1)} = \sigma(\boldsymbol{D}_{ea}^{-\frac{1}{2}} \boldsymbol{A}_{ea} \boldsymbol{D}_{ea}^{-\frac{1}{2}} \boldsymbol{X}_a^{(l)} \boldsymbol{W}^{(l)}) \tag{8}$$

where $\boldsymbol{A}_{ea}$ is the entity-attribute adjacency matrix; $\boldsymbol{D}_{ea}$ is the degree matrix of $\boldsymbol{A}_{ea}$.

E. Entity Alignment Training

To contain both structure embedding information and attribute embedding information of an entity, the outputs of both are subjected to the stitching operation:

$$\boldsymbol{X} = \left[\beta \boldsymbol{X}_e \| (1-\beta)\boldsymbol{X}_a\right] \tag{9}$$

To embed the two knowledge graphs in the same vector space, a boundary-based loss function is utilized as the training objective:

$$L = \sum_{(e_i, e_j \in E^+)} \sum_{(e_i^{'}, e_j^{'} \in E^-)} \max\left\{\left\|\boldsymbol{e}_i, \boldsymbol{e}_j\right\| - \left\|\boldsymbol{e}_i^{'}, \boldsymbol{e}_j^{'}\right\| + \gamma, 0\right\} \tag{10}$$

III. EXPERIMENTS

A. Dataset

To evaluate the performance of the model, the dataset for the experiments is the DBP15K dataset. DBP15K[16] contains three sub-datasets: the ZH-EN dataset, the JA-EN dataset, and the FR-EN dataset, and each of the datasets provides 15000 pre-aligned entity pairs for training, testing and evaluation.

B. Implementation Details

The model is constructed using the deep learning framework Tensorflow, the hyper-parameters of the model are set as follows: the entity and the attribute embedding layer are set to 300 dimensions respectively; the training process adopts Adam's algorithm for the optimization of the parameters, with a learning rate of 0.001, and the number of training rounds are all set to a maximum of 300 rounds, respectively; the splicing weights β is set to 0.3; the alignment seed is set to 30%.

C. Evaluation Metrices and Baselines

In this paper, we adopt Hits@k as the evaluation index of entity alignment effect. As with other methods, in this paper, the value of k is chosen to be 1 and 10.

Some classical baseline models and competitive entity alignment models are selected as comparisons, in order to validate the effectiveness of ARJE; including two classical baseline models based on TransE: MTransE[9], BootEA[12]; Three baseline models based on GCN: GCN-Align[14], RDCGCN[15], NMN[18].

Table 1 Performance of different entity alignment methods

Methods	DBP15K(ZH-EN)		DBP15K(JA - EN)		DBP15K(FR - EN)	
	Hits@1	Hits@10	Hits@1	Hits@10	Hits@1	Hits@10
MTransE	30.8	61.4	27.8	57.4	24.4	55.5
BootEA	62.9	84.8	62.2	85.4	65.3	87.4
GCN-Align	41.3	74.4	39.9	74.5	37.3	74.5
RDGCN	70.8	84.6	76.7	89.5	88.6	95.7
NMN	73.3	86.9	78.5	91.2	90.2	96.7
ARJE	**79.8**	**88.2**	**84.2**	**92.0**	**92.8**	**97.0**

Table 2 Results of the ablation study

Models	DBP15K(ZH-EN)		DBP15K(JA-EN)		DBP15K(FR-EN)	
	Hits@1	Hits@10	Hits@1	Hits@10	Hits@1	Hits@10
ARJE (-AR)	69.8	84.1	77.1	89.3	89.0	96.2
ARJE (-A)	74.1	86.2	80.5	89.7	89.5	96.4
ARJE (-R)	75.1	86.7	81.3	90.2	90.1	96.5
ARJE	**79.8**	**88.2**	**84.2**	**92.0**	**92.8**	**97.0**

D. Experimental Results and Analysis

The experimental results are shown in Table 1. As can be seen from the experimental results, the effect of the ARJE method is significantly better than other baseline models on all datasets. For the TransE-based embedding method, Its effectiveness is significantly inferior to other methods, as TransE may result in the loss of some structural information and lack consideration for the overall structure of the knowledge graph. Among them, BootEA obtains better results because of its iterative strategy of bootstrap training. For GCN-based methods, among them, GCN-Align has the worst results, which is because GCN-Align simply utilizes only relational triples and does not make use of other information; RDGCN produces better results due to its focus on the relationship information of interactions between entities; In addition, NMN has the best results among all baseline models, and its advantage is not only in the use of entity name information in the initialization stage, but also in its domain matching module. The ARJE method proposed in this paper compares favorably with the best-performing NMN, Hits@1 increased by 6.5%, 5.7%, and 2.6% in each of the datasets, which proves that attribute-relationship embedding can effectively improve the effect of entity alignment.

E. Ablation Study

To evaluate the effectiveness of each module of ARJE, Constructing ablation experiments on ARJE, and Table 2 shows the results. Where ARJE (-AR) indicates that ARJE removes all attribute-relation joint embedding modules; ARJE (-A) indicates that ARJE removes all attribute related modules. ARJE (- R) indicates ARJE removes all modules related to relation.

As can be seen from Table 2, both ARJE (-A) and ARJE (-R) effects have a significant decrease, however, the performance of ARJE (- A) and ARJE (- R) is superior to ARJE (- AR), indicating that fusing additional information can improve the performance of entity alignment based on structural embedding. In addition, the ARJE model that integrates relationship and attribute dual network has further improved compared to ARJE (- A) and ARJE (- R), indicating that further considering attribute information on the basis of integrating relationship information can effectively improve the performance of the model.

IV. Conclusion

In this paper, ARJE is proposed, in which attribute-relation joint embedding is to improve the entity alignment accuracy. Finally, ARJE is evaluated and the empirical results prove the effectiveness of ARJE. In the future, research will be conducted on how to effectively implement entity embedding.

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