

PAPER

Type-Enhanced Ensemble Triple Representation via Triple-Aware Attention for Cross-Lingual Entity Alignment

Zhishuo ZHANG[†], Chengxiang TAN^{†a)}, Xueyan ZHAO[†], and Min YANG[†], *Nonmembers*

SUMMARY Entity alignment (EA) is a crucial task for integrating cross-lingual and cross-domain knowledge graphs (KGs), which aims to discover entities referring to the same real-world object from different KGs. Most existing embedding-based methods generate aligning entity representation by mining the relevance of triple elements, paying little attention to triple indivisibility and entity role diversity. In this paper, a novel framework named TTEA – Type-enhanced Ensemble Triple Representation via Triple-aware Attention for Cross-lingual Entity Alignment is proposed to overcome the above shortcomings from the perspective of ensemble triple representation considering triple specificity and diversity features of entity role. Specifically, the ensemble triple representation is derived by regarding relation as information carrier between semantic and type spaces, and hence the noise influence during spatial transformation and information propagation can be smoothly controlled via specificity-aware triple attention. Moreover, the role diversity of triple elements is modeled via triple-aware entity enhancement in TTEA for EA-oriented entity representation. Extensive experiments on three real-world cross-lingual datasets demonstrate that our framework makes comparative results.

key words: *cross-lingual entity alignment, knowledge graph, ensemble triple representation, specificity-aware triple attention, role diversity*

1. Introduction

Knowledge Graphs (KGs) have been powerful platform for organizing plain text into regularized data formatted as (*head entity, relation, tail entity*), such as (*Beijing, Capital_of, China*) denoting that *Beijing is the capital of China*, in which *Capital_of* holds the directional relation from head entity *Beijing* to tail entity *China*. However, most of KGs are independently constructed in different languages or domains. Although these cross-lingual or cross-domain KGs such as DBpedia [1], YAGO [2] and ConceptNet [3] have been widely applied in many real-world scenarios, such as finance [4], medical care [5], [6], and artificial intelligence [7]–[9], the structural heterogeneity and rule specificity among these KGs make the knowledge cannot be effectively integrated. Entity alignment (EA) provides a crucial step for information fusion, which aims to discover equivalent entities from different KGs.

Recently, embedding-based methods have attracted wide attention, which embed entity and relation by encoding them into latent vector spaces and measure the embedding distance for EA [10]–[13]. There have been many efforts to obtain excellent representation of entity and relation for EA,

which can be roughly divided into two categories according to perspectives: Trans-based methods and GNNs-based methods.

Trans-based methods treat element interaction as a translation process $h + r \approx t$ for a triple (h, r, t) . These methods [14]–[16] are effective and simple, but unable to form the complete representation of triple elements as the internal correlation is complex and indescribable. Besides, noise will be introduced inevitably in the mapping process between different latent spaces. GNNs-based methods fall into two categories, GCNs-based and GATs-based. The former usually reflect EA via neighbor alignment and topology structure [17]–[19], and the latter integrate the surrounding information to enhance embedding [20], [21]. Although these methods can effectively improve performance by fusing neighbor information, they usually focused on the element itself and rarely considered the specificity of ensemble triple and role diversity, which may hold rich semantic information. For details, in case the entity pair (e^1, e_1) includes two entities to be aligned in Fig. 1. Then EA-oriented entity representations of e^1 in KG1 and e_1 in KG2 are optimally generated during training. On the one hand, the triple specificity tries to illustrate entity semantic from a triple perspective rather than in a element view. In the training process, the triple $(e^1, r1, e^2)$ and $(e^1, r2, e^3)$ should play important roles for generating EA-oriented entity representation of e^1 , and the triples $(e_1, R2, e_3)$ and $(e_2, R1, e_1)$ have the responsibility for the EA-oriented representation of e_1 as the same. On the other hand, the role diversity attempts to distinguish the influence of elements with different roles on triple. Specifically, for the entity e_1 attaching to more than one triple in KG2. It is intuitive that the influence of e_1 on triple $(e_1, R2, e_3)$ is inconsistent with the influence of e_1 on triple $(e_2, R1, e_1)$, in which the entity e_1 plays a role as head entity in the former while tail entity in the latter. Furthermore, there may be multiple relations holding different types between head entity and tail entity, as the entity pairs (e^3, e^5) in KG1 and (e_3, e_5) in KG2 show.

To address the above shortcomings, we propose TTEA – Type-enhanced Ensemble Triple Representation via Triple-aware Attention for Cross-lingual Entity Alignment in this paper with the intuitive assumption that relation is generic in semantic space and type space for a specific triple, which is capable of fully utilizing triple specificity and role diversity. Considering that triple elements are indivisible, TTEA introduces a type-enhanced ensemble triple representation module to capture semantic and type information while pre-

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[†]Department of Computer Science and Technology, Tongji University, Shanghai, China.

a) E-mail: Jerrytan@tongji.edu.cn

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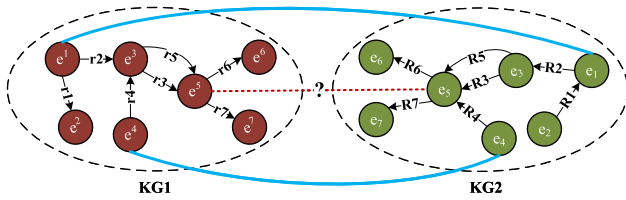


Fig. 1 A toy example of entity-role diversity and multiple relations between entities. The blue solid lines between entities in KG1 and KG2 refer to the alignments.

serving triple specificity. In terms of multiple relations and roles in a triple, we design a triple-aware entity enhancement mechanism to obtain cycle co-enhanced head-aware and tail-aware entity embedding. RAGA [21] is the closest work with this paper, the difference is that TTEA tries to exploit ensemble triple specificity and role diversity of head and tail entities while RAGA tackle EA from element perspective only. Experimental results on three cross-lingual KGs prove that TTEA made comparative results with baselines[†].

In summary, our main contributions are as follows:

- We provide a novel perspective to regard relation as information carrier during spatial transformation, which is capable to effectively alleviate the noise introduced during mapping.
- We propose a novel EA framework which sufficiently utilizes triple specificity and role diversity via ensemble triple representation and triple-aware entity enhancement.
- Extensive experiments conducted on public datasets demonstrate that TTEA makes comparative performance among corresponding EA baseline methods.

2. Related Work

Embedding-based methods have been the mainstream formula for EA in recent years. These methods can be roughly divided into two categories: Trans-based embedding methods and GNNs-based embedding methods. **Trans-based embedding methods:** A line of Trans-based works embed entity and relation in different latent spaces for different KGs [16], [22]–[25]. The second line of Trans-based works embed entity and relation from different KGs into a unified latent space via parameters sharing [26] and extending aligned relation [27]. Then these methods utilize TransE [28] and its variants [14], [15] to model internal correlations among triple elements as a linear equation to learn EA-oriented entity representation. However, this formula cannot comprehensively mining the complex interaction among triple components with the simple mode. **GNNs-based embedding methods:** GNNs-based embedding methods have obtained great improvement in EA. GCN-Align [10] is the first work to enhance entity embedding via GCNs, following which GCNs-based methods are extended to aggregate neighbor information. Some works use neighbor entities and relations alignment to tackle EA with the assumption

that equivalent entities sharing approximate neighbors [29], and some other related efforts utilize topology structure to reinforce entity embedding via GCNs [12], [19], [30]–[32]. While GCN-based methods treat neighbor relation equally, which is unreasonable. Thus GATs-based methods are designed considering different neighbor entities contribute different importance. Some works adopt neighbor attention for entity embedding [18], [33]–[36], in which to our best knowledge, RAGA [21] achieves state-of-the-art results by modeling correlation between entity and relation in embedding-based methods. And others utilize cross-KG attention to spread neighbor information of aligned pairs [20], [37], [38]. Existing GNNs-based methods have effectively improved the performance of EA, but not considered diversity of entities roles and the multi-level representation of ensemble triple. Our work in this paper is also a GNNs-based method from the perspective of ensemble triple and element roles diversity.

Besides, there are some techniques for EA. Some works tried to mine EA-oriented message contained in entity name, such as [39], [40] explored the effect of different levels of entity name on EA, [41] proposed a tree-view label propagation mechanism. And external resources such as entity attributes, images, and other string information are utilized [17], [19], [42]–[45]. However, on the one hand, the external sources are not available or inauthentic in some real scenarios such as user supervision cross social medias. On the other hand, structural heterogeneity among different KGs is the main issue being addressed in this paper. Therefore, unlike previous works [39], [46], external sources are not utilized in TTEA. Instead, it relies on topology structure and neighbor information for solving heterogeneity at its core. What is more, to handle the insufficient seed pairs, Bootstrapping learning [47] and iterative training strategy [23] are introduced. Specifically, bi-directional iterative training strategy [48] are widely applied recently [11], [13], [49], [50], which is also adopted in TTEA for improving performance.

3. Problem Formulation

A KG could be formalized as $KG = (E, R, T)$, where E and R are the sets of entity and relation respectively, $T \subset E \times R \times E$ is the set of relational triple. Given two cross-lingual KGs, $KG1 = (E1, R1, T1)$ and $KG2 = (E2, R2, T2)$, the task of EA is defined as identifying entity pairs composed of entities from $KG1$ and $KG2$ based on a set of seed entity pairs in this paper, in which each entity pair comprises two entities, originating from distinct KGs, that refer to the identical real-world object. The seed entity pairs are known aligned and can be denoted as $S = \{(e_1, e_2) | e_1 \in E1, e_2 \in E2\}$, where e_1 and e_2 are equivalent objects from $KG1$ and $KG2$, respectively.

4. TTEA Framework

We propose a framework TTEA based on type-enhanced ensemble triple representation and triple-aware entity enhancement via triple-aware attention mechanism. The overall ar-

[†] Available source codes in <https://github.com/CodesForNlp/TTEA>.

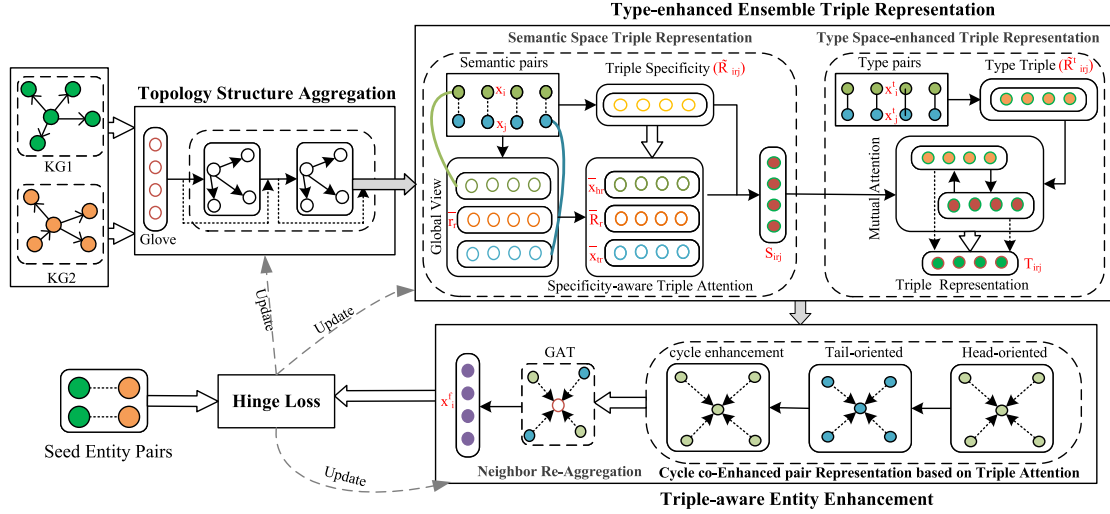


Fig. 2 An overall of TTEA framework, which consists of the following components: 1) topology structure aggregation for integrating neighbors, 2) type-enhanced ensemble triple representation for generating ensemble triple and fusing type information, and 3) triple-aware entity enhancement for obtaining EA-oriented entity representation.

architecture of TTEA is illustrated as Fig. 2, which mainly consists of four parts: Topology Structure Aggregation, Type-enhanced Ensemble Triple Representation, Triple-aware Entity Enhancement and Entity Alignment Strategy. Entity name-based embedding is enhanced via structural information for initialization in the first part, after that the ensemble triple representation with specificity is generated in Type-enhanced Ensemble Triple Representation part. Then, triple-aware representations of head and tail entities are respectively obtained and are circularly reinforced by each other in Triple-aware Entity Enhancement module. Finally, in the Entity Alignment Strategy part, the bi-direction iterative strategy is applied to enlarge seed pairs, meanwhile the entity embedding and the parameters are updated via back-propagation.

4.1 Topology Structure Aggregation

We firstly expand relation as a combination of original-relation, reverse-relation and self-relation to fully describe topology structure in KGs. We also use the entity name-based embedding as the initialized representation as RAGA does, following which a two-layer GCNs with Highway Networks [51] are deployed to aggregate topological information while preserving entity primary semantic. The l -th Highway-GCN layer is formulated as:

$$\mathbf{X}_{gcn}^{l+1} = \text{ReLU} \left(\tilde{\mathbf{D}}^{-\frac{1}{2}} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-\frac{1}{2}} \mathbf{X}^l \right) \quad (1)$$

$$T \left(\mathbf{X}^l \right) = \sigma \left(\mathbf{X}^l \mathbf{W}^l + \mathbf{b}^l \right) \quad (2)$$

$$\mathbf{X}^{l+1} = T \left(\mathbf{X}^l \right) \cdot \mathbf{X}_{gcn}^{l+1} + \left(1 - T \left(\mathbf{X}^l \right) \right) \cdot \mathbf{X}^l \quad (3)$$

where $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$, \mathbf{A} is the adjacency matrix of relation-expanded graph, \mathbf{I} is the identity matrix, $\tilde{\mathbf{D}}$ is the degree

matrix of $\tilde{\mathbf{A}}$ and $\mathbf{X}^l \in \mathbb{R}^{n \times d_e}$ denotes the input entity embedding in l -th hidden layer, n is the number of entities in a KG, d_e is the dimension of entity embedding, \mathbf{X}_{gcn}^{l+1} is the output of l -th GCN layer, and \mathbf{X}^{l+1} is the output from the l -th highway network. $\sigma(\cdot)$ is activation function, \cdot denotes the element-wise multiplication, \mathbf{W}^l and \mathbf{b}^l are the weight matrix and bias vector of the input embedding in l -th hidden layer.

4.2 Type-Enhanced Ensemble Triple Representation

The ensemble triple representation is generated in this module by mining the influence of element and type information on triple in semantic space and type space via ensemble triple attention mechanism.

4.2.1 Ensemble Triple Representation in Semantic Space

To describe relation's wholeness and multi-relation features, the global relation $\tilde{\mathbf{r}} \in \mathbb{R}^{2d_e}$ is computed as the average concatenation of head and tail entities with same relation.

$$\tilde{\mathbf{r}}_r = \frac{1}{|T_r|} \sum_{(e_i, r, e_j) \in T_r} (\mathbf{x}_i \oplus \mathbf{x}_j) \quad (4)$$

where \mathbf{x}_i is the embedding of e_i , \oplus denotes the concatenation operation, T_r is the set of triple with a specific relation r in KG.

Moreover, we utilize triple specificity to alleviate the redundancy and noise during element interaction. The local relation of a specific triple (e_i, r, e_j) is firstly defined as $\tilde{\mathbf{r}}_{irj} = \mathbf{x}_i \oplus \mathbf{x}_j$, based on which the triple specificity is denoted as $\tilde{\mathbf{R}}_{irj} = \mathbf{x}_i \oplus (\tilde{\mathbf{r}}_{irj} \mathbf{W}_e^l) \oplus \mathbf{x}_j$, where $\mathbf{W}_e^l \in \mathbb{R}^{2d_e \times d_r}$ is the mapping matrix, d_r is the relation dimension.

Then, we design a three-view ensemble triple attention

mechanism to legitimately incorporate global triple features, which includes head-aware attention, tail-aware attention and relation-aware attention. It is noteworthy that we use the overall relation $\tilde{\mathbf{r}}_r = \mathbf{W}_e^g \tilde{\mathbf{r}}_r + \mathbf{W}_e^l \tilde{\mathbf{r}}_{irj}$ for relation-aware triple attention mechanism, where $\mathbf{W}_e^g, \mathbf{W}_e^l \in \mathbb{R}^{2d_e \times d_r}$ are mapping matrices for global and local relation respectively. Specifically, the head-aware semantic triple representation $\bar{\mathbf{x}}_{hr}$ is obtained via head-aware triple attention:

$$c_{ir} = a^T (\mathbf{x}_i \mathbf{W}_h \oplus \tilde{\mathbf{R}}_{irj} \mathbf{W}_i^s) \quad (5)$$

$$\alpha_{ir} = \frac{\exp(\text{LReLU}(c_{ir}))}{\sum_{(e_i, r, e_j) \in T_r} \exp(\text{LReLU}(c_{i'r}))} \quad (6)$$

$$\bar{\mathbf{x}}_{hr} = \text{LReLU} \left(\sum_{T_r} (\alpha_{ir} \mathbf{x}_i \mathbf{W}_h) \right) \quad (7)$$

where $a \in \mathbb{R}^{2d_r \times 1}$ is a one-dimension vector to map the multi-dimension input into a scalar. $\mathbf{W}_h \in \mathbb{R}^{d_e \times d_r}$ and $\mathbf{W}_i^s \in \mathbb{R}^{(2d_e + d_r) \times d_r}$ are linear transition matrices for head entity and ensemble triple in semantic space. LReLU is the *Leaky_Relu* activation function, α_{ir} is the attention score from head entity \mathbf{x}_i to ensemble triple representation. Then the tail-aware semantic triple representation $\bar{\mathbf{x}}_{tr}$ and relation-aware semantic triple representation $\bar{\mathbf{R}}_r$ can be obtained in the same way.

Then, the fused ensemble triple representation in semantic space is computed as combining $\bar{\mathbf{x}}_{hr}$, $\bar{\mathbf{x}}_{tr}$ and $\bar{\mathbf{R}}_r$, which is added with the primary specificity as the final triple representation \mathbf{S}_{irj} in semantic space for $(e_i, r, e_j) \in T$ to fully retain the triple semantic specificity:

$$\mathbf{S}_{irj} = \bar{\mathbf{x}}_{hr} + \bar{\mathbf{x}}_{tr} + \bar{\mathbf{R}}_r + (\tilde{\mathbf{R}}_{irj} \mathbf{W}_i^s) \quad (8)$$

4.2.2 Type Space-Enhanced Triple Representation

In this module, we adopt nonlinear mapping to generate type embedding $\mathbf{X}^t \in \mathbb{R}^{n \times d_t}$ from semantic embedding $\mathbf{X} \in \mathbb{R}^{n \times d_e}$, where d_t is the type dimension:

$$\mathbf{X}^t = \tanh(\mathbf{X} \mathbf{W} + b) \quad (9)$$

To effectively characterize triple, we regard the elements of type triple as a whole to incorporate type information considering the type inseparability. For a triple (e_i, r, e_j) , the global relation representation $\tilde{\mathbf{r}}_r^t \in \mathbb{R}^{2d_t}$ is computed as averaging the concatenation of entity pair with the same relation r , which is added to the local relation $\tilde{\mathbf{r}}_{irj}^t = \mathbf{x}_i \oplus \mathbf{x}_j$ for generating type triple $\tilde{\mathbf{R}}_{irj}^t$ as Eq. (10)–(12), where $\mathbf{W}_i^r \in \mathbb{R}^{2d_t \times d_r}$ is the transition matrix:

$$\tilde{\mathbf{r}}_r^t = \frac{1}{|T_r|} \sum_{(e_i, r, e_j) \in T_r} (\mathbf{x}_i^t \oplus \mathbf{x}_j^t) \quad (10)$$

$$\mathbf{r}_{irj}^t = \tilde{\mathbf{r}}_r^t + \tilde{\mathbf{r}}_{irj}^t \quad (11)$$

$$\tilde{\mathbf{R}}_{irj}^t = \mathbf{x}_i^t \oplus (\mathbf{r}_{irj}^t \mathbf{W}_i^r) \oplus \mathbf{x}_j^t \quad (12)$$

Then a Semantic-Type mutual attention is designed, in

which the enhanced type-space triple representation $\bar{\mathbf{T}}_r$ can be obtained:

$$\alpha_{tr} = \frac{\exp(\text{LReLU}(a^T (\mathbf{S}_{irj} \oplus \tilde{\mathbf{R}}_{irj}^t \mathbf{W}_t)))}{\sum_{T_r} \exp(\text{LReLU}(a^T (\mathbf{S}_{i'rj'} \oplus \tilde{\mathbf{R}}_{i'rj'}^t \mathbf{W}_t)))} \quad (13)$$

$$\bar{\mathbf{T}}_r = \text{ReLU} \left(\sum_{(e_i, r, e_j) \in T_r} (\alpha_{tr} \mathbf{S}_{irj}) \right) \quad (14)$$

where $\mathbf{W}_t \in \mathbb{R}^{(2d_t + d_r) \times d_r}$ are the trainable parameter for type triple. And the enhanced global representation $\bar{\mathbf{S}}_r$ can be generated in the same way.

Finally, the type-enhanced ensemble triple representation $\mathbf{T}_{ijr} \in \mathbb{R}^{(d_r + d_t)}$ is obtained while preserving primary type features.

$$\mathbf{T}'_{ijr} = \mathbf{S}_{irj} + \bar{\mathbf{S}}_r + (\tilde{\mathbf{R}}_{irj}^t \mathbf{W}_t) + \bar{\mathbf{T}}_r \quad (15)$$

$$\mathbf{T}_{ijr} = \mathbf{T}'_{ijr} \oplus \bar{\mathbf{r}}_r^t \quad (16)$$

4.3 Triple-Aware Entity Enhancement

4.3.1 Cycle Co-Enhanced Entity Pair Representation Based on Triple Attention

An entity may play different roles as head or tail in different triples and the influences of a head entity e_i and a tail entity e_j on triple (e_i, r, e_j) are entirely different. In this module, head entity and tail entity are respectively generated via triple attention and get reinforced circularly.

Firstly, the head-oriented entity representation is enforced via triple attention, which can be formulated as Eq. (17)–(18).

$$\alpha_{th} = \frac{\exp(\text{LReLU}(a^T (\mathbf{T}_{ijr} \mathbf{W}_h^c \oplus \mathbf{x}_i)))}{\sum_{(e_i, r', e_j) \in T} \exp(\text{LReLU}(a^T (\mathbf{T}_{i'j'r'} \mathbf{W}_h^c \oplus \mathbf{x}_i)))} \quad (17)$$

$$\mathbf{x}_i = \mathbf{x}_i + \text{ReLU} \left(\sum_{(e_i, r, e_j) \in T} (\alpha_{th} \mathbf{T}_{ijr} \mathbf{W}_h^c) \right) \quad (18)$$

After that, the tail-oriented entity representation is carried out as the same of head-oriented procedure, which can be formulated as Eq. (19)–(20).

$$\alpha_{tt} = \frac{\exp(\text{LReLU}(a^T (\mathbf{T}_{ijr} \mathbf{W}_t^c \oplus \mathbf{x}_j)))}{\sum_{(e_i', r', e_j) \in T} \exp(\text{LReLU}(a^T (\mathbf{T}_{i'j'r'} \mathbf{W}_t^c \oplus \mathbf{x}_j)))} \quad (19)$$

$$\mathbf{x}_j = \mathbf{x}_j + \text{ReLU} \left(\sum_{(e_i, r, e_j) \in T} (\alpha_{tt} \mathbf{T}_{ijr} \mathbf{W}_t^c) \right) \quad (20)$$

where $\mathbf{W}_h^c, \mathbf{W}_t^c \in \mathbb{R}^{(d_r + d_t) \times d_e}$ are the trainable weight

parameters for triples.

Furthermore, it should be noted that the cycle enhancement between head and tail is accomplished by regarding the head-oriented entity representation as the participant of tail-oriented attention computation and vice versa. Specifically, the head-oriented entity representation generated by Eq. (18) will be the participant of the tail-oriented attention computation in Eq. (19). Similarly, the tail-oriented entity representation generated by Eq. (20) will be the participant of the head-oriented attention computation in Eq. (17) in the next cycle.

4.3.2 Neighbor Re-Aggregation

In the last part of TTEA, we apply a GAT layer to re-aggregate neighbor information with modeled representation and the final entity representation \mathbf{x}_i^f is generated for EA.

$$\alpha_{ij} = \frac{\exp(\text{LReLU}(a^T(\mathbf{x}_i \oplus \mathbf{x}_j)))}{\sum_{e_k \in N_i} \exp(\text{LReLU}(a^T(\mathbf{x}_i \oplus \mathbf{x}_k)))} \quad (21)$$

$$\mathbf{x}_i^f = \mathbf{x}_i \oplus \left(\text{ReLU} \left(\sum_{e_j \in N_i} (\alpha_{ij} \mathbf{x}_j) \right) \right) \quad (22)$$

where N_i is the set of neighbor entities of e_i .

4.4 Entity Alignment Strategy

To evaluate the confidence of entity pair being equivalent, the Manhattan distance is used to measure the semantic discrepancy between entity representations from different KGs for illustrating the similarity of entities as Eq. (23), based on which the metric in Chapter 5.5 is computed and the margin-based loss L is defined as Eq. (24). Moreover, we deploy a bi-direction iterative strategy following MRAGA [48] to expand training seed pairs based on negative-sample method, during which only the bi-directional aligned entity pairs can be regarded as new seed entity pairs in next training epoch.

$$\text{dis}(e_i, e_j) = \left\| \mathbf{x}_i^f - \mathbf{x}_j^f \right\|_1 \quad (23)$$

Algorithm 1 The Overall Training Process of TTEA

Require: Source KG_s , Target KG_t , Seed entity pairs S for Training, The Glove embedding vectors of entities E_s and E_t in KG_s, KG_t

- 1: **for** $epoch\ n = 1 \rightarrow E$ **do**
 - 2: Aggregating topology Structure with Equations (1)-(3)
 - 3: Generating Ensemble Triple in Semantic Space with Equations (4)-(8)
 - 4: Generating Final Triple Representation via Type-enhanced Co-Attention with Equations (9)-(16)
 - 5: Obtaining EA-oriented Entity Representation based on Triple Attention with Equations (17)-(20)
 - 6: Re-Aggregating Neighbor Information with Equations (21)-(22)
 - 7: Compute sample loss with Equations (23)-(24)
 - 8: **if** $n \% 5 == 0$ **then**
 - 9: Expanding Seed Training Sets S Following [48]
 - 10: **end if**
 - 11: **end for**
-

$$L = \sum_{(e_i, e_j) \in S} \max(\text{dis}(e_i, e_j) - \text{dis}(e'_i, e'_j) + \lambda, 0) \quad (24)$$

where (e_i, e_j) is a pre-aligned entity pair in training set S , (e'_i, e'_j) is the negative sample generated by randomly replacing e_i or e_j with their k -nearest neighbors, λ is the margin hyper-parameter.

The overall training process of TTEA framework can be described as Algorithm 1.

5. Experimental Setup

5.1 DataSets

In order to make the reliable and fair comparison, we evaluate TTEA on three real-world multi-lingual datasets from a simplified DBP15K described in Table 1, which are adopt by almost all the baselines and are constructed by removing lots of isolated entities and relations from primary DBP15K [52]. Each dataset in the simplified version contains 15000 aligned entity pairs.

5.2 Baselines

To comprehensively evaluate our approach, we choose some embedding-based methods as baselines to make comparison. These approaches are divided into three groups: Trans-based methods, GNNs-based methods and Semi-supervised based methods:

– **Trans-based methods:** MTransE [22], JAPE [52], BootEA [47], TransEdge [16], RpAlign [27].

– **GNNs-based methods:** (1) *GCN-based methods:* GCN-Align [10], HMAN [43], HGCN [30], MCEA [50]. (2) *GAT-based methods:* NAEA [36], RDGCN [20], KAGNN [33], MRGA [35], SHEA [37], RAGA-I [21].

– **Semi-supervised methods:** MRAEA [48], RREA-semi [11], RAGA-semi [21], MCEA-semi [50].

It should be noted that methods requiring additional information such as RAEA [42] and RNM [19] are not considered as baselines for fairness.

5.3 Model Variants

To make valid evaluation on different components in our framework, we implement three variants of TTEA to verify

Table 1 Statistical data of simplified DBP15K.

DBP15K		Entities	Relations	Rel Triples	Links
ZH-EN	ZH	19388	1700	70414	15000
	EN	19572	1322	95142	
JA-EN	JA	19814	1298	77214	15000
	EN	19780	1152	93484	
FR-EN	FR	19661	902	105998	15000
	EN	19993	1207	115722	

Table 2 Overall performance of entity alignment

Methods	ZH-EN			JA-EN			FR-EN		
	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
MTransE(2017)	30.8	61.4	0.364	27.8	57.4	0.349	24.4	55.5	0.335
JAPE(2017)	41.2	74.4	0.490	36.2	68.5	0.476	32.4	66.7	0.430
BootEA(2018)	62.9	84.7	0.703	62.2	85.4	0.701	65.3	87.4	0.731
TransEdge(2019)	73.5	91.9	0.801	71.9	93.2	0.795	71.0	94.1	0.796
RpAlign(2022)	74.8	88.8	0.794	72.9	89.0	0.872	75.2	89.9	0.801
GCN-Align(2018)	41.2	74.4	0.549	39.9	74.4	0.546	37.3	74.5	0.532
HMAN(2019)	56.1	85.9	0.67	55.7	86.0	0.67	55.0	87.6	0.66
HGCN(2019)	72.0	85.7	0.768	76.6	89.7	0.813	89.2	96.1	0.917
MCEA(2022)	72.4	93.4	0.800	71.9	94.0	0.800	73.9	95.3	0.820
NAEA(2019)	65.0	86.7	0.720	64.1	87.3	0.718	67.3	89.4	0.752
RDGCN(2019)	70.8	84.6	0.751	76.7	89.5	0.812	88.6	95.7	0.908
KAGNN(2022)	73.6	87.3	0.786	79.4	91.1	0.837	92.0	97.6	0.941
MRGA(2021)	75.5	90.5	0.783	73.4	90.3	0.771	75.7	91.7	0.791
SHEA(2021)	76.3	91.4	0.835	82.1	93.8	0.860	90.5	97.0	0.902
RAGA-I(2021)	79.8	93.3	0.847	82.9	95.0	0.875	91.4	98.2	0.940
TTEA-base(wo-E)	78.9	93.4	0.842	82.0	95.0	0.868	91.9	98.5	0.944
TTEA-base(wo-T)	78.7	93.4	0.841	81.4	95.1	0.864	91.4	98.4	0.940
TTEA-base(wo-C)	79.9	93.5	0.849	82.9	95.1	0.875	92.2	98.3	0.946
TTEA-base(ours)	80.2	93.8	0.852	83.1	95.4	0.876	92.4	98.6	0.947
MRAEA(2020)	75.2	92.3	0.824	75.3	93.3	0.825	78.1	94.7	0.843
RREA-semi(2020)	80.1	94.8	0.857	80.2	95.2	0.858	82.7	96.6	0.881
MCEA-semi(2022)	81.4	95.6	0.867	80.7	95.7	0.864	84.1	97.0	0.891
RAGA-semi(2021)	85.7	96.0	0.896	88.9	97.1	0.920	94.0	98.8	0.958
TTEA-semi(ours)	86.5	96.6	0.902	89.5	97.6	0.927	94.9	99.1	0.966

their effectiveness:

(1) wo-E: a simplified TTEA version without Ensemble Triple Attention.

(2) wo-T: a simplified TTEA version without Type Space-Enhanced module.

(3) wo-C: a simplified TTEA version without Cycle co-Enhanced module.

5.4 Implementation Details

We get the cross-lingual initial entity embedding from RAGA [21], which adopted translation technique to mapping Glove [53] embedding into different languages. For a fair comparison with the baselines, we use a 30% proportion of alignment seeds for training and the rest for testing as baselines do. The grid search strategy is used to manually tune the hyper-parameters. And we used the Adam optimizer [54] to train our model. The training epoch E is set to 80, and we make evaluation on test dataset every 5 epochs. The depth l of Highway-GCNs is 2, both the relation dimension d_r and type dimension d_t are 100. And the number of epochs p for updating negative samples is 5, the number of nearest negative samples k is 5. The margin hyper-parameter λ is 3.0.

5.5 Metrics

By convention, we report the Hits@1, Hits@10 and MRR results, which are widely used for the evaluation of alignment effectiveness. Specifically, Hits@k measures the percentage of correct alignment ranked at top k which can be ranked by

Eq. (23), and MRR is the average of the reciprocal ranks of results, which can be computed as Eq. (25). Higher Hits@k and MRR scores indicate better performance.

$$MRR = \frac{1}{|N|} \sum_{1 \leq i \leq |N|} \frac{1}{rank_i} \quad (25)$$

6. Results and Analysis

6.1 Overall Performance

The overall EA results are shown in Table 2, which are either implemented with the source codes or provided by original papers. To make a comprehensive comparison with baselines from different perspectives, experiments are employed in two settings: (1) -base: the training seed entity pairs are not expanded during training process, (2) -semi: the training seed entity pairs will be dynamically expanded with a bi-directional iterative training strategy. The solid lines separate Trans-based methods, GNNs-based methods and Semi supervised-based methods and dot line makes a distinction between GCNs-based methods and GATs-based methods and TTEA variants are under the dashed line.

For Trans-based methods, TransEdge and RpAlign outperform MTransE, JAPE, and BootEA with their unique representation for triple elements. In detail, RpAlign achieves better Hits@1 for its relation prediction and self-training mechanism, while TransEdge gets more excellent Hits@10 and MRR on ZH_EN and JA_EN via contextualizing relation representation in terms of specific head-tail entity pair. For GCNs-based methods, GCN-Align gets the worst results

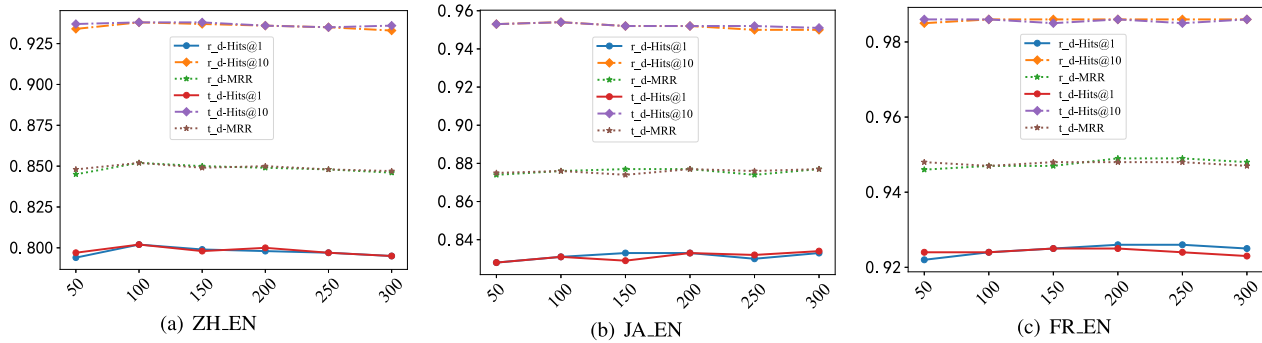


Fig. 3 EA performance with different relation and type dimensions from 50 to 300.

Table 3 Comparison of variants with semi setting.

Modes	ZH-EN			JA-EN			FR-EN		
	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
TTEA-semi(wo-E)	85.9	96.2	0.898	88.7	97.4	0.921	94.7	99.0	0.964
TTEA-semi(wo-T)	85.9	96.3	0.897	88.3	97.3	0.918	93.9	98.9	0.959
TTEA-semi(wo-C)	86.1	96.3	0.899	89.1	97.3	0.923	94.8	99.0	0.966
TTEA-semi	86.5	96.6	0.902	89.5	97.6	0.927	94.9	99.1	0.966

Table 4 Comparison of different modes of cycle co-enhanced module.

Modes	ZH-EN			JA-EN			FR-EN		
	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
mode1	79.8	93.5	0.849	83.1	95.0	0.875	92.2	98.4	0.946
mode2	80.2	93.8	0.852	83.1	95.4	0.876	92.4	98.6	0.947
mode3	79.9	93.6	0.849	83.1	95.4	0.877	92.3	98.5	0.947

as shallow utilization of relation triple while MCEA outperforms others for extending the convolution region of long-tail entities. Furthermore, NAEA, RDGCN, KAGNN, MRGA, SHEA, RAGA-l all adopt GATs to obtain fine-grained representation, which get excellent performance without doubt. Among them, RAGA-l achieves the best results, which generate relation from entity via attention mechanism and then aggregate relation to entity. Compared with baselines, TTEA performs best in all evaluation metrics on three datasets with the consideration of triple specificity and the role diversity.

6.2 Ablation Analysis

6.2.1 Effect of TTEA Components

The results of model variants with base setting, i.e. (TTEA-base(wo-E), TTEA-base(wo-T) and TTEA-base(wo-C) in Table 2) and semi setting, i.e. (TTEA-semi(wo-E), TTEA-semi(wo-T) and TTEA-semi(wo-C) in Table 3) both show that while ensemble triple attention, Type Space-enhanced module and Cycle co-Enhanced module in TTEA all make a improvement, Type Space-Enhanced module has a more significant effect. Moreover, three modes of Cycle co-Enhanced module with different cycle orders are compared in Table 4 to explore appropriate cycle form.

mode1: the mode of co-enhanced process with the head-tail order.

mode2: the mode of cycle co-enhanced process with the head-tail-head order.

Table 5 Comparison of different depths of Highway-GCNs.

Depths	ZH-EN			JA-EN			FR-EN		
	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
$l=1$	79.4	92.4	0.841	83.4	94.5	0.875	92.9	98.4	0.950
$l=2$	80.2	93.8	0.852	83.1	95.4	0.876	92.4	98.6	0.947
$l=3$	77.0	93.8	0.832	79.4	94.8	0.851	88.6	97.7	0.921

mode3: the mode of cycle co-enhanced process with the head-tail-head-tail order.

We can see from Table 4 that the mode2 adopted in TTEA is more effective on ZH_EN and FR_EN for reasonable cycle process while the mode3 gets the almost same performance on JA_EN.

6.2.2 Impact of GCN Depth

To explore the impact of different Highway-GCNs depth l , we compare TTEA variants with different depths with $l = 1$, $l = 2$ and $l = 3$ in Table 5. The results show that the TTEA variant with a two-layer Highway-GCNs obtains the greatest superiority on ZH_EN and JA_EN for their complex structure, while a one-layered Highway-GCNs get the best performance on FR_EN for its entity semantic reliance.

6.2.3 Impact of Relation and Type Dimensions

There are two dimensional hyper-parameters: relation dimension d_r and type dimension d_t in TTEA. We respectively evaluate TTEA on six different relation and type dimensions as 50, 100, 150, 200, 250 and 300 to explore dimensional impacts. The results in Fig. 3 show that different relation and type dimensions have approximate performance, which indicate that dimensions have little influence on TTEA. Especially, the best results can be obtained on ZH_EN when $d_r = d_t = 100$.

6.2.4 Impact of Seed Entity Pairs

To explore the impact of different training seeds, we compare RAGA-l and RAGA-semi with TTEA-base and TTEA-semi by varying the proportion of training seeds from 25% to 50% with a step size of 5%. The results in Fig. 4, Fig. 5 and Fig. 6 respectively depict Hits@1, Hits@10 and MRR with

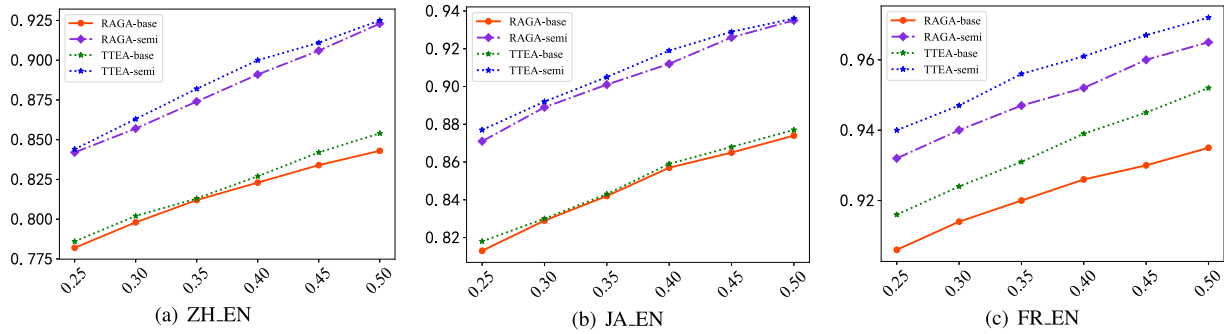


Fig. 4 Hits@1 with different training seed pairs.

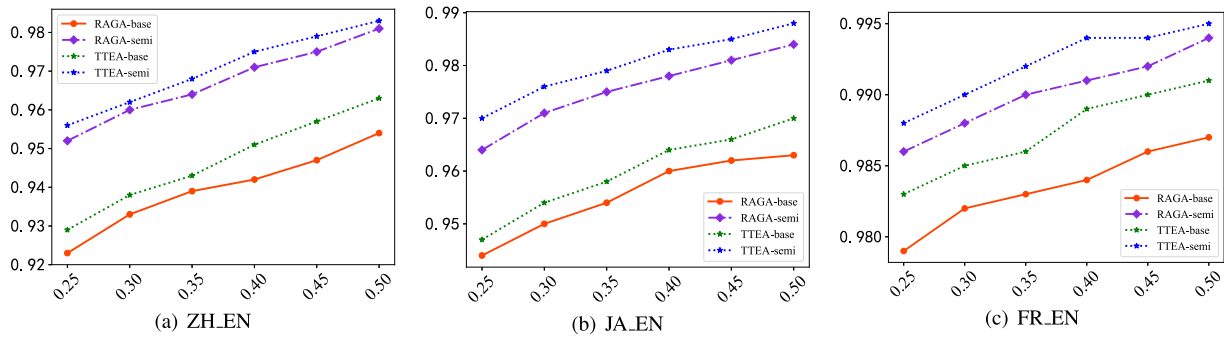


Fig. 5 Hits@10 with different training seed pairs.

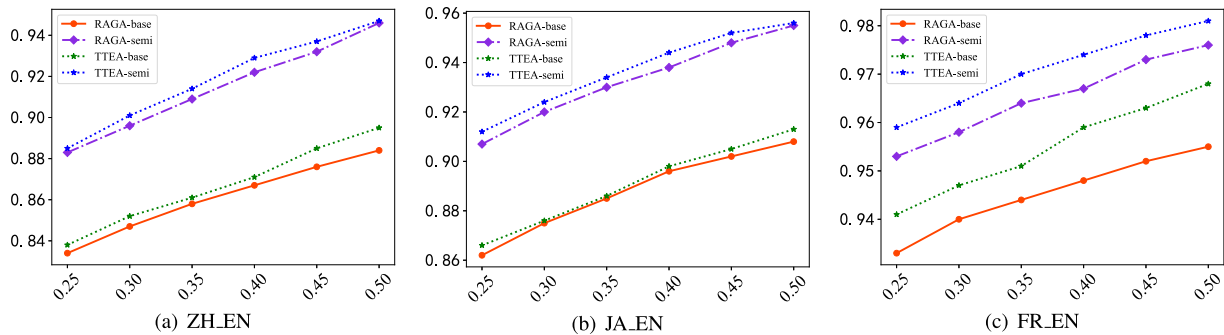


Fig. 6 MRR with different training seed pairs.

different seeds proportions. It is showed that TTEA is better than RAGA on both base and semi-supervised local alignment methods two modes for all metrics of three datasets. And as training seeds increase, the Hit@1, Hits@10 and MRR curves of TTEA-base on three datasets are steeper than RAGA-l, which draw the better performance and potentiality.

7. Conclusion

In this paper, to address insufficient utilization of triple specificity and the diversity of entity role, we present a novel framework TTEA – Type-enhanced Ensemble Triple Representation via Triple-aware attention for Cross-lingual Entity Alignment. By modeling role features and relational interaction between semantic space and type space, TTEA is

capable to incorporate ensemble triple specificity and learn cycle co-enhanced head and tail representations. Compared with baselines, our model achieves comparative performance on three real-world cross-lingual datasets.

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Zhishuo Zhang received the B.S. degree in School of Computer Science and Engineering, Tongji University, Shanghai, China, in 2019. He is currently pursuing his Ph.D. degree in Tongji University of Computer Science and Engineering, Shanghai, China.



Chengxiang Tan received the Ph.D. degree in engineering from Northwestern Polytechnic University, China, in 1994. He is currently a Professor of computer science with Tongji University.



Xueyan Zhao received the B.S. degree in School of Computer Science and Engineering, Tongji University, Shanghai, China, in 2017. He is currently pursuing his Ph.D. degree in Tongji University of Computer Science and Engineering, Shanghai, China.



Min Yang received the M.S. degree in School of Information and Communication Engineering, Dalian University for Nationalities, 2021. She is currently pursuing her Ph.D. degree in Tongji University of Computer Science and Engineering, Shanghai, China.