

Ensemble Semi-supervised Entity Alignment via Cycle-teaching

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Abstract

Entity alignment is to find identical entities in different knowledge graphs. Although embedding-based entity alignment has recently achieved remarkable progress, training data insufficiency remains a critical challenge. Conventional semi-supervised methods also suffer from the incorrect entity alignment in newly proposed training data. To resolve these issues, we design an iterative cycle-teaching framework for semi-supervised entity alignment. The key idea is to train multiple entity alignment models (called aligners) simultaneously and let each aligner iteratively teach its successor the proposed new entity alignment. We propose a diversity-aware alignment selection method to choose reliable entity alignment for each aligner. We also design a conflict resolution mechanism to resolve the alignment conflict when combining the new alignment of an aligner and that from its teacher. Besides, considering the influence of cycle-teaching order, we elaborately design a strategy to arrange the optimal order that can maximize the overall performance of multiple aligners. The cycle-teaching process can break the limitations of each model's learning capability and reduce the noise in new training data, leading to improved performance. Extensive experiments on benchmark datasets demonstrate the effectiveness of the proposed cycle-teaching framework, which significantly outperforms the state-of-the-art models when the training data is insufficient and the new entity alignment has much noise.

1 Introduction

Entity alignment seeks to find identical entities of different KGs that refer to the same real-world object. Recently, embedding-based entity alignment approaches have achieved great progress (Sun, Hu, and Li 2017; Sun et al. 2018; Cao et al. 2019; Wu et al. 2019a; Sun et al. 2020a; Zeng et al. 2020; Mao et al. 2020). One prime advantage of embedding techniques lies in relieving the heavy reliance on hand-craft features or rules. KG embeddings have also demonstrated their great strength to tackle the symbolic heterogeneity of different KGs (Wang et al. 2017). Especially for entity alignment, embedding-based approaches capture the similarity of entities in vector space. But these approaches highly rely on sufficient training data (i.e., seed entity alignment) to bridge different KG embedding spaces for alignment learning. The

training data insufficiency issue in real-world scenarios (Chen et al. 2017) prevents embedding-based approaches from effectively capturing entity similarities across different KGs.

The semi-supervised approach is an effective solution to the above issue. It iteratively proposes new “reliable” entity alignment to augment training data (Zhu et al. 2017; Sun et al. 2018; Chen et al. 2018). There are several shortcomings of existing semi-supervised approaches, and not all semi-supervised strategies can bring improved performance and stability to entity alignment in real scenarios (Sun et al. 2020b). For example, although the popular self-training approach BootEA (Sun et al. 2018) can alleviate the error-accumulation issue via a heuristic alignment editing method, the learning capability of its entity alignment model and the alignment selection bias still limit its performance. The co-training approach KDCoE (Chen et al. 2018) incorporates literal descriptions as side information to complement the structure view of entities. However, it requires a high complementarity of the two independent feature views and specific prior knowledge for feature selection. It usually fails to bring improvement due to the limited availability of descriptions.

In summary, the shortcomings of existing semi-supervised entity alignment approaches lie in the following aspects. (i) **Noisy alignment accumulation.** This is the critical challenge for semi-supervised approaches that the newly proposed entity alignment inevitably contains much noisy data. Iteratively accumulating new entity alignment as training data is also error-propagation. The incorrect entity alignment can spread to the following iterations with adverse effects on final performance. (ii) **Biased alignment selection.** The semi-supervised approach usually proposes the predicted high-confidence alignment to bootstrap itself, and such alignment will receive more training and higher confidence in the next iterations. The approach will then be more inclined to propose the same more and more “reliable” alignment, leading to a biased alignment selection. The performance improvement brought by retraining the entity alignment model with what it already knows is limited. (iii) **Performance bottleneck of the aligner.** Although the embedding-based entity alignment model (called aligner) can receive better optimization with more training data during semi-supervised learning, the aligner has its performance bottleneck due to its limited expressiveness on embedding learning. This can be reflected by the variable performance of the entity alignment approach

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when employing different embedding models, e.g., TransE (Bordes et al. 2013) and GCN (Kipf and Welling 2017).

To address the above shortcomings, we elaborately design a novel **Cycle-Teaching framework for Entity Alignment**, named **CycTEA**, which enables multiple entity alignment models (called aligners) to teach each other. CycTEA lets each aligner teach its selected new entity alignment to its subsequent aligner for robust semi-supervised training. The subsequent aligner can filter noisy alignment via alignment conflict resolution and get more reliable entity alignment to augment training data. The motivation behind our work is that, as different aligners have different alignment capacities, the selected new entity alignment of an aligner can benefit other aligners and help them filter the noisy alignment introduced by the biased alignment selection (Han et al. 2018).

Cycle-teaching possesses some critical advantages over the traditional ensemble semi-supervised method, e.g., Tri-Training (Zhou and Li 2005) that integrates three models in the “majority-teach-minority” way (i.e., majority vote). First, cycle-teaching can help each aligner break its performance bottleneck. It can produce more diverse and complementary entity alignment since the aligners have different capacities and are trained based on their own training data. Taught by the new “knowledge” from others, each aligner can overcome the ceiling of entity alignment performance. Second, cycle-teaching can reduce the risk of noise training data. In cycle-teaching, as different aligners have different learning abilities, they can filter different types of incorrect entity alignment by the proposed diversity-aware alignment selection and conflict resolution. The error flows from one aligner to its successor can be reduced during the iterations. Third, cycle-teaching can be easily extended to multiple aligners (more than three and also even number of aligners). It can avoid the problem that multiple models fail to reach an agreement by majority vote. Our contributions are summarized as follows:

- We propose a novel semi-supervised learning framework, i.e., cycle-teaching, for entity alignment. It seeks to build a strong and robust entity alignment approach by integrating multiple simple aligners. It does not require sufficient feature views of entities or high performance of each aligner, and is able to achieve better generalization ability.
- To guarantee the quality of new entity alignment, we propose a diversity-aware alignment selection method and resolve alignment conflict by re-matching. We determine the cycle-teaching order based on the complementarity and performance difference of neighboring aligners. The cycle-teaching paradigm helps the multiple aligners combat the noise alignment during iterative training. For each aligner, its new entity alignment combined with the new knowledge learned from others can bring significant performance gain.
- We show that conventional semi-supervised methods, e.g., self-training and co-training can be regarded as the special cases of cycle-teaching. The advantages of cycle-teaching lie in reducing noise alignment accumulation and markedly boosting each aligner by teaching it unknown alignment.
- Our framework can integrate any entity alignment models, including relation-based models such as AlignE (Sun et al. 2018), RSN4EA (Guo, Sun, and Hu 2019) and AliNet

(Sun et al. 2020a). Extensive experiments on the benchmark entity alignment datasets OpenEA (Sun et al. 2020b) demonstrate the effectiveness of our framework.

2 Related Work

Structure-based Entity Alignment. The assumption for structure-based entity alignment is that similar entities should have similar relational structures. Early studies such as MTransE (Chen et al. 2017), AlignE (Sun et al. 2018), SEA (Pei et al. 2019) exploit TransE (Bordes et al. 2013) as the base embedding model for relational structure learning. To capture entity alignment across different KGs, the two KGs are merged as one graph for joint embedding or separately embedded along with a linear mapping. Recent studies such as GCN-Align (Wang et al. 2018), AliNet (Sun et al. 2020a) and others (Cao et al. 2019; Zhu et al. 2019; Li et al. 2019; Fey et al. 2020; Ye et al. 2019; Xu et al. 2019) design various graph neural networks (GNNs) for neighborhood structure learning and alignment learning. Some approaches that exploit long-term relational dependency of entities like IPTransE (Zhu et al. 2017) and RSN4EA (Guo, Sun, and Hu 2019) have also achieved great progress.

Attribute-enhanced Entity Alignment. Other approaches enhance entity alignment by learning from side information such as attribute correlation (Sun, Hu, and Li 2017), attribute values (Trisedya, Qi, and Zhang 2019; Zhang et al. 2019), entity names (Wu et al. 2019a,b, 2020; Liu et al. 2020) and distant supervision information from pre-trained language models (Yang et al. 2019; Tang et al. 2020). Although achieving high performance, one major problem of these models lies in their limited generalizability since the side information is not always available in different KGs.

Semi-supervised Entity Alignment. As seed entity alignment is usually limited in real scenarios, some approaches explore to label new alignment to augment training data iteratively. IPTransE (Zhu et al. 2017) conducts self-training to propose new alignment. However, it fails to achieve satisfying performance because it accumulates much noise data during iterations. Some work (Chen et al. 2018; Yang et al. 2020) uses a co-training mechanism to propagate new alignment from two orthogonal views (e.g., relational structures and attributes). However, the improvement is also limited because some entities do not have attributes. BootEA (Sun et al. 2018) implements a heuristic editing method to mitigate the error-propagation issue, bringing significant improvement. However, the new seed selection is also limited by the model performance. When the accumulated new pairs can be aligned successfully by the embedding module itself, the improvement would be smaller. Therefore, we aim to design an approach that iteratively labels reliable entity alignment as training data and accumulates the new entity alignment that one model can hardly find by itself based on cycle-teaching.

3 Embedding-based Entity Alignment

We define a KG as a 3-tuple, i.e., $\mathcal{K} = (\mathcal{E}, \mathcal{R}, \mathcal{T})$. \mathcal{E} and \mathcal{R} denote entity and relation sets, respectively. $\mathcal{T} \subseteq \mathcal{E} \times \mathcal{R} \times \mathcal{E}$ is the set of relational triples. Following (Sun et al. 2018),

we consider entity alignment between a source KG $\mathcal{K}_1 = (\mathcal{E}_1, \mathcal{R}_1, \mathcal{T}_1)$ and a target one $\mathcal{K}_2 = (\mathcal{E}_2, \mathcal{R}_2, \mathcal{T}_2)$. Given a small set of seed entity alignment $\mathcal{A}_{train} = \{(e_1, e_2) \in \mathcal{E}_1 \times \mathcal{E}_2 \mid e_1 \equiv e_2\}$ as training data, the task seeks to find the remaining entity alignment. For embedding-based approaches, the typical inference process is via the nearest neighbor search in the embedding space, i.e., given an aligned entity pair (x, y) , embedding-based approaches seek to hold

$$\mathbf{y} = \arg \max_{\mathbf{y}' \in \mathcal{E}_2} \pi(\mathbf{x}, \mathbf{y}'), \quad (1)$$

where $\pi(\mathbf{x}, \mathbf{y})$ is a similarity measure to serve as the alignment confidence of entities and we use cosine in the paper. Hereafter, we use bold-faced letters to denote embeddings, e.g. \mathbf{x} and \mathbf{y} are the embeddings of entities x and y , respectively. To achieve the goal as in Eq. (1), an entity alignment framework usually employs two basic modules: knowledge embedding and alignment learning (Sun et al. 2020b).

3.1 Knowledge Embedding

This module seeks to learn an embedding function f to map an entity to its embedding, i.e., $f(x) = \mathbf{x}$. TransE (Bordes et al. 2013), RSN4EA (Guo, Sun, and Hu 2019) and GNN (Kipf and Welling 2017) are three popular KG embedding techniques. In TransE, the embeddings are learned by minimizing a energy function over each triple (h, r, t) :

$$\min_f \sum_{(h,r,t) \in \mathcal{T}_1 \cup \mathcal{T}_2} \|f(h) + f(r) - f(t)\|, \quad (2)$$

where $\|\cdot\|$ denotes L_1 or L_2 vector norm. KG embeddings can be learned by jointly optimizing the TransE’s objective and the alignment learning objective (in the next section). RSN4EA (Guo, Sun, and Hu 2019) proposes a recurrent skip mechanism to capture the long-term semantic information. It uses a biased random walk to generate relation paths such as (x_1, x_2, \dots, x_T) with entities and relations in an alternating order. It encodes the paths as the output hidden state in RNN, i.e., $\mathbf{o}_i = \tanh(\mathbf{W}_1 \mathbf{o}_{i-1} + \mathbf{W}_2 \mathbf{x}_i + \mathbf{b})$ at step i , where $\mathbf{W}_1, \mathbf{W}_2$ are the weight matrices and \mathbf{b} is the bias. The skipping connection is defined as follows to enhance the semantic representations between entities and relations:

$$\mathbf{o}'_i = \begin{cases} \mathbf{o}_i & x_i \in \mathcal{E} \\ \mathbf{S}_1 \mathbf{o}_i + \mathbf{S}_2 \mathbf{x}_{i-1} & x_i \in \mathcal{R} \end{cases}, \quad (3)$$

where \mathbf{S}_1 and \mathbf{S}_2 are weight matrices for entities and relations, respectively. For GNN, f is an aggregation function to combine the representations of central entity and neighbors:

$$f(e) = \text{comb}(\mathbf{e}, \text{agg}(\mathcal{N}_e)), \quad (4)$$

where \mathcal{N}_e are the embeddings of entity e ’s neighbors. Different aggregation strategies lead to different GNN variants. GNNs output entity representations for alignment learning.

All existing knowledge embedding techniques can be applied to our cycle-teaching framework. Specifically, TransE (e.g., AlignE (Sun et al. 2018)) captures the local semantics from relation triples, GNN (e.g., AliNet (Sun et al. 2020a)) models the global structure of KGs, and RSN4EA (Guo, Sun, and Hu 2019) leans the long-term semantic knowledge. In addition, other side information can also be considered by incorporating the attribute-enhanced aligners into the cycle-teaching framework, which is left for future work.

3.2 Alignment Learning

To capture the alignment information, some models directly maximize the embedding similarities of pre-aligned entities, whose objective can be formulated as follows:

$$\max \frac{1}{|\mathcal{A}_{train}|} \sum_{(x,y) \in \mathcal{A}_{train}} \pi(\mathbf{x}, \mathbf{y}). \quad (5)$$

Augmenting training data is our focus in this paper.

4 Cycle Teaching for Entity Alignment

Figure 1 illustrates the cycle-teaching framework. At each iteration, if training has not been terminated, our framework would automatically compute an optimal cycle-teaching order (Sect. 4.1). Each aligner proposes reliable entity alignment pairs (Sect. 4.2) and then transmits them to the successor. The successor aligner combines its own new entity alignment and the received ones via conflict resolution (Sect. 4.3). Then the resolved new entity alignment pairs are added into the training data set to train the aligner further, such that this aligner can be taught by the new entity alignment that it cannot find. Its peer can attenuate the effect of some noisy entity alignment from one model. When the training ends, the framework combines the results from all aligners to calculate the alignment ranking list for each source entity (Sect. 4.4).

4.1 Cycle-teaching Order Arrangement

There are multiple aligners in CycTEA. Intuitively, the adjacent aligners should have higher complementarity such that the successor can receive more reliable alignment beyond its capacity. Moreover, it is better to let the aligner with higher performance teach weaker aligners so that the student aligner (successor) can be promoted by the more excellent teacher aligner (predecessor). To this end, we formalize our order arrangement problem as a Travelling Salesman Problem (TSP). We first build a directed complete graph where each aligner works as a node, and the edge weight reveals how beneficial to connect the two nodes. Then, the task is to return the route starting from an aligner while ending with the same one and has the highest sum of edge weights. The resulted route indicates the order arrangement. The most important thing is to define the edge weight and we hereby consider two critical factors. The first factor is the complementarity of the alignment selection from M_i to M_j :

$$f_{\text{com}}(M_i, M_j) = |(\mathcal{A}_i - \mathcal{A}_i \cap \mathcal{A}_j)|/|(\mathcal{A}_j)|, \quad (6)$$

where \mathcal{A}_i and \mathcal{A}_j denote the new reliable alignment sets of M_i and M_j at current iteration, respectively. It is noted that $f_{\text{com}}(M_i, M_j) \neq f_{\text{com}}(M_j, M_i)$ as we measure the complementarity feature in an asymmetric way, which reflects the new alignment brought by aligner M_i to M_j . We also want the stronger aligner to teach the weaker one. Therefore, we define the weight of performance between aligners M_i and M_j as the current Hits@1 difference on valid dataset:

$$f_{\text{per}}(M_i, M_j) = \exp(\text{valid}(M_i) - \text{valid}(M_j)), \quad (7)$$

Note that $f_{\text{per}}(M_i, M_j) \neq f_{\text{per}}(M_j, M_i)$ since the subtraction operation is not symmetric. The final edge weight from aligner M_i to M_j is the combination of the two factors:

$$w(M_i, M_j) = f_{\text{com}}(M_i, M_j) + \epsilon * f_{\text{per}}(M_i, M_j), \quad (8)$$

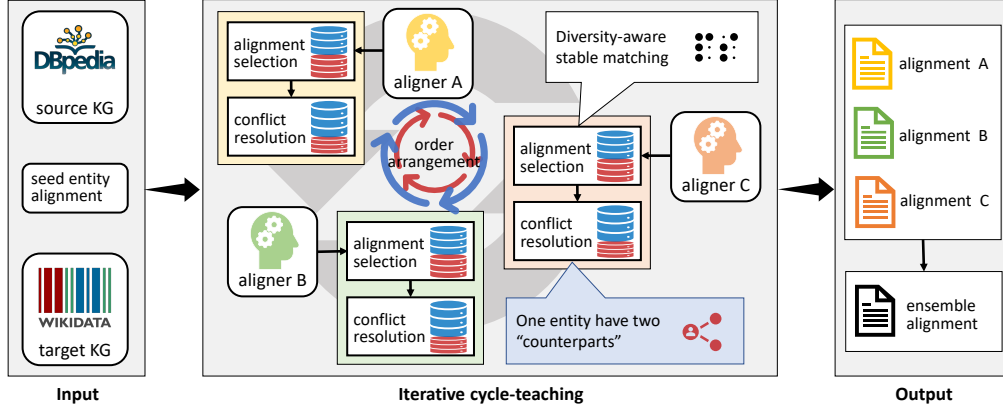


Figure 1: Cycle-teaching framework for entity alignment.

where ϵ is the combination weight. After calculating each edge weight in the aligner graph, we aim to find an optimal path to traverse the whole graph covering the maximized edge weights. This TSP problem is NP-hard as there are totally $(k-1)!$ choices of paths. We can utilize existing TSP approximate algorithms to derive sub-optimal solution when the number of aligners is very large. While in practice, we can enumerate all paths and pick the optimal one since the number of aligners is usually small.

4.2 Diversity-aware Alignment Selection

To pick out reliable entity alignment as new training data, we propose diversity-aware alignment selection, which considers both the embedding similarity and match diversity.

Match Diversity. Entity alignment is a 1 : 1 matching task, i.e., a source entity can be matched with at most one target entity, and vice versa (Suchanek, Abiteboul, and Senellart 2011). We expect a source entity to have very high embedding similarity with its counterpart in the target KG. Existing methods use nearest neighbor (NN) search to retrieve entity alignment, while ignoring the similarity distribution over other entities. In contrast, we consider the match diversity (Gal, Roitman, and Sagi 2016), which measures how much a predicted alignment pair (x, y) deviates from other competing pairs like (x', y) and (x, y') . We compute the average similarity of all competing pairs as:

$$\mu(x, y) = \frac{1}{(\|\mathcal{N}_x\| + \|\mathcal{N}_y\| - 1)} \left(\sum_{y' \in \mathcal{N}_x} \pi(x, y') + \sum_{x' \in \mathcal{N}_y} \pi(x', y) \right), \quad (9)$$

where \mathcal{N}_x denotes the set of all the candidate target entities for the source entity x (including y), and \mathcal{N}_y is the set of all candidate source entities for the target entity y (including x). Given the average similarity, we define the match diversity of (x, y) as the difference between its similarity and the average:

$$\tau(x, y) = \pi(x, y) - \mu(x, y). \quad (10)$$

We expect the correct entity alignment pair has a high match diversity, which indicates that the pairs have a high embedding similarity while its competing pairs have low similarity.

Alignment Selection via Stable Matching. We use match diversity as alignment confidence to select new alignment.

To guarantee the quality of the selected entity alignment and satisfy the constraint of 1 : 1 matching, we model alignment selection as a stable matching problem (SMP). We generate a sorted candidate list for each entity based on the alignment confidence. The SMP can be solved by the Gale-Shapley algorithm, which can produce a stable matching for all entities in time $O(n^2)$ where n is the number of source entities.

4.3 Conflict Resolution via Re-matching

For each aligner, it may have conflict selection between its predecessor and itself. For example, source entity x may have two different “counterparts” y_1 and y_2 predicted by itself and its predecessor, respectively. Our solution is to let the two aligners cooperate to resolve the alignment conflicts.

For the selected reliable entity alignment of two aligners, \mathcal{A}_1 and \mathcal{A}_2 , assuming that the conflict alignment set is \mathcal{C} , we collect the entities appearing in \mathcal{C} to conduct a re-matching process. Specifically, for the involved entities from the source KG $\mathcal{X} = \{x | (x, y_1, y_2) \in \mathcal{C}, x \in \mathcal{E}_1, y_1, y_2 \in \mathcal{E}_2\}$, and the entities that have not been matched from the target KG $\mathcal{Y} = \{y | y \in \mathcal{E}_2, y \notin \mathcal{A}_1 \cup \mathcal{A}_2\}$, we utilize them to build a bipartite graph with weights and conduct the alignment selection in 4.2 to select more reliable alignment pairs. Considering the conflict pairs are difficult, we combine the similarity of two aligners, to serve as bipartite graph edge weights:

$$\pi(x, y) = \alpha \cdot \pi_1(x, y) + (1 - \alpha) \cdot \pi_2(x, y), \quad (11)$$

where $\alpha = \text{valid}_1 / (\text{valid}_1 + \text{valid}_2)$ is a balance weight based on the two aligners’ validation performance (Hits@1).

Compared with other possible conflict resolution strategies, such as majority vote and ensemble training, our method has the following advantages. The majority vote is limited to odd numbers of aligners, and it does not consider the similarity distribution, so the final selection is limited to the choices of aligners. For ensemble training, it outputs the same selection for all the aligners, and these aligners will become increasingly similar as the training process continues, resulting in lower robustness of alignment noise. In contrast, our re-matching strategy considers similarity distribution to repair incorrect alignment pairs, and the cycle propagation prevents all aligners to rapidly become similar.

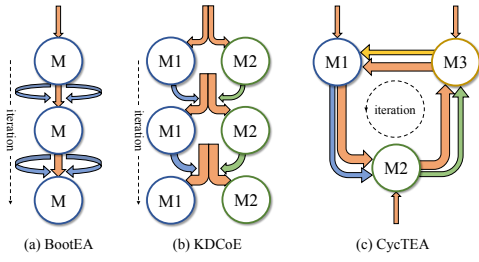


Figure 2: Comparison of BootEA, KDCoE, and the proposed CycTEA. “M” stands for an aligner. Orange arrows represent training data. Blue, green and yellow arrows denote the error flows in the new alignment proposed by different aligners.

4.4 Ensemble Entity Alignment Retrieval

To benefit from all aligners, we combine their embedding similarity to generate final alignment result. We firstly assign weights $\{\alpha_1, \alpha_2, \dots, \alpha_k\}$ to aligners $\{M_1, M_2, \dots, M_k\}$ based on their Hits@1 on validation data:

$$\alpha_i = \frac{\text{valid}(M_i)}{\sum_{j \in \{1, \dots, k\}} \text{valid}(M_j)}. \quad (12)$$

Then, the final similarity between entities is defined as the weighted sum of the similarity of each aligner:

$$\pi(x, y) = \sum_{i \in \{1, \dots, k\}} \alpha_i \cdot \pi_i(x, y). \quad (13)$$

Given the ensemble entity similarities, we obtain the candidate counterpart list for each source entity by the NN search.

4.5 Discussions

We compare CycTEA with two semi-supervised approaches in Figure 2. The self-training approach BootEA can be regarded as a special case of cycle-teaching with only one aligner. It directly feeds the selected entity alignment to itself. The noise is also transferred back to the aligner. The co-training approach KDCoE utilizes two independent aligners to propose new alignment. The noisy data from both aligners is also accumulated together. Therefore, it still suffers from the problem that each aligner’s noisy information is also transferred back to itself. By contrast, in our framework, a large part of the aligner’s noisy alignment is not directly sent back to itself due to the alignment cycle propagation. Instead, the noisy pairs are fed into the other model. As different aligners generate embeddings from different perspectives, one aligner’s noisy pairs may be easily handled by the other. In addition, we carefully design the training data accumulation procedure as a fine-tuned step by removing the negative sampling from alignment learning over selected new pairs, and set smaller semi-supervised training epochs. Therefore, the aligner will be adapted to the correct pairs from the other model firstly, and the influence of noisy data can be reduced.

5 Experiment

We build our framework on top of the OpenEA library (Sun et al. 2020b). We will release our source code in GitHub¹.

¹<https://github.com/JadeXIN/CycTEA>

5.1 Experimental Settings

Datasets. Current datasets such as DBP/DWY (Sun, Hu, and Li 2017) are quite different from real-word KGs (Sun et al. 2020b). Hence, we use the benchmark dataset released at the OpenEA library (Sun et al. 2020b) for evaluation, which follows the data distribution of real KGs. It contains two cross-lingual settings (English-to-French and English-to-German) and two monolingual settings (DBpedia-to-Wikidata and DBpedia-to-YAGO). Each setting has two sizes with 15K and 100K pairs of reference entity alignment, respectively. We follow the dataset splits in OpenEA, where 20% reference alignment is for training, 10% for validation and 70% for test.

Implementation Details. CycTEA can incorporate any number of aligners ($k \geq 2$). We choose three structure-based models as the aligners, i.e., AlignE, AliNet and RSN4EA. We follow their implementations settings used in OpenEA for a fair comparison. The order arrangement parameter $\epsilon = 0.2$. Performance is tested with 5-fold cross-validation to ensure an unbiased evaluation. Following the convention, we use Hits@1, Hits@5 and MRR as evaluation metrics, and higher scores of these metrics indicate better performance.

Baselines. Similarly, we compare with structure-based entity alignment models for a fair comparison:

- Triple-based models that capture the local semantics information of relation triples based on TransE, including MTransE (Chen et al. 2017), AlignE and BootEA (Sun et al. 2018) as well as SEA (Pei et al. 2019).
- Neighborhood-based models that use GNNs to exploit sub-graph structures for entity alignment, including GCNAlign (Wang et al. 2018), AliNet (Sun et al. 2020a), HyperKA (Sun et al. 2020a) and KE-GCN (Yu et al. 2021).
- Path-based models that explore the long-term dependency across relation paths, including IPTransE (Zhu et al. 2017) and RSN4EA (Guo, Sun, and Hu 2019).

We do not compare with some recent attribute-based models (Chen et al. 2018; Zhang et al. 2019; Wu et al. 2019a; Zhang et al. 2019) since they require side information that our framework, as well as other baselines, do not use. In addition, as RREA (Mao et al. 2020) failed in OpenEA 100K datasets (Ge et al. 2021), we do not include it in the baselines.

5.2 Main Results

Tables 1 and 2 present the entity alignment results. CycTEA outperforms all baselines, and is 4% to 11% higher than the strongest baseline BootEA on Hits@1. e.g., CycTEA outperforms BootEA by 11.5% on EN-FR-15K. BootEA achieves second-best results due to its bootstrapping strategy, but the limited ability of self-training prevents its further improvement. In the supervised setting, KE-GCN, AliNet and RSN4EA all acquire satisfactory results, but lack of training data limits their performance. On 100K datasets, many baselines fail to achieve promising results due to more complex KG structures and larger alignment space, but CycTEA maintains the best performance, demonstrating its practicability. The variant of an aligner in CycTEA is denoted as “aligner+” (e.g., “AlignE+” refers to the “AlignE” in CycTEA). Three

Table 1: Entity alignment results on 15K datasets. * means the results are produced by their source code.

Methods	EN-FR-15K			EN-DE-15K			D-W-15K			D-Y-15K		
	Hits@1	Hits@5	MRR	Hits@1	Hits@5	MRR	Hits@1	Hits@5	MRR	Hits@1	Hits@5	MRR
MTransE	0.247	0.467	0.351	0.307	0.518	0.407	0.259	0.461	0.354	0.463	0.675	0.559
AlignE	0.357	0.611	0.473	0.552	0.741	0.638	0.406	0.627	0.506	0.551	0.743	0.636
BootEA	0.507	0.718	0.603	0.675	0.820	0.740	0.572	0.744	0.649	0.739	0.849	0.788
SEA	0.280	0.530	0.397	0.530	0.718	0.617	0.360	0.572	0.458	0.500	0.706	0.591
GCN-Align	0.338	0.589	0.451	0.481	0.679	0.571	0.364	0.580	0.461	0.465	0.626	0.536
AliNet	0.364	0.597	0.467	0.604	0.759	0.673	0.440	0.628	0.522	0.559	0.690	0.617
HyperKA*	0.353	0.630	0.477	0.560	0.780	0.656	0.440	0.686	0.548	0.568	0.777	0.659
KE-GCN*	0.408	0.670	0.524	0.658	0.822	0.730	0.519	0.727	0.608	0.560	0.750	0.644
IPTransE	0.169	0.320	0.243	0.350	0.515	0.430	0.232	0.380	0.303	0.313	0.456	0.378
RSN4EA	0.393	0.595	0.487	0.587	0.752	0.662	0.441	0.615	0.521	0.514	0.655	0.580
AlignE+	0.563	0.765	0.653	0.707	0.859	0.775	0.633	0.798	0.706	0.742	0.854	0.791
AliNet+	0.609	0.778	0.684	0.751	0.874	0.805	0.673	0.809	0.731	0.783	0.863	0.818
RSN4EA+	0.524	0.721	0.612	0.697	0.846	0.762	0.595	0.746	0.663	0.670	0.770	0.715
CycTEA	0.622	0.814	0.708	0.756	0.892	0.816	0.686	0.838	0.753	0.777	0.871	0.820

Table 2: Entity alignment results on 100K datasets. * means the results are produced by their source code.

Methods	EN-FR-100K			EN-DE-100K			D-W-100K			D-Y-100K		
	Hits@1	Hits@5	MRR	Hits@1	Hits@5	MRR	Hits@1	Hits@5	MRR	Hits@1	Hits@5	MRR
MTransE	0.138	0.261	0.202	0.140	0.264	0.204	0.210	0.358	0.282	0.244	0.414	0.328
AlignE	0.294	0.483	0.388	0.423	0.593	0.505	0.385	0.587	0.478	0.617	0.776	0.691
BootEA	0.389	0.561	0.474	0.518	0.673	0.592	0.516	0.685	0.594	0.703	0.827	0.761
SEA	0.225	0.399	0.314	0.341	0.502	0.421	0.291	0.470	0.378	0.490	0.677	0.578
GCN-Align	0.230	0.412	0.319	0.317	0.485	0.399	0.324	0.507	0.409	0.528	0.695	0.605
AliNet	0.266	0.444	0.348	0.405	0.546	0.471	0.369	0.535	0.444	0.626	0.772	0.692
HyperKA*	0.231	0.426	0.324	0.239	0.432	0.332	0.312	0.535	0.417	0.473	0.696	0.574
KE-GCN*	0.305	0.513	0.405	0.459	0.634	0.541	0.426	0.620	0.515	0.625	0.791	0.700
IPTransE	0.158	0.277	0.219	0.226	0.357	0.292	0.221	0.352	0.285	0.396	0.558	0.474
RSN4EA	0.293	0.452	0.371	0.430	0.570	0.497	0.384	0.533	0.454	0.620	0.769	0.688
AlignE+	0.379	0.558	0.466	0.509	0.659	0.581	0.492	0.665	0.571	0.699	0.831	0.759
AliNet+	0.429	0.600	0.510	0.546	0.676	0.608	0.555	0.708	0.623	0.742	0.864	0.796
RSN4EA+	0.324	0.486	0.403	0.465	0.600	0.530	0.436	0.587	0.507	0.667	0.810	0.732
CycTEA	0.442	0.627	0.530	0.560	0.709	0.630	0.566	0.732	0.641	0.747	0.871	0.803

aligners all acquire large improvement in CycTEA. For example, AliNet benefits the most from cycle-teaching because it captures two-hop information and the high-quality new alignment can boost it largely. The result of CycTEA is a little lower than AliNet+ in D-Y-15K because the large performance variance of three aligners hurts the ensemble result.

5.3 Further Analyses

Effectiveness of Cycle-teaching. Table 3 compares CycTEA with other semi-supervised strategies. The first three model variants use self-training. CycTEA significantly outperforms the self-training models, because it can integrate knowledge from all aligners. Compared with other alignment selection strategies, i.e., keeping the alignment supported by all aligners (Intersection), or combining alignment from all aligners (Union), or selecting alignment supported by the highest number of aligners (Majority vote), CycTEA still achieves the best performance. The improvement achieved by “Intersection” is the smallest because entity pairs supported by all aligners are limited. But it has the best result in EN-FR by coincidence, as the noisy alignment proposed by all aligners is higher than other datasets, and “Intersection” can filter the noise thoroughly. “Union” achieves limited improvement

Table 3: Hits@1 scores w.r.t. different semi-supervised learning strategies on the 15K datasets.

Methods	EN-FR	EN-DE	D-W	D-Y
AlignE (semi)	0.507	0.675	0.572	0.739
RSN4EA (semi)	0.497	0.673	0.553	0.632
AliNet (semi)	0.452	0.685	0.570	0.753
CycTEA (Intersection)	0.632	0.726	0.631	0.752
CycTEA (Union)	0.594	0.736	0.657	0.750
CycTEA (Majority vote)	0.614	0.739	0.677	0.761
CycTEA	0.622	0.756	0.686	0.777

since it involves much noise. “Majority vote” is more considerable than them but still lower than CycTEA as it inevitably removes some correct entity alignment pairs.

Effectiveness of Re-matching. Table 4 evaluates the effect of our re-matching strategy for conflict resolution (cr). We can see that re-matching can significantly improve the precision of new alignment by 4% to 9%, while with a slight decrease in recall. This is because the filter process of re-matching inevitably breaks some correct entity pairs. Finally, re-matching can bring 1% to 3% improvement on F1-score to all aligners and further improve the overall performance.

Table 4: Quality of proposed new alignment on 15K datasets

Methods	EN-FR-15K			D-W-15K		
	Prec.	Rec.	F1	Prec.	Rec.	F1
AlignE+ (w/o cr)	0.650	0.569	0.606	0.718	0.639	0.676
AlignE+	0.696	0.541	0.609	0.761	0.622	0.685
RSN4EA+ (w/o cr)	0.619	0.538	0.575	0.649	0.607	0.627
RSN4EA+	0.684	0.528	0.596	0.717	0.602	0.655
AliNet+ (w/o cr)	0.601	0.560	0.579	0.675	0.640	0.657
AliNet+	0.687	0.534	0.601	0.766	0.608	0.678

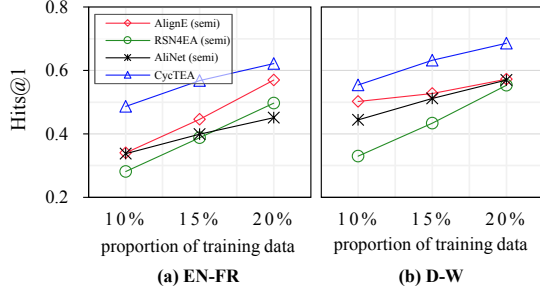


Figure 3: Hits@1 w.r.t different proportions of training data.

Robustness to Noisy Accumulated Entity Alignment. To evaluate the robustness of CycTEA to the accumulated noisy alignment, we evaluate the framework trained on different proportions of seed entity alignment from 10% to 20% to simulate this scenario, as less training data leads to worse performance and a larger ratio of noise in the proposed new alignment. Figure 3 depicts the trend of Hits@1 of three aligners in self-training (denoted as “aligner (semi)”). They all achieve better performance as the ratio increases. We can see AliNet (semi) is more sensitive to the training data ratio as its performance drops drastically when the training data size decreases. As GNNs capture the global structure information, the useful information it can capture reduces exponentially when the training data is meager. RSN4EA (semi) has poor robustness as it presents much worse results in the scenarios of heavy noise. CycTEA maintains promising performance over any training data ratio, which validates its superiority.

Effectiveness of Dynamic Order Arrangement. Figure 4 represents the performance with different cycle-teaching orders. There are two static orders in total given three aligners. We can see the first order is superior to the second one, and our dynamic order exceeds both static orders. In particular, the performance with the order “AlignE-AliNet-RSN4EA” is only slightly worse than ours. This is because the order appears much more frequent than the other one in our dynamic order arrangement during iteration. This shows that our dynamic order arrangement can effectively capture the optimal order during training and result in better performance.

Effectiveness of Diversity-aware Alignment Selection. Table 5 gives the ablation study on our diversity-aware selection method. We report the results of AliNet in CycTEA due to space limitation, where “w/o daas” denotes the variant without using the matching diversity for alignment selection. We can see that our diversity-aware method can improve the pre-

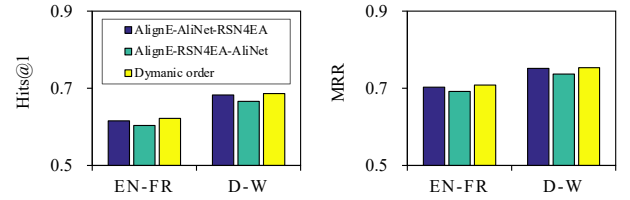


Figure 4: Hits@1 and MRR w.r.t different teaching orders.

Table 5: Quality of the new alignment proposed by AliNet in CycTEA w/ and w/o diversity-aware alignment selection.

Methods	EN-FR-15K			D-W-15K		
	Prec.	Rec.	F1	Prec.	Rec.	F1
AliNet+(w/o daas)	0.591	0.565	0.578	0.672	0.652	0.661
AliNet+	0.687	0.534	0.601	0.766	0.608	0.678

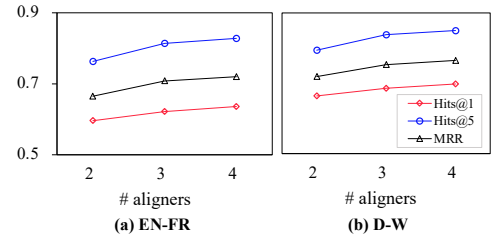


Figure 5: Entity alignment performance w.r.t. # aligners.

cision and F1-score of selected alignment and reduce noise.

Different numbers of aligners in CycTEA. Our framework can be implemented to any number of aligners. Due to space limitation, we test its performance with $k = 2, 3, 4$ aligners, respectively. We choose AlignE and AliNet for $k = 2$, and add RSN4EA for $k = 3$, and introduce KE-GCN for $k = 4$. These aligners are well-performing structure-based models, and these combinations are the optimal settings given these four aligners. Figure 5 indicates that the performance increases when integrating more aligners. But in the main setting, we choose AlignE, AliNet and RSN4EA, the structure-based aligners with high complementarity and good performance, for a trade-off between effectiveness and efficiency.

6 Conclusion

We present a novel and practical cycle-teaching framework for entity alignment. It utilizes multiple entity alignment models and iteratively cycle-teach each model by transmitting their proposed reliable alignment. Cycle-teaching can primarily remedy the effect of noisy data in the accumulated new alignment and extend all models’ alignment learning ability. Our diversity-aware alignment selection and re-matching based alignment conflict resolution strategies further improve the quality of the new alignment. We also consider the effect of teaching order and propose dynamic order arrangement. Experiments on benchmark datasets show that our approach can outperform SOTA methods and achieve promising results in the heavy noise-propagation scenario. For future work, we plan to extend our framework to multi-view features.

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