Conflict-Aware Pseudo Labeling via Optimal Transport for Entity Alignment

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Abstract—Entity alignment aims to discover unique equivalent entity pairs with the same meaning across different knowledge graphs (KGs). Existing models have focused on projecting KGs into a latent embedding space so that inherent semantics between entities can be captured for entity alignment. However, the adverse impacts of alignment conflicts have been largely overlooked during training, thereby limiting the entity alignment performance. To address this issue, we propose a novel Conflictaware Pseudo Labeling via Optimal Transport model (CPL-OT) for entity alignment. The key idea is to iteratively pseudo-label alignment pairs empowered with conflict-aware optimal transport (OT) modeling to boost the precision of entity alignment, CPL-OT is composed of two key components—entity embedding learning with global-local aggregation and iterative conflict-aware pseudo labeling-that mutually reinforce each other. To mitigate alignment conflicts during pseudo labeling, we propose to use optimal transport as an effective means to warrant one-to-one entity alignment between two KGs with the minimal overall transport cost. Extensive experiments on benchmark datasets validate the superiority of CPL-OT over state-of-the-art baselines under both settings with and without prior alignment seeds.

Index Terms—knowledge graph, entity alignment, pseudo labeling, optimal transport

I. INTRODUCTION

Knowledge Graphs (KGs) comprise of graph-structured semantic information about real-world concepts (or entities) and relations among these concepts. KGs are widely adopted in various AI-powered applications to provide strong inference capabilities. Yet, it is well recognized that real-world KGs suffer from incompleteness arising from their complex, semi-automatic construction processes. To enrich knowledge representation over incomplete KGs, entity alignment aims to link entities with the same real-world identity across KGs.

Mainstream entity alignment models are based on KG embedding, which embeds KGs into a latent vector space to capture inherent semantics regardless of the heterogeneity among KGs. To learn better KG embeddings, methods like GCN-Align [1] leverage graph convolutional networks (GCNs) [2] to capture structural and neighboring entity information for entity alignment. Recent studies [3]–[5] utilize a highway strategy [6] to alleviate the over-smoothing issue during GCN propagation, or jointly learn entity and relation embeddings for improving the precision of entity alignment. Other works tackle the shortage of pre-aligned entity pairs (known as *prior alignment*

seeds) provided for training. BootEA [7], IPTransE [8] and MRAEA [9] propose bootstrapping strategies to iteratively augment alignment seeds for improving subsequent training.

Despite making remarkable progress, current methods have largely overlooked the adverse impacts of alignment conflicts during training, i.e., multiple entities in one KG are simultaneously aligned with a single entity in another KG. The presence of alignment conflicts is mainly due to two reasons. First, although graph convolution enables to effectively encode entity neighborhood information into entity embeddings, GCN-based methods often incur more conflicting alignment pairs due to the innate feature smoothing effect. Second, conflicting alignment pairs would adversely impair the quantity of correctly pseudo-labeled alignment pairs, thus jeopardizing the efficacy of subsequent model training. This restricts the performance of pseudo labeling based KG alignment.

In this paper, we propose a novel <u>C</u>onflict-aware <u>P</u>seudo <u>L</u>abeling via <u>O</u>ptimal <u>T</u>ransport model (CPL-OT) for entity alignment. Our core idea is to pseudo-label alignment pairs via conflict-aware OT modeling to boost the precision of entity alignment. CPL-OT consists of two key components—entity embedding learning with global-local aggregation and iterative conflict-aware pseudo labeling—that alternately reinforce each other. Specifically, we make the following contributions.

- We propose an iterative conflict-aware pseudo labeling strategy that selects the most reliable alignment pairs via OT modeling. The OT models entity alignment as a process of transporting each entity in one KG to a unique entity in another KG with the minimal overall transport cost, warranting one-to-one entity alignment.
- We design graph convolution with global-local aggregation for learning expressive entity embeddings. The rectified distance between entity embeddings are used as the transport cost for OT modeling to mitigate alignment conflicts during pseudo labeling.
- Experimental results on benchmark datasets show that CPL-OT yields competitive results with or without prior alignment seeds, outperforming state-of-the-art baselines.

II. RELATED WORK

We review two streams of related work: entity alignment in knowledge graphs and optimal transport on graphs.

A. Entity Alignment in Knowledge Graphs

Most entity alignment models are embedding-based approaches, which embed KGs into a unified vector space by imposing the embeddings of pre-aligned entity pairs to be as close as possible. This ensures that alignment similarities between entities can be directly measured via their embeddings.

To leverage KG structural information, methods like GCN-Align [1] utilize GCNs to learn better entity embeddings for alignment. However, GCNs and their variants are inclined to result in alignment conflicts, because their feature smoothness schemes make entities have similar embeddings among local neighborhoods. To alleviate the over-smoothing issue, recent works [3]–[5] adopt a highway strategy [6] on GCN layers, which "mixes" the smoothed entity embeddings with the original features. Other models such as HGCN [3], RDGCN [4], and RNM [5] consider relations in KGs to reinforce GCN-based entity embeddings. Nonetheless, these models require an abundance of prior alignment seeds for training, which are labor-intensive and costly to obtain in real-world KGs.

To tackle the shortage of prior alignment seeds, semisupervised methods such as BootEA [7], IPTransE [8], RNM [5], and MRAEA [9] propose bootstrapping strategies to iteratively augment alignment seeds. These models, however, inevitably introduce alignment conflicts during bootstrapping, as they sample possible alignment pairs directly based on embedding distances. To handle alignment conflicts, RNM [5] and MRAEA [9] use simple heuristics to preserve only the most convincing alignment pairs. BootEA [7] adopts a bipartite graph max-weighted matching strategy to select a small number of the most likely aligned pairs at each iteration, and then accumulates pseudo labels across iterations, which inevitably incurs alignment conflicts. In our work, we model entity alignment as an OT process, warranting a larger quantity of correctly aligned entity pairs to be pseudo-labeled at each iteration without conflicts. This offers sufficient supervision to learn informative entity embeddings for alignment inference.

B. Optimal Transport on Graphs

Optimal transport (OT) aims to find an optimal plan to move one distribution of mass to another with the minimal cost [10]. Recently, OT has been studied for cross-lingual KG entity alignment [11] and cross-domain alignment on graphs [12]. The transport on the edges across graphs has also been used to define the Gromov-Wasserstein distance to measure graph matching similarity [13] or to boost the entity alignment performance [12]. However, these methods have primarily used OT to define a learning objective, involving bilevel optimization for model training with high computational cost. Thus, they cannot be directly applied to our context of iterative pseudo labeling.

III. PROBLEM DEFINITION

A knowledge graph can be denoted as $G = \{E, R, T\}$ with the entity set E, relation set R and triplet set T. We use $e \in E$, $r \in R$, $(e_i, r, e_j) \in T$ to represent an entity, a relation and a triplet, respectively. Each entity e is characterized by a

feature vector $x_e \in \mathbb{R}^d$, which can be obtained from its textual descriptions or entity name with semantic meanings. Formally, two individual KGs are given for the task of entity alignment, i.e., $G_1 = \{E_1, R_1, T_1\}$ and $G_2 = \{E_2, R_2, T_2\}$. An entity $e_i \in E_1$ in G_1 is likely to correspond to the same concept with another entity $e_j \in E_2$ in G_2 , denoted as $e_i \Leftrightarrow e_j$, and vice versa.

To provide supervision for entity alignment, a small number of pre-aligned entity pairs between G_1 and G_2 are sometimes provided as prior alignment seeds in the form of $\mathbb{L}^0_e = \{(e_i,e_j)|e_i\in E_1,e_j\in E_2,e_i\Leftrightarrow e_j\}$. In some cases, prior alignment seeds may be unavailable due to high labeling cost, such that $\mathbb{L}^0_e = \emptyset$. Along with prior alignment seeds, there are two sets of unaligned entities $E_1'\subseteq E_1$ and $E_2'\subseteq E_2$ in two KGs, with $E_1'=E_1$ and $E_2'=E_2$ when $\mathbb{L}^0_e = \emptyset$. The task of entity alignment is to discover unique equivalent entity pairs (e_i,e_j) with $e_i\in E_1'$, $e_j\in E_2'$ and $e_i\Leftrightarrow e_j$ across G_1 and G_2 , based on prior alignment seeds \mathbb{L}^0_e , KG structure, and entity features in G_1 and G_2 .

IV. THE PROPOSED METHOD

To effectively perform entity alignment with the shortage of prior alignment seeds, the proposed CPL-OT model uses an OT-based pseudo labeling to augment entity alignment seeds and provide more supervisions for entity alignment inference. CPL-OT comprises of two components: global-local aggregation for entity embedding and conflict-aware pseudo labeling for alignment augmentation. The two components are performed alternately in an iterative way until convergence.

A. Global-Local Aggregation for Entity Embedding

To leverage relational structures, we conduct two levels of neighborhood aggregation for each entity, i.e., global-level relation aggregation and local-level entity aggregation.

1) Global-Level Relation Aggregation: First, for each relation $r_i \in R_1 \cup R_2$, we construct its feature vector \boldsymbol{x}_{r_i} as the averaged concatenation of the feature vectors of its associated head and tail entities:

$$\boldsymbol{x}_{r_i} = \frac{1}{|\{(e_h, r_i, e_t) \in T_1 \cup T_2\}|} \sum_{(e_h, r_i, e_t) \in T_1 \cup T_2} [\boldsymbol{x}_{e_h} || \boldsymbol{x}_{e_t}],$$

where $[\cdot \| \cdot]$ denotes the concatenation operation, $\{(e_h, r_i, e_t) \in T_1 \cup T_2\}$ is the set of all triplets containing relation r_i , \boldsymbol{x}_{e_h} and $\boldsymbol{x}_{e_t} \in \mathbb{R}^d$ are the feature vectors of entity e_h and e_t , respectively. Then, for each entity $e_i \in E_1 \cup E_2$, we construct its averaged neighboring relation feature vector as

$$\boldsymbol{x}_{e_i_rels} = \frac{1}{|\mathcal{N}_r(e_i)|} \sum_{r_j \in \mathcal{N}_r(e_i)} \mathbb{I}_{e_i}(r_j) \cdot \boldsymbol{x}_{r_j},$$
 (2)

where $\mathcal{N}_r(e_i)$ is the set of one-hop neighboring relations of entity e_i , and $\mathbb{I}_{e_i}(r_j)$ indicates the direction of relation r_j with regards to e_i , with -1 for e_i being the successor and +1 for e_i being the predecessor. The consideration of the direction can incorporate richer relational neighborhood structures.

To perform global-level relation aggregation, we concatenate each entity's averaged neighboring relation feature vector

 $x_{e_i_rels} \in \mathbb{R}^{2d}$ with its original feature vector $x_{e_i} \in \mathbb{R}^d$, followed by a non-linear transformation:

$$\mathbf{h}_{e_i}^{(1)} = \text{ReLU}(W_1[\mathbf{x}_{e_i} || \mathbf{x}_{e_i_rels}] + b_1) + \mathbf{x}_{e_i},$$
 (3)

where $W_1 \in \mathbb{R}^{d \times 3d}$ and $b_1 \in \mathbb{R}^d$ are the weight matrix and the bias vector, respectively. To avoid over-smoothing, we add back the original entity feature vector \boldsymbol{x}_{e_i} .

2) Local-Level Entity Aggregation: After obtaining relation aggregated entity embeddings, we conduct local-level entity aggregation to capture neighboring entity structure.

To this end, we take advantage of a two-layer GCN [2] together with a highway gate strategy [6] to avoid oversmoothing. Formally, we first stack relation aggregated entity embeddings $\boldsymbol{h}_{e_i}^{(1)}$ for each entity $e_i \in E_1 \cup E_2$ into an embedding matrix $H_e^{(1)} \in \mathbb{R}^{(|E_1|+|E_2|)\times d}$. Then, the entity embedding matrix $H_e^{(1)}$ is updated as follows from l=1:

$$\begin{cases} \tilde{H}_{e}^{(l+1)} = \text{ReLU}(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H_{e}^{(l)}W_{l+1}), \\ H_{e}^{(l+1)} = T(H_{e}^{(l)}) \odot \tilde{H}_{e}^{(l+1)} + (1 - T(H_{e}^{(l)})) \odot H_{e}^{(l)}, \end{cases}$$
(4)

where $\tilde{A}=A+I_{|E_1|+|E_2|}$ is the undirected adjacency matrix of the two combined graphs $G_1\cup G_2$ augmented by self-connections that are represented by the $(|E_1|+|E_2|)\times(|E_1|+|E_2|)$ identity matrix $I_{|E_1|+|E_2|},\ \tilde{D}_{ii}=\sum_j \tilde{A}_{ij}$ is the degree matrix, $W_{l+1}\in\mathbb{R}^{d\times d}$ is the weight matrix at layer l and \odot is the Hadamard product (or element-wise multiplication). Specifically, $T(H_e^{(l)})\in\mathbb{R}^{(|E_1|+|E_2|)\times d}$ is the transformation gate obtained from $H_e^{(l)}$. The use of the transformation gate can effectively filter out over-smoothed feature dimensions. After neighboring entity aggregation, we can obtain entity embeddings $H_e^{(3)}$ for KG alignment.

Formally, we denote the final embedding for entity e_i as $\boldsymbol{h}_{e_i} = \boldsymbol{h}_{e_i}^{(3)} \in \mathbb{R}^d$, where $\boldsymbol{h}_{e_i}^{(3)} \in \mathbb{R}^d$ is the transpose of the row vector of $H_e^{(3)}$ indexed by entity e_i .

B. Conflict-Aware Pseudo Labeling for Alignment Augmentation with Optimal Transport

With the constructed entity embeddings, we perform pseudo labeling to identify new reliable alignment pairs. A simple approach is to calculate the embedding distance $d(e_i, e_j)$ between each entity pair (e_i, e_j) across two KGs:

$$d(e_i, e_j) = \|\mathbf{h}_{e_i} - \mathbf{h}_{e_j}\|_1, \tag{5}$$

where $\|\cdot\|$ denotes 1-norm. The entity pairs with a distance smaller than a pre-defined threshold are then identified as the pseudo-labeled alignment pairs. However, this simplistic pseudo labeling approach might lead to errors, especially when entity embeddings are not well learned in the presence of scarce prior alignment seeds.

To address this issue, we use the relational neighborhood matching [5] to rectify embedding based distance in Eq. (5):

$$\tilde{d}(e_i, e_j) = d(e_i, e_j) - \lambda s(e_i, e_j), \tag{6}$$

where λ is a trade-off parameter and $s(e_i, e_j)$ is the relational neighborhood matching similarity [5] calculated by comparing

neighborhoods, including neighboring entities and neighboring relations, between (e_i, e_j) .

For each unaligned entity $e_i \in E_1'$ in G_1 , we can find its alignment $e_i \in E_2'$ in G_2 with the shortest rectified distance:

$$e_i \Leftrightarrow \underset{e_j \in E_2}{\arg\min} \tilde{d}(e_i, e_j).$$
 (7)

Due to the smoothing effect of neighborhood aggregation, entities tend to have indistinguishable representations, resulting in alignment conflicts. To avoid this issue, we propose an OT-based strategy. The aim is to find an optimal plan to transport each unaligned entity in G_1 to a unique unaligned entity in G_2 . As such, a globally optimal alignment configuration can be discovered with the minimal overall inconsistency.

From the unaligned entity sets $E_1' \subseteq E_1$ and $E_2' \subseteq E_2$, we first identify the alignment candidates by considering only the cross-KG entity pairs with the rectified distance smaller than a pre-defined threshold θ :

$$C_{\theta} = \{ (e_i, e_j) | e_i \in E_1', e_j \in E_2', \ \tilde{d}(e_i, e_j) < \theta \}.$$
 (8)

The entity sets in alignment candidates are then denoted as:

$$E_{1}^{"} = \{ e_{i} \in E_{1}^{'} | \exists e_{j} \in E_{2}^{'}, (e_{i}, e_{j}) \in \mathcal{C}_{\theta} \}, E_{2}^{"} = \{ e_{j} \in E_{2}^{'} | \exists e_{i} \in E_{1}^{'}, (e_{i}, e_{j}) \in \mathcal{C}_{\theta} \},$$
(9)

where without loss of generality, we assume $|E_1''| < |E_2''|$. The alignment candidate set \mathcal{C}_θ inevitably involves some conflicting alignments. To warrant one-to-one alignment, we propose to model entity alignment as an OT process, i.e., transporting each entity $e_i \in E_1''$ to a unique entity $e_j \in E_2''$, with the minimal overall transport cost. Naturally, the rectified distance can be used to define the transport cost across KGs:

$$C(e_i, e_j) = \tilde{d}(e_i, e_j), \ e_i \in E_1'', e_j \in E_2'',$$
 (10)

where $C(e_i,e_j)$ is the transport cost between entity e_i and e_j . The transport plan is in the form of a bijection $T:E_1''\to E_2''$. In other words, each entity $e_i\in E_1''$ has exactly one transport to the target entity $T(e_i)\in E_2''$. The goal is to find the optimal transport plan T^* that minimises the overall transport cost:

$$T^* = \underset{T}{\arg\min} \sum_{e_i \in E_1''} C(e_i, T(e_i)). \tag{11}$$

The objective can be reformulated as:

$$\begin{split} & \underset{P \in \{0,1\}^{|E_1''| \times |E_2''|}}{\arg\min} \langle P, C \rangle_F, \text{ subject to:} \\ & \sum_{e_j \in E_2''} P_{e_i, e_j} = 1, \sum_{e_i \in E_1''} P_{e_i, e_j} \leq 1, \end{split} \tag{12}$$

where $\langle \cdot, \cdot \rangle_F$ is the Frobenius inner product between two matrices. $P \in \{0,1\}^{|E_1''| \times |E_2''|}$ is the transport indicating matrix and each element P_{e_i,e_j} denotes whether $e_i \in E_1''$ is aligned to $e_j \in E_2''$ with 1 for true and 0 for false. To achieve one-to-one alignments across E_1'' and E_2'' in two KGs, with $|E_1''| < |E_2''|$, the summation of each row in P is constrained to 1, while the summation of each column is bounded by 1.

To solve the OT problem above, some exact algorithms have been proposed, such as the Branch and Bound algorithm [14]. The exact algorithms guarantee to find a globally optimal transport plan but with prohibitively high computational cost for iterative pseudo labeling. Hence, we propose to use a greedy algorithm [15] as an efficient yet accurate approximation to exact algorithms, which is proven to have an at least 1/2 approximation ratio as compared to exact algorithms [16].

The overall process of our greedy algorithm for OT-based pseudo labeling is given in Algorithm 1. In Step 1, the pseudo-labeled alignment set $\hat{\mathbb{L}}_e$ and its increment $\Delta \hat{\mathbb{L}}_e$ are initialized as \emptyset . The greedy algorithm first expands $\Delta \hat{\mathbb{L}}_e$ with the bounded shortest distance principle in Steps 2-5. In Steps 6-10, the alignment conflicts in $\Delta \hat{\mathbb{L}}_e$ are eliminated through checking every two conflicting alignment pairs. As entity pairs can be sorted according to a lexicographic order, the operation can be finished in linear time. Newly aligned entity pairs are then removed from E_1' and E_2' in Steps 11-14. In Step 15, \mathbb{L}_e is expanded with $\Delta \hat{\mathbb{L}}_e$ and $\Delta \hat{\mathbb{L}}_e$ is set to \emptyset . We then repeat the entity alignment augmentation process on the updated E'_1 and E'_2 until no updates in \mathbb{L}_e in Step 16. Finally, the greedy algorithm returns pseudo-labeled alignment pairs \mathbb{L}_e . Take the number of iterations in Step 16 as a constant, the overall time complexity of Algorithm 1 is $O(|E_1| \cdot |E_2|)$.

C. Model Training for Entity Alignment

After determining pseudo-labeled alignment pairs $\hat{\mathbb{L}}_e$, the alignment seeds are augmented as: $\mathbb{L}_e \leftarrow \mathbb{L}_e^0 \cup \hat{\mathbb{L}}_e$. Accordingly, we define the entity alignment loss as:

$$L = \sum_{(e_i, e_j) \in \mathbb{L}_e} \sum_{(e_{i'}, e_{j'}) \in \mathbb{L}'_e} R(e_i, e_j) \cdot [d(e_i, e_j) - d(e_{i'}, e_{j'}) + \gamma]_+,$$
(13)

where $[\cdot]_+$ denotes $\max(0,\cdot)$, \mathbb{L}'_e is the set of sampled negative entity alignment pairs not included in \mathbb{L}_e , γ is a positive margin hyper-parameter, and $d(\cdot,\cdot)$ is the embedding distance between two entities, as defined in Eq. (5). $R(e_i,e_j)\in(0,1]$ is the soft alignment score, i.e., the reliability score of each alignment pair $(e_i,e_j)\in\mathbb{L}_e$. For any prior aligned entity pair, $R(e_i,e_j)=1$. For the augmented alignment,

$$R(e_i, e_j) = \sigma(w \cdot \theta - \tilde{d}(e_i, e_j)), \tag{14}$$

where $\sigma(\cdot)$ is the sigmoid function, θ is the threshold used to determine alignment candidates, and $w \in (0,1]$ is a hyperparameter that controls the lower bound of R.

To obtain the negative entity alignment set \mathbb{L}'_e , we adopt a *adaptive negative sampling* strategy, i.e., for each positive entity pair (e_i, e_j) in augmented alignment set \mathbb{L}_e , we select K nearest entities of e_i measured by the embedding distance in Eq.(5) to replace e_j and form K negative counterparts $(e_i, e_{j'})$. This strategy helps push entities in misaligned entity pairs far away from each other in the embedding space.

Note that, as a special case when there are no prior alignment seeds, initialized entity embeddings without training are used for pseudo labeling instead.

With iterative pseudo labeling and model training, the final learned entity embeddings h_e are informative enough to measure the similarity between entities. We thus directly

Algorithm 1: Optimal Transport based Pseudo Labeling with Greedy Algorithm

Data: Two unaligned entity sets $E'_1 \subseteq E_1$ and

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E_2' \subseteq E_2. The rectified distance d(\cdot, \cdot) and
                 distance threshold \theta.
     Result: Pseudo-labeled alignment pair set \mathbb{L}_e.
 1 Initialize \hat{\mathbb{L}}_e \leftarrow \emptyset and \Delta \hat{\mathbb{L}}_e \leftarrow \emptyset;
 2 for each e_i \in E_1' do
            Find e_j \in E_2' with minimal d(e_i, e_j);
            if \tilde{d}(e_i, e_i) < \theta then
            Expand \Delta \hat{\mathbb{L}}_e \leftarrow \Delta \hat{\mathbb{L}}_e \cup \{(e_i, e_i)\};
 6 for each (e_i, e_j), (e_{i'}, e_j) \in \Delta \hat{\mathbb{L}}_e do
           if d(e_i, e_j) \leq d(e_{i'}, e_j) then
                  Update \Delta \hat{\mathbb{L}}_e \leftarrow \Delta \hat{\mathbb{L}}_e \setminus \{(e_{i'}, e_j)\};
                 Update \Delta \hat{\mathbb{L}}_e \leftarrow \Delta \hat{\mathbb{L}}_e \setminus \{(e_i, e_j)\};
11 for each (e_i, e_j) \in \Delta \hat{\mathbb{L}}_e with e_i \in E_1' do
      Update E_1' \leftarrow E_1' \setminus \{e_i\};
13 for each (e_i, e_j) \in \Delta \hat{\mathbb{L}}_e with e_j \in E_2' do
     Update E_2' \leftarrow E_2' \setminus \{e_j\};
15 Expand \hat{\mathbb{L}}_e \leftarrow \hat{\mathbb{L}}_e \cup \Delta \hat{\mathbb{L}}_e and set \Delta \hat{\mathbb{L}}_e \leftarrow \emptyset;
16 Repeat Steps 2-15 until no updates in \hat{\mathbb{L}}_e;
17 return Pseudo-labeled alignment pair set \hat{\mathbb{L}}_e.
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use the embedding distance defined in Eq.(5) to infer aligned entities. Given two sets of unaligned entities, $E_1' \subseteq E_1$ and $E_2' \subseteq E_2$, for each entity $e_i \in E_1'$, we find the entity $e_j \in E_2'$ having the smallest embedding distance to e_i as its alignment.

V. EXPERIMENTS

A. Datasets and Baselines

We evaluate the performance of our CPL-OT¹ method on two benchmark datasets, DBP15K [17] and SRPRS [18]. The statistics of both datasets are provided in Table I.

TABLE I: Statistics of datasets

Datase	ts	Entities	Relations	Rel.triplets		
DBP15K _{ZH_EN}	Chinese	66,469	2,830	153,929		
	English	98,125	2,317	237,674		
DBP15K _{JA_EN}	Japanese	65,744	2,043	164,373		
	English	95,680	2,096	233,319		
DBP15K _{FR_EN}	French	66,858	1,379	192,191		
	English	105,889	2,209	278,590		
SRPRS _{EN_FR}	English	15,000	221	36,508		
	French	15,000	177	33,532		
SRPRS _{EN_DE}	English	15,000	222	38,363		
	German	15,000	120	37,377		

For evaluation, we compare CPL-OT with 12 state-of-theart entity alignment models categorized into three groups:

 Models that leverage KG structure only, including MTransE [19], JAPE [17] and GCN-Align [1] in their structure-only variants denoted as JAPE-Stru and GCN-Stru.

¹Source code: https://github.com/qdin4048/CPL-OT

Models	DBP15K _{ZH_EN}			DBP15K _{JA_EN}			DBP15K _{FR_EN}			SI	RPRS _{EN_F}	R	SRPRS _{EN_DE}		
	Hit@1	Hit@10	MRR												
30% Prior Alignment Seeds															
MtransE [19] JAPE-Stru [17] GCN-Stru [1]	20.9 37.2 39.8	51.2 68.9 72.0	0.31 0.48 0.51	25.0 32.9 40.0	57.2 63.8 72.9	0.36 0.43 0.51	24.7 29.3 38.9	57.7 61.7 74.9	0.36 0.40 0.51	21.3 24.1 24.3	44.7 53.3 52.2	0.29 0.34 0.34	10.7 30.2 38.5	24.8 57.8 60.0	0.16 0.40 0.46
IPTransE [8] BootEA [7] MRAEA [9]	33.2 61.4 75.7	64.5 84.1 93.0	0.43 0.69 0.83	29.0 57.3 75.8	59.5 82.9 93.4	0.39 0.66 0.83	24.5 58.5 78.0	56.8 84.5 94.8	0.35 0.68 0.85	12.4 36.5 46.0	30.1 64.9 76.8	0.18 0.46 0.56	13.5 50.3 59.4	31.6 73.2 81.5	0.20 0.58 0.66
GCN-Align [1] JAPE [17] HMAN [20] RDGCN [4] HGCN [3] RNM [5] CEA [21]	43.4 41.4 56.1 69.7 70.8 84.0 78.7	76.2 74.1 85.9 84.2 84.0 91.9	0.55 0.53 0.67 0.75 0.76 0.87	42.7 36.5 55.7 76.3 75.8 87.2 86.3	76.2 69.5 86.0 89.7 88.9 94.4	0.54 0.48 0.67 0.81 0.81 0.90	41.1 31.8 55.0 87.3 88.8 93.8 97.2	77.2 66.8 87.6 95.0 95.9 98.1	0.53 0.44 0.66 0.90 0.91 0.95	29.6 24.1 40.0 67.2 67.0 92.5 96.2	59.2 54.4 70.5 76.7 77.0 96.2	0.40 0.34 0.50 0.71 0.71 0.94	42.8 26.8 52.8 77.9 76.3 94.4 97.1	66.2 54.7 77.8 88.6 86.3 96.7	0.51 0.36 0.62 0.82 0.80 0.95
CPL-OT	92.7	96.4	0.94	95.6	98.3	0.97	99.0	99.4	0.99	97.4	98.8	0.98	97.4	98.9	0.98
No Prior Alignment Seeds															
MRAEA [9] SelfKG [22]	77.8 82.9	83.2 91.9	-	88.9 89.0	92.7 <u>95.3</u>	-	95.0 95.9	97.0 99.2	-	93.4	<u>96.0</u>	0.92	94.9	<u>96.3</u>	<u>0.92</u>
CPL-OT	91.1	95.0	0.93	94.4	97.7	0.96	98.6	99.1	0.99	97.1	98.7	0.98	97.2	98.6	0.98

TABLE II: Performance comparison on DBP15K and SRPRS

- Models based on bootstrapping, including IPTransE [8], BootEA [7], and MRAEA [9];
- Models that use auxiliary information with KG structure, including GCN-Align [1], JAPE [17], RDGCN [4], HGCN [3], RNM [5], HMAN [20], CEA [23], MRAEA [9] in its unsupervised variant, and SelfKG [22] in its variant using translated version of word embeddings.

We use $\mathrm{Hit}@k\ (k=1,10)$ and Mean Reciprocal Rank (MRR) as evaluation metrics. Higher $\mathrm{Hit}@k$ and MRR scores indicate better entity alignment performance.

B. Experimental Setup

We follow the conventional 30%-70% training-test split on DBP15K and SRPRS. We use semantic meanings of entity names to construct entity features. On DBP15K with big linguistic barriers, we first use Google Translate to translate non-English entity names into English, then look up 768-dimensional word embeddings pre-trained by BERT [24]. On SRPRS with small linguistic barriers, we directly look up word embeddings without translation. For each entity, we aggregate TF-IDF-weighted word embeddings to form its feature vector.

CPL-OT uses the following parameter settings: d=300, $\lambda=10$, w=0.25, $\theta=4$, $\gamma=1$ and K=125. For BERT pretrained word embeddings, we use a PCA-based technique [25] to reduce feature dimension from 768 to 300 with minimal information loss. The batch size is set to 256 and the number of training epochs is set to 80. The Adam optimizer is used with a learning rate of 0.001 and 0.00025 on DBP15K and SRPRS, respectively. All experiments are run in Pytorch on an RTX 2080 Ti (11GB memory) GPU.

We re-produce the results of RNM and the unsupervised variant of MRAEA on SRPRS using their open-sourced code. Since entity features are not originally provided by SRPRS, we directly use our BERT-based entity features weighted by TF-IDF for re-implementation. The results of MRAEA on both benchmarks, RNM on DBP15K, and SelfKG on DBP15K are obtained from their original papers. Results of other baselines

are obtained from [26]. For the proposed CPL-OT, we repeat the experiment five times and report the average results.

C. Performance Comparison with State-of-the-Art

Table II compares different models on five cross-lingual datasets from DBP15K and SRPRS. The results are reported under two settings: using 30% prior alignment seeds, and with no prior alignment seeds, where all aligned pairs are used for testing. The best and second best performing methods are marked in **boldface** and underlined, respectively.

- 1) 30% Prior Alignment Seeds: In this setting, CPL-OT significantly beats all existing models on five datasets. In particular, on DBP15K_{ZH_EN}, CPL-OT outperforms the second best model by nearly 9% in terms of Hit@1. We note that there are clear overall performance gaps among the five datasets, where the lowest accuracy is achieved on DBP15K_{ZH_EN} due to its large linguistic barriers. Thus, we regard entity alignment on DBP15K_{ZH_EN} as the most challenging task.
- 2) No Prior Alignment Seeds: In the case of no prior alignment seeds, CPL-OT also achieves superior results, significantly outperforming MRAEA and SelfKG. Benefiting from its conflict-aware pseudo-labelling, CPL-OT even outperforms all baselines using 30% prior alignment seeds. When prior alignment seeds are reduced from 30% to zero, the performance of CPL-OT retains stable. The maximum drop of Hit@1 for CPL-OT is only 1.6% on DBP15K_{ZH EN}.

D. Ablation Study

We conduct a series of ablation study to investigate the importance of different components of the proposed CPL-OT model on both settings of 30% prior alignment seeds and no prior alignment seeds. Table III compares the full CPL-OT model with its ablated variants, with the best performance highlighted by **boldface**. From Table III, we can find the full CPL-OT model overall performs the best in all cases.

1) Ablation on Global-Level Relation Aggregation: Without global-level relation aggregation (w.o. Global-level Rel. Aggr.), entities tend to be over-smoothed by neighboring

TABLE III: Ablation study of CPL-OT

Models	DB	P15K _{ZH}	EN	N DBP15K _{JA_E}		EN DBP15K _{FR}		EN SF		RPRS _{EN_FR}		SRPRS _{EN_D}		ЭE	
	Hit@1	Hit@10	MRR	Hit@1	Hit@10	MRR	Hit@1	Hit@10	MRR	Hit@1	Hit@10	MRR	Hit@1	Hit@10	MRR
30% Prior Alignment Seeds															
Full Model w.o. Global-level Rel. Aggr. w.o. Emb. Dist. Rect. w.o. Conflict-aware OT w.o. Soft Align.	92.7 89.3 84.2 91.7 92.9	96.4 94.1 91.9 95.3 96.2	0.94 0.91 0.87 0.93 0.94	95.6 94.2 90.4 94.8 95.2	98.3 97.2 95.6 97.8 98.0	0.97 0.95 0.92 0.96 0.96	99.0 99.1 96.9 98.5 98.9	99.4 99.6 98.4 99.2 99.4	0.99 0.99 0.98 0.99 0.99	97.4 96.3 95.0 96.9 97.6	98.8 97.6 97.3 98.5 98.7	0.98 0.97 0.96 0.98 0.98	97.4 96.7 96.4 96.8 97.4	98.9 98.0 98.2 98.6 98.7	0.98 0.97 0.97 0.98 0.98
No Prior Alignment Seeds															
Full Model w.o. Global-level Rel. Aggr. w.o. Emb. Dist. Rect. w.o. Conflict-aware OT w.o. Soft Align.	91.1 88.8 70.3 90.0 90.7	95.0 93.0 77.7 94.0 94.7	0.93 0.90 0.73 0.91 0.92	94.5 93.4 80.9 93.4 94.0	97.6 96.9 87.6 96.7 97.4	0.96 0.95 0.83 0.95 0.95	98.6 98.6 94.6 98.1 98.7	99.2 99.5 96.2 98.9 99.3	0.99 0.99 0.95 0.98 0.99	97.1 96.2 91.5 96.5 96.8	98.6 97.5 93.6 98.2 98.7	0.98 0.97 0.92 0.97 0.98	97.2 96.1 93.6 96.5 97.0	98.4 97.5 96.1 98.3 98.7	0.98 0.97 0.95 0.97 0.98

entity features, thereby incurring more conflicts during pseudo labeling and degrading model performance on both settings.

- 2) Ablation on Embedding Distance Rectification: As relational neighborhood matching can well complement embedding distance for entity alignment, by providing additional evidence contributed by aligned neighboring entities and relations. Ablating this component (w.o. Emb. Dist. Rect.) leads to a dramatic performance drop on both settings.
- 3) Ablation on Conflict-aware Alignment with OT: After replacing OT-based alignment with a naive alignment strategy that simply uses Eq.(7) to preserve only the most convincing aligned entity pairs for handling conflicts (w.o. Conflict-aware OT), the model fails to pseudo-label sufficient correct alignments, resulting in inferior performance on both settings.
- *4) Ablation on Soft Alignment:* On the setting with 30% prior alignment seeds, ablating soft alignment (w.o. Soft Align.) has comparable performance to the full model. However, on the setting with no prior alignment seeds, pseudo labeling is prone to errors due to the lack of high-quality entity embeddings, so the ablation of soft alignment degrades model performance on DBP15K_{ZH_EN} and DBP15K_{JA_EN}.

VI. CONCLUSION

We proposed a novel conflict-aware pseudo labeling model (CPL-OT) for entity alignment across KGs. CPL-OT augments the training data with sufficiently reliable alignment pairs via an OT modeling for alleviating alignment conflicts. Competitive performance of CPL-OT on two benchmark datasets demonstrates the superiority of OT-based pseudo-labeling strategy and its great potential for entity alignment in KGs.

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