Knowledge Graph Entity Alignment with Graph Convolutional Networks: Lessons Learned

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Abstract. In this work, we focus on the problem of entity alignment in Knowledge Graphs (KG) and we report on our experiences when applying a Graph Convolutional Network (GCN) based model for this task. Variants of GCN are used in multiple state-of-the-art approaches and therefore it is important to understand the specifics and limitations of GCN-based models. Despite serious efforts, we were not able to fully reproduce the results from the original paper and after a thorough audit of the code provided by authors, we concluded, that their implementation is different from the architecture described in the paper. In addition, several tricks are required to make the model work and some of them are not very intuitive. We provide an extensive ablation study to quantify the effects these tricks and changes of architecture have on final performance. Furthermore, we examine current evaluation approaches and systematize available benchmark datasets. We believe that people interested in KG matching might profit from our work, as well as novices entering the field.

Keywords: Entity Alignment · Knowledge Graph · Graph Neural Network.

1 Introduction

The success of information retrieval in a given task critically depends on the quality of the underlying data. Another issue is that in many domains knowledge bases are spread across various data sources [14] and it is crucial to be able to combine information from different sources. In this work, we focus on knowledge bases in the form of Knowledge Graphs (KGs), which are particularly suited for information retrieval [18]. Joining information from different KGs is non-trivial, as there is no unified schema or vocabulary. The goal of the entity alignment task

⁴ The code is available at https://github.com/Valentyn1997/kg-alignment-lessons-learned.
is to overcome this problem by learning a matching between entities in different KGs. In the typical setting some of the alignments are known in advance (seed alignments) and the task is therefore supervised. More formally, we are given graphs \( G_L = (V_L, E_L) \) and \( G_R = (V_R, E_R) \) with a seed alignment \( A = (l_i, r_i) \subseteq V_L \times V_R \). It is commonly assumed that an entity \( v \in V_L \) can match at most one entity \( v' \in V_R \). Thus the goal is to infer alignments for the remaining nodes only.

Graph Convolutional Networks (GCN) \([9,7]\), which have been recently become increasingly popular, are at the core of state-of-the-art methods for entity alignments in KGs \([24,4,26,30,1]\). In this paper, we thoroughly analyze one of the first GCN-based entity alignment methods, GCN-Align \([24]\). Since the other methods we are studying can be considered as extensions of this first paper and have a similar architecture, our goal is to understand the importance of its individual components and architecture choices. To this end, we investigate differences between the architecture proposed in the original paper and the implementation provided by the authors. We empirically quantify their effect and show that parts of these deviations are important to achieve the reported performance results. On the other hand other components proposed in the paper do not improve performance and therefore the model can be simplified. In summary, our contribution is as follows:

1. We investigate the reproducibility of the published results of a recent GCN-based method for entity alignment and uncover differences between the method’s description in the paper and the authors’ implementation.
2. We perform an ablation study to demonstrate the individual components’ contribution.
3. We apply the method to numerous additional datasets of different sizes to investigate the consistency of results across datasets.

2 Related work

In this section we review previous work for the entity alignment for Knowledge Graphs and revise datasets and current evaluation process. We believe this is useful for practitioners, since we discover some pitfalls, especially when implementing evaluation scores and selecting datasets for comparison. The overview of methods, datasets and metrics is provided in Table 1.

2.1 Methods

While the problem of entity alignments in Knowledge Graphs has been tackled historically by researching vocabularies which are as broad as possible, and establish them as a standard, recent approaches take a more data-driven view. Early methods use classical knowledge graph link prediction models such as TransE \([3]\) to embed the entities of the individual knowledge graphs using a intra-KG link prediction loss, and differ in what they do with the aligned entities. For instance MTransE \([6]\) learns a linear transformation between the embedding spaces of the individual graphs using \(L_2\)-loss. BootEA \([21]\) adopts a bootstrapping approach and iteratively labels the most likely alignments and utilizes them for further
Table 1. Overview of related work in the field of entity alignment for knowledge graphs with their used datasets and metrics.

| Method         | Datasets                  | Metrics          | Code |
|----------------|---------------------------|------------------|------|
| MTransE [6]    | WK3l-15K, WK3l-120K, CN3l | H@10, MR         | yes  |
| IPTransE [29]  | DFB-{1,2,3}               | H@10, MR         | yes  |
| JAPE [19]      | DBP15K(JAPE)              | H@10,50, MR      | yes  |
| KDCoE [5]      | WK3l-60K                  | H@10, MR         | yes  |
| BootEA [29]    | DBP15K(JAPE), DWY100K     | H@10, MRR        | yes  |
| SEA [15]       | WK3l-15K, WK3l-120K       | H@10,50, MRR     | yes  |
| MultiKE [28]   | DWY100K                   | H@10, MR, MRR    | yes  |
| AttrE [22]     | DBP-LGD, DBP-GEO, DBP-YAGO| H@10, MR         | yes  |
| RSN [8]        | custom DBP15K, DWY100K    | H@10, MRR        | yes  |
| GCN-Align [23] | DBP15K(JAPE)              | H@10,50          | yes  |
| CL-GNN [27]    | DBP15K(JAPE)              | H@10             | yes  |
| MuGNN [4]      | DBP15K(JAPE), DWY100K     | H@10             | yes  |
| NAEA [30]      | DBP15K(JAPE), DWY100K     | H@10, MRR        | no   |

In addition to the alignment loss, embeddings of aligned entities are swapped regularly to calibrate embedding spaces against each other. SEA [16] learns mapping between embedding spaces in both directions and additionally adds cycle-consistency loss. Therefore the distance between original embedding of an entity and its representation, which was first translated to another space and then back from it, is penalized. IPTransE [29] embeds both KGs into the same embedding space and uses a margin-based loss to enforce the embeddings of aligned entities to become similar. RSN [8] model generates sequences using different types of random walks which can move between graphs when visiting aligned entities. The generated sequences are feed to adapted recurrent model. JAPE [19], KDCoE [5], MultiKE [28] and AttrE [22] utilize attributes available for some entities and additional information like names of entities and relationships. Graph Neural Network (GNN) based models [24,4,26,30,1] have in common that they use GNN to create node representations by aggregating node representations together with representations of their neighbors. Most of GNN approaches do not distinguish between different relations and either consider all neighbors equally [24,26,1] or use attention [4] to weight the representations of the neighbors for the aggregation.

2.2 Datasets

The datasets used by entity alignments methods generally derive from large-scale open-source data source such as DBPedia [2], YAGO [13], or Wikidata [25]. While there is the DWY-100k dataset, which comprises 100k aligned entities across the three aforementioned individual knowledge graphs, most of the datasets, such as DBP15k, or WK3l derive from a single multi-lingual database. There, subsets are formed according to a specific language, and entities which occur in multiple languages and are linked accordingly are used as alignments.

As an interesting observation we found out that all papers which evaluate

5 Please note, that while [30] does not state explicitly that they use GNNs, their model is very similar to [23].
Table 2. Overview of used datasets with their sizes in the number of triples (edges), entities (nodes), relations (different edge types) and alignments. For WK3l, the alignment is provided as a directed mapping on a entity level. However, there are additional triple alignments. Following a common practice as e.g. [15] we can assume that an alignment should be symmetric, and that we can extract entity alignments from the triple alignments. Doing so, we obtain the number of alignments given in brackets.

| Dataset       | Subset | Graph | Triples | Entities | Relations | Alignments |
|---------------|--------|-------|---------|----------|-----------|------------|
| DBP15k (full) | fr-en  | fr    | 192,191 | 66,858   | 1,379     | 15,000     |
|               | en     | 278,590 | 105,889 | 2,209     |           |            |
|               | ja     | 164,373 | 65,744  | 2,043     |           | 15,000     |
|               | zh     | 153,929 | 66,469  | 2,830     |           | 15,000     |
|               | en     | 237,674 | 98,125  | 2,317     |           |            |
| DBP15k (JAPE) | fr-en  | fr    | 105,998 | 19,661   | 903       | 15,000     |
|               | en     | 115,722 | 19,993  | 1,208     |           |            |
|               | ja     | 77,214  | 19,814  | 1,299     |           | 15,000     |
|               | zh     | 70,414  | 19,388  | 1,153     |           | 15,000     |
|               | en     | 95,142  | 19,572  | 1,323     |           |            |
| WK3l-15k      | en-de  | en    | 209,041 | 15,127   | 1,841     | 1,289 (10,383) |
|               | de     | 144,244 | 14,603  | 596       | 1,140 (10,383) |
|               | en-fr  | en    | 203,356 | 15,170   | 2,228     | 2,998 (8,024) |
|               | fr     | 169,329 | 15,393  | 2,422     | 3,812 (8,024) |
| WK3l-120k     | en-de  | en    | 624,659 | 67,650   | 2,393     | 6,173 (50,280) |
|               | de     | 389,554 | 61,942  | 861       | 4,820 (50,280) |
|               | en-fr  | en    | 1,375,406 | 119,749 | 3,109    | 36,749 (87,836) |
|               | fr     | 760,497 | 118,592 | 2,336     | 36,013 (87,836) |
| DWY-100k      | dbp-wd | dbp   | 463,294 | 100,000  | 330       | 100,000    |
|               | wd     | 448,774 | 100,000 | 220       |           |            |
|               | dbp    | dbp   | 428,952 | 100,000  | 302       | 100,000    |
|               | yg     | 502,563 | 100,000 | 31        |           |            |

on DBP15k, do not evaluate on the full DBP15k dataset (which we refer to as DBP15k (full)), but rather use a smaller subset provided by the authors of JAPE [19] in their GitHub repository, which we call DBP15k-JAPE. The smaller subsets were created by selecting a portion of entities (around 20k of 100k) which are popular, i.e. appear in many triples as head or tail. The number of aligned entities stays the same (15k). As the paper only reports the dataset statistics of the larger dataset, and does not mention the reduction of the dataset, subsequent papers also report the statistics of the larger dataset, although experiments use the smaller variant [19, 21, 24, 29].

2.3 Scores

It is common practice to only consider the entities being part of the test alignment as potential matching candidates. Although we argue that ignoring entities exclusive to a single graph as potential candidates does not reflect well the use-
In the following description of evaluation measures we focus only on the case of aligning one node $l_i \in V_L$ with a ground truth alignment $r_i \in V_R$. The right-to-left alignment is handled analogously. Let $V_R^* = \{v_r \in V_R \mid \exists v_l \in V_L : (v_l, v_r) \in A_e\}$ denote the set of matching candidates in the right graph. For a node $l_i$, the entity alignment models generates a score $f(l_i, v_j)$ for each matching candidate $v_j \in V_R^*$. Afterwards, the candidates are sorted according to their score, and the rank $\text{rank}(l_i, r_i)$ is computed as the index of the ground truth match $r_i$ in this sorted list (1-based). The mean rank (MR) is simply the mean over the ranks for all alignments.

$$MR = \frac{1}{|A_e|} \sum_{i=1}^{|A_e|} \text{rank}(l_i, r_i)$$

The mean reciprocal rank (MRR) is the mean over all reciprocal ranks.

$$MRR = \frac{1}{|A_e|} \sum_{i=1}^{|A_e|} \frac{1}{\text{rank}(l_i, r_i)}$$

It is naturally bounded between 0 and 1, where 1 corresponds to a perfect score. Moreover, its value is dominated by small ranks, and it is less sensitive to larger ones. The hits at $k$ ($H@k$) is the percentage of alignments where the rank was at most $k$, i.e. equivalent to the recall at $k$.

$$H@k = \frac{|\{(l_i, r_i) \in A_e \mid \text{rank}(l_i, r_i) \leq k\}|}{|A_e|}$$

### 3 Method

GCN-Align \cite{24} is a GCN-based approach to embed all entities from both graphs into a common embedding space. Each entity $i$ is associated with structural features $h_i^s \in \mathbb{R}^d$, which are initialized randomly and updated during training. The features of all entities in a single graph are combined to the feature matrix $H^s$. Subsequently, a two-layer GCN is applied. A single GCN layer is described by

$$H^{(i+1)} = \sigma \left( \hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(i)} W^{(i)} \right)$$

with $\hat{A} = A + I$, where $A$ is the adjacency matrix, and $\hat{D}_{ii} = \sum_{j=1}^n \hat{A}_{ij}$ is the diagonal node degree matrix. The input of the first layer is set to $H^{(0)} = H^s$, and $\sigma$ is non-linear activation function. For the first layer, $\sigma = \text{ReLU}$, and the

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8 In the typical scenario it is not known in advance, which entities have matching and which not. Therefore the resulting score is too optimistic. However, we advocate to investigate this shortcoming further in future work.
second layer uses the identity. The output of the second layer is considered as
the structural embedding, denoted by \( s_i = H^{(2)}_i \in \mathbb{R}^d \). Both graphs are equipped
with its own node features, but the convolution weights \( W^{(i)} \) are shared across
the graphs.

The adjacency matrix is derived from the knowledge graph by first computing
a score, called functionality, for each relation as the ratio between the number
of different entities which occur as head, and the number of triples in which the
relation occurs

\[
\alpha_r := \frac{|\{v \in V \mid \exists v' : (v, r, v') \in T\}|}{|\{t \in T \mid \exists v, v' \in V : (v, r, v) \in T\}|}
\]

Analogously, the inverse functionality \( \alpha'_r \) is obtained by replacing the nominator
by the number of different tail entities. The final adjacency matrix is obtained
as

\[
A_{ij} = \sum_{(e_i, r, e_j)} \alpha'_r + \sum_{(e_j, r, e_j)} \alpha_r
\]

In addition, each entity \( i \) is also equipped with attributes \( h^a_i \in \mathbb{R}^{d'} \) which
are combined into a graph attribute matrix \( H^a \). Analogously, the attributes are
processed by a GCN for each graph with convolution weights shared across the
graphs, resulting in attribute embeddings \( a_i \in \mathbb{R}^{d'} \).

The attribute and structure GCNs are optimized separately using SGD. As
loss function, a margin-rank loss is used, exemplary for the structure embedding

\[
L = \sum_{(r_i, l_i) \in A} \sum_{(r_j, l_j) \in A^-} \left[ \|s^L_{i} - s^R_{i}\|_1 + \gamma - \|s^L_{j} - s^R_{j}\|_1 \right]_+
\]

where \([x]_+ = \max\{0, x\}\), and the margin \( \gamma \) is a hyperparameter chosen separately
for structure and attribute embeddings. \( A^- \) denotes a set of negative samples
constructed by either replacing the left or the right entity with a random entity
from the same graph.

In order to compare two nodes from both graphs, the \( L_1 \) distance between
their embeddings is used, normalised by the dimensionality.

\[
\text{score}(v^L_i, v^R_j) = -\left( \beta \frac{\|s^L_{i} - s^R_{i}\|_1}{d} + (1 - \beta) \frac{\|a^L_{i} - a^R_{j}\|_1}{d'} \right)
\]

Here, \( \beta \) is a hyperparameter for the tradeoff between structural and attribute
similarity.

3.1 Implementation Differences

The code\(^9\) provided by the authors differs in a few aspects from the method
described in the paper. First, instead of using the full DBP15k dataset having

\(^9\)https://github.com/1049451037/GCN-Align
the dataset sizes as reported in the paper, a smaller version is used. Second, when computing the adjacency matrix, \( \text{fun}(r) \) and \( \text{ifun}(f) \) are set to at least 0.3. Third, the node features are always normalised to unit Euclidean length before passing them into the network. Finally, there are no convolution weights. This fact is particularly interesting, as this means that the whole GCN does not contain a single parameter, but is just a fixed function on the learned node embeddings.

4 Experiments

In initial experiments we were able to reproduce the results reported in the paper using the implementation provided by the authors. Moreover, we are able to reproduce the results using our own implementation, and settings adjusted to the authors’ code. In addition, we replaced the adjacency matrix based on functionality and inverse functionality by a simpler version, where \( a_{ij} = \{(h, r, t) \in T \mid h = e_i, t = e_j\} \). We additionally use \( D^{-1}A \) instead of the symmetric normalization. In total, we see no difference in performance between our simplified adjacency matrix, and the authors’ one. We identified two aspects which affect the model’s performance: Not using convolutional weights, and normalizing the variance when initializing node embeddings. We provide empirical evidence for this finding across numerous datasets. Our results regarding Hits@1 (H@1), Hits@10 (H@10), mean rank (MR) and mean reciprocal rank (MRR) are summarised in Table 3.

Node Embedding Initialization Comparing the columns of Table 3, we can observe the influence of the node embedding initialization. Using the settings from the authors’ code, i.e. not using weights, a choosing a variance of \( n^{-1/2} \) actually results in inferior performance in terms of H@1, as compared to use a standard normal distribution. These findings are consistent across datasets.

Convolution Weights The first column of Table 3 corresponds to the weight usage and initialization settings used in the code for GCN-Align. We achieve slightly better results than published in [24], which we attribute to a more exhaustive parameter search. Interestingly, all best configurations use Adam optimizer instead of SGD. Adding convolution weights degrades the performance across all datasets and subsets thereof but one as witnessed by comparing the first two columns with the last two columns.

5 Conclusion

In this work, we reported our experiences when implementing the Knowledge Graph alignment method GCN-Align. We pointed at important differences between the model described in the paper and the actual implementation and quantified their effects in the ablation study. Furthermore, we discussed specifics and shortcomings of the current evaluation process. For future work, we plan to include other methods for entity alignments in our framework.
Table 3. Ablation study on using convolution weights and different embedding initialisation. We fix using convolution weights and the variance for the normal distribution from which the embedding vectors are initialized and optimize the other hyperparameters according to validation H@1 (80/20% train-validation split) on DBP15K (JAPE) zh-en in a large-scale hyperparameter search, comprising 1,440 experiments. (Hyperparameter Grid: optim. \(\in\) \{Adam, SGD\}, lr \(\in\) \{0.1, 0.5, 1, 10, 20\}, #layers \(\in\) \{1, 2, 3\}, #neg. samples \(\in\) \{5, 50, 100\}, #epochs \(\in\) \{10, 500, 2000, 3000\}. ) Hence, we obtain four sets of hyperparameters. For each dataset, we perform a smaller hyperparameter search to fine-tune LR, #epochs & #layers for each dataset (again 80/20 split) and evaluate the best models on the official test set.

|                      | H@1 | H@10 |
|----------------------|-----|------|
|                      | No  | Yes  | No  | Yes  | No  | Yes  |
|                      | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) |
| DBP15K (FULL) fr-en  | 24.0 | 28.0 | 15.0 | 21.0 | 58.0 | 63.0 |
| ja-en                | 25.0 | 30.0 | 20.0 | 26.0 | 56.0 | 65.0 |
| zh-en                | 22.0 | 28.0 | 17.0 | 22.0 | 53.0 | 63.0 |
| DBP15K (JAPE) fr-en  | 37.0 | 41.0 | 27.0 | 32.0 | 75.0 | 79.0 |
| ja-en                | 35.0 | 41.0 | 27.0 | 33.0 | 70.0 | 74.0 |
| zh-en                | 34.0 | 39.0 | 27.0 | 31.0 | 68.0 | 73.0 |
| DWY100K wd           | 49.0 | 54.0 | 34.0 | 46.0 | 76.0 | 83.0 |
| yg                   | 63.0 | 70.0 | 48.0 | 64.0 | 84.0 | 91.0 |
| WK3L120K en-de       | 8.0  | 9.0  | 6.0  | 9.0  | 23.0 | 25.0 |
| en-fr                | 7.0  | 8.0  | 5.0  | 7.0  | 20.0 | 22.0 |
| WK3L15K en-de        | 13.0 | 15.0 | 12.0 | 16.0 | 37.0 | 41.0 |
| en-fr                | 14.0 | 16.0 | 11.0 | 14.0 | 45.0 | 47.0 |

|                      | MR  | MRR  |
|----------------------|-----|------|
|                      | No  | Yes  | No  | Yes  | No  | Yes  |
|                      | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) | n\(^{-1/2}\) |
| DBP15K (FULL) fr-en  | 385.17 | 303.16 | 211.59 | 154.93 | 0.35 | 0.39 |
| ja-en                | 463.04 | 314.05 | 262.03 | 172.74 | 0.36 | 0.42 |
| zh-en                | 501.86 | 293.90 | 243.59 | 365.94 | 0.32 | 0.39 |
| DBP15K (JAPE) fr-en  | 162.67 | 169.36 | 195.54 | 163.71 | 0.50 | 0.54 |
| ja-en                | 286.48 | 231.00 | 277.97 | 209.43 | 0.47 | 0.52 |
| zh-en                | 306.51 | 273.39 | 293.60 | 228.11 | 0.46 | 0.51 |
| DWY100K wd           | 768.04 | 680.96 | 818.93 | 835.93 | 0.58 | 0.64 |
| yg                   | 151.83 | 113.90 | 197.23 | 193.12 | 0.70 | 0.78 |
| WK3L120K en-de       | 2484.10 | 3048.33 | 2484.60 | 3300.58 | 0.14 | 0.15 |
| en-fr                | 4356.30 | 4584.78 | 4120.80 | 4885.99 | 0.11 | 0.13 |
| WK3L15K en-de        | 256.65 | 273.20 | 219.33 | 294.10 | 0.21 | 0.24 |
| en-fr                | 198.02 | 243.63 | 212.07 | 284.53 | 0.25 | 0.26 |
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Appendix

Dataset Links

| Dataset        | Link                                                                 |
|----------------|----------------------------------------------------------------------|
| DBP15K-JAPE    | github.com/nju-websoft/JAPE/blob/master/data/dbp15k.tar.gz          |
| DBP15K-full    | ws.nju.edu.cn/jape/                                                  |
| DWY100K        | github.com/nju-websoft/BootEA/tree/master/dataset/DWY100K           |
| WK3l-15K       | drive.google.com/open?id=1AsPPU4ka1Rc9u-XYMGWtvV5hf3egi0z           |
| WK3l-60k       | github.com/muhaochen/MTransE-tf/blob/master/preprocess/wk3l60k.zip  |
| WK3l-120K      | drive.google.com/open?id=1AsPPU4ka1Rc9u-XYMGWtvV5hf3egi0z           |
| CN3l           | drive.google.com/open?id=1AsPPU4ka1Rc9u-XYMGWtvV5hf3egi0z           |
| DFB-1          | github.com/thunlp/IEAJKE/tree/master/data                          |

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