Multilingual Knowledge Graph Completion
with Joint Relation and Entity Alignment

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Abstract

Knowledge Graph Completion (KGC) predicts missing facts in an incomplete Knowledge Graph. Almost all of existing KGC research is applicable to only one KG at a time, and in one language only. However, different language speakers may maintain separate KGs in their language and no individual KG is expected to be complete. Moreover, common entities or relations in these KGs have different surface forms and IDs, leading to ID proliferation. Entity alignment (EA) and relation alignment (RA) tasks resolve this by recognizing pairs of entity (relation) IDs in different KGs that represent the same entity (relation). This can further help prediction of missing facts, since knowledge from one KG is likely to benefit completion of another. High confidence predictions may also add valuable information for the alignment tasks.

In response, we study the novel task of jointly training multilingual KGC, relation alignment and entity alignment models. We present ALIGNKGC, which uses some seed alignments to jointly optimize all three of KGC, EA and RA losses. A key component of ALIGNKGC is an embedding-based soft notion of asymmetric overlap defined on the (subject, object) set signatures of relations – this aids in better predicting relations that are equivalent to or implied by other relations. Extensive experiments with DBPedia in five languages establish the benefits of joint training for all tasks, achieving 10-32 MRR improvements of ALIGNKGC over a strong state-of-the-art single-KGC system completion model over each monolingual KG. Further, ALIGNKGC achieves reasonable gains in EA and RA tasks over a vanilla completion model over a KG that combines all facts without alignment, underscoring the value of joint training for these tasks.

1 Introduction

A knowledge graph (KG), also called as knowledge base (KB), has nodes representing entities and edges representing relations. Entities have unique canonical IDs. Relations also have canonical labels such as born-in or works-at, with associated IDs. A fact triple in a KG is of the form (subject entity, relation, object entity). A KG is usually associated with a human language. Each entity (or relation) ID is associated with one or more surface forms in the KG. E.g., the ID for the country USA may have aliases like “United States of America”.

KGs are usually very incomplete, as curators struggle to keep up with the real world. KG completion (KGC) is thus a strongly motivated problem and studies the prediction of true facts unknown to the KG. While the problem is well-researched, with dozens of approaches explored over the last few years (Bordes et al., 2013; Dettmers et al., 2018; Sun et al., 2019; Trouillon et al., 2016), most KGC research is applicable to only one KG in one language at a time. However, different language speakers would maintain separate KGs in their own languages. Independent completion of each KG may not be optimal, since information from one KG will likely help completion of the other.

A second issue is that each KG will give a different ID, and often also the surface form, to the same entity, such as “Estados Unidos de América” for the USA entity in a Spanish KG. This leads to the problem of ID proliferation. A recent line of research around entity alignment (EA) across KGs in different languages attempts to assign a unique ID to all IDs representing the same entity (Chen et al., 2017; Sun et al., 2017, 2018; Cao et al., 2019; Sun et al., 2020; Chen et al., 2021; Tang et al., 2020). A related task is relation alignment (RA), though relatively less attention has been given to this for multilingual KGs. We note that RA involves global evidence, because the decision
to merge two relations in two languages can have far-reaching consequences to many facts in both KGs.

Our key contribution is to recognize and exploit the synergy between Multilingual KGC, EA and RA tasks. It is not surprising that such alignments will allow a KG an access to more facts and will lead to better completion. Similarly, if a fact can be predicted with high confidence in one KG that may give additional support to alignment of its constituent entities and relations.

In this paper, we present ALIGNKGC, a multi-task system that learns to optimize for KGC, EA and RA jointly. At the heart of ALIGNKGC is the subject-object signature of each relation, which we represent as a bag of embeddings. These bags are compared for equivalence and implication between relations, and trained via an end-to-end training protocol for the multiple tasks.

We evaluate ALIGNKGC on slices of DBPedia in five languages. We compare it against a strong state-of-the-art single-KGC system trained over each monolingual KG separately. Compared to this monolingual baseline, we find that ALIGNKGC achieves substantial accuracy boost due to other KGs that get better aligned by our system, obtaining 10-32 pt MRR improvements across languages. For EA and RA, we compare it against a multilingual baseline trained over the single KG that has union of all (unaligned) facts. Joint training yields 22 pt HITS@1 gain on EA, and 26 pt HITS@1 gain in RA for frequent relations. Our code and data sets will be made publicly available.

2 Notation and preliminaries

Throughout, we use knowledge graph (KG) and knowledge base (KB), and similarly KBC and KGC interchangeably. A KG consists of entities $E$ and relations (aka relation types) $R$. A KG instance is a triple $(s, r, o)$ where $s, o \in E$ and $r \in R$. These are all canonical IDs, but each ID is associated with aliases in one or more languages.

2.1 KGC task

For any single KG, training data is provided as $(s, r, o)$ triples. A test instance has the form $(s, r, ?)$ or $(?, r, o)$ where the system has to predict $o$ or $s$. Multiple correct values are possible. The evaluation protocol usually has the system rank candidate $o$’s or $s$’s and then measures MRR or hits@$K$.

2.2 Alignment task

We consider a set $L = \{l_1, l_2, \ldots\}$ of languages. For simplicity of exposition, we consider two KGs called $K_{l_1}$ and $K_{l_2}$. Here $K_{l_1}$ represents the KG supported by the language $l_1$. An entity in this KG is called $e_{l_1}$. A relation in this KG is called $r_{l_1}$. For simplicity of exposition, we consider two KGs called $K_{l_1}$ and $K_{l_2}$ where $l, l' \in L$.

Although we cast the alignment task as between KGs in two different languages, alignment between diverse KGs even in the same language (such as Wikipedia and IMDB) are considered in the same spirit. Furthermore, it is possible for multiple KGs to take the place of $K_{l_1}$ to improve KGC in $K_{l_2}$.

An equivalence between entities $e_{l_1}$ and $e_{l_2}$ is specified as $e_{l_1} \equiv e_{l_2}$, also written as the triple $(e_{l_1}, \equiv, e_{l_2})$. This induces a graph by adding some more edges with label ‘$\equiv$’ to $K_{l_1} \cup K_{l_2}$. Similarly an equivalence between relations $r_{l_1}$ and $r_{l_2}$ is specified as $r_{l_1} \equiv r_{l_2}$; this is not easily represented in the graph $K_{l_1} \cup K_{l_2}$, however.

Other relations may be possible between relation pairs, such as $r_{l_1} \implies r_{l_2}$, which means, for all $s, o$ such that $(s, r_{l_1}, o)$ holds, so does $(s, r_{l_2}, o)$.

During training, a set of entity equivalences $\{(e^1_n, \equiv, e^2_n) : n = 1, \ldots, N\}$ and a set of relation equivalences $\{(r^1_m, \equiv, r^2_m) : m = 1, \ldots, M\}$ are revealed to the system. The goal of the system is to infer additional entity and relation equivalences. The system is usually called upon to produce a ranked list of equivalences, which is evaluated using HITS@$K$ or MRR.

To achieve KGC enhanced with alignment, the system has to infer additional triples in either KG, making best use of the revealed equivalences. For the KG alignment goal, the system has to infer additional alignment triples between an entity or relation in $K_{l_1}$ and an entity or relation in $K_{l_2}$.

3 Proposed methods

3.1 Baseline

Many KG embedding and KBC algorithms have been proposed in the last few years. ComplEx (Trouillon et al., 2016) with all negative instances (no sampling) gives the best predictions (Jain et al., 2020), so we use it as our baseline KGC gadget. ComplEx defines a triple score as

$$f(s, r, o) = \Re(\langle s, r, o^\star \rangle),$$

where $c^\star$ is complex conjugate, $\langle \cdot \cdot \cdot \rangle$ is a 3-way elementwise inner product and $\Re(\cdot)$ is the real part.
of a complex number. When applied to any one KG in isolation, we call this method **KGONE**.

Perhaps the most straight-forward way to apply a KGC system is to compute \( KG_1 \cup KG_2 \), collapse node pairs specified as equivalent in \( \{(e_i, e_j)\} \), and rename all equivalent \( r_1, r_2 \) relation IDs to a common new ID. A KGC system can work on the resulting KG, and this method is called **KG-UNION**. Of course, this scheme does not impute any equivalences beyond what are explicitly provided.

### 3.2 Joint alignment and completion

For both textual and structured inputs, the problem of inferring a predicate or relation as entailed by another has been studied (Lin and Pantel, 2001; Bhagat et al., 2007; Nakashole et al., 2012). With that work as our point of departure, we ask: How similar are two relations \( r_1, r_2 \) in one KG?

To build an estimate of similarity, we define the subject-object signature of a relation wrt a KG:

\[
SO(r) = \{(s, o) : (s, r, o) \in KG\}
\]

(2)

Here \( s, o \) are interpreted as canonical IDs.

#### 3.2.1 Jaccard similarity

Jaccard similarity can then be used as a standard symmetric belief that two relations are equivalent:

\[
b(r_1 \leftrightarrow r_2) = \frac{|SO(r_1) \cap SO(r_2)|}{|SO(r_1) \cup SO(r_2)|}.
\]

(3)

We add a threshold on these scores to reduce noise of false relation alignment signal.

#### 3.2.2 Asymmetric subsumption

The issue with Jaccard similarity is that it can give a symmetric high score to relation pairs having asymmetric implications between them. E.g., in the DBP5L data set, Jaccard similarity gives a large similarity score between locationCity and headquarter, or keyPerson and founders.

Therefore, we need a belief measure for one relation subsuming another, which we define as

\[
b(r_1 \Rightarrow r_2) = \frac{|SO(r_1) \cap SO(r_2)|}{|SO(r_1)|} \in [0, 1]
\]

(4)

\( b(r_2 \Rightarrow r_1) \) is defined likewise. Extending the logical statement

\[
(r_1 \leftrightarrow r_2) \iff (r_1 \Rightarrow r_2) \land (r_2 \Rightarrow r_1)
\]

(5)

to the fuzzy domain, we get

\[
b(r_1 \leftrightarrow r_2) = \min\{b(r_1 \Rightarrow r_2), b(r_2 \Rightarrow r_1)\}
\]

(6)

#### 3.2.3 Soft subsumption and equivalence

In the above definitions involving \( SO \), we assumed the \( (s, o) \) pairs were represented using canonical entity IDs. This may not be useful in the KG alignment task because canonical entity IDs will frequently not match.

Recall that the KBC system obtains embedding vectors \( e \) for each entity \( e \) in the KG. Reusing notation, we modify our earlier definition of subject-object signature to

\[
SO(r) = \{(s, o) : (s, r, o) \in KG\},
\]

i.e., where each element is the concatenation of the subject and object embedding vectors.

Now consider one relation from each of two KGs to be aligned, viz., \( r_1, r_2 \). Suppose the \( (s, o) \) pairs of \( r_1 \) are indexed by \( i \) and pairs of \( r_2 \) are indexed by \( j \). To generalize (6), we build a matrix \( A_{r_1,r_2} \) of pairwise cosine similarities:

\[
A_{r_1,r_2}[i,j] = \cos(SO(r_1)[i], SO(r_2)[j])
\]

(8)

The continuous extension of \( SO(r_1) \cap SO(r_2) \) involves solving a maximal bipartite matching problem using \( A_{r_1,r_2} \) as edge weights. Ideally, we should be able to backpropagate various KBC and alignment losses past the solution of the matching problem to the entity and relation embeddings. Gumbel-Sinkhorn matrix scaling (Cuturi, 2013; Mena et al., 2018) can be used for this purpose, but it is computationally expensive at KG scales.

Here we use a computationally cheaper approximation: only if \( i \) is \( j \)'s strongest partner and \( j \) is \( i \)'s strongest partner, we choose edge \( (i, j) \) and accrue toward the soft version of \( SO(r_1) \cap SO(r_2) \) the score increment

\[
\sigma(A_{r_1,r_2}[i,j] w + c),
\]

(9)

where \( \sigma \) is the sigmoid nonlinearity, and \( w > 0, b \in \mathbb{R} \) are model parameters trained along with all embeddings. Summarizing, we estimate

\[
|SO(r_1) \cap SO(r_2)| = \sum_{i,j} p(i,j) \sigma(A_{r_1,r_2}[i,j] w + c),
\]

(10)

where the partner test indicator is written as

\[
p(i, j) = [i = \text{argmax}_{i'} A[i', j]] \\
\]

\[
[j = \text{argmax}_{j'} A[i, j']] \]

(11)

We continue to use (4) and (6) as defined with the modified continuous definition of intersection.

#### 3.2.4 Assembling a joint loss function

We start with the ComplEx KBC loss and then augment with loss terms corresponding to entity...
alignment and relation alignment. Using \( f \) in Equation 1, ComplEx defines
\[
\Pr(o|s,r) = e^{f(s,r,o)} \sum_{o'} e^{f(s,r,o')}, \quad (12)
\]
\[
\Pr(s|o,r) = e^{f(s,r,o)} \sum_{s'} e^{f(s',r,o)}, \quad (13)
\]
and the log-likelihood KGC loss as
\[
L_{KGC} = \sum_{(s,r,o) \in \mathcal{KG}} - \log \Pr(o|s,r) - \log \Pr(s|o,r). \quad (14)
\]
In our experiments, we found that retaining the full negative sets \( \{s'\}, \{o'\} \) is better than negative sampling, which we implemented using 1-N scoring (Jain et al., 2020; Dettmers et al., 2018).

We have no counterpart to the entity alignment loss (Chen et al., 2017; Sun et al., 2018) because, for any pair \( e_i \equiv e_{i'} \), we force the two entities to share the same embedding vector. But we do introduce a novel relation alignment loss. If \( b(r_1 \leftrightarrow r_{i'}) \) is large, but the relation embeddings \( r_1 \) and \( r_{i'} \) are very dissimilar, we should assess a loss. This naturally suggests the additional relation alignment loss term \( L_{RA1} \)
\[
L_{RA1} = \sum_{c(r_1, r_{i'})} \|r_1 - r_{i'}\|_1. \quad (15)
\]
Other forms are possible, like
\[
\sum_{c(r_1, r_{i'})} BCE\left(b(r_1 \leftrightarrow r_{i'}), \sigma(\cos(r_1, r_{i'}))\right). \quad (16)
\]
where the corresponding relation test indicator is written as
\[
c(r_1, r_{i'}) = \begin{cases} r_1 \equiv \arg\max_{i'} b(r_1 \Rightarrow r_{i'}') \\ r_{i'} \equiv \arg\max_{i'} b(r_{i'} \Rightarrow r_1') \end{cases} \quad (17)
\]

3.2.5 Joint loss
We put together all the above loss components and also a L2-regularizer \( L_{reg} \) on entity and relation embeddings, each multiplied by tuned hyperparameters \( \alpha, \beta \):
\[
L_{KGC} + \alpha L_{reg} + \beta L_{RA1} \quad (18)
\]
We initialize all elements of entity and relation embeddings to \( \mathcal{N}(0, 0.05) \). Entity embeddings are not sensitive to alignment initially except those involved in seed alignment, hence we initialize the \( c = -90 \) and \( w = 100 \) in (4). Thus, only very high initial cosine similarities contribute to equivalence score computation. As a form of curriculum, we let relation alignments get stable for few iterations and then make the equivalence scores trainable.

4 Experiments
4.1 Dataset
Standard mono-lingual KGC datasets such as FB15k, FB15k-237, WN18, WN18RR, and Yago3-10, are not directly suited to evaluation of multi-lingual KGC task. Also, the focus on KG alignment is still relatively recent, with only a few suitable multi-lingual datasets that provide gold alignments between entity and relation pairs for training and evaluation. One such dataset is DBP5L, derived from DBpedia in five languages: English (En), Greek (El), Spanish (Es), Japanese (Ja) and French (Fr). Typically, about 40% of entities in one language are aligned to entities in the other language. We use the same 60-30-10 splits of the KG triples into train-dev-test folds as in Chen et al. (2020) and combine the train set of all languages for training. We also pick half of seed entity alignments randomly for training and rest is held for evaluation.

Because DBpedia uses a uniform relation vocabulary that is normalized across all languages, it cannot be directly used to test RA. To simulate that KBs in different languages come from different sources, we declare a unique ID for each relation in a language. This creates a testbed for the RA task.

4.1.1 Salient statistics
Table 1 lists the statistics of the five KGs in DBP5L. En is expectedly the most well-populated. Figure 2 shows that 60% of the relation labels have associated string descriptions in only one of five languages mostly English in DBP-5L. However, these relation labels account for only 8% of fact triples. Meanwhile, almost 80% of fact triples have relations expressed in all five languages.

4.2 Performance measures
We evaluate ALIGNKGC on DBP5L dataset, on three different tasks — KGC, EA and RA. As is common when evaluating the system for the task of KGC, we regard test instances \( (s, r, ?) \) as a task of ranking \( o \) (on the basis of scores computed in equations (12) and (13)), with gold \( o^* \) known. We report

| Language | Greek | Japanese | Spanish | French | English |
|----------|-------|----------|---------|--------|---------|
| #Entity  | 5,231 | 11,805   | 12,382  | 13,176 | 13,996  |
| #Relation| 111   | 128      | 144     | 178    | 831     |
| #Triples | 13,839| 28,774   | 54,066  | 49,015 | 80,167  |

Table 1: Salient statistics of KGs.
MRR (Mean Reciprocal Rank) and the fraction of queries where o* is recalled within rank 1 and rank 10 (HITS). The filtered evaluation removes valid train or test tuples ranking above (s, r, o*) for scoring purposes.

To evaluate the system for EA, we use the test instance (e_l, ≡, ?) as a task of ranking e_r, using the cosine distance between the entity embeddings of the language pair. We calculate Hits@1 and Hits@10 on the resulting rankings.

Similarly, to evaluate the system on the task of RA, we use the test instance (r_s, ≡, ?) as a task of ranking r_o, using the cosine distance between the relation embeddings of the language pair. We calculate Hits@1 and Hits@10 on the resulting rankings.

Note that we use l and l’ as placeholders for various language pairs we train/test on.

4.3 KGC performance

Table 3 shows the KGC performance on the five languages of DBP-5L namely Greek, Japanese, French, Spanish and English. Though train and test set of each language KG have no overlap (KG_l(train) ∩ KG_l(test) = ∅). But because we assign the same IDs for aligned entities during training, some form of overlap may exist in the combined training triples of all languages with test sets in any language. E.g., if (s_l, r_l, o_l) ∈ KG_l(train) and (s_r, r_r, o_r) ∈ KG_l(test), where s_l ≡ s_r, o_l ≡ o_r and r_l ≡ r_r (relation alignment may or may not be used).

Therefore, rather than report metrics only on whole test-split, which can be misleading, we split our test set into two components: seen test set with triples/facts as shown above, and unseen test as the remaining triples. Qualitatively, performance on the seen split represents the capacity of the model to memorize known facts in a language and align them to another language, whereas the unseen split gives a true sense of a system’s inference capability, since the fact has not been read in any language at train time.

Table 3 shows the results of various ALIGNKGC variations compared to the baseline. KGCUNION being our multilingual baseline shows gains of combining the different language KGs over the monolingual baseline KGONE. We find that each modification (Jaccard, Asymmetric scores and Soft Asymmetric scores) improves the results successively. Further analysis reveals that Jaccard significantly helps with seen split, since it is able to learn similar embeddings for two aligned relations and entities, and yields high scores for seen tuple in a different language. Asymmetric computations help further as they remove false positives in RA that appear in the Symmetric Jaccard version.

Finally, making these asymmetric implication scores trainable learns better implications scores, which significantly improve entity alignment, which in turn gives better relation alignment. So we get best results on the both unseen and seen test splits for this version.

4.4 Alignment performance

Table 4 reports the performance of the various models on RA and EA tasks. We use entity and relation alignment results of KGCUNION as our baseline. We find that all ALIGNKGC variants outperform the baseline by vast margins. We notice that performance gain in RA are higher for highly frequent relations, and for less frequent relations, decreases slightly compared to Jaccard. Since a much larger fraction of triples (see Figure 2) express these highly frequent relations, it overall improves the performance of KGC significantly.

We also note that Jaccard and Asymmetric Jaccard models perform Entity alignment based on KGC loss only, since they do not have any trainable alignment loss. Since those models significantly improve the performance of EA, it provides evidence that KGC can result in better alignment. Learnable asymmetric model, of course, incentivizes better alignment too, leading to a further improvement in performance.
Table 3: KGC Performance of Models on Five languages

| Language | KGONE | KGUNION | ALIGNKGK (Asymmetric) | ALIGNKGK (Soft Asymmetric) |
|----------|-------|---------|-----------------------|---------------------------|
| GREEK    | Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 |
| Hits@1    | 76.1   | 50.5   | 59.9   | 76.3   | 73.7   | 64.5   | 74.4   | 64.4   | 43.4   | 37.6   |
| Hits@3    | 22.7   | 19.4   | 7.7    | 19.8   | 2.3    | 12.5   | 4.5    | 12.5   | 0.8    | 0.2    |
| Hits@10   | 26.9   | 21.8   | 4.2    | 21.8   | 1.9    | 17.4   | 1.9    | 17.4   | 0.1    | 0.1    |

Table 4: Entity and relation alignment Performance of Models on Five languages

| Relation Alignment(<500) | Relation Alignment(>500) | Entity Alignment |
|--------------------------|--------------------------|-----------------|
| Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 |
| KGUNION | 19.8 | 28.7 | 42.8 | 66.5 | 23.5 | 42.8 |
| ALIGNKGK (Asymmetric) | 27.8 | 39.8 | 53.5 | 72.7 | 38.3 | 55.8 |
| ALIGNKGK (Soft Asymmetric) | 27.2 | 38.7 | 66.9 | 75.0 | 40.7 | 57.4 |
| AlignedGNN | 26.6 | 37.6 | 68.8 | 76.5 | 45.3 | 61.9 |

5 Related work

5.1 KBC

KBC through learning embeddings for KG artifacts is a densely-populated research landscape. Among the best performers are ComplEx (Jain et al., 2020; Trouillon et al., 2016), ConvE (Dettmers et al., 2018), and RotatE (Sun et al., 2019). Almost all such systems are designed for a single KG, or are agnostic to the language used in entity and relation aliases.

5.2 KG alignment

Although more recent interest in KG alignment is rapidly growing. MTransE (Chen et al., 2017), as the name suggests, uses TransE (Bordes et al., 2013) on each KG separately, and adds a loss term that penalizes large distance between embeddings of equivalent entities. BootEA (Sun et al., 2018) finds entity embeddings in their respective KGs and estimates a probability of equivalence by comparing their embeddings. This probability is then used for a semi-supervised bootstrapping of equivalent pairs. JAPe (Sun et al., 2017) builds attribute- and network neighborhood-based embeddings of entities and combines them with EA constraints. MuGNN (Cao et al., 2019) uses a graph neural network (GNN) to embed entities informed by entailment constraints of the form \((s, r, o) \Rightarrow (s, r', o) / s, o\). These constraints appear to be manually provided and are the only KBC mechanism. Afterward, tied GNNs obtain node embeddings which are compared to propose \(\equiv\) links. AliNet (Sun et al., 2020) is another GNN-based EA system. It uses an attention mechanism over larger node neighborhoods to build node representations. MultiKE (Zhang et al., 2019) is perhaps the only work that treats entity and relation alignments at par and combines multiple views to make decisions. However, they use relation names rather than their structural subject-object summaries. JEANS (Chen et al., 2021) is distinctive in that it links (‘grounds’) a text corpus to entities and uses TransE (Bordes et al., 2013) for the KG, skip-grams for the text, with additional alignment constraints as usual. BERT-INT (Tang et al., 2020) is another EA system that combines mBERT-obtained features from entity aliases and text descriptions with soft 1-hop graph neighborhood matching.

Except MultiKE, most systems focus on EA, assuming RA is unnecessary, or already accomplished. Chen et al. (2020) state so explicitly. At a high level, EA is a component of ALIGNKGK, and the precise EA method used is orthogonal to ALIGNKGK itself.

6 Conclusion

We have presented ALIGNKGK, a system that jointly learns to complete multiple KGs (KGC) and align their entities and relations. KGC and entity alignment were known tasks, but relation alignment was, to our knowledge, never integrated with them. In extensive experiments, ALIGNKGK significantly improves KGC accuracy, as well as
alignment scores, underscoring the value of joint alignment and completion.

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