Canonicalizing Open Knowledge Bases with Multi-Layered Meta-Graph Neural Network

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Abstract
Noun phrases and relational phrases in Open Knowledge Bases are often not canonical, leading to redundant and ambiguous facts. In this work, we integrate structural information (from which tuple, which sentence) and semantic information (semantic similarity) to do the canonicalization. We represent the two types of information as a multi-layered graph: the structural information forms the links across the sentence, relational phrase, and noun phrase layers; the semantic information forms weighted intra-layer links for each layer. We propose a graph neural network model to aggregate the representations of noun phrases and relational phrases through the multi-layered meta-graph structure. Experiments show that our model outperforms existing approaches on a public datasets in general domain.

1 Introduction
Open Knowledge Bases (Open KBs) do not require specification of ontology or relational schema, and thus can easily adapt to new domains or new data. They were named for being constructed by open information extraction (Open IE) systems such as ReVerb [Fader et al., 2011], OLLIE [Saha, 2017], and many others [Angeli et al., 2015; Stanovsky et al., 2018]. However, Galárraga et al. [2014] argue that the noun phrases (NPs) and relational phrases (RPs) in Open KBs are often not canonical as they may have various forms and can hardly be linked to standard KBs (e.g., Freebase, Wikipedia). For example, “CIFS (Common Internet File System)” is a general-purpose information-sharing protocol formerly known as “SMB (Server essage Block)”; however, Open KBs may often treat them as totally different NPs directly. The problem of canonicalization is to group NPs (those referring to the same entity) and RPs (those having the same semantic meaning) in the given Open KBs.

Existing methods use text embedding algorithms [Pennington et al., 2014; Mikolov et al., 2013] assuming that the NPs (RPs) with similar contexts or similar surface forms, e.g., “city_of_chicago” and “chicago_area”, “be_bear_in” and “be_bear_at”, can be grouped together. The semantic embeddings perform better than feature engineering methods [Vashishth et al., 2018]. However, as the examples in Fig. 1, (a) the NPs or RPs may look different but actually they refer to the same thing in the two tuples: (“CIFS”, “be_formally_known_as”, Server_Message_Block) and (“SMB”, “stand_for”, Server_Message_Block); (b) the same surface may refer to different things: (“Clinton”, “be_bear_in”, Arkansas) and (“Clinton”, “be_bear_in”, Illinois). We argue that a better sense of the NP/RP ambiguity needs integration of (1) sentence-to-tuple-to-phrase structural information and (2) semantic information of contexts.

We conduct the Open KB as a three-layered graph (see Fig. 1). The layers from bottom to top are of NP nodes, RP nodes, and sentence nodes. The structural information forms inter-layer links connecting NPs to the RP (with attributes “subject” and “object” as a tuple) and RPs to the sentences. The semantic information forms intra-layer links for each layer, weighted by the semantic similarity between the nodes. The semantic embedding can be obtained from GloVe, language models, or some open IE methods. In such three-layered knowledge graph, distinguishing (dis-)similar nodes for a given node is essential for canonicalization problem. Therefore we propose a novel structure, called multi-layered meta-graph, to collectively sample (dis-)similar nodes for Open KB canonicalization.
A multi-layered meta-graph is an induced sub-graph of inter-layer and intra-layer links. Various meta-graph can be defined, while a basic meta-graph is composed of all the nodes and links from two Open KB relation tuples. The (dis-)similar nodes can be selected and sampled via multi-layered meta-graph structures. For example (see Fig. 1), the meta-graph connecting “CIFS” and “SMB” has high positive weights on intra-layer links between sentences, RPs, and NPs – it indicates similarity; the meta graph connecting the two “Clinton” nodes has high positive weights on sentence and RP links but negative weights on the NP-NP link – it indicates dissimilarity. Note that most of the meta graphs are not strong indicators.

We propose a new graph neural network model, multi-layered meta-graph neural network (MGNN), to learn canonical embedding based on semantic information (induced into semantic embedding) and structural information (induced into meta-graph). Two phrases (i.e., NPs or RPs) of the similar canonical embeddings should be grouped together. Given one NP or RP, MGNN first concatenates the embeddings of its similar NPs or RPs sampled based on semantic embedding similarity and meta-graph structures. MGNN then aggregate these sampled nodes with a non-linear weighted transform of the concatenated embedding to update the canonical embedding of the target NP or RP node. The learning process is unsupervised, and we introduce a hybrid loss function to guide MGNN for effective canonical embedding learning.

We conduct experiments on a public Open KB (from Re-Verb) [Fader et al., 2011]. Results show that our model outperforms existing approaches on OpenKB canonicalization.

3 The Proposed Model

The model design of our proposed multi-layered meta-graph neural network (MGNN) is shown in Fig. 2. Open KBs are represented as multi-layered graphs. The structural information forms inter-layer links and the semantic information forms intra-layer links. MGNN learns the node’s canonical embeddings through the graph neural architecture, guided by semantic information (induced into semantic embedding) and structural information (induced into meta-graph). After that, we apply Hierarchical Agglomerative Clustering (HAC) [Tan et al., 2006] on the learned canonical embeddings of NPs and RPs to obtain the canonicalization for Open KBs.

3.1 Multi-Layered Graph for Open KBs

We use multi-layered graph instead of the traditional relational graphs (flatten network of entities) to represent Open KBs: \( G = \{ L_1, L_2, L_3, E_{1,2}^{subj}, E_{1,2}^{obj}, E_{2,3} \} \). \( L_i \) denotes the \( i \)-th layer (from bottom to top). All the three layers have
fully linked intra-layer links, inducing the semantic information from pre-learned semantic embeddings (e.g., word2vec, GloVe). \( E_{i,j} \) denotes the inter-layer links. We use \( v^x \) represents the corresponding node of relation tuple unit \( x \) (e.g., \( \{s, r, e_{\text{subj}}, e_{\text{obj}}\} \)), and \( v^y \) is to denote the semantic embedding of \( v^x \). \( V_X \) is to denote the nodes sets for \( X \), where \( X \) is a set of NPs, RPs or sentences from \( S, R \) or \( E \).

The first layer \( L_1 = \{V_c, E_{c,c}\} \) for NP nodes. An intra-layer link \( (v'^i, v'^j) \) exists between any two NP nodes \( v'^i \) and \( v'^j \). And the weight of the intra-layer link is defined as \( \Phi(v'^i, v'^j) = v'^i \cdot v'^j \).

The second layer \( L_2 = \{V_R, E_{R,R}\} \) for RP nodes. An intra-layer link \( (v'^r, v'^j) \) exists between any two RP nodes \( v'^r \) and \( v'^j \), and the link weight is \( \Phi(v'^r, v'^j) = v'^r \cdot v'^j \).

The third layer \( L_3 = \{V_S, E_{S,S}\} \) for sentence embeddings. An intra-layer link \( (v'^s, v'^s) \) exists between any two sentence nodes \( v'^s \), \( v'^s \). The link weight is \( \Phi(v'^s, v'^s) = v'^s \cdot v'^s \).

Between layers, we have sets of inter-layer links, where \( E_{1,2} = \{(v'^s, v'^r) | (s, r, e_{\text{subj}}, e_{\text{obj}}) \in D\}, E_{2,3} = \{(v'^r, v'^s) | (s, r, e_{\text{subj}}, e_{\text{obj}}) \in D\} \).

Note that two NPs of the same surface form (e.g., “Clinton”) are considered as two different nodes. So, one NP node connects only to one RP node in \( G \). For semantic embeddings, we use bag-of-words followed by SVD for sentences, GloVe for NPs (average vector for phrase), and BERT [Devlin et al., 2019] for RPs (average vector for phrase), and then do the normalization for all vectors.

### 3.2 Multi-Layered Meta Graph

We define a new graph structure, called multi-layered meta graph (simply named as meta-graph), which is used to sample (dis-)similar nodes for a given NP/RP node. These (dis)similar nodes will be utilized to aggregate their features for canonical embedding learning and canonicalization. For convenience, we first define that \( E_{G} = E_{1,2} \cup E_{2,3} \cup E_{3,2} \cup E_{E,E} \cup E_{R,R} \cup E_{S,S} \).

**Basic meta-graph.** As shown in Fig. 3, a basic meta-graph is composed of all the nodes and links from two Open KB relation tuples. Therefore a basic meta-graph is defined as \( G = (V, (V(V))) \) where \( V = \{v'^s_1, v'^s_2, v'^r_1, v'^r_2, v'^{subj}_1, v'^{subj}_2, v'^{obj}_1, v'^{obj}_2, v'^{obj}_3\} \).

**NP meta-graph.** For a pair of NP nodes (green), an NP meta-graph is an extension of basic meta-graph for multiple relevant sentences. Formally, given a pair of NP as subjects in certain tuples \( e_{\text{subj}}^{1}, e_{\text{subj}}^{2} \), suppose the corresponding RP are \( r_1, r_2 \). The NP meta-graph is defined as \( G_{1,2} = (VNP, \Delta(VNP)) \), where \( VNP = V_{S1} \cup V_{S2} \cup \{v'^s_1, v'^s_2, v'^{subj}_1, v'^{subj}_2, v'^{obj}_1, v'^{obj}_2, v'^{obj}_3\} \). For a pair of object nodes, \( VNP = V_{S1} \cup V_{S2} \cup \{v'^r_1, v'^r_2, v'^{subj}_1, v'^{subj}_2, v'^{obj}_1, v'^{obj}_2, v'^{obj}_3\} \), and so \( G_{1,2} = (VNP, \Delta(VNP)) \).

We simply write the NP meta-graph as \( G_{1,2} = (VNP, \Delta(VNP)) \) where \( VNP = V_{S1} \cup V_{S2} \cup \{v'^s_1, v'^s_2, v'^r_1, v'^r_2, v'^{subj}_1, v'^{subj}_2, v'^{obj}_1, v'^{obj}_2, v'^{obj}_3\} \) for later use.

**RP meta-graph.** For a pair of RP nodes (orange), the RP meta-graph includes all the relevant NP nodes and sentence nodes. Formally, suppose the RP pair are \( r_1 \) and \( r_2 \). The RP meta-graph is defined as \( G_{1,2} = (VNP, \Delta(VNP)) \), where \( VNP = V_{S1} \cup V_{S2} \cup \{v'^s_1, v'^s_2, v'^r_1, v'^r_2, v'^{subj}_1, v'^{subj}_2, v'^{obj}_1, v'^{obj}_2, v'^{obj}_3\} \).

**3.3 Phrase (Node) Pair Sampling via Meta-Graph**

In this section, we define the canonical weight \( \Psi(e_1, e_2) \) between a pair of phrases (NP/RP nodes in graph) using their meta-graphs. Higher canonical weight means higher probability to group the phrase (node) pair together. Given a pair of NP nodes \( v'^s_1 \) and \( v'^s_2 \) with the NP meta-graph \( G_{1,2} \). We define the canonical weight as the mean of the link weight between the sentence node sets \( V_{S1} \) and \( V_{S2} \), RP nodes \( (v'^r_1 \) and \( v'^r_2 \)), and NP nodes \( (v'^s_1 \) and \( v'^s_2 \)):

\[
\Psi(v'^s_1, v'^s_2) = \frac{1}{4} \left( \Phi(V_{S1}, V_{S2}) + \Psi(v'^r_1, v'^r_2) + \Phi(v'^s_1, v'^s_2) \right)
\]

(1) where \( \Psi(\cdot) \) is the canonical weight function and the link weight between two sentence sets is defined as follows,

\[
\hat{\Phi}(V_{S1}, V_{S2}) = \frac{\sum_{s_1 \in S1} \sum_{s_2 \in S2} \psi(v'^s_1, v'^s_2)}{|S1| \cdot |S2|}.
\]

(2)

On the other hand, given a pair of RP nodes \( v'^r_1 \) and \( v'^r_2 \), with the RP meta-graph \( G_{1,2} \). The canonical weight between the RP nodes is:

\[
\Psi(v'^r_1, v'^r_2) = \frac{1}{4} \left( \Phi(V_{S1}, V_{S2}) + \Phi(v'^r_1, v'^r_2) \right)
\]

(3)

where \( \Phi(V_{S1}, V_{S2}) \) is defined same as \( \Phi(V_{S1}, V_{S2}) \) by replacing \( S_i^1 \) with \( S_i^j \) (i = 1, 2). The link weight between two NP sets is defined as:

\[
\hat{\Phi}(V_{E1}, V_{E2}) = \frac{\sum_{e_1 \in E1} \sum_{e_2 \in E2} \psi(v'^s_1, v'^s_2)}{|E1| \cdot |E2|}.
\]

(4)
Next we discuss about finding negative phrase pairs for negative sampling in modeling training process. For example, the two NPs “Clinton” actually refer to different persons. In their NP meta-graph, we find that the intra-layer links on sentences, RPs, and subject NPs are positively high but the link between the object NPs (“Arkansas” and “Illinois”) is negative. So we define the negative canonical probability for a pair of NP nodes $v^1$ and $v^2$, where higher one means higher probability of NPs referring to different things:

$$
\Psi^{-}(v^1, v^2) = \sigma \left( -2 \cdot \Phi(v^1, v^2) \right),
$$

(5)

where we use $\Psi^{-}(\cdot)$ as a function to negative canonical probability and $\sigma$ is a sigmoid function. Given a meta-graph of a NP pair (e.g., both as subjects), when we found extremely high similarity in sentence pair and RP pair while extreme low similarity in the other NP pair (both as objects), it indicates high probability of the NP pair referring to different things (i.e., negative NP pair).

Similarly, given the RP meta-graph of $v^1$ and $v^2$, the function to negative canonical probability is

$$
\Psi^{-}(v^1, v^2) = \sigma \left( \frac{-2 \min(\Phi(v^1, v^2), \Phi(v^2, v^1))}{\max(\Phi(v^1, v^2), \Phi(v^2, v^1))} \right).
$$

(6)

**Complexity analysis.** It takes $O(N^2)$ time to compute canonical weights of all NP pairs and RP pairs. In practice, we first sort the similarity between sentences, RPs and NPs. Then we adopt early-stop strategy to refuse to calculate the canonical weight of the rest pairs. It cost a reasonable time in fact even has $O(N^2)$ time complexity.

### 3.4 Canonical Embedding Aggregation in Multi-Layered GNN

We extend GraphSAGE [Hamilton et al., 2017], a sampling and aggregation-based GNN model to the multi-layered graph settings. Given a phrase $x \in E \cup R$ along with its node $v^x \in V_E \cup V_R$, we initialize the canonical embedding with the semantic embedding:

$$
h^0_{y^x} \leftarrow v^x.
$$

(7)

The next step is to weighted sample a set of $v^x$’s “neighboring nodes” $N(v^x) = N^{\text{meta}}(v^x) \cup N^{\text{intra}}(v^x)$, where $N(v^x)$ includes the node samples from both the meta-graph based canonical weight distribution (obtained by $\Psi(v^x, \cdot)$) and intra-layer weight distribution (obtained by $\Phi(v^x, \cdot)$).

Suppose $h^{k-1}_{y^x}$ is the canonical embedding of node $v^x$ at the (k-1)-th GNN layer and the neighboring feature vector at the k-th layer and the neighboring feature vector at the k-th layer, and to multiply with a weighted matrix $W^k = W^{2d \times d}$ if $k = 1$; otherwise, $W^k \in \mathbb{R}^{2d \times d}$, do a non-linear transform with $\sigma$ and normalization.

$$
h^k_{y^x} = \sigma \left( W^k \cdot \text{CONCAT}(h^{k-1}_{y^x}, h_{N(v^x)}) \right),
$$

(10)

$$
h^k_{y^x} = h^k_{y^x} / \|h^k_{y^x}\|_2.
$$

After $K$ iterations, the final canonical embedding is denoted by $z^x \equiv h^K_{y^x}$. Finally, we apply the Hierarchical Agglomerative Clustering (HAC) on $z^x \in E \cup R$ for open KB canonicalization.

### 3.5 Hybrid Loss in Multi-Layered GNN

We introduce the loss function to supervise the multi-layered GNN for effective canonical embedding learning. To design the loss, we have the following assumptions: (1) As defined before, a pair of phrases, either NPs or RPs, would have similar canonical embeddings if they have high canonical weight $\Psi(v^1, v^2)$, $\Psi(v^2, v^1)$, because the meta-graph structure supports their grouping. (2) A pair of phrases should have dissimilar canonical embeddings if they have high negative canonical probability $\Psi^{-}(v^1, v^2)$, $\Psi^{-}(v^2, v^1)$, because the meta-graph structure supports the separation. (3) Besides the meta-graph structures, intra-layer link weights on $L_1$ or $L_2$ (semantic similarity) indicate the grouping/separation: positive, high link weight indicates grouping and thus similar canonical embeddings, and negative, low link weight indicates separation and dissimilar canonical embeddings. (4) Due to the phrase ambiguity, the pure semantic similarity is not as trustworthy as the meta-graph structure, and thus generates high recall but low precision. So, if we find four sets of phrase pairs:

- $D_{\text{meta},+}$: its phrase pairs $(x, y)$ have high canonical weight $\Psi(v^x, v^y)$;
- $D_{\text{meta},-}$: its phrase pairs $(x, y)$ have high negative canonical probability $\Psi^{-}(v^x, v^y)$;
- $D_{\text{intra},+}$: its phrase pairs $(x, y)$ have positive, high semantic similarity $\Phi(v^x, v^y)$;
- $D_{\text{intra},-}$: its phrase pairs $(x, y)$ have negative, low semantic similarity $\Phi(v^x, v^y)$.

We define a hybrid loss function as follows, which will be minimized to train the parameters (i.e., aggregation and matrix $W^k$) of MGN model:

$$
\mathcal{L} = \alpha \mathcal{L}_1 + \beta \mathcal{L}_2 + (1 - \alpha - \beta) \mathcal{L}_3
$$

(11)

where $\alpha$ and $\beta$ are hyper-parameters and

$$
\mathcal{L}_1 = \sum_{(x_1, y_1) \in D_{\text{meta},+}} \max(0, z^{x_1} \cdot z^{y_2} - z^{x_2} \cdot z^{y_1} + \gamma_1),
$$

$$
\mathcal{L}_2 = \sum_{(x_1, y_1) \in D_{\text{meta},-}} \max(0, z^{x_1} \cdot z^{y_2} - z^{x_2} \cdot z^{y_1} + \gamma_2),
$$

$$
\mathcal{L}_3 = \sum_{(x_1, y_1) \in D_{\text{intra},+}} \max(0, z^{x_2} \cdot z^{y_1} - z^{x_1} \cdot z^{y_2} + \gamma_3),
$$

where $\gamma_i$ ($i = 1, 2, 3$) are hyper-parameters.
4 Experiments

4.1 Experimental Setup

Datasets
ReVerb45K [Vashishth et al., 2018] has 45K relation tuples, 89K NPs, 21.6K RPs, and 106.4K sentences. The gold entities were obtained by linking NPs in the tuples to Freebase, resulting 7.5K gold entities. However, the dataset has no gold relation for canonical RPs. So we do quantitative analysis for NP canonicalization and qualitative analysis for RP canonicalization. We randomly sampled 20% entities and used the associated tuples as the validation set. And the rest of the data was used for both unsupervised learning and test (i.e., test set).

Evaluation Metrics
Following [Galárraga et al., 2014; Vashishth et al., 2018], we use macro-, micro- and pairwise metrics for evaluating Open KB canonicalization methods. In all cases, F1 measure is given as the harmonic mean of precision and recall.

Baseline Methods
For NP canonicalization, we compare MGNN with the following competitive methods:

- **Morphological Normalization** [Fader et al., 2011] applies normalization operations; **Paraphrase Database** (PPDB) grouped two NPs together if they share a common paraphrase in PPDB 2.0 [Pavlick et al., 2015];
- **Galárraga** [Galárraga et al., 2014] used IDF token similarity, Jaro-Winkler similarity metric and Attribute Overlap respectively, along with hierarchy clustering method to canonicalize OpenKB.
- **GloVe** [Pennington et al., 2014] method represented NPs with pre-trained embeddings;
- **HoIE** [Nickel et al., 2016] has been successfully applied for link prediction in KBs;
- **CESI** [Vashishth et al., 2018] is a novel side information based embedding learning method for canonicalizing Open KBs. CESI solves a joint objective to learn noun and relation phrase embeddings, while utilizing relevant side information in a principled manner. CESI is now the state-of-the-art method on Open KB canonicalization. HoIE is the main architecture of CESI, so we denote CESI as HoIE + Side Info.

4.2 Results on ReVerb45K

Overall Performance
Table 1 shows that the proposed MGNN outperforms all the competitive methods on the average result of the three evaluation metrics (i.e., macro-, micro- and pairwise-F1 score). Compared to GloVe, MGNN improves average F1 score relatively by 2.4% (by 1.4% on macro, by 0.6% on micro, and by 5.2% on pairwise, respectively). Investigating actual number of gold entities and precision/recall, MGNN successfully finds 225 more gold entities than GloVe and assigns 584 more NPs to the correct clusters. It significantly improves the precision of pairwise prediction (by 11.7%). HoIE only uses structure information to update embeddings, weakening the use of semantic information in Open KBs. Semantic embeddings (GloVe) are more effective to do NP canonicalization than HoIE. MGNN model performs the best on NP canonicalization in ReVerb45K.

The feature-based methods by Galárraga et al. [2014] have competitive macro-F1 score but extremely low pairwise-F1. This is because most of the gold entities have very few NPs in the ReVerb45K, so they can be captured by the feature-based methods. These methods missed the gold entities that were frequently mentioned in the corpus like person names. Another reason is that ReVerb45K has a considerably larger number of entities and a comparatively smaller number of relation tuples (89K vs 45K). These methods are more likely to put two NPs together if they share an uncommon token. So, the accuracy relies heavily on the quality of document frequency estimation though we may have a small number of tuples.

Side information could be useful as shown in previous work [Vashishth et al., 2018], including WordNet, PPDB, and information obtained from entity linking and morph normalization. We implement a MGNN model equipped with the side information. It improves average F1 score relatively by 2.6% over CESI (which is HoIE being equipped with the side information). The MGNN model achieves a significantly bigger macro-F1 score (by +6.4% over the best baseline). The MGNN achieves new state-of-the-art on ReVerb45K Open KB canonicalization.

Ablation Study
Table 2 compares the variants of the proposed model to evaluate the effectiveness of the following components: (1) **meta-graph based hybrid loss**, by discarding one of the three loss terms $L_i (i = 1, 2, 3)$; (2) **meta-graph based canonical embedding aggregation**, by removing the meta-graph based neighbor set $N^\psi$ in MGNN; (3) **graph neural network architecture**, by discarding GNN and only using the proposed loss function to update semantic embeddings.

| Methods                  | Macro | Micro | Pair | Aver. |
|-------------------------|-------|-------|------|-------|
| Galárraga-Attr           | 75.1  | 20.1  | 0.2  | 31.8  |
| Galárraga-StrSim         | 69.9  | 51.7  | 0.5  | 40.7  |
| Galárraga-IDF            | 71.6  | 50.8  | 0.5  | 41.0  |
| Morph Norm               | 1.4   | 77.7  | 75.1 | 51.4  |
| PPDB                    | 46.0  | 45.4  | 64.2 | 51.9  |
| HoIE (Random)           | 5.4   | 74.6  | 50.9 | 43.6  |
| HoIE (GloVe)            | 33.5  | 75.8  | 51.0 | 53.4  |
| GloVe                  | 56.3  | 81.8  | 77.0 | 71.7  |
| MGNN (Ours)             | 57.1  | 82.3  | 81.0 | 73.5  |
| HoIE (GloVe) + Side Info| 62.7  | 84.4  | 81.9 | 76.3  |
| MGNN + Side Info (Ours) | 66.7  | 86.3  | 81.2 | 78.3  |

Table 1: The MGNN model performs the best on NP canonicalization in ReVerb45K.
Table 2: Ablation study on the MGNN model.

| Loss Term | Macro | Micro | Pair | Average |
|-----------|-------|-------|------|---------|
| MGNN      | 57.1  | 82.3  | 81.0 | 73.5    |
| w/o loss $L_1$ | 56.1  | 81.0  | 79.5 | 72.2    |
| w/o loss $L_2$ | 41.3  | 74.6  | 68.4 | 61.4    |
| w/o loss $L_3$ | 55.8  | 80.9  | 79.3 | 72.0    |
| w/o loss $L_1, L_3$ | 54.9  | 80.3  | 77.6 | 70.9    |
| w/o $N^w$ | 53.1  | 80.2  | 77.0 | 70.1    |
| w/o GNN    | 58.3  | 79.1  | 69.5 | 69.0    |

Table 3: RP canonicalization cases on ReVerb45K.

Two pure RP clusters

{announce acquisition of, acquire the asset of, announce purchase of, become sole owner of, buy control interest in, announce takeover of}

{be the national language of, be the language of, be the primary language use in, be speak in, be the main language of, be an official ...}

Two impure RP clusters

{be an citizen of, may have be bear in, have grow up in, have be bear in}

{be president of, be crown king of, become leader of, become prime minister of}

Table 3: RP canonicalization cases on ReVerb45K.

MGNN may be confused by relevancy: “be a citizen of” and “have grow up in” refer to relevant but not the same relation. Grouping “be president of” and “become prime minister of” is wrong though makes some sense. This needs to be addressed in future work.

5 Related Work

Open IE: OpenIE systems extend information extraction to open domains without requiring any relation-specific schema in advance [Fader et al., 2011; Angeli et al., 2015; Stanovsky et al., 2018; Jiang et al., 2019]. ReVerb [Fader et al., 2011] restricted the relation to verbal phrases. Early systems prefer to apply rule-based techniques to extract fact tuples [Angeli et al., 2015]. Stanovsky et al. [2018] obtained labeled OpenIE data from semantic role labeling.

KB Canonicalization and Entity Linking: Ontological KB canonicalization has been studied for long [Krishnamurthy and Mitchell, 2011; Pujara et al., 2013]. Concept Resolver took use of the “one sense per category” assumption which states that an entity mention refers to at most one concept in ontology [Krishnamurthy and Mitchell, 2011]. Knowledge Graph Identification is to produce a consistent Knowledge Graph by performing entity resolution, entity classification, and link prediction jointly [Pujara et al., 2013]. Pujara et al. [2013] incorporated multiple extraction sources and ontological information to infer the most probable knowledge graph. These approaches require additional information in the form of an ontology of relations, which is not available for Open KB. For Open KB canonicalization, Galárraga et al. [2014] performed entity mention canonicalization over manually-defined feature spaces. Wu et al. [2018] speeded up the canonicalization methods in practice. Entity linking and named entity disambiguation aim at mapping entity mention to an existing KB such as Wikipedia or Freebase. Most approaches [Sil et al., 2018; Raiman and Raiman, 2018; Murty et al., 2018; Ng, 2017] generated a list of candidate entities for each entity mention and re-rank them.

Meta-Graph Analysis: Zhao et al. [2017] first introduced the concept of meta-graph to heterogeneous information network to build recommender systems. They used meta-graph as features to measure the node similarity. Yang et al. [2018] used meta-graph to learn the embedding of nodes in heterogeneous information networks. Most previous studies used meta-graph as a feature. We use meta-graph as an important structure indicating canonical properties in a multi-layered graph representation of Open KB.

6 Conclusions

We proposed a multi-layered meta-graph based graph neural network model (MGNN) for Open KB canonicalization. MGNN integrates semantic information (intra-layer links) and structural information (inter-layer links) through canonical embedding aggregation. It adapted a meta-graph based neighbor acquisition and learned node canonical embedding with meta-graph based hybrid loss. Our model outperforms baselines on a general Open KB dataset.
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