Type-augmented Relation Prediction in Knowledge Graphs

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Abstract

Knowledge graphs (KGs) are of great importance to many real world applications, but they generally suffer from incomplete information in the form of missing relations between entities. Knowledge graph completion (also known as relation prediction) is the task of inferring missing facts given existing ones. Most of the existing work is proposed by maximizing the likelihood of observed instance-level triples. Not much attention, however, is paid to the ontological information, such as type information of entities and relations. In this work, we propose a type-augmented relation prediction (TaRP) method, where we apply both the type information and instance-level information for relation prediction. In particular, type information and instance-level information are encoded as prior probabilities and likelihoods of relations respectively, and are combined by following Bayes' rule. Our proposed TaRP method achieves significantly better performance than state-of-the-art methods on three benchmark datasets: FB15K, YAGO26K-906, and DB111K-174. In addition, we show that TaRP achieves significantly improved data efficiency. More importantly, the type information extracted from a specific dataset can generalize well to other datasets through the proposed TaRP model.

1 Introduction

Knowledge graphs (KGs) have gained significant popularity due to successful applications to many different AI tasks such as question answering (Huang et al. 2019), recommendation (Wang et al. 2019), dialogue generation (Xu, Bao, and Zhang 2020), and scene graph generation (Zareian, Karaman, and Chang 2020). However, KGs are generally incomplete and suffer from missing relations between entities (Socher et al. 2013; West et al. 2014). The task of knowledge graph completion or relation prediction is aimed at tackling this issue, i.e., inferring missing facts given existing ones. For example, in Figure 1, given two entities, e.g., Helen_Mirren and The_Queen, the relation prediction task predicts if those entities are connected by any of the existing relations in the KG, e.g., actor.

Relation prediction methodologies are mostly based on KG embeddings, and can primarily be categorized based on the two kinds of information they use from KGs: (i) Instance-level information, i.e., existing triples connecting entities through relations, such as Helen_Mirren

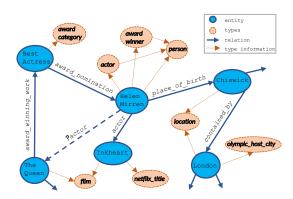


Figure 1: An example in a knowledge graph (KG).

 \rightarrow place_of_birth \rightarrow Chiswick; and (ii) Ontological information, i.e., meta information about entities and relations, such as the type information of entities e.g., Helen_Mirren is of types {actor, award_winner, person \}. The majority of existing methods use merely instancelevel information for learning the embeddings (Sun et al. 2019; Zhang et al. 2019), while a few other models use both instance-level information and ontological information (Hao et al. 2019; Garg et al. 2019; Xie et al. 2016). Ontological information such as type information can intuitively help relation prediction, as most relations may connect two distinct types of entities as domain and range. For example, the relation place_of_birth always connects entities of type *person* to entities of type *location*. Integrating such type information into instance-level training triples can benefit the relation prediction task, in particular when there is a lack of sufficient training data for learning embeddings.

A few existing embedding based models with such type information integrated have shown success (Guo et al. 2015; Xie, Liu, and Sun 2016; Ma et al. 2017; Garg et al. 2019; Hao et al. 2019). However, these models integrate the ontological information through the model training procedure for better learning the embeddings, and are hence prone to the following drawbacks: (i) the type information is not explicitly differentiated from the instance-level information, and a single set of model parameters are learned by considering

two kinds of information jointly; (ii) the type information is tightly encoded into the objective function, making the integration highly reliant on the training procedure and hence less flexible in augmenting new embedding techniques. We refer to such integration procedures as *feature-level integration*. Instead, we proposed an effective *decision-level integration*: given the type information and instance-level information encoded as prior probabilities and likelihoods respectively, the proposed decision-level integration combines the two kinds of information by following Bayes' rule.

In this paper, we propose a simple but effective framework to augment existing embedding based models with type information. The contributions of our work are as follows:

- The proposed decision-level integration framework is independent of the embedding based model, and can be flexibly applied for augmenting different embedding based models without additional training.
- The proposed type-augmented relation prediction (TaRP) method achieves better relation prediction performance than state-of-the-art models on three benchmark datasets. Furthermore, we show that by incorporating the type information, TaRP has less dependency on training data, and thus is more data efficient.
- We empirically demonstrate that the type information extracted from a specific dataset can generalize well to other, different datasets through the proposed TaRP model.

2 Related Work

KG embedding based methods have been widely explored for the KG completion task. The general methodology of the embedding based method is to define a score function for triples within a continuous embedding space. The score function usually takes the form $f_r(\mathbf{e}_h, \mathbf{e}_t)$, where $\mathbf{e}_h, \mathbf{e}_t$ are head and tail entity embeddings. The score function measures the salience of a candidate triple (e_h, r, e_t) , and embeddings of entities and relations are learned by optimizing the score function. TransE (Bordes et al. 2013) represents entities and relations in d-dimensional vector space, i.e., $\mathbf{e}_h, \mathbf{e}_r, \mathbf{r} \in \mathbb{R}^d$ and learns the embeddings by assuming the translation principle $\mathbf{e}_h + \mathbf{r} \approx \mathbf{e}_t$ with the proposed score function $f_r(\mathbf{e}_h, \mathbf{e}_t) = -||\mathbf{e}_h + \mathbf{r} - \mathbf{e}_t||$. Along the lines of the translation-based methods (first introduced by TransE), many more advanced methods have been proposed, such as TransH (Wang et al. 2014) and TransD (Ji et al. 2015). More recently, RotatE (Sun et al. 2019) and QuatE (Zhang et al. 2019) have been proposed by representing the entities and relations using complex vectors. In addition, neural networks have also been introduced to learn robust embedding based models, such as ConvE (Dettmers et al. 2018) and HypER (Balažević, Allen, and Hospedales 2019). These methods learn embeddings based on instance-level information observed from existing triples, without considering the rich ontological information that exists.

There are existing embedding based methods that explore the usage of the ontological information. Dist-Mult (Yang et al. 2014) considered semantic similarity and associated related entities using Hadamard product of embeddings. Guo et al. (2015) proposed semantically

smooth embedding, where the type information is encoded as smoothness constraints. Ma et al. (2017) measured the type-based semantic similarity between entities and relations, and that semantic similarity served as the prior probability. Besides semantic types of entities, underlying hierarchy structures among types are also considered. Xie, Liu, and Sun (2016) proposed type-specific entity projections by applying hierarchical type information, and devised type-embodied knowledge representation learning (TKRL). Hao et al. (2019) introduced instance-view KG and ontology-view KG, and the hierarchy structures among types are explicitly represented within the ontology-view KG. Universal embeddings are then learned by considering the two types of KGs jointly. In addition, hierarchical type information is extracted as logical propositions for the quantum embeddings (Garg et al. 2019), and symbolic KGs are represented with embedding vectors in a logic structure preserving manner. Besides the type information, other ontological information is also explored. DKRL (Xie et al. 2016) applies entity descriptions, which are represented as vectors. SSP (Xiao et al. 2017) uses the topic distribution of entity descriptions to construct semantic hyperplanes. All of these models integrate the ontological information into the instance-level information at the feature-level in order to learn the embeddings better.

Besides embedding based methods, path based methods have also been proposed for thhe KG completion task, e.g., (Lao, Mitchell, and Cohen 2011; Das et al. 2016; Chen et al. 2018). Path based methods infer missing facts based on multi-hop paths going from the head entity to tail entity in KGs, and hence offer logical insights into the underlying KG. Type information is also explored in recent path based methods. Lei et al. (2019) proposed to utilize type semantics from the relation to obtain attention that constrains the semantics of the entity. Path based methods suffer from high computational cost because of the path finding procedure; in this paper, we focus on embedding based approaches.

3 Proposed Method

To leverage the type information of entities and relations in improving the relation prediction performance, we propose a type-augmented relation prediction (TaRP) approach. We firstly propose a prior model where we encode the type information as prior probabilities. The existing embedding based models are employed to model the data likelihood of relations based on existing instance-level triples. In the end, we integrate the type information into the embedding based models at the decision level.

3.1 Type Information Encoding

We propose a prior model where we encode the type information as prior probabilities. We denote a knowledge graph as $\mathcal{G} = \{\mathcal{E}, \mathcal{R}, \mathcal{T}\}$, where \mathcal{E}, \mathcal{R} and \mathcal{T} indicates the entity set, the relation set, and the type set respectively. We firstly collect the type set regarding to each entity $e \in \mathcal{E}$ and each relation $r \in \mathcal{R}$ separately. For each triple (e_h, r, e_t) , we then define the type-based prior probability of relation r condition on the entity pair (e_h, e_t) by measuring the semantic

similarity. In particular, the semantic similarity is calculated based on the correlation between type sets of entities and relations.

Type collection for entities and relations Types of entities usually have underlying hierarchy structures, such as the structure among types $\{actor, award_winner, person\}$ in Figure 1. To take such a hierarchy into the consideration, we propose to use the hierarchy-based type weights. Given entity e, its type set is denoted as T_e . A hierarchy structure among a subset of types is denoted as $H = \frac{t_1}{t_2} \frac{1}{\dots} \frac{t_k}{\dots} \frac{t_k}{\dots}$, where $t_k \in T_e$, K is the total number of hierarchy levels, t_K is the most specific semantic type, and t_1 is the most general semantic type. Instead of treating the types in the hierarchy H equally, we weight the types based on their locations in the hierarchy. The weight of type t_k regarding to hierarchy H of entity e is defined as,

$$w_e^H(t_k) = \frac{\exp(k-1)}{\sum_{j=0}^{K-1} \exp(j)}$$
(1)

Multiple hierarchical structures can exist for one entity with each hierarchy including a subset of types. For example, in Figure 1, entity $e = \texttt{Hellen_Mirren}$ has three hierarchical structures among its types: $H_1 = |\textit{person/actor}, H_2| = |\textit{person/award_winner}|$, and $H_3 = |\textit{person}|$. Type person is included in all three hierarchies. Following Eq.1, we have $w_e^{H_i}(\textit{person}) = 0.27, i = \{1,2\}$ and $w_e^{H_3}(\textit{person}) = 1$.

For each type $t \in T_e$, we calculate its hierarchy-based weight as $w_e(t) = \min(w_e^{H_1}(t), w_e^{H_2}(t), ..., w_e^{H_N}(t))$, where N is the total number of hierarchies containing type t. In the example above, we thus have $w_e(\textit{person}) = 0.27$, $w_e(\textit{actor}) = 0.73$, and $w_e(\textit{award_winner}) = 0.73$.

For the type sets of relation, we consider both the head type set $T_{r,head}$ and tail type set $T_{r,tail}$ defined as

$$T_{r,head} = \bigcup_{e \in \text{Head}(r)} T_e$$

$$T_{r,tail} = \bigcup_{e \in \text{Tail}(r)} T_e$$
(2)

where $\operatorname{Head}(r) = \{e_h | (e_h, r, e_t) \in \mathcal{G}, \forall e_t \in \mathcal{E}\}$ indicating the set of head entities of relation r, and $\operatorname{Tail}(r) = \{e_t | (e_h, r, e_t) \in \mathcal{G}, \forall e_h \in \mathcal{E}\}$ indicating the set of tail entities of relation r. Correspondingly, we calculate the type weights as

$$w_{r,head}(t) = \sum_{e \in \text{Head}(r)} w_e(t), \quad \text{for } t \in T_{r,head}$$

$$w_{r,tail}(t) = \sum_{e \in \text{Tail}(r)} w_e(t), \quad \text{for } t \in T_{r,tail}$$
(3)

Type-based prior probability Given a triple $(e_h, r, e_t) \in \mathcal{G}$, we measure the semantic similarity between entities and relations based on the correlation between their type sets. The similarity score $s(\cdot, \cdot)$ is calculated as

$$s(e_h, r) = \frac{\sum_{t \in T_{r,head} \cap T_{e_h}} w_{r,head}(t)}{\sum_{t \in T_{r,head}} w_{r,head}(t)}$$

$$s(e_t, r) = \frac{\sum_{t \in T_{r,tail} \cap T_{e_t}} w_{r,tail}(t)}{\sum_{t \in T_{r,tail}} w_{r,tail}(t)}$$

$$(4)$$

where $T_{r,head} \cap T_{e_h} = \{t | t \in T_{r,head} \text{ and } t \in T_{e_h}\}$ and $T_{r,tail} \cap T_{e_t} = \{t | t \in T_{r,tail} \text{ and } t \in T_{e_t}\}$, and $0 \le s(\cdot, \cdot) \le 1$. The prior probability $p(r | \mathcal{T}(e_h, e_r, \mathcal{R}))$ is then defined based on similarity scores as,

$$p(r|\mathcal{T}(e_h, e_t, \mathcal{R})) \triangleq \frac{s(e_h, r)s(e_t, r)}{\sum_{r' \in \mathcal{R}} s(e_h, r')s(e_t, r')}$$
 (5)

where $\mathcal{T}(e_h,e_t,\mathcal{R})$ denotes the type information related to the entity pair (e_h,e_t) and the relation set \mathcal{R} . To obtain a valid prior probability, for $\forall r \in \mathcal{R}$, both the head type set $T_{r,head}$ and the tail type set $T_{r,tail}$ are required to be non-empty. For the cases there the type set of an entity e is empty (e can be either head entity e_h or the tail entity e_t), i.e., $T_e = \emptyset$, we assign uniform similarity scores, i.e., $s(e,r') = 1, \forall r' \in \mathcal{R}$. Different from the existing work (Ma et al. 2017) that measures semantic similarity by treating each type equally, our type-based prior probability with hierarchy-based type weights encode not only the type information but also the underlying hierarchies among types.

 $|T_{r,head}|$ or $|T_{r,tail}|$ of relation r can be large containing long tail noisy types, which may weaken the relation prediction performance of the prior model. To remove noisy types, we introduce a threshold η . Type $t \in T_{r,*}$ will be kept if

$$w_{r,*}(t) \ge W_{r,*}^{min} + \eta \times (W_{r,*}^{max} - W_{r,*}^{min})$$
 (6)

where $W_{r,*}^{max}$ and $W_{r,*}^{min}$ are the maximum and the minimal weight of the type set $T_{r,*}$ respectively. If $w_{r,*}(t)$ is not sufficiently high(i.e., Eq.6 is not satisfied), type t will be removed from $T_{r,*}$ without further consideration. $*=\{\text{head, tail}\}$. Threshold η varies from datasets to datasets and is chosen based on the performance on the validation set.

3.2 Embedding Based Models

Embedding based models represent relations and entities in a continuous embedding space. We denote the embedding of the head and tail entities as \mathbf{e}_h and \mathbf{e}_t respectively. The embedding of relation r is \mathbf{r} . A score function $f_r(\mathbf{e}_h,\mathbf{e}_t)$ is usually defined as a measurement of the salience of a triple (e_h,r,e_t) . Embeddings are then learned by optimizing the score function based on existing instance-level triples. We consider three embedding based models:

• **TransE** (Bordes et al. 2013):

$$f_r(\mathbf{e}_h, \mathbf{e}_t) = -||\mathbf{e}_h \cdot \mathbf{r} - \mathbf{e}_t|| \tag{7}$$

where $\mathbf{e}_h, \mathbf{e}_r \in \mathbb{R}^d$ and $\mathbf{r} \in \mathbb{R}^d$.

• **RotatE** (Sun et al. 2019):

$$f_r(\mathbf{e}_h, \mathbf{e}_t) = -||\mathbf{e}_h \circ \mathbf{r} - \mathbf{e}_t|| \tag{8}$$

where $\mathbf{e}_h, \mathbf{e}_r \in \mathbb{C}^d$ and $\mathbf{r} \in \mathbb{C}^d$.

• **QuatE** (Zhang et al. 2019):

$$f_r(\mathbf{e}_h, \mathbf{e}_t) = -||\mathbf{e}_h \otimes \frac{\mathbf{r}}{|\mathbf{r}|} - \mathbf{e}_t||$$
 (9)

where $\mathbf{e}_h, \mathbf{e}_r \in \mathbb{H}^d$ and $\mathbf{r} \in \mathbb{H}^d$.

All of these three models concentrate on existing triples to learn embedding vectors without considering any type information. The learned embeddings thus only contain instance-level information observed from existing triples. For each triple (e_h, r, e_t) , we define the likelihood of relation based on their corresponding embeddings as

$$p(e_h, e_t|r) \triangleq \exp(f_r(\mathbf{e}_h, \mathbf{e}_t)) \tag{10}$$

It is intuitive that the likelihood of relation will be small with a low score $f_r(\mathbf{e}_h, \mathbf{e}_t)$.

3.3 Type Information Integration

In the end, we propose to integrate the type information into the embedding based models at the decision-level. Given a triple (e_h, r, e_t) , we obtain the prior probability of relation r based on the type information, i.e., $p(r|\mathcal{T}(e_h, e_t, \mathcal{R}))$. On the other hand, we obtain the likelihood of relation based on embeddings learned from existing triples, i.e., $p(e_h, e_t|r)$. Combining them together, we obtain the posterior probability of relation r by following the Bayes rule, i.e.,

$$p(r|e_h, e_t, \mathcal{T}(e_h, e_t, \mathcal{R})) \propto p(e_h, e_t|r)p(r|\mathcal{T}(e_h, e_t, \mathcal{R}))$$
(11)

The posterior probability $p(r|e_h, e_t, \mathcal{T}(e_h, e_t, \mathcal{R}))$ thus contains both the type information and the instance-level information. Different from existing work, e.g., (Ma et al. 2017; Xie, Liu, and Sun 2016), that integrates the type information at the feature-level, we propose to integrate the type information at the decision-level and our proposed integration approach is independent of the embedding based models.

4 Experiments

To evaluate the performance of our type-augmented relation prediction (TaRP) approach, we first perform ablation studies on the prior model; and then evaluate the performance of the TaRP model. We demonstrate the effectiveness of the TaRP model by comparing it to three baseline embedding based models: TransE, RotatE, and QuatE. In addition, we show that by incorporating type information, TaRP is much more data efficient than existing methods. Furthermore, we demonstrate the generalization ability of type information. In the end, we compare our approach to state-of-the-art models that also apply ontological information.

Datasets We consider three benchmark datasets for the relation prediction task: FB15K (Bordes et al. 2013), YAGO26K-906 (Hao et al. 2019) and DB111K-74 (Hao et al. 2019). FB15K is a popular benchmark dataset for the KG completion task, and its type information has been explored by most of the prior work, such as (Ma et al. 2017; Guo et al. 2015; Xie, Liu, and Sun 2016). YAGO26K-906 and DB111K-906 are two very recent datasets containing explicit ontological information, and have not been widely considered by related work.

FB15K consists of triples extracted from the FreeBase knowledge graph (Bollacker et al. 2008). The same type information is applied as introduced in (Xie, Liu, and Sun

2016) for FB15K¹. Both YAGO26K-906 and DB111K-174 contain two types of KGs: instance KG and ontology KG, which are connected to each other through type links. The instance KGs of YAGO26K-906 and DB111K-174 consist of triples extracted from the YAGO knowledge graph (Rebele et al. 2016) and the DBpedia knowledge graph (Lehmann et al. 2015) respectively; and are applied for the relation prediction task. Type links and ontology KGs are collected as type information (see Appendix B for the details of the pre-processing). Statistical information about the three datasets is shown in Table 1.

Table 1: Statistics of dataset.

Dataset	#Rel.	#Ent.	#Types	#Train	#Valid	#Test
FB15K	1,345	14,951	663	483,142	50,000	59,071
YAGO26K-906	34	26,078	226	351,664	-	39,074
DB111K-174	298	98,336	242	592,654	-	65,851

On all three datasets, for each relation, the obtained head type set and tail type set are non-empty. For each entity from FB15K and DB111K-74, the type set is non-empty. On YAGO26K-906, only 8,948 entities have non-empty type sets. As a result, 4, 149(10.6%) testing triples have type information for both head and tail entities; 30, 839(78.9%) triples have type information for only head entity or only tail entity; and 4,086(10.5%) triples don't have type information for both head and tail entities. For the cases where the type set of entity e is empty (e can be either head entity e_h or tail entity e_t), we assign uniform similarity scores, i.e., $s(e,r')=1, \forall r'\in \mathcal{R}.$

Evaluation protocol For each triple (e_h, r, e_t) in the testing set, we replace the relation r with every relation $r' \in \mathcal{R}$. We calculate the posterior probabilities $p(r'|e_h, e_t, \mathcal{T}(e_h, e_t, \mathcal{R}))$ of all replacement triples and rank these probabilities in descending order. We apply the filter setting (Ma et al. 2017). Two standard measures are considered as evaluation matrices: mean rank (MR) and Hits@N. A higher Hits@N and a lower MR mean better performance. In all the experiments, we report both Hits@1 and Hits@10.

Experimental Settings TaRP has one hyper-parameter threshold η . On each dataset, we select the threshold η from $\{0,0.1,0.2,0.4,0.6,0.8,0.9\}$ that achieves the best relation prediction performance (Hits@1) on the validation set (See Appendix A for detailed analysis of η). On FB15K and YAGO26K-906, $\eta=0.1$. On DB111K-174, $\eta=0$. We report the averaged size of type set over all the entities or relations as shown in Table 2^2 . For baseline embedding based models, we directly reuse the best configurations provided by previous studies (Sun et al. 2019; Zhang et al. 2019).

4.1 Ablation Studies on the Prior Model

We perform ablation studies to show the effectiveness of: 1) the hierarchy-based type weights; 2) the type information.

Effectiveness of hierarchy-based type weights To demonstrate the effectiveness of the proposed hierarchy-based type

¹The hierarchical type /common/topic is removed as this is applied to every entity.

 $^{^{2}|}T_{r,head}|$ and $|T_{r,tail}|$ are calculated with optimal thresholds applied

Table 2: Averaged size of the type set.

Dataset	Entity	Relation			
Dataset	$ T_e $	$ T_{r,head} $	$ T_{r,tail} $		
FB15K	12	20	19		
YAGO26K-906	9	6	5		
DB111K-174	2	7	12		

weights, we consider uniform weights for comparison, and calculate the prior probabilities based on types with uniform weights. We compare the relation prediction performance of the prior model with hierarchy-based weights to the performance of the prior model with uniform weights. Results are shown in Table 3 where the prior model with hierarchy-based weights achieves much better performance than the prior model with uniform weights, particularly on FB15K and DB111K-174 datasets. These results empirically demonstrate the effectiveness of the hierarchy-based type weights.

Table 3: Effectiveness of the hierarchy-based type weights.

Type weights		FB15K		YAGO26K-906			
Type weights	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10	
Uniform	26	4.95	43.88	3.92	71.85	88.75	
Hierarchy-based	2.9	64.10	97.10	3.34	79.60	88.60	
Tyma yyaiahta		DB111K-	174				
Type weights	MR	Hits@1	Hits@10				
Uniform	13.67	19.62	63.61				
Hierarchy-based	2.6	55.00	96.60				

Effectiveness of type information To study the effectiveness of the type information, we evaluate the relation prediction performance of the prior model by considering the type information of 1) only head entity (H); 2) only tail entity (T); 3) both head and tail entities (H+T). For YAGO26K-906, only a subset of triples contain type information for both head and tail entities (4, 149 triples), and hence we perform the evaluation on this subset for fair comparison. Re-

Table 4: Effectiveness of the type information.

Tuna Info		FB15F	ζ	YAGO26K-906			
Type Info.	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10	
Н	23.2	8.00	46.90	4.2	56.20	86.30	
T	20.3	9.00	50.20	2.5	65.20	95.70	
H+T	2.9	64.10	97.10	1.7	71.40	99.40	
Type Info.		DB111K-	174				
Type IIIIo.	MR	Hits@1	Hits@10				
Н	8.9	7.00	70.80				
T	12.5	19.70	62.10				
H+T	2.6	55.00	96.60				

sults in Table 4 shows that considering the type information of head and tail entities jointly, the prior model achieves the best performance. These results depict that both the type information of head and tail entities are effective in relation prediction.

4.2 Evaluation of the TaRP Model

We evaluate the TaRP model by first comparing it to three baseline embedding based models. In addition, we show the data efficiency of the proposed TaRP model by reducing the number of training triples. More importantly, we perform cross-dataset evaluation and empirically demonstrate the generalization ability of the type information.

Comparisons to baseline models As introduced in Section 3, we consider three baseline embedding based models: TransE, RotatE, and QuatE. The embeddings of entities and relations are obtained by directly running baseline models with reported best hyper-parameter settings³⁴. In addition, to demonstrate the effectiveness of the proposed decision-level integration, we enrich the existing training sets by adding type information as addition training triples; and train the embedding based models on enriched training sets for comparison. On YAGO26K-906 and DB111K-174, triples from ontology KG and type links can be directly used as additional training triples. On FB15K, given an entity e and its hierarchical type $/t_1/t_2/.../t_K$, we collect type triples as (e, r_1, t_K) with $r_1 = \text{type}$ and $\{(t_k, r_2, t_{k-1})\}_{k=2}^K$ with $r_2 = is_a$. The embedding based models trained on enriched training sets can thus learn embeddings based on both existing triples and the type information. In other words, the type information is fused with instance-level information at the feature-level. We denote the embedding based models learned from enriched training sets as: TransE(w/Type), RotatE(w/Type) and QuatE(w/Type). By combining the prior model with three embedding based models separately, we obtain three TaRP models: TaRP-T, TaRP-R, and TaRP-Q. The results are shown in Table 5 (see Appendix C for additional visualization results).

From Table 5, we can see that all three TaRP models achieve performance improvement on all three benchmark datasets compared to the corresponding baseline embedding based models. In particular, on FB15K and DB111K-174, the improvement is significant. For instance, TaRP-R obtains 92.91% for Hits@1 on FB15K, achieving 12.71% improvement compared to RotatE. On the other hand, on both YAGO26K-906 and DB111K-174, embedding based models trained on enriched training sets achieve improved performance compared to baseline embedding based models. However, for most of the embedding based models trained on enriched training sets, the achieved performance improvement is not as significant as the improvement achieved by the proposed TaRP model. TaRP models achieve overall better performance than the embedding based models trained on enriched training sets. For example, on DB111K-174, QuatE(w/Type) obtains 60.49% for Hits@1; though higher than the 58.60% obtained by QuatE, this is still significantly worse than the 76.60% obtained by TaRP-Q. In addition, on FB15K, the embedding-based models trained with type triples perform worse than the embedding-based models trained without type triples. The reason may be that type triples collected from FB15K can contain errors⁵ which

³https://github.com/DeepGraphLearning/KnowledgeGraphEmbedding

⁴https://github.com/cheungdaven/QuatE

 $^{^5}$ For example, for type /book/author, the collected type triple $(author, is_a, book)$ is not true.

Table 5: Evaluation of the Type-augmented Relation Prediction(TaRP) model

Method		FB15K			YAGO26K-906			DB111K-174		
Method	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10	
TransE	3.64	76.50	92.30	1.12	90.70	99.92	4.76	66.60	86.70	
RotatE	2.38	80.20	97.80	1.10	92.84	99.90	4.53	65.90	93.80	
QuatE	4.01	82.20	94.90	1.33	91.65	98.96	8.56	58.60	88.90	
TransE(w/Type)	3.32	79.37	91.56	1.12	90.70	99.93	4.16	67.64	91.91	
RotatE(w/Type)	3.67	73.63	96.44	1.08	93.31	99.93	3.47	70.08	96.42	
QuatE(w/Type)	3.98	80.82	92.97	1.32	91.98	99.09	7.63	60.49	89.14	
TaRP-T	1.84	88.90	99.00	1.10	90.80	99.98	1.61	74.80	99.40	
TaRP-R	1.16	92.91	99.84	1.08	92.84	99.98	1.52	76.50	99.50	
TaRP-Q	1.64	91.60	99.50	1.14	92.93	99.79	1.56	76.60	99.40	

leads to decreased performance. Our proposed prior model directly applies the type information, and hence errors introduced by type triples do not affect the TaRP models.

These results show that by incorporating the type information, the TaRP model can always achieve better performance with different baseline embedding based models. More importantly, the TaRP models achieve overall better performance than the embedding based models trained with type triples, indicating that the proposed decision-level integration procedure is a more effective integration. In addition, through the proposed integration approach, the type information can be directly combined with embedding based models without additional training.

Data efficiency of the TaRP model We consider the embeddings that are learned from a small subset of training triples. Given insufficient training data, the quality of the learned embeddings will be lower. We compare the TaRP model where embeddings are learned from only a subset of training triples to the embedding based model that is trained on complete training sets. We perform this evaluation on FB15K and DB111K-174. RotatE is applied as the baseline embedding based model. We extract the subset of training triples with respect to each relation individually. Results are shown in Table 6. As shown, on FB15K, by integrating the type in-

Table 6: Data efficiency of the TaRP model(D:training data)

Method		FB15F	ζ	DB111K-174			
Method	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10	
RotatE(100% D)	2.38	80.20	97.80	4.53	65.90	93.80	
TaRP-R(20% D)	1.90	83.20	99.20	2.17	63.40	97.60	
TaRP-R(40% D)	1.74	85.90	99.60	1.78	70.90	98.70	
TaRP-R(60% D)	1.73	84.90	99.70	1.62	74.80	99.10	
TaRP-R(80% D)	1.71	85.50	99.70	1.55	76.00	99.40	

formation, TaRP-R achieves better performance than RotatE with only 20% of the training data. On DB111K-174, TaRP-R achieves better performance with 40% of the training data. These results show that TaRP achieves better performance than the embedding-based model using much lesser training data. By leveraging type information, TaRP has lesser dependency on the training triples, and thus is more data efficient.

Cross-dataset evaluation of the TaRP model To demonstrate the generalization ability of the type information, we perform cross-dataset evaluation. In particular, the type in-

formation is collected from outside of the dataset. Given two knowledge graphs $\mathcal{G}^1 = \{\mathcal{E}^1, \mathcal{R}^1, \mathcal{T}^1\}$ and $\mathcal{G}^2 =$ $\{\mathcal{E}^2, \mathcal{R}^2, \mathcal{T}^2\}$, for each entity $e \in \mathcal{E}^1$, we perform exact string matching to find if there exists a matched entity $e \in \mathcal{E}^2$. If so, we collect the type information for $e \in \mathcal{E}^1$ as $T_e = \{t_k\}_{k=1}^K$, where $t_k \in \mathcal{T}^2$ and K is the total number of types for entity e. For each dataset, we transfer the type information from the other two datasets individually. Given the transferred type information, we collect the relations whose head type set and tail type set are both nonempty in order to perform valid type information encoding. Only the testing triples that contain such relations are considered for the evaluation. In the end, on the FB15K dataset, 785 qualified relations are obtained resulting in 55, 804 testing triples. On the YAGO26K-906 dataset, 32 qualified relations are obtained resulting in 37, 401 testing triples. On the DB111K-27 dataset, 134 qualified relations are obtained resulting in 55, 037 testing triples. For comparison, we extract the type information from within-dataset. The prior models with type information extracted from FB15K, YAGO26K-906, and DB111K-174 are denoted as FB prior, YG prior, and DB prior respectively. In addition, for each dataset, we consider a union prior where we combine the type sets of each entity extracted from the other two datasets with the existing type set collected from within-dataset. The embedding based models are directly trained on the training triples from within-dataset. RotatE is applied as the baseline embedding based model. For each dataset, we combine the baseline embedding based model with four different prior models individually, resulting in four TaRP models: TaRP-R(FB prior), TaRP-R(YG prior), TaRP-R(DB prior) and TaRP-R(Union prior). Results are shown in Table 7. As we can see from the Table 7, TaRP-R with type information collected from crossdatasets can still achieve performance improvement compared to the baseline embedding based model. For example, on FB15K, 3.3% improvement is achieved with the type information transferred from YAGO26K-906. Furthermore, the TaRP-R with union-prior achieves better performance than the TaRP-R with type information collected withindatasets by leveraging additional type information collected from cross-datasets. From these results, we can see that the type information extracted from a specific dataset can generalize well to different datasets. In addition, through the proposed decision-level integration, the embedding based model can be easily combined with different type informa-

Table 7: Cross-dataset evaluation of the TaRP model

Method	FB15K			YAGO26K-906			DB111K-174		
Method	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10
RotatE	1.76	82.47	98.59	1.09	92.55	99.92	2.59	79.42	97.21
TaRP-R(FB prior)	1.37	92.88	99.79	1.06	94.29	99.98	2.06	80.55	97.88
TaRP-R(YG prior)	1.74	85.77	98.97	1.05	95.75	99.99	2.22	79.90	97.62
TaRP-R(DB prior)	5.99	84.95	98.25	1.06	94.62	99.99	1.39	86.20	99.22
TaRP-R(Union prior)	1.19	92.90	99.83	1.04	95.81	99.99	1.34	86.57	99.40

tion without additional training.

4.3 Comparisons to State-Of-The-Art Methods

We compare TaRP to additional SoTA models that also apply ontological information. In particular, on FB15K, we compared to DKRL (Xie et al. 2016), TKRL (Xie, Liu, and Sun 2016), SSP (Xiao et al. 2017), and TransT (Ma et al. 2017). TKRL and TransT apply type information. DKRL and SSP apply contextual information like descriptions of entities. The results are shown in Table 8. * indicates the reported performance. On YAGO26K-906 and DB111K-174, we compare to the state-of-the-art model, JOIE (Hao et al. 2019)⁶. We train JOIE on two datasets with its reported best hyper-parameter configurations, and the results are shown in Table 9. From Table 8 and Table 9, we can see that TaRP-R achieves the best performance, in particular for Hits@10. By integrating type information, the ranks of triples are concentrated within rank1- rank10 (see Appendix C for the visualizations). Hence, TaRP-R achieves very high Hits@10 and significantly outperforms SoTA methods on all three datasets.

Table 8: Comparisons with SOTA on FB15k

Methods	MR	Hits@1	Hits@10
DKRL(CNN)+TransE (Xie et al. 2016)	2.03*	-	90.8*
TKRL(RHE) (Xie, Liu, and Sun 2016)	1.73^*	92.8*	-
SSP(Std.) (Xiao et al. 2017)	1.22*	-	89.2*
SSP(Joint) (Xiao et al. 2017)	1.47^*	-	90.9*
TransT (Ma et al. 2017)	1.19*	-	94.1*
TaRP-R	1.16	92.9	99.8

Table 9: Comparisons with SOTA on YAGO26K-906 and DB111K-174

Method			YAGO26K	-906	DB111K-174		
		MR	Hits@1	Hits@10	MR	Hits@1	Hits@10
JOIE (Hao et al. 2019)	1.47	90.1	97.1	2.22	71.8	89.6
	TaRP-R	1.08	92.8	99.9	1.52	76.5	99.5

5 Discussion

To further analyze the effectiveness of TaRP, we consider the performance of each relation individually. In particular, we categorize each relation r based on the percentage of training triples containing the relation r. We consider five categories: $\{<0.5\%,0.5\%-1\%,1\%-5\%,5\%-10\%,>10\%\}$. For each category, we record the Hits@10 of each relation

within the category from all three datasets, and report the averaged Hits@10. We take RotatE as the baseline embedding based model, and results are visualized in Figure 2. We see that for the relations that are contained in very few training triples (e.g., <0.5%, or 0.5%-1%), the training data is not sufficient to learn robust embeddings. Thus the prediction performance is significantly worse than the performance of relations having sufficient training data (e.g., 5%-10% or >10%). On the other hand, relations with insufficient training triples can benefit more from type information, and thus TaRP achieves more significant improvement for relations with insufficient data (e.g., <0.5%).

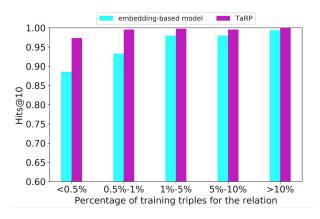


Figure 2: Performance per relation

6 Conclusion

In this paper, we propose an effective type-augmented relation prediction (TaRP) method, where we apply both type information and instance-level information for relation prediction in knowledge graphs. The type information and instance-level information are encoded as prior probabilities and likelihoods of relations respectively, and are combined at the decision-level. Our approach significantly outperforms state-of-the-art methods. Additionally, by leveraging type information, the TaRP model is able to be more data efficient than existing models. Furthermore, type information extracted from a specific dataset is shown to generalize well to other datasets.

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⁶https://github.com/JunhengH/joie-kdd19

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