Learning to Borrow – Relation Representation for Without-Mention Entity-Pairs for Knowledge Graph Completion

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Abstract

Prior work on integrating text corpora with knowledge graphs (KGs) to improve Knowledge Graph Embedding (KGE) have obtained good performance for entities that co-occur in sentences in text corpora. Such sentences (textual mentions of entity-pairs) are represented as Lexicalised Dependency Paths (LDPs) between two entities. However, it is not possible to represent relations between entities that do not co-occur in a single sentence using LDPs. In this paper, we propose and evaluate several methods to address this problem, where we borrow LDPs from the entity pairs that co-occur in sentences in the corpus (i.e. with mentions entity pairs) to represent entity pairs that do not co-occur in any sentence in the corpus (i.e. without mention entity pairs). We propose a supervised borrowing method, SuperBorrow, that learns to score the suitability of an LDP to represent a without-mentions entity pair using pre-trained entity embeddings and contextualised LDP representations. Experimental results show that SuperBorrow improves the link prediction performance of multiple widely-used prior KGE methods such as TransE, DistMult, ComplEx and RotatE.

1 Introduction

Knowledge Graphs (KGs) are a structured form of information that underlie the relationships between real-world entities (Ehrlinger and Wöß, 2016; Kroetsch and Weikum, 2016; Paulheim, 2017). A KG is represented using a set of relational tuples of the form \( (h, r, t) \), where \( r \) represents the relation between the head entity \( h \) and the tail entity \( t \). For example, the relational tuple (Joe Biden, president-of, US) indicates that the president-of relation holds between Joe Biden and US. There exists a large number of publicly available and widely used KGs, such as Freebase (Bollacker et al., 2008), DBpedia (Auer et al., 2007), and YAGO ontology (Suchanek et al., 2007). KGs have been effectively applied in various NLP tasks such as, relation extraction (Riedel et al., 2013; Weston et al., 2013), question answering (Das et al., 2017; Sydorova et al., 2019), and dialogue systems (Xu et al., 2020). However, most KGs suffer from data sparseness as many relations between entities are not explicitly represented (Min et al., 2013).

To overcome the sparsity problem, Knowledge Graph Embedding (KGE) methods learn representations (a.k.a. embeddings) for entities and relations in a given KG in a vector space, which can then be used to infer missing links between entities (Bordes et al., 2013; Nickel et al., 2015; Wang et al., 2017). Such models are trained to predict relations that are likely to exist between entities (known as link prediction or KG completion) according to some scoring formula. Although previously proposed KGE methods have shown good empirical performances for KG completion (Minervini et al., 2015), the KGEs are learnt from the KGs only, which might not represent all the relations that exist between the entities included in the KG. To overcome this limitation, prior work has used external text corpora in addition to the KGs (Toutanova et al., 2015; Xu et al., 2016; Long et al., 2016; An et al., 2018; Wang et al., 2019b,a; Lu et al., 2020). Compared to structured KGs, unstructured text corpora are abundantly available, up-to-date and have diverse linguistic expressions for extracting relational information.

The co-occurrences of two entities within sentences (a.k.a textual mentions) in a text corpus has shown its success for text-enhanced KGEs (Komninos and Manandhar, 2017; An et al., 2018). For example, the relational tuple in the Freebase KG (Joe Biden, president-of, US) is mentioned in the following sentence “Joseph Robinette Biden Jr. is an American politician who is the 46th and current president of the United States.” This sentence expresses the president-of relation between the two...
entities Joe Biden and US. As the entity-pair (Joe Biden, US) appears in a single sentence, we call it a with-mention entity-pair. However, even in a large text corpus, not every related entity pair co-occurs in a specified window, which are referred to as without-mention entity-pairs in previous studies. For instance, if we consider the widely used FB15K-237 KG (Toutanova et al., 2015) and the ClueWeb12 (Gabrilovich et al., 2013) text corpus with FB entity mention annotations, 1 33% of entity-pairs in FB15k-237 do not have textual mentions within the same sentences. This sparseness problem limits the generalisation capabilities of using textual mentions for enhancing KGEs. Specifically, Toutanova et al. (2015); Komninos and Manandhar (2017) have shown larger improvements in link prediction for with-mention entity-pairs over without-mention pairs.

In this paper, we propose a method to augment a given KG with additional textual relations extracted from a corpus and represented as LDPs. The augmented KG can then be used to train any KGE learning method. This is attractive from both scalability and compatibility point of views because our proposal is agnostic to the KGE learning method that is subsequently used for learning KGEs. Our main contribution in this paper is to improve link prediction for without-mention entity-pairs by borrowing LDPs from with-mentions entity-pairs to overcome the sparseness in co-occurrences of the without-mentions entity-pairs. We show that learning a supervised borrowing method, SuperBorrow, that scores suitable LDPs to represent without-mention entity-pairs based on pre-trained entity embeddings and contextualised LDP embeddings boosts the performance of link prediction using a series of KGE methods, compared to what would have been possible without textual relations.

2 Related Work

KGEs from a Multi-relational Graph: Typically, KG embedding models consist of two main steps: (a) defining a scoring function for a tuple, and (b) learning entity and relation representations. Entities are usually represented as vectors, whereas relations can be represented by vectors (e.g. TransE (Bordes et al., 2013), DistMult (Yang et al., 2014) and ComplEx (Trouillon et al., 2016)) matrices (e.g. RESCAL (Nickel et al., 2011)), or

| KGE method       | Score function       |
|------------------|----------------------|
| TransE (Bordes et al., 2013) | $||h + r - t||_{1/2}$ |
| DistMult (Yang et al., 2014) | $\langle h, r, t \rangle$ |
| ComplEx (Trouillon et al., 2016) | $\langle h, r, t \rangle$ |
| RotatE (Sun et al., 2019) | $||h \circ r - t||^2$ |

Table 1: Score functions proposed in KGE methods. Entity embeddings $h, t \in \mathbb{R}^d$ are vectors in all models, except in ComplEx where $h, t \in C^d$. Here, $\ell_{1/2}$ denotes either $\ell_1$ or $\ell_2$ norm of a vector. In ComplEx, $t$ is the element-wise complex conjugate.

by 3D tensors (e.g. Neural Tensor Network (Socher et al., 2013)).

Using some form of a representation, scoring functions are then defined to evaluate the strength of a relation $r$ between $h$ and $t$ entities in a triple. TransE is one of the earliest and well-known distance-based KGE method that performs a linear translation and its scoring function is given in Table 1. Alternatively, a bilinear function is used in several KGE models, such as RESCAL, DistMult and ComplEx, for which scoring functions are defined in Table 1. KGEs are learnt such that the observed facts (positive triples) are assigned higher scores compared to that of the negative triple (for example generated by perturbing a positive instance by replacing its head or tail entities by an entity randomly selected from the set of entities) by minimising a loss function, such as the logistic loss or the margin loss.

Conventional KGE models are trained using the facts in the KGs, which are often incomplete. Therefore, to overcome the sparsity of structured KGs, we propose to integrate information from a text corpus, thereby augmenting the KG. The augmented KG is then used as the input to existing KGE methods to learn accurate entity and relation embeddings. In particular, we do not modify the scoring functions nor optimisation objectives for the respective KGE methods, which makes our proposed approach applicable in many existing KGE methods without any modifications.

Text-Enhanced KGEs: Recently, a new line of research that combines textual information with relational graphs has emerged (Lu et al., 2020). Different combination methods have been proposed for this purpose. Wang et al. (2014) proposed a model to embed both entities and words (using entity names and Wikipedia anchors) into the same low-dimensional vector space to capture relational

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1 200 million sentences in CluWeb12 annotated with FB entity mention annotations.
information from a KG and the co-occurrences from the corpus. Rosso et al. (2019) control the amount of information shared between the two data sources in the joint embedding space using regularisation. This joint model is further enhanced by incorporating entity descriptions from an external corpus, which are jointly learnt with the KG (Zhong et al., 2015; Xie et al., 2016; Veira et al., 2019). In a different scenario, the text-enhanced knowledge embedding model by Wang et al. (2016) creates a co-occurrence network of words and entities from an entity-annotated corpus. The authors define point-wise and pair-wise contexts using the co-occurrence frequencies in the network. Then, entity and relation embeddings are enhanced using textual point-wise and pair-wise embeddings, respectively. Similarly, Rezayi et al. (2021) construct an augmented KG that has nodes from external text. The original and the augmented graphs are then aligned to suppress the noise and distil relevant information. In our work, we focus on adding extra edges to the KG rather than nodes as in Rezayi et al. (2021) and Wang et al. (2016).

In addition to contextual information and textual descriptions of individual words/entities, sentences where two entities co-occur have been used as contextual evidence to learn KGEs (Toutanova et al., 2015; Komninos and Manandhar, 2017; Tang et al., 2019). For example, Toutanova et al. (2015) extracted LDPs by parsing co-occurring sentences in a text corpus, which are then used as textual relations in the KG. This model can be seen as a special case of universal schema (Riedel et al., 2013), which combines textual and KG relations in the same entity-pair co-occurrence matrix, subsequently decomposed to obtain entity embeddings. Komninos and Manandhar (2017) proposed a novel triple scoring function where textual mentions are used as a source of supporting evidence for a triple.

Our problem setting differs from prior work on text-enhanced KGEs in two important ways. First, we do not modify the underlying structure of the KGE method, which is attractive from both scalability and compatibility of our proposal. Second, rather than considering only entity-pairs that are occurring within a specified context in the corpus (i.e. with-mention entity-pairs), we propose to borrow LDPs from with-mention entity-pairs to overcome the data sparseness in without-mention entity-pairs that never co-occur within any sentence in the corpus.

3 Method

A relational KG \( \mathcal{D} \) consists of a set of entities \( \mathcal{E} \) and a set of relations \( \mathcal{R} \). In \( \mathcal{D} \), knowledge is represented by relational tuples \((h, r, t)\in\mathcal{D}\), where the head entity \( h \) is related to the tail entity \( t \) by the KG relation \( r \). In this work, we assume relations to be asymmetric in general (if \((h, r, t) \in \mathcal{D}\) then it does not necessarily follow that \((t, r, h) \in \mathcal{D}\)). The goal is to learn representations for entities and relations such that missing tuples can be accurately inferred.

As KGs \( \mathcal{D} \) are often sparse with many missing edges between entities, the learnt KGEs are affected, which in return impacts the performance of KGEs on downstream tasks such as link prediction. To address this sparseness problem, we consider the availability of a text corpus \( \mathcal{T} \) where relational facts are expressed using contexts in which an entity-pair co-occurs. The textual relations that are extracted from \( \mathcal{T} \) can be injected into \( \mathcal{D} \) before applying a KGE method.

To align \( \mathcal{D} \) with \( \mathcal{T} \), entity linking is applied to resolve ambiguous entity mentions in the text with unique entities in the KG (Gabrilovich et al., 2013; Shen et al., 2014). Then, sentences of which two entities co-occurring with are considered as textual mentions of relations that exist between those entities. Assuming that the corpus is annotated using the entities in \( \mathcal{D} \), there are multiple possibilities to obtain relational features of sentences that mention the entities. Following previous work (Toutanova et al., 2015), we first run a dependency parser (Chen and Manning, 2014) on each sentence in the entity-annotated corpus to obtain LDPs. Then, if \( \mathcal{D} \) contains the head and tail entities of an LDP \( l \), we insert \( l \) into \( \mathcal{D} \) to form a textual triple \((h, l, t) \in \mathcal{D}\). The augmented KG is then used to learn embeddings for \( \mathcal{E} \) and \( \mathcal{R} \) using different KGE methods. During KGE processes, we treat both original relations in the KG and the augmented LDPs equally. In principle, any existing KGE learning method can be applied on the augmented KG as we later see in our experiments.

One obvious limitation of the above-described method is that entity-pairs that never co-occur in any contextual window (e.g. a sentence) will not be connected by any LDP during the augmentation process. This is fine if the two entities are truly unrelated. However, this is problematic for entities that are related but their relations were not sufficiently covered in the text corpus because of the coverage issues and small size of the corpus. As
Table 2: Statistics of the datasets. w-m and w/o-m denotes the number of test instances respectively in with-mention and without-mention entity-pair sets.

|          | Relations | Entities | Triples       | Train/Test |
|----------|-----------|----------|---------------|------------|
| FB       | 237       | 14,541   | 272,115/20,466| 2,344      | 18,122     |
| Text     | 1,100     | 12,930   | 404,009/-     | -          | -          |

where the input entity-pair to the MLP is encoded

\[
\phi(h, t) = [h \oplus t \oplus (h - t) \oplus (h \odot t)]
\]

Here, \(\oplus\) denotes the concatenation of vectors and \(\odot\) is the element-wise multiplication between two vectors. (1) considers the information in the head and tail entity embeddings independently as well as the interactions between their corresponding dimensions. The final output vector \(f(h, t; \theta)\) of the MLP is treated as the representation of the entity-pair \((h, t)\).

As an alternative to representing the relationship between two entities in an entity-pair \((h, t)\) by \(f(h, t; \theta)\) using the corresponding entity embeddings, we can use \(\mathcal{L}_{(h,t)}\), the set of LDPs co-occurring between \(h\) and \(t\) (Bollegala et al., 2010). Because an LDP is a sequence of textual tokens, we can use any sentence encoder to represent an LDP by a vector. Specifically, in our experiments later we use the pretrained sentence encoder SBERT (Reimers and Gurevych, 2019) to represent an LDP, \(l\), by a vector, \(l\).

We require LDPs that co-occur with an entity-pair \((h, t)\) to be similar to \(f(h, t; \theta)\) than LDPs that do not co-occur with \((h, t)\). Specifically, we use the set of with-mention entity-pairs with their associated LDPs as positive training instances \(S_{(h,t)}\). LDPs that are associated with either \(h\) or \(t\) alone (not both) are used as negative training instances \(S'_{(h,t)}\) as given by (2).

\[
S_{(h,t)} = \{(h, l, t)|\exists \epsilon(h, l, t) \in D \land t' \neq t, \exists h' (h', l, t) \in D \land h' \neq h\}
\]

(2)

We learn the parameters of \(f(h, t; \theta)\) by minimising the marginal loss over \(S_{(h,t)}\) and \(S'_{(h,t)}\) as shown in (3).

\[
\sum_{(h,l,t) \in S_{(h,t)}} \sum_{(h',l',t) \in S'_{(h,t)}} \max \left(0, \gamma - f(h, t; \theta)^T (l - l')\right)
\]

(3)

Here, \(\gamma \geq 0\) is the margin and is set to 1 in our experiments. To determine which LDPs to be borrowed for a particular without-mention entity pair, \((h^*, t^*)\), we first compute its representation, \(f(h^*, t^*; \theta)\) using the \(\theta\) found by minimising (3) above. We then score each LDP, \(l\), using the sentence encoder model, by the inner-product, \(f(h^*, t^*; \theta)^T l\). We then select the top-\(k\) LDPs with the highest inner-products with \(f(h^*, t^*; \theta)\) to augment the KG. The number of borrowed LDPs \((k)\) is a hyperparameter that is tuned using the validation triples selected from the KG.

4 Experimental Setup

4.1 Dataset and Training Details

Datasets: We use FB15k237 as the KG and ClueWeb12\(^2\) as the corpus for extracting LDPs for the entity-pairs in the FB157k237 KG. Specifically, we use the textual triples consisting of LDPs that are extracted and made available\(^3\) by Toutanova et al. (2015). The number of extracted unique LDPs and textual triples in this dataset are respectively 2,740,176 and 3,978,014. To make the training of KGE methods computationally efficient, we filter out LDPs that occur in less than 100 distinct entity-pairs in the corpus. The FB15k237 test set is split into with-mention (i.e. entity-pairs that co-occur in some LDP) and without-mention (i.e entity-pairs that do not co-occur in any LDP) sets as shown in Table 2. According to Table 2, there are 88.14\% without-mentions entity-pairs in the

\(^2\)https://lemurproject.org/clueweb12/
\(^3\)https://www.microsoft.com/en-us/download/details.aspx?id=52312
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We include the number of hidden layers \( \ell \), which are publicly available for the entities (KG only), and textual relations. The MLP has 400 features. The hyperparameters particularly used as an evaluation task to compare the overall with-mention without-mention activation \{ tanh, relu, sigmoid \} are tuned using the above-mentioned validation set. The MLP consists of two 768-dimensional layers, and the last layer represents the entity-pair to be mapped to the LDP embedding space that has 768 dimensions encoded using the SBERT paraphrase-distilroberta-base model, which has reported SoTA performance on various knowledge-intensive tasks (Warstadt et al., 2020). SuperBorrow is trained for 50 iterations using mini-batch Stochastic Gradient Descent with momentum and a batch size of 128.

### Evaluation Protocol
After augmenting FB15K237 with the borrowed \( k \) LDPs for each without-mention entity-pair, we train a KGE method to obtain embeddings for the entities in \( \mathcal{E} \), relations in \( \mathcal{R} \) and textual relations. The hyperparameter \( k \) is tuned on the validation set of FB15K237 for each KGE method from \( \{ 1, 3, 10, 15, 20, 25, 30 \} \).

We use Link Prediction, which has been popularly used as an evaluation task to compare the

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Table 3: Results of link prediction on FB15K237. Higher is better for all metrics except for the mean rank (MR) for which lower values indicate better performance. The best result for each metric and each KGE method is shown in bold.

| Model                      | MRR | MR H@10 | H@3 | H@10 | H@3 | H@10 | H@3 | H@10 | H@3 |
|----------------------------|-----|---------|-----|------|-----|------|-----|------|-----|
| TransE (KG only)           | 0.336 | 0.523 | 0.368 | 0.243 | 0.314 | 0.508 | 0.349 | 0.218 | 0.333 | 0.519 | 0.364 | 0.241 |
| KG+ExtractedLDPs           | 0.314 | 0.495 | 0.343 | 0.224 | 0.433 | 0.659 | 0.489 | 0.319 | 0.291 | 0.468 | 0.318 | 0.206 |
| LinkAll                    | 0.360 | 0.531 | 0.381 | 0.269 | 0.520 | 0.683 | 0.493 | 0.316 | 0.328 | 0.510 | 0.360 | 0.255 |
| Co-occurrence              | 0.302 | 0.47 | 0.353 | 0.202 | 0.412 | 0.639 | 0.464 | 0.297 | 0.506 | 0.479 | 0.557 | 0.408 |
| NeighbborBorrow            | 0.491 | 0.682 | 0.541 | 0.392 | 0.394 | 0.629 | 0.464 | 0.277 | 0.493 | 0.50 | 0.542 | 0.395 |
| SuperBorrow                | 0.751 | 0.868 | 0.799 | 0.681 | 0.787 | 0.918 | 0.748 | 0.606 | 0.787 | 0.898 | 0.825 | 0.723 |

DistMult (KG only)          | 0.302 | 0.489 | 0.333 | 0.209 | 0.257 | 0.436 | 0.289 | 0.165 | 0.302 | 0.489 | 0.333 | 0.209 |
| KG+ExtractedLDPs           | 0.325 | 0.512 | 0.357 | 0.232 | 0.427 | 0.656 | 0.483 | 0.311 | 0.306 | 0.488 | 0.335 | 0.216 |
| LinkAll                    | 0.527 | 0.707 | 0.536 | 0.325 | 0.663 | 0.676 | 0.54 | 0.175 | 0.786 | 0.797 | 0.715 | 0.511 |
| Co-occurrence              | 0.365 | 0.574 | 0.404 | 0.261 | 0.428 | 0.664 | 0.479 | 0.310 | 0.351 | 0.558 | 0.388 | 0.248 |
| NeighbborBorrow            | 0.415 | 0.639 | 0.465 | 0.392 | 0.412 | 0.645 | 0.463 | 0.297 | 0.408 | 0.563 | 0.458 | 0.295 |
| SuperBorrow                | 0.482 | 0.681 | 0.536 | 0.377 | 0.415 | 0.655 | 0.475 | 0.291 | 0.482 | 0.678 | 0.534 | 0.379 |

ComplEx (KG only)           | 0.312 | 0.493 | 0.342 | 0.222 | 0.275 | 0.459 | 0.299 | 0.185 | 0.312 | 0.493 | 0.342 | 0.222 |
| KG+ExtractedLDPs           | 0.321 | 0.505 | 0.349 | 0.229 | 0.407 | 0.637 | 0.458 | 0.291 | 0.304 | 0.482 | 0.329 | 0.216 |
| LinkAll                    | 0.528 | 0.707 | 0.536 | 0.325 | 0.663 | 0.676 | 0.54 | 0.175 | 0.786 | 0.797 | 0.715 | 0.511 |
| Co-occurrence              | 0.358 | 0.570 | 0.399 | 0.222 | 0.436 | 0.679 | 0.499 | 0.319 | 0.342 | 0.552 | 0.380 | 0.238 |
| NeighbborBorrow            | 0.428 | 0.650 | 0.479 | 0.315 | 0.418 | 0.656 | 0.478 | 0.298 | 0.422 | 0.563 | 0.472 | 0.309 |
| SuperBorrow                | 0.489 | 0.687 | 0.540 | 0.385 | 0.416 | 0.653 | 0.481 | 0.291 | 0.493 | 0.686 | 0.541 | 0.388 |

RotatE (KG only)            | 0.338 | 0.560 | 0.395 | 0.259 | 0.333 | 0.527 | 0.386 | 0.236 | 0.354 | 0.527 | 0.391 | 0.254 |
| KG+ExtractedLDPs           | 0.359 | 0.551 | 0.396 | 0.264 | 0.448 | 0.672 | 0.509 | 0.333 | 0.341 | 0.528 | 0.374 | 0.247 |
| LinkAll                    | 0.567 | 0.758 | 0.626 | 0.424 | 0.714 | 0.770 | 0.570 | 0.317 | 0.567 | 0.758 | 0.626 | 0.424 |
| Co-occurrence              | 0.435 | 0.639 | 0.484 | 0.329 | 0.441 | 0.663 | 0.499 | 0.327 | 0.426 | 0.629 | 0.473 | 0.321 |
| NeighbborBorrow            | 0.462 | 0.672 | 0.514 | 0.357 | 0.443 | 0.675 | 0.514 | 0.326 | 0.457 | 0.664 | 0.508 | 0.351 |
| SuperBorrow                | 0.682 | 0.836 | 0.739 | 0.594 | 0.412 | 0.652 | 0.473 | 0.290 | 0.706 | 0.851 | 0.764 | 0.621 |

4https://github.com/LivNLP/Relational-Walk-for-Knowledge-Graphs
We compare the proposed LDP borrowing method with vs. without-mention entity-pairs as opposed to simply connecting all without-mention entity-pairs that co-occurs in any sentence in the corpus (Co-occurrence) in the augmented KG and does not distinguish between different textual relations. This baseline is designed to highlight the importance of the context of entity-pair co-occurrences in the corpus beyond simply treating all co-occurrences equally during the augmenting process.

**NeighbBorrow:** Given a without-mention entity-pair \((h^*, t^*)\), we can borrow the LDPs from the first nearest neighbouring (1NN) with-mention entity-pair \((h, t)\). The similarity between entity-pairs can be computed using (4) in an unsupervised manner using pretrained entity embeddings such as RelWalk embeddings (Bollegala et al., 2021).

\[
sim((h, t), (h^*, t^*)) = \cos(h, h^*) \cos(t, t^*) \tag{4}
\]

Here, \(\cos\) is the cosine similarity between two vectors converted to nonnegative values (i.e. \([0, 1]\)) using the linear transformation \((x + 1)/2\). On average, when considering 1NN, we borrow 1.3 LDPs for each without-mention pair of entities. In contrast to the proposed SuperBorrow, NeighbBorrow is unsupervised and decouples entities in each pair when computing their similarity.

## 5 Results

**Link Prediction:** Table 3 shows the results of link prediction for different settings on FB15K237 under different KGE methods. Two translational distance-based KGE methods (i.e. TransE and RotatE) and two semantic matching-based models (i.e. DistMult and ComplEx) are used as the KGE learning methods (Rossi et al., 2021; Wang et al., 2021). We emphasize that our purpose here is not to compare the absolute performance among those KGE methods, but to evaluate the effect of using LDPs for augmenting the KG and representing the without-mention entity-pairs via different borrowing methods. For SuperBorrow, the optimal numbers of borrowed LDPs \((k)\) determined using the validation set for TransE, DistMult, ComplEx and RotatE respectively are 30, 20, 15 and 25.

As shown in Table 3, augmenting the KG with the extracted LDPs (i.e., KG+ExtractedLDPs) significantly improves the performance for with-mention entity-pairs for all KGE methods. However, the performance when predicting links for without-mention entity-pairs decreases slightly for all KGE methods, except for DistMult in the KG+ExtractedLDPs setting. For the borrowing models, even though the co-occurrence baseline improves the prediction for without-mention set, borrowing relevant LDPs from the 1NN entity-pairs (NeighbBorrow) or the proposed supervised borrowing (SuperBorrow) reports superior results.
We can see that the best performance for the overall and without-mention sets are achieved with the augmented KG using SuperBorrow, followed by NeighbBorrow.

Relation Prediction: Table 4 shows the accuracies for the relation prediction task. Experimentally, the best results for this task is obtained when corrupting \( r \), in addition to \( h \) and \( t \) corruptions, is applied to generate negative triples to train the KGE method. This negative sampling schedule follows the evaluation procedure of relation prediction. As shown in the table, SuperBorrow reports the best MR and Hits@3 for DistMult KGEs, while NeighbBorrow baseline performs better than SuperBorrow with ComplEx method. Further results for relation prediction are in the Supplementary Appendix A.

Comparisons against Prior Work: We compare our proposed method against prior work, namely Feature Rich Network (FRN) (Komninos and Mandhar, 2017) and Conv (E+DistMult) (Toutanova et al., 2015). In FRN, an MLP is trained to predict the probability of a given triple being true using different types of features such as the entity types and features extracted from textual relation mentions. Conv(E+DistMult) represents LDPs by vectors using a convolutional neural network, and combines DistMult scoring function with that of the Entity model (E) proposed by Riedel et al. (2013). E model learns a vector for each entity and two vectors for each relation corresponding to the two arguments \( r_h \) and \( r_t \) of a relation \( r \). The scoring function of a triple in E model is defined as \( h \cdot r_h + t \cdot r_t \). The combined model (E+DistMult) is trained on a linearly weighted combination of KG triples and textual triples. For a fair comparison, we consider the task of predicting missing tail entities and we avoid the type-constraint setting.

As shown in Table 5, for the overall test set of FB15K237 our models outperform both FRN and Conv models according to MRR and Hits@10. For with-mention entity-pairs, our models report higher scores compared to Conv(E+DistMult), while FRN performs best. For with-mention entity-pairs FRN can extract rich features from the contexts of co-occurrences, which helps it to obtain superior performances. However, both FRN and Conv models perform poorly on without-mention entity-pairs, where such contextual features are unavailable. On the other hand, by using the proposed SuperBorrow to augment LDPs for KGs we can overcome this limitation successfully.

6 Analysis

Borrowed LDPs: To provide examples of LDPs injected into FB15K237, Table 6 shows the borrowed LDPs by NeighbBorrow and SuperBorrow for some selected entity-pairs. We can see that representative LDPs of various relation types are ranked at the top by SuperBorrow. For example, for the film-distributor relation, NeighbBorrow selects LDPs containing specific tokens such as movie or film, whereas SuperBorrow retrieves LDPs that better express the target relation such as 20th Century Fox:(dobj):released:(nsubj):Lincoln.

Relation Categories: To better analyse the effect of the proposed SuperBorrow for KGEs, we evaluate the link prediction task on different relation categories including 1to1, 1toN, Nto1 and NtoN as defined in Bordes et al. (2013).

Table 7 presents the results of predicting head entities for all KGE methods considering KG only and SuperBorrow. We can see that SuperBorrow achieves higher performance over the original graph on all relation categories. In particular, our proposal significantly boosts the performance of predicting head entities for the Nto1 relation type where all KGE methods report the lowest H@10 for

Table 4: Results of relation prediction on FB15K237.

| Model                | MR      | H@3    | H@1    | MR      | H@3    | H@1    |
|----------------------|---------|--------|--------|---------|--------|--------|
| DistMult (KG only)   | 4.1     | 0.938  | 0.856  | 4.0     | 0.942  | 0.865  |
| KG+ExtractedLDPs     | 2.6     | 0.955  | 0.876  | 2.7     | 0.957  | 0.883  |
| LinAlt               | 7.2     | 0.887  | 0.752  | 7.4     | 0.880  | 0.742  |
| Co-occurrence        | 2.4     | 0.954  | 0.875  | 2.4     | 0.956  | 0.882  |
| NeighbBorrow         | 3.0     | 0.955  | 0.874  | 3.0     | 0.956  | 0.881  |
| SuperBorrow          | 2.2     | 0.960  | 0.875  | 2.2     | 0.962  | 0.882  |
| ComplEx (KG only)    | 3.1     | 0.954  | 0.910  | 2.8     | 0.957  | 0.908  |
| KG+ExtractedLDPs     | 1.9     | 0.967  | 0.917  | 1.9     | 0.967  | 0.922  |
| LinAlt               | 4.0     | 0.949  | 0.812  | 4.1     | 0.942  | 0.855  |
| Co-occurrence        | 1.8     | 0.967  | 0.916  | 1.8     | 0.967  | 0.920  |
| NeighbBorrow         | 1.7     | 0.972  | 0.921  | 1.7     | 0.974  | 0.925  |
| SuperBorrow          | 1.7     | 0.972  | 0.917  | 1.7     | 0.973  | 0.922  |

Table 5: Comparisons against prior work on link prediction on FB15K237. The results for prior work are taken from the original papers. The best results are in bold, while the second best results are underlined.

| Model                | MR      | H@10   | MR      | H@10   | MR      | H@10   |
|----------------------|---------|--------|---------|--------|---------|--------|
| Conv (E+DistMult)    | 0.401   | 0.581  | 0.379   | 0.499  | 0.424   | 0.611  |
| FRN                  | 0.403   | 0.620  | 0.441   | 0.683  | 0.387   | 0.595  |
| ours (DistMult)      | 0.460   | 0.714  | 0.378   | 0.649  | 0.468   | 0.720  |
| ours (RotatE)        | 0.499   | 0.712  | 0.439   | 0.674  | 0.504   | 0.715  |
Table 6: Borrowed LDPs of selected entity-pairs. Top 5 LDPs with our borrowing method and LDPs borrowed from 3NN entity-pairs are shown.

| Entity-pairs \((h, r, t)\) | Borrowed LDPs | SuperBorrow |
|---------------------------|----------------|-------------|
| \(h=\) Woodrow Wilson \(t=\) League of Nations \(r=\) organizations-founded | \(h;\langle\text{nsubj}\rangle;\text{joined};\langle\text{dobj}\rangle;t\) | \(h;\langle\text{poss}\rangle;t\) |
| \(h=\) 20th Century Fox \(t=\) Lincoln \(r=\) film-distributor | \(h;\langle\text{nn}\rangle;\text{movie};\langle\text{appos}\rangle;t\) | \(h;\langle\text{dep}\rangle;\text{released};\langle\text{subj}\rangle;t\) |
| \(h=\) Deep Impact \(t=\) Leslie Dilley \(r=\) film-production-design-by | \(h;\langle\text{obj}\rangle;\text{in};\langle\text{prep}\rangle;\text{work};\langle\text{poss}\rangle;t\) | \(h;\langle\text{dep}\rangle;\text{film};\langle\text{poss}\rangle;t\) |
| \(h=\) Idaho \(t=\) Christianity \(r=\) religion | \(h;\langle\text{appos}\rangle;\text{usa};\langle\text{appos}\rangle;t\) | \(h;\langle\text{poss}\rangle;t\) |

Table 7: Hits@10 of tail prediction for different relation categories.

| Method       | # Tuples | 1to1 | 1toN  | Nto1   | NtoN   |
|--------------|----------|------|-------|--------|--------|
| TransE       | 192      | 0.536| 0.597 | 0.124  | 0.418  |
| DistMult     | 1293     | 0.947| 0.984 | 0.377  | 0.829  |
| ComplEx      | 4289     | 0.300| 0.433 | 0.104  | 0.371  |
| RotatE       | 14,696   | 0.922| 0.856 | 0.338  | 0.547  |

Figure 1: t-SNE plots for DistMult entity embeddings comparing (a) KG-only and (b) KG with LDPs.

The KG only setting. Similar results are obtained for predicting the tail entities as in Appendix B. Overall, these results show that incorporating information from text corpora into KGs enables us to learn KGs that encode diverse relation types.

**Visualisation of Entity Embeddings:** In Figure 1, we visualise the entity embeddings of KGOnly and KG with LDPs using \(t\)-distributed stochastic neighbour embeddings (t-SNE) (Hinton and Roweis, 2002) method. Relations in FB15k237 are labelled as domain/type/property where domain/type represents the type of a head entity in the relation. Thus, for each entity in the KG, we extract its types from all training triples where the entity acts as the head. We label entities that belong to the two most frequent entity types, which are people/person (4,538 entities) and film/film (1,923 entities). From Figure 1, we see that the embeddings learnt from the augmented graph results in distinct clusters of the same type, compared to the clusters obtained from the KG alone. This emphasizes the importance of using textual mentions in KGE learning.

7 Conclusion

We considered the problem of representing without-mention entity-pairs in KGE learning. Specifically, we proposed a method (SuperBorrow) to determine which LDPs to borrow from with-mention entity-pairs to augment a KG using a corpus. Our proposed method improves the performance of several KGE learning methods in link and relation prediction tasks.
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**Supplementary Material**

### A Relation Prediction

Relation prediction results for all the KGE methods are shown in Table 8. As we see, unlike semantic matching-based KGE models, incorporating LDPs into the KG do not improve relation prediction for translational distance-based KGE methods (TransE and RotatE). For KG+ExtractedLDPs embeddings, the performance for with-mention set decreases by 0.045 and 0.012 on average for MRR and H@{10,3,1}, for TransE and RotatE respectively. In-depth analysis for this observation can be conducted in future research.

### B Tail Prediction for Relation Categories

Table 9 presents Hits@10 for tail prediction considering 1to1, 1toN, Nto1 and NtoN relation categories. As we see, SuperBorrow embeddings obtain the best results for all KGE methods and all the relation categories.

### C Training KGE Methods

For reproducability, we list the hyperparameter setting to train KGE methods in Table 10. AdaGrad (Duchi et al., 2011) with 100 batches is used to learn KGs. Table 11 shows the training time (in hours) to train KGE methods for KG only and SuperBorrow using OpenKE-Pytorch tool (Han et al., 2018).

| Method | #Tuples | 1to1 | 1toN | Nto1 | NtoN |
|--------|---------|------|------|------|------|
| TransE | KG only | 0.547 | 0.097 | 0.851 | 0.574 |
|        | SuperBorrow | 0.943 | 0.647 | 0.980 | 0.907 |
| DistMult | KG only | 0.521 | 0.055 | 0.774 | 0.507 |
|        | SuperBorrow | 0.880 | 0.424 | 0.898 | 0.657 |
| ComplEx | KG only | 0.500 | 0.034 | 0.787 | 0.518 |
|        | SuperBorrow | 0.869 | 0.456 | 0.964 | 0.753 |
| RotatE | KG only | 0.536 | 0.107 | 0.855 | 0.561 |
|        | SuperBorrow | 0.927 | 0.731 | 0.983 | 0.853 |

Table 9: Hits@10 of tail prediction for different relation categories.

| Method   | #Train tuples | Time (h) |
|----------|---------------|----------|
| TransE   | KG only       | 272,115  | 0.42    |
|          | SuperBorrow   | 1,217,294| 1.58    |
| DistMult | KG only       | 272,115  | 0.78    |
|          | SuperBorrow   | 1,036,904| 2.67    |
| ComplEx  | KG only       | 272,115  | 0.69    |
|          | SuperBorrow   | 946,709  | 2.11    |
| RotatE   | KG only       | 272,115  | 1.11    |
|          | SuperBorrow   | 1,127,099| 4.13    |

Table 11: Training time on FB15K237 in hours.
Table 8: Relation prediction on FB15K237.

| Model          | learning rate | embedding dimension | negative samples | loss function | margin | epochs |
|----------------|---------------|---------------------|------------------|---------------|--------|--------|
| TransE (KG only) | 1.0           | 300                 | 25               | Margin loss   | 5.0    | 1000   |
| KG+ExtractedLDPs | 0.5           | 300                 | 25               | SoftPlus loss | -      | 1000   |
| ComplEx (KG only) | 0.5           | 100                 | 25               | SoftPlus loss | -      | 1000   |
| RotatE (KG only) | 2e-5          | 300                 | 25               | SigmoidLoss   | 9.0    |        |

Table 10: The hyperparameter setting for KGE methods on link prediction task.