Incorporating Literals into Knowledge Graph Embeddings

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Abstract

Knowledge graphs, on top of entities and their relationships, contain another important element: literals. Literals encode interesting properties (e.g. the height) of entities that are not captured by links between entities alone. Most of the existing work on embedding (or latent feature) based knowledge graph modeling focuses mainly on the relations between entities. In this work, we study the effect of incorporating literal information into existing knowledge graph models. Our approach, which we name LiteralE, is an extension that can be plugged into existing latent feature methods. LiteralE merges entity embeddings with their literal information using a learnable, parametrized function, such as a simple linear or nonlinear transformation, or a multilayer neural network. We extend several popular embedding models using LiteralE and evaluate the performance on the task of link prediction. Despite its simplicity, LiteralE proves to be an effective way to incorporate literal information into existing embedding based models, improving their performance on different standard datasets, which we augmented with their literals and provide as testbed for further research.

1 Introduction

Knowledge graphs (KGs) form the backbone of a range of applications, for instance in the areas of search, question answering and data integration. Some well known knowledge graphs are DBpedia [Lehmann et al., 2015], Freebase [Bollacker et al., 2008], YAGO [Mahdisoltani et al., 2014] and the Google Knowledge Graph. There are different knowledge representation paradigms for modeling knowledge graphs such as the Resource Description Framework (RDF) and (labeled) property graphs. Within this paper, we consider a knowledge graph to be a set of triples, where each triple connects an entity (shown as circle in Figure 1) to another entity or a literal (the latter shown as rectangle in Figure 1) via relationships. Such knowledge graphs can be represented by the RDF as well as the property graph paradigms, i.e. the methods presented in this paper are applicable to both.

Knowledge graphs aim to capture factual knowledge within a particular domain. However, they are often incomplete since, e.g., more information is provided for popular entities or because the knowledge graph is partially or fully generated via an automatic extraction process. As a result, knowledge graphs rely heavily on methods predicting unknown triples given all known triples. This problem is usually referred to as link prediction. The closely related problem of detecting incorrect triples in knowledge graphs is referred to as link correction and relevant for improving the quality of knowledge graphs.

Due to the importance of the problem, many methods for link prediction and correction in knowledge graphs have been developed. The two main classes of these methods are graph feature and latent feature models. Graph feature models predict the existence of triples based on features directly ob-

Figure 1: Literals encode information that cannot be represented by relations alone, and are useful for link prediction task. For instance, by considering both birthYear literals and the fact that John and Jane both study at Doe High School, we can infer the relation friendOf between John and Jane is likely to exist.
served in the knowledge graph, such as the neighborhood of an entity and paths to other entities. They are well suited for modeling local graph patterns. In latent feature models, low-dimensional, latent representations (also called embeddings) of entities and relations are learned. These embeddings incorporate the structure of a knowledge graph, can capture global patterns and allow to compute the likelihood of a given triple in terms of a probability or score function.

However, most of the recent work on latent feature models only take entities and their relations to other entities into account. Therefore, they are potentially missing the additional information encoded in literals. For example, Figure 1 shows two entities with both structural (visiting the same school) as well as literal (birth years) information. To maximize the accuracy of predicting a friendOf relation between entities, structural and literal information should be combined as people visiting the same school and with similar age tend to have a higher probability of being friends.

In this paper, we investigate the advantage obtained by incorporating the additional information provided by literals into latent feature models. We introduce LiteralE, a method to enrich entity embeddings with their literal information. Given an entity embedding, we incorporate its corresponding literals using a learnable parametric function, e.g., an affine transformation or a neural network. The resulting literal-enriched embeddings can then replace the vanilla embeddings in any latent feature model. LiteralE can be seen as an extension module that can be universally combined with the score function of any existing latent feature model. The resulting system can be jointly trained with stochastic gradient descent in an end-to-end manner. Thus, LiteralE is a simple approach to incorporate literal information into existing models. Within this paper, we focus on numerical literal values. However, the principle can be directly generalized to other literal types, such as textual and image information. Our contributions in this paper are threefold:

- We introduce LiteralE, a universal approach to enrich latent feature models with literal information via a learnable parametric function. In contrast to other latent feature models including literals, our approach does not require hand-crafted features, does not rely on a fixed function to combine entity embeddings and literals, can model interactions between an embedding of an entity and all its literal values and can be trained end-to-end.

- We evaluate LiteralE on standard link prediction datasets (FB15k, FB15k-237 and YAGO3-10). We extended FB15k and FB15k-237 with literals, in order to allow for direct comparison against other methods on these standard datasets. We provide these literal-extended versions and hope they can serve as a test bed for future research on literals in KG modeling.

- Based on experimental results on the extended datasets, we show that by exploiting the information provided by literals, the link prediction performance of existing models can be increased significantly.

Our implementation and all datasets are publicly available at: [https://github.com/SmartDataAnalytics/LiteralE](https://github.com/SmartDataAnalytics/LiteralE)

2 Preliminaries

Problem Description Link prediction is defined as the task of deciding whether a fact (represented by a triple) is true or false given the knowledge graph. More formally, let $E = \{e_1, \cdots, e_N\}$ be the set of entities, $L = \{l_1, \cdots, l_M\}$ the set of literal values, $R = \{r_1, \cdots, r_N\}$ the set of relations connecting two entities and $D = \{d_1, \cdots, d_N\}$ the set of relations connecting an entity and a literal, i.e., the data relations. A knowledge graph $G$ is a subset of $(E \times R \times E) \cup (E \times D \times L)$ representing the facts that are assumed to hold. Then, link prediction can be formulated as the task of mapping each possible triple $(e_i, r_k, e_j) \in E \times R \times E$ to a score value, where a higher value implies the triple is more likely to be true.

Latent Feature Models In general, latent feature models are a class of methods in which low dimensional vector representations of entities and relations, called embeddings, are learned. Let $H$ be the dimension of latent variables. Let $E \in \mathbb{R}^{N \times H}$ be the entity embeddings matrix and $R \in \mathbb{R}^{N \times H}$ be the relation embeddings matrix for $E$ and $R$ respectively. The task of link prediction is then finding a function $f : \mathbb{R}^H \times \mathbb{R}^H \times \mathbb{R}^H \rightarrow \mathbb{R}$ that maps a triple’s embeddings $(e_i, e_j, r_k)$ to a score $f(e_i, e_j, r_k)$ that correlates with the truth value of the triple.

Latent feature models for link predictions are well studied. Examples of popular methods are DistMult [Yang et al., 2014], ComplEx [Trouillon et al., 2016], and ConvE [Dettmers et al., 2017]. These methods follow a score-based approach and differ in their parameterization of the entity and relation representations. Some use latent matrices instead of latent vectors or allow to use relation and entity embeddings to have different dimensions. The exact formulation of the scoring function $f$ that uses these embeddings also differs.

The DistMult scoring function is defined as diagonal bilinear interaction between two entities and a relation embedding in a given triple, as follows:

$$f_{\text{DistMult}}(e_i, e_j, r_k) = \langle e_i \odot e_j \odot r_k \rangle ,$$ (1)

where $e_i$ and $e_j$ denote the $i$-th and $j$-th row of $E$ respectively, and $r_k$ denotes the $k$-th row of $R$.

ComplEx can be seen as DistMult analogue in the complex space. The embedding matrices have two parts: the real part $\text{Re}(E)$ and $\text{Re}(R)$, and the imaginary part $\text{Im}(E)$ and $\text{Im}(R)$. The scoring function is defined as

$$f_{\text{ComplEx}}(e_i, e_j, r_k) = \langle \text{Re}(e_i), \text{Re}(e_j), \text{Re}(r_k) \rangle$$  
$$+ \langle \text{Im}(e_i), \text{Im}(e_j), \text{Re}(r_k) \rangle$$  
$$+ \langle \text{Re}(e_i), \text{Im}(e_j), \text{Im}(r_k) \rangle$$  
$$- \langle \text{Im}(e_i), \text{Re}(e_j), \text{Im}(r_k) \rangle .$$ (2)

\footnote{A literal-extended version of YAGO3-10 is provided by Pezeshkpour et al., 2017}
ComplEx thus has twice the number of parameters compared to DistMult but provides the benefit of modelling asymmetric relationships better, as discussed by Trouillon et al. [2016].

ConvE uses convolution operations to extract features from entity and relation embeddings. Let \( h \) be a nonlinear function, \( \omega \) be convolution filters, and \( W \) be a weight matrix. The ConvE score function is then defined as follows:

\[
f_{\text{convE}}(e_i, e_j, r_k) = h(\text{vec}(h((e_i, r_k) \ast \omega))W)e_a.
\]

In this work, we use DistMult, ComplEx, and ConvE as main models which we extend by LiteralE. Our hypothesis is that by incorporating LiteralE and thus literals information, we can significantly improve the performance of DistMult, ComplEx, and ConvE.

3 LiteralE

Our method of incorporating literals into existing latent feature models, which we call LiteralE, is a simple, modular, and universal extension which can enhance the performance of the base models.

Let \( L \in \mathbb{R}^{N_e \times N_e} \) be a matrix, where each entry \( L_{ik} \) contains the \( k \)-th literal value of \( i \)-th entity if a triple with the \( i \)-th entity and the \( k \)-th data relation exists in the knowledge graph and zero otherwise. At the core of LiteralE is a function \( g : \mathbb{R}^H \times \mathbb{R}^{N_e} \rightarrow \mathbb{R}^H \) that takes entity embeddings and their literal vectors as inputs and maps them onto another \( H \)-dimensional vector. The resulting vectors are (non-)linear transformations of both the entity embeddings and their literal vectors. Then, the original embedding vectors in the scoring function of any latent feature model can be replaced with these literal-enriched vectors. For example in our experiments, we replace every entity embedding \( e_i \) with \( e_{i}^{\text{lit}} = g(e_i, l_i) \) in the scoring functions of DistMult and ConvE. For ComplEx, where the embeddings have a real and an imaginary part, we replace \( \text{Re}(e_i) \) and \( \text{Im}(e_i) \) with \( \text{Re}(e_i)^{\text{lit}} = g_{\text{real}}(\text{Re}(e_i), l_i) \) and \( \text{Im}(e_i)^{\text{lit}} = g_{\text{im}}(\text{Im}(e_i), l_i) \), respectively. Aside of these changes in entities embeddings, the score functions are as described before in Equations (1), (2), and (3).

The transformation function \( g \) can be any fixed or learnable function. In this work, we focus on simple learnable functions: linear transformation, non-linear transformation and a multi-layer neural network (MLP), as specified in the following:

\[
\begin{align*}
g_{\text{real}}(e_i, l_i) &= W^T[e_i, l_i], \\
g_{\text{nonlin}}(e_i, l_i) &= h(W^T[e_i, l_i]), \\
g_{\text{MLP}}(e_i, l_i) &= h(W^T_ih(W^T[e_i, l_i]),
\end{align*}
\]

where \( W, W_1 \) and \( W_2 \) are trainable weight matrices and \( h \) is a non-linear function. More concretely, we concatenate the entity embedding vector with the corresponding literals vector and map it into an \( H \)-dimensional vector. In Eq. 4 the mapping is a simple linear combination with a learnable weight matrix, whereas in Eq. 5 we add nonlinearity on top of the linear combination. Finally, in Eq. 6 we use function composition for this mapping, i.e. MLP. We experiment with hyperbolic tangent and ReLU for the non-linear transformation (or activation function) and only ReLU for MLP.

In summary, we propose to replace the score function \( f_X(e_i, e_j, r_k) \) from the host method \( X \) with the function composition \( f_X(g(e_i, l_i), g(e_j, l_j), r_k) \) as illustrated in Figure 2. This new scoring function can be trained by gradient descent using the same training procedure as before.

4 Related Work

In the last years, several efforts to incorporate literals into knowledge graph embedding models have been made. Toutantova et al. [2015] and Tu et al. [2017] make use of textual literals of entities in addition to relational embeddings. More specifically they learn additional entity embeddings from their textual description and use them in an additive term in the score function of latent distant models. Xie et al. [2016] use image literals in their model by projecting entities’ image features into an entity embeddings space. However all of those approaches do not consider numerical literals. MultiModal [Pezeshkpour et al., 2017] extends DistMult to also predict the likeliness of (subject, predicate, literal) triples, by replacing the object embedding in standard DistMult by its literal embedding (where literals of different modalities are taken into account). By doing so literals are incorporated into entity embedding by multi-task learning scheme. In contrast, LiteralE combines the literals into the entity embedding directly and thus no additional task is required.

KBLRN [Garcia-Duran and Niepert, 2017] handles literals in a separate function added to the vanilla scoring function and thus does not incorporate literals in to the entity embeddings themselves. Moreover, KBLRN’s numerical features

\footnote{Note, that incorporating the literal information into the embeddings also seems advantageous for entity disambiguation or clustering.}
are handcrafted, which requires prior knowledge and manual intervention. In contrast, LiteralE learns to merge entity embeddings and its literals in a single representation in an end-to-end manner.

MTKGNN [Tay et al., 2017] extends ERMLP [Dong et al., 2014] and incorporates literals by introducing an additional learning task (i.e., predicting the literal value for a given entity). The multi-task learning approach of MTKGNN requires an additional attribute-specific training procedure. Scalability when adding another type or modality of literals is thus costly as another learning task needs to be devised.

Lastly, the model recently proposed by Thoma et al. [2017] can be seen as a special case of LiteralE where the function used to combine literals of entities is a concatenation followed by singular value decomposition. Thus, they use fixed functions to combine the representations, whereas LiteralE employs adaptable functions and is therefore more flexible. Furthermore, they only consider image and text literals and thus do not consider numerical literals.

5 Experiments

5.1 Training

In our experiments, we use the same training approach as Dettmers et al. [2017] for all the tested models. That is, for every given triple \((e_i, r_k, e_j)\), we compute scores for \((e_i, r_k, e_j', e_j)\), \(\forall e_j' \in E\) using the (original or LiteralE-extended) scoring function \(f\), and use the sigmoid function to produce probabilities \(p = \sigma(f(\cdot))\). The model is trained by minimizing the binary cross-entropy loss of the produced probability vector \(p \in \{0, 1\}^N_e\), \(N_e\) being the number of entities, w.r.t. the vector of truth values \(y \in \{0, 1\}^{N_e}\) for the scored triples:

\[
L(p, y) = -\frac{1}{N_e} \sum_{x=1}^{N_e} \left( y_x \log(p_x) + (1 - y_x) \log(1 - p_x) \right),
\]

where \(p_x\) and \(y_x\) are the predicted probability and the given truth value for the \(x\)-th element of our candidate set \(\{(e_i, r_k, e_j'), \forall e_j' \in E\}\). We use Adam [Kingma and Ba, 2014] to optimize this loss function.

5.2 Datasets

We use three widely used datasets for evaluating link prediction performance: FB15k, FB15k-237, and YAGO3-10. FB15k [Bordes et al., 2013] is a subset of Freebase where most triples are related to movies and sports. As discussed by Dettmers et al., [2017] FB15k has a large number of test triples which can simply be obtained by inverting training triples. This results in a biased test set, for which a simple model which is symmetric with respect to object and subject entity is capable of achieving excellent results. To address this problem, Toutanova and Chen [2015] created FB15k-237 by removing inverse relations from FB15k. YAGO3-10 [Mahdisoltani et al., 2014] is a subset of the YAGO3 knowledge graph which mostly consists of triples related to people.

In this work, we only consider numerical literals, e.g., longitude, latitude, population, age, date of birth, etc. To enrich FB15k and FB15k-237 with literals, we created a SPARQL endpoint for Freebase and extracted literals of all entities contained in FB15k. We further filtered the extracted literals based on their frequency, i.e., we only consider data relations \(r_k \in D\) that occur at least in 5 triples in FB15k. We also remove all key and ID relations since their values are not meaningful as quantities. For YAGO3-10, we use numerical literals provided by YAGO3-10-plus [Pezeshkpour et al., 2017], which is publicly available.

In case an entity has multiple literal values for a particular data relation, we arbitrarily select one of them. Some statistics of the datasets are provided in Table 1.

| Dataset       | FB15k | FB15k-237 | YAGO3-10 |
|---------------|-------|-----------|----------|
| # Entities \((N_e)\) | 14,951 | 14,541 | 123,182 |
| # Relations \((N_r)\) | 1,345 | 237 | 37 |
| # Rel. rel. \((N_d)\) | 121 | 121 | 5 |
| # Literals \(|L|\) | 18,741 | 18,741 | 111,406 |
| # Relational triples | 592,213 | 310,116 | 1,089,040 |
| # Literal triples | 70,257 | 70,257 | 111,406 |

Table 1: Statistics of number of entities, relations, and literals for all datasets used in this paper.

Our literal-extended versions of FB15k and FB15k-237 are available at: [https://github.com/TimDettmers/ConvE](https://github.com/TimDettmers/ConvE)

5.3 Experimental Setup

We build our LiteralE code on top of ConvE’s codebase, which is publicly available. The hyperparameters used in all of our experiments across all datasets are: learning rate 0.001, batch size 128, embedding size 100, embedding dropout probability 0.2, feature map dropout probability 0.2, projection layer dropout probability 0.3, and label smoothing 0.1. The hyperparameter values are the same as in the experiments of Dettmers et al. [2017] except for embedding dimensions for DistMult and ComplEx, which we set to 100 instead of 200 in all our experiments.

Except for ConvE, we run all of our experiments for a maximum of 100 epochs as we observed that this is sufficient for convergence in most cases. For ConvE, we used at most 1000 epochs, as described in the original paper [Dettmers et al., 2017]. We apply early stopping in all of the experiments by monitoring the Mean Reciprocal Rank (MRR) metric on the validation set every three epochs.

To validate our approach and to eliminate the effect of different environment setups, we reproduce the base models and compare them with their LiteralE-extension. Note that we were unable to reproduce the results reported by Garcia-Duran and Niepert [2017] and Pezeshkpour et al. [2017] as the code is not open-source at the time of this writing. We do not compare LiteralE to the work of Tay et al. [2017] since their results were obtained on an unpublished dataset and we

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3https://github.com/pouyapez/multim-kb-embeddings

4https://github.com/TimDettmers/ConvE

5We also tried with embedding size of 200 but it had little to no impact on the results.

6We could not obtain their dataset and thus unable to run our
| Models                          | MR   | MRR   | Hits@1   | Hits@3   | Hits@10  |
|--------------------------------|------|-------|----------|----------|----------|
| DistMult \cite{Dettmers et al., 2017} | 97   | 0.654 | 0.546    | 0.733    | 0.824    |
| ComplEx \cite{Dettmers et al., 2017}    | -    | 0.692 | 0.599    | 0.759    | 0.84     |
| ConvE \cite{Dettmers et al., 2017}      | 64   | 0.745 | 0.67     | 0.801    | 0.873    |
| KBL (DistMult) \cite{Garcia-Duran and Niepert, 2017} | 66   | 0.774 | 0.712    | -        | 0.876    |
| KBLN \cite{Garcia-Duran and Niepert, 2017} | 69   | 0.783 | 0.726    | -        | 0.878    |
| DistMult (Ours)                  | 108  | 0.671 | 0.589    | 0.723    | 0.818    |
| ComplEx (Ours)                   | 127  | 0.695 | 0.618    | 0.744    | 0.833    |
| ConvE (Ours)                     | 49   | 0.692 | 0.596    | 0.76     | 0.853    |
| DistMult+LiteralE               | 85   | 0.583 | 0.476    | 0.652    | 0.771    |
| ComplEx+LiteralE                | 92   | 0.765 | 0.705    | 0.806    | 0.871    |
| ConvE+LiteralE                  | 55   | 0.66  | 0.556    | 0.733    | 0.836    |
| DistMult+LiteralE-Tanh          | 94   | 0.557 | 0.448    | 0.626    | 0.748    |
| DistMult+LiteralE-ReLU          | 120  | 0.509 | 0.408    | 0.566    | 0.697    |
| DistMult+LiteralE-MLP           | 188  | 0.327 | 0.238    | 0.36     | 0.496    |

Table 2: Link prediction results on FB15k.

| Models                          | MR   | MRR   | Hits@1   | Hits@3   | Hits@10  |
|--------------------------------|------|-------|----------|----------|----------|
| DistMult \cite{Dettmers et al., 2017} | 254  | 0.241 | 0.155    | 0.263    | 0.419    |
| ComplEx \cite{Dettmers et al., 2017}    | 248  | 0.24  | 0.152    | 0.263    | 0.419    |
| ConvE \cite{Dettmers et al., 2017}      | 330  | 0.301 | 0.22     | 0.33     | 0.458    |
| KBL (DistMult) \cite{Garcia-Duran and Niepert, 2017} | 231  | 0.301 | 0.214    | -        | 0.475    |
| KBLN \cite{Garcia-Duran and Niepert, 2017} | 229  | 0.304 | 0.22     | -        | 0.47     |
| DistMult (Ours)                  | 641  | 0.28  | 0.2      | 0.307    | 0.438    |
| ComplEx (Ours)                   | 652  | 0.29  | 0.212    | 0.317    | 0.445    |
| ConvE (Ours)                     | 297  | 0.313 | 0.228    | 0.344    | 0.479    |
| DistMult+LiteralE               | 346  | 0.31  | 0.225    | 0.34     | 0.48     |
| ComplEx+LiteralE                | 441  | 0.297 | 0.215    | 0.327    | 0.458    |
| ConvE+LiteralE                  | 264  | 0.314 | 0.228    | 0.346    | 0.483    |
| DistMult+LiteralE-Tanh          | 300  | 0.321 | 0.234    | 0.355    | 0.494    |
| DistMult+LiteralE-ReLU          | 454  | 0.302 | 0.222    | 0.331    | 0.464    |
| DistMult+LiteralE-MLP           | 262  | 0.289 | 0.212    | 0.313    | 0.442    |

Table 3: Link prediction results on FB15k-237.

| Models                          | MR   | MRR   | Hits@1   | Hits@3   | Hits@10  |
|--------------------------------|------|-------|----------|----------|----------|
| DistMult \cite{Dettmers et al., 2017} | 5926 | 0.337 | 0.237    | 0.379    | 0.54     |
| ComplEx \cite{Dettmers et al., 2017}    | 6351 | 0.355 | 0.258    | 0.399    | 0.547    |
| ConvE \cite{Dettmers et al., 2017}      | 2792 | 0.523 | 0.448    | 0.564    | 0.658    |
| Multimodal S+N \cite{Pezeshkpour et al., 2017} | -    | 0.325 | 0.213    | 0.382    | 0.517    |
| DistMult (Ours)                  | 2943 | 0.466 | 0.377    | 0.514    | 0.653    |
| ComplEx (Ours)                   | 3768 | 0.493 | 0.411    | 0.536    | 0.649    |
| ConvE (Ours)                     | 2141 | 0.505 | 0.42     | 0.554    | 0.66     |
| DistMult+LiteralE               | 2705 | 0.504 | 0.422    | 0.551    | 0.653    |
| ComplEx+LiteralE                | 3072 | 0.509 | 0.433    | 0.552    | 0.653    |
| ConvE+LiteralE                  | 1720 | 0.506 | 0.422    | 0.556    | 0.664    |
| DistMult+LiteralE-Tanh          | 1685 | 0.417 | 0.322    | 0.464    | 0.595    |
| DistMult+LiteralE-ReLU          | 6839 | 0.427 | 0.343    | 0.473    | 0.582    |
| DistMult+LiteralE-MLP           | 3091 | 0.134 | 0.085    | 0.138    | 0.226    |

Table 4: Link prediction results on YAGO3-10.
cannot reproduce their approach on our datasets because their code is not publicly available.

We use the following standard evaluation metrics for link prediction: Mean Rank (MR), Mean Reciprocal Rank (MRR), Hits@1, Hits@3, and Hits@10 over the test set of each dataset.

6 Results

The results for our experiments on link prediction are summarized in Tables 2, 3 and 4. In general, we observe that incorporating literals using LiteralE results in an improvement over base models.

ComplEx with LiteralE results in improved performance across all datasets. Adding LiteralE to DistMult improves its performance on FB15k-237 and YAGO3-10 but deteriorates the performance on FB15k. Specifically, while ComplEx+LiteralE achieves 10% relative improvement on MRR on FB15k compared to basic ComplEx, DistMult+LiteralE drops 13% relative to basic DistMult on FB15k.

We hypothesize that this drop in performance of DistMult+LiteralE on FB15k happens due to the lower expressive power of DistMult, in particular its inability to capture asymmetry in relations. The score function of DistMult is symmetric, i.e. $f(h, r, t) = f(t, r, h)$, meaning it will assign exactly the same score to a triple if its head and tail were swapped. Since DistMult already has difficulties in modeling asymmetric relations on FB15k, adding literals might only introduce noise, resulting in more lower performance. ComplEx (the complex equivalent of DistMult) solves the symmetric score problem by using the complex conjugate of the entity embedding when used as the tail in a triple (and its normal embedding when being the head). This gives ComplEx more expressive power, which could allow it to more easily exploit the addition of literals to improve its predictions. Our hypothesis that DistMult+LiteralE degrades due to symmetric relations also seems to be confirmed by the fact that adding LiteralE improves DistMult on FB15k-237, where all symmetric relations are discarded.

On YAGO3-10, we observed noticeably better results for our reproductions of basic DistMult and ComplEx, while also observing slightly worse results on basic ConvE, compared to those reported by Dettmers et al. [2017]. We believe this is due to Dettmers et al. [2017] using a different training approach for ConvE compared to the other methods. Specifically, they use a 1-1 approach for DistMult and ComplEx, while using a 1-N approach for ConvE. We refer our readers to Dettmers et al. [2017] for more details regarding this.

We observed that LiteralE improves all the base models on YAGO3-10, although by a smaller margin than on the other datasets. This could be attributed to the lower number of literal relations and the relatively lower average literals per entity in YAGO3-10, compared to FB15k(-237): there are 5 literal relations and 0.9 literals per entity in YAGO3-10 compared to 121 literal relations and around 1.2 literals per entity in both FB15k and FB15k-237. A less pronounced improvement when fewer literal relations are available is consistent with the hypothesis that literals are useful for link prediction.

| Models   | MRR     | Hits@1   | Hits@10  |
|----------|---------|----------|----------|
| DistMult | 0.308±0.003 | 0.222±0.004 | 0.48±0.002 |
| ComplEx  | 0.296±0.001 | 0.213±0.002 | 0.459±0.002 |
| ConvE    | 0.313±0.002 | 0.227±0.002 | 0.481±0.004 |

Table 5: Mean and standard deviation of the results of various methods with LiteralE on FB15k-237. The samples used for calculating these statistics are obtained by performing five runs with different random seeds.

6.1 Functional Form of LiteralE

We show the effect of the choice of the functional form of $g$ in Table 2, 3 and 4. In particular, we experimented with DistMult for the three choices of functional form of $g$: linear, nonlinear, and MLP (Equations 4, 5 and 6, respectively, see Section 3).

Based on our experiments, we observed that the best results are achieved by defining LiteralE as a simple linear function. Adding nonlinearities (ReLU or hyperbolic tangent) generally renders the results worse on all evaluation metrics, except on FB15k-237, where using a hyperbolic tangent yields the best result. Using an MLP based transformation for LiteralE yields negative results, which might be attributed to overfitting.

6.2 Effect of Random Seeds

To estimate the uncertainty in the results we obtained, we ran LiteralE five times on FB15k-237 with all three base models. In each run, we picked a different random seed. In Table 5, we report the mean and standard deviation across different runs for different evaluation metrics. The low standard deviation of the metrics across different runs indicate that the obtained results are stable and thus reproducible.

7 Conclusion and Future Work

In this paper, we introduced LiteralE: a simple method to incorporate literals in latent feature models for knowledge graphs. LiteralE can be seen as an extension module for any latent feature model. We showed that by applying LiteralE to existing models such as DistMult, ComplEx, and ConvE, their link prediction performance can be improved. Furthermore, we showed that the simplest linear form of LiteralE performed best across most of the datasets. For future work, LiteralE could be extended to accommodate different modalities of literals, e.g. text, images etc. Furthermore, LiteralE could also be incorporated in other tasks besides link prediction, such as entity resolution and knowledge graph clustering.

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