Multiple Run Ensemble Learning with Low-Dimensional Knowledge Graph Embeddings

Chengjin Xu*, Mojtaba Nayyeri*, Sahar Vahdati† and Jens Lehmann*‡
*SDA Research, University of Bonn, Bonn, Germany
Email: {xuc, nayyeri, jens.lehmann}@cs.uni-bonn.de
‡University of Oxford, Oxford, UK
Email: sahar.vahdati@cs.ox.ac.uk
*‡Fraunhofer IAIS, Bonn, Germany
Email: jens.lehmann@iais.fraunhofer.de

Abstract—Knowledge graphs (KGs) represent world facts in a structured form. Although knowledge graphs are quantitatively huge and consist of millions of triples, the coverage is still only a small fraction of world’s knowledge. Among the top approaches of recent years, link prediction using knowledge graph embedding (KGE) models has gained significant attention for knowledge graph completion. Various embedding models have been proposed so far, among which, some recent KGE models obtain state-of-the-art performance on link prediction tasks by using embeddings with a high dimension (e.g. 1000) which accelerate the costs of training and evaluation considering the large scale of KGs. In this paper, we propose a simple but effective performance boosting strategy for KGE models by using multiple low dimensions in different repetition rounds of the same model. For example, instead of training a model one time with a large embedding size of 1200, we repeat the training of the model 6 times in parallel with an embedding size of 200 and then combine the 6 separate models for testing while the overall numbers of adjustable parameters are same (6*200=1200) and the total memory footprint remains the same. We show that our approach enables different models to better cope with their expressiveness issues on modeling various graph patterns such as symmetric, 1-n, n-1 and n-n. In order to justify our findings, we conduct experiments on various KGE models. Experimental results on standard benchmark datasets, namely FB15K, FB15K-237 and WN18RR, show that multiple low-dimensional models of the same kind outperform the corresponding single high-dimensional models on link prediction in a certain range and have advantages in training efficiency by using parallel training while the overall numbers of adjustable parameters are same.

Index Terms—Graph Embedding, Ensemble Learning, Statistical Relational Learning, Link Prediction

I. INTRODUCTION

Numerous knowledge graphs including lexical datasets and world’s knowledge, such as WordNet [1], FreeBase [2], YAGO [3], and DBpedia [4], have been published with different utilization purposes. These KGs have become a significant resource for many AI-based applications such as question answering and recommendation systems [5]. Therefore, a new horizon for using machine learning approaches on structured data at scale has been opened up for leading science and industry.

Despite all the advantages of KGs in down stream tasks, one of the main challenges of existing KGs is their incompleteness [6]. Knowledge graph completion using link prediction approaches aims at addressing the incompleteness of KGs. Among various link prediction approaches, knowledge graph embedding (KGE) has gained significant attention recently. A KGE model takes a KG in the form of triple facts \((h, r, t)\) where \(h, t\) are entities (nodes) and \(r\) is a relation (link) between the entities (e.g. \((\text{Berlin, Capital of, Germany})\)). A vector is assigned to each element of a triple \((h, r, t)\) in a KG and all vectors are then adjusted by optimizing a loss function. The likelihood of a triple is then measured by using a score function over the embedding vectors \((h, r, t)\). To evaluate the performances of KGE models on link prediction, several benchmarks including FB15K, WN18 [6], FB15K237 and WN18RR [7] are established by extracting subsets from large-scale KGs, e.g., WordNet [8] and FreeBase [9].

The score functions of models play an important role in the performance of KGE models. Numerous KGE models with a focus on score functions have been proposed. Among them, several recent models, including ComplExN3 [10], RotatE [11] and QuatE [14] take the advantage of hyper-complex representations and high-dimensional embeddings to achieve the state-of-the-art results. The high performances of RotatE, ComplExN3 and QuatE on FB15K are achieved by using embeddings with the dimensions of 1000, 1000 and 2000. Due to the usage of complex-valued vectors and quaternion vectors of ComplExN3 and QuatE, their best performing settings result in 4000 adjustable parameters for each entity and relation. On the other hand, for KGE models with higher embedding dimensions, there is a risk of the redundancy of parameters leading to unnecessary consumption on training time as well as memory space while the generalisation capabilities of the learned models are not improved. For example, the experimental results of ComplExN3 shows that the performances of a ComplExN3 with 500-dimensional embeddings on FB15K237 and WN18RR are almost same as a ComplExN3 with a embedding dimension of 2000.

Such observations show that the above mentioned state-of-the-art models take advantages of high embedding dimensions and multiple-vector representation resulting in a large embedding size \(d\) which is equal to the total number of adjustable parameters of each entity/relaion embedding. In other words, these models use single model with a multi-part high dimen-
sional embeddings (the total embedding size is $1 \times d_h$). In contrast to those models, we use the same model multiple ($k$) times in parallel trainings with low dimension (the overall embedding size is $k \times d_l$). In order to have a fair comparison, we enforce $k \times d_l = 1 \times d_h$ to guarantee that the overall numbers of adjustable parameters of multiple low-dimensional models is equal to the single high-dimensional model. Using multiple low dimensional model instead of a single high dimensional model improves the expressivity of various models in handling various patterns including symmetric, 1-n, n-1 and n-n. The experimental results on three benchmarks show that the ensemble of the same KGE model several times trained with low-dimensions results in a better performances than training that model once with a high dimension, regarding link prediction accuracy (higher expectations and lower standard deviations) and training time.

II. RELATED WORK

KGE models can be roughly classified into two groups, distance-based models and semantic matching models [5]. Here we review two distance-based KGE models, i.e., TransE, RotatE and three semantic matching models i.e., DistMult, ComplEx and ComplExN3. Each KGE model defines a score function $f(h, r, t)$ which takes embedding vectors of a triple $(h, r, t)$ and returns a value showing the degree of correctness of the triple.

TransE [6] computes the score of a triple $h, r, t$ by measuring the distance between relation-specific translated head $(h + r)$ and the tail $t$ as

$$f(h, r, t) = -\|h + r - t\|;$$  \hspace{1cm} (1)

to enforce $h + r \approx t$ for each positive triple $(h, r, t)$ in the vector space. The TransE model embeds entities/relation into $d$ dimensional real space, i.e., $h, r, t \in \mathbb{R}^d$.

RotatE [11] aims at mapping each element of the head embedding $(h_i)$ to the corresponding tail embedding $t_i$ by using relation-specific rotation $r_i = e^{i \theta}$. The score of each triple $(h, r, t)$ is computed as

$$f(h, r, t) = -\|h \circ r - t\|;$$  \hspace{1cm} (2)

where $\circ$ is the element-wise multiplication and $h, r, t \in \mathbb{C}^d$. This enforces $h \circ r \approx t$ for each positive triple $(h, r, t)$.

DistMult [15] is based on the Bilinear model [16] where each relation is represented by a diagonal matrix rather than a full matrix. The formulation of score function is

$$f(h, r, t) = h^\top \text{diag}(r)t = \sum_{i=0}^{d} h_i \cdot r_i \cdot t_i.$$  \hspace{1cm} (3)

This score captures pairwise interactions between only the components of $h$ and $t$ along the same dimension and thus can only deal with symmetric relations.

ComplEx [17] was proposed as an elegant way to solve the shortcoming of DistMult in modeling asymmetric relation. Its main contribution is to embed KGs in complex space. The score function is defined as

$$f(h, r, t) = \text{Re}(h^\top \text{diag}(r)t) = \text{Re} \left(\sum_{i=1}^{d} h_i r_i \bar{t}_i\right),$$  \hspace{1cm} (4)

where $r, h, t \in \mathbb{C}^d$, $t_i$ represents the complex conjugate of $t$. By using this scoring function, triples that have asymmetric relations can obtain different scores. ComplExN3 [10] extends ComplEx with weighted nuclear 3-norm (N3 regularization) and uses a multi-class logistic loss function as optimization objective to achieve the state-of-the-art results.

Krompass and Tresp [20] integer multiple different KGE models into one score function and combines them during the training phase. Likewise, Muroemagi et al. [22] combine different word embedding models using an iterative method. However, we focus on stretching and squeezing the dimensions of the same models which are trained separately and combined only for testing.

III. PROPOSED APPROACH

Compared to TransE and DistMult, ComplExN3, RotatE and QuatE take advantages of high-dimensional multi-part embeddings to achieve state-of-the-art performances on link prediction. In these models, all parts of embeddings are adjusted simultaneously. By contrast, in this part we propose a new approach which combines multiple models of the same kind where each model contains low-dimensional embeddings and is trained separately.

Let us have a model $M$ (e.g. RotatE) with the embedding size $d$ where $d$ is equal to the total number of adjustable parameters of each entity/relation embedding in a KGE model. Let $E$ denote the set of all entities and $R$ the set of all relations present in a knowledge graph. A triple is represented as $(h, r, t)$, with $h, t \in E$ denoting head and tail entities respectively and $r \in R$ the relation between them. We use $\Omega = \{(h, r, t)\} \subseteq E \times R \times E$ to denote the set of observed triples. We follow the steps below in our approach:

(a) We first generate $k$ times copies of an underlying model $M$. The $j$th copy of the model is denoted by $M_j$, $j = 1, \ldots, k$, and the corresponding $d_i$ dimensional embeddings of $(h, r, t)$ are denoted by $(h_j, r_j, t_j)$. The vectors are randomly initialized before training.

(b) We then train each of the models $M_j, j = 1, \ldots, k$ separately with the same loss function. The training process can speed up by using parallel computing.

(c) Finally, the testing is performed by using the following score function

$$f(h, r, t) = \frac{1}{k} \sum_{j=1}^{k} f_M(h_j, r_j, t_j),$$  \hspace{1cm} (5)

where $f_M(h_j, r_j, t_j)$ is the score of a triple $(h, r, t)$ computed by the $j$th copy of the model.

Figure 1 gives an example of representation learning with the ensemble of multiple DistMult models, named as MDistMult. Firstly, the entity Berlin is represented as a vector with
a dimension of $k \times d_l$. Then the vector is divided into $k$ separate vectors with dimensions of $d_l$. Each separate vector is trained with a single DistMult model. Given a triple $(\text{Berlin}, \text{Capital_of}, \text{Germany})$, its overall score is equal to the average of its scores computed from the $k$ separate DistMult models.

Note that all models are trained on the same dataset with same hyperparameters and the only two difference between the models is the random initialization of the embedding vectors and the random sampling during the training process. To verify the efficiency of our approach, we keep the overall embedding size $d_h$ of multiple low-dimensional models same as the embedding size $d_h$ of the single high-dimensional model, i.e. $k \times d_l = d_h$.

We follow the above steps to perform experiments on various state-of-the-art models, including TransE, RotatE, DistMult, ComplEx and ComplExN3. We also test DistMultN3, the extension of DistMult with the N3 regularizer. We will later elaborate on the embedding initialization and the optimization objectives of various models as well as the parallel training mechanism.

### A. Initialization

In this work, combined multiple models of the same kind are trained with same hyperparameters under the uniform experiment setting and the only two model variations are from the random initialization of embeddings before the training process and the random sampling during the training process.

Following the previous work on KGE, we use Xavier uniform initialization for semantic matching models and Xavier norm initialization for distance-based models. Xavier uniform initialization can make variances of each neuron layer remain the same and thus bring a faster converge speed. Xavier uniform initialization and Xavier norm initialization fill the input embedding with values drawn from the uniform distribution $\mathcal{U}(-a, a)$ and the normal distribution $\mathcal{N}(0, \sigma^2)$ respectively.

where

$$a = \sqrt{\frac{6}{d_{in} + d_{out}}}, \quad \sigma = \sqrt{\frac{2}{d_{in} + d_{out}}}.$$  \hfill (6)

For KGE model, $d_{in}$ is equal to the embedding size $d$ and $d_{out} = 0$. We follow the original experimental settings to uniformly initialize embeddings for TransE, RotatE and use Xavier norm initialization for DistMult and ComplEx. On the other hand, embeddings are initialized as sparse vectors for ComplExN3 and DistMultN3. Since the random seed is not fixed in the experiments, embeddings of different copies of the same model are initialized as different vectors.

### B. Optimization

An appropriate loss function is quite important for model optimization. Most of distance-based KGE models like TransE use a margin rank loss function as optimization objective [6] [18] [19]. The original work introducing ComplEx obtained the state-of-the-art results with a binary logistic loss function [17]. RotatE adds a margin parameter into the binary logistic loss function without the regularization term. This margin-based logistic loss function has been proven to be helpful to enhance the performance of distance-based models [11] [12] [13]. In this work, we utilize the binary logistic loss function to train TransE, RotatE, DistMult and ComplEx. Given a training triple $(h, r, t)$, the binary logistic loss function is defined as follows,

$$L_b = - \log \sigma(\gamma + f_M(h, r, t)) - \sum_{i=1}^{\eta} p(h_i', r, t_i') \log \sigma(-\gamma - f_M(h_i', r, t_i')) + \lambda(||h||^2 + ||r||^2 + ||t||^2).$$  \hfill (7)

where $f(\cdot)$ denotes the specific score function of the KGE model $M$ as defined in the previous section, $\sigma(\cdot)$ denotes the sigmoid function, $\gamma$ denotes the margin of distance-based model, $\eta$ is the number of negative samples per positive ones, $(h_i', r, t_i')$ is the $i$th negative sample corresponding to $(h, r, t)$ and $p(h_i', r, t_i')$ is the weight of the negative sample which is computed from the following equation,

$$p(h_i', r, t_i') = \frac{\exp(f_M(h_i', r, t_i'))}{\sum_{j=1}^{\eta} \exp(f_M(h_j', r, t_j'))}.$$  \hfill (8)

Notice that the above loss function is exactly same as the binary logistic loss function used in [17] when $\gamma = 0$ and $p(h_i', r, t_i') = 1/\eta$. It is also equivalent to margin-based logistic loss function defined in [11] when $\lambda = 0$.

Different from previous work, ComplExN3 performs link prediction as a multiclass classification task by using the full negative sampling and the multi-class log-loss with N3 regularization instead of random negative sampling and the binary logistic loss with L2 regularization [10] [21]. We follow such setting for DistMultN3. The multiclass log-loss of a training triple $(h, r, t)$ is defined as follows,

$$L_m = L_m^1 + L_m^2 + \lambda(||h||^2 + ||r||^2 + ||t||^2),$$

$$L_m^1 = -\log \left( \frac{\exp(f_M(h, r, t))}{\sum_{h' \in \mathcal{E}} \exp(f_M(h', r, t))} \right),$$

$$L_m^2 = -\log \left( \frac{\exp(f_M(h, r, t))}{\sum_{t' \in \mathcal{E}} \exp(f_M(h, r, t'))} \right).$$  \hfill (9)
C. Parallel Training

Data parallelism and task parallelism are two common forms of parallel computing. Data parallelism divides data equally among multiple processors and instantaneously execute the same function over multiple data inputs across multiple processors. In our case, the training process of each copy \( M_j \) of the model \( M \) is taken as a separate task. For each training task, since it is independent to each other, there is no risk of being stuck with double buffering or waiting other tasks. Thus, we can utilize task parallelism and data parallelism for training multiple KGE models at the same time in multi-GPU environments.

Multiple models can also be trained parallelly in a single-GPU environment. A single process may not utilize all the computation capacity and memory-bandwidth available on the GPU. Nvidia Multi-Process Service (MPS) \(^{[23]}\) allows kernel computation capacity and memory-bandwidth available on the GPU environment. A single process may not utilize all the parallelism for training multiple KGE models at the same time, but the relation vector is non-zero. Therefore, given \( h, r, t \) are embeddings which are associated to \((h_1, r_1, t_1)\) for the first slice and \((h_2, r_2, t_2)\) for the second slice. Therefore, we have

\[
\begin{align*}
\text{TransE1: } & \quad h_1 + r_1 \approx t_1, t_1 + r_1 \neq h_1, \quad \text{and} \\
\text{TransE2: } & \quad h_2 + r_2 \neq t_2, t_2 + r_2 \approx h_2.
\end{align*}
\]

where \((h_1, r_1, t_1)\) are embeddings which are associated to the first slice and \((h_2, r_2, t_2)\) are used for the second slice. The overall score of \((h, r, t)\) computed by MTransE becomes \( f(h, r, t) = 0 + \eta/2 = \eta/2 \) and for \((t, r, h)\), the score becomes \( f(t, r, h) = \eta/2 + 0 = \eta/2 \). Consequently, it is possible for MTransE to model symmetric pattern.

n-1 Relation Pattern

In addition to symmetric, TransE suffers from encoding other patterns such as 1-n, n-1 and n-n relations. Here we focus on 1-n relation encoding in TransE and our model. For simplicity of explanation, let \( n = 2 \). Assume \( h^1, h^2 \) are two different entities satisfying \((h^1, r, t)\) and \( \alpha(h^2, r, t) \) where \( r \) is an n-1 relation. Since it is less likely that \( h^1 = h^2 \). Therefore, for the relation \( r \) we have either

\[
\begin{align*}
\text{TransE1: } & \quad h^1 + r = t, h^2 + r \neq t, \quad \text{or} \\
\text{TransE2: } & \quad h^1 + r \neq t, h^2 + r = t.
\end{align*}
\]

Therefore, \((h^1, r, t)\) and \((h^2, r, t)\) get different scores while both are positive triples (ranked differently).

Using MTransE, it is possible for the model to learn

\[
\begin{align*}
\text{TransE1: } & \quad h^1_1 + r_1 = t_1, h^1_1 + r_1 \neq t_1. \\
\text{TransE2: } & \quad h^1_2 + r_2 \neq t_2, h^2_2 + r_2 = t_2.
\end{align*}
\]

for the first slice and

\[
\begin{align*}
\text{TransE1: } & \quad h^2_1 + r_1 = t_1, h^2_1 + r_1 \neq t_1. \\
\text{TransE2: } & \quad h^2_2 + r_2 \neq t_2, h^2_2 + r_2 = t_2.
\end{align*}
\]

for the second slice. Therefore, we have \( f(h^1, r, t) = 0 + \eta_1/2 \) and \( f(h^2, r, t) = \eta_2/2 + 0 \) for \((h^1, r, t), (h^2, r, t)\) respectively. As shown in Figure 2, these two triples have the possibility of getting more close scores and consequently are ranked more closely. The similar arguments can be used for other models and patterns.

IV. EXPERIMENTS

1) Dataset: We use FB15K \([^6]\), FB15K-237 and WN18RR \([^7]\) for evaluation. FB15K contains relation triples from Freebase, a large tuple database with structured general human knowledge. Another version of FB15K named as FB15K-237 has been created to provide a more challenging
The percentage of testing triples which are ranked lower than N is considered as Hits@N. To compute MRR, the following formula is used MRR = \frac{1}{|\Sigma|} \sum_{i=1}^{n} \frac{1}{RR_i} + \frac{1}{LR_i}, where n is the number of testing triples, RR_i and LR_i are the right rank and the left rank of the i-th test triple. To alleviate the noise from the random initialization and the random sampling, in this paper we train and evaluate each KGE model 10 times and compute the averages and the standard deviations of its MRRs and Hits@Ns. The standard deviations of MRR and Hits@3 support the intuition that the ensemble of multiple models can alleviate the noise from the random initialization of single models.

V. RESULTS AND DISCUSSION

A. Link Prediction Results

We first study the effect of k on the performance of the ensemble KGE models (e.g., MTransE, MRotatE, MDistMult, MComplEx, MDistMultN3 and MComplExN3) by fixing the overall embedding size d = 1200 and tuning k ∈ {1, 2, ..., 6}. As shown in Figure 4 when the embedding sizes are fixed on 1200, the number of combined KGE models of the same kind higher, the performance on FB15K of the combination KGE model better regarding the averages and the standard deviations of MRR and Hits@3. This observation supports the intuition that the ensemble of multiple models can alleviate the noise from the random initialization of single models.

We further compare the link prediction performances of single high-dimensional KGE models (e.g., TransE, RotatE, DistMult, ComplEx, DistMultN3 and ComplExN3) and the simple ensembles of multiple low-dimensional KGE models of the same kinds (e.g., MTransE, MRotatE, MDistMult, MComplEx, MDistMultN3 and MComplExN3) with the same dimension sizes. The embedding size of each low-dimensional KGE models are fixed as 200 and we change the embedding size d of an ensemble model, e.g., MTransE by tuning the number of the combined low-dimensional models k, i.e., d = 200 \times k, k = 1, 2, ..., 6.

Figure 4 and Figure 5 show the link prediction results of the single high-dimensional models and the multiple low-dimensional models.
dimensional models regarding MRR and Hits@3. Averagely, the ensembles of multiple low-dimensional models outperform the corresponding high-dimensional single models with the same overall embedding sizes. We notice that the performance of a single KGE model might decrease with the embedding size increasing, e.g., RotatE ($d = 1000$) and RotatE ($d = 800$) have lower MRRs and Hits@3s than RotatE ($d = 800$) on FB15K. This observation demonstrates that using embeddings with an overly large embedding size leads to a risk of overfitting, especially for distance-based KGE models.
models. By contrast, the ensemble of \( k + 1 \) KGE models of a
same kind always outperforms the ensemble of \( k \) KGE models
of the same kind since the new added model improves the
generalization ability of the ensemble model.

To clearly compare the ensemble KGE models and the single
KGE models which have the same overall embedding sizes
and scoring functions, Table IV lists the link prediction results
of all target KGE models with the same overall embedding
size of \( d = 1200 \) on FB15K and FB15K237 regarding MRR,
\( \text{Hits}@1 \), \( \text{Hits}@3 \) and \( \text{Hits}@10 \). For any kind of KGE approach,
his-high-dimensional model with \( d = 1200 \) underperforms the
ensemble of its low-dimensional models with the same overall
embedding size across all metrics. For instance, MComplExN3
with \( d = 1200 \) improves 1.6 points of MRR and 2.7 points of
\( \text{Hits}@1 \) compared to ComplExN3 with \( d = 1200 \).

### B. Quality Analysis

Table III reports the MRRs of TransE \((d = 200 \times 1)\), TransE
\((d = 1200 \times 1)\) and MTransE \((d = 200 \times 6)\) on link prediction
involving different relation patterns in FB15K. Following the
setting in \([24]\), we separate relations into 4 categories: 1-1, 1-n,
n-1 and n-n. Within the 1345 relations in FB15K, 24% are 1-1,
23% are 1-n, 29% are n-1, and 24% are n-n. We also employ
AMIE+ \([25]\) to extract 24 symmetric relations \((r(x,y)=r(y,x))\)
from FB15K with a confidence threshold of 0.8. A few typical
symmetric relations include person/sibling and person/spouse.
As shown in Table III, TransE \((d = 1200 \times 1)\) have the
close performance to MTransE \((d = 200 \times 6)\) on 1-1 relations,
whereas MTransE significantly outperforms both
TransE \((d = 1200 \times 1)\) and TransE \((d = 200 \times 1)\) on other
complex relation patterns. MTransE can enhance the
expressiveness and the generalization ability of TransE by
comprehensively considering the link prediction results of
multiple TransE models to alleviate the negative effect of
TransE’s limitation on modeling 1-n, n-1, n-n and symmetric
relations. More concretely, Table IV gives an example of how
MTransE improves the performance of TransE models on
modeling \( tv_{program/language} \), an n-1 relation. Given four
test triples involving the same relation \( tv_{program/language} \)
and the same tail entity \( English \) with different head entities,
the first TransE model predicts triples ("Parks and Reactions",
\( tv_{program/language}, English \)) well while the second TransE
model predicts ("Angel", \( tv_{program/language}, English \))
correctly. By combining these two models, the ensemble model
MTransE can predict both triples precisely. Meanwhile, the
ranks of other two head entities which are underrated by both
TransE models are improved by the MTransE model.

### C. Training Time

By using MPS, we can efficiently train multiple low-
dimensional KGE models on a single GPU simultaneously.
We conduct all experiments on a TITAN X (Pascal) GPU. As
shown in Figure 6, the time cost per epoch of training multiple
low-dimensional KGE models, e.g., MRotatE \((d = 200 \times k)\)
and MComplEx \((d = 200 \times k)\), is less than training a single
high-dimensional KGE model, e.g., ComplEx and RotatE, with
the same overall embedding size \( d \).

VI. CONCLUSION

In this work, we empirically study the effect of the embedding
size on the performance of several common KGE models and propose a performance boosting training strategy
for KGE models without enlarging the overall embedding
sizes of models. Concretely, we first divide a high-dimensional
embedding into several low-dimensional embedding and input
them into the respective KGE models of the same kind
which are separately trained. All models are combined only
at the query time. Given a triple \((h, r, t)\), its final overall

score is equal to the average of its scores computed from multiple models. We show that our approach can improve the generalization ability of KGE models on modeling various complex relation patterns. And the training processes of multiple KGE models can be completed efficiently by using parallel training. Experimental results demonstrate that the ensembles of multiple low-dimensional KGE models of the same kind outperform the corresponding single high-dimensional KGE models with the same embedding size.

ACKNOWLEDGMENT
This work is supported by the EC Horizon 2020 grant LAMBDA (GA no. 809965), the CLEOPATRA project (GA no. 812997) and the China Scholarship Council (CSC).

REFERENCES
[1] G. A. Miller. “WordNet: a lexical database for English,” Communications of the ACM 38, 1995, pp. 39-41.
[2] K. Bollacker, C. Evans, P. Paritosh, T. Sturge and J. Taylor. “Freebase: a collaboratively created graph database for structuring human knowledge,” In Proceedings of the 2008 ACM SIGMOD international conference on Management of data, 2008, pp. 1247-1250.
[3] F. M. Suchanek, G. Kasneci and G. Weikum, “Yago: a core of semantic knowledge,” In Proceedings of the 16th international conference on World Wide Web, 2007, pp. 697-706.
[4] S. Auer, C. Bizer, G. Kobilarov, J. Lehmann, R. Cyganiak, Z. Ives, “Dbpedia: A nucleus for a web of open data,” In The semantic web, 2007, pp. 722-735.
[5] Q. Wang, Z. Mao, B. Wang, L. Guo. “Knowledge graph embedding: A survey of approaches and applications,” IEEE Transactions on Knowledge and Data Engineering, 2017, no. 12, pp. 2724-2743.
[6] A. Bordes, N. Usunier, A. Garcia-Duran, J. Weston and O. Yakhnenko, “Translating embeddings for modeling multi-relational data,” Advances in neural information processing systems, 2013, pp. 2787-2795.
[7] T. Dettmers, P. Minervini, P. Stenetorp and S. Riedel, “Convolutional 2d knowledge graph embeddings;” In Proceedings of the AAAI Conference on Artificial Intelligence, 2018, vol. 32, no. 1.
[8] G. A. Miller. “WordNet: a lexical database for English,” Communications of the ACM 38, 1995, pp. 39-41.
[9] K. Bollacker, C. Evans, P. Paritosh, T. Sturge and J. Taylor. “Freebase: a collaboratively created graph database for structuring human knowledge,” In Proceedings of the 2008 ACM SIGMOD international conference on Management of data, 2008, pp. 1247-1250.
[10] T. Lacroix, N. Usunier, G. Obozinski, “Canonical tensor decomposition for knowledge base completion,” In International Conference on Machine Learning, 2018.
[11] Z. Sun, Z. Deng, J. Nie, and J. Tang. “Rotate: Knowledge graph embedding by relational rotation in50complex space,” In International Conference on Learning Representations, 2019.
[12] C. Xu, M. Nayeri, F. Alkhoury, H. Yazdi, J. Lehmann, “Temporal Knowledge Graph Completion Based on Time Series Gaussian Embedding,” In International Semantic Web Conference, 2020, pp. 654-671.
[13] C. Xu, M. Nayeri, F. Alkhoury, H. Yazdi, J. Lehmann, “TeRo: A Time-aware Knowledge Graph Embedding via Temporal Rotation.” arXiv: 2010.01029, 2020.
[14] S. Zhang, Y. Tay, L. Yao and Q. Liu, “Quaternion Knowledge Graph Embedding,” In Advances in neural information processing systems, 2019.
[15] B. Yang, W. T. Yih, X. He, J. Gao and L. Deng, “Embedding entities and relations for learning and inference in knowledge bases,” In International Conference on Learning Representations, 2014.
[16] M. Nickel, V. Tresp, H. P. Kriegel, “A three-way model for collective learning on multi-relational data,” In International Conference on Machine Learning (ICML), 2011, vol. 11, pp. 809-816.
[17] T. Trouillon, J. Welbl, S. Riedel, E. Gaussier and G. Bouchard, “Complex embeddings for simple link prediction,” In International Conference on Machine Learning (ICML), 2016.
[18] M. Nayeri, C. Xu, S. Vahdati, N. Vassilieva, E. Sallinger, H. Yazdi, J. Lehmann, ”Fantastic Knowledge Graph Embeddings and How to Find the Right Space for Them.” International Semantic Web Conference. Springer, Cham, 2020, pp. 438-455.
[19] M. Nayeri, C. Xu, S. Vahdati, E. Sallinger, H. Yazdi, J. Lehmann, ”On the knowledge graph completion using translation based embedding: the loss is as important as the score.” arXiv preprint arXiv: 1909.00519 , 2019.
[20] D. Krompaß, V. Tresp, “Ensemble solutions for link prediction in knowledge graph,” In Proceedings of the 2nd Workshop on Linked Data for Knowledge Discovery, 1-10.
[21] C. Xu, M. Nayeri, Y. Chen, J. Lehmann, ”Knowledge graph embeddings in geometric algebras.” arXiv preprint arXiv: 2010.00989, 2020.
[22] A. Muromígá, K. Sirts, S. Laur, “Linear ensembles of word embedding models,” arXiv preprint arXiv: 1704.01419, 2017.
[23] P. Sah, “Improving gpu utilization with multiprocess579service (MPS),” In GPU Technology Conference, 2015, vol. 5584.
[24] Z. Wang, J. Zhang, J. Feng and Z. Chen, “Knowledge Graph Embedding by Translating on Hyperplanes,” In Proceedings of the AAAI Conference on Artificial Intelligence, 2014, pp. 1112–1119.
[25] L. Galárraga, C. Teflioudi, K. Hose, F. M. Suchanek, “Fast rule mining in ontological knowledge bases with AMIE+,”” The VLDB Journal, 2015, no. 6, pp. 707-730.
[26] X. Glorot, Y. Bengio. “Understanding the difficulty of training deep feedforward neural networks,” In Proceedings of the thirteenth international conference on artificial intelligence and statistics, 2010, pp. 249-256.