Language Model-driven Negative Sampling

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Abstract

Knowledge Graph Embeddings (KGEs) encode the entities and relations of a knowledge graph (KG) into a vector space with a purpose of representation learning and reasoning for an ultimate downstream task (i.e., link prediction, question answering). Since KGEs follow closed-world assumption and assume all the present facts in KGs to be positive (correct), they also require negative samples as a counterpart for learning process for truthfulness test of existing triples. Therefore, there are several approaches for creating negative samples from the existing positive ones through a randomized distribution. This choice of generating negative sampling affects the performance of the embedding models as well as their generalization. In this paper, we propose an approach for generating negative sampling considering the existing rich textual knowledge in KGs. Particularly, a pre-trained Language Model (LM) is utilized to obtain the contextual representation of symbolic entities. Our approach is then capable of generating more meaningful negative samples in comparison to other state of the art methods. Our comprehensive evaluations demonstrate the effectiveness of the proposed approach across several benchmark datasets for like prediction task. In addition, we show cased our the functionality of our approach on a clustering task where other methods fall short.

1 Introduction

Knowledge graph (KG) can be viewed as an abstraction of real world where the facts are represented as triples in the form of (entity, relation, entity). Despite the growing quantity of KGs with billions of such triples, they remain incomplete capturing all relevant facts of domains from real world. Therefore, the last decade witnessed various AI-based approaches for KG completion. Knowledge Graph Embedding (KGE) models are the prominent approach in this regard that employ a link prediction method for graph completion. While the foundation of KGS follow closed world assumption where all the present triples are considered to be positive (correct), such AI-based approaches including KGEs need to be trained on not only positive samples but also negative ones. Therefore, a paradigm of creating negative samples from the existing positive ones has been formed for KGE models where a random triple corruption method has been employed in most of the cases. In this way, the significant role of negative sampling and its impact on the overall performance are not carefully considered. This is majorly due to the restrictions of the random distribution that affects the model generalization, specially on unseen data.

Recently, several negative sampling techniques have been proposed to improve the performance and efficiency of KGEs \cite{12, 14, 6, 21, 8, 3}. One of the early works named Uniform \cite{10} proposed a fixed distribution and another one uses a population-based distribution \cite{7}. In \cite{9}, Generative Adversarial networks (GANs) are used for generating negative samples for KGEs. Most of these works are computationally expensive as they either suffers from vanishing gradient problem or require high number of training parameters. Furthermore, these approaches mostly stay with learning the graph patterns rather than considering any complementary knowledge that are carried by entities and relations. Let us consider a target triple (Berlin, capital, Germany) for generating negative sample out of it. Aforementioned distributions may replace Germany by Apple or Car and generate a negative triple such as (Berlin, capital, Apple) and (Berlin, capital, Car), respectively. As visible, these triples are far from being effective negative samples as semantically there is no connection between the corrupted entity and the relation. Generating such negative samples reduces the generalization capabilities of KGE models and highly affects their performance.

To alleviate the aforementioned issues, we propose a novel method with the aid of Pre-trained Language Models (PLMs) for generating negative samples of KGEs which is not only run-time efficient but also improves the state-of-the-art performances. Additionally, we leverage K-means++ in a clustering task where the contextualized embedding of KG entities are transferred into a dense or vectorized space to generate negative samples. The motivation for obtaining the negative samples based on the output of PLMs highly relates to the richness of contextual knowledge associated to entities and relations. Naturally, during the training process of KGEs, the models learns the vector representation of the entities considering the structure of KG – ignoring complementary knowledge (in most of the cases). On the other hand, PLMs are not designed to consider such structural knowledge. Therefore, the vectorized representations of the contextual knowledge for each entities obtained from PLMs play great role for defining the similarities of the entities.

We employed Sentence-BERT \cite{13} to obtain the contextual representation of KG entities. In our approach, we also
apply a dimension reduction algorithm to transform the high-dimensional embeddings into low-dimensional representation. The low-dimensional contextualized entity embeddings are then clustered with K-Means++. This facilitates the model to cluster the similar entities closer together to each other into a dense space which allows for run-time efficient negative sampling. The PLM embedding carry contextual meanings meaning as they are trained with large corpora. Accordingly, we expected that such meaning-based negative candidates lead to better representation learning which was then confirmed by the evaluation results both on performance and clustering.

For a chosen entity in head or tail position to be corrupted, the model identifies an ideal cluster where this particular entity belongs to. This cluster then becomes the source cluster (or a desired nearest clusters.) to sample the negative triples from. In case of considering other nearest clusters, multiple chain of clusters are united as a hub from which negatives candidates are sampled. We shall note that, the distance to the other clusters also plays a role in this regards which is also studied.

We conduct experiments to evaluate the performance of our proposed method. We used two publicly available datasets, namely WN18, and WN18RR. Since our approach is model independent, we experimented the proposed negative sampling method on widely used KGs in the case of TransE [5], and RotatE [15]. Our proposed method achieves state-of-the-art performance.

2 Related Work

In this section, we provide a summary of relevant approaches which we classified as following: the approaches using Uniform Distribution-based, or Generative Adversarial Network-based, and Structure-aware Approaches.

Uniform Distribution-based Approaches. Many of the initial negative sampling approaches follow random distribution for selection of entities to be corrupted [12, 14]. In [20], Bernoulli distribution is considered to limit the appearance of false negative triples in the existing relationships between head and tail entities. Despite simplicity, such approaches focus on sampling from a fixed distribution and suffer from vanishing gradient problem [6, 21].

Generative Adversarial Network-based Approaches. Recently, Generative Adversarial Network (GAN) [9] has been explored for negative sampling to overcome the limitations of fixed distribution based sampling techniques [6, 21]. In the GAN-based approaches, the discriminator is trained to minimize the margin-based ranking loss, while the generator learns to sample high-quality negative samples [6]. Although, such techniques are capable of generating high-quality negative samples, they are expensive to train. However, much higher training time is required for these methods to learn the full distribution of negative triples. In [22], this issue is addressed by proposing a distilled version to reduce the number of parameters and training time. It stores the high scoring negative triples in a cache to get rid of the highly skewed negative sampling distribution issue that exists in the datasets. The pre-processed cache is later used to sample negative triples with high score to tackle the vanishing gradient problem and high training time problem.

Structure-aware Approaches. More recently, a structure-aware negative sampling technique (SANS) was proposed [2] to consider the neighborhood information for generating negative triples. To corrupt an entity of a triple for negative sampling, all the k-hop neighborhood nodes connected to the entity are considered as negative nodes. Thus, the negative triples are generated from the structural information (i.e., the k-hop neighborhood). However, it is crucial for the KGE models to know about possible connection beyond k-hop to perform link prediction.

In contrast to the previous works, we employ contextualized representation of the entity and relation and utilized a k-means++ algorithm to cluster similar entities and relations into a dense space. The contextualized vector representation and the clustering method allow our system to effectively and efficiently generated negative samples.

3 Approach

In this section, we propose a novel method of negative sampling generation that uses language model and neighborhood clustering for negative sample generation. As the initial step, we obtain the embedding from Sentence-BERT [13]. Obtaining the approximation of optimal number of cluster is optional in our case since the Elbow method [16] considered as a hyperparameter. Later, dimensionality reduction techniques such as PCA [1], Spectral Embedding [11] and TSNE [18] is used to reduce the dimension of the output embeddings from Sentence Transformer. This is done to eradicate the curse of dimensionality [19] in order to get rid of the larger embedding dimension of Sentence-BERT. In order to cluster the embeddings, we use KMeans++ [4] algorithm to build the neighborhood clusters. The method consists of two phases: Building the neighborhood clusters, and Negative sample generation.

3.1 Building the neighborhood clusters

This sub-phase of our execution demonstrates the construction of the neighborhood clusters. Building the neighborhood is considered as an crucial step as it puts the entities of the KG in different clusters based on the pre-trained embeddings from the text. Figure 1 provides the illustration of our neighborhood cluster creation.

In order to build the clusters consisting of member entities, output embeddings from sentence transformer is required. The input for the sentence transformer is the textual representation of the entities from the entity set $\mathcal{E}$. Lets consider it as $\mathcal{E}_{text}$. If we consider the sentence transformer as a function $\Omega$, the output of $\Omega$ is $n_e \times 786$ dimensional vector representation, where $n_e$ is the number of entities in $\mathcal{E}$, which is stated in equation 1. The output dimension is large in this regards and may not be able to form good cluster based on the semantic of the text due to the curse of dimensionality. For this reason, we have used dimensionality reduction techniques for reducing the dimension to $Z$ which is less than equal 768.

$$\Omega(\mathcal{E}_{text}) : \mathcal{E}_{ST} \in \mathbb{R}^{n_e \times 786} \quad (1)$$
Let's consider the dimensionality reduction function as $\phi$. The input of this function is the output of $\Omega$, additionally $\Omega$ requires the desired number of reduced dimension $Z$ as a hyperparameter. The output is a $n_e \times Z$ dimensional vector namely $E_{ST} \in \mathbb{R}^{n_e \times Z}$ (equation 2).

$$\phi(E_{ST}) : E_{ST} \in \mathbb{R}^{n_e \times Z}$$ (2)

KMeans++ is applied on $E_{ST}$ to obtain $K$ number of clusters consisting of entities $\{e\} \subseteq E$. Other KMeans attributes such as cluster centroids, distances between cluster centroids are retrieved as well.

Our objective function for building neighborhood can be aligned with the objective function of KMeans clustering algorithm, where $\mu$ is a variable which is optimized for each cluster centers $c_i$ (formulated in equation 3).

$$\text{Argmin}_c \sum_{i=1}^{K} \sum_{e_i \in E \subseteq c_i} \| E_{ST} - \mu_{c_i} \|^2$$ (3)

Finally, each entities that are mapped to their respective cluster centroid acts as the representative of the whole cluster. After assigning each entity $e$ to its respective clusters $c_i \subseteq C$, we construct the mapping dictionary $\text{dict}$, where the cluster assignment of all entities are preserved. In $\text{dict}$ the keys are the set of all the entity symbols $E$ and the values are associated representative cluster centroids $C$ (equation 4). The distances of the cluster centroids are preserved under the attribute of Kmeans namely $KM_0$. That is how basically our neighborhood cluster is built to be used in training.

$$\text{dict} : E \rightarrow C$$ (4)

### 3.2 Negative sample generation during training

Generally, KGE models create negative samples from the existing positive triples during training. Either the head or the tail is corrupted and replaced with candidate entities to form negative triples. Our approach follows the generalized structure to fetch the negative samples during the training phase. Previous subsection (subsection 3.1) talks about the neighborhood creation, which is used in this phase as the mean of generation of the negative samples. In this subsection, by utilizing the already created cluster dictionary $\text{dict}$ and KMeans attributes $KM_0$ to process negative triples generation is described. Our goal is to generate negative samples while preserving semantics of the text for the entities so that meaningful negatives are fetched. KGE model exhibits better performance if meaningful entities are selected for corruption.

The cluster dictionary $\text{dict}$ and KMeans attributes $KM_0$ from the subsection 3.1 is required regarding the information of the entities and their associated clusters. The KG training set $T_{h,r,t}$ where $h,r,t$ represents head, relation and tail. The stored information about the KMeans attributes $KM_0$ (information about the cluster centroids and distances between them) are used to obtain the distance between candidate entities to be corrupted and the cluster centroids. Our goal is to generate $N$ negative samples per positive triple $t_{h,r,t}$ in each given batch $B$. We consider only the entities $\{e\} \subseteq E$ which are in the same cluster or the member entities of clusters in $H$ hops within $d$ nearest distances. For each triple $t_{h,r,t}$, firstly the decision about the head or tail corruption is taken as a probabilistic manner. For the entity $e$ (which is to be corrupted), we compute the distances to other clusters namely the cluster centroids. From the neighborhood building function (discussed in subsection 3.1), we have the dictionary $\text{dict}$ consisting of the information about the entities along with their cluster centroids. Then, the clusters are sorted based on their distances $d$ to that particular entity and their members that are fetched from $\text{dict}$. If the distance function is considered as $CD$, the cluster centroids stored in

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**Algorithm 1: Building neighborhood.**

**INPUT:** Entity embedding $E$ from PLMs, Desired number of clusters $K$, dimensionality reduction function $\phi$, reduced dimensionality $Z$.

**OUTPUT:** Cluster Dictionary dict where keys: mapped entities $\{e\} \subseteq E \subseteq C$, values: cluster centroids $\{c\}$, $KM_0$ as KMeans Attributes such as distance to centroids, number of centroids etc.

**Function** Build entity clusters $(E, K, Z)$:

1. $E_Z \leftarrow \phi(E, Z)$
2. $KM \leftarrow$ Initialize Kmeans (number of clusters $= K$)
3. $D_{E_Z, C}, KMeans\_attributes \leftarrow KM(E_Z)$ // For each entities in $E_Z$ obtain assigned cluster number $C$

   $$\text{dict} \leftarrow \{}$$

   **for each entity $e \in E$ do**

   1. $\text{dict}[\{key : e, value : e\}] \leftarrow \text{map}(\{e\} \subseteq E_Z, c \in C) // \text{map the matching entities} \{e\} \subseteq E \text{ belonging to the centroid } c$

   **Return** dict, $KM_0$
KMeans attribute $K M_θ$ is defined as $C$, the desired number of clusters as $K$ and obtained distance vector is $M$, then the formulation (equation 5) can be considered as follows.

$$CD(e, C_{K,M_θ}) : M \in \mathbb{R}^{1 \times K}$$

Upon obtaining the sorted clusters and their member entities, it is possible to obtain $N$ negative entities randomly as the counterpart for a particular entity $e$. With those randomly picked entities $\{e’\}$ from the $\mathcal{H}$ within $d$ nearest hop clusters, $\mathcal{T}_{h’,r,t}$ is formed. If we consider obtaining $N$ negative samples $\{e_0, e_1, ... e_N\}$ for a particular entity and the number of clusters based on tolerated distances to clusters is $d_{max}$, then the set of possible negative entities resides in the union of all the clusters till that distance $d_{max}$ (equation 6).

$$\{e_0, e_1, ... e_N\} \in \mathcal{E}’ = \mathcal{E}_{H0} \cup \mathcal{E}_{H1} \cup ... \mathcal{E}_{H_{d_{max}}}$$

### Algorithm 2: LM-Driven Negative Sampling

**Input:** Training set $\mathcal{T}_{batch}$, cluster dictionary $\text{dict}$, $K$Means attributes $K M_θ$, Entity set $\mathcal{E}$, Relation set $\mathcal{R}$, Batch size $B$, Negative sample number $N$, Number of nearest $\mathcal{H}$ hops based on $d_{max}$ distance

**Output:** For given batch of triples $\mathcal{T}_{batch}$ generate batch of negatives $\mathcal{T}_{’batch}$ where $h’, r, t’ \in \mathcal{T}_{’batch}$

**Function**

**Sample Negative ($\mathcal{T}_{h, r, t, \mathcal{M}_θ, \mathcal{R}, \mathcal{B}, \mathcal{N}, \mathcal{H})$ :**

$\mathcal{T}_{batch} [\leftarrow 1]$

for triple $t_{h, r, t} \in \mathcal{T}_{batch}$ do

- corrupt_position $\leftarrow$ probability($h, t, 0.5$)
- entity2corrupt $\leftarrow$ $t_{h, r, t}$[corrupt_position]
- distance_to_clusters $\leftarrow$
- compute_distance(entity2corrupt, dict, $K M_θ$)
- sorted_clusters $\leftarrow$
- sort(dict, distance_to_clusters)
- corruption_candidates $\leftarrow$ dict[0 : $\mathcal{H}$]
- corrupted_entities $\leftarrow$
- random_choice(corruption_candidates, $\mathcal{N}$)
- Negative Triples
- $t’$ $\leftarrow$ tcorrupt_position = corrupted_entities
- $\mathcal{T}_{’batch}$ $\leftarrow$ $\mathcal{T}_{’batch}$ $\cup$ $t’$

**Return** $\mathcal{T}_{’batch}$

### 4 Experimental Set-up

In this section, we provide all the details of the experimental set-up including the datasets, hyper-parameters, and the chosen KGE models. In order to set up the evaluations, we chose benchmark knowledge graphs that contain textual knowledge for entities, namely WN18, and WN18RR. WN18 dataset contains lexical relations between words [15] where several patterns can be found from that dataset including symmetric, anti-symmetric and inverse. WN18RR is a subset of WN18 for which due to the leakage in the dataset many of the inverse relations are removed. The main patterns in this dataset is: asymmetric, symmetric, and composition [15]. The general statistics of these datasets are provided in table 1.

| Dataset    | $|E|$ | $|R|$ | #train | #valid. | #test |
|------------|------|------|--------|---------|-------|
| WN18       | 40,943 | 18 | 141,442 | 5,000 | 5,000 |
| WN18RR     | 40,943 | 11 | 86,835  | 3,034  | 3,134 |

Table 1: Dataset statistics. This table presents the number of entities, relation, triples as well as division of train, validation and test sets.

### 4.1 Hyper-parameter Settings

For WN18 and WN18RR many of the hyperparameters are taken from the best settings mentioned in RotatE paper [15] and their github repository. In WN18 for RotatE model we have used an embedding dimension $D=500$, gamma $\gamma = 12.0$, adversarial temperature (for training with adversarial negative sampling) $\tau = 0.5$, learning rate $\alpha = 0.0001$, batch size $B = 512$, Number of negative sample $N = 100$. Additionally, our models hyperparameters are: total number of clusters $K=10$, max hop $H = 3$.

In WN18RR for RotatE model we are using the same settings except the gamma $\gamma=0$, the learning rate $\alpha=0.00005$, and the number of negative samples $N=100$ (for adversarial case $N=50$).

In WN18 TransE model we have used an embedding dimension $D=500$, gamma $\gamma = 12.0$, adversarial temperature (for training with adversarial negative sampling) $\tau = 0.5$, learning rate $\alpha = 0.0001$, batch size $B = 512$, Number of negative sample $N = 100$ (without adversarial negative sampling), 50( with adversarial negative sampling). Using adversarial negative sampling the number of negative sample is $N=50$, the number of clusters $K=10$, and hop size $H = 3$. Using non adversarial/uniform negative sampling the number of negative sample is $N=100$, the number of clusters $K=20$, and hop size $H = 2$.

With uniform negative sampling in WN18RR dataset we use embedding dimension $D=400$, batch size $B = 1024$, number of clusters $K=10$, learning rate $\alpha = 0.00005$, number of negative samples $N = 50$, $\gamma = 6$, hop size $H = 2$.

With adversarial negative sampling in WN18RR dataset we use embedding dimension $D=500$, batch size $B = 512$, number of clusters $K=10$, learning rate $\alpha = 0.00005$, number of negative samples $N = 50$, hop size $H = 3$. In all the cases the reduced dimension parameter for PCA for the output from PLMs is $Z = 200$.

### 4.2 Baseline Models and Evaluation Metrics

We used our approach together with RotatE KGE model that is considered as it is known for its robustness. In RotatE, the head embedding is rotated towards the tail via the relation. The score function of RotatE is $||h \circ r - t||$. We also considered TransE which is a popular and widely used KGE model due to its simplicity, and high performance. In TransE, the head $h$ embedding is translated towards tail $t$ via the relation $r$ [5]. The score function of TransE is $||h + r - t||$.

**Evaluation Metrics** The performance measure is evaluated using standard performance metrics of link prediction.

[1]https://github.com/DeepGraphLearning/KnowledgeGraphEmbedding
task. We use Hit@10 and Mean Reciprocal Rank (MRR) as the performance metrics. MRR represents the inverse of the average rank obtained from the score of each test triple. In MRR a better performance can be indicated by the higher value. The Hit@10 represents the fact that where the actual entity appeared in the top 10 prediction for the embedding model. We have taken the average Hit@10 for the test triple to measure the performance.

## 5 Evaluation and Analysis

In this section we present the results of our evaluation on the mentioned datasets. Additionally, we provide several ablation studies that are also discussed here.

### Results

The results of the evaluations show improvements in the performance metrics specially for Hit@10. The results are presented for uniform, and adversarial negative sampling. In table 3, the results are shown without adversarial sampling. For RotatE embedding model, the achieved result for Hit@10 on WN18 by the proposed method is 96.18% and for WN18RR datasets, it is 57.33%. For WN18 dataset with our negative sampling technique TransE achieved the Hit@10 score of 95.57%. In table 4, a significant improvement in the result of RotatE is visible that is achieved with our negative sampling technique in both MRR (95.90%) and Hit@10 (96.09%) metrics. For WN18RR in RotatE, the results are improved in Hit@10. The results of the other models are taken from SANS paper [2].

### Ablation Study on Time Complexity

In the table 2, the complexity of our method is shown in terms of pre-processing, run-time and space complexity. Here, we computed these for our methods, the complexities for other approaches are re-used from SANS [2].

### Table 2

Comparison of different negative sampling techniques in terms of pre-processing, run-time and space complexity. While, we computed these for our methods, the complexities for other approaches are re-used from SANS [2].

### Table 3

Results of KGE models without adversarial sampling.

### Table 4

Result of KGE models with adversarial negative sampling.

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| Algorithm       | Preprocessing Complexity | Runtime Complexity | Space Complexity |
|-----------------|--------------------------|--------------------|-----------------|
| Uniform [5]     | O(1)                     | O(BN)              | O(t)            |
| KRGBAN [6]      | O(t)                     | O(BN + BE)         | O(t)            |
| NSCaching [22]  | O(1)                     | O(BN + BD + t)     | O(t)            |
| Self-Adv. [15]  | O(|E|)                   | O(|E|)             | O(|E|)          |
| Uniform SANS [2]| O(|V|^3)logH             | O(|V|^2)           | O(|V|^2)        |
| Self-Adv. SANS [2] | O(|V|^3)logH       | O(|V|^2)           | O(|V|^2)        |
| Uniform RW-SANS [2] | O(|V|)                   | O(|V|)             | O(|V|)          |
| Self-Adv. RW-SANS [2] | O(|V|)                   | O(|V|)             | O(|V|)          |
| KNS (our method) | O(D^2PLM|E| + D^3PLM + |E||K|=Z) | O(Hlog(H) + BN) | O(|H|)          |

| Algorithm       | WN18   | WN18RR |
|-----------------|--------|--------|
| RotatE Uniform  | 0.9098 | 96.05  | 0.4760 | 57.29 |
| RotatE Self-Adv. SANS | 0.9494 | 95.85  | 0.4745 | 57.12 |
| RotatE Self-Adv. RW-SANS | 0.9496 | 96.09  | 0.4805 | 56.94 |
| RotatE KNS (ours) | 0.9469 | 95.93  | 0.4770 | 57.35 |

| Algorithm       | WN18   | WN18RR |
|-----------------|--------|--------|
| KNS (our method) | 0.7947 | 94.92  | 0.2274 | 53.20 |

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**Ablation Study on Time Complexity.** In the table 2, the complexity of our method is shown in terms of pre-processing, run-time and space complexity. Here, \( t \) is the GAN parameters count, \( N \) denoted the number of negative samples, \( B \) stand for batch size, \( E \) as edge set, \( R \) for relation set, and \( D \) represents the embedding dimension. Additionally, \( H \) is used for hops count, \( r \) for randomwalks count, and \( Z \) for PCA dimensionality reduction parameter. In the pre-processing part, our method has dimensionality reduction complexity for PCA, and K-means. The time complexity of PCA algorithm can be stated as \( O(D^2PLM|E| + D^3PLM) \), where \( D^2PLM \) stands for the output feature dimension from PLM. The K-means algorithm time complexity is \(|E|\|K\|Z\). Since we use a reduced dimension for K-Means clustering we our feature dimension becomes \( Z \). Here, \( I \) is the number of iteration and \( |E| \) is the length of the entity set. Our run-time complexity is \( O(Hlog(H) + BN) \). In our training procedure we have a sorting mechanism to sort the desired number of Hops \( H \) based on distances and that is the only added complexity in comparison to Uniform negative sampling. In this case \( B \) and \( N \) stands for batch size and the number of negative sample. Our space complexity which is denoted as \( O(|H|) \), only depends on the number of desired hops since we do not consider the entities outside of desired range. The complexities of other methods are taken from SANS paper [2].

**Ablation Study on Trained Entity Embedding** In Figure 2, it can be seen that, there are certain entities that are not clustered in the expected group for Random (Uniform
Ablation Study on the Quality of Negative Samples

In table 5 we provide the assessment for the validity of the negative entities that are drawn in the cases of Uniform negative sampling, SANS and KNS. As already shown in [2], we also used WN18RR dataset for this purpose. The drawn candidate negative entities for Uniform and SANS are taken from [2]. Similar to SANS our method is also capable of generating meaningful negative samples. Semantic meaningfulness declines as we include distant hops.

6 Conclusion

In this paper, we addressed the problem of creating meaningful negative sampling for knowledge graph embedding models. Our approach replaces the old paradigm of creating negative sampling using a random distribution technique. KNS is the approach presented in this work that leverages rich textual complementary knowledge of the entities in the training phase of the embedding models. In order to do so, pre-trained language model are employed for generating embedding of

We used the RotatE model to obtain these embeddings. Rest of the hyperparameters to generate these embeddings are as follows: $D=200$, batch size $B=64$, number of clusters $K=6$, $N=3$, $\gamma=12$, hop size $H=2$ and learning rate $\alpha=0.1$.
textual knowledge. Our approach is mode-independent and have been integrated into two KG embedding models (TransE, and RotatE). We performed evaluations on existing benchmark knowledge graphs where entities are assigned with textual knowledge, namely WN18, AND WN18RR. The results show significant improvement in the performance of the underlying models. In addition, we performed clustering tasks and the results approve that using language models-driven negative sampling highly affects the effectiveness of the KGE models.

References
Abdi, H., and Williams, L. J. 2010. Principal component analysis. Wiley interdisciplinary reviews: computational statistics 2(4):433–459.
Ahrabian, K.; Feizi, A.; Salehi, Y.; Hamilton, W. L.; and Bose, A. J. 2020. Structure aware negative sampling in knowledge graphs. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), 6093–6101. Online: Association for Computational Linguistics.
Alam, M. M.; Jabeen, H.; Ali, M.; Mohiuddin, K.; and Lehmann, J. 2020. Affinity dependent negative sampling for knowledge graph embeddings. In DL4KG@ESWC.
Arthur, D., and Vassilvitskii, S. 2006. k-means++: The advantages of careful seeding. Technical report, Stanford.
Bordes, A.; Usunier, N.; Garcia-Duran, A.; Weston, J.; and Yakhnenko, O. 2013. Translating embeddings for modeling multi-relational data. Advances in neural information processing systems 26.
Cai, L., and Wang, W. Y. 2018. KBGAN: Adversarial learning for knowledge graph embeddings. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), 1470–1480. New Orleans, Louisiana: Association for Computational Linguistics.
Chen, T.; Sun, Y.; Shi, Y.; and Hong, L. 2017. On sampling strategies for neural network-based collaborative filtering. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 767–776.
Dash, S., and Gliozzo, A. 2019. Distributional negative sampling for knowledge base completion. Applied Sciences.
Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; and Bengio, Y. 2014. Generative adversarial nets. Advances in neural information processing systems 27.
He, X.; Liao, L.; Zhang, H.; Nie, L.; Hu, X.; and Chua, T.-S. 2017. Neural collaborative filtering. In Proceedings of the 26th international conference on world wide web, 173–182. Luxburg, U. V. 2007. A tutorial on spectral clustering.
Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, 3111–3119.
Reimers, N., and Gurevych, I. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics.
Sun, Z.; Deng, Z.-H.; Nie, J.-Y.; and Tang, J. 2019a. Rotate: Knowledge graph embedding by relational rotation in complex space. In International Conference on Learning Representations.
Sun, Z.; Deng, Z.-H.; Nie, J.-Y.; and Tang, J. 2019b. Rotate: Knowledge graph embedding by relational rotation in complex space.
Syakur, M. A.; Khotimah, B. K.; Rochman, E. M. S.; and Satoto, B. D. 2018. Integration k-means clustering method and elbow method for identification of the best customer profile cluster. IOP Conference Series: Materials Science and Engineering 336:012017.
Tenenbaum, J. B.; Silva, V. d.; and Langford, J. C. 2000. A global geometric framework for nonlinear dimensionality reduction. science 290(5500):2319–2323.
Van der Maaten, L., and Hinton, G. 2008. Visualizing data using t-sne. Journal of machine learning research 9(11).
Verleysen, M., and Francois, D. 2005. The curse of dimensionality in data mining and time series prediction. In International work-conference on artificial neural networks, 758–770. Springer.
Wang, Z.; Zhang, J.; Feng, J.; and Chen, Z. 2014. Knowledge graph embedding by translating on hyperplanes. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 28.
Wang, P.; Li, S.; and Pan, R. 2018. Incorporating gan for negative sampling in knowledge representation learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32.
Zhang, Y.; Yao, Q.; Shao, Y.; and Chen, L. 2019. Nscaching: Simple and efficient negative sampling for knowledge graph embedding. In 2019 IEEE 35th International Conference on Data Engineering (ICDE), 614–625. IEEE.