The past decade has witnessed great thrive in building web-scale knowledge graphs (KGs), which provide effective well-structured relational information between entities, have proven useful for many knowledge-driven AI and NLP tasks [2, 5, 48]. A typical KG usually consists of a huge amount of knowledge triples in the form of (head entity, relation, tail entity), or the abbreviation (h, r, t). The past decade has witnessed great thrive in building web-scale KGs, e.g., Freebase [3], Google Knowledge Graph [10] and other domain-specific KGs. However, these knowledge graphs cannot reasonably reach full coverage and always suffer from incompleteness due to a large volume increasing and even infinite real-world knowledge facts [32]. Accordingly, knowledge graph construction and completion are significant for KG-driven tasks. Recently, open information extraction (Open IE) [1, 36], automatic neural relation extraction [24] and crowd-sourcing mechanism are widely used for KG construction, while these approaches unfortunately may bring noises in KG due to insufficient human supervision [14, 21]. For instance, recent open IE model on benchmark achieves only 24% precision when the recall is 67% [36].

1 INTRODUCTION

Knowledge graphs (KGs), which provide effective well-structured relational information between entities, have proven useful for many knowledge-driven AI and NLP tasks [2, 5, 48]. A typical KG usually consists of a huge amount of knowledge triples in the form of (head entity, relation, tail entity), or the abbreviation (h, r, t). The past decade has witnessed great thrive in building web-scale KGs, e.g., Freebase [3], Google Knowledge Graph [10] and other domain-specific KGs. However, these knowledge graphs cannot reasonably reach full coverage and always suffer from incompleteness due to a large volume increasing and even infinite real-world knowledge facts [32]. Accordingly, knowledge graph construction and completion are significant for KG-driven tasks. Recently, open information extraction (Open IE) [1, 36], automatic neural relation extraction [24] and crowd-sourcing mechanism are widely used for KG construction, while these approaches unfortunately may bring noises in KG due to insufficient human supervision [14, 21]. For instance, recent open IE model on benchmark achieves only 24% precision when the recall is 67% [36].

To address those shortcomings, in this paper we focus on KG refinement [32], attempting to accomplish two targets simultaneously: (a) improving the coverage of KG, i.e., KG completion, by adding additional facts to KG, and (b) improving the correctness of KG, i.e., KG correction, by identifying and removing errors. KG refinement is critical to improve knowledge graph which is a backbone of many knowledge-driven intelligent systems [2, 5]. In recent years, various embedding models [4, 12, 15, 16, 23, 29, 30, 34, 35, 38, 40, 41] have been proposed for KG completion but with inappropriate assumption that no noise exists in KG, ignoring error detection which should be significant and essential for KG refinement as well [32].

In this paper, to refine KG, we propose a novel support-confidence-aware KG embedding framework (SCEF), which considers triple quality as well in contrast to conventional methods. We implement KG completion and correction simultaneously by learning knowledge representations with triple support and triple confidence. The framework with support-confidence has been widely studied in research field such as data mining [27]. Fig. 1 demonstrates a brief illustration of our support-confidence-aware framework, where KG suffers from incompleteness and noises after automatic KG construction. KG is expected to be improved via KG refinement by learning embeddings with our proposed SCEF model.

Specifically, SCEF follows the promising translation-based framework first proposed by [4], and builds final energy function by combining conventional translation-based model with support and confidence. We propose two triple supports considering two typical external textual evidence: entity types and entity descriptions respectively. Through extensive experiments on real-world datasets, we demonstrate SCEF’s effectiveness.

ABSTRACT

Knowledge graph (KG) refinement mainly aims at KG completion and correction (i.e., error detection). However, most conventional KG embedding models only focus on KG completion with an unreasonable assumption that all facts in KG hold without noises, ignoring error detection which also should be significant and essential for KG refinement. In this paper, we propose a novel support-confidence-aware KG embedding framework (SCEF), which implements KG completion and correction simultaneously by learning knowledge representations with both triple support and triple confidence. Specifically, we build model energy function by incorporating conventional translation-based model with support and confidence. To make our triple support-confidence more sufficient and robust, we not only consider the internal structural information in KG, studying the approximate relation entailment as triple confidence constraints, but also the external textual evidence, proposing two kinds of triple supports with entity types and descriptions respectively. Through extensive experiments on real-world datasets, we demonstrate SCEF’s effectiveness.

KEYWORDS

Knowledge Graph, Refinement, Completion, Error Detection, Support-Confidence, Embedding

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Specifically, SCEF follows the promising translation-based framework first proposed by [4], and builds final energy function by combining conventional translation-based model with support and confidence. We propose two triple supports considering two typical external textual evidence: entity types and entity descriptions respectively, which correspondingly provide rich pragmatic and semantic information for triple support estimation [42, 45]. Moreover, we further propose triple confidence constraints by studying the approximate relation entailment [9] according to internal structural information in KG, beyond the local and global confidence proposed by [44].

We evaluate our models on three tasks including KG noise detection, KG completion and triple classification. Experimental results demonstrate that our proposed model outperform the baseline on all tasks, which confirms the capability of SCEF in KG refinement. The main contributions of this work are concluded as follows:

- We propose a novel support-confidence-aware KG embedding framework for knowledge graph refinement, which uses both internal structural information in KG and external textual evidence.
- We evaluate our SCEF models on several datasets: FB15K-N1, FB15K-N2 and FB15K-N3, which have different noise rates extended from FB15K [4], and outperforms previous models on all tasks.

SCEF: A Support-Confidence-aware Embedding Framework for Knowledge Graph Refinement

Knowledge Graph, Refinement, Completion, Error Detection, Support-Confidence, Embedding

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1 INTRODUCTION

Knowledge graphs (KGs), which provide effective well-structured relational information between entities, have proven useful for many knowledge-driven AI and NLP tasks [2, 5, 48]. A typical KG usually consists of a huge amount of knowledge triples in the form of (head entity, relation, tail entity), or the abbreviation (h, r, t). The past decade has witnessed great thrive in building web-scale KGs, e.g., Freebase [3], Google Knowledge Graph [10] and other domain-specific KGs. However, these knowledge graphs cannot reasonably reach full coverage and always suffer from incompleteness due to a large volume increasing and even infinite real-world knowledge facts [32]. Accordingly, knowledge graph construction and completion are significant for KG-driven tasks. Recently, open information extraction (Open IE) [1, 36], automatic neural relation extraction [24] and crowd-sourcing mechanism are widely used for KG construction, while these approaches unfortunately may bring noises in KG due to insufficient human supervision [14, 21]. For instance, recent open IE model on benchmark achieves only 24% precision when the recall is 67% [36].
2 RELATED WORK

2.1 Knowledge Graph Refinement

Knowledge graph refinement (KGR) is essential after automatic KG construction [10], since the result may never be perfect whichever approach is taken for constructing knowledge graph [14, 26, 32]. Various methods for KGR have been proposed [32], which can differ along three distinct orthogonal dimensions: (i) the overall goal of the method, i.e., completion [4, 35] vs. correction [14, 26] of KG; (ii) the refinement target (e.g., relations between entities [35], entity types [31]), and (iii) the data used by the approach (i.e., only KG itself [4], or further external sources [43, 45]). However, most conventional approaches are only used for one goal as yet, while a combination between completion and error detection methods could be of great value [32]. Jia et al. [17] propose a crisscrossing neural network for KG completion and correction at the same time, while have high complexity and computational cost. In this paper, we concentrate on KG completion and correction simultaneously, and introduce two triple supports and a triple confidence constraints for KGR, by considering the typical external heterogeneous source (i.e., entity hierarchical types and descriptions) beyond the KG itself.

2.2 Knowledge Graph Embedding

Recent years knowledge graph embedding (see more in this survey [39]) has become a hot research topic. The key idea is to encode all the entities and relations in KG into a latent semantic vector space, so as to simplify manipulation without losing KG’s inherent structural information. Various embedding methods have been proposed in recent years, which can be roughly classified into two categories according to the information they used: (i) those which learn embeddings only with KG at hand, e.g., TransE [4] and its extensions [16, 23, 40, 41], the RESCAL [30] and its extensions [25], and the neural network models [8, 35]; (ii) those learning embeddings by combining existing KG with external heterogeneous information, e.g., entity hierarchical types [7, 45], entity descriptions [42, 43, 48], plain text [46], and relation paths [22]. However, all these methods assume that all the facts in KG hold without noise, which is unreasonable especially for KGs constructed automatically without sufficient human supervision. Recently, Xie et al. [44] propose a embedding method (CKRL) with confidence to deal with this issue, which is a pioneer work within KG embedding framework. But it ignores the rich semantic information in external textural information which is strong evidence to judge triple quality [42, 43, 45], and also very prone to overfitting since both the triple score and the confidence merely derive from internal structural information in KG [39]. To the best of our knowledge, our proposed model is the first knowledge graph embedding method in the second category to consider both the triple support and confidence for KG refinement. In this paper, we concentrate on refining noisy KGs on the basis of the promising translation-based knowledge graph embedding model (TransE), which is not difficult to be replaced with other enhanced KG embedding model [23, 40].

3 METHODOLOGY

We first give the notations used in this paper. For each triple $(h, r, t)$, the head and tail entities $h, t \in \mathcal{E}$ and the relation $r \in \mathcal{R}$, where $\mathcal{E}$ and $\mathcal{R}$ represent the sets of relations. $\mathcal{T}_h$ and $\mathcal{T}_t$ represent the hierarchical types of head and tail respectively. $\mathcal{D}_h$ and $\mathcal{D}_t$ denote the descriptions of them respectively. $\mathcal{T}$ stand for the overall training set with noises.

3.1 Support-Confidence-aware KG Embedding Framework

To refine knowledge graph (i.e., KG completion and error detection), we first introduce two promising concepts: triple support and triple confidence for each triple fact. Triple support, derived from the external textural evidence, reflects the reliability of a triple. Triple confidence, measured with internal structural information, describes the correctness of a triple. The fact with higher support and confidence possesses higher quality, and should be more considered reasonably. We set the triple model as the same of TransE [4]: $M(h, r, t) = ||h + r - t||$, which represent the dissimilarity score between head and tail with relation under translation assumption.
Here, the support-confidence-aware KG embedding energy function (see Figure 2) is correspondingly designed as follows:

$$E(T) = \sum_{(h, r, t) \in T} S(h, r, t) \cdot C(h, r, t) \cdot M(h, r, t).$$  \hspace{1cm} (1)

$S(h, r, t)$ stands for the triple support, which is showed in detail in Section 3.2. A higher triple support implies that the corresponding triple is more reliable. $C(h, r, t)$ represents the triple confidence. A higher triple confidence indicates the triple is more credible.

**Textual Evidence**

| Entity Type & Description |
|---------------------------|
| **Knowledge Graph**       |
| (h, r, t)                 |

**Figure 2: The support-confidence-aware KG embedding energy function.**

The support-confidence framework is generic and is not limited to a specific model of triple, which can be used for improving other knowledge graph embedding models. CKRL, proposed by Xie et al. [44], can be taken as a special case of our SCEF if $S(h, r, t)$ is set to 1, defectively ignoring the rich semantic information in external textual evidence. Actually triple quality can be labeled by human-being experts, but this work is much time-consuming and subjective [33]. In next section, we introduce automatic methods to estimate triplet support and confidence according to KG and external textual evidence respectively. In SCEF, we bring in triple support and confidence to learn more about the significant facts, and thus could obtain better knowledge embeddings for KG refinement.

**Figure 3: The example of triple, with entity hierarchical types and entity descriptions.**

### 3.2 Triple Support with Textual Evidence

#### 3.2.1 Triple Support with Entity Types

We first utilize the entity hierarchical types for the triple support (TS). Entity hierarchical types information implies different roles an entity may play in different scenarios [7]. Most typical knowledge graph (e.g. Freebase[3], DBpedia [20]) have entity type information. Entity types usually consist of hierarchical structures, in which the lower granularity of semantic concepts are considered as the sub-type of entities. Generally most entities possess more than one hierarchical type. For instance, in Fig. 3, State of Hawaii has a variety of types (e.g. people/place_of born, areas/sovereign state and areas/Administrative area) and shows different attributes under different types.

The head and tail entity hierarchical types are strong evidence to estimate the triple support. For instance, the incomplete triple (?,?, was_born_in, State of Hawaii), in which the head suppose to be filled with a living things (Type: people/person), is more creditable than which is filled with non-living things (Type: book/written_work). In other words, although both the triples (Donald Trump, was_born_in, State of Hawaii) and (Pride and Prejudice, was born_in, State of Hawaii) are not true, but we still believe that the support of the former is higher than the support of the latter due to their distinct types, i.e., the type of Donald Trump (people/person) is more reasonable.

Here, we build the entity type triple, by replacing both head and tail with their corresponding hierarchical types: $(h, r, t) \rightarrow (T_h, r, T_t)$, to estimate the triple support.

To build triple support with hierarchical types, inspired by TKRL [45], we first encode the hierarchical type information into representation learning with a general form. Generally most entities in KGs have more than one hierarchical type. The general form of type encoder, in which the type representation of entity $e$ will be the weighted summation of all type representations, is as follow:

$$T_e = \alpha_1 T_{c_1} + \alpha_2 T_{c_2} + \cdots + \alpha_n T_{c_n},$$  \hspace{1cm} (2)

where $n$ is the number of types of entity $e$, $c_i$ is the $i$-th type of entity $e$, $T_{c_i}$ and $\alpha_i$ is the representation and corresponding weight for $c_i$ respectively. Secondly, we utilize the promising weighted hierarchical embedding (WHE) method [45], considering that different granularities of sub-type in hierarchical structures may vary in significance in type representation, to build the representation of $T_e$ as follows:

$$T_e = \sum_{i=1}^{m} \beta_i \cdot T_{c(i)} = \beta_1 \cdot T_{c(1)} + \cdots + \beta_m \cdot T_{c(m)},$$  \hspace{1cm} (3)

in which $m$ is the number of layers in the hierarchical structure, $T_{c(i)}$ is the sub-type representation of $c^{(i)}$, $\beta_i$ is the corresponding weight of $c^{(i)}$. The more details can be find in [45].

Finally, we design a novel model of the triple support with entity hierarchical types. As we discussed above, following translation-assumption framework [4], we build the distance of the entity type triple: $G(T_h, r, T_t) = ||T_h + r - T_t||$, $T_h$ and $T_t$ stand for the representation of head type and tail type respectively which are calculated by WHE. The triple support with hierarchical types is designed as follows:

$$TS(h, r, t) = \sigma(-G(T_h, r, T_t)), \hspace{1cm} \forall (h, r, t) \in \mathcal{T}$$  \hspace{1cm} (4)

where $\sigma(x) = 1/(1+e^{-x})$ is the sigmoid or logistic function to convert the type triple score into triple support. A higher the TS implies that the triple is more probable to be true.
3.2.2 Triple support with Entity Descriptions. TS would fail to work if the types of head and tail exactly match but the fact is actually false, such as (Donald Trump, was-born-in, State of Hawaii). However, the textual descriptions can discover semantic relevance and offer precise semantic expression [42]. The semantic relevance between entities is capable to recognize the true triples, and precise semantic expression could promote the discriminative ability between two triples. Here, we design the entity description triple to estimate the triple support, by replacing both head and tail with their corresponding descriptions: (h, r, t) → (D_h, r, D_t). In the following, we introduce an novel approach to build triple support with entity descriptions (DS).

From each shot description, we generate a set of keywords which is capable of capturing the main ideas of entities. The assumption is that similar entities should have similar descriptions, and correspondingly have similar keywords. Those triple support may be detected in the internal contact of their keywords. We formulate entity descriptions as \( \mathcal{D}_e := \{w_1, w_2, \ldots, w_n\}\). \( \{w_1, w_2, \ldots, w_n\} \) is the set of keywords in entity description. \( n \) is the size of words set. We take advantage of conventional neural network (CNN) [18, 43] to model entity description \( \mathcal{D}_e \). The CNN model can takes word orders, i.e., complicated local interactions of keywords in entity description, into consideration.

CNN : The \( i \)-th output vector of convolution layer is calculated as:

\[
z_i^{(l)} = \sigma(W^{(l)}_{i}, w_i^{(l)} + b_i^{(l)}),
\]

where \( W^{(l)} \) is the convolution kernel for all input vectors of \( \ell \)-th convolution layer after window process and \( b_i^{(l)} \) is the optional bias. \( \sigma \) is the activation function such as \text{tanh} or \text{ReLU}. \( w_i^{(l)} \) is the \( i \)-th vector of \( W^{(l)} \) which is obtained by concatenating \( k \) column vectors in \( \ell \)-th window of the polling output of \((\ell -1)\)-th layer. The pooling process shrinks the parameter space of CNN and filter noises after every convolution layer. We use \( n \)-max-pooling and mean-pooling strategies respectively in different pooling layers. After the last pooling layer, we obtain the representation of entity description \( \mathcal{D}_e \).

Finally, we design a novel model of the triple support with entity descriptions. Under translation-assumption, we build the distance of the entity description triple: \( G(D_h, r, D_t) = \|D_h + r - D_t\| \). \( D_h \) and \( D_t \) stand for the representation of head type and tail descriptions respectively which are calculated by CNN. The triple support with entity descriptions is designed as follows:

\[
\text{DS}(h, r, t) = \sigma(-G(D_h, r, D_t)), \quad \forall (h, r, t) \in \mathcal{T}.
\]

A higher the DS implies that the triple is more probable to hold.

3.2.3 Overall Support Model. The overall triplet support combines with two kinds of support stated above. We have:

\[
\text{S}(h, r, t) = \lambda \cdot \text{TS}(h, r, t) + (1 - \lambda) \cdot \text{DS}(h, r, t),
\]

where \( \lambda \) is hyper-parameter.

3.3 Triple Confidence with KG

3.3.1 CKRL. As we introduced in Section 2, CKRL, proposed by Xie et al. [44], is a promising model to estimate the triple confidence with the internal structural information in KG. Inspired by their work, we take advantage of both the local triple confidence and global path confidence (see more in [44]). Furthermore, we also study approximate relation entailment constraints (EC) from internal KG for triple confidence estimation.

3.3.2 Approximate Relation Entailment as Confidence Constraint. Approximate relation entailment means that an ordered pair of relations that the former approximately entails the latter, e.g. \text{was-born-in} and \text{nationality}, stating that a person born in a country is very likely, but unnecessarily, to have a nationality of that country. Each such relation pair \((r_p, r_q)\) is associated with a weight \( \phi \) to indicate the confidence level of entailment: \( r_p \xrightarrow{\phi} r_q \). A higher weight stands for a higher level of confidence. Following Wang et al. [39], the relation entailments can be derived automatically from KG by modern rule mining systems [11]. Let \( V \) denotes the set of all approximate relation entailments. Therefore, we can denote the approximate entailment between relations \( r_p \) and \( r_q \) with confidence level \( \phi \) as follows:

\[
C(h, r_q, t) \geq \phi \cdot C(h, r_p, t), \quad \forall (r_p, r_q) \in V,
\]

\( (h, r_p, t), \quad (h, r_p, t) \in \mathcal{T} \).

3.4 Objective Formalization and Optimization

We introduce the training objective of our model. Following TransE [4], we use margin-based optimization criterion to train our model. The main idea is that the model scoring function value of true knowledge-triple in training set \( \mathcal{T} \) should be lower than the corrupt one, the head or tail of which is replaced by a random one. Note that we do not replace both head and tail with random one at the same time. A triple will not be considered as a negative sample if it is already in training set \( \mathcal{T} \). To learn embeddings, we minimize the hinge loss function \( L \) as follows:

\[
L = \sum_{(h, r, t) \in \mathcal{T}} \sum_{(h', r', t') \in \mathcal{T}'} [\gamma + M(h, r, t) - M(h', r', t')]_+, \quad S(h, r, t) \cdot C(h, r, t),
\]

\[
+ \mu \sum_{(h, r_p, t), (h, r_p, t) \in \mathcal{T}, (r_p, r_q) \in V} [\phi \cdot C(h, r_p, t) - C(h, r_q, t)]_+, \quad \forall (h, r_p, t) \in \mathcal{T}, \quad (r_p, r_q) \in \mathcal{V}.
\]

where \( M(h, r, t) \) is the dissimilarity score of positive triple and \( M(h', r, t') \) is that of negative triple, and \( \gamma > 0 \) is the margin hyperparameter. The triple support \( S(h, r, t) \) is determined by (7). \( \mathcal{T}' \) represents the negative triple set.

\[
\mathcal{T}' := \{(h', r, t)|(h, r, t) \in \mathcal{T} \cap h' \in \mathcal{E} \land h' \neq h \} \cup \{(h, r, t')|(h, r, t) \in \mathcal{T} \cap t' \in \mathcal{E} \land t' \neq t \}.
\]

It is not absolutely necessary to use hinge loss function [47]. However, it is very common to use hinge loss for learning embedding (like TransE, NTN, etc) just as our model did. The embeddings of all entities, relations, sub-types and keywords are denoted as \( \{E, R, T, W\} \) respectively initialized randomly. We use mini-batch stochastic gradient descent (SGD) for optimization.

As pointed out by [6], it would be uneconomical to save all negative properties of an entity or a concept. Therefore, we further require entities to have non-negative vectorial representations[9]. In most cases, non-negative will further induce sparsity and interpretability [19]. We perform the following procedure iteratively for a given number of iterations. First, we sample a small set (minibatch) of

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tripltes from the training set \( T \), and then for each positive triple in it, we construct a negative sample by replace the head or tail with random one. The parameters are then updated by taking a gradient descent step gradually.

4 EXPERIMENT

4.1 Datasets

Our experiments are conducted on a public benchmark dataset, FB15K [4] that is a typical knowledge graph extracted from Freebase [3], and three extended datasets (FB15K-N1, FB15K-N2 and FB15K-N3) which is generated based on FB15K with different noise rates (i.e., 10\%, 20\% and 40\% respectively) to simulate the real-world KG construction with errors [44].

Given a positive triple \((h, r, t)\) in KG, the head or tail is randomly replaced to form a negative one \((h', r, t)\) or \((h, r, t')\). In order to generate harder and more confusing noises, \(h'\) (or \(t'\)) should have appeared in the head (or tail) position with the same relation, which means that the tail entity of relation was_born_of in negative triples should also be a place. All three noisy datasets share same entities, relations, validation and test sets with FB15K, will all generated negative triples fused into the original training set of FB15K. The statistics are listed in Table 1.

Following [11], we use AMIE+\(^1\) to extract approximate relation entailment automatically from FB15K. As suggested by Guo et al. [13], we only consider entailments with PCA confidence\(^2\) higher than 0.8. As such, 535 approximate relation entailments are extracted from FB15K.\(^3\)

Table 1: Statistics of the datasets.

| Dataset | #Entities | #Rel.s | #Train | #Valid | #Test |
|---------|-----------|--------|--------|--------|-------|
| FB15k   | 14,951    | 1,345  | 483,142| 50,000 | 59,071|
|         | FB15k-N1  | FB15k-N2| FB15k-N3|
| #Neg triples | 46,408    | 93,782 | 187,925|

4.2 Experimental Settings

In experiment, we evaluate our SCEF model with three different combination strategies. SCEF (EC) represents the strategy which only considers triple confidence with relation entailment constraints. SCEF (EC+TS) considers both confidence constraints and type support, while SCEF(EC+TS+DS) considers confidence constraints and two kinds of triplet support. We choose TransE [4] and CKRL [44] as baseline for comparison. As the datasets are the same, we directly reprint the experimental results of several baselines from the literature. We train our SCEF model using mini-batch SGD. The margin \( \gamma \) is empirically set to 1. We select the learning rate \( \lambda \) in the stochastic gradient descent among \([0.0001, 0.001, 0.01]\), the dimension of entity, relation, entity type and keyword embedding \( \kappa \) in all models in a range of \([50, 100]\) on the validation set. For overall triple support model, the hyperparameter \( \lambda \) is set as 0.5. For triple confidence, we set the parameter of CNN are: \#window size=2, \#convolution layer = 2, \#dimension of feature map = \( \kappa \).

4.3 Knowledge Graph Noise Detection

This task aims to detect possible noises in knowledge graphs according to their triple scores, in order to verifying the capability of our SCEF models in identifying noises in KGs. We utilize translation- assumption method TransE: \( M(h, r, t) = ||h + r - t|| \) as our triple model. Following the triple classification protocol in [35], we rank all triples in training set with their model score. Therefore, the higher the model score, the more likely the triple is noise.

Results: Fig. 4 shows the evaluation results (precision/recall curves) of KG noise detection, from which we can observe that:

- Our proposed models outperform all the baselines on all noisy datasets, which confirms the capability of our SCEF models in error detection for KG refinement.
- SCEF (EC+TS+DS) has impressive improvement in error detection compare to other support-confidence-aware methods. It indicates that the triple support with entity descriptions can provide significant help for error detection.
- SCEF (EC+TS) achieves better performance than SCEF (EC). It indicates that the triple support with entity type can further boost KG correction beyond the triple confidence.
- SCEF (EC) performs better than CKRL (LT+PP+AP), which implies that the approximate relation entailment constraints can improve the learning of triple confidence, so as to help KG noise detection.

4.4 Knowledge Graph Completion

The classical knowledge base completion task aims to complete a triple when one of its head, tail or relation is missing, i.e., to predict how likely some additional facts (triples) are held. Here, we only focus on entity prediction, determined by TransE[4]: \( h + r \approx t \). We conduct two typical measures proposed by [4]: Mean Rank and Hits@10, and the different evaluation settings of “Raw” and “Filter” (See [4] for details).

Results: Table 2 shows the results of entity prediction with different noise rates, from which we observe that:

- All support-confidence-aware SCEF models achieve better performance comparing with baseline on all noisy datasets, which confirms the capability of our models in KG completion beyond KG error detection.
- Our methods achieve more significant improvement as the noise rate in KGs increases, comparing with evaluation results between the three noisy datasets. It verifies that considering the support-confidence in KG embedding is very essential especially when KGs have high rate of noises.
- Both SCEF (EC+TS) and SCEF (EC+TS+DS) perform better than SCEF (EC). It demonstrates that the external information (i.e., entity type and description) could further benefit KG completion.

\(^1\)https://www.mpi-inf.mpg.de/departments/databases-and-information-systems/research/yago-nage/amie

\(^2\)It denotes the confidence under the partial completeness assumption, see more in [11].

\(^3\)For instance, /people/place_of_birth \( \xrightarrow{1.00} /location/people_born_here; /film/directed_by \xrightarrow{0.98} /director/film \).
Table 2: Evaluation results on entity prediction. (The lower the better for Mean Rank, whereas Hits@10(%) is on the contrary.)

| Datasets  | FB15K-N1 | FB15K-N2 | FB15K-N3 |
|-----------|----------|----------|----------|
| TransE    | Mean Rank | Hits@10 (%) | Mean Rank | Hits@10 (%) | Mean Rank | Hits@10 (%) |
| Raw Filter | 240      | 144      | 44.9      | 59.8      | 250      | 155      | 42.8      | 56.3      | 265      | 171      | 40.2      | 51.8      |
| CKRL (LT)  | 237      | 140      | 45.5      | 61.8      | 243      | 146      | 44.3      | 59.3      | 244      | 148      | 42.7      | 56.9      |
| CKRL (LT+PP) | 236    | 139      | 45.3      | 61.6      | 241      | 144      | 44.2      | 59.4      | 245      | 149      | 42.8      | 56.8      |
| CKRL (LT+PP+AP) | 236 | 138      | 45.3      | 61.6      | 240      | 144      | 44.2      | 59.3      | 245      | 150      | 42.8      | 56.6      |
| SCEF (EC)  | 235      | 137      | 45.8      | 61.9      | 238      | 143      | 44.8      | 60.2      | 243      | 147      | 43.1      | 57.2      |
| SCEF (EC+TS) | 232     | 136      | 46.2      | 62.2      | 236      | 140      | 45.1      | 60.7      | 240      | 145      | 44.1      | 58.2      |
| SCEF (EC+TS+DS) | 231 | 136      | 46.2      | 62.8      | 235      | 140      | 45.3      | 60.9      | 240      | 144      | 44.2      | 58.2      |

Table 3: Evaluation results on triple classification

| Dataset    | FB15K-N1 | FB15K-N2 | FB15K-N3 |
|------------|----------|----------|----------|
| TransE     | 81.3     | 79.4     | 76.9     |
| CKRL(LT)   | 81.8     | 80.2     | 78.3     |
| CKRL(LT+PP) | 81.9   | 80.1     | 78.4     |
| CKRL(LT+PP+AP) | 81.7 | 80.2     | 78.3     |
| SCEF (EC)  | 82.1     | 80.9     | 79.2     |
| SCEF (EC+TS) | 82.4  | 81.0     | 80.3     |
| SCEF (EC+TS+DS) | 82.6 | 81.2     | 80.3     |

4.5 Triple Classification

Triple classification aims to predict correct facts in the test data, which could be viewed as a binary classification problem. Following the same protocol in [35], we use validate set to find a threshold \( \zeta_r \) for each relation such that if \( ||h + r - t|| \leq \zeta_r \), the triple will be classified to be positive, otherwise to be negative. Since there are no explicit negative triples in existing knowledge graphs, we construct negative triples in validation and test set following the same protocol in [35], with equal number of positive and negative examples. The final accuracy is based on how many triplets are classified correctly. **Results:** Table 3 shows the resulting accuracy of each model. We can find that:

- The SCEF models outperform baseline on all datasets, which proves that support-confidence-aware framework can be helpful for relation triple classification as well.
- More specifically, SCEF (EC+TS+DS) model improves 0.9%, 1.0% and 2.0% on FB15K-N1, FB15K-N2 and FB15K-N3 respectively, it reaffirms that our method become more significant with higher noise rates.

5 Conclusion and Future Work

Knowledge graph refinement (e.g., completion and correction), is an important but underexplored problem. In this paper, we propose SCEF, a novel support-confidence-aware framework for KG completion and correction simultaneously by learning embeddings with triple support and confidence. We not only consider the internal structural information in KG, studying the approximate relation entailment as triple confidence constraints, but also the external textual evidence, proposing two kinds of triple supports with entity types and descriptions respectively. Through extensive experiments on three real-world datasets, we demonstrate SCEF’s effectiveness over state-of-the-art baselines.

We will explore the following research directions in future: (i) more external source are expected to improve the triple quality. (ii) apply the support-confidence framework to improve network embedding which faces noise issue as well.
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