Knowledge-Graph-Enhanced Relation Extraction Datasets

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Abstract

Knowledge-enhanced methods that take advantage of auxiliary knowledge graphs have recently emerged in relation extraction, and they surpass traditional text-based relation extraction methods. However, there are no public datasets that contain both evidence sentences and knowledge graphs for knowledge-enhanced relation extraction. To solve this issue, we propose a knowledge-graph-enhanced relation extraction dataset (KGRED) based on widely used distantly supervised relation extraction datasets. We refined these datasets to improve the data quality and constructed auxiliary knowledge graphs for these datasets through entity linking to support knowledge-enhanced relation extraction tasks. We built baselines in two popular relation extraction settings, sentence-level and bag-level relation extraction, and made comparisons between the latest knowledge-enhanced relation extraction methods using the new datasets we curated. KGRED provided high-quality relation extraction datasets with auxiliary knowledge graphs for evaluating the performance of knowledge-enhanced relation extraction methods. Experiments on KGRED reveal the influence of knowledge graph information on relation extraction tasks.

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1. Introduction

Relation extraction (RE) aims to extract relations between entities from natural language sentences [1]. RE benefits various downstream tasks in natural language processing, such as question answering [2, 3], knowledge graph construction [4, 5], and reading comprehension [6, 7]. Knowledge graphs (KGs) store relational facts in the form of a subject entity, object entity, and the relation between two entities [8]. For example, the fact (James Joyce, country of citizenship, Ireland) means that James Joyce is (was) a citizen of Ireland. As a form of structured representation of facts, KGs have wide applications in the information technology (IT) industry, such as social network analysis [9, 10] and recommending systems [11, 12].

Recently, increasing number of researchers have integrated KGs into their RE methods to enhance the performance [13, 14, 15]. Meanwhile, abundant resources such as distantly supervised relation extraction (DSRE) datasets [16] and large knowledge databases [17, 18] have facilitated these studies. However, there are no unified public datasets that combine both sentences and the corresponding knowledge graphs for training and evaluating knowledge-enhanced RE methods. Researchers in this field have to build auxiliary KGs, create datasets from scratch, and retest previous baselines to make fair comparisons [14, 19, 15]. Therefore, it is difficult to report reproducible results or make comparisons between existing models owing to the lack of public datasets.

To solve these issues, we improved the data quality of three widely used RE datasets and constructed an auxiliary KG for each of them through entity linking. We refer to these improved datasets as KGRED. KGRED can be a public evaluative criterion for knowledge-enhanced RE methods, and we expect KGRED to promote the development of knowledge-enhanced RE in the future.

We begin with original DSRE datasets that are based on Wikidata [17] or Freebase [18]. DSRE generates large-scale data by aligning relational facts in KGs to raw text [16]. Therefore, entities in DSRE datasets naturally match their counterparts in databases, which facilitates locating the entities through their identifiers in the database and collecting additional relation facts for them. Thus, it is feasible to automatically construct a KG for each DSRE dataset. See Figure 1 for illustration. We collected three DSRE datasets: NYT10m [16], Wiki20m [16], and Wiki80
Ansel Easton Adams was an American landscape photographer. Adams participated in the club’s annual High Trips, later becoming official photographer for the trips. Imitating the example of photographer Alfred Stieglitz, Adams opened his own art and photography gallery in 1933.

Figure 1: An illustration of instances in a DSRE dataset and the auxiliary KG for the dataset. An instance consists of a sentence together with a relational fact expressed by the sentence. A batch of instances constitutes an RE dataset. A KG contains some or all entities in an RE dataset and relations between them. In this example, we link entities in the three instances to their counterparts in the auxiliary KG. Then, a knowledge-enhanced RE method can classify the relation between Ansel Adams and Photographer as Occupation by the virtue of the information provided by the sentences and the KG.

[20] and refined them by improving the data quality and constructing a KG for each of them. Thereafter, we performed a series of RE experiments on KGRED to evaluate the performance of existing RE methods. We also analyzed the experimental results to determine the influence of the auxiliary KG information on RE methods. Summarizing, KGRED provides the first standardized datasets for knowledge-enhanced RE methods.

The contributions of our study are two-fold. First, we create KGRED with three challenging KG-enhanced RE datasets, to potentially promote the develop-
ment of knowledge-enhanced RE research. We publish our datasets on Figshare; see Appendix A for access to KGRED. Second, we set metrics for knowledge-enhanced RE methods on KGRED and evaluate the latest RE methods on our datasets. According to our experiments, knowledge-enhanced RE methods can outperform traditional methods; however, the knowledge-enhanced RE task becomes more challenging when the scale of auxiliary KG is limited.

The remainder of the article is organized as follows. Section 2 reviews the widely-used DSRE datasets and the knowledge-enhanced RE methods. Section 3 describes the construction of KGRED. Section 4 presents the descriptive analysis of KGRED. Section 5 evaluates the RE models on KGRED. Section 6 presents the experimental results and discussion. Section 7 concludes the paper.

2. Related Works

In this section, we discuss widely used DSRE datasets and knowledge-enhanced RE methods that have been proposed in recent years.

**DSRE datasets.** Most existing DSRE datasets are constructed by recognizing entities mentioned in free text and then linking them to public databases such as Wikidata and Freebase. NYT10 is one of the earliest large-scale datasets constructed by DSRE automatically. However, Han et al. identified noisy labeling problems in NYT10 and other existing datasets. To alleviate this problem, Gao et al. provided two DSRE datasets with large manually annotated test sets, which significantly improved the data quality of previous NYT10 and Wiki20. Although noisy labeling problems were alleviated, data quality issues remain in NYT10m and Wiki20m. Therefore, we further denoised these datasets and enriched them with external KGs through entity linking. Our refined datasets will provide the community with a touchstone to evaluate knowledge-enhanced RE methods.

**Knowledge-enhanced RE.** A growing number of RE methods leverage auxiliary information, such as attributes and embeddings of entities, into their models, in which KG information plays an important role because it reveals the broad associations between entities. In virtue of KGs, CGRE derives constraint graphs from KG to model the intrinsic connections between relations. The model generates representations for entities and relations by encoding the graph into vectors and extracting node features. Xu and Barbosa proposed an RE frame-
work, HRERE, which jointly learns language representations and knowledge base. Moreover, KGPool [15] applied a graph pooling algorithm that dynamically selects KG context to enhance the model performance. Their method only considers names, categories, aliases, and descriptions of entities as their side information from KG. REMAP [26], a multimodal method for DSRE, fuses knowledge graph embeddings with deep language models to classify the relations between entities. However, currently, it is impossible to compare the performance of all the above methods because they have not been evaluated on a unified benchmark. Thus, we revisit the existing knowledge-enhanced RE methods and evaluate them on our datasets to obtain an objective comparison.

3. Construction of KGRED

In this section, we provide the problem definition and introduce previous DSRE datasets in Section 3.1 and Section 3.2. Thereafter, we describe the process of entity linking and dataset refinement for KGRED in Section 3.3 and Section 3.4.

3.1. Problem definition

Knowledge-enhanced RE methods classify relations between entity pairs from unstructured text with the help of knowledge base (KB) information [23, 25]. A dataset for RE comprises a batch of instances and a set of candidate relations. Each instance contains a sentence and a corresponding relation fact (an entity pair and the relation between them), as shown in Figure 1. All relations in the dataset are restricted in the set of candidate relations. Traditional RE methods classify the relation between two entities according to the sentence for each instance. In addition to traditional RE, knowledge-enhanced RE methods generally require an auxiliary KG as auxiliary information to enhance their RE performance. To set up datasets for knowledge-enhanced RE tasks, we improve the data quality of existing RE datasets and construct KGs for them to obtain KG-enhanced RE datasets.

Our experiments evaluate RE methods on two levels. Sentence-level RE implies that the method considers only one instance as the input at a time and predicts the relation of entities expressed by the sentence. On the contrary, bag-level RE implies that the method takes a bag at a time as the input. A bag contains instances with the same entity pairs in the dataset, such as the three instances shown in Figure 1. Bag-level methods classify the relation between the two entities considering all the instances in the bag.
The main notations used are as follows: $E$ represents the entity set containing all entities in an RE dataset. $R$ represents the relation set containing all relation labels in an RE dataset. N/A means not applicable, which is a label type that may appear in $R$. $r^i = (x^i, e^i_1, e^i_2)$ is the $i$-th instance in an RE dataset, where $e^i_1$ and $e^i_2$ delimit entity mentions in token sequence $x^i$. $(h^j, t^j, r^j)$ is the $j$-th relation fact in a KG, where $h^j$ and $t^j$ are subject entity and object entity with relation $r^j$, respectively.

3.2. Previous relation extraction datasets

We used three frequently-used relation extraction datasets: NYT10m [16], Wiki80 [20], and Wiki20m [16]. Wiki80 is a sentence-level dataset, while Wiki20m and NYT10m are bag-level datasets.

- **NYT10m** [16] is a bag-level dataset obtained from NYT10 [27] by cleaning the dataset and separating the validation set from the training set. NYT10m also provides a manually-annotated test set based on the original test set. N/A instances in NYT10m imply that there is no relation between entities.

- **Wiki80** [20] is a sentence-level dataset based on the few-shot dataset FewRel [28]. This human-labeled dataset contains 56,000 relation facts with 80 kinds of relations. N/A relation fact does not exist in Wiki80.

- **Wiki20m** [16] is derived from Wiki20 by reorganizing its relation facts and redividing its training, validation, and test sets. This bag-level RE dataset shares the same relation ontology with Wiki80, except that Wiki20m contains a N/A relation expressing unknown relation.

3.3. Entity linking

Entity linking implies locating entities in KB so that knowledge context can be extracted for each entity and constructing a KG for the dataset. We applied different entity linking methods to NYT10m [16], Wiki80 [20], and Wiki20m [16].

**NYT10m.** As NYT10 [27] is distantly supervised by Freebase [18], all its entities can naturally be retrieved in Freebase. However, Freebase was shut down in 2014; thus, we could not extract specific knowledge context from it. Therefore, we used FB15k [29], a subset of Freebase [18], to provide knowledge context for NYT10m instead.

**Wiki80 and Wiki20m.** All entities in Wiki80 [20] and Wiki20m [16] are directly extracted from Wikidata [17], implying that entities in these datasets naturally match entities in Wikidata. Therefore, we retrieved entities in Wiki80 and
Wiki20m from Wikidata according to the Wiki identifiers of the entities in Wikidata. After the retrieval, Wikidata provided external side information of entities, such as descriptions, aliases, and neighbor entities, which can be used to construct auxiliary KGs for RE datasets. However, some entities in these datasets were redirected, while some of them no longer existed in Wikidata anymore.

3.4. Dataset refinement

As previous datasets suffer from data quality issues and do not have unified auxiliary KGs, dataset refinement aims to improve the data quality of each RE dataset and construct a KG for the dataset according to the knowledge base.

Data Quality Improvement. To provide high-quality datasets, we denoised all the original datasets. We updated identifiers of redirected entities to the latest version and deleted those instances containing missing entities in Wiki80 [20] and Wiki20m [16]. Then, we deleted duplicate instances in each dataset. We found that some relation facts in Wiki80 and Wiki20m had the subject and object referring to the same entity such as:

\[(\text{soviet}[Q15180], \text{soviets union}[Q15180], \text{country}[P17]),\]

and we removed instances containing these relation facts. Eventually, in Wiki80, there were 162 redirected identifiers, and 32 entities were removed; in Wiki20m, there were 1,092 redirected identifiers, and 269 entities were removed.

KG for NYT10m. NYT10m [16] only provides instances with relational facts and not KG context for their entities. Thus, we constructed an informative KG for this dataset so that the dataset can serve as a benchmark for KG-enhanced RE tasks. After linking all the entities to FB15k as elaborated in Section 3.3, we extracted triplets of these entities from the knowledge base to construct the KG. Formally, let \( E \) be a set of entities containing all entities in NYT10m and let \( R \) be a set of relations containing all relations in NYT10m. Given every triplets \((h^j, t^j, r^j)\) in FB15k, where \(h^j\) and \(t^j\) are subject and object entities with relation \(r^j\). We construct the KG using every triplet that satisfies the following rules: (1) \(h^j\) and \(t^j\) can be found in \(E\), (2) \(r^j\) is a relation in \(R\). In addition, for every instance \(r^i = (x^i, e^i_1, e^i_2)\) in NYT10m, where \(e^i_1\) and \(e^i_2\) delimit entity mentions in token sequence \(x^i\), we can extract a triplet such as \((e^i_1, e^i_2, r^i)\). These triplets can be added in KG to avoid information shortage. In the final KG, the triplets extracted from validation/test sets must be excluded.

KGs for Wiki80 and Wiki20m. Identically, both Wiki80 and Wiki20m only provide instances with relational facts. We can also extract suitable information
from Wikidata [17] for KG construction. The KG construction method we used for Wiki80 and Wiki20m is the same as the one we used for NYT10m.

4. Data Analysis

In this section, we present the statistics of KGRED and analyze how these datasets support relation extraction tasks enhanced by knowledge graphs.

4.1. Analysis of instances

As discussed in Section 3.4, dataset refinement denoises the original DSRE datasets to guarantee data quality. Eventually, we obtained a modified version of NYT10m with 475,401 instances, Wiki80 with 55,547 instances, and Wiki20m with 743,703 instances. Wiki80 is smaller than the other datasets. The scale of NYT10m is close to that of Wiki20m. However, the amounts of entities and relational facts in Wiki20m are much higher than the ones in NYT10m, and the N/A proportion of NYT10m is higher than that in Wiki20m. The statistics of our modified datasets in KGRED are presented in Table 1.

| Dataset   | Manual | Instances | Entities | Facts    | N/A | Relations | KB          |
|-----------|--------|-----------|----------|----------|-----|-----------|-------------|
| NYT10m    | train  | No        | 417,893  | 61,112   | 17,137 | 80%       | Freebase    |
|           | valid  | No        | 46,422   | 20,850   | 4,062  | 80%       |             |
|           | test   | All       | 11,086   | 4,554    | 3,899  | 28%       |             |
| Wiki80    | train  | All       | 50,353   | 66,758   | 50,353 | 0%        | Wikiidata   |
|           | val    | All       | 5,194    | 8,662    | 5,194  | 0%        |             |
|           | test   | Part      | 123,122  | 89,925   | 53,755 | 23%       |             |
| Wiki20m   | train  | No        | 571,787  | 285,905  | 154,078| 55%       | Wikiidata   |
|           | valid  | No        | 48,794   | 44,082   | 16,489 | 66%       |             |
|           | test   | Part      | 123,122  | 89,925   | 53,755 | 23%       |             |

Table 1: Statistics of KGRED datasets. The Manual column indicates whether the instances are manually labeled. Instances, Entities, and Facts indicate the number of instances, entities, and relational facts, respectively. The N/A column shows the percentages of instances with N/A relation in the datasets. Relation indicates the number of relations in each dataset. KB indicates the knowledge base source of datasets in KGRED. Wiki80 and Wiki20m are our modified versions.

4.2. Analysis of knowledge graphs

In Section 3.4, we elaborated the process of KG generation for each DSRE dataset. For NYT10m, we used a subset of FB15k [29] as KG. This KG covers approximately 25% entities in NYT10m. For Wiki80 and Wiki20m, we extracted
the knowledge context of entities from Wikidata [17] and generated KGs with the context. These KGs contain large quantities of relational facts and almost all entities in wiki80 and Wiki20m.

All the aforementioned KGs provide abundant side information for KG-enhanced relation extraction tasks. To strengthen their performance, knowledge-enhanced RE methods can train knowledge embeddings with our KGs or consider relational facts in the KGs as input [19, 25, 26].

We present the statistics of KGs in KGRED in Table 2. The amounts of entities and facts reflect the scales of KGs. On one hand, the scales of Wiki20m dataset and KG are relatively large, implying that Wiki20m is eligible to measure the performance of knowledge-enhanced RE methods. On the other hand, the scales of Wiki80 dataset and KG are small, implying that we can measure the performance of models quickly with Wiki80. Moreover, the scale of KG for NYT10m is much smaller than that of the NYT10m dataset, and this KG can only provide knowledge context for approximately 25% of the entities in NYT10m. The degree of an entity is the number of triples containing that entity in the KG. The average degree of all entities shows the density of the KG. For Wiki80 and Wiki20m, the KGs provide 7.98 and 8.60 direct neighbors for each entity on average, implying that the information in these KGs is dense. Because KG embeddings are sensitive to the density of the KG [30], we believe that our dense KGs are helpful to KG enhanced RE methods which often rely on KG embeddings [19, 25, 26, 31]. For NYT10m, the average degree is 2.87, which is relatively low but acceptable. According to the number of connected components and the size of the maximal connected components, each KG consists of a very large connected component and a few small connected components. Relational information in large connected components is denser than the information in small ones. As the maximal component contains almost all entities in each KG, KG-enhanced methods can extract features of entities and relations from these KGs effectively.

5. Experimental Settings

To evaluate the performance of existing RE methods, especially knowledge-enhanced RE methods, we conduct a series of comprehensive experiments. In this section, we describe our baselines and evaluation strategy.

5.1. Baselines

We collected various current RE methods as our baselines to evaluate their performance on our datasets. Below, we provide a sketch of all RE baselines that
| Dataset    | Total En. | KG En. | Facts     | Degree | Comp. | Max Comp. | KB          |
|------------|-----------|--------|-----------|--------|-------|-----------|-------------|
| NYT10m     | 64,890    | 16,469 | 23,643    | 2.87   | 733   | 14,730    | FB15k       |
| Wiki80     | 72,358    | 72,353 | 288,750   | 7.98   | 513   | 70,477    | Wikidata    |
| Wiki20m    | 360,966   | 360,956| 1,551,694 | 8.60   | 621   | 359,145   | Wikidata    |

Table 2: Statistics of KG for each dataset in KGRED. Total En. is the total number of entities in the dataset. KG En. and Facts show the number of entities and relational facts in the KG (all entities and relations in the KG are also in the dataset). Degree is the average degree of all entities in the KG. Comp. is the number of connected components in the graph. Max Comp. is the size of the maximal connected component. KB is the knowledge base of each KG.

we evaluated on our KG-enhanced datasets, which include RE methods without KG, sentence-level, and bag-level RE methods with KG.

All methods were developed under supervised training or were fine-tuned on the training set and evaluated on the validation/test set. For PCNN [32] and BERT [33], we followed the experimental settings of [16, 20]. For the other baselines, we used their original settings and hyper-parameters except for the training epochs.

5.1.1. RE methods without KG

We selected two widely used RE models PCNN [32] and BERT [33] as our baselines. These methods classify relations between entities without the help of KG information. We conducted these experiments on original Wiki80, Wiki20m, and NYT10m or cited the experimental results from [16].

- **PCNN** [32] is a DSRE method proposed to learn features from text automatically. It relies on piece-wise convolutional neural networks to encode words in a sentence and provide sentence-level embeddings.

- **BERT** [33] and its variants have dominated a wide range of natural language processing tasks since 2019. This pretraining method has a great influence in various fields including relation extraction.

5.1.2. Sentence-level RE methods with KG

Sentence-level RE methods take advantage of the auxiliary KG for RE tasks in different ways, and the most common approach is to use embeddings derived from KG. We selected three methods to evaluate their sentence-level performance on our proposed datasets.

- **RECON** [19] uses a graph neural network to learn representations of both the sentence as well as facts stored in a KG. These facts include entity attributes and relational facts.
• **KGPool** [15] dynamically selects KG context with graph pooling to enhance the performance of RE. This method only considers attributes of entities as their side information from KG instead of relational facts. This side information, extracted from Wikidata [17] directly, is not a part of our datasets.

• **CoLAKE** [31] uses a word-knowledge graph, which is an unlabeled data structure that integrates language and knowledge context to learn contextualized representation. When fine-tuning the model, we used the label *unk* to represent N/A relation in Wiki20m.

### 5.1.3. Bag-level RE methods with KG

Bag-level RE methods classify relations between entities on the bag-level instead of sentence-level. We evaluated three bag-level methods on KGRED.

• **CGRE** [14] constructs a constraint graph to model the relation dependencies using entity type information. It generates representations for entities and relations by encoding the graph into vectors and extracting features of the nodes to support RE tasks.

• **HRERE** [25] is a neural framework that jointly learns knowledge and language representations. It integrates relation extraction and knowledge base embedding tasks in a unified way to increase the model performance.

• **REMAP** [26] is a multimodal method for DSRE task. It fuses knowledge graph embeddings with deep language models to extract and classify the relations between entities effectively.

### 5.2. Metrics

We used two metrics: the micro F1 and micro average precision (AP), to evaluate the model performance. Micro F1 is the harmonic mean of global micro precision and global micro recall. The formulas for micro F1 are:

\[
F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}},
\]

\[
\text{precision} = \frac{TP}{TP + FP},
\]

\[
\text{recall} = \frac{TP}{TP + FN},
\]
where TP is the global true positive rate, FP is the global false positive rate, and FN is the global false negative rate. AP is the weighted mean of precision at each threshold for all samples. The formula for micro AP is:

\[
AP = \sum_{i=2}^{n} \text{precision}_i \times (\text{recall}_i - \text{recall}_{i-1}),
\]

where \( \text{precision}_i \) and recall are the global precision and recall at the \( i \)th threshold, and \( n \) is the total number of samples. AP is also called AUC of PR curve in some articles [16, 20].

For sentence-level RE, we predicted the relation of each sentence directly and report the results on test sets. For bag-level RE, we grouped instances with the same entity pairs into bags and predicted the results of all bags in test sets. According to the settings of most RE experiments [15, 16, 19, 20, 25], all instances including those with N/A labels were considered for micro F1 calculation. Meanwhile, instances with N/A labels were excluded for micro AP calculation.

6. Results and Discussion

In the previous section, we described the settings of our baselines. In this section, we present the results of these RE experiments according to our settings. Furthermore, we analyze the results and discuss the impact of KG information on RE tasks.

6.1. Results

As observed from Table 3, some of the models are left unevaluated on some datasets. As for BERT and PCNN, we only provide results of PCNN+ONE and BERT+ONE on Wiki80. Average (AVG), at-least-one (ONE), and attention (ATT) are all methods used in bag-level RE to aggregate prediction results of each sentence to bag predictions. AVG averages the representations of all the sentences in the bag. ONE predicts relation scores for each sentence in the bag and then takes the highest score for each relation. ATT produces a weighted average over embeddings of sentences in the bag and determines weights by attention scores between sentences and relations. However, Wiki80 is a sentence-level RE dataset and the entity pairs are unique. Therefore, AVG and ATT do not fit this scenario. Regarding CoLAKE, as it is a pretrained model based on Wikidata5M [34], there are no learned representations for relations in NYT10m, we only evaluated it with Wiki80 and Wiki20m. Furthermore, there is a risk of information leakage, which
Table 3: Experimental results (%) of baselines. We report three-run micro F1 scores and micro average precision (AP) scores with standard deviations. RE w.o. KG indicates RE methods without using KG. S. RE and B. RE indicate sentence-level and bag-level RE methods with KG. As for PCNN and BERT, we only evaluate PCNN+ONE and BERT+ONE because the other two aggregation methods do not fit the sentence-level dataset Wiki80. CoLAKE was left untested on NYT10m because of the lack of learned relation representations and CGRE was only evaluated on NYT10m because the constraint graph it relies on only contains relations from Freebase.

| Model         | Wiki80 F1  | Wiki80 AP  | Wiki20m F1  | Wiki20m AP  | NYT10m F1  | NYT10m AP |
|---------------|------------|------------|-------------|-------------|------------|-----------|
|               |            |            |             |             |            |           |
| RE w/o. KG    |            |            |             |             |            |           |
| PCNN+AVG†     | —          | —          | 71.8        | 78.1        | 53.6       | 52.9      |
| PCNN+ONE†     | 77.43      | 84.68      | 70.3        | 76.6        | 54.8       | 53.4      |
| PCNN+ATT†     | —          | —          | 71.2        | 77.5        | 56.5       | 56.8      |
| BERT+AVG†     | —          | —          | 82.7        | 89.9        | 60.4       | 56.7      |
| BERT+ONE†     | 86.69      | 93.41      | 81.6        | 88.9        | 61.9       | 58.1      |
| BERT+ATT†     | —          | —          | 66.8        | 70.9        | 54.1       | 51.2      |
| S. RE         |            |            |             |             |            |           |
| RECON [19]    | 77.58±0.30 | 86.86±0.17 | 74.85±1.02  | 92.58±0.68  | 52.09±1.58 | 68.30±2.30|
| KGPool [15]   | 78.13±0.39 | 87.51±0.23 | 78.61±0.25  | 89.67±0.23  | 50.78±0.83 | 64.18±0.18|
| CoLAKE [31]   | 91.78±0.08 | 96.89±0.03 | 86.05±0.77  | 92.74±0.79  | —          | —         |
| B. RE         |            |            |             |             |            |           |
| CGRE [14]     | —          | —          | 51.48±0.66  | 53.51±0.40  | —          | —         |
| HRERE [25]    | 80.04±0.21 | 87.42±0.17 | 77.33±0.29  | 88.38±0.24  | 30.50±0.16 | 54.40±0.88|
| REMAP [26]    | 88.73±0.18 | 92.16±0.22 | 84.99±0.21  | 89.92±0.19  | 52.19±0.92 | 66.39±1.19|

† These experiments were conducted on original RE datasets under the settings of [16, 20]. We conducted the experiments for Wiki80, and the results of these models on Wiki20m and NYT10m have been cited from [16].‡ Since CoLake is pre-trained on Wikidata, there is a risk of information leakage. 

From the results, RE methods with KG generally outperformed those without KG, especially in AP scores. This is because extra KG information can provide more knowledge to the models. A noticeable exception is that all RE methods mean some triplets in the test set will appear in the KG of CoLAKE’s training data. Regarding CGRE, we evaluated it with NYT10m because the constraint graph provided by the author only contains relations from Freebase [18] but not in Wikidata [17].
with KG performed badly in micro F1 scores on NYT10m. This may be due to the small number of relational facts in KG built for NYT10m, and other information in KG such as entity attributes used by RECON and KGPool or constraint graphs used by CGRE may not provide the models with a useful predictive direction. Furthermore, the methods that use pre-training are significantly better than the other methods.

6.2. Analysis and discussion

We conduct various analyses and discuss the effect of KG we added to the original datasets, including basic statistics from the perspective of instances and the effect of KG on model performance.

6.2.1. Instance distribution of degree

This section analyzes the general statistics of the KGs we built from the perspective of instances. As shown in Figure 2 for Wiki80 and Wiki20m, the distributions are roughly similar, and the frequency of instances reaches its peak when the degree is approximately 16, after which the frequency tends to decrease with the increase in the degree. For NYT10m, the frequency of instances is high when the degree is 2, indicating that many entities do not have additional relational facts. Furthermore, we observe that the frequency of instances in Wiki20m is much higher, and the highest log-scaled frequency is greater than 6,000. This is due to the much more linked relational facts for Wiki20m.

In general, the distribution is similar between Wiki80 and Wiki20m. The difference is that the amount of data in Wiki80 is small, so the overall log-scaled
Figure 3: Micro F1 of instances with different degrees using different models on each dataset. The degree of each instance is obtained from the sum of the degrees of the subject and object entities in KG. We split the instances into ten groups according to their degrees. Degrees are maximum when the percentile of degree is 95 and minimum when it is 5.

frequency is small. However, the distribution of NYT10m is quite different; it is sparse and irregular.

6.2.2. Association between degree and instance performance

We further analyze the effect of the number of degrees on the prediction result of each instance. As shown in Figure 3, micro F1 scores tend to drop first and then increase in Wiki80 and Wiki20m using KGPool, RECON or HRERE. Interestingly, this trend appears to be the opposite of that in Figure 3. However, there is no such notable trend in NYT10m, owing to its small built KG. As mentioned in Section 6.1, the method that uses pre-training, CoLAKE, performs better than the other methods. Furthermore, CoLAKE and CGRE are not sensitive to the number of degrees. It is because these two methods do not use relational facts.

In most cases, model performance increases with the number of degrees, implying that the more the relational facts involved in an instance, the more precise the prediction result.

6.2.3. Association between degree and relation performance

We also analyze the effect of the number of degrees from the perspective of relations. As shown in Figure 4, a relation tends to be predicted correctly with the increase of involved relational facts. Different from the observation in Section 6.2.2, CoLAKE also has such a trend. This may be because, for each relation, if the degree of an instance is small, the entities in the instance are difficult to represent by the model. We also observe that the observation of NYT10m is quite
different from Wiki80 and Wiki20m, possibly due to the much fewer relational facts we built for it in KG. To further study how models perform on each relation, we plot several models and their micro F1 scores for each relation in Figure B.1 in Appendix B. We can see that the abilities of the models to correctly categorize each relation vary a lot. Some relations are easy to determine, for instance, voice type and position played on team/specialty in Wiki80 while the others are not. Besides, micro F1 scores can reach 1.0 for some of the relations in Wiki80 and Wiki20m, but this conclusion does not hold for the NYT10m dataset. Moreover,
many relations in NYT10m cannot be recognized by models. This may be due to the low data amounts these relations contain.

In conclusion, for each relation in Wiki80 and Wiki20m, low relational facts involved instances are difficult to predict. The relational facts help models predict the relation of each instance. However, even with a few relational facts, these models are not very accurate in predicting most of the relations in NYT10m.

6.2.4. Discussion

From the aforementioned analyses, we can conclude that knowledge-enhanced RE methods are effective, and intensive efforts are needed to improve them. Owing to the relatively small KG of NYT10m, the performance of most methods with KG is inferior to those without KG, which suggests that these models rely excessively on KG information in the design and even have a negative effect when KG information is insufficient. Therefore, knowledge-enhanced RE, in the presence of small-scale KG supplementation, is worthy of study. We believe these research directions are worth following: (1) Designing models effectively using KG information, especially relational facts. (2) Exploring methods that leverage insufficient relational facts to improve RE performance.

7. Conclusion

We created KGRED using three KG-enhanced RE datasets based on widely-used DSRE datasets. By linking entities in these datasets to large-scale knowledge bases, we identified problems in these datasets and further cleaned them to improve data quality. We also built auxiliary KGs for each dataset for knowledge-enhanced RE methods in both sentence-level and bag-level settings. Moreover, we discovered the association between auxiliary KGs and knowledge-enhanced RE methods that show that our auxiliary KGs consistently benefit these methods. In summary, we provided three high-quality datasets for fair comparisons between knowledge-enhanced RE methods and built baselines in various settings, which will further promote the development of RE research.

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**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
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Appendix A. Access to KGRED

We have posted our refined datasets Wiki80, Wiki20m, and NYT10m on Figshare: https://figshare.com/projects/KGRED/134459. Each dataset consists of four major components: a knowledge graph, training set, validation set, and a testing set (since the original Wiki80 has no testing set, we consider the validation set as the testing set for our experiments). The knowledge graphs are in CSV format. Each entry in the knowledge graphs represent a relational fact (a subject, an object, and a relation). For training/validation/testing sets, we follow the format of the original datasets. All instances in these sets are in json format, providing sentences, relations, and entities by key/value pairs.
Appendix B. Model Performance on Relations

(a) HRERE

(b) KGPool

(c) RECON

Figure B.1: Top-10 high and top-10 low micro F1 scores of different relations for HRERE, KGPool and RECON.