Revisiting DocRED – Addressing the Overlooked False Negative Problem in Relation Extraction

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Abstract

The DocRED dataset is one of the most popular and widely used benchmarks for document-level relation extraction (RE). It adopts a recommend-revise annotation scheme so as to have a large-scale annotated dataset. However, we find that the annotation of DocRED is incomplete, i.e., the false negative samples are prevalent. We analyze the causes and effects of the overwhelming false negative problem in the DocRED dataset. To address the shortcoming, we re-annotate 4,053 documents in the DocRED dataset by adding the missed relation triples back to the original DocRED. We name our revised DocRED dataset Re-DocRED. We conduct extensive experiments with state-of-the-art neural models on both datasets, and the experimental results show that the models trained and evaluated on our Re-DocRED achieve performance improvements of around 13 F1 points. Moreover, we propose different metrics to comprehensively evaluate the document-level RE task.

1 Introduction

The field of relation extraction (RE) is related to knowledge bases (KB). Most popular relation extraction datasets are constructed from knowledge triples in knowledge bases. For example, the TACRED dataset (Zhang et al., 2017) is constructed by the TAC Knowledge Base Population challenge. The NYT10 (Riedel et al., 2013) dataset matched the Freebase Knowledge base (Bollacker et al., 2008) to the New York Times corpus (Sandhaus, 2008). Wiki20 (Gao et al., 2021) and DocRED (Yao et al., 2019) originated from distant supervision from the Wikidata knowledge base and Wikipedia articles. By exploiting distant supervision, relation triple candidates can be retrieved from the knowledge bases for a given piece of text. The retrieved triples are based on co-occurrence only, and they may not be related to the context. Thereafter, most existing works (Yao et al., 2019; Alt et al., 2020) focus on reducing false positives.

However, the false negative problem in the relation extraction datasets is overlooked. Without resolving this issue, the annotations of the datasets are incomplete. Recent efforts on addressing the false negative problem are from the model perspective (Chen et al., 2021; Hao et al., 2021), which aims to denoise the false negative data during training. The challenge for these approaches is that both development and test sets can be incomplete at the same time. Without a complete annotated dataset, the current evaluation is ill-defined. Several re-annotation works revised the existing sentence-level relation extraction datasets. Alt et al. (2020)
re-annotated a small amount of challenging samples in the development and test sets of the TACRED dataset (Zhang et al., 2017). Stoica et al. (2021) extended this work and re-annotated the training, development, and test sets of TACRED with a semantically refined label space. Besides, Gao et al. (2021) re-annotated the test sets of two distantly supervised RE datasets. Even though their discussions and examples emphasized the efforts on correcting the false positive samples, all the revised versions of the datasets have a significant increase of positive samples. That is, many samples that are previously labeled as no_relation (NA) are re-annotated with relation labels in the revised datasets. We show the detailed statistics in Table 1, which indicates that the false negative problem is prevalent in sentence-level relation extraction. Compared to the sentence-level task, document-level relation extraction is more susceptible to the false negative problem. This is primarily because document-level RE involves significantly more entity pairs in a raw text, as shown in Table 1. Note that the objective of the RE task is to determine the relation types for all entity pairs, and the number of entity pairs is quadratic in the number of entities.

In this paper, we address the false negative problem in DocRED. We find that the false negative problem originates from two sources. First, although the Wikidata knowledge base provides a good starting point for annotation, it is highly sparse and far from complete. There are many relation triplets that are not in the Wikidata KB. For example, in Figure 1, the article reflects that the song “I Knew You Were Trouble” was produced by both “Max Martin” and “Shellback”, but “Shellback” is not included in both the knowledge base and the DocRED dataset. Second, the DocRED dataset employed the recommend-revise annotation scheme. However, the additional relation triples from the RE model and human annotations do not cover the remaining ground-truth relation triples, and a detailed discussion is given in Section 2. With the incomplete annotated development and test sets, the previous evaluation does not necessarily provide a fair reference. Therefore, we propose to revise the DocRED dataset to recover the incomplete annotations through an iterative approach with a human in the loop. Specifically, we use multiple state-of-the-art document-level RE models to generate relation candidates and ask human annotators to examine the recommended triples. The details of our annotation process are given in Section 3.

Most recently, Huang et al. (2022) also identify the false negative issue in DocRED (Yao et al., 2019), and they combat the problem by annotating 96 documents from scratch with two expert annotators. However, annotating relation triples from scratch is different from revising recommended triples, and it is difficult to scale up to a dataset of a larger size. We provide a comprehensive analysis between our approach and the annotating-from-scratch approach in Appendix A. Compared to Huang et al. (2022), our approach is better in the following aspects. First, our dataset is of significantly larger size (4,053 vs 96). Second, the precision of our annotation is higher. Third, our evaluation dataset contains more triples per document than Huang et al. (2022), indicating that our dataset better tackles the incompleteness problem of DocRED. Fourth, our dataset annotation approach is more scalable and can be extended to an arbitrary number of relation types.

Overall, our contributions can be summarized as follows:

• We identify the overwhelming but neglected false negative problem in relation extraction.

• We show that the false negative problem is the cause of performance bottleneck on many relation extraction datasets, and we also provide a high-quality revised version of the document-level relation extraction dataset, Re-DocRED.

• Moreover, we propose different metrics to have a more comprehensive evaluation for document-level RE research.

2 Preliminaries

2.1 Background of the DocRED Dataset

The DocRED dataset (Yao et al., 2019) is one of the popular and widely-studied benchmark datasets for document-level relation extraction. The dataset contains 5,053 Wikipedia documents, where each document has an average length of 196.7 words, and an average of 19.5 entities. With 97 predefined relation types (including no_relation) and an average of 393.6 entity pairs, there exist around 38,000 relation triple candidates per document to be annotated. To reduce the annotation workload, a recommend-revise scheme is adopted. Specifically, relation triple candidates are recommended from distantly supervised data and predictions of a RE
model. On average for each document, 19.9 triples are suggested from distantly supervised data and 7.8 triples are recommended by relation extraction models. Human annotators are asked to read the documents and review the relation triple candidates. Based on the final reported statistics, 57.2% of relation triples from entity linking and 48.2% from RE models are annotated. Besides filtering the wrong relation triples, human annotators are asked to add the omitted ones. However, we find that it is challenging to add the omitted relation triples, and it can be inferred that the annotators of the DocRED dataset mainly filtered out the false positive triples.

### 2.2 Problems of the DocRED Dataset

Based on our empirical analysis of the top-performing models (Tan et al., 2022; Zhang et al., 2021; Zhou et al., 2021b) on the DocRED leaderboard, many predicted triples are correct but are not annotated in the DocRED dataset. Therefore, it is important to review the dataset and identify the true bottleneck of document-level RE. We identify incomplete annotation as the major issue in the DocRED dataset.

#### Incomplete Annotation

As mentioned in Section 2.1, it is difficult to annotate a document-level RE dataset from scratch. The DocRED dataset is mainly created by human filtering the recommended relation triples from distantly supervised data and predictions from the RE model. It is worth noting that the construction procedure of the DocRED dataset relies on the underlying assumption that the combination of the recommended triples from the distantly supervised data and the RE model contains almost all the ground-truth relation triples in the documents. This assumption is not true since the relations in the Wikidata knowledge base are sparse and incomplete. In the original DocRED production process, only the distantly supervised data is used to train the RE model, which may lead to low-quality prediction. Furthermore, the performance of the previously used RE model is significantly worse than the recent approaches based on pre-trained language models. Therefore, the recommended relation triples from the RE model are likely not enough for covering the ground-truth relation triples for a given text.

By relying heavily on the relation triple candidates generated from the above two methods, the annotation of the previous DocRED dataset is incomplete. While the recommend-revise scheme is the major source of incompleteness of the original DocRED dataset (Yao et al., 2019), a secondary source of incompleteness comes from logical inconsistency. There are many inverse relation pairs in DocRED. For example, if entity A is annotated as a “sibling” of entity B, then entity B is also a “sibling” of entity A. The lack of inverse relation also contributes to the incompleteness problem.

#### 2.3 Preliminary Analysis

To identify the difficulty of relation extraction, we conduct a preliminary analysis on two evaluation tasks: Relation Extraction (RE) and Positive Relation Classification (PRC).

**Settings of Our Analysis**

Given a text $T$ and a set of $n$ entities $\{e_1, \ldots, e_n\}$, the objective of the RE task is to identify a relation type $r \in R$ for each entity pair $(e_i, e_j)$. $e_i$ and $e_j$ denote two different entities, and $R$ is a predefined set of relation types, including no_relation. Under the PRC setting, we do not use any entity pair in no_relation.
Datasets

| Sentence level | P   | R   | F1  |
|----------------|-----|-----|-----|
| TACRED         | 93.38 | 93.38 | 93.38 |
| Re-TACRED      | 96.83 | 96.83 | 96.83 |
| Incomplete Re-TACRED | 96.53 | 96.53 | 96.53 |

| Document level | P   | R   | F1  |
|----------------|-----|-----|-----|
| DocRED         | 93.84 | 89.68 | 91.71 |
| HacRED         | 95.87 | 90.13 | 94.23 |

Table 2: Preliminary experimental results of positive relation classification.

2.3.1 Preliminary Results of Positive Relation Classification

By assuming that there is a relation between the entity pairs, the positive relation classification (PRC) task shows the difficulty of classifying the relation types. Note that document-level PRC is a multi-label classification problem. Hence, precision and recall are not necessarily the same. From Table 2, we can see that all the models perform well. The performance of sentence-level RE and document-level RE are comparable, even though document-level RE has a significantly longer context and requires cross-sentence reasoning. This shows that the difficulty of positive relation classification is not severely affected by sentence boundary or context length. Another finding from Table 2 is that the revised version of TACRED has marginally higher performance than the original version. This is expected as the revised version receives an extra round of human annotation. The performance on Incomplete Re-TACRED is only marginally worse than the Re-TACRED, which shows that positive relation classification can achieve a comparatively high performance despite the reduction of training instances. Besides, it is worth noting that the performance on HacRED is higher than the performance on DocRED, even though HacRED claims that it is a semantically harder dataset. Although the baseline models are not exactly the same, we can still infer that the difficulty level of classifying the positive relation types on sentence-level and document-level datasets are not significantly different.

2.3.2 Preliminary Results of Relation Extraction

Compared to the setting of positive relation classification, the standard relation extraction task includes all the negative no_relation samples during training. We compare the performance of the previous best approaches on the sentence-level and document-level RE datasets in Table 3. We observe that the performance on the standard RE task is lower than that on the PRC task. For a specific dataset, the performance on PRC is the upper bound of RE performance, since the evaluation of PRC ignores no_relation. However, with a good quality annotation, the performance of relation extraction and positive relation classification should not have a large gap. For the sentence-level dataset, we can see that the performance on the revised ver-
Datasets | P   | R   | F1  
--- | --- | --- | ---
Sentence-level | | | |
TACRED | 75.70 | 73.40 | 74.50  
Re-TACRED | 90.60 | 91.30 | 90.90  
Incomplete Re-TACRED | 65.61 | 71.71 | 68.52  
Document-level | | | |
DocRED | 64.86 | 61.51 | 63.14  
HacRED | 77.89 | 76.55 | 77.21  

Table 3: Preliminary experimental results of relation extraction.

We adopt three top-performing models on the current DocRED leaderboard: KD-DocRE (Tan et al., 2022), DocuNET (Zhang et al., 2021), and AT-LOP (Zhou et al., 2021b). We split the datasets into four disjoint parts. We then train each model in a cross-validation manner, i.e., when three parts are used for training, the remaining one part is used for evaluation.

**Step 2 - Scoring the Unrecognized Triples** In this step, we aim to generate a large number of relation triple candidates, so that they could cover the missing annotations in the previous DocRED. With the trained scorer models, we can predict the scores for all the enumerated relation triples. To control the number of relation triple candidates for the next step, we define a threshold score to remove the less confident predictions. The predicted relation triples from all the models are then merged together. Due to the different characteristics of these models, we could generate a large and diverse pool of relation triple candidates for the next step.

**Step 3 - Human Filtration** After the relation triple candidates are generated from the previous step, each triple candidate will be annotated by humans. The human annotators are asked to read the document and check whether the triples can be inferred from the document. Unlike the annotation process of the original DocRED, we did not ask the annotators to explicitly label the supporting evidence of their judgment. This is mainly because the evidence annotations have a marginal effect on RE and they are hard to obtain during inference time. Each triple will be annotated by two annotators, and a third annotator will resolve the conflicting annotations.

The above three steps form one round of our iterative approach.

3.2 **Our Revised Re-DocRED**

We conducted two rounds of annotation in total. For the first round, we annotated 4,053 documents that include all training and evaluation documents. On average, we recommended 11.9 triples for each document and 9.4 triples were accepted, with an acceptance rate of 79.0%. The Fleiss Kappa (Fleiss, 1971) coefficient for round 1 annotation is 0.73, which is considered substantial agreement. To further improve the recall on the evaluation dataset, we conducted a second round of annotation for the 1,000 evaluation documents. We used the annotated 3,053 training samples from round 1 for round 2
Table 4: Statistics of our Re-DocRED dataset and the DocRED dataset (Yao et al., 2019).

|            | Re-DocRED |            | DocRED |            |
|------------|-----------|------------|--------|------------|
|            | Train     | Dev        | Test   | Train      | Dev       |
| # Documents| 3,053     | 500        | 500    | 3,053      | 1,000     |
| Avg. # Entities | 19.4     | 19.4       | 19.6   | 19.5       | 19.6      |
| Avg. # Triples | 28.1     | 34.6       | 34.9   | 12.5       | 12.3      |
| Avg. # Sentences | 7.9      | 8.2        | 7.9    | 7.9        | 8.1       |

In this round, 14.1 triples were recommended and only 6.0 triples were accepted, with an acceptance rate of only 42.55%. The Fleiss Kappa for round 2 annotation is 0.66. More details are given in Appendix B. After human annotation, we also add relation triples by manually defining logic rules. In this way, we are able to resolve the problem of logical inconsistency (described in Section 2.2) in the DocRED dataset. These rules mainly consist of inverse relations and co-occurring relations. On average, we added 6.4 triples for each document. See Appendix E for more details.

Since our main goal is to address the false negative problem in the DocRED dataset, we keep all the existing annotated triples in the original DocRED dataset. Overall, our training documents contain 28.1 triples on average, with 9.4 triples added from human annotation and 6.2 triples from logical rules. Our evaluation documents contain 34.7 triples on average, with 15.4 triples added from human annotation and 6.7 triples from logical rules. We divide the 1,000 evaluation documents into 500 development and 500 test documents. The average number of triples of the evaluation documents is higher than that of the training documents. This indicates that the evaluation data has more complete annotation compared to the training data. The detailed statistics of the Re-DocRED dataset are shown in Table 4. The average number of triples per document is significantly higher for Re-DocRED compared to the original DocRED. There are 12.3 triples per document in the original DocRED and 34.7 triples per document in Re-DocRED. This shows that there are approximately 64.6% triples missing in the original DocRED dataset.

4 Experiments
4.1 Comparison on Relation Extraction

To compare the previous DocRED and our Re-DocRED, we evaluate 4 different approaches on the two datasets. Apart from the three models that are used during our annotation process (Section 3.1), we also compare the performance with an additional approach, JEREX (Eberts and Ulges, 2021). Table 5 shows the experimental results, and the reported metrics are micro-averaged F1 scores and Ign_F1 scores. The latter refers to the F1 score that ignores the triples that appear in the training set. According to the statistics in Table 1, even though our revised Re-DocRED dataset contains many more relation triples, we observe that all the baseline models demonstrate significant performance improvement on both development and test sets. Compared to DocRED, the performance of the baseline models on Re-DocRED increased by more than 11 F1 points. When these models are pre-trained with distantly supervised data, we observe consistent performance improvement on Re-DocRED.

4.2 Comparison on Positive Relation Classification

Following the experimental setting in Section 2.3.1, we compare the positive relation classification performance between the original DocRED and our Re-DocRED with ATLOP (Zhou et al., 2021b) in and Table 6. We observe that the performance on Re-DocRED is comparable to the original version. This indicates that our added triples are of comparable quality to the original DocRED data.

5 More Analysis

Additional Evaluation Metrics As mentioned in Section 2, document-level relation extraction is a challenging task. Hence, it is necessary to have various performance evaluation metrics so as to conduct a comprehensive evaluation. On top of the standard F1 and Ign_F1 evaluation metrics, we define four additional metrics to assess the models. (1). **Freq. F1**, which only considers the 10 most common relation types in the training set of Re-DocRED, where these frequent relation types account for 60% of the relation triples. (2). **LT F1**, which only considers the long-tail (the remaining 86) relation types. (3). **Intra F1**, which evaluates on relation triples that appear in the same sentence. (4). **Inter F1**, which evaluates on cross-sentence relation triples.

We show the comprehensive evaluation results in Table 7. We observe that there exists a relatively large gap between the Freq. F1 and LT F1 metrics, and the difference is around 6–8 F1 points. Such
| Models    | DocRED Dev | DocRED Test | Re-DocRED Dev | Re-DocRED Test | Test Differences |
|-----------|------------|-------------|---------------|---------------|-----------------|
|           | Ign_F1     | F1          | Ign_F1        | F1            | Ign_F1          | F1              | ΔIgn_F1 | ΔF1   |
| JEREX     | 56.52      | 58.48       | 56.74         | 58.59         | 69.12           | 70.33           | +12.23  | +1.66 |
| ATLOP     | 61.47      | 63.32       | 61.34         | 63.26         | 76.88           | 77.63           | +15.60  | +14.47|
| DocuNET   | 62.01      | 63.76       | 62.03         | 63.82         | 77.53           | 78.16           | +15.24  | +14.10|
| KD-DocRE  | 62.19      | 64.24       | 62.49         | 64.09         | 77.92           | 78.65           | +15.14  | +14.26|

+ Pre-trained with distantly supervised data

| Models    | DocRED Dev | DocRED Test | Re-DocRED Dev | Re-DocRED Test | Test Differences |
|-----------|------------|-------------|---------------|---------------|-----------------|
|           | Ign_F1     | F1          | Ign_F1        | F1            | Ign_F1          | F1              | ΔIgn_F1 | ΔF1   |
| JEREX     | 60.73      | 62.68       | 60.64         | 62.53         | 73.65           | 75.07           | +12.94  | +12.49|
| ATLOP     | 63.53      | 65.42       | 63.39         | 65.36         | 78.15           | 79.13           | +15.03  | +14.03|
| DocuNET   | 63.32      | 65.43       | 63.17         | 65.28         | 78.40           | 78.95           | +15.34  | +13.74|
| KD-DocRE  | 65.24      | 67.19       | 65.07         | 66.98         | 79.31           | 79.88           | +15.02  | +13.64|

Table 5: Experimental results using the original DocRED and our revised Re-DocRED. For DocRED the reported results are using the same splits of development and test sets as Re-DocRED.

| Training | Test  | P     | R     | F1    |
|----------|-------|-------|-------|-------|
| DocRED   | DocRED| 93.84 | 89.68 | 91.71 |
| Re-DocRED| Re-DocRED| 94.48 | 90.12 | 92.25 |

Table 6: Positive relation classification performance with the original DocRED and our revised Re-DocRED (using ATLOP).

behavior shows that the frequent relation types are easier to be recognized compared to the long-tail relations. Furthermore, we also find that the performance on triples that appear in the same sentence (Intra F1) is better than that on the cross-sentence relation triples (Inter F1), by around 2–5 F1 points. This is because it is harder to encode long-distance interactions. Therefore, a promising future direction is to match the performance on the long-tail relation types to the frequent types, and also improve the model’s representation capability to capture long-distance interactions so as to reduce the differences between the inter-sentence and intra-sentence relation triples.

Effects of Distant Supervision Pre-training To further analyze the effects of distant supervision pre-training, we examine the performance of the KD-DocRE model with and without the pre-training step, and Table 8 shows the results. Under both settings, recall of the long-tail classes is significantly lower than their corresponding precision. Moreover, by comparing the performance of long-tail classes, we observe that pre-training with distantly supervised data improves the precision of the long-tail classes. We show additional error analysis and case studies in Appendix D.

6 Related Work

6.1 Relation Extraction

Relation extraction (RE) is an important task in information extraction and knowledge graph completion. There is a series of RE datasets built over the past decades, and they have significantly advanced the research on RE. The ACE 2005 dataset (Walker et al., 2006) and SemEval 2010 Task 8 (Hendrickx et al., 2010) are two sentence-level RE datasets created by human annotation. However, these two datasets have a relatively small number of relation types and instances. The large-scale TACRED (Zhang et al., 2017) dataset is created based on the 2009–2014 TAC knowledge base population (KBP) challenges and crowd-sourced human annotations. FewRel (Han et al., 2018) and FewRel 2.0 (Gao et al., 2019) have been proposed to study the transferability and few-shot capability of RE models. However, early relation extraction datasets mainly focus on sentence-level RE, whereas many relations can only be expressed by multiple sentences. The document-level relation extraction task has been proposed to build RE systems that are able to extract relations from multiple entities and sentences. Yao et al. (2019) have created the DocRED dataset by distant supervision from Wikipedia articles and the Wikidata knowledge base, then sampled 5,053 documents for human annotation. The annotation strategy of DocRED is mainly based on machine recommendation and human filtering. With a similar approach, Cheng et al. (2021) has created a Chinese document-level RE dataset that focuses on hard relation cases.
Table 7: Performance comparison under different metrics.

| Models       | Dev   | Test   |
|--------------|-------|--------|
|              | IgF1  | F1     | IgF1  | F1     | Freq. F1 | LT F1 | Intra F1 | Inter F1 |
| ATLOP        | 76.88 | 77.63  | 76.94 | 77.73  | 80.79    | 72.47 | 80.18    | 75.13    |
| DocuNET      | 77.53 | 78.16  | 77.27 | 77.92  | 81.16    | 73.41 | 79.91    | 76.64    |
| KD-DocRE     | 77.92 | 78.65  | 77.63 | 78.35  | 80.97    | 74.42 | 79.57    | 77.26    |
+ Pre-trained with distantly supervised data
| ATLOP        | 78.15 | 79.13  | 78.42 | 79.39  | 82.09    | 75.16 | 80.28    | 78.33    |
| DocuNET      | 78.4  | 78.95  | 78.51 | 79.02  | 81.98    | 74.37 | 80.18    | 78.01    |
| KD-DocRE     | 79.31 | 79.88  | 80.09 | 80.62  | 82.76    | 76.35 | 81.78    | 79.61    |

Table 8: Detailed analysis of KD-DocRE on the test set of Re-DocRED.

| Type       | P     | R     | F1     |
|------------|-------|-------|--------|
| KD-DocRE   | Freq. | 87.23 | 75.55  | 80.97  |
|            | LT    | 80.90 | 68.90  | 74.42  |
| KD-DocRE   | Freq. | 89.76 | 76.78  | 82.76  |
| +Pre-training | LT | 86.14 | 68.53  | 76.35  |

## 6.2 Machine-Assisted Data Generation

Since labeled data is expensive to obtain for complex NLP tasks, there is much research on generating labeled data in an automatic fashion. Distant supervision was first used by Mintz et al. (2009) to generate large amounts of relation extraction data without human efforts. Prior work on automatic data generation mainly relies on rule-based pattern matching (Lehmann et al., 2015) and web crawling (Buck et al., 2014). These types of rule-based methods are susceptible to noise propagation. With the rapid development of pre-trained language models (PLMs; Devlin et al., 2019; Liu et al., 2019; Brown et al., 2020), much recent research explores methods that leverage PLMs for automatic data generation (Anaby-Tavor et al., 2020; Zhou et al., 2021a; Yang et al., 2020; Kumar et al., 2020). However, these methods typically depend on a certain set of supervised source data. Another line of work utilizes manually designed prompts and instructions to generate data in an unsupervised manner (Schick and Schütze, 2021; Chia et al., 2022). Although these methods improve the performance of certain downstream tasks, the quality of the machine-generated data still does not match human annotation. To mitigate noise from the machine-generated data, West et al. (2021) generate a large amount of commonsense knowledge data and employ human annotators to filter the generated candidates.

## 7 Conclusion

In conclusion, this paper identifies the causes and effects of the overwhelming but neglected false negative problem in relation extraction. We show that the false negative problem is the cause of the performance bottleneck on many RE datasets. We have also provided a high-quality revised version of the document-level RE dataset DocRED. Moreover, we have proposed different metrics to achieve a more comprehensive evaluation for document-level RE. We have also conducted a thorough error analysis on state-of-the-art RE models.

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Table 9: Examples for the common error types by Huang et al. (2022). We use blue to color the entities and green to color the relations.
Our Machine-Guided Annotation vs. Annotation From Scratch

In this section, we compare our Re-DocRED dataset with a concurrent work (Huang et al., 2022) on revising the DocRED dataset. Our work uses machine-guided annotation methods, whereas their work asks the annotators to annotate from scratch (denoted as “From Scratch”). As mentioned in Huang et al. (2022), annotating from scratch is an extremely challenging task. This is mainly due to the quadratic complexity of the document-level RE task. Suppose there are \( N \) entities in one document and the label space of interest contains \( R \) relations. The search space for human annotation is \( N \times (N - 1) \times R \). In particular, for an average case of DocRED (\( N=20, R=96 \)), annotators will need to make around 36,480 classification decisions for one document. In contrast, for machine-guided generation, annotators will only need to make decisions on the recommended candidates, averaging only 25.5 decisions per document. This is primarily due to the pattern recognition capability of deep neural models, which significantly reduces the search space for human annotators. The size of our re-annotated dataset is much larger, and we have conducted significantly more experimental analysis.

We examined and analyzed all the annotated 96 documents of “From Scratch”. We found that there are several types of systematic errors in Huang et al. (2022) and we show the error types in Table 10. Firstly, annotation from scratch is susceptible to annotators’ misunderstanding of relation definition (25.5%). For the first example in Table 9, the relation between architect and its designed building is architect\(^3\), whereas annotators in Huang et al. (2022) deem such relation as creator\(^4\). This is imprecise as the architect relation was not in the label space of DocRED, therefore, it is not possible to find this relation between the architect and its design. Secondly, annotating from scratch is susceptible to human commonsense bias (19.0%). This is primarily due to human’s memorization of popular entities, such as countries and geographical locations (example 3 in Table 9). The third major error type is due to the slippery slope logical fallacy, as shown by example 4 in Table 9. The numbers within brackets were falsely identified as the date of birth and date of death, whereas the passage is about a renowned high school. It can be inferred that the numbers behind the alumni names are indicating the time periods that they were in this school. This error arises because most date of birth and date of death are described by brackets and numbers. However, such a pattern does not necessarily mean all numbers in brackets are indicating such relations.

Error Types Percentage

| Error Types                      | Percentage |
|----------------------------------|------------|
| Misunderstanding of Definition   | 25.5%      |
| Commonsense Bias                 | 19.0%      |
| Slippery Slope Reasoning         | 22.1%      |
| Others                           | 33.4%      |

Table 10: Common error types of Huang et al. (2022).

| Added Triples | Errors | Precision |
|---------------|--------|-----------|
| Scratch       | 681    | 54        | 92.4      |
| Re-DocRED     | 733    | 17        | 97.7      |

Table 11: Error rates of Re-DocRED and the Scratch dataset (Huang et al., 2022) based on examining 20 randomly sampled documents. We observe that Re-DocRED has higher precision.

It is worth noting that the annotators in Huang et al. (2022) are already experts in English and the annotators went through discussion after annotation. However, there are still a considerable number of errors from their dataset. We believe that this is due to the complex nature of this annotation task. In the meantime, we also conducted human-evaluation on our Re-DocRED dataset and compared the precision of the two datasets in Table 11. We can see that our Re-DocRED dataset has significantly higher precision for the added triples. Moreover, we compare the unit price and unit time for different annotation strategies in Table 12. We can see that annotating from scratch costs three times more than our machine-guided annotation. Hence, by comparing the two approaches for annotating document-level relation extraction datasets, we conclude that:

1. Even though the annotation “From Scratch” is conducted by human experts, there are still missing triples in the annotated 96 documents. That is, annotating from scratch does not completely eliminate the incompleteness problem when the number of entities \( N \) and relation types \( R \) are large.
2. Annotation from scratch is not as precise
Table 12: Costs and unit time required for different annotation strategies.

| Annotation Strategy                  | Unit Price | Unit Time |
|--------------------------------------|------------|-----------|
| Annotating from Scratch             | 48 CNY     | 40 mins   |
| One Round of Revision               | 7.8 CNY    | 10 mins   |
| Two Rounds of Revision              | 15.8 CNY   | 15 mins   |

as recommend-revise. As Table 9 shows, human annotation of Huang et al. (2022) contains several types of systematic errors.

3. Annotating from scratch is hard to scale. According to Huang et al. (2022) and feedback from our annotators, it takes more than 30 minutes by experts to annotate one document. Then the two experts will still spend extra time discussing and resolving the conflicts.

4. The recommend-revise scheme is able to mitigate the false negative problem and is easier to scale up.

B Details of Relation Annotation

As mentioned in Section 3.1, we use three top-performing models on the DocRED leaderboard for relation candidate generation, and the three models are: (1) KD-DocRE (Tan et al., 2022), (2) DocuNET (Zhang et al., 2021), and (3) AT-LOP (Zhou et al., 2021b). To obtain relation triple candidates for all 4,053 documents, we split the human-annotated subset into 4 different splits (Table 14), with the first split as the original DocRED development set. This is to ensure that the number of training samples is comparable to the original DocRED when any three of the splits are used for training our scorer models, and then the remaining one is used for prediction. Following the training paradigm of Tan et al. (2022), we first pre-train each model with the distantly supervised data in DocRED. Then, the pre-trained model is continue-trained on any three splits of DocRED, and we then use the trained models to make predictions on the remaining split set. Therefore, it requires four times of training and inference so that we can get the predictions for all the four split sets. To further increase the number of relation candidates, we set the dynamic threshold to 0.9 of the models for the Adaptive Threshold class (Zhou et al., 2021b) for all models.

C Coreferential Error Annotation

Coreferential Errors Besides the major problem of incomplete annotation, coreferential errors are also detrimental to the evaluation of DocRED. Note that an entity in the DocRED dataset can have multiple mention appearances in a document. If some mentions that are referring to the same entity are not included in the entity cluster, a redundant entity cluster will be formed. This kind of coreferential error will affect the relation predictions involving the redundant entity. Since the complexity of the DocRE task is quadratic in the number of entities, it is important to make sure that the coreferential annotations are correct. Errors in the coreferential annotation can be propagated and amplified during relation extraction.

Coreferential Annotation As mentioned above, there are a considerable number of entities of DocRED that have the same surface names but refer to different entities. In such cases, we examined all entities that contain the same surface name and entity types in the DocRED dataset. For these entities, annotators will need to decide whether: (1) the two entities are coreferential to each other, (2) the overlapping mentions are wrongly grouped to a certain entity cluster, and (3) the two mentions are indeed referring to two separate entities. As a result, we merged 102 coreferential entity pairs in the evaluation documents and 122 pairs in the training documents. Therefore, the average number of entities per document of Re-DocRED is slightly lower than the original DocRED.

D Common Model Error Examples

In this section, similar to Tan et al. (2022), we split the union of ground-truth triples and predicted triples into four categories: (1) Correct (C), where predicted triples are in the ground truth. (2) Wrong (W), where the output relation type is wrong but the predicted head and tail entities are in the ground truth. (3) Missed (MS), where the model predicts no relation for a pair of head and tail entities but there is some relation in the ground truth. (4) More (MR), where the model predicts an extraneous relation for a pair of head and tail entities that is not in the ground truth. The performance breakdown is shown in Table 15. We observe that the majority of the errors were in the MS and MR categories. On the other hand, we found that predictions on popular relations tend to fall under the MR category. We further show this popularity bias pattern
Example 1  
**Error Type 1: Extraneous Prediction (MR)**

**Error Cause:** Popular pattern bias

**Document:** "Lookin Ass" is a song by American rapper and singer Nicki Minaj. It was produced by Detail and Choppa Boi. It was recorded by Minaj for the Young Money Entertainment compilation album (2014). The music video for the track was released on February 14, 2014. On March 11, 2014, "Lookin Ass" was serviced to urban contemporary radio in the United States as Young Money: Rise of an Empires third official single. It was sent to US rhythmic radio stations on March 18, 2014, two weeks after its predecessor, "Trophies".

**More Triples:** (Young Money Entertainment, Nicki Minaj, *performer*), (Trophies, Nicki Minaj, *performer*)

Example 2  
**Error Type 1: Extraneous Prediction (MR)**

**Error Cause:** Popular pattern bias

**Document:** The Portland Golf Club is a private golf club in the northwest United States, in suburban Portland, Oregon. It is located in the unincorporated Raleigh Hills area of eastern Washington County, southwest of downtown Portland and east of Beaverton. PGC was established in the winter of 1914, when a group of nine businessmen assembled to form a new club after leaving their respective clubs. The present site was chosen due to its relation to the Spokane, Portland and Seattle Railway’s interurban railroad line with frequent passenger service to the site because automobiles and roads were few. ...

**More Triples:** (Portland, Washington County, located in the administrative territorial entity), (Washington County, Portland, contains administrative territorial entity)

Example 3  
**Error Type 2: Missing Triples (MS)**

**Error Cause:** Failed in coreferential reasoning

**Document:** Kurt Tucholsky (; 9 January 1890 – 21 December 1935) was a German-Jewish journalist, satirist, and writer. He also wrote under the pseudonyms Kaspar Hauser (after the historical figure), Peter Panter, Theobald Tiger and Ignaz Wrobel. Born in Berlin-Moabit, he moved to Paris in 1924 and then to Sweden in 1929. Tucholsky was one of the most important journalists of the Weimar Republic. As a politically engaged journalist and temporary co-editor of the weekly magazine Die Weltbühne he proved himself to be a social critic in the tradition of Heinrich Heine.

**Missing Triples:** (Kurt Tucholsky, Die Weltbühne, employer)

Example 4  
**Error Type 2: Missing Triples (MS)**

**Error Cause:** Fail to find long-tail relations

**Document:** CBBC (short for Children’s BBC) is a British children’s television strand owned by the BBC and aimed for children aged from 6 to 12. BBC programming aimed at under six year old children is broadcast on the CBeebies channel. CBBC broadcasts from 7 am to 9 pm on the digital CBBC Channel, available on most UK digital platforms. The CBBC brand was used for the broadcast of children’s programmes on BBC One on weekday afternoons and on BBC Two mornings until these strands were phased out in 2012 and 2013 respectively, as part of the BBC’s “Delivering Quality First” cost-cutting initiative. CBBC programmes were also broadcast in high definition alongside other BBC content on BBC HD, generally at afternoons on weekends, unless the channel was covering other events. This ended when BBC HD closed on 26 March 2013, but CBBC HD launched on 10 December 2013.

**Missing Triples:** (BBC HD, 26 March 2013, dissolved, abolished or demolished)

Table 13: Examples of the two most common error types. We use blue and green to color the **entities** and **relations**, respectively.

| Split 0 | Split 1 | Split 2 | Split 3 |
|--------|--------|--------|--------|
| 1,000  | 1,000  | 1,000  | 1,053  |

Table 14: Dataset statistics of each split. The split 0 is the original DocRED development set.

Table 15: Statistics of our error distribution on the development set of Re-DocRED. The final evaluation score is evaluated on \( r \in R \) triples, hence the correct predictions of **NA** are ignored when calculating the final scores.

E  **Details of Logical Rules**

In this section, we show the logical rules that we used. After examining the DocRED dataset (Yao et al., 2019), we found that there are two types of logical inconsistencies. The first type is the incompleteness of inverse relations, and the sec-
ond is the inconsistency in co-occurring relations. The inverse relations are logical relations that can be implied by reversing the direction of relation triplets. For example, if entity 1 is the participant of an event (entity 2), this event should have a participant relation with entity 1. We show all the inverse relation pairs that we used in Table 17. Besides inverse relations, we also added triples by co-occurring rules. This is mainly because we found that these relations are logically correlated and their co-occurrence is inconsistent in the original DocRED dataset. For example, when describing the relation between entities and wars, there are two involved relations: relation conflict and participant of. For such cases, we deem that the two relations shall all be present when conflict is present. We show the list of co-occurring relations in Table 16.

| Relation       | Co-occurring relation     |
|----------------|---------------------------|
| country        | located in                |
| conflict       | participant of            |

Table 16: List of co-occurring relations.

| Relation        | Inverse Relation          |
|-----------------|---------------------------|
| author          | notable work              |
| performer       | notable work              |
| producer        | notable work              |
| composer        | notable work              |
| director        | notable work              |
| lyrics by       | notable work              |
| participant     | participant of            |
| participant of  | participant               |
| has part        | part of                   |
| sibling         | sibling                   |
| series          | has part                  |
| spouse          | spouse                    |
| characters      | present in work           |
| conflict        | participant               |
| parent organization | subsidiary            |
| subsidiary      | parent organization       |
| follows         | followed by               |
| followed by     | follows                   |
| father          | child                     |
| replaced by     | replaces                  |
| head of government | applies to jurisdiction |
| replaces        | replaced by               |
| legislative body | applies to jurisdiction  |
| head of state   | applies to jurisdiction   |
| mother          | child                     |
| part of         | has part                  |
| sister city     | sister city               |
| capital         | capital of                |

Table 17: List of inverse relations.

5https://www.wikidata.org/wiki/Property:P607
6https://www.wikidata.org/wiki/Property:P1344