A Relational Triple Extraction Method Based on Feature Reasoning for Technological Patents

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Abstract: The relation triples extraction method based on table filling can address the issues of relation overlap and bias propagation. However, most of them only establish separate table features for each relationship, which ignores the implicit relationship between different entity pairs and different relationship features. Therefore, a feature reasoning relational triple extraction method based on table filling for technological patents is proposed to explore the integration of entity recognition and entity relationship, and to extract entity relationship triples from multi-source scientific and technological patents data. Compared with the previous methods, the method we proposed for relational triple extraction has the following advantages: 1) The table filling method that saves more running space enhances the speed and efficiency of the model. 2) Based on the features of existing token pairs and table relations, reasoning the implicit relationship features, and improve the accuracy of triple extraction. On three benchmark datasets, we evaluated the model we suggested. The result suggest that our model is advanced and effective, and it performed well on most of these datasets.

Keywords: Technological patents; Joint extraction; Reasoning features

1 Introduction

Entity relation triples extraction is a basic task in information extraction. It attempts to extract triples from unstructured text [1]. Relational Triple Extraction (RTE) is useful for many downstream applications, such as knowledge reasoning and knowledge graph [2].

The conventional pipeline method extracts entities firstly, then categorizes the different types of relationships in predefined set of relationships. However, these models neglect the connection between the two tasks and are vulnerable to bias propagation. As a result of the total separation of entity recognition and relationship classification [3].

At present, the main method of RTE is the method of extracting entities and relationships simultaneously, which is called the joint extraction method as well [4]. This approach addresses the issue of bias propagation. On several benchmark datasets, some of the most recent joint extraction methods demonstrate remarkable extraction capabilities, particularly when it comes to complicated phrases which contain numerous or overlapping triples.

Among these current methods for joint extraction, a method based on table filling [5] performs exceptionally well. Each item in the table is used to determine if the token pair has a matching relationship in these methods, which normally keep a table for each relationship. As a result, the core to these methods is to precisely complete the relational table, and extract triples based on the full table. However, the existing methods to populate the relationship table [6] are mainly based on extracting features from a single token pair or a single relationship table, but ignore the associations and different relationships between various entity pairs in the same input sentence.

To make full advantage of the relationships between different entity pairs and between different relational tables, we provide a table filling based feature reasoning relational triple extraction model. Based on the model, the historical features of token pairs and table relations are integrated. The features can better reveal the differences between relationships and token pairs, which can not only improve the accuracy of triplet extraction through multiple mutual verification, but also improve the recall rate of triplet extraction by helping to derive new triples. For each relationship, we first create a table feature. In a related table feature and a subject object related feature, all relational tables’ features are then combined. On this basis, the method based on transformer is used to reasoning entity relationship features.

In summary, the following are the primary contributions of our work:

We suggest an entity relationship extraction method for the technological patent data set.

We proposed a new table filling strategy and triple decoding method.

We integrate previous relationship table features and subject object features to reasoning the implicit relationship features.

2 Related Work

Early studies often adopted a pipeline based RTE method [7]. This approach initially identifies every entity in the input text before predicting the relationships between every pair of entities. However, pipeline-based methods have two serious drawbacks [8]. The correlation between entity recognition and relationship prediction is ignored. They also frequently encounter the issue of error propagation. Researchers started investigating joint extraction methods that concurrently extract entities and
connections in attempt to address these drawbacks [9].

One of joint extraction methods is tagging based methods [10], which usually extracts entities through labels first, and then predicts relationships. These models [11] often employ binary mark sequences to establish the beginning and ending locations of the entities, as well as often to establish the connection between two entities. Takanobu [12] used reinforcement learning to first identify relations and then recognize entity pairings. Sequence-to-sequence methods [13] belong to extraction methods as well. This type of approach [14] frequently transforms the relational triple extraction into a task of producing triples in a certain order, such as generating relationships and then generating entities. To decode overlapping connections, Zeng [15] presented a sequence-to-sequence model, however it was unable to produce multiword entities [16] [17]. Nayak and Ng provide an enhancement by using an encoder decoder model that extracts words simultaneously, similar to the machine translation approach [18].

The newer method is table filling based methods [19]. This approach will maintain a table for each relationship, with the entries typically representing the beginning and ending locations of the two entities that have this particular relationship. Consequently, the RTE work is changed into a task that accurately fills these tables. Wang [20] proposed TPLinker based on table filling that considers the problem of mark pair linking in joint extraction and presents a new handshake marking method that aligns the border marks of entities under each connection type.

3 Method

We proposed a feature reasoning relational triple extraction model (TEFR). The framework of TEFR is shown in Figure 1. The historical features of token pairs are integrated in the framework which can better extracting module. Execute table features filling module and feature reasoning module several times through iteration, and gradually refine the table features. Finally, based on the updated table attributes, triple extracting module fills each table and generates total triples from these filled tables.

In encoder module, the encoder is a pretrained Bert base model. The module initially encodes a sentence into a symbolic representation sequence I. Input I into different feed-forward networks (FNN) and create initial subject features and object features through one-way propagation (represented by $I^{(1)}_s$ and $I^{(1)}_o$, respectively), as described in Eq (1) and Eq (2).

$$I^{(1)}_s = W_1I + b_1$$

$$I^{(1)}_o = W_2I + b_2$$

In table features filling module, we record the subject and object features at iteration $t$ as $I^{(t)}_s$ and $I^{(t)}_o$. Then, the module accepts them as input and creates a table feature for each item which in predefined set of relationships. The table feature of relationship $r$ at $t$ is marked as $T^{(t)}_r$, and its size is the same as that of table. Each item in $T^{(t)}_r$ represents the tag characteristics of a token pair. Specifically, for a pair $(w_i, w_j)$, we record its tag feature as $T^{(t)}_r(i,j)$, which is calculated by Eq (3).

$$T^{(t)}_r(i,j) = W_rReLU(I^{(t)}_s(i,j) \odot I^{(t)}_o(i,j)) + b_r$$

where $\odot$ represents the Hadamard Product, $I^{(t)}_s$ and $I^{(t)}_o$ represent the subject and object feature of tokens $(w_i, w_j)$ at the $t$-th iteration respectively.

In feature reasoning module, the module generates implicit subject and object features based on the existing features. The freshly created features will then be returned to TFF for the following iteration. The module specifically comprises the three stages listed below.

In the first stage, table attributes should be combined. Assuming that the round of iteration is $t$, we integrate all connection table features to create a unified table feature ($T^{(t)}$), which will reveal a lot about token pairs and relationships. We apply the maximum pooling and the

![Figure 1: Model architecture. $I^{(1)}_{s/o}$ represents initial feature.](image)

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FFN model on $T_r^{(t)}$ to create a table feature ($T_s^{(t)}$) and an object related table feature ($T_o^{(t)}$), as shown in Eq (4).

$$T_{s/o}^{(t)} = W_{s/o} \text{maxpool}(T^{(t)}) + b_{s/o}$$  (4)

Where $W_{s/o}$ is the trainable weight and $b_{s/o}$ is the trainable bias. The maximum pool is used to extract important features of topics and objects from existing features.

In the second stage, we mine expected reasoning features. Here, we mainly use the model based on transformer to reason the implicit features between relationships and token pairs. We use the multi-head-self-attention approach on $T_{s/o}^{(t)}$ to mine implicit relationships. The sentence relationship is also used as part of the input. Next, we use FFN to generate new subject and object features. The whole process of subject object feature reasoning can be written with the following Eq (5), (6), (7)

$$T_s^{(t)} = \text{MultiHeadSelfAtt}(T_{s/o}^{(t)})$$  (5)

$$f_{s/o}^{(t+1)} = \text{MultiHeadAtt}(T_{s/o}^{(t)}, I, I)$$  (6)

$$I_{s/o}^{(t+1)} = \text{ReLU}(f_{s/o}^{(t+1)}W + b)$$  (7)

In the third stage, in order to avoid the vanishing gradient problem and develop the final theme and object features, we employ the residual network. Finally, the features of the subjects and objects are sent to table features filling module as the features in the next iteration.

In triple extracting module, taking the last iteration's table feature ($T_r^{(N)}$) as input, it returns all triples. Then, triple extracting module decodes the filled table to derive all triples. Specifically, for each relationship, first fill its table with the method shown in Eq (8) and Eq (9).

$$table_{r}(i, j) = \text{softmax}(T_r^{(N)}(i, j))$$  (8)

$$table_{r}(i, j) = \text{argmax}_{i \in L}(table_{r}(i, j)[i])$$  (9)

The triple extracting module then decodes all triples by decoding the entire table. In our decoding method, different search paths are created according to different token pair types. If the subject and object are complex entities, the search order from beginning to end will be based on the direction of CCH and CCT in the table, and the search order from end to begin will be based on the direction of CCT and CCH in the table. If it is a simple entity pair, it will be searched according to the EE tag in the table.

4 Experiments

4.1 Dataset

In order to facilitate the comparison of our model with previous work, we followed the popular data set selection: NYT* and WebNLG*. In addition to the above four datasets, we also used TFH_Annnotated_Dataset as technological patents datasets. TFH_Annnotated_Dataset is an annotated patent data set related to thin film head technology in hard disk, which is used to annotate semantic relationships between entities. The well-designed information pattern for patent annotation contains 15 semantic relationships. The basic information of these datasets is shown in Table 1.

| & NYT* & WebNLG* & TFH_Annnotated_Dataset |
|---|---|---|---|
| **Normal** | 37013 | 3266 | 1596 | 246 | 3259 | 722 |
| **ALL** | 56195 | 5000 | 5019 | 703 | 3259 | 722 |
| **Relation** | 24 | 171 | & |

4.2 Baselines

For comparison, we use the following model as the benchmark: (1) CopyRE [21] is a joint relation extraction model based on copying mechanism and seq2seq; (2) GraphRel [22] considers the interaction between named entities and relationships through relationship weighted GCN to better extract relationships; (3) ETL-Span [23] using span based labeling scheme, the joint extraction task is decomposed into several sequence label problems. This model can fully capture the semantic dependency between different steps, and reduce the noise of unrelated entity pairs; (4) CasRel [24] is a new cascading binary annotation framework model, in which the relationship is modeled as a function that maps from the beginning entity to the end entity, which turns the previous classification task into the problem of finding triples; (5) Based on the Bert decoder, TPLinker [25] is best performing model on the NYT* and WebNLG* datasets. It has obvious improvement in dealing with difficult sentences with overlapping relations or sentences with more than two relations. The main of these baseline experimental results are taken straight from their original journals. In this section, we show the best results of the above baseline models. For consistency, we refer to the model proposed by us as TEFR.

4.3 Evaluation Metrics

In our experiments, If the extracted triplet's subject entity and object entity's relationship and header are accurate, the extracted triplet is regarded correct. We followed the popular selection reporting standards of micro precision (prec.), recall (rec.), and F1 scores to meet all baselines.

4.4 Main Results and Analysis

The primary results are in the Table 2, indicating that TEFR is extremely effective. When compared to the model utilizing the same encoder (BERT based encoder), it obtains the top result on most of datasets. The results also reveal that TEFR performed better on all datasets, its
F1 score was 0.9%, 1.7%, and 4.0% higher than the previous best model on NYT24*, WebNLG* and TFH_Annotated_Dataset.

|               | NYT24* |          |          |
|---------------|--------|----------|----------|
|               | Prec.  | Rec.     | F1       |
| CopyRE        | 61.0   | 56.6     | 58.7     |
| GraphRel      | 63.9   | 60.0     | 61.9     |
| ETL-Span      | 84.9   | 72.3     | 78.1     |
| CasRel        | 89.7   | 89.5     | 89.6     |
| TPLinker      | 91.3   | 92.5     | 91.9     |
| TEFR          | 92.5   | 93.0     | 92.8     |

|               |        |          |          |
|---------------|--------|----------|----------|
|               |        |          |          |
| CopyRE        | 37.7   | 36.4     | 37.1     |
| GraphRel      | 44.7   | 41.1     | 42.9     |
| ETL-Span      | 84.0   | 91.5     | 87.6     |
| CasRel        | 93.4   | 90.1     | 91.8     |
| TPLinker      | 91.8   | 92.0     | 91.9     |
| TEFR          | 93.2   | 93.9     | 93.5     |

We can also observe that when compared to the previous best model, the performance improvement of TEFR on WebNLG* is better than that on other datasets. We believe this is mostly due to the fact that WebNLG has considerably more relations than NYT. This means that there are more implicit associations to be inferred. This also means that more relationship table information can integrate more implicit features, providing a more complete semantic representation of subject and object for the next iteration.

Compared with other datasets, TEFR does not perform as well on TFH_Annotated_Dataset. The main reason is that the number of TFH_Annotated_Dataset is small, and manual annotation is a time-consuming and labor-consuming work. The amount of data that can be trained on the model is not as large as other data sets. However, compared with the previous benchmark model, TEFR still performs better.

The reasons for TEFR's excellent performance are as follows. First, TEFR is based on the table filling strategy with more information, each marked table cell not only represents the head and tail position of the entity pair, but also represents whether the entity pair is a composite type. Second, the multi-head attention method in feature reasoning module is effective for reasoning implicit feature. The disadvantage of the single-head attention method is that the model will excessively focus on its own position when encoding the current position information. However, the multi-head attention method can solve this problem which conducts feature mining from different angles, and the information expressed by the feature is richer than that of the single head self-attention method.

4.5 Detailed Results

We conducted detailed experiments from the following two aspects to prove the effectiveness of our model.

The influence of the number of iterations N was analyzed, and the results are displayed in and Figure 2, from which the following conclusions may be taken.

On all data sets, when N = 2, feature reasoning module starts to play a role, and the performance of TEFR has been significantly improved, which again shows that the iterative use of historical table features can significantly improve the performance of the model. In the case of N = 3, the performance of TEFR is the best. However, when N > 3, the performance of TEFR decreases, which indicates that the more iterations, inferable information will not increase. This also shows that feature reasoning can only play its best role in a specific number of iterations, and the more iterations, the more useful implicit information cannot be inferred.

5 Conclusions

We proposed a new RTE method based on feature reasoning in this research. The method we proposed based on the features of existing token pairs and table relationships, reasoning the implicit features of subject and object, and enhances the accuracy of triple extraction.

The method can extract triples from complicated phrases that comprise numerous or overlapping triples as well. The model TEFR is tested on different datasets. A vast number of experiments suggest TEFR is always better than all relatively strong baselines, and has obtained the best results. Furthermore, our model has a fast reasoning speed and a small number of parameters.

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