A Novel Few-Shot Relation Extraction Pipeline Based on Adaptive Prototype Fusion

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Abstract

Few-shot relation extraction (FSRE) aims at recognizing unseen relations by learning with merely a handful of annotated instances. To more effectively generalize to new relations, this paper proposes a novel pipeline for the FSRE task based on adaptive prototype fusion. Specifically, for each relation class, the pipeline fully explores the relation information by concatenating two types of embedding, and then elaborately combine the relation representation with the adaptive prototype fusion mechanism. The whole framework can be effectively and efficiently optimized in an end-to-end fashion. Experiments on the benchmark dataset FewRel 1.0 show a significant improvement of our method against state-of-the-art methods.

1 Introduction

Relation extraction (RE) is an important part of information extraction in the field of natural language processing (Bach and Badaskar, 2007). It aims at extracting and classifying the relation between two entities contained in a given text and can be applied in other advanced tasks (Li et al., 2021; Hu et al., 2021), such as knowledge graph (Zhao et al., 2020), machine reading comprehension (Ding et al., 2019; Dua et al., 2020), and question answering (Karpukhin et al., 2020; Zhang et al., 2021). Currently, most researches on RE start from deep learning methods, but these methods rely on large-scale and high-quality annotated datasets. In many real-world applications, it is not possible to collect sufficient instances for model training, which makes them difficult to apply. In order to solve the problem of data scarcity, Few-shot relation extraction (FSRE) task has been widely studied in recent years. The task first trains a model on a large-scale annotated data with known relation types, and then quickly adapts to a small amount of data with new relation types.

Recent works expect to get better results by utilizing the relation information, including relation labels and descriptions, as the external knowledge to assist model training. Yang et al. (2020) proposed TD-Proto model, which is an enhanced prototypical network with both relation and entity descriptions. Wang et al. (2020) proposed CTEG model that learns to decouple relations by adding two types of external information. There also exists another track to improve model performance. Its target is to hope that the model can learn good prototypes, that is, to learn intra-class similarity and inter-class dissimilarity (Peng et al., 2020; Han et al., 2021). Peng et al. (2020) proposed a contrastive pre-training framework for RE to enhance the ability to grasp entity types and extract relational facts from contexts. Han et al. (2021) introduced a novel supervised contrastive learning method that obtains better prototypes by combining the prototypes, relation labels and descriptions to support model training.

Inspired by the modern approaches, we utilize relation information derived from external knowledge in our model training process to achieve a better performance on the FSRE task. We propose a novel adaptive prototype fusion strategy to dynamically combine the relation prototype utilizing external knowledge and the original relation prototype, in the hope of boosting the FSRE task performance as much as possible. Our proposed model achieves a significant improvement against state-of-the-art methods in the application to a benchmark dataset.

2 Methodology

This section provides the details of our proposed approach. Figure 1 shows the overall model structure. First, we encode the sentences and relation by a shared encoder in order to map their information into the same embedding space. Then, for the relation representation, we concatenate two aspects of
the relation representations in order to obtain the same dimension as prototypes and make a direct interaction with the prototypes. Next, we integrate relation representations into the original prototypes by the proposed adaptive prototype fusion mechanism.

Consider the general $N$ way $K$ shot setting. We employ BERT (Kenton and Toutanova, 2019) as the encoder to map the instances into a low-dimensional vector space and to better capture the semantic information of support set $S$ and $Q$. For instances in $S$ and $Q$, we concatenate the hidden states corresponding to start tokens of two entity mentions following Soares et al. (2019), i.e., $h = \text{concat}(h_1, h_2) \in \mathbb{R}^{2d}$, where $h_i \in \mathbb{R}^d, i = 1, 2$ and $d$ is the size of the representation vector. Then, we average intermediate states of each relation which has the same dimension as $p$.

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\[ \text{concat} \in \mathbb{R}^{2d}, \]

which has the same dimension as $p_i$.

The final prototype representations are obtained by the adaptive prototype fusion, which is an weighted average of $P_i$ and $r_i$ formulated as

\[ P_i^w = wp_i + (1 - w)r_i, \]

where $w$ is a learnable scale weight. With the representation of query and final prototypes of $N$ relations, the model computes the probability of the relations for the query instance $q_j$ as follows:

\[ P(y = i|q_j) = \frac{\exp(q_j^T p_i^w)}{\sum_{n=1}^{N} \exp(q_j^T p_n^w)}. \]

3 Experiments

3.1 Dataset and Baselines

Dataset Our proposed pipeline is evaluated on the benchmark dataset FewRel 1.0 (Han et al., 2018). The dataset consists of 100 relations with 700 labeled instances for each relation. Our experiments follow the splits used in official benchmarks, including 64 classes for training, 16 classes for validation, and 20 novel classes for testing.

Baselines Three CNN-based models (i.e., Proto-CNN (Snell et al., 2017), Proto-HATT (Gao et al., 2019a), and MLMAN (Ye and Ling, 2019)) and eight BERT-based models (i.e., Proto-BERT (Snell et al., 2017), MAML (Finn et al., 2017), GNN (Satorras and Estrach, 2018), BERT-PAIR (Gao et al., 2019b), REGRAB (Qu et al., 2020), TD-Proto (Yang et al., 2020), CTEG (Wang et al., 2020), and HCRP (Han et al., 2021)) are included for the purpose of comparison.

3.2 Training and Evaluation

Training We use BERT-base-uncased as the sentence encoder, with some parameters being fixed as follows: training iteration number = 30,000, validation iteration number = 1000, batch size = 4, and learning rate = $1 \times 10^{-5}$.

Evaluation We consider the general settings including 5-way-1-shot, 5-way-5-shot, 10-way-1-shot, and 10-way-5-shot. For each scenario, we use accuracy as a performance metric. We report the metrics on the FewRel 1.0 validation set. We also evaluate our model on the test set stored in CodaLab, which is not public available.

3.3 Results

All experiment results are shown in Table 1. Evidently, our proposed model achieves the best predictive capability compared with the state-of-the-art methods, demonstrating the effectiveness of our approach.

4 Conclusion

We propose a novel FSRE pipeline using an adaptive prototype fusion strategy. This strategy allows the model to adaptively exploit external knowledge by learning a dynamic weight to balance the original prototype and the relation representation. Our experiments on the FewRel 1.0 dataset show that our proposed model achieves a significant improvement against the modern state-of-the-art methods.

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Figure 1: The pipeline of our proposed model. First, the sentence and relation information share the same encoder. Then, two types of relation representation are concatenated directly as the prototype of relation. Finally, the relation prototype and the original class prototype are comprehensively combined by the adaptive prototype fusion mechanism to get the final prototype.

| Encoder | Model                  | 5-way-1-shot     | 5-way-5-shot     | 10-way-1-shot    | 10-way-5-shot    |
|---------|------------------------|------------------|------------------|------------------|------------------|
| CNN     | Proto-CNN♣ (Snell et al., 2017) | 72.65 / 74.52    | 86.15 / 88.40    | 60.13 / 62.38    | 76.20 / 80.45    |
|         | Proto-HATT (Gao et al., 2019a) | 75.01 / —       | 87.09 / 90.12    | 62.48 / —        | 77.50 / 83.05    |
|         | MLMAN (Ye and Ling, 2019) | 79.01 / 82.98    | 88.86 / 92.66    | 67.37 / 75.59    | 80.07 / 87.29    |
|         | Proto-BERT* (Snell et al., 2017) | 82.92 / 80.68    | 91.32 / 89.60    | 73.24 / 71.48    | 83.68 / 82.89    |
|         | MAML* (Finn et al., 2017) | 82.93 / 89.70    | 86.21 / 93.55    | 73.20 / 83.17    | 76.06 / 88.51    |
|         | GNN* (Satorras and Estrach, 2018) | — / 75.66       | — / 89.06        | — / 70.08        | — / 76.93        |
|         | BERT-PAIR♣ (Gao et al., 2019b) | 85.66 / 88.32    | 89.48 / 93.22    | 76.84 / 80.63    | 81.76 / 87.02    |
|         | REGRAB (Qu et al., 2020) | 87.95 / 90.30    | 92.54 / 94.25    | 80.26 / 84.09    | 86.72 / 89.93    |
|         | TD-Proto (Yang et al., 2020) | — / 84.76        | — / 92.38        | — / 74.32        | — / 85.92        |
|         | CTEG (Wang et al., 2020) | 84.72 / 88.11    | 92.52 / 95.25    | 76.01 / 81.29    | 84.89 / 91.33    |
|         | HCRP (Han et al., 2021) | 90.90 / 93.76    | 93.22 / 95.66    | 84.11 / 89.95    | 87.79 / 92.10    |
|         | Ours                  | **91.93 / 94.48** | **94.08 / 96.45** | **86.70 / 90.54** | **89.78 / 93.45** |

Table 1: Accuracy (%) of few-shot classification on the FewRel 1.0 validation / test set. ♣The results of Proto-CNN and BERT-PAIR are from FewRel public leaderboard (https://thunlp.github.io/fewrel.html), *the results of Proto-BERT and MAML are reported in Qu et al. (2020), and the results of our method on the test dataset is available at https://codalab.lisn.upsaclay.fr/competitions/7395. Our method introduces additional relation label name and description information, as done in TD-Proto. Other baseline methods also use different external knowledge.
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