Dependency-aware Prototype Learning for Few-shot Relation Classification

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Abstract

Few-shot relation classification aims to classify the relation type between two given entities in a sentence by training with a few labeled instances for each relation. However, most of existing models fail to distinguish multiple relations that co-exist in one sentence. This paper presents a novel dependency-aware prototype learning (DAPL) method for few-shot relation classification. Concretely, we utilize dependency trees and shortest dependency paths (SDP) as structural information to complement the contextualized representations of input sentences by using the dependency-aware embedding as attention inputs to learn attentive sentence representations. In addition, we introduce a gate controlled update mechanism to update the dependency-aware representations according to the output of each network layer. Extensive experiments on the FewRel dataset show that DAPL achieves substantially better performance than strong baselines. For reproducibility, we will release our code and data upon the publication of this paper at https://github.com/publicstaticvo/DAPL.

1 Introduction

Relation classification, which aims to classify the relation between two entities in a sentence, is a fundamental task for information retrieval (Kadry and Dietz, 2017), knowledge graph construction (Shen et al., 2020; Ji et al., 2021) and question answering (Luo et al., 2018). Most of existing relation classification methods (Wang et al., 2016; Guo et al., 2019; Shen et al., 2020; Tian et al., 2021; Zhao et al., 2022a) focus on the supervised scenario where sufficient labeled training data is available. However, it is time-consuming and labor-intensive to collect large-scale labeled data in many real-world applications, especially in the low-resource settings (Geng et al., 2019, 2020; Fan et al., 2021; Zhao et al., 2022b).

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Recently, few-shot relation classification (FSRC), which explores relation extraction methods by training with a few labeled examples in each relation, has become a hot research topic (Gao et al., 2019; Qu et al., 2020; Gao et al., 2020; Wang et al., 2020; Xu and Xiang, 2021; Ding et al., 2021; Fan et al., 2021). For instance, Han et al. (2018) introduce a large-scale FSRC dataset and implement several well-known few-shot learning techniques (Finn et al., 2017; Snell et al., 2017) for FSRC. Qu et al. (2020) propose a Bayesian meta learning approach for FSRC, which learns the posterior distributions of prototype vectors among different relations.

Despite the remarkable progress of FSRC methods, there is still a technical challenge which is not addressed well in prior work. Specifically, there can be multiple relations that co-exist in a sentence, while only one relation corresponds to the given entity pairs. The other existed relations may mislead the classifier to the wrong relation class, which is called the misleading relation. Taking Figure 1 as an example, the gold relation between two target entities “Mitsubishi toppo” and “minica” is “derivative-model” marked by the term “derived from”, while most prior FSRC methods incorrectly predict the misleading relation “products-producer” marked by the term “produced by”.

One possible solution is to leverage the dependency tree as auxiliary information to facilitate the representation learning. Recently, several studies have incorporated dependency tree into supervised relation classification models and obtained significant performance improvement (Sun et al., 2020; Yu et al., 2020; Pouran Ben Veyseh et al., 2020; Chen et al., 2021; Fan et al., 2021; Tian et al., 2021). However, few studies investigate the effectiveness of dependency trees in FSRC task. In addition, most existing works either solely focus on the terms that have direct dependency with target entities or involve redundant information by using...
the entire dependency tree, failing to get other information such as shortest dependency paths (SDP) of two entities thus cannot tackle the misleading relation problem. For example, as illustrated in Figure 1, the SDP (marked as red lines) of the two entities can help the relation classification model obtain the correct relation “derived from”. Therefore, it is necessary to fully exploit dependency information as auxiliary structural information, which can help identify useful terms and misleading terms via their relative positions to the given entities.

In this paper, we propose a novel dependency-aware prototype learning (DAPL) method for FSRC. DAPL is based on the framework of prototypical networks (Snell et al., 2017) with the BERT (Devlin et al., 2018) encoder, motivated by the effectiveness of prototypical networks in few-shot classification tasks. In our method, we leverage dependency trees as structural information to complement the contextualized representations of input sentences. Specifically, we assign each input token with a dependency label, according to whether the token is adjacent to the target entities or on the SDP between the two target entities. We highlight the tokens on the SDP by assigning a unified sdp dependency label for each token. Then, we convert these dependency labels into dependency embeddings, which are used as attention inputs of the contextualized sentence representations to learn dependency-aware sentence representations. Furthermore, we introduce a gate-controlled update mechanism to update the dependency-aware representations based on the output of each BERT layer, inspired by the effectiveness of the gate update functions in GRU (Cho et al., 2014). This mechanism provides a feedback to dependency states about whether they are reflecting the importance of each token and related to the ground truth labels.

The main contributions of this work are three-fold:

- We propose a novel dependency-aware prototype learning method for FSRC, which fully exploit the dependency and contextualized information to alleviate the misleading relation problem and improve the overall performance of FSRC.
- We present a gate-controlled update mechanism to adaptively adjust the dependency-aware representations according to the output of each network layer.
- Experiments on a benchmark FSRC dataset (i.e., FewRel) show that our method outperforms the strong baselines by a noticeable margin.

2 Methodology

Problem Definition In the RC task, each instance consists of an input sequence x (including a input sentence z, a head entity e1, a tail entity e2) and a relation label y for the two entities. We adopt a typical N-way-K-shot setting for FSRC (Qu et al., 2020). Under N-way-K-shot configuration, the training data is further split into a support set S and a query set Q which have disjoint labels, where S contains N relation classes and each with K labeled examples. The goal of FSRC is to learn a model using D_train, which is then used to predict the relation y for each input x in testing set.

2.1 Dependency Labels

Given an input example x ∈ D_train, we denote its dependency tree as G = (V, E), where V contains the tokens in the sentence and E contains the set of edges (dependencies) of tokens. Each triplet (wi, wj, d) ∈ E denotes that there is a dependency of type d between tokens wi and wj in x. Note that G is an undirected graph. Given the head entity e1 and the tail entity e2, we denote the set of all tokens on the SDP between e1 and e2 except themselves as P. We assign two dependency labels li(1) and li(2) to each token wi of the sentence x, where li(1) and li(2) denote the dependency relations between the token wi to the head entity and the tail entity respectively by the following four steps:
1. We initialize the \( l_i^{(1)} \) and \( l_i^{(2)} \) labels of each token as \textit{none}.

2. The \( l_i^{(1)} \) label of \( e_1 \) and the \( l_i^{(2)} \) label of \( e_2 \) are set to \textit{self}.

3. For each token \( w_i \in P \) on SDP except \( e_1 \) and \( e_2 \), we set its \( l_i^{(1)} \) and \( l_i^{(2)} \) labels as \textit{sdp}.

4. For each token \( w_i \not\in P \) that is not on SDP, we set \( l_i^{(1)} \) to the corresponding dependency parsing type if \( l_i^{(1)} \) is \textit{none} and \( w_i \) has an edge connected to \( e_1 \) on the dependency tree. We can get the \( l_i^{(2)} \) label for \( e_2 \) in a similar way.

To better illustrate the above process, we take the sentence “[CLS] the school <e1> master <e1> teaches the lesson with a <e2> steak </e2> [SEP]” as an example. We show how the two labels of each token are obtained as follows:

1. We initialize the \( l_i^{(1)} \) and \( l_i^{(2)} \) labels of each token as \textit{none}.

2. The \( l_i^{(1)} \) labels of “<e1>”, “master”, “<e1>” and the \( l_i^{(2)} \) labels of “<e2>”, “steak”, “<e2>” are assigned with \textit{self}.

3. The dependency path between the two entities (i.e., “master” and “steak”) is “master-teaches-steak”, so both \( l_i^{(1)} \) and \( l_i^{(2)} \) labels of “teaches” are set as \textit{sdp}.

4. For the remaining tokens, “the” and “school” are adjacent to “master” on the dependency tree, so the \( l_i^{(1)} \) label of “the” is \textit{det}, and the \( l_i^{(1)} \) label of “school” is \textit{compound}. Meanwhile, “with” and “a” are adjacent to “steak”, so the \( l_i^{(2)} \) label of “with” is \textit{case}, and the \( l_i^{(2)} \) label of “a” is \textit{det}.

Afterwards, we use an embedding layer to convert the dependency labels \( l_i^{(1)} \) and \( l_i^{(2)} \) into dependency embeddings \( d_i^{(1)} \) and \( d_i^{(2)} \) with an embedding dimension of \( d_h/2 \), where \( d_h \) is the hidden vector size of the encoder. The dependency embedding \( d_i \) of each token \( w_i \) is formed by concatenating \( d_i^{(1)} \) and \( d_i^{(2)} \) together, whose length is \( d_h \).

2.2 Dependency-aware Attention

Figure 2 shows the structure of our model DAPL. Our model takes each token representation \{\( w_i \)\} and dependency embedding \{\( d_i \)\} in the sentence as input. Inspired by the remarkable success of pre-trained language models (PLMs) on most of NLP tasks, we employ BERT (Devlin et al., 2018) as the basic framework of our model. To learn the importance of each token to the given entities, we modify the self-attention mechanism in original BERT by adding together the contextual representation and dependency representation when generating query and key matrices at the \( l \)-th layer:

\[
Q(l) = (h_i^{(l-1)} + d_i^{(l-1)})W_Q(l) \tag{1}
\]

\[
K(l) = (h_i^{(l-1)} + d_i^{(l-1)})W_K(l) \tag{2}
\]

\[
V(l) = h_i^{(l-1)}W_V(l) \tag{3}
\]

\[
\tilde{h}(l) = \text{softmax} \left( \frac{Q(l)K(l)^T}{\sqrt{d_K}} \right)V(l) \tag{4}
\]

where \( W_Q(l), W_K(l), W_V(l) \in \mathbb{R}_{d_h \times d_h} \) are learnable attention weights in scaled dot-product attention. Here, \( h_i^{(l)} = w_i \) and \( d_i^{(l)} = d_i \). Then, a two-layer feed-forward neural network with a ReLU activation takes the weighted sum \( \tilde{h}(l) \) as input to learn the output hidden states \( h(l) \) at the \( l \)-th layer:

\[
h(l) = \max(0, \tilde{h}(l)W_1(l) + b_1(l))W_2(l) + b_2(l) \tag{5}
\]

where \( W_1(l), W_2(l), b_1(l), b_2(l) \) are learnable parameters in BERT.

2.3 Gate-controlled Update

We propose a gate-controlled update to the dependency states \( d_i^{(l-1)} \) at the end of each layer by using the previous dependency representation \( d_i^{(l-1)} \) and the output hidden states \( h_i^{(l)} \). Inspired by the Gate Recurrent Unit (GRU) (Cho et al., 2014), we devise an update gate and a control gate. Specifically, the
control gate is a single fully-connected layer with a sigmoid activate function, which is defined as:

$$z_i^{(l)} = \text{sigmoid}( [h_i^{(l)}; d_i^{(l-1)}]W_Z^{(l)})$$

(6)

where $W_Z^{(l)} \in \mathbb{R}^{d_h \times d_b}$ is a learnable parameter. The update gate is a single fully-connected layer with a tanh activate function, which is defined as:

$$u_i^{(l)} = \tanh(h_i^{(l)}W_U^{(l)})$$

(7)

where $W_U^{(l)} \in \mathbb{R}^{d_h \times d_b}$ is a learnable parameter.

Finally, the output dependency representations are learned by considering the last dependency state $d_i^{(l-1)}$ and the update gate output $u_i^{(l)}$ under the control of $z_i^{(l)}$:

$$d_i^{(l)} = (1 - z_i^{(l)}) \odot d_i^{(l-1)} + z_i^{(l)} \odot u_i^{(l)}$$

(8)

where $\odot$ represents the element-wise product.

2.4 Relation Classification

We apply a max-pooling operation on the position $K$ where $\odot W$ with a tanh activate function, which is defined as:

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$$W^{(l)} \in \mathbb{R}^{d_h \times d_b}$$

where $W^{(l)} \in \mathbb{R}^{d_h \times d_b}$ is a learnable parameter.

Inference Stage

In inference phase, we compute the relation $\hat{y}_i$ of each input $x_i$ in testing set as:

$$\hat{y}_i = \arg\min_c d(h_{x_i}, p_c), \quad c \in [1, \ldots, N]$$

(10)

3 Experiments

3.1 Experimental Setup

Dataset

We use the benchmark FSRC dataset FewRel (Han et al., 2018) to evaluate the effectiveness of our model. FewRel contains 100 different relations, with 64 relations in training set, 16 relations in validation set and 20 relations in testing set. For each type of relation, there are 700 different examples. Since the 20 testing relations are unpublished, we re-split the published 64 training relations into 50 relations and 14 relations for training and validation respectively, and employ the original validation set with 16 relations for testing, following previous studies (Yang et al., 2020).

Baselines

We compare DAPL with several state-of-the-art baselines for FSRC, including Proto (Snell et al., 2017), Proto-GAT (Snell et al., 2017), BERT-PAIR (Gao et al., 2019), CTEG (Wang et al., 2020), TD-Proto (Yang et al., 2020), and a simple version of ConceptFERE (Yang et al., 2021) that involves an external concept database.

Implementation Details

For the PLM, the proposed DAPL is implemented based on BERTbase for all experiments. We conduct $N$-way-$K$-shot (denoted as $N$-w-$K$-s) to study the performance in different situations. Here, we adopt four different settings, i.e., 5-w-1-s, 5-w-5-s, 10-w-1-s, and 10-w-5-s. We tune the entire model and select the checkpoint with best validation performance. The maximum length of the sentence is 90. We follow Soares et al. (2019) to insert four special tokens <e1>, </e1>, <e2> and </e2> to mark the boundaries of the entities. The dependency trees are obtained using the external Stanford CoreNLP Toolkit proposed by StanfordNLP. The size of the dependency embedding is 384. DAPL is optimized with AdamW (Loshchilov and Hutter, 2018) and warmup mechanism (Popel and Bojar, 2018).

3.2 Experimental Results

Overall Results

We adopt classification accuracy as the evaluation metric. Table 1 reports the experimental results of our model and four baselines in four few-shot settings. Our DAPL model achieves significantly better performance than the baselines in all settings. Specifically, our method improves the best performance of baselines by 0.28%/1.76%/0.75%/3.34% under the four settings respectively. The performance gain of our method comes from the auxiliary dependency information.
| Model          | 5 way 1 shot | 5 way 5 shot | 10 way 1 shot | 10 way 5 shot |
|---------------|-------------|-------------|---------------|--------------|
| Proto         | 72.65       | 86.15       | 60.13         | 76.20        |
| Proto-GAT     | 79.14       | 88.46       | 68.87         | 79.45        |
| BERT-PAIR     | 85.66       | 89.48       | 76.84         | 81.76        |
| ConceptFERE   | 84.28       | 90.34       | 74.00         | 81.82        |
| CTEG          | 84.72       | 92.52       | 76.01         | 84.89        |
| TD-Proto      | 84.76       | 92.38       | 74.32         | 85.92        |
| DAPL (Ours)   | **85.94**   | **94.28**   | **77.59**     | **89.26**    |
| DAPL w/o Gate | 85.44       | 93.68       | 76.29         | 88.27        |
| DAPL w/o SDP  | 85.30       | 93.10       | 76.04         | 87.43        |
| DAPL w/o DT   | 85.06       | 92.46       | 75.13         | 86.54        |

Table 1: The main evaluation results and the ablation results on the test set.

| Ground-truth   | By DAPL       | By CTEG       | Input Example                                                                 |
|----------------|---------------|---------------|-------------------------------------------------------------------------------|
| Husband-Wife   | Husband-Wife  | Children-Parent| He was born in Kristiania as a son of Gerda Ring and Halfdan Christensen and brother of Bab Christensen. |
| Parent-Children| Parent-Children| Husband-Wife  | On March 8, 1852 he married Kapi'olani, daughter of Kūhiō Kalaniana'ole and Kinoiki Kekaulike. |

Table 2: Prediction results on the test samples. We use the red and blue colors to indicate the head and tail entities.

**Ablation Study** To analyze the impact of different components in DAPL, we also conduct ablation test in terms of discarding the dependency tree (denoted as w/o DT), the SDP dependency label (denoted as w/o SDP) and the gate-controlled update mechanism (denoted as w/o Gate). The ablation test results are reported in Table 1. The accuracy scores decrease sharply when removing the dependency tree. This is within our expectation since the dependency tree provides rich information of entities and relations between them. Not surprisingly, combining all the factors achieves the best performance over the four experimental settings.

**Case Study** In Table 2, we provide a case study to illustrate the effectiveness of our model for alleviating the misleading relation problem qualitatively. Specifically, we provide two examples from the test set that are incorrectly predicted by CTEG while being correctly predicted by our method. By fully exploiting the auxiliary dependency information, our DAPL can correctly predict the correct relation even being disturbed by the misleading relation “Husband-wife”. However, CTEG has a propensity to confuse the co-exist relations in a sentence, since the misleading terms are close to the given entities.

**4 Conclusion**

In this paper, we proposed a dependency-aware prototype learning method for FSRC, which leveraged dependency trees and shortest dependency paths as structural information to complement the contextualized representations of input sentences. A gate-controlled update mechanism was further devised to adaptively update the dependency-aware representations according to the output of each network layer. Experimental results showed that DAPL outperformed strong baselines for FSRC.

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