Using a Penalty-based Loss Re-estimation Method to Improve Implicit Discourse Relation Classification

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Abstract

We tackle implicit discourse relation classification, a task of automatically determining semantic relationships between arguments. The attention-worthy words in arguments are crucial clues for classifying the discourse relations. Attention mechanisms have been proven effective in highlighting the attention-worthy words during encoding. However, our survey shows that some inessential words are unintentionally misjudged as the attention-worthy words and, therefore, assigned heavier attention weights than should be. We propose a penalty-based loss re-estimation method to regulate the attention learning process, integrating penalty coefficients into the computation of loss by means of overstability of attention weight distributions. We conduct experiments on the Penn Discourse TreeBank (PDTB) corpus. The test results show that our loss re-estimation method leads to substantial improvements for a variety of attention mechanisms.

1 Introduction

The goal of pairwise sentence-level discourse analysis is to determine the relation that is held by a pair of arguments (Prasad et al., 2008), where an argument generally stands for a narrative sentence. Implicit discourse relation classification is a challenging subtask. It is required to determine the relation on the condition that the explicit connective (i.e., a syntactic conjunction) is not given. For example, the arguments in Figure 1 are a pair of semantically-related arguments, where the possible connective “but” that may signal the comparison relation has been omitted.

Argument 1 (Arg1): Robert S. Enrlich resigned as chairman, president and chief executive.
Argument 2 (Arg2): Mr. Enrlich will continue as a director and a consultant.
Ground-truth relation: Comparison (sub-relation—concession)
Omitted connective: but

Figure 1: Example of arguments, connective and relationship, as well as attention weight distributions

Detecting the content words that imply correlations between arguments contributes to the relation determination (Marcu and Echihabi, 2002). We refer such kind of content words to attention-worthy words, such as the words shown in bold in Figure 1. The current attention mechanisms have been proven effective in recognizing and utilizing attention-worthy words. They generally assign heavier weights to attention-worthy words conditioned on either internal (Lin et al., 2017) or external context.
Table 1: The equations of different attention mechanisms as well as parameters (where, $\Phi$ denotes the non-linear transformation and $\text{cls}$ is a special classification token in BERT, $k(k=1,2,3)$ is the attention-layer number, the memory vector $M$ is used to preserve the information of previous layer, $M_k \otimes e$ is the operation that repeatedly expands the dimensions of encoder states).

(Ma et al., 2017). Benefiting from the positive effects of the heavily weighted attention-worthy words on representation learning, the existing attention-based neural networks obtains considerable performance gains for discourse relation classification.

However, our survey shows that some of inessential words are highlighted with heavier weights by the attention mechanisms. As a result, the attention weight distributions fall into the over-smooth transition state (as shown in Figure 1). This makes it difficult to sensitively perceive the effects of attention-worthy words or even misleads the encoder during encoding. To solve the problem, we propose to estimate attention-oriented penalty coefficients by means of overstability of attention weight distributions. On the basis, we integrate the penalty coefficients into the loss measurement process (Section 2), so as to optimize the parameters of attention mechanisms by backward propagation of penalty. Briefly, we aim to use penalty coefficients to obtain distinguishable attention weights. In Figure 1, we show the jagged attention weight distributions obtained after using our penalty coefficients. We carry out experiments on PDTB v2.0 (Prasad et al., 2008), a corpus that comprises a large-scale pairwise argument instances, along with pre-annotated implicit relation tags. The test results show that our method substantially improves the attention-based discourse relation classification (Section 3).

2 Approach

We utilize BERT (Devlin et al., 2019) as the baseline encoder, and connect it with a multi-layer perceptron (MLP) to form the discourse relation classifier. In addition, we reproduce three attention mechanisms, including self (Lin et al., 2017), interactive (Ma et al., 2017) and multi-layer (Liu and Li, 2016) attention mechanisms. On the basis, we couple them with the baseline (BERT) encoder. Similarly, they are also connected with a MLP respectively for discourse relation classification. It is noteworthy that the attention mechanisms mentioned above have been carefully studied on PDTB v2.0. Though, they were built over some slightly weak word embeddings. For fair comparison, we choose to couple them with the pre-trained BERT encoder. BERT is fine-tuned in all of our experiments.

Assume that a certain neural attention mechanism is defined as $\mathcal{F}(H_1, H_2, \theta)$, we tend to optimize $\theta$. In the equation, $H_1$ and $H_2$ denotes the encoder states of a pair of arguments which are obtained using the pre-trained BERT, and $\theta$ stands for the shorthand of all parameters of the attention mechanism. We specify the parameters of all the considered attention-based computational models in Table 1. We optimize $\theta$ by re-estimating the loss $J(\theta)$ using penalty coefficients. The penalty coefficients are measured by means of mean deviations among different attention weights. Backward propagation is used as usual to tune the parameters in $\theta$ conditioned on the re-estimated loss. The loss $J(\theta)$ is calculated as follows:

$$J(\theta) = \frac{1}{n} \sum_{i=1}^{n} L(y^{(i)}, \hat{y}^{(i)}) - \chi(\theta); \quad L(y^{(i)}, \hat{y}^{(i)}) = - \sum_{j=1}^{C} P(y^{(i)}_j) \log(P(\hat{y}^{(i)}_j))$$

(1)

$$\chi(\theta) = \lambda[(\sigma_1)^2 + (\sigma_2)^2]$$

(2)

where, $C$ denotes the relation class number, $P(\hat{y}^{(i)}_j)$ stands for the probability that the relation class is predicted as the $i$-th class, $\sigma_1$ denotes the scalar deviation value that is calculated over the attention
| Systems                          | COM  | CON  | EXP  | TEM  |
|---------------------------------|------|------|------|------|
| Bert (Baseline) (Devlin et al., 2019) | 45.67| 56.46| 73.84| 37.01|
| + Self (Lin et al., 2017)       | 46.66| 56.75| 73.40| 38.94|
| + Self + Penalty                | 50.45| 58.27| 75.45| 39.02|
| + Interactive (Ma et al., 2017) | 48.11| 57.02| 74.66| 38.44|
| + Interactive (Ours)            | 48.85| 57.96| 74.90| 39.23|
| + Interactive (Ours) + Penalty  | 49.29| 58.46| 75.41| 40.40|
| + Multi-layer (two layers) (Liu and Li, 2016) | 47.02| 57.97| 74.96| 39.61|
| + Multi-layer (two layers) + Penalty | 49.87| 58.38| 75.33| 41.25|
| + Multi-layer (three layers) (Liu and Li, 2016) | 48.47| 58.09| 74.27| 38.70|
| + Multi-layer (three layers) + Penalty | 50.11| 58.77| 76.26| 43.26|

Table 2: Test results for different attention mechanisms which are coupled with our penalty mechanism.

| Model                                         | COM  | CON  | EXP  | TEM  |
|-----------------------------------------------|------|------|------|------|
| Bert (Baseline) (Devlin et al., 2019)         | 45.67| 56.46| 73.84| 37.01|
| + Self (Lin et al., 2017)                     | 46.66| 56.75| 73.40| 38.94|
| + Self + Interactive (ours)                   | 49.40| 58.48| 75.37| 39.77|
| + Self + Interactive (ours) + Penalty         | 50.91| 58.88| 76.35| 43.51|

Table 3: The test results for the combination of attention mechanisms and shareable penalty mechanism.

weights for $H_1$, while $\sigma_2$ is calculated for $H_2$, and $\lambda$ denotes a hyperparameter which is separately set for different attention mechanisms (section 3). It can be preconceived that a smaller deviation will lead to a relatively larger loss. In other words, if the attention weight distribution is smooth (corresponding to a small deviation), the loss will relatively be increased, and as a result, the attention parameters $\theta$ will be dramatically changed by backward propagation.

3 Experimentation

We evaluated our model on the benchmark PDTB v2.0 (Prasad et al., 2008). The four main relation classes are considered in the experiments, including Comparison (abbr., COM), Contingency (CON), Expansion (EXP) and Temporality (TEM). We follow the previous work (Ji and Eisenstein, 2015) to split datasets, using sections 02-20 as the training set, sections 00-01 the development set and sections 21-22 the test set. For comparison purpose, we use F1 as the evaluation metric.

We utilize BERT that outputs word embeddings with the hidden size of 768. There are 12 self-attention heads considered in BERT. The max length of the input sequence is set to 163, in which the maximum length $N$ of an argument is set to 80. In addition, the batch size is set to 15, and gradient descent is set separately: $\beta_1=0.9$ and $\beta_2=0.999$. The learning rate is set to 5e-5 and dropout rate is set to 0.1. We set the hyperparameter $\lambda$ to 1e-3 for both the multi-layer and self-attention mechanisms, and 1e-2 for the interactive attention mechanism.

The main test results are shown in Table 2, in which various attention mechanisms are coupled with our penalty-based loss re-estimation model (penalty mechanism for short). Note that the label of “Interactive (Ours)” denotes the reproduced interactive attention mechanism which introduces the special classification token “cls” (see Table 1) into the encoder state. It can be observed that the proposed penalty mechanism yields substantial improvements for every attention model. Besides, we combine the self and interactive attention mechanisms and utilize a shareable penalty mechanism to improve them. The performance is shown in Table 3. It can be found that the F1 scores obtained for all the four relation classes are increased further. It proves that our penalty mechanism is capable of producing shareable penalty coefficients for different attention models.

We compare our method to the state-of-the-art. As shown in Table 4, our best model (i.e., the combined attention models coupled with the shareable penalty mechanisms) outperforms the previous work for the comparison (COM) and expansion (EXP) relations. In addition, it achieves comparable performance to
Table 4: Comparison to the State-of-the-art approaches.

| Model             | COM  | CON  | EXP  | TEM  |
|-------------------|------|------|------|------|
| Zhang et al (2015)| 33.22| 52.04| 69.59| 30.54|
| Qin et al (2016)  | 41.55| 57.32| 71.50| 35.43|
| Liu and Li (2016) | 36.70| 54.48| 70.43| 38.84|
| Qin et al (2017)  | 40.87| 54.56| 72.38| 36.20|
| Lan et al (2017)  | 40.73| 58.96| 72.47| 38.50|
| Dai and Huang (2018)| 46.79| 57.09| 70.41| 45.61|
| Guo et al (2018)  | 40.35| 55.81| 71.12| 36.65|
| Bai and Zhao (2018)| 47.85| 54.47| 70.60| 36.87|
| Nguyen et al (2019)| 48.44| 56.84| 73.66| 38.60|
| He et al (2020)   | 47.98| 55.62| 69.37| 39.84|
| Our best          | **50.91** | **58.88** | **76.35** | 43.51|

that of Lan et al. (2017)’s work for the contingency (CON) relation, which was being at the top of the list for years. For the temporality (TEM) relation, our method results in less severe performance reduction when it improves the performance for other three relation classes.

4 Related work

Recently, neural networks have been widely studied for argument representation learning (Zhang et al., 2015), which is admitted to be the crucial issue for discourse relation recognition. Due to the capacity of generating low-dimensional continuous representations for arguments, RNNs with Bi-LSTM are used during encoding. Chen et al (2016) couple Bi-LSTM with a gated relevance model. Liu and Li (2016) use multi-layer attention computation over the output of Bi-LSTM. Meanwhile, Liu et al (2016) build a multi-task learning framework with Convolutional Neural Network (CNN) for argument encoding. By contrast, Lan et al (2017) integrate Bi-LSTM into the multi-task framework and couple it with the attention mechanism. Guo et al (2018) utilize the interaction mechanism to weight the representations emitted by Bi-LSTM, and perform a deeper encoding by tensor network. Dai and Huang (2018) use Bi-LSTM to bring paragraph-level contextual information into argument representations.

In addition, Qin et al (2016) build a hybrid neural model which couples two gated CNNs to extract both word-level and semantic-level convolutional features. Further, Qin et al (2017) integrate generative adversarial networks into multi-task learning network. Hereafter, Bai and Zhao (2018) establish multi-task network using multi-layer gated CNNs. The network is additionally coupled with residual networks and interactive attention mechanisms. Nguyen et al (2019) enhance Bai and Zhao (2018)’s multi-layer CNNs-based multi-task learning by minimizing the divergence between connective-level embeddings and relation-level embeddings. He et al (2020) develop a joint learning architecture which updates both geometric and semantic features during encoding.

5 Conclusion

Our experiments demonstrate that the utilization of penalty coefficients for loss re-estimation can effectively strengthen the attention-based implicit discourse relation classification. Nevertheless, our survey shows that some attention-worthy words fails to be effectively perceived by the current attention mechanisms. More importantly, the semantics of such kind of attention-worthy words can be well-encoded only through the understanding of related common sense. Therefore, in the future, we will utilize commonsense knowledge graph to enhance the attention modeling method.

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