Memorizing All for Implicit Discourse Relation Recognition

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Abstract

Implicit discourse relation recognition is a challenging task due to the absence of the necessary informative clue from explicit connectives. The prediction of relations requires a deep understanding of the semantic meanings of sentence pairs. As implicit discourse relation recognizer has to carefully tackle the semantic similarity of the given sentence pairs and the severe data sparsity issue exists in the meantime, it is supposed to be beneficial from mastering the entire training data. Thus in this paper, we propose a novel memory mechanism to tackle the challenges for further performance improvement. The memory mechanism is adequately memorizing information by pairing representations and discourse relations of all training instances, which right fills the slot of the data-hungry issue in the current implicit discourse relation recognizer. Our experiments show that our full model with memorizing the entire training set reaches new stateof-the-art against strong baselines, which especially for the first time exceeds the milestone of 60% accuracy in the 4-way task.

1 Introduction

Implicit discourse relation recognition is one of the critical components of discourse parsing. This task is to identify the relationship between two adjacent discourse units (sentence or clause) without explicit connectives (e.g. *because*, *whereas*, etc.). This task is tough because relation recognition requires a deep understanding of the two discourse units. Previous works have shown that this task is instrumental to many downstream tasks such as text summarization (Gerani et al., 2014) and question answering (Jansen et al., 2014).

The most important benchmark datasets until now for this task is Penn Discourse Treebank 2.0

(PDTB 2.0) (Prasad et al., 2008), in which an instance is a tetrad $\{Arg_1, Arg_2, implicit connective, discourse relation\}$, where the argument pair Arg_1 and Arg_2 are discourse related sentences or clauses, the implicit connectives are annotated by humans and are not known during testing. Implicit discourse relation recognition is to disclose discourse relation for any given Arg_1 and Arg_2 without knowing implicit connective. Here is an example for the instance,

 $[Arg_1]$: Never mind.

 $[Arg_2]$: You already know the answer.

[Implicit connective]: Because

[Discourse relation]: Cause

Numerous works have been do

Numerous works have been done for this task. Lin et al. (2009) and Pitler et al. (2009) first practiced conventional methods with artificial linguistic features. Since 2015, neural networks dominate the mainstreams by introducing convolutional neural network (CNN) (Zhang et al., 2015; Qin et al., 2016b), recurrent neural network (RNN) (Ji et al., 2016; Rönnqvist et al., 2017), attention mechanism (Liu and Li, 2016; Rönnqvist et al., 2017), and other network methods (Qin et al., 2016c; Schenk et al., 2016; Lan et al., 2017; Dai and Huang, 2018; Guo et al., 2018).

For neural network methods, the parameters learned from the training data capture the semantic features. However, due to the data sparsity issue, these captured features may not well semantically link arguments and their relations, which thus will heavily affect the performance.

So in this work, we propose a novel memory component storing all the semantic representations of training instances and their corresponding relations. During testing, the model could consult the memory component and find out the similar semantic patterns and utilize the memorized re-

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lations. The hypothesis is that if the similar instances in the training set can be retrieved, the relations of these instances must be helpful. The training instances are stored through their encoded representations. These memorized instances can also be considered as a sort of knowledge source, which reflects the links between semantic representations and discourse relations. The adopted memory component can be theoretically applied to any existing suitable models.

To implement and evaluate the memory component, we integrate the memory component into the state-of-the-art model from Bai and Zhao (2018) and let the augmented model be evaluated on the benchmark PDTB 2.0, which shows that the appended memory mechanism can further promote the performance over strong baseline.

This paper is organized as follows. Section 2 reviews the related works. Section 3 introduces the baseline model and our proposed memory component. Section 4 demonstrates the experiments and analyses. Section 5 states the conclusion.

2 Related Works

2.1 Implicit Discourse Relation Recognition

Since the PDTB 2.0 corpus was released, a surge of works focusing on implicit discourse relation recognition have been proposed. And after two shared tasks (Xue et al., 2015, 2016) on CoNLL are held, this task attracted more researchers. Feature-based methods (Pitler et al., 2009; Lin et al., 2009; Zhou et al., 2010) mainly focused on extracting linguistic, or semantic features from the discourse units, or the relations between unit pairs. Then these features are distilled and sent to a classifier for relation prediction. Lin et al. (2009) explored several common features and their combination. Lei et al. (2018) considered some semantic and cohesion features. Recent years, most of the works focused on using neural networks to extract the features, or to produce more suitable representations for prediction. Braud and Denis (2015) found that embeddings trained with neural networks are very useful. Chen et al. (2016a) and Lei et al. (2017) used the relationship between words to help the classification. Zhang et al. (2015) and Qin et al. (2016b) used CNN to encode the discourse units to representations. Qin et al. (2016c) used a gated mechanism to enhance their classifier. Ji et al. (2016) used RNN to model sentences and used graphical models to do inference. Liu and Li (2016), Rönnqvist et al. (2017), and Guo et al. (2018) deployed attention mechanism for better semantic extraction. Rutherford et al. (2017) compared several network architectures. Liu et al. (2016), Lan et al. (2017), Kishimoto et al. (2018), and Xu et al. (2018) tried to use extra information to help the training procedure. Dai and Huang (2018) put discourse units to their context and made prediction in series.

Our work is orthogonal and complementary to them. Our motivation of introducing this is to lighten the existing data-hungry bottleneck of discourse relation recognition problem which only counts on an extremely small dataset. As the implicit task is more semantically difficult than the explicit one, the state-of-the-art performance of the former only reaches around 50% until the very recent days, while the latter may reach 80% or higher. There are a few existing works trying to alleviate the data sparsity issue. Rutherford and Xue (2015) directly relabeled explicit instances into implicit ones by manually removing the explicit connectives. Qin et al. (2017) used a generative adversarial training method to force the implicit module to learn from the explicit module. Xu et al. (2018) utilized active learning to lead more data into training. In this paper, we straightforwardly apply a memory component to store all possible training instances for this challenging task, which is never explored before.

2.2 Memory Network

Weston et al. (2015) first proposed memory networks to store relevant information. The memory networks can reduce the long-term forgetting issues or can be used for a knowledge base. Sukhbaatar et al. (2015) optimized the memory network and trained it end-to-end which eases the training significantly. Miller et al. (2016) extended this mechanism to a key-value memory for machine reading comprehension. However, our proposed memory component is not the same. Their memory networks are to tackle the long-term dependency issue, and the memory is used for each instance temporarily, while our memory component is used for the whole system to store the training set and is fixed after training.

3 Method

The relation recognition model usually encodes the arguments first and classifies the encoded rep-

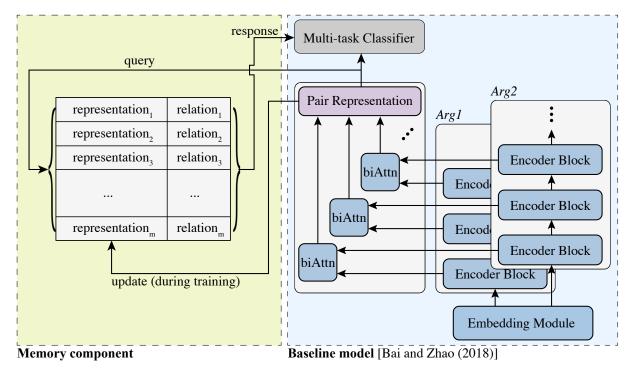


Figure 1: Model overview.

resentations. Our overall model architecture is given in Figure 1, in which a baseline module (Bai and Zhao, 2018) and a memory component are contained. The baseline model is the current state-of-the-art model for this task and can provide better representations for higher performance. Besides, we store the pair representations to the memory component to augment the whole system.

3.1 Baseline Model

In this section, we briefly introduce the baseline model¹, which reaches the current state-of-the-art results for both 11-way and 4-way implicit tasks, and consists of the following four parts.

We adopt the latest deep enhanced representation model in Bai and Zhao (2018) as our baseline, which is the current state-of-the-art model which first exceeds the milestone of 48% accuracy and 50% F_1 in 11-way and 4-way implicit tasks, respectively. Implementing this strong baseline, we store the representations of discourse unit pairs to the memory. It provides better representations and leads to a higher performance gain.

The right part of Figure 1 shows our baseline model. It demonstrates the four parts. The first part is the embedding module or the word-level module. The second part is the encoding module or the sentence-level module. The third part

is the attention module or the pair-level module. The fourth part is multi-task classifiers.

Embedding Module

The k-th word of an input sentence is embedded into a vector \mathbf{e}_k , which is concatenated from three parts, $\mathbf{e}_k = [\mathbf{e}_k^w; \mathbf{e}_k^s; \mathbf{e}_k^c] \in \mathbb{R}^{d_e}$. \mathbf{e}_k^w is pre-trained word embedding (word2vec) (Mikolov et al., 2013). \mathbf{e}_k^s is subword-level embedding. \mathbf{e}_k^c is the ELMo embedding (Peters et al., 2018).

Subword units are segmented from training data using byte pair encoding (BPE) (Sennrich et al., 2016). For each word, the subword sequence of the word is mapped to the subword embedding sequence. Then convolutional operations are applied to the embedding sequence followed by max pooling operation. Finally, the outputs are concatenated and fed to a highway network (Srivastava et al., 2015) for subword-level embedding \mathbf{e}_k^s .

ELMo (Embeddings from Language Models) is a pre-trained contextualized word embedding. The outputs of this pre-trained ELMo encoder are two 1024-dimension vectors for each word. Given this output, a self-adjusted weighted average is calculated. Following these processes, the vector is fed to a feed forward network to reduce its dimension.

Encoding Module

The encoding module encodes each argument separately and is composed of stacked encoder

¹Please refer to the original paper for more model details.

blocks. The output of each layer is delivered to the next layer and the attention module. Bai and Zhao (2018) considers two types of encoder blocks, and we only use the convolutional type here as both types of blocks give similar performance.

Assuming the input for the encoder block is $\mathbf{x}_k \in \mathbb{R}^{d_e}$ $(k=1,\cdots,N)$, the input is sent to a convolutional layer and mapped to output $[\mathbf{A}_k;\mathbf{B}_k] \in \mathbb{R}^{2d_e}$. After the convolutional operation, a gated linear units (GLU) (Dauphin et al., 2016) is applied, i.e.,

$$\mathbf{z}_k = \mathbf{A}_k \otimes \sigma(\mathbf{B}_k) \in \mathbb{R}^{d_e}$$

There is a residual connection in this block, which adds the output and the input of the block. Therefore, $\mathbf{z}_k + \mathbf{x}_k$ is the final output of the block corresponding to the input \mathbf{x}_k . The output is delivered to the next layer and the attention module.

Attention Module

The outputs of each layer are sent to the attention module. Supposing the encoder block layer number is L, and the outputs of l-th block layer for Arg_1 and Arg_2 are $\mathbf{u}_1^l, \mathbf{u}_2^l \in \mathbb{R}^{N \times d_e}$, N is the sentence length. They are addressed by a bi-attention module, where the attention matrix is

$$\mathbf{M}_{l} = (FFN(\mathbf{u}_{1}^{l}))\mathbf{u}_{2}^{l} \in \mathbb{R}^{N \times N}$$

FFN is a feed forward network applied to the last dimension corresponding to the word. Then

$$\mathbf{o}_{2}^{l} = softmax(\mathbf{M}_{l})\mathbf{u}_{2}^{l} \in \mathbb{R}^{N \times d_{e}}$$

$$\mathbf{o}_{1}^{l} = softmax(\mathbf{M}_{l}^{T})\mathbf{u}_{1}^{l} \in \mathbb{R}^{N \times d_{e}}$$

the *softmax* is applied to each row of the matrix. We apply 2-max pooling on each of them and concatenate them as output

$$\mathbf{r}_l = [top2(\mathbf{y}_1^l); \ top2(\mathbf{o}_2^l)] \in \mathbb{R}^{4d_e}$$

The final pair representation is (we let $d_r = 4d_e L$)

$$\mathbf{r} = [\mathbf{r}_1; \mathbf{r}_2; \cdots; \mathbf{r}_L] \in \mathbb{R}^{d_r}$$

This representation is applied as the input of both the classifiers and the memory component.

Classifiers

In this model, two classifiers are used. One is for the relation prediction, and the other one is for the connective prediction. Qin et al. (2017) and Bai and Zhao (2018) demonstrated that connective aware information is essentially useful for the training. The two classifiers predict the relations and the connectives simultaneously.

The classifiers are multilayer perceptrons (MLPs) with a *softmax* layer. The connective classifier helps the model produce better representations, and only works during training. The output of the connective classifier is

$$\mathbf{o}_c = softmax[MLP_c(\mathbf{r})] \in \mathbb{R}^{n_c},$$

and the output of the relation classifier is

$$\mathbf{o}_r = softmax[MLP_r(\mathbf{r})] \in \mathbb{R}^{n_r},$$
 (1)

where n_c and n_r are the number of connectives and discourse relations respectively. The loss function for both classifiers is cross entropy loss, and the total loss is the sum of the two losses

$$Loss = Loss_{relation} + Loss_{connective}$$
.

3.2 Memory Component

The left part in Figure 1 shows a key-value memory component S to memorize the (representation, relation) pairs of all the training instances. The keys S^k are the semantic representations of discourse unit pairs in the training set, and the values S^v are the corresponding relations. The keys are updated during training for better retrieval, and the memorized keys are retained for testing.

Supposing there are m slots in the memory S, which can contain m training instances. We intend to sample out m training instances and index them with $1, \dots, m$. Therefore, the i-th training instance will be stored at the i-th memory slot S_i . (In our experiments, we set m with the number of all training instances, namely, we memorize the entire training set.)

The key part \mathcal{S}^k of the memory component is initialized randomly and is updated during training. Simultaneously, the value part \mathcal{S}^v is initialized with the one-hot encodings which represent the relations. These encodings are fixed all the time. Given n_r relations, the one-hot representation of the j-th relation $(j=1,\cdots,n_r)$ is

$$[0, \cdots, 1, \cdots, 0] \in \mathbb{R}^{n_r},$$

that is, assign the whole vector to 0 and the j-th number to 1.

Update

The key part S^k of the memory is updated during training. The baseline module can produce a pair representation \mathbf{r} for classification, which is used as the semantic representation to update the key part S^k in the memory.

In each epoch of the training procedure, every instance in the training set will be input once. Then one representation for each instance is produced in one epoch. Supposing there is one presampled training instance, for example, the i-th instance, then the corresponding output pair representation \mathbf{r}_i will fill the i-th key slot \mathcal{S}_i^k of the memory. In each epoch, all the key slots \mathcal{S}^k of the memory are updated precisely once.

After the training procedure, the memorized information in memory is fixed and can be queried during testing. The memorized information is the correspondence between fine-tuned representations and discourse relations in the training set. Through updating, the representations can carry semantic information about discourse arguments and are better for value retrieval.

Query

In this stage, the relevant memorized information is retrieved and delivered to the classifier. For the query, each candidate in the memory is assigned to a relevance weight reflecting the semantic similarity with the query representation. Then the useful information in the memory is retrieved by taking their weighted sum using the relevance weights for the response, which reflects the discourse relations of the most similar instances.

Supposing that the pair representation to be classified is $\mathbf{r}_q \in \mathbb{R}^{d_r}$, which is also used for the query, and the representation key in memory slot \mathcal{S}_i^k is $\mathbf{r}_i \in \mathbb{R}^{d_r}$. The query can be seen as two steps.

The first step is to assign a coefficient to each candidate in the memory component respectively. During training, our model is kept evaluated on the whole training set. Supposing after one of the training epochs, the number of correctly predicted training instances for the j-th relation ($j = 1, \dots, n_r$) is m_j . For the i-th training instance, if it is mispredicted, then we assign the coefficient c_i with 0. Otherwise, if it is correctly predicted, and the relation of it is the j-th relation, then we assign $c_i = 1/m_j$. In other words, we only select out the correctly predicted instances and assign a coefficient to it to balance the result since the number of

different relations is not the same.

The second step is to calculate the relevance weight corresponding to \mathbf{r}_j ,

$$w_j = f(\mathbf{r}_q, \mathbf{r}_j), \tag{2}$$

where f is an attention function. The f can have different choices, such as dot product:

$$f(\mathbf{r}_q, \mathbf{r}_j) = \mathbf{r}_q^T \mathbf{r}_j; \tag{3}$$

biaffine attention (Dozat and Manning, 2017; Cai et al., 2018):

$$f(\mathbf{r}_q, \mathbf{r}_j) = \mathbf{r}_q^T \mathbf{U} \mathbf{r}_j + \mathbf{w}_1^T \mathbf{r}_q + \mathbf{w}_2^T \mathbf{r}_j + b, \quad (4)$$

where $\mathbf{U} \in \mathbb{R}^{d_r \times d_r}$, $\mathbf{w}_1, \mathbf{w}_2 \in \mathbb{R}^{d_r}$ and $b \in \mathbb{R}$ are parameters; or other attention methods. The advanced attention mechanism such as biaffine can learn more query patterns while dot product attention returns the most similar one according to cosine distance without training.

After that, these relevance weights are normalized with *softmax* and used for the response.

Response and Classification

Supposing the value in slot S_i^v is \mathbf{v}_i , which is the one-hot vector for discourse relation, then the final response vector will be

$$\mathbf{v} = \sum_{i=1}^{m} softmax(w_i)c_i \mathbf{v}_i \in \mathbb{R}^{n_r}, \quad (5)$$

where n_r is the number of discourse relations introduced before. Then this vector is sent to an MLP, and we modify the output of the relation classifier (Eq. 1) to

$$\mathbf{o}_r = softmax[(1 - \lambda) MLP_r(\mathbf{r}) + \lambda MLP_m(\mathbf{v})],$$

where λ is a hyperparameter and MLP_m is the MLP for memory response vector. This response contains the true label information and reflects the links between representations and relations.

Though \mathbf{r}_i $(i=1,\cdots,m)$ is used as the key in the memory component, it is also a semantic representation of the corresponding training instance. So we can still use it as another choice for memory response vector

$$\mathbf{v}' = \sum_{i=1}^{m} softmax(w_i)c_i \mathbf{r}_i \in \mathbb{R}^{d_r}, \quad (6)$$

then the output of the relation classifier will be

$$\mathbf{o}_r = softmax[(1 - \lambda) MLP_r(\mathbf{r}) + \lambda MLP_r(\mathbf{v}')],$$

here we use the MLP of relation classification for response vector. This response is the representation from training arguments, and since we use coefficient to filter the memory, so the classifier can correctly classify them. This response can also help the learning procedure of the classifier.

4 Experiments²

4.1 Dataset Settings

Recent works mainly use PDTB 2.0 as the benchmark dataset and we follow them. The adopted benchmark PDTB 2.0 has three levels of relations: Level-1 *Class*, Level-2 *Type*, and Level-3 *Subtypes*. The first level consists of four major relation Classes and the second level contains 16 Types. According to Ji and Eisenstein (2015), on the second level five relation types have no dev and test instances, thus they are removed, so there are 11 types in total. We conduct evaluations on two levels: 11-way classification on level 2 and 4-way classification on level 1.

We follow the dataset settings of the previous works. For the 11-way classification, we use two splitting methods: the first is PDTB-Lin's splitting (Lin et al., 2009), which uses section 2-21, 22 and 23 as training, dev and test sets respectively. the second is PDTB-Ji's splitting (Ji and Eisenstein, 2015), which uses section 2-20, 0-1, and 21-22 as training, dev and test sets respectively. For 4-way classifications, the splitting is the same as the PDTB-Ji's splitting in 11-way classification without eliminating instances.

During training, the instances with more than one annotated relation types are considered as multiple instances. At test time, a prediction matching one of the gold types is taken as the correct answer. All sentences in the dataset are padded or truncated to keep the uniform 100-word length.

4.2 Model Details

Most of the hyperparameter settings in our experiments are the same as the baseline model of Bai and Zhao (2018). For Lin's splitting, we change the layer number of classifiers to 2, the hidden dim of the classifiers to 2048, and the learning rate of it to 0.0012. We set $\lambda=0.3$ and the memory dropout to 0.2.

4.3 Results

Table 1 is the comparison on 11-way classification and Table 2 is the comparison on 4-way classification. Our memory method yields performance gain and achieves a new state-of-the-art performance in both 11-way and 4-way classification. For binary classification, three out of four results of our method are better than the baseline.

All the results are averaged from multiple runs. For Lin's splitting, the result is achieved with the dot product attention (Eq. 3) and the response from values (Eq. 5), and for Ji's splitting, the result is achieved with the biaffine attention (Eq. 4) and the response from keys (Eq. 6). For 4-way and binary classifications, the results are achieved with the biaffine attention (Eq. 4) and the response from keys (Eq. 6). The analyses about the choice of attention methods and responses are in the next subsection.

4.4 Analysis

We have conducted some analyses and ablation studies on our memory component to illustrate the effectiveness of our method. These experiments are conducted with the PTDB-Ji splitting on 11-way classification if not specified.

Time Consumption

The first analysis is about the training time of our method. We conduct a comparative experiment and find that even with the biaffine attention (which is more complex than the dot product attention), the consumed time of our new model is 7% more than the baseline model since the training set is relatively small. So the memory component only brings little impact on training time.

Key-part Strategy

Besides the updating strategy mentioned before, we also examine a fixed key scheme to show the advantage of our method, this scheme can only be used with the value response. In this scheme, we concatenate the pre-trained word2vec embeddings and ELMo to a 2348-dimension vector for each word. Then for each argument (Arg_1 and Arg_2), we average the word embeddings as its representation. Then the two representations are concatenated to the pair representation. This representation is memorized in the key part and fixed all the time. The query vector uses the same scheme as the keys. We use biaffine attention here.

 $^{^2} The \ code \ is \ available \ at \ https://github.com/hxbai/IDRR_mem$

Model	PDTB-Lin	PDTB-Ji
Lin et al. (2009)	40.20	-
Lin et al. (2009) + Brown clusters	-	40.66
Ji and Eisenstein (2015)	-	44.59
Qin et al. (2016a)	43.81	45.04
Qin et al. (2017)	44.65	46.23
Bai and Zhao (2018)	45.73	48.22
Ours	46.08	49.15

Table 1: Accuracy (%) for 11-way classification.

Model	Comp.	Cont.	Exp.	Temp.	4 -way (F_1)	4-way (Acc)
Rutherford and Xue (2015)	34.20	43.90	69.10	14.7	40.50	57.10
Zhang et al. (2015)	33.22	52.04	69.59	30.54	-	-
Ji and Eisenstein (2015)	35.93	52.78	-	27.63	-	-
Chen et al. (2016b)	40.17	54.76	-	31.32	-	-
Qin et al. (2016c)	41.55	57.32	71.50	35.43	-	-
Liu et al. (2016)	34.65	46.09	69.88	31.82	44.98	57.27
Liu and Li (2016)	39.86	54.48	70.43	38.84	46.29	57.57
Qin et al. (2017)	40.87	54.56	72.38	36.20	-	-
Lan et al. (2017)	40.73	58.96	72.47	38.50	47.80	57.39
Lei et al. (2018)	43.24	57.82	72.88	29.10	47.15	-
Dai and Huang (2018)	-	-	-	-	48.82	58.20
Bai and Zhao (2018)	47.85	54.47	70.60	36.87	51.06	-
Ours	47.15	55.24	70.82	38.20	52.19	60.69

Table 2: F_1 score (%) comparison on binary classification. F_1 score (%) and accuracy (%) comparison on 4-way classification. (Only single models are compared.)

For the query, we test two schemes. The first examines a fixed query representation, which is the same as the representations used in updating. The second applies the encoded representation \mathbf{r}_q which is introduced before, and we use a one layer MLP to make its dimension the same as the keys. Then such a setting receives much lower accuracy 47.83% and 48.32% respectively compared to our dynamic key results 49.09%, which indicates that the fixed representation fails to successfully extract features about discourse relations. The concatenated word embeddings and ELMo are indeed semantic representations, whereas they still lack effective informative clues on the connection between argument pairs, which even makes the performance worse. Contrarily, the dynamic keys and queries in our memory component can capture more salient relation features for better performance.

Coefficient

As introduced in Section 3.2, we assign each training instance in the memory component a coef-

ficient, which is used to select out the correctly predicted training instances and balance the instance number of different classes. For example, the numbers of instances of different classes in the training set of 4-way classification are 689, 3288, 1898, 6900 respectively, which are extremely unbalanced. Without a balancing control, the class with much more instances will have an overwhelming impact. The unbalancing issue also exists for 11-way classification.

Then, we try to fix the coefficient, that is, all the training instances can be queried during testing and the coefficient only works for balancing. The result of this experiment is 48.93%, which is lower than dynamic coefficient (49.15%), but higher than the baseline model (48.22%). It means that incorporating all the training instances in the memory component can bring useful information, but will have more noise than the memory filtered by the coefficient.

Attention and Response

Section 3.2 mentions two attention strategies and two response methods. Here we did several experiments for them in different settings. The results are in Table 3. Here we did not have results on combined key and value response (add the two types of responses as the final response) since its performance is similar to that only with the key response.

From the table, we can find the performance is heavily related to the dataset settings. The performance gain on Lin's splitting is smallest and the results with different settings on it are extremely unstable. With the key response, the performances are even drastically worse than the baseline. Except for Lin's splitting, the biaffine attention with key response can achieve the best performance.

As introduced before, Ji's splitting for 11-way classification and the splitting on 4-way classification are the same, which has a larger test set than Lin's splitting. Thus it is not surprising that a smaller test set makes the results on Lin's splitting insignificant and maybe hardly query from the memory component, or the queried information may be too noisy to promote the performance.

The choice of the combination method of the attention and the response needs to consider the dataset settings and the attention and the response can affect each other.

M - 1 - 1	11-	way	4-way		
Model	Lin	Ji	F_1	Acc.	
baseline	45.73	48.22	51.06	-	
D + K	40.86	48.63	50.51	59.66	
D + V	46.08	48.99	51.69	60.39	
B + K	38.47	49.15	52.19	60.69	
B + V	45.92	49.09	51.22	60.15	

Table 3: Comparison for attention and response methods on different settings. D denotes dot product attention, B denotes biaffine attention, K denotes use key response, and V denotes use value response.

Example

Table 4 shows an example for the queried instances. We find that the model pays attention to instances of relevant relations and the weight assigned to it is nearly 1, that is, the model focuses on exactly one instance in the memory. These retrieved instances indeed help the prediction of the test instance.

Test instance

Relation 1: Contingency.Cause **Relation 2:** Expansion.List

 \mathbf{Arg}_1 : The HUD budget has dropped by more

than 70% since 1980.

 Arg_2 : We've taken more than our fair share.

Queried training instance top 1

Relation: Contingency.Cause

Arg₁: At 11.1% of gross national product, U.S. health costs already are the highest in the world. By contrast, Japan's equal 6.7% of GNP, a nation's total output of goods and services.

Arg₂: Management and labor worry that the gap makes U.S. companies less competitive.

Table 4: A example for the queried training instances.

4.5 Discussion

The proposed memory component seems to work like the nearest neighbor method. However, the whole component is dynamically adjusted rather than the static data setting for the nearest neighbor method. The keys are updated with optimized pair representations. If the keys are fixed, the performance will be worse according to our empirical verification. Eq. 2 is differentiable, which means the loss can back-propagate through the memory component to facilitate the baseline model, and if f in Eq. 2 has parameters (such as the biaffine attention), they can also be tuned. In the meantime, it is not easy for the nearest neighbor method to design a dynamic distance function and a data update method, which are the right powerful designs in our propose memory mechanism according to our discussion in Section 4.4.

5 Conclusion

In this paper, we propose a novel memory component to enhance state-of-the-art implicit discourse relation recognition model. The augmented memory component can memorize useful salient knowledge about the pair representations and the discourse relations in the training set. This knowledge can benefit the prediction performance during the testing procedure. Our system can dynamically adjust so that query and response can be better during training. Our experiments show that putting the whole training set into the memory lets our model receive the most favorable results and achieves new state-of-the-art performance for the concerned challenging task.

References

- Hongxiao Bai and Hai Zhao. 2018. Deep enhanced representation for implicit discourse relation recognition. In *Proceedings of the 27th International Conference on Computational Linguistics (COL-ING)*, pages 571–583, Santa Fe, New Mexico, USA.
- Chloé Braud and Pascal Denis. 2015. Comparing word representations for implicit discourse relation classification. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2201–2211, Lisbon, Portugal.
- Jiaxun Cai, Shexia He, Zuchao Li, and Hai Zhao. 2018. A full end-to-end semantic role labeler, syntactic-agnostic over syntactic-aware? In Proceedings of the 27th International Conference on Computational Linguistics (COLING), pages 2753–2765, Santa Fe, New Mexico, USA.
- Jifan Chen, Qi Zhang, Pengfei Liu, and Xuanjing Huang. 2016a. Discourse relations detection via a mixed generative-discriminative framework. In *Proceedings of the thirtieth AAAI Conference on Artificial Intelligence (AAAI)*, pages 2921–2927, Phoenix, Arizona, USA.
- Jifan Chen, Qi Zhang, Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. 2016b. Implicit discourse relation detection via a deep architecture with gated relevance network. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 1: Long Papers)*, pages 1726–1735, Berlin, Germany.
- Zeyu Dai and Ruihong Huang. 2018. Improving implicit discourse relation classification by modeling inter-dependencies of discourse units in a paragraph. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT), Volume 1 (Long Papers), pages 141–151, New Orleans, Louisiana.
- Yann N. Dauphin, Angela Fan, Michael Auli, and David Grangier. 2016. Language modeling with gated convolutional networks. arXiv preprint arXiv:1612.08083.
- Timothy Dozat and Christopher D Manning. 2017. Deep biaffine attention for neural dependency parsing. In *Proceedings of the International Conference on Learning Representations (ICLR)*, Toulon, France.
- Shima Gerani, Yashar Mehdad, Giuseppe Carenini, Raymond T. Ng, and Bita Nejat. 2014. Abstractive summarization of product reviews using discourse structure. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1602–1613, Doha, Qatar.
- Fengyu Guo, Ruifang He, Di Jin, Jianwu Dang, Longbiao Wang, and Xiangang Li. 2018. Implicit discourse relation recognition using neural tensor net-

- work with interactive attention and sparse learning. In *Proceedings of the 27th International Conference on Computational Linguistics (COLING)*, pages 547–558, Santa Fe, New Mexico, USA.
- Peter Jansen, Mihai Surdeanu, and Peter Clark. 2014. Discourse complements lexical semantics for non-factoid answer reranking. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 977–986, Baltimore, Maryland.
- Yangfeng Ji and Jacob Eisenstein. 2015. One vector is not enough: Entity-augmented distributed semantics for discourse relations. *Transactions of the Association for Computational Linguistics (TACL)*, 3:329–344.
- Yangfeng Ji, Gholamreza Haffari, and Jacob Eisenstein. 2016. A latent variable recurrent neural network for discourse-driven language models. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT), pages 332–342, San Diego, California.
- Yudai Kishimoto, Yugo Murawaki, and Sadao Kurohashi. 2018. A knowledge-augmented neural network model for implicit discourse relation classification. In *Proceedings of the 27th International Conference on Computational Linguistics (COLING)*, pages 584–595, Santa Fe, New Mexico, USA.
- Man Lan, Jianxiang Wang, Yuanbin Wu, Zheng-Yu Niu, and Haifeng Wang. 2017. Multi-task attention-based neural networks for implicit discourse relationship representation and identification. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1299–1308, Copenhagen, Denmark.
- Wenqiang Lei, Xuancong Wang, Meichun Liu, Ilija Ilievski, Xiangan He, and Min-Yen Kan. 2017. SWIM: A simple word interaction model for implicit discourse relation recognition. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI)*, pages 4026–4032, Melbourne, Australia.
- Wenqiang Lei, Yuanxin Xiang, Yuwei Wang, Qian Zhong, Meichun Liu, and Min-Yen Kan. 2018. Linguistic properties matter for implicit discourse relation recognition: Combining semantic interaction, topic continuity and attribution. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence (AAAI)*, pages 4848–4855, New Orleans, USA.
- Ziheng Lin, Min-Yen Kan, and Hwee Tou Ng. 2009. Recognizing implicit discourse relations in the Penn Discourse Treebank. In *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 343–351, Singapore.

- Yang Liu and Sujian Li. 2016. Recognizing implicit discourse relations via repeated reading: Neural networks with multi-level attention. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1224–1233, Austin, Texas.
- Yang Liu, Sujian Li, Xiaodong Zhang, and Zhifang Sui. 2016. Implicit discourse relation classification via multi-task neural networks. In *Proceedings of the thirtieth AAAI Conference on Artificial Intelligence (AAAI)*, pages 2750–2756, Phoenix, Arizona, USA.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information Processing Systems (NIPS)* 26, pages 3111–3119.
- Alexander Miller, Adam Fisch, Jesse Dodge, Amir-Hossein Karimi, Antoine Bordes, and Jason Weston. 2016. Key-value memory networks for directly reading documents. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1400–1409, Austin, Texas.
- Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT), Volume 1 (Long Papers)*, pages 2227–2237, New Orleans, Louisiana.
- Emily Pitler, Annie Louis, and Ani Nenkova. 2009. Automatic sense prediction for implicit discourse relations in text. In *Proceedings of the Joint Conference of the 47th Annual Meeting of he Association for Computational Linguistics and the 4th International Joint Conference on Natural Language Processing (ACL-IJCNLP)*, pages 683–691, Suntec, Singapore.
- Rashmi Prasad, Nikhil Dinesh, Alan Lee, Eleni Miltsakaki, Livio Robaldo, Aravind K Joshi, and Bonnie L Webber. 2008. The Penn Discourse Tree-Bank 2.0. In *Proceedings of the Sixth conference on International Language Resources and Evaluation (LREC-2008)*, pages 2961–2968, Marrakech, Morocco.
- Lianhui Qin, Zhisong Zhang, and Hai Zhao. 2016a. Implicit discourse relation recognition with context-aware character-enhanced embeddings. In *Proceedings of the 26th International Conference on Computational Linguistics (COLING): Technical Papers*, pages 1914–1924, Osaka, Japan.
- Lianhui Qin, Zhisong Zhang, and Hai Zhao. 2016b. Shallow discourse parsing using convolutional neural network. In *Proceedings of the CoNLL-16 shared task*, pages 70–77, Berlin, Germany.

- Lianhui Qin, Zhisong Zhang, and Hai Zhao. 2016c. A stacking gated neural architecture for implicit discourse relation classification. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2263–2270, Austin, Texas.
- Lianhui Qin, Zhisong Zhang, Hai Zhao, Zhiting Hu, and Eric Xing. 2017. Adversarial connective-exploiting networks for implicit discourse relation classification. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 1: Long Papers)*, pages 1006–1017, Vancouver, Canada.
- Samuel Rönnqvist, Niko Schenk, and Christian Chiarcos. 2017. A recurrent neural model with attention for the recognition of Chinese implicit discourse relations. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 2: Short Papers)*, pages 256–262, Vancouver, Canada.
- Attapol Rutherford, Vera Demberg, and Nianwen Xue. 2017. A systematic study of neural discourse models for implicit discourse relation. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL): Volume 1, Long Papers*, pages 281–291, Valencia, Spain.
- Attapol Rutherford and Nianwen Xue. 2015. Improving the inference of implicit discourse relations via classifying explicit discourse connectives. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT), pages 799–808, Denver, Colorado.
- Niko Schenk, Christian Chiarcos, Kathrin Donandt, Samuel Rönnqvist, Evgeny Stepanov, and Giuseppe Riccardi. 2016. Do we really need all those rich linguistic features? a neural network-based approach to implicit sense labeling. In *Proceedings of the CoNLL-16 shared task*, pages 41–49, Berlin, Germany.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany.
- Rupesh Kumar Srivastava, Klaus Greff, and Jürgen Schmidhuber. 2015. Training very deep networks. *arXiv preprint arXiv:1507.06228*.
- Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, and Rob Fergus. 2015. End-to-end memory networks. In *Advances in Neural Information Processing Systems (NIPS)* 28, pages 2440–2448. Montreal, Canada.

- Jason Weston, Sumit Chopra, and Antoine Bordes. 2015. Memory networks. In *Proceedings of the International Conference on Learning Representations (ICLR)*, San Diego, CA.
- Yang Xu, Yu Hong, Huibin Ruan, Jianmin Yao, Min Zhang, and Guodong Zhou. 2018. Using active learning to expand training data for implicit discourse relation recognition. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 725–731, Brussels, Belgium.
- Nianwen Xue, Hwee Tou Ng, Sameer Pradhan, Rashmi Prasad, Christopher Bryant, and Attapol Rutherford. 2015. The CoNLL-2015 shared task on shallow discourse parsing. In *Proceedings of the Nineteenth Conference on Computational Natural Language Learning (CoNLL) Shared Task*, pages 1–16, Beijing, China.
- Nianwen Xue, Hwee Tou Ng, Sameer Pradhan, Attapol Rutherford, Bonnie Webber, Chuan Wang, and Hongmin Wang. 2016. CoNLL 2016 shared task on multilingual shallow discourse parsing. In *Proceedings of the CoNLL-16 shared task*, pages 1–19, Berlin, Germany.
- Biao Zhang, Jinsong Su, Deyi Xiong, Yaojie Lu, Hong Duan, and Junfeng Yao. 2015. Shallow convolutional neural network for implicit discourse relation recognition. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2230–2235, Lisbon, Portugal.
- Zhi-Min Zhou, Yu Xu, Zheng-Yu Niu, Man Lan, Jian Su, and Chew Lim Tan. 2010. Predicting discourse connectives for implicit discourse relation recognition. In *Proceedings of the 23rd International Conference on Computational Linguistics (COLING)*, pages 1507–1514, Beijing, China.