Exploiting Contextual Information via Dynamic Memory Network for Event Detection

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Abstract

The task of event detection involves identifying and categorizing event triggers. Contextual information has been shown effective on the task. However, existing methods which utilize contextual information only process the context once. We argue that the context can be better exploited by processing the context multiple times, allowing the model to perform complex reasoning and to generate better context representation, thus improving the overall performance. Meanwhile, dynamic memory network (DMN) has demonstrated promising capability in capturing contextual information and has been applied successfully to various tasks. In light of the multi-hop mechanism of the DMN to model the context, we propose the trigger detection dynamic memory network (TD-DMN) to tackle the event detection problem. We performed a five-fold cross-validation on the ACE-2005 dataset and experimental results show that the multi-hop mechanism does improve the performance and the proposed model achieves best $F_1$ score compared to the state-of-the-art methods.

1 Introduction

According to ACE (Automatic Content Extraction) event extraction program, an event is identified by a word or a phrase called event trigger which most represents that event. For example, in the sentence “No major explosion we are aware of”, an event trigger detection model is able to identify the word “explosion” as the event trigger word and further categorize it as an Attack event. The ACE-2005 dataset also includes annotations for event arguments, which are a set of words or phrases that describe the event. However, in this work, we do not tackle the event argument classification and focus on event trigger detection.

The difficulty of the event trigger detection task lies in the complicated interaction between the event trigger candidate and its context. For instance, given a sentence at the end of a passage:

they are going over there to do a mission they believe in and as we said, 250 left yesterday.

It’s hard to directly classify the trigger word “left” as an “End-Position” event or a “Transport” event because we are not certain about what the number “250” and the pronoun “they” are referring to. But if we see the sentence:

we are seeing these soldiers head out.

which is several sentences away from the former one, we now know the “250” and “they” refer to “the soldiers”, and from the clue “these soldiers head out” we are more confident to classify the trigger word “left” as the “Transport” event.

From the above, we can see that the event trigger detection task involves complex reasoning across the given context. Existing methods (Liu et al., 2017; Chen et al., 2015; Li et al., 2013; Nguyen et al., 2016; Venugopal et al., 2014) mainly exploited sentence-level features and (Liao and Grishman, 2010; Zhao et al., 2018) proposed document-level models to utilize the context.

The methods mentioned above either not directly utilize the context or only process the context once while classifying an event trigger candidate. We argue that processing the context multiple times with later steps re-evaluating the context with information acquired from the previous steps improves the model performance. Such a mechanism allows the model to perform complicated reasoning across the context. As in the example, we are more confident to classify “left” as a “Transport” event if we know “250” and “they” refer to “soldiers” in previous steps.

We utilize the dynamic memory network (DMN) (Xiong et al., 2016; Kumar et al., 2016) to capture the contextual information of the given trigger word. It contains four modules: the input module for encoding reference text where the an-
2.1 Input Module

The input module further contains two layers: the sentence encoder layer and the fusion layer. The sentence encoder layer encodes each sentence into a vector independently, while the fusion layer gives these encoded vectors a chance to exchange information between sentences.

Sentence encoder layer Given document \( d \) with \( l \) sentences \( (s_1, \ldots, s_l) \), let \( s_i \) denotes the \( i \)-th sentence in \( d \) with \( n \) words \( (w_{i1}, \ldots, w_{in}) \). For the \( j \)-th word \( w_{ij} \) in \( s_i \), we concatenate its word embedding \( w_{ij} \) with its entity type embedding\(^2\) \( e_{ij} \) to form the vector \( W_{ij} \) as the input to the sentence encoder Bi-GRU(Cho et al., 2014) of size \( H_s \). We obtain the hidden state \( h_{ij} \) by merging the forward and backward hidden states from the Bi-GRU:

\[
    h_{ij} = \text{GRU}_s(W_{ij}) + \text{GRU}_s(W_{ij})^{-1}
\]

where + denotes element-wise addition.

We feed \( h_{ij} \) into a two-layer perceptron to generate the unnormalized attention scalar \( u_{ij} \):

\[
    u_{ij} = \tanh(h_{ij} \cdot W_{s1}) \cdot W_{s2}
\]

where \( W_{s1} \) and \( W_{s2} \) are weight parameters of the perceptron and we omitted bias terms. \( u_{ij} \) is then normalized to obtain scalar attention weight \( \alpha_{ij} \):

\[
    \alpha_{ij} = \frac{\exp(u_{ij})}{\sum_{k=1}^{n} \exp(u_{ik})}
\]

The sentence representation \( s_i \) is obtained by:

\[
    s_i = \sum_{j=1}^{n} \alpha_{ij} h_{ij}
\]

Fusion layer The fusion layer processes the encoded sentences and outputs fact vectors which contain exchanged information among sentences. Let \( s_i \) denotes the \( i \)-th sentence representation obtained from the sentence encoder layer. We generate fact vector \( f_i \) by merging the forward and backward states from fusion GRU:

\[
    f_i = \text{GRU}_f(s_i) + \text{GRU}_f(s_i)^{-1}
\]

Let \( H_f \) denotes the hidden size of the fusion GRU, we concatenate fact vectors \( f_1 \) to \( f_l \) to obtain the matrix \( F \) of size \( l \) by \( H_f \), where the \( i \)-th row in \( F \) stores the \( i \)-th fact vector \( f_i \).

\(^2\)The ACE-2005 includes entity type (including type “NA” for none-entity) annotations for each word, the entity type embedding is a vector associated with each entity type.
The memory module has three components: the attention gate, the attentional GRU (Xiong et al., 2016) and the memory update gate. The attention gate determines how much the memory module should attend to each fact given the facts $F$, the question $q^*$, and the acquired knowledge stored in the memory vector $m_{t-1}$ from the previous step.

The three inputs are transformed by:

$$u = [F \ast q^*; |F - q^*|; F \ast m_{t-1}; |F - m_{t-1}|]$$ \hspace{1cm} (8)

where $\ast$ is concatenation, $\cdot$, $-$ and $|$ are element-wise product, subtraction and absolute value respectively. $F$ is a matrix of size $(m, H_f)$, while $q^*$ and $m_{t-1}$ are vectors of size $(1, H_q)$ and $(1, H_m)$, where $H_m$ is the output size of the memory update gate. To allow element-wise operation, $H_f, H_q$ and $H_m$ are set to a same value $H$. Meanwhile, $q^*$ and $m_{t-1}$ are broadcasted to the size of $(m, H)$.

In equation 8, the first two terms measure the similarity and difference between facts and the question. The last two terms have the same functionality for facts and the last memory state.

Let $\beta$ of size $l$ denotes the generated attention vector. The $i$-th element in $\beta$ is the attention weight for fact $f_i$. $\beta$ is obtained by transforming $u$ using a two-layer perceptron:

$$\beta = \text{softmax}(\tanh(u \cdot W_{m_1}) \cdot W_{m_2})$$ \hspace{1cm} (9)
Table 1: 5-fold cross-validation results on the ACE-2005 dataset. The results are rounded to a single digit. The \( F_1 \) of the last column are calculated by averaging \( F_1 \) scores of all folds.

| Methods       | Fold 1   | Fold 2   | Fold 3   | Fold 4   | Fold 5   | Avg      |
|---------------|----------|----------|----------|----------|----------|----------|
|               | \( P \) | \( R \) | \( F_1 \) | \( P \) | \( R \) | \( F_1 \) | \( P \) | \( R \) | \( F_1 \) | \( P \) | \( R \) | \( F_1 \) |
| DMCNN         | 67.6     | 60.5     | 63.9     | 62.6     | 63.1     | 62.9     | 68.9     | 62.1     | 65.3     | 68.9     | 63.0     | 66.9     | 66.0     | 65.5     | 65.8     | 64.9     |
| DEEB-RNN      | 64.9     | 64.1     | 64.5     | 63.4     | 64.7     | 64.0     | 66.1     | 64.3     | 65.2     | 66.0     | 67.3     | 66.6     | 65.5     | 67.2     | 66.3     | 65.3     |
| TD-DMN 1-hop  | 67.3     | 62.1     | 64.6     | 65.4     | 61.7     | 63.5     | 72.0     | 60.0     | 65.4     | 66.6     | 68.0     | 67.3     | 68.3     | 65.0     | 66.6     | 65.5     |
| TD-DMN 2-hop  | 69.2     | 61.0     | 64.8     | 64.6     | 63.4     | 64.0     | 64.3     | 66.4     | 65.3     | 68.7     | 65.9     | 67.3     | 68.5     | 65.7     | 67.1     | 65.7     |
| TD-DMN 3-hop  | 66.3     | 63.7     | 64.9     | 66.9     | 60.6     | 63.6     | 68.3     | 64.0     | 66.1     | 67.9     | 66.3     | 67.1     | 70.2     | 64.3     | 67.1     | 65.8     |
| TD-DMN 4-hop  | 66.7     | 63.4     | 65.0     | 61.4     | 65.5     | 63.4     | 66.4     | 66.0     | 66.2     | 64.7     | 69.1     | 66.8     | 70.0     | 63.4     | 66.5     | 65.6     |

where \( W_{m1} \) and \( W_{m2} \) are parameters of the percep-ron and we omitted bias terms.

The attentional GRU takes facts \( F \), fact attention \( \beta \) as input and produces context vector \( c \) of size \( H_c \). At each time step \( t \), the attentional GRU picks the \( f_t \) as input and uses \( \beta_t \) as its update gate weight. For space limitation, we refer reader to (Xiong et al., 2016) for the detailed computation.

The memory update gate outputs the updated memory \( m_t \) using question \( q^* \), previous memory state \( m_{t-1} \) and context \( c \):

\[
m_t = \text{relu}([q^*; m_{t-1}; c] \cdot W_a) \tag{10}
\]

where \( W_a \) is the parameter of the linear layer.

The memory module could be iterated several times with a new \( \beta \) generated for each time. This allows the model to attend to different parts of the facts in different iterations, which enables the model to perform complicated reasoning across sentences. The memory module produces \( m_t \) as the output at the last iteration.

### 2.4 Answer Module

Answer module predicts the event type for each word in a sentence. For each question GRU hidden state \( q_{ij} \), the answer module concatenates it with the memory vector \( m_t \) as the input to the answer GRU with hidden size \( H_a \). The answer GRU outputs \( a_{ij} \) by merging its forward and backward hidden states. The fully connected dense layer then transforms \( a_{ij} \) to the size of the number of event labels \( O \) and the softmax layer is applied to output the probability vector \( p_{ij} \). The \( k \)-th element in \( p_{ij} \) is the probability for the word \( w_{ij} \) being the \( k \)-th event type. Let \( y_{ij} \) be the true event type label for word \( w_{ij} \). Assuming all sentences are padded to the same length \( n \), the cross-entropy loss for the single document \( d \) is applied as:

\[
J(y, p) = - \sum_{i=1}^{l} \sum_{j=1}^{n} \sum_{k=1}^{O} I(y_{ij} = k) \log p_{ij}^{(k)} \tag{11}
\]

where \( I(\cdot) \) is the indicator function.

### 3 Experiments

#### 3.1 Dataset and Experimental Setup

**Dataset**

Different from prior work, we performed a 5-fold cross-validation on the ACE 2005 dataset. We partitioned 599 files into 5 parts. The file names of each fold can be found online\(^3\). We chose a different fold each time as the testing set and used the remaining four folds as the training set.

**Baselines**

We compared our model with two other models: DMCNN (Chen et al., 2015) and DEEB-RNN (Zhao et al., 2018). DMCNN is a sentence-level event detection model which enhances traditional convolutional networks with dynamic multiple pooling mechanism customized for the task. The DEEB-RNN is a state-of-the-art document-level event detection model which firstly generate a document embedding and then use it to aid the event detection task.

**Evaluation**

We report precision, recall and \( F_1 \) score of each fold along with the averaged \( F_1 \) score of all folds. We evaluated all the candidate trigger words in each testing set. A candidate trigger word is correctly classified if its event subtype and offsets match its human annotated label.

**Implementation Details**

To avoid overfitting, we fixed the word embedding and added a 1 by 1 convolution after the embedding layer to serve as a way of fine tuning but with a much smaller number of parameters. We removed punctuations, stop words and sentences which have length less equal than 2. We used the Stanford corenlp toolkit (Manning et al., 2014) to

\(^3\)https://github.com/AveryLiu/TD-DMN/data/splits
separate sentences. We down-sampled negative samples to ease the unbalanced classes problem.

The setting of the hyperparameters is the same for different hops of the TD-DMN model. We set $H$, $H_s$, $H_c$, and $H_a$ to 300, the entity type embedding size to 50, $W_{s1}$ to 300 by 600, $W_{s2}$ to 600 by 1, $W_{m1}$ to 1200 by 600, $W_{m2}$ to 600 by 1, $W_q$ to 900 by 300, the batch size to 10. We set the down-sampling ratio to 9.5 and we used Adam optimizer (Kingma and Ba, 2014) with weight decay set to $1e^{-5}$. We set the dropout rate before the answer GRU to 0.4 and we set all other dropout rates to 0.2. We used the pre-trained word embedding from (Le and Mikolov, 2014).

| Methods          | $F_1$ | $F_1^*$ |
|------------------|-------|---------|
| TD-DMN 1-hop     | 65.48 | 65.52   |
| TD-DMN 2-hop     | 65.69 | 65.46   |
| TD-DMN 3-hop     | 65.78 | 65.51   |
| TD-DMN 4-hop     | 65.57 | 65.40   |

Table 2: The impact of the question module, $F_1^*$ indicates results with empty questions.

We still observe the increase and drop pattern of the $F_1$ for the untouched model. However, such a pattern is not obvious with empty questions. This implies that we are unable to have a steady gain without the question module in this specific task.

4. Future Work

In this work, we explored the TD-DMN architecture to exploit document context. Extending the model to include wider contexts across several similar documents may also be of interest. The detected event trigger information can be incorporated into question module when extending the TD-DMN to the argument classification problem. Other tasks with document context but without explicit questions may also benefit from this work.

5. Conclusion

In this paper, we proposed the TD-DMN model which utilizes the multi-hop mechanism of the dynamic memory network to better capture the contextual information for the event trigger detection task. We cast the event trigger detection as a question answering problem. We carried five-fold cross-validation experiments on the ACE-2005 dataset and results show that such multi-hop mechanism does improve the model performance and we achieved the best $F_1$ score compared to the state-of-the-art models.

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