Event Detection with Relation-Aware Graph Convolutional Networks

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Abstract

Event detection (ED), a key subtask of information extraction, aims to recognize instances of specific types of events in text. Recently, graph convolutional networks (GCNs) over dependency trees have been widely used to capture syntactic structure information and get convincing performances in event detection. However, these works ignore the syntactic relation labels on the tree, which convey rich and useful linguistic knowledge for event detection. In this paper, we investigate a novel architecture named Relation-Aware GCN (RA-GCN), which efficiently exploits syntactic relation labels and models the relation between words specifically. We first propose a relation-aware aggregation module to produce expressive word representation by aggregating syntactically connected words through specific relation. Furthermore, a context-aware relation update module is designed to explicitly update the relation representation between words, and these two modules work in the mutual promotion way. Experimental results on the ACE2005 dataset show that our model achieves a new state-of-the-art performance for event detection.

1 Introduction

Event Detection (ED), a key subtask of information extraction, aims to detect event of specific type from given text. Specifically, each event in a sentence is marked by a word or phrase called "event trigger", which expresses the occurence of an event. The task of event detection is to detect event triggers in a sentence and classify them into the corresponding event types. Taking Figure 1 as an example, ED is supposed to recognize the event trigger "visited" and classify it to the event type "Meet".

Syntactic dependency, which expresses interdependence relationship between words in a sentence, is capable of providing key information for event detection. Syntactic dependency includes syntactic structure information, which indicates syntactic connection between two words, and syntactic dependency relation which depicts the specific type of syntactic relation between two words. Figure 1 is an example of syntactic dependency parsing and we can see that syntactic dependency structure is often represented as tree structure. As shown in Figure 1, the words "Putin", "visited" and "Bush" connected by syntactic structure constitute an event, which means that syntactic structure can help to provide key evidence for event detection. Furthermore, we think that the syntactic dependency relations of one word are the significant indicators to decide whether the word is a trigger or not. For example in Figure 1, "nsubj", "dobj" and "nmod" are all trigger-related syntactic relations. Specifically, "nsubj" and "dobj" show that "Putin" and "Bush" are the subject and object of "visited" respectively, words connected by "nmod" expresses when and where the event happened. This implies that the word "visited" is more likely to be the trigger of an event. Additionally, according to our statistics on the benchmark ACE2005 dataset, "nsubj", "dobj" and "nmod" take up 25% of trigger-related syntactic relations (2.5% on average). Therefore, it is important to consider syntactic dependency structure and relation label simultaneously for ED.

Recently, Graph Convolutional Networks (GCN) based models (Nguyen and Grishman, 2018; Liu et al., 2018; Yan et al., 2019) have been proposed to introduce syntactic dependency structure to improve the performance of event detection. These models outperform previous sequence-based models (Chen et al., 2015; Nguyen et al., 2016; Liu et al., 2017; Chen et al., 2018) without using syntactic structure

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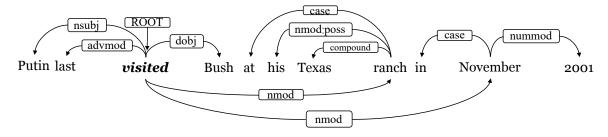


Figure 1: An example of syntactic dependency parsing. The sentence contains an event of "Meet" triggered by "visited".

information. However, these GCN-based models ignore specific syntactic dependency relation labels. In order to introduce relation labels into GCN, one intuitive approach is to encode different types of syntactic relation with different relation-specific convolutional filters. However, two technical challenges exist in the approach. The first challenge is parameter explosion, since the number of parameters grow rapidly with the number of relation types. Given the size of dataset for event detection is just moderate, models with large amounts of parameters are easy to overfit, which is the reason why existing GCN-based methods for ED (Nguyen and Grishman, 2018; Liu et al., 2018; Yan et al., 2019) ignore specific syntactic relation label. The second challenge is context-free representation of relation. Since syntactic relation label is encoded in the form of relation-specific convolutional filter parameters, each relation label keeps the same representation across all graphs. Actually, the same relation under different contexts convey different information. For example in Figure 1, "nmod" connected with "ranch" conveys where the event happens but "nmod" connected with "November" conveys when the event happens. Preferably, each relation between different word pairs should have context-aware representation, so that different clues for event detection can be expressed.

In this paper, we propose a model named Relation-Aware Graph Convolutional Network (RA-GCN) to overcome above challenges simultaneously. To model the relation between words without parameter explosion, we construct a relation-aware adjacency tensor by extending the element of traditional adjacency matrix to be a vector, which is representation of corresponding relation. Specifically, the element of tensor is initialized as syntactic relation label embedding. Since each type of syntactic relation is distinguished by the label embedding rather than GCN filter, the amount of parameters can be reduced. In this way, a relation-aware aggregation module is designed to aggregate syntactically connected words through specific relation label. Besides, a context-aware relation update module is designed to update relation representation with context semantic information, so that each relation between words holds a context-aware representation of its own. These two modules update word and relation representation respectively, and they work in a mutual promotion way.

To summary, our contributions are as follows.

- We propose RA-GCN for ED, which can introduce specific syntactic relation into GCN and is the first study to exploit syntactic dependency structure and relation label in GCN simultaneously.
- We design a relation-aware aggregation module to aggregate syntactically connected words through specific relation label and design a context-aware relation update module to update relation representation specifically.
- We conduct extensive experiments on a standard ED dataset ACE2005 and experiments show that RA-GCN achieves a new state-of-the-art. Qualitative analysis is conducted to understand how our model works.

2 Related Works

Early methods (Ji and Grishman, 2008; Hong et al., 2011; Li et al., 2013) used elaborately designed lexical and syntactic features to finish event detection as a classification problem, which are called features-based models. These approaches rely on discriminative features to train the model, thus feature designing

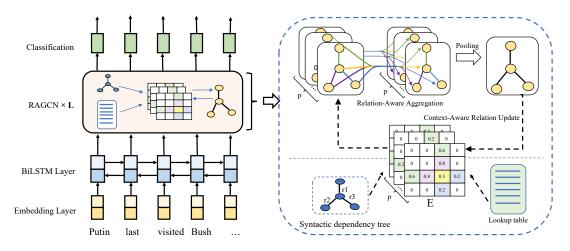


Figure 2: Model architecture shown with example "Putin last visited Bush at his Taxes ranch in November 2001", where words after "Bush" is omitted. In RA-GCN, relation-aware adjacency tensor $\mathbf{E} \in \mathbb{R}^{n \times n \times p}$ is initialized according to syntactic dependency parsing. Relation-aware aggregation module is to produce word representation by aggregating syntactically connected words through specific relation and context-aware relation update module is to update the relation representation in \mathbf{E} .

strategy can influence the performance of model.

Recent studies have shown that neural network based ED models outperform previous feature-based models. (Chen et al., 2015) proposed Convolutional Neural Network (CNN) to capture sentence clues without designing complicated features. (Nguyen et al., 2016) introduced Recurrent Neural Network (RNN) to capture sequential contextual information of each word to perform ED task. (Liu et al., 2017) exploited event argument information through supervised attention to improve the detection of triggers. (Chen et al., 2018) investigated gated multi-level attention and hierarchical tagging to detect multiple events in one sentence simultaneously.

Sequence-based neural network models mentioned above does not take syntactic dependency information into consideration, which can provide important clues for event detection. Consequently, (Sha et al., 2018) added a novel dependency bridge to BiLSTM, which can help to exploit syntactic tree structure and sequence structure simultaneously. With the rise of GCN (Kipf and Welling, 2017), syntactic structure information can be introduced by constructing graph of sentence according to syntactic connectivity between words. GCN can make good use of syntactic structure between words in sentence, which has been proved effectively for event detection. (Nguyen and Grishman, 2018) investigated GCN on syntactic dependency trees and adopted a novel pooling method to detect event triggers. (Liu et al., 2018) introduced syntactic shortcut arcs to enhance information flow and attention-based GCN to perform event detection. (Yan et al., 2019) proposed a dependency tree based GCN model with aggregative attention to combine multi-order word representation from different GCN layers. However, these GCN-based models ignore the specific syntactic relation label due to the limitation of parameter capacity. In this paper, we propose a model which exploits syntactic relation label effectively, so that the performance can be improved.

3 Methods

In this section, we will describe the preliminary and detail of our method. Figure 2 shows the overall architecture of our proposed model.

3.1 Preliminary

Graph Convolutional Networks GCN (Kipf and Welling, 2017), which can be operated to encode graphs, is an extension of convolutional neural network. Normally, a graph with n nodes can be represented by an adjacency matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$, where $\mathbf{A}_{ij} = 1$ if an edge exists between $\operatorname{node}_{i_{th}}$ and $\operatorname{node}_{j_{th}}$, otherwise 0. Graph convolution operation aims to gather information from neighbor nodes in the graph,

and the operation in l_{th} GCN layer can be formulated as follows:

$$\mathbf{H}^{l} = GCN(\mathbf{A}, \mathbf{H}^{l-1}, \mathbf{W})$$

$$= \sigma(\mathbf{A}\mathbf{H}^{l-1}\mathbf{W})$$
(1)

where $\mathbf{A} \in \mathbb{R}^{n \times n}$ is an adjacency matrix expressing connectivity between nodes, $\mathbf{H}^{l-1} \in \mathbb{R}^{n \times d}$ is the input node representations where n means the number of nodes and d means the input dimension of node representation, $\mathbf{W} \in \mathbb{R}^{d \times h}$ is a learnable convolutional filter where h means hidden dimension of GCN node representation, σ is a activation function chosen as ReLU.

Task Description Event detection aims to locate and classify the word or phrase, which expresses the occurence of an event, into the corresponding event type. The word or phrase is also called **Event Trigger**. Following existing works, we formulate event detection as a sequence labeling task. Each word in a sentence is annotated with a tag by "BIO" schema, which includes "O", "B-EventType" and "I-EventType". Tag "O" means that the corresponing word does not trigger any event and "EventType" means a specific type of event, where "B-EventType" means the word is the begining token of an event trigger and "I-EventType" means the inside token of an event trigger. "BIO" schema is proposed because there exist triggers which contain several words, such as "take off". Therefore, the total number of tags is $2 \times N_{EventType} + 1$, where $N_{EventType}$ is the number of predefined event types and "+1" means "O".

3.2 Embedding Layer

Embedding layer aims to transform each word to a real-valued embedding vector, which contains semantic information and entity type information of the word.

Word embedding is able to capture meaningful semantic information. Following previous works (Chen et al., 2015; Liu et al., 2017; Chen et al., 2018; Yan et al., 2019), we use the pretrained word embeddings by Skip-gram model on NYT Corpus.

Entities in the sentences are annotated with BIO schema and we transform each entity type label to a real-valued embedding by looking up an entity-type lookup table.

Each word w_i is represented as the concatation of its word embedding \mathbf{w}_i and entity type embedding \mathbf{e}_i , namely that the input embedding of w_i is $\mathbf{x}_i = [\mathbf{w}_i; \mathbf{e}_i] \in \mathbb{R}^{d_w + d_e}$, where d_w and d_e denote the dimension of word embedding and entity type embedding respectively.

3.3 BiLSTM Layer

BiLSTM layer is exploited to capture the contextual information for each word. The operation of an LSTM unit can be formulated as

$$\mathbf{h}_i = [\overrightarrow{\text{LSTM}}(\mathbf{x}_i); \overleftarrow{\text{LSTM}}(\mathbf{x}_i)], i \in [1, n]$$
(2)

where LSTM(\mathbf{x}_i) means the operation of LSTM cell on word input embedding \mathbf{x}_i , $\mathbf{h}_i \in \mathbb{R}^{2 \times d_h}$ and d_h means the hidden dimension of LSTM cell. BiLSTM operates LSTM from forward and backward directions, which can capture past and future sequential contextual information of a word at each time step. The output of BiLSTM layer is concatation of bi-directional representation, which is used as initial input word representation for RA-GCN Layer.

3.4 Relation-Aware GCN

To introduce syntactic structure information, previous GCN-based event detection methods transform each sentence to a graph according to syntactic dependency parsing. Each word in the sentence is regarded as a node of graph and an adjacency matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ of boolean type is constructed for the sentence to represent syntactic connectivity between words, where n means the number of words in the sentence, $\mathbf{A}_{ij}=1$ if an syntactic relation exist between word i_{th} and word i_{th} , otherwise 0. Syntactic relation is not distinguished from each other in \mathbf{A} .

To model the relation between words, we extend the element of adjacency matrix to be a multidimensional vector. Accordingly, a relation-aware adjacency tensor $\mathbf{E} \in \mathbb{R}^{n \times n \times p}$ is constructed, the element of which is relation representation vector of dimension p and p can also be understood as channels of E. The relation-aware adjacency tensor is initialized according to syntactic relation between words and a lookup table is introduced to transform each type of syntactic relation label into a real-valued embedding. If an syntactic relation exists between word_{i_{th}} and word_{j_{th}}, E_{ij*} is initialized as the corresponding p-dimensional embedding obtained from the lookup table, otherwise a zero vector of dimension p. Following previous works (Marcheggiani and Titov, 2017; Zhang et al., 2018; Guo et al., 2019), we construct graph of sentence undirectly, where E_{ji*} and E_{ij*} are initialized as the same syntactic relation embedding so that opposite relation can be included. For ROOT word in dependency tree, we add a self loop to itself with a special relation ROOT.

RA-GCN aims to produce expressive representation for each word. Each layer of RA-GCN contains two parts, relation-aware aggregation module and context-aware relation update module, which work in the mutual promotion way. Two modules of RA-GCN are described as follows.

3.4.1 Relation-Aware Aggregation Module

Relation-aware aggregation module is to produce representation for each word by aggregating syntactically connected words through relation-aware adjacency tensor **E**. Each element of **E** denotes relation representation between words, thus relation information can be embedded during aggregating. Each dimension of relation representation is regarded as a channel of the tensor **E** and RA-GCN aggregates words from different channels respectively. Relation-aware aggregation operation is defined as follows:

$$\begin{split} \mathbf{H}^{l} &= \operatorname{RAGCN}(\mathbf{E}^{l-1}, \mathbf{H}^{l-1}, \mathbf{W}) \\ &= \sigma(\operatorname{Pooling}(\mathbf{E}_{**1}^{l-1} \mathbf{H}^{l-1} \mathbf{W}, \mathbf{E}_{**2}^{l-1} \mathbf{H}^{l-1} \mathbf{W}, \\ &\dots, \mathbf{E}_{**p}^{l-1} \mathbf{H}^{l-1} \mathbf{W})) \end{split} \tag{3}$$

where $\mathbf{E}^{l-1} \in \mathbb{R}^{n \times n \times p}$ is relation-aware adjacency tensor from initialization or last RA-GCN layer, $\mathbf{E}^{l-1}_{**i} \in \mathbb{R}^{n \times n}$ is i_{th} channel slice of \mathbf{E}^{l-1} and n is the number of words in the sentence; $\mathbf{H}^{l-1} \in \mathbb{R}^{n \times d}$ is input word representation, where d means the input dimension of words; $\mathbf{W} \in \mathbb{R}^{d \times h}$ is a learnable filter and h is hidden dimension of RA-GCN, σ means activation function ReLU. Average pooling is exploited because it can cover information from all channels.

3.4.2 Context-Aware Relation Update Module

To produce context-aware relation representation, we use adjacency word representations to update relation representation in adjacency tensor. The operation is defined as follows:

$$\mathbf{E}_{ij*}^{l} = \mathbf{W}_{\mathbf{u}}[\mathbf{E}_{ij*}^{l-1} \oplus \mathbf{h}_{i}^{l} \oplus \mathbf{h}_{j}^{l}], i, j \in [1, n]$$

$$\tag{4}$$

where \oplus means the operation of concatation, \mathbf{h}_i^l , \mathbf{h}_j^l means the representation of $\operatorname{word}_{i_{th}}$ and $\operatorname{word}_{j_{th}}$ in current RA-GCN layer after aggregation, $\mathbf{E}_{ij*}^{l-1} \in \mathbb{R}^p$ is the relation representation between $\operatorname{word}_{i_{th}}$ and $\operatorname{word}_{j_{th}}$ where p is the dimension of relation representation, $\mathbf{W}_{\mathbf{u}} \in \mathbb{R}^{(2 \times h + p) \times p}$ is a learnable transformation matrix where h is the hidden dimension of RA-GCN. This operation combines the context semantic information with syntactic relation embedding, so that different information behind relation can be expressed. The updated relation-aware adjacency tensor is fed into the next layer of RA-GCN for relation-aware aggregation.

3.5 Classification Layer

Finally, we feed the representation of each word into a fully-connected network, which is followed by a softmax operation to compute distribution $p(t|\mathbf{h})$ over all event labels:

$$p(t|\mathbf{h}) = \operatorname{softmax}(\mathbf{W}_{t} \cdot \mathbf{h} + \mathbf{b}_{t})$$
(5)

where \mathbf{W}_t transforms word representation \mathbf{h} to feature score for each event label and \mathbf{b}_t is a bias term. After softmax, event label with the largest probability is chosen as the classification result.

3.6 Bias Loss Function

Following (Chen et al., 2018; Yan et al., 2019), we adopt a bias loss function to strengthen the influence of EventType labels during training, since the number of "O" tags is much lager than that of EventType tags. The bias loss function is formulated as follows:

$$J(\theta) = -\sum_{i=1}^{N_s} \sum_{j=1}^{n_i} \log p(y_j^t | s_i, \theta) \cdot I(O) +$$

$$\alpha \log p(y_j^t | s_i, \theta) \cdot (1 - I(O))$$

$$(6)$$

where N_s is the number of sentences, n_i is the number of words in the i_{th} sentence; I(O) is a swifting function which equals to 0 if the tag of word is one of EventType labels, otherwise 1; α is a bias weight which can help to enhance the influence of EventType tags.

4 Experiments

4.1 Dataset and Evaluation Metrics

We conduct experiments on the standard event detection dataset, ACE2005, which contains 599 documents annotated with 33 types of events. Following previous works (Li et al., 2013; Chen et al., 2015; Nguyen et al., 2016; Liu et al., 2017; Chen et al., 2018; Yan et al., 2019), we use the same 529 documents for training, the same 40 documents for test and the rest 30 documents for dev. The syntactic dependency parsing is operated by Stanford CoreNLP toolkit.

Finally, Precision (P), Recall (R) and F_1 -measure (F_1) are used to evaluate experiment results in the same way as previous works ((Chen et al., 2015; Nguyen et al., 2016; Liu et al., 2017; Chen et al., 2018; Yan et al., 2019)).

4.2 Hyper-parameter Setting

The hyper-parameters are tuned on the dev dataset. The word embeddings are pretrained on New York Times corpus with the Skip-gram algorithm and the dimension of word embedding is 100. The dimension of entity type embedding is 25. We set the hidden dimension of BiLSTM to be 100 and the hidden dimension of RA-GCN to be 150 with relation embedding of dimension 50. Following (Yan et al., 2019), the max length of sentence is set to be 50 by padding shorter sentences and cutting longer ones. We set batch size to be 30, SGD for optimization with learning rate of 0.1. The dropout rate is 0.6 and L2-norm is 1e-5. The bias loss parameter α is 5. Additionally, we set RA-GCN to be 2 layers, since GCN suffers from over-smoothing which means the node representation will get more and more similar with the number of GCN layers increase.

4.3 Baselines

We select following models for comparison, which can be classified as three types: feature-based models, sequence-based neural network models and GCN-based neural network models.

4.3.1 Feature-based Models

Feature-based models use human designed features to perform event detection. 1) **MaxEnt** is proposed by (Li et al., 2013) using only lexical features, basic features and syntactic features desinged by human; 2) **CrossEntity** is proposed by (Hong et al., 2011) using cross-entity information to perform event detection.

4.3.2 Sequence-based Neural Network Models

1) **DMCNN**, proposed by (Chen et al., 2015), uses dynamic multi-pooling convolutional network; 2) **JRNN**, proposed by (Nguyen et al., 2016), employs bidirectional RNN for the task; 3) **ANN-AugAtt**, proposed by (Liu et al., 2017), uses annotated event argument information with supervised attention, where words describing Time, Place and Person of event get larger attention score; 4) **dbRNN**, proposed by (Sha et al., 2018) adds dependency arcs with weight to BiLSTM to make use of tree structure and sequence structure simultaneously; 5) **HBTNGMA**, proposed by (Chen et al., 2018), uses hierarchical and bias tagging networks to detect multiple events in one sentence collectively.

Model	P	R	F_1
MaxEnt (Li et al., 2013)	74.5	59.1	65.9
CrossEntity (Hong et al., 2011)	72.9	64.3	68.3
DMCNN (Chen et al., 2015)	75.6	63.6	69.1
JRNN (Nguyen et al., 2016)	66.0	73.0	69.3
ANN-AugAtt (Liu et al., 2017)	78.0	66.3	71.7
dbRNN ^{†‡} (Sha et al., 2018)	74.1	69.8	71.9
HBTNGMA (Chen et al., 2018)	77.9	69.1	73.3
GCN-ED [†] (Nguyen and Grishman, 2018)	77.9	68.8	73.1
JMEE [†] (Liu et al., 2018)	76.3	71.3	73.7
MOGANED [†] (Yan et al., 2019)	79.5	72.3	75.7
RGCN ^{†‡} (Schlichtkrull et al., 2018)	70.6	80.8	75.4
RA-GCN ^{†‡}	76.7	78.6	77.6

Table 1: Performance on blind test data. † means models using syntactic dependency structure only and †‡ means models using syntactic dependency structure and relation simultaneously; Bold marks the highest score among all models.

Model	F_1
RA-GCN	77.62
- RAAM	75.51
– MdR	73.51
– CARUM	75.23
– RAAM & CARUM	74.82
– BiLSTM	65.84

Table 2: Ablation study of RA-GCN, where "-" means "remove", "RAAM" means "relation-aware aggregation module", "MdR" means multi-dimensional representation of relation, "CARUM" means "context-aware relation update module".

4.3.3 GCN-based Models

1) **GCN-ED** is proposed by (Nguyen and Grishman, 2018), which investigates GCN on syntactic dependency tree structure to improve performance; 2) **JMEE** is proposed by (Liu et al., 2018), which uses GCN with self-attention and highway network to improve performance of GCN for event detection; 3) **MOGANED** is proposed by (Yan et al., 2019), which uses GCN with aggregated attention to combine multi-order word representation from different GCN layers.

RGCN (Schlichtkrull et al., 2018), which models relation data with relation-specific adjacency matrix $\mathbf{A}_r \in \mathbb{R}^{n \times n}$ and convolutional filter \mathbf{W}_r , has been implemented for knowledge completion. We adapt RGCN for the task of event detection and the result is shown in Table 1.

4.4 Overall Performance

Table 1 shows the performance of our model and other comparable baseline models. We can see that RA-GCN achieves the best performance among all models above, which improves the best beseline 1.9% on F_1 -measure. Besides, we also have observations as follows:

1) RA-GCN outperforms the best GCN-based models, which demonstrates that syntactic relation label can provide key information for event detection. 2) RA-GCN outperforms RGCN and the reasons can be analyzed from two aspects. First, the amount of parameters is smaller than that of RGCN, thus the model can be trained better on limited data. Second, context-aware relation representation can provide more information for event detection to improve performance. 3) Comparing RA-GCN with **dbRNN**, which adds syntactic dependency arcs with a weight to BiLSTM, our model gains improvement on both P and R. The reason is that GCN can capture dependency tree structure more effectively and the multi-dimensional embedding of syntactic relation in RA-GCN can learn more information than just a weight in **dbRNN**. 4) RA-GCN outperforms all sequence-based neural network models, which demonstrates that reasonable use of syntactic dependency information can improve performance.

5 Analysis

5.1 Ablation Study

To study the contribution of RA-GCN core components, we design ablation experiments. Based on experiment results in Table 2, we have analysis as follows. 1) –RAAM: To study whether syntactic label

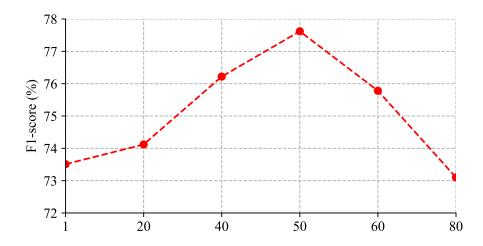


Figure 3: Dimension influence of relation representation.

help to improve the performance of RA-GCN, we initialize each element of relation-aware adjacency tensor as the same representation, which means only syntactic dependency structure is exploited. The result drops nearly 2.1% on F_1 -measure, which demonstrates that syntactic dependency label can provide information to improve the performance of RA-GCN. 2) -MdR: To study whether multi-dimensional representation of relation help to enhance the ability to capturing information, we set the dimension of relation representation to be 1, which means the relation-aware adjacency tensor $\mathbf{E} \in \mathbb{R}^{n \times n \times p}$ is compressed to be $\mathbf{E} \in \mathbb{R}^{n \times n \times 1}$. We can see that F_1 -measure drops 4% approximately, which demonstrates that multidimensional representation can learn more information than just a scalar weight. 3) -CARUM: To study whether context-aware relation representation help to improve performance, we remove context-aware relation update module in RA-GCN. The performance degrades 2.4%, which illustrates that contextaware relation representation can provide more evident information for event detection. 4) -RAAM & CARUM: To study whether "relation" can help GCN to work better, we remove relation-aware aggregation module and context-aware relation update module simultaneously, which means only vallina GCN is used. We can see that the performance reduces by 2.8%, which illustrates that "relation" can help to capture information which vallina GCN can not capture. 5) -BiLSTM: BiLSTM is removed before RA-GCN and the performance drops terribly. This illustrates that BiLSTM can capture important sequential information which GCN miss. Therefore, GCN and BiLSTM can be complementary to each other for event detection task.

5.2 Effect of Relation Representation Dimension

Since performance of RA-GCN drops when the dimension of relation representation is 1, we investigate the influence of multi-dimensional representation of relation. As shown in Figure 3, F_1 -measure increases with the increasing dimension of relation representation at first, but degrades when the dimension is up to 50. Reasons for this phenomenon can be explained as follows. If the dimension of relation representation is too small, it can not capture full information of relation between words. On the contrary, if the dimension is large, which may also hurt the performance because of overfitting.

5.3 Efficiency Advantage

To prove that RA-GCN architecture can model relation data more effectively, we compare RA-GCN architecture with RGCN architecture from two aspects: space consumption and inference speed. According to our statistics, the amount of parameters of RA-GCN architecture and RGCN architecture are 2,385,584 and 4,115,184 respectively. Since RA-GCN initializes syntactic dependency label as parameters of look up table rather than those of GCN filters, the amount of parameters is reduced significantly. We can see that the amount of parameters of RA-GCN architecture is only 57.9% that of RGCN, which means that RA-GCN has superiority of space complexity. Besides, the inference speed of RA-GCN architecture is 7.67 times that of RGCN, which means that RA-GCN is more light-weight. Since RA-GCN

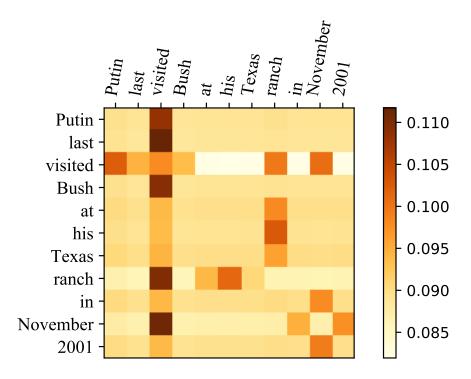


Figure 4: Visualization of connection strength between words. Length of relation representation vector is used as connection strength score. Darker red means higher score for connection strength.

is more efficient in both inference speed and space consumption, RA-GCN has better applicability when modeling relation data.

5.4 Case Study

We use a sentence "Putin last visited Bush at his Texas ranch in November 2001" as an example to illustrate the connection strength between words. Following (Sabour et al., 2017), we use the length of relation representation vector in adjacency tensor to represent the corresponding connection strength score. As we can see from each row in Figure 4, each word has the strongest connection with "visited", which is exactly the event trigger and ROOT in syntactic dependency tree. In the row of "visited", it has strongest connections with "Putin", "ranch", "November" and "Bush", which shows that "nsubj", "nmod" and "dobj" are strong relations for event trigger. Strong connection with event-related words ("Putin", "Bush", "ranch" and "November") means that these words contribute more information in relation-aware aggregation to produce expressive representation for the event trigger "visited", which can provide evident clue for event detection.

6 Conclusion and Future Works

In this paper, we propose a novel model named Relation-Aware Graph Convolutional Network (RA-GCN) for event detection, which can exploit syntactic dependency relation label efficiently and model the relation between words specifically. Experiments on the standard event detection dataset ACE2005 show that our proposed model outperforms all baseline models. In the future, we will take into account the direction of syntactic dependency in RA-GCN. Besides, we will attempt to exploit RA-GCN model for relation extraction and other subtasks of information extraction.

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