EDUs Representation Learning for RST Discourse Parsing

**Abstract.** Discourse structure has a central role in several NLP tasks, such as dialogue generation or discourse translation. Also, Text-Level discourse parsing is notoriously difficult for the long distance of discourse and deep structure of discourse trees. In this paper, we take discourse parsing task back to tree’s representation problem and build a tree-structured model for RST discourse parsing. What’s more, we compare those popular methods for sentence representation along with a tree structured neural network to find a best EDUs encoder in RST discourse parsing task.

**Keywords:** Discourse Parsing, RST-DT, Tree LSTM, EDUs Representation.

Introduction

Documents are usually formed as a long sequence text which could also be analyzed as constituency trees, as shown in figure 1. Discourse structures can detailedly describe the organization of a document which is central to a number of NLP applications like sentiment analysis [1], text summarization [2] and question answering [3].

Rhetorical Structure Theory (RST) [4] is a representative linguistic theory of discourse structures, This theory guided the annotation of the RST Discourse Treebank (RST-DT) [5], from which several text level discourse parsers have been proposed [6, 7, 8, 9].

However, the RST-DT discourse corpora are limited in size, since annotation is time consuming and complex. Many measures have been taken to solve the problem. For example, Braud [9] harmonized some existing corpora to leverage information by combining dataset in different languages. Due to the limitation of training data, the methods of discourse parsing are still weak: those state-of-the-art jobs at present like Ji et al. [10] and Wang [8] are still based on traditional methods like support vector machine (SVM) instead of neural networks. We think it meaningful to do this research over neural network based discourse parsing for the fast development of Deep Learning.

In this paper, our model is implemented as shift-reduce discourse parser. The core idea of our work is to learn better representation for each subtree, so we present a tree-structured neural network to discourse parsing. What’s more, sentence representation is inevitable an essential part in deep models. We will compare those popular methods for sentence representation along with this neural network strictly. We make the code and preprocessing scripts available for download at <https://github.com/ArlenZhang/Data_share>.

**Fig. 1.** An example of RST discourse structure

Mr. Vaux said

that

if no agreement is reached,

other buyers will be

sought by bid or auction.

condition

Same-Unit

attribution

2 Related Work

The task of discourse parsing are mainly divided into two aspects. The first one focus on relation recognition, the other is full discourse parsing that identifies discourse relation and structure. The RST discourse parsing focus on the later one and many RST discourse parsers have been proposed up to now. The first text-level discourse parser relays mainly on heuristics and hand-crafted rules [11, 5]. Hernaulth et al. [6] built a greedy model using SVM to transform this task into a labeling decision problem. Feng and Hirst [7] built a bottom-up, two stage (sentence- then document-level), greedy parser with linear-chain CRF models.

Recently, many more researchers have focused on building models with good representations of the limited data. Li et al. [12] used a recursive neural network that builds a representation for each clause based on the syntactic tree, and then apply tw**o classifiers as Hernault et al. [6].** The system presented by Ji and Eisenstein [10] jointly learns the representation of the discourse units and a shift-reduce parser. This system, however, uses Tree LSTM to represent each discourse tree node and focus on the representation learning for each EDU.

3 Parsing Model

3.1 Background: Shift-reduce parsing

A shift-reduce discourse parser [maintain](file:///D:\%E6%9C%89%E9%81%93%E8%AF%8D%E5%85%B8%E5%AE%89%E8%A3%85%E8%B7%AF%E5%BE%84\Dict\7.2.0.0703\resultui\dict\?keyword=maintain)s two data structures: a stack of partially completed subtrees and a buffer of EDUs yet to be parsed. The parser is initialized with the stack empty and the buffer contains the EDUs of the document in order. During parsing process, the parser consumes transitions constantly, where . The state of buffer and stack will change according to the predicted action label. The shift-reduce parsing procedure is detailedly described in Table 1.

**Table 1.** Shift-reduce discourse parsing

|  |
| --- |
| **Algorithm 1** Shift-reduce discourse parsing |
| **Input:** EDUs of a discourse    **while** buffer has more than 0 element **or** stack has more than 1 element **do**  = Predict the action label according to  **if** is **then**  Pop an element from and push it onto  **else**  Pop tow elements and from  Merge and into  Push onto  **endif**  **endwhile**  Pop the last element from  **Output:** A discourse parsing tree |

3.2 Elements in Buffer

We use a learned linear transformation to map all these encoded EDUs of a document into a vector pair that stored in the buffer. The vector of those encoded EDUs will be display in section 4.

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

3.3 Composition Function

Figure 2 shows a derivative of the bottom-up Tree-LSTM [13], illustrating the input (), memory cell () and hidden state () at the time. It extends the sequence LSTM by splitting the previous state vector into a left child state vector and a right child state vector , splitting the previous cell vector into and .

*ct*

*ht*

**Fig. 2.** Topology of tree LSTM. Shaded nodes represent the input vectors from our two trackers. White nodes represent hidden state vectors and memory cell vectors.

When the action is performed, the vector representations of two child nodes are popped off the stack and fed into a *composition function* which is also a neural network function that produces a representation for the new parent node at time step . The composition function of us calculating and as :

|  |  |  |
| --- | --- | --- |
|  |  | (2) |
|  |  | (3) |

where is an optional vector valued input argument which is either empty or comes from an external source like the trackers (see section 3.4), is the forget gate, is the input gate, is the output gate, and is the elementwise product. The new pair which represents a subtree is pushed onto the stack.

3.4 Trackers

State tracker [14] and connective tracker are two simple sequence-based LSTM. The state tracker’s inputs at the step is the top element of the buffer and the top two elements of the stack and . The connective tracker’s input at the step is the connectives in the next EDU to be popped in the buffer. So, the connective works only when the next transition is . The connectives we use are those artificially tagged connectives in PDTB [22]. We combine the outputs of two trackers into as shown in figure 3.We use these two tracker in two purpose: the composed hidden states supplies a representation of the to the transition classifier and it is also used as a input vector for the composition function (see 3.3).

**Fig. 3.** Network architecture of two trackers we use. The left one is the connective tracker. The right one is the state tracker. **We use two colors to reflect the switch of the LSTM gate**.

4 Methods for EDU Representation

We use word representation based on the 100D vectors provided by GloVe [15]. We do not update the weights of these vectors during training for we aim at comparing these encoders strictly. We still use POS embedding which is obtained over a whole sentence as a supplement representation for each word in EDUs. In this paper, we focus on finding a most appropriate sentence encoder for EDU representation. These most popular encoders used in our experiments are listed below.

4.1 CNN based encoder

Convolutional Neural Network (CNN) is an efficient model for encoding, it can capture some important local information of a sentence which could be helpful in structure building. As we know, sometimes, it is lexical information like connectives, specific words and phrase that counts. As we care about word level vector information when we apply CNN in NLP, so we set the size of filters as . The structure of CNN encoder with is designed in figure 2.

*You will win at last*

*embedding*

*convolution*

*max\_pooling*

POS

Words

**Fig. 4.** EDUs encoder based on CNN

4.2 Bi LSTM & Self-Attention based encoder

Bi LSTM is a variant of RNN, it is meant to maintain a low-resolution summary of the portion of the sentence has been processed so far. However, it only provides a final hidden state to represent the sentence which will be invalid for we need to capture some decisive local hidden state. Self-attention mechanism will put attention on all the hidden states of a sequence and can extract relevant information of the sequence. It performs well on many tasks like Reading comprehension [16]、Natural language inference [17]、Text summary [18] and so on. We introduce self-attention into this Bi LSTM encoder with the purpose of obtaining decisive local information for discourse parsing. We formulate our vision of attention as:

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

where as shown in figure 3, and are weights to learn.

**……**

**……**

**…**

**……**

Attention layer

Bi LSTM layer

embedding

**Fig. 5.** EDUs encoder based on **Bi LSTM & Self-Attention**

4.3 Bag of word model

Continuous Bag of Word model is a neural network for efficient estimation of high-quality sentence embedding proposed by Siamese [19]. Averaging the embedding of words in a sentence has proven to be a surprisingly successful and efficient way of obtaining sentence embedding. In this paper, we use this bag of word model to represent EDUs. We describe the representation of a EDU as:

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

where is the length of a EDU, is the word embedding weights of the word in the EDU.

4.4 Features for Data Driven Model

Feature engineering is a traditional method in discourse parsing task. Many classical and effective discourse parsers are based on this. Nowadays, features are still useful in face of limited data. Wang [8] extracted a lot of features from the top 2 elements in the stack and firstEDU in the queue to train a SVM classifier which achieves the highest score at the level of Span. Ji et al. [10] transformed these extracted features by multiplying them with a specific weight matrix which makes their model work as a data driven model. However, they use these representations to train a SVM classifier which is still a traditional method. Braud et al. [9] extracted almost the same features as DPLP and trained a feed-forward neural network as their parser model. They proposed a cross-lingual discourse parser which improves the performance with lots of external data.

**Table 2.** Features selected for RST parsing

|  |
| --- |
| Feature |
| Words at the beginning and end of the EDU |
| POS tag at the beginning and end of the EDU  The head words the first three words in the EDU  Boolean value of whether the center word of temporary sentence is in the temporary EDU |
| Length of tokens in the EDU (l1<=5, 5<l2<=12, 12<l3)  Position of EDU in a discourse (position of the EDU divided by the total number of EDU) |

These successful parsers have a similarity that they all use some simple but effective feature to represent EDU. **To improve this experiment,** we select some typical features in table 2. The usual way of using these features in neural network is to automatically learn vectors for these features. In this paper, we combine the last 3 sets of features into 18 groups and assign different feature vectors to each group. We describe the representation of a EDU as:

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

5 Experiments

5.1 Setup

The RST-DT annotates 385 documents from the Wall Street Journal. It was mainly divided into 2 data sets (347 for training and 38 for testing). Conventionally, we binarize those non-binary subtrees with right-branching [20] and use 18 coarse-grained relations as our relation set. We use the evaluation metrics defined by Marcu [21], i.e. the precision, recall and F-score with respect to span and nuclearity.

5.2 Results and Analysis

In this paper, we aim at finding a better way of EDU representation for neural network based discourse parsing. We hold the purpos**e that relation labeling should be done separately due to data sparsity. Thus we put our attention only on span (S) and nuclearity (N) in this paper.**

**Table 3.** Performance of our parser based on different **encoders**

|  |  |  |
| --- | --- | --- |
| Encoding Model | S | N |
| CNN | 78.32 | 55.63 |
| Bi LSTM & Self-attention | **84.01** | **68.97** |
| BOW | 83.35 | 67.83 |
| Feature Vectors Learning | 83.56 | 67.92 |

We choose the Ji et al. [10] to compare with in three reasons: 1. the DPLP has a state-of-art result in discourse parsing; 2. it is also a data driven model different from others; 3. Our parsers are all built on the limited data RST-DT without other external data.

**Table 4.** Final performance compared with DPLP

|  |  |  |
| --- | --- | --- |
| Approach | S | N |
| Ji and Eisenstein | 82.1 | 71.1 |
| Ours | 84.01 | 68.97 |

Comparing with Ji, our discourse parsing based on tree-structured neural network is a dynamic process, we don’t need to prepare all data before. We introduce a novel Tree structured neural network instead of SVM in DPLP. What’s more, DPLP learns the representation matrix and the SVM classifier at the same time which is harder to train than ours. From the F-score at the Span level, our parser are better than theirs.

6 Conclusion

We conduct a series of experiments to find out a better method for EDUs representation in data driven model. We introduce connective tracker and state tracker into constituent tree LSTMs to build a novel RST discourse parser. We have presented a framework to perform discourse parsing while jointly training the EDUs encoders to output better representations for EDUs. Our shift-reduce parsing system substantially outperforms existing data driven parsers like DPLP on span detection.

One big problem of our model is data sparsity which has limited the performance of the model. Our future work will focus on simplifying our model and introducing external data to alleviate the problem of data sparsity.

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