Chinese Discourse Segmentation Using Bilingual Discourse Commonality

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Abstract

Discourse segmentation aims to segment Elementary Discourse Units (EDUs) and is a fundamental task in discourse analysis. For Chinese, previous researches identify EDUs just through discriminating the functions of punctuations. In this paper, we argue that Chinese EDUs may not end at the punctuation positions and should follow the definition of EDU in RST-DT. With this definition, we conduct Chinese discourse segmentation with the help of English labeled data. Using discourse commonality between English and Chinese, we design an adversarial neural network framework to extract common language-independent features and language-specific features which are useful for discourse segmentation, when there is no or only a small scale of Chinese labeled data available. Experiments on discourse segmentation demonstrate that our models can leverage common features from bilingual data, and learn efficient Chinese-specific features from a small amount of Chinese labeled data, outperforming the baseline models.

Introduction

Discourse segmentation aims to segment Elementary Discourse Units (EDUs) which are defined as the minimal building blocks of constituting a text (Mann and Thompson 1988). There exist many controversies about what constitutes an EDU. A generally acceptable practice takes EDUs to be non-overlapping clauses (Carlson and Marcu 2001), which has been verified a reasonable language unit and used successfully in some downstream applications such as automatic summarization (Hirao et al. 2013; Li, Thadani, and Stent 2016; Durrett, Berg-Kirkpatrick, and Klein 2016).

For research on Chinese discourse, several discourse corpus have been constructed (Zhou and Xue 2012; Li, Kong, and Zhou 2014; Zhang, Qin, and Liu 2014). Zhou and Xue (2012) built a predicate-argument style Chinese discourse treebank, following the annotation scheme of English Penn Discourse Treebank (PDTB) (Prasad et al. 2007). Motivated by Rhetorical Structure Theory (RST) (Li, Kong, and Zhou 2014) constructed a RST-like discourse treebank. These work directly treated EDUs as Chinese clauses segmented by some punctuations, e.g., comma, semicolon and period. At the same time, there are some work to research whether punctuations especially commas are boundary marks of EDUs (Xue and Yang 2011; Yang and Xue 2012; Xu and Li 2013; Li, Feng, and Feng 2015). In our opinion, Chinese EDUs (or clauses) may not always end at the punctuation positions. Fig. 1 shows two Chinese examples of discourse segmentation (1a and 2a). From the examples we can see that, besides punctuations, some intra-sentential words may be the boundaries of EDUs, e.g., “美尼指出 (Armenia state)” in 1a and “在制定下一个比表” (when developing the next scale)” in 2a.

As we know, the discourse guidelines defined by Carlson and Marcu (2001) compile a series of rules for segmenting English EDUs, which can also apply on Chinese text. However, compared to English, it is relatively difficult to identify Chinese EDUs under this guideline, because Chinese phrase structure is syntactically similar to sentence structure, and relative pronouns and subordinating conjunctions are rarely used to introduce clauses (Tsao 1990). Thus, in this paper we argue to adopt the EDU segmentation guideline proposed by Carlson and Marcu (2001) and aim to conduct Chinese discourse segmentation with a more appropriate way.

For our work, the main problem is the absence of labeled...
Chinese data which conforms to this segmentation guideline. It is fortunate that there exist some discourse commonalities between Chinese and English as we observe. Figure 1 gives two English discourse segmentation examples (i.e., 1a and 2b) which are translations of 1a and 2a respectively. We can see that each EDU in either language contains a verb-like word and other similar syntactic and lexical features in judging the EDU boundary. In such cases, we come up with the idea that Chinese EDU segmentation can be conducted with the help of the discourse commonality summarized from substantial English discourse data such as RST Discourse Treebank (RST-DT) [Carlson and Marcu 2001].

As for cross-lingual discourse segmentation, [Braud, Lacroix, and Søgaard 2017] designed a multi-task learning framework for five languages (i.e., English, Spanish, German, Dutch and Brazilian Portuguese) which belong to the Indo-European family and are very similar. Their model is relatively simple and can not well extract common features for discourse segmentation sharing in much different languages such as Chinese and English, since Chinese belongs to Sino-Tibetan language family and English. To transfer English segmentation information to Chinese, inspired by the work of Ganin and Lempitsky [2015], we design the adversarial neural network framework which can leverage both language-specific features and shared language-independent features for discourse segmentation. We propose to use English labeled data to train a discourse segmenter and simultaneously transfer the learned discourse segmentation features to Chinese. A common Bidirectional Long-short term memory (BiLSTM) network is designed with language-adversarial training to exploit the language-independent knowledge which can be transferred from English to Chinese. At the same time, two private BiLSTMs are used to extract language-specific knowledge.

To the best of our knowledge, we are the first to propose that Chinese EDU segmentation can not be limited to only judging the functions of punctuations and contribute to providing a small scale of Chinese labeled corpus. We also contribute to using an adversarial neural network framework to conduct Chinese discourse segmentation with the help of English labeled data. Experiments show that our models can leverage common features from English data, and learn efficient Chinese-specific features from a small amount of Chinese labeled data, outperforming the baseline models.

Chinese Elementary Discourse Units

In this section, we briefly introduce the definition of Chinese EDUs in our work. Generally, the basic principle is to treat an EDU as a clause. However, since a discourse unit is a semantic concept while a clause is syntactically defined, researchers further made some refinements on EDU segmentation. We mainly followed the guidelines defined by Carlson and Marcu [2001] and manually labeled a small corpus according to the characteristics of Chinese. Next we list some criteria of segmenting EDUs as follows.

1. Subjective clauses, objective clauses of non-attributive verbs and verb complement clauses are not segmented as EDUs.
2. A prepositional clause is an EDU.
3. Complements of attribution verbs, including both speech acts and other cognitive acts, are treated as EDUs.
4. Coordinated sentences and clauses are broken into separate EDUs.
5. Coordinated verb phrases are not separated into EDUs.
6. Temporal expressions are marked as separate EDUs.
7. Correlative subordinators consist of two separate EDUs, provided that the subordinate clause contains a verbal element.
8. Strong discourse cues can start a new EDU no matter they are followed by a clause or a phrase.
9. There are some embedded discourse units where one EDU is separated by a subordinate clause.

We also show some EDU segmentation examples in Fig. 2 which correspond to the above segmentation criteria in bold face. Due to space limitation, we do not explain the segmentation criteria in detail. Following the EDU segmentation guideline, we manually segment 782 sentences from People’s Daily for training, validation and test.

Method

Model Architecture

To conduct Chinese discourse segmentation by exploiting English labeled data, we design our model as in Fig. 3. The whole architecture is mainly composed of four modules: a common feature extractor (F) that extracts the shared language-independent features for discourse segmentation, private feature extractors (H_e and H_p) that learns language-specific features respectively for Chinese and English, an EDU segmenter (P) that conducts discourse segmentation for a sequence, and a language discriminator (Q) that judges whether a sequence is in Chinese or English language.

To be specific, given a sentence x composed of N words, we look up the pre-trained bilingual word embeddings W_1, W_2, ..., W_N and Universal POS tag embeddings P_1, P_2, ..., P_N, and use their concatenation (X = T_1, T_2, ..., T_N) as the input of three feature extractors (i.e., F, H_e and H_p), each of which is modeled using the bidirectional LSTM (BiLSTM) models. Knowing the used language of x, X is inputted into the common feature extractor and the corresponding language-specific feature extractor. The common feature extractor maps X into the hidden states \( F(x) = h^c_1, h^c_2, ..., h^c_N \) which contains both forward and backward information learned by LSTMs. Similarly, the private feature extractor converts X into the hidden states \( H_e(x) = h^e_1, h^e_2, ..., h^e_N \) and \( H_p(x) = h^p_1, h^p_2, ..., h^p_N \) if x is in Chinese, \( H_e(x) = h^e_1, h^e_2, ..., h^e_N \) if x is in English. Next, with the hidden states as input, we design two tasks: one task is discourse segmentation and the other is a language-adversarial task.

- Discourse segmentation task. Discourse segmentation is regarded as a sequence labeling problem with two labels (i.e., 0 and 1) indicating whether to segment the current word. With the concatenation of \( F(x) \) with \( H(x) \) (i.e., \( H_e(x) \) or \( H_p(x) \)), a BiLSTM layer is applied to obtain the abstract hidden states \( h^1_1, h^1_2, ..., h^1_N \) for the following CRF...
1': [王芳实施偷窃行为是既定事实。] (That Wang Fang committed theft is an established fact)

2': [通过加强宣传教育。] (By strengthening publicity and education.)
[学校提高了学生们的安全意识。] (the school has improved students’ safety awareness.)

3': [中央相信] (China believes)
[两国关系能够稳定发展。] (relations between the two countries can develop steadily.)

4': [智利西部海岸发生强烈地震] (A strong earthquake struck the western coast of Chile)
[并引发海啸。] (and triggered a tsunami.)

5': [中央关注并赞成朝鲜对该事件的处理方案。] (China cares and approves North Korea’s handling of the incident.)

6': [在会见中国国家领导人后。] (After meeting with the Chinese national leaders,)
[金正恩还将与韩国首相举行会晤。] (Kim Jong-un will also hold a meeting with the Korean Prime Minister.)

7': [他的思想太过前卫] (His ideas are so avant-garde)
[以至于没有同时代的人能够理解他。] (that no contemporary person can understand him)

8': [根据外交网站消息。] (According to the website of the Ministry of Foreign Affairs website.)
[9月17日，外交部发言人洪磊主持例行记者会。] (Foreign Ministry spokesman Hong Lei hosted a regular press conference on September 17.)

9': [画展共展出] (The exhibition totally exhibits)
[由中俄两国艺术家精心合作的] (carefully created by Chinese and Russian artists)
[油画和中国画60余幅。] (more than 60 paintings and Chinese paintings.)

Figure 2: Examples 1’~9’ of EDU segmentation correspond to the criteria 1~9.

layer which outputs the final labeling results. Suppose $T$ is the transition matrix of a linear-CRF and $c, b$ are score vectors that capture the cost of beginning and ending with a given label. Then, the global score of a given label sequence $y$ is represent by

$$ J_p \equiv \min_{\Theta_p} \mathbb{E}_{x,y} \log \frac{P(x) P(F(x), y) \prod_{i=1}^{m} e^{P(F(x), y) + c[y_i] + \sum_{i=1}^{m-1} T[y_i, y_{i+1}] + e[y_m]}}{\sum_{y} e^{P(F(x), y) + c[y_i] + \sum_{i=1}^{m-1} T[y_i, y_{i+1}] + e[y_m]}} \quad (2) $$

\textbf{Language-adversarial task.} The language-adversarial task aims to train the language-independent features which make the language discriminator difficult to distinguish what language is used. The idea is inspired by domain adversarial training and Generative Adversarial Network (GAN), which has been applied on sentiment classification and POS tagging (Chen et al. 2016; Kim et al. 2017). The language discriminator is composed of convolution neural networks (CNNs) and a fully-connected layer with sigmoid activation function, with reference to the text classification model (Kim 2014).

First, the common language-independent features $F(x) = h_1^x, h_2^x, ..., h_N^x$ are inputted to three convolution filters whose activation function is leaky ReLU (Maas, Hannun, and Ng 2013) and window sizes are set to 3, 4 and 5 respectively. Then, the max-over-time pooling (MaxPool) operation is applied to obtain three fixed-length vectors which are concatenated as a vector. Next, the fully connected layer takes the concatenated vector as input and outputs a scalar value. The higher the value is, the more probable the language is in English.

When training the language discriminator, we expect the scores for English instances to be higher and the scores for Chinese to be lower. Here, we define the distribution of the common language-independent features $F$ for English and Chinese instances as:

$$ P_{Ch}^F \equiv P(F(x)|x \in \text{Chinese}) $$
$$ P_{En}^F \equiv P(F(x)|x \in \text{English}) $$

We train $F(x)$ to make these two distributions as close as possible so that $F(x)$ is independent of language. Following (Chen et al. 2016) and (Arjovsky, Chintala, and Bottou 2017), we minimize the Wasserstein distance between $P_{Ch}^F$ and $P_{En}^F$ since the Wasserstein distance is relatively stable for hyperparameter selection. We notate the language discriminator as the function $Q$, according to the Kantorovich-Rubinstein duality (Villani 2008) we get the Wasserstein distance $W(P_{Ch}^F, P_{En}^F)$:

$$ W(P_{Ch}^F, P_{En}^F) = \sup_{Q} \mathbb{E}_{F(x) \sim P_{Ch}^F}[Q(F(x))] - \mathbb{E}_{F(x') \sim P_{En}^F}[Q(F(x'))] \quad (3) $$

Let the discriminator $Q$ be parameterized by $\Theta_q$, and the objective function $J_q$ given $\Theta_q$ is:

$$ J_q \equiv \max_{\Theta_q} \mathbb{E}_{F(x) \sim P_{Ch}^F}[Q(F(x))] - \mathbb{E}_{F(x') \sim P_{En}^F}[Q(F(x'))] \quad (4) $$

Finally, when training the parameters of the common feature extractor $F(x)$, we minimize the objective function $J_q$ given that the discriminator has been trained well. This means that the common features between English and Chinese are language-independent and the discriminator have no capacity to distinguish the two languages. At the same
time, we need to consider the discourse segmentation task with \( F(x) \) and \( H(x) \) as input. Let the feature extractors be parameterized as \((\Theta_f, \Theta_h)\), and we train the features with the objective function:

\[
J_{f,h} \equiv \min_{\Theta_f, \Theta_h} J_p(\Theta_f, \Theta_h) + \lambda J_q(\Theta_f)
\]

(5)

**Model Training**

To train our model, we use English labeled data, Chinese unlabeled data and zero (or a little) Chinese labeled data. The English labeled corpus is important for learning language-independent features. According to the Chinese resource we use, two ways of training are designed.

- **With zero Chinese labeled data (ZL).** We only use English labeled corpus and Chinese unlabeled corpus to train the language discriminator \((\Theta_g)\), common feature extractor \((\Theta_f)\) and EDU segmenter \((\Theta_p)\). Since no labeled Chinese data is used, the private Chinese-specific feature extractor can not be trained. Only the common language-independent features are fed into the segmenter for Chinese discourse segmentation.

- **Only with a little Chinese labeled data (LL).** We use English and Chinese labeled data to train our model and do not use Chinese unlabeled data. To balance the scale of Chinese data with that of English data, we keep duplicating the small amount of Chinese labeled data until it has a similar scale with the English labeled data. The duplicated Chinese labeled data and English labeled data are used to train our model until the Chinese validation data reaches the highest performance.

**Experiments**

**Resources**

- **Chinese data.** In this work of Chinese discourse segmentation, there are totally 782 manually labeled Chinese sentences, which were introduced in section. Among these data, we choose 182 sentences to compose of a test set and 200 sentences a validation set, and use the rest 400 sentences as training data when needed. Besides, another 9236 sentences from *People’s Daily* serves as unlabeled Chinese training data.

- **English data.** We use the RST-DT corpus composed of 385 discourse-segmented articles from Wall Street Journal (WSJ) and 500 segmented articles from *Yang and Li 2018*. Finally, we totally get 9636 segmented English sentences.

- **Bilingual word embeddings (BWE).** To obtain cross-lingual word embeddings which share the same space between Chinese and English, we use BiLBOWA \(\text{[Gouws, Bengio, and Corrado 2015]}\) to obtain the 200-dimensional bilingual word embeddings. To train BiLBOWA, we use 570,499 Chinese sentences from *People’s Daily*, 700,000 English sentences from CNN/DailyMail \(\text{[Hermann et al. 2015]}\), and a parallel corpus composed of 50,000 pairs of aligned Chinese and English sentences.

- **Universal POS tags.** In order to assure that Chinese and English adopt the same POS tagset, we use Universal POS tagset \(\text{[Nivre et al. 2016]}\). For English text, we use pre-trained UDPipe model \(\text{[Straka, Hajic, and Straková 2016]}\) to postag. For Chinese text, we use Stanford CoreNLP toolkit \(\text{[Manning et al. 2014]}\) to postag with the UPenn tagset and then convert the tag to Universal POS tag with a conversion mask\(^1\) because UDPipe lacks Chinese training data and performs poorly.

**Setup**

When training our model, we train the feature extractors \((F, H)\) and the discourse segmenter \((P)\) together, and train the language discriminator \((Q)\) separately. \(F, H\) and \(P\) are trained \(k\) iterations per \(Q\) iteration. Following the ANDN

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\(^1\)Refer to [http://universaldependencies.org/tagset-conversion/zh-conll-uposf.html](http://universaldependencies.org/tagset-conversion/zh-conll-uposf.html) and make some modifications.
network (Chen et al. 2016), we set $k$ to be the value of 5. For the parameter $\lambda$ which balances the influence of $\mathcal{P}$ and $\mathcal{Q}$, we experiment the values of $\{0.2, 0.1, 0.05\}$ on the validation data and finally set it to be 0.1. All the models are optimized using RMSProp with learning rate of 0.001 and decaying rate of 0.9. The reason why we do not use Adam is that momentum-based optimizers are unreliable when training weight-clipped WGAN (Arjovsky and Bottou 2017). When training $\mathcal{Q}$, the threshold of weight-clipping is set as 0.01. The word embeddings dimension is set 200. The POS tag embeddings are initialized randomly and their dimension is set 50. The dimensions of the hidden states in the BiLSTMs are set the same as the dimensions of their corresponding input vectors. Besides, the outputs of all BiLSTMs are regularized with dropout rate of 0.5 (Pham et al. 2014). The size of minibatch is set 20.

To verify the effectiveness of our model, we design two sets of experiments. In the first set of experiments, we compare our models with several baselines and exhibit the performance improvement brought by the discourse commonality between Chinese and English and the adversarial language training model. In the second set of experiments, we analyze the factors such as size of the labeled Chinese data which may influence the performance of our model. In the experiments, we use Precision, Recall and F-measure to evaluate the performance and F-measure is the main metric of measuring the quality of a model.

**Results**

Since there is no available tools which follow the RST-DT criteria to segment Chinese EDUs, here we design several baselines for comparison. First, considering when there is no Chinese labeled training data, we use three baselines to contrast with our model of $\mathcal{ZL}$. The first baseline is named S-baseline in which we directly see each sentence as an EDU. The second baseline is named P-baseline which segments the sentences whenever it meets a punctuation except quotation marks (i.e., “”) and slight-pause mark (i.e., , ). The third is a baseline named NoAdvers-Z which is identical to our model except the adversarial training part is removed. In another view, NoAdvers-Z can be seen as a segmenter which is composed of two-layer LSTM and one layer of CRF. We use English labeled data to train NoAdvers-Z and test it on Chinese text which is similar to the method of (Braud, Lacroix, and Søgaard 2017). When we use the small amount of Chinese labeled data, we design a baseline NoAdvers-L to contrast with our model $\mathcal{LL}$. The only difference between NoAdvers-L and NoAdvers-Z is that we train NoAdvers-L using the duplicated Chinese data as training set.

Table 1 shows the results of our models with the baselines. From the table, we can see S-baseline achieves the worst performance, though its precision is 100 percent because each sentence boundary must be an EDU boundary. The recall of 48.46% means that only 48.46% of all EDU boundaries belong to the sentence boundaries. P-baseline achieves a high F-measure of 79.41%, though it is simple. According to the performance of P-baseline, we know that 71.2% of EDU boundaries belong to the punctuations and most of the punctuations (89.76%) prefer to be EDU boundaries. Thus, the most challenging in Chinese discourse segmentation is to recall the rest 28.8% EDU boundaries and pick out those punctuations which do not serve as EDU boundaries. We can also see that NoAdvers-Z performs worse than P-baseline with regard to the three metrics of Precision, Recall and F-measure. This means that we can not directly use the English training data to train a Chinese discourse segmenter even if bilingual embeddings of two languages share the same space. $\mathcal{ZL}$ significantly outperforms the other three baselines when no labeled Chinese data is available and achieves the F-measure of 82.35% by leveraging the common feature extractor adversarial network. Compared to P-baseline, $\mathcal{ZL}$ can identify more EDU boundaries because the shared language-independent features learned from English labeled data are more appropriate to recognizing Chinese EDUs. This can be verified from several segmentation examples which are shown in Figure 4. We can see that Example (3a) can identify the attribution verb “提醒 (remind)”, which indicates an EDU boundary following a subordinate clause. This means that “提醒 (remind)” is also an attribution verb in the English training data and the Chinese segmenter learns the feature. Example (4a) correctly judges the functions of two commas where the content before the first comma is a temporal expression and the second comma is a real EDU boundary, because our model

![Table 1: Results Comparison](image)

| Method    | F-measure | Precision | Recall   |
|-----------|-----------|-----------|----------|
| S-baseline| 48.46%    | 100.00%   | 48.46%   |
| P-baseline| 79.41%    | 89.76%    | 71.20%   |
| NoAdvers-Z| 71.13%    | 77.50%    | 65.72%   |
| $\mathcal{ZL}$ | 82.35%    | 87.33%    | 77.92%   |
| NoAdvers-L | 86.54%    | 91.19%    | 82.33%   |
| $\mathcal{LL}$ | 87.70%    | 93.59%    | 82.51%   |

Figure 4: Examples of EDU segmentation by $\mathcal{ZL}$ model. For each EDU, we give its literal English translation in parenthesis. 3a, 4a and 5a are system results. 3a and 4a are correct while 5a is wrong.
Figure 5: Examples of EDU segmentation by LL model. For each EDU, we give its literal English translation in parenthesis. 6a and 7a are system results. 6a is correct while 7a is wrong. 7a’ is the gold segmentation result of 7a.

may learn the language-independent features that a temporal clause can not be a separate EDU and verb-like words should be contained in an EDU. It is obvious that ZL has its limitations. Example (5a) is wrongly segmented and each segmented EDU does not have a complete meaning, though the model learns to contain a verb-like word in each EDU. This is because Chinese is a language of parataxis and use the passive voice with adding a function word (e.g., "为...作(be created)"") in this example, which is different from English. It is difficult for ZL to learn the Chinese-specific features without any Chinese labeled data.

Table 1 also shows the performance of NoAdvers-L and LL, which use the 400 Chinese labeled sentences to supervise the training. From the table, we can see that NoAdvers-L and LL both outperform over the methods using zero Chinese labeled data. With Chinese and English labeled data together, LL can effectively train the Chinese-specific features as well as the common language-independent features which are useful to labeling the EDU boundaries. At the same time, NoAdvers-L achieves satisfactory results and again verifies that labeled data can provide effective supervision. LL outperforms NoAdvers-L, since the common features learned through the adversarial language discrimination and cross-lingual resources remedy training insufficiency of Chinese-specific features caused by the small Chinese labeled data. Figure 6 shows two segmentation examples by the LL model. Here LL correctly segments Example (6a) which has been wrongly segmented by ZL (i.e., 5a). From this example, we can see that the Chinese labeled data can train more Chinese-specific features such as the embedded attributive clause. Example (7a) is still wrongly segmented by LL. Here "告 (report)" and "亡 (casualty)" are seen as noun words. In fact, when our annotators read this sentence, "亡" is always understood as a verb phrase "be killed or injured". This is because verbs and verb phrases in Chinese can be nominalized without any overt marker for it. Without a large amount of Chinese labeled data, it is difficult to learn such ambiguous knowledge which is crucial to discourse segmentation.

Figure 6: Impact of labeled Chinese resource scale

| POS tagset | ZL | LL |
|------------|----|----|
| Universal  | 82.35% | 87.70% |
| Different  | 79.40% | 86.37% |

Table 2: Impact of POS tagset

Impact of Resources

In this subsection, we mainly investigate the influence of size of Chinese labeled data and Universal POS tagset. To figure out to what extend our model can remedy the lack of labeled Chinese data, we explore the performance change with regard to the size of these data and compare our models with the NoAdvers model. Figure 6 displays the performance change. With zero Chinese labeled data, there is a large performance gap between our ZL model and the NoAdvers-Z model, because the common features learned from the adversarial mechanism contribute much to Chinese discourse segmentation in ZL. With Chinese labeled data increasing, the performance gap between our LL model and the NoAdvers-L model first becomes decreased and then keeps stable when the size of Chinese labeled data reaches 200 sentences. The performance tendency means that Chinese labeled data when available is more effective for training the Chinese discourse segmenter than English data. The more Chinese labeled data a model has, the higher performance it can boost. From the performance gaps between our model and the NoAdvers model, we can say that the common language-independent features learned from cross-lingual discourse commonality also contributes to Chinese discourse segmentation. Since we do not have a large amount of Chinese labeled data, we are not sure whether the two performance lines will intersect and whether the common features learned from English data will not contribute to Chinese discourse segmentation when Chinese labeled data is large enough. At least, with the small-scale Chinese training data in hand, the common language-independent features learned from the adversarial discrimination are still important to the performance of a Chinese discourse segmenter. To show the necessity of using Universal POS tagset, we do the contrast experiments with language-specific POS
tagsets (English Penn Treebank POS tagset and Chinese Penn Treebank POS tagset) as input in the ZL and LL models respectively. In the experiments, all settings are the same as introduced above except using different POS tagsets and POS tag embeddings in the network. The results are shown in Table 2. We can see that both ZL and LL models with the Universal POS tagset show superior results to the models with different POS tagsets. These results suggest that Universal POS tagsets provide a good basis for learning cross-lingual knowledge which is important for discourse segmentation.

Related Work
Recently, much work have been conducted on English EDU segmentation. Most of those segmenters are based on statistical classifiers and leverage many manually extracted features in which lexical syntactic subtree features play an important role (Soricut and Marcu 2003). Some modifications to the statistic model and features have made great improvements (Fisher and Roark 2007; Joty, Carennini, and Ng 2015) and (Bach, Minh, and Shimazu 2012) achieved the best results ever. Besides, (Subba and Di Eugenio 2007) first used neural networks on this task and some neural network models have achieved comparable results using less artificial features. Since (Sporleder and Lapata 2005) see the EDU segmentation task as a sequence labeling problem, we leverage the LSTM-CRF model (Huang, Xu, and Yu 2015; Ma and Hovy 2016) which is proved effective in this problem.

As for Chinese EDU segmentation, previous work mainly focused on identifying EDU boundaries by punctuations and saw this task as comma classification (Li, Feng, and Hovy 2016) which is proved effective in this problem. However, it is difficult to obtain parallel corpus. Then, one kind of the alternative methods is statistic model based and require cross-lingual features (Ando and Zhang 2005; Darwish 2013); and the other kind of methods are neural network based, since word embeddings in different languages have the capability of representing semantic meanings in the same space. Besides bilingual word embeddings, bilingual character embeddings also improve the performance (Yang, Salakhutdinov, and Cohen 2016; Cotterell and Duh 2017). However, these work are usually constrained to a language family such as Indo-European languages which share some same characters (Braud, Lacroix, and Søgaard 2017). For Chinese and English which belong to different language families, we propose a method to get Universal Chinese POS tags and use adversarial network to solve the language adaption problem inspired by (Ganin and Lempitsky 2015), (Chen et al. 2016) and (Kim et al. 2017).

Conclusions
In this paper, we propose to segment EDUs in Chinese based on RST and identify those EDU boundaries where there is no punctuations. Further more, we design an adversarial network to exploit abundant English discourse data to help segment Chinese EDUs because of the lack of labeled Chinese data which follows the criterion above. Based on cross-lingual discourse commonality, we use an adversarial language discrimination task to extract common language-independent features and language-specific features which are useful for discourse segmentation. Experimental results verify the efficiency of our models.

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