Chinese Grammatical Error Diagnosis by Conditional Random Fields

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Abstract

This paper reports how to build a Chinese Grammatical Error Diagnosis system based on the conditional random fields (CRF). The system can find four types of grammatical errors in learners’ essays. The four types of errors are redundant words, missing words, bad word selection, and disorder words. Our system presents the best false positive rate in 2015 NLP-TEA-2 CGED shared task, and also the best precision rate in three diagnosis levels.

1 Introduction

Learning Chinese as foreign language is on the rising trend. Since Chinese has its own unique grammar, it is hard for a foreign learner to write a correct sentence. A computer system that can diagnose the grammatical errors will help the learners to learn Chinese fast (Yu et al., 2014; Wu et al., 2010; Yeh et al., 2014; Chang et al., 2014).

In the NLP-TEA-2 CGED shared task data set, there are four types of errors in the learners’ sentences: Redundant, Selection, Disorder, and Missing. The research goal is to build a system that can detect the errors, identify the type of the error, and point out the position of the error in the sentence.

2 Methodology

Our system is based on the conditional random field (CRF) (Lafferty, 2001). CRF has been used in many natural language processing applications, such as named entity recognition, word segmentation, information extraction, and parsing (Wu and Hsieh, 2012). For different task, it requires different feature set and different labeled training data. The CRF can be regarded as a sequential labeling tagger. Given a sequence data X, the CRF can generate the corresponding label sequence Y, based on the trained model. Each label Y is taken from a specific tag set, which needs to be defined in different task. How to define and interpret the label is a task-dependent work for the developers.

Mathematically, the model can be defined as:

\[
P(Y|X) = \frac{1}{Z(X)} \exp(\sum \lambda_k f_k) \tag{1}
\]

where Z(X) is the normalization factor, \(f_k\) is a set of features, \(\lambda_k\) is the corresponding weight. In this task, X is the input sentence, and Y is the corresponding error type label. We define the tag set as: \(\{O, R, M, S, D\}\), corresponding to no error, redundant, missing, selection, and disorder respectively. Figure 1 shows a snapshot of our working file. The first column is the input sentence X, and the third column is the labeled tag sequence Y. Note that the second column is the Part-of-speech (POS) of the word in the first column. The combination of words and the POSs will be the features in our system. The POS set used in our system is listed in Table 1, which is a simplified POS set provided by CKIP\(^1\).

Figure 2 (at the end of the paper) shows the framework of the proposed system. The system is built based on the CRF++, a linear-chain CRF model software, developed by Kudo\(^2\).

Figure 1: A snapshot of our CRF sequential labeling working file

\[^{1}\hspace{1cm} \text{http://ckipsvr.iis.sinica.edu.tw/}\]
\[^{2}\hspace{1cm} \text{http://crfpp.sourceforge.net/index.html}\]
Table 1: Simplified CKIP POS

2.1 Training phase

In the training phase, a training sentence is first segmented into terms. Each term is labeled with the corresponding POS tag and error type tag. Then our system uses the CRF++ leaning algorithm to train a model. The features used in CRF++ can be expressed by templates. Table 12 (at the end of the paper) shows one sentence in our training set. Table 13 (at the end of the paper) shows all the templates of the feature set used in our system and the corresponding value for the example. The format of each template is %X[row, col], where row is the number of rows in a sentence and column is the number of column as we shown in Figure 1. The feature templates used in our system are the combination of terms and POS of the input sentences. For example, the first feature template is “Term+POS”, if an input sentence contains the same term with the same POS, the feature value will be 1, otherwise the feature value will be 0. The second feature template is “Term+Previous Term”, if an input sentence contains the same term bi-gram, the feature value will be 1, otherwise the feature value will be 0.

2.2 Test phase

In the Test phase, our system use the trained model to detect and identify the error of an input sentence. Table 2, Table 3, and Table 4 show the labeling results of examples of sentences with error types Redundant, Selection, Disorder, and Missing respectively.

| Word | POS | tag | Predict tag |
|------|-----|-----|-------------|
| 他   | N   | O   | O           |
| 是   | Vt  | O   | O           |
| 真   | ADV | R   | R           |
| 很   | ADV | O   | O           |
| 好   | Vi  | O   | O           |
| 的   | T   | O   | O           |
| 人   | N   | O   | O           |

Table 2: A tagging result sample of a sentence with error type Redundant
你 千萬 不要 在意
千萬 千萬 不要 在意

Table 3: A tagging result sample of a sentence with error type Selection

Table 3: A tagging result sample of a sentence with error type Selection

你 什麼 要 玩
什麼 D D D
要 ADV D D
玩 Vt D D

Table 4: A tagging result sample of a sentence with error type Disorder

看 電影 時候
Vt N M M

Table 5: A tagging result sample of a sentence with error type Missing example

Term POS tag Predict tag
你 N O O
千萬 DET O O
不要 ADV O O
在意 Vt O O
這 DET O O
個 M S S
事情 N O O

Table 6: The confusion matrix.

| System predict tag | A | B |
|--------------------|---|---|
| Known tag A | tpA | eAB |
| B | eBA | tpB |

F1-Score A = \( \frac{2 \times \text{Precision A} \times \text{Recall A}}{\text{Precision A} + \text{Recall A}} \)
Accuracy = \( \frac{tpA + tpB}{All \ Data} \)

3 Experiments

3.1 Data set

Our training data consists of data from NLP-TEA1(Chang et al.,2012)Training Data, Test Data, and the Training Data from NLP-TEA2. Figure 3 (at the end of the paper) shows the format of the data set. Table 7 shows the number of sentences in our training set.

Table 7: Training set size

| size | NLP-TEA1 | NLP-TEA2 |
|------|----------|----------|
| Redundant | 1830     | 434      |
| Correct   | 874      | 0        |
| Selection | 827      | 849      |
| Disorder  | 724      | 306      |
| Missing   | 225      | 622      |

3.2 Experiments result

In the formal run of NLP-TEA-2 CGED shared task, there are 6 participants and each team submits 3 runs. Table 8 shows the false positive rate. Our system has the lowest false positive rate 0.082, which is much lower than the average. Table 9, Table 10, and Table 11 show the formal run result of our system compared to the average in Detection level, Identification level, and Position level respectively. Our system achieved the highest precision in all the three levels, but the accuracy of our system is fare. However, the recall of our system is relatively low. The numbers in boldface are the best performance amount 18 runs in the formal run this year.

Table 8: The false positive rate.

| Submission       | False Positive Rate |
|------------------|---------------------|
| CYUT-Run1        | 0.096               |
| CYUT-Run2        | 0.082               |
| CYUT-Run3        | 0.132               |
| Average of all 18 runs | 0.538               |
| Detection Level | Accuracy | Precision | Recall | F1     |
|-----------------|----------|-----------|--------|--------|
| CYUT-Run1       | 0.584    | 0.7333    | 0.264  | 0.3882 |
| CYUT-Run2       | 0.579    | 0.7453    | 0.24   | 0.3631 |
| CYUT-Run3       | 0.579    | 0.6872    | 0.29   | 0.4079 |
| Average of all 18 runs | 0.534    | 0.560     | 0.607  | 0.533  |

Table 9: Performance evaluation in Detection Level.

| Identification Level | Accuracy | Precision | Recall | F1     |
|----------------------|----------|-----------|--------|--------|
| CYUT-Run1            | 0.522    | 0.5932    | 0.14   | 0.2265 |
| CYUT-Run2            | 0.525    | 0.6168    | 0.132  | 0.2175 |
| CYUT-Run3            | 0.505    | 0.5182    | 0.142  | 0.2229 |
| Average of all 18 runs | 0.335    | 0.329     | 0.208  | 0.233  |

Table 10: Performance evaluation in Identification Level.

| Position Level      | Accuracy | Precision | Recall | F1     |
|---------------------|----------|-----------|--------|--------|
| CYUT-Run1           | 0.504    | 0.52      | 0.104  | 0.1733 |
| CYUT-Run2           | 0.505    | 0.5287    | 0.092  | 0.1567 |
| CYUT-Run3           | 0.488    | 0.45      | 0.108  | 0.1742 |
| Average of all 18 runs | 0.263    | 0.166     | 0.064  | 0.085  |

Table 11: Performance evaluation in Position Level.

4 Error analysis on the official test result

There are 1000 sentences in the official test set of the 2015 CGED shared task. Our system labeled them according to the CRF model that we trained based on the official training set and the available data set from last year.

The number of tag O dominates the number of other tags in the training set for sentences with or without an error. For example, sentence no. B1-0436, a sentence without error:

{上次我坐了 MRT 去了圓山站參觀寺廟了，O(上次) , O(坐), O(MRT), O(去了), O(圓山), O(站), O(參觀), O(寺廟), O(了)}

And, sentence no. A2-0322, a sentence with an error:

{他們從公車站走路走二十分鐘才到電影院了，O(他們), O(從), O(公車站), O(走路), O(二十), O(分鐘), O(到), O(電影院), R(了)}

Therefore, our system tends to label words with tag O and it is part of the reason that our system gives the lowest false positive rate this year. Our system also has high accuracy and precision rate, but the Recall rate is lower than other systems. We will analyze the causes and discuss how to improve the fallbacks.

We find that there are 11 major mistake types of our system result.
1. Give two error tags in one sentence.
2. Fail to label the Missing tag.
3. Fail to label the Disorder tag.
4. Fail to label the Redundant tag.
5. Fail to label the Selection tag.
6. Label a correct sentence with Missing tag.
7. Label a correct sentence with Redundant tag.
8. Label a correct sentence with Disorder tag.
9. Label a correct sentence with Redundant tag.
10. Fail to label a Disorder type with Missing tag.

Analysis of the error cases:
1. Give two error tags in one sentence: In the official training set and test set, a sentence has at most one error type. However, our method might label more than one error tags in one sentence. For example, a system output: {他是很聰明學生, O(他), R(是), O(很), O(聰明), M(學生)}. Currently, we do not rule out the possibility that a sentence might contain more than one errors. We believe that in the real application, there might be a need for such situation. However, our system might compare the confidence value of each tag and retain only one error tag in one sentence.

2. Fail to label the Missing tag: The missing words might be recovered by rules. For example, a system output: {需要一些東西修理好，O(需要), O(一些), O(東西), O(修理好)} should be {需要一些東西修理好，O(需要), M(一些), O(東西), O(修理好)}. and the missing word should be “被” or “把”.

A set of rule for “被” or “把” can be helpful.

3. Fail to label the Disorder tag: The disorder
error is also hard for CRF model, since the named entity (NE) is not recognized first. For example, a system output: {離台北車站淡水不太近} should be {離台北車站淡水不太近, D(離), D(台北), D(車站), D(淡水), O(不), O(太), O(近)}. The disorder error can only be recognized once the named entities "台北車站" and "淡水" are recognized and then the grammar rule "NE1+離+NE2+近" can be applied.

4. Fail to label the Redundant tag: Some adjacent words are regarded as redundant due to the semantics. Two adjacent words with almost the same meaning can be reduced to one. For example: a system output: {那公園是在台北北部最近新有的, O(那), O(公園), O(是), O(在), O(台北), O(北部), O(最近), O(新), O(有的)} fail to recognize the redundant word R(台北) or R(北部). In this case, "新有的" is also bad Chinese, it should be "新建的". However, the word segmentation result makes our system hard to detect the error.

5. Fail to label the Selection tag: We believe that it required more knowledge to recognize the selection error than limited training set. For example, a system output: {這是一個很好的新聞, O(這), O(很好), O(的), O(新聞)} fail to recognize the classifiers (also called measure words) for"新聞" should not be "個", the most common Mandarin classifier. It should be "則". A list of the noun to classifier table is necessary to recognize this kind of errors.

6. Label a correct sentence with Missing tag: This case is relative rare in our system. For example, a system output: {一個小時以前我決定休息一下, M(一), O(個), O(小時), O(以前), M(我), O(決定), O(休息), O(一下)} accurately contains no error. However our system regard a single "－" should be a missing error according to the trained model.

7. Label a correct sentence with Redundant tag: There are cases that we think our system perform well. For example, our system output: {平常下了課以後他馬上回家, O(平 常), O(下), R(了), O(課), O(以後), O(他), O(馬上), O(回家)}. Where "了" can be regarded as redundant in some similar cases.

8. Label a correct sentence with Disorder tag: This is a rare case in our system. For example, a system output: {以後慢慢知道他這種方式其實是很普通的交朋友的方式, O(以後), O(慢), O(知道), O(他), O(這), O(種), O(方式), O(其), O(是), O(很), O(普通), O(的), O(交), O(朋友), O(的), O(方式)} is a sentence that cannot be judged alone without enough contexts.

9. Label a correct sentence with Selection tag: In one case, our system output: {今天是個很重要的天, O(今天), O(重要), S(個), O(的), R(重要), O(的), O(一), O(天)}， where "個" is also not a good measure word.

10. Label a Selection type with Redundant tag: Sometimes there are more than one way to improve a sentence. For example, a system output: {下了課王大衛本來馬上回家, O(下), R(了), O(課), O(王大衛), O(本來), O(馬上), O(回家)}， which is no better than {下了課王大衛本來馬上回家, O(下), O(了), O(課), O(王大衛), S(本來), O(馬上), O(回家)}， where “本來” should be “就”. However, in a different context, it could be “本來想”+”但是…”.

11. Label a Disorder type with Missing tag: Since a Disorder error might involve more than two words, comparing to other types, it is hard to train a good model. For example, a system output: {中國新年到了的時候, O(中國), O(新年), O(到), O(了), M(的), O(時候)} should be {中國新年到了的時候, O(中國), O(新), O(年), O(到), O(了), M(的), O(時候)}, and the correct sentence should be “到了中國新年的時候”. A grammar rule such as “到了”+Event+”的時候” might be help.

5 Conclusion and Future work

This paper reports our approach to the NLP-TEA-2 CGED Shared Task evaluation. Based on the CRF model, we built a system that can achieve the lowest false positive rate and the highest precision at the official run. The
According to our error analysis, the difficult cases suggest that to build a better system requires more features and more training data. The system can be improved by integrating rule based system in the future.

Due to the limitation of time and resource, our system is not tested under different experimental settings. In the future, we will test our system with more feature combination on both POS labeling and sentence parsing.

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Figure 3: An example of the source data.

| col0 | col1 | col2 |
|------|------|------|
| r-2  | 他   | O    |
| r-1  | 是   | Vt   |
| r0   | 真   | ADV  |
| r1   | 好   | O    |
| r2   | 的   | Vi   |
| r3   | 人   | O    |
| r4   | N    | O    |

Table 12: A sample training sentence.

| Template Meaning | Template | Feature rule |
|------------------|----------|--------------|
| Term+POS         | %x[0,0]/%x[0,1] | 真/ADV |
| Term+Previous Term | %x[0,0]/%x[-1,0] | 真/是 |
| Term+Previous POS  | %x[0,0]/%x[-1,1] | 真/Vt |
| POS+Previous Term | %x[0,1]/%x[-1,0] | ADV/是 |
| POS+Previous POS  | %x[0,1]/%x[-1,1] | ADV/Vt |
| Term+Previous POS  | Term+Previous |
| POS+Previous POS  | %x[0,1]/%x[-1,0]/%x[-1,1] | 真/是/Vt |
| Term+Second Previous Term | %x[0,0]/%x[-2,0] | 真/他 |
| Term+Second Previous POS | %x[0,0]/%x[-2,1] | 真/N |
| POS+Second Previous Term | %x[0,1]/%x[-2,0] | ADV/他 |
|--------------------------|------------------|-------|
| POS+Second Previous POS  | %x[0,1]/%x[-2,1] | ADV/N |
| Term+Second Previous Term+Second Previous POS | %x[0,0]/%x[-2,0]/%x[-2,1] | 真/他/N |
| POS+Second Term+Second Previous POS | %x[0,1]/%x[-2,0]/%x[-2,1] | ADV/他/N |
| Term+Next Term           | %x[0,0]%x[1,0]   | 真/很 |
| Term+Next POS            | %x[0,0]%x[1,1]   | 真/ADV |
| POS+Next Term            | %x[0,1]%x[1,0]   | ADV/很 |
| POS+Next POS             | %x[0,1]%x[1,1]   | ADV/ADV |
| Term+Next Term+Next POS  | %x[0,0]%x[1,0]%x[1,1] | 真/很/ADV |
| POS+Next Term+Next POS   | %x[0,1]%x[1,0]%x[1,1] | ADV/很/ADV |
| Term+Second Next Term    | %x[0,0]%x[2,0]   | 真/好 |
| Term+Second Next POS     | %x[0,0]%x[2,1]   | 真/Vi |
| POS+Second Next Term     | %x[0,1]%x[2,0]   | ADV/好 |
| POS+Second Next POS      | %x[0,1]%x[2,1]   | ADV/Vi |
| Term+Second Next Term+Second Next POS | %x[0,0]%x[2,0]%x[2,1] | 真/好/Vi |
| POS+Second Next Term+Second Next POS | %x[0,1]%x[2,0]%x[2,1] | ADV/好/Vi |

Table 13: All the templates and the corresponding value for the sample sentence.