Pretraining Chinese BERT for Detecting Word Insertion and Deletion Errors

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Abstract

Chinese BERT models achieve remarkable progress in dealing with grammatical errors of word substitution. However, they fail to handle word insertion and deletion because BERT assumes the existence of a word at each position. To address this, we present a simple and effective Chinese pretrained model. The basic idea is to enable the model to determine whether a word exists at a particular position. We achieve this by introducing a special token [null], the prediction of which stands for the non-existence of a word. In the training stage, we design pretraining tasks such that the model learns to predict [null] and real words jointly given the surrounding context. In the inference stage, the model readily detects whether a word should be inserted or deleted with the standard masked language modeling function. We further create an evaluation dataset to foster research on word insertion and deletion. It includes human-annotated corrections for 7,726 erroneous sentences. Results show that existing Chinese BERT performs poorly on detecting insertion and deletion errors. Our approach significantly improves the F1 scores from 24.1% to 78.1% for word insertion and from 26.5% to 68.5% for word deletion, respectively.

1 Introduction

Grammatical Error Correction (GEC), which aims to detect and correct grammatical errors of text, is an important and active research area in natural language processing (Ng et al., 2014; Napoles et al., 2017; Ge et al., 2018; Awasthi et al., 2019; Omelianchuk et al., 2020; Rothe et al., 2021). In this work, we study Chinese GEC (Chang, 1995; Huang et al., 2000; Yu and Li, 2014; Yu et al., 2014; Zhang et al., 2015; Li et al., 2021), which has unique challenges as Chinese language does not have word delimiters (i.e., spaces) in written sentences. Major types of grammatical errors include word substitution, insertion and deletion. Recently, BERT and its model variations (Hong et al., 2019; Zhang et al., 2020; Liu et al., 2021) show promising results on handling grammatical errors related to word substitution. However, they fail to handle word insertion and deletion errors, both of which are crucial and the sum of these two types account for 44.7% of the grammatical errors in the CGED dataset (Rao et al., 2020). The reason why it can’t be handled well is that the learning objective of BERT assumes the existence of a word at each position, thus it is incapable of determining whether no word exists at a position. Take word insertion as an example. If a word needs to be inserted between two words (i.e., $w_i$ and $w_{i+1}$), the standard BERT hardly detects anomalies because $w_i$ fits well to its preceding context and $w_{i+1}$ fits well to its following context.

We present a new Chinese pretrained model to address the aforementioned issue. Our model inherits from BERT the power of contextual word prediction, and is further enhanced with the ability to determine whether no word should be predicted. We achieve this by introducing a special token [null], the prediction of which represents the non-existence of a word. Our model is trained with masked language modeling (MLM), where a [mask] token can be inserted between two input words or substituted from an input word. For the former, the pretraining task is to predict [null]. For the latter, the pretraining task falls back to the original MLM objective of BERT. Since our model is a tailored BERT, we initialize both Transformer blocks and the head layer at top with a public Chinese BERT. The training of our model converges fast in practice. Our model can be easily adopted to handle word insertion and deletion with the stan-
standard MLM function. When examining whether a word needs to be inserted between $w_i$ and $w_{i+1}$, we insert a [mask] token between them and check if the probability of [null] being predicted at the position of [mask] is low (e.g., lower than a threshold of 10.0%). An additional advantage of the model is that it conducts detection and correction simultaneously because the top ranked prediction can be directly used for correction. When detecting whether a word $w_i$ needs to be deleted, we check if the probability of [null] being predicted at the position of $w_i$ is high (e.g., higher than a threshold of 99.0%).

We further contribute by creating an evaluation set of human-annotated sentences. It consists of 4,969 and 2,757 sentences with annotated corrections for insertion and deletion errors, respectively. We find that the standard Chinese BERT performs poorly on the detection of insertion and deletion errors. On detecting insertion errors, our approach improves the F1 score from 24.1% to 78.1%. On detecting deletion errors, our approach improves the F1 score from 26.5% to 68.5%.

## 2 Background on MLM and Notation

To make the paper self-contained, we briefly describe the standard learning objective of MLM in this subsection. The basic idea of MLM is to reconstruct the corrupted words of a sequence given the surrounding context. Specifically, given an original sentence $x = (x_1, x_2, ..., x_n)$ consisting of $n$ words, a part of words are “corrupted” through being replaced by special [mask] tokens or replaced by randomly sampled words from a vocabulary of tens of thousands words. Let’s denote the corrupted input sequence as $\tilde{x} = (\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_m)$, which is composed of $m$ words, and denote the set of the indexes of corrupted words as $I(\tilde{x})$. It is worth noting that $\tilde{x}$ and $x$ have the same amount of words (i.e., $m = n$) and the words whose indexes do not fall into $I(\tilde{x})$ are identical in $\tilde{x}$ and $x$.

The goal of MLM is to produce $x$ given $\tilde{x}$. This is typically formulated as a cloze task, which only reconstructs the corrupted words given context. The loss function is formulated as follows,

$$L_{\text{MLM}} = - \sum_{i \in I(\tilde{x})} \log p(y_i = t_i | h(\tilde{x}))$$  \hspace{1cm} (1)

where $h(\tilde{x})_i$ is the contextual representation of the $i$-th word in $\tilde{x}$ calculated by Transformer (Vaswani et al., 2017) and $p(y_i = t_i | h(\tilde{x}))$ is the conditional probability of the ground truth $t_i$ to be predicted.

In the standard BERT, $t_i$ is equal to $x_i$. In the implementation of BERT, corrupted words account for 15% tokens of the input sequence. A corrupted word can be substituted with a [mask] token (80% of the time), substituted with a random word (10% of the time), and unchanged (10% of the time).

## 3 Method

In this section, we first introduce our pretraining task. Then, we present the application of our model to word insertion and deletion, respectively.

### 3.1 Learning to Predict [null]

We introduce our pre-training task in this subsection. The basic idea is that our model inherits from BERT the ability to select the most suitable word from the vocabulary given context, and is further enhanced with the ability to detect whether no word should occur at a particular position.

We achieve this by introducing a special token [null], the prediction of which stands for the non-existence of a word. Different from BERT that corrects the input only with word substitution, we produce a corrupted sequence with both word insertion and substitution operations. Consider an original input sequence $x = (x_1, x_2, ..., x_n)$ consisting of $n$ words. If word insertion is applied to word $x_i$, we keep $x_i$ unchanged and insert a word $\tilde{x}^{\text{ins}}_i$ after $x_i$ (details about $\tilde{x}^{\text{ins}}_i$ are introduced next). As a result, the corrupted sequence $\tilde{x}$ includes a subsequence of $(x_i, \tilde{x}^{\text{ins}}_i, x_{i+1})$ and the length of $\tilde{x}$ is no less than the length of $x$ (i.e., $m \geq n$). In the training stage, the goal is predicting [null] at the position of $\tilde{x}^{\text{ins}}_i$, which means that there is no word between $x_i$ and $x_{i+1}$. If word substitution is applied to word $x_i$, we largely follow the training process of BERT to replace $x_i$ with [mask] or keep $x_i$ unchanged.

The overall loss function is given as follows, where $I_{\text{sub}}(\tilde{x})$ and $I_{\text{ins}}(\tilde{x})$ are the indexes of the corrupted words produced with substitution and insertion operations, respectively.

$$L_{\text{ours}} = - \sum_{i \in I_{\text{sub}}(\tilde{x})} \log p(y_i = t_i | h(\tilde{x})) - \sum_{i \in I_{\text{ins}}(\tilde{x})} \log p(y_i = \text{[null]} | h(\tilde{x}))$$  \hspace{1cm} (2)

The former part of the loss helps the model inherit the ability of contextual word prediction from
B. BERT, and the latter part helps to learn whether a word should exist.

An illustration of the data corruption process is depicted in Figure 1. We perform the following strategies to corrupt original texts:

- **R1.** We randomly sample 15% of input words for corruption, among which half of them are corrupted with the substitution operation and the other half are obtained with the insertion operation.

- **R2.** For the insertion operation, the newly inserted word $x_{ins}^i$ is [mask] 50% of the time and is randomly selected from the vocabulary 15% of the time. For the remaining 35%, we use a mask-and-generate pipeline to produce a real word as $x_{ins}^i$. Specifically, we first insert a [mask] token at the position of $x_{ins}^i$, and then adopt MLM of a standard BERT model (Devlin et al., 2018) to produce top 10 words. Finally, we randomly select one of them as $x_{ins}^i$. This is effective for handling word deletion (see results at Section 5.4).

- **R3.** For the substitution operation, a word has a fifty-fifty chance of being replaced with [mask] or keeping unchanged.

### 3.2 Application to Word Insertion

In this subsection, we present how to apply our model to handling the grammatical error of word insertion. Given a sentence as the input, the task is to detect whether a word needs to be inserted between any two words and if so, generate the word to be inserted. We divide the whole process into two stages: detection and correction. We use one model to accomplish two stages. An illustration is given in Figure 2.

The goal of detection is to predict whether or not a word should be inserted between two words. In the inference phase, we first insert a [mask] token between $x_i$ and $x_{i+1}$, resulting in a new sequence of $n + 1$ words. Afterwards, we use our model to compute the probability of [null] to be predicted. If the probability is lower than a threshold (e.g., 10%), a word needs to be inserted here. An advantage of the model is that the correction result can be obtained at the same time. We regard the word with the highest probability as the word to be inserted.

Figure 2: An example of the inference process for word insertion. The translation is “Prevent heatstroke and keep calm.”. When determining whether a word should be inserted between “保” and “清”, we insert a [mask] token between them and check the probability of [null] with MLM.
3.3 Application to Word Deletion

We present how to apply our model to dealing with grammatical errors of word deletion. Given a sentence, the task is to detect whether a word should be deleted or not. Compared to word insertion, correction is not needed for this task.

Unlike the use of our model in word insertion, we do not insert [mask] tokens to the input. Here, we directly take the original sentence as the input and make predictions on top of the contextual representation of each word. This is efficient in practice because detecting all tokens can be done in one forward pass. Specifically, we check the probability of [null] being predicted for each word. If the probability is higher than a threshold (e.g., 99%), the word should be deleted. Figure 3 shows an example of the inference process. For reduplication errors (e.g. “的的”), we delete the last word.

Figure 3: An example of the inference process for word deletion. The translation is “They worry that their mistakes will affect the growth of their children.”. We directly conduct MLM without masking words and check the probability of [null] for each position.

4 Dataset Annotation

Existing datasets for Chinese grammatical error correction are either composed of sentences written by non-naive speakers of Chinese language (Zhao et al., 2018; Rao et al., 2020) or dominated by errors of word substitution (Tseng et al., 2015; Wang et al., 2018a). Our new dataset differs from the previous ones in that the sentences in our dataset are written by native Chinese speakers and contain a lot of insertion and deletion errors. Therefore our dataset is more suitable for studying the problem of detecting insertion and deletion errors. In this section, we describe how our dataset is built.

4.1 Annotation Process

An intuitive annotation pipeline is to first randomly sample sentences from the data source, and then dispatch them to human annotators to correct sentences with grammatical errors. However, this is impractical because the majority of randomly sampled sentences do not contain grammatical errors. To improve the annotation efficiency and make the experimental results convincing, we train a dedicated BERT model to select sentences for annotation. We train this model by corrupting a sentence with an inserted [mask] and is trained to predict [null]. Thus, this model is capable of producing warning positions (i.e., where the errors may occur). We apply this model to web news and blog articles of many Gigabytes, resulting in sentences with the probabilities of having insertion/deletion errors as well as the warning positions. We rank these sentence with the probabilities in descending order and send each sentence together with the warning position to at least one human annotator and one judge. Annotators are asked to rewrite the sentence if there are grammatical errors. Annotators are reminded to avoid making huge changes to the sentence structure and are allowed to ignore some warning positions. An instance is discarded if any of the following three situations is satisfied: (1) the judge does not agree on the annotated results; (2) the meaning of the sentence is confusing; (3) there are no insertion or deletion errors.

4.2 Annotation Results

Figure 4 gives examples of insertion and deletion types as well as some special cases. We can see that (d1) is a normal case of word deletion and (d2) shows a special case where a comma is deleted. A general case of insertion is given in (i1). Sometimes, people may use abbreviated expressions in written sentences (e.g., i2), our criterion is that annotators are encouraged to insert a word if carry out insertion leads to a better sentence. We also given two special cases. In (s1), the suggested position is a part of an named entity, so that no action needs to be taken. In (s2), the whole sentence is discarded because the meaning of the sentence is unclear to both annotators and judges. From a randomly sampled set of discarded sentences, we find that most of them are written in traditional Chinese, are largely composed of ancient Chinese poems, or include many colloquial and slang words.

After the annotation process is completed, we implement a text alignment toolkit for Chinese language on top of ERRANT (Bryant et al., 2017)\(^3\).

\(^3\)https://github.com/chrisjbryant/errant
Deletion
(d1) 所以决定让他来完成这个任务。
(d2) 因为她从小，就知道自己最想要的是什么。

Insertion
(i1) 那么它们是否符合你的要求呢？
(i2) 大家谁也没当回事儿，觉得可能是一场意外。

Special Cases
(s1) 比起年少阳光的满江，如今蓄起了胡须的他再度开嗓，有了时光的魅力。
(s2) 夏天，白昼，明治的红豆。

Table 1: Statistics of the annotated dataset.

| Dataset | Deletion | Insertion |
|---------|----------|-----------|
| Count   | 2,757    | 4,969     |
| No. words per sentence | 59.4 | 55.6 |
| Erroneous positions per sentence | 1.06 | 1.24 |
| No. sentence w/ one error | 2,612 | 3,900 |
| No. sentence w/ two errors | 116  | 874 |
| No. sentence w/ three errors | 15   | 153 |

5 Experiments

We report results and model analysis in this section.

5.1 Setting

We evaluate on our annotated dataset. For each insertion and deletion type, we keep a subset of 500 instances as the development set and leave the remaining as the test set. We don’t conduct experiments in a supervised setting, so no data points remain for fine-tuning. The development set is only used for selecting a threshold. Evaluation results are reported on the test set. The model can be easily used in a supervised setting, where a binary classifier is learned on top of the representation of [mask], we leave this as a future work.

We evaluate in terms of two subtasks: error detection and error correction. Detection is required for both word insertion and deletion. Following previous work (Wang et al., 2019; Cheng et al., 2020; Liu et al., 2021), we use character-level precision, recall, and F1 scores as the evaluation metrics. We calculate these metrics based on the script of Wang et al. (2019)⁴. Correction is only applicable to word insertion. We evaluate in an end-to-end manner: an output is correct only if both the detected position and the revised word are correct.

Our model largely follows BERT-base (Devlin et al., 2018). It has 12 Transformer encoder blocks, 12 self-attention heads and 768 hidden state dimensions. We increase the vocabulary size of BERT by one (i.e., adding a special token of [null]). The parameters of the embedding layer, the Transformer blocks, and the head layer except for parameters related to [null] are initialized from an existing Chinese BERT (Devlin et al., 2018)⁤. We collect web news and blog articles as the pre-training data, which has about 800 Gigabytes after data processing. We set batch size as 10,240 and train the model on 32 Tesla V100 GPUs. We set the learning rate as 1e-4 and use the Adam optimizer (Kingma and Ba, 2014) with a linear warmup scheduler. We find that the model converges fast after about 4K training steps.

Figures and tables

Figure 4: Examples of the annotated dataset. Each row stands for an instance sent to annotators. The word with wave underline in the 2nd column is the warning position which is also given to annotators.

Dataset Deletion Insertion
| Count | 2,757 | 4,969 |
| No. words per sentence | 59.4 | 55.6 |
| Erroneous positions per sentence | 1.06 | 1.24 |
| No. sentence w/ one error | 2,612 | 3,900 |
| No. sentence w/ two errors | 116  | 874 |
| No. sentence w/ three errors | 15   | 153 |

⁴https://github.com/wdimmy/Automatic-Corpus-Generation
⁤https://github.com/google-research/bert
| Method                      | Insertion |          |          | Deletion |          |          |
|-----------------------------|-----------|----------|----------|----------|----------|----------|
|                             | Precision | Recall   | F1       | Precision | Recall   | F1       |
| BERT w/ substituted [mask]  | 13.1      | 22.7     | 16.5     | 17.1      | 21.0     | 18.8     |
| BERT w/o [mask]             | 14.3      | 16.5     | 15.3     | 23.0      | 31.3     | 26.5     |
| BERT w/ inserted [mask]     | 28.0      | 21.2     | 24.1     | -         | -        | -        |
| MacBERT                     | 6.4       | 21.2     | 9.8      | 10.8      | 33.5     | 16.3     |
| PLOME                       | 6.7       | 26.5     | 10.7     | 10.6      | 35.2     | 16.3     |
| Flying                      | 62.8      | 19.2     | 29.4     | 56.2      | 29.9     | 39.1     |
| Our approach                | 77.6      | 78.6     | 78.1     | 71.4      | 65.9     | 68.5     |

Table 2: Results of grammatical error detection for word insertion and word deletion.

5.2 Baseline Models

We implement the following baselines for model comparison. For fair comparison, we continue pretraining a stronger Chinese BERT model (also initialized with the checkpoint of Devlin et al. (2018)) with the the same dataset used to train our approach, and use that to build the first three baselines given below.

- **BERT w/ substituted [mask]**. When we detect whether a word is erroneous, we replace it with [mask] and check whether the probability of the original word being predicted by MLM is lower than a threshold. For correction, we insert a [mask] token when the detection model decides to insert a word. We run MLM with the same BERT model and output the word with the highest probability.

- **BERT w/o [mask]**. Compared to the first baseline, the only difference is that this baseline does not use [mask] token. The original word remains the same in the detection phase. This baseline is not applicable to correction. We also implement a baseline with the same pipeline using MacBERT (Cui et al., 2020).

- **BERT w/ inserted [mask]**. We build this baseline for handling insertion. In the detection stage, we insert a [mask] token between two words and check if the probability of the top predicted word is lower than a threshold. In the correction stage, the top predicted word for the inserted [mask] token is returned.

- **PLOME** (Liu et al., 2021) is the first BERT-style pretrained model for Chinese spelling correction. It is trained by corrupting the input with phonologically and visually similar characters instead of [mask] tokens. We develop baselines based on their pipeline and tune thresholds on the development sets to detect for insertion and deletion. Since the training of PLOME does not use [mask], we don’t apply it to correction.

- **Flying** (Wang et al., 2020b) is the leading system in the challenge of Chinese Grammatical Error Diagnosis (CGED). It detects error types of words via sequence labeling. The feature of each word is computed based on the word embedding and the output of Transformers. We collect sentences with insertion and deletion errors from CGED, and use them to train two baseline systems for detecting insertion and deletion errors, respectively.

5.3 Results on Error Detection

Table 7 shows the results of error detection for both insertion and deletion types. Among these unsupervised baselines, inserting [mask] on top of BERT is the strongest for detecting insertion type of error. This makes sense because the task is to detect whether a word should be added, and this baseline gives the potentially real word a real position. For the deletion error type, the strongest unsupervised baseline is to directly make the prediction without masking words. It is not surprising that PLOME does not perform well on dealing with insertion and deletion errors because it is optimized for the task of word substitution. Flying system is the only supervised baseline which is trained on a public dataset. We can see that it has a very low recall because the style of the training data is different from our dataset. Overall, our approach consistently outperforms baselines by large margins.

We show the performance of our approach on error detection with different thresholds in Appendix. For each task, we select the threshold that obtains the best performance based on their pipeline and tune thresholds on the development sets to detect for insertion and deletion. Since the training of PLOME does not use [mask], we don’t apply it to correction.

We find that using datasets of both types to train a joint detector performs worse (by about 5% F1 score) than training two task-specific detectors.
the best F1 score on the dev set, and use it for testing. Appendix gives the performance of all baselines with different thresholds.

5.4 Effects of Corrupted Word Generation

We show how the sampling strategy of mask-and-generate (R of insertion operation in Section 3.1) plays an important role in word deletion. It is worth to note that when our approach takes the original sentence as the input (instead of replacing words with \([\text{mask}]\)) and detects all the words of the input sentence at once. This strategy has a big advantage in terms of inference speed (see section 5.8 below). From Table 5.4, we can see that mask-and-generate significantly improves the accuracy of word deletion. We believe the reason is that corrupting text via inserting a random word gives an easy training instance, whereas inserting a word via mask-and-generate produces more difficult context-dependent instances.

| Method                     | Insertion | Deletion |
|----------------------------|-----------|----------|
| BERT w/ substituted [mask] | 1.3       | 6.2      |
| BERT w/o [mask]            | 12.2      | 28.2     |
| BERT w/ inserted [mask]    | 11.8      | -        |
| Flying                     | 17.2      | 20.8     |
| Our approach               | 41.5      | 40.4     |

Table 5: Results on CGED in F1 score.

5.5 Results on Error Correction

We report the end-to-end performance of error correction in Table 4. Since generating a word via MLM needs to insert a \([\text{mask}]\) token, the baselines without using \([\text{mask}]\) are not considered here. Unsurprisingly, our approach performs better than baselines because our detection model shows huge gains over the baselines. The point is that our approach is capable of detecting and correcting an error with one model and one forward pass.

| Method                     | P        | R        | F1       |
|----------------------------|----------|----------|----------|
| BERT w/ substituted [mask] | 8.4      | 14.8     | 10.8     |
| BERT w/ inserted [mask]    | 26.6     | 20.1     | 22.9     |
| Our approach               | 58.3     | 59.1     | 58.7     |

Table 4: Results of error correction for word insertion.

5.6 Results on CGED Dataset

To further demonstrate the broad effectiveness of our model, we conduct extended experiments on another widely adopted benchmark CGED (Rao et al., 2020). Baseline systems described in Section 5.2 are used. We evaluate on the sentences containing insertion and deletion errors from CGED, respectively. As Table 5 shows, our approach is obviously superior to baseline models in F1. Detailed results in P, R and F1 are given in the appendix.

5.7 Case Study and Error Analysis

Figure 5 shows the correctly and wrongly predicted examples detected by our model. We can see that the model is capable of handling both normal words (o1 and o5) and punctuations (o2 and o6).

In o3, our second-ranked prediction (“数百人”, hundreds of people) is same with the ground truth. Although the top prediction is incorrect, the result (“数十人”, dozens of people) also fits well to the context. In o4, the probability of [null] is as high as 95.44%. However, our model does not detect any errors because our threshold is strict (i.e., 99.1%). In o7 and o8, although both second-ranked predictions are same with the ground truth, the top predictions also make sense.

5.8 Analysis on Inference Time Cost

We report the time costs of our approach in word deletion and insertion, respectively. For word deletion, our approach runs one forward pass to detect all the words of a sentence. For word insertion, our approach runs one forward pass for each word, since detecting for a word (i.e., a position) needs to insert a \([\text{mask}]\) token at the particular position and remaining other contexts untouched. On average, the inference time costs for deletion and insertion are respectively 9.2ms and 106.3ms on one V100 GPU machine (the average sentence length is shown in Table 1). We attempted to speed up the inference speed for word insertion by inserting a \([\text{mask}]\) between every two words, so that running one forward pass could handle all words. This improves the inference speed by almost 10 times, but with the cost of accuracy decrease (from 78.1 to 72.3 in terms of F1).
Category | Correctly Predicted Examples | Wrongly Predicted Examples
---|---|---
Deletion | (o1) 在这次袭击当中，大使馆中有三人死亡，数百人受伤。 (Translation: In this bombing, three people were killed in the embassy and hundreds were injured.) Ground truth: delete the 21th word ‘十’ Prediction: delete the 20th word ‘(’ p(‘十’) = 3.66% p([null]) = 99.61%
| (o3) 在这次袭击当中，大使馆中有三人死亡，数百人受伤。 (Translation: In this bombing, three people were killed in the embassy and hundreds were injured.) Ground truth: delete the 21th word ‘十’ Prediction: delete the 20th word ‘(’ p(‘十’) = 3.66% p([null]) = 99.61%
| (o5) 她也申请了参加。 (Translation: She also applied.) Ground truth: insert a word ‘时’ between the 17th word ‘时’ Prediction: insert a word ‘时’ between the 17th word ‘时’ p(‘时’) = 65.34% p(‘0’) = 21.57% p([null]) = 4.04% p([null]) = 0.07%
| (o7) 陈道明非常重视这个角色，早早的把剧本研究透。 (Translation: Daoming Chen attached great importance to this role and thoroughly studied the script at home in advance.) Ground truth: insert a word ‘即’ before the 17th word ‘即’ Prediction: insert a word ‘即’ before the 17th word ‘即’ p(‘即’) = 66.42% p(‘0’) = 15.12% p(‘大’) = 2.45% p([null]) = 0.19%

Insertion | (o2) 周浩要追我，被身后的警察拦了下来。 (Translation: Hao Zong wanted to chase me, but was stopped by the police behind him.) Ground truth: delete the 12th word, which is a punctuation ‘/’ Prediction: delete the 12th word, which is a punctuation ‘/’ p(‘0’) = 0.19% p([null]) = 99.80%
| (o4) 想必镜子，我不愿意逃离这座城市？ (Translation: I don’t know if Hamburg is willing to upgrade.) Ground truth: delete the 9th word ‘即’ Prediction: no error is detected. p(‘即’) = 4.53% p([null]) = 95.44%
| (o6) 邻里的妈妈听不进去，也只好让小军在那里不下去。 (Translation: The honest mother doesn’t listen to any advice. She is so stubborn so that I can only call in advance and tell my cousin to visit them on May Day.) Ground truth: insert a word ‘即’ before the 17th word ‘即’ Prediction: insert a word ‘即’ before the 17th word ‘即’ p(‘即’) = 67.58% p(‘0’) = 25.34% p([null]) = 2.49% p([null]) = 0.97%
| (o8) 建设15万个充电桩，到2023年将电动车数量提到250,000辆。 (Translation: Build 150,000 new charging piles and increase the number of electric vehicles to 250,000 by 2023.) Ground truth: insert a word ‘即’ before the 24th word ‘即’ Prediction: insert a word ‘即’ before the 24th word ‘即’ p(‘即’) = 67.23% p(‘0’) = 30.70% p([null]) = 0.95%

Figure 5: Correctly and wrongly predicted examples for word deletion and insertion. The word highlighted in blue in the 2nd column is where the error occurs.

6 Related Work

We describe related works on Chinese GEC and pretrained models.

Recent methods for Chinese GEC can be generally categorized into sequence translation and sequence tagging. Sequence translation methods (Wang et al., 2018b, 2019, 2020a; Li and Shi, 2021) typically use sequence-to-sequence models based on LSTM or Transformer, where the encoder consumes grammatically erroneous sentences and the decoder generates correct sentences in an autoregressive or non-autoregressive manner. Although these models are able to handle various error types, the generated results might not be faithful to the input because of the exposure bias issue (Zhang et al., 2019). Recent sequence tagging methods (Zhang et al., 2020; Cheng et al., 2020; Zhang et al., 2021; Xu et al., 2021) usually use neural network architectures to first tag the error positions and then correct them. Among them, BERT-based models are capable of conducting detection and correction of substitution error at once, however, they fail to deal with insertion and deletion errors.

PLOME (Liu et al., 2021) is the first pretrained model developed for Chinese grammatical error correction with a focus on handling word substitution. They use GRU to encode phonic and shape of Chinese character as additional input to the model. Our experimental results indicate that PLOME does not adapt well to word insertion or deletion. It is an interesting future work to develop a versatile model that combines the advantages of PLOME and our approach. There are general-purpose Chinese BERT models whose learning processing relates to GEC in some sense. For example, MacBERT (Cui et al., 2020) regards MLM as correction, where corrupted words are replaced with synonyms instead of [MASK] tokens.

7 Conclusion

This work proposes a pretrained model for dealing with grammatical errors of word insertion and deletion. A special token [null] is introduced to facilitate the model to handleably detect the existence of a word. We further contribute by creating an evaluation dataset with human-labeled corrections. Results show that existing BERT models perform poorly on detection the insertion and deletion of words. Our approach obtains significant gains on both tasks. In the future, we plan to develop a versatile model with the ability to handle many other types of grammatical errors.

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Table 6: The thresholds that selected for each method.

| Method                      | Threshold | Insertion-dev |   |   | Deletion-dev |   |   |
|-----------------------------|-----------|---------------|---|---|-------------|---|---|
|                             |           | Precision     | Recall | F1    | Precision     | Recall | F1   |
| BERT w/ substituted [mask]  | 1e-4      | 19.6          | 9.2  | 12.6 | 1e-4          | 21.9  | 12.1 | 15.6 |
|                             | 5e-4      | 16.3          | 14.7 | 15.5 | 3e-4          | 19.3  | 17.6 | 18.4 |
|                             | 1e-3      | 14.9          | 17.4 | 16.1 | 5e-4          | 18.6  | 19.9 | 19.3 |
|                             | 3e-3      | **24.0**      | **16.9** |      | 1e-3          | **26.1** | **21.7** |      |
|                             | 5e-3      | 12.0          | 24.9 | 16.2 | 3e-3          | 15.6  | 34.3 | 21.4 |
|                             | 1e-2      | 11.1          | 28.4 | 15.9 | 5e-3          | 14.8  | 37.6 | 21.2 |
| BERT w/o [mask]             | 0.8       | 21.8          | 6.2  | 9.7  | 0.3           | 44.4  | 8.4  | 14.2 |
|                             | 0.9       | 20.5          | 8.3  | 11.8 | 0.5           | 38.6  | 10.3 | 16.3 |
|                             | 0.98      | 17.2          | 14.4 | 15.7 | 0.7           | 35.8  | 11.9 | 17.8 |
|                             | 0.992     | 14.2          | 17.7 | 15.7 | 0.9           | 34.7  | 18.4 | 24.0 |
|                             | **0.994** | **20.0**      | **16.4** |      | **0.99**      | **22.8** | **34.5** | **27.5** |
|                             | 0.996     | 13.1          | 22.1 | 16.4 | 0.992         | 21.8  | 36.6 | 27.3 |
| BERT w/ inserted [mask]     | 0.8       | 5.0           | 42.5 | 8.9  | -             | -     | -    | -    |
|                             | 0.9       | 7.0           | 46.0 | 12.2 | -             | -     | -    | -    |
|                             | 0.95      | 9.2           | 43.0 | 15.2 | -             | -     | -    | -    |
|                             | **0.998** | **30.9**      | **23.8** | **26.9** | -             | -     | -    | -    |
|                             | 0.999     | 36.9          | 18.9 | 25.3 | -             | -     | -    | -    |
| MacBERT                     | 0.01      | 6.4           | 11.8 | 8.3  | 0.01          | 11.2  | 28.2 | 16.0 |
|                             | 0.03      | 6.7           | 16   | 9.5  | **0.02**      | **11.3** | **33.9** | **17.0** |
|                             | 0.05      | 7.1           | 19.1 | 10.4 | 0.03          | 10.9  | 35.4 | 16.7 |
|                             | 0.07      | 6.9           | 20.1 | 10.2 | 0.05          | 10.3  | 37.9 | 16.2 |
|                             | **0.1**   | **6.7**       | **22.4** | **10.4** | 0.1         | 9.4   | 43.1 | 15.5 |
|                             | 0.2       | 5.7           | 25.6 | 9.4  | 0.2           | 8.1   | 49.8 | 13.9 |
| PLOME                       | 0.07      | 6.8           | 21.6 | 10.3 | 0.7           | 10.4  | 29.8 | 15.4 |
|                             | 0.05      | 6.6           | 26.2 | 10.5 | 0.8           | 10.3  | 34.0 | 15.8 |
|                             | **0.08**  | **6.4**       | **34.2** | **10.8** | **0.85**    | **10.2** | **37.2** | **16.0** |
|                             | 0.09      | 6.0           | 40.2 | 10.5 | 0.9           | 9.9   | 41.5 | 16.0 |
| Our Approach                | 0.06      | 7.0           | 73.2 | 75.0 | 0.8           | 33.2  | 92.2 | 48.8 |
|                             | **0.07**  | **76.2**      | **75.2** | **75.7** | 0.9         | 41.8  | 88.9 | 56.8 |
|                             | 0.08      | 74.9          | 76.3 | 75.6 | 0.98         | 59.9  | 78.4 | 67.9 |
|                             | 0.09      | 73.8          | 76.7 | 75.2 | 0.99         | 66.3  | 72.0 | 69.1 |
|                             | 0.1       | 72.7          | 77.6 | 75.1 | **0.991**    | **67.3** | **71.1** | **69.3** |
|                             | 0.12      | 70.1          | 79.0 | 74.3 | 0.992        | 68.3  | 69.4 | 68.8 |

Figure 6: The performance of our approach on detecting deletion and insertion errors with different thresholds. Numbers are reported on the dev set. The finally selected thresholds are marked with dot lines.
| Method                  | Insertion |        |        | Deletion |        |        |
|------------------------|-----------|--------|--------|----------|--------|--------|
|                        | P  | R  | F1 | P  | R  | F1  |
| BERT w/ substituted [mask] | 12.2 | 0.8 | 1.5 | 55.9 | 3.3 | 6.2  |
| BERT w/o [mask]        | 8.9 | 19.7 | 12.2 | 27.4 | 29.0 | 28.2 |
| BERT w/ inserted [mask] | 12.6 | 11.6 | 11.8 | -    | -    | -    |
| Flying                 | 35.3 | 11.4 | 17.2 | 40.9 | 13.9 | 20.8 |
| Our approach           | **43.7** | **39.5** | **41.5** | **41.2** | **39.7** | **40.4** |

Table 7: Results on CGED.