A Simple but Effective Classification Model for Grammatical Error Correction

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Abstract

We treat grammatical error correction (GEC) as a classification problem in this study, where for different types of errors, a target word is identified, and the classifier predicts the correct word form from a set of possible choices. We propose a novel neural network based feature representation and classification model, trained using large text corpora without human annotations. Specifically we use RNNs with attention to represent both the left and right context of a target word. All feature embeddings are learned jointly in an end-to-end fashion. Experimental results show that our novel approach outperforms other classifier methods on the CoNLL-2014 test set (F0.5 45.05%). Our model is simple but effective, and is suitable for industrial production.

1 Introduction

In recent years, many promising approaches have been proposed for grammatical error correction. They can be categorized into two types: classification and machine translation (MT). In the classification approach, for a specific error type, GEC is cast as a classification task (possibly with multiple classes), where the class labels represent the correct forms of the words in the sentence. Rozovskaya et al. (2014) proposed a classification system CUUI that used different combinations of averaged perceptron, naïve Bayes, and pattern-based learning, and was the best classifier method in the CoNLL-2014 shared task (Ng et al., 2014). Wang et al. (2017) proposed a deep context model that used neural networks to extract the context information of input sentences, without complex feature engineering, and outperformed the previous classifier methods. Another widely used method is based on MT, which aims to translate the incorrect text into correct text directly. Junczys-Dowmunt and Grundkiewicz (2016) used a statistical MT (SMT) framework Moses and investigated interactions of dense and sparse features, different optimizers, and tuning strategies, and showed good performance. Chollampatt and Ng (2018) used a neural MT (NMT) system, with a multilayer convolutional encoder-decoder neural network initialized with embeddings that make use of character N-gram information, and achieved outstanding results among all the systems.

One problem with the MT based methods is that these models need a large amount of parallel data, where each sentence with grammatical errors has its corresponding correct sentence. Annotated training data (with errors labeled) is also needed for standard classifier based approaches. However, in this work we use neural networks to learn sentence/context representations for the classifier approach, and instead of relying on labeled training data, we generate data for model training from large amount of regular English text. Furthermore, we use different attention schemes to capture the dependency among words in the sentences. Our simple method does not require elaborated feature engineering for different error types, and can be trained effectively in an end-to-end fashion. Experimental results show that our approach achieves state-of-the-art results on the CoNLL-2014 data among all the classifier methods proposed before.
2 Classification Task Definition

We consider five error types: article, preposition, verb form, noun number, and subjective agreement. A neural classification model is trained for each error type. Table 1 illustrates the specific classes used for different kinds of errors. We treat article error correction as a three-category classification problem: _a/an, the_ and no article. The position where the article can appear should be in front of a noun phrase (a combination of noun words and adjective words). For preposition type, we pick 8 most common prepositions: _in, to, of, on, by, for, with, and about_. When the input sentence contains these words, we make a preposition prediction for correction. As shown in the table, verb form, noun number, and subjective agreement type can be viewed as a three-way, two-way and two-way classification problem respectively.

| Error Type          | Classes                                      |
|---------------------|----------------------------------------------|
| article             | 0 = a/an, 1 = the, 2 = None                  |
| preposition         | label = preposition index                    |
| verb form           | 0 = base form, 1 = gerund or present participle, 2 = past participle |
| noun number         | 0 = singular, 1 = plural                     |
| subjective agreement| 0 = non-3rd person singular present, 1 = 3rd person singular present |

Table 1: Classification labels for different error types.

For each error type, we first use the stanford Corenlp toolkit (Manning et al., 2014) to locate the target words that need to be checked in the given sentence. Take sentence (_she eat an apple everyday_. ) as an example. Its POS tags are (PRP VBP DT NN NN .). For subject agreement error type, we locate the POS tag VBP (verb, non-3rd person singular present) and its corresponding word _eat_, so _eat_ is the target word that we check for errors. Our model predicts a class label that stands for the relative form of the target word, and thus we can get the corresponding predicted word. For target word _eat_, if the predicted class label is 1, then the corresponding predicted word is _eats_. If the final predicted word is different from the original target word, then the original word will be marked as a mistake and be replaced by the predicted word for correction. For the given input sentence, we apply the five models corresponding to the five error types in the following order: verb form, noun number, article, preposition and subjective agreement.

3 Neural Model

Figure 1 illustrates our model architecture. We use GloVe (Pennington et al., 2014) to initialize the embedding of each input word. After we identify the target word for an error type (e.g., _eat_ in the example sentence), we split the sentence into two parts, its left context (i.e., _she_), and its right context (i.e., _an apple everyday_.), and use gated recurrent unit (GRU) (Cho et al., 2014) layer to represent them respectively. That is, given an embedded sentence _e_\_1:n and a target word _w_i_, we have the left GRU outputs _lo_\_1:i−1, and the right GRU outputs _ro_\_i+1:n.

We propose two kinds of attention mechanism to better represent the context and the target word. The difference between them is whether to use the target word information.

The first attention uses context words only, without the target word. This is to model the inner connection among the input context words. The following equations show how attention is calculated for the left GRU outputs _lo_\_1:i−1.

\[
\text{score}(lo_t) = lo_t^TWa_{lo_{t-1}} \\
a(t) = \frac{\exp(\text{score}(lo_t))}{\sum_{j=1}^{i-1} \exp(\text{score}(lo_j))} \\
lstate = (\sum_{t=1}^{i-1} a(t)lo_t) \oplus lo_{i-1}
\]

Figure 1: Model Architecture. From bottom to top are embeddings, RNN layer, RNN outputs, attention states and MLP.
where $W_a$ is a matrix. The final left context is then represented as a weighted average vector, concatenated with the last GRU output. The formula for right context state is similar, except that $ro_{i+1}$ is the last GRU output, because we feed the right context words into the GRU layer from right to left.

The second kind of attention uses the target word to model the relationship between it and its context. The following equations are for the left context.

$$score(lo_i) = lo_i^T W_b \hat{e}_i$$

$$a(t) = \frac{\exp(score(lo_i))}{\sum_{j=1}^{t-1} \exp(score(lo_j))}$$

$$lstate = \sum_{t=1}^{i-1} a(t)lo_t \oplus \hat{e}_i \oplus lo_{i-1}$$

where $W_b$ is a matrix, and $\hat{e}_i$ is the embedding of the base form of the target word. The left context state is the weighted average vector, concatenated with the target word embedding, and the last GRU output. Again similar attention is applied to the right context. We only use this target word dependent attention to noun number and verb form error types, because when deciding the correct word form for these two types, the interaction between the word itself and its contexts is crucial; whereas for the other three types, the target word information is not necessary or not correct to be useful, so we only use the first attention for them. For preposition error type, the target word itself may be wrong (e.g., the target word is of, and the right word may be to). For subjective agreement or article error types, the information about the target word (the verb, article location) is not needed to predict the correct form.

After calculating the left and right states, we concatenate them and feed it to a multilayer perceptron (MLP). At the last layer of the MLP, we use a softmax function to calculate the probability of each class for an error type:

$$L(x) = Wx + b$$
$$MLP(x) = \text{softmax}(L(ReLU(L(x))))$$

where ReLU is the Rectified Linear Unit activation function (Nair and Hinton, 2010), and $L(x)$ is a fully connected linear operation. The output of our model is the label with the highest probability.

To train the model, we use cross entropy loss:

$$\text{loss} = \frac{1}{n} \sum_{i=1}^{n} y_i \log \hat{y}_i$$  \hspace{1cm} (4)

where $n$ is the number of training samples, $\hat{y}_i$ is the predicted label, and $y_i$ is the true label.

## 4 Experiments

### 4.1 Setup

We use the wiki dump\(^1\) and COCA\(^2\) corpora to generate training data for five grammatical types separately. For example, for subjective agreement type, we locate the VBP and VBZ POS tags and the corresponding target word in a sentence, and then the word and its left/right context can be used for model training. All the input text is lowercased. The vocabulary is made up of the most $40K$ common words in the corpora, and all tokens that are not in the vocabulary are represented as a single unk token.

We use part of the CoNLL-2014 training dataset as our validation dataset. We evaluate our model on the CoNLL-2014 test set, and report $F_{0.5}$ result that is a standard metric for this error correction task. $F_{0.5}$ combines precision (P) and recall (R), while emphasizing precision twice as much as recall, since accurate feedback is often more important than coverage in error correction.

We trained the classifiers separately for each error type. Some important model settings are provided in appendix (Table A.1).

After we obtain the model’s prediction, we set a threshold (e.g., 0.9) for each error type in the final error correction process. If the probability for the predicted label is higher than the threshold and the corresponding word form is different from that of the original target word, we use the predicted one as the correction.

### 4.2 Results

#### 4.2.1 Type-specific Results

Table 2 shows the results of our model for different error types, with and without attention. For all the error types, we can see that using attention achieves better performance, suggesting the effectiveness of modeling the interaction among words in the context, or between the target word and other words.

\(^1\)https://dumps.wikimedia.org/enwiki/

\(^2\)https://corpus.byu.edu/coca/
Table 3 compares our model, CUUI, and the deep context model. The deep context model uses only the wiki dump data and the base form of the target noun word as extra context information, without attention. Our model achieves the highest $F_{0.5}$ scores for all the error types except the preposition one that has a small performance degradation. Some example corrections from our model are provided in appendix (Table A.2).

| Error Type   | Baseline | Attention |
|--------------|----------|-----------|
| article      | 46.80    | 48.83     |
| preposition  | 17.44    | 18.57     |
| verb form    | 27.71    | 33.42     |
| noun number  | 25.24    | 50.30     |
| subjective agreement | 52.95 | 57.79 |

Table 2: Results of our neural classification model, with and without attention, on CoNLL-2014 data (based on the combination of two annotators without alternative answers).

| Error Type   | A       | B       | Ours     | +/-   |
|--------------|---------|---------|----------|-------|
| article      | 33.7    | 42.1    | 48.83    | +6.7  |
| preposition  | 19.0    | 19.1    | 18.57    | -0.5  |
| verb form    | 19.2    | 15.3    | 33.42    | +14.2 |
| noun number  | 41.0    | 42.4    | 50.30    | +7.9  |
| subjective agreement | 49.3 | 49.9 | 57.79 | +7.9 |

Table 3: Results of our model, in comparison with the best classifier CUUI (A) in CoNLL-2014 and the deep context model (B). The last column means the difference with the previous highest score. Again the data is the combination of two annotators without alternative answers in CoNLL-2014.

4.2.2 Overall Results

Finally we fix the mechanical errors (punctuation, spelling and capitalization errors) using existing resources and rule-based methods similar to (Rozovskaya and Roth, 2016), since these errors are different from the grammatical mistakes and not specific to GEC. After that, our model corrects five type errors in order. In addition, we also combine our model with the public SMT system from (Rozovskaya and Roth, 2016) to build a hybrid system by letting our model and the SMT take turns to correct grammatical errors until there is no change for the input sentence. Table 4 presents the results of ours in comparison to several previously published best results on the CoNLL-2014 shared task data.

Our neural classification model outperforms the CUUI system and the deep context model, and has similar performance as (Ji et al., 2017), the first best fully neural MT method. Our hybrid method consisting of our neural classification model and the public SMT system (that is, replacing the classifier method in (Rozovskaya and Roth, 2016)) has a better performance with a 50.16 $F_{0.5}$ score. (Chollampatt and Ng, 2018) achieved the best performance as we can see, but our model is a single model without re-scoring using edit operation and language model features, and is more suitable for industrial production.

| System                          | P   | R   | $F_{0.5}$ |
|---------------------------------|-----|-----|-----------|
| CUUI                            | 41.78 | 24.88 | 36.79    |
| The public SMT                  | 66.02 | 15.11 | 39.44    |
| (Wang et al., 2017)             | 54.5 | 21.3 | 41.6    |
| Our neural model                | 58.18 | 23.68 | 45.05    |
| (Ji et al., 2017)               | N/A | N/A | 45.15    |
| (Rozovskaya and Roth, 2016)     | 60.17 | 25.64 | 47.40    |
| Our system                      | 59.36 | 30.97 | 50.16    |
| (Chollampatt and Ng, 2018)      | 65.49 | 33.14 | 54.79    |

Table 4: Overall performance of our model and other systems.

5 Conclusions

We propose a neural classification model to learn context representation of sentences for grammatical error correction. Attention mechanisms are designed to properly model characteristics of different error types. Compared to the traditional classifier methods, our approach does not need complex feature engineering, the context representation is learned jointly with classification in an end-to-end fashion, and we can effectively utilize enormous and easy-to-get native data. This method outperforms other classifier approaches, and is more suitable for industrial production compared with the state-of-the-arts.
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A Supplemental Material
| Error Type        | Attention Type | Optimizer | LR  | GRU | Threshold |
|------------------|----------------|-----------|-----|-----|-----------|
| article          | first          | SGD       | 0.08| 128 | 0.9       |
| preposition      | first          | SGD       | 0.08| 128 | 0.85      |
| verb form        | second         | Adam      | 0.001| 256| 0.9       |
| noun number      | second         | Adam      | 0.001| 256| 0.9       |
| subjective agreement | first     | SGD       | 0.08| 256 | 0.9       |

Table A.1: Important model settings of each error type. SGD means stochastic gradient descent algorithm, Adam means the algorithm from (Kingma and Ba, 2014), LR means learning rate, GRU means GRU hidden size. Other parameters are the same for all types: the word embedding size is 300, MLP hidden size is 512.

| No. | Original                                      | Proposed                                      |
|-----|-----------------------------------------------|-----------------------------------------------|
| 1.  | then how does car come into being ...         | then how does the car come into being ...     |
| 2.  | especially for the young people without marriage | especially for young people without marriage |
| 3.  | for the case of marriage, people should be honest. | in the case of marriage, people should be honest. |
| 4.  | ... negative impacts to the family            | ... negative impacts on the family            |
| 5.  | he might end up dishartened his family.       | he might end up dishartening his family.      |
| 6.  | it will just adding on their misery.           | it will just add on their misery.             |
| 7.  | ... be honest with his or her feeling.         | ... be honest with his or her feelings.        |
| 8.  | ... after realising his or her conditions.     | ... after realising his or her condition.     |
| 9.  | the popularity of social media sites have made ... | the popularity of social media sites has made ... |
| 10. | these skills are important to know, but is difficult ... | these skills are important to know, but are difficult ... |

Table A.2: Examples of our model corrections. Article errors are demonstrated in the 1st and 2nd sentences. Preposition errors are corrected in 3rd and 4th sentences. The 5th and 6th sentences show that verb form errors can be corrected. Even though the surrounding words are similar in 7th and 8th sentences, our model still successfully corrects these noun number errors. And even though the subjects are not near the verbs, errors are still corrected in the 9th and 10th sentences.