A Syntax-Guided Grammatical Error Correction Model with Dependency Tree Correction

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Abstract

Grammatical Error Correction (GEC) is a task of detecting and correcting grammatical errors in sentences. Recently, neural machine translation systems have become popular approaches for this task. However, these methods lack the use of syntactic knowledge which plays an important role in the correction of grammatical errors. In this work, we propose a syntax-guided GEC model (SG-GEC) which adopts the graph attention mechanism to utilize the syntactic knowledge of dependency trees. Considering the dependency trees of the grammatically incorrect source sentences might provide incorrect syntactic knowledge, we propose a dependency tree correction task to deal with it. Combining with data augmentation method, our model achieves strong performances without using any large pre-trained models. We evaluate our model on public benchmarks of GEC task and it achieves competitive results.

1 Introduction

Grammatical Error Correction (GEC) is a task of detecting and correcting grammatical errors in sentences. Due to the growing number of language learners of English, there has been increasing attention to the English GEC in the past few years.

Considering the outstanding performance of neural network models in machine translation tasks, numerous studies have applied cutting-edge neural machine translation models to GEC task (Zhao et al., 2019; Junczys-Dowmunt et al., 2018). Besides, the adoption of large pre-trained models becomes popular as well (Kaneko et al., 2020; Omelianchuk et al., 2020a). These works have achieved great success, but lack the use of syntactic knowledge which plays an important role in the correction of grammatical errors.

In this work, we propose a syntax-guided GEC model (SG-GEC) with dependency tree correction task to exploit the syntactic knowledge of dependency trees. A dependency tree is a directed graph representing syntactic knowledge of several words towards each other. Inspired by Veličković et al. (2017), we adopt the graph attention mechanism to utilize the syntactic knowledge within dependency trees.

Especially, the source sentences in GEC task are sentences with grammatical errors which means the dependency trees of source sentences might provide incorrect syntactic knowledge. So simply applying the graph attention mechanism over source sentences would not work well. Given that, we proposed a dependency tree correction task to construct dependency trees of corrected sentences. Considering a tree can be uniquely determined by relations of nodes, we construct the dependency trees of corrected sentences by predicting the relations of nodes instead of the entire tree. By applying this additional task, the model can construct dependency trees of corrected sentences and enrich the model with the corrected syntactic knowledge.

We apply the data augmentation method to further improve the performance of the model. Experiments are conducted on the following widely used benchmarks: CoNLL-2014 (Ng et al., 2014), FCE (Yannakoudakis et al., 2011), BEA-2019 (Bryant et al., 2019). Among models without using the large pre-trained models, our model achieves the best F-score on all benchmarks. Comparing with models which incorporate the large pre-trained models, our model achieves very competitive performance as well. In general, our model achieves strong performance without using any large pre-trained models.

Our contributions are summarized as follows:

1. To the best of our knowledge, we introduce syntactic knowledge into neural GEC model for the first time, by applying graph attention mechanism to utilize the dependency tree.
2. We propose a dependency tree correction task
to deal with the problem that the dependency trees of grammatically incorrect source sentences might provide incorrect syntactic knowledge.

3. Without using any large pre-trained model, our SG-GEC model achieves strong performances on public GEC benchmarks.

2 Related Work

Early published works in GEC developed models based on manually designed grammar rules (Murata and Nagao, 1994; Bond et al., 1996; Siegel, 1996). After Han et al. (2006) pointed out the limitation of rule-based method, some researchers turned their attention to the statistical machine learning method (Knight and Chander, 1994; Minnen et al., 2000; Izumi et al., 2003).

With the development of deep learning, recent works proposed various neural network models to solve GEC task. Some regarded the GEC task as a translation problem and applied cutting-edge neural machine translation model to deal with it (Yuan and Briscoe, 2016; Chollampatt and Ng, 2018). Many recent works (Junczys-Dowmunt et al., 2018; Zhao et al., 2019) made use of the powerful machine translation architecture Transformer (Vaswani et al., 2017). Considering the tremendous performance of pre-trained methods, pre-trained language model, such as BERT (Devlin et al., 2019),RoBERTa (Liu et al., 2019) and XLNet (Yang et al., 2019), have been adopted in GEC models (Kaneko et al., 2020; Omelianchuk et al., 2020a).

A challenge in applying neural machine translation models to GEC task is the requirement of the large training data. Given that, many works incorporated data augmentation methods to address this problem. Many works adopted pre-defined rules to generate synthetic samples with grammatical errors. (Grundkiewicz et al., 2019; Lichtarge et al., 2018; Choe et al., 2019). Kiyono et al. (2019) further studied the data augmentation methods and showed the efficacy of back-translation procedure.

Recently, dependency parsing has been further developed with neural network (Dozat and Manning, 2016; Li et al., 2018). Benefiting from it, models could receive syntactic knowledge with higher accuracy. Many works showed the potential of using syntactic knowledge in various tasks (Zhang et al., 2020; Wang et al., 2020; Jin et al., 2020). Inspired by previous works, we proposed the SG-GEC model to utilize the syntactic knowledge within dependency trees.

3 Our Approach

In this section, we will introduce our proposed approach. Firstly, we begin by providing the notations we use. Then we introduce the syntax-guided model which consists of a sentence encoder, a syntax-guided encoder and a sentence decoder. Next, we show the proposed dependency tree correction task. Finally, the objective functions will be presented. The overall architecture is shown in Figure 1.

3.1 Notations

Given GEC training data $D$ that comprise pairs of grammatically incorrect source sentence $X = (x_1, x_2, ..., x_N)$ and grammatically correct target sentence $Y = (y_1, y_2, ..., y_M)$, where $N$ is the length of source sentence and $M$ is the length of target sentence.

With a dependency parser, we can get the dependency trees $G_x = (V_x, E_x)$ of the source sentence $X$ and $G_y = (V_y, E_y)$ of the target sentence $Y$, where $V_x, V_y$ are sets of nodes, $E_x, E_y$ are sets of edges, respectively. Each node represents a token in the sentence. We denote $R$ as the set of dependency relation labels. Each edge of dependency tree is denoted as a triple $(i, j, r_{i,j})$, which means a dependency relation from the node $v_i$ to the node $v_j$ with the relation label $r_{i,j} \in R$.

3.2 Sentence Encoder

Our model adopts Transformer architecture as sentence encoder to construct the context-aware representations of source sentence. The sentence encoder encodes the source sentence $X = (x_1, x_2, ..., x_N)$ with a stack of $L_1$ identical layers which applies multi-head attention mechanism to tokens followed by feed-forward layers.

Let $H^l = (h^l_1, h^l_2, ..., h^l_N)$ denote the representations of tokens at layer $l$. In particular, the input of sentence encoder $H^0 = (h^0_1, h^0_2, ..., h^0_N)$ is the sum of the token embedding and position encoding.

It performs the multi-head attention to get the values and adopts residual connection (He et al., 2016) and layer normalization (Ba et al., 2016) to connect adjacent layers. The final contextual representation is denoted as $H^{L_1}$.

3.3 Syntax-Guided Encoder

In order to incorporate the syntactic knowledge of dependency tree, we proposed a syntax-guided encoder. It is a stack of $L_2$ identical graph layers.
which consist of graph attention mechanism and fully connected feed-forward network.

Let \( H^l = (\hat{h}^1, \hat{h}^2, ..., \hat{h}^n) \) denote the representation of tokens at layer \( l \). In particular, the input of syntax-guided encoder is the output of sentence encoder \( H^{L_1} \).

Inspired by Veličković et al. (2017), we adopt the graph attention mechanism to exploit the syntactic knowledge within the dependency tree \( G_x \) of source sentence \( X \). However, this proposed graph attention mechanism is designed for undirected graphs without labels, while the dependency tree is a directed graph with relation labels. So we treat the dependency relations as the nodes as well, and get the representation of each node by aggregating the neighbor relations.

Firstly, we get the representation of a relation \((i, j, r_{i,j})\) from the representations of nodes \(v_i\) and \(v_j\), and the learnable embedding of relation label \(r_{i,j}\). Considering incoming edges and outgoing edges might play different roles to a node, we apply different mappings over incoming relations and outgoing relations, respectively. The representation of outgoing relation \((i, j, r_{i,j})\) for node \(v_i\) is computed as follows:

\[
\overline{u}_{i,j}^{r_{i,j}} = \text{ReLU} \left( \left[ \bar{h}^i \parallel e^r_{i,j} \parallel \hat{h}^j \right] W_{\text{out}} + b_{\text{out}} \right)
\]  

(1)

where \(e^r_{i,j} \in \mathbb{R}^{d_{\text{model}}}\) is the embedding of relation label \(r_{i,j}\), \(W_{\text{out}} \in \mathbb{R}^{d_{\text{model}} \times 3d_{\text{model}}}\) and \(b_{\text{out}} \in \mathbb{R}^{d_{\text{model}}}\) are the parameters.

Similarly, the representation of incoming relation \((j, i, r_{j,i})\) for node \(v_i\) is computed as follows:

\[
\hat{h}_{j,i} = \text{ReLU} \left( \left[ \hat{h}^j \parallel e^r_{j,i} \parallel \hat{h}^i \right] W_{\text{in}} + b_{\text{in}} \right)
\]  

(2)

where \(e^r_{j,i} \in \mathbb{R}^{d_{\text{model}}}\) is the embedding of relation label \(r_{j,i}\), \(W_{\text{in}} \in \mathbb{R}^{d_{\text{model}} \times d_{\text{model}}}\) and \(b_{\text{in}} \in \mathbb{R}^{d_{\text{model}}}\).

With graph attention mechanism, we can get a new representation \(\hat{h}_i^*\) of node \(v_i\), by aggregating the representation of its neighbor outgoing relations and neighbor incoming relations. This process can be formulated as follows:

\[
\hat{h}_i^* = \sum_{u \in \mathcal{N}R_x(v_i)} \alpha(u, \hat{h}_i) uW^V
\]  

(3)

\[
\alpha(u, \hat{h}_i) = \frac{\exp \left( (uW^K)^T \hat{h}_i W^Q \right)}{\sum_{z \in \mathcal{N}R_x(v_i)} \exp \left( (zW^K)^T \hat{h}_i W^Q \right)}
\]  

(4)

where \(\mathcal{N}R_x(v_i)\) denotes all neighbor relations of \(v_i\) in dependency tree of source sentence \(G_x\), including incoming relations and outgoing relations.

Multi-head operation was adopted in graph attention as well:

\[
\text{MHGAT} \left( \hat{h}_i \right) = \left( \parallel_{t=1} S^{ht}_t \right) W^O
\]  

(5)
where $\parallel$ denotes the concatenation of the $T$ attention heads and $\hat{h}_i^{L_t}$ is the result $\hat{h}_i$ of graph attention in head $t$. Each head $t$ learns independent transformations $W_i^{L_t}, W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}, W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}, W_O \in \mathbb{R}^{td_{\text{src}} \times d_{\text{model}}}$ respectively.

The fully connected feed-forward network adopts residual connection and layer normalization for connecting the adjacent layers.

$$\hat{H}' = \text{LayerNorm} \left( \hat{H}^{l-1} + \text{MHGAT} \left( \hat{H}^{l-1} \right) \right) \quad (6)$$

$$\hat{H}^l = \text{LayerNorm} \left( \hat{H}' + \text{FFN}(\hat{H}') \right) \quad (7)$$

where $l \in [1, L_2]$, and the final representation of syntax-guided encoder is $\hat{H}^{L_2}$.

### 3.4 Dual Context Aggregation

Considering that we have two representations: one is the contextual representation $\hat{H}^{L_1} = (h_1^{L_1}, h_2^{L_1}, ..., h_N^{L_1})$ from the sentence encoder, the other is syntax-guided representation $\hat{H}^{L_2} = (\hat{h}_1^{L_2}, \hat{h}_2^{L_2}, ..., \hat{h}_N^{L_2})$ from syntax-guided encoder. Formally, the output $O = (o_1, o_2, ..., o_N)$ of the whole encoder is computed by:

$$o_i = \beta h_i^{L_1} + (1 - \beta) \hat{h}_i^{L_2} \quad (8)$$

where $\beta \in (0, 1)$ is a hyper-parameter.

### 3.5 Sentence Decoder

The sentence decoder has an architecture similar to Transformer. It is composed of $L_3$ identical layers. Each layer has three sub-layers: a masked multi-head self-attention mechanism, a multi-head attention mechanism and a feed-forward network.

Let $\overline{H}$ denotes the representations of tokens at layer $l$. Similar to the sentence encoder, the input $\overline{H}^0$ of sentence decoder is the sum of positional encoding and token embedding.

Firstly, we use the masked multi-head self-attention mechanism to encode the sequences. Then, the encoded sequence and the output of encoder $O$ are fed to the multi-head attention mechanism and feed-forward network.

For convenience, we denote the final output of the decoder $\overline{H}^{L_3}$ as $\overline{H}$. It is passed through a softmax layer to generate the probability distribution $p_i^c$ of the next word over the target vocabulary at step $i$.

Considering the similarity between input and output, we adopt copy mechanism to improve the performance of our model, which can deal with the problem of out-of-vocabulary words as well.

At each generation step $i$, we obtain copy distribution $p_i^c$ from the output of decoder $\overline{H}$ and the output of encoder $O$. Then, we calculate the generation probability $\eta_i \in [0, 1]$ from the output of decoder $\overline{H}$.

The final distribution $p_i$ at step $i$ is the weighted average of the two probability distributions:

$$p_i = \eta_i * p_i^c + (1 - \eta_i) * p_i^g \quad (9)$$

### 3.6 Dependency Tree Correction

Unlike other tasks, the source sentences in GEC task are sentences with grammatical errors. It means the dependency trees of source sentences might have errors as well. So only applying the graph attention mechanism over source sentences would get the syntactic knowledge with errors. To remedy this, we propose an auxiliary dependency tree correction task to construct dependency trees of corrected sentences and enrich the model with the corrected syntactic knowledge.

As for any two nodes in a dependency tree, there are three groups of relations between them: dependency relation, distance and ancestor-descendant relation. The tree can be uniquely determined by these relations of nodes. So we can construct the dependency trees of corrected sentences by using the final representations of the decoder to predict these relations of nodes.

The proposed dependency tree correction task consists of three sub-tasks. Each sub-task corresponds to one of the three relations between two nodes.

The first sub-task requires the model to predict the dependency relations for the given node pairs. Given the outputs $\overline{h}_i \in \overline{H}, \overline{h}_j \in \overline{H}$ of the decoder for two nodes $v_i$ and $v_j$, we adopt a multi-layer perceptron to predict the corresponding dependency relation.

$$\hat{r}_{i,j} = \text{softmax} \left( W_r \left[ \text{MLP} \left( \left[ \overline{h}_i || \overline{h}_j \right] \right) \right] + b_r \right) \quad (10)$$

where $W_r \in \mathbb{R}^{(L+1) \times d_{\text{model}}}, b_r \in \mathbb{R}^{L+1}$, and $L$ is the number of dependency relation label types in the dependency tree.

For a pair of nodes that are adjacent in the dependency tree, the gold label is the given dependency
We denote $a_{i,j}$ where $W$ maximized: the following negative log-likelihood function is optimization objective is to maximize the probability dependency tree $G$. Given a source sentence $X$, the ground truth is the ancestor-descendant relation of nodes $v_i$ and $v_j$. The distance prediction objective is defined as follows:

$$\hat{d}_{i,j} = \text{softmax} \left( W_d \left[ \text{MLP} \left( \left[ h_i \| h_j \right] \right) \right] + b_d \right)$$

where $W_d \in \mathbb{R}^{(D+1) \times d_{model}}$, $b_d \in \mathbb{R}^{D+1}$, and $D$ is the maximum distance of the dependency graphs in the dataset. $d_{i,j}$ is the ground truth.

The last sub-task requires the model to predict the ancestor-descendant relation between a pair of nodes. Given a node $v_i$, if any node $v'$ is on the path from root to node $v_i$, then node $v'$ is the ancestor of node $v$ and node $v$ is the descendant of node $v'$. We denote $a_{i,j}$ as the ancestor-descendant relation from node $v_i$ to node $v_j$. If node $v_i$ is the ancestor of node $v_j$, the ancestor-descendant relation $a_{i,j}$ is ancestor. If node $v_j$ is the ancestor of node $v_i$, the ancestor-descendant relation $a_{i,j}$ is descendant. Otherwise, there is no ancestor-descendant relation between two nodes.

It is an important syntactic knowledge and we predict the relation as follows:

$$\hat{a}_{i,j} = \text{softmax} \left( W_a \left[ \text{MLP} \left( \left[ h_i \| h_j \right] \right) \right] + b_a \right)$$

where $W_a \in \mathbb{R}^{3 \times d_{model}}$, $b_a \in \mathbb{R}^3$. For a pair of nodes on the same path from root to a leaf node, the ground truth is the ancestor-descendant relation $a_{i,j}$. Otherwise, the ground truth is non-relation.

### 3.7 Objective Function

Given a source sentence $X$ and the corresponding dependency tree $G_x$, the grammatical error correction objective is to maximize the probability of grammatically correct target sentence $Y$. The following negative log-likelihood function is optimized:

$$L_g = - \sum_{i=1}^{M} \log P \left( y_i \mid y_{1:i-1}, X, G_x, \theta \right)$$

where $\theta$ represents the parameters of model.

To construct the dependency tree of corrected sentence and enrich the model with the corrected syntactic knowledge. We also optimize the three proposed dependency tree correction objectives. Considering the inconsistency between the tokens of generated sentence and the target sentence, we only compute the loss function on the overlapped nodes. For convenience, we denote $S(\hat{Y}, Y)$ as the set of pairs of overlapped nodes.

The dependency relation prediction objective is defined as follows:

$$L_r = - \frac{M}{|S|} \sum_{(i,j) \in S(\hat{Y}, Y)} \log P \left( r_{i,j} \mid X, Y, G_x, \theta \right)$$

where $|S|$ is the size of $S(\hat{Y}, Y)$, $r_{i,j}$ is the ground truth for the relation of nodes $v_i$ and $v_j$ in dependency tree $G_y$.

The distance prediction objective is defined as follows:

$$L_d = - \frac{M}{|S|} \sum_{(i,j) \in S(\hat{Y}, Y)} \log P \left( d_{i,j} \mid X, Y, G_x, \theta \right)$$

where $d_{i,j}$ is the ground truth for the distance of nodes $v_i$ and $v_j$ in dependency tree $G_y$.

The ancestor-descendant relation prediction objective is defined as follows:

$$L_a = - \frac{M}{|S|} \sum_{(i,j) \in S(\hat{Y}, Y)} \log P \left( a_{i,j} \mid X, Y, G_x, \theta \right)$$

where $a_{i,j}$ is the ground truth for the ancestor-descendant relation of nodes $v_i$ and $v_j$ in dependency tree $G_y$.

Thus, the overall loss is the weighted sum of the grammatical error correction objective and dependency tree correction objectives:

$$L = L_g + \lambda_1 \ast L_r + \lambda_2 \ast L_d + \lambda_3 \ast L_a$$

where $\lambda_1$, $\lambda_2$ and $\lambda_3$ are the hyper-parameters.

### 4 Experiment Setup

#### 4.1 Datasets

We use the following GEC datasets as original training corpus: National University of Singapore Corpus of Learner English (NUCLE)(Dahlmeier et al.,
2013), Lang-8 Corpus of Learner English (Lang-8)(Tajiri et al., 2012), FCE dataset(Yannakoudakis et al., 2011), and Write & Improve + LOCNESS Corpus(W&I+LOCNESS)(Bryant et al., 2019).

We report results on CoNLL-2014 benchmark evaluated by official M2 scorer1(Dahlmeier and Ng, 2012), and on BEA-2019 and FCE benchmarks evaluated by ERRANT2.

4.2 Model Details

In this paper, we use the public toolkit Fairseq (Ott et al., 2019) to build our model.

We set 4 heads for multi-head graph attention and 8 heads for multi-head self-attention, masked multi-head self-attention. The dimension of word embedding and hidden units is 512. For the inner layer in the feed-forward network, the size is 2048. The numbers of layers $L_1$, $L_2$, $L_3$ are set to 6, 3 and 6, respectively. The weight $\beta$ in the dual context aggregation is 0.5. The weight coefficients of loss $\lambda_1$, $\lambda_2$, $\lambda_3$ are set to 0.5, 0.1, 0.1.

To avoid unknown tokens in datasets, we apply byte-pair encoding (BPE) (Sennrich et al., 2016b) to sentences before feeding the texts into models. This operation may divide a word into several sub-words, which might lead to the mismatch between the nodes in the dependency tree and the tokens in the source sequence. Considering that, we take the average of the word embeddings of all sub-words corresponding to a word as the input representation of this word.

The model is trained by using the Adam optimization method (Kingma and Ba, 2015) with initially learning rate 0.0001, momentum $\beta_1 = 0.9$, $\beta_2 = 0.999$ and weight decay $10^{-5}$. To avoid overfitting, we adopt dropout mechanism (Srivastava et al., 2014) with dropout rate 0.1. Beam search with beam size of 5 is used for decoding.

4.3 Training Stages

Following Omelianchuk et al. (2020b), we train the GEC model in three stages.

Firstly, we train the model on synthetic sentences generated by data augmentation method. Then, we extract sentence pairs containing grammatical errors from four training datasets (NUCLE, Lang-8, FCE and W&I+LOCNESS) and fine-tune the model on these sentence pairs. Finally, we fine-tune the model on the respective entire training dataset corresponding to each test set.

4.4 Implementation Details

The incorporation of data augmentation method has been one of the most effective ways to improve the performance of GEC models. Following previous work, we use 10M parallel sentences with synthetically generated grammatical errors (Awasthi et al., 2019).

We parse the sentences of these datasets with a dependency parser(Dozat and Manning, 2016), which is a neural graph-based model and achieves very competitive results on standard treebanks for six different languages.

To further improve the performance, we incorporate the following techniques that are widely used in GEC task. Following Choe et al. (2019), we use spellcheck Enchant3 to assist the correction of spelling errors. Following Sennrich et al. (2016a, 2017), we use the right-to-left re-ranking(R2L) method to build the ensemble of independently trained models. We pass n-best candidates generated from four left-to-right models to four right-to-left models, and re-rank the n-best candidates based on their corresponding scores.

5 Results and Analysis

5.1 Comparison Results

We evaluate the performance of our SG-GEC model on public benchmarks and compare the scores with the current top models in GEC task. Table 1 shows the results.

Comparing with previous models without using the large pre-trained models, our SG-GEC achieves the best F-score on all benchmarks. It outperforms not only all previous single models but also all ensemble models with less augmented data.

Comparing with models which incorporate the large pre-trained models, our model achieves very competitive performance as well. As for single models, our model outperforms the method that adopts pre-trained model BERT and large amounts of augmented data(Kaneko et al., 2020). As for ensemble models, our model achieves the best F-score on CoNLL-2014 benchmark and FCE benchmark. Besides, it achieves very strong performance on BEA-2019 benchmark without using any large pre-trained models. Comparing with the method (Omelianchuk et al., 2020a) that adopts three large pre-trained models which leads to huge computing costs, the results of our ensemble model are

1https://github.com/nusnlp/m2scorer
2https://github.com/chrisjbryant/errant
3https://github.com/pyenchant/pyenchant
Table 1: Comparison results of GEC methods. The top group shows the results of the single models. The second group shows the results of the ensemble models. Pre-trained model column shows whether the method adopts any large pre-trained models. Augmented data sizes show the amounts of additional training sentences used in each method. **Bold** indicates the highest score in each column.

Table 2: Results of ablation study on CoNLL-2014 benchmark. For the last three models, we do the significance tests of F-score between these model and Copy-Transformer respectively. * means the p-value < 0.1. ** means the p-value < 0.05. *** means the p-value < 0.01

5.2 Ablation Study

Firstly, we perform an ablation study on the CoNLL-2014 benchmark to evaluate the influence of different modules in our proposed SG-GEC model. Four ensemble models are investigated in this part: the baseline model Copy-Transformer, the model with dependency tree correction, the model with syntax-guided encoder, the full model SG-GEC. All models apply the data augmentation and techniques mentioned in previous parts. In order to ensure the reliability of the results, we do the significance tests of F-score between models. We randomly divide the test set into ten subsets and get the F-scores of the models on each of them. Then we apply paired-samples t-test to test the significance of results.

Table 2 shows the results. As we can see, both graph attention mechanism and dependency tree correction task significantly improve the performance of model. We find that the additional dependency tree correction task can increase both precision and recall of the model. The model can achieve better performance by adding dependency tree correction loss. Besides, we can find that applying syntax-guided encoder with graph attention mechanism can greatly improve the performance of model as well. In particular, the precision of model increases by 5.2. It shows that graph attention mechanism can capture the syntactic knowledge within dependency tree and adopting this syntactic knowledge can significantly improve the precision of the model in grammatical error correction.

Utilizing both syntax-guided encoder and dependency tree correction task can further improve the model performance. By constructing the dependency trees of corrected sentences, we can enrich the model with the corrected syntactic knowledge. As we can see, our full model SG-GEC with both syntax-guided encoder and dependency tree correction task achieves the best precision, recall and F-score on the benchmark.
Table 3: Ablation results of sub-tasks for dependency tree correction on CoNLL-2014 benchmark.

| Model                                      | P   | R   | $F_{0.5}$ |
|--------------------------------------------|-----|-----|-----------|
| SG-GEC                                     | 78.7| 41.7| 66.8      |
| SG-GEC – Dependency relation prediction    | 77.5| 41.0| 65.8      |
| SG-GEC – Distance prediction               | 78.3| 41.5| 66.5      |
| SG-GEC – Ancestor-descendant relation prediction | 78.1| 41.2| 66.2      |

Table 4: Example of corrections. Brackets mark the spans of errors. The text on the right of the arrow is the correction of the error on the left.

![Dependency tree of the source sentence in the case.](image)

We further perform an ablation study to investigate the influence of proposed sub-tasks. We evaluate the performance of the ensemble models that remove a sub-task on the CoNLL-2014 benchmark respectively. Table 3 presents the results.

We can find out that all sub-tasks, dependency relation prediction, distance prediction and ancestor-descendant relation prediction, are useful for improving the performance of the model. Specifically, the removing of dependency relation prediction sub-task has the greatest impact on the performance of the model. The F-score of the model without dependency relation prediction sub-task decreases by 1.0. It may indicate that the importance of dependency relations between the nodes. In addition, the F-score of the models without distance prediction and ancestor-descendant relation sub-task decreases by 0.3 and 0.6 respectively. We can see the effects of these two sub-tasks from the results.

5.3 Case Study

In this section, we use a specific case to analyze our proposed SG-GEC model. In Table 4, we show an example of our proposed model.

In this case, we can see how syntactic knowledge improves the performance of the model. The dependency tree of source sentence is shown as Figure 2. The source sentence contains two grammatical errors: one is subject-verb agreement (SVA) error, and the other is verb tense (Vt) error. Copy-Transformer can only detect and correct the SVA errors. With the help of graph attention mechanism, SG-GEC model can capture the dependency relation rcmod (relative clause) between verb "suffered" and noun "one", and the dependency relation nsubj (nominal subject) between verb "keep" and noun "one". Considering the tense of verb "keep", present tense is proper in this sentence. With the help of syntactic knowledge, our model can detect and correct both errors in this source sentence.

6 Conclusion

In this work, we propose a syntax-guided GEC model (SG-GEC) which adopts the graph attention mechanism to utilize the syntactic knowledge of dependency tree. Considering the dependency trees of the grammatically incorrect source sentences might provide incorrect syntactic knowledge, we propose a dependency tree correction task to deal with it. Combining with data augmentation method, our model achieves strong performances without using any large pre-trained models. We evaluate our model on public benchmarks of GEC task and it achieves competitive results.

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