Erroneous data generation for Grammatical Error Correction

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Abstract

It has been demonstrated that the utilization of a monolingual corpus in neural Grammatical Error Correction (GEC) systems can significantly improve the system performance. The previous state-of-the-art neural GEC system is an ensemble of four Transformer models pretrained on a large amount of Wikipedia Edits. The Singsound GEC system follows a similar approach but is equipped with a sophisticated erroneous data generating component. Our system achieved an $F_{0.5}$ of 66.61 in the BEA 2019 Shared Task: Grammatical Error Correction. With our novel erroneous data generating component, the Singsound neural GEC system yielded an $M^2$ of 63.2 on the CoNLL-2014 benchmark (8.4% relative improvement over the previous state-of-the-art system).

1 Introduction

The most effective approaches to Grammatical Error Correction (GEC) task are machine translation based methods. Both Statistical Machine Translation (SMT) approaches and Neural Machine Translation (NMT) methods have achieved promising results in the GEC task.

Pretraining a decoder as a language model is an effective method to improve the performance of neural GEC systems (Junczys-Dowmunt et al., 2018). As an extension of this work, Lichtarge et al. (2018) showed pretraining on 4 billion tokens of Wikipedia edits to be beneficial for the GEC task.

In this work, we investigate a similar approach by systematically generating parallel data for pretraining. As shown in Table 1, in addition to spelling errors (price → puice), transposition errors (independent voters → voters independent) and concatenation errors (the man → theman), our method also introduces errors such as ramped → ramping. Our approach obtained competitive results compared to the top systems in the BEA 2019 GEC Shared Task. Both our single model and ensemble models have exceeded the previous state-of-the-art systems on the CoNLL-2014 (Ng et al., 2014) benchmark and our system reaches human-level performance on the JFLEG (Napoles et al., 2017) benchmark.

2 Related Work

Chollampatt and Ng (2018) used a convolutional sequence-to-sequence (seq2seq) model (Gehring et al., 2017) with a large language model for rescoring. Their model was the first NMT based GEC system that exceeded the strong SMT baseline system (Junczys-Dowmunt and Grundkiewicz, 2016) which combined a Phrase-based Machine Translation (PBMT) with a large language model. Then a hybrid PBMT-NMT system (Grundkiewicz and Junczys-Dowmunt, 2018) appeared to reach the new state-of-the-art on the CoNLL-2014 benchmark. Later, various pure neu-

| Origin | Generated |
|--------|-----------|
| the primary is open to independent voters . | the primary is opens to voters independhent . |
| the price of alcohol is ramped up at every budget . | the puice of alcool is ramping up at every budget . |
| they say the police shot and killed the man after he had fired at them . | they say the polices shot and killed theman after he had firing at them . |

Table 1: Examples of generated data.
ral systems (Ge et al., 2018; Junczys-Dowmunt et al., 2018; Lichtarge et al., 2018) reported state-of-the-art results successively. Ge et al. presented the fluency boosting method which was demonstrated to be effective to improve performance of GEC seq2seq models. The system proposed by Junczys-Dowmunt et al. (2018) is an ensemble of Transformer models (Vaswani et al., 2017); they pretrained the decoder of transformer as a language model on a large monolingual corpus. To our best knowledge, the current state-of-the-art GEC system on both the CoNLL-2014 benchmark and the JFLEG benchmark is the system presented by Lichtarge et al. (2018), which is an ensemble of four Transformer models pretrained on Wikipedia revisions and then fine-tuned on Lang-8 (Mizumoto et al., 2011).

Table 3 shows the development and test data sets in our experiments. We choose the ABCN dev set as our development set and the ABCN test, the CoNLL-2014 test, the JFLEG as our benchmark. For these benchmarks, we report precision ($P$), recall ($R$) and $F_{0.5}$ with ERRANT (Bryant et al., 2017) on the ABCN test, GLEU (Sakaguchi et al., 2016) on the JFLEG test set (Napoles et al., 2017). To compare with previous state-of-the-art systems, we provide results of MaxMatch (M2) Scorer (Dahlmeier and Ng, 2012) on the CoNLL-2014 test set.

## 4 Erroneous Data Generation

In this section, we describe our error generating method. For each sentence, we assign a probability distribution as shown in Table 4 to determine the number of errors according to the sentence length. The parameters in Table 4 are determined empirically, as well as the parameters in Table 5, Table 6 and Table 7. Because of the time limitation of the GEC competition, we did not optimize these parameters.

After the number of errors ($E$) in a sentence has been determined, we randomly select $E$ tokens from all the tokens of the sentence with equal probability to be errors. And for each error, we apply a random variable (Table 5) to determine which error type it should be.

We introduce five error types:

- Concatenation: combine two consecutive tokens, e.g., hello world $\rightarrow$ helloworld.
- Misspelling: introduce spelling errors into

### Table 2: Statistics for training data sets.

| Corpus      | Sentences | Tokens | Anno. |
|-------------|-----------|--------|-------|
| WMT11       | 115M      | 2362M  | No    |
| 1B words    | 30M       | 769M   | No    |
| Lang-8      | 1037K     | 12M    | Yes   |
| NUCLE       | 57K       | 1.2M   | Yes   |
| FCE         | 28K       | 455K   | Yes   |
| ABCN        | 34K       | 628K   | Yes   |

### Table 3: Statistics for test and development data.

| Corpus       | Sentences | Scorer |
|--------------|-----------|--------|
| ABCN dev     | 4384      | ERRANT |
| ABCN test    | 4477      | ERRANT |
| JFLEG test   | 747       | GLEU   |
| CoNLL-2014 test | 1312       | M² Scorer |

### Table 4: Probability distribution of sentence errors.

| Length | Err. Prob. |
|--------|------------|
| $[1, 3)$ | 0.50       |
| $[3, 6)$ | 0.50       |
| $[6, 9)$ | 0.50       |
| $[9, 16)$ | 0.15, 0.25 |
| $[16, 20)$ | 0.15, 0.15 |
| $[20, 30)$ | 0.10, 0.15 |
| $[30, \infty)$ | 0.10, 0.30 |

### Table 5: Error types.

- Concatenation
- Misspelling
- Insertion
- Deletion
- Substitution

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1http://statmt.org/wmt11/training-monolingual.tgz
| Type   | Prob. |
|-------|-------|
| Concatenation | 0.12  |
| Misspell   | 0.45  |
| Substitution | 0.40  |
| Deletion  | 0.00  |
| Transposition | 0.03  |

Table 5: Error types.

| Tok. length | Err. | Prob. |
|-------------|------|-------|
| [1, 3)      | 0    | 1.00  |
| (3, 5)      | 1    | 1.00  |
| [5, 10)     | 1    | 0.80  |
| 2           | 0.20 |
| [10, ∞)     | 1    | 0.75  |
| 2           | 0.15 |
| 3           | 0.10 |

Table 6: Number of misspells in a token.

| Type         | Prob. |
|--------------|-------|
| Deletion     | 0.30  |
| Insertion    | 0.15  |
| Transposition | 0.25  |
| Replacement  | 0.30  |

Table 7: Mispell types.

- Substitution: computer → camputer.
- Deletion: delete the token.
- Transposition: the token exchange position with a consecutive token.

### 4.1 Misspelling

To generate misspellings, we introduce a random variable to determine how many errors in the token according to the token length (parameters are shown in Table 6.), and we randomly insert errors into the token.

For each spelling error, we apply another random variable to determine which error type should be. We introduce four spelling error types (Table 7 lists the parameters.).

- Deletion: delete the character.
- Insertion: insert a random English letter into the current position.

- Transposition: exchange position with the consecutive character.
- Replacement: replace the current character with a random English character.

We only introduce spelling errors into words belonging to a vocabulary list of 32k ordinary words which does not include numerals (e.g., 2019), tokens that contain digits (e.g., Lang8), URLs or non-word symbols (e.g., ≥ ▽ ≤).

### 4.2 Substitution

We introduce seven types of substitutions according to token and its part-of-speech (POS).

- Substitution between Prepositions. E.g., in, on, at, through, for, with.
- Substitution between Articles. E.g., a, an, the.
- Substitution between Pronouns (Singular). E.g., he, she, his, him, her, hers.
- Substitution between Pronouns (Plural). E.g., their, them, they, theirs.
- Substitution between Wh words. E.g., which, where, what, how, when, who, whose, whom.
- Substitution between Modal verbs. E.g., will, shall, can, may, would, could, might.
- Substitution in a Word Tree (see 4.3 for details).

### 4.3 Word Tree

We want to make substitutions such as going → gone, useful → usable, administration → administrative. To make such substitution possible, we introduce the Word Tree.

A Word Tree represents a group of words that share the same stem but have different suffixes. Figure 1 shows an example of Word Tree of “use”. A node denotes a word (e.g., usable) and corresponding Extended part-of-speech (EPOS) (e.g., VBPJJBLE) (see 4.4 for details.), and an edge indicates the root from which the word is derived (e.g., “usable” is derived from “use”).

With EPOS, we can easily set rules or assign probability distributions to determine which substitutions are more likely to happen, (e.g., singular ↔ plural, VBD ↔ VBZ ↔ VBP ↔ VBN ↔

\[ \text{We manually created this vocabulary for building the Word Tree (see 4.3 for details).} \]
VBG, adjective $\leftrightarrow$ adverb), and which substitutions are less likely to happen (e.g., happiest JJS $\leftrightarrow$ happiness JJ,NN). In our experiments, due to the time limitation of the competition, we simply assigned a uniform distribution to all existing words in a Word Tree, excluding substitutions that were definitely unlikely to occur such as substitutions between the words in an NN JJ F branch (e.g., careful) and the words in an NN JJ L branch (e.g., carelessness).

### 4.4 Extended part-of-speech

A Word Tree can contain multiple words of the same POS. As shown in the example in Figure 1, use, user and usefulness can all be nouns. Therefore, in order to identify the different roles for words in a Word Tree, we propose EPOS, derived from part-of-speech (POS) and the surface form of the word.

POS explains how a word is used (mostly syntactically) in a sentence. Compared to POS, EPOS also reflects some semantic role of a word in a sentence.

We define EPOS in Table 11 in the Appendix. We used NLTK (Bird, 2006) as our POS tagger, and use NLTK-style tags in this paper.

We briefly describe our method of creating word trees.

a. Extract the vocabulary from a text corpus which is tagged with NLTK POS tagger.

b. Create three tables for Noun, Verb, and Adjective respectively. The Noun table contains two columns: singular and plural; the Verb table has six columns: original verb form (VB), non-third person present (VBP), third person present (VBZ), past tense (VBD), past participle (VBN) and present participle (VBG); the Adjective table has four columns: adjective, adverb, comparative degree and superlative degree.
| #  | System     | P     | R     | F₀.₅ |
|----|------------|-------|-------|------|
| 1  | UEDIN-MS   | 72.28 | 60.12 | 69.47|
| 4  | CAMB-CLED  | 70.49 | 55.07 | 66.75|
| 5  | Singsound  | 70.17 | 55.39 | 66.61|

Table 8: Results of BEA 2019 GEC competition.

| dev | test |
|-----|------|
| P   | R    | F₀.₅ |
|-----|------|------|
| 52.29 | 66.06 | 56.68 | 63.94 |
| 44.60 | 50.59 | 43.60 | 49.02 |
| 55.37 | 70.14 | 57.57 | 67.21 |
| 47.01 | 56.05 | 44.33 | 53.24 |

Table 9: Results of ABCN set. "w/o pretrain" refers to models without pretraining.

gree. Then we fill words into corresponding entries according to their POS tags. Words that cannot be filled in any of the above tables are filled into a list.

c. Manually check and correct all entries of the three tables, and fill missing entries as well.

d. Define EPOS as listed in Table 11 in the Appendix according to suffix transforming rules.

e. Extract a RAW list from the vocabulary according to the suffix transforming rules.

f. Create an EPOS tree structure for each token in the RAW list, and then fill each word from the vocabulary into the corresponding entry of the corresponding EPOS tree (The full structure of the EPOS Tree is described in Table 12 in the Appendix, and Figure 2 shows the Verb branch); then prune empty entries in the trees.

g. Manually check every entry of every word tree, and fix all incorrect entries.

h. Update the defined EPOS (final version in Table 11) and the EPOS tree (Table 12); recreate word trees.

i. Repeat step g and h until satisfied.

5 Experiments

In our experiments, we generated a corpus of 3 billion tokens, of which about 24% were errors.

Following Lichtarge et al. (2018), we also use Transformer as our encoder-decoder model, using Tensor2Tensor open source implementation.

The models are trained on words, and rare words are segmented into sub-words with the byte pair encoding (BPE) (Sennrich et al., 2015). We use 6 layers for both encoder and decoder, and 4 attention heads. The embedding size and hidden size are 1024, and the filter size for all position-wise feed forward network is 4096. We set dropout rate to 0.3, and source word dropout is set to 0.2 as a noising technique. Following Junczys-Dowmunt et al. (2018), source, target and output embeddings are tied in our models.

Following Lichtarge et al. (2018), we first trained our model on an artificially generated parallel corpus with a batch size of approximately 3072 tokens. Then we set the batch size to 2048 tokens and fine-tuned on human annotated data for 20 epochs, and we averaged the 5 best checkpoints. Finally, the averaged model was fine-tuned on the ABCN and FCE training data for 1000 steps as domain adaptation (Junczys-Dowmunt et al., 2018).

There are about 50% sentence pairs without any correction in the Lang-8 dataset, and we noticed that training with too many error-free sentence pairs had a negative effect. Therefore, we filtered out these error-free sentence pairs in the Lang-8 dataset. Since the NUCLE, FCE and ABCN datasets are much smaller than the Lang-8 set, we did not filter out the error-free sentence pairs in these datasets.

We used beam search for decoding with a beam size of 4 at evaluation time. For the ensemble, we averaged logits from 4 Transformer models with identical hyper-parameters at each decoding step. Following (Grundkiewicz and Junczys-Dowmunt, 2018; Junczys-Dowmunt et al., 2018; Lichtarge et al., 2018), we preprocessed the JF-LEG dataset with spell-checking. We did not apply spell-checking to the ABCN and CoNLL-2014 datasets.

6 Results and Discussion

The results of the Singsound System in the GEC competition (Table 8) were obtained by an ensemble of four models. Because of the time limitation, we only trained two independent models.
Table 10: Comparison with top performing systems on CoNLL and JFLEG datasets. (1): Chollampatt and Ng (2017) (2): Chollampatt and Ng (2018); (3): Junczys-Dowmunt et al. (2018); (4): Grundkiewicz and Junczys-Dowmunt (2018); (5): Lichtarge et al.(2018).

from scratch. The other two were based on existing trained models. Concretely, after we got a model trained from scratch, we kept training it on the generated corpus for 0.2 epoch; then fine-tuned the model on the annotated data and ABCN and FCE training sets as before.

We provide the performance of our single model and the ensemble of 4 independently trained models on the ABCN dev and test datasets in Table 9. As the results shown in Table 9, models pretrained on the generated corpus significantly outperform the models without pretraining.

To compare with previous state-of-the-art GEC systems, we evaluated our systems on the CoNLL-2014 and JFLEG datasets. As the results shown in Table 10, our single model exceeded previous state-of-the-art systems on the CoNLL-2014 dataset. Our ensemble models achieved 8.4% relative improvement over the latest state-of-the-art results on the CoNLL-2014 benchmark.

We also report the results on the CoNLL-2014 10 annotation dataset (denoted as CoNLL-10) (Bryant and Ng, 2015) which is an extension of the CoNLL-2014 test set with 10 annotators. The human-level scores are calculated by averaging the scores for each annotator with regard to the remaining annotators. Following Chollampatt and Ng (2017), scores on CoNLL-10 (SvH) are calculated by removing one set of human annotations at a time and evaluating the system against the remaining sets. Our models reach human-level performance on both CoNLL-10 and JFLEG benchmarks.

7 Conclusion

In this work, we present a novel erroneous data generating method for training English GEC models. Our experiments show that Transformer models pretrained on generated corpus significantly outperform the previous GEC systems that are also based on Transformer. We also present a novel tool: the Word Tree, which represents a group of words that share the same stem but have different suffixes; and we show that one possible application of the Word Tree is generating erroneous text for training GEC models.

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## A Appendix

| EPOS        | POS | Annotation                      | Examples |
|-------------|-----|---------------------------------|----------|
| RAW         |     | Root of word trees, original form | use      |
| NN          | NN  | Noun                            | use      |
| NNS         | NNS | Plural form of Noun             | uses     |
| NN_JJ_F     | JJ  | NN + ful                       | useful   |
| NN_JJ_F_NN  | NN  | NN_JJ_F + ness                 | usefulness |
| NN_JJ_F_NNS | NNS | Plural form of NN_JJ_F_NN      |          |
| NN_JJ_F_NNS_ORI | NN     | Adjective used as Noun       | dreadful |
| NN_RB_F     | RB  | Adverb form of NN_JJ_F         | usefully |
| NN_JJ_L     | JJ  | NN + less                      | useless  |
| NN_JJ_L_NN  | NN  | NN_JJ_L + ness                 | uselessness |
| NN_JJ_L_NNS | NNS | Plural form of NN_JJ_L_NN      |          |
| NN_JJ_L_NNS_ORI | NN     | Adjective used as Noun       | wireless |
| NN_RB_L     | RB  | Adverb form of NN_JJ_L         | uselessly |
| NN_JJ_OUS   | JJ  | NN + ous                       | dangerous |
| NN_JJ_OUS_NN | NN   | NN_JJ_OUS + ness               | dangerousness |
| NN_JJ_OUS_NNS | NNS | Plural form of NN_JJ_OUS_NN    |          |
| NN_RB_OUS   | RB  | Adverb form of NN_JJ_OUS       | dangerously |
| NN_JJ_AL    | JJ  | NN + al                        | rational |
| NN_JJ_AL_NN | NN  | NN_JJ_AL + ness                | rationalness |
| NN_JJ_AL_NNS | NNS | Plural form of NN_JJ_AL_NN     |          |
| NN_RB_AL    | RB  | Adverb form of NN_JJ_AL        | rationally |
| NN_JJ_Y     | JJ  | NN + y                         | lucky    |
| NN_JJR_Y    | JJR | Comparative degree of NN_JJ_Y  | luckier  |
| NN_JJS_Y    | JJS | Superlative degree of NN_JJ_Y  | luckiest |
| NN_JJ_Y_NN  | NN  | NN_JJ_Y + ness                 | luckiness |
| NN_JJ_Y_NNS | NNS | Plural form of NN_JJ_Y_NN      |          |
| NN_JJ_Y_NNS_ORI | NN     | Adjective used as Noun       | safety   |
| NN_RB_Y     | RB  | Adverb form of NN_JJ_Y         | luckily  |
| NN_JJ_D     | JJ  | NN + ed                        | warmhearted |
| NN_JJ_D_NN  | NN  | NN_JJ_D + ness                 | warmheartedness |
| NN_JJ_D_NNS | NNS | Plural form of NN_JJ_D_NN      |          |
| NN_RB_D     | RB  | Adverb form of NN_JJ_D         | warmheartedly |
| VB          | VB  | Original form of verbs         | go       |
| VBD         | VBD | Past tense                     | went     |
| VBZ         | VBZ | Present third person singular  | goes     |
| VBN         | VBN | Past participle                | gone     |
| VBN_NN      | NN  | VBN + ness                     | limitedness |
| VBN_NNS     | NNS | Plural form of VBN_NN          |          |
| VBN_NNS_ORI | NNS | Plural form of VBN when VBN used as Noun | shots, thoughts |
| VBN_RB      | RB  | Adverb form of VBN             | excitedly |
| VBG         | VBG | Present participle             | baking   |
| VBG_NNS_ORI | NNS | Plural form of VBG when VBG used as Noun | bakings |
| VBG_RB      | RB  | Adverb form of VBG             | excitingly |
| VBP         | VBP | non-third person present       | go       |
By abuse notation, “+” denotes “with some suffix”.

| POS         | Definition                                                                 | Example       |
|-------------|-----------------------------------------------------------------------------|---------------|
| VBP         | Verb base form                                                               | VBP + ion     |
| NNS         | Plural form of VBP + ion                                                     | connections   |
| NN          | Verb base form                                                               | VBP + er / or / ar |
| VBP         | Verb base form                                                               |ancers, editors |
| NNS         | Plural form of VBP + ion                                                     |usable         |
| JJ          | Adjective                                                                    | usable         |
| ORI         | Adjective                                                                    | usable         |
| M           | Movement                                                                    | usable         |
| JJR         | Comparative degree of Adjective                                             | happiest       |
| JJ_NN       | JJ + ness                                                                    | happier        |
| JJ_NNS      | Plural form of JJ + ness                                                    | happiness      |
| RB          | Adverb                                                                      | happily        |
| RBR         | Comparative degree of Adverb                                               | harder         |
| RBS         | Superlative degree of Adverb                                               | hardest        |
| CD          | Cardinal digits                                                             | one            |
| CD_JJ       | Adjective form of CD                                                        | first          |
| CD_RB       | Adverb form of numbers                                                     | firstly        |
| CD_JJ_NN_ORI| Adjective used as Noun                                                      | first          |
| CD_JJ_NNS_ORI| Plural form of CD_JJ + ness                                               | firsts         |
| CD_RB_ORI   | Adverbs that are same as CD_JJ                                             | firsts         |
| CD_NNS      | Plural form of CD                                                           | ones           |
| DT          | Determiner                                                                   | the            |
| WRB         | Wh-adverb                                                                   | how, where     |
| PRP         | Personal pronoun                                                            | I, you, they   |
| IN          | Preposition or subordinating conjunction                                   | in, from, after|
| CC          | Coordinating conjunction                                                   | and            |
| MD          | Modal verb                                                                  | can            |
| OFS         | Any POS out of the POS column                                              |                |

Table 11: EPOS table.
| Parent | Children |
|--------|----------|
| RAW    | NN, JJ, VB, IN, OFS, CC, MD, DT, PRP, CD, WDT, WP, WRB |
| NN     | NNS, NN JJ F, NN JJ L, NN JJ Y, NN JJ D, NN JJ OUS, NN JJ AL |
| NN JJ D| NN RB D, NN JJ D NN |
| NN JJ Y| NN RB Y, NN JJ R Y, NN JJS Y, NN JJ Y NN, NN JJ Y NN ORI |
| NN JJ Y NN | NN JJ Y NNS |
| NN JJ Y NN ORI | NN JJ Y NNS ORI |
| NN JJ F | NN RB F, NN JJ F NN, NN JJ R F, NN JJS F, NN JJ F NN ORI |
| NN JJ F NN | NN JJ F NNS |
| NN JJ F NN ORI | NN JJ F NNS ORI |
| NN JJ L | NN RB L, NN JJ L NN, NN JJ R L, NN JJS L, NN JJ L NN ORI |
| NN JJ L NN | NN JJ L NNS |
| NN JJ L NN ORI | NN JJ L NNS ORI |
| NN JJ AL | NN RB AL, NN JJ AL NN |
| NN JJ AL NN | NN JJ AL NNS |
| NN JJ OUS | NN RB OUS, NN JJ OUS NNS |
| NN JJ OUS NN | NN JJ OUS NNS |
| VB     | VBP, VBD, VBZ, VBG, VBN |
| VBP    | VBP JJ, VBP NN R, VBP NN M, VBP NN O, VBP JJ BLE |
| VBP JJ | VBP RB, VBP JJ NN, VBP JJ NN ORI |
| VBP JJ NN | VBP JJ NNS |
| VBP JJ NN ORI | VBP JJ NNS ORI |
| VBP JJ BLE | VBP RB BLE VBP JJ BLE NN |
| VBP JJ BLE NN | VBP JJ BLE NNS |
| VBP NN R | VBP NNS R |
| VBP NN M | VBP NNS M |
| VBP NN O | VBP NNS O |
| VBG    | VBG RB, VBG NNS |
| VBN    | VBN RB, VBN NN |
| VBN NN | VBN NNS |
| JJ     | JJR, JJS, RB, JJ NN, JJ NN ORI |
| JJ NN  | JJ NNS |
| JJ NN ORI | JJ NNS ORI |
| RB     | RBR, RBS |
| CD     | CD JJ, CD JJ NN ORI, CD NNS |
| CD JJ  | CD RB, CD RB ORI |
| CD JJ NN ORI | CD JJ NNS ORI |

Table 12: Structure of the EPOS Tree.