Stronger Baselines for Grammatical Error Correction Using Pretrained Encoder–Decoder Model

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Abstract  
Grammatical error correction (GEC) literature has reported on the effectiveness of pretraining a Seq2Seq model with a large amount of pseudo data. In this study, we explored two generic pretrained encoder–decoder (Enc–Dec) models, including BART, which reported the state-of-the-art (SOTA) results for several Seq2Seq tasks other than GEC. We found that monolingual and multilingual BART models achieve high performance in GEC, including a competitive result compared with the current SOTA result in English GEC. Our implementations will be publicly available at GitHub.

1 Introduction  
Grammatical error correction (GEC) takes sentences written by language learners as inputs and corrects errors included in the inputs. Most work regard this task as a translation task and use encoder–decoder (Enc–Dec) architectures in order to convert ungrammatical sentences to grammatical ones. State-of-the-art (SOTA) Enc–Dec models for GEC are often pretrained with a large amount of pseudo data (Kiyono et al., 2019; Grundkiewicz et al., 2019; Náplava and Straka, 2019; Kaneko et al., 2020). For example, Kiyono et al. (2019) generated a pseudo corpus using back translation and achieved previous SOTA results for English GEC. Náplava and Straka (2019) generated a pseudo corpus by introducing artificial errors into monolingual corpora and achieved best scores for GEC in several languages by adopting the methods proposed by Grundkiewicz et al. (2019).

These pretrained approach needs to use a lot of a pseudo parallel corpus. Specifically, Grundkiewicz et al. (2019) uses 100M ungrammatical and grammatical sentence pairs; and Kiyono et al. (2019) and Kaneko et al. (2020) use 70M sentence pairs, which require time-consuming pretraining of GEC models using the pseudo corpus. Therefore, we studied whether publicly available pretrained Enc–Dec models without the need for pseudo data are effective for GEC.

Specifically, we investigated two proposed pretrained models using a large amount of monolingual corpora. First, we used a pretrained Enc–Dec model, masked sequence to sequence (MASS) pretraining, proposed by Song et al. (2019). This model was pretrained by reconstructing the masked tokens, given the remaining part of the sentence. Second, we explored the pretrained model called bidirectional and auto-regressive Transformer (BART) proposed by Lewis et al. (2019). This model was pretrained by predicting the original sequence, given the masked and shuffled sentence. Although these models achieved SOTA results for various tasks, none of them has been applied to GEC tasks.

We used these two generic pretrained models to compare with GEC models using a pseudo corpus approach (Kiyono et al., 2019; Kaneko et al., 2020; Náplava and Straka, 2019). We conducted GEC experiments for four languages: English, German, Czech, and Russian. The Enc–Dec model based on BART achieved competitive results with the current SOTA models in English GEC. The multilingual model also shows high performance in other languages despite only needing fine-tuning. These results suggest that BART can be used as a simple baseline for GEC. We also investigated why the BART initialization is superior compared to that of MASS.

2 Previous Work  
Grundkiewicz et al. (2019) reported that pretraining of the Enc–Dec model using a pseudo corpus is effective for the GEC task. In particular, they introduced word- and character-level errors into a
sentence in monolingual corpora. They developed a confusion set derived from a spellchecker and randomly replaced a word in a sentence. They also randomly deleted a word, inserted a random word, and swapped a word with an adjacent word. They performed these same operations, i.e., replacing, deleting, inserting, and swapping, for characters. They won the BEA2019 shared task (Bryant et al., 2019) by pretraining Transformer (Vaswani et al., 2017) using this method.

Kiyono et al. (2019) explored the generation of a pseudo corpus by introducing random errors or using back translation. They reported that a pretrained model with back-translation data is better than that with pseudo data based on random errors. They achieved previous SOTA results using this corpus in English GEC. Kaneko et al. (2020) combined Kiyono et al. (2019)’s pretrained model and BERT (Devlin et al., 2019) and achieved current SOTA results. The Kaneko et al. (2020)’s research is most similar to our research in that these researches use the publicly available pretrained model to GEC. The difference between these researches is the architecture of pretrained model; Kaneko et al. (2020) used pretrained encoder. Therefore, their method did not solve the problem that it requires pretraining with a large amount of pseudo data.

Náplava and Straka (2019) used methods proposed by Grundkiewicz et al. (2019) for several languages, including German, Czech, and Russian. They trained Transformer with pseudo corpora (10M sentence pairs), and achieved current SOTA results for German, Czech, and Russian GEC.

3 Pretrained Model

In this paper, we investigated two pretrained models: MASS and BART. These models are inputted with the masked sequence, but the way to mask tokens and the output length is different. This section discusses the difference between the models.

MASS. The MASS (Song et al., 2019) model is pretrained by predicting only the masked tokens given a masked sequence using Transformer. They replaced the original tokens in a sentence over a span length with masked tokens. This span length was set to roughly 50% of the total number of tokens in the sentence.

The authors released several pretrained models for NLP tasks, such as machine translation, text summarization, and conversational response generation. We used the MASS model pretrained for English generation tasks, such as summarization, for English GEC. They also pretrained a MASS model by using English and German monolingual data for the English–German translation. This model was based on the XLM (Conneau and Lample, 2019) implementation1, which uses a language embedding to distinguish the language of a sentence. Therefore, we fine-tuned this model with the language embedding representing German, for German GEC.

BART. BART (Lewis et al., 2019) is pretrained by predicting original sequence given a masked and shuffled sequence using Transformer. They introduced masked tokens with various lengths based on Poisson’s distribution, inspired by Span-BERT (Joshi et al., 2020), at multiple positions. BART is pretrained with large monolingual corpora (160 GB), including news, books, stories, and web-text domains.

They released the pretrained model using English monolingual corpora for several tasks, including summarization, and we used the model for English GEC. Liu et al. (2020) proposed multilingual BART (mBART) for machine translation task, which we used for GEC of several languages. This model is trained using monolingual corpora for 25 languages simultaneously. They used a special token for representing the language of a sentence. For example, they added <en_XX> as the encoder inputs and <ja_XX> into the initial token of decoder for En–Ja translation. To fine-tune mBART for German, Czech, and Russian GEC, we set the target language for the special token referring to that language.

4 Experiment

4.1 Settings

Common Settings. As shown in Table 1, we used learner corpora including BEA (Bryant et al., 2019; Granger, 1998; Mizumoto et al., 2011; Tajiri et al., 2012; Yannakoudakis et al., 2011; Dahlmeier et al., 2013), JFLEG (Náplava et al., 2017), and CoNLL-14 (Ng et al., 2014) data for English; Falko+MERLIN data (Boyd et al., 2014) for German; AKCES-GEC (Náplava and Straka, 2019) for Czech; and RULEC-GEC (Rozovskaya and Roth, 2019) for Russian.

1https://github.com/facebookresearch/XLM
Table 1: Data statistics.

| lang | Corpus     | Train | Dev  | Test  |
|------|------------|-------|------|-------|
| En   | BEA        | 1,157,370 | 4,384 | 4,477 |
|      | JFLEG      | -     | -    | 747   |
|      | CoNLL-2014 | -     | -    | 1,312 |
| De   | Falko+MERLIN | 19,237 | 2,503 | 2,337 |
| Cz   | AKCES-GEC  | 42,210 | 2,485 | 2,676 |
| Ru   | RULEC-GEC  | 4,980  | 2,500 | 5,000 |

Our models were fine-tuned with a single GPU (TITAN RTX), and our implementations were based on publicly available codes. We used the hyperparameters used in the previous work (Song et al., 2019; Lewis et al., 2019; Liu et al., 2020), unless otherwise noted.

The models without the ensemble method were averaged in five experiments with random seeds.

**English.** Our setting to the English datasets is almost the same as that of Kiyono et al. (2019). We extracted the training data from the BEA-train for English GEC. Similar to Kiyono et al. (2019), we did not use the unchanged sentences in the source and target sides; thus, the training data consist of 561,525 sentences. We split the BEA-dev into tuning data (2,191 sentences) and validation data (BEA-valid; 2,193 sentences) and used the former for deciding the best model.

We trained the MASS- and BART-based models by using MASS-middle-uncased and bart.large, respectively. These models are proposed for the summarization task, which requires some constraints in inference to ensure appropriate outputs; however, we did not impose any constraints because our task is different. For the MASS-based model, we followed the preprocessing used by Song et al. (2019). We applied byte-pair-encoding (BPE) (Sennrich et al., 2016) to training data for the BART-based model by using the BPE model of Lewis et al. (2019).

We used the $M^2$ scorer (Dahlmeier and Ng, 2012) and GLEU (Napoles et al., 2015) for CoNLL-14 and JFLEG, respectively, and used the ERRANT scorer (Bryant et al., 2017) for BEA-valid and BEA-test. We compared these scores with SOTA results (Kiyono et al., 2019; Kaneko et al., 2020).

**German, Czech, and Russian.** The dataset settings in this study are almost the same as those used by Náplava and Straka (2019) for each language. We used official training data and decided the best model by using the development data.

In addition, we trained the MASS- and mBART-based models for German GEC and trained only the mBART-based model for GEC tasks of other languages. We used mass_ende_1024 and mbart.cc25 for the MASS- and mBART-based models, respectively. For the MASS-based model, we followed the preprocessing of Song et al. (2019) and set German for the language embedding. For the mBART-based model, we followed Liu et al. (2020); we detokenized the GEC training data for the mBART-based model and applied SentencePiece (Kudo and Richardson, 2018). For evaluation, we tokenized outputs after recovering the subwords. We then used spaCy-based tokenizer for German and the MorphoDiTa tokenizer for Czech.

Moreover, the $M^2$ scorer was used for each language. We compared these scores with the current SOTA results (Náplava and Straka, 2019).

### 4.2 Result

**English.** Table 2 shows the results of the English GEC task, where the BART-based model is shown to achieve much better results than those of MASS-based model for CoNLL-14, JFLEG, and BEA-valid. BART is observed to achieve better initial weights for the GEC tasks than those achieved by MASS. In Section 5, we discuss in detail why these results are achieved.

When using a single model, the BART-based model is better than the model by Kiyono et al. (2019) and competitive to Kaneko et al. (2020)’s results in terms of CoNLL-14 and BEA-test. Kiyono et al. (2019) and Kaneko et al. (2020) incorporated several techniques to improve the accuracy of GEC. To compare these models, we experimented with an ensemble of five models. Our ensemble model is slightly better than our single model but worse than ensemble models by Kiyono et al. (2019) and Kaneko et al. (2020). The BART-based model along with the ensemble...
model achieves competitive results than the current SOTA results despite only needing the fine-tuning of the BART model.

**German, Czech, and Russian.** Table 3 shows the result of German, Czech, and Russian GEC.

Considering German GEC, the mBART-based model shows higher performance than that of the MASS-based model. mBART also provides appropriate initial weights for GEC tasks for languages other than English. Therefore, the pretraining method of BART is considered superior compared to that of the MASS model for the GEC task.

In the German GEC task, the mBART-based model achieves 4.45 $F_{0.5}$ points lower than the model by Náplava and Straka (2019). This could be because Náplava and Straka (2019) pretrained the GEC model with only the target language, while mBART is pretrained with 25 languages, resulting in the information of other languages being included as noise.

In the Czech GEC task, the m-BART-based model achieves 6.65 $F_{0.5}$ points lower than the model by Náplava and Straka (2019). Similar to the case of the German GEC results, we suppose that mBART includes noisy information.

Considering Russian GEC, the mBART-based model shows much lower scores than Náplava and Straka (2019)'s model. This could be because the training data for Russian GEC are scarce compared to those of German or Czech. To investigate the effect of corpus size, we additionally trained mBART model with a 10M pseudo corpus, using the Grundkiewicz et al. (2019)'s method, and fine-tuned it with the learner corpus to compensate the low-resource scenario. The result shown in Table 3 supports our hypothesis.

### 5 Discussion

**BART as a simple baseline model.** According to the German and Czech GEC results, the mBART-based model, in which we only fine-tuned the pretrained mBART model, achieves competitive scores with current SOTA models. In other words, mBART-based models are considered to show sufficiently high performance for several languages without using any pseudo corpus. These results indicate that the mBART-based model can be used as a simple GEC baseline for several languages.

**Comparison of MASS- and BART-based models** We compare the pretrained MASS- and BART-based models for each error type by using ERRANT (Bryant et al., 2017). Table 4 shows
the results for BEA-valid, where the BART-based model achieves much higher scores than those obtained by the MASS-based model for missing and replacement error types. However, the BART-based model slightly improves the correction performance for unnecessary words (+5.35 $F_{0.5}$).

When pretraining BART, the input words with various lengths were replaced with a single masked token and the fine-tuned model tended to predict the original sentence. Thus, BART could be used as a generative model. For pretraining MASS, the input and output sequences for MASS differed considerably because a part of the inputs was masked and the model predicted only the original masked words. Thus, MASS fails to learn edit operations typical to GEC, such as a replacement, effectively.

6 Conclusion

We introduced two generic pretrained Enc–Dec models, MASS and BART, into GEC. The experimental results indicate that BART better initializes Enc–Dec model parameters than MASS. The fine-tuned BART achieved competitive results compared with current SOTA results in English GEC, and the fine-tuned mBART showed a high performance in other languages. These results indicate that BART is a simple baseline model for pretraining GEC methods because it only needs fine-tuning as training. For future work, we would like to try other pretraining methods such as UniLM (Dong et al., 2019) and investigate the property of pretrained language models effective in the GEC training.

References

Adriane Boyd, Jirka Hana, Lionel Nicolas, Detmar Meurers, Katrin Wisniewski, Andrea Abel, Karin Schöne, Barbora Štindlová, and Chiara Vettori. 2014. The MERLIN corpus: Learner language and the CEFR. In Proc. of LREC, pages 1281–1288.

Christopher Bryant, Mariano Felice, Øistein E. Andersen, and Ted Briscoe. 2019. The BEA-2019 shared task on grammatical error correction. In Proc. of BEA, pages 52–75.

Christopher Bryant, Mariano Felice, and Ted Briscoe. 2017. Automatic annotation and evaluation of error types for grammatical error correction. In Proc. of ACL, pages 793–805.

Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Proc. of NeurIPS, pages 7057–7067.

Daniel Dahlmeier and Hwee Tou Ng. 2012. Better evaluation for grammatical error correction. In Proc. of NAACL-HLT, pages 568–572.

Daniel Dahlmeier, Hwee Tou Ng, and Siew Mei Wu. 2013. Building a large annotated corpus of learner English: The NUS corpus of learner English. In Proc. of BEA, pages 22–31.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proc. of NAACL-HLT, pages 4171–4186.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. In Proc. of NeurIPS, pages 13063–13075.

Sylviane Granger. 1998. The computer learner corpus: A versatile new source of data for SLA research. In Sylviane Granger, editor, Learner English on Computer, pages 3–18. Addison Wesley Longman.

Roman Grundkiewicz, Marcin Junczys-Dowmunt, and Kenneth Heafield. 2019. Neural grammatical error correction systems with unsupervised pre-training on synthetic data. In Proc. of BEA, pages 252–263.

Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S Weld, Luke Zettlemoyer, and Omer Levy. 2020. Span-BERT: Improving pre-training by representing and predicting spans. Transactions of the Association for Computational Linguistics, 8:64–77.

Masahiro Kaneko, Masato Mita, Shun Kiyono, Jun Suzuki, and Kentaro Inui. 2020. Can encoder-decoder models benefit from pre-trained language representation in grammatical error correction? In Proc. of ACL.

Shun Kiyono, Jun Suzuki, Masato Mita, Tomoya Mizumoto, and Kentaro Inui. 2019. An empirical study of incorporating pseudo data into grammatical error correction. In Proc. of EMNLP-IJCNLP, pages 1236–1242.

Philipp Koehn, Hue Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondrej Bojar, Alexandra Constantin, and Evan Herbst. 2007. Moses: Open source toolkit for statistical machine translation. In Proc. of ACL Demo Sessions, pages 177–180.

Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In Proc. of EMNLP: System Demonstrations, pages 66–71.
Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. ArXiv, abs/1910.13461.

Yinhan Liu, Jiatao Gu, Naman Goyal, Xiongmin Li, Sergey Edunov, Marjan Ghazvininejad, Mike Lewis, and Luke Zettlemoyer. 2020. Multilingual denoising pre-training for neural machine translation. ArXiv, abs/2001.08210.

Tomoya Mizumoto, Mamoru Komachi, Masaaki Nagata, and Yuji Matsumoto. 2011. Mining revision log of language learning SNS for automated Japanese error correction of second language learners. In Proc. of IJCNLP, pages 147–155.

Jakub Náplava and Milan Straka. 2019. Grammatical error correction in low-resource scenarios. In Proc. of W-NUT, pages 346–356.

Courtney Napoles, Keisuke Sakaguchi, Matt Post, and Joel Tetreault. 2015. Ground truth for grammatical error correction metrics. In Proc. of ACL-IJCNLP, pages 588–593.

Courtney Napoles, Keisuke Sakaguchi, and Joel Tetreault. 2017. JFLEG: A fluency corpus and benchmark for grammatical error correction. In Proc. of EACL, pages 229–234.

Hwee Tou Ng, Siew Mei Wu, Ted Briscoe, Christian Hadiwinoto, Raymond Hendy Susanto, and Christopher Bryant. 2014. The CoNLL-2014 shared task on grammatical error correction. In Proc. of CoNLL Shared Task, pages 1–14.

Alla Rozovskaya and Dan Roth. 2019. Grammar error correction in morphologically rich languages: The case of Russian. Transactions of the Association for Computational Linguistics, 7:1–17.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proc. of ACL, pages 1715–1725.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2019. MASS: Masked sequence to sequence pre-training for language generation. In Proc. of ICML, pages 5926–5936.

Toshikazu Tajiri, Mamoru Komachi, and Yuji Matsumoto. 2012. Tense and aspect error correction for ESL learners using global context. In Proc. of ACL, pages 198–202.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proc. of NeurIPS, pages 5998–6008.

Helen Yannakoudakis, Ted Briscoe, and Ben Medlock. 2011. A new dataset and method for automatically grading ESOL texts. In Proc. of ACL-HLT, pages 180–189.