Synthetic Data Generation for Grammatical Error Correction with Tagged Corruption Models

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Abstract

Synthetic data generation is widely known to boost the accuracy of neural grammatical error correction (GEC) systems, but existing methods often lack diversity or are too simplistic to generate the broad range of grammatical errors made by human writers. In this work, we use error type tags from automatic annotation tools such as ERRANT to guide synthetic data generation. We compare several models that can produce an ungrammatical sentence given a clean sentence and an error type tag. We use these models to build a new, large synthetic pre-training data set with error tag frequency distributions matching a given development set. Our synthetic data set yields large and consistent gains, improving the state-of-the-art on the BEA-19 and CoNLL-14 test sets. We also show that our approach is particularly effective in adapting a GEC system, trained on mixed native and non-native English, to a native English test set, even surpassing real training data consisting of high-quality sentence pairs.

1 Introduction

Grammatical error correction (GEC) systems aim to automatically correct grammatical and other types of writing errors in text. It is common to view this problem as a sequence-to-sequence task (i.e. ungrammatical sentence → grammatical sentence) and borrow models that were originally developed for neural machine translation (NMT) (Chollampatt and Ng, 2018; Junczys-Dowmunt et al., 2018; Ge et al., 2018b). Back-translation (Sennrich et al., 2016) is a synthetic data generation technique for NMT that employs a translation system trained in the reverse direction to synthesize source sentences from sentences in the target language, and is still one of the most effective strategies to use monolingual data in NMT training. Similarly, synthetic training data generation for GEC has also been widely studied in the literature (Brockett et al., 2006; Foster and Andersen, 2009; Rozovskaya and Roth, 2010; Felice et al., 2014; Rei et al., 2017; Kasewa et al., 2018; Xie et al., 2018; Ge et al., 2018a,b; Kiyono et al., 2019; Lichtarge et al., 2019; Stahlberg and Byrne, 2019; Zhao et al., 2019; Xu et al., 2019; Grundkiewicz et al., 2019; Choe et al., 2019; Takahashi et al., 2020). This work is inspired by previous efforts to use ideas from back-translation for GEC (Kasewa et al., 2018; Xie et al., 2018; Kiyono et al., 2019). In contrast to prior work, we use error type tags such as SPELL (spelling error) or SVA (subject-verb agreement error) to control the output of our corruption models and generate more realistic as well as diverse grammatical errors. Our tagged corruption models are trained to output the corrupted sentence given a clean sentence and an error tag, e.g.:

“NOUN: INFL There were a lot of sheep.”

→ “There were a lot of sheeps.”

The tags mitigate the tendency of untagged corruption models to produce simplistic corruptions since many error type tags require more complex rewrites. In general, there is a one-to-many mapping from a clean sentence to a noisy sentence. Using a regular corruption model, many of these synthetic errors tend to be simplistic, but adding tag information allows the model to generate specific patterns of errors that can be found in actual GEC corpora. The benefit of covering a wide range of error types when generating pseudo data for GEC has also been demonstrated by Takahashi et al. (2020); Wan et al. (2020). Moreover, the tag distribution in the synthetic data can be made to match the distribution of a specific target domain. We use this distribution matching technique to adapt a GEC system to better correct errors by native speakers.

1Example outputs from untagged and tagged corruption models can be found in Appendix B.
As an alternative to adding the tag directly to the input sequence, we add inference-time constraints to the recently proposed Seq2Edits model (Stahlberg and Kumar, 2020) to force the generation of a particular tag. We implement such constraints using Finite State Transducers (FSTs). We then use these corruption models to generate synthetic training data that follows a desired tag distribution, for example the tag distribution on the development set. Using our new synthetic pretraining sets\(^2\) we report state-of-the-art results on two popular GEC test sets (BEA-test: 74.9 F\(_0\), CoNLL-14: 68.3 F\(_0\)). In our experiments on GEC for native English, a model fine-tuned on synthetic data that follows a native English error-tag distribution can even surpass a model fine-tuned on high-quality, real (i.e. non-synthetic) data.

### 2 Tagged Corruption Models

At the core of our approach is a model that generates an ungrammatical sentence from a clean sentence given an error tag \(t \in T\) that describes the desired type of error. \(T\) is the set of 25 error type tags supported by the automatic annotation toolkit ERRANT (Felice et al., 2016; Bryant et al., 2017).

A straightforward way to train such a tagged corruption model is to annotate a parallel corpus with ERRANT, prepend the ERRANT tag to the clean sentence, and train a model such as a standard Transformer (Vaswani et al., 2017) to generate the ungrammatical sentence.\(^3\) This idea is similar to the multi-lingual NMT system of Johnson et al. (2017) that adds the target language ID tag to the source sentence.

Alternatively, the recently proposed Seq2Edits\(^4\) (Stahlberg and Kumar, 2020) model is able to directly predict error tags along with the edits, and does not need to be provided error tags in the input sequence. Instead, during beam search we constrain the tag output tape of Seq2Edits with an FST that forces the generation of a certain tag. Fig. 1 illustrates three types of constraint FSTs with the example tag, SPELL. All FSTs require at least one occurrence of the SPELL tag. NoSigma (Fig. 1a) is the most restrictive constraint as it only allows SPELL and SELF (used by Seq2Edits for unmodified source spans). PostSigma (Fig. 1b) allows other tags after SPELL, but constrains the hypothesis to start with either SELF or SPELL to prevent beam search from committing to a corruption that

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\(^2\)https://github.com/google-research-datasets/C4_200M-synthetic-dataset-for-grammatical-error-correction

\(^3\)If a sentence pair has multiple tags we duplicate it in the training set for each unique tag. This potentially enables the corruption model to learn co-occurrences of error categories since multiple errors may be labelled with a single tag.

\(^4\)A short description of the Seq2Edits model is provided in Appendix A for convenience.

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**Table 1:** Outputs of a tagged Seq2Edits corruption model for the example input sentence “There were a lot of sheep.” The ERRANT error type tags for native English, a model fine-tuned on synthetic data that follows a native English error-tag distribution can even surpass a model fine-tuned on high-quality, real (i.e. non-synthetic) data.

| Tag       | Log-prob | Corruption model output |
|-----------|----------|-------------------------|
| ADJ       | -3.06    | There were a lot of many sheep. |
| ADJ:FORM  | -2.49    | There were a more better of sheep. |
| ADV       | -2.63    | There were a lot of sheep there. |
| CONJ      | -1.39    | And there were a lot of sheep. |
| CONTR     | -0.90    | ’There’re a lot of sheep. |
| DET       | -1.06    | There were lot of sheep. |
| K         | -1.45    | There were a lot of. |
| MORPH     | -0.67    | There were a lot of sheep. |
| NOUN      | -2.51    | There were a lot of sheep. |
| NOUN:INFL | -0.61    | There were a lot of sheep. |
| NOUN:NUM  | -1.33    | There were a lot of sheep. |
| NOUN:POSS | -0.92    | There were a lot of sheep’s. |
| ORTH      | -0.79    | There were a lot of sheep. |
| OTHER     | -2.60    | There were a lot of sheep. |
| PART      | -1.22    | There were a lot off sheep. |
| PREP      | -1.08    | There were a lot sheep. |
| PRON      | -1.55    | It was a lot of sheep. |
| PUNCT     | -1.00    | There were a lot of sheep |
| SPELL     | -2.79    | There were a lot of sheep. |
| VERB      | -2.58    | There were a lot of sheep. |
| VERB:FORM | -2.34    | There were a lot of sheep. |
| VERB:INFL | -1.09    | There were a lot of sheep. |
| VERB:SVA  | -0.44    | There was a lot of sheep. |
| VERB:TENSE| -0.57    | There are a lot of sheep. |
| WO        | -1.87    | There were a lot sheep of. |
We compare three different methods: **Optimal**, **Offline-Optimal**, **Online**, and **Offline-Probabilistic**.

**Optimal** The **Optimal** method frames this task as a constrained optimization problem:

$$\max_{t^*} \sum_{n=1}^{N} \log P(y_{t^*,n}|t_{n}^*,x_n)$$  \hspace{1cm} (2)

under the constraint that the observed distribution of tags matches the desired distribution, i.e. Eq. 1 is satisfied. Fig. 2 illustrates that this is an instance of a well-studied problem called maximum weighted bipartite matching (Schrijver, 2003) and can be solved efficiently with a standard minimum-cost flow solver.

**Offline-Probabilistic** The intuition behind the **Offline-Probabilistic** method is to first draw a tag according to the desired tag distribution $P^*(x)$ and then sample sentences which are most likely to contain this tag, i.e. draw $N$ sentences from the distribution $P((x,y)|t)$.

$$P((x,y)|t) = \frac{P(x,y)P(t|x,y)}{\sum_{n=1}^{N} P(x_n,y_n)P(t|x_n,y_n)} = \frac{P(t|x,y)}{\sum_{n=1}^{N} P(t|x_n,y_n)},$$

where we assume each sentence-pair has the same probability $P(x,y) = \frac{1}{N}$.

$$P(t|x,y) = \frac{P(t,x,y)}{P(x,y)} = \frac{P(x)P(t|x)P(y|t,x)}{P(x,y)} \approx \frac{1}{|T|} \frac{1}{N} P(y|t,x),$$

where we assume that a) each sample has equal probability i.e. $P(x) \approx P(x,y) = \frac{1}{N}$, b) each tag is equally likely given the source sentence, $P(t|x) = \frac{1}{|T|}$, where $|T|$ is the size of the tag.

is incompatible with SPELL.\(^5\) PREPOSTSIGMA (Fig. 1c) allows other tags both before and after SPELL.

Table 1 lists example outputs of a tagged Seq2Edits corruption model for all 25 ERRANT tags and demonstrates the model’s capability to generate a broad variety of realistic errors.

### 3 Synthetic Data Generation with Tagged Corruption Models

For a grammatical input sentence $x_n$ ($n \in [1,N]$ where $N$ is the training set size), we denote the corrupted sentence according to the tag $t \in T$ as $y_{t,n}$. Our goal is to assign a single tag $t_{n}^*$ to each training sentence such that the overall distribution follows a certain desired tag distribution $P^*(t)$:

$$\forall t \in T : P^*(t) \approx \frac{|\{t_{n}^* = t|n \in [1,N]\}|}{N}$$  \hspace{1cm} (1)

We compare three different methods: **Offline-Optimal**, **Offline-Probabilistic**, and **Online**.

**Offline-Optimal** The **Offline-Optimal** method frames this task as a constrained optimization problem:

$$\max_{t^*} \sum_{n=1}^{N} \log P(y_{t^*,n}|t_{n}^*,x_n)$$  \hspace{1cm} (2)

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$$P((x,y)|t) = \frac{P(x,y)P(t|x,y)}{\sum_{n=1}^{N} P(x_n,y_n)P(t|x_n,y_n)} = \frac{P(t|x,y)}{\sum_{n=1}^{N} P(t|x_n,y_n)},$$

where we assume each sentence-pair has the same probability $P(x,y) = \frac{1}{N}$.

$$P(t|x,y) = \frac{P(t,x,y)}{P(x,y)} = \frac{P(x)P(t|x)P(y|t,x)}{P(x,y)} \approx \frac{1}{|T|} \frac{1}{N} P(y|t,x),$$

where we assume that a) each sample has equal probability i.e. $P(x) \approx P(x,y) = \frac{1}{N}$, b) each tag is equally likely given the source sentence, $P(t|x) = \frac{1}{|T|}$, where $|T|$ is the size of the tag.

\(^5\)An example of this garden-path problem would be a subject-verb-agreement (SVA) constraint, but all active hypotheses in the beam already contain an adjective error and the correct subject and verb (e.g.: “SVA He owns a large bike with tiny wheels” → “He owns a wide bike with . . .”).
vocabulary. $P(y|t, x)$ is the probability assigned by the corruption model to the target sequence $y$ given the source $x$ and tag $t$.

Unlike the *Offline-Optimal* approach, this method does not guarantee that each sentence from the original training set will be included in the sample. However, this may not matter in practice when drawing from a large pool of examples.

**Online** A major limitation that prevents the *Offline-Optimal* and *Offline-Probabilistic* methods from scaling up efficiently is that we need to run the corruption model for every combination of tag and source sentence ($\Omega(N|T|)$ runtime).\(^6\) The *Online* method avoids this computational complexity by drawing the tag $t^*_n$ for each example from the desired tag distribution $P^*(\cdot)$, and then generating the target $y_n$ given the source $x_n$ and tag $t^*_n$.

\[ \forall n \in [1, N]: t^*_n \sim P^*. \tag{3} \]

Thus, it does not rely on the corruption model probabilities. The *Online* method assigns tags on-the-fly to each sentence independently and hence runs in $\Theta(N)$.

## 4 Results

For comparability to related work, we report span-based ERRANT $F_{0.5}$-scores on the development and test sets (BEA-dev and BEA-test) of the BEA-2019 shared task (Bryant et al., 2019). We use the M2 scorer (Dahlmeier and Ng, 2012) to compute $F_{0.5}$-scores on the CoNLL-13 (Ng et al., 2013) and CoNLL-14 (Ng et al., 2013) sets, and the GLEU metric (Napoles et al., 2015) on JFLEG-dev and JFLEG-test (Napoles et al., 2017).

### 4.1 Training Setup

All our grammar *correction* models are standard Seq2Seq (not Seq2Edits) Transformers (Vaswani et al., 2017) trained with Adafactor (Shazeer and Stern, 2018) using the Tensor2Tensor (Vaswani et al., 2018) TensorFlow (Abadi et al., 2015) library. Our *corruption* models are either standard Transformers or Seq2Edits models (Stahlberg and Kumar, 2020).\(^7\) We use a Tensor2Tensor joint 32K subword vocabulary and the ‘Big’ hyper-parameter set for all our models. For our tagged corruption models we extend the subword vocabulary by the 25 ERRANT error tags.

We use both existing and new data sets to train our models (Table 2). WikiEdits and RoundTripGerman are large but noisy pre-training sets described by Lichtarge et al. (2019). In this work we introduce a new synthetic pre-training corpus – C4\(_{200M}\) – that we generated by applying our corruption methods to 200M sentences sampled randomly from the Colossal Clean Crawled Corpus (Raffel et al., 2020, C4).\(^8\) Our final *correction* models are trained using the two stage fine-tuning recipe of Lichtarge et al. (2020): after pre-training we first fine-tune on Lang-8 (Mizumoto et al., 2011) and then on BEA+FCE which is the combination of the FCE corpus (Yannakoudakis et al., 2011) and the training split of the Cambridge English Write & Improve corpus used in the BEA-2019 shared task (Bryant et al., 2019). Our *corruption* models are trained using a similar setup but do not use C4\(_{200M}\) in pre-training. In our ablation experiments, however, we modify specific stages of this training pipeline to gain more insight into our methods.

### 4.2 Synthetic vs. Real Parallel Data

In initial experiments (Tables 3 to 5) we explore how well our synthetic data generation methods can replace real parallel data. The corruption models used in this section are fine-tuned on Lang-8 but not on BEA+FCE. The seed correction model is pre-trained on WikiEdits and RoundTripGerman and fine-tuned on Lang-8. We discard the source sentences in BEA+FCE, replace them with synthetic

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\(^6\)We ignore the runtime of beam search when describing the asymptotic time complexity for simplification.

\(^7\)The focus of our work was to examine techniques for synthetic data correction while keeping the *correction* model fixed. Hence, we do not use Seq2Edits models for *correction*.

\(^8\)We filtered C4 with language ID and removed sentences longer than 250 words before selecting the 200M sentences.

| Data set                        | Synthetic | Number of sentences | Used for     |
|---------------------------------|-----------|---------------------|--------------|
| WikiEdits (Lichtarge et al., 2019) | No        | 170M                | Pre-training |
| RoundTripGerman (Lichtarge et al., 2019) | Yes       | 176M                | Pre-training |
| Lang-8 (Mizumoto et al., 2011)  | No        | 1.9M                | Stage 1 fine-tuning |
| FCE-train (Yannakoudakis et al., 2011) | No        | 26K                 | Stage 2 fine-tuning |
| BEA-train (Bryant et al., 2019) | No        | 34K                 | Stage 2 fine-tuning |
| This work: C4\(_{200M}\)       | Yes       | 200M                | Pre-training |

Table 2: Training data sets used in this work.
corruptions of the target sentences, and fine-tune the seed correction model on this synthetic data, i.e. all models in Tables 3 to 5 are trained by fine-tuning the same seed model (Table 4a and 5a) on the same set of target sentences but different sets of source sentences.

### Data generation without tags

Fine-tuning the seed model on the real parallel data improves the $F_{0.5}$-score on BEA-dev by 16.7 points (33.7 → 50.4 in rows a and b of Table 4). Our goal is to close the gap relative to the $F_{0.5}$ of 50.4 using synthetic source sentences. The corruption models in rows c and d of Table 4 do not use any error tags, which is similar to previous attempts to apply back-translation to GEC (Kasewa et al., 2018).

### Data generation with tags

Table 3 reports results from the tag-based corruption methods introduced in this work. Seq2Edits (rows b-e) is more amenable to tag-based corruption than a standard full sequence Transformer model (row a) because tag prediction is a component of the Seq2Edits model. Interestingly, the Offline-Optimal method tends to perform worse than Offline-Probabilistic and Online in the constrained Seq2Edits experiments (rows b-e). We hypothesize that Offline-Optimal might generate duller and more systematic errors because the corruption model score is used to pair tags with sentences. Increasing the diversity of synthetic errors by selecting non-optimal tag-sentence pairs ultimately improves the usefulness of the synthetic data.  

Comparing Table 4 with Table 3 we observe that controlling the tag distribution of the synthetic data from a Seq2Edits model outperforms traditional back-translation without tags. Our best model (Online column in Table 3c) achieves an $F_{0.5}$-score of 48.0 which is much better than our best system without tags (42.4 $F_{0.5}$ in Table 4c) and remarkably close to the oracle score of 50.4 $F_{0.5}$ (Table 4b) obtained using a model trained on real parallel data.

For all experiments in the remainder of this paper we used the unconstrained tagged Seq2Edits corruption models (Table 3e) because it yields reasonable gains across all methods (Offline-Optimal, Offline-Probabilistic, and Online) and is easiest and most practical to run on a large scale. Furthermore, we will only use the Online method to avoid the computational overhead of Offline-Optimal and Offline-Probabilistic.

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## Table 3: Tagged synthetic data generation where tags are chosen according to the BEA-dev tag distribution. The GEC seed model (Table 4a) is fine-tuned on BEA+FCE with synthetic source sentences and evaluated on the BEA-dev set. Rows a and e prepend the desired tag to the input sequence while rows b-d use FST constraints.

| Corruption model | Constraint | Tagged input? | Offline-Optimal | Offline-Probabilistic | Online |
|------------------|------------|---------------|-----------------|----------------------|--------|
| a Full sequence  | -          | ✓             | 54.5            | 16.7                 | 37.5   |
| b Seq2Edits      | NoSIGMA    |               | 57.2            | 21.8                 | 43.2   |
| c Seq2Edits      | POSIGMA    |               | 56.5            | 21.6                 | 42.7   |
| d Seq2Edits      | PREPOSIGMA |               | 56.3            | 22.4                 | 43.3   |
| e Seq2Edits      |            | ✓             | 55.3            | 26.7                 | 45.5   |

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## Table 4: Untagged synthetic data generation. The seed GEC model (row a) is fine-tuned on BEA+FCE target sentences that are either paired with the real source sentences (row b) or with back-translated source sentences using either a full sequence Transformer (row c) or a Seq2Edits (row d) corruption model.

| Source | Target | Offline-Optimal |
|--------|--------|-----------------|
| a N/A (Seed model) | 57.0 | 12.8 | 33.7 |
| b Real data | BEA+FCE | 56.5 | 35.2 | 50.4 |
| c Synthetic (Full seq.) | BEA+FCE | 57.5 | 20.6 | 42.4 |
| d Synthetic (Seq2Edits) | BEA+FCE | 53.4 | 20.6 | 40.5 |

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## Table 5: Adapting GEC to non-native or native English. In rows c-f the GEC seed model (row a) is fine-tuned on BEA+FCE with source sentences synthesized by a tagged Seq2Edits corruption model by following proficiency-dependent tag distributions (A1, B1, C1, or N1). FT denotes fine-tuning.

| System | Test set ($F_{0.5}$) |
|--------|----------------------|
| a Seed model | 37.6 | 34.1 | 31.4 | 22.2 |
| b FT on real data | 50.3 | 51.5 | 44.1 | 42.1 |

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$^9$The same intuition motivates our experiments in Sec. 4.3 that replace beam search with sampling.

$^{10}$We noticed that constrained decoding (Table 3b-d) often fails in large-scale experiments if the selected tag and source sentence are incompatible.
Adapting GEC to English proficiency levels  A potential use case for tagged corruption models is to adapt a GEC model to the proficiency level of the user by changing the target tag distribution $P'(t)$ of the synthetic fine-tuning set. Each sentence in the BEA-dev development set is annotated with English proficiency labels (CEFR-levels A, B, C, and ‘N’ for native English). We split BEA-dev using these labels, and then split each set again into two parts (development/test), resulting in eight disjoint subsets A1, A2, B1, B2, C1, C2, N1, N2 with about 500 sentences each. We use A1, B1, C1, and N1 to estimate proficiency-dependent target tag distributions. As before we fine-tune the seed model on the BEA-train target sentences with synthetic source sentences that follow one of these tag distributions, but evaluate the fine-tuned models on the A2, B2, C2, and N2 splits. Table 5 shows that the tag distributions from A1, B1, and C1 yield similar performance (rows c-e in Table 5) across most test sets. This suggests that our method is not effective at discriminating between the different CEFR-levels of non-native English. However, using the tag distribution from native speakers (N1 in Table 5f) does yield substantial gains on the native English test set (42.9 $F_{0.5}$ on N2), even surpassing the real parallel data (42.1 $F_{0.5}$ Table 5b). This demonstrates the potential of tag-based corruption for improving GEC of native English.

Fig. 3 shows that the error tag distribution for native English differs significantly from the non-native distributions. Native speakers (orange bar) tend to make more punctuation (PUNCT), and spelling (SPELL) mistakes whereas the determiner errors (DET) are more common in non-native text.

4.3 The C4200M Synthetic Data Set

We showed in the previous section that using an unconstrained tagged Seq2Edits corruption model that follows the BEA-dev tag distribution works well in a controlled setup (corrupting ∼60K clean target sentences from BEA+FCE). We now apply the same corruption model to a much larger, clean data set (C4200M) consisting of 200M sentences and use the resulting synthetic data set as an additional pre-training set for our GEC models. Fig. 4 reports performance from three different GEC models with different pre-training sets, each using the 2-stage fine-tuning pipeline described in Sec. 4.1. The RoundTripGerman+WikiEdits model resembles the baseline of Lichtarge et al. (2020). Using C4200M instead of RoundTripGerman+WikiEdits
Table 6: Using different target tag distributions to corrupt C4
trained using RoundTripGerman+WikiEdits and C4
followed by the 2-stage fine-tuning, i.e. row b corresponds to row 3 in Fig. 4. All tagged corruption models improve upon the untagged models (rows a and f). In contrast to our adaptation experiments in Table 5, the variations between different tag distributions are small. This indicates that even though choosing the correct tag distribution is crucial for adapting GEC to native English, at the pre-training stage the ability of tagged corruption models to generate diverse errors is more important than matching a particular distribution.

Previous work on back-translation has found that it can be beneficial to use sampling instead of beam search for synthetic data generation (Edunov et al., 2018; Kiyono et al., 2019). We confirm these findings for our tagged corruption models: Sampling (Table 6g-j) outperforms beam search (Table 6b-e) for all tag distributions except CoNLL-13. Using sampling and the BEA-dev tag distribution (Table 6g) yields good performance across all development sets. The BEA-dev tag distribution reflects a wide range of grammatical errors across various proficiency levels compared to other corpora such as CoNLL-14 (mostly beginner) or FCE (School) (Bryant et al., 2019, 2020); Stahlberg and Kumar (2020) and multiply the model score of the identity mapping with a factor (tuned on the development set) to balance precision and recall. Our single model outperforms other single models on CoNLL-14 and JFLEG-

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Table 6: Using different target tag distributions to corrupt C4
with a tagged Seq2Edits corruption model, either using beam search or sampling. We report the best of five training runs after two-stage fine-tuning according to the performance on the development set.

| Tag distribution | Decoding | BEA-dev | CoNLL-13 | JFLEG-dev |
|------------------|----------|---------|----------|-----------|
|                  |          | P       | R        | F0.5      | P       | R        | F0.5      | GLEU  |
| a None (no tags) | Beam search | 58.1 | 36.5 | 51.9 | 58.5 | 29.0 | 48.6 | 57.2 |
| b BEA-dev        | Beam search | 58.0 | 39.3 | 52.9 | 58.5 | 33.0 | 50.7 | 57.9 |
| c CoNLL-13       | Beam search | 58.8 | 39.6 | 53.6 | 58.9 | 33.3 | 51.0 | 57.9 |
| d JFLEG-dev      | Beam search | 58.3 | 39.1 | 53.1 | 58.9 | 31.6 | 50.2 | 57.6 |
| e Uniform        | Beam search | 59.1 | 39.6 | 53.8 | 58.3 | 33.4 | 50.7 | 57.7 |
| f None (no tags) | Sampling | 57.5 | 36.0 | 51.4 | 56.9 | 29.4 | 47.9 | 57.1 |
| g BEA-dev        | Sampling | 59.5 | 41.3 | 54.7 | 59.2 | 34.7 | 51.9 | 58.5 |
| h CoNLL-13       | Sampling | 58.6 | 40.7 | 53.9 | 58.5 | 33.3 | 50.8 | 58.1 |
| i JFLEG-dev      | Sampling | 59.0 | 39.7 | 53.8 | 58.2 | 34.0 | 51.0 | 58.4 |
| j Uniform        | Sampling | 59.6 | 40.6 | 54.5 | 58.3 | 34.3 | 51.1 | 58.3 |

Table 7: Data generation on WikiEdits for pre-training. Models are pre-trained on a mix of the original WikiEdits data set and a synthetic data set that consists of WikiEdits target sentences corrupted with either (1) an untagged Seq2Edits corruption model (row a), (2) round-trip translation via German (row b, or row 1 in Fig. 4), or (3) a tagged Seq2Edits corruption model (row c) following the BEA-dev tag distribution.

| GEC data (pre-training) | Synthetic source | BEA-dev |
|-------------------------|------------------|---------|
|                         |                  | P       | R        | F0.5 |
| a Untagged corruption   | WikiEdits        | 40.8 | 4.0 | 14.3 |
| b RoundTripGerman       | WikiEdits        | 33.6 | 11.6 | 24.3 |
| c Tagged corruption     | WikiEdits        | 39.7 | 20.2 | 33.3 |

Improves the final F0.5-score to 52.1. Combining all three pre-training sets leads to a large jump in F0.5 to 32.4 after pre-training. The gains are reduced after fine-tuning, but our best model still uses all three pre-training sets (52.9 F0.5 after the second fine-tuning stage). The gains in Fig. 4 from using C4200M can be attributed to a) the tagged corruption method, or b) the use of C4 rather than Wikipedia which covers a broader range of text types. In the ablation experiment in Table 7, rather than using C4200M, we corrupted the WikiRevision target sentences with various corruption methods. Tagged corruption (row c) outperforms both untagged corruption (row a) and round-trip translation (row b) when the target sentences are kept constant.

A crucial practical question is whether our approach is sensitive to the particular target tag distribution P*(t), and if the synthetic C4200M training data can help generalization to other development sets. Rows b-e in Table 6 show the performance after fine-tuning for four different tag distributions: BEA-dev, CoNLL-13, JFLEG-dev, and Uniform. Each row reports the performance of a model pre-trained using RoundTripGerman+WikiEdits and C4200M corrupted using the desired tag distribution followed by the 2-stage fine-tuning, i.e. row b corresponds to row 3 in Fig. 4. All tagged corruption models improve upon the untagged models (rows a and f). In contrast to our adaptation experiments in Table 5, the variations between different tag distributions are small. This indicates that even though choosing the correct tag distribution is crucial for adapting GEC to native English, at the pre-training stage the ability of tagged corruption models to generate diverse errors is more important than matching a particular distribution.

Previous work on back-translation has found that it can be beneficial to use sampling instead of beam search for synthetic data generation (Edunov et al., 2018; Kiyono et al., 2019). We confirm these findings for our tagged corruption models: Sampling (Table 6g-j) outperforms beam search (Table 6b-e) for all tag distributions except CoNLL-13. Using sampling and the BEA-dev tag distribution (Table 6g) yields good performance across all development sets. The BEA-dev tag distribution reflects a wide range of grammatical errors across various proficiency levels compared to other corpora such as CoNLL-14 (mostly beginner) or FCE (School) (Bryant et al., 2019, 2020); Stahlberg and Kumar (2020) and multiply the model score of the identity mapping with a factor (tuned on the development set) to balance precision and recall. Our single model outperforms other single models on CoNLL-14 and JFLEG-

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11For more insight into the difference between untagged and tagged corruptions see Appendix B.

12This factor is around 1.0 for BEA-dev and CoNLL-13 (i.e. no impact) but it helps to re-balance precision and recall on JFLEG (around 2.0).
Table 8: Comparison of our final system with related work.

| System                  | BEA-test | CoNLL-14 | JFLEG-test |
|-------------------------|----------|----------|------------|
|                         | P R F0.5 | P R F0.5 | GLEU       |
| **Single systems**      |          |          |            |
| Kiyono et al. (2019)    | 65.5     | 59.4     | 64.2       |
| Omelianchuk et al. (2020)| 79.2    | 53.9     | 72.4       |
| Lichtarge et al. (2020) | 67.6     | 62.5     | 66.5       |
| Kaneko et al. (2020)    | 67.1     | 60.1     | 65.6       |
| Wan et al. (2020)       | 66.9     | 60.6     | 65.5       |
| **This work**           | 72.1     | 64.4     | 70.4       |
| **Ensembles**           |          |          |            |
| Grundkiewicz et al. (2019)| 72.3  | 60.1     | 69.5       |
| Kiyono et al. (2019)    | 74.7     | 56.7     | 70.2       |
| Omelianchuk et al. (2020)| 79.4    | 57.2     | 73.7       |
| Lichtarge et al. (2020) | 75.4     | 64.7     | 73.0       |
| Kaneko et al. (2020)    | 72.3     | 61.4     | 69.8       |
| Wan et al. (2020)       | 72.6     | 61.3     | 70.0       |
| **This work**           | 77.7     | 65.4     | 74.9       |

5 Related Work

The body of literature on synthetic data generation for GEC is large. Various heuristics have been proposed to inject synthetic noise into grammatical sentences such as random word- or character-level insertion, substitution, deletion, or shuffling operations (Lichtarge et al., 2019; Zhao et al., 2019; Xu et al., 2019), using spell checkers (Grundkiewicz et al., 2019), or randomly applying word edits extracted from the training data (Choe et al., 2019). Kasewa et al. (2018); Stahlberg and Byrne (2019) applied back-translation (Sennrich et al., 2016) to GEC and reported substantial gains. Similar to MT (Edunov et al., 2018), back-translation for GEC can be further improved by adding noise to the decoding process (Xie et al., 2018) or by using sampling instead of beam search (Kiyono et al., 2019). Fluency-boost learning (Ge et al., 2018a,b) can also be used to generate additional sentence pairs during training. Lichtarge et al. (2019) proposed to generate noisy counterparts of grammatical English sentences by translating them to another language (e.g. German) and back (“round-trip translation”), a technique we also use in this work. The use of tags for back-translation in MT has been explored by Caswell et al. (2019). Our tagged corruption models are inspired by Wan et al. (2020) who generated synthetic sentences from latent representations that are perturbed using explicit error type tags. Our approach of adding the tags to the input sequence is simpler as it requires no modifications to the model architecture or training procedure.

6 Conclusion

We have introduced a synthetic data generation method for grammatical error correction that is able to produce a wide range of realistic grammatical errors. Our method is based on grammar corruption models that corrupt a clean sentence given an error type tag. Conditioning on the error type tag enables us to control synthetic data generation much more precisely than alternative methods such as round-trip translations or tag-independent back-translation. We explored different ways of using these tagged corruption models to generate synthetic data that follows a certain error tag distribution. We found that fine-tuning a model on synthetic data that follows a native English error tag distribution can even outperform fine-tuning on genuine parallel data from a mixture of proficiency levels. Along with this paper we published a new 200M sentence data set for GEC – C4200M. Using C4200M in pre-training of vanilla Transformer GEC models yields state-of-the-art performance on two standard GEC test sets (BEA-test and CoNLL-14). We expect this corpus to further stimulate the development of new data-driven approaches in GEC.
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**A The Seq2Edits Model**

This section contains a short description of the key elements of the Seq2Edits model which we use extensively in this work. For a detailed discussion we refer the reader to the full paper from Stahlberg and Kumar (2020).

Seq2Edits represents sequence transduction as a sequence of edit operations. Each edit operation is applied to a span in the source sentence which is either copied (labelled with SELF) or replaced by replacement tokens. Fig. 5 shows that each edit is represented by a 3-tuple consisting of an error tag $t_n$, the source span end position $p_n$ (the implicit source span start position is $p_{n-1}$), and the replacement token $r_n$. The sequence of 3-tuples is predicted auto-regressively by a modified Transformer with multiple target tapes.

Unlike Stahlberg and Kumar (2020), in this work we use Seq2Edits as a corruption model. Thus, each edit corresponds to an artificial error of a certain type (represented by the error tag $t_n$) rather than a correction. In Sec. 2 we constrain the error tag tape with FSTs (Fig. 1) to force the generation of a specific error type.

**B Example Corruptions**

The main contribution of this work is using explicit error type tags to control and diversify the output of corruption models since conventional corruption models without tags tend to generate dull and monotonous output. In the examples in Table 9 the untagged corruption model simply deletes a determiner while the tagged corruption model is able to produce a wide variety of human-like writing errors. This observation is supported by Fig. 6 which shows that the untagged corruption model mainly outputs simplistic punctuation errors while the untagged model has a much better coverage of other more complex error types.

**C Example Corrections**

Table 10 shows example outputs from two systems: with and without using our new $\text{C4}_{200M}$ pre-training data set.\(^{13}\) The system with $\text{C4}_{200M}$ tends to be more fluent because it is trained on much more English text from diverse sources. The first example in Table 10 demonstrates that pre-training on $\text{C4}_{200M}$ also seems to help learning semantics – the non-$\text{C4}_{200M}$ output (“we always stock up on traffic”) is grammatically correct, but the $\text{C4}_{200M}$ model has learned that “stocking up on traffic” is nonsensical, and that being “stuck in traffic” is probably a better match for the author’s intent.

The system with $\text{C4}_{200M}$ is able to work well across a wider range of domains by proposing more radical changes such as long-range reorderings to improve the fluency as demonstrated by the movement of “well” in the second example or the major rewrite in the third example of Table 10. However, this can make the $\text{C4}_{200M}$ model more prone to subtle changes in semantics, as shown in the last example (“public transport is a cost effective (..) allocation” → “public transport is cost effective and ..”).

\(^{13}\)https://github.com/google-research-datasets/C4\_200M-synthetic-dataset-for-grammatical-error-correction
Figure 5: Representing grammatical error correction as a sequence of span-based edit operations. The implicit start position for a source span is the end position of the previous edit operation. Self indicates spans that are copied over from the source sentence (x). The probability of the first two edits is given by:

\[
P(\text{After many years}, x) = P(t_1 = \text{SELF}|x) \cdot P(p_1 = 3|\text{SELF}, x) \cdot P(r_1 = \text{SELF}|\text{SELF}, 3, x) \cdot P(t_2 = \text{PUNCT}|\text{SELF}, 3, \text{SELF}, x) \cdot P(p_2 = 3|\text{SELF}, 3, \text{SELF}, \text{PUNCT}, x) \cdot P(r_2 = |\text{SELF}, 3, \text{SELF}, \text{PUNCT}, 3, x).
\]

Figure and caption are taken from Stahlberg and Kumar (2020).

Figure 6: Error tag distributions for untagged and tagged Seq2Edits corruption models. Most of the untagged corruptions are dull punctuation errors (PUNCT) whereas the tagged corruptions are more diverse as they follow the BEA-dev tag distribution in Fig. 3.
I'm learning a lot and the students are very friendly.

The British summertime was first introduced in England in 1908.
Table 10: Example outputs on BEA-dev (Bryant et al., 2019) after two stage fine-tuning. The system without C4200M corresponds to the first row in Fig. 4. The outputs with C4200M were generated from the system in Table 6e.