Abstract

We present FELIX – a flexible text-editing approach for generation, designed to derive the maximum benefit from the ideas of decoding with bi-directional contexts and self-supervised pre-training. In contrast to conventional sequence-to-sequence (seq2seq) models, FELIX is efficient in low-resource settings and fast at inference time, while being capable of modeling flexible input-output transformations. We achieve this by decomposing the text-editing task into two sub-tasks: *tagging* to decide on the subset of input tokens and their order in the output text and *insertion* to in-fill the missing tokens in the output not present in the input. The *tagging* model employs a novel Pointer mechanism, while the *insertion* model is based on a Masked Language Model. Both of these models are chosen to be non-autoregressive to guarantee faster inference. FELIX performs favourably when compared to recent text-editing methods and strong seq2seq baselines when evaluated on four NLG tasks: Sentence Fusion, Machine Translation Automatic Post-Editing, Summarization, and Text Simplification.

1 Introduction

The idea of text in-filling when coupled with the self-supervised pre-training of deep Transformer networks on large text corpora have dramatically changed the landscape in Natural Language Understanding. BERT (Devlin et al., 2018) and its successive refinements RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2019) implement this recipe and have significantly pushed the state-of-the-art on multiple NLU benchmarks such as GLUE (Wang et al., 2018) and SQuAD (Rajpurkar et al., 2016).

More recently, the idea of using masked or infilling style objective for model pretraining has also been applied to sequence-to-sequence tasks and has significantly pushed the state-of-the-art on a number of text generation tasks, e.g. KERMIT (Chan et al., 2019), MASS (Song et al., 2019), Bert2Bert (Rothe et al., 2019), BART (Lewis et al., 2019) and T5 (Raffel et al., 2019).

While sequence-to-sequence frameworks offer a generic tool for modeling almost any kind of text-to-text transduction, there are still many real-world tasks where generating target texts completely from scratch—as it is done with the seq2seq approaches—can be unnecessary. This is especially true for monolingual settings where input and output texts have relatively high degrees of overlap. In such cases a natural approach is to cast the task of conditional text generation into a text-editing task, where the model learns to reconstruct target texts by applying a set of edit operations to the inputs. Typically, the set of edit operations is fixed and predefined ahead of time, which on one hand limits the flexibility of the model to reconstruct arbitrary output texts from their inputs, but on the other leads
to higher sample-efficiency as the limited set of allowed operations significantly reduces the search space. Based on this observation, text-editing approaches have recently re-gained significant interest (Gu et al., 2019; Dong et al., 2019; Awasthi et al., 2019; Malmi et al., 2019).

In this paper we present a novel text-editing framework, FELIX, which is heavily inspired by the ideas of bi-directional decoding (slot in-filling) and self-supervised pre-training. In particular, we have designed FELIX with the following requirements in mind:

**Sample efficiency.** Training a high precision text generation model typically requires large amounts of high-quality supervised data. Self-supervised techniques based on text in-filling have been shown to provide a crucial advantage in low-resource settings. Hence, we focus on approaches able to benefit from already existing pre-trained language models such as BERT, where the final model is directly fine-tuned on the down-stream task.

**Fast inference time.** Achieving low latencies when serving text generation models typically requires specialized hardware and finding a trade-off between model size and accuracy. One of the major reasons for slow inference times is that text generation models typically employ an autoregressive decoder, i.e., output texts are generated in a sequential non-parallel fashion. To ensure faster inference times we opt for keeping FELIX fully non-autoregressive. Even though it is well-known that autoregressive decoding leads to higher accuracy scores, fast inference was one of our top priority features for FELIX.

**Flexible text editing.** While simplifying the learning task, text-editing models are not as powerful as general purpose sequence-to-sequence approaches when it comes to modeling arbitrary input-output text transductions. Hence, we strive to strike a balance between the complexity of learned edit operations and the percentage of input-output transformations the model can capture.

**FELIX.** To meet the aforementioned desiderata, we propose to tackle text editing by decomposing it into two sub-problems: tagging and insertion (see Fig. 1). Our tagger is a Transformer-based network that implements a novel Pointing mechanism (Vinyals et al., 2015). It decides which source tokens to preserve and in which order they appear in the output, thus allowing for arbitrary word re-ordering.

The target words not present in the source are represented by the generic slot predictions to be in-filled by the insertion model. To benefit from self-supervised pre-training, we chose our insertion model to be fully compatible with the BERT architecture, such that we can easily re-use the publicly available pre-trained checkpoints.

By decomposing text-editing tasks in this way we redistribute the complexity load of generating an output text between the two models: the source text already provides most of the building blocks required to reconstruct the target, which is handled by the tagging model. The missing pieces are then in-filled by the insertion model, whose job becomes much easier as most of the output text is already in-place. Moreover, such a two-step approach is the key for being able to use completely non-autoregressive decoding for both models and still achieve competitive results compared to fully autoregressive approaches.

We evaluate FELIX on four distinct text generation tasks: Sentence Fusion, Text Simplification, Summarization, and Automatic Post-Editing for Machine Translation and compare it to recent text-editing and seq2seq approaches. Each task is unique in the editing operations required and the amount of training data available, which helps to better quantify the value of solutions we have integrated into FELIX.

## 2 Model description

FELIX decomposes the conditional probability of generating an output sequence $y$ from an input $x$ as follows: $p(y|x) = p_{\text{ins}}(y|y^m)p_{\text{tag}}(y^t, \pi|x)$, where the two terms correspond to the tagging and the insertion model. Term $y^m$, which denotes an intermediate sequence with masked spans $y^m$ fed into the insertion model, is constructed from $y^t$, a sequence of tags assigned to each input token $x$, and a permutation $\pi$, which reorders the input tokens. Given this factorization, both models can be trained independently.

### 2.1 Tagging

The tag sequence $y^t$ is constructed as follows: source tokens that must be copied are assigned the KEEP tag, tokens not present in the output are marked by the DELETE tag, token spans present in the output but missing from the input are modeled

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1The code is publicly available at: URL to be added
### 2.2 Pointing

**FELIX** explicitly models word reordering to allow for larger global edits, as well as smaller local changes, such as swapping nearby words, *John and Mary* → *Mary and John*. Without word reordering step a vanilla editing model based on just tagging such as (Malmi et al., 2019; Dong et al., 2019), would first need to delete a span (*and Mary*) and then insert *Mary and* before *John*. **FELIX** is able to model this without the need for deletions or insertions.

Given a sequence $x$ and the predicted tags $y^t$, the re-ordering model generates a permutation $\pi$ so that from $\pi$ and $y^t$ we can reconstruct the insertion model input $y^m$. Thus we have: $p(y^m|x) = \prod_i p(\pi(i)|x_i, y^t)p(y^t|x)$. We highlight that each $\pi(i)$ is predicted independently in a non-autoregressive fashion. The output of this model is a series of predicted pointers (source token → next target token). $y^m$ can easily be constructed by daisy chaining the pointers together, as seen in Fig. 3. As highlighted by this figure, **FELIX**’s reordering process is similar to non-projective dependency parsing (Dozat and Manning, 2017), where head relationships are non-autoregressively predicted to form a tree. Similarly **FELIX** predicts next word relationship and instead forms a sequence.

Our implementation is based on a pointer network (Vinyals et al., 2015), where an attention mechanism points to the next token. Unlike previous approaches where a decoder state attends over an encoder sequence, our setup applies intra-attention, where source tokens attend to all other source tokens.

When constructing the training data there are many possible combinations of $\pi$ and $y^t$ which could produce $y^m$, as trivially all source tokens can be deleted and then target tokens inserted. Hence, we construct the dataset using a greedy method to maximize the number of kept tokens, minimize the number of inserted token, and minimize the amount of reordering, keeping source tokens in continuous sequences where possible. Since each token can only point to one other token, loops will be formed if the same token is pointed to multiple times. When constructing the dataset, we ensure that each token is only pointed to at most once. At inference time a constrained beam search is used to ensure no loops are created.

### 2.3 Insertion

An input to the insertion model $y^m$ contains a subset of the input tokens in the order determined by the tagging model, as well as masked token spans that it needs to in-fill.

To represent masked token spans we consider two options: *masking* and *infilling* (see Fig. 2). In the former case the tagging model predicts how

| Src: | The | big | very | loud | cat |
|-----|-----|-----|------|------|-----|
| $y^t$: | KEEP | DEL | DEL  | DEL  | KEEP |
| Mask $y^m$: | The | [REPL] big very loud | [REPL] MASK | MASK | cat |
| Pred: | The | noisy | large | cat |

| Infill $y^m$: | The | [REPL] big very loud | [REPL] MASK | MASK | MASK | MASK | cat |
| Pred: | The | noisy | large | PAD | PAD | PAD | cat |

Figure 2: An example of two ways to model inputs to the insertion model: via token masking (Mask) or infilling (Infill). In the former case the tagging model predicts the number of masked tokens (*INS*), while in the latter it is delegated to the insertion model, which replaces the generic *INS* tag with a fixed length span (length 4). Note that the insertion model predicts a special *PAD* symbol to mark the end of the predicted span. Replacements are modeled by keeping the deleted spans between the [REPL] tags. This transforms the source text *The big very loud cat* into the target *The noisy large cat*. Note that for simplicity this example does not include reordering.

Figure 3: Pointing mechanism to transform “the big very loud cat” into “the very big cat”. 

| CLS | The | big | very | loud | cat |
|-----|-----|-----|------|------|-----|
| [CLS] | The | big | very | loud | cat |
many tokens need to be inserted by specializing the \texttt{INSERT} tag into \texttt{INS}$_k$, where $k$ translates the span into $k$ \texttt{MASK} tokens.

For the \textit{infilling} case the \textit{tagging} model predicts a generic \texttt{INS} tag, which signals the \textit{insertion} model to infill it with a span of tokens of an arbitrary length. If we were to use an autoregressive \textit{insertion} model, the natural way to model it would be to run the decoder until it decides to stop by producing a special \textit{stop} symbol, e.g., \texttt{eos}. Since by design we opted for using a non-autoregressive model, to represent variable-length insertions we use a \texttt{PAD} symbol to pad all insertions to a fixed-length sequence of \texttt{MASK} tokens.

Note that we preserve the deleted span in the input to the \textit{insertion} model by enclosing it between \texttt{[REPL]} and \texttt{[/REPL]} tags. Even though this introduces an undesired discrepancy between the pretraining and fine-tuning data that the \textit{insertion} model observes, we found that making the model aware of the text it needs to replace significantly boosts the accuracy of the \textit{insertion} model.

### 2.4 FELIX as Insertion Transformer

Another intuitive way to picture how FELIX works is to draw a connection with the Insertion Transformer (Stern et al., 2019). In the latter the decoder starts with a blank output text (canvas) and iteratively infills it by deciding which token and in which position it should appear in the output. Multiple tokens can be inserted at a time thus achieving sub-linear decoding times. In contrast, FELIX trains a separate \texttt{tagger} model to pre-fill\textsuperscript{3} the output canvas with the input tokens in a single step. As the second and final step FELIX does the insertion into the slots predicted by the \texttt{tagger}. This is equivalent to a single decoding step of the Insertion Transformer. Hence, FELIX requires significantly fewer (namely, two) decoding steps than Insertion Transformer, and through the \texttt{tagging/insertion} decomposition of the task it is straightforward to directly take advantage of existing pre-trained masked language models.

\footnote{In all our experiments the maximum lengths of 8 was sufficient to represent over 99\% of insertion spans from the training set.}

\footnote{In the text edit tasks reported in this paper this corresponds to more than 80\% of the output tokens.}

### 3 Model implementation

#### 3.1 Tagging Model

**Tagger.** Our \texttt{tagger} is a 12-layer BERT-base model. Tags are predicted by applying a single feed-forward layer $f$ to the output of the encoder $h^L$, as such $T = \arg\max f(h^L)$.

**Pointer.** The input to the Pointer layer at position $i$ is a combination of the encoder hidden state $h^L_i$, the embedding of the predicted tag $e(T_i)$ and the positional embedding $e(p_i)^4$ as follows: $h^{L+1}_i = f([h^L_i; e(T_i); e(p_i)])$.

Next token prediction uses a pointer network attending over all hidden states, as such:

$$ p(i|\pi_i) = \text{attention}(h^{L+1}_i, h^{L+1}_{\pi(i)}) $$  
(1)

Attention between hidden states is calculated using a query-key network with a scaled dot-product:

$$ \text{Attention}(Q, K) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}}) $$  
(2)

Where $K$ and $Q$ linear projections of $h^{L+1}$ and $d_k$ is the hidden dimension. We found the optional inclusion of an additional Transformer layer prior to the query projection increased the performance on movement heavy datasets.

When realizing the pointers, we use a constrained beam search where we ensure no loops are created. We note that loops only form in $<3\%$ of the case\textsuperscript{5}.

#### 3.2 Insertion Model

Similar to the \texttt{tagger}, our \textit{insertion} model is also based on a 12-layer BERT-base and is initialized from a public pretrained checkpoint.

When using the \textit{masking} approach, the \textit{insertion} model is essentially solving a masked language modeling task and, hence, we can directly take advantage of the BERT-style pretrained checkpoints. This is a considerable advantage especially in the low-resource settings as we do not waste training data on learning a language model component of the text-editing model. With the task decomposition where \textit{tagging} and \textit{insertion} can be trained

\footnote{Voita et al. (2019) have shown that models trained with masked language modeling objectives lose positional information, a property we consider important for reordering.}

\footnote{We fix the beam size to 5. For a batch size of 32 and maximum sequence length of 128, beam search incurs an additional penalty of about 12ms when run on a Xeon CPU@3.7GHz.}
We evaluate FELIX with no reordering (FELIX) on four distinct text editing tasks: Sentence Fusion, Text Simplification, Summarization, and Automatic Post-Editing for Machine Translation. In addition to reporting previously published results for each task, we also compare to a recent text-editing approach LASERTAGGER (Malmi et al., 2019). We follow their setup and set the phrase vocabulary size to 500 and run all experiments using their most accurate autoregressive model. For all tasks we run an ablation study, examining the effect of an open vocabulary with no reordering (FELIXINSERT), and a fixed vocabulary\(^7\) with reordering model (FELIXPOINT).

**Task analysis.** The chosen tasks cover a diverse set of edit operations and a wide range of dataset sizes, varying from under 30,000 data points to over 5 million. Table 1 provides dataset statistics including: the size, sentence length, and the translation error rate (TER) (Snover et al., 2006) between the source and target sentences. We use TER to highlight unique properties of each task. The summarization dataset is a deletion heavy dataset, with the highest number of deletion edits and the largest reduction in sentence length. It contains moderate amounts of substitutions and large number of shift edits, caused by sentence re-ordering. Both the simplification and post-editing datasets contain a large number of insertions and substitutions, while simplification contains a greater number of deletion edits. Post-editing, however, is a much larger dataset covering multiple languages. Sentence fusion has the lowest TER, indicating that obtaining the fused targets requires only a limited number of local edits. However, these edits require modeling

the discourse relation between the two input sentences, since a common edit type is predicting the correct discourse connective (Geva et al., 2019).

Additionally, we provide coverage statistics and the percentage of training instances for which an editing model can fully reconstruct the output from the input of our proposed model in Table 2, contrasting it against LASERTAGGER. As both FELIX and FELIXINSERT use an open vocabulary, they cover 100% of the test data, whereas FELIXPOINT and LASERTAGGER often cover less than half. For every dataset FELIXPOINT covers a significantly higher percentage than LASERTAGGER, with the noticeable case being summarization, where there is a 3x increase in coverage. This can be explained by the high number of shift edits within summarization (Table 1), something FELIXPOINT is explicitly designed to model. We found that the difference in coverage between FELIXPOINT and LASERTAGGER correlates strongly (correlation 0.99, p<0.001) with the number of shift edits. Comparing the average percentage of MASKs inserted, we see that FELIX always inserts (~50%) less MASKs than FELIXINSERT, since no word reordering requires more deletions and insertions for the latter.

4 Experiments

We evaluate FELIX on four distinct text editing tasks: Sentence Fusion, Text Simplification, Summarization, and Automatic Post-Editing for Machine Translation. For simplicity we use the LASERTAGGER phrase vocabulary.

4.1 Sentence Fusion

Sentence Fusion is the problem of fusing independent sentences into a coherent output sentence(s).

**Data.** We use the balanced Wikipedia portion of the DiscoFuse dataset (Geva et al., 2019) and also study the effect of the training data size by creating four increasingly smaller subsets of DiscoFuse: 450,000 (10%), 45,000 (1%), 4,500 (0.1%) and 450 (0.01%) data points.

**Metrics.** Following Geva et al. (2019), we report two metrics: *Exact score*, which is the percentage of exactly correctly predicted fusions, and *SARI* (Xu et al., 2016), which computes the average F1 scores of the added, kept, and deleted n-grams.

**Results.** Table 3 includes additional BERT-based seq2seq baselines: BERT2BERT from (Rothe et al., 2019) and SEQ2SEQBERT from (Malmi et al., 2019). For all FELIX variants we further break down the scores based on how the INSERTION is modelled: via token-masking (Mask) or Infilling (Infill). Additionally, to better understand the contribution of *tagging* and *insertion* models to the final accuracy, we report scores assuming oracle *insertion* and *tagging* predictions respectively (highlighted rows).

\(^6\)We still fine-tune the insertion model to accommodate for the additional token spans between the [REPL] and [/REPL] such that it learns to condition the prediction of masked tokens on those spans.

\(^7\)For simplicity we use the LASERTAGGER phrase vocabulary.
The results show that FELIX and its variants significantly outperform the baselines LASERTAGGER and seq2seqBERT, across all data conditions. Under the 100% condition BERT2BERT achieves the highest SARI and Exact score, however for all other data conditions FELIX outperforms BERT2BERT. The results highlights that both seq2seq models perform poorly with less than 4500 (0.1%) datapoints, whereas all editing models achieve relatively good performance.

When comparing FELIX variants we see that in the 100% case FELIXINSERT outperforms FELIX, however we note that for FELIXINSERT we followed (Malmi et al., 2019) and used an additional sentence re-ordering tag, a hand crafted feature tailored to DiscOFuse which swaps the sentence order. It was included in (Malmi et al., 2019) and resulted in a significant (6% Exact) increase. However, in the low resource setting FELIXoutperforms FELIXINSERT, suggesting that FELIX is more data efficient than FELIXINSERT.

**Ablation.** We first contrast the impact of the insertion model and the tagging model, noticing that for all models Infill achieves better tagging scores and worse insertion scores than Mask. Secondly, FELIX achieves worse tagging scores but better insertion scores than FELIXINSERT. This highlights the amount of pressure each model is doing, by making the tagging task harder, such as the inclusion of reordering, the insertion task becomes easier. Finally, the insertion models even under very low data conditions achieve impressive performance. This suggests that under low data conditions, most pressure should be applied to the insertion model.

### 4.2 Simplification

Sentence simplification is the problem of simplifying sentences such that they are easier to understand. Simplification can be both lexical, replacing or deleting complex words, or syntactic, replacing complex syntactic constructions.

**Data.** Training is performed on WikiLarge, (Zhang and Lapata, 2017a) a large simplification corpus which consists of a mixture of three Wikipedia simplification datasets collected by (Kauchak, 2013; Woodsend and Lapata, 2011; Zhu et al., 2010). The test set was created by Xu et al. (2016) and consists of 359 source sentences taken from Wikipedia, and then simplified using Amazon Mechanical Turkers to create eight references per source sentence.

**Metrics.** We report SARI, as well as breaking it down into each component KEEP, DELETE, and ADD, as we found the scores were uneven across these metrics. We include a readability metrics (FKGL), and the percentage of unchanged source sentences (copy).

**Results.** In Table 4 we compare against three state-of-the-art SMT based simplification systems: (1) PBMT-R (Wubben et al., 2012), a phrase-based machine translation model. (2) Hybrid (Narayan and Gardent, 2014), a model which performs sentence splitting and deletions and then simplifies with PBMT-R. (3) SBMT-SARI (Xu et al., 2016), a syntax-based translation model trained on PPDB and which is then tuned using SARI. Four neural seq2seq approaches: (1) DRESS (Zhang and Lap-

### Table 1: Statistics across tasks: size of the dataset (Size), source length in tokens ($L_{src}$), target length in tokens ($L_{tgt}$), and TER score (Snover et al., 2006) along with its components, including number of insertions (Ins), deletions (Del), substitutions (Sub), and shifts (Shift).

| Dataset          | Size   | $L_{src}$ | $L_{tgt}$ | TER | Ins  | Del  | Sub  | Shift  |
|------------------|--------|-----------|-----------|-----|------|------|------|--------|
| Post-editing     | 5M     | 18.10     | 17.74     | 24.97| 04.24| 06.25| 11.30| 02.69  |
| Simplification   | 296K   | 22.61     | 21.65     | 26.02| 04.75| 08.97| 09.90| 02.41  |
| Summarization    | 26K    | 32.48     | 22.16     | 42.33| 00.29| 32.06| 09.34| 10.71  |
| Sentence fusion  | 4.5M   | 30.51     | 30.04     | 30.04| 10.92| 02.49| 04.91| 03.75  |

### Table 2: Coverage and MASK statistics. Coverage is the percentage of training examples that the models are able to generate. Both FELIXINSERT and FELIX have full coverage of all test sets. MASK % is the ratio of masked tokens to target tokens.

| Dataset            | Coverage | LASERTAGGER | FELIXPOINT | MASK % | FELIXINSERT | FELIX |
|--------------------|----------|-------------|------------|--------|-------------|-------|
| Postediting        | 35.10    | 40.40       | 42.39      | 17.30  |
| Simplification     | 36.87    | 42.27       | 18.23      | 13.85  |
| Summarization      | 16.71    | 48.33       | 15.92      | 11.91  |
| Sentence fusion    | 85.39    | 95.25       | 14.69      | 09.20  |
Table 3: Sentence Fusion results on DiscoFuse using the full and subsets 10%, 1%, 0.1% and 0.01% of the training set. We report three model variants: FELIXPOINT, FELIXINSERT and FELIX using either Mask or Infill insertion modes. Rows in gray background report scores assuming oracle tagging (TAG) or insertion (INS) predictions.

| Model         | Insertion Oracle | SARI | Exact | 10% | 1%  | 0.1% | 0.01% |
|---------------|------------------|------|-------|-----|-----|------|-------|
| BERT2BERT     |                  |      |       |     |     |      |       |
| SEQ2SEQBERT   |                  |      |       |     |     |      |       |
| LASERTAGGER   |                  |      |       |     |     |      |       |
| FELIXPOINT    |                  | 88.20| 60.76 | 53.75| 44.90| 31.87| 13.82 |
| FELIXINSERT   |                  | 88.72| 63.37 | 56.67| 48.85| 33.32| 13.99 |
| FELIX         |                  | 88.86| 61.31 | 52.85| 45.45| 36.87| 16.96 |

Table 4: Sentence Simplification results on WikiLarge.

| WikiLarge | SARI | ADD | DEL | KEEP | FKGL | Copy  |
|-----------|------|-----|-----|------|------|-------|
| SBMT-SARI | 37.94| 05.60| 37.96| 70.27| 8.89 | 0.10  |
| DMASS+DCSS| 37.01| 05.16| 40.90| 64.96| 9.24 | 0.06  |
| PBMT-R    | 35.92| 05.44| 32.07| 70.26| 10.16| 0.11  |
| HYBRID     | 28.75| 01.38| 41.45| 43.42| 7.85 | 0.04  |
| NTS       | 33.97| 03.57| 30.02| 68.31| 9.63 | 0.21  |
| DRESS     | 33.30| 02.74| 32.93| 64.23| 8.79 | 0.22  |
| DRESS-Ls  | 32.98| 02.57| 30.77| 65.60| 8.94 | 0.27  |
| EditNTS   | 34.94| 03.23| 32.37| 69.22| 9.42 | 0.12  |
| LASERTAGGER| 32.31| 03.02| 33.63| 60.27| 9.82 | 0.21  |
| FELIXPOINT| 34.37| 02.35| 34.80| 65.97| 9.47 | 0.18  |
| FELIXINSERT| 35.79| 04.03| 39.70| 63.64| 8.14 | 0.09  |
| FELIX     | 38.13| 03.55| 40.45| 70.39| 8.98 | 0.08  |

4.3 Summarization

Data. We use the dataset from (Toutanova et al., 2016), which contains 6,168 short input texts (one or two sentences) and one or more human-written summaries, resulting in 26,000 total training pairs. The human experts were not restricted to just deleting words when generating a summary, but were allowed to also insert new words and reorder parts of the sentence, which makes this dataset particularly suited for abstractive summarization models.

Metrics. In addition to SARI we include ROUGE-L and BLEU-4, as these metrics are commonly used in the summarization literature.

Results. The results in Table 5 show that FELIX achieves the highest SARI, ROUGE and BLEU score. All ablated models achieve higher SARI scores than all other models. Interestingly, the difference between FELIXPOINT and LASERTAGGER is modest, even though FELIXPOINT covers twice as much data as LASERTAGGER. With LASERTAGGER being trained on 4500 data points and FELIXPOINT trained on 13000. In Table 3 we see that LASERTAGGER and FELIXPOINT perform similarly under such low data conditions.

4.4 Post-Editing

Automatic Post-Editing (APE) is the task of automatically correcting common and repetitive errors found in machine translation (MT) outputs.
Data. APE approaches are trained on triples: the source sentence, the machine translation output, and the target translation. We experiment on the WMT17 EN-DE IT post-editing task, where the goal is to improve the output of an MT system that translates from English to German and is applied to documents from the IT domain. We follow the procedures introduced in [Junczys-Dowmunt and Grundkiewicz, 2016] and train our models using two synthetic corpora of 4M and 500K examples merged with a corpus of 11K real examples oversampled 10 times. The models that we study expect a single input string. To obtain this and to give the models a possibility to attend to the English source text, we append the source text to the German translation separated by a special token. Since the model input consists of two different languages, we use the multilingual BERT checkpoint for the proposed methods and for LASERTAGGER.

Metrics. We follow the evaluation procedure of WMT17 APE task and report translation error rate (TER) [Snover et al., 2006] as the primary metric and BLEU as a secondary metric.

Results. We consider the following baselines: COPY, which is a competitive baseline given that the required edits are typically very limited, LASERTAGGER [Malmi et al., 2019], LEVENShteIN TRANSFORMER (LeVT) [Gu et al., 2019], which is a partially autoregressive model that also employs a deletion and an insertion mechanisms, a standard TRANSFORMER evaluated by [Gu et al., 2019], and a state-of-the-art method by [Lee et al., 2019]. Unlike the other methods, the last baseline is tailored specifically for the APE task by encoding the source separately and conditioning the MT output encoding on the source encoding [Lee et al., 2019].

The results are shown in Table 6. First, we can see that using a custom method (Lee et al., 2019) brings significant improvements over generic text transduction methods. Second, FELIX performs very competitively, yielding comparative results to LEVENSHTEIN TRANSFORMER (Gu et al., 2019) which is a partially autoregressive model, and outperforming the other generic models in terms of TER. Third, FELIXINSERT performs considerably worse than FELIX and FELIXPOINT, suggesting that the pointing mechanism is important for the APE task. This observation is further backed by Table 2 which shows that without the pointing mechanism the average proportion of masked tokens in a target is 42.39% whereas with pointing it is only 17.30%. Therefore, removing the pointing mechanism shifts the responsibility too heavily from the tagging model to the insertion model.

5 Related work

Seq2seq models [Sutskever et al., 2014] have been applied to many text generation tasks that can be cast as monolingual translation, but they suffer from well-known drawbacks [Wiseman et al., 2018]: they require large amounts of training data, and their outputs are difficult to control. Whenever input and output sequences have a large overlap, it is reasonable to cast the problem as a text editing task, rather than full-fledged sequence to sequence generation. Ribeiro et al. (2018) argued that the general problem of string transduction can be reduced to sequence labeling. Their approach applied only to character deletion and insertion and was based on simple patterns. LaserTagger [Malmi et al., 2019] is a general approach that has been shown to perform well on a number of text editing tasks, but it has two limitations: it does not allow for arbitrary reordering of the input tokens; and insertions are restricted to a fixed phrase vocabulary that is derived from the training data. Similarly, Ed-

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Table 5: Summarization. Copy is not included as all models copied less than 2% of the time.

| Metrics | SARI | ADD | DEL | KEEP | Rouge | BLEU |
|---------|------|-----|-----|------|-------|------|
| SEQ2SEQ | 32.10 | 52.70 | 08.30 |      |       |      |
| LASERTAGGER | 40.36 | 06.04 | 54.47 | 60.57 | 81.68 | 35.47 |
| FELIXPOINT | 40.97 | 05.94 | 58.30 | 58.67 | 79.47 | 31.34 |
| FELIXINSERT | 41.85 | 06.45 | 61.37 | 57.73 | 78.12 | 29.78 |
| FELIX | 42.60 | 07.65 | 57.26 | 62.89 | 83.54 | 36.23 |

Table 6: WMT17 En→De post-editing results.

| Methods | TER ↓ | BLEU ↑ |
|---------|-------|--------|
| COPY | 24.48 | 62.49 |
| TRANSFORMER | 22.1 | 67.2 |
| LASERTAGGER | 24.29 | 63.83 |
| LeVT | 21.9 | 66.9 |
| SOTA (Lee et al., 2019) | 18.13 | 71.80 |
| FELIXPOINT | 22.51 | 65.61 |
| FELIXINSERT | 29.09 | 57.42 |
| FELIX | 21.87 | 66.74 |

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8http://statmt.org/wmt17/ape-task.html
9https://storage.googleapis.com/bert_models/2018_11_23/multi_cased_L-12_H-768_A-12.zip
itNTS (Dong et al., 2019) and PIE (Awasthi et al., 2019) are two other text-editing models that predict tokens to keep, delete, and add, which are developed specifically for the tasks of text simplification and grammatical error correction, respectively. In contrast to the aforementioned models, FELIX allows more flexible rewriting, using a pointer network that points into the source to decide which tokens should be preserved in the output and in which order.

Pointer networks have been previously proposed as a way to copy parts of the input in hybrid sequence-to-sequence models. Gulcehre et al. (2016) and Nallapati et al. (2016) trained a pointer network to specifically deal with out-of-vocabulary words or named entities. See et al. (2017) hybrid approach learns when to use the pointer to copy parts of the input. Chen and Bansal (2018) proposed a summarization model that first selects salient sentences and then rewrites them abstractively, using a pointer mechanism to directly copy some out-of-vocabulary words. These methods still typically require large amounts of training data and they are inherently slow at inference time due to autoregressive decoding.

Previous approaches have proposed alternatives to autoregressive decoding (Gu et al., 2018; Lee et al., 2018; Chan et al., 2019; Wang and Cho, 2019). Instead of the left-to-right autoregressive decoding, Insertion Transformer (Stern et al., 2019) and BLM (Shen et al., 2020) generate the output sequence through insertion operations, whereas Levenshtein Transformer (LEV T) (Gu et al., 2019) additionally incorporates a deletion operation.

These methods produce the output iteratively, while FELIX requires only two steps: tagging and insertion.

The differences between the proposed model, FELIX, its ablated variants, and a selection of related works is summarized in Table 7.

| Model       | Type     | Non-autoregressive | Pretrained | Reordering | Open vocab |
|-------------|----------|---------------------|------------|------------|------------|
| Transformer | + Copying| seq2seq             | ✓          | ✓          | ✓          |
| T5          |          |                     | ✓          | ✓          | ✓          |
| LEV T       |          |                     | ✓          | ✓          | ✓          |
| PIE         |          |                     | ✓          | ✓          | ✓          |
| EditNTS     |          |                     | ✓          | ✓          | ✓          |
| LASERTAGGER | Text edit |                    | ✓          | ✓          | ✓          |
| FELIXINSERT |          |                     | ✓          | ✓          | ✓          |
| FELIXPOINT  |          |                     | ✓          | ✓          | ✓          |
| FELIX       |          |                     | ✓          | ✓          | ✓          |

Table 7: Model comparison along five dimensions: model type, whether the decoder is non-autoregressive (LEV T is partially autoregressive), whether the model uses a pretrained checkpoint, a word reordering mechanism (T5 uses a reordering pretrained task but it does not have a dedicated copying mechanism for performing reordering), and whether the model can generate any possible output (Open vocab).

when compared to strong seq2seq baselines and other recent text editing approaches.

In the future work we plan to investigate the following ideas: (i) how to effectively share representations between the tagging and insertion models using a single shared encoder, (ii) how to perform joint training of insertion and tagging models instead of training them separately, (iii) strategies for unsupervised pre-training of the tagging model which appears to be the bottleneck in highly low-resource settings, and (iv) distillations recipes.

Acknowledgments

We thank Aleksandr Chuklin, Daniil Mirylenka, Ryan McDonald, and Sebastian Krause for useful discussions, running early experiments and paper suggestions.

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