Abstract

In this work, we train a text repair model as a post-processor for neural machine translation (NMT). The goal of the repair model is to correct typical errors introduced by the translation process, and convert the “translationese” output into natural text. The repair model is trained on monolingual data that has been round-trip translated through English, to mimic errors that are similar to the ones introduced by NMT. Having a trained repair model, we apply it to the output of existing NMT systems. We run experiments for both the WMT18 English→German and the WMT16 English→Romanian task. Furthermore, we apply the repair model on the output of the top submissions of the most recent WMT evaluation campaigns. We see quality improvements on all tasks of up to 2.5 BLEU points.

1 Introduction

Recent work in Neural Machine Translation (NMT) (Bahdanau et al., 2015; Gehring et al., 2017; Vaswani et al., 2017) has improved the state-of-the-art in Machine Translation. NMT relies mainly on parallel training data, which can be an expensive and scarce resource. There are several approaches to leverage monolingual data for NMT: Language model fusion for both phrase-based (Brants et al., 2007) and neural MT (Gülçehre et al., 2015, 2017), back-translation (Sennrich et al., 2016b), unsupervised NMT (Lample et al., 2018a; Artetxe et al., 2018a), dual learning (Cheng et al., 2016; Di He and Ma, 2016; Yingce Xia and Liu, 2017), and multi-task learning (Domhan and Hieber, 2017).

In this paper, we present a different approach to leverage monolingual data, which can be used as a post-processor for any existing translation. The idea is to train a text repair model that fixes typical errors introduced by the translation process. During training, the repair model uses a noisy version of each sentence as input and learns how to reconstruct the original sentence. In this work, we model a noisy version with round-trip translations (RTT) through English, translating a sentence in the target language into English, then translating the result back into the original language. We train the repair model with a standard transformer model on the WMT18 English→German and WMT16 English→Romanian monolingual News Crawl data and apply this repair model on the output of NMT models that are either trained on all available bitext or trained on a combination of bitext and back-translated monolingual data. Furthermore, we show that our repair model can be used as a post-processor for the best output of the recent WMT evaluation campaigns, where it improves even the output of these well engineered translation systems.

In addition to measuring quality in terms of BLEU scores on the standard WMT test sets, we split each test set into two subsets based on whether the source or target is the original sentence (each sentence is either originally written in the source or target language and human-translated into the other). We call these the source-language-original and target-language-original halves, respectively. We find that evaluating our repaired output on the source-language-original half actually decreases the BLEU scores, whereas the BLEU scores improve for the target-language-original half. This is in line with results from Koppel and Ordan (2011), who demonstrate that the mere fact of being translated plays a crucial role in the makeup of a translated text, making the actual (human) translation a less natural
example of the target language. We hypothesize that, given these findings, the consistent decreases in BLEU scores on test sets whose source side are natural text does not mean that the actual output is of lower quality. To verify this hypothesis, we run human evaluations for different outputs with and without the repair model. The human ratings demonstrate that the output of the repair model is both consistently more accurate and consistently more fluent, regardless of whether the source or the target language is the original language, contradicting the corresponding BLEU scores.

To summarize the contributions of the paper:

- We introduce the text repair model as post-processor for fixing typical translation errors from NMT output.
- We improve the BLEU of top submissions of the recent WMT evaluation campaigns.
- We show that the BLEU scores of the repair model only have high correlation with human ratings when they are calculated with target-original references.
- We propose separately reporting scores on test sets whose source sentences are translated and whose target sentences are translated, and call for higher-quality test sets.

2 Text Repair Model

2.1 Definition and Training

We formalize the repair model as a translation model from synthetic “translationese” (Gellerman, 1988) text in one language to natural text in the same language. For a language pair \((X, Y)\) and a monolingual corpus \(M_Y\) in language \(Y\), the training procedure for the text repair model is as follows:

1. Train two translation models on bitext for \(X \rightarrow Y\) and \(Y \rightarrow X\).
2. Use these models to generate round-trip translations for every target-language sentence \(y\) in \(M_Y\), resulting in the synthetic dataset \(RTT(M_Y)\).
3. Train a translation model on pairs of \((RTT(y), y)\), that translates from the round-tripped version of a sentence to its original form.

This procedure is illustrated in Figure 1.

![Figure 1: Training procedure of the text repair model in language \(Y\).](image)

2.2 Application

Given a trained translation model and a trained repair model, the procedure is simply to a) translate any source text from language \(X\) to language \(Y\) with the translation model, and b) repair the output of the translation by passing it through the text repair model. In this sense, the repair model may also be viewed as a paraphrasing model to produce “naturalized” text. This procedure is illustrated in Figure 2.

![Figure 2: The repair model as post-processor of NMT.](image)

3 Experimental Setup

3.1 Architecture

For the translation models, we use the transformer implementation in lingvo (Shen et al., 2019), using the transformer-base and transformer-big model sizes (Vaswani et al., 2017) for Romanian→English and German→English, respectively. The reverse models, English→Romanian and English→German, are both the transformer-big. Both use a vocabulary of 32k subword units, and exponentially moving averaging of checkpoints (EMA decay) with the weight decrease parameter set to \(\alpha = 0.999\).

The repair models are also transformer models with 32k subword units and EMA decay trained with lingvo. For the German repair model, we use the transformer-big size, whereas for the Romanian repair model, we use the smaller transformer-base setup as we have less monolingual data.
3.2 Evaluation
We report BLEU (Papineni et al., 2002) and human evaluations. All BLEU scores are calculated with sacreBLEU (Post, 2018)\(^1\).

Since 2014, the organizers of the WMT evaluation campaign (Bojar et al., 2017) have created test sets with the following method: first, they crawled monolingual data in both English and the target language from news stories from online sources. Thereafter they took about 1500 English sentences and translated them into the target language, and an additional 1500 sentences from the target language and translated them into English. This results in test sets of about 3000 sentences for each English-X language pair. The sgm files of each WMT test set include the original language for each sentence.

In addition to reporting overall BLEU scores on the different test sets, we also report results on the two subsets (based on the original language) of each newstest20XX, which we call the \{German,Romanian\}-original and English-original halves of the test set. This is motivated by Koppel and Ordan (2011), who demonstrated that they can train a simple classifier to distinguish human-translated text from natural text with high accuracy. These text categorization experiments suggest that both the source language and the mere fact of being translated play a crucial role in the makeup of a translated text. One of the major goals of the text repair model is to rephrase the NMT output in a more natural way, aiming to remove undesirable translation artifacts that have been introduced.

To collect human rankings, we present each output to crowd-workers, who were asked to score each sentence on a 5-point scale for:

- **fluency**: How do you judge the overall naturalness of the utterance in terms of its grammatical correctness and fluency?

Further, we included the source sentence and asked the raters to evaluate each sentence on a 2-point scale (binary decision) for:

- **accuracy**: Does the statement factually contradict anything in the reference information?

Each task was given to three different raters. Consequently, each output has a separate score for each question that is the average of 3 different ratings.

3.3 Data
For the round-trip experiments we use the monolingual News Crawl data. We remove duplicates and apply a max-length filter on the source sentences and the round-trip translations, filtering to the minimum of 500 characters or 70 tokens. For German, we concatenate all News Crawl data from 2007 to 2017, comprising 216.5M sentences after filtering and removing duplicates. For Romanian, we use News Crawl ’16, comprising 2.2M sentences after filtering and deduplication.

Our translation models are trained on WMT18 and WMT16 bitext (~5M sentences for German and ~0.5M sentences for Romanian), for English→German and English→Romanian, respectively. We filter sentences pairs that have empty source or target, that have source or target longer than 250 tokens, or the ratio of whose length is greater than 2.0. For English→German, we also build a system based on noised back-translation, as in Edunov et al. (2018). We use the same 216.5M monolingual sentences that we used for the repair model for generating the noisy back-translation data.

4 Experiments
4.1 English→German
The results of our English→German experiments are shown in Table 1. We trained the repair model on RTT produced by English→German and German→English NMT models that are only trained on bitext. Applying the repair model on the output of our NMT model also trained on only bitext improves the BLEU scores by up to 1.5 BLEU points for newstest2014 and 0.7 BLEU points for newstest2017. Nevertheless, the score drops by 1.4 points on newstest2016. To investigate the differing impact on the two test sets, we split each test set by its original language in Table 2. The repair model consistently increases the BLEU on the German-original half of the test set, but decreases the BLEU on the English-original half. Consequently, we applied the repair model only on the sentences with original language in German (+repair de-orig only) and see consistent improvements over all test sets with an average BLEU improvement of 2.2 points.
Table 1: BLEU scores for WMT18 English→German. We apply the same repair model (trained on RTT with bitext models) for both an NMT system based on pure bitext and an NMT system that uses noised back-translation (NBT) in addition to bitext.

Table 2: BLEU scores for WMT18 English→German. Test sets are divided by their original source language (either German or English).

Table 3: English→German human evaluation results split by original language.

To verify that the drop in BLEU score is because of the unnatural reference translations, we run a human evaluation (see Section 3.2) for both fluency/grammatical correctness and accuracy. Based on the human ratings (Table 3), the text repair model also improves on the English-original half of the test set (which is a more realistic use case).

Without re-training the repair model, we use the repair model that is trained on the bitext RTT and apply it to a stronger NMT system that also includes all the available monolingual data in the form of noised back-translation. We see a very similar pattern to the previous experiments. Regarding automatic scores, the repair model only improves on the German-original part of the test sets, with an average improvement of 1.3 BLEU points. The human evaluations show the same inconsistency with the automatic scores for the English-original half. As with the weaker baseline, humans rate the output of the repair model as more fluent and more accurate compared to the output without the repair model (Table 3). Further, we also run a human evaluation on the reference sentence and found that the scores for both fluency and accuracy are only minimal higher than for the repaired NBT output.

As the repair model seems to be agnostic to the model which produced the RTT, we applied it to the best submissions of the recent WMT18
evaluation campaign, applying the repair model to German-original half of the test set. Table 4 shows the results for the 2 top submissions of Microsoft (Junczys-Dowmunt, 2018) and Cambridge (Stahlberg et al., 2018). Both systems improved by up to 0.8 points in BLEU.

|                       | Microsoft | Cambridge |
|-----------------------|-----------|-----------|
| WMT18 submission      | 48.7      | 47.2      |
| + repair only de-orig | 49.5      | 47.7      |

Table 4: BLEU scores for WMT18 English→German newstest2018. We apply the repair model only on the German-original half of the test set. BLEU scores are calculated on the full newstest2018 set and the English-original half is just copied from the submission.

Finally, we train the text repair model on different random subsets of the available 216.5M monolingual data (see Figure 3). The average BLEU scores on newstest2014-newstest2017 show that we can achieve similar performance by using 24 million training examples only.

4.2 English→Romanian

Experimental results for the WMT16 English→Romanian task are summarized in Table 5. By applying the repair model on top of a baseline that is only trained on bitext, we see improvements of 3.0 BLEU (dev) and 0.3 BLEU (test) over our baseline system when we apply the repair process only to the Romanian-original half of the test-set. Similar to English→German, we apply the repair model on the top 2 submissions of the WMT16 evaluation campaign (Table 6). Both the QT21 submission (Peter et al., 2016), which is a system combination of several NMT systems, and the ensemble of the University of Edinburgh (Sennrich et al., 2016a) improve, by 0.3 BLEU and 0.2 BLEU on test, respectively.

|                       | dev  | test |
|-----------------------|------|------|
| Sennrich et al. (2016a) | 28.8 |      |
| our bitext            | 27.0 | 28.9 |
| + text repair         | 27.3 | 29.0 |
| + repair only ro-orig | 30.0 | 29.2 |

Table 5: BLEU scores for WMT16 English→Romanian.

|                       | QT21 | Edinburgh |
|-----------------------|------|-----------|
| WMT16 submission      | 29.4 | 28.8      |
| + repair only ro-orig | 29.7 | 29.0      |

Table 6: BLEU scores for WMT16 English→Romanian test set. The repair model was applied on top of the best WMT16 submissions.

5 Example Output

We would like to highlight a few short examples where the repair model improves the NMT translation in German. Although the repair model is also quite helpful for long sentences, we will focus on short examples for the sake of simplicity. In Table 7 there are examples from the English→German noised back-translated (NBT) setup (see Table 1), with and without the repair model. In the first example, NMT translates club (i.e. cudgel) incorrectly into Club (i.e. organization). Based on the context of the sentence, the repair model learned that club has to be translated into Schlagstock (i.e. cudgel). The next two examples are very similar as the repair model improves the word choice of the translations by taking the context of the sentence into account. The NMT translations of the last two examples make little sense and the repair model rephrases the output into a fluent, meaningful sentence.

6 Discussion

In this section, we discuss the results on the English-original subset of newstest16 (Table 2 and Table 3), where the repair model lowered the score by 6 BLEU, yet improved human evaluations. A
Using a club, they beat the victim in the face and upper leg.

NBT Mit einem Club schlagen sie das Opfer in Gesicht und Oberschenkel.

+ repair Mit einem Schlagstock schlagen sie dem Opfer ins Gesicht und in den Oberschenkel.

Müller put another one in with a penalty.

NBT Müller setzte einen weiteren mit einer Strafe ein.

+ repair Müller netzte einen weiteren per Elfmeter ein.

Obama receives Netanyahu

NBT Obama erhält Netanjahu

+ repair Obama empfängt Netanjahu

At least one Bayern fan was taken injured from the stadium.

NBT Mindestens ein Bayern-Fan wurde vom Stadion verletzt.

+ repair Mindestens ein Bayern-Fan wurde verletzt aus dem Stadion gebracht.

The archaeologists made a find in the third construction phase of the Rhein Boulevard.

NBT Die Archäologen haben in der dritten Bauphase des Rheinboulevards gefunden.

+ repair Die Archäologen sind im dritten Bauabschnitt des Rheinboulevards fündig geworden.

Table 7: Example output for English→German.

 naïve take-away from this result would be that evaluation sets whose target side is natural text are inherently superior. However, translating from translationese also has its own problems, including 1) it does not represent any real-world translation task, and 2) translationese sources may be much easier to translate “correctly”, and reward MT biases like word-for-word translation. The take-away, therefore, must be to report scores both on the source-language-original and the target-language-original test sets, rather than lumping two test-sets together into one as has heretofore been done. This gives a higher-precision glimpse into the strengths and weaknesses of different modeling techniques, and may prevent some effects (like improvements in naturalness of output) from being hidden.

Going forward, this result should also be seen as a call for higher-quality test sets. Multi reference BLEU is one option and less likely to suffer these biases as acutely, and has previously been used in the NIST projects. Another option could be to align sentence pairs from monolingual data sets in two languages and run human evaluation to exclude bad sentence pairs.

7 Related Work

Back-translation

Back-translation (Sennrich et al., 2016b; Ponceelas et al., 2018) augments relatively scarce parallel data with plentiful monolingual data, allowing one to train source-to-target (S2T) models with the help of target-to-source (T2S) models. Specifically, given a set of sentences in the target language, a pre-constructed T2S translation system is used to generate translations to the source language. These synthetic sentence pairs are combined with the original bilingual data when training the S2T NMT model.

Iterative Back-translation

Iterative back-translation (Zhang et al., 2018; Cotterell and Kreutzer, 2018; Vu Cong Duy Hoang and Cohn, 2018) is a joint training algorithm to enhance the effect of monolingual source and target data by iteratively boosting the source-to-target and target-to-source translation models. The joint training method uses the monolingual data and updates NMT models through several iterations. A variety of flavors of iterative back-translation have been proposed, including Niu et al. (2018), who simultaneously perform iterative S2T and T2S back-translation in a multilingual model, and Di He and Ma (2016); Yingce Xia and Liu (2017), who combine dual learning with phases of back- and forward-translation.

Artetxe et al. (2018a,b) and Lample et al. (2018a,b) used iterative back-translation to train two unsupervised translation systems in both directions (X→Y and Y→X) in parallel. Further, they used back-translation to generate a synthetic source to construct a dev set for tuning the parameters of their unsupervised statistical machine translation system. In a similar formulation, Cheng et al. (2016) jointly learn a translation system with a round-trip autoencoder.

Round-tripping and Paraphrasing
Round-trip translation approach has seen success as a method to generate paraphrases. Bannard and Callison-Burch (2005) extracted paraphrases by using alternative phase translations from bilingual phrase tables from Statistical Machine Translation. Mallinson et al. (2017) presented PARANET, a neural paraphrasing model based on round-trip translations with NMT. They showed that their paraphrase model outperforms all traditional paraphrase models.

Perhaps most similar to this work, though in the reverse direction, Tian Wu (2018) train a paraphrasing model on $(X, \text{RTT}(X))$ pairs, translating from natural text into a simplified version. They apply this sentence-simplifier on the source sentences of the training data and report quality gains for IWSLT.

### Translationese and Artifacts from NMT

The difference between translated sentence pairs based on whether the source or the target is the original sentence has long been recognized by the human translation community, but only partially investigated by the machine translation community. An introduction to the latter is presented in Koppel and Ordan (2011), who train a high-accuracy classifier to distinguish human-translated text from natural text in the Europarl corpus. This is in line with research from the professional translation community, which has seen various works investigating both systematic biases inherent to translated texts (Baker, 1993; Selinker, 1972), as well as biases resulting specifically from interference from the source text (Toury, 1995). There has similarly long been a focus on the conflict between Fidelity (the extent to which the translation is faithful to the source) and Transparency (the extent to which the translation appears to be a natural sentence in the target language) (Warner, 2018; Schleiermacher, 1816; Dryden, 1685). To frame our hypotheses in these terms, the present work hypothesizes that outputs from NMT systems often err on the side of disfluent fidelity, or word-by-word translation.

### 8 Conclusion

We propose a text repair model that increases the quality of NMT translations, measured both by BLEU and human evaluation. We see improvements both when repairing our model translations and when repairing existing outputs from the winning submissions to the WMT competition. The repair model has the advantage that it is agnostic to the model which produced the translations, and so can be used on top of any new advance in the field, without need for re-training. Further, we demonstrate that we need only a subset of 24M training examples to train the repair model. We furthermore use this model as a tool to reveal systematic problems with reference translations, and propose finer-grained BLEU reporting on both source-language-original test sets and target-language-original test sets, as well as calling for higher-quality test sets.

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