Translationese as a Language in “Multilingual” NMT

Parker Riley△*, Isaac Caswell▽, Markus Freitag▽, David Grangier▽
△ University of Rochester
▽ Google Research

Abstract

Machine translation has an undesirable propensity to produce “translationese” artifacts, which can lead to higher BLEU scores while being liked less by human raters. Motivated by this, we model translationese and original (i.e., natural) text as separate languages in a multilingual model, and pose the question: can we perform zero-shot translation between original source text and original target text? There is no data with original source and original target, so we train sentence-level classifiers to distinguish translationese from original target text, and use this classifier to tag the training data for an NMT model. Using this technique we bias the model to produce more natural outputs at test time, yielding gains in human evaluation scores on both accuracy and fluency. Additionally, we demonstrate that it is possible to bias the model to produce translationese and game the BLEU score, increasing it while decreasing human-rated quality. We analyze these models using metrics to measure the degree of translationese in the output, and present an analysis of the capriciousness of heuristically-based train-data tagging.

1 Introduction

“Translationese” is a term that refers to artifacts present in text that was translated into a given language that distinguish it from text originally written in that language (Gellerstam, 1986). These artifacts include lexical and word order choices that are influenced by the source language (Gellerstam, 1996) as well as the use of more explicit and simpler constructions (Baker et al., 1993).

These differences between translated and original text mean that the direction in which parallel data (bitext) was translated is potentially important for machine translation (MT) systems. Most parallel data is either source-original (the source was translated into the target; “forward” data) or target-original (the target was translated into the source; “reverse” data), though sometimes neither side is original because both were translated from a third language.

Figure 1 illustrates the four possible combinations of translated and original source and target data. Recent work has examined the impact of translationese in MT evaluation, using the WMT evaluation campaign as the most prominent example. From 2014 through 2018, WMT test sets were constructed such that 50% of the sentence pairs are source-original (upper right quadrant of Figure 1) and the rest are target-original (lower left quadrant). Toral et al. (2018), Zhang and Toral (2019), and Graham et al. (2019) have all examined the effect of this testing setup on MT evaluation, and have all argued that target-original test data should not be included in future evaluation campaigns because the translationese source is too easy to translate. While target-original test data does have the down-
side of a translationese source side, recent work has shown that human raters prefer MT output that is closer in distribution to original target text than translationese (Freitag et al., 2019). This indicates that the target side of test data should also be original (upper left quadrant of Figure 1); however, it is unclear how to produce high-quality test data (let alone training data) that is simultaneously source- and target-original.

Because of this lack of original-to-original sentence pairs, we frame this as a zero-shot translation task, where translationese and original text are distinct languages or domains. We adapt techniques from zero-shot translation with multilingual models (Johnson et al., 2016), where the training pairs are tagged with a reserved token corresponding to the domain of the target side: translationese or original text. Tagging is helpful when the training set mixes data of different types by allowing the model to 1) indicate each pair’s type at training to preserve distinct behaviors and avoid the model regressing to a mean/dominant prediction across data types, and 2) to elicit different behavior in inference, i.e. providing a tag at test time yields predictions resembling a specific data type. We then investigate what happens when the input is an original sentence in the source language and the model’s output is also biased to be original, a scenario never observed in training.

Tagging in this fashion is not trivial, as most MT training sets do not annotate which pairs are source-original and which are target-original, so in order to distinguish them we train binary classifiers that predict whether the target side of a sentence pair is original text in that language or translated. This follows several prior works attempting to identify translated text (Kurokawa et al., 2009; Koppel and Ordan, 2011; Lembersky et al., 2012).

For the same reasons that we need a translationese classifier (i.e. labeled data is scarce), we require a large corpus of target-language text annotated by whether it is original or translated. We use News Crawl data from WMT as target-original data. It consists of news articles crawled from the internet, and so we assume that most of them are not translations. Getting translated data is trickier; most human-translated pairs where the original language is annotated are only present in test sets, which are generally small. To sidestep this, we adopt the following argument:

**Premises**

1. [known] Human translators produce translationese.
2. [known] Machine translation also produces translationese.

3. We demonstrate with human evaluations that this technique improves translation quality, both in terms of fluency and accuracy.
4. We show that biasing the model to instead produce translationese outputs inflates BLEU scores while harming quality as measured by human evaluations.

## 2 Classifier Training + Tagging

Motivated by prior work detailing the importance of distinguishing translationese from original text (Kurokawa et al., 2009; Lembersky et al., 2012; Toral et al., 2018; Zhang and Toral, 2019; Graham et al., 2019; Freitag et al., 2019; Edunov et al., 2019) as well as work in zero-shot translation (Johnson et al., 2016), we hypothesize that performance on the source-original translation task can be improved by distinguishing target-original and target-translationese examples in the training data and constructing an NMT model to perform zero-shot original→original translation.

The problem is that most machine translation training sets do not annotate the original language for the sentence pairs; to address this, we train a binary classifier that predicts whether the target side of a sentence pair is original text in that language or translated from the source language. This follows several prior works attempting to identify translated text (Kurokawa et al., 2009; Koppel and Ordan, 2011; Lembersky et al., 2012).

For the same reasons that we need a translationese classifier (i.e. labeled data is scarce), we require a large corpus of target-language text annotated by whether it is original or translated. We use News Crawl data from WMT as target-original data. It consists of news articles crawled from the internet, and so we assume that most of them are not translations. Getting translated data is trickier; most human-translated pairs where the original language is annotated are only present in test sets, which are generally small. To sidestep this, we adopt the following argument:

**Premises**

1. [known] Human translators produce translationese.
2. [known] Machine translation also produces translationese.

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1Europarl (Koehn, 2005) is a notable exception, but we found it to be too small for our purposes, and it is not in the news domain, which is what is used for the WMT translation task.

2http://www.statmt.org/wmt18/translation-task.html
3. **[our assumption]** Human translationese and machine translationese are similar.

**Conclusion**

1. Therefore, we can model human translationese with machine translationese.

As a result, we choose to use machine translation output as a proxy for human translationese, meaning we construct a classifier training data set using only unannotated monolingual data. We propose two ways of doing this: using forward translation (FT) or round-trip translation (RTT). Both are illustrated in Figure 2.

To generate FT data, we take source-language News Crawl data and translate it into the target language using a machine translation model trained on WMT training bitext. We can then train a classifier to distinguish the FT target-language data and monolingual target-language data.

One potential problem with the FT data set is that the original and translated pairs may differ not only in the respects we care about (i.e. translationese), but also in content. Taking English→French as an example language pair, one could imagine that certain topics are more commonly reported on in original English language news than in French, and vice versa, e.g. news about American or French politics, respectively. The words and phrases representing those topics could then act as signals to the classifier to distinguish the original language.

To address this, we also experiment with RTT data. For this approach we take target-language monolingual data and round-trip translate it with two machine translation models (target→source and then source→target), resulting in another target-language sentence that should contain the same content as the original sentence, alleviating the concern with FT data. Here we hope that the noise introduced by round-trip translation will be similar enough to human translationese to be useful for our downstream task.

In both settings, we use the trained binary classifier to detect and tag training bitext pairs where the classifier predicted that the target side is original.

### 3 Experimental Set-up

#### 3.1 Data

We perform our experiments on WMT18 English→German bitext and WMT15 English→French bitext. We use WMT News Crawl for monolingual data (2007–2017 for German and 2007–2014 for French). We filter out sentences longer than 250 subwords and remove pairs whose length ratio is greater than 2. This results in about 5M pairs for English→German. We do not filter the English→French bitext, resulting in 41M sentence pairs.

For monolingual data, we deduplicate and filter sentences with more than 70 tokens or 500 characters. For the experiments described later in Section 5.3, this monolingual data is back-translated with a target-to-source translation model; after doing so, we remove any sentence pairs where the back-translated source is longer than 75 tokens or 550 characters. This results in 216.5M sentences for English→German (of which we only use 24M) and 39M for English→French.

The classifiers were trained on the target language monolingual data in addition to either an equal amount of source language monolingual data machine-translated into the target language (for the FT classifiers) or the same target sentences round-trip translated through the source language with MT (for the RTT classifiers). In both cases, the MT models were trained only with WMT bitext.

The models used to generate the synthetic data have BLEU\(^3\) performance as follows on newstest2014/full: German→English 31.8; English→German 28.5; French→English 39.2; English→French 40.6.

#### 3.2 Architecture

Our NMT models use the transformer-big architecture (Vaswani et al., 2017) implemented in lingvo (Shen et al., 2019) with a shared source- target byte-pair-encoding (BPE) vocabulary (Sen-

\(^3\)BLEU + case.mixed + lang.LANGUAGE_PAIR + num- refs.1 + smooth.exp + test.SET + tok.13a + version.1.2.15
Table 1: Performance of our own translationese classifiers and those reported by Kurokawa et al. (2009). All classifiers only saw the target side of each sentence pair. See Figure 2 for an overview of data used for the FT and RTT classifiers. The “Content-Aware?” column indicates whether the classifier was able to use content differences between the two classes to identify translations, or whether it was restricted to intrinsic textual features. *Kurokawa et al. (2009) A - word-based; B - mixed word/POS-based.

Table 2: Percentage of training data where the target side was classified as original. The English→German bitext was much smaller than the English→French bitext, so we upsampled the pairs with predicted original German (marked with a * here) to make both subsets of the bitext the same size.

4 Results and Discussion

4.1 Classifier Accuracy

Before evaluating the usefulness of our translationese classifiers for the downstream task of machine translation, we can first evaluate how accurate they are at distinguishing original text from human translations. We use WMT test sets for this evaluation, because they consist of source-original and target-original sentence pairs in equal number. The F1 scores for the various classifiers are shown in Table 1. Table 2 reports how much of the training data was classified as having original text on the target side. The back-translation (BT) classification proportions pertain to the experiments (Section 5.3). We note that while the classifiers trained to distinguish forward translations from original text perform reasonably well, the ones trained to identify round-trip translations are less effective. This result is in line with prior work by Kurokawa et al. (2009), who trained an SVM classifier on French sentences to detect translations from English. They used word n-gram features for their classifier, but were worried about a potential content effect and so also trained a classifier

3.3 Evaluation

We report BLEU (Papineni et al., 2002) scores with SacreBLEU (Post, 2018)\(^4\) and run human evaluations for the best performing systems (Section 4.3).

\(^4\)BLEU + case.mixed + lang.LANGUAGE_PAIR + num.refs.1 + smooth.exp + test.SET + tok.intl + version.1.2.15
where nouns and verbs were replaced with corresponding part-of-speech (POS) tags. Note that they tested on the Canadian Hansard corpus (containing Canadian parliamentary transcripts in English and French) while we tested on WMT test sets, so the numbers are not directly comparable, but it is interesting to see the similar trends in comparing content-aware and content-unaware versions of the same method. We also point out that Kurokawa et al. (2009) both trained and tested with human-translated sentences, while we trained our classifiers with machine-translated sentences while still testing on human-translated data.

### 4.2 NMT with Translationese-Classified Bitext

Table 3 shows the BLEU scores of three models all trained on WMT 2014 English→French bitext. The difference is in how the pairs with original target sides vs. translationese targets were distinguished from each other: either no distinction was made, or tags were applied to those sentence-pairs with a target side that a classifier predicted to be original French. We first note that the model trained on data tagged by the round-trip translation (RTT) classifier slightly underperforms the baseline. However, the model trained with data tagged by the forward translation (FT) classifier is able to achieve an improvement of 0.5 BLEU on both halves of the test set when biased toward translationese on the source-original half and original text on the target-original half. This, coupled with the observation that the BLEU score on the source-original half sharply drops when adding the tag, indicates that the two halves of the test set represent quite different tasks, and that the model has learned to associate the tag with some aspects specific to generating original text as opposed to translationese. However, we were not able to replicate this positive result on the English→German language pair; those results are reported in Table 4. Interestingly, in this scenario the relative ordering of the FT and RTT classifiers is reversed, with the German RTT classifier outperforming the FT classifier. This is also interesting because the German classifiers achieved higher F1 scores than the French ones, indicating that a classifier’s performance alone is not a sufficient indicator of its effect on translation performance. One possible explanation for the negative result is that the English→German bitext only contains 5M pairs, as opposed to the 41M for English→French, so splitting the data into two portions could make it difficult to learn both portions’ output distributions properly.

### Table 4: Average BLEU over newstest20\{14/full,16,17,18\} for models trained on WMT 2018 English→German bitext, with tags added according to classifier predictions on the target side. Our baseline has no tags, and is just the transformer-big architecture of Vaswani et al. (2017). Newstest2015 was used as development data.

| Test set | Decode as if | Train data tagging | Src-Orig | Trg-Orig | Combined |
|----------|--------------|-------------------|---------|---------|----------|
|          |              |                   | Natural | Transl. | Transl. | Natural | Transl. | Domain match |
| Untagged |              |                   | 36.3    | 36.3    | 30.0    | 30.0    | 34.0    |            |
| FT clf.  |              |                   | 28.3    | 36.0    | 29.4    | 29.8    | 33.6    |            |
| RTT clf. |              |                   | 32.3    | 36.2    | 30.0    | 30.2    | 33.9    |            |
4.3 Human Evaluation Experiments

In the previous subsection, we saw that BLEU for the source-original half of the test set went down when the model trained with FT classifications (FT clf.) was decoded as if it were target-original (Table 3). Prior work has shown that BLEU has a low correlation with human judgments when the reference contains translationese but the system output is biased toward original/natural text (Freitag et al., 2019). This is the very situation we find ourselves in now. Consequently, we run a human evaluation to see if the output truly is more natural and thereby preferred by human raters, despite the loss in BLEU. We run both a fluency and an accuracy evaluation for English→French to compare the quality of this system when decoding as if source-original vs. target-original. We also compare the system with the Untagged baseline. All evaluations are conducted with bilingual speakers whose native language is French. Our two evaluations are as follows:

- **Accuracy**: We do a direct assessment for all outputs to measure translation accuracy. Each output was scored on a 6-point scale by 3 different raters, with the average taken as the final score. Raters were shown only the source sentence and the model output.

- **Fluency**: We do a side-by-side evaluation to measure fluency. As in the accuracy evaluation, each output is rated by 3 different humans. However, in this evaluation the source sentence is not shown, and raters are shown two different model outputs for the same (hidden) source. Raters were asked to select which output was more fluent, or whether they were equally good.

Fluency human evaluation results are shown in Table 5. In both evaluations, humans show a preference for the tagged model output when it is decoded as natural text (with the tag). This shows that the natural decodes are more fluent than both the translationese (untagged) decodes from the same model and the baseline tagless model, despite the drop in BLEU compared to each. Accuracy human ratings are summarised in Table 6. Humans prefer decoding as natural text, demonstrating that the model does not suffer a loss in accuracy by generating more fluent output.

5 Supplemental Experiments

5.1 Measuring Translationese

Translationese tends to be simpler, more standardised and more explicit (Baker et al., 1993) compared to original text and can retain typical characteristics of the source language (Toury, 2012). Toral (2019) proposed metrics attempting to quantify the degree of translationese present in a translation. Following their work, we quantify lexical simplicity with two metrics: lexical variety and lexical density. We also calculate the length ratio between the source sentence and the generated translations to measure interference from the source.

5.1.1 Lexical Variety

An output is simpler when it uses a lower number of unique tokens/words. By generating output closer
Table 7: Measuring the degree of translationese for WMT English→French newstest2014/full on the source-original half. Higher lexical variety, higher lexical density, and higher length ratio indicates less translationese output. The least translationese value for each metric is bolded.

| Test set → | Stc-Orig | Decode | lexical variety | lexical density | length ratio |
|------------|----------|--------|-----------------|-----------------|-------------|
| Untagged   |          | 0.258  | 0.393           | 0.246           |             |
| FT clf.    | Translationese | 0.255  | 0.396           | 0.264           |             |
| FT clf.    | Natural  | 0.260  | 0.397           | 0.245           |             |

5.1.2 Lexical Density

Scarpa (2006) found that translationese tends to be lexically simpler and have a lower percentage of content words (adverbs, adjectives, nouns and verbs) than original written text. Lexical density is calculated as follows:

\[
\text{lex. density} = \frac{\text{number of content words}}{\text{number of total words}}
\] (2)

5.1.3 Length Ratio

Both MT and humans tend to avoid restructuring the source sentence and stick to sentence structures popular in the source language. This results in a translation with similar length to that of the source sentence. By measuring the length ratio, we measure interference in the translation because its length is guided by the source sentence’s structure. We compute the length ratio at the sentence level and average the scores over the test set of source-target pairs \((x, y)\):

\[
\text{length ratio} = \frac{|x| - |y|}{|x|}
\] (3)

5.1.4 Results

Results for all three different translationese measurements are shown in Table 7.

- **Lexical Variety**

Using the tag to decode as natural text (i.e. more like original target text) increases lexical variety. This is expected as original sentences tend to use a larger vocabulary than simpler outputs.

- **Lexical Density**

We also increase lexical density when decoding as natural text. In other words, the model has a higher percentage of content words in its output, which is an indication that it is more like original target-language text.

- **Length Ratio**

Unlike the previous two metrics, decoding as natural text does not lead to a more “natural” distribution of length-ratios. However, there is a clear difference between this metric and the previous two: length ratio also takes the source sentence into account. This hints at an interesting subtlety of our tagging scheme: since all of our training pairs have translationese on either the source or the target side, the model never fully learns to model the aspects of translationese that relate the source and target sentences, and can only model the naturalness of the target language in isolation. This comes back to the problem of the lack of original→original training data noted in the introduction.

5.2 Tagging using Translationese Heuristics

Rather than tagging training data with a trained classifier, as explored in the previous sections, it might be possible to tag using much simpler heuristics, and achieve a similar effect. We explore two options here:

5.2.1 Simple-length-ratio tagging

We tag all sentence-pairs \((x, y)\) in the training data where the ratio of token lengths \(\frac{|x|}{|y|}\) is greater than the empirical ratio of token lengths \(\hat{\rho}_{\text{length}}\) in two monolingual corpora, \(M_x\) and \(M_y\):

\[
\hat{\rho}_{\text{length}} = \frac{1}{|M_x|} \sum_{x_i \in M_x} \frac{|x_i|}{|y|}
\] (4)

In this case, the tag indicates that the output is shorter than expected. For English→French, we
Table 8: Comparing heuristic-based tagging with classifier-based tagging. BLEU scores are averaged for newstest2014/full and newstest2015 English→French. Neither heuristic performs as well as the trained classifier, and length-ratio tagging actually has the reverse effect from what we expect.

5.3 Back-Translation Experiments

We also investigated whether using a classifier to tag training data improved model performance in the presence of back-translated (BT) data. Caswell et al. (2019) introduced tagged back-translation (TBT), where all back-translated pairs are tagged and no bitext pairs are. They experimented with decoding the model with a tag (“as-if-back-translated”) but found it harmed BLEU score. However, in our early experiments we discovered that doing this actually improved the model’s performance on the target-original portion of the test set, while harming it on the source-original half. Thus, we frame TBT as a heuristic method for identifying target-original pairs: the monolingual data used for the back-translations is assumed to be original, and the target side of the bitext is assumed to be translated. We wish to know whether we can find a better tagging scheme for the combined BT and bitext data, based on a classifier or some other heuristic. We are confident that at least some of the training bitext is target-original, and it is even possible that some of the monolingual target data is not original, as it could have been translated from another language. Because of this, we perform experiments with MT models trained with bitext and BT data tagged by a classifier or heuristic.

Results for English→French models trained with BT data are presented in Table 9. While combining the bitext classified by the FT classifier with all-tagged BT data yields a minor gain of 0.2 BLEU over the TBT baseline of Caswell et al. (2019), the other methods do not beat the baseline. This indi-
Table 9: Average BLEU (newstest2014/full and newstest2015) scores for models trained on WMT 2014 English→French bitext and 39M back-translated monolingual sentences, with tags added according to heuristics and/or classifier predictions on the target (French) side. The first result row represents tagged back-translation (Caswell et al., 2019) and is our baseline. All data was filtered by an automatic language identification tool, retaining only pairs with English source and French target. Newstest2013 was used as development data.

Table 10: Average BLEU scores (newstest2018{14/full,16,17,18}) for models trained on WMT 2018 English→German bitext and 24 million back-translated monolingual sentences, with tags added according to heuristics and/or classifier predictions on the target (German) side. The first result row represents tagged back-translation (Caswell et al., 2019) and is our baseline. All data was filtered by an automatic language identification tool, retaining only pairs with English source and German target. Newstest2015 was used as development data. For the last two rows, the back-translations consisted of 12 million untagged and 12 million tagged pairs.

Indicates that assuming all of the target monolingual data to be original is not as harmful as the error introduced by the classifiers.

English→German results are presented in Table 10. Combining the bitext classified by the RTT classifier with all-tagged BT data matched the performance of the TBT baseline, but none of the models outperformed it. This is expected, given the poor performance of the bitext-only models for this language pair.

6 Example Output

In Table 11, we show example outputs for WMT English→French comparing the Untagged baseline with the FT clf. inference output when decoding with tags (force the model to generate natural output). In the first example, *avec suffisamment d’art* is an incorrect word-for-word translation, as the French word *art* cannot be used in that context. Here the word *habilement*, which is close to “skilfully” in English, sounds more natural. In the second example, *libre d’impôt* is the literal translation of “tax-free”, but French documents rarely use it, they prefer *pas imposable*, meaning “not taxable”.

In the last example, *arriéré* in French can be used only for backlog in the sense of a late payment and cannot be used in this context; *retard*, which means lateness/delay, is appropriate here.

7 Related Work

7.1 Translationese

The effects of translationese on MT training and evaluation have been investigated by many prior authors (Kurokawa et al., 2009; Lembersky et al., 2012; Toral et al., 2018; Zhang and Toral, 2019; Graham et al., 2019; Freitag et al., 2019; Edunov et al., 2019). Training classifiers to detect translationese has also been done (Kurokawa et al., 2009; Koppel and Ordan, 2011). Similarly to this work, Kurokawa et al. (2009) used their classifier to preprocess MT training data; however, they merely filtered out target-original pairs. In contrast, Lembersky et al. (2012) used both types of data (without explicitly distinguishing them with a classifier), and used entropy-based measures to cause their phrase-based system to favor phrase table entries with target phrases that are more similar to a corpus
of translationese than original text. In this work, we combine aspects from each of these: we train a classifier to partition the training data, and use both subsets to train a single model with a mechanism allowing control over the degree of translationese to produce in the output. We also use more modern neural MT methods instead of a phrase-based system, and show with human evaluations that source-original test sentence pairs result in BLEU scores that do not correlate well with translation quality when evaluating models trained to produce more original output.

### 7.2 Training Data Tagging for NMT

In addition to tagging methods as in Caswell et al. (2019), inserting tags in training data and using them to control output is a technique that has been growing in popularity. Tags on the source sentence have been used to indicate target language in multilingual models (Johnson et al., 2016), formality level in English→Japanese (Yamagishi et al., 2016), politeness in English→German (Sennrich et al., 2016a), gender from a gender-neutral language (Kuczmarski and Johnson, 2018), as well as to produce domain-targeted translation (Kobus et al., 2016). Shu et al. (2019) use tags at training and inference time to increase the syntactic diversity of their output while maintaining translation quality; similarly, Agarwal and Carpuat (2019) and Marchisio et al. (2019) use tags to control the reading level (e.g. simplicity/complexity) of the output. Overall, tagging can be seen as domain adaptation (Freitag and Al-Onaizan, 2016; Luong and Manning, 2015).

### 8 Conclusion

We have demonstrated that translationese and original text can be treated as separate target languages in a “multilingual” model, distinguished by a classifier trained using only monolingual and synthetic data. The resulting model has improved performance in the ideal, zero-shot scenario of original→original translation, as measured by human evaluation of accuracy and fluency. However, this is associated with a drop in BLEU score, indicating that better automatic evaluation is needed.

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