Domain, Translationese and Noise in Synthetic Data for Neural Machine Translation

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Abstract

The quality of neural machine translation can be improved by leveraging additional monolingual resources to create synthetic training data. Source-side monolingual data can be (forward-)translated into the target language for self-training; target-side monolingual data can be back-translated. It has been widely reported that back-translation delivers superior results, but could this be due to artefacts in the test sets? We perform a case study using French-English news translation task and separate test sets based on their original languages. We show that forward translation delivers superior gains in terms of BLEU on sentences that were originally in the source language, complementing previous studies which show large improvements with back-translation on sentences that were originally in the target language. To better understand when and why forward and back-translation are effective, we study the role of domains, translationese, and noise. While translationese effects are well known to influence MT evaluation, we also find evidence that news data from different languages shows subtle domain differences, which is another explanation for varying performance on different portions of the test set. We perform additional low-resource experiments which demonstrate that forward translation is more sensitive to the quality of the initial translation system than back-translation, and tends to perform worse in low-resource settings.

1 Introduction

The quality of neural machine translation can be improved by leveraging additional monolingual resources in various different ways (Sennrich et al., 2016b; Zhang and Zong, 2016; Gulcehre et al., 2017; Ramachandran et al., 2017; Freitag et al., 2019). Among these, back-translation is the most widely used technique in shared translation tasks (Barrault et al., 2019, p. 15), and it has been reported that it outperforms self-training with forward translation (Burlot and Yvon, 2018). However, in the past year, attention was drawn to the fact that standard test sets are often shared between translation directions and thus contain both portions where the original text is on the source side (original), as well as portions where the original text is used as the reference translation, with the source text being a human translation (reverse) (See Figure 1). This use of original and “reverse” test sets heavily affects empirical results for back-translation. When augmenting the model with back-translation, improvements in BLEU (Papineni et al., 2002) are a lot more evident if the sentence was translated in the reverse direction, that is to say with naturally produced reference and human translation source on the source side (Edunov et al., 2019). Freitag et al. (2019) explore automatic post editing (APE), which heavily relies on synthetic training data, and find that there is a loss in BLEU score on the original portion, despite humans perceiving improvement in the translation quality. Zhang and Toral (2019) show that the ranking of submissions to the news translation task changes when evaluating only the portion with original sources, or only that with translationese sources. Interestingly, systems that rely heavily on large-scale back-translation, such as that by Edunov et al. (2019), are more dominant on the reverse portion.

We focus on three factors that we hypothesise play a large role in explaining the observed differences in effectiveness between forward and back-translation, and between performance on the original and reverse portion of standard test sets: differences in the domains between source-side and target-side monolingual texts\textsuperscript{1}, differences in lan-

\textsuperscript{1}here, we use domain in a broad sense to refer to various
language style between naturally produced text and translationese text, and differences in how noise in the synthetic data will affect the final system, depending on whether it is on the source-side (back-translation) or target side (forward translation). We perform the following experiments to verify our claims:

- We show that when the test sets are split according to original language, forward translation is better at improving BLEU scores on the original portion, complementing the findings of (Edunov et al., 2019), who find that back-translation is better at improving BLEU on the reverse portion.

- We perform language model experiments where we contrast language style and language domain and evaluate on the test sets.

- We show that the language between original and translationese French is sufficiently different to be reliably detected by a neural network on a document level.

- We perform human evaluation on a subset of our translation, comparing a baseline system, one augmented with back-translation and one augmented with forward translation. We see some evidence of domain adaptation, but overall forward and back-translation achieve similar levels of adequacy and BLEU is far more sensitive to the original translation direction of the test set than human judgements.

- We explore the effectiveness of forward and back-translation in a low-resource scenario, where the quality of the synthetic data produced is poor, and find that forward translation is more sensitive to the quality of the initial translation system than back-translation.

2 Background

Statistical machine translation relies on the noisy channel model, which makes large-scale language models, and hence extensive monolingual target-language data, very valuable (e.g. Brants et al., 2007). In neural machine translation (Bahdanau et al., 2015; Vaswani et al., 2017) however, it is not immediately clear how to make use of monolingual target-language resources. This led to the development of different methods such as language model fusion (Gulcehre et al., 2017), language model pretraining (Ramachandran et al., 2017), back-translation (Sennrich et al., 2016b), but also the exploration of methods to incorporate source-language data via forward translation (Zhang and Zong, 2016). Out of these, back-translation is the most widely used (see Barault et al., 2019), and has been reported to work better than forward translation in particular (Burlot and Yvon, 2018).

2.1 Back-translation

Given a translation task $L_1 \rightarrow L_2$, where large-scale monolingual $L_2$ data is available, back-translation refers to training a translation model $L_2 \rightarrow L_1$ and using it to translate the $L_2$ data into $L_1$, creating a synthetic parallel corpus that can be added to the true bilingual data for the purpose of training a $L_1 \rightarrow L_2$ model.

While this technique was first explored for statistical machine translation (Bertoldi and Federico, 2009; Lambert et al., 2011; Bojar and Turchyna, 2011), it has a different effect on training, and was found to be much more effective, in neural machine translation, particularly in low-resource scenarios (Sennrich et al., 2016b,a). However, it is not entirely clear what causes the large improvement in translation quality. Previous work has analysed increases in fluency when training on back-translated data (e.g. Sennrich et al., 2016b; Edunov et al., 2019), and domain adaptation effects (e.g. Sennrich et al., 2016b; Chinea-Rios et al., 2017a), which can be attributed to the target-side data, but the properties of synthetic source sentences have also been investigated. Burlot and Yvon (2018) have found that automatic translations tend to be more monotonic and simpler than natural parallel data, which could make learning easier, but these biases also make the training distribution less similar to natural input. While there is some evidence that the quality of the back-translation system matters (Burlot and Yvon, 2018), models are relatively robust to noise, and Edunov et al. (2018) even find that they obtain better models when using sampling rather than standard beam search for back-translation, or explicitly add noise, even if this reduces the quality of back-translations. Caswell et al. (2019) argue that if the model is given means to distinguish real from synthetic parallel data, either via noise or more simply a special tag, it can avoid learning detrimental biases from synthetic training data.
2.2 Forward translation

Given a translation task $L_1 \rightarrow L_2$, where large-scale monolingual $L_1$ data is present, forward translation refers to training a translation model $L_1 \rightarrow L_2$ and using it to translate the $L_1$ data into $L_2$, creating a synthetic parallel corpus that can be added to the true bilingual data for the purpose of training an improved $L_1 \rightarrow L_2$ model.

Self-training with forward translation was also pioneered in statistical machine translation (Ueffing et al., 2007), but attracted new interest in neural machine translation, where improvements in BLEU were demonstrated (Zhang and Zong, 2016; Chinea-Ríos et al., 2017b). Compared to back-translation, biases and errors in synthetic data are intuitively more problematic in forward translation since they directly affect the gold labels, making attempts to treat real and synthetic data differently less effective (Caswell et al., 2019). Also, there is no clear theoretical link between forward-translated synthetic training data and a model’s fluency. However, other effects, such as domain adaptation and improved learnability of translation from synthetic data remain plausible.2

Burlot and Yvon (2018) perform a systematic study which shows that forward translation leads to some improvements in translation quality, but not nearly as much as back-translation. In very recent work, Wu et al. (2019) show large-scale experiments where a combination of synthetic data produced by both forward and backward translation delivers superior results to just using one or the other. The amount of research on forward translation is however significantly smaller than that on back-translation.

3 Domains and Translationese

Based on these studies, let us now consider how the original and reverse portion of standard test sets differ, and how this can partially explain the observed differences between forward and back-translation.

3.1 Domains

It has previously been shown that back-translation can be used for domain adaptation (Sennrich et al., 2016b; Chinea-Ríos et al., 2017a), and the effectiveness of back-translation and forward translation heavily depends on the availability of relevant, in-domain monolingual data. Even if we have both source-side and target-side data from the same general domain, we believe that there can be subtle differences between them. Even in restricted domain tasks, such WMT news translation (Barrault et al., 2019), newspaper articles in different languages talk about different topics.3 For ex-

\footnote{Also consider the effectiveness of sequence-level knowledge distillation (Kim and Rush, 2016), which is similar to forward translation, but different in that for knowledge distillation, the source side of the parallel training data is re-translated, while we focus on integrating additional monolingual data.}

\footnote{Obviously, there will also be differences between newspapers in the same language, but we expect that a large-scale}
ample, French news article cover subjects of local interest, such as the Quebec local elections. On the other hand, English language news in WMT test sets talk about mostly American or international topics. Therefore when performing back-translation, which is based on target-side data, this implicitly adapts systems to this target-side news domain, while forward translation would adapt systems to the source-side news domain.

### 3.2 Translationese

A second important distinction between the original and reverse portion of test sets comes from their creation, i.e. the process of translation. Human translations show systematic differences to natural text, and this dialect has been termed translationese. Translationese has been extensively studied in the context of natural language processing (Baroni and Bernardini, 2005; He et al., 2016). Translationese texts tend to have different word distribution than naturally produced text due to interference from the source language (Koppel and Ordan, 2011), and other translation strategies such as simplification and explicitation. While translationese is hard to spot for humans, machine learning methods can reliably identify it (Ilisei et al., 2010; Koppel and Ordan, 2011; Rabinovich and Wintner, 2015).

Translationese and its effect have been studied in the context of statistical machine translation: Kurokawa et al. (2009); Lembersky et al. (2012) observe that systems reach higher BLEU on test sets if the direction of the test set is the same as the direction of the training set and Stymne (2017) show how one can tune a system specifically to translationese. Due to the directional nature of the WMT19 test sets (Barrault et al., 2019), research on translationese now in the context of neural machine translation has been revitalized (Freitag et al., 2019; Edunov et al., 2019; Zhang and Toral, 2019; Graham et al., 2019).

One of our goals in this paper is to isolate domain effects and translationese effects in the analysis of synthetic training corpora.

### 4 Experimental setup

We performed our case study using the WMT 15 English-French news translation task dataset (Bojar et al., 2015), consisting of 35.8M parallel sentences from the same language will better match topics at test time than one from another language. In addition to that, in order to perform back and forward translation we used 49.8M English monolingual sentences and 46.1M French monolingual sentences from the respective News Crawl corpora. For training the back-translation and forward translation systems we used shallow bidirectional RNN (Bahdanau et al., 2015), equivalent to the one used by (Sennrich et al., 2016a). For producing the synthetic data we used sampling from the softmax distribution (Edunov et al., 2018). Byte pair encoding (BPE) (Sennrich et al., 2016c) was used to produce a shared vocabulary of 88k tokens.

For training the baseline model, as well as the ones augmented with synthetic data, we used the transformer base architecture (Vaswani et al., 2017). The models denoted as BT and FWD are trained by augmenting the parallel dataset with back-translation and forward translation respectively, while keeping the model hyperparameters the same as those of the baseline. All training and decoding was done using the Marian machine translation toolkit (Junczys-Dowmunt et al., 2018). All models were trained with early stopping on a dev set (newstest2014) with patience 10.

### 4.1 Directional test sets

We used all available datasets from the news translation task and split them by direction, based on the source language, equivalent to the way done by Post (2018), and we evaluated each dataset with all of our models.

### 5 Translation experiments

We present our experimental results on Table 1. On the original portion, the system augmented with forward translated data performs the best on all test sets. It is important to note that the back-translation system is worse than the baseline on some test sets, suggesting it harms the translation quality.

We observe the opposite on the reverse portion: the back-translation system is always the best, and by quite some margin, but unlike in the previous case, the forward translation system clearly shows improvements over the baseline.

On the full datasets, the overall trend is that forward translation improves translation quality, but not as much as back-translation, which is consistent with previous work (Burlot and Yvon, 2018).

We note that overall back-translation had rela-
| System          | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|-----------------|------|------|------|------|------|------|
| Original (French source) |      |      |      |      |      |      |
| Baseline        | 26.3 | 40.3 | 28.7 | 30.5 | 34.6 | 45.2 |
| BT              | 26.6 | 39   | 28.6 | 27.8 | 32.5 | 45.5 |
| FWD             | **28.4** | **42.9** | **30.5** | **31.8** | **37** | **47.2** |
| Reverse (Translationese French source) |      |      |      |      |      |      |
| Baseline        | 23.7 | 24.7 | 33.8 | 38.9 | 30.5 | 31.9 |
| BT              | **31.1** | **31.5** | **41.5** | **47.4** | **36** | **36.8** |
| FWD             | 25.6 | 26.9 | 34.6 | 40.7 | 31   | 33.1 |
| Full test set*  |      |      |      |      |      |      |
| Baseline        | 24.8 | 33   | 31.2 | 34.6 | 32.5 | 38.5 |
| BT              | **29.2** | **35.5** | **34.8** | **37.5** | **34.3** | **41** |
| FWD             | 26.7 | 35.5 | 32.5 | 36.2 | 34   | 40   |

Table 1: French→English BLEU scores on newstest. BT and FWD denote baseline system augmented with backward-translation and forward translation respectively.

*For some test sets, some of the sentences are originally in neither French nor English, so we removed them from the test set.

We observe a relative gain of 6.8 BLEU on average on the reverse test sets, whereas forward translation improved them with just about 1.4 BLEU. On test sets that were originally in the source language however, forward translation brought improvements of 2 BLEU, whereas back-translation obtained an average loss of 1 BLEU. We hypothesize that apart from the domain adaptation effect that the two data augmentations bring, back-translation has an additional advantage: It explicitly models original target side language, which is what is used to compute the BLEU score. On the other hand, forward translation only provides domain adaptation, as its target side text is of markedly poorer quality.

6 Language model experiments

BLEU scores are insufficient to draw conclusions about the nature of the improvements both data augmentation methods bring, so we designed a language modelling experiment in order to approach the problem from a different angle. Specifically, we measure the similarity between training and test sets by training language models on our training data, and measuring perplexity to variants of the test sets.

We trained four language models using the data that we had prepared for forward and back-translation: two native English and French language models and two English and French translationese models (we denote the latter two ENMT and FRMT, respectively). The language models computed on the machine translated data exhibit specific features: They are trained on sampled data so we expect below average fluency, but good adaptation to the domain (source-side news or target-side news). Therefore we expect that the native French language model will perform better (i.e. have lower perplexity) on native French text compared to a translationese French language model, as the style and the domain of the native text match with those of the native language model. We expect that we will observe the same effect when evaluating native vs translationese English language model on native English text.

When considering translated test sets, we will expect them to be closer to the translationese language models – this is both compatible with the interpretation that the two types of texts are similar because they are both translationese, as well as the interpretation that they are similar because they are from the same source-language domain.

But what if we have native English data that has been human translated into French and then automatically translated into English? In this case it will share the domain with native English, but after the intermediate human translation, we expect the style to be closer to the language model trained on the translationese text. This variant of the test set gives us the most direct answer as to what extent translationese or domain effects affect the similarity between training and test data.

| test set | FRnative | FRMT |
|----------|----------|------|
| native FR | **99.22** | 118.83 |
| HTEN→FR  | **113.98** | 117.97 |

Table 2: Language model perplexity on the French side of the combined directional datasets, normalised by number of sentences. We distinguish whether test sets are native French or human translation (HT).

Table 2 shows the language model performance of the native French language model and the translationese French language model. We observe that unsurprisingly, the language model trained on original French data shows lower perplexity on the original French data than the one trained on MT translated French. Somewhat surprisingly the trend is maintained in the translationese French dataset, even if the two perplexity scores are closer to each other. This is unlike the results on the English language models on Table 3, where the lan-
Table 3: Language model perplexity on the English side of the combined directional datasets, normalised by number of sentences. We distinguish whether test sets are native English, human translation (HT), machine translation (MT), or roundtrip translation with multiple translation steps.

| test set     | EN\text{\textsubscript{native}} | EN\text{\textsubscript{MT}} |
|--------------|----------------------------------|-----------------------------|
| native EN    | 101.90                           | 118.71                      |
| HT\text{\textsubscript{EN→FR}}, MT\text{\textsubscript{FR→EN}} | 98.01                          | 99.71                       |
| MT\text{\textsubscript{FR→EN}} | 102.28                           | 94.43                       |
| HT\text{\textsubscript{FR→EN}} | 113.99                           | 111.90                      |

Of most interest are the result for HT\text{\textsubscript{EN→FR}}, MT\text{\textsubscript{FR→EN}}, i.e. the roundtrip translation of native English text. Based on our hypothesis that source-language and target-language domains are slightly different, we expect the EN\text{\textsubscript{native}} LM to perform better than EN\text{\textsubscript{MT}}. Based on the more established explanation that the main distinguishing feature of translated text are translationese artefacts, we would expect EN\text{\textsubscript{MT}} to perform better than EN\text{\textsubscript{native}}. In fact, perplexities are very close to each other, suggesting that domain effects and translationese effects both come into play, and roughly balance each other out.

7 Domain identification experiments

Inspired by the work of Caswell et al. (2019), we explore if translation models can learn whether training instances come from the source-language or target-language “domain”. To this end, we train a French→English translation model only using synthetic training data (both forward translations and back-translations), and we add a tag at the beginning of the target sentence indicating the original language. The resulting model is able to correctly identify the original language in 83% of the sentences of the training set. When evaluating it on test sets, the model has a marked preference to identify the original language as French. On the originally French portion, the model found 89.4% of the sentences be native French, whereas on the human translated French side, the model predicts 51% of the sentences to be native French. It is possible that the model has learned to partially rely on translation errors and other biases of machine translation for the discrimination, which lowers its accuracy on human translations, but the overall accuracy of 70% is still remarkable and points at systematic differences between the original and reverse portion of WMT test sets that the model picks up on without being trained on any human-translated data.

8 Human Evaluation

Table 1 shows big discrepancies in the BLEU scores based on the type of synthetic data and directionality of the datasets, but BLEU does not tell the full story. The main author performed manual evaluation on 1008 uniformly selected sentences from all the newstest datasets, 504 from the forward direction and 504 from the reverse direction. We evaluated MT output on adequacy and fluency on a scale from 0 to 5. In the adequacy category we measure how intelligible the sentence is, regardless of the grammar. The scale we used is the following:

- 0 No translation produced/ single word.
- 1 Obviously incomplete translation/nonsense words.
- 2 A small part of the sentence is translated, but not enough to get the meaning across.
- 3 The sentence is translated but a crucial word is mistranslated or missing in such a way that the meaning is very different from the reference.
- 4 Minor mistake, missing non crucial word or imprecise word used.
- 5 Perfect translation.

The fluency evaluation measures how fluent the sentence reads in English, regardless of whether the meaning is translated correctly or not. We expect the back-translation system to have better fluency, because it has access to extra gold target side data. We used the following fluency scale:

- 0 No translation produced/ single word.
- 1 Obviously incomplete translation or nonsense words.
- 2 A soup of words, individual bigrams or trigrams make sense.
3 Major grammatical mistakes.

4 Minor grammatical mistakes.

5 Perfectly fluent.

Our human evaluation results are presented on Table 4. We see that adding extra back and forward translated data always improves the adequacy and fluency of the translation over the baseline. This is contrary to the results in table 1, which show that on the original portion of some test sets, back-translation produces worse BLEU score than the baseline, but consistent with findings of Edunov et al. (2019); Freitag et al. (2019). We see that in terms of adequacy, human judges prefer the forward translation system on the original portion, and the back-translation system on the reverse portion, but in terms of fluency, the results are more conflicting: On the original portion, back-translation and forward translation perform almost identically, while in the reverse portion, there is a strong preference for using back-translation. We also note that the baseline results are much better on the original portion, rather than the reverse. We show the three-way $p$-values and statistics scores computed using the ANOVA test (Heiberger and Neuwirth, 2009). When performing $t$-test on just the forward and back-translation systems, only the results on the reverse dataset show significant difference between the two systems.

9 Other Language Pairs

In order to see if our findings generalise to other language pairs, we trained Estonian→English and Finnish→English translation models, following the same procedure as the one described in Section 4. In order to better control for domain and style, we only use the parallel news crawl data from the WMT18 (Bojar et al., 2018) translation task, which resulted in 3.1M sentence pairs for Finnish→English and 0.9M sentence pairs for Estonian→English.

For data augmentation, we use all the available news-crawl on the Estonian/Finnish side for forward translation and the equivalent amount of English news-crawl for back-translation. This resulted in 14.5M monolingual sentences used for Finnish-English back/forward translation and 2.9M sentences used for Estonian-English back/forward translation. We produced two versions of the synthetic data: One with a shallow RNN as the one for the English–French experiments, described in section 4, and one with a transformer system with the same hyperparameters as the baseline from section 4.

We present our results on tables 5 and 6. In the case of Estonian (Table 5), we have a low resource scenario which produced particularly poor synthetic data: The RNN English–Estonian system that was used for generating back-translation reaches just 12 BLEU on the dev set. On the other hand a transformer English–Estonian achieves 18 BLEU. For contrast, the difference between the RNN and the transformer Estonian–English that were used to produce the forward translation was just 2 BLEU (15-17). We see that the quality of the back-translation system in this case does actually matter: The systems augmented with transformer back-translation gained 4.7 BLEU points on average against the RNN back-translation. Relatively, the forward translation system has improved significantly more: Just 2 BLEU points of difference between the RNN and transformer models used to create the synthetic data resulted in 3.2 points increase in BLEU. This suggests that data augmentation via forward translation is substantially more sensitive to the translation quality of the initial translation system than back-translation.

Our observations are confirmed in the slightly higher-resource experiment on Finnish→English (Table 6). The quality of the translation model used for back-translation was improved by 9 BLEU (from 17 to 26) when using a transformer instead of RNN, but on the final system, this yielded just 1.1 BLEU increase on average. On the other hand, the quality of the translation system used for forward translation was improved from 17 to 23 BLEU, which improved the final system by 2 BLEU on average.

We see that in a very low-resource scenario (Table 5) where it may be difficult to produce sufficiently high quality of forward translation, back-translation always yields superior gains. However forward translation benefits much more from increased model quality in the initial translation system than back-translation. We can see that in the Finnish→English experiment, where forward translation does produce the best BLEU scores on 2 out of 4 test sets. We predict that, as the quality of translation systems continues to improve, this will favour forward translation as a data augmen-
| System | Adequacy | Fluency |
|--------|----------|---------|
|        | Original | Reverse | Original | Reverse |
| Baseline | 4.01     | 3.88    | 4.36     | 4.34    |
| BT      | 4.12     | 4.30    | 4.43     | 4.61    |
| FWD     | 4.23     | 4.15    | 4.44     | 4.47    |

$p$-value: 0.008 $<$ 0.00001, 0.3 $<$ 0.00001

$t$-test on FWD and BT

$p$-value: 0.11, 0.009, 0.83, 0.0006

Table 4: French $\rightarrow$ English human evaluation of 1008 sentences (504 in original and reverse portion, respectively). Three way statistics test was computed using the ANOVA test (Heiberger and Neuwirth, 2009). Standard $t$-test was used for the two way comparison between FWD and BT.

| System | 2018dev | 2018test |
|--------|---------|----------|
|        | Original (Estonian source) |        | Original (Estonian source) |
| Baseline | 18.0     | 19.4     | Baseline | 22.6     | 24.2     | 24.2     | 19.4     |
| $\text{BT}_{\text{rnn}}$ | 17.1     | 17.9     | $\text{BT}_{\text{rnn}}$ | 20.9     | 21.7     | 21.7     | 19.4     |
| $\text{BT}_{\text{transformer}}$ | **20.8** | **21.5** | $\text{BT}_{\text{transformer}}$ | 21.5     | 22.9     | 22.2     | **20.0** |
| $\text{FWD}_{\text{rnn}}$ | 16.2     | 17.4     | $\text{FWD}_{\text{rnn}}$ | 19.6     | 22.2     | 22.4     | 13.9     |
| $\text{FWD}_{\text{transformer}}$ | 19.6     | 20.8     | $\text{FWD}_{\text{transformer}}$ | 22.4     | **24.3** | **24.2** | 15.0     |

| Reverse (Translationese Estonian source) |
|-----------------------------------------|
| Baseline | 20.2     | 20.6     |
| $\text{BT}_{\text{rnn}}$ | 23.2     | 22.8     |
| $\text{BT}_{\text{transformer}}$ | **29.4** | **28.0** |
| $\text{FWD}_{\text{rnn}}$ | 17.9     | 18.3     |
| $\text{FWD}_{\text{transformer}}$ | 20.5     | 20.8     |

| Full test set |
|---------------|
| Baseline | 19.1     | 20.0     |
| $\text{BT}_{\text{rnn}}$ | 20.1     | 20.5     |
| $\text{BT}_{\text{transformer}}$ | **25.1** | **24.9** |
| $\text{FWD}_{\text{rnn}}$ | 17.1     | 17.8     |
| $\text{FWD}_{\text{transformer}}$ | 20.6     | 20.8     |

Table 5: BLEU scores on Estonian $\rightarrow$ English. The RNN and Transformer subscripts refer to the system used for producing backtranslation.

| System | 2015 | 2016 | 2017 | 2018 |
|--------|------|------|------|------|
|        | Original (Finnish source) |
| Baseline | 22.6     | 24.2     | 24.2     | 19.4     |
| $\text{BT}_{\text{rnn}}$ | 20.9     | 21.7     | 21.7     | 19.4     |
| $\text{BT}_{\text{transformer}}$ | 21.5     | 22.9     | 22.2     | **20.0** |
| $\text{FWD}_{\text{rnn}}$ | 19.6     | 22.2     | 22.4     | 13.9     |
| $\text{FWD}_{\text{transformer}}$ | 22.4     | **24.3** | **24.2** | 15.0     |

| Reverse (Translationese Finnish source) |
|-----------------------------------------|
| Baseline | 18.9     | 22.7     | 26.1     | 22.1     |
| $\text{BT}_{\text{rnn}}$ | 22.6     | 28.8     | 31.5     | 20.3     |
| $\text{BT}_{\text{transformer}}$ | **24.1** | **30.4** | **33.3** | 21.4     |
| $\text{FWD}_{\text{rnn}}$ | 16.8     | 20.4     | 23.4     | 20.1     |
| $\text{FWD}_{\text{transformer}}$ | 18.3     | 22.5     | 26.0     | **22.2** |

| Full test set |
|---------------|
| Baseline | 20.6     | 23.4     | 25.2     | 18.3     |
| $\text{BT}_{\text{rnn}}$ | 21.9     | 25.7     | 27.2     | 19.8     |
| $\text{BT}_{\text{transformer}}$ | **23.0** | **27.1** | **28.4** | **20.6** |
| $\text{FWD}_{\text{rnn}}$ | 18.1     | 21.2     | 22.9     | 16.5     |
| $\text{FWD}_{\text{transformer}}$ | 20.2     | 23.3     | 25.2     | 18.1     |

Table 6: BLEU scores on Finnish $\rightarrow$ English. The RNN and Transformer subscripts refer to the system used for producing backtranslation.

10 Conclusions

In this paper we reviewed the effect of directionality on machine translation results, focusing both on the direction of data augmentation (forward and back-translation), and the original language of test sets, focusing on French $\rightarrow$ English as a case study, with additional experiments on Estonian $\rightarrow$ English and Finnish $\rightarrow$ English. We confirm that the original language of parallel test sets affects BLEU scores, particularly when data augmentation approaches such as forward and back-translation are compared. We find that back-translation is more effective than forward translation in the somewhat artificial setting where the input to the translation system is itself a human translation, and the original text is used as reference. In the more natural setting where the input is native text, and the reference a human translation, forward translation can...
perform better in terms of BLEU, although it still trails behind back-translation if the forward translations in the synthetic data sets are very poor.

Manual evaluation shows that better BLEU scores do not necessarily correspond to better translation quality according to human judgments. Despite wildly differing BLEU results depending on the original language of test sentences, forward translation and back-translation systems both yield similar improvements in terms of human judgments.

To better understand the differences between forward and back-translation, we consider both translationese effects and subtle domain differences between source-language and target-language monolingual data. Language model experiments indicate that both of these play a role, and partially explain why back-translation is so suitable for reverse test sets. Experiments with translation systems trained on only synthetic data (forward and back-translation) also show that the provenance of test set sentences is predictable with 70% accuracy.

Our findings are in agreement with concurrent and independent work by Shen et al. (2019), who perform low-resource translation experiments with back-translation and self-learning, an iterative form of forward translation. They also find that the original language of parallel test data determines whether back-translation or forward translation is a more effective strategy for data augmentation.

Based on our findings, we can make several recommendations for the use of forward translation and back-translation to augment neural machine translation. Firstly, both strategies are viable. While BLEU is very sensitive to the choice of data augmentation, with up to 5 BLEU difference between the two choices in our French→English experiments, depending on the make-up of the test set, our human evaluation indicates that both strategies can yield similar results, with back-translation having a small edge in fluency. Secondly, we observe subtle domain differences between corpora in different languages, even if they cover the same general domain (news) and were collected with the same methods. Following the general heuristic to use training data that matches the test domain as closely as possible, this is an argument for using forward translation. Lastly, our results indicate that the success of forward translation for data augmentation is heavily dependent on the quality of the forward translations, while back-translation is more robust. Hence, we expect forward translation to be most suitable for translation directions where translation quality is already high, while back-translation is suitable for low-resource scenarios or other settings with relatively low translation quality. Of course, the use of forward and back-translation is not mutually exclusive, and in settings with access to suitable monolingual corpora in both the source and target language, combining the two is another viable strategy (Wu et al., 2019).

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