Fully Synthetic Data Improves Neural Machine Translation with Knowledge Distillation

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Abstract
This paper explores augmenting monolingual data for knowledge distillation in neural machine translation. Source language monolingual text can be incorporated as a forward-translation. Interestingly, we find the best way to incorporate target language monolingual text is to translate it to the source language and round-trip translate it back to the target language, resulting in a fully synthetic corpus. We find that combining monolingual data from both source and target languages yields better performance than a corpus twice as large only in one language. Moreover, experiments reveal that the improvement depends upon the provenance of the test set. If the test set was originally in the source language (with the target side written by translators), then forward translating source monolingual data matters. If the test set was originally in the target language (with the source written by translators), then incorporating target monolingual data matters.

1 Introduction
When we used knowledge distillation (Ba and Caruana, 2014; Hinton et al., 2015; Kim and Rush, 2016) to build faster neural machine translation (NMT) (Bahdanau et al., 2014; Sutskever et al., 2014) models, the quality loss depended on the test set. Test sets collected in the source language then professionally translated to the target language showed little change in BLEU (Papineni et al., 2002). However, test sets collected in the target language then professionally translated to the source language showed larger losses in BLEU due to knowledge distillation. This led us to examine source and target monolingual data augmentation methods and their relationship with translationese.

Target monolingual data is normally incorporated by back translation (Sennrich et al., 2016), which adds a pseudo-parallel corpus of real target-language text paired with their machine translations to the source language. Sequence-level knowledge distillation uses forward translation: source language text is translated to the target language to form a pseudo-parallel corpus, which the student then learns from (Kim and Rush, 2016). The two methods can be composed: authentic text in the target language can be translated to the source language then translated again to the target language, resulting in a completely synthetic parallel corpus consisting solely of machine translation output. Oddly, our experiments show that this completely synthetic corpus is better for training students in knowledge distillation compared to concatenating a back-translated corpus. We can incorporate source monolingual data by simply forward translating it with a teacher model.

This paper explores the interaction of monolingual data augmentation in knowledge distillation. We find that the BLEU improvement depends on the provenance of the test set. Augmenting target monolingual data improves BLEU for test set originated in target language. Inversely, source monolingual data improves BLEU for a test set originally in the source language. Augmenting both source and target monolingual data yields the best result.

We also investigate whether forward-translating seen data is necessary, as some research suggests forward-translating the same corpus used by the teacher (Kim and Rush, 2016; Freitag et al., 2017; Yim et al., 2017). We find that the student trained on new unseen monolingual data performs equally as the one with one trained on the same dataset as the teacher, as long as they share the same domain.

The amount of training data, including the augmented one affects model performance (Edunov et al., 2018; Sennrich and Zhang, 2019; Araabi and Monz, 2020). Therefore, we also explore the augmented monolingual data size. We find that augmenting more monolingual data is generally better. However, having more varied data based on the monolingual language origin is much more im-
important. Using monolingual data from both source and target languages is better than having more data in total from one language.

![Diagram of teacher model setup](image1)

**Figure 1:** Illustration for setting up a teacher model. The teacher is trained with parallel corpus + back-translation data.

![Diagram of student model setup](image2)

**Figure 2:** Illustration for setting up a student model with interpolated knowledge distillation. The student is trained with forward-translated data by the teacher.

## 2 Related Work

### 2.1 Knowledge Distillation

Smaller neural models usually have an advantage in terms of efficiency (Kim et al., 2019; Bogoychev et al., 2020; Aji and Heafield, 2020). However, they are usually of poorer quality than large models. Smaller models have shown to perform better if trained with knowledge distillation (Ba and Caruana, 2014; Hinton et al., 2015; Kim and Rush, 2016) than trained from scratch, which we confirm. In knowledge distillation, the small model is trained by learning the output distribution of a larger model.

Kim and Rush (2016) proposed interpolated knowledge distillation for sequence-to-sequence models. In interpolated knowledge distillation, students learn directly from the output produced by their teachers. This interpolated knowledge distillation is easy to apply, as practically we simply produce forward translated synthetic data using a teacher model once. Despite its simplicity, interpolated knowledge distillation has been shown to be useful for training small models without compromising quality (Kim et al., 2019; Bogoychev et al., 2020).

### 2.2 Translationese Evaluation

Human-written translations, sometimes called translationese, show different characteristics compared to naturally written text. The word distribution differs from natural text, as the translators are influenced by the original language when producing the translation (Koppel and Ordan, 2011). In the context of machine translation, sentences in the test set may originally come from the source language or the target language, which was then translated by annotators.

Several studies have found that the performance of the NMT model is sensitive to translationese (Zhang and Toral, 2019; Bogoychev and Sennrich, 2019; Edunov et al., 2020). The ranking of a news translation shared task changes depending on which part of the test set is used (Zhang and Toral, 2019). The training data used also affects the performance of NMT. Edunov et al. (2020) have found that leveraging back translation data improves the performance of test sets derived from target-side data that are translated to source-side. Bogoychev and Sennrich (2019) found otherwise that the forward translation synthesis data achieved better BLEU in the test set from the source-side. Given that our research in knowledge distillation makes use of monolingual data from both languages, we will conduct a performance evaluation based on the original source of the test set as well.

## 3 Knowledge Distillation With Monolingual Data

To perform a knowledge distillation, we first have to prepare a teacher model. The teacher model is trained as usual by using parallel data ($\text{Par}_{\text{src}} – \text{Par}_{\text{tgt}}$) and back translation data ($\text{BT}(\text{Mono}_{\text{tgt}}) – \text{Mono}_{\text{tgt}}$). An illustration for setting up the teacher model can be seen in Figure 1.

In interpolated knowledge distillation, the student learns to mimic the teacher’s translations. So we take source language text, forward translate (FT) it with the teacher, and train the student on a pseudo-parallel corpus of source text and the teacher’s translations. An illustration for this approach can be seen in Figure 2. There are sev-
eral options for source-side monolingual data to be forward-translated by the teacher model, which we will explore further in this paper:

- **Forward-translated source-side parallel data:** \( \text{Par}_{\text{src}} \rightarrow \text{FT}(\text{Par}_{\text{src}}) \). We can take the source side of the available parallel data. Naturally, this data is learnt by the teacher and follows prior work’s (Kim and Rush, 2016; Freitag et al., 2017; Yim et al., 2017) suggestion to use the same data for the student.

- **Forward-translated back translation:** \( \text{BT}(\text{Mono}_{\text{tgt}}) \rightarrow \text{FT}(\text{BT}(\text{Mono}_{\text{tgt}})) \). We can forward-translate back translation (BT) data (i.e., target-side monolingual data that has been translated to the opposite direction). Similar to the previous data, we can use the same BT data as the one used by the teacher. Though, we also explore using BT that teachers have never seen before. It should be noted that in this case, both the source and target are synthetic data.

- **Forward-translated source-side monolingual data:** \( \text{Mono}_{\text{src}} \rightarrow \text{FT}(\text{Mono}_{\text{src}}) \). Lastly, we can take advantage of the source-side monolingual data by directly translating it. Different from the previous data sources, this data has never been seen before by the teacher.

| Training set | Source → Target |
|--------------|-----------------|
| Used by teacher | \( \text{Par}_{\text{src}} \rightarrow \text{Par}_{\text{tgt}} \) |
| \( \text{BT} \) | \( \text{BT}(\text{Mono}_{\text{tgt}}) \rightarrow \text{Mono}_{\text{tgt}} \) |
| Used by student | \( \text{FT}(\text{Par}) \rightarrow \text{FT}(\text{Par}_{\text{src}}) \) |
| \( \text{FT}(\text{BT}) \) | \( \text{FT}(\text{BT}(\text{Mono}_{\text{tgt}})) \rightarrow \text{BT}(\text{Mono}_{\text{tgt}}) \) |
| \( \text{FT}(\text{Mono}) \) | \( \text{Mono}_{\text{src}} \rightarrow \text{FT}(\text{Mono}_{\text{src}}) \) |

Table 1: Dataset summary for the experiments.

To summarize, we define the following training sets, shown in Table 1. Some research (Kim and Rush, 2016; Freitag et al., 2017; Yim et al., 2017) suggests training the student model with the same data as the teacher model, namely \( \text{FT}(\text{Par}) \) and \( \text{FT}(\text{BT}) \). We also have access to source-side monolingual data which can be used as \( \text{FT}(\text{Mono}) \). We will explore whether each of these datasets can be used in interpolated knowledge distillation. Since prior work has shown that NMT evaluation is sensitive towards training data direction (Bogoychev and Sennrich, 2019; Edunov et al., 2020), we also split the test set based on the original language.

4 Experiment Setup

4.1 Model Configuration

Our teacher model uses a Transformer Big architecture (Vaswani et al., 2017) with 6 encoder and decoder layers, with the embedding 1024 and a feed-forward network (FFN) size of 4096. Following Bogoychev et al. (2020), most of our students use the Tiny architecture with 6 standard Transformer layers for the encoder and 2 RNN-based Simpler Simple Recurrent Unit (SSRU) layers (Kim et al., 2019) for the decoder. We also use a unit size of 256 and filter size of 1536. Beside the Tiny architecture, in section 5.3 we also explore student model of different layer sizes and unit sizes.

The text is pre-processed into subword units with SentencePiece (Kudo and Richardson, 2018). We also use a tied-embeddings layer (Press and Wolf, 2017). The model is trained using the Marian toolkit (Junczys-Dowmunt et al., 2018) until no improvement is found for 20 consecutive validation steps. We evaluate once every 1k steps, and the training ends after 200k steps. We use SacreBLEU (Post, 2018) to measure the model’s performance.

Our model is trained on 4 GPUs\(^1\) with 10 GB dynamic mini-batch. Training time depends on the size of the model and data. Teacher model takes up to about 8 days, while student model can be trained in 1-2 days.

4.2 Data

**Turkish-English (Tr-En)** Tr-En parallel data comes from the WMT17 news translation task, which consists of 207k pairs. Monolingual English data for back-translation is collected from NewsCrawl 2017. Monolingual Turkish data for forward translation is collected from NewsCrawl 2018 and 2019.

**Estonian-English (Et-En)** Similarly, our Et-En parallel data comes from WMT18 news translation task (over-sampled to 10M pairs). English and Estonian monolingual data were obtained from NewsCrawl from 2017 to 2014. In addition, we used the BigEst Estonian Corpus for additional monolingual Estonian. We clean the data by removing sentences that are too short (less than 3 words) or too long (more than 150 words).

\(^1\)P100 or GeForce RTX 2080 Ti, depending on availability
Spanish-English (Es-En) Lastly, the Es-En parallel data is a combination of data from ParaCrawl release-5 and Opus, totalling 102M pairs. Monolingual data for English is taken from NewsCrawl 2014-2017. Spanish monolingual data is a combination of NewsCrawl 2007-2018, Europarl v9, and Gigaword corpus.

5 Experiments and Discussion

5.1 Monolingual Data for Knowledge Distillation

We start the experiment by training several knowledge-distilled systems on different subsets of training data according to Table 1. As a baseline, we also compare the performance with our Big teacher model, and Tiny non-distilled model. Both models are trained with the same training set of parallel corpus and back-translation corpus. The results can be seen in Table 2. Following Bogoychev and Sennrich (2019), we break down the test set by the language in which the text was originally written.

As expected, the quality of the non-distilled Tiny model is much lower than the Big model. This result confirms that knowledge distillation significantly improves the quality of smaller model.

The students vary in performance depending on the data set and the original language of the test set. The Tiny student model trained with parallel data and back-translation ($\text{FT(Par + BT)}$) performs well on test sets originating from the target language, but poorly on test sets originating from the source language. In contrast, the model trained with parallel data and source-side monolingual data ($\text{FT(Par + Mono)}$) works well on test sets originating from the source language, but poorly if originating from the target language. Combining all sets ($\text{FT(Par + Mono + BT)}$) generally yields the best result, regardless of the data origin. Since these patterns are consistent among different test sets, hence we simply report the averaged BLEU for the next experiments.

Older Workshop on Machine Translation campaigns created test sets by gathering text in a variety of languages then translating to all the other languages pivoting through English. So, for example, a sentence originally written in Czech was translated to English and again from English to Spanish, forming part of the Spanish–English test set. We label these cases as “other” in Table 2. The model trained with $\text{FT(Par + Mono)}$ achieves marginally better BLEU than our recommended $\text{FT(Par + Mono + BT)}$. We are unsure why, but the difference is small enough relative to the size of the test set to conclude anything.

We try two ways to combine forward translation and back translation: composition and concatenation. In composition, target language monolingual text is translated to the source language then translated again to the target language in a round-trip. Curiously, this $\text{FT(BT)}$ data is fully synthetic. In contrast, we can simply concatenate the back-translated and forward-translated parallel corpora. The result in Table 2 (Last row) shows that apparently using $\text{FT(BT)}$ is slightly better than $\text{BT}$. We further confirm that this improvement significant, according to (Koehn, 2004) (p-value 0.002). Hence, we recommend to use composition: fully synthetic forward-translated back-translation data. This makes sense because concatenation bypasses the teacher and exposes the student to real target language data, which is more difficult to learn from.

5.2 Using Unseen Monolingual Data

There is a confounding factor in the use of source monolingual data: it was never seen by the teacher and, consequently, did not have a chance to overfit. Separating this confound directly would require inventing a way to use source data to train the teacher. But we can test a related question: does it matter if the teacher and student use the same target monolingual data?

To recall, the teacher model is trained with the parallel corpus (Par) and back translation data (BT). Following results from the previous section, to train the student we back translate the target monolingual data and then forward translate it to form a synthetic parallel corpus (FT(BT)). Both teacher and student require BT data, which is coming from the target monolingual data. Do we need to use the same target monolingual data for both of them?

As shown in Table 4, we explore training students with different target monolingual data. We divide NewsCrawl 2017 into equally-sized chunks. The teacher is trained with back translation of the first chunk. One student is trained with forward translation of back translation from the same chunk. Another student is trained on forward translated back translations from a second chunk of NewsCrawl 2017 (unseen by the teacher). We find that both students perform equally well.
Table 2: Experiment results in terms of BLEU, divided based on the test-set's original language. The Big model is our teacher model. Models trained with forward-translated data (denoted with FT(...)) are our student models. For the training data, please refer to Table 1.

Furthermore, we also train students using forward-translated back translation constructed from different corpora: NewsCrawl 2010, CommonCrawl, and OpenSubtitle. We find that among those, NewsCrawl 2010 works best (and performs comparably with NewsCrawl 2017), whereas OpenSubtitle achieves worst BLEU. From these results, we conclude that the training data for students does not have to be the same as the teacher, as long as the domain agrees. Though, using CommonCrawl or OpenSubtitles\(^2\) monolingual data is still better than not using any monolingual data at all.

Likewise, we also explored the effects of selecting the forward-translated monolingual data (FT(Mono)). However, different from the back translation that comes from the target-side monolingual data, the source-side monolingual data is not used when training the teacher. So, in this experiment we only explore the domain from the data. In Table 3, we find that the best monolingual source-side data for student is the one with the same domain as the teacher (news domain) model.

### 5.3 Monolingual Data Size

In Table 2, the best student model is trained with the combination of forward-translated back-translation and forward-translated source-side monolingual data (FT(Par + Mono + BT)). However, that model is trained with the most amount of data compared to others. In this subsection, we further explore the effect of back-translation and source-side monolingual data under more controlled data size, to remove any artefact of different data size from interfering with the result.

Generally, more training data often leads to better performance. However, in our case, mixing our synthetic data is more important, than as shown in Table 5, given the same total amount of augmented data size, mixing back-translation and source-side monolingual data achieves the best BLEU, compared to the models trained exclusively on either data. In fact, our Tr-En model trained with

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\(^2\)http://opus.nlpl.eu/download.php?f=OpenSubtitles/v2018/mono/OpenSubtitles.raw.{en,et}.gz
Table 3: Exploring different back-translation data sources when the student model is trained with FT(Par + BT) training data. None is trained only with FT(Par).

| source                     | src | tgt | all |
|----------------------------|-----|-----|-----|
| None                       | 4.5 | 5.0 | 4.9 |
| NewsCrawl-17 (same as Teacher) | 16.2 | 25.6 | 21.2 |
| NewsCrawl-17 (diff. w/ Teacher) | 16.3 | 25.9 | 21.4 |
| NewsCrawl-10               | 15.9 | 25.7 | 21.1 |
| English CommonCrawl        | 15.7 | 23.3 | 19.7 |
| Opensub v2018              | 10.6 | 14.8 | 12.8 |

Table 4: Exploring different source-side monolingual data when the student model is trained with FT(Par + Mono) training data. None is trained only with FT(Par).

| source                     | src | tgt | all |
|----------------------------|-----|-----|-----|
| None                       | 4.5 | 5.0 | 4.9 |
| NewsCrawl-18 + 19          | 17.8 | 24.1 | 21.3 |
| Turkish CommonCrawl        | 17.0 | 22.8 | 20.2 |
| Opensub v2018              | 11.4 | 15.8 | 13.3 |

Table 5: Evaluating model’s performance over various monolingual dataset size. Models trained with mixture FT(BT) + FT(Mono) generally perform best.

| augment size | src | tgt | all |
|--------------|-----|-----|-----|
| 5M           | 16.2 | 25.6 | 21.2 |
| 2.5M         | 17.9 | 25.8 | 22.0 |
| 10M          | 16.5 | 25.9 | 21.8 |
| 5M           | 18.1 | 25.2 | 21.4 |
| 10M          | 18.2 | 27.5 | 23.2 |

(a) Tr→En model.

| augment size | src | tgt | all |
|--------------|-----|-----|-----|
| 32M          | 26.4 | 33.4 | 30.3 |
| 16M          | 28.6 | 31.7 | 30.6 |
| 32M          | 28.1 | 34.5 | 31.6 |

(b) Et→En model.

| augment size | src | tgt | all |
|--------------|-----|-----|-----|
| 96M          | 44.1 | 53.9 | 35.9 |
| 43M          | 45.8 | 52.1 | 36.3 |
| 96M          | 45.6 | 53.6 | 36.4 |

(c) Es→En model.

2.5M FT(BT) + 2.5M FT(Mono) achieves overall BLEU comparable to the models trained with 10M data exclusively on either side (22.0 BLEU vs 21.9 BLEU). Soto et al. (2020) has shown similar result with back-translation data, where augmenting from multiple sources is better than relying on one source of data.

5.4 Exploring Different Student Sizes

From Table 2, we only see small BLEU-gap between teachers and students in the test set originating from the source. In some cases, we find that students perform equally or even better than teachers in that test set. On contrary, students lose BLEU significantly (can be more than −5 points) when handling a test set originally written in the target language. In this subsection, we confirm this pattern by training student models with different sizes.

We explore 4 variations of student size (Base, Small, Tiny, and Micro) as shown in Table 6. The Base model uses Transformer encoder and decoder, whereas the other models use RNN-based Simpler Simple Recurrent Unit (SSRU) for decoders. We also stack the students with 8-bit fixed point quantization (Kim et al., 2019) and 4-bit log quantization (Aji and Heafield, 2020) to achieve even smaller model size. Our 8-bit and 4-bit models are trained with full 32-bit precision first before continuing training under lower precision.

The result shown in Table 6 confirms that the student models handle test sets with original source sentences better, compared to the opposite side. A Similar pattern can be observed for both Et→En and En→En models, as shown in Table 7. In our extremely small 4-bit Micro student, we “only” lose −1.6 BLEU points on the test set originating in the source language compared to −6.8 BLEU points on the test set originated in the target language. Moreover, our largest student (Base) already loses −1.4 BLEU points on that target-originated test set.

Model quantization can shrink the size more effectively than just using a smaller network. For example, the Micro model is bigger (47MB, 21.4
Table 6: Performances of different Tr→En student sizes, according to test set’s original language. The teacher and non-distilled models are trained with Par+BT, whereas all student models are trained with FT(Par+BT+Mono) data.

| Model          | Size (MB) | Embed. size | FFN Enc./Dec. Prec | Tr→En avg. BLEU |
|---------------|-----------|-------------|-------------------|----------------|
|               |           | src (△)    | tgt (△)           | all (△)        |
| Big (Teacher) | 781       | 1024        | 4096              | 6/6            |
|               |           | 32          | 18.2              | 29.6           |
| Base (non-distill) | 232      | 512         | 2048              | 6/6            |
|               |           | 32          | 18.1 (-0.1)       | 29.1 (-0.5)    |
| Base          | 232       | 512         | 2048              | 6/6            |
|               |           | 32          | 18.3 (0.1)        | 28.2 (-1.4)    |
| Small         | 83        | 256         | 1536              | 6/6            |
|               |           | 32          | 18.0 (-0.1)       | 27.2 (-2.4)    |
| Tiny          | 65        | 256         | 1536              | 6/2            |
|               |           | 32          | 18.3 (0.1)        | 26.6 (-3.0)    |
| Micro         | 47        | 256         | 1024              | 4/2            |
|               |           | 8           | 17.3 (-0.9)       | 24.9 (-4.7)    |
| Small-8bit    | 21        | 256         | 1536              | 6/6            |
|               |           | 8           | 18.0 (-0.2)       | 27.1 (-2.5)    |
| Tiny-8bit     | 17        | 256         | 1536              | 6/2            |
|               |           | 8           | 17.8 (-0.4)       | 25.9 (-3.7)    |
| Micro-8bit    | 12        | 256         | 1024              | 4/2            |
|               |           | 8           | 17.7 (-0.5)       | 24.1 (-5.5)    |
| Small-4bit    | 10        | 256         | 1536              | 6/6            |
|               |           | 4           | 17.7 (-0.5)       | 25.8 (-3.8)    |
| Tiny-4bit     | 8         | 256         | 1536              | 6/2            |
|               |           | 4           | 17.9 (-0.3)       | 25.2 (-4.4)    |
| Micro-4bit    | 6         | 256         | 1024              | 4/2            |
|               |           | 4           | 16.6 (-1.6)       | 22.8 (-6.8)    |

We train a non-distilled Base model, to find out whether this performance decline is due to knowledge distillation or the small size of the model. As in Table 6, we see that the distilled Base model yields worse BLEU on target-originated test (−1.4 BLEU) compared to the non-distilled variant (−0.5 BLEU). Therefore we confirm that distilled models somehow have difficulty handling a test set originally written in the target language.

5.5 Student Output vs Translationese

Student models perform better when the source text is original and the target text is translationese. This makes some intuitive sense: all student training data is forward translated from some source sentence, just as translationese is forward translations. To make this comparison more rigorous, we examined indicia of translationese from the literature.

Translationese differs from original text in type-token ratio (TTR), length, and part-of-speech tag rate (Lembersky et al., 2012; Daems et al., 2017). In Table 8, we show that indeed the student models are closer to translationese in type-token ratio than their teacher. However, we found no difference in text length and part-of-speech tag rate.

Based on the human reference from Table 8, we can see that human translationese shows lower TTR, compared to the natural text. Interestingly, our non-distilled Big and Base model show the same TTR regardless the original language. Performing knowledge distillation reduces TTR, confirming that the student models are more biased.
Table 8: Type-token ratio of English translation produced by our model and human reference, divided based on the input’s original language. For human reference, Translation originated from English is the natural text, whereas translation originated from Turkish is the translationese.

| Generated by             | origlang= | tr  | en  |
|--------------------------|-----------|-----|-----|
| Human reference          |           | 0.151 | 0.176 |
| Big model (teacher)      |           | 0.164 | 0.164 |
| Base model (non-distil)  |           | 0.164 | 0.165 |
| Base model (student)     |           | 0.158 | 0.163 |
| Tiny model (student)     |           | 0.158 | 0.160 |

This result is also consistent with (Vanmassenhove et al., 2019; Toral, 2019), where translation output is losing its linguistic richness. Deeper investigation towards model’s output would be interesting. For example, by using human evaluation to analyze model output directly.

6 Conclusion

We have conducted experiments on data augmentation in NMT with knowledge distillation through: (1) Forward translating source-originated text, and (2) Forward translating back-translated target-originated text. We found that both types of augmentation data had an impact on performance (in terms of BLEU score), depending on the test set’s original language. Forward translating source-originated text worked well if the test set was also originated from the source language. In contrast, forward translating back translation data worked well if the test set was originated from the target language. Combining both data achieved the best overall performance, even under the same total data size. For example, a student trained with 5M of data (1) + 5M of data (1) achieved overall better BLEU compared to a student trained with 10M of only with data (1) or (2) exclusively.

Prior work often used the same back translation data for the teacher and the student. However, we found that this is not required, provided that the domain is the same. Since our student is trained on forward-translated data, our student models are more robust on handling the test set originated from the source language. Such test set is essentially a forward translation as well. Our 8 MB student model degraded only -0.5 BLEU compared to its 781 MB teacher model.

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A Evaluation with CHRF and TER

To see whether our findings is consistent with other metrics, we re-evaluate our result in Table 2 with CHRF and TER, in which we find a consistent pattern, compared to the result with BLEU.
**CHRF by original language (higher is better)**

| Training Data | Test original language | WMT16 | WMT17 | WMT18 | WMT13 |
|---------------|------------------------|-------|-------|-------|-------|
|               | src tgt all            | src tgt all | src tgt all | src tgt all | src tgt all |
| Big Model     | Par + BT               | .478  | .559  | .521  | .550  | .644  | .600  |
| Tiny Model    | Par + BT               | .400  | .455  | .429  | .516  | .606  | .564  |
|               | FT (Par + BT)          | .452  | .526  | .491  | .531  | .609  | .572  |
|               | FT (Par + Mono)        | .469  | .517  | .495  | .551  | .604  | .579  |
|               | FT (Par + Mono + BT)   | .476  | .535  | .508  | .553  | .613  | .584  |
|               | FT (Par + Mono + BT)   | .479  | .536  | .509  | .545  | .610  | .579  |

**TER by original language (lower is better)**

| Training Data | Test original language | WMT16 | WMT17 | WMT18 | WMT13 |
|---------------|------------------------|-------|-------|-------|-------|
|               | src tgt all            | src tgt all | src tgt all | src tgt all | src tgt all |
| Big Model     | Par + BT               | .708  | .618  | .661  | .578  | .495  | .535  |
| Tiny Model    | Par + BT               | .800  | .765  | .781  | .615  | .548  | .581  |
|               | FT (Par + BT)          | .722  | .657  | .688  | .599  | .542  | .570  |
|               | FT (Par + Mono)        | .707  | .687  | .696  | .581  | .561  | .570  |
|               | FT (Par + Mono + BT)   | .698  | .648  | .672  | .576  | .536  | .555  |
|               | FT (Par + Mono + BT)   | .698  | .651  | .673  | .589  | .540  | .564  |

Table 9: Experiment results in terms of TER and CHRF, divided based on the test-set’s original language. This is the same experiment as Table 2. Generally, they follow the same pattern as BLEU whereas FT (Mono) improves source-originated test, and FT (BT) helps target-originated test.