Towards Character-Level Transformer NMT
by Finetuning Subword Systems

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Abstract
Applying the Transformer architecture on the character level usually requires very deep architectures that are difficult and slow to train. A few approaches have been proposed that partially overcome this problem by using explicit segmentation into tokens. We show that by initially training a subword model based on this segmentation and then finetuning it on characters, we can obtain a neural machine translation model that works at the character level without requiring segmentation. Without changing the vanilla 6-layer Transformer Base architecture, we train purely character-level models. Our character-level models better capture morphological phenomena and show much higher robustness towards source-side noise at the expense of somewhat worse overall translation quality. Our study is a significant step towards high-performance character-based models that are not extremely large.

1 Introduction
State-of-the-art neural machine translation (NMT) models operate almost end-to-end with the exception of input and output text segmentation. The segmentation is done by first employing rule-based tokenization and then splitting into subword units using statistical heuristics such as byte-pair encoding (BPE; Sennrich et al., 2016) or SentencePiece (Kudo and Richardson, 2018).

Recurrent sequence-to-sequence (S2S) models can learn translation end-to-end (at the character level) without changes in the architecture (Cherry et al., 2018), given sufficient model depth. Training character-level Transformer S2S models (Vaswani et al., 2017) is more complicated because the self-attention size is quadratic in the sequence length.

In this paper, we empirically evaluate the Transformer S2S models. We observe that training a character-level model directly from random initialization suffers from instabilities often preventing the model from converging. Instead, we propose finetuning subword-based models to get a model without explicit segmentation. Our character-level models show slightly worse translation quality, but have better robustness towards input noise and better capture morphological phenomena. Our approach is important to many research groups because previous approaches have relied on very large transformers, which are out of reach for much of the research community.

2 Related Work
Character-level decoding seemed to be relatively easy with recurrent S2S models (Chung et al., 2016). Early attempts at achieving segmentation-free NMT with recurrent networks required a deep network processing the input hidden states covering a constant character span (Lee et al., 2017). Cherry et al. (2018) showed that with a sufficiently deep recurrent model, no changes in the model are necessary, and they can still reach translation quality that is on par with sub-word models. Other methods (Luong and Manning, 2016; Ataman et al., 2019) can leverage character-level information, however they require tokenized text as an input and only have access to the character-level embeddings of predefined tokens.

Training character-level transformers appears to be more challenging. Choe et al. (2019) succeeded in training a character-level left-to-right Transformer language model that performs on par with a subword-level model. However, to reach this performance they needed a large model with 40 layers and trained on a billion-word corpus, with prohibitive computational cost.

In the most related work to ours, Gupta et al. (2019) managed to train a character-level NMT with Transformer model by using Transparent Attention (Bapna et al., 2018). Transparent attention
The cat sleeps on a mat.

Table 1: Examples of text tokenization and subword segmentation with different numbers of BPE merges.

| # merges | segm. / sent. | segm. / token | avg. unit size |
|----------|--------------|---------------|---------------|
| 126.1    | 5.6          | 1.00          | 1.00          |
| 61.4     | 2.7          | 2.03          | 2.08          |
| 54.0     | 2.4          | 2.32          | 2.36          |
| 47.4     | 2.1          | 2.66          | 2.67          |
| 41.5     | 1.9          | 3.03          | 3.04          |
| 36.2     | 1.6          | 3.46          | 3.50          |
| 31.8     | 1.4          | 3.95          | 3.98          |
| 28.4     | 1.3          | 4.37          | 4.51          |

Table 2: Statistics of English-German parallel data under different segmentations.

Table 2 showing that character sequences are on average more than 4 times longer subword sequences with 32k vocabulary.

We test two methods for finetuning subword models to reach character-level models: first, direct finetuning of sub-word models, and second, iteratively removing BPE merges in several steps in a curriculum learning setup (Bengio et al., 2009). In both cases we always finetune models until they are fully converged, using early stopping.

4 Experiments

To cover target languages of various morphological complexity, we conduct our main experiments on two resource-rich language pairs: translation between English-German and English-Czech. Both Czech and German contain phenomena that might be better modeled with character-level models: rich inflection in Czech and compounding in German.

We train and evaluate the English-German translation using the 4.5M parallel sentences of the WMT14 data (Bojar et al., 2014). Czech-English is trained on 15.8M sentence pairs of the CzEng 1.7 corpus (Bojar et al., 2016) and tested on WMT18 data (Bojar et al., 2018).

Additionally, we test our method in low-resource English-to-Turkish trained on 207k sentences of the SETIMES2 corpus (Tiedemann, 2012) and evaluated on the WMT18 test set.

To assess the effect of the number of parameters, we also present results of character-level English-German having approximately the same number of parameters as the best-performing subword models.

We follow the original hyperparameters for the Transformer Base model (Vaswani et al., 2017) in-
including the learning rate schedule. For fine-tuning, we use Adam (Kingma and Ba, 2015) with constant learning rate $10^{-5}$. All models are trained using Marian (Junczys-Dowmunt et al., 2018).

We evaluate the translation quality using BLEU (Papineni et al., 2002), chrF (Popović, 2015) and METEOR 1.5 (Denkowski and Lavie, 2014).

Following Gupta et al. (2019), we also conduct a noise-sensitivity evaluation to natural noise as introduced by Belinkov and Bisk (2018). With a probability $p \in \{0, 0.1, \ldots, 1.0\}$ words are replaced with their variants from a misspelling corpus. Like Gupta et al. (2019), we assume the BLEU scored measured with noisy data input can be explained by a linear approximation using the noise probability: $\text{BLEU} \approx \beta p + \alpha$. However unlike them, we report the relative translation quality degradation $\beta/\alpha$ instead of only $\beta$. Parameter $\beta$ corresponds to absolute BLEU score degradation and is thus higher given lower-quality systems, making them seemingly more robust.

To look at morphological generalization, we evaluate translation into Czech and German using MorphEval (Burlot and Yvon, 2017). MorphEval consists of 13k sentence pairs that differ in exactly one morphological category. The evaluation metric is a proportion of sentence pairs where morphological contrast was correctly captured in the preferred translation.

## 5 Results

The results of the experiments are presented in Table 3. The translation quality only slightly decreases when drastically decreasing the vocabulary. However there is a gap between the character-level and subword-level model of 1–2 BLEU points. With the exception of Turkish, models trained by finetuning reach a large margin better translation quality than character-level models trained from scratch.

For English-to-Czech translation, we observe a large drop in BLEU score with the decreasing vocabulary size, but almost no drop in terms of METEOR score, whereas for other language pairs all metrics are in agreement. The differences between the subword and character-level models are less pronounced in the low-resourced English-to-Turkish translation.

Whereas the number of parameters in transformer layers in all models is constant at 35 million, the number of parameters in the embeddings decreases $30 \times$ from over 15M to only slightly over 0.5M, with overall a $30\%$ parameter count reduction. However, increasing matching the number of

| From random initialization | Direct finetuning from | In steps |
|---------------------------|----------------------|---------|
| **BLEU**                  | **EN-DE**            | **fr**  |
| 26.86                     | 26.66                | 26.39   |
| 26.58                     | 26.36                | 26.08   |
| 25.79                     | 25.00                | 24.63   |
| **chrF**                  |                      |         |
| -0.10                     | +                    | +       |
| **METEOR**                |                      |         |
| 47.68                     | 47.95                | 47.75   |
| 47.91                     | 47.71                | 45.00   |
| Noise sens.               | -1.074               | -1.051  |
| MorphEval                 | 89.97                | 89.52   |
| **BEU**                  | **en-tr**            | **es**  |
| 29.79                     | 30.13                | 29.26   |
| 28.61                     | 28.46                | 28.14   |
| 26.62                     | 26.36                | 26.08   |
| ** chrF**                |                      |         |
| -0.34                     | +                    | +       |
| **METEOR**                |                      |         |
| 37.07                     | 37.41                | 37.22   |
| 36.92                     | 36.71                | 36.60   |
| Noise sens.               | +0.450               | +0.435  |
| MorphEval                 | 83.86                | 84.55   |
| **BEU**                  | **en-cs**            | **es**  |
| 21.06                     | 20.81                | 20.93   |
| 20.60                     | 20.01                | 19.52   |
| 18.24                     | 19.25                | 19.25   |
| ** chrF**                |                      |         |
| +0.25                     | +                    | +       |
| **METEOR**                |                      |         |
| 25.98                     | 25.79                | 25.58   |
| 25.36                     | 25.18                | 25.08   |
| Noise sens.               | -1.031               | -1.009  |
| MorphEval                 | 83.26                | 84.55   |
| **BEU**                  | **en-fr**            | **es**  |
| 12.62                     | 13.29                | 12.68   |
| 12.24                     | 12.02                | 11.56   |
| ** chrF**                |                      |         |
| +0.48                     | +                    | +       |
| **Noise sens.**           | -0.216               | -0.194  |

Table 3: Quantitative results of the experiments. Small numbers denote the difference from the best model. For finetuning experiments we report difference from the best model and from the parent model.
paramters by increasing the model capacity does close the performance gap.

In our first set experiments, we finetuned the model using directly the character-level input. Experiments with parent models of various vocabulary sizes (column “Direct finetuning” in Table 3) suggest the larger the parent vocabulary, the worse the character-level translation quality. This led us to the hypothesis that gradually decreasing the vocabulary size in several steps might lead to better translation quality. This hypothesis, however, did not prove true as we observed a small drop in translation quality. The character-level approach does not require computationally expensive finetuning already trained sub-word models. Our approach does not require dramatically increased model depth. Our experiments show that subword-based models can be fine-tuned to work on the character level without explicit segmentation with somewhat of a drop in translation quality. The character-level models, on the other hand, are more robust to input noise and better capture some morphological phenomena. Our approach is important to research groups which wish to train character Transformer models but do not have access to very large computational resources.

### Table 4: Effect of model size on translation quality for English-to-German translation.

| vocab. | architecture | # param. | BLEU |
|--------|--------------|----------|------|
| BPE 16 | Base         | 42.6M    | 26.86|
| char.  | Base         | 35.2M    | 25.21|
| char.  | Base + FF dim. 2650 | 42.6M    | 25.37|

Figure 1: Degradation of the translation quality of the subword (gray) and character-based systems (red) for English-German translation with increasing noise.

### Table 5: Quantitative results of MorphEval on English to German.

|          | 32k | 16k | 8k  | 4k  | 2k  | 1k  | 500 | 0   |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|
| T        | 1297| 1378| 1331| 1151| 1048| 903 | 776 | 242 |
| I        | 21.79| 18.34| 17.17| 12.33| 12.25| 8.75| 7.28| 3.87|

|          | BPE 16k | char  |
|----------|---------|-------|
| Adj. strong | 95.5    | 97.2  |
| Comparative | 93.4    | 91.5  |
| Compounds   | 63.6    | 60.4  |
| Conditional | 92.7    | 92.3  |
| Coordverb-number | 96.2    | 98.1  |
| Coordverb-person | 96.4    | 98.1  |
| Coordverb-tense | 96.6    | 97.8  |
| Coreference gender | 94.8    | 92.8  |
| Future      | 82.1    | 89.0  |
| Negation    | 98.8    | 98.4  |
| Noun number | 65.5    | 66.6  |
| Past        | 89.9    | 90.1  |
| Pron. plur. | 98.4    | 98.8  |
| Superlative | 98.9    | 99.8  |
| Verb position | 95.4    | 94.2  |

Table 6: Training (T) and inference (I) speed in sentences processed per second on a single GPU.

6 Conclusions

We presented a simple approach for training character-level Transformer NMT models by finetuning already trained sub-word models. Our approach does not require computationally expensive changes in the Transformer architecture and does not require dramatically increased model depth. Our experiments show that subword-based models can be fine-tuned to work on the character level without explicit segmentation with somewhat of a drop in translation quality. The character-level models, on the other hand, are more robust to input noise and better capture some morphological phenomena. Our approach is important to research groups which wish to train character Transformer models but do not have access to very large computational resources.
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