Why don’t people use character-level machine translation?

Jindřich Libovický and Helmut Schmid and Alexander Fraser
Center for Information and Speech Processing, LMU Munich
Munich, Germany
{libovicky, schmid, fraser}@cis.lmu.de

Abstract

We present a literature and empirical survey that critically assesses the state of the art in character-level modeling for machine translation (MT). Despite evidence in the literature that character-level systems are comparable with subword systems, they are virtually never used in competitive setups in WMT competitions. We empirically show that even with recent modeling innovations in character-level natural language processing, character-level MT systems still struggle to match their subword-based counterparts both in terms of translation quality and training and inference speed. Character-level MT systems show neither better domain robustness, nor better morphological generalization, despite being often so motivated. On the other hand, they tend to be more robust towards source side noise and the translation quality does not degrade with increasing beam size at decoding time.

1 Introduction

The progress in natural language processing brought by deep learning methods is often narrated as removing assumptions about the input data and letting the models learn everything end-to-end. One of the assumptions about input data that seems to resist this trend is (at least partially) linguistically motivated segmentation of input data in machine translation (MT) and natural language processing (NLP) in general.

Several papers in the past claimed parity of character-based methods with subword models, highlighting advantageous features of such systems. Very recent examples include Gao et al. (2020); Banar et al. (2020); Li et al. (2021). Despite this, character-level methods are rarely used as strong baselines in research papers and shared task submissions, suggesting that character-level models might have drawbacks that are not sufficiently addressed in the literature.

In this paper, we examine what the state of the art in character-level machine translation really is. We survey existing methods and conduct a meta-analysis of the input segmentation methods used in WMT shared task submissions. We systematically compare the most recent character-processing architectures, some of them for the first time in MT. Further, we propose a two-step decoder architecture that unlike standard decoders does not suffer from a slow-down due to the length of character sequences. Following the recent literature on MT decoding, we explore how their findings generalize to character-level methods.

Many previous studies on character-level MT drew their conclusions from experiments on rather small datasets and focused mostly on translation quality. To compensate for this, we revisit and systematically evaluate the state-of-the-art approaches to character-level neural machine translation (NMT) and identify their major strengths and weaknesses on competitively large datasets.

2 Character-Level NMT

Character-level processing was hardly possible within the statistical MT paradigm that assumed the existence of phrases consisting of semantically rich tokens that roughly correspond to words. Neural sequence-to-sequence models (Sutskever et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017) do not explicitly work with this assumption. In theory, they can learn to transform any sequence into any sequence.

The original sequence-to-sequence models used word-based vocabularies of a limited size, which necessarily lead to the relatively frequent occurrence of out-of-vocabulary tokens. A typical solution to that problem is subword segmentation (Sennrich et al., 2016; Kudo and Richardson, 2018), which keeps frequent tokens intact and splits less frequent ones into smaller units, even down to the character level.
Modeling language on the character level is attractive because it can help overcome several problems of subword models. One-hot representation of words or subwords do not reflect systematic character-level similarities between words, potentially harming morphologically rich languages. With subwords, minor typos on the source side lead to radically different input representations resulting in low robustness towards source-side noise (Provilkov et al., 2020; Libovický and Fraser, 2020).

Models using recurrent neural networks (RNN) showed early success with character-level segmentation on the decoder side (Chung et al., 2016). Using character-level processing on the encoder side proved harder which was attributed to the features of the attention mechanism which can presumably benefit from semantically rich units (such as subwords) in the encoder. Following this line of thinking, Lee et al. (2017) introduced 1D convolutions with max-pooling that pre-process the character sequence into a sequence of latent word-like states that was used as an input to the standard encoder. Coupled with a character-level decoder, they claimed to match the state-of-the-art subword-based models. Even though this architecture works well on the character level for European languages, it does not generalize further to the byte level (Costa-jussà et al., 2017). Hybrid approaches combining tokenization into words followed by the computation of character-based word representations were successfully used with RNNs (Luong and Manning, 2016; Grónroos et al., 2017; Ataman et al., 2019). Later, Cherry et al. (2018) showed that with RNNs, sufficiently large models do not need architecture modification and perform on par with subword models.

Character-level modeling with Transformers appears to be more difficult. Gupta et al. (2019) used Transparent Attention (Bapna et al., 2018) to train deep character-level models and needed up to 32 layers to close the gap between the BPE and character models. Libovický and Fraser (2020) narrowed the gap between subword and character modeling using curriculum learning by finetuning the subword models to character-level.

Gao et al. (2020) proposed adding a convolutional sub-layer in the Transformer layers. At the cost of a 30% increase of model parameter count, they managed to narrow the gap between subword- and character-based models by half. Banar et al. (2020) reused the convolutional preprocessing layer with constant step segments of Lee et al. (2017) in a Transformer model for translation into English. They made no changes to the decoder and reached comparable, usually slightly worse, translation quality as the BPE-based models.

Shaham and Levy (2021a) revisited character- and byte-level MT on rather small WSLT datasets. Their results show that although character-level and byte-level models are usually worse than BPE models, byte-based models without embedding layers often outperform BPE-based models in the out-of-English direction. Using similarly small datasets, Li et al. (2021) claim that character-level modeling outperforms BPE when translating into fusional, agglutinative, and introflexive languages.

Nikolov et al. (2018) experimented with character-level models for romanized Chinese. However, their results were comparable to using logographic signs and significantly worse than using subwords. Zhang and Komachi (2018) argued that signs in logographic languages carry too much information and were able to improve the translation quality by segmenting Chinese and Japanese into sub-character units while keeping subword segmentation on the English side.

Little is known about other properties of character-level MT beyond the overall translation quality. Sennrich (2017) prepared a set of contrastive English-German sentence pairs and tested them using shallow RNN-based models. They observed that character-based models transliterated better, but captured morphosyntactic agreement worse. Libovický and Fraser (2020) evaluated Transformer-based character-level models using MorphEval and came to mixed conclusions.

Gupta et al. (2019) and Libovický and Fraser (2020) make claims about the noise robustness of the character-level models using synthetic noise.
Li et al. (2021) evaluated domain robustness by training models on small domain-specific datasets and evaluating them on unrelated domains, claiming the superiority of character-level models in this setup. We argue that this is a very unnatural setup and rather evaluate the domain robustness by evaluating general models on domain-specific test sets. In such a setup, the results of Gupta et al. (2019) do not show a clear advantage of character modeling over BPE in English-to-German translation.

Due to the increased sequence length, character-level systems are significantly slower. Libovický and Fraser (2020) reported a $5.6 \times$ slowdown at training time and a $4.7 \times$ slowdown at inference time compared to subword models.

Recent research on character-level modeling goes beyond MT. Pre-trained multilingual representations are a particularly active area. Clark et al. (2021) proposes CANINE, an architecture for shrinking character sequences into less hidden states (similar to Lee et al., 2017). They use local self-attention and strided convolutions instead of highway layers and max-pooling (as in Lee’s work). Their model is trained using the masked-language-modeling objective (Devlin et al., 2019) with subword supervision or in an encoder-decoder setup similar to T5 (Raffel et al., 2020), with both reaching a similar representation quality to similar models built on subwords.

ByT5 (Xue et al., 2021a) and Charformer (Tay et al., 2021) are based on the mT5 model (Xue et al., 2021b) which uses sequence-to-sequence denoising pre-training. Whereas byT5 only uses byte sequences instead of subwords and differs in hyperparameters, Charformer uses convolution and combines character blocks to obtain latent subword representations. These models mostly reach similar results to sub-word models, occasionally outperforming some of them, in the case of Charformer without a significant slowdown.

3 WMT submissions

The Conference on Machine Translation (WMT) organizes annual shared tasks in various use cases of MT. The shared task submissions focus entirely on translation quality rather than the novelty of the presented ideas, as most other research papers do. Therefore, we assume that, if character-level models were a fully-fledged alternative to subword models, at least some systems submitted to the shared tasks would use character-level models.

![Figure 2: A boxplot of vocabulary sizes of WMT systems from 2018–2020, the median is denoted with the orange line.](image)

We annotated all recent system description papers with what input and output segmentation they used. We focused on information about experiments with character-level models. Since we are primarily interested in the Transformer architecture that became the standard after 2017, we only included system description papers from 2018–2020 (Bojar et al., 2018; Barrault et al., 2019, 2020). Transformers were used in 81%, 87%, and 97% of the systems in the respective years. We included the main task on WMT, news translation, and two minor tasks where character-level modeling might be useful: translation robustness (Li et al., 2019; Specia et al., 2020) and translation between similar languages.

Almost all systems use subword-based vocabulary (BPE: 81%, 71%, 66% in the respective years; SentencePiece: None in 2018, 9% and 25% in the following ones). Purely word-based (none in 2018, 2% and 3% in the later years) or morphological segmentation (4%, 2%, 3% in the respective years) are rarely used. The average vocabulary size decreases over time (see Figure 2) with a median size remaining at 32k in the last two years. The reason behind decreasing average is probably a higher proportion of systems for low-resource languages where smaller vocabulary leads to better translation quality (Sennrich and Zhang, 2019).

Among the 145 annotated system description papers, there were only two that used a character-level segmentation. Mahata et al. (2018) used a character-level model for Finnish-to-English translation. This system however makes many unusual and suboptimal design choices and ended up as the last one in the manual evaluation. Scherrer et al. (2019) experimented with character-level systems for similar language translation and observed that characters outperform other segmentations for Spanish-Portuguese translation, but not Czech-Polish.

Knowles et al. (2020) experimented with differ-
ent subword vocabulary sizes for English-Inuktikut translation and reached the best results used a subword vocabulary of size 1k, which makes it close to the character level. Most of the papers do not even mention character-level segmentation as a viable alternative they would like to pursue in future work (7% in 2018, 2% in 2019, none in 2020).

Character-level methods were more frequently used in WMT17 with RNN-based systems, especially for translation of Finnish (Escolano et al., 2017; Östling et al., 2017) and less successfully for Chinese (Holtz et al., 2017) and the automatic post-editing task (Variš and Bojar, 2017).

On the other hand, Figure 1 shows that the research interest in character-level methods remains approximately the same, or might be slightly increasing. For practical solutions in WMT systems, we clearly show that system designers in the WMT community have avoided character-level models.

We speculate that the main reason for not considering character-level modeling is the lower efficiency in combination with none of the literature showing clearly superior translation quality. Most of the WMT submissions use back-translation (85%, 82%, and 94% in the respective years) often iterated several times (11%, 20%, and 16%), with requires both training and inference on large datasets. With the approximately $5 \times$ slowdown, WMT-scale experiments on character models are not easily tractable.

4 Evaluated Models

We evaluate several Transformer-based architectures for character-level MT. A major issue with character-level sequence processing is the sequence length and low information density compared to subword sequences. Architectures for character-level sequence processing typically address this issue by locally processing and shrinking the sequences into latent word-like units. In our experiments, we explore several ways to do this.

First, we directly use character embeddings as input to the Transformer layers. Second, following Banar et al. (2020), we use the convolutional character processing layers proposed by Lee et al. (2017). Third, we replace the convolutions with local self-attention as proposed in the CANINE model (Clark et al., 2021). Finally, we use the recently proposed Charformer architecture (Tay et al., 2021).

Lee-style encoding. Lee et al. (2017) process the sequence of character embeddings with convolutions of different kernel sizes and output channels. The original paper used kernel sizes from 1 to 8. For simpler implementation, we only use even-sized kernels up to size 9. In the original paper, this was followed by 4 highway layers (Srivastava et al., 2015). In our preliminary experiments, we observed that a too deep stack of highway layers leads to diminishing gradients and we replaced the two Highway layers with feedforward sublayers as used in the Transformer architecture (Vaswani et al., 2017).

CANINE. Clark et al. (2021) experiment with character-level pre-trained sentence representations. The character-processing architecture is in principle similar to Lee et al. (2017) but uses more modern building blocks. Character embeddings are processed by a Transformer layer with local self-attention which only allows the states to attend to states in their neighborhood. This is followed by downsampling using strided convolution.

Charformer. Unlike the previous two approaches, Charformer (Tay et al., 2021), does not apply a nonlinear function on the embeddings and gets latent subword representations by repeated averaging of character embeddings. First, it processes the sequence using a 1D convolution, so the states are aware of their mutual local positions. Second, non-overlapping character $n$-grams of length up to $N$ are represented by averages of the respective embeddings. I.e., for each character, there is a vector that represents the character as a member of $n$-grams of length 1 to $N$. In the third step, the character blocks are scored with a scoring function (a linear transformation), which can be interpreted as attention over $N$ $n$-gram lengths. The attention scores are used to compute a weighted average over the $n$-gram representations. Finally, the sequence is downsampled using mean-pooling with window size $N$.

Whereas Lee-style encoding allows using low-dimensional character embeddings and keeps most parameters in the convolutional layers, CANINE and Charformer need to have the same dimension as the following Transformer layer stack.

Two-step decoding. The architectures mentioned above allow the Transformer layers to operate more efficiently with a shorter and more information-dense sequence of states. However, while decoding, we need to generate the target char-
character sequence in the original length, by outputting a block of characters in each decoding step. Our preliminary experiments showed that generating blocks of characters non-autoregressively leads to incoherent output. Therefore, we propose a two-step decoding architecture where the stack of Transformer layers operating over the downsampled sequence is followed by a lightweight LSTM autoregressive decoder (see Figure 3).

The input to the lightweight decoder is a concatenation of the embedding of the previously generated character and a projection of the Transformer decoder output state. At inference time, the lightweight decoder generates a block of characters, which are then provided as an input to the character-level processing layer, and the Transformer decoder which computes an output state that the lightweight LSTM decoder uses to generate another block of characters. More details are in Appendix A.

First, we conduct all our experiments on the small IWSLT datasets. Second, we evaluate the most promising architecture combinations on larger datasets.

5 Experiments on Small Data

We implement the models using Huggingface Transformers (Wolf et al., 2020). We take the CANINE layer from Huggingface Transformers and use an independent implementation of Charformer\(^1\). Hyperparameters and other experimental details are in the Appendix B.

5.1 Experimental Setup

We evaluate the models on translation between English on one side and German, French, and Arabic on the other side using the IWSLT 2017 datasets (Cettolo et al., 2017) with a training data size of around 200k sentences for each language pair (see Appendix B for details).

For the subword models, we tokenize the input using the Moses tokenizer (Koehn et al., 2007) and then further split the words into subword units using BPE (Sennrich et al., 2016) with 16k merge operations. For the character models, we limit the vocabulary to 300 UTF-8 characters.

We use the Transformer Base architecture (Vaswani et al., 2017) in all experiments. We do not make any changes in the subword and baseline character experiments. We replace the embedding lookup with the character processing architectures in the later experiments. For the Lee-style encoder, we chose similar hyperparameters as related work (Banar et al., 2020).

For experiments with Charformer and CANINE models, we set the hyperparameters such that they cover the same character span before downsampling as the Lee-style encoder, which causes the models to have fewer parameters than a Lee-style encoder. Note however that for both the Charformer and the CANINE models, the number of parameters is almost independent of the character window width. For all three character processing architectures, we experiment with downsampling factors of 3 and 5 (a 16k BPE vocabulary corresponds to a downsampling factor of about 4 in English).

5.2 Translation Quality

We evaluate the translation quality using the BLEU score (Papineni et al., 2002), the chrF score (Popović, 2015) (as implemented in SacreBLEU; Post, 2018), and the COMET score (Rei et al., 2020). We run each experiment 4 times and report the mean value and standard deviation.

The results are presented in Table 1. Except for translation into Arabic (which is consistent with the findings of Shaham and Levy, 2021a and Li et al., 2021), where character methods outperform BPEs, subword methods are always better than characters.

The comparison of the character processing architectures shows that the Lee-style encoder outperforms the two more recent methods and the method of using the character embeddings directly. Charformer performs similarly to using character embeddings directly, CANINE is significantly worse. The results are mostly consistent across the language pairs.

Increasing the downsampling from 3 to 5 de-
grades the translation quality for all architectures. Employing the two-step decoder matches the decoding speed of subword models, however, the overall translation quality is much worse.

The three metrics that we use give consistent results in most cases. Often, relatively small differences in BLEU and chrF scores correspond to much bigger differences in the COMET score.

### 5.3 Inference

After Stahlberg and Byrne (2019) showed that the MAP estimate in sequence-to-sequence processing often leads to an empty sequence and that search errors during beam search are crucial in reaching high translation quality, inference heuristics in sequence-to-sequence models have been recently intensively discussed (Meister et al., 2020; Massarelli et al., 2020; Shi et al., 2020; Shaham and Levy, 2021b).

It is clear that translation quality quickly degrades beyond a certain beam width unless heuristically defined length normalization is applied.

Eikema and Aziz (2020) conclude Minimum Bayes Risk (MBR; Goel and Byrne 2000) estimation is more appropriate and propose an approximation based on sampling from the model and show that their method performs comparably with standard beam search. This was later confirmed by Müller and Sennrich (2021) and they observed higher robustness to copy noise and domain shift, as well.

Intuitive arguments about the inference algorithms are often based on the properties of the subword output distribution. On average, character models will produce distributions with lower perplexity and thus likely suffer more from the exposure bias problem which might harm sampling from the model. Therefore, there is a risk that these empirical findings do not apply to character-level models.

For this reason, we explore what decoding strategies are best suited for the character-level models. We compare the translation quality of beam search decoding with different degrees of length normalization.² Further, we compare beam search decoding with MBR (with 100 samples), greedy decoding, and random sampling. We use the chrF as a comparison metric which allows pre-computing of the character n-grams and thus faster comparison of sentence pairs than the originally proposed.

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²As we increase beam size, the number of search errors is decreasing, but here we are evaluating modeling errors, not search errors.
METEOR metric (Denkowski and Lavie, 2011).

Figure 4 shows the translation quality of the selected models for different beam sizes. The dotted lines denoting the translation quality without length normalization show that whereas the quality of the subword models quickly deteriorates without length normalization, character-level models do not seem to suffer from this problem. We hypothesize this is because of the significantly different sizes of output distributions which in the case of subword models lead to smaller values on average.

Table 2 presents the translation quality for different decoding methods. In all cases, beam search is the best strategy. Sampling from character-level models leads to very poor translation quality that in turn also influences the MBR decoding that leads to much worse results than beam search. This suggests that character-level models learn correctly the mode of the distributions, but fail to learn good conditional distributions, so the initial assumption behind MBR decoding that Eikema and Aziz (2020) made for the subword models does not hold on the character level.

Moreover, we found that MBR decoding performs comparably with beam search in terms of chrF score for our best models, but gets much worse COMET scores. This raises concerns that the previous results of MBR decoding reaching parity with beam search might have been an artifact of n-gram based metrics.

6 Experiments on WMT Data

Based on the results of the experiments with the IWSLT data, we further experimented only with the Lee-style encoder using a downsampling factor of 3 on the source side. Additionally, we experiment with hybrid systems with a subword encoder and character decoder. We train translation systems of competitive quality on two high-resource language pairs: English-Czech and English-German and perform an extensive evaluation.

6.1 Experimental Setup

For English-to-Czech translation, we use the CzEng 2.0 corpus (Kocmi et al., 2020b) that aggregates and curates all available sources for this language pair. We use all 66M authentic parallel sentence pairs and 50M back-translated Czech sentences.

For the English-to-German translation, we use a subset of the training data used by Chen et al. (2021). The data consists of 66M authentic sentence pairs filtered from the available data for WMT
were unseen at training time. We tokenize and lemmatize all data with UDPipe (Straka and Straková, 2017). On the WMT20 test set, we compute the recall of test lemmas that were not in the training set and recall of word forms that were not in the training data, but forms of the same lemma were. Note that not generating a particular lemma or form is not necessarily an error. Therefore, we report the recall in contrast with the recall of lemmas and forms that were represented in the training data.

Character-level models are also supposed to be more robust towards source-side noise. We evaluate the noise robustness of the systems using synthetic noise. We use TextFlint (Wang et al., 2021) to generate synthetic noise in the source text with simulated typos and spelling errors. We generate 20 noisy versions of the WMT20 test set and report the average COMET score.

### 6.2 Results

The main results are presented in Table 3. The main trends in the translation quality are the same as in the case of IWSLT data: Subword models outperform character models. Using Lee-style encoding narrows the quality gap and performs similarly to models with subword tokens on the source side. Although domain robustness often motivates character-level experiments, our experiments show that the trends are domain-independent, except for English-German IT Domain translation.

The similar performance of the subword encoder and the Lee-style encoder suggests that the hidden states of the Lee-style encoder can efficiently emulate the subword segmentation. We speculate that the main weaknesses remain on the decoder side.

In the English-to-Czech direction, the character-level models perform worse in gender bias evaluation, although they better capture grammatical gender agreement according to the MorphEval benchmarks.
mark. On the other hand, character-level models make more frequent errors in the tense of coordinated verbs, so the average performance on the MorphEval benchmark remains the same. There are no major differences in recall of novel forms and lemmas.

For the English-to-German translation, character-level methods reach better results on the gender bias benchmark. We speculate that getting gender correct in German might be easier because unlike Czech it does not require subject-verb agreement. The average performance on the MorphEval benchmark is also slightly better for character models. Detailed results on the MorphEval set are in Tables 7 and 8 in the Appendix. Recall of novel forms suggest also slightly better morphological generalization.

The only clear advantage of the character-level models is the robustness towards the source side noise. This is the only setup where character-level models showed a clear advantage, outperforming both the fully subword model and the model with subword encoder.

7 Conclusions

In our extensive literature survey, we found evidence that character-level methods should reach comparative translation quality as subword methods, typically at the expense of much higher computation costs. We speculate that the computation cost is the reason why virtually none of the recent WMT systems used character-level methods nor mention them as a reasonable alternative.

Recently, most innovations in character-level modeling were introduced in the context of pretrained representations. In our comparison of character processing architectures (two of them used for the first time in the context of MT), we showed that 1D convolutions followed by highway layers still deliver the best results for MT.

Character-level systems are still mostly worse than subword systems. Moreover, the recent character-level architectures do not show advantages over vanilla character models, other than improved speed.

To overcome efficiency issues, we proposed a two-step decoding architecture that matches the speed of subword models, however at the expense of a further drop in translation quality.

Further, we found that conclusions of recent literature on decoding in MT do not generalize for character models. Character models do not suffer from the beam search curse and decoding methods based on sampling from the model perform poorly.

Evaluation on competitively large datasets showed that there is still a small quality gap between character and subword models. Character models do not show better domain robustness, and only slightly better morphological generalization in German, although this is often mentioned as important motivation for character-level modeling. The only clear advantage of character models is high robustness towards source-side noise.

Unlike the early attempts on character-level MT, which claimed that decoding is straightforward and focus on the encoder part of the model, our conclusions are that Lee-style encoding is comparable to subword encoders. Even now, most modeling innovations focuses on encoding. Both accurate and efficient character-level decoding remains an open research question.

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A Two-step decoder

Here, we describe details of the architecture of the two step decoder shown in Figure 3. The input of the decoder are hidden states of the character processing architecture, i.e., for a downsampling factor $s$, a sequence that is $s$ times shorter than the input sequence. The output of the Transformer stack is a sequence of the same length.

For each Transformer decoder state $h_i$, the decoder needs to produce $s$ characters. This is done by a light-weight autoregressive LSTM decoder. In each step, it has two inputs: the embedding of the previously decoded character and a projection of the decoder state $h_i$. There are $s$ different linear projections for each of the output character generated from a single Transformer state.

At inference time, the LSTM decoder gets one Transformer state and generates $s$ output characters. The characters are fed to the character processing architecture, which is in turn used to generate the next Transformer decoder state.

B IWSLT Experiments

B.1 Dataset details

We used the tst2010 part of the dataset for validation and tst2015 for testing and did not use any other test sets. The data sizes are presented in Table 4.

B.2 Model Hyperparameters

All models are trained with initial learning rate: $5 \cdot 10^{-4}$ with 4k warmup steps. The batch size is 20k tokens for both BPE and character experiments with update after 3 batches. Label smoothing is set to 0.1.

Lee-style. The character embedding dimension is 64. The encoder uses 1D convolutions of kernel size 1, 3, 5, 7, 9 with 128, 256, 512, 512, 256 filters. Their output is concatenated and projected to the model dimension, followed by 2 highway layers and 2 Transformer feed-forward layers.

CANINE. The local self-attention span in the encoder is $4 \times$ the downsampling factor, in the decoder, equal to the downsampling factor.

Two-step decoder. The decoder uses character embeddings with dimension of 64, which is also the size of the projection of the Transformer decoder state. The hidden state size of the LSTM is 128.

B.3 Validation Performance

The validation BLEU and chrF scores and training and inference times are in Table 5. The training times were measured on machines with GeForce GTX 1080 Ti GPUs and with Intel Xeon E5–2630v4 CPUs (2.20GHz), a single GPU was used.

Note that the experiments on IWSLT were not optimized for speed and are thus not comparable with the times reported with FairSeq.

C WMT Experiments

C.1 Training Details

We use the Transformer Big architecture as defined FairSeq’s standard transformer_wmt_en_de_big_t2t. The Lee-style encoder uses filters sizes 1, 3, 5, 7, 9 of dimensions 256, 512, 1024, 1024, 512. The other parameters remains the same as in the IWSLT experiments.

We set the beta parameters of Adam optimizer to 0.9 and 0.998 and gradient clipping to 5. The learning rate is $5 \cdot 10^{-4}$ with 16k warmup steps. Early stopping is with respect to negative log likelihood with patience 10. We save 5 best checkpoints and do checkpoint averaging before evaluation. The maximum batch size is 1800 tokens for the BPE experiments and 500 for character-level experiments. We train the models on 4 GPUs, so the effective batch size is 4 times bigger.

C.2 Validation Performance

During training, we evaluated the models by measuring the cross-entropy on the validation set. After model training, we use grid search to estimate the best value of length normalization on a validation set. The translation quality on the validation data is tabulated in Table 6.
Table 4: IWSLT data statistics in terms of number of parallel sentences and number of characters.

| Model          | From English | Into English |
|----------------|--------------|--------------|
|                | Train        | Validation   | Test         |
|                | Sent. Char.  | Sent. Char.  | Sent. Char.  |
|                | src          | tgt          | src          | tgt          |
| BPE 16k        | 9.9 ± 9.4    | 10.8 ± 12.4  | 11.5 ± 13.0  |
| Vanilla char.  | 14.5 ± 22.2  | 13.7 ± 20.3  | 14.9 ± 21.3  |
| Lee-style enc. | 5.9 ± 5.5    | 4.9 ± 4.9    | 5.3 ± 4.9    |
| Vanilla char.  | 14.5 ± 22.2  | 13.7 ± 20.3  | 14.9 ± 21.3  |
| Lee-style enc. | 5.9 ± 5.5    | 4.9 ± 4.9    | 5.3 ± 4.9    |

Table 5: Training time (hours), inference time on the validation set (seconds) and translation quality in terms of the noise evaluation are in Table 9.

| Model          | BPE 16k | BPE2char | char | lee |
|----------------|---------|----------|------|-----|
| BPE 16k        | 24.4 ± 22.9 | .524 ± .513 | .753 ± .687 | 0.8 ± 1.2 |
| BPE to char    | 24.4 ± 22.9 | .524 ± .513 | .753 ± .687 | 0.8 ± 1.2 |
| Lee-style enc. | 24.4 ± 22.9 | .524 ± .513 | .753 ± .687 | 0.8 ± 1.2 |

Table 6: Translation quality on the validation data and the value of length normalization that led to the best quality on the data.

Table 7: Detailed MorphEval results for English-Czech translation.

C.3 Detailed Results

The detailed results on the MorphEval benchmark are in Tables 7 (Czech) and 8 (German). The details of the noise evaluation are in Table 9.
| BPE | BPE2char | Char | Lee |
|-----|----------|------|-----|
| dj strong | 97.9% | 98.7% | 99.6% | 99.2% |
| comparative | 96.9% | 96.8% | 95.6% | 96.3% |
| compounds syns | 65.9% | 66.0% | 65.4% | 66.7% |
| conditional | 90.5% | 95.4% | 97.0% | 97.0% |
| coordverb-number | 98.0% | 98.7% | 99.1% | 99.3% |
| coordverb-person | 98.3% | 99.1% | 99.5% | 99.8% |
| coordverb-tense | 98.0% | 98.7% | 99.3% | 99.3% |
| coref-gender | 94.5% | 93.2% | 95.1% | 91.9% |
| future | 87.3% | 90.8% | 87.6% | 88.9% |
| negation | 98.8% | 98.8% | 99.4% | 99.4% |
| noun number | 67.0% | 69.3% | 71.5% | 68.4% |
| past | 94.7% | 97.1% | 96.0% | 96.5% |
| pron2nouns-gender | 100.0% | 100.0% | 100.0% | 100.0% |
| pronplus | 99.2% | 99.2% | 98.6% | 98.2% |
| pron relative-gender | 69.4% | 69.1% | 68.8% | 71.0% |
| pron relative-number | 69.4% | 69.1% | 68.8% | 71.0% |
| superlative | 99.8% | 99.8% | 99.8% | 99.6% |
| verb position | 96.0% | 95.2% | 95.2% | 95.8% |

| ADJ gender | .006 | .002 | .002 | .003 |
| ADJ number | .004 | .001 | .002 | .001 |
| NOUN case | .018 | .011 | .013 | .011 |
| VERB number | .022 | .017 | .015 | .020 |
| VERB person | .010 | .010 | .006 | .008 |
| VERB tense/mode | .046 | .041 | .049 | .050 |

Average | 90.6 | 91.3 | 91.4 | 91.5 |

Table 8: Detailed MorphEval results for English-German translation.

| BLEU | chrF | COMET |
|------|------|-------|
| BPE 16k | 15.1 ±0.2 | .436 ±.002 | -1.863 ±.010 |
| BPE to char | 14.4 ±0.2 | .436 ±.001 | -1.836 ±.009 |
| Vanilla char. | 19.5 ±0.2 | .493 ±.001 | -1.307 ±.009 |
| Lee-style enc. | 20.2 ±0.2 | .497 ±.001 | -1.308 ±.009 |
| BPE 16k | 16.0 ±0.2 | .464 ±.002 | -1.127 ±.012 |
| BPE to char | 15.5 ±0.2 | .465 ±.001 | -1.112 ±.008 |
| Vanilla char. | 18.5 ±0.1 | .504 ±.001 | -1.742 ±.013 |
| Lee-style enc. | 19.6 ±0.1 | .515 ±.001 | -1.743 ±.014 |

Table 9: Detailed results on the datasets with generated noise. Average and standard deviation for 20 evaluations.