Improving Fluency of Non-Autoregressive Machine Translation

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Abstract

Non-autoregressive (nAR) models for machine translation (MT) manifest superior decoding speed when compared to autoregressive (AR) models, at the expense of impaired fluency of their outputs. We improve the fluency of a nAR model with connectionist temporal classification (CTC) by employing additional features in the scoring model used during beam search decoding. Since the beam search decoding in our model only requires to run the network in a single forward pass, the decoding speed is still notably higher than in standard AR models. We train models for three language pairs: German, Czech, and Romanian from and into English. The results show that our proposed models can be more efficient in terms of decoding speed and still achieve a competitive BLEU score relative to AR models.

1 Introduction

One of the challenges that the research community faces today is improving the latency of neural machine translation (NMT) models. The decoders in modern NMT models operate autoregressively, which means that the target sentence is generated in steps from left to right (Bahdanau et al., 2015; Vaswani et al., 2017). In each step, a token is generated and it is supplied as the input for the next step.

Recently, nAR models for NMT tackled this issue by reformulating translation as sequence labeling. As long as the model and the data fit in a GPU memory, all computation steps can be done in parallel (Gu et al., 2018; Lee et al., 2018; Libovický and Helcl, 2018; Ghazvininejad et al., 2019). However, such models suffer from less fluent outputs.

In phrase-based statistical machine translation (SMT; Koehn, 2009), the translation fluency is handled by a language model component, which is responsible for arranging the phrases selected by the decoder into a coherent sentence. In AR NMT, there is no external language model. The decoder part of the neural model plays the role of a conditional language model, which estimates the probability of the translation given the source sentence signal as processed by the encoder part.

In automatic speech recognition (ASR), Graves and Jaitly (2014) proposed a beam search algorithm which combines an n-gram language model with scores from a model trained using CTC (Graves et al., 2006).

In this paper, we adopt and generalize this approach for nAR NMT by extending a CTC-based model by Libovický and Helcl (2018). We experiment with these models on six language pairs and we find that the generalized decoding algorithm helps narrowing the performance gap between the CTC-based and the standard AR models.

2 Non-autoregressive MT with CTC

Non-autoregressive models for MT formulate the translation problem as sequence labeling. The states of the final decoder layer are independently labeled with target sentence tokens. The models can parallelize all steps of the computation and thus reduce the decoding time substantially. The nAR models were enabled by the invention of the self-attentive Transformer model (Vaswani et al., 2017), which allows arbitrary reordering of the states in each layer. Most of the nAR models need a prior estimate of the sentence length, either explicitly (Lee et al., 2018) or via a specialized fertility model (Gu et al., 2018) and rely on the attention mechanism for re-ordering.

We base our work on an alternative approach that does not depend on the target length estimation. Instead, it constrains the upper bound of
We tackle the reduced fluency problem using beam search and employing additional features in its scoring model. Our approach is inspired by statistical MT and ASR.

3.1 Beam Search with CTC

Unlike greedy decoding, which can be performed in parallel by selecting tokens with the highest probability in each step independently, beam search operates sequentially. However, the speedup gained from the parallelization is preserved because the output probability distributions are still conditionally independent and thus can be computed in a single pass through the network—as opposed to the AR models, which need to re-run the entire stack of decoder layers every step.

The beam search algorithm for the CTC-based model (Graves and Jaitly, 2014) is shown in Algorithm 1. Unlike standard beam search in NMT, the algorithm needs to deal with the issue that a single hypothesis may have various derivations, depending on the positions of the blank symbols. The score of a single derivation is the product of the conditionally independent probabilities of the output tokens (line 7).

The beam search score of a hypothesis is then the sum of the scores of its derivations formed in the current beam search step (line 8).

3.2 Scoring Model

For selecting $n$ best hypotheses (line 9 in Algorithm 1), we employ a linear model to compute the score:

$$score = \log P(y|x) + w \cdot \Phi(y)$$  

(1)

where $P(y|x)$ is the CTC score of the generated sentence $y$ given a source sentence $x$, $\Phi$ is a feature function of $y$ and $w$ is a trainable feature weight vector.

We use structured perceptron for beam search to learn the feature weights (Huang et al., 2012). During training, we run the beam search algorithm and if the reference translation falls off the beam, we apply the perceptron update rule:

$$w \leftarrow w + \alpha (\Phi(y) - \Phi(\hat{y}))$$  

(2)

where $\alpha$ is the learning rate, $\Phi(y)$ are the feature values of the prefix of the reference translation in the given time step, and $\Phi(\hat{y})$ are the feature values of the highest-scoring hypothesis in the beam. Alternatively, we found that applying the perceptron update rule multiple times with all hypotheses that scored higher than the reference leads to faster convergence. In order to stabilize the training, we do not train the weight of the CTC score and set it to 1.
### Table 1: Quantitative results of the models in terms of BLEU score and average decoding times per sentence in milliseconds. Results on WMT14 English-German translation and results without back-translation are in the Appendix.

| Method                      | German WMT15 | Romanian WMT16 | Czech WMT18 | Decoding time [ms] |
|-----------------------------|--------------|----------------|-------------|-------------------|
|                             | en → de      | en → ro        | en → cs     |                   |
| Non-autoregressive          | 21.67        | 19.88          | 16.27       | 233               |
| Transformer, greedy         | 29.84        | 25.89          | 21.57       | 1664              |
| Transformer, beam 5         | 30.23        | 26.46          | 22.20       | 3848              |
| Ours, beam 1                | 22.68        | 19.74          | 16.98       | 337               |
| Ours, beam 5                | 25.50        | 22.46          | 19.31       | 408               |
| Ours, beam 10               | 25.93        | 23.33          | 19.47       | 526               |
| Ours, beam 20               | 26.03        | 24.11          | 19.58       | 1097              |

Language Model. The main component improving the fluency is a language model (LM). For efficiency, we use an \( n \)-gram LM. Since the hypotheses contain blank symbols, the beam may consist of hypotheses of different lengths. Because shorter sequences are favored by the LM, we divide the log-probability of each hypothesis by its length in order to normalize the scores.

Blank/non-blank symbols. To guide the decoding towards sentences of correct length, we compute the ratio of blank vs. non-blank symbols as follows:

\[
\max \left( 0, \frac{\# \text{blanks}}{\# \text{non-blanks}} - \delta \right)
\]

where \( \delta \) is a hyperparameter that thresholds the penalization for too high blank/non-blank symbol ratio. Based on the distribution properties of the ratio, we use \( \delta = 4 \).

Trailing blank symbols. We observed that the outputs produced by the CTC-based model tend to be too short. To prevent that, we count the trailing blank symbols:

\[
\max \left( 0, \# \text{trailing blanks} - \text{source length} \right).
\]

### 4 Experiments

We perform experiments on three language pairs in both directions: English-Romanian, English-German, and English-Czech.

For training the base NMT models, we use WMT parallel data,\(^1\) which consists of 0.6M sentences for English-Romanian, 4.5M sentences for English-German, and 57M sentences for English-Czech.

Further, we use the WMT monolingual data: 20M sentences for English, German and Czech and 2.2M sentences for Romanian for training the LM and for back-translation.

We preprocess all data using SentencePiece\(^2\) (Kudo and Richardson, 2018). We train the SentencePiece models with a vocabulary size of 50,000.

We implement the proposed architecture using Neural Monkey\(^3\) (Helcl and Libovický, 2017). The parameters we used for the training are listed in Appendix A. We will release the code upon publication.

We used the AR baselines trained on the parallel data for generating back-translated synthetic training data (Sennrich et al., 2016). When training on back-translated data, authentic parallel data are upsampled to match the size of the back-translated data. We thus train our final models using the mix of authentic and backtranslated data, so both AR baselines and the proposed models use the same amount of data for training. If we only used the parallel data for training the neural models and kept the monolingual data only for the language model, the proposed model would have benefited from having access to more data than the AR baselines.

We train a 5-gram KenLM model (Heafield, 2011) on the monolingual data tokenized using the same SentencePiece vocabulary as the parallel data.

For the perceptron training, we split the valida-

\(^1\)http://statmt.org/wmt19/translation-task.html

\(^2\)https://github.com/google/sentencepiece

\(^3\)https://github.com/ufal/neuralmonkey
tion data for each language pair in halves and use one half as the training set and the second half as a held-out set. We use the score on the held-out set during the perceptron training as an early-stopping criterion. The scoring model is initialized with zero weights for all features and a fixed weight of 1 for the CTC score.

5 Results

We evaluate our models on the standard WMT test sets that were previously used for evaluation of nAR NMT. We use newstest2015 for English-German, newstest2016 for English-Romanian, and newstest2018 for English-Czech (Bojar et al., 2015, 2016, 2018). We compute the BLEU scores (Papineni et al., 2002) as implemented in SacreBLEU⁴ (Post, 2018). We also measure the average decoding time for a single sentence.

Table 1 shows the measured quantitative results of the experiments. We observe that the beam search greatly improves the translation quality over the CTC-based nAR models (“Non-autoregressive” vs. “Ours”). Additionally, we have control over the speed/quality trade-off by either lowering or increasing the beam size.

Increasing the beam size from 1 to 5 systematically increases the translation quality by at least 3 BLEU points. Decoding with a beam size of 20 matches the quality of greedy autoregressive decoding while maintaining 1.5× speedup.

Figure 1 plots the time required to translate a sentence with respect to its length. As expected, beam search decoding is more time-consuming than the CTC-based labeling (greedy). However, our method is still substantially faster than the AR model, especially for longer sentences.

Table 2 shows how features used in the scoring model contribute to the BLEU score. We can see that combining the features is beneficial and that the improvement is substantial with larger beam sizes. The feature weights were trained separately for each beam size.

Our cursory manual evaluation indicates that additional features help to tackle the most significant problems of nAR NMT – repeated or malformed words and too short sentences (see Appendix C for examples).

6 Related Work

The earliest work on nAR translation includes work by Gu et al. (2018) and Lee et al. (2018) which are the closest to our model beside our baseline. Unlike our approach, they do not include state splitting. Gu et al. (2018) used a latent fertility model to copy a sequence of embeddings which is then used for the target sentence generation. Lee et al. (2018) use two decoders. The first decoder generates a candidate translation, which is then iteratively refined by the second decoder a denoising auto-encoder or a masked LM (Ghazvininejad et al., 2019).

Junczys-Dowmunt et al. (2018) exploit the autoregressive architectures (Bahdanau et al., 2015; Vaswani et al., 2017) and try to optimize the decoding speed. Using model quantization and state memoization they achieve a two-times speedup.

7 Conclusions

We introduced a MT model with beam search that combines nAR CTC-based NMT model with an

| Beam Size | 1   | 5   | 10  | 20  |
|-----------|-----|-----|-----|-----|
| c + l + r + t | 22.68 | 25.50 | 25.93 | 26.03 |
| c + l + r     | 22.21 | 24.92 | 25.12 | 25.35 |
| c + l         | 22.05 | 24.64 | 24.77 | 25.12 |
| c             | 21.67 | 22.06 | 22.13 | 22.17 |

Table 2: BLEU scores for English-to-German translation for different beam sizes and feature sets: CTC score (c), language model (l), ratio of the blank symbols (r), and the number of trailing blank symbols (t).

⁴https://github.com/mjpost/sacreBLEU
We performed experiments on six language pairs and evaluated the models on the standard WMT sets. Our approach narrows the quality gap between the nAR and AR models while still maintaining a substantial speedup.

The experiments show that the main benefit of the proposed approach is the opportunity to balance the trade-off between translation quality and translation speed. The autoregressive models are still superior in translation quality for most of the language pairs, even though by a narrow margin. In contrast, the non-autoregressive models are very fast, but often lack in translation quality. Our approach enhances constant-time neural network run with a fast beam search utilizing a scoring model to improve the translation quality. By altering the beam size, we can adjust the speed and the quality ratio to achieve acceptable results both in terms of speed and translation quality.

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A Appendix: Parameters

The autoregressive baseline models use roughly the same set of hyperparameters as the Transformer base model (Vaswani et al., 2017). Encoder and decoder have 6 layers each, model dimension is 512, and the dimension of the feed-forward layer is 2,048. We use 16 attention heads in both self-attention and encoder-decoder attention. During training, we use label smoothing of 0.1 and we use dropout rate of 0.1. We use Adam optimizer (Kingma and Ba, 2015) with parameters $\beta_1 = 0.9$, $\beta_2 = 0.997$, and $\epsilon = 10^{-9}$ with fixed learning rate of $10^{-4}$. Due to the GPU memory limitations, we use batches of 20 sentences each, but we accumulate the gradients and perform the only update the model parameters every 10 steps. (This makes our batch to have an effective size of 200 sentences.)

The hyperparameters of the CTC-based models were selected to be as comparative as possible to the autoregressive models, with the following exceptions. The splitting factor between the encoder and the decoder was selected to be $k = 3$, following the setup of Libovický and Helcl (2018). We lowered the number of attention heads between the encoder and the decoder to 8 instead of 16. We changed the hyperparameter because it lead to better results in preliminary experiments. For training, instead of batching by a fixed number of sentences, we use batches of maximum size of 400 tokens. We use the same delayed update interval of 10 steps per update.
B Appendix: Additional Results

Quantitative results without the use back-translation, i.e., when the monolingual data are used only for training the target-side language model are shown in in Table 4.

Quantitative results on WMT14 English-to-German Data for comparison with related work are presented in Table 3.

| Method              | German WMT14 en → de | German WMT14 de → en |
|---------------------|-----------------------|-----------------------|
| Non-autoregressive  | 19.55                 | 23.04                 |
| Transformer, greedy | 27.29                 | 31.06                 |
| Transformer, beam 5 | 27.71                 | 31.85                 |
| Ours, beam 1        | 20.59                 | 24.11                 |
| Ours, beam 5        | 23.61                 | 27.19                 |
| Ours, beam 10       | 24.27                 | 27.83                 |
| Ours, beam 20       | 24.41                 | 28.14                 |

Table 3: Quantitative results of the models in terms of BLEU on the WTM14 data.

C Appendix: Examples

We include a few selected examples from the English-to-German (Table 5), German-to-English (Table 6), and Czech-to-English (Table 7) system outputs.

| Method             | German WMT15 en → de | German WMT15 de → en | Romanian WMT16 en → ro | Romanian WMT16 ro → en | Czech WMT18 en → cs | Czech WMT18 cs → en | Decoding time [ms] |
|--------------------|-----------------------|-----------------------|-------------------------|------------------------|---------------------|---------------------|---------------------|
| Non-autoregressive | 19.71                 | 21.64                 | 18.45                   | 25.48                  | 13.92               | 14.87               | 314                 |
| Transformer, greedy| 26.39                 | 28.56                 | 19.91                   | 27.33                  | 16.00               | 22.72               | 1637                |
| Transformer, beam 5| 26.99                 | 29.39                 | 20.81                   | 27.99                  | 17.08               | 23.54               | 4093                |
| Ours, beam 1       | 20.81                 | 22.68                 | 18.45                   | 26.52                  | 14.86               | 16.11               | 326                 |
| Ours, beam 5       | 23.29                 | 25.96                 | 20.88                   | 29.67                  | 17.16               | 20.87               | 398                 |
| Ours, beam 10      | 23.99                 | 26.19                 | 21.52                   | 29.88                  | 17.20               | 21.52               | 518                 |
| Ours, beam 20      | 24.01                 | 26.59                 | 22.02                   | 29.94                  | 17.24               | 21.87               | 1162                |

Table 4: Quantitative results in terms of BLEU without the use of back-translation.
On account of their innate aggressiveness, songs of that sort were no longer played on the console.

Aufgrund ihrer Angriffslust wurden Lieder dieser Art nicht mehr auf der Konsole gespielt.

Further trails are signposted, which lead up towards Hochrhön and offer an extensive hike.

Weitere Wege sind ausgeschildert, die Richtung Hochrhön führen und eine gedehnte Wanderung bieten.

Aber diese Selbstzufriedenheit ist unangebracht.

But such complacency is misplaced.
| Source | Problémem mohou být také jednorázové pleny. |
|--------|---------------------------------------------|
| nAR    | Singleapersalso be problem. |
| nAR + LM | One can diapers be the problem. |
| AR     | Single diapers may also be the problem. |
| Reference | Disposable incontinence pants may also be a problem. |

| Source | Pere se ve mně adolescentní potřeba uchechtí se s obdivem nad tím, s jakým vážným tónem je mi výklad podáván. |
|--------|--------------------------------------------------------------------------------------------------|
| nAR    | I adolescent need to chuck with admiration the serious tone my interpret. |
| nAR + LM | I have a adolescent need to chuck with wonderation of the serious tone my interpret. |
| AR     | I’m asking for an adolescent need to laugh at the admiration of the serious tone of my interpretation. |
| Reference | I feel the adolescent need to chuckle with admiration for the serious tone with which my comment is handled. |

Table 7: Czech-to-English examples.