

Efficient Inference For Neural Machine Translation

Yi-Te Hsu^{1*} Sarthak Garg² Yi-Hsiu Liao² Ilya Chatsviorkin²

¹Johns Hopkins University

²Apple Inc.

yhsul6@jhu.edu, {sarthak_garg, yihsiu_liao, ilych}@apple.com

Abstract

Large Transformer models have achieved state-of-the-art results in neural machine translation and have become standard in the field. In this work, we look for the optimal combination of known techniques to optimize inference speed without sacrificing translation quality. We conduct an empirical study that stacks various approaches and demonstrates that combination of replacing decoder self-attention with simplified recurrent units, adopting a deep encoder and a shallow decoder architecture and multi-head attention pruning can achieve up to 109% and 84% speedup on CPU and GPU respectively and reduce the number of parameters by 25% while maintaining the same translation quality in terms of BLEU.

1 Introduction and Related Work

Transformer models (Vaswani et al., 2017) have outperformed previously used RNN models and traditional statistical MT techniques. This improvement, though, comes at the cost of higher computation complexity. The decoder computation often remains the bottleneck due to its autoregressive nature, large depth and self-attention structure.

There has been a recent trend towards making the models larger and ensembling multiple models to achieve the best possible translation quality (Lepikhin et al., 2020; Huang et al., 2019). Leading solutions on common benchmarks (Zhu et al., 2020; Brown et al., 2020) usually use an ensemble of Transformer big models, which combined can have more than 1 billion parameters.

Previous works suggest replacing the expensive self-attention layer in the decoder with simpler alternatives like the Average Attention Network (AAN) (Zhang et al., 2018), Simple Recurrent Unit (SRU) (Lei et al., 2018) and Simpler Simple Recurrent Unit (SSRU) (Kim et al., 2019). AAN is

a simpler version of the self-attention layer which places equal attention weights on all previously decoded words instead of dynamically computing them. SRU and SSRU are lightweight recurrent networks, with SSRU consisting of only 2 matrix multiplications per decoded token.

Because of the autoregressive property of the decoder in a standard Transformer model, reducing computation cost in the decoder is much more important than in the encoder. Recent publications (Miceli Barone et al., 2017; Wang et al., 2019a; Kasai et al., 2020) thus suggest that a deep encoder, shallow decoder architecture can speed up inference while maintaining a similar BLEU score.

Another line of research focuses on model pruning techniques to make NMT models smaller and more efficient. In this paper, we only explore structured pruning methods, in which smaller components of the network are pruned away. Applications of structured pruning to NMT include works by Voita et al. (2019) and Michel et al. (2019) which show that most of the attention heads in the network learn redundant information and can be pruned. Michel et al. (2019) proposed the idea of pruning heads by head importance scoring. Voita et al. (2019) uses a relaxation of L_0 regularization (Louizos et al., 2018) to prune the attention heads.

All of the above mentioned methods use the vanilla Transformer architecture as their baseline, so it is not clear if these approaches can give complimentary results when combined together. In this work, we explore and benchmark, combining all of the above techniques, with the goal of maximizing inference speed without hurting translation quality.

After carefully stacking the approaches, our proposed architecture is able to achieve a significant speed improvement of 84% on GPU and 109% on CPU architectures without any degradation of translation quality in terms of BLEU.

* Work done during internship at Apple Inc.

2 Efficient Inference for Neural Machine Translation

This section presents the proposed efficient inference architecture for neural machine translation. First, we outline the overall procedure of building an efficient inference architecture. Then, we detail each step in the process.

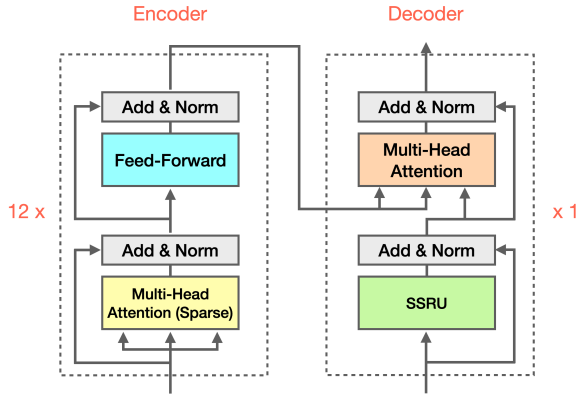


Figure 1: Efficient Transformer Architecture

First, we use sequence-level knowledge distillation (Kim and Rush, 2016) to transfer knowledge from a strong teacher model to a smaller student model. This approach allows the student model to learn from a simpler target distribution and therefore enables us to use a simpler architecture.

Then, to simplify the decoder of the student model, the self-attention mechanism is replaced by lightweight recurrent units (Kim et al., 2019), and the feed-forward network is removed. To further reduce the decoder computation, we adopt the deep encoder, shallow decoder architecture (Kasai et al., 2020). Lastly, we prune redundant attention heads through L_0 regularization (Voita et al., 2019). Each architecture modification is performed by retraining the student model. Figure 1 shows the proposed efficient Transformer architecture.

2.1 Teacher-student Training

We follow the procedure described in Kim et al. (2019), to train an ensemble of 8 Transformer-big models, 4 forward, 4 reverse direction, as the first round of teacher models (T). Without the help of extra monolingual corpora, we apply multi-agent dual learning (MADL) (Wang et al., 2019b) to train another 8 Transformer big teacher models (T-MADL) by re-decoded bitext with ensemble teacher models (T) in both directions. Then we use noisy backward-forward translation (Edunov et al., 2018) with the

T-MADL model to, again, re-decode the original bitext, but with more variance on the source side. Finally, we use the above generated synthetic data along with the original bitext to train our student model.

We use interpolated sequence-level knowledge distillation (Kim and Rush, 2016) in most of the described re-decoding runs except the noisy backward-forward translation where sampling is used in the reverse direction. More details about model training and architecture can be found in Kim et al. (2019).

2.2 Replacing Self-attention with Lightweight Recurrent Units

Inspired by Kim et al. (2019), we replace the decoder self-attention with an RNN, reducing its time complexity from $O(N^2)$ to $O(N)$, where N is the length of the output sentence. We compare replacing self-attention with two lightweight layers: SSRU and AAN, in Section 3.1. The SSRU layer is as follows:

$$\begin{aligned} f_t &= \sigma(W_t x_t + b_f) \\ c_t &= f_t \odot c_{t-1} + (1 - f_t) \odot W x_t \\ o_t &= \text{ReLU}(c_t) \end{aligned} \quad (1)$$

where the \odot is element-wise multiplication. x_t , o_t , f_t and c_t are the input, output, forget-gate and cell-state, respectively. We optimized the SSRU by combining the two matrix multiplications, $W_t x_t$ and $W x_t$, into one. We find this simple trick can improve speed by 6% on GPU.

For AAN, we found that removing the gating layer does not degrade the translation quality while reducing the computation. In our experiments, we use the following implementation of AAN (without a gating layer):

$$o_t = \text{FFN}\left(\frac{1}{t} \sum_{k=1}^t \mathbf{x}_k\right) \quad (2)$$

where $\text{FFN}(\cdot)$ is a position-wise two-layer feed-forward network. t , o_t and x_k denote the current position, output at position t and input at position k respectively.

2.3 Removing the Feed-forward Layer

Each decoder layer consists of a lightweight recurrent unit, followed by an encoder-decoder multi-head attention component and a pointwise feed-forward layer. The feed-forward sub-layer is responsible for 33% of parameters within the 6-layer

decoder; however, we found that it can be removed entirely from the decoder without hurting the translation quality with our implementation of SSRU (Section 3.1).

2.4 Deep Encoder, Shallow Decoder

In order to further reduce the decoder computation, we decrease the number of decoder layers. In line with the work done by Kasai et al. (2020), to maintain the same model capacity, we increase the number of encoder layers. We explore the speed-accuracy trade-off while varying the depth of both components in Section 3.2, and find that using 12 encoder layers and 1 decoder layer gives a significant speedup without losing translation quality.

2.5 Pruning Attention Heads

Adopting a deep encoder, shallow decoder architecture achieves a good speed-quality tradeoff; however, it increases the number of parameters in the encoder. To further improve efficiency and reduce parameters, we apply multi-head attention pruning proposed by Voita et al. (2019) to our architecture. The output of each head h_i across all attention layers is multiplied by a learnable gate g_i , before it is passed to subsequent layers of the network. To switch off less informative heads (i.e. $g_i = 0$), we applied L_0 regularization to the gates. L_0 norm is the number of non-zero gates across the model. However, because of the non-differentiable property of the L_0 norm, a differentiable approximation is used. Each gate g_i , is modeled as a random variable sampled from a Hard Concrete Distribution (Louizos et al., 2018) parameterized by ϕ_i , and takes values in the range $[0, 1]$. We then minimize the differentiable approximation of L_0 regularization loss, L_c :

$$L_c(\phi) = \sum_{i=1}^h (1 - P(g_i = 0 | \phi_i)), \quad (3)$$

where h denotes the total number of heads, ϕ is the set of gate parameters, and $P(g_i = 0 | \phi_i)$ is computed according to the Hard Concrete Distribution.

The model is initially trained with the standard cross entropy loss L_{xent} and then fine-tuned with the additional regularization loss as follows:

$$L(\theta, \phi) = L_{xent}(\theta, \phi) + \lambda L_c(\phi), \quad (4)$$

where θ denotes the set of original model parameters, and λ is a hyperparameter which controls

how aggressively the attention heads are pruned. During inference time, all heads h_j , where $P(g_j = 0 | \phi_j) = 1$ are completely removed from the network. Our experiments in Section 3.3 show that we can effectively prune out a large portion of redundant self-attention heads from the deep-encoder.

3 Experiments

We use the Transformer base model (Vaswani et al., 2017) trained on teacher decoded data as our baseline. All the described methods are stacked on top of this baseline model. Following Kim et al. (2019), we use 4 million bitext from the WMT’14 English-German news translation task. All sentences are encoded with 32K subword units using SentencePiece (Kudo and Richardson, 2018). We report BLEU on the newstest2014 in all the experiments and use newstest2015 for the final evaluation in Section 3.4

All experiments are implemented in fairseq (Ott et al., 2019). The configuration of teacher-student training follows the settings in Kim et al. (2019). We use an effective batch size of 458k words and 16 GPUs for training. Adam optimizer is applied with $\beta = (0.9, 0.98)$. We use label smoothing with $\varepsilon = 0.1$, inverse square root learning rate schedule with 2500 warmup steps and peak learning rate of 0.0007. The models are trained with 50k updates except for the models with pruning, where additional fine-tuning with 100-150k updates is applied. We use a beam size of 5 during inference. We evaluate the inference speed with batch size of 128 sentences on GPU, batch size 1 on CPU and report speed in words per second (wps), averaged over 10 decoding runs.

Hardware: We evaluate our performance on 1 GPU (NVIDIA Tesla V100-SXM2-32GB) and 1 core CPU (Intel Xeon E5-2640 v4 @ 2.40GHz)

3.1 Replacing Self-Attention with RNN

From Table 1, we can observe that replacing the self-attention with lightweight recurrent units gives significant speed improvements (18-25%) without any impact on BLEU score.

Removing the feed-forward network in the decoder leads to an additional 10-13% speedup for both AAN and SSRU, but results in 0.9 BLEU degradation for AAN. Therefore, we use SSRU as our main architecture in further experiments.

	BLEU	wps	speedup
Baseline	28.9	4510	-
AAN	28.9	5323	18%
SSRU	28.7	5629	25%
AAN w/o ffn	28.0	5915	31%
SSRU w/o ffn	28.5	6079	35%

Table 1: Results of replacing self-attention with lightweight recurrent units and removing the feed-forward network (ffn) in the decoder. Decoding on a GPU with batch-size 128.

3.2 Number of Layers

We evaluate different combinations of depths in the encoder and decoder. In the decoder, the self-attention mechanism is replaced by the SSRU, and the feed-forward network is removed.

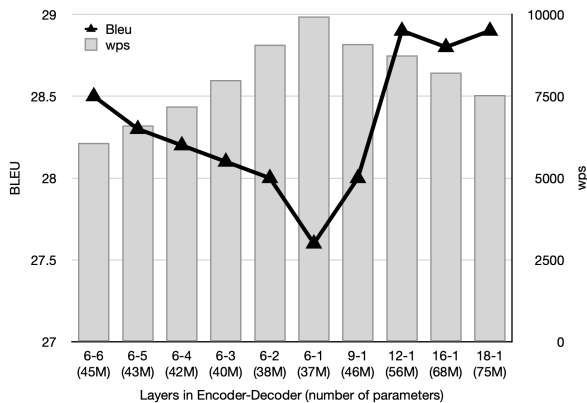


Figure 2: Translation quality – inference speed trade-off over different number of encoder – decoder layers.

From Figure 2, removing one decoder layer at a time from the baseline model increases wps by 10% at a cost of BLEU score degradation since model capacity goes down. As we increase the number of encoder layers to 12 or more, we observe up to 45% speedup, better BLEU score but higher number of parameters than the original 6-6 structure.

3.3 Pruning Attention Heads

Pruning allows us to remove up to 75% of attention heads with slight BLEU degradation. We observe from the remaining heads that for the pruned baseline (22/7/8) model, the self-attention heads are more important in the deeper layers rather than the lower layers. On the other hand, in our best configuration (SSRU 18/8/-), there is no clear pattern of remaining heads.

	attention heads (enc/enc-dec/dec)	BLEU
Baseline	96/8/8	29.2
+ pruned	22/7/8	29.0
SSRU w/o ffn	96/8/-	28.9
+ pruned	18/8/-	28.6

Table 2: Head pruning through L_0 regularization on the 12 – 1 layer (encoder-decoder) structure. The (enc/enc-dec/dec) refers to the total number of attention heads in encoder self-attention, encoder-decoder attention and decoder self-attention respectively.

3.4 Combined Results

We combine all of the methods and evaluate our model on the newstest2015 testset.

	BLEU	speedup GPU/CPU	#params
Baseline	31.1	-	61M
SSRU	31.1	14/12%	57M
+ Remove ffn	31.0	28/49%	45M
+ 12-1	31.5	82/103%	56M
+ Prune heads	31.4	84/109%	46M

Table 3: Decoding on a GPU with batch-size 128, and a single CPU core with batch-size 1. [12-1] refers to the number of layers in the encoder and the decoder.

Table 3 shows that by using all of the techniques in combination, the model achieves 84% and 109% speed improvement on GPU and CPU, respectively compared to the baseline model (Transformer-base). There are only 25% heads remain in the deep-encoder after pruning and the total number of parameters is 25% fewer.

4 Conclusion

In this paper we explored the combination of techniques aimed at improving inference speed which lead to the discovery of a very efficient architecture. The best architecture has a deep 12-layer encoder, and a shallow decoder with only one single lightweight recurrent unit layer and one encoder-decoder attention mechanism. 75% of the encoder heads were pruned giving rise to a model with 25% fewer parameters than the baseline Transformer. In terms of inference speed, the proposed architecture is 84% faster on a GPU, and 109% faster on a CPU.

Acknowledgments

We would like to thank Andrew Finch, Stephan Peitz, Udhay Nallasamy, Matthias Paulik and Russ Webb for their helpful comments and reviews. Many thanks to the rest of the Machine Translation Team for interesting discussions and support.

References

- Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. [Language models are few-shot learners](#). *arXiv preprint arXiv:2005.14165*.
- Sergey Edunov, Myle Ott, Michael Auli, and David Grangier. 2018. [Understanding back-translation at scale](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, page 489–500, Brussels, Belgium.
- Yanping Huang, Youlong Cheng, Ankur Bapna, Orhan Firat, Dehao Chen, Mia Chen, HyoukJoong Lee, Jiquan Ngiam, Quoc V Le, Yonghui Wu, and Zhifeng Chen. 2019. [Gpipe: Efficient training of giant neural networks using pipeline parallelism](#). In *Advances in Neural Information Processing Systems 32*, pages 103–112, Vancouver, Canada.
- Jungo Kasai, Nikolaos Pappas, Hao Peng, James Cross, and Noah A Smith. 2020. [Deep encoder, shallow decoder: Reevaluating the speed-quality tradeoff in machine translation](#). *arXiv preprint arXiv:2006.10369*.
- Yoon Kim and Alexander M. Rush. 2016. [Sequence-level knowledge distillation](#). In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1317–1327, Austin, Texas. Association for Computational Linguistics.
- Young Jin Kim, Marcin Junczys-Dowmunt, Hany Hassan, Alham Fikri Aji, Kenneth Heafield, Roman Grundkiewicz, and Nikolay Bogoychev. 2019. [From research to production and back: Ludicrously fast neural machine translation](#). In *Proceedings of the 3rd Workshop on Neural Generation and Translation*, pages 280–288, Hong Kong. Association for Computational Linguistics.
- Taku Kudo and John Richardson. 2018. [SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 66–71, Brussels, Belgium.
- Tao Lei, Yu Zhang, Sida I. Wang, Hui Dai, and Yoav Artzi. 2018. [Simple recurrent units for highly parallelizable recurrence](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4470–4481, Brussels, Belgium.
- Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. 2020. [Gshard: Scaling giant models with conditional computation and automatic sharding](#). *arXiv preprint arXiv:2006.16668*.
- Christos Louizos, Max Welling, and Diederik P. Kingma. 2018. [Learning sparse neural networks through \$l_0\$ regularization](#). In *International Conference on Learning Representations*, Vancouver, Canada.
- Antonio Valerio Miceli Barone, Jindřich Helcl, Rico Sennrich, Barry Haddow, and Alexandra Birch. 2017. [Deep architectures for neural machine translation](#). In *Proceedings of the Second Conference on Machine Translation*, pages 99–107, Copenhagen, Denmark. Association for Computational Linguistics.
- Paul Michel, Omer Levy, and Graham Neubig. 2019. [Are sixteen heads really better than one?](#) In *Advances in Neural Information Processing Systems 32*, pages 14014–14024. Vancouver, Canada.
- Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. [fairseq: A fast, extensible toolkit for sequence modeling](#). In *Proceedings of Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Demonstrations*, Minneapolis, USA.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. [Attention is all you need](#). In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, page 6000–6010, Red Hook, NY, USA. Curran Associates Inc.
- Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. 2019. [Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5797–5808, Florence, Italy. Association for Computational Linguistics.
- Qiang Wang, Bei Li, Tong Xiao, Jingbo Zhu, Changliang Li, Derek F. Wong, and Lidia S. Chao. 2019a. [Learning deep transformer models for machine translation](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1810–1822, Florence, Italy. Association for Computational Linguistics.
- Yiren Wang, Yingce Xia, Tianyu He, Fei Tian, Tao Qin, ChengXiang Zhai, and Tie-Yan Liu. 2019b. [Multi-agent dual learning](#). In *International Conference on Learning Representations*, New Orleans, Louisiana, United States.

Biao Zhang, Deyi Xiong, and Jinsong Su. 2018. [Accelerating neural transformer via an average attention network](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, Melbourne, Australia. Association for Computational Linguistics.

Jinhua Zhu, Yingce Xia, Lijun Wu, Di He, Tao Qin, Wengang Zhou, Houqiang Li, and Tiejun Liu. 2020. [Incorporating bert into neural machine translation](#). In *International Conference on Learning Representations*, Addis Ababa, Ethiopia.