Lessons on Parameter Sharing across Layers in Transformers

Sho Takase

Tokyo Institute of Technology

sho.takase@nlp.c.titech.ac.jp

Shun Kiyono

RIKEN / Tohoku University

shun.kiyono@riken.jp

Abstract

We propose a parameter sharing method for Transformers (Vaswani et al., 2017). The proposed approach relaxes a widely used technique, which shares parameters for one layer with all layers such as Universal Transformers (Dehghani et al., 2019), to increase the efficiency in the computational time. We propose three strategies: SEQUENCE, CYCLE, and CY-CLE (REV) to assign parameters to each layer. Experimental results show that the proposed strategies are efficient in the parameter size and computational time. Moreover, we indicate that the proposed strategies are also effective in the configuration where we use many training data such as the recent WMT competition.

1 Introduction

Transformer-based methods have achieved notable performance in various NLP tasks (Vaswani et al., 2017; Devlin et al., 2019; Brown et al., 2020). In particular, Brown et al. (2020) indicated that the larger parameter size we prepare, the better performance the model achieves. However, the model which is composed of many parameters occupies a large part of a GPU memory capacity. Thus, it is important to explore a parameter efficient way, which achieves better performance than a basic model with the same parameter size.

Parameter sharing is a widely used technique as a parameter efficient way (Dehghani et al., 2019; Dabre and Fujita, 2019; Lan et al., 2020). Dehghani et al. (2019) proposed Universal Transformer which consists of parameters for only one layer of a Transformer-based encoder-decoder, and uses the parameters N times for an N-layered encoder-decoder. Dabre and Fujita (2019) and Lan et al. (2020) also used such parameter sharing across layers for their Transformers.

Dehghani et al. (2019) reported that Universal Transformer achieved better performance than

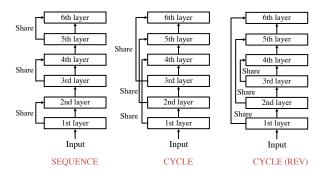


Figure 1: Examples of three parameter assignment strategies proposed by this study when we set M=3 and N=6.

the vanilla Transformer in machine translation if they consist of the same number of parameters. However, when we prepare the same number of parameters for Universal Transformer and basic Transformer, Universal Transformer requires much more computational time because weight matrices for each layer in Universal Transformer are much larger. For example, we demonstrate that Universal Transformer requires twice as much training time as the basic Transformer in WMT En-De, which is a widely used machine translation dataset.

In this paper, we propose a new parameter sharing method which is faster than using the same parameters for all layers such as Universal Transformer. Instead of preparing parameters for only one layer, we prepare parameters for M layers to construct an N-layered encoder-decoder, where $1 \le M \le N$. In other words, the proposed method relaxes the parameter sharing strategy used in previous studies (Dehghani et al., 2019; Dabre and Fujita, 2019; Lan et al., 2020). For the parameter assignment to each layer, we provide several strategies and compare them empirically. Experimental results show that the proposed method achieves comparable scores to the method assigning parameters of one layer to all layers with smaller computational time.

Algorithm Encoder Construction

Input: the total number of layers N, the number of independent layers M, the sharing strategy TYPE \in {SEQUENCE, CYCLE, CYCLE (REV)}

```
Output: enc_1, ..., enc_N
  1: for i in [1, ..., N] do
          if i == 1 then
               enc_i \leftarrow CreateNewLayer
 3:
 4:
          else if Type == Sequence then
               if (i-1) \mod |N/M| == 0 then
 5:
 6:
                    enc_i \leftarrow CreateNewLayer
               else
 7:
 8:
                     enc_i \leftarrow enc_{i-1}
          else if Type == Cycle then
 9:
10:
               if i \leq M then
                     enc_i \leftarrow CreateNewLayer
11:
12:
               else
13:
                     \operatorname{enc}_i \leftarrow \operatorname{enc}_{((i-1) \bmod M)+1}
          else if Type == Cycle (REV) then
14:
               if i \leq M then
15:
16:
                     enc_i \leftarrow CreateNewLayer
               else if i \leq (M * (\lceil N/M \rceil - 1)) then
17:
                     \operatorname{enc}_i \leftarrow \operatorname{enc}_{((i-1) \bmod M)+1}
18:
19:
               else
20:
                     \operatorname{enc}_i \leftarrow \operatorname{enc}_{M-((i-1) \bmod M)}
```

Figure 2: The proposed parameter assignment strategies for an encoder construction. CreateNewLayer is a function which creates a new encoder layer.

2 Proposed Method

As described in Section 1, we use parameters for M layers in the construction of an N-layered Transformer-based encoder-decoder. For the parameter assignment, we provide three strategies: SEQUENCE, CYCLE, and CYCLE (REV). We describe these strategies in this section.

Figure 1 shows examples of three parameter assignment strategies for an encoder-side when we set M=3 and N=6. Let enc_i be the i-th layer of an encoder. Figure 2 describes the algorithm to assign each parameter to each layer for the encoder. For the decoder-side, we assign each parameter with the same manner.

2.1 SEQUENCE

The simplest strategy is to assign the same parameters to sequential $\lfloor N/M \rfloor$ layers. We name this

strategy SEQUENCE. For example, when we set M=3 and N=6, sequential 2 layers share their parameters as illustrated in Figure 1.

2.2 CYCLE

In CYCLE, we stack M layers whose parameters are independent from each other. Then, we repeat stacking the M layers with the identical order to the first M layers until the total number of layers reaches N. When we set M=3 and N=6, we stack 3 layers twice as illustrated in Figure 1.

2.3 CYCLE (REV)

Liu et al. (2020) reported that higher decoder layers obtain larger gradient norms when we use the post layer normalization setting, which is originally used in Vaswani et al. (2017) and widely used in machine translation. Their report implies that higher layers require more degrees of freedom than lower layers for their expressiveness. In other words, lower layers probably have redundant parameters in comparison with higher layers. Thus, we propose the strategy CYCLE (REV) reusing parameters of lower layers in higher layers.

In this strategy, we repeat stacking M layers in the same as CYCLE until $M*(\lceil N/M \rceil-1)$ layers. For the rest of the layers, we stack M layers in reverse order. When we set M=3 and N=6, we stack 3 layers and then stack the 3 layers in reverse order as illustrated in Figure 1. Thus, the lowest layer and highest layer share their parameters.

3 Layer Normalization in Transformers

For layer normalizations in Transformers, most recent studies used the pre layer normalization setting (Pre-LN) when they stacked many layers (Wang et al., 2019; Brown et al., 2020) because Pre-LN makes a training more stable than the post layer normalization setting (Post-LN) (Nguyen and Salazar, 2019; Xiong et al., 2020). However, Transformers with Post-LN achieve better performance if we succeed in their training (Nguyen and Salazar, 2019; Liu et al., 2020). To make a training Transformers with Post-LN stable, Liu et al. (2020) proposed Admin which smooths the impacts of each parameter in the early stage of training. In this study, we also use Admin for the stable training.

4 Experiments

We focus on the English-to-German translation task in the same as previous studies (Vaswani et al.,

Setting	Genuine	Synthetic
Standard	4.5M	-
High Resource	44.2M	284.3M

Table 1: The number of translation sentence pairs in training datasets for each experiment.

2017; Dehghani et al., 2019; Kiyono et al., 2020). We conduct experiments on two types of English-to-German translation tasks. The difference is the amount of training data. Table 1 summarizes the number of training data in each configuration.

4.1 Standard Setting

Datasets We used WMT 2016 training dataset, which is widely used in previous studies (Vaswani et al., 2017; Ott et al., 2018). The dataset contains 4.5M English-German sentence pairs. Following the previous studies, we constructed a vocabulary set with BPE (Sennrich et al., 2016b) in the same manner. We set the number of BPE merge operations at 32K and shared the vocabulary between both the source and target languages. We measured case-sensitive detokenized BLEU with Sacre-BLEU (Post, 2018)¹.

Methods For the proposed parameter assignment strategies, we fixed M=6 and set N=12,18 based on the Transformer (base) setting in Vaswani et al. (2017). We compare the proposed strategies with the following baselines.

Original and **Original** (big): These are the original Transformer (base) and (big) settings in Vaswani et al. (2017), respectively.

Admin: We applied Admin (Liu et al., 2020) to the Transformer (base) setting.

Universal: As the parameter sharing strategy in previous studies such as Universal Transformers (Dehghani et al., 2019), we set $M=1^2$. In this setting, we increased the dimension of each layer for a fair comparison in terms of the number of parameters. We used the Universal Transformer

base setting in Dehghani et al. (2019).

Results Table 2 shows BLEU scores on newstest2010-2016 for each method. We trained three models with different random seeds, and reported the averaged scores. In addition, Table 2 shows the total number of parameters and computational speeds³. The computational speeds are based on the speed of Original.

In the comparison between Universal and Original, Universal achieved better scores although their parameter sizes are almost the same. This result is consistent with the report in Dehghani et al. (2019). Moreover, Universal outperformed Original (big) in the averaged score even though the parameter size of Universal is much smaller than the one of Original (big). On the other hand, the proposed strategies (SEQUENCE, CYCLE, and CYCLE (REV)) were faster and achieved slightly better scores than Universal when we set M=6 and N=12. Since Admin did not have positive influence on the BLEU scores as shown in Table 2, our strategies caused the improvements. Thus, our proposed parameter sharing strategies are more efficient in terms of the parameter size and computational time.

In M=6 and N=12, SEQUENCE, CYCLE, and CYCLE (REV) achieved almost the same scores. In contrast, the scores of SEQUENCE were lower than other two strategies in M=6 and N=18. This result indicates that CYCLE and CYCLE (REV) are better strategies when we construct a deep Transformer with small M. In M=6 and N=18, CYCLE (REV) improved 0.41 from Universal in the averaged BLEU score even though their computational speeds were almost the same.

4.2 High Resource Setting

Datasets In the high resource setting, we constructed 44.2M translation sentence pairs as a training dataset with the procedures of Kiyono et al. (2020) which achieved the best result in the WMT 2020 news translation task. In addition, we augmented the training data by using the backtranslation technique (Sennrich et al., 2016a) in the same manner as Kiyono et al. (2020). We obtained 284.3M pairs as the synthetic training data.

Methods We used the original Transformer (big) setting (Vaswani et al., 2017) as our baseline in using genuine training data. For the proposed strategies, we used N=12 and M=6.

¹The BLEU score computed by SacreBLEU is often lower than the score by the procedure of Vaswani et al. (2017) as reported in Ott et al. (2018). In fact, when we used the same procedure as Vaswani et al. (2017), the best model in Table 3 achieved 35.14 in the averaged BLEU score in newstest2014. However, Post (2018) encouraged using SacreBLEU for the compatibility of WMT results.

²The original Universal Transformers (Dehghani et al., 2019) use the sinusoidal positional encoding for each layer and adaptive computation time technique (Graves, 2017) but we omitted them in this study to focus on the difference among parameter sharing strategies.

³We regard processed tokens per second during the training as the conputational speed.

Method	M	N	#Params	Speed	2010	2011	2012	2013	2014	2015	2016	Average
Original	6	6	61M	×1.00	24.16	22.01	22.33	26.13	27.13	29.83	34.41	26.57
Admin	6	6	61M	$\times 0.97$	24.14	21.93	22.25	26.14	27.05	29.59	34.23	26.48
Universal	1	6	63M	$\times 0.48$	24.37	22.33	22.70	26.40	27.65	30.24	34.60	26.90
Original (big)	6	6	210M	$\times 0.39$	24.31	22.21	22.75	26.39	28.28	30.35	33.40	26.81
SEQUENCE	6	12	61M	$\times 0.63$	24.65	22.32	22.83	26.98	27.88	30.27	34.99	27.13
CYCLE	6	12	61M	$\times 0.63$	24.51	22.43	22.69	26.61	27.91	30.37	34.77	27.04
CYCLE (REV)	6	12	61M	$\times 0.63$	24.66	22.47	22.87	26.68	27.72	30.37	34.81	27.08
SEQUENCE	6	18	61M	$\times 0.47$	24.53	22.44	22.73	26.59	27.73	30.30	34.80	27.02
CYCLE	6	18	61M	$\times 0.47$	24.74	22.60	23.04	26.89	28.14	30.54	34.79	27.25
CYCLE (REV)	6	18	61M	$\times 0.47$	24.93	22.77	23.09	26.88	28.09	30.60	34.84	27.31

Table 2: The number of layers, the number of parameters, computational speeds based on the original Transformer, BLEU scores on newstest2010-2016, and averaged scores when we trained each method on widely used WMT 2016 training dataset. Scores in bold denote the best result for each set.

Method	#Params	2014	2018	2019				
Genuine training data								
Original (big)	242M	31.40	47.11	42.80				
SEQUENCE	242M	31.90	48.15	43.12				
CYCLE	242M	32.10	48.11	43.19				
CYCLE (REV)	242M	32.06	48.34	43.43				
+ Synthetic (back-translated) data								
Kiyono et al. (2020)	514M	33.1	49.6	42.7				
CYCLE (REV)	343M	33.54	49.55	42.18				

Table 3: BLEU scores on newstest2014, 2018, and 2019. We focused these test sets to compare the top system on WMT 2020 (Kiyono et al., 2020).

In using both of the genuine and synthetic (backtranslated) dataset, we applied CYCLE (REV) to the BASE setting in Kiyono et al. (2020) because CYCLE (REV) achieved the best BLEU scores on most test sets in Table 2. We also used N=12 and M=6 in this configuration. We compare the reported score of the best model described in Kiyono et al. (2020). Their model is composed of 9 layers (N=9 and M=1, in other words), and thus, it contains much more parameters than ours.

Results Table 3 shows BLEU scores on new-stest2014, 2018, and 2019. We focused on these test data to compare Kiyono et al. (2020). In the same as experiments in Section 4.1, we reported the averaged scores of three morels trained with different random seeds. Table 3 also shows the total number of parameters⁴.

Table 3 shows that our proposed strategies achieved better BLEU scores than Original (big) when we prepared the same number of parameters. This result indicates that our proposed strategies are also useful in the high resource setting.

When we used additional synthetic data for the training in the same manner as Kiyono et al. (2020), CYCLE (REV) achieved comparable BLEU scores to the best system of Kiyono et al. (2020) except for newstest2019⁵ even though the parameter size of CYCLE (REV) were smaller than theirs. This result indicates that CYCLE (REV) is also efficient in the construction of models for the recent competitive tasks. In addition, this result implies that our proposed strategies can be used in the configuration where we train many parameters with a tremendous amount of data such as recent pre-trained language models, e.g., GPT series (Brown et al., 2020).

5 Conclusion

We proposed three parameter sharing strategies: SE-QUENCE, CYCLE, and CYCLE (REV), for internal layers in Transformers. In contrast to the previous strategy, which prepares parameters for only one layer and shares them across layers such as Universal Transformers (Dehghani et al., 2019), our proposed strategies prepare parameters for Mlayers to construct N layers. Experimental results show that the proposed strategies achieved comparable BLEU scores to ones of Universal with small computational time when we prepare almost the same parameters for each method. In other words, the proposed strategies are efficient in the parameter size and computational time. Moreover, CYCLE and CYCLE (REV) are appropriate to the construction of a deep model. Through experiments on the high resource setting, we demonstrated that CYCLE (REV) can achieve the comparable scores to the top system of WMT 2020 news translation task (Kiyono et al., 2020) with smaller parameters.

⁴The parameter sizes of Original (big) in Tables 2 and 3 are different from each other due to the difference of sharing embeddings. Following Kiyono et al. (2020), we did not share embeddings in the high resource setting.

⁵For newstest2019, synthetic data might harm the quality of a model because models trained with only genuine data outperformed models trained with both data.

References

- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems 33 (NeurIPS), pages 1877–1901.
- Raj Dabre and Atsushi Fujita. 2019. Recurrent stacking of layers for compact neural machine translation models. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33:6292–6299.
- Mostafa Dehghani, Stephan Gouws, Oriol Vinyals, Jakob Uszkoreit, and Łukasz Kaiser. 2019. Universal transformers. In *Proceedings of the 7th International Conference on Learning Representations (ICLR)*.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT), pages 4171–4186.
- Alex Graves. 2017. Adaptive computation time for recurrent neural networks.
- Shun Kiyono, Takumi Ito, Ryuto Konno, Makoto Morishita, and Jun Suzuki. 2020. Tohoku-AIP-NTT at WMT 2020 news translation task. In *Proceedings of the Fifth Conference on Machine Translation (WMT)*, pages 145–155.
- Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A lite bert for self-supervised learning of language representations. In *Proceedings of the 8th International Conference on Learning Representations (ICLR)*.
- Liyuan Liu, Xiaodong Liu, Jianfeng Gao, Weizhu Chen, and Jiawei Han. 2020. Understanding the difficulty of training transformers. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5747–5763.
- Toan Q. Nguyen and Julian Salazar. 2019. Transformers without tears: Improving the normalization of self-attention. In *Proceedings of the 16th International Conference on Spoken Language Translation (IWSLT)*.

- Myle Ott, Sergey Edunov, David Grangier, and Michael Auli. 2018. Scaling neural machine translation. In *Proceedings of the Third Conference on Machine Translation (WMT)*, pages 1–9.
- Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation (WMT)*, pages 186–191.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. Improving neural machine translation models with monolingual data. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 86–96.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 1715–1725.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30 (NIPS)*, pages 5998–6008.
- Qiang Wang, Bei Li, Tong Xiao, Jingbo Zhu, Changliang Li, Derek F. Wong, and Lidia S. Chao. 2019. Learning deep transformer models for machine translation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 1810–1822.
- Ruibin Xiong, Yunchang Yang, Di He, Kai Zheng, Shuxin Zheng, Chen Xing, Huishuai Zhang, Yanyan Lan, Liwei Wang, and Tie-Yan Liu. 2020. On layer normalization in the transformer architecture. In *Proceedings of the 37th International Conference on Machine Learning (ICML)*.