On Layer Normalizations and Residual Connections in Transformers

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Abstract

In the perspective of a layer normalization (LN) position, the architecture of Transformers can be categorized into two types: Post-LN and Pre-LN. Recent Transformers prefer to select Pre-LN because the training in Post-LN with deep Transformers, e.g., ten or more layers, often becomes unstable, resulting in useless models. However, in contrast, Post-LN has also consistently achieved better performance than Pre-LN in relatively shallow Transformers, e.g., six or fewer layers. This study first investigates the reason for these discrepant observations empirically and theoretically and discovers 1, the LN in Post-LN is the source of the vanishing gradient problem that mainly leads the unstable training whereas Pre-LN prevents it, and 2, Post-LN tends to preserve larger gradient norms in higher layers during the back-propagation that may lead an effective training. Exploiting the new findings, we propose a method that can equip both higher stability and effective training by a simple modification from Post-LN. We conduct experiments on a wide range of text generation tasks and demonstrate that our method outperforms Pre-LN, and stable training regardless of the shallow or deep layer settings.

1 Introduction

To prevent the vanishing/exploding gradient problem in the training of a deep neural network (DNN), various techniques, such as batch normalization [10, 8] and residual connection [24], have been proposed and widely used in almost all recent DNNs. Transformer [28] employs the layer normalization [1] for this purpose. Transformer is currently the most successful model architecture in DNNs. This was firstly developed for applying sequence-to-sequence tasks, such as machine translation [28], summarization [27], and automatic speech recognition [30], and currently used in speech, vision, and many other information processing research fields.

As discussed in batch normalization literature [7], the position of the normalization layers primarily affects both the stability and resultant performance of a trained model. Similarly, in Transformers, some previous studies have investigated...
the impact of the layer normalization positions [32, 33]. There are currently two major layer normalization positions in Transformers: Pre-Layer Normalization (Pre-LN) and Post-Layer Normalization (Post-LN). Pre-LN applies the layer normalization to an input for each sub-layer, and Post-LN places the layer normalization after each residual connection. The original Transformer [28] employs Post-LN. However, recent studies often suggest using Pre-LN [32, 2, 5] because the training in Post-LN with deep Transformers (e.g., ten or more layers) often becomes unstable, resulting in useless models. Figure 1 shows an actual example; loss curves of training 18L-18L Transformer encoder-decoders on a widely used WMT English-to-German machine translation dataset. Here, $X_l$-$Y_l$ represents the number of layers in encoder and decoder, where $X$ and $Y$ correspond to encoder and decoder, respectively. These figures clearly show that 18L-18L Post-LN Transformer encoder-decoder fails to train the model. However, in contrast, Liu et al. [13] reported that Post-LN consistently achieved better performance than Pre-LN in the machine translation task when they used 6L-6L (relatively shallow) Transformers.

This paper focuses specifically on such discrepant observations between Pre-LN and Post-LN in configurations with different layer sizes. We then investigate the sources of the instability of training in deep-layer configurations and the superior performance in shallow-layer configurations for Post-LN compared with Pre-LN to understand the essentials of the Pre-LN and Post-LN difference. We discover that the layer normalization in Post-LN is the source of the vanishing gradient problem that mainly leads the unstable training, whereas Pre-LN prevents it as shown in Figure 1. In particular, we clarify that the layer normalization is a significant factor in the vanishing gradient problem by comparing the input/output vector norms of gradient flows for each layer normalization during back-propagation. These analyses bring us a novel idea that can satisfy higher stability by skipping over layer normalizations and provide better performance than Pre-LN regardless of their layer sizes. Specifically, we propose a method that is based on Post-LN Transformers but has additional residual connections to the stable training.

We conduct experiments on a wide range of text generation tasks, namely machine translation, summarization, language modeling, and automatic speech recognition. We obtain the following three new major findings from our experiments:

1. Post-LN Transformers achieve better performance than Pre-LN Transformers in text generation tasks (not only machine translation [13] but also other tasks). Thus, Post-LN is superior to Pre-LN if we can solve its unstable training.

2. Our modification enables Post-LN Transformers to stack many layers.
3. Our method can maintain the advantage of Post-LN in performance and mitigate unstable training property, and thus provide better performance than Pre-LN regardless of their layer sizes.

2 Post-LN and Pre-LN Transformers

We briefly describe Post-LN and Pre-LN Transformers. The original Transformer [28] uses Post-LN in which layer normalizations are located after each residual connection. Let \( x \) be an input of sub-layer, and \( F(\cdot) \) be a sub-layer of Transformers such as a feed-forward network and multi-head attention. Post-LN is defined as follows:

\[
\text{PostLN}(x) = \text{LN}(x + F(x)),
\]

(1)

where \( \text{LN}(\cdot) \) is the layer normalization function.

In contrast, Pre-LN places the layer normalization before an input of each sub-layer;

\[
\text{PreLN}(x) = x + F(\text{LN}(x)).
\]

(2)

Figure 2 (a) and (b) illustrate Post-LN and Pre-LN Transformer architectures respectively.

3 Gradients of Transformer Layers

As described in Liu et al. [13], the vanishing gradient problem often occurs in Post-LN Transformers. Figure 3 shows gradient norms of each layer for the (a) encoder-side and (b) decoder-side at the beginning of training when we train 18L-18L Transformer encoder-decoders on widely used machine translation dataset (WMT English-to-German dataset). Focus on the decoder-side of Post-LN as illustrated in Figure 3 (b). This figure shows that shallower layer is, smaller its gradient norm is. Thus, the vanishing gradient occurs in the decoder-side of Post-LN because its gradient norms are exponentially decayed as back-propagated to shallower layers. This result is consistent with the previous study [13]. We consider that this vanishing gradient causes the difficulty in stacking many layers with the Post-LN setting as shown in Figure 1.

To explore more details of the vanishing gradient empirically, we check gradient norms of parts (1) - (5) in Figure 2 (a). Figure 4 shows the gradient norms of each part at 18th layer. This figure indicates that the gradient norms from (4) to (3) and (2) to (1) drastically decrease. These parts correspond to layer normalizations as in Figure 4. Thus, layer normalizations in Post-LN Transformers probably cause the vanishing gradient problem.

To investigate the difference of gradient flows between Post-LN and Pre-LN theoretically, we calculate derivatives of equations (1) and (2). The derivatives are as follows:

\[
\frac{\partial \text{PostLN}(x)}{\partial x} = \frac{\partial \text{LN}(x + F(x))}{\partial (x + F(x))} \left( I + \frac{\partial F(x)}{\partial x} \right),
\]

(3)

\[
\frac{\partial \text{PreLN}(x)}{\partial x} = I + \frac{\partial F(\text{LN}(x))}{\partial \text{LN}(x)} \frac{\partial \text{LN}(x)}{\partial x},
\]

(4)

where \( I \) is the identity matrix. As Equation (3), the derivative of Post-LN is equal to the product of two derivatives; one is the layer normalization, and the other

![Figure 3: Gradient norms of 18L-18L Transformer-based encoder-decoder architectures.](image)

![Figure 4: Gradient norms of each location in the 18th decoder for the 18L-18L Post-LN Transformer encoder-decoder on WMT English-to-German translation training data.](image)
consists of the residual connection and sub-layer $\mathcal{F}$. In contrast, in Pre-LN, the derivative of the residual connection is isolated from the term related to the derivative of the layer normalization. The difference between these equations implies that the residual connection in Pre-LN prevents the vanishing gradient because it keeps gradients of upper layers even if the derivative of the layer normalization drastically decreases gradients.

4 Transformations by Each Layer

As described, it is difficult to stack many layers in Post-LN Transformers because the vanishing gradient problem occurs. Although Pre-LN is more stable in training, Post-LN can achieve better performance if we succeed their trainings (see Section 6). In this Section, we explore the reason on the difference on their performance.

Focus Pre-LN in Figure 3. In contrast to Post-LN, deeper (higher) layer is, smaller its gradient norm is. Thus, higher layers are not required drastically changing their parameters from initial values. This implies that higher layers in Pre-LN are not effective enough.

To investigate the effectiveness of higher layers, we focus on transformations by each layer. Figure 5 shows averaged cosine similarities among outputs of each layer for 6L-6L Transformer encoder-decoders trained on the WMT dataset when we input several sequences. This figure indicates that the lower-left similarities of Pre-LN are higher than ones of Post-LN. This result means that the outputs of shallow layers are similar to the final layer output in Pre-LN in comparison with Post-LN. In other words, higher layers in Pre-LN are less effective than ones in Post-LN if we succeed their trainings.

We consider that the residual connection in Pre-LN causes this phenomenon. As Equation (2), in Pre-LN, an input $x$ skips over the sub-layer $\mathcal{F}(\cdot)$ by the residual connection. Thus, the input $x$ is directly connected to the final layer output. This property makes the training stable as described in Section 3 but causes such high similarities among outputs from each layer. Therefore, we consider that Pre-LN underperforms Post-LN because the residual connection in Pre-LN inhibits the effectiveness of its higher layers. In contrast, for Post-LN, larger gradient norms in higher layers as in Figure 3 make higher layers more effective as in Figure 5, but we have to prevent the vanishing gradient problem in shallow layers when we stack many layers.

5 Modification for Stable Training in Post-LN: Bottom-to-Top Connection

This section introduces a modification that makes the training of Post-LN more stable while its better performance remains. In detail, we describe an additional residual connection to mitigate the vanishing gradient in Post-LN. This additional residual connection enables to stack many layers in Post-LN.

Based on discussions in previous sections, we need a term keeping gradients in the derivatives such as Equation (4) to prevent the vanishing gradient. To satisfy this requirement, we propose a residual connection that skips over layer normalizations except for the final one in each layer. Our introduced connection ties an input of a layer to the result of the feed-forward network (FFN) as red arrows in Figure 2 (c)\textsuperscript{1}. We call this connection **Bottom-to-Top (B2T) connection.** We formalize this

\textsuperscript{1}We tried a connection that skips over all layer normalizations including the final one in each layer but it significantly harmed the performance. When we prepare such a connection, the connection ties an input to the output directly. Because the connection inhibits transformations by each layer as described in Section 4, it is reasonable to harm the performance. Thus, we exclude the final layer normalization to take the advantage of Post-LN.
Table 1: BLEU scores of each method on WMT newstest2010-2016 and their averages.

| Method            | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | Average |
|-------------------|------|------|------|------|------|------|------|---------|
| Enc-Dec: 6L-6L     |      |      |      |      |      |      |      |         |
| Post-LN           | 24.27| 22.06| 22.43| 26.11| 27.13| 29.70| 34.40| 26.59   |
| Pre-LN            | 24.03| 21.77| 22.08| 25.63| 26.27| 29.07| 33.84| 26.10   |
| B2T connection    | 24.12| 21.93| 22.29| 26.31| 26.84| 29.48| 34.73| 26.53   |
| Enc-Dec: 18L-18L   |      |      |      |      |      |      |      |         |
| Post-LN           | 24.07| 21.98| 22.40| 26.28| 27.36| 29.74| 34.16| 26.57   |
| Pre-LN            |      |      |      |      |      |      |      |         |
| B2T connection    | 24.62| 22.51| 22.86| 26.74| 28.48| 30.99| 34.93| 27.30   |
| Enc-Dec: 60L-12L   |      |      |      |      |      |      |      |         |
| Post-LN           | 23.99| 21.99| 22.65| 26.42| 27.96| 29.45| 32.49| 26.42   |
| Pre-LN            |      |      |      |      |      |      |      |         |
| B2T connection    | 24.75| 22.88| 23.09| 27.12| 28.82| 30.99| 33.64| 27.33   |

connection as the following equation:

\[ x_{inp} + x_{ffn} + \text{FFN}(x_{ffn}), \tag{5} \]

where \( x_{inp} \) is an input of a layer, \( x_{ffn} \) is an input of FFN, and \( \text{FFN}(\cdot) \) is a feed-forward network. In short, \( x_{inp} \) skips layer normalizations after self and encoder-decoder cross attentions, and thus it keeps gradients as in Pre-LN. In fact, Figure 3 (b) indicates that B2T connection mitigates the vanishing gradient of 18L-18L encoder-decoders. Moreover, B2T connection keeps the property of Post-LN on transformations by each layer as in Figure 5 (c).

6 Experiments

Through experiments, we indicate following three findings.

- Post-LN Transformers achieve better performance than Pre-LN Transformers if we succeed in their trainings.
- B2T connection enables to train deep Transformers with the Post-LN configuration.
- Our modifications keep the advantage of Post-LN in the performance, and thus outperform Pre-LN Transformers.

6.1 Machine Translation

6.1.1 Dataset

The machine translation task is widely used to investigate the performance of Transformer-based methods since the original Transformer [28, 17, 32, 33, 13]. We adopted the widely used WMT English-to-German (EnDe) training dataset [28, 17] that contains 4.5M sentence pairs. We applied the byte-pair-encoding (BPE) algorithm [23] to construct a vocabulary set in the same manner with previous studies. We set the number of BPE merge operations at 32K and shared the vocabulary between the source and target languages. We used newstest2010-2016 to investigate the performance as in Takase and Kiyono [26].

6.1.2 Methods

We compare Post-LN, Pre-LN and Post-LN with our B2T connection (B2T connection) Transformers. We used fairseq\footnote{https://github.com/pytorch/fairseq} \[18\] as an implementation of Transformers. We stacked layers of encoders and decoders in 6L-6L and 18L-18L as typical or deep configurations, respectively. In addition, we prepared the 60L-12L configuration, that is described as “very deep Transformers” in Liu et al. [14]. We used the Transformer (base) setting for dimension sizes of internal layers.
6.1.3 Results

We measured case-sensitive detokenized BLEU scores with SacreBLEU [20]. Table 1 shows BLEU scores of each method on newstest2010-2016 and the averaged score of them. BLEU score is precision-based n-gram overlapping between the model output and correct examples; larger is better.

The upper part of Table 1 shows results in the 6L-6L configuration. This part indicates that Post-LN achieved better scores than ones of Pre-LN in all test sets. In addition, B2T connection also outperformed Pre-LN in all test sets. Thus, they are superior to Pre-LN when we set the total number of layers shallow.

The middle part of Table 1 shows results in the 18L-18L configuration. This part shows that the training of Post-LN failed, and thus we cannot stack 18L-18L in the vanilla Post-LN. Focus on B2T connection, its training succeeded and they outperformed Pre-LN in the 18L-18L configuration. Figure 6 shows negative log-likelihood values (NLL) of each method when we regard newstest2013 as validation data. This figure indicates that NLLs of Pre-LN are worse than ones of B2T connection. As the stacking more total layers, the lower part of Table 1 shows results in the 60L-12L configuration. The results of this part are consistent with results in the 18L-18L configuration. These results indicate that our modification enabled to stack many layers without harm to its performance such as Pre-LN.

6.2 Abstractive Summarization

6.2.1 Dataset

The abstractive summarization task is one of the most famous sequence-to-sequence problems in NLP. In this study, we conduct the experiment on the headline generation task which is the task to generate a headline from a given sentence [21]. We used headline-sentence pairs extracted from Annotated English Gigaword [16] by Rush et al. [21]. The dataset contains 3.8M headline-sentence pairs as the training set and 1951 pairs as the test set. In addition, we used additional 13M headline-sentence pairs extracted from REALNEWS [35] and NewsCrawl [4] for training deep Transformers as in Takase and Kiyono [26]. We applied BPE [23] to construct a vocabulary set. In the same as the machine translation experiment, We set the number of BPE merge operations at 32K and shared the vocabulary between both the encoder and decoder sides.

6.2.2 Methods

We compare Post-LN, Pre-LN, and B2T connection Transformers in the same as Section 6.1. We set the layers of encoders and decoders in 6L-6L as the base configuration and 18L-18L as the deep configuration.

6.2.3 Results

Table 2 shows ROUGE-1, 2, and L scores of each method on the test set. These scores are computed based on n-gram overlapping between generated and correct headlines; larger is better.

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3The BLEU scores based on SacreBLEU are often lower than the scores based on the procedure of Vaswani et al. [28] as reported in Ott et al. [17]. However, we used SacreBLEU to enhance the compatibility of results as described in Post [20].
4The signature of SacreBLEU is BLEU+nrefs:1+case:mixed+ eff:no+tok:13a+smooth:exp+version:2.0.0.
5Appendix C indicates the results when we stack more total layers.
In the 6L-6L configuration, Post-LN achieved better performance than Pre-LN. Thus, Post-LN also outperformed Pre-LN in the headline generation task if their trainings succeeded. Moreover, B2T connection achieved comparable scores to Post-LN.

In the 18L-18L configuration, the training of Post-LN failed. In contrast, B2T connection succeeded in training, and outperformed Pre-LN. Thus, our modification is also more suitable than Pre-LN in training deep Transformers for the headline generation task.

### 6.3 Language Model

In addition to encoder-decoders, we investigate the effect of our B2T connection in the decoder side only, i.e., a neural language model. Because recent pre-trained models such as the GPT series are language models trained on a large amount of training data, experimental results on language modeling give insight as a pre-trained model.

#### 6.3.1 Dataset

We used WikiText-103 [15] that consists of a large amount of tokens. The training, validation, test sets contain 103M, 0.2M, 0.2M tokens respectively. The vocabulary set consists of 0.3M words.

#### 6.3.2 Methods

We used Transformer with adaptive input representations [2] which is implemented in fairseq as the base architecture in this experiment. We stacked 6 layers as the base configuration in the same as in machine translation and summarization experiments. For the deep configuration, we used 16 layers by following Baevski and Auli [2]. For the dimension sizes of internal layers, we used the same values as in Baevski and Auli [2]. We compare Post-LN, Pre-LN, and B2T connection.

#### 6.3.3 Results

Table 3 shows perplexities of each method on validation and test sets of WikiText-103. Perplexity is computed based on negative log-likelihood, and thus, smaller is better. The upper part of this table indicates that Post-LN and our B2T connection outperformed Pre-LN when the total number of layers is 6. When we stacked 16 layers, the training of Post-LN failed. In contrast, B2T connection achieved better performance than Pre-LN. These results are consistent with results on machine translation and summarization tasks. Thus, our modification also enables to train deep Transformers on language modeling, and they are more effective than Transformers with Pre-LN.

### 6.4 Automatic Speech Recognition

In addition to experiments on natural language processing tasks, we conduct an experiment on another modality: automatic speech recognition (ASR).

#### 6.4.1 Dataset

We used LibriSpeech [19] that is the standard English ASR benchmark dataset. The dataset contains 1,000 hours of English speech from audiobooks. We used the standard splits of LibriSpeech: used all available training data for training and two configurations (clean and other) of development and
test sets for evaluation. We applied the same pre-processing as in Wang et al. [30]. In detail, we constructed a vocabulary set for the decoder-side with SentencePiece [12] by setting the vocabulary size 10,000. To obtain speech features, we used torchaudio.

6.4.2 Methods

We used a Transformer-based speech-to-text model described in Wang et al. [30] as the base architecture in this experiment. This model contains a convolutional layer to construct an embedding for the encoder-side but the other parts are identical to Transformers used in machine translation and summarization tasks. We used the same dimension sizes as in T-Md described in Wang et al. [30]. We set the number of layers 6L-6L and 12L-6L as the base and deep configurations respectively because Wang et al. [30] stacked many layers for the encoder-side only. We compare Post-LN, Pre-LN, and B2T connection.

6.4.3 Results

Table 4 shows word error rates (WERs) of each method on each set. In WER, smaller is better. The upper part of this table indicates that Post-LN and B2T connection outperformed Pre-LN on all sets in the 6L-6L configuration. In addition, the lower part of this table indicates that B2T connection succeeded in training and achieved better (or comparable) performance\(^7\) to Pre-LN in the 12L-6L configuration. These results are consistent with other experiments in this study.

| Method            | Dev Clean | Other Clean | Test Clean | Other Clean |
|-------------------|-----------|-------------|------------|-------------|
| Enc-Dec: 6L-6L    |           |             |            |             |
| Post-LN           | 3.78      | 8.76        | 4.19       | 8.74        |
| Pre-LN            | 3.89      | 9.69        | 4.22       | 9.65        |
| B2T connection    | **3.69**  | **8.97**    | **3.86**   | **8.94**    |
| Enc-Dec: 12L-6L   |           |             |            |             |
| Post-LN           | Training failed |          |            |             |
| Pre-LN            | **3.21**  | 7.91        | **3.49**   | 8.22        |
| B2T connection    | **3.26**  | **7.74**    | **3.48**   | **7.68**    |

7 Related Work

Layer normalization [1] is a useful technique to train neural networks but its mechanism has been unclear essentially [34]. Transformer, that is the standard architecture for various tasks, also contains layer normalizations. The original Transformer architecture adopted the Post-LN configuration [28]. On the other hand, recent Transformer implementations adopt Pre-LN configurations [11, 29, 18, 2].

To construct deep Transformers that achieve better performance, recent studies have focused on the behavior of layer normalizations. Wang et al. [32] indicated the difficulty in training deep Transformers with Post-LN due to the vanishing gradient problem, and indicated that Pre-LN enables to stack many layers through machine translation experiments. In addition, they proposed dynamic linear combination of layers (DLCL) that uses the weighted sum of lower layers as an input of a layer for effective deep Transformers. Bapna et al. [3] and Dou et al. [6] also proposed such connection methods to stack many layers. Xiong et al. [33] explored the relation between the warm-up strategy and layer normalizations in Transformers. Through theoretical and empirical analyses, they indicated that Post-LN requires the warm-up strategy to stabilize the training.

Meanwhile, some studies proposed initialization methods to make the training of deep neural networks stable [36, 37, 9]. Zhang et al. [36] proposed the depth-scaled initialization to prevent the vanishing gradient problem in Transformers. Zhang et al. [37] proposed the fixed-update initialization to remove normalizations in neural networks. Inspired by these studies, Huang et al. [9] proposed T-Fixup, that enables to remove both warmup and layer normalizations from Transformers. In addition to the initialization scheme, Wang et al. [31] proposed DeepNorm that uses a weight in a residual connection before layer normalizations to stabilize Post-LN based Transformers. They provided the combination of the initialization scheme and DeepNorm as DeepNet.

Liu et al. [13] is strongly related to our study. They analyzed the training dynamics of Post-LN and Pre-LN Transformers, and claimed that the vanishing gradient is not the direct reason of unstable training.

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\(^6\)https://github.com/pytorch/audio

\(^7\)Wang et al. [30] reported that the improvement was small even if they increased the number of parameters. Thus, we emphasize that B2T connection achieved better WERs on dev-other and test-other although their parameter sizes are (almost) equal to one of Pre-LN.
They assumed that the large variances of outputs from each sub-layer cause the unstable training, and proposed Admin that consists of additional parameters to control the variances. Moreover, this method processes several forward steps for the initialization, and then conducts the actual training. In a nutshell, this method requires additional computational costs. In contrast, we indicated that we can stabilize the training of Post-LN Transformers by only adding a residual connection skipping over layer normalizations that cause the vanishing gradient.

As a comparison with recent methods, we compare our B2T connection with DLCL\(^8\), T-Fixup\(^9\), DeepNet, and Admin\(^10\) on machine translation and abstractive summarization tasks. Although the recent studies conducted comparisons on only machine translation task \([32, 13, 9, 31]\), we conduct the comparison on the summarization for reliable findings. We used the same datasets as Sections 6.1 and 6.2. We prepared 6L-6L and 18L-18L configurations. We used the official implementations except for DeepNet\(^11\). For hyper-parameters we used the same values for each method excluding T-Fixup, and hyper-parameters reported in Huang et al. \([9]\) for T-Fixup to prevent divergence.

Tables 5 and 6 show the results of machine translation and abstractive summarization respectively. Table 5 indicates that B2T connection outperformed others in the averaged BLEU score in both of 6L-6L and 18L-18L configurations. Table 6 indicates that B2T connection also outperformed others in the abstractive summarization tasks. Based on these results, B2T connection can achieved better or comparable performance to previous methods. In addition to the performance, we emphasize that our modification does not require additional computational costs such as DLCL and Admin.

### 8 Conclusion

In this study, we addressed the stability of training Post-LN Transformers. Through theoretical and empirical analyses, we indicated that layer normalizations cause unstable training in stacking many layers. Moreover, we revealed the reason for the different performances of Pre-LN and Post-LN through transformations by each layer. Based on the analyses, we introduced the B2T connection to mitigate the vanishing gradient of Post-LN while maintaining all the advantages of Post-LN.

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\(^8\)https://github.com/wangqiangneu/dlcl

\(^9\)https://github.com/layer6ai-labs/T-Fixup

\(^10\)https://github.com/LiyuanLucasLiu/Transformer-Clinic

\(^11\)The paper on DeepNet was uploaded to arXiv on 1st Mar 2022. The authors described work in progress, and the official implementation is not publicly available yet. However, we selected this method as a comparison with the latest method.
We conducted experiments on various tasks, i.e., machine translation, abstractive summarization, language model, and speech recognition. Our experimental results discovered the following three findings: 1, Post-LN achieves better performance than Pre-LN if Post-LN succeeds in its training. 2, Our proposal, B2T connection, enables successful training of deep Post-LN Transformers in at least 18L-18L and 60L-12L configurations. 3, Post-LN with B2T connection consistently outperforms Pre-LN in all the deep Transformer configurations. In addition, the performance of Post-LN with B2T connection showed comparative or even superior among several related methods proposed recently.

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Table 7: Hyper-parameters used in our experiments.

| Params            | Machine Translation | Abstractive Summarization | Language Model | ASR |
|-------------------|---------------------|---------------------------|----------------|-----|
| Hidden dim size   | 512                 | 512                       | 1024           | 512 |
| FFN dim size      | 2048                | 2048                      | 4096           | 2048|
| Attention heads   | 8                   | 8                         | 8              | 8   |
| Learning rate     | 0.001               | 0.001                     | 0.001          | 0.001|
| Scheduler         | inverse sqrt        | inverse sqrt              | inverse sqrt   | inverse sqrt |
| Adam β            | (0.9, 0.98)         | (0.9, 0.98)               | (0.9, 0.98)    | (0.9, 0.98) |
| Warmup updates    | 4k                  | 4k                        | 2k             | 4k  |
| Max updates       | 50k                 | 50k                       | 50k            | 150k|
| Max tokens / GPU  | 3584                | 3584                      | 1024           | 40k |

Table 8: The number of GPUs and computational time to construct one model in our experiments.

|                      | Machine Translation | Abstractive Summarization | Language Model | ASR |
|----------------------|---------------------|---------------------------|----------------|-----|
|                      | 6L-6L               | 18L-18L                   | 6L-6L          | 18L-18L |
| #GPU                 | 128                 | 128                       | 64             | 144  |
| Time (hour)          | 5                   | 13                        | 4              | 17   |

Figure 7: Gradient norms of each part in the (a) 1st decoder and (b) 9th decoder for the 18L-18L Post-LN Transformer encoder-decoder on WMT English-to-German translation training data.

A Details of Experimental Settings

A.1 Hyper-parameters

As described in Section 6, our hyper-parameters follow previous studies. Table 7 shows hyper-parameters for each experiment. For fair comparisons, we used the same hyper-parameters for each method except for T-Fixup. For T-Fixup, we used hyper-parameters reported in Huang et al. [9] to prevent divergence.

A.2 Computational Resources

We mainly used Tesla P100 GPUs for our experiments. Table 8 shows the number of GPUs and computational time to construct one model in our experiments.
B Supplementary of Gradient Norms of Each Location

For gradient norms of each part in a layer, we also check 1st and 9th decoders in addition to the 18th decoder in the 18L-18L Post-LN Transformer encoder-decoder as in Figure 4. Figure 7 shows the gradient norms of each part. This figure also indicates that the gradient norms drastically decrease through layer normalizations in the same as in the 18th decoder (Figure 4). Thus, the vanishing gradient problem in Post-LN Transformers is probably caused by layer normalizations.

C Stacking the Total Number of Layers to 100

We stacked the total number of layers to 72, i.e. 60L-12L Transformers, in the experiments in Section 6.1. In this section, we investigate the performance when we stack more total layers. Figure 8 shows the best NLL values on validation data in the WMT English-to-German dataset when we varied the total number of layers. In this experiments, we divided the total number of layers between the encoder and decoder equally. For example, 100 in the horizontal axis represents 50L-50L Transformers. We prepared 6L-6L, 12L-12L, 18L-18L, 36L-36L, and 50L-50L Transformers.

Figure 8 indicates that our findings are valid if we stack the total number of layers to 100. For Post-LN Transformers, the training of the 12L-12L configuration succeeded but the NLL values on validation data diverged in stacking 18L-18L or more layers. For B2T connection, its training succeeded and it outperforms Pre-LN Transformers in all configurations. These results are consistent with results in Section 6.

On the other hand, Figure 8 indicates that stacking more layers than the 18L-18L configuration did not improve the performance because the overfitting occurred. Figure 9 shows that NLL on validation data in the 36L-36L configuration. As shown in this figure, NLL began to increase from the middle of training. If we increase the amount of training data, we can prevent this overfitting. However, increasing the training data size probably requires much more computational resources even though we have to prepare a large amount of computational resources to train deep Transformers.

D B2T Connection without Layer Normalization

In addition to B2T connection, we also consider a modification to prevent the vanishing gradient problem. Since layer normalizations drastically decrease gradients as described in Section 3, removing layer normalizations might provide stable gradients during back-propagation. However, the values in the forward pass exponentially grow if we remove layer normalizations. Thus, we introduce weights that prevent the explosive increase in the forward pass while mitigate decreasing gradients in back-propagation as an alternative of the layer normalization. In using the alternative, we replace...
Table 9: BLEU scores of our modifications on WMT newstest2010-2016 and their averages.

| Method                  | 2010  | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | Average |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|---------|
| Enc-Dec: 6L-6L          |       |       |       |       |       |       |       |         |
| B2T connection          | 24.12 | 21.93 | 22.29 | 26.31 | 26.84 | 29.48 | 34.73 | 26.53   |
| + w/o LN                | 24.17 | 22.07 | 22.24 | 25.83 | 26.96 | 29.70 | 34.42 | 26.48   |
| Enc-Dec: 18L-18L        |       |       |       |       |       |       |       |         |
| B2T connection          | 24.75 | 22.88 | 23.09 | 27.12 | 28.82 | 30.99 | 33.64 | 27.33   |
| + w/o LN                | 24.47 | 22.37 | 22.58 | 27.04 | 28.34 | 30.49 | 34.38 | 27.10   |

Equation (5) with the following equation:

\[ \alpha x_{\text{inp}} + \beta (x_{\text{ffn}} + \text{FFN}(x_{\text{ffn}})). \]  

(6)

Through several experiments\(^\text{12}\), we found that the following values are suitable as \(\alpha, \beta\):

\[
\alpha = \min \left( \frac{N}{12}, N^{-0.15} \right),
\]  

(7)

\[
\beta = d^{-0.2},
\]  

(8)

where \(N\) is the number of layers and \(d\) is the dimension size of input vectors \(x_{\text{inp}}\). For example, we assign 60 and 12 to \(N\) of the encoder and decoder in the 60L-12L configuration. Therefore, more layers we stack, larger value \(\alpha\) is during small \(N\) (until \(N = 9\) in detail), and then \(\alpha\) decreases. In short, \(\alpha\) prevents the explosive increase in the forward pass when we stack many layers. For \(\beta\), it decreases in accordance with the increase of the dimension size \(d\), and thus it prevents the explosive increase when we use a large dimension size. When we use Equation (6), we can remove all layer normalizations in internal layers. Thus, we solve the vanishing gradient problem due to layer normalizations.

Tables 9 and 10 shows results of B2T connection without layer normalizations (w/o LN) on machine translation and summarization tasks. These tables indicate that B2T connection without layer normalizations achieved comparable scores to B2T connection with layer normalizations. However, since results of B2T connection without layer normalizations are slightly worse than ones of B2T connection, we recommend using B2T connection with layer normalizations basically.

Table 10: F-1 based ROUGE scores of our modifications on headline generation.

| Method                  | R-1   | R-2   | R-L   |
|-------------------------|-------|-------|-------|
| Enc-Dec: 6L-6L          |       |       |       |
| B2T connection          | 38.43 | 19.37 | 35.72 |
| + w/o LN                | 38.63 | 19.75 | 35.77 |
| Enc-Dec: 18L-18L        |       |       |       |
| B2T connection          | 39.61 | 20.28 | 36.66 |
| + w/o LN                | 39.29 | 20.01 | 36.48 |

E  Ethical Concerns on Data and Codes

The datasets used in our experiments are publicly available. LibriSpeech [19] is derived from read audiobooks. Other datasets are mainly constructed from newswire texts and Wikipedia. Thus, in our understanding, our used datasets don’t contain personally identifiable information and offensive contents.

For licenses, DLCL, Admin, and T-Fixup are licensed under BSD, Apache 2.0, and MIT licenses, respectively. For other methods, we used fairseq, which is licensed under the MIT license, as a base toolkit.

F  Limitations and Potential Negative Societal Impacts

In this paper, we indicated the vanishing gradient problem makes the training of deep Post-LN Transformers unstable. We proposed the B2T connection to mitigate the vanishing gradient problem

\(^{12}\)We can tune \(\alpha, \beta\) to improve the performance for each task but we introduce values that are useful for various tasks.
due to layer normalizations. Section 6 and Appendix C show that the B2T connection enables successful training of deep Post-LN Transformers in at least 18L-18L, 60L-12L, and 50L-50L configurations. However, the proposed B2T connection does not perfectly prevent the vanishing gradient, as shown in Figure 3. Thus, the vanishing gradient might harm the training in extremely deep Transformers even if we use the B2T connection. In such cases, we may be able to train models more stably by combining a parameter initialization approach such as depth-scaled initialization [36].

The proposed method helps to construct deep Transformers. As discussed in Strubell et al. [25] and Schwartz et al. [22], such deep neural networks require substantial energy consumption. Thus, we also have to explore an efficient way while maintaining good performance in addition to the direction to improve the performance by stacking many layers.