Learning Light-Weight Translation Models from Deep Transformer

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Abstract
Recently, deep models have shown tremendous improvements in neural machine translation (NMT). However, systems of this kind are computationally expensive and memory intensive. In this paper, we take a natural step towards learning strong but light-weight NMT systems. We proposed a novel group-permutation based knowledge distillation approach to compressing the deep Transformer model into a shallow model. The experimental results on several benchmarks validate the effectiveness of our method. Our compressed model is 8× shallower than the deep model, with almost no loss in BLEU. To further enhance the teacher model, we present a Skipping Sub-Layer method to randomly omit sub-layers to introduce perturbation into training, which achieves a BLEU score of 30.63 on English-German newstest2014. The code is publicly available at https://github.com/libei/neu/GPKD.

Introduction
Neural machine translation (NMT) has advanced significantly in recent years (Bahdanau, Cho, and Bengio 2015). In particular, the Transformer model has become popular for its well-designed architecture and the ability to capture the dependency among positions over the entire sequence (Vaswani et al. 2017). Early systems of this kind stack 4-8 layers on both the encoder and decoder sides (Wu et al. 2016; Gehring et al. 2017), and the improvement often comes from the use of wider networks (a.k.a., Transformer-Big). More recently, researchers try to explore deeper models for Transformer. Encouraging results appeared in architecture improvements by creating direct pass from the low-level encoder layers to the decoder (Bapna et al. 2018; Wang et al. 2019; Wei et al. 2020; Wu et al. 2019b; Li et al. 2019), and proper initialization strategies (Zhang, Titov, and Sennrich 2019; Xu et al. 2020; Liu et al. 2020; Huang et al. 2020).

Despite promising improvements, problems still remain in deep NMT. Deep Transformer stacked by dozens of encoder layers always have a large number of parameters, which are computationally expensive and memory intensive. For example, a 48-layer Transformer is 3× larger than a 6-layer system and 1.5× slower for inference. It is difficult to deploy such models on resource-restricted devices, such as mobile phones. Therefore, it is crucial to compress such heavy systems into light-weight ones while keeping their performance.

Knowledge distillation is a promising method to address the issue. Although several studies (Sun et al. 2019; Jiao et al. 2020) have attempted to compress the 12-layer BERT model through knowledge distillation, effectively compressing extremely deep Transformer NMT systems is still an open question in the MT community. In addition, these methods leverage sophisticated layer-wise distillation loss functions to minimize the distance between the teacher and the student models, which requires huge memory consumption and enormous training cost.

In this paper, we investigate simple and efficient compression strategies for deep Transformer. We propose a novel Transformer compression approach (named as group-permutation based knowledge distillation method (GPKD)) to transfer the knowledge from an extremely deep teacher model into a shallower student model. We disturb the computation order among each layer group during the teacher training phase, which is easy to implement and memory friendly. Moreover, to further enhance the performance of the teacher network, we introduce a vertical “dropout” (named as skipping sub-layer method) into training by randomly omitting sub-layers to prevent co-adaptations of the over-parameterized teacher network. Although similar technique has been discussed in Fan, Grave, and Joulin (2020)’s work, we believe that the finding here is complementary to theirs. Both GPKD and regularization training methods can be well incorporated into the teacher training process, which is essential for obtaining a strong but light-weight student model.

We ran experiments on the WMT16 English-German, NIST OpenMT12 Chinese-English and WMT19 Chinese-English translation tasks. The GPKD method compressed a 48-layer Transformer into a 6-layer system with almost no loss in BLEU. It outperformed the baseline with the same depth by +2.46 BLEU points. Through skipping sub-layer method, the teacher network achieved a BLEU score of 30.63 BLEU on the newstest2014 English-German task, and the student obtains additional improvements of 0.50 BLEU points.

Compressio of Deep Transformer
In this section, we first introduce the formulation of knowledge distillation (KD), then present the group-permutation...
based knowledge distillation (GPKD) approach to compressing deep Transformer.

Knowledge Distillation

The purpose of KD is to transfer knowledge from a complex teacher network to a light-weight student network by encouraging the student network reproducing the performance of the teacher network. Let $F^T(x, y)$ and $F^S(x, y)$ represent the predictions of the teacher network and the student network, respectively. Then KD can be formulated as follows:

$$L_{KD} = \sum_{x \in X, y \in Y} L(F^T(x, y), F^S(x, y))$$

(1)

where $L(\cdot)$ is a loss function to evaluate the distance between $F^T(x, y)$ and $F^S(x, y)$. $x$ and $y$ represent the source inputs and target inputs, respectively. $(X, Y)$ denotes the whole training dataset. The objective can be seen as minimizing the loss function to bridge the gap between the student and its teacher.

To advance the student model, a promising method is to learn from the intermediate layer representations of the teacher network via additional loss functions (Sun et al. 2019; Jiao et al. 2020). However, the additional loss functions require large memory footprint due to the logits computation of both the teacher and student networks in each mini-batch training phase. This is quite challenging when the teacher is extremely deep. Alternatively, we choose sequence-level knowledge distillation (SKD), proposed in Kim and Rush (2016)’s work to simplify the training procedure. Through their results, SKD achieves comparable or even higher translation performance than word-level KD method. Concretely, SKD uses the translation results of the teacher network as the gold instead of the ground truth. In this work, we build our student systems upon SKD method.

Group-Permutation Based Knowledge Distillation

Through preliminary experimental results, the student network trained with the SKD data still significantly underperforms its teacher. A possible explanation is directly shrinking the encoder depth is harmful to the translation performance. To further bridge the gap between the teacher network and the student work, we propose a group-permutation based knowledge distillation method, including three stages: (i) group-permutation training strategy which rectifies the information flow of the teacher network during training phase. (ii) generate the SKD data through the teacher network. (iii) train the student network with the SKD data. Instead of randomly initializing the parameters of the student network, we selected layers from the teacher network to form the student network, which provides a better initialization. Figure 1 exhibits the whole training process.

Group-Permutation Training  Assuming that the teacher model has $N$ Transformer layers, we aim to extract $M$ layers to form a student model. This can be characterized as learning the mapping between $layer_m$ and $layer_n$, where $m \in \{1, 2, ..., M\}$ and $n = N/M \times m$. To achieve this goal, the stacking layers are first divided into $M$ groups and every adjacent $h = N/M$ layers form a group. The core idea of the proposed method is to make the selected single layer mimic the behavior of its group output. Instead of employing additional loss functions to reduce the distance of the intermediate layer representations between the student network and the teacher network, we simply disturbing the computation order in each group when training the teacher network.

In each mini-batch of training, we randomly disturb the order of the layers in each group. Suppose that $G_i = \{L_1, L_2, L_3\}$ is the set of intermediate layers in each group. The left part of Figure 1 shows the computation order of the layers during the teacher training phase. Note
that each group is independent with others in ordering the layers. In this work, we sample the layer order uniformly from all the permutation choices.

**Generating SKD Data**  As shown in Stage 2 (the top right part in Figure [1]), given the training dataset \( \{X, Y\} \), the teacher network translates the source inputs into the target sentences \( Z \). Then the SKD data is the collection of \( \{X, Z\} \).

**Student Training**  After obtaining the teacher network and the SKD data, we begin optimizing the student network with the supervision of the teacher. As illustrated in Stage 1, each single layer imitates the logits of its group output and every layer in each group behave similar with each other. Then we randomly choose one layer from each group to form a “new” encoder which the encoder depth is reduced from \( N \) to \( M \). It can be regarded as the student model with fewer layers. The compression rate is controlled by the hyper-parameter \( h \). One can compress a 48-layer teacher into a 6-layer network by setting \( h = 8 \), or progressively achieve this goal with \( h = 2 \) for three times of compression.

**The DESDAR Architecture**

The GPDKD method also fits into the decoder. Hence we design a heterogeneous NMT model consisting of a deep encoder and a shallow decoder, abbreviated as (DESDAR). Such an architecture can enjoy high translation quality due to the deep encoder and fast inference due to the light decoder. Similar findings were observed in previous work (Zhang, Titov, and Sennrich 2019; Xiao et al. 2019), which could speed up the Transformer inference by simplifying the decoder architecture. This is due to the fact that the heavy use of dot-product attention in the decoder and the nature of auto-regressive decoding slows down the system.

Moreover, it offers a way of balancing the translation quality and the inference. This is promising for industrial applications. For example, one can maximize the speedup by using one decoder layer or two, or can yield further BLEU improvements by enlarging the decoder depth. The experimental results in the following sections show the effectiveness of the DESDAR architecture.

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1For a 3-layer group, the computation order includes \( \{L_1, L_2, L_3\}, \{L_1, L_3, L_2\}, \{L_2, L_1, L_3\}, \{L_2, L_3, L_1\}, \{L_3, L_1, L_2\} \) and \( \{L_3, L_2, L_1\} \).
In addition, Greff, Srivastava, and Schmidhuber (2017) have shown that the lower-level sub-layers of a deep neural network provide the core representation of the input and the subsequent sub-layers refine that representation. Therefore, it is natural to skip fewer sub-layers if they are close to the input, instead of using the same dropping rate for each single layer in Fan, Grave, and Joulin (2020). To this end, we design a method that makes the lower-level sub-layers seldom to be dropped. Let \( L \) be the number of layers of the stack, and \( l \) be the current sub-layer. Then, we define \( M \) as

\[
M = \begin{cases} 
0, & P \leq p_l \\
1, & P > p_l 
\end{cases}
\] (4)

where

\[
p_l = \frac{l}{2L} \cdot \phi, \quad \text{for } 1 \leq l \leq 2L
\] (5)

In this model, \( \phi \) is a hyper-parameter that is set to 0.4 in our experiments. \( p_l \) is the rate of omitting the sub-layer. For sub-layer \( l \), we first draw a variable \( P \) from the uniform distribution in \([0, 1] \). Then, \( M \) is set to 1 if \( P > p_l \), and 0 otherwise. Thus the lower-level sub-layers are more likely to survive.

Note that the Skipping Sub-Layer method is doing something like sampling a sub-network from a full network. For a model with \( 2L \) sub-layers, it encodes \( 2^{2L} \) sub-networks and each configuration of sub-layer omission represents a sub-network. These sub-models are learned efficiently because they share the parameters. For inference, all these sub-models behave like an ensemble model. Following the work in Hinton et al. (2012), we rescale the output representation of each sub-layer by the survival rate \( 1 - p_l \), like this:

\[
x_{t+1} = (1 - p_l) \cdot \text{F}(\text{LN}(x_t)) + x_t
\] (6)

Factor \( 1 - p_l \) is used to scale-down the output of the sub-layer, so the expected output of the sub-layer is the same as the actual output at test time. Then, the final model can make a more accurate prediction by averaging the predictions from \( 2^{2L} \) sub-models.

**Two-stage Training**

Our Skipping Sub-Layer method is straightforwardly applicable to the training phase of Transformer. However, we found in our preliminary experiments that the learned model even underperformed the baseline if we introduced sub-layer omission into training from the beginning. This might be due to the fact that deep Transformer is complex and the training is fragile to the perturbation if the model does not get to the smoothed region of the error surface.

Here, we instead adopt a two-stage training method to learn the deep Transformer model with omitting sub-layers. First, we train the model as usual but early stop it when the model converges on the validation set. Then, we apply our Skipping Sub-Layer method to the model and continue training until the model converges again. As is shown in Table 4, the two-stage training is helpful for making better use of random sub-layer omission and producing better results. To our knowledge, we are the first to emphasize the importance of the two-stage training in building deep Transformer with omitting layers or sub-layers.

**Experiments**

We conducted experiments on the WMT’16 English-German, NIST’12 Chinese-English and WMT19’ Chinese-English tasks.

**Experimental Setups**

The bilingual and evaluation data mainly came from three sources:

- **WMT’16 English-German (En-De).** We used the same datasets as in Vaswani et al. (2017), Wu et al. (2019), Wang et al. (2019). They consisted of approximately 4.5M tokenized sentence pairs. All sentences were segmented into sequences of sub-word units (Sennrich, Haddow, and Birch 2016) with 32K merge operations using a vocabulary shared by the source and target sides. newstest2016 and newstest2014 was the validation and test data, respectively.

- **NIST’12 Chinese-English (NIST Zh-En).** We randomly extracted nearly 1.9M bilingual corpus from NIST’12 OpenMT+ MT06 was the validation set and the concatenation of MT04 and MT08 was the test set.

- **WMT’19 Chinese-English (WMT Zh-En).** For more convincing results, we also experimented on a larger dataset extracted from the mixture of the CMT and UN corpora, provided by Wang et al. (2019). We selected newstest2017 as the validation data and reported the BLEU scores on newstest2018 and newstest2019.

We adopted the compound split strategy for En-De, which was a common post-processing step used in previous work (Vaswani et al. 2017, Wang et al. 2019, Wu et al. 2019). For Zh-En tasks, all the sentences were segmented by the tool provided within Niutrans (Xiao et al. 2012). Translation quality was measured by case-sensitive tokenized BLEU for En-De task, and case-insensitive tokenized BLEU for NIST Zh-En task. The BLEU script was multi-bleu.perl. We also reported the sacrebleu-results on the En-De and the WMT Zh-En tasks, respectively.

For training, we used Adam optimizer (Kingma and Ba 2015), and followed the hyper-parameters used in Wang et al. (2019). As suggested in Shaw, Uszkoreit, and Vaswani (2018), we incorporated the relative position representation into the self-attention mechanism to enhance the positional information. This is quite crucial when building extremely deep Transformer. Then, we batched sentence pairs by approximate length, and limited input/output tokens per batch to 4,096/GPU and updated the parameters every two steps. The hidden size of Base and Deep models was 512, and 1024 for

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3 There are \( 2L \) sub-layers for \( L \) layers.

4 BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.2.12
The results of the GPR method applied on En-De and Zh-En tasks. We set \( h = 4 \) and \( h = 8 \) to compress the 24-layer and 48-layer systems, respectively. RPR denotes the Transformer incorporating by relative positional information.

Table 1: The results of the GPR method applied on En-De and Zh-En tasks. Table 1 shows the results when applying the GPKD method to the encoder side. Deep Transformer systems outperform the shallow baselines by a large margin, but the model capacities are 2 or 3 times larger. And 6-layer models trained through SKD outperform the shallow baselines by 0.63-1.39 BLEU scores, but there is still a nonnegligible gap between them and their deep teachers. As we expect, our GPKD method can enable the baselines to perform similarly with the deep teacher systems, and outperforms SKD by 0.41-1.10 BLEU scores on three benchmarks. Note that, although the compressed systems are 4 or 8 × shallower, they only underperform the deep baselines by a small margin. Similar phenomenon is observed when switching to a wide network, that 6-layer RPR-Big systems match with its shallow baselines by a wide network, that 6-layer RPR-Big systems match with its

Big-RPR-12L 12-6 286M 29.91 - 332M 54.19 56.89 49.29 53.45 - 335M 27.00 27.50 28.70 27.73 -
Big-RPR-6L 6-6 211M 29.39 - 256M 53.88 56.55 49.16 53.35 - 258M 26.50 27.00 28.30 27.26 -
+SKD
+GPKD

Big-RPR-6L 6-6 211M 29.21 ref 256M 52.80 55.57 47.54 51.97 ref 258M 26.50 27.00 28.30 27.26 -
+GPKD

Figure 4: The training loss of applying the GPKD (blue) and SKD (red) methods on the WMT En-De, NIST Zh-En tasks, respectively.

Figure 5: BLEU scores [%] and translation speed [tokens/sec] against decoder depth on the En-De task.

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Figure 5 plots the BLEU scores [%] and translation speeds [tokens/sec] on the WMT En-De task.

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Experimental Results

The Effect of GPKD Method We successfully trained 24-layer/48-layer Transformer-Deep systems and 12-layer Transformer-Big systems incorporating the relative position representation (RPR) on three tasks. Table 1 shows the results when applying the GPKD method to the encoder side. Deep Transformer systems outperform the shallow baselines by a large margin, but the model capacities are 2 or 3 times larger. And 6-layer models trained through SKD outperform the shallow baselines by 0.63-1.39 BLEU scores, but there is still a nonnegligible gap between them and their deep teachers. As we expect, our GPKD method can enable the baselines to perform similarly with the deep teacher systems, and outperforms SKD by 0.41-1.10 BLEU scores on three benchmarks. Note that, although the compressed systems are 4 or 8 × shallower, they only underperform the deep baselines by a small margin. Similar phenomenon is observed when switching to a wide network, that 6-layer RPR-Big systems match with its teacher with almost no loss in BLEU, indicating the GPKD method is applicable in different model capacities. Moreover, Figure 5 plots the training loss of SKD and GPKD methods. We observe that GPKD obtains a much lower training loss than SKD on the WMT En-De and NIST Zh-En tasks, which further verifies the effectiveness of GPKD.

Figure 5 plots the BLEU scores [%] and translation speeds [tokens/sec] on the WMT En-De task.
improvement is observed when we switch to a strong Deep-RPR-48L model.

Table 2 exhibits several DESDAR systems with different settings. DESDAR 48-3 achieves comparable performance with the 48-6 baseline, but speeds up the inference by \(1.52 \times\). However, a shallower decoder makes a great decrease compact on BLEU, though it obtains a \(1.97 \times\) speedup. Through the SKD method, the DESDAR 48-1 system can even outperform the RPR-Base by 2.10 BLEU scores and speeds up the inference by 2.18. Moreover, our GPKD method can enable the DESDAR 48-1 system to perform similarly with the deep baseline, outperforms SKD by nearly +0.31 BLEU scores. Interestingly, after knowledge distillation, the beam search seems like to be not important for the DESDAR systems, which can achieve a 3.2 \(\times\) speedup with no performance sacrifice with the greedy search. This may be due to the fact that the student network learns the soft distribution generated by the teacher network, which has already limited the search space to the max beam margin (Kim and Rush 2016).

The Effect of Skipping Sub-Layer Method The red curves in Figure 6 show that the 48-layer RPR model converges quickly on three tasks, and the validation PPL goes up later. At the same time, the training PPL is still going down (see Figure 3). As we expect, the Skipping Sub-Layer method reduces the overfitting problem and thus achieves a lower PPL (3.39) on the validation set. The similar phenomena are observed on the other two tasks. In addition, the last row of Table 3 shows that the strong Deep-RPR model trained through the Skipping Sub-Layer approach obtains +0.40-0.72 BLEU improvements on three benchmarks.

Comparison with Related Methods Table 4 exhibits the BLEU scores and the validation PPL of several related systems trained through two optimization ways. Interestingly, all these systems underperform the deep baseline when we trained them from scratch. This is reasonable because the skipped connections make disturbances to the optimization when the model is still in the early stage of training, and the parameters are in the non-smoothed region of the loss function. The phenomena here verify the importance of the two-stage training strategy.

On the other hand, our Skipping Sub-Layer method and Stochastic Layers (Pham et al. 2019) trained by the finetuning schema both beat the strong baseline. This confirms that dropping sub-layers randomly is helpful for reducing the overfitting when we train deep Transformer models. However, the deep models trained with LayerDrop method cannot gain more benefit and we attribute this to the fact that LayerDrop uses the same probability to omit sub-layers throughout the stack. This is harmful to the performance because omitting many lower-level layers reduces the representation ability of the deep model significantly (Huang et al. 2016; Greff, Srivastava, and Schmidhuber 2017).

Ablation Study Table 5 shows the ablation study of omitting different components, including randomly skipping the feed-forward (FFN) sub-layer, the self-attention (SAN) sub-layer, all sub-layers and the whole layer. As shown in Table 5 the performance of the single checkpoint and the checkpoint averaging model is reported. First, we can see that all these systems obtain lower validation PPLs and higher BLEU scores for the single model than the baseline. And our default
strategy beats the baseline by a larger margin in terms of both PPL and BLEU. There is no significant difference when we skip FFN or SAN only, and they all surpass the system that randomly omits the entire layer. This is mainly due to the fact that we can sample more diverse sub-networks in training. Note that the results here were mainly experimented on deep Transformer, rather than a shallow but wide counterpart reported in Fan, Grave, and Joulin (2020), which is complementary to the community.

The Overall Results  Table 6 shows the results of incorporating both the GPKD and Skipping Sub-Layer approaches. Note that, these systems are obtained upon the strong Deep-RPR-48L system. As we can see that a 6-6 system achieves comparable performance with the state-of-the-art, though the parameter is only 4 times less than theirs. In addition, it beats the shallow baseline by +2.56 BLEU scores at the same scale. This offers a way of selecting the proper system considering the trade-off between the translation performance and the model storage. For example, one can choose GPKD 6-3 system with satisfactory performance and fast inference speed, or GPKD 24-3 system with both high translation quality and competitive inference speed. Another interesting finding here is that shrinking the decoder depth may hurt the BLEU score when the encoder is not strong enough.

### Related Work

Deep neural networks play an important role in the resurgence of deep learning. It has been observed that increasing the depth of neural networks can drastically improve the performance of convolutional neural network-based systems (He et al. 2016). The machine translation communities follow this trend. For example, Bapna et al. (2018) and Wang et al. (2019) shortened the path from upper-level layers to lower-level layers so as to avoid gradient vanishing/exploding. Wu et al. (2019b) designed a two-stage approach with three specially designed components to build a 6-layer Transformer-Big system. Zhang, Titov, and Sennrich (2019) successfully trained a deep Post-Norm Transformer with carefully designed layer-wise initialization strategy. More attempts on initialization strategy emerged recently (Xu et al. 2020; Liu et al. 2020; Huang et al. 2020). Perhaps the most relevant work with us is Fan, Grave, and Joulin (2020)’s work. They employed Layer-Drop mechanism to train a 12-6 Transformer-Big and pruned sub-networks during inference without finetuning. Here we address a similar issue in deep Transformer, which has not been discussed yet. Beyond this, we present a new training strategy that can boost the deep system in a robust manner.

For model compression, there are many successful methods, such as quantization (Gong et al. 2014), knowledge distillation (KD) (Kim and Rush 2016), weight pruning (Han et al. 2015) and efficient Transformer architecture (Mehta et al. 2020a,b). For Transformer models, Sun et al. (2019) proposed a novel approach to compressing a large BERT model into a shallow one via the Patient Knowledge Distillation method. Jiao et al. (2020) achieved a better compression rate by richer supervision signals between the teacher network and the student network. However, these methods are not straightforwardly applicable to machine translation, they need simultaneously compute the logits of each layer in both the teacher and student networks, which consumes large GPU memory. In this work, we propose the GPKD method to compress an extremely deep model into a baseline-like system, without any additional computation cost.

### Conclusions

Our contributions in this work are two folds. (i) We propose a GPKD method to compress the deep model into a shallower one with minor performance sacrifice, which outperforms the SKD method by a large margin. (ii) The proposed Skipping Sub-Layer method reduces the overfitting problem when training extremely deep encoder systems by randomly omitting sub-layers during training phase. The experimental results on three widely-used benchmarks validate the effectiveness of the proposed methods. After the incorporating of two methods, the strong but light-weight student models show competitive performance which is application friendly.
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