Fractional Skipping: Towards Finer-Grained Dynamic CNN Inference

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Abstract
While increasingly deep networks are still in general desired for achieving state-of-the-art performance, for many specific inputs a simpler network might already suffice. Existing works exploited this observation by learning to skip convolutional layers in an input-dependent manner. However, we argue their binary decision scheme, i.e., either fully executing or completely bypassing one layer for a specific input, can be enhanced by introducing finer-grained, softer decisions. We therefore propose a Dynamic Fractional Skipping (DFS) framework. The core idea of DFS is to hypothesize layer-wise quantization (to different bitwidths) as intermediate “soft” choices to be made between fully utilizing and skipping a layer. For each input, DFS dynamically assigns a bitwidth to both weights and activations of each layer, where fully executing and skipping could be viewed as two “extremes” (i.e., full bitwidth and zero bitwidth). In this way, DFS can fractionally exploit a layer's expressive power during input-adaptive inference, enabling finer-grained accuracy-computational cost trade-offs. It presents a unified view to link input-adaptive layer skipping and input-adaptive hybrid quantization. Extensive experimental results demonstrate the superior tradeoff between computational cost and model expressive power (accuracy) achieved by DFS. More visualizations also indicate a smooth and consistent transition in the DFS behaviors, especially the learned choices between layer skipping and different quantizations when the total computational budgets vary, validating our hypothesis that layer quantization could be viewed as intermediate variants of layer skipping. Our source code and supplementary material are available at [https://github.com/Torment123/DFS](https://github.com/Torment123/DFS).

1 Introduction

Although convolutional neural networks (CNNs) have shown state-of-the-art performance in many visual perception tasks (Krizhevsky, Sutskever, and Hinton 2012; Taigman et al. 2014), the high computational cost has limited their application in resource-constrained platforms such as drones, self-driving cars, wearables and many more. The growing demand of unleashing the intelligent power of CNN into these devices has posed unique challenges in developing algorithms that enable more computationally efficient inference of CNNs. Earlier resource-efficient implementations assumed that CNNs are first compressed before being deployed, thus being “static” and unable to adjust their own complexity at inference. Later on, a series of works (Figurnov et al. 2017; Wang et al. 2018a) pointed out that the continuous improvements in accuracy, while significant, are marginal compared to the growth in model complexity. This implies that computationally intensive models may only be necessary to classify a handful of difficult inputs correctly, and they might become “wasteful” for many simple inputs.

Motivated by this observation, several works have tackled the problem of input-dependent adaptive inference, by dynamically bypassing unnecessary computations on the layer-level, i.e., selectively executing a subset of layers (Figurnov et al. 2017; Wu et al. 2018b). However, the binary decision scheme of either executing a layer fully, or skipping it completely, leaves no room for intermediate options. We conjecture that finer-grained dynamic execution options can contribute to better calibrating the inference accuracy of CNNs w.r.t. the complexity consumed.

On a separate note, CNN quantization appears to exploit model redundancy at the finest level - by reducing the bitwidth of the element-level numerical representations of weights and activations. Earlier works (Han, Mao, and Dally 2015; Zhu et al. 2016) presented to quantize all layer-wise weights and activations to the same low bitwidth, yet ignored the fact that different layers can have different importance. The latest work (Wang et al. 2019) learned to assign different bitwidths for each layer. However, no work has yet discussed an input-adaptive, layer-wise bitwidth allocation at the inference time, not to mention linking between quantization with dynamic inference.

In an effort to enable finer-grained dynamic inference beyond “binary” layer skipping, we propose a Dynamic Fractional Skipping (DFS) framework, that treats layer quantization (to different bitwidths) as softer, intermediate versions of layer-wise skipping. Below are our contributions:

- We propose to link two efficient CNN inference mindsets: dynamic layer skipping and static quantization, and show that they can be unified into one framework. Specifically, DFS considers a quantized layer to be a “fractionally executed” layer, in contrast to either a fully executed (selected) or non-executed (bypassed) layer in the existing layer skipping regime. In this way, DFS can more flexibly calibrate the trade-off between the inference accuracy and...
the total computational costs.

- We introduce input-adaptive quantization at inference for the first time. Based on each input, DFS learns to dynamically assign different bitwidths to both weights and activations of different layers, using a two-step training procedure. That is in contrast to [Wang et al. 2019] that learns layer-wise bit allocation during training, which is then fixed for inference regardless of inputs. The existing layer skipping could be viewed as DFS’s coarse-grained version, i.e., allowing only to select between full bits (executing without quantization) and zero bit (bypassing).

- We conduct extensive experiments to illustrate that DFS strikes a better computational cost and inference accuracy balance, compared to dynamic layer skipping and other relevant competitors. Moreover, we visualize the skipping behaviors of DFS when varying the total inference computations in a controlled way, and observe a smooth transition from selecting, to quantizing, and to bypassing layers. The observation empirically supports our conjecture that layer quantization can be viewed as soft and intermediate variants of layer skipping.

2 Related Works

Model Compression. Model compression has been widely studied to speedup CNN inference by reducing model size (Wu et al. 2018a). Existing works focus on pruning unimportant model weights, or quantizing the model into low bitwidths.

Pruning: There has been extensive studies on model pruning in different granularities. (Han, Mao, and Dally 2015) [Han et al. 2015] reduce the redundant parameters by performing element-wise weight pruning. Coarser-grained channel level pruning has been explored in (Yu et al. 2017) [Liu et al. 2017; He, Zhang, and Sun 2017] by enforcing group sparsity. (Wen et al. 2016) exploits parameter redundancy in a multi-grained manner by grouping weights into structured groups during pruning, each with a Lasso regularization. (Xu, Park, and Brick 2018) proposes a hybrid pruning by performing element-wise pruning on top of the filter-wise pruned model. (Kim, Ahn, and Oh 2018) performs multi-grained model pruning by adding explicit objectives for different levels. (Cheng et al. 2017) presents a comprehensive review on pruning techniques. These methods are applied to well-trained networks and do not dynamically adjust the model complexity conditioned on the input.

Network Quantization: Quantizing network weights and activations has been proven to be an effective approach to reduce the memory and computational budgets. Most of the existing works quantize the model to varied bitwidths with a marginal accuracy loss. (Rastegari et al. 2016) binarized each convolution filter into \{-w, +w\}. (Zhou et al. 2016) used one bit for network weights and two bits for activations. (Jacob et al. 2018) made use of 8-bit integers for both weights and activations. With the recent development of hardware design, it becomes possible to use flexible bitwidths for different layers (Wang et al. 2019). (Han, Mao, and Dally 2015) determines the layer-wise bit allocation policy based on domain experts; (Wang et al. 2019) further enhanced the idea by automating the decision process with a reinforcement learning method. These works either empirically find fixed bitwidths or automatically learn fixed layer-wise bit allocation regardless of input, ignoring that the importance of each layer may vary with different inputs. Our proposed DFS models are orthogonal to existing static quantization methods.

Dynamic Inference. While model compression presents “static” solutions, i.e., the compressed models cannot adaptively adjust their complexity at inference, for improving inference efficiency, the recently developed dynamic inference methods offer a different option to execute partial inference, conditioned on input complicity or resource constraints.

Dynamic Channel Selection/Pruning: Since layer skipping only works well in network architectures with residual connections, channel pruning methods have been developed to exploit the redundancy in CNNs at a finer level. (Lin et al. 2017) formulates the channel pruning problem as a Markov decision process, and apply RNN gating network to determine which channel to prune conditioned on the input. GaterNet (Chen et al. 2018) uses a separate network to calculate the channel activation strategy. The slimmable neural network (Yu et al. 2018) trains the network with varied layer widths, and adjust channel number during inference to meet resource budgets. (Teerapittayanon, McDanel, and Kung 2016) adds additional branch classi-
fiers to the backbone CNNs, forcing a large portion of inputs to exit at the branches in order to meet resource demands. (Huang et al. 2017) further boosts the performance of early exiting by aggregating features from different scale for early prediction. The early exiting works have been developed for resource-dependent inference, which is orthogonal to our input-dependent inference, and the two can be combined to yield further resource savings.

3 The Proposed Framework

In resource-constrained platforms, the ideal efficient CNN inference should save as much resource as possible without non-negligible accuracy degradation. This requires the algorithm to maximize the model’s expressive power, while dropping any redundant parts. Existing works like SkipNet exploit the model redundancy on the layer level, the binary decision of either executing a layer fully or skipping it completely makes it impossible to make use of the layer’s representational power in any finer levels. In contrast, CNN quantization exploits the model redundancy in the finest level - by reducing the bitwidth of the numerical representation of weights and activations. Thus, a natural thought is to use bitwidth options to fill in the gap between the binary options of layer skipping, striking an optimal tradeoff between computational cost and accuracy.

We hereby propose a Dynamic Fractional Skipping (DFS) framework that combines the following two schemes into one continuous fine-grained decision spectrum:

- **Input-Dependent Layer Skipping.** On the coarse-grained level, the “executed” option of the layer skip decision is equivalent to the full bitwidth option of layer quantization in the DFS framework, and the “skip” option is equivalent to a zero-bit option of layer quantization.

- **Input-Dependent Network Quantization.** On the fine-grained level, any lower than full bitwidth execution can be viewed as “fractionally” executing a layer, enabling the model to take advantage of the expressive power of the layer in its low bitwidth version.

To our best knowledge, DFS is the first attempt to unify binary layer skipping design and one alternative of its intermediate “soft” variants, i.e., quantization, into one dynamic inference framework. Together they achieve optimal tradeoffs between accuracy and computational usage by skipping layers if possible or executing varied “fractions” of the layers. Meanwhile, state-of-the-art hardware design of CNNs have shown that such DFS schemes are hardware friendly. For example, (Sharma et al. 2018) proposed a bit-flexible CNN accelerator that constitutes an array of bit-level processing elements to dynamically match the bitwidth of each individual layer. With such dedicated accelerators, the proposed DFS’s energy savings would be maximized.

**DFS Overview.** We here introduce how the DFS framework is implemented in ResNet-style models, which has been the most popular backbone CNNs for dynamic inference (Wang et al. 2018a, Wu et al. 2018b). Figure 1 illustrates the operation of our DFS framework. Specifically, for the i-th layer, we let \( F_i \in \mathbb{R}^{s \times s \times m} \) denote its output feature maps and therefore \( F_{i-1} \) as its input ones, where \( m \) denotes the total number of channels and \( s \times s \) denote the feature map size. Also, we employ \( C_k \) to denote the convolutional operation in the i-th layer executed in \( k \) bits (e.g., \( k = 32 \) corresponds to the full bitwidth) and design a gating network \( G_i \) for determining fractional skipping of the i-th layer. Suppose there are a total of \( n \) decision options, including the two binary skipping options (i.e., SkipNet) and a set of varied bitwidth options for quantization, and then \( G_i \) outputs a gating probability vector of length \( n \). The operation of a convolutional layer under the DFS framework can then be formulated as:

\[
F_i = \sum_{k=1}^{n-1} G_k^i C_k^i (F_{i-1}) + G_0^i F_{i-1}
\]

Where \( G_i \) is the gating probability vector of the i-th layer, \( G_k^i \) denotes the value of its \( k \)-th entry, and \( b_k \) represents the bitwidth option corresponding to the \( k \)-th entry. When \( k = 0 \), we let \( G_0^i \) represent the probability of a complete skip.

**Gating Design of DFS.** In the DFS framework, the execution decision of a layer is calculated based on the output of the previous layer. Therefore, the gating network should be able to capture the relevance between consecutive layers in order to make informative decision. As discussed in (Wang et al. 2018a), recurrent neural networks (RNNs) have the advantages of both light weight (due to its parameter sharing design, which accounts for only 0.04% of the computational cost of a residual block) and being able to learn sequential tasks (due to its recurrent structure), thus, we adopt this convention and implement the gating function \( G \) as a Long Short Term Memory (LSTM) network, as depicted in Figure 2. Specifically, suppose there are \( n \) options including the binary skipping options and the intermediate bitwidth options, then the LSTM output will be projected into a skipping probability vector of length \( n \) via softmax function. During inference, the largest element of the vector will be quantized to 1 and selected for execution; during training, the skipping probability will be used for backpropagation, which will be introduced in more detail in the subsection of DFS training.

**Training of DFS.** Objective Function: The learning objective of DFS is to boost the prediction accuracy while min-
We evaluate the training of DFS follows the two-step procedure as described in Section 3. For the first step, we set the initial learning rate as 0.1, and train the gating network with a total of 64000 iterations; the learning rate is reduced by $10 \times$ after the 32000-th iteration, and further reduced by $10 \times$ after the 48000-th iteration. The specified computation budget is set to 100%. The hyperparameters including the momentum, weight decaying factor, and batch size are set to be 0.9, 1e-4, and 128, respectively, and the absolute value of $\alpha$ in Equation (2) is set to 5e-6.

After the first step is finished, we use the resulting LSTM gate as the initialization for the second step, where we jointly train the backbone model and gating network to reach the specified computation budget. Here we use an initial learning rate of 0.01, with pre-specified target $cp$, and all other settings are the same as the first step.

**DPS Performance Evaluation.** We evaluate the proposed DPS against the competitive dynamic inference technique SkipNet (Wang et al. 2018a) and two state-of-the-art static CNN quantization techniques proposed in (Banner et al. 2018) and (Wang et al. 2019).

Comparison with SkipNet (Dynamic Inference Method): In this subsection, we compare the performance of DFS with that of the SkipNet method. Specifically, we compare the performance of DFS on ResNet38 and ResNet74 with that of SkipNet38 and SkipNet74, respectively, on both the CIFAR-10 and CIFAR-100 datasets. We denote the largest vector element will be selected to be executed.

Figure 2: An illustration of the RNN gate used in DFS. The output is a skipping probability vector, where the green arrows denote the layer skip options (skip/keep), and the blue arrows represent the quantization options. During inference, the skip/keep/quantization options corresponding to the parameters will adapt to the new feature statistics. Motivated by this idea, we use a two-step training procedure:

1) Fix the parameters of $\mathcal{A}$ and train the gating network to reach the state of executing all the layers with full bitwidth.

2) With the initialization obtained from the first step, we jointly train $\mathcal{A}$ and the gating network to achieve the targeted computational budget.

The computational cost is controlled via computation percentage ($cp$), which is defined as the ratio between the FLOPs of executed layers and the FLOPs of the full bitwidth model. During training, we dynamically change the sign of $\alpha$ in Equation (2) to stabilize the $cp$ of the model: for each iteration, if the $cp$ of the current batch of samples is above the targeted $cp$, we set $\alpha$ to be positive, encouraging the model to reduce its $cp$ by suppressing the resource loss $E$ in Equation (2); if the $cp$ is below the targeted $cp$, we set $\alpha$ to be negative, encouraging the model to increase its $cp$ by reinforcing $E$. In the end the $cp$ of the model will be stabilized around the targeted $cp$. The absolute value of $\alpha$ is the step size to adjust the $cp$, since we empirically found out that the performance of our model is robust to a wide range of step sizes, we fix the absolute value of $\alpha$. More detailed experiments of the choice of $\alpha$ will be presented in section 4.
DFS-ResNet38x as the models with DFS applied on top of ResNet38x backbone. Experimental results on CIFAR-10 are shown in Figure 3 (vs. ResNet38) and Figure 4 (vs. ResNet74). Specifically, Figures 3-4 show that (1) **given the same computation budget**, DFS-ResNet38/74 consistently achieves a higher prediction accuracy than that of SkipNet38/74 under a wide range of computation percentage (20%-80%), with the largest margin being about 4% (93.61% vs. 89.26%) at the computation percentage of 20%; (2) **given the same or even a higher accuracy**, DFS-ResNet38/74 achieves more than 60% computational saving as compared to SkipNet38/74; (3) interestingly, DFS-ResNet38/74 even achieves better accuracies than the original full bitwidth ResNet38/74. We conjecture that this is because DFS can help in relieving model overfitting thanks to its finer-grained dynamic feature.

Figure 5 (vs. ResNet38) and Figure 6 (vs. ResNet74) show the results on CIFAR-100. We can see that the accuracy improvement (or computational savings) achieved by DFS-ResNet38/74 over SkipNet38/74 is even more pronounced given the same computation percentage (or the same/higher accuracy). For example, as shown in Figure 5 DFS-ResNet38 achieves 8% (68.91% and 60.38%) better prediction accuracy than SkipNet38 under the computation percentage of 20%; and Figure 6 shows that DFS-ResNet74 outperforms SkipNet74 with 6% (70.94% and 65.09%) accuracy when computation percentage is 20%.

The four sets of experimental results above (i.e., Figures 3-6) show that (1) **CNNs with DFS outperform the corresponding SkipNets even at a high computation percentage of 80%** (i.e., small computational savings of 20% over the original ResNet backbones); (2) as the computation percentage decreases from 80% to 20% (corresponding to computational savings from 20% to 80%), the prediction accuracy of CNNs with DFS stays relatively stable (slightly fluctuate within a range of 0.5% while being consistently higher than that of SkipNet under the same computation percentage), whereas the accuracy of SkipNet decreases drastically. These observations validate our conjecture that DFS’s finer-grained dynamic execution options can better calibrate the inference accuracy of CNNs w.r.t. the complexity consumed.

Comparison with Statically Quantized CNNs: In this section, we compare DFS with two state-of-the-art static CNN quantization methods: the scalable network (Banner et al. 2018) and HAQ (Wang et al. 2019), with ResNet38 as the backbone on CIFAR-10. Specifically, for the scalable network (Banner et al. 2018), we train it under a set of bitwidths of (8bit, 10bit, 12bit, 14bit, 16bit, 18bit, 20bit, 22bit); according to HAQ’s official implementation, only the weights are quantized, we control HAQ quantized models’ computation percentage via compression ratio (the ratio between the size of the quantized weights and the full bitwidth weights). The bitwidth allocation of HAQ is shown in the supplementary material, it can be seen that HAQ learns fine-grained quantization options, the smallest difference between two options is 1 bit. Note that (1) DFS is orthogonal to static CNN quantization methods, and thus can be applied on top of quantized models for further reducing CNNs’ required computational cost; and (2) This set of experiments are not
We conduct two sets of experiments to demonstrate how dynamically changing the sign of $\alpha$ as described in section 3 is necessary for reaching the targeted performance. Table 1 compares two training scenarios of DFS-ResNet74 on CIFAR10, DFS-ResNet74-D denotes the case where dynamic changing sign of $\alpha$ is enforced. When the computational saving requirement is mild, the model shows a strong tendency to “fractionally” skip all its layers.

We demonstrate that quantization options are indeed natural candidates as intermediate “fractional” skipping choices. Specifically, we investigate how these decisions gradually change to layer quantization at different bitwidths. In general, the (full) layer skip options are likely to be taken only when a very low $cp$ is enforced. When the computational saving requirement is mild, the model shows a strong tendency to “fractionally” skip all its layers.

Table 2: Performance of DFS models under different $\alpha$. The ‘abs’ in the leftmost column represents absolute value.

| Model                  | Target $cp$ | Actual $cp$ | Acc   |
|------------------------|-------------|-------------|-------|
| DFS-ResNet74-D         | 40%         | 40.20%      | 93.53%|
| DFS-ResNet74-C         | 40%         | 8.20%       | 93.12%|
| Base-ResNet74          |             |             | 93.55%|

Figure 7: Accuracy vs. computation percentage of DFS-ResNet38, the scalable quantized ResNet38 and HAQ quantized ResNet38.

to show that DFS is better than static CNN quantization methods. Instead, the motivation is that it can be insightful to observe the behaviors of static and dynamic quantization methods under the same settings.

Figure 7 shows the results. It can be seen that DFS-ResNet38 achieves similar or slightly better accuracy (up to 1.2% over the scalable method and 0.2% over HAQ) than both the scalable and HAQ methods, even with a much more coarser-grained quantization options (keep, skip, 8bits, and 16bits). Furthermore, among the three methods, the prediction accuracy of the scalable method fluctuates the most as the computation percentage changes, showing that CNNs with layer-wise adaptive bitwidths can achieve better trade-offs between accuracy and computational cost.

Choice of Parameter $\alpha$: We conduct two sets of experiments to demonstrate how dynamically changing the sign of $\alpha$ affects the model’s performance. Table 1 compares two training scenarios of DFS-ResNet74 on CIFAR10. DFS-ResNet74-D denotes the case where dynamic changing sign of $\alpha$ is applied, and DFS-ResNet74-C denotes the case where $\alpha$ is a positive constant, and we set the absolute value of $\alpha$ to 1e-5. It can be seen that when $\alpha$ is constant, the resulting actual $cp$ significantly deviates from the targeted $cp$, since a positive $\alpha$ will keep enforcing the model to reduce $cp$ without constraint, while the dynamic case achieves the desired $cp$. Table 2 shows how the performance of the DFS-ResNet74 model varies with the absolute value of $\alpha$ on CIFAR10. During training, the dynamic changing sign of $\alpha$ is applied. It can be seen that there is an obvious accuracy drop (0.2%) under both targeted $cps$ when the absolute value of $\alpha$ increases to (1e-4,1e-3), where the actual $cp$ deviated from the target $cp$ by around 3%. This is because a larger step size will cause the $cp$ of the model to fluctuate, and thus the unstable training will results in degraded accuracy, while the stable performance in the range (1e-6,1e-5) proves that the model is robust to smaller step size under different targeted $cps$.

Decision Behavior Analysis and Visualization

We then visualize and study the learned layer-wise decision behaviors of DFS, and how they evolve as $cp$ increases.

Table 1: DFS performance under dynamic changing $\alpha$ and constant $\alpha$.

| abs of $\alpha$ | Target $cp$ = 40 % | Actual $cp$ | Acc   |
|-----------------|---------------------|-------------|-------|
| 1e-6            | 40.10%              | 93.53%      | 50.08%| 93.72%|
| 1e-5            | 40.93%              | 93.54%      | 50.20%| 93.74%|
| 1e-4            | 40.80%              | 93.31%      | 51.01%| 93.52%|
| 1e-3            | 43.75%              | 93.27%      | 53.40%| 93.42%|

Figures 8-10 show the layer-wise “decision distributions” (e.g., the skip option taken per layer) of DFS-ResNet74 trained on CIFAR-10, as the computation percentage increases from 4% to 6.25%. In this specific case and (quite low) percentage range, the model is observed to only choose between “skip” and “8bit” in a vast majority of input cases. Therefore, we only plot “skip” and “8bit” columns for compact display. We can observe a smooth transition of decision behaviors as the computational percentage varies: from a mixture of layer skipping and quantization, gradually to all layer quantization. Specifically, from Figure 8 to Figure 9 within the first residual group, the percentage of skipping options for blocks 2,4,9 remains roughly unchanged, while we observe an obvious drop of skipping percentages at block 5 (from 55% to 0%) and block 8 (from 100% to 10%). Similarly, for the second and third residual groups, the skipping percentage of most residual blocks gradually reduces to 0%, with that of the remaining blocks (20,22,23,24) stays roughly unchanged. From Figure 9 to Figure 10, the decisions of all the layers shift to 8bit. The smooth transition empirically endorses our hypothesis made in Section 3 that the layer quantization options can serve as a “fractional” intermediate stage between the binary layer skipping options.

As $cp$ increases, DFS apparently favors the finer-grained layer quantization options than the coarser-grained layer skipping. Figure 11 shows the accuracy of DFS-ResNet74 when the computation percentage increases from 4% to 30%. From 4% to 6.25% (when the layer skipping options gradually change to all-quantization options), there is a notable accuracy increase from 92.91% to 93.54%. The performance then reaches a plateau after the computation percentage of 6.25%, while we observe DFS now tends to choose quantization for all layers (see supplementary ma-

https://github.com/mit-han-lab/haq-release
Figure 8: Visualization of layerwise decision distribution of DFS-ResNet74 on CIFAR10: computation percentage = 4 %.

Figure 9: Visualization of layerwise decision distribution of DFS-ResNet74 on CIFAR10: computation percentage = 5 %.

Figure 10: Visualization of layerwise decision distribution of DFS-ResNet74 on CIFAR10: computation percentage = 6.25 %.

Figure 11: DFS-ResNet74 under lower $cps$.

5 Conclusion

We proposed a novel DFS framework, which extends binary layer skipping options with the “fractional skipping” ability - by quantizing the layer weights and activations into different bitwidths. The DFS framework exploits model redundancy in a much finer-grained level, leading to more flexible and effective calibration between inference accuracy and complexity. We evaluate DFS on the CIFAR-10 and CIFAR-100 benchmarks, and it was shown to compare favorably against both state-of-the-art dynamic inference method and static quantization techniques.

While we demonstrate that quantization indeed can be viewed as “fractional” intermediate states in-between binary layer skip options (by both achieved results, and the visualizations of skipping decision transitions), we recognize that more possible alternatives to “fractionally” execute a layer could be explored, such as channel slimming (Yu et al. 2018). We leave this as a future work.

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