NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications

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Abstract. This work proposes an automated algorithm, called NetAdapt, that adapts a pre-trained deep neural network to a mobile platform given a resource budget. While many existing algorithms simplify networks based on the number of MACs or the number of parameters, optimizing those indirect metrics may not necessarily reduce the direct metrics, such as latency and energy consumption. To solve this problem, NetAdapt incorporates direct metrics into its adaptation algorithm. These direct metrics are evaluated using *empirical measurements*, so that detailed knowledge of the platform and toolchain is not required. NetAdapt automatically and progressively simplifies a pre-trained network until the resource budget (e.g., latency) is met while maximizing the accuracy. Experiment results show that NetAdapt achieves better accuracy versus latency trade-offs on both mobile CPU and mobile GPU, compared with the state-of-the-art automated network simplification algorithms. For image classification on the ImageNet dataset, NetAdapt achieves up to a 1.66× speedup in *measured inference latency* with higher accuracy.

1 Introduction

Deep neural networks (DNNs or networks) have become an indispensable component of artificial intelligence, boasting near or super-human accuracy on common vision tasks such as image classification and object detection. However, DNN-based AI applications are typically too computationally intensive to be deployed on resource-constrained platforms such as mobile phones. This hinders the enrichment of a large set of user experiences.

In the literature, great efforts have been made to improve the efficiency of networks. However, the majority of works are based on optimizing the "indirect metrics" such as the number of multiply-accumulate operations (MACs) or the number of weights as proxies for the resource consumption of a network. Although these indirect metrics are convenient to compute and integrate into the optimization framework, they may not be good approximations to the "direct metrics" that matter for the real applications, such as latency and energy consumption. The relationship between an indirect metric and the corresponding

* This work was done while Tien-Ju Yang was an intern at Google.

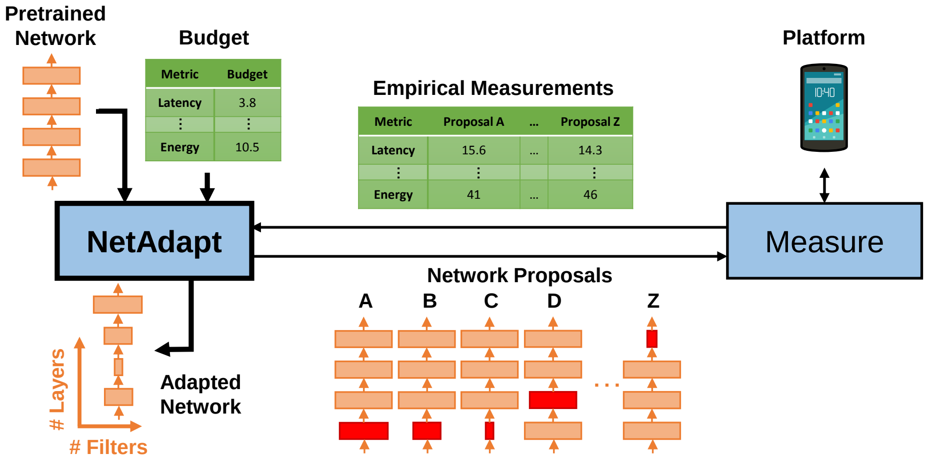

Fig. 1. NetAdapt automatically adapts a pretrained network to a mobile platform given a resource budget. This algorithm is guided by the direct metrics for resource consumption. NetAdapt eliminates the requirement of platform-specific knowledge by using empirical measurements to evaluate the direct metrics. At each iteration, NetAdapt generates many network proposals and measures the proposals on the target platform. The measurements are used to guide NetAdapt to generate the next set of network proposals at the next iteration.

direct metric can be highly non-linear and platform-dependent as observed by [1–3]. In Table 4, we also demonstrate empirically that a network with a fewer number of MACs can be slower when actually running on mobile devices. In one case, a network of 19% less MACs incurs 29% longer latency in practice.

There are two common practices to design efficient network architectures. The first is designing a single architecture with no regard to the underlying platform. It is hard for a single architecture to run optimally on all the platforms due to the different platform characteristics. For example, the fastest architecture on a desktop GPU may not be the fastest one on a mobile CPU with the same accuracy. Moreover, there is little guarantee that the architecture could meet the resource budget (e.g., latency) on all platforms of interest. The second practice is manually crafting architectures for a given target platform based on the platform's characteristics. However, this practice requires deep knowledge about the implementation details of the platform, including the toolchains, the configuration and the hardware architecture, which are generally unavailable given the proprietary nature of hardware and the high complexity of modern systems. Furthermore, manually designing a different architecture for each platform could be taxing for researchers and engineers.

In this work, we propose a platform-aware algorithm, called *NetAdapt*, to address the aforementioned issues and facilitate platform-specific DNN deployment. NetAdapt (Fig. 1) incorporates *direct metrics* in the optimization loop, so it does not suffer from the discrepancy between the indirect and direct metrics. The direct metrics are evaluated by the empirical measurements taken from the target platform. This enables the algorithm to support any platform without detailed knowledge of the platform itself, although such knowledge could still be incorporated into the algorithm for potentially better results. In this paper, we use latency as the running example even though our algorithm is generalizable to other metrics or a combination of them (Sec. 4.3).

The network optimization of NetAdapt is carried out in an automatic way to gradually reduce the resource consumption of a pretrained network while maximizing the accuracy. The optimization runs iteratively until the latency budget is met. Through this design, NetAdapt can generate not only a network that meets the budget, but also a family of simplified networks with different tradeoffs, which allows dynamic network selection and further study. Finally, instead of being a black box, NetAdapt is designed to be easy to interpret. For example, through studying the proposed network architectures and the corresponding empirical measurements, we can understand why a proposal is chosen and this sheds light on how to improve the platform and network design.

The main contributions of this paper are:

- We propose a framework that is guided by direct metrics when optimizing a pretrained network to meet a given resource budget. By using the empirical measurements to evaluate the direct metrics, no platform-specific knowledge is required.
- We propose an automated constrained network optimization algorithm that maximizes accuracy while satisfying the constraints (i.e., the predefined resource budget). The algorithm outperforms the state-of-the-art automatic network simplification algorithms by up to 1.66$\times$ in terms of reduction in *measured inference latency* while delivering higher accuracy.
- We perform experiments that demonstrate the effectiveness of NetAdapt on multiple platforms, with measured results on a mobile CPU with Google's toolchain or a mobile GPU with Qualcomm's toolchain.

2 Related Work

There is a large body of work that aims to simplify DNNs. We refer the readers to [4] for a comprehensive survey, and summarize the main approaches below.

The most related works are pruning-based methods. [5–7] aim to remove individual redundant weights from DNNs. However, most platforms cannot fully take advantage of unstructured sparse filters [2]. Hu et al. [8] and Srinivas et al. [9] focus on removing entire filters instead of individual weights. The drawback of these methods is the requirement of *manually* choosing the compression rate for each layer. MorphNet [10] leverages the sparsifying regularizers to automatically determine the layerwise compression rate. ADC [11] uses reinforcement learning to learn a policy for choosing the compression rates. The crucial difference between all the aforementioned methods and ours is that they are not guided by the direct metrics, and thus may lead to sub-optimal performance, as we see in Sec. 4.3.

Energy-aware pruning [1] uses an energy model [12] and incorporates the estimated energy numbers into the pruning algorithm. However, this requires designing models to estimate the direct metrics of each target platform, which requires detailed knowledge of the platform including its hardware architecture [13], and the network-to-array mapping used in the toolchain [14]. NetAdapt does not have this requirement since it can directly use empirical measurements.

DNNs can also be simplified by approaches that involve directly designing efficient network architectures, decomposition or quantization. MobileNets [15] and ShuffleNets [16] provide efficient layer operations and reference architecture design. Layer-decomposition-based algorithms [17, 18] exploit matrix decomposition to reduce the number of operations. Quantization [19–21] reduces the complexity by decreasing the computation accuracy. The proposed algorithm, NetAdapt, is complementary to these methods. For example, NetAdapt can adapt MobileNets to further push the frontier of efficient networks as shown in Sec. 4 even though MobileNets are more compact and much harder to simplify than the other larger networks, such as VGG [22].

3 Methodology: NetAdapt

We propose an algorithm, called NetAdapt, that will allow a user to automatically simplify a pretrained network to meet the resource budget of a platform while maximizing the accuracy. NetAdapt is guided by direct metrics for resource consumption and the direct metrics are evaluated by using empirical measurements, thus eliminating the requirement of detailed platform-specific knowledge.

3.1 Problem Formulation

NetAdapt aims to solve the following non-convex constrained problem:

$$\begin{aligned} \underset{Net}{\text{maximize}} \quad & Acc(Net) \\ \text{subject to} \quad & Res_j(Net) \le Bud_j, \; j = 1, \ldots, m, \end{aligned} \tag{1}$$

where Net is a simplified network from the initial pretrained network, $Acc(\cdot)$ computes the accuracy, $Res_j(\cdot)$ evaluates the direct metric for resource consumption of the j^{th} resource, and Bud_j is the budget of the j^{th} resource and the constraint on the optimization. The resource can be latency, energy, memory footprint, etc., or a combination of these metrics.

Based on an idea similar to progressive barrier methods [23], NetAdapt breaks this problem into the following series of easier problems and solves it iteratively:

$$\begin{aligned} \underset{Net_i}{\text{maximize}} \quad & Acc(Net_i) \\ \text{subject to} \quad & Res_j(Net_i) \le Res_j(Net_{i-1}) - \Delta R_{i,j}, \; j = 1, \ldots, m, \end{aligned} \tag{2}$$

where Net_i is the network generated by the i^{th} iteration and Net_0 is the initial pretrained network. As the number of iterations increases, the constraints (i.e.,

Algorithm 1: NetAdapt

Input: Pretrained Network: Net_0 (with K CONV and FC layers), Resource Budget: Bud, Resource Reduction Schedule: ΔR_i

Output: Adapted Network Meeting the Resource Budget: $\hat{Net}$

i = 0;
Res_i = TakeEmpiricalMeasurement(Net_i);
while $Res_i > Bud$ **do**
    Con = Res_i - ΔR_i;
    for *k from 1 to K* **do**
        `/* TakeEmpiricalMeasurement is also called inside ChooseNumFilters for choosing the correct number of filters that satisfies the constraint (i.e., current budget). */`
        N_Filt_k, Res_Simp_k = ChooseNumFilters(Net_i, k, Con);
        Net_Simp_k = ChooseWhichFilters(Net_i, k, N_Filt_k);
        Net_Simp_k = ShortTermFineTune(Net_Simp_k);
    Net_{i+1}, Res_{i+1} = PickHighestAccuracy($Net\_Simp_:$, $Res\_Simp_:$);
    i = i + 1;
$\hat{Net}$ = LongTermFineTune(Net_i);
return $\hat{Net}$;

current resource budget $Res_j(Net_{i-1}) - \Delta R_{i,j})$ gradually become tighter. $\Delta R_{i,j}$, which is larger than zero, indicates how much the constraint tightens for the j^{th} resource in the i^{th} iteration and can vary from iteration to iteration. This is referred to as "resource reduction scheduling", which is similar to the concept of learning rate scheduling. The algorithm terminates when $Res_j(Net_{i-1}) - \Delta R_{i,j}$ is equal to or smaller than Bud_j for every resource type. It outputs the final adapted network and can also generate a sequence of simplified networks (i.e., the highest accuracy network from each iteration $Net_1, ..., Net_i$) to provide the efficient frontier of accuracy and resource consumption tradeoffs.

3.2 Algorithm Overview

For simplicity, we assume that we only need to meet the budget of one resource, specifically latency. One method to reduce the latency is to remove filters from the convolutional (CONV) or fully-connected (FC) layers. While there are other ways to reduce latency, we will use this approach to demonstrate NetAdapt.

The NetAdapt algorithm is detailed in pseudo code in Algorithm 1 and in Fig. 2. Each iteration solves Eq. 2 by reducing the number of filters in a *single* CONV or FC layer (the **Choose # of Filters** and **Choose Which Filters** blocks in Fig. 2). The number of filters to remove from a layer is guided by empirical measurements. NetAdapt removes entire filters instead of individual weights because most platforms can take advantage of removing entire filters and this strategy allows reducing both filters and feature maps, which play an important role in resource consumption [1]. The simplified network is then fine-

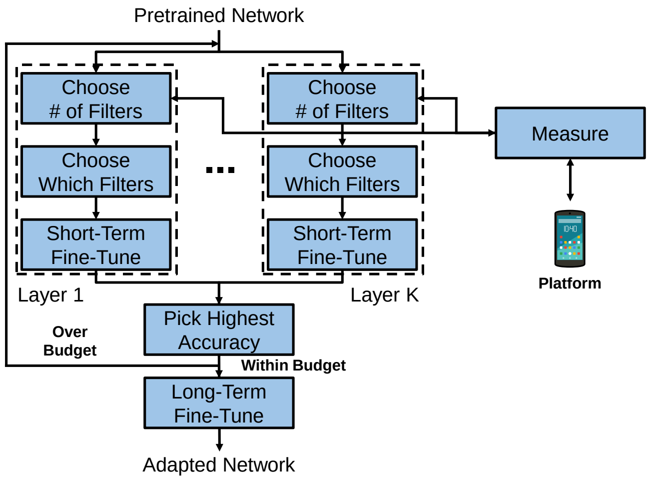

Fig. 2. This figure visualizes the algorithm flow of NetAdapt. At each iteration, NetAdapt decreases the resource consumption by simplifying (i.e., removing filters from) one layer. In order to maximize accuracy, it tries to simplify each layer individually and picks the simplified network that has the highest accuracy. Once the target budget is met, the chosen network is then fine-tuned again until convergence.

tuned for a short length of time in order to restore some accuracy (the **Short-Term Fine-Tune** block).

In each iteration, the previous three steps (highlighted in bold) are applied on each of the CONV or FC layers individually[3]. As a result, NetAdapt generates K (i.e., the number of CONV and FC layers) network candidates in one iteration, each of which has a single layer modified from previous iteration. The proposed network candidate with the highest accuracy is carried over to the next iteration (the **Pick Highest Accuracy** block). Note that the selection of the network for the next iteration should not be made based on the test set to avoid overfitted results. Finally, once the target budget is met, the chosen network is fine-tuned again until convergence (the **Long-Term Fine-Tune** block).

3.3 Algorithm Details

This section describes the key blocks in the *NetAdapt* algorithm (Fig. 2).

Choose Number of Filters This step focuses on determining *how many* filters to preserve in a specific layer based on empirical measurements. NetAdapt gradually reduces the number of filters in the target layer and measures the resource consumption of each of the simplified networks. The maximum number of filters that can satisfy the current resource constraint will be chosen. Note

[3] The algorithm can also be applied to a group of multiple layers as a single unit (instead of a single layer). For example, in ResNet [24], we can treat a residual block as a single unit to speed up the adaptation process.

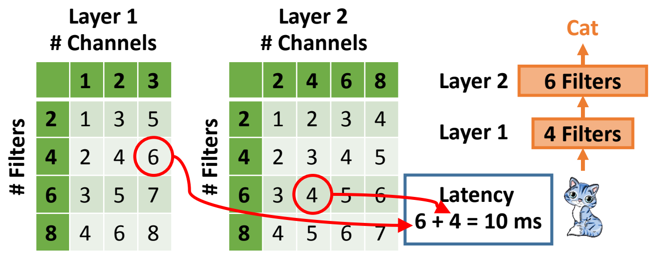

Fig. 3. This figure illustrates how layer-wise look-up tables are used for fast resource consumption estimation.

that when some filters are removed from a layer, the associated channels in the following layers should also be removed. Therefore, the change in the resource consumption of other layers needs to be factored in.

Choose Which Filters This step is responsible for choosing *which* filters to preserve based on the architecture from the previous step. There are many methods proposed in the literature and we choose the magnitude-based method to keep the algorithm simple. In this work, the N filters that have the largest $\ell 2$-norm magnitude will be kept, where N is the number of filters determined by the previous step. More complex methods can be adopted to potentially further increase the accuracy, such as removing the filters based on their joint influence on the feature maps [1].

Short-/Long-Term Fine-Tune Both the short-term fine-tune and long-term fine-tune steps in NetAdapt involve network-wise end-to-end fine-tuning. The only difference is that they fine-tune the network with different numbers of iterations.

At each iteration of the algorithm, we fine-tune the simplified networks with a relatively smaller number of iterations (i.e., short-term) to regain accuracy. This step can be carried out in parallel or in sequence. As shown in Sec. 4.3, without short-term fine-tuning, the accuracy will drop to zero in a few iterations and misleads the algorithm to choose the wrong architecture.

As the algorithm proceeds, the network is continuously trained but does not converge. Once the final adapted network is obtained, we fine-tune the network with more iterations until convergence (i.e., long-term) as the final step.

3.4 Fast Resource Consumption Estimation

As mentioned in Sec. 3.3, NetAdapt uses empirical measurements to determine the number of filters to keep in a layer given the resource constraint. In theory, we can measure the resource consumption of each of the simplified networks on the fly during adaptation. However, taking measurements can be slow and difficult to parallelize due to the limited number of available devices. Therefore, it may be prohibitively expensive and become the computation bottleneck.

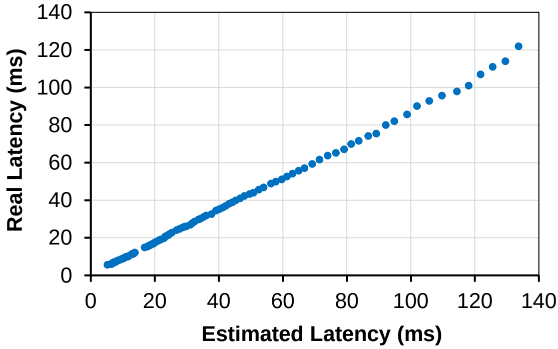

Fig. 4. The comparison between the estimated latency (using layer-wise look-up tables) and the real latency on a single large core of Google Pixel 1 CPU while adapting the 100% MobileNet with the input resolution of 224 [15].

We solve this problem by building layer-wise look-up tables with pre-measured resource consumption of each layer. When executing the algorithm, we look up the table of each layer, and sum up the layer-wise measurements to estimate the network-wise resource consumption, which is illustrated in Fig. 3. The reason of not using a network-wise table is that the size of the table will grow exponentially with the number of layers, which makes it intractable for deep networks. Moreover, layers with the same shape and feature map size only need to be measured once, which is common for modern deep networks.

Fig. 4 compares the estimated latency (the sum of layer-wise latency from the layer-wise look-up tables) and the real latency on a single large core of Google Pixel 1 CPU while adapting the 100% MobileNet with the input resolution of 224 [15]. The difference between them is sufficiently small to be used in our NetAdapt algorithm.

4 Experiment Results

In this section, we apply the proposed NetAdapt algorithm to MobileNets [15], which are designed for mobile applications, and experiment on the ImageNet dataset [25]. We didn't apply NetAdapt on larger networks like ResNet [24] and VGG [22] because these networks are seldom deployed on mobile platforms; it is also more difficult to simplify an already efficient network such as MobileNet than larger networks. We benchmark NetAdapt against three state-of-the-art network simplification methods:

– **MobileNet Family** [15] consists of networks that are simplified from a reference MobileNet architecture using two simple but effective hyper-parameters, the width multiplier and the resolution multiplier. Width multiplier scales the number of filters by a percentage across all convolutional (CONV) and fully-connected (FC) layers, and resolution multiplier scales the resolution of the input image. The two multipliers can be used together. We use the notation "50% MobileNet (128)" to denote applying the width multiplier of 50% on MobileNet with the input image resolution of 128.

– **MorphNet** [10] is an automatic network simplification algorithm based on sparsifying regularization.
– **ADC** [11] is an automatic network simplification algorithm based on reinforcement learning.

To demonstrate the effectiveness of NetAdapt, we adapted the largest MobileNet (100% MobileNet (224)) and a much smaller MobileNet (50% MobileNet (128)). We also tested NetAdapt on two different platforms: mobile CPUs and mobile GPUs. In addition, we performed ablation studies to investigate the impact of different components.

4.1 Detailed Settings

NetAdapt Configuration MobileNets [15] are based on depthwise separable convolutions, which factorize a $m \times m$ standard convolution layer into a $m \times m$ depthwise layer and a 1×1 standard convolution layer called a pointwise layer. In the experiments, we adapt each depthwise layer with the corresponding pointwise layer and choose which filters to keep based on the pointwise layer. When adapting 50% MobileNet (128), the initial latency reduction ($\Delta R_{0,0}$ in Eq. 2) at the first iteration is 0.5 and it decays at the rate of 0.96 per iteration. When adapting other networks, we use the same decay rate but scale the initial latency reduction proportional to the latency of the initial pretrained network. One example can be found in Sec. 4.2.

Training Configuration To avoid overfitting to the test set (in this case, the ImageNet validation set), we preserved ten thousand images from the training set, 10 images per class, as the holdout set. The new training set without the holdout images was used to perform short-term fine-tuning and the holdout set was used to pick the highest accuracy network out of the simplified networks at each iteration. The whole training set is used for the long-term fine-tuning, which is performed once in the last step of NetAdapt. The training configuration is the same as MorphNet [10] except that the batch size is 128 instead of 96. We used 0.045 as the learning rate for the long-term fine-tuning and 0.0045 for the short-term fine-tuning. All accuracy numbers are reported on the validation set to show the true performance.

Mobile Inference and Latency Measurement We used Google's TensorFlow Lite engine [26] for inference on mobile CPUs and Qualcomm's Snapdragon Neural Processing Engine (SNPE) for inference on mobile GPUs. For experiments on mobile CPUs, the latency was measured on a single large core of a Google Pixel 1 phone. For experiments on mobile GPUs, the latency was measured on the mobile GPU on a Samsung Galaxy S8 with SNPE's benchmarking tool. For each latency number, we report the median of 11 latency measurements.

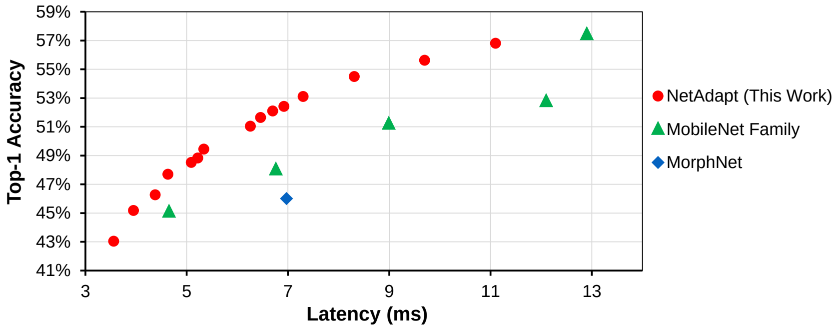

Fig. 5. The figure compares NetAdapt (adapting 50% MobileNet (128)) with the MobileNet family [15] and MorphNet [10] on a mobile CPU of Google Pixel 1[4].

Network	Top-1 Accuracy (%)		Latency (ms)	
25% MobileNet (224) [15]	52.8	(+0)	12.1	(100%)
NetAdapt	53.1	(+0.3)	7.3	(60%)
MorphNet [10]	46.0	(+0)	7.0	(100%)
NetAdapt	46.3	(+0.3)	4.4	(63%)

Table 1. A pairwise comparison between NetAdapt (adapting 50% MobileNet (128)) and the other two benchmark algorithms, the MobileNet family [15] and MorphNet [10] on a mobile CPU of Google Pixel 1. We compare the latency at similar accuracy.

Network	Top-1 Accuracy (%)		Latency (ms)	
100% MobileNet (192) [15]	69.3	(+0)	90.4	(100%)
NetAdapt	69.6	(+0.3)	67.1	(74%)
ADC [11]	68.8	(+0)	79.2	(100%)
NetAdapt	68.9	(+0.1)	55.7	(70%)

Table 2. A pairwise comparison between NetAdapt (adapting 100% MobileNet (224)) and the other two benchmark algorithms, the MobileNet family [15] and ADC [11] on a mobile CPU of Google Pixel 1. We compare the latency at similar accuracy.

4.2 Comparison with Benchmark Algorithms

Adapting 50% MobileNet (128) on a Mobile CPU In this experiment, we apply NetAdapt to adapt 50% MobileNet (128) to a mobile CPU. 50% MobileNet (128) is one of the most compact networks and much harder to simplify than other larger networks. The results are summarized and compared with the MobileNet family [15] and MorphNet [10] in Fig. 5 and Table 1. We observe that NetAdapt outperforms the MobileNet family by up to 1.66× faster with the same or higher accuracy. For MorphNet, NetAdapt's result is 1.59× faster with 0.3% higher accuracy.

[4] For the MobileNet family, we report the accuracy numbers of our trained version. Except for one network whose accuracy is decreased by 0.2%, all other networks achieve the same or higher accuracy compared to the numbers reported in [15].

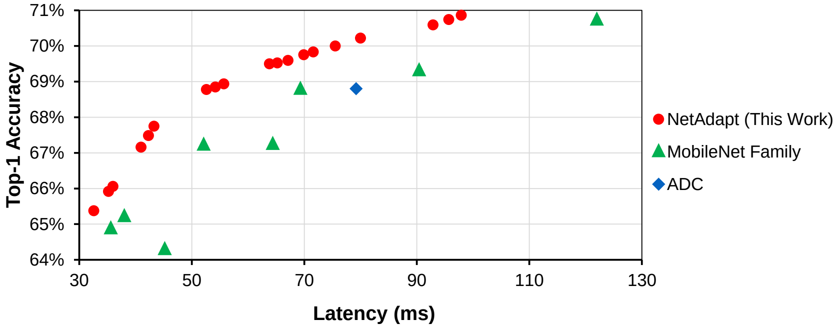

Fig. 6. The figure compares NetAdapt (adapting 100% MobileNet (224)) with the MobileNet family [15] and ADC [11] on a mobile CPU of Google Pixel 1.

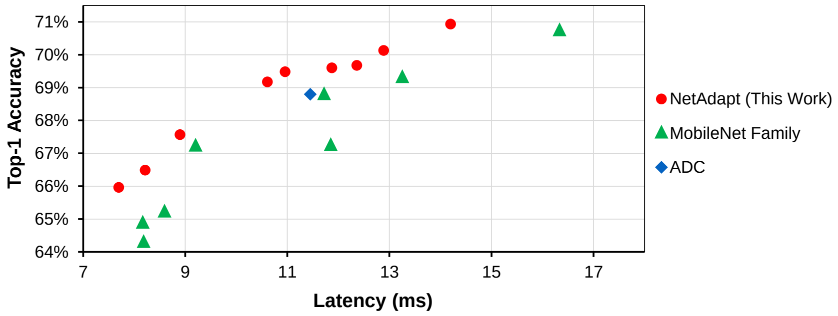

Fig. 7. This figure compares NetAdapt (adapting 100% MobileNet (224)) with the MobileNet family [15] and ADC [11] on a mobile GPU of Samsung Galaxy S8.

Network	Top-1 Accuracy (%)		Latency (ms)	
100% MobileNet (192) [15]	69.3	(+0)	13.3	(100%)
NetAdapt	69.5	(+0.2)	11.0	(83%)
ADC [11]	68.8	(+0)	11.4	(100%)
NetAdapt	69.2	(+0.4)	10.6	(93%)

Table 3. A pairwise comparison between NetAdapt (adapting 100% MobileNet (224)) and the other two benchmark algorithms, the MobileNet family [15] and ADC [11] on a mobile GPU of Samsung Galaxy S8. We compare the latency at similar accuracy.

Adapting 100% MobileNet (224) on a Mobile CPU In this experiment, we apply NetAdapt to adapt 100% MobileNet (224) on a mobile CPU. 100% MobileNet (224) is the largest MobileNet and achieves the highest accuracy. Because its latency is approximately 8× higher than that of 50% MobileNet (128), we scale the initial latency reduction by 8×. The results are shown and compared with the MobileNet family [15] and ADC [11] in Fig. 6 and Table 2. NetAdapt achieves higher accuracy than 100% MobileNet (192) and ADC while increasing the speed by 1.34× and 1.42×, respectively.

Network	Top-1 Accuracy (%)		# of MACs ($\times 10^6$)		Latency (ms)	
25% MobileNet (128) [15]	45.1	(+0)	13.6	(100%)	4.65	(100%)
MorphNet [10]	46.0	(+0.9)	15.0	(110%)	6.52	(140%)
NetAdapt	46.3	(+1.2)	11.0	(81%)	6.01	(129%)
75% MobileNet (224) [15]	68.8	(+0)	325.4	(100%)	69.3	(100%)
ADC [11]	68.8	(+0)	304.2	(93%)	79.2	(114%)
NetAdapt	69.1	(+0.3)	284.3	(87%)	74.9	(108%)

Table 4. The comparison between NetAdapt (adapting 50% MobileNet (128) or 100% MobileNet (224)) and the three benchmark algorithms on image classification when targeting the number of MACs. The latency numbers were measured on a mobile CPU of Google Pixel 1. We roughly match their accuracy and compare their latency.

Adapting 100% MobileNet (224) on a Mobile GPU In this experiment, we apply NetAdapt to adapt 100% MobileNet (224) on a mobile GPU to show the generality of NetAdapt. Fig. 7 and Table 3 show that NetAdapt outperforms other benchmark algorithms by up to 1.21× speed-up with higher accuracy. Due to the limitation of the SNPE tool, the layerwise latency breakdown only considers the computation time and does not include other latency, such as feature map movement, which can be expensive [1]. This affects the precision of the look-up tables used for this experiment. Moreover, we observe that there is an approximate 6.2ms (47% for 100% MobileNet (192)) non-reducible latency. These factors cause a smaller improvement on the mobile GPU compared with the experiments on the mobile CPU.

4.3 Ablation Studies

Impact of Direct Metrics In this experiment, we use the indirect metric (i.e., the number of MACs) instead of the direct metric (i.e., the latency) to guide NetAdapt to investigate the importance of using direct metrics. When computing the number of MACs, we only consider the CONV and FC layers because batch normalization layers can be folded into the corresponding CONV layers and the other layers are negligibly small. Table 4 shows that NetAdapt outperforms the benchmark algorithms with lower numbers of MACs and higher accuracy. This demonstrates the effectiveness of the proposed progressive optimization algorithm. However, we can observe that the network with lower numbers of MACs may not necessarily be faster. This demonstrates the necessity of incorporating direct measurements into the optimization flow.

Impact of Short-Term Fine-Tuning Fig. 8 shows the accuracy of different short-term fine-tuning iterations (without long-term fine-tuning). The accuracy rapidly drops to nearly zero if no short-term fine-tuning is performed (i.e., zero iterations). In this low accuracy region, the algorithm picks the best architecture solely based on noise and hence gives bad performance. After fine-tuning a network for a short amount of time (10k iterations), the accuracy is always kept above 20%, which allows the algorithm to make a better decision. Although further increasing the number of iterations improves the accuracy, we find that using 40k iterations leads to a good accuracy versus speed tradeoff.

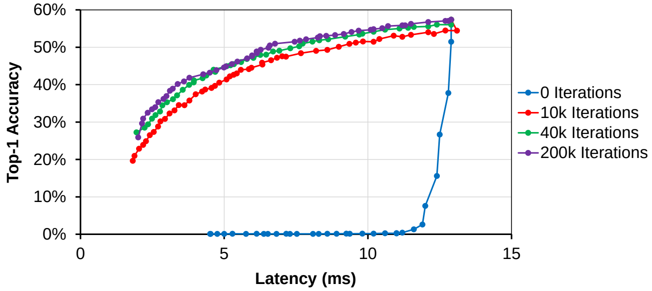

Fig. 8. This figure shows the accuracy of different short-term fine-tuning iterations when adapting 50% MobileNet (128) (without long-term fine-tuning) on a mobile CPU of Google Pixel 1. Zero iterations means no short-term fine-tuning.

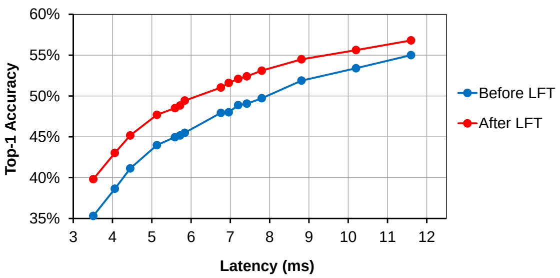

Fig. 9. The comparison between with and without long-term fine-tuning when adapting 50% MobileNet (128) on a mobile CPU of Google Pixel 1. Although the short-term fine-tuning preserves the accuracy well, the long-term fine-tuning gives the extra 3.4% in average (from 1.8% to 4.5%).

Initialization (ms)	Decay Rate	# of Total Iterations	Top-1 Accuracy (%)	Latency (ms)
0.5	0.96	28	47.7	4.63
0.5	1.0	20	47.4	4.71
0.8	0.95	20	46.7	4.65

Table 5. The influence of resource reduction scheduling.

Impact of Long-Term Fine-Tuning Fig. 9 illustrates the importance of performing the long-term fine-tuning. Although the short-term fine-tuning preserves the accuracy well, the long-term fine-tuning can still increase the accuracy by up to another 4.5% or 3.4% in average. Moreover, the long-term fine-tuning becomes more important as the network adaptation goes. Because the short training time of the short-term fine-tuning, the training is terminated far before convergence. Therefore, it is not surprising that the final long-term fine-tuning can further increase the accuracy.

Impact of Resource Reduction Schedules Table 5 shows the impact of using three different resource reduction schedules, which are defined in Sec. 3.1. Empirically, using a larger resource reduction at each iteration increases the

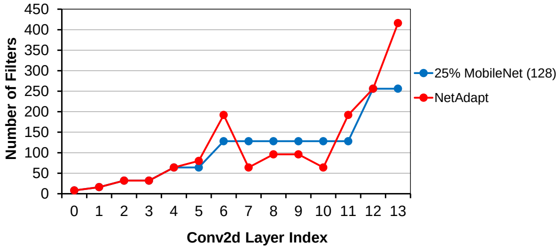

Fig. 10. The comparison between 25% MobileNet (128) and the adapted network starting from 50% MobileNet (128). Both of them have similar latency.

adaptation speed (i.e., reducing the total number of adaptation iterations) at the cost of accuracy. With the same number of total iterations, the result suggests that a smaller initial resource reduction with a slower decay is preferable.

4.4 Analysis of Adapted Network Architecture

The architecture of the adapted 50% MobileNet (128) is shown and compared with 25% MobileNet (128) in Fig. 10. Both of them have similar latency. There are two interesting observations.

First, NetAdapt removes more filters in layers 7 to 10, but fewer in layers 6. Since the feature map resolution is reduced in layer 6 but not in layers 7 to 10, we hypothesize that when the feature map resolution is reduced, more filters are needed to avoid creating an information bottleneck.

The second observation is that NetAdapt keeps more filters in layer 13 (i.e. the last CONV layer). One possible explanation is that the ImageNet dataset contains one thousand classes, so more feature maps are needed by the last FC layer to do the correct classification.

5 Conclusion

In summary, we proposed an automated algorithm, called NetAdapt, to adapt a pretrained network to a mobile platform given a real resource budget. NetAdapt can incorporate direct metrics, such as latency and energy, into the optimization to maximize the adaptation performance based on the characteristics of the platform. By using empirical measurements, NetAdapt can be applied to any platform as long as we can measure the desired metrics, without any knowledge of the underlying implementation of the platform. We demonstrated empirically that the proposed algorithm can achieve better accuracy versus latency tradeoff (by up to 1.66× faster with higher accuracy) compared with other state-of-the-art network simplification algorithms. In this work, we aimed to highlight the importance of using direct metrics in the optimization of efficient networks; we hope that future research efforts will take direct metrics into account in order to further improve the performance of efficient networks.

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