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# Pareto-Frontier-aware Neural Architecture Generation for Diverse Budgets

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## Abstract

Designing feasible and effective architectures under diverse computation budgets incurred by different applications/devices is essential for deploying deep models in practice. Existing methods often perform an independent architecture search for each target budget, which is very inefficient yet unnecessary. Moreover, the repeated independent search manner would inevitably ignore the common knowledge among different search processes and hamper the search performance. To address these issues, we seek to train a general architecture generator that automatically produces effective architectures for an arbitrary budget merely via model inference. To this end, we propose a Pareto-Frontier-aware Neural Architecture Generator (NAG) which takes an arbitrary budget as input and produces the Pareto optimal architecture for the target budget. We train NAG by learning the Pareto frontier (*i.e.*, the set of Pareto optimal architectures) over model performance and computational cost (*e.g.*, latency). Extensive experiments on three platforms (*i.e.*, mobile, CPU, and GPU) show the superiority of the proposed method over existing NAS methods.

## 1. Introduction

Deep neural networks (DNNs) (LeCun et al., 1989) have been the workhorse of many challenging tasks, including image classification (Krizhevsky et al., 2012) and semantic segmentation (Long et al., 2015). However, designing effective architectures often relies heavily on human expertise. To alleviate this, neural architecture search (NAS) has been proposed to automatically design architectures (Zoph & Le, 2017). Existing studies show that the automatically searched architectures often outperform the manually designed ones (Liu et al., 2019; 2018).

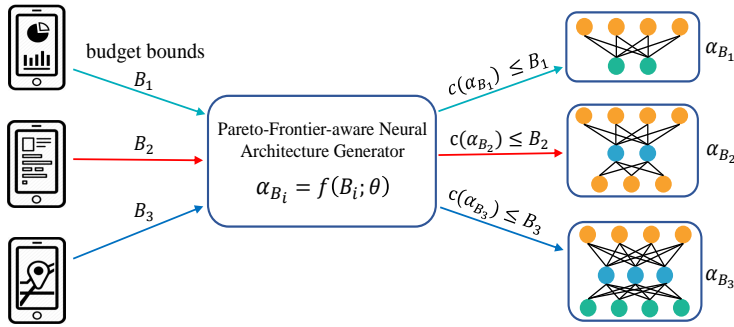
However, deep models often contain a large number of parameters and come with a high computational cost. As a result, it is hard to deploy deep models to real-world scenarios with limited computation resources. Thus, we have to carefully design architectures to fulfill a specific budget. More critically, we may have different budgets of computation resources in the real world. For example, a company may develop/maintain multiple applications and each of them has a specific budget of latency.

Existing methods (Tan et al., 2019; Stamoulis et al., 2019) seek to design a model to obtain an architecture under a single budget. When we consider diverse budgets, they have to conduct multiple search processes for each budget (Tan et al., 2019), which is very inefficient yet unnecessary. Besides finding a single architecture, one can learn a generator model that produces architectures according to a learnable distribution (Xie et al., 2019; Ru et al., 2020). However, the produced architectures tend to have a low variance in terms of model performance and computational cost (Xie et al., 2019; Ru et al., 2020). As a result, these methods still have to learn a generator for each budget. Unlike these methods, one can also exploit the population-based methods to simultaneously find multiple architectures and then select an appropriate one from them to fulfill a specific budget (Lu et al., 2019; 2020a). However, due to the limited population size, the selected architecture does not necessarily satisfy the considered budget. Thus, how to design architectures under diverse budgets remains an open question.

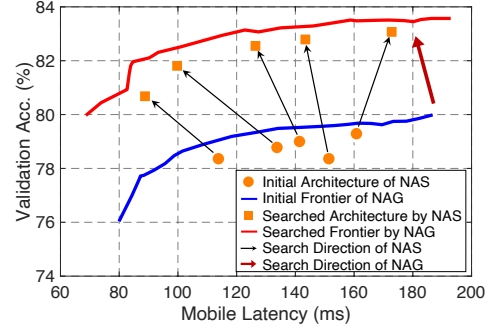
In this paper, rather than finding an architecture for a specific budget, we seek to learn an architecture generator to produce feasible architectures under diverse budgets. Note that we consider the same search space when designing architectures for different budgets. One may find some common architectures that perform well across multiple budgets. For example, based on a common architecture under some budgets, we may easily obtain promising architectures for a larger/smaller budget by slightly modifying some of its elements/layers. In this sense, it is possible to find effective architectures for diverse budgets simultaneously. More critically, the knowledge provided by these common architectures may also benefit the search process (See results in Table 1). Inspired by this, we propose a Pareto-Frontier-aware Neural Architecture Generator (NAG) which takes a budget as input and produces architectures satisfying the

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(a) Diverse application scenarios with different budgets.



(b) Comparisons of NAG and conventional NAS methods.

Figure 1. An illustration of the applications of NAG and the comparisons of search strategies. (a) NAG takes an arbitrary budget as input and outputs the corresponding architecture. (b) NAG learns the Pareto frontier rather than optimizing a specific architecture.

considered budget (See Figure 1(a)). Note that the Pareto optimal architectures under different budgets should lie on a distribution, *i.e.*, the Pareto frontier over model performance and computational cost (Kim & De Weck, 2005). We propose to learn the Pareto frontier (*i.e.*, improving the blue curve to the red curve in Figure 1(b)) instead of finding multiple discrete Pareto optimal architectures independently. To achieve this, we evenly sample a set of discrete budgets from the range of possible values and maximize the expected reward of the searched architectures over these budgets to approximate the Pareto frontier. To evaluate architectures under diverse budgets, we design an architecture evaluator to learn a Pareto dominance rule which determines whether an architecture is better than another. During inference, given an arbitrary budget, we are able to produce promising architectures merely via model inference, which is very efficient.

We summarize the contributions of our paper as follows.

- Rather than designing architectures for a specific budget, we consider learning to generate optimal architectures for any given budget. To this end, we propose a Pareto-Frontier-aware Neural Architecture Generator (NAG) method to learn the Pareto frontier of architectures over model performance and computational cost (as shown in Figure 2).
- To learn the generator, we propose an architecture evaluator to evaluate architectures under diverse budgets. Moreover, to make the Pareto frontier learning feasible, we propose a Pareto dominance rule to determine whether an architecture is better than another.
- Extensive experiments on three hardware platforms show that the architectures produced by our NAG consistently outperform the architectures searched by existing methods under different budgets.

## 2. Related Work

**Neural Architecture Search (NAS).** Unlike manually designing architectures with expert knowledge, NAS seeks to automatically design more effective architectures. However, solving the NAS problem is challenging due to the non-convex nature and the large search space (Pham et al., 2018; Guo et al., 2020a). Existing NAS methods can be roughly divided into three categories, namely, reinforcement-learning-based methods, evolutionary approaches, and gradient-based methods. Specifically, reinforcement-learning-based methods (Zoph & Le, 2017; Pham et al., 2018; Tan et al., 2019) learn a controller to produce architectures. Evolutionary approaches (Real et al., 2017; Liu et al., 2018; Real et al., 2019) search for promising architectures by gradually evolving a population. Gradient-based methods (Liu et al., 2019; Chen et al., 2019; Xu et al., 2020) relax the search space to be continuous and optimize architectures by gradient descent. Unlike these methods that find a single architecture, one can design different architectures by training an architecture generator. RandWire (Xie et al., 2019) designs stochastic network generators to generate randomly wired architectures. NAGO (Ru et al., 2020) proposes a hierarchical and graph-based search space to reduce the optimization difficulty. However, these generated architectures tend to have a low variance of both model performance and computational cost (Xie et al., 2019; Ru et al., 2020). Besides, given diverse budgets, they also have to learn a generator model for each budget to produce feasible architectures.

**Architecture Design under Resource Constraints.** Many efforts have been made in designing architectures under a resource constraint (Cai et al., 2020; Huang & Chu, 2020; Thomas Elsken & Hutter, 2019; Bender et al., 2020; Guo et al., 2020b). To reduce training budget, OFA (Cai et al., 2020) trains a powerful supernet, from which we can directly get a specialized sub-network without additional training.

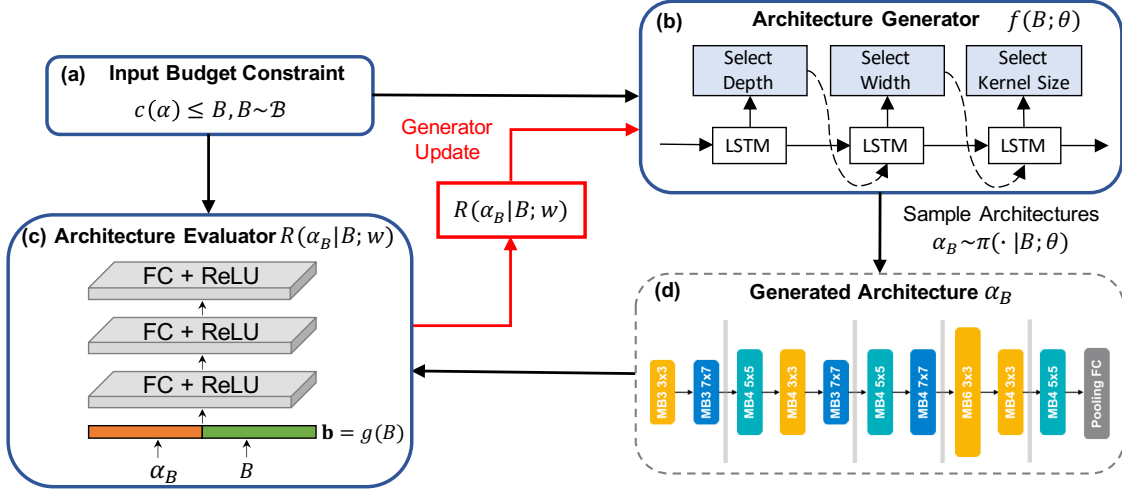


Figure 2. Overview of the proposed NAG. Our NAG mainly consists of two modules: an architecture generator  $f(\cdot; \theta)$  and an architecture evaluator  $R(\cdot; w)$ . Specifically, we build the generator model based on an LSTM network, which takes a budget constraint  $B$  as input and produces a promising architecture  $\alpha_B$  that satisfies the budget constraint, *i.e.*,  $c(\alpha)$ . To optimize the generator model, we design the evaluator using three fully connected (FC) layers to estimate the performance of the generated architectures  $\alpha_B$ . The orange and green boxes in (c) denote the embeddings of architecture  $\alpha_B$  and the budget w.r.t.  $B$ , respectively.

Moreover, PONAS (Huang & Chu, 2020) builds an accuracy table to find architectures satisfying a single budget constraint. TuNAS (Bender et al., 2020) proposes a reward function to restrict the latency of the searched architecture, which omits additional hyper-parameter tuning. However, given various computation budgets, these methods need to repeat the architecture search process for each budget. By contrast, our NAG only needs to search once to produce architectures that satisfy arbitrary budgets.

**Pareto Frontier Learning.** Given multiple objectives, Pareto frontier learning aims to find a set of Pareto optimal solutions over them. Most methods exploit evolutionary algorithms (Deb et al., 2002; Kim et al., 2004) to solve this problem. Inspired by them, many efforts have been made to simultaneously find a set of Pareto optimal architectures over accuracy and computational cost (Cheng et al., 2018; Dong et al., 2018). Recently, NSGANetV1 (Lu et al., 2020c) presents an evolutionary approach to find a set of trade-off architectures over multiple objectives in a single run. NSGANetV2 (Lu et al., 2020a) further presents two surrogates (at the architecture and weights level) to produce task-specific models under multiple competing objectives. Given a target budget, these methods may manually select an appropriate architecture from a set of searched architectures. However, given limited population size, the selected architectures do not necessarily satisfy the considered budget. More critically, due to the limited population size, these methods may only find a small number of architectures on the Pareto frontier. Thus, how to learn the entire Pareto frontier of architectures still remains an open question.

### 3. Pareto Neural Architecture Generation

**Notation.** In this paper, we consider producing architectures under diverse budgets simultaneously. For convenience, let  $B$  be a computation budget (*e.g.*, latency and MAdds) which can be considered as a random variable drawn from some distribution  $\mathcal{B}$ , namely  $B \sim \mathcal{B}$ . Let  $\Omega$  be an architecture search space. For any architecture  $\alpha \in \Omega$ , we use  $c(\alpha)$  and  $\text{Acc}(\alpha)$  to measure the cost and validation accuracy of  $\alpha$ , respectively. Without loss of generality, we use  $\alpha_B^{(i)}$  to denote the  $i$ -th generated architecture under the budget constraint  $c(\alpha_B^{(i)}) \leq B$ .

We focus on the architecture generation problem that aims to produce effective architectures for real-world applications/devices with diverse computation budgets. Note that the optimal architectures under different budgets lie on the Pareto frontier over model performance and computational cost (Kim & De Weck, 2005). Thus, we propose to learn the whole Pareto frontier to enable the generator to produce architectures for the budget with any possible value. In this way, we can easily find a promising architecture from the learned frontier by restricting the computational cost to be less than the considered budget.

Formally, we generate architectures by determining which architecture should be the optimal one w.r.t. any given budget. Specifically, we seek to learn a transformation mapping  $B \rightarrow \alpha_B$  to produce an architecture whose computational cost satisfies the constraint  $c(\alpha_B) \leq B$ . Note that both accuracy and computational cost in the objective are non-differentiable. We use reinforcement learning (Williams, 1992) to train the generator model (See Algorithm 1).

### 3.1. Learning the Architecture Generator $f(B; \theta)$

In this section, we propose an architecture generator model to automatically produce effective architectures for any given computation budget. As shown in Figure 2, we develop a conditional model  $f(B; \theta)$  based on an LSTM network. The  $f(B; \theta)$  takes a budget  $B$  as input and outputs an architecture  $\alpha_B = f(B; \theta)$  satisfying the budget constraint  $c(\alpha_B) \leq B$ . Here,  $\theta$  denotes the learnable parameters of  $f(\cdot)$ . Note that the optimal architecture under a specific budget should lie on the Pareto frontier over model performance and computational cost. To learn a general generator for an arbitrary budget, we seek to learn the Pareto frontier rather than optimizing a specific architecture.

**NAS under a single budget.** To illustrate our method, we first revisit the NAS problem with a single budget and then generalize it to the problem with diverse budgets. Note that it is non-trivial to directly find the optimal architecture (Zoph & Le, 2017). By contrast, one can first learn a policy  $\pi(\cdot; \theta)$  and then conduct sampling from it to find promising architectures, *i.e.*,  $\alpha \sim \pi(\cdot; \theta)$ . Given a budget  $B$ , the optimization problem becomes

$$\max_{\theta} \mathbb{E}_{\alpha \sim \pi(\cdot; \theta)} [R(\alpha|B; w)], \text{ s.t. } c(\alpha) \leq B. \quad (1)$$

Here,  $\pi(\cdot; \theta)$  is the learned policy parameterized by  $\theta$ , and  $R(\alpha|B; w)$  is the reward function parameterized by  $w$  that measures the joint performance on both the accuracy and the latency of  $\alpha$ . We use  $\mathbb{E}_{\alpha \sim \pi(\cdot; \theta)} [\cdot]$  to denote the expectation over the searched architectures.

**NAS under multiple budgets.** Problem (1) only focuses on one specific budget constraint. In fact, we seek to learn the Pareto frontier over the whole range of budgets (*e.g.*, latency). However, this problem is hard to solve since there may exist infinite Pareto optimal architectures with different computational cost. To address this, one can learn the approximated Pareto frontier by finding a set of uniformly distributed Pareto optimal points (Grosan & Abraham, 2008). In this paper, we evenly sample  $K$  budgets from the range of latency and maximize the expected reward over them. Thus, the optimization problem becomes

$$\begin{aligned} \max_{\theta} \mathbb{E}_{B \sim \mathcal{B}} \left[ \mathbb{E}_{\alpha_B \sim \pi(\cdot|B; \theta)} [R(\alpha_B|B; w)] \right], \\ \text{s.t. } c(\alpha_B) \leq B, B \sim \mathcal{B}, \end{aligned} \quad (2)$$

where  $\mathbb{E}_{B \sim \mathcal{B}} [\cdot]$  denotes the expectation over the budget. Unlike Eqn. (1),  $\pi(\cdot|B; \theta)$  is the learned policy conditioned on the budget of  $B$ . To find the architectures satisfying the budget constraint, we take  $B$  into account to compute the reward  $R(\cdot|B; w)$ . We will illustrate this in Section 3.3.

In practice, we use a policy gradient method to learn the architecture generator. To encourage exploration, we introduce an entropy regularization term  $H(\cdot)$  to measure the

### Algorithm 1 Training method of NAG.

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**Require:** Search space  $\Omega$ , latency distribution  $\mathcal{B}$ , learning rate  $\eta$ , training data set  $\mathcal{D}$ , parameters  $M, N$  and  $K$ .

- 1: Initialize model parameters  $\theta$  for the generator and  $w$  for the architecture evaluator.
- // Collect the architectures with accuracy and latency*
- 2: Train a supernet  $S$  on  $\mathcal{D}$ .
- 3: Randomly sample architectures  $\{\beta_i\}_{i=1}^M$  from  $\Omega$ .
- 4: Construct tuples  $\{(\beta_i, c(\beta_i), \text{Acc}(\beta_i))\}_{i=1}^M$  using  $S$ .
- // Learn the architecture evaluator*
- 5: **while** not convergent **do**
- 6: Sample a set of latencies  $\{B_k\}_{k=1}^K$  from  $\mathcal{B}$ .
- 7: Update the architecture evaluator by:
- $w \leftarrow w - \eta \nabla_w L(w)$ .
- 9: **end while**
- // Learn the architecture generator*
- 10: **while** not convergent **do**
- 11: Sample a set of latencies  $\{B_k\}_{k=1}^K$  from  $\mathcal{B}$ .
- 12: Obtain  $\{\alpha_{B_k}^{(i)}\}_{i=1}^N$  from  $\pi(\cdot|B_k; \theta)$  for each  $B_k$ .
- 13: Update the generator via policy gradient by:
- $\theta \leftarrow \theta + \eta \nabla_{\theta} J(\theta)$ .
- 15: **end while**

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entropy of the policy. Thus, the objective becomes

$$J(\theta) = \mathbb{E}_{B \sim \mathcal{B}} \left[ \mathbb{E}_{\alpha_B \sim \pi(\cdot|B; \theta)} [R(\alpha_B|B; w)] + \lambda H(\pi(\cdot|B; \theta)) \right], \quad (3)$$

where  $\lambda$  is a hyper-parameter. In each iteration, we first sample  $\{B_k\}_{k=1}^K$  from the distribution  $\mathcal{B}$ , and then sample  $N$  architectures  $\{\alpha_{B_k}^{(i)}\}_{i=1}^N$  for each budget  $B_k$ . Thus, the gradient of the objective for the generator w.r.t.  $\theta$  becomes<sup>1</sup>

$$\begin{aligned} \nabla_{\theta} J(\theta) \approx \frac{1}{KN} \sum_{k=1}^K \sum_{i=1}^N \left[ \nabla_{\theta} \log \pi(\alpha_{B_k}^{(i)}|B_k; \theta) R(\alpha_{B_k}^{(i)}|B_k; w) \right. \\ \left. + \lambda \nabla_{\theta} H(\pi(\cdot|B_k; \theta)) \right]. \end{aligned} \quad (4)$$

To learn the architecture generator, we still have to answer two questions. 1) How to represent the budget bound  $B$  as the inputs of NAG? As mentioned before, our NAG consider  $K$  discrete budgets during training. To represent different budgets, we use an embedding vector (Pham et al., 2018) to represent different budgets (See details in Section 3.2). 2) How to define the reward function  $R(\cdot|B; w)$  in Eqn. (4) to evaluate the generated architectures? Given diverse budgets, an architecture should be assigned a specific reward score for each budget. However, it is non-trivial to manually design the reward function. Instead, we propose to learn an architecture evaluator to automatically predict the score (See details in Section 3.3).

### 3.2. Vector Representation of Budget Bounds

To represent different budgets, following (Pham et al., 2018; Guo et al., 2019), we build a learnable embedding vector

<sup>1</sup>We put the derivations of the gradient in the supplementary.

$\mathbf{b} = g(B)$  for each sampled budget  $B$ . We incorporate these learnable embedding vectors into the parameters of the architecture generator and train them jointly. In this way, we are able to automatically learn the vectors of these budgets and encourage NAG to produce feasible architectures.

As mentioned before, we only sample a set of discrete budgets to train NAG. To accommodate all the budgets belong to a continuous space, we propose an embedding interpolation method to represent a budget with any possible value. Specifically, we perform a linear interpolation between the embedding of two adjacent discrete budgets to represent the considered budgets. For a target budget  $B$  between two sampled budgets  $B_1 < B < B_2$ , the linear interpolation of the budget vector  $\mathbf{b}$  can be computed by

$$\mathbf{b} = g(B) = \xi g(B_1) + (1 - \xi)g(B_2), \text{ where } \xi = \frac{B_2 - B}{B_2 - B_1},$$

Here,  $\xi \in [0, 1]$  denotes the weight of  $B_1$  in interpolation.

### 3.3. Learning the Architecture Evaluator $R(\cdot|B; w)$

To guide the training of NAG, we shall propose a reward function to estimate the performance of architectures. Given any architecture  $\beta$  and a budget  $B$ , we build an evaluator with three fully connected layers to predict the performance  $R(\beta|B; w)$  of  $\beta$  under the budget  $B$ . Since we have no labeled data for training, we learn the evaluator via pairwise comparisons between any two architectures.

**Pairwise ranking loss function.** To obtain a promising evaluator, we train the architecture evaluator using a pairwise ranking loss, which has been widely used in ranking problems (Freund et al., 2003; Burges et al., 2005; Chen et al., 2009). Specifically, we collect  $M$  architectures with accuracy and latency, and record these architectures as a set of triplets  $\{(\beta_i, c(\beta_i), \text{Acc}(\beta_i))\}_{i=1}^M$ . Thus, given  $M$  architectures, we have  $M(M-1)$  architecture pairs  $\{(\beta_i, \beta_j)\}$  in total after omitting the pairs with the same architecture. Assuming that we have  $K$  budgets, the pairwise ranking loss becomes

$$L(w) = \frac{1}{KM(M-1)} \sum_{k=1}^K \sum_{i=1}^M \sum_{j=1, j \neq i}^M \phi \left( d(\beta_i, \beta_j, B_k) \cdot [R(\beta_i|B_k; w) - R(\beta_j|B_k; w)] \right), \quad (5)$$

where  $d(\beta_1, \beta_2, B_k)$  denotes a function to indicate whether  $\beta_i$  is better than  $\beta_j$  under the budget  $B_k$ . The  $\phi(z) = \max(0, 1 - z)$  is a hinge loss function. We use the hinge loss  $\phi(\cdot)$  to enforce the predicted ranking results  $R(\beta_i|B_k; w) - R(\beta_j|B_k; w)$  to be consistent with the results of  $d(\beta_i, \beta_j, B_k)$  obtained by a comparison rule based on Pareto dominance.

According to Eqn. (5), based on collected training data

$\{(\beta_i, c(\beta_i), \text{Acc}(\beta_i))\}_{i=1}^M$  and  $\{B_k\}_{k=1}^K$ , the gradient w.r.t.  $w$  becomes

$$\nabla_w L(w) = \frac{1}{KM(M-1)} \sum_{k=1}^K \sum_{i=1}^M \sum_{j=1, j \neq i}^M \nabla_w \phi \left( d(\beta_i, \beta_j, B_k) \cdot [R(\beta_i|B_k; w) - R(\beta_j|B_k; w)] \right).$$

### 3.4. Pareto Dominance Design

To compare the performance between two architectures, we need to define a reasonable function  $d(\beta_1, \beta_2, B)$  in Eqn. (5). To this end, we define a Pareto dominance to guide the design of this function. Specifically, Pareto dominance requires that the quality of an architecture should depend on both the satisfaction of budget and accuracy. That means, given a specific budget  $B$ , a good architecture should be the one with the cost lower than or equal to  $B$  and with high accuracy. In this sense, we use Pareto dominance to compare two architectures and judge which one is dominative.

Given any two architectures  $\beta_1, \beta_2$ , if both of them satisfy the budget constraints (namely  $c(\beta_1) \leq B$  and  $c(\beta_2) \leq B$ ), then  $\beta_1$  dominates  $\beta_2$  if  $\text{Acc}(\beta_1) \geq \text{Acc}(\beta_2)$ . Moreover, when at least one of  $\beta_1, \beta_2$  violates the budget constraint, clearly we have that  $\beta_1$  dominates  $\beta_2$  if  $c(\beta_1) \leq c(\beta_2)$ . Formally, we define the Pareto dominance function  $d(\beta_1, \beta_2, B)$  to reflect the above rules:

$$d(\beta_1, \beta_2, B) = \begin{cases} 1, & \text{if } (c(\beta_1) \leq B \wedge c(\beta_2) \leq B) \\ & \wedge (\text{Acc}(\beta_1) \geq \text{Acc}(\beta_2)); \\ -1, & \text{else if } (c(\beta_1) \leq B \wedge c(\beta_2) \leq B) \\ & \wedge (\text{Acc}(\beta_1) < \text{Acc}(\beta_2)); \\ 1, & \text{else if } c(\beta_1) \leq c(\beta_2); \\ -1, & \text{otherwise.} \end{cases} \quad (6)$$

Based on Eqn. (6), we have  $d(\beta_1, \beta_2, B) = -d(\beta_2, \beta_1, B)$  if  $\beta_1 \neq \beta_2$ .

**Remark 1** *The accuracy constraint  $\text{Acc}(\beta_1) \geq \text{Acc}(\beta_2)$  plays an important role in the proposed Pareto dominance function  $d(\beta_1, \beta_2, B)$ . Without the accuracy constraint, we may easily find the architectures with very low computation cost and poor performance (See results in Table 2).*

### 3.5. Inferring Architecture for Required Budgets

During inference, we allow the input budget to be any value. Based on the set of discrete budgets in training, we first use linear interpolation to obtain the desired budget, and then perform inference using NAG to produce architectures. Specifically, given an arbitrary budget  $B$ , we first sample several candidate architectures from the learned policy  $\pi(\cdot|B; \theta)$ . If all the sampled architectures violate the

Table 1. Comparisons with state-of-the-art architectures on mobile devices. \* denotes the best architecture reported in the original paper. “-” denotes the results that are not reported. All the models are evaluated on  $224 \times 224$  images of ImageNet.

Architecture	Latency (ms)	Test Accuracy (%)		#Params (M)	#MAdds (M)	Search Cost (GPU Days)
		Top-1	Top-5			
MobileNetV3-Large (0.75 $\times$ ) (Howard et al., 2019)	93.0	73.3	-	4.0	155	-
MobileNetV2 (1.0 $\times$ ) (Sandler et al., 2018)	90.3	72.0	-	3.4	300	-
FBNetV2 (Wan et al., 2020)	-	76.3	92.9	-	321	30.0
OFA-80 (Cai et al., 2020)	76.8	76.8	93.3	6.1	350	51.7
NAG-80	79.9	<b>78.4</b>	<b>94.0</b>	7.3	349	0.7
FBNet-A (Wu et al., 2019)	91.7	73.0	-	4.3	249	9.0
ProxylessNAS-Mobile (Cai et al., 2019)	97.3	74.6	-	4.1	319	8.3
ProxylessNAS-CPU (Cai et al., 2019)	98.5	75.3	-	4.4	438	8.3
MobileNetV3-Large (1.0 $\times$ ) (Howard et al., 2019)	107.7	75.2	-	5.4	219	-
OFA-110 (Cai et al., 2020)	109.3	78.1	94.0	10.2	482	51.7
NAG-110	106.8	<b>79.5</b>	<b>94.5</b>	9.9	451	0.7
RandWire (Xie et al., 2019)	-	74.7	92.2	5.6	583	-
ProxylessNAS-GPU (Cai et al., 2019)	123.3	75.1	-	7.1	463	8.3
MobileNetV2 (1.4 $\times$ ) (Sandler et al., 2018)	139.6	74.7	-	6.9	585	-
MnasNet-A1 (1.0 $\times$ ) (Tan et al., 2019)	120.7	75.2	92.5	3.4	300	$\sim$ 3792
FBNet-C (Wu et al., 2019)	135.2	74.9	-	5.5	375	9.0
OFA-140 (Cai et al., 2020)	133.7	78.4	94.1	9.1	488	51.7
NAG-140	127.8	<b>79.8</b>	<b>94.7</b>	9.2	492	0.7
NSGANetV1 (Lu et al., 2020c)	-	76.2	93.0	5.0	585	27
PONAS-C (Huang & Chu, 2020)	145.1	75.2	-	5.6	376	8.8
DARTS (Liu et al., 2019)	176.6	73.1	91.0	4.7	574	4.0
P-DARTS (Chen et al., 2019)	168.7	75.6	92.6	4.9	577	3.8
OFA-170 (Cai et al., 2020)	168.3	78.9	94.4	10.7	661	51.7
NAG-170	167.1	<b>80.3</b>	<b>95.1</b>	10.0	606	0.7
NSGANetV2 (Lu et al., 2020a)	-	79.1	94.5	8.0	400	1
NAGO (Ru et al., 2020)	-	76.8	93.4	5.7	-	20.0
ENAS (Pham et al., 2018)	232.4	73.8	91.7	5.6	607	0.5
PC-DARTS (Xu et al., 2020)	194.1	75.8	92.7	5.3	597	0.1
MnasNet-A1 (1.4 $\times$ ) (Tan et al., 2019)	205.5	77.2	93.5	6.1	592	$\sim$ 3792
EfficientNet B0 (Tan & Le, 2019)	237.7	77.3	93.5	5.3	390	-
Cream-L (Peng et al., 2020)	-	80.0	94.7	9.7	604	12
OFA* (Cai et al., 2020)	201.9	80.2	95.1	9.1	743	51.7
OFA-200 (Cai et al., 2020)	195.9	79.0	94.5	11.0	783	51.7
NAG-200	193.9	<b>80.5</b>	<b>95.3</b>	10.4	724	0.7

budget constraint, we will repeat the sampling process until finding a feasible architecture. Then, we select the feasible architecture with the highest validation accuracy.

## 4. Experiments

We apply NAG to produce architectures under diverse latency budgets on three kinds of hardware platforms, including mobile devices (equipped with a Qualcomm Snapdragon 821 processor), CPU devices (Intel Core i5-7400), and GPU devices (NVIDIA TITAN X). For convenience, we use “Architecture- $B$ ” to represent the generated architecture that satisfies the latency budget w.r.t.  $B$ , e.g., NAG-80. Due to the page limit, we put the experimental results on CPU and GPU devices and visualizations of the generated architectures in the supplementary.

**Implementation details.** We use MobileNetV3 (Howard et al., 2019) as the backbone to build the search space. Following (Wu et al., 2019), we randomly choose 10% classes from ImageNet as the training set and train the supernet with progressive shrinking strategy (Cai et al., 2020) for 90 epochs. To obtain the range of latency, we randomly sample  $M=16,000$  architectures from the search space (See Figure 3(a)). Then, we evenly sample  $K=10$  discrete budgets to divide the range of latency (See the discussions on  $K$  in Section 4.4). Note that we share the same search space with OFA (Cai et al., 2020). We set the dimension of the embedding vector of budgets to 64. To accelerate model evaluation, following (Cai et al., 2020; Lu et al., 2020b), we first obtain the parameters from the full network of OFA and then finetune them for 75 epochs to obtain the final performance. We put more details in the supplementary.

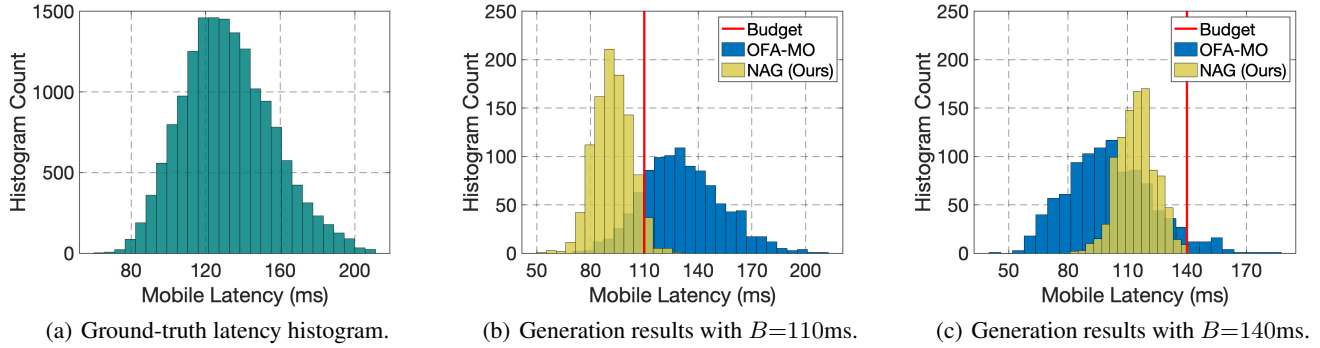


Figure 3. Latency histograms of sampled architectures on mobile devices. (a) Ground-truth latency histogram of 16,000 architectures that are uniformly sampled from the search space. (b) The latency histogram of 1,000 architectures sampled by different methods given  $B=110$ ms. (c) The latency histogram of 1,000 architectures sampled by different methods given  $B=140$ ms.

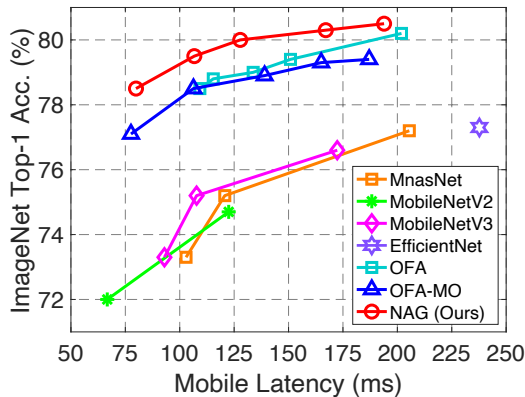


Figure 4. Comparisons of the architectures obtained by different methods on mobile devices.

#### 4.1. Comparisons with State-of-the-art Methods

We compare NAG with state-of-the-art methods on mobile device. We also consider the following baselines: 1) **OFA** uses the evolutionary search method (Real et al., 2019) used in the OFA paper (Cai et al., 2020) to perform architecture search. 2) **OFA-MO** conducts architecture search based on OFA super network by exploiting the multi-objective reward (Tan et al., 2019). From Table 1 and Figure 4, our NAG consistently achieves higher accuracy than other methods. Compared with the methods that find architectures for each budget independently (e.g., OFA and OFA-MO), our NAG only needs to search once to generate the architectures with arbitrary target latency.

We also visualize the latency histograms of the architectures generated on mobile devices in Figure 3(b) and Figure 3(c). Given latency budgets of 110ms and 140ms, OFA-MO is prone to produce a large number of architectures that cannot satisfy the target budgets. These results show that it

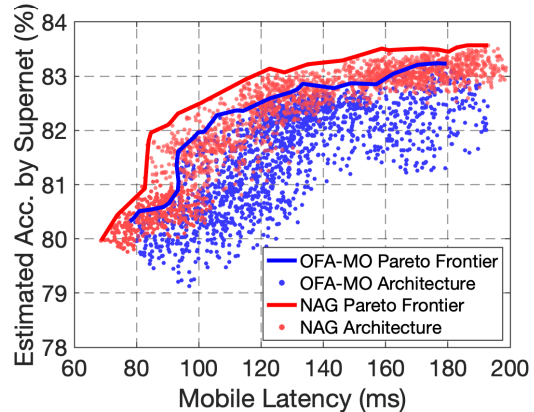


Figure 5. Comparisons of the Pareto frontiers of the generated architectures using different methods.

is hard to design the multi-objective reward to obtain the preferred architectures. Instead, NAG uses the Pareto dominance reward to encourage the architectures to satisfy the desired budget constraints. In this sense, most architectures generated by our NAG are able to fulfill the target budgets. We put more visual results of latency histograms with other target latencies in the supplementary.

Moreover, we compare the learned/searched frontiers of different methods and show the comparisons of Pareto frontiers in Figure 5. We plot all the architectures produced by different methods to form the Pareto frontier. Specifically, we use the architectures searched by multiple independent runs under different budgets for OFA-MO. For NAG, we use linear interpolation to generate architectures that satisfy different budgets. From Figure 5, our NAG finds a better frontier than OFA-MO due to the shared knowledge across the search process under different budgets.

Table 2. Comparisons of different reward functions based on NAG. We report the latency on mobile devices.

Reward	$B_1=80\text{ms}$		$B_2=110\text{ms}$		$B_3=140\text{ms}$		$B_4=170\text{ms}$		$B_5=200\text{ms}$	
	Acc. (%)	Lat. (ms)	Acc.	Lat. (ms)	Acc.	Lat. (ms)	Acc.	Lat. (ms)	Acc.	Lat. (ms)
Multi-objective Reward (Tan et al., 2019)	77.0	77.6	78.5	106.3	78.9	139.0	79.3	165.1	79.5	187.3
Multi-objective Absolute Reward (Bender et al., 2020)	78.1	76.8	78.9	109.2	79.2	130.1	79.5	163.6	79.9	197.5
Pareto Dominance Reward (w/o accuracy constraint)	73.8	74.4	73.6	64.9	74.3	66.5	73.9	70.0	74.0	70.8
Pareto Dominance Reward (Ours)	<b>78.4</b>	79.9	<b>79.5</b>	106.8	<b>79.8</b>	127.8	<b>80.3</b>	167.1	<b>80.5</b>	193.9

Table 3. Effect of different search strategies on the performance of NAG. We report the accuracy on ImageNet.

Search Strategy	$B_1=80\text{ms}$	$B_2=110\text{ms}$	$B_3=140\text{ms}$	$B_4=170\text{ms}$	$B_5=200\text{ms}$
Repeated Independent Search	76.7	78.6	79.1	79.4	79.7
Pareto Frontier Search	<b>78.4</b>	<b>79.5</b>	<b>79.8</b>	<b>80.3</b>	<b>80.5</b>

Table 4. Comparisons of the time cost for architecture generation/design among different methods.

Method	NAG	PC-DARTS	ENAS	DARTS
Time Cost	$\leq 5$ s	2 hours	12 hours	4 days

 Table 5. Effect of  $K$  on the generation performance of NAG. We compare the generated architectures using different values of  $K$  with the target latency  $B=140\text{ms}$  on ImageNet.

$K$	2	5	10	30
Top-1 Acc. (%)	79.1	79.4	<b>79.8</b>	79.7

## 4.2. Ablation Studies

Here, we investigate the effectiveness of the Pareto frontier learning strategy and the Pareto dominance reward. From Table 2, the Pareto frontier learning strategy tends to find better architectures than the independent search process due to the shared knowledge across the search processes under different budgets. Compared with two existing multi-objective rewards (Tan et al., 2019; Bender et al., 2020), the Pareto dominance reward encourages the generator to produce architectures that satisfy the considered budget constraints. Moreover, if we do not consider accuracy constraint in the Pareto dominance reward, the generated architectures have low latency and poor accuracy. With both the Pareto frontier learning strategy and the Pareto dominance reward, our method yields the best results under all budgets.

## 4.3. Comparisons of Architecture Generation Cost

In this part, we compare the architecture generation cost of different methods for 5 different budgets and show the comparison results in Table 4. Given an arbitrary target budget, existing NAS methods need to perform an independent search to find feasible architectures. By contrast, since NAG directly learns the whole Pareto frontier, we are able to generate promising architectures based on a learned generator model via inference. Thus, the architecture gener-

ation cost of NAG is much less than other existing methods (See results in Table 4). In this sense, we are able to greatly accelerate the architecture design process in real-world scenarios. These results demonstrate the efficiency of our NAG in generating architectures.

## 4.4. Effect of $K$ on the Generation Performance

In this part, we investigate the effect of  $K$  on the generation performance of NAG based on mobile device. Note that we evenly select  $K$  budgets from the range of latency. To investigate the effect of  $K$ , we consider several candidate values of  $K \in \{2, 5, 10, 30\}$ . We show the Top-1 accuracies of the architectures generated by NAG with different  $K$  on ImageNet in Table 5. Since a small number of selected budgets  $K$  cannot accurately approximate the ground-truth Pareto frontier or provide enough shared knowledge between different search processes, our method yields poor results with  $K = 2$ . When we increase  $K$  larger than 5, we are able to greatly improve the performance of the generated architectures. From Table 5, our method yields the best result with  $K = 10$ . Therefore, we select  $K = 10$  discrete budgets to train our NAG model in the experiments.

## 5. Conclusion

In this paper, we have proposed a novel Pareto-Frontier-aware Neural Architecture Generator (NAG) method to produce effective architectures for any given budget. Specifically, we train the NAG model to learn the Pareto frontier by maximizing the expected reward over a set of budgets. Moreover, we propose an embedding interpolation method to adapt the learned generator model to any possible budget. To provide accurate rewards to guide the learning of NAG, we propose a Pareto dominance reward that is able to judge whether an architecture is better than another. Based on the learned Pareto frontier, NAG is able to produce promising architectures under diverse budgets. Extensive experiments on three platforms (*i.e.*, mobile, CPU, and GPU devices) demonstrate the effectiveness of the proposed method.



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