WPNAS: Neural Architecture Search by jointly using Weight Sharing and Predictor

Ke Lin\(^1\) Yong A\(^2\) Zhuoxin Gan\(^2\) Yingying Jiang\(^2\)
\(^1\)Huawei \(^2\)Samsung Research China, Beijing (SRC-B)

Abstract

Weight sharing based and predictor based methods are two major types of fast neural architecture search methods. In this paper, we propose to jointly use weight sharing and predictor in a unified framework. First, we construct a SuperNet in a weight-sharing way and probabilistically sample architectures from the SuperNet. To increase the correctness of the evaluation of architectures, besides direct evaluation using the inherited weights, we further apply a few-shot predictor to assess the architecture on the other hand. The final evaluation of the architecture is the combination of direct evaluation, the prediction from the predictor and the cost of the architecture. We regard the evaluation as a reward and apply a self-critical policy gradient approach to update the architecture probabilities. To further reduce the side effects of weight sharing, we propose a weakly weight sharing method by introducing another HyperNet. We conduct experiments on datasets including CIFAR-10, CIFAR-100 and ImageNet under NATS-Bench, DARTS and MobileNet search space. The proposed WPNAS method achieves state-of-the-art performance on these datasets.

1. Introduction

Neural Architecture Search (NAS) is proposed to make the computer automatically search for an optimal neural network architecture, whose performance can surpass the manually designed state-of-the-art neural network architectures and has similar or less computational complexity (e.g., latency, FLOPs) [51]. Early NAS methods usually sample architectures from a pre-defined search space, obtain the performance of the architecture after training from scratch, and update the search algorithm through reinforcement learning [34, 51] or evolution algorithm [27, 46] until one or a cluster of optimal architectures are obtained. Although these methods have achieved amazing performances, they often need thousands of GPU-day to run the searching algorithm.

Weight-sharing [23, 26] and predictor [25, 38] are two most commonly used methods to solve the above problem of excessive resource consumption.

Weight sharing refers to building a SuperNet and all sub-architectures in the search space can inherit weights from the SuperNet. Therefore, the amount of parameters to be trained in the search process and the search time can be greatly reduced. Weight sharing NAS algorithms can be divided into two categories: i) Gradient based which parametrize architecture parameter as part of the SuperNet and update the parameter of the SuperNet (architecture parameters and weight parameters) in a differentiable way [8, 23, 42, 43], ii) Sampling based algorithms including uniform sampling [7, 14] and learning based sampling [1, 5, 44]. Because all sub-architectures are deeply coupled with each other, the evaluation of the performance of each architecture have large gaps between those architectures obtained by stand-alone training [7]. Therefore, in order to improve the ranking consistency between the architectures of weight sharing and the architectures obtained by stand-alone training, there are still two major problems to be solved: i) how to improve the correctness of the evaluation of each architecture and ii) is there any way to reduce the degree of weight sharing.

Predictor based NAS algorithms [25, 38] are proposed thanks to the introduction of several excellent benchmarking datasets such as NAS-Bench-101 [48], NAS-Bench-201 [11] and NATS-Bench [9]. Predictor based NAS collects several architecture-accuracy pairs as training data in advance, and uses MLP [38] or GCN [25] as predictor to train the direct mapping from architecture to accuracy. However, collecting architecture-accuracy pairs is a resource consuming issue, because it needs to fully train each architecture from scratch of the training pairs. How to improve the training efficiency of the predictor to reduce the dependence on training data is also an important question to be answered.

In this paper, we attempt to answer the above questions using a Weight-sharing and Predictor based NAS (WPNAS) method. First, we construct a SuperNet in a weight-sharing way and probabilistic sampling architectures from the SuperNet with inherited weights. To increase the correctness of
Figure 1. Overview of the proposed WPNAS. We apply a probabilistic sampling strategy to sample architectures from the SuperNet and use a HyperNet to alleviate the influence of weight sharing. The evaluation of the sampled architecture comes from three parts: direct evaluation, prediction from the few-shot predictor and the FLOPs of the architecture. Then we regard the evaluation of the architecture as reward and use a policy gradient algorithm to update architecture probabilities. The combined reward contains information from both SuperNet and predictor, thus may lead better evaluation. Few-shot learning is proposed to reduce the demand for training data of the predictor.

the evaluation of architectures, besides direct evaluation, we further apply a predictor to predict the performance the architecture on the other hand. Direct evaluation from SuperNet, the prediction from the predictor and the cost of the architecture are regarded as the reward and we apply a self-critical policy gradient approach to update the architecture probabilities. To increase the training efficiency of the predictor, we propose a few-shot learning based strategy to train the predictor. Besides, to further reduce the negative effects of weight sharing, we propose a weakly weight sharing method. Namely, we feed the sampled architecture into a HyperNet and generate different offset-weights, the final weights is the product of the offset-weights and weights from SuperNet. By this way, the degree of weight sharing is reduced.

In summary, the contribution of this work contains four major parts:

- We jointly use weight-sharing and predictor and use a self-critical policy gradient algorithm with probabilistic sampling to update architecture parameters.
- We propose a few-shot learning based predictor to increase the training efficiency of the predictor.
- HyperNet based weakly weight sharing strategy is proposed to alleviate the influence of weight sharing.
- We conduct comprehensive experiments on CIFAR and ImageNet datasets under several search space and the results demonstrate the superiority of the proposed method.

2. Related Work

**Weight sharing based NAS.** ENAS [26] is the first NAS paper to apply weight sharing to address the high searching cost problem. ENAS [26] applies reinforcement learning to train a controller to sample architectures and it does not need to train each sampled architecture from scratch, but directly inherit parameters from the Supernet, so the architecture search time can be reduced from thousands of GPU-day to only less than a single GPU-day. DARTS [23] uses a continuous relaxation on the categorical choices of inputs and operations. The weight parameters and architecture parameters can be updated based on the gradient, and the search time can be further reduced. DARTS has received a lot of attention and follow-up research because of its high simplicity and effectiveness [3, 6, 8, 42, 43]. The above gradient based methods still face two important problems: high GPU memory occupation and lack of theoretical support for discretization. [10] and [2] propose to apply Gumbel-Softmax trick to reduce the GPU memory occupation. Sampling based methods are proposed to solve the above two problems at the same time. SPOS [14] proposes a two-stage algorithm that abandoning the architecture parameters, using only uniform sampling to train the Supernet, and applying evolution algorithm to search optimal architectures on the
Figure 2. Few-shot learning based predictor.

3.1. Probabilistic Sampling

Suppose the SuperNet with model weights $\omega$ with a macro search space has $L$ layers, each layer have $K$ candidate operations $\{o_1, ..., o_K\}$. An individual architecture $A$ from the SuperNet can be denoted as $A = (A^1, ..., A^L)$, $A^l \in \{o_1, ..., o_K\}$. Like [1, 44], we also introduce architecture parameters (i.e. architecture probabilities) $\alpha$ and a prior distribution $p(A | \alpha)$. Each architecture $A$ is sampled based on $p(A | \alpha)$, thus the task of architecture search is to learn the distribution $p(A | \alpha)$ which prefers better architectures. Suppose the probabilities at different layers are independent to each other, the probability of architecture $A$ being sampled can be calculated as below:

$$p(A | \alpha) = \prod_l p(A^l | \alpha^l)$$  \hspace{1cm} (1)

3.2. Few-shot Predictor

Traditional accuracy predictor of NAS always needs thousands of training data pairs which require tremendous computing resources to obtain. To address this problem, we borrow the idea from few-shot learning on image classification for more efficient predictor training. Specifically, we construct a simple yet effective Relation Network [32]-like predictor by learning to compare query architectures and support architectures. The predictor has two major modules: architecture encoding module and architecture decoder module (see Figure 2.). The architecture encoding module embeds the support architectures and query architecture into the hidden representations with the same dimension. The embeddings from support set and query architecture are concatenated and are fed to the architecture decoder module to learn the accuracy offset between each architecture in the support set and the query architecture. The encoding and decoding modules can be MLP based, RNN based, Transformer based or GCN based. During training, the support set and the query set are randomly chosen from the training data. Once trained, the few-shot predictor is able to predict...
new architectures by computing relation offsets between the query architecture and the few examples of training set. For simplicity, we denote the output of the few-shot predictor as $FSP(A)$. In the following section, we will demonstrate the superiority of the proposed few-shot predictor than supervised learning based predictor.

### 3.3. Weakly weight sharing

Although weight sharing brings benefits such as reducing search consumption, it also leads to the fatal problem of the ranking gap between architectures trained by weight sharing and stand-alone training. To relieve this problem, we apply a weakly weight sharing strategy by introducing a HyperNet (see Figure 3.). Specifically, for a sampled architecture $A = (A^1, ..., A^L)$, the weights of the architecture can be inherit from the SuperNet, and we call these weights as base weights $\omega_b = [\omega^1_b, ..., \omega^L_b]$. A bidirectional LSTM (bi-LSTM) with $L$ time steps is used as the HyperNet to generate several weights for each edge (or layer) given the architecture, and these weights are called offset weights $\omega_o = [\omega^1_o, ..., \omega^L_o]$. The final weights for evaluation and back-propagation are the product of the based weights and offset weights:

$$\omega = [\omega^1, ..., \omega^L], \omega^l = \omega^l_b \omega^l_o$$ (2)

Suppose two architectures choose the same operation in a certain layer. If there is no weakly weight sharing, the two architectures have exactly the same weights on that layer. After the introduction of HyperNet, different architectures will generate different offset weights, if the two architectures have the same operation in a certain layer, their weights at that layer will be different. Thus, the introduction of HyperNet will reduce the degree of weight sharing among architectures, which may alleviate the problem of the ranking gap. The weights of HyperNet can be fixed or updated simultaneously with the SuperNet.

The maximum kernel size we used in this study is 5, so the dimension of $\omega^l_o$ is $5 \times 5 = 25$. For operations with smaller kernel size such as $3 \times 3$, the weights of the top left corner are cropped and used.

### 3.4. Optimization

Given a classification task with input $X$ and targets $y$, the goal of optimization can be present as:
\[ p(y | X, \alpha, \omega) = \int p(y | X, A, \omega)p(A | \alpha)dA \]  \hspace{1cm} (3)

We can simplify the optimization through Monte Carlo sampling and policy gradient algorithm. For \( \omega \), the optimization is straight forward. For a sampled architecture \( A \) with weights \( \tilde{\omega} \), we can directly optimize \( \tilde{\omega} \) by \( \nabla_{\tilde{\omega}} \log p(y | X, A, \tilde{\omega}) \).

For \( \alpha \), the gradient of loss can be estimated by policy gradient:
\[ \nabla_{\alpha}L = -r \nabla_{\alpha} \log p(\hat{A} | \alpha) \]  \hspace{1cm} (4)
where \( r \) is the reward function. The reward function contains three parts: 1) direct evaluation, i.e. the negative cross-entropy loss of the architecture \( \log p(y | X, \hat{A}, \tilde{\omega}) \); 2) the output of the few-shot predictor \( FSP(\hat{A}) \); and the negative FLOPs of the sampled architecture \( -FLOPs(\hat{A}, X) \).

Thus, we get:
\[ \nabla_{\alpha}L = -[\log p(y | X, \tilde{\omega}) + \beta_1 FSP(\hat{A}) - \beta_2 FLOPs(\hat{A}, X)] \times \nabla_{\alpha} \log p(\hat{A} | \alpha) \]  \hspace{1cm} (5)
where \( \beta_1 \) and \( \beta_2 \) are two hyper-parameters to control the weights of each part. Because the reward function of policy gradient is scalar, the information from predictor and FLOPs can be easily included when updating the architecture probabilities.

Inspired by [28], we also add a baseline item in the reward function from the architecture obtained by greedy decoding. Specifically, we apply an \( \arg \max \) operation on the probability distribution: \( \hat{A} = \arg \max A p(A | \alpha) \) to get the architecture \( \hat{A} \) and weights \( \tilde{\omega} \). The baseline item is:
\[ \hat{r} = \log p(y | X, \hat{A}, \tilde{\omega}) + \beta_1 FSP(\hat{A}) - \beta_2 FLOPs(\hat{A}, X) \]  \hspace{1cm} (6)

Thus, the final optimization equation of self-critical training is:
\[ \nabla_{\alpha}L = -[r - \hat{r}] \nabla_{\alpha} \log p(\hat{A} | \alpha) \]  \hspace{1cm} (7)

At initialization, the probability distribution is set to uniform distribution for fair search. During training, the probability distribution \( \alpha \) is optimized to prefer architectures with higher accuracy from both SuperNet and the predictor, and lower FLOPs. Once trained, the final architecture is discretized by \( A_{\text{final}} = \arg \max A p(A | \alpha) \). Unlike SPOS [14], our method does not require a second stage to find the optimal architecture.

4. Experiments

To validate the advantages of the proposed algorithm, we conduct experiments on three commonly used search spaces:

- NATS-Bench search space [9] (section 4.1), DARTS search space [23] (section 4.2) and MobileNet search space [30] (section 4.3).

**WPNAS procedure.** The whole process of our WP-NAS algorithm contains 5 steps. 1) WarmUp. We train the SuperNet without optimizing the architecture probabilities for 200 epochs. Only weights are updated in this step. We apply SGD optimizer with initial learning rate 0.1 and follow a cosine schedule to decay the learning rate to 0.01. 2) Acquisition of the ground truth of the Predictor. Uniform sampling 200 architectures, inheriting weights from the SuperNet and train these architectures for 30 epochs. Thus, we can obtain 200 architecture-accuracy data pairs as the ground truth of the predictor. We use the proposed way to get the ground truth instead of training from scratch for the sake of saving time. The Kendall Tau between our GT and that obtained by training from scratch is: Kendall Tau = 0.7, but the training time reduced by 85\%. 3) Train the Predictor. We use the proposed few-shot learning based algorithm to train the predictor. We split the 200 GTs with 170 architectures for training and 30 architectures for validation. The support size is set to 30. We train the predictor for 100 epochs. 4) WPNAS Search. Alternatively updating the weights and architecture probabilities for 300 epochs. Architecture probabilities are updated based on equation (7) by self-critical policy gradient training with a combined reward of direct evaluation, output of the predictor and the FLOPs. We also apply an SGD optimizer with cosine decay scheduler from 0.01 to 1e-5. 5) Evaluation. Obtain the final searched architecture with an argmax operation and train this architecture from scratch for 600 epochs.

**4.1. NATS-Bench experiments**

**NATS-Bench.** NATS-Bench [9] is an extension version of NAS-Bench-201 [11] and it is a unified benchmark on searching for both topology and size. For topology search space (TSS), it is a cell-based search space inspired by some cell-based algorithms [23, 26]. A cell is represented as a densely-connected directed acyclic graph (DAG) and all cells have the same topology. The DAG contains 4 nodes and 6 edges, and each edge of the DAG has 5 candidate operations. Thus, there are \( 5^6 = 15625 \) different architectures in the TSS search space. For size search space (SSS), the cell is the best one in the TSS search space on CIFAR-100 dataset. Each architecture contains five layers with a unique configuration based on the number of channels in each layer. There are 8 candidate channel numbers for searching: \{8, 16, 24, 32, 40, 48, 56, 64\}. Therefore, the search space size are \( 8^5 = 32768 \). We perform experiments on CIFAR-10 and CIFAR-100 datasets [21].

**Results on NATS-Bench.** Table 1. shows the results on NATS-Bench. **Baselines.** We apply single-path one-shot (SPOS) [14], the most representative sampling based algo-
Methods

| Methods                          | Kendall-Tau | MSE  | Best Rank | Best Acc. | Cost (GPU-day) |
|---------------------------------|-------------|------|-----------|-----------|----------------|
| SPOS [14]                       | 0.614       | 0.159| 5301      | 91.9      | 0.11           |
| SPOS + landmark [50]            | 0.632       | 0.153| 4801      | 92.02     | 0.124          |
| SPOS + landmark + PS            | 0.666       | 0.157| 559       | 93.38     | 0.27           |
| SPOS + landmark + PS + predictor| 0.698       | 0.140| 167       | 93.76     | 0.29           |
| SPOS + landmark + PS + predictor + WWS| 0.701 | 0.135| 94        | 93.86     | 0.33           |

Methods

| Methods                          | Kendall-Tau | MSE  | Best Rank | Best Acc. | Cost (GPU-day) |
|---------------------------------|-------------|------|-----------|-----------|----------------|
| SPOS [14]                       | 0.576       | 0.089| 6529      | 92.13     | 0.10           |
| SPOS + landmark [50]            | 0.579       | 0.093| 3352      | 92.45     | 0.13           |
| SPOS + landmark + PS            | 0.587       | 0.099| 1805      | 92.67     | 0.20           |
| SPOS + landmark + PS + predictor| 0.623       | 0.117| 37        | 93.34     | 0.22           |
| SPOS + landmark + PS + predictor + WWS| 0.634 | 0.099| 22        | 93.40     | 0.25           |

Table 1. Search results on NATS-Bench TSS and SSS search space. Cost is tested on a TITAN-RTX GPU. PS represents probabilistic sampling, WWS represents weak weight sharing.

Figure 4. Searched architectures of WPNAS-A ((a) and (b)) and WPNAS-B ((c) and (d)).
which are MLP, RNN and Transformer based. For both supervised learning and few-shot learning, the training / validation set are both 170/30. We train the predictor for 10 epochs using SGD with learning rate 1e-4. We apply a ranking loss similar as [41]. We report three metrics: Kendall-Tau, Pearson Correlation Coefficient and Mean Square Error (MSE). The results show that few-shot predictor has consistent better Kendall-Tau and MSE on CIFAR-10 and CIFAR-100 under TSS and SSS search spaces. The MSEs of few-shot predictor are extremely lower than that of supervised learning, because the proposed few-shot predictor can better learn the relationships between architectures, even only ranking loss is used without any other regression guidance.

### 4.2. DARTS search space

To compare with other NAS algorithms, we also conduct experiments on the commonly used DARTS search space [23] on CIFAR-10 and ImageNet [29] datasets. DARTS search space is also a cell based search space. The DAG contains 4 inner nodes, and each node has two parents nodes. The search space size is \(3.3 \times 10^{13}\). We set two types of architecture parameters for each node of the DAG: operation selection and parent node selection. Operation selection is used to select one operation from 8 candidates. Parent node selection is designed to select two parents nodes from the current node’s all previous nodes. Suppose the current node has \(N\) previous nodes, the number of candidate combinations are \(C_N^2\). Suppose operation selection and parent node selection are independent to each other, equation (1) remains valid as well. All the rest experiment settings are identical to DARTS for fair comparison. We compare our method with several manual networks such as DenseNet [19] and MobileNet [17] and some SOTA NAS algorithms on DARTS search space [3, 8, 23]. Similar as DARTS, we conduct the search experiment on CIFAR-10 dataset and validate the performance of the searched architecture on CIFAR-10 and ImageNet dataset. The channel number is expanded on ImageNet. Similar as [8,23], we also run 3 times evaluation on CIFAR-10 to get a more accurate result.

Table 3. shows the results on DARTS search space. WPNAS-A and WPNAS-B are two searched architectures with different \(\beta_2\) (WPNAS-A: \(\beta_2 = 1^{-3}\). WPNAS-B: \(\beta_2 = 1^{-5}\)). Figure 4. shows the searched architectures of WPNAS-A and WPNAS-B. Larger \(\beta_2\) can lead to find smaller architectures, the accuracy of WPNAS-A on CIFAR-10 dataset is 97.45 which is comparable with other SOTA methods, but with a smaller model size (2.4M). The larger architecture WPNAS-B has better accuracy 97.70 which is better than other methods. The results of our method on ImageNet (WPNAS-A:76.22, WPNAS-B:76.61) is comparable with other methods with comparable Params and FLOPs. Similar with [7, 8], we also add some tricks such as Swish, SE and AutoAugment, the performances of WPNAS-A and WPNAS-B are all improved significantly and achieves SOTA performance.

### 4.3. MobileNet search space

MobileNet search space is another commonly used macro search space for NAS benchmarking. Following [31], we construct the MobileNet-like SuperNet with 17 search blocks, and each block is a MobileNetV2 inverted bottleneck [30]. For each search block, the candidate set of convolutional kernel size is \(\{3,5\}\), the expansion ratio candidate set is \(\{1,3,6\}\), nonlinearities is selected in \{ReLU, HardSwish\} and each block can choose to use Squeeze-and-Excitation (SE) [18] module or not. The search space size is \(24^{17} \approx 2.9 \times 10^{23}\). We compare our NAS algorithm with some SOTA algorithms on this search space including SPOS [14], FBNet [36, 39], FairNas [7], FP-NAS [44] and MCT-NAS [31]. We also conduct the search experiment on CIFAR-10 dataset and transfer the architecture on ImageNet. The channel number is expanded on ImageNet.

Table 4. shows the results on MobileNet search space. We also obtain two final architectures WPNAS-A and WPNAS-B (WPNAS-A: \(\beta_2 = 1^{-3}\). WPNAS-B: \(\beta_2 = 1^{-5}\)). On ImageNet dataset, WPNAS-A has higher top-1 accuracy (75.6) compared with other methods (SPOS, FBNet and FairNAS) with similar Params and FLOPs. WPNAS-A is a bit lower than MCT-NAS-C, but MCT-NAS use other training tricks including WarmUp and EMA [15]. WPNAS-B also has higher accuracy than FP-NAS with similar Params. FBNetV2 has higher accuracy, but its cost (0.6k) is also much higher than ours. With the help of AutoAugment, WPNAS-B (77.8) also surpass FairNAS [77.5].

| Methods          | NATS-Bench TSS search space | CIFAR-10 | Kendall-Tau | Corr | MSE | Kendall-Tau | Corr | MSE |
|------------------|-----------------------------|---------|-------------|------|-----|-------------|------|-----|
| MLP              | 0.550                       | 0.595   | 0.838       | 0.582 | 0.546 | 0.694       |      |     |
| few-shot MLP     | 0.561                       | 0.539   | 0.083       | 0.617 | 0.561 | 0.132       |      |     |
| RNN              | 0.517                       | 0.493   | 0.885       | 0.524 | 0.492 | 0.707       |      |     |
| few-shot RNN     | 0.531                       | 0.502   | 0.078       | 0.562 | 0.542 | 0.132       |      |     |
| Transformer      | 0.582                       | 0.609   | 1.424       | 0.587 | 0.564 | 0.407       |      |     |
| few-shot Transformer | 0.588                | 0.601   | 0.097       | 0.595 | 0.538 | 0.122       |      |     |

| Methods          | NATS-Bench SSS search space | CIFAR-10 | Kendall-Tau | Corr | MSE | Kendall-Tau | Corr | MSE |
|------------------|-----------------------------|---------|-------------|------|-----|-------------|------|-----|
| MLP              | 0.705                       | 0.734   | 0.687       | 0.630 | 0.739 | 0.630       |      |     |
| few-shot MLP     | 0.804                       | 0.926   | 0.007       | 0.637 | 0.669 | 0.046       |      |     |
| RNN              | 0.773                       | 0.928   | 0.942       | 0.790 | 0.863 | 0.643       |      |     |
| few-shot RNN     | 0.786                       | 0.861   | 0.006       | 0.812 | 0.844 | 0.048       |      |     |
| Transformer      | 0.790                       | 0.937   | 0.486       | 0.849 | 0.852 | 1.161       |      |     |
| few-shot Transformer | 0.795                | 0.855   | 0.117       | 0.834 | 0.826 | 0.092       |      |     |
### Table 3. Search results on CIFAR-10 and ImageNet under DARTS search space and comparison with state-of-the-art methods. Cost is tested on a TITAN-RTX GPU. † represents using Swish, SE and Autoaugment.

| Methods | CIFAR-10 | ImageNet | Search Method |
|---------|----------|----------|---------------|
|         | Accuracy (%) | Params (M) | Search Cost (GPU-day) | FLOPs (M) | Search Cost (GPU-day) | |
| DenseNet-BC [19] | 96.54 | 25.6 | - | - | - | - | manual |
| Inception-v1 [33] | - | - | - | 69.8 | 89.9 | 6.6 | 1448 | - | manual |
| MobileNet [17] | - | - | - | 70.6 | 89.5 | 4.2 | 569 | - | manual |
| ShuffleNet 2 × (v2) [24] | - | - | - | 74.9 | - | - | 591 | - | manual |
| NASNet-A + cutout [52] | 97.35 | 3.3 | 1800 | 74.0 | 91.6 | 5.3 | 564 | 1800 | RL |
| AmoebaNet +cutout [27] | 97.45 ± 0.05 | 2.8 | 3150 | 75.7 | 92.4 | 6.4 | 570 | 3150 | evolution |
| PNAS [22] | 96.59 ± 0.09 | 3.2 | 225 | 74.2 | 91.2 | 5.1 | 588 | 225 | SMBO |
| ENAS + cutout [26] | 97.11 | 4.6 | 0.5 | - | - | - | - | - | RL |
| DARTS (1st order) + cutout [23] | 97.00 ± 0.14 | 3.3 | 0.4 | - | - | - | - | - | gradient |
| DARTS (2nd order) + cutout [23] | 97.24 ± 0.09 | 3.3 | 4.0 | 73.2 | 91.3 | 4.7 | 574 | 4.0 | gradient |
| PARSEC + cutout [1] | 97.19 ± 0.03 | 3.7 | 1.0 | 74.0 | 91.6 | 5.6 | - | 1.0 | gradient |
| SNAS (moderate) + cutout [40] | 97.02 ± 0.02 | 2.8 | 1.5 | 72.7 | 90.8 | 4.3 | 522 | 1.5 | gradient |
| F-DARTS-cutout [3] | 97.5 | 3.4 | 0.3 | 75.6 | 92.6 | 4.9 | 557 | 0.3 | gradient |
| NASP + cutout [47] | 97.17 ± 0.09 | 3.3 | 0.1 | - | - | - | - | - | gradient |
| PC-DARTS + cutout [42] | 97.43 ± 0.07 | 3.6 | 0.1 | 74.9 | 92.2 | 5.3 | 597 | 3.8 | gradient |
| FairDARTS + cutout [9] | 97.46 ± 0.05 | 3.3 | 0.1 | 75.6 | 92.6 | 4.3 | 440 | 3 | gradient |
| ISTA-NAS + cutout [45] | 97.64 ± 0.06 | 3.37 | 2.3 | 76.0 | 92.9 | 5.65 | 638 | 4.2 | gradient |
| DOTS + cutout [13] | 97.51 ± 0.06 | 3.5 | 0.26 | 76.0 | 92.8 | 5.3 | 596 | 1.3 | gradient |
| IDARTS + cutout [43] | 97.68 | 4.16 | 0.1 | 76.52 | 93.0 | 6.18 | 714 | 3.8 | gradient |
| VIM-NAS + cutout [37] | 97.55 ± 0.04 | 3.9 | 0.007 | 76.2 | 92.9 | - | 660 | 0.26 | gradient |
| WPNAS-A + cutout | 97.45 ± 0.10 | 2.4 | 1.5 | 76.22 | 92.70 | 5.03 | 550 | 1.5 | probabilistic sample |
| WPNAS-B + cutout | 97.70 ± 0.05 | 4.8 | 2.0 | 76.61 | 92.98 | 7.56 | 848 | 2.0 | probabilistic sample |
| WPNAS-A + cutout † | 98.00 ± 0.12 | 2.5 | 1.5 | 76.65 | 93.01 | 5.30 | 553 | 1.5 | probabilistic sample |
| WPNAS-B + cutout † | 98.12 ± 0.08 | 5.2 | 2.0 | 76.81 | 93.16 | 7.90 | 852 | 2.0 | probabilistic sample |

### Table 4. Search results on CIFAR-10 and ImageNet under MobileNet search space and comparison with state-of-the-art methods. † represents using Swish, SE and Autoaugment. ⋄ represents using training tricks including WarmUp and EMA [15].

| Methods | CIFAR-10 | ImageNet | Search Method |
|---------|----------|----------|---------------|
|         | Accuracy (%) | Params (M) | Search Cost (GPU-day) | FLOPs (M) | Search Cost (GPU-day) | |
| DenseNet-BC [19] | 96.54 | 25.6 | - | - | - | - | manual |
| Inception-v1 [33] | - | - | - | 69.8 | 89.9 | 6.6 | 1448 | - | manual |
| MobileNetV2 [30] | - | - | - | 74.9 | - | - | 591 | - | manual |
| MobileNetV3 [16] | - | - | - | 70.6 | 89.5 | 4.2 | 569 | - | manual |
| SPOS [14] | - | - | - | 72.0 | - | - | 300 | - | manual |
| FBNet [39] | - | - | - | 75.6 | 92.6 | 4.9 | 557 | 0.3 | gradient |
| FBNetV2 [36] | - | - | - | 75.6 | 92.6 | 4.9 | 557 | 0.3 | gradient |
| FairNAS [7] | - | - | - | 77.2 | - | - | 325 | 0.4 | gradient |
| FairNAS † [7] | - | - | - | 77.5 | - | - | 375 | 0.4 | gradient |
| FP-NAS + AutoAugment [44] | - | - | - | 77.5 | - | - | 375 | 0.4 | gradient |
| MCT-NAS-C † [31] | - | - | - | 77.5 | - | - | 375 | 0.4 | gradient |
| WPNAS-A + AutoAugment | 96.4 ± 0.06 | 5.4 | 1.0 | 75.6 | 92.4 | 4.7 | 390 | 1.0 | probabilistic sample |
| WPNAS-B | 96.06 ± 0.04 | 5.7 | 1.3 | 77.0 | 93.4 | 6.9 | 492 | 1.3 | probabilistic sample |
| WPNAS-A + AutoAugment | 96.4 ± 0.10 | 3.4 | 1.0 | 76.4 | 92.8 | 4.7 | 390 | 1.0 | probabilistic sample |
| WPNAS-B + AutoAugment | 96.52 ± 0.12 | 5.7 | 1.3 | 77.8 | 93.6 | 6.9 | 492 | 1.3 | probabilistic sample |

### 5. Conclusion

In this paper, we propose to jointly use weight sharing and predictor in a unified framework. Architecture coupling caused by weight sharing can lead to big evaluation ranking gap between architectures using weight sharing training and stand-alone training. To increase the correctness of the evaluation of architectures, besides the direct evaluation using the weights from SuperNet, we also introduce a predictor to evaluate the architecture from another perspective. The evaluations from these two parts are combined as the final prediction of the architecture, and are used as the reward of a self-critical policy gradient algorithm. After the introduction of predictor, the evaluation of architecture will be more accurate, which can also better guide the NAS algorithm to find better architectures. Besides, we propose a novel few-shot learning based predictor to enhance the performance of the predictor. Furthermore, we propose a weakly weight
sharing strategy by introducing a HyperNet to reduce the degree of weight sharing, thus leading to more stand-alone-training like SuperNet training. We conduct comprehensive experiments on CIFAR and ImageNet datasets under NATS-Bench, DARTS and MobileNet search space and our algorithm achieves SOTA performances on these datasets.

References

[1] Francesco Paolo Casale, Jonathan Gordon, and Nicolo’ Fusi. Probabilistic neural architecture search. In arXiv:1902.05116, 2019. 1, 3, 8
[2] Jianlong Chang, Yiwen Guo, GAOFENG Meng, SHIMING Xiang, Chunhong Pan, et al. Data: Differentiable architecture approximation. In NeurIPS, pages 874–884, 2019. 2
[3] Xin Chen, Lingxi Xie, Jun Wu, and Qi Tian. Progressive differentiable architecture search: Bridging the depth gap between search and evaluation. In ICCV, pages 1294–1303, 2019. 2, 7, 8
[4] Yaofo Chen, Yong Guo, Qi Chen, Minli Li, Wei Zeng, Yaowei Wang, and Mingkui Tan. Contrastive neural architecture search with neural architecture comparators. In CVPR, 2021. 3
[5] Zewei Chen, Fengwei Zhou, George Trimponias, and Li Zhenguo. Multi-objective neural architecture search via non-stationary policy gradient. In arXiv:2001.08437, 2020. 1
[6] Xiangxiang Chu, Xiaoxing Wang, Zhang Bo, Shun Lu, Xiaolin Wei, and Junchi Yan. Darts-: robustly stepping out of performance collapse without indicators. In ICLR, 2021. 2
[7] Xiangxiang Chu, Bo Zhang, and Xu Ruijun. Fairnas: Rethinking evaluation fairness of weight sharing neural architecture search. In ICCV, 2021. 1, 3, 7, 8
[8] Xianyi Dong, Lu Liu, Katarzyna Musial, and Bogdan Gabrys. Nats-bench: Benchmarking nas algorithms for architecture search. In IEEE transactions on pattern analysis and machine intelligence, 2021. 1, 5
[9] Xuanxi Dong and Yi Yang. Searching for a robust neural architecture in four gpu hours. In CVPR, pages 1761–1770, 2019. 2
[10] Xuanyi Dong and Yi Yang. Nas-bench-201: Extending the scope of reproducible neural architecture search. In ICLR, 2020. 1, 5
[11] Łukasz Dudziak, Thomas Chau, Mohamed S. Abdelfattah, Royson Lee, Hyeji Kim, and Nicholas D. Lane. Brp-nas: Prediction-based nas using gcns. In arXiv:2007.08668, 2020. 3
[12] Yu-Chao Gu, Li-Juan Wang, Yun Liu, Yi Yang, Yu-Huan Wu, Shao-Ping Lu, and Ming-Ming Cheng. Dots: Decoupling operation and topology in differentiable architecture search. In CVPR, 2021. 8
[13] Zichao Guo, Xiangyu Zhang, Haoyuan Mu, Wen Heng, Zechun Liu, Yichen Wei, and Jian Sun. Single path one-shot neural architecture search with uniform sampling. arXiv preprint arXiv:1904.00420, 2019. 1, 2, 5, 6, 7, 8
[14] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In CVPR, 2020. 7, 8
[15] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, Quoc V. Le, and Hartwig Adam. Searching for mobileienetv3. In ICCV, 2019. 7, 8
[16] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861, 2017. 7, 8
[17] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In CVPR, 2018. 7
[18] G. Huang, Z. Liu, L. van der Maaten, and K. Weinberger. Densely connected convolutional networks. In CVPR, 2017. 7, 8
[19] Sian-Yao Huang and Wei-Ta Chu. Searching by generating: Flexible and efficient one-shot nas with architecture generator. In CVPR, 2021. 3
[20] Alex Krizhevsky and Geoffrey Hinton. Learning multiple layers of features from tiny images. In Citeseer, Tech. Rep, 2009. 5
[21] Chenxi Liu, Barret Zoph, Maxim Neumann, Jonathon Shlens, Wei Hua, Li-Jia Li, Fei-Fei Li, Alan Yuille, Jonathan Huang, and Kevin Murphy. Progressive neural architecture search. In ECCV, pages 19–34, 2018. 8
[22] Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. In ICLR, 2019. 1, 2, 5, 7, 8
[23] Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In ECCV, pages 116–131, 2018. 8
[24] Xuefei Ning, Yin Zheng, Tianchen Zhao, Yu Wang, and Huazhong Yang. A generic graph-based neural architecture encoding scheme for predictor-based nas. In ECCV, 2020. 1, 3
[25] Hieu Pham, Melody Y Guan, Barret Zoph, Quoc V Le, and Jeff Dean. Efficient neural architecture search via parameter sharing. In ICML, 2018. 1, 2, 5, 8
[26] Esteban Real, Alok Aggarwal, Yanping Huang, and Quoc V Le. Regularized evolution for image classifier architecture search. In AAAI, volume 33, pages 4780–4789, 2019. 1, 8
[27] Steven J. Rennie, Etienne Marcheret, Youssef Mroueh, Jarret Le. Regularized evolution for image classifier architecture search. In AAAI, volume 33, pages 4780–4789, 2019. 1, 8
[28] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Fei-Fei Li. Imagenet large scale visual recognition challenge. In IJCV, 2015. 7
[29] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In CVPR, 2018. 5, 7, 8
[30] Xiu Su, Tao Huang, Yanxi Li, Shan You, Fei Wang, Chen Qian, Changshui Zhang, and Chang Xu. Prioritized architecture sampling with monte-carlo tree search. In CVPR, 2021. 3, 7, 8
[32] Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip H.S. Torr, and Timothy M. Hospedales. Learning to compare: Relation network for few-shot learning. In CVPR, 2018. 3

[33] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In CVPR, 2015. 8

[34] Mingxing Tan, Bo Chen, Ruoming Pang, Vijay Vasudevan, Mark Sandler, Andrew Howard, and Quoc V Le. Mnasnet: Platform-aware neural architecture search for mobile. In CVPR, pages 2820–2828, 2019. 1

[35] Yehui Tang, Yunhe Wang, Yixing Xu, Hanting Chen, and Boxin Shi. A semi-supervised assessor of neural architectures. In CVPR, 2020. 3

[36] Alvin Wan, Xiaoliang Dai, Peizhao Zhang, Zijian He, Yuandong Tian, Saining Xie, Bichen Wu, Matthew Yu, Kan Chen, Peter Vajda, and Joseph E. Gonzalez. Fbnetv2: Differentiable neural architecture search for spatial and channel dimensions. In CVPR, 2020. 7, 8

[37] Yuhui Xu, Yuchen Liu, Yixing Xu, Hanting Chen, and Chang Xu. Renas: Relativistic evaluation of neural architecture search. In CVPR, 2021. 3, 7

[38] Bichen Wu, Xiaoliang Dai, Peizhao Zhang, Yanghan Wang, Fei Sun, Yiming Wu, Yuandong Tian, Peter Vajda, Yangqing Jia, and Kurt Keutzer. Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search. In CVPR, pages 10734–10742, 2019. 7, 8

[39] Song Xue, Runqi Wang, Baochang Zhang, Tian Wang, Guodong Guo, and David Doermann. Idarts: Interactive differentiable architecture search. In ICCV, 2021. 1, 2, 8

[40] Zhaohui Yang, Yunhe Wang, Xinghao Chen, Boxin Shi, Chao Xu, Chunjing Xu, Qi Tian, and Chang Xu. Cars: Continuous evolution for efficient neural architecture search. In CVPR, 2020. 1

[41] Yibo Yang, Hongyang Li, Shan You, Fei Wang, Chen Qian, and Zhouchen Lin. Ista-nas: Efficient and consistent neural architecture search by sparse coding. In NeurIPS, 2020. 8

[42] Zhaohui Yang, Yunhe Wang, Xinghao Chen, Boxin Shi, Chao Xu, Chunjing Xu, Qi Tian, and Chang Xu. Cars: Continuous evolution for efficient neural architecture search. In CVPR, 2020. 1

[43] Quanming Yao, Ju Xu, Wei-Wei Tu, and Zhanxing Zhu. Efficient neural architecture search via proximal iterations. In AAAI, 2020. 8

[44] Chris Ying, Aaron Klein, Esteban Real, Eric Christiansen, Kevin Murphy, and Frank Hutter. Nas-bench-101: Towards reproducible neural architecture search. In ICML, 2019. 1