Neural Architecture Refinement: A Practical Way for Avoiding Overfitting in NAS

Yang Jiang
jiangyang218@sina.com

Cong Zhao
zhaocong.hk@gmail.com

Zeyang Dou
douzeyang@qq.com

Lei Pang
pang101@pcl.ac.cn

Abstract

Neural architecture search (NAS) is proposed to automate the architecture design process and attracts overwhelming interest from both academia and industry. However, it is confronted with overfitting issue due to the high-dimensional search space composed by operator selection and skip connection of each layer. This paper explores the architecture overfitting issue in depth based on the reinforcement learning-based NAS framework. We show that the policy gradient method has deep correlations with the cross entropy minimization. Based on this correlation, we further demonstrate that, though the reward of NAS is sparse, the policy gradient method implicitly assign the reward to all operations and skip connections based on the sampling frequency. However, due to the inaccurate reward estimation, curse of dimensionality problem and the hierarchical structure of neural networks, reward characteristics for operators and skip connections have intrinsic differences, the assigned rewards for the skip connections are extremely noisy and inaccurate. To alleviate this problem, we propose a neural architecture refinement approach that working with an initial state-of-the-art network structure and only refining its operators. Extensive experiments have demonstrated that the proposed method can achieve fascinated results, including classification, face recognition etc.

1 Introduction

Due to the amazing feature representation power of deep neural networks (DNNs), DNNs have enabled remarkable progress on a variety of tasks, such as object detection[1][2][3], natural language processing[4][5][6], speech recognition[7][8], face recognition[9][10][11] etc. Nevertheless, the optimal network architecture designs vary dramatically for different tasks and hardware platforms, it is time-consuming and error-prone for machine learning experts to design different architectures. To address this problem, neural architecture search (NAS) [12][13][14][15] has been proposed, it has attracted much attention in recent years.

NAS searches the optimal neural architecture in a search space. The element in the search space is a vector $\tau = [O_1, S_1, O_2, \ldots, O_n, S_n]$, where $O_m$ is a one hot coding sub-vector representing the operation selection for node $m$, and $S_m$ is a binary sub-vector illustrating the skip connection between node $m$ and the previous nodes. The operators refer to either atomic operators such as conv3x3 or max-pooling, or fused operator composite such as conv3x3-relu-maxpooling. The skips are merely the connections between arbitrary two layers of operators. Because of the high dimensionality of the search space, searching an optimal architecture turns to be a difficult optimization problem. Numerous works therefore have been proposed to either reduce the search space or use a better optimization backend. For instance, [13][16][17] restricted the diversity of the operator candidates and combined atomic operators into composite operators. [18][14] proposed to search a structured cell rather than the...
whole architecture in a pre-defined manner. As for optimization algorithm, [19, 20, 21, 16] employ
the evolution algorithm, which is computational expensive. Recently, reinforcement learning based
methods (RL-based methods)[15, 22, 23] and gradient-based method[24, 23, 25, 26] are proposed,
which requires much less computational resources and draw the attention of the field. Due to the
large datasets and heavy computational cost of training, most of recent NAS can only search over
a small sub dataset (which usually contains 1/10 samples), then transfer the found architecture to
whole dataset. This strategy is known as “proxy task”.

Though the above discussed methods help to improve efficiencies of NAS, we argue that recent
NAS frameworks suffer from the architecture overfitting problem, which prevent NAS from practical
applications. Taking ENAS as an example, during the optimization of the architecture, the controller
prefers to select architectures with dense skip connections, indicating that NAS easily falls into
plateaus of over-complicated architectures, the search architectures would overfit the training task
and perform poorly on unseen tasks.

In this paper, we explore the architecture overfitting problem in depth based on the RL-based NAS
framework. We show that the policy gradient method has deep correlations with the cross entropy
minimization. Based on this correlation, we further demonstrate that, though the reward of NAS is
sparse, the policy gradient method implicitly assign the reward to all operations and skip connections.
The assignment process is based on the final reward and the sampling frequency. Because these
assigned rewards guide the optimization of the meta controller, it is important to build the reliable
sampling strategy and estimate the final reward accurately. However, recent sampling strategies have
strong bias, resulting in the inaccurate final reward estimation. Due to the limitations of computational
resources, the architecture search process is often conducted on the proxy tasks, and the sampled
architectures cannot be well trained. This approximation creates the search bias, because different
architectures have different convergence rates. Given insufficient training steps, neural networks with
shallow depths and intensive skip connections generally tend to achieve higher accuracy than those
with deep depths and sparse skip connections. Besides, most of recent RL-based NAS framework
jointly optimize operators and skip connections. However, as we will show, due to the curse of
dimensionality of the skip connection space, the assigned reward suffers from the severe noise. This
problem makes the loss surfaces of operators and skip connections have different characteristics, the
optimization path of operators is smooth while that of skip connection is highly chaotic. This training
gap would lead the model easily stuck into inferior local minima, raising the architecture overfitting
issue. Moreover, due to the hierarchical structure of neural networks, the operator space and the skip
connection space have different reward charateristics, using one controller is hard to model the joint
search space.

Based on the above analysis, we propose a simple but effective method, which models the operator
domain and the skip connection domain separately and optimizes them alternatively, to alleviate the
architecture overfitting problem. For optimizing the skip connection domain, because of the search
bias and the chaotic optimization path of the skip connections domain, in principle we can optimize
this domain using non-gradient methods (e.g., sampling), well evaluate all candidates and use the
best one as the structure of the final model. However, this solution is computational expensive. In
this paper, we propose a simple method which works with a initial network architecture and fixes its
skip connections. In terms of the operator domain, due to the smoothness of its optimization path,
we optimize this domain via policy gradient approach. We call this method Network Architecture
Refinement (NAR). Because the skip connections is fixed during architecture search, NAR not only
eliminates the search bias and curse of dimension problems, but also largely reduces the overfitting
problem. Besides, the proposed method is easy and fast to converge.

We experimentally demonstrate that NAR can make many computer vision tasks achieve fascinated
results, including classification, face recognition task (more results and tasks will present later on).
In our experiment, NAR optimize the LResNet50E-IR[9] and gain accuracy with 99.75%, 97.61%
and 97.13% compared to that with 99.68%, 97.54% and 96.86% over LFW, CFP-FP, AgeDB-30 face
recognition dataset with 24% fewer FLOPS.

2 Related Work

For designing state-of-the-art architecture, NAS become the basic optimizer. Evolution-based
NAS methods explore the network topological transformation by applying evolitional methods
like crossover, mutation or recombination[20][21][16]. Alternatively RL-based NAS and gradient-based NAS methods build a directed acyclic graph (DAG) and search a subgraph as the optimal architecture[24][23][25]. But current NAS methods are difficult to optimize because of the high dimensional search space.

Based on pre-defined search space that consists of the candidate operations and skip connections, NAS methods aim to find an optimal combination. The initial definition of operations is fine elements like ReLU activations, convolution layer, batch normalization, etc., which leads to huge search space so as to make NAS unpractical[12]. For reducing search space, [14] and [13] combine fine elements to build higher-level operations based on the hand-designed architectures like Conv-BN-ReLU, Depthwise convolution, etc. and obtain impressive performance. Meanwhile [17][18] manually define some skip connection rules like recursive way etc. to constrain the connection degree of freedom. The attention of researcher turns from search space to topology[16][25]. Although the academic performance keep improved, the searched topologies may still suffer from overfitting as NAS still does not yet work in many practical tasks like face recognition.

### 3 Methodology

#### 3.1 Definition of Architecture Overfitting

Overfitting in machine learning refers to the problem that the well trained model cannot generalize well on the test data, because the model learns the non-robust patterns in the training data rather than the robust patterns of data. Architecture overfitting is defined in the same spirit, which means that the neural architecture models the training task so well that its performance drops on the similar task. To investigate the architecture overfitting in NAS, we compare two neural architectures with similar number of layers on two closely related tasks. The first architecture is a layer-wise searched architecture denoted as NAS-Arch[15], and the second is the handcrafted architecture ResNet-20[27]. The channels of ResNet-20 blocks is expanded to 64, 128 and 256 for fair comparison with NAS-Arch. The NAS-Arch is searched on CIFAR10. Then NAS-Arch and ResNet-20 are trained and tested on CIFAR 10. Finally, we train NAS-Arch and ResNet-20 on face-emore[28][9] and test them on LFW[29], CFP-FP[30] and AgeDB30[31][32]. Bear in mind that we use the same training strategy for NAS-Arch and ResNet-20. The result is shown in table 1. We see the NAS-Arch achieves better performance than that of ResNet-20 on Cifar, while ResNet-20 consistently outperforms NAS-Arch on three face recognition datasets. Since NAS-Arch has comparable parameters with ResNet-20, the performance gap doesn’t come from the gaps of model capacities. This example demonstrates that NAS indeed suffers from the architecture overfitting problem.

#### 3.2 Understanding Architecture Overfitting

We first show the relationships between the policy gradient method and the cross entropy minimization. Let $\tau^i = [O_1^i, S_1^i, O_2^i \ldots O_n^i, S_n^i]$ be the $i$ th sampled architecture, and $R^i$ is the corresponding reward. The policy gradient of reward expectation $ER$ is:

\[
\nabla_\theta ER(\theta) = \frac{1}{N} \sum_i R^i \nabla_\theta \log p(\tau^i|\theta),
\]

(1)

where $\theta$ is parameters of the controller and $N$ is the number of sampled architectures. We factorize $p(\tau^i|\theta)$ as

\[
p(\tau^i|\theta) = \prod_j p(O_j^i|Z_{1:j}^i, \theta)p(S_j^i|Z_{1:j}^i, O_j^i, \theta)
\]

(2)

where $Z_{1:j}$ represents the sampled operators and skip connections before node $j$. For notation simplicity, we use $p(O_j)$ and $p(S_j)$ to represent $p(O_j|Z_{1:j}, \theta)$ and $p(S_j|Z_{1:j}, O_j, \theta)$ respectively.
Figure 1: Gradient magnitudes plot during architecture search. X- and Y-axis represent the training steps of meta-controller and the corresponding gradient magnitudes. The smoothness of two curves are totally different, indicating that operator and skip connections have different training difficulties.

Substituting equation 2 into equation 1 yields

\[ \nabla_\theta ER(\theta) = \frac{1}{N} \sum_j \sum_i R^i (\nabla_\theta \log p(O^j_i) + \nabla_\theta \log p(S^j_i)). \]  

(3)

Equation 3 can be considered as the gradient of the following cross entropy loss

\[ ER(\theta) = -\frac{1}{N} \sum_j \sum_i R^i \cdot CE(O^j_i, p(O^j_i)) - \frac{1}{N} \sum_j \sum_i \sum_{t \leq j - 2} R^i \cdot BCE(S^j_{i,t}, p(S^i_{j,t})), \]  

(4)

where \( CE(x, y) \) and \( BCE(x, y) \) are the cross entropy and the binary cross entropy with target distribution \( x \) and predicted distribution \( y \), and \( S^j_{i,t} \in \{0, 1\} \) is the binary number representing whether a skip connection exists between node \( j \) and node \( t \). We use \( O^j_{i,k} \in \{0, 1\} \) to denote whether the \( j \) th node samples the \( k \) th operator. Suppose we have \( K \) operator candidates for each node, then the loss 4 can be rewritten as

\[ ER(\theta) = \sum_{k=1}^{K} \sum_j \left( \sum_i \frac{O^j_{i,k} R^i}{N} \right) \log p(O^j_{i,k}) + \sum_{n=1}^{2} \sum_j \sum_{t \leq j - 2} \left( \sum_i \frac{R^i \cdot S^j_{i,t,n}}{N} \right) \log p(S^j_{i,t,n}), \]  

(5)

where \( S^j_{i,t,n}(n = 1, 2) \) is the one hot coding of \( S^j_{i,t} \). The loss function 5 illustrates that the policy gradient implicitly assigns the final rewards to operators and skip connections based on their sampling frequency. Specifically, The reward for operator \( O^j_{i,k} \) and \( S^j_{i,t} \) are

\[ R_{O^j_{i,k}} = \frac{\sum_i O^j_{i,k} R^i}{N}, \]  

(6)

\[ R_{S^j_{i,t}} = \begin{cases} \sum_i R^i |S^j_{i,t} = 1| & \text{if } S^j_{i,t} = 1 \\ \sum_i R^i |S^j_{i,t} = 0| & \text{if } S^j_{i,t} = 0 \end{cases}, \]  

(7)

where

\[ |S^j_{i,t} = 1| = \begin{cases} 1 & \text{if } S^j_{i,t} = 1 \\ 0 & \text{if } S^j_{i,t} = 0 \end{cases}. \]  

(8)

Obviously, the qualities of these assigned rewards heavily rely on the accurate estimation of \( R^i \) and large \( N \). However, recent sampling strategies have strong bias, resulting in the inaccurate \( R^i \). Due to the limitations of computational resources, the architecture search process is often conducted on the proxy tasks, and the sampled architectures cannot be well trained. This approximation creates the search bias, because the networks with shallow depths and intensive skip connections usually have high validation accuracy at the early stage of training [33, 27].

Besides, \( N \) is usually small because of the expensive training cost. However, the dimensionality of skip connection space is often much higher than that of operator space. For example, we assume that the architecture consists of 12 nodes, and each node has 6 operator candidates. The dimensionality of the operator space is \( 2 \times 10^9 \), while that of the skip connection space is \( 4 \times 10^{16} \). Sampling
from this space suffers from the curse of dimensionality problem. Therefore, given small \( N \), the sampling frequency is rather noisy and unstable. This problem brings optimization difficulty when the controller learns the optimal skip connections from the highly noisy samples. As shown in Figure 1, the gradient of skip connections is oscillating while that of operators is far smoother. Therefore, the current reinforcement learning or continuous relaxation (e.g., DARTS) framework with one meta-controller is hard to model the joint space of operators and skips and the found architecture may overfit to the noisy skips in the training task and perform poorly on testing task.

### 3.3 Neural Architecture Refinement

Based on the above analysis, we see that the search bias and the curse of dimensionality problem yield the optimization difficulty of skip connection space. For the operator space, the search dimension of each node is the same, the assigned reward has the similar-level noise. However, for the skip connection space, the search dimension of the deep layers is much higher than that of shallow ones due to the hierarchical structure of the network, the noise of the assigned reward become severe as the layer goes deep. Therefore, due to the different reward characteristics of the operator space and the skip connection space, using one LSTM meta-controller is hard to model the joint space.

From the perspective of feature representation learning, skip are usually expected for offering the different depth-level features, and operator is mainly designed as the transformation-level function. Based on this fact, we argue that operator of each layer is related with the parameter complexity and skip connection accounts for the architecture complexity. Therefore, we define the operator and skip as parameter-overfitting related and architecture-overfitting related respectively, the operator and skip could be naturally considered as two domains.

Based on above analysis, we split the operator and skip connections as two individual spaces, and alternatively optimize one space while fix another. Basically, the alternative search is searching the optima along two directions in the joint space of operator and skip. When searching alternatively, the reward in step \( s-1 \) for skip optimization is denoted as \( ER_{\text{S}}^{s-1} \) and \( ER_{\text{O}}^{s} \) represents the reward in step \( s \) for operator optimization. Since our optimization strategy is optimizing one space by fixing another, we can reformulate as

\[
ER_{\text{O}}(\theta) = \sum_{k=1}^{K} \sum_{j} \frac{1}{N} \sum_{i} O_{j,k}^{i} R_{i}^{i} \log p(O_{j,k}^{i}) + C_{2},
\]

\[
ER_{\text{S}}(\theta) = C_{1} + \sum_{n=1}^{2} \sum_{j} \sum_{t \leq j-2} \left( \frac{1}{N} \sum_{i} R_{i}^{i} \cdot S_{j,t,n}^{i} \right) \log p(S_{j,t,n}^{i}),
\]

Where \( C_{1} \) and \( C_{2} \) are constants due to the fixed skips and operators. Suppose we begin the iteration from sampling the operation with fixed skips. We denote \( O^{i} (S^{i}) \) as the sampled nodes (skips) at \( i \)th iteration. By using the policy gradient optimization framework, we can find \((O^{i+1}, S^{i})\) such that \( ER(O^{i+1}, S^{i}) \geq ER(O^{i}, S^{i}) \). Besides, the optimal nodes (skips) searched from the last iteration served as the initialization of the next iteration. Thus, by alternatively minimizing \( E_{O} \) and \( E_{S} \), we have

\[
ER_{O}^{1} \leq ER_{O}^{2} \leq \cdots \leq ER_{S}^{N} \leq \max ER.
\]

The inequality shows that \( \{ER_{X}\}_{X \in \{O,S\}} \) is a monotone increasing bounded sequence, which indicates that we can find a Cauchy subsequence. This shows the convergence of the alternative optimization framework.

For optimizing the skip connection space, in principle we can optimize this domain using non-gradient methods (e.g., sampling), well evaluate all candidates and use the best one as the structure of the final model. However, this solution is computational expensive. Because the hand-crafted model structure has been verified its effectiveness, we propose a simple method that works with a initial network architecture and fixes its skip connections. In terms of the operator domain, due to the smoothness of its optimization path, we optimize this domain via policy gradient approach. Note that, due to the existence of \( R^{i} \) in the operator reward \( E_{O} \), optimizing operators also have the search bias which might lead to less diversity of operations. To address this problem, we pre-train the graph randomly for few epochs before starting to search. The pretraining would help to alleviate the search bias of the early stage of training. In the experiments, we denote the method using pre-train with suffix “PreTrain”.
We choose RL-based NAS as our operator optimizer. Following ENAS\cite{15}, we use LSTM\cite{39} as meta-controller that generate combination of operations and train the shared parameters of child models. The proposed method largely reduces the search space. Besides, since the skip connections and the model depth are fixed, we don’t have the curse of dimensionality problem and the search bias is largely reduced.

3.4 The Definition of Search Space

We define the rules that how to build search space. First, given the task that need to be applied by NAS, we take the state-of-the-art architecture that based on current research as our base model and do not modify the skip connections. Non-modified skips can be seen as higher level kind of high level combined operations, like the combination of skips and operations. Then, the search space composed by operator and skip is reduced to operator only.

Following the works\cite{15} we take their operations as our operator candidates, \(\text{conv}^3 \times 3\), \(\text{conv}^5 \times 5\), \(\text{depthwise}^3 \times 3\), \(\text{depthwise}^5 \times 5\), \(\text{max}^3 \times 3\), \(\text{avg}^3 \times 3\). Note that we treat the \(\text{max}^3 \times 3\) and \(\text{avg}^3 \times 3\) as non-parameterized convolution-like operator. Given one architecture, we prefer to choose the candidate operators with no more parameters than the architecture operators to avoid parameter-overfitting.

For example, we take face recognition as our task in this paper and follow the rules, we take \(\text{conv}^3 \times 3\), \(\text{depthwise}^3 \times 3\), \(\text{max}^3 \times 3\), \(\text{avg}^3 \times 3\) as candidate operations since the face model only use \(\text{conv}^3 \times 3\).

4 Experiment

We evaluate our proposed method on two kinds of tasks, face recognition and image classification. The initial architectures used in these two tasks have distinctive characteristics, such as number of parameters, number of layers etc. From the experiment, we want to demonstrate that our method have wide adaptability for both small and large architectures. All of our architecture refinements are conducted on one NVIDIA 1080Ti and implemented with PyTorch.

4.1 Face Recognition

For face recognition, ArcFace\cite{9} model is chosen as our baseline. We use NAR with and without pre-train to refine LResNet50E-IR \cite{9} and name the refined models as LResNet50E-IR-R and LResNet50E-IR-RP. The refinement is conducted on a proxy task and the refined architectures are trained over the whole dataset. The generalizability of the refined architecture is verified by training on two different tasks with performance reserving.

4.1.1 Dataset and Proxy Task

We choose face emore V1\cite{28,32} and V2\cite{28,9} as our training data, which consist 384,846 images with 85,164 identities and 5,822,653 images with 85,742 identities respectively. Distribution of face emore V1 and V2 are both non-uniform. Since face emore datasets are large, we build our proxy task for efficiency. We only randomly collect 160k images from face emore V2 as our proxy data. The proxy dataset contains 4k identities and each identity consists of 40 images. We random select 36 images as the training data for each identity and the rest images are used for validation. We use SGDR\cite{40} optimizer with \(T_{mult}=2, T_0=10\), max learning rate = 0.1 and min learning rate = 0.0001. The training stops after 150 epochs. As for data augmentation, we follow the same strategy as \cite{9}.

We use LFW, CFP and AgeDB dataset as our test data:

- **LFW\cite{29}**: LFW dataset contains 5749 different identities with 12,233 web-collected images. These images vary in pose, expression and illuminations. We use 6,000 face pairs by the standard protocol of unrestricted with labeled outside data.
- **CFP\cite{30}**: CFP contains 500 subjects, each of which consists of 10 frontal and 4 profile images. There are 10 folders with 350 same-person pairs and 350 different-person pairs in each of the evaluation protocol and the protocol includes frontal-frontal (FF) and frontal-
### Baseline and searched architectures

| Model          | Architecture |
|----------------|--------------|
| LResNet50E-IR  | [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0] |
| LResNet50E-IR-R | [0,1,2,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,3] |
| LResNet50E-IR-RP| [0,0,2,0,0,0,1,0,0,0,0,0,0,0,0,1,1,0,2,2,1,0,1,0] |

Table 2: Baseline and searched architectures

| Methods        | LFW(%) | CFP-FP(%) | AgeDB-30(%) | Parameter Number | FLOPS  |
|----------------|--------|-----------|-------------|------------------|--------|
| LResNet50E-IR  | 99.68  | 97.54     | 96.86       | 4.35 x 10^7      | 6.32 x 10^9 |
| LResNet50E-IR-R| 99.73  | 97.59     | 97.32       | 3.40 x 10^7      | 5.31 x 10^9 |
| LResNet50E-IR-RP| 99.75 | 97.61     | 97.13       | 3.38 x 10^7      | 4.69 x 10^9 |

Table 3: LResNet50E-IR, LResNet50E-IR-R and LResNet50E-IR-RP trained over Face-emore V2 profile (FP) face verification. We only choose CFP-FP, which is the challenging subset of CFP.

- **AgeDB** [31, 32]: AgeDB contains 440 subjects with 12,240 images of varied pose, expression, illuminations, and age. The average age is 49 years with the minimum of 3 and maximum of 101. Test data of AgeDB divided into four groups with different year gaps, that is 5 years, 10 years, 20 years and 30 years. There are 10 split images in each group, and each split includes 300 positive examples and 300 negative examples. We evaluate our model on AgeDB, that is the challenging subset.

#### 4.1.2 Architecture Analysis

The refined architecture vectors are shown in Table 2, where we denote $conv3 \times 3; depthwise3 \times 3; maxpool3 \times 3; avgpool3 \times 3$ as 0,1,2,3 respectively. Obviously, the vector of baseline is full of zero. In addition, architecture with more diverse operators are generated with pretrain strategy. Table 3 shows the computational load comparisons of all models, including the number of parameters and the FLOPS. We see that the refined models have less Flops and parameters than their baselines.

#### 4.1.3 Performance Analysis

We train the refined architectures on face emore V2 and test them on LFW, CFP, and AgeDB respectively. For comparison, we train LResNet50E-IR in the same environment as our benchmark. The hyper-parameter configuration is the same as ArcFace. We use SGDR training strategy with $T_{mult}=2, T_0=5$, max learning rate = 0.1 and min learning rate = 0.0001, and train for total 35 epochs. From Table 3, we can see that the LResNet50E-IR-RP trained on face emore V2 gain 99.75%, 97.61% and 97.13% compared to 99.68%, 97.54% and 96.86% over LFW, CFP-FP, AgeDB-30 face recognition dataset with 24% fewer FLOPS. LResNet50E-IR-R obtains the similar results. The refined models maintain the regular performance over variation in pose and illumination. Furthermore, they are robust to the frontal-profile and wide age range of the same person. It is important to note that NAR improves the baseline on all test datasets with much less FLOPS, indicating that NAR eases the architecture-overfitting issue in handcrafted architecture.

#### 4.1.4 Generalization

To further verify the generalization, we directly train the refined architectures on face emore V1. Note that the architectures are searched on proxy task of a different dataset, face emore V2. The results are shown in Table 4. We can see that both LResNet50E-IR-R and LResNet50E-IR-RP that trained over V1 can also achieve better performance over three datasets, which indicates that the searched architectures have better capability of generalization.

#### 4.2 Classification Task

For the classification task, we select ResNet-18 [27] as our baseline and refine it on CIFAR-10 [41]. We evaluate the searched model on CIFAR-10 and then transfer the refined model to ImageNet [42].
| Methods          | LFW(%) | CFP-FF(%) | AgeDB-30(%) | Parameter Number | FLOPS       |
|------------------|--------|-----------|-------------|------------------|-------------|
| LResNet50E-IR    | 99.55  | 93.64     | 95.51       | 4.35 × 10⁷       | 6.32 × 10⁹ |
| LResNet50E-IR-R  | 99.55  | 93.76     | 95.55       | 3.40 × 10⁷       | 5.31 × 10⁹ |
| LResNet50E-IR-RP | 99.56  | 94.42     | 95.60       | 3.38 × 10⁷       | 4.69 × 10⁹ |

Table 4: LResNet50E-IR, LResNet50E-IR-R and LResNet50E-IR-RP trained over Face-emore V1

| Model         | Architecture         | Parameter Number | FLOPS       |
|---------------|----------------------|------------------|-------------|
| ResNet-18     | [0,0,0,0,0,0,0]      | 1.17 × 10⁹       | 1.76 × 10⁹ |
| ResNet-18-8   | [0,0,0,0,0,0,0]      | 1.16 × 10⁹       | 1.57 × 10⁹ |
| ResNet-18-16  | [1,0,0,2,0]          | 0.92 × 10⁹       | 1.41 × 10⁹ |

Table 5: Architecture of ResNet-18 and ResNet-18-8, ResNet-18-16

4.2.1 Architecture Analysis

Our experiment follows the search strategy [27]. We search the residual block in two ways: 1) treat the whole residual block as one element in search space, 2) treat each CONV-BN-RELU as one element in search space. There are 8 depth layers for the first strategy and 16 for the second. We call the first architecture as ResNet-18-8 and the second as ResNet-18-16. The searched architectures are shown in Table 5. Because the search space of ResNet-18-8 is relatively small, there is just one operator being replaced. When we search using the second strategy, four operators are changed. ResNet-18-8 and ResNet-18-16 have 11% and 20% less FLOPS than baseline, even though ResNet-18 is already relatively small.

We see that NAR works better when we optimize a large and deep model. Literally, Large and deep model is much easier to overfit, which also demonstrate that NAR is practical for easing overfitting issues.

4.2.2 Results for classification

We evaluate ResNet-18-8 and ResNet-18-16 over CIFAR-10 and then transfer them to ImageNet for generalization test. The results are shown in Table 6. The refined models obtain slightly better performance on CIFAR-10 and comparable results on ImageNet but with fewer FLOPS.

The results of the classification task also demonstrate that NAR can not only improve the model but also has good capability of generalization.

5 Conclusion

In this paper, we explored the architecture overfitting problem in depth based on the reinforcement learning NAS framework. We showed that the policy gradient method has deep correlations with the cross entropy minimization. Though the reward of NAS is sparse, the policy gradient method implicitly assigns the reward to all operations and skip connections based on the reward and the sampling frequency. However, due to the inaccurate reward estimation, curse of dimensionality problem and the hierarchical structure of neural networks, reward characteristics for operators and skip connections have intrinsic differences, the assigned rewards for the skip connections are extremely noisy and inaccurate. Based on this analysis, we proposed a simple method, named as neural architecture refinement (NAR), to refine neural architectures. NAR only focuses on optimizing operator space while keep the skip connections fixed. NAR largely reduces FLOPs and parameters in the refined architecture, estimates the reward more accurate and alleviates the curse of dimensionality problem. Several transfer learning studies were conducted to further verify the generalization ability. Finally, despite that NAR achieved consistent performance in different computer vision tasks, skip connection, as the basic elemental elements of neural architecture, could be better modeled and sampled. Since operators and skips have different contributions to architecture design, searching the optimal architecture in an alternative way worth further investigation.
| Model          | CIFAR-10(%) | ImageNet Top-1(%) | ImageNet Top-5(%) |
|---------------|------------|-------------------|-------------------|
| ResNet-18     | 93.46      | 69.39             | 89.09             |
| ResNet-18-8   | 93.72      | 69.42             | 89.10             |
| ResNet-18-16  | 93.71      | 69.18             | 88.81             |

Table 6: Results of ResNet-18 and ResNet-18-8, ResNet-18-16 over CIFAR and ImageNet

References

[1] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: towards real-time object detection with region proposal networks. In *International Conference on Neural Information Processing Systems*, 2015.

[2] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng Yang Fu, and Alexander C. Berg. Ssd: Single shot multibox detector. In *European Conference on Computer Vision*, 2016.

[3] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Computer Vision and Pattern Recognition*, 2016.

[4] Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N Dauphin. Convolutional sequence to sequence learning. In *Proceedings of the 34th International Conference on Machine Learning*, pages 1243–1252, 2017.

[5] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, 2017.

[6] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[7] Alex Graves, Abdelrahman Mohamed, and Geoffrey Hinton. Speech recognition with deep recurrent neural networks. In *IEEE International Conference on Acoustics*, 2013.

[8] Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu. Wavenet: A generative model for raw audio, 2016.

[9] Jiankang Deng, Jia Guo, Niannan Xue, and Stefanos Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. *arXiv preprint arXiv:1801.07698*, 2018.

[10] O. M. Parkhi, A. Vedaldi, and A." Zisserman. Deep face recognition. In *British Machine Vision Conference*, 2015.

[11] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman. Vggface2: A dataset for recognising faces across pose and age. In *International Conference on Automatic Face and Gesture Recognition*, 2018.

[12] Irwan Bello, Barret Zoph, Vijay Vasudevan, and Quoc V Le. Neural optimizer search with reinforcement learning. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, 2017.

[13] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. Learning transferable architectures for scalable image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018.

[14] Zhao Zhong, Junjie Yan, Wei Wu, Jing Shao, and Cheng-Lin Liu. Practical block-wise neural network architecture generation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018.

[15] Hieu Pham, Melody Y Guan, Barret Zoph, Quoc V Le, and Jeff Dean. Efficient neural architecture search via parameter sharing. *arXiv preprint arXiv:1802.03268*, 2018.
[16] Hanxiao Liu, Karen Simonyan, Oriol Vinyals, Chrisantha Fernando, and Koray Kavukcuoglu. Hierarchical representations for efficient architecture search. arXiv preprint arXiv:1711.00436, 2017.

[17] Chenxi Liu, Liang-Chieh Chen, Florian Schroff, Hartwig Adam, Wei Hua, Alan Yuille, and Li Fei-Fei. Auto-deeplab: Hierarchical neural architecture search for semantic image segmentation. arXiv preprint arXiv:1901.02985, 2019.

[18] Liang-Chieh Chen, Maxwell Collins, Yukun Zhu, George Papandreou, Barret Zoph, Florian Schroff, Hartwig Adam, and Jon Shlens. Searching for efficient multi-scale architectures for dense image prediction. In Advances in Neural Information Processing Systems, 2018.

[19] Chenxi Liu, Barret Zoph, Maxim Neumann, Jonathon Shlens, Wei Hua, Li-Jia Li, Li Fei-Fei, Alan Yuille, Jonathan Huang, and Kevin Murphy. Progressive neural architecture search. In Proceedings of the European Conference on Computer Vision (ECCV), 2018.

[20] Gerard Jacques van Wyk and Anna Sergeevna Bosman. Evolutionary neural architecture search for image restoration. arXiv preprint arXiv:1812.05866, 2018.

[21] Esteban Real, Alok Aggarwal, Yanping Huang, and Quoc V Le. Regularized evolution for image classifier architecture search. arXiv preprint arXiv:1802.01548, 2018.

[22] Han Cai, Jiacheng Yang, Weinan Zhang, Song Han, and Yong Yu. Path-level network transformation for efficient architecture search. arXiv preprint arXiv:1806.02639, 2018.

[23] Han Cai, Ligeng Zhu, and Song Han. Proxylessnas: Direct neural architecture search on target task and hardware. arXiv preprint arXiv:1812.00332, 2018.

[24] Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. arXiv preprint arXiv:1806.09055, 2018.

[25] Sirui Xie, Hehui Zheng, Chunxiao Liu, and Liang Lin. Snas: stochastic neural architecture search. arXiv preprint arXiv:1812.09926, 2018.

[26] 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. arXiv preprint arXiv:1812.03443, 2018.

[27] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2016.

[28] Yandong Guo, Lei Zhang, Yuxiao Hu, Xiaodong He, and Jianfeng Gao. Ms-celeb-1m: A dataset and benchmark for large-scale face recognition. In European Conference on Computer Vision, pages 87–102, 2016.

[29] Lina J. Karam and Zhu Tong. Quality labeled faces in the wild (qlfw): a database for studying face recognition in real-world environments. Proceedings of SPIE - The International Society for Optical Engineering, 2015.

[30] Soumyadip Sengupta, Jun Cheng Chen, Carlos Castillo, Vishal M. Patel, Rama Chellappa, and David W. Jacobs. Frontal to profile face verification in the wild. In Applications of Computer Vision, 2016.

[31] Stylianos Moschoglou, Athanasios Papaioannou, Christos Sagonas, Jiankang Deng, Irene Kotsia, and Stefanos Zafeiriou. Agedb: The first manually collected, in-the-wild age database. In Computer Vision and Pattern Recognition Workshops, 2017.

[32] Jiankang Deng, Yuxiang Zhou, and Stefanos Zafeiriou. Marginal loss for deep face recognition. In IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2017.

[33] Xin Chen, Lingxi Xie, Jun Wu, and Qi Tian. Progressive differentiable architecture search: Bridging the depth gap between search and evaluation. arXiv preprint arXiv:1904.12760, 2019.
[34] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700–4708, 2017.

[35] Gao Huang, Yu Sun, Zhuang Liu, Daniel Sedra, and Kilian Q Weinberger. Deep networks with stochastic depth. In European conference on computer vision, pages 646–661, 2016.

[36] Tara N. Sainath, Brian Kingsbury, George Saon, Hagen Soltau, Abdel Rahman Mohamed, George Dahl, and Bhuvana Ramabhadran. Deep convolutional neural networks for large-scale speech tasks. Neural Networks, 64:39–48, 2015.

[37] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. Imagenet classification with deep convolutional neural networks. In International Conference on Neural Information Processing Systems, 2012.

[38] Matthew D Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In European conference on computer vision, pages 818–833, 2014.

[39] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[40] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. arXiv preprint arXiv:1608.03983, 2016.

[41] Alex Krizhevsky and Geoffrey Hinton. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.

[42] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. International journal of computer vision, 115(3):211–252, 2015.