UENAS: A UNIFIED EVOLUTION-BASED NAS FRAMEWORK

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ABSTRACT

Neural architecture search (NAS) has gained significant attention for automatic network design in recent years. Previous NAS methods suffer from limited search spaces, which may lead to sub-optimal results. In this paper, we propose UENAS, an evolution-based NAS framework with a broader search space that supports optimizing network architectures, pruning strategies, and hyperparameters simultaneously. To alleviate the huge search cost caused by the expanded search space, three strategies are adopted: First, an adaptive pruning strategy that iteratively trims the average model size in the population without compromising performance. Second, child networks share weights of overlapping layers with pre-trained parent networks to reduce the training epochs. Third, an online predictor scores the joint representations of architecture, pruning strategy, and hyperparameters to filter out inferior combos. By the proposed three strategies, the search efficiency is significantly improved and more well-performed compact networks with tailored hyper-parameters are derived. In experiments, UENAS achieves error rates of 2.81% on CIFAR-10, 20.24% on CIFAR-100, and 33% on Tiny-ImageNet, which shows the effectiveness of our method.

Index Terms—NAS, evolution, pruning, online predictor.

1. INTRODUCTION

The significant success of deep learning in many tasks, like image classification and object detection, is largely due to the outstanding neural network architectures. Along with this success, many online predictor have delivered efforts in designing more effective neural networks, i.e. VGGNet [1], ResNet [2] and etc. However, manually designing a powerful architecture is tedious and requires a lot of human endeavors.

Neural architecture search (NAS), which is emerged to discover excellent neural architectures automatically, has drawn growing interest. Different solutions to tackle the NAS problem have been explored in past few years, including RL-based [3], EA-based [4], and Gradient-based [5] approaches. More recently, [6] proposes a one-shot NAS method, which trains an all-in-one supernet by updating a single path in each step. Although some feasible achievement has been made, it suffers from a limited search space to constrain the supernet for fast convergence. Besides, these methods focus on only topology and building blocks of architectures while ignoring other configurations like training hyperparameters and channel number of each layer, which are also crucial for model evaluation.

Network pruning, on the other hand, is another way to intervene in the human-network-design procedure via automatically removing some useless parts of the network structure. [7] introduces sparsity regularization training and prune channels by the scaling factors in batch normalization layers. [8] first train a supernet with the largest channel sets and then greedily trim each layer with minimal accuracy drop. Such methods can alleviate model redundancy without much performance loss. However, they only consider channel dimensions and work on top of several existing human-designed network structures, which is sub-optimal.

In this paper, we propose UENAS, a Unified Evolution-based NAS framework that jointly optimizes for architectures, pruning strategies (can be converted to a fine-grained channel configuration), and hyperparameters (batch size and learning rate). The advantages of UENAS are three folds: (1) UENAS can jointly optimize hyperparameters, pruning configurations, and network architectures in an efficient single-trial paradigm. (2) UENAS allows each network architecture in the search space to be tailored with its own hyperparameters and pruning configuration which provides the best accuracy-efficiency trade-off. (3) UENAS conquers the problem of searching in a much larger search space by an evolutionary algorithm for its powerful capacity in jointly optimizing tasks. Besides, we introduce three practical strategies including adaptive pruning, partly weight inheriting, and online performance predicting to significantly improve the search efficiency of the evolutionary search.

Compared with previous evolution-based NAS methods [4, 9] which require thousands of GPU days, UENAS only costs 12 GPU days, largely reducing the search cost by orders of magnitude. Meanwhile, UENAS achieves excellent performance with top-1 accuracy of 97.19% on CIFAR-10, 79.76% on CIFAR-100, and 67% on Tiny-ImageNet.

Generally, the contributions of our proposed method are as follows:
1. We propose a unified evolution-based NAS framework with a broader search space that supports joint optimization of architectures, pruning strategies, and hyperparameters.

2. We considerably alleviate the evolutionary search cost by adaptive pruning strategy, weight inheritance, and online accuracy predictor.

3. We conduct extensive experiments on CIFAR-10, CIFAR-100, and Tiny-ImageNet to evaluate UENAS. The experimental results show the superiority and effectiveness of our proposed method.

2. PROPOSED METHOD

2.1. Problem Formulation

Given target datasets $D_{\text{train}}, D_{\text{val}}$, we denote the training loss on $D_{\text{train}}$ as $\mathcal{L}_{\text{train}}$ and the validation accuracy on $D_{\text{val}}$ as $\text{Acc}_{\text{val}}$. The target of NAS is to search for an optimal architecture $\alpha^*$, with weights $w^*$ obtained from minimizing $\mathcal{L}_{\text{train}}$, achieves the largest $\text{Acc}_{\text{val}}$. It can be formulated as following bi-level problem:

$$
\max_{\alpha^*, H^*} \quad \text{Acc}_{\text{val}}(w^*(\alpha^*, H^*))
$$

s.t. $w^*(\alpha^*, H^*) = \arg \min \mathcal{L}_{\text{train}}(w(\alpha^*, H))$

$$
\alpha^* = \text{Pruning}((p_1, p_2, ..., p_l), \alpha)
$$

$$
C(\alpha^*) < \text{Constrains}
$$

where $H$ is the training hyperparameter including batch size and learning rate. $(p_1, p_2, ..., p_l)$ is the non-uniform pruning strategy that applied to architecture $\alpha$. $w$ is the weights of pruned network $\alpha^P$, which is also related to training hyperparameters. $C(\alpha^P)$ is the resource constrain of pruned architecture, for example, FLOPs or latency.

The overall framework of UENAS is illustrated in Fig. 1.

We will elucidate UENAS from four components: search space and encoding, adaptive pruning strategy, evolution process, and online predictor.

2.2. Search Space and Encoding

Search space is a key component in NAS to get prominent results. Inspired from precedent state-of-the-art network structures VGG [1] and ResNet [2], We define a family of networks that consists of five stages with increased channels and up to three fully connected layers. A candidate architecture is depicted in Fig. 2. Max-pooling operation is applied between neighboring stages to reduce the spatial size of the feature map. We allow each stage to be connected with subsequent ones by shortcut connection.

Each layer in stages comprises a plain convolution layer, a batch normalization, and a ReLU operation. Channel numbers of both convolution and fully connected layers are obtained by multiplying pruning rates with predefined initial values.

Detailed searchable components is presented in Table 4 in which we term our search space as Arch+Pruning+ Hyp. Each component is represented by a fixed-length binary list and then concatenated to generate an integral representation. Specifically, we introduce discrete encoding to represent components with several definite choices (e.g. choose from \{C_1, C_2, ..., C_n\}) while use continuous encoding to represent components that take values from a continuous interval (e.g. optional value range in $[V_{\text{min}}, V_{\text{max}}]$). Therefore the encoding of a randomly generated value $C_i$ can be represented as follows:

$$
E(C_i) = \begin{cases} 
\text{Bin}(i)_m, & C_i \in \{C_1, C_2, ..., C_n\} \\
\text{Bin}(\text{int}\left(\frac{C_i - V_{\text{min}}}{V_{\text{max}} - V_{\text{min}}} \cdot 2^m\right))_m, & C_i \in [V_{\text{min}}, V_{\text{max}}]
\end{cases}
$$

where $i$ is the index of $C_i$. $\text{Bin()}_m$ represent for a fixed $m$-length binary list with 0 padding in the left if not attain. $m$ is a predefined length of the binary list to encode $C_i$. We apply the discrete encoding method to stages, the number of FC layers, and shortcut connections, while using the continuous encoding method for pruning strategy and training hyperparameters.

2.3. Adaptive Pruning Strategy

We apply an adaptive pruning strategy to balance model cost and accuracy. We show how we prune for each layer first and then how to choose promising pruning strategies.

We conduct pruning by building a new model with pruned channel numbers and copying the corresponding weights from the unpruned network. Similar to [10], we always keep the low-index channel weights. Details are as follows:

The weight matrix $W$ of the $i$-th unpruned layer is a four-dimension tensor with shape $(C_{out}, C_{in}, K, K)$ for convolution layers or a two-dimension tensor with shape $(C_{out}, C_{in})$ for fully connected layers. $C_{out}$ and $C_{in}$ are output and input channel numbers of the $i$-th layer, respectively. $K$ is the kernel size of the convolution layer. Therefore the weight matrix $W^*$ of the corresponding pruned layer is obtained as follows:

$$
W^* = \begin{cases} 
W[:, C_{out} \times p_{i-1}, C_{in} \times p_{i-1}, ..., ], & W \in \mathbb{R}(C_{out}, C_{in}, K, K) \\
W[:, C_{out} \times p_{i}, C_{in} \times p_{i}], & W \in \mathbb{R}(C_{out}, C_{in})
\end{cases}
$$

where $p_{i-1}$ and $p_i$ are pruning rates of the $(i-1)$-th and $i$-th layer, respectively. For convolution layers in stages and FC layers, the input channel number of the $i$-th layer is the output channel number of the $(i-1)$-th layer. We exclude the last fully connected layer when conducting pruning since it depends on the task label.
Online Predictor

Unpruned Networks
Child Population
Filter < Joint Encoding, Accuracy

Unpruned Network
Adaptive Pruning
Child Population
Average Model in Populations
N/2 N
Pruned Networks
Crossover Mutation

Fig. 1: The framework of UENAS. The search space contains architecture, pruning strategy, and hyperparameter. They are jointly optimized by the evolution process. Referring to [10], adaptive pruning strategy consists of batch norm re-calibration and inference process. Parent population is built by $\frac{1}{3}N$ unpruned networks and $\frac{2}{3}N$ pruned networks with the best performance. Additionally, an online accuracy predictor is applied to filter out inferior child individuals.

Fig. 2: A candidate network in our architecture family. It consists of five stages, several fully connected layers, and shortcut connections. Each convolution or fully connected layer is attached with a pruning rate.

We apply a non-uniform pruning schedule (the pruning rate of each layer is different), which may lead to channel number mismatch in shortcut connections. If the shortcut is a skip identity, we delete it when the corresponding two channel numbers are different after pruning. Otherwise if shortcut is a $1 \times 1$ convolution layer, $C_{in}$ and $p_{i-1}$ in Eq. 3 are obtained from the last layers of precedent stages.

As possible combinations of pruning rates are huge, we need to spot the most potential pruning strategies before actually finetuning them. An intuitive methodology is to rank the inference accuracy of pruned networks generated by different pruning strategies. Unfortunately, we found empirically that inference accuracy without retraining is poor and may lead to a wrong ranking list. As mentioned in [10], the reason may lie in the outdated global BN statistics that are copied from unpruned networks. Therefore we forward-propagation a few iterations on training data to re-calibrate the statistics in batch normalization. Note that when we update the statistics of batch normalization, the trainable parameters of pruned networks are fixed. In such case, we can fast evaluate the potential of pruned networks by inference accuracy and select superior ones to guarantee comparable performance.

2.4. Evolutionary Process

To progressively reduce the average model size in each generation, we select parents by $\frac{1}{3}$ from unpruned candidates and $\frac{2}{3}$ from pruned candidates with top performance. Then crossover and mutation operations will be conducted on the parent population to produce child candidates for the next generation. Before crossover, the parent population is divided into three groups denoted as $A$, $B$, and $C$ with declining top-1 accuracy. We conduct intra-group and inter-group crossover with possibilities $p_{\text{intra}}$ and $p_{\text{inter}}$, respectively. The intra-group cross is performed on individuals within one group, e.g., $A$ or $B$. Inter-group cross is applied on individuals from different groups e.g. $(A, B)$, $(A, C)$ and $(B, C)$. The crossover will exchange homologous segments of two-parent individuals at random places. After the crossover process is finished, the remaining unchanged parent individuals will be mutated. Each element in the binary list will be randomly flipped with a possibility $p_{\text{mutate}}$. The child networks generated by the crossover and mutation operation will copy weights of overlapped layers from their trained parents, while randomly initializing newly generated layers. In this way, the
training epochs of child networks will be largely reduced.

2.5. Online Predictor

We build the online predictor with a three-layer feed-forward neural network that has 2048 hidden units. The input of the predictor is the joint encoding, and the output is the predicted accuracy. We apply the root-mean-square error (RMSE) to supervise the training of the predictor. Instead of training offline with enormous accumulated data, we intuitively plug the accuracy predictor in the search process and refine it iteratively, which is more efficient. Specifically, after each generation is finished, a new predictor will be trained with all available \(<\text{encoding, accuracy}>\) pairs. Then the predictor is applied to filter out half of the newly generated individuals with the worst predicted accuracy. Compared with our candidate networks, the training cost of the predictor is negligible. With reduced population number, the computation burden of UENAS will be mitigated a step further.

3. EXPERIMENTS

3.1. Experimental Setup

When searching on CIFAR-10, we follow the common practice of NAS methods (5), (11) by randomly holding out 20% of the original training set for validation while using the remaining 80% for training. In the first generation, we randomly sample 60 candidates with channel configuration initialized as [64, 128, 256, 512, 512] for 5 stages. Then each candidate is trained for 30 epochs with randomly generated batch size and initial learning rate. We use optimizer in (12) and cosine schedule for network training. After one generation finishes, the online predictor is trained with the Adam optimizer for 300 epochs. The learning rate is set as 0.001 and batch size is 10. Afterward, the online predictor is used to filter out half of the child candidates with worse predicted accuracy, reduce the population size to 30 for the 2 ~ 5 generations. Meanwhile, 3 out of 100 pruning strategies are selected by adaptive pruning strategy, as presented in section 2.3. We fine-tune the pruned networks for 8 epochs to obtain their performance. Since the parent population is largely built (\(\frac{2}{3}\)) by iteratively pruned networks with comparable performance, the average model size in the child population is progressively reduced. We further decrease the training epochs of child populations in 2 ~ 5 generations to 15 epochs after coping weights from their parents. The total search process takes around 12 GPU days (96 hours on 3 NV-3090 GPUs). We plot the best architectures discovered by UENAS in Fig. 3 under constraints of no more than 15M parameters.

3.2. Experimental Results

To evaluate the performance of UENAS, we first train the obtained candidate (architecture with pruned channels, hyperparameters) on the full training dataset of CIFAR-10 for 600 epochs. On CIFAR-10, we apply Mixup (18) with interpolation coefficient \(\alpha\) as 1. DropBlock (19) is adopted with drop probability as 0.2 after the first and second max-pooling layer. We set the block size as 7 and 5 for the first and second DropBlock. The batch size and the learning rate are set as 128 and 0.05, which are obtained from the search stage. We observe that UENAS achieves a feasible search cost of 12 GPU days with comparable performance with other state-of-the-art methods. Although Arch2Vec (17) achieves slightly better accuracy than our method, its search cost is larger by one order of magnitude. When comparing with (15), which takes only 10 GPU days, UENAS achieves 1.42% higher accuracy with nearly 50% smaller model parameters.

We further transfer the candidate that searched on CIFAR-10 to CIFAR-100 and Tiny-ImageNet datasets to validate the generality of our method. When training on CIFAR-100, we alter the block sizes of two DropBlocks as 3 and 2, respectively. We use the same training hyperparameters as CIFAR-10 when training on Tiny-ImageNet. Table 1 presents the comparison results with other methods on CIFAR-100 and Tiny-ImageNet. On both two datasets, UENAS shows the best accuracy-efficiency trade-off. On CIFAR-100, our method improves the top1 accuracy of RepVGG A2 (20)
### Table 2: Comparison with state-of-the-art architectures when transferring to CIFAR-100 and Tiny-ImageNet datasets.

| Dataset       | Architecture          | Params (M) | Test Err. (%) |
|---------------|------------------------|------------|---------------|
| Cifar 100     | VGG16 bn [1]           | 135        | 26.00         |
|               | PreActResNet18 [21]    | 11.2       | 21.51         |
|               | RepVGG A2 [20]         | 26.94      | 22.82         |
|               | UENAS                  | 12.7       | 20.24         |
| Tiny-ImageNet | PreActResNets18 [21]   | 11.2       | 36.52         |
|               | Inception-Resnet [22]  | 8.3        | 37.56         |
|               | VGG16 bn [1]           | 135        | 35.05         |
|               | UENAS                  | 12.7       | 33            |

Table 3: K Tau of online predictor after each generation.

| Metric | Gen 1 | Gen 2 | Gen 3 | Gen 4 | Gen 5 |
|--------|-------|-------|-------|-------|-------|
| K Tau  | 0.50  | 0.58  | 0.59  | 0.60  | 0.63  |

by 2.58% while reducing 14.24M model size. On Tiny-ImageNet, UENAS is 3.52% higher than PreActResNets18 with minor model size increase by 1.5M.

#### 3.3. Online Predictor

We validate the effectiveness of the online predictor by Kendalls Tau (K Tau) [23], which measures the correlation between the predicted and the true accuracy ranks. We report the average value of 5-fold cross-validation in Table 3. Gen 1 to Gen 5 represent the online predictor that is trained with all available encoding and accuracy pairs after each generation. The results show that the online manner helps the predictor refine itself while searching.

#### 3.4. Adaptive Pruning Strategy

To examine the performance drop brought by the adaptive pruning strategy, we randomly sample one architecture, generate its three pruned networks, then train both the unpruned and 3 pruned networks for 300 epochs with the same training hyperparameters. The training curve is depicted in Fig. 4 (left). We observe that the pruned networks show a small performance decrease (0.19% ~ 0.74% accuracy drop) when compared to the unpruned network with nearly 50% parameters trimmed off. Fig. 4 (right) present the average model size of each generation. We can infer that by iteratively pruning from the last generation, the average model size is reduced progressively. Therefore, we conclude that the adaptive pruning strategy can help UENAS to design more efficient but performance comparable architectures.

#### 3.5. Ablation Study

We conduct statistical analysis on each component of UENAS for ablation studies. Specifically, we first evaluate the improvement in performance brought by the joint search space, then we verify the acceleration on search cost by the predictor and the pruning strategy.

#### 3.5.1. Effect of the Jointly Search Space

We conduct comparison experiments on three progressively enlarged search spaces, which are abbreviated as Arch, Arch+Pruning, and Arch+Pruning+ Hyper (search space in UENAS). Their searchable components are summarized in Table 4. To produce random search results in each search space, we replace the search algorithm of UENAS by randomly sampling and picking up the best one for an entire 600-epoch re-training. Since pruning strategy is not included in the Arch search space, we fix the stage channel configuration as [32, 64, 128, 256, 256] to fit in the computation constrain.

The results in Table 5 show that our jointly search is non-trivial. The same table also proves the effectiveness of our search method over random search.

#### 3.5.2. Acceleration on Search Cost

To evaluate the acceleration of online predictor (MLP) and adaptive pruning strategy on the evolution algorithm, we compare the search cost (GPU days) under three experiment settings: (1) UENAS without MLP and pruning strategy; (2) UENAS without pruning strategy and (3) UENAS. We perform 5 runs for each experiment setting and present the average value in Table 6. It is evident that our method accelerates the search process by around 4×, which shows the advantages of the predictor and pruning.

![Fig. 4: The effectiveness of the adaptive pruning strategy. Left: training curves of a randomly sampled network and its corresponding three pruned networks; Right: the average model size in each generation.](image-url)
In this paper, we propose UENAS, a unified NAS framework that jointly optimizes for architectures, pruning strategies, and hyperparameters. To address the dilemma of searching in such a huge search space, we further introduce adaptive pruning strategy, weight inheritance, and online accuracy predictor to largely reduce the search cost. With 96 hours on 3 GPUs, UENAS achieves excellent performance on CIFAR-10, CIFAR-100, and Tiny-ImageNet. For future work, we would evaluate UENAS on ImageNet benchmarks. We hope our findings in UENAS can shed light on a new paradigm of NAS where search spaces are less limited.

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Table 5: The comparison of our method with the random search on different search spaces.

| Search Space | Random Search | Our Search |
|--------------|---------------|------------|
| Arch         | 3.54          | 3.24       |
| Arch+Pruning | 3.11          | 3.01       |
| Arch+Pruning+Hyp | 2.94     | 2.81       |

Table 6: Comparison results under different experimental settings on CIFAR-10. We always keep weight sharing since the search space is too large.

| WS Predictor Pruning GPU Days Test Err |
|---------------------------------------|
| ✅ ❌ ❌ ❌ 40 2.86                       |
| ✅ ✔ ❌ 21 2.84                        |
| ✅ ✔ ✔ 12 2.81                        |
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