PR-DARTS: PRUNING-BASED DIFFERENTIABLE ARCHITECTURE SEARCH

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ABSTRACT

The deployment of Convolutional Neural Networks (CNNs) on edge devices is hindered by the substantial gap between performance requirements and available processing power. While recent research has made large strides in developing network pruning methods for reducing the computing overhead of CNNs, there remains considerable accuracy loss, especially at high pruning ratios. Questioning that the architectures designed for non-pruned networks might not be effective for pruned networks, we propose to search architectures for pruning methods by defining a new search space and a novel search objective. To improve the generalization of the pruned networks, we propose two novel PrunedConv and PrunedLinear operations. Specifically, these operations mitigate the problem of unstable gradients by regularizing the objective function of the pruned networks. The proposed search objective enables us to train architecture parameters regarding the pruned weight elements. Quantitative analyses demonstrate that our searched architectures outperform those used in the state-of-the-art pruning networks on CIFAR-10 and ImageNet. In terms of hardware effectiveness, PR-DARTS increases MobileNet-v2’s accuracy from 73.44% to 81.35% (+7.91% improvement) and runs 3.87× faster.

Keywords Neural Architecture Search, Pruning, Network Compression

1 Introduction

Convolutional Neural Networks (CNNs) provide an excellent avenue in obtaining the maximum feature extraction capacities required to resolve highly complex computer vision tasks [1,2,3,4]. There is an increasing demand for CNNs to become more efficient in order to be deployed on extremely resource-constrained edge devices. However, CNNs are not intrinsically tailored for the limited computing and memory capacities of tiny edge devices, making the deployment of CNN applications prohibited [5,6,7,8,9].

To democratize CNN acceleration, a variety of optimization approaches have been proposed, including network pruning [10,11,12], efficient architecture design [6], network quantization [13,14,15], knowledge distillation [16,17], and low-rank decomposition [18]. Particularly, network pruning is known to provide remarkable computational and memory savings by removing redundant weight parameters in the unstructured scenario [10,19,11,12], and the entire filter in the structured scenario [20,21,22,23]. Recently, unstructured pruning methods reported to provide extreme network size reduction. HYDRA [10] as the state-of-the-art unstructured pruning method provides up to 99% pruning ratio which is an excellent scenario for tiny edge devices.
Nevertheless, these methods suffer from a substantial accuracy drop, hampering them from being applied in practice (≈19% accuracy drop for MobileNet-v2 compared to non-pruned one [10]). Current pruning methods use handcrafted architectures designed for non-pruned filters [19, 11, 12, 23, 10]. We hypothesize that the backbone architecture may not be optimal for scenarios with extreme pruning ratios as they were initially designed for non-pruned ones. Instead, we can learn more efficient backbone architectures by exploring the space of pruned networks.

Neural Architecture Search (NAS) has achieved great success in automated designing high-performance CNN architectures. DARTS [24] is a popular cell-based NAS method that uses a gradient-based search algorithm to expedite the search speed. Motivated by the promising results of NAS, we came up with the idea of designing customized backbone architectures for pruning methods.

First, as the HYDRA pruning method [10] provides an extreme pruning ratio, we select it to prune the best architectures designed by DARTS. Disappointingly, the pruned searched architectures perform poorly with up to ≈21% accuracy loss (Section 4). This failure is due to DARTS’s lack of support for specific pruned network characteristics leading to low generalization performance. Based on the above hypothesis and empirical observations, we formulate a cell-based search space that is explicitly defined for pruned networks. Further, the original DARTS convolution and linear operations have been replaced by PrunedConv and PrunedLinear operations, respectively. Moreover, we propose a novel four-step gradient-based optimization algorithm to learn network architecture and weight parameters. We call this method pruning-based differentiable architecture search or PR-DARTS.

We show explicitly integrating pruning into the search procedure can lead to finding pruned networks with significant accuracy improvement. In Fig. 1, we compare the CIFAR-10 Top-1 accuracy and the number of parameters of PR-DARTS with the state-of-the-art pruned (by HYDRA [10]) and non-pruned networks. Results show PR-DARTS outperforms all competing architectures that employ HYDRA as a post pruning method. PR-DARTS-Small demonstrates its consistent effectiveness by achieving 15%, 10%, and 8% accuracy improvement over MobileNet-v2pruned [25], EfficientNet-v2pruned [26], and DARTSpruned [24], respectively. In addition, compared to networks with similar accuracy, PR-DARTS-Large has a significant reduction in network complexity ( Params) by 3.5 × , 30.0 × , 105.2 × over PDO-eConv [27], CCT-6/3 ×1 [28], and MomentumNet [29], respectively. Section 6 provides a comprehensive experimental study to evaluate different aspects of PR-DARTS.

Our main contributions are summarized as follows:

1. We perform extensive experiments to identify the limitations of applying pruning methods with extreme pruning ratios to the existing NAS algorithms.

2. We define a new search space for pruned networks; a new set of operations (PrunedConv and PrunedLinear) to improve the generalization of the pruned networks by regularizing the loss function to find architecture parameters.

3. We propose a novel search objective and a four-step gradient-based algorithm to learn architecture parameters, network weights, and pruning parameters.

2 Related Work

2.1 Neural Architecture Search and DARTS Variants

Neural Architecture Search (NAS) has recently attracted remarkable attention by relieving human experts from the laborious effort of designing neural networks. Early NAS methods mainly utilized evolutionary-based [30, 31, 9, 32] or reinforcement-learning-based methods [33, 34, 35]. Despite the efficiencies over handcrafted designs, they require tremendous computing resources. For example, the proposed method in [33] evaluates 20,000 neural candidates across 500 NVIDIA® P100 GPUs over four days. One-shot architecture search methods [36, 37, 38] have been proposed to identify optimal neural architectures within a few GPU days (>1 GPU day [39]). In particular, Differentiable Architecture Search (DARTS) [24] is a variation of one-shot NAS methods that relaxes the search space to be continuous and differentiable. The detailed description of DARTS can be found in Section 3.1. Despite the broad successes of DARTS in advancing NAS applicability, achieving optimal results remains a challenge for real-world problems. Many subsequent works investigate some of these challenges by focusing on (i) increasing search speed [40, 41], (ii) improving generalization performance [42, 43], (iii) addressing the robustness issues [44, 45, 46], (iv) reducing quantization error [15, 13], and (v) designing hardware-aware architectures [47, 48, 49]. As an orthogonal direction, few works attempt to prune the search space by removing inferior network operations [50, 51, 52, 53]. Yet, there is a lack of research on pruning weight parameters when designing neural architectures. PR-DARTS searches for neural operations that are most effective for pruned weight parameters in order to achieve higher generalizing performance.
2.2 Network Pruning

Network pruning is an effective method for reducing the size of CNNs, enabling them to be effectively deployed on devices with limited resource capacity. Prior works on network pruning can be classified into two categories: structured and unstructured pruning methods. The purpose of structured pruning is to remove redundant channels or filters to preserve the entire structure of weight tensors with dimension reduction [20, 21, 54, 22, 23]. While the structured pruning is famous for hardware acceleration, it sacrifices a certain degree of flexibility as well as weight sparsity [55].

On the other hand, unstructured pruning methods offer superior flexibility and compression rate by removing parameters with the least impact on the network accuracy from the weight tensors [56, 57, 20, 55, 58, 10, 19, 11, 12]. In general, unstructured pruning entails three stages, including (i) pre-training, (ii) pruning, and (iii) fine-tuning. Prior unstructured pruning methods proposed various criteria for selecting the lowest significant pruning weight parameters. [59, 60] pruned weight parameters based on the second-derivative values of the loss function. Several studies proposed to remove the weight parameters below a fixed pruning threshold, regardless of the training objective [56, 57, 58, 61, 62, 63]. To address the limitation of fixed thresholding methods, [19] proposed layer-wise trainable thresholds to determine the optimal value for each layer separately. To make the pruning techniques aware of robustness against adversarial attacks, HYDRA [10] proposed to formulate the pruning objective as empirical risk minimization and integrate it with the robustness training objective. HYDRA has been described in Section 3.2. Despite the success of HYDRA in achieving a significant compression rate and a higher degree of robustness, classification accuracy is compromised, notably when the pruning ratio is extremely high (up to 99%).

3 Preliminaries

3.1 DARTS

Differentiable Architecture Search (DARTS) [24] is a NAS method that significantly reduces the search cost by relaxing the search space to be continuous and differentiable. DARTS cell template is represented by a Directed Acyclic
Graph (DAG) containing $N$ intra-nodes. The edge $(i, j)$ between two nodes is associated with an operation $o^{(i,j)}$ (e.g., skip connection or $3 \times 3$ max-pooling) within $O$ search space. Eq. 1 computes the output of intermediate nodes.

$$\bar{o}^{(i,j)}(x^{(i)}) = \sum_{o \in O} \frac{\exp(\alpha^{(i,j)}_{o})}{\sum_{o' \in O} \exp(\alpha^{(i,j)}_{o'})} \cdot o(x^{(i)})$$

where $O$ and $\alpha^{(i,j)}_{o}$ denote the set of all candidate operations and the selection probability of $o$, respectively. The output node in the cell is the concatenation of all intermediate nodes. DARTS optimizes architecture parameters ($\alpha$) and network weights ($\theta$) with the following bi-level objective function:

$$\min_{\alpha} L_{\text{val}}(\theta^*, \alpha) \text{ s.t. } \theta^* = \arg\min_{\theta} L_{\text{train}}(\theta, \alpha)$$

where $L_{\text{train}} = \sum_{(x,y) \in (X_{\text{train}}, Y_{\text{train}})} l(\theta, x, y)$ and $L_{\text{val}} = \sum_{(x,y) \in (X_{\text{val}}, Y_{\text{val}})} l(\theta, x, y)$. The operation with the largest $\alpha_o$ is selected for each edge. $X_{\text{train}}$ and $Y_{\text{train}}$ represent the training dataset and corresponding labels, respectively. Similarly, the validation dataset and labels are indicated by $X_{\text{val}}$ and $Y_{\text{val}}$, respectively. After the search process has been completed, the final architecture is re-trained from scratch to obtain maximum accuracy.

### 3.2 HYDRA

Pruning is considered unstructured if it removes low-importance parameters from the weight tensors [55]. This paper employs HYDRA [10] as an unstructured network pruning method to provide higher flexibility and an extreme compression rate compared to structured pruning methods. HYDRA includes three main optimization stages: (i) pre-training: training the network on the target dataset, (ii) pruning: pruning unimportant weights from the pre-trained network, and (iii) fine-tuning: the pruned network is re-trained to recover its original accuracy. The pruning stage of HYDRA works as follows: First, according to Eq. 3, HYDRA initializes the pruning parameters ($s^0$).

$$s^0_i \propto \frac{1}{\max(\{|\theta_{\text{pre},i}|\})} \times \theta_{\text{pre},i}$$

where $\theta_{\text{pre},i}$ denotes the corresponding weight of $i$th layer in the pre-trained network. Next, to learn the pruning parameters ($\hat{s}$), HYDRA formulates the optimization problem as Eq. 4 which is then solved by the stochastic gradient descent (SGD) algorithm [64].

$$\hat{s} = \arg\min_{\theta_{\text{pre}}} \mathbb{E}_{(x,y) \sim D} [L_{\text{prune}}(\theta_{\text{pre}}, s, x, y)]$$

$\theta_{\text{pre}}$ and $\mathbb{E}$ refers to the pre-trained network parameters and mathematical expectation, respectively. Finally, HYDRA creates a binary pruning mask based on selecting top-$k$ weights with the highest magnitude of pruning parameters.

Figure 2: Comparison of PR-DARTS-Small and DARTS$_{\text{pruned}}$ on CIFAR-10 for (a) train and (b) test learning curves.
4 Research Motivation

It is inefficient to prune networks that are initially designed by NAS methods. To demonstrate this assertion, we first apply HYDRA [10] to the best architecture designed by DARTS [24] for CIFAR-10. We call this solution DARTS\_pruned. Then, we compare the performance of PR-DARTS with DARTS\_pruned. Fig. 2 illustrates the train and test accuracy curves for PR-DARTS and DARTS\_pruned architectures trained on the CIFAR-10 dataset. Disappointingly, the network designed by DARTS\_pruned results in reduced generalization performance. This implies that pruning backbone architectures designed by NAS methods is ineffective (PR-DARTS delivers 8% higher test accuracy compared to DARTS\_pruned). According to our investigations, we find two issues involved in the training failure of DARTS\_pruned: (i) DARTS does not support characteristics of pruned operations in its search space; and (ii) DARTS optimizes the search objective that is specialized for non-pruned networks. Section 5.2 addresses the first issue, while the second issue is addressed in Section 5.3.

5 PR-DARTS Method

5.1 PR-DARTS: Overview

PR-DARTS consists of three main steps: (1) Pre-training: we pre-train a random non-pruned architecture from the PR-DARTS search space. (2) Pruning and Architecture Design: we remove redundant weight parameters of candidate operations by learning a pruning mask. To this end, we propose two novel operations to enable the pruning-aware architecture search (Section 5.2). Further, we reformulate the DARTS objective to consider pruning in the search algorithm and generate the final searched architecture (Section 5.3). To solve the optimization problem, we propose a four-step gradient-based algorithm (Section 5.4). (3) Fine-tuning: we re-train the best-pruned architecture from scratch to achieve the maximum classification performance.

5.2 PR-DARTS Search Space

To support pruning operations, PR-DARTS proposes the pruned version of convolution and linear operations called PrunedConv and PrunedLinear, respectively. These operations learn a mask (m) to remove redundant weight parameters from the network. Fig. 3 illustrates the functionality of these two operations. In addition, Appendix A presents the PR-DARTS search operations.

![Diagram showing the functionality of linear and convolution operations](image)

Figure 3: Illustrating the (a) PrunedLinear and (b) PrunedConv operations.

To empirically investigate the behavior of the proposed pruning operations, we compare the similarity of non-pruned DARTS cells output with PR-DARTS and DARTS\_pruned methods. We use Kendall’s τ [65] metric to measure the similarity between output feature maps. The τ correlation coefficient returns a value between -1 and 1. Closer values to one indicate stronger positive similarity between the feature maps. Fig. 4 summarizes the results. Our observations reveal a strong similarity between PR-DARTS and non-pruned DARTS (up to 16%). On the other hand, the correlation between DARTS\_pruned and non-pruned DARTS is insignificant. Therefore, the cell’s behavior of PR-DARTS is more similar to non-pruned DARTS than DARTS\_pruned.
5.3 PR-DARTS Objective

PR-DARTS aims to search for the optimal architecture parameters ($\alpha^*$) to minimize the validation loss of the pruned network weight parameters. Thus, we formulate the entire search objective function as:

$$\alpha^* = \min_{\alpha} (L_{val}(\hat{\theta}(\alpha), \alpha))$$

subject to

$$\begin{align*}
\theta^*(\alpha) &= \arg\min_{\theta} L_{train}(\theta, \alpha) \\
\hat{m} &= \arg\min_{m \in \{0, 1\}^N} [L_{prune}(\theta^*(\alpha) \odot m, \alpha)] \\
\hat{\theta}(\alpha) &= \arg\min_{\theta} L_{fine-tune}(\theta^*(\alpha) \odot \hat{m}, \alpha).
\end{align*}$$

Eq. (5) is a bi-level optimization problem. The lower-level problem consists of three main optimization steps, including: (i) pre-training, (ii) pruning, and (iii) fine-tuning. Section 5.4 proposes a new multi-step optimization algorithm to solve the optimization problem of Eq. (5).

5.4 Optimization Algorithm

As shown in Fig. 5, the optimization algorithm consists of four main steps, which are described as follows.

5.4.1 Step 1: pre-train (learn $\theta^*$).

Given the $\alpha_t$ architecture parameters in the $t_{th}$ iteration, the network weight parameters ($\theta^*$) will be updated by using the SGD algorithm (Eq. (6)).

$$\theta_{t+1}^* = \theta_t^* - \eta_\theta \nabla_{\theta} L_{train}(\theta_t^*, \alpha_t)$$

where $\eta_\theta$ denotes the learning rate, $L_{train}$ denotes the loss function for the pre-training step, and $\nabla_{\theta} L_{train}(\theta_t^*, \alpha_t)$ denotes its gradient with respect to $\theta^*$.

5.4.2 Step 2: prune (learn $m$).

Learning mask parameters ($m$) is a challenging binary optimization problem. HYDRA solves this binary optimization problem by introducing pruning parameters $s$ and initializing them based on Eq. (3). Similar to step 1, we use SGD to find the best pruning parameters (Eq. (7)):

$$s_{t+1} = s_t - \eta_s \nabla_s L_{prune}(s_t, \alpha_t)$$

where $\eta_s$ and $L_{prune}$ indicate the learning rate and the loss function for the pruning step, respectively. Based on the pruning parameters, we select the top-$k$ weight parameters with the highest values. $k$ is based on the pruning ratio ($p$) as $k = 100 - p$ and therefore $\hat{m} = \mathbb{1}(|s| > |s|_k)$.

![Figure 4: Comparing the Kendall’s $\tau$ similarity metric of architectures designed by both DARTS$_{pruned}$ and PR-DARTS methods with non-pruned DARTS.](image)
5.4.3 Step 3: fine-tune (learn $\hat{\theta}$).

In the fine-tuning step, we only update the non-zero weight parameters using SGD to improve network accuracy (Eq. 8).

$$\hat{\theta}_{t+1} = \hat{\theta}_t - \eta_{\hat{\theta}} \nabla_{\hat{\theta}} \mathcal{L}_{\text{fine-tune}}(\hat{\theta}_t \odot \hat{m}, \alpha)$$  \hspace{1cm} (8)

where $\eta_{\hat{\theta}}$ and $\mathcal{L}_{\text{fine-tune}}$ denote the learning rate and the loss function for the fine-tuning step.

5.4.4 Step 4: train (learn $\alpha$).

After obtaining $\hat{\theta}_{t+1}$, we can optimize the upper-level optimization problem (Eq. 5) using the SGD algorithm (Eq. 9) to update the architecture parameters ($\alpha$).

$$\alpha_{t+1} = \alpha_t - \eta_{\alpha} \nabla_{\alpha} \mathcal{L}_{\text{val}}(\hat{\theta}(\alpha), \alpha)$$  \hspace{1cm} (9)

where $\eta_{\alpha}$ denotes the learning rate for updating architecture parameters. Similar to DARTS [24] method, we approximate the gradients of architecture parameters. Appendix B provides the PR-DARTS optimization algorithm.

We show that the proposed four-step optimization algorithm finds better architecture parameters with higher generalization performance. Fig. 6 compares the learning curves of PR-DARTS with DARTS pruned on the CIFAR-10 dataset. As shown, the PR-DARTS optimization algorithm significantly reduces the validation loss for pruned networks. Fig. 7 compares the behavior of generalization gap (train minus test accuracy) for PR-DARTS and DARTS pruned. PR-DARTS has a lower generalization gap (up to 22%), indicating PR-DARTS better regularizes the validation loss across all epochs compared to DARTS pruned.

6 Experiments

6.1 Experimental Setup

To evaluate PR-DARTS, we use CIFAR-10 [66] and ImageNet [67] public classification datasets. For the search process, we split the CIFAR-10 dataset into 30k data points for training and 30k for validation. We transfer the best-learned cells on CIFAR-10 to ImageNet [24] and re-train the final pruned network from scratch. Appendix C presents details on network design and fine-tuning steps. Appendix D presents specifications of hardware devices utilized for evaluating the performance of PR-DARTS at inference time. Table I provides the configuration details of the PR-DARTS variants. Each variation is built by stacking a different number of PR-DARTS cells and the output channels of the first layer to generate networks for various resource budgets. In Appendix E, we provide a qualitative comparison of the PR-DARTS searched cell with the DARTS searched cell.
Table 1: Configuration of the PR-DARTS variants. #Cells: the number of stacked cells. #Channels: the number of output channels for the first PrunedConv operation.

| PR-DARTS      | CIFAR-10 |                      | ImageNet |
|---------------|----------|----------------------|----------|
|               | Tiny     | Small | Medium | Large | Small | Medium | Large |
| #Cells        | 16       | 20    | 12     | 14    | 14    | 15     | 16    |
| #Channels     | 30       | 36    | 86     | 108   | 48    | 86     | 128   |

6.2 PR-DARTS Compared to Non-pruned Networks

Table 2 compares the performance of PR-DARTS against the state-of-the-art and the state-of-the-practice CNNs. We select the CNN architecture with the highest accuracy, DrNAS [42], as the baseline for comparing compression rates. In comparison with DrNAS [42], PR-DARTS-Large provides 37.73× and 29.23× higher network compression rates while delivering a comparable accuracy (less than 2.5% accuracy loss) on the CIFAR-10 and ImageNet datasets, respectively. Compared to the best handcrafted designed network [28] on the CIFAR-10 (CCT-6/3x1), PR-DARTS-Large significantly decreases the parameters of the network by 29.9× with providing slightly higher accuracy.

Table 2: Comparing the PR-DARTS method with the state-of-the-art non-pruned networks on the CIFAR-10 and ImageNet datasets.

| Architecture | Year | Search Method | CIFAR-10 | ImageNet | |
|--------------|------|---------------|----------|----------|
|              |      |               | Top-1 Acc. (%) | #Params (×10<sup>6</sup>) | Compression |
|              |      |               | Top-5 Acc. (%) | #Params (×10<sup>6</sup>) | Compression |
| ResNet-18* [2] | 2016 | - | 91.0 | 11.1 | -2.77× |
| PDO-eConv [27] | 2020 | - | 94.62 | 0.37 | +10.81× |
| FlexTCN-7 [28] | 2021 | - | 92.2 | 0.67 | +5.97× |
| CCT-6/3x1 [28] | 2021 | - | 95.29 | 3.17 | +1.26× |
| MomentumNet [29] | 2021 | - | 95.18 | 11.1 | -2.77× |
| DARTS (1<sup>st</sup> order) [24] | 2018 | gradient | 96.86 | 3.3 | +1.21× |
| DARTS (2<sup>nd</sup> order) [24] | 2018 | gradient | 97.24 | 3.7 | +1.08× |
| SGAS (Cri 1. avg) [68] | 2020 | | 97.34 | 3.7 | +1.08× |
| SDARTS-RS [69] | 2020 | | 97.39 | 3.4 | +1.17× |
| DrNAS [42] | 2020 | gradient | 97.46 | 4.0 | 1.0× |
| PR-DARTS-Small | 2022 | gradient | 89.06 | 0.017 | +235.29× |
| PR-DARTS-Medium | 2022 | gradient | 92.18 | 0.054 | +74.07× |
| PR-DARTS-Large | 2022 | gradient | 95.31 | 0.106 | +37.37× |

† The baseline for comparing the #params compressing rate is Non-pruned DrNAS [42] as the most accurate architecture.
† ResNet-18 results are trained in Torch, July 10, 2018.

Figure 6: Comparing learning curves (validation loss) of PR-DARTS and DARTS<sub>pruned</sub> on the searched architectures trained with the CIFAR-10 dataset.

Figure 7: Comparing the generalization gap of PR-DARTS and DARTS<sub>pruned</sub> over the CIFAR-10 dataset. The lower values for the generalization gap are better.
Table 3: Comparing the PR-DARTS method with pruned networks on the CIFAR-10 and ImageNet datasets.

| Architecture   | CIFAR-10 | ImageNet |
|----------------|----------|----------|
|                | Top-1 (%) | #Params (×10³) | Compression Rate | NID  | Top-1 (%) | #Params (×10³) | Compression Rate | NID  |
| DARTSpruned    | 81.25    | 21.0     | 100.47× | 3.86 | 38.67    | 61.33     | 33.0            | 100×  | 1.11 |
| MobileNet-v2pruned | 74.44    | 22.2     | 95.04×  | 3.30 | 17.97    | 36.72     | 34.87           | 94.63× | 0.515 |
| ResNet-18pruned | 90.62    | 111.6    | 18.90×  | 0.81 | 67.58    | 80.86     | 116.84         | 28.24× | 0.578 |
| EfficientNetpruned | 75.92    | 102.3    | 10.43×  | 0.39 | 70.57    | 85.94     | 194.6          | 40.54× | 0.281 |
| PR-DARTS-Small | 94.06    | 105.5    | 20×     | 0.91 | 73.78    | 85.94     | 194.6          | 16.95× | 0.38 |
| PR-DARTS-Medium| 92.18    | 53.65    | 39.32×  | 1.71 | 68.34    | 82.24     | 81.95          | 40.26× | 0.841 |
| PR-DARTS-Large | 95.31    | 105.5    | 20×     | 0.91 | 73.83    | 85.94     | 194.6          | 16.95× | 0.38 |

† The baseline for comparing the compressing rate is full-precision and dense DARTS architecture.
‡ NID = Accuracy/#Parameters [70]. NID measures how efficiently each network uses its parameters.

6.3 PR-DARTS Compared to Pruned Networks with HYDRA

As we focus on improving the accuracy of pruned networks at extremely high pruning ratios, we compare PR-DARTS with other networks pruned with HYDRA [10] at 99% pruning ratio (Table 3). In comparison with DARTSpruned, PR-DARTS-Small yields 7.81% and 7.81% higher top-1 accuracies with 1.23× and 1.05× reduction in network size on the CIFAR-10 and ImageNet datasets, respectively. In comparison with ResNet-18pruned on the CIFAR-10 dataset, we provide 1.56% and 4.7% higher accuracy with 2.08× and 1.05× network size reduction for PR-DARTS-Medium and PR-DARTS-Large, respectively. Compared to ResNet-18pruned on the ImageNet dataset, PR-DARTS-Medium provides 0.76% higher accuracy with 1.42×. We can conclude that PR-DARTS can effectively increase pruned networks’ accuracy at extremely high pruning ratios compared to the post pruned NAS-based and handcrafted networks.

6.4 Evaluation of PR-DARTS with Various Pruning Ratios

Table 4 compares PR-DARTS and the DARTSpruned method with three different pruning ratios including 90%, 95%, and 99% on the CIFAR-10 dataset. PR-DARTS achieves 1.57%, 1.04%, and 7.8% higher accuracies with 7%, 6.9%, and 23% network size reduction compared to the DARTSpruned at 90%, 95%, and 99% pruning ratios, respectively. Thus, PR-DARTS is significantly more effective at extremely higher pruning ratios (99%) than lower pruning ratios (90%).

6.5 PR-DARTS Compared to Other Pruning Methods

Table 5 compares PR-DARTS with the state-of-the-art pruning algorithms. The results indicate that PR-DARTS outperforms other pruning algorithms with different backbone architectures on CIFAR-10 and ImageNet datasets. On CIFAR-10, PR-DARTS-Large shows a 1.6% higher accuracy and 3.8× reduction in the network size compared to the most accurate results provided by TAS pruning [71]. PR-DARTS-Large also provides 4.68% accuracy improvement with 38.14× reduction in the network size over TAS pruning [71] on ImageNet. In light of PR-DARTS’ higher efficiency compared to other pruning methods, we can conclude that the pruning method was not the only reason for the PR-DARTS effectiveness.

6.6 PR-DARTS Compared to Quantized Networks

Network quantization emerged as a promising research direction to reduce the intensive computation of neural networks. Recently, [15, 14, 13] proposed to integrate the quantization mechanism into the differentiable NAS procedure to improve the performance of quantized networks. Table 6 compares PR-DARTS with the best results of NAS-based quantized networks. The compression rate is calculated as \( \frac{\sum_{l=1}^{L} \#W_l \times 32}{\sum_{l=1}^{L} \#W_l \times q} \), where \( \#W_l \) and \( \#W_l^q \) are the number of weights in layer \( l \) for full-precision (32-bit) and quantization network with \( q \)-bit resolution [13]. PR-DARTS-Medium

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Table 4: Evaluating the effectiveness of PR-DARTS at various pruning ratios.

| Architecture   | 90% | 95% | 99% |
|----------------|-----|-----|-----|
|                | Accuracy | #Params (×10³) | Accuracy | #Params (×10³) | Accuracy | #Params (×10³) |
| DARTSpruned    | 95.31% | 421 | 93.75% | 210.5 | 81.25% | 21.0 |
| PR-DARTS-Small | 96.88% | 391 | 94.79% | 196.75 | 89.06% | 17.0 |
Table 5: Comparing PR-DARTS with other pruning algorithms.

| Pruning Method | CIFAR-10 | ImageNet |
|----------------|----------|----------|
|                | Backbone Arch. | Top-1 Acc.(%) | #Params (×10^4) | Backbone Arch. | Top-1 Acc.(%) | Top-5 Acc.(%) | #Params (×10^6) |
| SFP [20]       | ResNet-20 | 92.08 | 2.69 | 68.10 | 87.78 | 6.46 |
| FPGM [21]      | -        | 92.31 | 2.69 | -    | 68.41 | 88.48 | 6.46 |
| TAS pruning [71] | -        | 93.16 | 2.32 | -    | 69.15 | 88.48 | 7.40 |
| PR-DARTS-Small | -        | 89.06 | 0.017 | -    | 46.48 | 68.36 | 0.029 |
| PR-DARTS-Medium | -       | 92.18 | 0.054 | -    | 68.34 | 82.24 | 0.082 |
| PR-DARTS-Large | -        | 95.31 | 0.106 | -    | 73.83 | 85.94 | 0.194 |

yields 0.24% and 3.24% higher accuracies and significantly higher compression rate by 2.7× and 4.24× compared to TAS [13] as the most accurate quantized network on the CIFAR-10 and ImageNet datasets, respectively.

Table 6: Comparing the PR-DARTS method with quantized networks on CIFAR-10.

| Architecture | #bits (W/A) | CIFAR-10 | ImageNet | CIFAR-10 | ImageNet |
|--------------|-------------|----------|----------|----------|----------|
|              | Top-1 Acc.(%) | #Params (×10^4) | Compression | Top-1 Acc.(%) | Top-5 Acc.(%) | #Params (×10^6) | Compression |
| Binary NAS (A) [15] | 1/1 | 90.66 | 2.4 | 44.0× | 57.69 | 79.89 | 5.57 | 32.74× |
| TAS [13]     | 2/2 | 91.94 | 2.4 | 22.0× | 65.1 | 86.3 | 5.57 | 16.37× |
| PR-DARTS-Small | 32/32 | 89.06 | 0.017 | 194.11× | 46.48 | 68.36 | 0.029 | 196.55× |
| PR-DARTS-Medium | 32/32 | 92.18 | 0.054 | 61.1× | 68.34 | 82.24 | 0.082 | 69.51× |
| PR-DARTS-Large | 32/32 | 95.31 | 0.106 | 31.13× | 73.83 | 85.94 | 0.194 | 29.38× |

† The baseline for comparison is full-precision DARTS with 3.3M and 5.7M parameters for CIFAR-10 and ImageNet.
‡ (Weights/Activation Function).

6.7 Hardware Performance Results of PR-DARTS

We extensively study the effectiveness of PR-DARTS in the context of hardware efficiency by computing the inference time (latency) of various state-of-the-art networks pruned with HYDRA [10] for a wide range of resource-constrained edge devices on the CIFAR-10 dataset (Fig. 8). The batch size is equal to 1 for all experiments. It is worth noting that we did not utilize any simplification techniques, such as [72], to compact the sparse filters by fusing weight parameters. Our results reveal that the Pareto-frontier of PR-DARTS consistently outperforms all other counterparts by a significant margin, especially on CPUs that have very limited parallelism. PR-DARTS-Tiny as the fastest network improves the accuracy from MobileNet-v2’s 73.44% to 81.35% (+7.91% improvement) and accelerates the inference by up to 3.87×. More importantly, PR-DARTS-Tiny runs much faster than DARTS pruned by 1.67-4.74× with slightly better accuracy. Compared to ResNet-18 pruned as the closest network to PR-DARTS in terms of accuracy, PR-DARTS-Medium provides 1.46% accuracy improvement and up to 1.94× acceleration on hardware.

6.8 Analyzing the Discrimination Power of PR-DARTS

We use t-distributed stochastic neighbor embedding (t-SNE) method [73] for visualizing decision boundaries of non-pruned DARTS, DARTS pruned, and PR-DARTS on the CIFAR-10 dataset. Fig. 9 illustrates the decision boundaries of classification for each network. According to the results, PR-DARTS has a higher discrimination power than DARTS pruned, and PR-DARTS behaves very similarly to non-pruned DARTS.
6.9 Reproducibility Analysis.

To verify the reproducibility of results, the PR-DARTS-Small search procedure was run five times with different random seeds. Fig. 6.9 plots the average of accuracy and loss variations as well as the shades to indicate the confidence intervals. Results show that, while the confidence interval is wide at first, the average of multiple runs converges to neural architectures with similar performance with an average standard deviation (STDEV) of 2.22%.

Figure 8: Trade-off: accuracy v.s. measured latency. PR-DARTS-Tiny, PR-DARTS-Small, PR-DARTS-Medium, PR-DARTS-Large are variants of PR-DARTS designed for different computational budgets (Table 1). PR-DARTS-Tiny consistently achieves higher accuracy with similar latency than MobileNet-v2 pruned and provides lower latency while achieving better accuracy as DARTS pruned.

Figure 9: Visualize decision boundary of (a) DARTS, (b) DARTS pruned, (c) PR-DARTS-Large with t-SNE embedding method.

Figure 10: Demonstrating the reproducibility of PR-DARTS results.
7 Conclusion

To design better performing pruned network architectures, we proposed the first variation of NAS to prune network weights and design network architecture simultaneously, called PR-DARTS. PR-DARTS significantly improves the performance of pruned architectures by proposing: (i) new cell operations specialized for pruned networks; and (ii) a new search objective that improves the generalization performance by regularizing the loss function. Our experimental results reveal that the learned architectures outperform the architectures used in the state-of-the-art pruned networks on both CIFAR-10 and ImageNet datasets. In the long term, we foresee that our designed networks can effectively contribute to the goal of green artificial intelligence by efficiently utilizing resource-constrained devices as the edge accelerating solutions. A promising avenue for future work is to design a pruned network that is robust against adversarial attacks.

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Supplementary Material

A PR-DARTS Search Operations

Table A.1 summarizes the operations of the PR-DARTS search space.

| Operation Type | Separable Pruned Convolution | Dilated Pruned Convolution | Max Pooling | Average pooling | Skip connect |
|----------------|------------------------------|----------------------------|-------------|----------------|--------------|
| Kernel Size    | 3 × 3, 5 × 5                 | 3 × 3, 5 × 5               | 3 × 3       | 3 × 3          | N/A          |

B Pseudo-code of the PR-DARTS Optimization Algorithm

Algorithm 1 presents the PR-DARTS optimization algorithm.

C Details on Configuration Setup on Network Design and Fine-tuning Steps

Details on Searching Networks. We create a network with 16 initial channels and eight cells. Each cell consists of seven nodes equipped with a depth-wise concatenation operation as the output node. The PrunedConv operations follow the ReLU+PrunedConv+Batch Normalization order. We train the network using SGD for 50 epochs with the batch size of 64 in the PR-DARTS pre-train step. Then, we update the value of pruning parameters for 20 epochs in the PR-DARTS pruning step. Finally, we fine-tune the network for 50 epochs and update architecture parameters in the PR-DARTS fine-tuning step. The initial learning rate for the PR-DARTS pre-train, pruning, and fine-tuning steps is 0.025, 0.1, 0.01, respectively. In our experiments, we use the cosine annealing learning rate [1]. We use weight decay=3×10^{-4} and momentum=0.9 in all steps. The search process takes ≈3 GPU-days on a single NVIDIA® RTX A4000 that produces 4.35 Kg CO₂.

Details on Training the Searched Networks. For CIFAR-10, we use three main stages to design the best network. First, we train the dense network for 200 epochs. Then, we prune the network and find the best pruning parameters for 20 epochs. Finally, to achieve maximum accuracy, we fine-tune the network for 200 epochs. We use the batch size of 64 for all three stages. To train the network, we employ the SGD algorithm with weight decay=3×10^{-6}, momentum=0.1, and the learning rate equal to the configuration of the search algorithm. For ImageNet, we pre-train, prune, and fine-tune the best network for 90 epochs with batch size=256. As before, we use the SGD algorithm with weight decay=3×10^{-5}, momentum=0.9, initial learning rate=0.1, and one-cycle learning rate updating policy [1] with the length of 50 epochs.
Table D.1: Hardware Specification.

| Platform          | Specification      | Value                          |
|-------------------|--------------------|-------------------------------|
| **Search & Train**| GPU                | NVIDIA® RTX A4000 (735 MHz)   |
|                   | GPU Memory         | 16 GB GDDR6                   |
|                   | GPU Compiler       | cuDNN version 11.1            |
|                   | System Memory      | 64 GB                         |
|                   | Operating System   | Ubuntu 18.04                  |
|                   | $CO_2$ Emission/Day | 1.45 Kg                       |
| **Real Hardware** | Embedded GPU       | NVIDIA® Jetson TX2 (735 MHz)  |
|                   |                    | 256 CUDA Cores                |
|                   |                    | NVIDIA® Quadro M1200 (735 MHz)|
|                   |                    | 640 CUDA Cores                |
|                   | Embedded CPU       | ARM Cortex™-A7 (1.2 GHz)       |
|                   |                    | 4/4 (Cores/Total Thread)      |
|                   |                    | Intel® i5-3210M Mobile CPU     |
|                   |                    | 5/4 (Cores/Total Thread)      |
| **Estimation**†‡  | Xiaomi Mi9 GPU     | Adreno 640 GPU (750 MHz)       |
|                   |                    | 986 GFLOPs FP32 (Single Precision) |
|                   | Myriad VPU         | Intel Movidius NCS2 (700 MHz)  |
|                   |                    | 28-nm Co-processor            |

† Calculated using the ML $CO_2$ impact framework: [https://mlco2.github.io/impact/][2]
‡ Performance Estimation using the nn-Meter framework [3].

D Details on Hardware Configuration Setup.

Table D.1 presents specifications of hardware devices utilized for evaluating the performance of PR-DARTS at inference time.

E Qualitative Analysis of the Searched Cell.

Fig. E.1 shows the best cells searched by PR-DARTS-Small. An interesting finding is that, for the normal cell, PR-DARTS-Small tends to select PrunedConv operation with larger kernel sizes ($5 \times 5$), providing more pruning candidates. PR-DARTS-Small tends to leverage max-pooling operations in the reduction cell instead of avg-pooling operations. This is because the max-pooling operation has a higher feature extraction capability with pruned filters [4].

![Figure E.1: The illustration of (a) normal cell and (b) reduction cell.](image-url)
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