VP-DARTS: Validated Pruning Differentiable Architecture Search

Tai-Che Feng and Sheng-De Wang
Department of Electrical Engineering, National Taiwan University, Taipei, Taiwan

Keywords: Deep Learning, Model Optimization, Neural Architecture Search, Differentiable Architecture Search, Model Compression, Model Pruning, Soft Pruning.

Abstract: Recently Differentiable Architecture Search (DARTS) has gained increasing attention due to its simplicity and efficient search capability. However, such search methods have a significant chance of encountering overfitting, which can result in the performance collapse problem of the discovered models. In this paper, we proposed VP-DARTS, a validated pruning-based differentiable architecture search method using soft pruning, to address this issue. Firstly, unlike previous search methods, we consider the differentiable architecture search process as a model pruning problem. It prunes or removes unimportant operations from the supernet that contains all possible architectures to obtain the final model. We also show that the traditional hard pruning method would gradually reduce the capacity of the search space during training, leading to local optimal results. To get better architectures than hard pruning, we proposed using a parameterized soft pruning approach in our training process. Secondly, the original DARTS method selects the operation with the maximum architecture parameter on each edge to form the final architecture after training. But we found that this approach cannot truly reflect their importance. Therefore, we estimate the impact on the supernet of each candidate operation by using a subset of the validation set to evaluate its degree of importance. Finally, we implement our method on the NAS-Bench-201 search space, and the experimental results show that VP-DARTS is a robust search method that can obtain architectures with good performance and stable results.

1 INTRODUCTION

Early machine learning models were all manually crafted by experts, and these models achieved great success in tasks such as image recognition, including ResNet (He et al., 2016), VGG (Simonyan and Zisserman, 2015), MobileNet (Howard et al., 2017; Sandler et al., 2018), and others. However, designing these neural networks requires a lot of expertise and time. To address this issue, neural architecture search (NAS) has gradually gained attention. Its main objective is automatically to search for the most suitable model architecture without requiring specialized knowledge.

However, since the search space of NAS is not continuous, early methods could only rely on Reinforcement Learning (Zoph and Le, 2017) or Genetic Algorithms (Real et al., 2019), which require a lot of computing resources and time. H. Liu (Liu et al., 2019b) proposed a differentiable method called DARTS to reduce search costs. The method still has some limitations. First, during the training process, skip connections are more likely to appear in the final architecture. This phenomenon is called performance collapse, which can decrease the stability and accuracy of the network. Secondly, since the training is done through continuous relaxation, each candidate operation is assigned a trainable architecture parameter, which is used to determine the final architecture by choosing the one with the highest value after training. However, we found that these parameters do not truly represent the importance of the operations. In this paper, we propose using a portion of validating set to estimate the degree of importance of operations in the supernet.

The proposed approach is called VP-DARTS and includes the following three main concepts: 1) considering the differentiable architecture search training process as a model pruning problem, 2) using a general parameterized soft pruning techniques based on soft pruning (He et al., 2018) to solve the problem, and 3) using a portion of validating set to estimate the degree of importance of operations in the supernet. In summary, our contributions are as follows:

- We found that the training process of the differentiable architecture search method can be viewed as a model pruning problem. And, a generalized

Feng, T. and Wang, S.
VP-DARTS: Validated Pruning Differentiable Architecture Search.
DOI: 10.5220/0012296700003636

In *Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART 2024) - Volume 2*, pages 47-57
ISBN: 978-989-758-680-4; ISSN: 2184-433X

software pruning approach is proposed to solve the problem.

- The previous methods of selecting operations cannot correctly reflect their true importance. Therefore, we propose estimating the impact of each candidate operation on the supernet by using a subset of the validation set to validate the supernet rather than simply using the values of their architecture parameters.

2 RELATED WORKS

2.1 DARTS

DARTS (Liu et al., 2019b) aims to solve the problem of discontinuous search space for NAS. It uses the cell-based search space to narrow the search range and maps the discrete optimization space to a continuous interval.

In this cell-based search space, each searched cell can be viewed as a directed acyclic graph (DAG), where each node represents a feature map, and each edge represents a type of operation performed. The method first constructs a supernet that contains all possible architectures, where each edge (i, j) becomes a mixed operation $\overline{o}^{(i,j)}(x)$ of all candidate operations $o \in O$, with an architecture parameter $\alpha_o^{(i,j)}$ assigned to it. These architecture parameters α on the same edge will pass through a Softmax activation function, as shown in Equation 1. Through the continuous relaxation approach, NAS can be trained simply using gradient descent. This reduces the training cost significantly compared to the Reinforcement Learning or Genetic Algorithm approaches.

$$\overline{o}^{(i,j)}(x) = \sum_{o \in O} \frac{\exp(\alpha_o^{(i,j)})}{\sum_{o' \in O} \exp(\alpha_{o'}^{(i,j)})} o(x) \qquad (1)$$

At the end of the search, these architecture parameters can be regarded as the index of importance of each operation on the corresponding edge since a larger value α represents a higher proportion of the results produced by that operation on the edge. Therefore, we only need to select the best one based on the maximum architecture parameter on each edge after training to form the final architecture. This approach reduces the search cost from thousands of GPU days to just hours and achieves comparable or even better results to other non-differentiable NAS methods.

2.2 Soft Pruning

Hard pruning (Han et al., 2015; Han et al., 2016; Guo et al., 2020; Liu et al., 2019a; Liu et al., 2019c; He et al., 2020) is the most common pruning technique. Generally, the importance scores are computed based on certain criteria at a specific stage, and those weights that do not satisfy are directly removed. Afterward, the remaining weights are fine-tuned to recover the performance of the pruned model.

Soft pruning (He et al., 2018; He et al., 2019; Cai et al., 2021) is another pruning technique. The main difference between soft and hard pruning is that the pruned weights are not permanently removed but were allowed to participate in the iterative update of the next epoch. Those considered unimportant components have a second chance to regain their importance at the latter training stage. Therefore, the model capacity can be restored from the pruned model during training, allowing the discovery of better models that achieve higher accuracy. On the other hand, in hard pruning, the pruned weights are permanently removed, reducing the model's capacity during training and causing a loss in performance. It also increases the probability that the final search result will be unstable. Since if different components are removed, the subsequent training will search from diverse remaining search spaces, resulting in significant differences in the search result. Furthermore, soft pruning does not need to fine-tune the pruned model after training. This approach significantly saves time compared to the fine-tuning stage required by hard pruning.

In the original soft pruning method (He et al., 2018), the unimportant weights are set to zero for the next epoch. However, directly setting the pruned weights to zero may be too aggressive. Thus, to gradually discard the pruned weights, SofteR Pruning (Cai et al., 2021) is introduced, which gradually increases the pruning strength for these pruned weights during the training process with a monotonic decreasing parameter, leading to better pruning results.

3 APPROACH

3.1 DARTS Pruning

While in the differentiable architecture search method, the goal is to choose the most considerable operation on each edge to form the final architecture. Assuming we look from a different perspective, the operation selection problem can be considered a model pruning problem. In other words, we prune the

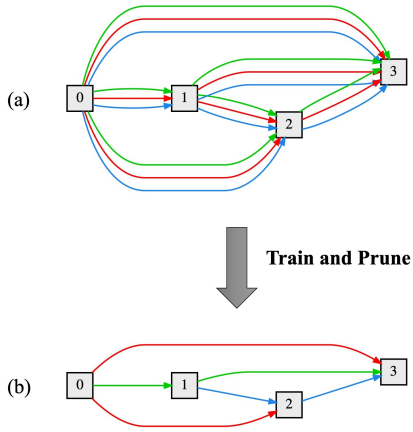


Figure 1: The pruning concept of DARTS (a) DARTS constructs a supernet that contains all possible sub-networks and is trained using continuous relaxation (b) After training, operation-level pruning is performed to remove all unimportant operations at once from the supernet, leaving only one between each pair of nodes.

unimportant operations on each edge and keep the best one, and these remaining operations become the final architecture. In the case of DARTS (Liu et al., 2019b), as shown in Figure 1, the simplest pruning method was employed. It sets the pruning ratio to the maximum and prunes all unimportant operations at the same time. However, the drawback of this approach is that it may easily remove some crucial components and lead to unstabilized results.

Therefore, it is necessary to change the pruning technique to improve the search for more suitable architectures in DARTS. One possible solution is to avoid directly setting the pruning ratio to the maximum but use a progressive approach, increasing the pruning ratio step by step so that unimportant operations can be removed gradually from the supernet in the training process. This approach is adopted in the Search Space Approximation of PDARTS (Chen et al., 2019) and SGAS (Li et al., 2020), which aims to search for better architectures by gradually selecting the edge operations.

However, these various hard pruning approaches still cannot solve the problem of excessive skip connections. After conducting experiments, we found that although the gradual pruning approach can indeed find better combinations of operations than the original DARTS with one-time pruning, skip connections still frequently appear in the final architecture, which suffers from the performance collapse problem. Moreover, these gradual pruning approaches use a similar greedy algorithm to decide which operations to prune at each step and heavily rely on the current training results. Once the unimportant ones are pruned, they are permanently removed and cannot appear in the final architecture. This reduces the search space and compromises the performance during training, leading to an unstable search result.

3.2 Soft Pruning-Based DARTS

Therefore, to address the problem of performance collapse and stabilize the search results, we adopts the soft pruning (He et al., 2018; He et al., 2019; Cai et al., 2021) approach as the pruning technique in differentiable architecture search. The reason is that in this type of model architecture search, our goal is to find the best combination of operations. If we use the traditional hard pruning, those considered unimportant operations at the selection moment will be permanently removed. It reduces the capacity of the search space and the diversity of operation combinations in the later stages of training.

These unimportant operations will not permanently remove if soft pruning is used. Instead, the values of their coefficients will reduce or set to 0 in each epoch and continue to be trained. As shown in Figure 2, these operations still exist in the supernet and allow iterative updates giving those unimportant ones to regain their importance. This approach also ensures the capacity of the search space and the diversity of operations combination during training, avoiding the aforementioned problems and enabling us to search for better architectures.

The generalized soft pruning decay strategy formula can be written as Equation 2.

$$\alpha_1 = \alpha_0(1 - \frac{K}{max\_epoch}) \ , \ 0 \leq K < max\_epoch \quad (2)$$

where α_0 represents the original value, α_1 represents the pruned value, max_epoch represents the total number of pruning epochs, and the coefficient K represents the reduced rate of value, which can control the decaying speed in each epoch. As we fixed the value of K as max_epoch during the training process, the original soft pruning (He et al., 2018) approach is used. That is, the unimportant operation coefficients will be set to zero at the beginning of each epoch. On the other hand, since directly setting the pruned weights to zero may be too aggressive, SofteR Pruning (Cai et al., 2021) gradually increases the pruning strength during the training process, in which the value of K is adjustable. This approach improves the drawbacks of the original soft pruning since the value of the operation coefficients will not be directly set to 0. In this case, the operation can regain their importance more easily and the search can retain more promising architectures.

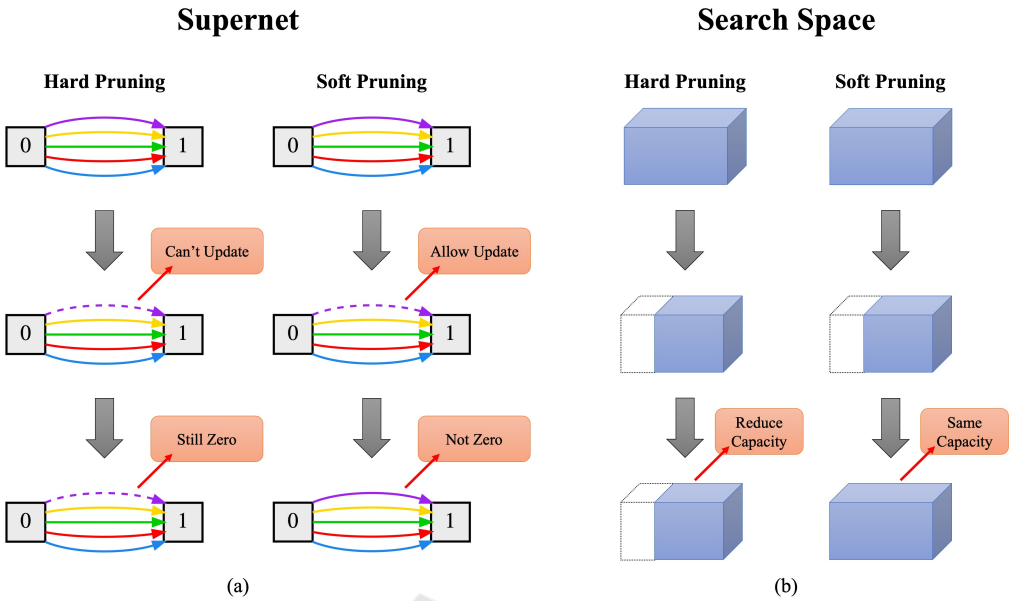


Figure 2: Hard pruning vs. soft pruning in DARTS. In the soft pruning training process, (a) no operation is removed from the supernet during the middle of the training. Instead it is allowed to be continuously updated and let the unimportant operations recover their importance; (b) the capacity of the search space will not decrease, and all possible architectures will exist throughout the training process.

For example, as shown in Figure 3(a), the pruning strength can be set up as the ratio between the current epoch and the total number of pruning epochs. This method is known as the linear decay strategy in SofteR Pruning. Another strategy is called the exponential decay strategy. However, compared to filter pruning, the convergence speed is significantly slower in the differentiable architecture search training process, where operation-based pruning is performed. If the exponential decay strategy is used, the coefficient values will drop in the early stages of training significantly, as shown in Figure 3(b), reducing the chances of recovering operations that are considered unimportant. Therefore, we only consider using the linear decay strategy to attempt to train better architectures. The difference between these two approaches is shown in Figure 4, where the fixed value K will directly set the coefficient to 0, and the adjustable K will set the value according to the decaying strategy.

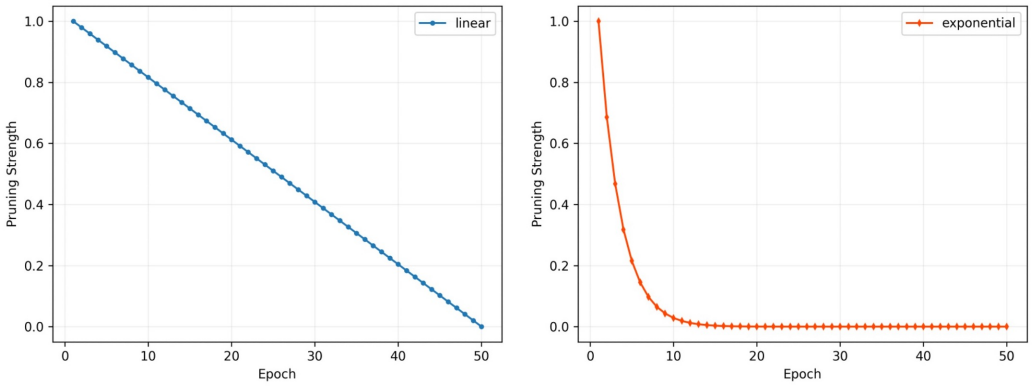
Furthermore, since we treat the selection of operations in DARTS as a model pruning problem, we consider the architecture parameters as general model weights just like others, rather than the probability distribution on each edge. Therefore, we do not use softmax to normalize the architecture parameters. Instead, we train the unnormalized weights directly, as shown in Equation 3.

$$\overline{o}^{(i,j)}(x) = \sum_{o \in O} \alpha_o^{(i,j)} o(x) \tag{3}$$

There are two benefits while not using Softmax. First, since softmax normalizes the weights and forces the sum of all values to 1, when one value increases, the others are compressed and become smaller. This emphasizes the importance of the operations having higher values. While this is fine for fair competition in other methods, skip connections make the competition unfair in DARTS, as some papers (Chen et al., 2019; Chu et al., 2020) have pointed out that its convergence speed is much faster than other operations. Therefore, using softmax only makes the architecture parameters of skip connections grow faster, making it difficult for other operations to be selected. Moreover, since softmax is applied to the architecture parameters on the same edge, it's unable to distinguish the importance between two operations located on different edges and leads to unfair comparisons between operations in the search process.

3.3 Determine Operation Strength Using Validation Set

In the original DARTS method, the importance of each operation is determined based on the magnitude of its architecture parameter. However, according to



(a) Linear Decay Strategy (b) Exponential Decay Strategy

Figure 3: Different decay strategy while using adjustable K.

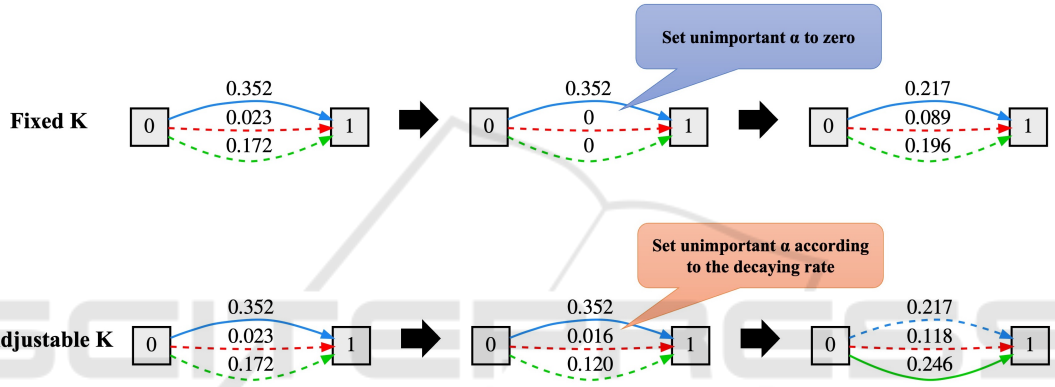


Figure 4: Comparison of using fixed K and adjustable K.

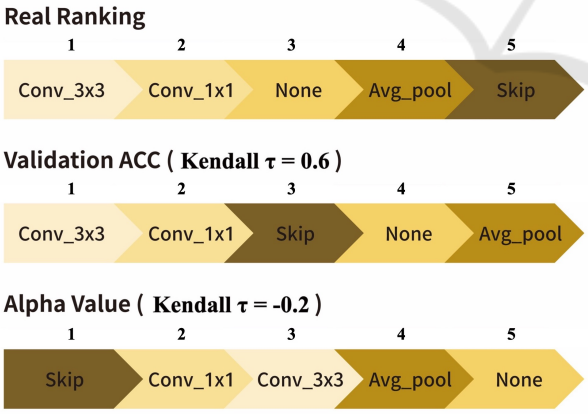


Figure 5: Comparison of Kendall τ coefficient between using the magnitude of architecture parameters α, the remaining supernet validation accuracy without the operation, and the real ranking.

some studies (Zhou et al., 2021; Wang et al., 2021), these coefficients do not accurately reflect their true importance. The operation with the highest coefficient may not be the most important one. Therefore, we attempt to address this issue by estimating the impact of all operations on the supernet instead of directly looking at their architecture parameters.

Algorithm 1: Determine Operation Strength Using Validation Accuracy.

Input : Supernet S; Two operations o_1, o_2
Output: The more important operation o_1, o_2

Val_{o_1} = Validation accuracy of the remaining supernet S when o_1 is removed;
Val_{o_2} = Validation accuracy of the remaining supernet S when o_2 is removed;

if $Val_{o_1} > Val_{o_2}$ **then**
  o_2 is more important than o_1;
  return o_2;
end
else
  o_1 is more important than o_2;
  return o_1;
end

We used the Kendall τ coefficient (Kendall, 1938) to verify the above situation. The Kendall τ coefficient is a commonly used measurement of the correlation between two rankings. It can be calculated as

$$Kendall\ \tau = \frac{C-D}{C+D} \tag{4}$$

where C represents the number of concordant pairs, and D represents the number of discordant pairs. The resulting correlation value always falls between -1 and 1, where -1 and 1 represent perfect negative and positive correlations, respectively, and 0 indicates that the two rankings are completely independent.

Therefore, if we wish the predicted ranking to be similar to the actual rank, the calculated Kendall τ coefficient should be as high as possible. As shown in Figure 5, we calculated the Kendall τ coefficient between the magnitude of architecture parameters, the supernet validation accuracy without the operation, and the actual rank after the DARTS training method. We random sample 100 cell architectures and replace the edges to be evaluated for importance with all candidate operations. We sort them based on the accuracy of the models they construct and calculate the average rank, which serves as the actual ranking for those operations on that edge.

After experiments, we found that using the validation accuracy to determine the importance can better reflect the operations ranking. Using the magnitude of architecture parameters resulted in a Kendall τ value of -0.2 while using validation accuracy as the measurement achieved a value of 0.6. This result shows that using the original magnitude of the architecture parameters cannot correctly determine the importance, leading to select the wrong operations to form the final architecture.

Therefore, according to the above findings, we propose estimating the impact on the supernet of each candidate operation to determine their importance. The overall process is summarized in Algorithm 1. If the validation accuracy decreases significantly after removing one of the operations from the supernet, it indicates that the removed one is quite important because the model performance can only improve by adding it back. On the other hand, if the difference in accuracy before and after removing an operation is negligible, the importance of that operation is relatively low because even without it, the model can still maintain its performance.

3.4 VP-DARTS: Validated Pruning Differentiable Architecture Search

In summary, this study uses the soft pruning approach to conduct the differentiable architecture search method and change the way of determining the importance of operations by estimating their impact on the supernet using the validation set. We name the approach Validated Pruning Differentiable Architecture Search (VP-DARTS). The whole VP-DARTS method is shown in Figure 6, with the following steps:

- To ensure fair competition between all operations, a warmup strategy is employed in the early training, where all architecture parameters are frozen, and only the weights on the model are trained.
- While the warmup stage is completed, at the beginning of each epoch, all candidate operations are removed individually from the supernet, and the validation accuracy of the remaining model is measured to determine their importance. Since testing with the entire validation set is time-consuming, we randomly sample a subset in each epoch to reduce the search cost.
- After every operation strength has been determined, the soft pruning method is used to remove all operations that are considered unimportant temporarily. This approach sets their architecture parameters to α_1 with parameter K as shown in Equation 2, which allows them to participate in the next iteration update to regain their importance. It ensures the search space and the model capacity are not reduced during training, which allows all possible operation combinations to continue existing and find better architectures.
- Repeat the above two steps in each epoch until the training is complete. After training, remove each operation and test the validation set accuracy again to determine the importance of each one, and select the best one with the lowest accuracy to form the final cell architecture.

4 EXPERIMENTS

4.1 Search Space: NAS-Bench-201

NAS-Bench-201 (Dong and Yang, 2020) is a widely-used benchmark for neural architecture search, which fixes the hyperparameters such as the size of search space, the number of candidate operations, the value of learning rate, and data augmentation techniques

Table 1: Results of VP-DARTS on NAS-Bench-201.

Method	CIFAR-10		CIFAR-100		ImageNet16-120		Search Cost
	validation	test	validation	test	validation	test	(h)
Random (baseline)	90.93 ± 0.36	93.70 ± 0.36	70.93 ± 1.09	71.04 ± 1.07	44.45 ± 1.10	44.57 ± 1.25	-
Reinforce (Zoph and Le, 2017)	91.09 ± 0.37	93.85 ± 0.37	71.61 ± 1.12	71.71 ± 1.09	45.05 ± 1.02	45.24 ± 1.18	-
Genetic (Real et al., 2019)	91.19 ± 0.31	93.92 ± 0.30	71.81 ± 1.12	71.84 ± 0.99	45.15 ± 0.89	45.54 ± 1.03	-
DARTS (1st) (Liu et al., 2019b)	39.77 ± 0.00	54.30 ± 0.00	15.03 ± 0.00	15.61 ± 0.00	16.43 ± 0.00	16.32 ± 0.00	2.0
DARTS (2nd) (Liu et al., 2019b)	39.77 ± 0.00	54.30 ± 0.00	15.03 ± 0.00	15.61 ± 0.00	16.43 ± 0.00	16.32 ± 0.00	-
SNAS (Xie et al., 2019)	90.10 ± 1.04	92.77 ± 0.83	69.69 ± 2.39	69.34 ± 1.98	42.84 ± 1.79	43.16 ± 2.64	-
PCDARTS (Xu et al., 2020)	89.96 ± 0.15	93.41 ± 0.30	67.12 ± 0.39	67.48 ± 0.89	40.83 ± 0.08	41.31 ± 0.22	-
SGAS (Li et al., 2020)	85.06 ± 0.00	88.33 ± 0.03	70.80 ± 0.65	70.76 ± 1.29	42.97 ± 2.53	43.04 ± 2.76	-
iDARTS (Zhang et al., 2021)	89.86 ± 0.60	93.58 ± 0.32	70.57 ± 0.24	70.83 ± 0.48	40.38 ± 0.59	40.89 ± 0.68	-
ReNAS (Xu et al., 2021)	90.90 ± 0.31	93.99 ± 0.25	71.96 ± 0.99	72.12 ± 0.79	45.85 ± 0.47	45.97 ± 0.49	-
DARTS- (Chu et al., 2021)	91.03 ± 0.44	93.80 ± 0.40	71.36 ± 1.51	71.53 ± 1.51	44.87 ± 1.46	45.12 ± 0.82	-
DrNAS (Chen et al., 2021)	91.55 ± 0.00	94.36 ± 0.00	73.49 ± 0.00	73.51 ± 0.00	46.37 ± 0.00	46.34 ± 0.00	3.9
β-DARTS (Ye et al., 2022)	91.55 ± 0.00	94.36 ± 0.00	73.49 ± 0.00	73.51 ± 0.00	46.37 ± 0.00	46.34 ± 0.00	3.2
VP-DARTS (Fixed K)	**91.34 ± 0.06**	**94.15 ± 0.07**	**72.64 ± 0.94**	**72.77 ± 0.57**	**45.81 ± 0.28**	**45.91 ± 0.43**	**2.8**
VP-DARTS (Adjustable K)	**91.55 ± 0.00**	**94.36 ± 0.00**	**73.49 ± 0.00**	**73.51 ± 0.00**	**46.37 ± 0.00**	**46.34 ± 0.00**	**2.8**
Optimal	91.61	94.37	73.49	73.51	46.77	47.31	

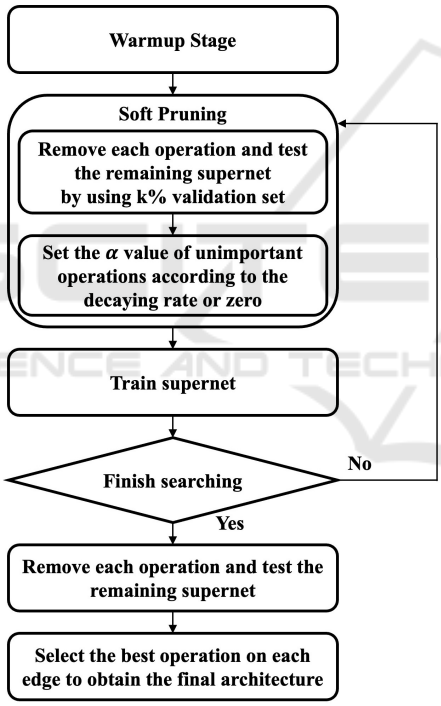


Figure 6: Overview of VP-DARTS.

during the search stage, providing a fair competition platform for all NAS methods in three datasets: CIFAR-10, CIFAR-100 and ImageNet16-120, an ImageNet subset down-sampled version. The objective of the search space is to find the best cell architecture, which can be represented as a directed acyclic graph (DAG) consisting of four nodes and six edges. The search space consists of five candidate operations: Zeroize, Skip Connection, 1x1 Convolution, 3x3 Convolution, and 3x3 Avg Pooling. For more detailed settings, please refer to the NAS-Bench-201 paper (Dong and Yang, 2020).

4.2 Implementation Details

We conducted 20 warmup epochs at the beginning of the search, where we froze all architecture parameters and only trained the weights of the supernet itself, and since skip connection has a faster convergence speed, we added dropout with the probability of 0.2 behind to suppress it, to ensure fair competition among all operations. After the warmup stage, we applied the soft pruning approach for the last 30 epochs by random sampling 50% of validation sets accuracy in each epoch to determine the importance. The final pruning ratio is used during the whole search phase, which means that the training is performed by considering four unimportant operations to be masked on each edge in every epoch. We set $K = max\_epoch$ in Equation 2 as the fixed K approach. For the adjustable K approach, we use the linear decay strategy mentioned in Section 3.2 to determine the strength of pruning in each epoch. We performed both search methods on CIFAR-10 and evaluated the performance on all datasets.

4.3 Search Results

The experimental results are shown in Table 1, where we conducted five search processes with different random seeds and reported their average accuracy ± variance. The results show that VP-DARTS, while using the fixed parameter K achieves comparable performance on all datasets in NAS-Bench-201 with 94.15% test accuracy on CIFAR-10, 72.77% test accuracy on CIFAR-100, and 45.91% test accuracy

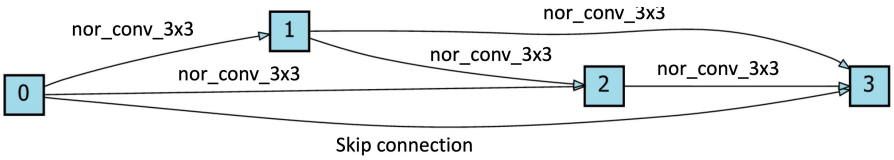


Figure 7: The searched cell of VP-DARTS (adjustable K) on NAS-Bench-201 with CIFAR-10.

on ImageNet16-120, which is better than most of the search methods using the hard pruning approach, such as DARTS and SGAS.

Furthermore, VP-DARTS using the adjustable K approach can achieve even better results than the fixed value K, which could find better architectures on all datasets with 94.36% test accuracy on CIFAR-10, 73.51% test accuracy on CIFAR-100 and 46.34% test accuracy on ImageNet16-120. This approach achieves state-of-the-art performance and completes the search process in just 2.8 hours, requiring less time than other methods. The searched architecture of VP-DARTS using adjustable K is shown in Figure 7, from which we observe that VP-DARTS effectively solves the problem of excessive skip connections in DARTS, resulting in well-performing searched architectures. Moreover, since using the adjustable K does not directly set the architecture parameters of unimportant operations to zero, it is easier to let them regain importance at the beginning of the training process and select the more suitable and stable one. Therefore, adjustable K can get more stable results than the fixed value.

In summary, compared to using hard pruning methods like DARTS or SGAS, VP-DARTS, which uses the soft pruning approach, maintains the capacity of the search space unchanged during training, enabling the discovery of better and more stable architectures. Moreover, using the adjustable K approach, VP-DARTS achieves superior results by gradually increasing the pruning strength during the search process with less training cost than other search methods. These results indicate that applying soft pruning in differentiable architecture search with directly estimating the impact on the supernet can obtain excellent architectures.

5 ABLATION STUDY

5.1 Soft Pruning vs. Hard Pruning

In this paper, we proposed VP-DARTS, which utilizes the technique of generalized soft pruning to reduce unimportant weights and the validated accuracy as the operation selection criterion. In contrast, traditional hard pruning methods determine the strength of the operations by the architecture parameter on the current training status and permanently remove them from the search space.

Here we conducted an ablation study to compare the differences between soft pruning and hard pruning in DARTS on NAS-Bench-201 search space. Both methods are trained with the same settings mentioned in Section 4.2, 50 epochs search phase with a 20 epochs warmup at the beginning, dropout rate of 0.2, and using 50% of the validation set accuracy to determine the importance of operations. In traditional hard pruning, we prune all unimportant ones at the end of the training, similar to DARTS. In progressive hard pruning, we use the Search Space Approximation from PDARTS (Chen et al., 2019) and divide the later search phase into three stages. The search space size is set to 5, 3, and 2, respectively, gradually pruning unimportant operations in the search phase.

We used different random seeds for five search processes and reported their average accuracy ± variance. As shown in Table 2, the experiment results demonstrate that utilizing hard pruning as the search strategy in DARTS leads to lower performance in the obtained network architecture, regardless of whether traditional hard pruning or progressive hard pruning is employed. Moreover, using soft pruning also shows a more stable result. The experiment shows that using the soft pruning approach to maintain the capacity of the search space during training is helpful for the differentiable architecture search method.

5.2 Validation Accuracy vs. Alpha Value

In Section 3.3, we mentioned that using the same approach as DARTS to directly determine the importance of operations based on the magnitude of α may not accurately reflect the actual ranking compared to using validation accuracy. Here, we compare the impact of using these two approaches again. We use the fixed value K approach in VP-DARTS while changing the way of directly determining the importance of operations based on the magnitude of α and compare it with the original method of using

Table 2: Comparison between using hard pruning and soft pruning approach.

Method	CIFAR-10		CIFAR-100		ImageNet16-120	
	validation	test	validation	test	validation	test
Hard Pruning	87.97 ± 3.58	91.41 ± 2.24	67.67 ± 5.10	67.97 ± 5.23	40.42 ± 7.95	37.99 ± 53.90
Gradually Hard Pruning	89.79 ± 0.15	93.11 ± 0.10	69.88 ± 1.04	70.29 ± 1.66	42.74 ± 5.36	43.55 ± 4.93
Soft Pruning (Fixed *K*)	$\mathbf{91.34 \pm 0.06}$	$\mathbf{94.15 \pm 0.07}$	$\mathbf{72.64 \pm 0.94}$	$\mathbf{72.77 \pm 0.57}$	$\mathbf{45.81 \pm 0.28}$	$\mathbf{45.91 \pm 0.43}$

Table 3: Comparison of using the magnitude of α and validation accuracy determining the importance of operations.

Method	CIFAR-10		CIFAR-100		ImageNet16-120	
	validation	test	validation	test	validation	test
α Value	85.27 ± 1.50	88.86 ± 1.49	62.47 ± 7.53	62.99 ± 9.45	35.90 ± 11.78	35.11 ± 12.37
Val Accuracy	$\mathbf{91.34 \pm 0.06}$	$\mathbf{94.15 \pm 0.07}$	$\mathbf{72.64 \pm 0.94}$	$\mathbf{72.77 \pm 0.57}$	$\mathbf{45.81 \pm 0.28}$	$\mathbf{45.91 \pm 0.43}$

validation accuracy.

The experimental results are shown in Table 3. From the result, we can observe that utilizing validation accuracy enables us to discover architectures with superior performance. It achieves accuracy rates exceeding 5% across all datasets and even 10% accuracy boosts on CIFAR-100 and ImageNet16-120. This once again confirms that directly determining the importance of operations based on the magnitude of α cannot accurately represent the actual ranking.

5.3 The Impact of Validation Set Proportion

Since we use validation accuracy to determine the importance of operations, a large amount of validation set testing is required in each epoch. Here we compare the influence of using different proportions of validation set sizes to determine the importance of operations on the final results. For the cases that use a partial subset, we randomly sampled the validation set during each epoch instead of using a fixed subset.

The results are shown in Figure 8. We can observe that employing a higher proportion of the validation set for testing leads to better and more stable results of the searched architecture. On the contrary, a smaller proportion of the validation set results in decreased accuracy and stability of the searched architecture since different parts of the validation set are used each time. However, it can significantly reduce the search time since fewer data are used for testing each time when determining the importance of operations.

The search results are relatively consistent when the proportion is 50% or above but would experience a significant drop when it is below 50%. Therefore, our method chooses to use the 50% ratio, which strikes a balance between training cost and accuracy.

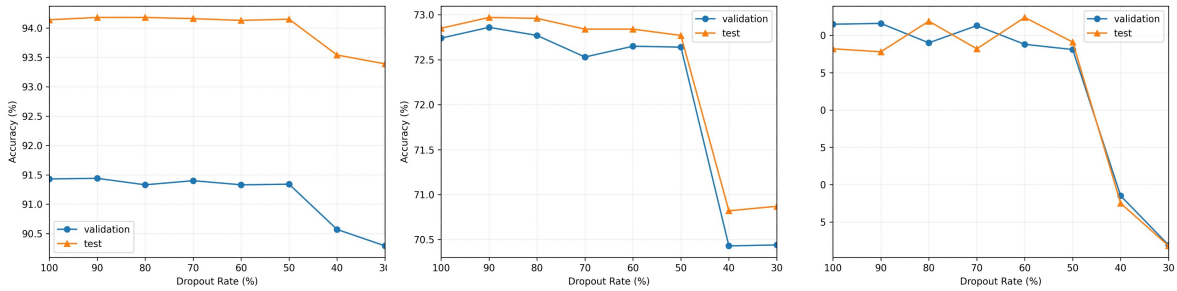
6 CONCLUSION

In this paper, we propose VP-DARTS, a differentiable architecture search method based on soft pruning, and determining the importance of each operation by directly estimating its impact on the supernet using validation accuracy. This method effectively solves the issue of excessive skip connections causing the performance collapse problem and can result in better architectures. With the fixed value *K* of VP-DARTS, we achieved a comparable result on the NAS-Bench-201 search space, with accuracy rates of 94.15%, 72.77%, and 45.91% on CIFAR-10, CIFAR-100, and ImageNet-16-120, respectively. It outperformed other NAS methods using the hard pruning approach in the training process.

Moreover, using the adjustable value K, VP-DARTS can achieve even better results than the fixed value, obtaining accuracy rates of 94.36% on CIFAR-10, 73.51% on CIFAR-100, and 46.34% on ImageNet-16-120. It achieves state-of-the-art performance with stable results and lower search costs than other NAS methods. Furthermore, in the ablation study, we showed that soft pruning could obtain better and stable results than traditional hard pruning among differentiable architecture search methods. The main reason is that the software pruning does not reduce the capacity of search space during training while hard pruning does. The experiments show that VP-DARTS is a robust search method and can find neural architectures with good performance.

REFERENCES

Cai, L., An, Z., Yang, C., and Xu, Y. (2021). Softer pruning, incremental regularization. In *25th International*



(a) CIFAR-10 (b) CIFAR-100 (c) ImageNet16-120

Figure 8: Comparison of VP-DARTS with fixed value K using different validation set proportions.

Conference on Pattern Recognition (ICPR), pages 224–230. IEEE.

Chen, X., Wang, R., Tang, X., and Hsieh, C.-J. (2021). DrNAS: Dirichlet neural architecture search. In *International Conference on Learning Representation (ICLR)*.

Chen, X., Xie, L., Wu, J., and Tian, Q. (2019). Progressive differentiable architecture search: Bridging the depth gap between search and evaluation. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1294–1303.

Chu, X., Wang, X., Zhang, B., Lu, S., Wei, X., and Yan, J. (2021). DARTS-: Robustly stepping out of performance collapse without indicators. In *International Conference on Learning Representations (ICLR)*.

Chu, X., Zhou, T., Zhang, B., and Li, J. (2020). Fair DARTS: Eliminating Unfair Advantages in Differentiable Architecture Search. In *16th European Conference On Computer Vision (ECCV)*.

Dong, X. and Yang, Y. (2020). Nas-bench-201: Extending the scope of reproducible neural architecture search. In *International Conference on Learning Representations (ICLR)*.

Guo, J., Zhang, W., Ouyang, W., and Xu, D. (2020). Model compression using progressive channel pruning. *IEEE Transactions on Circuits and Systems for Video Technology*, 31(3):1114–1124.

Han, S., Mao, H., and Dally, W. J. (2016). Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. *International Conference on Learning Representations (ICLR)*.

Han, S., Pool, J., Tran, J., and Dally, W. J. (2015). Learning both weights and connections for efficient neural networks. In *Proceedings of the 28th International Conference on Neural Information Processing Systems-Volume 1*, pages 1135–1143.

He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR)*, pages 770–778.

He, Y., Ding, Y., Liu, P., Zhu, L., Zhang, H., and Yang, Y. (2020). Learning filter pruning criteria for deep convolutional neural networks acceleration. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2006–2015. IEEE.

He, Y., Dong, X., Kang, G., Fu, Y., Yan, C., and Yang, Y. (2019). Asymptotic soft filter pruning for deep convolutional neural networks. *IEEE Transactions on Cybernetics*, pages 1–11.

He, Y., Kang, G., Dong, X., Fu, Y., and Yang, Y. (2018). Soft filter pruning for accelerating deep convolutional neural networks. In *International Joint Conference on Artificial Intelligence (IJCAI)*, pages 2234–2240.

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., and Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*.

Kendall, M. (1938). A new measure of rank correlation. *Biometrika*, 30(1/2):81–93.

Li, G., Qian, G., Delgadillo, I. C., Müller, M., Thabet, A., and Ghanem, B. (2020). SGAS: Sequential greedy architecture search. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Liu, C., Liu, P., Zhao, W., and Tang, X. (2019a). Visual tracking by structurally optimizing pre-trained cnn. *IEEE Transactions on Circuits and Systems for Video Technology*, 30(9):3153–3166.

Liu, H., Simonyan, K., and Yang, Y. (2019b). DARTS: Differentiable architecture search. In *International Conference on Learning Representations (ICLR)*.

Liu, Z., Sun, M., Zhou, T., Huang, G., and Darrell, T. (2019c). Rethinking the value of network pruning. In *International Conference on Learning Representations (ICLR)*.

Real, E., Aggarwal, A., Huang, Y., and Le, Q. V. (2019). Regularized evolution for image classifier architecture search. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 4780–4789.

Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., and Chen, L.-C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520.

Simonyan, K. and Zisserman, A. (2015). Very deep convolutional networks for large-scale image recog-

nition. In *International Conference on Learning Representations (ICLR)*.

Wang, R., Cheng, M., Chen, X., Tang, X., and Hsieh, C.-J. (2021). Rethinking architecture selection in differentiable NAS. In *International Conference on Learning Representations (ICLR)*.

Xie, S., Zheng, H., Liu, C., and Lin, L. (2019). SNAS: stochastic neural architecture search. In *International Conference on Learning Representations (ICLR)*.

Xu, Y., Wang, Y., Han, K., Tang, Y., Jui, S., Xu, C., and Xu, C. (2021). ReNAS: Relativistic evaluation of neural architecture search. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 4411–4420.

Xu, Y., Xie, L., Zhang, X., Chen, X., Qi, G.-J., Tian, Q., and Xiong, H. (2020). PC-DARTS: Partial channel connections for memory-efficient architecture search. In *International Conference on Learning Representations (ICLR)*.

Ye, P., Li, B., Li, Y., Chen, T., Fan, J., and Ouyang, W. (2022). β-DARTS: Beta-decay regularization for differentiable architecture search. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10864–10873. IEEE.

Zhang, M., Su, S. W., Pan, S., Chang, X., Abbasnejad, E. M., and Haffari, R. (2021). iDARTS: Differentiable architecture search with stochastic implicit gradients. In *International Conference on Machine Learning*, pages 12557–12566. PMLR.

Zhou, Y., Xie, X., and Kung, S.-Y. (2021). Exploiting operation importance for differentiable neural architecture search. *IEEE Transactions on Neural Networks and Learning Systems*, 33(11):6235–6248.

Zoph, B. and Le, Q. (2017). Neural architecture search with reinforcement learning. In *International Conference on Learning Representations (ICLR)*.