BARS: Joint Search of Cell Topology and Layout for Accurate and Efficient Binary ARchitectures

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Abstract

Binary Neural Networks (BNNs) have received significant attention due to its promising efficiency. Currently, most BNN studies directly adopt widely-used CNN architectures, which can be suboptimal for BNNs. This paper proposes a novel Binary ARchitecture Search (BARS) flow to discover superior binary architecture in a large design space. Specifically, we design a two-level (Macro & Micro) search space tailored for BNNs, and apply differentiable neural architecture search (NAS) to explore this search space efficiently. The macro-level search space includes depth and width decisions, which is required for better balancing the model performance and capacity. And we also make modifications to the micro-level search space to strengthen the information flow for BNN. A notable challenge of BNN architecture search lies in that binary operations exacerbate the “collapse” problem of differentiable NAS, and we incorporate various search and derive strategies to stabilize the search process. On CIFAR-10, BARS achieves 1.5\% higher accuracy with 2/3 binary Ops and 1/10 floating-point Ops. On ImageNet, with similar resource consumption, BARS-discovered architecture achieves 3\% accuracy gain than hand-crafted architectures, while removing the full-precision downsample layer.

1. Introduction

Convolutional Neural Networks (CNNs) have demonstrated great performances in computer vision tasks. However, CNNs require intensive computation and storage, which hinders their deployments on low-end devices or under resource-constrained scenarios. Approaches like network pruning [13, 31], efficient architecture design [26, 37, 29], and quantization [15] are proposed to alleviate this problem. Among quantization researches, designing binarizing neural networks (BNNs) (1-bit quantization) is a promising direction. Via binarizing network parameters and activations, the resource-consuming 32-bit floating-point multiplication could be replaced by efficient bitwise operations (e.g., XNOR, bitcount). In this way, both the computation and the memory burden could be significantly reduced. Despite their computational efficiency, BNNs still suffer from several major problems. Firstly, the performance is still unsatisfactory. Secondly, certain operations of the computation flow still require full-precision. (e.g., the down-sampling operations), which brings difficulty to hardware acceleration.

There exist numerous studies that work on mitigating BNNs’ accuracy gap by minimizing the quantization error [36], improving the training loss [20], or customizing the gradient calculation [19]. Others focus on binary architecture designs. They adapt established CNN architectures to the binary domain, while making adjustments like reordering layers [2] or adding more shortcuts [19]. However, BNNs have unique architectural preferences. For example, depthwise convolution is not suitable [3, 28], and BNNs will often favor width over depth. Therefore, we propose a differentiable neural architecture search (NAS) flow, BARS, in order to discover more favorable BNN architectures. Similar to our work, recent studies [3, 28] also employ differentiable NAS techniques in binary architecture design. However, they solely focus on one of the two important aspects that affect model performance: cell topology [28, 3] and cell layout [27]. In contrast, BARS takes both aspects into consideration and jointly searches for the intra-cell topology and the inter-cell layout.

BARS involves several considerations to facilitate an effective architecture search process for BNN architectures. Firstly, the original DARTS [17] search space’s cell design fails to provide adequate information flow for proper binary network training. BARS proposes to adapt the micro-level search space to better preserve the information flow. Secondly, for BNNs, increasing the operation width brings ac-
Accuracy gain. Thus, instead of using a pre-defined cell layout and model augmentation scheme, BARS incorporates the cell layout (depth/width) into the search space, and utilizes capacity regularization to strike a proper performance-capacity trade-off without model proxy during the search. Thirdly, differentiable NAS suffers from the well-known “collapse” problem: “shortcut” operations have unfair advantages over parameterized operations. This problem originates from the parameterized operations (e.g., Conv) require more training to perform well while parameter-free ones (e.g., shortcuts) do not. This problem is further exacerbated in BNN architecture search, since binary convolutions are even harder to train than floating-point ones. BARS makes a series of adjustments on the search space, search strategy, and derive strategy to stabilizing the search process.

To summarize, the contributions of this paper are as follows.

• We propose a novel BNN-oriented NAS flow - BARS, in which the search space, along with the search and derive strategies are carefully designed and developed according to the characteristics of BNNs.

• We find that the cell-based search space (Sec. 4.1.1) adopted by recent studies [28, 3] is not suitable for BNN, and craft a new search space which contains all the dimensions that are crucial to BNN architecture design, including depth, width, connection pattern, and operation choices. It also strengthens connections to better preserve the information flow for BNN.

• We adopt search strategy (Sec. 4.1.2) improvements including Gumbel-Softmax sampling and entropy regularization to stabilize the search and bridge the search-derive gap in differentiable NAS. And instead of using a model proxy in the search process and relying on pre-defined model augmentation (e.g., uniform width expansion) [28, 3], we directly search for the performance-capacity trade-off.

• Our method can discover superior BNN architectures that outperform state-of-the-art baseline architectures with smaller capacity. And the full-precision operations can be reduced to the maximum extent in BARS-discovered architectures.

2. Related Works

2.1. Binary Neural Networks

Binarization Scheme Network binarization could be viewed as an extreme case of network quantization. It could replace the original FP32 multiplications with efficient bitwise operations, gaining dozens of times of acceleration. However, due to the lack of representation ability, binary neural networks often suffers from noticeable accuracy degradation. A number of methods are proposed for improving the performance of BNN. XNORNet[25] uses shared scaling factors to improve the representation ability without introducing much computational overhead. Many recent works [18, 3, 28] follow its binarization scheme, and so do we. Some other binarization schemes are also proposed, such as: [12] uses projection convolutional layers, [4] fuses the weight and activation scaling factor together before inference. Other aspects for improving BNN performance focuses on improving the loss function like [36], or amend the gradient estimation as [19, 24].

Binary Architectural Advances The above-mentioned methods mainly focus on improving the binarization or training scheme. Apart from that, the network architecture also plays a critical role in determining the performance of a BNN. Prior works [25, 19, 22], have shown that proper modification of the network architecture could result in notable performance improvement. [25] proposes applying binarization after the batchnorm layer. [19] adds an extra shortcut across binary convolution. [22] modifies the separable convolutions in the mobilenet architecture to make it suitable for BNN. Other works like [2, 1] also adapts famous CNN architectures to binary ones.

2.2. Neural Architecture Search (NAS)

NAS Search Space NAS search space design in recent studies can be divided into two hierarchies: the macro-level, and the micro-level (cell-level) search space. The macro-level describes how cells are organized to construct the entire architecture, and methods are developed to search for the layout decisions, including depth and width [32, 14]. On the other hand, the micro-level describes the operation-level connection inside each cell, and aims at finding su-
Considerable efforts have been devoted into applying and developing gradient-based NAS (a.k.a., Differentiable NAS) methods \cite{DARTS, SNAS, XNORNet} due to its high search efficiency. DARTS \cite{DARTS} first modeled the NAS problem as a bi-level optimization problem, in which the architecture parameters are updated using gradient methods. Later on, SNAS \cite{SNAS} proposed to incorporate operation sampling in the differentiable NAS process with the Gumbel-Softmax \cite{Gumbel-Softmax} relaxed reparametrization trick. Recent studies extend search space dimensions to connection \cite{Connection}, width \cite{Width}, kernel size \cite{KernelSize}, depth \cite{Depth} and so on.

Cell-based search spaces \cite{Cell-based} are designed to facilitate a more efficient NAS process and are widely used \cite{DARTS, SNAS}. Usually, there are two types of cells in cell-based search spaces: normal ones and reduce ones (stride > 1). And these two types of cells are stacked in a pre-defined order to construct a complete architecture. In this work, we identify that when searching for binary architecture, the commonly-used cell constraints will exacerbate the collapse problem \cite{Collapse} of differentiable NAS. We propose to alleviate this issue by searching for layer-wise or stage-wise micro architectures.

NAS for Binary Architecture Previous works on improving binary network architecture design often adopt minor modifications to existing well-performing CNN models. Applying NAS to the binary domain could be an effective solution to discover more suitable architecture for BNN. \cite{Sign} strikes a balance between accuracy and resource consumption for BNN via applying evolutionary search on network width. \cite{Faster} adopts a similar approach on groups in convolutions. \cite{Faster, XNORNet} introduce gradient-based search for binary network. They prove that traditional gradient-based NAS methods such as \cite{DARTS, SNAS} could not be directly applied for BNN search. Thus, they modify the operations in search space and the searching strategy. These methods make advances in searching for efficient binary architectures. However, they still have the following drawbacks. Firstly, they solely focus on only one out of two closely related aspects: network topology and capacity. Secondly, full-precision layers still exist in the main body of the architecture. \cite{XNORNet} uses a full-precision preprocess layer in each cell, \cite{Faster} uses full-precision shortcut for reduction cell, which takes up the majority of the computation. BARS aims to search for both the topology and capacity of the binary architecture. Also, pursue the full binarization of the main body of the architecture.

3. Preliminary

3.1. Network Binarization

BARS follows the binarization scheme proposed in XNORNet \cite{XNORNet} with the modification of using a single scaling factor instead of channel-wise for more efficiency. The binary convolution of weights \( W \in \mathbb{R}^{C_{\text{out}} \times C_{\text{in}} \times K_w \times K_h} \) and the input feature map \( X \in \mathbb{R}^{bs \times C_{\text{in}} \times W \times H} \) can be written as in Eq. 1, where \( C_{\text{out}} \) and \( C_{\text{in}} \) represents the input and out channels, \((K_w, K_h)\) and \((W, H)\) are the size of the convolution kernel and the feature map, and \( bs \) is the batch size.

\[
W \ast X = (\text{Sign}(W) \circ \text{Sign}(X)) \otimes \beta, \tag{1}
\]

where \( \circ \) denotes the binary multiplication, which could be simplified into the XNOR and bitcount operation, \( \otimes \) means full precision element-wise multiplication. \( \beta \) is a scalar real-valued scaling factor. During inference, the binarization takes place before the convolution. During training, the gradient of the non-differentiable binarization (\( \text{Sign}(w) \)) is acquired with the Straight-Through \cite{Straight-Through} scheme, and are used for updating the real-valued weights \( W \).

3.2. Differentiable NAS

BARS adopts a differentiable architecture search flow \cite{DARTS, SNAS, XNORNet}. In differentiable NAS, a supernet is constructed such that all possible architectures are sub-architecture of this supernet. Then, architectural choices parameterized by architectural parameters \( \alpha \) are optimized following the gradients of the validation loss \( L_{\text{val}} \). The bi-level optimization problem can be written as

\[
\min_{\alpha} L_{\text{val}}(w^*(\alpha), \alpha) \quad \text{s.t. } w^*(\alpha) = \arg\min_w L_{\text{train}}(w, \alpha). \tag{2}
\]

After the search, one needs to derive a discrete architecture using the relaxed architecture parameter \( \alpha \). In the original differentiable NAS method \cite{DARTS}, for the normal and reduction cell type, the operation with the maximum \( \alpha \) (except for the “none” operation) is chosen on each edge. Then the normal and reduction cells are stacked to construct the final model. Studies \cite{Collapse, Derive} have pointed out that the derive process introduces a large discrepancy. BARS proposes a few modifications to bridge the search-derive gap.

4. BARS Framework

BARS seeks to acquire accurate and efficient binary architectures through gradient-based searching of both the cell topology and the layout. To achieve that, we make modifications to two crucial components of the NAS algorithm - search space and search strategy. For search space,
BARS uses a skippable macro search space (Sec. 4.1.1) with a learnable width to search for the cell layout, and uses a densely-connected micro-level search space (Sec. 4.1.2) to preserve information flow for BNN. For search strategy, Gumbel-Softmax sampling (Sec. 4.2.1), along with entropy and capacity regularization (Sec. 4.2.2-4.2.3) are employed to stabilize the search.

### 4.1. Search Space Design

Earlier studies [1, 27] reveal two important factors concerning BNN’s performance: model capacity (depth/width) and information flow. In light of the above, BARS improves the search space from two aspects. We modify the micro-level cell template to better preserve the information flow, and introduce the macro-level depth/width search to strike a better balance between accuracy and efficiency.

#### 4.1.1 Macro-level: Search for Network Depth / Width

**Depth Search** As illustrated in Fig. 2, we use a skippable macro-level search space construction to search for the network depth. Within a stage, we introduce extra “skip” paths from cell outputs to the aggregation node. The aggregation node is placed at the end of the stage before the reduction cell. For example, if there are three cells (Cell-1, Cell-2, Cell-3) in one stage, the probabilities of choosing different depth ∈ {0, 1, 2, 3} can be calculated as the softmax of the four-dimensional depth parameter αpath = [αp0, αp1, αp2, αp3]: P(depth = i) = \(\frac{\exp(\alpha_{pi})}{\sum_{j} \exp(\alpha_{pj})}\). Denoting the input feature map of this stage and the out feature map at each cell as \(y_0, \ldots, y_3\), the feature map of the aggregation node \(y_{aggr}\) is calculated as Eq. 3. Compared with the previous studies that use a similar depth search scheme [14], we sample path choices with...


| Techniques                      | Acc.  |
|---------------------------------|-------|
| Macro-Level                     |       |
| Normal/Reduction Cell [17]      | 91.70%|
| Without Width Search            | 92.27%|
| Without Depth Search            | 91.92%|
| Micro-Level                     |       |
| Without Gumbel-Softmax          | Failed|
| Without Cell-Shortcut           | 52.83%|
| Without Ent-erg                 | 92.56%|
| Without FLOPs-reg               | 92.44%|
| Derive                          |       |
| Without sample when derive      | 90.68%|
| BARS                            | 92.97%|

Table 1. Ablation study of search space design, search & derive strategies. Gumbel-Softmax sampling and cell-wise shortcut is critical for an effective search process. The search space design, including stage-wise cell topologies, depth and width search also helps get better results.

Gumbel-Softmax [16] sampling instead of plain softmax to stabilize the depth search.

\[
m_i = \text{Gumbel-Softmax}(\alpha_{\text{path}})
\]

\[
y_{\text{aggr}} = \sum_i m_i \times y_i.
\]

Width Search The network width plays an important role in improving the performance of binary architectures [27, 28]. Since the representation power of BNN is restricted, expanding the network width is an effective way to improve the performance at the cost of increasing model capacity. Thus it is natural to employ the NAS technique to strike a proper trade-off between performance and efficiency. To achieve that, BARS directly searches for the stagewise width of the layout. Specifically, for all cells in one stage, we use a width architecture parameter \( \alpha_{\text{width}} \) to denote the logits of the probability of selecting several discretized width choices (e.g., \([0.25, 0.5, 0.75, 1.0]\) in our experiments). As shown in Fig. 2 and Eq. 4, during the forward process, we sample a relaxed width choice from the distribution parameterized by \( \alpha_{\text{width}} \) with Gumbel-Softmax sampling, and multiply the weighted mask onto all the feature maps in that stage.

\[
m_i = \text{Gumbel-Softmax}(\alpha_{\text{width}})
\]

\[
y = \sum_i m_i \times M_i \odot x
\]

where \( M_i \) is the mask corresponding to the \( i \)-th width choice in \([0.25, 0.5, 0.75, 1.0]\). For example, if \( i = 0 \) (the relative width choice is 0.25), the first quarter of the elements in \( M_i \) are 1s and the other elements are 0s.

**4.1.2 Micro-level: Search for Cell Topology**

The micro search space is the main part of the DARTS search space, which focuses on the operation-level searching for cell topology. It describes the architecture as a DAG (directed acyclic graph). All possible operations are computed on the edge and aggregated at each node, weighted by the architectural parameter \( \alpha \). Outputs of each node is concatenated at the output node. A preprocess layer is used to align the width of the inputs and operations on edge. (See Fig. 2)

Operation level We choose 3 candidate operations - [binary convolution 3x3, shortcut, None]. Previous work [28] has shown that sometimes binary convolution can cause intense information loss, even worse than the “none” operation. Thus we focus on how to process the information on a certain edge. To preserve all information through the shortcut, or process the information through binary convolution, or simply discard the “harmful” information through “none”. Many recent works on binary networks [1, 19] have concluded that adding an extra shortcut for binary convolution could improve performance with little overhead. So we add one extra shortcut for binary conv 3x3.

Cell Template Design We aim to preserve the information flow of BNN to the maximum extent for proper training. Firstly, we reduce the number of preprocess layers to one instead of two in previous works. The preprocess layer involves width change, so operational-level shortcuts could not be easily added. Thus it is relatively sensitive to binarization and could be regarded as the “information bottleneck”. ([3] uses full-precision preprocess to avoid this). Secondly, we add an extra shortcut across the cell to encourage the inter-cell information flow. As could be seen
from Tab. 1, Cell-level shortcut ensures proper BNN training. Thirdly, strided binary convolution is also known to be a sensitive part [1] since it reduces the spatial size, which causes information loss and brings difficulty for adding the shortcut. [28] uses full-precision convolution on downsampled cell shortcut to amend this. In BARS, we concatenate the outputs of two strided convolution with shortcut and spatially staggered input. In this way, the information flow for strided convolution is maintained.

4.2. Search Strategy

Differentiable NAS [17] has been challenged due to that it is likely to produce degenerated architectures containing too many shortcuts, which is known as the “collapse” problem. This section describes several key techniques we identified to alleviate the “collapse” problem, including Gumbel-Softmax sampling, entropy regularization, and warmup training of the supernet weights.

4.2.1 Gumbel-Softmax Sampling for Differentiable Architecture Optimization

For all the architectural parameters (depth \( \alpha_{\text{path}} \), width \( \alpha_{\text{width}} \), operation type \( \alpha \) ), we sample a relaxed architecture \( m \) from the corresponding multinomial architectural distribution Multinomial(\( m(\alpha) \)) with the Gumbel-Softmax technique [16]. Denoting the number of choices as \( D \), the logits of the Multinomial distribution as \( \alpha \), each dimension \( m_i \) in the relaxed architecture decision \( m \in [0,1]^D \) can be represented as

\[
m_i = \frac{\exp((\alpha_i + g_i)/\tau)}{\sum_{j=1}^{D} \exp((\alpha_j + g_j)/\tau)} \text{ for } i = 1, \cdots, D, \tag{5}
\]

where \( g_i \) is a standard Gumbel-distributed random variable. We emphasize that using Gumbel-Softmax sampling with a proper temperature schedule is important for differentiable NAS methods to work properly. First, incorporating sampling in the differentiable search process help alleviate the well-known collapse phenomenon [38]. Specifically, if no sampling is incorporated as in the original DARTS [17], the output of a searchable block \( O \) with \( D \) discrete operation choices \( \alpha_i, i = 1, \cdots, D \) can be represented as \( O(x) = \sum_{i=1}^{D} p_i \alpha_i(x) = \sum_{i=1}^{D} p_i \alpha_i(x) \). Since there is no discrete architecture sampling in the search process, the weights can be scaled and to mask the effect of \( p_{\alpha=1, \cdots, D} \), which could make the search process go in a wrong direction. For example, when there is a FLOPs objective, the search process would learn to cheat by decreasing the probability of \( p_\alpha \) corresponding to parameterized operations (e.g., Conv) and increasing the weight scale accordingly. That would cause the search to collapse into assigning high probability to cheap operations. Secondly, another well-known failing reason for differentiable NAS [35, 7] is that the final projection step to derive the discrete architecture from the continuous mixture architecture can introduce large discrepancy. By using Gumbel-Softmax sampling, if we anneal the temperature to a low value, the introduced bias is minimized, and the derive discrepancy is reduced.

4.2.2 Entropy Regularization and Supernet Warm-up

A widely-acknowledged cause of the “collapse” problem is that parameterized operations (e.g., Conv) are usually under-trained in the early search stage [9], and the search process will favor operation-free operations. And this gap in the optimization sufficiency will be amplified if the architecture parameters are updated towards the parameter-free operations. In BNN, this problem is further exacerbated since binary convolutions are even harder to train than floating-point ones [3].

To tackle the “collapse” caused by insufficient optimization of parameterized operations, we conduct warmup training of the supernet weights for several epochs. Also, we impose an entropy regularization on the architecture distribution to encourage exploration in the early search stage and confident architecture decision in the late search stage.

\[
L_{\text{ent}} = \lambda_{\text{ent}} \left( - \sum_i \alpha_i \log(\alpha_i) \right) \tag{6}
\]

where \( \lambda_{\text{ent}} \) is a hyperparameter that follows an increasing schedule. In the early search stage, it remains negative to encourage search exploration and avoid collapsing. \( \lambda_{\text{ent}} \) gradually adds up to positive to drive the \( \alpha \) towards confident one-hot choices. Thus the discrepancy between searching and deriving is reduced.

4.2.3 Capacity Regularization

Expanding the width of binary networks can increase their performances [1], and different parts of the network might have different sensitivity to the width choices [11]. Earlier studies [28, 3] neglect this aspect in the search process and use post-search uniform width expansion, which would lead to suboptimal results (See Fig. 3). In contrast, BARS seeks to balance the performance and efficiency directly in the search process, by incorporating the width search decision and imposing a capacity (FLOPs) regularization [29].

\[
L = L_0 \times \left( \frac{\text{FLOPs}(\alpha)}{F} \right)^\theta \tag{7}
\]

where \( L_0 \) is the original loss and \( F \) is the FLOPs budget, \( \text{FLOPs}(\alpha) \) is the current expected flops. \( \gamma \) and \( \theta \) are hyperparameters and \( \gamma \) is set as 0 in our experiments.
| Dataset      | Method                  | FLOPs | BiOps   | Equivalent Ops | Params | Fully-Binarized | Acc.  |
|--------------|-------------------------|-------|---------|----------------|--------|-----------------|-------|
| CIFAR-10     | ResNet-18 (XNOR)        | 16M   | 1094M   | 50.2M          | 11.17M | FP Downsample   | 91.12%|
|              | ResNet-18 (Bireal)      | 11M   | 1123M   | 46.1M          | 11.34M | FP Downsample   | 91.23%|
|              | ResNet-34 (XNOR)        | 27M   | 2302M   | 98.9M          | 21.81M | FP Downsample   | 91.49%|
|              | WRN-40 (XNOR)           | ~27M  | ~3000M  | 120.7M         | -      | FP Downsample   | 91.58%|
|              | NiN (XNOR)              | ~27M  | ~400M   | 41.5M          | -      | ✓               | 86.28%|
|              | ResNet-18 (CBCN)        | ~27M  | ~1000M  | 58.2M          | -      | FP Downsample   | 91.9% |
|              | ResNet-18 (IRNet)       | ~27M  | ~1000M  | 58.2M          | -      | FP Downsample   | 91.5% |
|              | BNAS (XNOR)             | 175M  | 1393M   | 218.53M        | 5.57M  | FP Cell Shortcut| 92.7% |
|              | BARS-A                  | 2M    | 1027M   | 34.1M          | 2.77M  | ✓               | 91.25%|
|              | BARS-B                  | 2M    | 2096M   | 67.5M          | 6.07M  | ✓               | 92.98%|
|              | BARS-C                  | 3M    | 3747M   | 119.5M         | 10.76M | ✓               | 93.43%|
| ImageNet     | ResNet-18 (ABC)         | ~100M | ~4000M  | 225.0M         | -      | ✓               | 42.7% |
|              | ResNet-18 (XNOR)        | 138M  | 3699M   | 253.6M         | 12.54M | ✓               | 48.3% |
|              | BiDenseNet (XNOR)       | 167M  | 3557M   | 278.1M         | 12.80M | FP Downsample   | 53.1% |
|              | ResNet-18 (Bireal)      | ~160M | ~4000M  | 285.0M         | -      | FP Downsample   | 56.4% |
|              | ResNet-18 (PCNN)        | ~160M | ~4000M  | 285.0M         | -      | FP Downsample   | 57.3% |
|              | BNAS (XNOR)             | 195M  | 6274M   | 391.1M         | 28.41M | FP Cell Shortcut| 57.6% |
|              | BARS-D                  | 129M  | 1499M   | 122.8M         | 9.46M  | ✓               | 52.5% |
|              | BARS-E                  | 194M  | 2526M   | 275.9M         | 14.04M | ✓               | 56.1% |

Table 2. Performance and capacity comparison of BARS-discovered architectures and baselines on CIFAR-10 and ImageNet. BARS-discovered architectures outperform baseline architectures with much lower resource consumption. “Equivalent Ops” are calculated as $FLOPs + \frac{1}{64} * BiOps$ [1]. “Fully-Binarized” means all network components except for the first and last layer remains binary. Unlike recent studies [19, 18, 28] on binary architectures use full-precision downsampling operations, BARS-discovered architectures only use binary operations in the major architecture backbone, which is beneficial for hardware acceleration.

4.3. Derive Strategy

Original DARTS [17] enforces several constraints in the derive process to acquire valid architecture, e.g., only selecting two input nodes for each inner node and excluding the “none” op during deriving. However, cell architecture suitable for BNN might have more dense connections, and “none” operation might be the best choice on some edges in a BNN [28], thus one should not exclude the “none” operation when deriving the final architecture. After searching, BARS samples $K = 8$ candidate architectures using the architecture distribution parameterized by $\alpha$, and choose the one with the minimum validation loss (evaluated using the supernet weights) as the final architecture.

5. Experiments and Analysis

We run BARS on CIFAR-10 and ImageNet datasets with different FLOPs target, and acquire a series of models of different size (BARS-A/B/C on CIFAR, BARS-D/E on ImageNet). Detailed experimental settings are elaborated in the appendix. Note that unlike previous studies [28, 3] that transfer architectures discovered on CIFAR-10 to ImageNet, we directly apply search on the 100-class subset of ImageNet.
5.1. Results on CIFAR-10 and ImageNet

Tab. 4.2 and Fig. 1 show the comparison of BARS-discovered architectures and the baseline ones. We can see that BARS discovers architectures with superior performance and efficiency. Note that in order to demonstrate the performance gain brought by the architectural design. All our models are trained from scratch with XNOR-Net [25] binarization scheme. Neither additional tricks [24], nor full-precision pre-training models [19, 12] are used. Moreover, we emphasize that BARS binarizes all operations in the major architecture (except the stem and the final layer), whereas previous studies use full-precision downsample (FP downsample) layers to maintain acceptable performances. For example, the accuracy of ResNet-18 on ImageNet dropped from 53.1% to 48.3% if no FP downsample is used. On CIFAR-10, BARS-B achieves higher accuracy (1.5%) than the hand-crafted binary model with 2/3 binary operations (BiOps), much less (1/10) floating-point operations (FLOPs) and parameters. On ImageNet, BARS-D outperforms the “fully-binarized” ResNet-18 by a large margin with notably less resource consumption. With similar resource consumption, BARS-E achieves 3% higher accuracy than ResNet-18, and no FP downsample is used.

5.2. Search Dynamics

As could be witnessed from Fig. 5, the entropy regularization and Gumbel-softmax sampling with a high temperature encourage exploration in the early stage of searching, so the α’s distribution is relatively uniform and changes intensely. It effectively avoids the “collapsing”. When reaching the end of the search, the Gumbel temperature is close to zero, making the sampling close to one-hot sampling. Also, entropy regularization encourages architecture distribution to be more confident. The final architecture distribution is close to a one-hot form, and the derive gap is reduced.

5.3. Ablation Study of strategies

We perform ablation studies on proposed techniques. From the results shown in Tab. 1, we conclude that: 1) Gumbel-softmax sampling is crucial for stable search. 2) Allowing cells in different stages to have distinct topology is important for finding well-performing architectures. 3) Cell-wise shortcut enables inter-cell information flow and is the key to proper BNN training. 4) Directly search for the layout (width/depth) further improves performance under certain resource constraints.

5.4. Discovered Cell

We compare the searched cells of BARS and a failed search using two cell types and four candidate operations on CIFAR in Fig. 6. The normal cell of the failed search has “collapsed” to contain only shortcuts. In BARS, no cell type has collapsed to all shortcuts. Instead, the cells in the early stages contain more binary convolutions, while the latter ones have fewer convolutions and more shortcuts. Forcing all normal cells in different stages to have the same topology would prevent the search from discovering this pattern and aggravate the collapse problem. It is also witnessed that in the operation search, the convolution with a bigger kernel size (binary conv 5x5) is dominant among parameterized operations. It reflects that binary search favors bigger kernel size for its better representation ability.

6. Conclusion

Designed to better explore BNN architectures that are both accurate and efficient, BARS proposes improvements
to both the search space and the search strategy of differentiable NAS: Firstly, we make modifications to the micro-level cell template to adapt to the binary domain. Second, we introduce a macro-level depth/width search to strike a better balance between model accuracy and capacity. Furthermore, improvements in the search strategy are adopted to alleviate the “collapse” problem. BARS discovers binary architecture which outperforms baseline methods with significantly less resource consumption.
References

[1] Joseph Bethge, Marvin Bornstein, Adrian Loy, Haojin Yang, and C. Meinel. Training competitive binary neural networks from scratch. *ArXiv*, abs/1812.01965, 2018. 2, 4, 5, 6, 7

[2] J. Bethge, H. Yang, M. Bornstein, and C. Meinel. Binarydensenet: Developing an architecture for binary neural networks. In *2019 IEEE/CVF International Conference on Computer Vision (ICCVW)*, pages 1951–1960, 2019. 1, 2

[3] Adrian Bulat, B. Martínez, and Georgios Tzimiropoulos. Bats: Binary architecture search. *ArXiv*, abs/2003.01711, 2020. 1, 2, 3, 4, 5, 6, 7

[4] Adrian Bulat and Georgios Tzimiropoulos. Xnor-net++: Improved binary neural networks. In *BMVC*, 2019. 2

[5] Jianlong Chang, Xinbang Zhang, Yiwen Guo, Gaofeng Meng, S. Xiang, and C. Pan. Data: Differentiable architecture approximation. In *NeurIPS*, 2019. 3

[6] Hanlin Chen, Li’an Zhuo, B. Zhang, Xiawu Zheng, J. Liu, D. Doermann, and Rongrong Ji. Binarized neural architecture search. In *AAAI*, 2020. 4

[7] Xiangning Chen and Cho-Jui Hsieh. Stabilizing differentiable architecture search via perturbation-based regularization. *ArXiv*, abs/2002.05283, 2020. 6

[8] X. Chen, Lingxi Xie, J. Wu, and Q. Tian. Progressive differentiable architecture search: Bridging the depth gap between search and evaluation. *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 1294–1303, 2019. 3

[9] Xiangxiang Chu, Tianbao Zhou, B. Zhang, and J. Li. Fair darts: Eliminating unfair advantages in differentiable architecture search. *ArXiv*, abs/1911.12126, 2019. 3, 6

[10] Matthieu Courbariaux, Itay Hubara, Daniel Soudry, Ran El-Yaniv, and Yoshua Bengio. Binarized neural networks: Training deep neural networks with weights and activations constrained to +1 or -1. *arXiv: Learning*, 2016. 3

[11] Zhen Dong, Zhewei Yao, A. Gholami, M. Mahoney, and K. Keutzer. Hawq: Hessian aware quantization of neural networks with mixed-precision. *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 293–302, 2019. 6

[12] Jiaxin Gu, C. Li, B. Zhang, J. Han, Xianbin Cao, J. Liu, and D. Doermann. Projection convolutional neural networks for 1-bit cnns via discrete back propagation. *ArXiv*, abs/1811.12755, 2019. 2, 8

[13] Song Han, Huizi Mao, and William J Dally. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. In *International Conference on Learning Representations (ICLR)*, 2016. 1

[14] Y. Hu, X. Wu, and R. He. Tr-nas: Rethinking three search freedoms of latency-constrained differentiable neural architecture search. In *The European Conference on Computer Vision (ECCV)*, 2020. 2, 3, 4

[15] Itay Hubara, Matthieu Courbariaux, Daniel Soudry, Ran El-Yaniv, and Yoshua Bengio. Quantized neural networks: Training neural networks with low precision weights and activations. *J. Mach. Learn. Res.*, 18:187:1–187:30, 2017. 1

[16] Eric Jang, Shixiang Gu, and Ben Poole. Categorical reparameterization with gumbel-softmax. *arXiv preprint arXiv:1611.01144*, 2016. 3, 5, 6

[17] Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. *arXiv preprint arXiv:1806.09055*, 2018. 1, 3, 4, 5, 6, 7

[18] Z. Liu, Zhiqiang Shen, M. Savvides, and K. Cheng. Reactnet: Towards precise binary neural network with generalized activation functions. *ArXiv*, abs/2003.03488, 2020. 2, 7

[19] Zechun Liu, Baoyuan Wu, Wenhao Luo, Xin Yang, Wei Liu, and Kwang-Ting Cheng. Bi-real net: Enhancing the performance of 1-bit cnns with improved representational capability and advanced training algorithm. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 722–737, 2018. 1, 2, 5, 7, 8

[20] A. Mishra and Debbie Marr. Apprentice: Using knowledge distillation techniques to improve low-precision network accuracy. *ArXiv*, abs/1711.05852, 2018. 1

[21] Xuefei Ning, Tianchen Zhao, Wenshuo Li, Peng Lei, Yu Wang, and Huazhong Yang. Dsa: More efficient budgeted pruning via differentiable sparsity allocation. In *ECCV*, 2020. 3

[22] Hai Phan, D. Huynh, Yihui He, M. Savvides, and Zhiqiang Shen. Mobinet: A mobile binary network for image classification. *2020 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 3442–3451, 2020. 2

[23] H. Phan, Z. Liu, D. Huynh, M. Savvides, K. Cheng, and Zhiqiang Shen. Binarizing mobilenet via evolution-based searching. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13417–13426, 2020. 3

[24] Haotong Qin, Ruihao Gong, Xianglong Liu, Mingzhu Shen, Ziran Wei, Fengwei Yu, and Jingkuan Song. Forward and backward information retention for accurate binary neural networks. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2247–2256, 2020. 2, 8

[25] Mohammad Rastegari, Vicente Ordonez, Joseph Redmon, and Ali Farhadi. Xnor-net: Imagenet classification using binary convolutional neural networks. In *ECCV*, 2016. 2, 3, 8

[26] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4510–4520, 2018. 1

[27] Mingzhu Shen, Kai Han, Chunjing Xu, and Yunhe Wang. Searching for accurate binary neural architectures. *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*, pages 2041–2044, 2019. 1, 3, 4, 5

[28] Kunal Pratap Singh, Dahyun Kim, and Jonghyun Choi. Learning architectures for binary networks. In *ECCV*, 2020. 1, 2, 3, 5, 6, 7

[29] M. Tan, B. Chen, R. Pang, V. Vasudevan, M. Sandler, A. Howard, and Q. V. Le. Mnasnet: Platform-aware neural architecture search for mobile. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2815–2823, 2019. 1, 6
[30] X. Wang, Chao Xue, Junchi Yan, Xiaokang Yang, Yonggang Hu, and K. Sun. Mergenas: Merge operations into one for differentiable architecture search. In *IJCAI*, 2020.

[31] Wei Wen, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. Learning structured sparsity in deep neural networks. In *Advances in neural information processing systems*, pages 2074–2082, 2016.

[32] B. Wu, Xiaoliang Dai, P. Zhang, Y. Wang, Fei Sun, Yiming Wu, Yuandong Tian, P. Vajda, Y. Jia, and K. Keutzer. Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search. *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10726–10734, 2019.

[33] S. Xie, H. Zheng, Chunxiao Liu, and L. Lin. Snas: Stochastic neural architecture search. *ArXiv*, abs/1812.09926, 2019.

[34] Yuhui Xu, Lingxi Xie, Xiaopeng Zhang, X. Chen, Guo-Jun Qi, Q. Tian, and Hongkai Xiong. Pc-darts: Partial channel connections for memory-efficient differentiable architecture search. *ArXiv*, abs/1907.05737, 2019.

[35] Arber Zela, T. Elsken, Tonmoy Saikia, Yassine Marrakchi, T. Brox, and F. Hutter. Understanding and robustifying differentiable architecture search. In *International Conference on Learning Representations (ICLR)*, 2020.

[36] D. Zhang, J. Yang, Dongqiangzi Ye, and Gang Hua. Lq-nets: Learned quantization for highly accurate and compact deep neural networks. *ArXiv*, abs/1807.10029, 2018.

[37] X. Zhang, X. Zhou, M. Lin, and J. Sun. Shufflenet: An extremely efficient convolutional neural network for mobile devices. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6848–6856, 2018.

[38] Pan Zhou, Caiming Xiong, R. Socher, and S. Hoi. Theory-inspired path-regularized differential network architecture search. In *NeurIPS*, 2019.

[39] Barret Zoph, V. Vasudevan, Jonathon Shlens, and Quoc V. Le. Learning transferable architectures for scalable image recognition. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8697–8710, 2018.