Searching for Low-Bit Weights in Quantized Neural Networks

Zhaohui Yang[1,2], **Yunhe Wang**[2], **Kai Han**[2], **Chunjing Xu**[2],
Chao Xu[1], **Dacheng Tao**[3]*, **Chang Xu**[3]
[1] Key Lab of Machine Perception (MOE), Dept. of Machine Intelligence, Peking University.
[2] Noah's Ark Lab, Huawei Technologies.
[3] School of Computer Science, Faculty of Engineering, University of Sydney.
zhaohuiyang@pku.edu.cn; {yunhe.wang,kai.han,xuchunjing}@huawei.com
xuchao@cis.pku.edu.cn; {dacheng.tao, c.xu}@sydney.edu.au

Abstract

Quantized neural networks with low-bit weights and activations are attractive for developing AI accelerators. However, the quantization functions used in most conventional quantization methods are non-differentiable, which increases the optimization difficulty of quantized networks. Compared with full-precision parameters (*i.e.*, 32-bit floating numbers), low-bit values are selected from a much smaller set. For example, there are only 16 possibilities in 4-bit space. Thus, we present to regard the discrete weights in an arbitrary quantized neural network as searchable variables, and utilize a differential method to search them accurately. In particular, each weight is represented as a probability distribution over the discrete value set. The probabilities are optimized during training and the values with the highest probability are selected to establish the desired quantized network. Experimental results on benchmarks demonstrate that the proposed method is able to produce quantized neural networks with higher performance over the state-of-the-art methods on both image classification and super-resolution tasks. The PyTorch code will be made available at `https://github.com/huawei-noah/Binary-Neural-Networks/tree/main/SLB` and the MindSpore code will be made available at `https://www.mindspore.cn/resources/hub`.

1 Introduction

The huge success of deep learning is well demonstrated in considerable computer vision tasks, including image recognition [27, 61, 62], object detection [15, 53], visual segmentation [25], and image processing [35, 72]. On the other side, these deep neural architectures are often oversized for accuracy reason. A great number of network compression and acceleration methods have been proposed to eliminate the redundancy and explore the efficiency in neural networks , including pruning [23, 67], distillation [69, 6, 70, 44, 14], low-bit quantization [8, 52, 78], weight decomposition [75, 42, 71], neural architecture search [46, 68] and efficient block design [30, 54, 50, 21, 64].

Among these algorithms, quantization is very particular which represents parameters in deep neural networks as low-bit values. Since the low costs of quantized networks on both memory usage and computation, they can be easily deployed on mobile devices with specific hardware design. For example, compared with conventional 32-bit networks, binary neural networks (BNNs) can directly obtain a 32$\times$ compression ratio, and an extreme computational complexity reduction by executing

*Corresponding Author.

bit-wise operations (*e.g.*, 57× speed-up ratio in XNORNet [52]). However, the performance of the low-bit neural networks is usually worse than that of full-precision baselines, due to the optimization difficulty raised by the low-bit quantization functions.

To reduce the accuracy drop of quantized neural networks, some methods have been proposed in recent years. BiRealNet [48] inserts more shortcuts to help optimization. Structured Binary [81] and ABCNet [43] explore some sophisticated binary blocks and achieve comparable performance to that of full-precision networks, *etc*.

Admittedly, the aforementioned methods have made great efforts to improve the performance of the quantized neural networks. However, the accuracy gap between the full-precision network and its quantized version is still very huge, especially the binarized model. For example, the state-of-the-art accuracy of binarized ResNet-18 is about 10% lower than that of the full-precision baseline. A common problem in existing quantization methods is the estimated gradients for quantization functions, using either STE [8, 52, 29, 47, 59, 4] or self-designed gradient computation manner [46]. The estimated gradients may provide inaccurate optimization direction and consequently lead to worse performance. Therefore, an effective approach for learning quantized neural networks without estimated gradients is urgently required.

In this paper, we present a novel weight searching method for training the quantized deep neural network without gradient estimation. Since there are only a few values of low-bit weights (*e.g.*, +1 and -1 in binary networks), we develop a weight searching algorithm to avoid the non-differentiable problem of quantization functions. All low-bit values of an arbitrary weight in the given network are preserved with different probabilities. These probabilities will be optimized during the training phase. To further eliminate the performance gap after searching, we explore the temperature factor and a state batch normalization for seeking consistency in both training and testing. The effectiveness of the proposed differentiable optimization method is then verified on image classification and super-resolution tasks, in terms of accuracy and PSNR values.

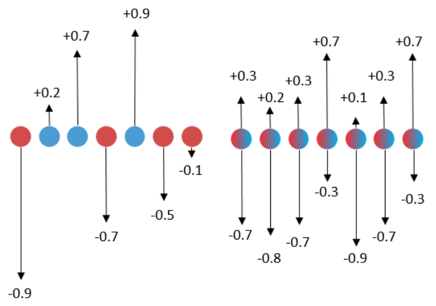


Figure 1: The binary case of the proposed method SLB. Conventional BNN (left) binarize full-precision proxy weights during training and update proxy weights by inaccurate gradients. For SLB (right), the training period is to optimize the distribution over discrete weights and the specific binary values will be determined after training.

2 Related Works

To reduce memory usage and computational complexity of deep neural networks, a series of methods are explored, including efficient block design, network pruning, weight decomposition, and network quantization. MobileNet [30, 54] and ShuffleNet [50] design novel blocks and construct the networks with high efficiency. Weight pruning methods such as DeepCompression [23] propose to remove redundant neurons in pre-trained models, while requires specific hardware for acceleration. Structured pruning methods [28, 67, 73] discard a group of weights (*e.g.*, an entire filter) in pre-trained networks so that the compressed model can be directly accelerated in any off-the-shelf platforms. Lxow-rank decomposition methods [10, 34, 75, 71] explore the relationship between weights and filters and explore more compact representations. Gradient-based neural architecture search methods [46, 66, 20, 60, 38, 39] use the continuous relaxation strategy to search discrete operations for each layer. All the candidate operations are mixed with a learnable distribution during searching and the operation with the highest probability is selected as the final operation. Quantization methods [40, 1, 51, 16, 11, 65, 77, 22] represent weights or activations in a given neural architecture as low-bit values. The model size and computational complexity of the quantized network are much smaller than those of its original version. Compared with previous model compression methods, network quantization does not change the architecture and the calculation process of original ones, which is supported by some mainstream platforms.

To maintain the high performance of quantized neural networks, considerable approaches have been explored for training low-bit weights and activations. For instance, Fixed point quantization [41] reduces about 20% complexity without loss of accuracy on CIFAR-10 dataset. BinaryConnect [8] represents weights by binary values $\{-1, +1\}$, TTQ [79] uses the ternary weights $\{-1, 0, +1\}$. Activations in these two methods are still full-precision values. DoReFa [78] quantizes both weights and activations to low-bit values. Among all the quantization methods, in extreme cases, if activations and weights are both 1 bit, the binary neural network not only occupies less storage space but also utilizes low-level bit operations xnor and bitcount to accelerate inference. ABCNet [43], CBCN [45], BENN [80] and SBNN [81] explored how to modify the BNN to match the performance with full-precision networks. In [82], a clearly different viewpoint is investigated into gradient descent, which provides the first attempt for the field and is worth further exploration. The hidden relationship between different variables is carefully studied, which will benefit many applications.

Nevertheless, most of the quantization functions in existing methods are non-differentiable, which increases the optimization difficulty. Thus, this paper aims to explore a more effective algorithm for quantizing deep neural networks.

3 Methods

In this section, we first briefly introduce the optimization approach in the conventional weight quantization methods and the existing problems. Then, a low-bit weight search approach is developed for accurately learning quantized deep neural networks. The strategies, including gradually decreasing temperature and state batch normalization, are proposed to eliminate the quantization gap.

3.1 Optimization Difficulty in Network Quantization

Representing massive weights and activations in deep neural networks using low-bit values is effective for reducing memory usage and computational complexity. However, it is very hard to learn these low-bit weights in practice.

For the case of q-bit quantization, the coordinate axis is divided into $m = 2^q$ intervals, and each interval corresponds to one discrete value in set $\mathbb{V} = \{v_1, v_2, \cdots, v_m\}, v_1 < \cdots < v_m$. Denoting the thresholdsas $T = \{t_1, \ldots, t_{m-1}\}, v_1 < t_1 \le v_2 \ldots v_{m-1} < t_{m-1} \le v_m$, the quantization function $\mathcal{Q}(x)$ can be defined as,

$$\mathcal{Q}(x) = \begin{cases} v_1 \ \text{ if } \ x < t_1, \\ v_2 \ \text{ if } \ t_1 \le x < t_2, \\ \cdots \\ v_m \ \text{ if } \ t_{m-1} \le x, \end{cases} \tag{1}$$

where $x \in \mathbb{R}$ is the original full-precision values. Given full-precision latent convolutional filters W_q^{lat}, the weights are quantized as $W_q = \mathcal{Q}(W_q^{lat})$, which are used to calculate the output features (*i.e.*, activations). In the training phase, the gradients ∇_{W_q} w.r.t the quantized filters W_q can be calculated with standard back-propagation algorithm. However, the gradients $\nabla_{W_q^{lat}}$ is hard to obtain, because the derivative of $\mathcal{Q}$ is zero almost everywhere and infinite at zero point. The Straight Through Estimator (STE) [8] is a widely used strategy to estimate the gradient of W_q^{lat}, *i.e.*,

$$\nabla_{W_q^{lat}} = \nabla_{W_q} \tag{2}$$

where the approximate gradients $\nabla_{W_q^{lat}}$ are use to update weights W_q^{lat},

$$\hat{W_q^{lat}} = W_q^{lat} - \eta \cdot \nabla_{W_q^{lat}} \cdot \sigma(\nabla_{W_q^{lat}}), \tag{3}$$

where η is the learning rate and $\sigma(\cdot)$ is the gradient clip function. Although Eq. 2 can provide the approximate gradients of W_q^{lat}, the estimation error cannot be ignored if we aim to further improve the performance of quantized networks. Considering that there are a number of layers and learnable parameters in modern neural networks, the optimization difficulty for learning accurate quantized models is still very large.

3.2 Low-bit Weight Searching

The parameters in a quantized neural network can be divided into two parts: the non-quantized parameters W_f (*e.g.*, in batch normalization, fully connected layer), and the quantized convolutional parameters W_q. The target of training the network is to find W_f^*, W_q^* that minimizes

$$W_f^*, W_q^* = \underset{W_f \in \mathbb{R}, W_q \in \mathbb{V}}{\arg\min} \mathcal{L}(W_f, W_q), \tag{4}$$

where the W_f and W_q belong to different domains, which are real number $\mathbb{R}$ and discrete set $\mathbb{V}$, respectively.

To optimize modern neural networks, the stochastic gradient descent (SGD) strategy is usually utilized. However, the discrete variables W_q are not feasible to be optimized by SGD. The previously described solution (Eq. 2- 3) by introducing the latent variables can be viewed as a heuristic solution that enables updating all the parameters in an end-to-end manner. However, the estimated and inaccurate gradients limit the upper bound of the performance. In contrast, inspired by gradient-based neural architecture search methods [46, 68, 24, 74, 12], we introduce the continuous relaxation strategy to search discrete weights.

Consider optimizing an n-dimensional discrete variable W of size $(d_1, \ldots, d_n)$, where each element w in W is chosen from the m discrete values $\mathbb{V} = \{v_1, v_2, \cdots, v_m\}$. A new auxiliary tensor $A \in \mathbb{R}^{m \times d_1 \times \cdots \times d_n}$ is created to learn the distribution of W, and the probability over m discrete variables is computed according to the following formula,

$$P_i = \frac{\exp^{A_i/\tau}}{\sum_j \exp^{A_j/\tau}}, \quad i \in \{1, \cdots, m\}, \tag{5}$$

where P_i is probability that the elements in W belong to the i-th discrete value v_i, and τ is the temperature controlling the entropy of this system. The expectation of the quantized values for W can be obtained:

$$W_c = \sum_i P_i \cdot v_i, \tag{6}$$

where the continuous state tensor W_c is calculated according to the probability over all the discrete values. W_c is used for convolution during training, and the process of Eq. 6 is differentiable and friendly for end-to-end training. Here we optimize the auxiliary tensor A whose gradients can be accurately calculated so that we avoid the gradient estimation in previous works.

In the inference stage, the weights are quantized by selecting the discrete value with the maximum probability for each position. In formal, the quantized state weights are

$$W_q = \sum_i I_i \cdot v_i, \tag{7}$$

where $I = \text{onehot}(\arg\max_i(P_i)), \ i \in \{1, \cdots, m\}$ indicates the one-hot vectors with the maximum probability.

For a convolution layer in neural networks, a four-dimensional weight tensor W of size $M \times N \times D_K \times D_K$ is to be learned, where M, N, and D_K are output channels, input channels, and kernel size, respectively. By using the proposed method to search for q-bit quantized weight W, the problem can be transformed into a special case of dimension $n = 4$ and discrete values $m = 2^q$ (Eq. 1). The tensor $A \in \mathbb{R}^{m \times M \times N \times D_K \times D_K}$ is constructed to learn the distribution over the discrete value set $\mathbb{V}$ according to Eq. 5. By using the continuous relaxation, the learning of Eq. 4 could be transformed to learn the tensor A,

$$W_f^*, A^* = \underset{W_f \in \mathbb{R}, A \in \mathbb{R}}{\arg\min} \mathcal{L}(W_f, A), \tag{8}$$

where the entire network is differentiable and can be optimized end-to-end with accurate gradients.

3.3 Optimization Details

We use the full-precision tensor W_c for training and quantized tensor W_q for inference. Although the continuous relaxation method solves the problem of inaccurate gradient during training, there is still a quantization gap after converting W_c to W_q. This will lead to the mismatch between the W_q and other parameters trained according to W_c, such as the statistics in the batch normalization layers.

Algorithm 1 Training algorithm of SLB

```
Input: The network $\mathcal{N}$ constructed by convolution and state batch normalization, training iterations
    $I$, dataset $\mathcal{D}$, initialize temperature $\tau_s$, end temperature $\tau_e$ and temperature decay scheduler $\mathcal{T}$.
1: for iter $i$ in $1, \dots, I$ do
2:     Update temperature parameter $\tau$ according to the temperature decay scheduler $\mathcal{T}$.
3:     Get minibatch data $X$ and target $Y$ from dataset $\mathcal{D}$, calculate continuous weights $W_c$ and
       quantized weights $W_q$ of $\mathcal{N}$ according to the current temperature $\tau$.
4:     The continuous state weights $W_c$ (Eq. 6) is computed and prediction $P = \mathcal{N}(X)$. The
       continuous state statistics in SBN are also updated.
5:     Compute the discrete weights $W_q$ (Eq. 7) and the discrete state statistics in SBN layer are
       updated (Eq. 13).
6:     The loss is calculated according to the prediction $P$ and target $Y$, and the back-propogated
       gradients are used to update auxiliary matrix $A$.
7: end for
8: Record quantized tensors $W_q$ and the discrete state statistics in SBN.
Output: A trained quantized neural network $\mathcal{N}^*$.
```

3.3.1 Reducing the Quantization Gap

In the proposed low-bit weight searching scheme, the continuous W_c for training and the discrete W_q for inference are not exactly the same. The quantization gap is introduced to measure the quantization error in the process of transforming the softmax distribution to the one-hot vector (Eq. 6- 7),

$$W_{gap} = W_q - W_c. \tag{9}$$

Fortunately, As stated in the temperature limit Theorem 1, the quantization gap W_{gap} could be an infinitesimal quantity if the temperature τ is small enough.

Theorem 1 (Temperature Limit Theorem). *Assuming $a \in \mathbb{R}^m$ is a vector in tensor A. If the temperature τ is gradually decreasing to zero, then the quantization gap is an infinitesimal quantity.*

Proof. The distribution p is computed as,

$$p_i = \frac{\exp^{a_i/\tau}}{\sum_j \exp^{a_j/\tau}} = \frac{1}{\sum_j \exp^{(a_j - a_i)/\tau}}, \tag{10}$$

by gradually decreasing τ to zero, the index of the maximum value is $k = \arg\max_i p_i$, the quantization gap w_{gap} is computed as,

$$\begin{aligned}
&\lim_{\tau \to 0} p_k = 1, \quad \lim_{\tau \to 0} p_{i,\, i \neq k} = 0 \\
&\lim_{\tau \to 0} w_{gap} = v_k - \sum_i p_i \cdot v_i \\
&\qquad = (1 - p_k) \cdot v_k + \sum_{i,\, i \neq k} p_i \cdot v_i \\
&\qquad = 0.
\end{aligned} \tag{11}$$

□

We propose the gradually decreasing temperature strategy during training so that $\lim_{\tau \to 0} W_c = W_q$. In particular, at the beginning of optimization, the temperature factor τ is high, and the distribution P is relatively smooth. With the change of temperature τ, the distribution P becomes sharper. In this way, the quantization gap will gradually decrease as τ changes.

3.3.2 State Batch Normalization

With the gradually decreasing temperature strategy, the continuous W_c will converge to the discrete W_q. Nevertheless, one problem that cannot be ignored is that the temperature cannot be decreased to a minimal value, *i.e.*, 0. If a neuron w's probability of choosing its value to be a discrete value is greater than a relatively high threshold (*e.g.*, $\max(p) > 0.999$), we may infer that the discrete value will not change as we continue to decrease the temperature and make the distribution sharper. Under this assumption, the quantized weights are well optimized and the only difference between training and inference is the statistics difference for batch normalization layers. Thus we proceed to develop a corresponding state batch normalization that acts as a bridge between a sharp softmax distribution and a one-hot distribution.

Batch Normalization (BN) [33] is a widely-used module for increasing the training stability of deep neural networks. The conventional BN for a given input feature y can be written as,

$$\hat{y_i} = \frac{1}{\sigma_i}(y_i - \mu_i), \tag{12}$$

where i is the index of channel and μ_i, σ_i are the mean and standard deviation values for the i-th channel, respectively. In the proposed method, W_c is used for convolution during training, so the normalization is formulated as,

$$y_c = x \otimes W_c, \;\; \hat{y_{c,i}} = \frac{1}{\sigma_{c,i}}(y_{c,i} - \mu_{c,i}), \tag{13}$$

where x is the input data, $\otimes$ is the convolution operation and y_c is the output. $\mu_{c,i}$ and $\sigma_{c,i}$ are the mean value and standard deviation of the i-th channel in y_c.

Therefore, the statistics of the quantized weights W_q does not match with the statistics σ_c and μ_c of BN , which results in a precision decline in inference. To address this problem, we proposed the State Batch Normalization (SBN). To be specific, the SBN calculates two groups of statistics during training, one is for y_c and the other is for y_q where y_q is the convolution output using quantized weights W_q. The normalization process of y_q is

$$y_q = x \otimes W_q, \;\; \hat{y_{q,i}} = \frac{1}{\sigma_{q,i}}(y_{q,i} - \mu_{q,i}), \tag{14}$$

where $\mu_{q,i}$ and $\sigma_{q,i}$ are the mean and standard deviation of the i-th channel in y_q.

Both $\hat{y_c}$ and $\hat{y_q}$ have a mean of zero and a standard deviation of one. We make they share the same group of affine coefficients,

$$z_{c,i} = \gamma_i \hat{y_{c,i}} + \beta_i, \;\; z_{q,i} = \gamma_i \hat{y_{q,i}} + \beta_i \tag{15}$$

In this case, the proposed SBN eliminates the small quantization gap in the statistics for batch normalization layers.

3.3.3 Overall Algorithm

We view the training for quantized networks as a search problem, and utilize a differentiable method for learning the distribution of quantized weights. The strategies including gradually decreasing temperature and state batch normalization are proposed to eliminate the quantization gap. The overall training algorithm of searching for low-bit weights (SLB) is summarized in Algorithm 1.

4 Experiments

We examine our proposed method on quantized neural networks with different bitwidths. Following common practice in most works, we use the CIFAR-10 [37] and large scale ILSVRC2012 [9] recognition datasets to demonstrate the effectiveness of our method. For all the quantized neural networks, following previous methods [48, 76, 78], all convolution layers except for the first one are quantized. The low-bit set $\mathbb{V}$ is constructed by uniform distribution from -1 to 1.

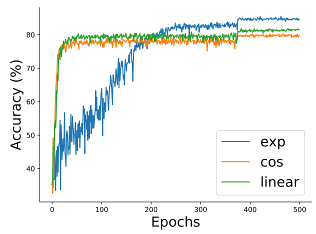


Figure 2: The diagram of different temperature scheduler.

4.1 Experiments on CIFAR-10

In this section, we first examine different temperature decay schedulers and then compare the results with other methods. We train the network for 500 epochs in total and decay the learning rate by a factor of 10 at 350, 440, and 475 epochs. The matrix A is initialized by kaiming initialization [26]. The quantization function for the activations is the same as DoReFa [78].

We test several different decay schedulers for temperature changing, including *sin*, *linear* and *exp*, which are widely used in adjusting the learning rate [49, 30, 49]. For convenience, we used T in this section to represent $\frac{1}{\tau}$ in Eq. 5. The temperature T is used to control the entropy of the system. Given the start temperature factor T_s, the end temperature T_e and the total number of training iterations I. At iteration i, the temperature T_t in different schedulers is calculated as follow,

$$T_{t,linear} = T_s + \frac{i}{I} \times (T_e - T_s),\;\; T_{t,sin} = T_s + \sin(\frac{i\pi}{2I}) \times (T_e - T_s),\;\; T_{t,exp} = T_s \times (\frac{T_e}{T_s})^{\frac{i}{I}}.$$

In Figure 2, we comprehensively compare different schedulers on binary ResNet20. We set $T_s = 0.01$ and $T_e = 10$. For *sin* and *linear* schedulers, the accuracies converge rapidly. However, some weights are not adequately trained, which results in relatively low accuracies. For the *exp* scheduler, the accuracies are much higher which indicates the weights converge to better local minima. In the following experiments, we adopt the *exp* scheduler for temperature adjusting.

Table 1: Results of ResNet20 on CIFAR-10.

Methods	**Bit-width (W/A)**	**Acc. (%)**
FP32 [27]	32/32	92.1
DoReFa [78, 17]	1/1	79.3
DSQ [16]	1/1	84.1
SQ [17]	1/1	84.1
SLB	1/1	**85.5**
LQ-Net [76]	1/2	88.4
SLB	1/2	**89.5**
SLB	1/4	**90.3**
SLB	1/8	**90.5**
LQ-Net [76]	1/32	90.1
DSQ [16]	1/32	90.2
SLB	1/32	**90.6**
LQ-Net [76]	2/2	90.2
SLB	2/2	**90.6**
SLB	2/4	**91.3**
SLB	2/8	**91.7**
SLB	2/32	**92.0**
SLB	4/4	**91.6**
SLB	4/8	**91.8**
SLB	4/32	**92.1**

Table 2: Results of VGG-Small on CIFAR-10.

Methods	**Bit-width (W/A)**	**Acc. (%)**
FP32 [58]	32/32	94.1
BNN [32]	1/1	89.9
XNORNet [52]	1/1	89.8
DoReFa [78, 17]	1/1	90.2
SQ [17]	1/1	91.7
SLB	1/1	**92.0**
LQ-Net [76]	1/2	93.4
SLB	1/2	**93.4**
SLB	1/4	**93.5**
SLB	1/8	**93.8**
LQ-Net [76]	1/32	93.5
SLB	1/32	**93.8**
LQ-Net [76]	2/2	93.5
SLB	2/2	**93.5**
SLB	2/4	**93.9**
SLB	2/8	**94.0**
SLB	2/32	**94.0**
SLB	4/4	**93.8**
SLB	4/8	**94.0**
SLB	4/32	**94.1**

We compare our results with other SOTA quantization methods including BNN, XNORNet, DoReFa, DSQ, SQ, and LQ-Net, on two different network architectures, *i.e.*, VGG-Small [58] and ResNet20 [27]. As shown in Table 1 and Table 2, our method outperforms other methods and achieves state-of-the-art results on different bit-widths.

4.2 Experiments on ILSVRC2012

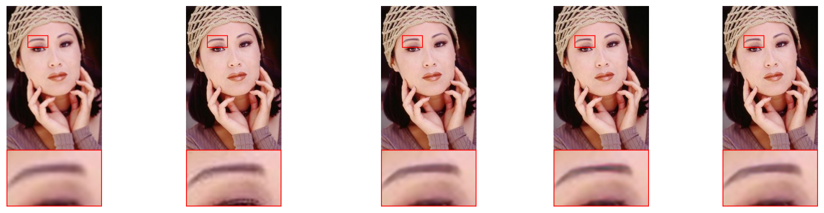
In the ILSVRC2012 classification experiments, we use ResNet18 [27, 48, 56, 57] as our backbone and compare the results with other state-of-the-art methods. The learning rate starts from 1e-3, weight decay is set to 0, and Adam optimizer is used to update parameters. Table 3 presents the results of our method and a number of other quantization methods.

The binary neural network is the most potential method because the xnor and bitcount operations are relatively efficient. Our proposed method on the binary case achieves state-of-the-art accuracy with a

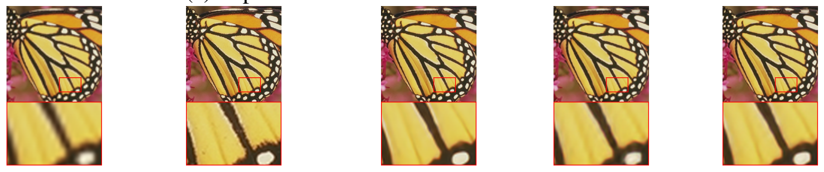
Table 3: Overall comparison of quantized ResNet18 on ILSVRC2012 large scale classification dataset. 'W/A' denotes the bitwidth of weights and activations, respectively.

Methods	Bit-width (W/A)	Top-1 (%)	Top-5 (%)
FP32 [27]	32/32	69.3	89.2
BNN [32]	1/1	42.2	67.1
ABCNet [43]	1/1	42.7	67.6
XNORNet [52]	1/1	51.2	73.2
BiRealNet [48]	1/1	56.4	79.5
PCNN [18]	1/1	57.3	80.0
SQ [17]	1/1	53.6	75.3
ResNetE [2]	1/1	58.1	80.6
BONN [19]	1/1	59.3	81.6
SLB	1/1	**61.3**	**83.1**
SLB (w/o SBN)	1/1	61.0	82.9
DoReFa [78]	1/2	53.4	-
LQ-Net [76]	1/2	62.6	84.3
HWGQ [5]	1/2	59.6	82.2
TBN [63]	1/2	55.6	79.0
HWGQ [5]	1/2	59.6	82.2
SLB	1/2	**64.8**	**85.5**
DoReFa [78]	1/4	59.2	-
SLB	1/4	**66.0**	**86.4**
SYQ [13]	1/8	62.9	84.6
SLB	1/8	**66.2**	**86.5**

Methods	Bit-width (W/A)	Top-1 (%)	Top-5 (%)
FP32 [27]	32/32	69.3	89.2
BWN [52]	1/32	60.8	83.0
DSQ [16]	1/32	63.7	-
SQ [17]	1/32	66.5	87.3
SLB	1/32	**67.1**	**87.2**
PACT [7]	2/2	64.4	-
LQ-Net [76]	2/2	64.9	85.9
DSQ [16]	2/2	65.2	-
SLB	2/2	**66.1**	**86.3**
SLB	2/4	**67.5**	**87.4**
SYQ [13]	2/8	67.7	87.8
SLB	2/8	**68.2**	**87.7**
TTQ [79]	2/32	66.6	87.2
LQ-Net [76]	2/32	68.0	88.0
SLB	2/32	**68.4**	**88.1**



(a) Super-resolution results with scale factor $\times 2$.



(b) Super-resolution results with scale factor $\times 3$.

Figure 3: Super-resolution results on Set5 dataset with different scale factors.

Top-1 accuracy of 61.3% . When using more bits on the activations, the Top-1 accuracies gradually increase. Our method consistently outperforms other methods by a significant margin. By adding the bitwidth of weights, the proposed SLB also achieves state-of-the-art accuracies on different settings.

4.2.1 The Impact on State Batch Normalization

We further verify the importance of state batch normalization by removing it in binary ResNet18. In particular, the discrete weights and discrete state statistics are not calculated during training, and the continuous state statistics are used after training. Because of the quantization gap, the SLB (w/o SBN) in Table 3 decreases the Top-1 accuracy by 0.3%. This indicates the essentiality to maintain two groups of statistics, which are estimated by the continuous state outputs and discrete state outputs, respectively.

4.3 Experiment on Super Resolution

To verify the generalization of the proposed method, we apply SLB to the image super-resolution task. The typical model VDSR [36] is selected as the baseline model. Following the original paper, we use the 291 images as in [55] for training and test on Set5 dataset [3]. Each image in the training data is split into patches and augmented with rotation or flip. The baseline model and the binarized models using DoReFa and SLB algorithms are trained with the same setting as in [36].

The models are compared at different scale factors, *i.e.* $\times 2$ and $\times 3$. From the results in Figure 3, we can see that SLB achieves much higher PSNR than DoReFa at both $\times 2$ and $\times 3$ scale factors. In Figure 3(a), the eyebrow in DoReFa's result is somewhat red while the result of SLB is normal and closer to the raw image. In Figure 3(b), the texture on the wing in DoReFa's result is blurry and hard to see clearly. SLB could well recover the texture and performs close to the full-precision model.

5 Conclusions

In this paper, we use the continuous relaxation strategy which addresses the gradient mismatch problem. To learn the discrete convolution kernels, an auxiliary probability matrix is constructed to learn the distribution for each weight from soft to hard, and the gradients are calculated to update the distribution. The state batch normalization is also proposed to minimize the gap between continuous state outputs and discrete state outputs. Our SLB can be applied to optimize quantized networks on a number of bitwidth cases and achieved state-of-the-art performance, which demonstrates the effectiveness of our method.

Acknowledgement

This work is supported by National Natural Science Foundation of China under Grant No. 61876007, Australian Research Council under Project DE180101438.

Broader Impact

Compared with full-precision networks, the quantized neural networks have the advantages of small model size, fast inference speed, low energy cost and efficient runtime memory occupation. The methods for training high-precision quantized neural networks help the deployment of computer vision models on mobile devices. Our proposed searching scheme provides a novel and feasible method for training high-precision quantized networks.

References

[1] Thalaiyasingam Ajanthan, Puneet Dokania, Richard Hartley, and Philip Torr. Proximal mean-field for neural network quantization. *ICCV*, 2019.

[2] Joseph Bethge, Haojin Yang, Marvin Bornstein, and Christoph Meinel. Back to simplicity: How to train accurate bnns from scratch? *arXiv*, 2019.

[3] Marco Bevilacqua, Aline Roumy, Christine Guillemot, and Marie Line Alberi-Morel. Low-complexity single-image super-resolution based on nonnegative neighbor embedding. *BMVC*, 2012.

[4] Adrian Bulat, Brais Martinez, and Georgios Tzimiropoulos. Bats: Binary architecture search. *ECCV*, 2020.

[5] Zhaowei Cai, Xiaodong He, Jian Sun, and Nuno Vasconcelos. Deep learning with low precision by half-wave gaussian quantization. *CVPR*, 2017.

[6] Hanting Chen, Yunhe Wang, Chang Xu, Zhaohui Yang, Chuanjian Liu, Boxin Shi, Chunjing Xu, Chao Xu, and Qi Tian. Data-free learning of student networks. *ICCV*, 2019.

[7] Jungwook Choi. Pact: Parameterized clipping activation for quantized neural networks. *arXiv*, 2018.

[8] Matthieu Courbariaux, Yoshua Bengio, and Jean-Pierre David. Binaryconnect: training deep neural networks with binary weights during propagations. *NeurIPS*, 2015.

[9] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. *CVPR*, 2009.

[10] Emily Denton, Wojciech Zaremba, Joan Bruna, Yann LeCun, and Rob Fergus. Exploiting linear structure within convolutional networks for efficient evaluation. *arXiv*, 2014.

[11] Ruizhou Ding, Ting-Wu Chin, Zeye Liu, and Diana Marculescu. Regularizing activation distribution for training binarized deep networks. *CVPR*, 2019.

[12] Shaojin Ding, Tianlong Chen, Xinyu Gong, Weiwei Zha, and Zhangyang Wang. Autospeech: Neural architecture search for speaker recognition. *arXiv*, 2020.

[13] Julian Faraone, Nicholas Fraser, Michaela Blott, and Philip H.W. Leong. Syq: Learning symmetric quantization for efficient deep neural networks. *CVPR*, 2018.

[14] Yonggan Fu, Wuyang Chen, Haotao Wang, Haoran Li, Yingyan Lin, and Zhangyang Wang. Autogan-distiller: Searching to compress generative adversarial networks. *ICML*, 2020.

[15] Ross Girshick. Fast r-cnn. *ICCV*, 2015.

[16] Ruihao Gong, Xianglong Liu, Shenghu Jiang, Tianxiang Li, Peng Hu, Jiazhen Lin, Fengwei Yu, and Junjie Yan. Differentiable soft quantization: Bridging full-precision and low-bit neural networks. *CVPR*, 2019.

[17] Ruihao Gong, Xianglong Liu, Shenghu Jiang, Tianxiang Li, Peng Hu, Jiazhen Lin, Fengwei Yu, and Junjie Yan. Differentiable soft quantization: Bridging full-precision and low-bit neural networks. *ICCV*, 2019.

[18] Jiaxin Gu, Ce Li, Baochang Zhang, Jungong Han, Xianbin Cao, Jianzhuang Liu, and David Doermann. Projection convolutional neural networks for 1-bit cnns via discrete back propagation. *arXiv*, 2018.

[19] Jiaxin Gu, Junhe Zhao, Xiaolong Jiang, Baochang Zhang, Liu Jianzhuang, Guodong Guo, and Rongrong Ji. Bayesian optimized 1-bit cnns. *ICCV*, 2019.

[20] Jianyuan Guo, Kai Han, Yunhe Wang, Chao Zhang, Zhaohui Yang, Han Wu, Xinghao Chen, and Chang Xu. Hit-detector: Hierarchical trinity architecture search for object detection. *CVPR*, 2020.

[21] Kai Han, Yunhe Wang, Qi Tian, Jianyuan Guo, Chunjing Xu, and Chang Xu. Ghostnet: More features from cheap operations. *CVPR*, 2020.

[22] Kai Han, Yunhe Wang, Yixing Xu, Chunjing Xu, Enhua Wu, and Chang Xu. Training binary neural networks through learning with noisy supervision. *ICML*, 2020.

[23] Song Han, Huizi Mao, and William J. Dally. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. *ICLR*, 2016.

[24] Chaoyang He, Haishan Ye, Li Shen, and Tong Zhang. Milenas: Efficient neural architecture search via mixed-level reformulation. *arXiv*, 2020.

[25] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. *ICCV*, 2017.

[26] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. *ICCV*, 2015.

[27] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *CVPR*, 2016.

[28] Yihui He, Xiangyu Zhang, and Jian Sun. Channel pruning for accelerating very deep neural networks. *ICCV*, 2017.

[29] Koen Helwegen, James Widdicombe, Lukas Geiger, Zechun Liu, and Kwang-Ting Cheng. Latent weights do not exist: Rethinking binarized neural network optimization. *NeurIPS*, 2019.

[30] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv*, 2017.

[31] Huawei. Mindspore. `https://www.mindspore.cn/`, 2020.

[32] Itay Hubara, Matthieu Courbariaux, Daniel Soudry, Ran El-Yaniv, and Yoshua Bengio. Binarized neural networks. *NeurIPS*, 2016.

[33] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *ICML*, 2015.

[34] Max Jaderberg, Andrea Vedaldi, and Andrew Zisserman. Speeding up convolutional neural networks with low rank expansions. *BMVC*, 2014.

[35] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. *ECCV*, 2016.

[36] Jiwon Kim, Jung Kwon Lee, and Kyoung Mu Lee. Accurate image super-resolution using very deep convolutional networks. *CVPR*, 2016.

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

[38] Yanxi Li, Minjing Dong, Yunhe Wang, and Chang Xu. Neural architecture search in a proxy validation loss landscape. *ICML*, 2020.

[39] Yanxi Li, Zhaohui Yang, Yunhe Wang, and Chang Xu. Adapting neural architectures between domains. *NeurIPS*, 2020.

[40] Zefan Li, Bingbing Ni, Wenjun Zhang, Xiaokang Yang, and Wen Gao. Performance guaranteed network acceleration via high-order residual quantization. *ICCV*, 2017.

[41] Darryl D. Lin, Sachin S. Talathi, and V. Sreekanth Annapureddy. Fixed point quantization of deep convolutional networks. *ICML*, 2016.

[42] Shaohui Lin, Rongrong Ji, Chao Chen, Dacheng Tao, and Jiebo Luo. Holistic cnn compression via low-rank decomposition with knowledge transfer. *TPAMI*, 2018.

[43] Xiaofan Lin, Cong Zhao, and Wei Pan. Towards accurate binary convolutional neural network. *NeurIPS*, 2017.

[44] Benlin Liu, Yongming Rao, Jiwen Lu, Jie Zhou, and Cho jui Hsieh. Metadistiller: Network self-boosting via meta-learned top-down distillation. *ECCV*, 2020.

[45] Chunlei Liu, Wenrui Ding, Xin Xia, Baochang Zhang, Jiaxin Gu, Jianzhuang Liu, Rongrong Ji, and David Doermann. Circulant binary convolutional networks: Enhancing the performance of 1-bit dcnns with circulant back propagation. *CVPR*, 2019.

[46] Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. *ICLR*, 2019.

[47] Zechun Liu, Zhiqiang Shen, Marios Savvides, and Kwang-Ting Cheng. Reactnet: Towards precise binary neural network with generalized activation functions. *ECCV*, 2020.

[48] Zechun Liu, Baoyuan Wu, Wenhan Luo, Xiaodong Yang, Weiwei Liu, and Kwang-Ting Cheng. Bi-real net: Enhancing the performance of 1-bit cnns with improved representational capability and advanced training algorithm. *ECCV*, 2018.

[49] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *ICLR*, 2017.

[50] Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. *ECCV*, 2018.

[51] Hai Phan, Dang Huynh, Yihui He, Marios Savvides, and Zhiqiang Shen. Mobinet: A mobile binary network for image classification. *arXiv*, 2019.

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

[53] Joseph Redmon, Santosh Kumar Divvala, Ross B. Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. *CVPR*, 2016.

[54] Mark B. Sandler, Andrew G. Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. *CVPR*, 2018.

[55] Samuel Schulter, Christian Leistner, and Horst Bischof. Fast and accurate image upscaling with super-resolution forests. *CVPR*, 2015.

[56] Mingzhu Shen, Kai Han, Chunjing Xu, and Yunhe Wang. Searching for accurate binary neural architectures. *ICCVW*, 2019.

[57] Mingzhu Shen, Xianglong Liu, Ruihao Gong, and Kai Han. Balanced binary neural networks with gated residual. *ICASSP*, 2020.

[58] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *ICLR*, 2015.

[59] Kunal Pratap Singh, Dahyun Kim, and Jonghyun Choi. Learning architectures for binary networks. *ECCV*, 2020.

[60] Yehui Tang, Yunhe Wang, Yixing Xu, Hanting Chen, Boxin Shi, Chao Xu, Chunjing Xu, Qi Tian, and Chang Xu. A semi-supervised assessor of neural architectures. *CVPR*, 2020.

[61] Yehui Tang, Yunhe Wang, Yixing Xu, Boxin Shi, Chao Xu, Chunjing Xu, and Chang Xu. Beyond dropout: Feature map distortion to regularize deep neural networks. *AAAI*, 2020.

[62] Yehui Tang, Shan You, Chang Xu, Jin Han, Chen Qian, Boxin Shi, Chao Xu, and Changshui Zhang. Reborn filters: Pruning convolutional neural networks with limited data. *AAAI*, 2020.

[63] Diwen Wan, Fumin Shen, Li Liu, Fan Zhu, Jie Qin, Ling Shao, and Heng Tao Shen. Tbn: Convolutional neural network with ternary inputs and binary weights. *ECCV*, 2018.

[64] Haotao Wang, Shupeng Gui, Haichuan Yang, Ji Liu, and Zhangyang Wang. Gan slimming: All-in-one gan compression by a unified optimization framework. *ECCV*, 2020.

[65] Ziwei Wang, Jiwen Lu, Chenxin Tao, Jie Zhou, and Qi Tian. Learning channel-wise interactions for binary convolutional neural networks. *CVPR*, 2019.

[66] Bichen Wu, Xiaoliang Dai, Peizhao Zhang, Yanghan Wang, Fei Sun, Yiming Wu, Yuandong Tian, Peter Vajda, Yangqing Jia, and Kurt Keutzer. Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search. *CVPR*, 2019.

[67] Zuxuan Wu, Tushar Nagarajan, Abhishek Kumar, Steven Rennie, Larry S. Davis, Kristen Grauman, and Rogério Schmidt Feris. Blockdrop: Dynamic inference paths in residual networks. *CVPR*, 2018.

[68] Sirui Xie, Hehui Zheng, Chunxiao Liu, and Liang Lin. Snas: stochastic neural architecture search. *ICLR*, 2019.

[69] Yixing Xu, Yunhe Wang, Hanting Chen, Kai Han, Chunjing Xu, Dacheng Tao, and Chang Xu. Positive-unlabeled compression on the cloud. *NeurIPS*, 2019.

[70] Yiding Yang, Jiayan Qiu, Mingli Song, Dacheng Tao, and Xinchao Wang. Distilling knowledge from graph convolutional networks. *CVPR*, 2020.

[71] Zhaohui Yang, Yunhe Wang, Chuanjian Liu, Hanting Chen, Chunjing Xu, Boxin Shi, Chao Xu, and Chang Xu. Legonet: Efficient convolutional neural networks with lego filters. *ICML*, 2019.

[72] Zhaohui Yang, Yunhe Wang, Chang Xu, Peng Du, Chao Xu, Chunjing Xu, and Qi Tian. Discernible image compression. *arXiv*, 2020.

[73] Jiahui Yu and Thomas Huang. Autoslim: Towards one-shot architecture search for channel numbers. *arXiv*, 2019.

[74] Jiahui Yu, Pengchong Jin, Hanxiao Liu, Gabriel Bender, Pieter-Jan Kindermans, Mingxing Tan, Thomas S. Huang, Xiaodan Song, Ruoming Pang, and Quoc Le. Bignas: Scaling up neural architecture search with big single-stage models. *arXiv*, 2020.

[75] Xiyu Yu, Tongliang Liu, Xinchao Wang, and Dacheng Tao. On compressing deep models by low rank and sparse decomposition. *CVPR*, 2017.

[76] Dongqing Zhang, Jiaolong Yang, Dongqiangzi Ye, and Gang Hua. Lq-nets: Learned quantization for highly accurate and compact deep neural networks. *ECCV*, 2018.

[77] Feng Zheng, Cheng Deng, and Heng Huang. Binarized neural networks for resource-efficient hashing with minimizing quantization loss. *IJCAI*, 2019.

[78] Shuchang Zhou, Zekun Ni, Xinyu Zhou, He Wen, Yuxin Wu, and Yuheng Zou. Dorefa-net: Training low bitwidth convolutional neural networks with low bitwidth gradients. *arXiv*, 2016.

[79] Chenzhuo Zhu, Song Han, Huizi Mao, and William J. Dally. Trained ternary quantization. *ICLR*, 2017.

[80] Shilin Zhu, Xin Dong, and Hao Su. Binary ensemble neural network: More bits per network or more networks per bit? *CVPR*, 2018.

[81] Bohan Zhuang, Chunhua Shen, Mingkui Tan, Lingqiao Liu, and Ian D. Reid. Structured binary neural networks for accurate image classification and semantic segmentation. *CVPR*, 2018.

[82] Li'an Zhuo, Baochang Zhang, Linlin Yang, Hanlin Chen, Qixiang Ye, David Doermann, Rongrong Ji, and Guodong Guo. Cogradient descent for bilinear optimization. *CVPR*, 2020.