BiViT: Extremely Compressed Binary Vision Transformer

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Abstract

Model binarization can significantly compress model size, reduce energy consumption, and accelerate inference through efficient bit-wise operations. Although binarizing convolutional neural networks have been extensively studied, there is little work on exploring binarization on vision Transformers which underpin most recent breakthroughs in visual recognition. To this end, we propose to solve two fundamental challenges to push the horizon of **Bi**nary **Vi**sion Transformers (BiViT). First, the traditional binary method does not take the long-tailed distribution of softmax attention into consideration, bringing large binarization errors in the attention module. To solve this, we propose Softmaxaware Binarization, which dynamically adapts to the data distribution and reduces the error caused by binarization. Second, to better exploit the information of the pretrained model and restore accuracy, we propose a Cross-layer Binarization scheme and introduce learnable channel-wise scaling factors for weight binarization. The former decouples the binarization of self-attention and MLP to avoid mutual interference while the latter enhances the representation capacity of binarized models. Overall, our method performs favorably against state-of-the-arts by 19.8% on the TinyImageNet dataset. On ImageNet, BiViT achieves a competitive 70.8% Top-1 accuracy over Swin-T model, outperforming the existing SOTA methods by a clear margin.

1. Introduction

Vision Transformer (ViT) [18] and its variants have achieved great success in a variety of computer vision tasks, such as image classification [18, 21, 41], object detection [10, 19, 31], semantic segmentation [11, 56, 75], etc. How-

ever, massive parameters and calculations of the Transformer model hinder its applications on portable devices such as mobile phones. To address this, various model compression algorithms have been widely studied, such as distillation [28, 57, 59], pruning [50, 67, 77] and quantization [35–37]. Among them, binary Transformers aggressively compress weights and activations to a single bit, which gives 32× saving on memory consumption. Meanwhile, efficient bit-wise operations can greatly accelerate model inference and reduce energy consumption.

However, the performance degradation restricts the wide application of binary networks, which is mainly caused by the limited representation ability and difficulty in optimization. To tackle these bottlenecks, binarized convolutional neural networks (CNN) literature has been proposed to minimize the binarization error [8,54,76], enhance the representation ability [44,46,79] and relieve the gradient approximation error in optimization [4, 26, 53]. Also, many attempts have been made in previous studies to binarize BERT [16] for natural language processing (NLP) tasks, such as correcting the attention value range mismatch [52], stronger distillation and migrating some methods on binary CNNs to Transformers [42]. However, there are few studies on the binarization of vision Transformers yet.

In addition to the common challenges mentioned above, binarizing Transformers presents two new technical challenges. **Firstly, it lacks effective methods for accurately binarizing softmax attention.** Self-attention module aims to find pairwise similarity between all the tokens [61], which is very different from convolutional or fully-connected layers as the values of attention scores are all positive values between (0, 1) while the ordinary weights have both positive and negative values, as shown in Figure 3. Therefore, its functionality and data distribution are quite different from the ordinary weights. The recent study

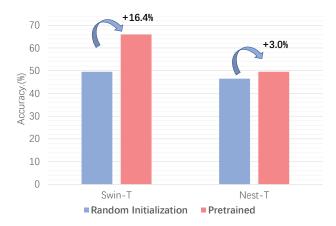


Figure 1. **Impact of pretrained model when binarizing Transformers.** The experiment is conducted on TinyImageNet dataset. Initiating Transformers from the pretrained models greatly boosts the accuracy.

BiBERT [52] simply binarizes the attention score before Softmax to $\{0, 1\}$ to maximize the information entropy. However, it ignores the impact of Softmax on the distribution and will lead to huge quantization errors or even damage the attention mechanism. Secondly, how to preserve the information in the pretrained model during binarization is under explored. Unlike binary CNNs that perform well when training from scratch [44, 53, 60], we observe that BiViTs heavily rely on pretrained model and are sensitive to quantization, as shown in Figure 1. Even the initial weights are derived from pretrained model, directly binarizing all parameters still causes a huge loss of pretrained information, which then leads to a severe performance drop. Also, the loss of pretrained information is difficult for Transformers to recover through quantizationaware training (QAT). In particular, MLP modules account for nearly half of the computations and parameters within a Transformer [39]. It is composed of an activation layer and two fully-connected layers, which are equivalent to 1×1 convolutions and are widely known to be difficult to optimize due to the limited representational capability [20, 46, 79]. How to binarize the attention more effectively and how to retain the information of the pretrained model remains an open question.

To reduce the quantization error in binarizing attentions, we first analyze the long-tailed distribution of attention scores and discover their inner variety between different attention vectors. To adaptively search the optimal threshold for binarization, we propose an optimization algorithm based on sparse coding and block coordinate descent and further propose an efficient approximation called Softmax-aware Binarization to avoid conducting the optimization on each forward pass. To retain pretrained information and further enhance model representation ability, we then propose Cross-layer Binarization to decouple the quantization

of self-attention and MLPs to avoid mutual interference and adopt parameterized scaling factors for weights binarization. To our best knowledge, we are the first to successfully binarize Transformers for vision tasks.

In summary, our contributions are as follows:

- We design Softmax-aware Binarization for the selfattention module, which adapts to the long-tailed data distribution and greatly reduces the quantization error.
- We propose Cross-layer Binarization and Learnable Weight Binarization to retain pretrained information and further enhance the representation ability of binary Transformers, which facilitates BiViTs to converge and improve the accuracy.
- Combining the above contributions, we propose the first applicable BiViT. Experiments on TinyImageNet and ImageNet datasets show that it consistently outperforms current state-of-the-arts by great margins.

2. Related Work

2.1. Vision Transformers

Transformer [61] is initially used to process long sequences in NLP tasks. ViT [18] first adapts Transformers to vision tasks by splitting images into grids and constructing vision token sequences. DeiT [58] further improves the data efficiency of vision Transformers. Benefiting from the global receptive field and the powerful longrange modeling capabilities of Transformer models, ViTs demonstrate promising performance against CNN counterparts. Many follow-up works are proposed to explore hierarchical structures [41, 62, 74], inject convolutional layers [14, 22, 34] and apply ViTs to different vision tasks [19, 69, 73]. However, the inference speed of ViTs is usually slower than that of CNNs in practical applications [33]. The reasons mainly include the lack of special optimization (such as Winograd [40] for convolutional layers) and the quadratic computational complexity of the self-attention module. To reduce the computational complexity of ViTs, many methods have been proposed, including linear attention [9, 55, 63], redundancy reduction [50, 66, 71] and quantization [36, 37, 45]. However, current Transformer quantization work mainly focuses on fixed-point quantization, whether through Quantization-Aware Training (QAT) [32, 36] or Post-Training Quantization (PTQ) [37, 45, 68]. Research on ternary or binary quantization remains to be studied.

2.2. Binary Neural Networks

Binary neural network (BNN) quantizes both weights and activations to 1-bit, which greatly reduces the complexity of the model. The binarization of models usually requires QAT to restore accuracy. To overcome the non-differentiability of quantizer during training and the limited

representation capacity, many methods have been proposed to help binarize CNNs, such as binary-friendly model structure [6,7,38,46,49,78], knowledge distillation [44,47,48], soft function [17,24,53,72], optimizer selection [1,13,43], etc. Although some of them are also effective for Transformer models, as analyzed in BiT [42], methods focusing on binary Transformers still need to be developed to relieve accuracy degradation.

The literature closely related to our work includes BinaryBERT [3], BiBERT [52] and BiT [42]. They put forward some improvements on the binarization of BERT [16] model, including binarization function and model distillation, and evaluated them on NLP tasks. However, none of these methods are evaluated on computer vision tasks. In the following sections, we will migrate these methods to Swin [41] and NesT [74] as our baselines to test their performance and analyze their drawbacks. Then we propose to improve BiViT's performance by accurate attention binarization and pretrained information preservation. To the best of our knowledge, we are the pioneering work in the field of BiViTs.

3. Method

3.1. Preliminaries

Generally, BNNs follow [54] to use Sign function to binarize weights and activations to {-1, +1}, and use Straight-Through Estimator (STE) [5] to overcome the non-differentiability of the Sign function, as follows:

$$\hat{x} = \operatorname{Sign}(x) = \begin{cases} +1, & \text{if } x > 0\\ -1, & \text{otherwise,} \end{cases}$$
 (1)

$$\frac{\partial \mathcal{L}}{\partial x} \approx \begin{cases} \frac{\partial \mathcal{L}}{\partial \hat{x}}, & \text{if } |x| < 1\\ 0, & \text{otherwise.} \end{cases}$$
 (2)

To estimate the full-precision $\mathbf{x} \in \mathbb{R}^n$, BNNs further use a scaling factor $\alpha \in \mathbb{R}^+$ to reduce the quantization error:

$$\alpha = \frac{\|\mathbf{x}\|_{\ell_1}}{n}, \quad \mathbf{x} \approx \alpha \hat{\mathbf{x}}.$$
 (3)

With both weights and activations binarized, Binary GEneral Matrix Multiplication (BGEMM) can be used to accelerate the inference, which can be efficiently implemented by XNOR and bitcount operations [54]. In special cases, if only one operand is binarized, the multiplication can still be replaced by addition to accelerate the calculation akin to BinaryConnect [12].

However, binarization using Sign can be problematic in Transformers. In the self-attention mechanism [61], the cal-

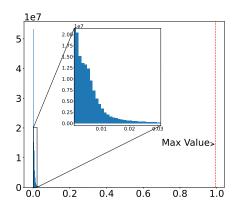


Figure 2. The long-tailed distribution of attention scores. Most attention scores are around zero but the maximum values can reach 0.99

culation formula of attention is defined by:

Attention(
$$\mathbf{Q}, \mathbf{K}, \mathbf{V}$$
) = Softmax $\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right) \mathbf{V}$, (4)

where \mathbf{Q} , \mathbf{K} , \mathbf{V} are respectively query, key and value matrics and d_k is the dimension of the key.

We can see that Softmax operation is used in the last dimension to obtain the attention scores. According to the definition of Softmax, the results are non-negative and they will all be +1 after Sign function. In order to solve the problem of value range mismatch, BiBERT [52] proposes to use the Bool function to binarize the attention scores without Softmax operation:

$$Bool(x) = \begin{cases} 1, & \text{if } x > 0\\ 0, & \text{otherwise.} \end{cases}$$
 (5)

However, this will lead to huge quantization errors since Softmax is totally discarded, as we will analyze in Section 3.2.

3.2. Softmax-aware Binarization

Self-attention mechanism [61] is designed to model global relationship among different patches (tokens) and focuses on important token pairs. Figure 2 presents the distribution of attention scores in the pretrained NesT-T [74] model. It is obvious that after Softmax operation, attention scores follow a long-tailed distribution and more than 99.5% of them are less than 0.05, which is highly sparse. For a more detailed explanation, we take a deep look at an actual attention vector (*i.e.*, one row of the attention matrix) from the NesT-T pretrained model, as shown in Figure 3(a). In this case, if we directly use Bool function to binarize, nearly half of the attention scores are set to 1 and they have the same contribution to binarization (Figure 3(c)), which is inconsistent with the actual distribution of softmax attention scores where few values dominate (see Figure 3(b)).

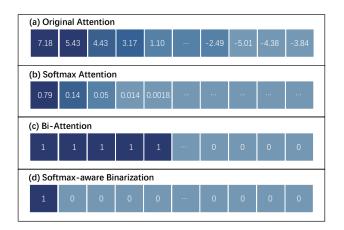


Figure 3. **Details of attention binarization.** (a) Original attention from NesT-T pretrained model. (b) Attention processed by Softmax operation. (c) Attention binarized with BiBERT's Bi-Attention techniques. (d) Attention binarized by our method.

In order to reduce the quantization error while binarizing attention scores, the ideal binarization method must satisfy the following two properties: 1) Compared with using Bool function, the proportion of activated attention scores (set to 1) should be smaller. As shown in Figure 2, most values are around 0, which can be ignored during calculation, and only a few significant values are considered. 2) The activation threshold should not be a fixed value. Softmax is operated on every row-wise attention vector (*i.e.*, each row of the attention matrix) while different attention vectors follow different distributions. For example, the maximum value of some of them can reach 0.99, while the others are only about 0.05. Empirically, even though most attentions are dominated by only a few elements, the threshold to activate should be different across all attention vectors.

To achieve this, the key is to find the optimal threshold T for each attention vector binarization (i.e., T is different for each row). Inspired by sparse coding [30] and LQ-Nets [70], we formulate the quantized vector $\mathbf{x}_q \in \mathbb{R}^n$ by the inner product between a basis vector $\mathbf{v} \in \mathbb{R}^k$ and the binary encoding vector $\mathbf{b} \in \{0,1\}^{k \times n}$:

$$\mathbf{x}_q = \mathbf{v}^T \mathbf{b},\tag{6}$$

where k is the target bit-width. Then the optimization problem can be formulated as:

$$\mathbf{v}^*, \mathbf{b}^* = \underset{\mathbf{v}, \mathbf{b}}{\operatorname{argmin}} \|\mathbf{v}^T \mathbf{b} - \mathbf{x}\|_2^2, \quad s.t. \ \mathbf{b} \in \{0, 1\}^{k \times n}.$$
(7)

In this paper, the bit-width k is set to 1, thus the basis vector \mathbf{v} becomes a scalar v. However, with both v and \mathbf{b} to be solved, brute-force search can be computationally expensive. Instead, the optimization problem can be efficiently solved in a block coordinate descent approach. Specifically,

we alternatively optimize the basis v and binary encoding vector \mathbf{b} while keeping another fixed:

Update v: With fixed binary encoding vector **b**, the optimization problem will degenerate to a special case of linear regression. Therefore, the optimal v can be derived by:

$$v^* = \frac{\mathbf{x} \cdot \mathbf{b}}{\|\mathbf{b}\|_2^2},\tag{8}$$

where \cdot represents dot product between two vectors.

Update b: Since we get the optimal v with Eq. (8), the two values for binarization becomes $\{0, v^*\}$. The optimal transition point (threshold) can be simply calculated as:

$$T = \frac{0 + v^*}{2}.\tag{9}$$

Then we binarize the real-valued attention vector with the threshold to update the binary encoding b:

$$\mathbf{b}^* = \text{Bool}(\mathbf{x} - T). \tag{10}$$

After iterating for N times, the quantization error between binary attention and the full-precision counterpart decreases significantly, as shown in line 2 of Table 1.

Table 1. Quantization error under different methods. We set N=5 and $\beta=0.25$ in practice.

Method	Quantization Error
BiBERT	0.683
Optimal T	2.58e-05
Approximate T	2.72e-05
Approximate T w/o scales	0.141

Although this optimization strategy minimizes the quantization error, it is impractical to optimize each generated attention vector during inference. Besides, we calculate an optimal \boldsymbol{v} for each attention vector, which introduces an extra computational burden.

To simplify optimization and maintain similar computational complexity as the previous methods [3, 42, 52], we try to seek a relationship between the optimal T (calculated by Eq. (9)) and the distribution of the attention scores. As shown in Figure 4, the optimal T is highly related to the maximum value of the attention scores. Therefore, we approximate T using a fixed coefficient β (shared in the model) and the maximum value of the attention vector \mathbf{x} to greatly accelerate the inference:

$$T = \beta \text{Max}(\mathbf{x}). \tag{11}$$

Experimental result demonstrates that this approximation barely increases the quantization error, as shown in line 3 of Table 1.

However, compared with the previous methods [3, 42, 52], multiplying the basis scalar v by the binary encoding

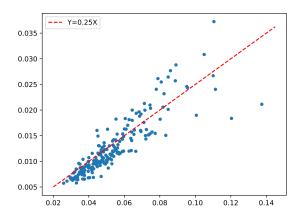


Figure 4. Relation between the maximum value of attention (Xaxis) and optimal T (Y-axis). Blue dots are maximum value of each attention vector sampled from the pretrained NesT-T model and red dashed line represents the result of linear regression on these attention scores.

vector b to get x_q in Eq. (6) still introduces extra computation. To keep the same computational complexity as previous methods, we make a second approximation and further discard the basis scalar v in Eq. (6) since the obtained binary attention scores b already satisfy the two properties mentioned in Section 3.2. In this case, the quantization error is shown in line 4 of Table 1. It should be noted that this step is simply a trade-off between accuracy and complexity. By default, we use the algorithm with two approximations for experiments.

Since our binary strategy mimics the Softmax operation, we use Softmax to approximate the gradient instead of STE in the backward pass. Specifically, the gradients are backpropagated as if the elements are processed by Softmax during the forward pass.

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = \frac{\partial \mathcal{L}}{\partial \mathbf{b}} \frac{\partial \mathbf{b}}{\partial \mathbf{x}} \approx \frac{\partial \mathcal{L}}{\partial \mathbf{b}} \frac{\partial \text{Softmax}(\mathbf{x})}{\partial \mathbf{x}}.$$
 (12)

This can effectively address the mismatch between the forward quantizer and its backward approximator.

Overall, the training process of our Softmax-aware Binarization is summarized in Algorithm 1.

3.3. Information Preservation

3.3.1 Cross-layer Binarization

The pretrained model is crucial for BiViTs, as empirically justified in Figure 1. However, compared with binary BERT [3,42,52], BiViTs are rather difficult to optimize. To prove this, we directly migrate BiBERT [52] to Swin-T [41] and NesT-T [74] to verify its performance on vision tasks. The results are shown in Table 6. We observe that its accuracy degradation in image classification tasks can reach 40%,

Algorithm 1 Softmax-aware Binarization for self-attention modules.

- 1: **Input**: the softmax attention scores $\mathbf{x} \in \mathbb{R}^n$
- 2: Forward propagation
- Approximate the transition point T by the maximum value of attentions with Eq. (11):

$$T = \beta \text{Max}(\mathbf{x});$$

- Binarize attentions with transition point T by Eq. (10): $\hat{\mathbf{x}} = \text{Bool}(\mathbf{x} - T);$
- 5: Backward propagation
- Calculate the gradients w.r.t. x with Eq. (12): $\frac{\partial \mathcal{L}}{\partial \mathbf{x}} \approx \frac{\partial \mathcal{L}}{\partial \hat{\mathbf{x}}} \; \frac{\breve{\partial} \mathrm{Softmax}(\mathbf{x})}{\partial \mathbf{x}}.$

which indicates that vanilla BiViTs cannot make good use of the pretrained information and is difficult to optimize on vision tasks.

To explore the reasons, we present the architecture and parameters of Swin-T in Figure 5. The MLP, which is equivalent to 1×1 convolutions, is hard to quantize (as analyzed in Section 1) and has more parameters than the self-attention module. To tackle this problem, we propose Cross-layer Binarization (CB), which is analogous to the previous two-stage training scheme [47, 80], to decouple the quantization of self-attention and MLP module to reduce mutual interference. In the first stage, we keep MLP to full precision and binarize all the self-attention modules with Softmax-aware Binarization. Then in the second stage, we binarize MLPs to get the final model.

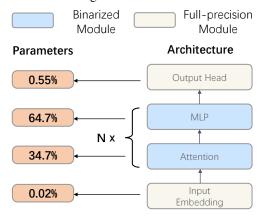


Figure 5. The architecture and parameters of Swin-T model. MLP is difficult to binarize due to 1×1 convolutions and has far more parameters than other modules.

Compared with previous two-stage training schemes that first binarize activations and then weights [2, 44, 47], CB is designed for Transformers to relieve the mutual interference and mitigate information loss caused by binarizing MLPs. The experimental results demonstrate that using CB brings more accuracy improvement than the traditional two-step training scheme. Also, the rich reserved information of the pretrained model makes it possible to perform fine-tuning on the binary Transformer. As we will show in Section 4.2.2, training with CB provides more competitive performance under the same number of training iterations.

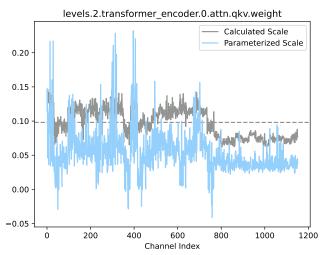


Figure 6. Parameterized and calculated scaling factors in **NesT-T model.** The dashed line represents the mean value of calculated scaling factors.

3.3.2 Learnable Weight Binarization

To further narrow the performance gap between the binarized model and the full-precision counterpart, an intuitive idea is to increase the representation ability of the binarized model. However, this usually results in increased number of model parameters. To this end, we propose to parameterize scaling factors (as defined in Eq. (3)) to enhance the representation ability of the binarized model.

Motivated by SE-Net [27], channel-wise scaling factors can be regarded as the importance of each channel, rather than an approximation of its distribution. In order to preserve the model structure and complexity, we directly replace the scaling factor by a learnable parameter. The parameterized scaling factors could be optimized in conjunction with other network parameters via backward propagation during training. As shown in Figure 6, the deviation of the scaling factors obtained by Eq. (3) across channels is small, indicating that weight distribution of each channel is similar. On the contrary, the parameterized scaling factors vary greatly from channel to channel, showing that it learns to pay more attention to specific channels and thus enhancing the representation capacity of the model.

4. Experiment

4.1. Implementation Details

Dataset and architecture. We conduct experiments on two standard benchmarks: TinyImageNet [65] and ImageNet (ILSVRC12) [15]. The input resolution is 224×224 . For data augmentation, we follow the settings in DeiT [58],

which are common practices in ViTs. To demonstrate the versatility of our method, we adopt two widely-used efficient architectures: Swin-T [41] and NesT-T [74]. We do not conduct experiments on full-attention models (like ViT [18]) because of their low data efficiency in visual tasks. All the blocks in Transformer models are binarized without exception. For binary attention modules, all weights and intermediate results including Q, K, V and projection layers, are binarized. For binary MLP modules, weights are binarized in all experiments. We leave the input embedding layer and output layer unbinarized as it is the common practice of BNNs [54].

Training setup. All experiments are implemented with Py-Torch [51] and timm [64] library. For both datasets, we employ Adam [29] optimizers without weight decay and train models for 300 epochs using a cosine annealing schedule with 5 epochs of warm-up. The initial learning rate is set to 5e-4. When training is split into two stages, we train 150 epochs at each stage to keep the number of total iterations the same. Knowledge distillation (KD) [25] is used in all experiments. Specifically, we use the distribution loss proposed in [44] for optimization. Before training, all parameters are initialized with the pretrained model.

4.2. Ablation Studies

4.2.1 Effect of Softmax-aware Binarization

First, we conducted ablation experiments over Swin-T and NesT-T models on TinyImageNet to prove the effectiveness of the proposed Softmax-aware Binarization. To eliminate the impact of MLPs, we keep them full-precision and only binarize attention modules. As shown in Table 2, Softmax-aware Binarization consistently narrows the accuracy gap between the teacher and the binary Transformer model, indicating that the quantization error in the self-attention module is effectively suppressed.

Table 2. Ablation study on Softmax-aware Binarization.

Arch	Method	ATTN BitWidth (W/A)	Top-1 (%)
	FP	32/32	80.57
Swin-T	BiBERT	1/1	73.39
	+ Softmax-aware Binarization	1/1	74.62
NesT-T	FP	32/32	80.31
	BiBERT	1/1	68.51
	+ Softmax-aware Binarization	1/1	70.73

Also, we conduct experiments to verify the impact of β estimation (see Eq. (11)) on the accuracy of the model. The results in Table 3 show that the model is not sensitive to β within a reasonable interval (about 0.25 to 0.45). In the following experiments, β is set to 0.25 to enable efficient bit-shift operation in Eq. (11). However, the accuracy of the model decreases when β is too small (less than 0.2). This indicates that as the threshold becomes too small, the Softmax-aware Binarization is less effective and too many

attention scores are activated.

Table 3. Comparisons of binary attention's performance under different thresholds. The experiment is conduct over NesT-T model on TinyImageNet.

Method	Top-1 Acc.(%)
FP	80.31
BiBERT	68.51
Ours (β =0.20)	69.18
Ours (β =0.25)	70.73
Ours (β =0.35)	70.81
Ours (β =0.45)	70.68

4.2.2 Effect of Information Preservation

To demonstrate the effectiveness of Cross-layer Binarization (CB), we compare the accuracy of training with CB schemes with that of directly training fully-binarized networks and training with traditional two-step schemes [47]. The experiments are conducted with activations in MLP modules remaining full-precision. As shown in the Table 4, using CB can improve the accuracy by 11.6% compared with one-step training, making it more applicable. Moreover, CB outperforms the traditional two-step training scheme by 4.1%, demonstrating its strong ability to retain pretrained information. We expect that the two methods can be combined to further improve the accuracy since they are orthogonal, but will leave it for future work.

Table 4. Ablation study on Cross-layer Binarization. Here, "CB" denotes Cross-layer Binarization and "TS" denotes traditional two-stage training scheme.

Method	ATTN BitWidth (W/A)	MLP BitWidth (W/A)	Top-1 (%)
FP	32/32	32/32	80.31
Ours (w/o CB)	1/1	1/32	58.20
Ours (w/TS)	1/1	1/32	65.64
Ours (w/ CB)	1/1	1/32	69.83

With the pretrained information well preserved, CB also accelerates the convergence process of the binary model. As shown in Figure 7, training binary models on ImageNet with CB requires fewer iterations to achieve ideal results. For instance, when CB is not used for training, 70 epochs are required to reach a Top-1 accuracy of 50%. However, it only takes 30 epochs for CB to reach the same accuracy, which significantly improves the training efficiency.

Parameterized scaling factors can be applied to both self-attention and MLP modules. To show the improvement brought by parameterized scaling factors, we conduct the experiments by starting with a BiBERT-based baseline and then adding parameterized scaling factors to its self-attention and MLP modules separately. As shown in Table 5, parameterized scaling factors are effective in both

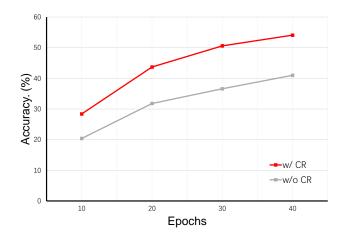


Figure 7. Training accuracy curve with less training epochs. The experiment is conducted over NesT-T model on TineImageNet dataset.

modules, getting 4.2% and 1.3% accuracy improvement respectively. Therefore, we use parameterized scaling factors in both modules by default if they are binarized.

Table 5. Ablation study on parameterized scaling factors.

Method	ATTN BitWidth (W/A)	MLP BitWidth (W/A)	Top-1 (%)
FP	32/32	32/32	80.31
BiBERT	1/1	32/32	68.51
+Parameterized Scales	1/1	32/32	72.75
FP	32/32	32/32	80.31
BiBERT	32/32	1/1	70.02
+Parameterized Scales	32/32	1/1	71.35

4.3. Comparison with SOTA methods

4.3.1 Evaluation On TinyImgnet

Table 6. Comparisons of different network architectures on Tiny-ImageNet. Here, "FP" means full-precision pretrained model, "ATTN" denotes attention module and (W/A) represents the number of bits used in weights or activations.

Arch	Method	ATTN	MLP	Top-1 (%)
		BitWidth (W/A)	BitWidth (W/A)	
Swin-T	FP	32/32	32/32	80.57
	BiBERT	1/1	1/1	41.89
	BiT	1/1	1/1	40.52
	Ours	1/1	1/1	58.66
	FP	32/32	32/32	80.57
	BiBERT	1/1	1/32	65.93
	BiT	1/1	1/32	61.82
	Ours	1/1	1/32	71.20
NesT-T	FP	32/32	32/32	80.31
	BiBERT	1/1	1/1	32.39
	BiT	1/1	1/1	34.72
	Ours	1/1	1/1	52.21
	FP	32/32	32/32	80.31
	BiBERT	1/1	1/32	49.53
	BiT	1/1	1/32	46.43
	Ours	1/1	1/32	69.83

We first evaluate our performance on the TinyImageNet

dataset. As shown in Table 6, previous Transformer binarization methods have severe accuracy degradation (more than 40%) on image classification tasks, which makes it barely usable in real applications. With our proposed method, the performance gap between the binary and fullprecision model is greatly narrowed. For models with all weights and activations binarized, our method can improve the accuracy by nearly 20% (52.21% vs. 32.39% for NesT-T). However, this result is still not ideal. One reason is that the MLP module accounts for a large part of parameters and is hard to compress, as analyzed in Section 1. Therefore, we reserve the activations in MLP modules as full-precision to make it more applicable. The experimental results show that leaving activations unbinarized can greatly reduce the performance degradation caused by binary MLPs (69.83% vs. 52.21%), achieving a better trade-off between accuracy and complexity. In this case, the model size is also reduced and we can still use addition to replace multiplication for more efficient inference. For models with 1W32A in MLP modules, the accuracy of our method is also much better than current SOTA methods.

Another finding is that the accuracy of binary Swin-T is clearly better than binary NesT-T, while the performance of their full-precision models is similar. This may be attributed to the mask mechanism in the local window attention of Swin, which has the effect of restraining the number of original attentions greater than zero and thus helps the model to binarize. However, for most Transformers with standard self-attention (like NesT), our method brings huge accuracy gains.

4.3.2 Evaluation On ImageNet

We further evaluate the effectiveness of our method on the ImageNet dataset, and the results are shown in Table 7. To preserve the accuracy, we binarize all weights while leaving the activations in MLP modules full-precision. For Swin-T, our method outperforms previous SOTA by a margin of 2.5%, achieving a competitive 70.8% Top-1 accuracy. For NesT-T, where the previous method even fails to converge, our method obtains a 68.7% Top-1 accuracy. The improvement can be attributed to the effective binarization for self-attention modules and the information well preserved from full-precision model. The results also demonstrate the feasibility of binary Transformers in real-world visual tasks for the first time.

4.4. Comparison with Binary CNNs

We list the amount of model parameters and accuracy of binary ResNet [23] in Table 7, so that we can compare the

Table 7. Comparisons of different network architectures on ImageNet, "*" denotes the model fails to converge. In particular, we list the parameters of the model for comparison between different architectures. It is worth noting that **the attention module** of the Transformer model is under 1W1A configuration.

Arch	Method	MLP BitWidth (W/A)	Top-1 (%)
DagNat 10	FP	/	69.6
ResNet-18 (Params: 11.7M)	AdaBin ¹	/	63.1
	IR-Net ²	/	66.5
ResNet-34 (Params: 21.8M)	FP	/	73.3
	AdaBin ¹	/	66.4
	IR-Net ²	/	70.4
Swin-T (Params: 28.3M)	FP	32/32	81.2
	BiBERT	1/32	68.3
	Ours	1/32	70.8
NesT-T (Params: 17.1M)	FP	32/32	81.1
	BiBERT	1/32	0.27*
	Ours	1/32	68.7

two model structures. CNN is mainly composed of convolutional layers, which only contains a small amount of 1×1 convolution layers, so most of the models can be compressed efficiently. The accuracy degradation of ResNet-34 in 1W32A configuration is less than 3% compared with the full-precision model. On the other hand, Transformers also have their advantages. The global receptive field and attention mechanism have strong representation capability, which makes the accuracy of the full-precision ViT models much higher than that of ResNet under the similar number of parameters. Since we inherit the information of the pretrained model, a stronger teacher model will undoubtedly help the training of the BiViT. For example, when the attention maintains 1W1A (while the MLP module remains 1W32A), BiViT can still provide better accuracy than ResNet with the 1W32A configuration (70.8% vs. 70.4%). Moreover, BiViT provides a strong baseline for future research on binarizing ViTs, whether for image classification or other vision tasks.

5. Conclusion and Discussion

In this paper, we have proposed to tackle two fundamental challenges with customized solutions for BiViT, and have successfully applied binary Transformers to visual tasks for the first time. Inspired by the long-tailed distribution of softmax attention, we have proposed the Softmax-aware Binarization for self-attention, the core module of Transformers, which greatly reduces the quantization error. To preserve information from pretrained model and enhance representation ability, we have proposed the Cross-layer Binarization scheme that decouples the quantization of self-attention and MLPs, and parameterized scaling factors for weight binarization. Combined with the above points, our BiViT has achieved significant accuracy improvement on

¹CNNs with binary weights and activations.

²CNNs with binary weights and full-precision activations.

the image classification task, with up to 70.8% Top-1 accuracy on ImageNet. In the future, we will extend BiViT to more downstream vision tasks such as dense detection and segmentation.

Limitations and societal impact. The performance gap between BiViT and full-precision counterparts needs to be further narrowed. Also, there are many factors that affect the accuracy of binary Transformers that have not been studied in this paper, such as the binary-friendly Transformer structure design and the impact of soft functions. Our BiViT does not have any potential negative societal impacts.

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