Visual Transformer Pruning

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Abstract

Visual transformer has achieved competitive performance on a variety of computer vision applications. However, their storage, run-time memory, and computational demands are hindering the deployment on mobile devices. Here we present an visual transformer pruning approach, which identifies the impacts of channels in each layer and then executes pruning accordingly. By encouraging channel-wise sparsity in the Transformer, important channels automatically emerge. A great number of channels with small coefficients can be discarded to achieve a high pruning ratio without significantly compromising accuracy. The pipeline for visual transformer pruning is as follows: 1) training with sparsity regularization; 2) pruning channels; 3) finetuning. The reduced parameters and FLOPs ratios of the proposed algorithm are well evaluated and analyzed on ImageNet dataset to demonstrate its effectiveness.

1 Introduction

Recently, transformer [21] has attracted much attention and shed light on various computer vision applications [7] such as image classification [4, 20, 8], object detection [1, 27], and image processing [2]. However, most of the proposed transformer variants highly demand storage, run-time memory, and computational resource requirements, which impede their wide deployment on edge devices, e.g., robotics and mobile phones. Although massive effective techniques have been developed for compressing and accelerating convolutional neural networks (CNNs) including low-rank decomposition [18], quantization [23], network pruning [19], and knowledge distillation [14], there still exists an urgency to develop and deploy efficient visual transformer.

Taking advantage of different designs [25, 9, 16], transformer can be compressed and accelerated to varying degrees. ALBERT [10] reduces network parameter and speed up training time by decomposing embedding parameters into smaller matrices and enabling cross-layer parameter sharing. Star-Transformer [6] sparsifies the standard transformer by moving fully-connected structure to the star-shaped topology. Based on knowledge distillation techniques, the student networks in [17, 9] learn from the logits in the larger pre-trained teacher networks. Some effective pruning algorithms have been proposed to reduce the attention head [13] or individual weights [5]. The previous methods focus on compressing and accelerating the transformer for the natural language processing tasks. With the emergence of visual transformers such as ViT [4], PVT [22], and TNT [8], an efficient transformer is urgently need for computer vision applications.

To address the aforementioned problems, we propose to prune the visual transformer according to the learnable importance scores. Inspired by the pruning scheme in network slimmming [11], we add the learning coefficients before the layers to be prune and sparsify them by training the network with \mathcal{L}_1 regulation. The channels with smaller coefficient values will be pruned and the compact network can be obtained. Experimental results on the benchmark demonstrate the effectiveness of the proposed algorithm. Our visual transformer pruning (VTP) method largely compresses and accelerates the

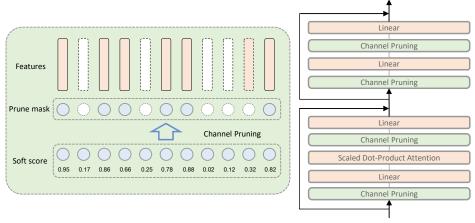


Figure 1: Visual Transformer Pruning.

original ViT (DeiT) models. As the first pruning method for visual transformers, this work will provide a solid baseline and experience for future research.

2 Approach

2.1 Complexity Analysis

The typical visual transformer architecture [21, 4] consists of Multi-Head Self-Attention (MHSA), Multi-Layer Perceptron (MLP), layer normalization, activation function, and shortcut connection. MHSA is the characteristic component of transformer to perform information interaction among tokens. In particular, the input $X \in \mathbb{R}^{n \times d}$ is transformed to query $Q \in \mathbb{R}^{n \times d}$, key $K \in \mathbb{R}^{n \times d}$ and value $V \in \mathbb{R}^{n \times d}$ via fully-connected layers, where n is the number of patches and d is the embedding dimension. The self-attention mechanism is utilized to model the relationship between patches:

$$Attention(Q, K, V) = Softmax\left(QK^{T}/\sqrt{d}\right)V. \tag{1}$$

Finally, a linear transformation is applied to generate the output of MHSA:

$$Y = X + FC_{out}(Attention(FC_q(X), FC_k(X), FC_v(X))),$$
(2)

where the layer normalization and activation function are omitted for simplification. The number of parameters and FLOPs of MHSA are 4nd and $4nd^2+2n^2d$, respectively. As for the two-layer MLP, it can be formulated as

$$Z = Z + FC_2(FC_1(Y)). \tag{3}$$

The hidden dimension is usually set as 4d, so its parameters and FLOPs values are $8d^2$ and $8nd^2$, respectively. The parameters or FLOPs of layer normalization, activation function, and shortcut can be ignored compared to those of MHSA and MLP. A transformer block has about $4nd+8d^2$ parameters and $12nd^2+2n^2d$ FLOPs in total where MHSA and MLP occupy the vast majority.

2.2 Visual Transformer Pruning

To slim the transformer architecture, we focus on decreasing the FLOPs of MHSA and MLP. We propose to reduce the dimension of features by learning the importance score of each dimension. For the features $X \in \mathbb{R}^{n \times d}$, where n denotes the number of channels that need to be pruned and d denotes the dimension of each channel, we aim to preserve the important features and remove the useless ones. Suppose the optimal importance scores are $\mathbf{a}^* \in \{0,1\}^d$, that is, the scores for important features are ones while the scores for useless ones are zeros. With the importance scores, we can obtain the pruned features:

$$X^* = X \operatorname{diag}(\mathbf{a}^*). \tag{4}$$

However, it's hard to optimize \mathbf{a}^* in the neural network through a back-propagation algorithm due to its discrete values. Thus, we propose to relax \mathbf{a}^* to real values as $\hat{\mathbf{a}} \in \mathbb{R}^d$. The soft pruned features is obtained as

$$\hat{X} = X \operatorname{diag}(\hat{\mathbf{a}}) \tag{5}$$

Then, the relaxed importance scores $\hat{\mathbf{a}}$ can be learned together with the transformer network end-to-end. In order to enforce sparsity of importance scores, we apply ℓ_1 regularization on the coefficients: $\lambda \|\hat{\mathbf{a}}\|_1$ and optimize it by adding on the training objective, where λ is the sparsity hyper-parameter. After training with sparsity penalty, we obtain the transformer with some importance scores near zero. We rank all the values of regularized coefficients in the transformer and obtain a threshold τ according to a pre-defined pruning rate. With the threshold τ , we obtain the discrete \mathbf{a}^* by setting the values below the threshold as zero and higher values as ones:

$$\mathbf{a}^* = \hat{\mathbf{a}} > \tau. \tag{6}$$

After pruning according to the importance scores a^* , the total pruned transformer is fine-tuned to diminish the accuracy drop. The above pruning procedure is denoted as

$$X^* = Prune(X). (7)$$

As shown in Figure 1, we apply the pruning operation on all the MHSA and MLP blocks. The pruning process for them can be formulated as

$$Q, K, V = FC_q(Prune(X)), FC_k(Prune(X)), FC_v(Prune(X)),$$
(8)

$$Y = X + FC_{out}(Prune(Attention(Q, K, V))), \tag{9}$$

$$Z = Z + FC_2(Prune(FC_1(Prune(Y)))). \tag{10}$$

The proposed visual transformer pruning (VTP) method provides a simple yet effective way to slim visual transformer models. We hope that this work will serve as a solid baseline for future research and provide useful experience for the practical deployment of visual transformers.

3 Experiments

In this section, we verify the effectiveness of the proposed VTP methods to prune visual transformer models on ImageNet dataset.

3.1 Datasets

ImageNet-1K. ImageNet ILSVRC2012 dataset [15] is a large-scale image classification dataset including 1.2 million images for training and 50,000 validation images belonging to 1,000 classes. The common data augmentation strategy in DeiT [20] is adopted for model development, including Rand-Augment [3], Mixup [26], and CutMix [24].

ImageNet-100. ImageNet-100 is collected as a subset of ImageNet-1K. We first randomly sampled 100 classes and their corresponding images for training and validation. We adopt the same data augmentation strategy for ImageNet-100 as ImageNet-1K.

3.2 Implementation Details

Baseline. We evaluate our pruning method on a popular visual transformer implementation, i.e., DeiT-base [20]. In our experiments, a 12-layer transformer with 12 heads and 768 embedding dimensions is evaluated on both ImageNet-1K and Imagenet-100. For a fair comparison, we utilize the official implementation of DeiT and do not use techniques like distillation. On the ImageNet-1K, we take the released model of DeiT-base as the baseline. We finetune the model on the ImageNet-1K using batch size 64 for 30 epochs. The initial learning rate is set to 6.25×10^{-7} . Following Deit [20], we use AdamW [12] with cosine learning rate decay strategy to train and finetune the models.

Training with Sparsity Regularization and Pruning. Based on the baseline model, we train the visual transformer with ℓ_1 regularization using different sparse regularization rates. We select the optimal sparse regularization rate (i.e. 0.0001) on Imagenet-100 and apply it on ImageNet-1K. The learning rate for training with sparsity is 6.25×10^{-6} and the number of epochs is 100. The other training setting follows the baseline model. After sparsity, we prune the transformer by setting different pruning thresholds and the threshold is computed by the predefined pruning rate, e.g., 0.2.

Finetuning. We finetune the pruned transformer with the same optimization setting as in training, except for removing the ℓ_1 regularization.

3.3 Results and Analysis

Imagenet-100 Experiments and Ablation Study. We firstly conduct ablation studies on Imagenet-100, as shown in Table 1. From the results, the amount of pruning rate matches the ratio of parameters saving and FLOPs saving. For example, when we prune 40% channels of the models trained with 0.0001 sparse rate, the parameter saving is 45.3% and the FLOPs saving is 43.0%. We can see that the Parameters and FLOPs drop while the accuracy maintains. Besides, the sparse ratio does not highly influence the effectiveness of the pruning method. In Table 2, we compare the baseline model with two VTP models, i.e., 20% pruned and 40% pruned models. The accuracy drops slightly with large FLOPs decrease. When we prune 20% channels, 22.0% FLOPs are saved and the accuracy drops by 0.96%. When we prune 40% channels, 45.3% FLOPs are saved and the accuracy drops by 1.92%.

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Sparse Penalty	Pruning Rate	Params (M)	Params Reduced	FLOPs (B)	FLOPs Reduced	Top1 (%)
0.0001	0.6	29.0	↓66.4%	6.4	↓63.5%	90.00
	0.5	38.0	↓56.0%	8.2	↓53.4%	91.46
	0.4	47.3	↓45.3%	10.0	↓43.0%	92.58
	0.2	66.1	↓23.5%	13.7	↓22.0%	93.54
0.00001	0.6	28.2	↓67.4%	6.3	↓64.4%	89.88
	0.5	37.5	↓56.6%	8.1	↓54.0%	91.40
	0.4	47.1	↓45.5%	10.0	↓43.2%	92.38
	0.2	66.1	↓23.5%	13.7	↓22.0%	93.44

Table 1: Ablation Study on ImageNet-100.

Table 2: Results on ImageNet-100.

Model	Params (M)	FLOPs (B)	Top1 (%)	Top5 (%)
Deit-B (Baseline)	86.4	17.6	94.50	98.94
VTP (20% pruned)	66.1	13.7	93.54	98.36
VTP (40% pruned)	47.3	10.0	92.58	98.04

Imagenet-1K Experiments. We also evaluate the proposed VTP method on the large-scale ImageNet-1K benchmark. The results are shown in Table 3. Compared to the base model DeiT-B, the accuracy of VTP only decreases by 1.1% when 40% channels are pruned. The accuracy only drops by 0.5% while 20% channels are pruned. The effectiveness of VTP can be generalized to large-scale datasets.

Table 3: Results on ImageNet-1K.

Model	Params (M)	FLOPs (B)	Top1 (%)	Top5 (%)
CNN based ResNet-152	60.2	11.5	78.3	94.1
RegNetY-16GF	83.6	15.9	80.4	- -
Transformer based				
ViT-B/16	86.4	55.5	77.9	-
DeiT-B (Baseline)	86.4	17.6	81.8	-
VTP (20% pruned)	67.3	13.8	81.3	95.3
VTP (40% pruned)	48.0	10.0	80.7	95.0

4 Conclusion

In this paper, we introduce a simple yet efficient visual transformer pruning method. \mathcal{L}_1 regulation is applied to sparse the channels of the transformer and the important channels appear automatically. The experiments conducted on Imagenet-100 and ImageNet-1K demonstrate that the pruning method can largely reduce the computation costs and model parameters while maintaining the high accuracy of original visual transformers. In the future, the important components such as the number of heads and the number of layers can also be reduced with this method, which is a promising attempt to further compress visual transformers.

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