Abstract

Since the vision transformer (ViT) has achieved impressive performance in image classification, an increasing number of researchers pay their attentions to designing more efficient vision transformer models. A general research line is reducing computational cost of self attention modules by adopting sparse attention or using local attention windows. In contrast, we propose to design high performance transformer based architectures by densifying the attention pattern. Specifically, we propose cross attention among blocks of ViT (CabViT), which uses tokens from previous blocks in the same stage as extra input to the multi-head attention of transformers. The proposed CabViT enhances the interactions of tokens across blocks with potentially different semantics, and encourages more information flows to the lower levels, which together improves model performance and model convergence with limited extra cost. Based on the proposed CabViT, we design a series of CabViT models which achieve the best trade-off between model size, computational cost and accuracy. For instance without the need of knowledge distillation to strength the training, CabViT achieves 83.0% top-1 accuracy on Imagenet with only 16.3 million parameters and about 3.9G FLOPs, saving almost half parameters and 13% computational cost while gaining 0.9% higher accuracy compared with ConvNext, use 52% of parameters but gaining 0.6% accuracy compared with distilled EfficientFormer. Source code is available at https://github.com/hkzhang91/CabViT.

1. Introduction

With the fast adoption of transformer structures in computer vision community, various types of attention patterns are proposed to improve the performance or the speed of transformer models. For example, the vanilla global multi-head self attention in ViT [3], the local windowed attention in swin transformers [13], the grid attention across interleaved tokens in MaxViT [22], and the attention on progressively pruned tokens in Dynamic ViT [18]. These works seek to sparsify the attention patterns of the vanilla ViT to achieve better speed accuracy trade off.

In contrast, we propose a new model block as well as a family of models called CabViT, which improves the performance of vision transformers by further densifying the attention patterns with limited extra cost. Specifically, we propose to connect the input of standard multi-head attention (MHA) module with extra tokens transformed from previous blocks in the same stage, while still restrict the attention module to output the original amount of tokens. To further reduce the computational cost, we merge the tokens from previous blocks by using depthwise convolutions with large strides. These tokens are further calibrated by scaling them with learned parameters, before being taken into the attention units in subsequent blocks.

The new CaB connection has several advantages. 1) It helps transformers further exploit the interactions of tokens across different levels. 2) It reuses the previously generated tokens so that some of the information no longer needs to be preserved by the subsequent transformer operations, leading to potentially smaller models with similar accuracy. 3) Similar to the residual connections in ResNet, this extra cross layer connection encourages more information flows...
to the lower levels of the network, which at the same time further alleviates vanishing-gradient problems.

The newly densified connections bring in limited extra computational cost. As is detailed in Section 3.3 1) The number of output tokens are kept the same as in standard ViTs, which makes the extra computation cost increases linearly instead of quadratically. 2) In existing vision transformer architectures, majority of the computation cost lies in the feed forward network (FFN) part instead of the MHA part of transformer blocks. This linear growth of computational complexity does not significantly increase the overall computation cost. 3) We use depthwise convolutions with large kernels and long strides to aggregate the tokens from previous blocks to reduce the number of extra inputs.

We adopted the proposed CabViT design in two typical classes of transformer models, the plain ViT model as used in DeiT, and the ConvNet and transformer hybrid structures that are seen in many recent works [15, 7, 12]. Experiments show that the proposed CaB block can be seamlessly used to replace the corresponding transformer blocks in these architectures, and achieve significantly better results than their corresponding baselines. Specifically, CabViT achieves 80.3% top-1 accuracy with about 6.2 million parameters and about 1.5G FLOPs, saving almost half parameters but gaining 1.2% higher accuracy compared with the recently proposed EfficientFormer. Fig 1 displays the comparison result.

The contribution of this paper is summarized as follows.

1. Opposite to many recent works that use sparse attention to improve transformer models, we propose to design more efficient models by densifying the attention connection patterns.

2. We propose the CabViT block with cross attention among blocks in the same stage. CabViT block reuses existing tokens and enhances the interactions of tokens from different levels. In the CabViT block, we design a light-weight token merge and enhancement (TME) module to control its computational complexity.

3. Based on the proposed CabViT block, we build several new models, which achieve better performance than state-of-the-arts.

2. Related Works

2.1. Pure vision transformers

Dosovitskiy et al. introduced transformer model into vision tasks and proposed the ViT [3]. It cropped an image into 16 × 16 patches as an input token sequence to the transformer and used positional encoding to model spatial relations among tokens. DeiT [21] lowered the difficulty of ViT model training by knowledge distillation, and achieved competitive accuracy with less pretraining data. To further improve the model architecture, researchers attempted to optimize the ViT toward improving its computational efficiency. Among them, the Swin transformer [13] computes self attention among shifted local windows. The MaxViT [22] uses block attention and grid attention alternatively to keep spatially global information exchange while significantly reduce the number of tokens involved in the self attention computation. The DynamicViT [18] prunes redundant tokens progressively and dynamically depending on the input features. Mohsen et al. [5] proposed a differentiable parameter-free adaptive token sampler and plugged it into ViTs to sample part tokens for attention computation.

Except for the DeiT, all methods above keep pure vision transformer architectures and seek to achieve better accuracy speed trade-off by using sparse attention via reducing the number of tokens in attention patterns. In contrast, we propose to achieve this goal by densifying the attention pattern, reusing existing tokens from previous blocks. Such interactions promote attentions across features of different scales and semantic levels, which is very common in ConvNets and many methods before the wide adoption of deep learning.

2.2. Hybrid ConvNet and vision transformers

Rather than simplifying ViTs, another popular line of research is to combine elements of ViTs and ConvNets to form new backbones. Two early attempts can be found in [7, 28], where ConvNet blocks are employed to extract low level information in early stages and ViT blocks are adopted in deep stages. Such a hybrid structure improves optimization stability and model performance. Similarly, BoTNet [20] replaces the standard convolution with multihead attention in the last few blocks of ResNet. In [15], the deeper stages of MobileNetv2 [19] are replaced with their proposed MobileViT block. There are other hybrid models which mix convolution operation with self attention and channel mixer operations. For example, ConViT[4] incorporates soft convolutional inductive biases via a gated positional self-attention. CMT [8] and Next-ViT [11] insert both convolution operation and self attention module into a single block. PVT v1 [25], PVT v2 [26], LIT [17] and LIT v2 [16] insert convolutional operations into each stage of ViT models to reduce the number of tokens, and build hierarchical multi-stage structures.

Hybrid models achieve better trade-off between model cost and accuracy compared with pure vision transformer models, while they usually have more complex architectures. Therefore, both pure ViTs and hybrid models have their own advantages for different applications. Our work is complementary to these hybrid design attempts, and can be used to replace the transformer part for most of these
methods.

2.3. Skip connections in ConvNets

In retrospect, our work is also related to several key improvements in ConvNets design that introduces extra connections to improve the information flows.

ResNet [9] employs shortcut connections to overcome the degradation problem, where accuracy gets saturated and then degrades rapidly with the increasing convolutional network depth. DenseNet [10] connects each layer to every other layer in a feedforward fashion. As with ResNet that builds the whole network by stacking several residual units, DenseNet consists of multiple dense blocks. Wang et al. [24] further improve DenseNet by using two-way dense layers to obtain different receptive fields. With limited extra computational cost, these model design choices solved bottlenecks existed in ConvNets and are still widely used in both academia and industry.

Our proposed cross attention is similar to the works above in that it reuses existing intermediate results and introduces extra connections to the overall network structure. As experiments show, our work introduces similar benefits to transformer models such as better model performance and faster model convergence.

2.4. Cross attention transformers

In transformers, cross attention is usually used to mix two different embedding sequences. In [23, 6], the output of encoder is fed to decoder via cross attention. CrossViT [1] mixes small-patch and large-patch tokens with cross attention to extract multi-scale features.

Our proposed CabViT shares the basic idea of integrating information with cross attention and uses it to enhances the interactions of tokens on potentially different semantic levels.

3. The proposed CabViT

3.1. CabViT block and CabViT stage

Fig.2 shows the major parts and connection relations of a CabViT stage which consists of L CabViT blocks. Each CabViT block is composed of three major parts, which are named multi-head attention (MHA), token merge and enhancement (TME), and feed forward network (FFN) respectively.

**MHA.** Different from the standard ViT block, our proposed CabViT block receives two sets of tokens as input. The block in turn generates two sets of tokens as well, which are denoted as \(x_l\) and \(\bar{x}_l\) respectively. Taking the block at depth \(l\) as an example, the inputs are the regular features from its previous block \(x_{l-1}\) and a set of block digest tokens \((\bar{x}_{l-2}, \bar{x}_{l-3}, \ldots, \bar{x}_1)\) from earlier blocks in the stage.

The **MHA** takes both \(x_{l-1}\) and \((\bar{x}_{l-2}, \bar{x}_{l-3}, \ldots, \bar{x}_1)\) as input, but only generates \(n\) tokens \(y_l^s\) as its output. Specifically, given the inputs above, the query, key, and value for multi-head attention modules are constructed as follows:

\[
Q = W^Q x_{l-1} \\
K = W^K [x_{l-1}, (1\alpha^T) \odot (\bar{x}_{l-2}, \ldots, \bar{x}_1)] \\
V = W^V [x_{l-1}, (1\alpha^T) \odot (\bar{x}_{l-2}, \ldots, \bar{x}_1)]
\]

where \(W^K, W^V, W^Q\) are the three weight matrices transforming input into key, value and query tokens respectively. Elements in \(\alpha\in \mathbb{R}^{s\times 1}\) are the learnable scale factors for digest tokens and \(\odot\) denotes the element-wise multiplication where each token in \(\bar{x}\) is multiplied by a corresponding scaling scalar in \(\alpha\). \(s\) is the stride size in the depth wise convolutions that will be introduced shortly.

The computed \(Q, K, V\) are then connected to the standard dot product attention operators as in the original transformer [23], which computes the globally mixed intermediate tokens \(y_l^s\).
Token merge branch

Token enhance branch

Figure 3: The detailed structure of the token merge and enhancement (TME) module.

\[ y_l^l = x_{l-1}^l + W^P \left[ \text{softmax} \left( \frac{QK^T}{\sqrt{d}} + B \right) V \right] \] (4)

The \( B \) in Eqn.4 is a learnable matrix consisting of two parts, which are relative position bias for \( x \) and relative depth bias for \( \bar{x} \). The query has only \( n \) tokens, so the output \( y^l \) is of size \( n \times d \).

TME. The intermediate tokens \( y^l \) are then passed to the added token merge and enhancement (TME) part, which computes the digest tokens \( \bar{x}^l \) and locally enhanced tokens \( z^l \) using two separate depthwise convolutions. As shown in Fig 3, our TME has two branches. In the token merge branch, we use a large kernel \((7 \times 7)\) large stride \((s = 4)\) depthwise convolution to generate \( \bar{x}^l \), resulting in a small number of tokens to be used by subsequent blocks. In token enhancement branch, a standard depth wise convolution \((3 \times 3, s = 1)\) is used to locally mix the tokens so as to enhance the 2d spatial relations in the token sequence.

FFN. The locally enhanced tokens \( z^l \) are then used in the standard FFN part of ViT to compute the output token \( x^l \), which together with \( \bar{x}^l \) are the entire output of a CabViT block at depth \( l \).

In summary, our CabViT are different from vanilla ViT in the following ways:

- **Asymmetric input and output.** In our CabViT, MHA part takes both regular tokens and digest tokens as input but keep the output sequence length fixed to \( n \) as in regular transformers. This is the key point that why our proposed CabViT only introduce limited extra computational cost. More details are explained in section 3.3.

- **Digest token scale.** It is worth noting that the digest tokens are scaled by a learned calibration factor \( \alpha \) before they are used in the multi-head attention. We believe that the characteristics of tokens in different semantic levels (different blocks) are different. Without this calibration operation, digest tokens are hard to integrate to regular tokens in current blocks to work as we expected. A visual comparison shows this phenomenon in ablation study part.

- **Relative depth embedding.** In the MHA part, we choose to use relative positional encoding instead of absolute ones. Apart from its generally better performance, the choice also gives model the flexibility to encode relative depth of the digest tokens, which simplifies the model design.

3.2. CabViT Models

The CabViT block is a generic block that can be grouped as CabViT stages to construct models. To demonstrate the universal effectiveness of our new attention pattern, we build two types of CabViT based models, each falls into one of the major categories of transformer related computer vision models as described in Sec. 2. The overall structure of these models for classification task are illustrated in Fig.4.

- **CabViT-P.** As shown in Fig 4 (a), following the style of vanilla ViT, we construct our plain CabViT model (denoted as CabViT-P). The model essentially uses one block of CabViT after the patch embedding layer that crops \( 16 \times 16 \) patches and converts them into a token sequence. The corresponding task related head is kept unchanged compared with the original ViT model.

- **CabViT-H.** As illustrated in Fig 4 (b). Following the trend of combining ConvNet structures and transformer structures to build hybrid models, we also propose to build hybrid CabViT models, denoted as CabViT-H in the experiments. Following LeViT [7] and ViT-C[28], we adopt
In vision transformer model families, the FFN part actually constitutes the majority of computations. This is paradoxical to the fact that MHA scales at $O(n^2)$ while FFN scales at $O(1)$, largely because that the neglected constant token size $d$ in big O analysis is rather large and scales poorly. Fig. 5 details the exact adds and multiplications (FLOPs) of a standard ViT block in terms of the number of tokens $n$ and the dimension of tokens $d$. Taking the transformer block DeiT-Tiny as an example, because $n = 196$ and $d = 192$ are at the same scale, the $2n^2d$ FLOPs in MHA is much less compared with that $(8nd^2)$ of FFN (15% vs 56% respectively). For models in pyramid shapes such as swin transformers where $n < d$, the majority skews even more towards FFN because of the local windowing effect. Compared with the reference models, our CabViT variants only introduce about 13% extra computational cost.

It looks like that the proposed CabViT is heavier than its reference model as it introduces extra computations. However, the counter-intuitive fact is that CabViT can be more light-weight than its reference model. As is mentioned in introduction, CabViT reuses tokens from previous blocks, enhances interaction of tokens across blocks and improve information flow. Compared with the vanilla ViT, CabViT has better parameter efficiency. Therefore, CabViT can get comparable or even better performance with fewer layers and channels. Our experiments further verifies this advantage.

In addition to the detailed analysis above, we want to point out that the prior efforts to sparsify the attention patterns spatially in Sec. 2.1 and our proposal to densify the attention patterns across semantic levels are complementary to each other. While not the key emphasis of this paper, it is definitely worth exploring if the two types of designs can be combined to yield even more efficient and performant models.

4. Experiments

In this section, we conduct image classification experiments on ImageNet-1K [2], and semantic segmentation experiments on ADE20K [29] to evaluate our proposed models. We first compare the proposed CabViTs with our baseline and the previous SOTA methods. Then, we conduct detailed study to show the effectiveness of our design choices.

4.1. ImageNet classification

Experiment settings. The CabViT-P is implemented based on code of DeiT \(^1\). The CabViT-H models are implemented based on code of ConvNext \(^2\) and Swin \(^3\). We follow the training recipes in DeiT [21] to train our CabViT-P.

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1. https://github.com/facebookresearch/deit
2. https://github.com/facebookresearch/ConvNeXt
3. https://github.com/microsoft/Swin-Transformer
Table 1: Comparison with baselines. The plain version CabViT-P is based on DeiT-T. The hybrid ViT CabViT-H models are based on ConvNext and Swin Transformers.

| Models            | # params. (M) | FLOPs (G) | Top1 acc (%) |
|-------------------|---------------|-----------|--------------|
| DeiT-T            | 5.5           | 72.2      |
| CabViT-P-L0       | 5.9           | 74.3      |
| ConvNext-T (× 0.5)| 7.4           | 1.2       | 77.5         |
| Swin-2G           | 12.8          | 2.0       | 79.2         |
| CabViT-H-L1       | 6.2           | 1.5       | 80.3         |
| ConvNext-T        | 29            | 4.5       | 82.1         |
| Swin-T            | 29            | 4.5       | 81.3         |
| CabViT-H-L2       | 16.3          | 3.9       | 83.0         |

Comparison with baselines. The results are summarized in Table 1, from which we can see that both types of our proposed CabViT models outperform their reference models by a significant margin. Compared with DeiT-T, CabViT-P-L0 does have 0.4 M more parameters, but it achieves 2.1% higher accuracy. Our CabViT-H models achieve better performance in all three metrics: accuracy, model size, and computational cost. CabViT-H-L1 achieves 80.3% top-1 accuracy with about 6.2 million parameters and 1.5 billion FLOPs, saving about half parameters and 25% computational cost but gaining 1.1% higher accuracy compared with similarly sized Swin-2G. CabViT-H-L1 also has good scalability. The scaled up version CabViT-H-L2 outperforms the ConvNext by 0.9% with 13% less computational cost and 44% fewer parameters. CabViT-H-L2 also surpasses Swin-T by 1.7% while using fewer parameters and less computation.

In summary, our proposed CabViT design universally improves performances of both plain version and hybrid ViT models without increasing too much extra computation cost or even saving parameters and FLOPs.

Comparison with other models. In Table 2, we make a comparison with other models proposed in recent two years. Compared to the latest state-of-the-arts, including ConvNets, ViTs and Hybrid models, our proposed CabViT models achieve the best accuracy under the condition of having similar model sizes. In addition, the proposed models beat models strengthened by knowledge distillation in classification accuracy.

Specifically, CabViT-H-L1 outperforms MobileOne and EdgeNext by 0.9% in classification accuracy, while keeping comparable or smaller model size and fewer computational cost. Among models having about 25 million parameters, CabViT-H-L2 achieves the highest classification
| Method  | Backbone   | mIOU | # params. | FLOPs |
|---------|------------|------|-----------|-------|
| DANet   | ResNet-101 | 45.2 | 69        | 1119  |
| DpLab.v3+ | ResNet-101 | 44.1 | 63        | 1021  |
| ACNet   | ResNet-101 | 45.9 | -         | -     |
| DNL     | ResNet-101 | 46.0 | 69        | 1249  |
| OCRNet  | ResNet-101 | 45.3 | 56        | 923   |
| UperNet | ResNet-101 | 44.9 | 86        | 1029  |
| UperNet | Swin-T     | 46.1 | 60        | 945   |
| UperNet | ConvNext-T | 46.7 | 60        | 939   |
| UperNet | CabViT-H-L2 | 46.7 | 46        | 730   |

Table 3: Semantic segmentation on the ADE20K dataset. We use UperNet as our segmentation method and compare our performance using the same method with other popular backbones.

accuracy with the fewest parameters. Compared with Next-ViT-S which achieves the second highest accuracy, CabViT-H-L2 saves about half parameters and 32% computational cost, while gaining 0.5 percentage points higher accuracy. Also, note that both EfficientFormer-L3 and LeViT-256 are trained with knowledge distillation, which has been verified to improve accuracy significantly [21]. Even so, CabViT-H-L2 still has better accuracy and smaller model size compared with these two models.

4.2. Semantic segmentation

**Training setting.** To evaluate the proposed CabViTs on downstream tasks. We apply them on the ADE20K semantic segmentation task. Following Swin and ConvNext, we adopt UperNet [27] as our base framework and implement segmentation experiments on mmseg⁴. CabViT-H-L2 is trained for 160K iterations with a batch size of 16. Model pretrained on ImageNet-1K is used to initialize segmentation model. More details are presented in supplementary materials.

**Comparison with baselines.** The results are summarized in Tab.3, compared with Swin-T, CabViT-H-L2 achieves 0.6% higher mIoU. Compared with ConvNext-T, CabViT-H-L2 has no advantage in mIoU but saves about a quarter parameters and computational cost. Compared with Swin-T and ConvNext-T, the last two stages of CabViT-H-L2 are narrower (384 vs 320, 768 vs 480). Correspondingly, the segmentation head for CabViT-H-L2 is also narrower, which saves parameters and computation, but may harm the final result. We suspect introducing a bridge such as point wise conv may solve this problem, and will investigate this direction in our future work.

4.3. Ablation study

In this section, we conduct ablation analysis on components proposed in our CabViT.

⁴https://github.com/open-mmlab/mmsegmentation

Effects of the digest token scale factor. Fig 6 shows the attention score maps of several CabViT blocks trained with and without digest token scale factors. It can be seen that without this factor, the attention between digest tokens and regular tokens are generally weak, and become weaker as the depth goes deeper (down on the figure). This verifies our hypothesis that characteristics of tokens in different levels can be very different. Comparing the two columns of attention maps, it clearly shows that the scale factor helps increasing the correlation between regular tokens and the digest tokens, thus encourages the reuse of previously generated tokens.
| Steps | Models       | Model differences                                      | # Param. (M) | FLOPs (G) | Top1 acc (%) |
|-------|--------------|--------------------------------------------------------|-------------|-----------|--------------|
| 0     | ConvNext-T   | Baseline.                                              | 29          | 4.5       | 82.1         |
| 1     | ConvNext-T \times 0.5 | Reduce channel width to half.                          | 7.4         | 1.06      | 77.5         |
| 2     | ConvSwin     | Replace last two stages with swin                      | 10.5        | 1.38      | 79.2         |
| 3     | ConvViT      | Replace window attention with global. attention        | 10.5        | 1.47      | 79.8         |
| 4     | ConvViT      | Cross attention among blocks.                          | 10.5        | 1.52      | 79.9         |
| 5     | ConvViT      | Add learnable scale factors.                           | 10.5        | 1.52      | 80.3         |
| 6     | CabViT-H-L1  | Reduce width and depth, and add TME.                   | 6.2         | 1.46      | 80.3         |
| 7     | CabViT-H-L2  | Scale up.                                              | 16.3        | 3.9       | 83.0         |

Table 4: Ablation study on Imagenet-1K. Steps 1-7 shows the process of deriving our CabViT-H models from the ConvNext-T.

**Faster convergence.** We show the loss curves of several models in Fig 7, which verifies our claim that our model converges faster. Compared with ConvNext, ConvSwin loss drops slower in the first 25 epochs but has lower final loss. Similarly, ConvViT also does not drop fast in early stage. Benefiting from dense connection design, the loss of our CabViT-H is always the lowest.

**From baseline to CabViT-Hs.** The high performance of CabViT-H models are based on two key points, 1) combining strengths of ConvNets and ViTs; 2) dense but not heavy cross block attention design. Table 4 displays the process of how we integrate the two key points in designing our models. Step 1 provides a baseline micro model to speed up experiments. Step 2 uses the simplest way to build a hybrid model, which inherits some advantages of ConvNets and ViTs, achieving promising performance. In step 3, based on computational complexity analysis in section 3.3, window attention is replaced with global attention, which improves 0.6% accuracy while introducing very limited extra cost. Step 4 attempts to add cross attention among blocks without adjusting digest tokens, which slightly improves performance. Step 5 adopts learnable scale factors to adjust digest tokens and improves by 0.4%. Up to now, the modified model outperforms our baseline by 2.8%, at the cost of more parameters and higher computational cost compared with baseline. Step 6 introduces TME module to enhance models and also reduces width and depth to get a light weight model. Benefiting from TME module, the new light weight model has fewer parameters and acceptable computational cost, while keeping high accuracy. Finally, we scale up the light weight model and get CabViT-H-L2, which achieves the best trade-off between accuracy, model size and computational cost in its model size class.

**4.4. Inference speed comparison**

Here, we compare our model with other two recently proposed hybrid models to verify its inference efficiency. As shown in Fig 8, EfficientFormer-L3 and CabViT-H-L2 achieve faster speed compared with NextViT. EfficientFormer-L3 and our model have similar computational cost, but our CabViT-H-L2 has faster speed. Benefiting from the cross attention design has better parameter efficiency, CabViT-H-L2 is build with fewer layers and channels. We conjecture this is the main reason that why CabViT-H-L2 has faster speed than EfficientFormer-L3. From CabViT-H-L2 to EfficientFormer-L3, inference speed drops by 57.5%, 11.6% and 11.0% on three devices.

**5. Discussions**

In this paper, we present a new type of attention patterns in transformer based models for computer vision. The new pattern reuses existing tokens from previous blocks to create attentions across potentially different semantic levels, and is proved to be effective in different model scales and different vision tasks. For future directions, we propose to further mix the design with prior work that sparsify spatial attention patterns, which may produce even more efficient model backbones for various applications.

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