MetaFormer Baselines for Vision

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https://github.com/sail-sg/metaformer

Abstract

MetaFormer, the abstracted architecture of Transformer, has been found to play a significant role in achieving competitive performance. In this paper, we further explore the capacity of MetaFormer, again, by migrating our focus away from the token mixer design: we introduce several baseline models under MetaFormer using the most basic or common mixers, and demonstrate their gratifying performance. We summarize our observations as follows:

- (1) **MetaFormer ensures solid lower bound of performance**. By merely adopting identity mapping as the token mixer, the MetaFormer model, termed *IdentityFormer*, achieves >80% accuracy on ImageNet-1K.
- (2) MetaFormer works well with arbitrary token mixers. When specifying the token mixer as even a random matrix to mix tokens, the resulting model *RandFormer* yields an accuracy of >81%, outperforming IdentityFormer. Rest assured of MetaFormer's results when new token mixers are adopted.
- (3) MetaFormer effortlessly offers state-of-the-art results. With just conventional token mixers dated back five years ago, the models instantiated from MetaFormer already beat state of the art.
 - (a) ConvFormer outperforms ConvNeXt. Taking the common depthwise separable convolutions as the token mixer, the model termed ConvFormer, which can be regarded as pure CNNs, outperforms the strong CNN model ConvNeXt.
 - (b) CAFormer sets new record on ImageNet-1K. By simply applying depthwise separable convolutions as token mixer in the bottom stages and vanilla selfattention in the top stages, the resulting model CAFormer sets a new record on ImageNet-1K: it achieves an accuracy of 85.5% at 224 × 224 resolution, under normal supervised training without external data or distillation.

In our expedition to probe MetaFormer, we also find that a new activation, *StarReLU*, reduces 71% FLOPs of activation compared with commonly-used GELU yet achieves better performance. Specifically, StarReLU is a variant of Squared ReLU dedicated to alleviating distribution shift. We expect StarReLU to find great potential in MetaFormer-like models alongside other neural networks.

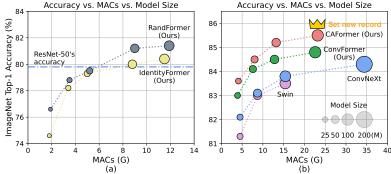


Figure 1: **Performance of MetaFormer baselines and other state-of-the-art models on ImageNet-1K at** 224^2 **resolution.** The architectures of our proposed models are shown in Figure 2. (a) IdentityFormer/RandFormer achieve over 80%/81% accuracy, indicating MetaFormer has solid lower bound of performance and works well on arbitrary token mixers. The accuracy of well-trained ResNet-50 [24] is from [75]. (b) Without novel token mixers, pure CNN-based ConvFormer outperforms ConvNeXt [46], while CAFormer sets a new record of 85.5% accuracy on ImageNet-1K at 224^2 resolution under normal supervised training without external data or distillation.

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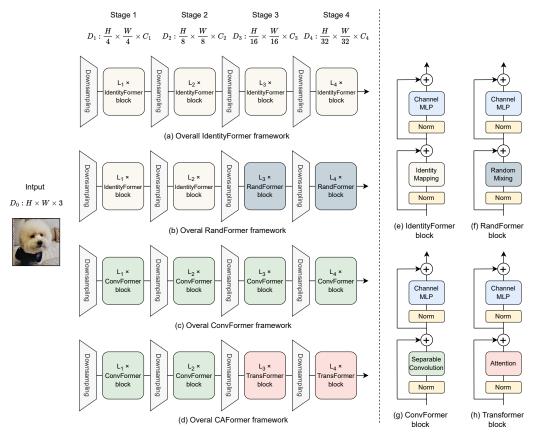


Figure 2: (a-d) Overall frameworks of IdentityFormer, RandForemr, ConvFormer and CAFormer. Similar to [24, 73, 45], the models adopt hierarchical architecture of 4 stages, and stage i has L_i blocks with feature dimension D_i . Each downsampling module is implemented by a layer of convolution. The first downsampling has kernel size of 7 and stride of 4, while the last three ones have kernel size of 3 and stride of 2. (e-h) Architectures of IdentityFormer, RandForemr, ConvFormer and Transformer blocks, which have token mixer of identity mapping, global random mixing (Equation 15), separable depthwise convolutions [9, 48, 59] (Equation 16) or vanilla self-attention [72], respectively.

1 Introduction

In recent years, Transformers [72] have demonstrated unprecedented success in various computer vision tasks [5, 17, 4, 86]. The competence of Transformers has been long attributed to its attention module. As such, many attention-based token mixers [82, 21, 73, 45, 88] have been proposed in the aim to strengthen the Vision Transformers (ViTs) [17]. Nevertheless, some work [66, 36, 85, 22, 56] found that, by replacing the attention module in Transformers with simple operators like spatial MLP [66, 67, 65] or Fourier transform [36], the resultant models still produce encouraging performance.

Along this line, the work [81] abstracts Transformer into a general architecture termed *MetaFormer*, and hypothesizes that it is MetaFormer that plays an essential role for models in achieving competitive performance. To verify this hypothesis, [81] adopts embarrassingly simple operator, pooling, to be the token mixer, and discovers that *PoolFormer* effectively outperforms the delicate ResNet/ViT/MLP-like baselines [24, 75, 17, 68, 73, 66, 67, 42], which confirms the significance of MetaFormer.

In this paper, we make further steps exploring the boundaries of MetaFormer, through, again, deliberately taking our eyes off the token mixers. Our goal is to push the limits of MetaFomer, based on which we may have a comprehensive picture of its capacity. To this end, we adopt the most basic or common token mixers, and study the performance of the resultant MetaFormer models on the large-scale ImageNet-1K image classification. Specifically, we examine the token mixers being bare

operators such as identity mapping or global random mixing, and being the common techniques dated back years ago such as separable convolution [9, 48, 59] and vanilla self-attention [72], as shown in Figure 2. We summarize our key experimental results in Figure 1, and our main observations are as follows.

- MetaFormer secures solid lower bound of performance. By specifying the token mixer to be the plainest operator, identity mapping, we build a MetaFormer model termed *IdentityFormer* to probe the performance lower bound. This crude model, surprisingly, already achieves gratifying accuracy. For example, with 73M parameters and 11.5G MACs, IdentityFormer attains top-1 accuracy of 80.4% on ImageNet-1K. Results of IdentityFormer demonstrate that MetaFormer is indeed a dependable architecture that ensures a favorable performance, even when the lowest degree of token mixing is involved.
- MetaFormer works well with arbitrary token mixers. To explore MetaFormer's universality to token mixers, we further cast the token mixer to be random, with which the message passing between tokens is enabled but largely arbitrary. Specifically, we equip the token mixers with random mixing in the top two stages and preserve the identity mapping in the bottom two stages, to avoid bringing excessive computation cost and frozen parameters. The derived model, termed *RandFormer*, turns out to be efficacious and improves IdentityFormer by 1.0%, yielding an accuracy of 81.4%. This result validates the MetaFormer's universal compatibility with token mixers. As such, please rest assured of MetaFormer's performance when exotic token mixers are introduced.
- MetaFormer effortlessly offers state-of-the-art performance. We make further attempts by injecting more informative operators into MetaFormer to probe its performance. Again, without introducing novel token mixers, MetaFormer models equipped with "'old-fashioned" token mixers invented years ago, including inverted separable convolutions [9, 48, 59] and vanilla self-attention [72], readily delivers state-of-the-art results. Specifically,
 - ConvFormer outperforms ConvNeXt. By instantiating the token mixer as separable depthwise convolutions, the resultant model, termed *ConvFormer*, can be treated as a pure-CNN model without channel or spatial attention [28, 76, 72, 17]. Experiments results showcase that ConvFormer consistently outperforms the strong pure-CNN model ConvNeXt [46].
 - CAFormer sets new record on ImageNet-1K. If we are to introduce attention into ConvFormer by even adopting the vanilla self-attention [72], the derived model, termed CAFormer, readily yields record-setting performance on ImageNet-1K. Specifically, CAFormer replaces the token mixer of ConvFormer in the top two stages with vanilla self-attention, and hits a new record of 85.5% top-1 accuracy at 224² resolution on ImageNet-1K under the normal supervised setting (without extra data or distillation).

These MetaFormer models, with most basic or commonly-used token mixers, readily serve as dependable and competitive baselines for vision applications. When delicate token mixers or advanced training strategies are introduced, we will not be surprised at all to see the performance of MetaFormer-like models hitting new records.

Along our exploration, we also find that a new activation, *StarReLU*, largely reduces the activation FLOPs up to 71%, when compared with the commonly-adopted GELU. StarReLU is a variant of Squared ReLU, but particularly designed for alleviating distribution shifts. In our experiments, specifically, StarReLU outperforms GELU by 0.3%/0.2% accuracy on ConvFormer-S18/CAFormer-S18, respectively. We therefore expect StarReLU to find great potential in MetaFormer-like models alongside other neural networks.

2 Method

2.1 Recap the concept of MetaFormer

The concept MetaFormer [81] is a general architecture instead of a specific model, which is abstracted from Transformer [72] by not specifying token mixer. Specifically, the input is first embedded as a sequence of features (or called tokens) [72, 17]:

$$X = \text{InputEmbedding}(I). \tag{1}$$

Then the token sequence $X \in \mathbb{R}^{N \times C}$ with length N and channel dimension C is fed into repeated MetaFormer blocks, one of which can be expressed as

$$X' = X + \text{TokenMixer}\left(\text{Norm}_1(X)\right),\tag{2}$$

$$X'' = X' + \sigma \left(\text{Norm}_2(X') W_1 \right) W_2, \tag{3}$$

where $\operatorname{Norm}_1(\cdot)$ and $\operatorname{Norm}_2(\cdot)$ are normalizations [31, 1]; TokenMixer(·) means token mixer mainly for propagating information among tokens; $\sigma(\cdot)$ denotes activation function; W_1 and W_2 are learnable parameters in channel MLP. By specifying token mixers as concrete modules, MetaFormer is then instantiated into specific models.

2.2 Techniques to improve MetaFormer

This paper does not introduce complicated token mixers. Instead, we introduce a new activation StarReLU and other two modifications [60, 55, 10] to improve MetaFormer.

2.2.1 StarReLU

In vanilla Transformer [72], ReLU [49] is chosen as the activation function that can be expressed as

$$ReLU(x) = \max(0, x), \tag{4}$$

where x denotes any one neural unit of the input. This activation costs 1 FLOP for each unit. Later, GPT [53] uses GELU [25] as activation and then many subsequent Transformer models (e.g., BERT [14], GPT-3 [3] and ViT [17]) employ this activation by default. GELU can be approximated as,

GELU(x) =
$$x\Phi(x) \approx 0.5 \times x(1 + \tanh(\sqrt{2/\pi}(x + 0.044715 \times x^3))),$$
 (5)

where $\Phi(\cdot)$ is the Cumulative Distribution Function for Gaussian Distribution (CDFGD). Although revealing better performance than ReLU [62, 81], GELU approximately brings 14 FLOPs ¹, much larger then ReLU's 1 FLOP of cost. To simplify GELU, [62] finds that CDFGD can be replaced by ReLU.

$$SquaredReLU(x) = xReLU(x) = (ReLU(x))^{2}.$$
 (6)

This activation is called Squared ReLU [62], only costing 2 FLOPs for each input unit. Despite the simplicity of Squared ReLU, we find its performance can not match that of GELU for some models on image classification task as shown in Section 3.4. We hypothesize the worse performance may be resulted from the distribution shift of the output [34]. Assuming input x obeys normal distribution with mean 0 and variance 1, i.e. $x \sim N(0,1)$, we have:

$$E((ReLU(x))^2) = 0.5, \quad Var((ReLU(x))^2) = 1.25,$$
 (7)

where $E(\cdot)$ and $Var(\cdot)$ denote expectation and variance, respectively. See Appendix A.1 for the derivation process of Equation 7. Therefore the distribution shift can be solved by

$$\operatorname{StarReLU}(x) = \frac{\left(\operatorname{ReLU}(x)\right)^2 - \operatorname{E}\left(\left(\operatorname{ReLU}(x)\right)^2\right)}{\sqrt{\operatorname{Var}\left(\left(\operatorname{ReLU}(x)\right)^2\right)}} = \frac{\left(\operatorname{ReLU}(x)\right)^2 - 0.5}{\sqrt{1.25}}$$
(8)

$$\approx 0.8944 \cdot (\text{ReLU}(x))^2 - 0.4472.$$
 (9)

We name the above activation *StarReLU* as multiplications (*) is heavily used. However, the assumption of standard normal distribution for input is strong [34]. To make the activation adaptable to different situations, like different models or initialization, scale and bias can be set to be learnable [23, 8]. We uniformly re-write the activation as

$$StarReLU(x) = s \times (ReLU(x))^{2} + b, \tag{10}$$

where $s \in \mathbb{R}$ and $b \in \mathbb{R}$ are scalars of scale and bias respectively, which are shared for all channels and can be set to be constant or learnable to attain different StarReLU variants. StarReLU only costs 4 FLOPs (or 3 FlOPs with only s or b), much fewer than GELU's 14 FLOPs but achieving better performance as shown in Section 3.4. For convenience, we utilize StarReLU with learnable scale and bias as default activation in this paper as intuitively this variant can more widely adapt to different situations [23, 8]. We leave the study of StarReLU variant selection for different situations in the future.

¹tanh is counted 6 FLOPs for simplicity [71]

Algorithm 1 Token mixers of identity mapping and random mixing, PyTorch-like Code

```
import torch
import torch.nn as nn
# Identity mapping
from torch.nn import Identity
# Random mixing
class RandomMixing(nn.Module):
   def __init__(self, num_tokens=196):
       super(). init ()
       self.random_matrix = nn.parameter.Parameter(
          data=torch.softmax(torch.rand(num tokens, num tokens), dim=-1),
          requires_grad=False)
   def forward(self, x):
       B. H. W. C = x.shape
       x = x.reshape(B, H*W, C)
       x = torch.einsum('mn, bnc -> bmc', self.random_matrix, x)
       x = x.reshape(B, H, W, C)
       return x
```

2.2.2 Other modifications

Scaling branch output. To scale up Transformer model size from depth, [69] proposes *LayerScale* that multiplies layer output by a learnable vector:

$$X' = X + \lambda_l \odot \mathcal{F}(\text{Norm}(X)), \tag{11}$$

where $X \in \mathbb{R}^{N \times C}$ denotes the input features with sequence length N and channel dimension C, $\operatorname{Norm}(\cdot)$ is the normalization, $\mathcal{F}(\cdot)$ means the token mixer or channel MLP module, $\lambda_l \in \mathbb{R}^C$ represents the learnable LayerScale parameters initialized by a small value like 1e-5, and \odot means element multiplication. Similar to LayerScale, [89, 43, 60] attempt to stabilize architectures by scaling the residual branch (*ResScale* [60]):

$$X' = \lambda_r \odot X + \mathcal{F}(\text{Norm}(X)), \tag{12}$$

where $\lambda_r \in \mathbb{R}^C$ denotes learnable parameters initialized as 1. Apparently, we can merge the above two techniques into *BranchScale* by scaling all branches:

$$X' = \lambda_r \odot X + \lambda_l \odot \mathcal{F}(\text{Norm}(X)). \tag{13}$$

Among these three scaling techniques, we find ResScale performs best according to our experiments in Section 3.4. Thus, we adopt ResScale [60] by default in this paper.

Disabling biases. Following [55, 10], we disable the biases of fully-connected layers, convolutions (if have) and normalization in the MetaFormer blocks, finding it does not hurt performance and even can bring slight improvement for specific models as shown in the ablation study. For simplicity, we disable biases in MetaFormer blocks by default.

2.3 IdentityFormer and RandFormer

Following [81], we would like to instantiate token mixer as basic operators, to further probe the capacity of MetaFormer. The first one we considered is the identity mapping,

$$IdentityMapping(X) = X. (14)$$

Identity mapping does not conduct any token mixing, so actually, it can not be regarded as token mixer. For convenience, we still treat it as one type of token mixer to compare with other ones.

Another basic token mixer we utilize is global random mixing,

$$RandomMixing(X) = XW_R, (15)$$

where $X \in \mathbb{R}^{N \times C}$ is the input with sequence length N and channel dimension C, and $W_R \in \mathbb{R}^{N \times N}$ is a matrix that are frozen after random initialization. This token mixer will bring extra frozen parameters and computation cost quadratic to the token number, so it is not suitable for large token

Model		IdentityFormer	RandFormer	PoolFormerV2
	S12	C = (64)	(128, 320, 512), L =	=(2,2,6,2)
Size	S24	C = (64)	128, 320, 512, $L =$	=(4,4,12,4)
Size	S36	C = (64.64)	(128, 320, 512), L =	= (6, 6, 18, 6)
	M36	C = (96)	(192, 384, 768), L =	=(6,6,18,6)
	M48	C = (96)	(192, 384, 768), L =	=(8,8,24,8)
Token Mixer		$T = (\mathrm{Id}, \mathrm{Id}, \mathrm{Id}, \mathrm{Id})$	$T = (\mathrm{Id}, \mathrm{Id}, \mathrm{Rand}, \mathrm{Rand})$	T = (Pool, Pool, Pool, Pool)
Classifier Head			Global average pooling, N	orm, FC

Table 1: Model configurations of IdentityFormer, RandFormer and PoolFormerV2. "C", "L" and "T" means channel number, block number and token mixer type, respectively. "Id", "Rand" and "Pool" denotes token mixer of identity mapping, random mixing and pooling, respectively. The contents in the tuples represent the configurations in the four stages of the models.

Model		ConvFormer	CAFormer		
	S18	C = (64, 128, 320, 512),	L = (3, 3, 9, 3)		
Size	S36	C = (64, 128, 320, 512),	L = (3, 12, 18, 3)		
Size	M36	C = (96, 192, 384, 576),	L = (3, 12, 18, 3)		
	B36	C = (128, 256, 512, 768),	L = (3, 12, 18, 3)		
Token Mixer		T = (Conv, Conv, Conv, Conv)	T = (Conv, Conv, Attn, Attn)		
Classifier Head		Global average poo	oling, Norm, MLP		

Table 2: Model configurations of ConvFormer and CAFormer. "C", "L" and "T" means channel number, block number and token mixer type. "Conv" and "Attn" denotes token mixer of separable convolution and vanilla self-attention, respectively. The contents in the tuples represent the configurations in the four stages of the models.

number. The PyTorch-like code of the identity mapping and random mixing are shown in Algorithm 1.

To build the overall framework, we simply follow the 4-stage model [35, 24] configurations of PoolFormer [81] to build models of different sizes. Specifically, we specify token mixer as identity mapping in all four stages and name the derived model IdentityFormer. To build RandFormer, considering that the token mixer of random mixing will bring much extra frozen parameters and computation cost for long token length, we thus remain identity mapping in the first two stages but set global random mixing as token mixer in the last two stages.

To compare IdentityFormer/RandFormer with PoolFormer [81] fairly, we also apply the techniques mentioned above to PoolFormer and name the new model PoolFormerV2. The model configurations are shown in Table 1 and the overall frameworks are shown in Figure 2.

2.4 ConvFormer and CAFormer

The above section utilizes basic token mixers to probe the lower bound of performance and model universality in terms of token mixers. In this section, without designing novel token mixers, we just specify the token mixer as commonly-used operators to probe the model potential for achieving state-of-the-art performance. The first token mixer we choose is depthwise separable convolution [9, 48]. Specifically, we follow the inverted separable convolution module in MobileNetV2 [59],

$$Convolutions(X) = Conv_{pw2}(Conv_{dw}(\sigma(Conv_{pw1}(X)))), \tag{16}$$

where $\operatorname{Conv_{pw1}}(\cdot)$ and $\operatorname{Conv_{pw2}}(\cdot)$ are pointwise convolutions, $\operatorname{Conv_{dw}}(\cdot)$ is the depthwise convolution, and $\sigma(\cdot)$ means the non-linear activation function. The PyTorch-like code of this module is shown in Algorithm 2 in the appendix. In practice, we set the kernel size as 7 following [46] and the expansion ratio as 2. We instantiate the MetaFormer as $\operatorname{ConvFormer}$ by specifying the token mixers as the above separable convolutions. ConvFormer also adopts 4-stage framework [24, 73, 45] (Figure 2) and the model configurations of different sizes are shown in the Table 2.

Besides convolutions, another common token mixer is vanilla self-attention [72] used in Transformer. This global operator is expected to have better ability to capture long-range dependency. However, since the computational complexity of self-attention is quadratic to the number of tokens, it will be cumbersome to adopt vanilla self-attention in the first two stages that have many tokens. As a

Model	Params (M)	MACs (G)	Top-1 (%)
RSB-ResNet-18 [24, 75]	11.7	1.8	70.6
IdentityFormer-S12	11.9	1.8	74.6
RandFormer-S12	11.9 + <u>0.2</u>	1.9	76.6
PoolFormerV2-S12 [81]	11.9	1.8	78.0
RSB-ResNet-34 [24, 75]	21.8	3.7	75.5
IdentityFormer-S24	21.3	3.4	78.2
RandFormer-S24	21.3 + 0.5	3.5	78.8
PoolFormerV2-S24 [81]	21.3	3.4	80.7
RSB-ResNet-50 [24, 75]	25.6	4.1	79.8
IdentityFormer-S36	30.8	5.0	79.3
RandFormer-S36	30.8 + 0.7	5.2	79.5
PoolFormerV2-S36 [81]	30.8	5.0	81.6
RSB-ResNet-101 [24, 75]	44.5	7.9	81.3
IdentityFormer-M36	56.1	8.8	80.0
RandFormer-M36	56.1 + 0.7	9.0	81.2
PoolFormerV2-M36 [81]	56.1	8.8	82.2
RSB-ResNet-152 [24, 75]	60.2	11.6	81.8
IdentityFormer-M48	73.3	11.5	80.4
RandFormer-M48	73.3 + 0.9	11.9	81.4
PoolFormerV2-M48 [81]	73.3	11.5	82.6

Table 3: Performance on ImageNet-1K of RSB-ResNet and MetaFormer models with basic tokens of identity mapping, random maxing and pooling. The underlined numbers mean the numbers of parameters that are frozen after random initialization.

comparison, convolution is a local operator with computational complexity linear to token length. Inspired by [4, 17, 12, 81], we adopt 4-stage framework and specify token mixer as convolutions in the first two stages and attention in the last two stages to build *CAFormer*, as shown in Figure 2. See Table 2 for model configurations of different sizes.

3 Experiments

3.1 Setup

ImageNet-1K [13] image classification is utilized to benchmark these baseline models. ImageNet-1K is one of the most widely-used datasets in computer vision which contains about 1.3M images of 1K classes on training set, and 50K images on validation set. For ConvFormer-B36 and CAFormer-B36, we also conduct pre-training on ImageNet-21K [13, 58], a much larger dataset containing \sim 14M images of 21841 classes, and then fine-tune the pretrained model on ImageNet-1K for evaluation. Our implementation is based on PyTorch library [50] and Timm codebase [74] and the experiments are run on TPUs.

Training and fine-tuning on ImageNet-1K. We mainly follow the hyper-parameters of DeiT [68]. Specifically, models are trained for 300 epochs at 224^2 resolution. Data augmentation and regularization techniques include RandAugment [11], Mixup [84], CutMix [83], Random Erasing [87], weight decay, Label Smoothing [63] and Stochastic Depth [30]. We do not use repeated augmentation [2, 26] and LayerScale [69], but use ResScale [60] for the last two stages. We adopt AdamW [33, 47] optimizer with batch size of 4096 for most models except CAFormer since we found it is not stable to train CAFormer under this setting. The problem may be caused by the large batch size, so we use a large-batch-size-friendly optimizer LAMB [80] for CAFormer. For 384^2 resolution, we fine-tune the models trained at 224^2 resolution for 30 epochs with Exponential Moving Average (EMA) [52]. The details of hyper-parameters are shown in Table 7 and 8 of the appendix.

Pre-training on ImageNet-21K and fine-tuning on ImageNet-1K. To probe the scaling capacity with a larger dataset, we pre-train ConvFormer-B36 and CAFormer-B36 on ImageNet-21K for 90 epochs at the resolution of 224². Then the pre-trained models are fine-tuned on ImageNet-1K at the

Testing at resolution							
	Meta-	Mixing	Params (M)	@224 \ \^384			
Model	Former	Type		MACs	Top-1	MACs	Top-1
	Tormer	13 pc	(111)	(G)	(%)	(G)	(%)
RSB-ResNet-50 [24, 75]	Х	Conv	26	4.1	79.8	-	
RegNetY-4G [54, 75]	X	Conv	21	4.0	81.3	_	_
ConvNeXt-T [46]	X	Conv	29	4.5	82.1	_	_
VAN-B2 [19]		Conv	27	5.0	82.8	_	_
ConvFormer-S18	/	Conv	27	3.9	83.0	11.6	84.4
DeiT-S [68]	/	Attn	$-\frac{27}{22}$	4.6	$-\frac{35.5}{79.8}$		
T2T-ViT-14 [82]	/	Attn	22	4.8	81.5	17.1	83.3
Swin-T [45]	/	Attn	29	4.5	81.3	-	-
CSWin-T [16]	/	Attn	23	4.3	82.7	_	_
MViTv2-T [40]	/	Attn	24	4.7	82.3	_	_
CoAtNet-0 [12]	/	Conv + Attn	25	4.2	81.6	13.4	83.9
UniFormer-S [37]	/	Conv + Attn	22	3.6	82.9	-	-
iFormer-S [61]	/	Conv + Attn	20	4.8	83.4	16.1	84.6
CAFormer-S18	1	Conv + Attn	26	4.1	83.6	13.4	85.0
RSB-ResNet-101 [24, 75]	X	Conv	45	7.9	81.3	-	-
RegNetY-8G [54, 75]	X	Conv	39	8.0	82.1	_	_
ConvNeXt-S [46]	X	Conv	50	8.7	83.1	_	-
VAN-B3 [19]	ĵ.	Conv	45	9.0	83.9	_	-
ConvFormer-S36	1	Conv	40	7.6	84.1	22.4	85.4
T2T-ViT-19 [82]		Attn	39	8.5	81.9		
Swin-S [45]	/	Attn	50	8.7	83.0	_	_
CSWin-S [16]	/	Attn	35	6.9	83.6	_	_
MViTv2-S [40]	/	Attn	35	7.0	83.6	_	_
CoAtNet-1 [12]	/	Conv + Attn	42	8.4	83.3	27.4	85.1
UniFormer-B [37]	/	Conv + Attn	50	8.3	83.9	27.4	05.1
CAFormer-S36	/	Conv + Attn	39	8.0	84.5	26.0	85.7
RSB-ResNet-152 [24, 75]	Х	Conv	60	11.6	81.8	20.0	-
RegNetY-16G [54, 75]	X	Conv	84	15.9	82.2	_	
ConvNeXt-B [46]	X	Conv	89	15.4	83.8	45.0	85.1
RepLKNet-31B [15]	1	Conv	79	15.3	83.5	45.1	84.8
VAN-B4 [19]	/	Conv	60	12.2	84.2	-	-
ConvFormer-M36	/	Conv	57	12.8	84.5	37.7	85.6
DeiT-B [68]	/	Attn	86	$-\frac{12.6}{17.5}$	81.8	55.4	$-\frac{83.0}{83.1}$
T2T-ViT-24 [82]	/	Attn	64	13.8	82.3	-	-
Swin-B [45]	/	Attn	88	15.4	83.5	47.1	84.5
CSwin-B [16]	/	Attn	78	15.4	84.2	47.1	85.4
MViTv2-B [40]	/	Attn	52	10.2	84.4	36.7	85.6
CoAtNet-2 [12]	/	Conv + Attn	75	15.7	84.1	49.8	85.7
MaxViT-S [70]	/	Conv + Attn	69	11.7	84.5	36.1	85.2
iFormer-L [61]	/	Conv + Attn	87	14.0	84.8	45.3	85.8
CAFormer-M36	/	Conv + Attn	56	13.2	85.2	42.0	86.2
RegNetY-32G [54, 75]	X	Conv	145	32.3	82.4	72.0	50.2
ConvNeXt-L [46]	X	Conv	198	34.4	84.3	101.0	85.5
ConvFormer-B36	7	Conv	100	22.6	84.8	66.5	85.7
MViTv2-L [40]	/	Attn	$-\frac{100}{218}$ -	$-\frac{22.0}{42.1}$	85.3	140.2	$-\frac{85.7}{86.3}$
CoAtNet-3 [12]	/	Conv + Attn	168	34.7	84.5	107.4	85.8
MaxViT-B [70]	/	Conv + Attn	120	23.4	85.0	74.2	86.3
CAFormer-B36	✓ ✓	Conv + Attn	99	23.4	85.5*	72.2	86.4
CATOINCI-D30	V	Conv + Aun	27	23.2	00.0	12.2	00.4

Table 4: **Performance of models trained on ImageNet-1K at the resolution of** 224^2 **and fine-tuned at** 384^2 . Model highlighted with blue background are proposed in this paper. The column "MetaFormer" denotes whether models adopt MetaFormer architecture (partially). * To the best of our knowledge, the model **sets a new record on ImageNet-1K** with the accuracy of 85.5% at 224^2 resolution under normal supervised setting (without external data or distillation), surpassing the previous best record of 85.3% set by MViTv2-L [40] with 55% fewer parameters and 45% fewer MACs.

resolution of 224^2 and 384^2 for 30 epochs with EMA [52]. See Table 9 in the appendix for more details of hyper-parameters.

3.2 Results of Models with basic token mixers

Table 3 shows the performance of models with basic token mixers on ImageNet-1K. Surprisingly, with bare identity mapping as token mixer, IdentityFormer already performs very well, especially for small model sizes. For example, IdentityFormer-S12/S24 outperforms RSB-ResNet-18/34 [24, 75] by 4.0%/2.7%, respectively. We further scale up the model size of IdentityFormer to see what accuracy it can achieve. By scaling up model size to \sim 73M parameters and \sim 12G MACs, IdentityFormer-M48 can achieve accuracy of 80.4%. Without considering the comparability of model size, this accuracy already surpasses 79.8% of RSB-ResNet-50. The results of IdentityFormer indicate that MetaFormer ensures solid lower bound of performance. The is to say, if you adopt MetaFormer as general framework to develop your own models, the accuracy will not be below 80% with similar parameter numbers and MACs of IdentityFormer-M48.

Another surprising finding is that by replacing token mixer of IdentityFormer with random mixing in the top two stages, RandFormer can consistently improve IdentityFormer. For example, RandFormer-S12/M48 obtains accuracy of 76.6%/81.4%, surpassing IdentityFormer-S12/M48 by 2.0%/1.0%, respectively. For medium and large model sizes, RandFormer can also achieve accuracy comparable to RSB-ResNet, like RandFormer-M36's 81.2% vs.RSB-ResNet-101's 81.3%. The promising performance of RandFormer, especially its consistent improvement over IdentityFormer, demonstrates MetaFormer can work well with arbitrary token mixers and validates MetaFormer's universal compatibility with token mixers. Therefore, rest assured of MetaFormer's performance when exotic token mixers are equipped.

Compared with PoolFormerV2 [81] with basic token mixer of pooling, neither of IdentityFormer nor RandFormer can match its performance. The worse performance of IdentityFormer makes sense as identity mapping does not conduct any token mixing. The performance gap between RandFormer and PoolFormerV2 may be resulted from the local inductive bias of pooling.

3.3 Results of models with commonly-used token mixers

We build ConvFormer by specifying the token mixer in MetaFormer as separable convolutions [9, 48] used in MobileNetV2 [59]. Meanwhile, CAFormer is built with token mixers of separable convolutions in the bottom two stages and vanilla self-attention in the top two stages. The results of models trained on ImageNet-1K are shown in Table 4.

ConvFormer actually can be regarded as pure CNN-based model without any attention mechanism [28, 76, 72, 17]. It can be observed that ConvFormer outperforms strong CNN model ConvNeXt [46] significantly. For example, at the resolution of 224², ConvFomer-B36 (100M parameters and 22.6G MACs) surpasses ConvNeXt-B (198M parameters and 34.4G MACs) by 0.5% top-1 accuracy while only requiring 51% parameters and 66% MACs. Also, ConvFormer outperforms various strong attention-based or hybrid models. For instance, ConvFormer-M36 outperforms Swin-B [45]/CoAtNet-2 [12] by 1.0%/0.4% with 35%/24% fewer parameters and 17%/18% fewer MACs.

Besides ConvFormer, CAFormer achieves more remarkable performance. Although CAFormer is just built by equipping token mixers of separable convolutions [9, 48, 59] in bottom stages and vanilla self-attention [72] in top stages, it already consistently outperforms other models in different sizes, as clearly shown in Figure 3. Remarkably, to the best of our knowledge, CAFormer sets new record on ImageNet-1K with top-1 accuracy of 85.5% at 224² resolution under normal supervised setting (without external data or distillation models).

When pre-trained on ImageNet-21K, the performance of ConvFormer-B36 and CAFormer-B36 surges to 87.0% and 87.4%, with 2.2% and 1.9% accuracy improvement compared with the results of ImageNet-1K training only. Both models keep superior to Swin-L [45]/ConvNeXt-L [46], showing the promising scaling capacity with a larger pre-training dataset. For example, ConvFormer-B36 outperforms ConvNeXt-L by 0.2% with 49% fewer parameters and 34% fewer MACs.

Just equipped with "old-fashioned" token mixers, ConvFormer and CAFormer instantiated from MetaForemr already can achieve remarkable performance, especially CAFormer sets a new record on ImageNet-1K. These results demonstrate MetaFormer can offer high potential for achieving

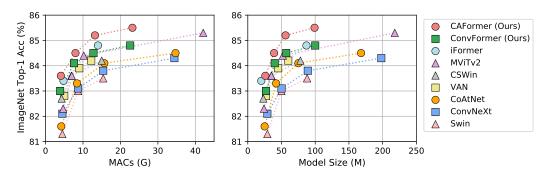


Figure 3: ImageNet-1K validation accuracy vs.MACs/Model Size at the resolution of 224^2 . Models with token (feature) mixing based on convolution, attention or hybrid are presented by \Box , \triangle or \bigcirc respectively.

				Testing at resolution			
Model	Meta-	Mixing	Params	@224		↑384	
Model	Former	Type	(M)	MACs	Top-1	MACs	Top-1
				(G)	(%)	(G)	(%)
Swin-L [45]	√	Attn	197	34.5	86.3	103.9	87.3
ConvNeXt-L [46]	X	Conv	198	34.4	86.8	101.0	87.5
ConvFormer-B36	✓	Conv	100	22.6	87.0	66.5	87.6
CAFormer-B36	✓	Conv + Attn	99	23.2	87.4	72.2	88.1

Table 5: **Performance of models pre-trained on ImageNet-21K and fine-tuned on ImageNet-1K for evaluation.** More ImageNet-21K pre-trained models of Convformer and CAFormer of other model sizes will release in the future.

state-of-the-art performance. When advanced token mixers or training strategies are introduced, we will not be surprised to see the performance of MetaFormer-like models setting new records. We expect ConvFormer and CAFormer as well as IdentityFormer and RandFormer to be dependable baselines for future neural architecture design.

3.4 Ablation

This paper does not design novel token mixers but utilizes three techniques to MetaFormer. Therefore, we conduct ablation study for them, respectively. ConvFormer-S18 and CAFormer-S18 on ImageNet-1K are taken as the baselines. When the StarReLU is replaced with ReLU [49], the performance of ConvFormer-S18/CAFormer significantly drops from 83.0%/83.6% to 82.1%/82.9%, respectively. When the activation is Squared ReLU [62], the performance is already satisfied. But for ConvFormer-18, it can not match that of GELU [25]. As for the StarReLU, it not only can reduce 71% activation FLOPs compared with GELU, but also achieves better performance with 0.3%/0.2% accuracy improvement for ConvFormer-S18/CAForemr-S18, respectively. This result expresses the promising application potential of StarReLU in MetaFormer-like models and other neural networks. We further observe the performance of different StarReLU variants on ConvFormer-S18. We adopt StarReLU with learnable scale and bias by default because it does not need to meet the assumption of standard normal distribution for input [34] and can be conveniently applied for different models and initialization [23, 8]. But for specific model ConvFormer-18, StarReLU with learnable or frozen bias is enough since it can already match the accuracy of the default StarReLU version. We leave the study of StarReLU variant selection in the future.

For other techniques, we find ResScale [60] performs best among the branch output scaling techniques; disabling biases [55, 10] in each block does not affect the performance for ConvFormer-S18 and can bring improvement of 0.1% for CAFormer-S18. We thus employ ResScale and disabling biases of each block by default.

Ablation	Variant	Top-1	(%)
Abiation	Variant	ConvFormer-S18	CAFormer-S18
_	Baseline	83.0	83.6
Activation	StarReLU → ReLU [49]	82.1	82.9
	StarReLU → Squared ReLU [62]	82.6	83.4
types	StarReLU → GELU [25]	82.7	83.4
	$\alpha \cdot (ReLU(x))^2 + \beta^*$		
	$\rightarrow \alpha \cdot (ReLU(x))^2$	82.6	83.6
StarReLU	$\rightarrow (ReLU(x))^2 + \beta$	83.0	83.5
variants	$\rightarrow 1/\sqrt{1.25} \cdot (ReLU(x))^2 - 0.5/\sqrt{1.25}$	83.0	83.5
	$\rightarrow 1/\sqrt{1.25} \cdot (ReLU(x))^2$	82.6	83.4
	$\rightarrow (ReLU(x))^2 - 0.5/\sqrt{1.25}$	83.0	83.3
Branch output	ResScale [60] \rightarrow None	82.8	83.2
	ResScale [60] \rightarrow LayerScale [69]	82.8	83.0
scaling	ResScale [60] \rightarrow BranchScale	82.9	83.3
Biases in each block	Disable biases of Norm, FC and Conv → Enable biases	83.0	83.5

Table 6: **Ablation for ConvFormer-S18/CAFormer-S18 on ImageNet-1K.** * α and β denotes learnable scalars shared for all channels.

4 Related work

Transformer, since being introduced in [72], has become a popular backbone for various tasks in NLP [53, 3, 44, 78, 55], computer vision [5, 17, 68, 82, 73, 45] and other domains [18, 51, 39, 32, 29, 38, 7]. In computer vision, iGPT [5] and ViT [17] introduce pure Transformer for self-supervised learning and supervised learning, attracting great attention in the research community to further improve Transformers. The success of Transformers had long been attributed to the attention module, and thus many research endeavors have been focused on improving attention-based token mixers [82, 73, 45]. However, it is shown in MLP-Mixer [66] and FNet [36] that, by replacing attention in Transformer with spatial MLP [65] and Fourier transform, the resulting models still deliver competitive results. Along this line, [81] abstracts the Transformer into a general architecture termed MetaFormer, and meanwhile proposes the hypothesis that, it is the MetaFormer that really plays a critical role in achieving promising performance. To this end, [81] specifies the token mixer to be as embarrassingly simple as pooling, and observes that the resultant model PoolFormer surpasses the well-tuned ResNet/ViT/MLP-like baselines [24, 75, 17, 68, 73, 66, 42, 67]. The power of MetaFormer can also be verified by the recent models adopting MetaFormer as the general architecture but with different attention-based [40, 57, 70], MLP-based [66, 67, 27, 6, 41], convolution-based [15, 19, 79, 56, 77], hybrid [61, 12, 37, 70] or other types of [64, 20] token mixers. Unlike these works, we do not attempt to introduce novel token mixers, but merely specify token mixers as the most basic or commonly-used operators to probe the capacity of MetaFormer.

5 Conclusion

In this paper, we make our exploration to study the capacity of MetaFormer, the abstracted architecture of Transformer. We take our eyes off the token-mixer design, and merely rely on the most basic or "old-fashioned" token mixers dated back years ago to build the MetaFormer models, namely IdentityFormer, RandFormer, ConvFormer, and CAFormer. The former two models, built upon identify mapping and randomized mixing, demonstrate the solid lower bound of MetaFormer and its universality to token mixers; the latter two models, built upon conventional separable convolutions and vanilla self-attention, readily offer recording-setting results. In our investigation, we also discover that a new activation, StarReLU, not only achieve better performance but also greatly reduces FLOPs of the activation function when compared with GELU. We expect MetaFormer to find its even boarder domain of vision applications in the future work, and cheerfully invite readers to try out the proposed MetaFormer baselines.

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A Appendix

A.1 Expectation and variance of Squared ReLU

Assuming the input x of Squared ReLU [62] (Equation 6) follows normal distribution with mean 0 and variance 1, i.e. $x \sim N(0, 1)$, we have:

$$E(x^2) = Var(x) = 1 \tag{17}$$

$$E((ReLU(x))^2) = \frac{1}{2}E(x^2) = 0.5$$
 (18)

$$E(x^4) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} z^4 \exp\left(-\frac{z^2}{2}\right) dz \tag{19}$$

$$= -\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} z^3 d\left(\exp\left(-\frac{z^2}{2}\right)\right) \tag{20}$$

$$= \left(-z^3 \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)\right) \Big|_{-\infty}^{+\infty} + 3 \int_{-\infty}^{+\infty} z^2 \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz \quad (21)$$

$$= 0 + 3E(x^2) = 3 (22)$$

$$E((ReLU(x))^4) = \frac{1}{2}E(x^4) = 1.5$$
 (23)

$$Var ((ReLU(x))^{2}) = E ((ReLU(x))^{4}) - (E ((ReLU(x))^{2}))^{2} = 1.5 - 0.5^{2} = 1.25$$
(24)

Thus, we can obtain the expectation $\mathrm{E}\left((\mathrm{ReLU}(x))^2\right)=0.5$ and variance $\mathrm{Var}\left((\mathrm{ReLU}(x))^2\right)=1.25$.

A.2 Code of separable convolution

Algorithm 2 shows the PyTorch-like code of inverted separable convolution from MobileNetV2 [59].

Algorithm 2 Token mixers of separable convolution, PyTorch-like Code

```
import torch
import torch.nn as nn
# Separable Convolution
class SepConv(nn.Module):
    "Inverted separable convolution from MobileNetV2"
   def __init__(self, dim, kernel_size=7, padding=3, expansion_ratio=2, act1=nn.ReLU, act2=nn.Identity,
       bias=True):
       super().__init__()
       med_channels = int(expansion_ratio * dim)
self.pwconv1 = nn.Linear(dim, med_channels, bias=bias) # pointwise conv implemented by FC
       self.act1 = preconv_act()
       self.dwcony = nn.Cony2d(med channels, med channels, kernel size=kernel size.
           padding=padding, groups=med_channels, bias=bias) # depthwise conv
       self.act2 = act_layer()
       self.pwconv2 = nn.Linear(med_channels, dim, bias=bias) # pointwise conv implemented by FC
   def forward(self, x):
    # [B, H, W, C] = x.shape
       x = self.pwconv1(x)
       x = self.act1(x)
       x = x.permute(0, 3, 1, 2) # [B, H, W, D] -> [B, D, H, W]
       x = self.dwconv(x)
       x = x.permute(0, 2, 3, 1) # [B, D, H, W] -> [B, H, W, D]
       x = self.act2(x)
       x = self.pwconv2(x)
```

A.3 Hyper-parameters

The hyper-parameters of IdentityFormer, RandFormer and PoolFormerV2 trained on ImageNet-1K [13] are shown in Table 7, while those of ConvFormer and CAFormer are shown in Table 8 for training on ImageNet-1K and Table 9 for pre-training on ImageNet-1K and fine-tuning on ImageNet-1K.

Hyper-parameter	IdentityFormer	RandFormer	PoolFormerV2			
Model size	S12/S24/S36/M36/M48					
Epochs	300					
Resolution	224^{2}					
Batch size		4096				
Optimizer		AdamW				
Learning rate		4e-3				
Learning rate decay	Cosine					
Warmup epochs	5					
Weight decay	0.05					
Rand Augment	9/0.5					
Mixup	0.8					
Cutmix	1.0					
Erasing prob		0.25				
Peak stochastic depth rate	0.1/0.1/0.2/0.3/0.4	0.1/0.1/0.2/0.3/0.3	0.1/0.1/0.2/0.3/0.4			
Label smoothing		0.1				

Table 7: Hyper-parameters of IdentityFormer, RandFormer, PoolFormerV2 trained on ImageNet-1K.

Uypar paramatar	ConvI	Former	CAFo	ormer		
Hyper-parameter	Train	Finetune	Train	Finetune		
Model size		S18/S36	/M36/B36			
Epochs	300	30	300	30		
Resolution	224^{2}	384^{2}	224^{2}	384^{2}		
Batch size	4096	1024	4096	1024		
Optimizer	AdamW	AdamW	LAMB	LAMB		
Learning rate	4e-3	5e-5	8e-3	1e-4		
Learning rate decay	Cosine	None	Cosine	None		
Warmup epochs	20	None	20	None		
Weight decay	0.05					
Rand Augment		9/0.5				
Mixup	0.8	None	0.8	None		
Cutmix	1.0	None	1.0	None		
Erasing prob	0.25					
Peak stochastic depth rate	0.2/0.3/0.4/0.6	0.3/0.5/0.8/0.8	0.15/0.3/0.4/0.6	0.3/0.5/0.7/0.8		
MLP head dropout rate	0/0/0/0	0.4/0.4/0.5/0.5	0/0.4/0.4/0.5	0.4/0.4/0.4/0.5		
Label smoothing	0.1					
EMA decay rate	None	0.9999	None	0.9999		

Table 8: Hyper-parameters of ConvFormer and CAFormer trained on ImageNet-1K and finetuned at larger resolution of 384^2 .

	Conv	Former	CAFormer			
Hyper-parameter	Pretrain	Finetune	Pretrain	Finetune		
Model size		B36				
Epochs	90	30	90	30		
Resolution	224^{2}	$224^2/384^2$	224^{2}	$224^2/384^2$		
Batch size	4096	1024	4096	1024		
Optimizer	AdamW	AdamW	LAMB	LAMB		
Learning rate	1e-3	5e-5	2e-3	1e-3		
Learning rate decay	Cosine	None	Cosine	None		
Warmup epochs	5	None 5	None			
Weight decay	0.05					
Rand Augment	9/0.5					
Mixup	0.8	None	0.8	None		
Cutmix	1.0	None	1.0	None		
Erasing prob	0.25					
Peak stochastic depth rate	0.2	0.3	0.3	0.3		
MLP head dropout rate	0.3	0.5	0.4	0.5		
Label smoothing	0.1					
EMA decay rate	None	0.9999	None	0.9999		

Table 9: Hyper-parameters of ConvFormer and CAFormer pre-trained on ImageNet-21K and fine-tuned on ImageNet-1K at resolution of 224² and 384².

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