

# MetaFormer is Actually What You Need for Vision

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Code: <https://github.com/sail-sg/poolformer>

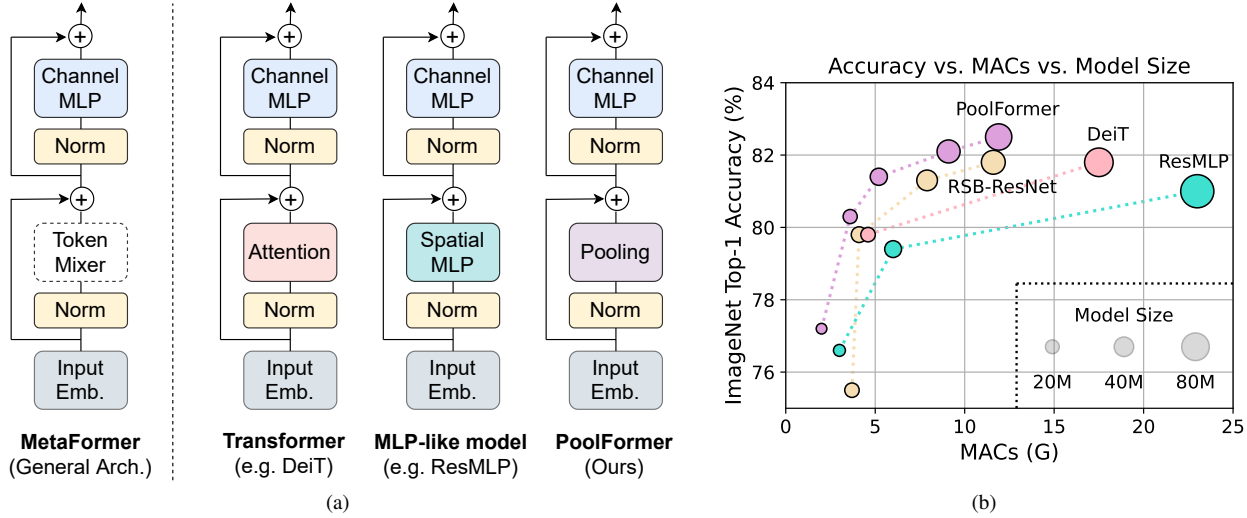


Figure 1. **MetaFormer and performance of MetaFormer-based models on ImageNet-1K validation set.** As shown in (a), we present *MetaFormer* as a general architecture abstracted from transformers [49] by not specifying the token mixer. When using attention/spatial MLP as the token mixer, MetaFormer is instantiated as transformer/MLP-like models. We argue that the competence of transformer/MLP-like models primarily stems from the general architecture MetaFormer instead of the equipped specific token mixers. To demonstrate this, we exploit an embarrassingly simple non-parametric operator, *pooling*, to conduct extremely basic token mixing. Surprisingly, the resulted model *PoolFormer* consistently outperforms the well-tuned vision transformer [16] baseline (DeiT [46]) and MLP-like [44] baseline (ResMLP [45]) as shown in (b), which well supports that MetaFormer is actually what we need to achieve competitive performance. RSB-ResNet in (b) means the results are from “ResNet Strikes Back” [52] where ResNet [22] is trained with improved training procedure for 300 epochs.

## Abstract

Transformers have shown great potential in computer vision tasks. A common belief is their attention-based token mixer module contributes most to their competence. However, recent works show the attention-based module in transformers can be replaced by spatial MLPs and the resulted models still perform quite well. Based on this observation, we hypothesize that the general architecture of the transformers, instead of the specific token mixer module, is more essential to the model’s performance. To verify this, we deliberately replace the attention module in transformers with an embarrassingly simple spatial pooling operator to conduct only the most basic token mixing. Surprisingly, we observe that the derived model, termed as *PoolFormer*, achieves competitive performance on mul-

ti-ple computer vision tasks. For example, on ImageNet-1K, *PoolFormer* achieves 82.1% top-1 accuracy, surpassing well-tuned vision transformer/MLP-like baselines DeiT-B/ResMLP-B24 by 0.3%/1.1% accuracy with 35%/52% fewer parameters and 48%/60% fewer MACs. The effectiveness of *PoolFormer* verifies our hypothesis and urges us to initiate the concept of “MetaFormer”, a general architecture abstracted from transformers without specifying the token mixer. Based on the extensive experiments, we argue that *MetaFormer is the key player in achieving superior results for recent transformer and MLP-like models on vision tasks*. This work calls for more future research dedicated to improving MetaFormer instead of focusing on the token mixer modules. Additionally, our proposed *PoolFormer* could serve as a starting baseline for future MetaFormer architecture design.

What is the Key to Transformer:

1. above statement
2. Attention is not all you need ICML’21 (skip connection & MLP)

## 1. Introduction

Transformers have gained much interest and success in the computer vision field [3, 8, 40, 48]. Since the seminal work of vision transformer (ViT) [16] that adapts pure transformers to image classification tasks, many follow-up models are developed to make further improvements and achieve promising performance in various computer vision tasks [34, 46, 57].

The transformer encoder, as shown in Figure 1(a), consists of two components. One is the attention module for mixing information among tokens and we term it as *token mixer*. The other component contains the remaining modules, such as channel MLPs and residual connections. By regarding the attention module as a specific token mixer, we further abstract the overall transformer into a general architecture *MetaFormer* where the token mixer is not specified, as shown in Figure 1(a).

The success of transformers has been long attributed to the attention-based token mixer [49]. Based on this common belief, many variants of the attention modules [12, 20, 50, 62] have been developed to improve the vision transformer. However, a very recent work [44] replaces the attention module completely with spatial MLPs as token mixers, and finds the derived MLP-like model can readily attain competitive performance on image classification benchmarks. The follow-up works [24, 33, 45] further improve MLP-like models by data-efficient training and specific MLP module design, gradually narrowing the performance gap to ViT and challenging the dominance of attention as token mixers.

Some recent approaches [30, 36, 37, 41] explore other types of token mixers within the MetaFormer architecture, and have demonstrated encouraging performance. For example, [30] replaces attention with Fourier Transform and still achieves around 97% of the accuracy of vanilla transformers. Taking all these results together, it seems as long as a model adopts MetaFormer as the general architecture, promising results could be attained. We thus hypothesize *compared with specific token mixers, MetaFormer is more essential for the model to achieve competitive performance*.

To verify this hypothesis, we apply an extremely simple non-parametric operator, *pooling*, as the token mixer to conduct the most basic token mixing. Astonishingly, this derived model, termed *PoolFormer*, achieves competitive performance, and even consistently outperforms well-tuned transformer and MLP-like models, including DeiT [46] and ResMLP [45], as shown in Figure 1(b). More specifically, PoolFormer-M36 achieves 82.1% top-1 accuracy on ImageNet-1K classification benchmark, surpassing well-tuned vision transformer/MLP-like baselines DeiT-B/ResMLP-B24 by 0.3%/1.1% accuracy with 35%/52% fewer parameters and 48%/60% fewer MACs. These results demonstrate that MetaFormer, even with a naive token

mixer, can still deliver promising performance. We thus argue that MetaFormer is our *de facto* need for vision models that deserved more future research.

The contributions of our paper are two-fold. Firstly, we abstract transformers into a general architecture MetaFormer, and empirically demonstrate that the success of transformer/MLP-like models is largely attributed to the MetaFormer architecture. Specifically, by only employing a simple non-parametric operator, pooling, as an extremely weak token mixer for MetaFormer, we build a simple model named PoolFormer and find it can still achieve highly competitive performance. We hope our findings inspire more future research dedicated to improving MetaFormer instead of focusing on the token mixer modules. Secondly, we evaluate the proposed PoolFormer on multiple vision tasks including image classification [13], object detection [32], instance segmentation [32], and semantic segmentation [61], and find it achieves competitive performance compared with the SOTA models using sophisticated design of token mixers. The PoolFormer can readily serve as a good starting baseline for future MetaFormer architecture design.

## 2. Related work

Transformers are first proposed by [49] for translation tasks and then rapidly become popular in various NLP tasks. In language pre-training tasks, transformers are trained on large-scale unlabeled text corpus and achieve amazing performance [2, 14]. Inspired by the success of transformers in NLP, many researchers apply attention mechanism and transformers to vision tasks [3, 8, 40, 48]. Notably, Chen *et al.* introduce iGPT [6] where the transformer is trained to auto-regressively predict pixels on images for self-supervised learning. Dosovitskiy *et al.* propose vision transformer (ViT) with hard patch embedding as input [16]. They show that on supervised image classification tasks, a ViT pre-trained on a large propriety dataset (JFT dataset with 300 million images) can achieve excellent performance. DeiT [46] and T2T-ViT [57] further demonstrate that the ViT pre-trained on only ImageNet-1K ( $\sim 1.3$  million images) from scratch can achieve promising performance. A lot of works have been focusing on improving the token mixing approach of transformers by shifted windows [34], relative position encoding [54], refining attention map [62], or incorporating convolution [11, 19, 53], *etc.* In addition to attention-like token mixers, [44, 45] surprisingly find that merely adopting MLPs as token mixers can still achieve competitive performance. This discovery challenges the dominance of attention-based token mixers and triggers a heated discussion in the research community about which token mixer is better [7, 24]. However, the target of this work is neither to be engaged in this debate nor to design new complicated token mixers to achieve new state of the art. Instead, we examine a fundamental question:

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**Algorithm 1** Pooling for PoolFormer, PyTorch-like Code

---

```
import torch.nn as nn

class Pooling(nn.Module):
    def __init__(self, pool_size=3):
        super().__init__()
        self.pool = nn.AvgPool2d(
            pool_size, stride=1,
            padding=pool_size//2,
            count_include_pad=False,
        )
    def forward(self, x):
        """
        [B, C, H, W] = x.shape
        Subtraction of the input itself is added
        since the block already has a
        residual connection.
        """
        return self.pool(x) - x
```

---

What is truly responsible for the success of the transformers and their variants? Our answer is the general architecture *i.e.*, MetaFormer. We simply utilize pooling as basic token mixers to probe the power of MetaFormer.

Contemporarily, some works contribute to answering the same question. Dong *et al.* prove that without residual connections or MLPs, the output converges doubly exponentially to a rank-1 matrix [15]. Raghu *et al.* [39] compare the feature difference between ViT and CNNs, finding that self-attention enables early aggregation of global information while residual connections strongly propagate features from lower to higher layers. Unfortunately, they neither abstract transformers into a general architecture nor give an explicit explanation of the origin of transformers' power.

### 3. Method

#### 3.1. MetaFormer

We present the core concept "MetaFormer" for this work at first. As shown in Figure 1, abstracted from transformers [49], MetaFormer is a general architecture where the token mixer is not specified while the other components are kept the same as transformers. The input  $I$  is first processed by input embedding, such as patch embedding for ViTs [16],

$$X = \text{InputEmb}(I), \quad (1)$$

where  $X \in \mathbb{R}^{N \times C}$  denotes the embedding tokens with sequence length  $N$  and embedding dimension  $C$ .

Then, embedding tokens are fed to repeated MetaFormer blocks, each of which includes two residual sub-blocks. Specifically, the first sub-block mainly contains a token mixer to communicate information among tokens and this sub-block can be expressed as

$$Y = \text{TokenMixer}(\text{Norm}(X)) + X, \quad (2)$$

where  $\text{Norm}(\cdot)$  denotes the normalization such as Layer Normalization [1] or Batch Normalization [26];

$\text{TokenMixer}(\cdot)$  means a module mainly working for mixing token information. It is implemented by various attention mechanism in recent vision transformer models [16, 57, 62] or spatial MLP in MLP-like models [44, 45]. Note that the main function of the token mixer is to propagate token information although some token mixers can also mix channels, like attention.

The second sub-block primarily consists of a two-layered MLP with non-linear activation,

$$Z = \sigma(\text{Norm}(Y)W_1)W_2 + Y, \quad (3)$$

where  $W_1 \in \mathbb{R}^{C \times rC}$  and  $W_2 \in \mathbb{R}^{rC \times C}$  are learnable parameters with MLP expansion ratio  $r$ ;  $\sigma(\cdot)$  is a non-linear activation function, such as GELU [23] or ReLU [38].

**Instantiations of MetaFormer.** MetaFormer describes a general architecture with which different models can be obtained immediately by specifying the concrete design of the token mixers. As shown in Figure 1(a), if the token mixer is specified as attention or spatial MLP, MetaFormer then becomes a transformer or MLP-like model respectively.

#### 3.2. PoolFormer

From the introduction of transformers [49], lots of works attach much importance to the attention and focus on designing various attention-based token mixer components. In contrast, these works pay little attention to the general architecture, *i.e.*, the MetaFormer.

In this work, we argue that this MetaFormer general architecture contributes mostly to the success of the recent transformer and MLP-like models. To demonstrate it, we deliberately employ an embarrassingly simple operator, pooling, as the token mixer. This operator has no learnable parameters and it just makes each token averagely aggregate its nearby token features.

Since this work is targeted at vision tasks, we assume the input is in channel-first data format, *i.e.*,  $T \in \mathbb{R}^{C \times H \times W}$ . The pooling operator can be expressed as

$$T'_{:,i,j} = \frac{1}{K \times K} \sum_{p,q=1}^K T_{:,i+p-\frac{K+1}{2},i+q-\frac{K+1}{2}} - T_{:,i,j}, \quad (4)$$

where  $K$  is the pooling size. Since the MetaFormer block already has a residual connection, subtraction of the input itself is added in Equation (4). The PyTorch-like code of the pooling is shown in Algorithm 1.

As well known, self-attention and spatial MLP has computational complexity quadratic to the number of tokens to mix. Even worse, spatial MLPs bring much more parameters when handling longer sequences. As a result, self-attention and spatial MLPs usually can only process hundreds of tokens. In contrast, the pooling needs a computational complexity linear to the sequence length without

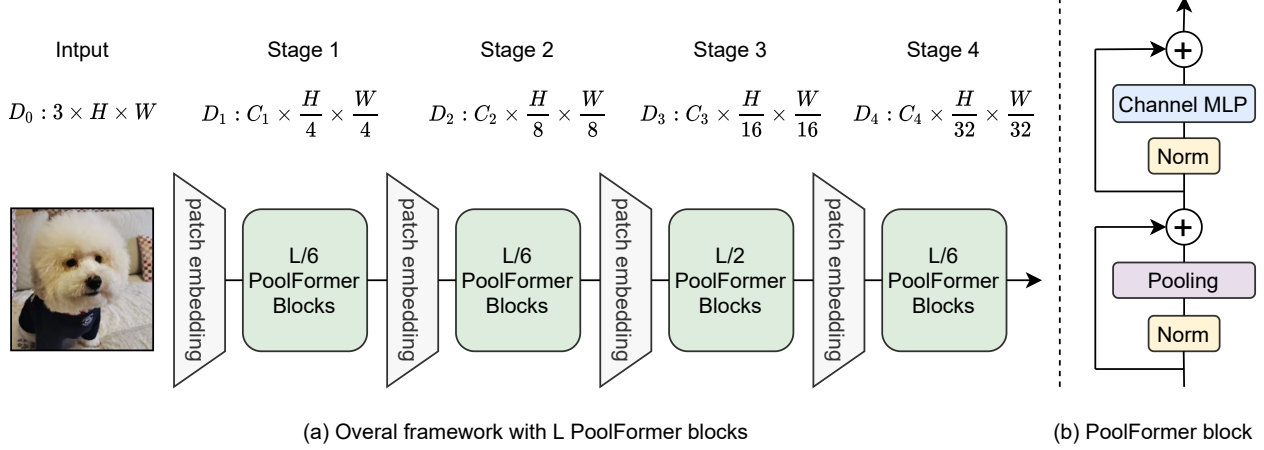


Figure 2. **(a) The overall framework of PoolFormer.** Similar to [22, 34, 50], PoolFormer adopts hierarchical architecture with 4 stages. For a model with  $L$  PoolFormer blocks, stage [1, 2, 3, 4] have  $[L/6, L/6, L/2, L/6]$  blocks, respectively. The feature dimension  $D_i$  of stage  $i$  is shown in the figure. **(b) The architecture of PoolFormer block.** Compared with transformer block, it replaces attention with extremely simple non-parametric operator, pooling, to conduct only basic token mixing.

any learnable parameters. Thus, we take advantage of pooling by adopting a hierarchical structure similar to traditional CNNs [22, 29, 42] and recent hierarchical transformer variants [34, 50]. Figure 2 shows the overall framework of PoolFormer. Specifically, PoolFormer has 4 stages with  $\frac{H}{4} \times \frac{W}{4}$ ,  $\frac{H}{8} \times \frac{W}{8}$ ,  $\frac{H}{16} \times \frac{W}{16}$ , and  $\frac{H}{32} \times \frac{W}{32}$  tokens respectively, where  $H$  and  $W$  represent the width and height of the input image. There are two groups of embedding size: 1) small-sized models with embedding dimensions of 64, 128, 320, and 512 responding to the four stages; 2) medium-sized models with embedding dimensions 96, 192, 384, and 768. Assuming there are  $L$  PoolFormer blocks in total, stages 1, 2, 3, and 4 will contain  $L/6$ ,  $L/6$ ,  $L/2$ , and  $L/6$  PoolFormer blocks respectively. The MLP expansion ratio is set as 4. According to the above simple model scaling rule, we obtain 5 different model sizes of PoolFormer and their hyper-parameters are shown in Table 1.

## 4. Experiments

### 4.1. Image classification

**Setup.** ImageNet-1K [13] is one of the most widely used datasets in computer vision. It contains about 1.3M training images and 50K validation images, covering common 1K classes. Our training scheme mainly follows [46] and [47]. Specifically, MixUp [59], CutMix [58], CutOut [60] and RandAugment [10] are used for data augmentation. The models are trained for 300 epochs using AdamW optimizer [27, 35] with weight decay 0.05 and peak learning rate  $lr = 1e^{-3} \cdot \text{batch size}/1024$  (batch size 4096 and learning rate  $4e^{-3}$  are used in this paper). The number of warmup epochs is 5 and cosine schedule is used to decay the learning rate. Label Smoothing [43] is set as 0.1. Dropout is disabled

but stochastic depth [25] and LayerScale [47] are used to help train deep models. Group Normalization (group number is set as 1 for simplicity) is adopted since it is preferred by PoolFormer as shown in Section 4.4. See the appendix for more details of hyper-parameters. Our implementation is based on the Timm codebase [51] and the experiments are run on TPUs.

**Results.** Table 2 shows the performance of PoolFormers on ImageNet classification. Surprisingly, despite the simple pooling token mixer, PoolFormers can still achieve highly competitive performance compared with CNNs and other MetaFormer-like models. For example, PoolFormer-S24 reaches the top-1 accuracy of more than 80 while only requiring 21M parameters and 3.6G MACs. Comparatively, the well-established ViT baseline DeiT-S [46], attains slightly worse accuracy of 79.8 but requires 28% more MACs (4.6G). To obtain similar accuracy, MLP-like model ResMLP-S24 [45] needs 43% more parameters (30M) as well as 67% more computation (6.0G) while only 79.4 accuracy is attained. Even compared with more improved ViT and MLP-like variants [33, 50], PoolFormer still shows better performance. Specifically, the pyramid transformer PVT-Medium obtains 81.2 top-1 accuracy with 44M parameters and 6.7G MACs while PoolFormer-S36 reaches 81.5 with 30% fewer parameters (31M) and 22% fewer MACs (5.2G) than those of PVT-Medium. Besides, compared with RSB-ResNet (“ResNet Strikes Back”) [52] where ResNet [22] is trained with improved training procedure for the same 300 epochs, PoolFormer is still not undefeated. With  $\sim 22$ M parameters/3.7G MACs, RSB-ResNet-34 [52] gets 75.5 accuracy while PoolFormer-S24 can obtain 80.3.

With the pooling operator, each token aggregates the features from its nearby tokens averagely. Thus it is the most

Stage	# Tokens	Layer Specification		PoolFormer				
				S12	S24	S36	M36	M48
1	$\frac{H}{4} \times \frac{W}{4}$	Patch Embedding	Patch Size	$7 \times 7$ , stride 4				
			Embed. Dim.	64		96		
		PoolFormer Block	Pooling Size	$3 \times 3$ , stride 1				
			MLP Ratio	4				
			# Block	2	4	6	6	8
2	$\frac{H}{8} \times \frac{W}{8}$	Patch Embedding	Patch Size	$3 \times 3$ , stride 2				
			Embed. Dim.	128		192		
		PoolFormer Block	Pooling Size	$3 \times 3$ , stride 1				
			MLP Ratio	4				
			# Block	2	4	6	6	8
3	$\frac{H}{16} \times \frac{W}{16}$	Patch Embedding	Patch Size	$3 \times 3$ , stride 2				
			Embed. Dim.	320		384		
		PoolFormer Block	Pooling Size	$3 \times 3$ , stride 1				
			MLP Ratio	4				
			# Block	6	12	18	18	24
4	$\frac{H}{32} \times \frac{W}{32}$	Patch Embedding	Patch Size	$3 \times 3$ , stride 2				
			Embed. Dim.	512		768		
		PoolFormer Block	Pooling Size	$3 \times 3$ , stride 1				
			MLP Ratio	4				
			# Block	2	4	6	6	8
Parameters (M)				11.9	21.4	30.8	56.1	73.4
MACs (G)				2.0	3.6	5.2	9.1	11.9

Table 1. **Configurations of different PoolFormer models.** There are two groups of embedding dimensions, *i.e.*, small size with [64, 128, 320, 512] dimensions and medium size with [96, 196, 384, 768]. Notation “S24” means the model is in small size of embedding dimensions with 24 PoolFormer blocks in total.

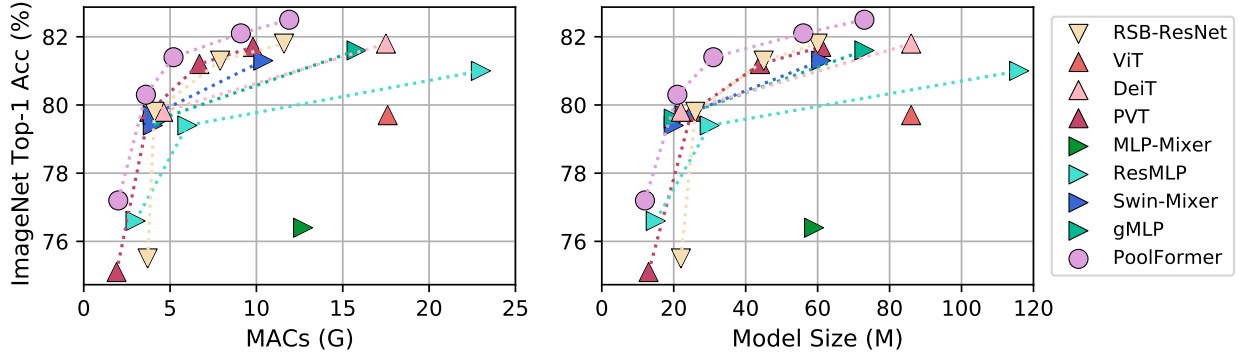


Figure 3. **ImageNet-1K validation accuracy vs. MACs/Model Size.** RSB-ResNet means the results are from “ResNet Strikes Back” [52] where ResNet [22] is trained with improved training procedure for 300 epochs.

basic token mixing operation. However, the experiment results show that even with this extremely simple token mixer, MetaFormer still obtains highly competitive performance. Figure 3 clearly shows that PoolFormer surpasses other models with fewer MACs and parameters. This finding conveys that the general architecture MetaFormer is actually what we need when designing vision models. By adopting

MetaFormer, it is guaranteed that the derived models would have the potential to achieve reasonable performance.

## 4.2. Object detection and instance segmentation

**Setup.** We evaluate PoolFormer on the challenging COCO benchmark [32] that includes 118K training images



General Arch.	Token Mixer	Outcome Model	Image Size	Params (M)	MACs (G)	Top-1 (%)
Convolutional Neural Netowrks	—	▼ RSB-ResNet-18 [22]	224	12	1.8	70.6
		▼ RSB-ResNet-34 [52]	224	22	3.7	75.5
		▼ RSB-ResNet-50 [52]	224	26	4.1	79.8
		▼ RSB-ResNet-101 [52]	224	45	7.9	81.3
		▼ RSB-ResNet-152 [52]	224	60	11.6	81.8
MetaFormer	Attention	▲ ViT-B/16* [16]	224	86	17.6	79.7
		▲ ViT-L/16* [16]	224	307	63.6	76.1
		▲ DeiT-S [46]	224	22	4.6	79.8
		▲ DeiT-B [46]	224	86	17.5	81.8
		▲ PVT-Tiny [50]	224	13	1.9	75.1
		▲ PVT-Small [50]	224	25	3.8	79.8
		▲ PVT-Medium [50]	224	44	6.7	81.2
		▲ PVT-Large [50]	224	61	9.8	81.7
	Spatial MLP	► MLP-Mixer-B/16 [44]	224	59	12.7	76.4
		► ResMLP-S12 [45]	224	15	3.0	76.6
		► ResMLP-S24 [45]	224	30	6.0	79.4
		► ResMLP-B24 [45]	224	116	23.0	81.0
		► Swin-Mixer-T/D24 [34]	256	20	4.0	79.4
		► Swin-Mixer-T/D6 [34]	256	23	4.0	79.7
		► Swin-Mixer-B/D24 [34]	224	61	10.4	81.3
		► gMLP-S [33]	224	20	4.5	79.6
		► gMLP-B [33]	224	73	15.8	81.6
	Pooling	● PoolFormer-S12	224	12	2.0	77.2
		● PoolFormer-S24	224	21	3.6	80.3
		● PoolFormer-S36	224	31	5.2	81.4
		● PoolFormer-M36	224	56	9.1	82.1
		● PoolFormer-M48	224	73	11.9	82.5

Table 2. **Performance of different types of models on ImageNet-1K classification.** All these models are only trained on the ImageNet-1K training set and the accuracy on the validation set is reported. RSB-ResNet means the results are from “ResNet Strikes Back” [52] where ResNet [22] is trained with improved training procedure for 300 epochs. \* denotes results of ViT trained with extra regularization from [44].

Backbone	Params (M)	AP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>S</sub>	AP <sub>M</sub>	AP <sub>L</sub>
▼ ResNet-18 [22]	21.3	31.8	49.6	33.6	16.3	34.3	43.2
● PoolFormer-S12	21.7	36.2	56.2	38.2	20.8	39.1	48.0
▼ ResNet-50 [22]	37.7	36.3	55.3	38.6	19.3	40.0	48.8
● PoolFormer-S24	31.1	38.9	59.7	41.3	23.3	42.1	51.8
▼ ResNet-101 [22]	56.7	38.5	57.8	41.2	21.4	42.6	51.1
● PoolFormer-S36	40.6	39.5	60.5	41.8	22.5	42.9	52.4

Table 3. **Performance of object detection on COCO val2017 [32].** All models are based on RetinaNet and  $1 \times$  training schedule (*i.e.* 12 epochs) is used for training detection models.

(train2017) and 5K validation images (val2017). The models are trained on training set and the performance on validation set is reported. PoolFormer is employed as the backbone for two standard detectors, *i.e.*, RetinaNet [31] and Mask R-CNN [21]. ImageNet pre-trained weights are utilized to initialize the backbones and Xavier [18] to initial-

ize the added layers. AdamW [27, 35] is adopted for training with an initial learning rate of  $1 \times 10^{-4}$  and batch size of 16. Following [21, 31], we employ  $1 \times$  training schedule, *i.e.*, training the detection models for 12 epochs. The training images are resized into shorter side of 800 pixels and longer side of no more than 1,333 pixels. For testing, the shorter

Backbone	Params (M)	AP <sup>b</sup>	AP <sup>b</sup> <sub>50</sub>	AP <sup>b</sup> <sub>75</sub>	AP <sup>m</sup>	AP <sup>m</sup> <sub>50</sub>	AP <sup>m</sup> <sub>75</sub>
▼ ResNet-18 [22]	31.2	34.0	54.0	36.7	31.2	51.0	32.7
● PoolFormer-S12	31.6	37.3	59.0	40.1	34.6	55.8	36.9
▼ ResNet-50 [22]	44.2	38.0	58.6	41.4	34.4	55.1	36.7
● PoolFormer-S24	41.0	40.1	62.2	43.4	37.0	59.1	39.6
▼ ResNet-101 [22]	63.2	40.4	61.1	44.2	36.4	57.7	38.8
● PoolFormer-S36	50.5	41.0	63.1	44.8	37.7	60.1	40.0

Table 4. **Performance of object detection and instance segmentation on COCO val2017 [32]**.  $AP^b$  and  $AP^m$  represent bounding box AP and mask AP, respectively. All models are based on Mask R-CNN and trained by  $1 \times$  training schedule (*i.e.* 12 epochs).

Backbone	Params (M)	mIoU (%)
▼ ResNet-18 [22]	15.5	32.9
▲ PVT-Tiny [50]	17.0	35.7
● PoolFormer-S12	15.7	37.2
▼ ResNet-50 [22]	28.5	36.7
▲ PVT-Small [50]	28.2	39.8
● PoolFormer-S24	23.2	40.3
▼ ResNet-101 [22]	47.5	38.8
▼ ResNeXt-101-32x4d [56]	47.1	39.7
▲ PVT-Medium [50]	48.0	41.6
● PoolFormer-S36	34.6	42.0
▲ PVT-Large [50]	65.1	42.1
● PoolFormer-M36	59.8	42.4
▼ ResNeXt-101-64x4d [56]	86.4	40.2
● PoolFormer-M48	77.1	42.7

Table 5. **Performance of Semantic segmentation on ADE20K [61] validation set.** All models are equipped with Semantic FPN [28].

side of the images is also resized to 800 pixels. The implementation is based on the `mmDetection` [4] codebase and the experiments are run on 8 NVIDIA A100 GPUs.

**Results.** Equipped with RetinaNet for object detection, PoolFormer-based models consistently outperform their comparable ResNet counterparts as shown in Table 3. For instance, PoolFormer-S12 achieves 36.2 AP, largely surpassing that of ResNet-18 (31.8 AP). Similar results are observed for those models based on Mask R-CNN on object detection and instance segmentation. For example, PoolFormer-S12 largely surpasses ResNet-18 (bounding box AP 37.3 vs. 34.0, and mask AP 34.6 vs. 31.2). Overall, for COCO object detection and instance segmentation, PoolFormers achieve competitive performance, consistently outperforming those counterparts of ResNet.

### 4.3. Semantic segmentation

**Setup.** ADE20K [61], a challenging scene parsing benchmark, is selected to evaluate the models for semantic seg-

mentation. The dataset includes 20K and 2K images in the training and validation set, respectively, covering 150 fine-grained semantic categories. PoolFormers are evaluated as backbones equipped with Semantic FPN [28]. ImageNet-1K trained checkpoints are used to initialize the backbones while Xavier [18] is utilized to initialize other newly added layers. Common practices [5, 28] train models for 80K iterations with a batch size of 16. To speed up training, we double batch size to 32 and decrease the iteration number to 40K. The AdamW [27, 35] is employed with an initial learning rate of  $2 \times 10^{-4}$  that will decay in the polynomial decay schedule with a power of 0.9. Images are resized and cropped into  $512 \times 512$  for training and are resized to shorter side of 512 pixels for testing. Our implementation is based on the `mmsegmentation` [9] codebase and the experiments are conducted on 8 NVIDIA A100 GPUs.

**Results.** Table 5 shows the ADE20K semantic segmentation performance of different backbones using FPN [28]. PoolFormer-based models consistently outperform the models with backbones of CNN-based ResNet [22] and ResNeXt [56] as well as transformer-based PVT. For instance, PoolFormer-12 achieves mIoU of 37.1, 4.3 and 1.5 better than ResNet-18 and PVT-Tiny, respectively.

These results demonstrate that our PoolFormer that serves as backbone can attain competitive performance on semantic segmentation although it only utilizes pooling for basically communicating information among tokens. This further indicates the great potential of MetaFormer and supports our claim that MetaFormer is actually what we need.

### 4.4. Ablation studies

The experiments of ablation studies are conducted on ImageNet-1K [13]. Table 6 reports the ablation study of PoolFormer. We discuss the ablation below according to the following aspects.

**Pooling.** Compared with transformers, the main change made by PoolFormer is using simple pooling as a token mixer. We first conduct ablation for this operator by directly replacing pooling with identity mapping. Surprisingly,

Ablation	Variant	Params (M)	MACs (G)	Top-1 (%)
Baseline	None (PoolFormer-S12)	11.9	2.0	77.2
Polling	Pooling → Identity mapping	11.9	2.0	74.3
	Pooling size 3 → 5	11.9	2.0	77.2
	Pooling size 3 → 7	11.9	2.0	77.1
	Pooling size 3 → 9	11.9	2.0	76.8
Normalization	Group Normalization [55] → Layer Normalization [1]	11.9	2.0	76.5
	Group Normalization [55] → Batch Normalization [26]	11.9	2.0	76.4
Activation	GELU [23] → ReLU [38]	11.9	2.0	76.4
	GELU → SiLU [17]	11.9	2.0	77.2
Hybrid Stages	[Pool, Pool, Pool, Pool] → [Pool, Pool, Pool, Attention]	14.0	2.1	78.3
	[Pool, Pool, Pool, Pool] → [Pool, Pool, Attention, Attention]	16.5	2.7	81.0
	[Pool, Pool, Pool, Pool] → [Pool, Pool, Pool, SpatialFC]	11.9	2.0	77.5
	[Pool, Pool, Pool, Pool] → [Pool, Pool, SpatialFC, SpatialFC]	12.2	2.1	77.9

GAP: 2.9

Table 6. **Ablation for PoolFormer on ImageNet-1K classification benchmark.** PoolFormer-S12 is utilized as the baseline to conduct ablation study. The top-1 accuracy on the validation set is reported.

MetaFormer with identity mapping can still achieve 74.3% top-1 accuracy, supporting the claim that MetaFormer is actually what we need to guarantee reasonable performance.

We test the effects of pooling size on PoolFormer. We observe similar performance when pooling sizes are 3, 5 and 7. However, when the pooling size increases to 9, there is an obvious performance drop of 0.5%. Thus, we adopt the default pooling size of 3 for PoolFormer.

**Normalization.** Three types of normalization are employed for PoolFormer, *i.e.*, Group Normalization [55] (group number is set as 1 for simplicity), Layer Normalization [1] and Batch Normalization [26]. We find PoolFormer prefers Group Normalization with 0.7% or 0.8% higher than Layer Normalization or Batch Normalization. Thus, Group Normalization is set as default for PoolFormer.

**Activation.** We change GELU [23] to ReLU [38] or SiLU [17]. When ReLU is adopted for activation, an obvious performance drop of 0.8 % is observed. For SiLU, its performance is almost the same as that of GELU. Thus, we still adopt GELU as default activation.

**Hybrid stages.** Among token mixers based on pooling, attention, and spatial MLP, the pooling-based one can handle much longer input sequences while attention and spatial MLP are good at capturing global information. Therefore, it is intuitive to stack MetaFormers with pooling in the bottom stages to handle long sequences and use attention or spatial MLP-based mixer in the top stages, considering the sequences have been largely shortened. Thus, we replace the token mixer pooling with attention or spatial FC<sup>1</sup> in the top one or two stages in PoolFormer. From Ta-

ble 6, the hybrid models perform quite well. The variant with pooling in the bottom two stages and attention in the top two stages delivers highly competitive performance. It achieves 81.0% accuracy with only 16.5M parameters and 2.7G MACs. As a comparison, ResMLP-B24 needs  $7.0\times$  parameters (116M) and  $8.5\times$  MACs (23.0G) to achieve the same accuracy. These results indicate that combining pooling with other token mixers for MetaFormer may be a promising direction to further improve the performance.

## 5. Conclusion and future work

In this work, we abstracted the attention in transformers as a token mixer, and the overall transformer as a general architecture termed MetaFormer where the token mixer is not specified. Instead of focusing on specific token mixers, we point out that MetaFormer is actually what we need to guarantee achieving reasonable performance. To verify this, we deliberately specify token mixer as extremely simple pooling for MetaFormer. It is found that the derived PoolFormer model can achieve competitive performance on different vision tasks, which well supports that “MetaFormer is actually what you need for vision”.

In the future, we will further evaluate PoolFormer under more different learning settings, such as self-supervised learning and transfer learning. Moreover, it is interesting to see whether PoolFormer still works on NLP tasks to further support the claim “MetaFormer is actually what you need” in the NLP domain. We hope that this work can inspire more future research devoted to improving the fundamental architecture MetaFormer instead of paying too much on the token mixer modules.

<sup>1</sup>Following [45], we use only one spatial fully connected layer as a

token mixer, so we call it FC.



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## References

- [1] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *arXiv preprint arXiv:1607.06450*, 2016. 3, 8, 11
- [2] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc., 2020. 2
- [3] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In *European Conference on Computer Vision*, pages 213–229. Springer, 2020. 2
- [4] Kai Chen, Jiaqi Wang, Jiangmiao Pang, Yuhang Cao, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jiarui Xu, Zheng Zhang, Dazhi Cheng, Chenchen Zhu, Tianheng Cheng, Qijie Zhao, Buyu Li, Xin Lu, Rui Zhu, Yue Wu, Jifeng Dai, Jingdong Wang, Jianping Shi, Wanli Ouyang, Chen Change Loy, and Dahua Lin. MMDetection: Open mmlab detection toolbox and benchmark. *arXiv preprint arXiv:1906.07155*, 2019. 7
- [5] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, 40(4):834–848, 2017. 7
- [6] Mark Chen, Alec Radford, Rewon Child, Jeffrey Wu, Heewoo Jun, David Luan, and Ilya Sutskever. Generative pre-training from pixels. In *International Conference on Machine Learning*, pages 1691–1703. PMLR, 2020. 2
- [7] Shoufa Chen, Enze Xie, Chongjian Ge, Ding Liang, and Ping Luo. Cyclemlp: A mlp-like architecture for dense prediction. *arXiv preprint arXiv:2107.10224*, 2021. 2
- [8] Yunpeng Chen, Yannis Kalantidis, Jianshu Li, Shuicheng Yan, and Jiashi Feng. A<sup>2</sup>-nets: Double attention networks. *Advances in Neural Information Processing Systems*, 31:352–361, 2018. 2
- [9] MMSegmentation Contributors. MMSegmentation: Openmmlab semantic segmentation toolbox and benchmark. <https://github.com/open-mmlab/mmdetection>, 2020. 7
- [10] Ekin D Cubuk, Barret Zoph, Jonathon Shlens, and Quoc V Le. Randaugment: Practical automated data augmentation with a reduced search space. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 702–703, 2020. 4
- [11] Stéphane d’Ascoli, Hugo Touvron, Matthew Leavitt, Ari Morcos, Giulio Biroli, and Levent Sagun. Convit: Improving vision transformers with soft convolutional inductive biases. *arXiv preprint arXiv:2103.10697*, 2021. 2
- [12] Stéphane D’Ascoli, Hugo Touvron, Matthew L Leavitt, Ari S Morcos, Giulio Biroli, and Levent Sagun. Convit: Improving vision transformers with soft convolutional inductive biases. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 2286–2296. PMLR, 18–24 Jul 2021. 2
- [13] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009. 2, 4, 7
- [14] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *NAACL-HLT (1)*, 2019. 2
- [15] Yihe Dong, Jean-Baptiste Cordonnier, and Andreas Loukas. Attention is not all you need: Pure attention loses rank doubly exponentially with depth. *arXiv preprint arXiv:2103.03404*, 2021. 3
- [16] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2020. 1, 2, 3, 6
- [17] Stefan Elfving, Eiji Uchibe, and Kenji Doya. Sigmoid-weighted linear units for neural network function approximation in reinforcement learning. *Neural Networks*, 107:3–11, 2018. 8
- [18] Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pages 249–256. JMLR Workshop and Conference Proceedings, 2010. 6, 7
- [19] Jianyuan Guo, Kai Han, Han Wu, Chang Xu, Yehui Tang, Chunjing Xu, and Yunhe Wang. Cmt: Convolutional neural networks meet vision transformers. *arXiv preprint arXiv:2107.06263*, 2021. 2
- [20] Kai Han, An Xiao, Enhua Wu, Jianyuan Guo, Chunjing Xu, and Yunhe Wang. Transformer in transformer. *arXiv preprint arXiv:2103.00112*, 2021. 2
- [21] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017. 6
- [22] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceed-*

- ings of the *IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. 1, 4, 5, 6, 7
- [23] Dan Hendrycks and Kevin Gimpel. Gaussian error linear units (gelus). *arXiv preprint arXiv:1606.08415*, 2016. 3, 8
- [24] Qibin Hou, Zihang Jiang, Li Yuan, Ming-Ming Cheng, Shuicheng Yan, and Jiashi Feng. Vision permutator: A permutable mlp-like architecture for visual recognition. *arXiv preprint arXiv:2106.12368*, 2021. 2
- [25] Gao Huang, Yu Sun, Zhuang Liu, Daniel Sedra, and Kilian Q Weinberger. Deep networks with stochastic depth. In *European conference on computer vision*, pages 646–661. Springer, 2016. 4, 11
- [26] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning*, pages 448–456. PMLR, 2015. 3, 8
- [27] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014. 4, 6, 7
- [28] Alexander Kirillov, Ross Girshick, Kaiming He, and Piotr Dollár. Panoptic feature pyramid networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6399–6408, 2019. 7
- [29] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25:1097–1105, 2012. 4
- [30] James Lee-Thorp, Joshua Ainslie, Ilya Eckstein, and Santiago Ontanon. Fnet: Mixing tokens with fourier transforms. *arXiv preprint arXiv:2105.03824*, 2021. 2
- [31] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision*, pages 2980–2988, 2017. 6
- [32] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014. 2, 5, 6, 7
- [33] Hanxiao Liu, Zihang Dai, David R So, and Quoc V Le. Pay attention to mlps. *arXiv preprint arXiv:2105.08050*, 2021. 2, 4, 6
- [34] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 10012–10022, October 2021. 2, 4, 6
- [35] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *International Conference on Learning Representations*, 2018. 4, 6, 7
- [36] André Martins, António Farinhas, Marcos Treviso, Vlad Niculae, Pedro Aguiar, and Mario Figueiredo. Sparse and continuous attention mechanisms. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 20989–21001. Curran Associates, Inc., 2020. 2
- [37] Pedro Henrique Martins, Zita Marinho, and André FT Martins.  $\infty$ -former: Infinite memory transformer. *arXiv preprint arXiv:2109.00301*, 2021. 2
- [38] Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *ICML*, 2010. 3, 8
- [39] Maithra Raghu, Thomas Unterthiner, Simon Kornblith, Chiyuan Zhang, and Alexey Dosovitskiy. Do vision transformers see like convolutional neural networks? *arXiv preprint arXiv:2108.08810*, 2021. 3
- [40] Prajit Ramachandran, Niki Parmar, Ashish Vaswani, Irwan Bello, Anselm Levskaya, and Jon Shlens. Stand-alone self-attention in vision models. *Advances in Neural Information Processing Systems*, 32, 2019. 2
- [41] Yongming Rao, Wenliang Zhao, Zheng Zhu, Jiwen Lu, and Jie Zhou. Global filter networks for image classification. *arXiv preprint arXiv:2107.00645*, 2021. 2
- [42] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015. 4
- [43] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826, 2016. 4
- [44] Ilya Tolstikhin, Neil Houlsby, Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Thomas Unterthiner, Jessica Yung, Andreas Steiner, Daniel Keysers, Jakob Uszkoreit, et al. Mlp-mixer: An all-mlp architecture for vision. *arXiv preprint arXiv:2105.01601*, 2021. 1, 2, 3, 6
- [45] Hugo Touvron, Piotr Bojanowski, Mathilde Caron, Matthieu Cord, Alaaeldin El-Nouby, Edouard Grave, Gautier Izacard, Armand Joulin, Gabriel Synnaeve, Jakob Verbeek, et al. Resmlp: Feedforward networks for image classification with data-efficient training. *arXiv preprint arXiv:2105.03404*, 2021. 1, 2, 3, 4, 6, 8, 11
- [46] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. In *International Conference on Machine Learning*, pages 10347–10357. PMLR, 2021. 1, 2, 4, 6, 11
- [47] Hugo Touvron, Matthieu Cord, Alexandre Sablayrolles, Gabriel Synnaeve, and Hervé Jégou. Going deeper with image transformers. *arXiv preprint arXiv:2103.17239*, 2021. 4
- [48] Ashish Vaswani, Prajit Ramachandran, Aravind Srinivas, Niki Parmar, Blake Hechtman, and Jonathon Shlens. Scaling local self-attention for parameter efficient visual backbones. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12894–12904, 2021. 2
- [49] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017. 1, 2, 3

- [50] Wenhai Wang, Enze Xie, Xiang Li, Deng-Ping Fan, Kaitao Song, Ding Liang, Tong Lu, Ping Luo, and Ling Shao. Pyramid vision transformer: A versatile backbone for dense prediction without convolutions. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 568–578, October 2021. 2, 4, 6, 7
- [51] Ross Wightman. Pytorch image models. <https://github.com/rwightman/pytorch-image-models>, 2019. 4
- [52] Ross Wightman, Hugo Touvron, and Hervé Jégou. Resnet strikes back: An improved training procedure in timm. *arXiv preprint arXiv:2110.00476*, 2021. 1, 4, 5, 6
- [53] Haiping Wu, Bin Xiao, Noel Codella, Mengchen Liu, Xiyang Dai, Lu Yuan, and Lei Zhang. Cvt: Introducing convolutions to vision transformers. *arXiv preprint arXiv:2103.15808*, 2021. 2
- [54] Kan Wu, Houwen Peng, Minghao Chen, Jianlong Fu, and Hongyang Chao. Rethinking and improving relative position encoding for vision transformer. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 10033–10041, 2021. 2
- [55] Yuxin Wu and Kaiming He. Group normalization. In *Proceedings of the European conference on computer vision (ECCV)*, pages 3–19, 2018. 8
- [56] Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1492–1500, 2017. 7
- [57] Li Yuan, Yunpeng Chen, Tao Wang, Weihao Yu, Yujun Shi, Zi-Hang Jiang, Francis E.H. Tay, Jiashi Feng, and Shuicheng Yan. Tokens-to-token vit: Training vision transformers from scratch on imagenet. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 558–567, October 2021. 2, 3
- [58] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 6023–6032, 2019. 4
- [59] Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In *International Conference on Learning Representations*, 2018. 4
- [60] Zhun Zhong, Liang Zheng, Guoliang Kang, Shaozi Li, and Yi Yang. Random erasing data augmentation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 13001–13008, 2020. 4
- [61] Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 633–641, 2017. 2, 7
- [62] Daquan Zhou, Yujun Shi, Bingyi Kang, Weihao Yu, Zihang Jiang, Yuan Li, Xiaojie Jin, Qibin Hou, and Jiashi Feng. Refiner: Refining self-attention for vision transformers. *arXiv preprint arXiv:2106.03714*, 2021. 2, 3

## A. Detailed hyper-parameters on ImageNet-1K

**PoolFormer.** On ImageNet-1K classification benchmark, we utilize the hyper-parameters shown in Table 7 to train models in our paper. Based on the relation between batch size and learning rate in Table 7, we set the batch size as 4096 and learning rate as  $4 \times 10^{-3}$ . For stochastic depth, following the original paper [25], we linearly increase the probability of dropping a layer from 0.0 for the bottom block to  $d_r$  for the top block.

**Hybrid Models.** We use the hyper-parameters for all models except for the hybrid models with token mixers of pooling and attention. For these hybrid models, we find that they achieve much better performances by setting batch size as 1024, learning rate as  $10^{-3}$ , and normalization as Layer Normalization [1].

## B. Training for longer epochs

In our paper, PoolFormer models are trained for the default 300 epochs on ImageNet-1K. For DeiT [46]/ResMLP [45], it is observed that the performance saturates after 400/800 epochs. Thus, we also conduct the experiments of training longer for PoolFormer-S12 and the results are shown in Table 8. We observe that PoolFormer-S12 obtains saturated performance after around 2000 epochs with a top-1 accuracy improvement of 1.8%. However, for fair comparison with other ViT/MLP-like models, we still train PoolFormers with 300 epochs by default.

## C. Code in PyTorch

We provide the PyTorch-like code in Algorithm 2 associated with the modules used in the PoolFormer block. Algorithm 3 further shows the PoolFormer block built with these modules.

	PoolFormer				
	S12	S24	S36	M36	M48
Peak drop rate of stoch. depth $d_r$	0.1	0.1	0.2	0.3	0.4
LayerScale initialization $\epsilon$	$10^{-5}$	$10^{-5}$	$10^{-6}$	$10^{-6}$	$10^{-6}$
Data augmentation	AutoAugment				
Repeated Augmentation	off				
Input resolution	224				
Epochs	300				
Warmup epochs	5				
Hidden dropout	0				
GeLU dropout	0				
Classification dropout	0				
Random erasing prob	0.25				
EMA decay	0				
Cutmix $\alpha$	1.0				
Mixup $\alpha$	0.8				
Cutmix-Mixup switch prob	0.5				
Label smoothing	0.1				
Relation between peak learning rate and batch size	$\text{lr} = \frac{\text{batch\_size}}{1024} \times 10^{-3}$				
Batch size used in the paper	4096				
Peak learning rate used in the paper	$4 \times 10^{-4}$				
Learning rate decay	cosine				
Optimizer	AdamW				
Adam $\epsilon$	1e-8				
Adam $(\beta_1, \beta_2)$	(0.9, 0.999)				
Weight decay	0.05				
Gradient clipping	None				

Table 7. **Hyper-parameters for image classification on ImageNet-1K**

# Epochs	300 (default)	400	500	1000	1500	2000	2500	3000
PoolFormer-S12	77.2	77.5	77.9	78.4	78.6	78.8	78.8	78.8

Table 8. **Performance of PoolFormer trained for different numbers of epochs.**

---

**Algorithm 2** Modules for PoolFormer block, PyTorch-like Code

---

```
import torch.nn as nn

class GroupNorm(nn.GroupNorm):
    """
    Group Normalization with 1 group.
    Input: tensor in shape [B, C, H, W]
    """
    def __init__(self, num_channels, **kwargs):
        super().__init__(1, num_channels, **kwargs)

class Pooling(nn.Module):
    """
    Implementation of pooling for PoolFormer
    --pool_size: pooling size
    Input: tensor with shape [B, C, H, W]
    """
    def __init__(self, pool_size=3):
        super().__init__()
        self.pool = nn.AvgPool2d(
            pool_size, stride=1, padding=pool_size//2, count_include_pad=False)

    def forward(self, x):
        # Subtraction of the input itself is added
        # since the block already has a residual connection.
        return self.pool(x) - x

class Mlp(nn.Module):
    """
    Implementation of MLP with 1*1 convolutions.
    Input: tensor with shape [B, C, H, W]
    """
    def __init__(self, in_features, hidden_features=None,
                 out_features=None, act_layer=nn.GELU, drop=0.):
        super().__init__()
        out_features = out_features or in_features
        hidden_features = hidden_features or in_features
        self.fc1 = nn.Conv2d(in_features, hidden_features, 1)
        self.act = act_layer()
        self.fc2 = nn.Conv2d(hidden_features, out_features, 1)
        self.drop = nn.Dropout(drop)
        self.apply(self._init_weights)

    def _init_weights(self, m):
        if isinstance(m, nn.Conv2d):
            trunc_normal_(m.weight, std=.02)
            if m.bias is not None:
                nn.init.constant_(m.bias, 0)

    def forward(self, x):
        x = self.fc1(x)
        x = self.act(x)
        x = self.drop(x)
        x = self.fc2(x)
        x = self.drop(x)
        return x
```

---



---

**Algorithm 3** PoolFormer block, PyTorch-like Code

---

```
import torch.nn as nn

class PoolFormerBlock(nn.Module):
    """
    Implementation of one PoolFormer block.
    --dim: embedding dim
    --pool_size: pooling size
    --mlp_ratio: mlp expansion ratio
    --act_layer: activation
    --norm_layer: normalization
    --drop: dropout rate
    --drop_path: Stochastic Depth,
        refer to https://arxiv.org/abs/1603.09382
    --use_layer_scale, --layer_scale_init_value: LayerScale,
        refer to https://arxiv.org/abs/2103.17239
    """
    def __init__(self, dim, pool_size=3, mlp_ratio=4.,
                act_layer=nn.GELU, norm_layer=GroupNorm,
                drop=0., drop_path=0.,
                use_layer_scale=True, layer_scale_init_value=1e-5):

        super().__init__()

        self.norm1 = norm_layer(dim)
        self.token_mixer = Pooling(pool_size=pool_size)
        self.norm2 = norm_layer(dim)
        mlp_hidden_dim = int(dim * mlp_ratio)
        self.mlp = Mlp(in_features=dim, hidden_features=mlp_hidden_dim,
                       act_layer=act_layer, drop=drop)

        # The following two techniques are useful to train deep PoolFormers.
        self.drop_path = DropPath(drop_path) if drop_path > 0. \
            else nn.Identity()
        self.use_layer_scale = use_layer_scale
        if use_layer_scale:
            self.layer_scale_1 = nn.Parameter(
                layer_scale_init_value * torch.ones((dim)), requires_grad=True)
            self.layer_scale_2 = nn.Parameter(
                layer_scale_init_value * torch.ones((dim)), requires_grad=True)

    def forward(self, x):
        if self.use_layer_scale:
            x = x + self.drop_path(
                self.layer_scale_1.unsqueeze(-1).unsqueeze(-1)
                * self.token_mixer(self.norm1(x)))
            x = x + self.drop_path(
                self.layer_scale_2.unsqueeze(-1).unsqueeze(-1)
                * self.mlp(self.norm2(x)))
        else:
            x = x + self.drop_path(self.token_mixer(self.norm1(x)))
            x = x + self.drop_path(self.mlp(self.norm2(x)))
        return x
```

---