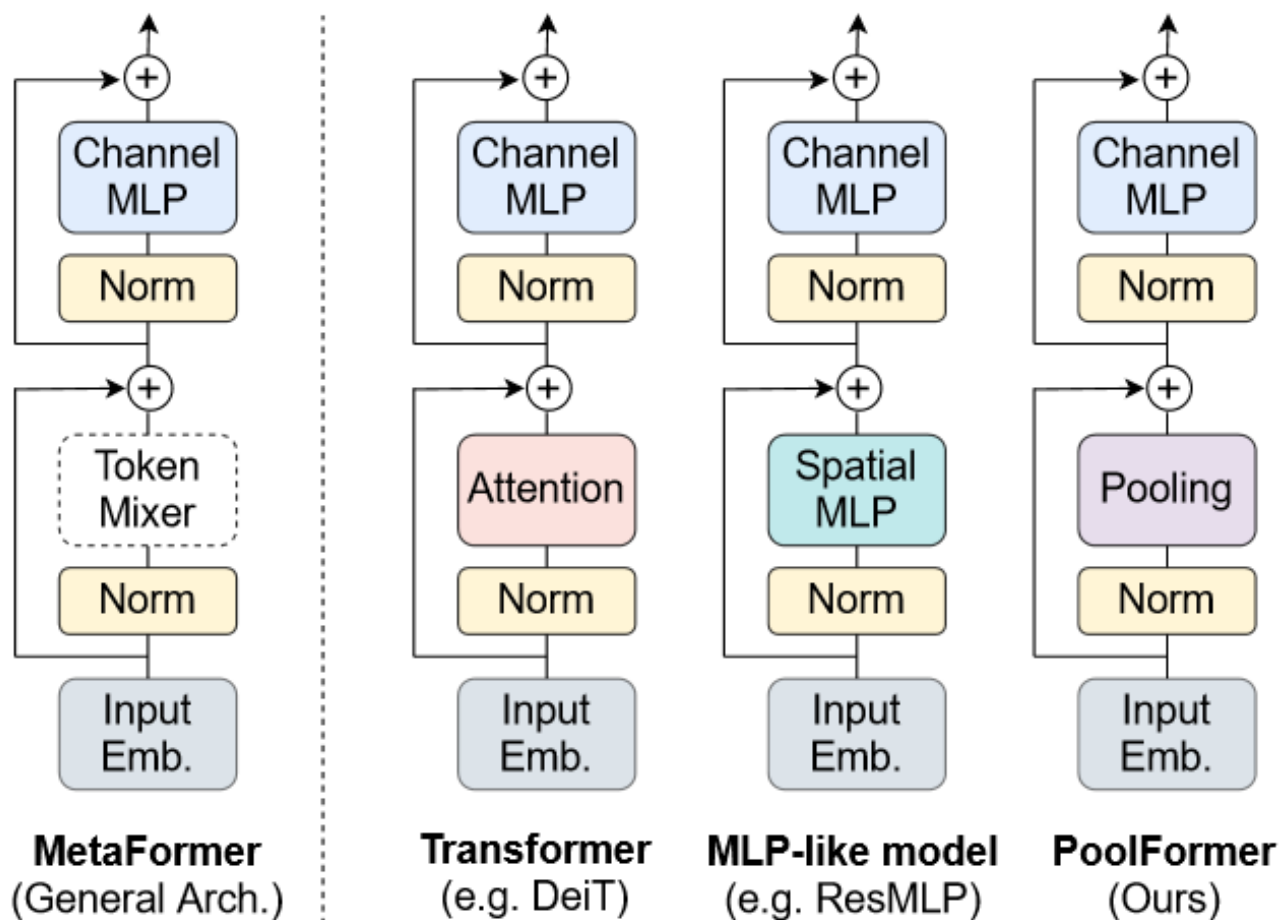

MetaFormer is Actually What You Need for Vision

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Outline

- analysis
 - attention-based token mixer module contributes most to their competence.
 - They can be replaced by spatial MLPs and the resulted models still perform quite well.
 - replace the attention module in transformers with an embarrassingly simple spatial pooling operator to conduct only the most basic token mixing.
- MetaFormer
- Experiments

MetaFormer



embedding tokens $X = \text{InputEmb}(I), X \in \mathbb{R}^{N \times C}$ (embedding dimension C)

sub-block 1 $Y = \text{TokenMixer}(\text{Norm}(X)) + X,$

sub-block 2 $Z = \sigma(\text{Norm}(Y)W_1)W_2 + Y,$ (Activation Function σ)

$$W_1 \in \mathbb{R}^{C \times rC}$$
$$W_2 \in \mathbb{R}^{rC \times C}$$

learnable parameters with MLP expansion ratio r

PoolFormer

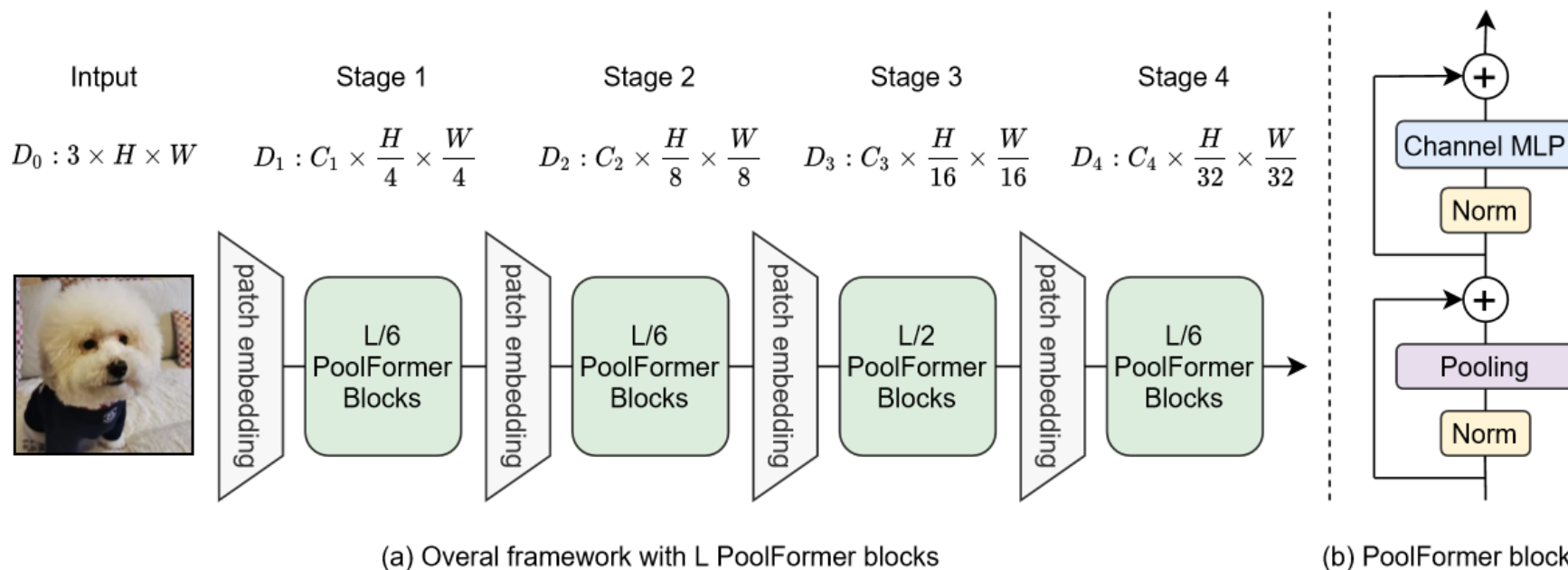
$$\text{Pooling operator } T'_{:,i,j} = \frac{1}{K \times K} \sum_{p,q=1}^K T_{:,i+p-\frac{K+1}{2},i+q-\frac{K+1}{2}} - T_{:,i,j},$$

pool size

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
        return self.pool(x) - x
```



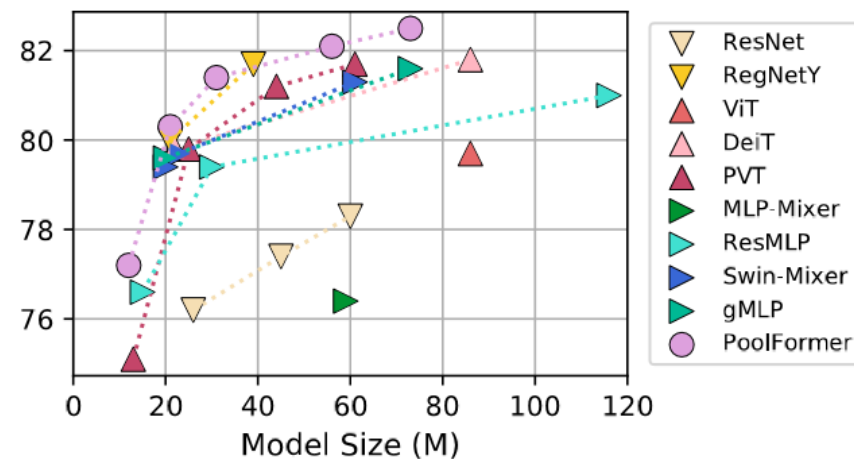
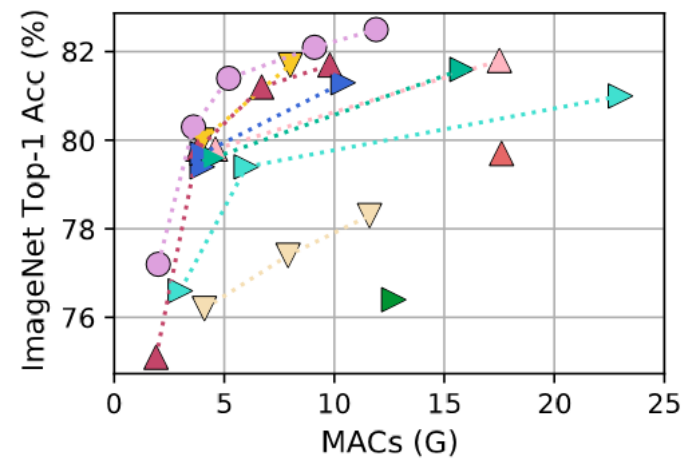
PoolFormer

Stage	# Tokens	Layer Specification		PoolFormer				
				S12	S24	S36	M36	M48
1	$\frac{H}{4} \times \frac{W}{4}$	Patch Embedding	Patch Size	7×7 , stride 4				
			Embed. Dim.	64		96		
		PoolFormer Block	Pooling Size	3×3 , stride 1				
			MLP Ratio	4				
			# Block	2	4	6	6	8
2	$\frac{H}{8} \times \frac{W}{8}$	Patch Embedding	Patch Size	3×3 , stride 2				
			Embed. Dim.	128		192		
		PoolFormer Block	Pooling Size	3×3 , stride 1				
			MLP Ratio	4				
			# Block	2	4	6	6	8
3	$\frac{H}{16} \times \frac{W}{16}$	Patch Embedding	Patch Size	3×3 , stride 2				
			Embed. Dim.	320		384		
		PoolFormer Block	Pooling Size	3×3 , stride 1				
			MLP Ratio	4				
			# Block	6	12	18	18	24
4	$\frac{H}{32} \times \frac{W}{32}$	Patch Embedding	Patch Size	3×3 , stride 2				
			Embed. Dim.	512		768		
		PoolFormer Block	Pooling Size	3×3 , 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

ImageNet Classification

Dataset: ImageNet-1k

General Arch.	Token Mixer	Outcome Model	Image Size	Params (M)	MACs (G)	Top-1 (%)
Convolutional Neural Networks	—	ResNet-50 [22]	224	26	4.1	76.2
		ResNet-101 [22]	224	45	7.9	77.4
		ResNet-152 [22]	224	60	11.6	78.3
		RegNetY-4GF [39]	224	21	4.0	80.0
		RegNetY-8GF [39]	224	39	8.0	81.7
MetaFormer	Attention	ViT-B/16* [16]	224	86	17.6	79.7
		ViT-L/16* [16]	224	307	63.6	76.1
		DeiT-S [47]	224	22	4.6	79.8
		DeiT-B [47]	224	86	17.5	81.8
		PVT-Tiny [51]	224	13	1.9	75.1
		PVT-Small [51]	224	25	3.8	79.8
		PVT-Medium [51]	224	44	6.7	81.2
		PVT-Large [51]	224	61	9.8	81.7
	Spatial MLP	MLP-Mixer-B/16 [45]	224	59	12.7	76.4
		ResMLP-S12 [46]	224	15	3.0	76.6
		ResMLP-S24 [46]	224	30	6.0	79.4
		ResMLP-B24 [46]	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



Object Detection and instance Segmentation

Dataset: COCO

Object Detection

Model	Params (M)	AP	AP ₅₀	AP ₇₅	AP _S	AP _M	AP _L
▼ 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

Instance Segmentation

Model	Params (M)	AP ^b	AP ^b ₅₀	AP ^b ₇₅	AP ^m	AP ^m ₅₀	AP ^m ₇₅
▼ 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

Dataset: ADE20K

Sementic Segmentation

Model	Params (M)	mIoU (%)
▼ ResNet-18 [22]	15.5	32.9
▲ PVT-Tiny [51]	17.0	35.7
● PoolFormer-S12	15.7	37.2
▼ ResNet-50 [22]	28.5	36.7
▲ PVT-Small [51]	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 [51]	48.0	41.6
● PoolFormer-S36	34.6	42.0
▲ PVT-Large [51]	65.1	42.1
● PoolFormer-M36	59.8	42.4
▼ ResNeXt-101-64x4d [56]	86.4	40.2
● PoolFormer-M48	77.1	42.7

Ablation Studies

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