PyramidTNT: Improved Transformer-in-Transformer Baselines with Pyramid Architecture

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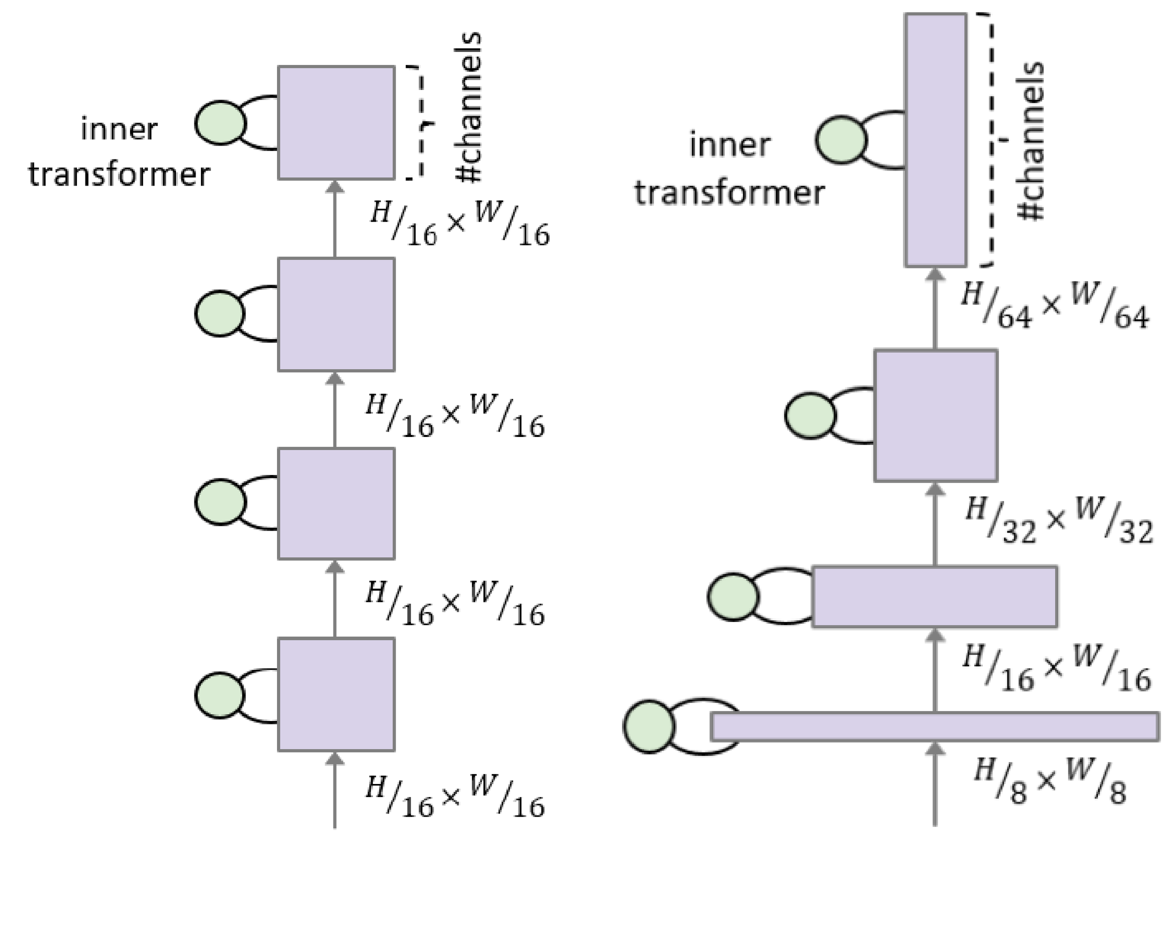
Abstract

Transformer networks have achieved great progress for computer vision tasks. Transformer-in-Transformer (TNT) architecture utilizes inner transformer and outer transformer to extract both local and global representations. In this work, we present new TNT baselines by introducing two advanced designs: 1) pyramid architecture, and 2) convolutional stem. The new ``PyramidTNT'' significantly improves the original TNT by establishing hierarchical representations. PyramidTNT achieves better performances than the previous state-of-the-art vision transformers such as Swin Transformer. We hope this new baseline will be helpful to the further research and application of vision transformer. Code is available at https://github.com/huawei-noah/CV-Backbones.

PyramidTNT Architecture



(a) TNT (b) PyramidTNT

Stage	Output size	PyramidTNT-Ti		PyramidTNT-S		PyramidTNT-M		PyramidTNT-B	
Stem	$\frac{H}{8}\times\frac{W}{8}$	Conv×5		Conv×5		Conv×5		Conv×5	
		Outer	Inner	Outer	Inner	Outer	Inner	Outer	Inner
Stage 1	$\frac{H}{8}\times\frac{W}{8}$	$\begin{bmatrix}D=80\\H_o=2\\R=4\end{bmatrix}\times2$	$\begin{bmatrix}C=5\\H_i=1\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=128\\H_o=4\\R=4\end{bmatrix}\times2$	$\begin{bmatrix}C=8\\H_i=2\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=192\\H_o=4\\R=4\end{bmatrix}\times2$	$\begin{bmatrix}C=12\\H_i=2\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=256\\H_o=4\\R=4\end{bmatrix}\times2$	$\begin{bmatrix}C=16\\H_i=2\\R=1\end{bmatrix}\times1$
Downsample	$\frac{H}{16}\times\frac{W}{16}$	Patch Merging		Patch Merging		Patch Merging		Patch Merging	
		Outer	Inner	Outer	Inner	Outer	Inner	Outer	Inner
Stage 2	$\frac{H}{16}\times\frac{W}{16}$	$\begin{bmatrix}D=160\\H_o=4\\R=2\end{bmatrix}\times6$	$\begin{bmatrix}C=10\\H_i=2\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=256\\H_o=8\\R=2\end{bmatrix}\times8$	$\begin{bmatrix}C=16\\H_i=4\\R=1\end{bmatrix}\times2$	$\begin{bmatrix}D=384\\H_o=8\\R=2\end{bmatrix}\times8$	$\begin{bmatrix}C=24\\H_i=4\\R=1\end{bmatrix}\times2$	$\begin{bmatrix}D=512\\H_o=8\\R=2\end{bmatrix}\times10$	$\begin{bmatrix}C=32\\H_i=4\\R=1\end{bmatrix}\times2$
Downsample	$\frac{H}{32}\times\frac{W}{32}$	Patch Merging		Patch Merging		Patch Merging		Patch Merging	
		Outer	Inner	Outer	Inner	Outer	Inner	Outer	Inner
Stage 3	$\frac{H}{32}\times\frac{W}{32}$	$\begin{bmatrix}D=320\\H_o=8\\R=1\end{bmatrix}\times3$	$\begin{bmatrix}C=20\\H_i=4\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=512\\H_o=16\\R=1\end{bmatrix}\times4$	$\begin{bmatrix}C=32\\H_i=8\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=768\\H_o=16\\R=1\end{bmatrix}\times6$	$\begin{bmatrix}C=48\\H_i=8\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=1024\\H_o=16\\R=1\end{bmatrix}\times6$	$\begin{bmatrix}C=64\\H_i=8\\R=1\end{bmatrix}\times1$
Downsample	$\frac{H}{64}\times\frac{W}{64}$	Patch Merging		Patch Merging		Patch Merging		Patch Merging	
		Outer	Inner	Outer	Inner	Outer	Inner	Outer	Inner
Stage 4	$\frac{H}{64}\times\frac{W}{64}$	$\begin{bmatrix}D=320\\H_o=8\\R=1\end{bmatrix}\times2$	$\begin{bmatrix}C=20\\H_i=4\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=512\\H_o=16\\R=1\end{bmatrix}\times2$	$\begin{bmatrix}C=32\\H_i=8\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=768\\H_o=16\\R=1\end{bmatrix}\times2$	$\begin{bmatrix}C=48\\H_i=8\\R=1\end{bmatrix}\times1$	$\begin{bmatrix}D=1024\\H_o=16\\R=1\end{bmatrix}\times2$	$\begin{bmatrix}C=64\\H_i=8\\R=1\end{bmatrix}\times1$
Head	1 × 1	Pooling & FC		Pooling & FC		Pooling & FC		Pooling & FC	
Input resolution		192×192		256×256		256×256		256×256	
Parameters (M)		10.6		32.0		85.0		157.0	
FLOPs (B)		0.6		3.3		8.2		16.0	

Experiments

- ImageNet classification

Model	Params (M)	FLOPs (B)	Throughput (image/s)	Top-1 (%)
T2T-ViT-14 [41]	21.5	5.2	-	81.5
T2T-ViT-19 [41]	39.2	8.9	-	81.9
T2T-ViT-24 [41]	64.1	14.1	-	82.3
PVT-Small [36]	24.5	3.8	820	79.8
PVT-Medium [36]	44.2	6.7	526	81.2
PVT-Large [36]	61.4	9.8	367	81.7
PVTv2-B0 [35]	3.4	0.6	-	70.5
PVTv2-B2 [35]	25.4	4.0	-	82.0
PVTv2-B4 [35]	62.6	10.1	-	83.6
Swin-T [22]	29	4.5	755	81.3
Swin-S [22]	50	8.7	437	83.0
Swin-B [22]	88	15.4	278	83.3
TNT-S [11]	23.8	5.2	428	81.5
TNT-S-2 [11]	22.4	4.7	704	81.4
TNT-B [11]	65.6	14.1	246	82.9
PyramidTNT-Ti	10.6	0.6	2423	**75.2**
PyramidTNT-S	32.0	3.3	721	**82.0**
PyramidTNT-M	85.0	8.2	413	**83.5**
PyramidTNT-B	157.0	16.0	263	**84.1**

- COCO object detection

Table 4. Object detection and instance segmentation results on COCO val2017. FLOPs is calculated on 1280×800 input.

Backbone	RetinaNet 1×						Mask R-CNN 1×						
	# FLOPs	AP	AP_{50}	AP_S	AP_M	AP_L	# FLOPs	AP^b	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^m_{75}
ResNet50 [13]	239.3G	36.3	55.3	19.3	40.0	48.8	260.1G	38.0	58.6	41.4	34.4	55.1	36.7
PVT-Small [36]	226.5G	40.4	61.3	25.0	42.9	55.7	245.1G	40.4	62.9	43.8	37.8	60.1	40.3
CycleMLP-B2 [3]	230.9G	40.6	61.4	22.9	44.4	54.5	249.5G	42.1	64.0	45.7	38.9	61.2	41.8
Swin-T [22]	244.8G	41.5	62.1	25.1	44.9	55.5	264.0G	42.2	64.6	46.2	39.1	61.6	42.0
Hire-MLP-Small [8]	237.6G	41.7	-	**25.3**	**45.4**	54.6	256.2G	42.8	65.0	46.7	39.3	62.0	42.1
PyramidTNT-S	225.9G	**42.0**	**63.1**	25.0	44.9	**57.7**	255.9G	**43.4**	**65.3**	**47.3**	**39.5**	**62.3**	**42.2**

Table 5. Instance segmentation results on COCO val2017.

Backbone	Mask R-CNN 3×							Cascade Mask R-CNN 3×						
	# FLOPs	AP^b	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^m_{75}	# FLOPs	AP^b	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^m_{75}
ResNet50 [13]	260.1G	41.0	61.7	44.9	37.1	58.4	40.1	738.7G	46.3	64.3	50.5	40.1	61.7	43.4
AS-MLP-T [18]	260.1G	46.0	67.5	50.7	41.5	64.6	44.5	739.0G	50.1	68.8	54.3	43.5	66.3	46.9
Swin-T [22]	264.0G	46.0	68.2	50.2	41.6	65.1	44.8	742.4G	50.5	69.3	54.9	43.7	66.6	47.1
Hire-MLP-S [8]	256.2G	46.2	68.2	50.9	42.0	65.6	45.3	734.6G	50.7	69.4	55.1	**44.2**	66.9	**48.1**
PyramidTNT-S	255.9G	**47.1**	**68.9**	**51.6**	**42.2**	**65.8**	**45.4**	794.1G	**51.0**	**69.7**	**55.3**	**44.2**	**67.0**	**48.1**