Transformer for Computer Vision

Wenhai Wang

Outline

- Transformer
- Transformer-Based Head
  - DEtection TRansformer (DETR) *(detection)*
  - Deformable DETR *(detection)*
  - Trans2Seg *(segmentation)*
- Transformer-Based Backbone
  - Vision Transformer (ViT)
  - Pyramid Vision (PVT)
- Future Work

Transformer

1. Multi-head Attention

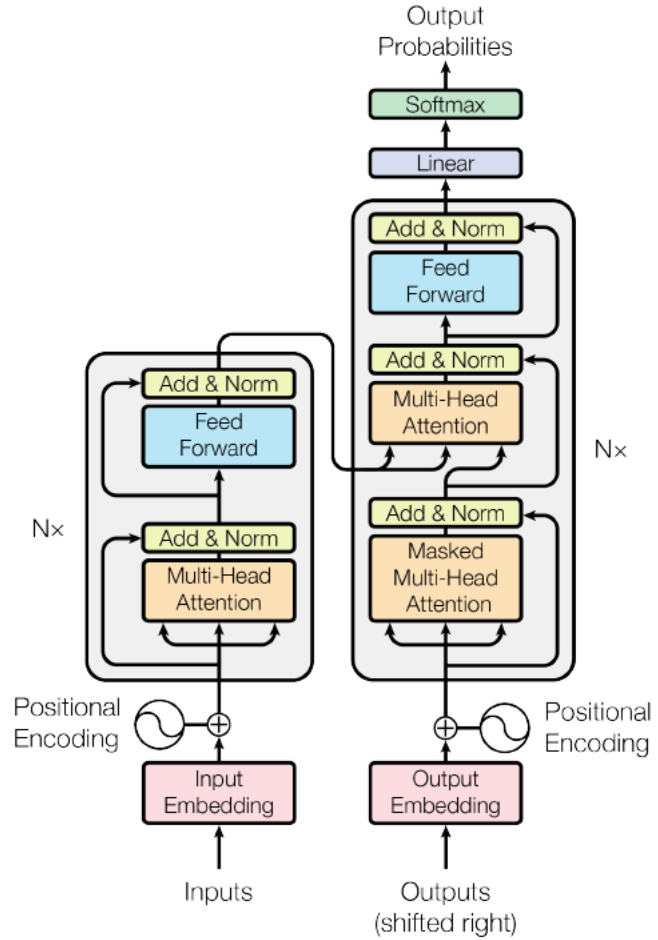
$$\text{MultiHead}(Q,K,V) = \text{Concat}(\text{head}_1,...,\text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$
$$\text{Attention}(Q,K,V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

2. Feed Forward

3. Position Embedding

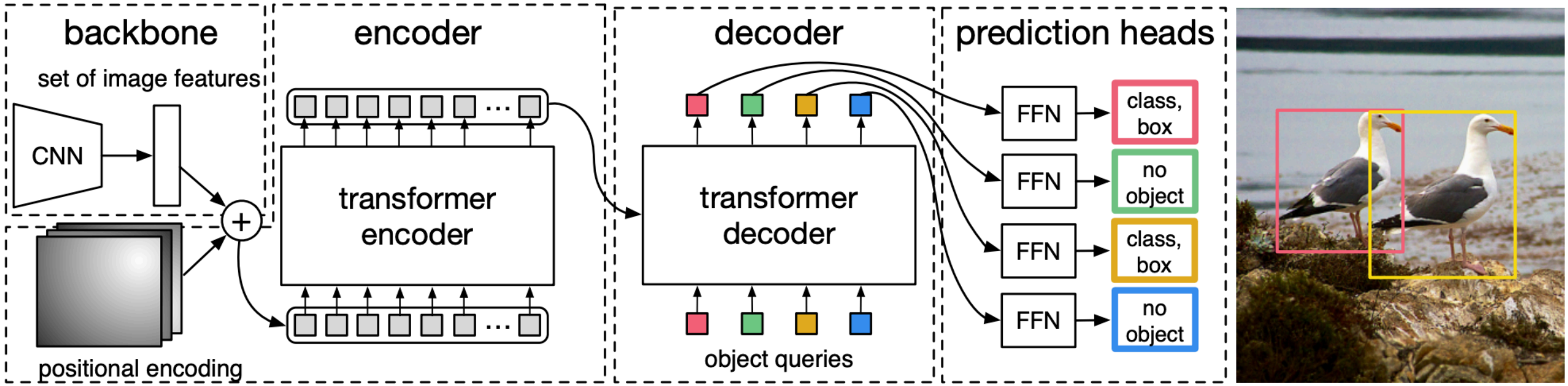
$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

4. Dropout/Residual Connection/Layer Normalization (LN)



Vaswani, Ashish, et al. "Attention is all you need." in NeurIPS, 2017.

DEtection TRansformer (DETR)



1. *Object Detection -> Dictionary Lookup*
2. Query + Bipartite Matching Loss
3. No NMS

Carion, Nicolas, et al. "End-to-end object detection with transformers." In ECCV, 2020.

Deformable DETR

- DeformAttn

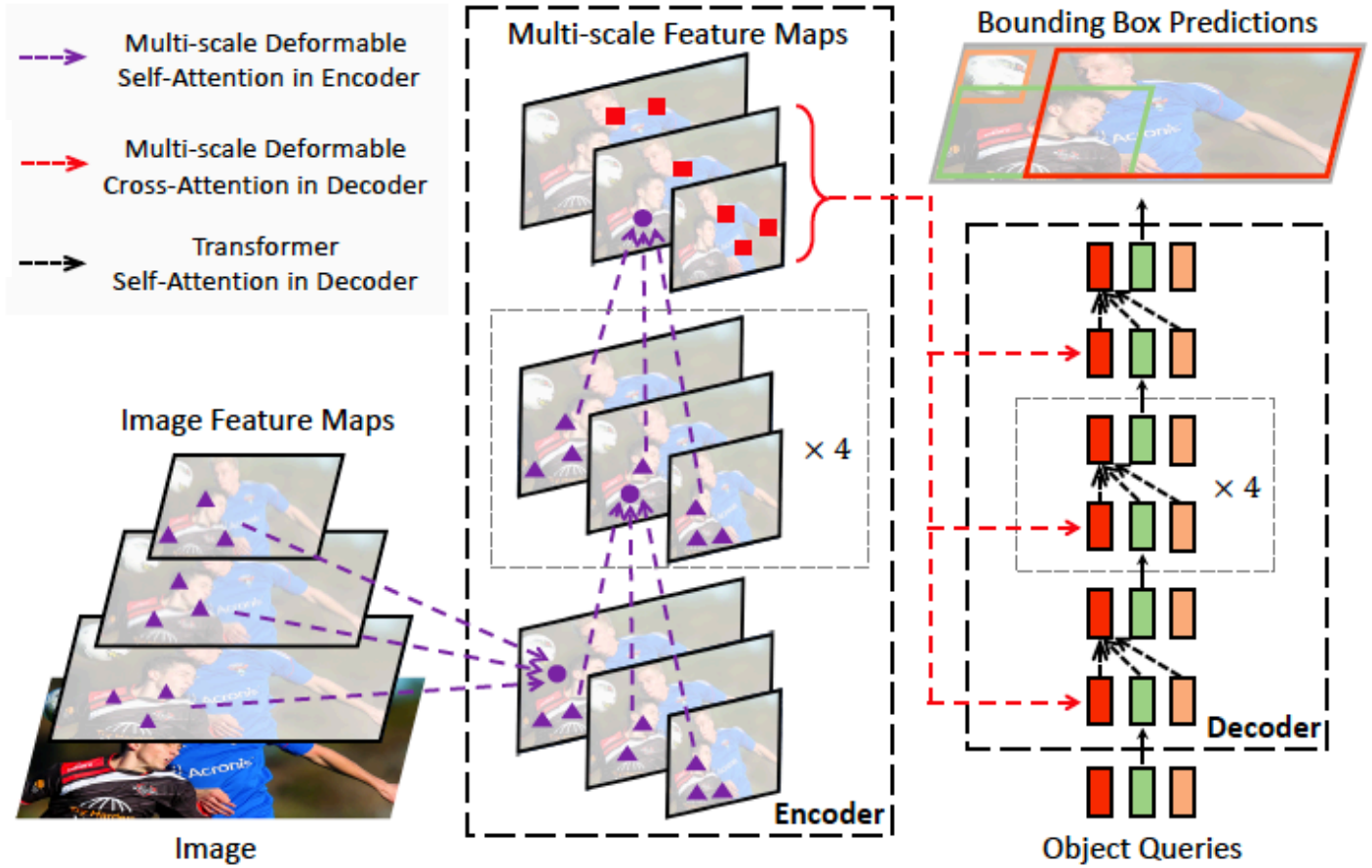
$$\sum_{m=1}^{M} \boldsymbol{W}_m \Big[\sum_{k=1}^{K} A_{mqk} \cdot \boldsymbol{W}'_m \boldsymbol{x}(\boldsymbol{p}_q + \Delta \boldsymbol{p}_{mqk}) \Big],$$

where $A_{mpk}, \Delta p_{mqk}$

is predicted by p_q.

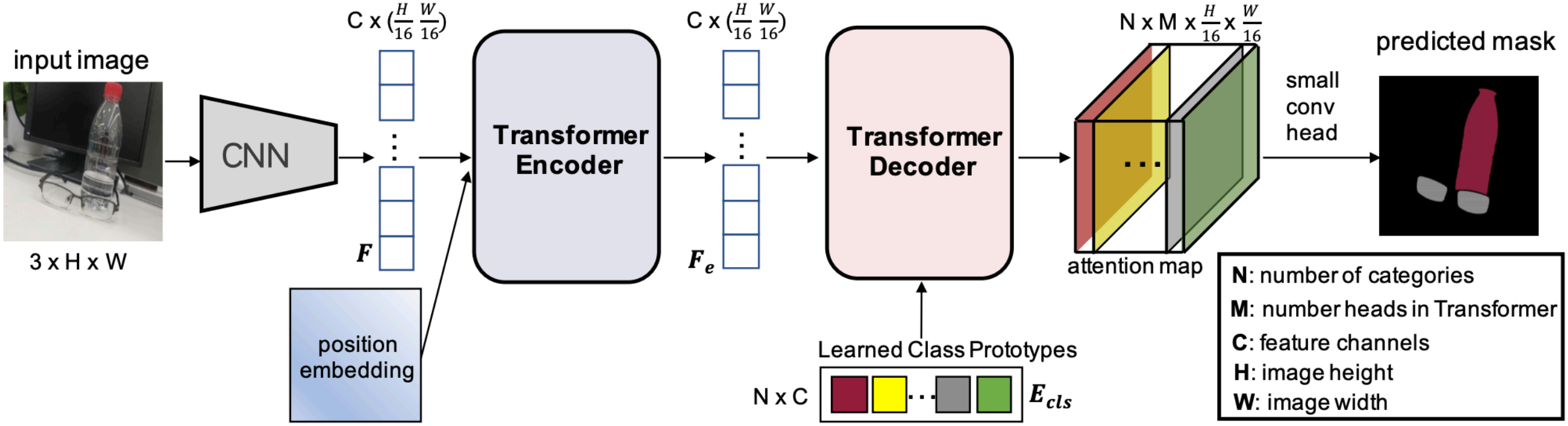
- Advantages

1. Faster Convergence Speed
2. Lower Computational Cost



Zhu, Xizhou, et al. "Deformable DETR: Deformable Transformers for End-to-End Object Detection." in ICLR, 2020.

Trans2Seg



Semantic Segmentation -> Dictionary Lookup

Xie, Enze, et al. "Segmenting transparent object in the wild with transformer." arXiv preprint arXiv:2101.08461 (2021).

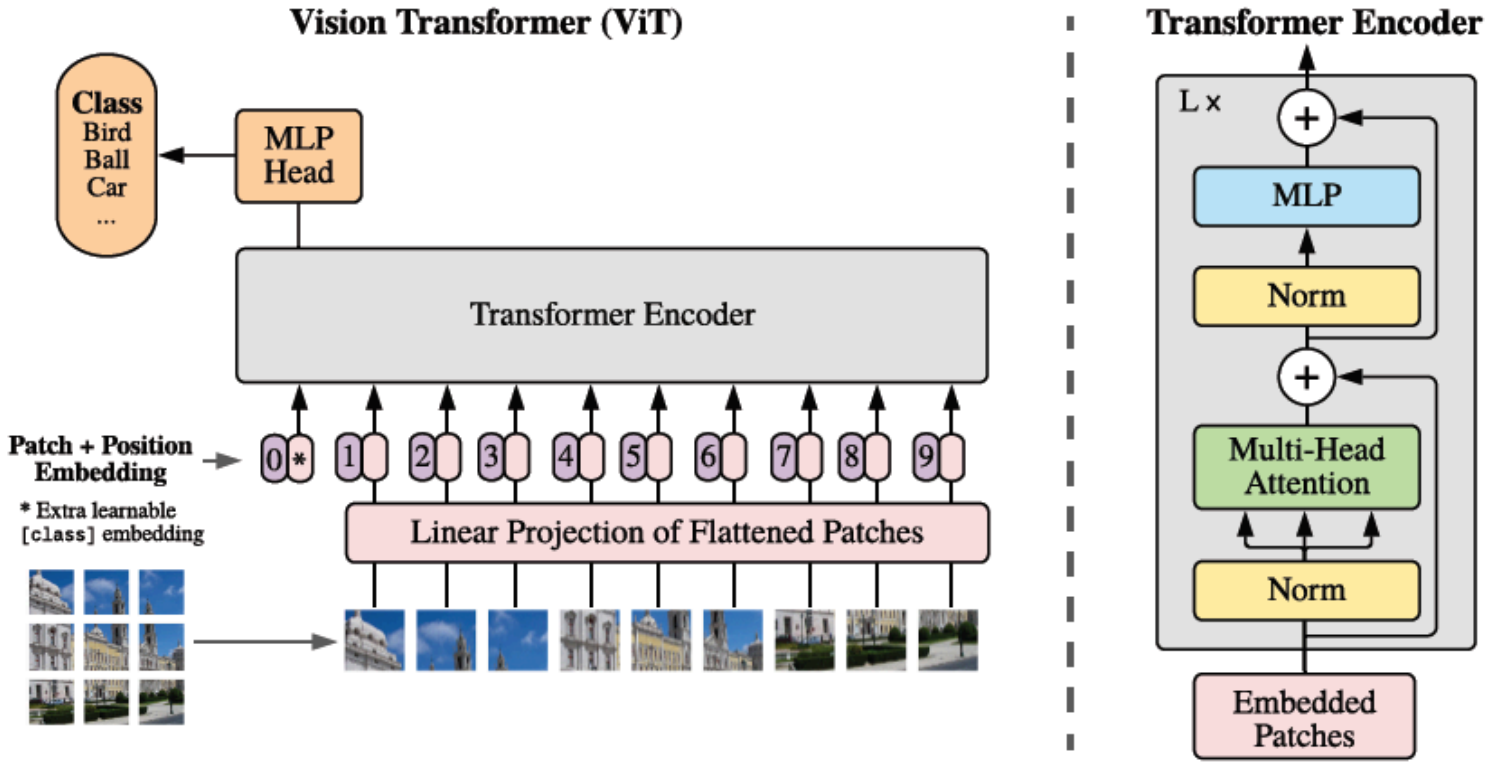
Vision Transformer (ViT)

- Some Tricks

1. Randomly-Initialized Position Embedding

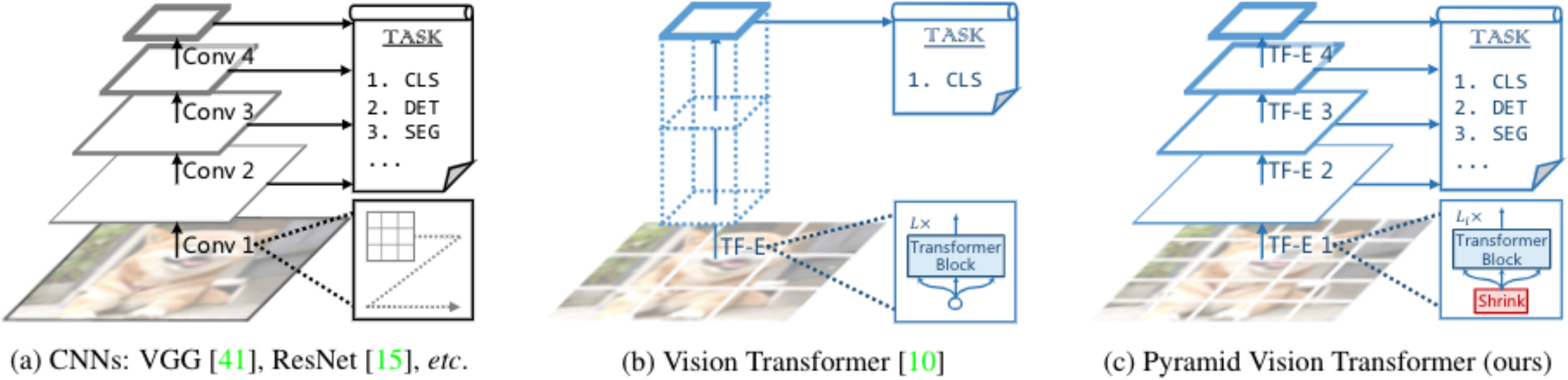
2. *Residual Connection w/ Drop Path*

3. ReLU -> GeLU



Dosovitskiy, Alexey, et al. "An image is worth 16x16 words: Transformers for image recognition at scale." in ICLR, 2020.

Pyramid Vision Transformer (PVT)



(a) CNNs: VGG [41], ResNet [15], *etc.* (b) Vision Transformer [10] (c) Pyramid Vision Transformer (ours)

- Limitations of CNN

1. Local Receptive Field

- Limitations of ViT

1. Columnar Structure
2. Single-Scale/Low-Resolution Output
3. *Unsuitable for Detection/Segmentation*

Wang, Wenhai, et al. "Pyramid Vision Transformer: A Versatile Backbone for Dense Prediction without Convolutions." arXiv preprint arXiv:2102.12122 (2021).

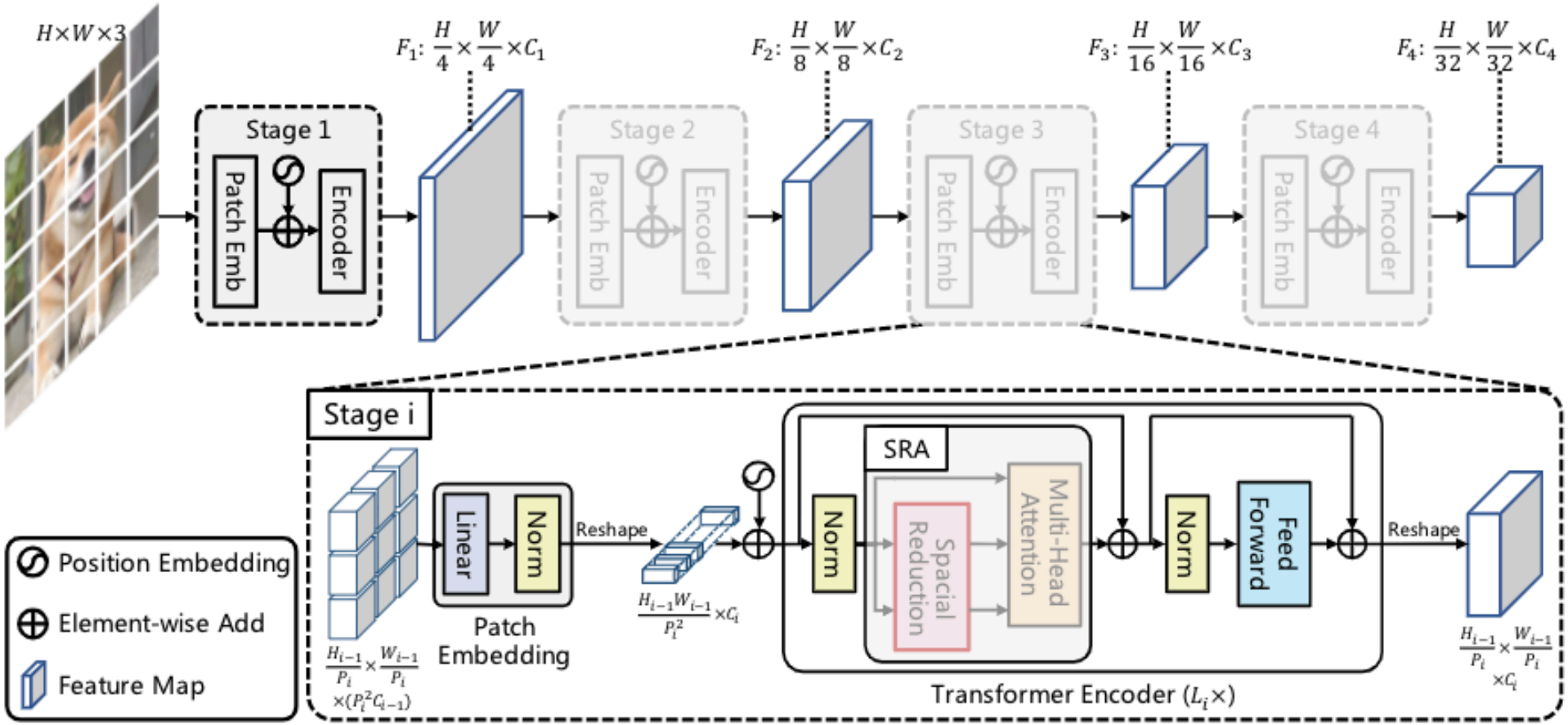
Overall Architecture

- Key Points

1. Four Stages for *Pyramid Structure*

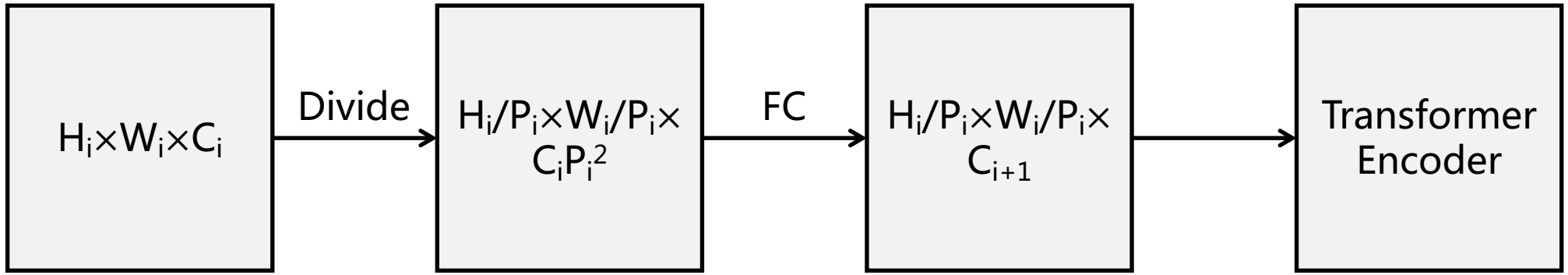
2. Each Stage:
   (1) Patch Emb.
   (2) Transformer Enc.

3. Spatial-Reduction Attention (SRA) for *high-resolution feature map*



How PVT obtains the feature pyramid?

- Adjusting the *patch size* (P_i) in Stage i



The process of the patch embedding in Stage i

Spatial-Reduction Attention

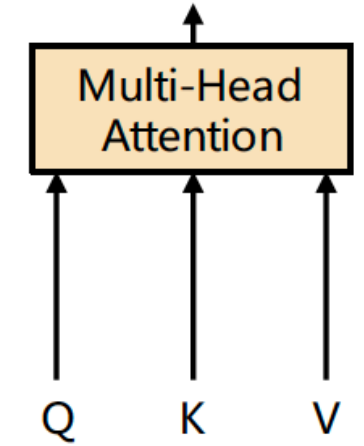
- SRA

$$\mathrm{SRA}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_0, ..., \mathrm{head}_{N_i})W^O$$

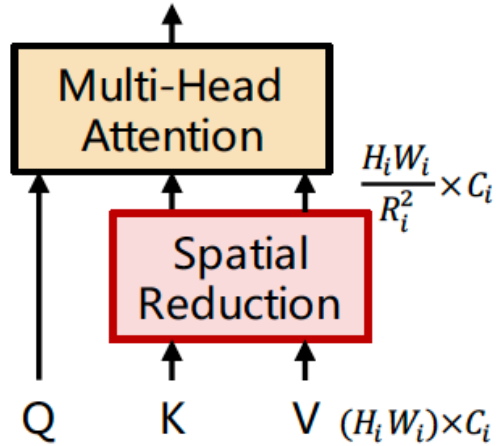
$$\mathrm{head}_j = \mathrm{Attention}(QW_j^Q, \mathrm{SR}(K)W_j^K, \mathrm{SR}(V)W_j^V)$$

$$\boxed{\mathrm{SR}(\mathbf{x}) = \mathrm{Norm}(\mathrm{Reshape}(\mathbf{x}, R_i)W^S)}$$

$$\mathrm{Attention}(\mathbf{q}, \mathbf{k}, \mathbf{v}) = \mathrm{Softmax}(\frac{\mathbf{q}\mathbf{k}^\mathsf{T}}{\sqrt{d_{\mathbf{head}}}})\mathbf{v}$$



Multi-Head Attention



Spatial-Reduction Attention (ours)

Compared to MHA, the resource cost of our SRA is R_i^2 times lower!

Detailed settings

- P_i: the patch size of the stage i;
- C_i: the channel number of the output of the stage i;
- L_i: the number of encoder layers in the stage i;
- R_i: the reduction ratio of the SRA in the stage i;
- N_i: the head number of the SRA in the stage i;
- E_i: the expansion ratio of the feed-forward layer [51] in the stage i;

	Output Size	Layer Name	PVT-Tiny	PVT-Small	PVT-Medium	PVT-Large
Stage 1	$\frac{H}{4} \times \frac{W}{4}$	Patch Embedding	$P_1 = 4;\ C_1 = 64$			
		Transformer Encoder	$\begin{bmatrix} R_1 = 8 \\ N_1 = 1 \\ E_1 = 8 \end{bmatrix} \times 2$	$\begin{bmatrix} R_1 = 8 \\ N_1 = 1 \\ E_1 = 8 \end{bmatrix} \times 3$	$\begin{bmatrix} R_1 = 8 \\ N_1 = 1 \\ E_1 = 8 \end{bmatrix} \times 3$	$\begin{bmatrix} R_1 = 8 \\ N_1 = 1 \\ E_1 = 8 \end{bmatrix} \times 3$
Stage 2	$\frac{H}{8} \times \frac{W}{8}$	Patch Embedding	$P_2 = 2;\ C_2 = 128$			
		Transformer Encoder	$\begin{bmatrix} R_2 = 4 \\ N_2 = 2 \\ E_2 = 8 \end{bmatrix} \times 2$	$\begin{bmatrix} R_2 = 4 \\ N_2 = 2 \\ E_2 = 8 \end{bmatrix} \times 3$	$\begin{bmatrix} R_2 = 4 \\ N_2 = 2 \\ E_2 = 8 \end{bmatrix} \times 3$	$\begin{bmatrix} R_2 = 4 \\ N_2 = 2 \\ E_2 = 8 \end{bmatrix} \times 8$
Stage 3	$\frac{H}{16} \times \frac{W}{16}$	Patch Embedding	$P_3 = 2;\ C_3 = 320$			
		Transformer Encoder	$\begin{bmatrix} R_3 = 2 \\ N_3 = 5 \\ E_3 = 4 \end{bmatrix} \times 2$	$\begin{bmatrix} R_3 = 2 \\ N_3 = 5 \\ E_3 = 4 \end{bmatrix} \times 6$	$\begin{bmatrix} R_3 = 2 \\ N_3 = 5 \\ E_3 = 4 \end{bmatrix} \times 18$	$\begin{bmatrix} R_3 = 2 \\ N_3 = 5 \\ E_3 = 4 \end{bmatrix} \times 27$
Stage 4	$\frac{H}{32} \times \frac{W}{32}$	Patch Embedding	$P_4 = 2;\ C_4 = 512$			
		Transformer Encoder	$\begin{bmatrix} R_4 = 1 \\ N_4 = 8 \\ E_4 = 4 \end{bmatrix} \times 2$	$\begin{bmatrix} R_4 = 1 \\ N_4 = 8 \\ E_4 = 4 \end{bmatrix} \times 3$	$\begin{bmatrix} R_4 = 1 \\ N_4 = 8 \\ E_4 = 4 \end{bmatrix} \times 3$	$\begin{bmatrix} R_4 = 1 \\ N_4 = 8 \\ E_4 = 4 \end{bmatrix} \times 3$

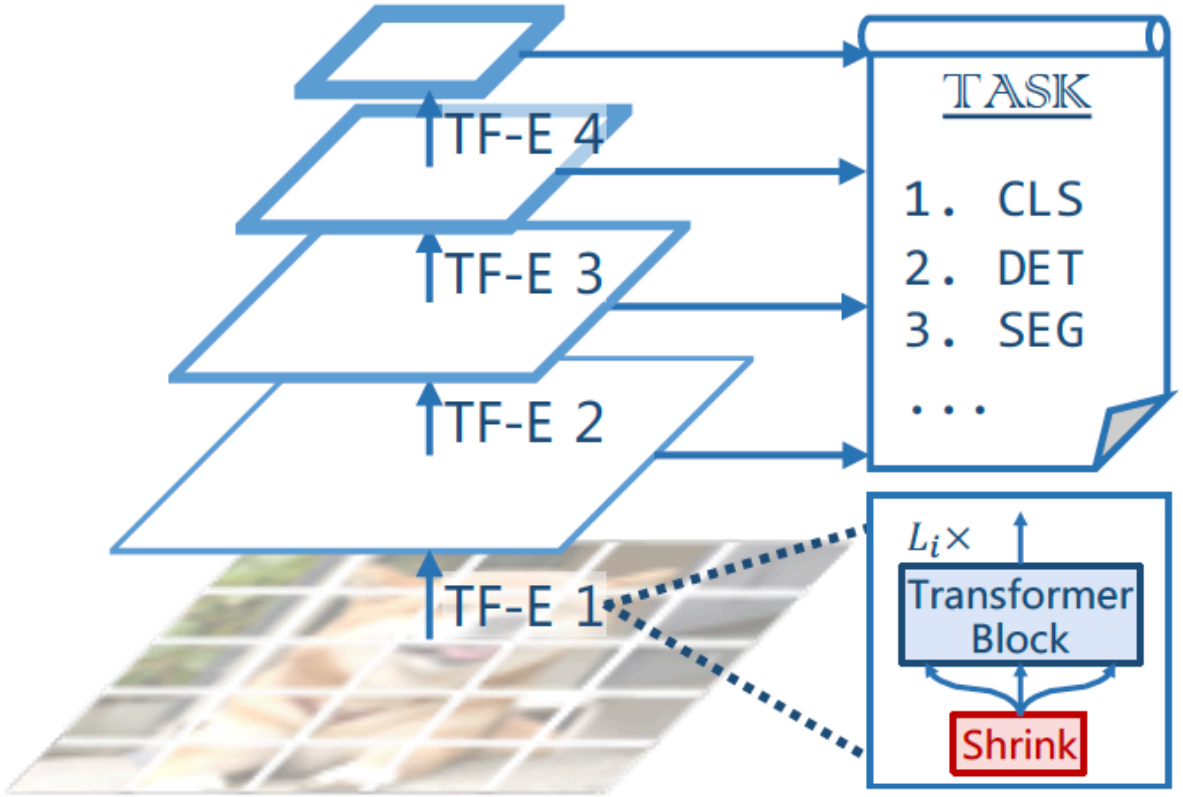
Table A1: **Detailed settings of Pyramid Vision Transformer (PVT) series.** The design follows the two rules of ResNet [5]. (1) With the growth of network depth, the hidden dimension gradually increases, and the output resolution progressively shrinks; (2) The major computation resource is concentrated in Stage 3.

Advantages

1. Multi-Scale/High-Resolution Output

2. *As versatile as ResNet, can be apply to detection/segmentation*

3. Making pure Transformer detection/ segmentation possible, for example
   (1) PVT + DETR
   (2) PVT + Trans2Seg



Performance

- PVT-S vs. R50

AP: 40.4 vs. 36.3 (+4.1)

#P: 34.2 vs. 37.7

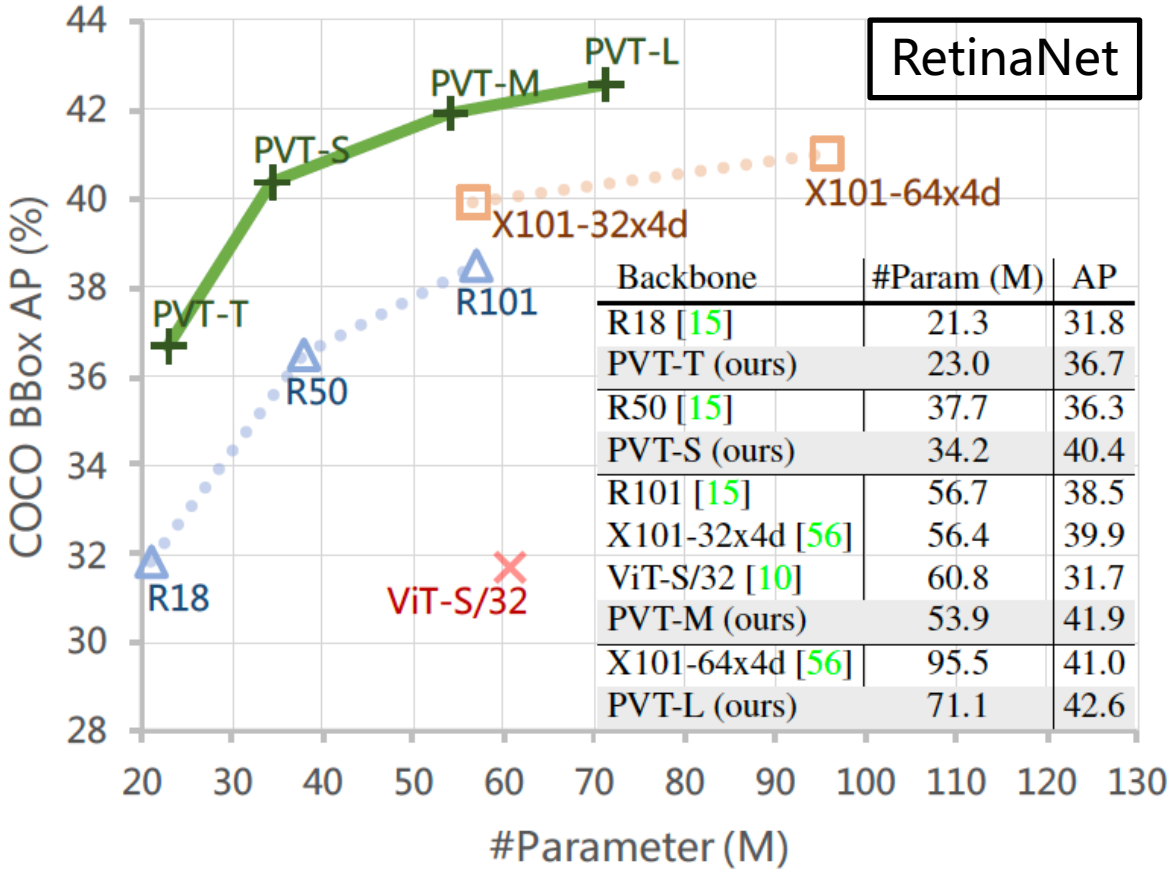
- PVT-L vs. X101-64x4d

AP: 42.6 vs. 41.0 (+1.6)

#P: 71.1 vs. 95.5 (20% fewer)

- [New] + Some New Tricks

PVT-S AP: 36.3 -> 40.4 -> 43.3 (+7.0)



Backbone	#Param (M)	AP
R18 [15]	21.3	31.8
PVT-T (ours)	23.0	36.7
R50 [15]	37.7	36.3
PVT-S (ours)	34.2	40.4
R101 [15]	56.7	38.5
X101-32x4d [56]	56.4	39.9
ViT-S/32 [10]	60.8	31.7
PVT-M (ours)	53.9	41.9
X101-64x4d [56]	95.5	41.0
PVT-L (ours)	71.1	42.6

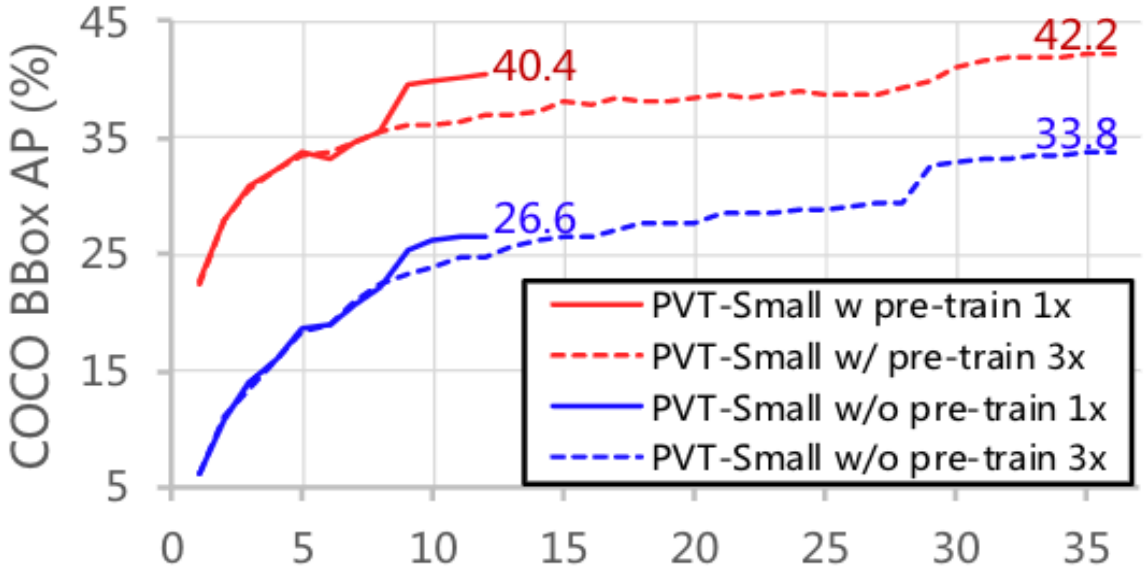
Ablation Study

1. *Going deeper is better than going wider*

2. *Pretrained weights can help PVT converge faster and better*

Method	#Param (M)	Top-1	RetinaNet 1x		
			AP	AP_{50}	AP_{75}
Wider PVT-Small	46.8	19.3	40.8	61.8	43.3
Deeper PVT-Small	44.2	18.8	41.9	63.1	44.3

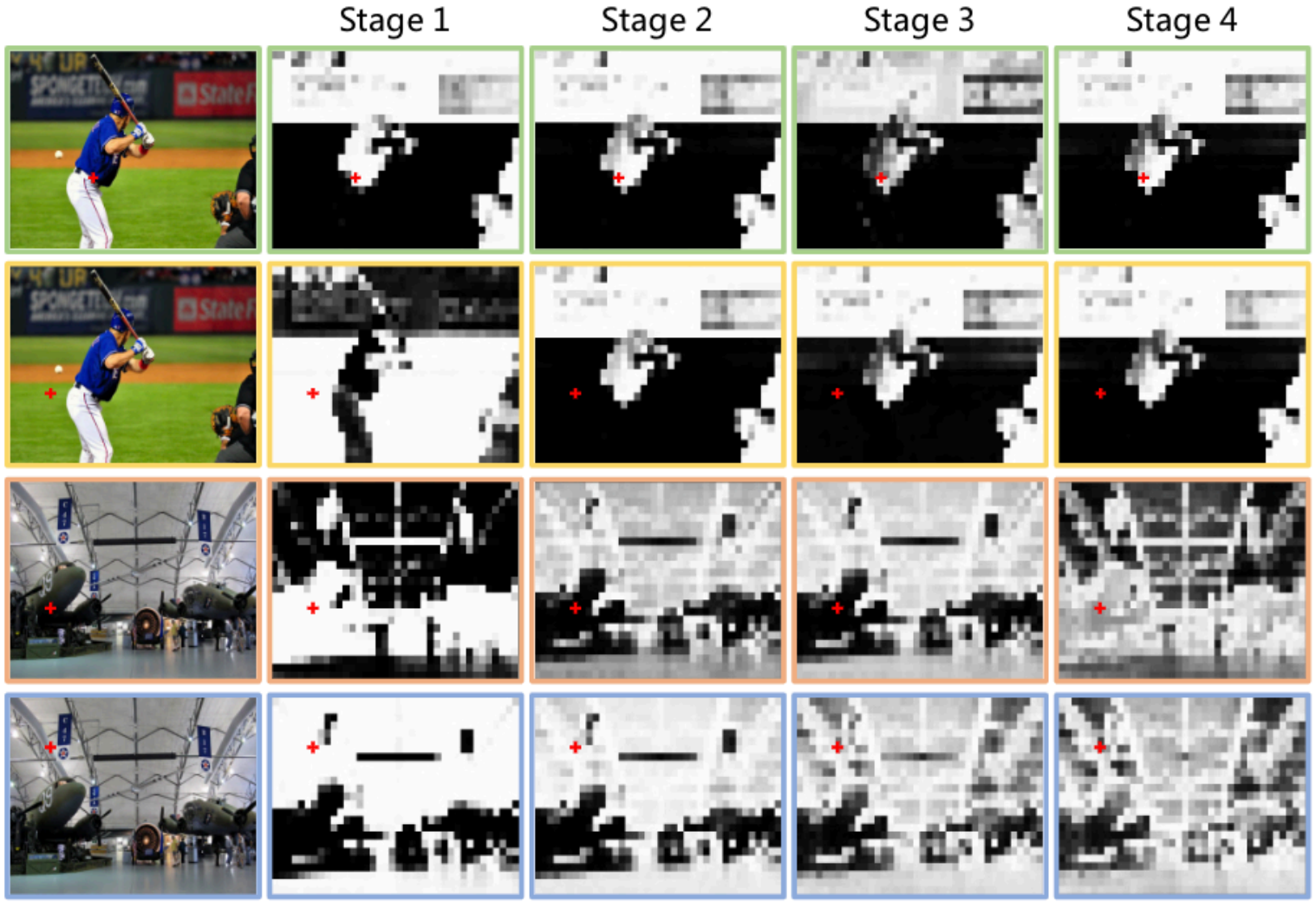
Table A3: **Deeper *vs*. Wider.** "Top-1" denotes the top-1 error on the ImageNet validation set. "AP" denotes the bounding box AP on COCO `val2017`. The deeper model obtains better performance than the wider model under comparable parameter number.



Ablation Study

1. The attention layer at the *shallow* stage mainly focuses on *appearance feature (e.g., color)*

2. The attention layer at the *deep* stage encodes *the global pattern of entire image,* and is *insensitive to the query pixel*

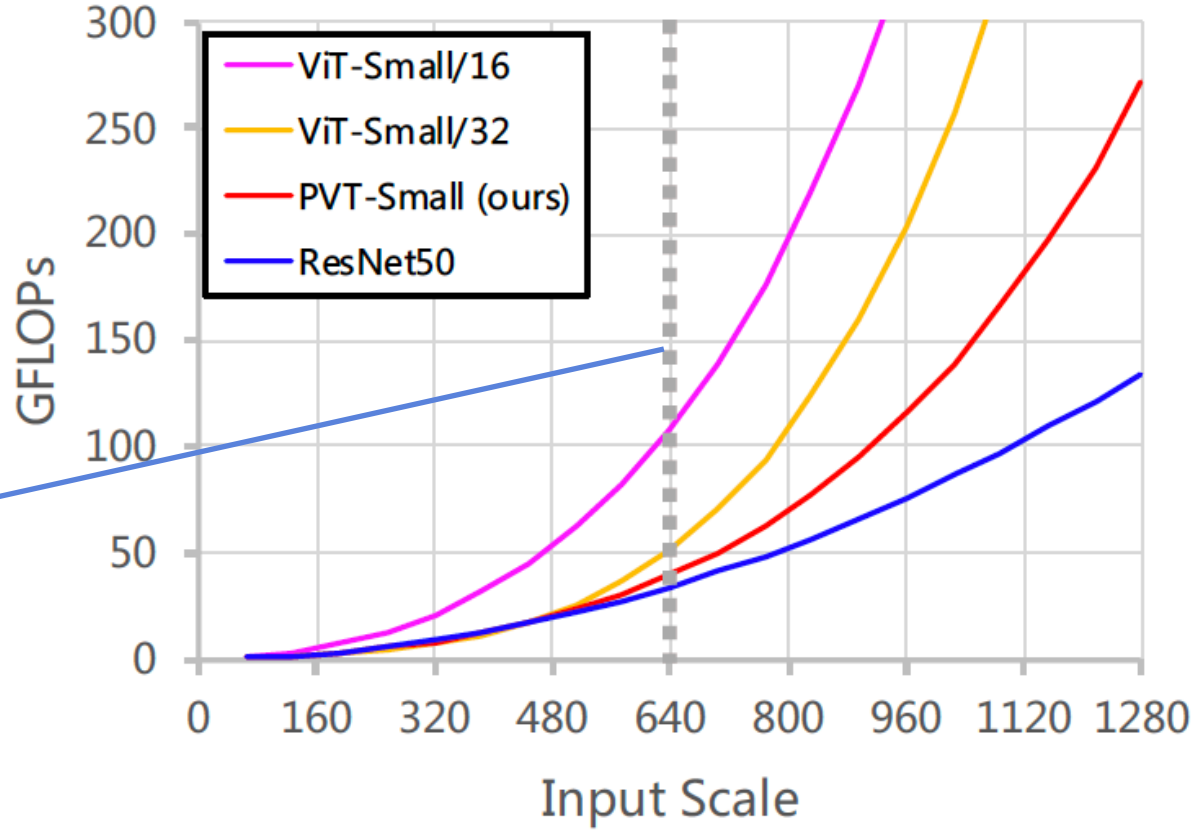


Computation Cost

- FLOPs Growth Rate

ViT-S/16 > ViT-S/32 > PVT-S > R50

PVT is more suitable for medium-resolution input (640×640 pixels)



Future Work

- Efficient Attention Layer;
- Position Embedding for 2D/3D Images;
- Pure Transformer Vision Models;
- Transformer + NAS/Pruning/Distillation/Quantification;
- Multimodal Transformer (*e.g.,* CV+NLP);
- …

Thanks

Q&A