PVTv2: Improved Baselines with Pyramid Vision Transformer

Wenhai Wang[1], Enze Xie[2], Xiang Li[3], Deng-Ping Fan[4],
Kaitao Song[3], Ding Liang[5], Tong Lu[1], Ping Luo[2], Ling Shao[4]
[1]Nanjing University [2]The University of Hong Kong
[3]Nanjing University of Science and Technology [4]IIAI [5]SenseTime Research
wangwenhai362@smail.nju.edu.cn,

Abstract

Transformer recently has presented encouraging progress in computer vision. In this work, we present new baselines by improving the original Pyramid Vision Transformer (PVTv1) by adding three designs, including (1) overlapping patch embedding, (2) convolutional feed-forward networks, and (3) linear complexity attention layers.

With these modifications, our PVTv2 significantly improves PVTv1 on three tasks e.g.*, classification, detection, and segmentation. Moreover, PVTv2 achieves comparable or better performances than recent works such as Swin Transformer. We hope this work will facilitate state-of-the-art Transformer researches in computer vision. Code is available at* https://github.com/whai362/PVT.

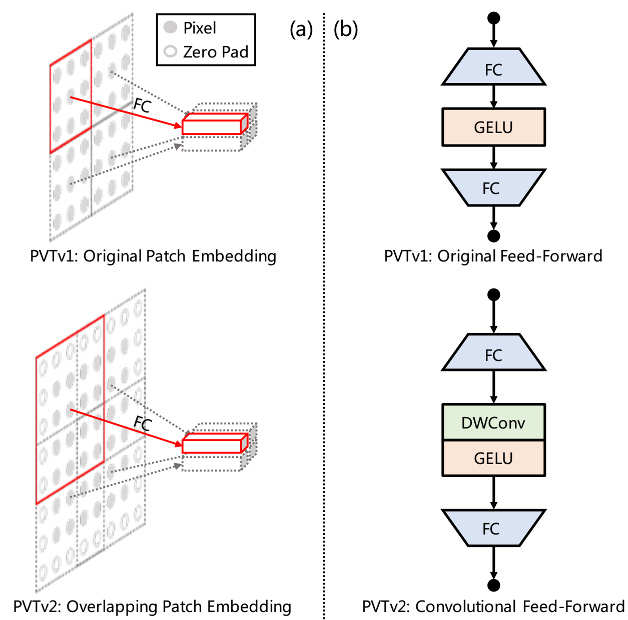

Figure 1: **Two improvements in PVTv2.** (1) Overlapping Patch Embedding. (2) Convolutional Feed Forward Network.

1. Introduction

Recent studies on vision Transformer are converging on the backbone network [8, 30, 32, 33, 23, 35, 10, 5] designed for downstream vision tasks, such as image classification, object detection, instance and semantic segmentation. To date, there have been some promising results. For example, Vision Transformer (ViT) [8] first proves that a pure Transformer can archive state-of-the-art performance in image classification. Pyramid Vision Transformer (PVT) [32] shows that a pure Transformer backbone can also surpass CNN counterparts in several detection and segmentation tasks [22, 40, **?**]. After that, Swin Transformer [23], CoaT [35], LeViT [10], and Twins [5] further improve the classification, detection, and segmentation performance with Transformer backbones.

This work aims to establish stronger and more feasible baselines built on the PVTv1 framework. We report that three design improvements, namely (1) overlapping patch embedding, (2) convolutional feed-forward networks, and (3) linear complexity attention layers are orthogonal to the PVTv1 framework, and when used with PVT, they can bring better image classification, object detection, instance and semantic segmentation performance. Specifically, PVTv2-B5[1] yields 83.8% top-1 error on ImageNet, which is significantly better than Swin-B [23] and Twins-SVT-L [5], while PVTv2-B5 has fewer parameters and GFLOPs. Moreover, GFL [19] with PVT-B2 archives 50.2 AP on COCO `val2017`, 2.6 AP higher than the one with Swin-T [23], 5.7 AP higher than the one with ResNet50 [13]. We hope these improved baselines will provide a reference for future research in vision Transformer.

[1]PVTv2 has 6 different size variants, from B0 to B5 according to the parameter number.

2. Related Work

We mainly discuss transformer backbones related to this work. ViT [8] treats each image as a sequence of tokens (patches) with a fixed length, and then feeds them to multiple Transformer layers to perform classification. It is the first work to prove that a pure Transformer can also archive state-of-the-art performance in image classification when training data is sufficient (*e.g.*, ImageNet-22k [7], JFT-300M). DeiT [30] further explores a data-efficient training strategy and a distillation approach for ViT.

To improve image classification performance, recent methods make tailored changes to ViT. T2T ViT [36] concatenates tokens within an overlapping sliding window into one token progressively. TNT [11] utilizes inner and outer Transformer blocks to generate pixel and patch embeddings respectively. CPVT [6] replaces the fixed size position embedding in ViT with conditional position encodings, making it easier to process images of arbitrary resolution. CrossViT [2] processes image patches of different sizes via a dual-branch Transformer. LocalViT [20] incorporates depth-wise convolution into vision Transformers to improve the local continuity of features.

To adapt to dense prediction tasks such as object detection, instance and semantic segmentation, there are also some methods [32, 23, 33, 35, 10, 5] to introduce the pyramid structure in CNNs to the design of Transformer backbones. PVTv1 is the first pyramid structure Transformer, which presents a hierarchical Transformer with four stages, showing that a pure Transformer backbone can be as versatile as CNN counterparts and performs better in detection and segmentation tasks. After that, some improvements [23, 33, 35, 10, 5] are made to enhance the local continuity of features and to remove fixed size position embedding. For example, Swin Transformer [23] replaces fixed size position embedding with relative position biases, and restricts self-attention within shifted windows. CvT [33], CoaT [35], and LeViT [10] introduce convolution-like operations into vision Transformers. Twins [5] combines local attention and global attention mechanisms to obtain stronger feature representation.

3. Methodology

3.1. Limitations in PVTv1

There are three main limitations in PVTv1 [32] as follows: (1) Similar to ViT [8], PVTv1 [32] treats an image as a sequence of non-overlapping patches, which loses the local continuity of the image to a certain extent; (2) The position encoding in PVTv1 is fixed-size, which is inflexible for process images of arbitrary size; (3) When processing high-resolution input (*e.g.*, shorter side being 800 pixels), the computational complexity of PVTv1 is relatively large. These problems limit the performance of PVTv1 on vision tasks.

To address these issues, we propose PVTv2, which improves PVTv1 through designs including overlapping patch embedding, convolutional feed-forward networks, and linear spatial reduction attention layer.

3.2. Overlapping Patch Embedding

We utilize overlapping patch embedding to tokenize images. As shown in Fig. 1(a), we enlarge the patch window, making adjacent windows overlap by half of the area, and pad the feature map with zeros to keep the resolution. In this work, we use convolution with zero paddings to implement overlapping patch embedding. Specifically, given an input of size $h \times w \times c$, we feed it to a convolution with the stride of S, the kernel size of $2S-1$, the padding size of $S-1$, and the kernel number of c'. The output size is $\frac{h}{S} \times \frac{w}{S} \times C'$.

3.3. Convolutional Feed-Forward

Inspired by [17, 6, 20], we remove the fixed-size position encoding [8], and introduce zero padding position encoding into PVT. As shown in Fig. 1(b), we add a 3×3 depth-wise convolution [16] with the padding size of 1 between the first fully-connected (FC) layer and GELU [15] in feed-forward networks.

3.4. Linear Spatial Reduction Attention

To further reduce the computation cost of PVT, we propose linear spatial reduction attention (SRA) as illustrated in Fig. 2. Different from SRA [32], linear SRA enjoys linear computational and memory costs like a convolutional layer. Specifically, given an input of size $h \times w \times c$, the complexity of SRA and linear SRA are:

$$\Omega(\text{SRA}) = \frac{2h^2w^2c}{R^2} + hwc^2R^2, \tag{1}$$

$$\Omega(\text{Linear SRA}) = 2hwP^2c, \tag{2}$$

where R is the spatial reduction ratio of SRA [32]. P is the pooling size of linear SRA, which is set to 7 by default.

Combining the three improvements, PVTv2 can (1) obtain more local continuity of images and feature maps; (2) process variable-resolution input more flexibly; (3) enjoy the same linear complexity as CNN.

4. Details of PVTv2 Series

We scale up PVTv2 from B0 to B5 By changing the hyper-parameters. which are listed as follows:

- S_i: the stride of the overlapping patch embedding in Stage i;
- C_i: the channel number of the output of Stage i;
- L_i: the number of encoder layers in 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 1: **Detailed settings of PVTv2 series.** "-Li" denotes PVTv2 with linear SRA.

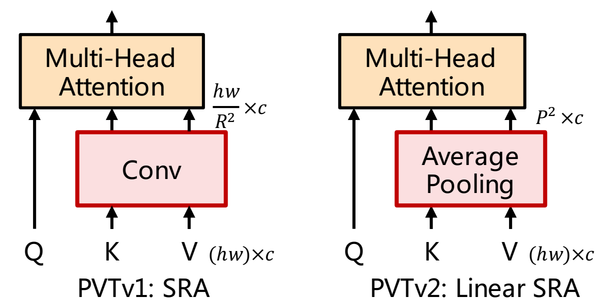

Figure 2: **Comparison of SRA in PVTv1 and linear SRA in PVTv2.**

- R_i: the reduction ratio of the SRA in Stage i;
- P_i: the adaptive average pooling size of the linear SRA in Stage i;
- N_i: the head number of the Efficient Self-Attention in Stage i;
- E_i: the expansion ratio of the feed-forward layer [31] in Stage i;

Tab. 1 shows the detailed information of PVTv2 series. Our design follows the principles of ResNet [14]. (1) the channel dimension increase while the spatial resolution shrink with the layer goes deeper. (2) Stage 3 is assigned to most of the computation cost.

5. Experiment

5.1. Image Classification

Settings. Image classification experiments are performed on the ImageNet-1K dataset [26], which comprises 1.28 million training images and 50K validation images from 1,000 categories. All models are trained on the training set for fair comparison and report the top-1 error on the validation set. We follow DeiT [30] and apply random cropping,

Method	#Param (M)	GFLOPs	Top-1 (%)
R18* [14]	11.7	1.8	30.2
R18 [14]	11.7	1.8	31.5
DeiT-Tiny/16 [30]	**5.7**	**1.3**	27.8
PVT-Tiny (ours)	13.2	1.9	**24.9**
R50* [14]	25.6	4.1	23.9
R50 [14]	25.6	4.1	21.5
X50-32x4d* [34]	25.0	4.3	22.4
X50-32x4d [34]	25.0	4.3	20.5
DeiT-Small/16 [30]	**22.1**	4.6	**20.1**
PVT-Small (ours)	24.5	**3.8**	20.2
R101* [14]	44.7	7.9	22.6
R101 [14]	44.7	7.9	20.2
X101-32x4d* [34]	**44.2**	8.0	21.2
X101-32x4d [34]	**44.2**	8.0	19.4
ViT-Small/16 [8]	48.8	9.9	19.2
PVT-Medium (ours)	**44.2**	**6.7**	**18.8**
X101-64x4d* [34]	83.5	15.6	20.4
X101-64x4d [34]	83.5	15.6	18.5
ViT-Base/16 [8]	86.6	17.6	**18.2**
DeiT-Base/16 [30]	86.6	17.6	**18.2**
PVT-Large (ours)	**61.4**	**9.8**	18.3

Table 2: **Image classification performance on the ImageNet validation set.** "#Param" refers to the number of parameters. "GFLOPs" is calculated under the input scale of 224×224. "*" indicates the performance of the method trained under the strategy of its original paper. "-Li" denotes PVTv2 with linear SRA.

random horizontal flipping [28], label-smoothing regularization [29], mixup [37], and random erasing [39] as data augmentations. During training, we employ AdamW [25] with a momentum of 0.9, a mini-batch size of 128, and a weight decay of 5×10^{-2} to optimize models. The initial learning rate is set to 1×10^{-3} and decreases following the cosine schedule [24]. All models are trained for 300 epochs from scratch on 8 V100 GPUs. We apply a center crop on the validation set to benchmark, where a 224×224 patch is cropped to evaluate the classification accuracy.

Results. In Tab. 2, we see that PVTv2 is the state-of-the-art method on ImageNet-1K classification. Compared to

Backbone	RetinaNet 1×							Mask R-CNN 1×						
	#P (M)	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	#P (M)	AP^b	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^m_{75}
PVTv2-B0	**13.0**	**37.2**	**57.2**	**39.5**	**23.1**	**40.4**	**49.7**	**23.5**	**38.2**	**60.5**	**40.7**	**36.2**	**57.8**	**38.6**
ResNet18 [14]	**21.3**	31.8	49.6	33.6	16.3	34.3	43.2	**31.2**	34.0	54.0	36.7	31.2	51.0	32.7
PVTv1-Tiny [32]	23.0	36.7	56.9	38.9	22.6	38.8	50.0	32.9	36.7	59.2	39.3	35.1	56.7	37.3
PVTv2-B1 (ours)	23.8	**41.2**	**61.9**	**43.9**	**25.4**	**44.5**	**54.3**	33.7	**41.8**	**64.3**	**45.9**	**38.8**	**61.2**	**41.6**
ResNet50 [14]	37.7	36.3	55.3	38.6	19.3	40.0	48.8	44.2	38.0	58.6	41.4	34.4	55.1	36.7
PVTv1-Small [32]	34.2	40.4	61.3	43.0	25.0	42.9	55.7	44.1	40.4	62.9	43.8	37.8	60.1	40.3
PVTv2-B2-Li (ours)	**32.3**	43.6	64.7	46.8	28.3	47.6	57.4	**42.2**	44.1	66.3	48.4	40.5	63.2	43.6
PVTv2-B2 (ours)	35.1	**44.6**	**65.6**	**47.6**	**27.4**	**48.8**	**58.6**	45.0	**45.3**	**67.1**	**49.6**	**41.2**	**64.2**	**44.4**
ResNet101 [14]	56.7	38.5	57.8	41.2	21.4	42.6	51.1	63.2	40.4	61.1	44.2	36.4	57.7	38.8
ResNeXt101-32x4d [34]	56.4	39.9	59.6	42.7	22.3	44.2	52.5	**62.8**	41.9	62.5	45.9	37.5	59.4	40.2
PVTv1-Medium [32]	**53.9**	41.9	63.1	44.3	25.0	44.9	57.6	63.9	42.0	64.4	45.6	39.0	61.6	42.1
PVTv2-B3 (ours)	55.0	**45.9**	**66.8**	**49.3**	**28.6**	**49.8**	**61.4**	64.9	**47.0**	**68.1**	**51.7**	**42.5**	**65.7**	**45.7**
PVTv1-Large [32]	**71.1**	42.6	63.7	45.4	25.8	46.0	58.4	**81.0**	42.9	65.0	46.6	39.5	61.9	42.5
PVTv2-B4 (ours)	72.3	**46.1**	**66.9**	**49.2**	**28.4**	**50.0**	**62.2**	82.2	**47.5**	**68.7**	**52.0**	**42.7**	**66.1**	**46.1**
ResNeXt101-64x4d [34]	95.5	41.0	60.9	44.0	23.9	45.2	54.0	101.9	42.8	63.8	47.3	38.4	60.6	41.3
PVTv2-B5 (ours)	**91.7**	**46.2**	**67.1**	**49.5**	**28.5**	**50.0**	**62.5**	**101.6**	**47.4**	**68.6**	**51.9**	**42.5**	**65.7**	**46.0**

Table 3: **Object detection and instance segmentation on COCO `val2017`.** "#P" refers to parameter number. AP^b and AP^m denote bounding box AP and mask AP, respectively. "-Li" denotes PVTv2 with linear SRA.

PVT, PVTv2 has similar flops and parameters, but the image classification accuracy is greatly improved. For example, PVTv2-B1 is 3.6% higher than PVTv1-Tiny, and PVTv2-B4 is 1.9% higher than PVT-Large.

Compared to other recent counterparts, PVTv2 series also has large advantages in terms of accuracy and model size. For example, PVTv2-B5 achieves 83.8% ImageNet top-1 accuracy, which is 0.5% higher than Swin Transformer [23] and Twins [5], while our parameters and FLOPS are fewer.

5.2. Object Detection

Settings. Object detection experiments are conducted on the challenging COCO benchmark [22]. All models are trained on COCO `train2017` (118k images) and evaluated on `val2017` (5k images). We verify the effectiveness of PVTv2 backbones on top of mainstream detectors, including RetinaNet [21], Mask R-CNN [12], Cascade Mask R-CNN [1], ATSS [38], GFL [19], and Sparse R-CNN [27]. Before training, we use the weights pre-trained on ImageNet to initialize the backbone and Xavier [9] to initialize the newly added layers. We train all the models with batch size 16 on 8 V100 GPUs, and adopt AdamW [25] with an initial learning rate of 1×10^{-4} as optimizer. Following common practices [21, 12, 3], we adopt 1× or 3× training schedule (*i.e.*, 12 or 36 epochs) to train all detection models. The training image is resized to have a shorter side of 800 pixels, while the longer side does not exceed 1,333 pixels. When using the 3× training schedule, we randomly resize the shorter side of the input image within the range of $[640, 800]$. In the testing phase, the shorter side of the input image is fixed to 800 pixels.

Results. As reported in Tab. 3, PVTv2 significantly outperforms PVTv1 on both one-stage and two-stage object detectors with similar model size. For example, PVTv2-B4 archive 46.1 AP on top of RetinaNet [21], and 47.5 AP^b on top of Mask R-CNN [12], surpassing the models with PVTv1 by 3.5 AP and 4.6 AP^b, respectively. We present some qualitative object detection and instance segmentation results on COCO `val2017` [22] in Fig. 3, which also shows the good performance of our models.

For a fair comparison between PVTv2 and Swin Transformer [23], we keep all settings the same, including ImageNet-1K pre-training and COCO fine-tuning strategies. We evaluate Swin Transformer and PVTv2 on four state-of-the-arts detectors, including Cascade R-CNN [1], ATSS [38], GFL [19], and Sparse R-CNN [27]. We see PVTv2 obtain much better AP than Swin Transformer among all the detectors, showing its better feature representation ability. For example, on ATSS, PVTv2 has similar parameters and flops compared to Swin-T, but PVTv2 achieves 49.9 AP, which is 2.7 higher than Swin-T. Our PVTv2-Li can largely reduce the computation from 258 to 194 GFLOPs, while only sacrificing a little performance.

5.3. Semantic Segmentation

Settings. Following PVTv1 [32], we choose ADE20K [40] to benchmark the performance of semantic segmentation. For a fair comparison, we test the performance of PVTv2 backbones by applying it to Semantic FPN [18]. In the training phase, the backbone is initialized with the weights pre-trained on ImageNet [7], and the newly added layers are initialized with Xavier [9]. We optimize our models using AdamW [25] with an initial learning rate of 1e-4. Following common practices [18, 4], we train our models for 40k iterations with a batch size of 16 on 4 V100 GPUs. The learning rate is decayed following the polynomial decay schedule with a power of 0.9. We randomly resize and crop the im-

Backbone	Method	AP^b	AP^b_{50}	AP^b_{75}	#P (M)	GFLOPs
ResNet50 [14]	Cascade Mask R-CNN [1]	46.3	64.3	50.5	82	739
Swin-T [23]		50.5	69.3	54.9	86	745
PVTv2-B2-Li (ours)		50.9	69.5	55.2	**80**	**725**
PVTv2-B2 (ours)		**51.1**	**69.8**	**55.3**	83	788
ResNet50 [14]	ATSS [38]	43.5	61.9	47.0	32	205
Swin-T [23]		47.2	66.5	51.3	36	215
PVTv2-B2-Li (ours)		48.9	68.1	53.4	**30**	**194**
PVTv2-B2 (ours)		**49.9**	**69.1**	**54.1**	33	258
ResNet50 [14]	GFL [19]	44.5	63.0	48.3	32	208
Swin-T [23]		47.6	66.8	51.7	36	215
PVTv2-B2-Li (ours)		49.2	68.2	53.7	**30**	**197**
PVTv2-B2 (ours)		**50.2**	**69.4**	**54.7**	33	261
ResNet50 [14]	Sparse R-CNN [27]	44.5	63.4	48.2	106	166
Swin-T [23]		47.9	67.3	52.3	110	172
PVTv2-B2-Li (ours)		48.9	68.3	53.4	**104**	**151**
PVTv2-B2 (ours)		**50.1**	**69.5**	**54.9**	107	215

Table 4: **Compare with Swin Transformer on object detection.** "AP^b" denotes bounding box AP. "#P" refers to parameter number. "GFLOPs" is calculated under the input scale of 1280×800. "-Li" denotes PVTv2 with linear SRA.

Backbone	Semantic FPN		
	#Param (M)	GFLOPs	mIoU (%)
PVTv2-B0 (ours)	**7.6**	**25.0**	**37.2**
ResNet18 [14]	**15.5**	**32.2**	32.9
PVTv1-Tiny [32]	17.0	33.2	35.7
PVTv2-B1 (ours)	17.8	34.2	**42.5**
ResNet50 [14]	28.5	45.6	36.7
PVTv1-Small [32]	28.2	44.5	39.8
PVTv2-B2-Li (ours)	**26.3**	**41.0**	45.1
PVTv2-B2 (ours)	29.1	45.8	**45.2**
ResNet101 [14]	47.5	65.1	38.8
ResNeXt101-32x4d [34]	**47.1**	64.7	39.7
PVTv1-Medium [32]	48.0	**61.0**	41.6
PVTv2-B3 (ours)	49.0	62.4	**47.3**
PVTv1-Large [32]	**65.1**	**79.6**	42.1
PVTv2-B4 (ours)	66.3	81.3	**47.9**
ResNeXt101-64x4d [34]	86.4	103.9	40.2
PVTv2-B5 (ours)	**85.7**	**91.1**	**48.7**

Table 5: **Semantic segmentation performance of different backbones on the ADE20K validation set.** "GFLOPs" is calculated under the input scale of 512×512. "-Li" denotes PVTv2 with linear SRA.

age to 512×512 for training, and rescale to have a shorter side of 512 pixels during testing.

Results. As shown in Tab. 5, when using Semantic FPN [18] for semantic segmentation, PVTv2 consistently outperforms PVTv1 [32] and other counterparts. For example, with almost the same number of parameters and GFLOPs, our PVTv2-B1/B2/B3/B4 are at least 5.3 points higher than PVTv1-Tiny/Small/Medium/Large. Moreover, although the GFLOPs of our PVT-Large are 12% lower than those of ResNeXt101-64x4d, the mIoU is still 8.5 points higher (48.7 *vs* 40.2). In Fig. 3, we also visualize some qualitative semantic segmentation results on ADE20K [40]. These results demonstrate that our PVTv2 backbones can extract powerful features for semantic segmentation, benefiting from the improved designs.

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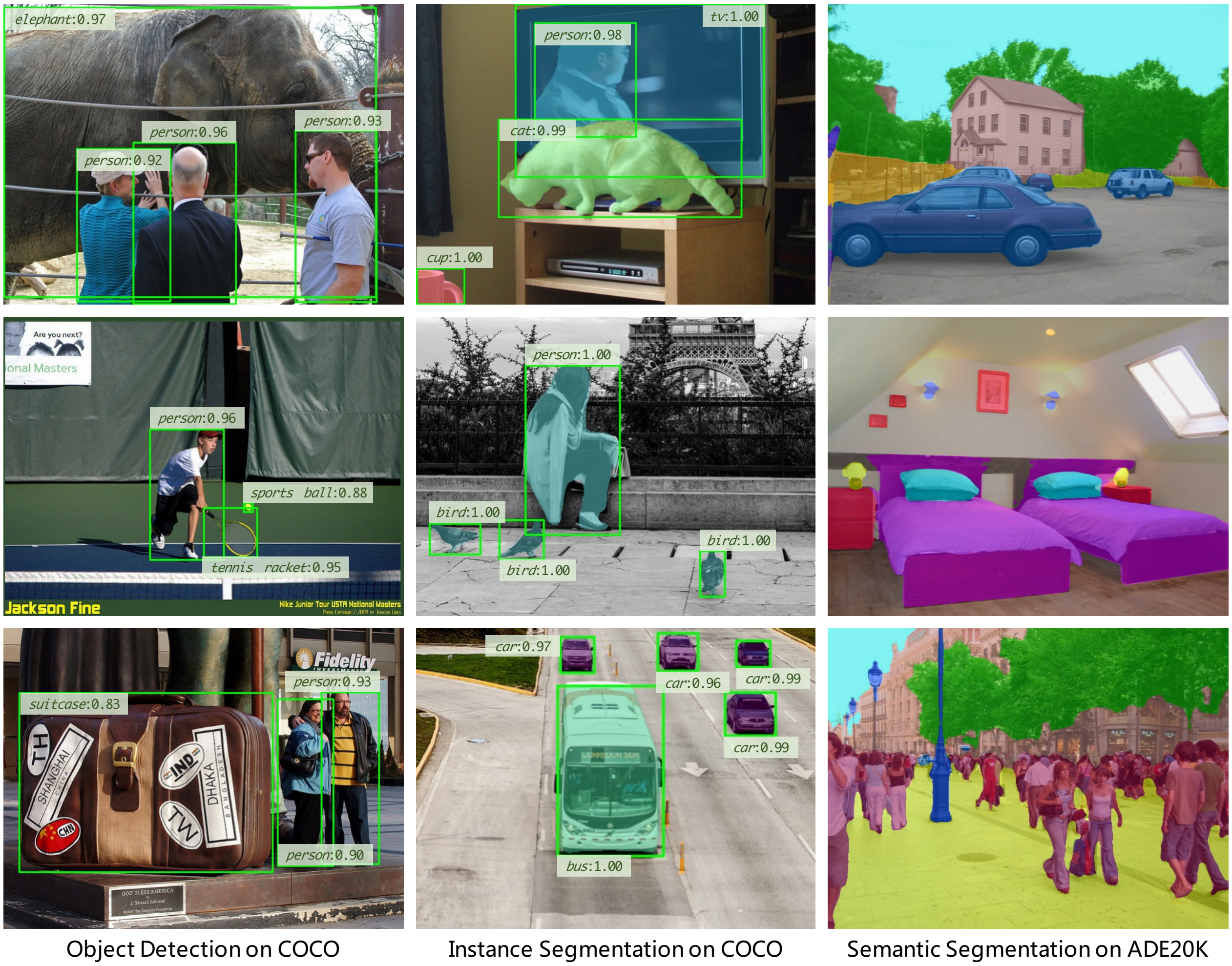

Figure 3: **Qualitative results of object detection and instance segmentation on COCO `val2017` [22], and semantic segmentation on ADE20K [40].** The results (from left to right) are generated by PVTv2-B2-based RetinaNet [21], Mask R-CNN [12], and Semantic FPN [18], respectively.

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