PSANet: Point-wise Spatial Attention Network for Scene Parsing – Supplementary Material

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More Numerical Results In Table 1, we give a comparison with current top ranked approaches on ADE20K test set. Our single PSANet101 gets final score as 55.46%, surpasses PSPNet269, the winner in challenge 2016 with a deeper backbone, and matches CASIA_IVA_JD, the winner entry in 2017 with multiple models ensembling. In Table 2, we compare PSANet with several state-of-the-art methods on VOC 2012 validation set. Table 3 and Table 4 list the detailed per-class results.

More Visual Results Fig. 1 shows the visual improvements on validation set of VOC 2012. Fig. 2 and Fig. 3 contain visual comparisons between different methods. Fig. 4 includes several visual predictions on Cityscapes dataset.

Table 1. Methods comparison on ADE20K *test* set. Score is the average of mean IoU and pixel accuracy.

Method	score
CASIA_IVA	54.33
360+MCG-ICT-CAS_SP	54.68
Adelaide/WiderNet[32]	56.41
SenseCUSceneParsing/PSPNet269[6]	55.38
WinterIsComing	55.44
CASIA_IVA_JD	55.47
PSANet101	55.46

Table 2. Methods comparison with models trained on *train_aug* set and evaluated on *val* set of VOC 2012.

Method	mIoU(%)
DeepLabv2[5]	77.69
PSPNet[6]	78.83
DeepLabv3[37]	79.77
PSANet	79.77

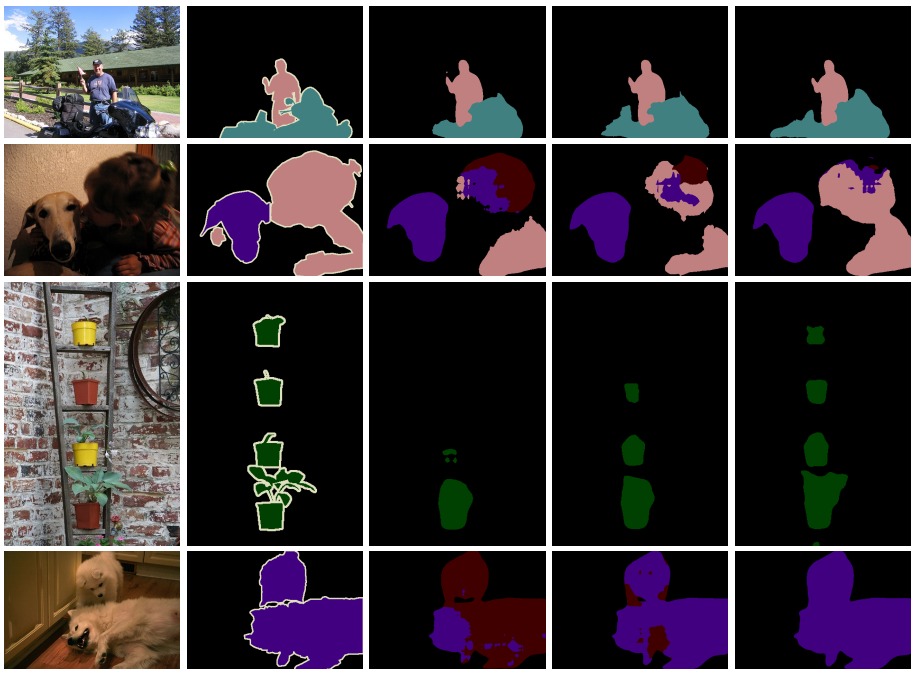
⋆ indicates equal contribution.

Table 3. Detailed per-class results on VOC 2012 *test* set.

Method	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mIoU
LRR [4]	92.4	45.1	94.6	65.2	75.8	95.1	89.1	92.3	39.0	85.7	70.4	88.6	89.4	88.6	86.6	65.8	86.2	57.4	85.7	77.3	79.3
DeepLabv2 [1]	92.6	60.4	91.6	63.4	76.3	95.0	88.4	92.6	32.7	88.5	67.6	89.6	92.1	87.0	87.4	63.3	88.3	60.0	86.8	74.5	79.7
SegModel [10]	93.6	60.2	93.6	69.1	76.4	96.3	88.2	95.5	37.9	90.8	73.3	91.1	94.3	88.6	88.6	64.8	90.1	63.7	87.3	78.2	81.8
LC [5]	85.5	66.7	94.5	67.2	84.0	96.1	89.8	93.5	47.2	90.4	71.5	88.9	91.7	89.2	89.1	70.4	89.4	70.7	84.2	79.6	82.7
DUC_HDC [11]	92.1	64.6	94.7	71.0	81.0	94.6	89.7	94.9	45.6	93.7	74.4	92.0	95.1	90.0	88.7	69.1	90.4	62.7	86.4	78.2	83.1
LKM [8]	95.3	68.7	94.1	72.6	82.4	96.0	89.3	93.0	47.8	89.6	70.8	89.2	93.3	90.1	91.2	72.0	89.8	67.8	88.9	76.9	83.6
RefineNet [6]	95.0	73.2	93.5	78.1	84.8	95.6	89.8	94.1	43.7	92.0	77.2	90.8	93.4	88.6	88.1	70.1	92.9	64.3	87.7	78.8	84.2
ResNet-38 [12]	96.2	75.2	95.4	74.4	81.7	93.7	89.9	92.5	48.2	92.0	79.9	90.1	95.5	91.8	91.2	73.0	90.5	65.4	88.7	80.6	84.9
PSPNet [13]	95.8	72.7	95.0	78.9	84.4	94.7	92.0	95.7	43.1	91.0	80.3	91.3	96.3	92.3	90.1	71.5	94.4	66.9	88.8	82.0	85.4
DeepLabv3 [2]	96.4	76.6	92.7	77.8	87.6	96.7	90.2	95.4	47.5	93.4	76.3	91.4	97.2	91.0	92.1	71.3	90.9	68.9	90.8	79.3	85.7
PSANet	95.8	76.1	94.1	78.2	84.6	96.5	92.2	94.6	44.7	92.4	78.8	90.2	97.1	93.2	91.5	70.5	94.8	66.0	88.7	83.5	85.7

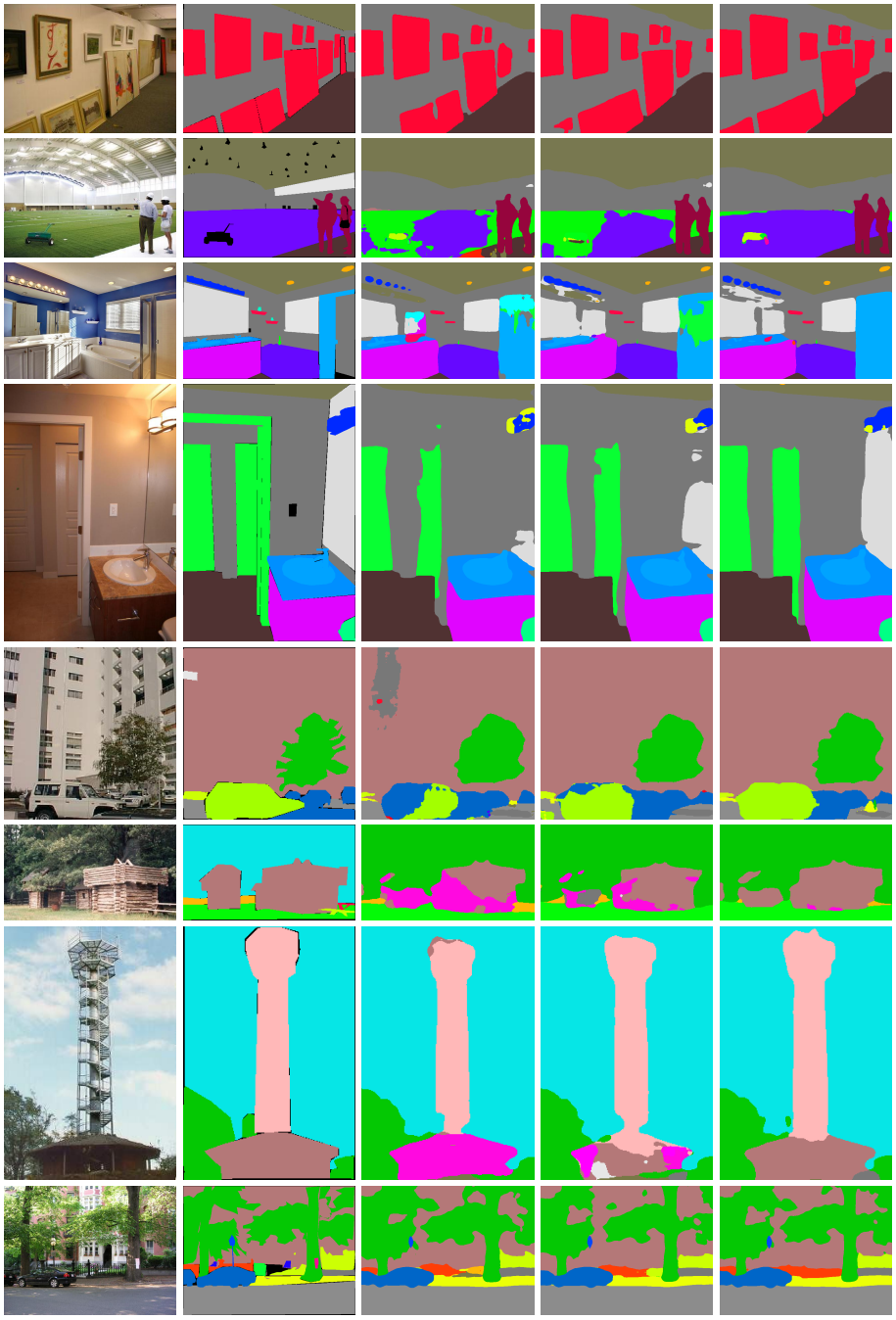
Table 4. Detailed per-class results on Cityscapes *test* set. Methods are trained using both *fine* and *coarse* data.

Method	road	swalk	build.	wall	fence	pole	tlight	sign	veg.	terrain	sky	person	rider	car	truck	bus	train	mbike	bike	mIoU
LRR-4x [4]	97.9	81.5	91.4	50.5	52.7	59.4	66.8	72.7	92.5	70.1	95.0	81.3	60.1	94.3	51.2	67.7	54.6	55.6	69.6	71.8
SegModel [9]	98.6	86.2	93.0	53.7	60.4	64.2	73.5	78.5	93.4	72.2	95.5	85.3	68.6	95.8	77.9	87.0	78.0	68.0	75.1	79.2
DUC_HDC [11]	98.5	85.9	93.2	57.7	61.1	67.2	73.7	78.0	93.4	72.3	95.4	85.9	70.5	95.9	76.1	90.6	83.7	67.4	75.7	80.1
Netwarp [3]	98.6	86.7	93.4	60.6	62.6	68.6	75.9	80.0	93.5	72.0	95.3	86.5	72.1	95.9	72.9	89.9	77.4	70.5	76.4	80.5
ResNet-38 [12]	98.7	86.9	93.3	60.4	62.9	67.6	75.0	78.7	93.7	73.7	95.5	86.8	71.1	96.1	75.2	87.6	81.9	69.8	76.7	80.6
PSPNet [13]	98.7	86.9	93.5	58.4	63.7	67.7	76.1	80.5	93.6	72.2	95.3	86.8	71.9	96.2	77.7	91.5	83.6	70.8	77.5	81.2
DeepLabv3 [2]	98.6	86.2	93.5	55.2	63.2	70.0	77.1	81.3	93.8	72.3	95.9	87.6	73.4	96.3	75.1	90.4	85.1	72.1	78.3	81.3
PSANet	98.7	87.0	93.5	58.9	62.5	67.8	76.0	80.0	93.7	72.6	95.4	87.0	73.0	96.2	79.3	91.2	84.9	71.1	77.9	81.4



(a) Image (b) Ground Truth (c) Baseline (d) PSA-COL (e) PSA-COL-DIS

Fig. 1. Visual improvements on *val* set of VOC 2012.



(a) Image (b) Ground Truth (c) DeepLab (d) PSPNet (e) PSANet

Fig. 2. Visual comparison on ADE20K dataset. (a) Image. (b) Ground Truth. (c) DeepLab [1]. (d) PSPNet [13]. (e) PSANet.

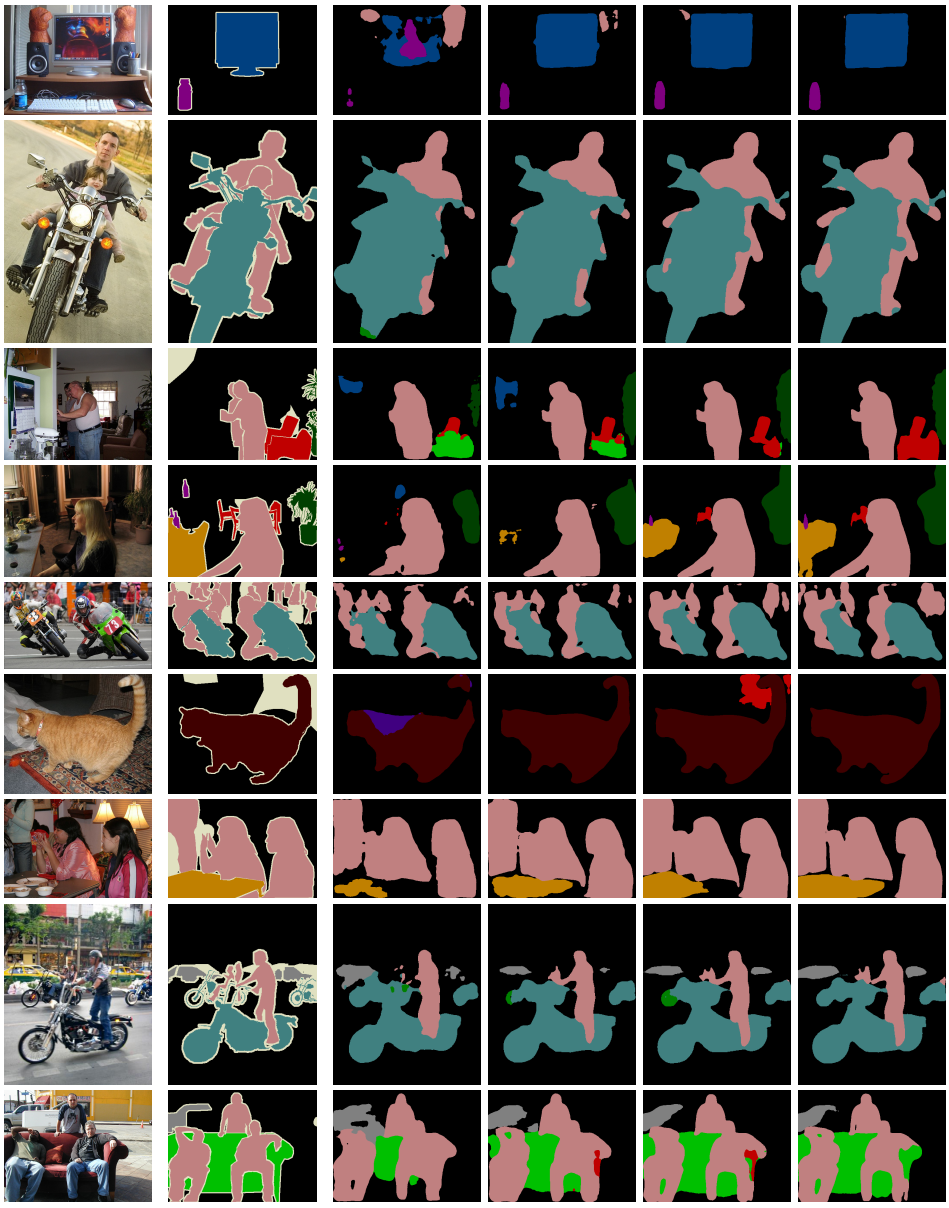
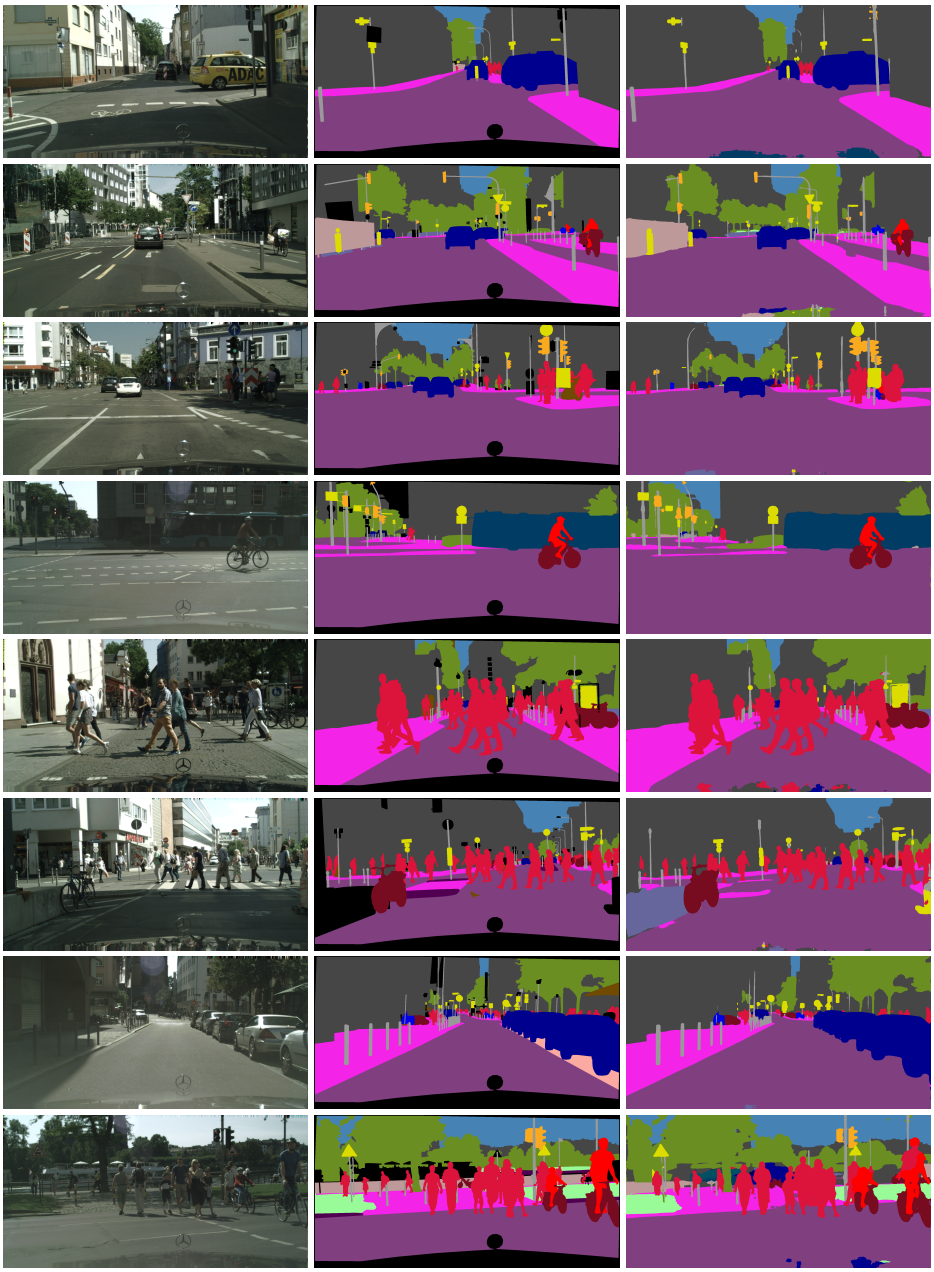


Fig. 3. Visual comparison on PSACAL VOC 2012 dataset. (a) Image. (b) Ground Truth. (c) FCN [7]. (d) DeepLab [1]. (e) PSPNet [13]. (f) PSANet.



(a) Image (b) Ground Truth (c) PSANet

Fig. 4. Visual prediction on Cityscapes dataset. (a) Image. (b) Ground Truth. (c) PSANet.

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