Dual Attention Network for Scene Segmentation

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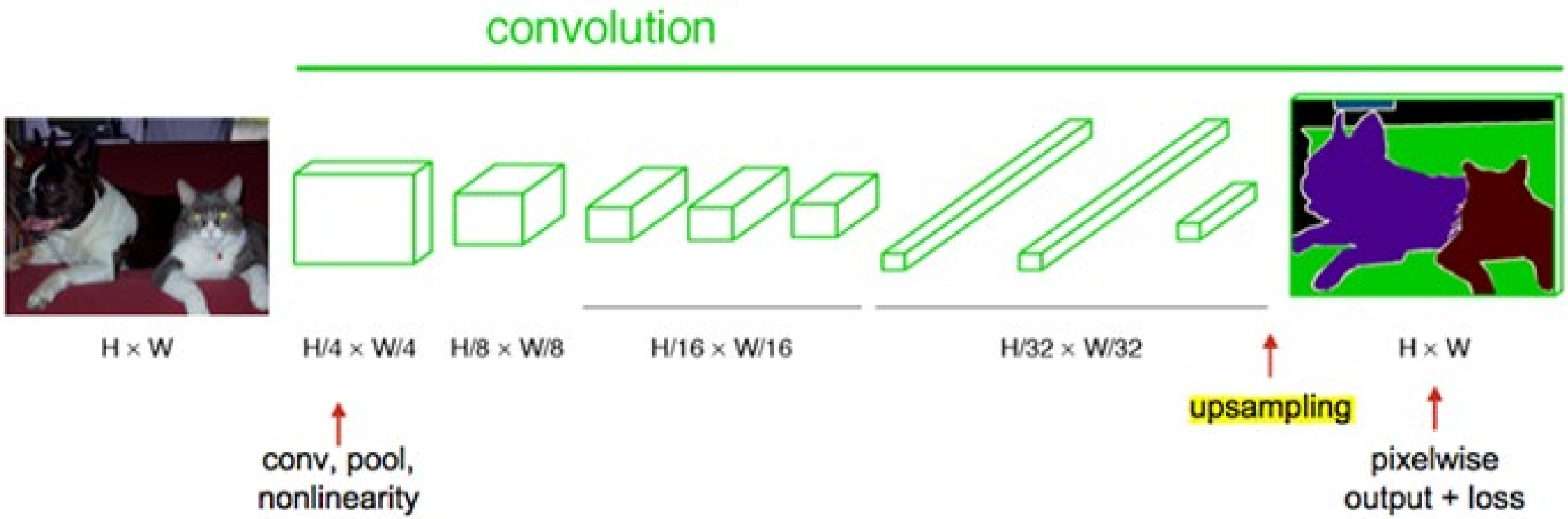
Contents

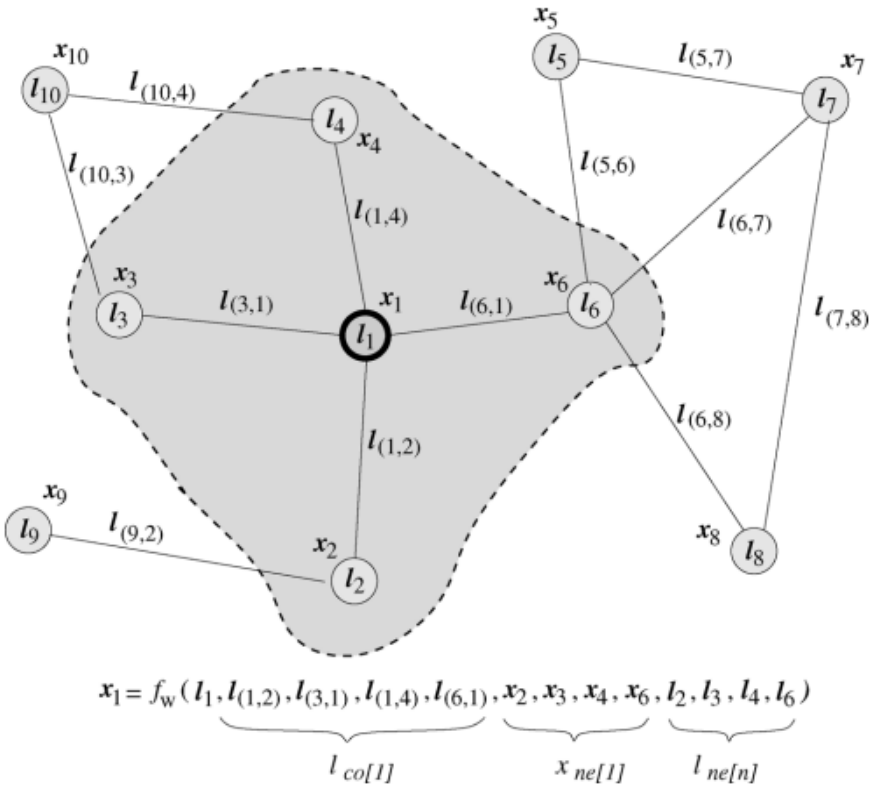
Goal

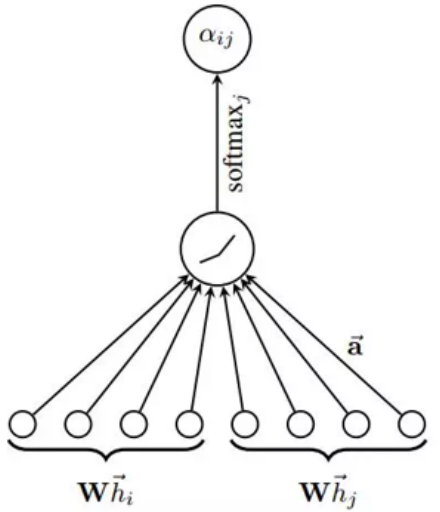
The goal of scene segmentation is to recognize each pixel including stuff, diverse objects

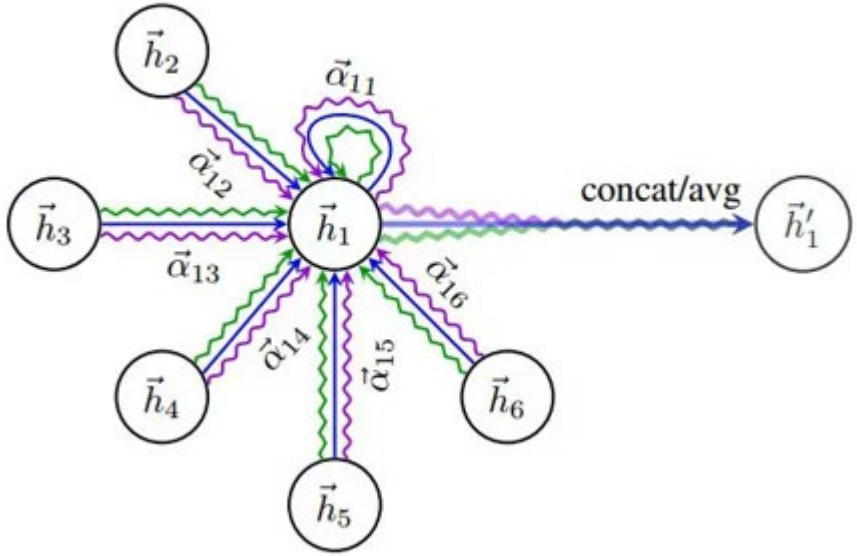
Related work： FCN(Fully Convolutional Networks)



Attention Network







Dual Attention Network

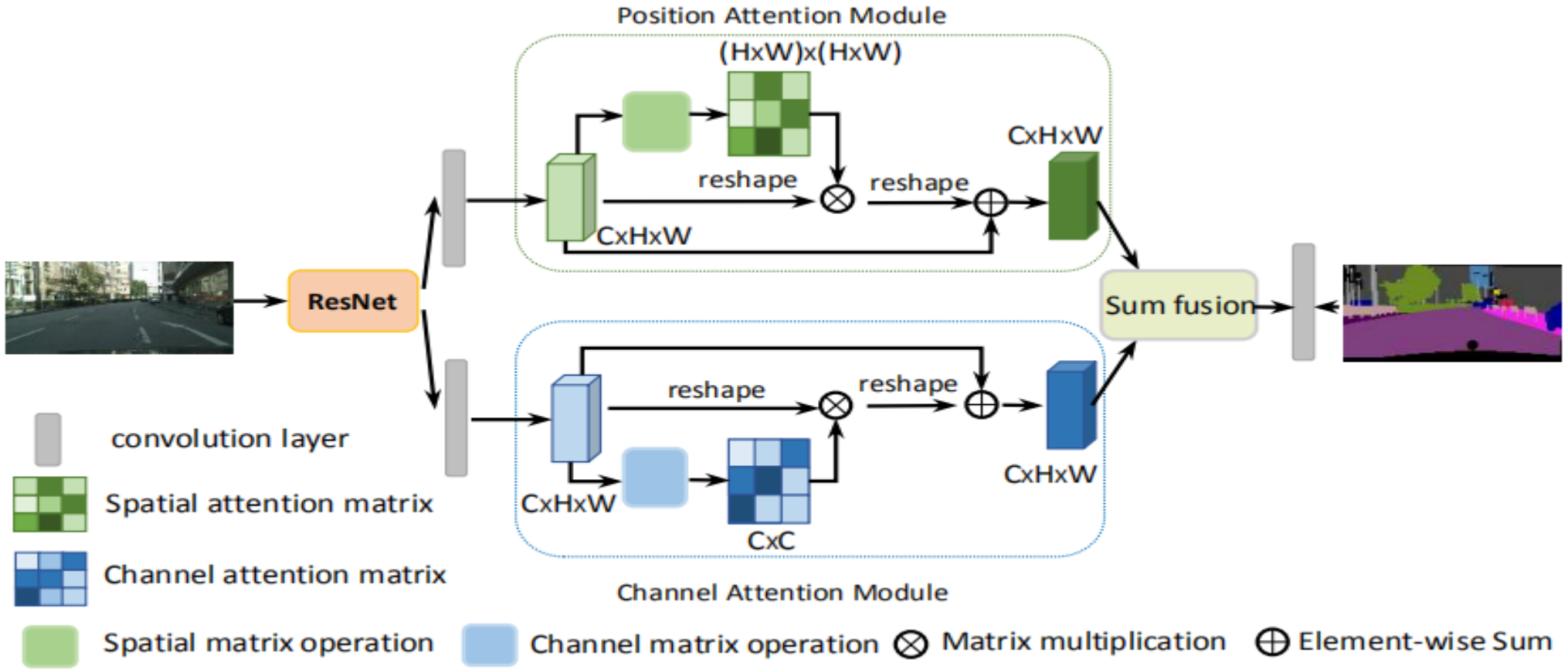
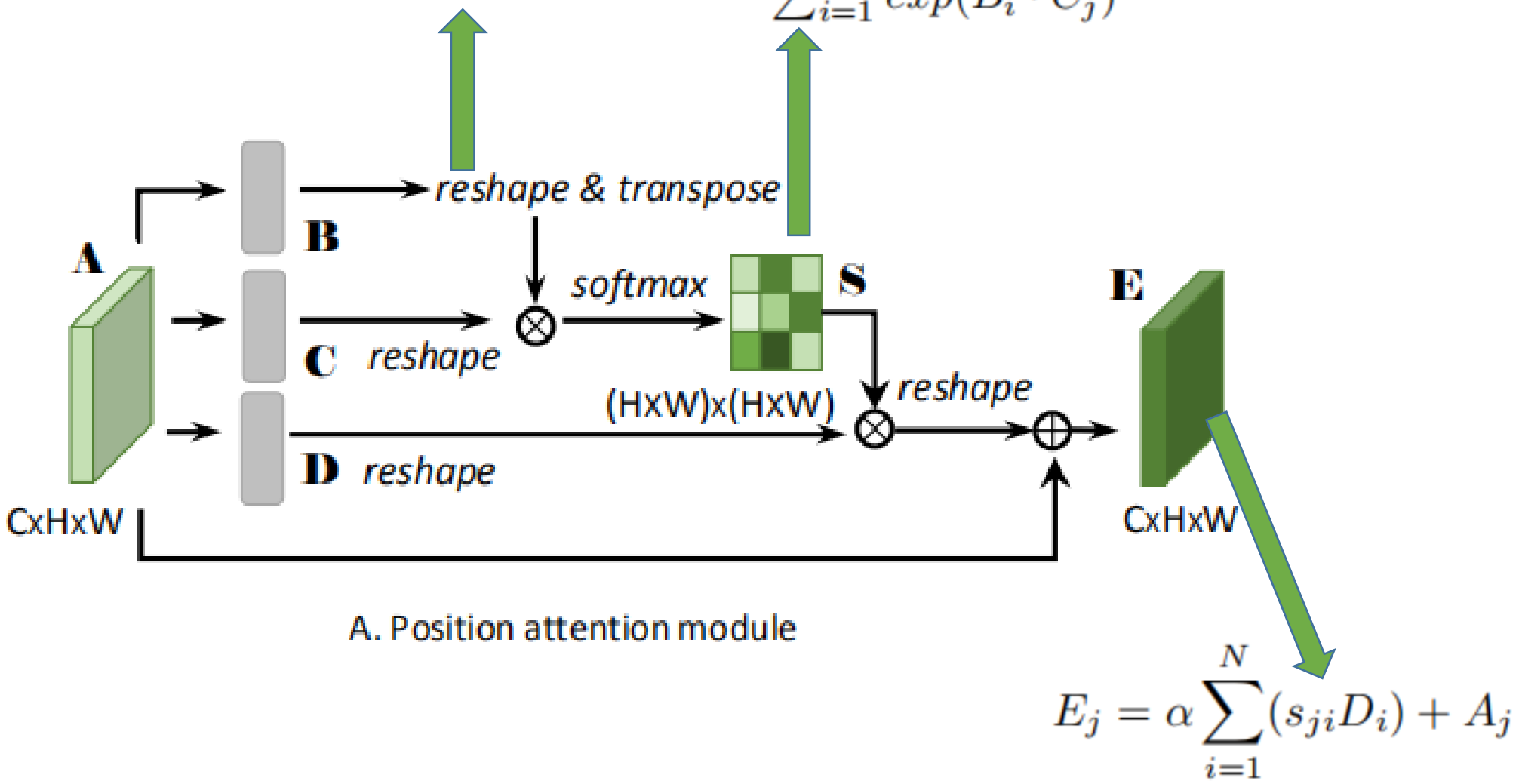


Figure 2: An overview of the Dual Attention Network. (Best viewed in color)

Position Attention Module

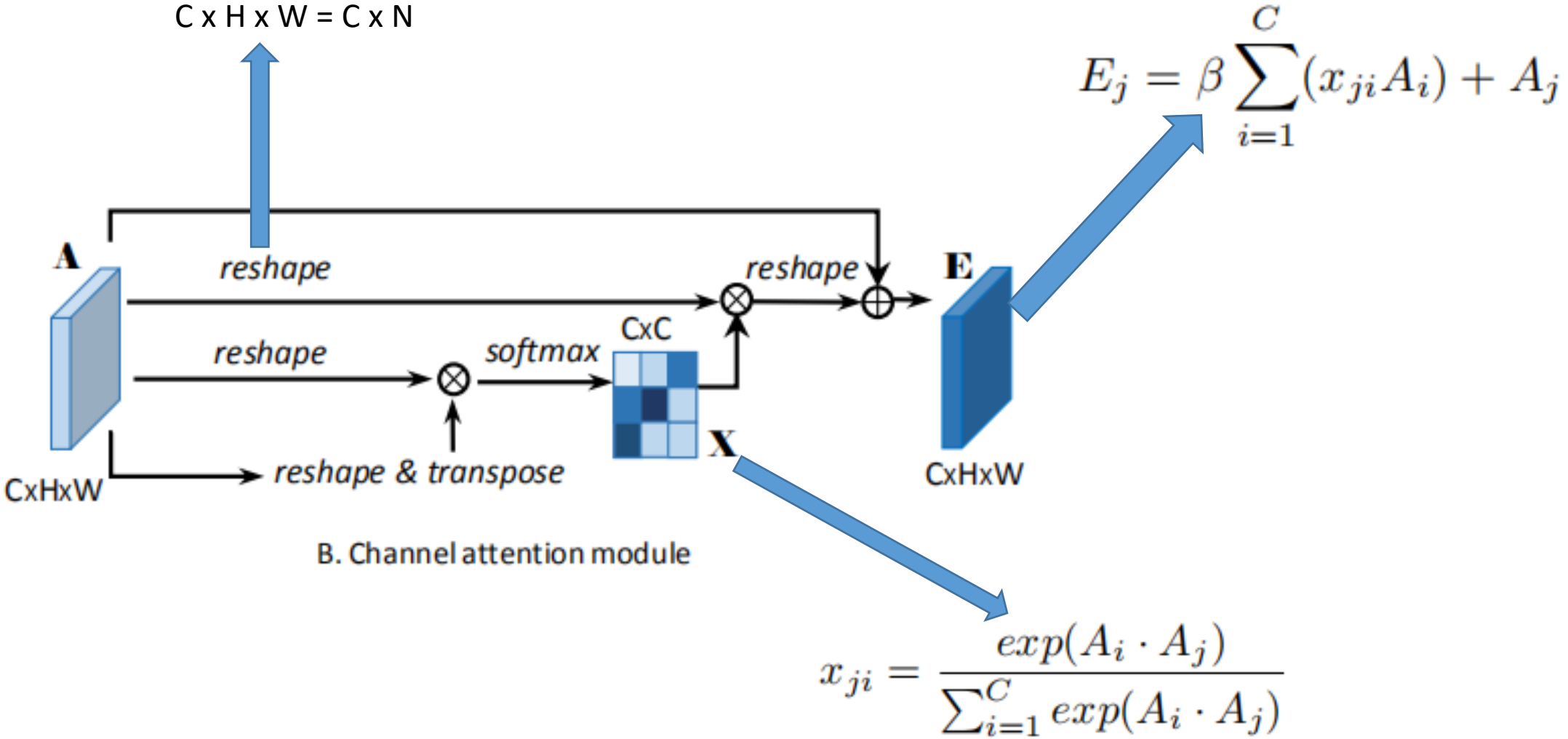
$$s_{ji} = \frac{exp(B_i \cdot C_j)}{\sum_{i=1}^{N} exp(B_i \cdot C_j)}$$



A. Position attention module

$$E_j = \alpha \sum_{i=1}^{N} (s_{ji} D_i) + A_j$$

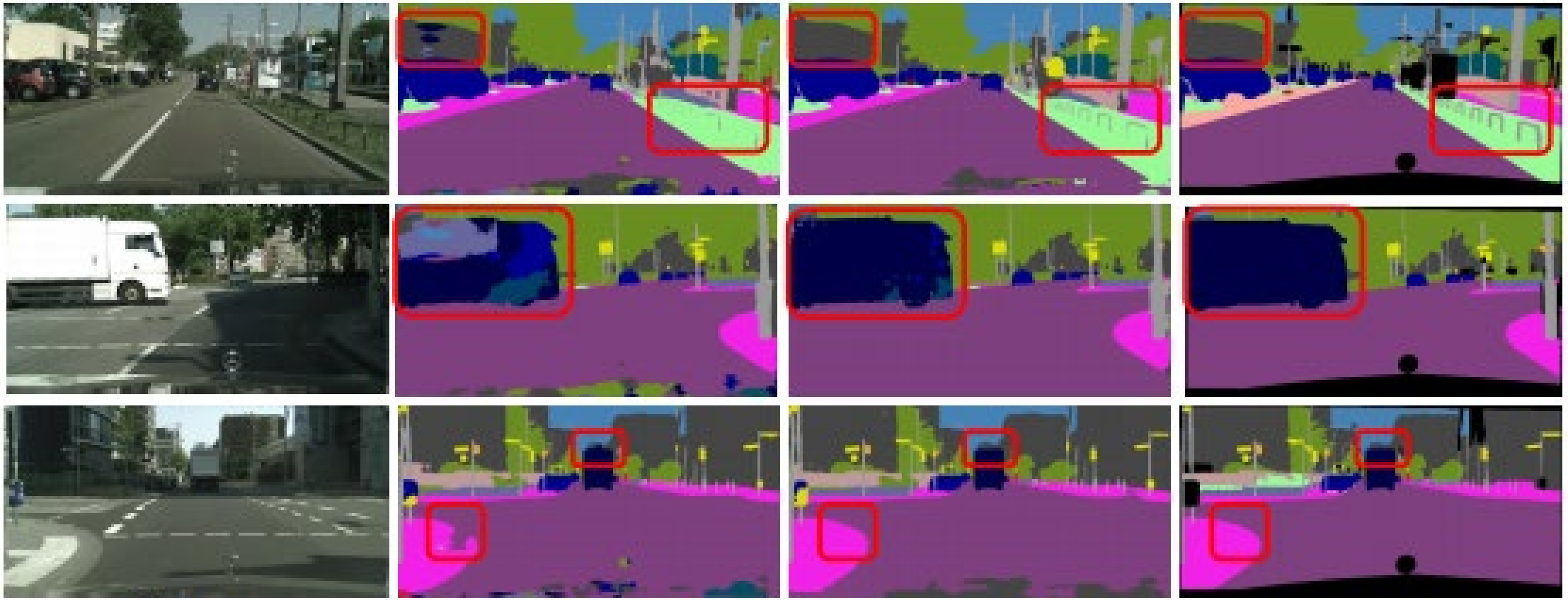
Channel Attention Module



$$E_j = \beta \sum_{i=1}^{C} (x_{ji} A_i) + A_j$$

$$x_{ji} = \frac{exp(A_i \cdot A_j)}{\sum_{i=1}^{C} exp(A_i \cdot A_j)}$$

Expriments



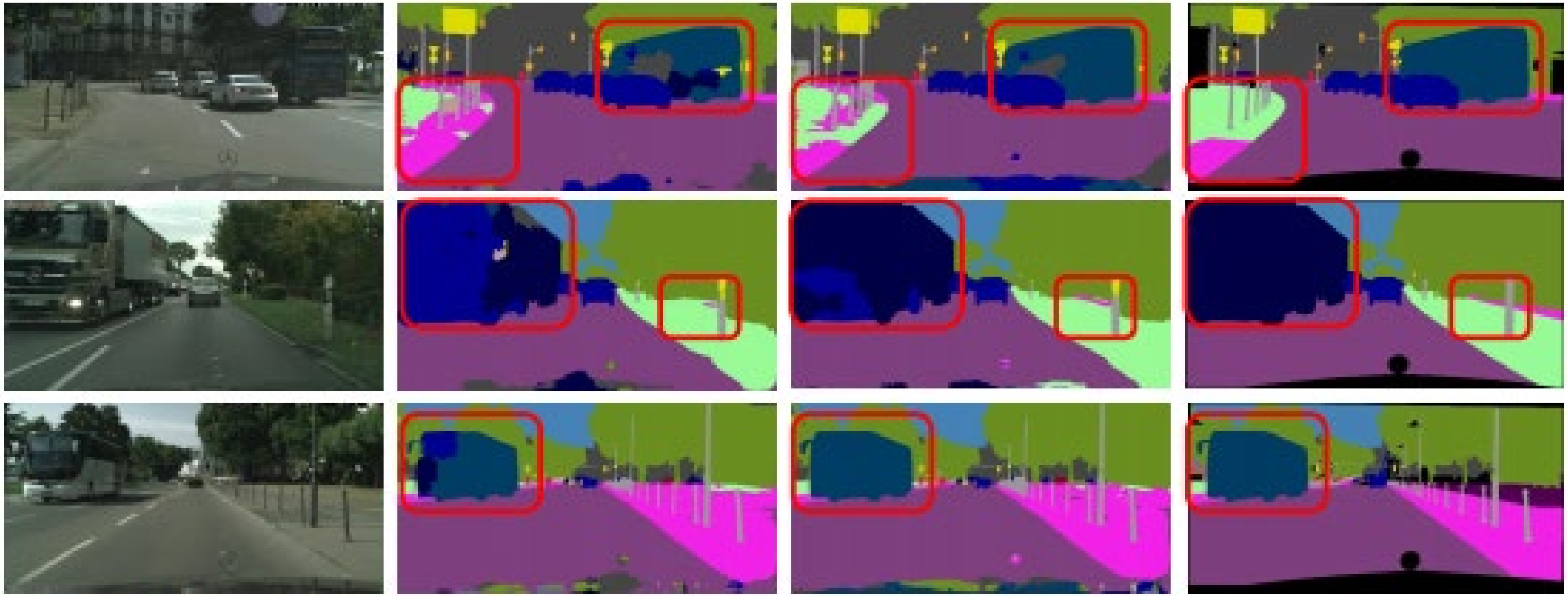


Image
Without CAM
With CAM
Groundtruth

Method	BaseNet	PAM	CAM	Mean IoU%
Dilated FCN	Res50			70.03
DANet	Res50	✓		75.74
DANet	Res50		✓	74.28
DANet	Res50	✓	✓	76.34
Dilated FCN	Res101			72.54
DANet	Res101	✓		77.03
DANet	Res101		✓	76.55
DANet	Res101	✓	✓	77.57

Table 1: Ablation study on Cityscapes val set. *PAM* represents Position Attention Module, *CAM* represents Channel Attention Module.

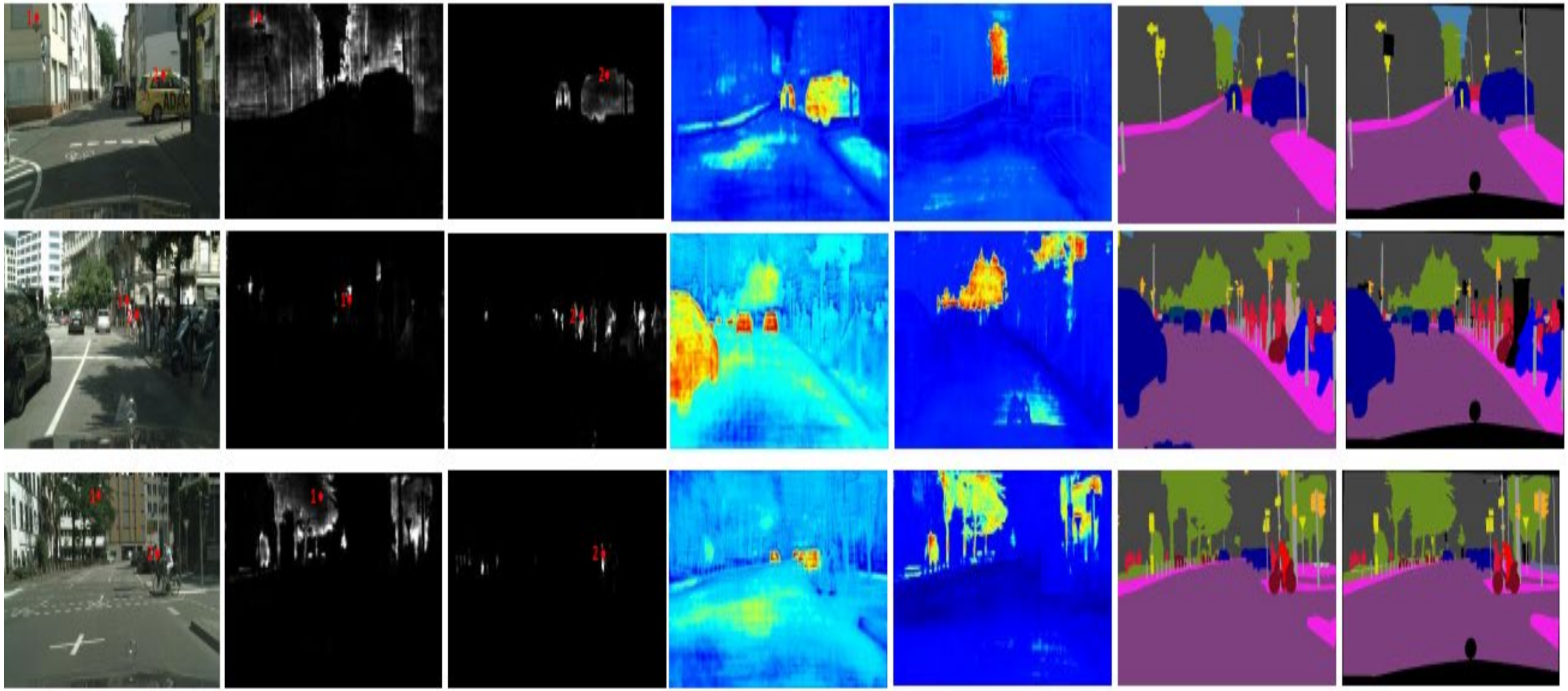


Image
Sub-attention map #1
Sub-attention map #2
Channel map #11
Channel map #4
Result
Groundtruth

Methods	Mean IoU	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetation	terrain	sky	person	rider	car	truck	bus	train	motorcycle	bicycle
DeepLab-v2 [3]	70.4	97.9	81.3	90.3	48.8	47.4	49.6	57.9	67.3	91.9	69.4	94.2	79.8	59.8	93.7	56.5	67.5	57.5	57.7	68.8
RefineNet [10]	73.6	98.2	83.3	91.3	47.8	50.4	56.1	66.9	71.3	92.3	70.3	94.8	80.9	63.3	94.5	64.6	76.1	64.3	62.2	70
GCN [15]	76.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DUC [22]	77.6	98.5	85.5	92.8	58.6	55.5	65	73.5	77.9	93.3	72	95.2	84.8	68.5	95.4	70.9	78.8	68.7	65.9	73.8
ResNet-38 [24]	78.4	98.5	85.7	93.1	55.5	59.1	67.1	74.8	78.7	93.7	72.6	95.5	86.6	69.2	95.7	64.5	78.8	74.1	69	76.7
PSPNet [29]	78.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BiSeNet [26]	78.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
PSANet [30]	80.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DenseASPP [25]	80.6	**98.7**	**87.1**	93.4	**60.7**	62.7	65.6	74.6	78.5	93.6	72.5	95.4	86.2	71.9	96.0	**78.0**	**90.3**	80.7	69.7	76.8
DANet	**81.5**	98.6	86.1	**93.5**	56.1	**63.3**	**69.7**	**77.3**	**81.3**	**93.9**	**72.9**	**95.7**	**87.3**	**72.9**	**96.2**	76.8	89.4	**86.5**	**72.2**	**78.2**

Method	**Mean IoU%**
FCN-8s [13]	37.8
Piecewise [11]	43.3
DeepLab-v2 (Res101-COCO) [3]	45.7
RefineNet (Res152) [10]	47.3
PSPNet (Res101) [29]	47.8
Ding et al.(Res101) [6]	51.6
EncNet (Res101) [27]	51.7
Dilated FCN(Res50)	44.3
DANet (Res50)	50.1
DANet (Res101)	**52.6**

Table 6: Segmentation results on PASCAL Context testing set.

Method	**Mean IoU%**
FCN-8s [13]	22.7
DeepLab-v2(Res101) [3]	26.9
DAG-RNN [18]	31.2
RefineNet (Res101) [10]	33.6
Ding et al.(Res101) [6]	35.7
Dilated FCN (Res50)	31.9
DANet (Res50)	37.2
DANet (Res101)	**39.7**

Table 7: Segmentation results on COCO Stuff testing set.