

Learning Lightweight Lane Detection CNNs by Self Attention Distillation (Supplementary Material)

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1. Details of Architecture

Table 1 summarizes the architecture of the lane existence prediction branch for ENet-SAD, ResNet-18-SAD and ResNet-34-SAD. As to ResNet-18-SAD and ResNet-34-SAD, we also use dilated convolution [10] to replace the original convolution layers in the last two blocks for ResNet-18 [1] and ResNet-34 [1].

Table 1. The architecture of the the lane existence prediction branch. Assuming the input is $3 \times 288 \times 800$. Note that the output size is $c \times h \times w$ before "Flatten", where c , h and w denote channel, height and width, respectively. The number in the bracket besides the layer name is the parameter for that layer. For instance, the four numbers besides dilated convolution denote kernel size, stride, padding and dilated rate, respectively.

Layer Name	Output Size
Dilated Convolution (3, 1, 4, 4)	$32 \times 36 \times 100$
Batch Normalization	$32 \times 36 \times 100$
Relu	$32 \times 36 \times 100$
Spatial Dropout (0.1)	$32 \times 36 \times 100$
Convolution (1, 1)	$5 \times 36 \times 100$
Spatial SoftMax	$5 \times 36 \times 100$
Average Pooling	$5 \times 18 \times 50$
Flatten	4500
Fully Connected	128
Relu	128
Fully Connected	4
Sigmoid	4

2. Lane Post-processing in CULane

For CULane, in the inference stage, we feed the image into the ENet model. Then the multi-channel probability maps and the lane existence vector are obtained. Following [7, 3], the final output is obtained as follows: First, we use a 9×9 kernel to smooth the probability maps. Then, for each lane whose existence probability is larger than 0.5, we search the corresponding probability map every 20 rows for the position with the highest probability value. Finally, we use cubic splines to connect these positions to get the

final output. The process improves the final lane prediction results as it removes noises in the probability maps. The process is depicted in Figure 1. Here, we differentiate different lane instances with different colors.

3. More Qualitative Results in Lane Detection

Figures 2 and 3 depict the qualitative results of different algorithms on TuSimple [9], CULane [7] and BDD100K [11]. As can be seen in Fig. 2, ENet-SAD can detect lanes more precisely than ENet [8] in TuSimple and CULane. Besides, the detection of ENet-SAD [5] is less affected by the irrelevant objects on the road compared with SCNN [7]. As can be seen in Fig. 3, the output probability maps of ENet-SAD are more compact and contain less noise compared with those of SCNN in poor light conditions. Compared with conventional knowledge distillation methods [2, 4], SAD is more memory-efficient since it does not require a teacher model. Besides, ENet-SAD can also be applied to much larger lane detection datasets, e.g., ApolloScape dataset [6].

References

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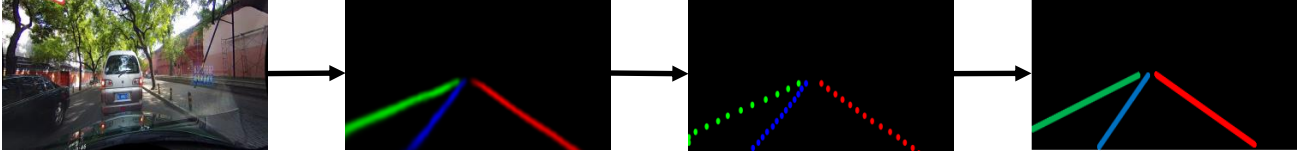


Figure 1. The process of obtaining lanes from probability maps on the CULane dataset. From left to right: original image, probability map, extracted lane points and final lane prediction.

	input	ENet-SAD	ENet	SCNN
(a)				
		99.6 %	95.4 %	93.8 %
(b)				
		96.0 %	89.6 %	95.8 %
(b)				
		100 %	66.6 %	66.6 %
		75 %	50 %	50 %

Figure 2. Performance of different algorithms on (a) TuSimple and (b) CULane testing sets. The number below each image denotes the accuracy. Ground-truth lanes are drawn on the input image.

	input	ENet-SAD	ENet	SCNN
		39.15 %	31.73 %	35.42 %
		35.49 %	32.08 %	32.36 %

Figure 3. Performance of different algorithms on BDD100K testing set. We visualize the probability maps to better showcase the effect of adding self attention distillation. The brightness of the pixel indicates the probability of this pixel belonging to lanes. The number below each image denotes the pixel accuracy of lanes. Ground-truth lanes are drawn on the input image.

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