Boundary-aware Graph Convolution for Semantic Segmentation

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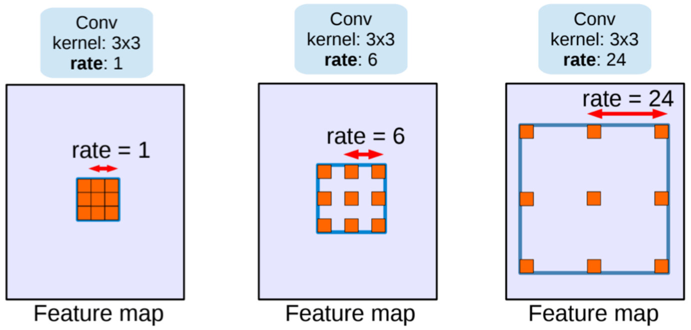
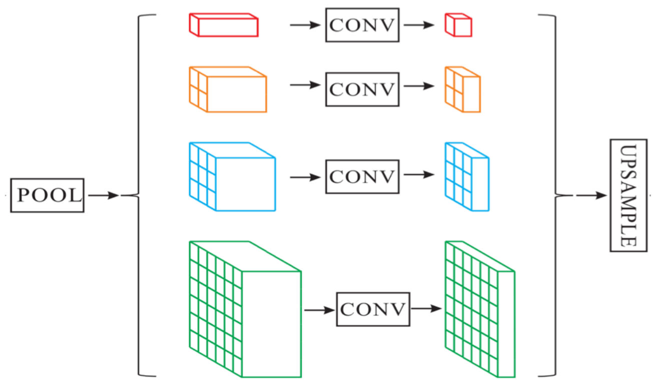
01 Background

Context-based methods

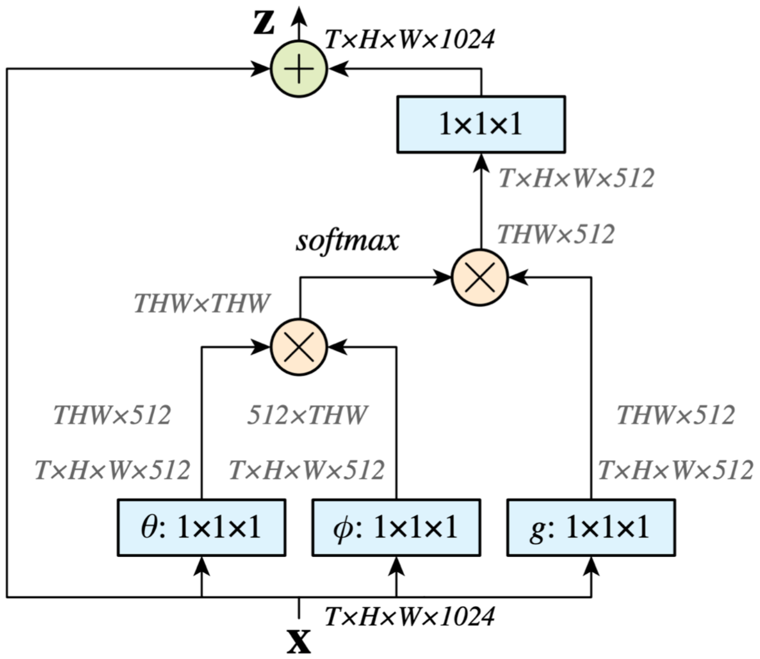
Dilated convolution



Pyramid pooling



Non-local block



02 Motivation

- Enhance the similarity of the same object .
- Keep the discrimination of other objects .
- Graph convolution is good at passing information with the design of adjacency matrix and proves to be a good reasoning method.

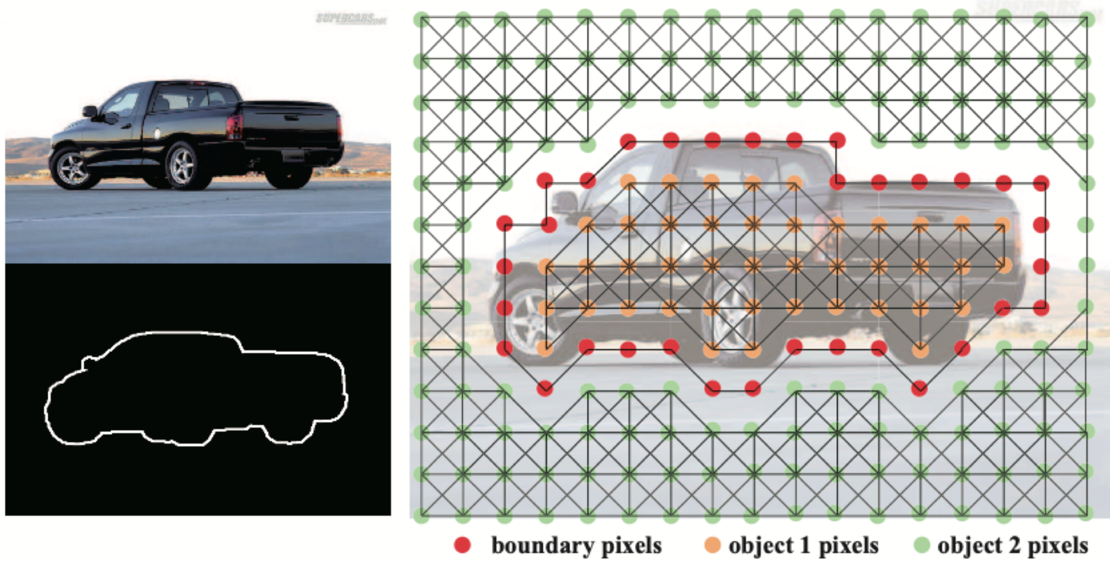
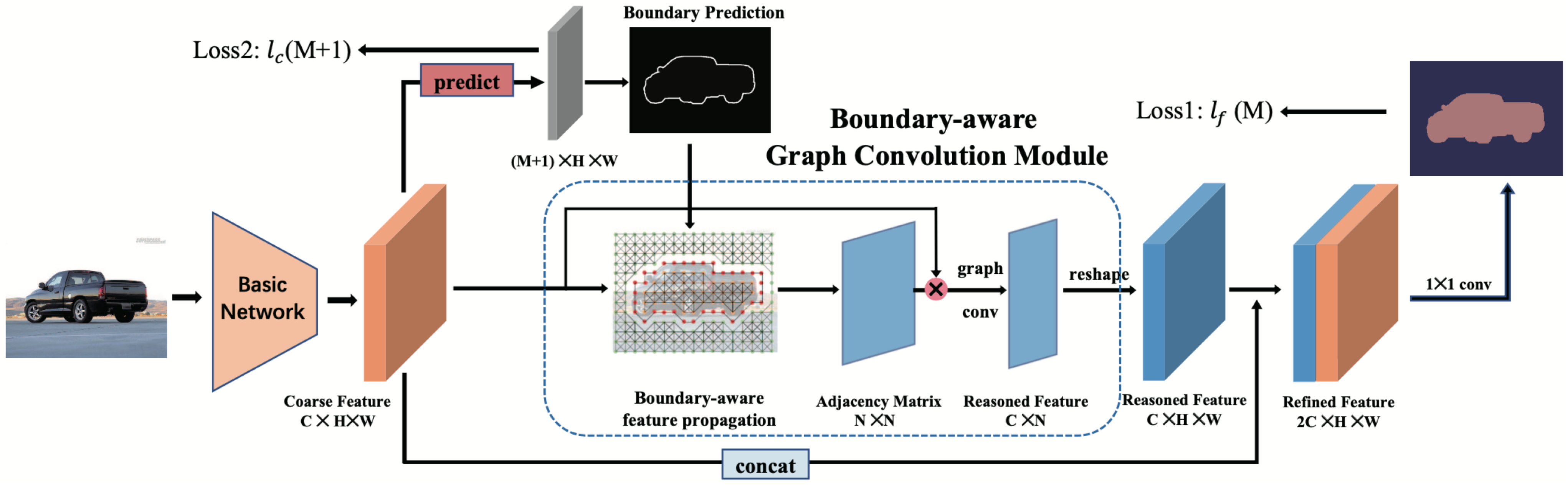


Illustration of our proposed feature propagation design. The connections only exists within the same object (pixels of object 1 are not connected to pixels of object 2), which helps to enhance the feature similarity of the same object and keep discrimination of others.

03 Method

Coarse-to-fine Framework



03

Method

Graph Construction:

We treat pixels in the feature map as nodes in the defined graph.

- Similarity Graph.

Each weight of edge which connecting two nodes in the graph is similarity function between two node features:

$$F(\boldsymbol{x_i}, \boldsymbol{x_j}) = \phi(\boldsymbol{x_i})^T \phi'(\boldsymbol{x_j})$$

$$A_{ij} = \frac{exp(F(\boldsymbol{x_i}, \boldsymbol{x_j}))}{\sum_{j=1}^{N} exp(F(\boldsymbol{x_i}, \boldsymbol{x_j}))}$$

- Boundary-aware Sampling.

Specifically, for every node in the graph, if it belongs to the boundary, the edges connecting it with other nodes are canceled whose weights equal to 0.

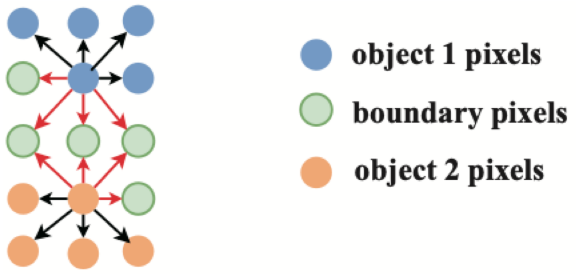


Illustration of boundary-aware sampling method. Black line denotes the normal connection and red line denotes the canceled connection.

Graph Reasoning:

$$Z = \sigma(AXW)$$ (Z: reasoned feature, A: adjacency matrix, X: input feature, W: learned weight)

04

Experiments

Ablation studies on Cityscapes validation set.

1. Performance comparisons of our proposed boundary-aware GCN and plain-GCN.

Method	mIOU(%)
ResNet-101 Baseline	76.3
ResNet-101 + plain GCN	78.2
ResNet-101 + boundary-aware GCN	79.9

2. Detailed performance comparisons of our proposed Boundary-aware Graph Convolution module.

Method	mIOU(%)
ResNet-101 Baseline	76.3
ResNet-101 + ASPP	78.4
ResNet-101 + BGC	79.9
ResNet-101 + ASPP + BGC	81.1

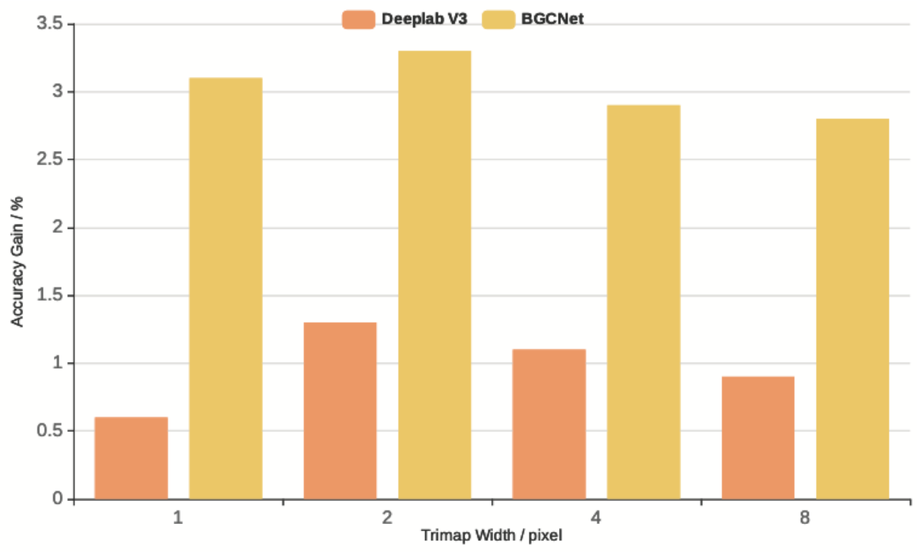
3. Impact of evaluation strategies.

Method	MS	Flip	mIOU(%)
BGCNet			81.1
BGCNet	✓		81.6
BGCNet		✓	81.4
BGCNet	✓	✓	**81.9**

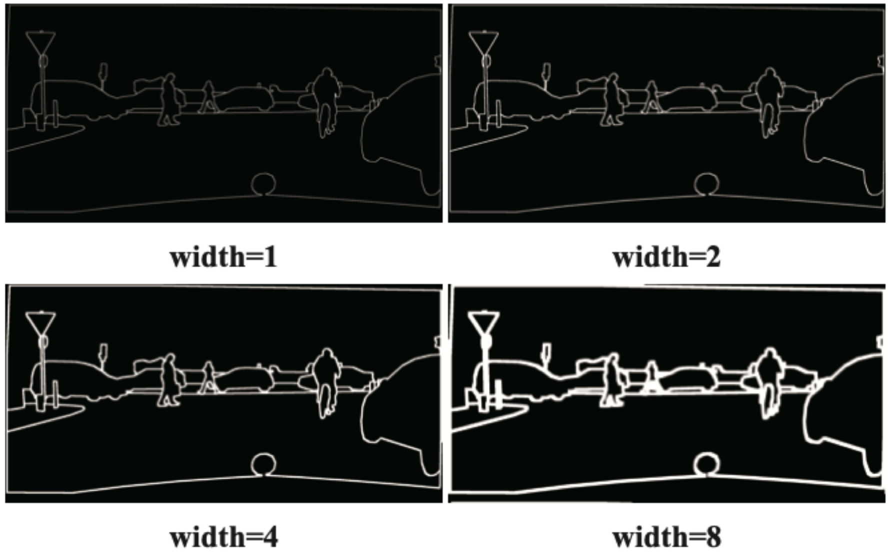
04

Experiments

Impact on boundary accuracy.



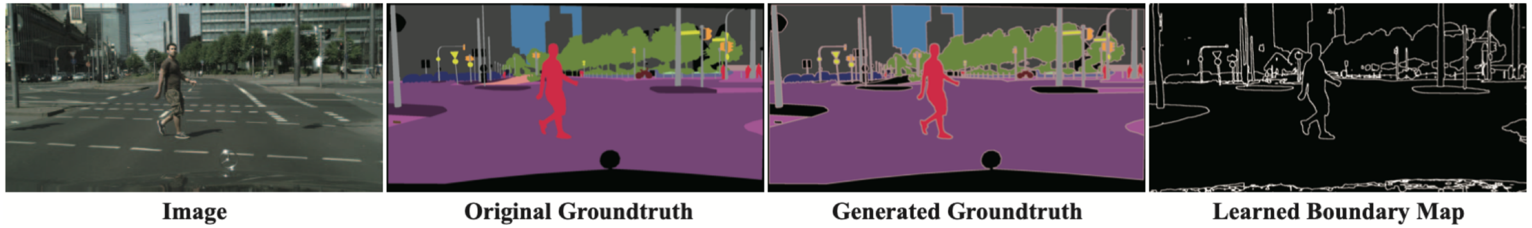
Boundary accuracy gain over baseline for two methods on Cityscapes validation set.



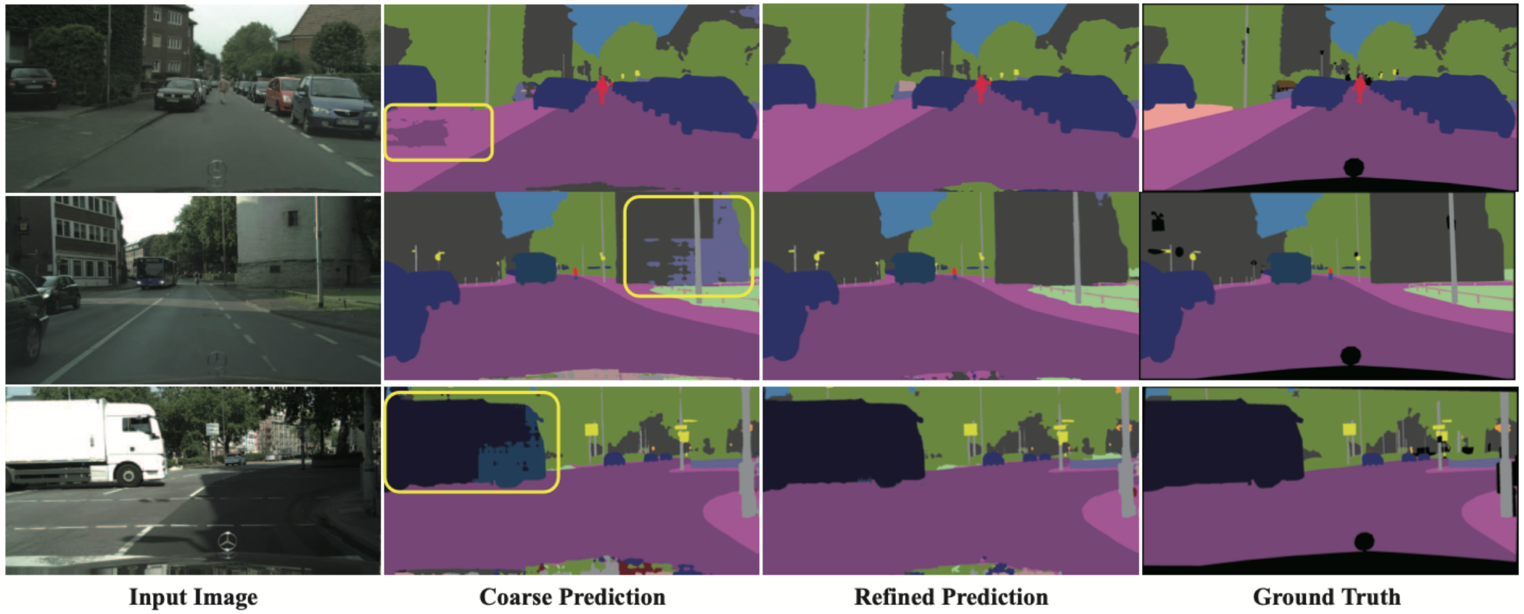
Trimaps used for boundary accuracy evaluation with different band width from Cityscapes validation set .

04 Experiments

Visualizations



Visualization results of boundary learning.



Visualization results on Cityscapes validation set.

04 Experiments

Comparisons with state-of-the-art methods on three benchmark datasets.

Method	Backbone	mIOU(%)
DeepLab-v2 [16]	ResNet-101	70.4
RefineNet [14]	ResNet-101	73.6
GCN [45]	ResNet-101	76.9
SAC [46]	ResNet-101	78.1
PSPNet [3]	ResNet-101	78.4
BiSeNet [47]	ResNet-101	78.9
AAF [48]	ResNet-101	79.1
DFN [49]	ResNet-101	79.3
PSANet [4]	ResNet-101	80.1
DenseASPP [42]	DenseNet-161	80.6
GloRe [22]	ResNet-101	80.9
DANet [43]	ResNet-101	81.5
BGCNet(Ours)	ResNet-101	**82.1**

Method	Backbone	mIOU(%)
FCN [1]	VGG-16	62.2
DeepLab-CRF [16]	VGG-16	71.6
PSPNet [3]	ResNet-101	82.6
DFN [49]	ResNet-101	82.7
DANet [43]	ResNet-101	82.6
EncNet [50]	ResNet-101	82.9
BGCNet(Ours)	ResNet-101	**84.2**

Method	Backbone	mIOU(%)
FCN-8s [1]	VGG-16	22.7
DAG-RNN [33]	VGG-16	31.2
RefineNet [14]	ResNet-101	33.6
CCL [51]	ResNet-101	35.7
DSSPN [52]	ResNet-101	37.3
SGR [23]	ResNet-101	39.1
BGCNet(Ours)	ResNet-101	**41.7**

Thanks for Watching

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