

STRUCT

Learning Dynamic Routing for Semantic Segmentation

CVPR 2020 (Oral)

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Presented by Yuzhang Hu
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Outline

- Authorship
- Background
- Method
- Experiment
- Conclusion

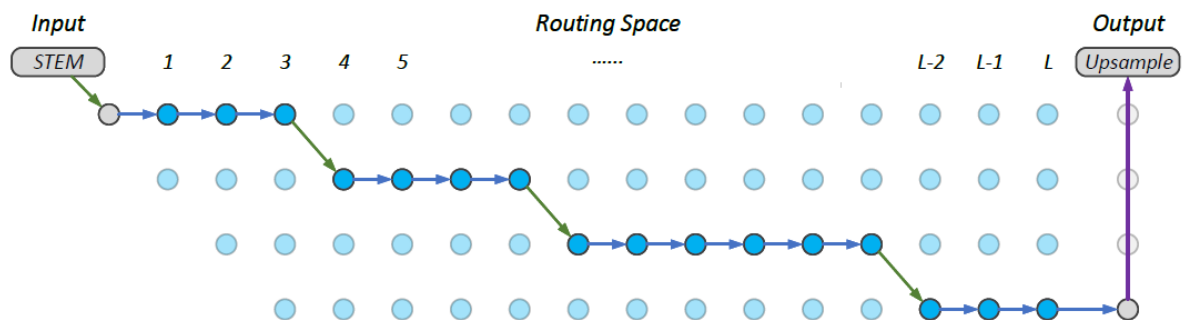
Background



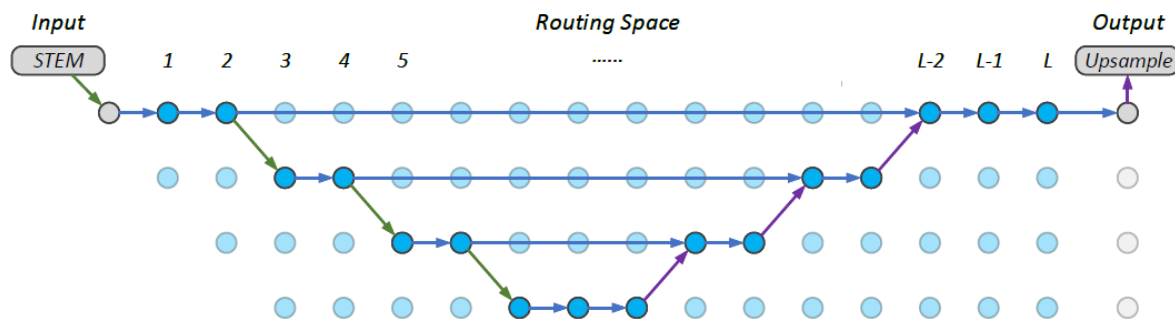
- Semantic Segmentation
 - Assign class label for each pixel
 - Diverse scale distributions of different object

Background

- Previous Network Architecture



FCN [1]



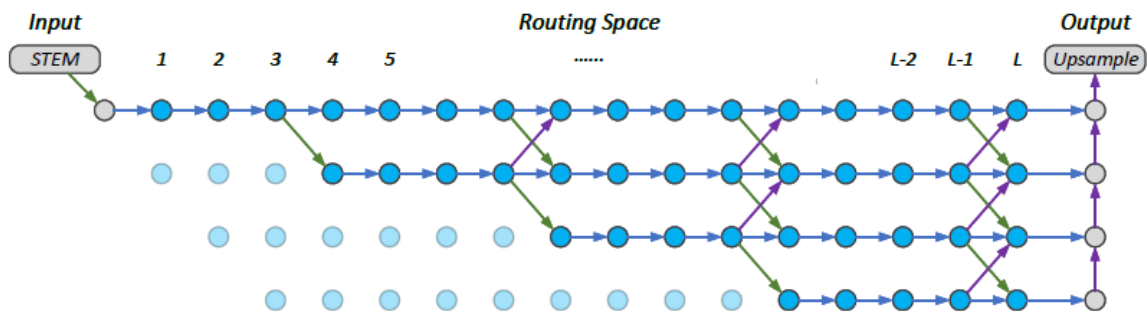
U-Net [2]

[1] Jonathan et al. Fully Convolutional Networks for Semantic Segmentation, CVPR2015

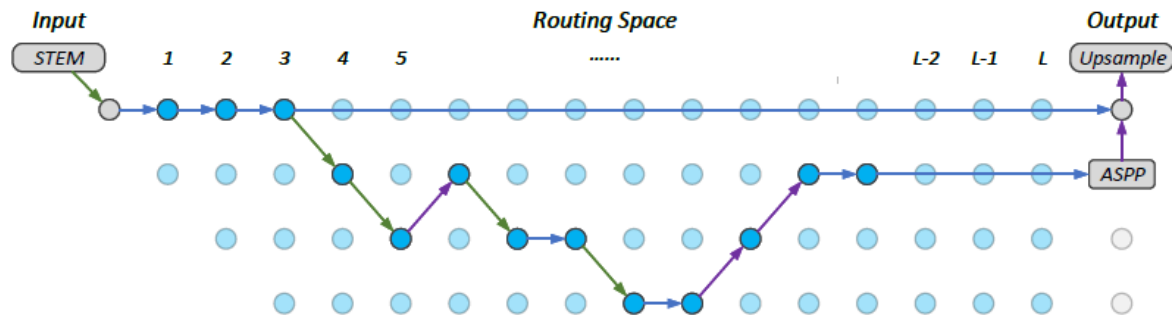
[2] Olaf et al. U-net: Convolutional Networks for Biomedical Image Segmentation, MICCAI2015

Background

- Previous Network Architecture



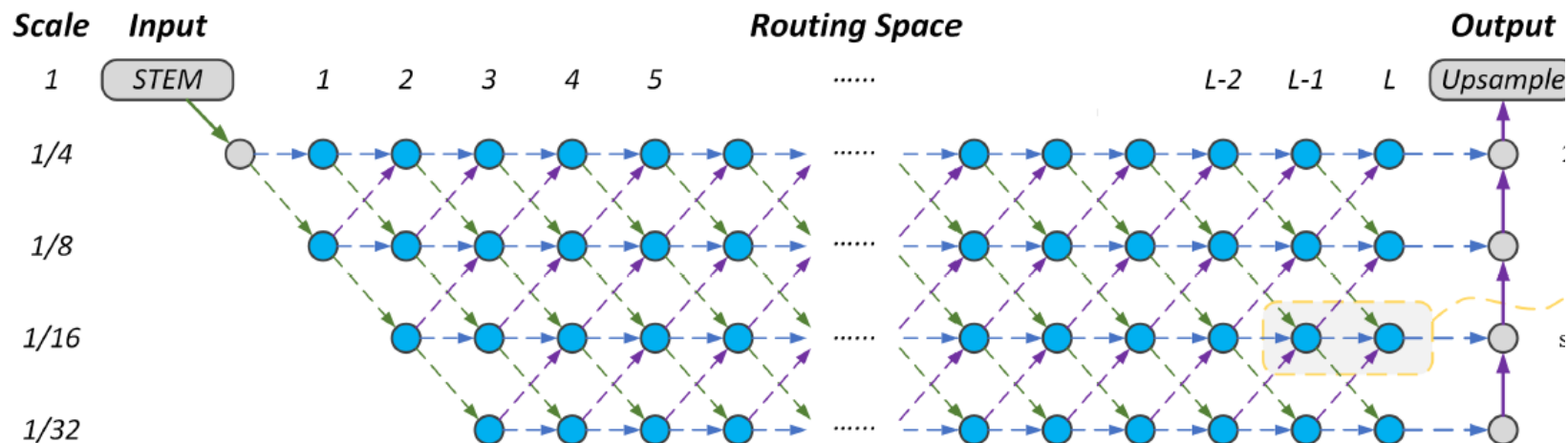
HRNet [1]



Auto-DeepLab [2]

Method

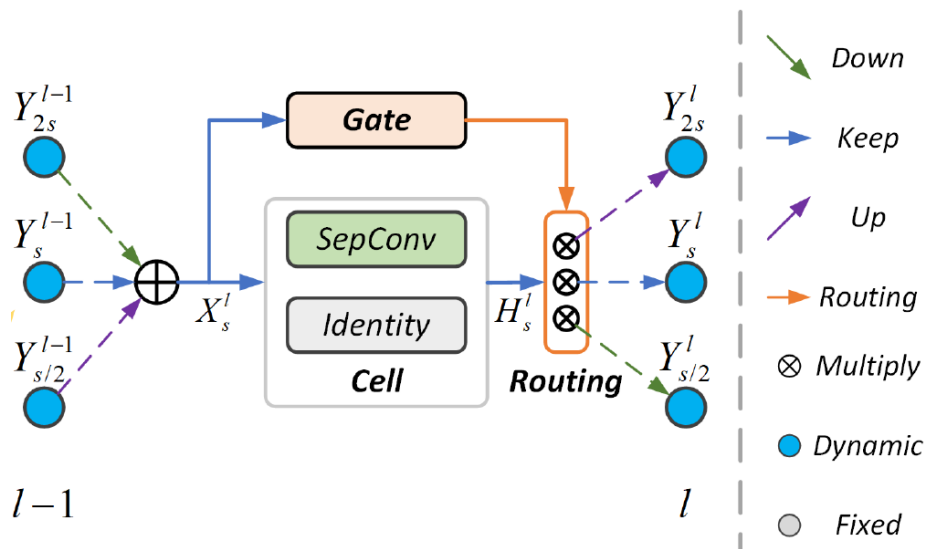
- Overall Structure



- Data-dependent forward routing
 - Cell of different scale.
 - Conditional gate control the routing.
 - Flexibility with the budgeted resource consumption.

Method

- Cell Structure



- Input Aggregation

$$\mathbf{X}_s^l = \mathbf{Y}_{s/2}^{l-1} + \mathbf{Y}_s^{l-1} + \mathbf{Y}_{2s}^{l-1}$$

- Cell Hidden State

$$\mathbf{H}_s^l = \sum_{O^i \in \mathcal{O}} O^i(\mathbf{X}_s^l)$$

- Gate Vector

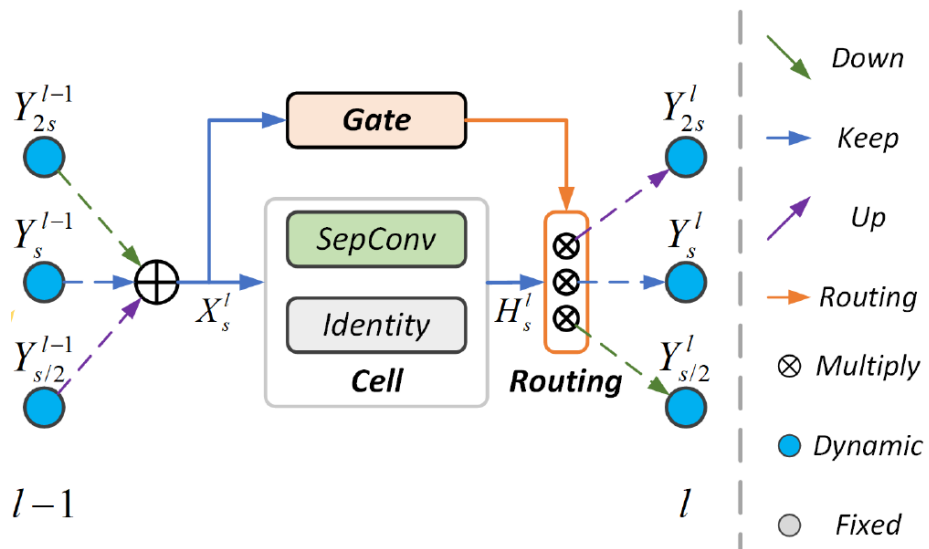
$$\mathbf{G}_s^l = \mathcal{F}(\omega_{s,2}^l, \mathcal{G}(\sigma(\mathcal{N}(\mathcal{F}(w_{s,1}^l, \mathbf{X}_s^l)))))) + \beta_s^l$$

$$\delta(\cdot) = \max(0, \text{Tanh}(\cdot))$$

$$\alpha_s^l \in \mathbb{R}^{B \times 3 \times 1 \times 1}$$

Method

- Cell Structure



- Forward Propagation

$$\mathbf{Y}_j^l = \alpha_{s \rightarrow j}^l \mathcal{T}_{s \rightarrow j}(\mathbf{H}_s^l)$$

$$\sum_j \alpha_{s \rightarrow j}^l > 0$$

- Cell Closing

$$\sum_j \alpha_{s \rightarrow j}^l = 0$$

Method

- Budget Constraint
 - Cell Cost

$$\begin{aligned}\mathcal{C}(\text{Node}_s^l) &= \mathcal{C}(\text{Cell}_s^l) + \mathcal{C}(\text{Gate}_s^l) + \mathcal{C}(\text{Trans}_s^l) \\ &= \max(\alpha_s^l) \sum_{O^i \in \mathcal{O}} \mathcal{C}(O^i) + \mathcal{C}(\text{Gate}_s^l) \\ &+ \sum_j \alpha_{s \rightarrow j}^l \mathcal{C}(\mathcal{T}_{s \rightarrow j})\end{aligned}$$

- Overall Cost

$$\mathcal{C}(\text{Space}) = \sum_{l \leq L} \sum_{s \leq 1/4} \mathcal{C}(\text{Node}_s^l)$$

Method

- Loss Function
 - Budget Cost

$$\mathcal{L}_C = (\mathcal{C}(\text{Space})/C - \mu)^2$$

- Overall Loss

$$\mathcal{L} = \lambda_1 \mathcal{L}_N + \lambda_2 \mathcal{L}_C$$

Experiment

Segmentation Performance for the Cityscapes Dataset

Method	Dynamic	Modeled from	mIoU(%)	FLOPs _{Avg} (G)	FLOPs _{Max} (G)	FLOPs _{Min} (G)	Params(M)
Handcrafted	✗	FCN-32s [24]	66.9	35.1	35.1	35.1	2.9
	✗	DeepLabV3 [5]	67.0	42.5	42.5	42.5	3.7
	✗	U-Net [28]	71.6	53.9	53.9	53.9	6.1
	✗	HRNetV2 [32]	72.5	62.5	62.5	62.5	5.4
Searched	✗	Auto-DeepLab [22]	67.2	33.1	33.1	33.1	2.5
Common-A	✗	Dynamic-A	71.6	41.6	41.6	41.6	4.1
Common-B	✗	Dynamic-B	73.0	53.7	53.7	53.7	4.3
Common-C	✗	Dynamic-C	73.2	57.1	57.1	57.1	4.5
Dynamic-A	✓	Routing-Space	72.8	44.9	48.2	43.5	17.8
Dynamic-B	✓	Routing-Space	73.8	58.7	63.5	56.8	17.8
Dynamic-C	✓	Routing-Space	74.6	66.6	71.6	64.3	17.8

- A/B/C stands for different budget constraint.
- Extracted fundamental routes to formulate common network.

Experiment

- Cell Component

- Cell operation Comparison.

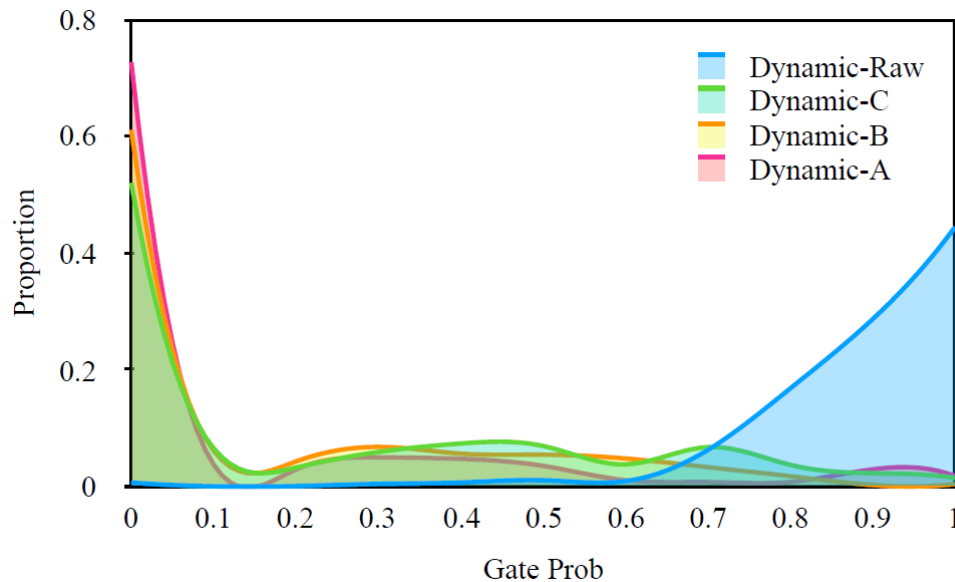
Cell Operation	mIoU(%)	FLOPs(G)	Params(M)
BottleNeck [16]	73.7	1134.8	203.9
MBCConv [29]	75.0	323.8	48.2
SepConv3×3	71.2	81.4	12.6
SepConv3×3 ×2	76.1	119.5	17.8
SepConv3×3 ×3	75.2	153.8	22.9

- Gate function comparison.

Activation	mIoU(%)	FLOPs(G)	Params(M)
Fix	74.5	103.1	15.3
Softmax	74.1	120.0	17.8
Sigmoid	75.9	120.0	17.8
max(0, Tanh)	76.1	119.5	17.8

Experiment

- Route activating probabilities



- Dynamic-Raw is without any budget constraint.
- Useless paths are cut under the budget constraint.

Conclusion

- Adaptively construct data-dependent forward routing for diverse scale distributions.
- Design budget constraint to for practical application and joint optimization with the original task.

Thanks!