

AL5.A.01 - Techniques IA

Deep learning-based semantic segmentation

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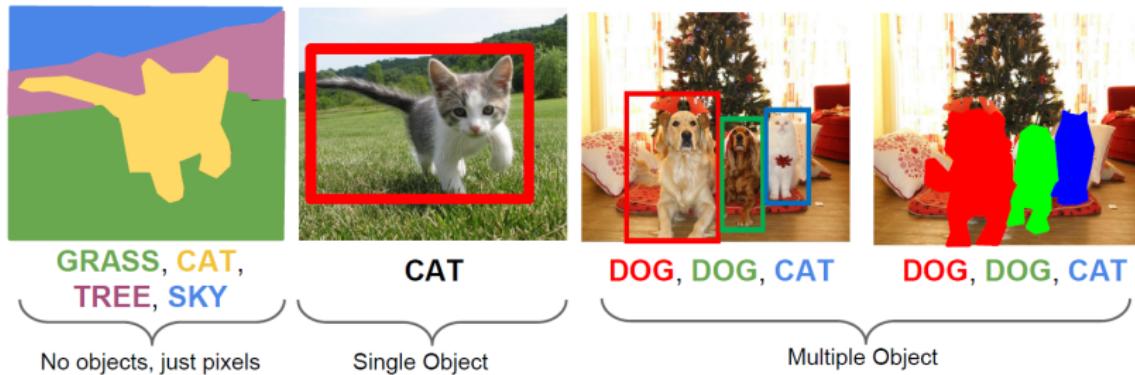
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Introduction Main computer vision tasks

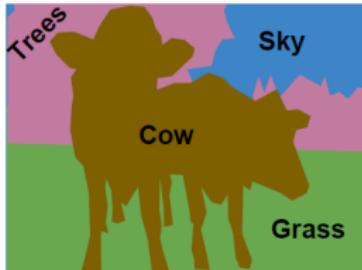
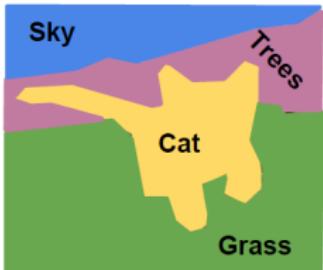
Reminder of main vision tasks: classification/recognition, classification+localization, object detection, semantic segmentation and instance segmentation¹



¹Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Today's focus: Semantic segmentation

- Predict a label for each pixel from the image (= pixel-wise classification)
- Not differentiate the instances, only the semantic²



²Image credit: <https://cs23in.github.io/>, Lecture 11, 2017

Introduction Semantic segmentation

Today's focus: Semantic segmentation

- Input: image of size $H \times W \times 3$ (for RGB images as usual)
- Output: segmentation map of size $H \times W \times 1$ (with class label at each pixel position)²



→ segmented

1: Person
2: Purse
3: Plants/Grass
4: Sidewalk
5: Building/Structures

Input

Semantic Labels

3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5
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5	5	3	3	3	3	3	3	1	1	1	1	1	3	3	3	3	3	3	3	3	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4	4	4	5	5	5	5
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4	4	4	1	1	1	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4	4	4	4	4	4
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3	3	3	1	2	2	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4	4	4	4	4	4

²Image credit: <https://www.jeremyjordan.me/semantic-segmentation/#loss>

Semantic segmentation Applications³

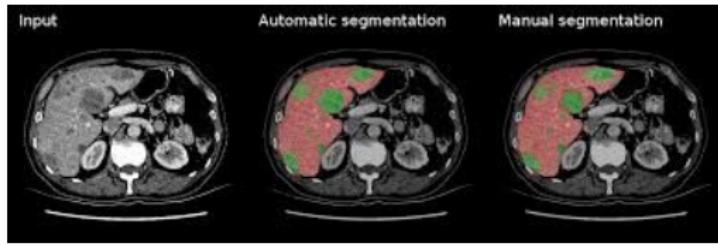
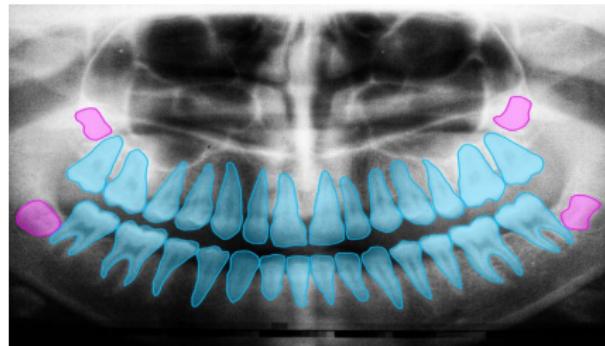
- **Autonomous driving.** Popular datasets: Cityscapes (30 classes, 5k images), KITTI (11, 400), Mapillary Vistas (66, 25k) , CamVid (32, 700), etc.



³Image credit: <https://keymakr.com/blog/semantic-segmentation-uses-and-applications/>

Semantic segmentation Applications³

- **Medical imaging.** Many sub-tasks: tumor segmentation, retinal vessel extraction, MRI-based various disease scanning, etc.



³Image credit: <https://keymakr.com/blog/semantic-segmentation-uses-and-applications/>

Semantic segmentation Applications³

- **Scene understanding (for image captioning/description).** Indoor and outdoor; street-view, panorama, aerial views. Popular datasets: ADE20K, SceneNet, UAVid, TorontoCity, etc.

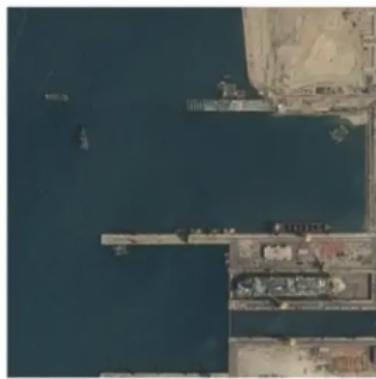


³Image credit: <https://keymakr.com/blog/semantic-segmentation-uses-and-applications/>

Metrics for evaluation

- Pixel accuracy: overall accuracy, average (class) accuracy, confusion matrix
- Mean IOU (Intersection-over-Union)
- For binary maps: Recall, Precision, F1-score

Remarks: using pixel accuracy is sometime dangerous: class imbalance, high portion of background, etc.⁴



⁴Image credit: <https://medium.com/towards-data-science/image-segmentation-kaggle-experience-9a41cb8924f0>

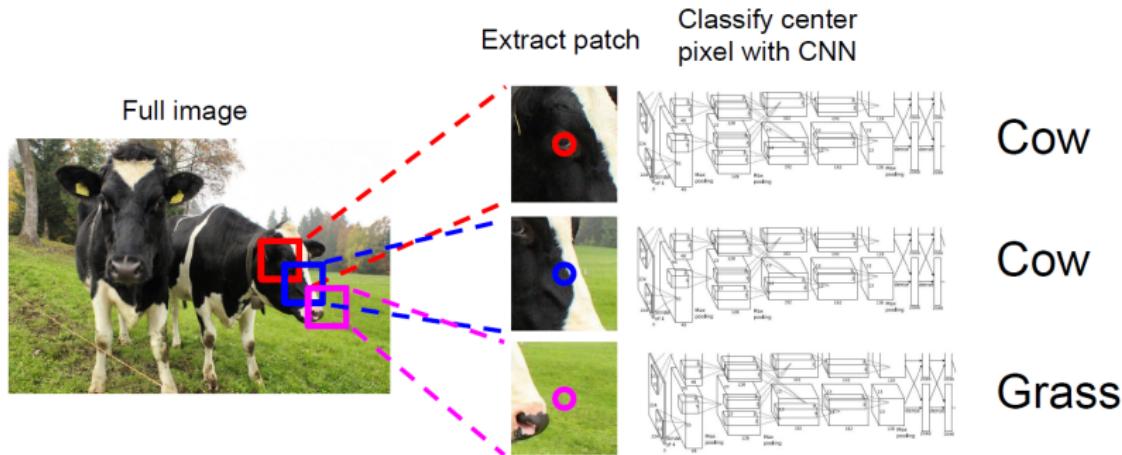
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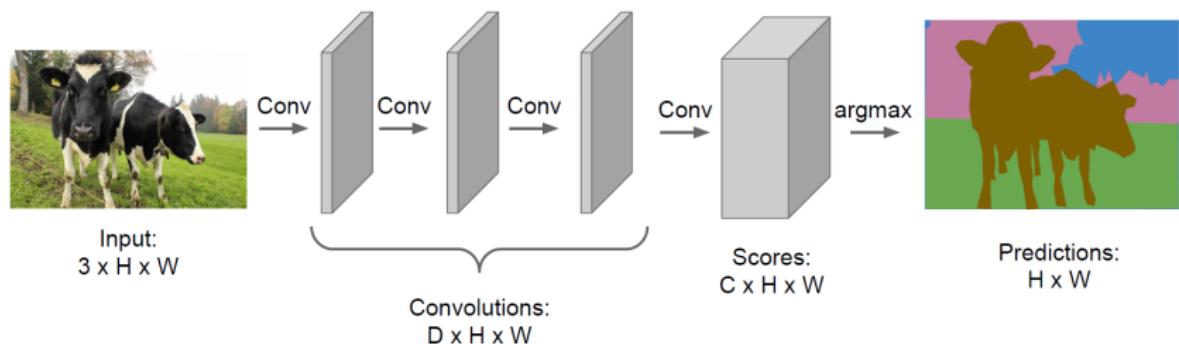
Segmentation networks Very first idea⁵

Sliding window: very very slow (inefficient) without reusing shared features from the ConvNet



⁵Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Fully convolutional: to fully share ConvNet features, design a network with only convolutional layers (no pooling, no fully-connected)



Problem: convolutions at the original image resolution are very expensive !

⁵Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Fully convolutional with downsampling and upsampling:

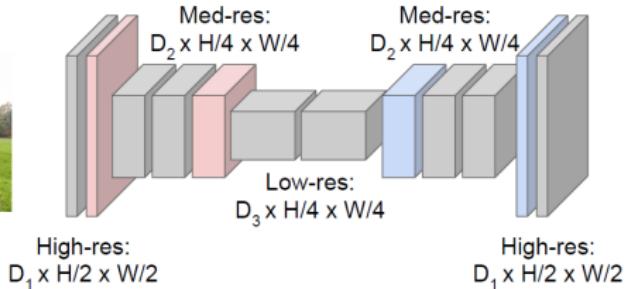
- allow to share features at multiple scales (low-level to high level)
- allow to learn deeper features (with more layers) without exploding the computational cost

Downsampling:
Pooling, strided convolution



Input:
 $3 \times H \times W$

Design network as a bunch of convolutional layers, with
downsampling and **upsampling** inside the network!



Upsampling:
???



Predictions:
 $H \times W$

⁵Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Read & discuss:

- An overview of semantic image segmentation, Jeremy Jordan
<https://www.jeremyjordan.me/semantic-segmentation/>

Questions for discussion:

- How to upsample ?
- What are the main architectures ?
- Which loss functions that could be used ?

Segmentation networks Upsampling⁶

Nearest neighbor or “Bed of nails”

- very simple method
- no parameters
- not efficient

Nearest Neighbor

1	2
3	4



Input: 2 x 2

“Bed of Nails”

1	2
3	4



Output: 4 x 4

Input: 2 x 2

1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

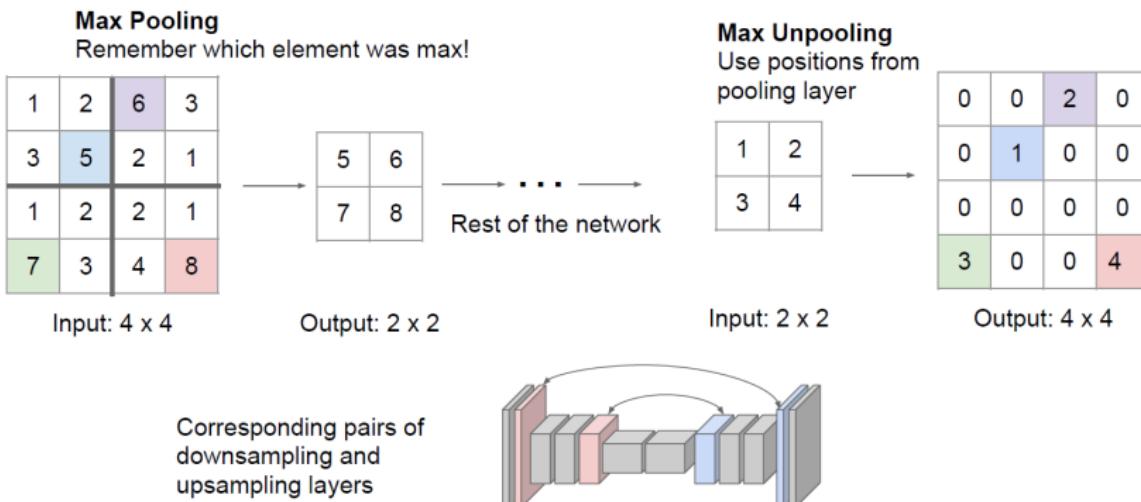
Output: 4 x 4

⁶Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Segmentation networks Upsampling⁶

Max unpooling

- remember the max element within max-pooling
- use the position in unpooling layers
- no parameter, better than Nearest neighbor or "Bed of nails"



⁶Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

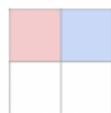
Segmentation networks Upsampling⁶

Transpose convolutions

- popular approach
- trainable parameters
- multiply the single value from the input with the filter weights and project into the output with summing at overlapped positions

Other names:

- Deconvolution (bad)
- Upconvolution
- Fractionally strided convolution
- Backward strided convolution

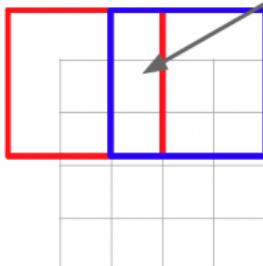


Input: 2 x 2

3 x 3 transpose convolution, stride 2 pad 1



Input gives weight for filter



Output: 4 x 4

Sum where output overlaps

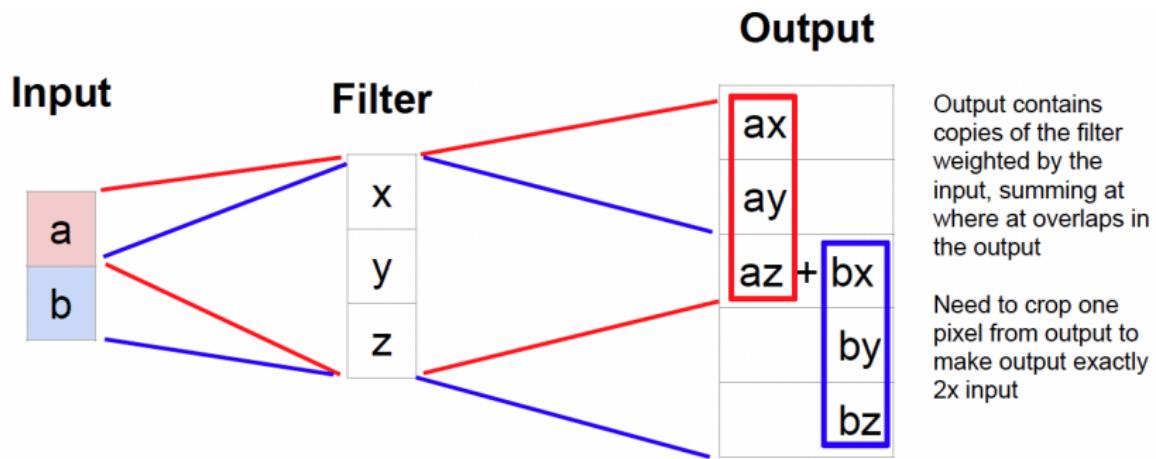
Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

⁶Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Transpose convolutions

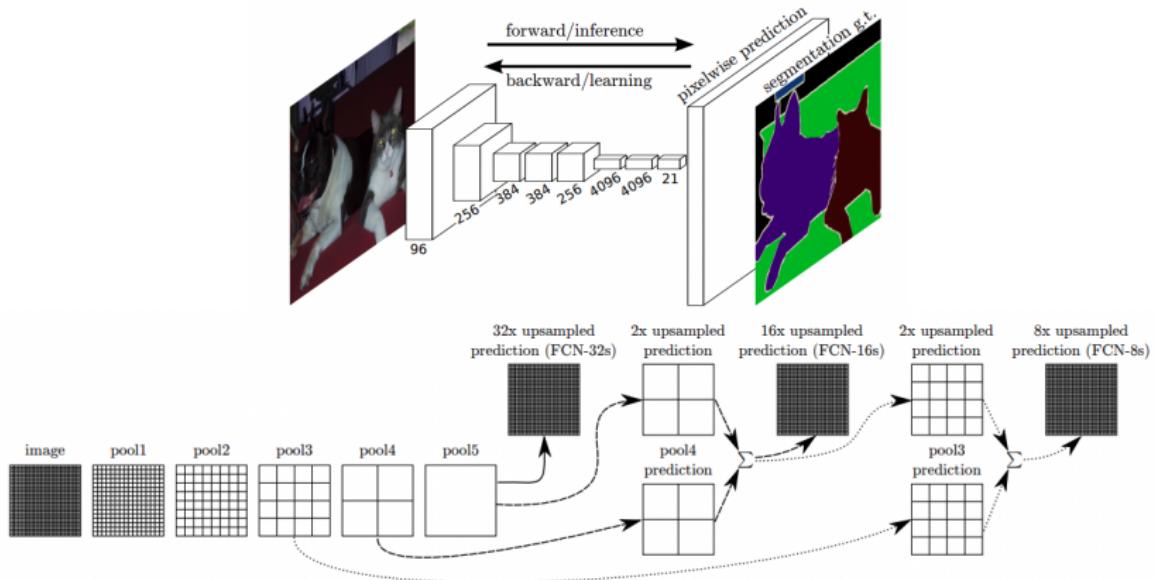
- 1D example for easy understanding



⁶Image credit: <https://cs231n.github.io/>, Lecture 11, 2017

Fully convolutional network ⁷

- first every deep seg network
- **skip connections** to upsample the feature maps of the final layers and fuse with earlier maps



⁷Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Decovolutional network⁷

- combine unpooling and deconvolution layer (transpose convolution) for upsampling

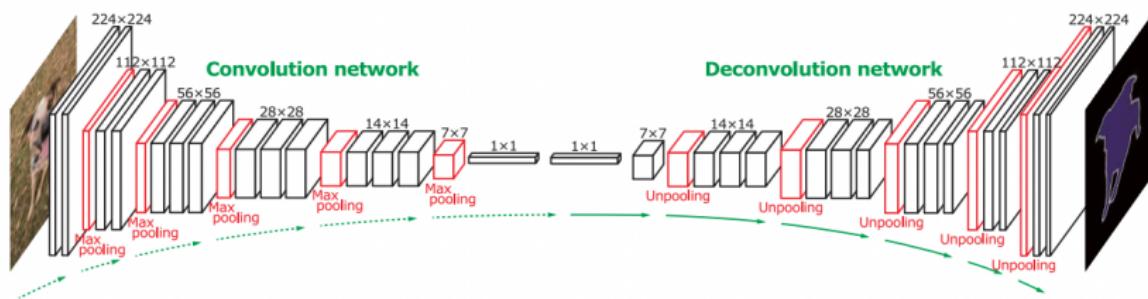


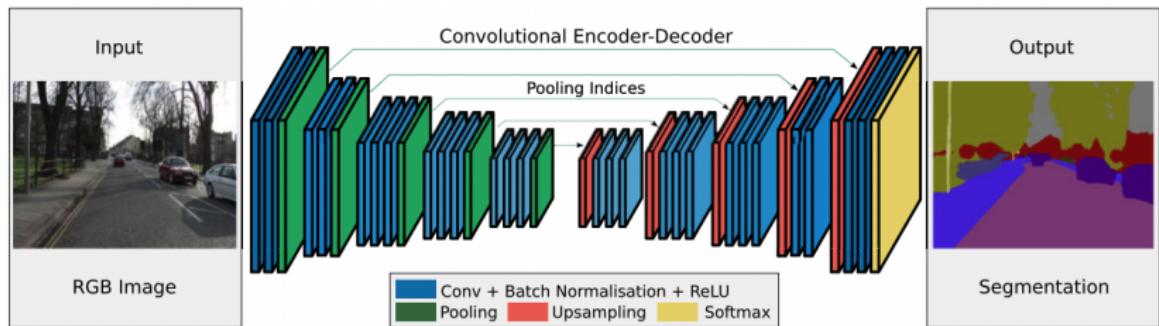
Figure 2. Overall architecture of the proposed network. On top of the convolution network based on VGG 16-layer net, we put a multi-layer deconvolution network to generate the accurate segmentation map of an input proposal. Given a feature representation obtained from the convolution network, dense pixel-wise class prediction map is constructed through multiple series of unpooling, deconvolution and rectification operations.

⁷ Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Segmentation networks Popular architectures

SegNet⁷

- popular approach in remote sensing
- max unpooling to remember the position of max element from pooling layer (pooling indices)

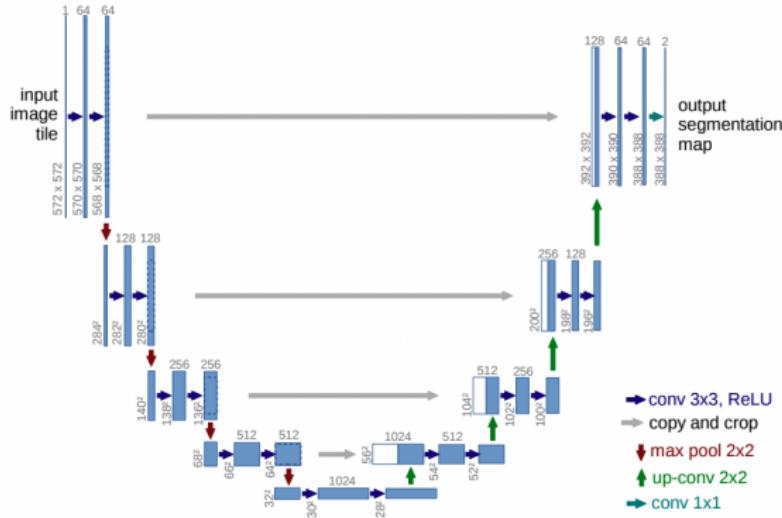


⁷SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation, IEEE PAMI 2017

Segmentation networks Popular architectures

U-net⁷

- proposed in the context of medical biomedical image segmentation
- skip connections for symmetric expanding path
- use transposed convolutions
- **very popular and efficient approach**



⁷U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

Other architectures⁷

Pretrained models available on Pytorch: DeepLabV3, FCN

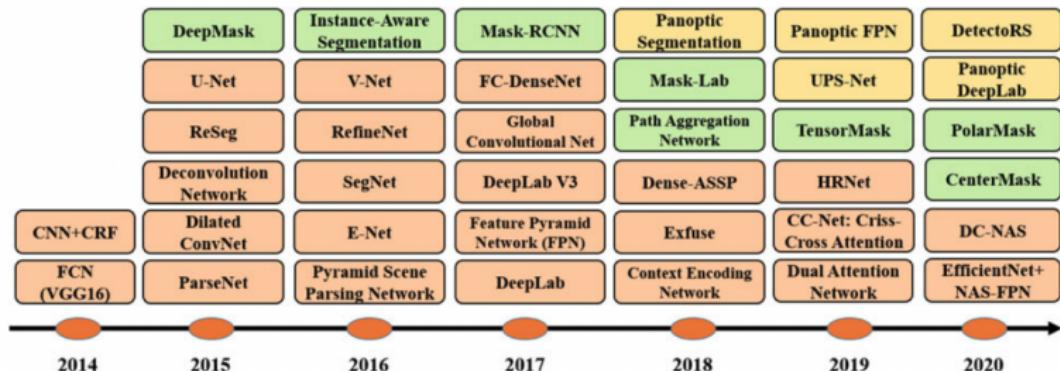


Fig. 33. Timeline of representative DL-based image segmentation algorithms. Orange, green, and yellow blocks indicate semantic, instance, and panoptic segmentation algorithms, respectively.

⁷Image Segmentation Using Deep Learning: A Survey, IEEE PAMI 2022

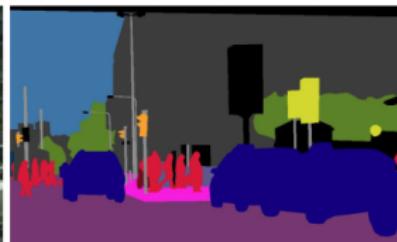
Segmentation networks Popular architectures

Remark Do no confuse tasks⁸

- Semantic segmentation
- Instance segmentation
- Panoptic segmentation (combination of the 2 others)



(a) image



(b) semantic segmentation



(c) instance segmentation



(d) panoptic segmentation

⁸Panoptic Segmentation, CVPR 2019

References I

Books & articles:

1. Minaee, S., Boykov, Y.Y., Porikli, F., Plaza, A.J., Kehtarnavaz, N. and Terzopoulos, D., 2021. Image segmentation using deep learning: A survey. IEEE PAMI.

Courses and blogs:

1. Lecture 11: Segmentation and Detection
<https://cs231n.github.io/transfer-learning/>
2. An overview of semantic image segmentation, 2018
<https://www.jeremyjordan.me/semantic-segmentation/#loss>
3. Image segmentation with DeepLabV3
https://pytorch.org/tutorials/beginner/deeplabv3_on_ios.html
4. Semantic segmentation benchmarks
<https://paperswithcode.com/task/semantic-segmentation>