Deep Learning

Lecture 7

Recap

Architectures for classification

- ResNet
- VGG
- MobileNet
- EfficientNet
- ViT

Object detection

- RCNN
- Fast-RCNN
- Faster-RCNN

Semantic segmentation

Motivation

We have car, building on both images, but scenes are different!

Semantic segmentation

Through semantic segmentation we really understand the image

How to make semantic segmentation

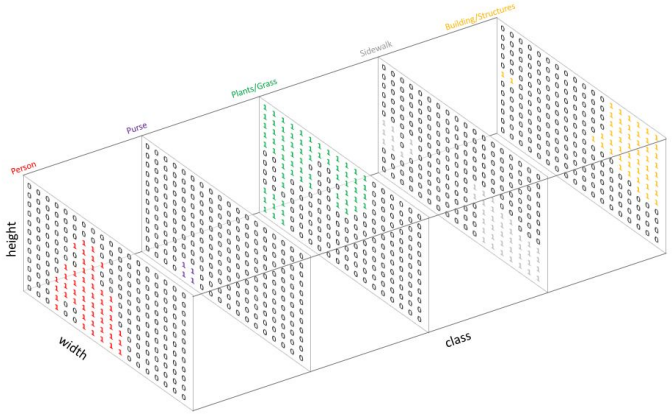
Input

segmented

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

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

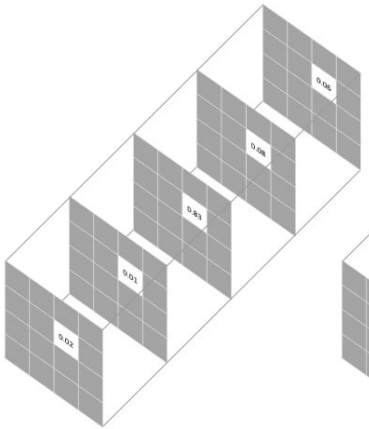
Semantic Labels



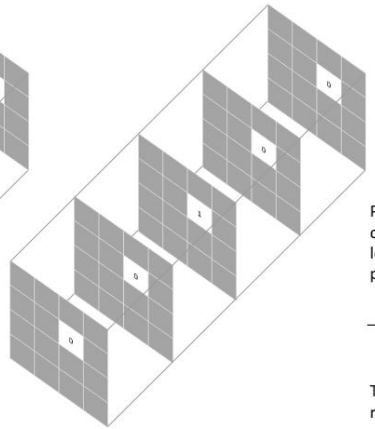
We set every pixel with class value -> Output HxWx1

But neural network work poorly with discrete values? How to parametrize predictions?

Loss functions



Prediction for a selected pixel

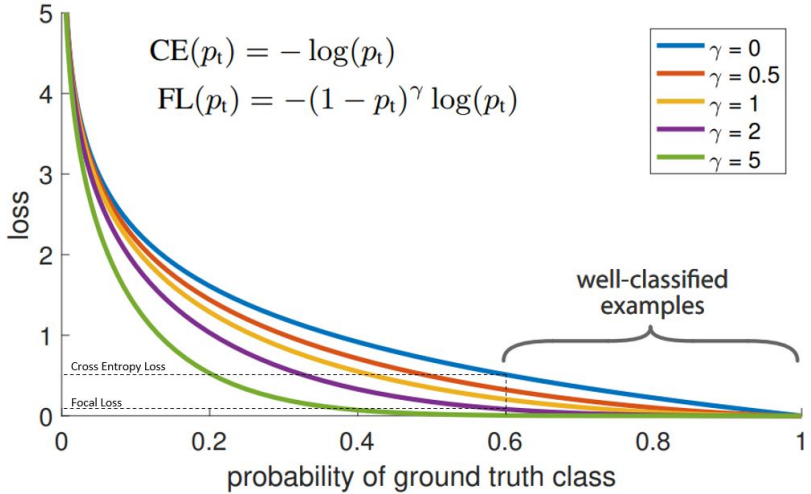


Target for the corresponding pixel

Pixel-wise loss is calculated as the log loss, summed over all possible classes

$$-\sum_{classes} y_{true} \log\left(y_{pred}\right)$$

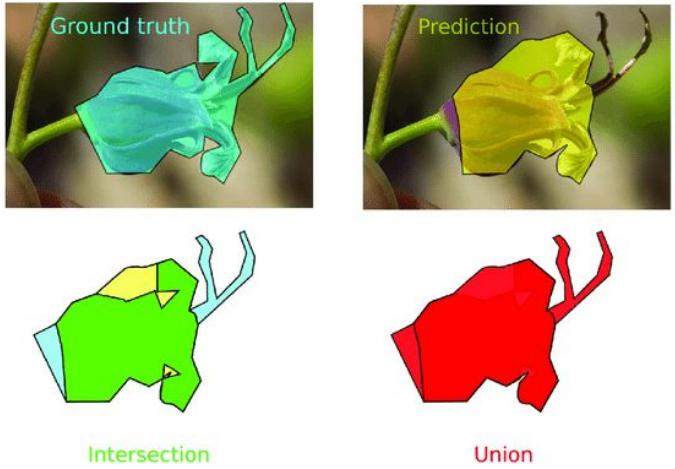
This scoring is repeated over all **pixels** and averaged



$$\mathrm{FL}\left(p_t\right) = -\alpha_t \left(1-p_t\right)^{\gamma} \log\left(p_t\right)$$

Why do we need alphas?

Metrics



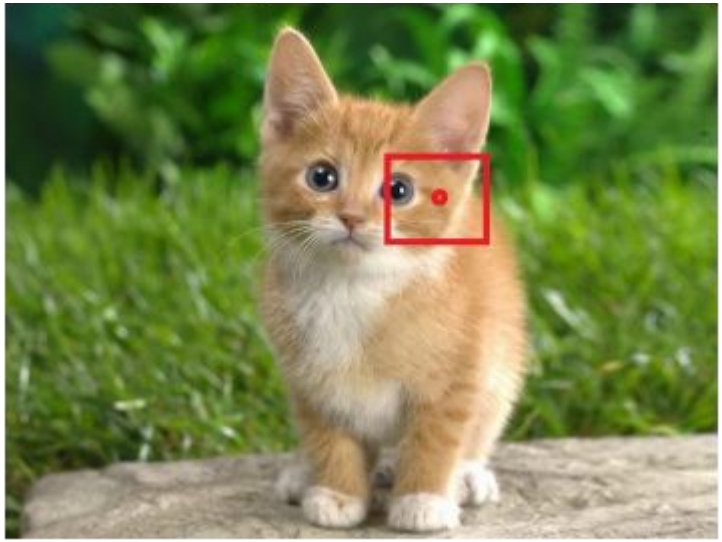
$$\text{IoU} = \frac{\text{Intersection}}{\text{Union}}$$

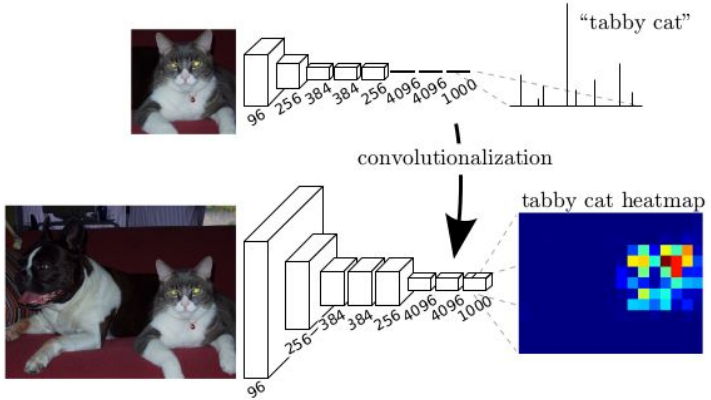
Averaging over classes → $mIoU$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Averaging over classes → $mAcc$

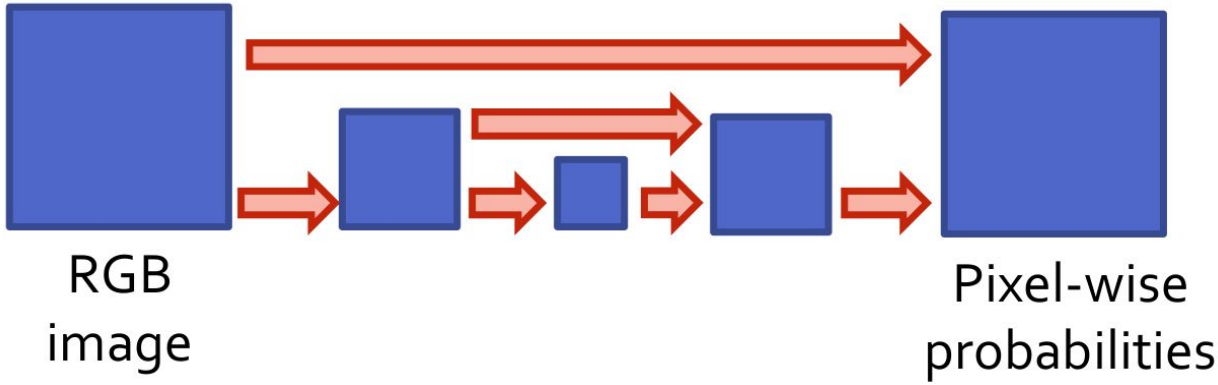
Simple solution





- Works too long
- Resolution is very bad

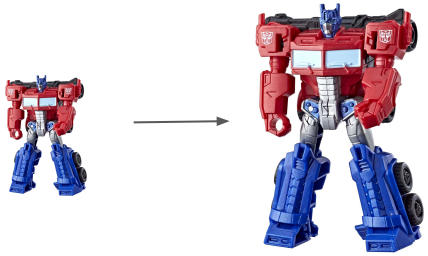
Better solution

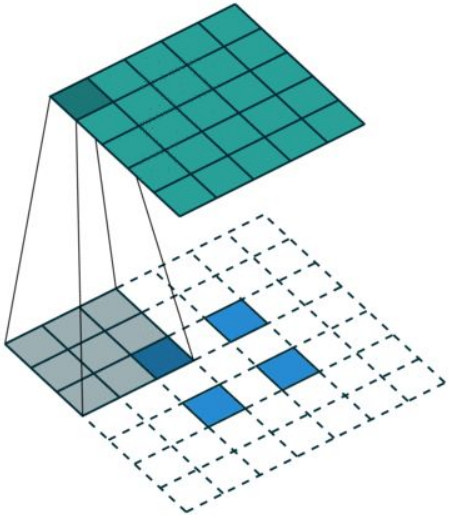


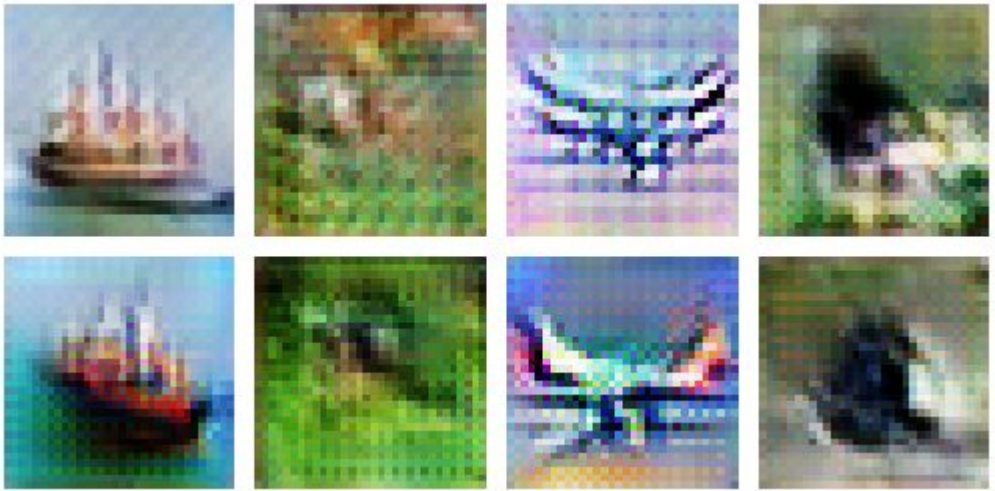
This solution solves both problems:

- Big receptive field
- Fine details due to top information

Upsampling

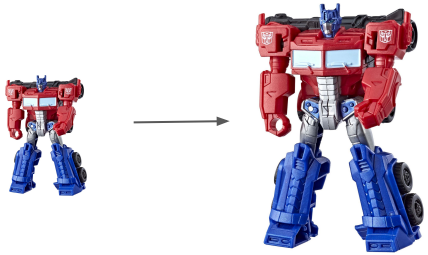






Transposed convolution can be use as upsampling function. But it can produce checkerboard artifacts

Upsampling



10	20
30	40

2x2

2x

10	10	20	20
10	10	20	20
30	30	40	40
30	30	40	40

4x4

Nearest neighbor upsampling

10	20
30	40

2x2

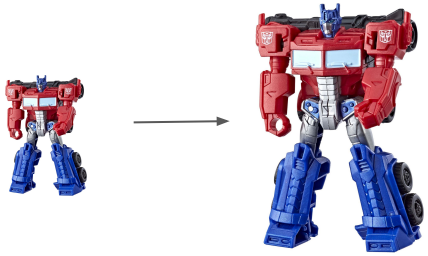
2x

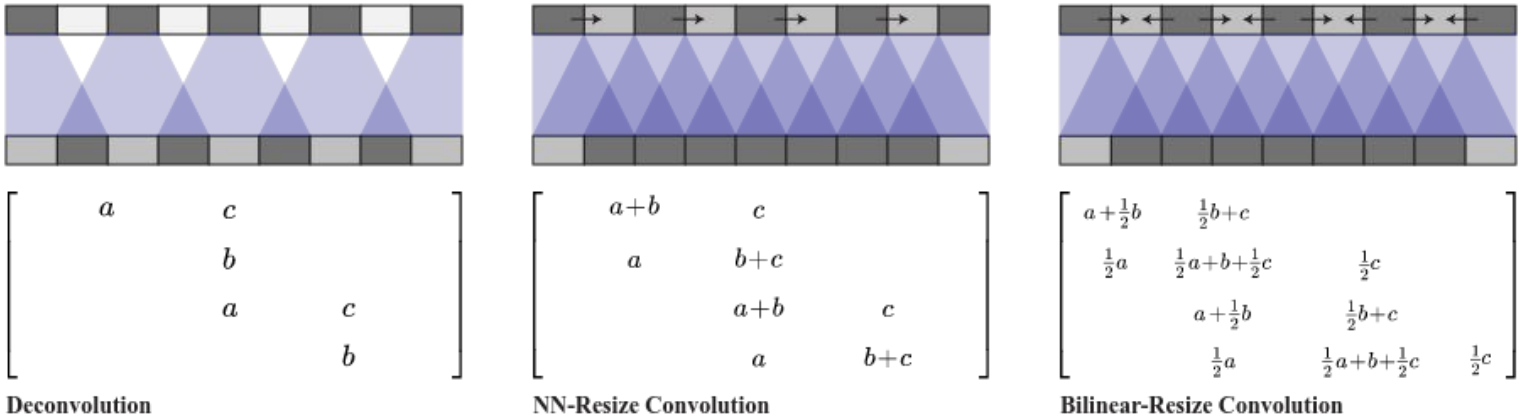
10	12	17	20
15	17	22	25
25	27	32	35
30	32	37	40

4x4

Bilinear interpolation upsampling

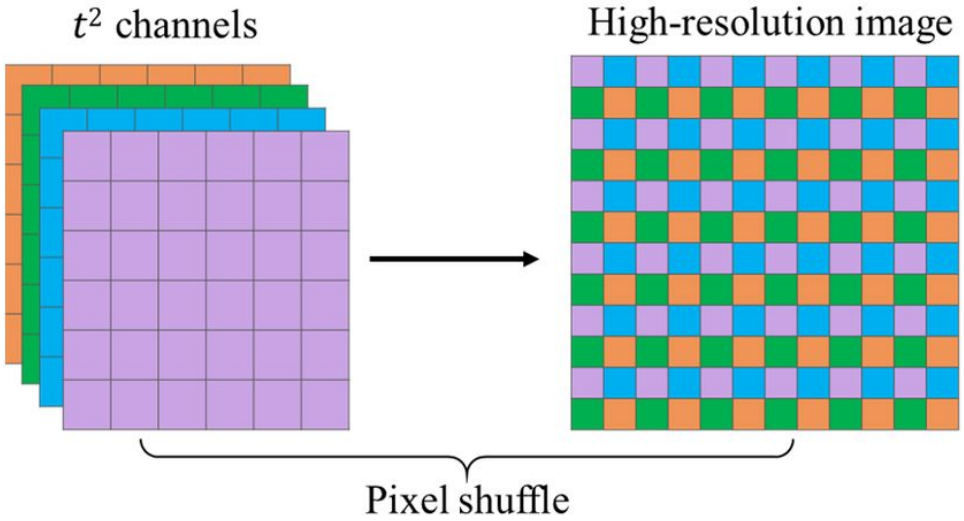
Upsampling





Voilà!

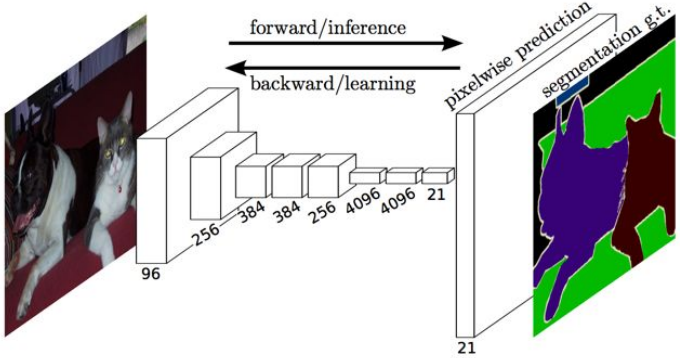
Pixel Shuffle

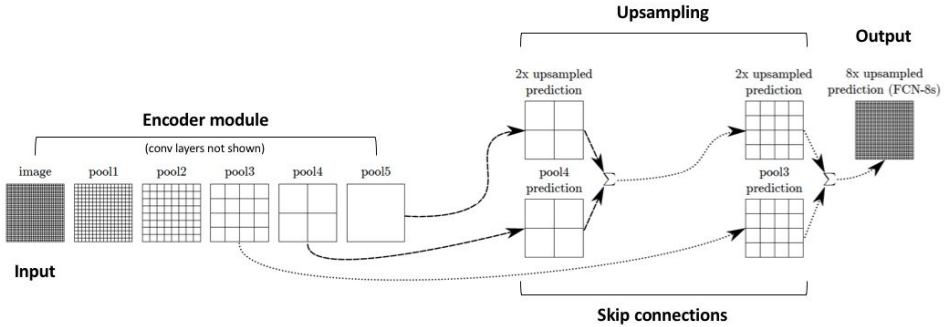


Transforms additional channels to spatial resolution (usually we do reverse)!

Architectures

FCN


forward/inference
backward/learning
pixelwise prediction
segmentation g.t.
96
256
384
384
256
4096
4096
21
21


Upsampling
Output
2x upsampled prediction
2x upsampled prediction
8x upsampled prediction (FCN-8s)
Encoder module
(conv layers not shown)
image
pool1
pool2
pool3
pool4
pool5
pool4 prediction
pool3 prediction
Input
Skip connections

FCN

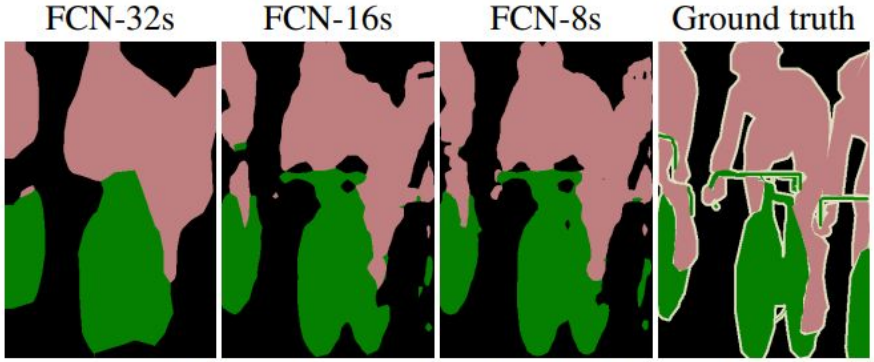
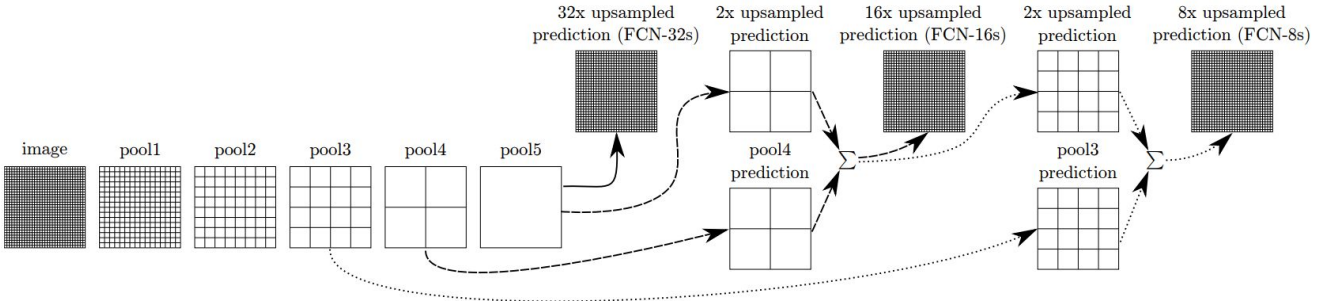
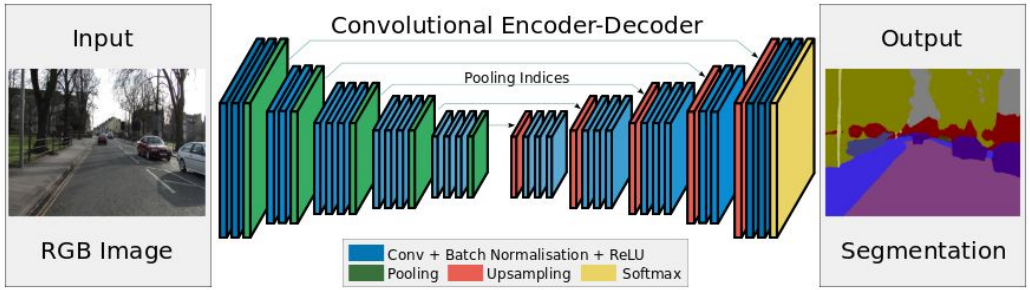


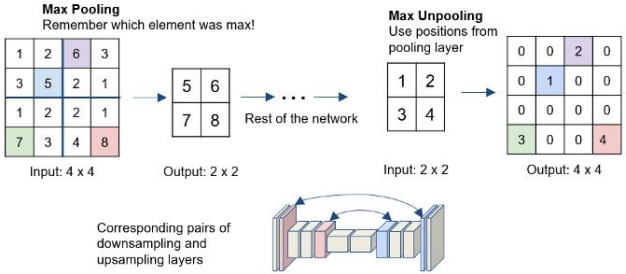
Figure 4. Refining fully convolutional nets by fusing information from layers with different strides improves segmentation detail. The first three images show the output from our 32, 16, and 8 pixel stride nets (see Figure 3).

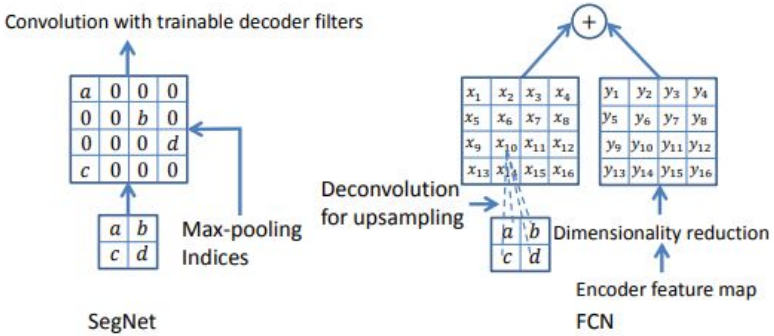
If we use more top information we get the better quality



SegNet

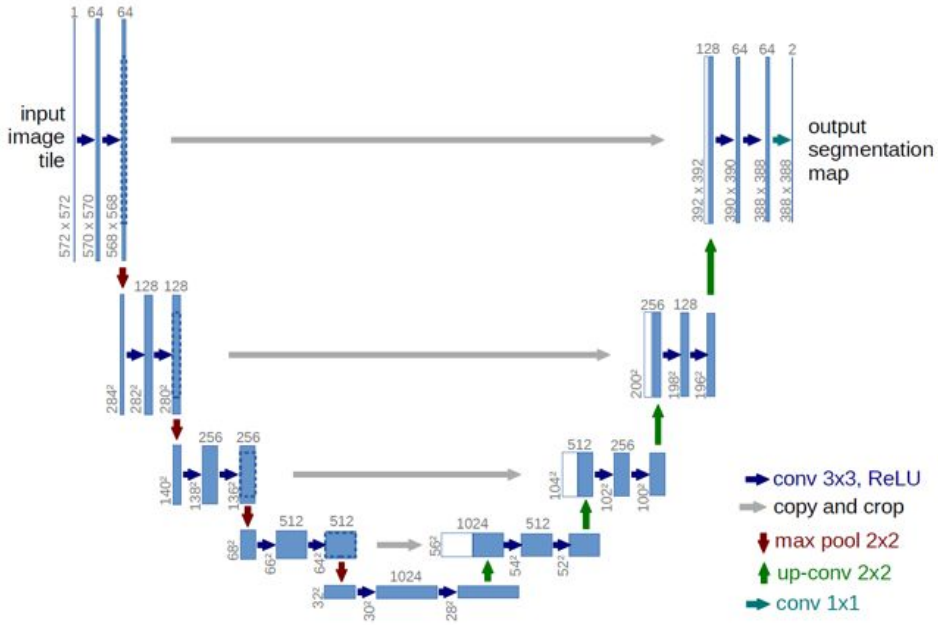






- Making encoder and decoder equal in terms of parameters
- Saving more information from encoder

UNet


input image tile
output segmentation map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

UNet

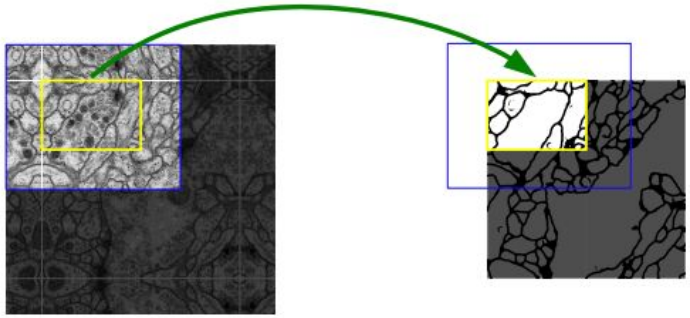
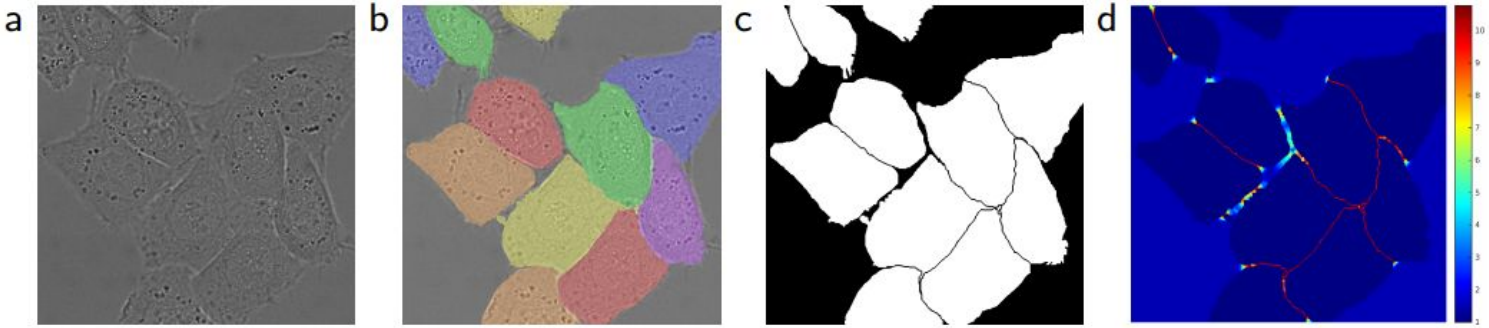


Fig. 2. Overlap-tile strategy for seamless segmentation of arbitrary large images (here segmentation of neuronal structures in EM stacks). Prediction of the segmentation in the yellow area, requires image data within the blue area as input. Missing input data is extrapolated by mirroring



HRNet

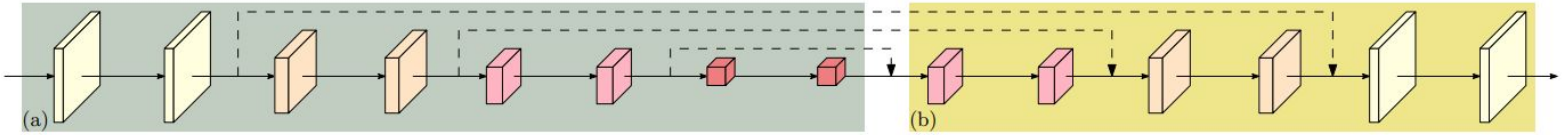
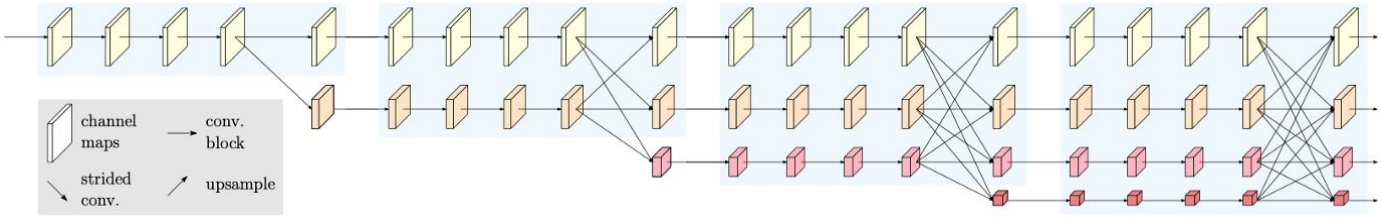


Fig. 1. The structure of recovering high resolution from low resolution. (a) A low-resolution representation learning subnetwork (such as VGGNet [126], ResNet [54]), which is formed by connecting high-to-low convolutions in series. (b) A high-resolution representation recovering subnetwork, which is formed by connecting low-to-high convolutions in series. Representative examples include SegNet [3], DeconvNet [107], U-Net [119] and Hourglass [105], encoder-decoder [112], and SimpleBaseline [152].

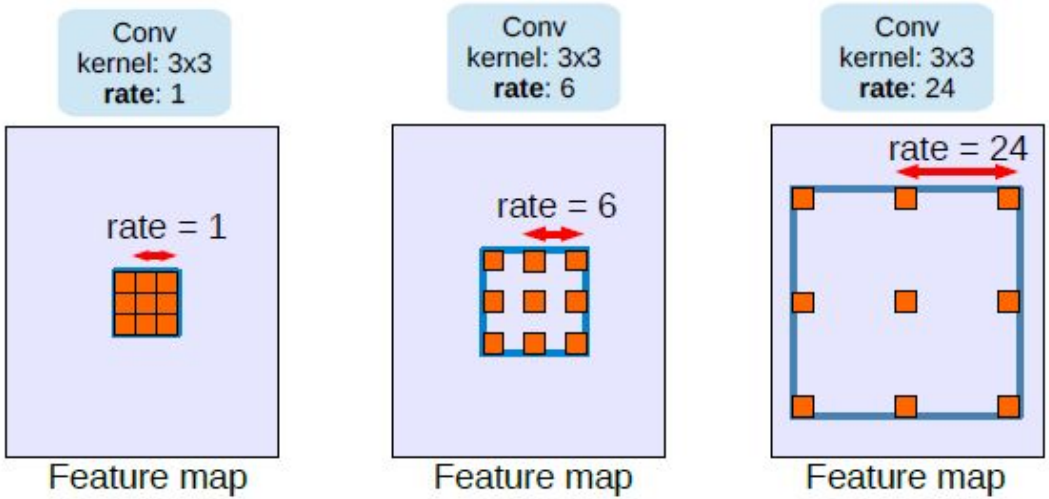
Base template for segmentation architecture



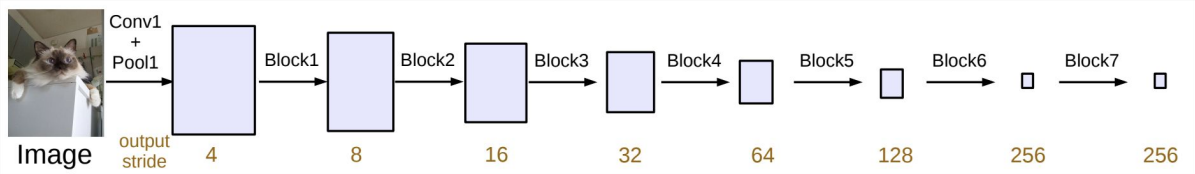
HRNet

Atrous convolution

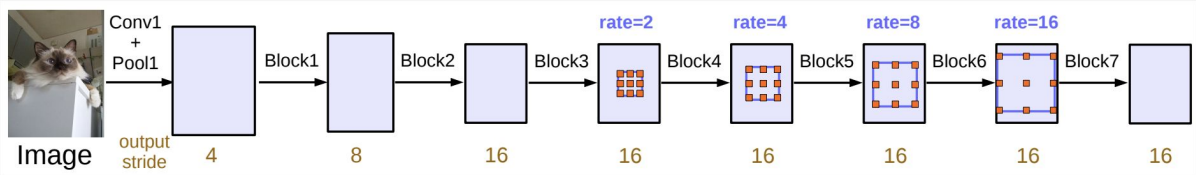
How to increase receptive field w/o lowering image resolution



Atrous convolution



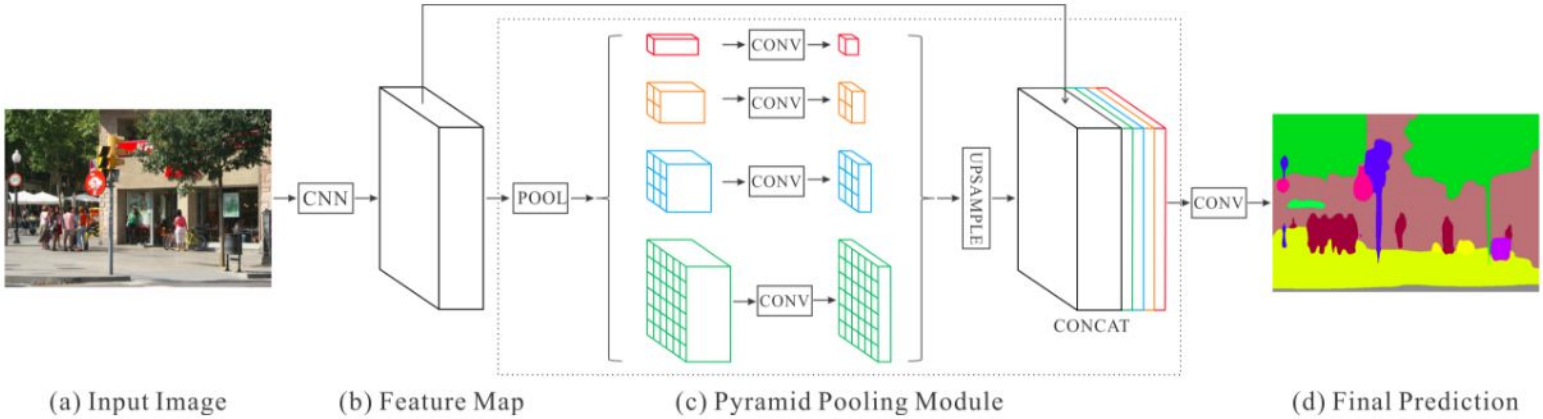
(a) Going deeper without atrous convolution.

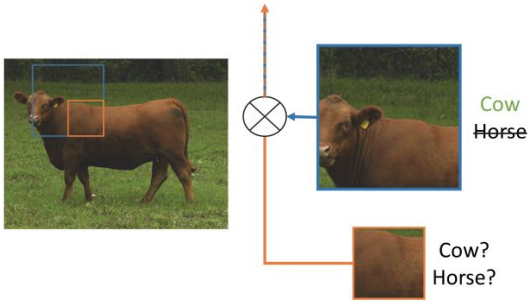


(b) Going deeper with atrous convolution. Atrous convolution with $rate > 1$ is applied after block3 when $output\_stride = 16$.

Figure 3. Cascaded modules without and with atrous convolution.

PSPNet


CNN
POOL
CONV
CONV
CONV
CONV
UPSAMPLE
CONCAT
CONV
(a) Input Image
(b) Feature Map
(c) Pyramid Pooling Module
(d) Final Prediction


Cow
Horse
Cow?
Horse?

DeepLab

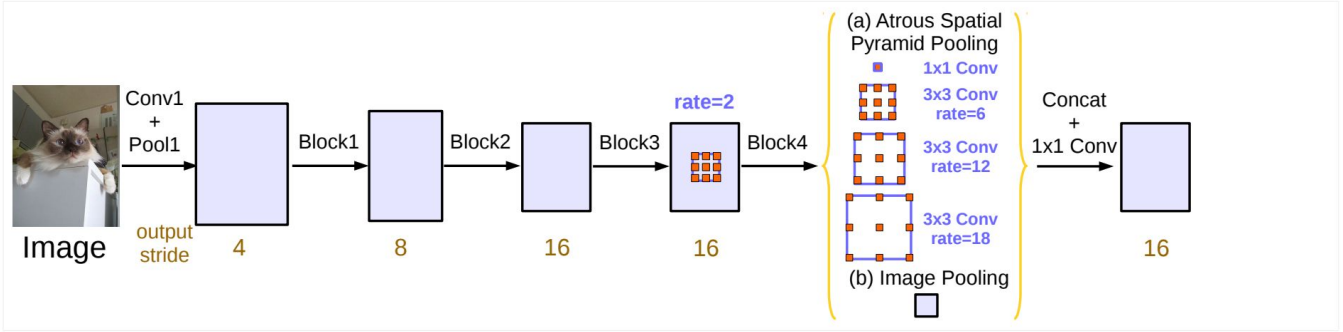
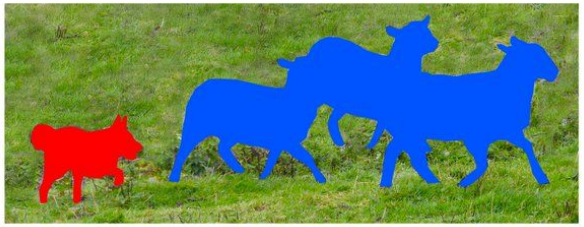


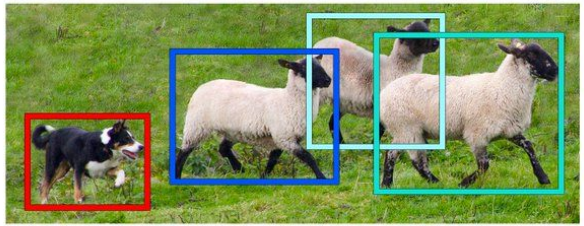
Figure 5. Parallel modules with atrous convolution (ASPP), augmented with image-level features.

Instance Segmentation

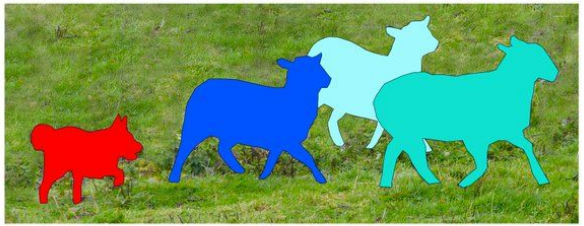
Image Recognition



Semantic Segmentation

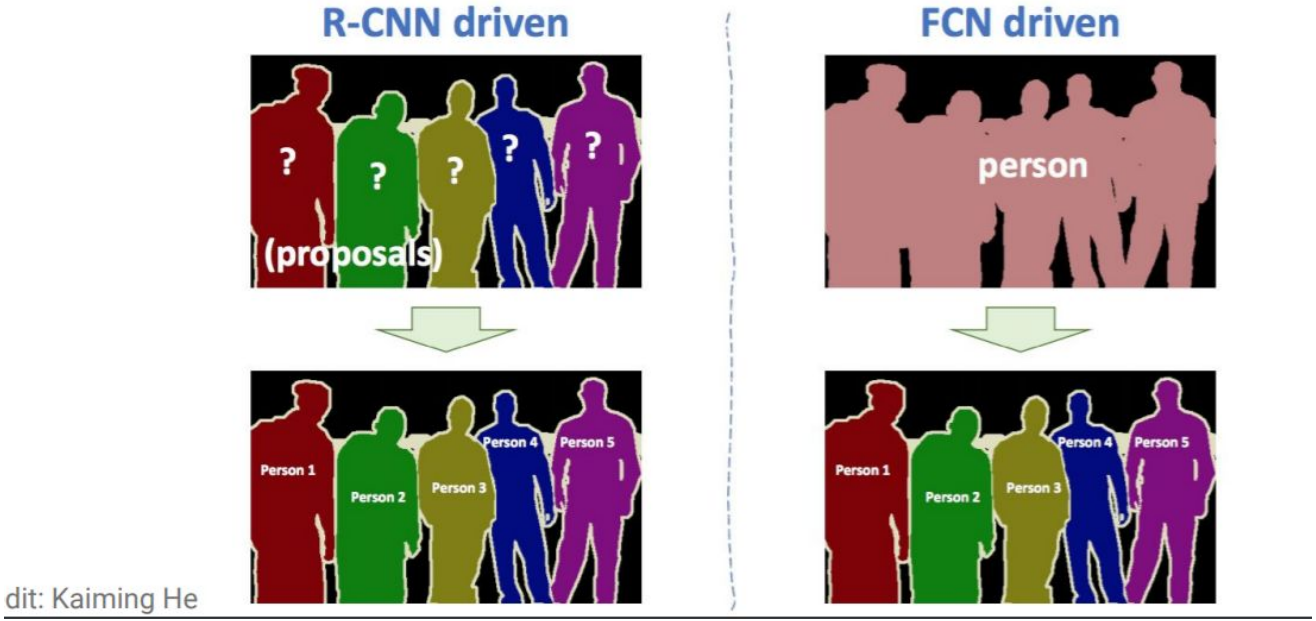


Object Detection



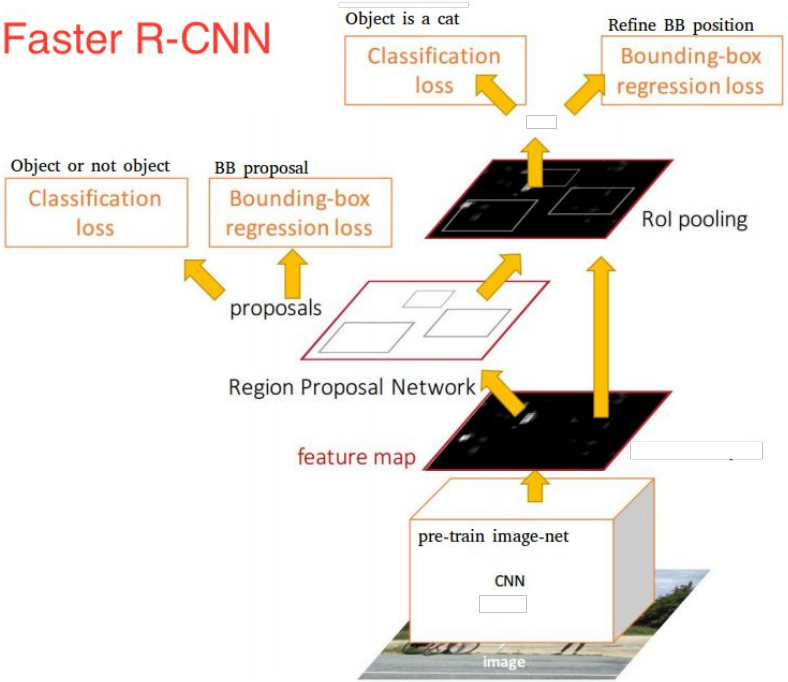
Instance Segmentation

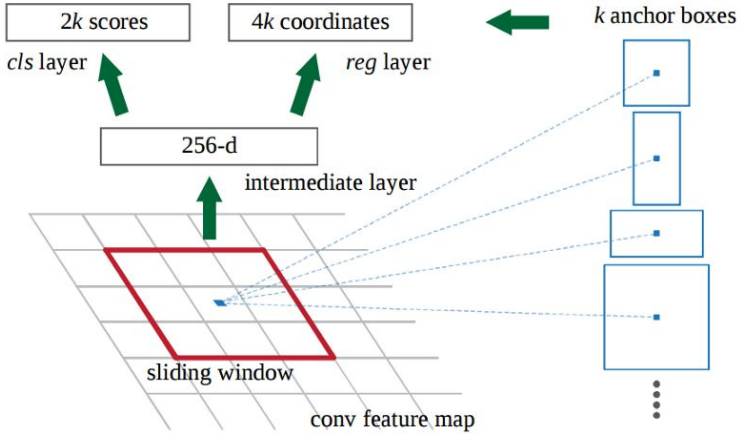
Instance Segmentation



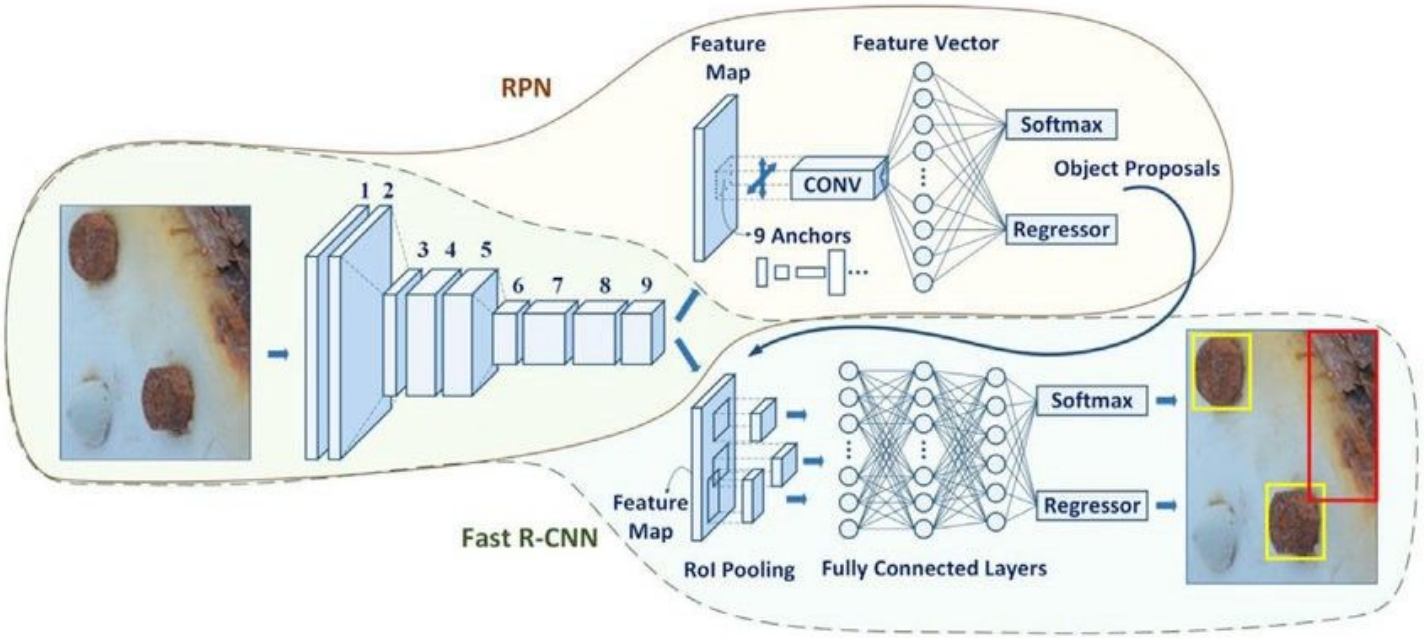
dit: Kaiming He

Reminder:

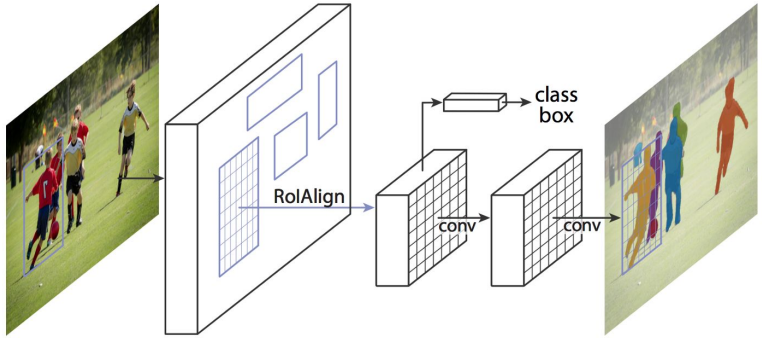

Faster R-CNN
Object is a cat
Classification loss
Refine BB position
Bounding-box regression loss
Object or not object
Classification loss
BB proposal
Bounding-box regression loss
RoI pooling
proposals
Region Proposal Network
feature map
pre-train image-net
CNN
image


2k scores
4k coordinates
k anchor boxes
cls layer
reg layer
256-d
intermediate layer
sliding window
conv feature map

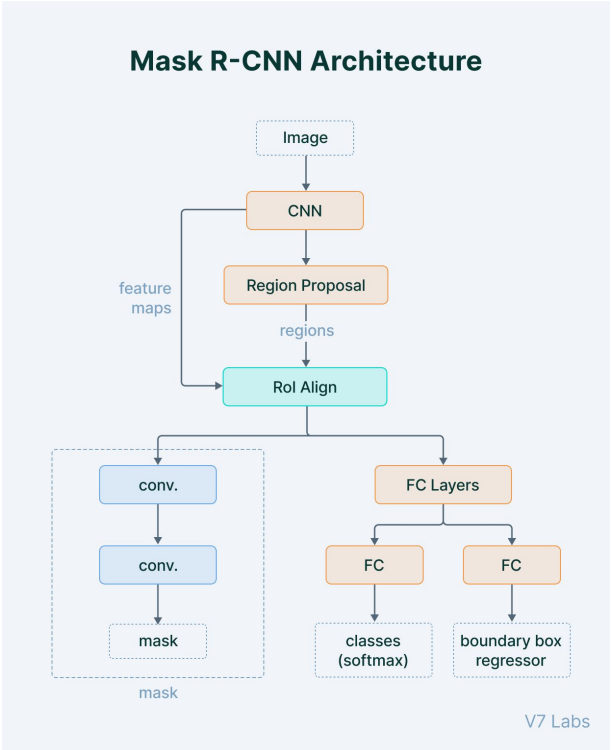
Faster RCNN


RPN
Feature Map
Feature Vector
Softmax
Object Proposals
CONV
Regressor
9 Anchors
1 2
3 4 5
6 7 8 9
Feature Map
Softmax
Regressor
Fast R-CNN
RoI Pooling
Fully Connected Layers

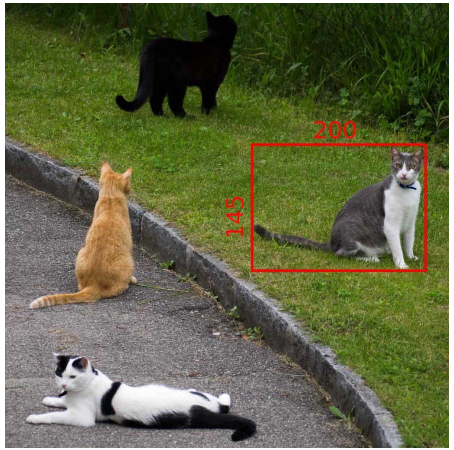
Mask R-CNN

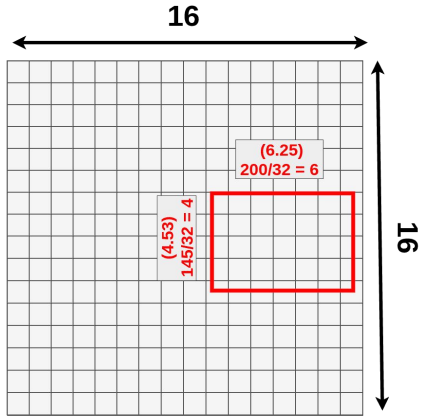


Adding mask prediction head



RoI Pooling

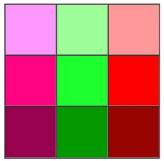




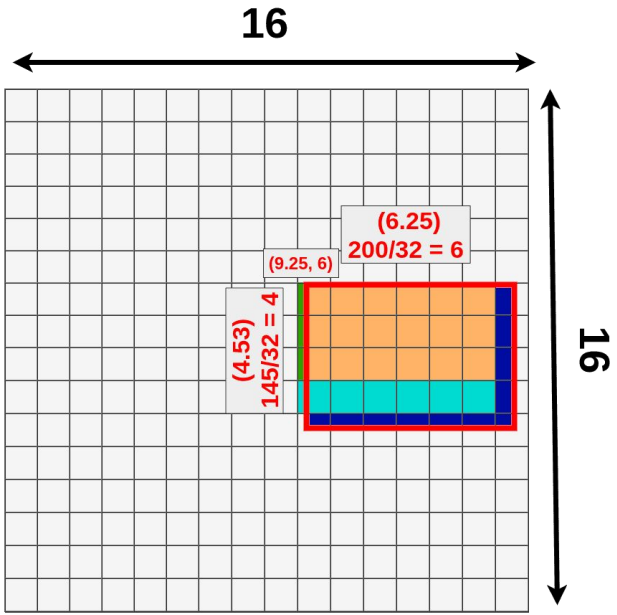
4x6 RoI

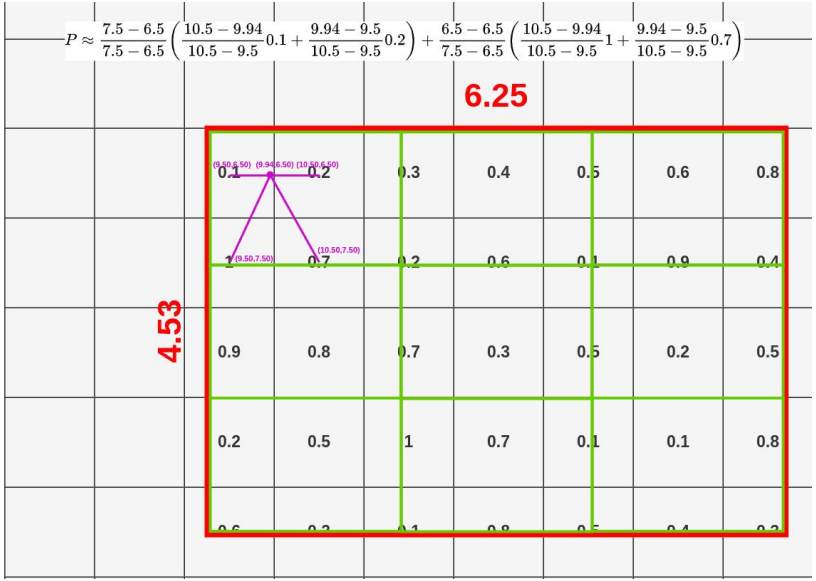
0.1	0.2	0.3	0.4	0.5	0.6
1	0.7	0.2	0.6	0.1	0.9
0.9	0.8	0.7	0.3	0.5	0.2

3x3 RoI Pooling

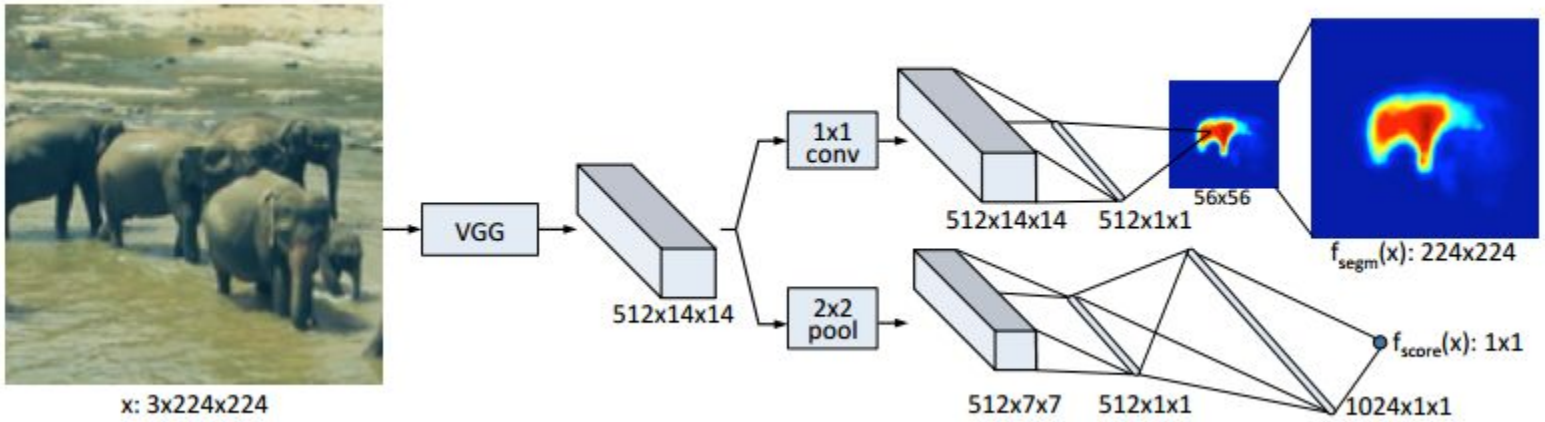


RoI Align


16
16
(6.25)
200/32 = 6
(9.25, 6)
(4.53)
145/32 = 4


$P \approx \frac{7.5-6.5}{7.5-6.5}\left(\frac{10.5-9.94}{10.5-9.5}0.1+\frac{9.94-9.5}{10.5-9.5}0.2\right)+\frac{6.5-6.5}{7.5-6.5}\left(\frac{10.5-9.94}{10.5-9.5}1+\frac{9.94-9.5}{10.5-9.5}0.7\right)$
6.25
4.53
0.1 0.2 0.3 0.4 0.5 0.6 0.8
1 0.7 0.2 0.6 0.1 0.9 0.4
0.9 0.8 0.7 0.3 0.5 0.2 0.5
0.2 0.5 1 0.7 0.1 0.1 0.8

DeepMask


x: 3x224x224
VGG
512x14x14
1x1 conv
2x2 pool
512x14x14
512x1x1
56x56
f_{segm}(x): 224x224
512x7x7
512x1x1
1024x1x1
f_{score}(x): 1x1

Panoptic Segmentation

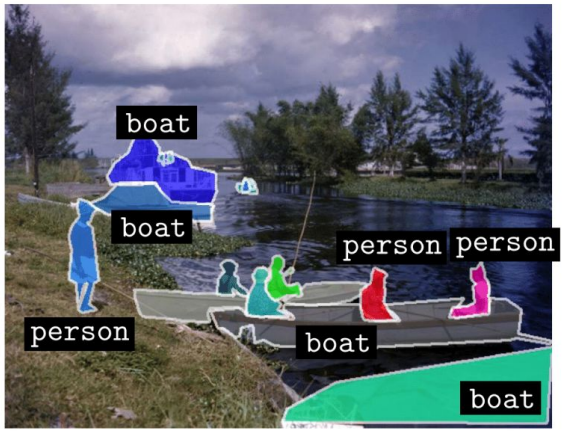
Semantic

Instance

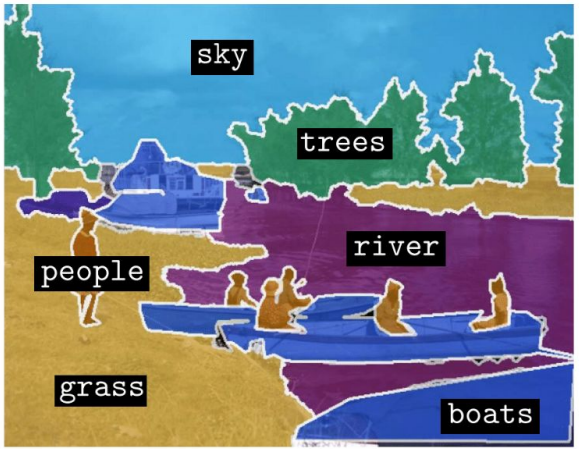
Panoptic

Panoptic Segmentation

What do every segmentation do?



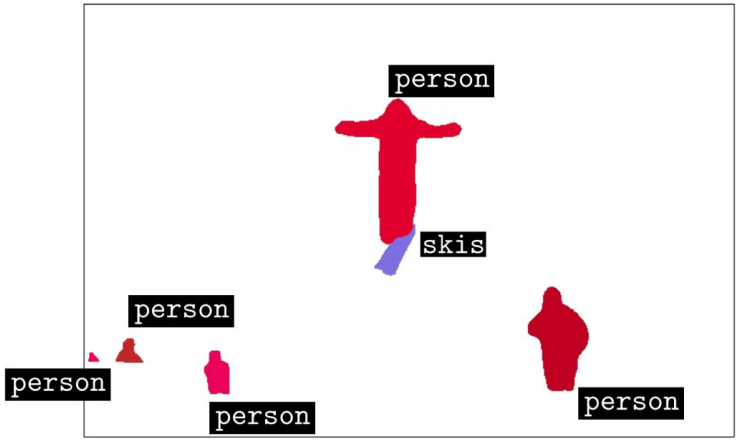
instance segmentation

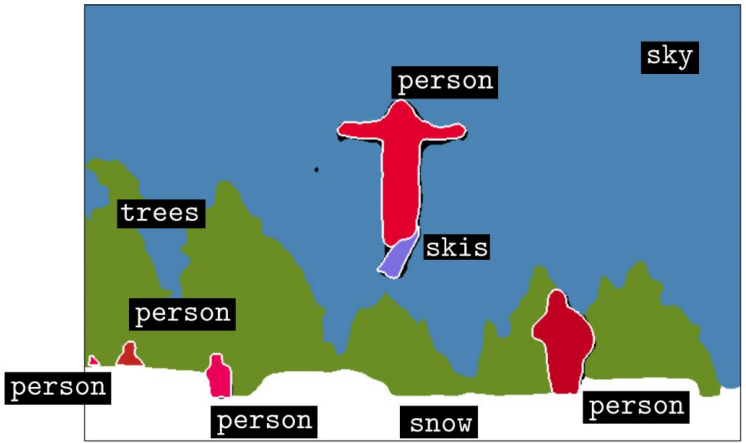


semantic segmentation

Panoptic Segmentation

What do instance segmentation see?

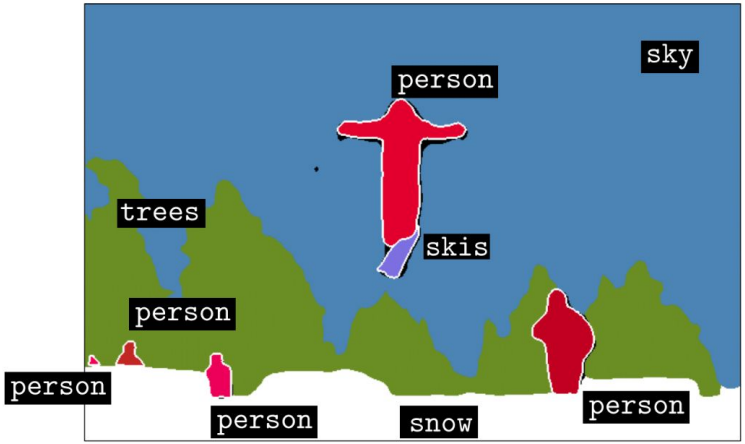


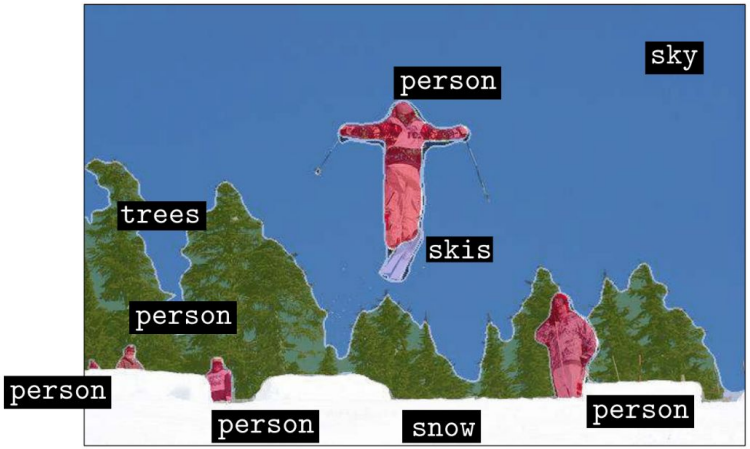


Let’s add semantic segmentation information

Panoptic Segmentation

How does the real image looks like?





Metric

Semantic segmentation

- IoU, per-pixel metric

Instance segmentation

- mAP, object-size agnostic

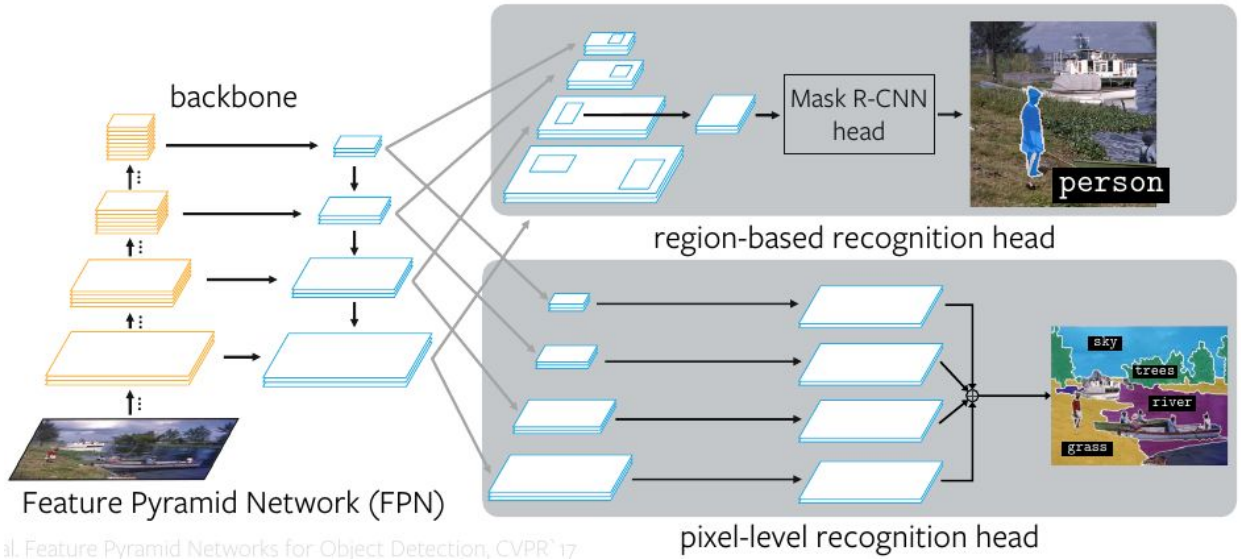
Panoptic segmentation should include both metrics simultaneously

Panoptic Segmentation

How to evaluate performance of panoptic segmentation model?

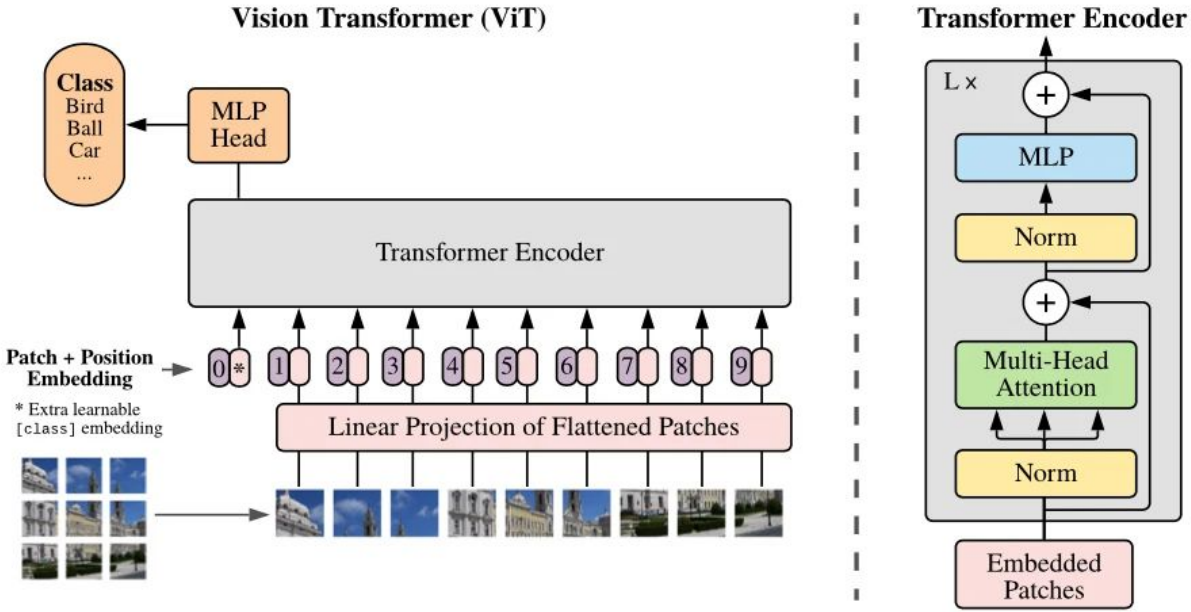
$$\begin{aligned}\mathrm{PQ} &= \frac{\sum_{(p,g)\in TP} \mathrm{IoU}(p,g)}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|} \\ &= \underbrace{\frac{\sum_{(p,g)\in TP} \mathrm{IoU}(p,g)}{|TP|}}_{\text{segmentation quality (SQ)}} \times \underbrace{\frac{|TP|}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|}}_{\text{recognition quality (RQ)}}\end{aligned}$$

Panoptic architecture

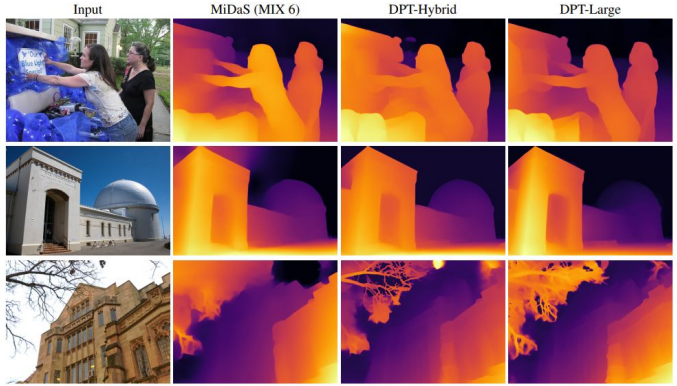


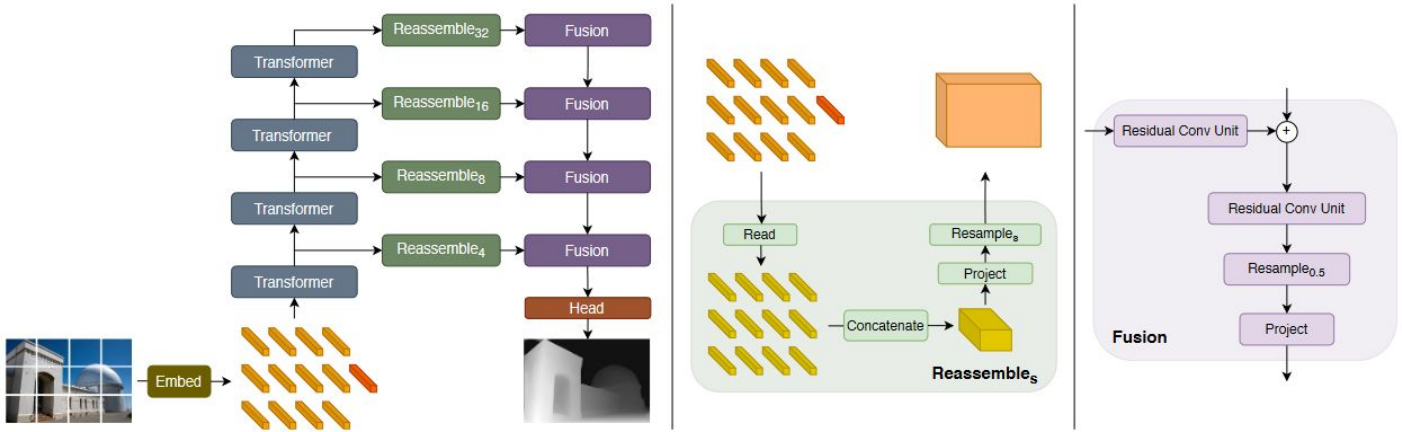
al. Feature Pyramid Networks for Object Detection, CVPR`17

Reminder: ViT

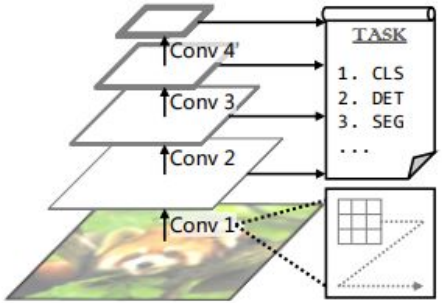


DPT (Vision Transformers for Dense Prediction)

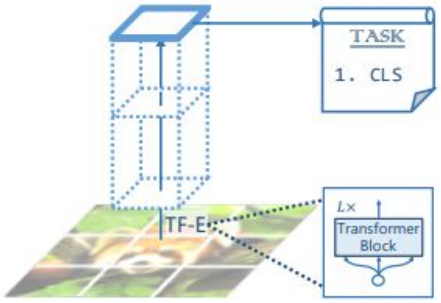




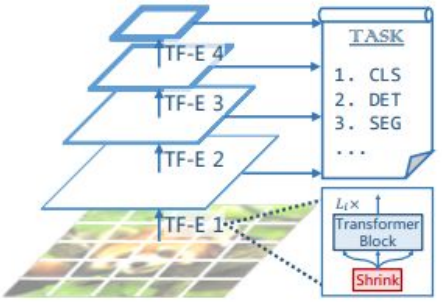
Pyramid Vision Transformer



(a) CNNs: VGG [54], ResNet [22], *etc.*

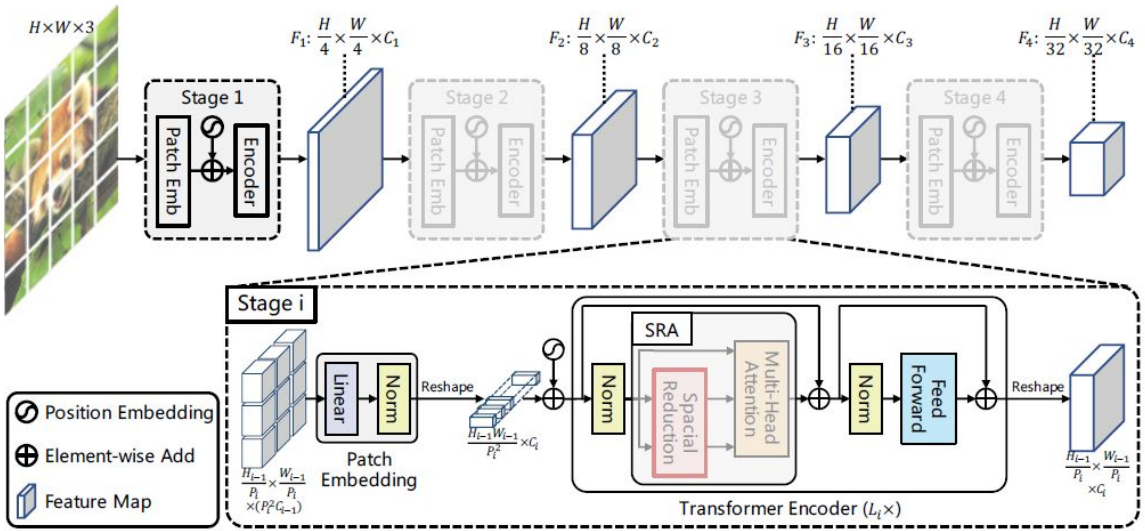


(b) Vision Transformer [13]

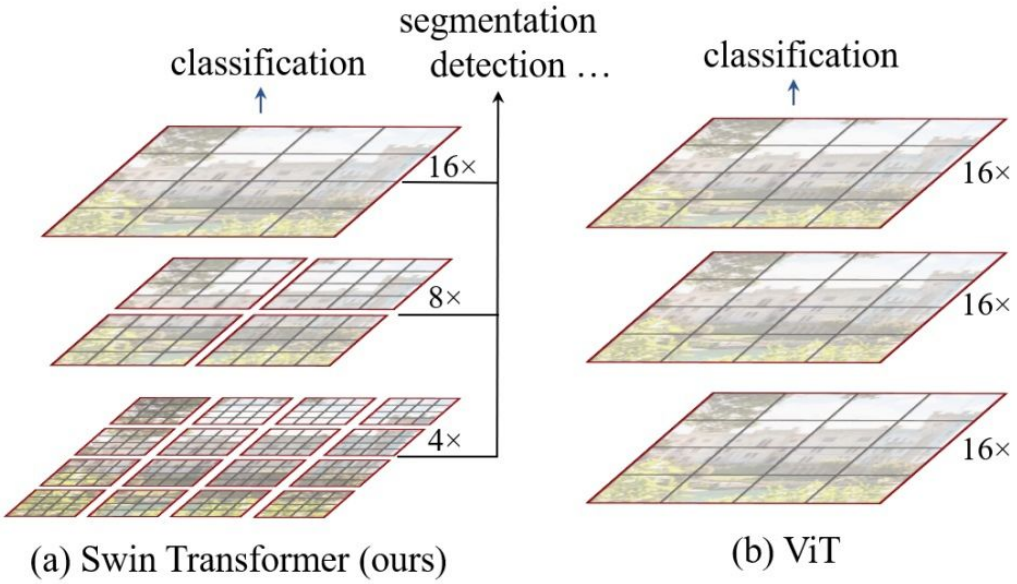


(c) Pyramid Vision Transformer (ours)

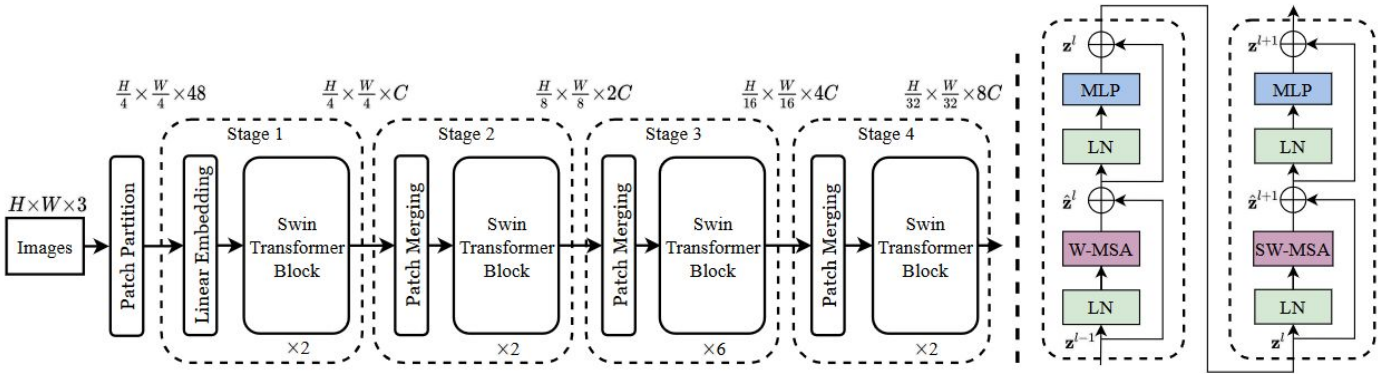
Pyramid Vision Transformer

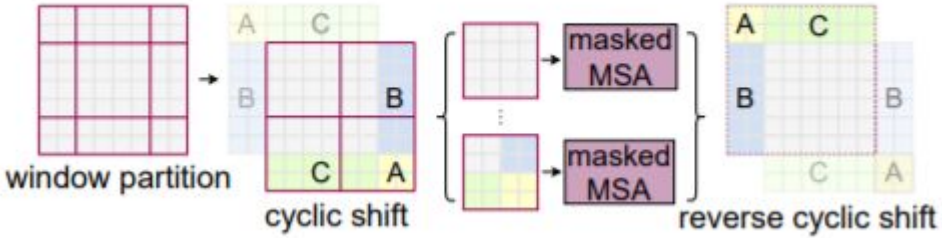


Swin


classification
segmentation
detection …
16×
8×
4×
(a) Swin Transformer (ours)
classification
16×
16×
16×
(b) ViT

Swin


$H \times W \times 3$
Images
Patch Partition
$\frac{H}{4} \times \frac{W}{4} \times 48$
Linear Embedding
Stage 1
Swin Transformer Block
×2
$\frac{H}{4} \times \frac{W}{4} \times C$
Patch Merging
Stage 2
Swin Transformer Block
×2
$\frac{H}{8} \times \frac{W}{8} \times 2C$
Patch Merging
Stage 3
Swin Transformer Block
×6
$\frac{H}{16} \times \frac{W}{16} \times 4C$
Patch Merging
Stage 4
Swin Transformer Block
×2
$\frac{H}{32} \times \frac{W}{32} \times 8C$
$\mathbf{z}^{l}$
MLP
LN
$\hat{\mathbf{z}}^{l}$
W-MSA
LN
$\mathbf{z}^{l-1}$
$\mathbf{z}^{l+1}$
MLP
LN
$\hat{\mathbf{z}}^{l+1}$
SW-MSA
LN
$\mathbf{z}^{l}$


window partition
A
C
B
B
C
A
cyclic shift
masked MSA
masked MSA
A
C
B
B
C
A
reverse cyclic shift

HRFormer

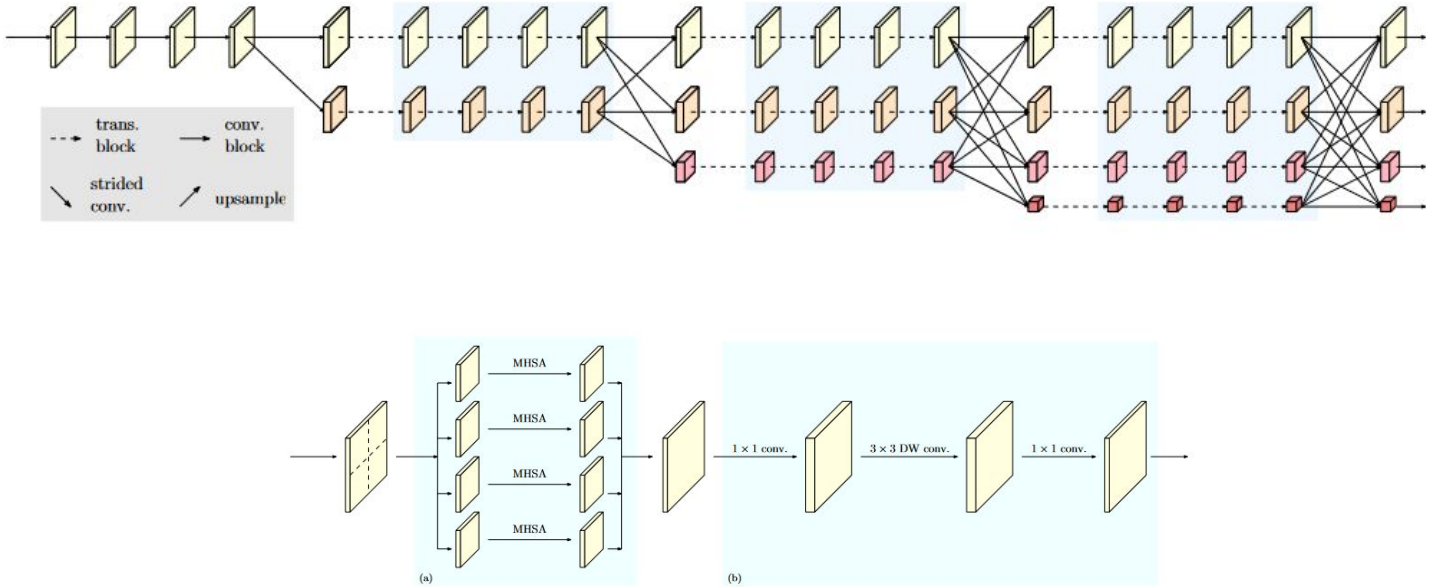
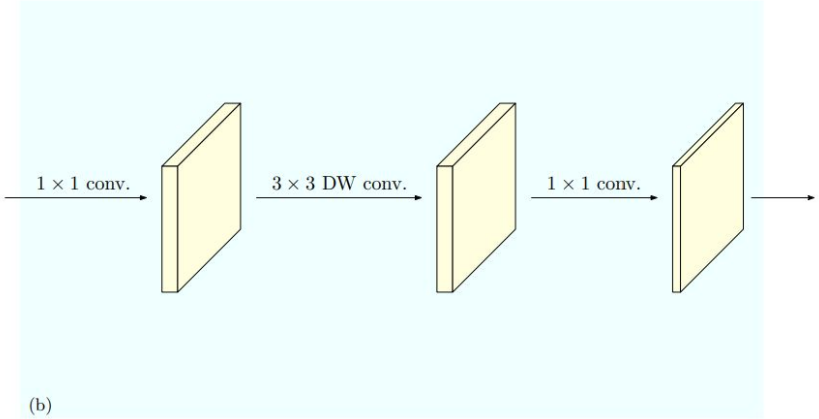


Figure 1: **Illustrating the HRFormer block.** The HRFormer block is composed of (a) local-window self-attentionm and (b) feed-forward network (FFN) with depth-wise convolution. The local-window self-attention scheme is inspired by the interlaced sparse self-attention [56, 21].

HRFormer



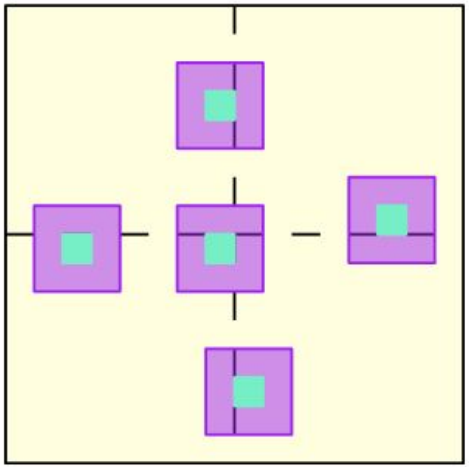


Figure 3: Illustrating that FFN with 3×3 depth-wise convolution connects the non-overlapping windows.

Recap

- Semantic segmentation problem
- Upsampling
- Architectures
- Panoptic / Instance segmentation