

Semantic Segmentation

Computer Vision

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Outline

- Semantic Segmentation
- Approaches
- Sliding window, fully convolutional, upSampling
- U-Net
- Depthwise Separable Convolutions
- MobileNet
- Hands-on

Semantic Segmentation

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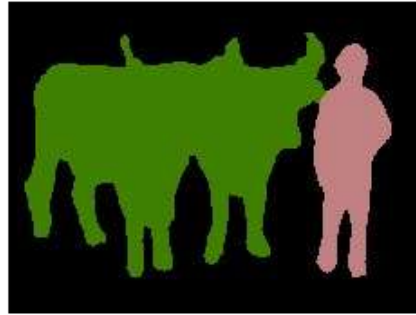
Semantic Segmentation

- Put label on each pixel in the image
- No need to specify the difference between the instances

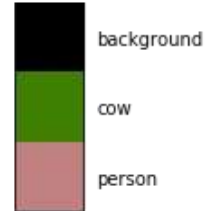
input image



segmentation map



segmentation overlay



Example



Background Rose Glass Die Teddy bear Unlabeled

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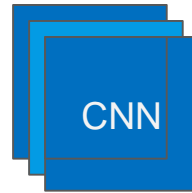
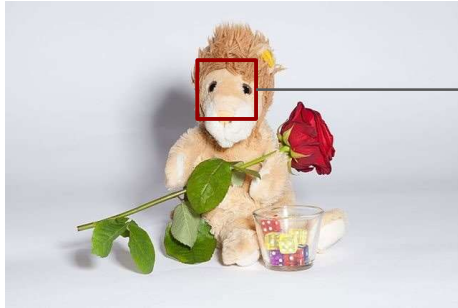
Semantic Segmentation

Extract
path

Run through a
CNN

Classify center
pixel

Repeat for every
pixel

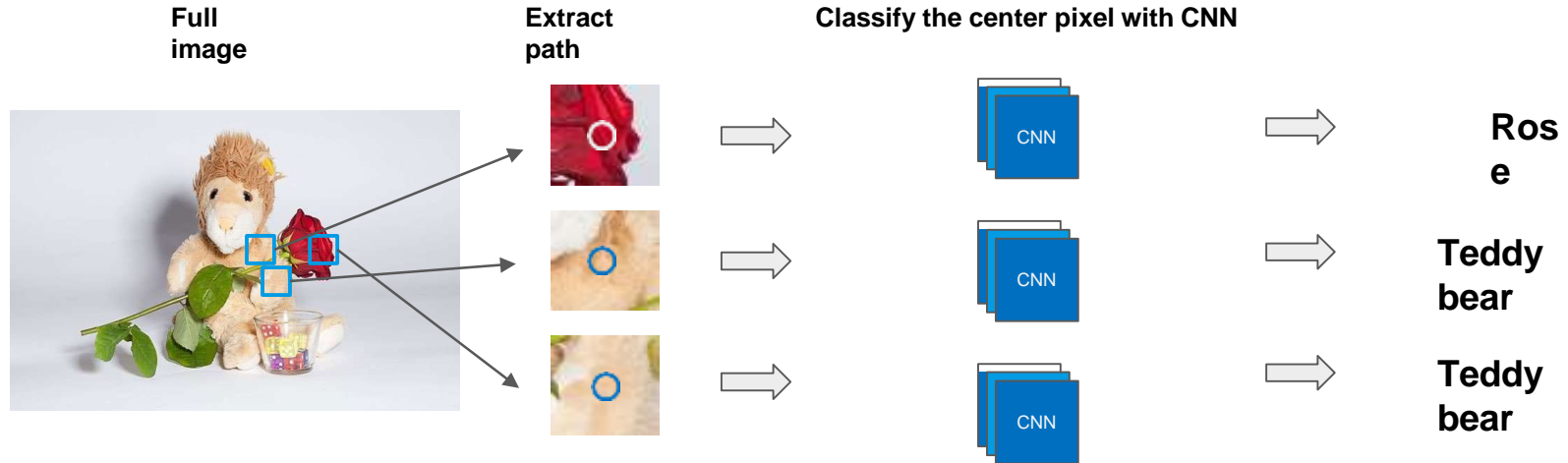


Tedd
y
bear



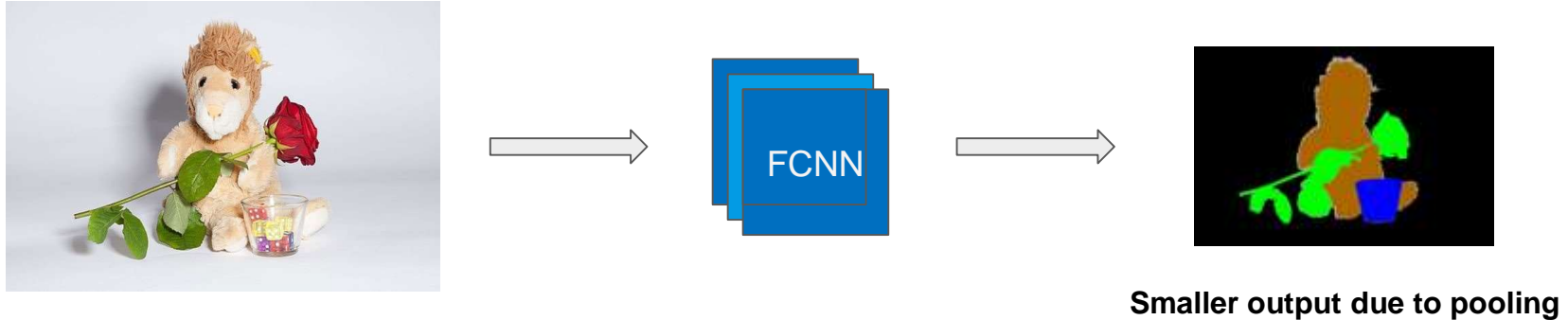
Background	Rose
Glass	Die
Unlabeled	Teddy bear

Semantic segmentation: sliding window



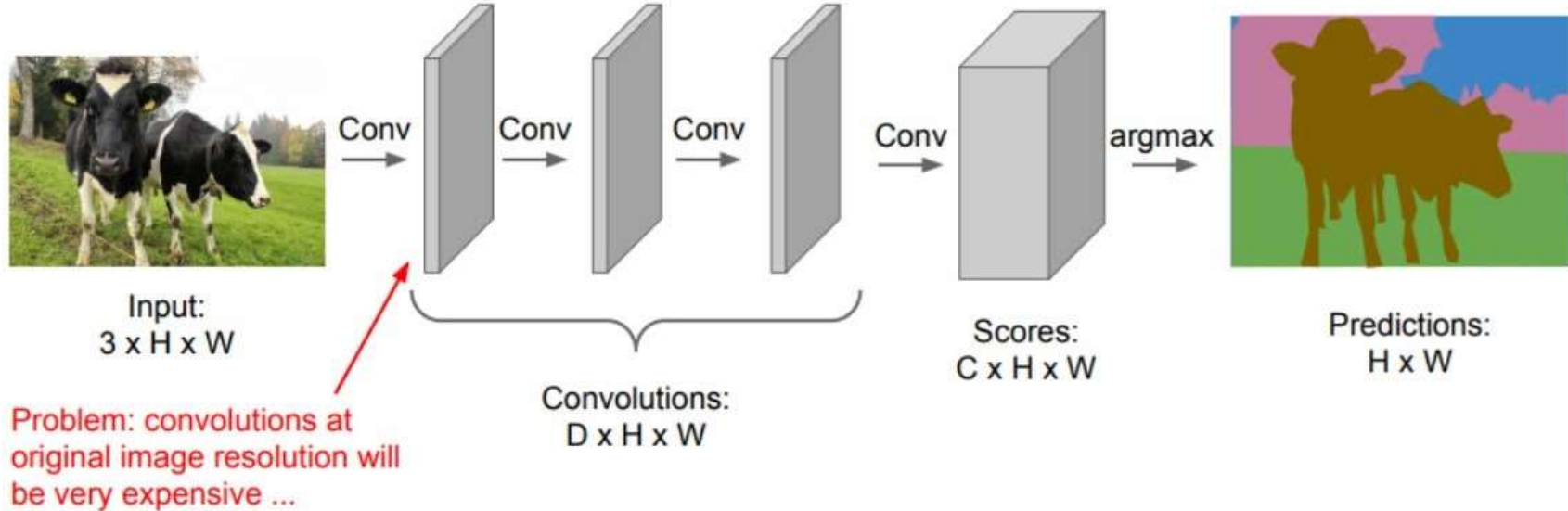
Semantic Segmentation

- Run through a fully convolutional network to get all pixels at once



Semantic Segmentation Idea : FCN

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



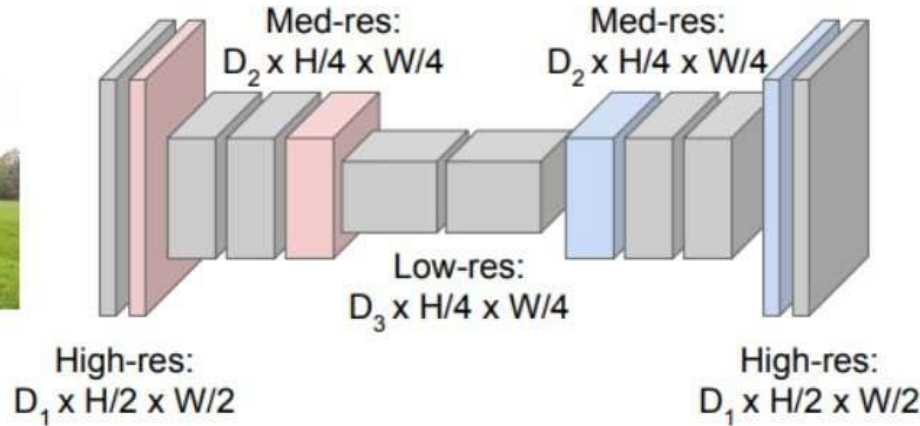
Semantic Segmentation Idea : FCN

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:
Unpooling or strided transpose convolution



Predictions:
 $H \times W$

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

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

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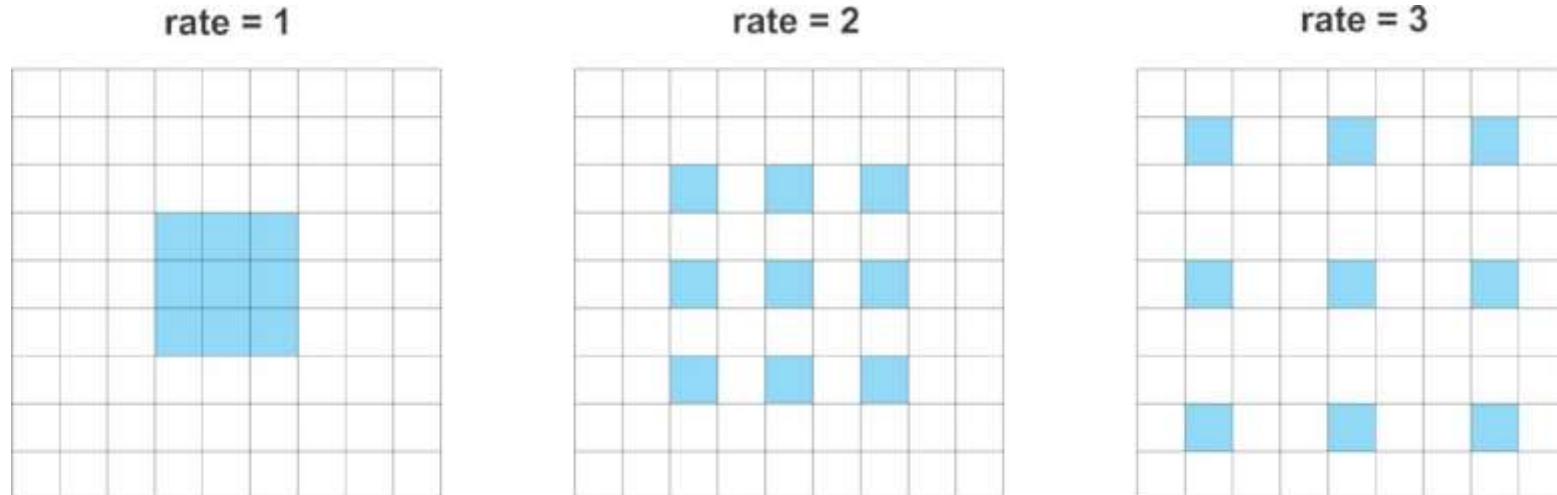
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Atrous/Dilated Convolutions

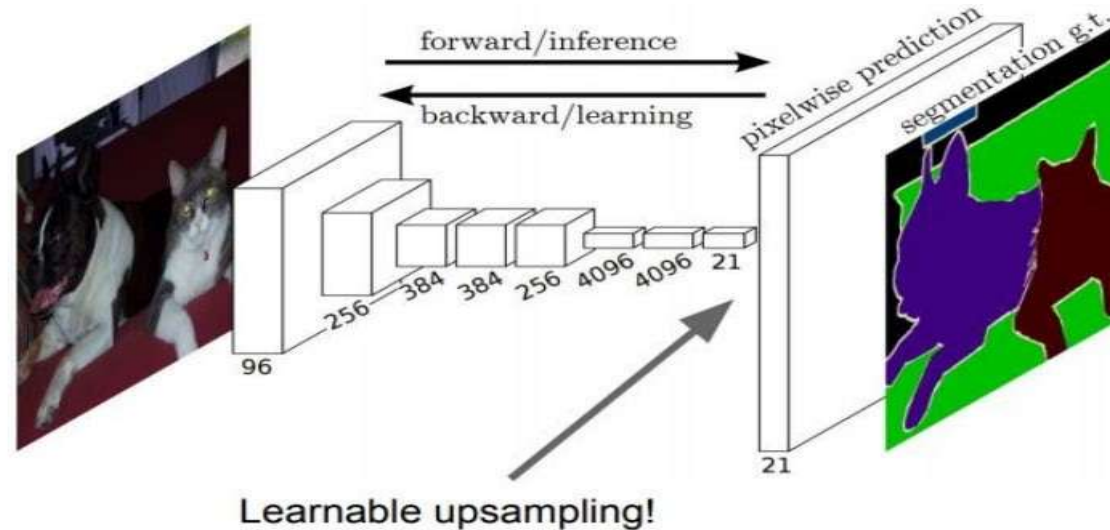
Atrous (or dilated) convolutions are regular convolutions with a factor that allows us to expand the filter's field of view.

Consider a 3×3 convolution filter for instance. When the dilation rate is equal to 1, it behaves like a standard convolution. But, if we set the dilation factor to 2, it has the effect of enlarging the convolution kernel.



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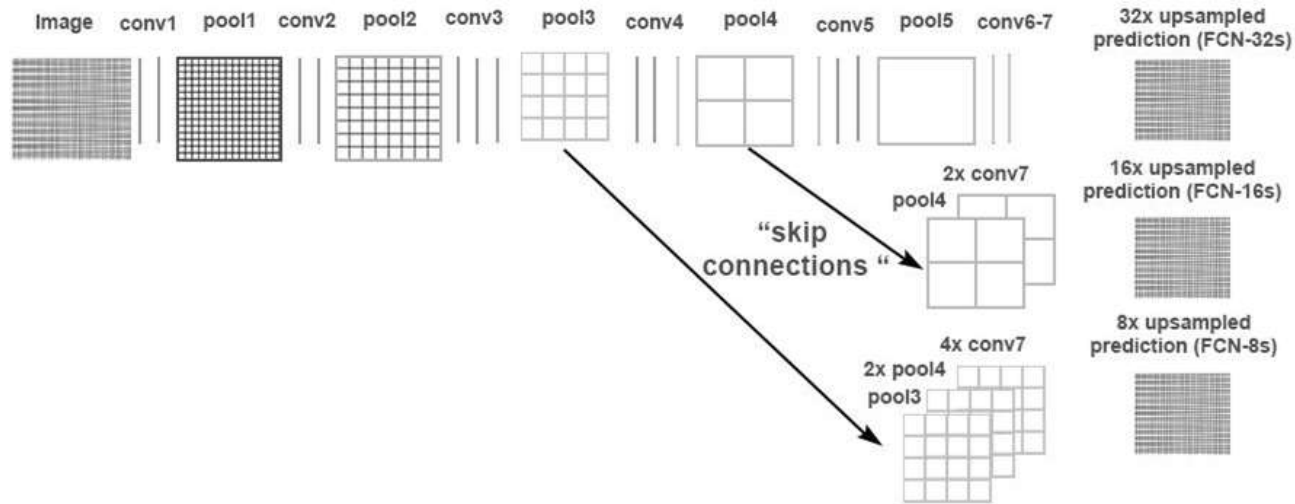
Semantic Segmentation : UpSampling



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

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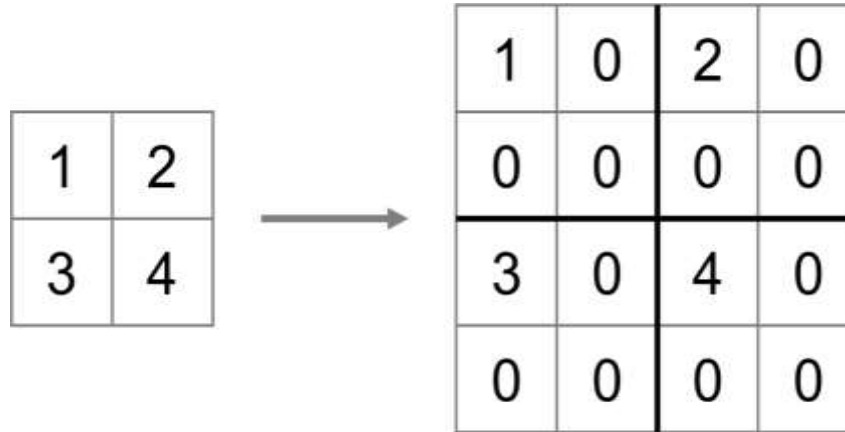
Semantic Segmentation : UpSampling



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UpSampling

- Transposed convolution / Deconvolution
- Fractionally strided convolution
- Max-unpooling: Preserves spatial information



In-Network upsampling: “Max Unpooling”

Max Pooling

Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

...
Rest of the network

Max Unpooling

Use positions from pooling layer

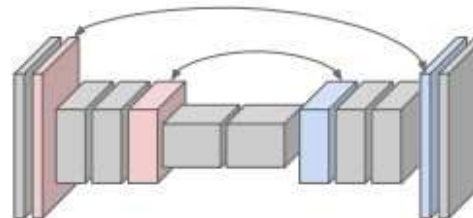
1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

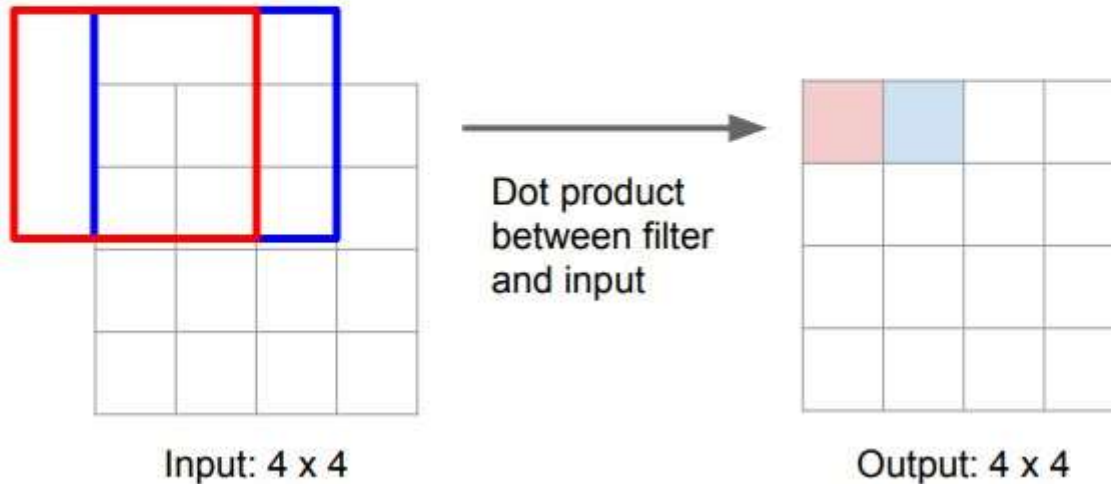
Corresponding pairs of
downsampling and
upsampling layers



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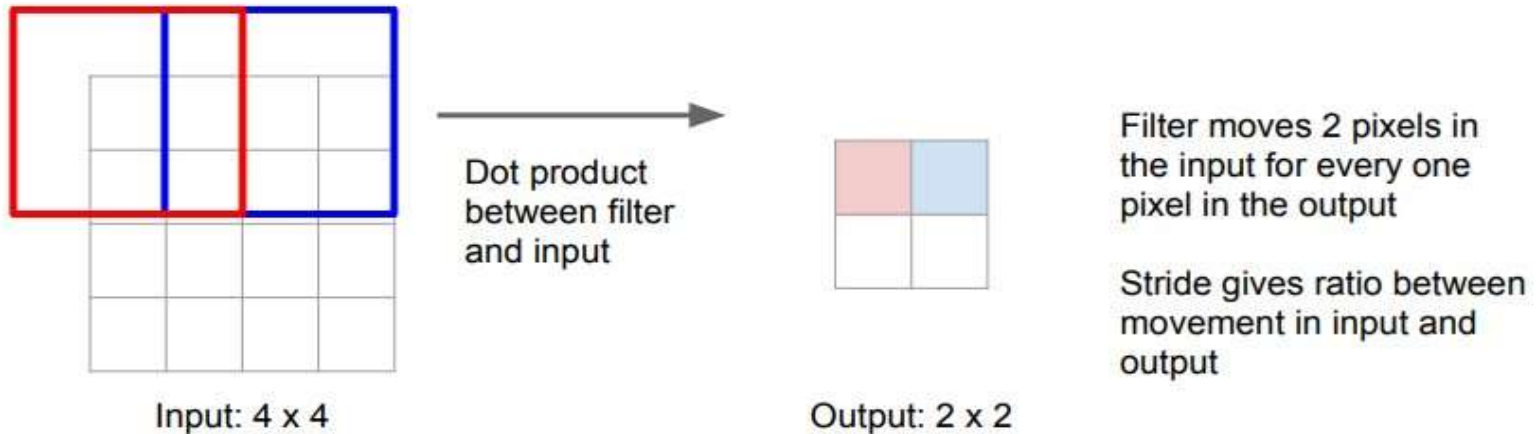
Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1



Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1

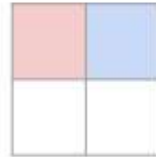


Learnable Upsampling: Transpose Convolution

Other names:

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

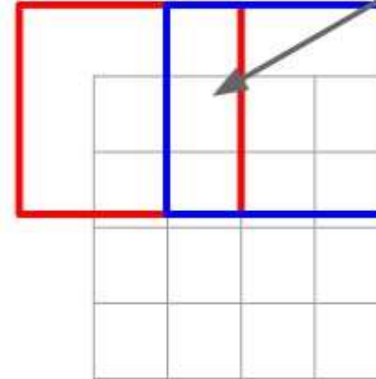
3 x 3 **transpose** convolution, stride 2 pad 1



Input: 2 x 2



Input gives
weight for
filter



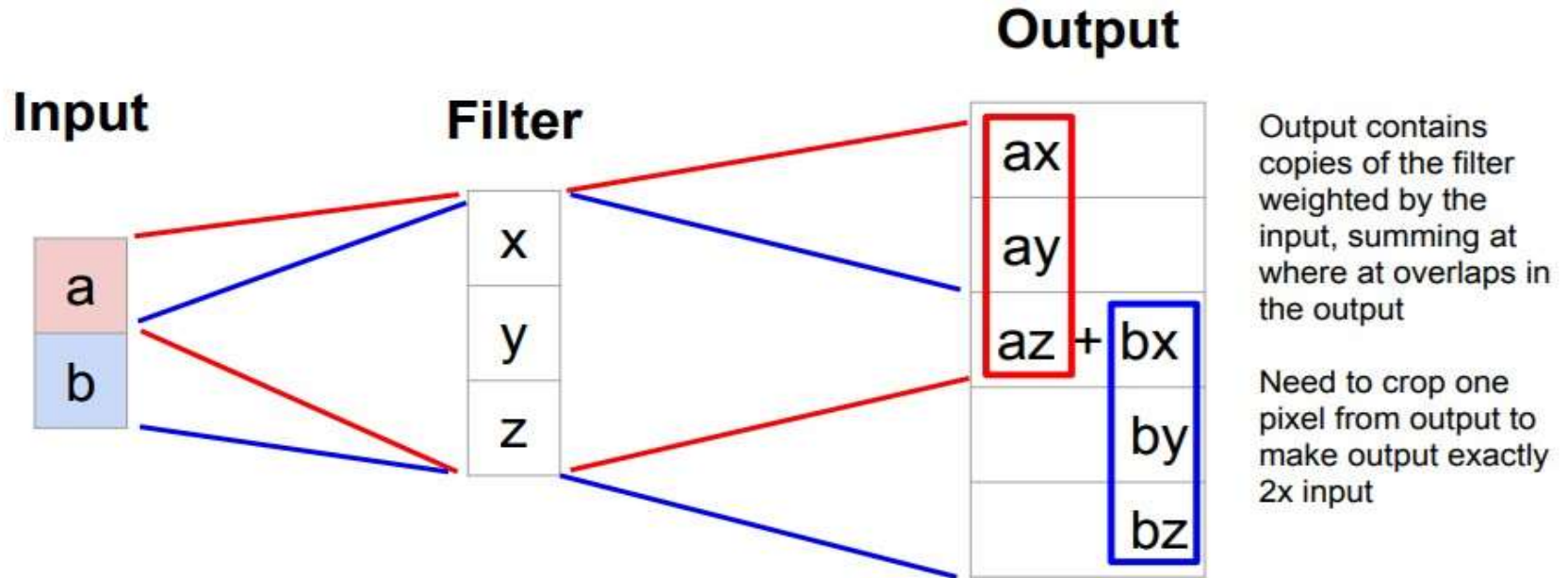
Output: 4 x 4

Sum where
output overlaps

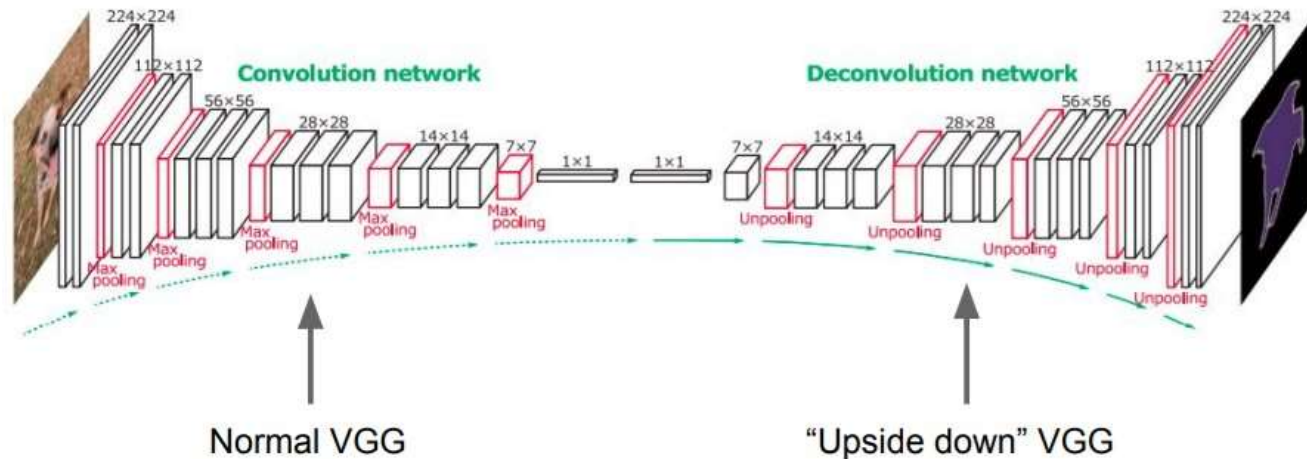
Filter moves 2 pixels in
the output for every one
pixel in the input

Stride gives ratio between
movement in output and
input

Learnable Upsampling: 1D Example



Semantic Segmentation: Upsampling



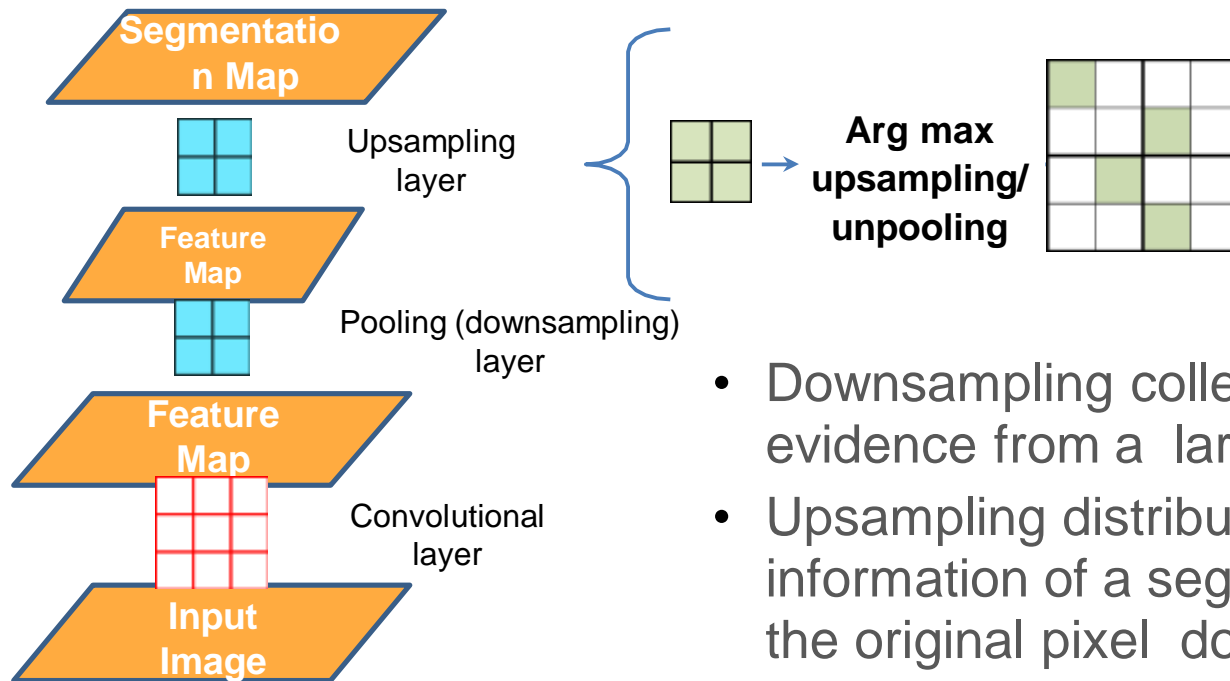
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

6 days of training on Titan X...

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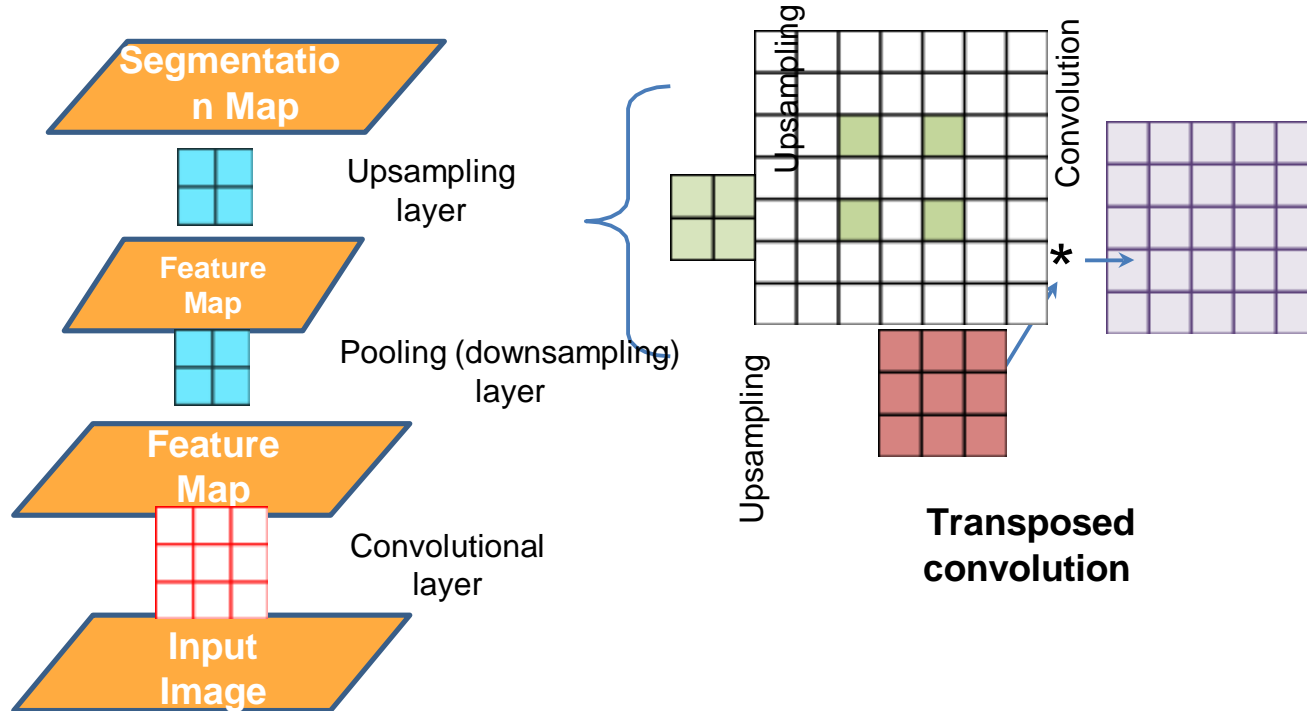
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To produce a segmentation map downsampling is followed by upsampling

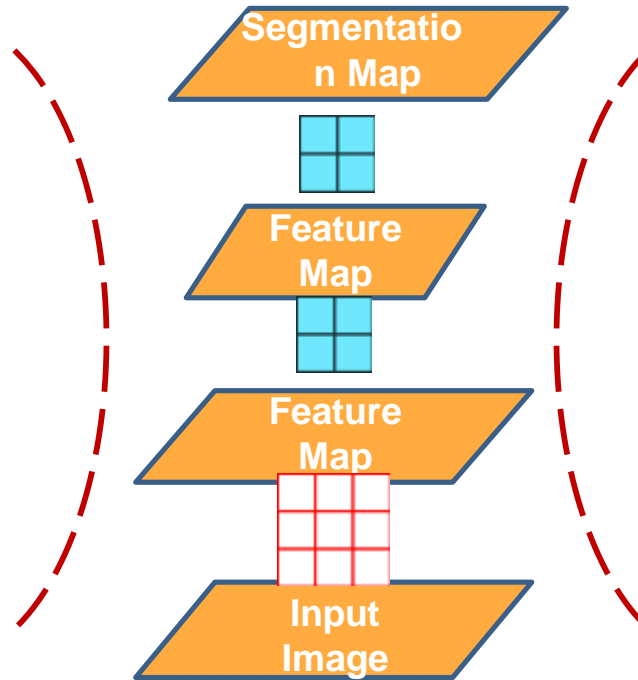


- Downsampling collects feature evidence from a larger area
- Upsampling distributes the information of a segment back to the original pixel domain

Upsampling can also be learned

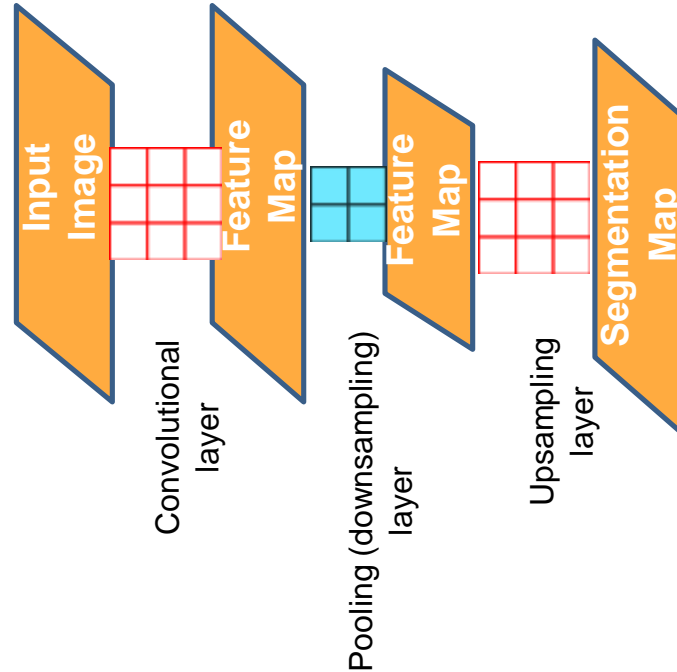


Downsampling and upsampling leads to an hour-glass structure



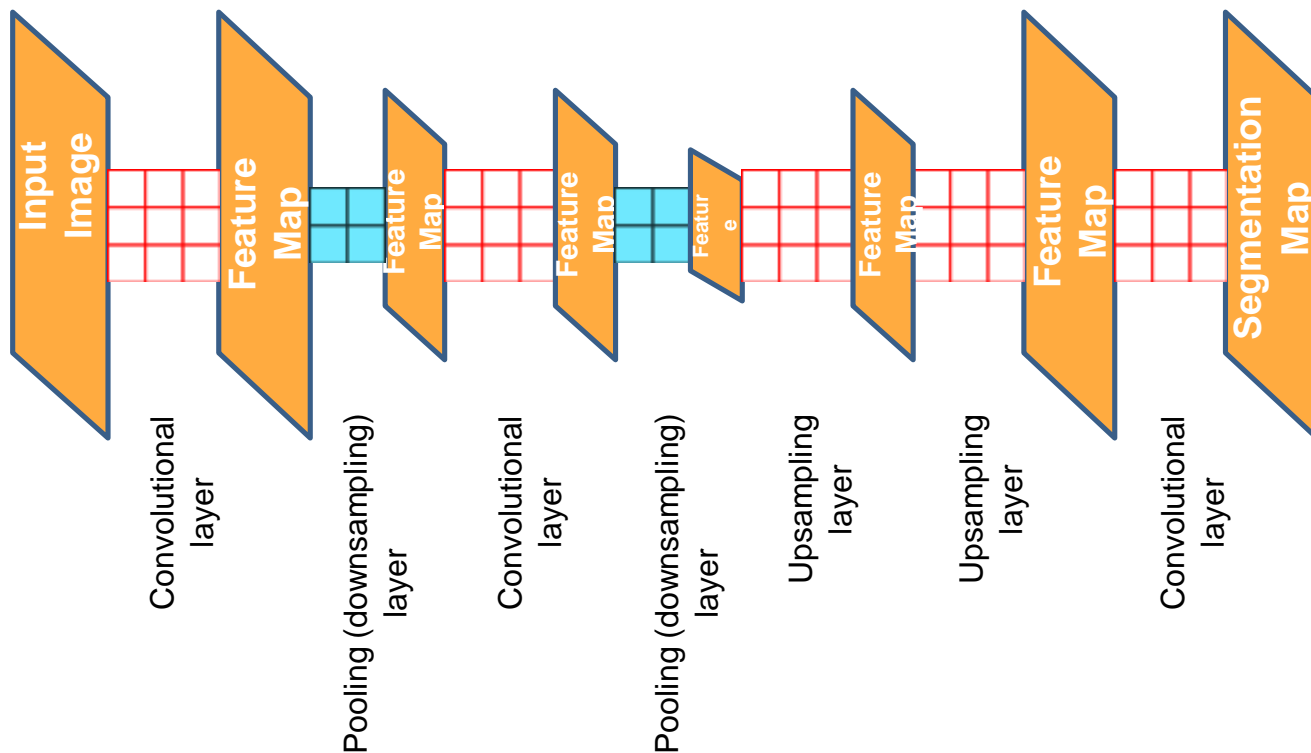
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Let us re-arrange the layers horizontally



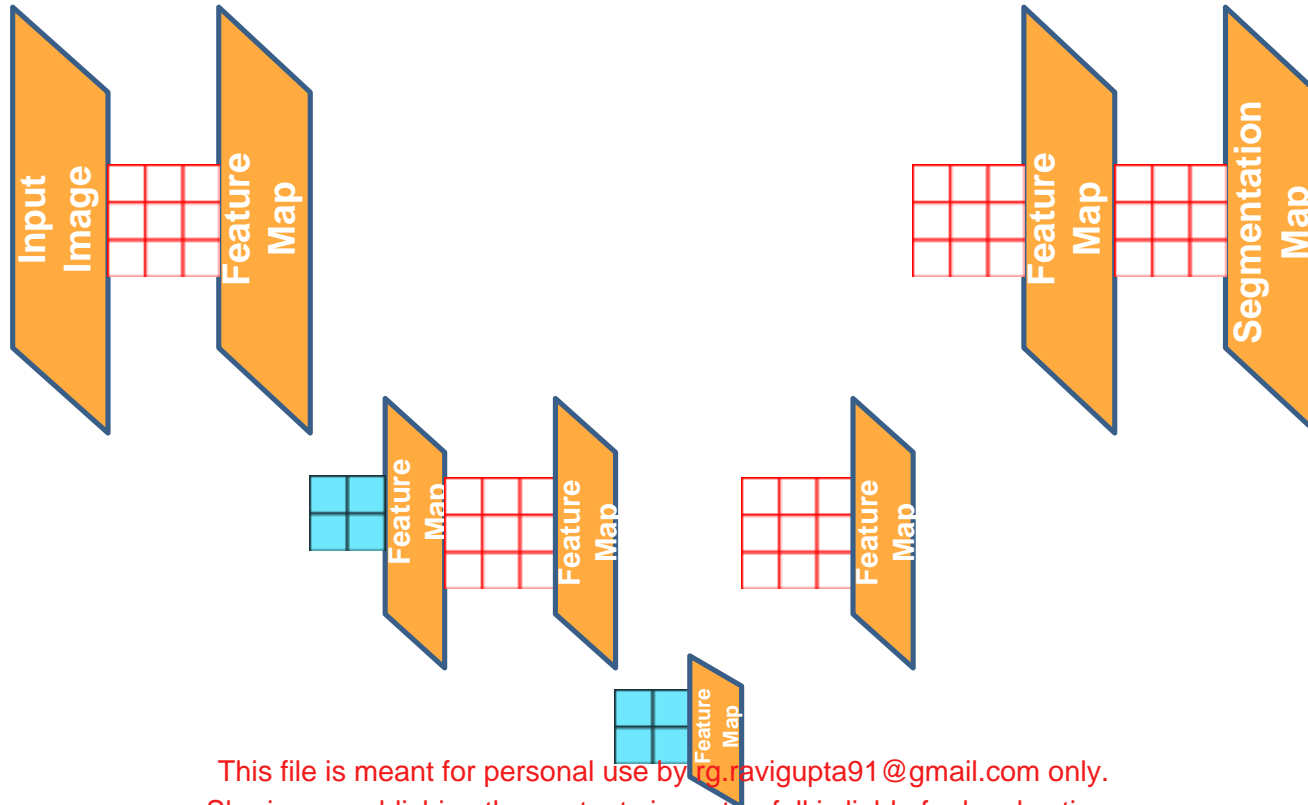
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More layers can be added



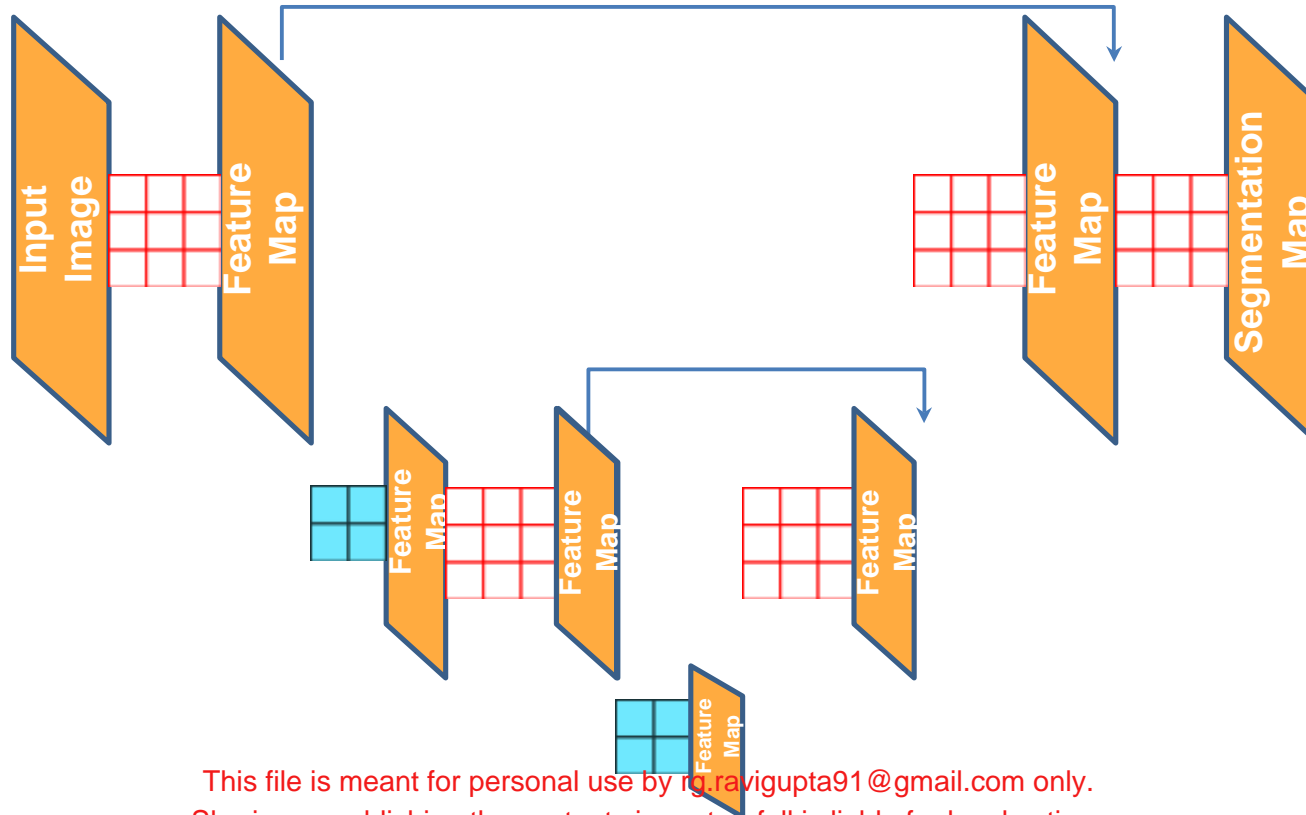
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Visually rearrange layers in a big U



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Concatenate previous feature maps for finer spatial context



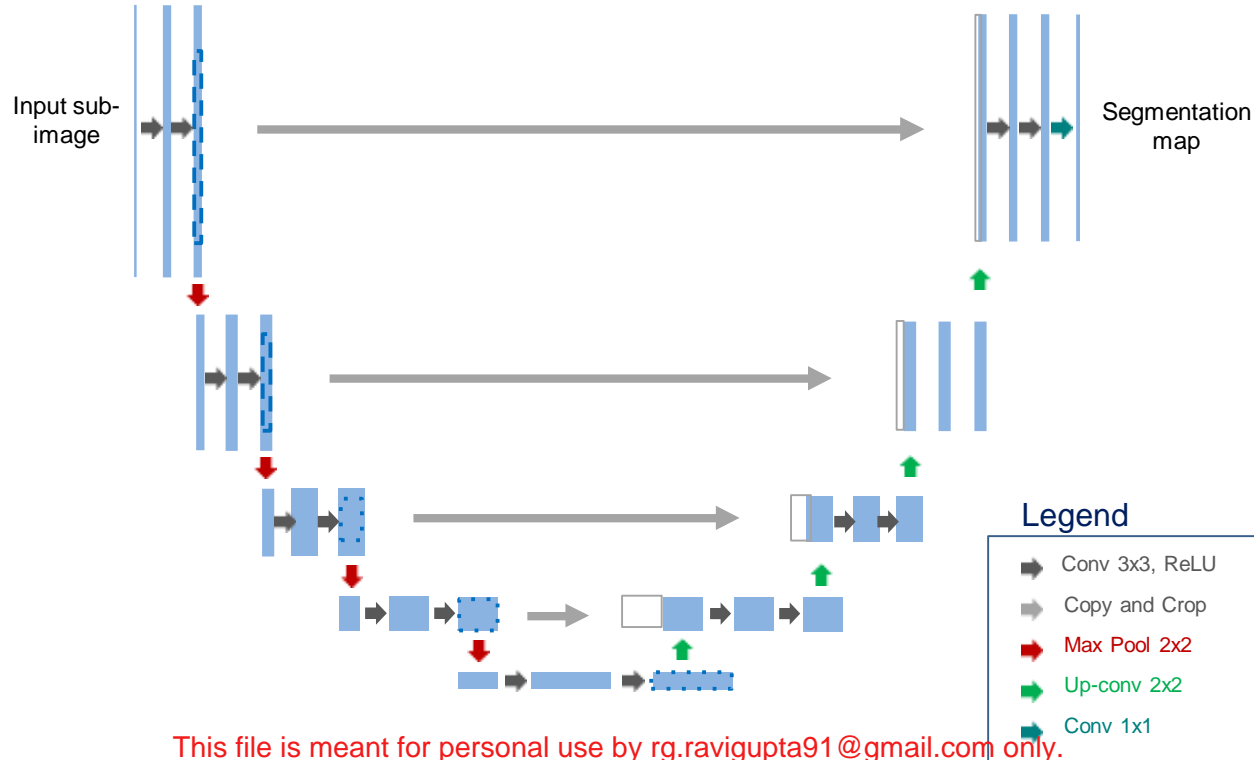
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U-Net

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U-Net is based on the ideas described in the previous slides



U-Net

2

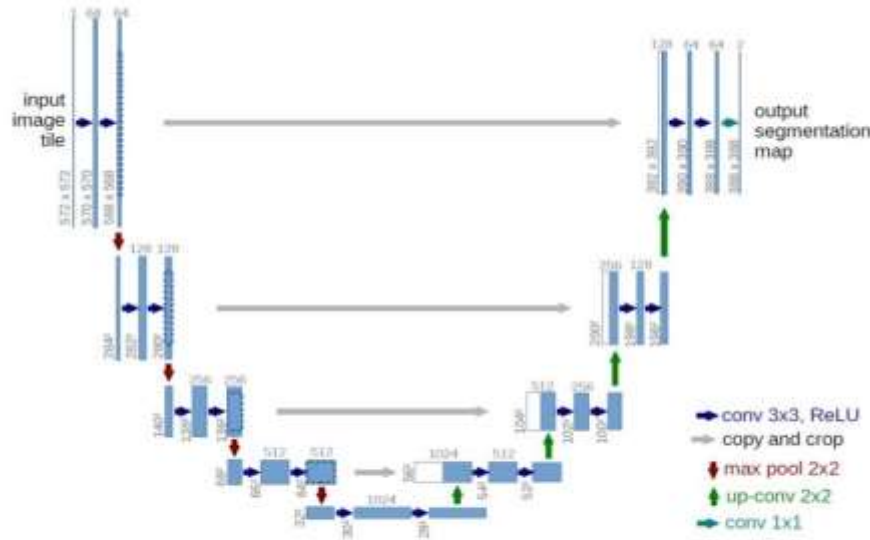


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

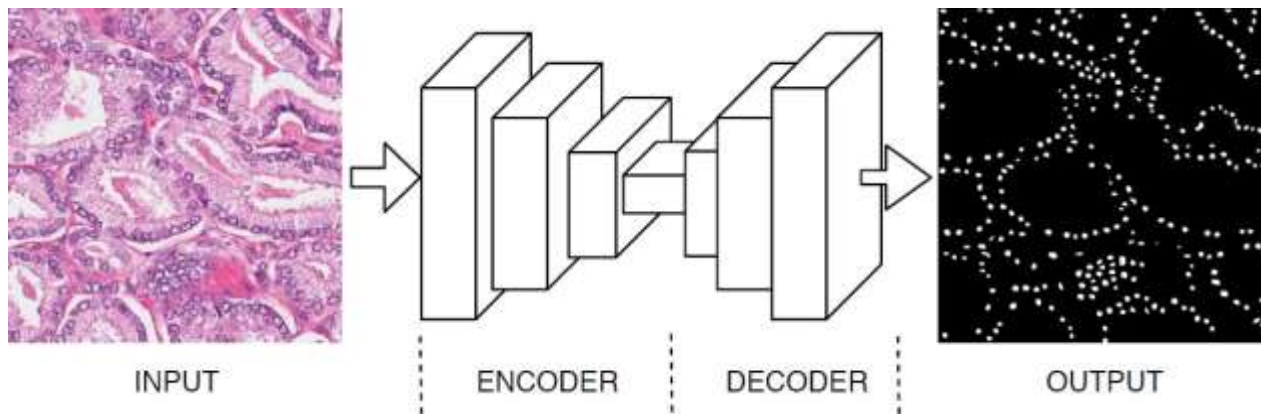
The architecture has -

An Encoder - Downsampling part. It is used to get context in the image. It is just a stack of convolutional and max pooling layers.

A Decoder - Symmetric Upsampling part. It is used for precise localization. Transposed convolution is used for upsampling.

It is a fully convolutional network (FCN). it has Convolutional layers and it does not have any dense layer so it can work for image of any size.

A sample output for nucleus segmentation in pathology



A general representation of fully convolutional networks. The encoder is composed of convolutional and pooling layers for downsampling and the decoder is composed of deconvolutional layers for upsampling.

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Dice coefficient

Dice coefficient is defined as follows:

X is the predicted set of pixels and Y is the ground truth.

$$\frac{2 * |X \cap Y|}{|X| + |Y|}$$

A higher dice coefficient is better. A dice coefficient of 1 can be achieved when there is perfect overlap between X and Y. Since the denominator is constant, the only way to maximize this metric is to increase overlap between X and Y.

For more info on Dice coefficient: <https://www.kaggle.com/c/carvana-image-masking-challenge#evaluation> -

References

<https://arxiv.org/pdf/1803.02758.pdf>

https://people.eecs.berkeley.edu/~jonlong/long_shelhamer_fcn.pdf

Paper - U-Net: Convolutional Networks for Biomedical Image Segmentation

Thank you!

Happy Learning :)