Lecture 8: CNNs in Vision I: Semantic Segmentation

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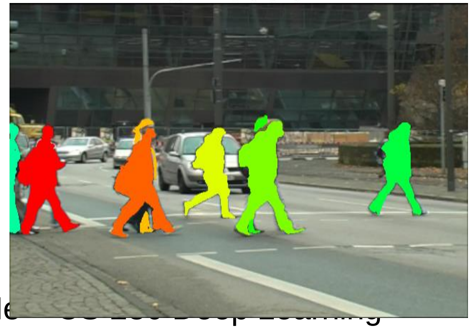
Review

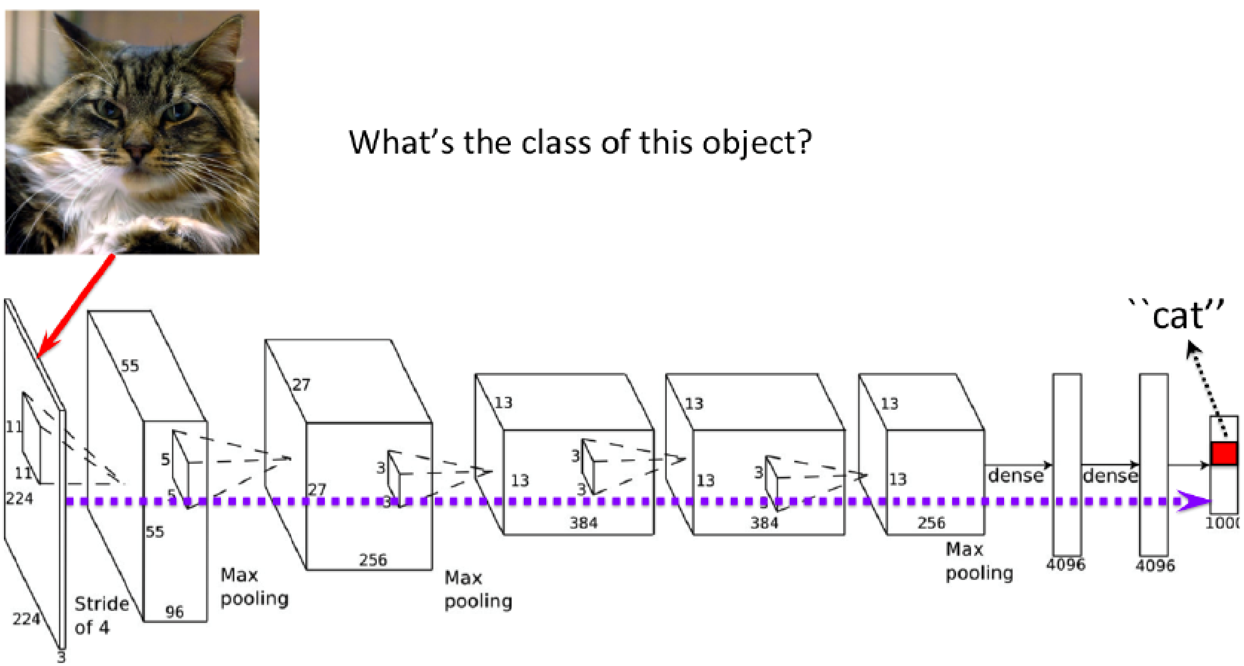
- In general, our goal is to learn a mapping from a signal to a ‘semantically meaningful’ representation.
  - Output can have many different forms:

red panda (*Ailurus fulgens*)



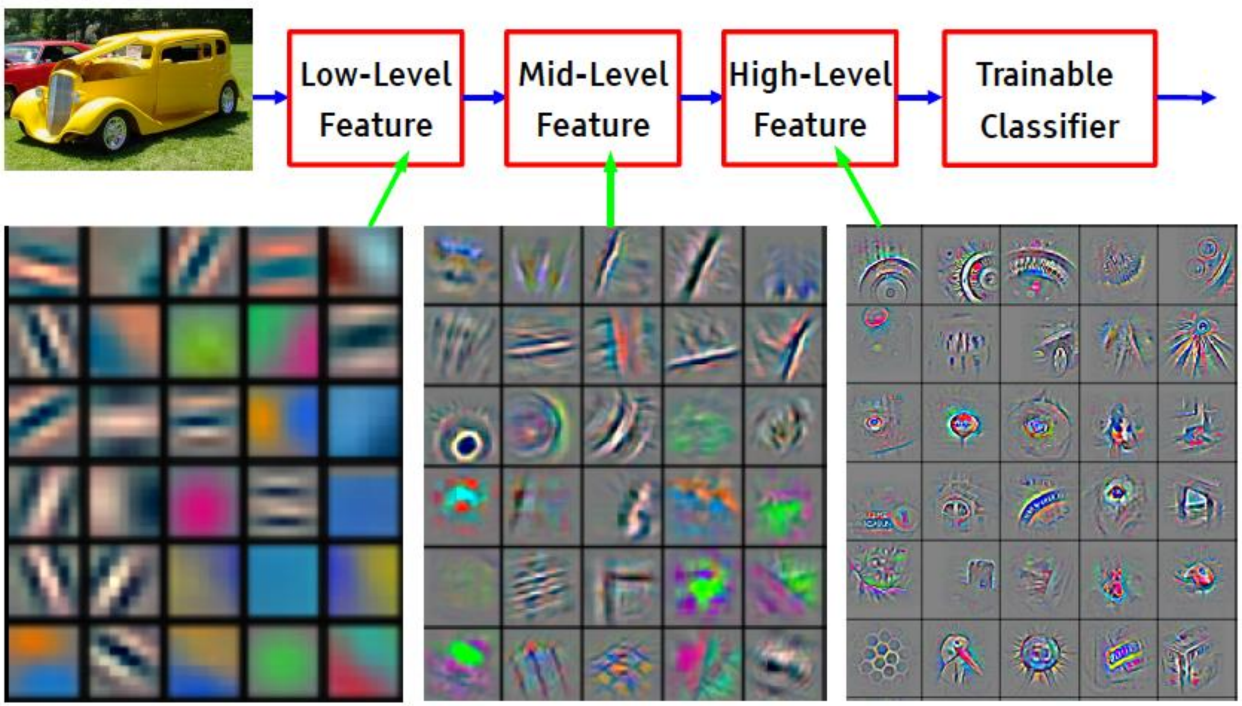
Previously on CNNs

- CNNs for image/object classification
  - AlexNet, VGGNet, GoogLeNet, ResNet, DenseNet
  - Trend towards deeper networks with more flexible network architecture
  - Better representation and more effective learning strategies



More on classification

- Why it works well for image classification?
  - Built-in translation and small deformation invariance
  - Hierarchical feature learning – shared representation
  - End-to-end training for the target problem



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

More on classification

- Is image classification a solved problem?
  - "(Super-)Human level" performance on some benchmarks
    - Face identification
    - ImageNet 1000 classes
- But compared to human vision…
  - Limitations in learning
    - We can learn new classes using one or two examples
    - We can also handle label noises
    - We can generalize to unfamiliar scenes
  - Limitation in prediction
    - We can also predict the uncertainty
    - We can easily handle adversarial examples
    - We are much more efficient in power consumption

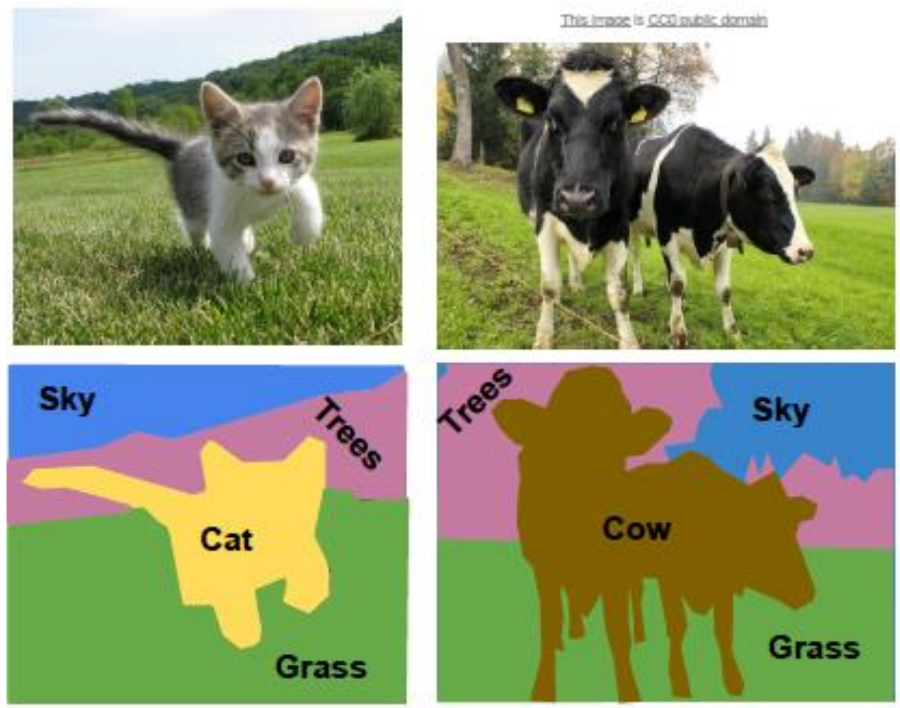
Outline

- What is semantic segmentation?
- Network architecture for semantic segmentation
  - Main idea for dense prediction
  - Fully convolutional network
  - Upsampling operators
  - Multiscale context modeling
- Network training losses

Acknowledgement: Feifei Li et al's cs231n notes

Semantic Segmentation

- Problem setup
  - Label each pixel in the image with an object category label
  - Do not differentiate object instances

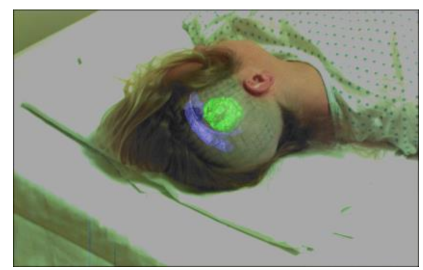


Key to many applications

- Autonomous robots and cars

- Safety and security

- Medical analysis and health

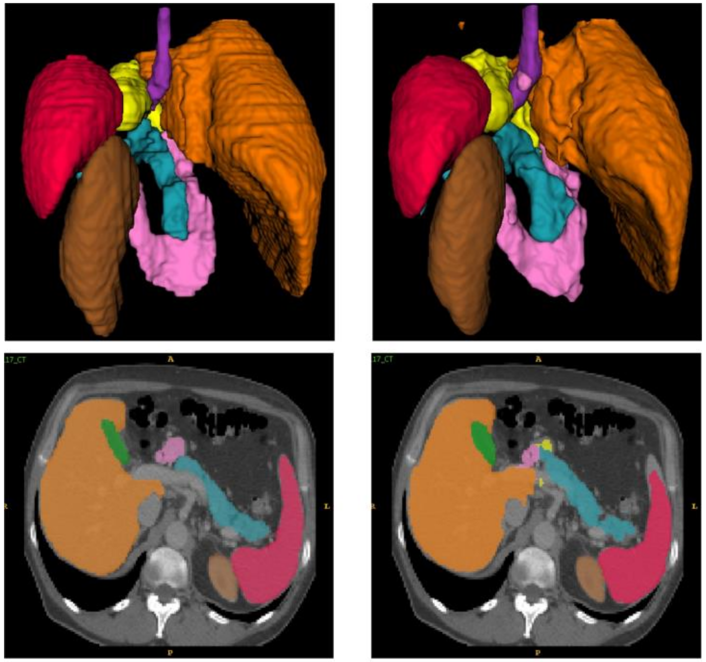


- etc…

Key to many applications

Autonomous driving
https://youtu.be/qWl9idsCuLQ

Multi-organ abdominal
CT segmentation
https://doi.org/10.1016/j.cmpb.2018.01.025



Reference standard NiftyNet segmentation

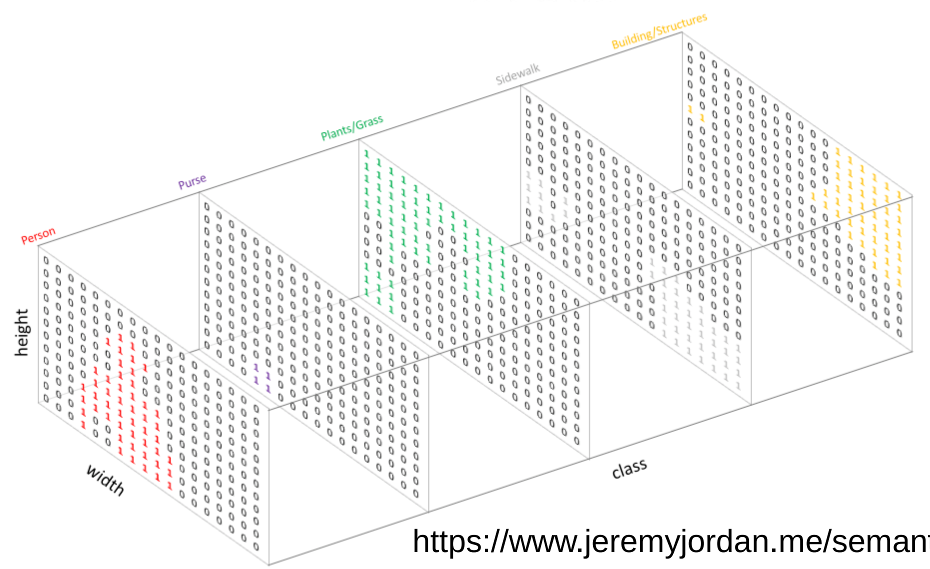
Semantic Segmentation

- Problem formulation
  - Pixel-wise object classification task

Input

Semantic Labels

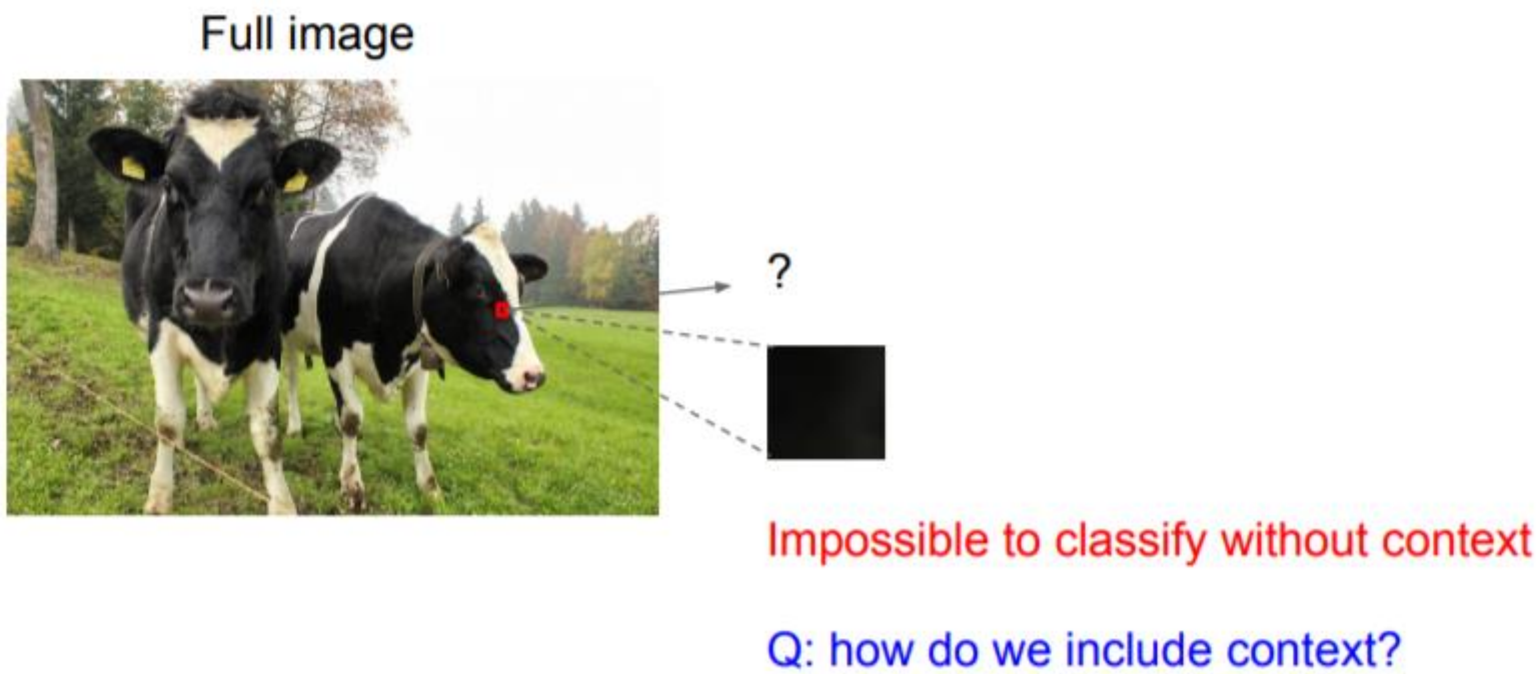
  - One-hot encoding



https://www.jeremyjordan.me/semantic-segmentation/

Why this is challenging?

- A naïve approach



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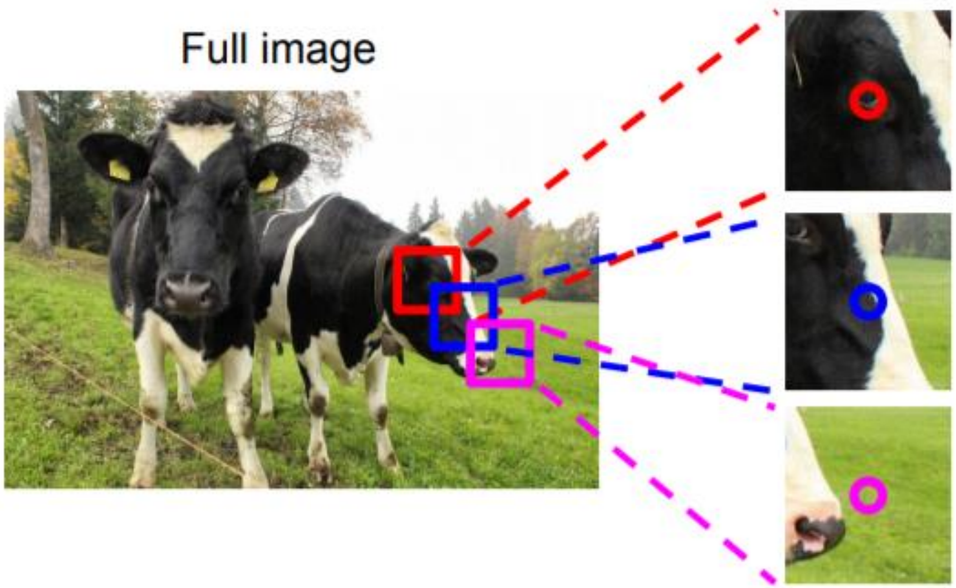
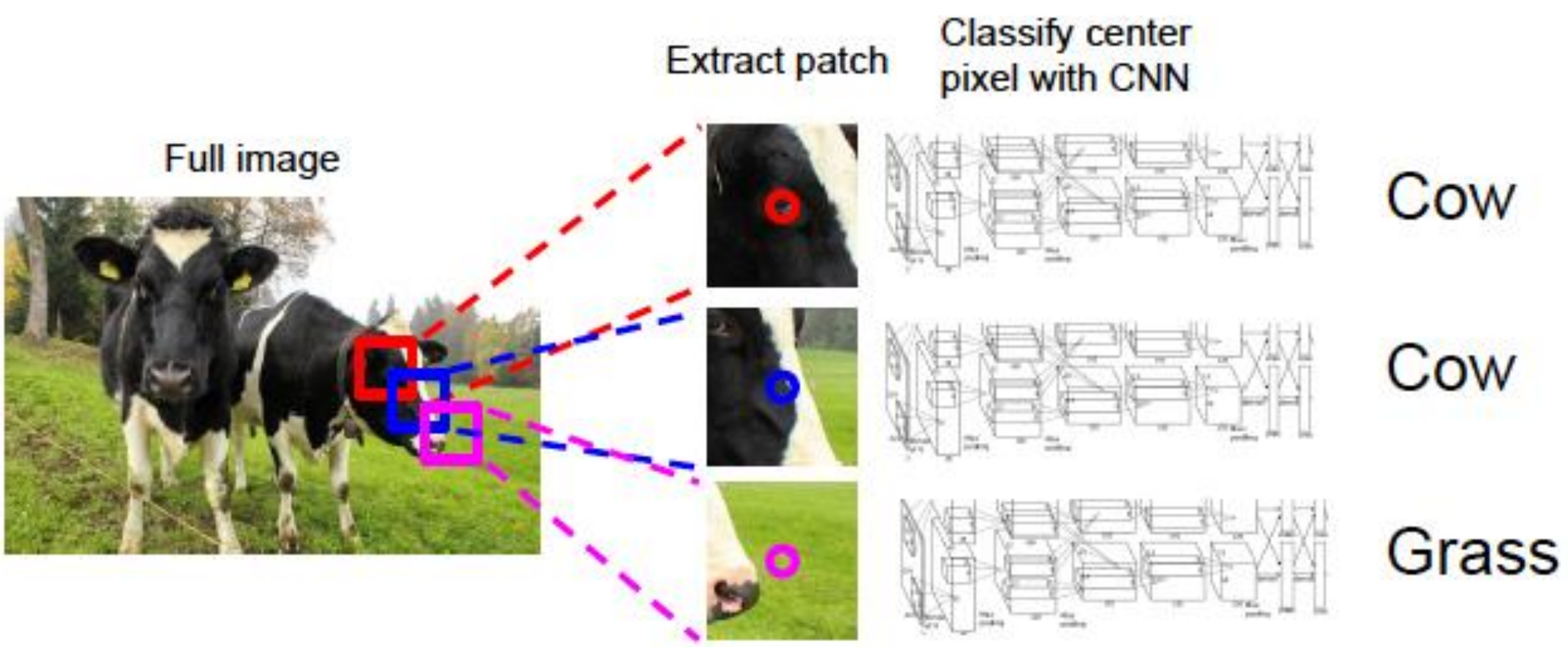


Q: how do we model this?

Why this is challenging?

- A naïve approach



Problem: Very inefficient! Not reusing shared features between overlapping patches

Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

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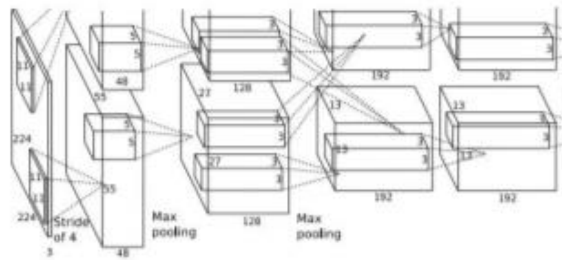
Several Ideas for SS

- First idea

Full image

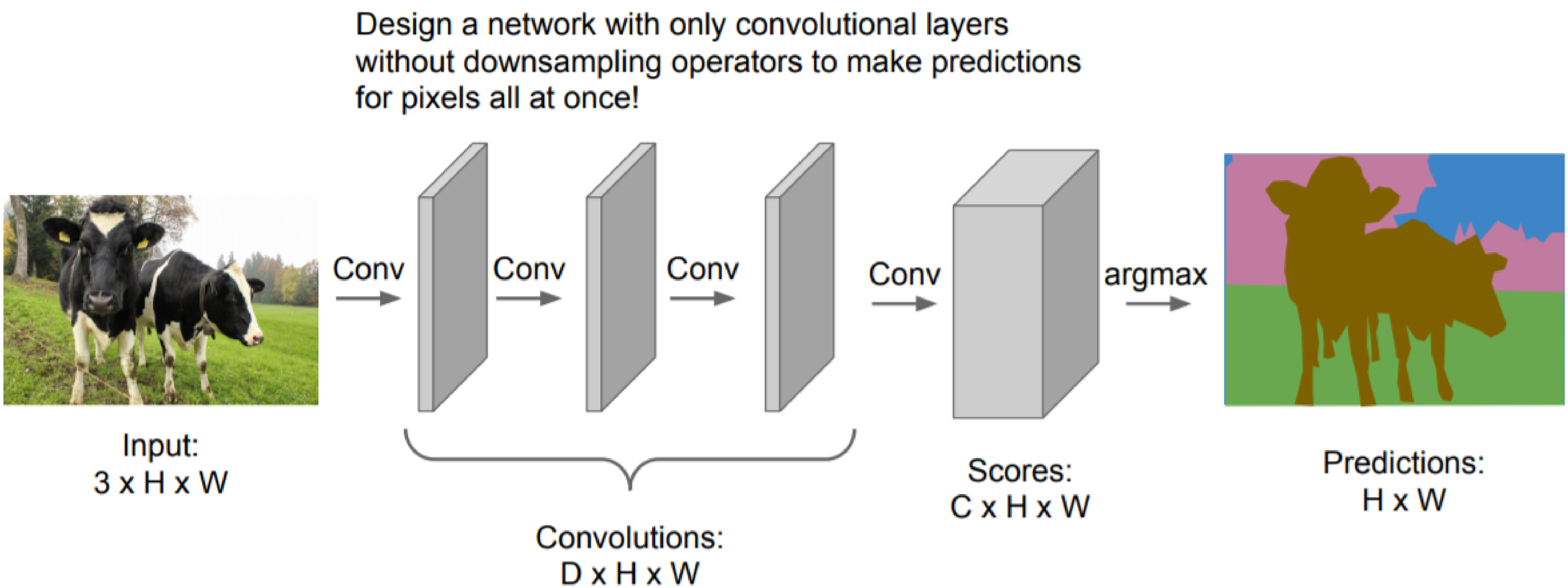


An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

Problem: classification architectures often reduce feature spatial sizes to go deeper, but semantic segmentation requires the output size to be the same as input size.

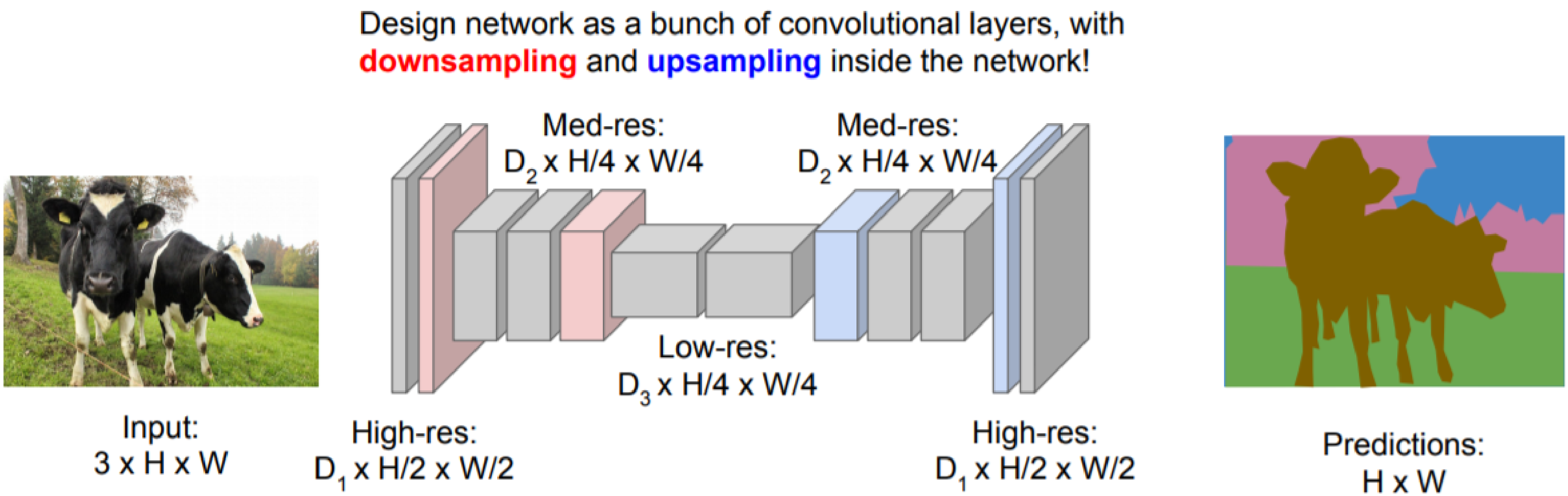
Several Ideas for SS

- Second idea



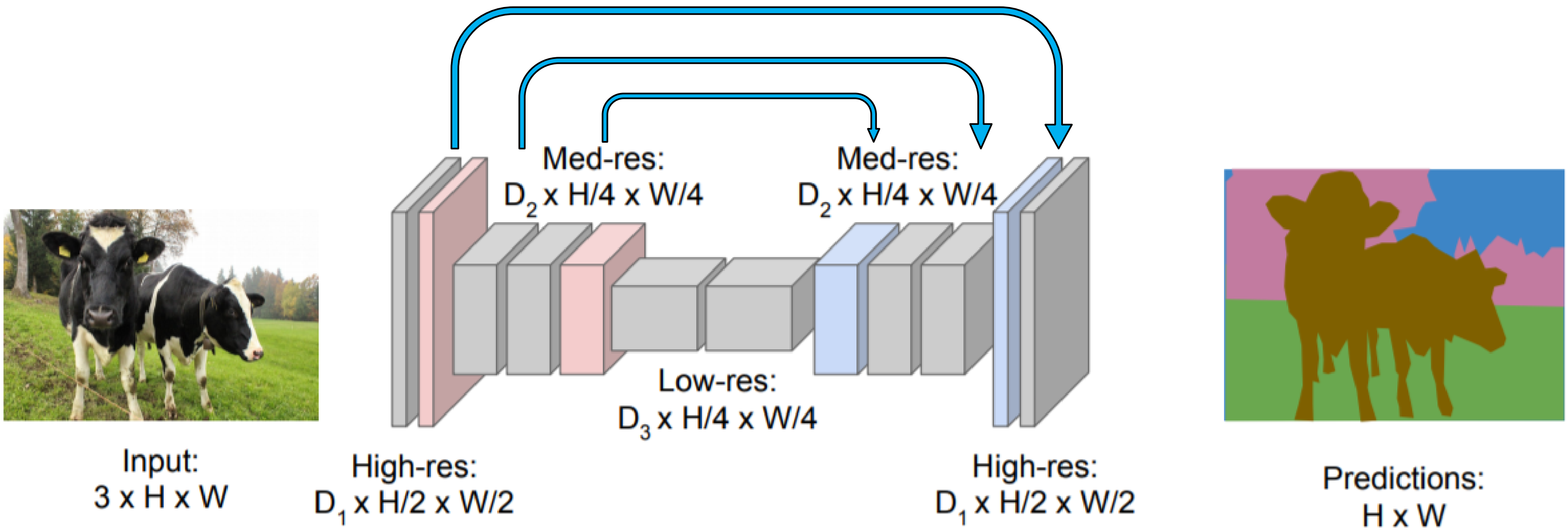
Several Ideas for SS

- Second idea improved



Several Ideas for SS

- Third idea



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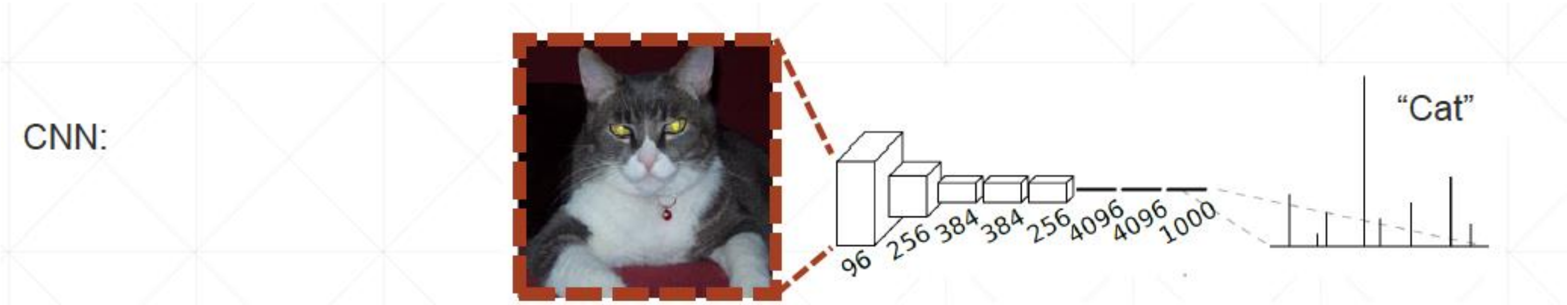
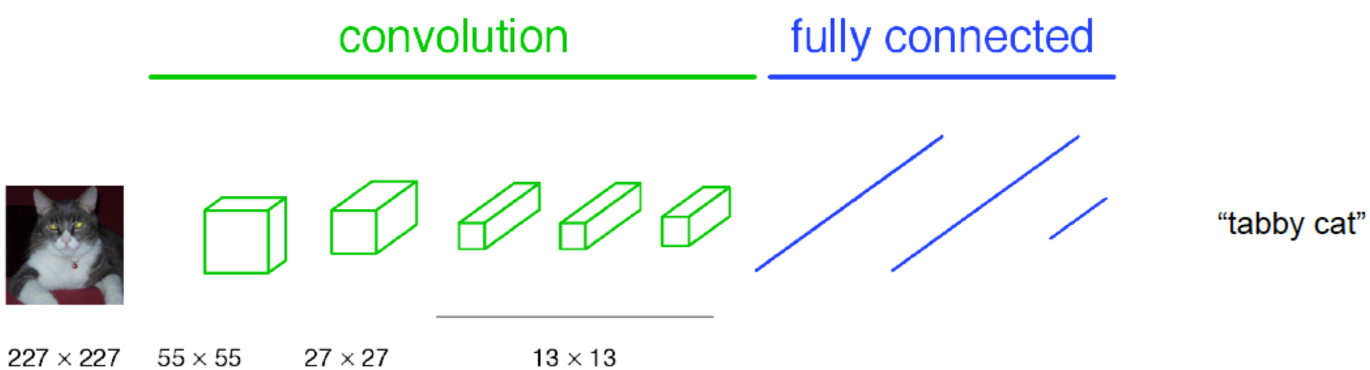
Network Design I: Efficiency

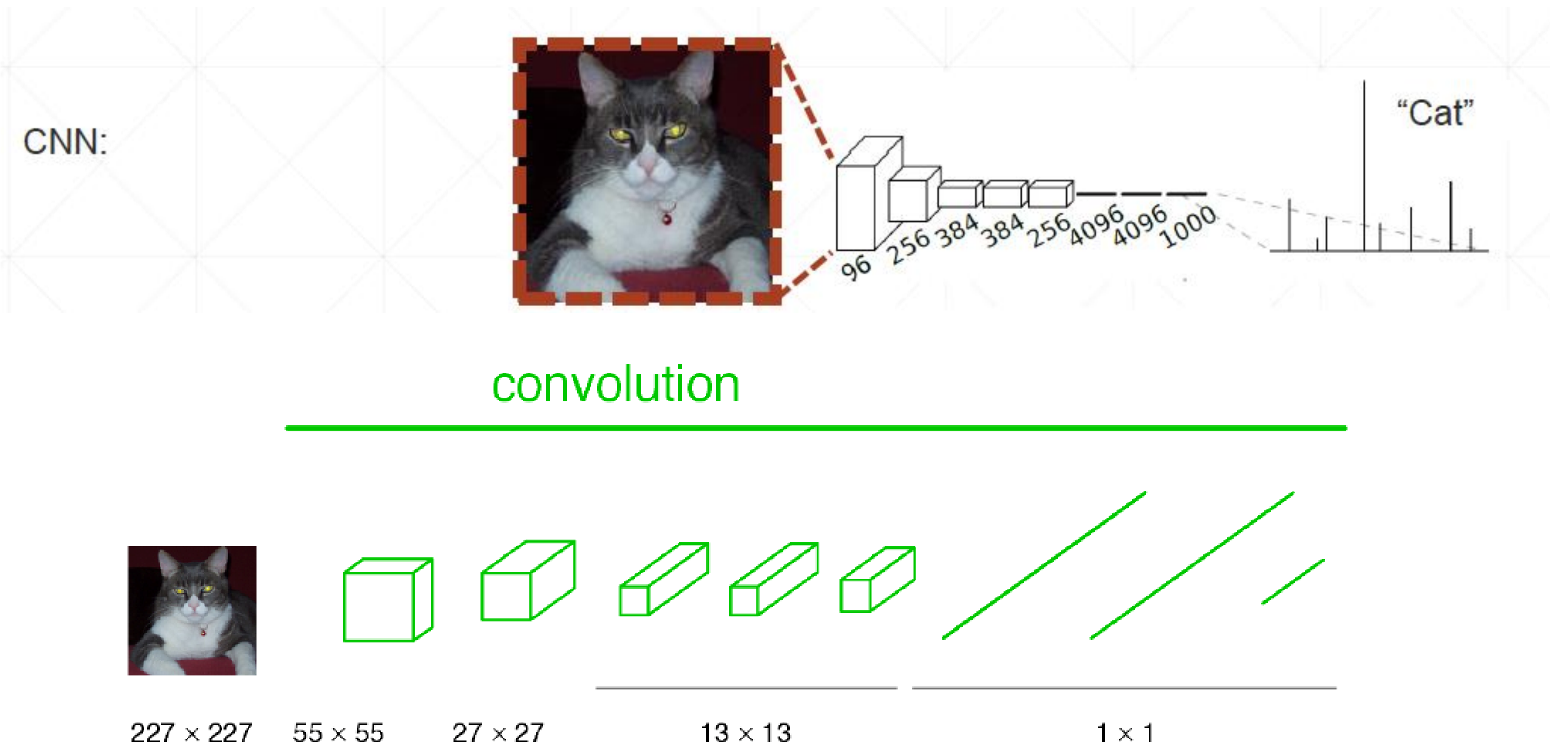
- Starting from a classification network





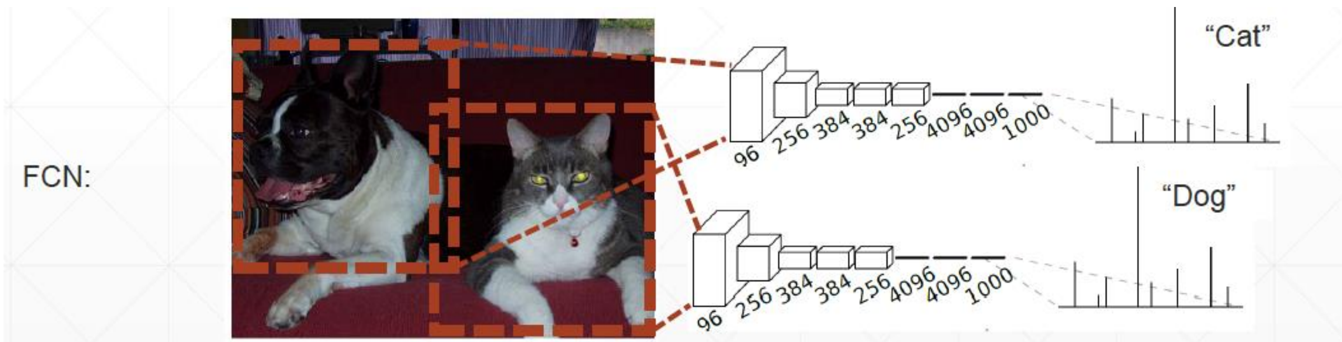
Network Design I: Efficiency

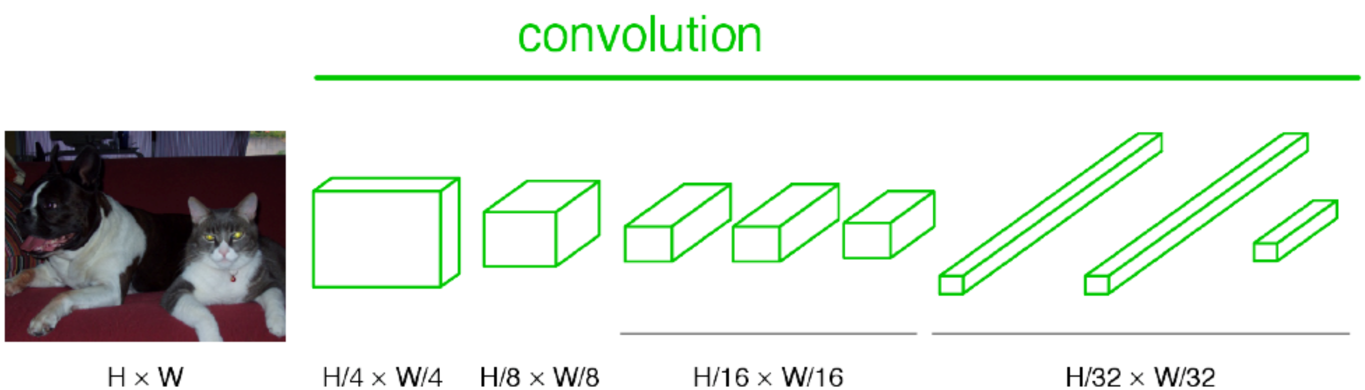
- Interpreting fully connected layers as 1x1 convolution (after reshaping)



Network Design I: Efficiency

- Extending to a complete image

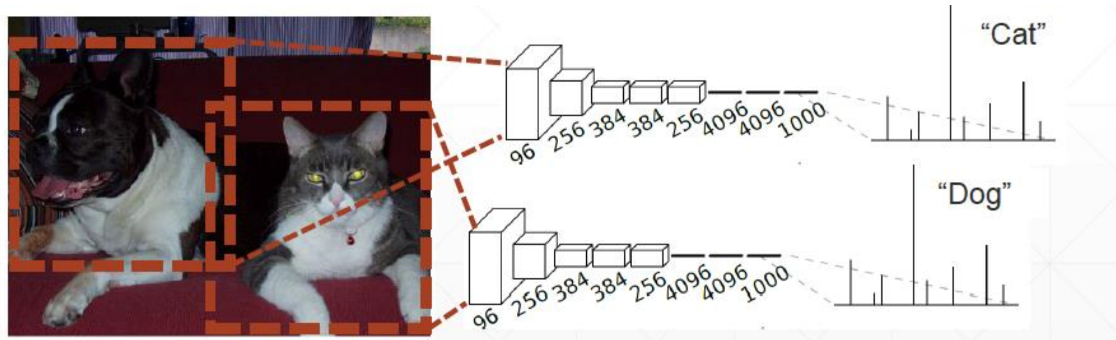


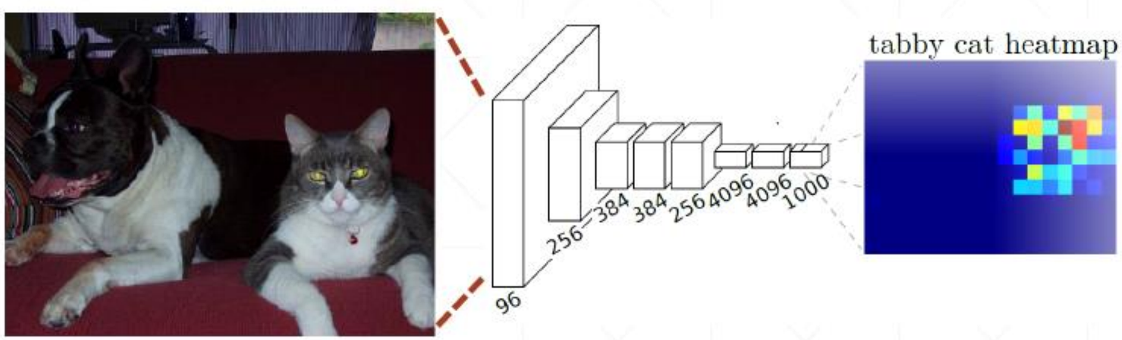


Network Design I: Efficiency

- Extending to a complete image

FCN:





- Keep kernel sizes and strides
- Replace dense layer with convolution

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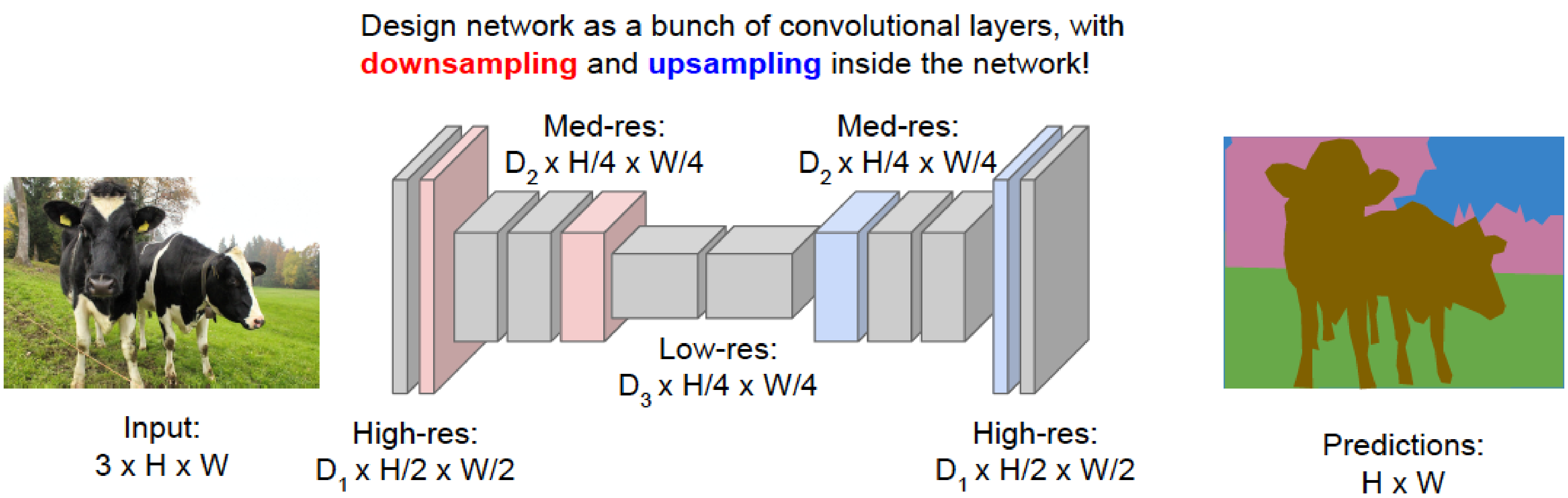
Network Design II: Spatial resolution

- General encoder-decoder architecture



In-Network upsampling

- Unpooling

Nearest Neighbor

1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

“Bed of Nails”

1	2
3	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

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

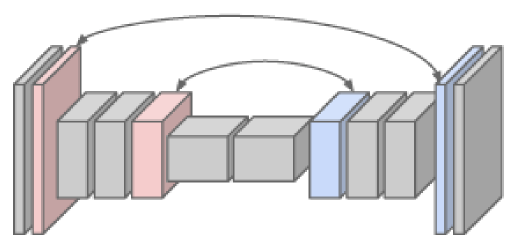
1	2
3	4

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



In-Network upsampling

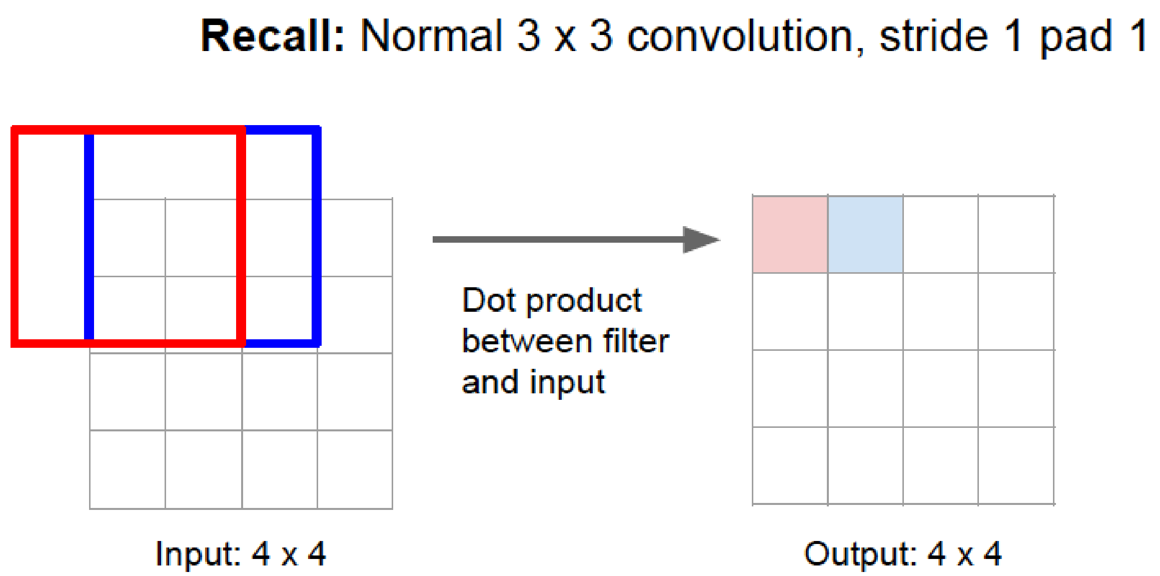
- Learnable Upsampling: Transpose convolution

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

Input: 4 x 4 Output: 4 x 4

In-Network upsampling

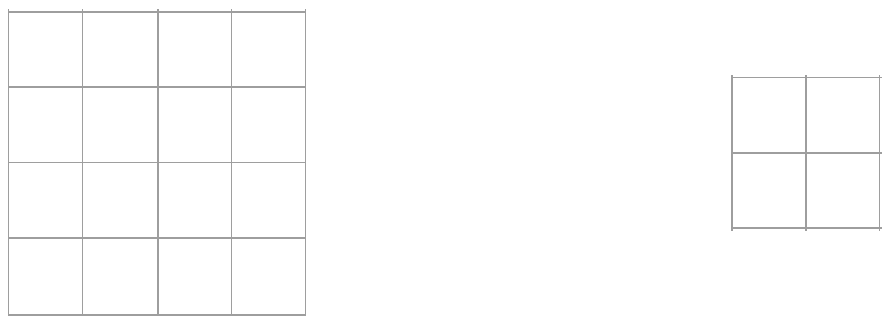
- Learnable Upsampling: Transpose convolution



In-Network upsampling

- Learnable Upsampling: Transpose convolution

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



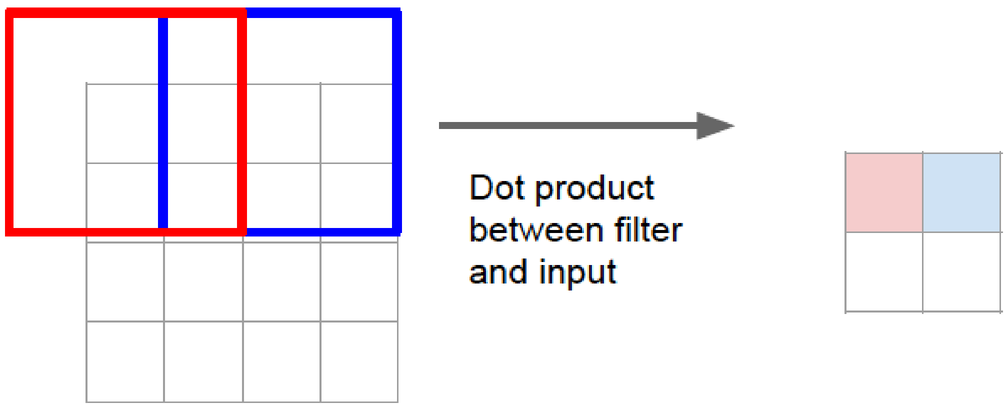
Input: 4 x 4

Output: 2 x 2

In-Network upsampling

- Learnable Upsampling: Transpose convolution

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



Input: 4 x 4

Output: 2 x 2

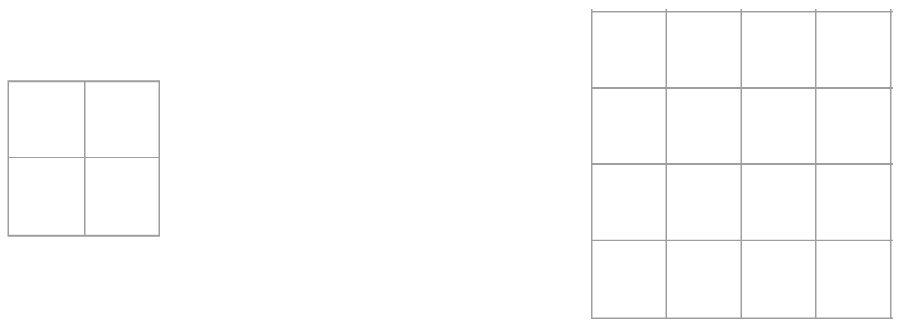
Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

In-Network upsampling

- Learnable Upsampling: Transpose convolution

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



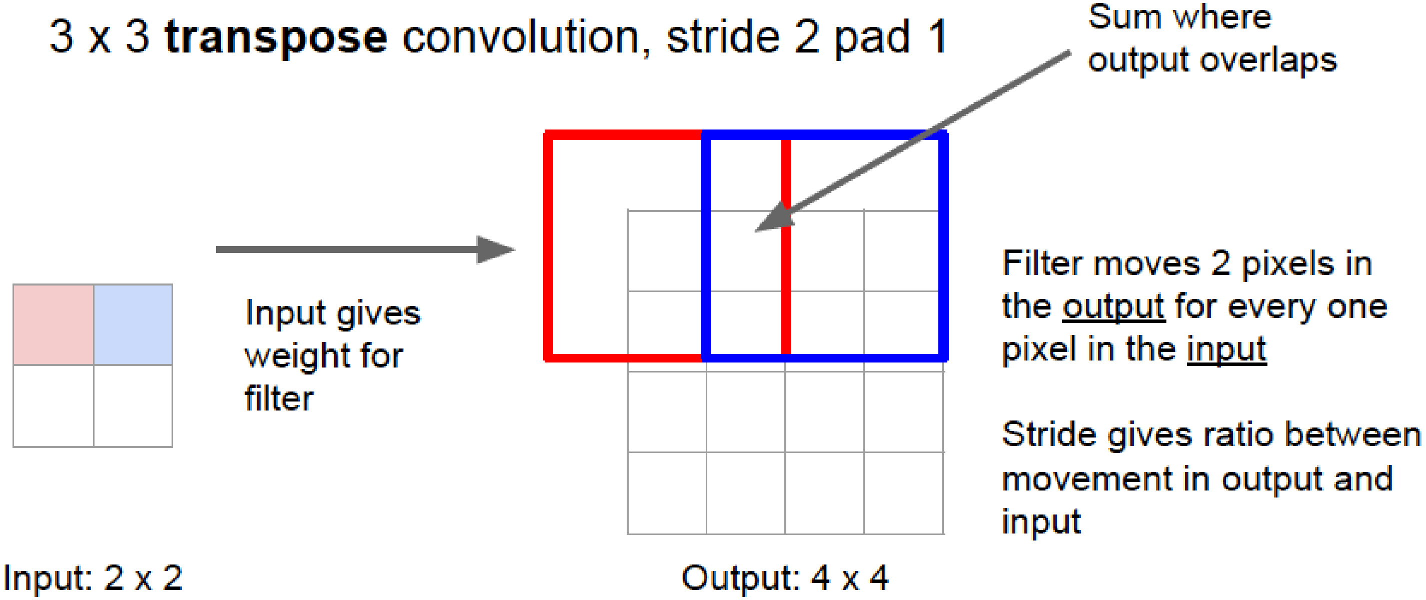
Input: 2 x 2

Output: 4 x 4

In-Network upsampling

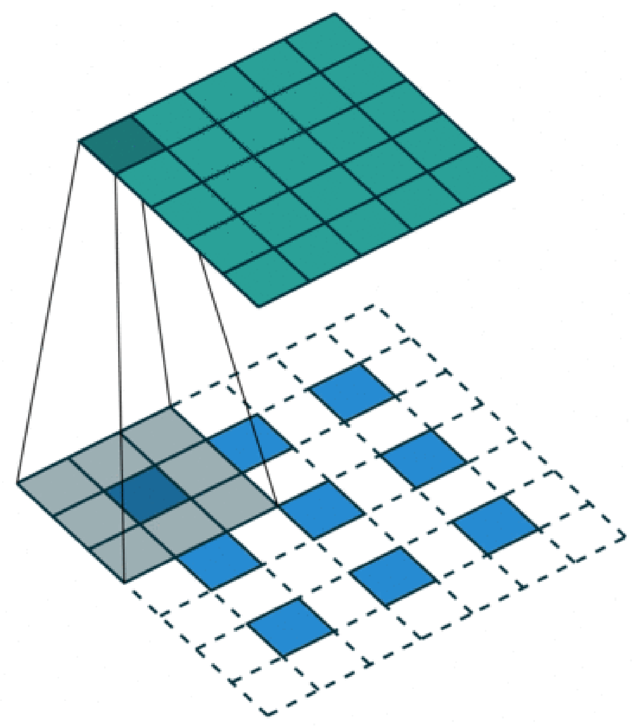
- Learnable Upsampling: Transpose convolution

Other names:
-Deconvolution (bad)
-Upconvolution
-Fractionally strided convolution
-Backward strided convolution



In-Network upsampling

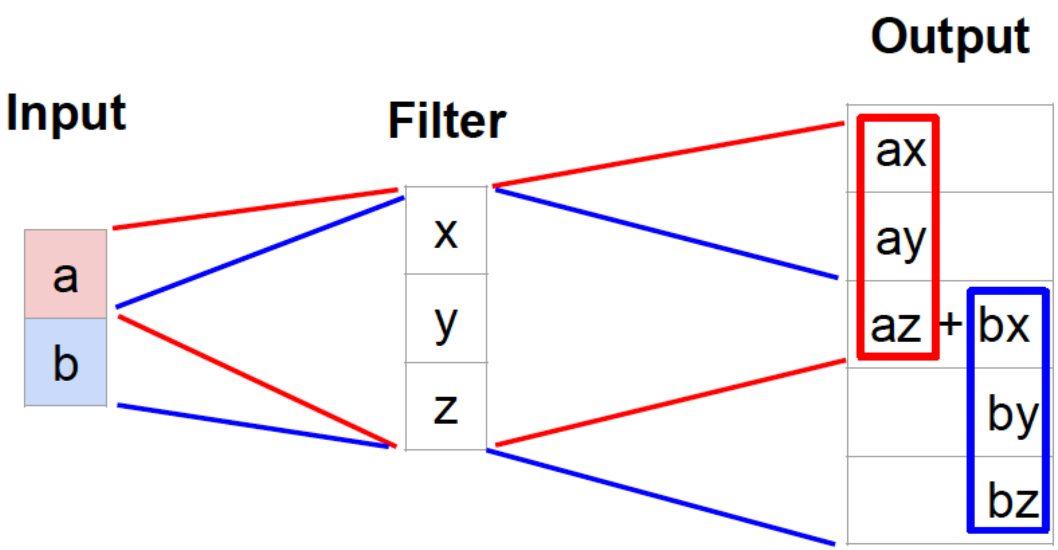
- 2D animation



https://github.com/vdumoulin/conv_arithmetic

In-Network upsampling

- Learnable Upsampling: Transpose convolution
  - 1D example



Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

Need to crop one pixel from output to make output exactly 2x input

In-Network upsampling

- Learnable Upsampling: Transpose convolution
  - 1D example

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & 0 & x & y & z & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=2, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

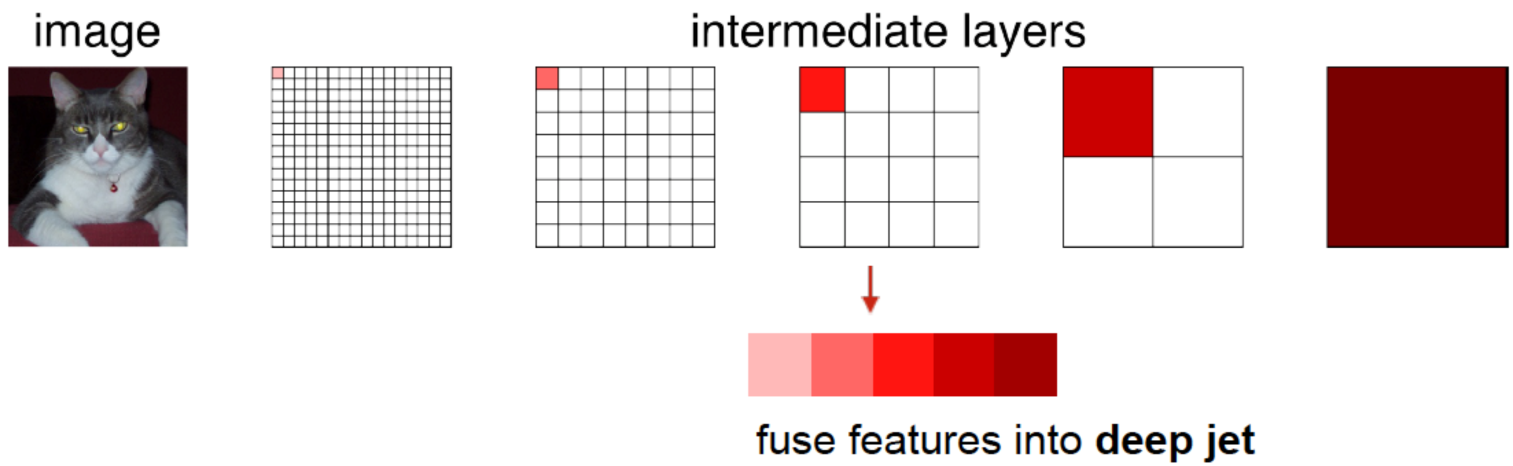
$$\vec{x} *^T \vec{a} = X^T \vec{a}$$

$$\begin{bmatrix} x & 0 \\ y & 0 \\ z & x \\ 0 & y \\ 0 & z \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} ax \\ ay \\ az + bx \\ by \\ bz \\ 0 \end{bmatrix}$$

When stride>1, convolution transpose is no longer a normal convolution!

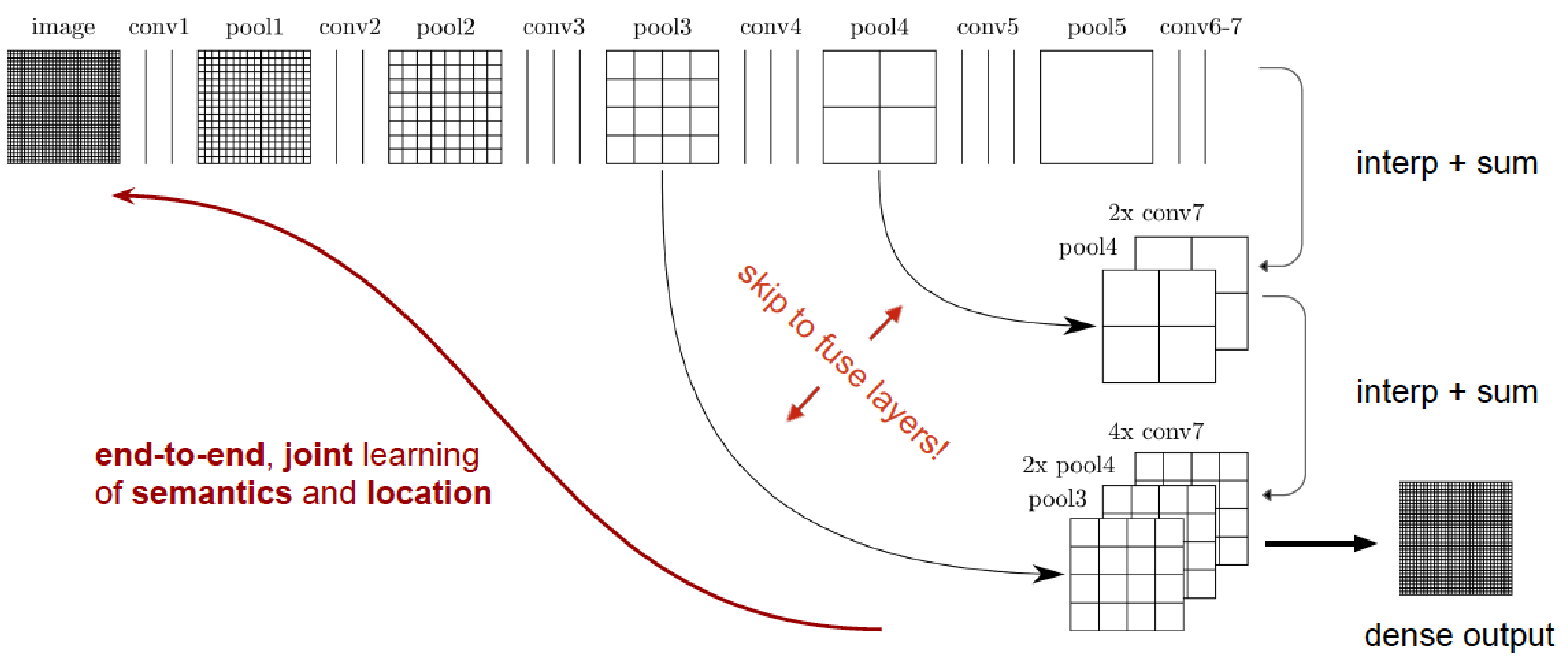
Network Design II: Examples

- Fully Convolutional Network [Long et al, CVPR 2015]
  - Upsampling: low-resolution, lack spatial details
  - Combining *where (local, shallow)* with *what (global, deep)*



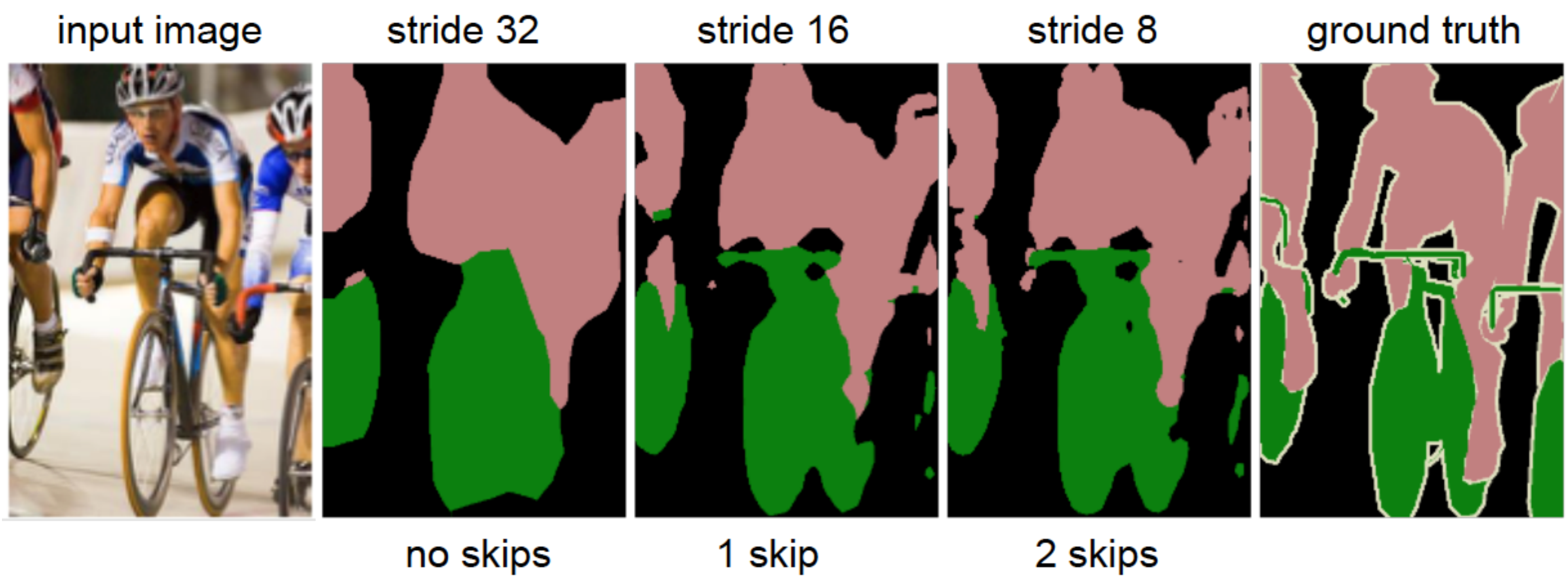
Network Design II: Examples

- Fully Convolutional Network [Long et al, CVPR 2015]
  - Upsampling: low-resolution, lack spatial details
  - Introducing ***skip layers***



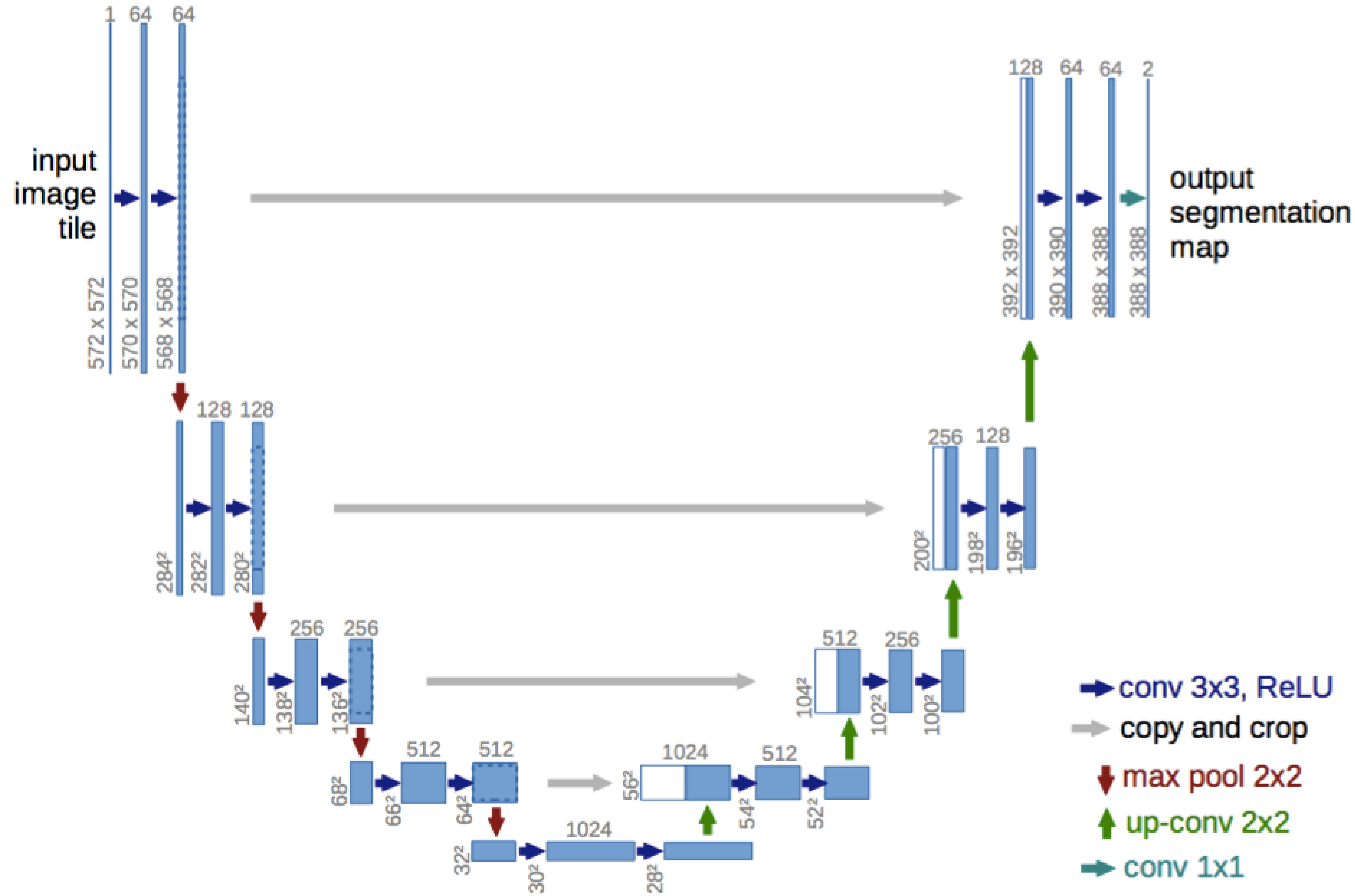
Network Design II: Examples

- Fully Convolutional Network [Long et al, CVPR 2015]
  - Upsampling: low-resolution, lack spatial details
  - Skip layer refinement



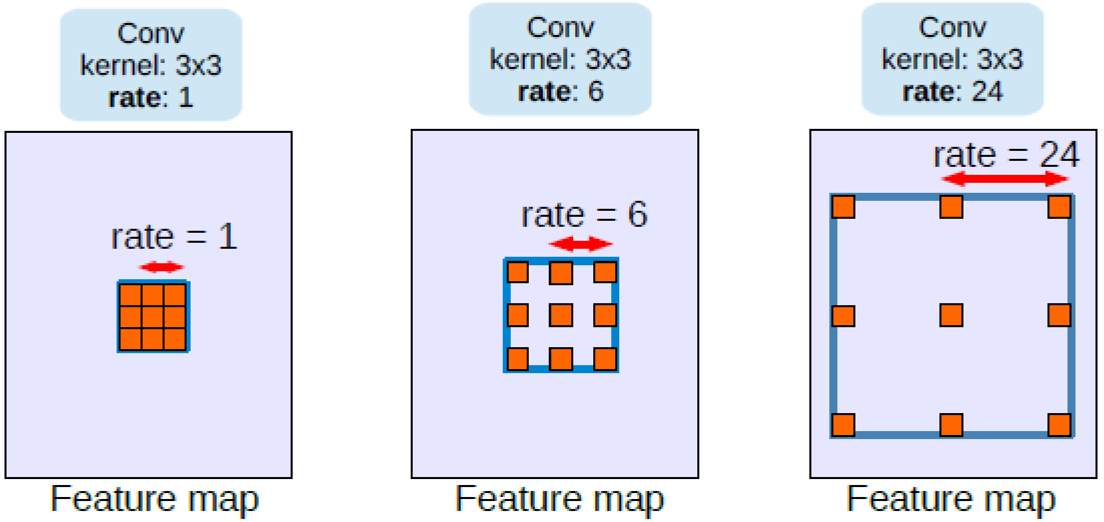
Network Design II: Examples

- U-Net [Ronneberger et al, MICCAI 2015]



Network Design II: Spatial resolution

- Dilated Convolutional Network [Yu and Koltun, ICLR 2016]
  - Dense feature map without upsampling
  - ***Dilated (or Atrous) convolution***



$$y[i] = \sum_{k=1}^{K} x[i + r \cdot k] w[k].$$

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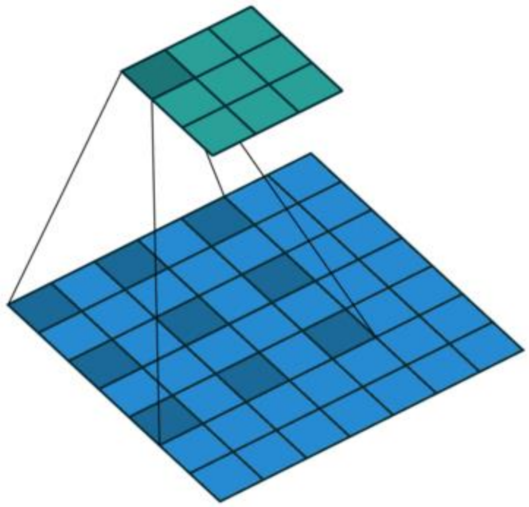

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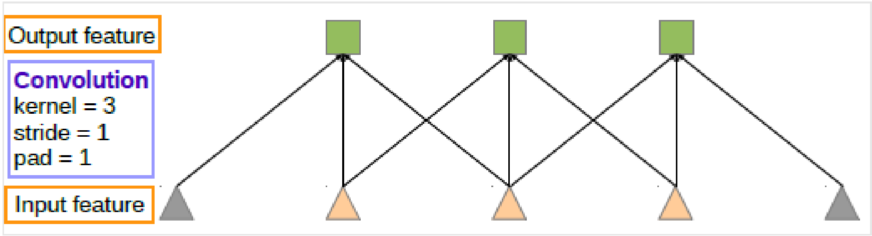
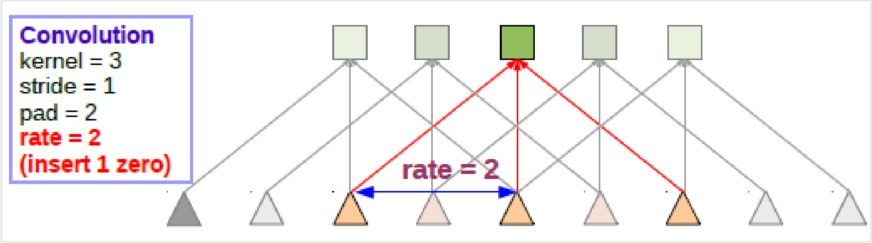


(a) Sparse feature extraction



(b) Dense feature extraction

$$y[i] = \sum_{k=1}^{K} x[i + r \cdot k]w[k].$$

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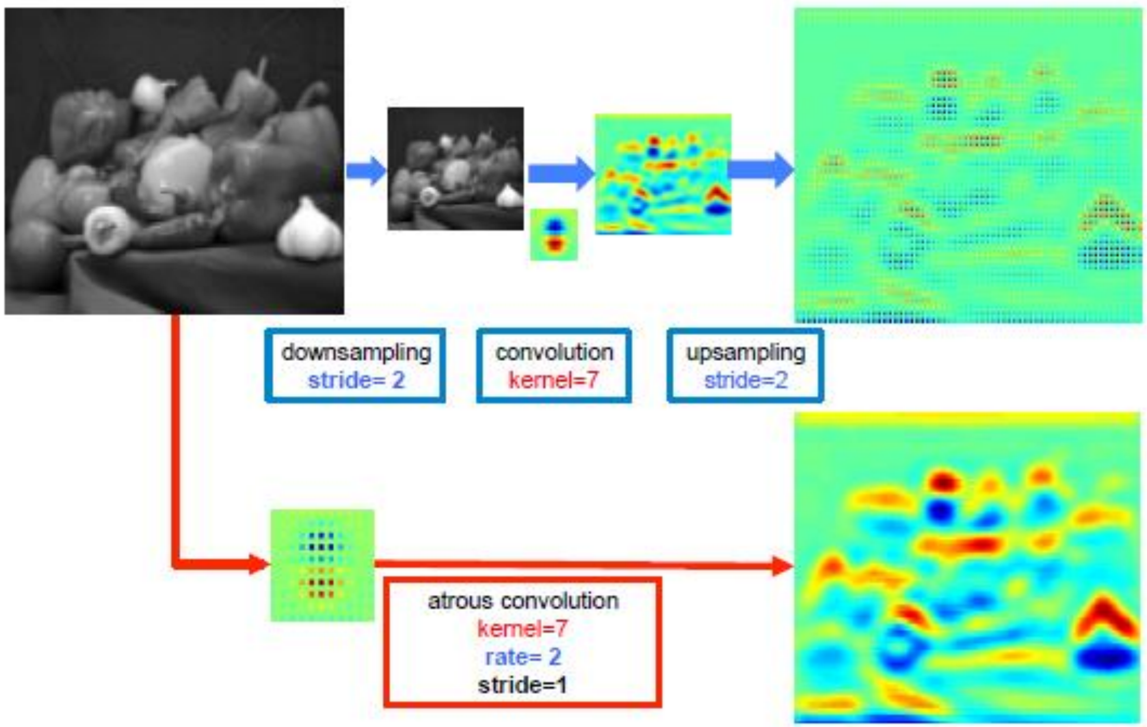

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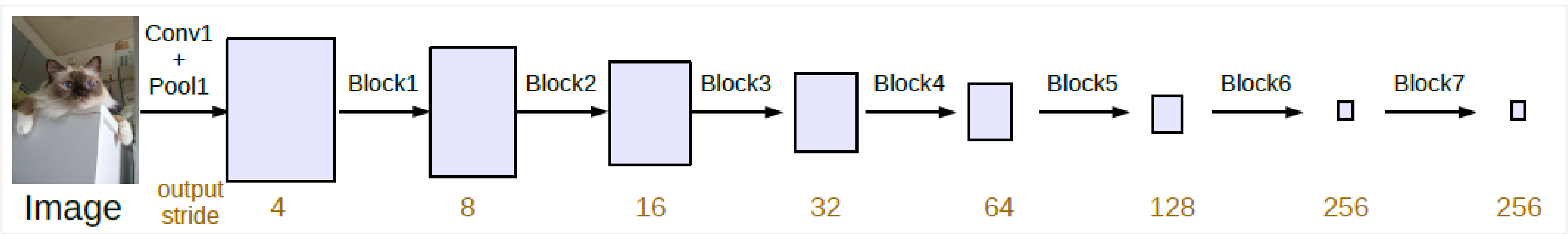
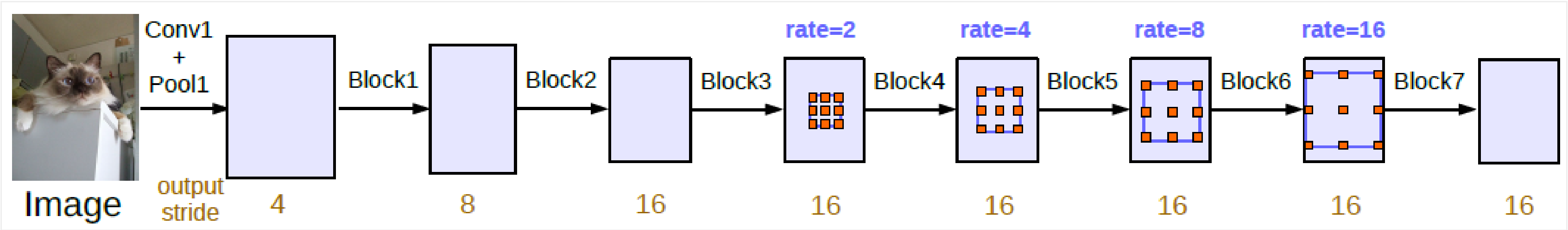


(a) Going deeper without atrous convolution.



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

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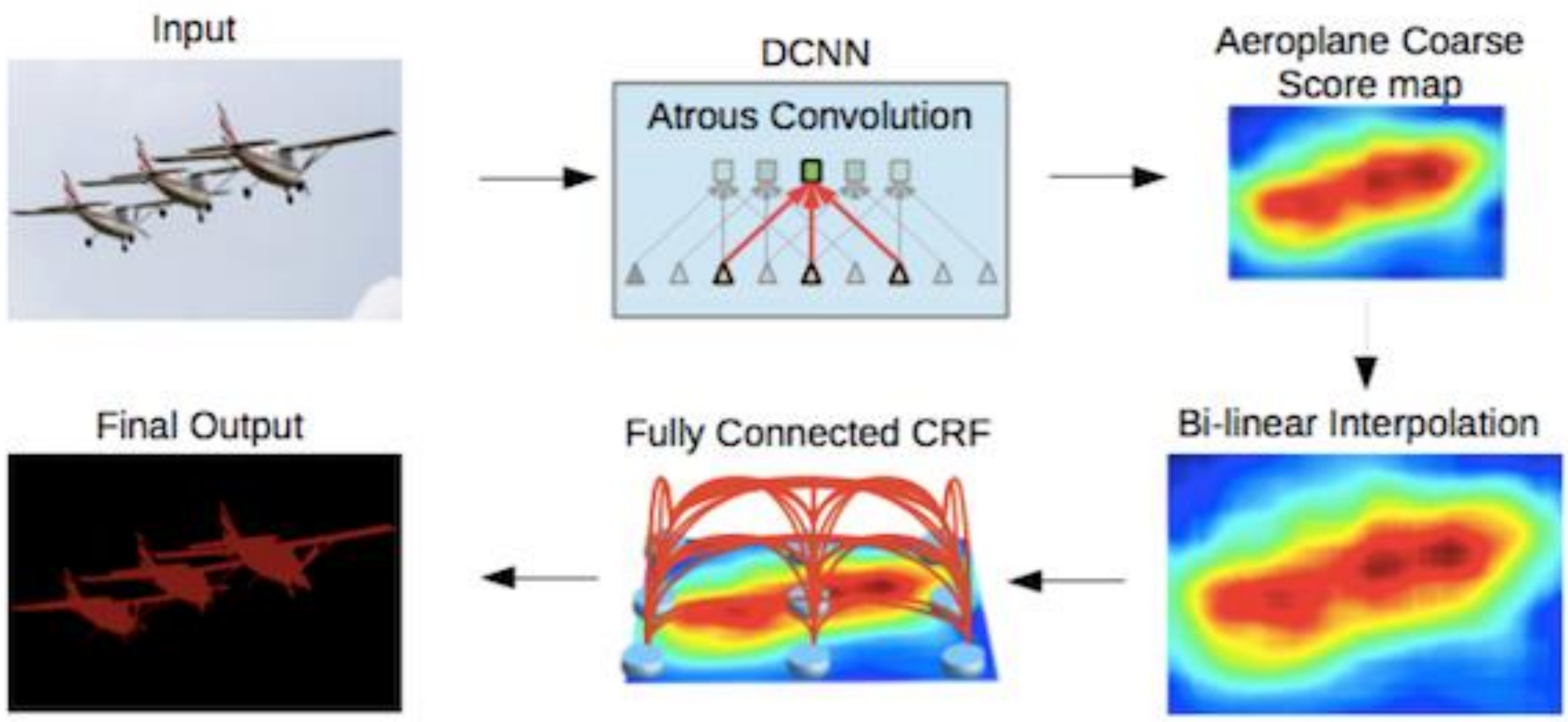
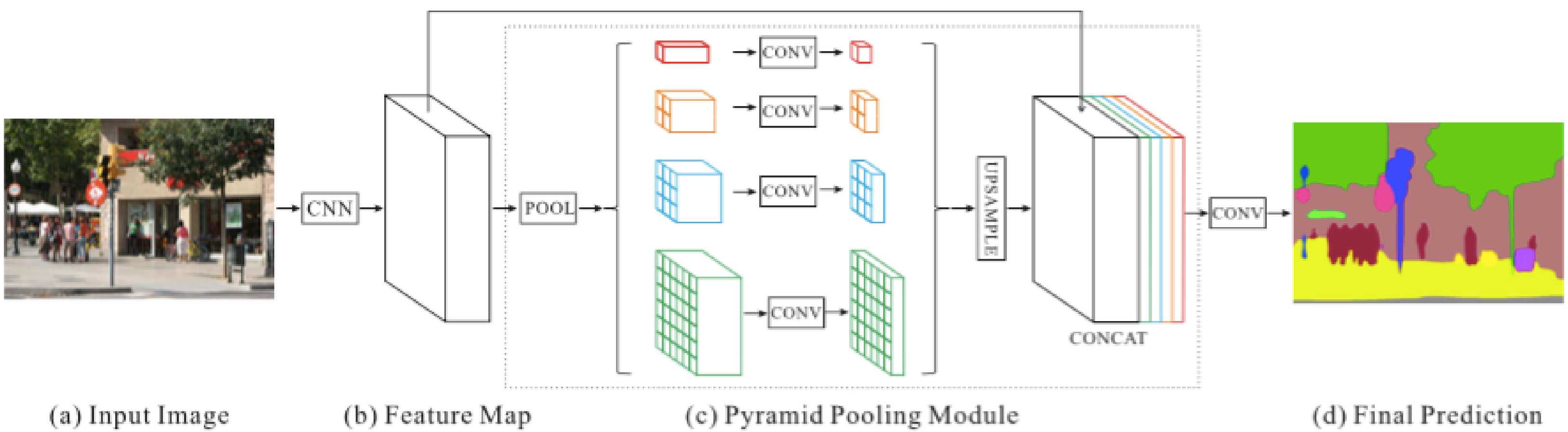
Network Design III: Multi-scale context

- DeepLab v1&v2
  - Post-processing with dense CRFs.



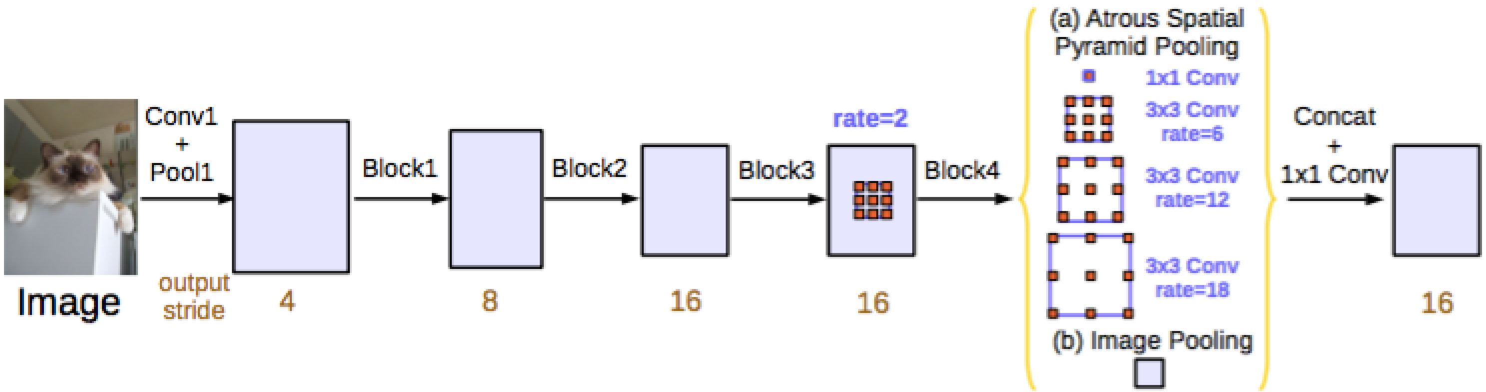
Network Design III: Multi-scale context

- PSPNet [Zhao et al CVPR 2017]
  - A pyramid parsing module that carries both local and global context information

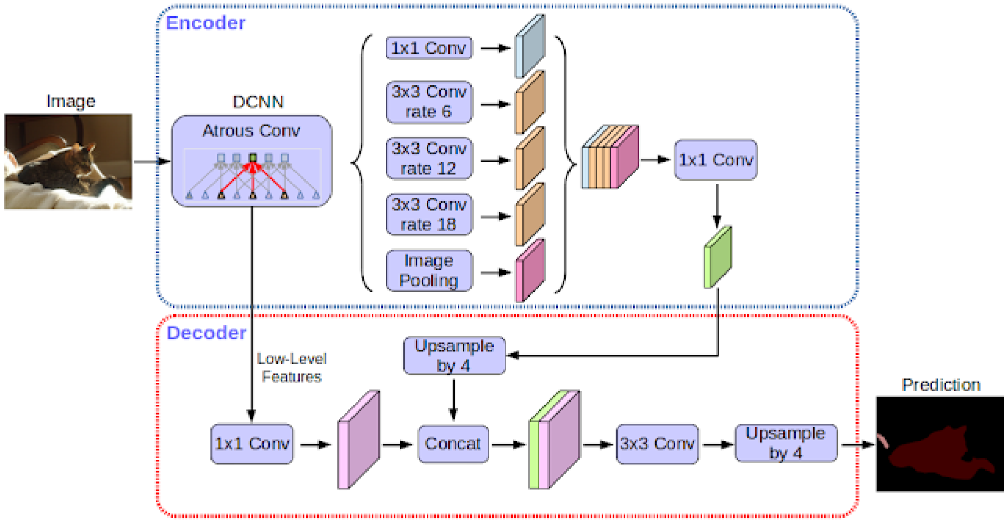


Network Design III: Multi-scale context

- DeepLab v3



- Deeplab v3+



https://ai.googleblog.com/2018/03/semantic-image-segmentation-with.html

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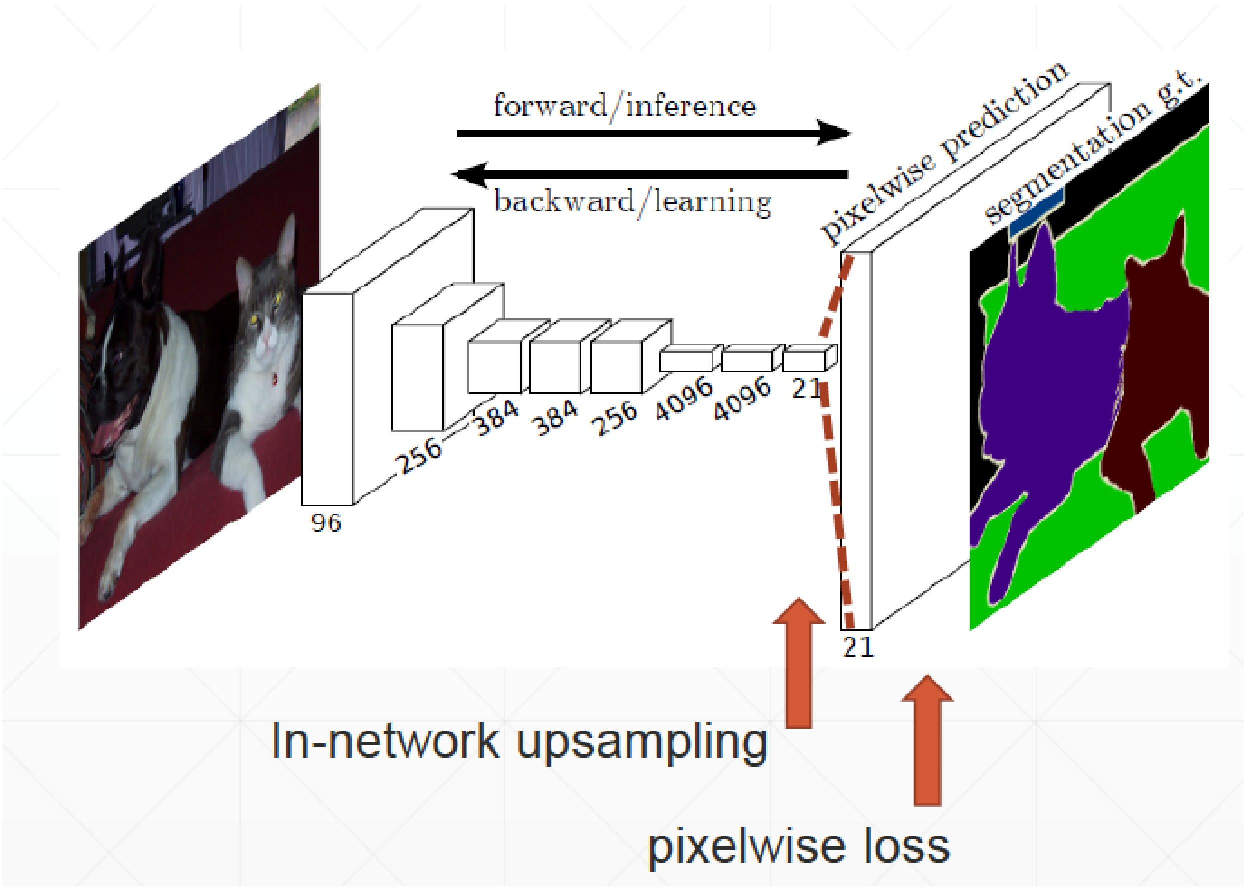
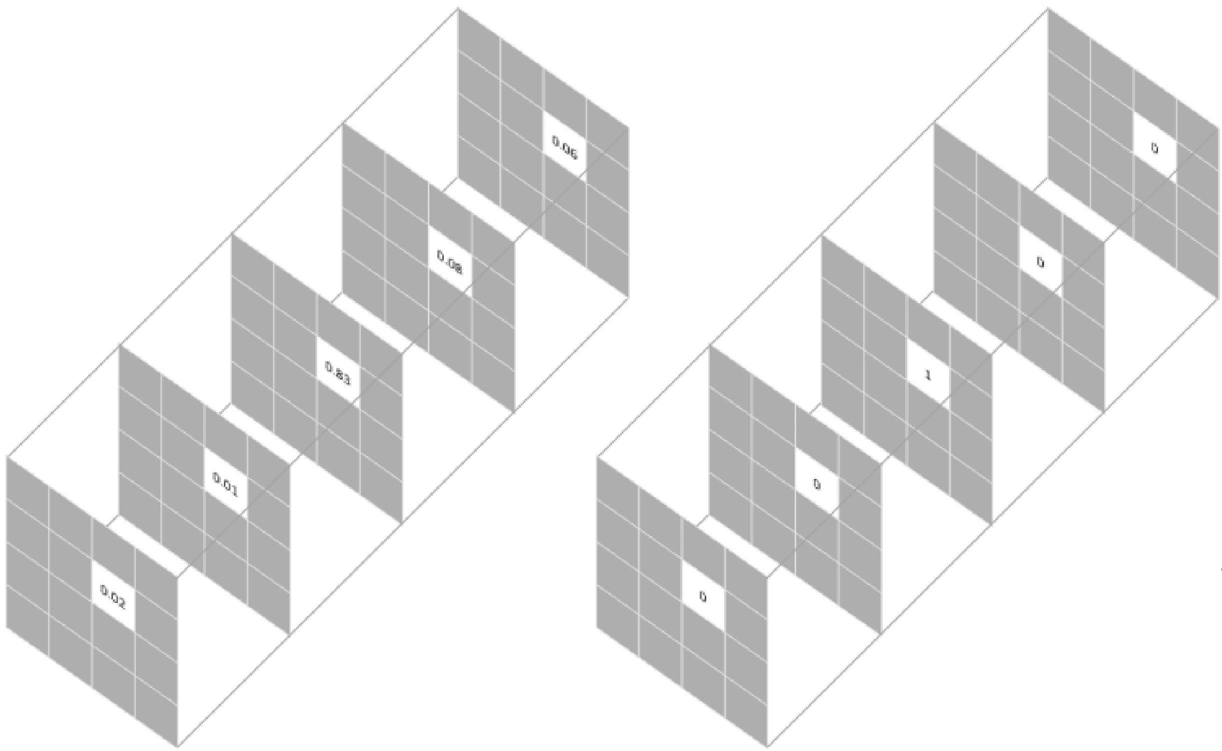
Semantic segmentation: loss function

- Main idea: pixel-wise classification



Semantic segmentation: loss function

- Pixel-wise loss



Prediction for a selected pixel

Target for the corresponding pixel

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

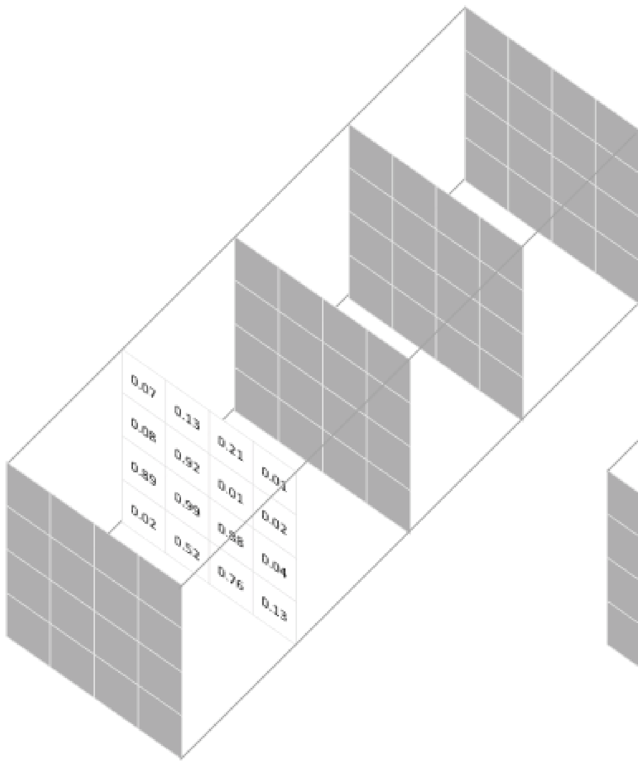
$$-\sum_{classes} y_{true} \log\left(y_{pred}\right)$$

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

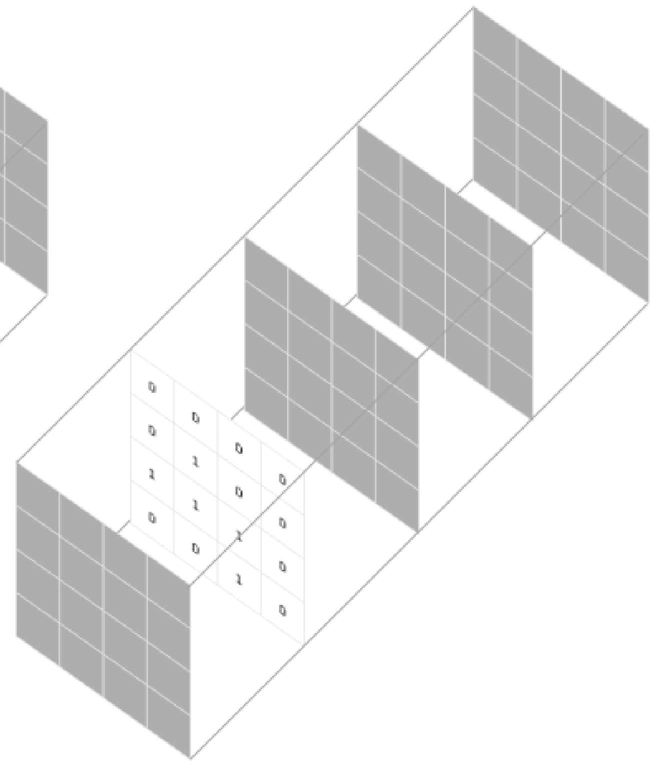
Semantic segmentation: loss function

- Region-based loss

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|}$$



Prediction for a selected class



Target for the corresponding class

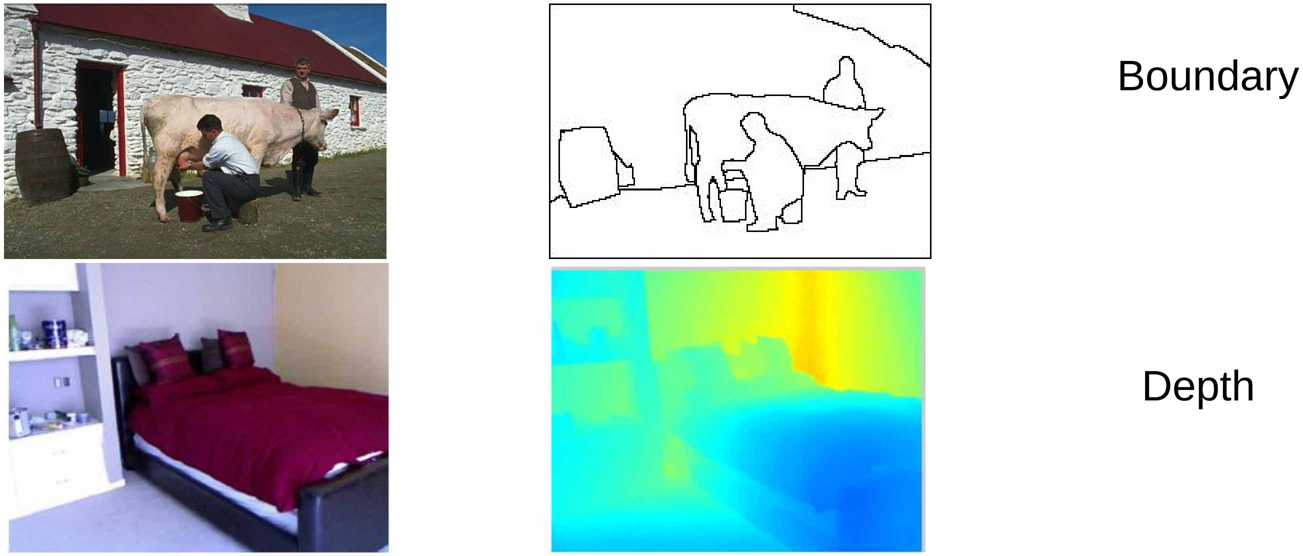
Soft Dice coefficient is calculated for each class mask

$$1 - \frac{2 \sum_{pixels} y_{true} y_{pred}}{\sum_{pixels} y_{true}^2 + \sum_{pixels} y_{pred}^2}$$

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

Semantic Segmentation: Summary

- Pixel-wise annotation of images
  - An instance of scene understanding



- Many questions remain unanswered
  - Training data?
  - Things vs. Stuff?
  - Boundary vs Region?

Semantic Segmentation: Summary

- Other research topics (not discussed)
  - *Low-level vision: superresolution, deblurring, inpainting, depth*
  - *Video: optical flow, action and activity recognition and detection*
  - *Volumetric/Multimodality: RGB-D images, medical imaging, etc.*

- Next time:
  - Instance detection and segmentation