RWTH AACHEN UNIVERSITY

Computer Vision – Lecture 13

Deep Learning IV

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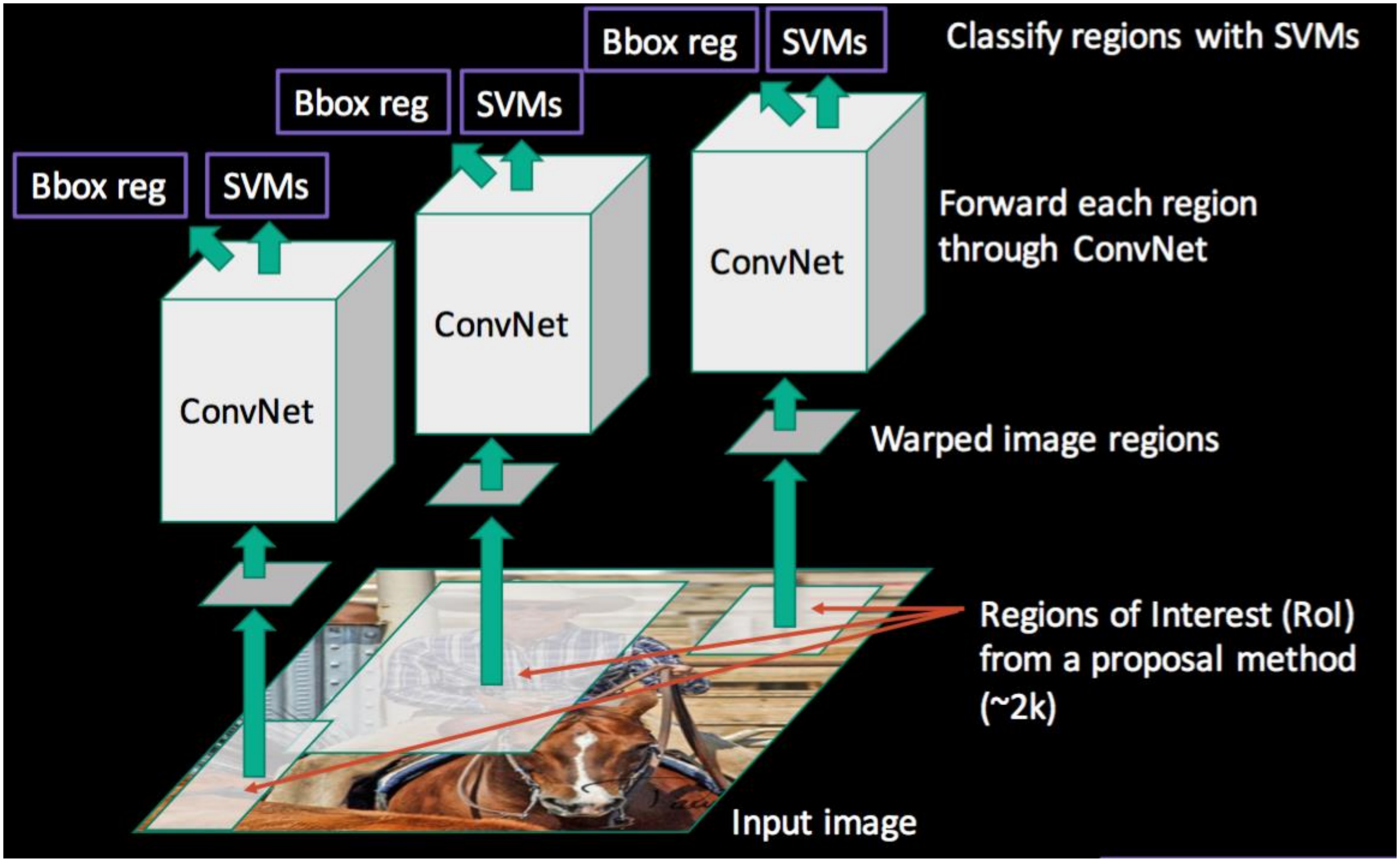
Course Outline

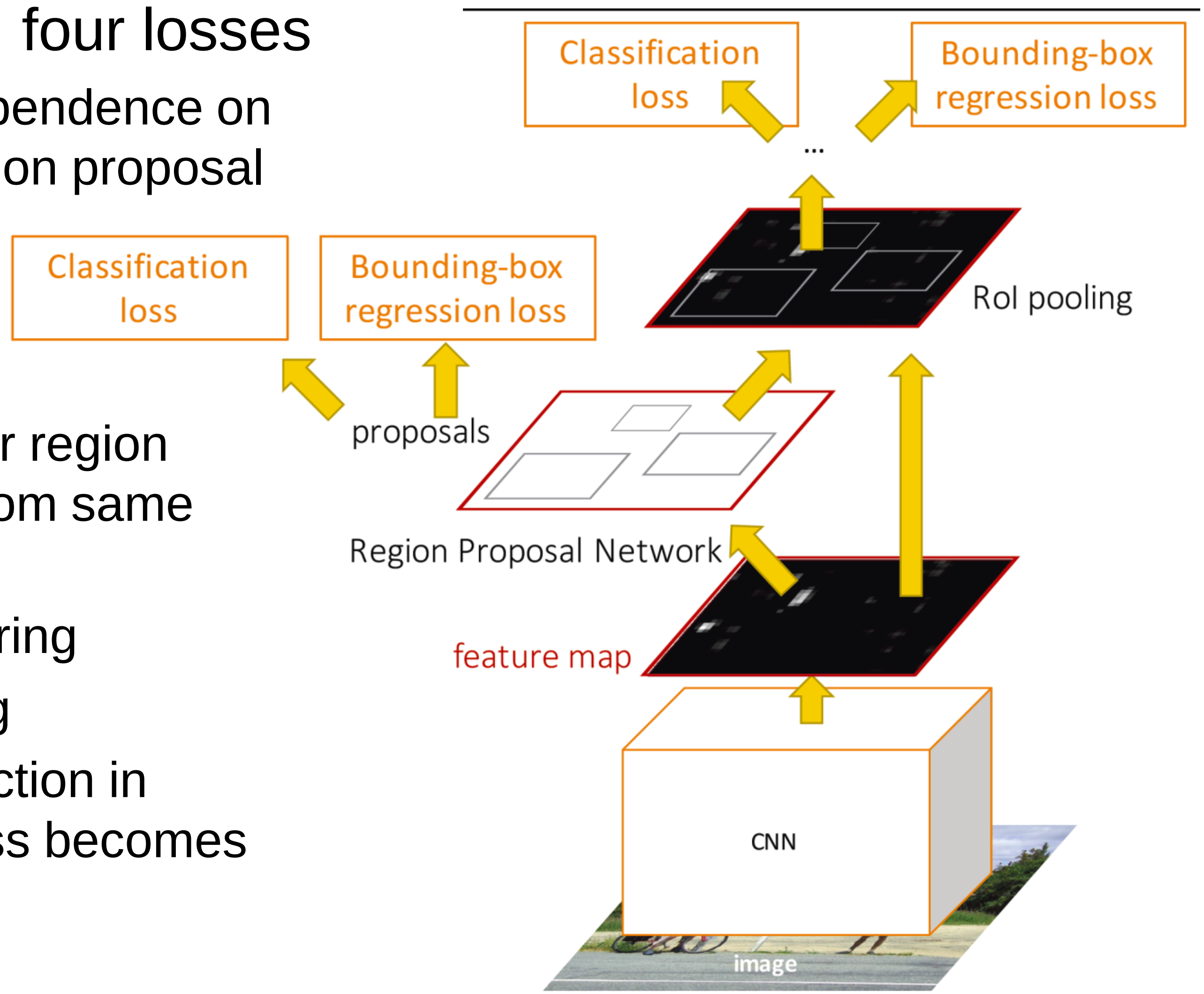
- Image Processing Basics
- Segmentation & Grouping
- Object Recognition & Categorization
  - Sliding Window based Object Detection
- Local Features & Matching
- Deep Learning
  - Convolutional Neural Networks (CNNs)
  - Deep Learning Background
  - CNNs for Object Detection
  - CNNs for Semantic Segmentation
  - CNNs for Matching
- 3D Reconstruction

Recap: R-CNN for Object Detection



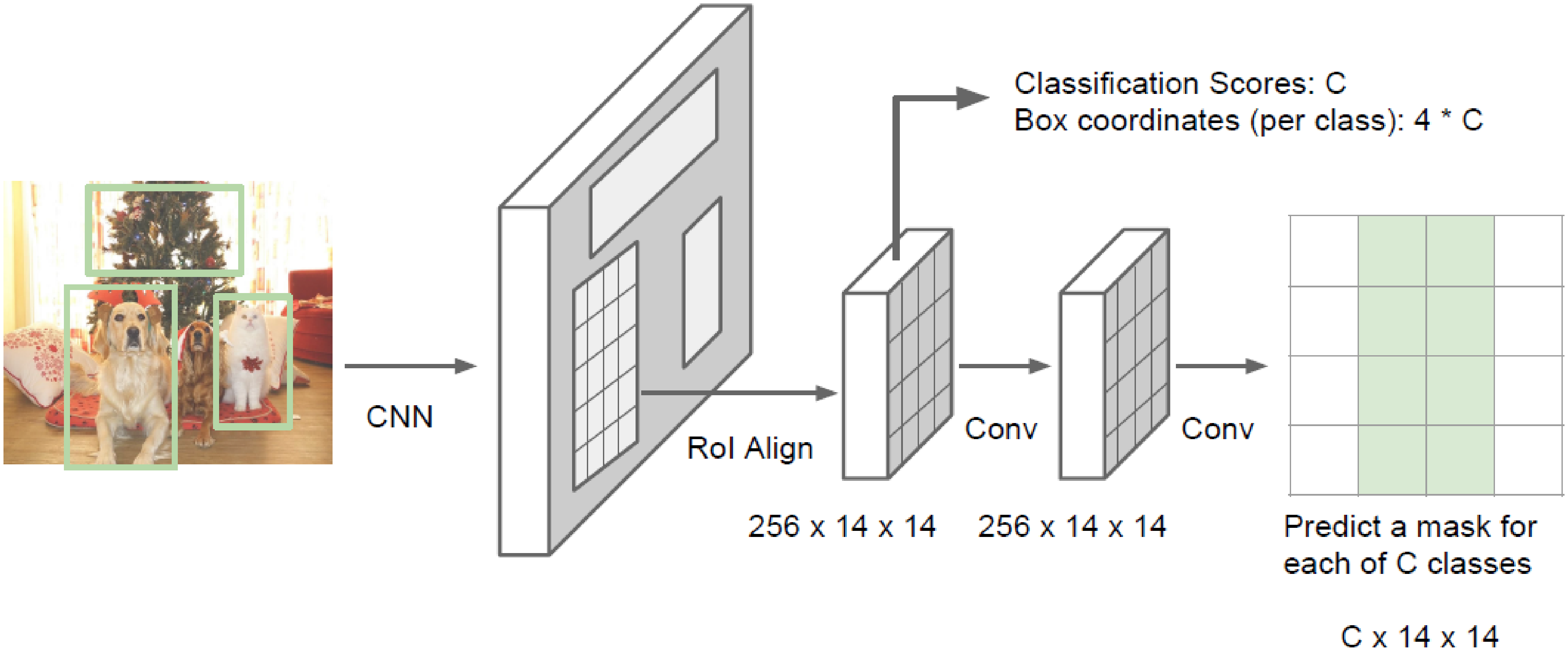
Recap: Faster R-CNN

- One network, four losses
  - Remove dependence on external region proposal algorithm.
  - Instead, infer region proposals from same CNN.
  - Feature sharing
  - Joint training
  - ⇒ Object detection in a single pass becomes possible.



Slide credit: Ross Girshick

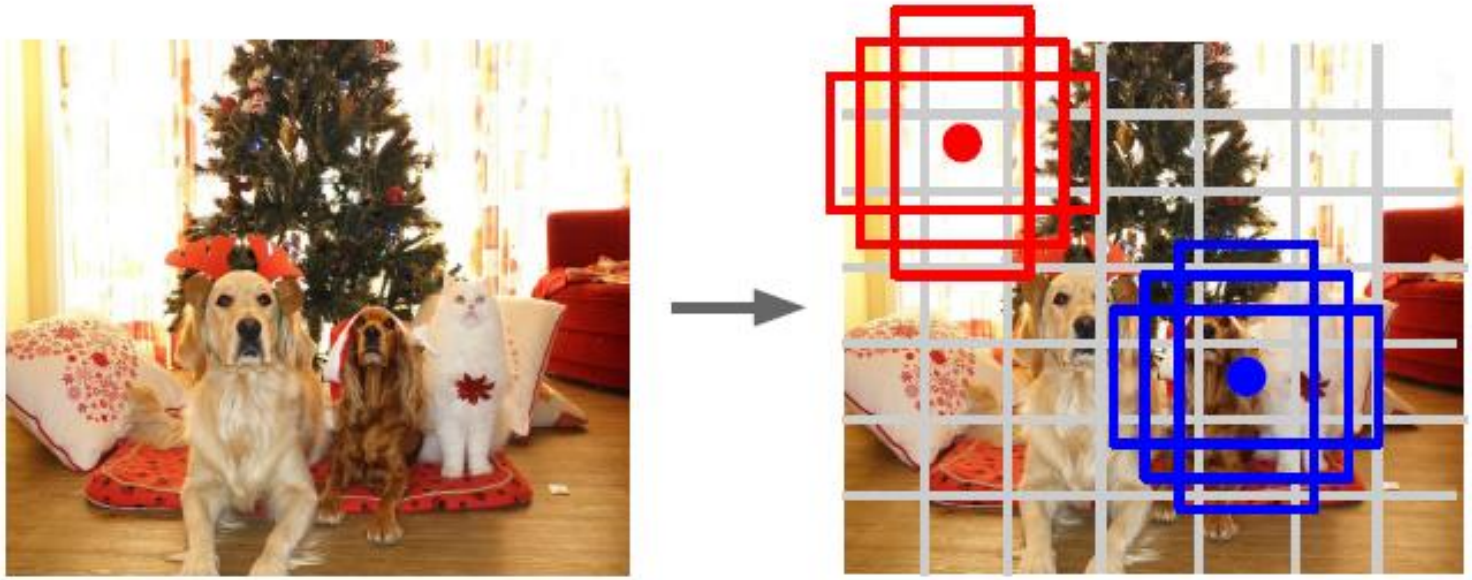
Recap: Mask R-CNN



K. He, G. Gkioxari, P. Dollar, R. Girshick, [Mask R-CNN](), arXiv 1703.06870.

Slide credit: FeiFei Li

Recap: YOLO / SSD



Input image
3 x H x W

Divide image into grid
7 x 7

- Idea: Directly go from image to detection scores
- Within each grid cell
  - Start from a set of anchor boxes
  - Regress from each of the B anchor boxes to a final box
  - Predict scores for each of C classes (including background)

Slide credit: FeiFei Li

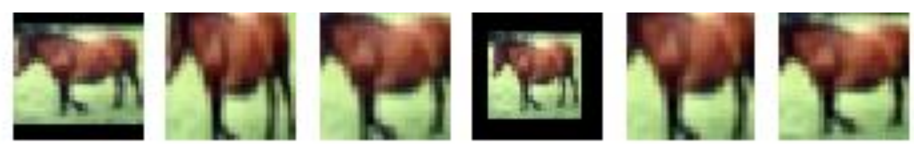
Topics of This Lecture

- Practical Advice on CNN training
  - Data Augmentation
  - Initialization
  - Batch Normalization
  - Dropout
  - Learning Rate Schedules
- CNNs for Segmentation
  - Fully Convolutional Networks (FCN)
  - Encoder-Decoder architecture
  - Transpose convolutions
  - Skip connections
- CNNs for Human Body Pose Estimation

Data Augmentation

- Idea
  - Augment original data with synthetic variations to reduce overfitting
- Example augmentations for images
  - Cropping

  - Zooming



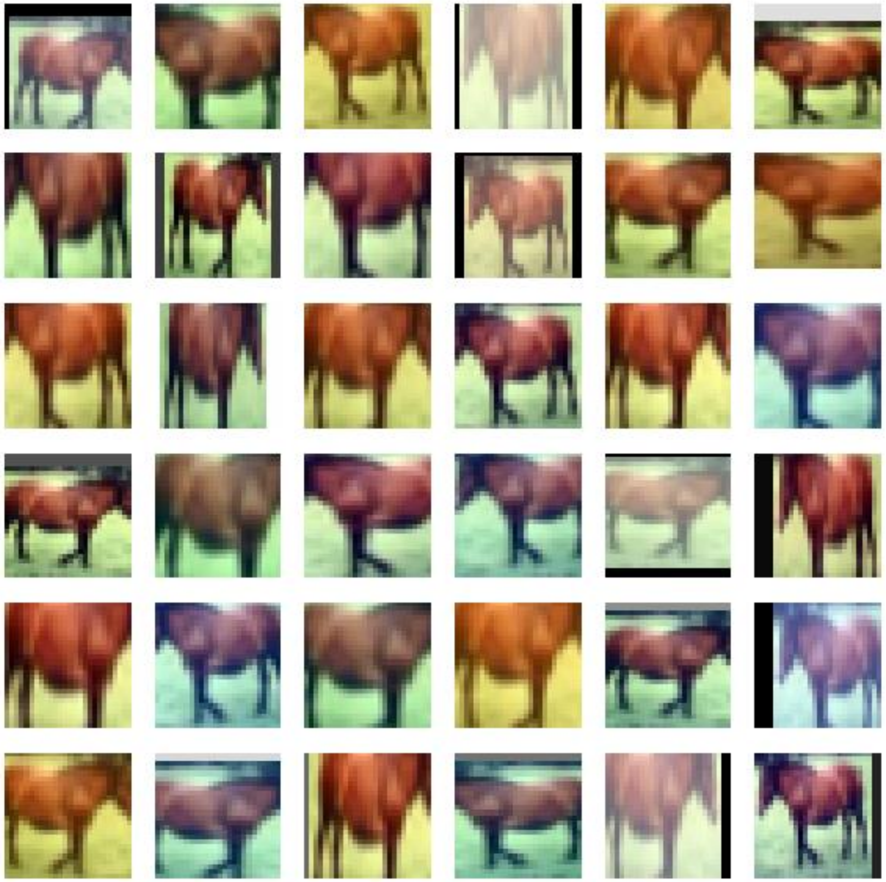
  - Flipping

  - Color PCA

Image source: Lucas Beyer

Data Augmentation

- Effect
  - Much larger training set
  - Robustness against expected variations
- During testing
  - When cropping was used during training, need to again apply crops to get same image size.
  - Beneficial to also apply flipping during test.
  - Applying several ColorPCA variations can bring another ~1% improvement, but at a significantly increased runtime.



Augmented training data (from one original image)

Image source: Lucas Beyer

Glorot Initialization

[Glorot & Bengio, '10]

- Variance of neuron activations
  - Suppose we have an input X with n components and a linear neuron with random weights W that spits out a number Y.
  - We *want the variance of the input and output of a unit to be the same*, therefore $n \operatorname{Var}(W_i)$ should be 1. This means

$$\operatorname{Var}(W_i) = \frac{1}{n} = \frac{1}{n_{\text{in}}}$$

  - Or for the backpropagated gradient

$$\operatorname{Var}(W_i) = \frac{1}{n_{\text{out}}}$$

  - As a compromise, Glorot & Bengio propose to use

$$\operatorname{Var}(W) = \frac{2}{n_{\text{in}} + n_{\text{out}}}$$

$\Rightarrow$ Randomly sample the initial weights with this variance.

He Initialization

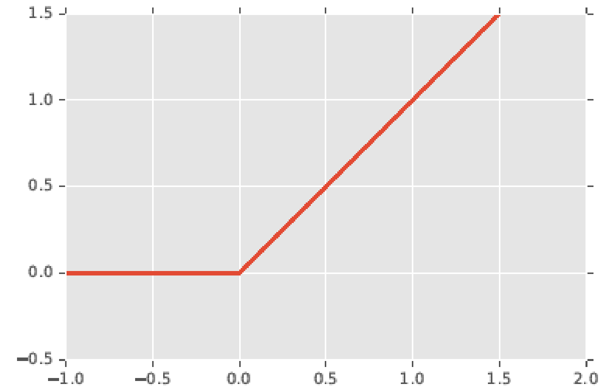
[He et al., '15]

- Extension of Glorot Initialization to ReLU units
  - Use Rectified Linear Units (ReLU)

$$g(a) = \max\{0, a\}$$

  - Effect: gradient is propagated with a constant factor

$$\frac{\partial g(a)}{\partial a} = \begin{cases} 1, & a > 0 \\ 0, & \text{else} \end{cases}$$



- Same basic idea: Output should have the input variance
  - However, the Glorot derivation was based on *tanh* units, linearity assumption around zero does not hold for *ReLU*.
  - He *et al.* made the derivations, proposed to use instead

$$\mathrm{Var}(W) = \frac{2}{n_{\text{in}}}$$

Practical Advice

- Initializing the weights
  - Draw them randomly from a zero-mean distribution.
  - Common choices in practice: Gaussian or uniform.
  - Common trick: add a small positive bias $(+\varepsilon)$ to avoid units with ReLu nonlinearities getting stuck-at-zero.

- When sampling weights from a uniform distribution $[a,b]$
  - Keep in mind that the standard deviation is computed as

$$\sigma^2 = \frac{1}{12}(b-a)^2$$

  - Glorot initialization with uniform distribution

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}, \frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}\right]$$

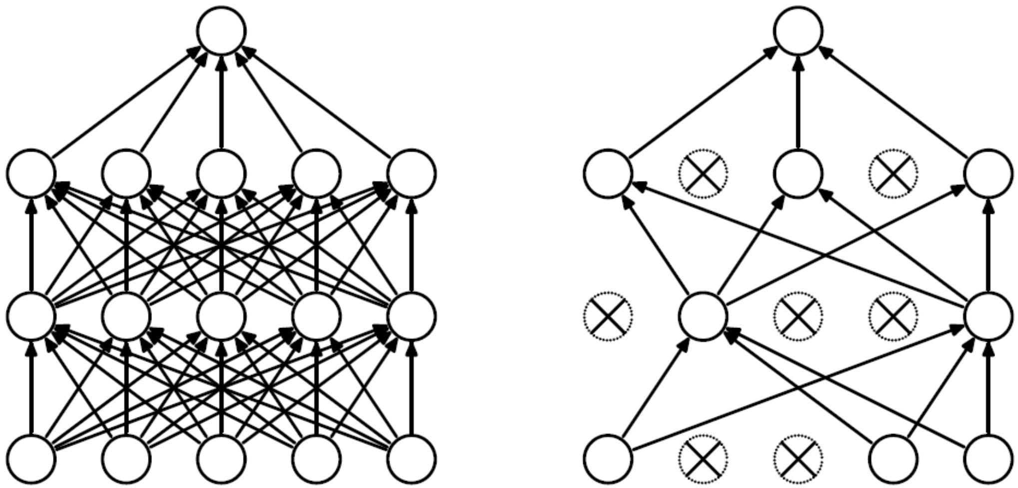
Batch Normalization

[Ioffe & Szegedy '14]

- Motivation
  - Optimization works best if all inputs of a layer are normalized.
- Idea
  - Introduce intermediate layer that centers the activations of the previous layer per minibatch.
  - I.e., perform transformations on all activations and undo those transformations when backpropagating gradients
  - Complication: centering + normalization also needs to be done at test time, but minibatches are no longer available at that point.
    - Learn the normalization parameters to compensate for the expected bias of the previous layer (usually a simple moving average)
- Effect
  - Much improved convergence (but parameter values are important!)
  - Widely used in practice

Dropout

[Srivastava, Hinton ’12]



(a) Standard Neural Net (b) After applying dropout.

- Idea
  - Randomly switch off units during training.
  - Change network architecture for each data point, effectively training many different variants of the network.
  - When applying the trained network, multiply activations with the probability that the unit was set to zero.

  $\Rightarrow$ Greatly improved performance

Choosing the Right Learning Rate

- Behavior for different learning rates

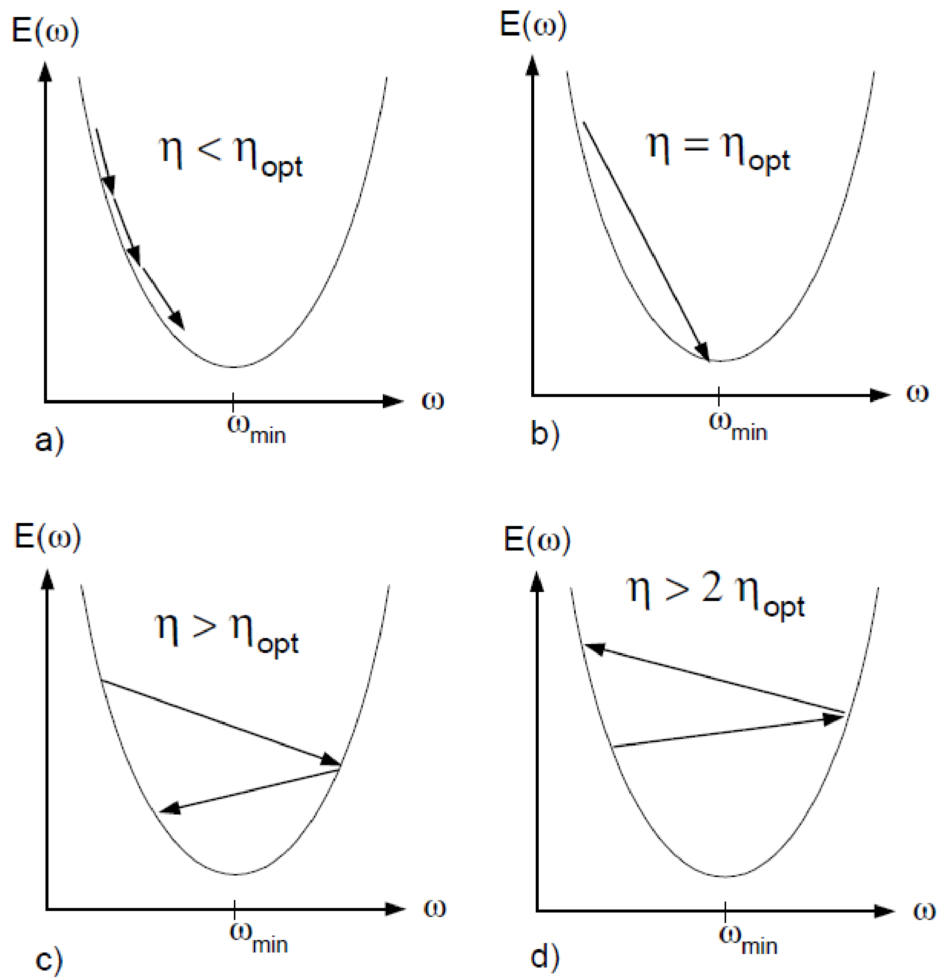


Image source: Yann LeCun et al., Efficient BackProp (1998)

Learning Rate vs. Training Error

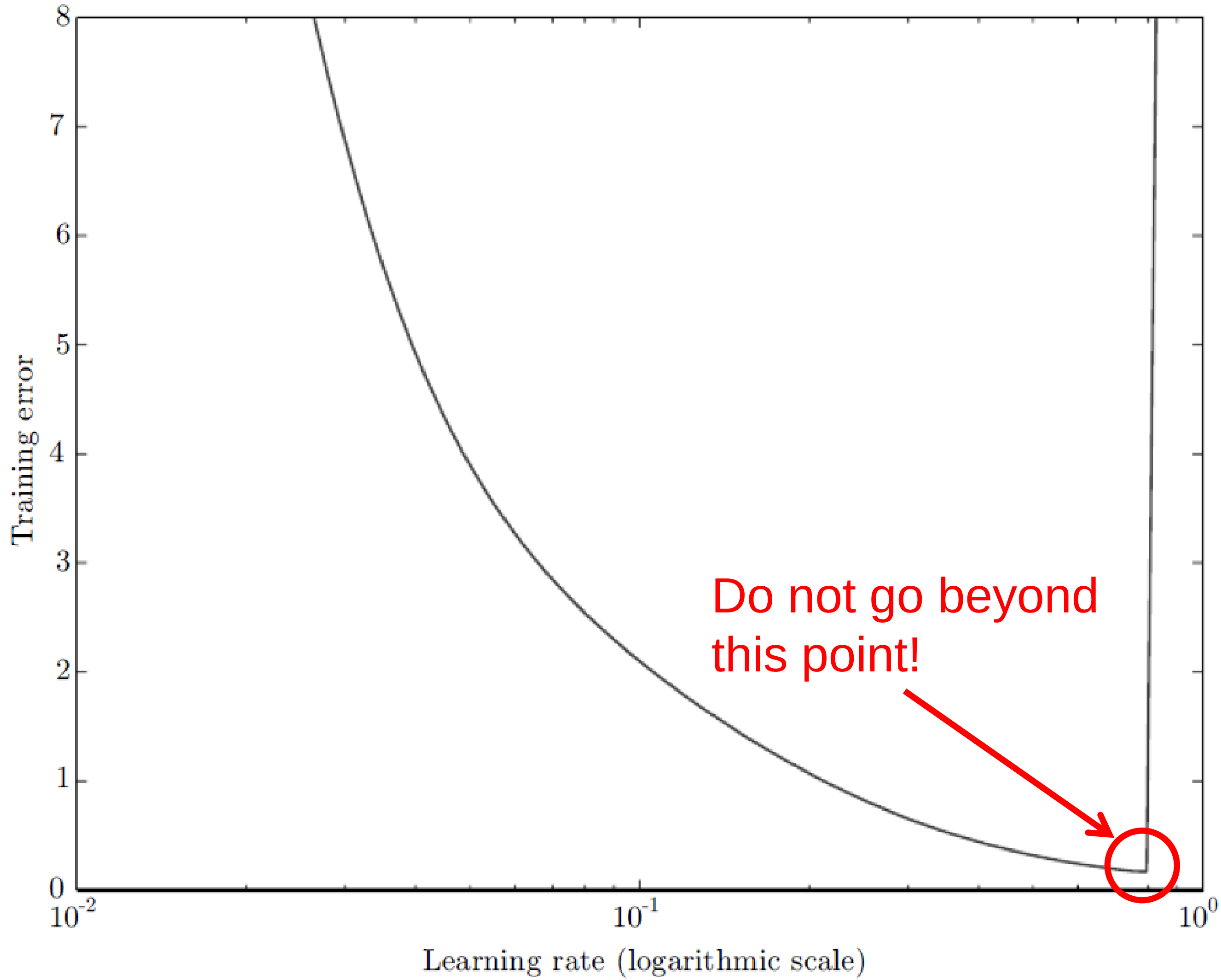
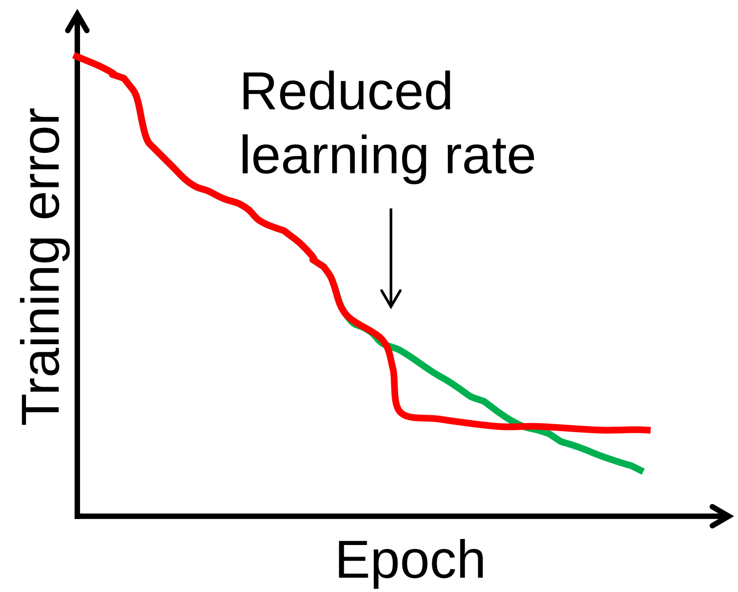


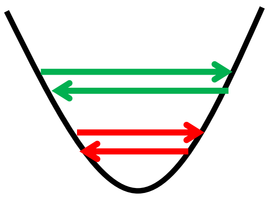
Image source: Goodfellow & Bengio book

Reducing the Learning Rate

- Final improvement step after convergence is reached
  - Reduce learning rate by a factor of 10.
  - Continue training for a few epochs.
  - Do this 1-3 times, then stop training.



- Effect
  - Turning down the learning rate will reduce the random fluctuations in the error due to different gradients on different minibatches.



- *Be careful: Do not turn down the learning rate too soon!*
  - Further progress will be much slower/impossible after that.

Summary

- Deep multi-layer networks are very powerful.
- But training them is hard!
  - Complex, non-convex learning problem
  - Local optimization with stochastic gradient descent
- Main issue: getting good gradient updates for the lower layers of the network
  - Many seemingly small details matter!
  - Weight initialization, normalization, data augmentation, choice of nonlinearities, choice of learning rate, choice of optimizer,…

$\Rightarrow$ *Exercise 5 will guide you through those steps. Take advantage of it!*

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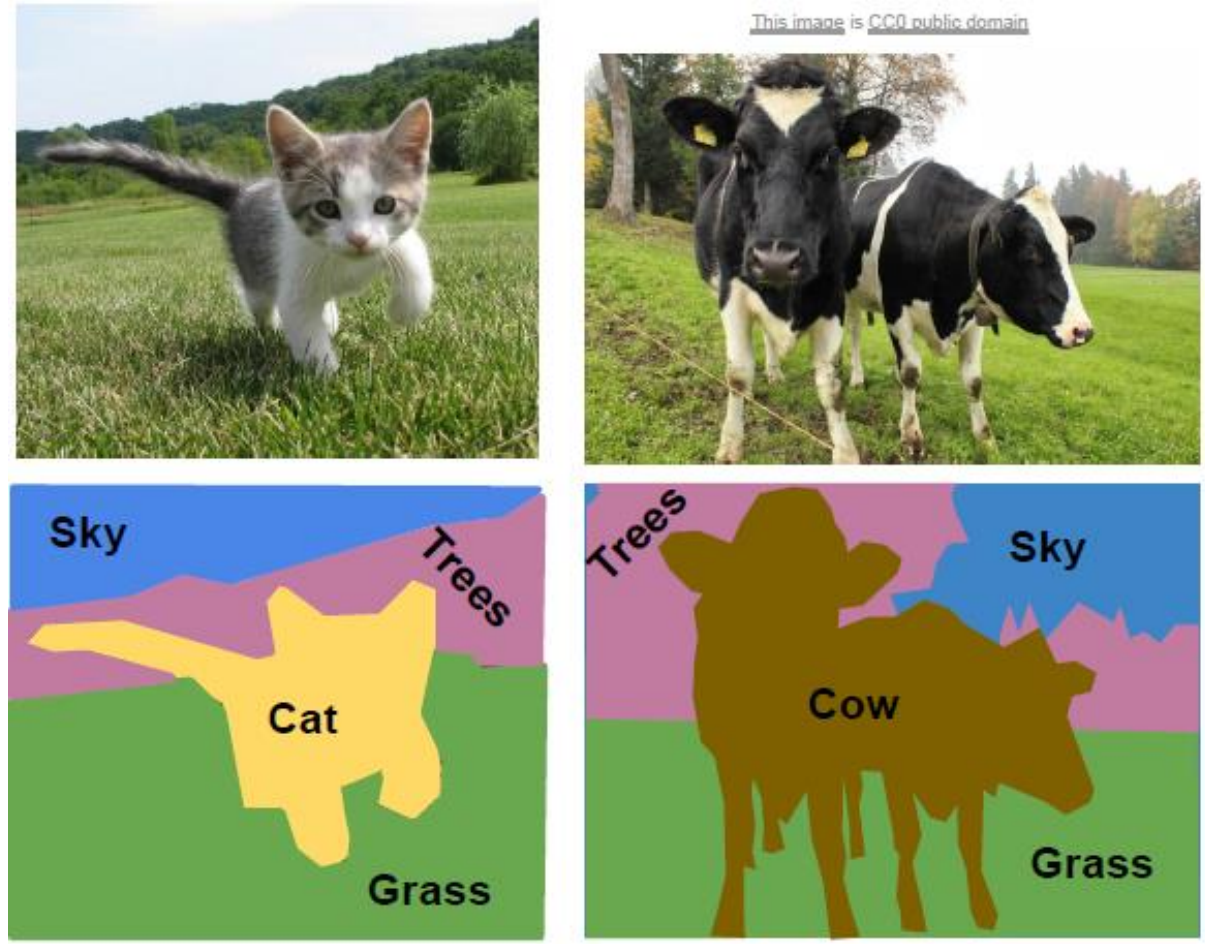
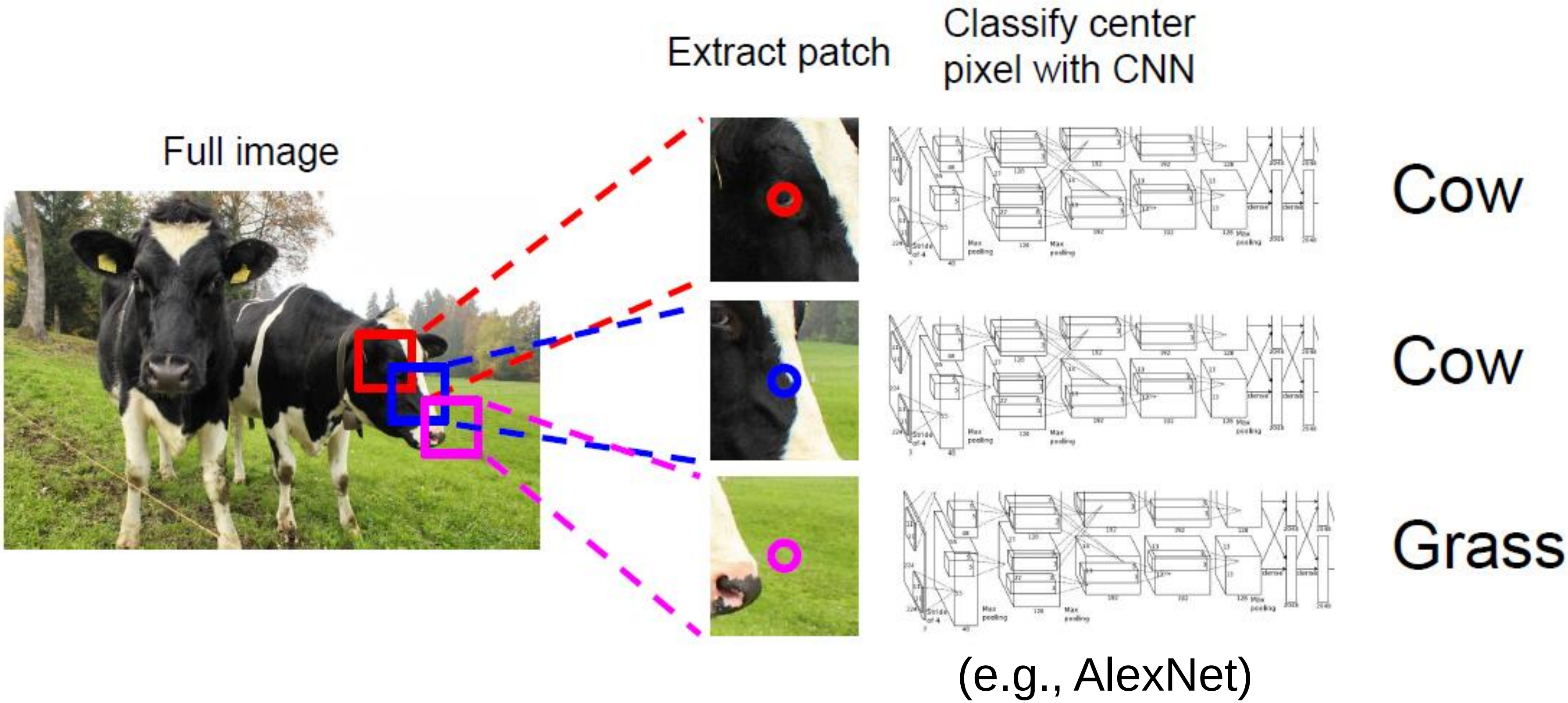
  - Batch Normalization
  - Dropout
  - Learning Rate Schedules
- CNNs for Segmentation
  - Fully Convolutional Networks (FCN)
  - Encoder-Decoder architecture
  - Transpose convolutions
  - Skip connections
- CNNs for Human Body Pose Estimation

Semantic Segmentation

- Semantic Segmentation
  - Label each pixel in the image with a category label
  - Don’t differentiate instances, only care about pixels
- Instance segmentation
  - Also give an instance label per pixel

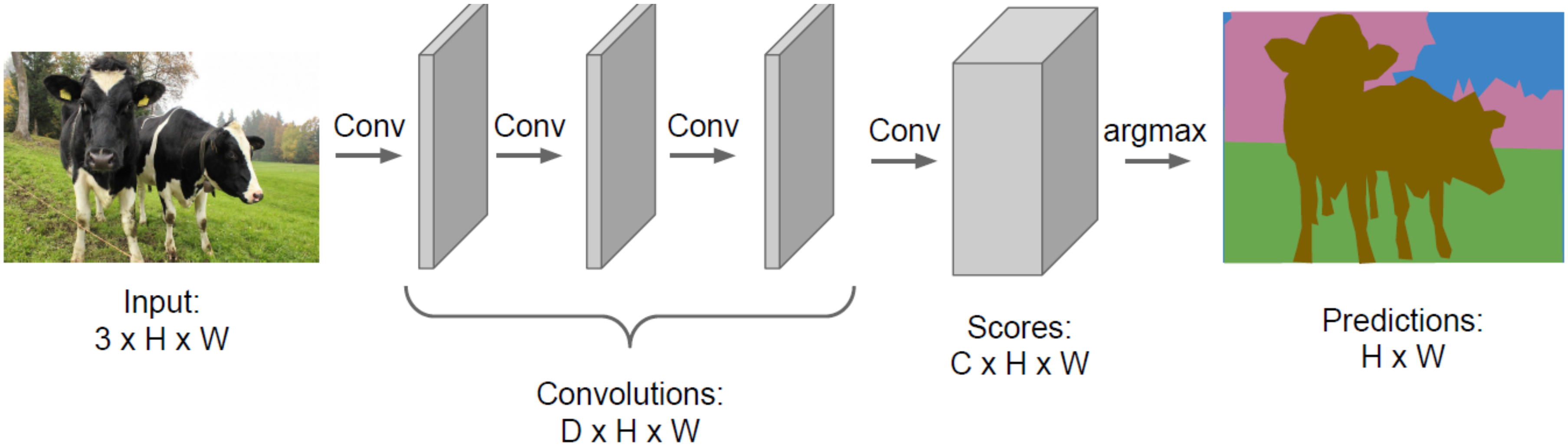


Segmentation Idea: Sliding Window



- Problem
  - Very inefficient
  - No reuse of features between shared patches

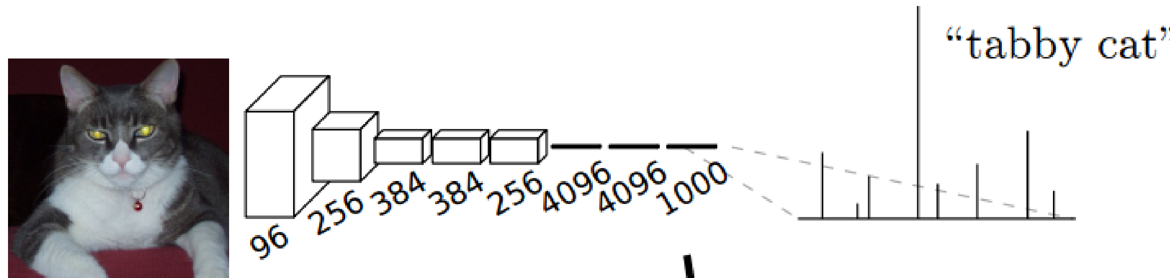
Segmentation Idea: Fully-Convolutional Nets



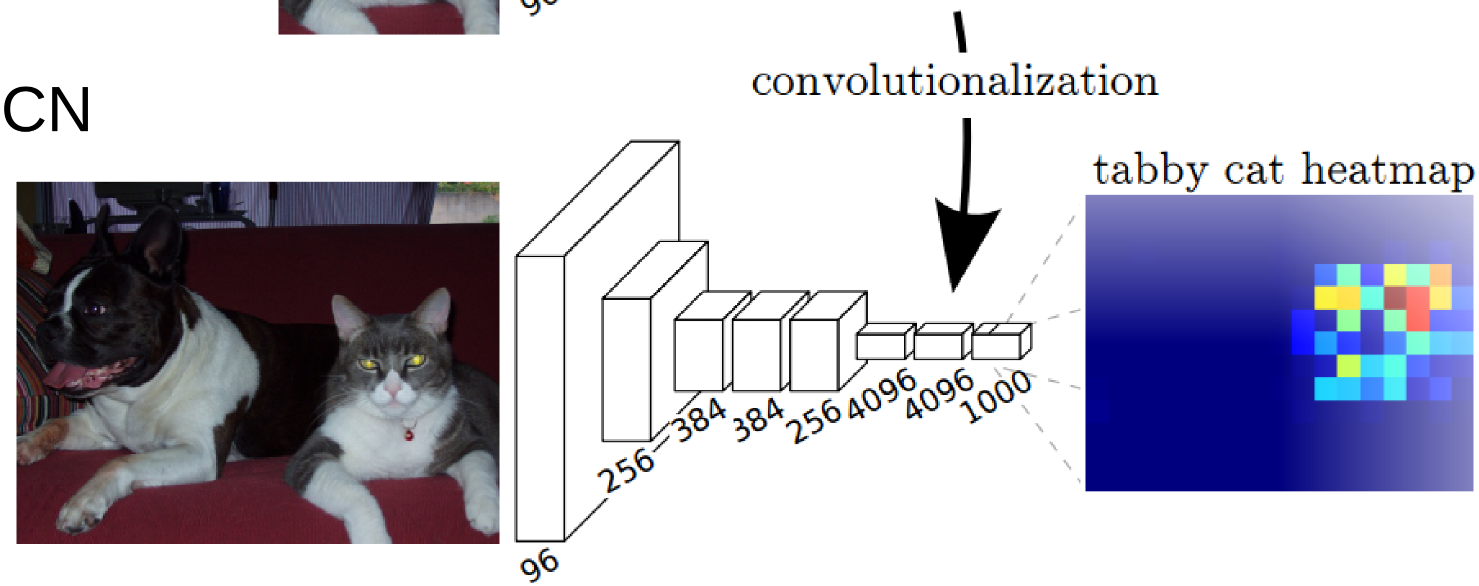
- Design a network as a sequence of convolutional layers
  - To make predictions for all pixels at once
  - Fully Convolutional Networks (FCNs)
    - All operations formulated as convolutions
    - Fully-connected layers become 1×1 convolutions
    - Advantage: can process arbitrarily sized images

CNNs vs. FCNs

- CNN



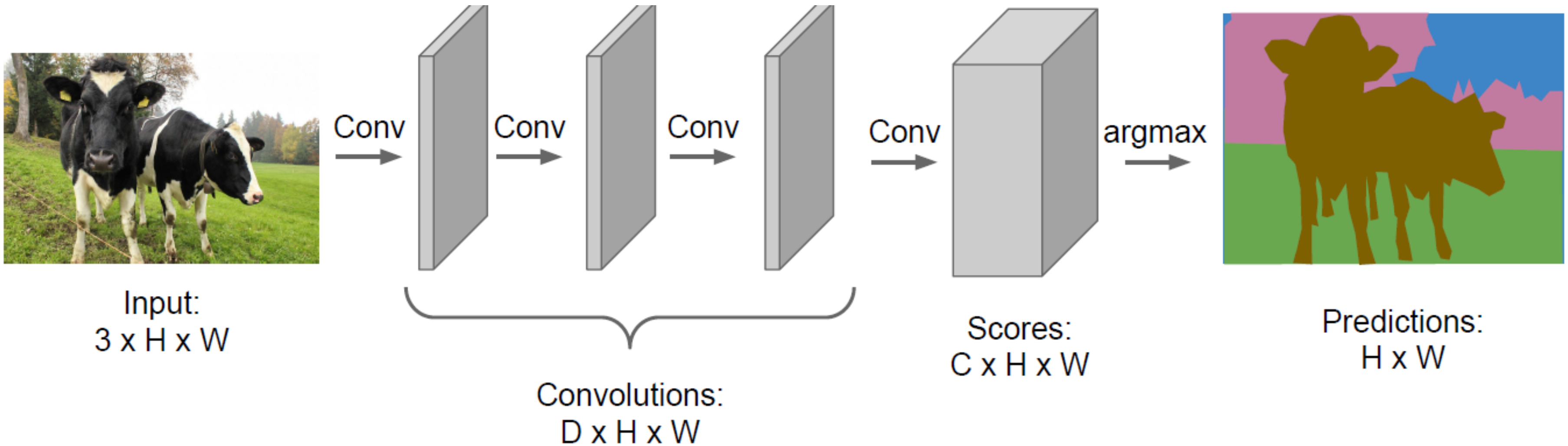
- FCN



- Intuition
  - Think of FCNs as performing a sliding-window classification, producing a heatmap of output scores for each class
  - But: more efficient, since computations are reused between windows

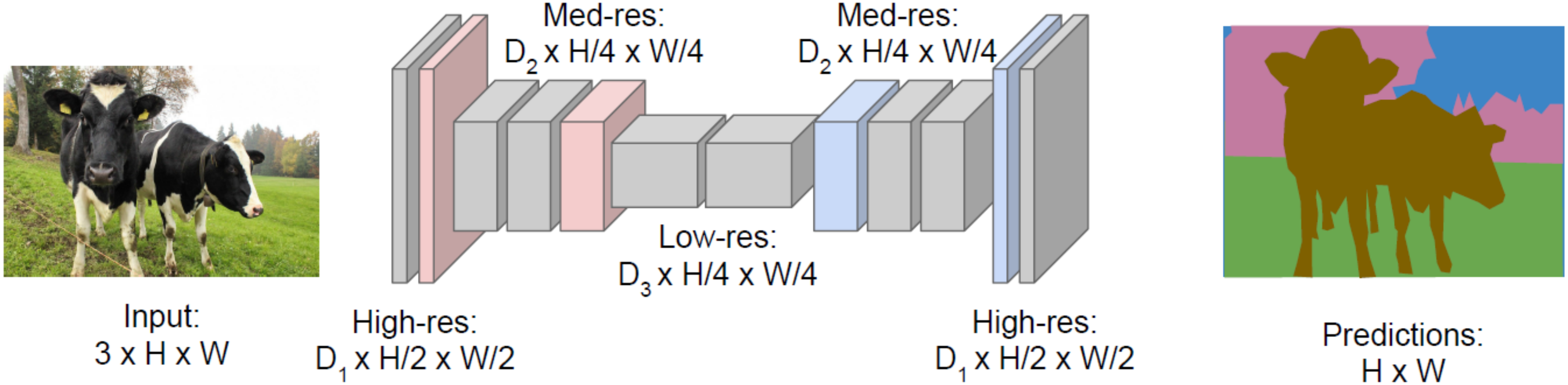
Image source: Long, Shelhamer, Darrell

Segmentation Idea: Fully-Convolutional Nets



- Design a network as a sequence of convolutional layers
  - To make predictions for all pixels at once
- Problem
  - Convolutions at original image resolution will be very expensive!

Segmentation Idea: Fully-Convolutional Nets



- Design a network as a sequence of convolutional layers
  - With downsampling and upsampling inside the network!
  - Downsampling
    - Pooling, strided convolution
  - Upsampling
    - ???

In-Network Upsampling: "Unpooling"

Nearest Neighbor

Input: 2 x 2

1	2
3	4

→

Output: 4 x 4

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

"Bed of Nails"

Input: 2 x 2

1	2
3	4

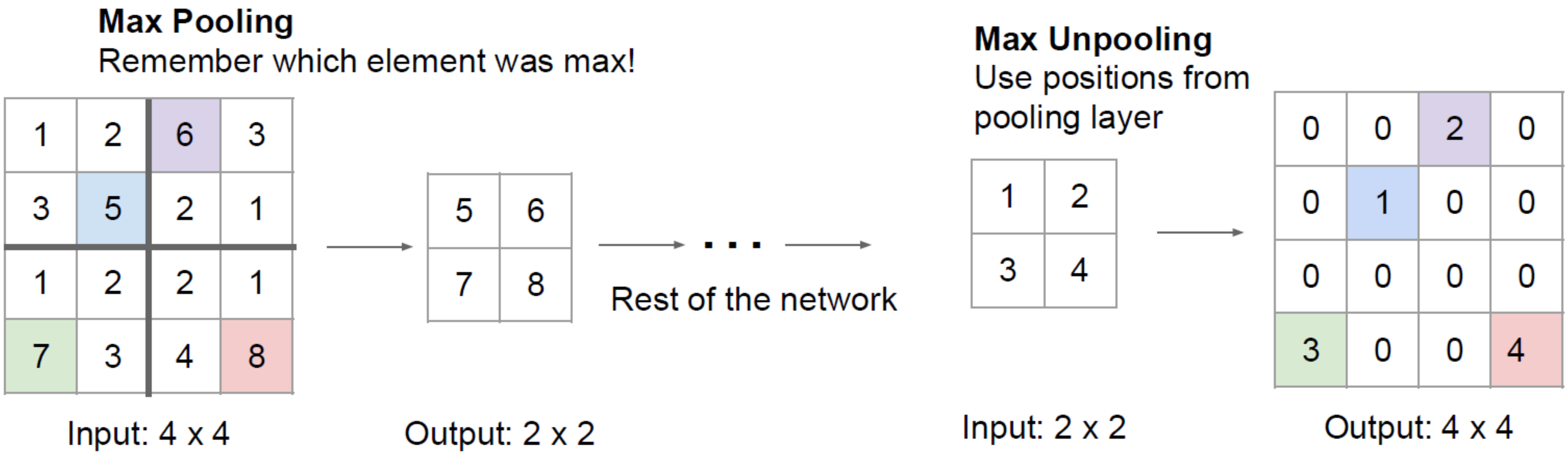
→

Output: 4 x 4

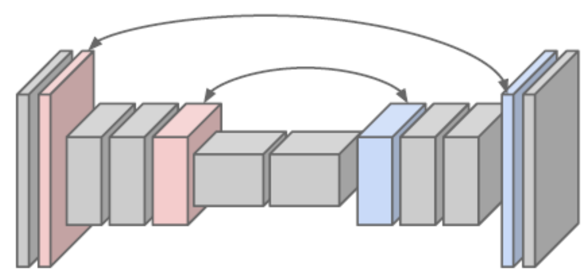
1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

- Nearest-Neighbor
  - Simplest version
  - Problem: blocky output structure
- "Bed of Nails"
  - Preserve fine-grained structure of the output
  - Problem: fixed location for upsampled stimuli

In-Network Upsampling: “Max Unpooling”

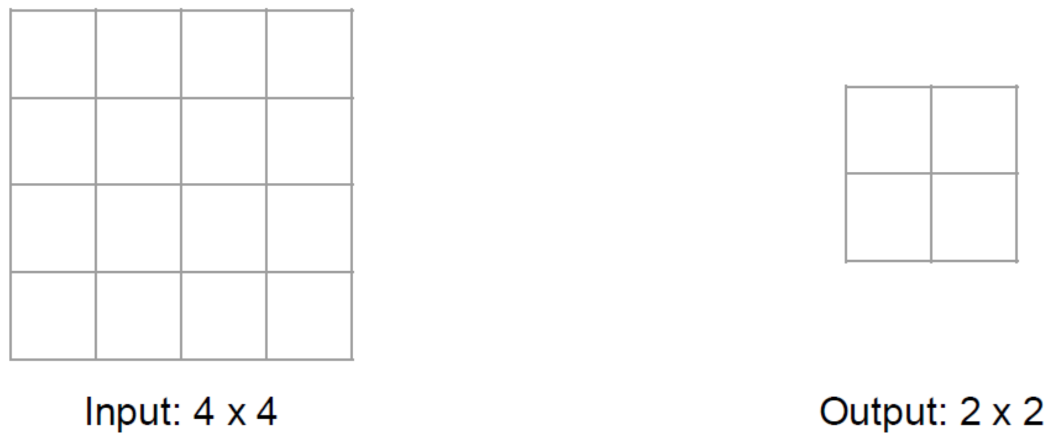


- Max Unpooling
  - Use corresponding pairs of downsampling and upsampling layers together
  - Remember which elements were max



Learnable Upsampling: Transpose Convolution

- Recall: Normal convolution, stride 2, pad 1

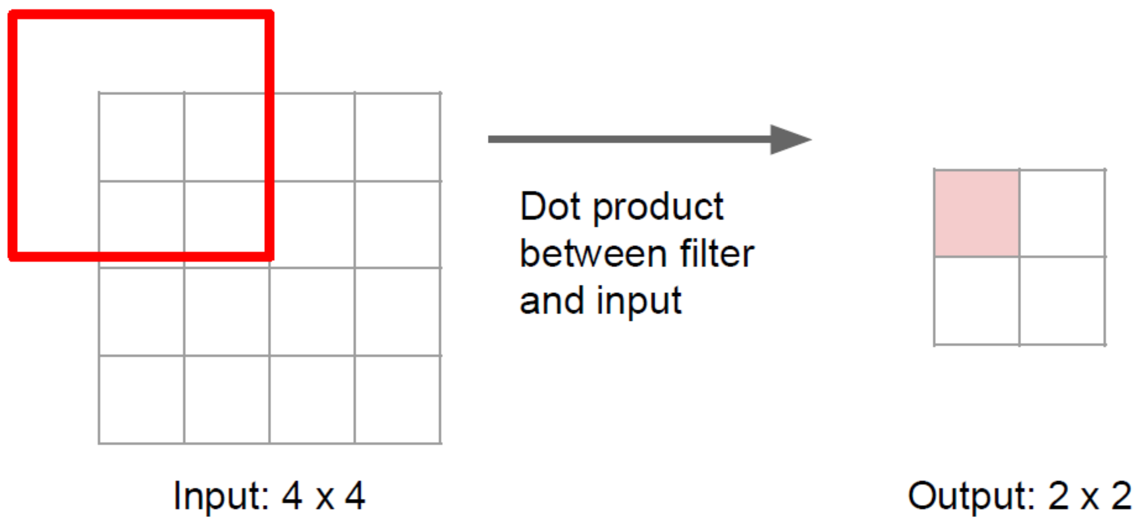


- Effect
  - Filter moves 2 pixels in the input for every one pixel in the output
  - Stride gives ration between movement in input and output

Slide credit: FeiFei Li

Learnable Upsampling: Transpose Convolution

- Recall: Normal convolution, stride 2 pad 1



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Learnable Upsampling: Transpose Convolution

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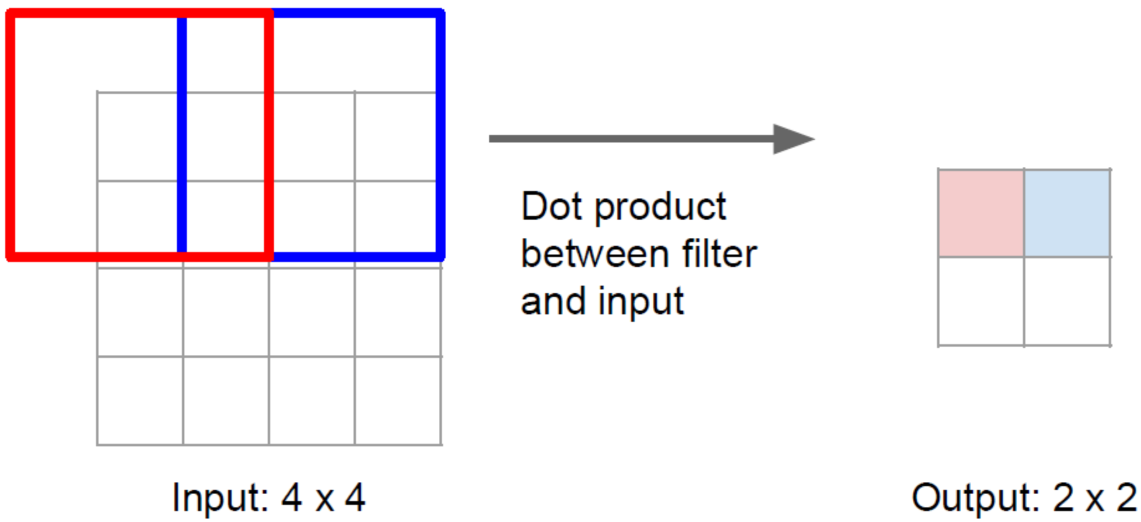
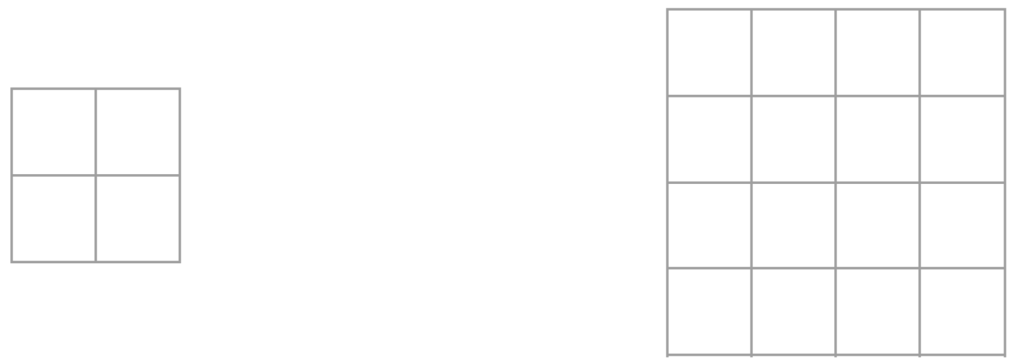


- Effect
  - Filter moves 2 pixels in the input for every one pixel in the output
  - Stride gives ration between movement in input and output

Slide credit: FeiFei Li

Learnable Upsampling: Transpose Convolution

- Now: 3x3 transpose convolution, <u>stride 2</u> pad 1

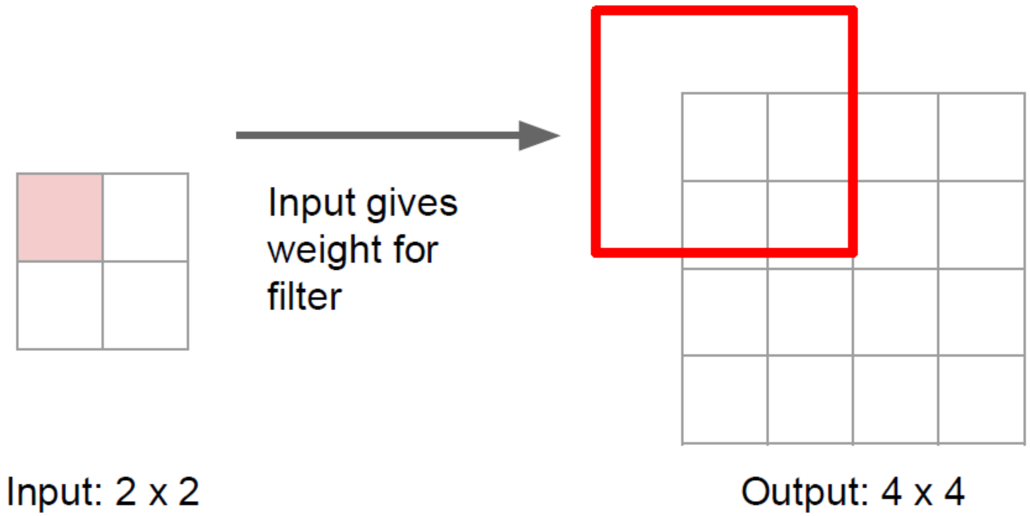


Input: 2 x 2

Output: 4 x 4

Learnable Upsampling: Transpose Convolution

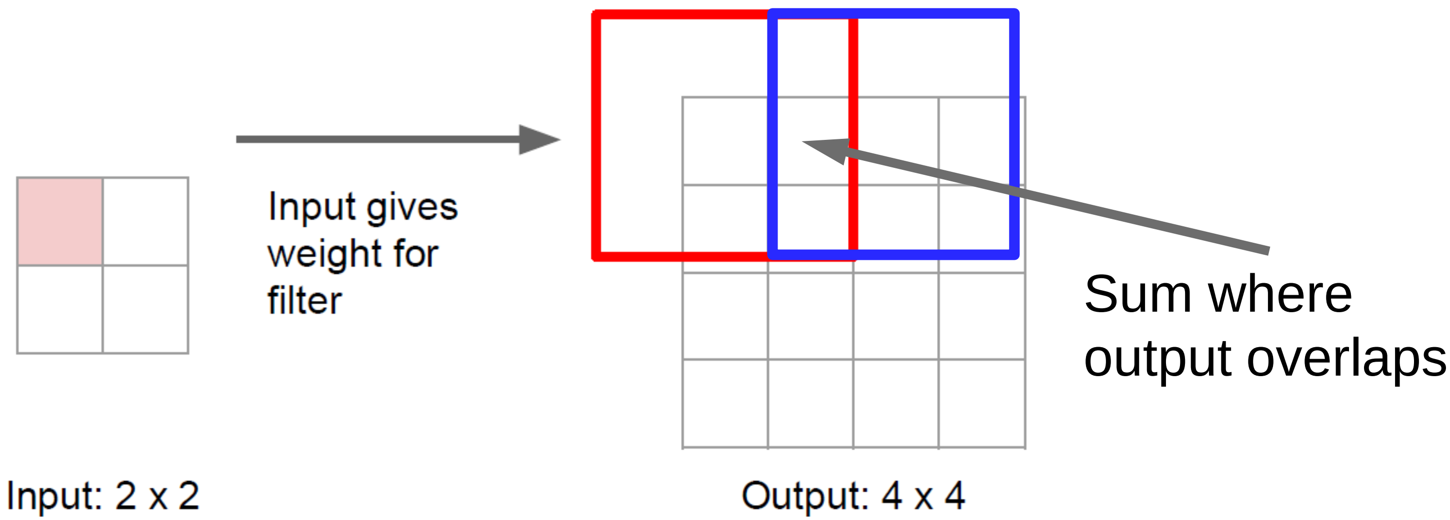
- Now: 3x3 transpose convolution, stride 2 pad 1



Slide credit: FeiFei Li

Learnable Upsampling: Transpose Convolution

- Now: 3x3 transpose convolution, stride 2 pad 1

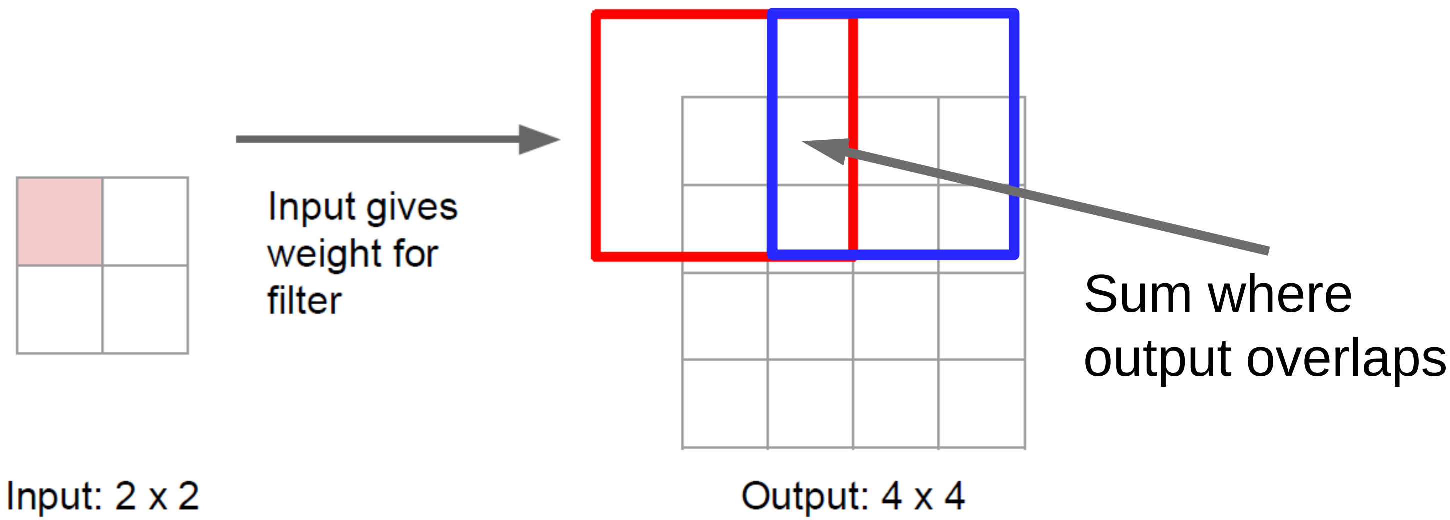


- Effect
  - Filter moves 2 pixels in the *output* for every one pixel in the *input*
  - Stride gives ration between movement in output and input

Slide credit: FeiFei Li

Learnable Upsampling: Transpose Convolution

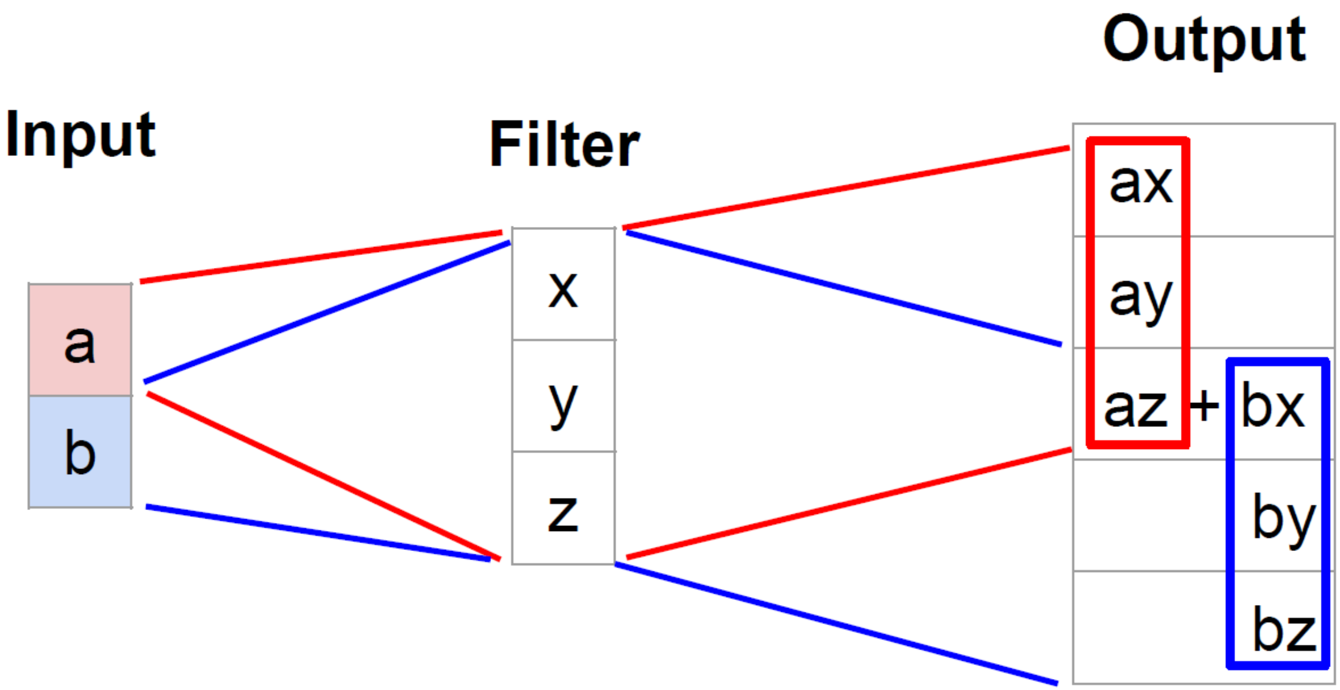
- Now: 3x3 transpose convolution, <u>stride 2</u> pad 1



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

Slide credit: FeiFei Li

Learnable Upsampling: 1D Example



- Observations
  - Output contains copies of the filter weighted by the input, summing overlaps in the output
  - Need to crop one pixel from output to make output exactly 2x input

Slide credit: FeiFei Li

Convolution as Matrix Multiplication (1D Example)

- Express convolution in terms of matrix multiplication
  - Example:
    - 1D conv
    - Kernel size = 3
    - Stride 1, padding = 1

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

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

- Convolution transpose multiplies by the transpose of the same matrix
  - When stride = 1, convolution transpose is just a regular convolution (with different padding rules)

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

$$\begin{bmatrix} x & 0 & 0 & 0 \\ y & x & 0 & 0 \\ z & y & x & 0 \\ 0 & z & y & x \\ 0 & 0 & z & y \\ 0 & 0 & 0 & z \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} ax \\ ay + bx \\ az + by + cx \\ bz + cy + dx \\ cz + dy \\ dz \end{bmatrix}$$

Slide credit: FeiFei Li

Convolution as Matrix Multiplication (1D Example)

- Express convolution in terms of matrix multiplication
  - Example:
    - 1D conv
    - Kernel size = 3
    - Stride 2, padding = 1

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

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

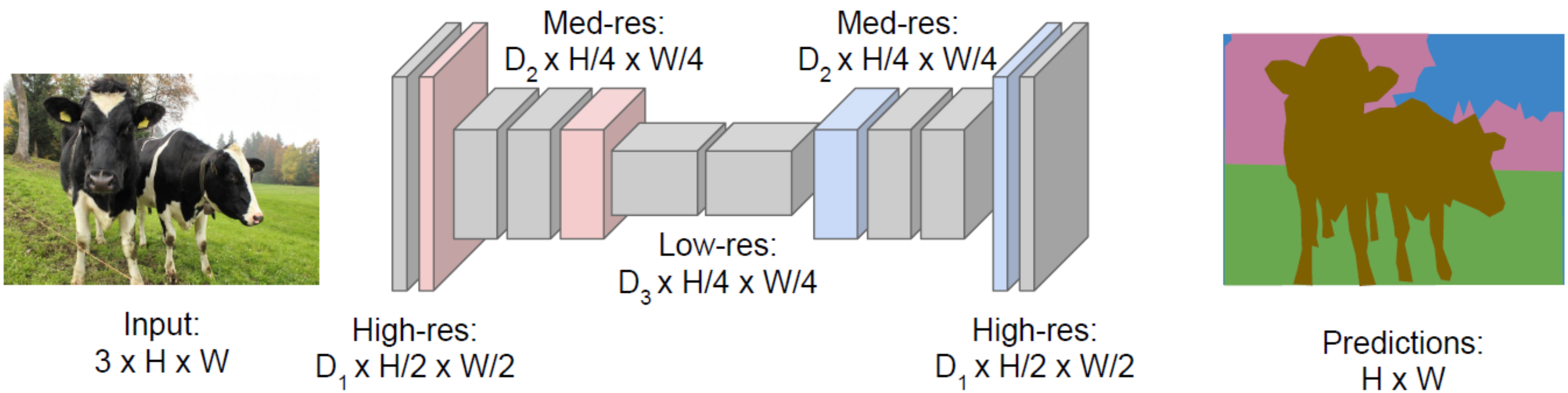
- Convolution transpose multiplies by the transpose of the same matrix
  - When stride > 1, convolution transpose is **no longer a normal convolution!**

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

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

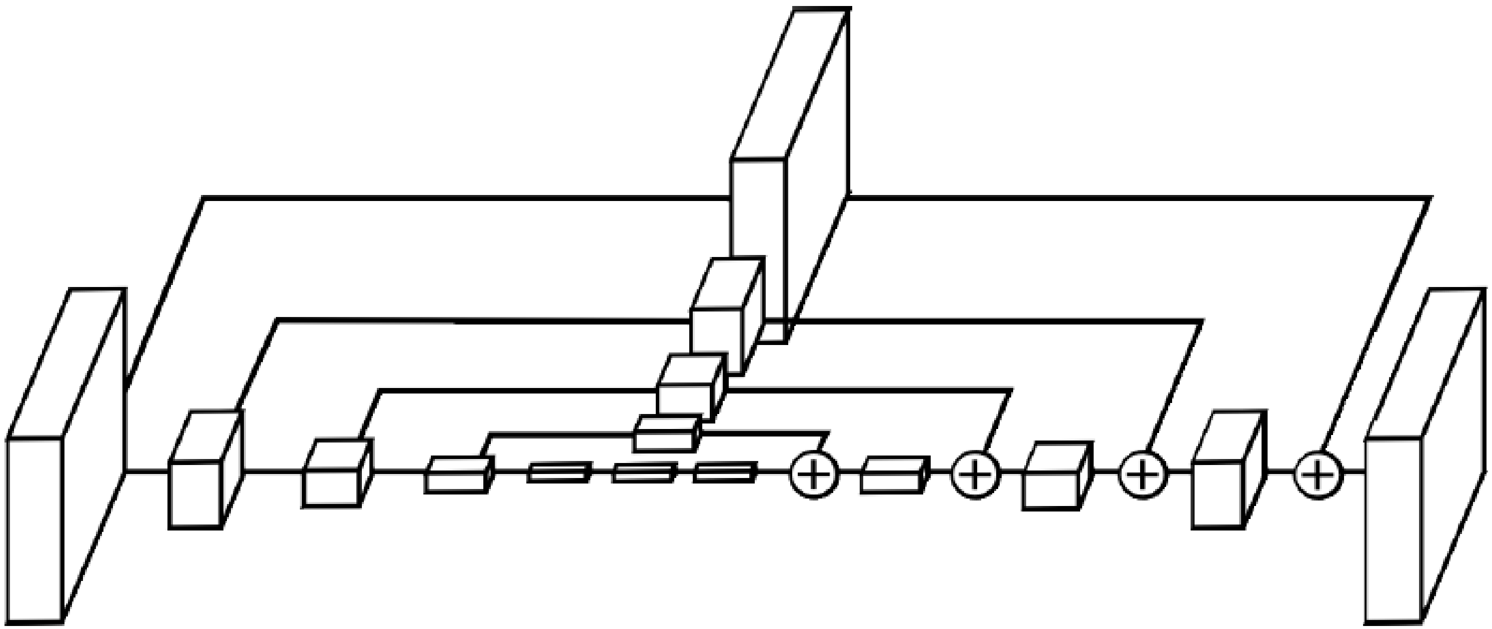
Slide credit: FeiFei Li

Segmentation Idea: Fully-Convolutional Nets



- Design a network as a sequence of convolutional layers
  - With downsampling and upsampling inside the network!
  - Downsampling
    - Pooling, strided convolution
  - Upsampling
    - Unpooling or strided transpose convolution

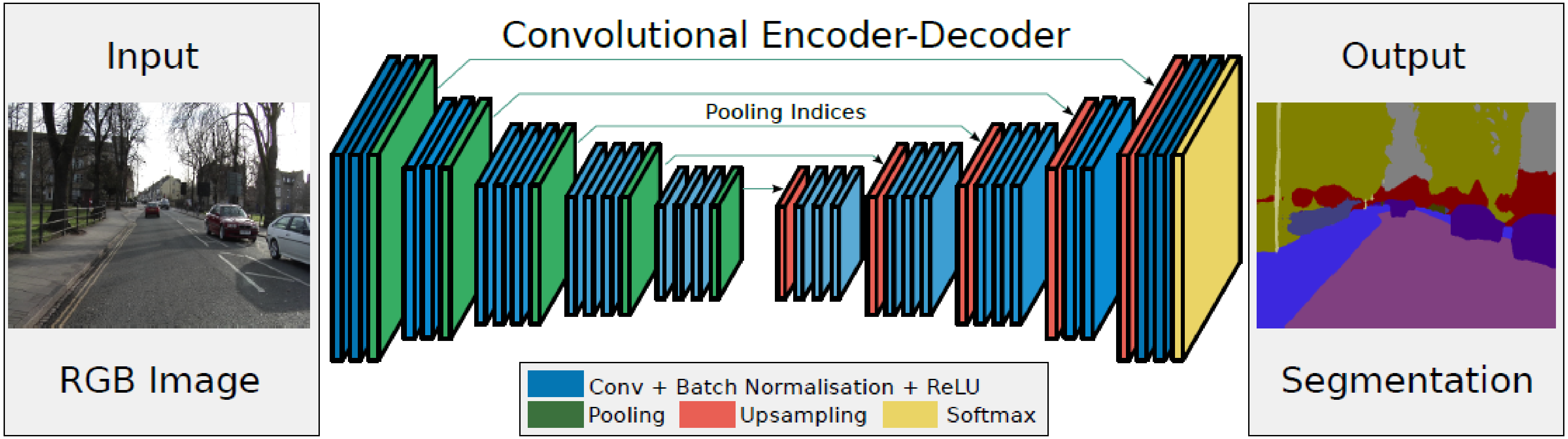
Extension: Skip Connections



- Encoder-Decoder Architecture with skip connections
  - Problem: downsampling loses high-resolution information
  - Use skip connections to preserve this higher-resolution information

Image source: Newell et al.

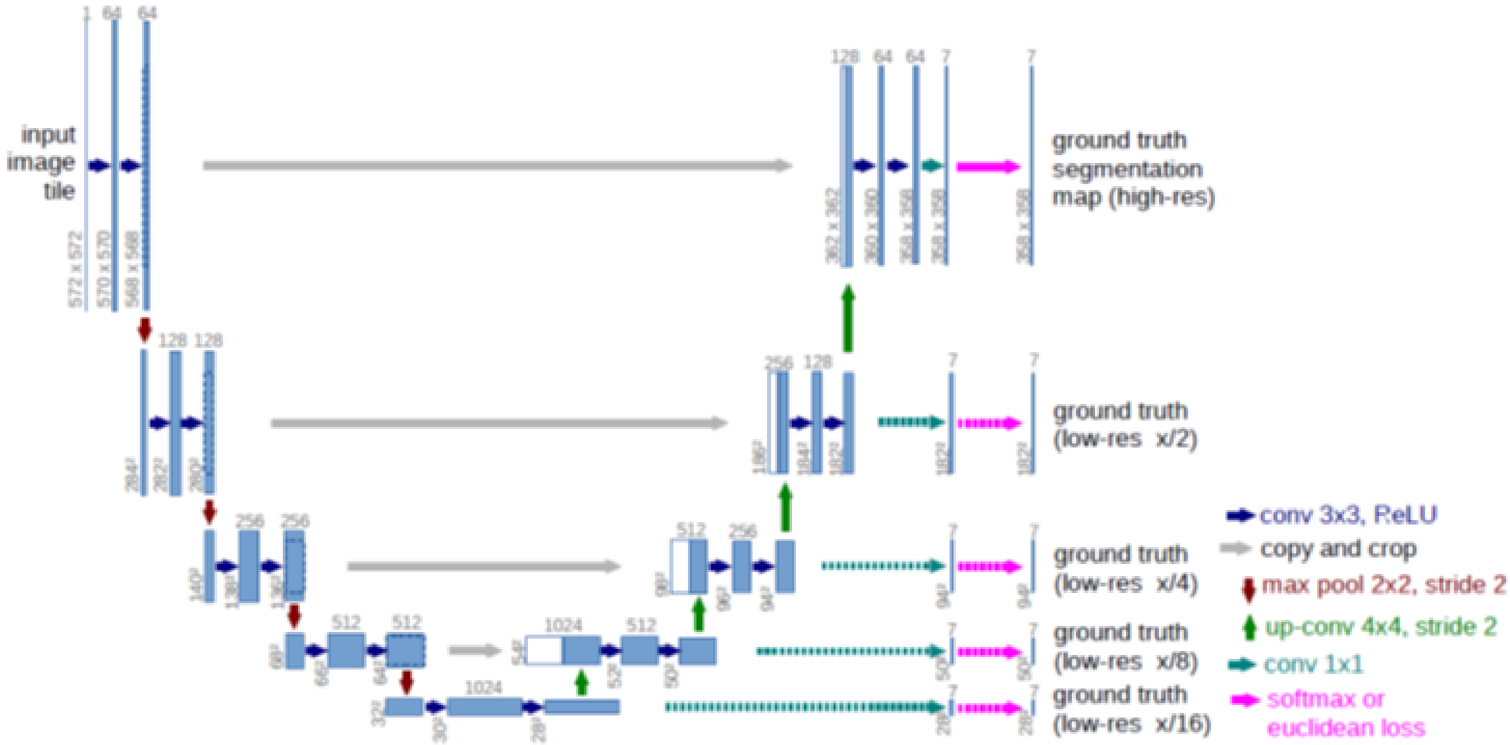
Example: SegNet



- SegNet
  - Encoder-Decoder architecture with skip connections
  - Encoder based on VGG-16
  - Decoder using Max Unpooling
  - Output with K-class Softmax classification

V. Badrinarayanan, A. Kendall, R. Cipolla, SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation, arXiv 1511.00561, IEEE Trans. PAMI 2017.

Example: U-Net



- U-Net
  - Similar idea, popular in biomedical image processing
  - Encoder-Decoder architecture with skip connections

O. Ronneberger, P. Fischer, T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

Semantic Segmentation

- Recent results
  - Based on an extension of ResNets for high-resolution segmentation

[Pohlen, Hermans, Mathias, Leibe, CVPR 2017]

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  - Learning Rate Schedules
- CNNs for Segmentation
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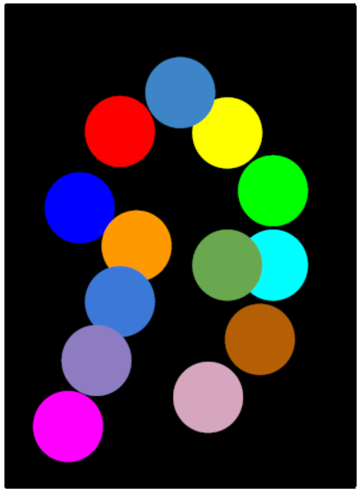
FCNs for Human Pose Estimation

- Input data

Image

Keypoints

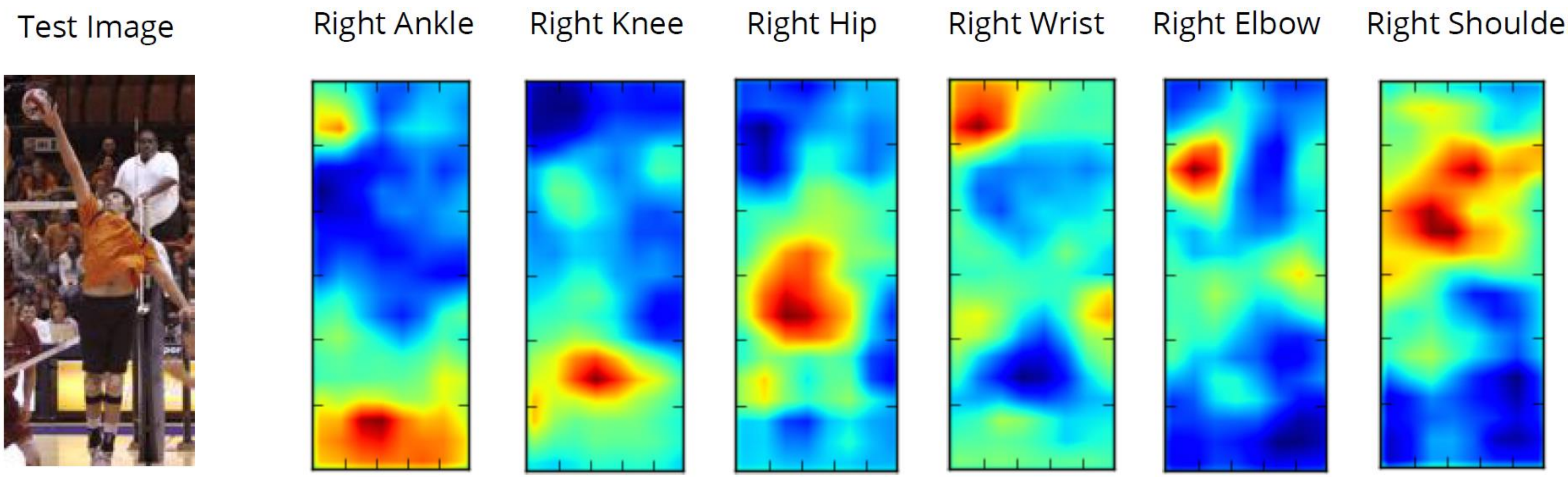
Labels



- Task setup
  - Annotate images with keypoints for skeleton joints
  - Define a target disk around each keypoint with radius r
  - Set the ground-truth label to 1 within each such disk
  - Infer heatmaps for the joints as in semantic segmentation

Slide adapted from Georgia Gkioxari

Heat Map Predictions from FCN



Slide adapted from Georgia Gkioxari

Example Results: Human Pose Estimation

[Rafi, Gall, Leibe, BMVC 2016]

More Recently: Parts Affinity Fields

- https://www.youtube.com/watch?v=pW6nZXeWlGM

References

- ReLu
  - X. Glorot, A. Bordes, Y. Bengio, Deep sparse rectifier neural networks, AISTATS 2011.
- Initialization
  - X. Glorot, Y. Bengio, Understanding the difficulty of training deep feedforward neural networks, AISTATS 2010.
  - K. He, X.Y. Zhang, S.Q. Ren, J. Sun, Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification, ArXiV 1502.01852v1, 2015.
  - A.M. Saxe, J.L. McClelland, S. Ganguli, Exact solutions to the nonlinear dynamics of learning in deep linear neural networks, ArXiV 1312.6120v3, 2014.

References and Further Reading

- Batch Normalization
  - S. Ioffe, C. Szegedy, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, ArXiV 1502.03167, 2015.
- Dropout
  - N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, Dropout: A Simple Way to Prevent Neural Networks from Overfitting, JMLR, Vol. 15:1929-1958, 2014.

References: Computer Vision Tasks

- Semantic Segmentation
  - J. Long, E. Shelhamer, T. Darrell, Fully Convolutional Networks for Semantic Segmentation, CVPR 2015.
  - O. Ronneberger, P. Fischer, T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015
  - V. Badrinarayanan, A. Kendall, R. Cipolla, SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation, arXiv 1511.00561, IEEE Trans. PAMI 2017.
  - T-Y. Lin P. Dollar, R. Girshick, K. He, B. Hariharan, S. Belongie, Feature Pyramid Networks for Object Detection, CVPR 2017.
  - L-C. Chen, G. Papandreou, F. Schroff, H. Adam, Rethinking Atrous Convolutions for Semantic Segmentation, arXiv 1706.05587 2017.

References: Computer Vision Tasks

- Human Body Pose Estimation
  - A. Toshev, C. Szegedy, DeepPose: Human Pose Estimation via Deep Neural Networks, CVPR 2014.
  - S.E. Wei, V. Ramakrishna, T. Kanade, Y. Sheikh, Convolutional Pose Machines, CVPR 2016.
  - A. Newell, K. Yang, J. Deng, Stacked Hourglass Networks for Human Pose Estimation, ECCV 2016.
  - Z. Cao, T. Simon, S.-E. Wei, Y. Sheikh, Realtime Multi-Person 2D Pose Estimation using Parts Affinity Fields, CVPR 2017.
  - B. Xiao, H. Wu, Y. Wei, Simple Baselines for Human Pose Estimation and Tracking, ECCV 2018. (Code)