Pixel Labeling

EECS 442 – Jeong Joon Park

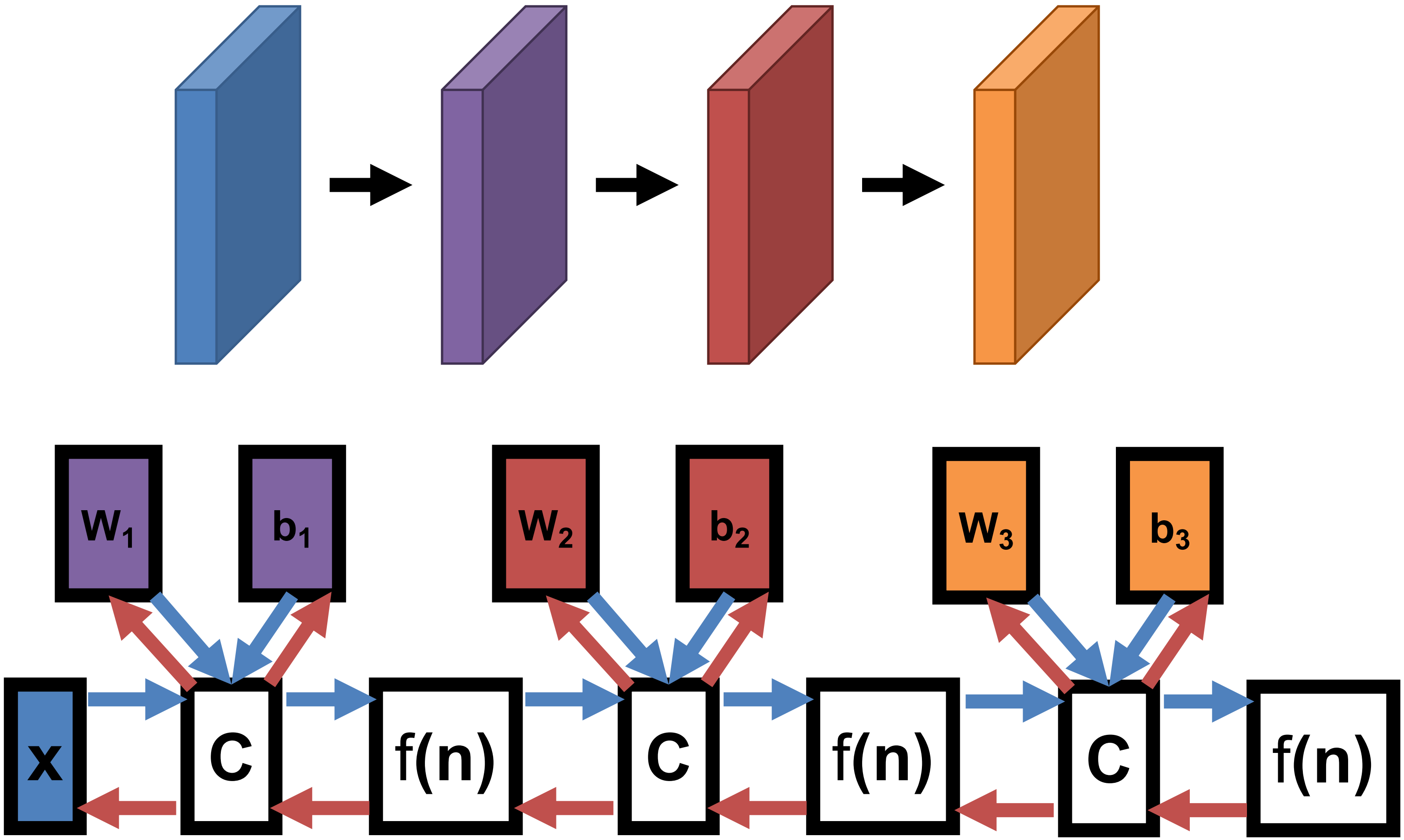
Winter 2024, University of Michigan

Administrivia

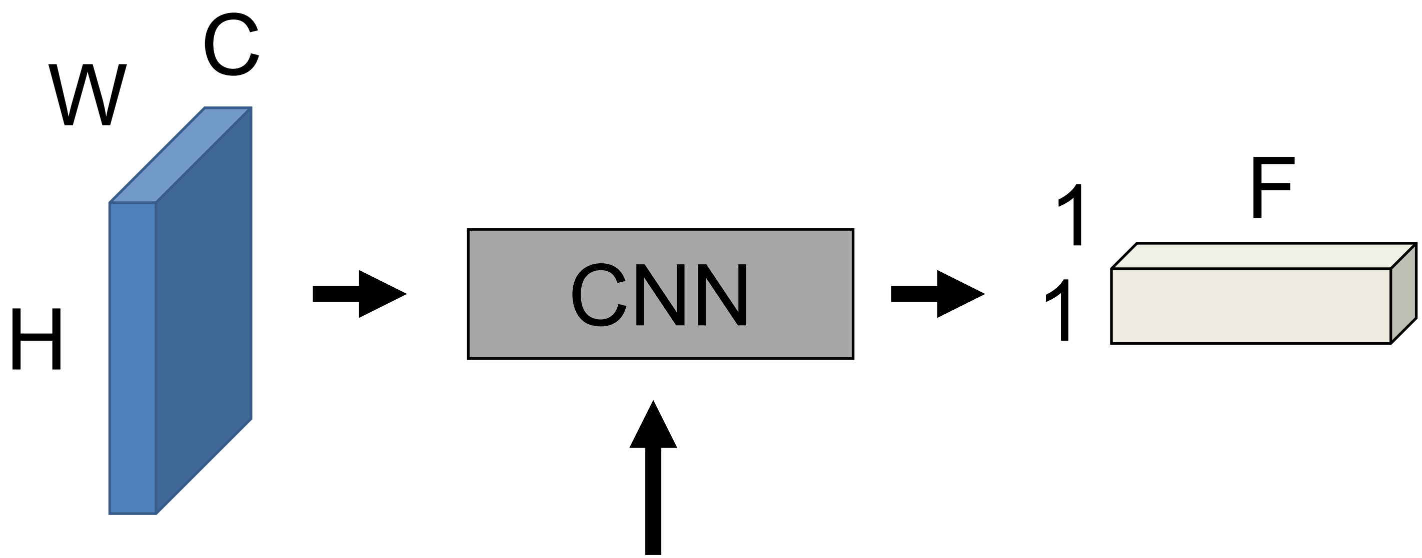
- Project team declaration: link
  Due this Wednesday. Email us if you have problem finding a team
- Briefly check your ideas at discussion/OH with GSIs or Me
- Project proposal (due Mar. 27th) – purely meant to help your scheduling
- Mid-term practice exam will be out on Wed

Recap

Convolutional Neural Network (CNN)



Mental Model



Function of the image that is parameterized by the convolutional filter weights and biases. We design the form of the function and fit the parameters to data.

Training a CNN

- Download a big dataset
- Initialize network weights randomly
- for epoch in range(epochs):
  - Shuffle dataset
  - for each minibatch in datsaet.:
    - Put data on GPU
    - Compute gradient with respect to loss
    - Update gradient with SGD

Training a CNN from Scratch

Need to start **w** somewhere

- AlexNet: weights ~ Normal(0,0.01), bias = 1
- “Xavier” or ”Kaiming” initialization: Initialize weights as a function of number of input/output channels

Take-home: important, but use defaults

Training a ConvNet

- Convnets typically have millions of parameters:
  - AlexNet: 62 million
  - VGG16: 138 million
  - ConvNeXt-L: 198M
- Convnets typically fit on ~1.2 million images
- Remember least squares: if we have fewer data points than parameters, we're in trouble
- Solution: need regularization / more data

Training a CNN – Weight Decay

SGD Update

$$\boldsymbol{w_{t+1}} = \boldsymbol{w_t} - \epsilon \frac{\partial L}{\partial \boldsymbol{w_t}}$$

+Weight Decay

$$\boldsymbol{w_{t+1}} = \boldsymbol{w_t} - \eta\epsilon\boldsymbol{w_t} - \epsilon \frac{\partial L}{\partial \boldsymbol{w_t}}$$

What does this remind you of?

Weight decay is similar to regularization but is not be the same for more complex optimization techniques.

See “Decoupled Weight Decay Regularization”, Loshchilov and Hutter.

Augmentataion

Horizontal Flip

Color Jitter

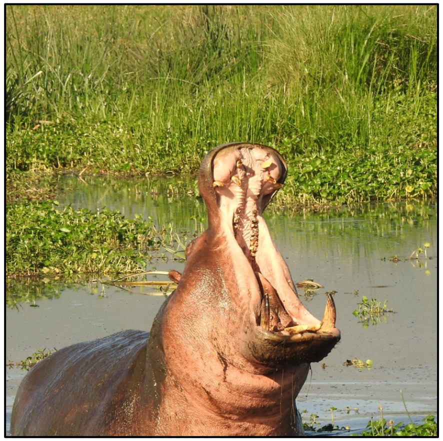


Image Cropping

Training a CNN –Augmentation

- Apply transformations that don't affect the output
- Produces more data but you have to be careful that it doesn't change the meaning of the output

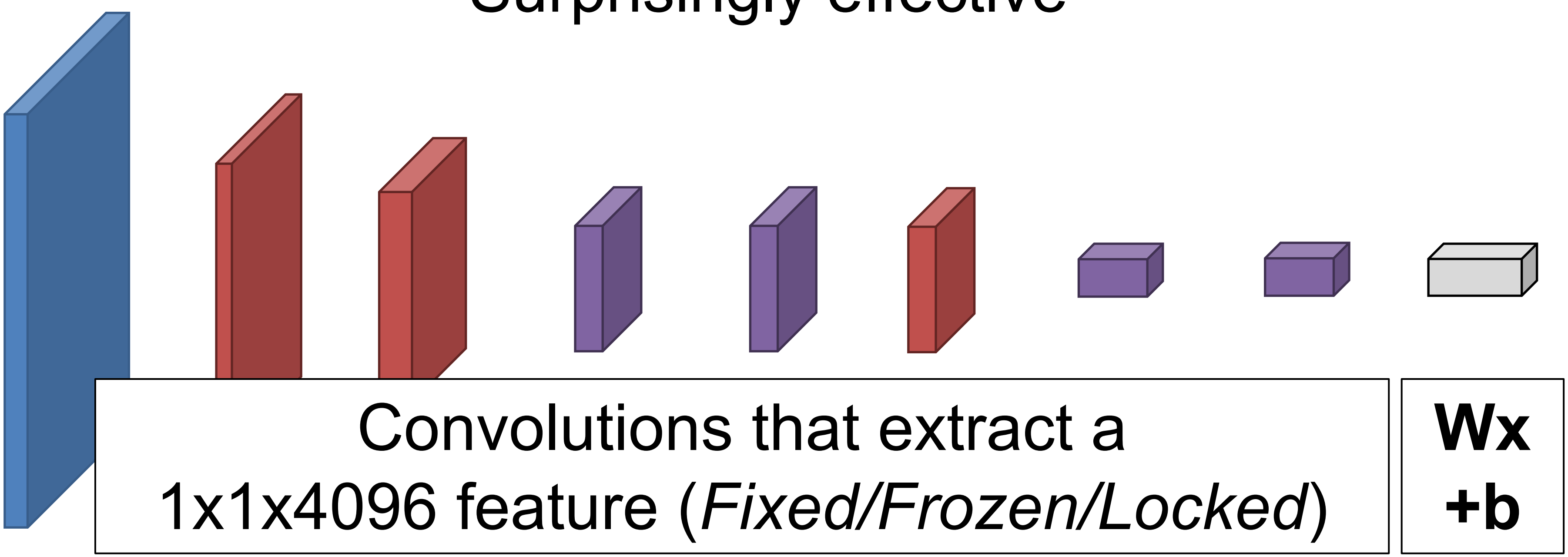
Training a CNN – Fine-tuning

- What if you don't have data?
- Reuse weights learned from other data!
- (Often) Works like magic

Fine-Tuning: Pre-trained Features

1. Extract some layer from an existing network
2. Use as your new feature.
3. Learn a linear model.

Surprisingly effective



Fine-Tuning: Transfer Learning

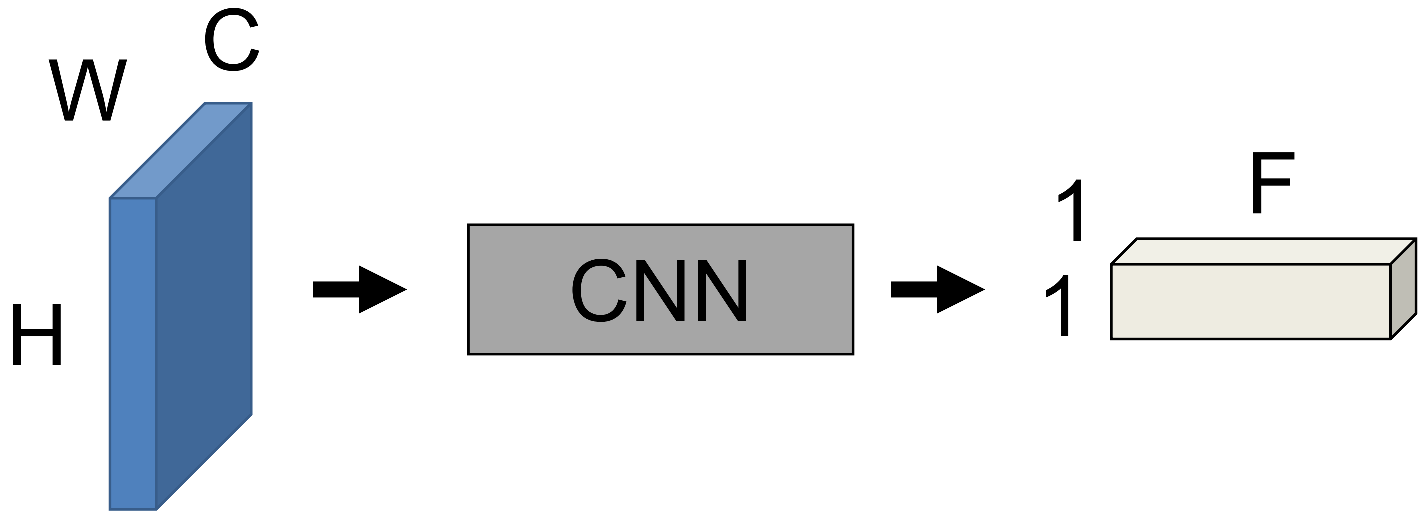
- Rather than initialize from random weights, initialize from some “pre-trained” model that does something else.
- Most common model is trained on ImageNet.
- Other pretraining tasks exist but are less popular.

Fine-Tuning: Transfer Learning

Why should this work?
Transferring from objects (dog) to scenes (waterfall)

Bau and Zhou et al. Network Dissection: Quantifying Interpretability of Deep Visual Representations. CVPR 2017.

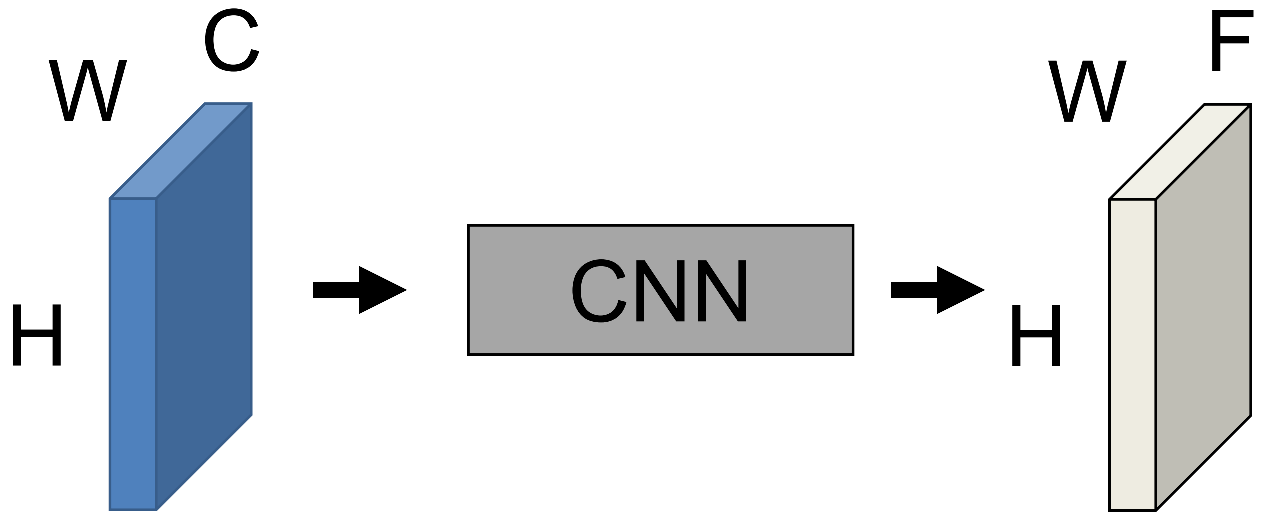
So Far



Convert HxW image into a F-dimensional vector

Is this image a cat?
At what distance was this photo taken?
Is this image fake?

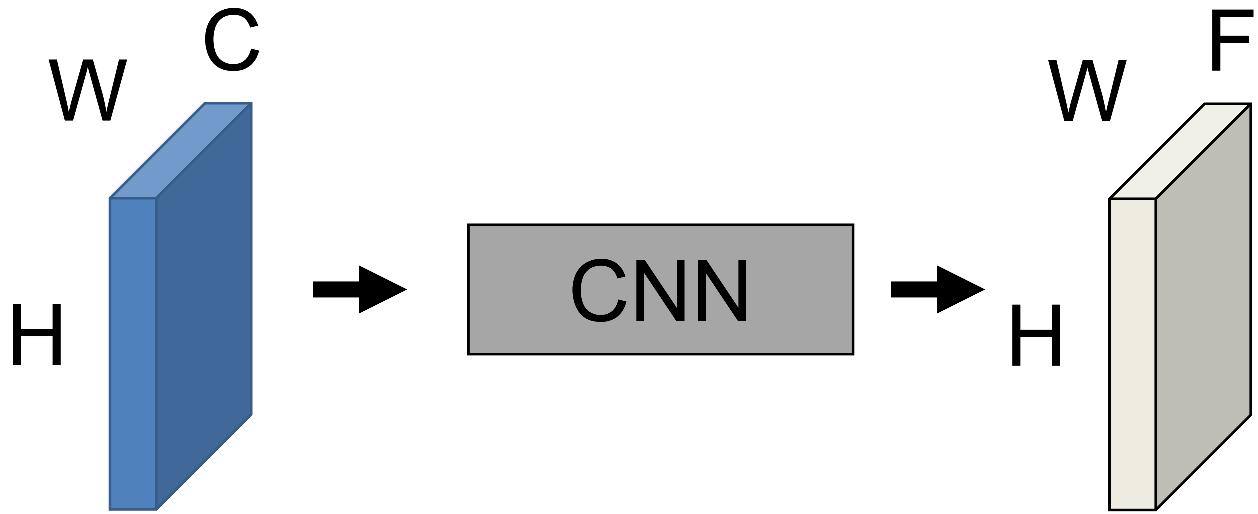
Now



Convert HxW image into a F-dimensional vector

Which pixels in this image are a cat?
How far is each pixel away from the camera?
Which pixels of this image are fake?

Semantic Segmentation



Today's Running Example

- Predict F-dimensional vector representing probability of each of F classes at every pixel
- Loss computed/backprop'd at *every* pixel.

Semantic Segmentation

Each pixel has label, inc. **background**, and unknown

Usually visualized by colors.

Note: don't distinguish between object *instances*

Input Label Input Label

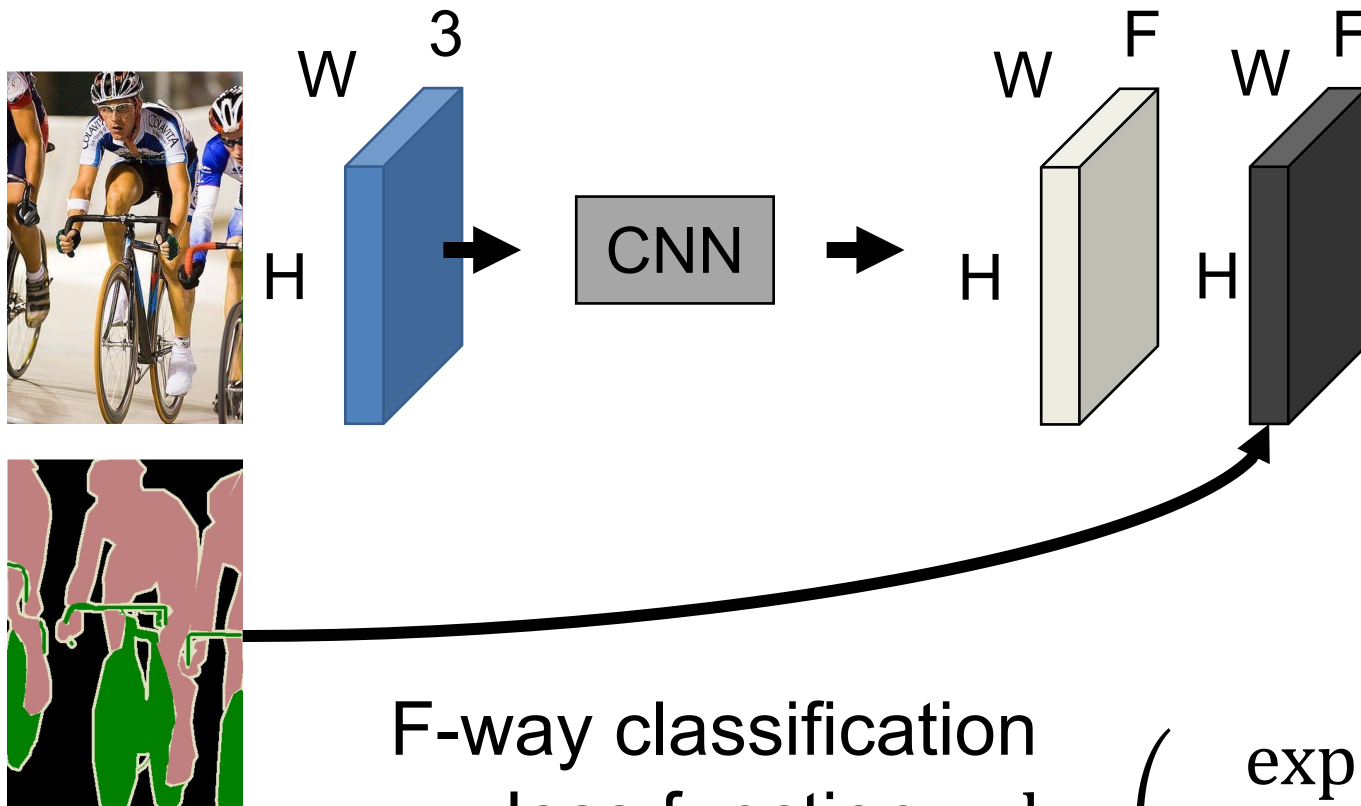
Image Credit: Everingham et al. Pascal VOC 2012.

Semantic Segmentation

"Semantic": ~~a usually meaningless word.~~
Meant to indicate here that we're **naming** things
using language (instead of numbers, e.g.)

Input	Label	Input	Label
			

Semantic Segmentation



F-way classification
loss function
at every pixel:

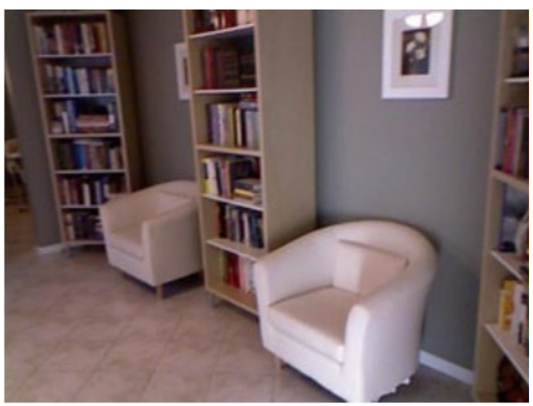
$$-\log\left(\frac{\exp((Wx)_{y_i})}{\sum_k \exp((Wx)_k))}\right)$$

Image Credit: Everingham et al. Pascal VOC 2012.

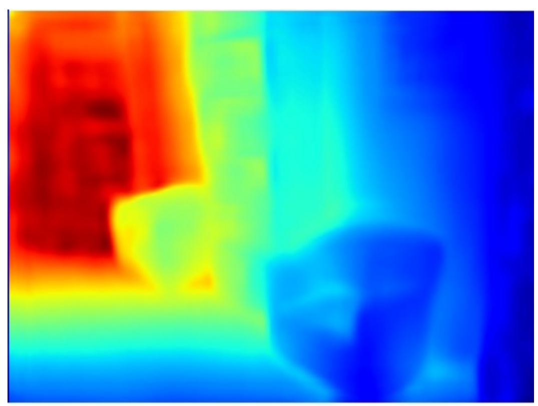
Other Tasks – Depth Prediction

Instead: give label of depthmap, train network to do regression (e.g., $||z_i - \widehat{z_i}||$ where z_i is the ground-truth and $\widehat{z_i}$ the prediction of the network at pixel i).

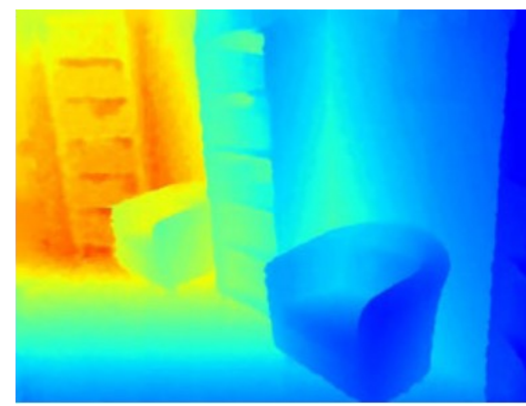
Input HxWx3
RGB Image



Output HxWx1
Depth Image

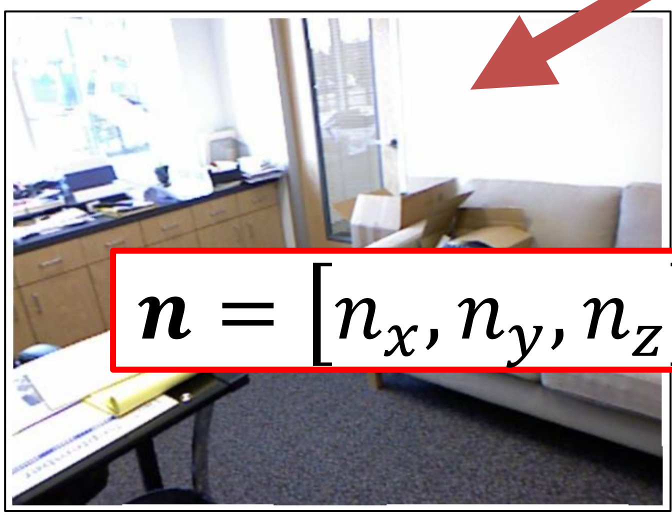


True HxWx1
Depth Image

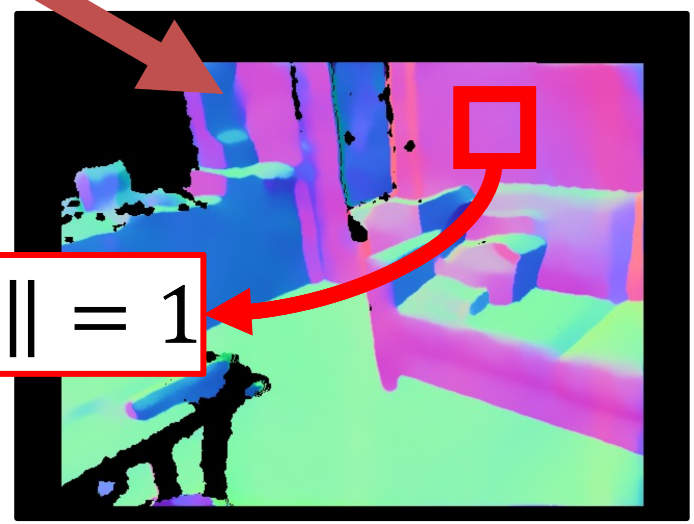


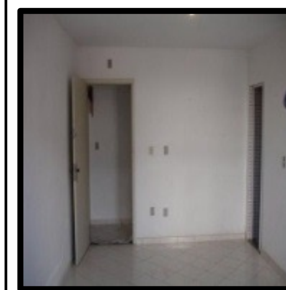
Result credit: Eigen and Fergus, ICCV 2015

Other Tasks – Surface Normals

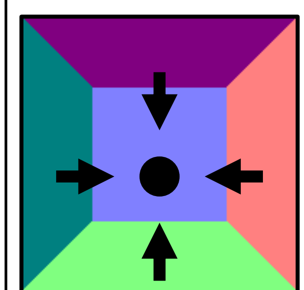


$$\boxed{\boldsymbol{n} = [n_x, n_y, n_z], \|\boldsymbol{n}\| = 1}$$





Room



Legend

Color Image

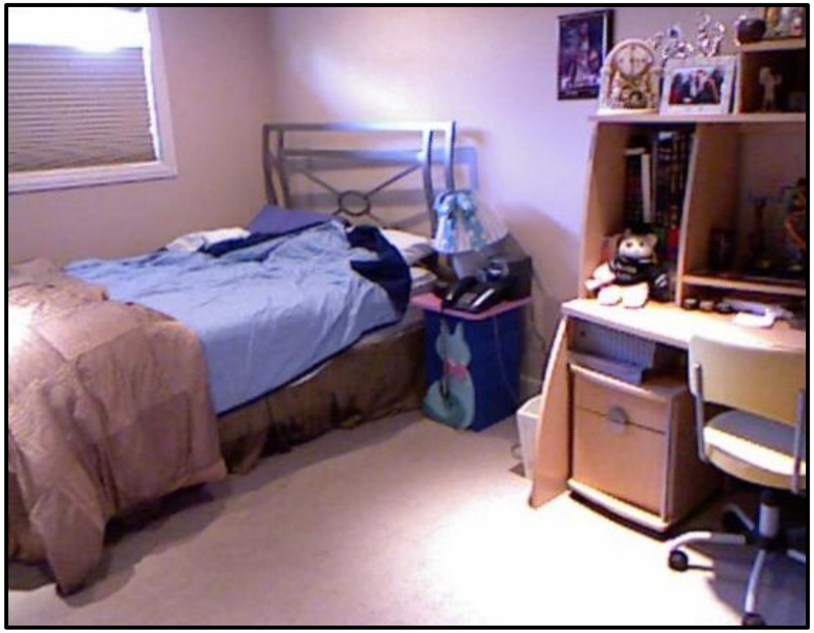
Normals

Image credit: NYU Dataset, Silberman et al. ECCV 2012

Surface Normals

Instead: train normal network to minimize $||\boldsymbol{n}_i - \widehat{\boldsymbol{n}_i}||$ where $\boldsymbol{n}_i$ is ground-truth and $\widehat{\boldsymbol{n}_i}$ prediction at pixel i.

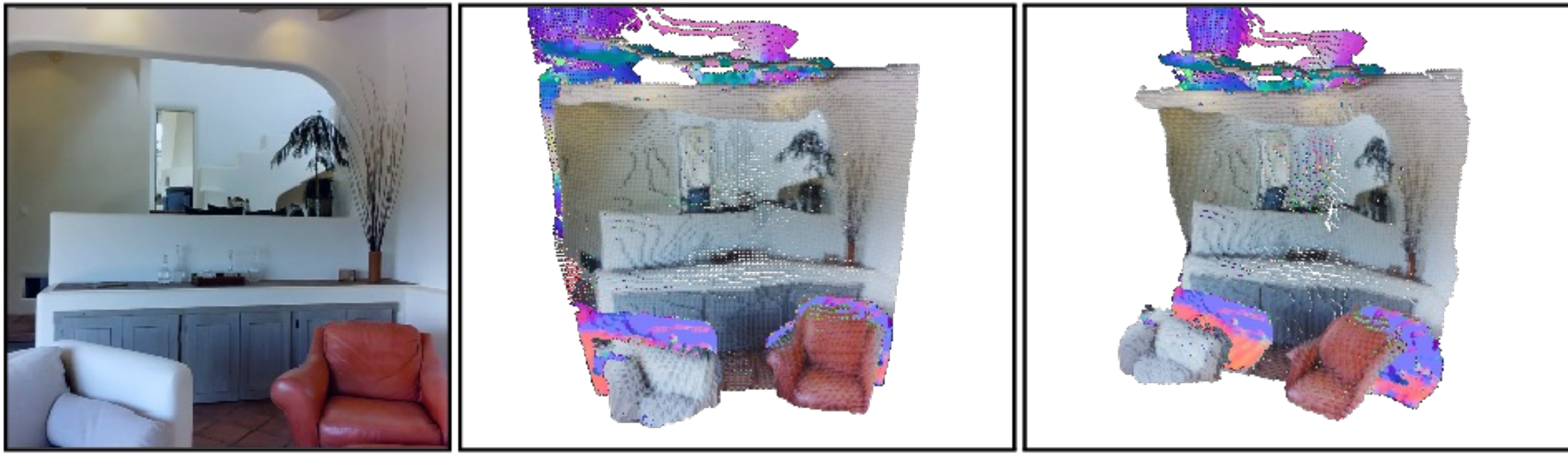
Input: HxWx3
RGB Image



Output: HxWx3
Normals

Result credit: X. Wang, D. Fouhey, A. Gupta, *Designing Deep Networks for Surface Normal Estimation.* CVPR 2014

3D Reconstruction



Result credit: N. Kulkarni, J. Johnson, D.F. Fouhey, *What's Behind The Couch: Directed Ray Distance Functions for 3D Reconstruction.* ???, 2022.

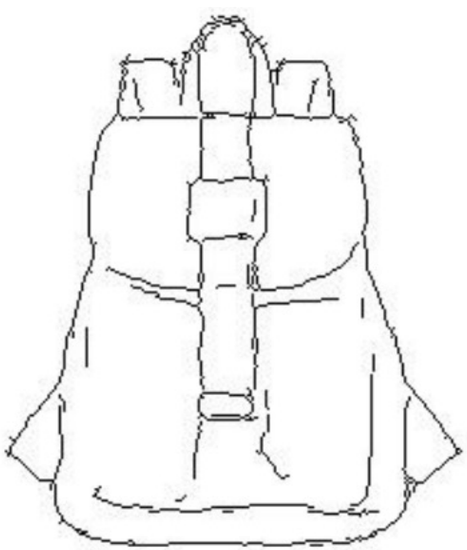
Other Tasks – Human Pose Estimation

Result credit: Z. Cao et al. *Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields*. CVPR 2017.

Other Task – Edges to Cats

Train network to minimize $\|I_j - \hat{I}_j\|$ where I_j is GT and $\hat{I}_j$ prediction at pixel j (*plus other magic*).

Input: HxWx1
Sketch Image



Output: HxWx3
Image

https://affinelayer.com/pixsrv/

Result credit: Isola et al. *Image-to-Image Translation with Conditional Adversarial Networks*. CVPR 2017.

Why Is This Task Hard?

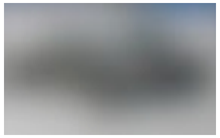


Image credit: A. Torralba

Why Is This Task Hard?

What's this? (No Cheating!)

(1) Keyboard?

(2) Hammer?

(3) Old cell phone?

(4) Xbox controller?

Image credit: COCO dataset

Why Is This Task Hard?

Image credit: COCO dataset

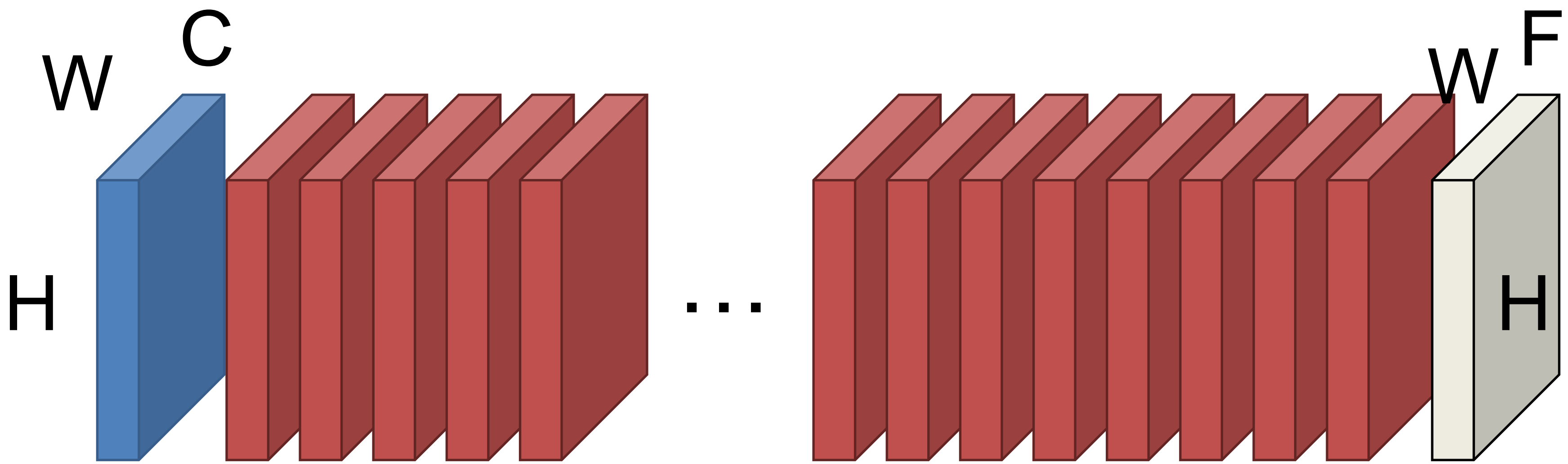
Why Is This Task Hard?

- Low-resolution features
- Need large context window

Why Is This Task Hard?

- It’s helpful to see two “wrong” ways to do this.

Why Not Stack Convolutions?

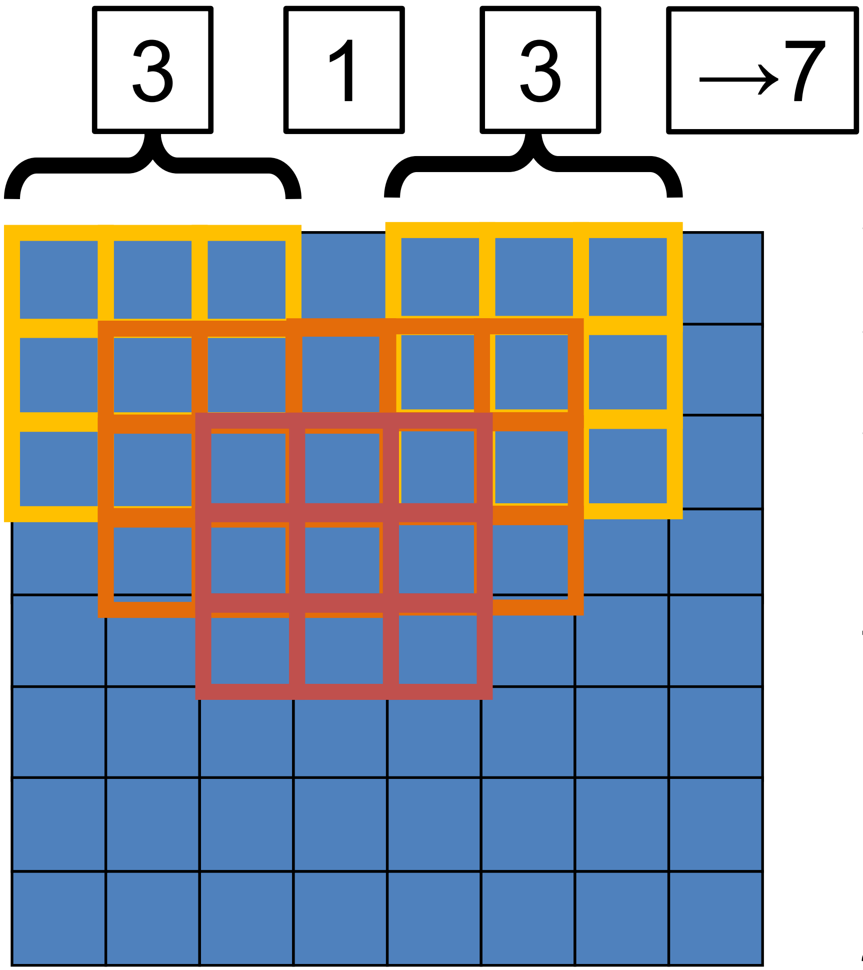


n 3x3 convs have a receptive field of 2n+1 pixels

How many convolutions until >=200 pixels?

100

3x3 Filters

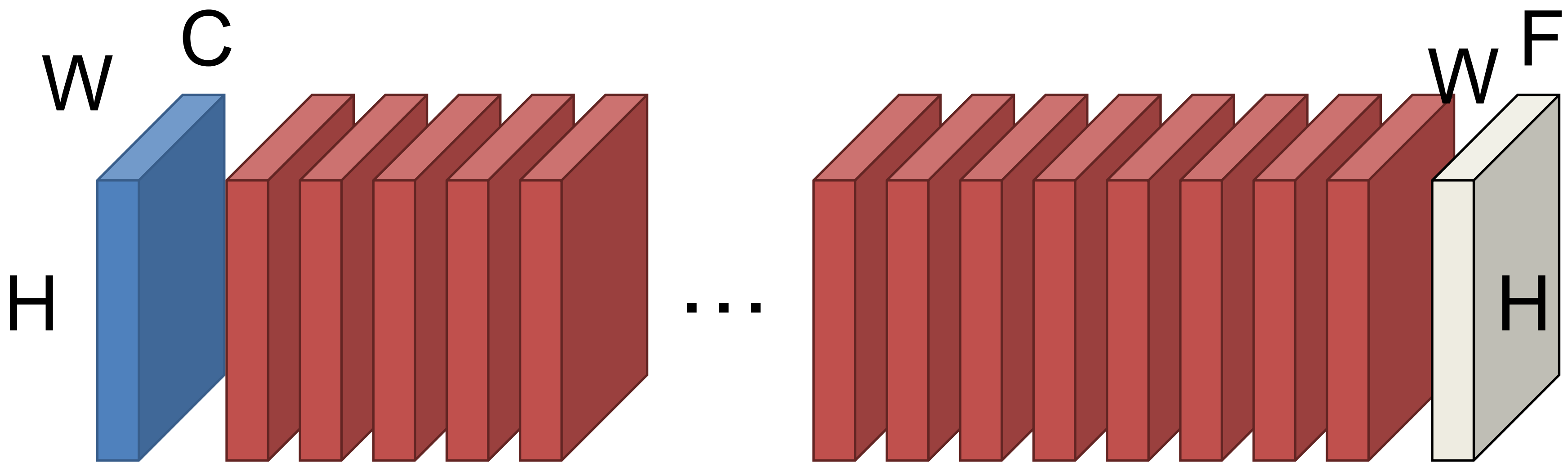


3x3 filter followed by
3x3 filter followed by
3x3 filter

→

Filter with 7x7
receptive field
2n+1

Why Not Stack Convolutions?



Suppose 200 3x3 filters/layer, H=W=400

Storage/layer/image: 200 * 400 * 400 * 4 bytes = 122MB

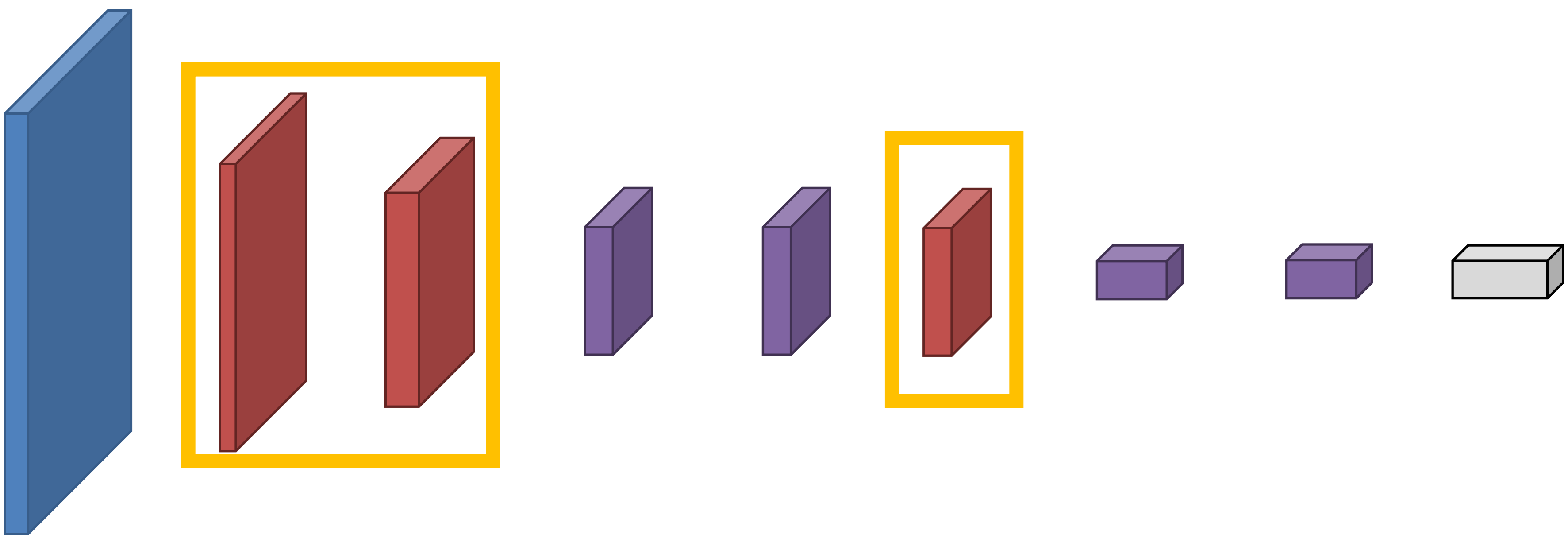
Uh oh!*

*100 layers, batch size of 20 = 238GB of memory!

Any Solutions?

Hence Need Low-Resolution

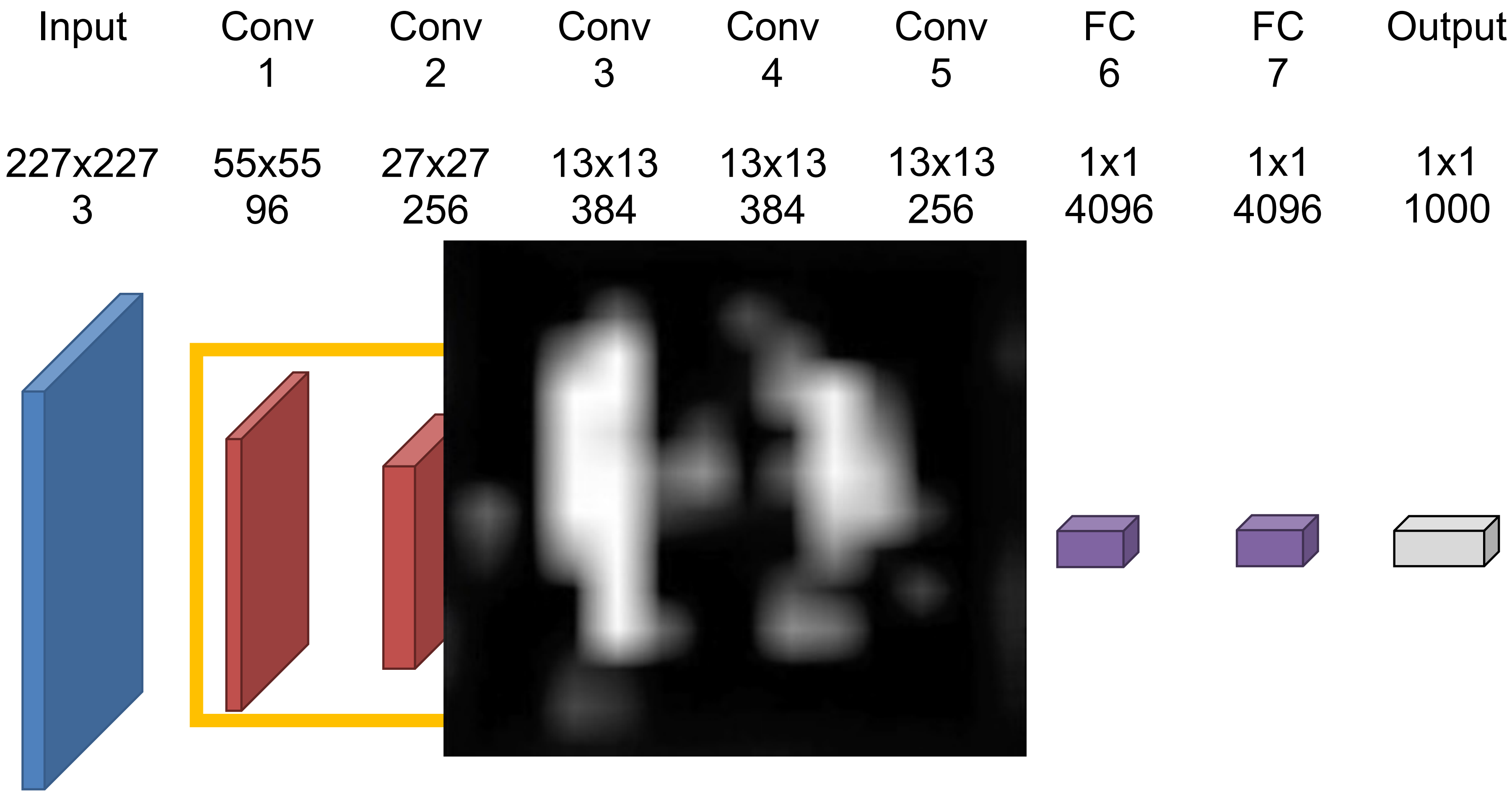
Input	Conv 1	Conv 2	Conv 3	Conv 4	Conv 5	FC 6	FC 7	Output
227x227 3	55x55 96	27x27 256	13x13 384	13x13 384	13x13 256	1x1 4096	1x1 4096	1x1 1000



Need to reduce resolution to save memory.

$1/8^{th}$ resolution → 1/64 memory

Hence Need Low-Resolution



Problem: Segmentation output is also low-resolution

If Memory's the Issue…

Crop out every sub-window and predict the label in the middle.

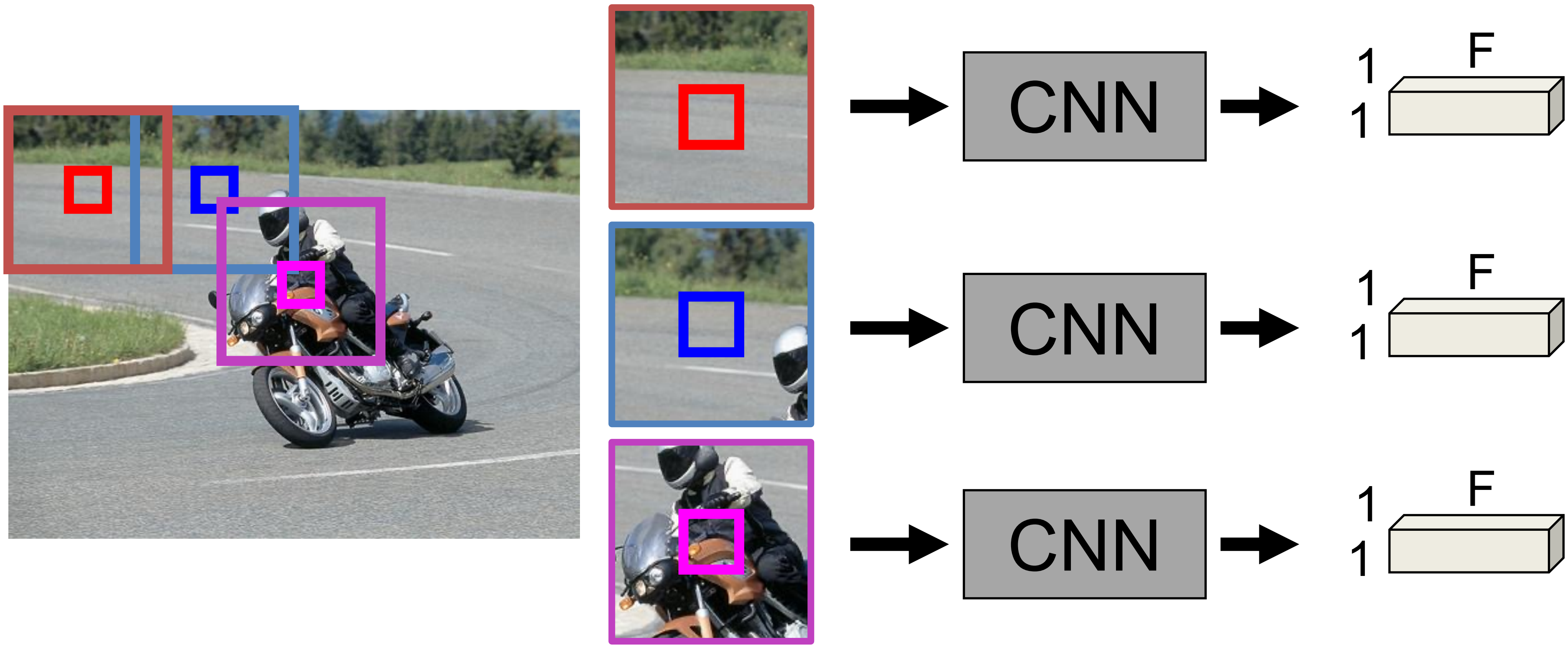


Image credit: PASCAL VOC, Everingham et al.

If Memory's the Issue…

Crop out every sub-window and predict the label in the middle.

What are these patches? Paved or not?

Context is very important! Need a large receptive fields

Image credit: PASCAL VOC, Everingham et al.

The Big Issue

We need to:

1. Have large receptive fields to figure out what we're looking at
2. Not waste a ton of time or memory while doing so

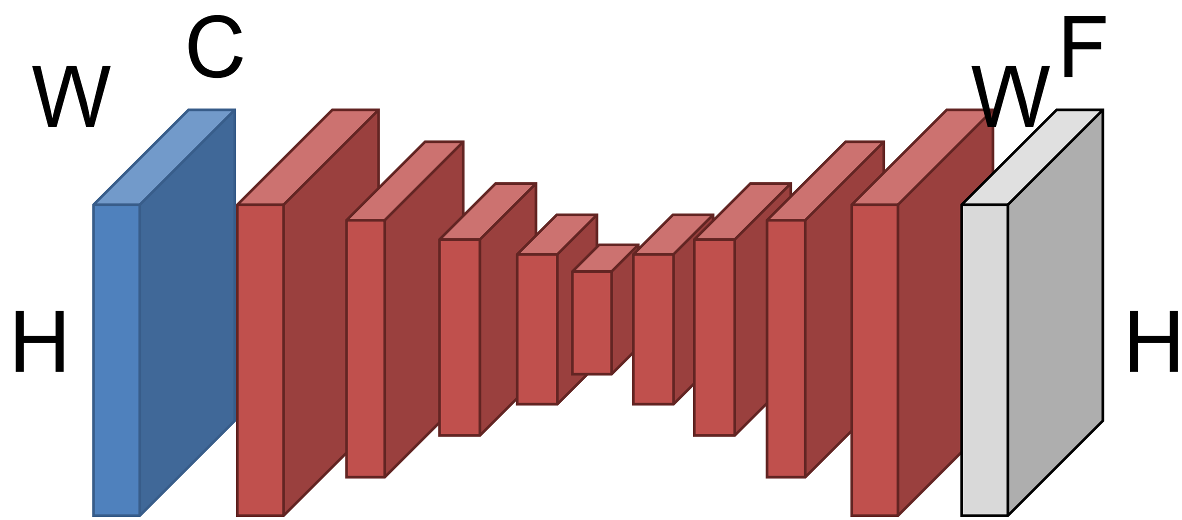
These two objectives are in total conflict

Encoder-Decoder

Key idea: First **downsample** towards middle of network. Then **upsample** from middle.

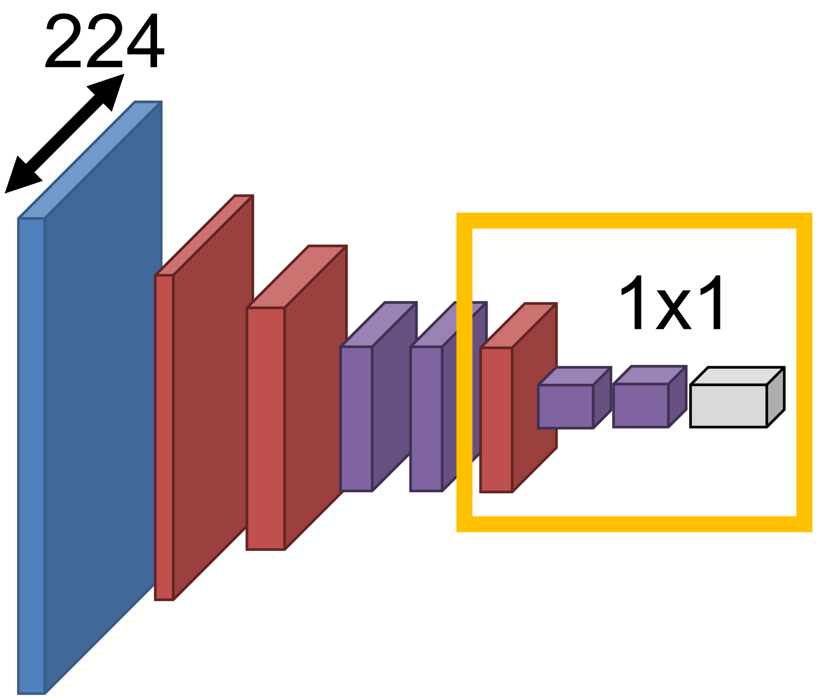
How do we downsample?

Strided-convolutions, pooling

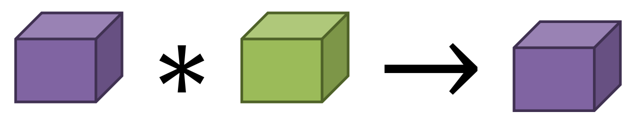


Fully Convolutional Network

Convnet that maps images to vectors



Fully-connected network has a fixed input-output dimensions

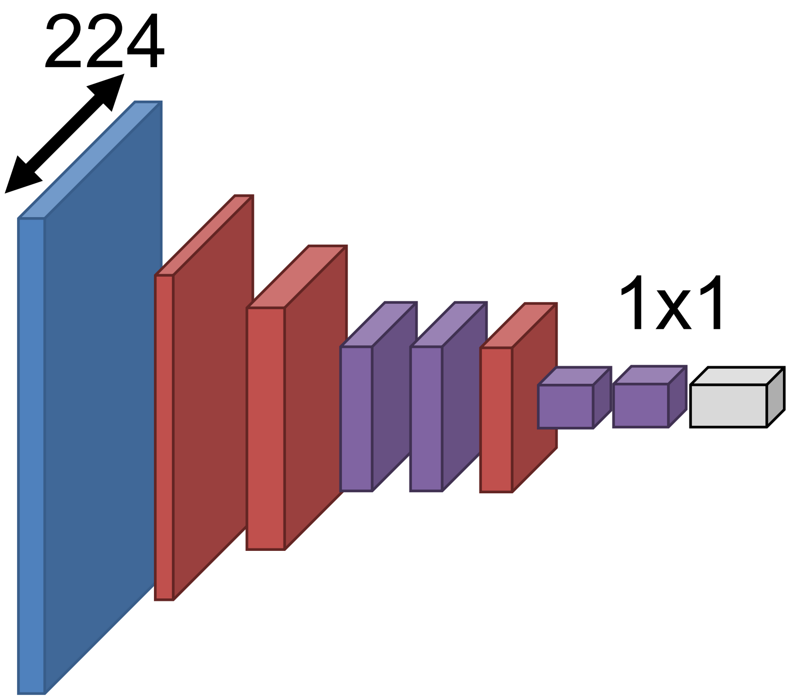


Recall that we can rewrite any vector-vector operations via 1x1 convolutions

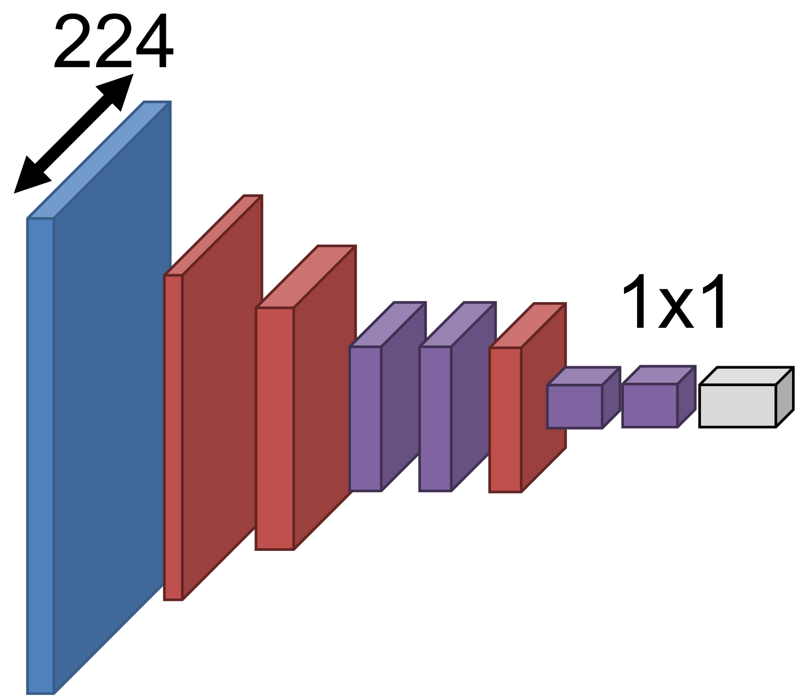
Long et al. *Fully Convolutional Networks For Semantic Segmentation*. CVPR 2014

Fully Convolutional Network

Convnet that maps images to vectors



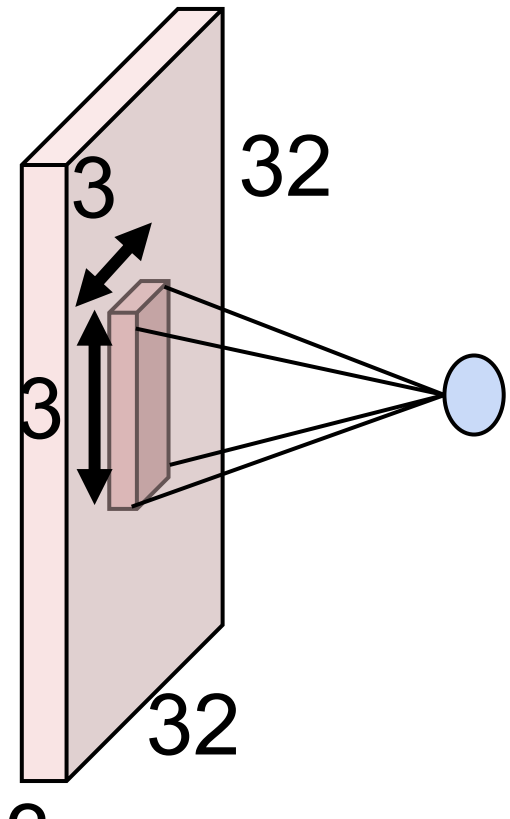
Convnet that maps images to images



What if we make the input bigger?

Convolution Layer

How big is the output?

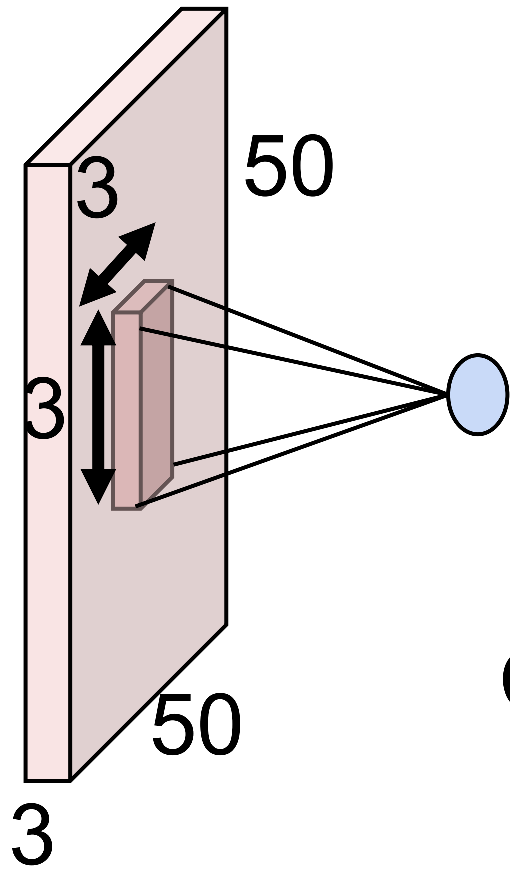


Height? 32-3+1=30
Width? 32-3+1=30

Slide credit: Karpathy and Fei-Fei

Convolution Layer

How big is the output?



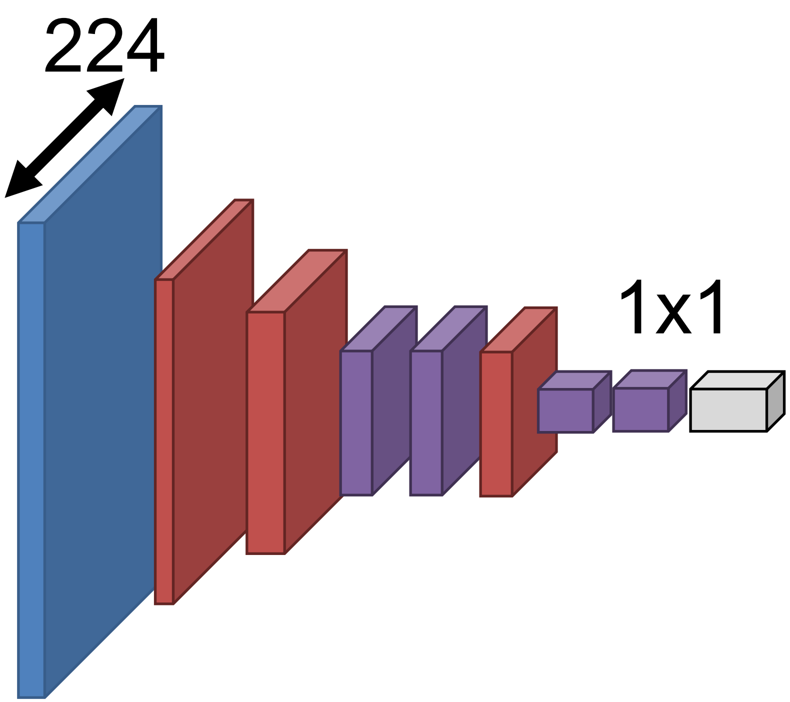
Height? 50-3+1=48
Width? 50-3+1=48

Can apply convolution layers to an image of any resolution

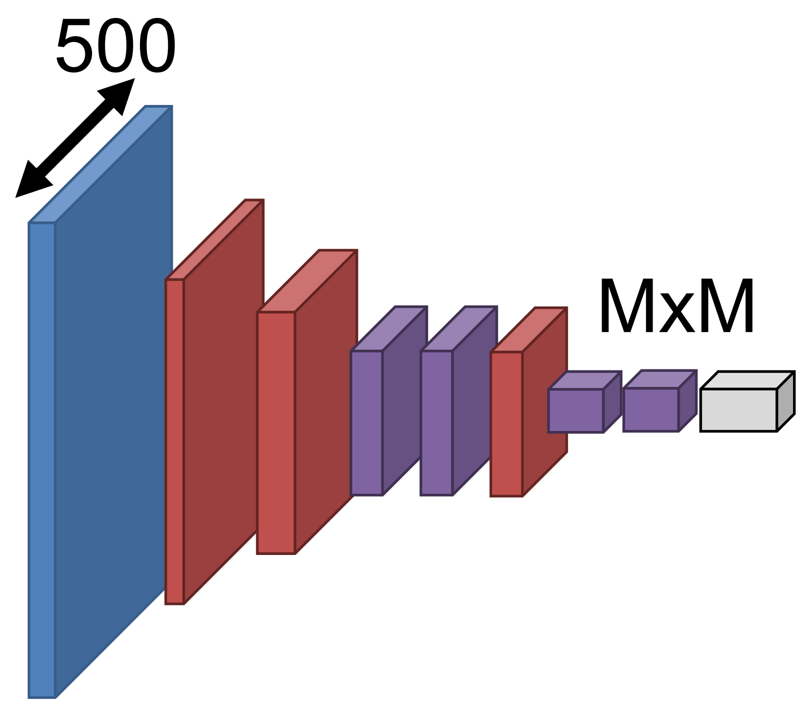
Slide credit: Karpathy and Fei-Fei

Fully Convolutional Network

Convnet that maps images to vectors



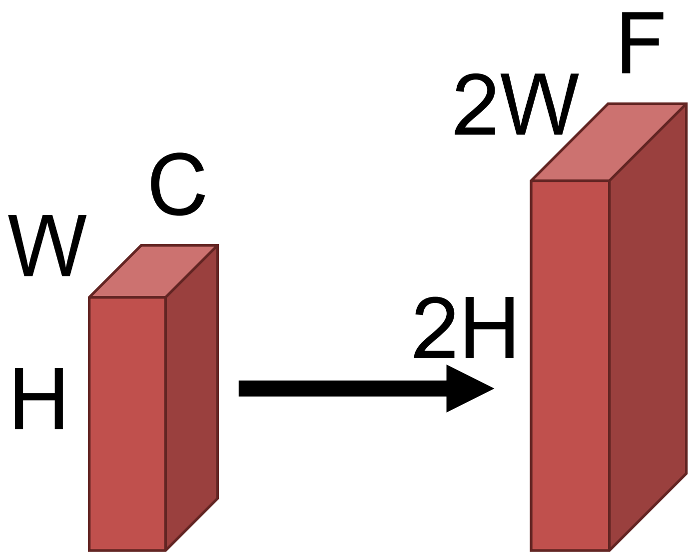
Convnet that maps images to images



Since it’s convolution, can reuse an image network

E.g., train on 224 ImageNet, test on COCO Dataset

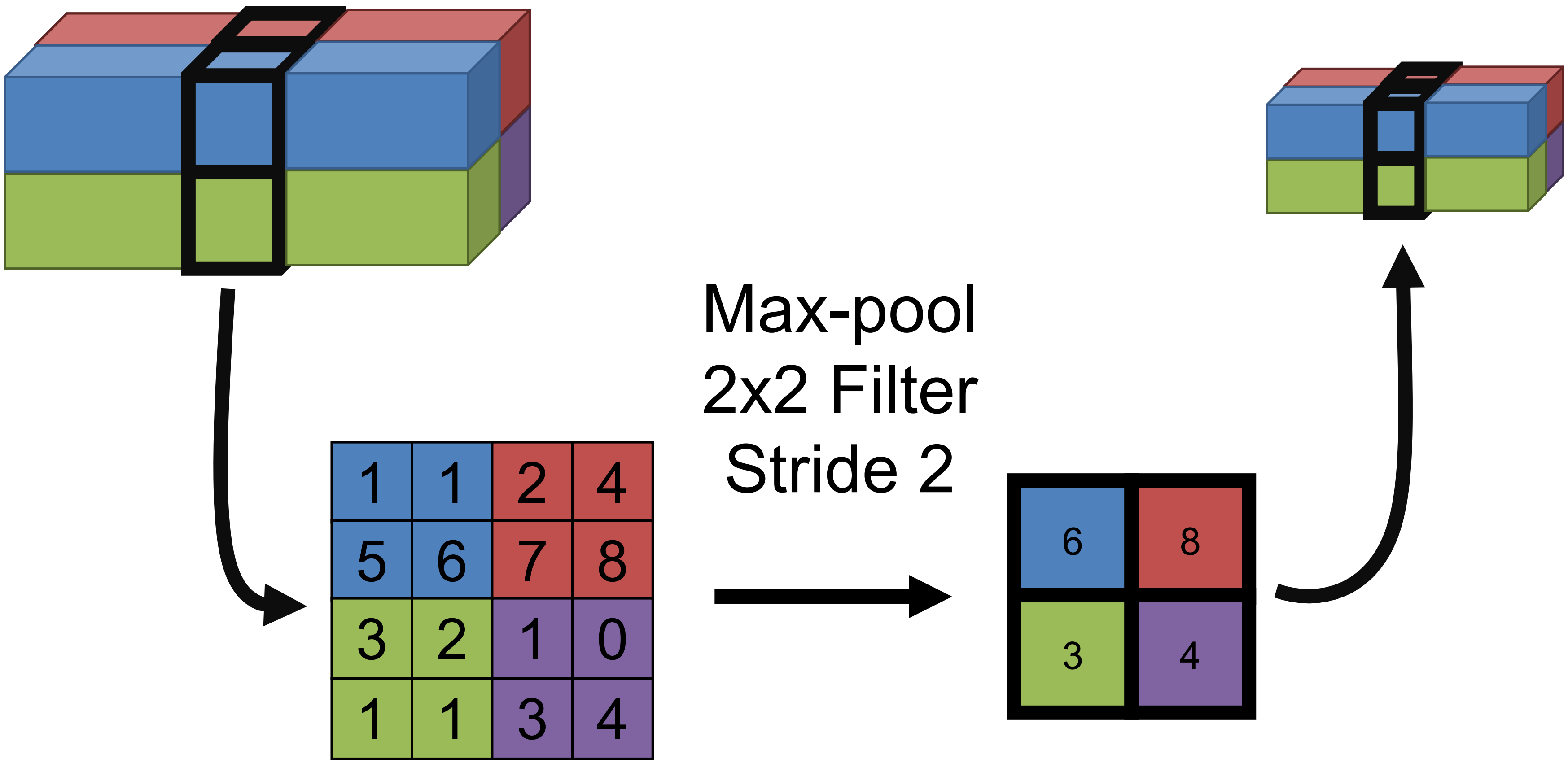
How Do We Upsample?



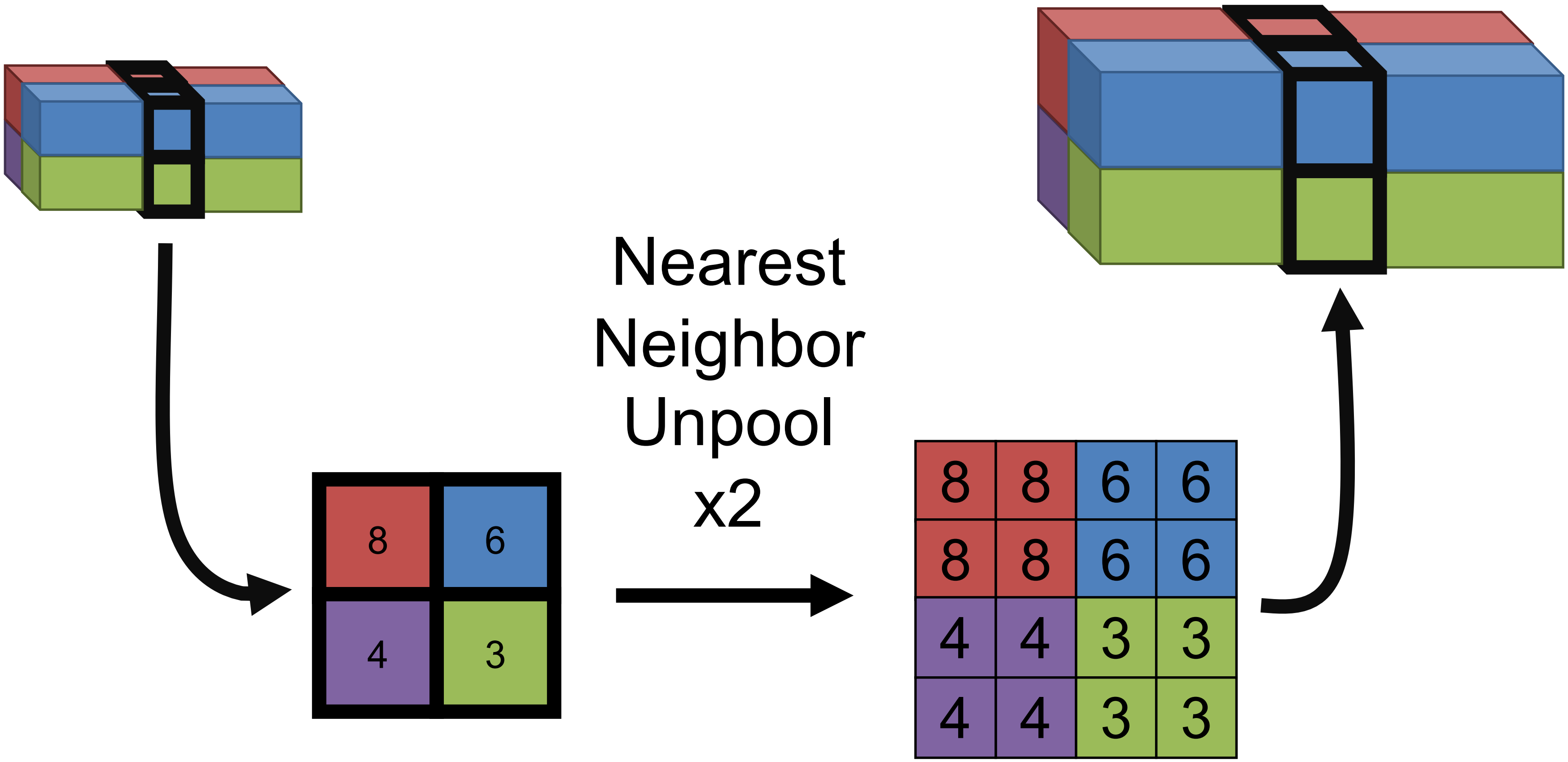
Do the opposite of how we downsample:

1. Pooling → "Unpooling"
2. Convolution → "Transpose Convolution"

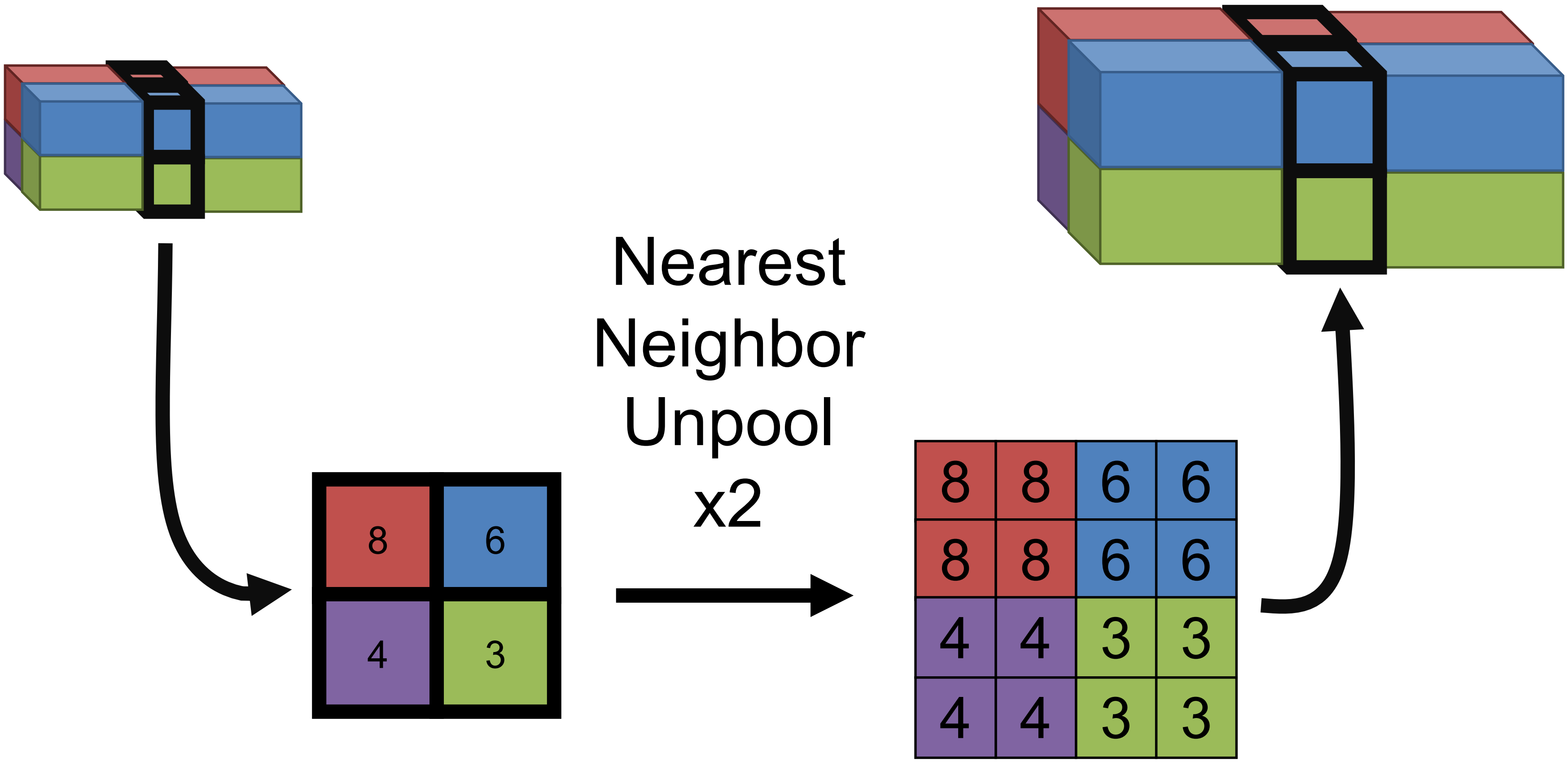
Recall: Pooling



Now: Unpooling



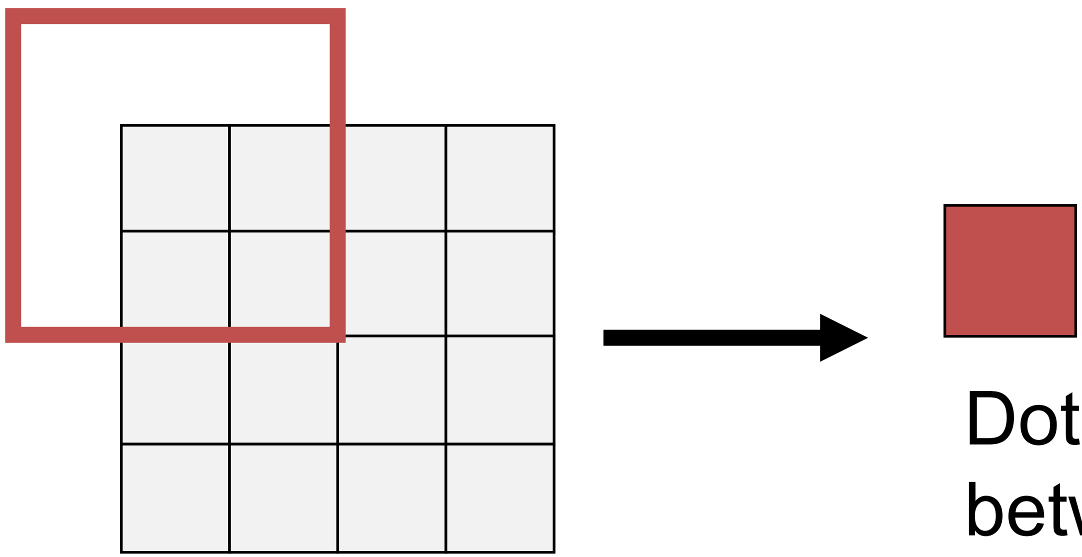
Now: Unpooling



Other interpolations possible: bilinear, bicubic, etc

Recall: Convolution

3x3 Convolution, Stride 2, Pad 1

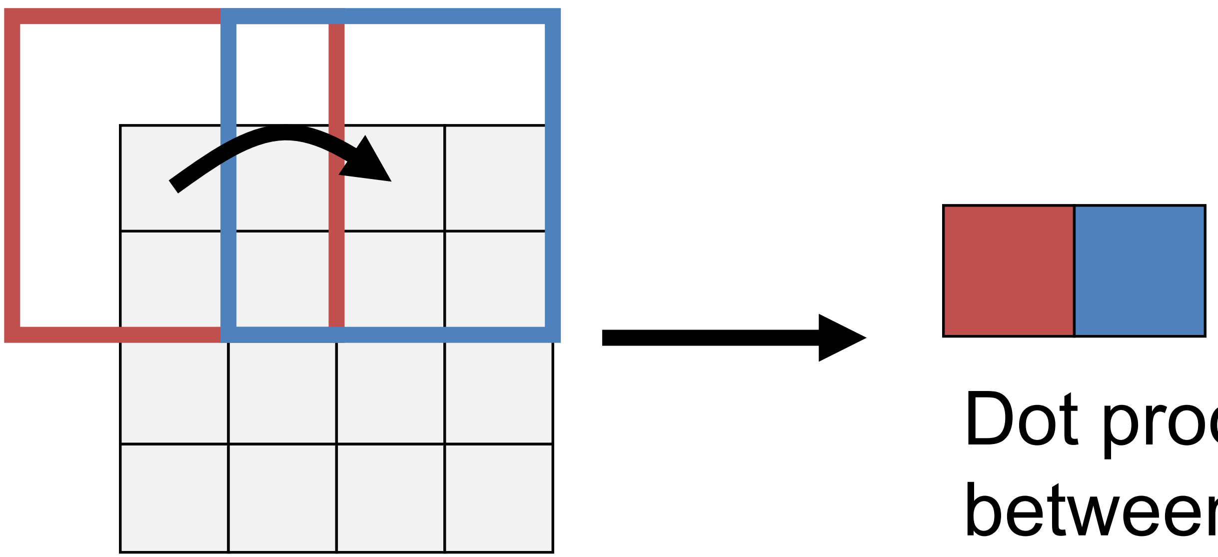


Dot product between filter f and input

Example Credit: L. Fei-Fei, J. Johnson, S. Yeung

Recall: Convolution

3x3 Convolution, Stride 2, Pad 1



Dot product between filter f and input

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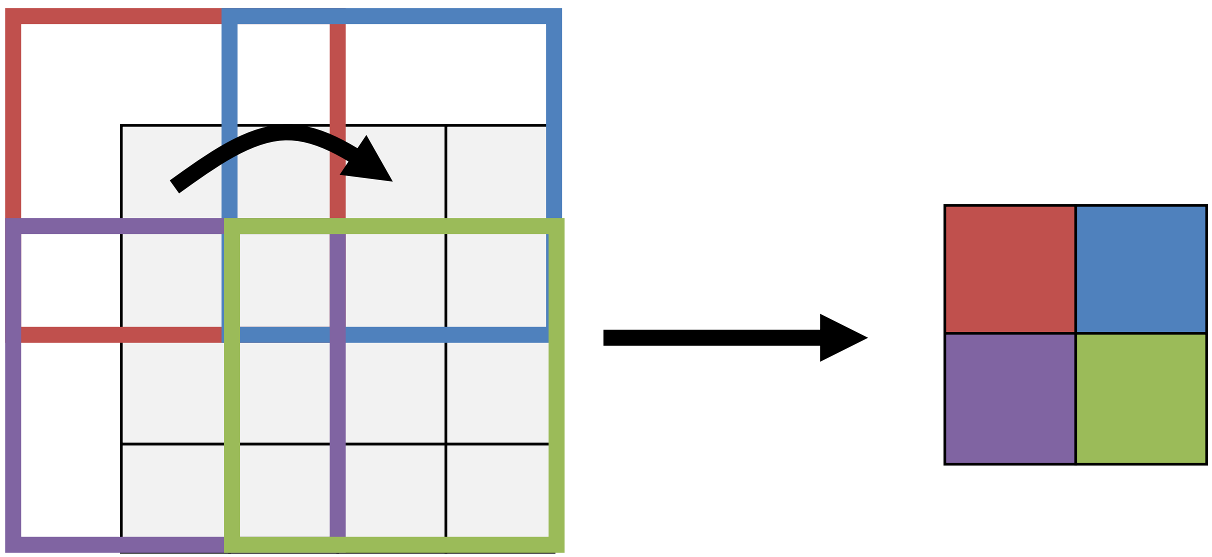
Recall: Convolution

3x3 Convolution, Stride 2, Pad 1

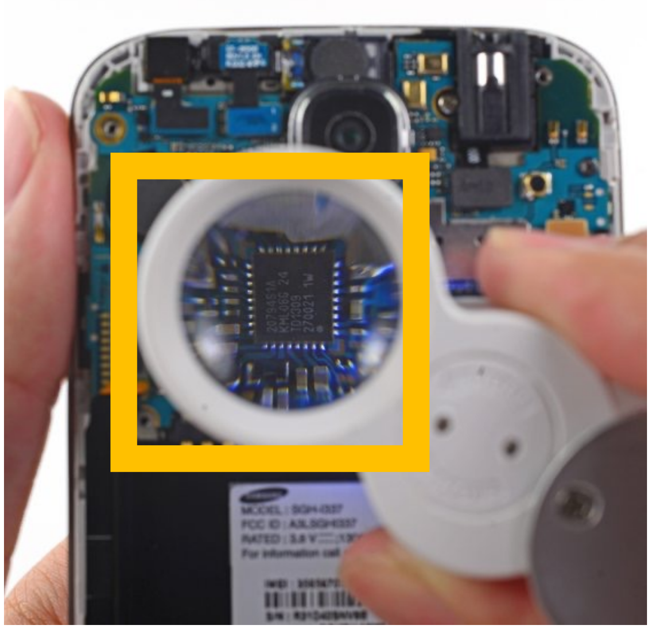


Example Credit: L. Fei-Fei, J. Johnson, S. Yeung

Transpose Convolution

Convolution

Filter: little (sliding) lens that looks at a pixel.



Transpose Conv.

Filter: tiles used to make image

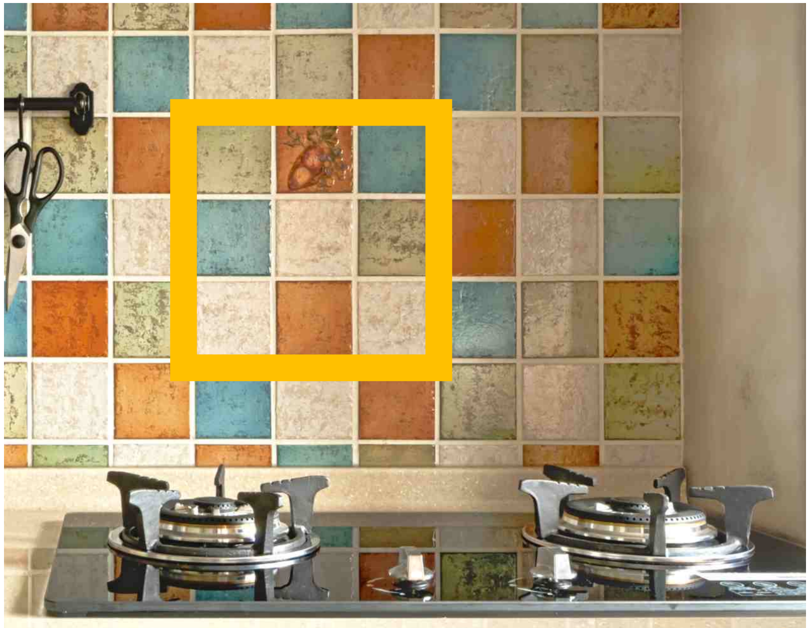
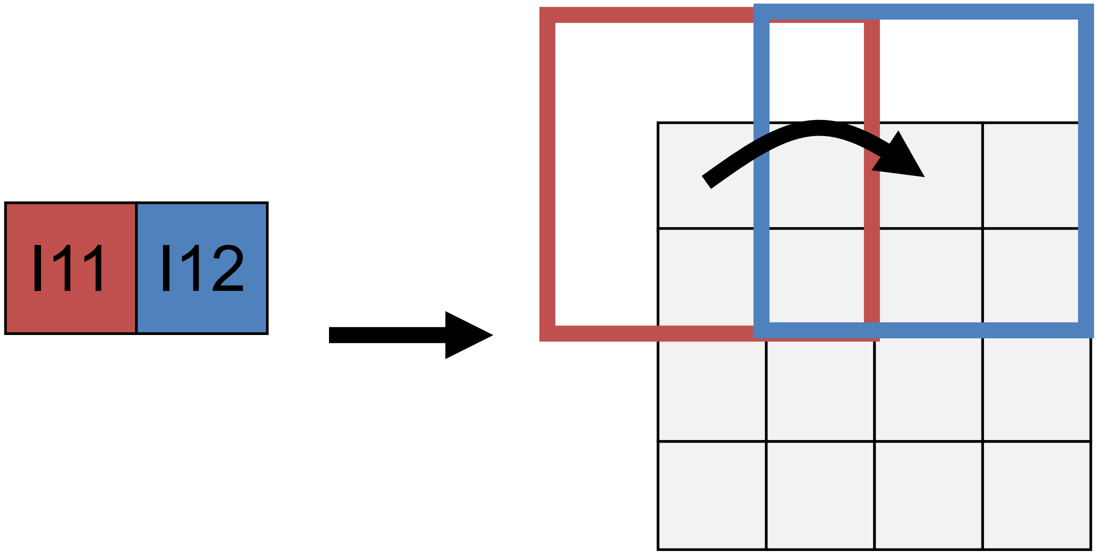


Image credit: ifixit.com, thespruce.com

Transpose Convolution

3x3 Transpose Convolution, Stride 2, Pad 1



Output is filter F weighted by input I

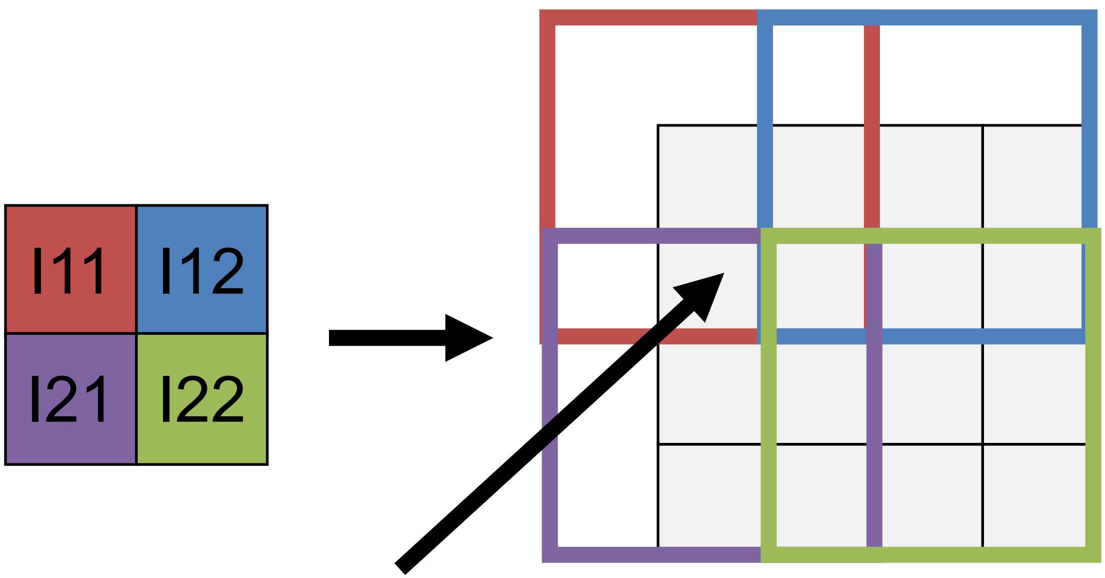
$$I_{11}\boldsymbol{F} \quad I_{12}\boldsymbol{F}$$

Each low-res pixel maps to a tile

Example Credit: L. Fei-Fei, J. Johnson, S. Yeung

Transpose Convolution

3x3 Transpose Convolution, Stride 2, Pad 1



Output is filter F weighted by input I

$I_{11}F$ $I_{12}F$

$I_{21}F$ $I_{22}F$

Sum outputs at overlap
(e.g., from $I_{11}F$ and $I_{21}F$)

Example Credit: L. Fei-Fei, J. Johnson, S. Yeung

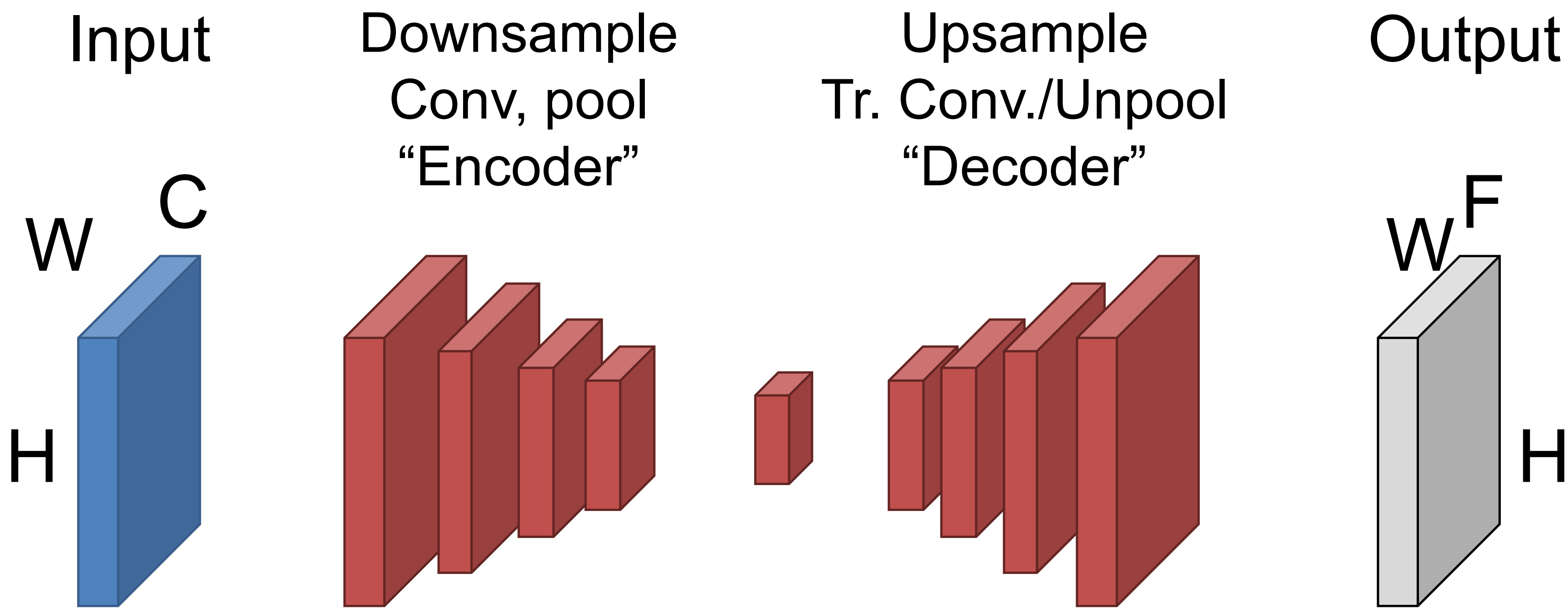
Transpose Convolution

Demo

Resource (for the curious)

Putting it Together

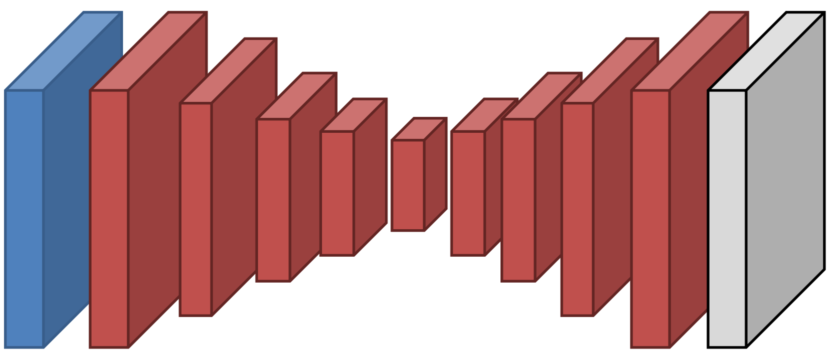
Convolutions + pooling downsample/compress/encode
Transpose convs./unpoolings upsample/uncompress/decode



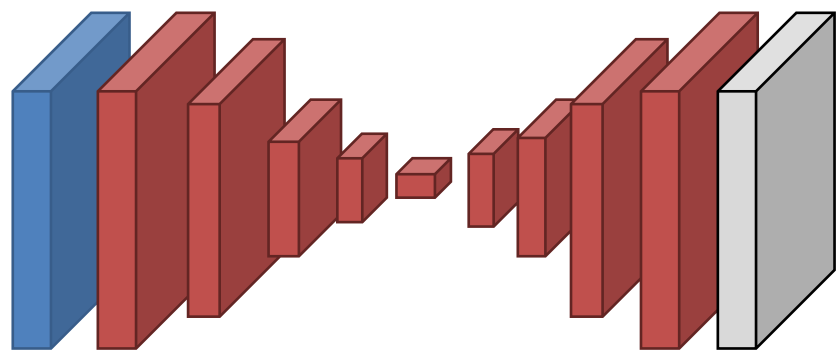
Putting It Together – Block Sizes

- Networks come in lots of forms
- **Don’t take any block sizes literally.**
- Often (not always) keep some spatial resolution

Encode to spatially smaller tensor, then decode.

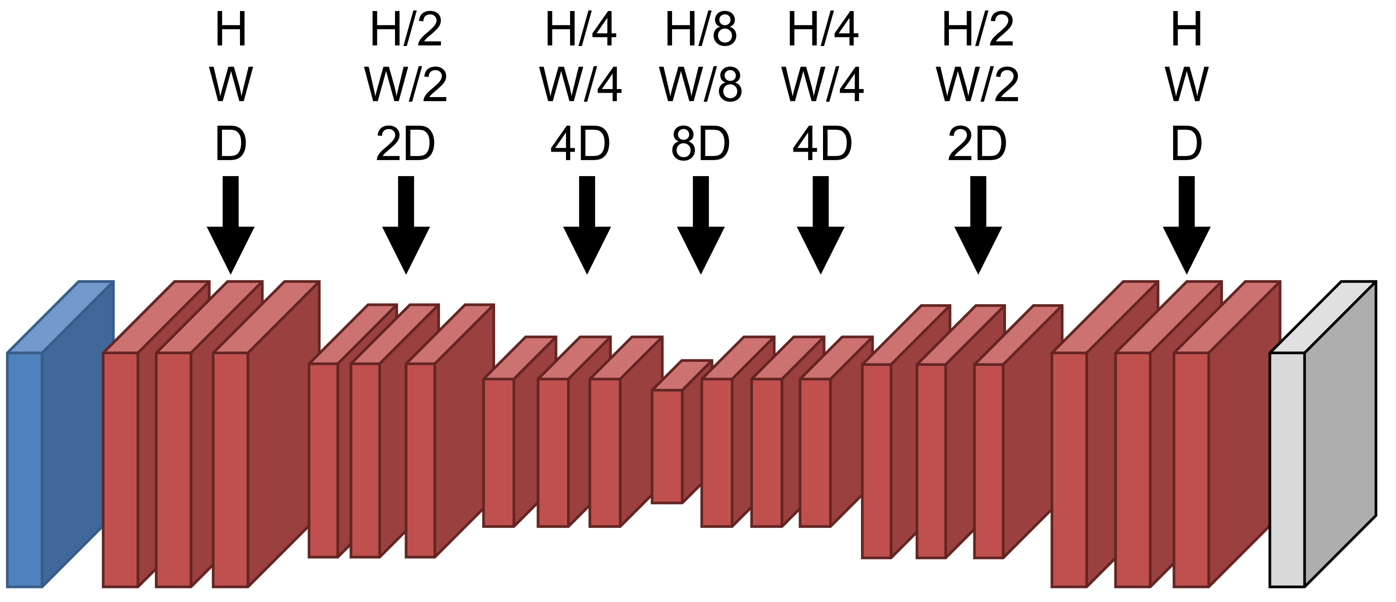


Encode to 1D vector then decode



Putting It Together – Block Sizes

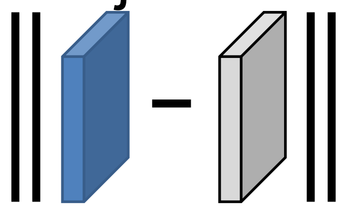
- Often multiple layers at each spatial resolution.
  - Often halve spatial resolution and double feature depth every few layers



An Aside: Autoencoders

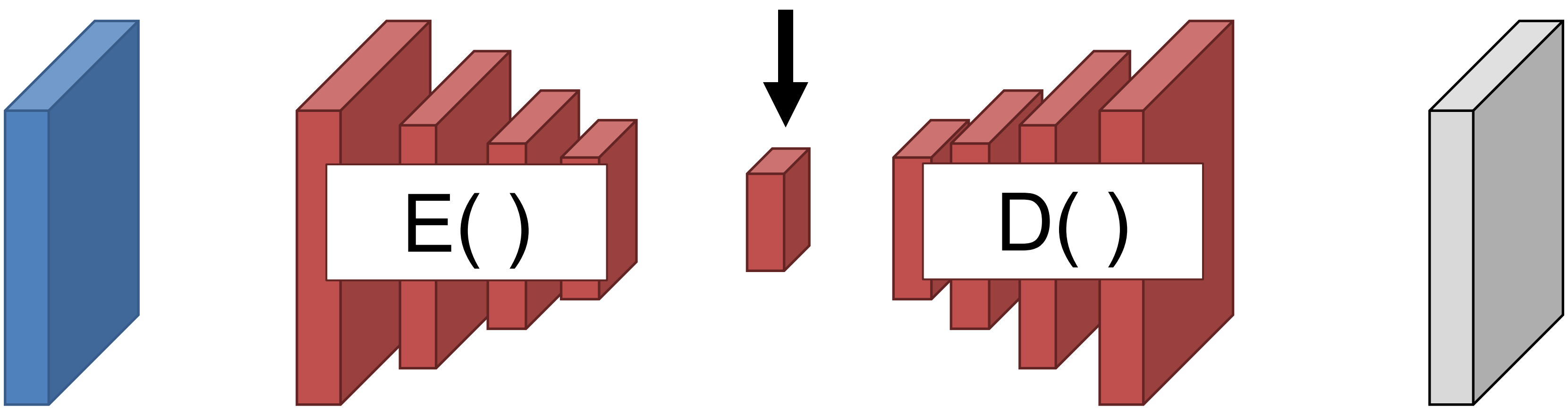
Network compresses input to “bottleneck”, decodes it back to input. Abstract latent space contrast to “Data Space.”

Objective:



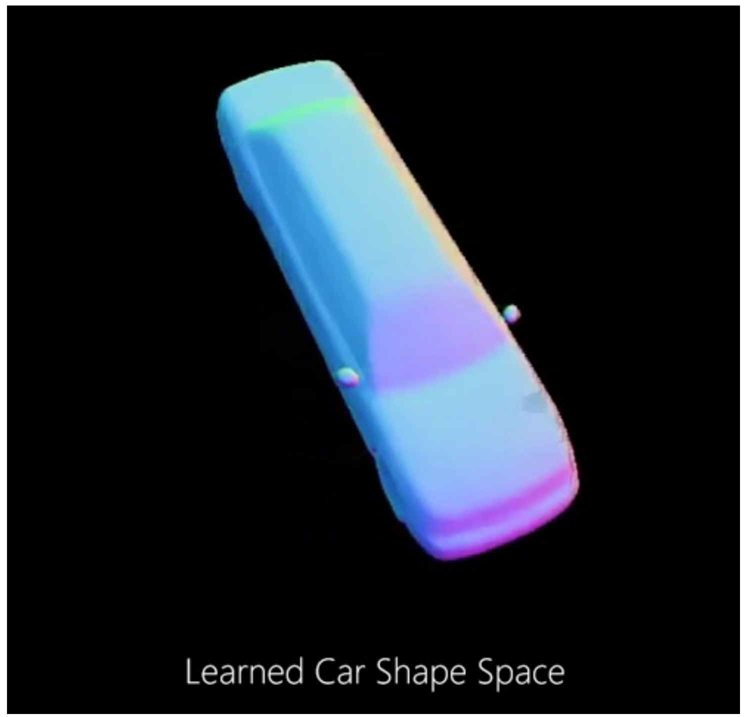
$$\left\| D\left(E\left(\boldsymbol{X}\right)\right) - \boldsymbol{X} \right\|$$

Bottleneck/
Latent Space/
Latent Code



Walking the Latent Space*

Linear Interpolation in the latent space



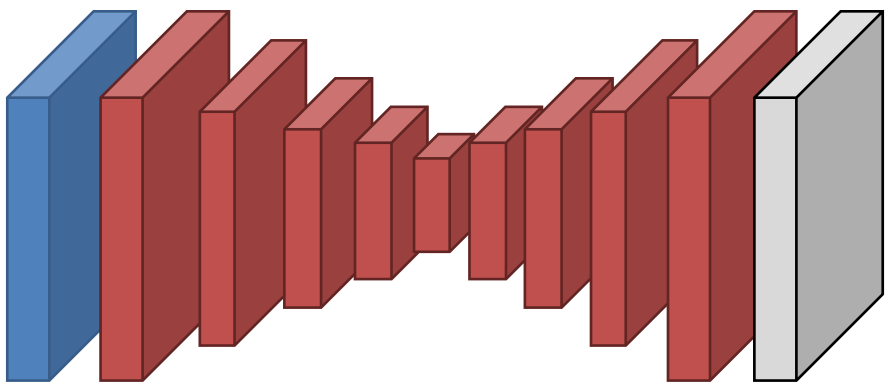
*In the interest of honesty in advertising: not an autoencoder, but a similar method with the same goal of learning a latent space

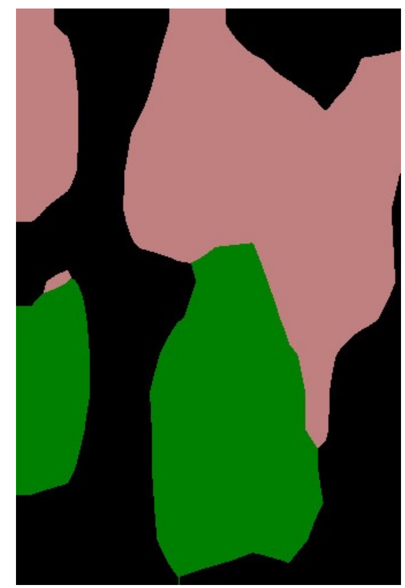
Result from Park et al. DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation. CVPR 2019

Missing Spatial Details

While the output *is* HxW, just upsampling often produces results without details/not aligned with the image.
Why?

Information about details lost when downsampling!

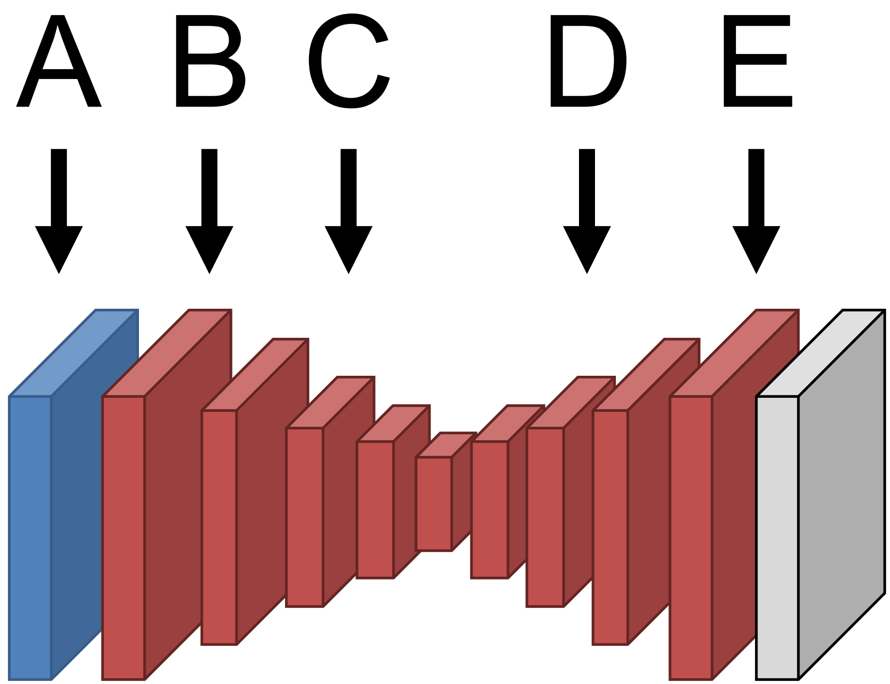


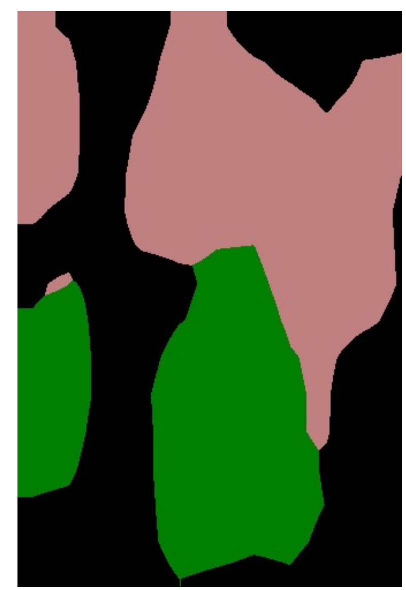


Result from Long et al. *Fully Convolutional Networks For Semantic Segmentation*. CVPR 2014

Missing Spatial Details

Where is the most useful information about the high-frequency details of the image?





Result from Long et al. *Fully Convolutional Networks For Semantic Segmentation*. CVPR 2014

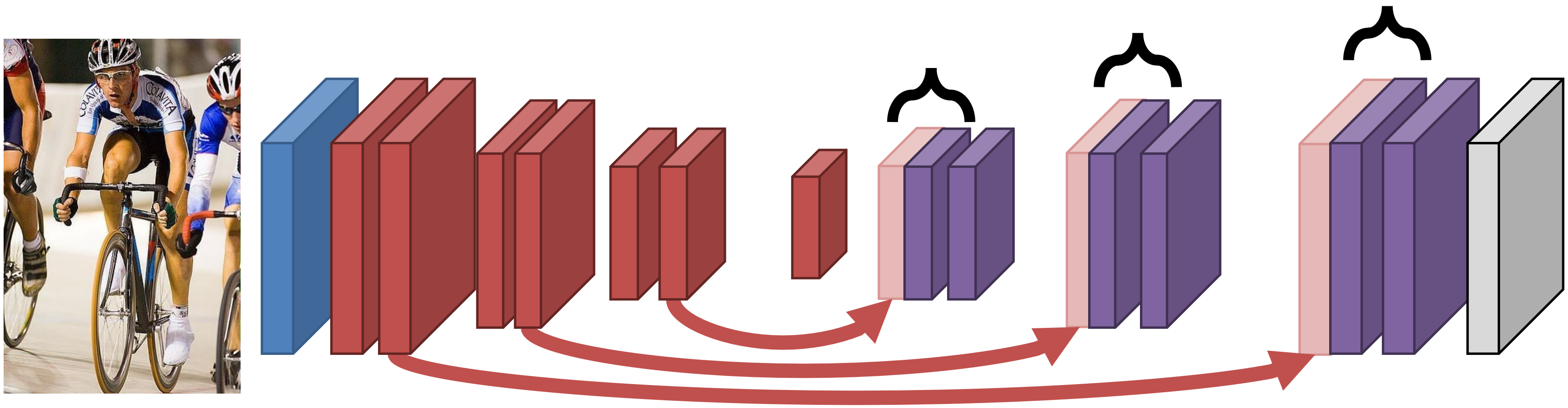
Missing Spatial Details

How do you send details forward in the network?

You copy the activations forward.

Subsequent layers at the same resolution figure out how to fuse things.

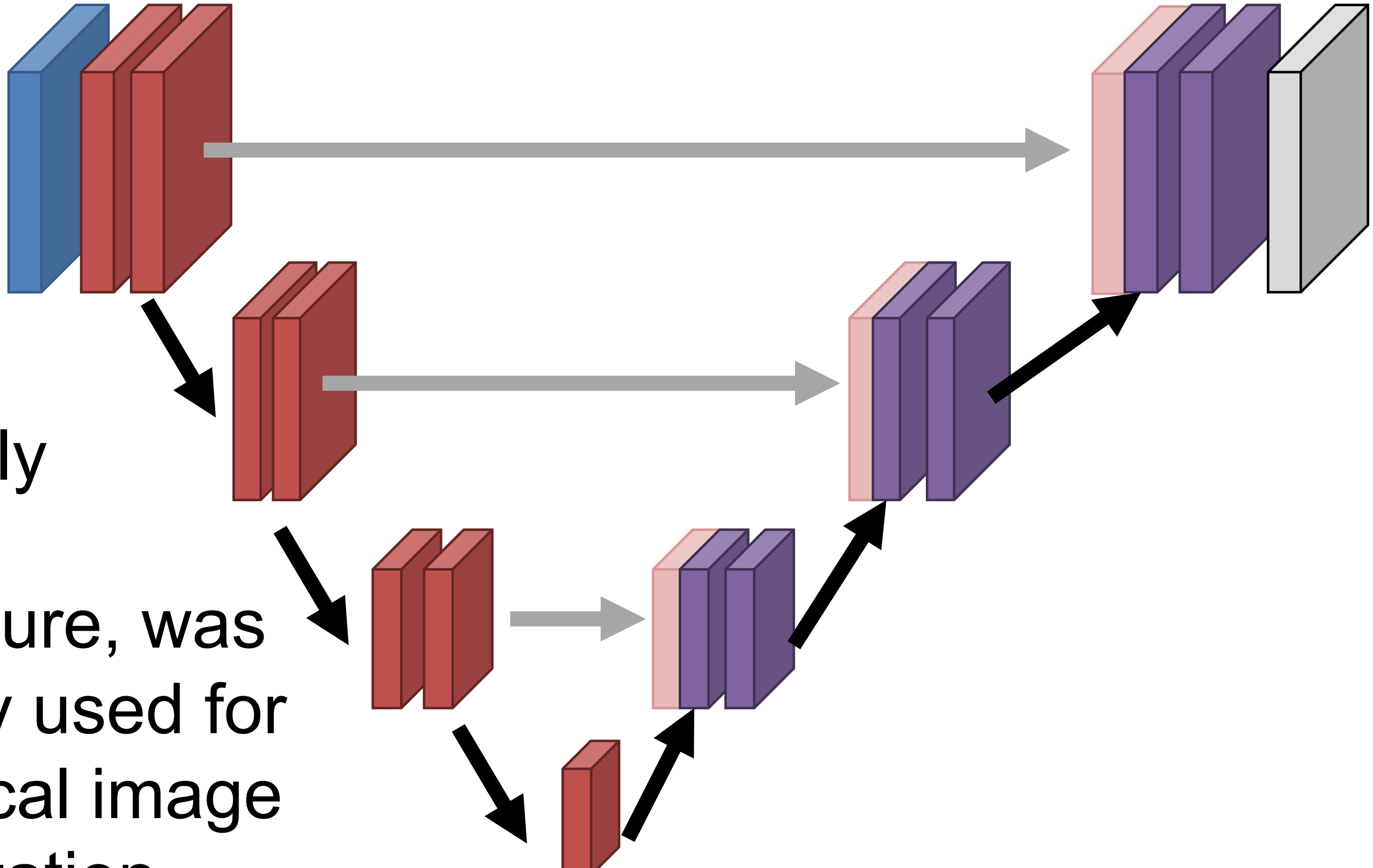
Often called Residual Connections as in ResNet



Copy

Result from Long et al. *Fully Convolutional Networks For Semantic Segmentation*. CVPR 2014

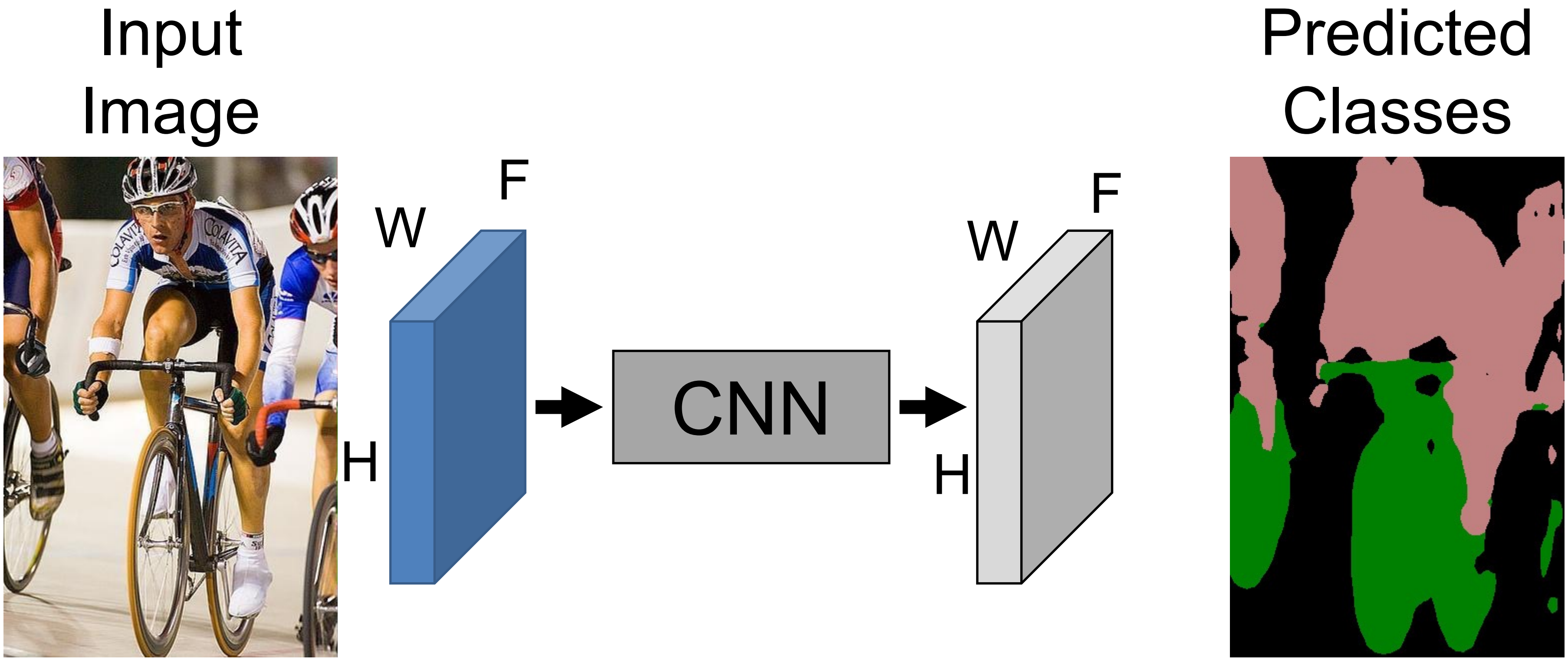
U-Net



Extremely popular architecture, was originally used for biomedical image segmentation.

Ronneberger et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation. MICCAI 2015

Evaluating Pixel Labels



How do we convert final HxWxF into labels?

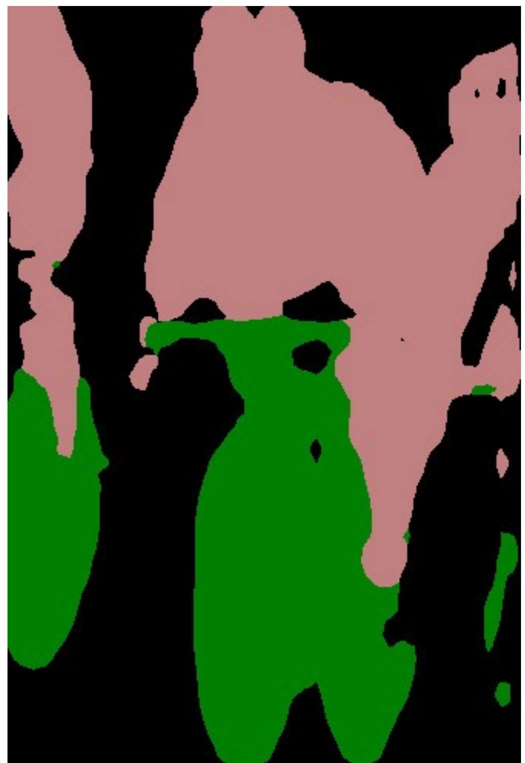
argmax over labels

Evaluating Semantic Segmentation

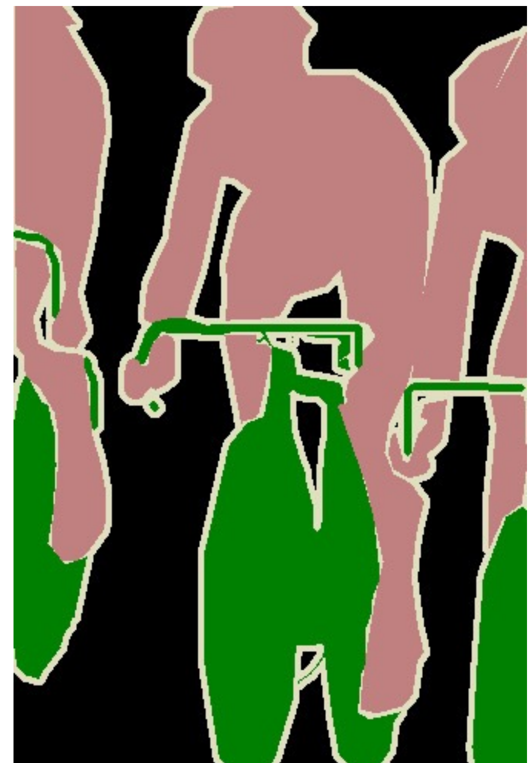
Given predictions, how well did we do?

Input

Prediction ($\hat{y}$)



Ground-Truth (y)



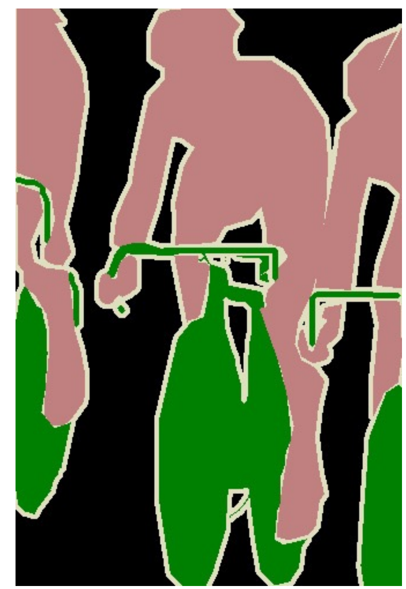
Evaluating Semantic Segmentation

Prediction and ground-truth are images where each pixel is one of F classes.

Accuracy: mean($\hat{\boldsymbol{y}} = y$)

Prediction ($\hat{\boldsymbol{y}}$)

Ground-Truth ($\boldsymbol{y}$)

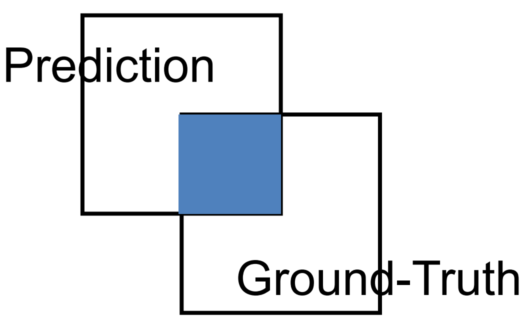


Evaluating Semantic Segmentation

Prediction and ground-truth are images where each pixel is one of F classes.

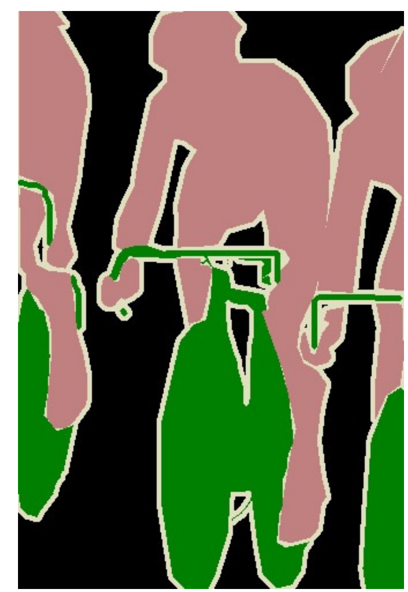
Accuracy: mean$(\hat{\boldsymbol{y}} = y)$

Intersection over union, averaged over classes



Prediction $(\hat{\boldsymbol{y}})$

Ground-Truth $(\boldsymbol{y})$



Evaluating Semantic Segmentation

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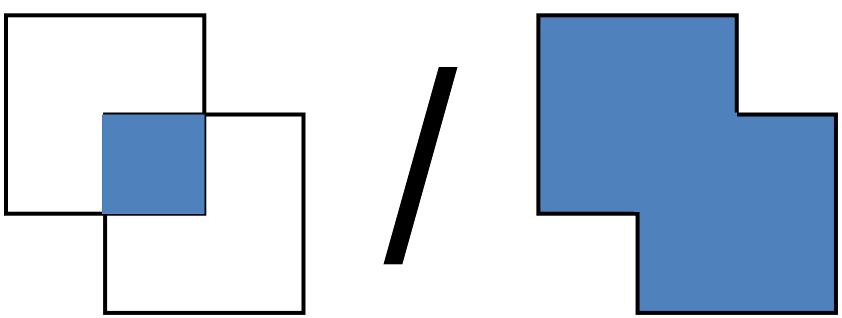
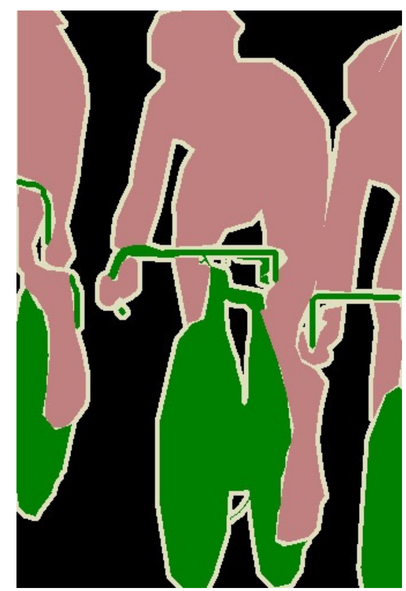


Prediction
($\hat{\boldsymbol{y}}$)

Ground-Truth
($\boldsymbol{y}$)



Next Time

- Detecting Objects (drawing boxes around them)

More Info

Why “Transpose Convolution”?

Can write convolution as matrix-multiply
Input: 4, Filter: 3, Stride: 1, Pad: 1

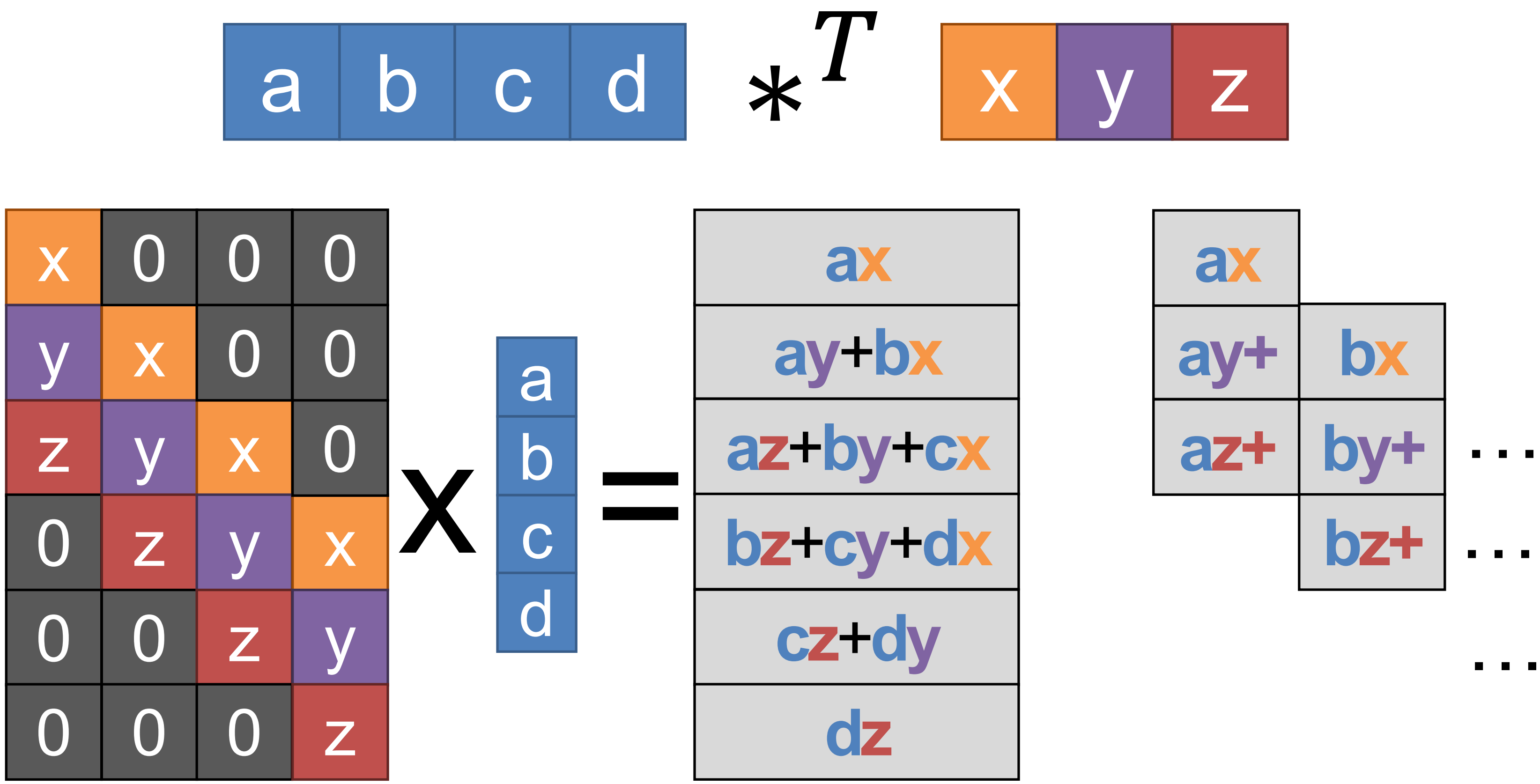
$$\begin{bmatrix} a & b & c & d \end{bmatrix} * \begin{bmatrix} x & y & z \end{bmatrix}$$

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

Example Credit: L. Fei-Fei, J. Johnson, S. Yeung

Why "Transpose Convolution"?

Transpose convolution is convolution transposed



Example Credit: L. Fei-Fei, J. Johnson, S. Yeung