Computer Vision

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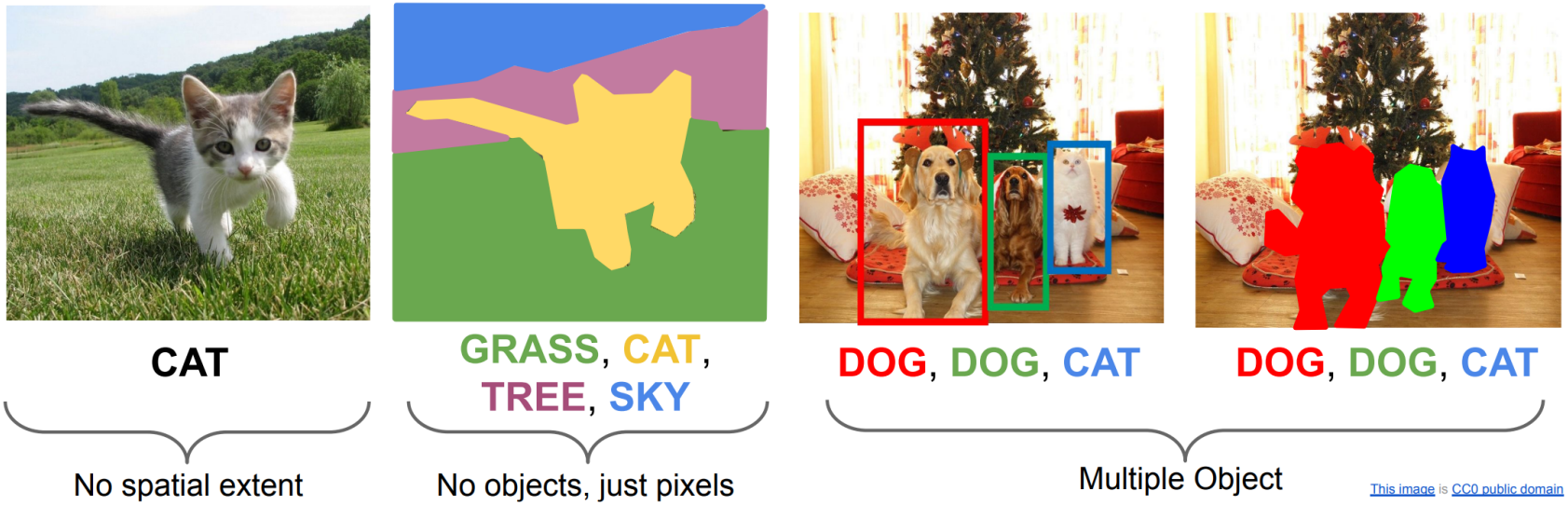
Image Classification

- Previously, we discussed Image Classification
- A core task in Computer Vision

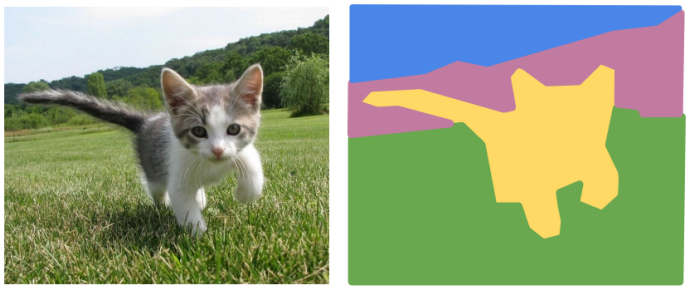
(assume given a set of possible labels)
{dog, cat, truck, plane, ...}

cat

Computer Vision Tasks

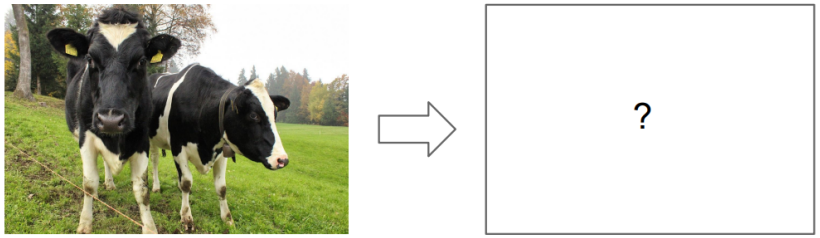


Semantic Segmentation



GRASS, CAT,
TREE, SKY, ...

Paired training data: for each training image,
each pixel is labeled with a semantic category.



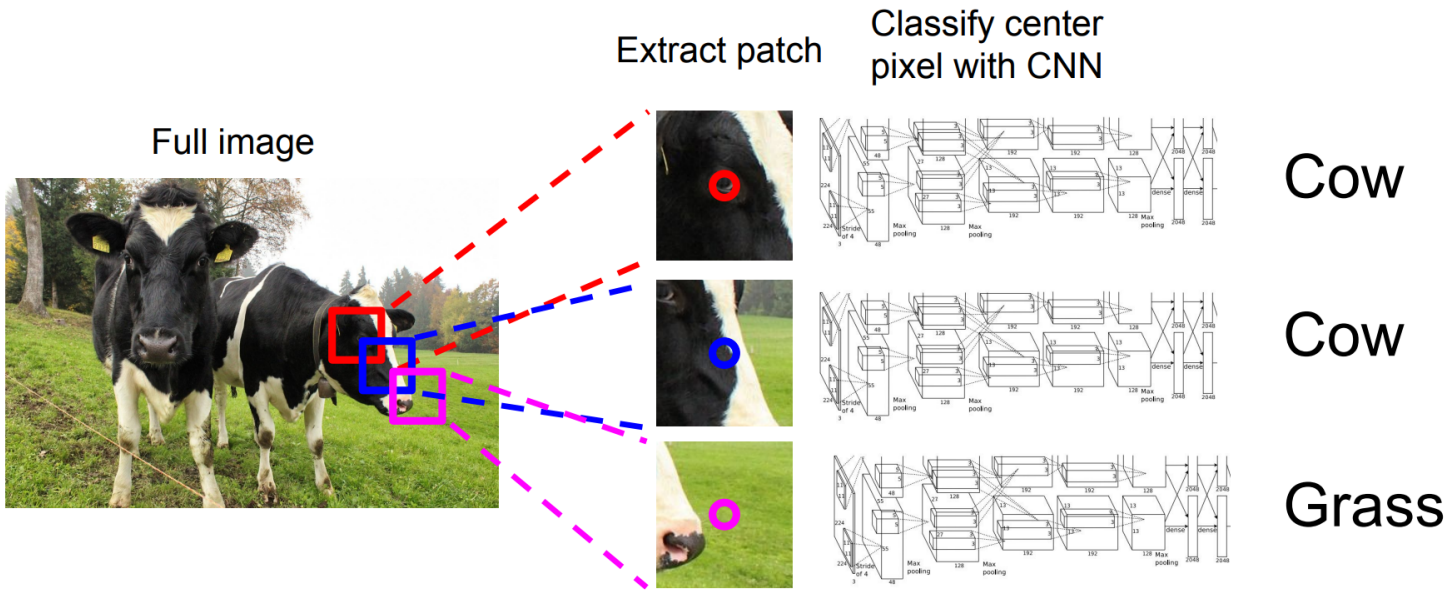
At test time, classify each pixel of a new image.

Semantic Segmentation

Semantic Segmentation

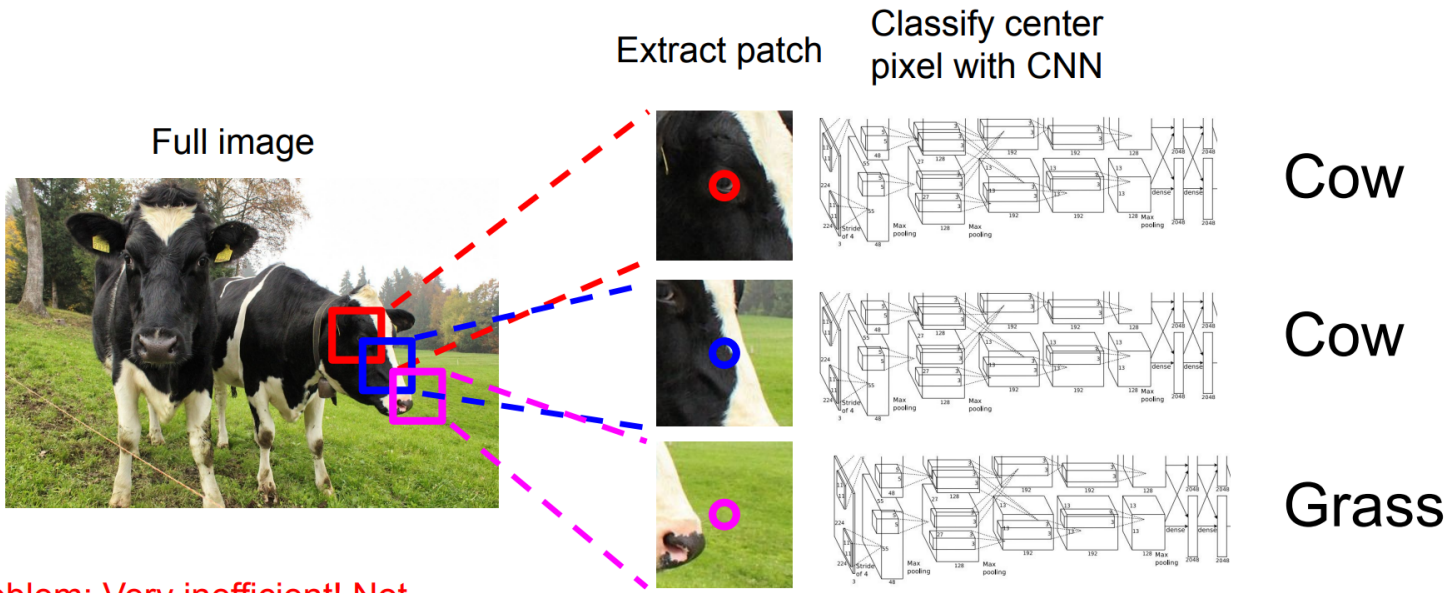
- Impossible to classify without context
- How do we include context?

Semantic Segmentation Idea: Sliding Window



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

Semantic Segmentation Idea: Sliding Window (cont.)

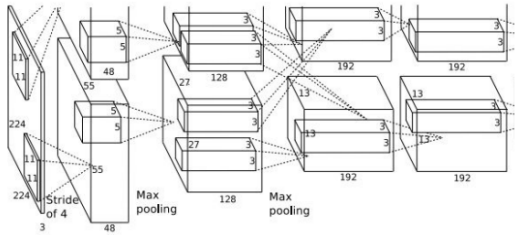


Problem: Very inefficient! Not reusing shared features between overlapping patches

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

Semantic Segmentation Idea: Convolution

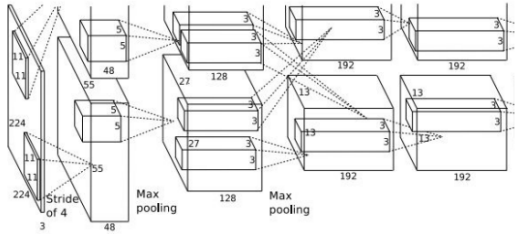
Full image



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

Semantic Segmentation Idea: Convolution (cont.)

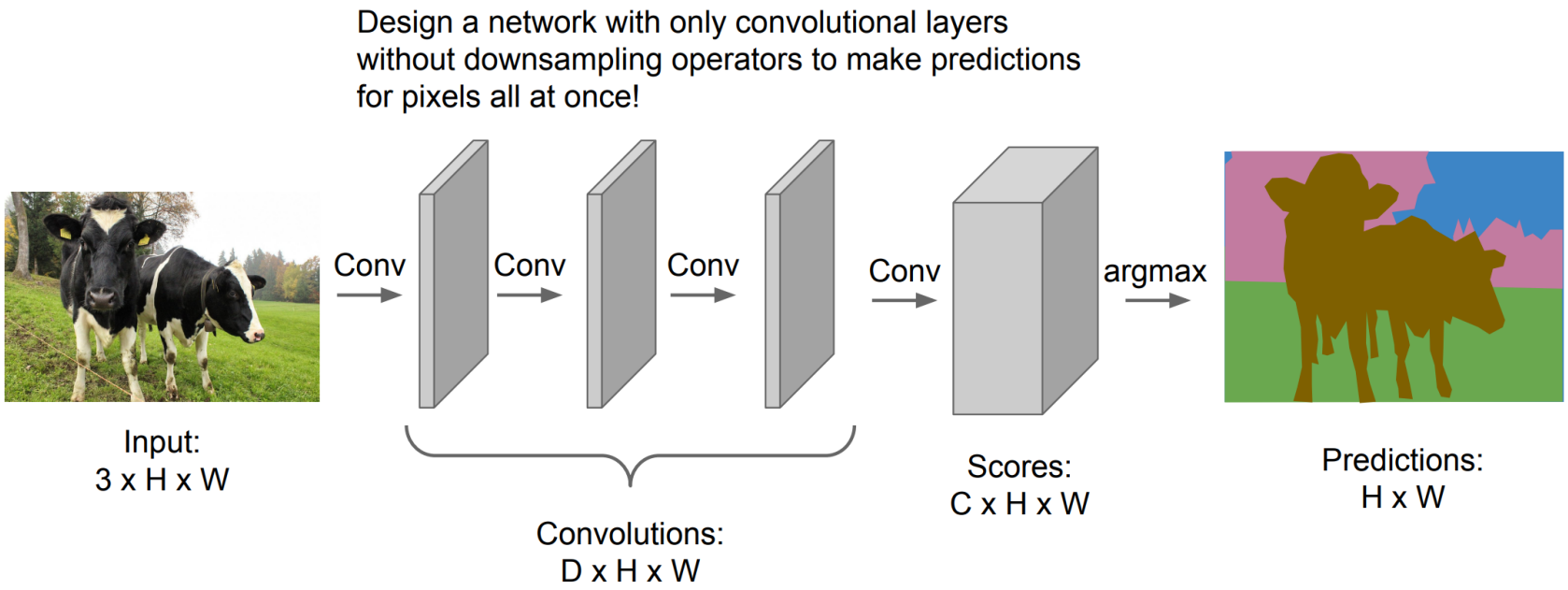
Full image



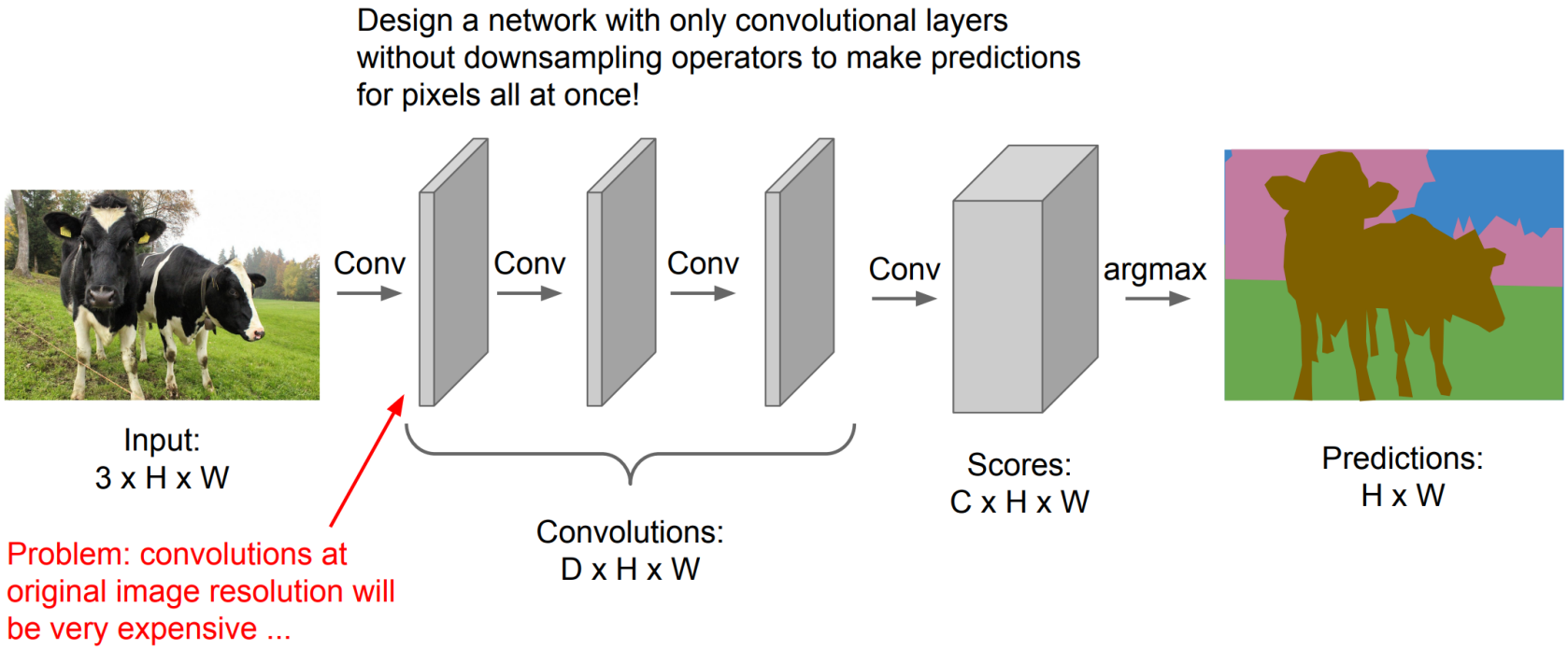
An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

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.

Semantic Segmentation Idea: Fully Convolutional



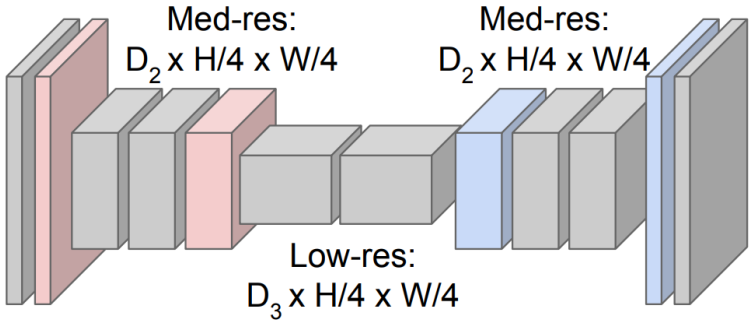
Semantic Segmentation Idea: Fully Convolutional (cont.)



Semantic Segmentation Idea: Fully Convolutional (cont.)

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

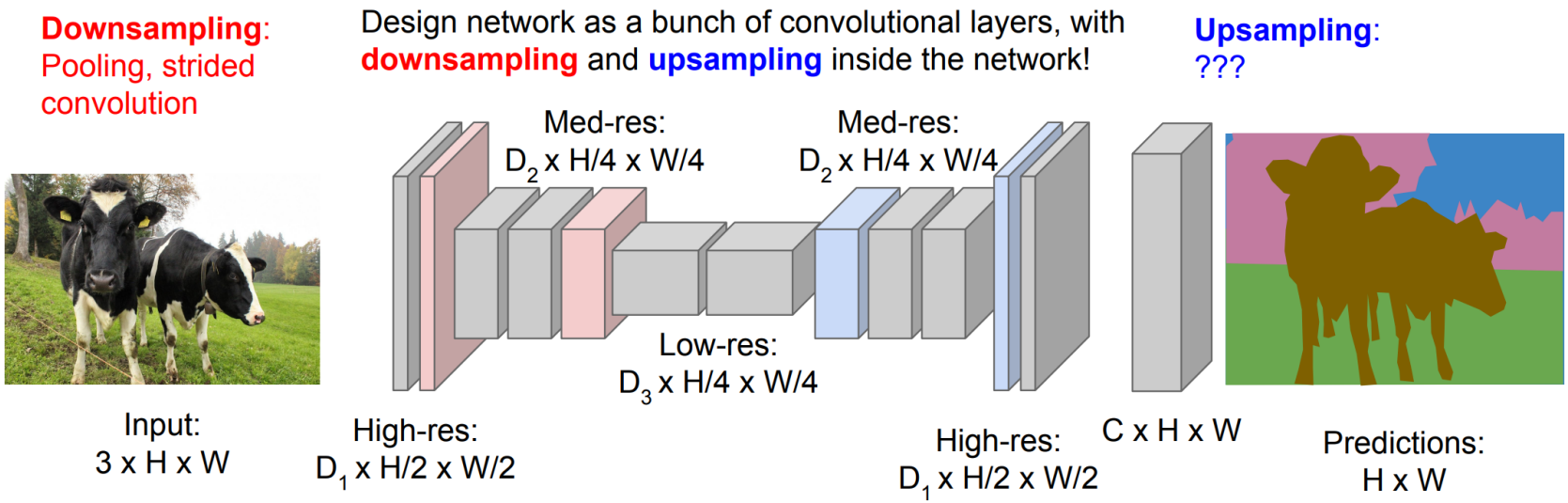
High-res:
D_1 x H/2 x W/2

C x H x W

Predictions:
H x W

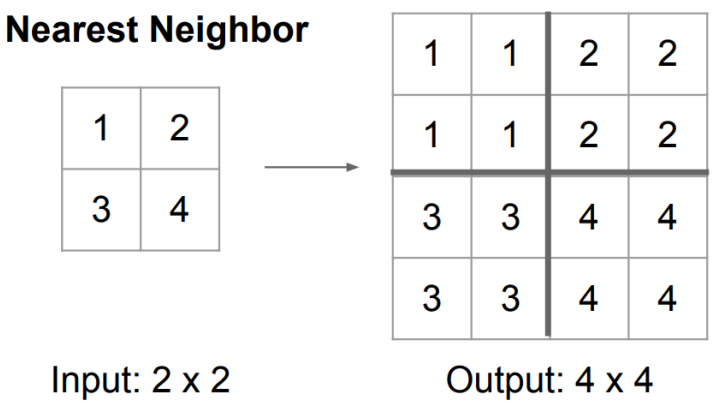
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

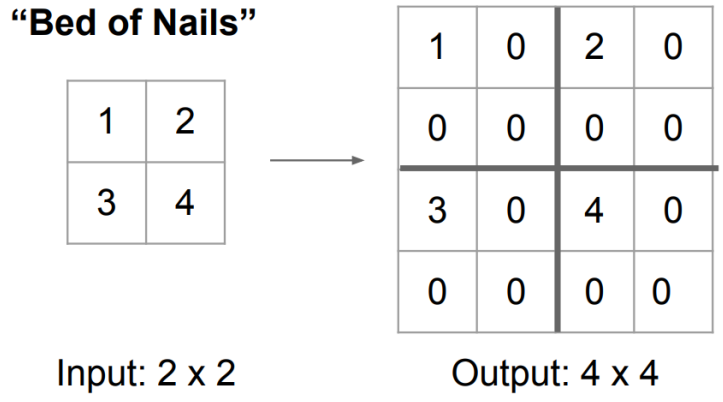
Semantic Segmentation Idea: Fully Convolutional (cont.)



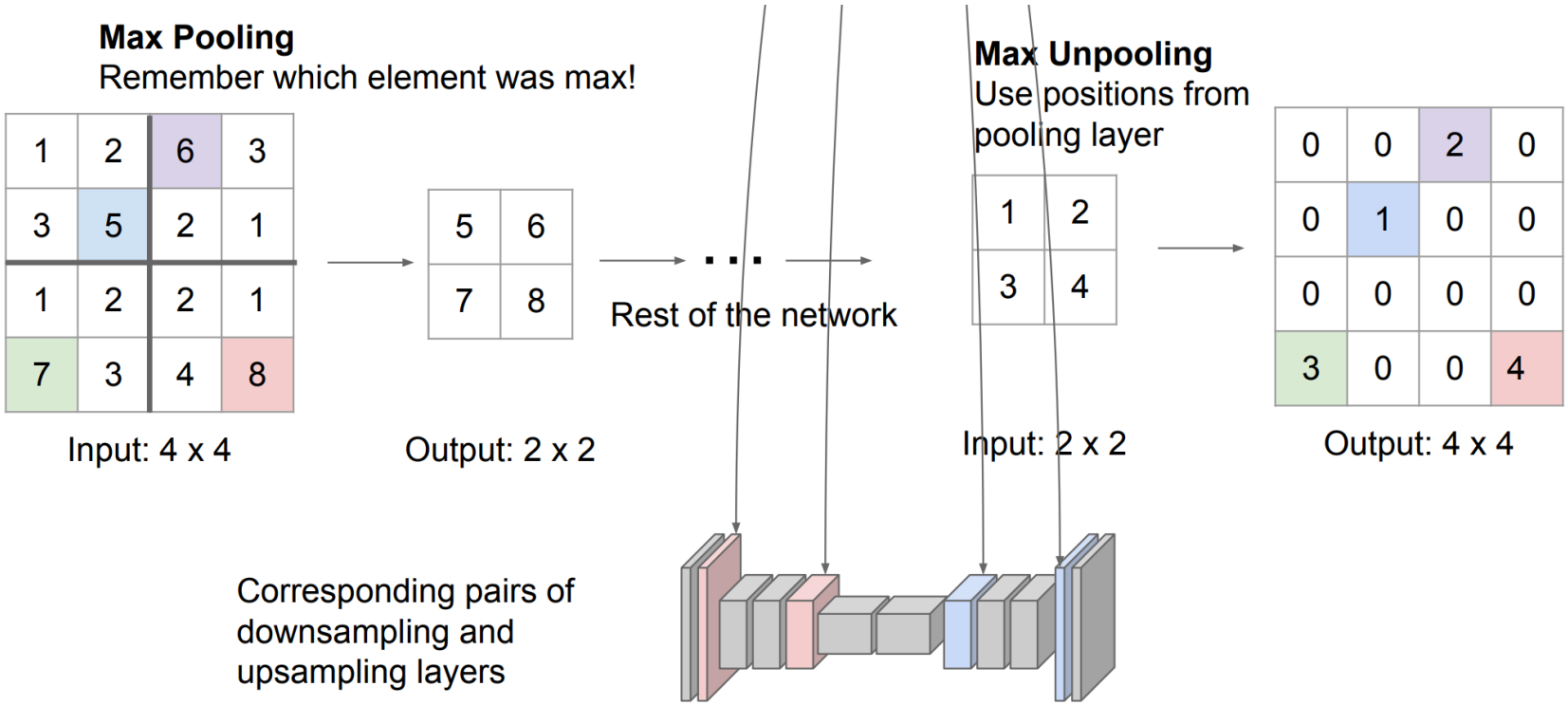
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

In-Network Upsampling: Unpooling



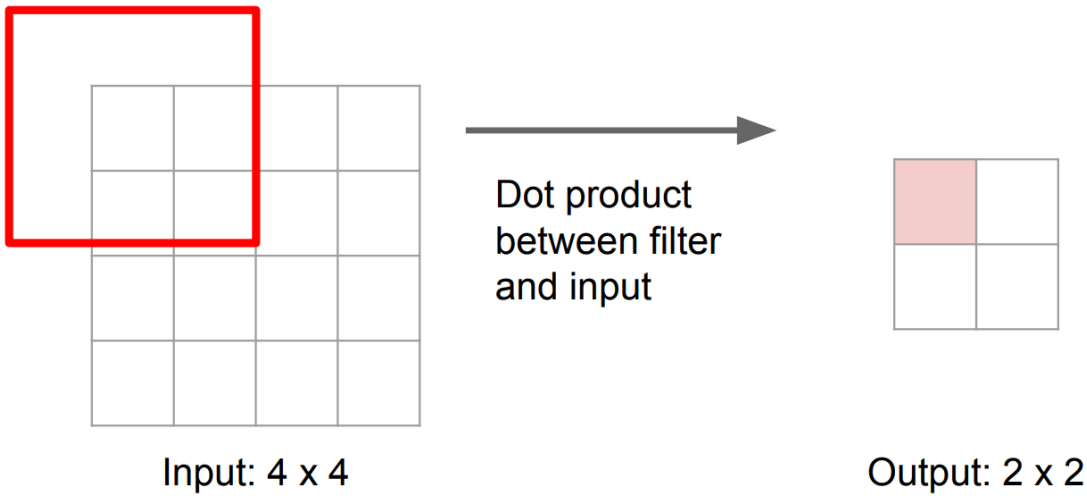


In-Network Upsampling: Max Unpooling



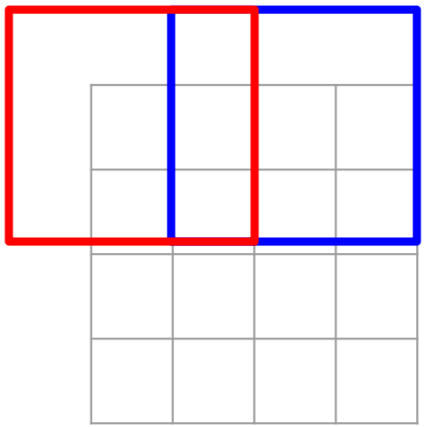
Learnable Upsampling: Transposed Convolution

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



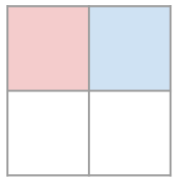
Learnable Upsampling: Transposed Convolution (cont.)

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



Input: 4 x 4

Dot product between filter and input



Output: 2 x 2

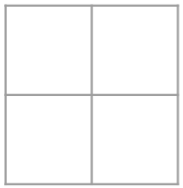
Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

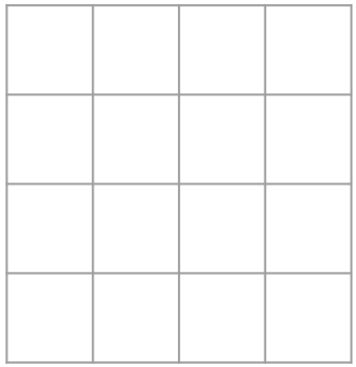
We can interpret strided convolution as “learnable downsampling”.

Learnable Upsampling: Transposed Convolution (cont.)

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

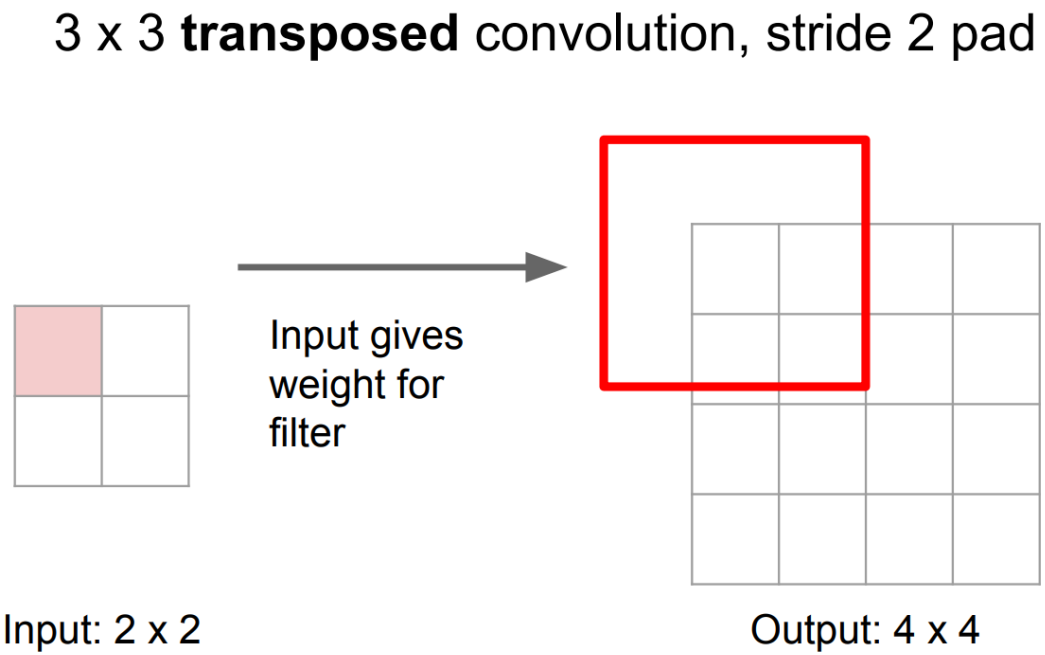


Input: 2 x 2

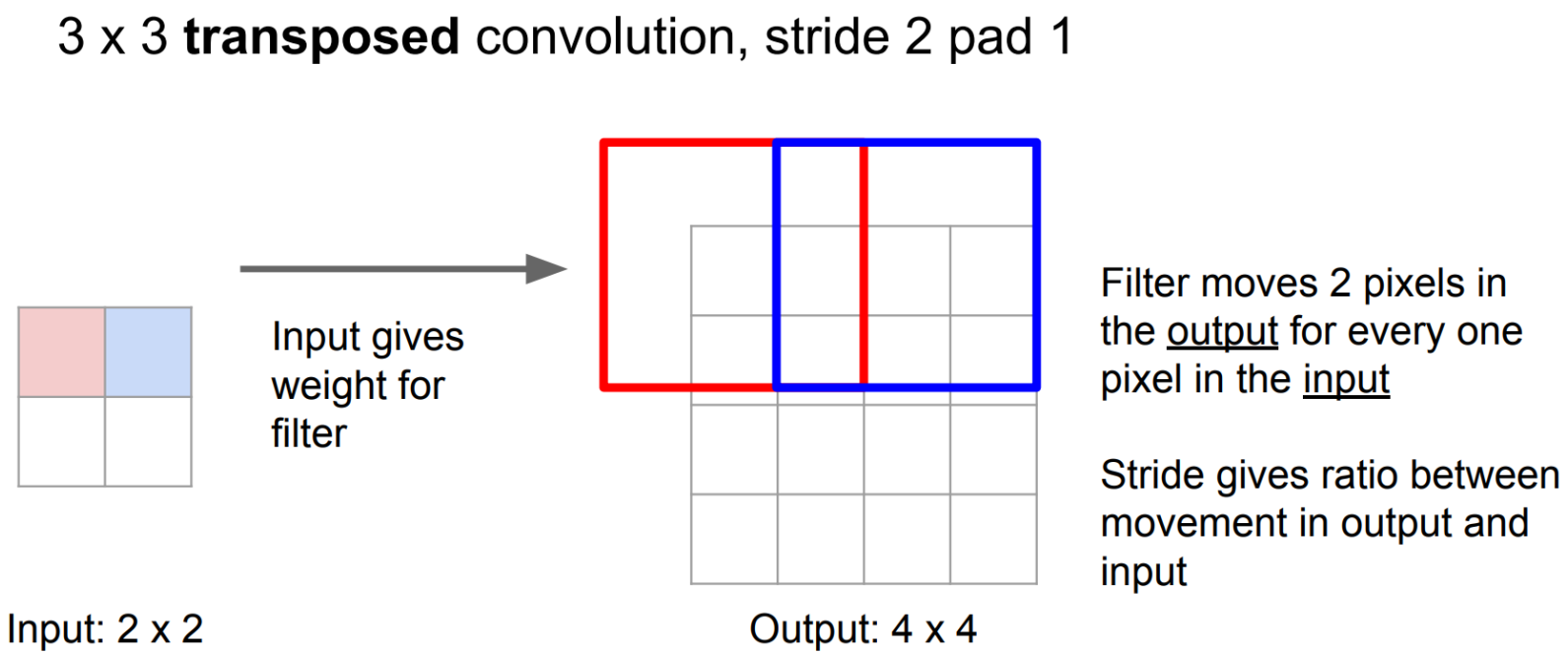


Output: 4 x 4

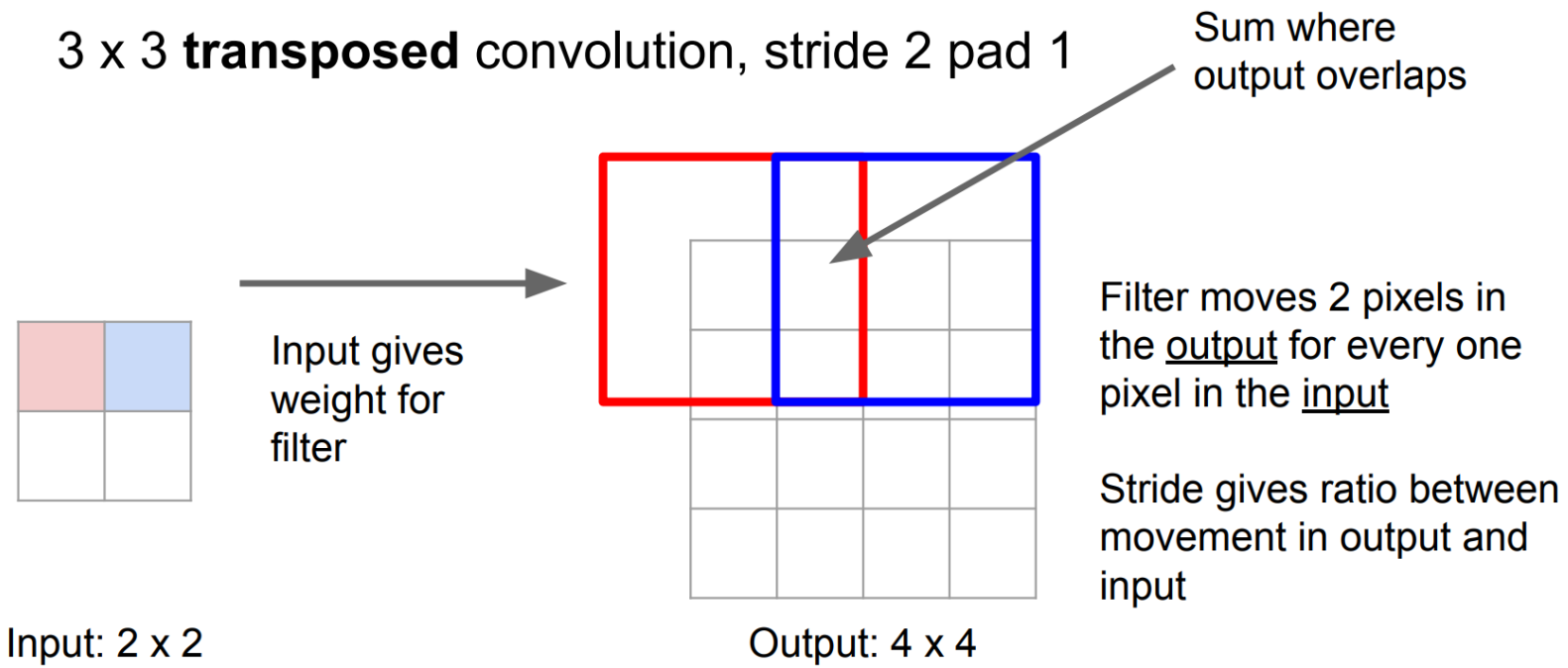
Learnable Upsampling: Transposed Convolution (cont.)



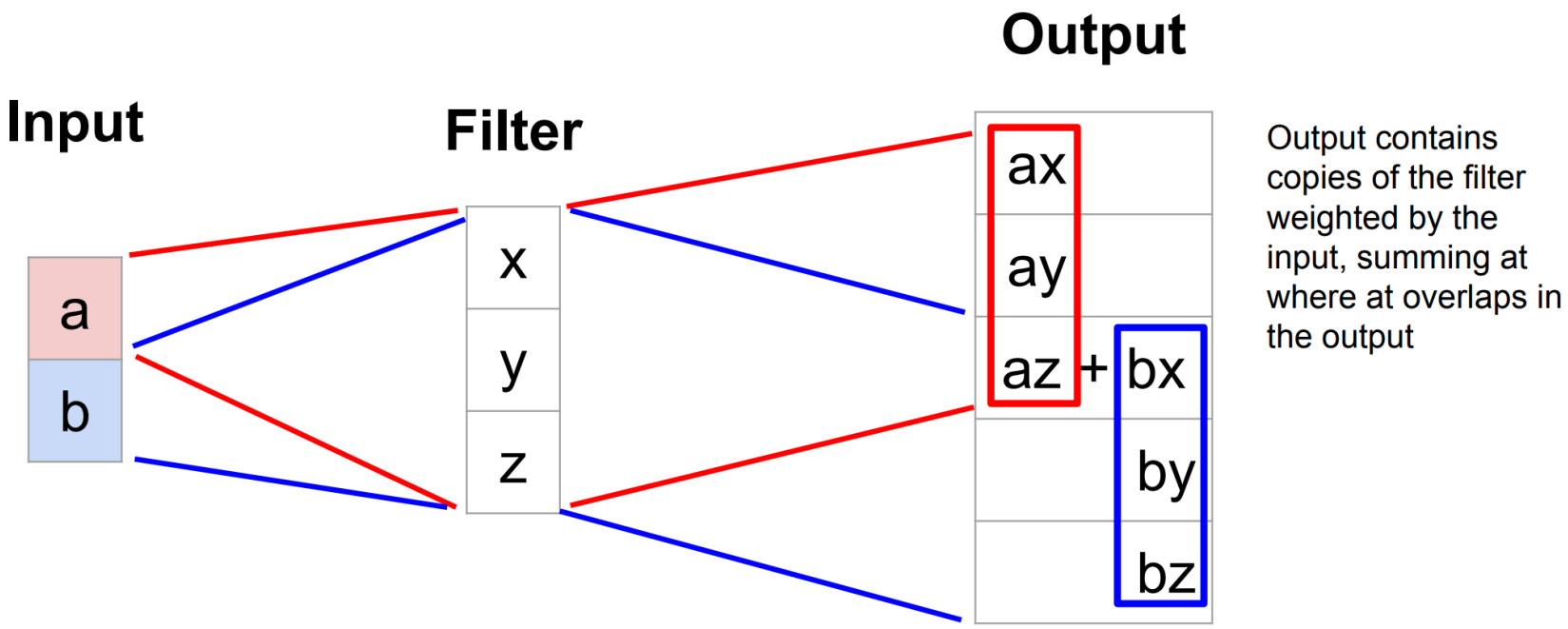
Learnable Upsampling: Transposed Convolution (cont.)



Learnable Upsampling: Transposed Convolution (cont.)



Transposed Convolution: 1D Example



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

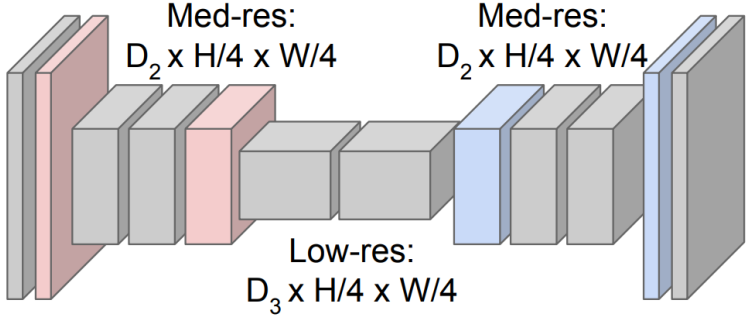
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling:
Unpooling or strided transposed convolution

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

High-res:
D_1 x H/2 x W/2

Predictions:
H x W

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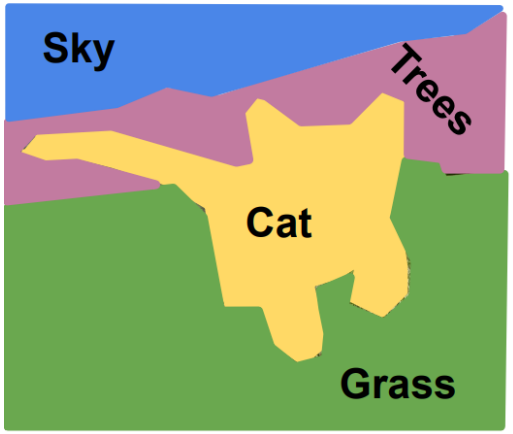
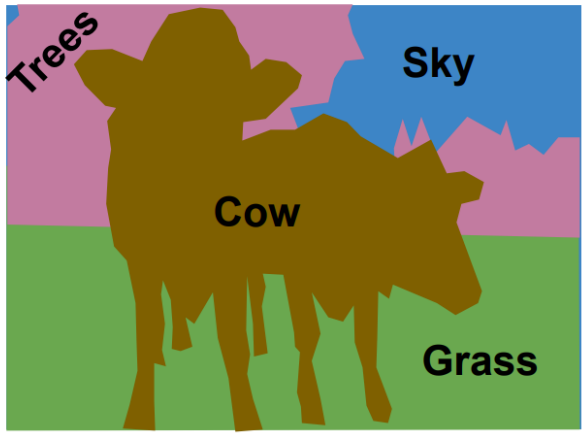
Semantic Segmentation

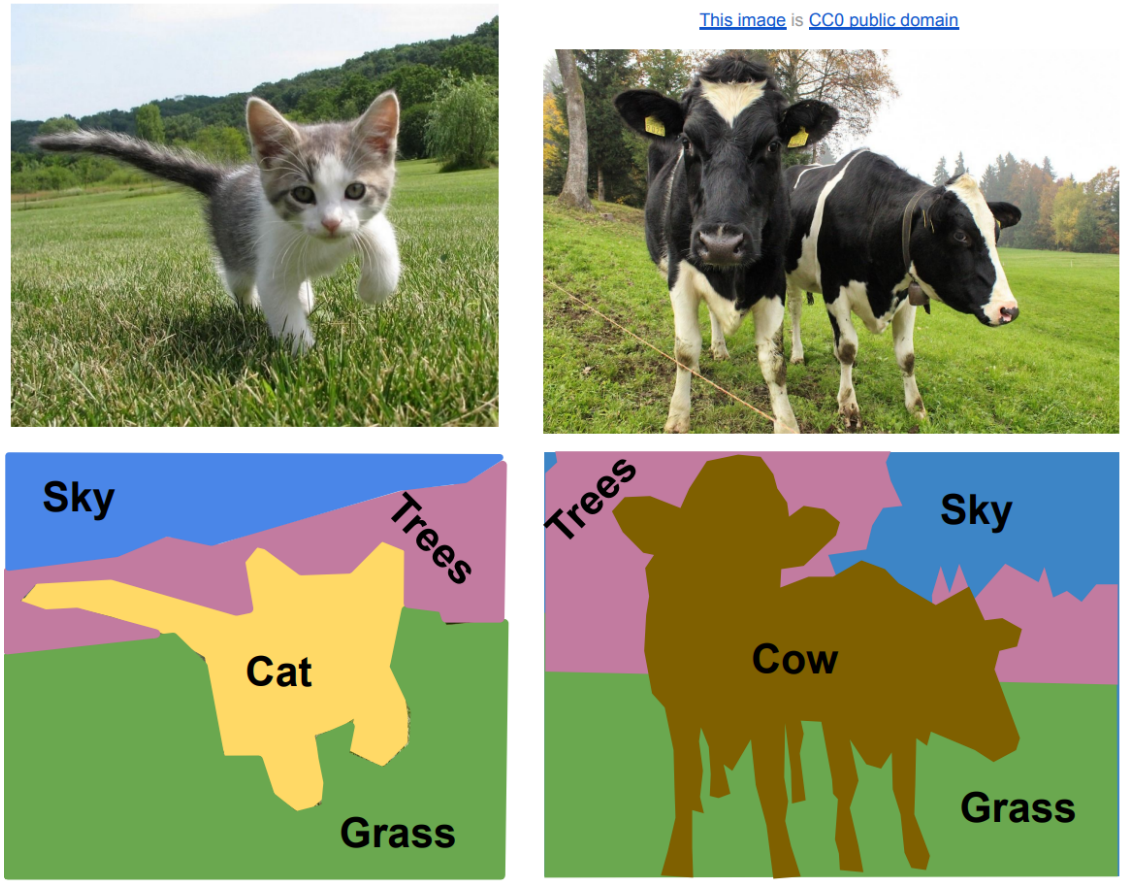
- Label each pixel in the image with a category label





Semantic Segmentation

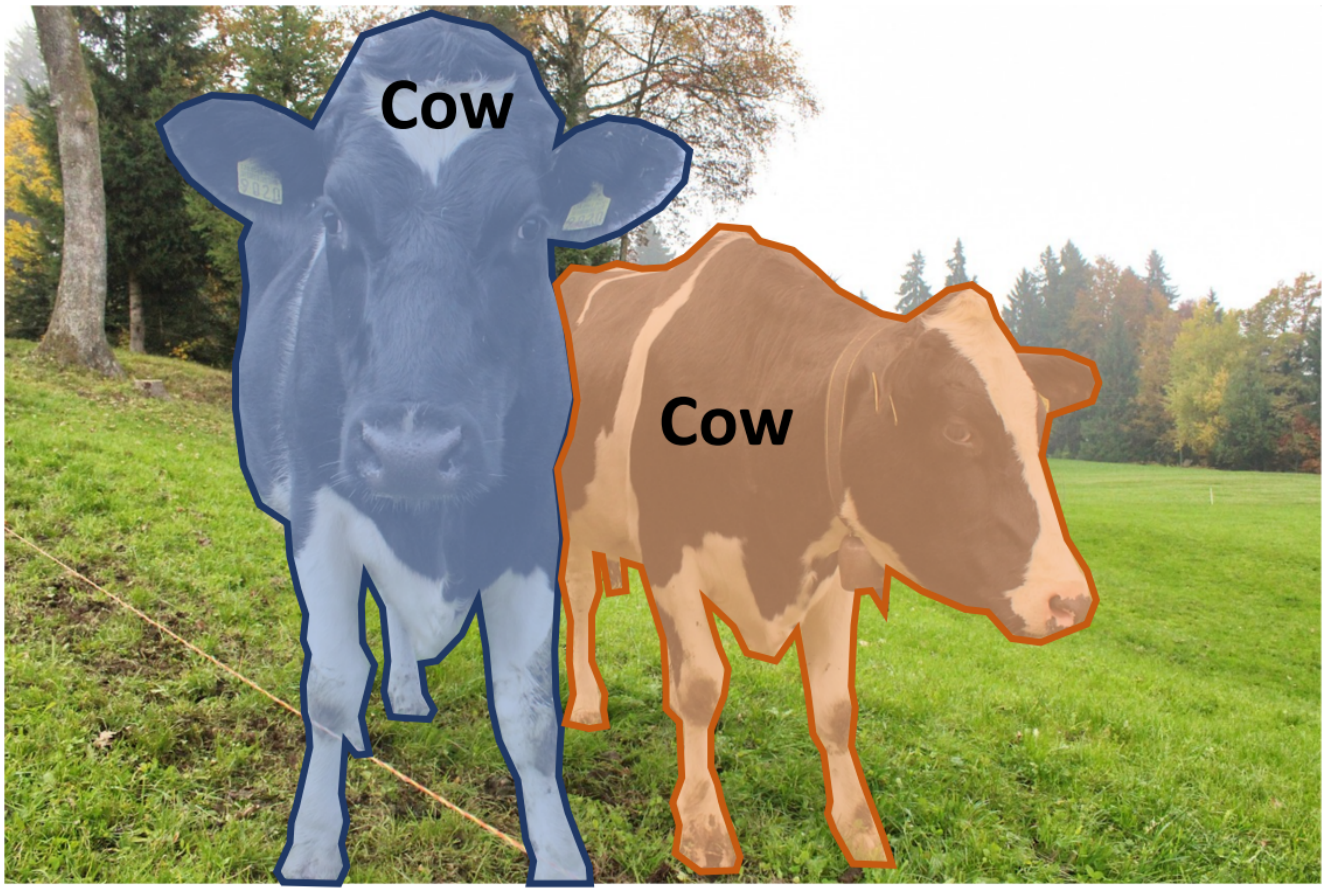
- Label each pixel in the image with a category label



- **Does not differentiate instances, only care about pixels**

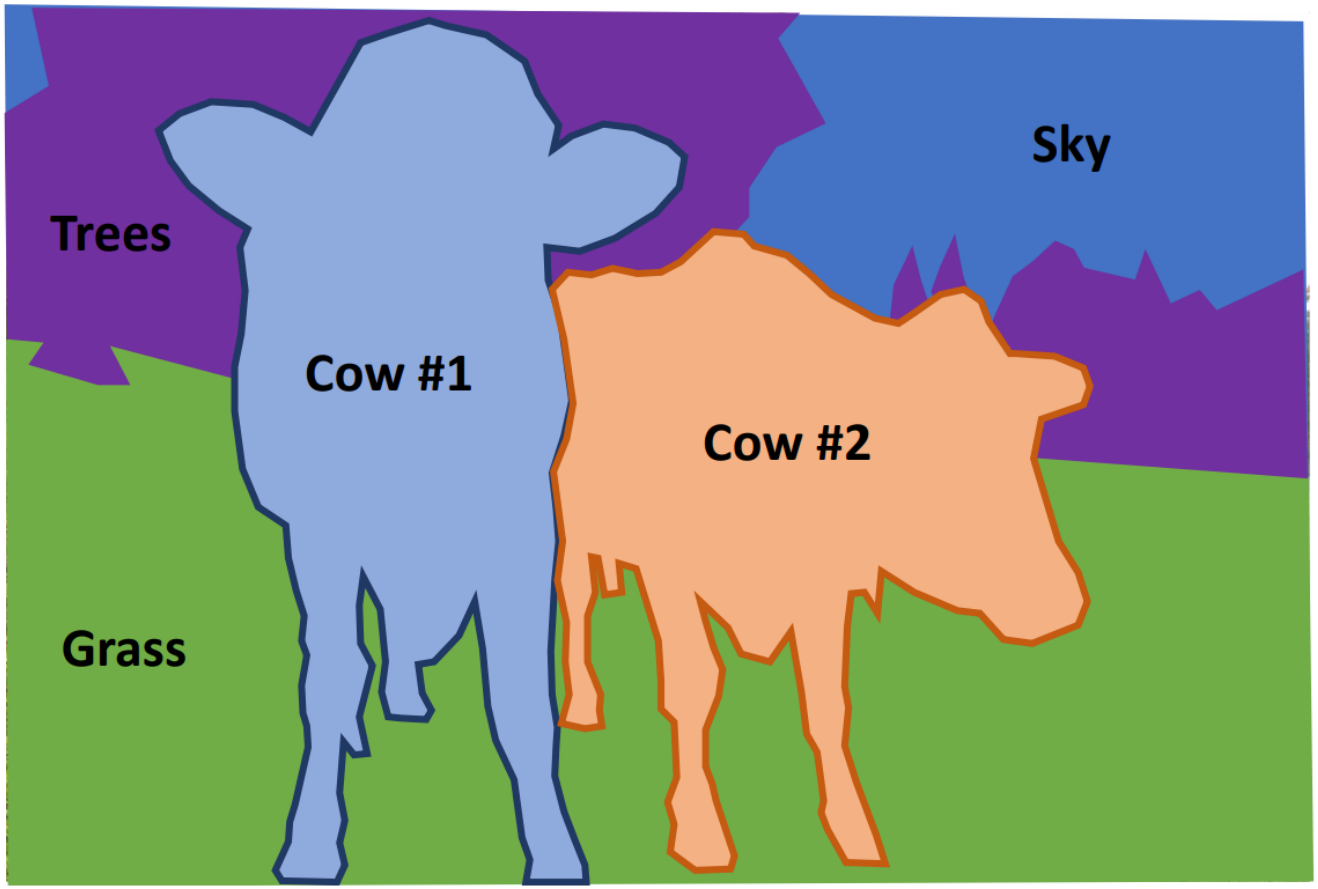
Instance Segmentation

- Separate object instances, but only things



Panoptic Segmentation

- Label all pixels in the image (both things and stuff)



References

These slides have been adapted from

- Fei-Fei Li, Yunzhu Li & Ruohan Gao, Stanford CS231n: Deep Learning for Computer Vision
- Assaf Shocher, Shai Bagon, Meirav Galun & Tali Dekel, WAIC DL4CV Deep Learning for Computer Vision: Fundamentals and Applications
- Justin Johnson, UMich EECS 498.008/598.008: Deep Learning for Computer Vision