# Lecture 10:
# Spatial Localization and Image Segmentation

# Computer Vision Tasks

Classification



CAT

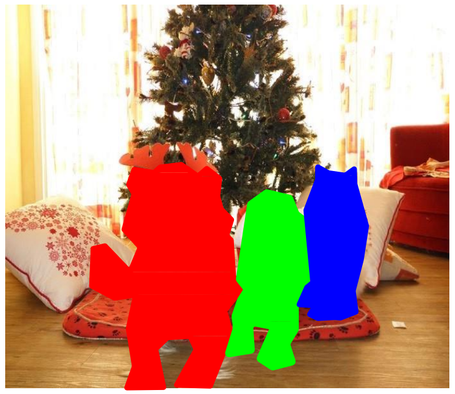
No spatial extent

Object Detection



DOG, DOG, CAT

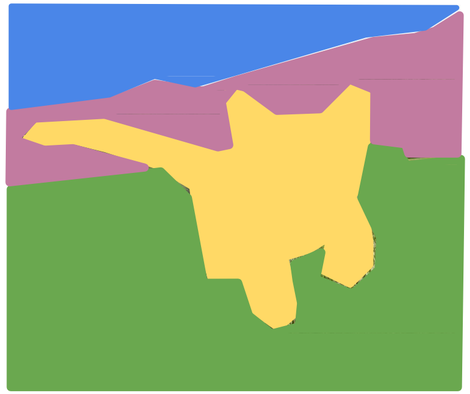
Instance Segmentation



DOG, DOG, CAT

Multiple Objects

Semantic Segmentation



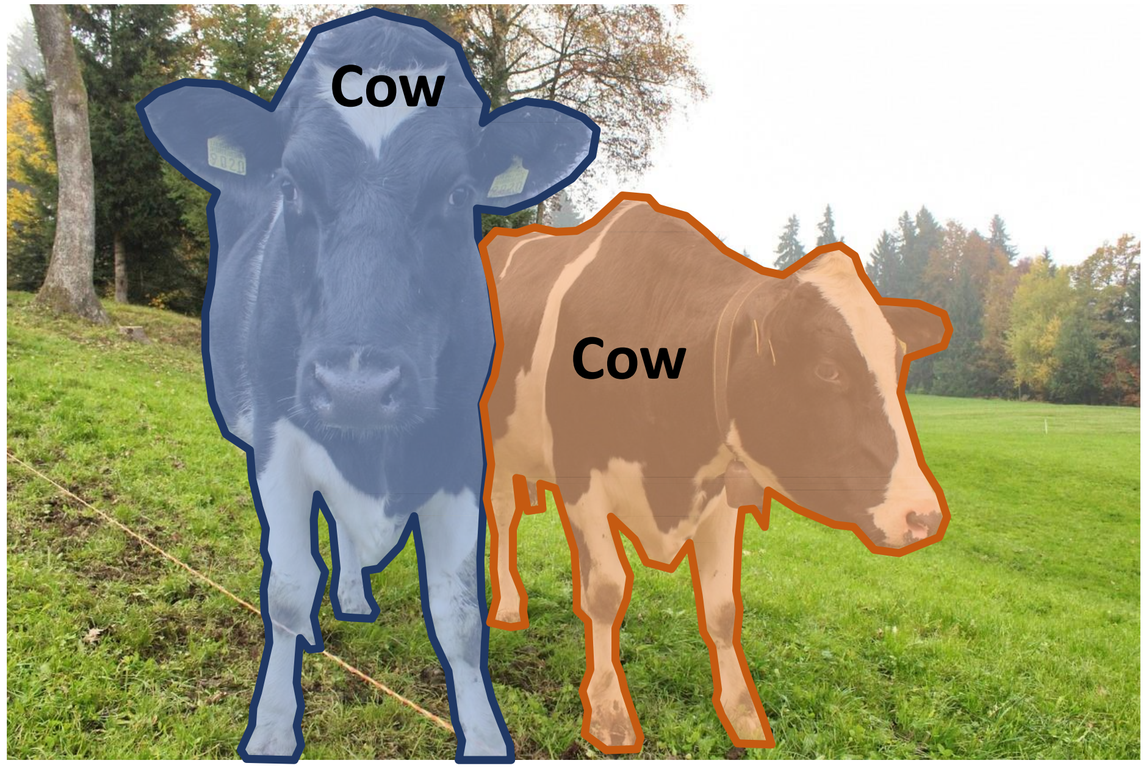
GRASS, CAT, TREE, SKY

No objects, just pixels

Slide adapted from: D Fouhey & J Johnson

# Instance segmentation

**Instance Segmentation**: Detect all objects in the image, and identify the pixels that belong to each object

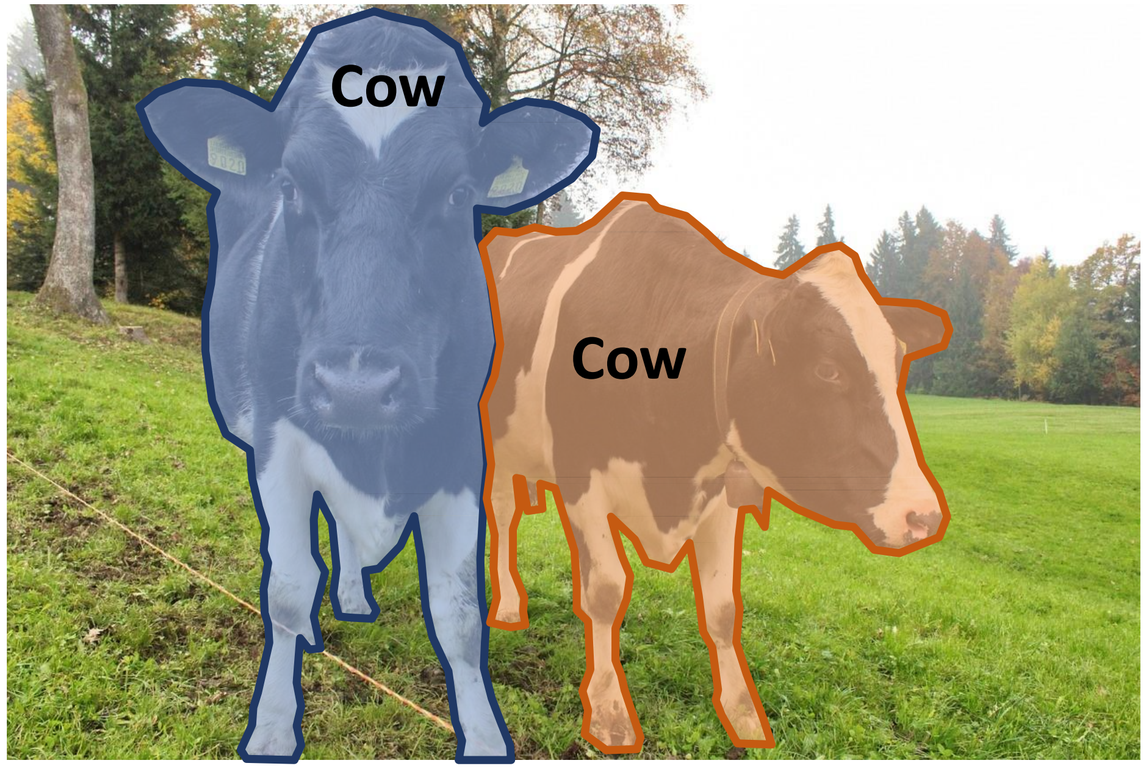



This image is CC0 public domain

# Instance segmentation

**Instance Segmentation**: Detect all objects in the image, and identify the pixels that belong to each object

**Approach:** Perform object detection, then predict a segmentation mask for each object!




This image is CC0 public domain

# Object Detection: Faster R-CNN

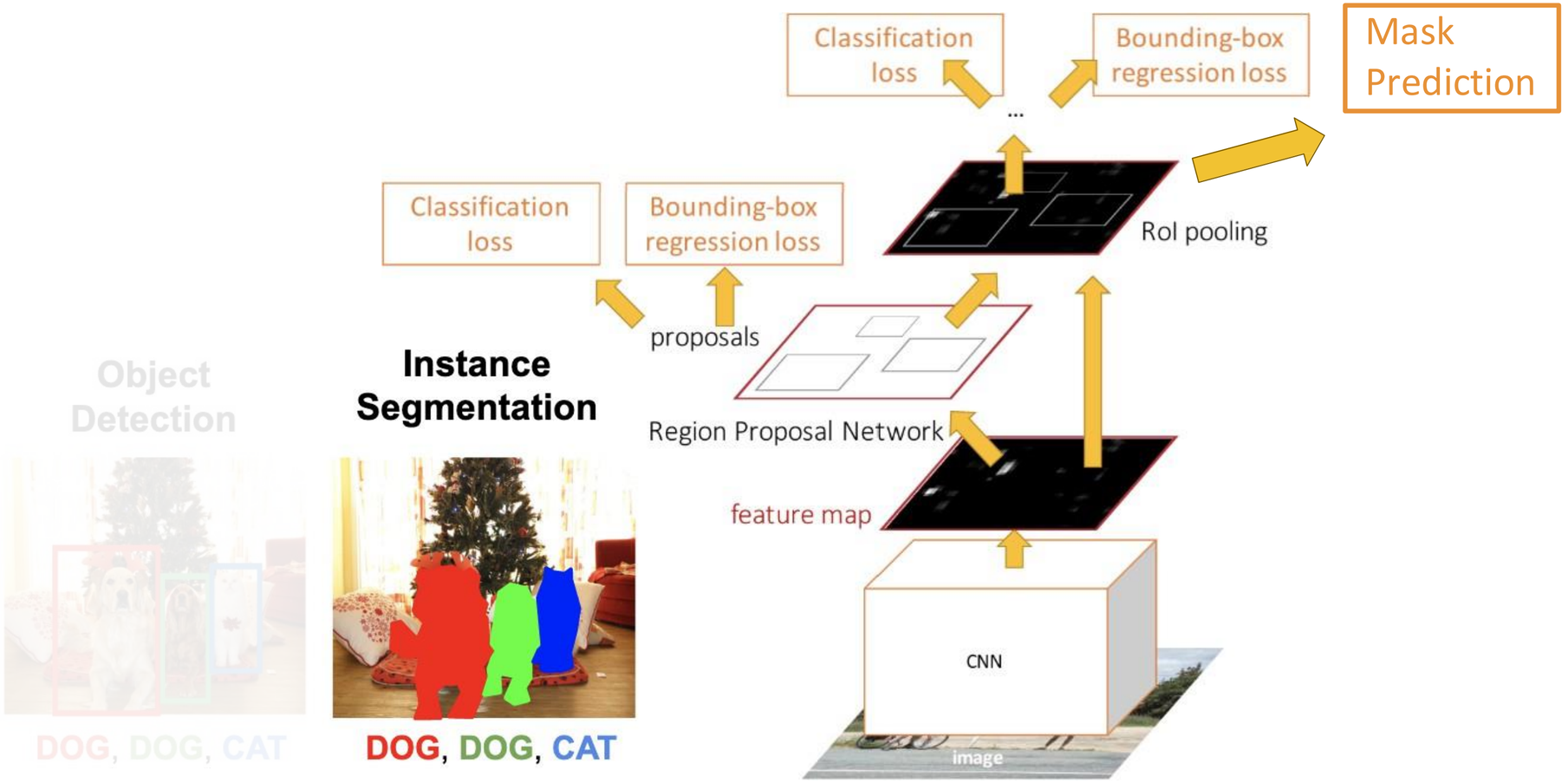






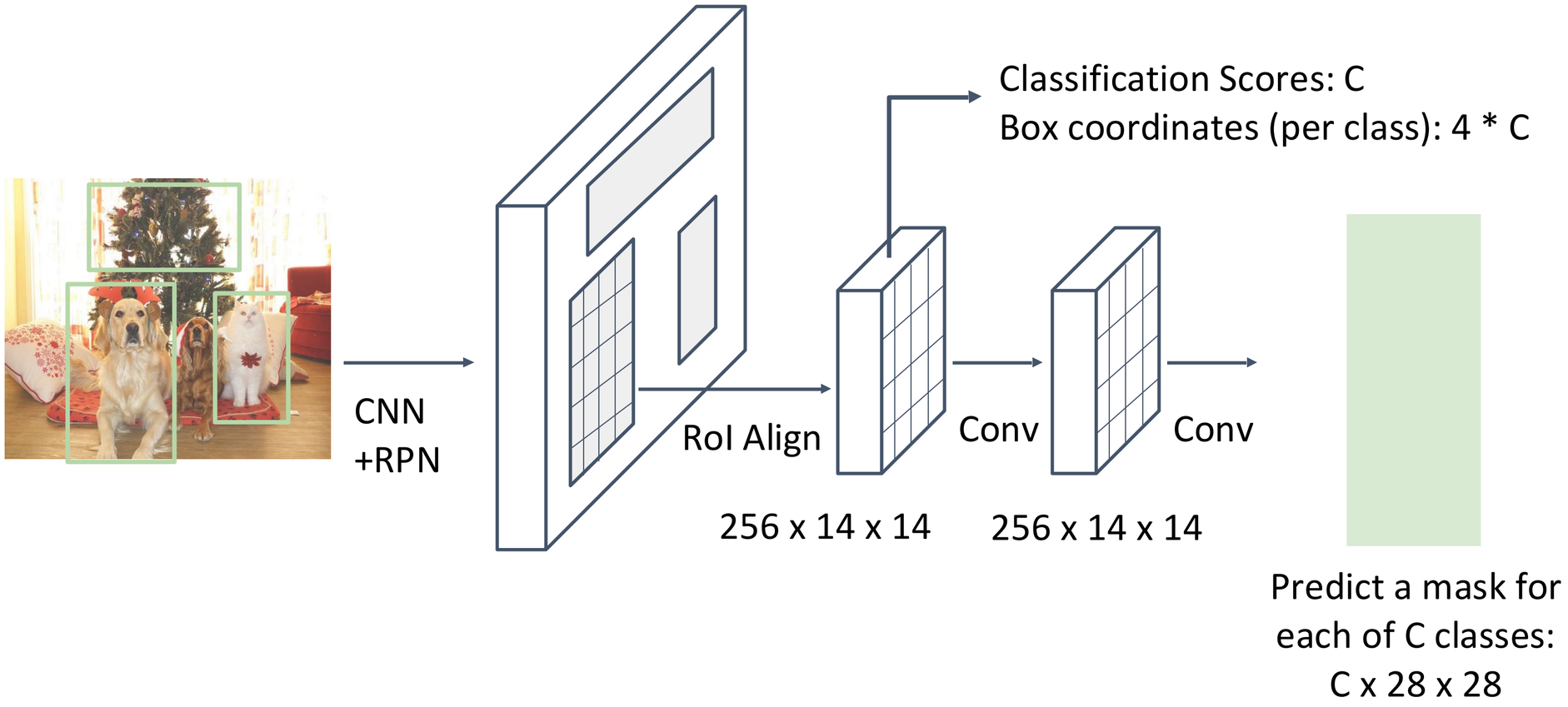

Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NeurIPS 2015

# Instance Segmentation: Mask R-CNN




He et al, "Mask R-CNN", ICCV 2017

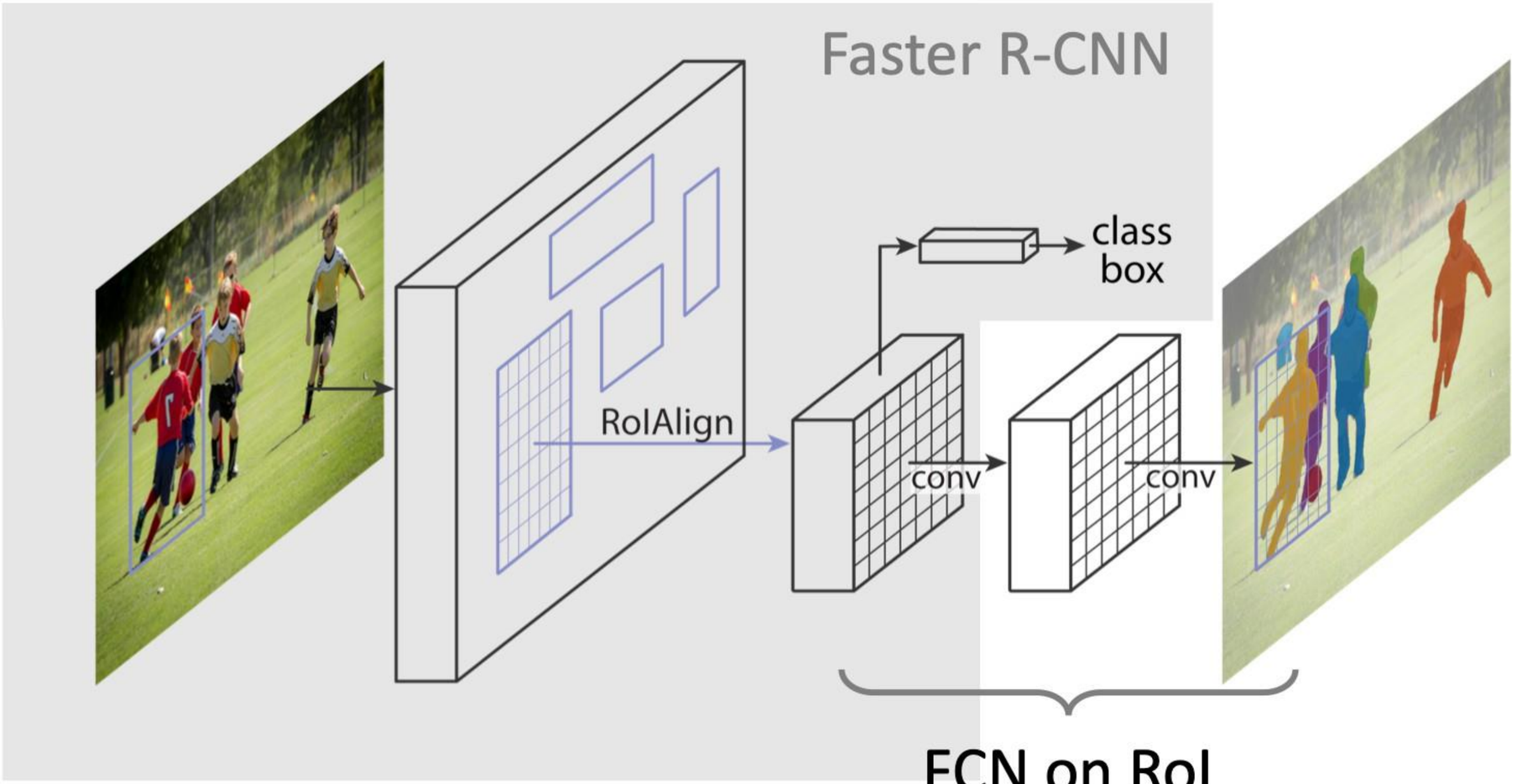
# Mask R-CNN




He et al, “Mask R-CNN”, ICCV 2017

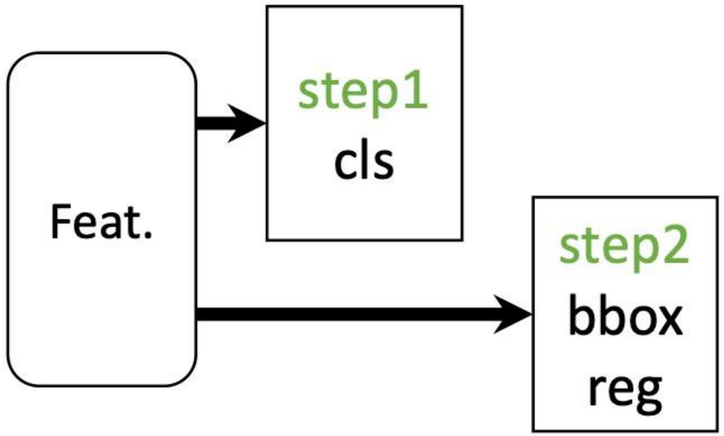
# Mask R-CNN

- Mask R-CNN = **Faster R-CNN** with **FCN** on RoIs

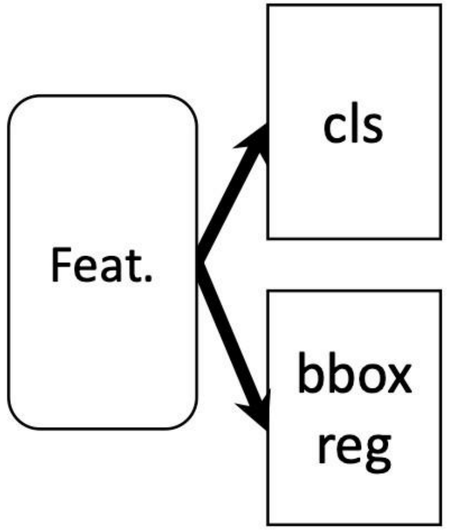


# Parallel Heads

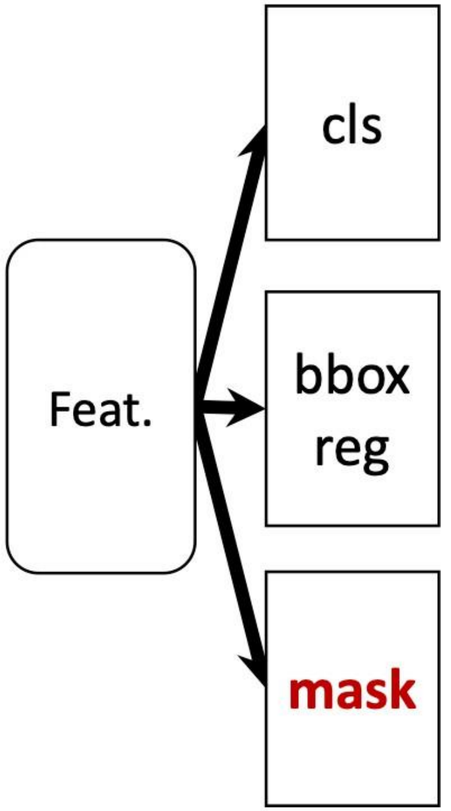
- Easy, fast to implement and train




(slow) R-CNN

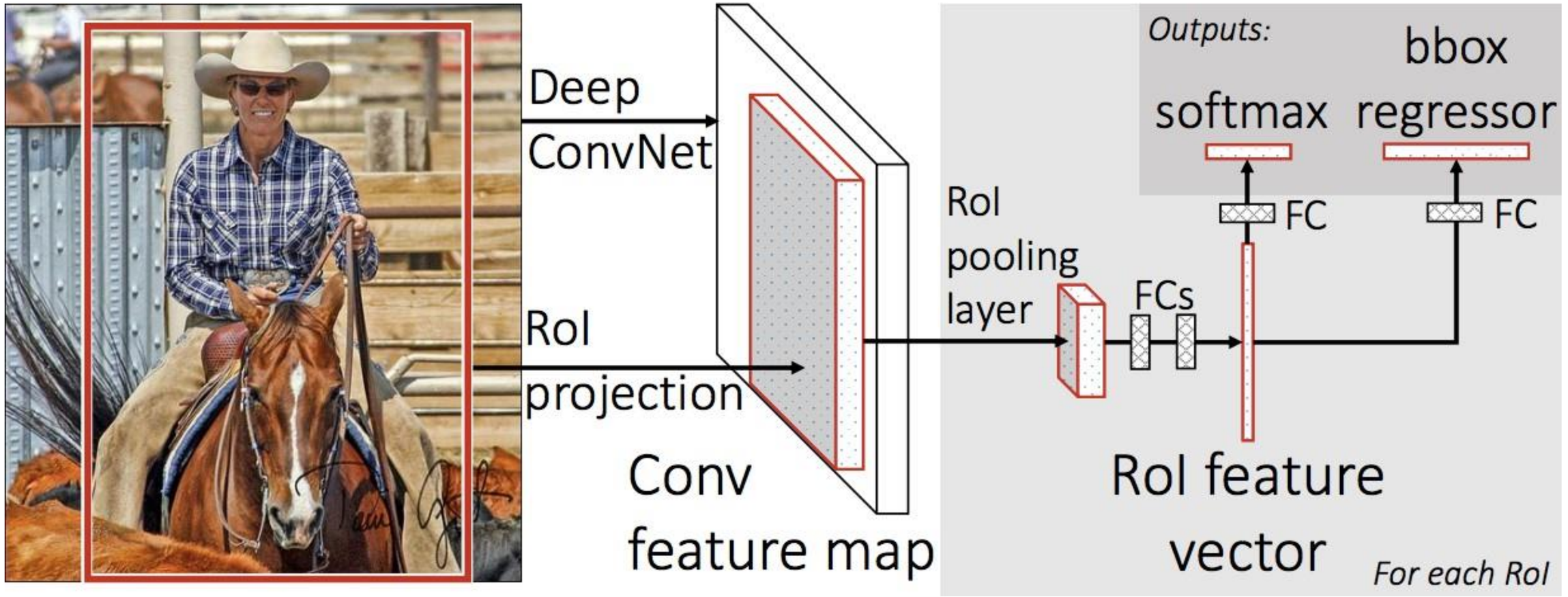



Fast/er R-CNN



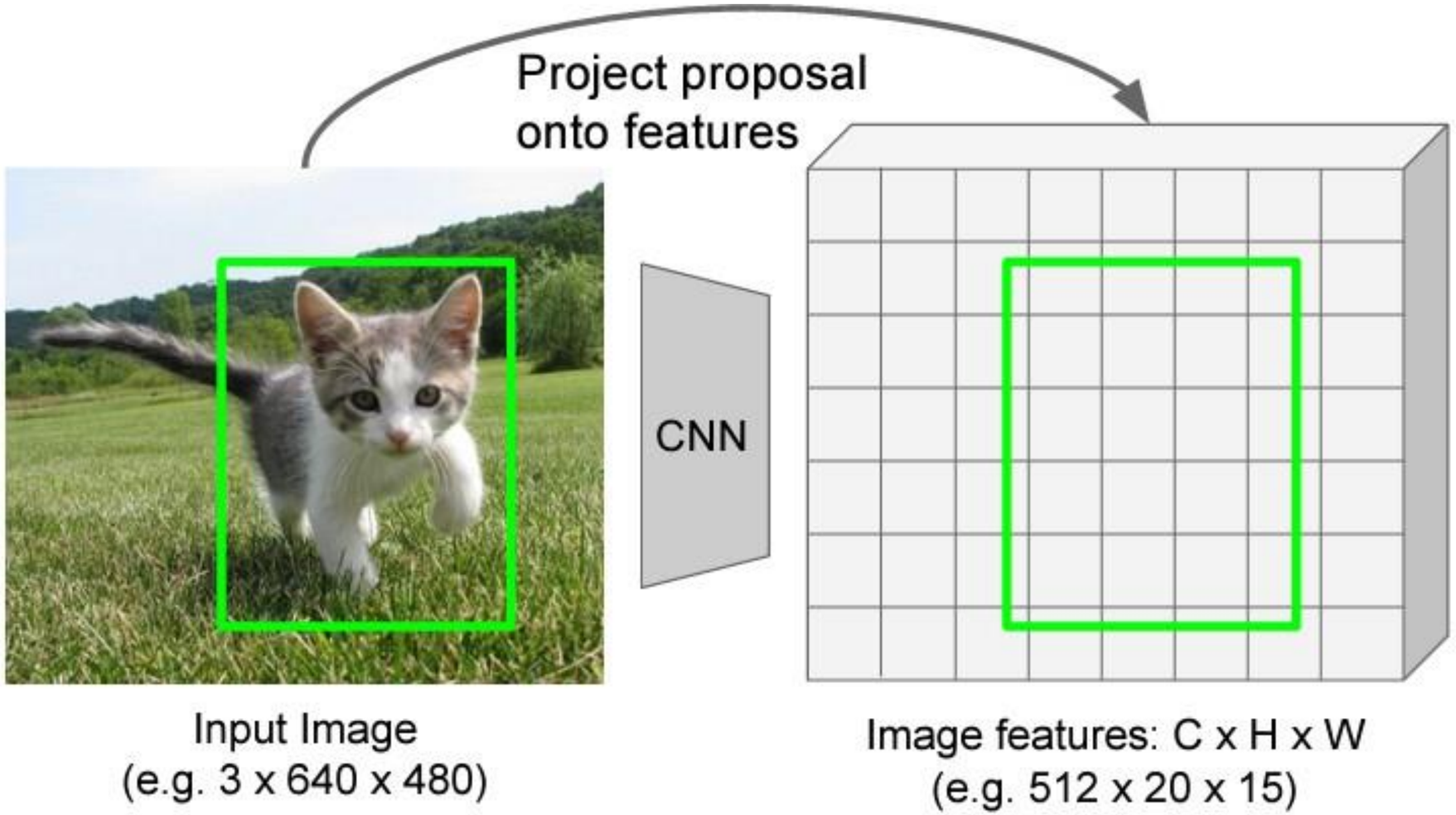

Mask R-CNN

# RoIPool and RoIAlign




R. Girshick, [Fast R-CNN](), ICCV 2015

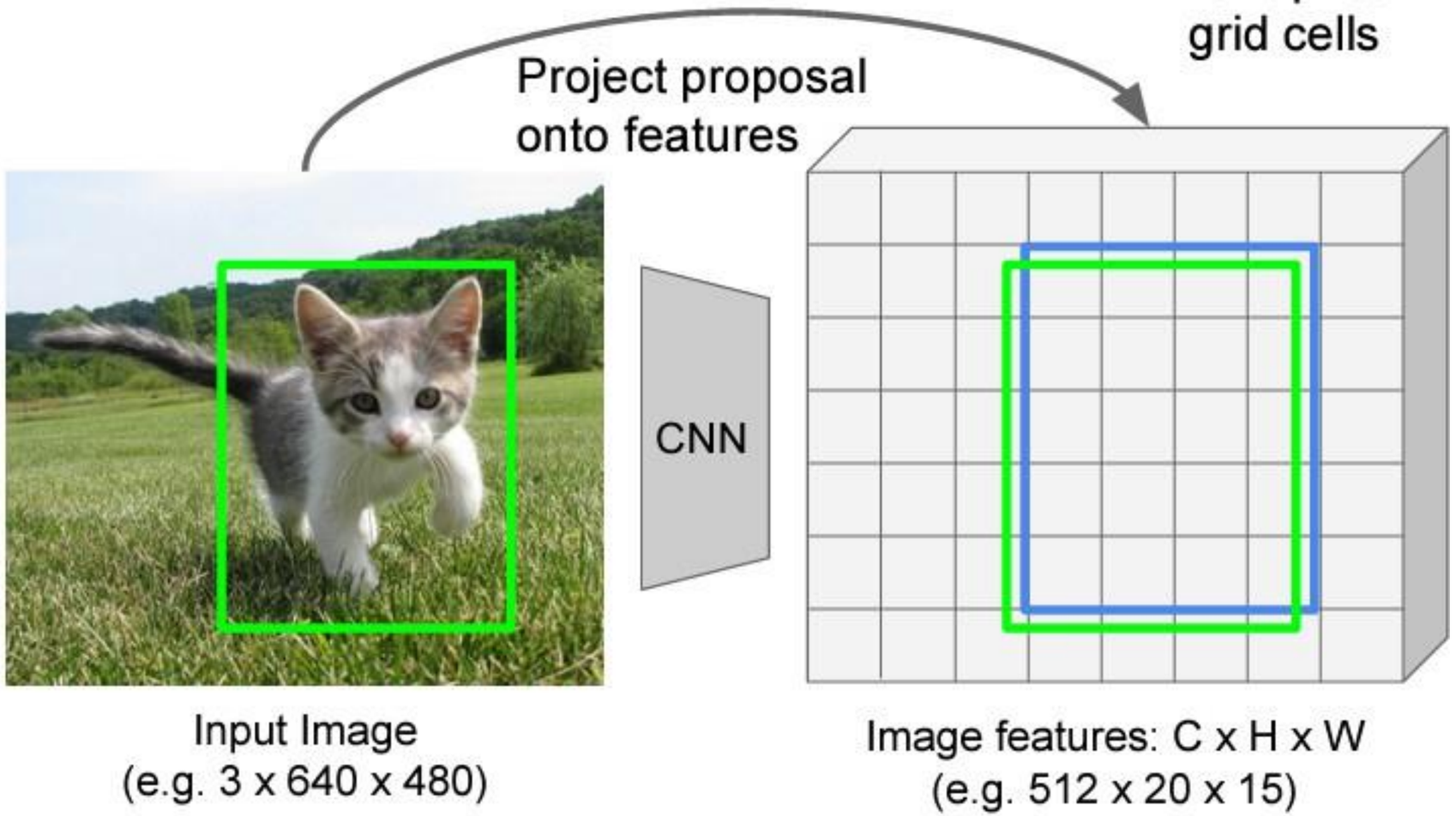
# Cropping Features: RoI Pool




Girshick, "Fast R-CNN", ICCV 2015.

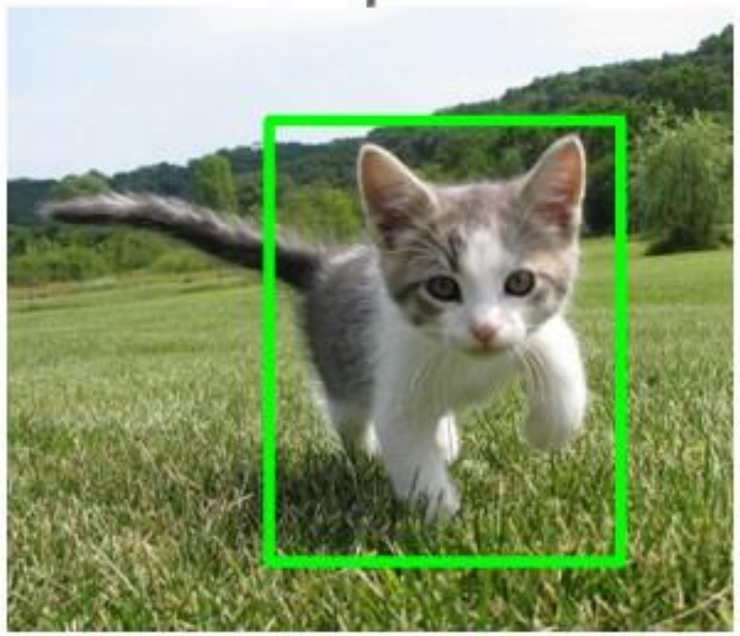
Girshick, "Fast R-CNN", ICCV 2015.

# Cropping Features: RoI Pool




Girshick, "Fast R-CNN", ICCV 2015.

# Cropping Features: RoI Pool



Input Image
(e.g. 3 x 640 x 480)

Project proposal onto features

CNN

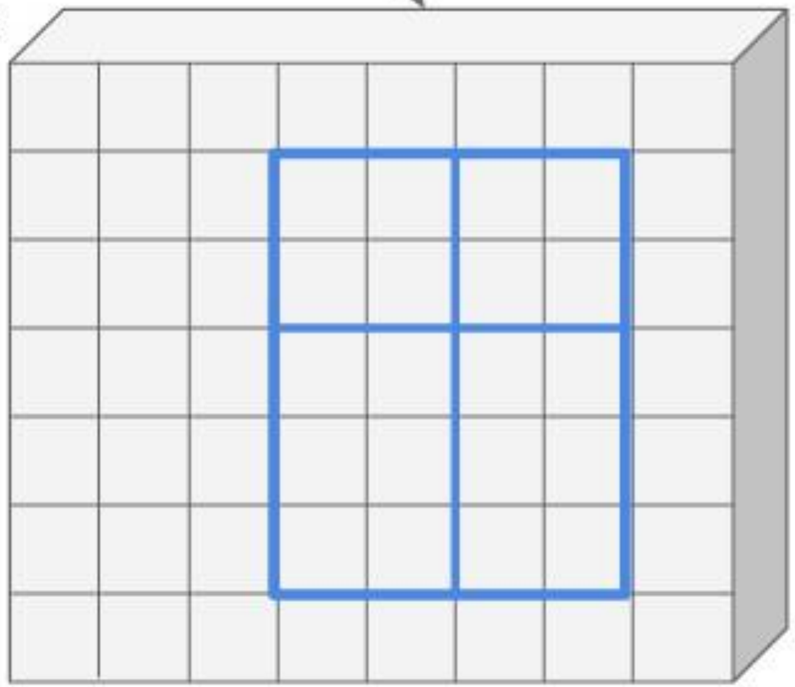
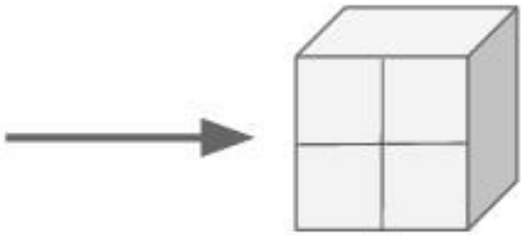


Image features: C x H x W
(e.g. 512 x 20 x 15)

"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion



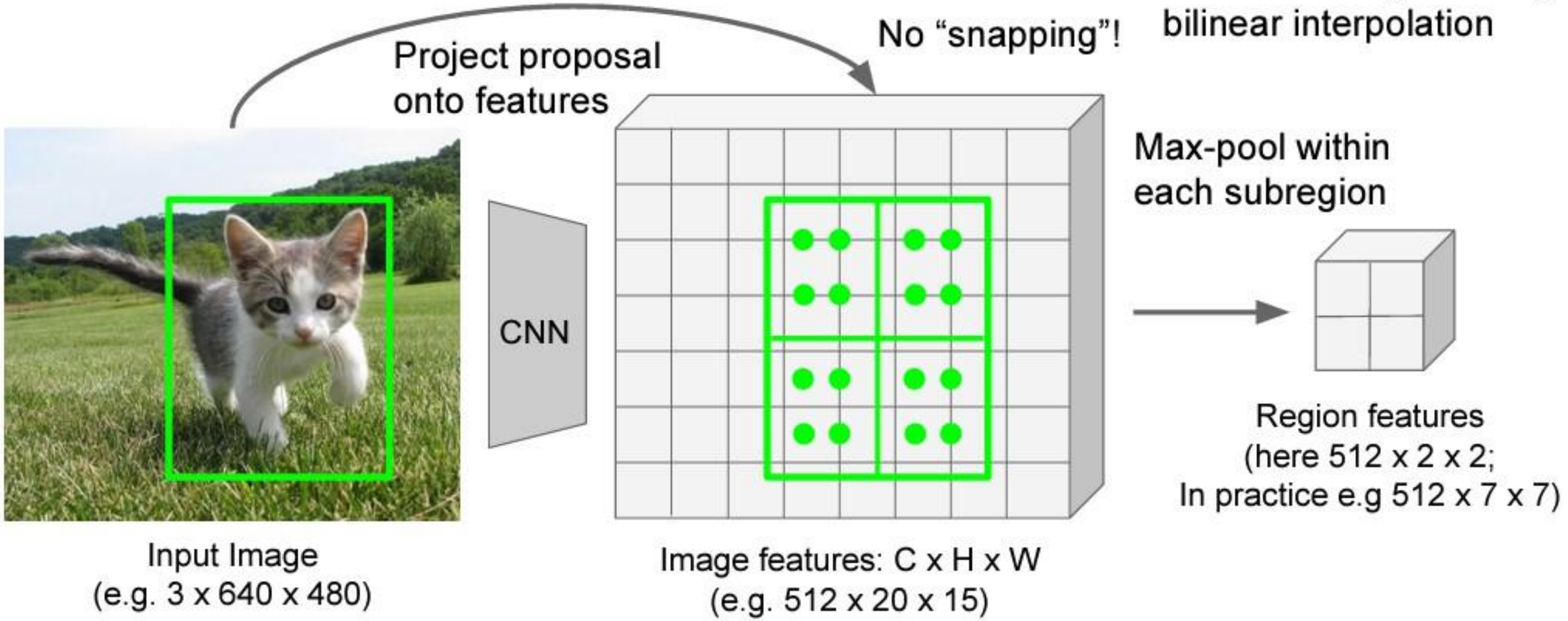
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

Region features always the same size even if input regions have different sizes!

Girshick, "Fast R-CNN", ICCV 2015.

# Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation




He et al, “Mask R-CNN”, ICCV 2017

# Ablation: RoIPool vs RoIAlign

baseline: ResNet-50-Conv5 backbone, **stride=32**

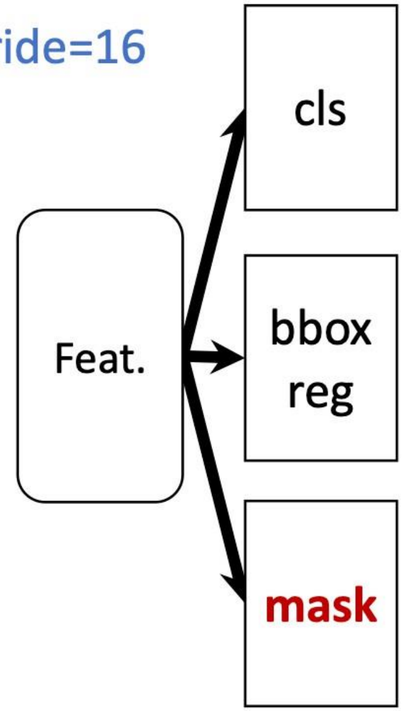
| | mask AP | | | box AP | | |
|---|---|---|---|---|---|---|
| | AP | $AP_{50}$ | $AP_{75}$ | $AP^{bb}$ | $AP^{bb}_{50}$ | $AP^{bb}_{75}$ |
| *RoIPool* | 23.6 | 46.5 | 21.6 | 28.2 | 52.7 | 26.9 |
| *RoIAlign* | **30.9** | **51.8** | **32.1** | **34.0** | **55.3** | **36.4** |
| | *+7.3* | *+ 5.3* | *+10.5* | *+5.8* | *+2.6* | *+9.5* |

- huge gain at high IoU, in case of big stride (32)

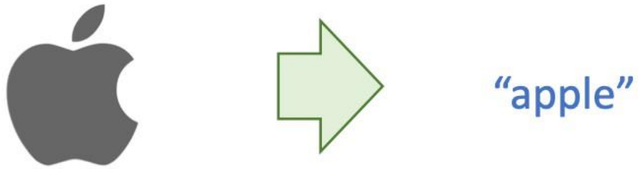
# Ablation: Multinomial vs Binary Segmentation

baseline: ResNet-50-Conv4 backbone, stride=16

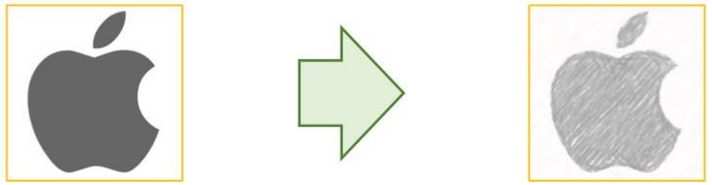
| | AP | $AP_{50}$ | $AP_{75}$ |
|---|---|---|---|
| *softmax* | 24.8 | 44.1 | 25.1 |
| *sigmoid* | **30.3** | **51.2** | **31.5** |
| | *+5.5* | *+7.1* | *+6.4* |




- cls head: did recognition

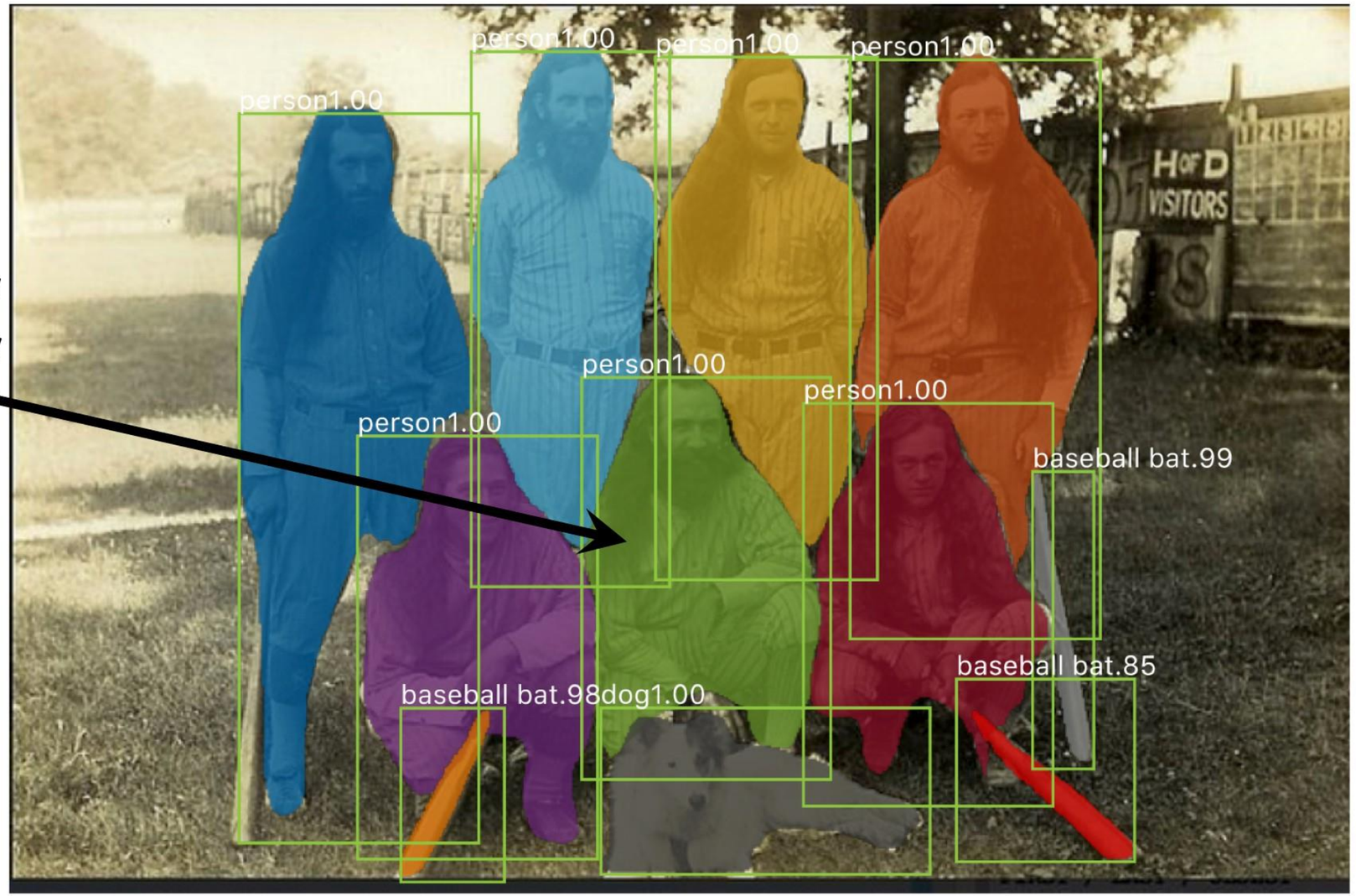



- mask head: no need to recognize again



# Mask R-CNN: Very Good Results!

object surrounded by same-category objects

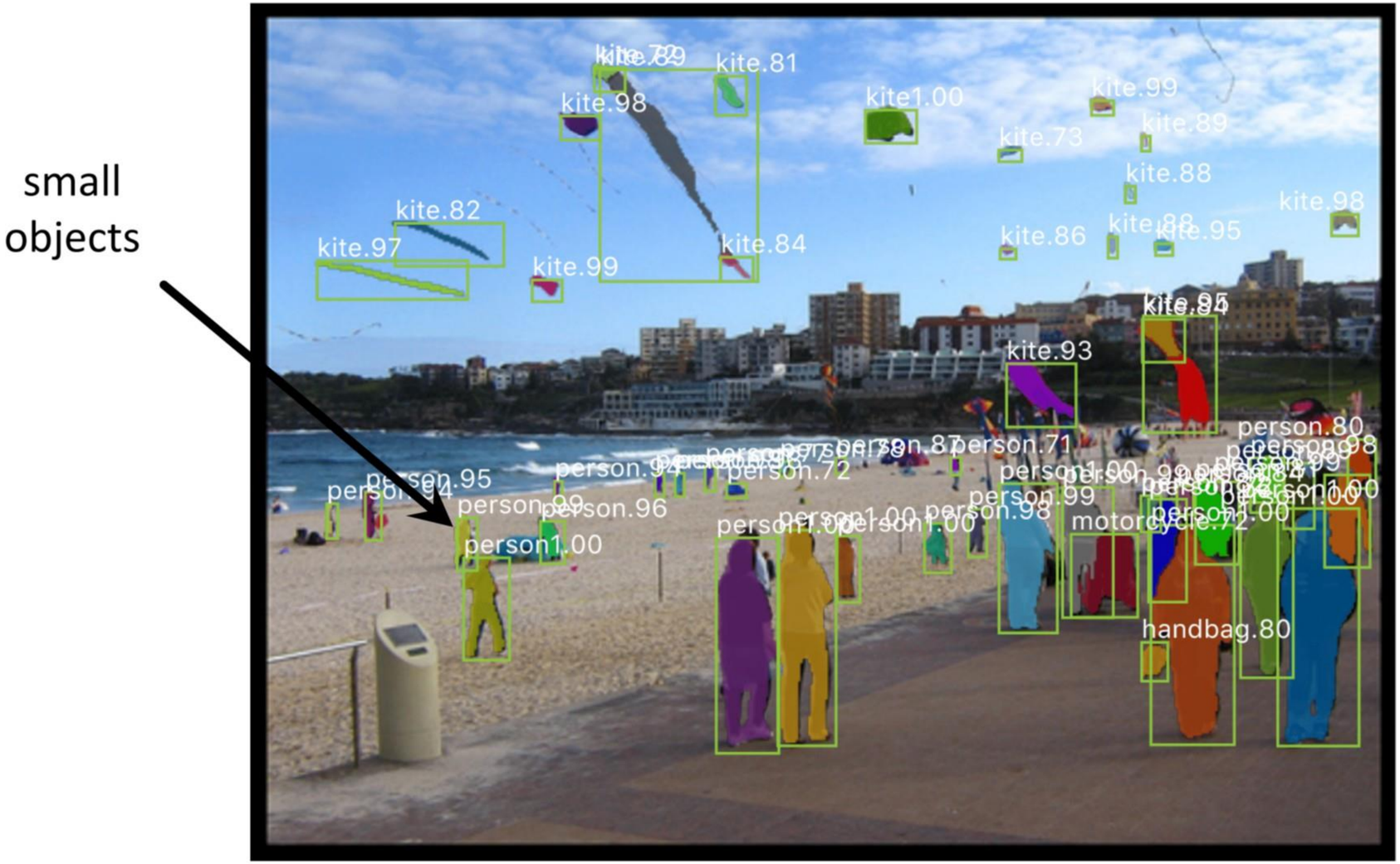



Mask R-CNN results on COCO

# Mask R-CNN: Very Good Results!


Mask R-CNN results on COCO

# Mask R-CNN: Very Good Results!




Mask R-CNN results on COCO

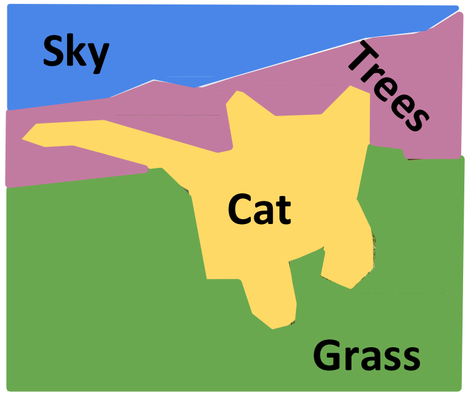
# Mask R-CNN: Failure Case

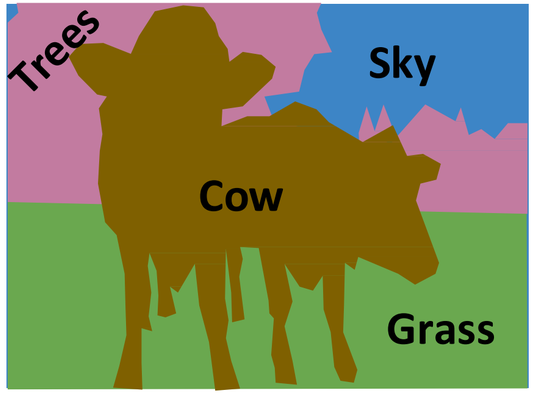

Mask R-CNN results on COCO

# Semantic Segmentation

Label each pixel in the image with a category label

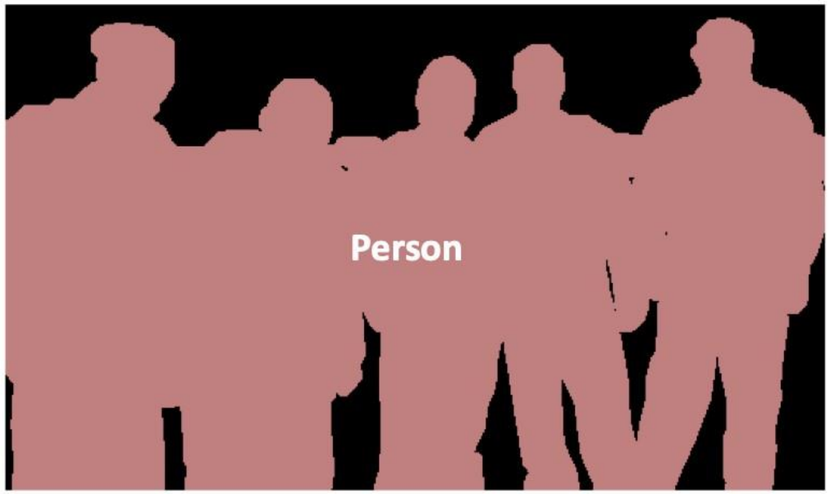
Don’t differentiate instances, only care about pixels

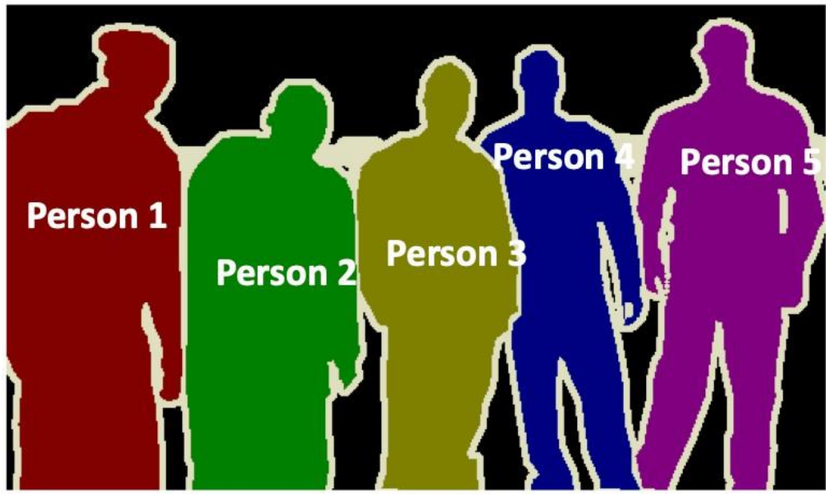



# Semantic vs Instance Segmentation

Object Detection

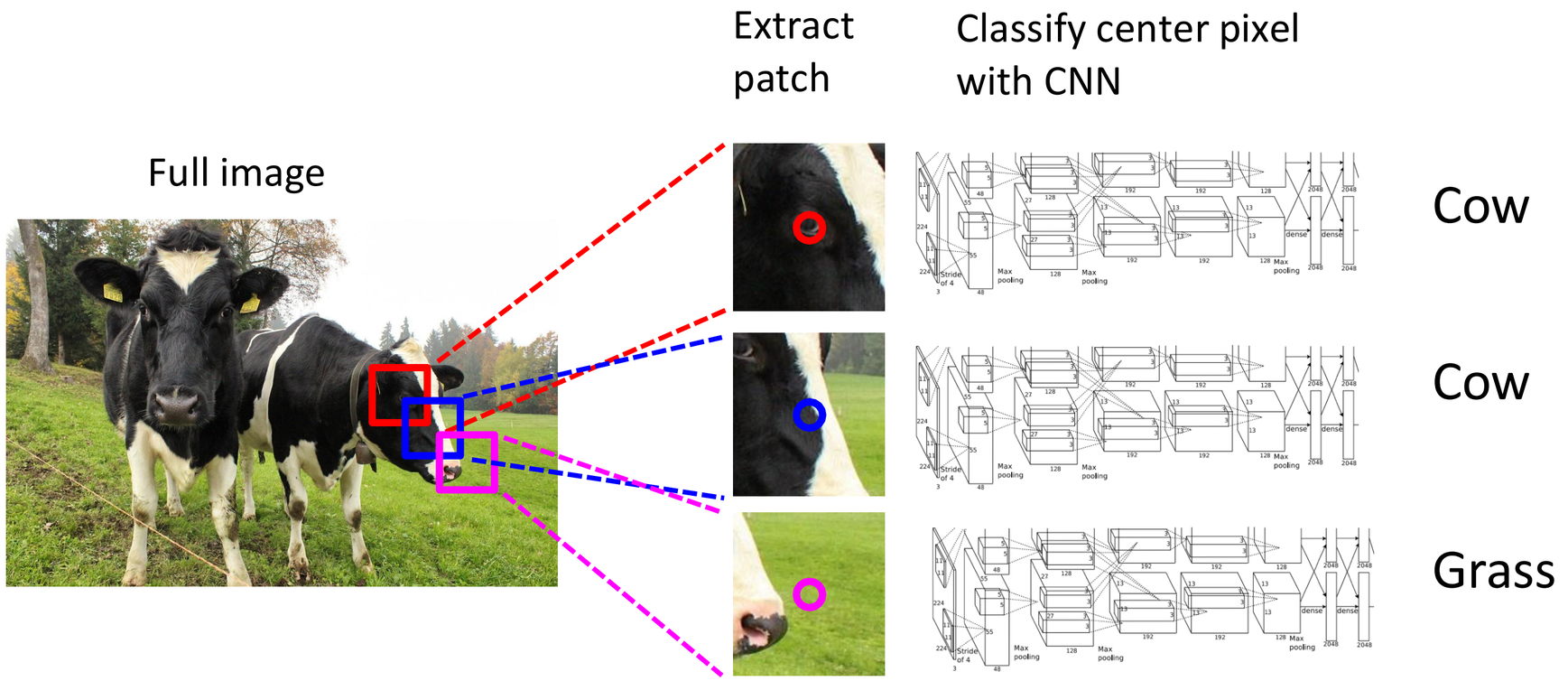



Semantic Segmentation




**Instance Segmentation**

# Segmentation: Sliding Window

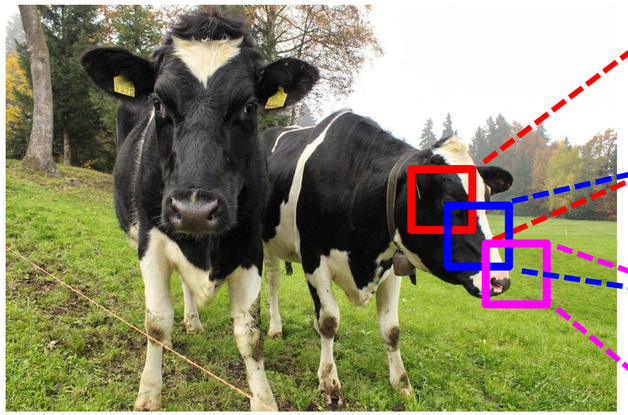



Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013

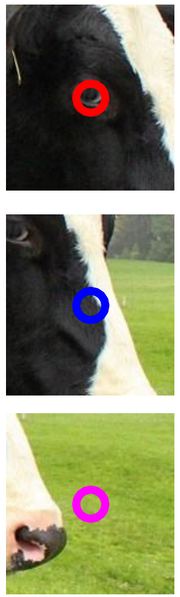
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

# Segmentation: Sliding Window

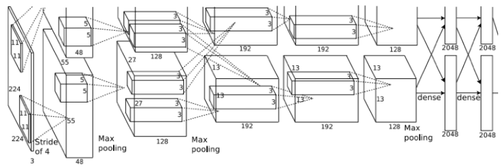
Full image



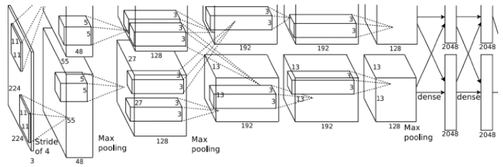
Extract patch



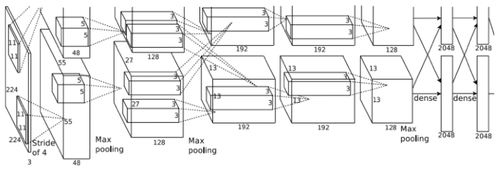
Classify center pixel with CNN




Cow



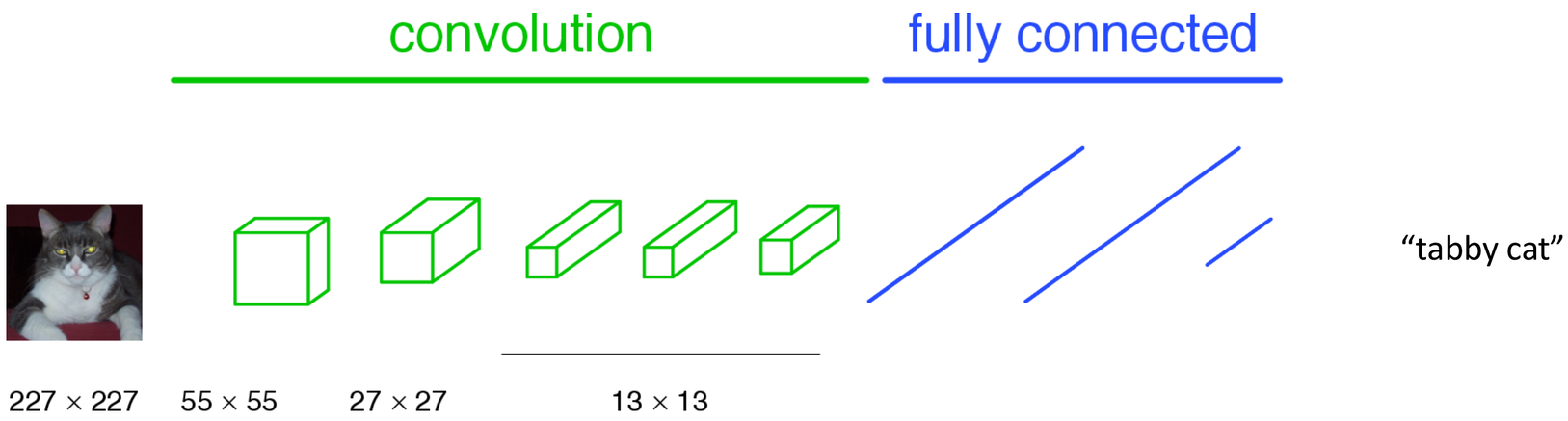

Cow




Grass

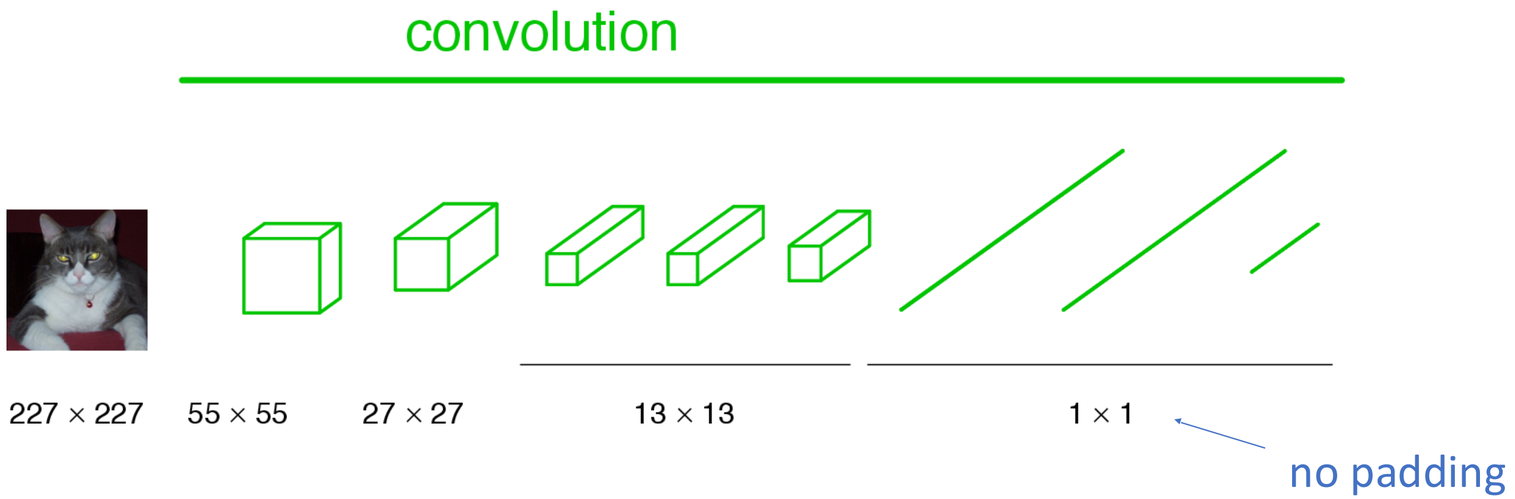
Problem: Very inefficient! Not reusing shared features between overlapping patches

# A Classification Network




Fully Convolutional Networks for Semantic Segmentation.
Jon Long, Evan Shelhamer, Trevor Darrell. CVPR 2015

# Becoming Fully Convolutional

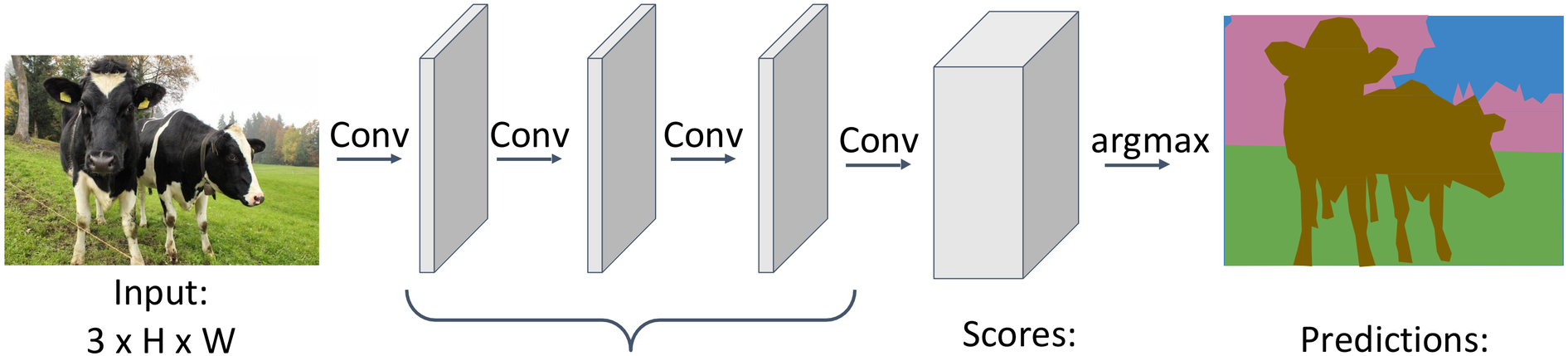



A fully-connected layer is equivalent to a convolution layer.

Note: “Fully Convolutional” and “Fully Connected” aren’t the same thing.
They’re almost opposites, in fact.

# Fully Convolutional Network

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

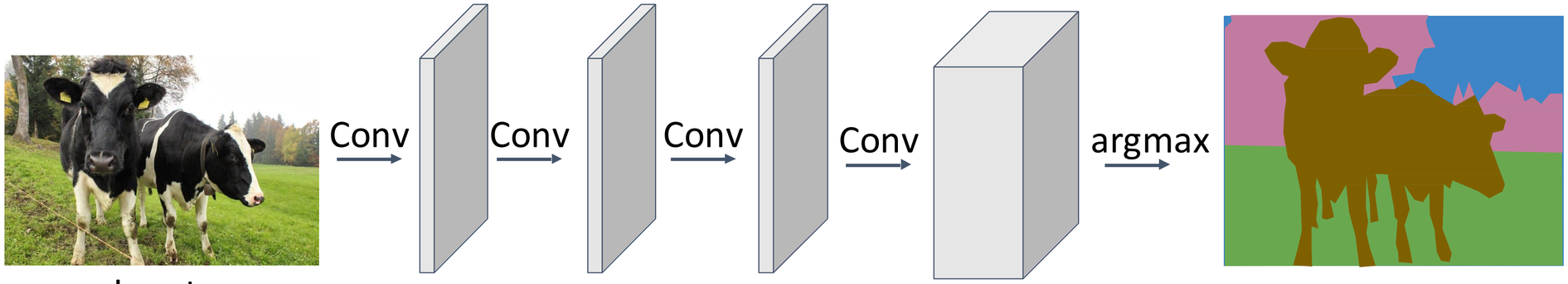



Loss function: Per-Pixel cross-entropy

Long et al, “Fully convolutional networks for semantic segmentation”, CVPR 2015

# Fully Convolutional Network

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



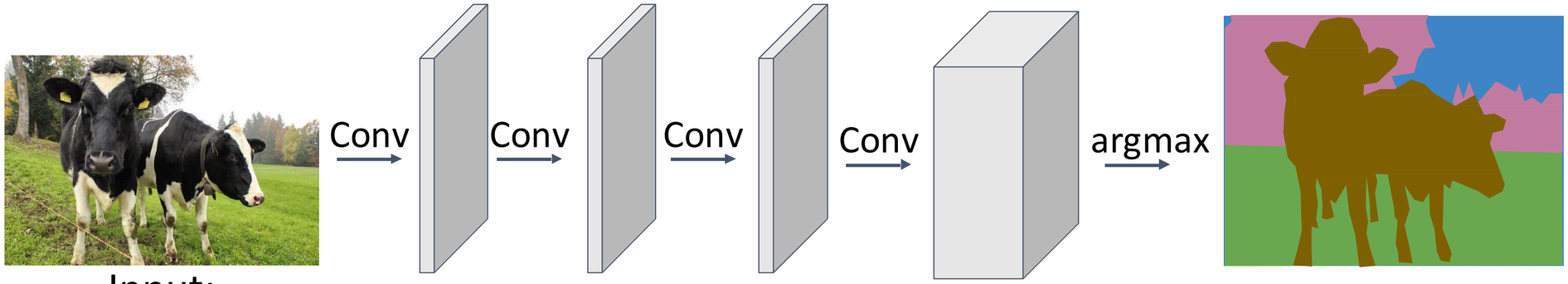

Input:
3 x H x W

**Problem #1**: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

Long et al, "Fully convolutional networks for semantic segmentation", CVPR 2015

# Fully Convolutional Network

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




Input:
3 x H x W

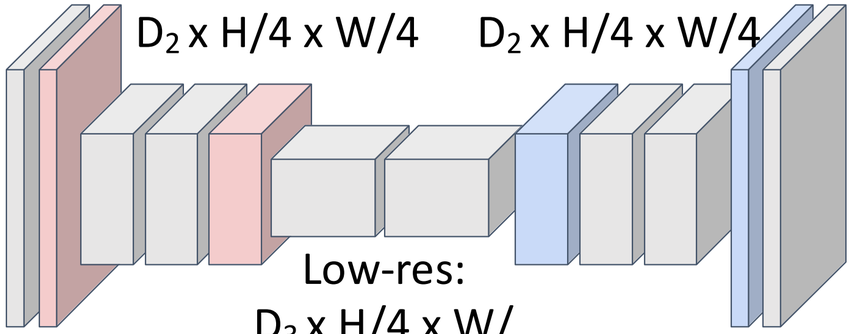
**Problem #1**: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

**Problem #2:** Convolution on high res images is expensive!

# Fully Convolutional Network

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

Input:
3 x H x W



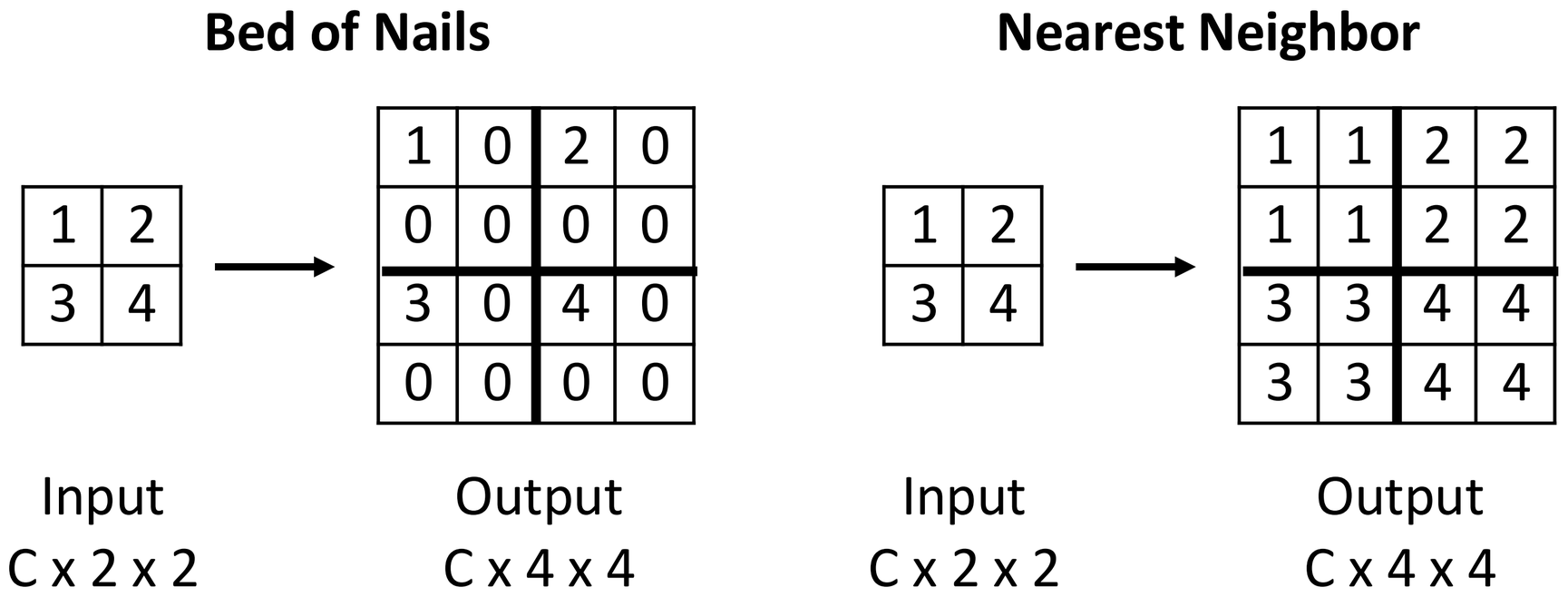

**Downsampling**:
Pooling, strided convolution

**Upsampling**:
???

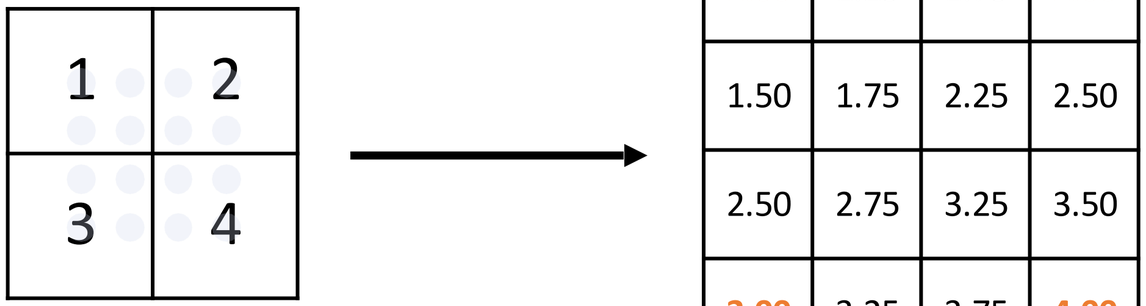
Predictions:
H x W

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

# In-Network Upsampling: “Unpooling”



# Upsampling: Bilinear Interpolation




Input: C x 2 x 2

Output: C x 4 x 4

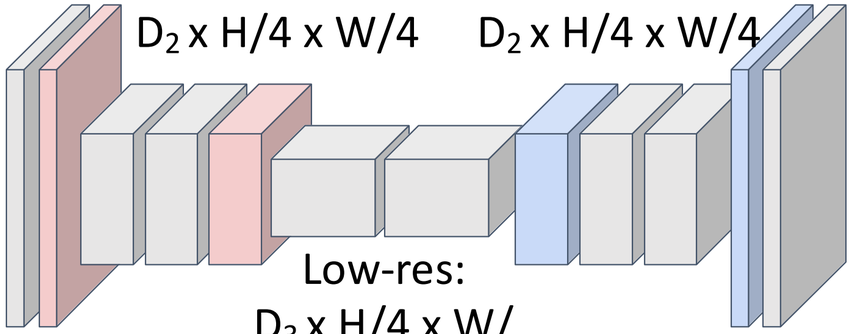
$$f_{x,y} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - i|) \max(0, 1 - |y - j|) \quad \begin{array}{l} i \in \{\lfloor x \rfloor - 1, \ldots, \lceil x \rceil + 1\} \\ j \in \{\lfloor y \rfloor - 1, \ldots, \lceil y \rceil + 1\} \end{array}$$

Use two closest neighbors in x and y
to construct linear approximations

# Fully Convolutional Network

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

Input:
3 x H x W




**Downsampling**:
Pooling, strided convolution

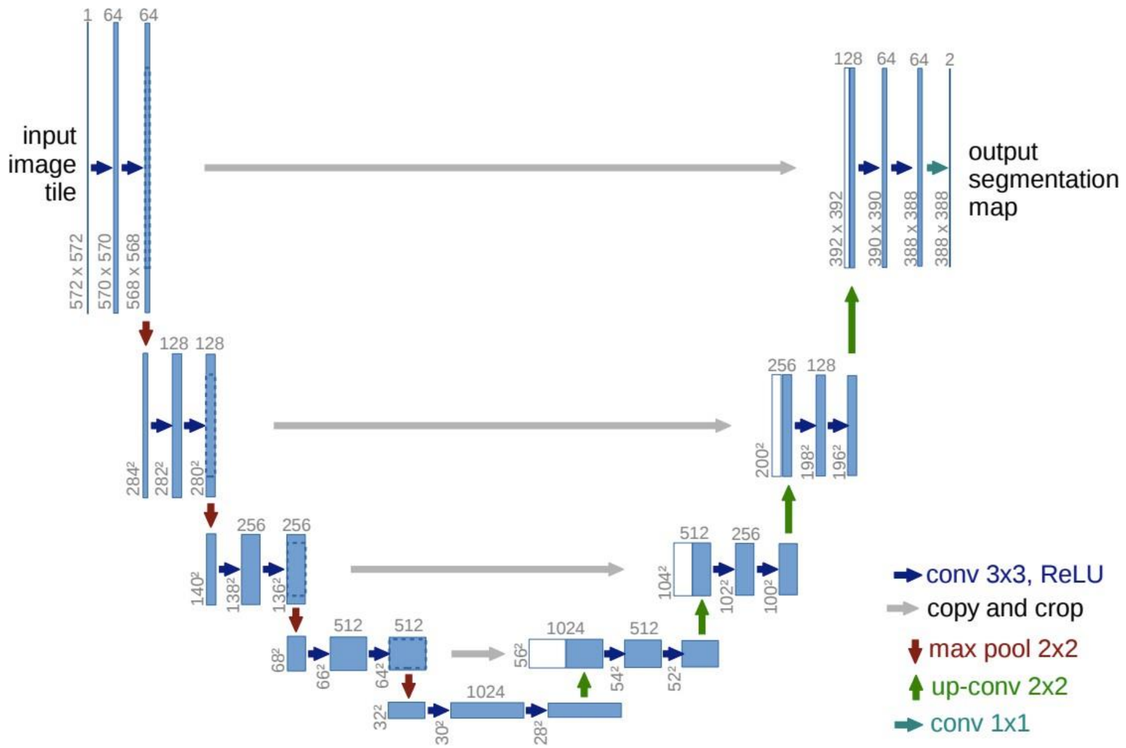
**Upsampling**:
???

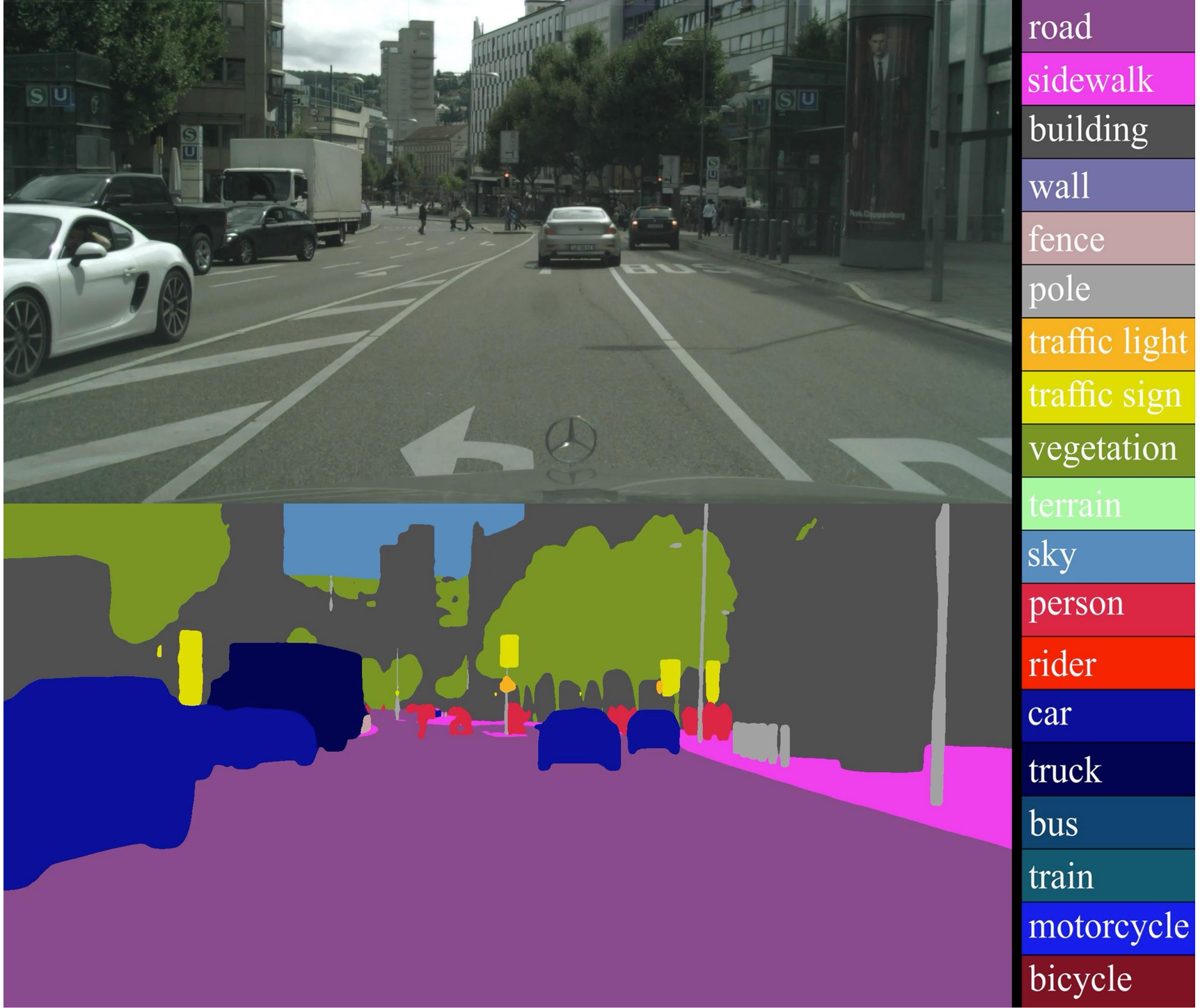
Predictions:
H x W

# U-Net

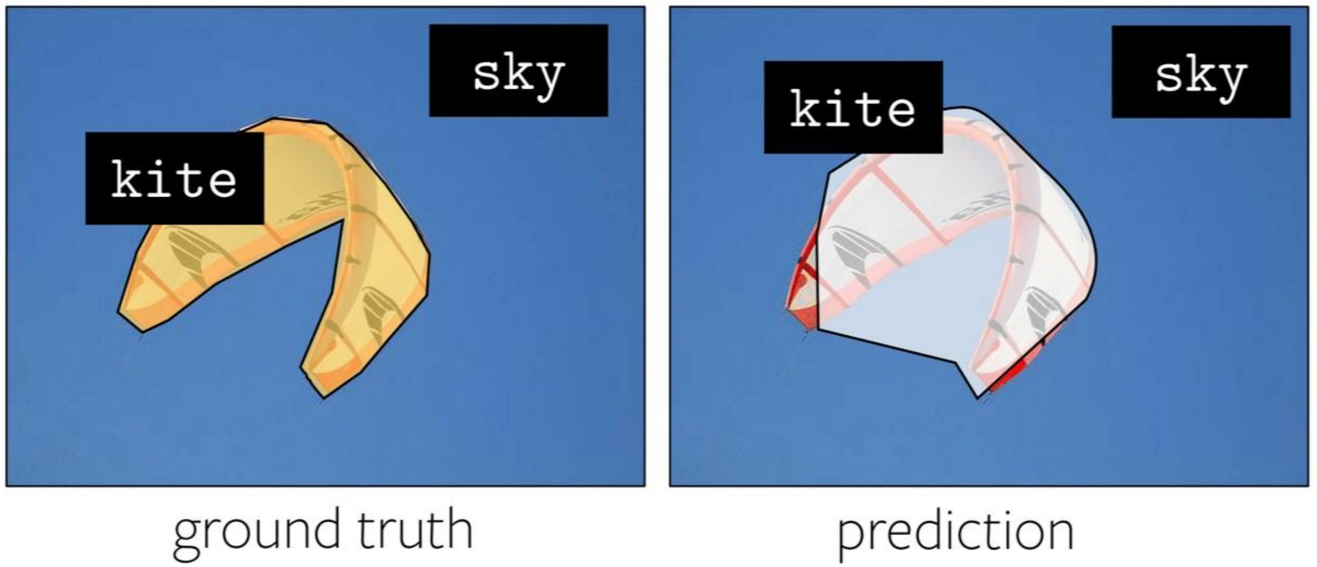
O. Ronneberger, P. Fischer, T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

- Like FCN, fuse upsampled higher-level feature maps with higher-res, lower-level feature maps
- Unlike FCN, fuse by concatenation, predict at the end




road
sidewalk
building
wall
fence
pole
traffic light
traffic sign
vegetation
terrain
sky
person
rider
car
truck
bus
train
motorcycle
bicycle

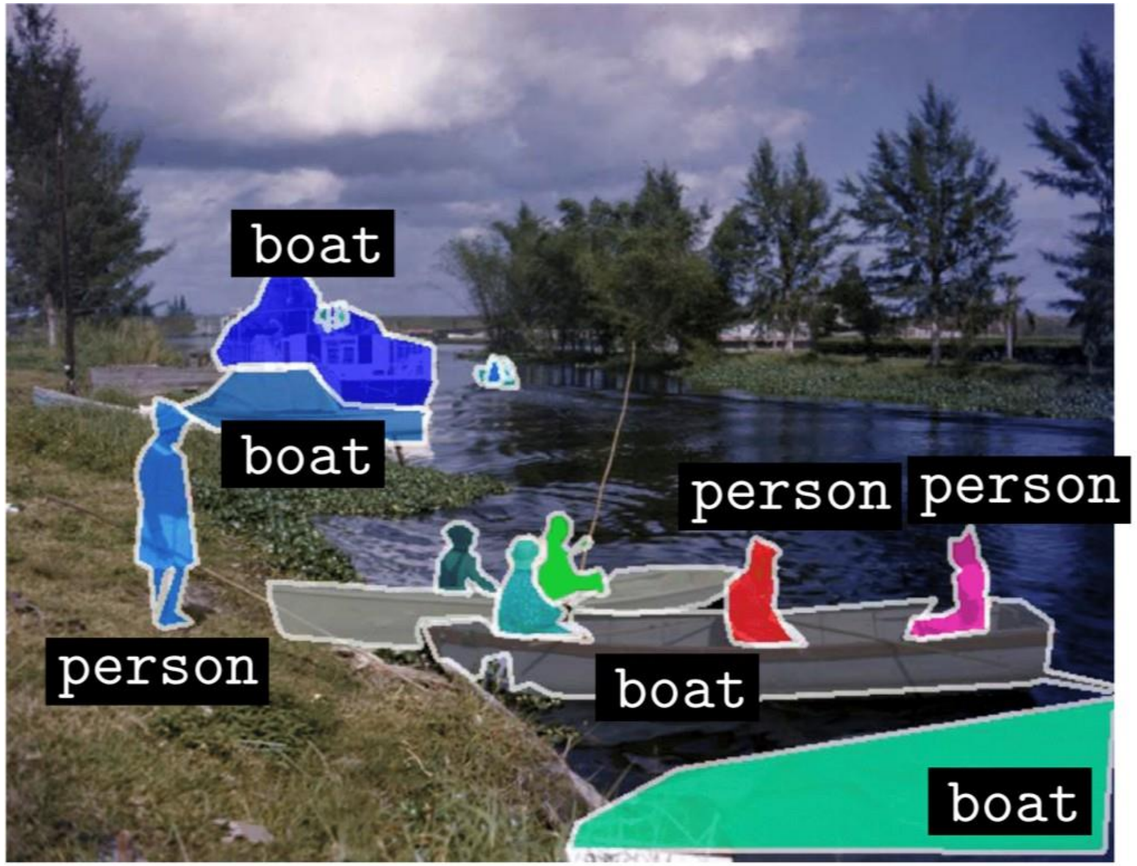
# Evaluation of Semantic Segmentation



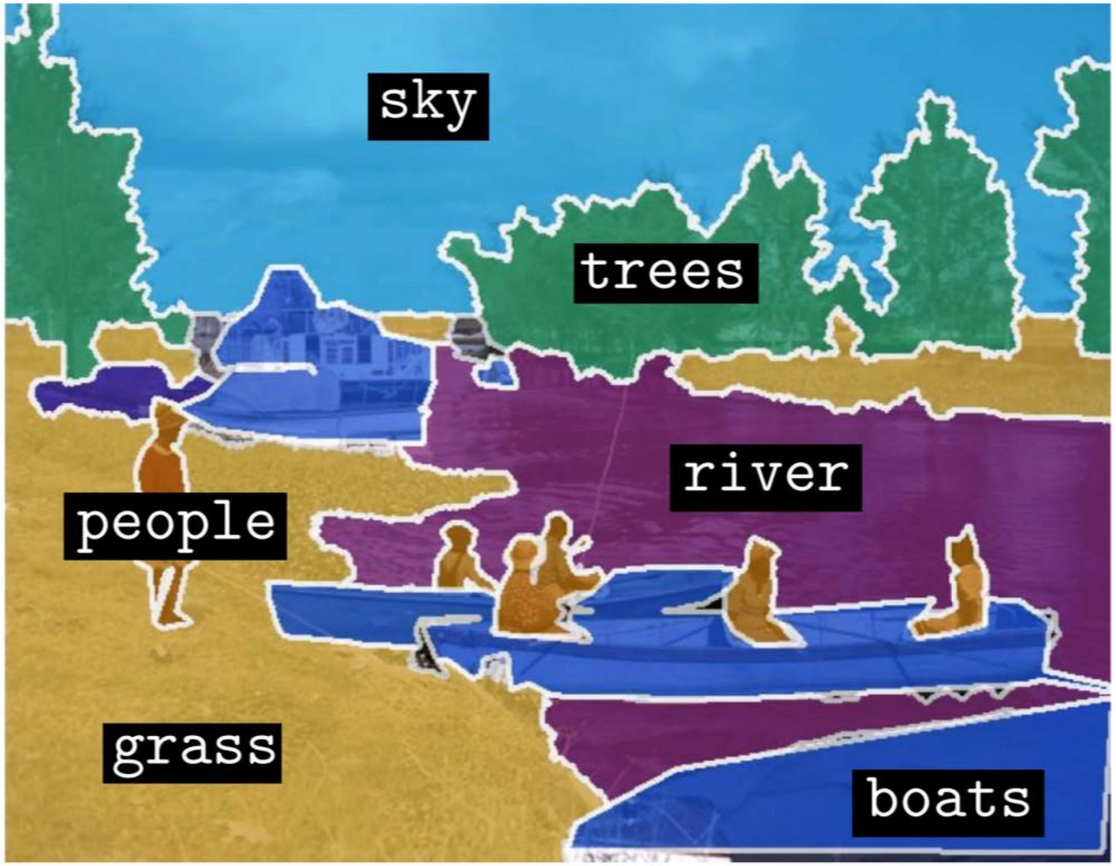

$$\text{IoU (kite)} = \frac{\text{area}(\quad)}{\text{area}(\quad)}$$

mIoU (mean IoU) per class

# Instance and Semantic Segmentation



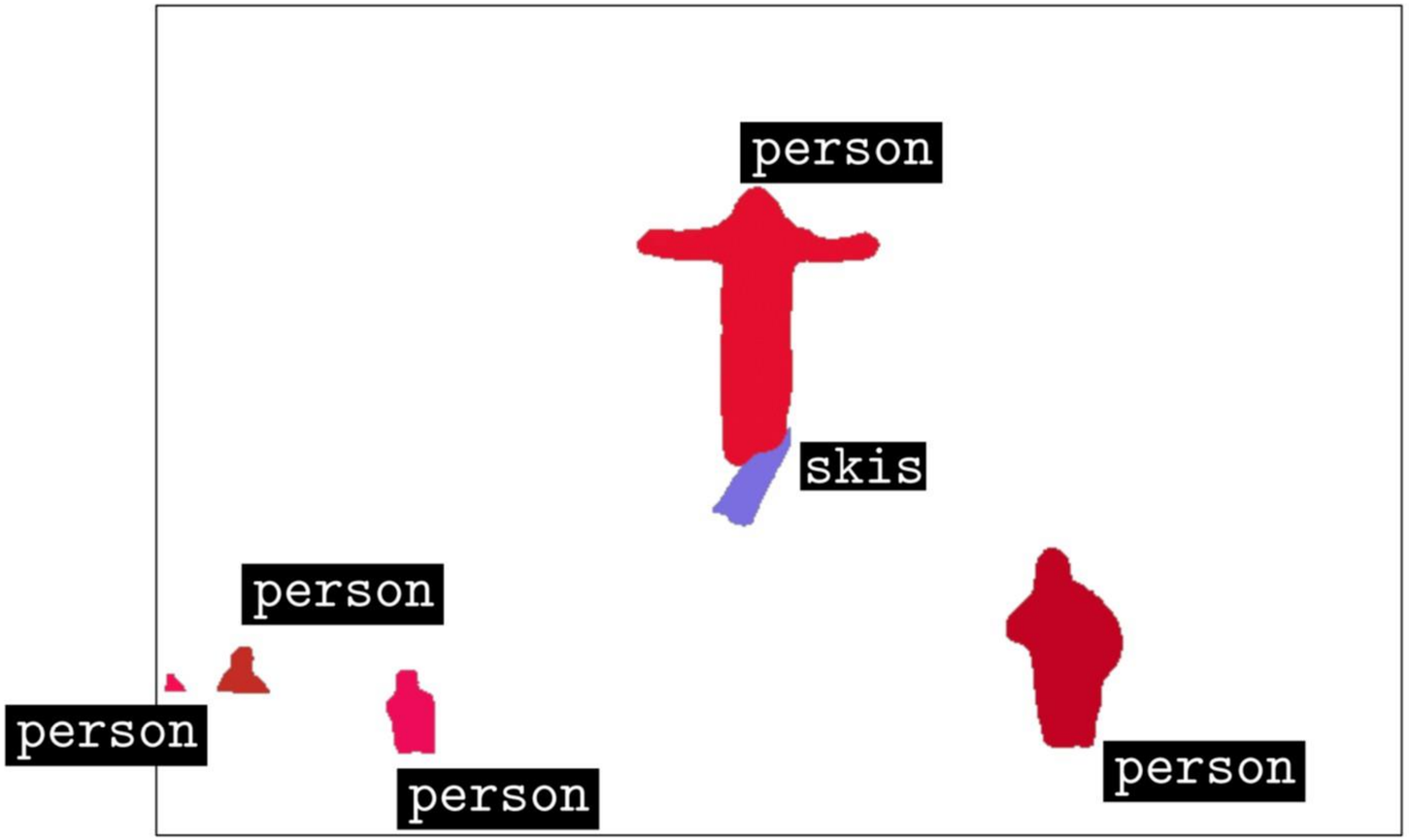

instance segmentation




semantic segmentation

real-world application likely requires both modalities

# What do instance segmentation models see?

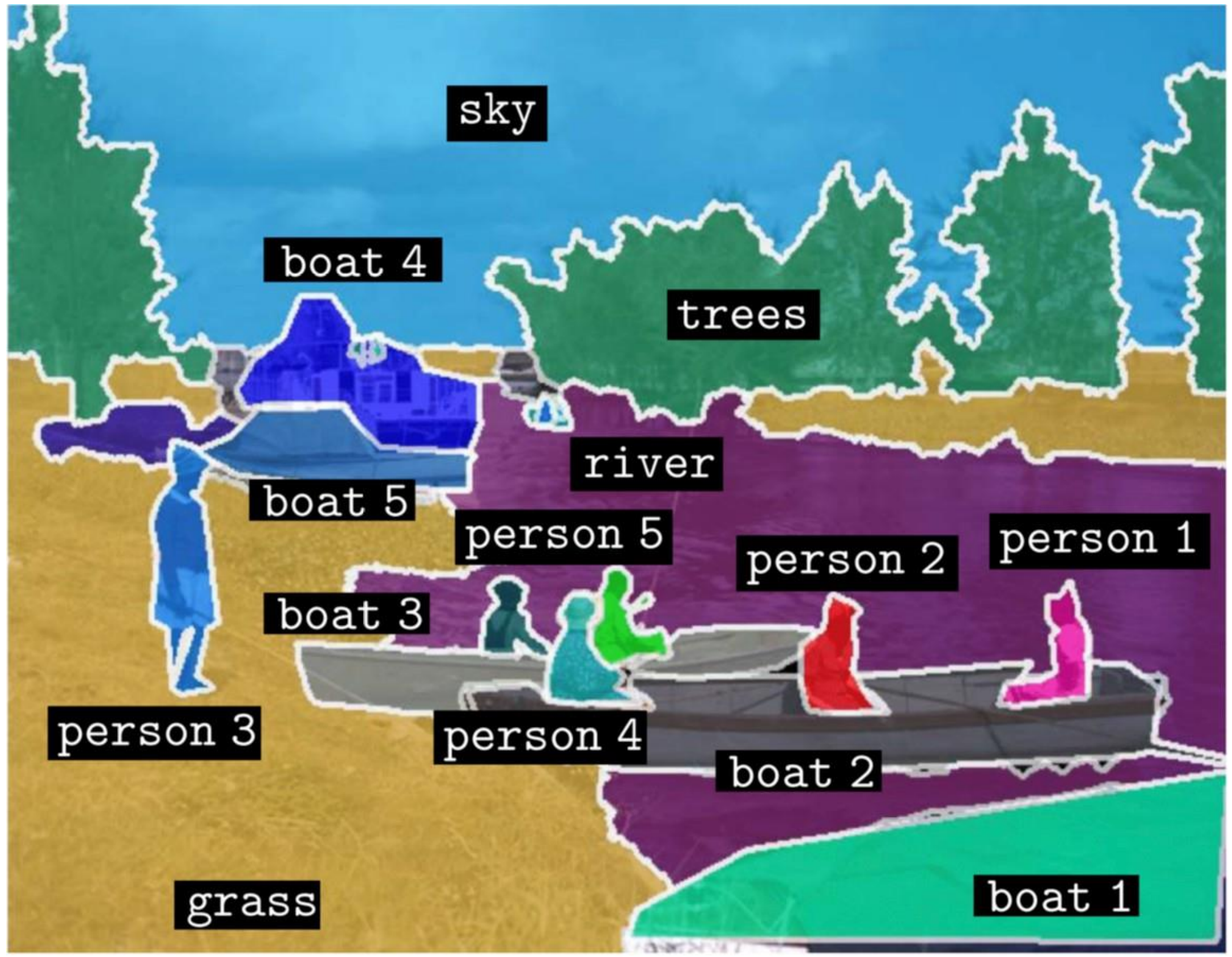



no understanding of the general scene layout

# What do semantic segmentation models see?

Does not differentiate different instances

# Panoptic Segmentation: Unified Segmentation



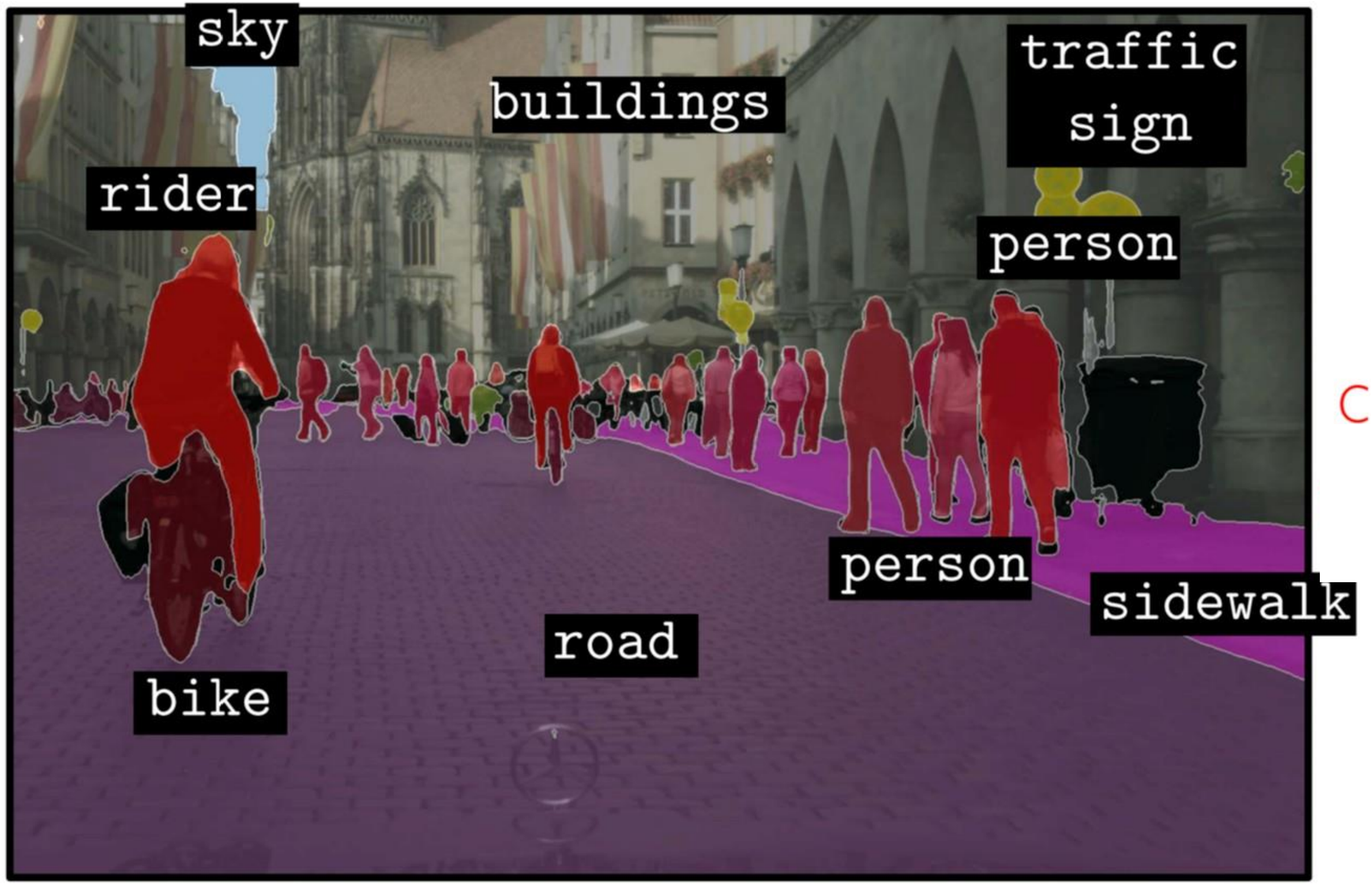

single task that combines semantic and instance segmentation

**things:** categories with instance-level annotation (person, boat)

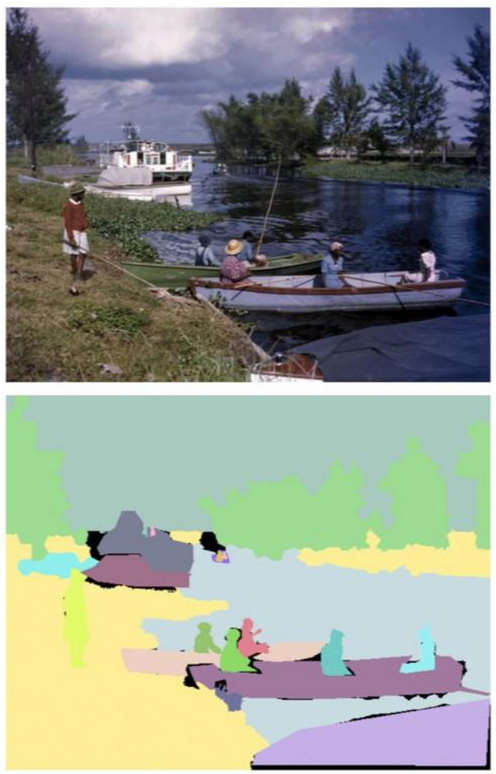
**stuff:** categories without the notion of instances (sky, road)

Panoptic: see everything at once

# Panoptic Segmentation



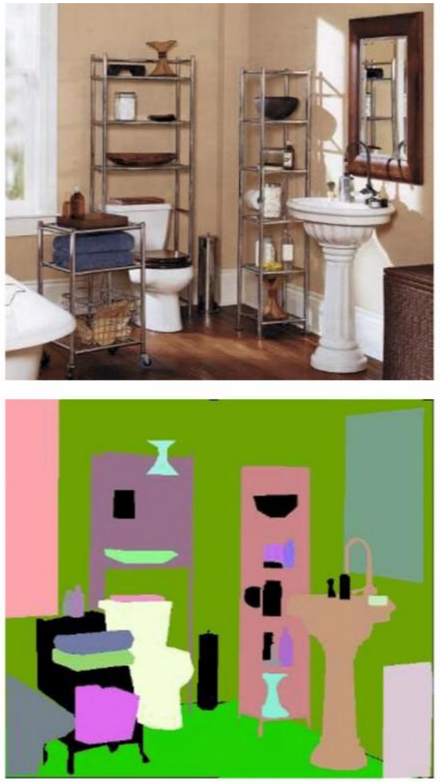
# Available Panoptic Segmentation Datasets



CO (2014) + COCO-stuff (2017)
COCO-panoptic challenges:
ECCV`18, **ICCV`19**

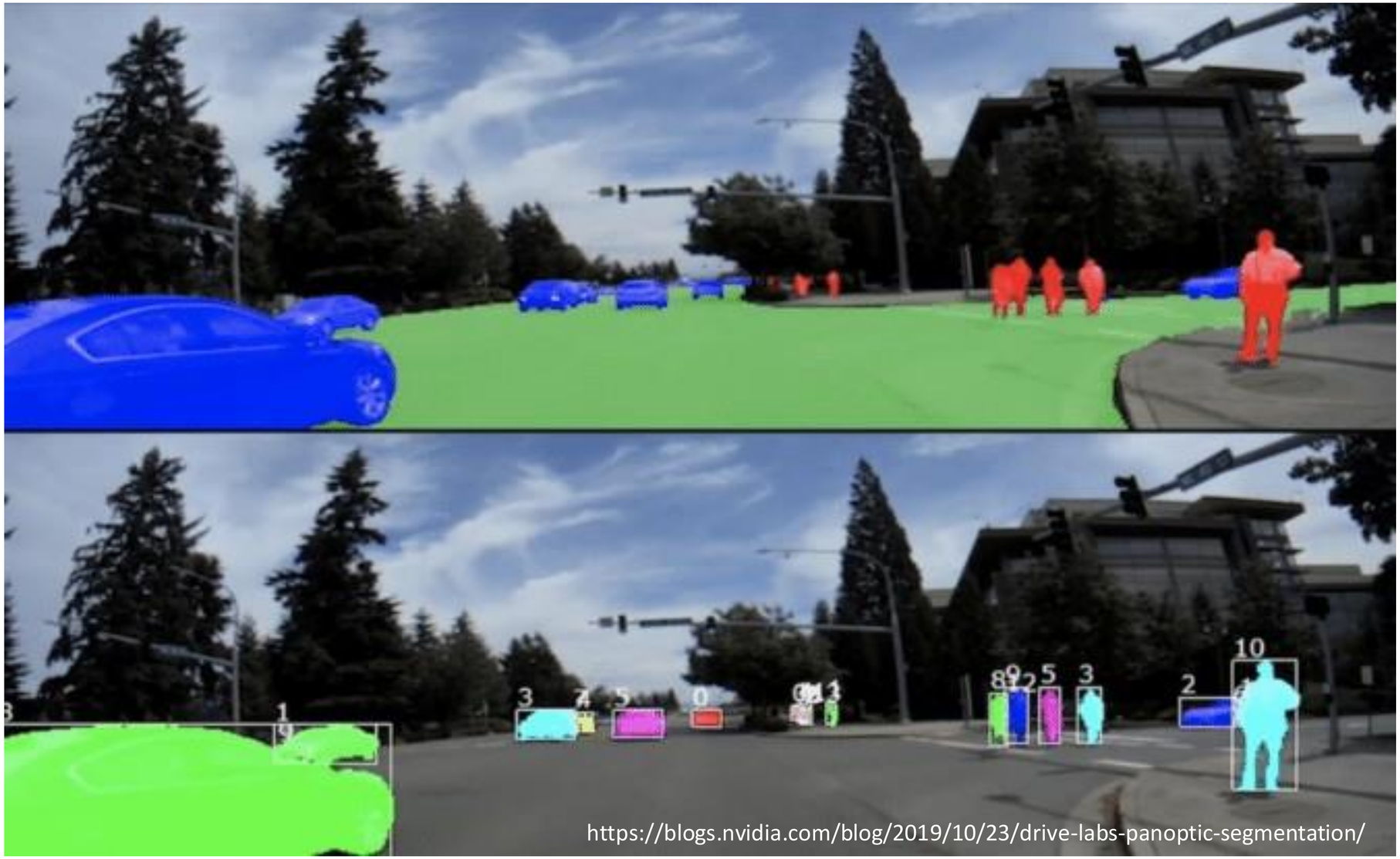
Mapillary Vistas (2017)
Vistas-panoptic challenges:
ECCV`18, **ICCV`19**

Cityscapes (2015)
panoptic test set
leaderboard (2019)

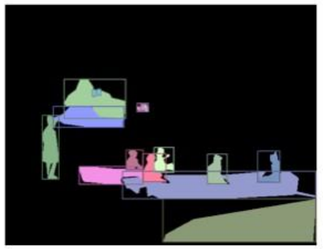


ADE20k (2016)
>22k images, 150 categories

# Panoptic Segmentation for Autonomous Driving

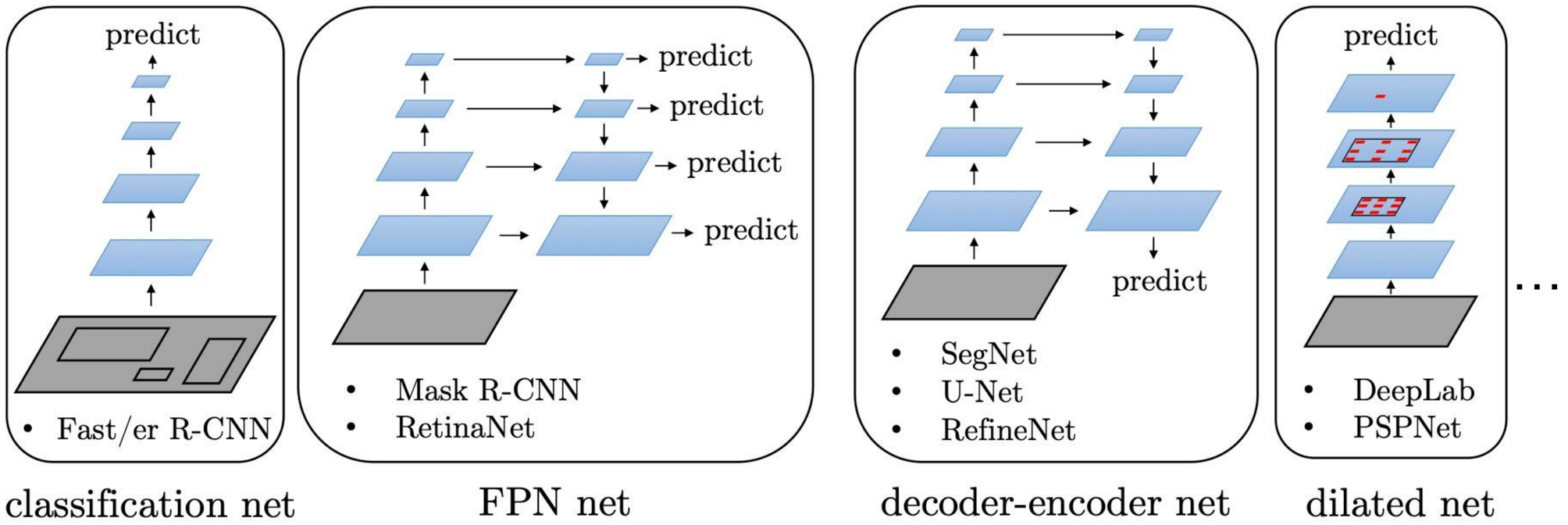


# Deep Networks for Segmentation Tasks



Object Detection/Seg

Semantic Segmentation




classification net | FPN net | decoder-encoder net | dilated net

# Panoptic FPN

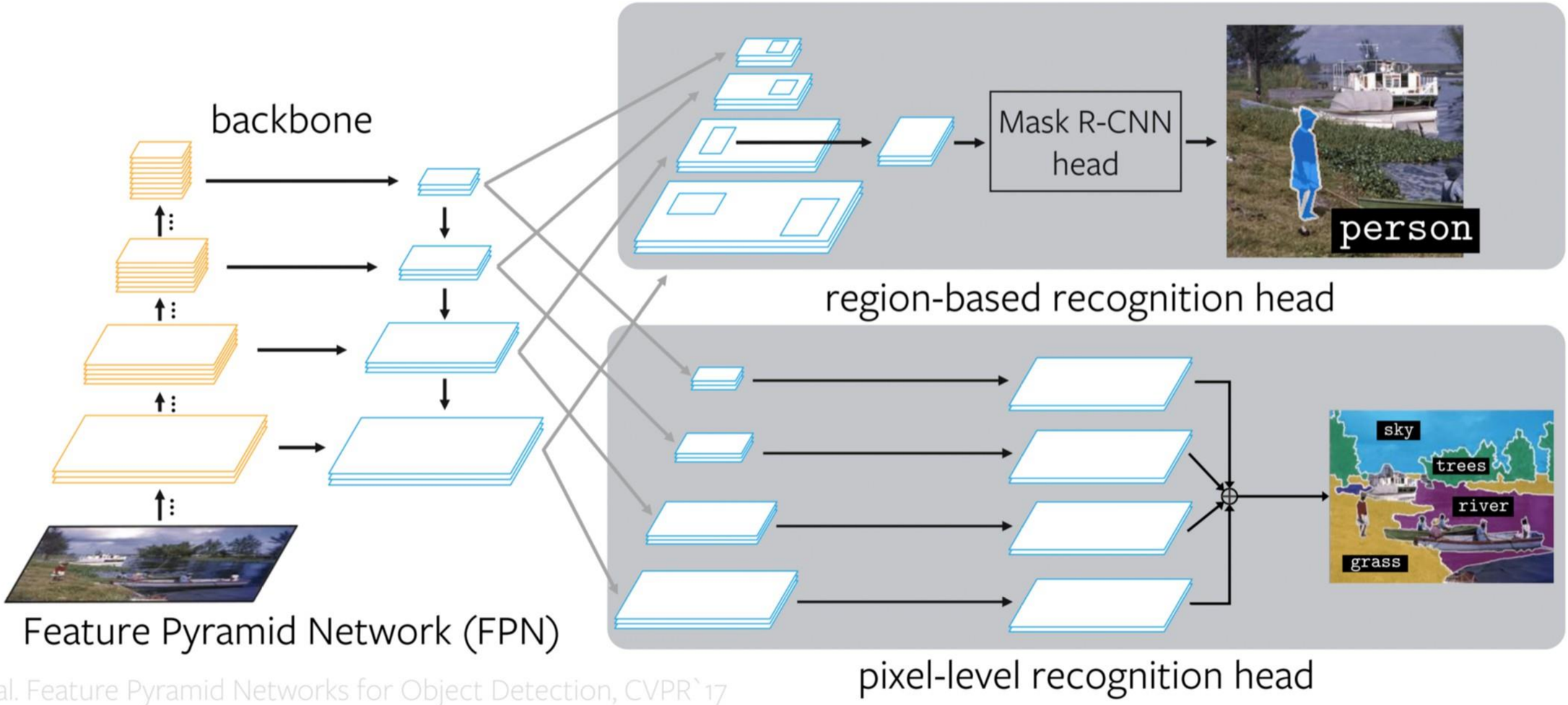
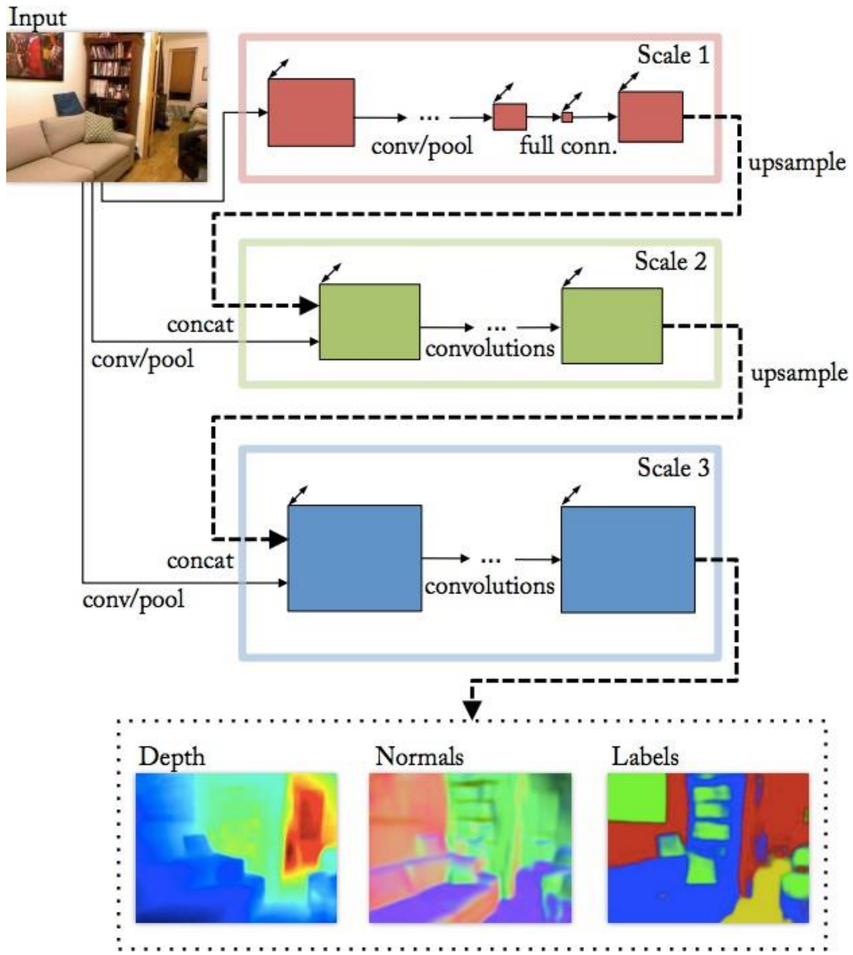
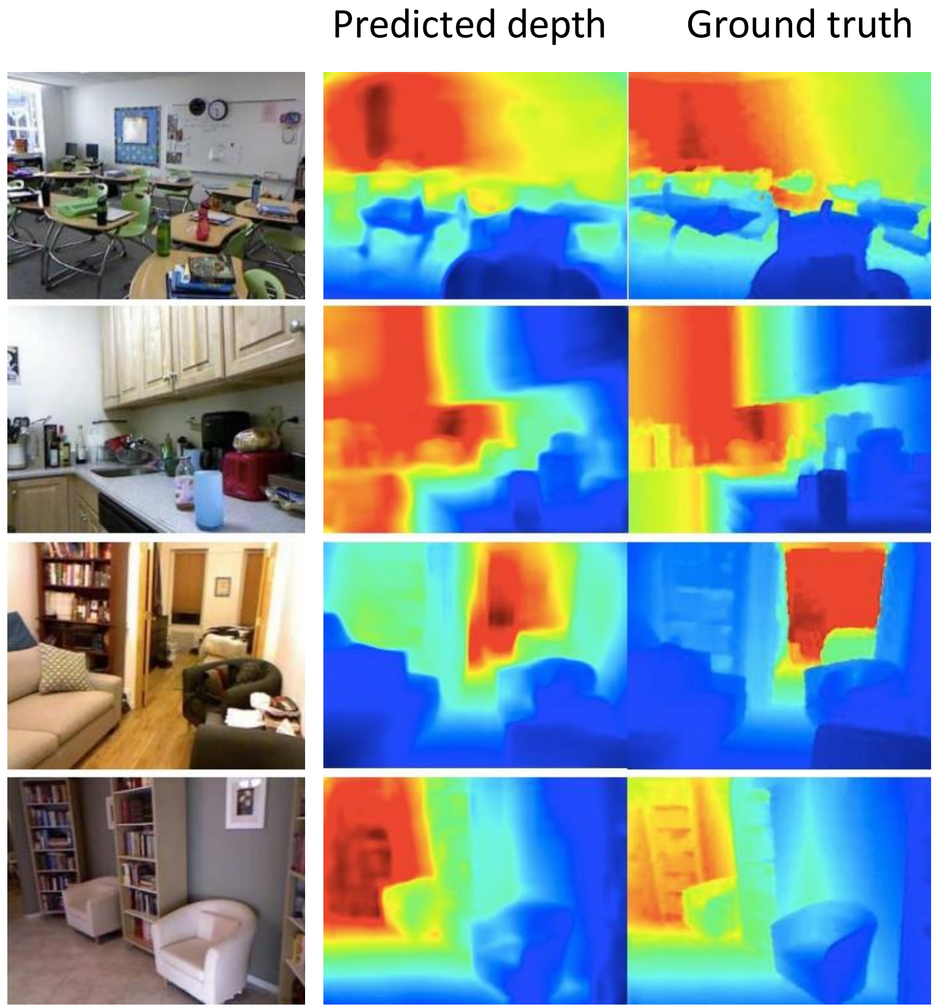



Figure Credit: Alexander Kirillov

# Dense Prediction: Depth and normal estimation

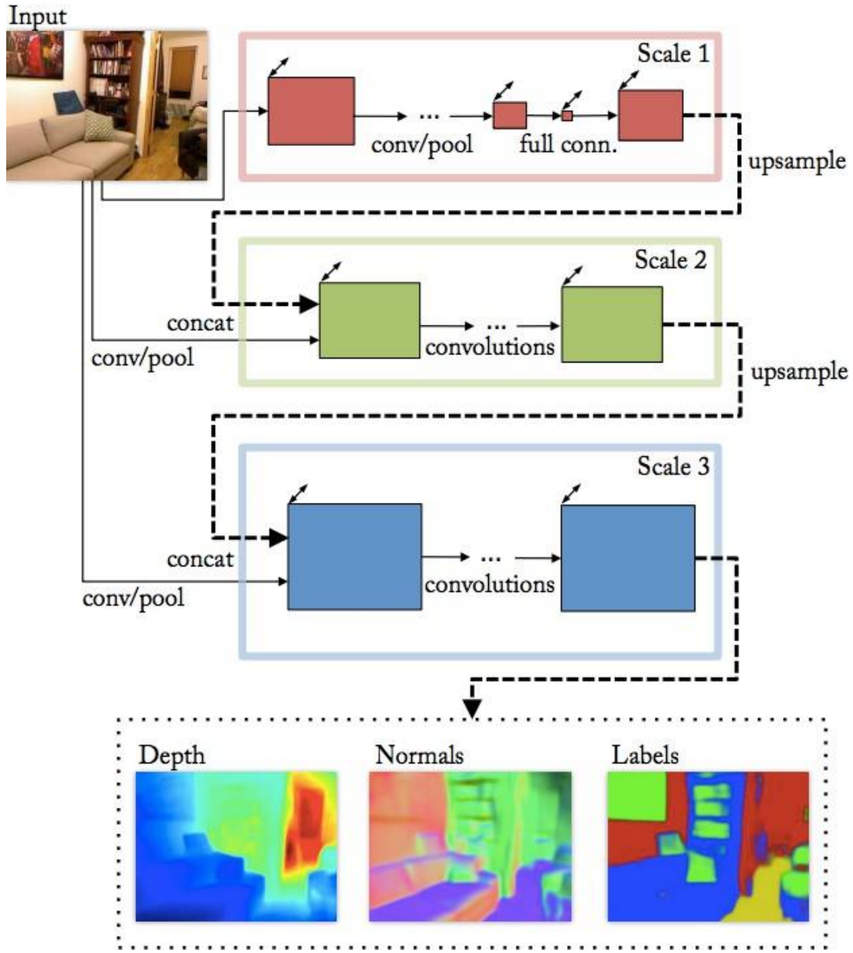


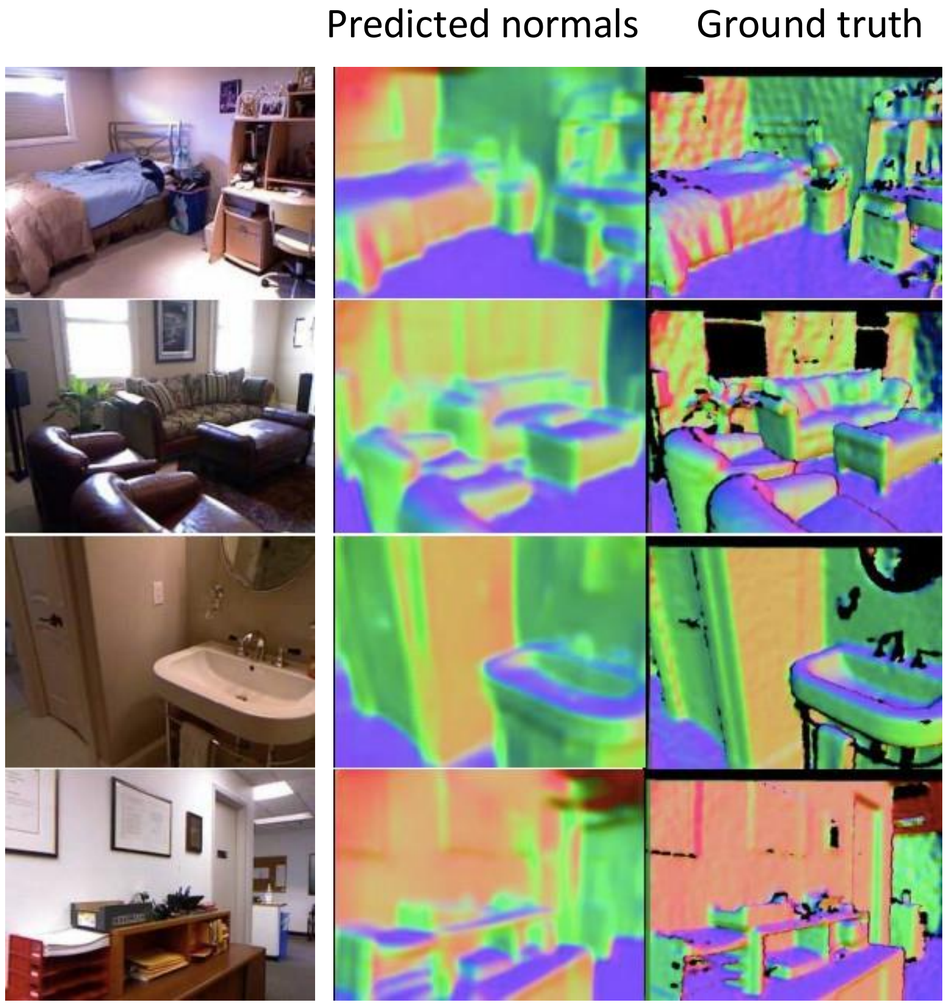




D. Eigen and R. Fergus, [Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture](), ICCV 2015

Slide credit: S. Lazebnik

# Dense Prediction: Depth and normal estimation

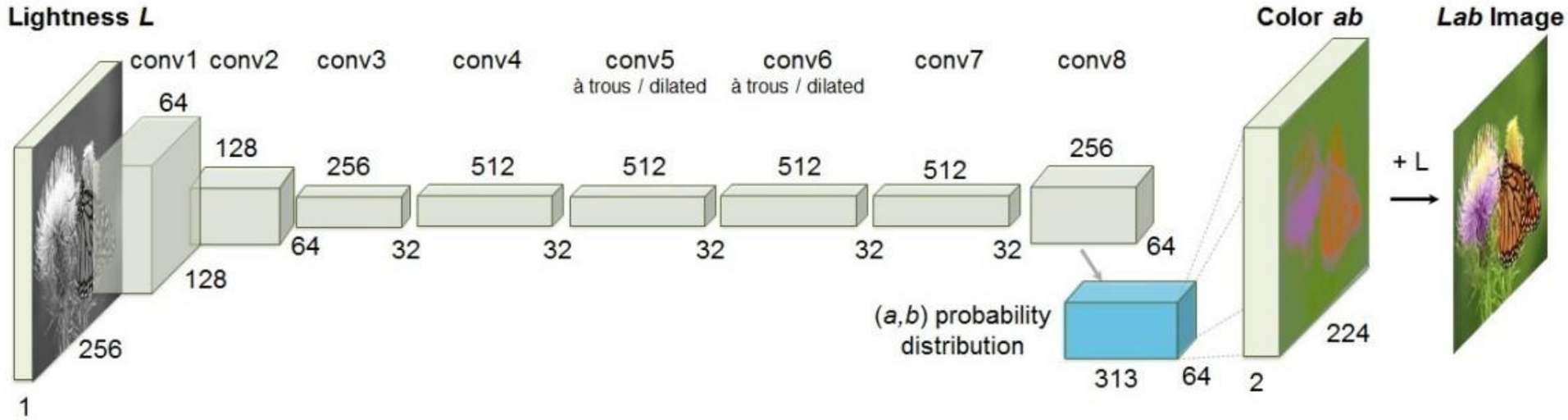



D. Eigen and R. Fergus, [Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture](), ICCV 2015

Slide credit: S. Lazebnik

# Dense Prediction: Colorization




R. Zhang, P. Isola, and A. Efros, Colorful Image Colorization, ECCV 2016

Slide credit: S. Lazebnik