Lecture 13: Spatial Localization and Image Segmentation

Administrivia

Expect TA feedback on **project proposal** by 9/30

Reminder, that **Homework 2** is due 9/29

Midterm

— Nov 16, in class

— Closed book

— Syllabus includes everything till the Nov. 9 lecture

Happy Dusshera / Vijaydashami (may you defeat the non-converging networks)

Project milestone (due 11/5)

Your project milestone report should be between **2 - 3 pages** using the provided template. The following is a suggested structure for your report:

- Title, Author(s)
- Introduction: this section introduces your problem, and the overall plan for approaching your problem
- Problem statement: Describe your problem precisely specifying the dataset to be used, expected results and evaluation
- Technical Approach: Describe the methods you intend to apply to solve the given problem
- Intermediate/Preliminary Results: State and evaluate your results upto the milestone

Submission: Please upload a PDF file to Gradescope. Please coordinate with your teammate and **submit only under ONE of your accounts**, and add your teammate on Gradescope.

Computer Vision Tasks

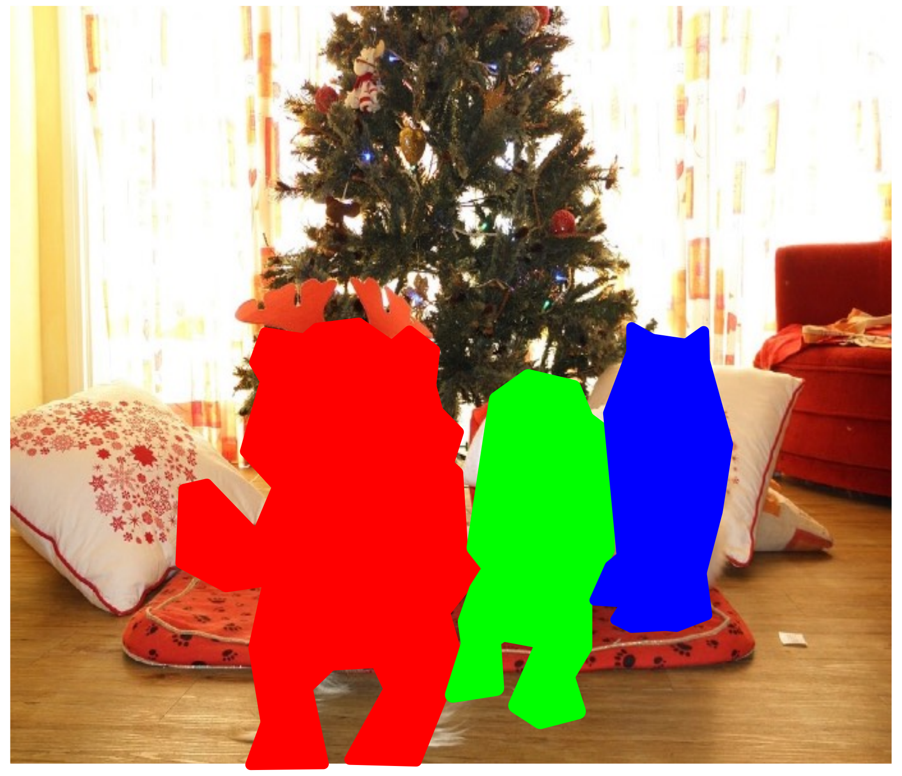
Classification

CAT

Object Detection

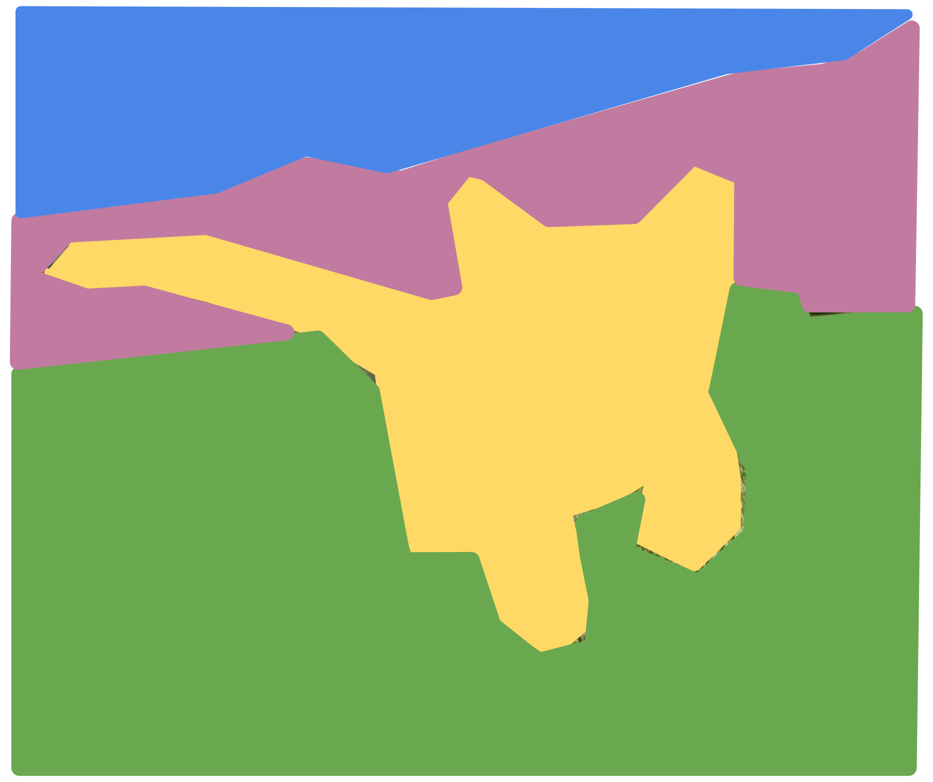
DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Semantic Segmentation



GRASS, CAT, TREE, SKY

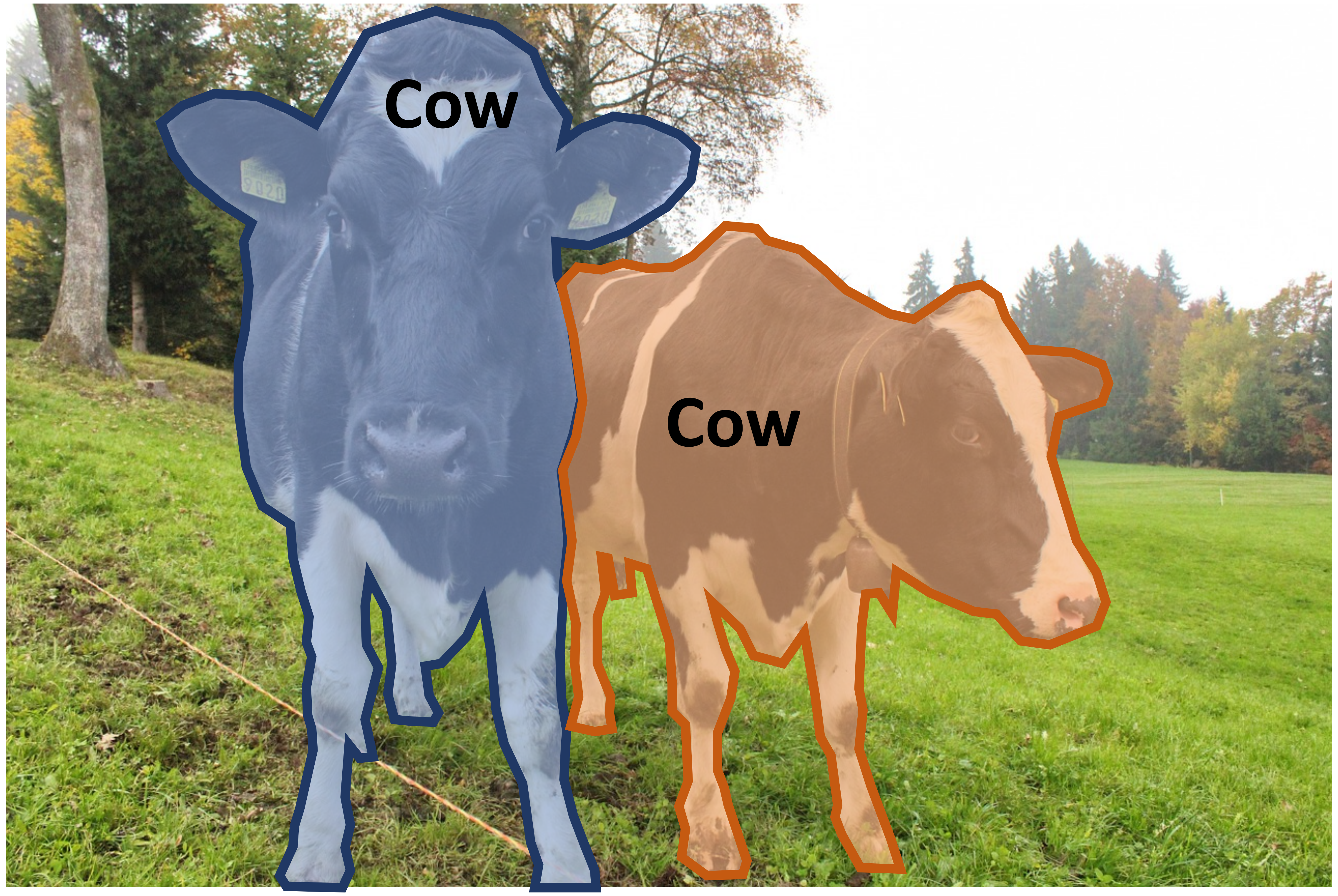
No spatial extent

Multiple Objects

No objects, just pixels

Instance segmentation

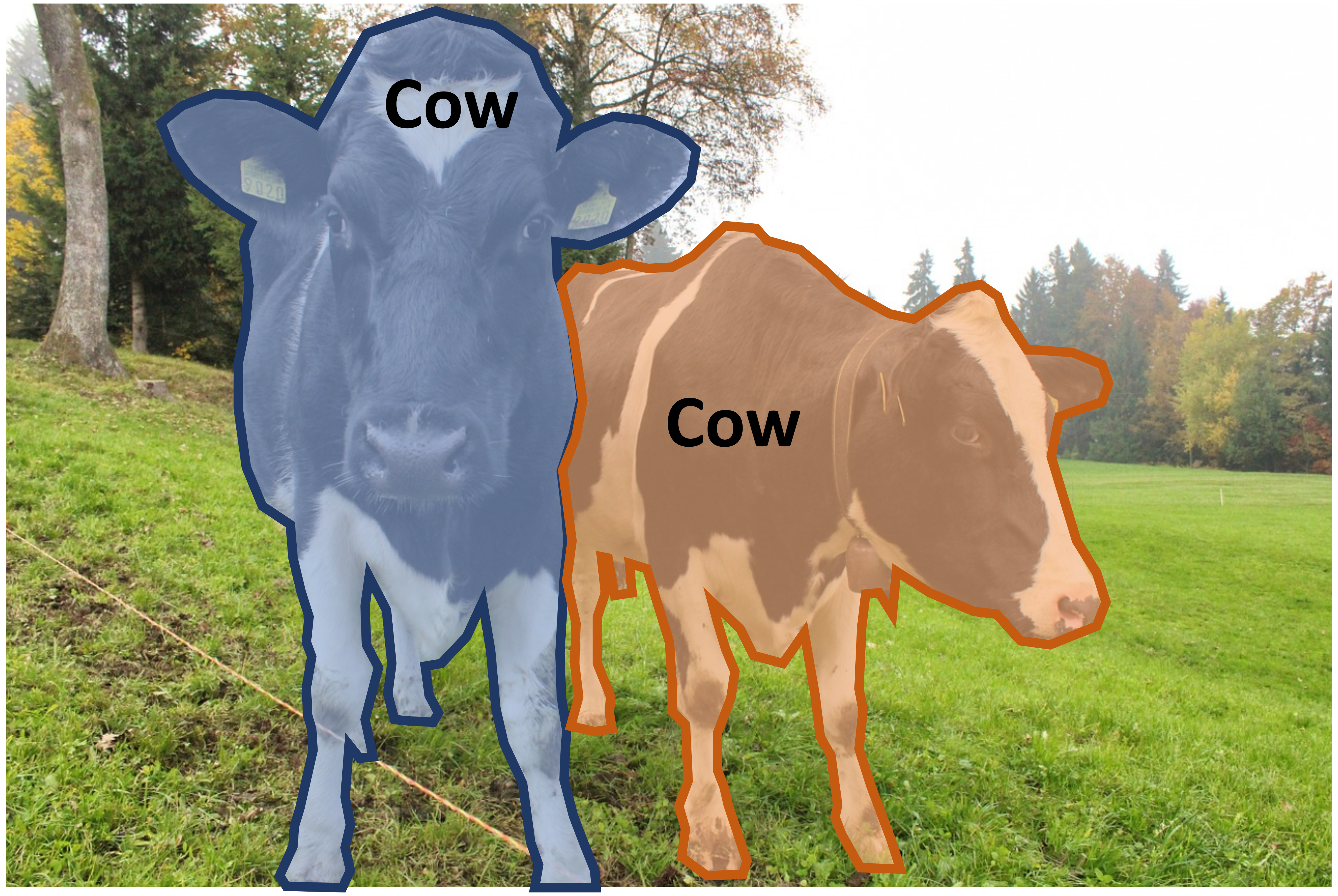
Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object



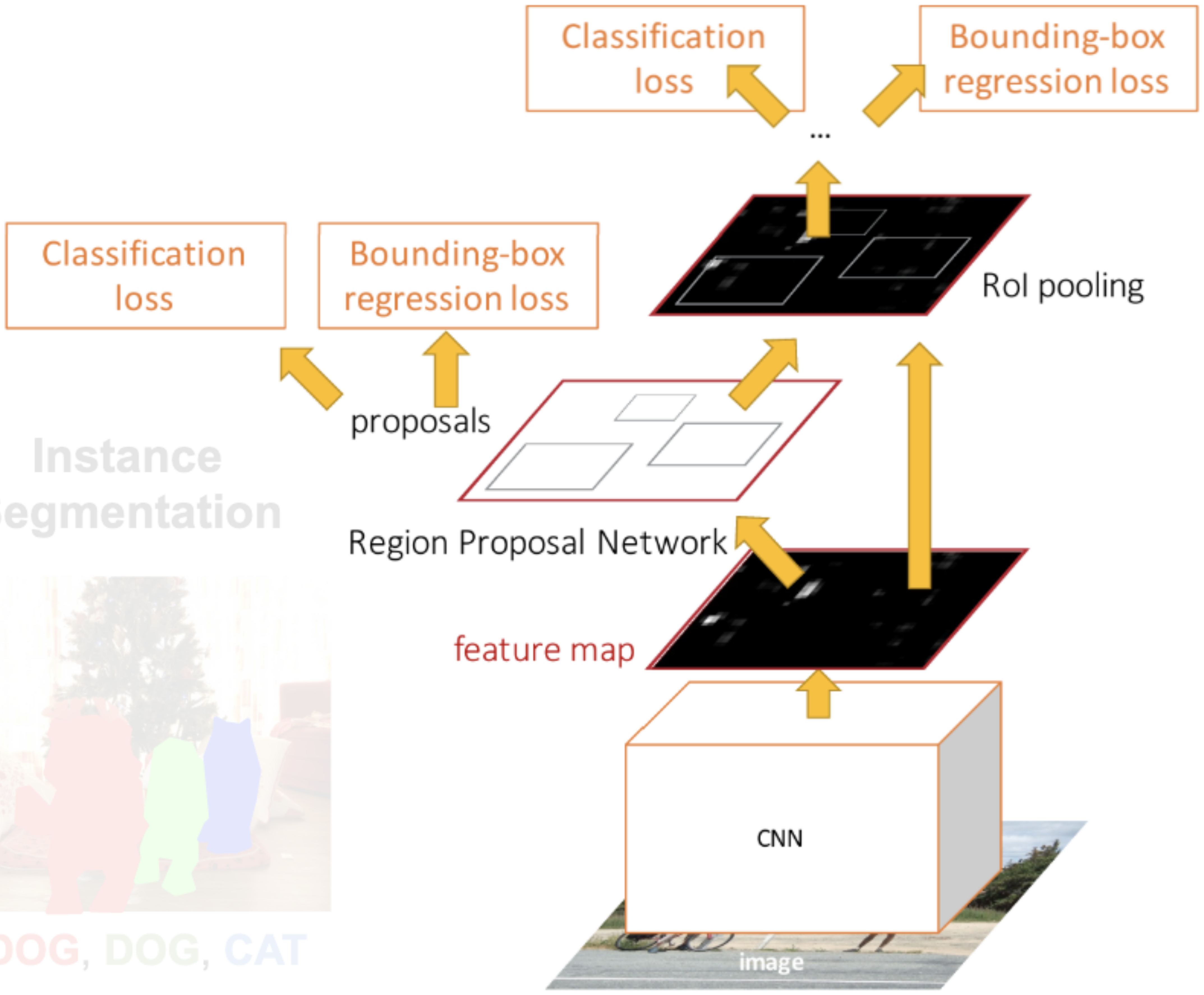
Instance segmentation

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!

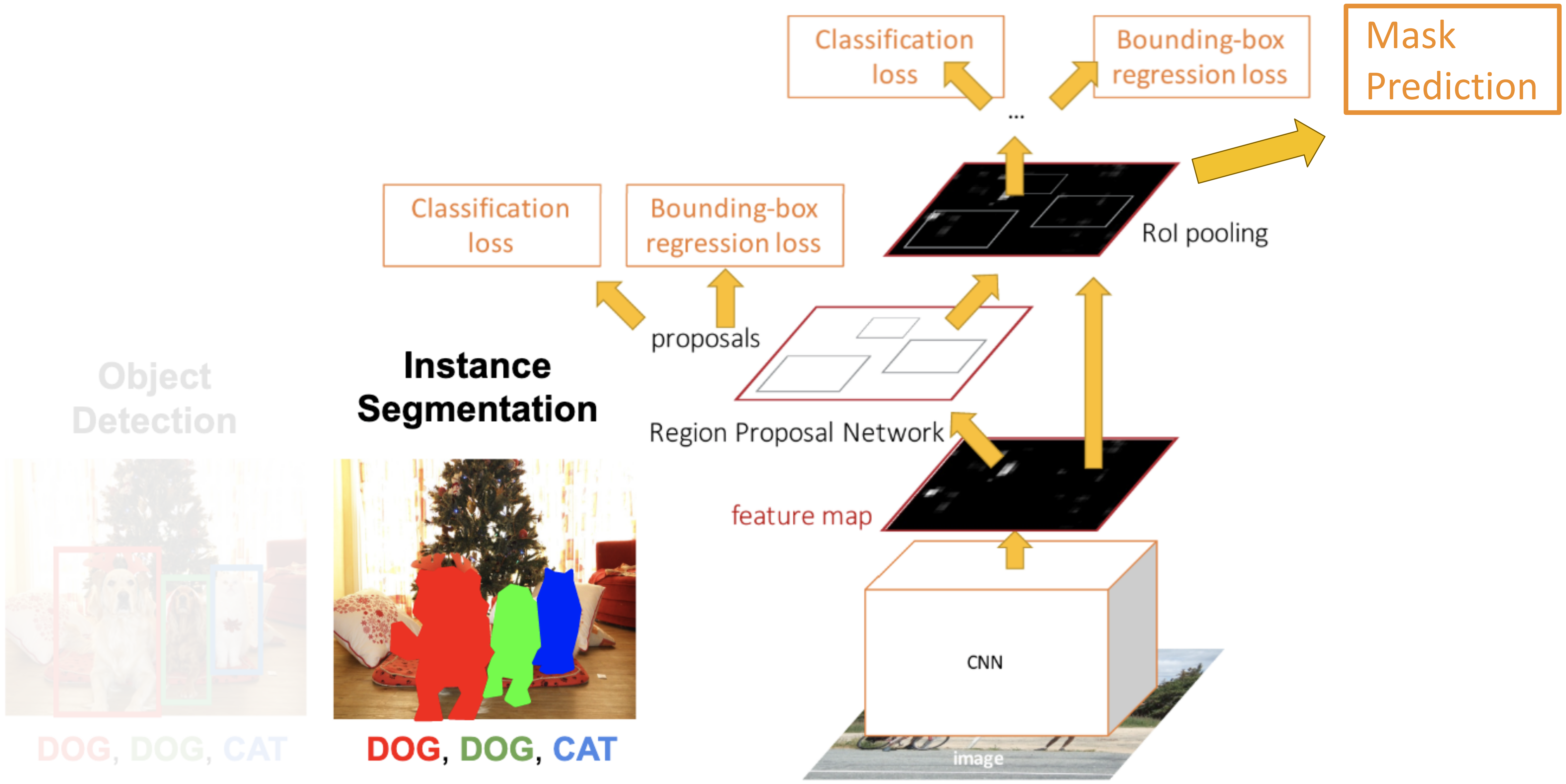


Object Detection: Faster R-CNN



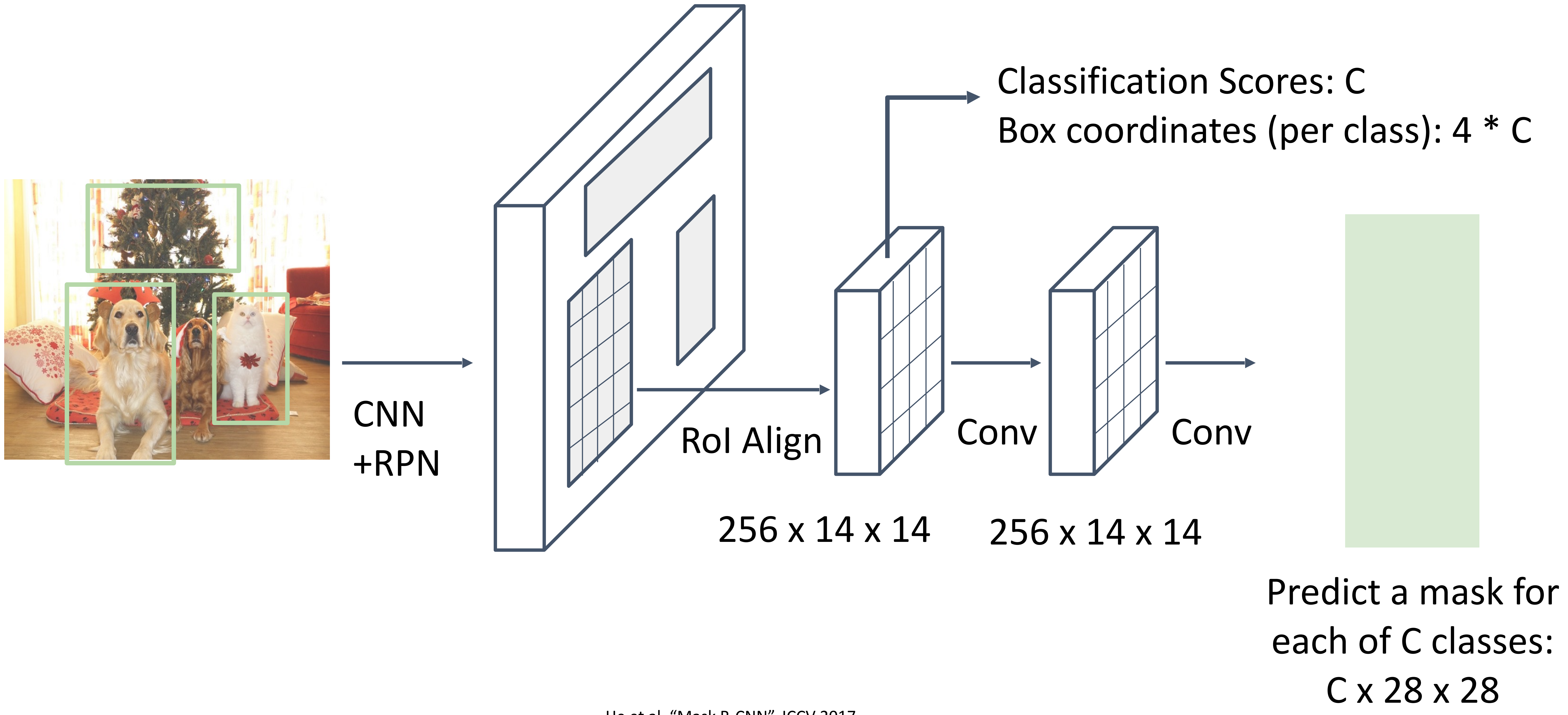
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NeurIPS 2015

Instance Segmentation: Mask R-CNN



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

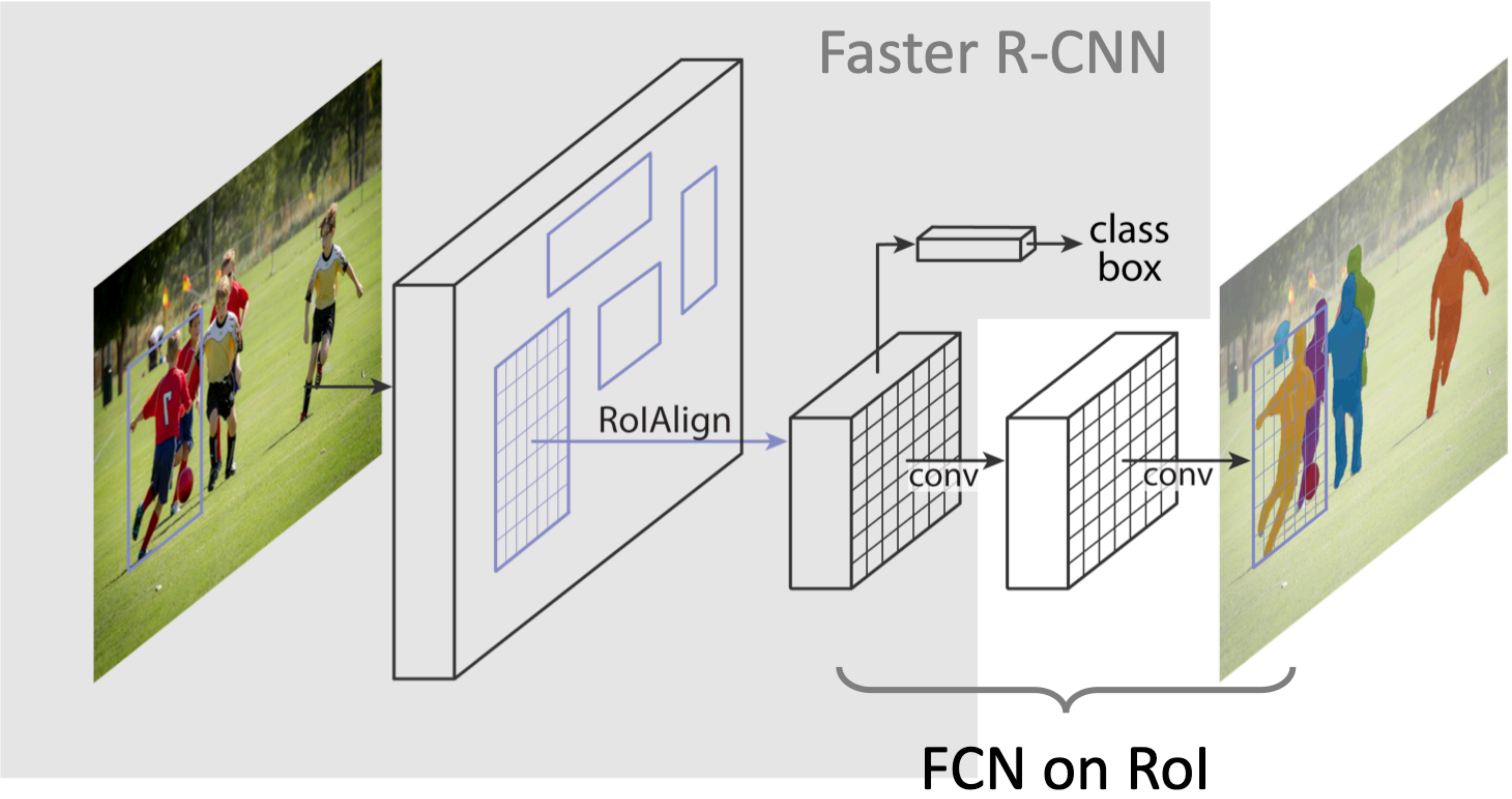
Mask R-CNN



He et al, “Mask R-CNN”, ICCV 2017

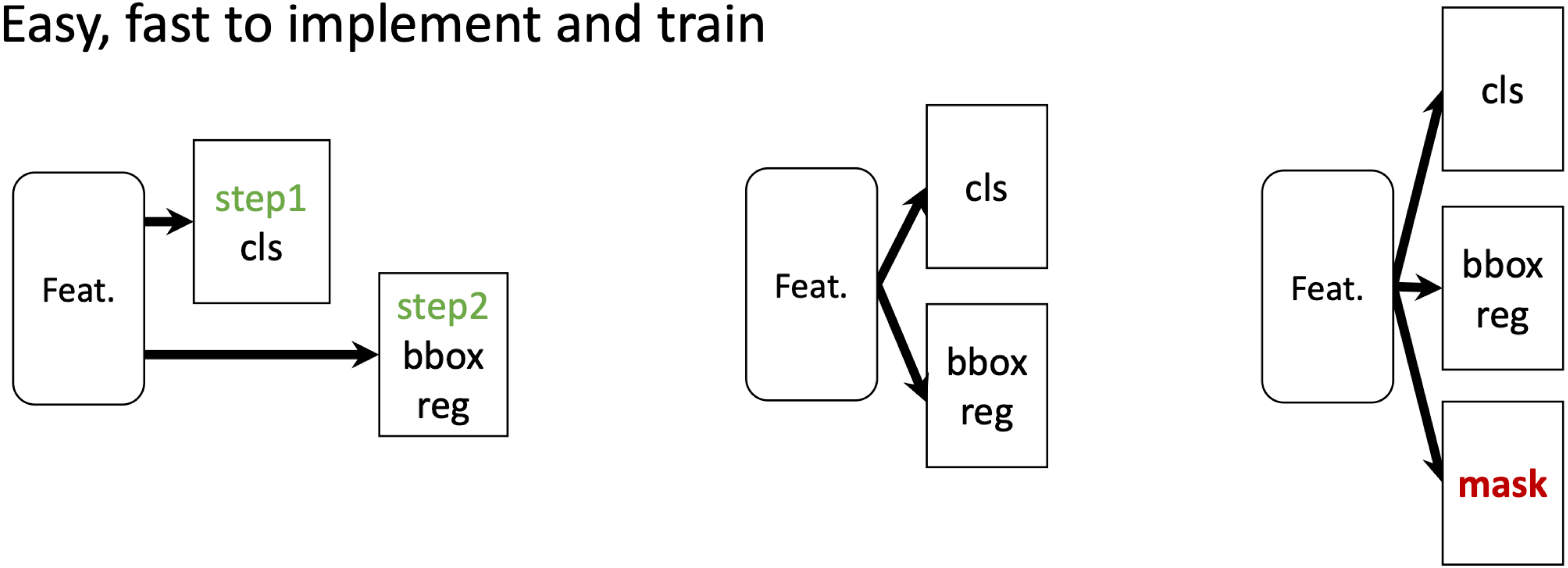
Mask R-CNN

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



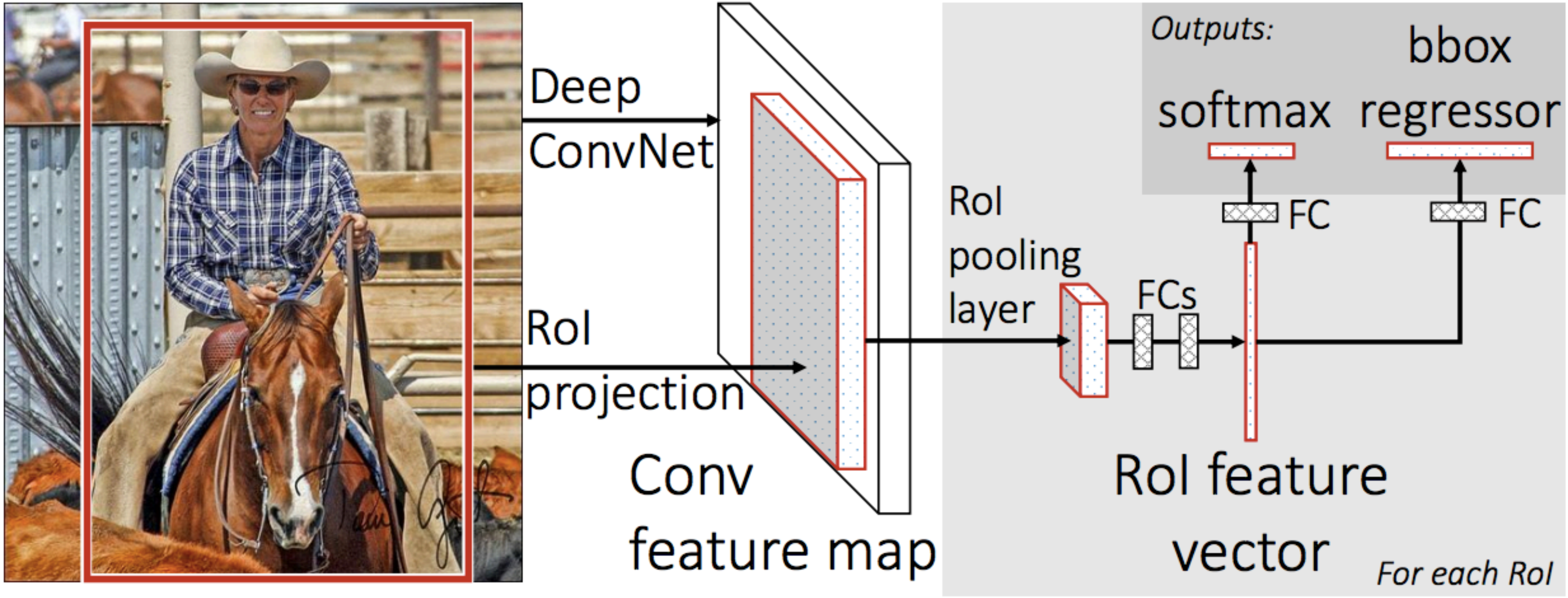
Parallel Heads

- Easy, fast to implement and train



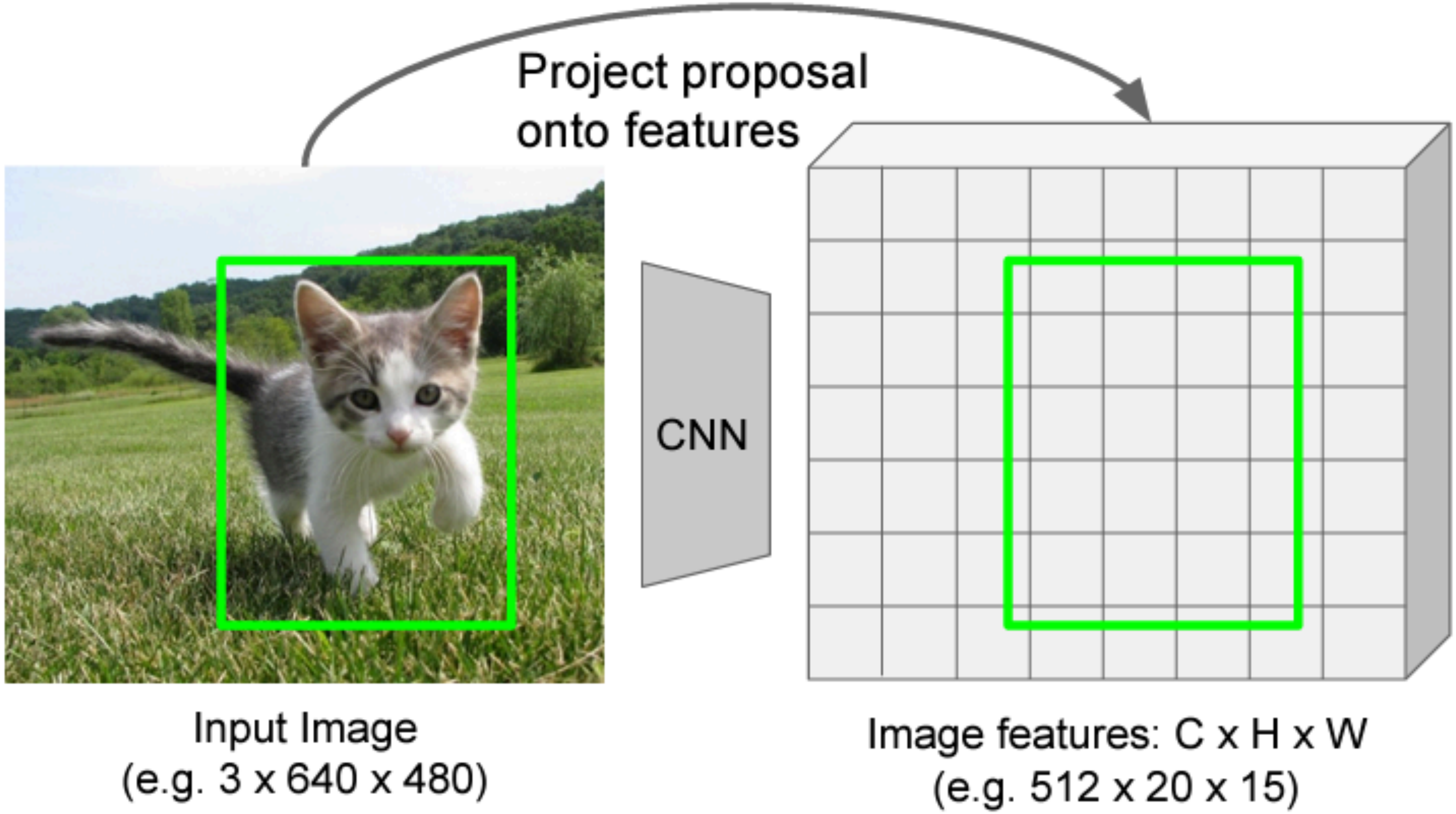
(slow) R-CNN | Fast/er R-CNN | Mask R-CNN

RoIPool and RoIAlign



R. Girshick, Fast R-CNN, ICCV 2015

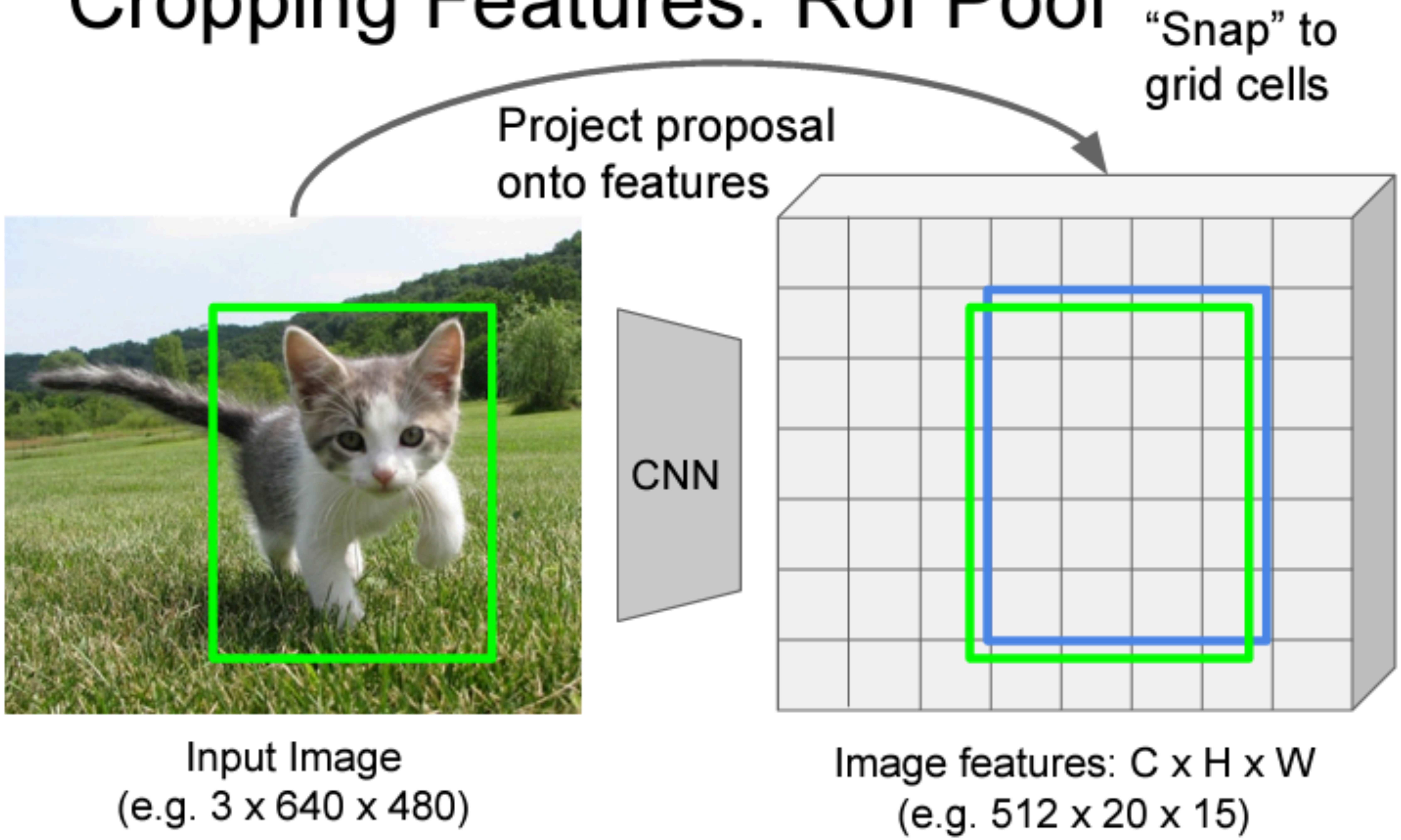
Cropping Features: RoI Pool



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

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

Cropping Features: RoI Pool

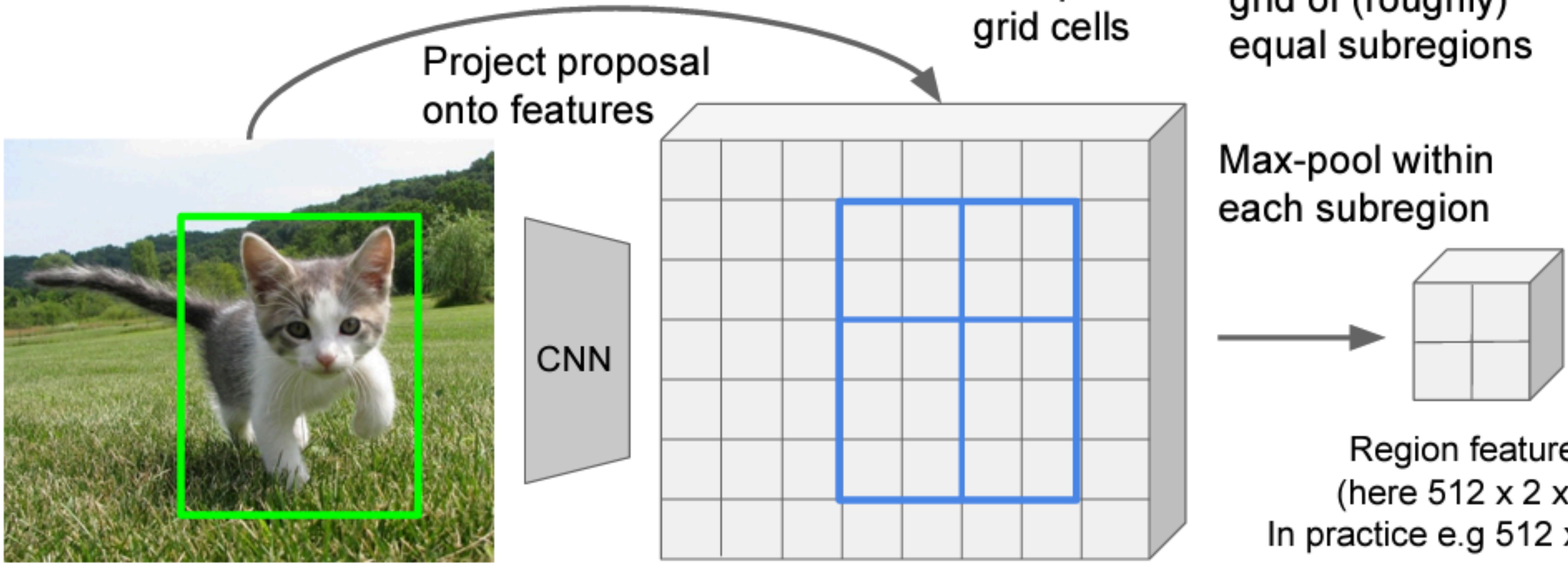


Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool

“Snap” to grid cells

Divide into 2x2 grid of (roughly) equal subregions



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

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

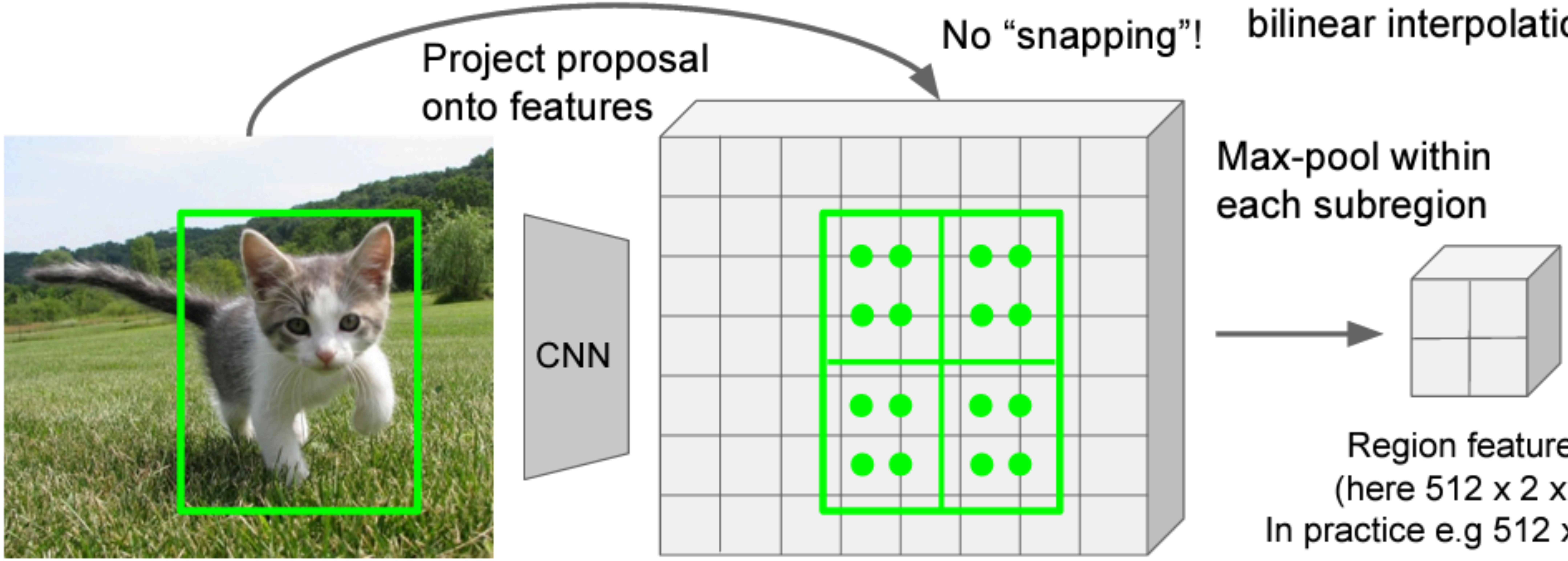
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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



Input Image
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(e.g. 512 x 20 x 15)

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

He et al, “Mask R-CNN”, ICCV 2017

Ablation: RoIPool vs RoIAlign

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

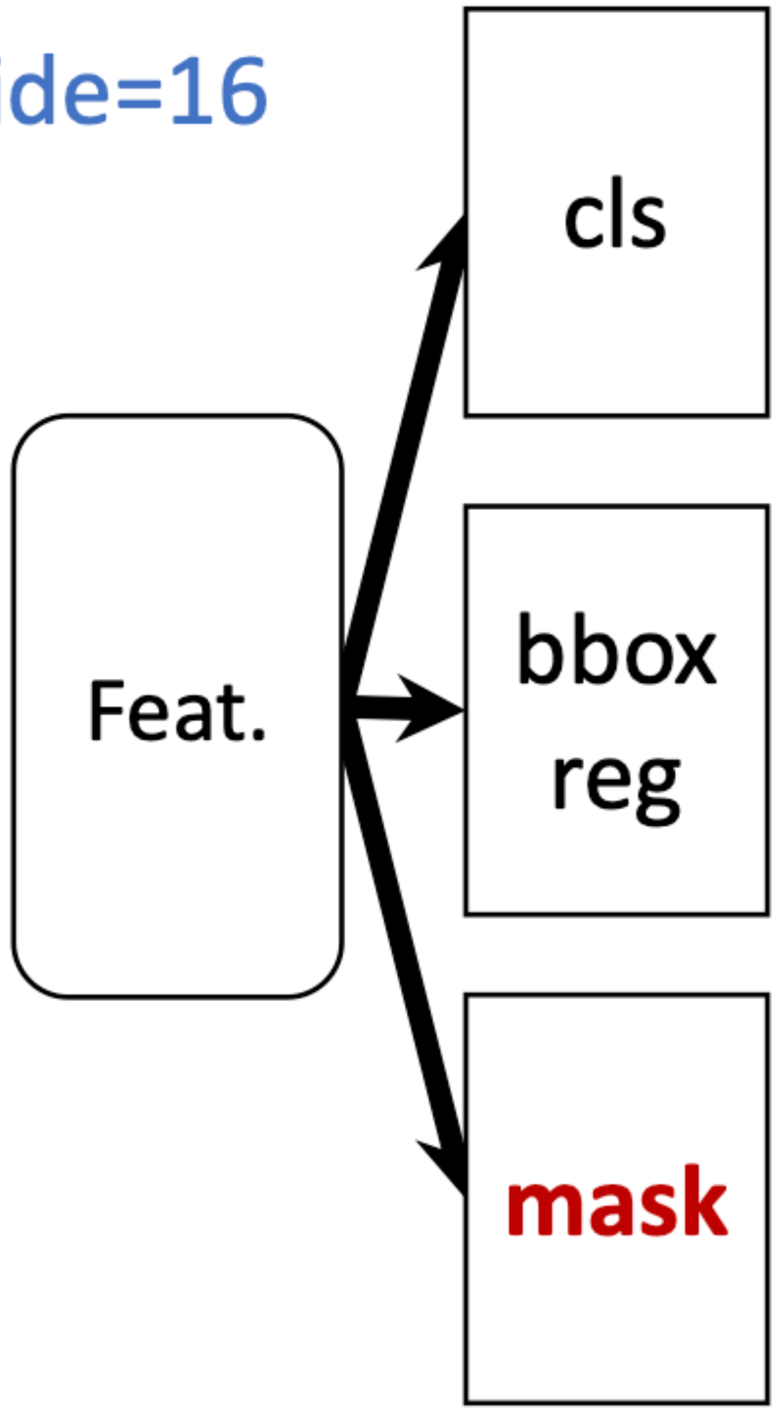
	mask AP			box AP		
	AP	AP_{50}	AP_{75}	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}
RoIPool	23.6	46.5	21.6	28.2	52.7	26.9
RoIAlign	**30.9**	**51.8**	**32.1**	**34.0**	**55.3**	**36.4**
	+7.3	*+ 5.3*	$\boxed{+10.5}$	*+5.8*	*+2.6*	*+9.5*

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

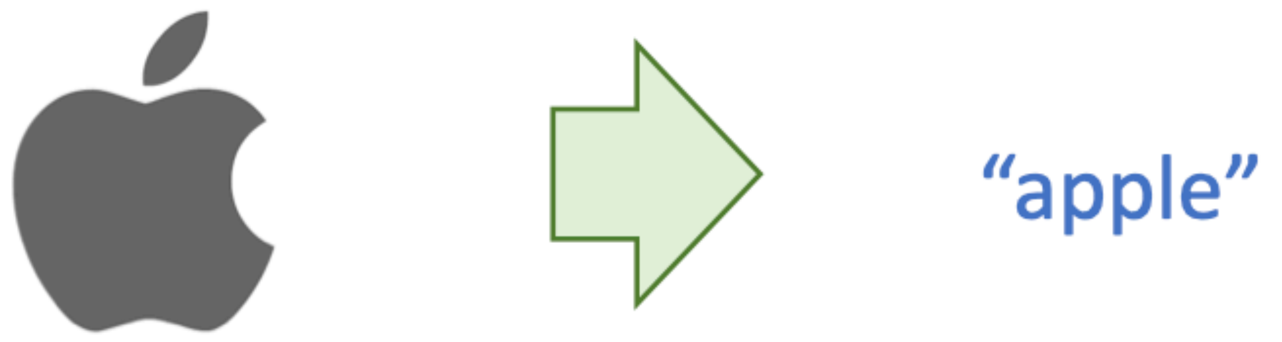
Ablation: Multinomial vs Binary Segmentation

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*



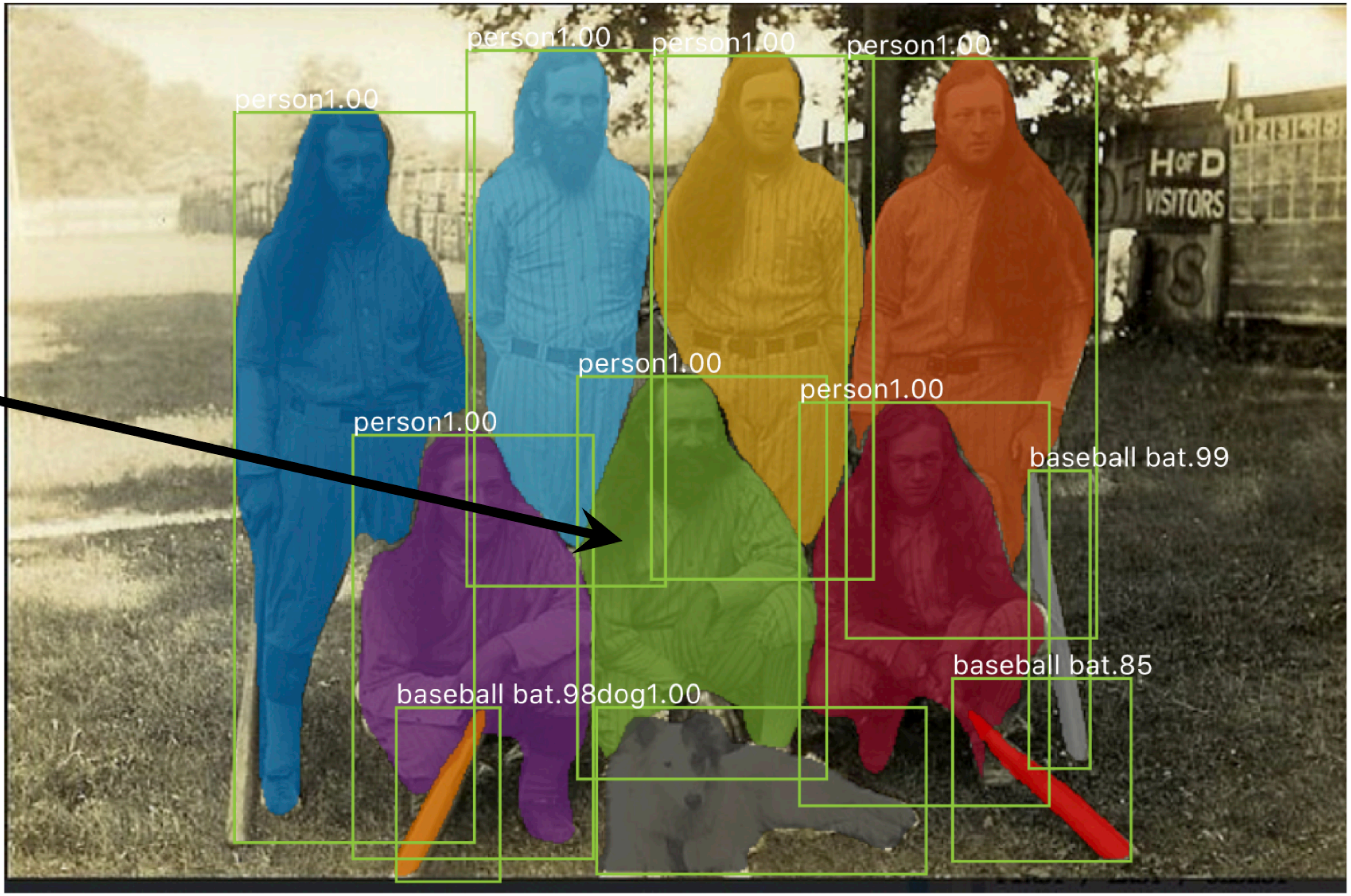
- cls head: did recognition



- mask head: no need to recognize again

Mask R-CNN: Very Good Results!

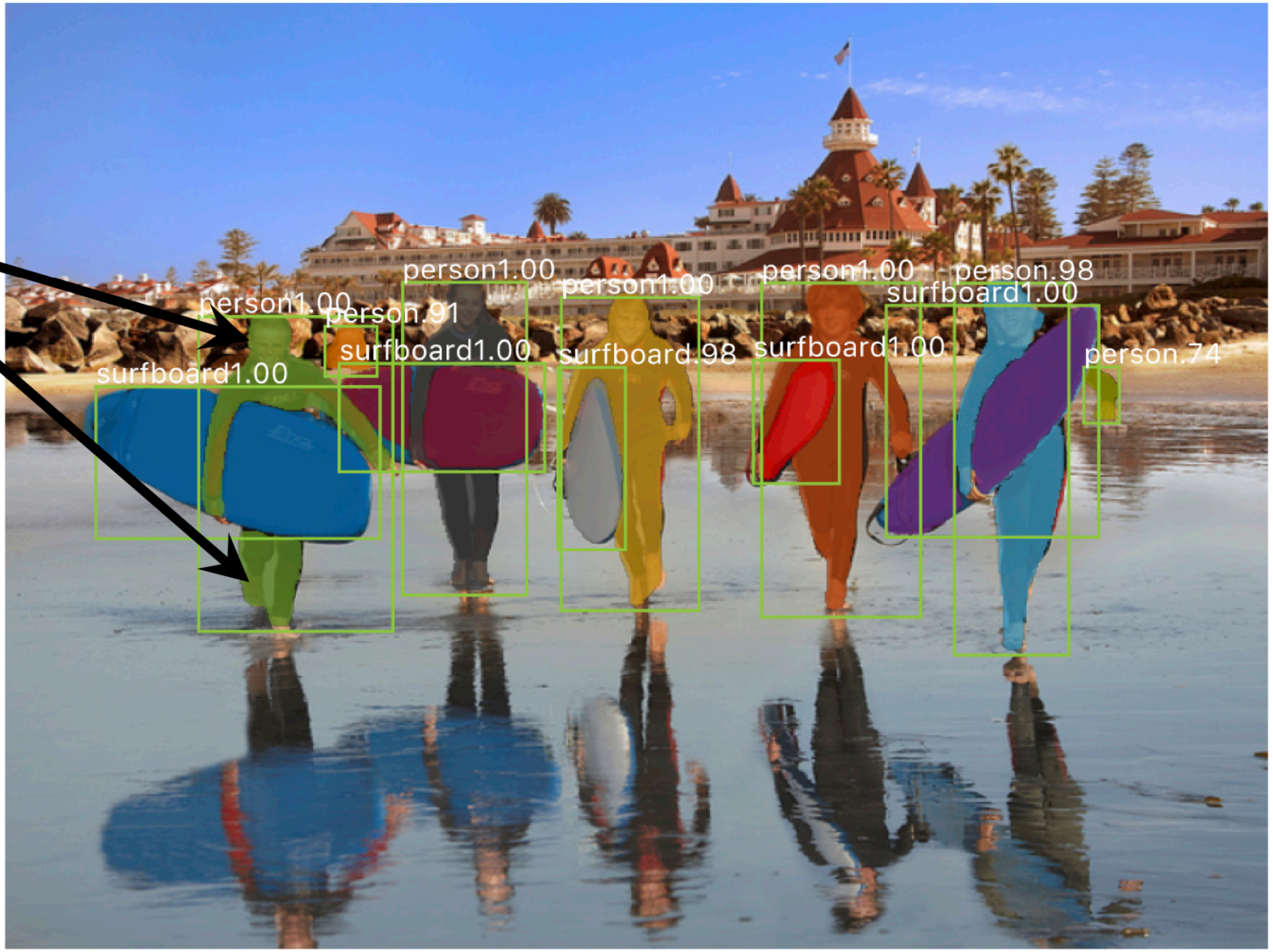
object
surrounded by
same-category
objects



Mask R-CNN results on COCO

Mask R-CNN: Very Good Results!

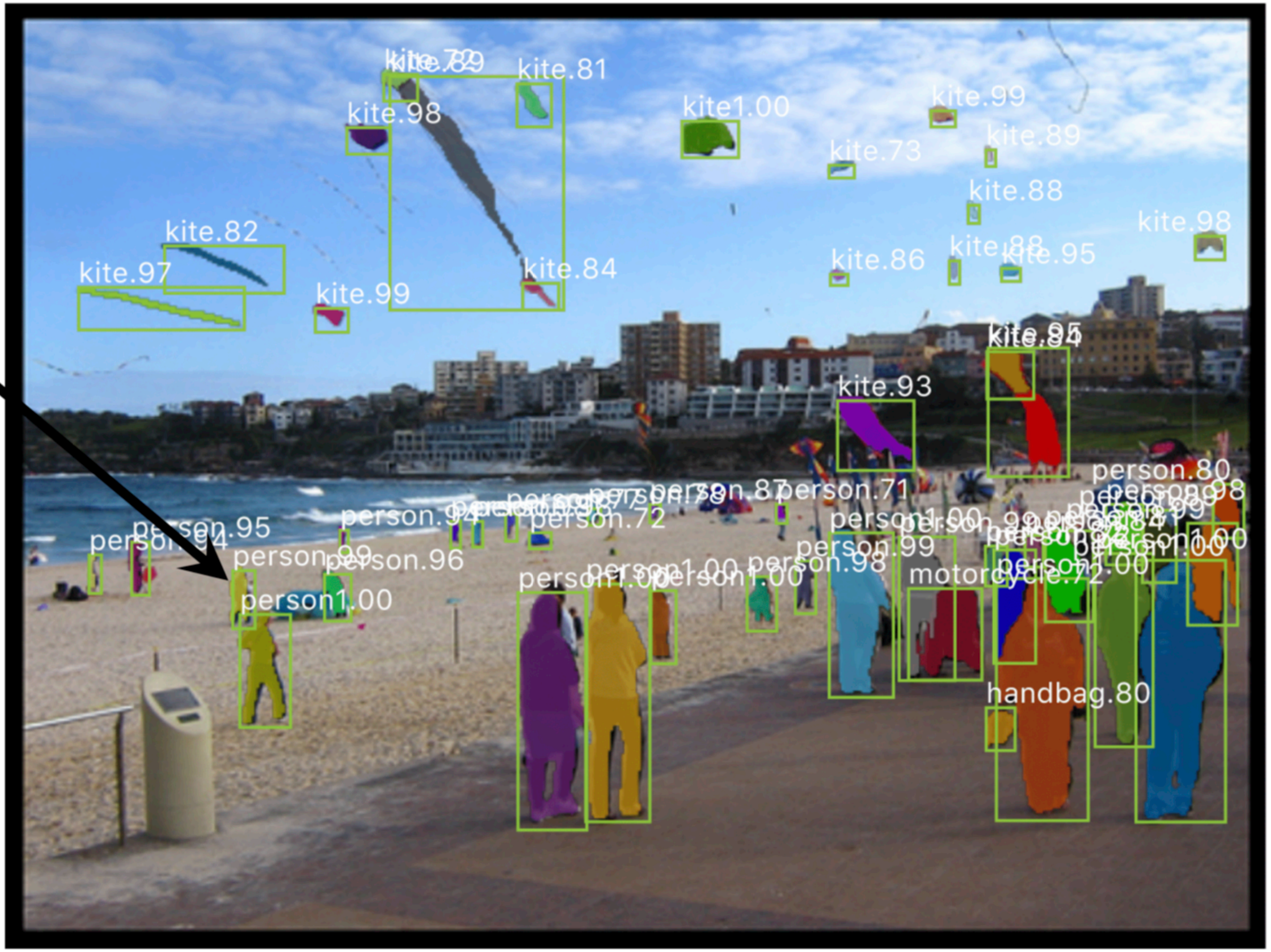
disconnected object



Mask R-CNN results on COCO

Mask R-CNN: Very Good Results!

small
objects

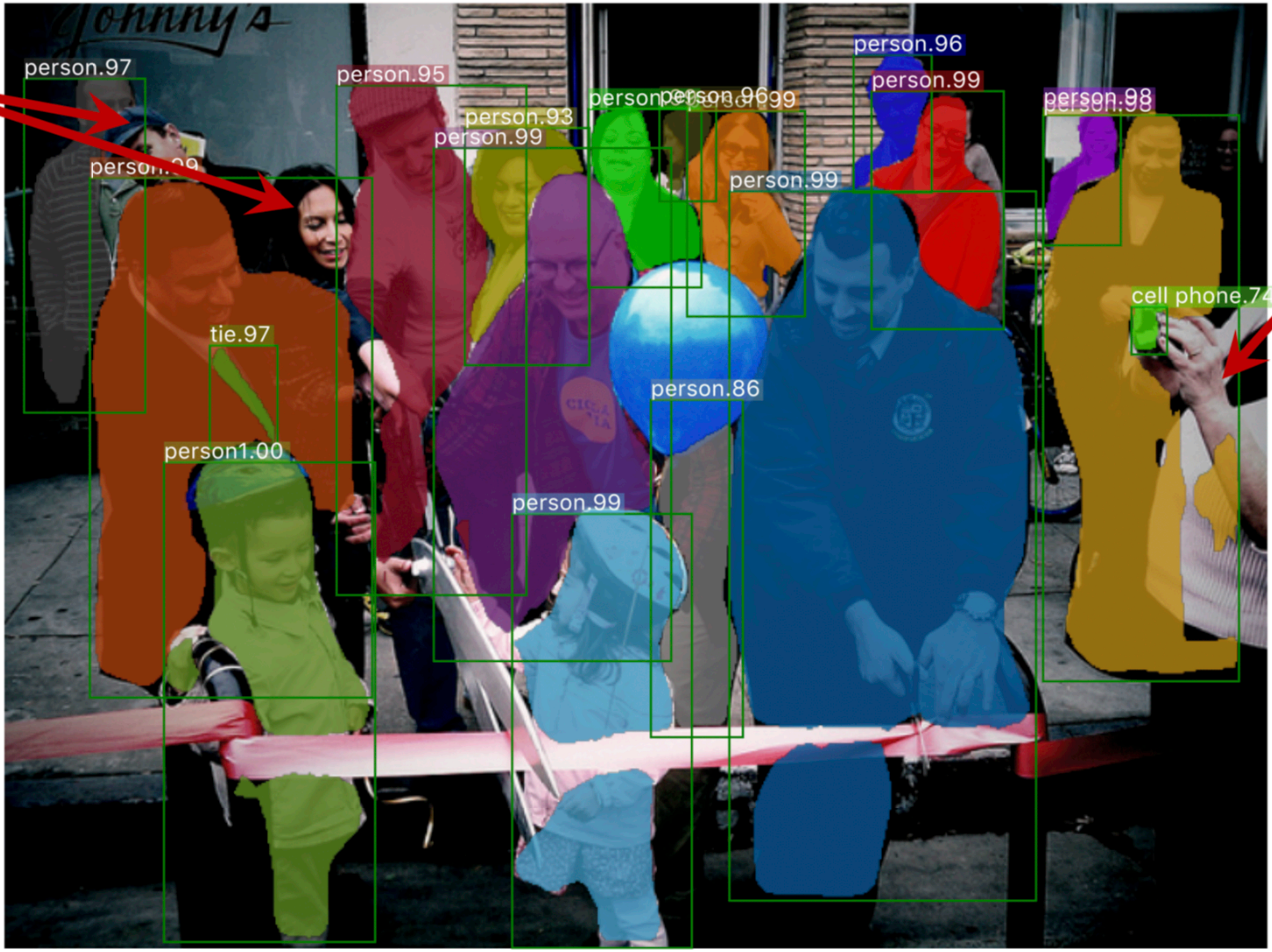


Mask R-CNN results on COCO

Figure Credit: Kaiming He

Mask R-CNN: Failure Case

missing



missing,
false mask

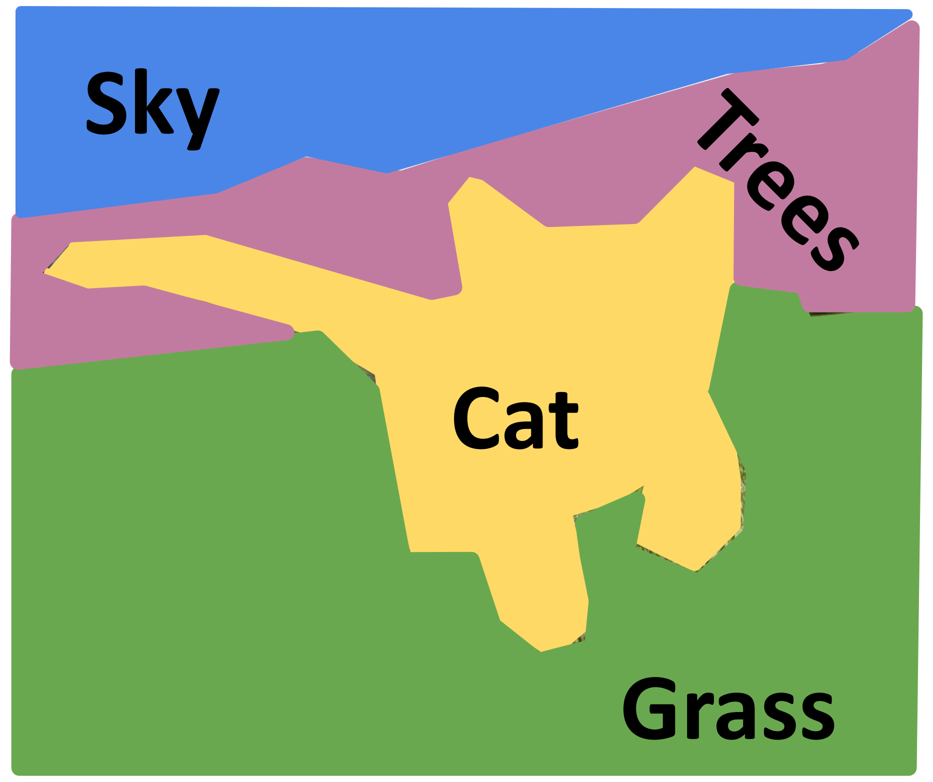
Mask R-CNN results on COCO

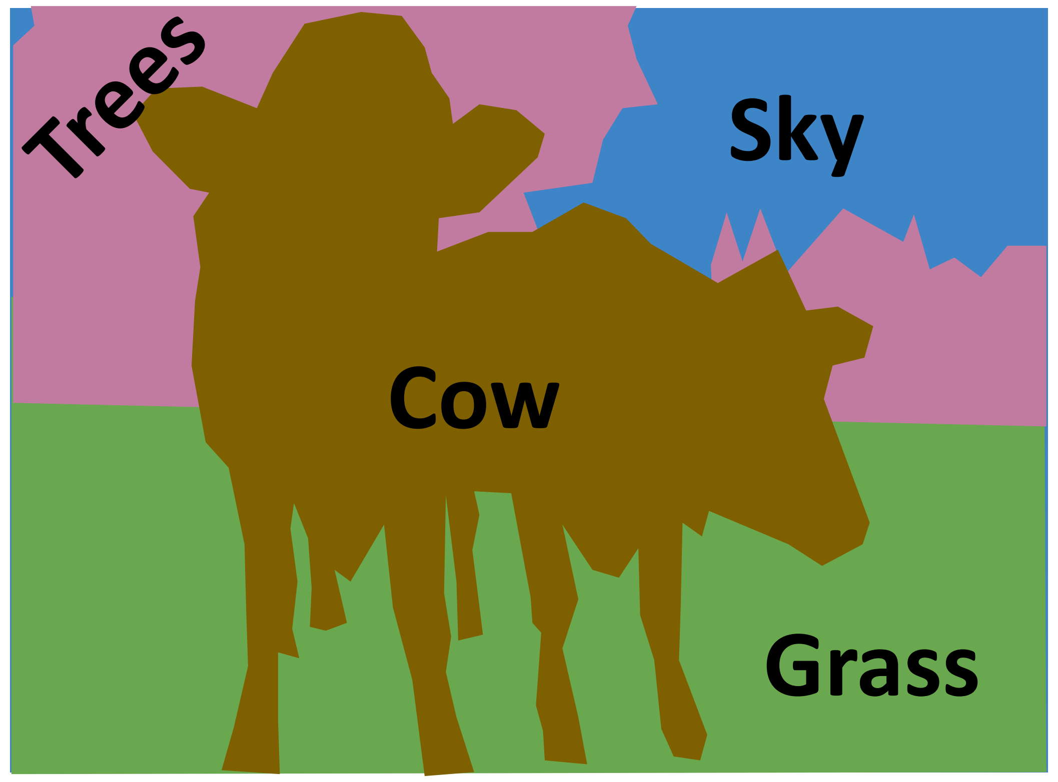
Semantic Segmentation

Label each pixel in the image with a category label

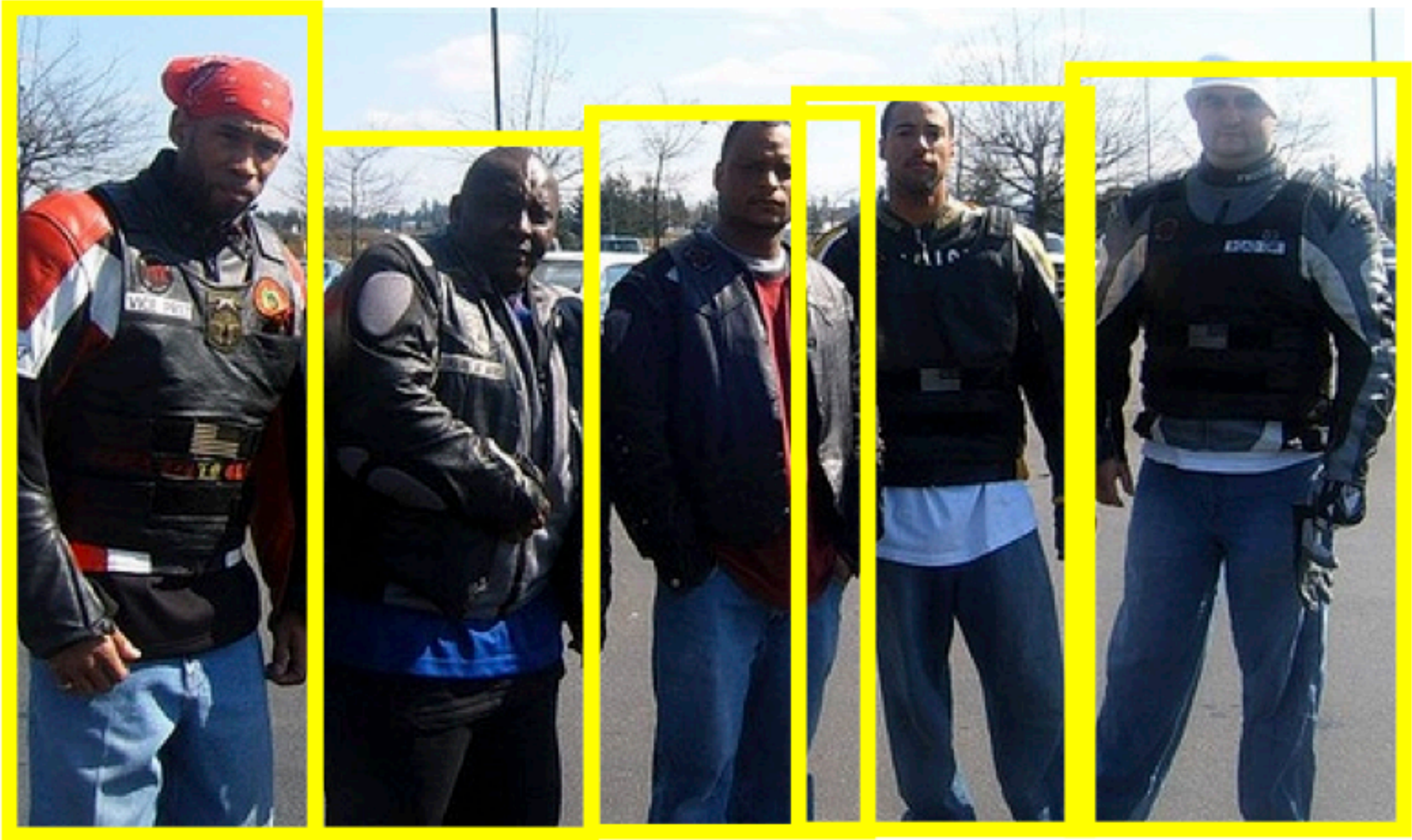
Don’t differentiate instances, only care about pixels

This image is CC0 public domain

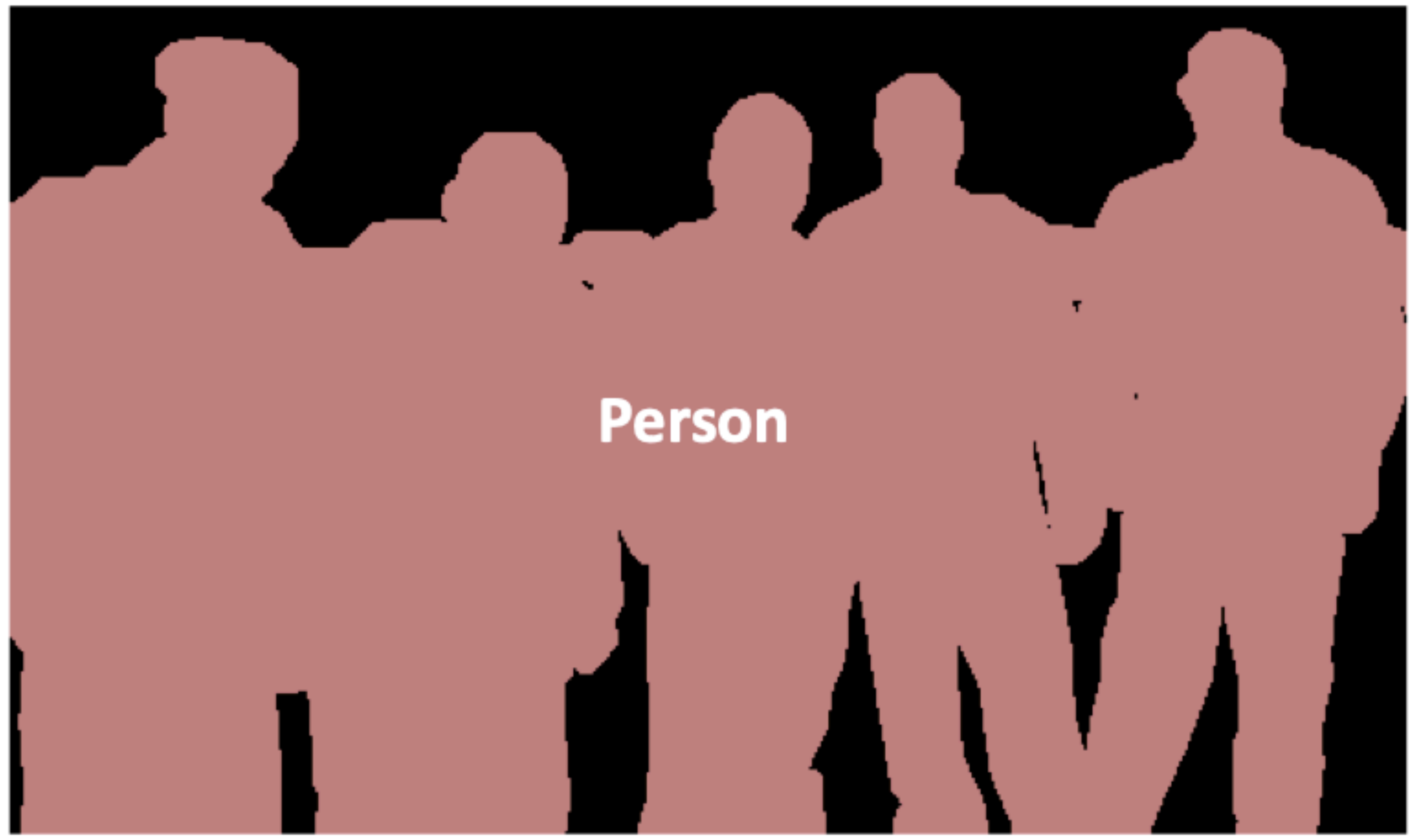




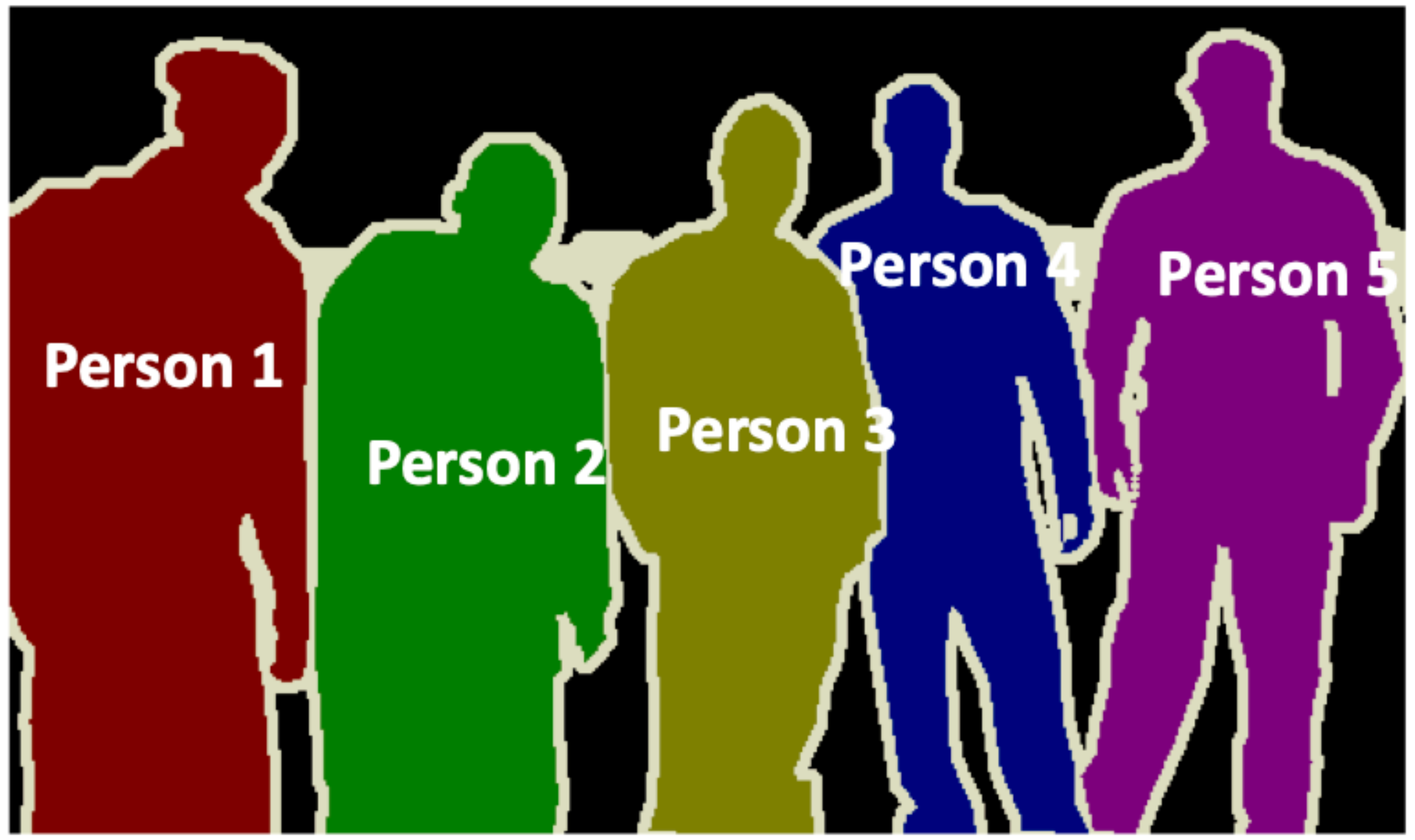
Semantic vs Instance Segmentation



Object Detection



Semantic Segmentation



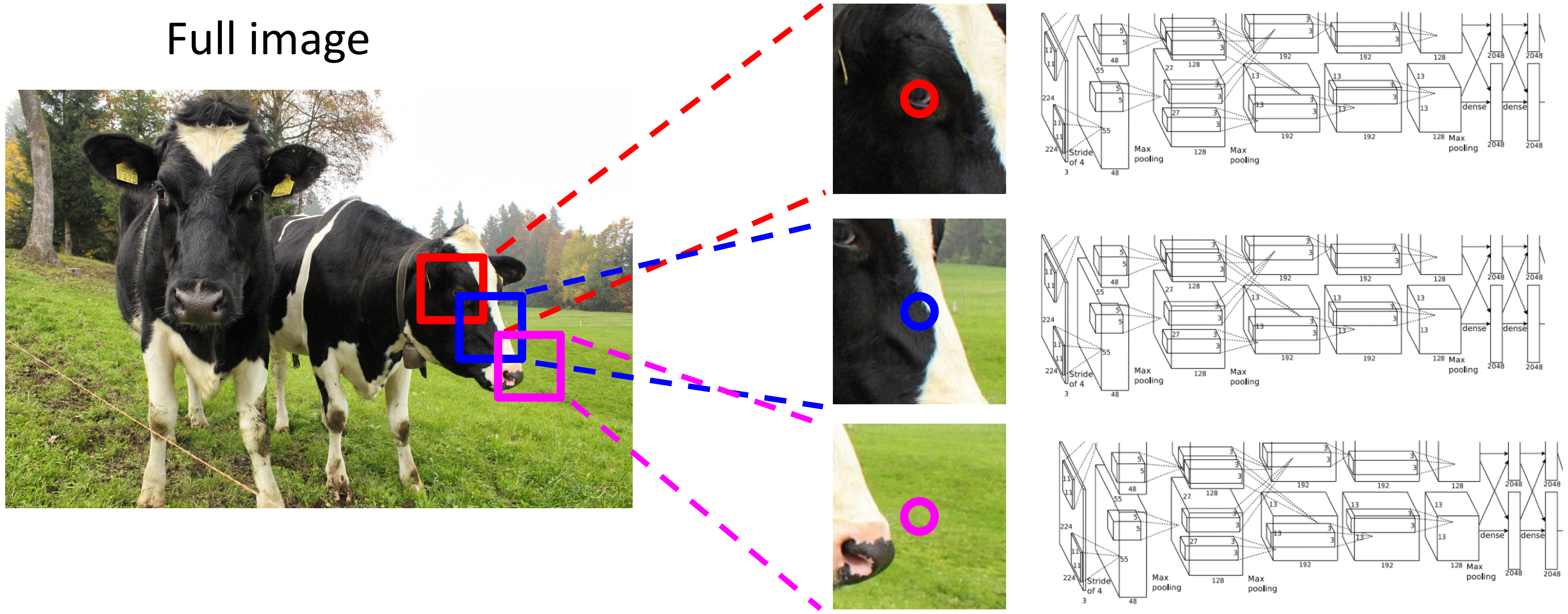
Instance Segmentation

Segmentation: Sliding Window

Extract patch

Classify center pixel with CNN

Full image



Cow

Cow

Grass

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

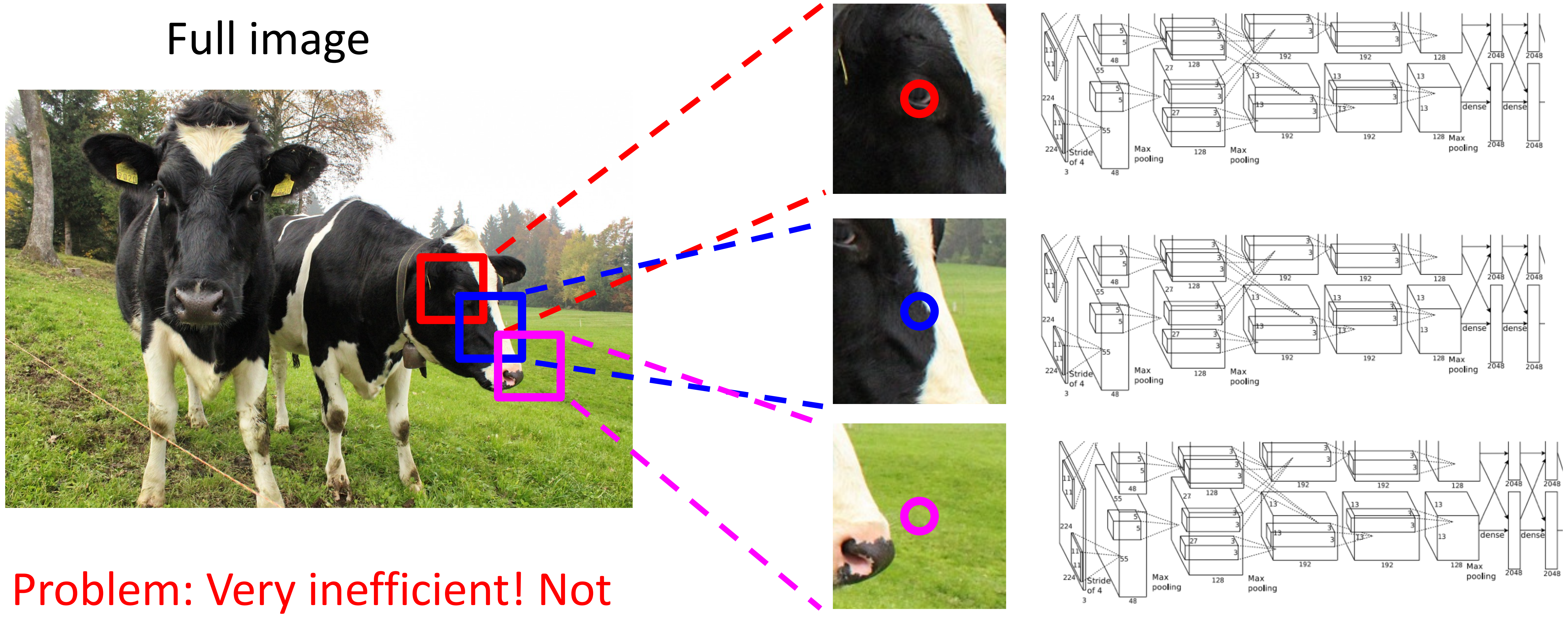
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Segmentation: Sliding Window

Extract patch

Classify center pixel with CNN

Full image



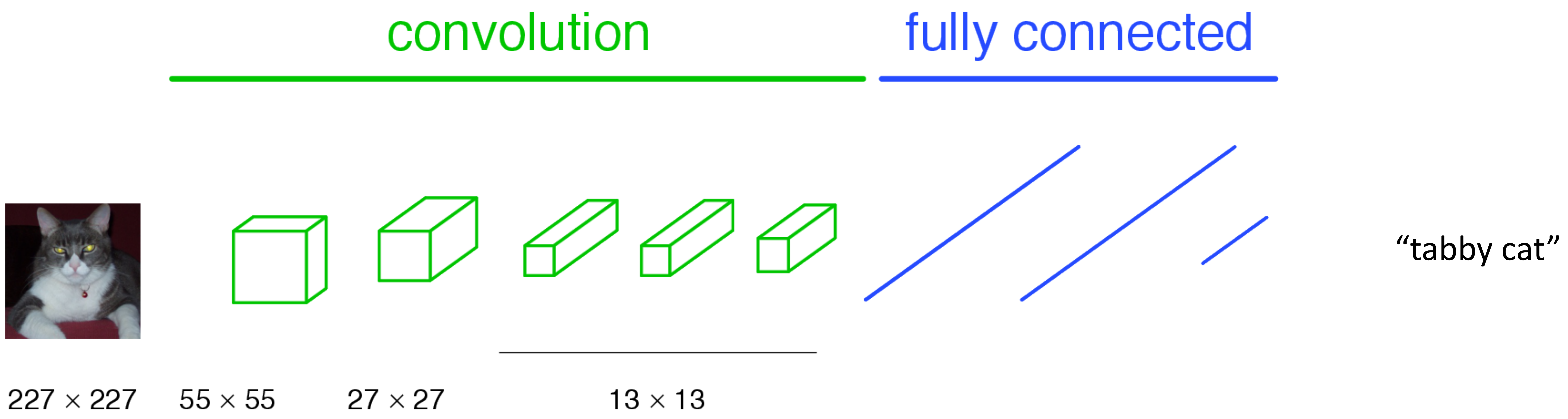
Cow

Cow

Grass

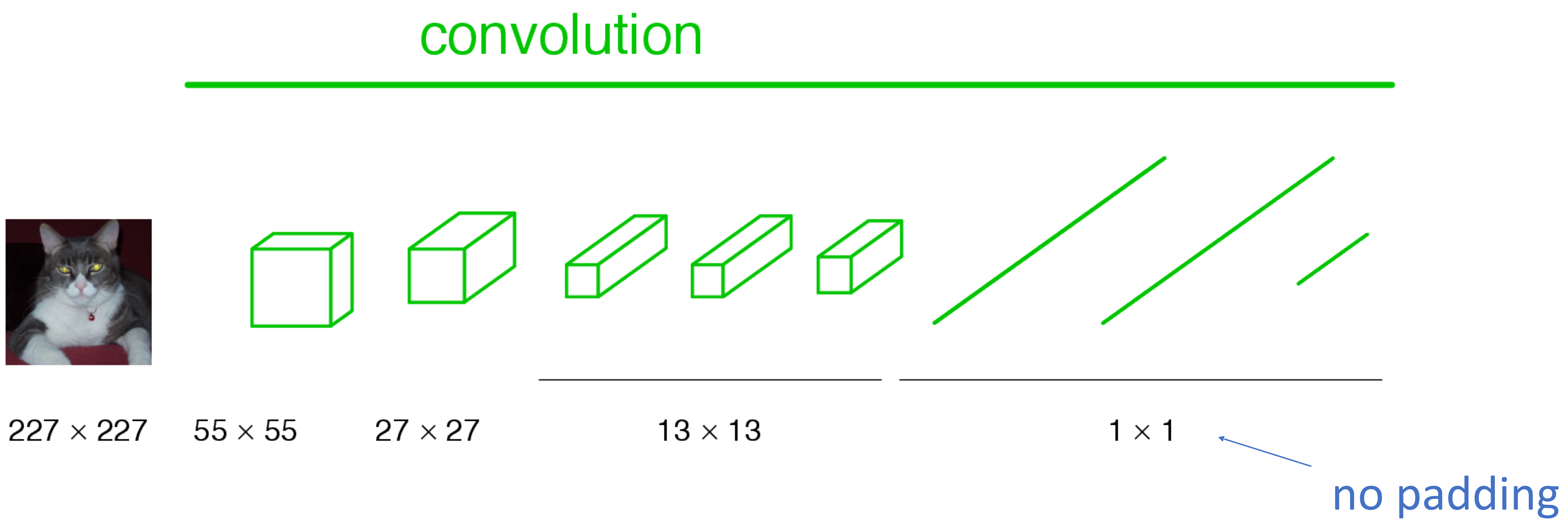
Problem: Very inefficient! Not reusing shared features between overlapping patches

A Classification Network



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

Becoming Fully Convolutional

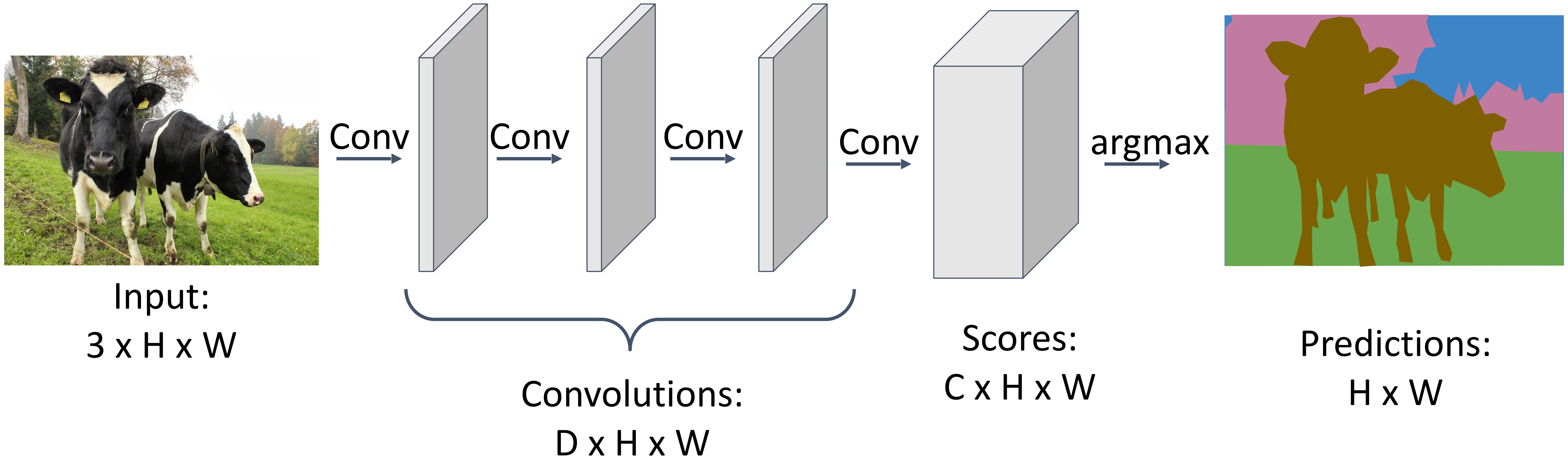


A fully-connected layer is equivalent to a convolution layer.

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!

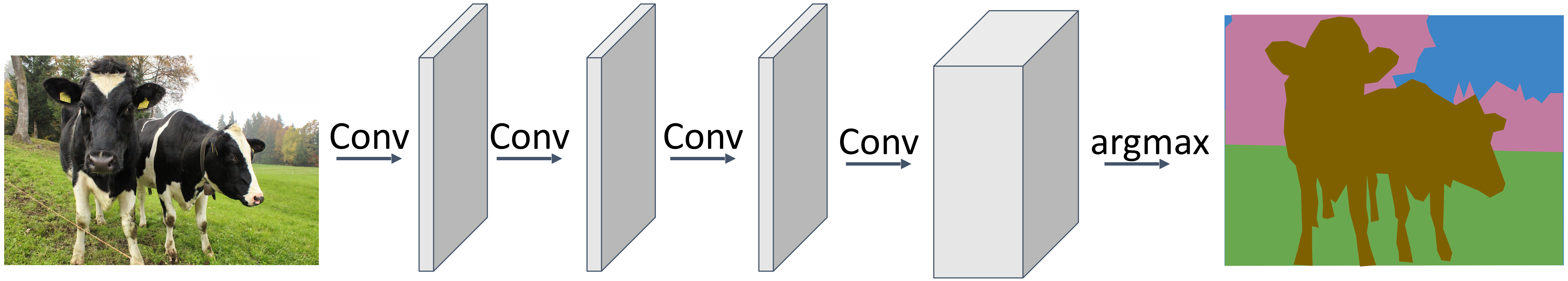


Loss function: Per-Pixel cross-entropy

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

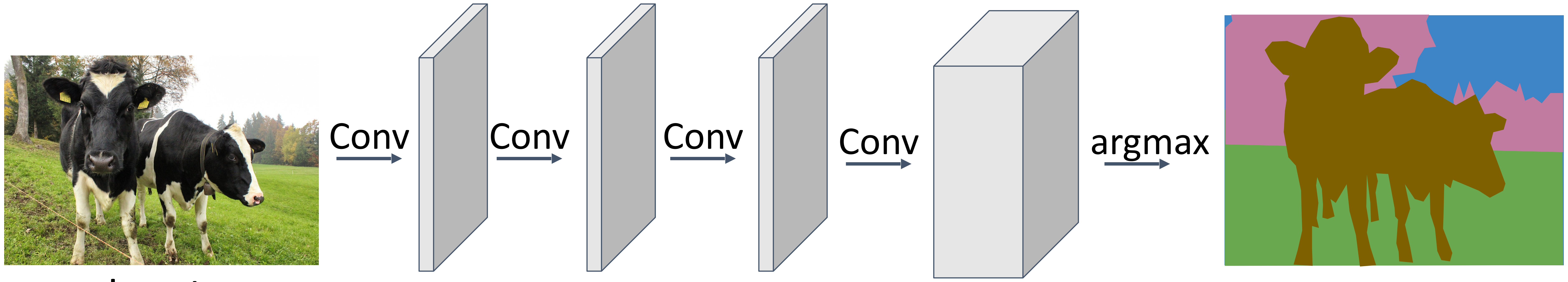
Problem #1: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

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

Slide credit: D Fouhey & J Johnson

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

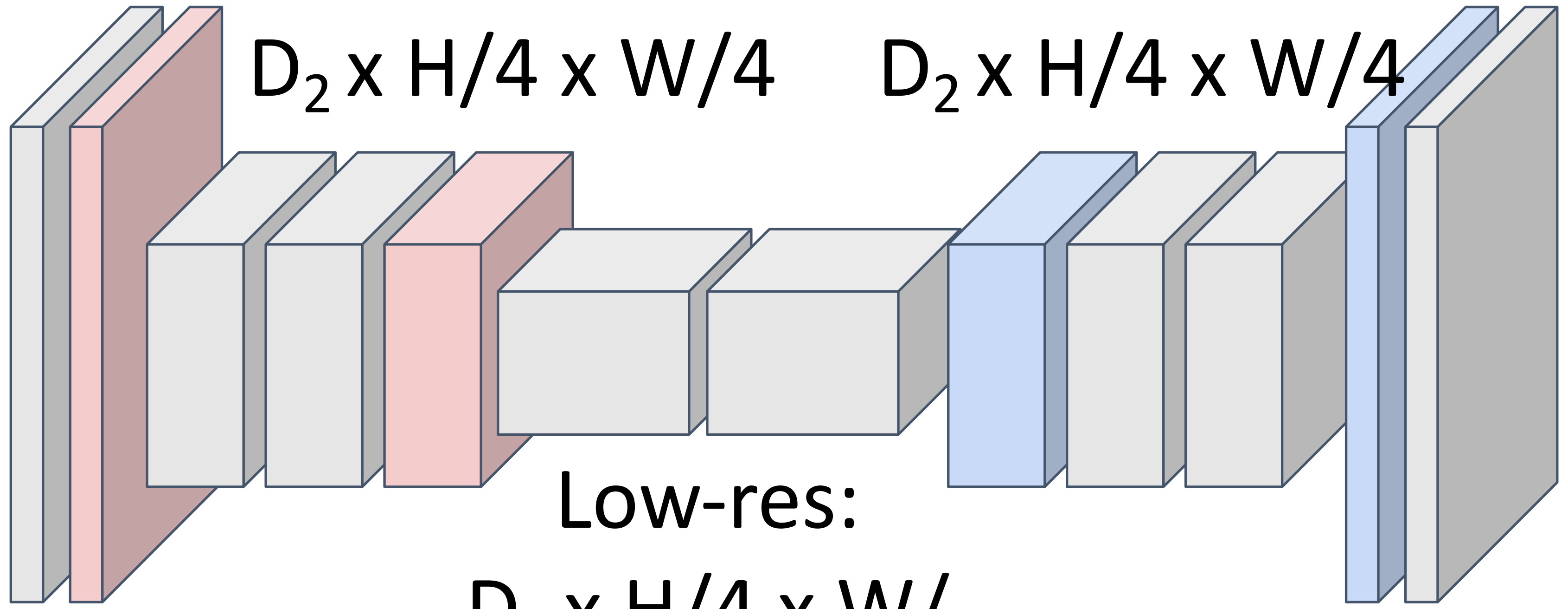
Problem #1: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

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



Med-res:
D_2 x H/4 x W/4

Med-res:
D_2 x H/4 x W/4

Low-res:
D_3 x H/4 x W/4

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

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

Predictions:
H x W

Downsampling:
Pooling, strided convolution

Upsampling:
???

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”

Bed of Nails

1	2
3	4

Input
C x 2 x 2

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

Output
C x 4 x 4

Nearest Neighbor

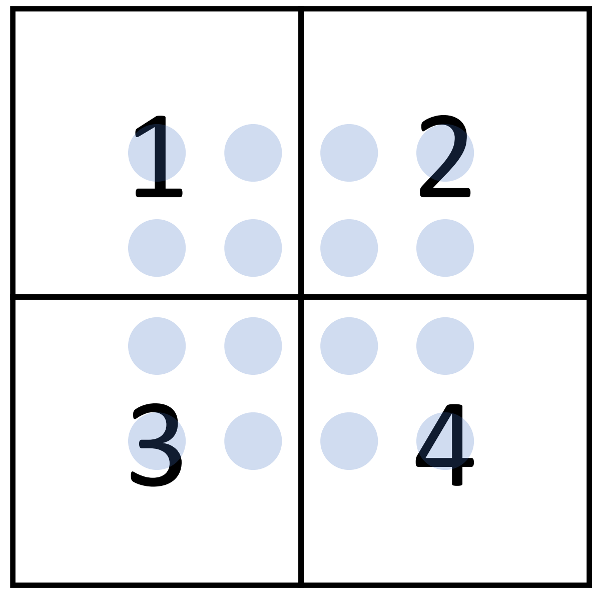
1	2
3	4

Input
C x 2 x 2

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

Output
C x 4 x 4

Upsampling: Bilinear Interpolation



Input: C x 2 x 2

1.00	1.25	1.75	2.00
1.50	1.75	2.25	2.50
2.50	2.75	3.25	3.50
3.00	3.25	3.75	4.00

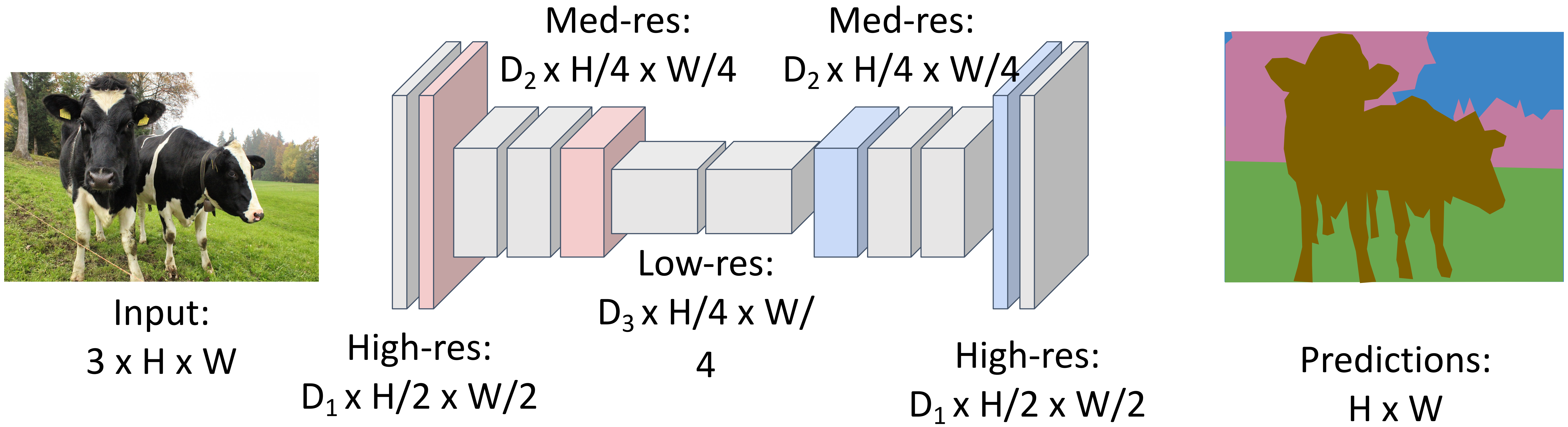
Output: C x 4 x 4

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

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!



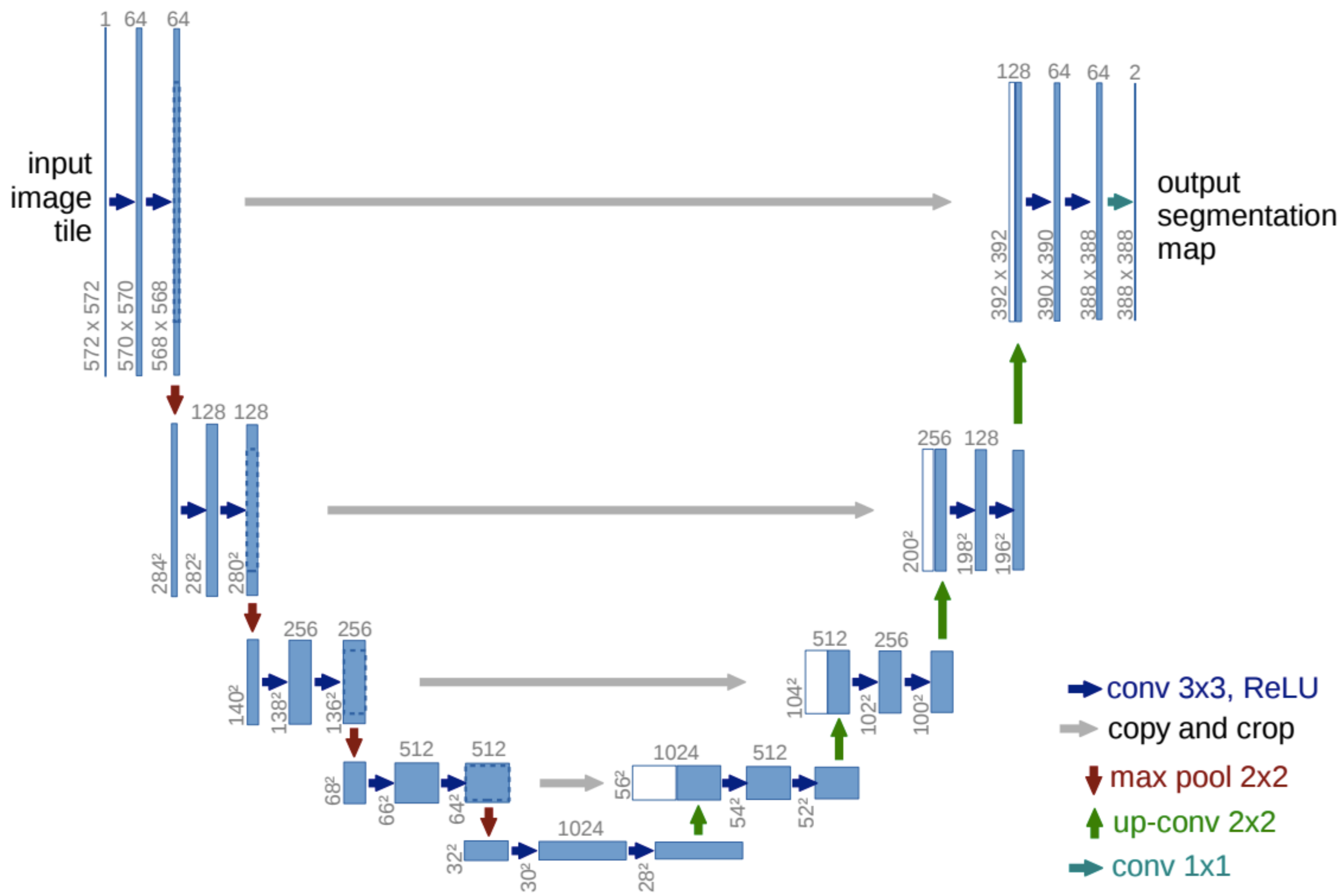
Downsampling: Pooling, strided convolution

Upsampling: ???

U-Net

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

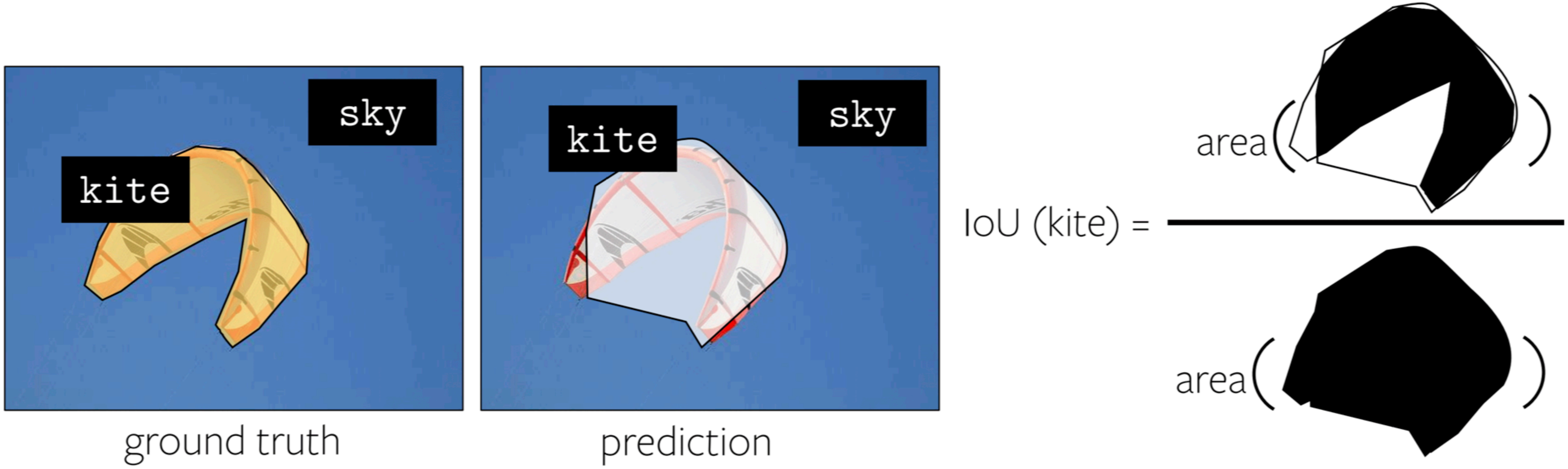
- Like FCN, fuse upsampled higher-level feature maps with higher-res, lower-level feature maps
- Unlike FCN, fuse by concatenation, predict at the end



Slide credit: S. Lazebnik

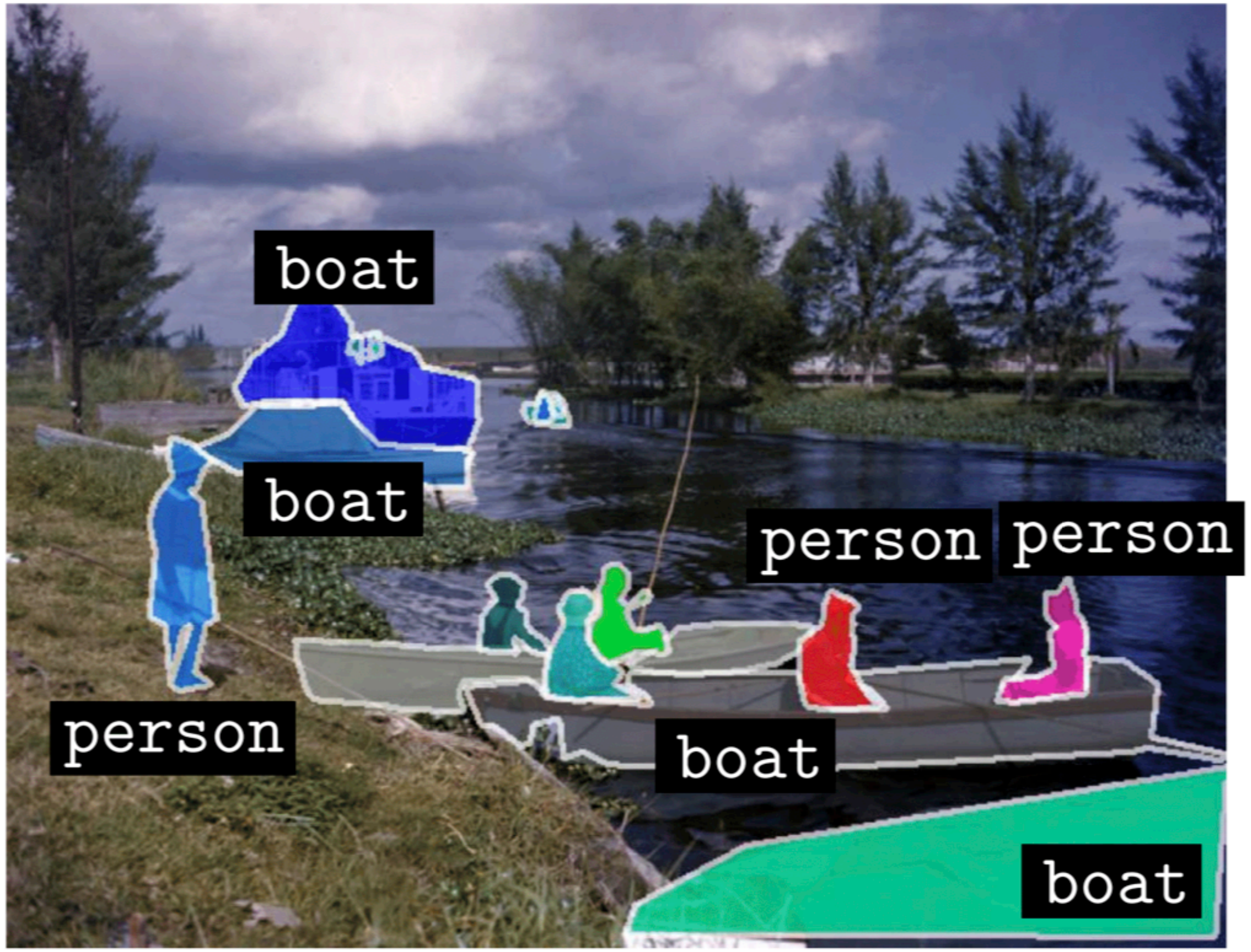

road
sidewalk
building
wall
fence
pole
traffic light
traffic sign
vegetation
terrain
sky
person
rider
car
truck
bus
train
motorcycle
bicycle

Evaluation of Semantic Segmentation

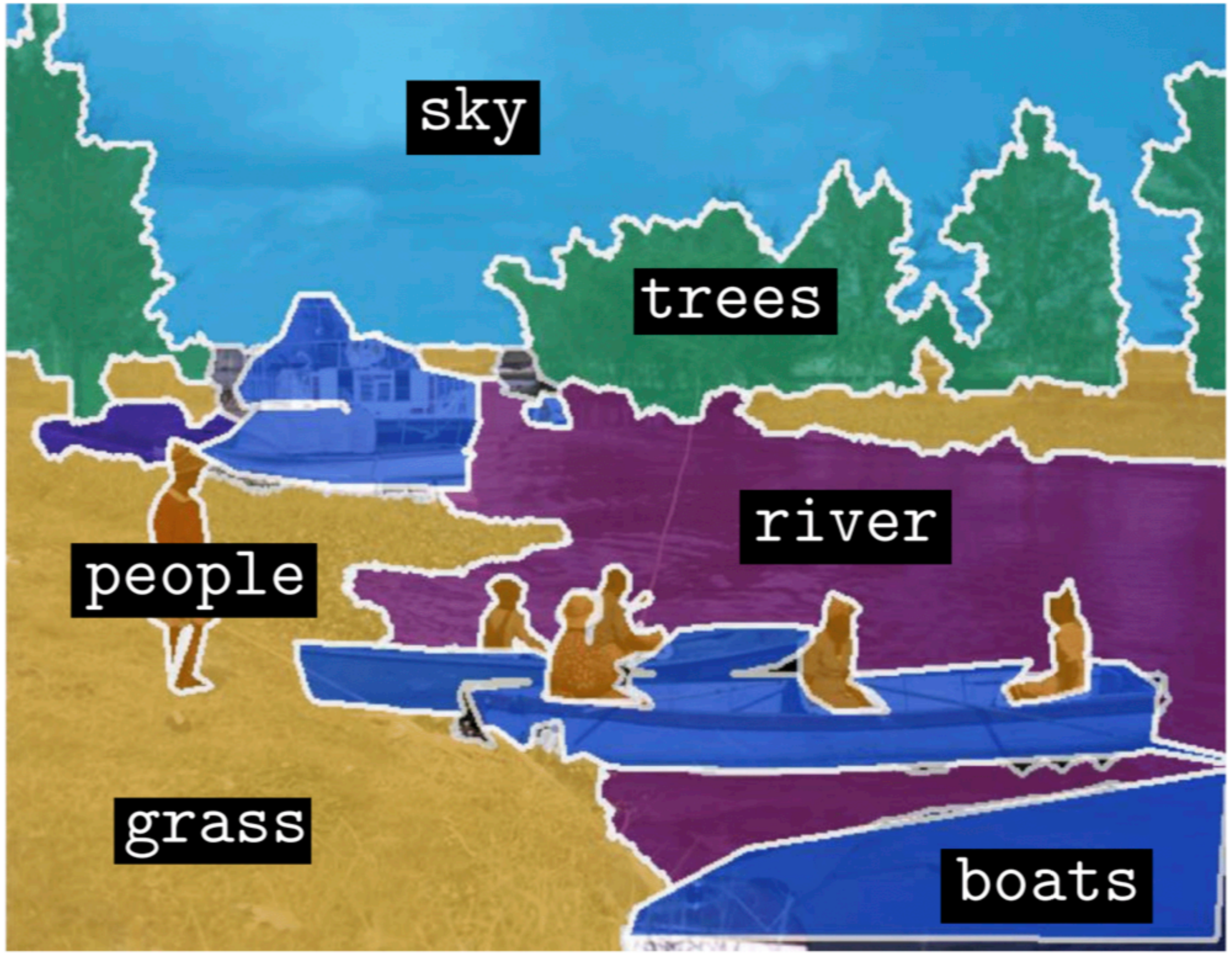


mIoU (mean IoU) per class

Instance and Semantic Segmentation



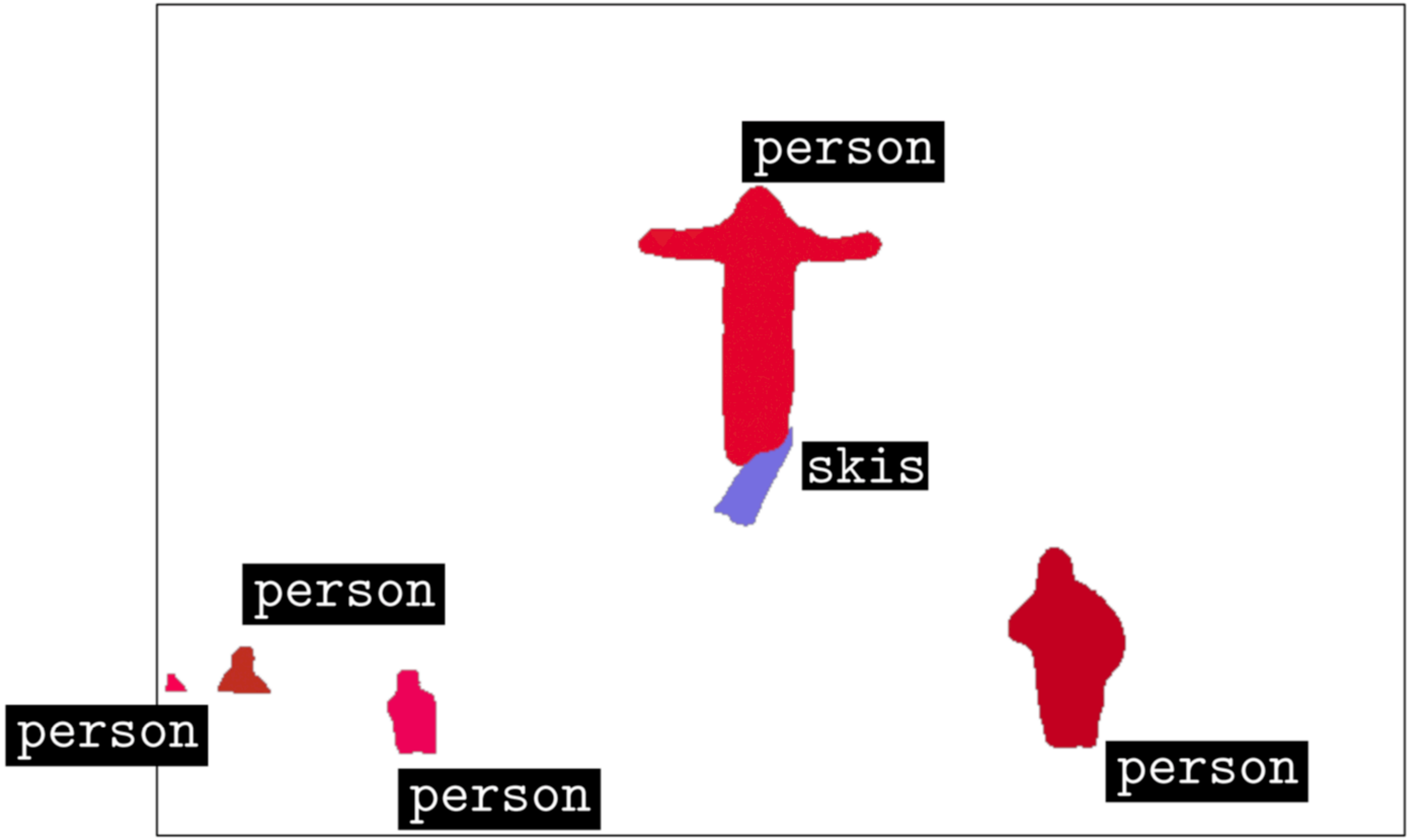
instance segmentation



semantic segmentation

real-world application likely requires both modalities

What do instance segmentation models see?



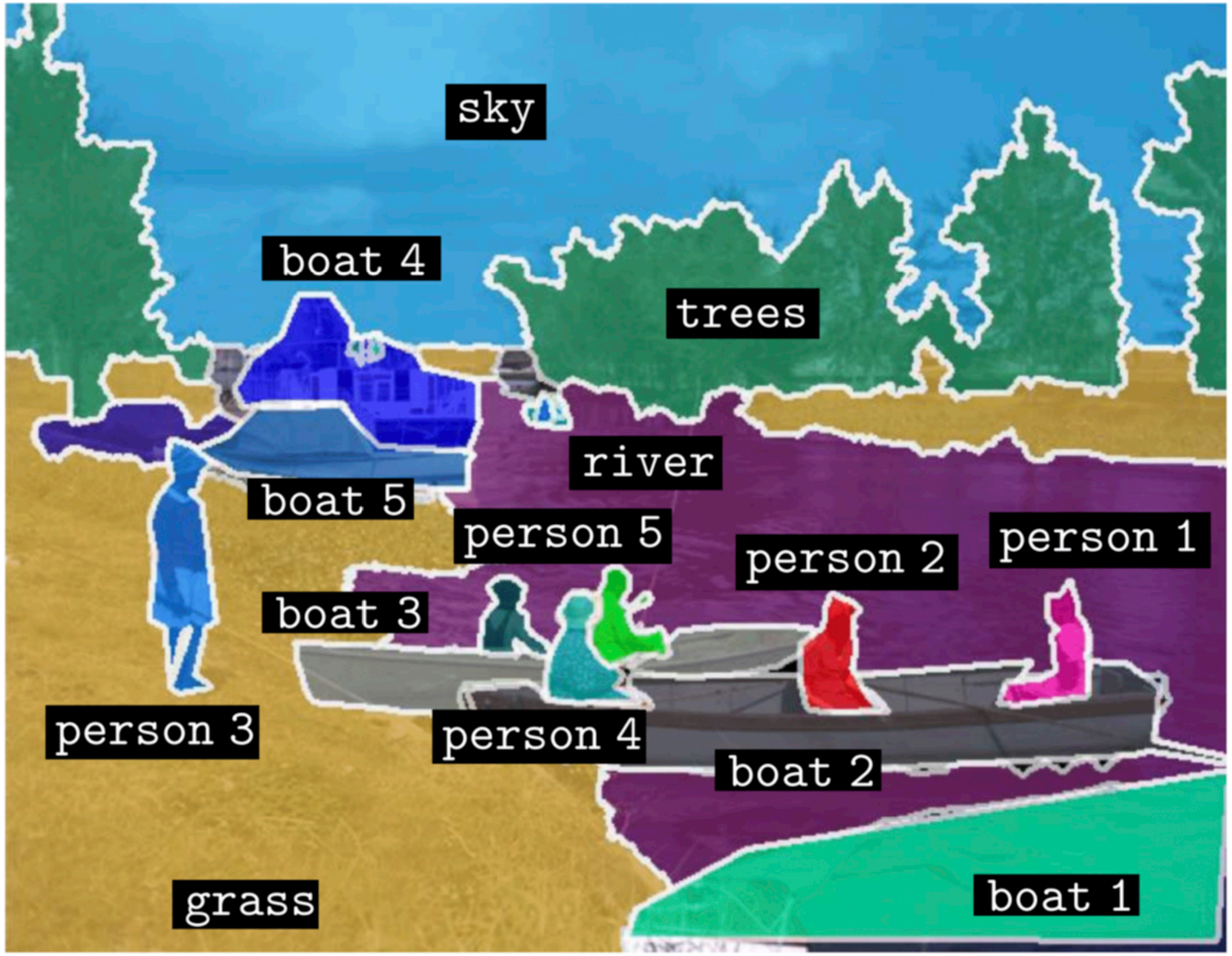
no understanding of the general scene layout

Figure Credit: Alexander Kirillov

What do semantic segmentation models see?

Does not differentiate different instances

Panoptic Segmentation: Unified Segmentation



single task that combines semantic and instance segmentation

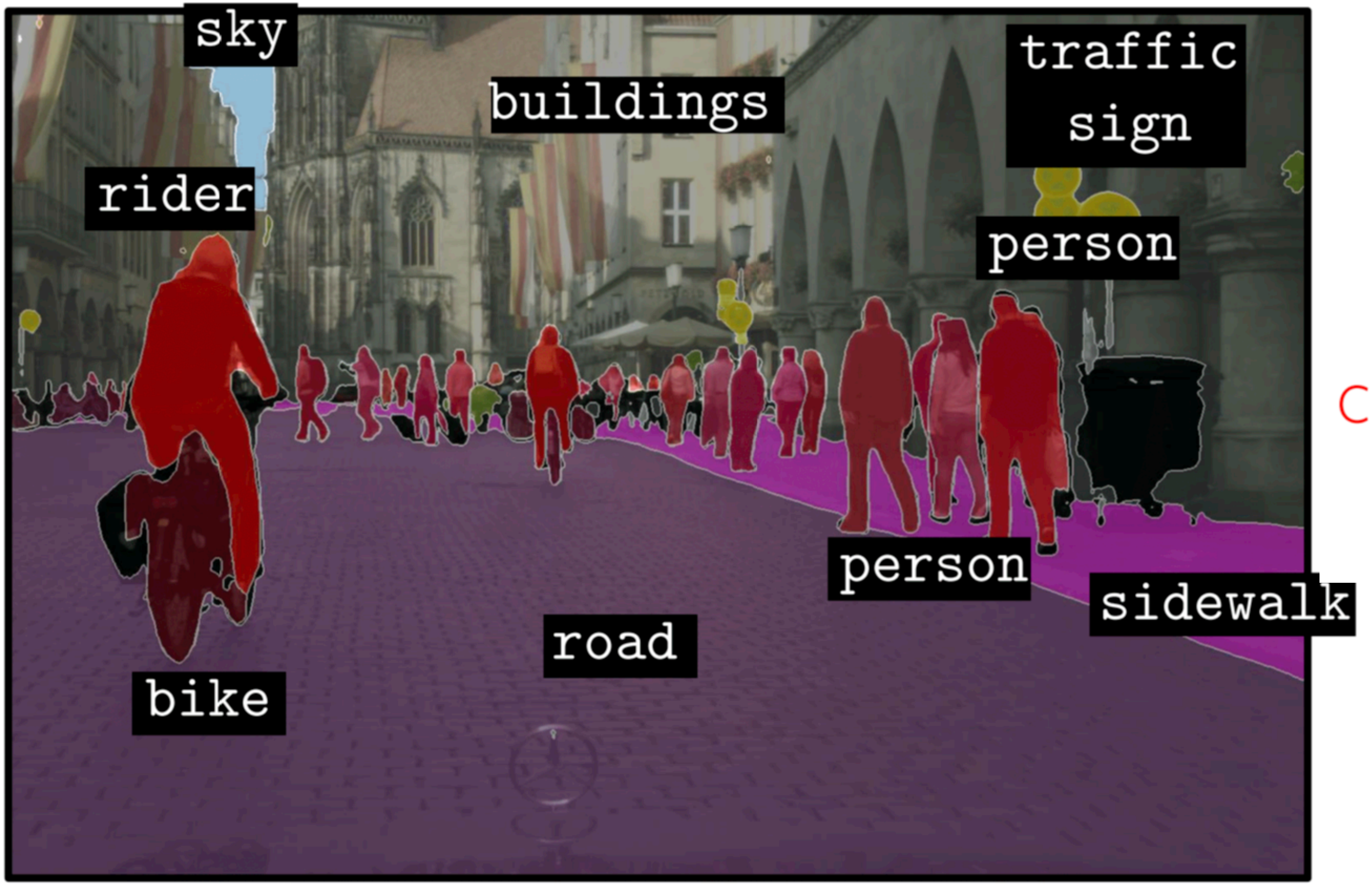
things: categories with instance-level annotation (person, boat)

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

Panoptic: see everything at once

Figure Credit: Alexander Kirillov

Panoptic Segmentation



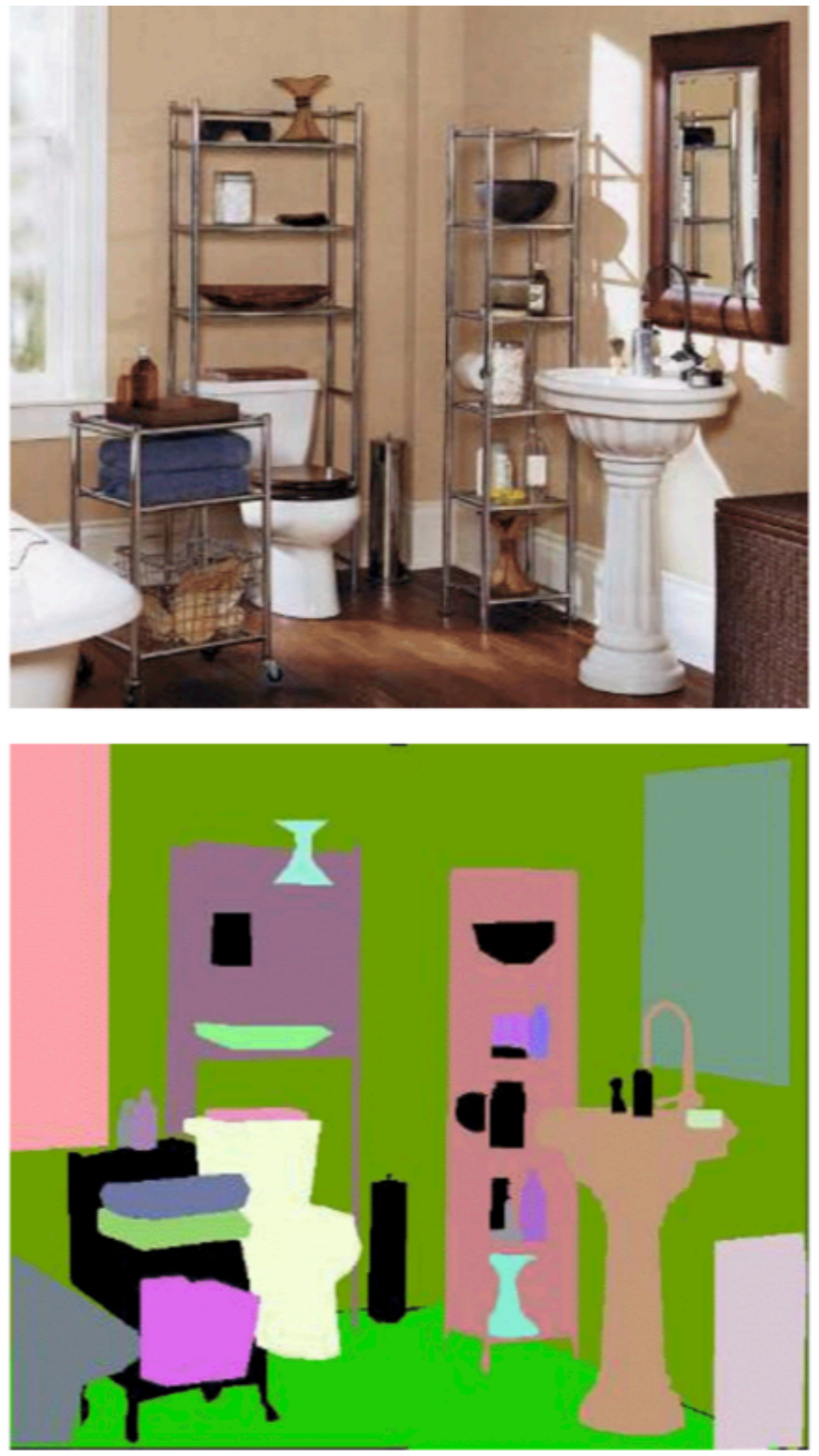
C

Available Panoptic Segmentation Datasets

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

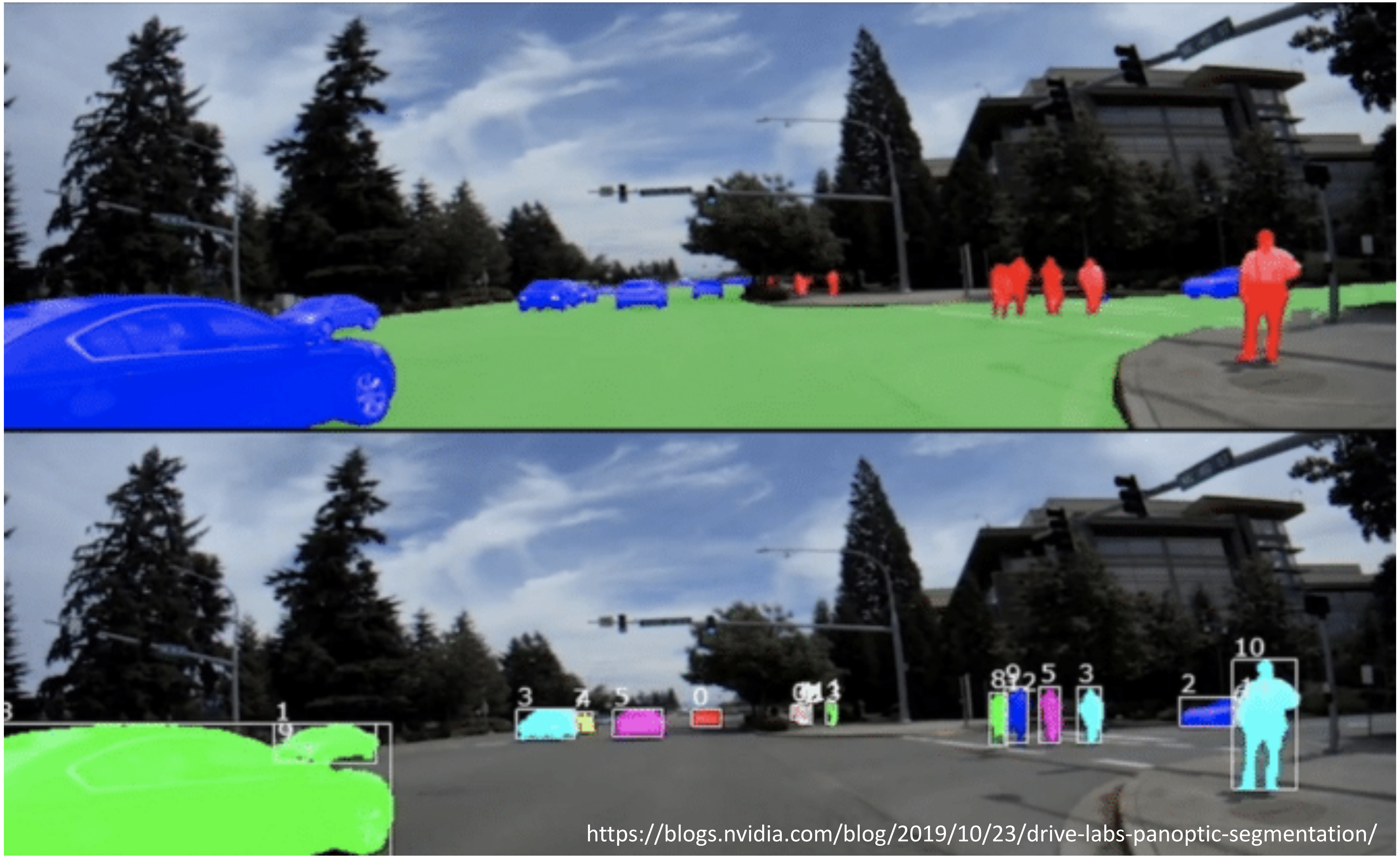
Mapillary Vistas (2017)
Vistas-panoptic challenges:
ECCV`18, **ICCV`19**

Cityscapes (2015)
panoptic test set
leaderboard (2019)

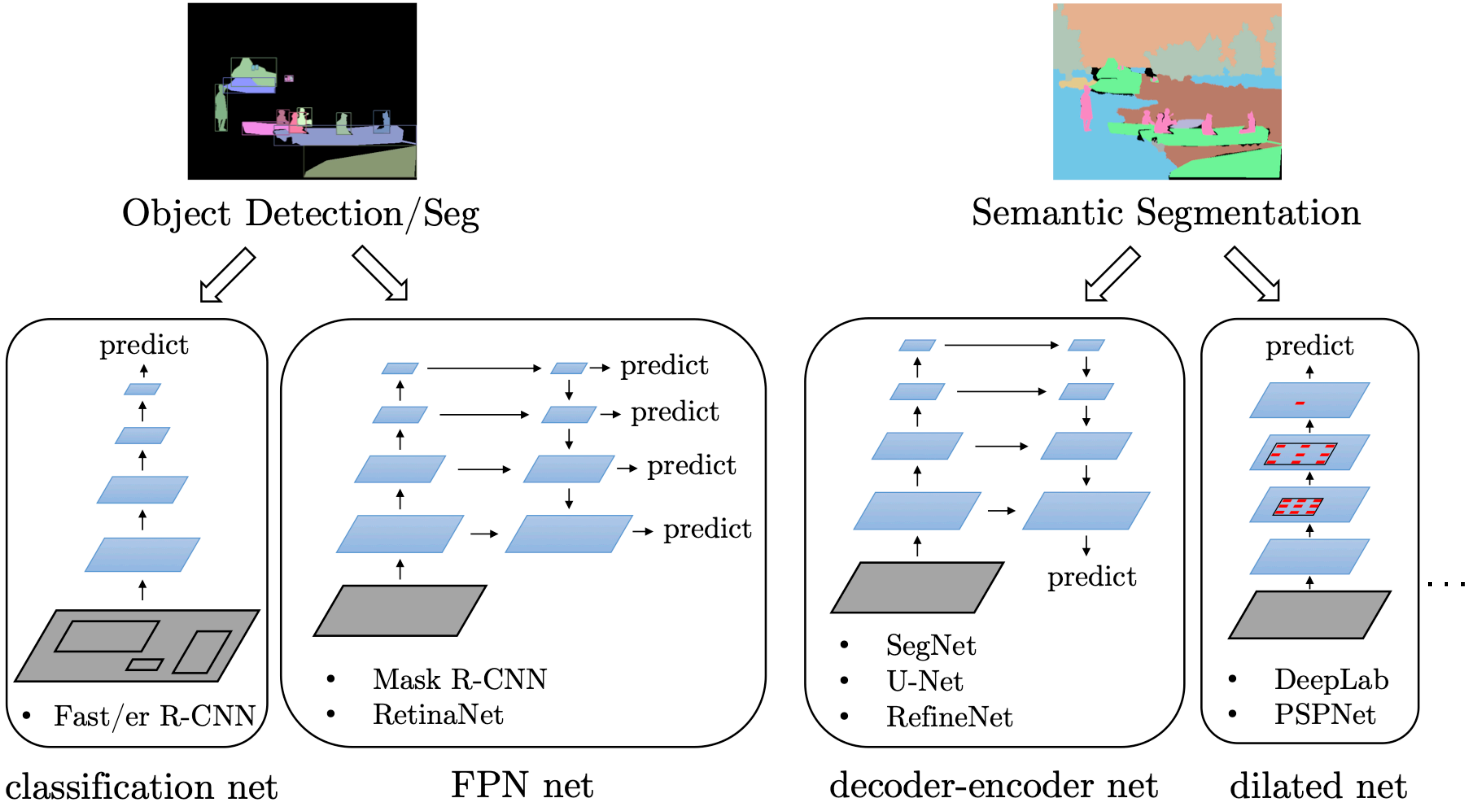


ADE20k (2016)
>22k images, 150 categories

Panoptic Segmentation for Autonomous Driving



Deep Networks for Segmentation Tasks



Panoptic FPN

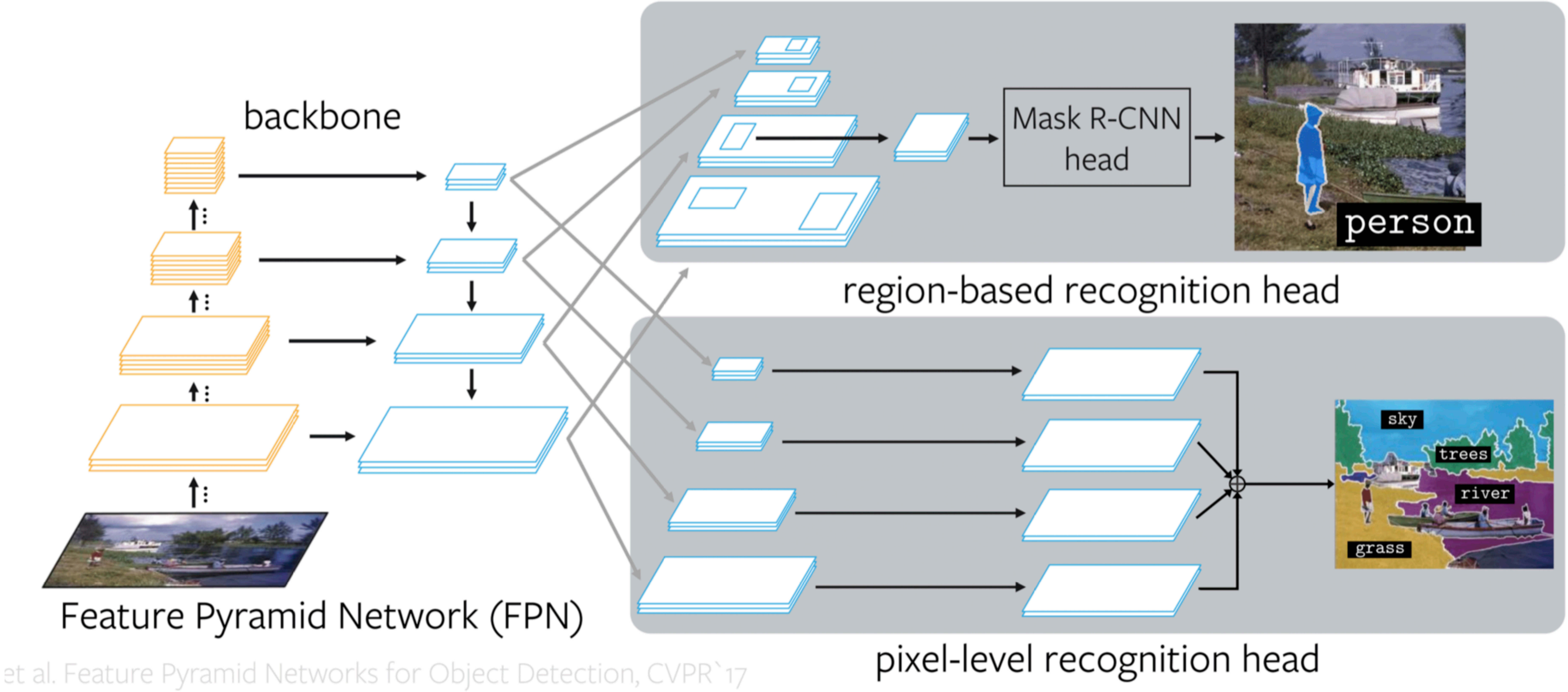
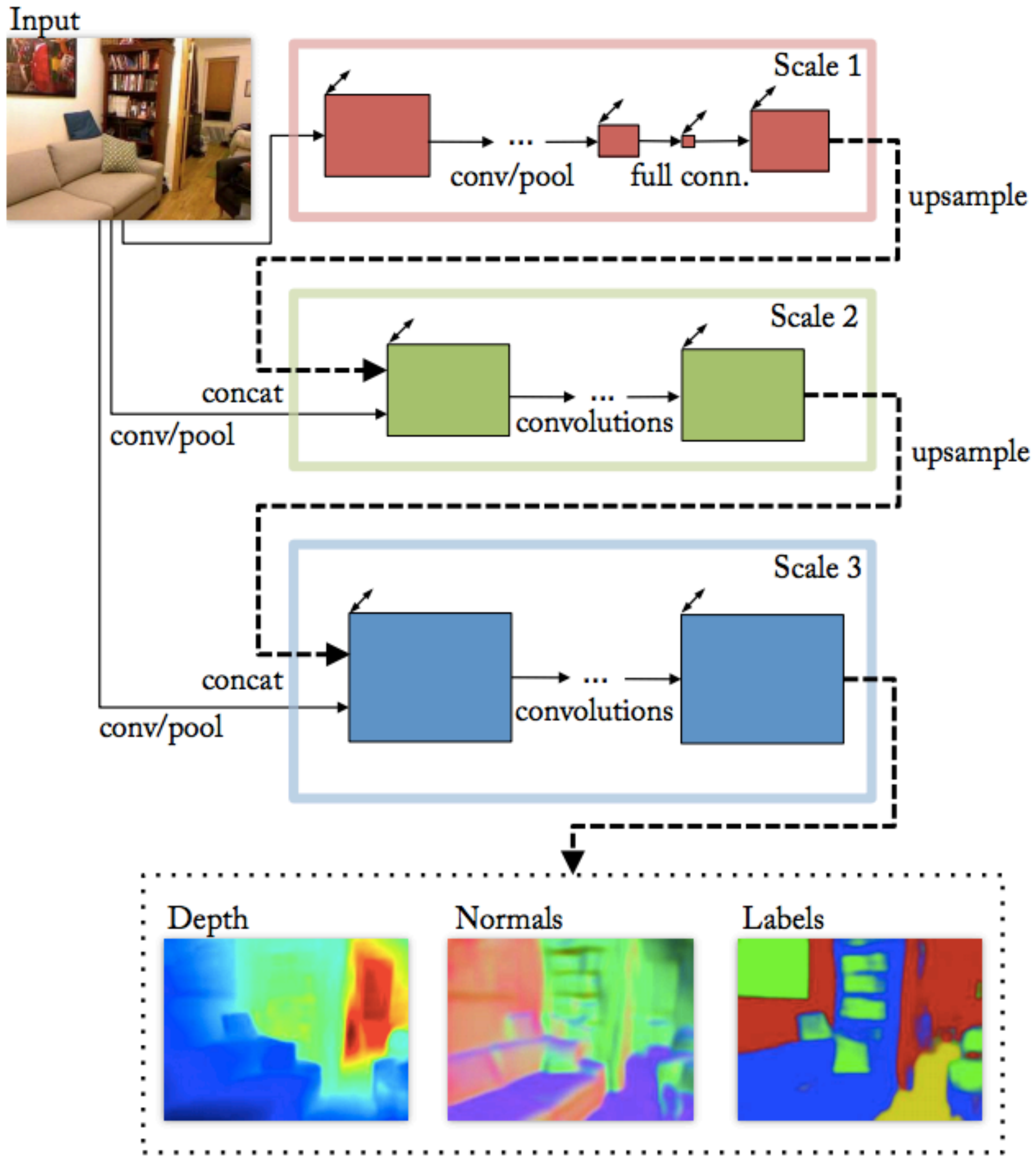
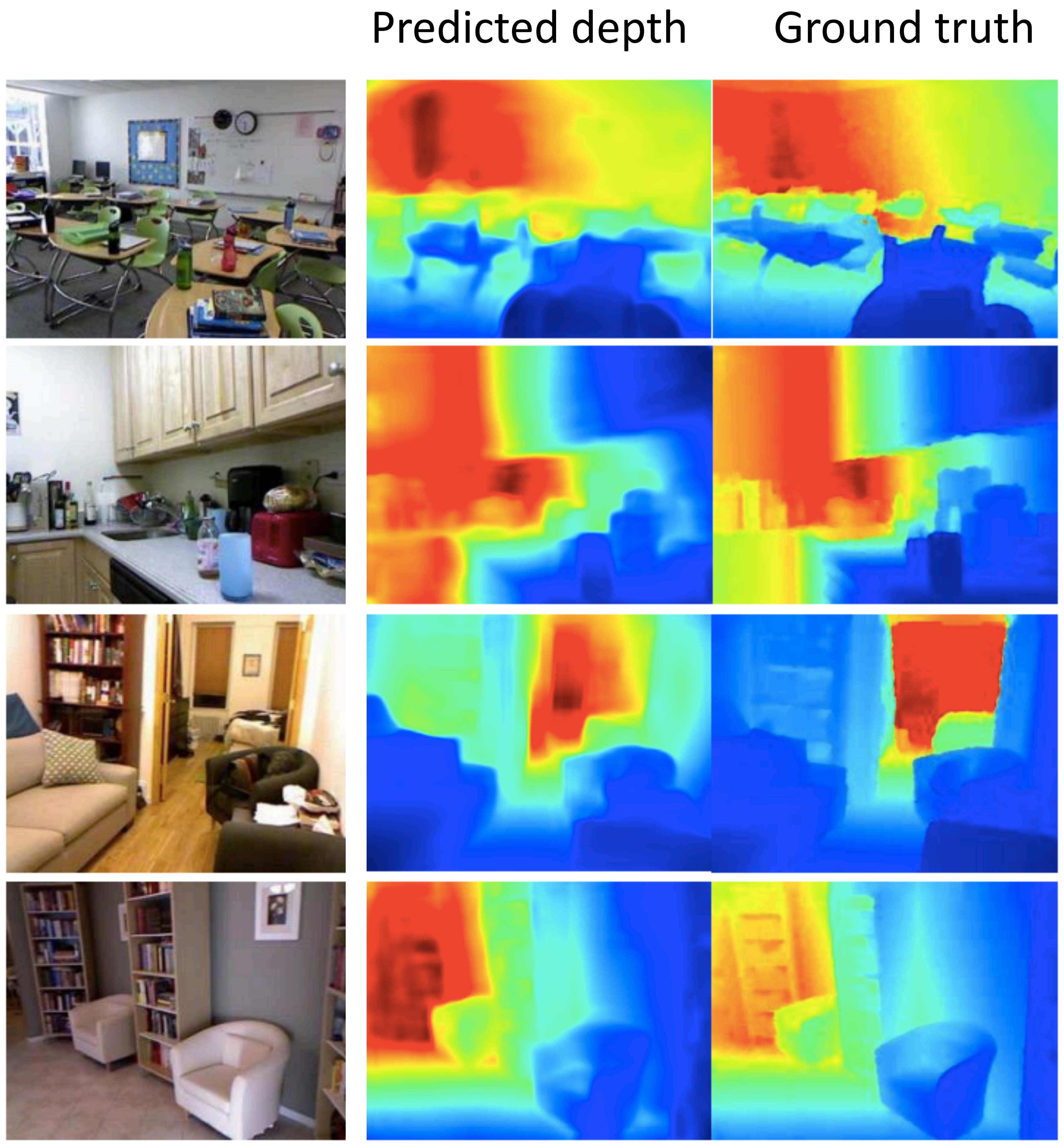


Figure Credit: Alexander Kirillov

Dense Prediction: Depth and normal estimation

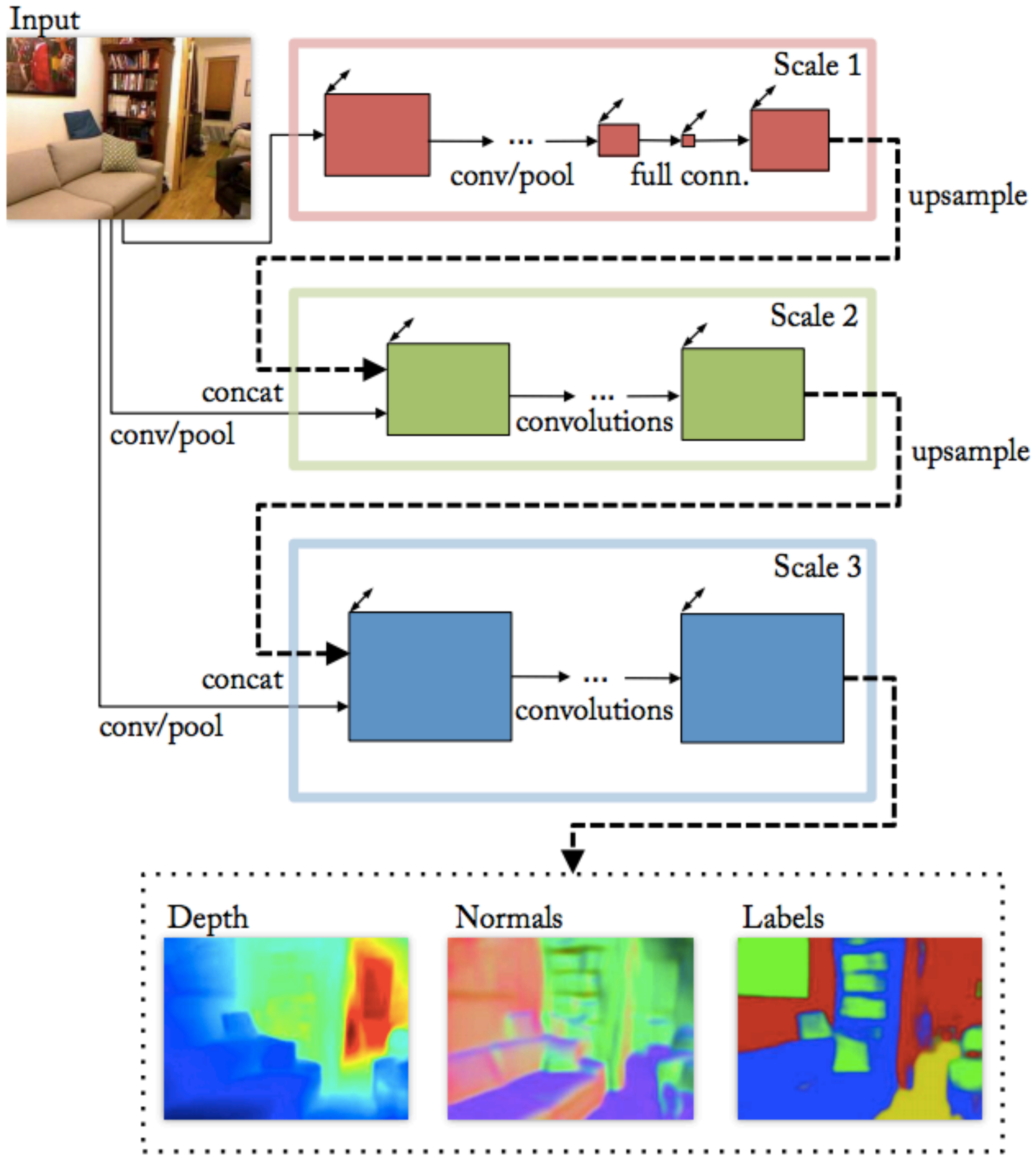


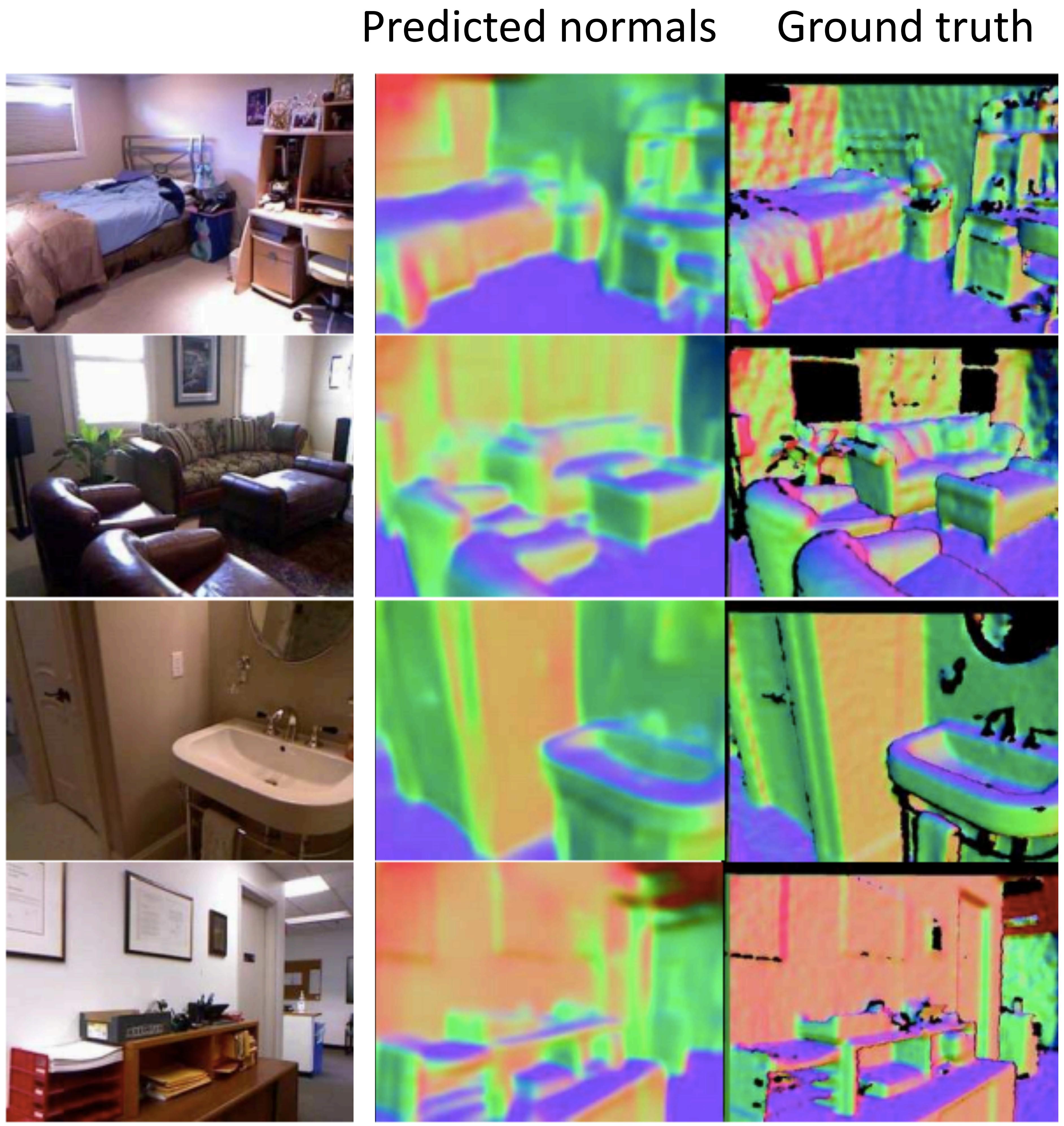


D. Eigen and R. Fergus, [Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture](), ICCV 2015

Slide credit: S. Lazebnik

Dense Prediction: Depth and normal estimation

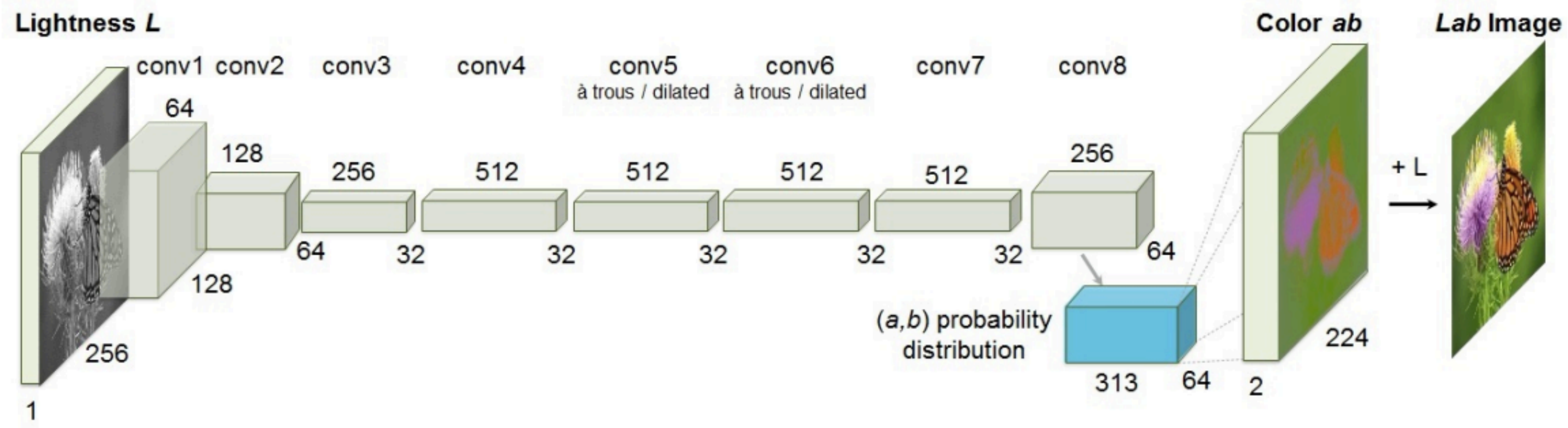


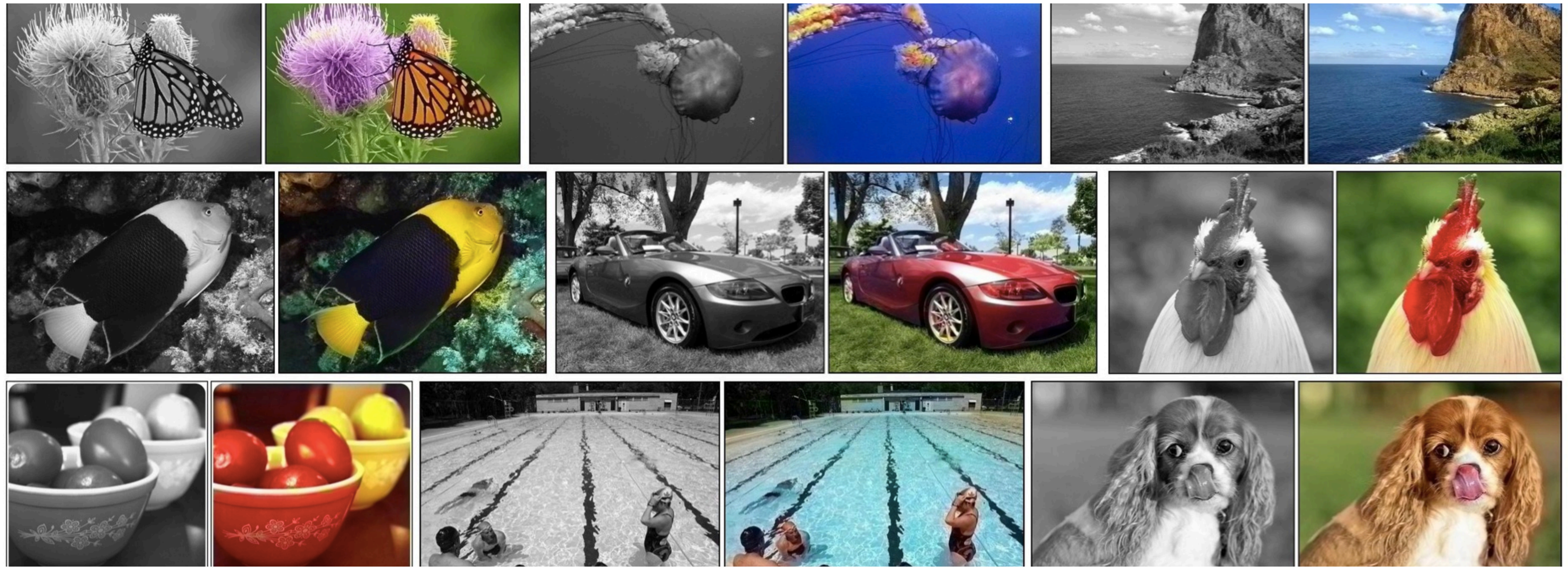


D. Eigen and R. Fergus, [Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture](), ICCV 2015

Slide credit: S. Lazebnik

Dense Prediction: Colorization





R. Zhang, P. Isola, and A. Efros, [Colorful Image Colorization](), ECCV 2016

Slide credit: S. Lazebnik