Lecture 16:
Image Segmentation

Computer Vision Tasks: Object Detection

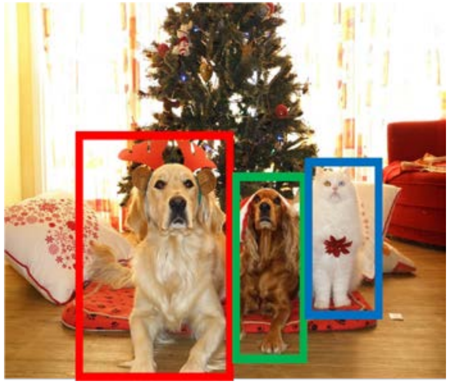
Classification

CAT

Semantic Segmentation

GRASS, CAT, TREE, SKY

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

No spatial extent

No objects, just pixels

Multiple Objects

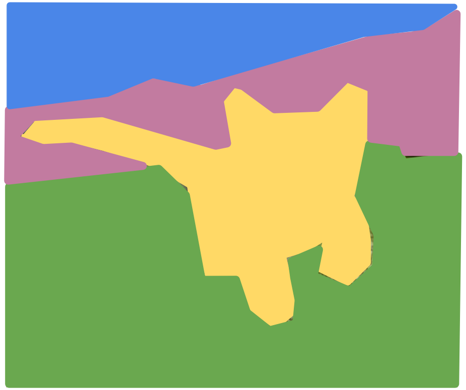
Computer Vision Tasks: Semantic Segmentation

Classification

CAT

No spatial extent

Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation

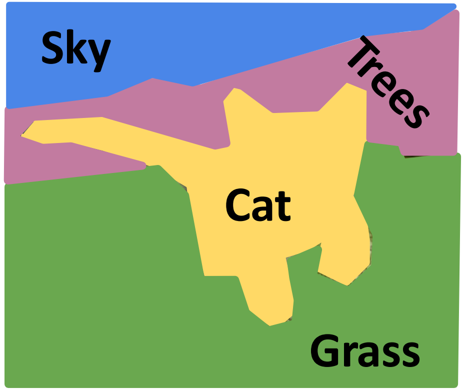
DOG, DOG, CAT

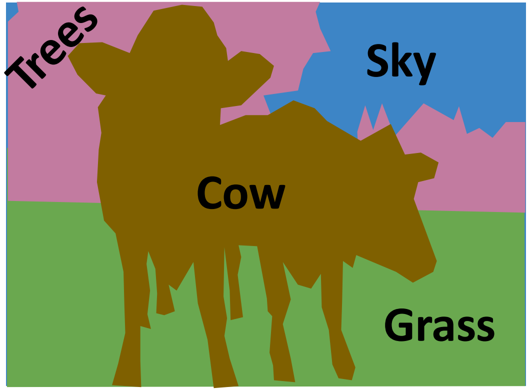
Multiple Objects

Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels



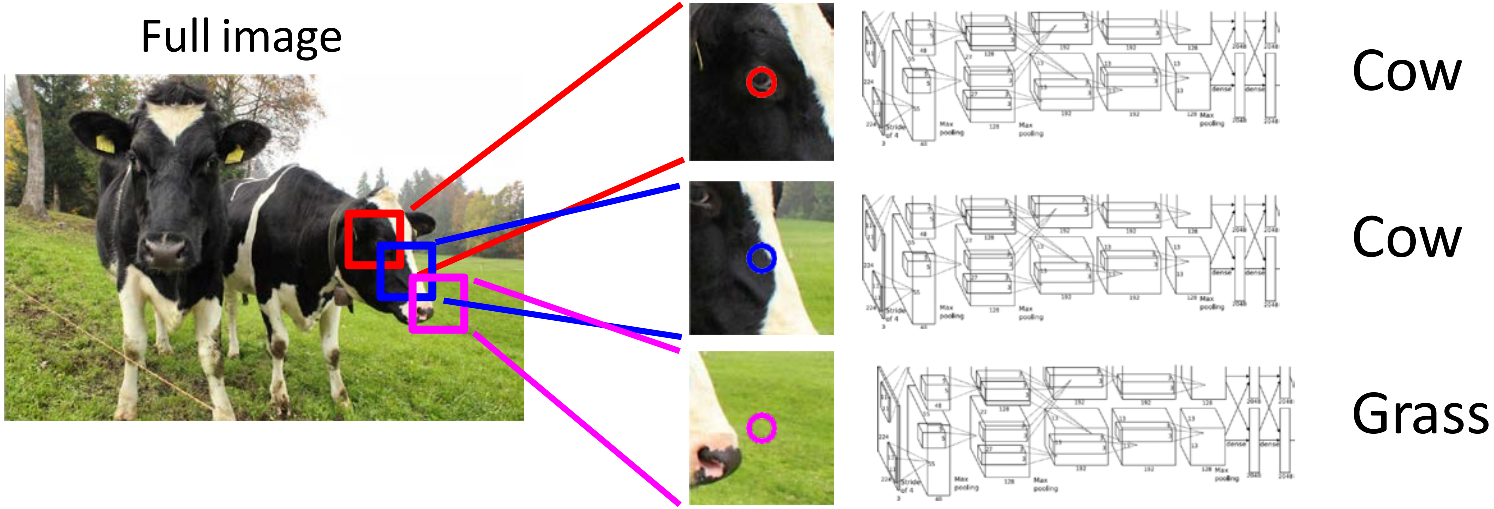


Semantic Segmentation Idea: Sliding Window

Full image

Extract patch

Classify center pixel with CNN

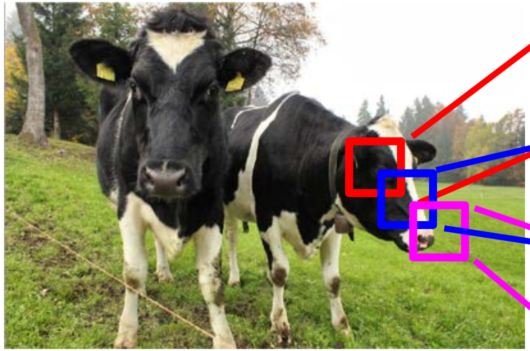


Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013

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

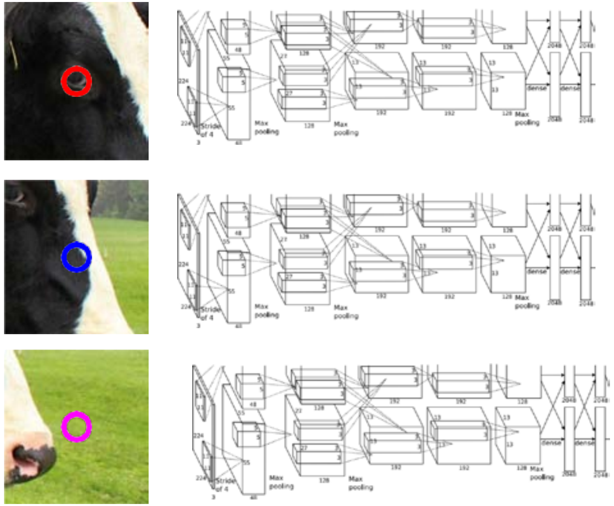
Semantic Segmentation Idea: Sliding Window

Full image



Extract patch

Classify center pixel with CNN



Cow

Cow

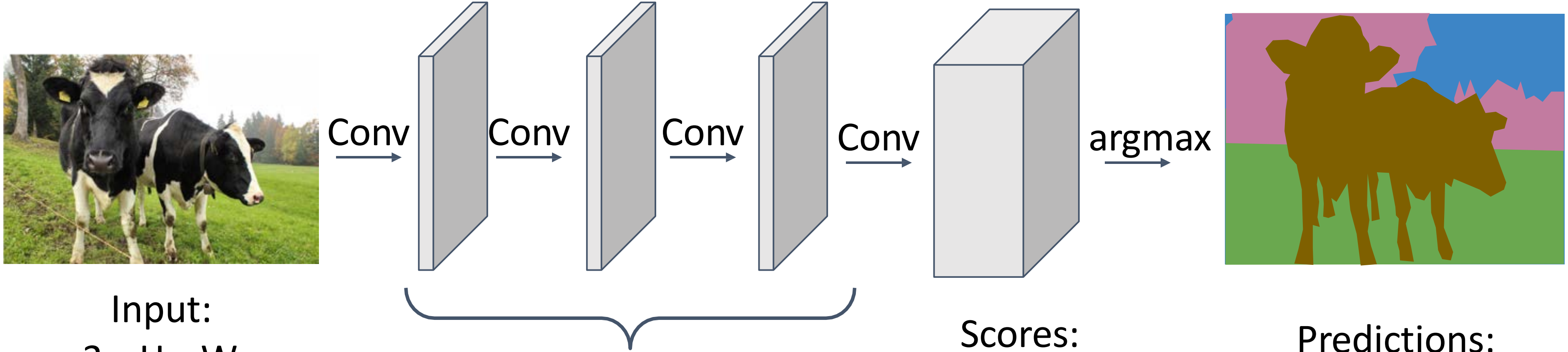
Grass

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: Fully Convolutional Network

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

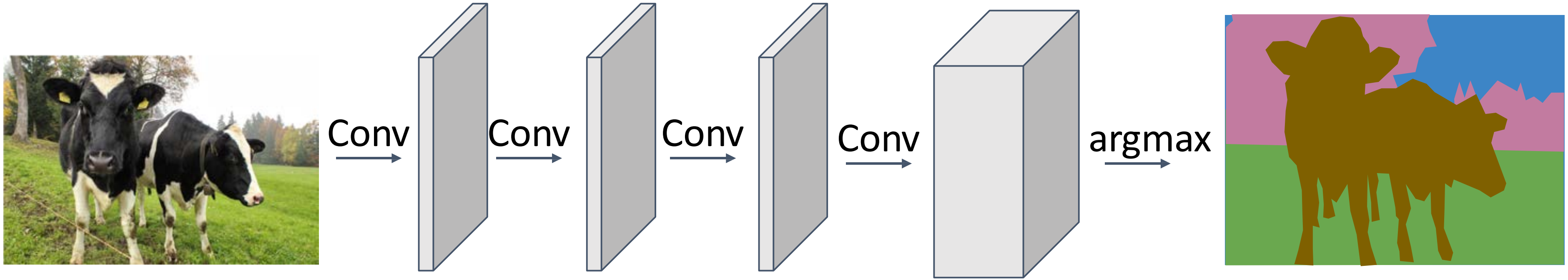


Loss function: Per-Pixel cross-entropy

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

Semantic Segmentation: Fully Convolutional Network

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



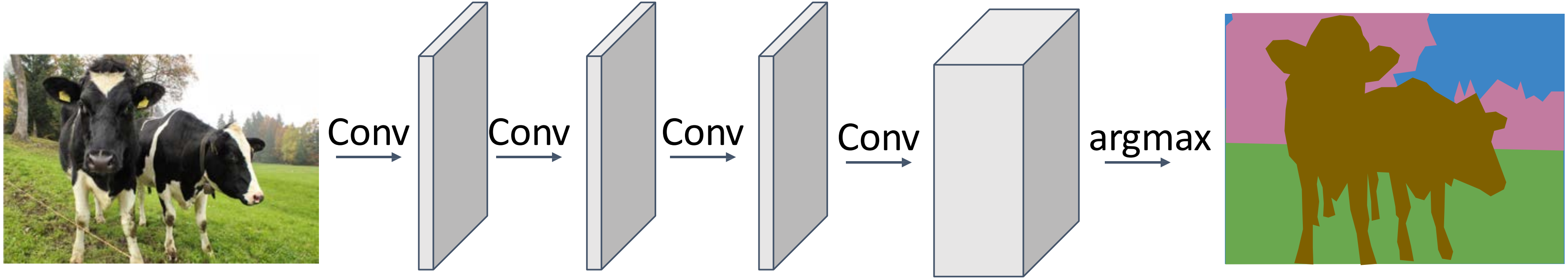
Input:
3 x H x W

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

Semantic Segmentation: 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

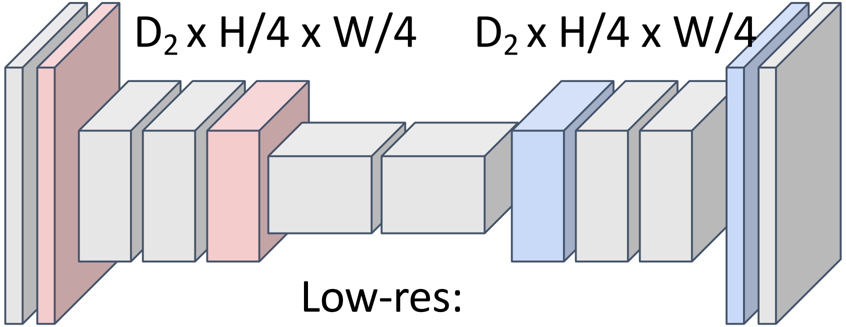
Problem #2: Convolution on high res images is expensive! Recall ResNet stem aggressively downsamples

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

Semantic Segmentation: Fully Convolutional Network

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

Input:
$3 \times H \times W$



Med-res:
$D_2 \times H/4 \times W/4$

Med-res:
$D_2 \times H/4 \times W/4$

High-res:
$D_1 \times H/2 \times W/2$

Low-res:
$D_3 \times H/8 \times W/8$

High-res:
$D_1 \times H/2 \times W/2$

Predictions:
$H \times W$

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: Fully Convolutional Network

Downsampling: Pooling, strided convolution

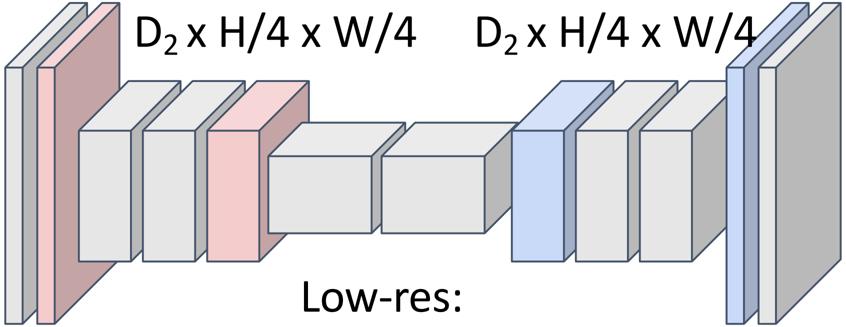
Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: ???

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



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

Low-res:
D_3 x H/8 x W/8

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
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

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

In-Network Upsampling: Bilinear Interpolation

1	2
3	4

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

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

$$j \in \{\lfloor y \rfloor - 1, \ldots, \lceil y \rceil + 1\}$$

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

In-Network Upsampling: Bicubic Interpolation

1	2
3	4

Input: C x 2 x 2

0.68	1.02	1.56	1.89
1.35	1.68	2.23	2.56
2.44	2.77	3.32	3.65
3.11	3.44	3.98	4.32

Output: C x 4 x 4

Use **three** closest neighbors in x and y to construct **cubic** approximations
(This is how we normally resize images!)

In-Network Upsampling: “Max Unpooling”

Max Pooling: Remember which position had the max

Max Unpooling: Place into remembered positions

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

→

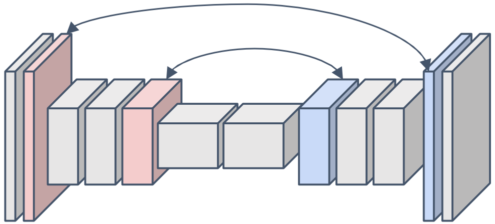
5	6
7	8

→ Rest of net →

1	2
3	4

→

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

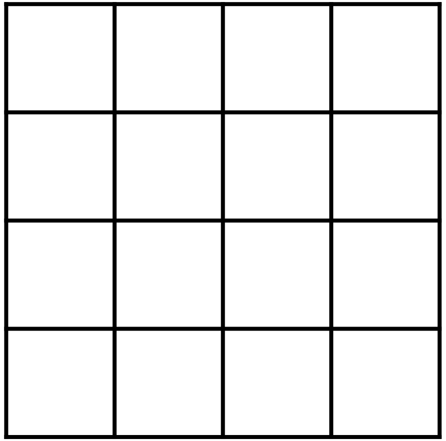


Pair each downsampling layer with an upsampling layer

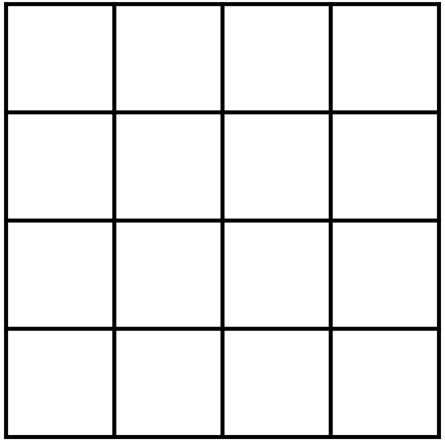
Noh et al, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Learnable Upsampling: Transposed Convolution

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



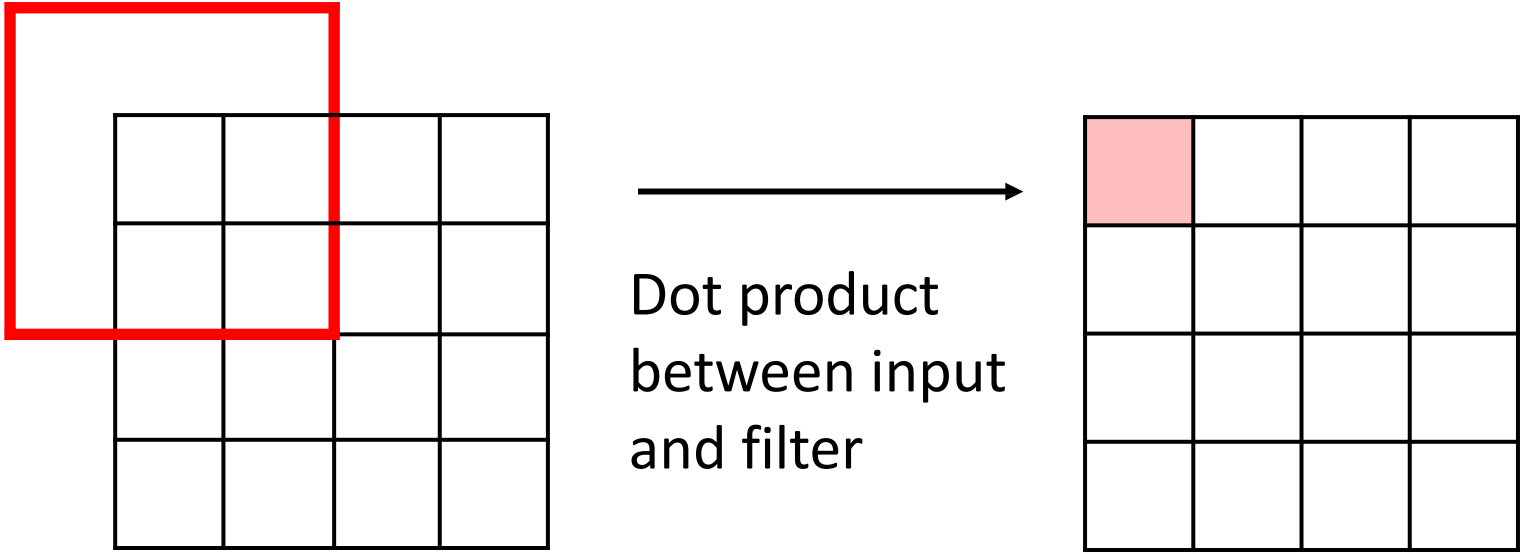
Input: 4 x 4



Output: 4 x 4

Learnable Upsampling: Transposed Convolution

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

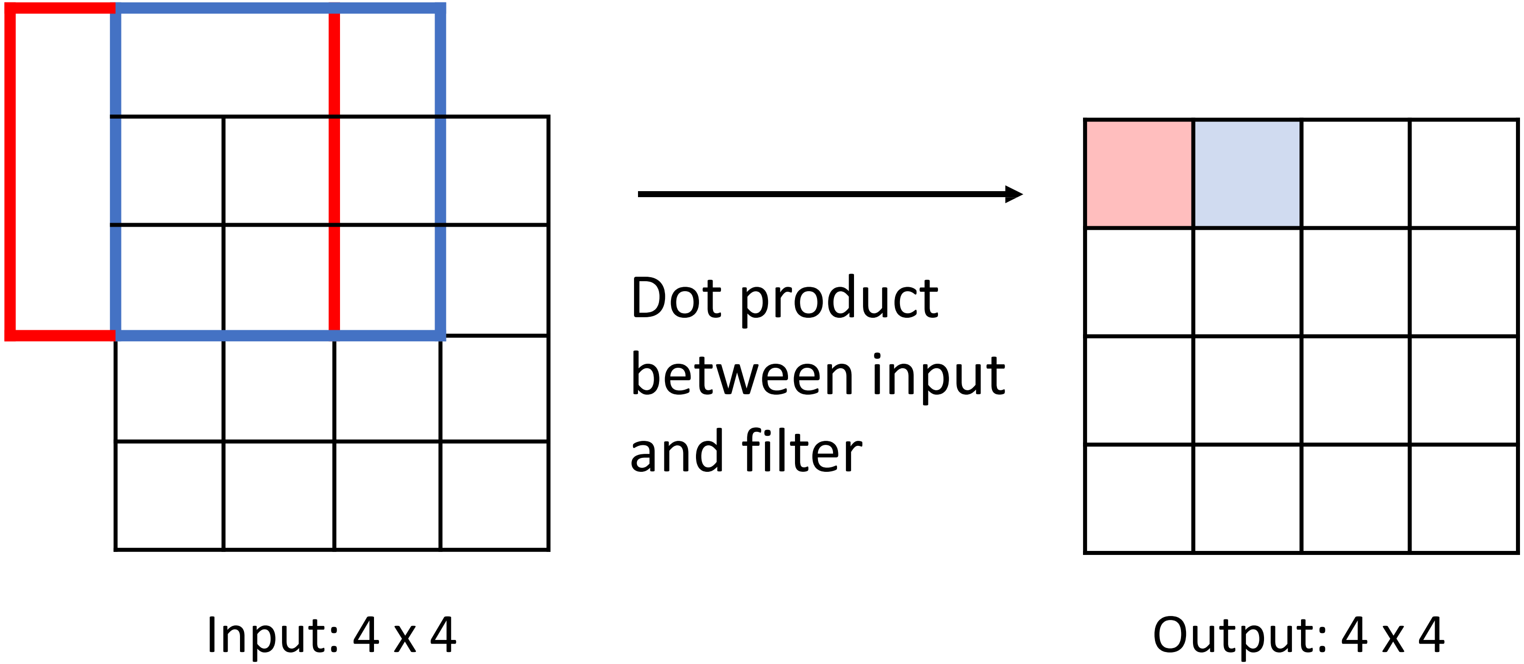


Input: 4 x 4

Output: 4 x 4

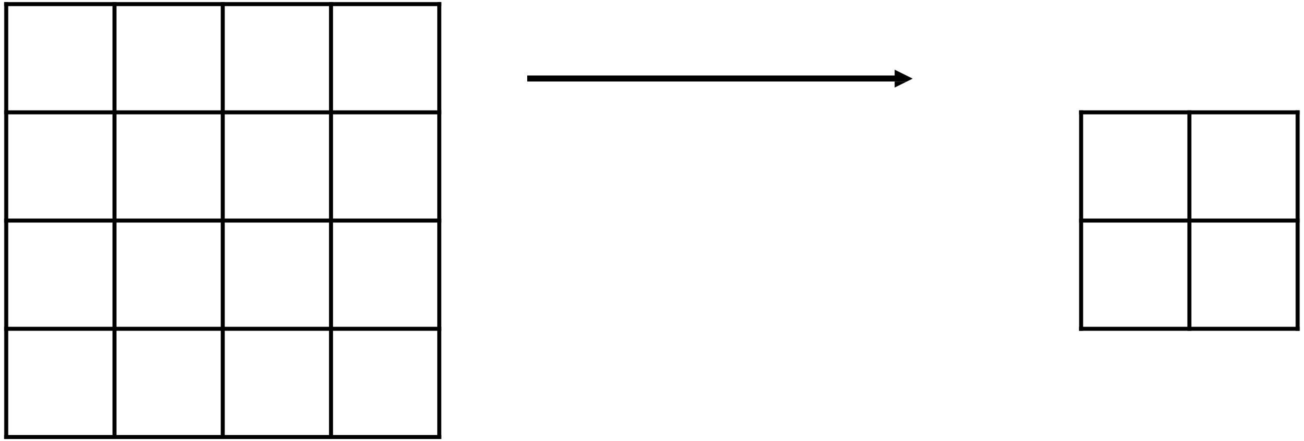
Learnable Upsampling: Transposed Convolution

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



Learnable Upsampling: Transposed Convolution

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

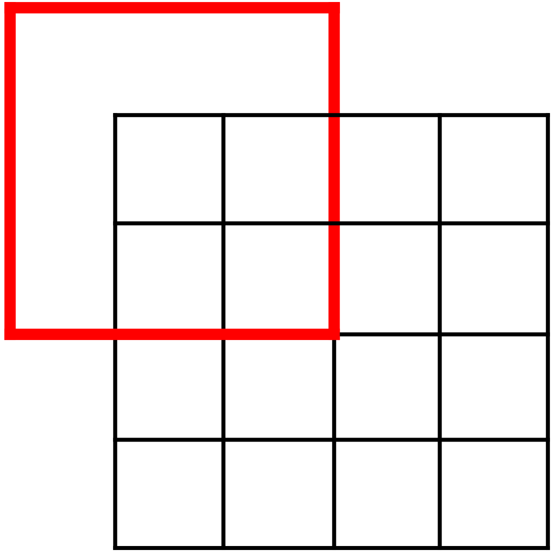


Input: 4 x 4

Output: 2 x 2

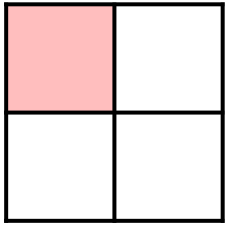
Learnable Upsampling: Transposed Convolution

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



Input: 4 x 4

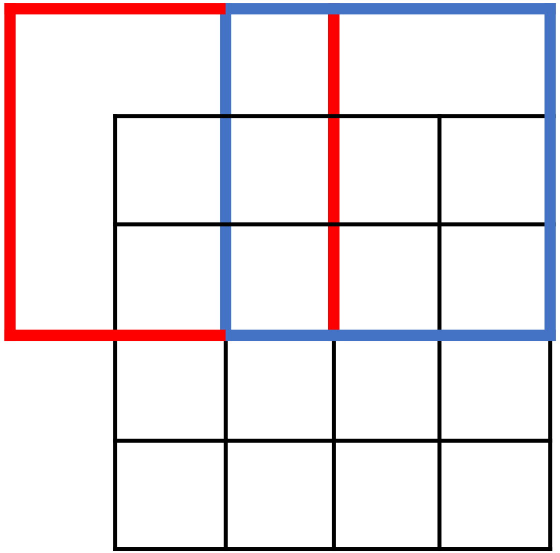
Dot product between input and filter



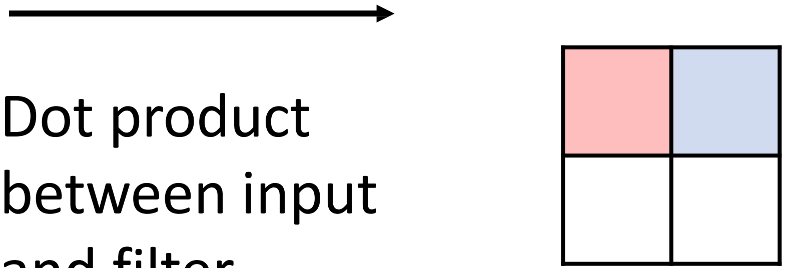
Output: 2 x 2

Learnable Upsampling: Transposed Convolution

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



Dot product between input and filter

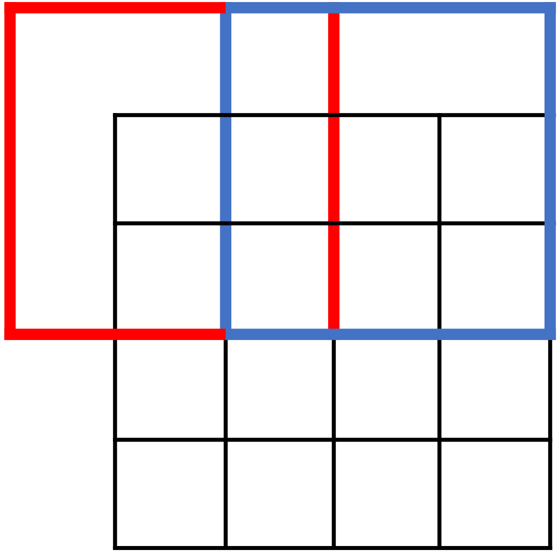


Input: 4 x 4

Output: 2 x 2

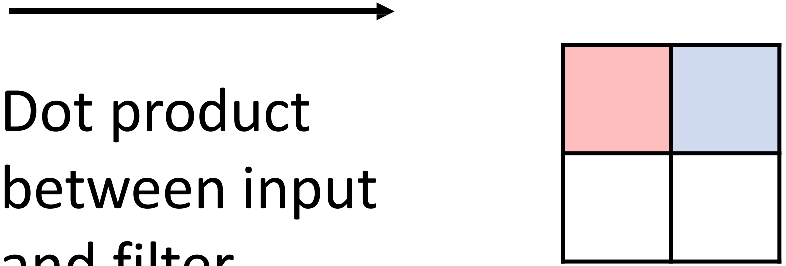
Learnable Upsampling: Transposed Convolution

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



Convolution with stride > 1 is "Learnable Downsampling"
Can we use stride < 1 for "Learnable Upsampling"?

Dot product between input and filter

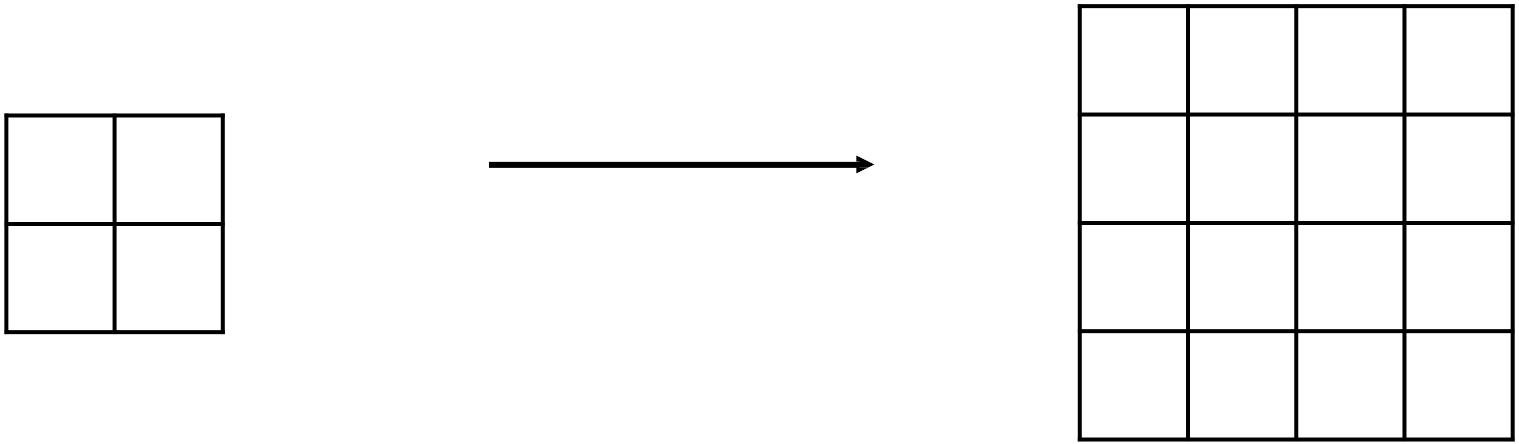


Input: 4 x 4

Output: 2 x 2

Learnable Upsampling: Transposed Convolution

3 x 3 **convolution transpose**, stride 2

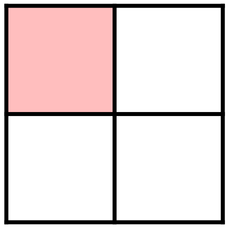


Input: 2 x 2

Output: 4 x 4

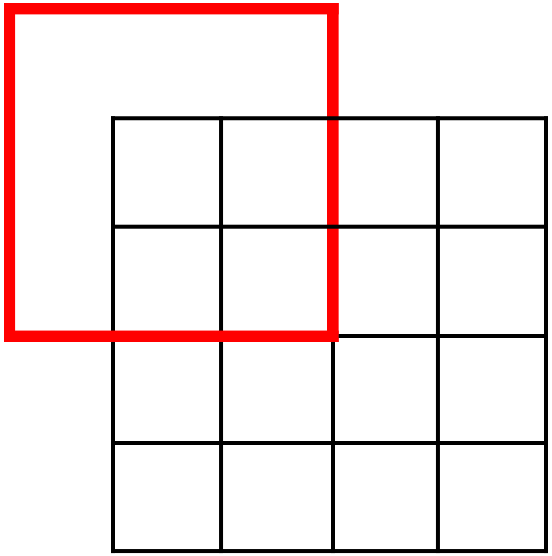
Learnable Upsampling: Transposed Convolution

3 x 3 **convolution transpose**, stride 2



Input: 2 x 2

Weight filter by input value and copy to output

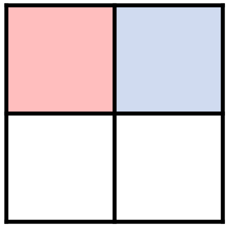


Output: 4 x 4

Learnable Upsampling: Transposed Convolution

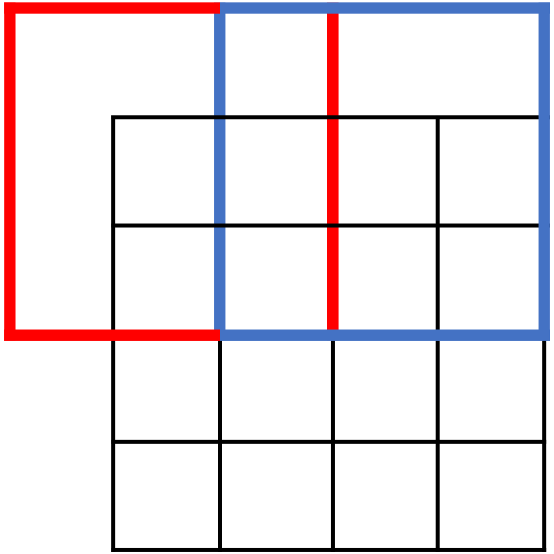
3 x 3 **convolution transpose**, stride 2

Filter moves 2 pixels in <u>output</u>
for every 1 pixel in <u>input</u>



Input: 2 x 2

Weight filter by
input value and
copy to output



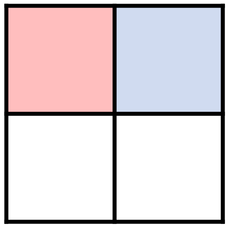
Output: 4 x 4

Learnable Upsampling: Transposed Convolution

3 x 3 **convolution transpose**, stride 2

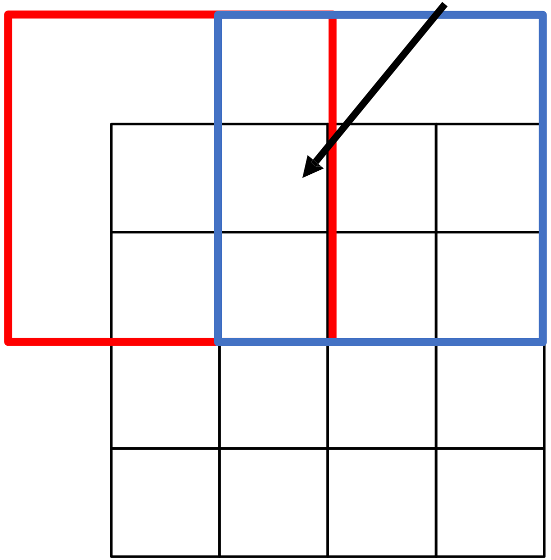
Sum where output overlaps

Filter moves 2 pixels in output for every 1 pixel in input



Input: 2 x 2

Weight filter by input value and copy to output

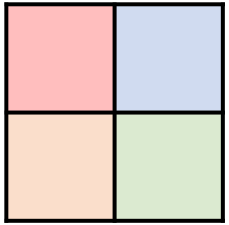


Output: 4 x 4

Learnable Upsampling: Transposed Convolution

3 x 3 **convolution transpose**, stride 2

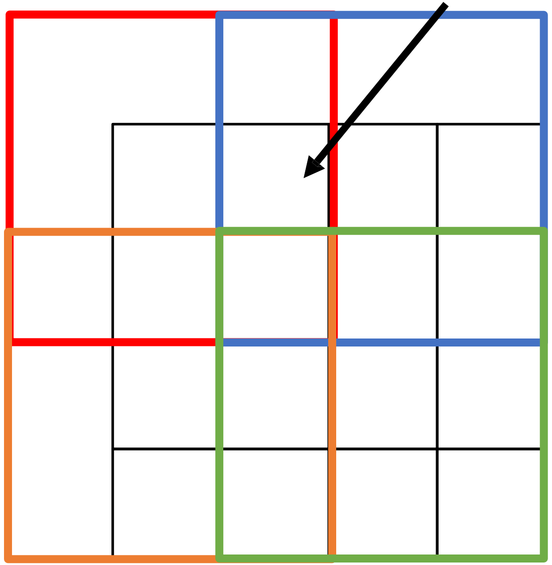
This gives 5x5 output – need to trim one pixel from top and left to give 4x4 output



Input: 2 x 2

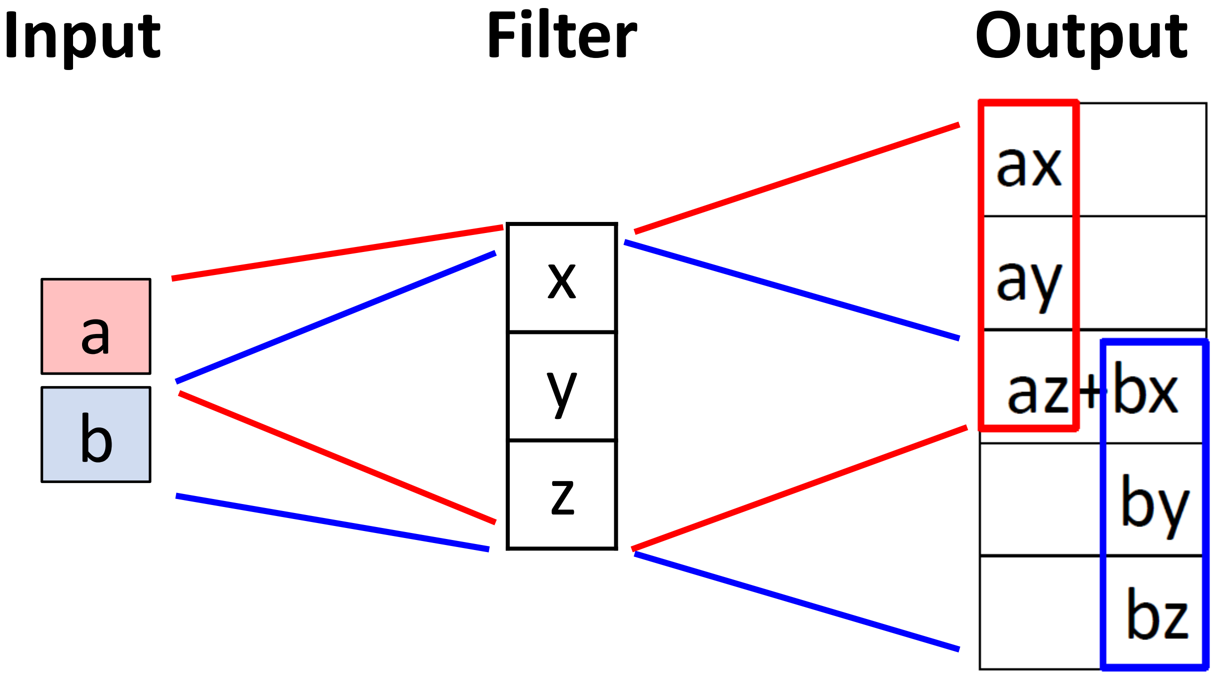
Weight filter by input value and copy to output

Sum where output overlaps



Output: 4 x 4

Transposed Convolution: 1D example

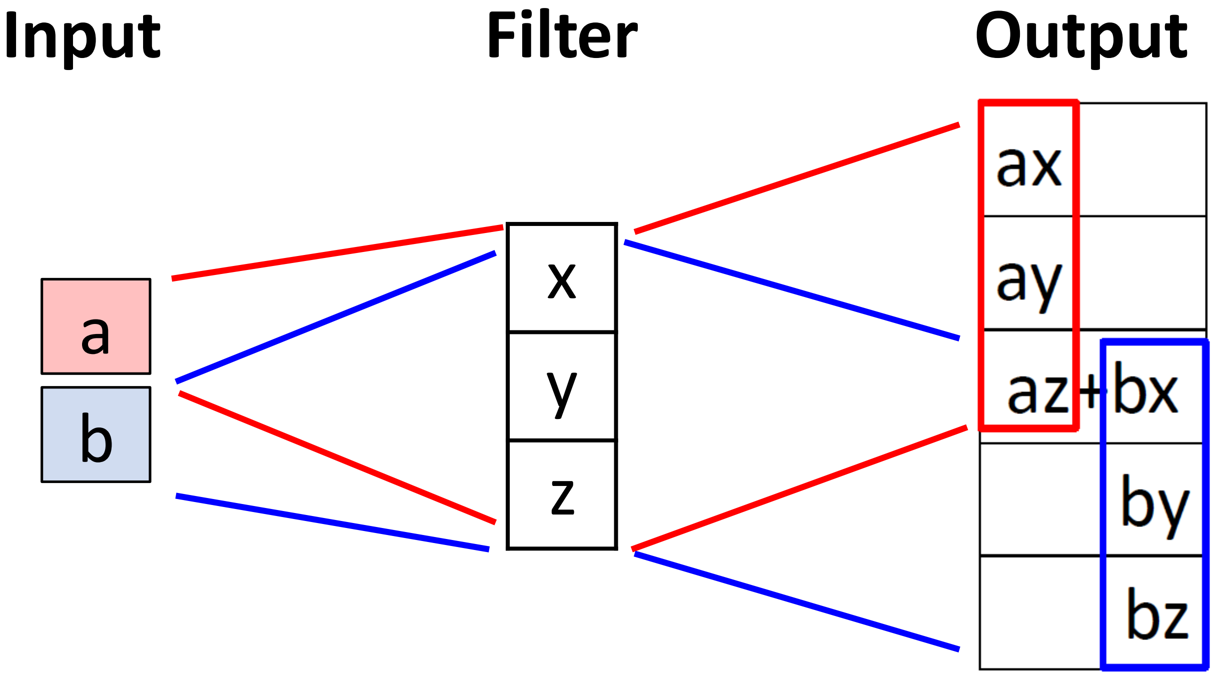


Output has copies of filter weighted by input

Stride 2: Move 2 pixels output for each pixel in input

Sum at overlaps

Transposed Convolution: 1D example



This has many names:

- Deconvolution (bad)!
- Upconvolution
-Fractionally strided convolution
-Backward strided convolution
- <u>Transposed Convolution</u> (best name)

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

Example: 1D conv, kernel size=3, stride=1, padding=1

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

Example: 1D conv, kernel size=3, stride=1, padding=1

Transposed convolution multiplies by the transpose of the same matrix:

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

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

When stride=1, transposed conv is just a regular conv (with different padding rules)

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

Example: 1D conv, kernel size=3, <u>stride=2</u>, padding=1

Transposed convolution multiplies by the transpose of the same matrix:

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

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

Example: 1D conv, kernel size=3, <u>stride=2</u>, padding=1

Transposed convolution multiplies by the transpose of the same matrix:

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

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

When stride>1, transposed convolution cannot be expressed as normal conv

Semantic Segmentation: Fully Convolutional Network

Downsampling:
Pooling, strided convolution

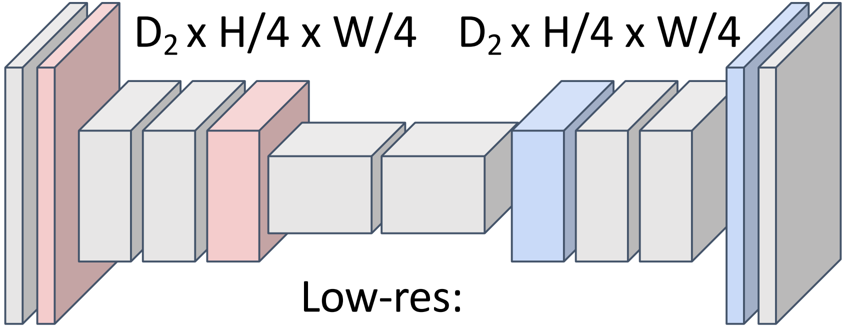
Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling:
Iinterpolation, transposed conv

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



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

Low-res:
D_3 x H/8 x W/8

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

Predictions:
H x W

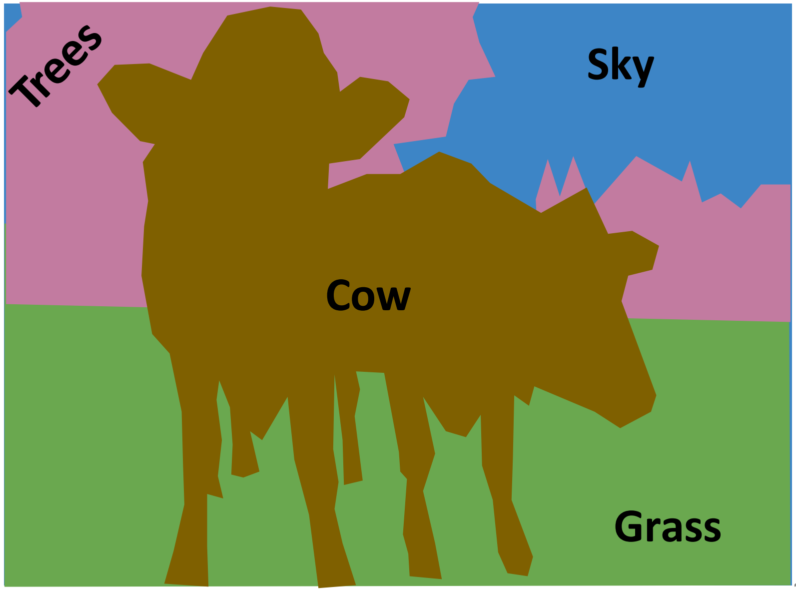
Loss function: Per-Pixel cross-entropy

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

Computer Vision Tasks

Object Detection: Detects individual object instances, but only gives box

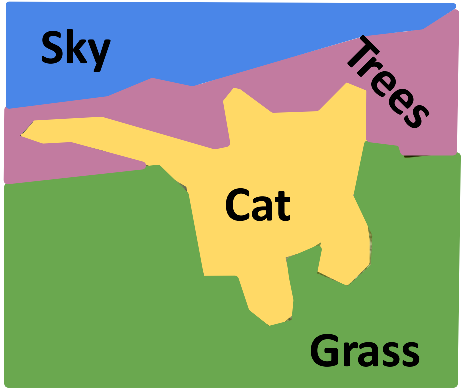
Semantic Segmentation: Gives per-pixel labels, but merges instances

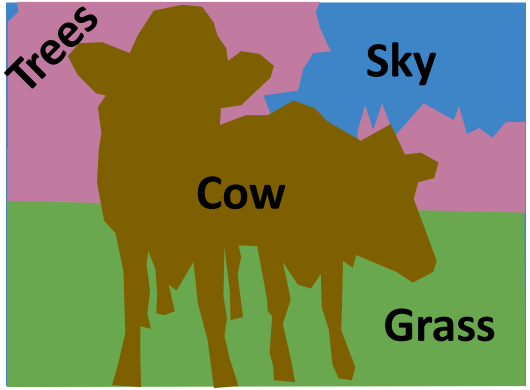


Things and Stuff

Things: Object categories that can be separated into object instances (e.g. cats, cars, person)

Stuff: Object categories that cannot be separated into instances (e.g. sky, grass, water, trees)

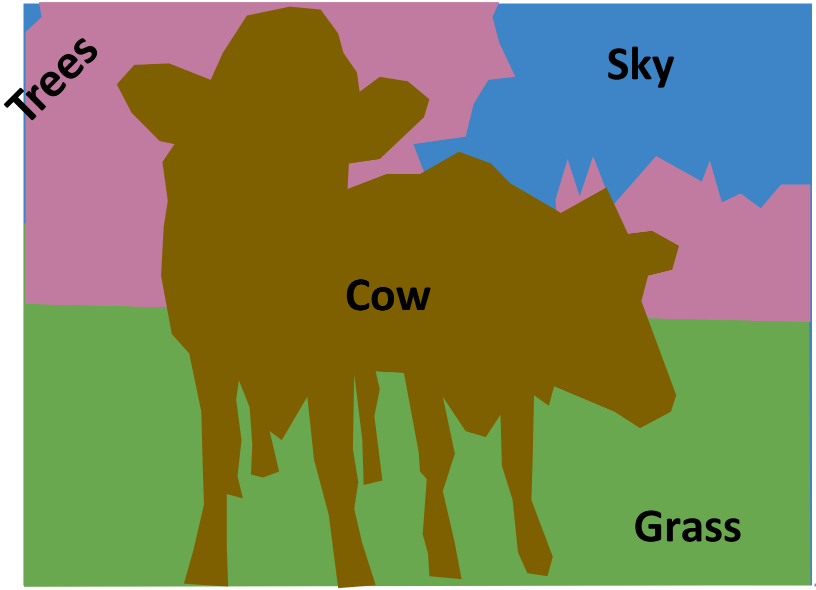




Computer Vision Tasks

Object Detection: Detects individual object instances, but only gives box (Only things!)

Semantic Segmentation: Gives per-pixel labels, but merges instances (Both things and stuff)



Computer Vision Tasks: Instance Segmentation

Classification

CAT

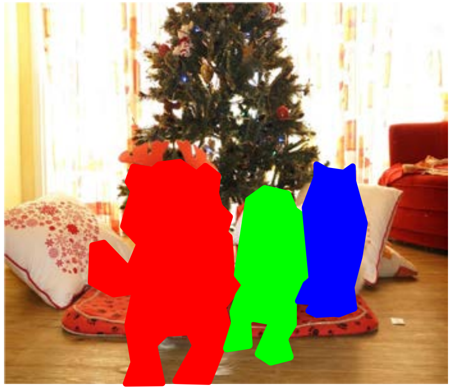
Semantic Segmentation

GRASS, CAT, TREE, SKY

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

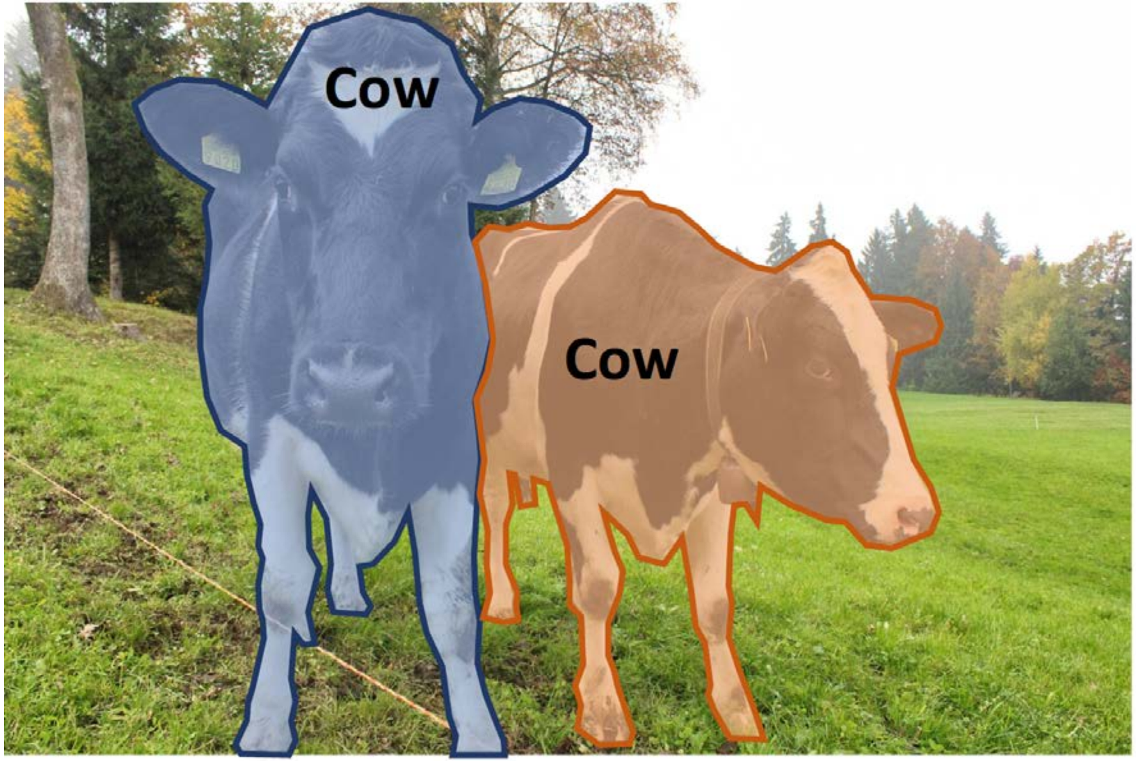
No spatial extent

No objects, just pixels

Multiple Objects

Computer Vision Tasks: Instance Segmentation

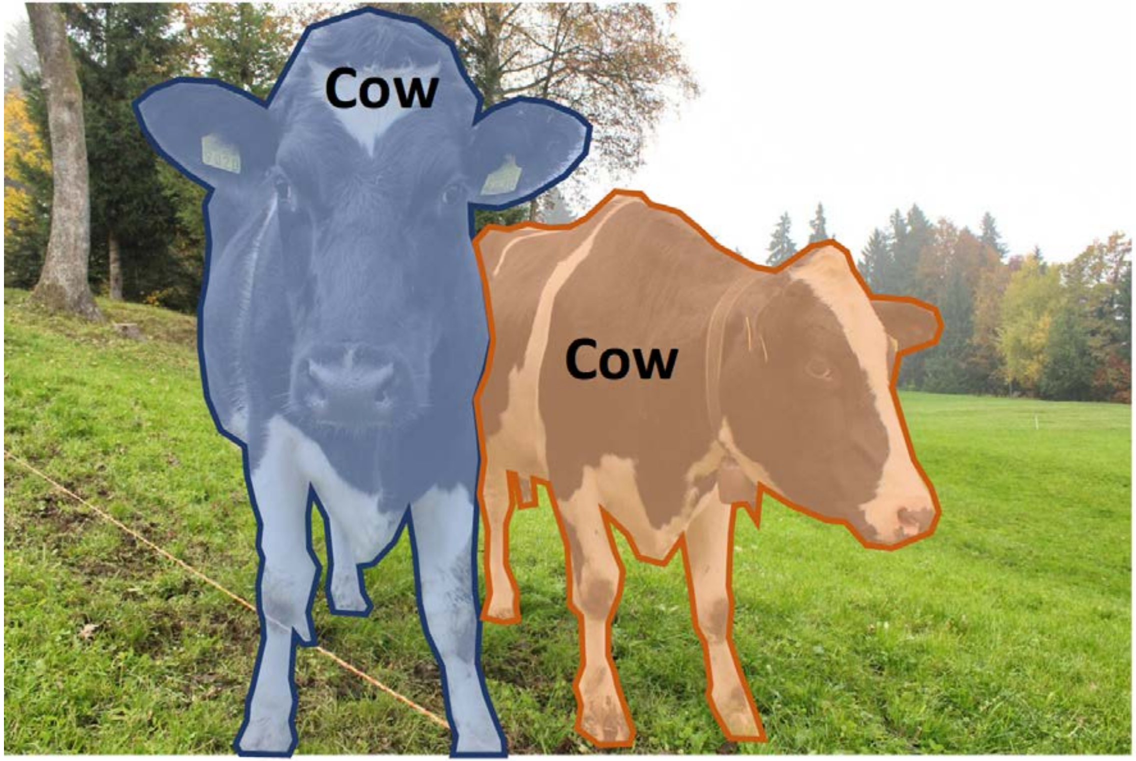
Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object (Only things!)



Computer Vision Tasks: Instance Segmentation

Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object (Only things!)

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



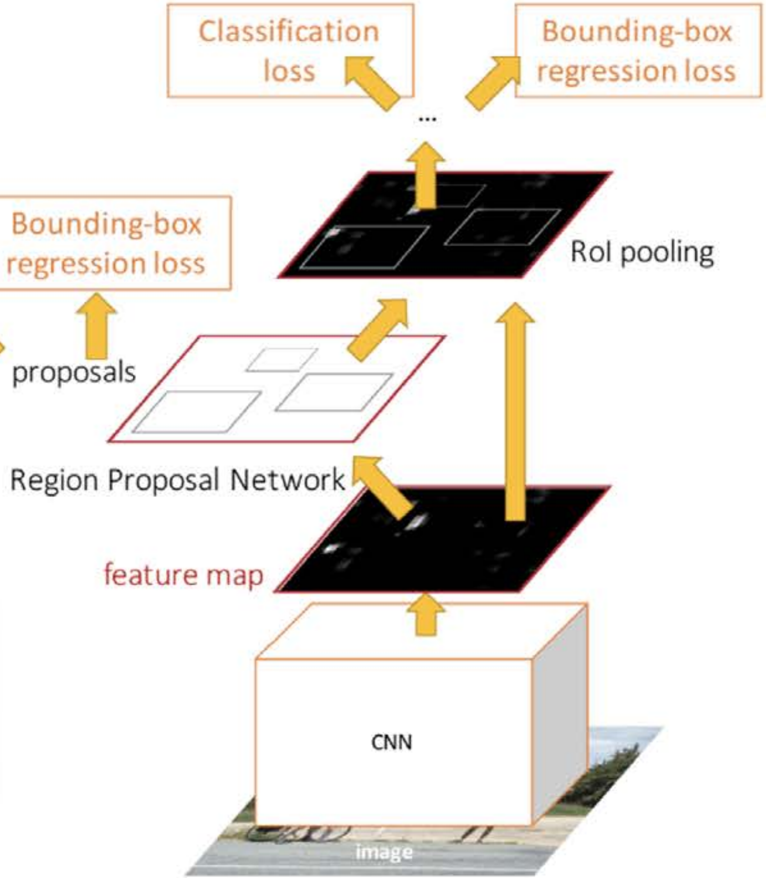
Object Detection: Faster R-CNN

Object Detection

DOG, DOG, CAT

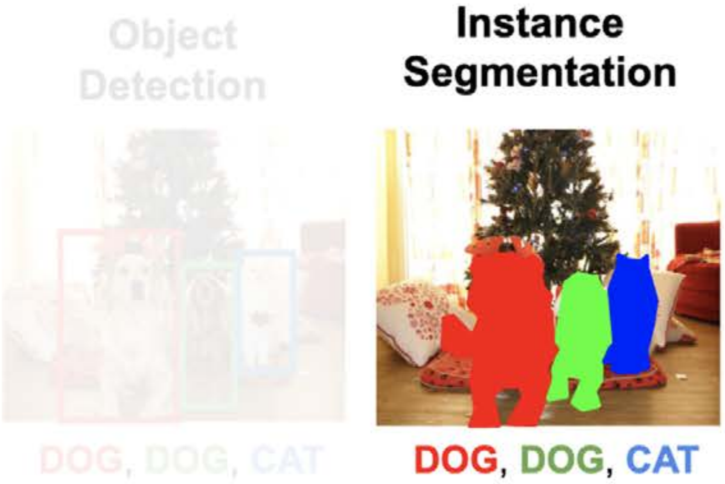
Instance Segmentation

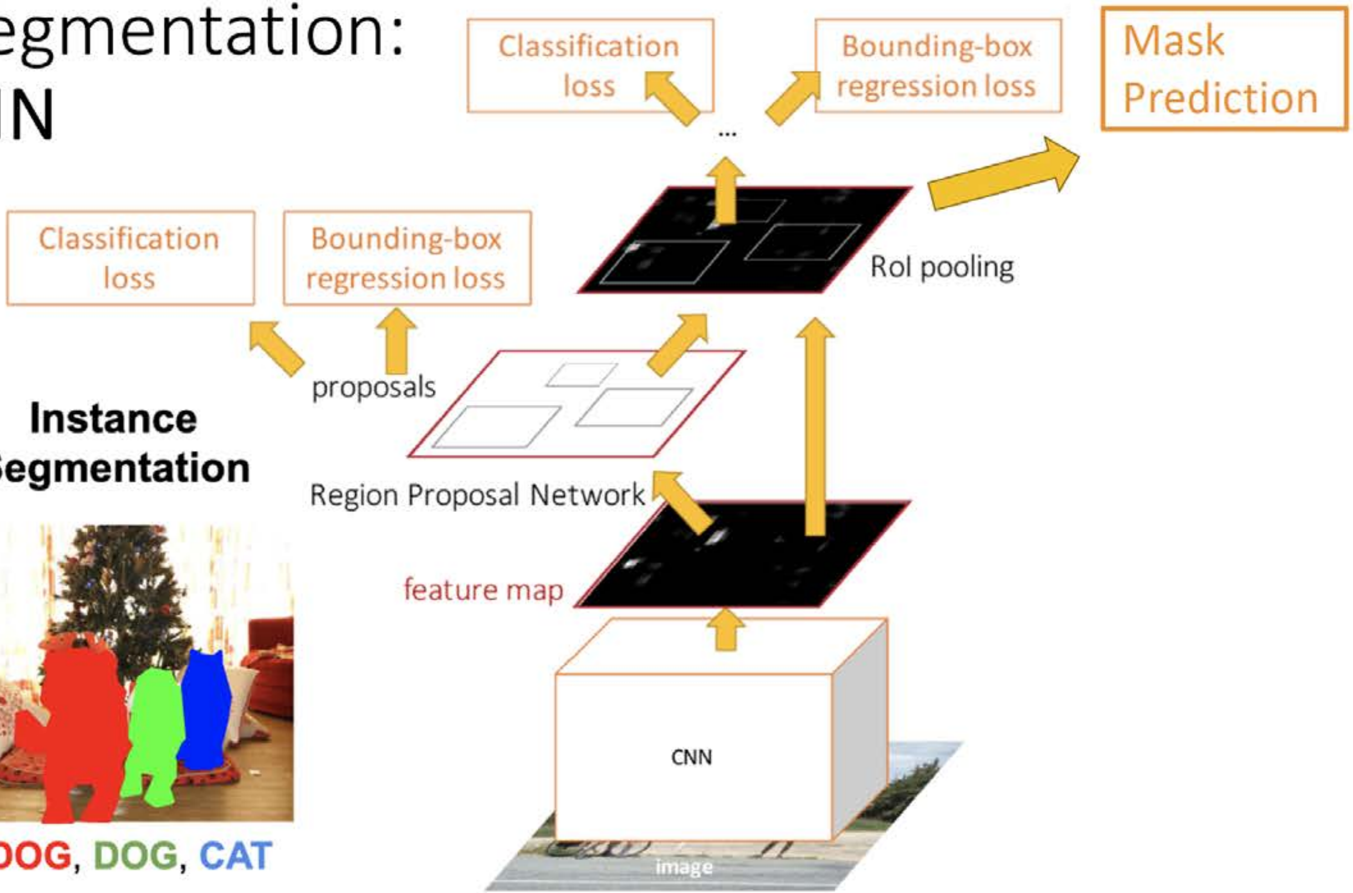
DOG, DOG, CAT



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

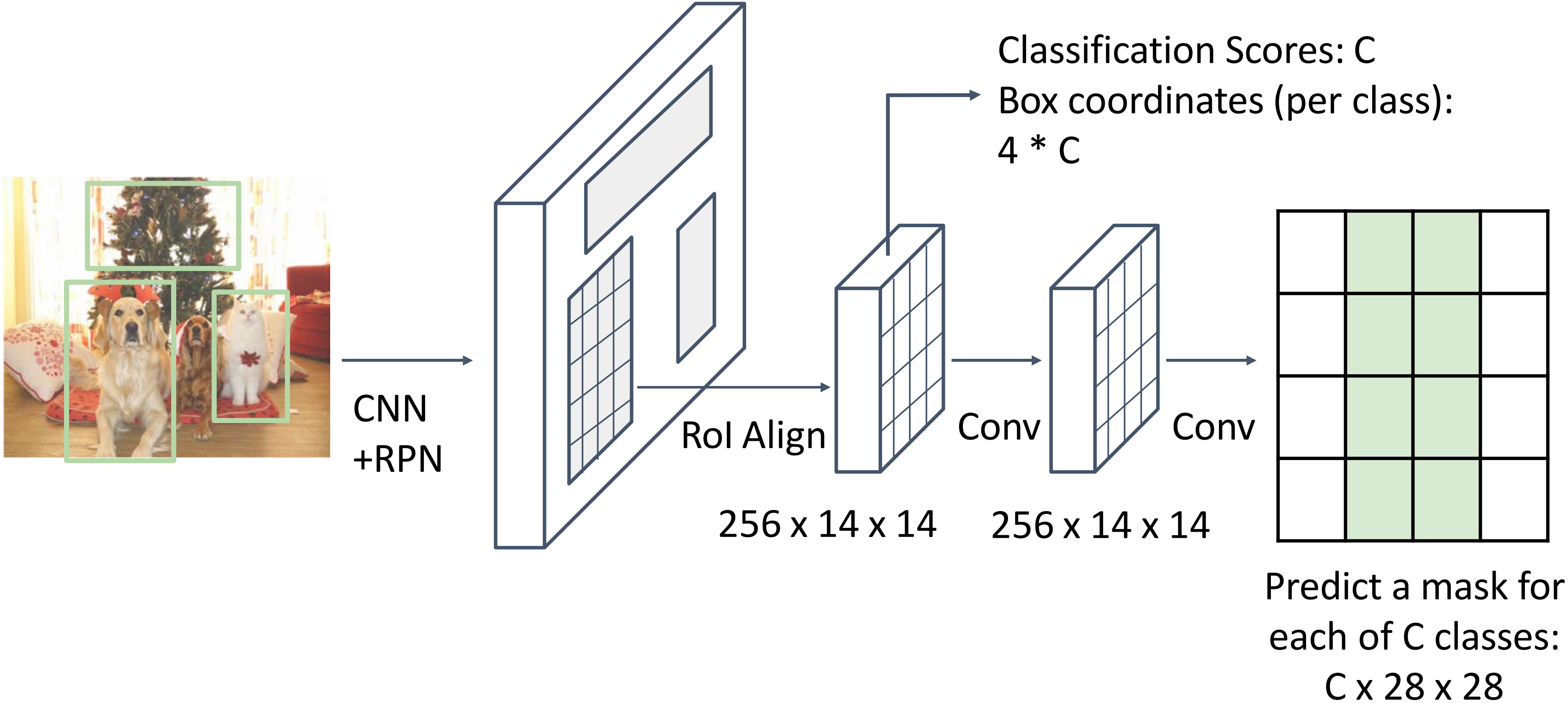
Instance Segmentation: Mask R-CNN





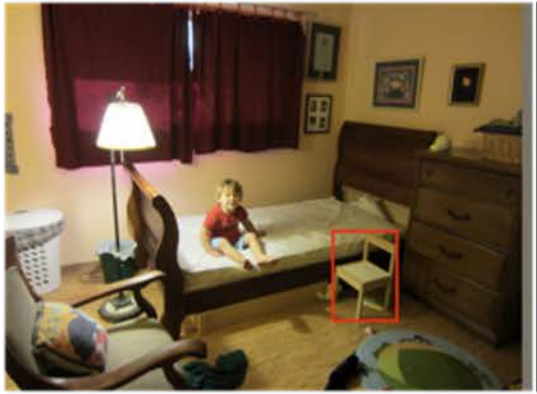
He et al, "Mask R-CNN", ICCV 2017

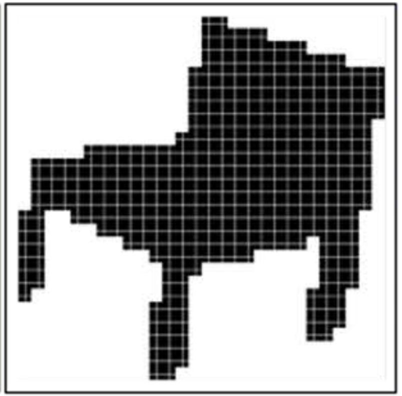
Mask R-CNN



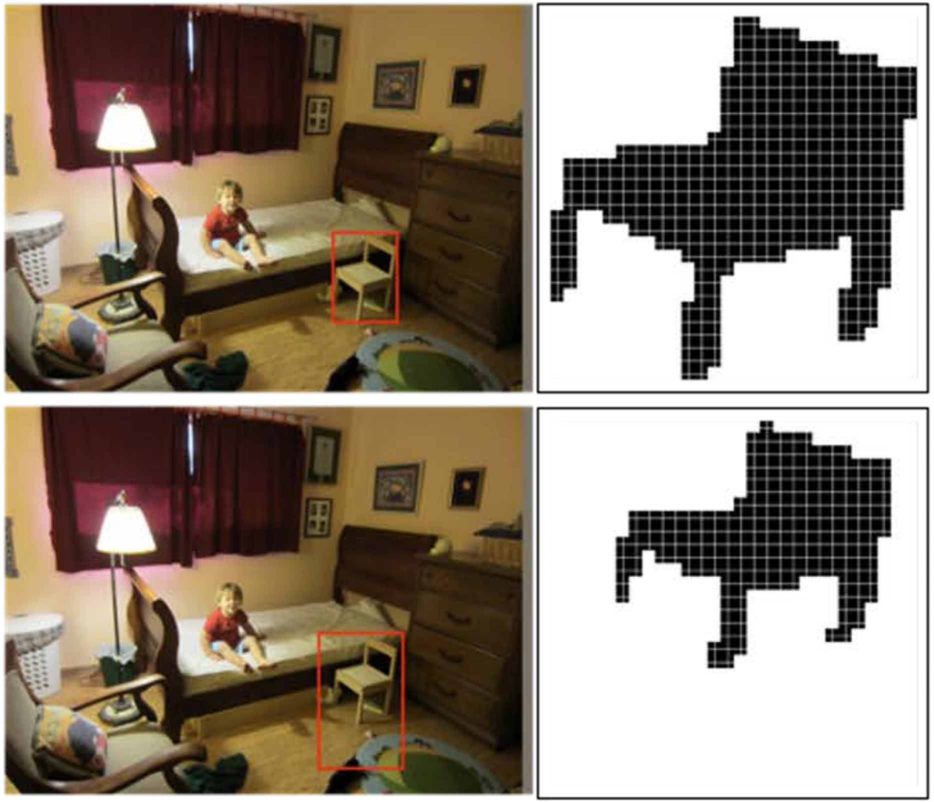
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN: Example Training Targets

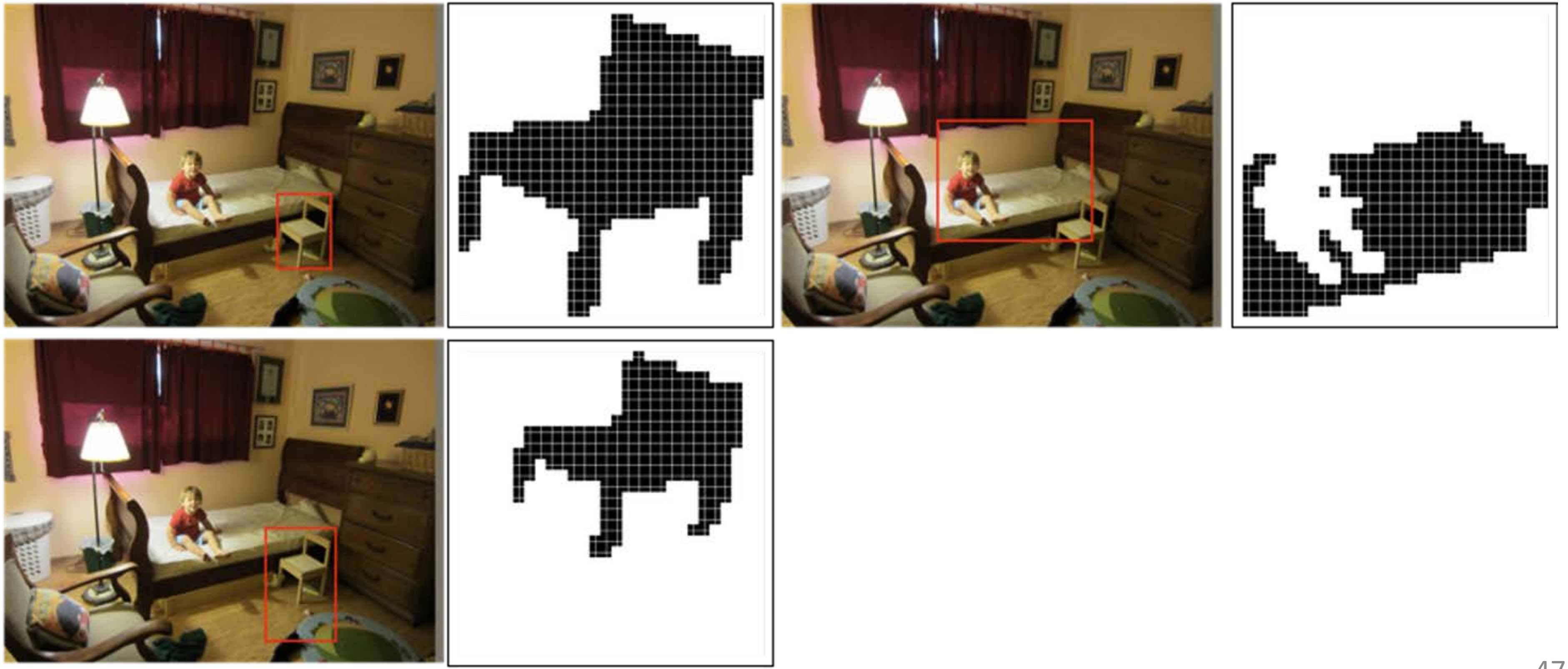




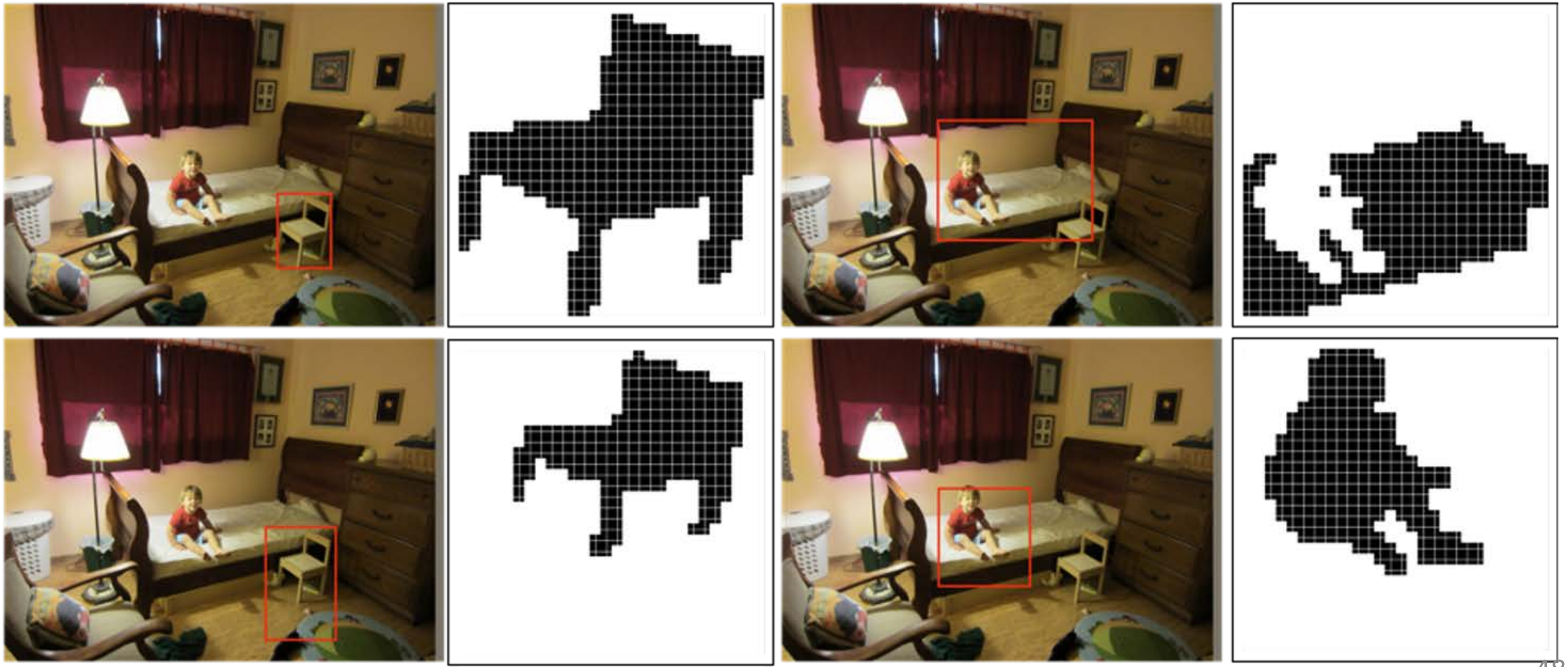
Mask R-CNN: Example Training Targets



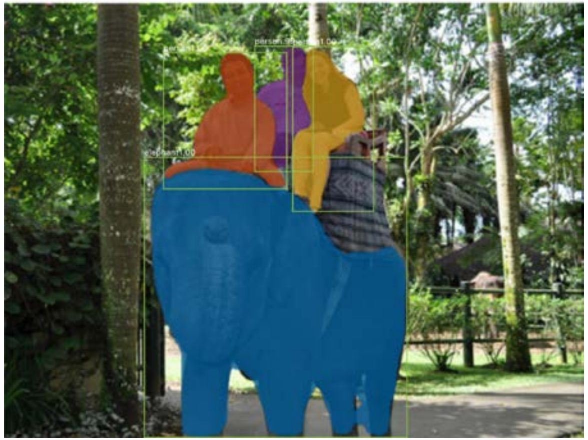
Mask R-CNN: Example Training Targets

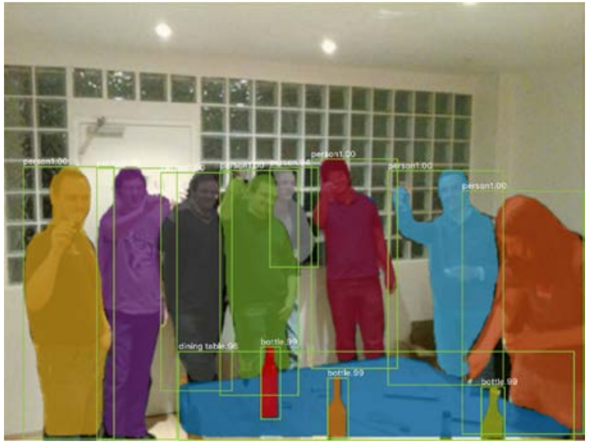


Mask R-CNN: Example Training Targets



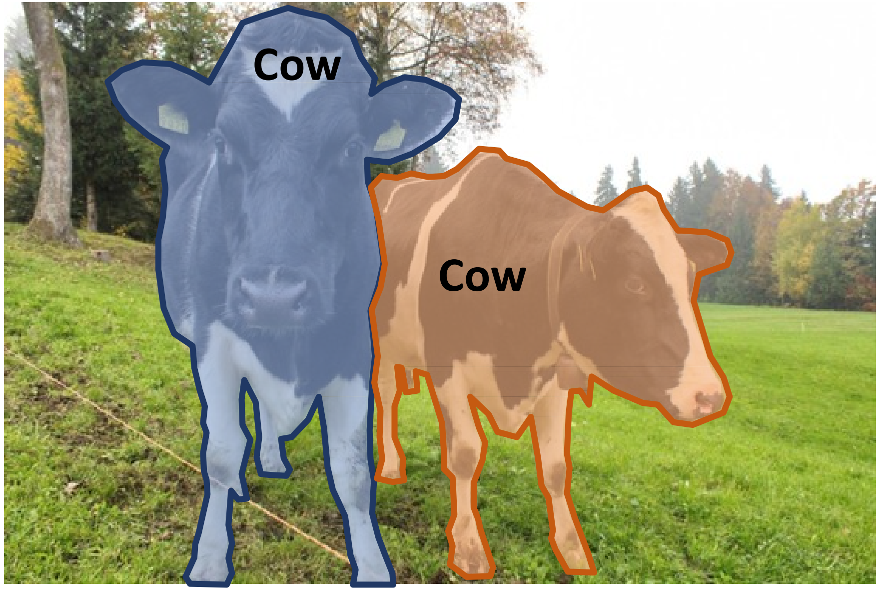
Mask R-CNN: Very Good Results!



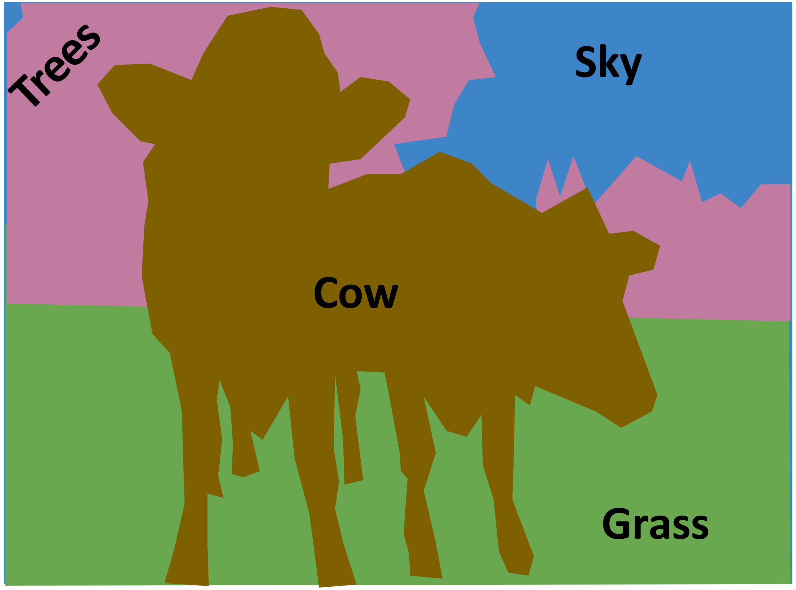


Beyond Instance Segmentation

Instance Segmentation: Separate object instances, but only things



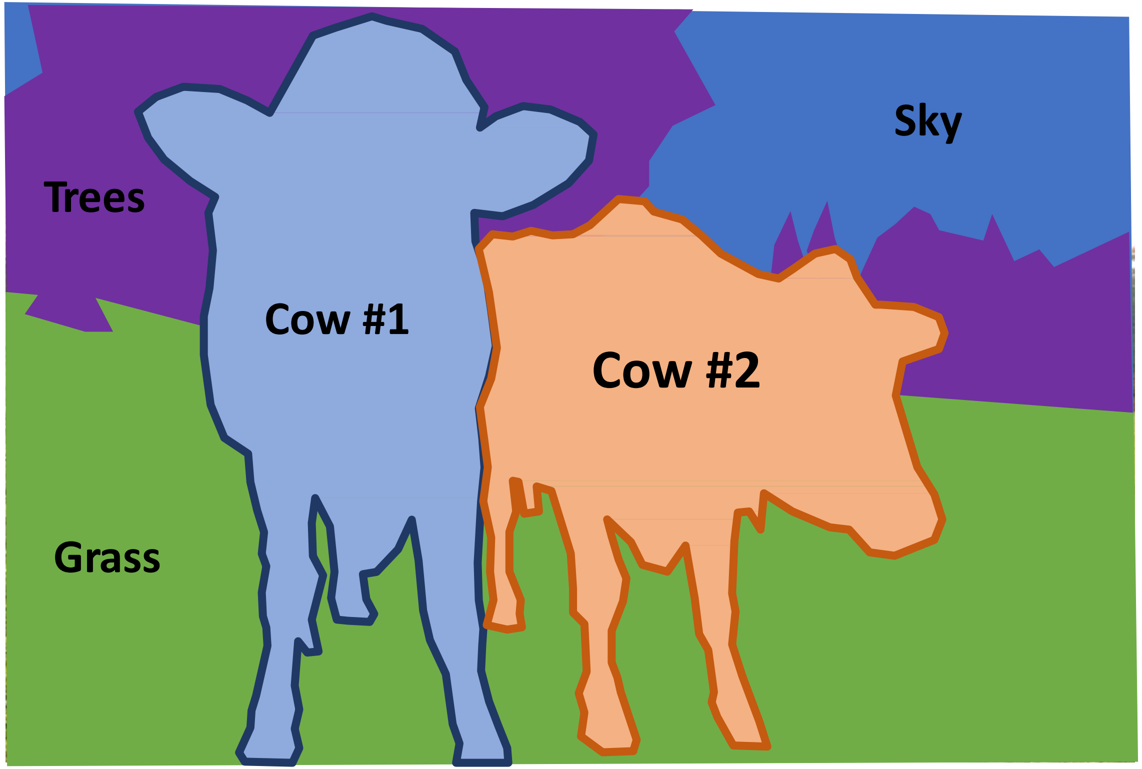
Semantic Segmentation: Identify both things and stuff, but doesn't separate instances



Beyond Instance Segmentation: Panoptic Segmentation

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

For “thing” categories also separate into instances



Kirillov et al, “Panoptic Segmentation”, CVPR 2019
Kirillov et al, “Panoptic Feature Pyramid Networks”, CVPR 2019

Beyond Instance Segmentation: **Panoptic Segmentation**

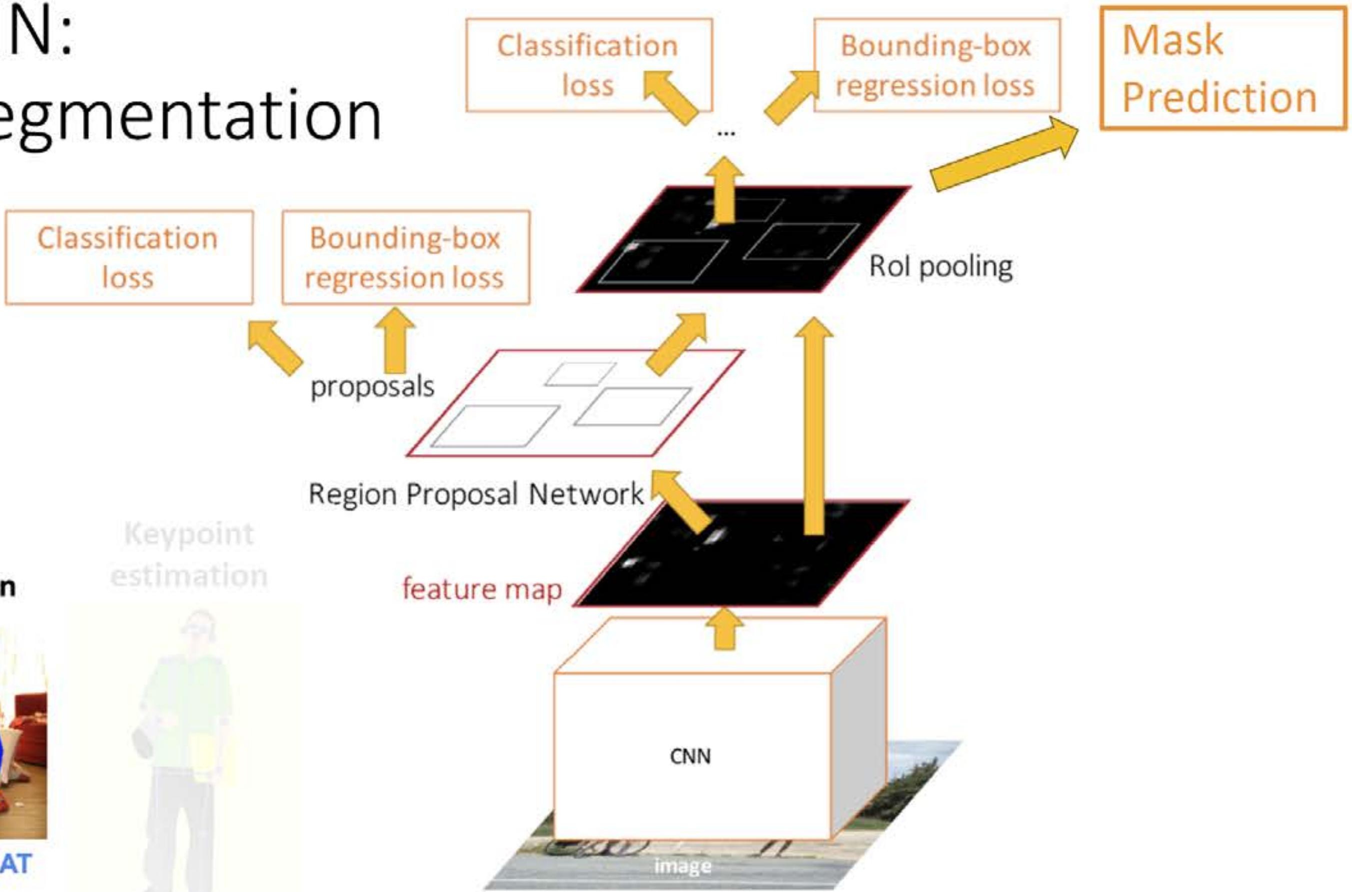
Kirillov et al, "Panoptic Feature Pyramid Networks", CVPR 2019

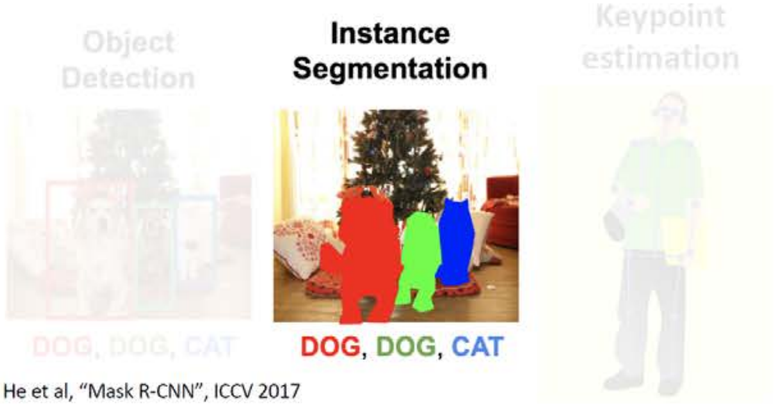
Beyond Instance Segmentation: Human Keypoints

Represent the pose of a human by locating a set of **keypoints**

e.g. 17 keypoints:
- Nose
- Left / Right eye
- Left / Right ear
- Left / Right shoulder
- Left / Right elbow
- Left / Right wrist
- Left / Right hip
- Left / Right knee
- Left / Right ankle

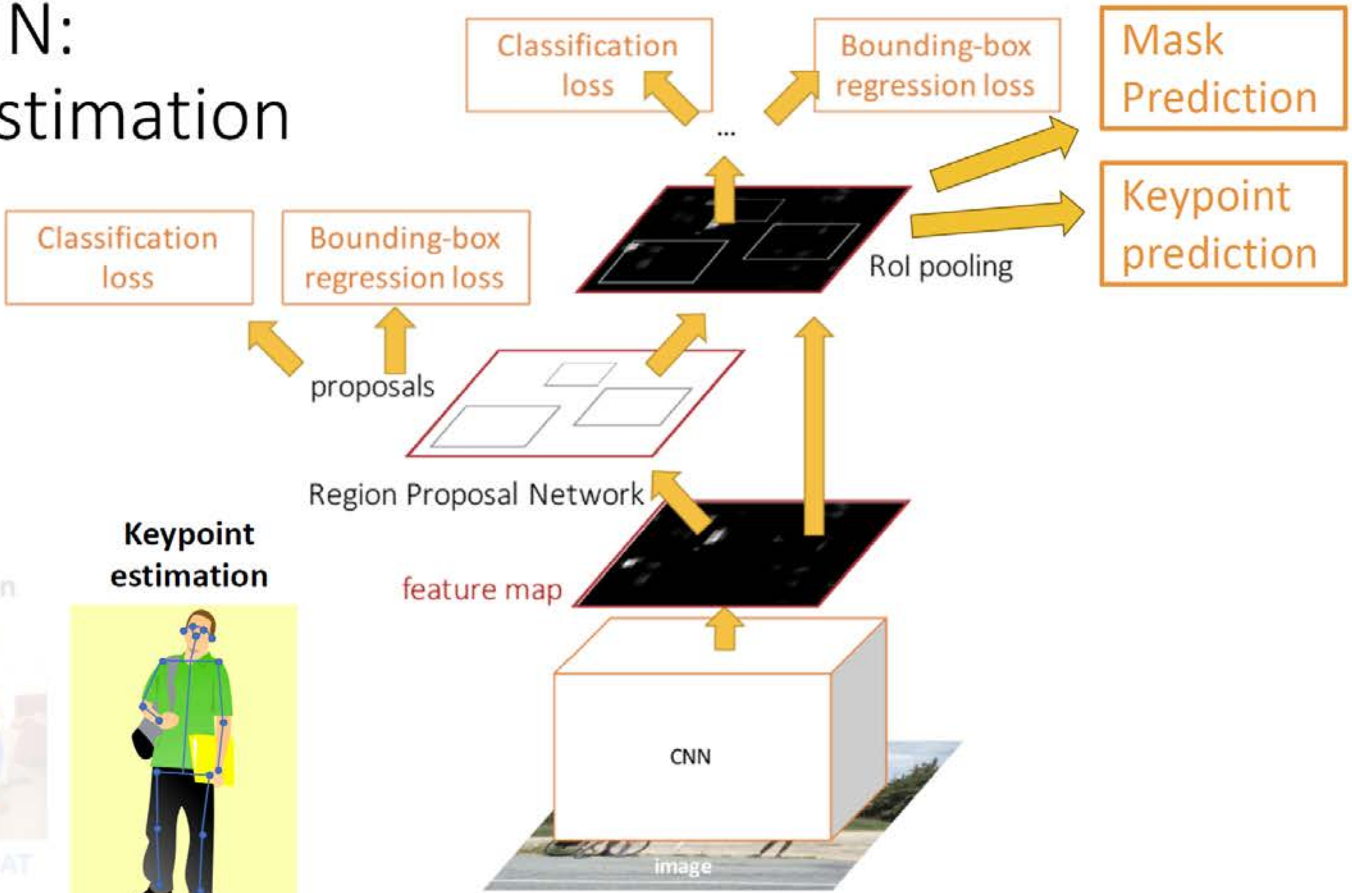
Mask R-CNN: Instance Segmentation





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

Mask R-CNN: Keypoint Estimation

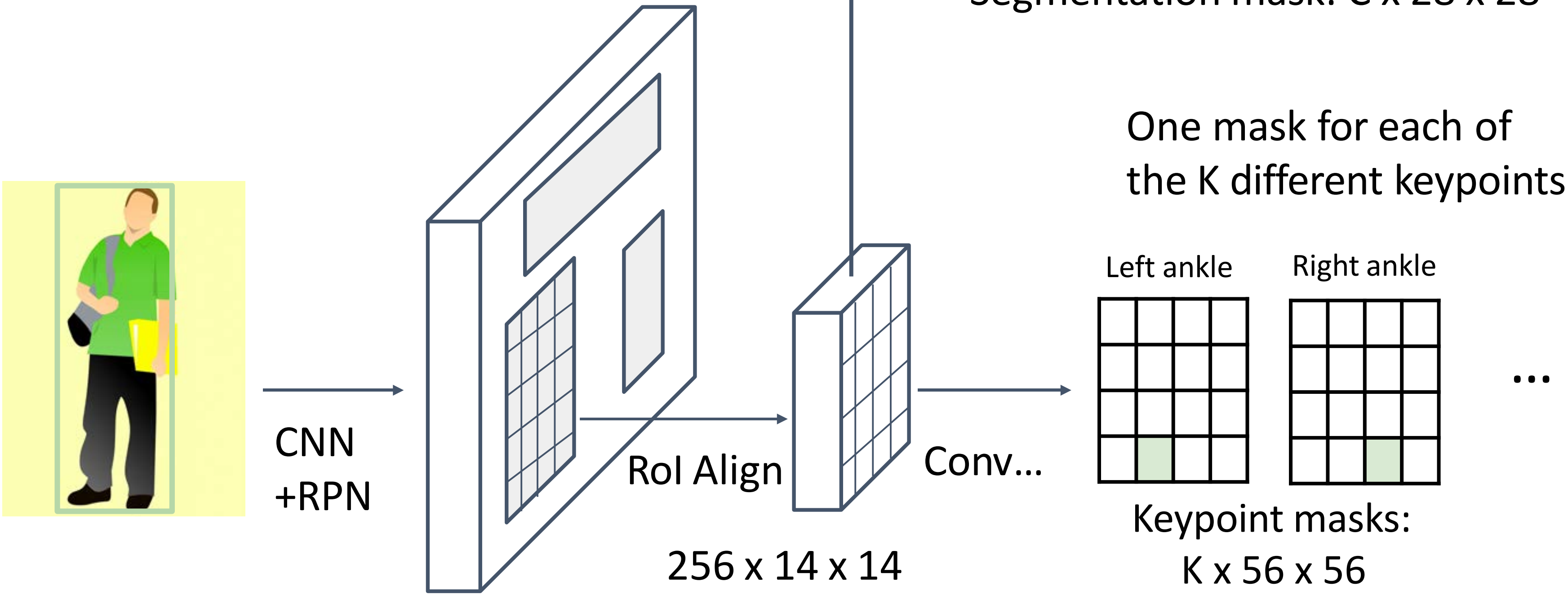


He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN: Keypoints

Classification Scores: C
Box coordinates (per class): 4 * C
Segmentation mask: C x 28 x 28

One mask for each of the K different keypoints



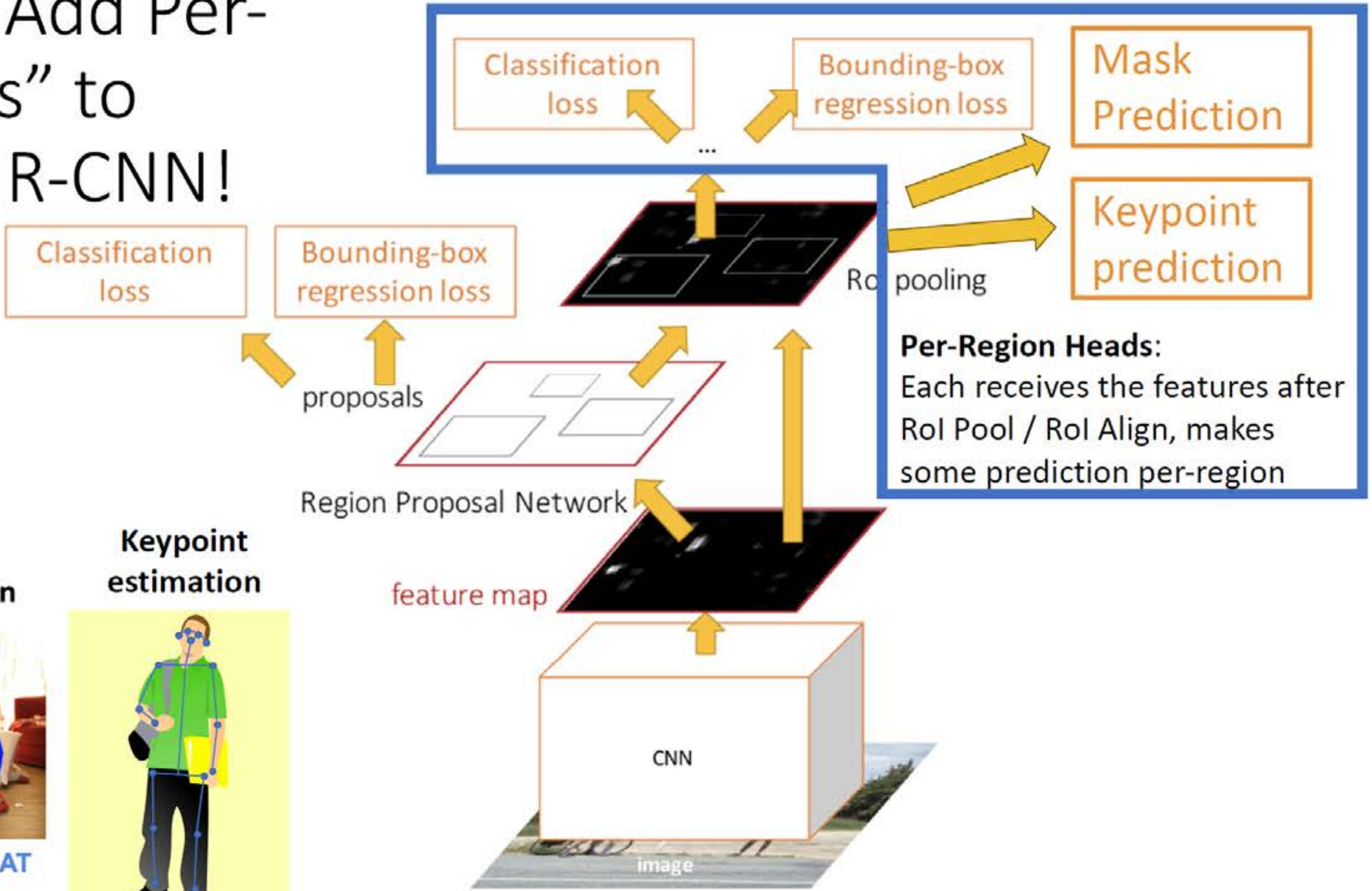
Ground-truth has one "pixel" turned on per keypoint. Train with softmax loss

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

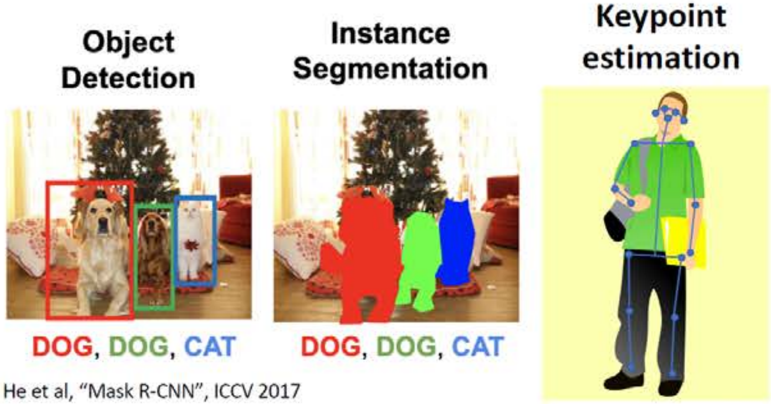
Joint Instance Segmentation and Pose Estimation

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

General Idea: Add Per-Region "Heads" to Faster / Mask R-CNN!

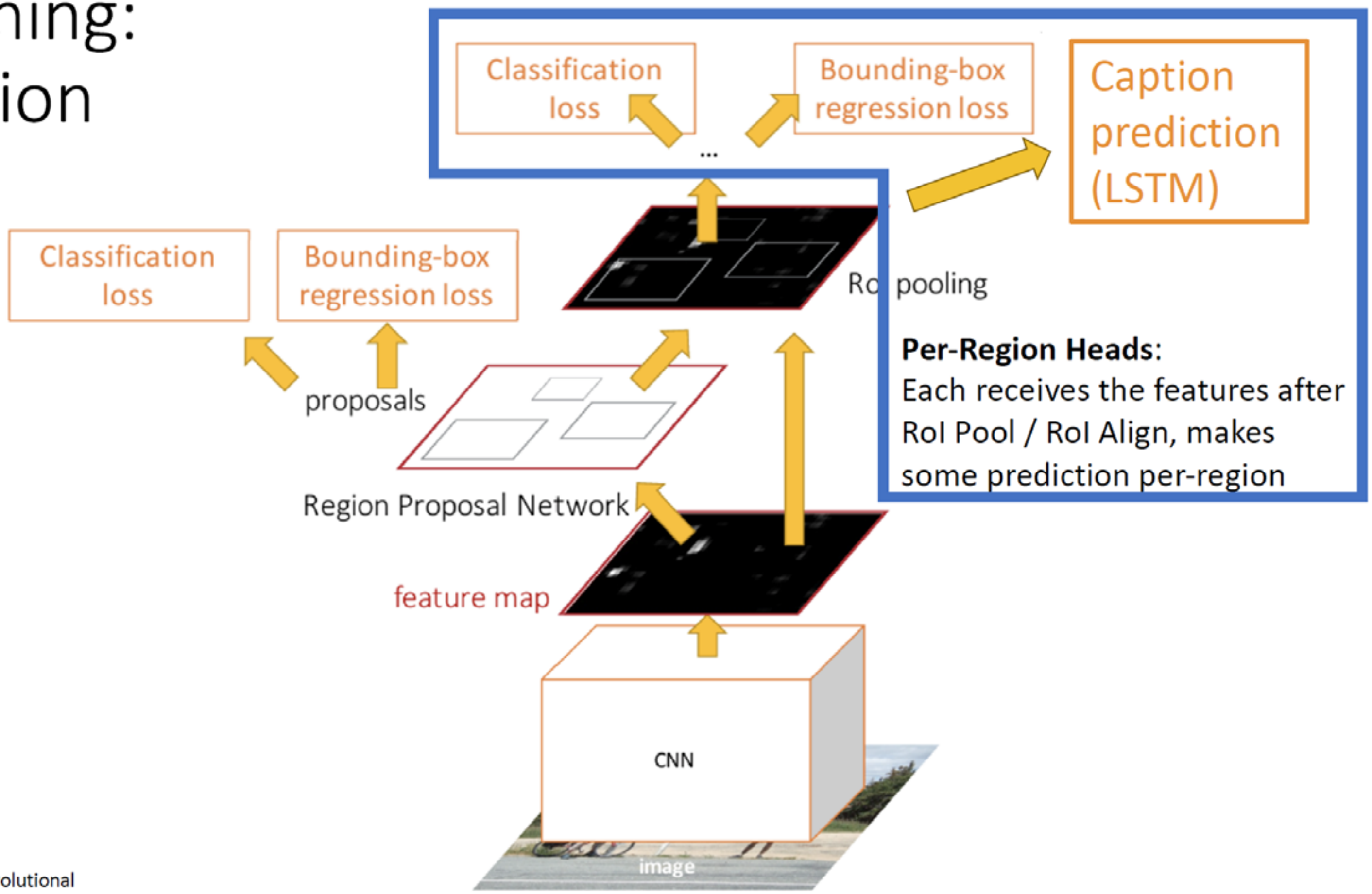


Per-Region Heads:
Each receives the features after RoI Pool / RoI Align, makes some prediction per-region



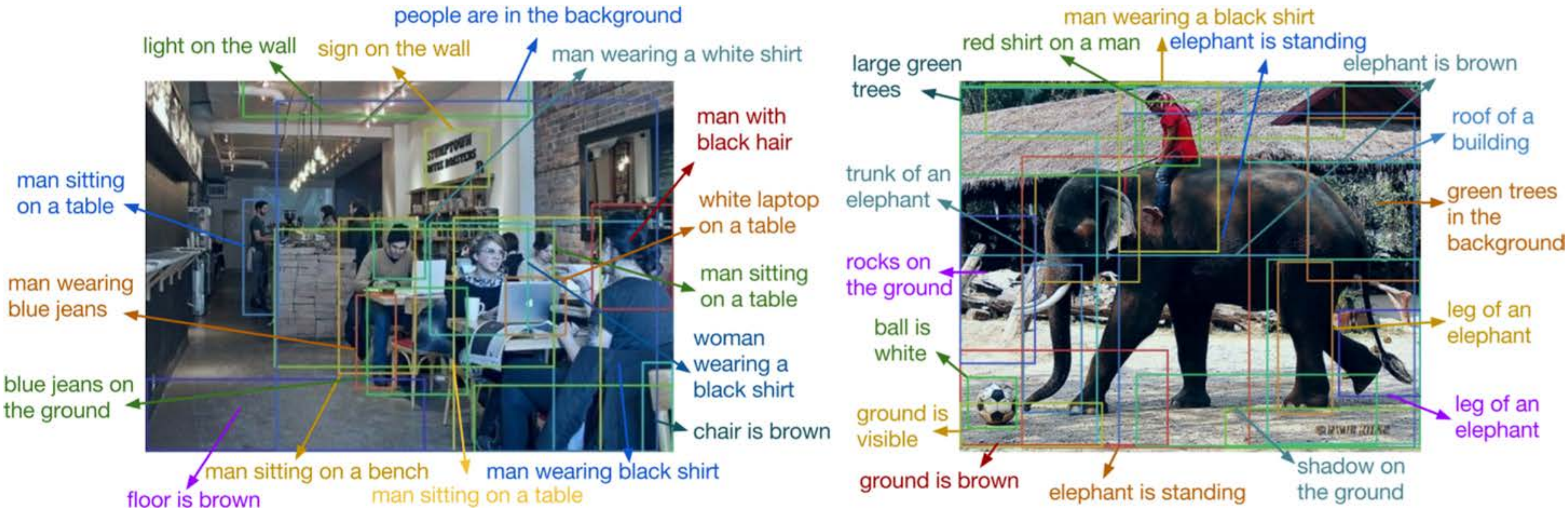
He et al, "Mask R-CNN", ICCV 2017

Dense Captioning: Predict a caption per region!



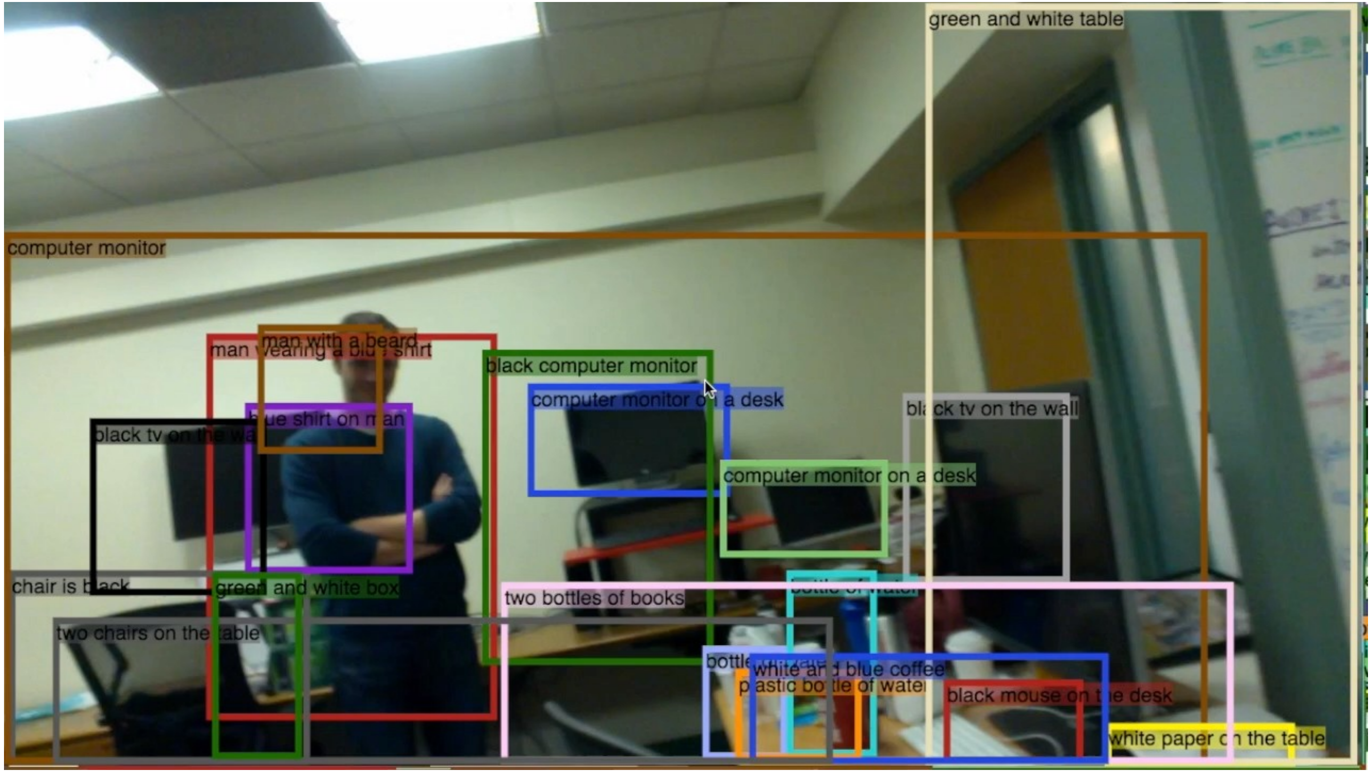
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Dense Captioning



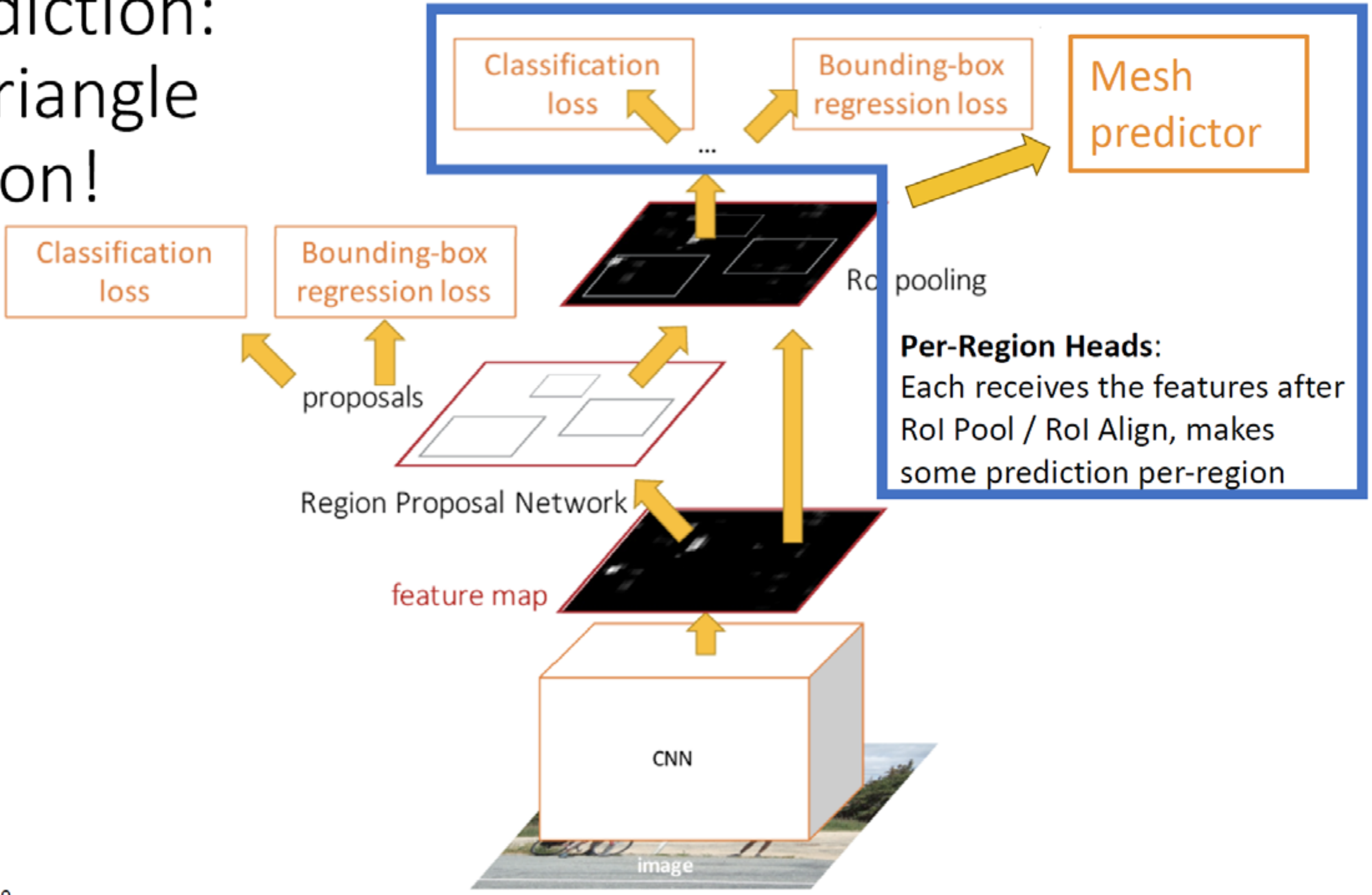
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Dense Captioning



Johnson, Karpathy, and Fei-Fei, “DenseCap: Fully Convolutional Localization Networks for Dense Captioning”, CVPR 2016

3D Shape Prediction: Predict a 3D triangle mesh per region!

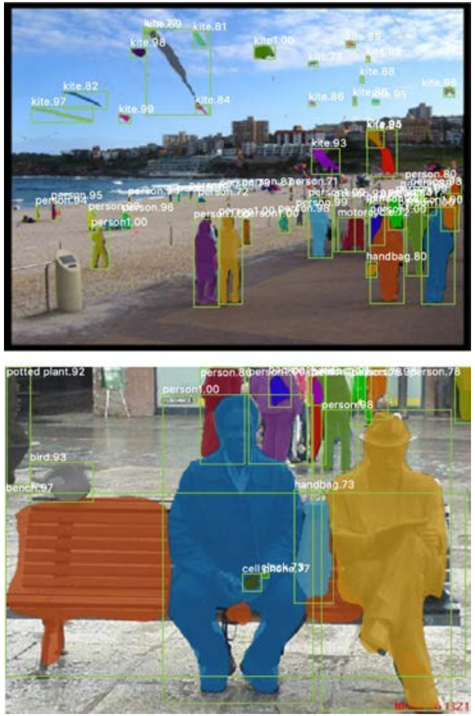


Per-Region Heads:
Each receives the features after RoI Pool / RoI Align, makes some prediction per-region

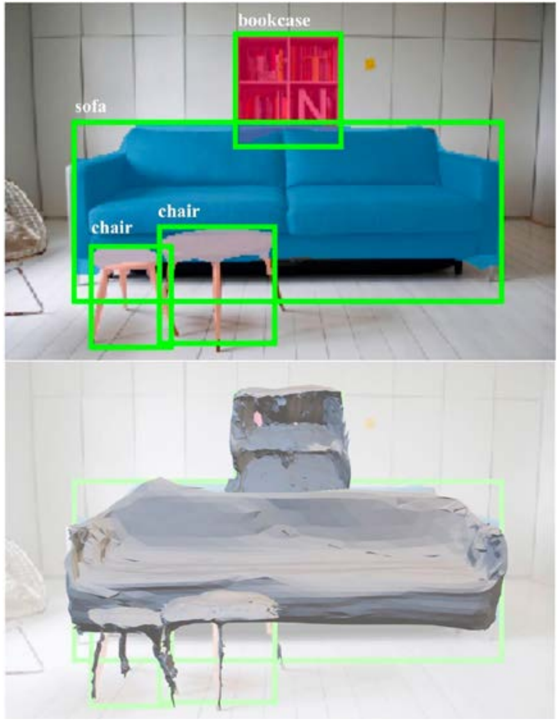
Gkioxari, Malik, and Johnson, "Mesh R-CNN", ICCV 2019

3D Shape Prediction: Mask R-CNN + Mesh Head

Mask R-CNN:
2D Image -> 2D shapes



Mesh R-CNN:
2D Image -> **3D** shapes



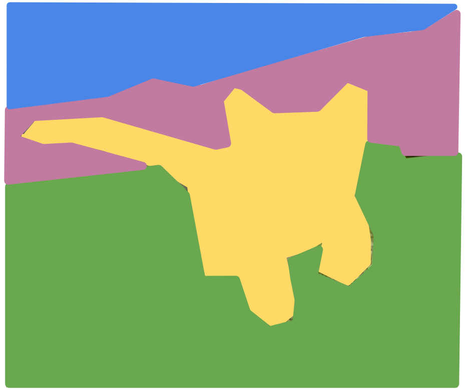
He, Gkioxari, Dollár, and Girshick, "Mask R-CNN", ICCV 2017

Gkioxari, Malik, and Johnson, "Mesh R-CNN", ICCV 2019

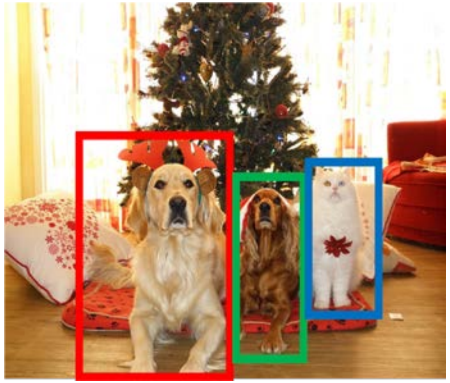
Summary: Many Computer Vision Tasks!

Classification | **Semantic Segmentation** | **Object Detection** | **Instance Segmentation**

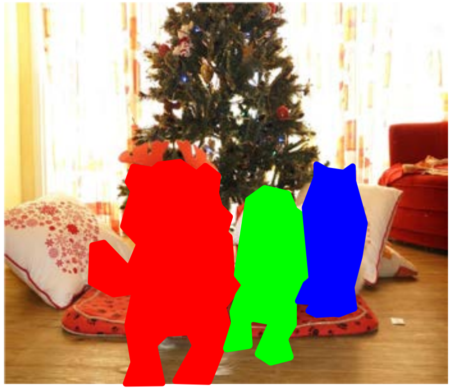
CAT



GRASS, CAT, TREE, SKY



DOG, DOG, CAT



DOG, DOG, CAT

No spatial extent

No objects, just pixels

Multiple Objects