Lecture 16:
Detection + Segmentation

Reminder: A4

A4 due **Wednesday, November 13, 11:59pm**

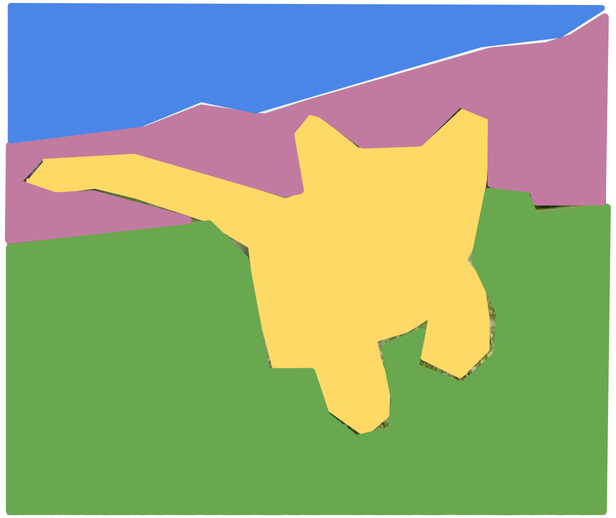
A4 covers:
- PyTorch autograd
- Residual networks
- Recurrent neural networks
- Attention
- Feature visualization
- Style transfer
- Adversarial examples

Last Time: Computer Vision Tasks

Classification

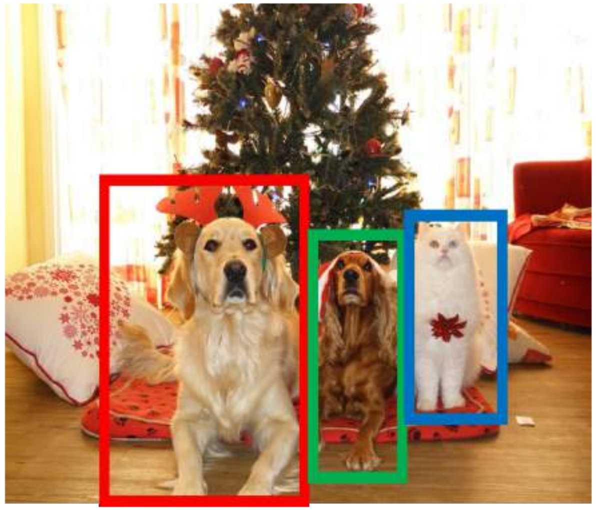
CAT

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

This image is CC0 public domain

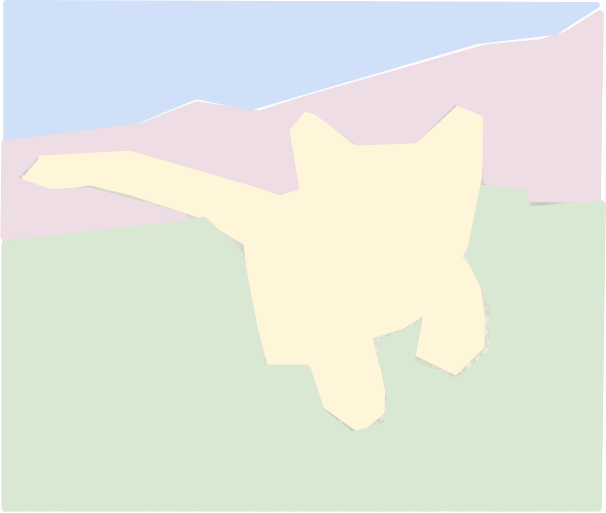
Last Time: Object Detection

Classification

CAT

No spatial extent

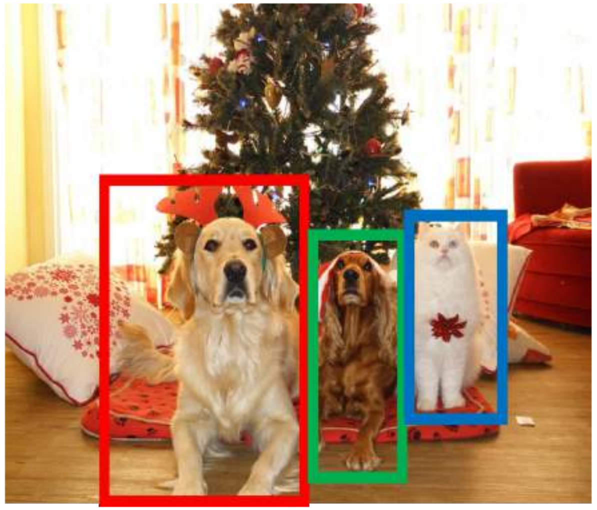
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection



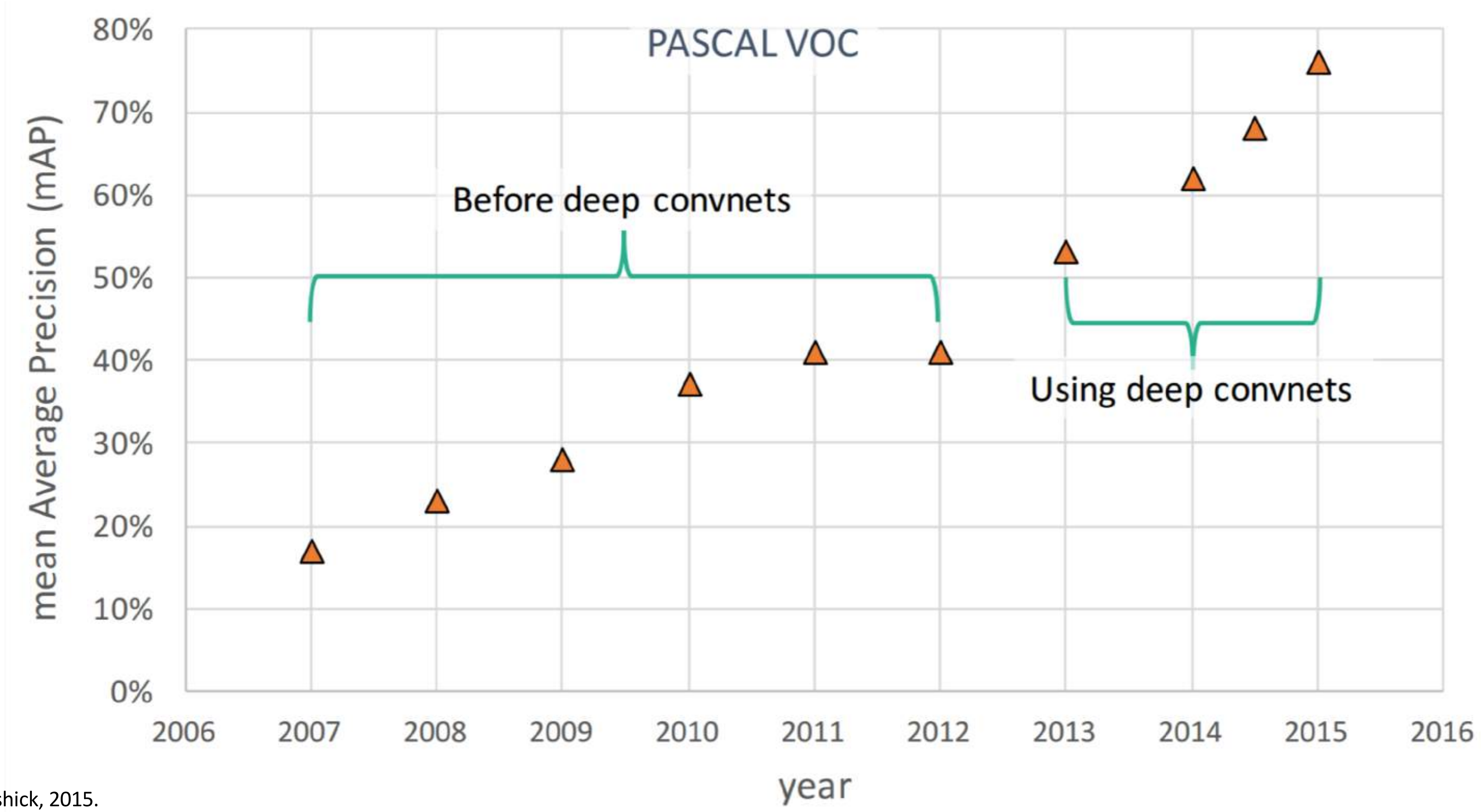
DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

Multiple Objects

Object Detection: Impact of Deep Learning



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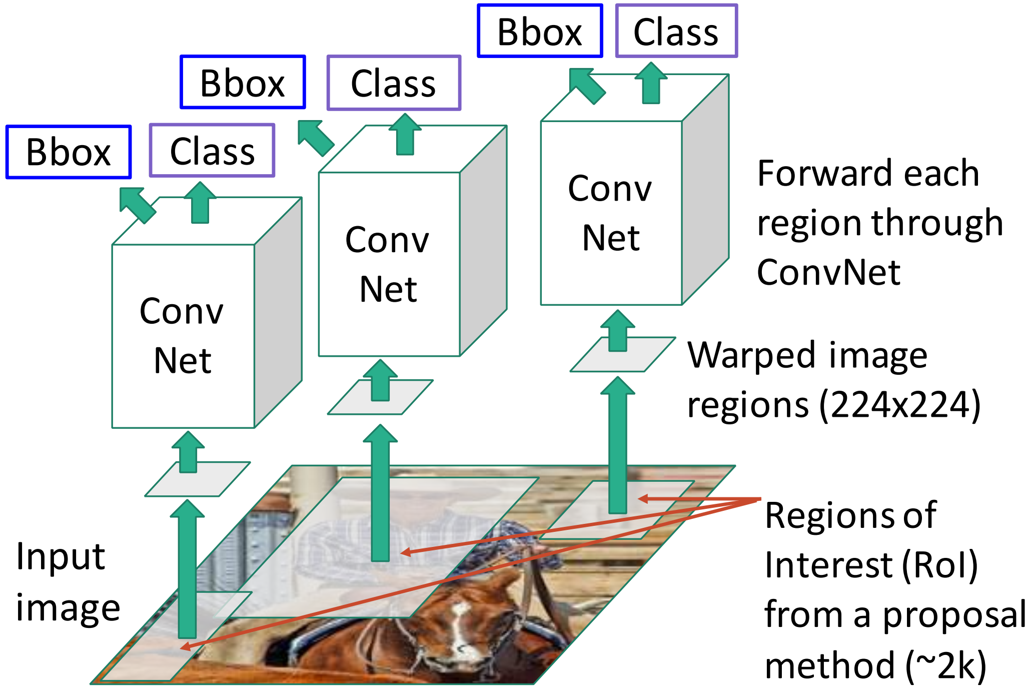
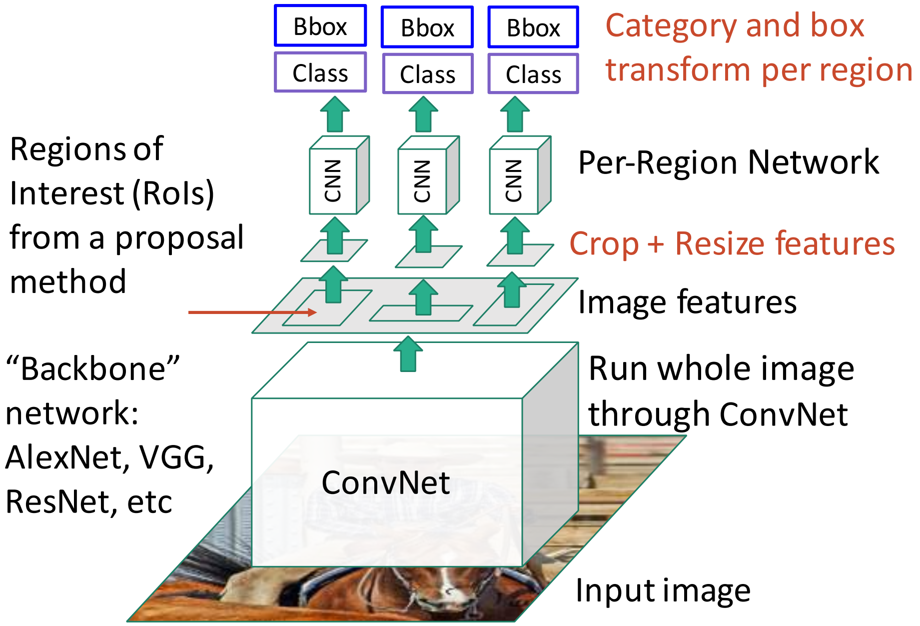
Last Time: Object Detection Methods

“Slow” R-CNN: Run CNN independently for each region

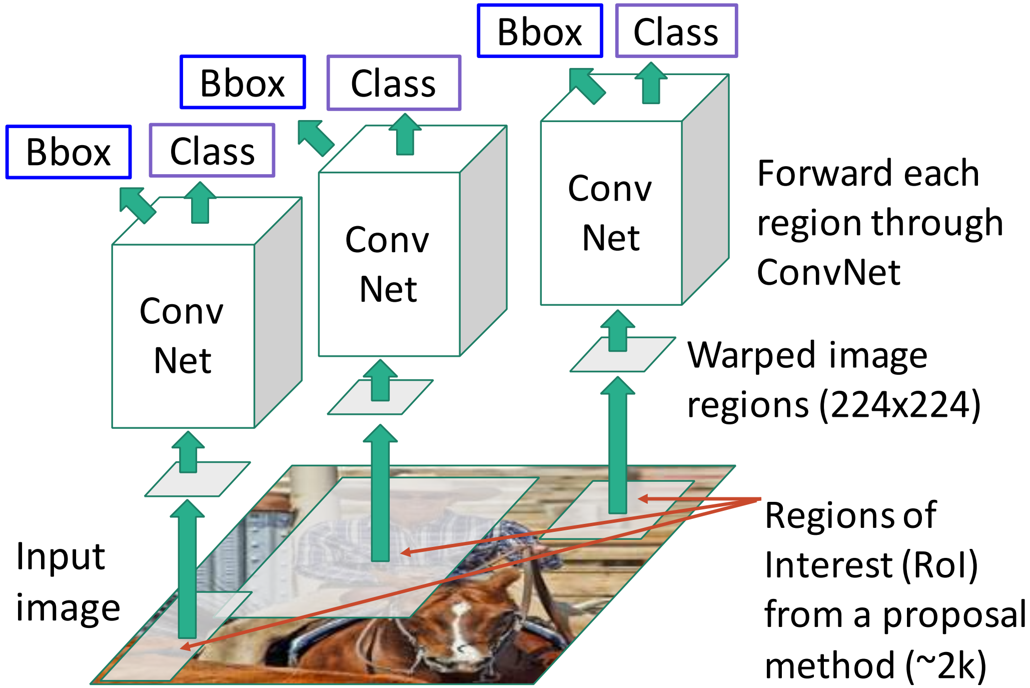


Fast R-CNN: Apply differentiable cropping to shared image features

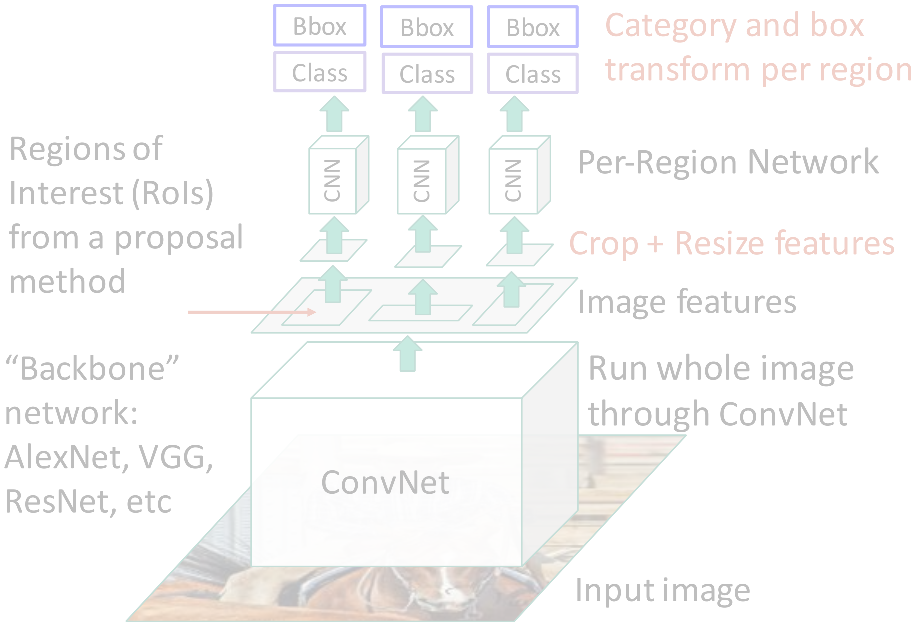


Recap: Slow R-CNN Training

"Slow" R-CNN: Run CNN independently for each region

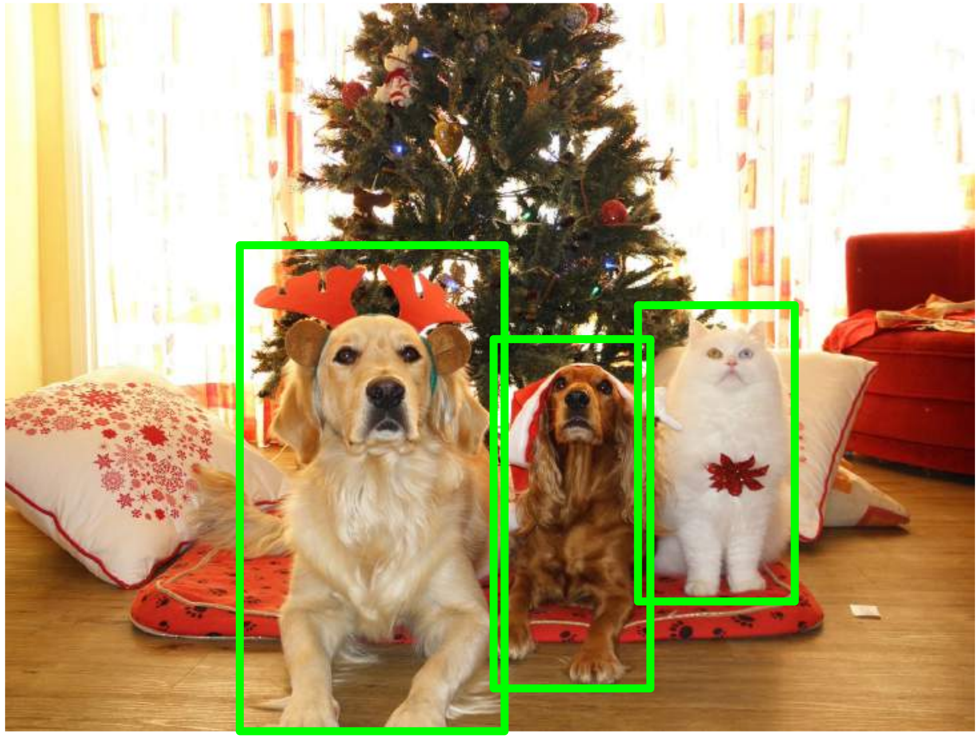


Fast R-CNN: Apply differentiable cropping to shared image features



”Slow” R-CNN Training

Input Image



Ground-Truth boxes

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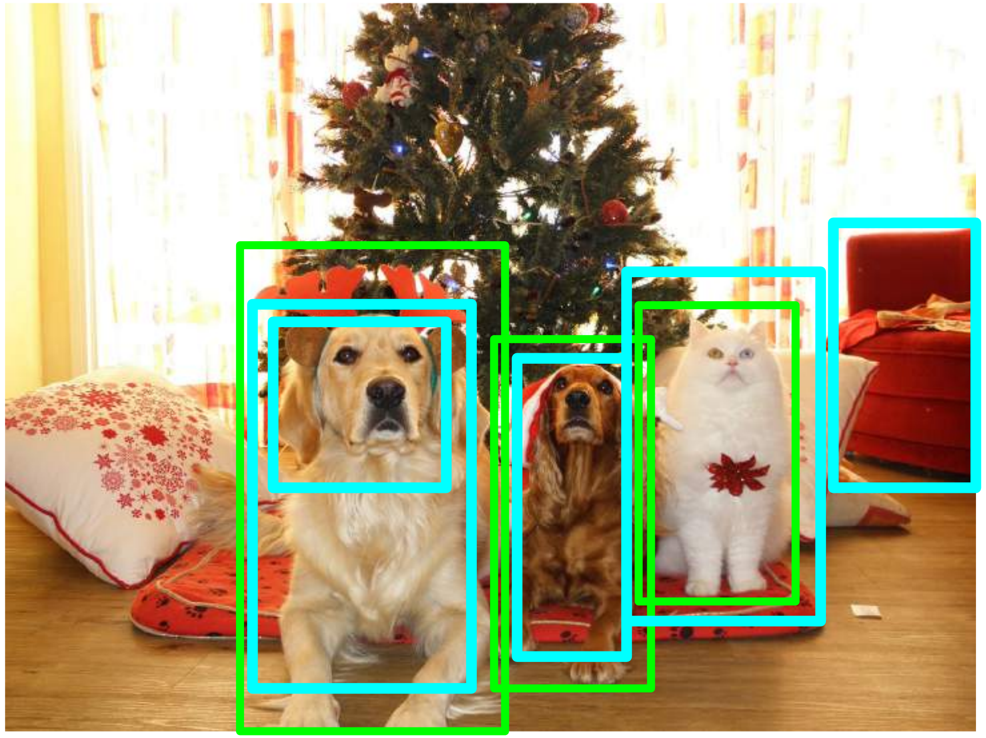
"Slow" R-CNN Training

Input Image



Ground-Truth boxes

Region Proposals

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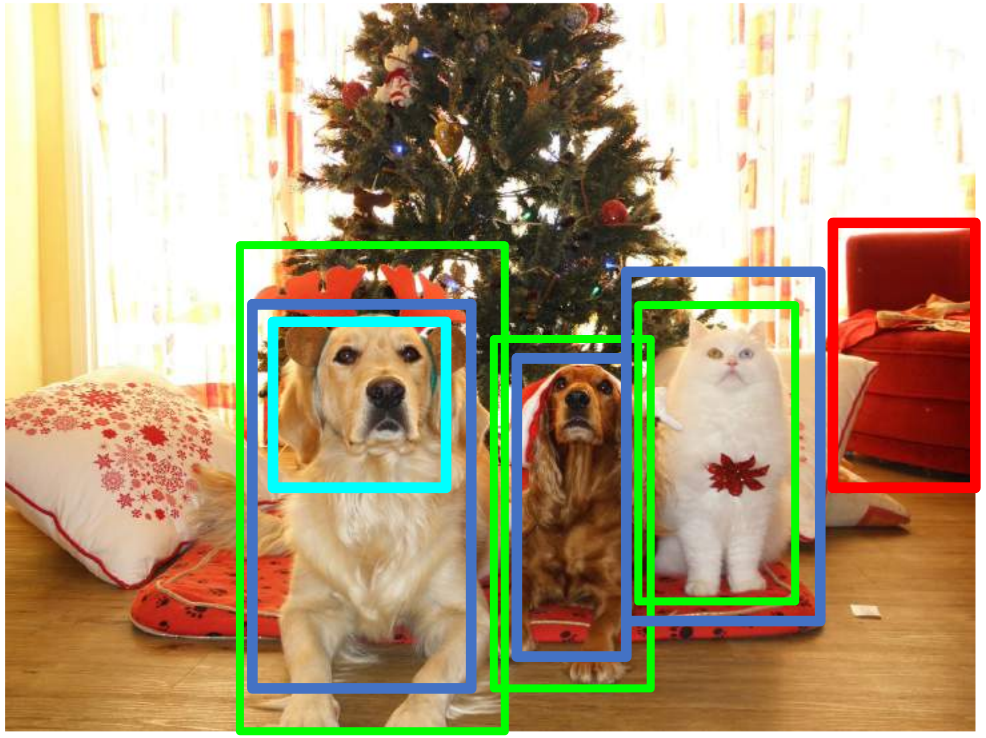
”Slow” R-CNN Training

Input Image



GT Boxes

Positive

Neutral

Negative

Categorize each region proposal as positive, negative, or neutral based on overlap with ground-truth boxes

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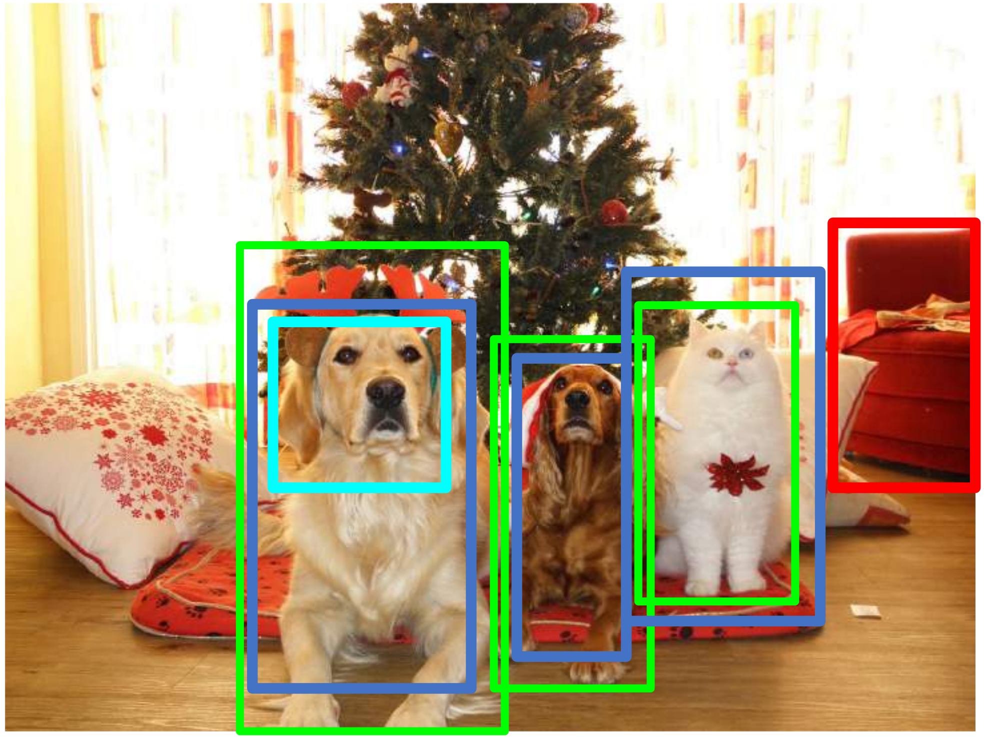
"Slow" R-CNN Training

Input Image

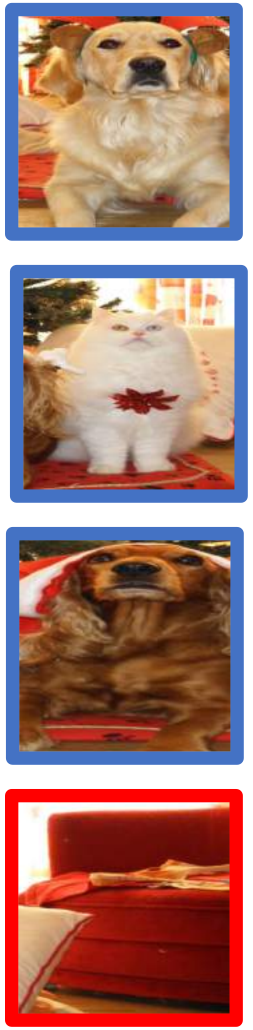


GT Boxes

Positive

Neutral

Negative



Crop pixels from each positive and negative proposal, resize to 224 x 224

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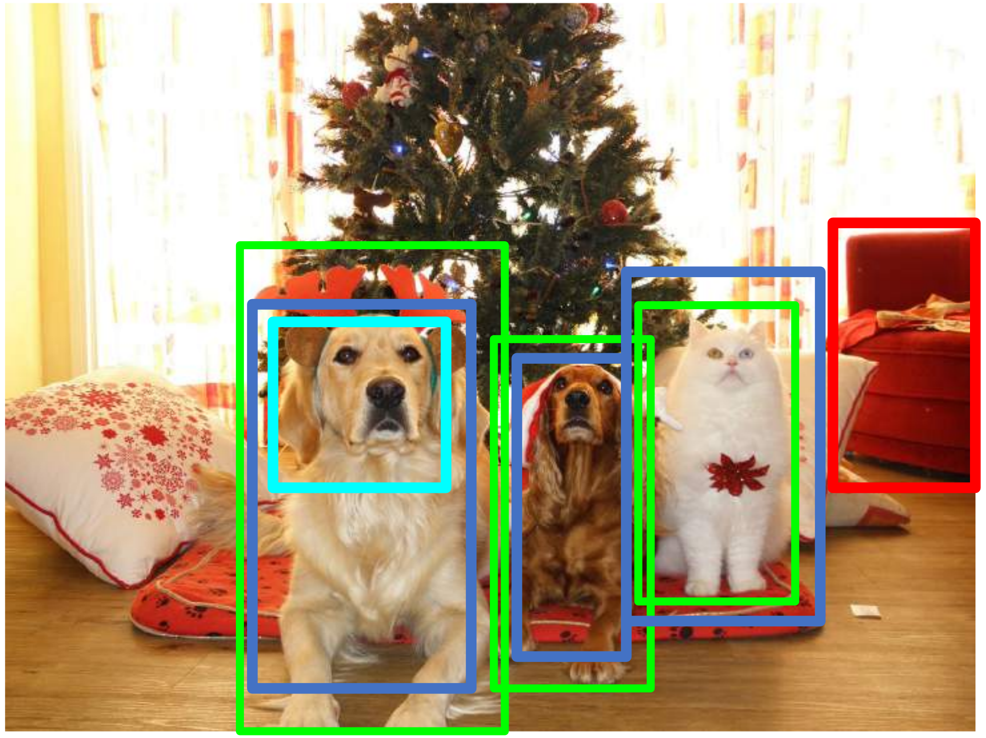
”Slow” R-CNN Training

Run each region through CNN. For positive boxes predict class and box offset; for negative boxes just predict background class

Input Image

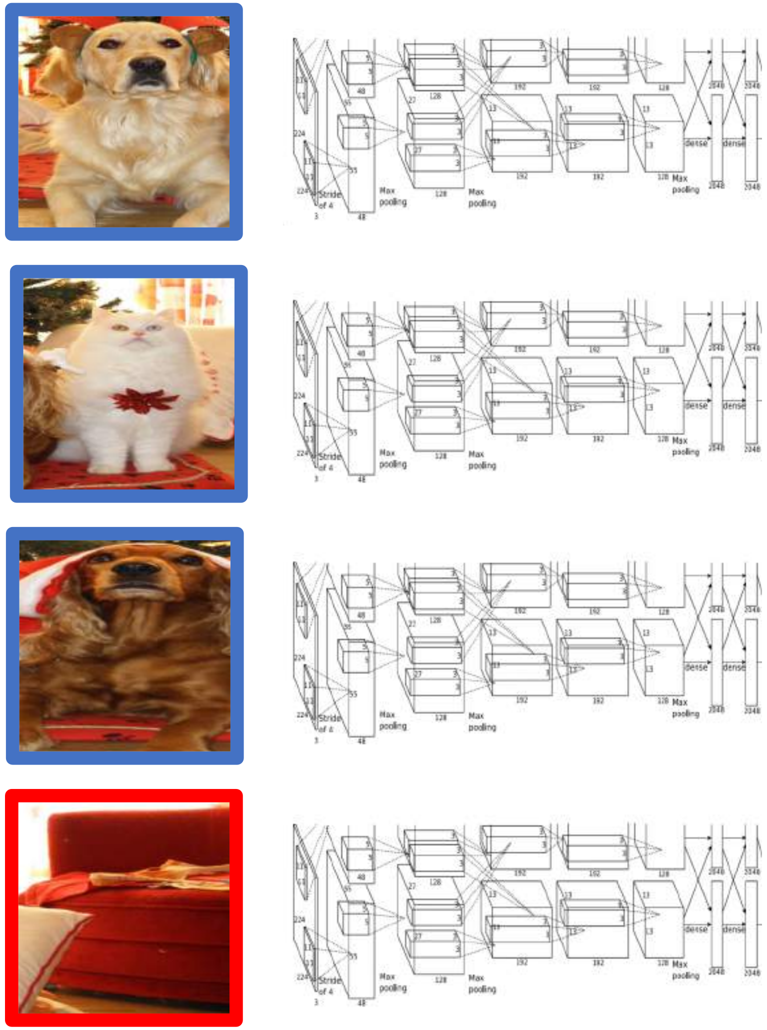


GT Boxes

Positive

Neutral

Negative



Class target: Dog

Box target:

Class target: Cat

Box target:

Class target: Dog

Box target:

Class target: Background

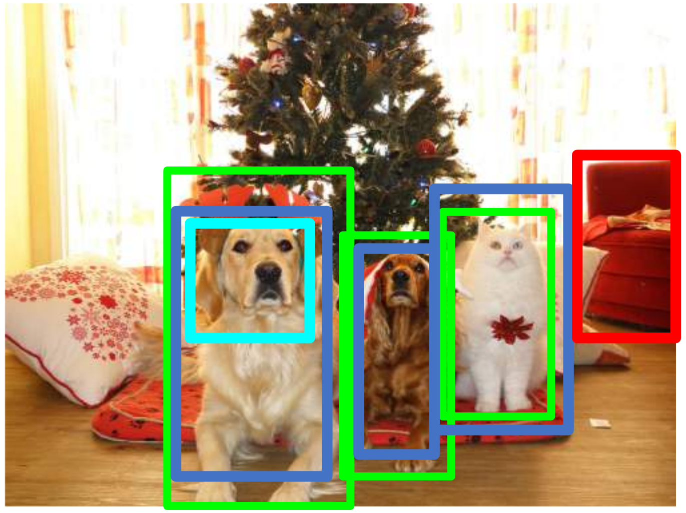
Box target: None

This image is CC0 public domain

Fast R-CNN Training

Crop features for each region, use them to predict class and box targets per region

Input Image



Backbone CNN

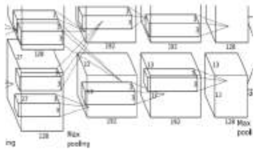
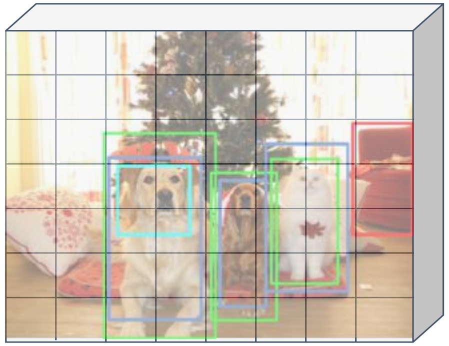
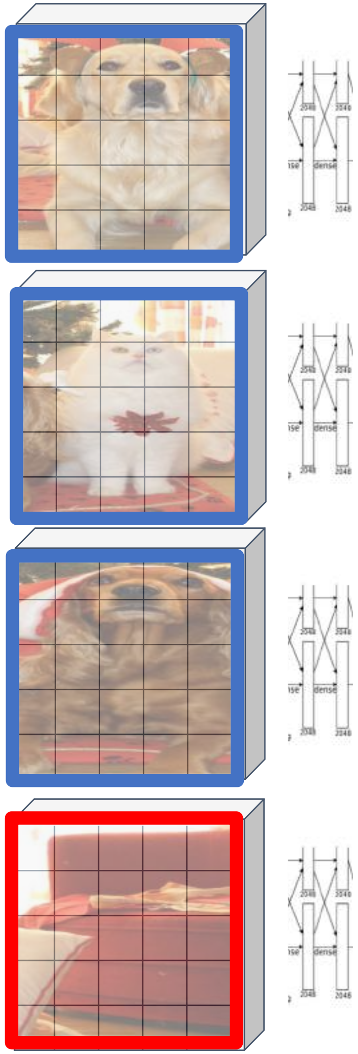


Image Features





Class target: Dog
Box target: →

Class target: Cat
Box target: →

Class target: Dog
Box target: →

Class target: Background
Box target: None

GT Boxes | Positive

Neutral | Negative

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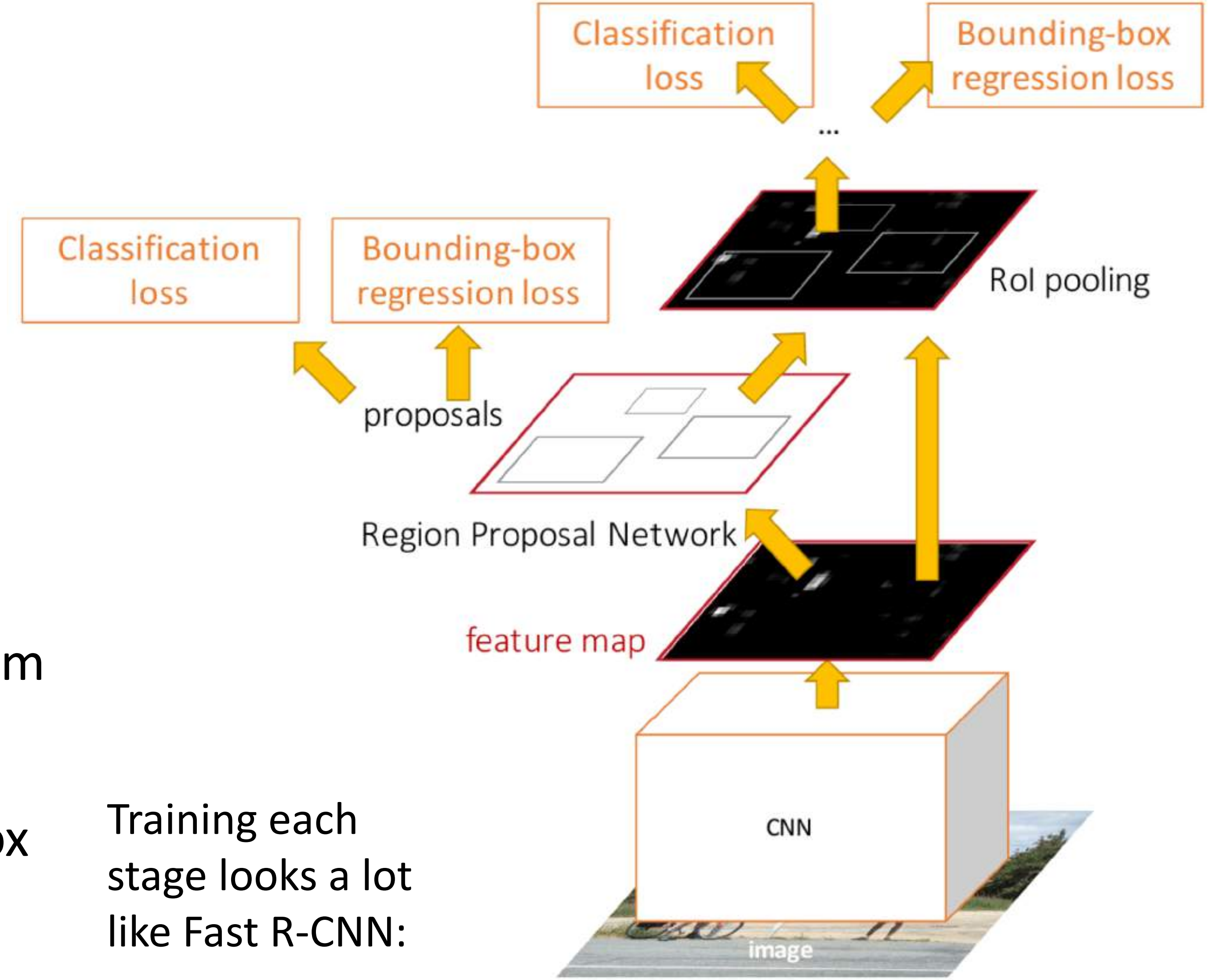
Faster R-CNN: Learnable Region Proposals

Jointly train with 4 losses:

1. **RPN classification**: anchor box is object / not an object
2. **RPN regression**: predict transform from anchor box to proposal box
3. **Object classification**: classify proposals as background / object class
4. **Object regression**: predict transform from proposal box to object box



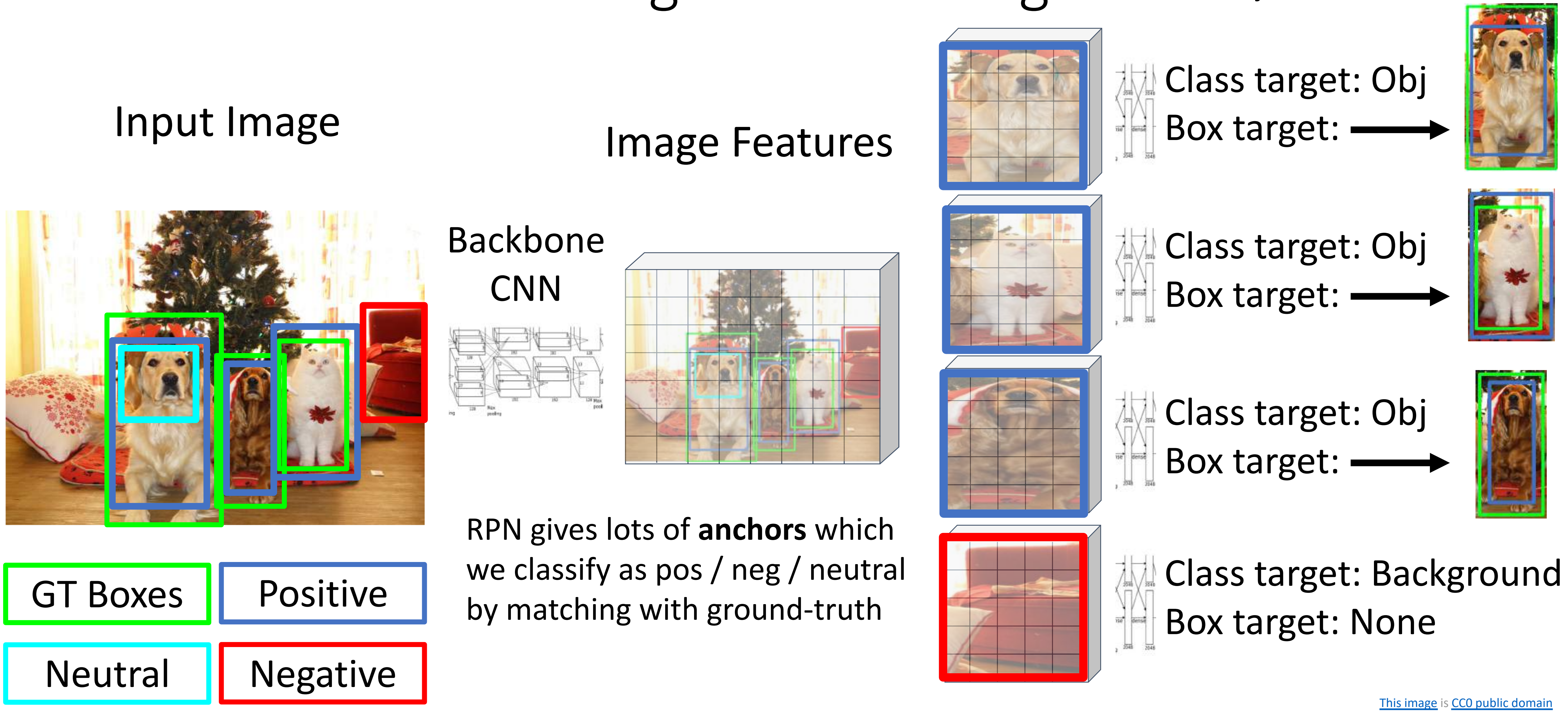
Anchor -> Region Proposal -> Object Box

(Stage 1) (Stage 2)

Training each stage looks a lot like Fast R-CNN:

Faster R-CNN Training: RPN Training

RPN predicts Object / Background for each anchor, as well as regresses from anchor to object box



RPN gives lots of **anchors** which we classify as pos / neg / neutral by matching with ground-truth

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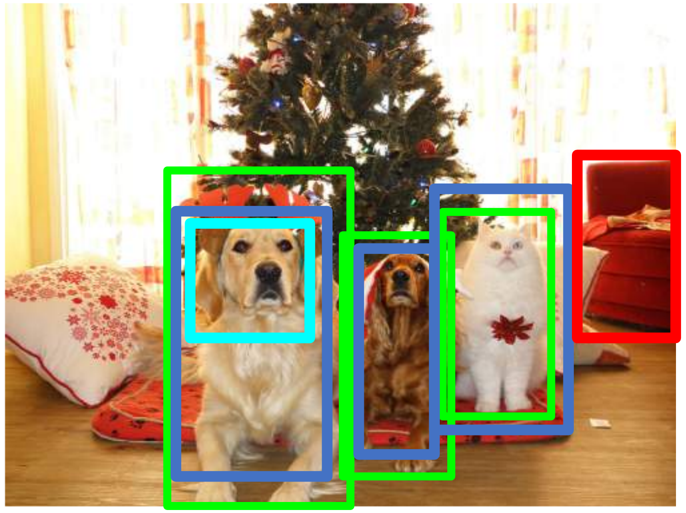
Faster R-CNN Training: Stage 2

Crop features for each proposal, use them to predict class and box targets per region

Input Image



GT Boxes | Positive | Neutral | Negative

Backbone CNN

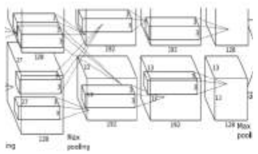
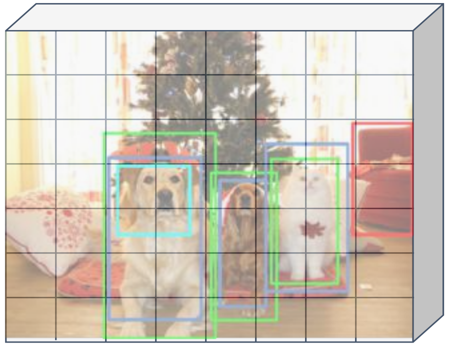
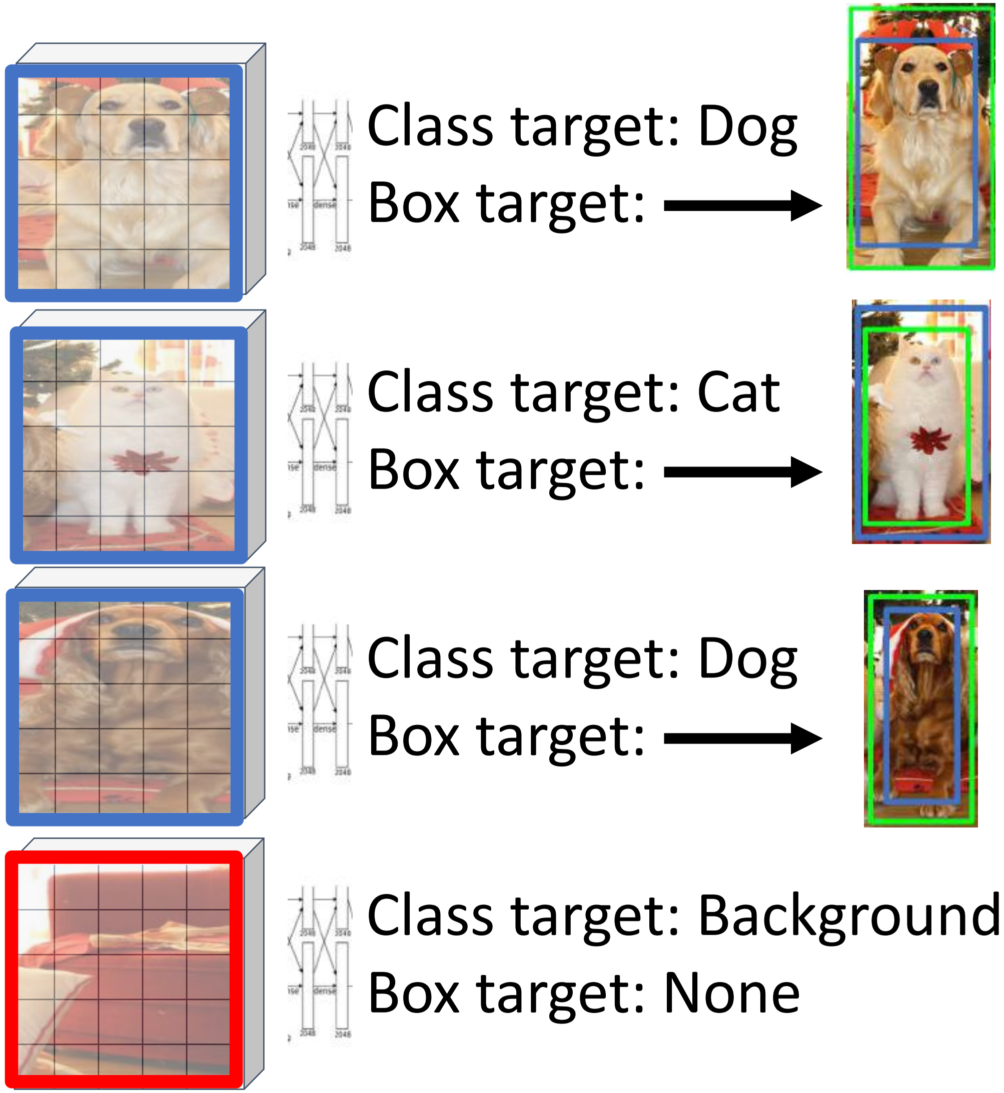


Image Features





Now proposals come from RPN rather than selective search, but otherwise this works the same as Fast R-CNN training

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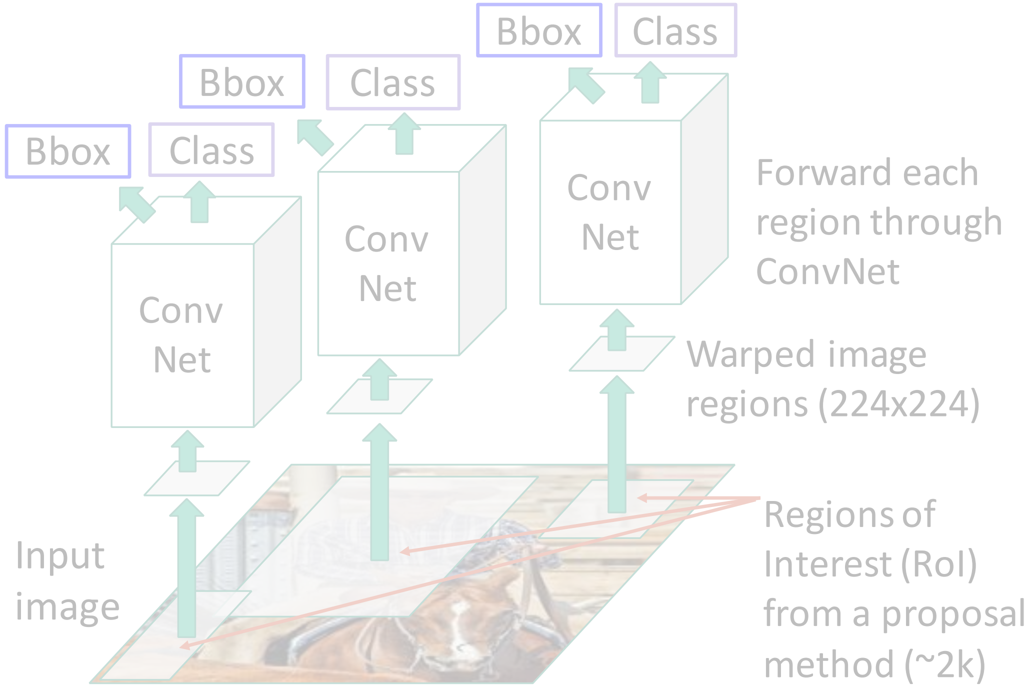
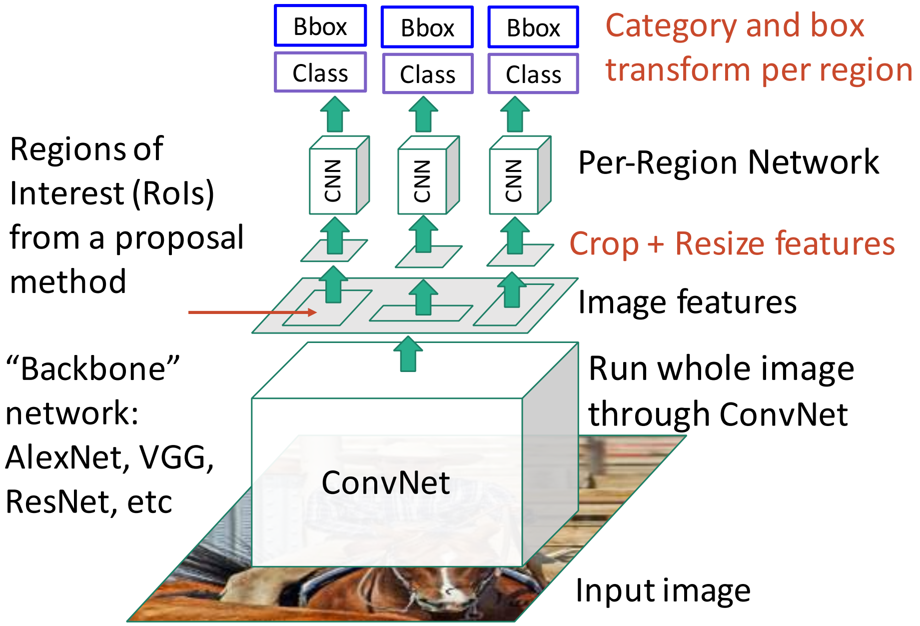
Recap: Fast R-CNN Feature Cropping

"Slow" R-CNN: Run CNN independently for each region

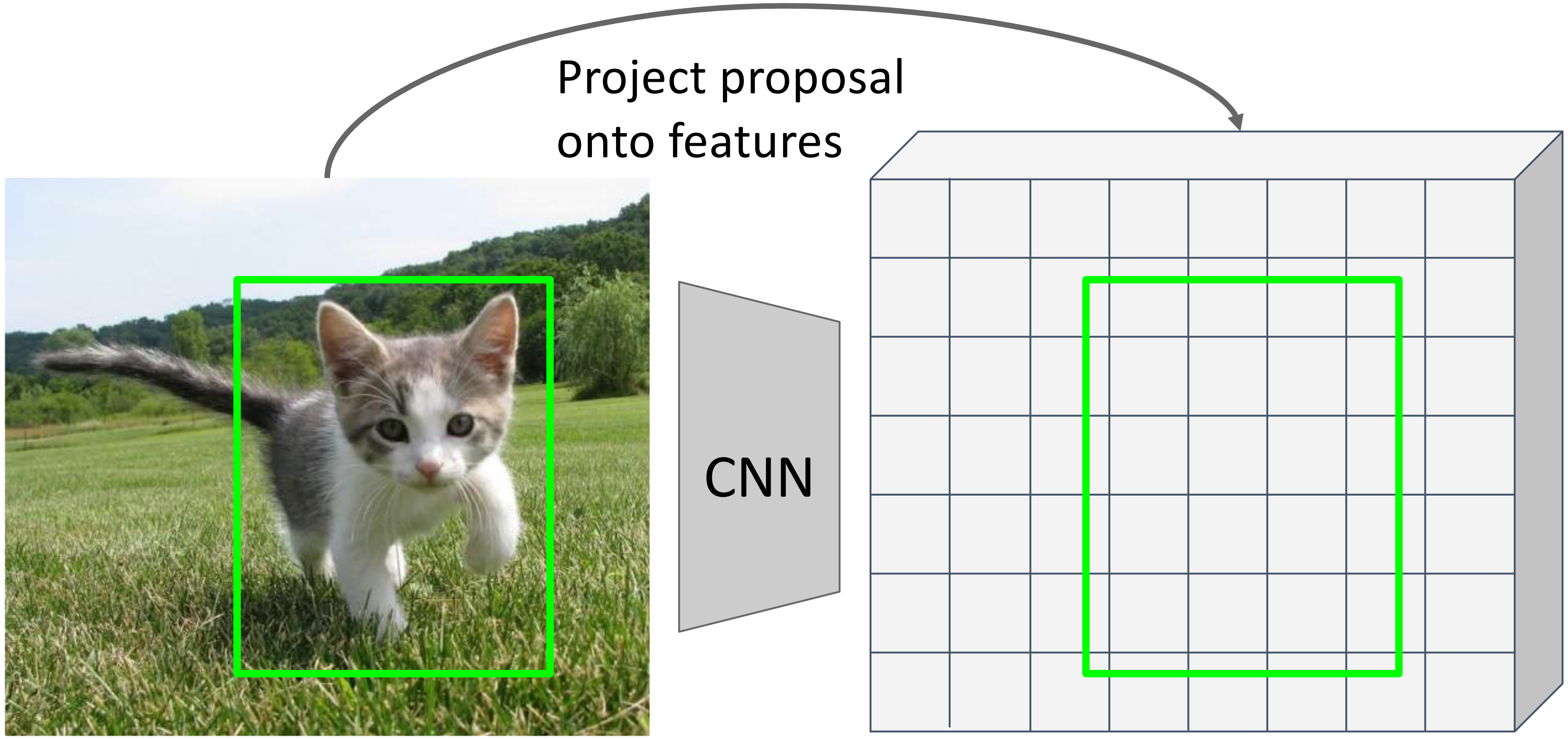


Fast R-CNN: Apply differentiable cropping to shared image features



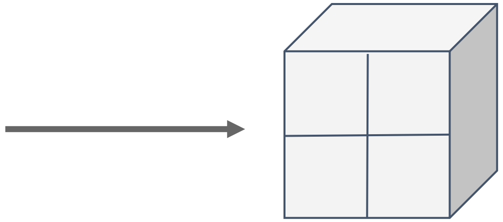
Cropping Features

Goal: Crop features for region proposal, and resize to a fixed size for downstream processing, in a differentiable way



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

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



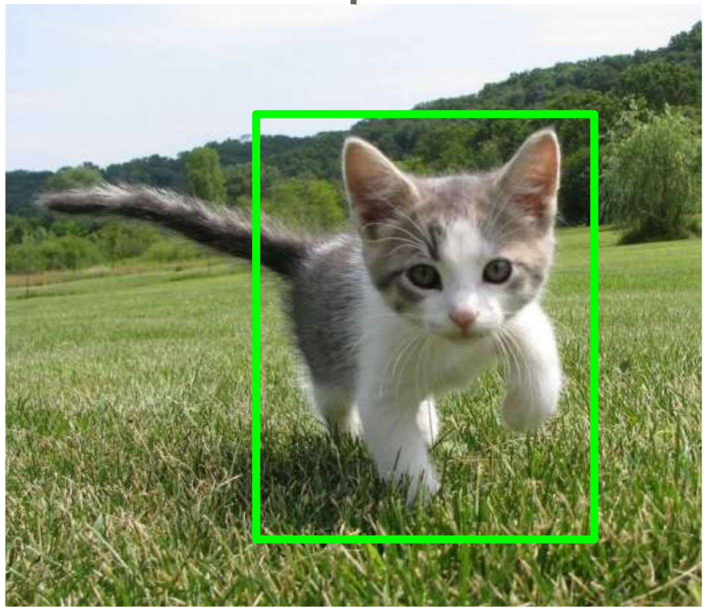
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool

Project proposal
onto features

"Snap" to grid cells



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

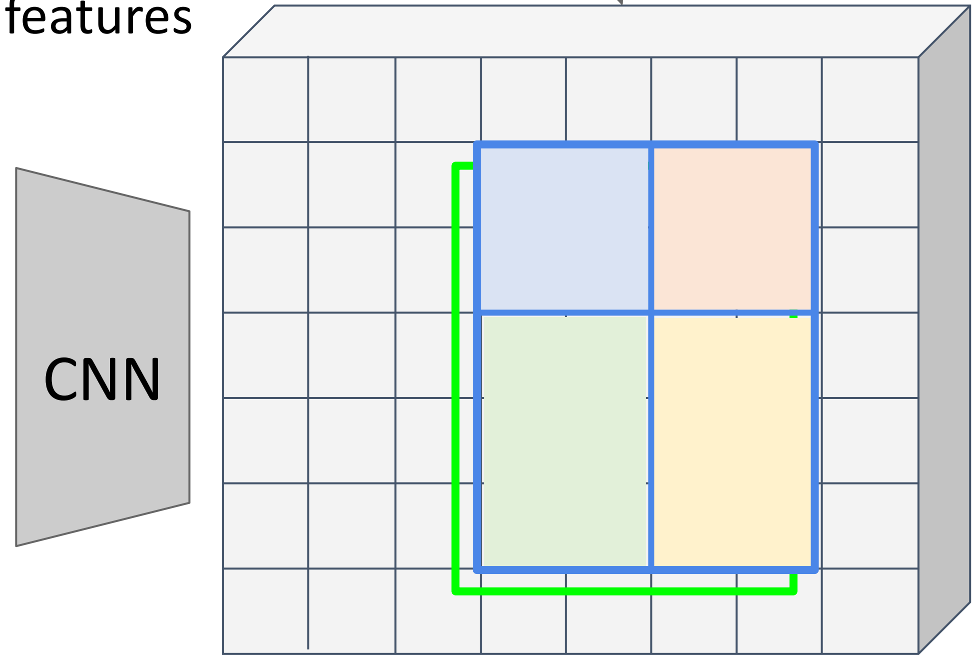
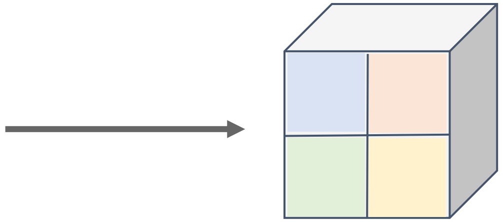


Image features
(e.g. 512 x 20 x 15)

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!

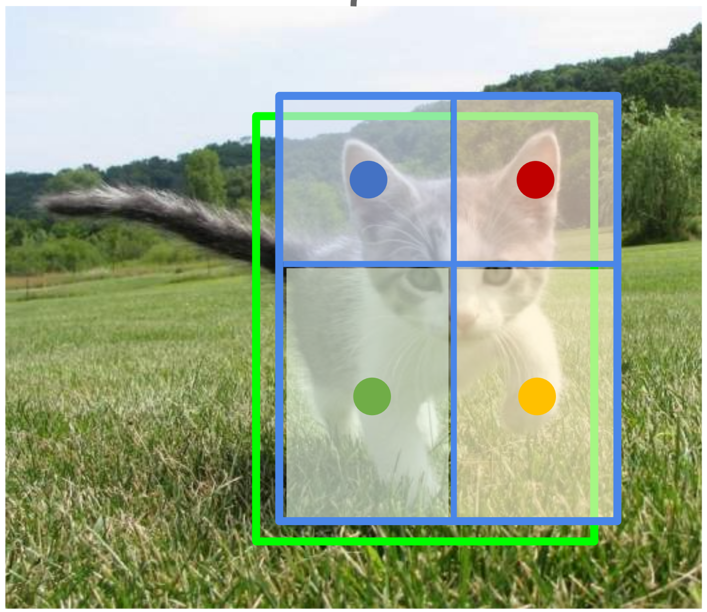
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool

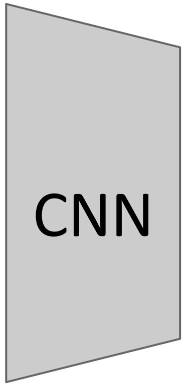
Divide into 2x2 grid of (roughly) equal subregions

Project proposal onto features

"Snap" to grid cells



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



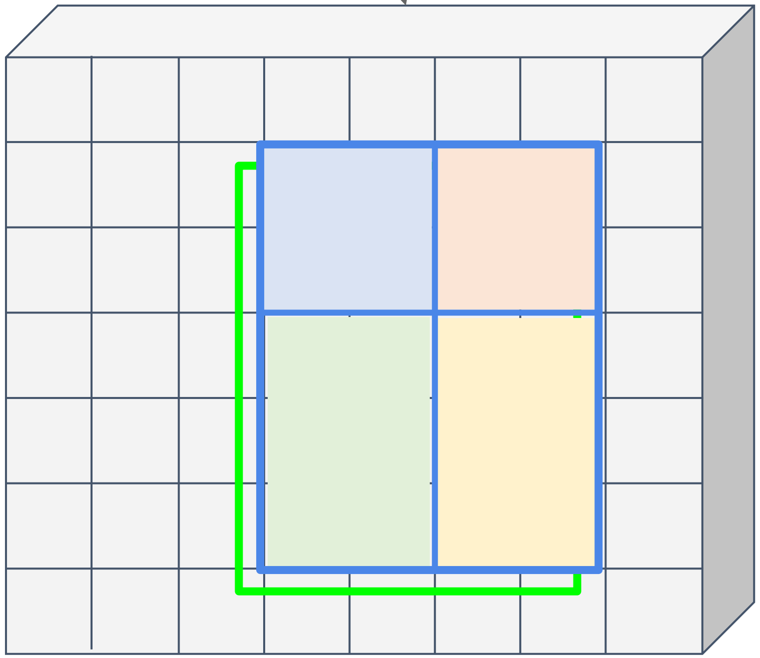
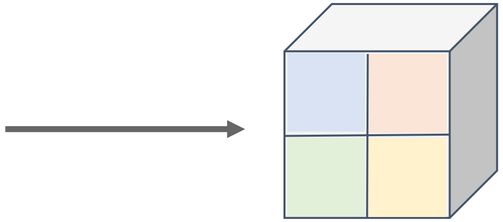


Image features
(e.g. 512 x 20 x 15)

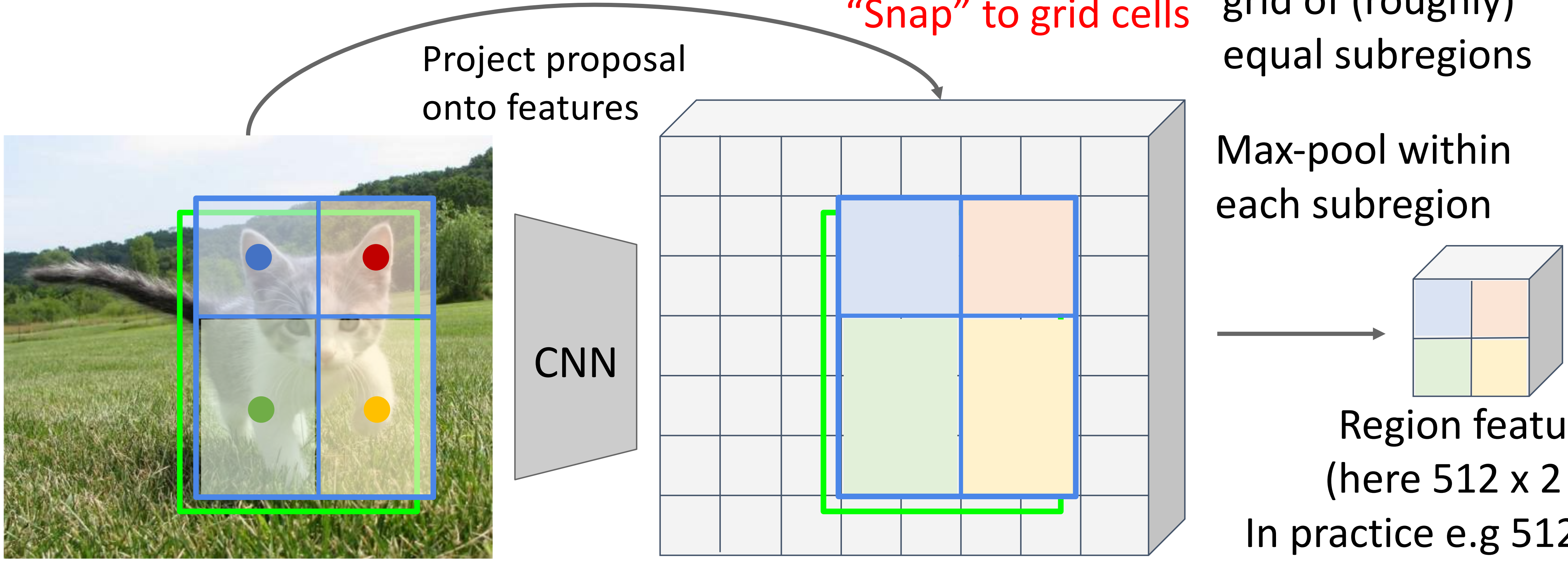
Max-pool within each subregion



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

Problem #1: Misaligned features due to snapping

Cropping Features: RoI Pool



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

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

Region Features = f(image features, box coordinates)

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)

Problem #1: Misaligned features due to snapping

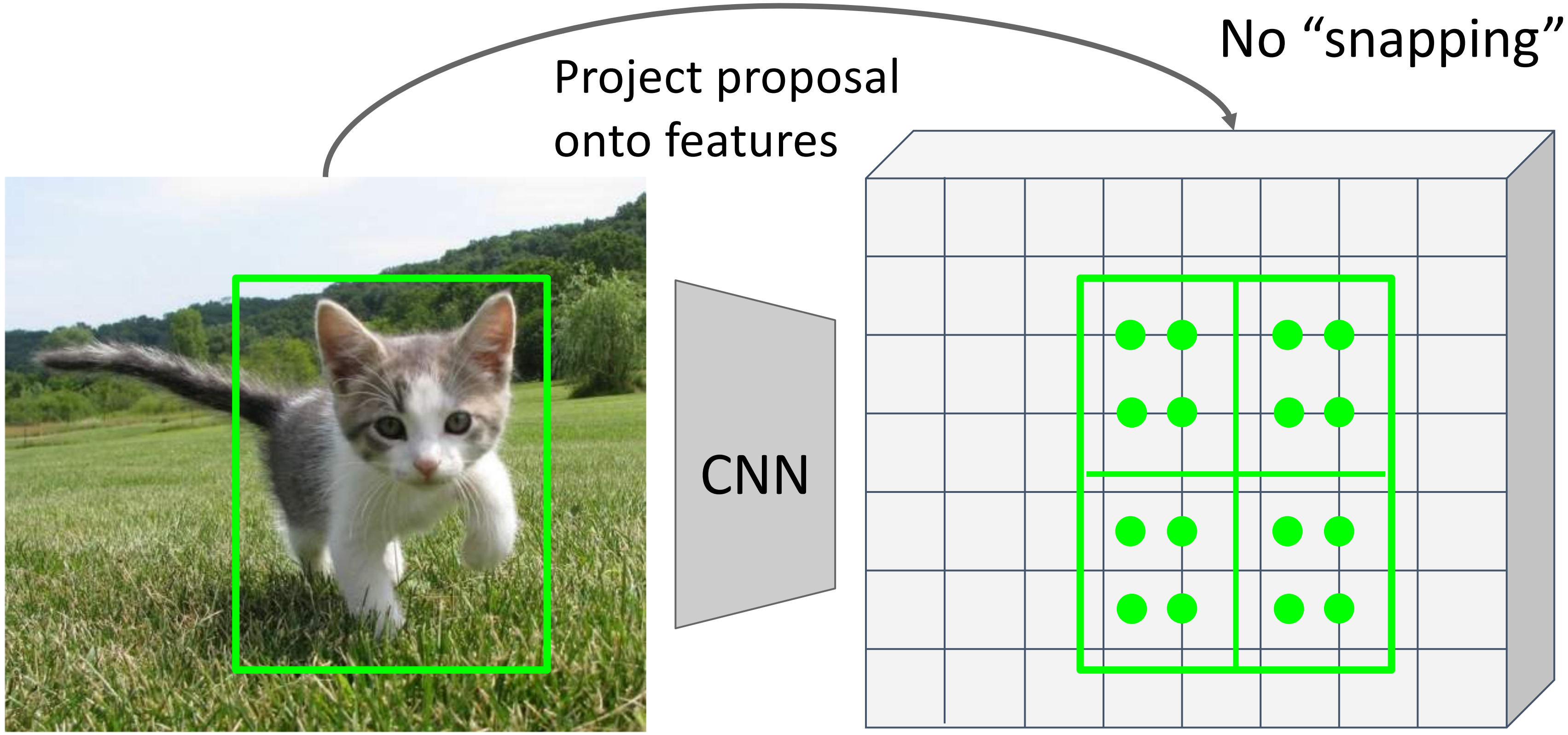
Problem #2: Can't backprop to box coordinates

Cropping Features: RoI Align

Divide into equal-sized subregions (may not be aligned to grid!)

No “snapping”!

Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



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

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

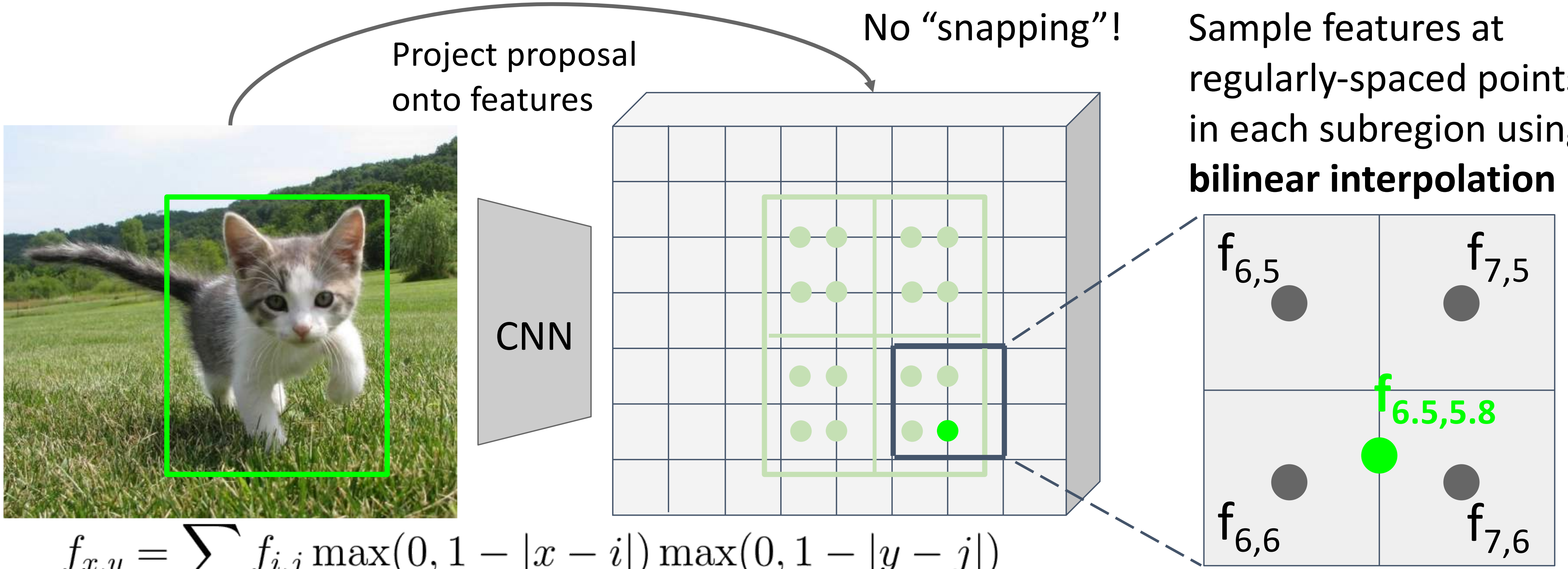
He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

Divide into equal-sized subregions (may not be aligned to grid!)

No "snapping"!

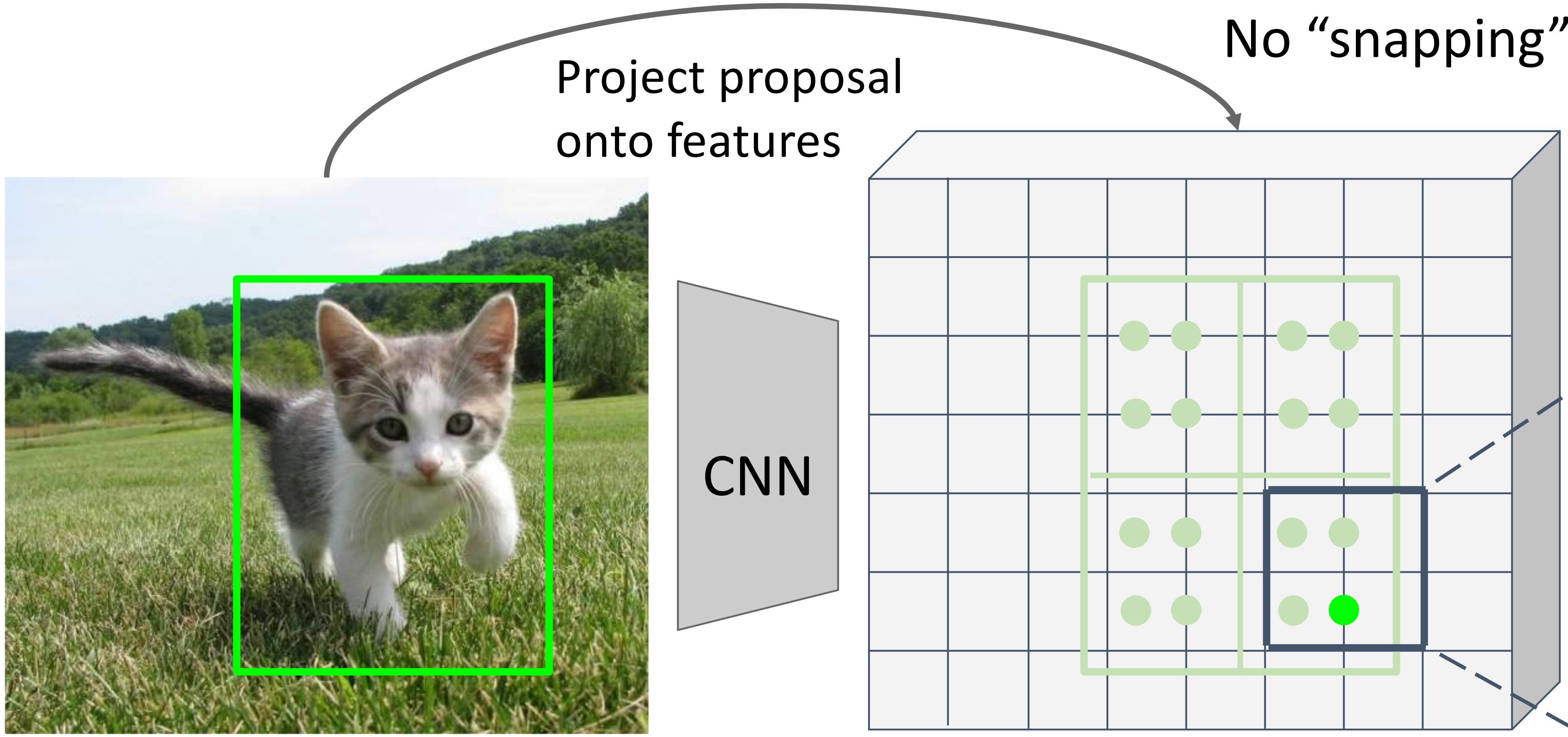
Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



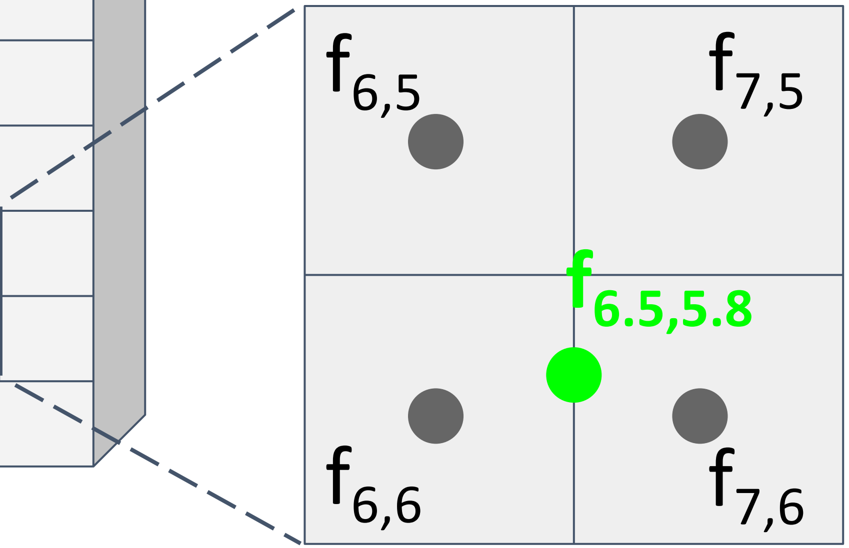
$$f_{x,y} = \sum_{i,j} f_{i,j} \max(0, 1-|x-i|) \max(0, 1-|y-j|)$$
$$i \in \{\lfloor x \rfloor - 1, \dots, \lceil x \rceil + 1\}$$
$$j \in \{\lfloor y \rfloor - 1, \dots, \lceil y \rceil + 1\}$$

Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align



Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



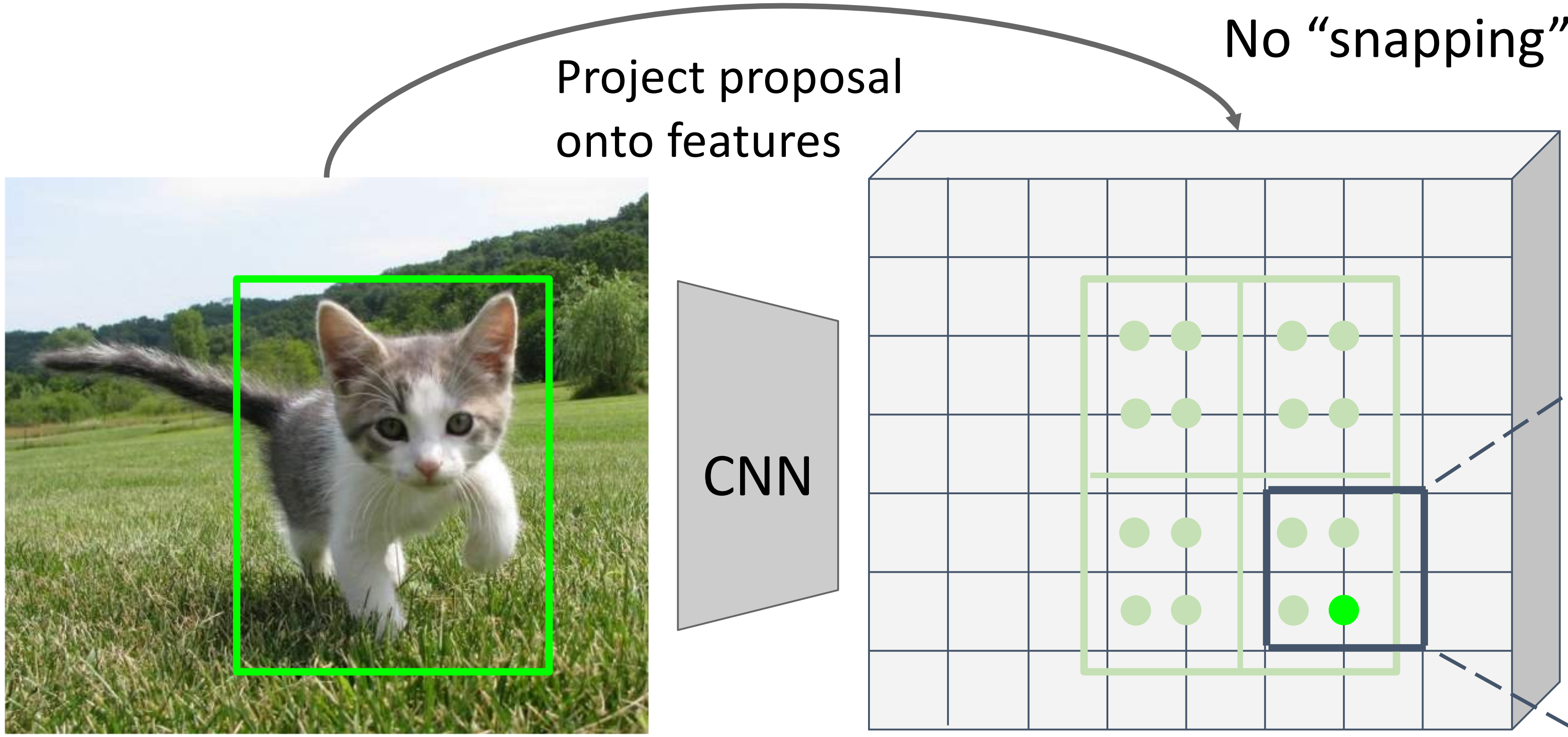
$$f_{x,y} = \sum f_{i,j} \max(0, 1 - |x - i|) \max(0, 1 - |y - j|)$$

$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

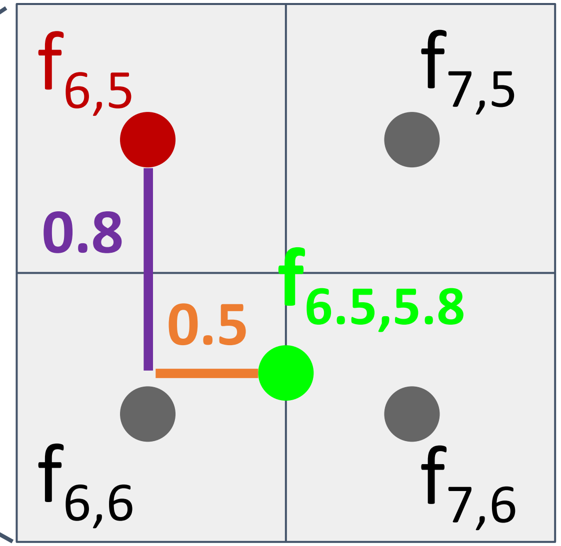
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align

Divide into equal-sized subregions (may not be aligned to grid!)



Sample features at regularly-spaced points in each subregion using **bilinear interpolation**

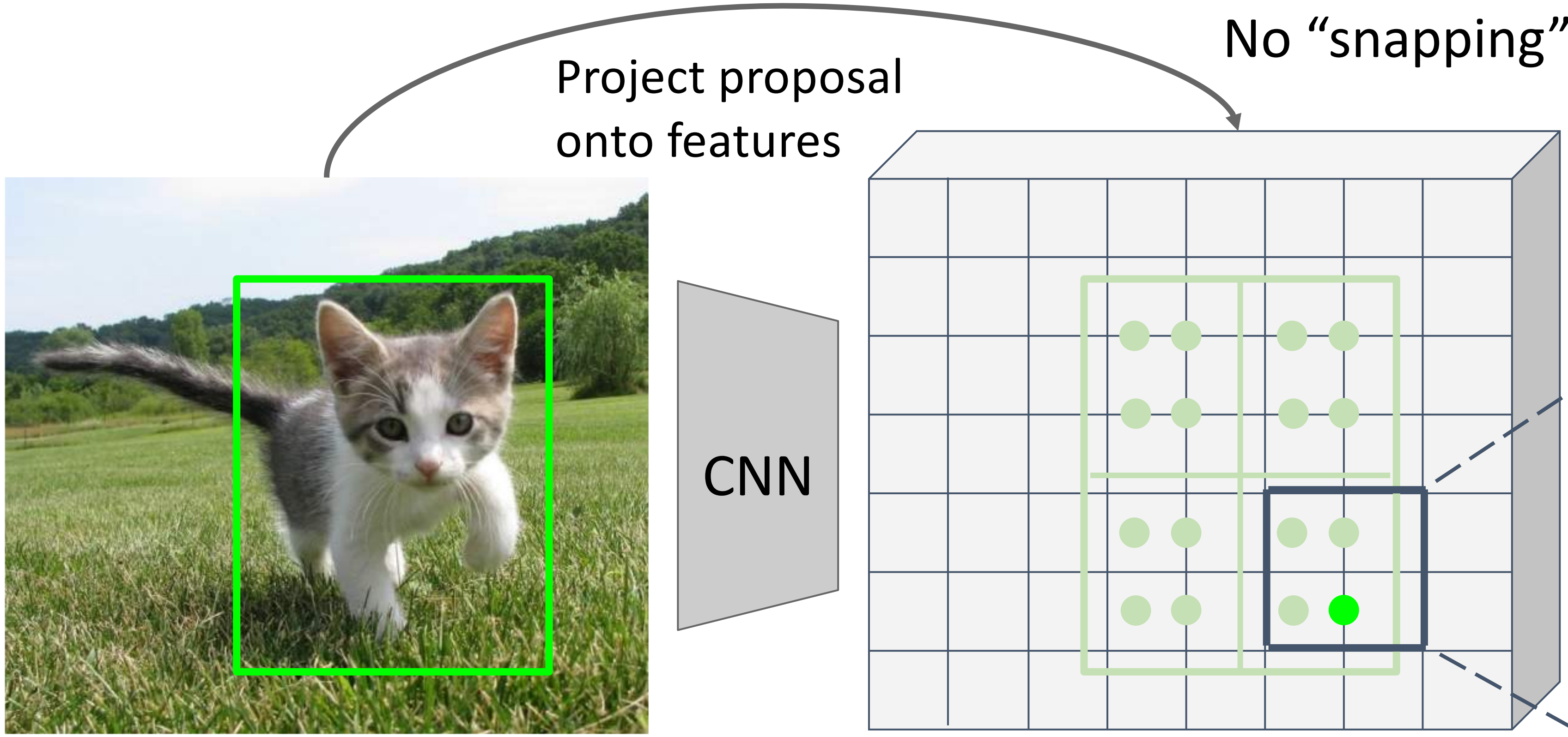


$$f_{x,y} = \sum \boxed{f_{i,j}} \boxed{\max(0, 1 - |x - i|)} \boxed{\max(0, 1 - |y - j|)}$$

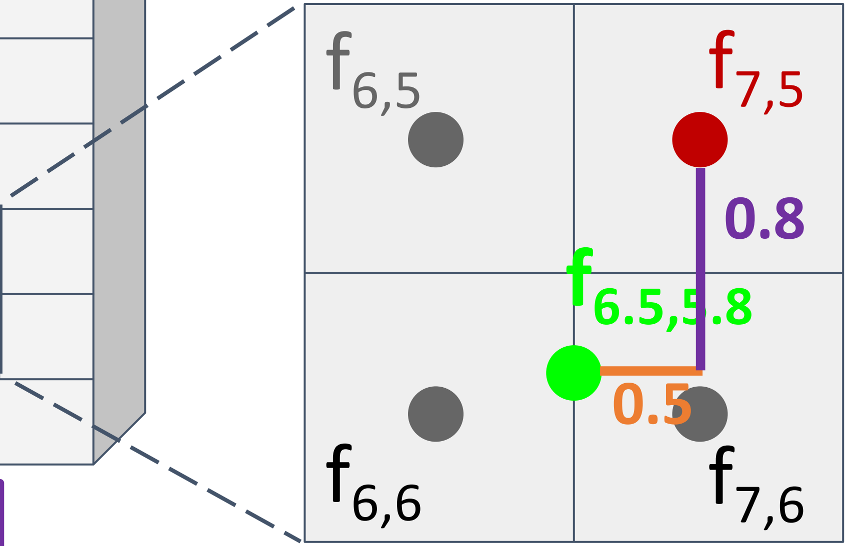
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align



Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



$$f_{x,y} = \sum \boxed{f_{i,j}} \boxed{\max(0, 1 - |x - i|)} \boxed{\max(0, 1 - |y - j|)}$$

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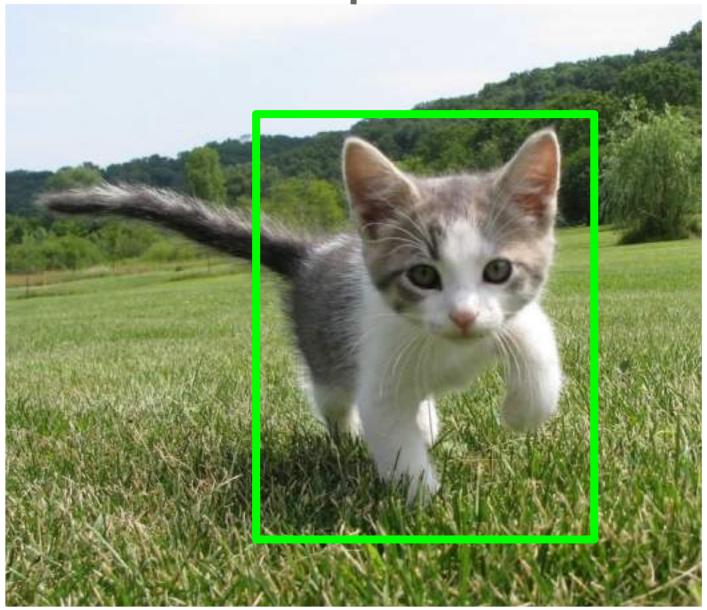
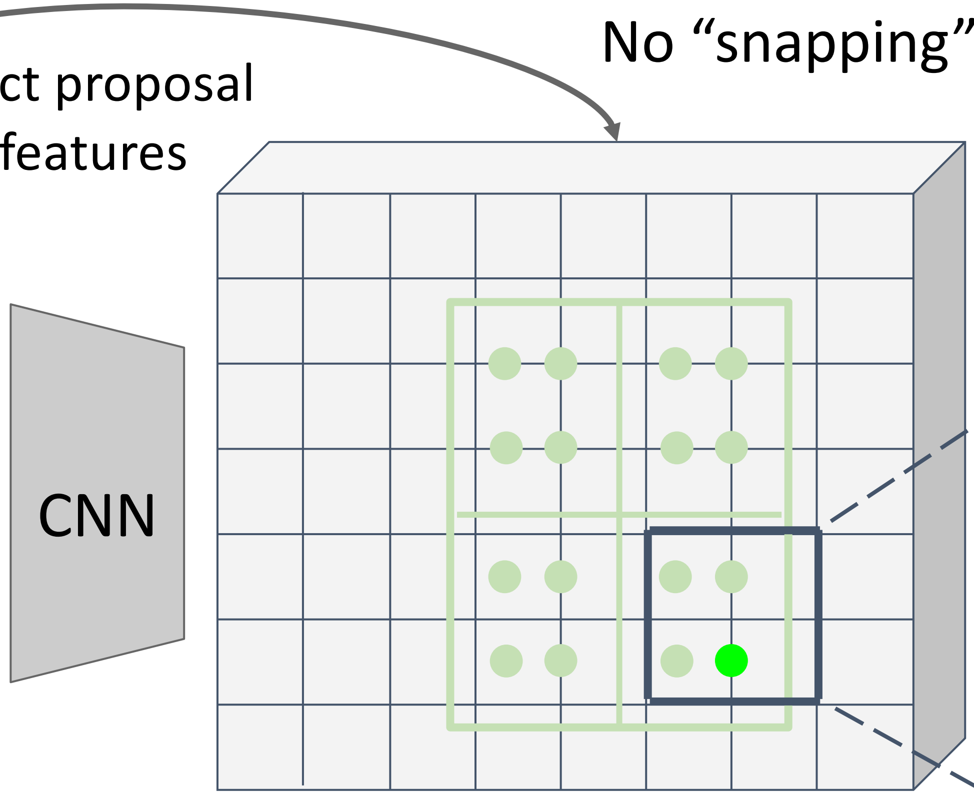
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

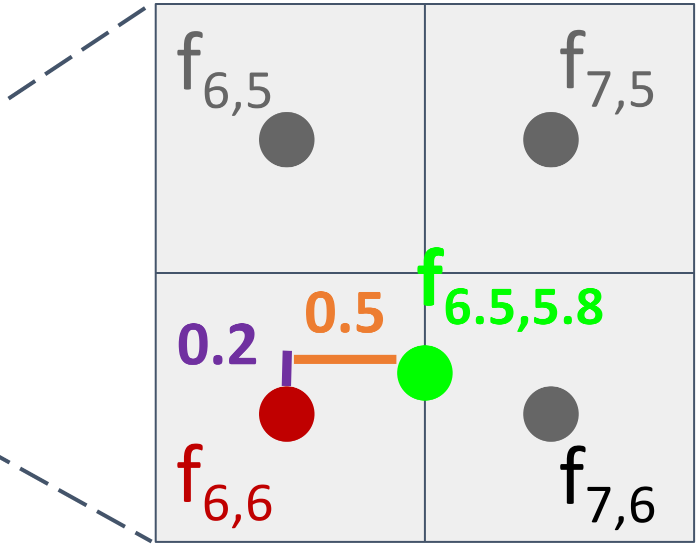
Cropping Features: RoI Align

Divide into equal-sized subregions (may not be aligned to grid!)





Sample features at regularly-spaced points in each subregion using **bilinear interpolation**

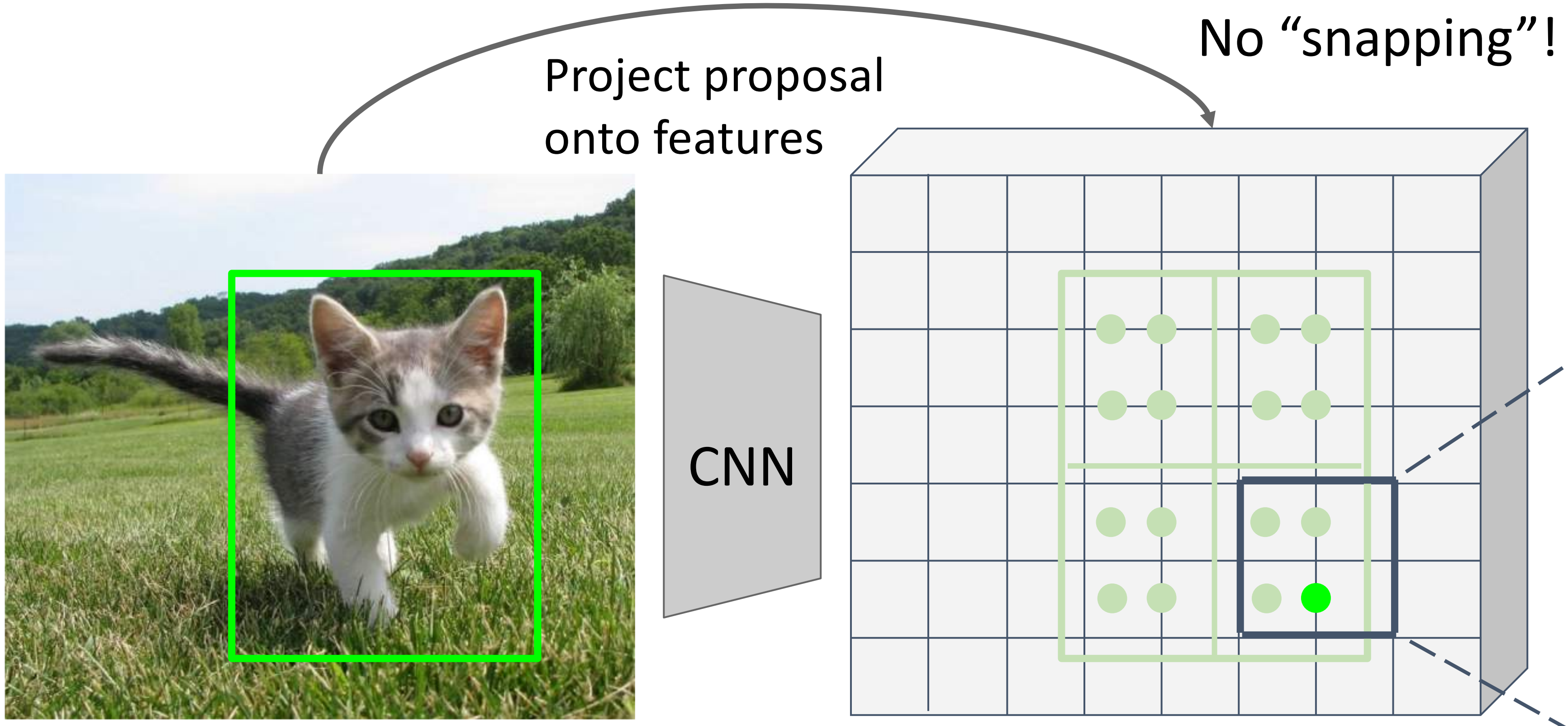


$$f_{x,y} = \sum \boxed{f_{i,j}} \boxed{\max(0, 1 - |x - i|)} \boxed{\max(0, 1 - |y - j|)}$$

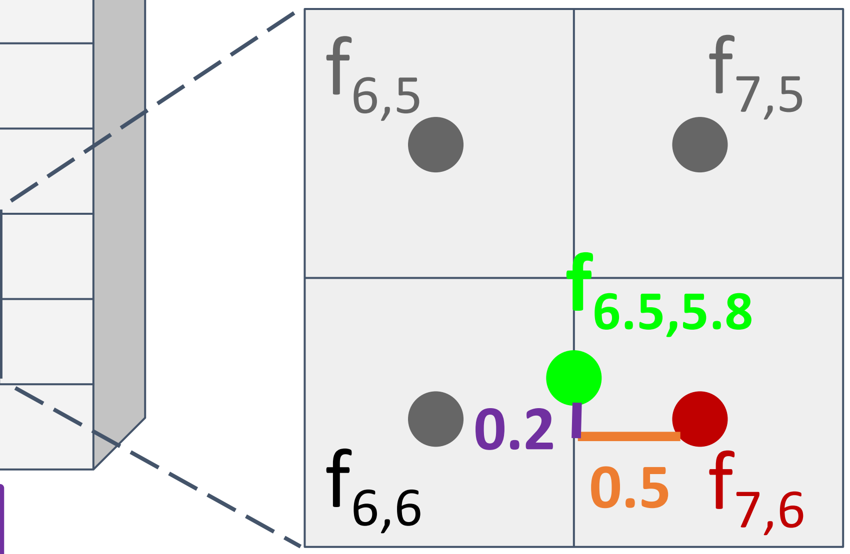
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align



Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



$$f_{x,y} = \sum \boxed{f_{i,j}} \boxed{\max(0, 1 - |x - i|)} \boxed{\max(0, 1 - |y - j|)}$$

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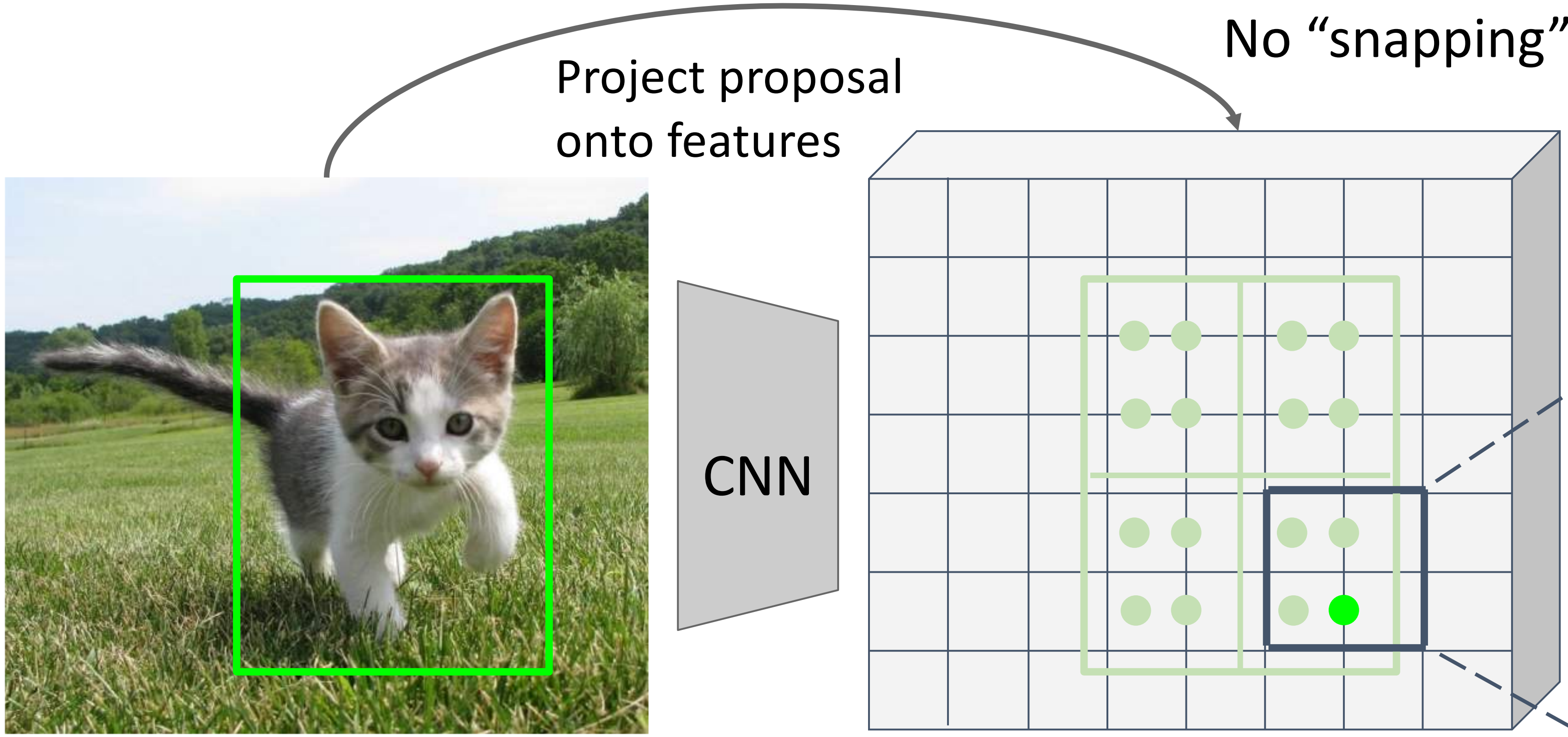
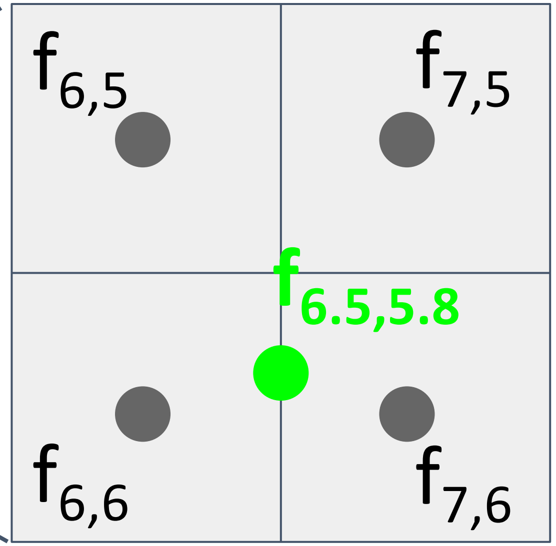
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align

Divide into equal-sized subregions (may not be aligned to grid!)



Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



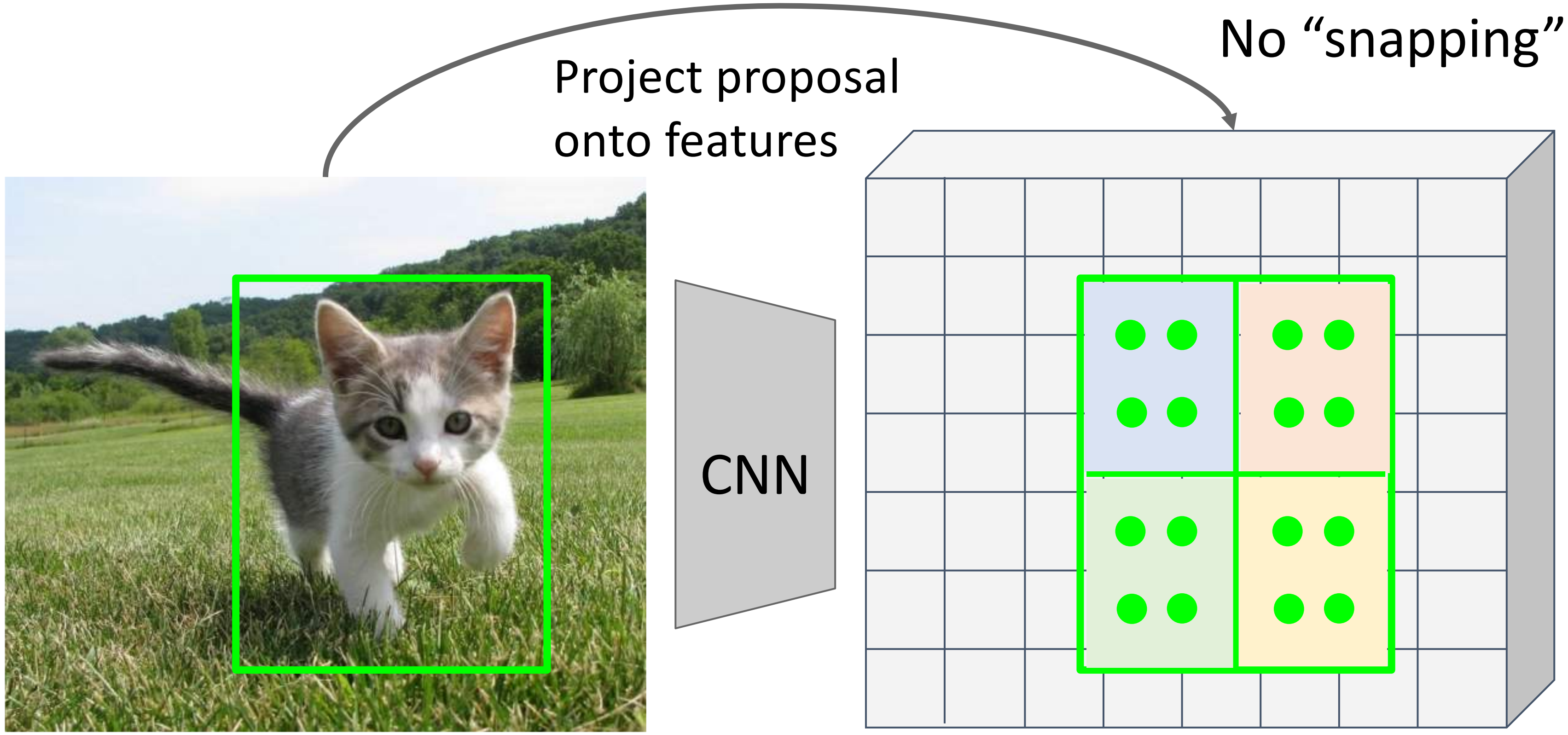
$$f_{x,y} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - i|) \max(0, 1 - |y - j|)$$

This is differentiable! Upstream gradient for sampled feature will flow backward into each of the four nearest-neighbor gridpoints

Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align

Divide into equal-sized subregions (may not be aligned to grid!)

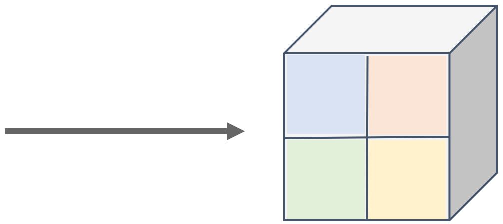


Input Image
(e.g. 3 x 640 x 480)

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

Sample features at regularly-spaced points in each subregion using **bilinear interpolation**

After sampling, max-pool in each subregion



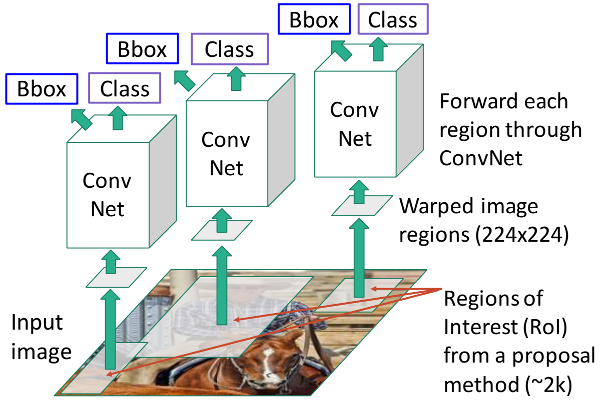
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

Output features now aligned to input box! And we can backprop to box coordinates!

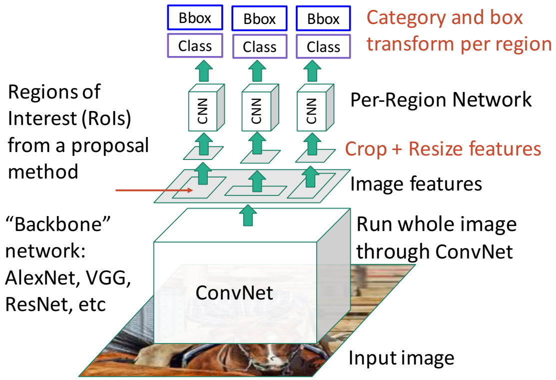
Object Detection Methods

Both of these rely on anchor boxes.
Can we do detection without anchors?

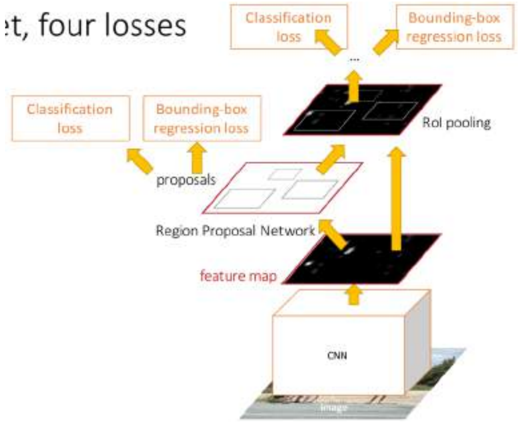
"Slow" R-CNN: Run CNN independently for each region



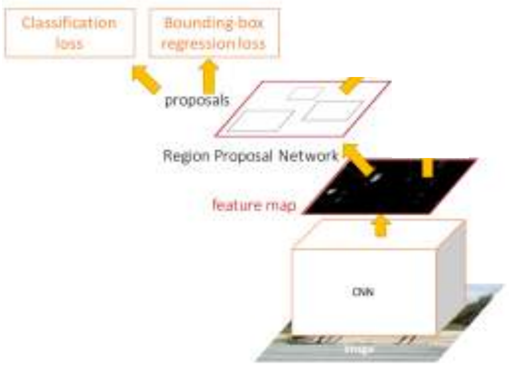
Fast R-CNN: Apply differentiable cropping to shared image features



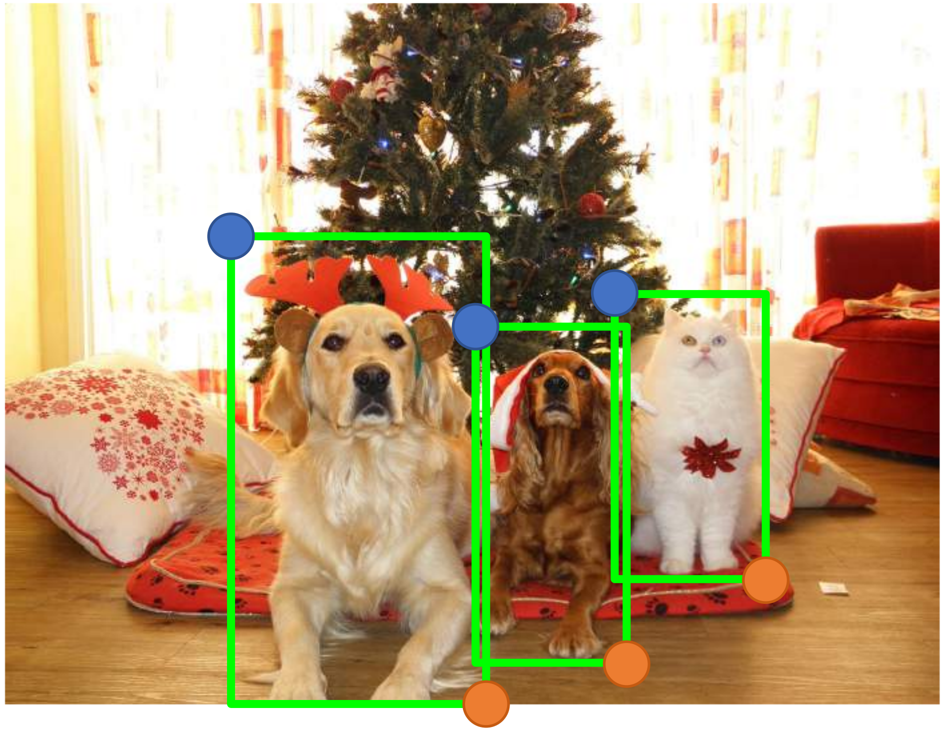
Faster R-CNN: Compute proposals with CNN



Single-Stage: Fully convolutional detector

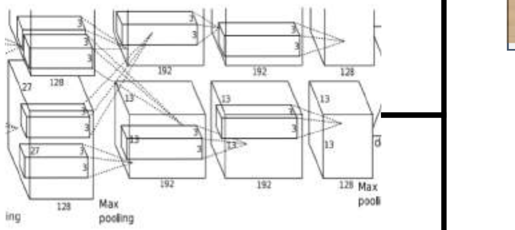


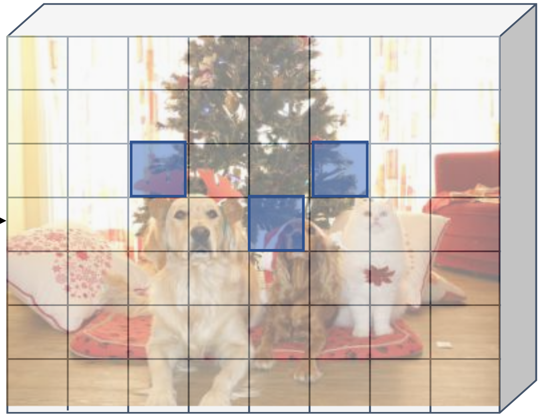
Detection without Anchors: CornerNet



Represent bounding boxes by pairs of corners

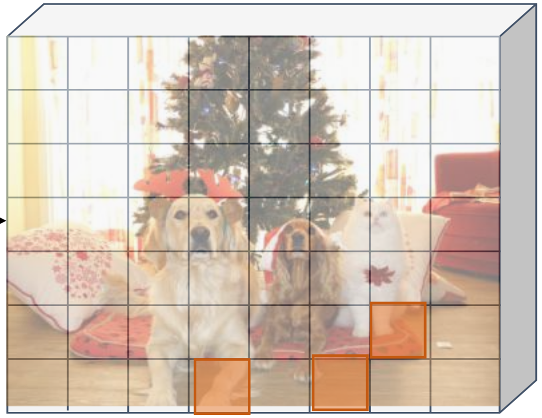
Backbone CNN





Upper left corners
Heatmap: C x H x W
Embeddings: D x H x W

Matching corners are trained to have similar embeddings



Lower right corners
Heatmap: C x H x W
Embeddings: D x H x W

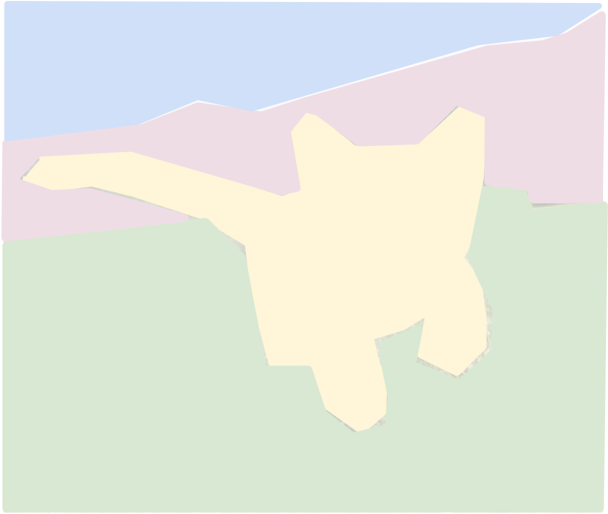
Law and Deng, “CornerNet: Detecting Objects as Paired Keypoints”, ECCV 2018

Computer Vision Tasks: Object Detection

Classification

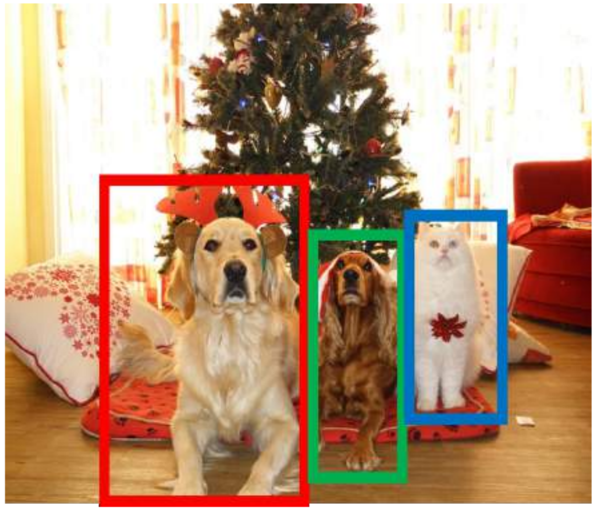
CAT

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

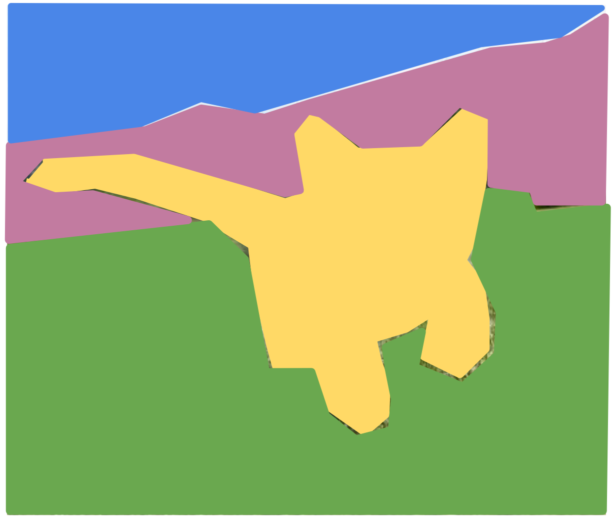
Computer Vision Tasks: Semantic Segmentation

Classification

CAT

No spatial extent

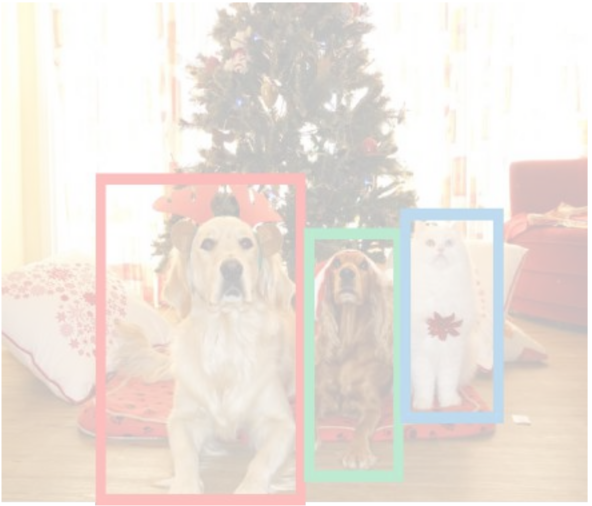
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

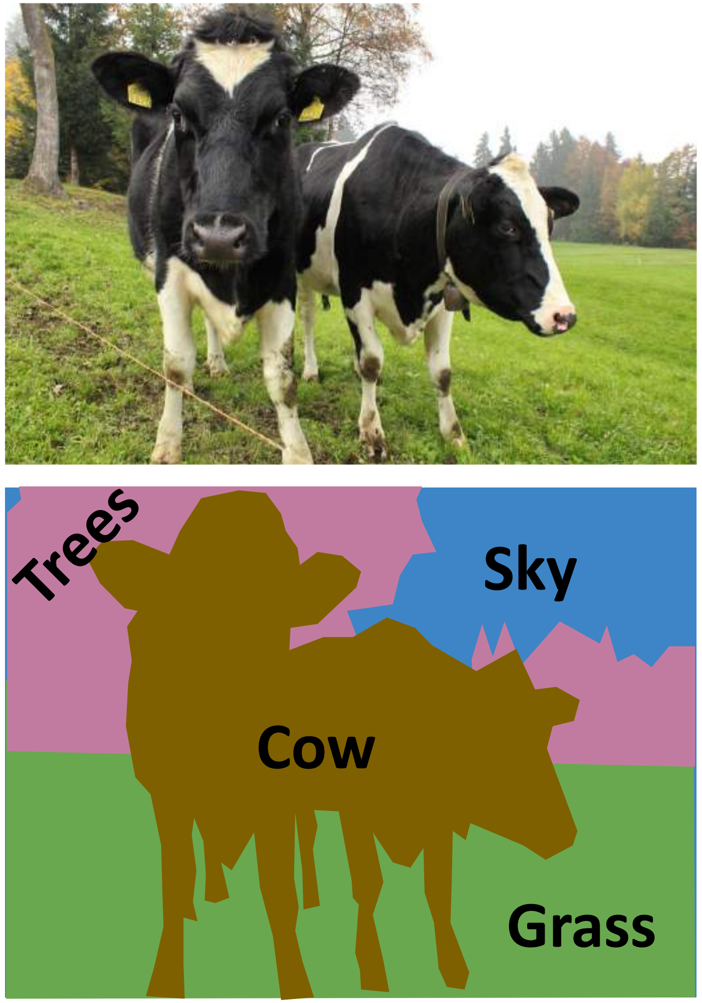
Multiple Objects

Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

This image is CC0 public domain

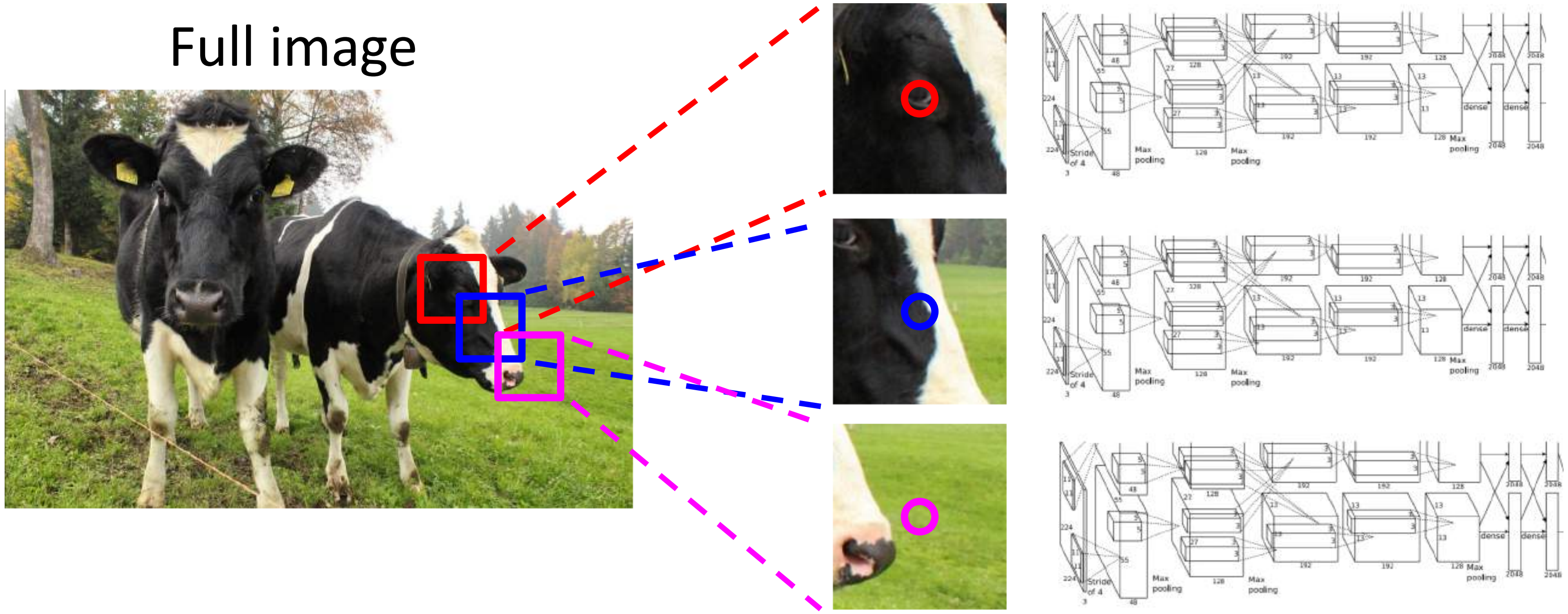


Semantic Segmentation Idea: Sliding Window

Full image

Extract patch

Classify center pixel with CNN



Cow

Cow

Grass

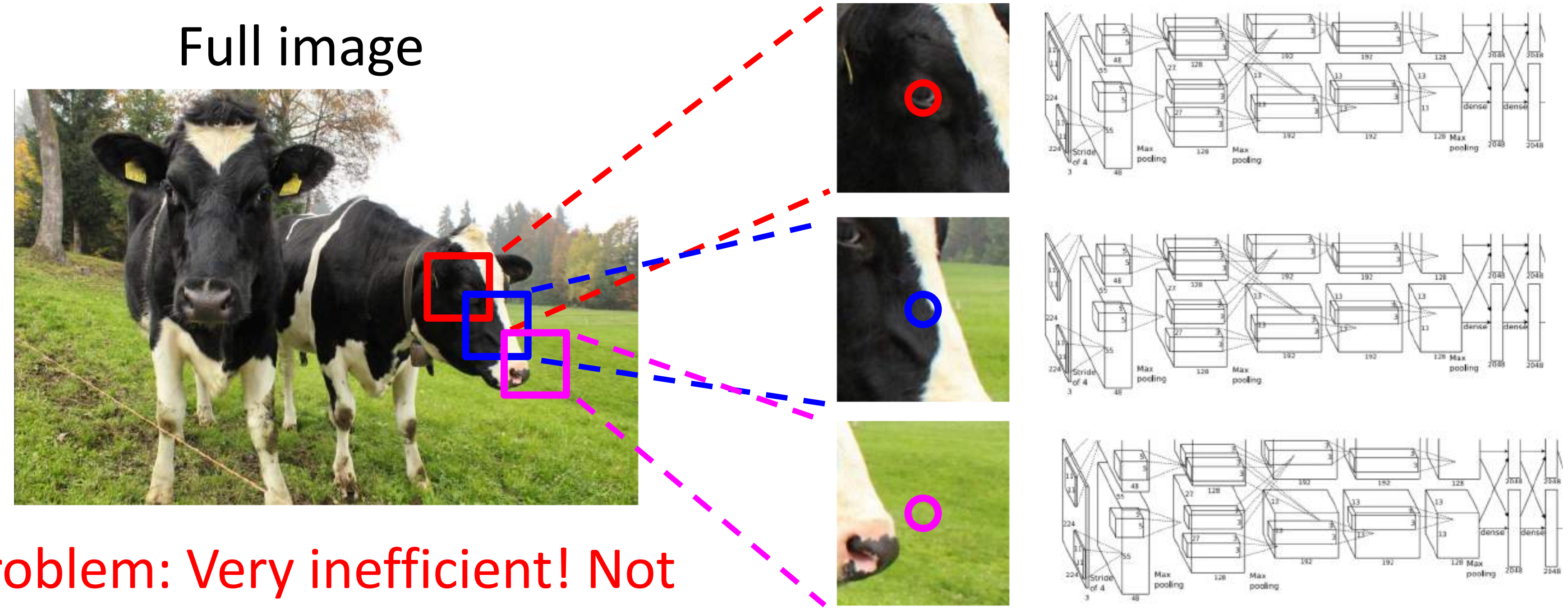
Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Semantic Segmentation Idea: Sliding Window

Full image

Extract patch

Classify center pixel with CNN

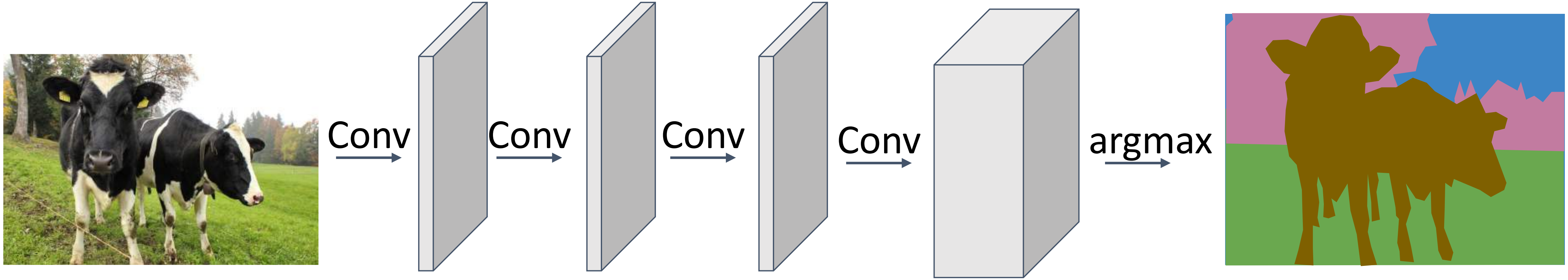


Problem: Very inefficient! Not reusing shared features between overlapping patches

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!



Input:
3 x H x W

Convolutions:
D x H x W

Scores:
C x H x W

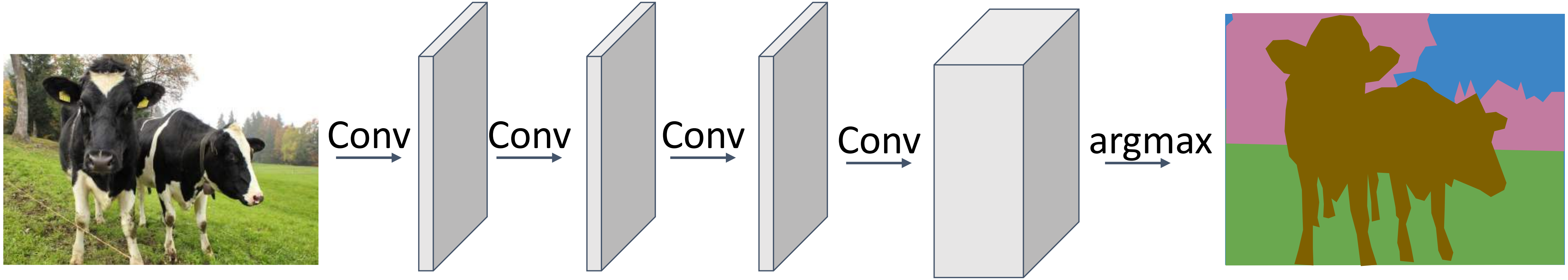
Predictions:
H x W

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!



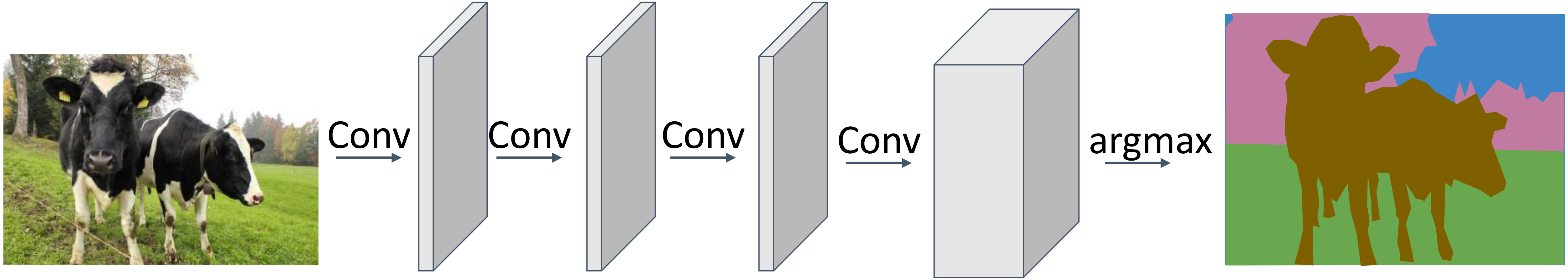
Input:
3 x H x W

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

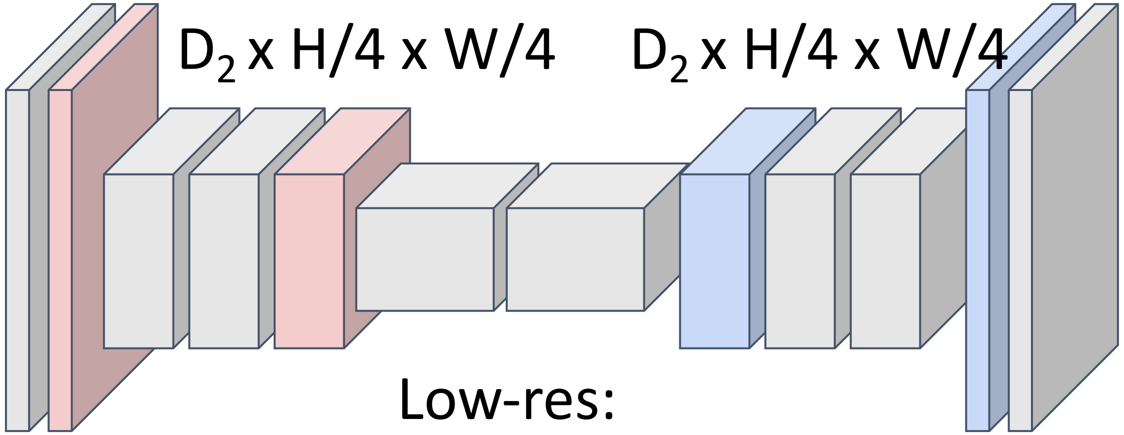
Semantic Segmentation: Fully Convolutional Network

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

Input:
3 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/4 x W/4

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

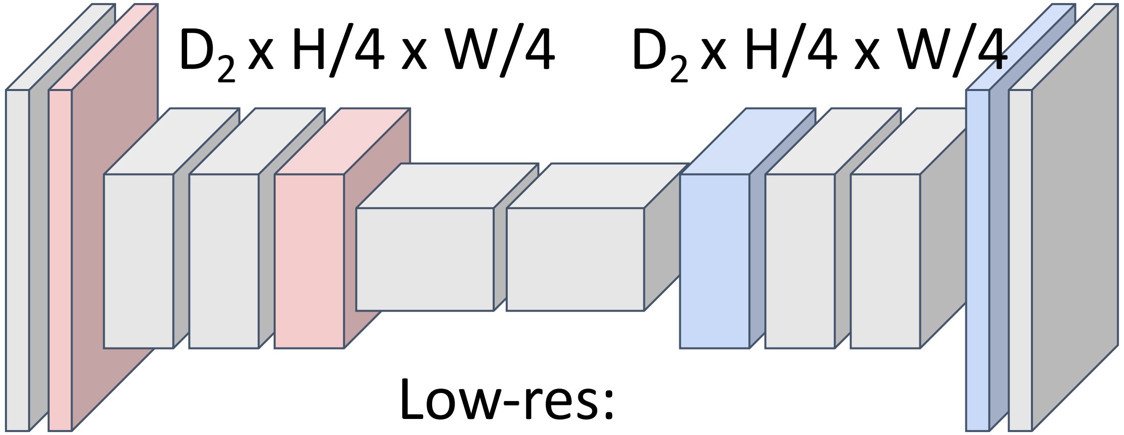
Semantic Segmentation: Fully Convolutional Network

Downsampling: Pooling, strided convolution

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

Upsampling: ???

Input:
$3 \times H \times W$



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:
$D_3 \times H/4 \times W/4$

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

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

→

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

Input
C x 2 x 2

Output
C x 4 x 4

Nearest Neighbor

1	2
3	4

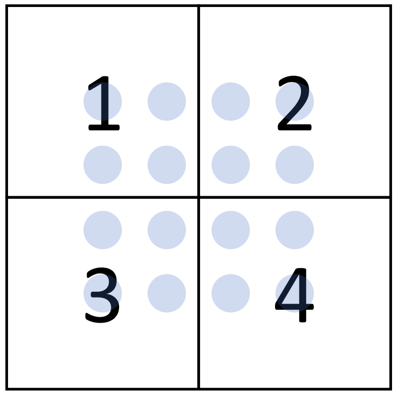
→

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

Input
C x 2 x 2

Output
C x 4 x 4

In-Network Upsampling: Bilinear Interpolation



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

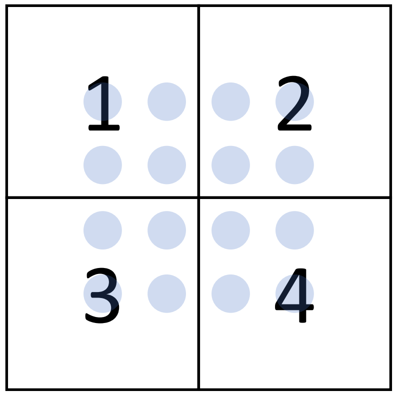
Input: C x 2 x 2

Output: C x 4 x 4

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

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

In-Network Upsampling: Bicubic Interpolation



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

Input: C x 2 x 2

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

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

→

5	6
7	8

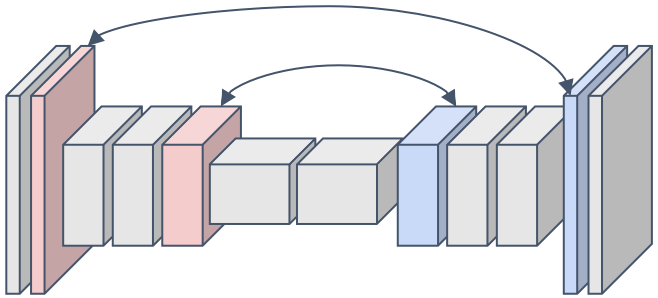
→ Rest of net →

Max Unpooling: Place into remembered positions

1	2
3	4

→

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

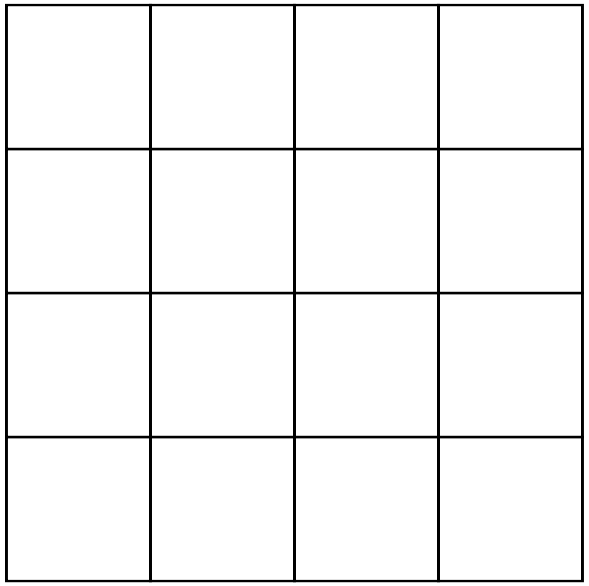


Pair each downsampling layer with an upsampling layer

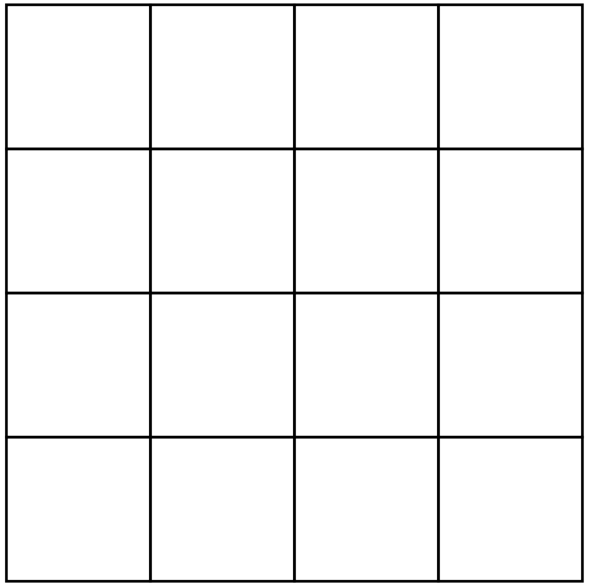
Noh et al, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Learnable Upsampling: Transposed Convolution

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



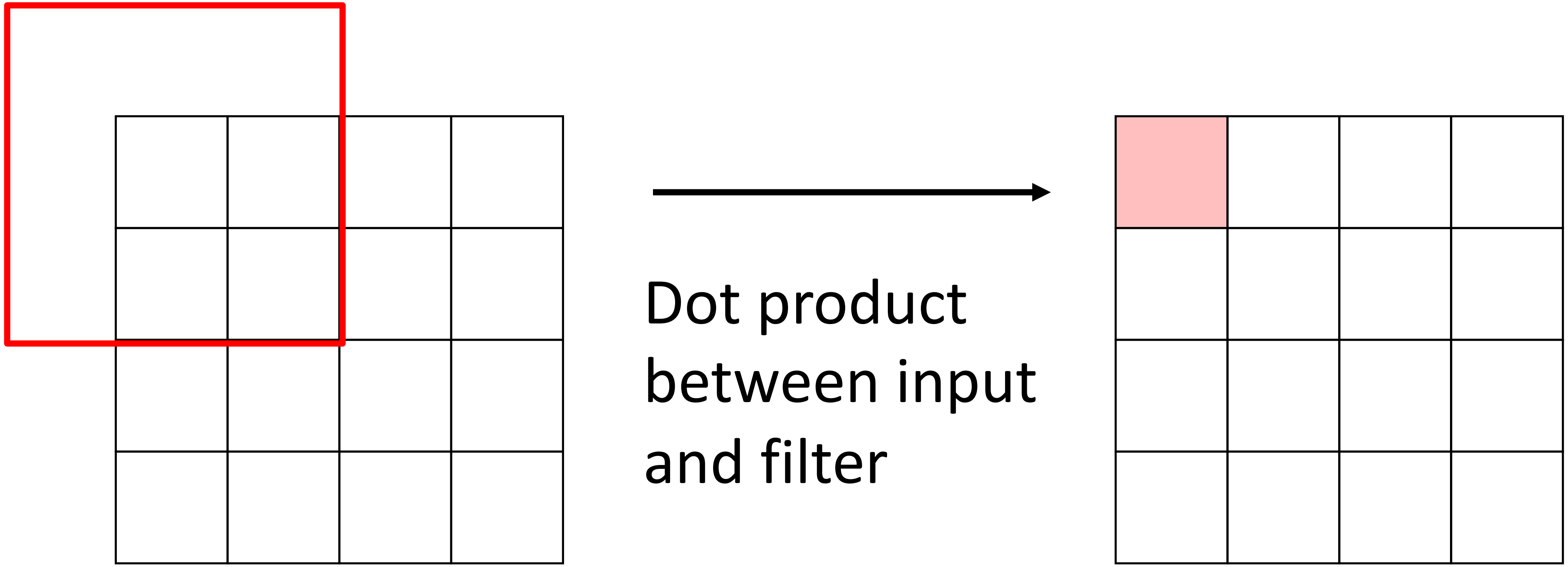
Input: 4 x 4



Output: 4 x 4

Learnable Upsampling: Transposed Convolution

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

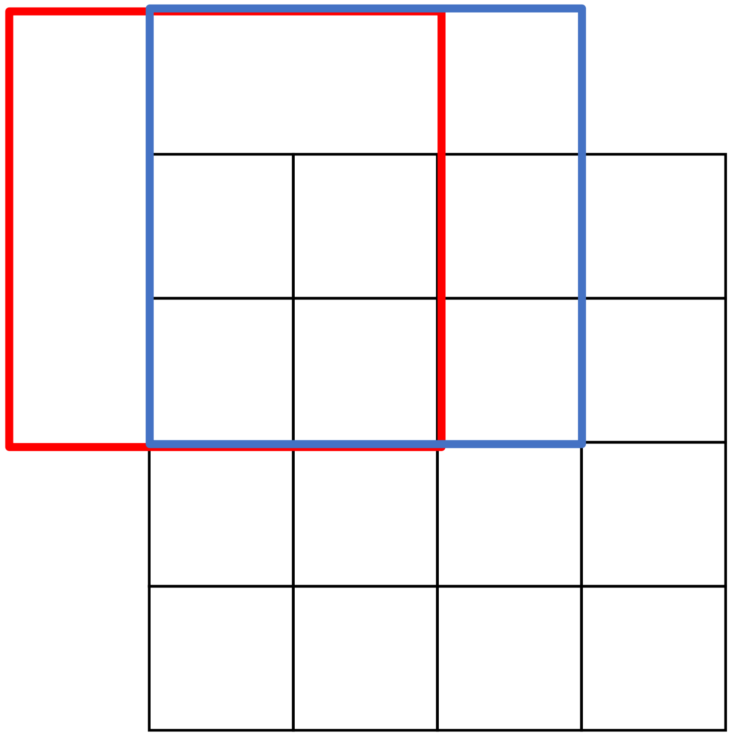


Input: 4 x 4

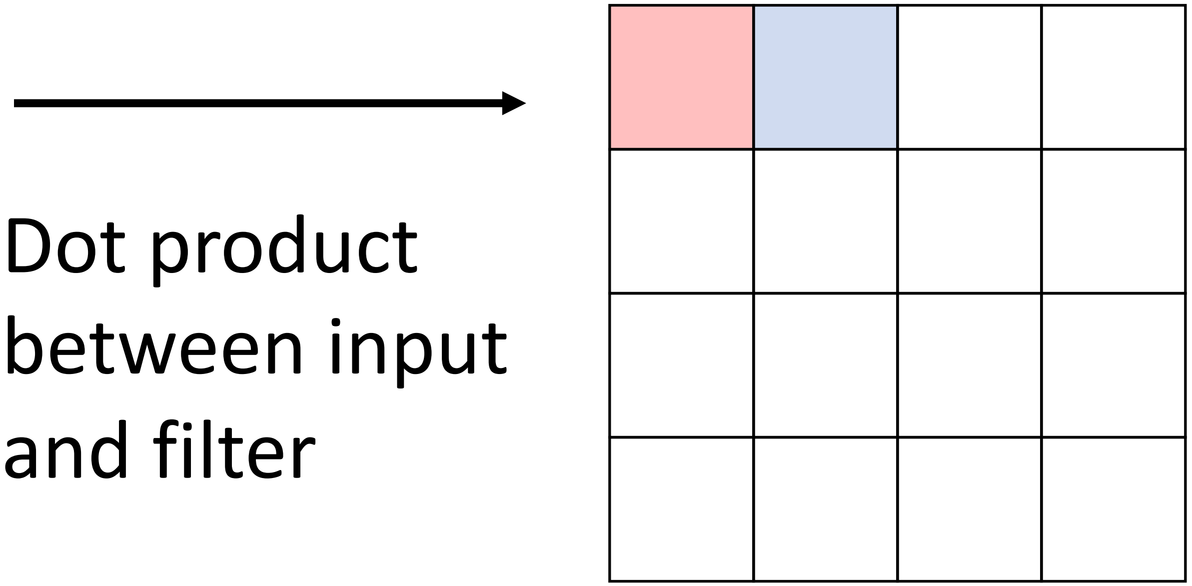
Output: 4 x 4

Learnable Upsampling: Transposed Convolution

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



Dot product between input and filter



Input: 4 x 4

Output: 4 x 4

Learnable Upsampling: Transposed Convolution

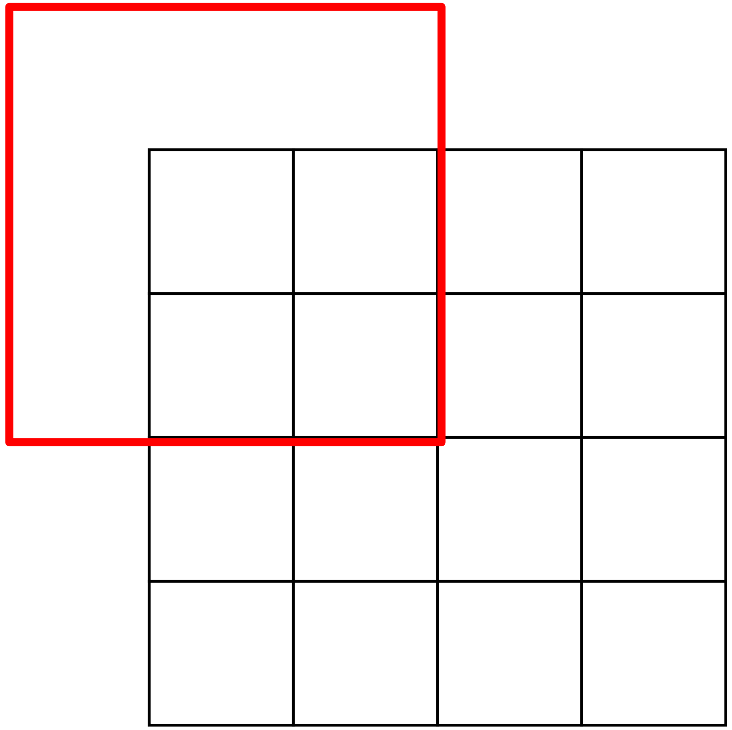
Recall: Normal 3 x 3 convolution, stride 2, pad 1

Input: 4 x 4

Output: 2 x 2

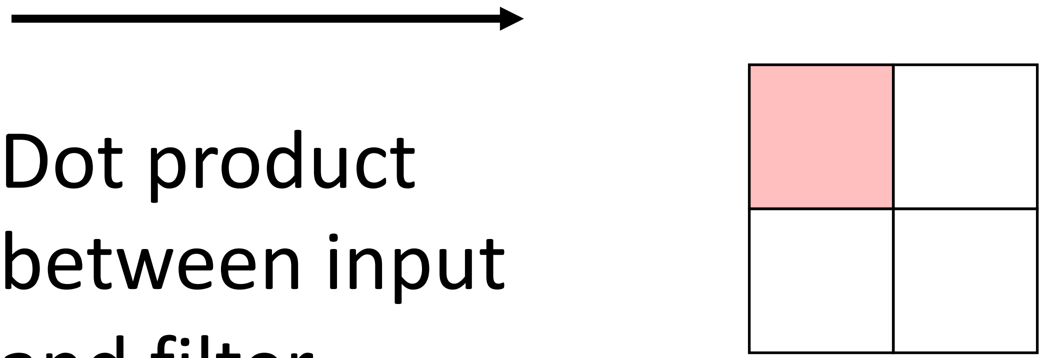
Learnable Upsampling: Transposed Convolution

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



Input: 4 x 4

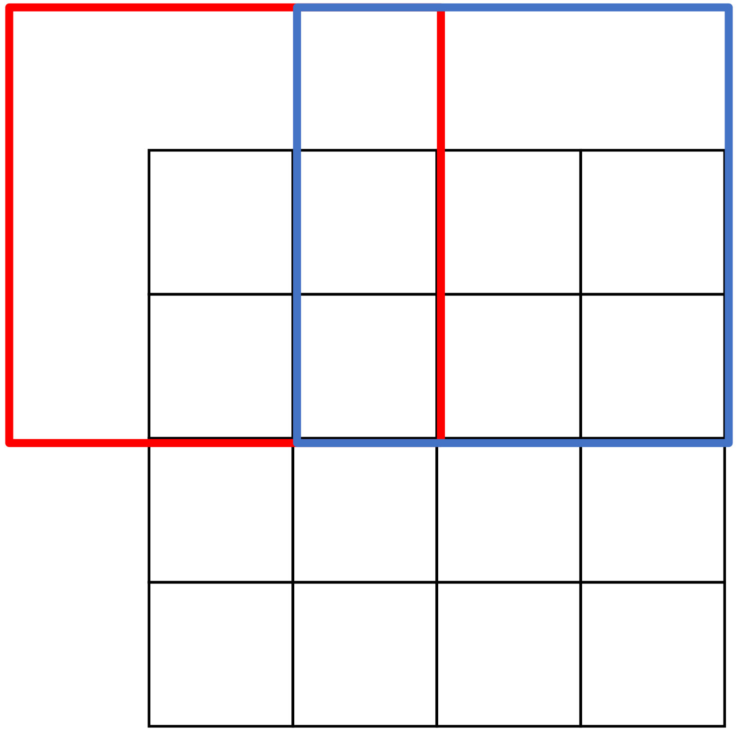
Dot product between input and filter



Output: 2 x 2

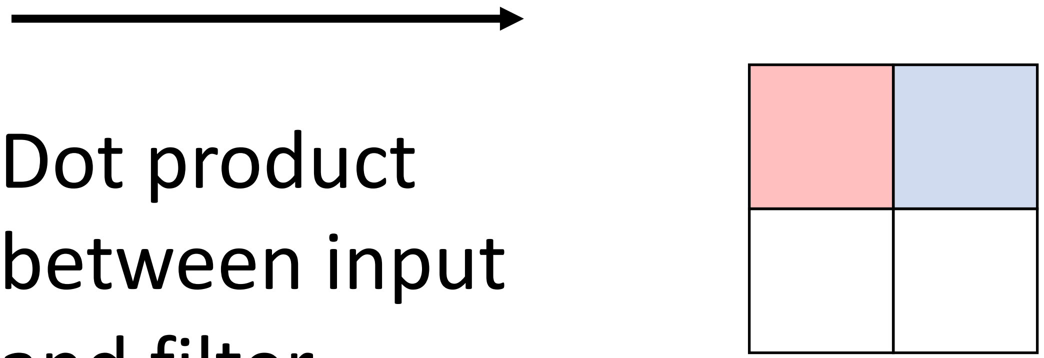
Learnable Upsampling: Transposed Convolution

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



Input: 4 x 4

Dot product between input and filter

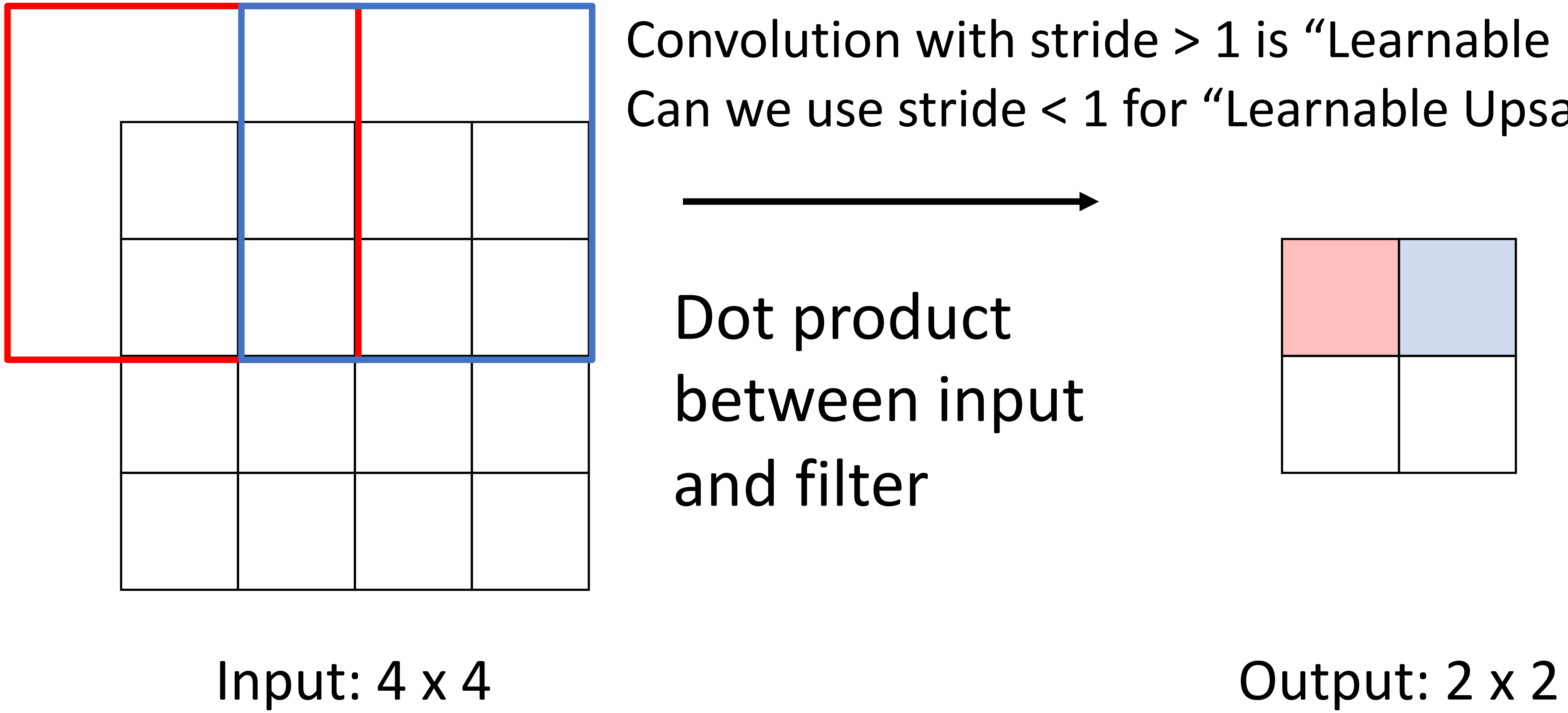


Output: 2 x 2

Learnable Upsampling: Transposed Convolution

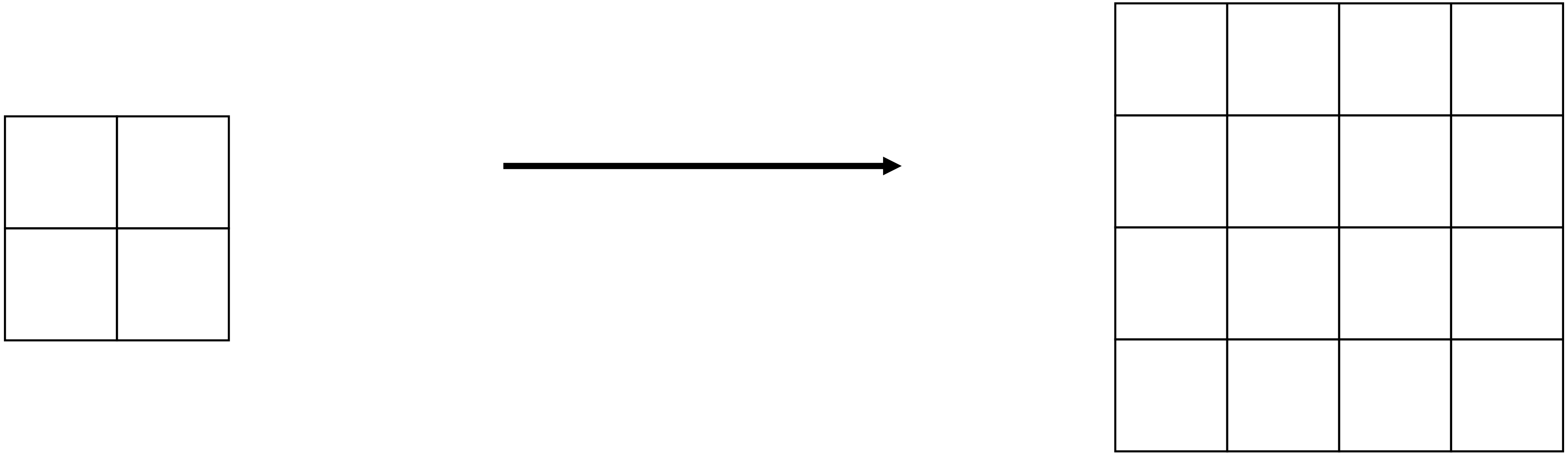
Recall: Normal 3 x 3 convolution, stride 2, pad 1

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



Learnable Upsampling: Transposed Convolution

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

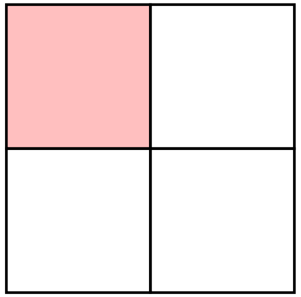


Input: 2 x 2

Output: 4 x 4

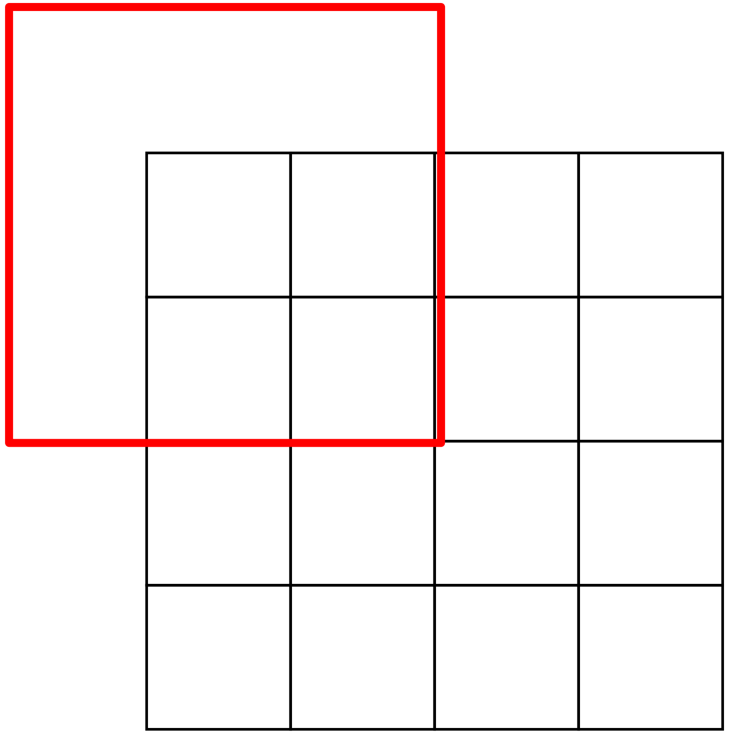
Learnable Upsampling: Transposed Convolution

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



Input: 2 x 2

Weight filter by input value and copy to output

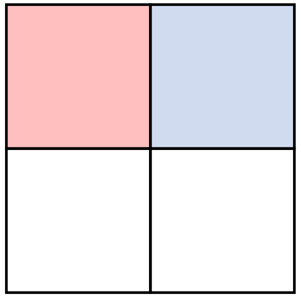


Output: 4 x 4

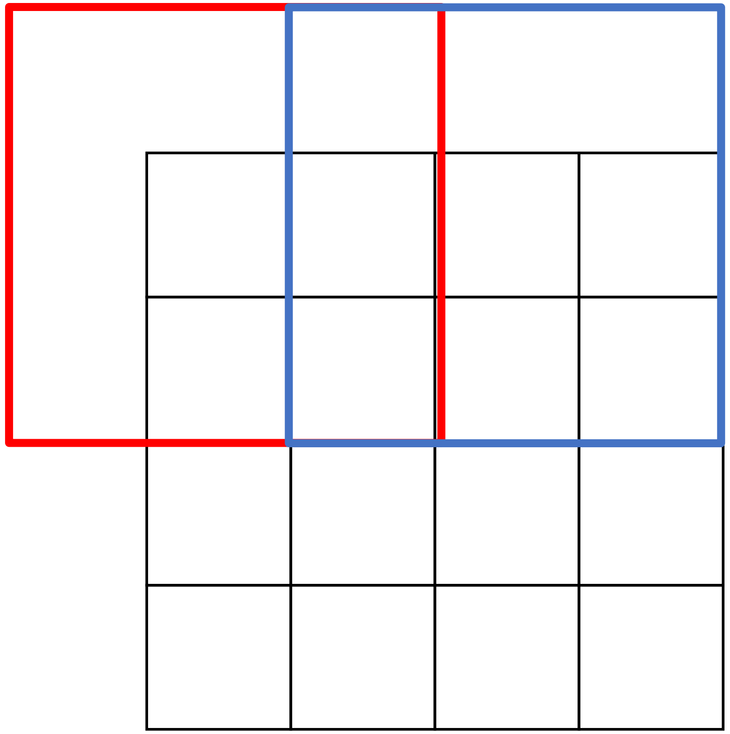
Learnable Upsampling: Transposed Convolution

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

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



Weight filter by input value and copy to output



Input: 2 x 2

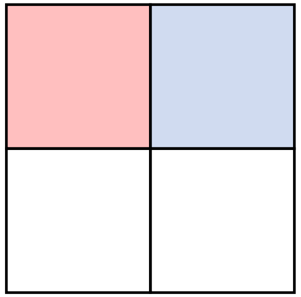
Output: 4 x 4

Learnable Upsampling: Transposed Convolution

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

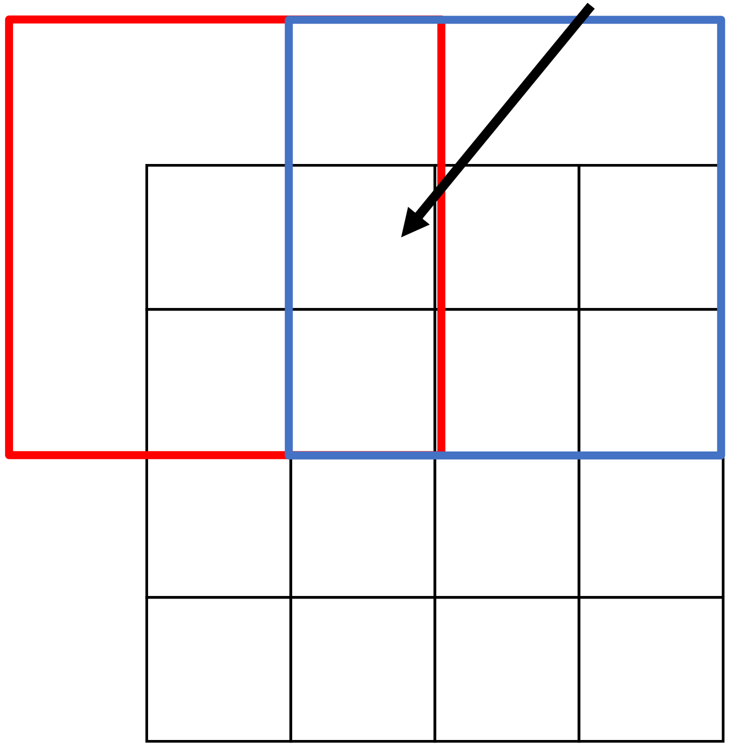
Sum where output overlaps

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

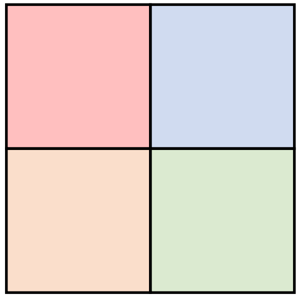


Output: 4 x 4

Learnable Upsampling: Transposed Convolution

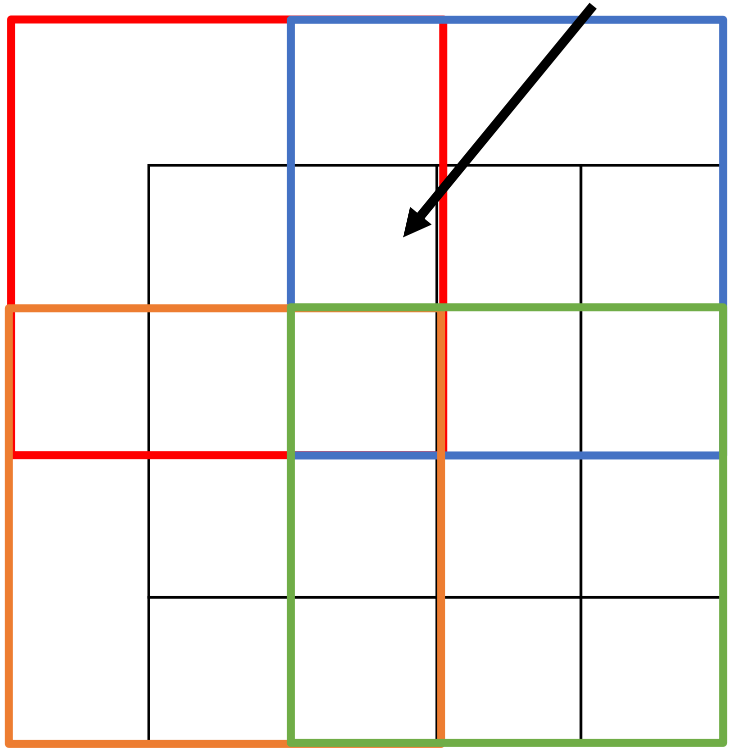
3 x 3 **convolution transpose**, stride 2

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



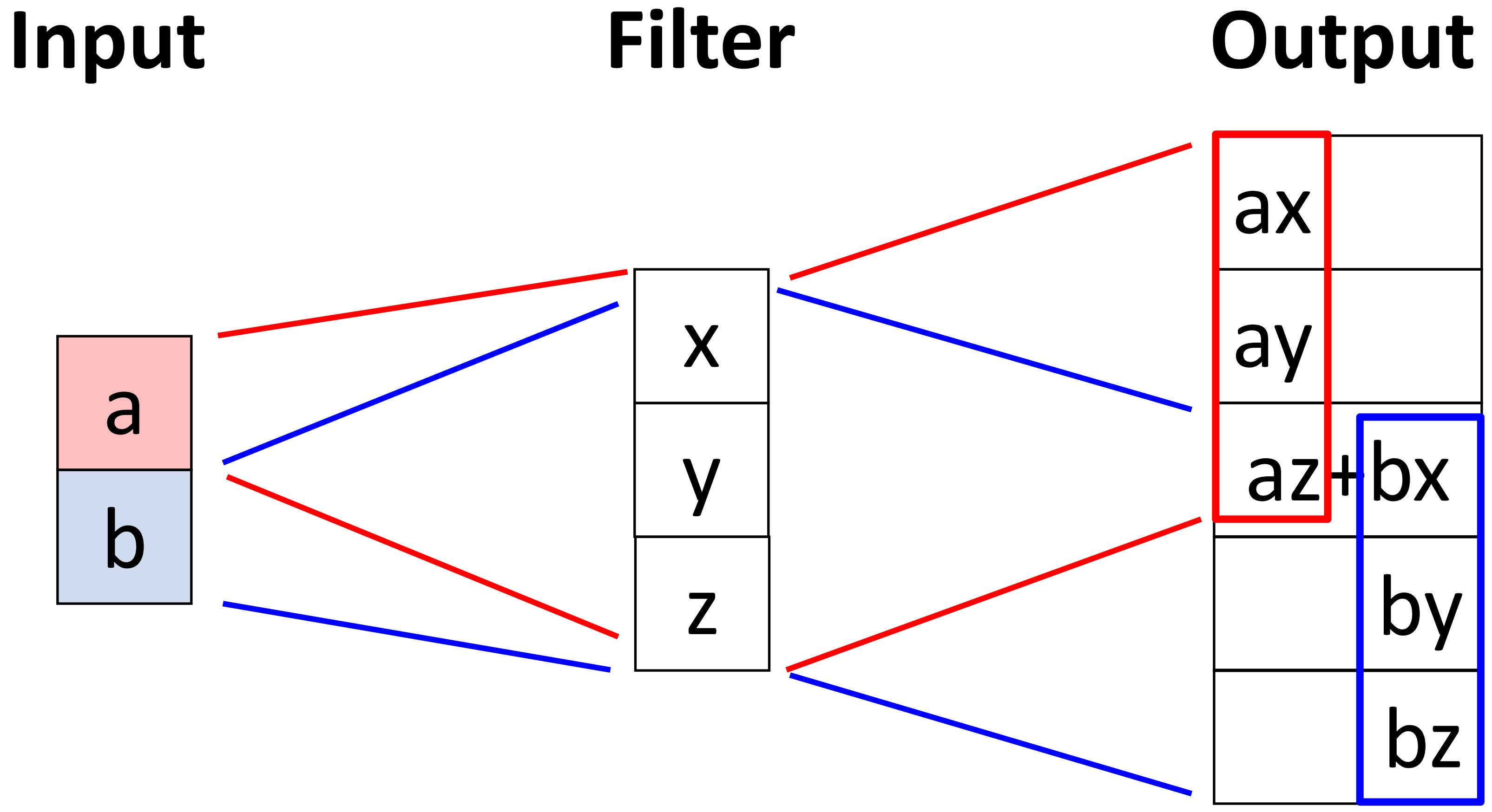
Input: 2 x 2

Weight filter by input value and copy to output



Output: 4 x 4

Transposed Convolution: 1D example

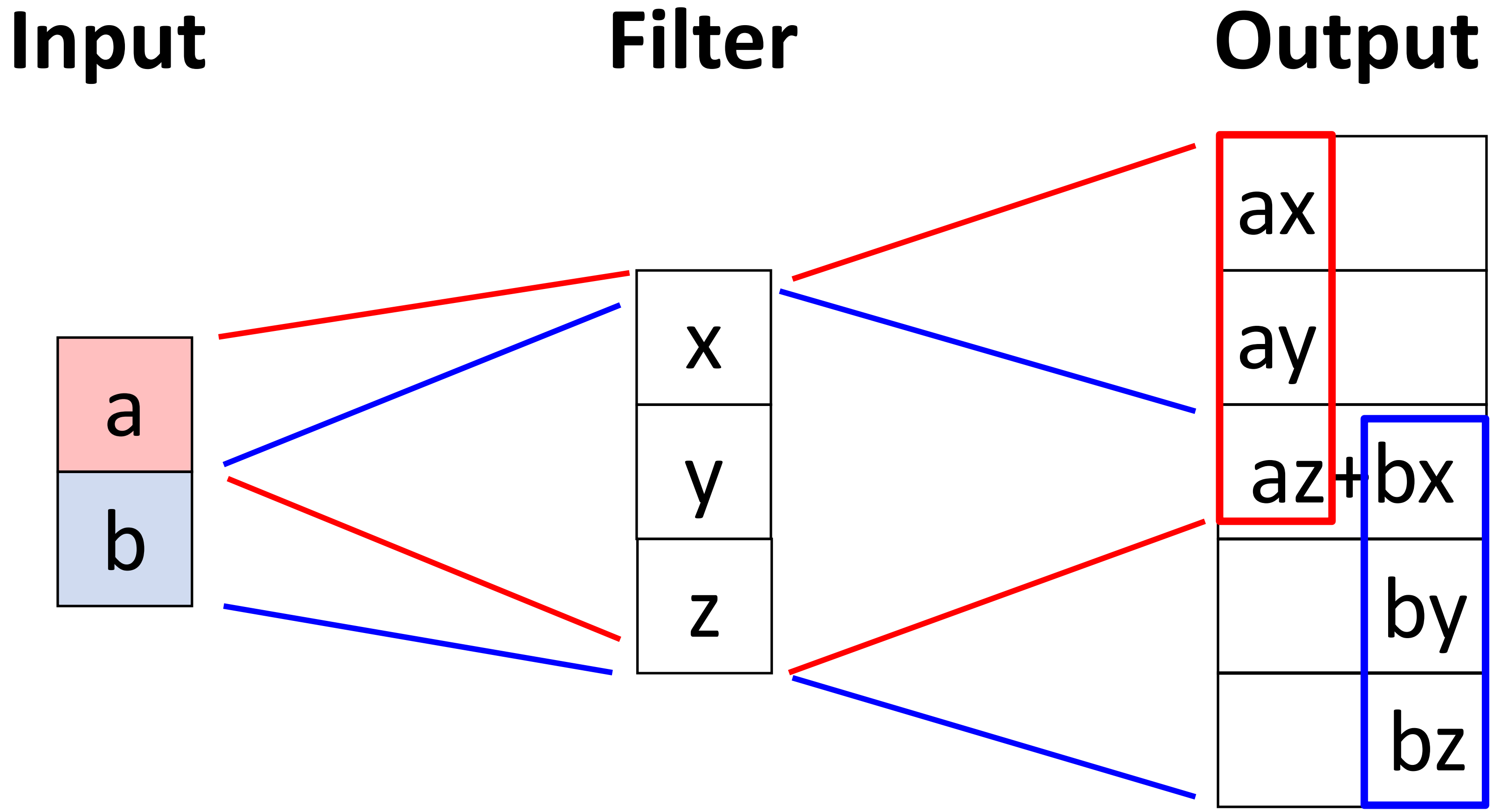


Output has copies of filter weighted by input

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

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

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

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

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

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

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

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

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

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

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

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

Example: 1D conv, kernel size=3, stride=2, 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

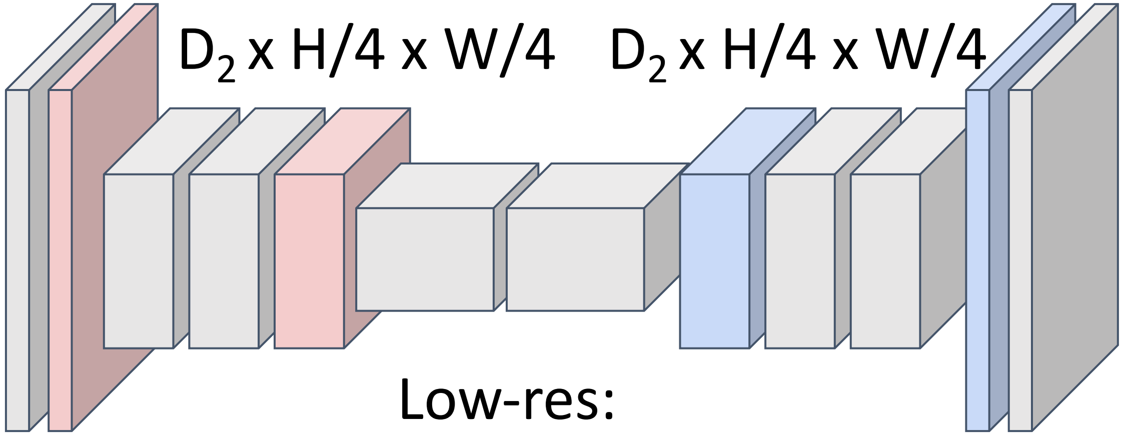
Semantic Segmentation: Fully Convolutional Network

Downsampling: Pooling, strided convolution

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

Upsampling: linterpolation, transposed conv

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: $D_3 \times H/4 \times W/4$

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

Predictions: $H \times W$

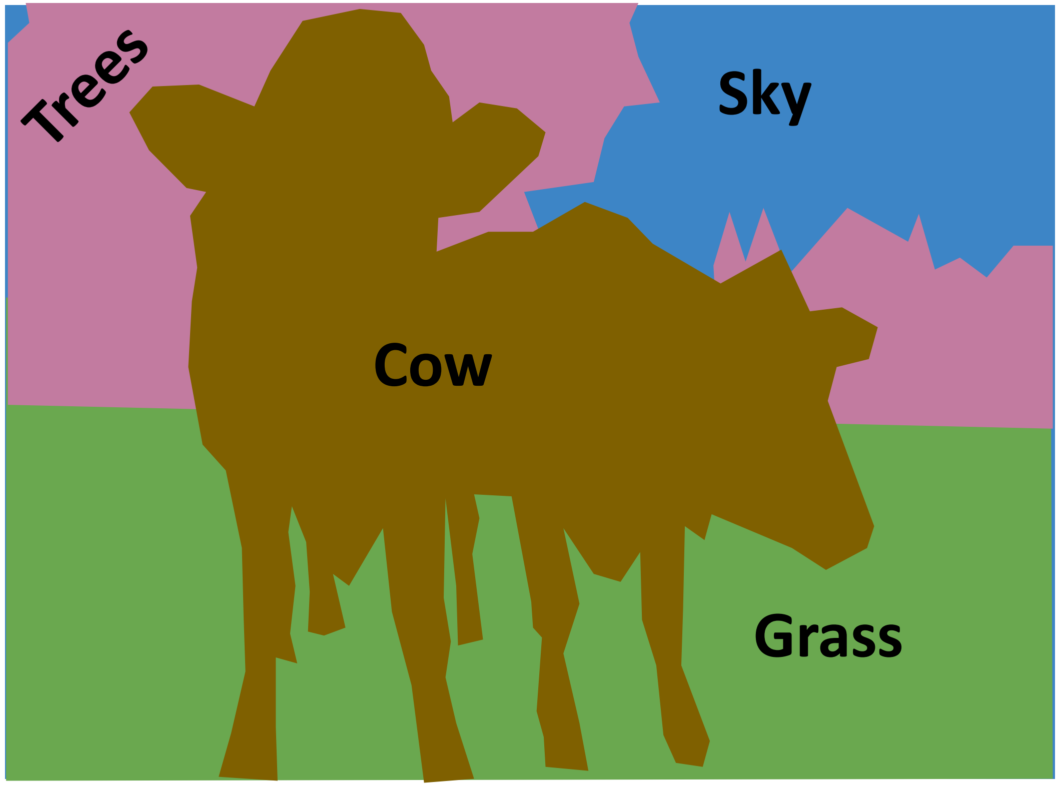
Loss function: Per-Pixel cross-entropy

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

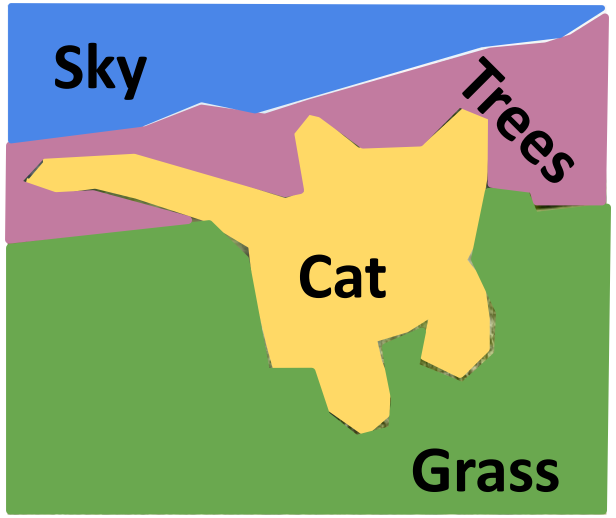


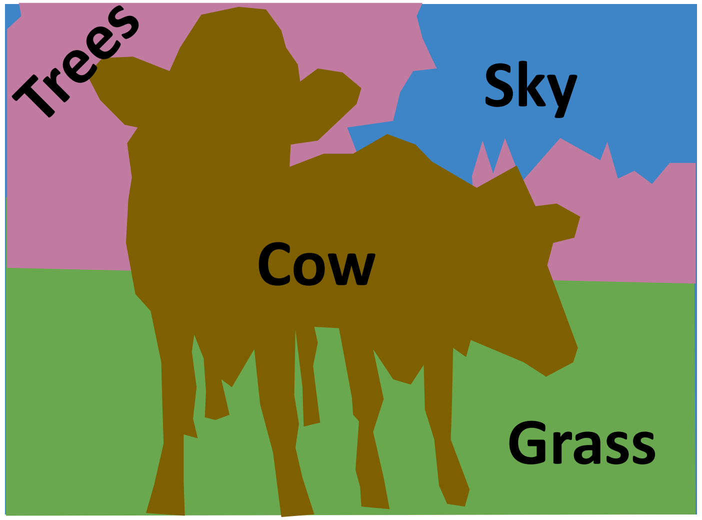
Things and Stuff

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)

[This image](#) is [CC0 public domain](#)

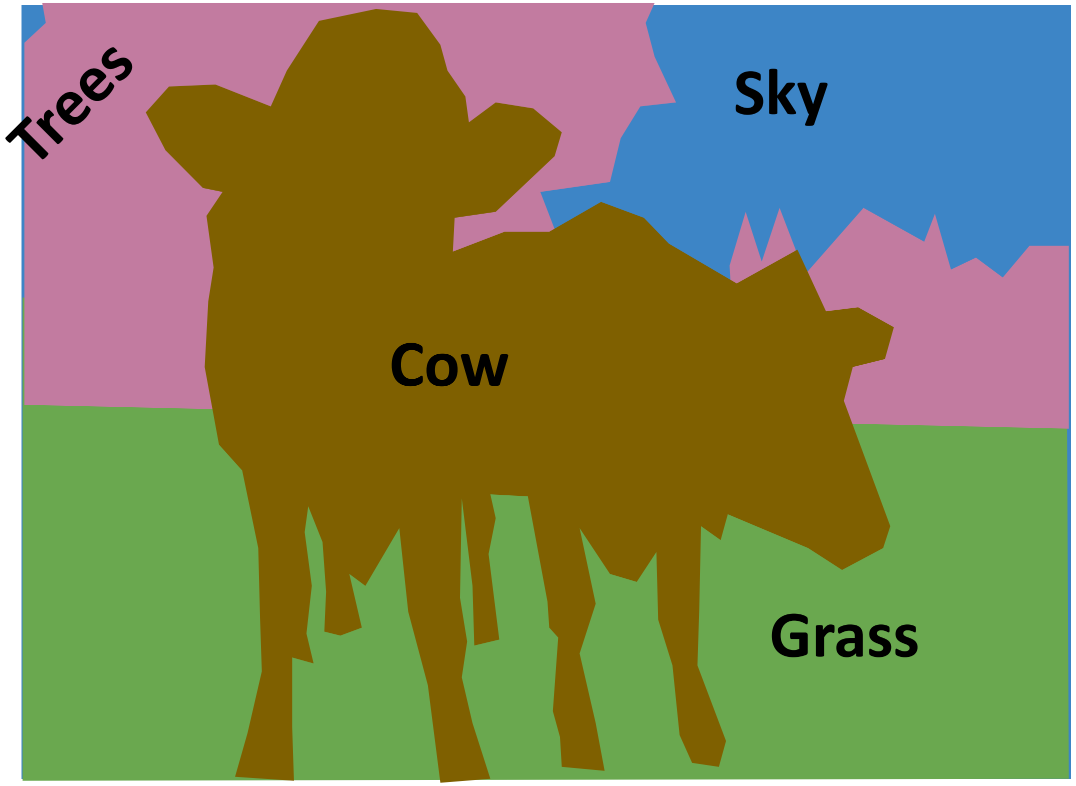




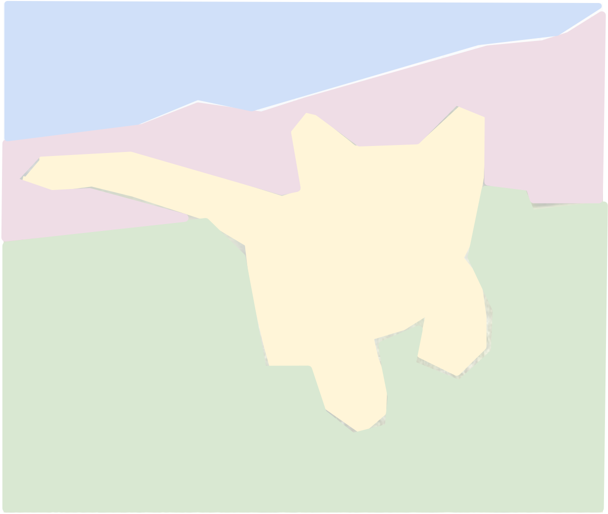
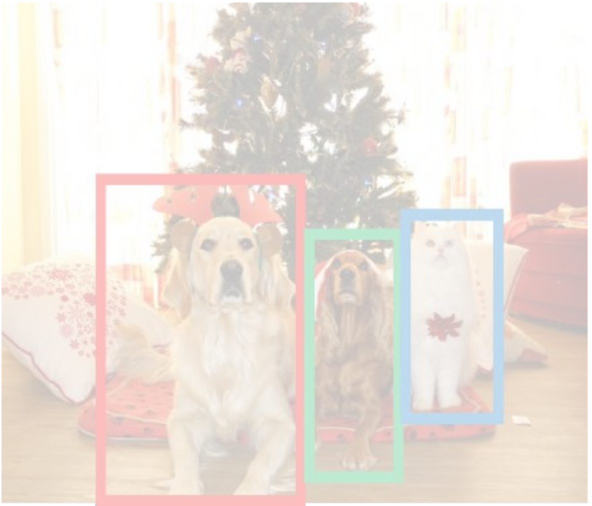
Computer Vision Tasks

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)

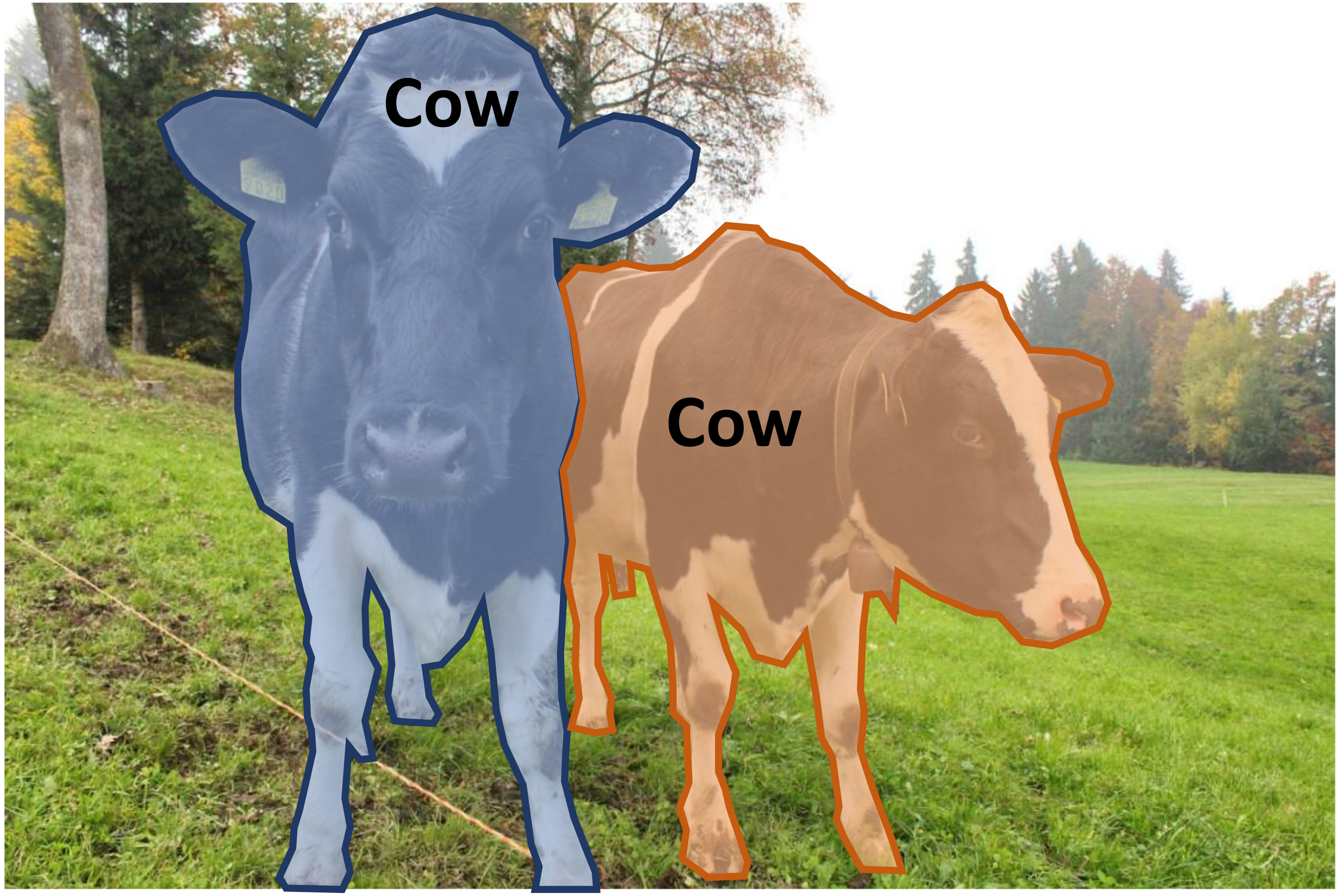


Computer Vision Tasks: Instance Segmentation

Classification	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	

Computer Vision Tasks: Instance Segmentation

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

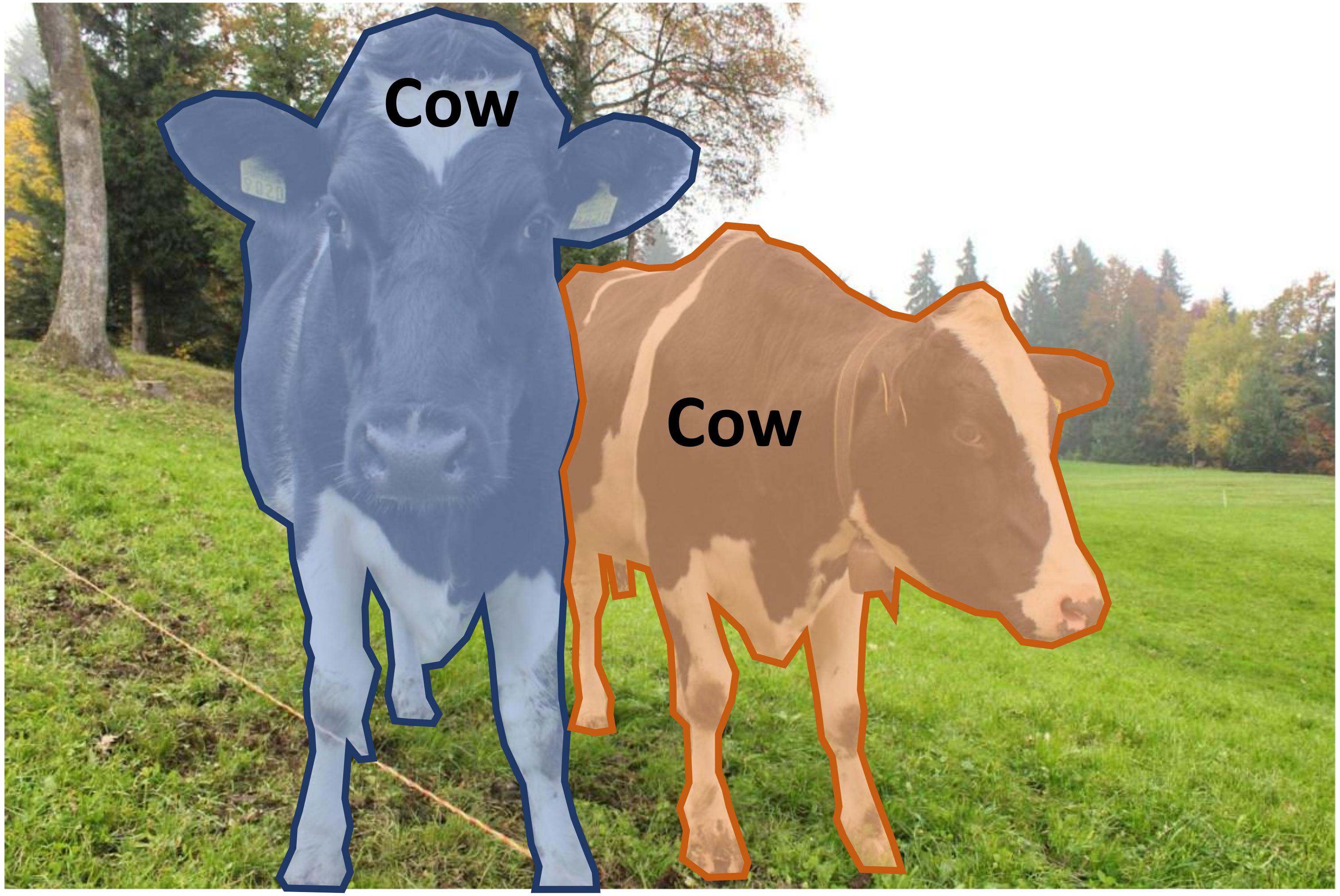


This image is CC0 public domain

Computer Vision Tasks: Instance Segmentation

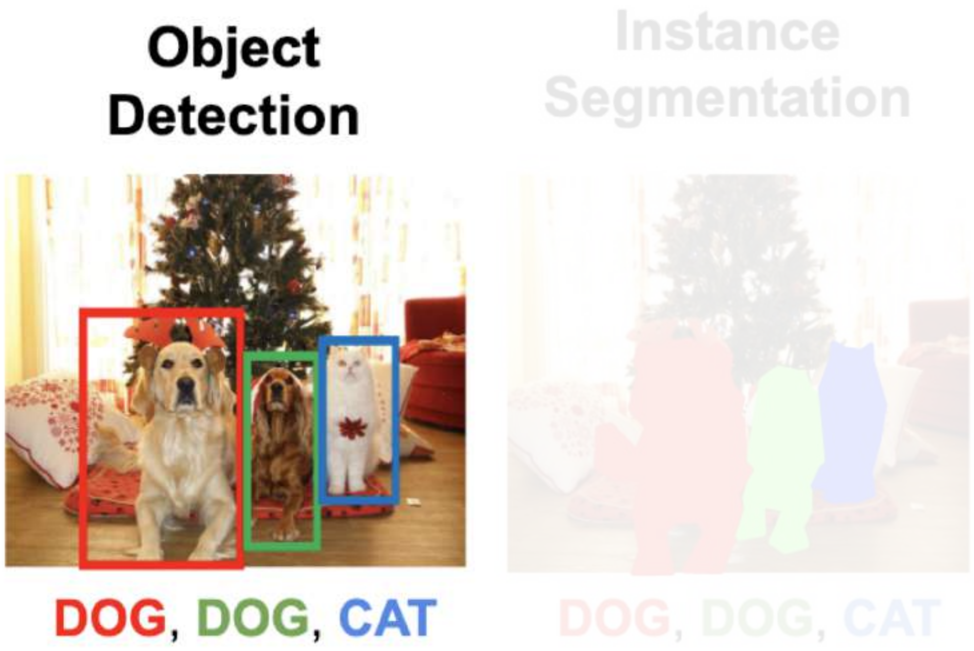
Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object (Only things!)

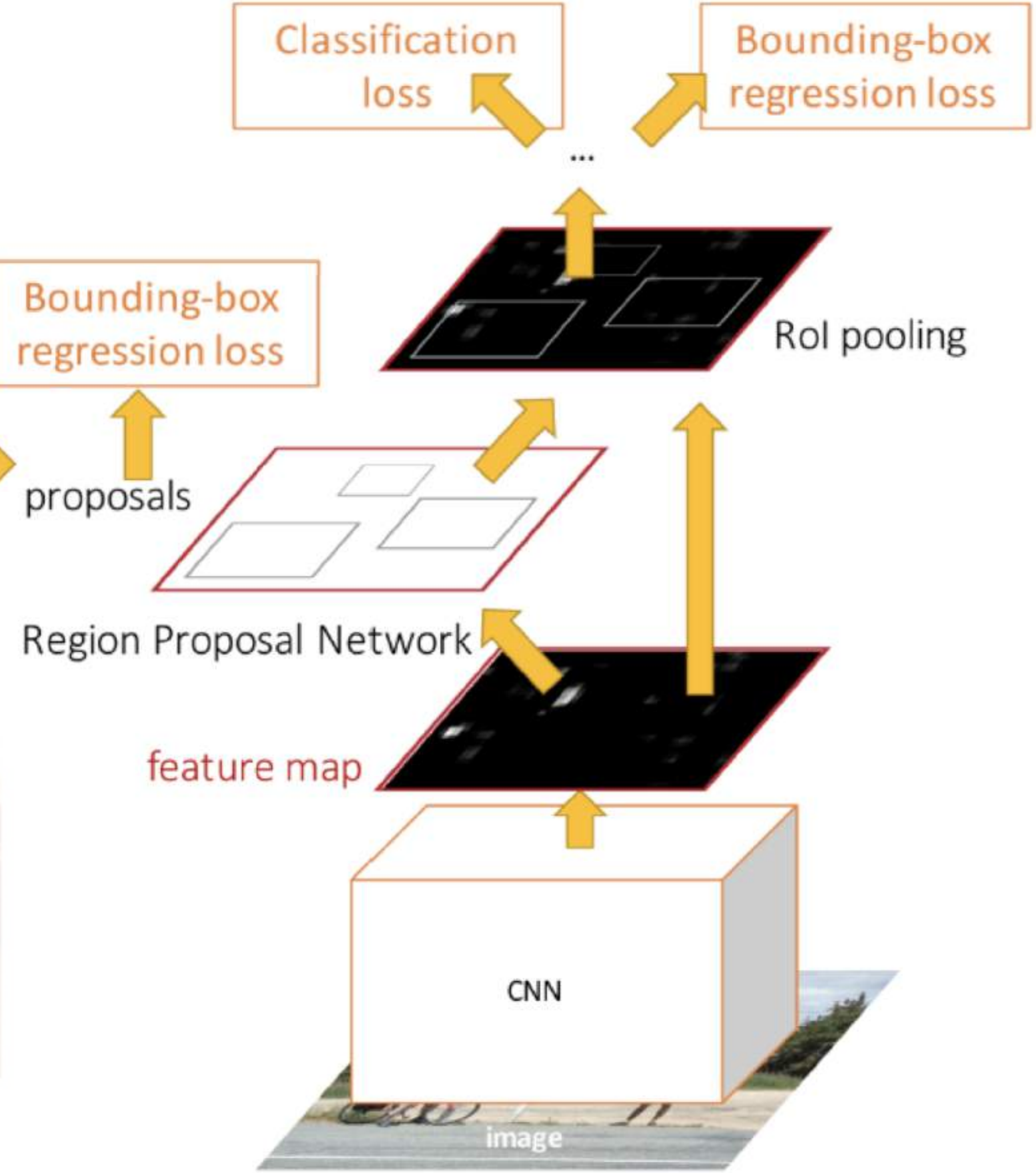
Approach: Perform object detection, then predict a segmentation mask for each object!



This image is CC0 public domain

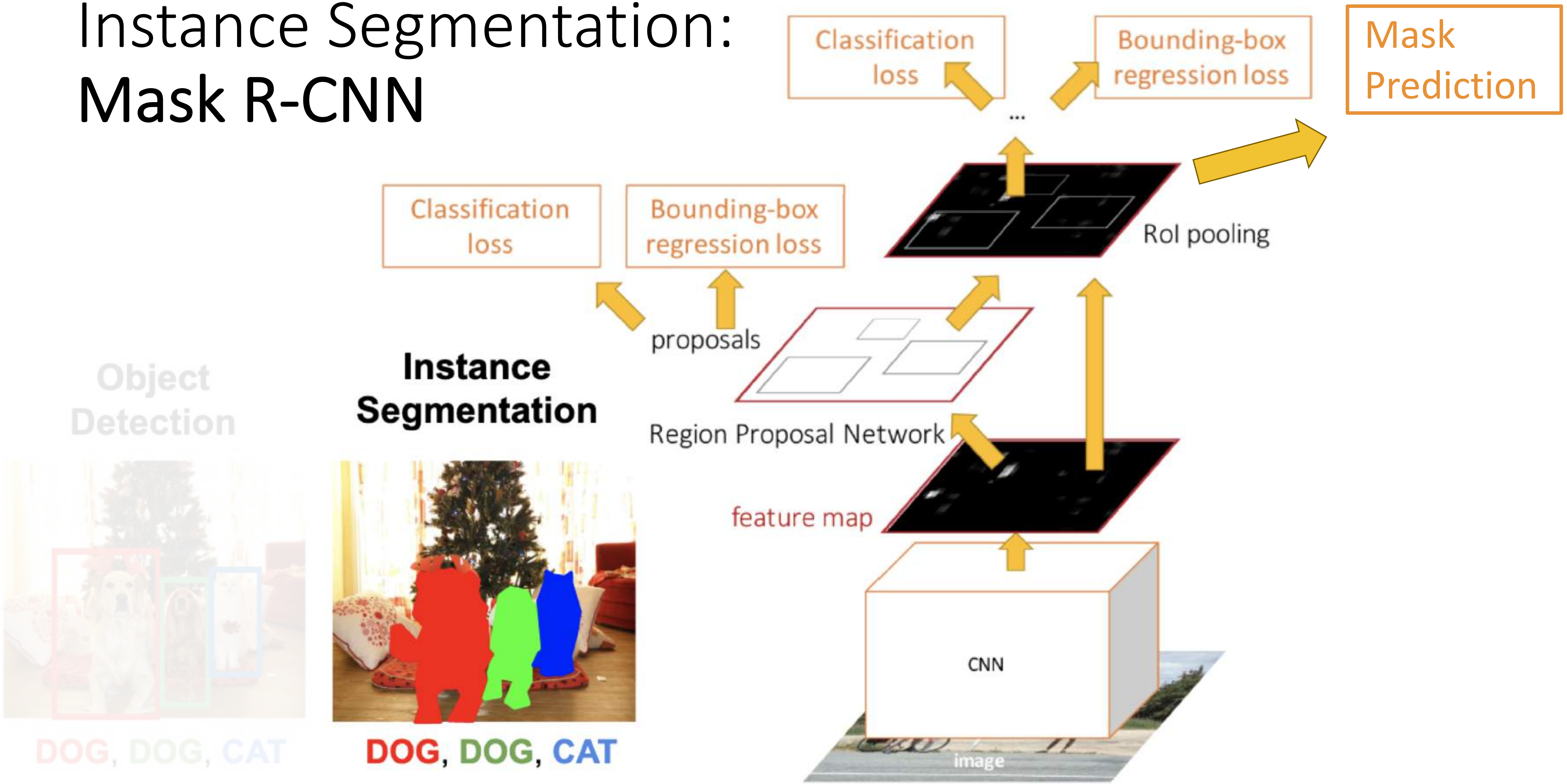
Object Detection: Faster R-CNN





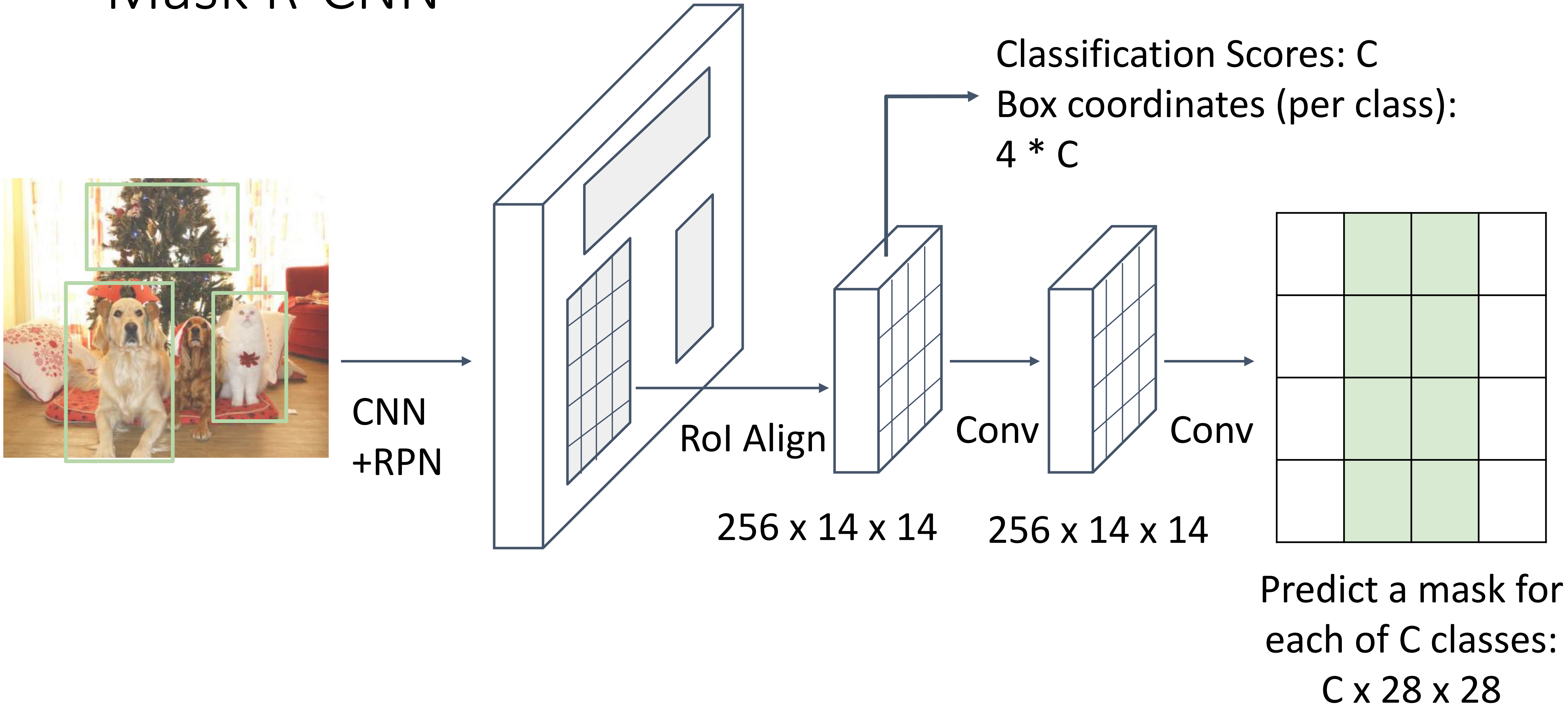
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NeurIPS 2015

Instance Segmentation: **Mask R-CNN**



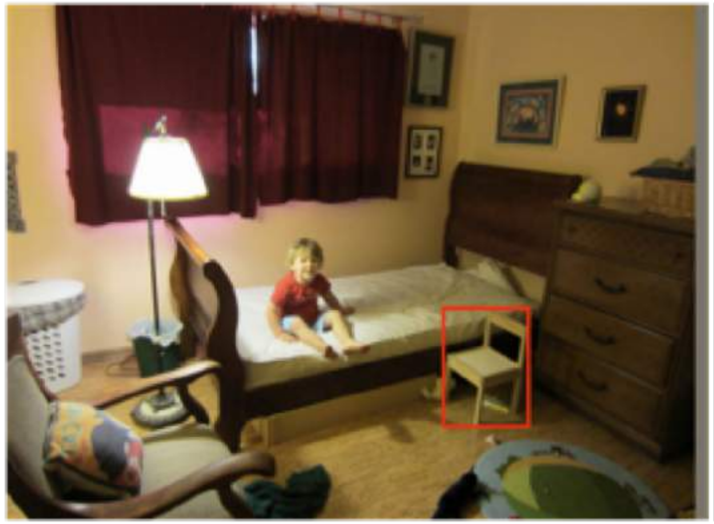
He et al, "Mask R-CNN", ICCV 2017

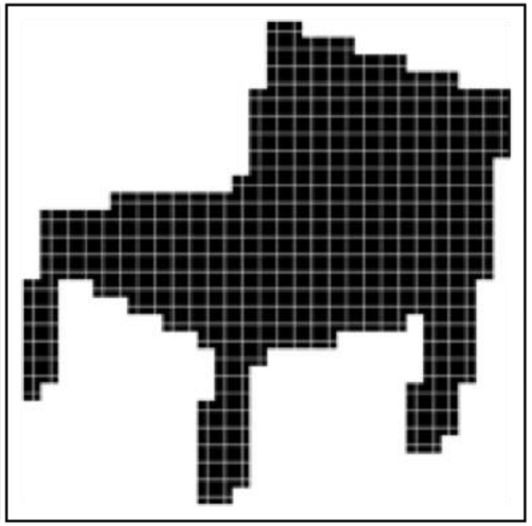
Mask R-CNN



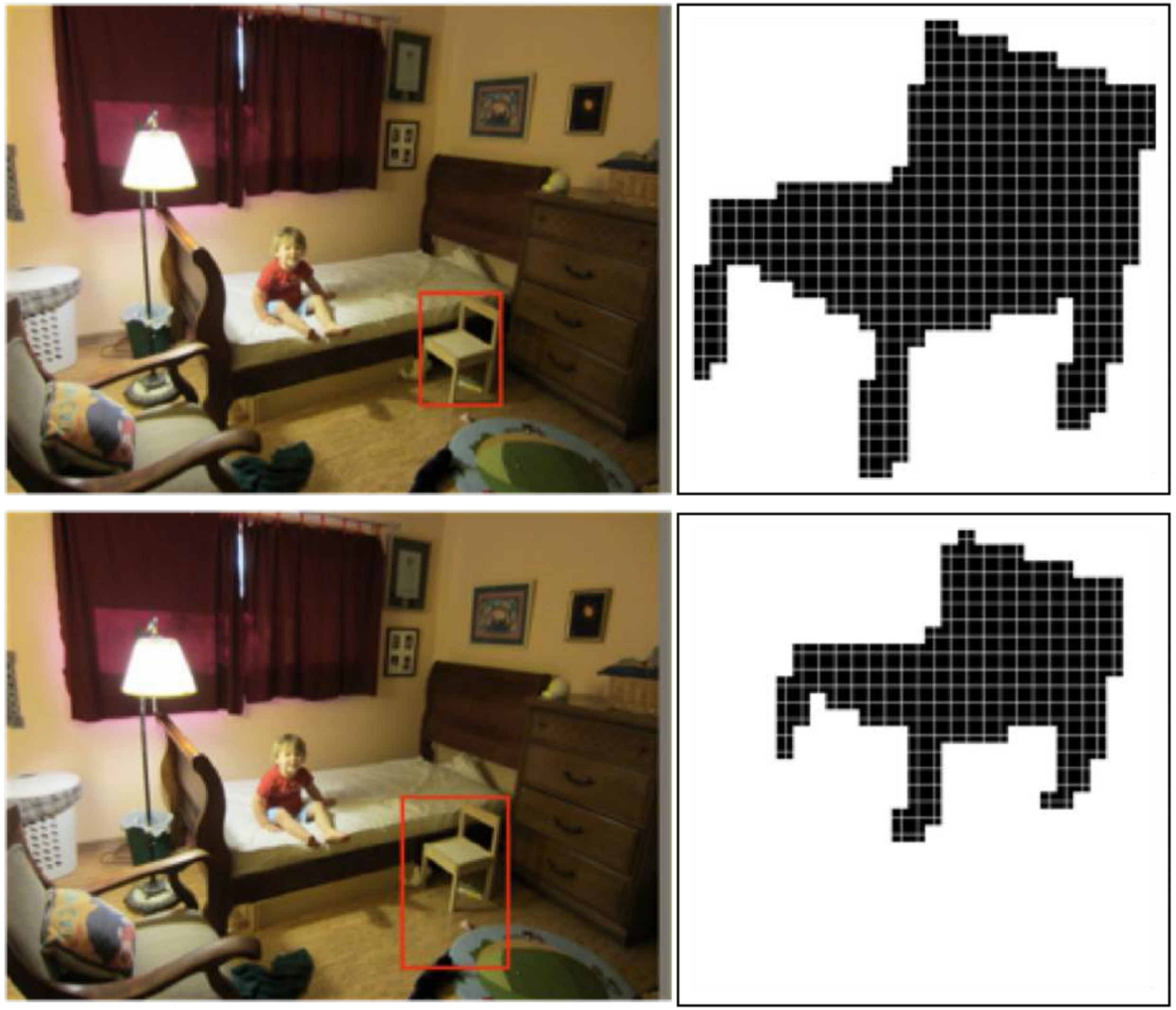
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN: Example Training Targets

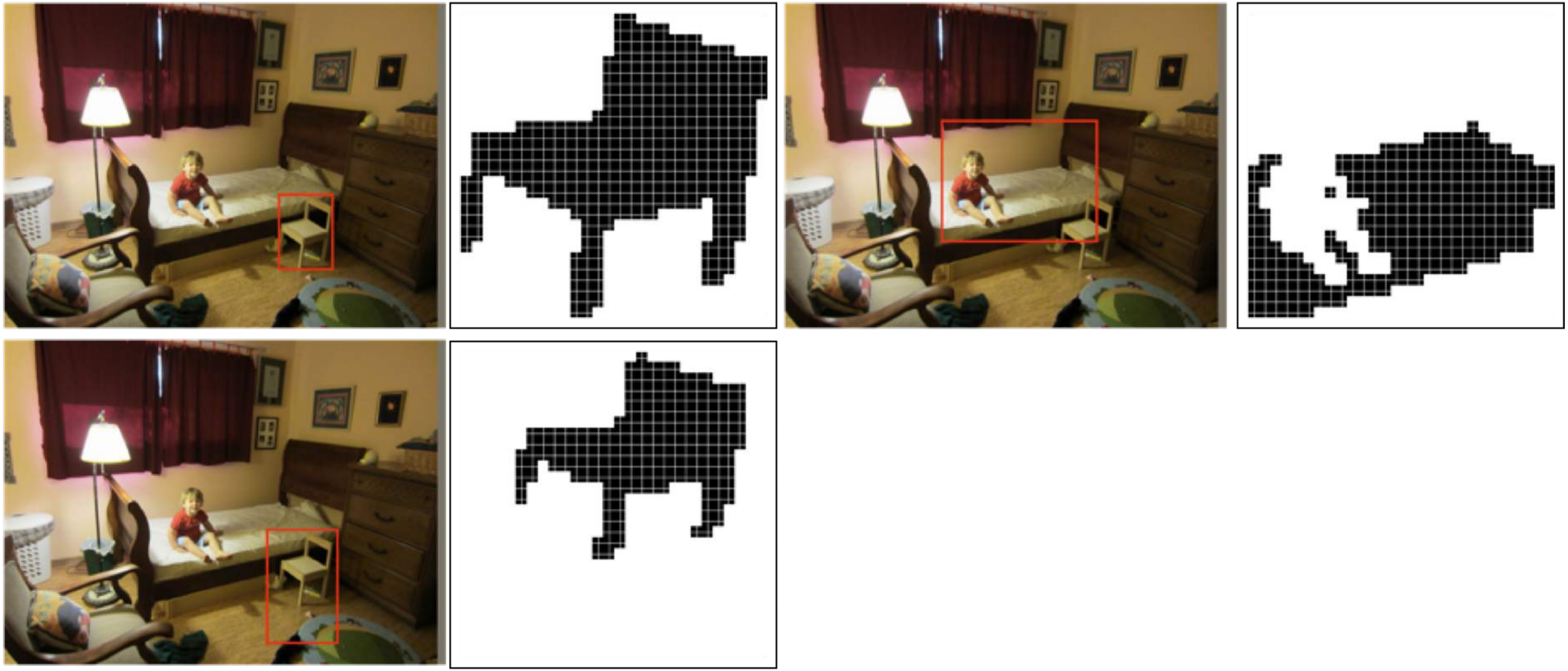




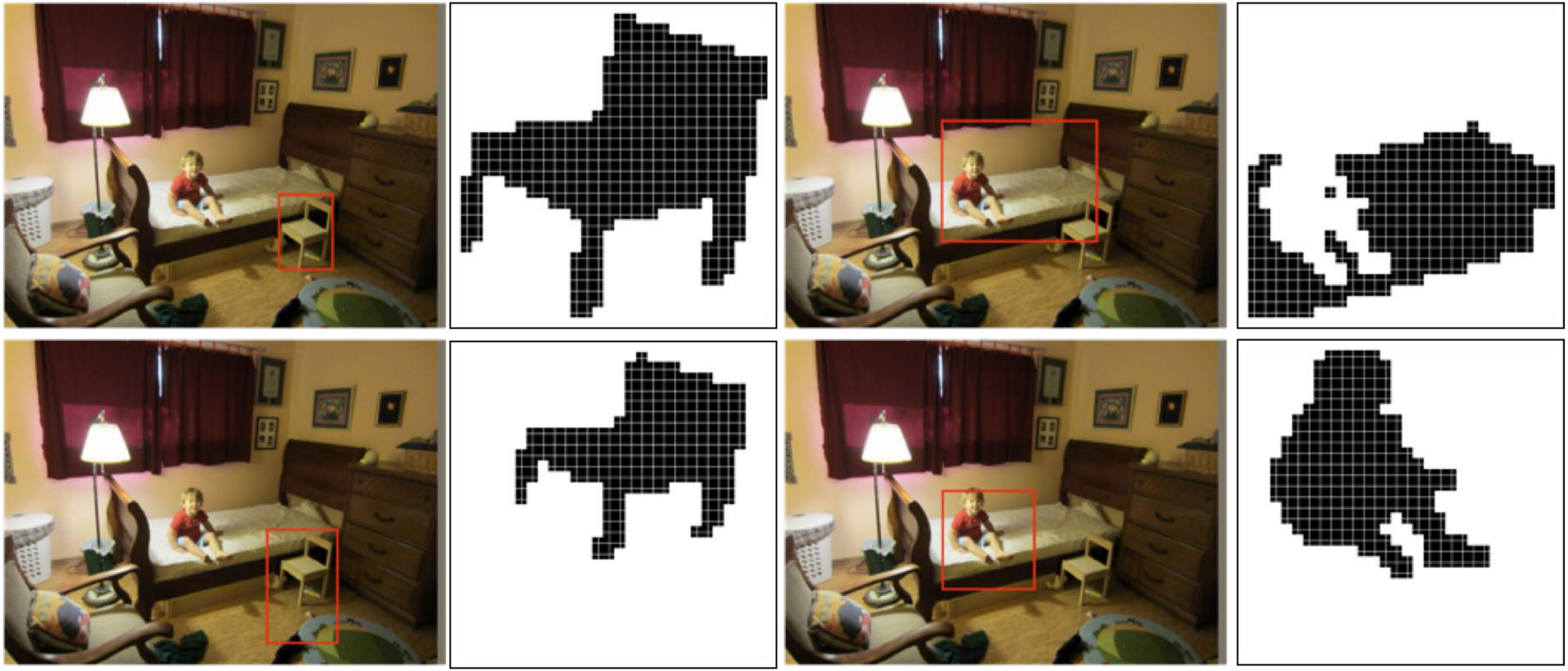
Mask R-CNN: Example Training Targets



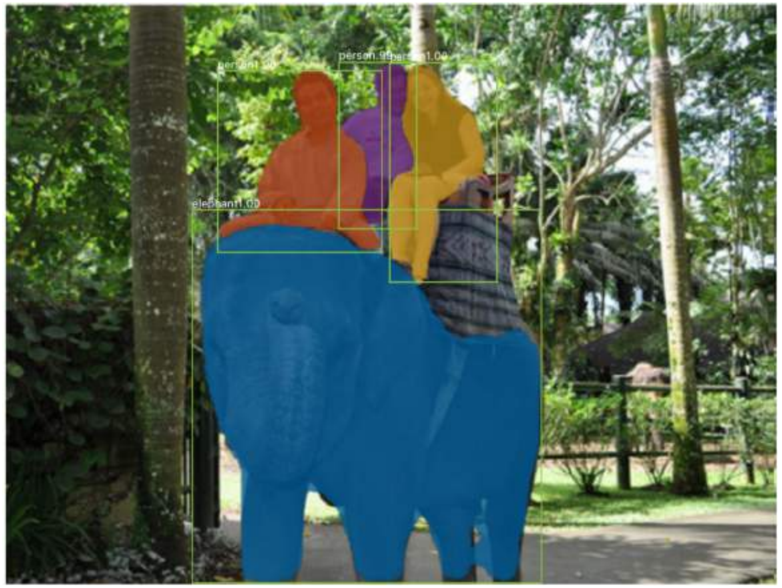
Mask R-CNN: Example Training Targets

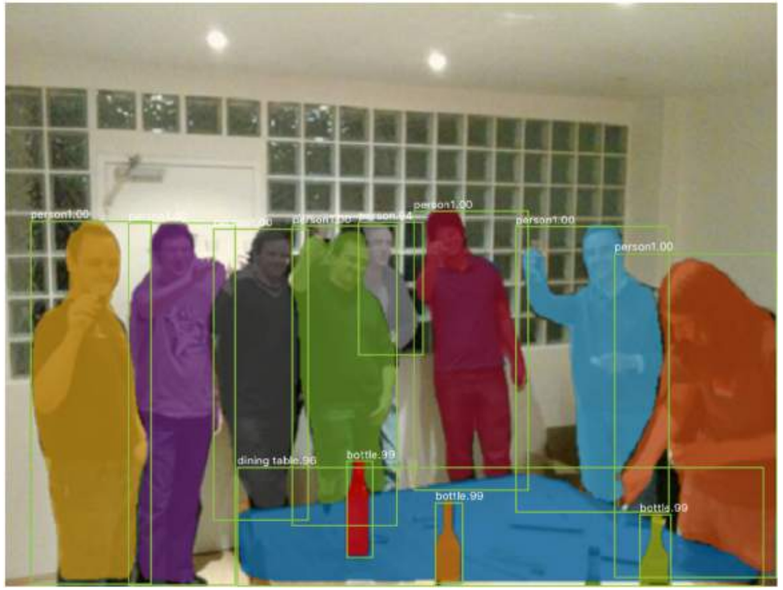


Mask R-CNN: Example Training Targets



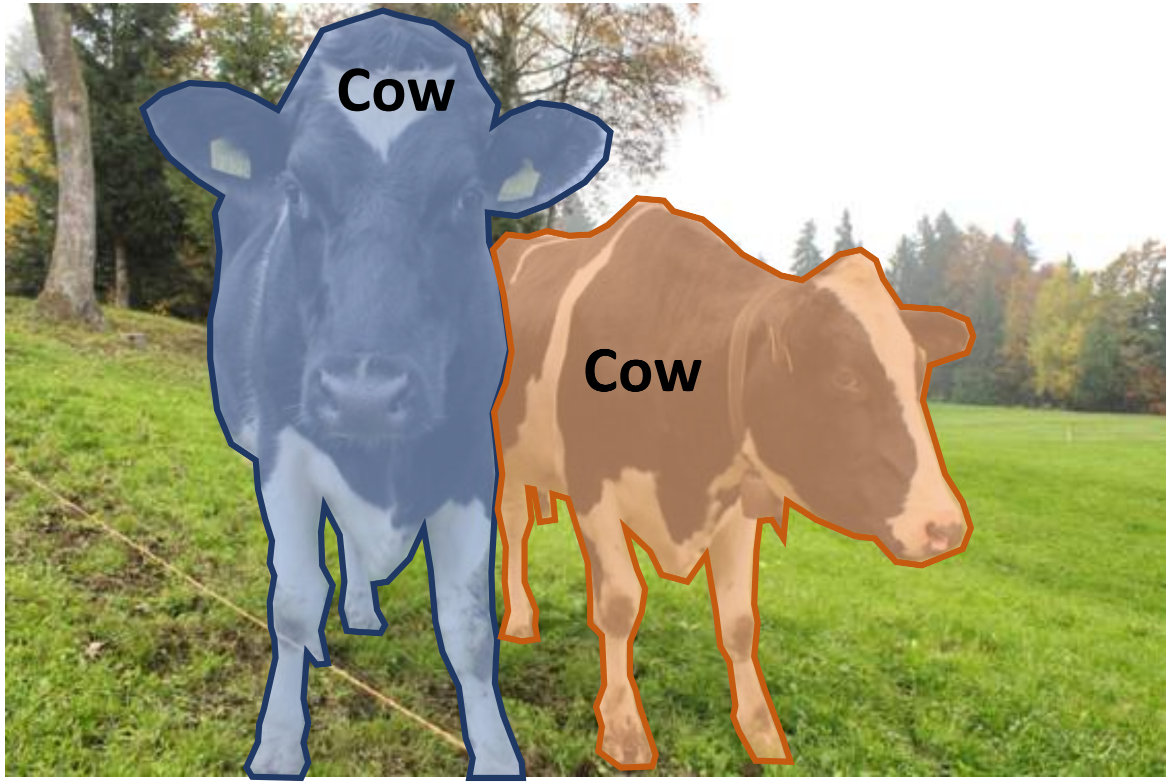
Mask R-CNN: Very Good Results!



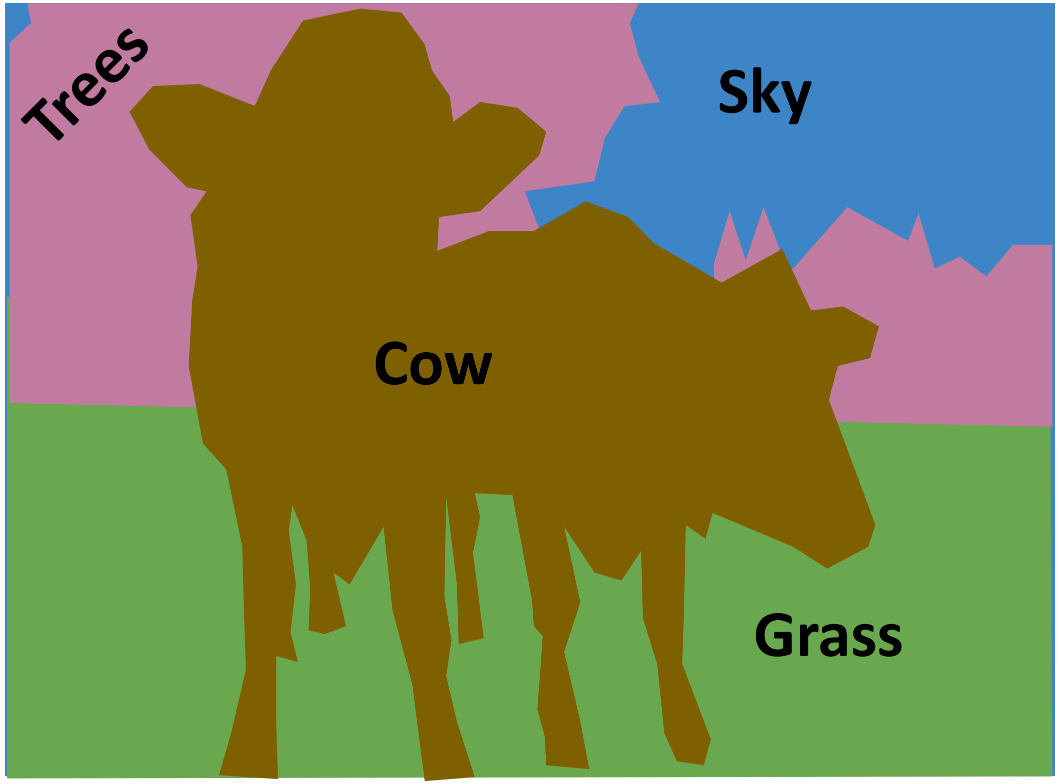


Beyond Instance Segmentation

Instance Segmentation: Separate object instances, but only things



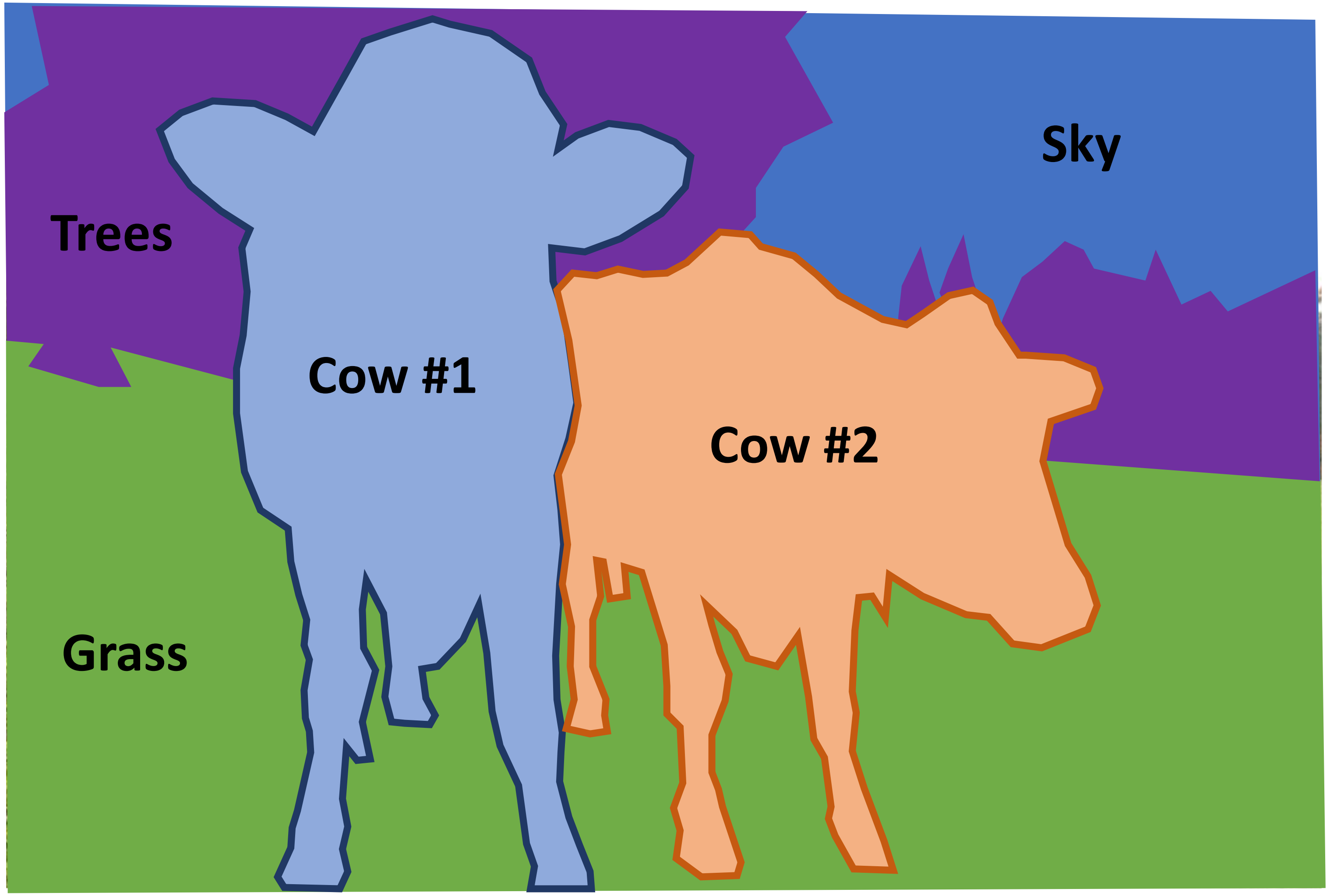
Semantic Segmentation: Identify both things and stuff, but doesn't separate instances



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

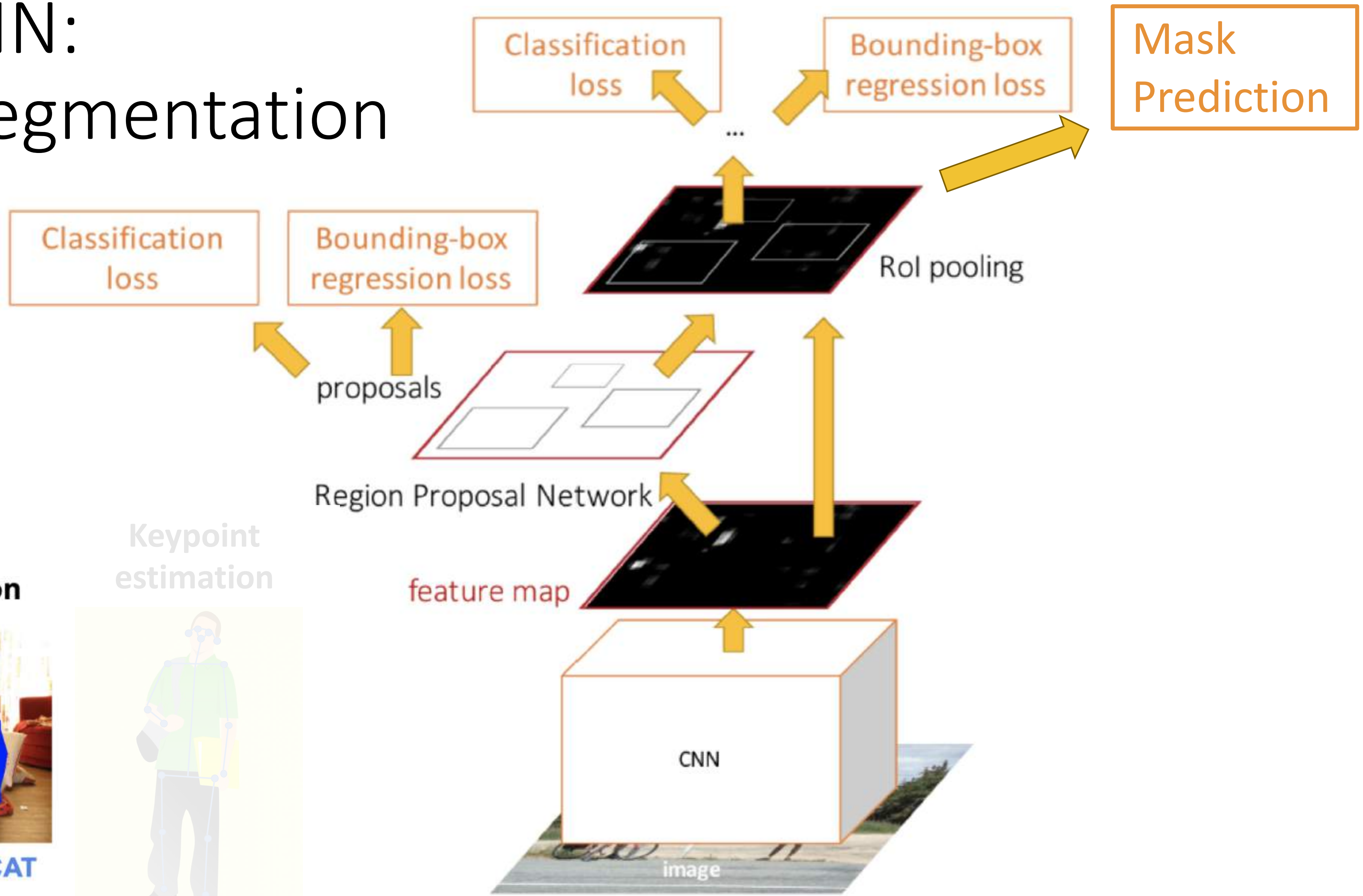
Beyond Instance Segmentation: Human Keypoints

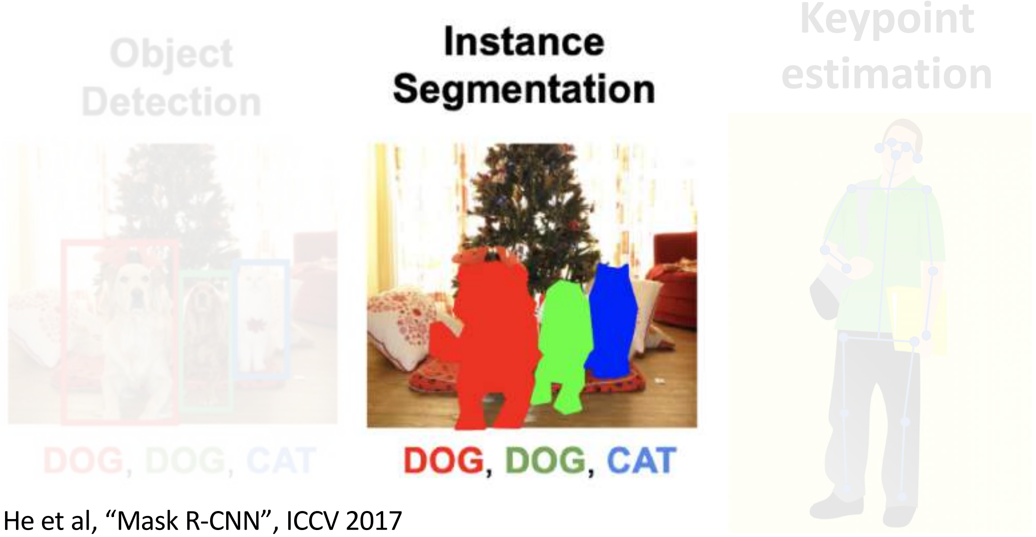
Represent the pose of a human by locating a set of **keypoints**

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

Person image is CC0 public domain

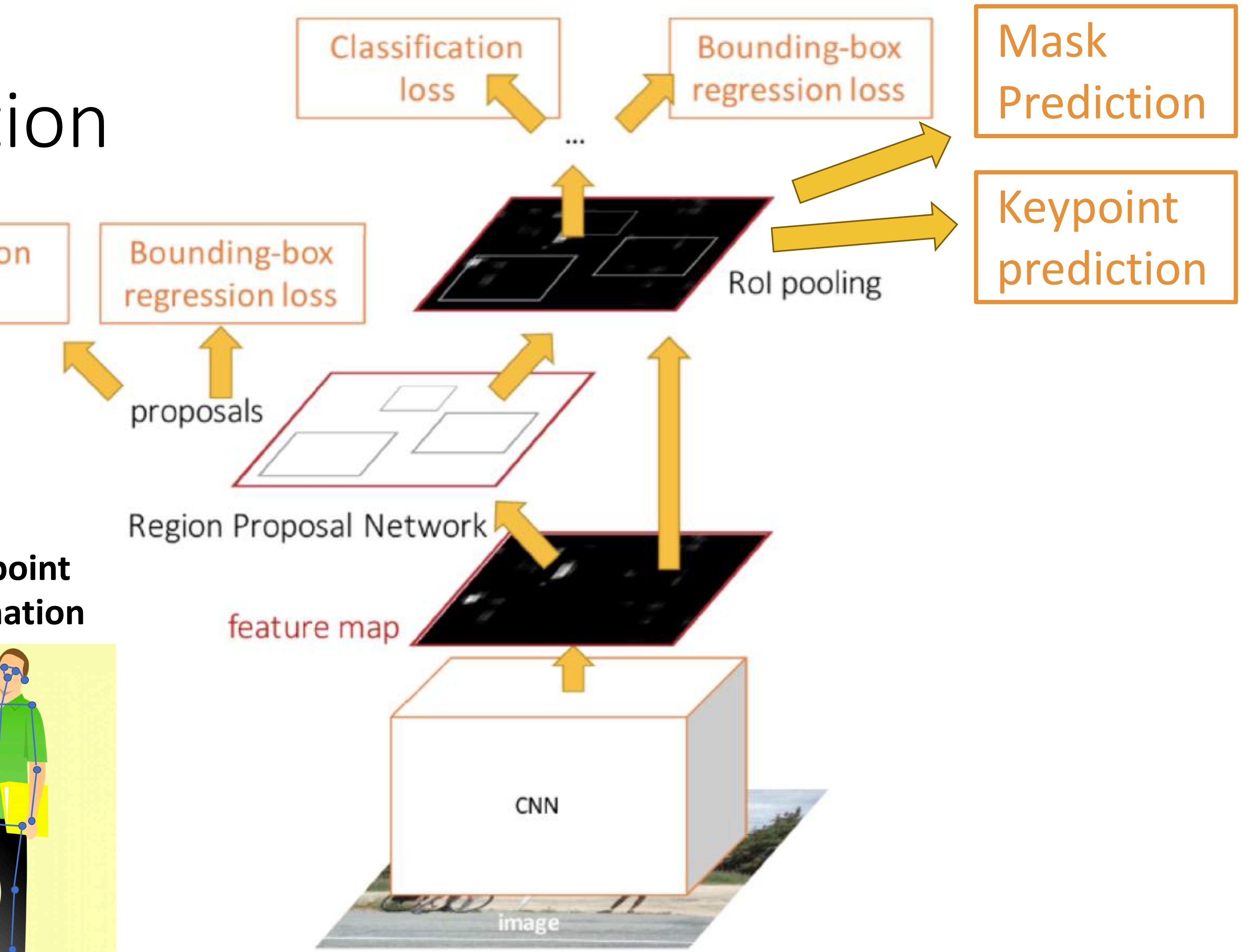
Mask R-CNN: Instance Segmentation





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

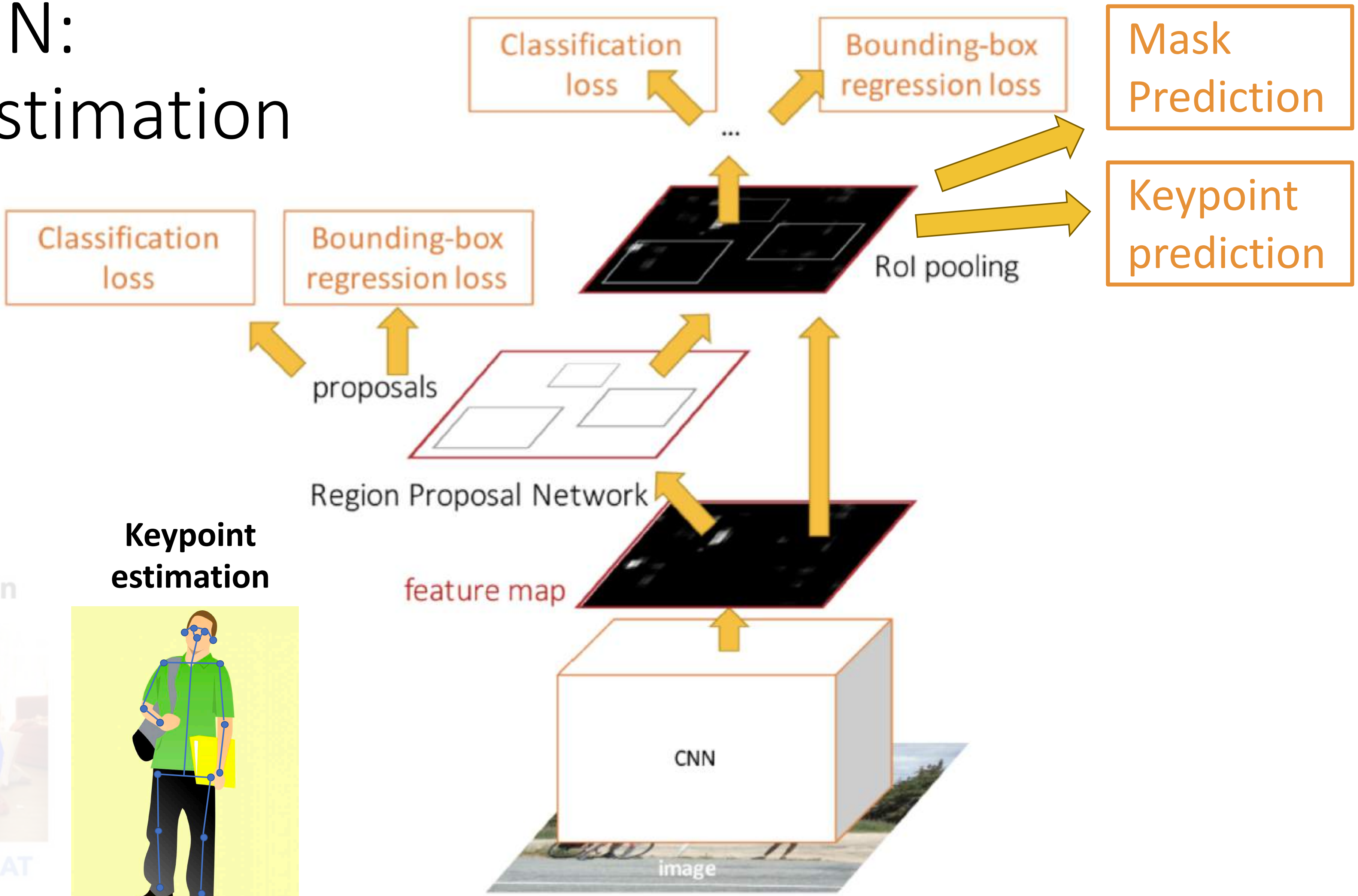
Mask R-CNN: Keypoint Estimation



Keypoint estimation

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

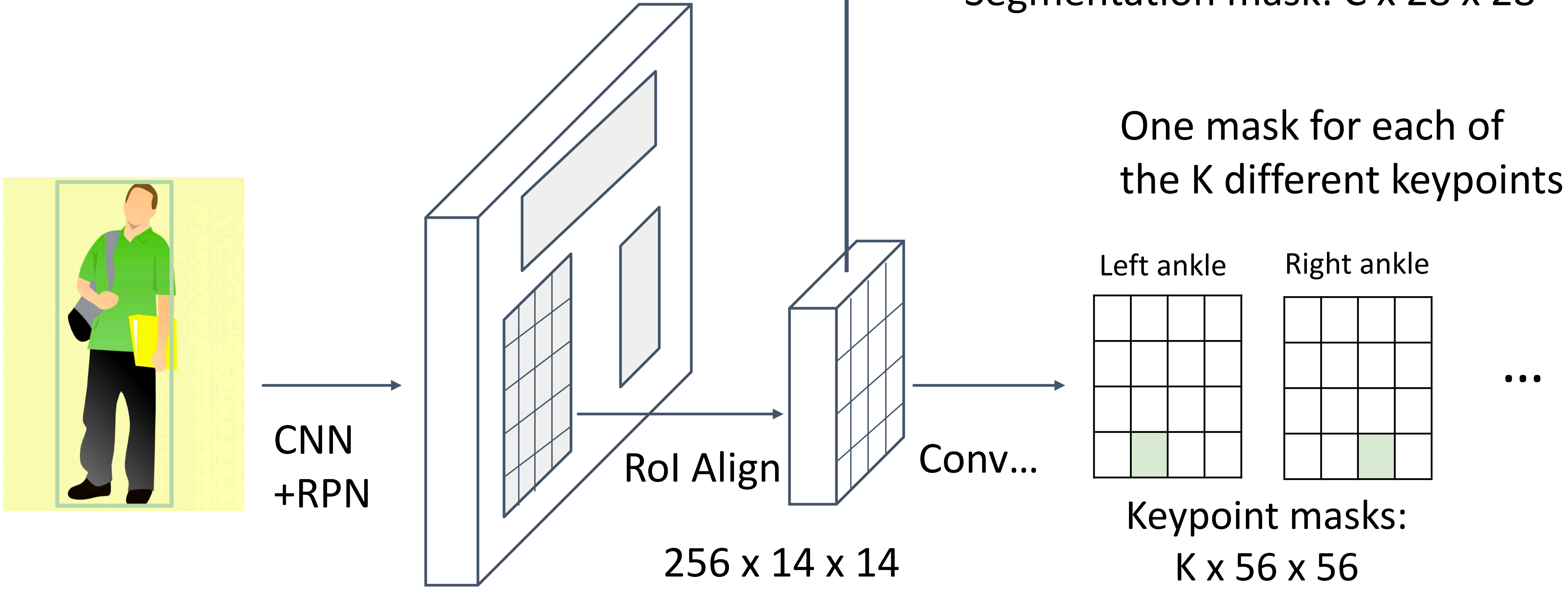
Mask R-CNN: Keypoint Estimation



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



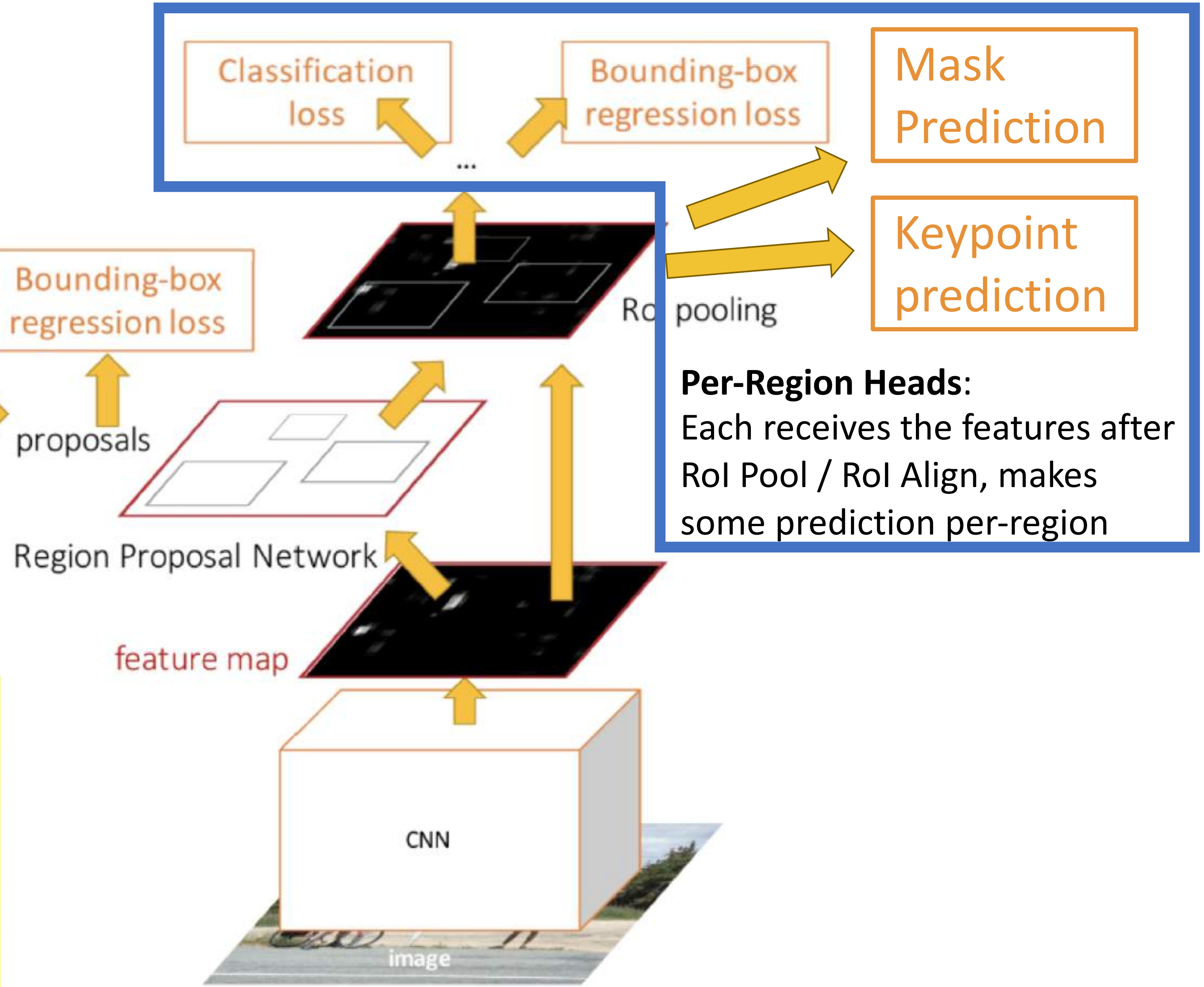
Ground-truth has one "pixel" turned on per keypoint. Train with softmax loss

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

Object Detection

DOG, DOG, CAT

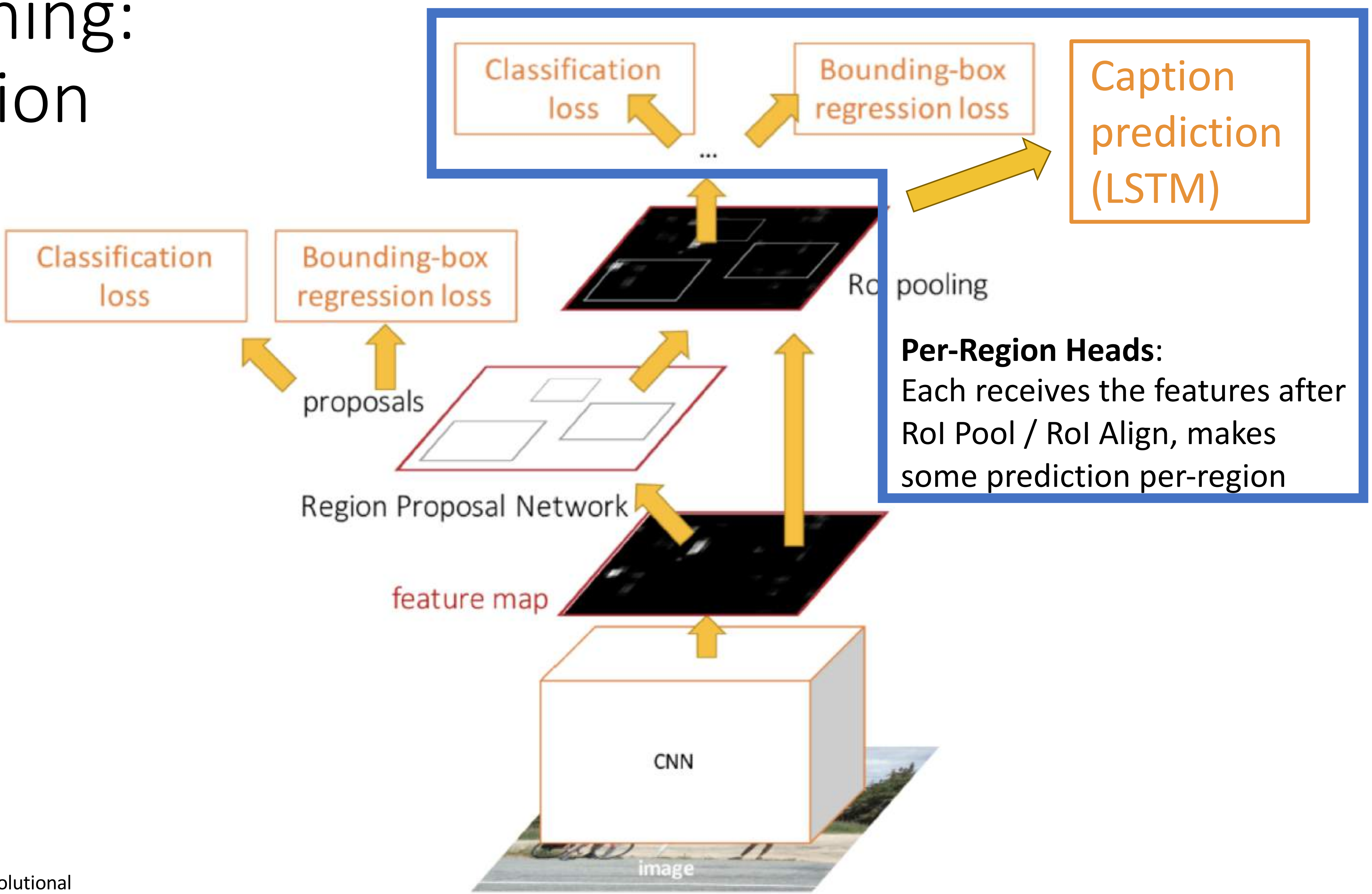
Instance Segmentation

DOG, DOG, CAT

Keypoint estimation

He et al, “Mask R-CNN”, ICCV 2017

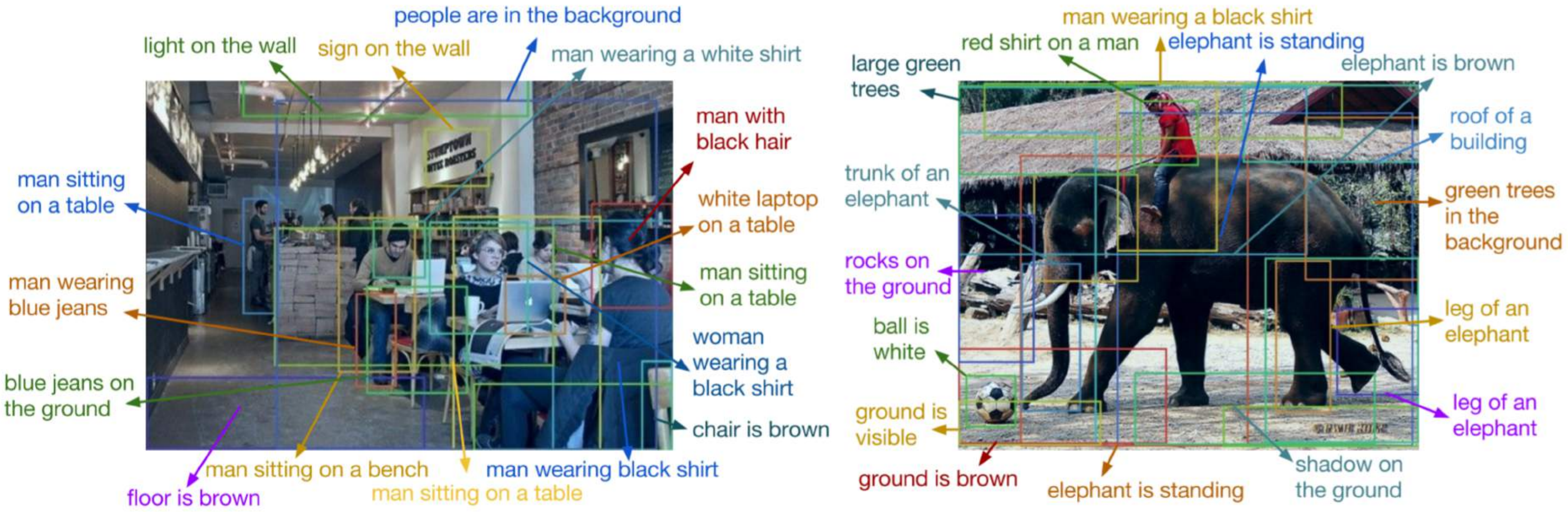
Dense Captioning: Predict a caption per region!



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

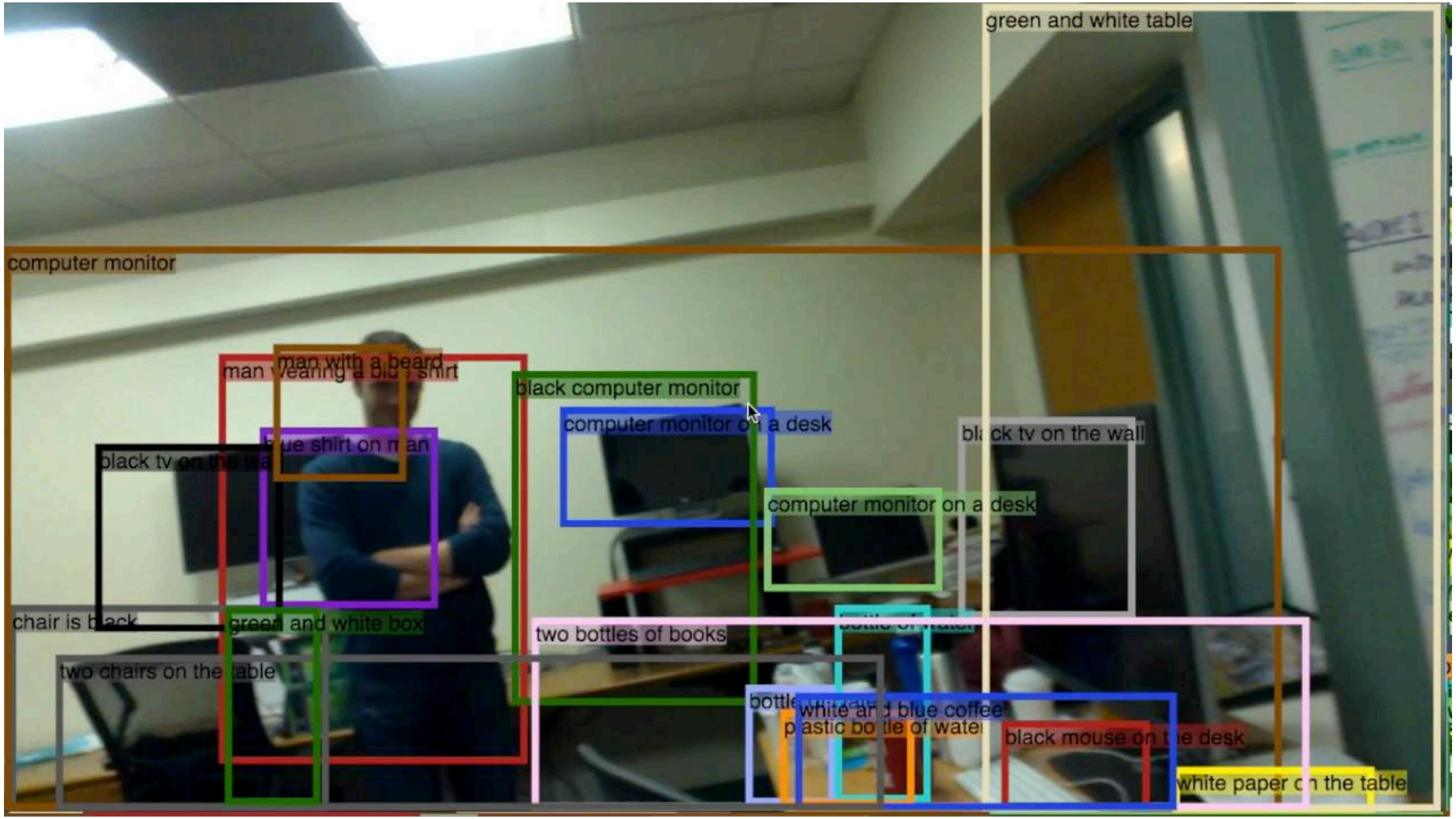
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Dense Captioning



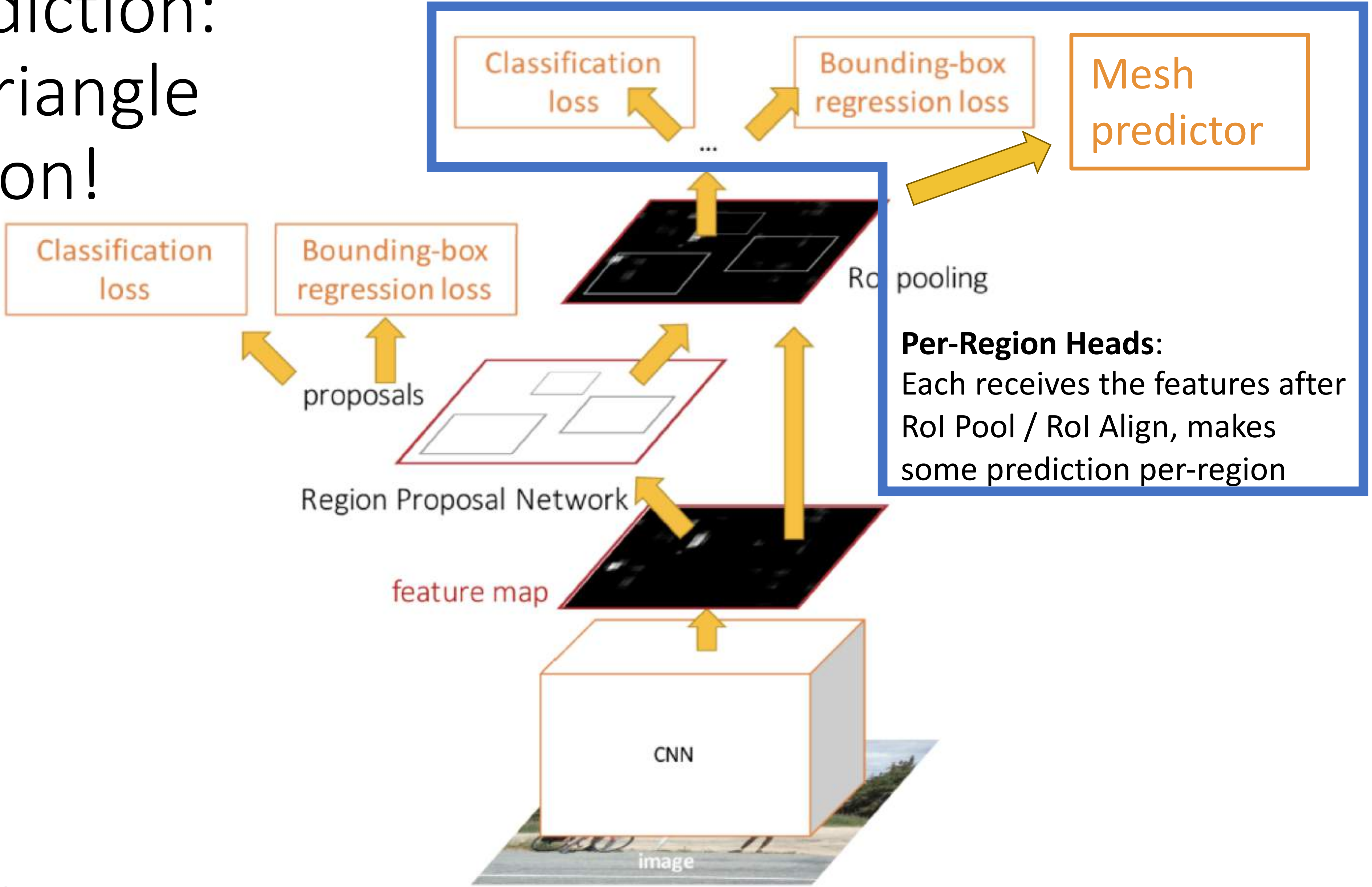
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Dense Captioning



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

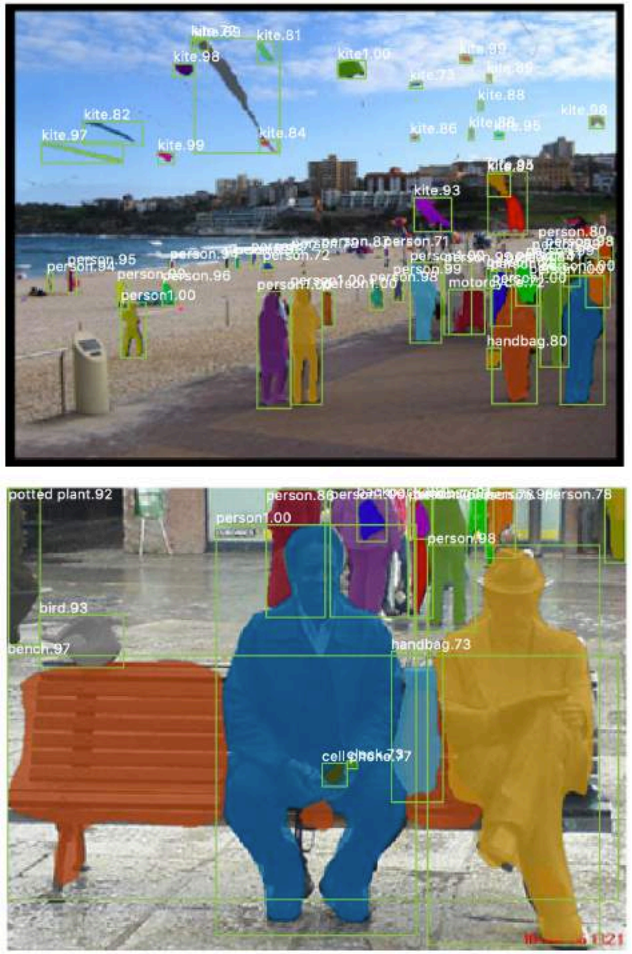
3D Shape Prediction: Predict a 3D triangle mesh per region!



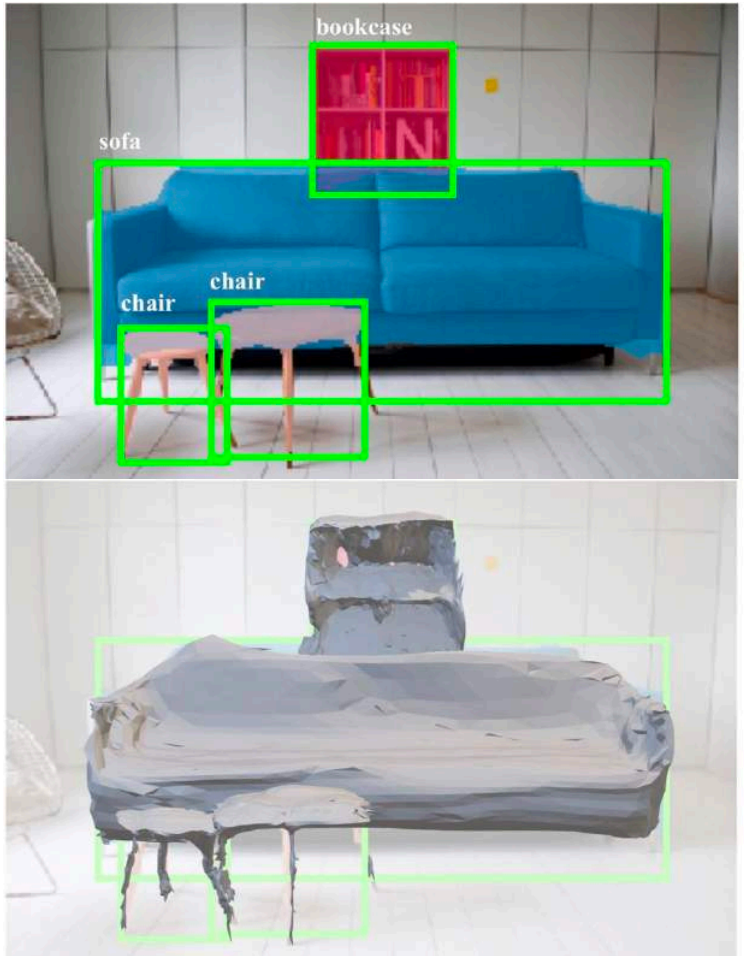
Gkioxari, Malik, and Johnson, "Mesh R-CNN", ICCV 2019

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

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



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

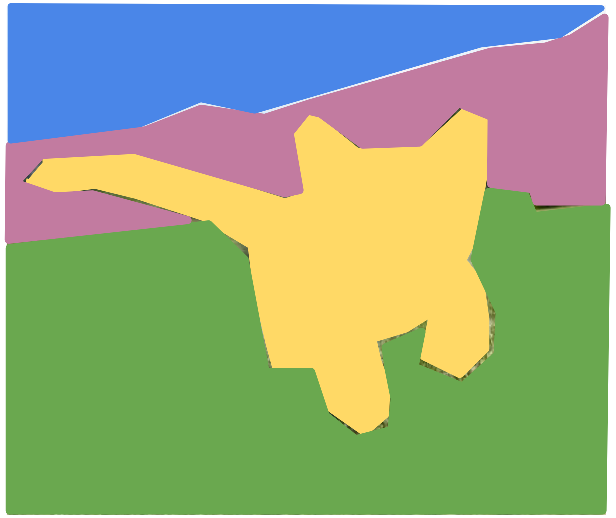
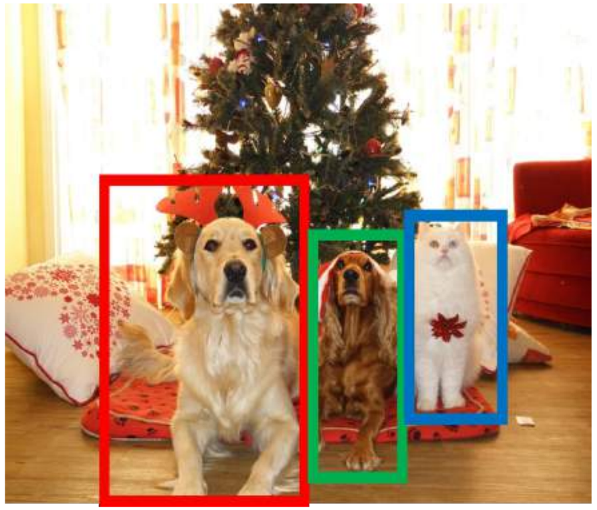


More details next time!

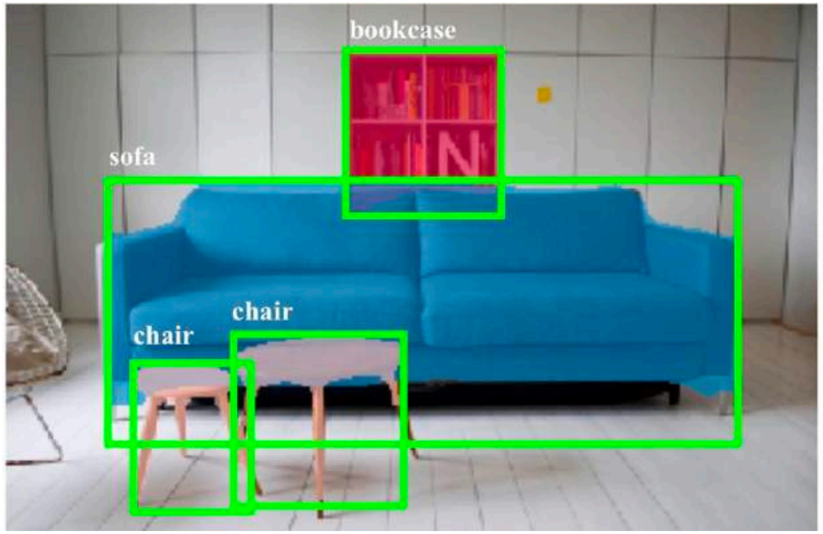
He, Gkioxari, Dollár, and Girshick, "Mask R-CNN", ICCV 2017

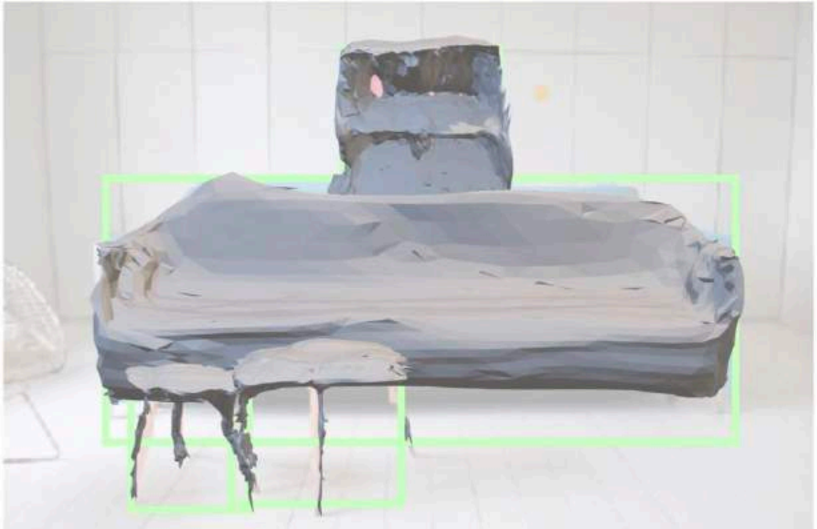
Gkioxari, Malik, and Johnson, "Mesh R-CNN", ICCV 2019

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	

This image is CC0 public domain





Next Time:
3D Vision