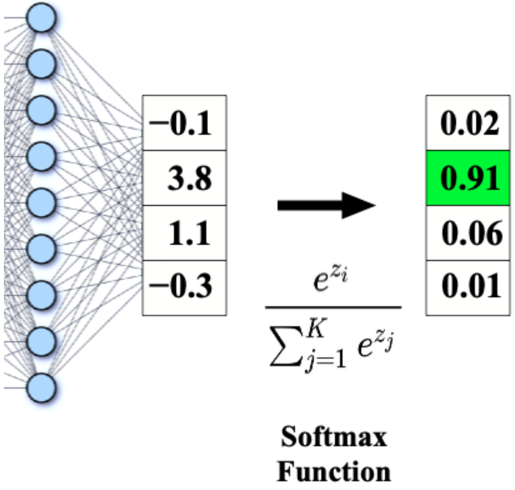
Lecture 9:
Object Detection and Image Segmentation

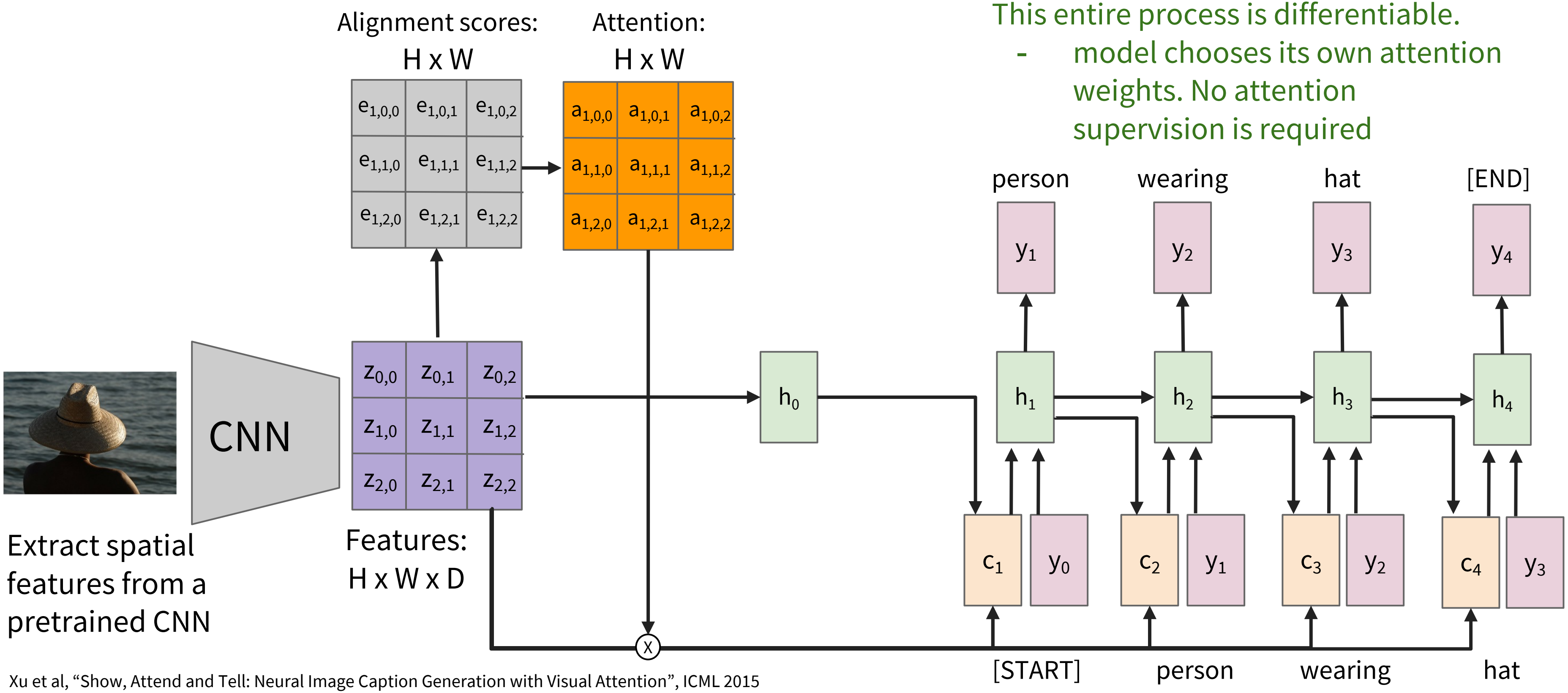
Softmax – Assignment 1



Can we have a data point that has a zero CE loss in softmax classifier?

- Correct answer:
    - No. It is very rare or unlikely. For every datapoint, softmax normalizes scores of all classes to turn it into a probability distribution (no probability can be exactly 0 or 1). Hence the CE loss can never be zero.
- Wrong answers by many students:
    - In softmax, adding a new datapoint perturbs the denominator of the softmax, which affects all the probabilities.
    - By adding a datapoint, the softmax loss can change because the log prob of the correct class for the new datapoint is likely different from the log prob of the correct class for existing datapoints.

Last time: Image Captioning with RNNs and Attention

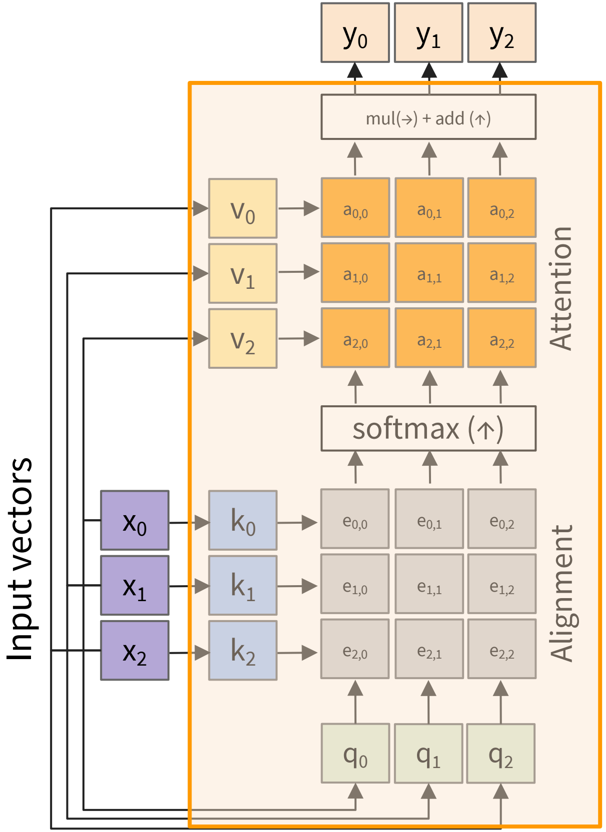


This entire process is differentiable.

- model chooses its own attention weights. No attention supervision is required

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

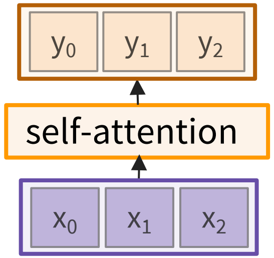
Last time: Self-Attention



Outputs:
context vectors: y (shape: D_v)

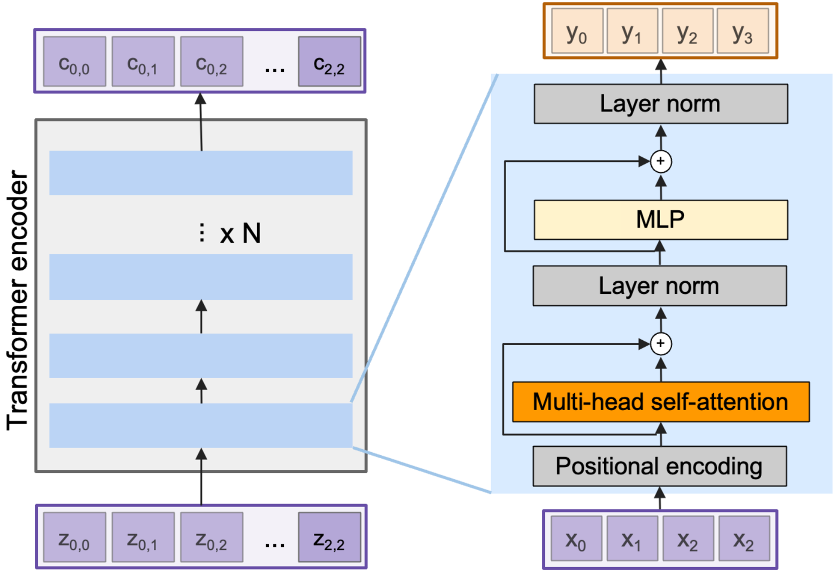
Operations:
Key vectors: $k = xW_k$
Value vectors: $v = xW_v$
Query vectors: $q = xW_q$
Alignment: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
Attention: $a = \text{softmax}(e)$
Output: $y_j = \sum_i a_{i,j} v_i$

Inputs:
Input vectors: x (shape: N x D)

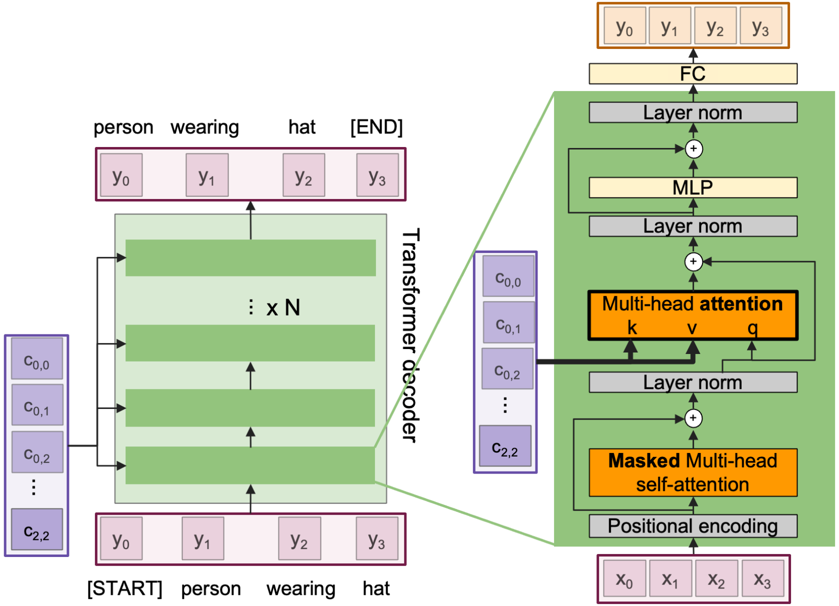


Last time: Transformer

Watch supplementary videos on Canvas (posted yesterday)



Encoder



Decoder

Recall: Image Classification: A core task in Computer Vision

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

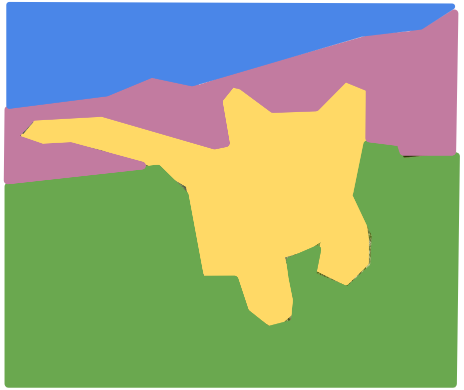
→ cat

Computer Vision Tasks

Classification

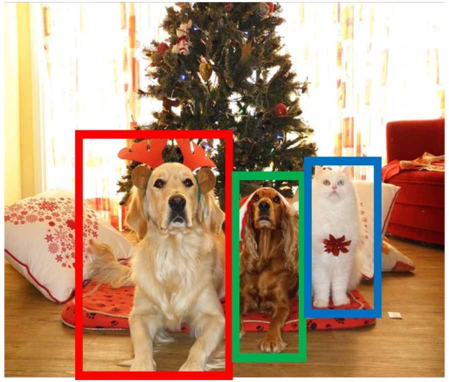
CAT

Semantic Segmentation



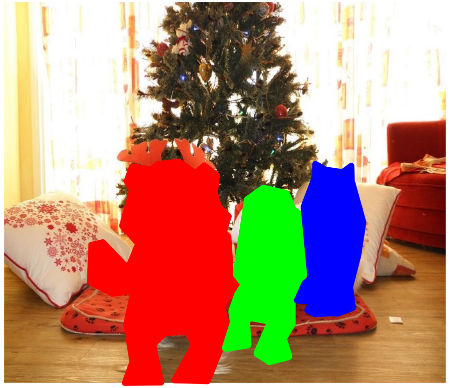
GRASS, CAT, TREE, SKY

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

No spatial extent

No objects, just pixels

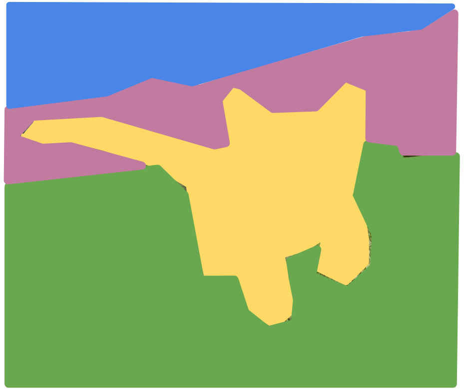
Multiple Object

Semantic Segmentation

Classification

CAT

Semantic Segmentation



GRASS, CAT, TREE, SKY

Object Detection

DOG, DOG, CAT

Instance Segmentation

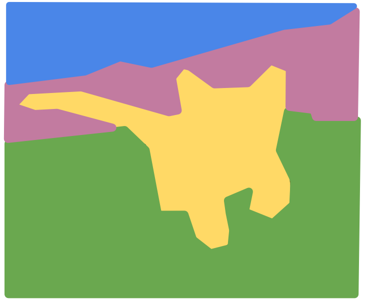
DOG, DOG, CAT

No spatial extent

No objects, just pixels

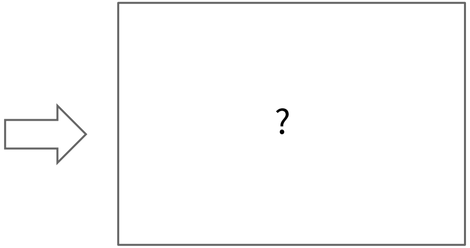
Multiple Object

Semantic Segmentation: The Problem



GRASS, CAT, TREE,
SKY, ...

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



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

Semantic Segmentation Idea: Sliding Window

Full image

Semantic Segmentation Idea: Sliding Window

Full image

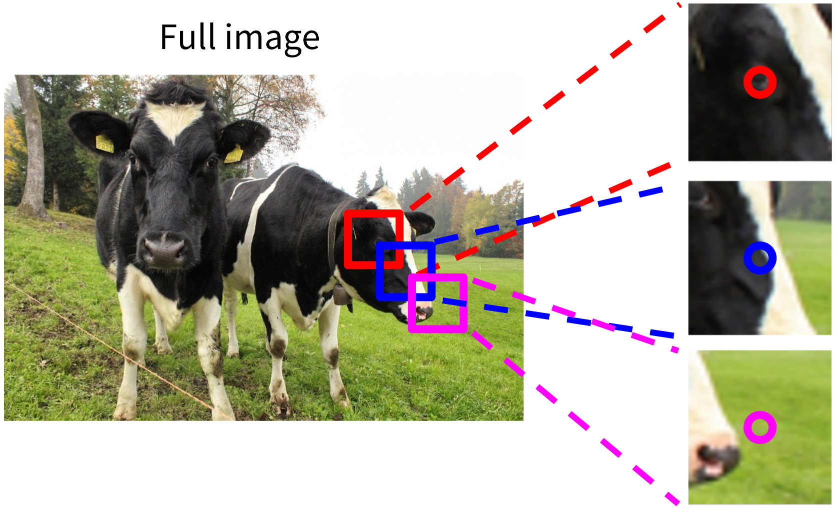
?

Impossible to classify without context

Q: how do we include context?

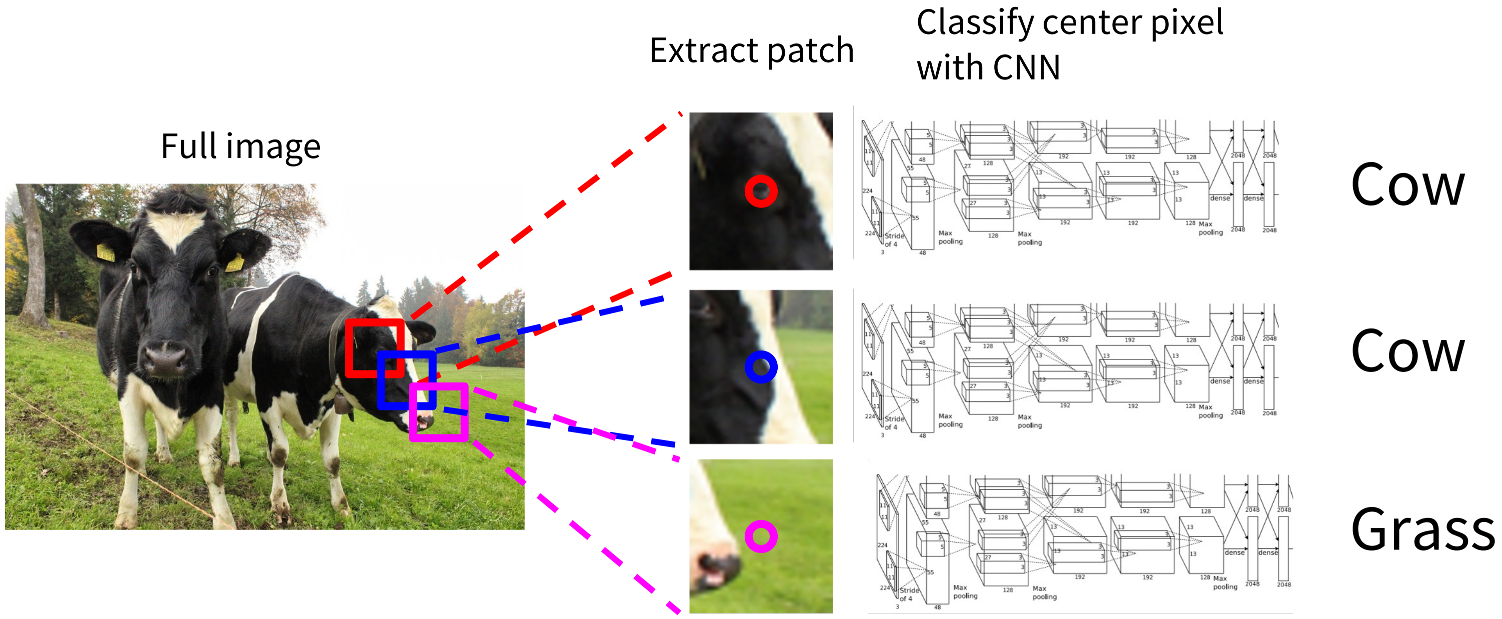
Semantic Segmentation Idea: Sliding Window

Full image



Q: how do we model this?

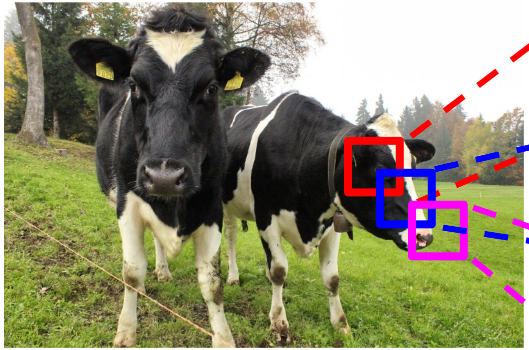
Semantic Segmentation Idea: Sliding Window



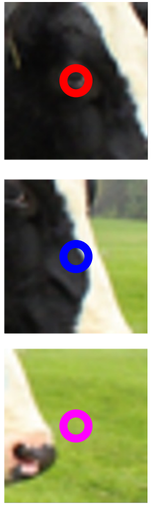
Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Semantic Segmentation Idea: Sliding Window

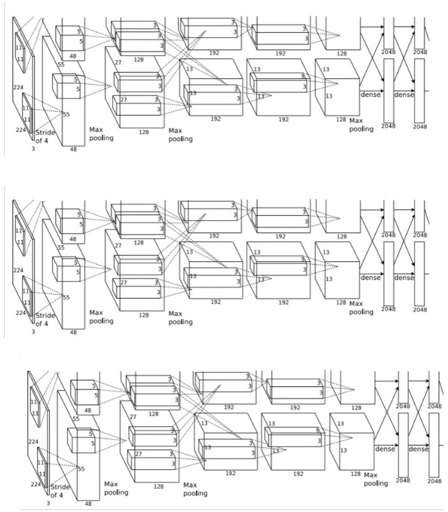
Full image



Extract patch



Classify center pixel with CNN



Cow

Cow

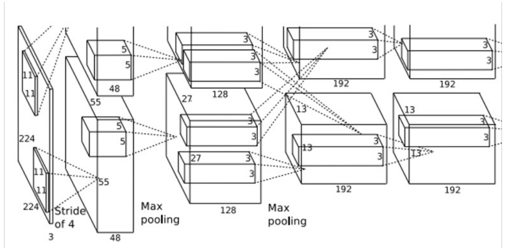
Grass

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 Idea: Convolution

Full image

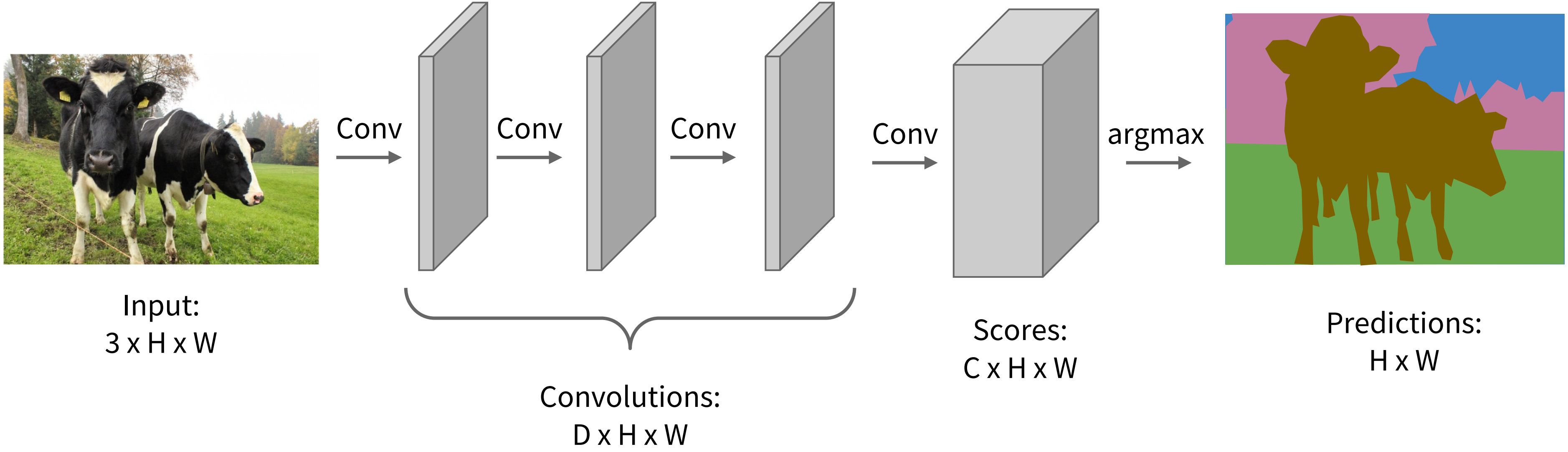


An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

Problem: classification architectures often reduce feature spatial sizes to go deeper, but semantic segmentation requires the output size to be the same as input size.

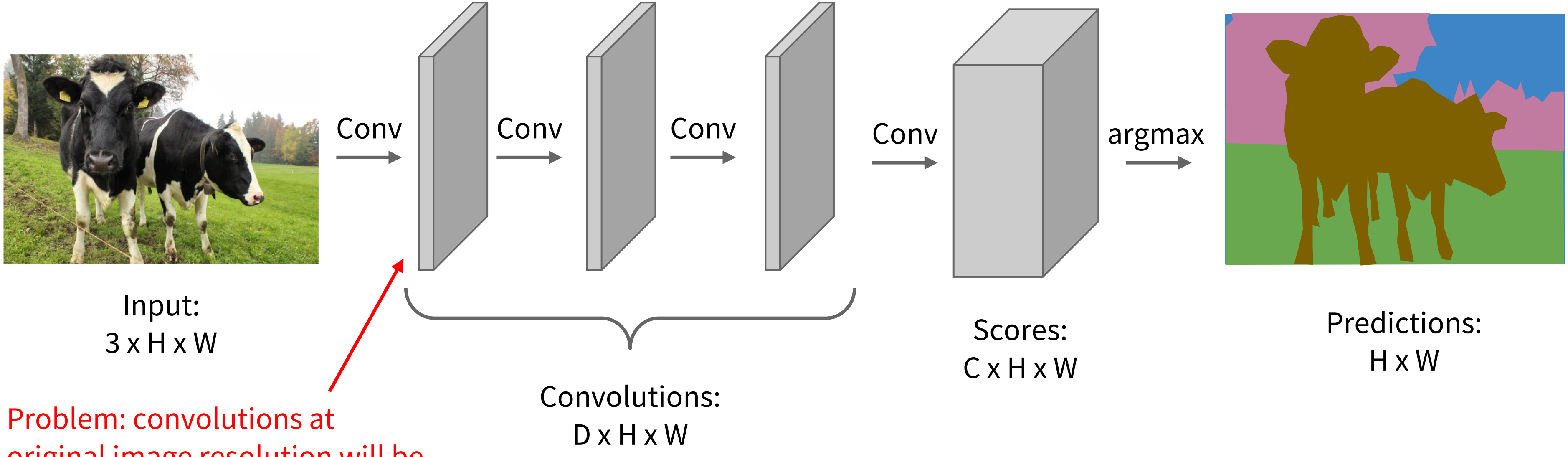
Semantic Segmentation Idea: Fully Convolutional

Design a network with only convolutional layers
without downsampling operators to make predictions
for pixels all at once!



Semantic Segmentation Idea: Fully Convolutional

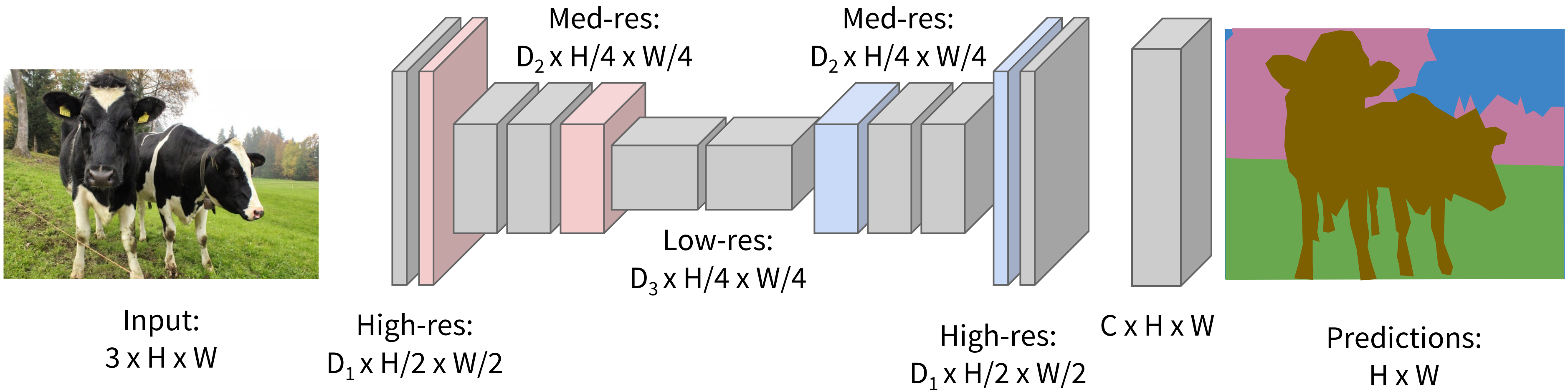
Design a network with only convolutional layers without downsampling operators to make predictions for pixels all at once!



Problem: convolutions at original image resolution will be very expensive ...

Semantic Segmentation Idea: Fully Convolutional

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



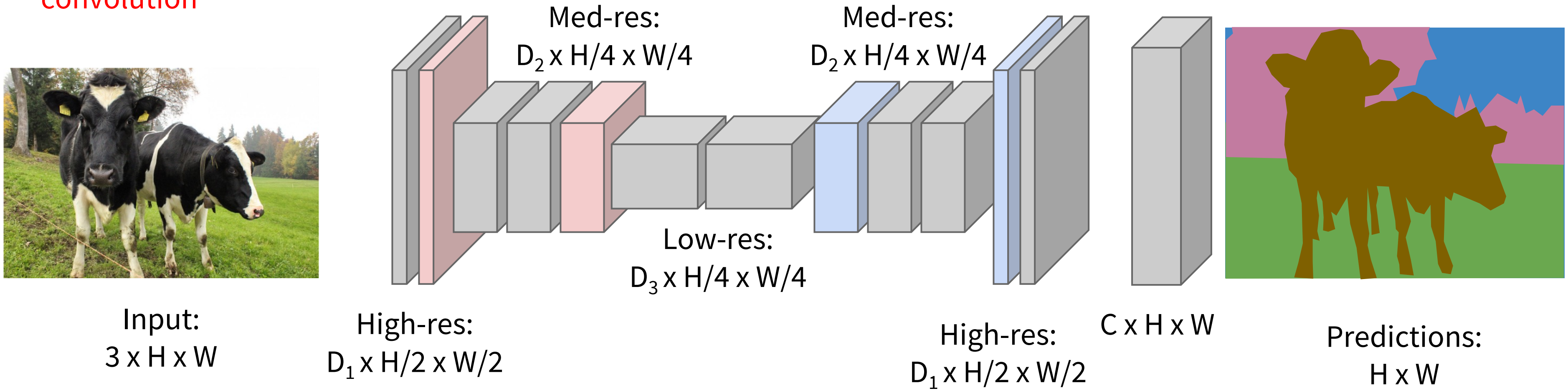
Long, Shelhamer, and Darrell, “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015
Noh et al, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

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

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”

Nearest Neighbor

1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

“Bed of Nails”

1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

In-Network upsampling: “Max Unpooling”

Max Pooling
Remember which element was max!

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

Input: 4 x 4

5	6
7	8

Output: 2 x 2

…

Rest of the network

Max Unpooling
Use positions from pooling layer

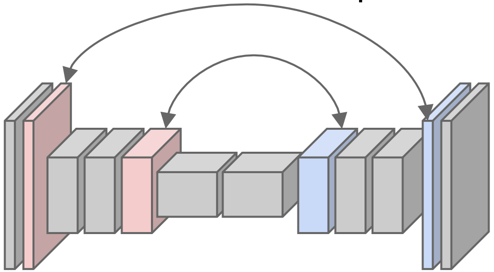
1	2
3	4

Input: 2 x 2

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

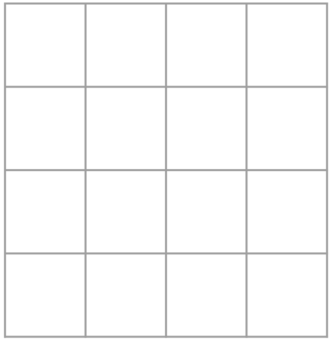
Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

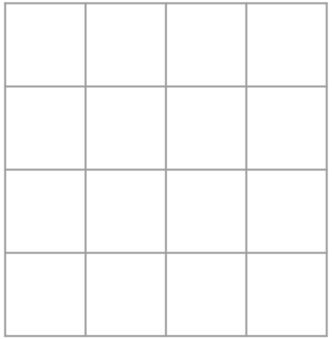


Learnable Upsampling

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



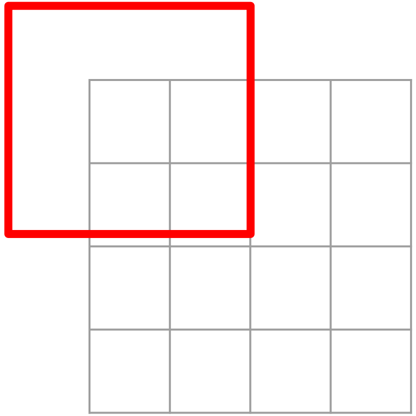
Input: 4 x 4



Output: 4 x 4

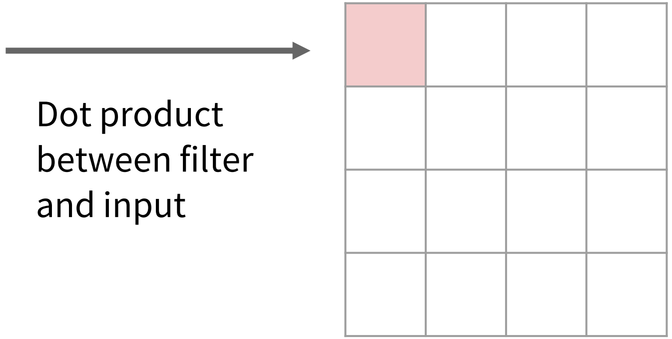
Learnable Upsampling

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



Input: 4 x 4

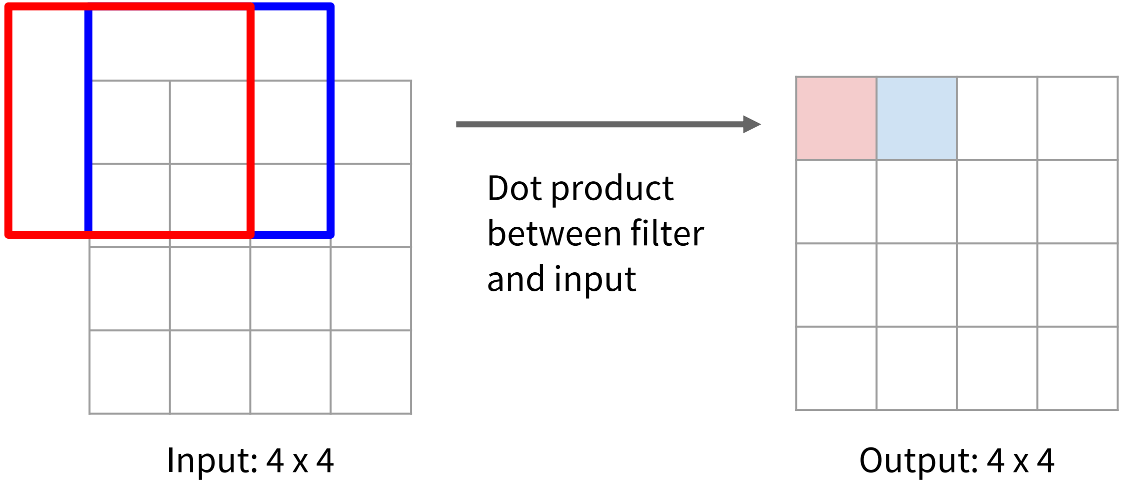
Dot product between filter and input



Output: 4 x 4

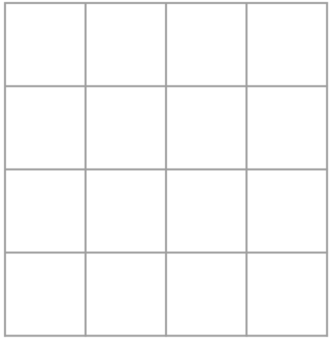
Learnable Upsampling

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

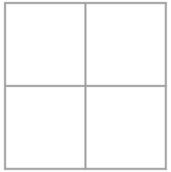


Learnable Upsampling

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



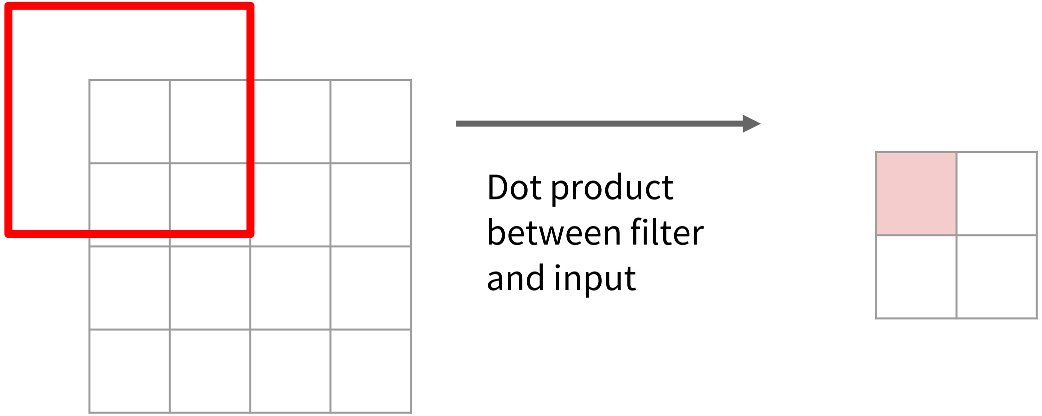
Input: 4 x 4



Output: 2 x 2

Learnable Upsampling

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

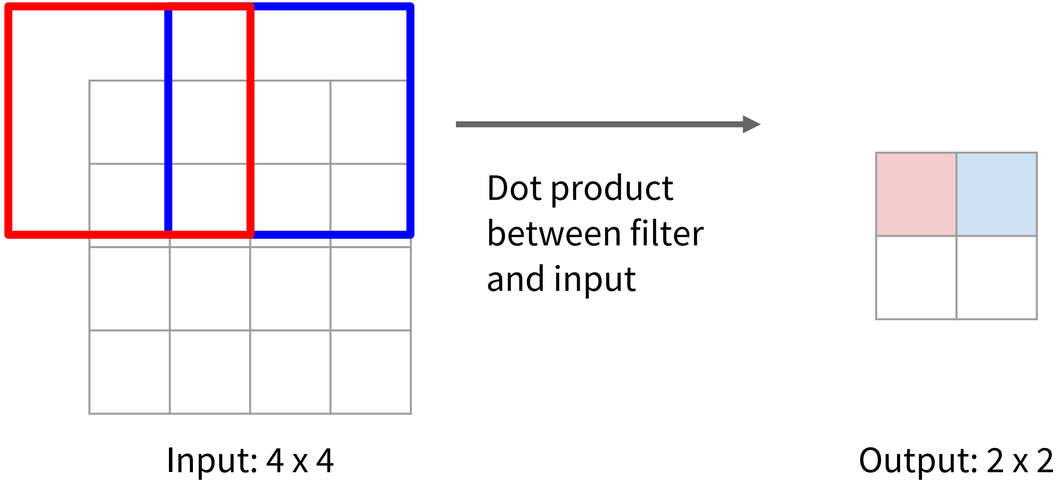


Input: 4 x 4

Output: 2 x 2

Learnable Upsampling

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



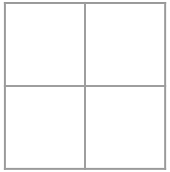
Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

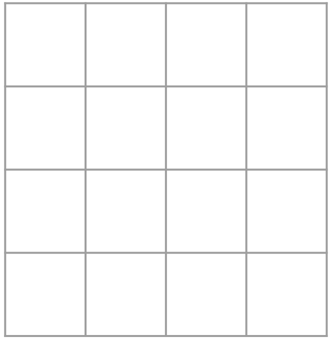
We can interpret strided convolution as “learnable downsampling”.

Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



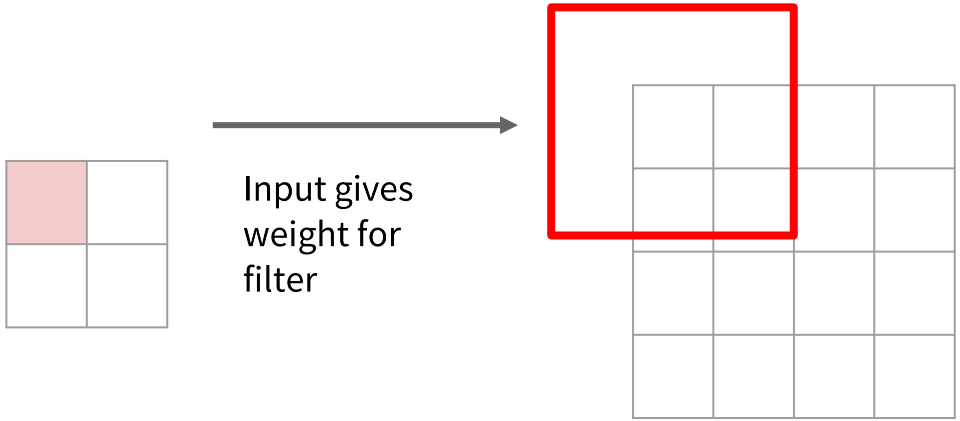
Input: 2 x 2



Output: 4 x 4

Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1

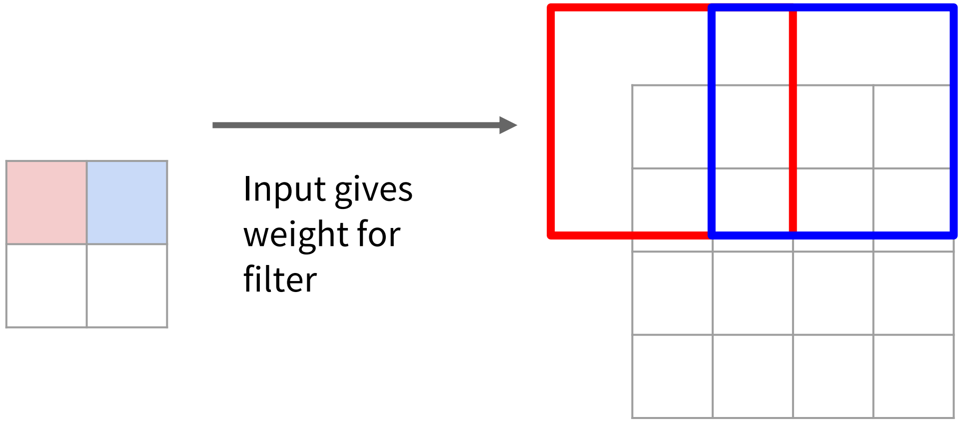


Input: 2 x 2

Output: 4 x 4

Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



Input gives weight for filter

Input: 2 x 2

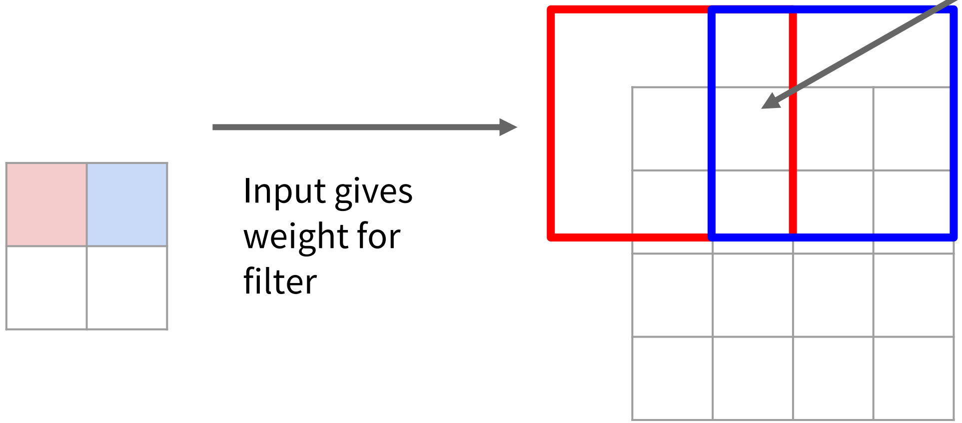
Output: 4 x 4

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

Stride gives ratio between movement in output and input

Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



Input: 2 x 2

Output: 4 x 4

Sum where output overlaps

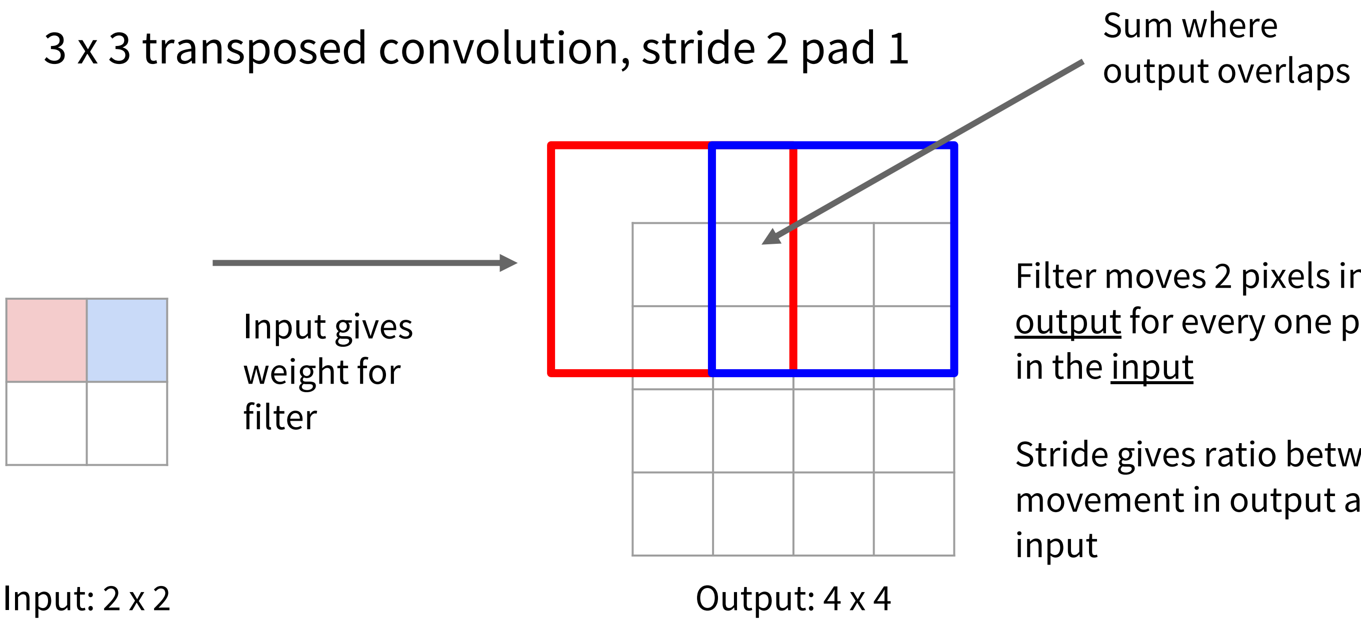
Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: Transposed Convolution

Q: Why is it called transposed convolution?

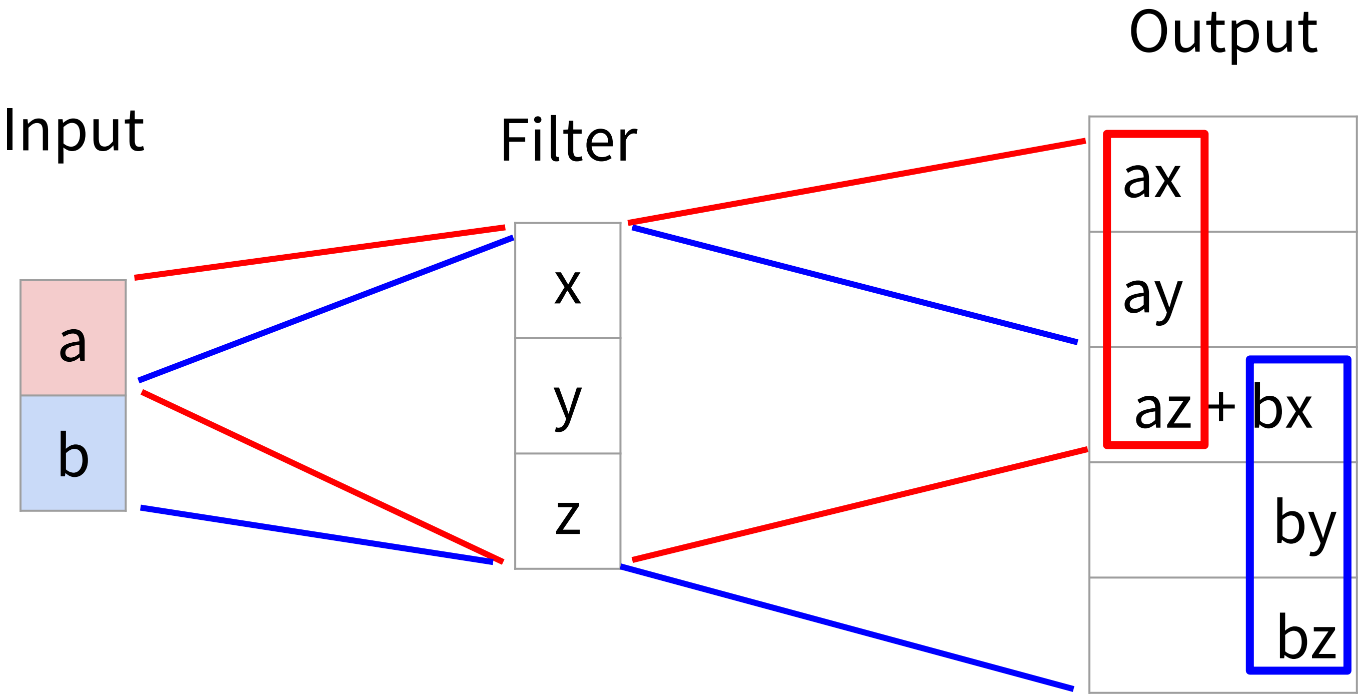
3 x 3 transposed convolution, stride 2 pad 1



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

Stride gives ratio between movement in output and input

Learnable Upsampling: 1D Example



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

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

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:

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

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

Example: 1D transposed conv, kernel size=3, <u>stride=2</u>, padding=0

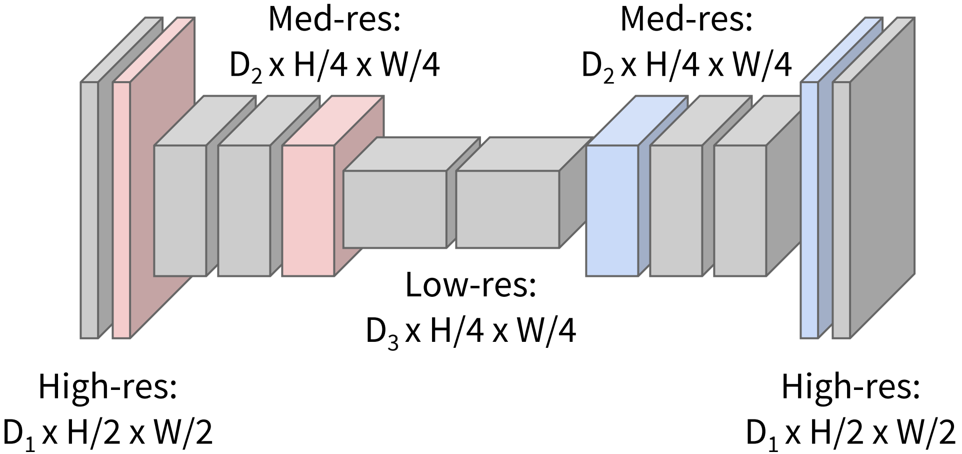
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

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

Upsampling: Unpooling or strided transposed convolution

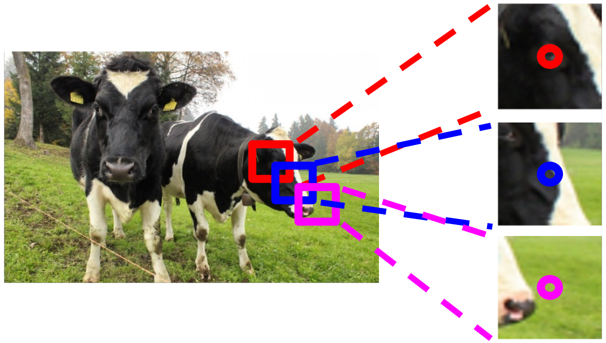
Input:
3 x H x W

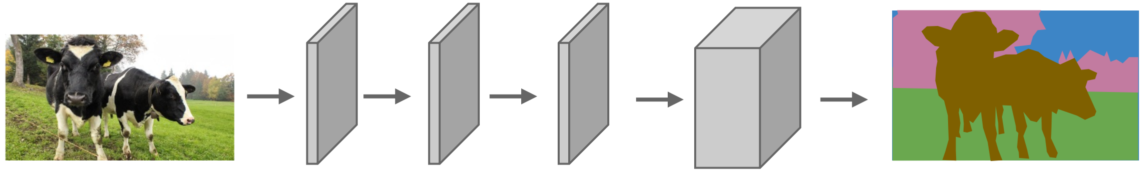


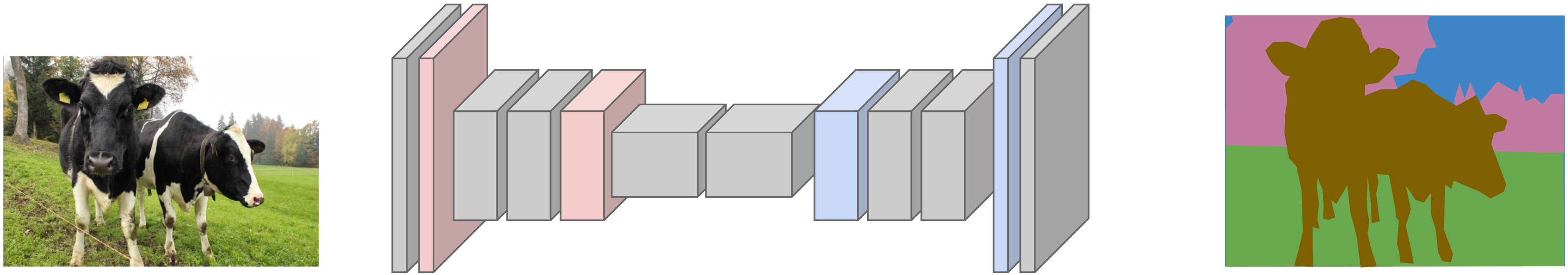
Predictions:
H x W

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

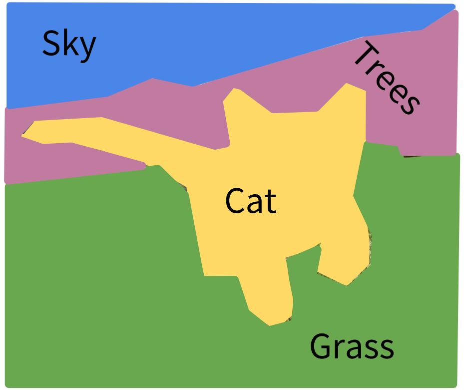
Semantic Segmentation: Summary

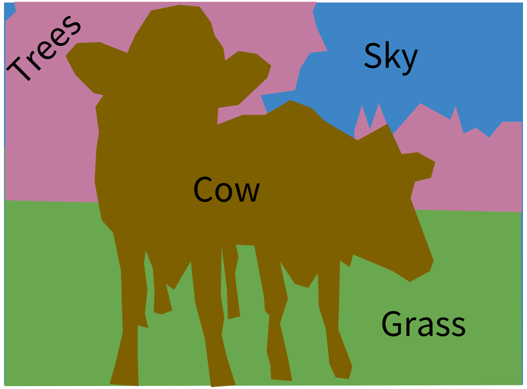






Semantic Segmentation





Label each pixel in the image with a category label

Don’t differentiate instances, only care about pixels

Object Detection

Classification

CAT

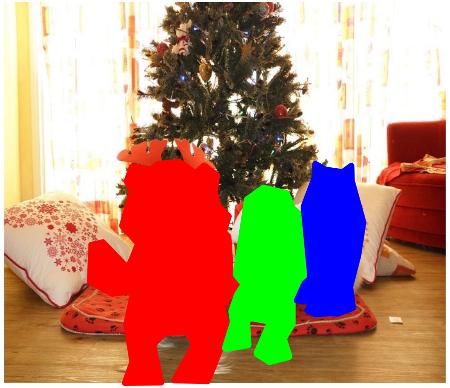
Semantic Segmentation

GRASS, CAT, TREE, SKY

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

No spatial extent

No objects, just pixels

Multiple Object

Object Detection

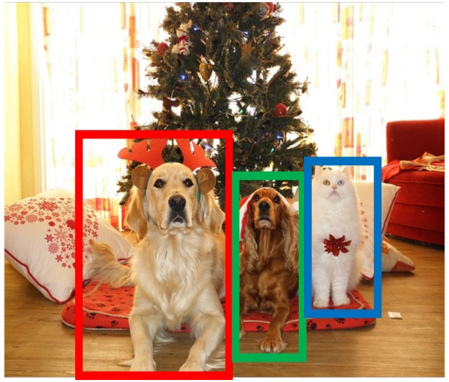
Classification

CAT

Semantic Segmentation

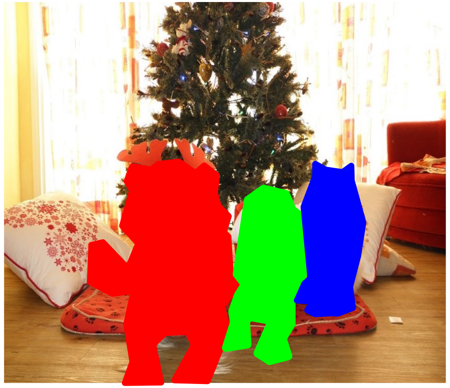
GRASS, CAT, TREE, SKY

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

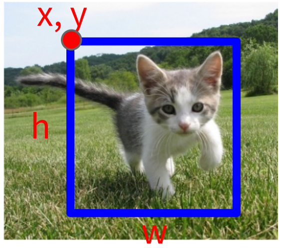
No spatial extent

No objects, just pixels

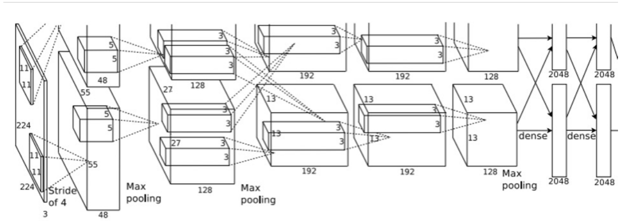
Multiple Object

Object Detection: Single Object

(Classification + Localization)



This image is CC0 public domain



Vector: 4096

Fully Connected: 4096 to 1000

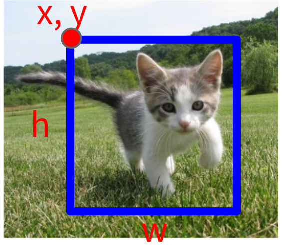
Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Fully Connected: 4096 to 4

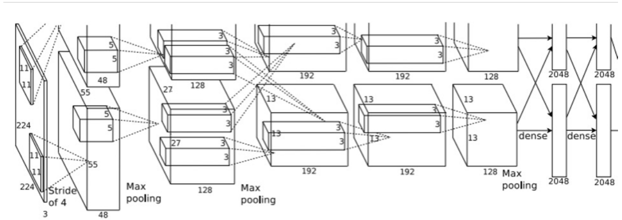
Box Coordinates
(x, y, w, h)

Object Detection: Single Object

(Classification + Localization)



This image is CC0 public domain



Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Correct label: Cat

Fully Connected: 4096 to 4

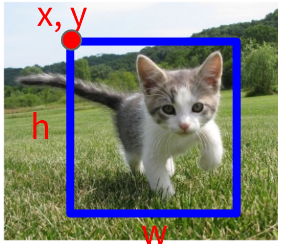
Box Coordinates (x, y, w, h)

L2 Loss

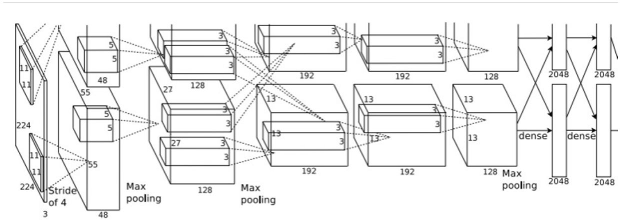
Correct box: (x', y', w', h')

Treat localization as a regression problem!

Object Detection: Single Object
(Classification + Localization)



This image is CC0 public domain



Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label: Cat

Softmax Loss

Multitask Loss

\+ → Loss

Fully Connected: 4096 to 4

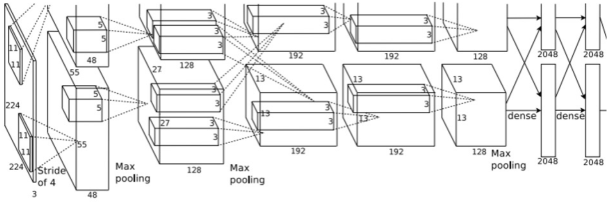
Box Coordinates (x, y, w, h)

L2 Loss

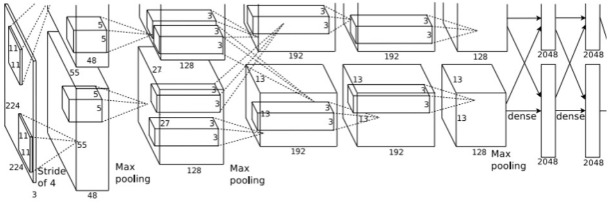
Correct box: (x’, y’, w’, h’)

Treat localization as a regression problem!

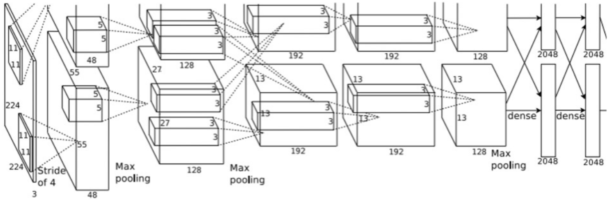
Object Detection: Multiple Objects



CAT: (x, y, w, h)



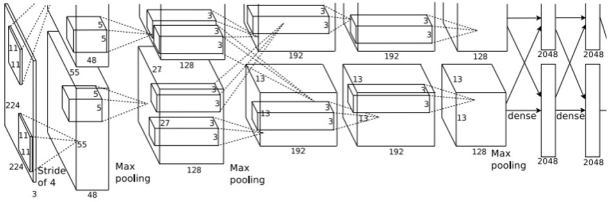
DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)



DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

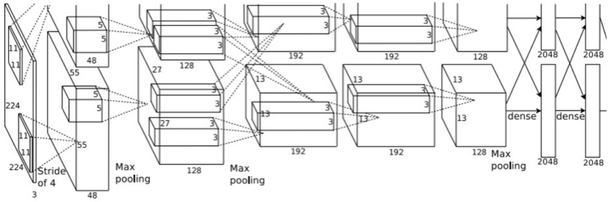
Object Detection: Multiple Objects

Each image needs a different number of outputs!



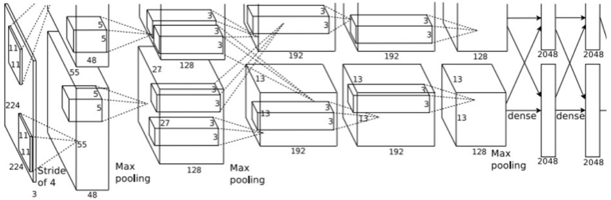
CAT: (x, y, w, h)

4 numbers



DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

12 numbers

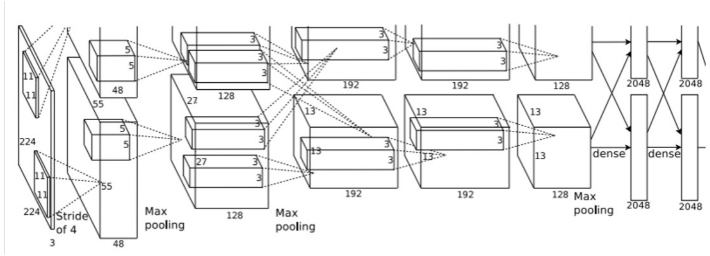


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Many numbers!

Object Detection: Multiple Objects

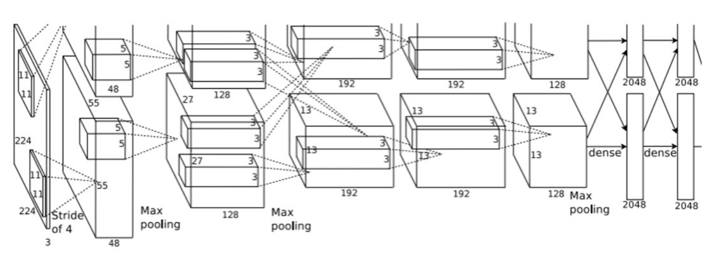
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

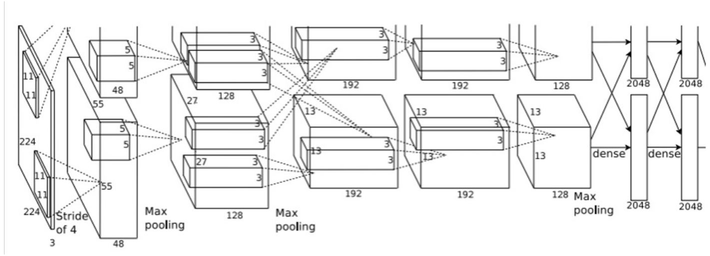
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

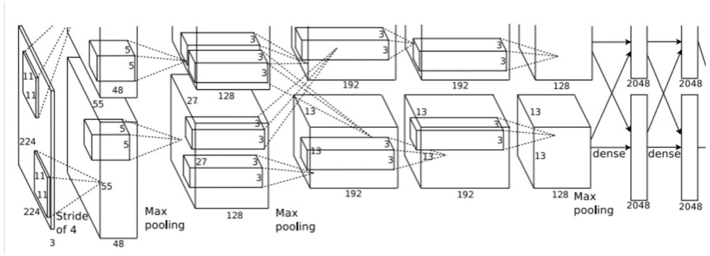
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

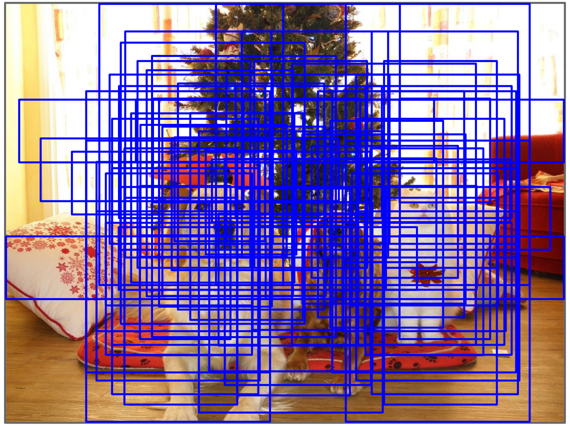
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



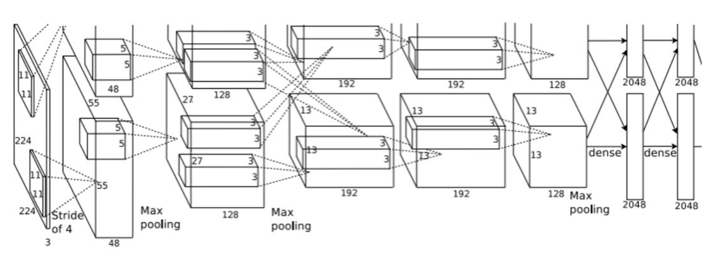
Dog? NO
Cat? YES
Background? NO

Q: What's the problem with this approach?

Object Detection: Multiple Objects



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

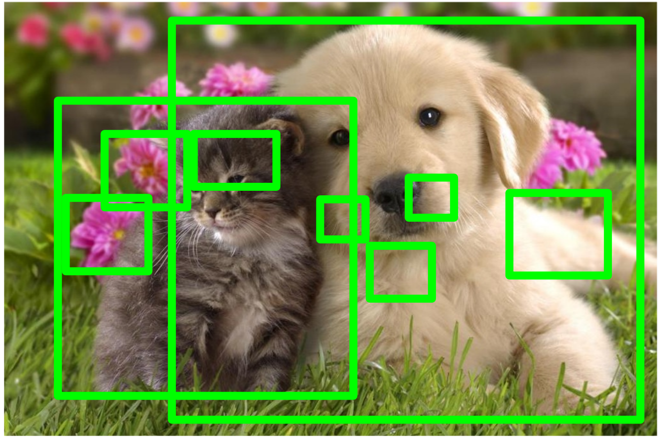


Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!

Region Proposals: Selective Search

- Find "blobby" image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



Alexe et al, "Measuring the objectness of image windows", TPAMI 2012
Uijlings et al, "Selective Search for Object Recognition", IJCV 2013
Cheng et al, "BING: Binarized normed gradients for objectness estimation at 300fps", CVPR 2014
Zitnick and Dollar, "Edge boxes: Locating object proposals from edges", ECCV 2014

R-CNN

Input image

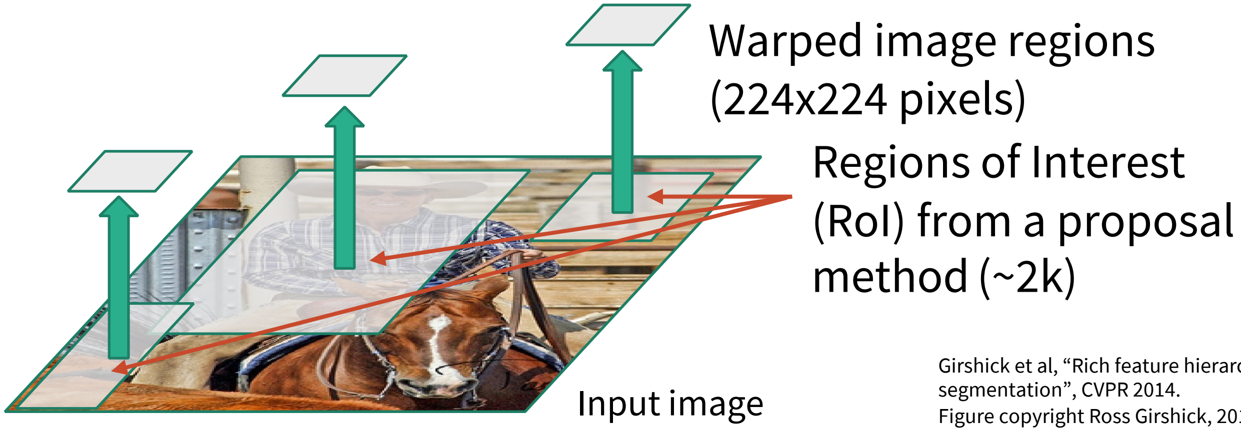
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN

Regions of Interest (RoI) from a proposal method (~2k)

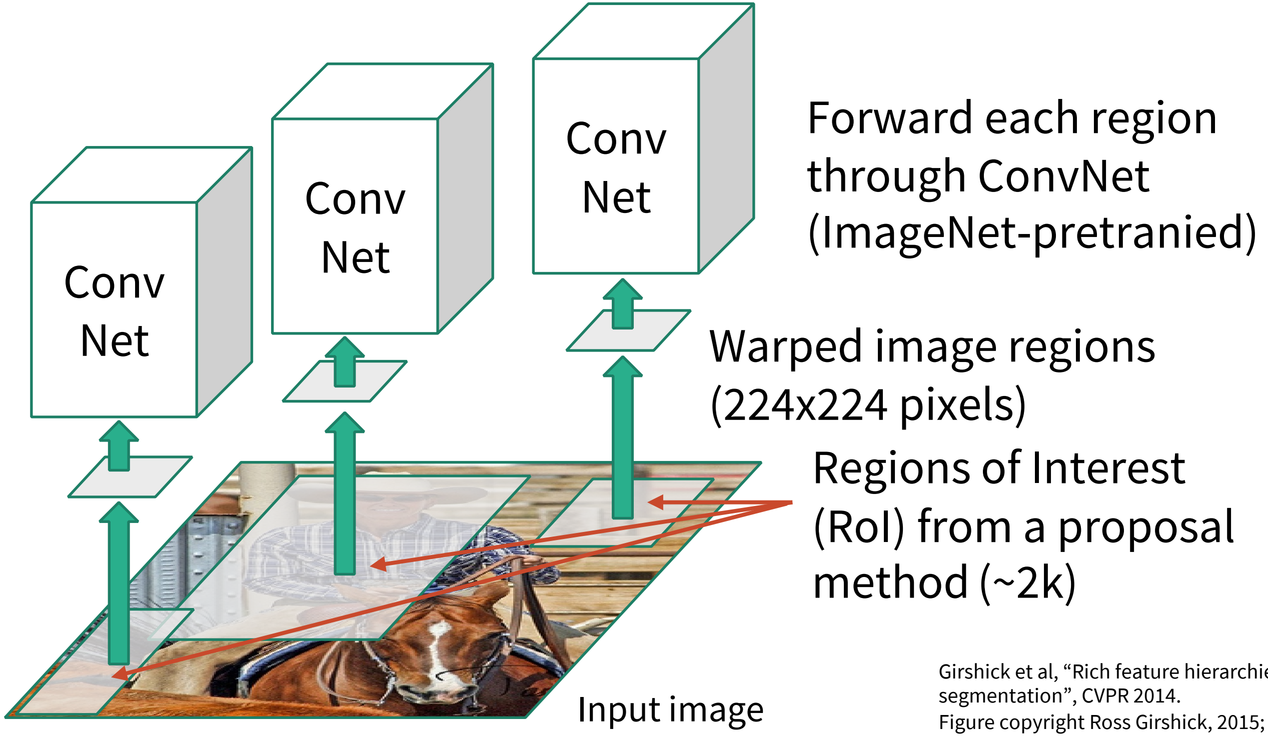
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN



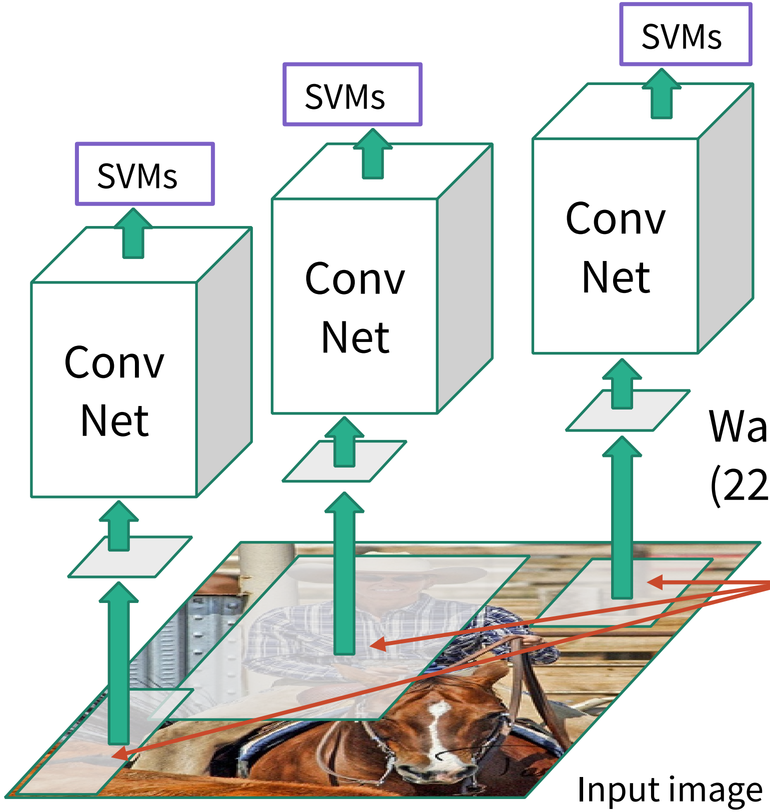
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN



Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN



Classify regions with SVMs

Forward each region through ConvNet (ImageNet-pretranied)

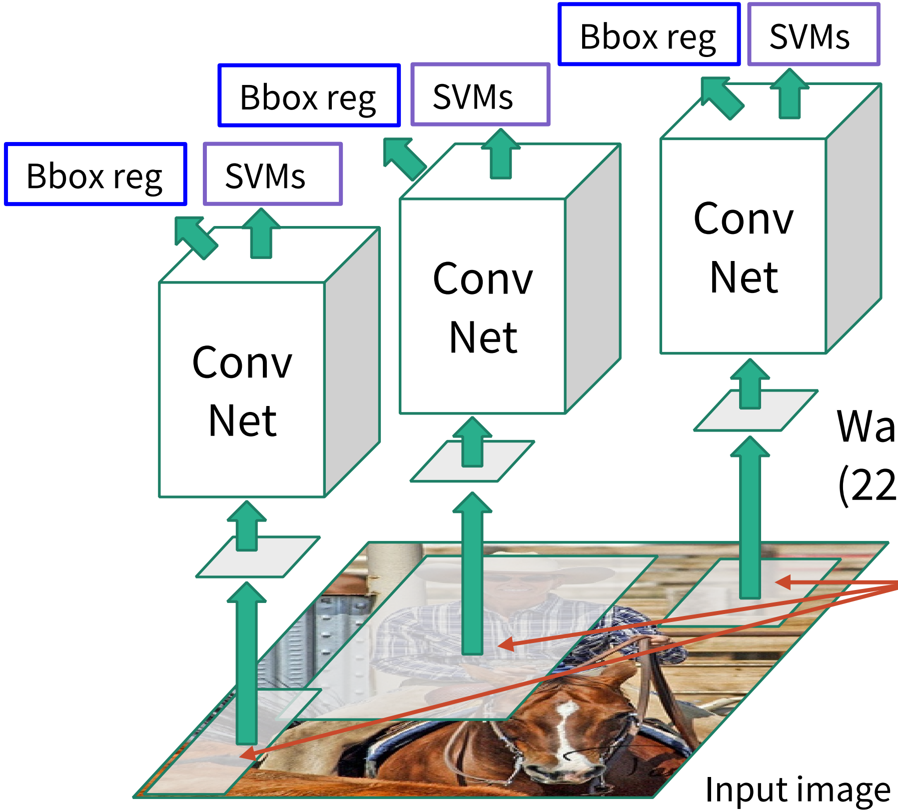
Warped image regions (224x224 pixels)

Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN

Predict "corrections" to the RoI: 4 numbers: (dx, dy, dw, dh)



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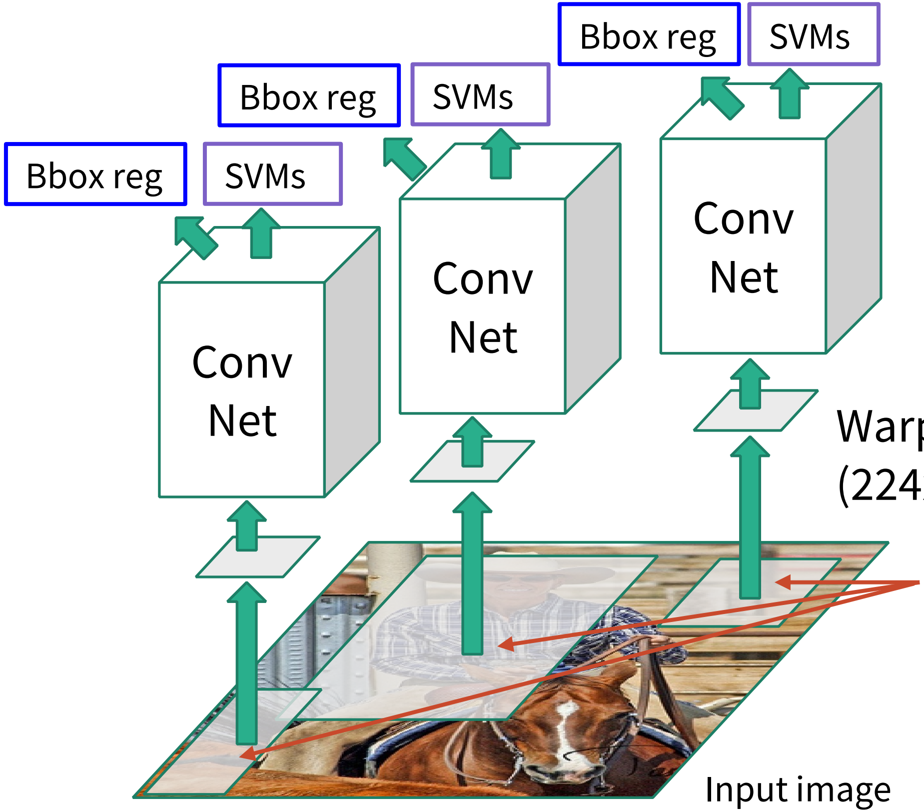
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN



Predict "corrections" to the RoI: 4 numbers: (dx, dy, dw, dh)

Classify regions with SVMs

Forward each region through ConvNet

Warped image regions (224x224 pixels)

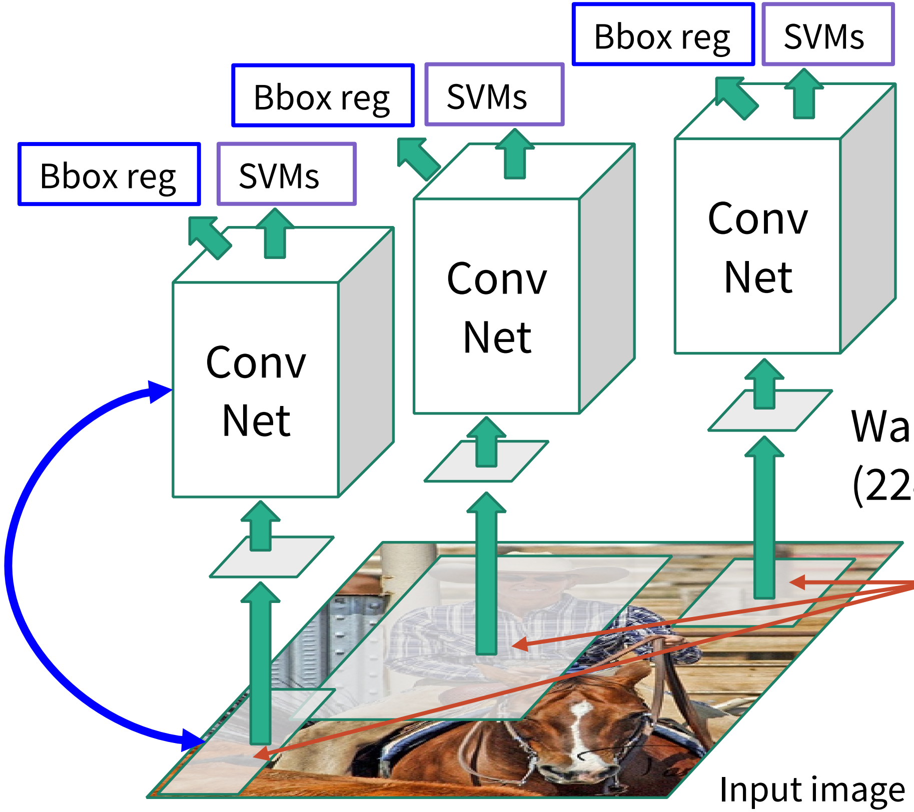
Regions of Interest (RoI) from a proposal method (~2k)

Problem: Very slow! Need to do ~2k independent forward passes for each image!

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

“Slow” R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)



Classify regions with SVMs

Forward each region through ConvNet

Warped image regions (224x224 pixels)

Regions of Interest (RoI) from a proposal method (~2k)

Problem: Very slow! Need to do ~2k independent forward passes for each image!

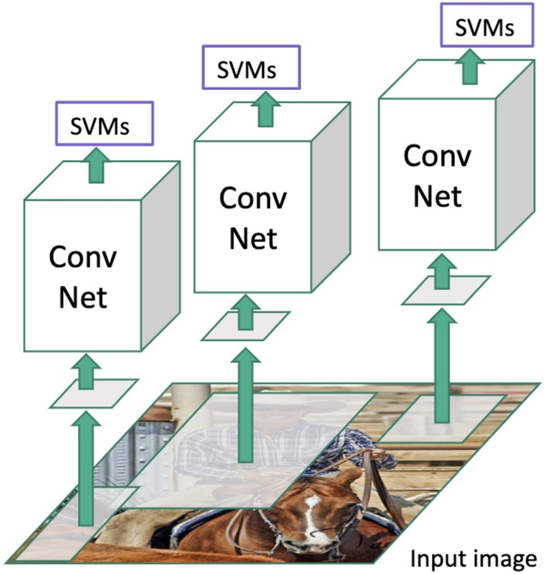
Idea: Pass the image through convnet before cropping! Crop the conv feature instead!

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

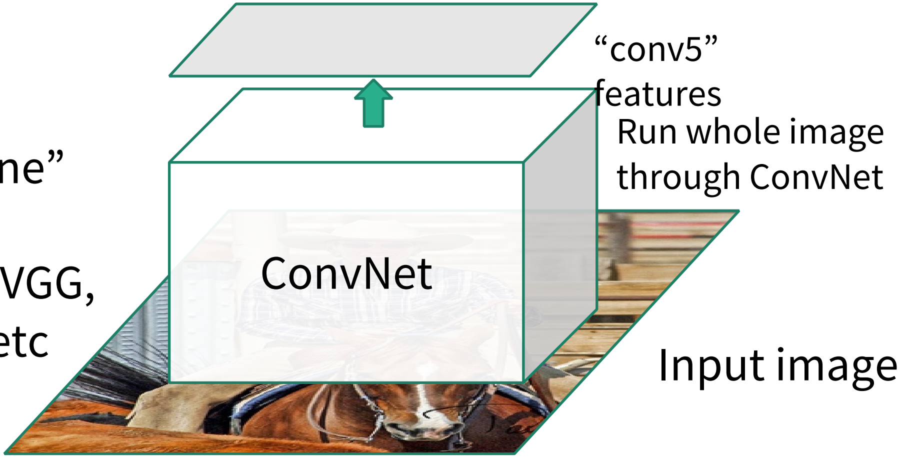
Fast R-CNN

Input image

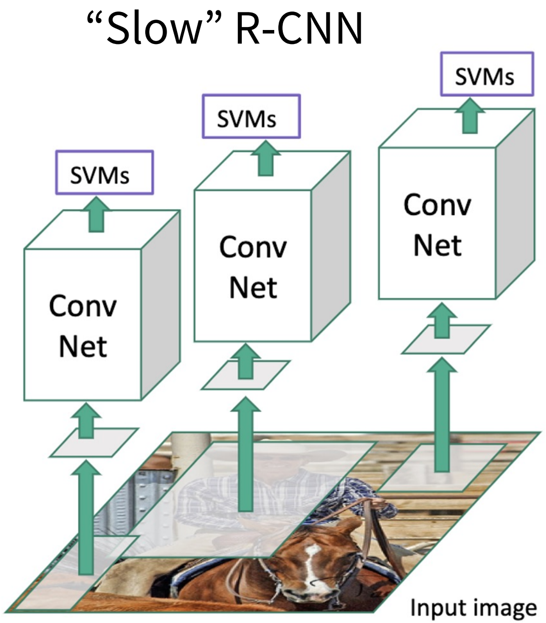
"Slow" R-CNN



Fast R-CNN



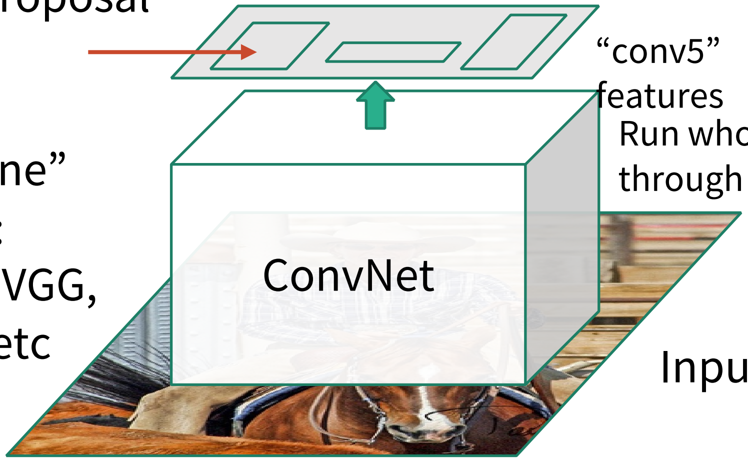
"Backbone" network: AlexNet, VGG, ResNet, etc



Fast R-CNN

Regions of Interest (RoIs) from a proposal method

“Backbone” network: AlexNet, VGG, ResNet, etc

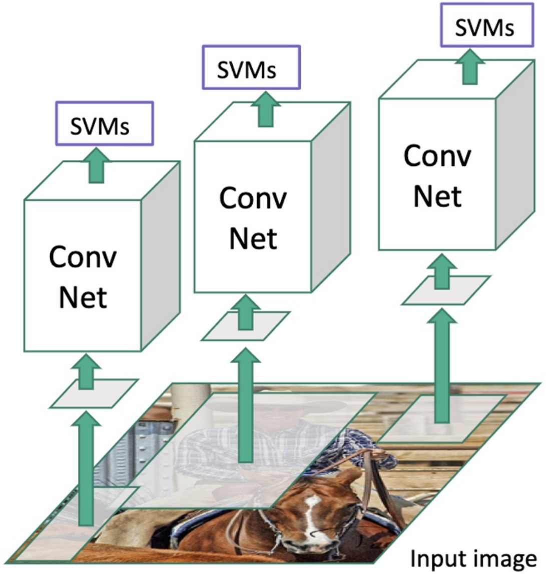


“conv5” features

Run whole image through ConvNet

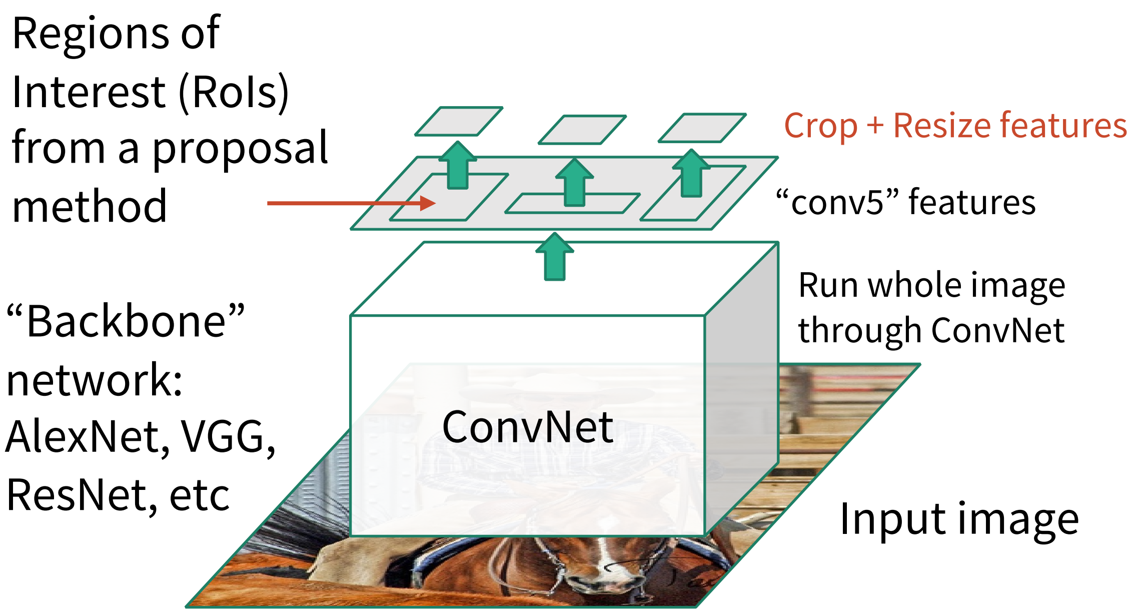
Input image

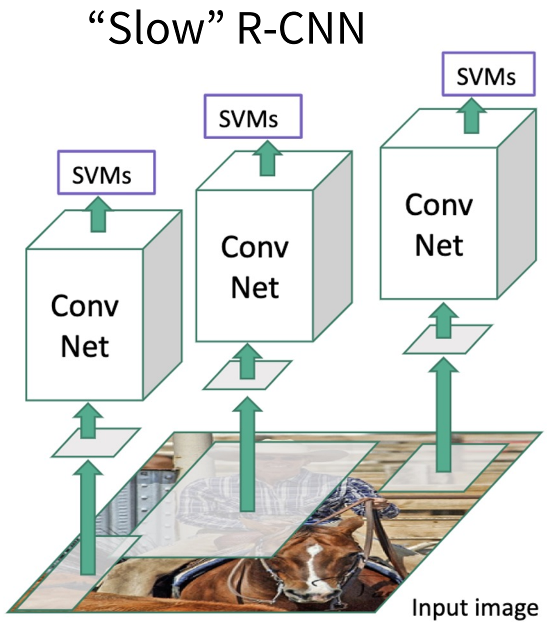
“Slow” R-CNN



Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

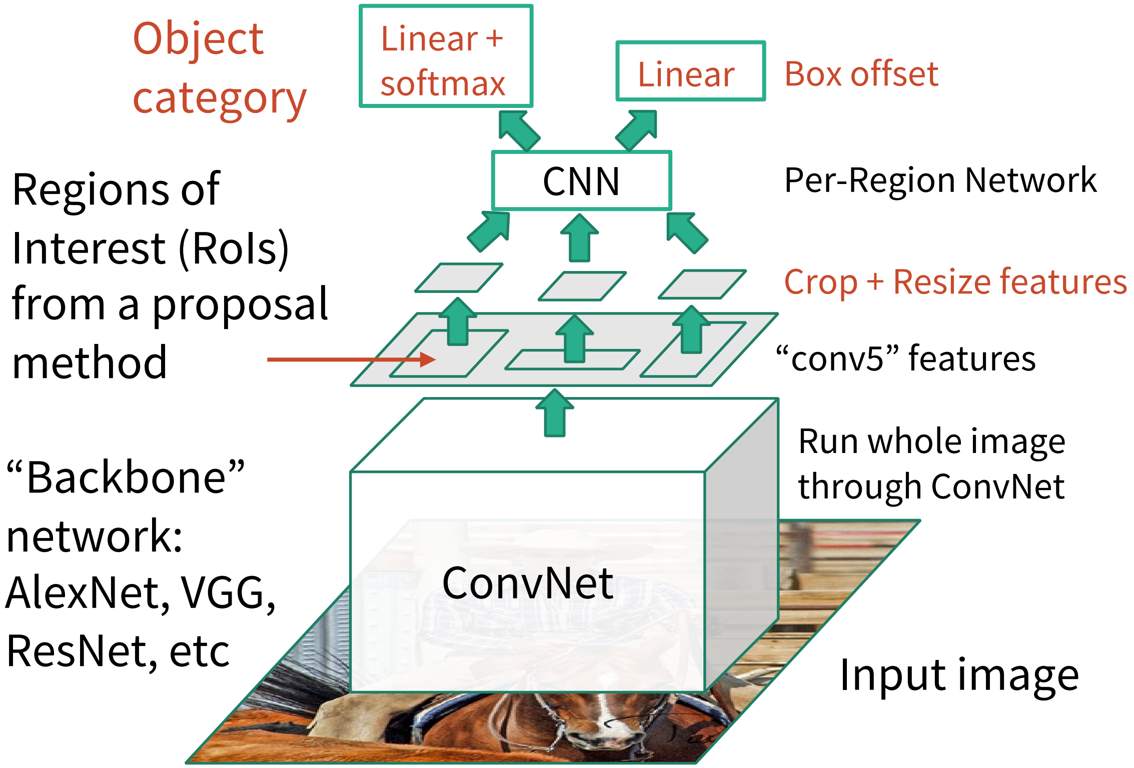
Fast R-CNN

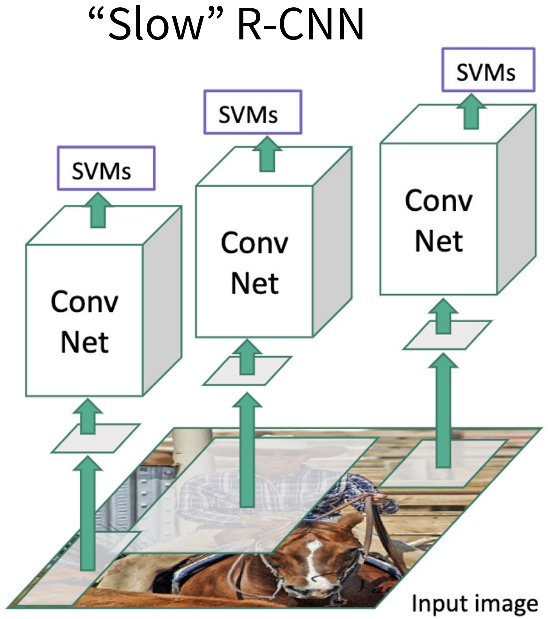




Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

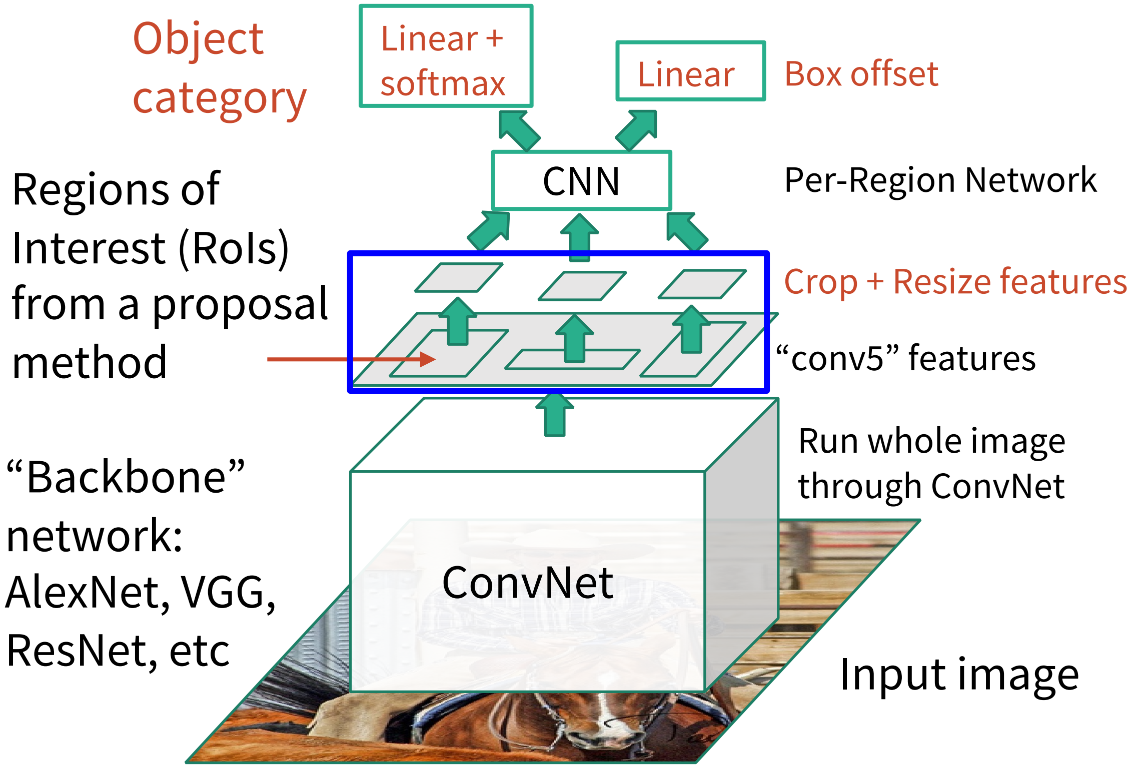
Fast R-CNN

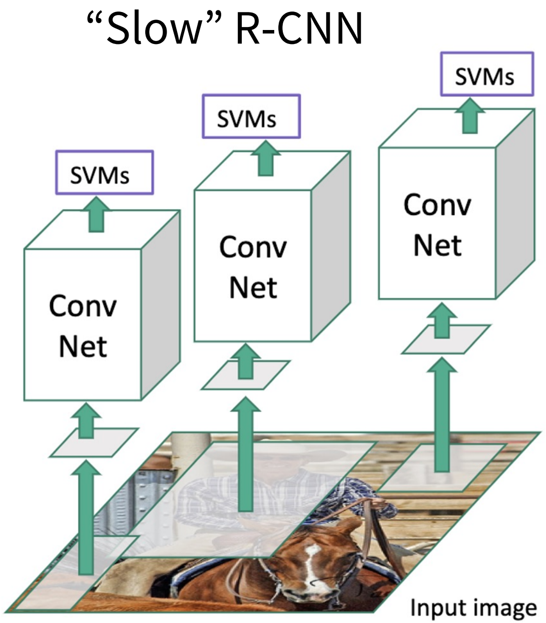




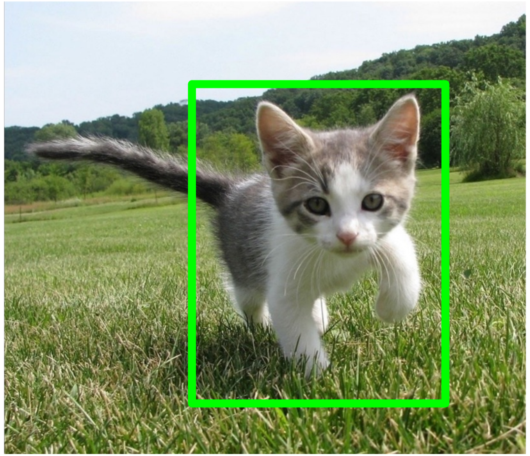
Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN


Object category
Linear + softmax
Linear
Box offset
CNN
Per-Region Network
Regions of Interest (RoIs) from a proposal method
Crop + Resize features
"conv5" features
Run whole image through ConvNet
"Backbone" network: AlexNet, VGG, ResNet, etc
ConvNet
Input image


"Slow" R-CNN
SVMs
SVMs
SVMs
Conv Net
Conv Net
Conv Net
Input image

Cropping Features: RoI Pool



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

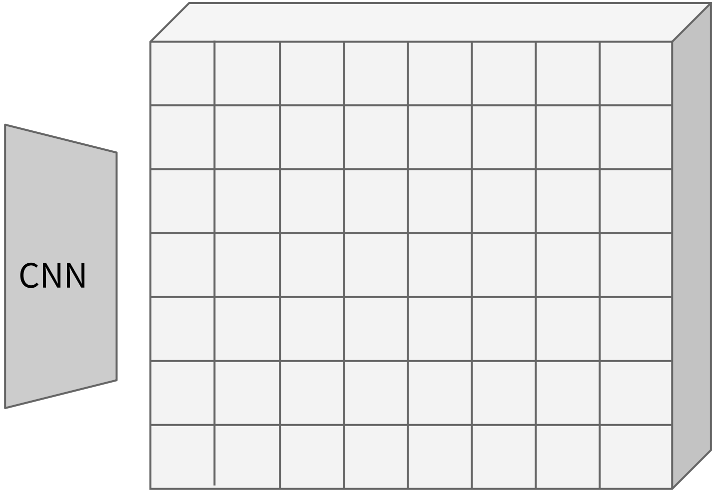
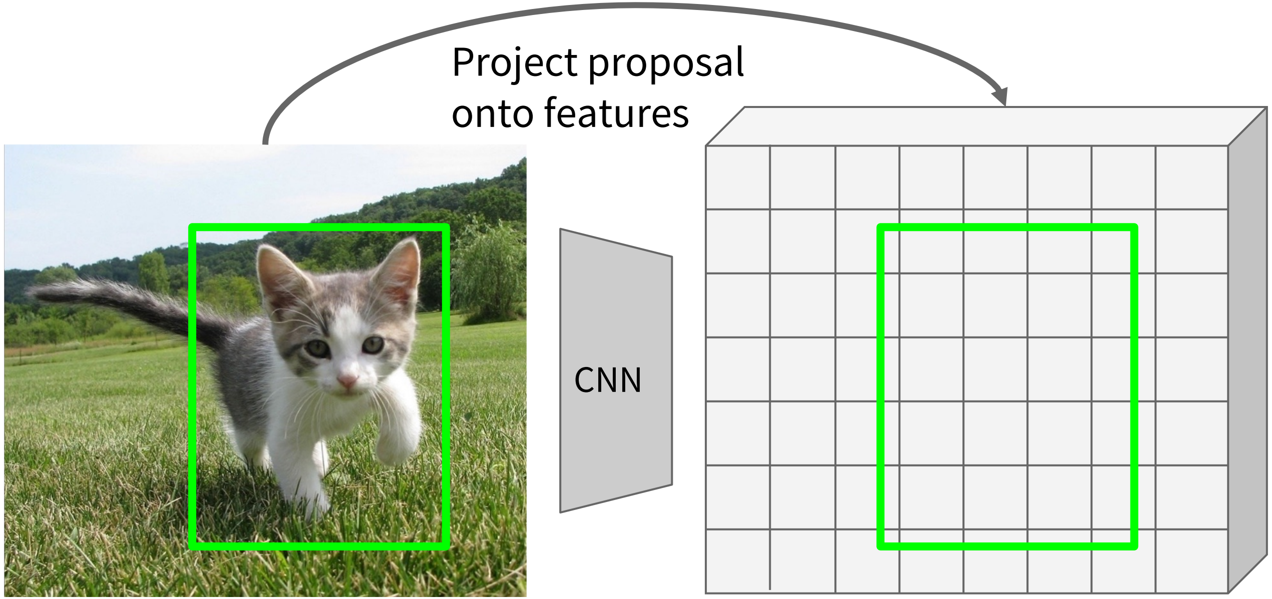


Image features: C x H x W
(e.g. 512 x 20 x 15)

Girshick, “Fast R-CNN”, ICCV 2015.

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

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

Girshick, “Fast R-CNN”, ICCV 2015.

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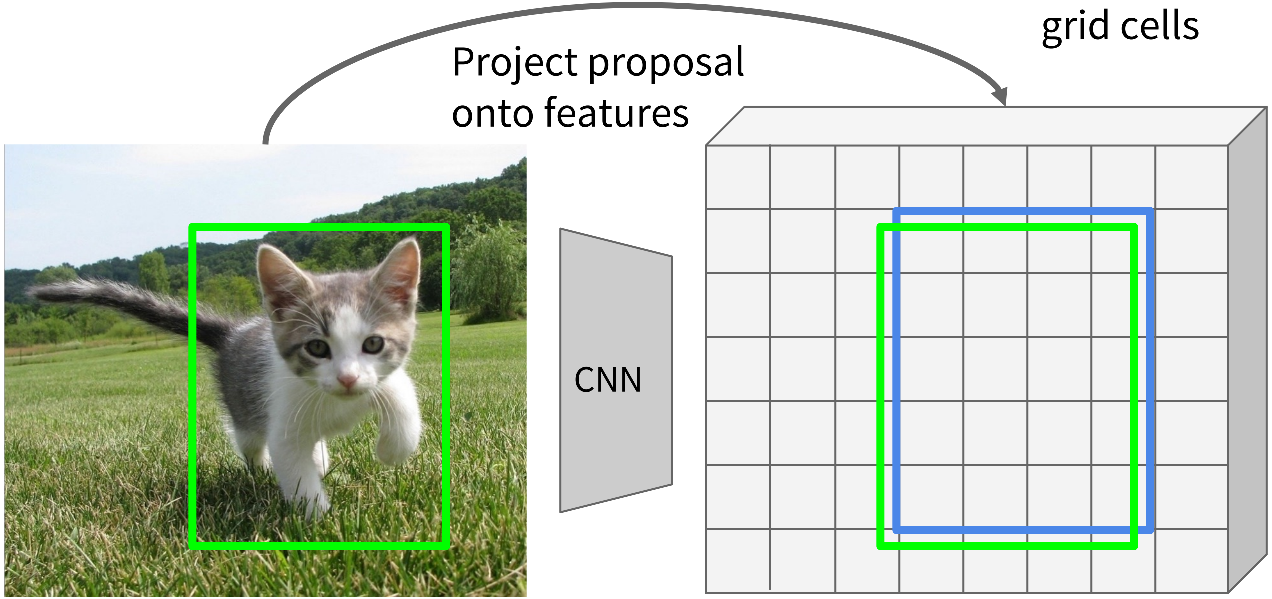
Cropping Features: RoI Pool

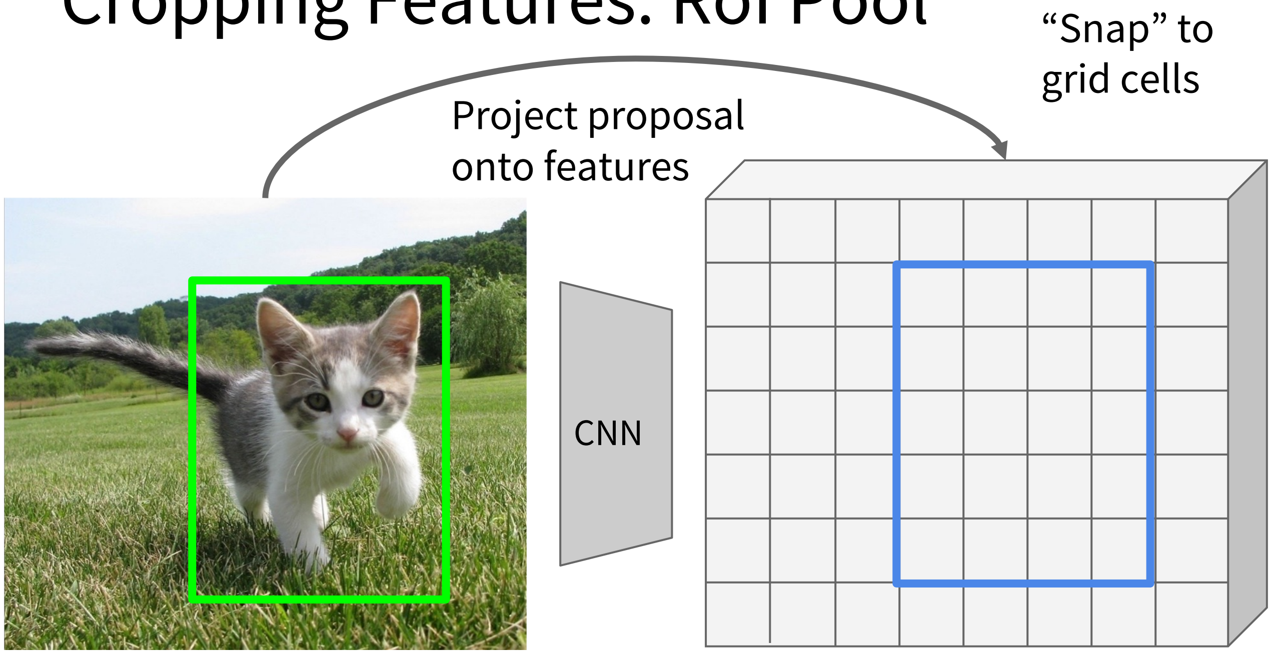


Input Image
(e.g. 3 x 640 x 480)

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

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

Cropping Features: RoI Pool



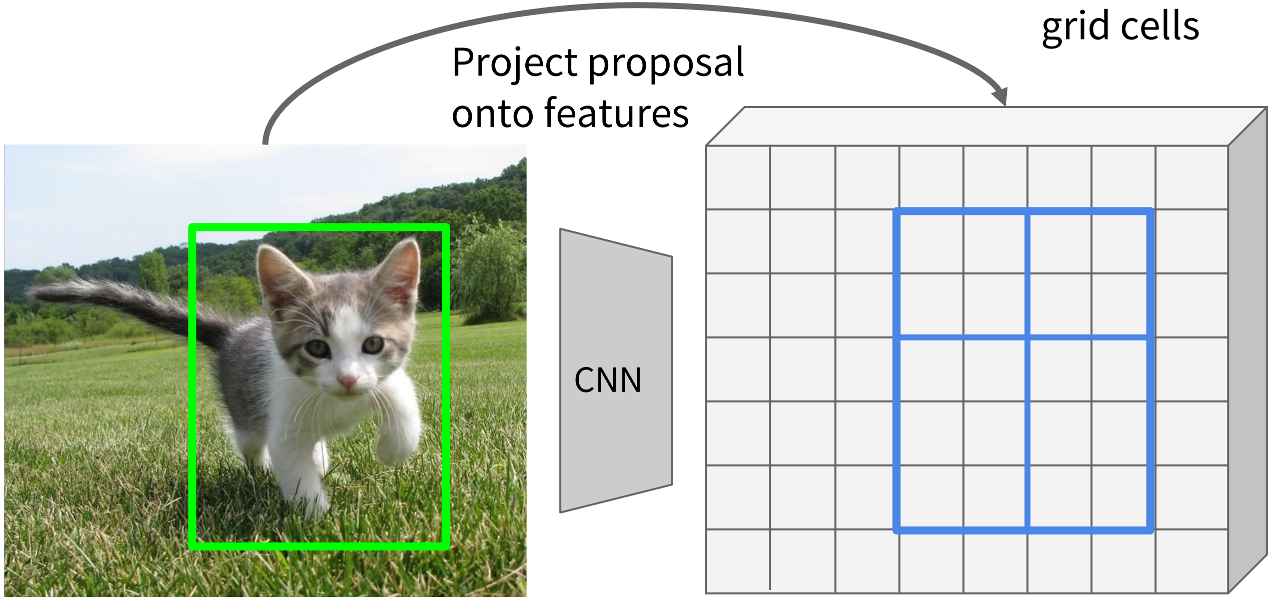
Input Image
(e.g. 3 x 640 x 480)

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

Q: how do we resize the 512 x 5 x 4 region to, e.g., a 512 x 2 x 2 tensor?.

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

Cropping Features: RoI Pool



Divide into 2x2 grid of (roughly) equal subregions

Q: how do we resize the 512 x 5 x 4 region to, e.g., a 512 x 2 x 2 tensor?.

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

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

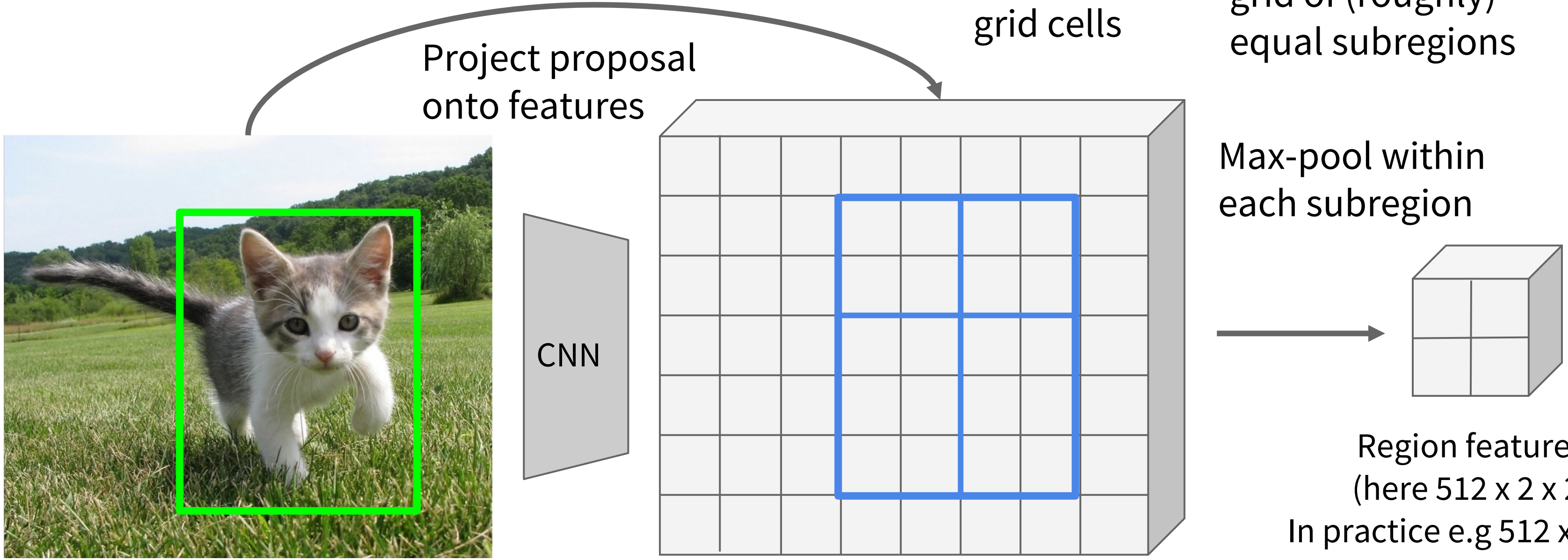
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool

"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion



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.

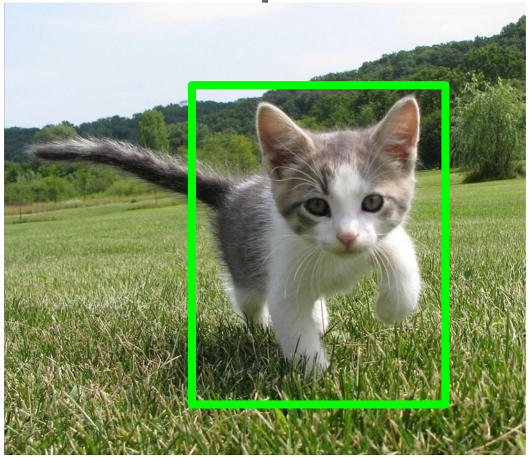
Cropping Features: RoI Pool

Project proposal
onto features

"Snap" to
grid cells

Divide into 2x2
grid of (roughly)
equal subregions

Max-pool within
each subregion



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

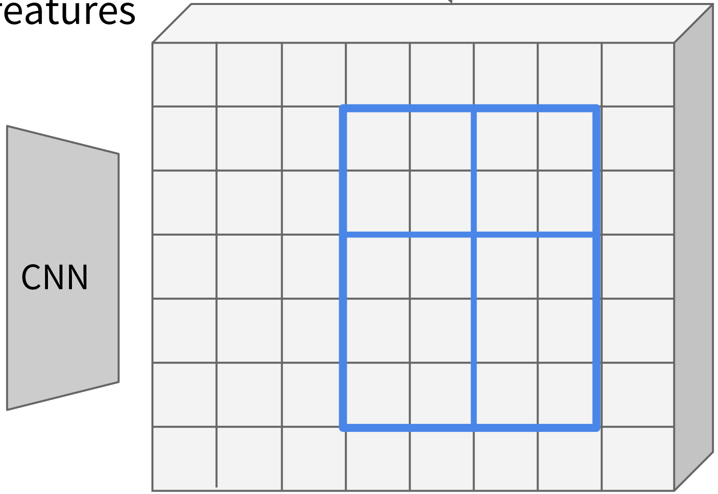
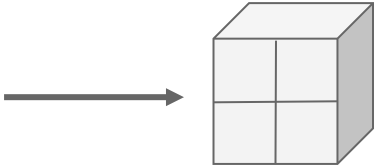


Image features: C x H x W
(e.g. 512 x 20 x 15)



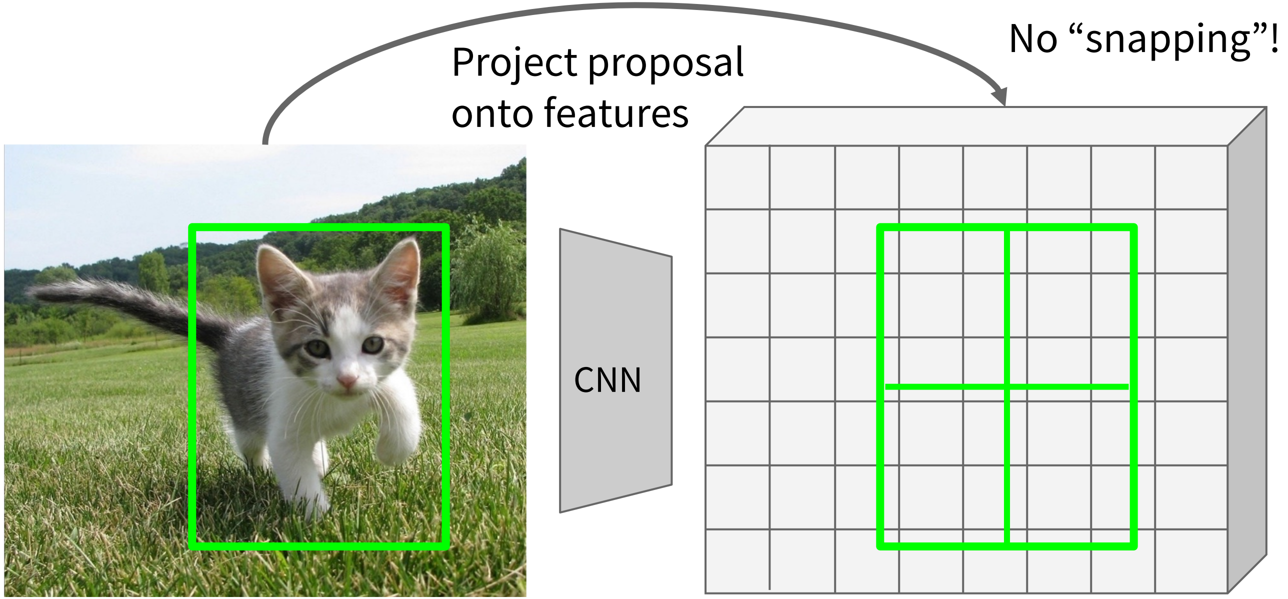
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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

Problem: Region features slightly misaligned

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

Cropping Features: RoI Align



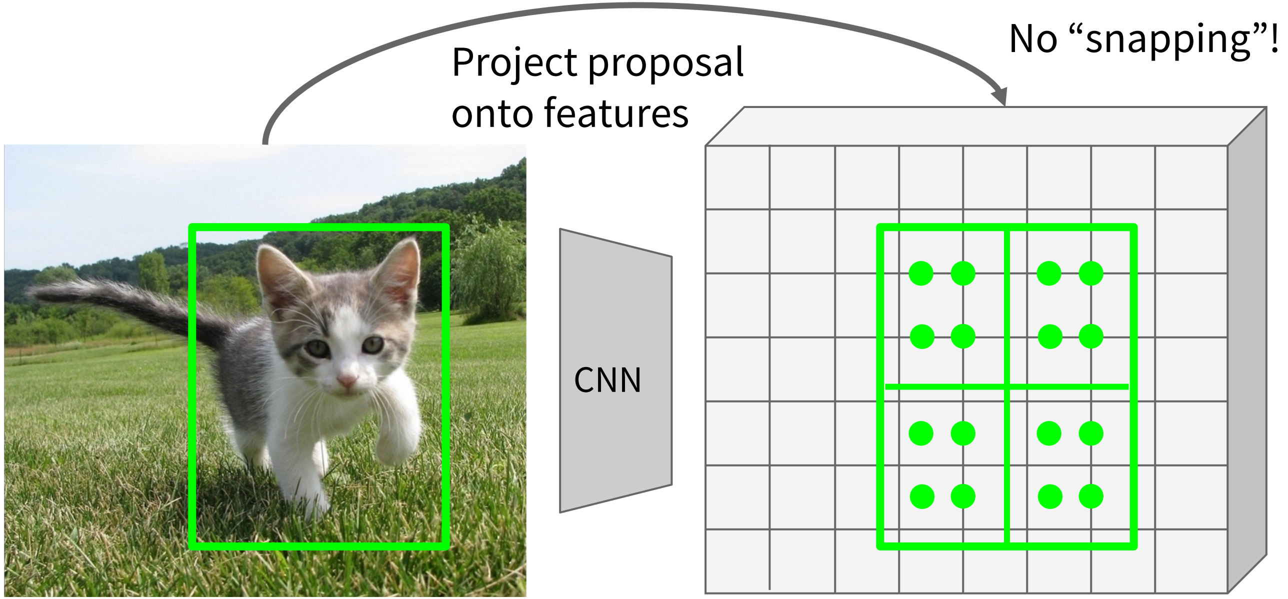
Input Image
(e.g. 3 x 640 x 480)

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

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

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



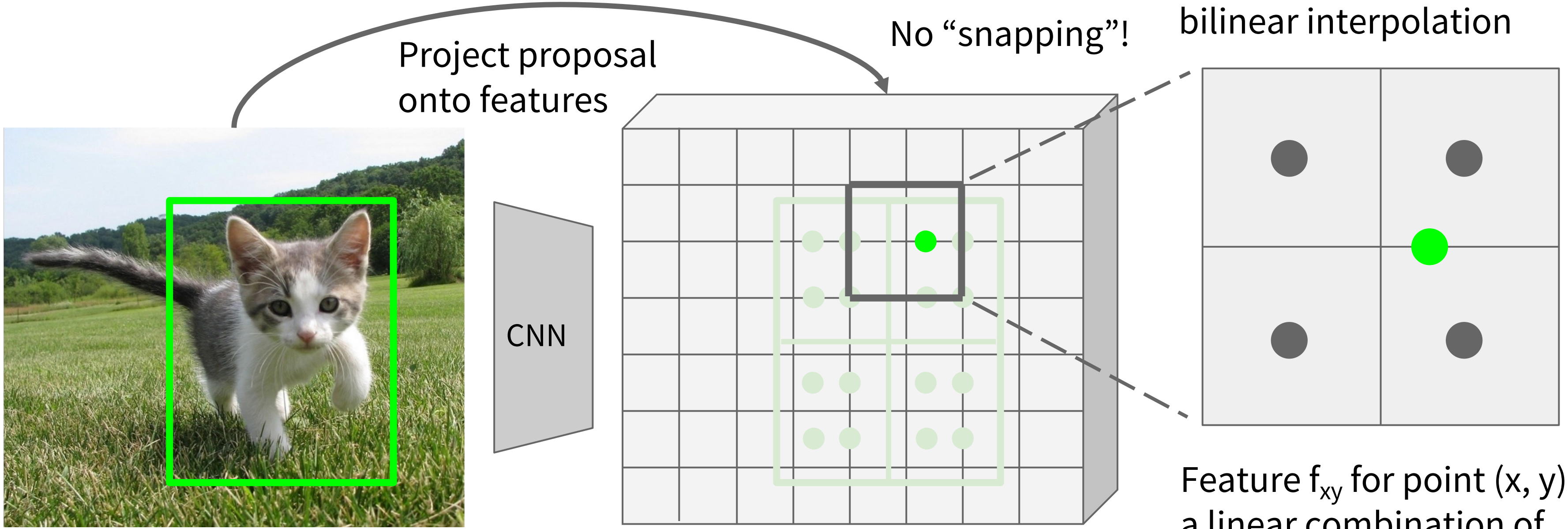
Input Image
(e.g. 3 x 640 x 480)

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

He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



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

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

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

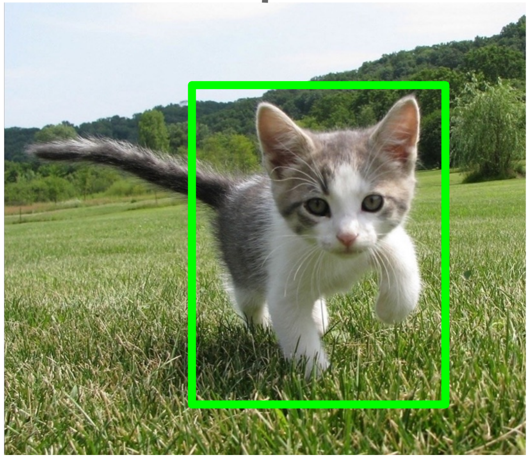
He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

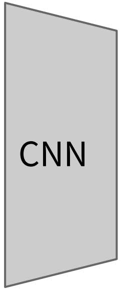
Project proposal onto features

No "snapping"!

Sample at regular points in each subregion using bilinear interpolation



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



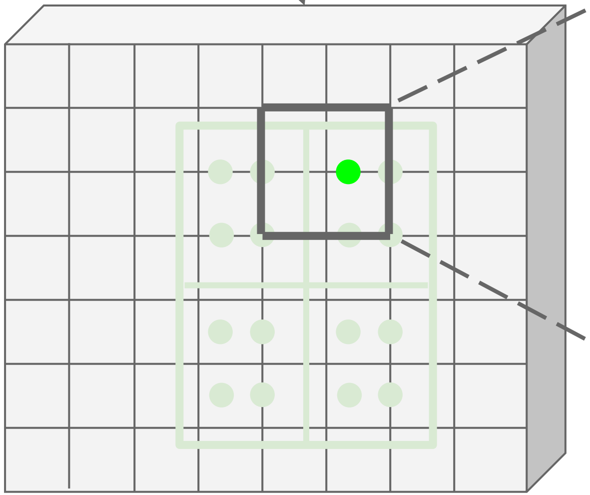
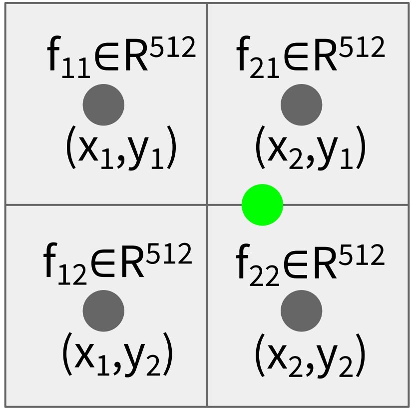


Image features: C x H x W
(e.g. 512 x 20 x 15)



(x,y)

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

$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

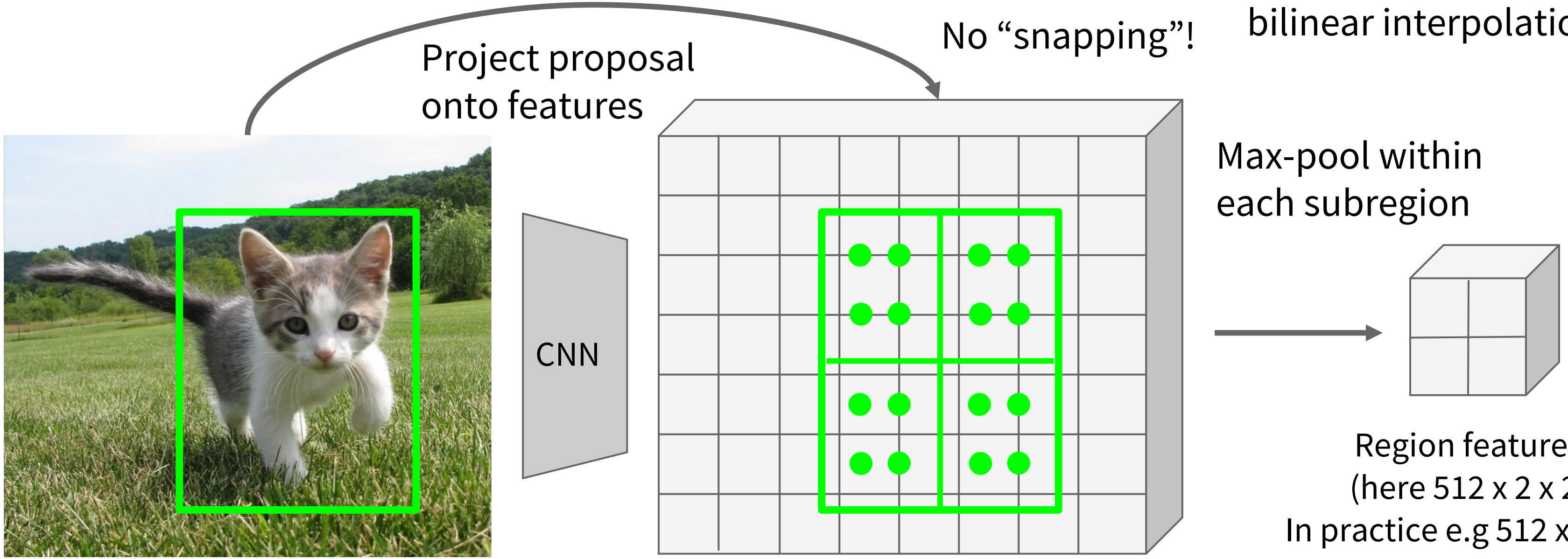
He et al, "Mask R-CNN", ICCV 2017

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation

No "snapping"!

Project proposal onto features



Max-pool within each subregion

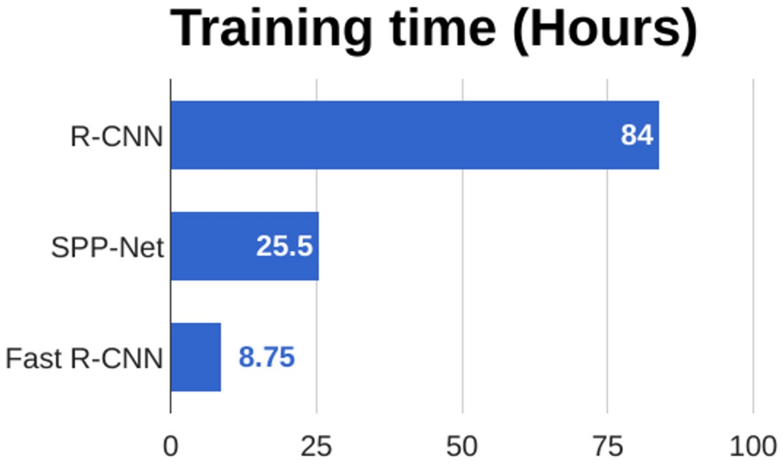
Input Image
(e.g. 3 x 640 x 480)

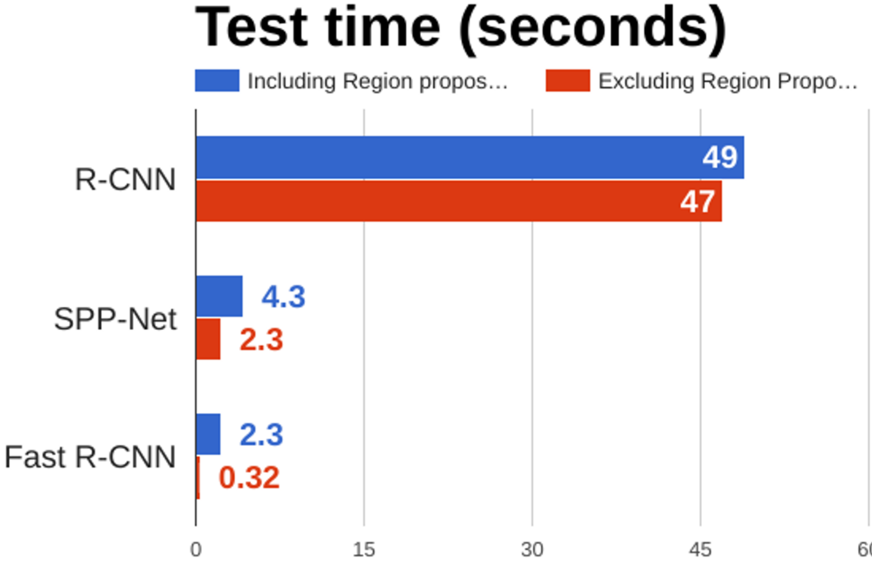
Image features: C x H x W
(e.g. 512 x 20 x 15)

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

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

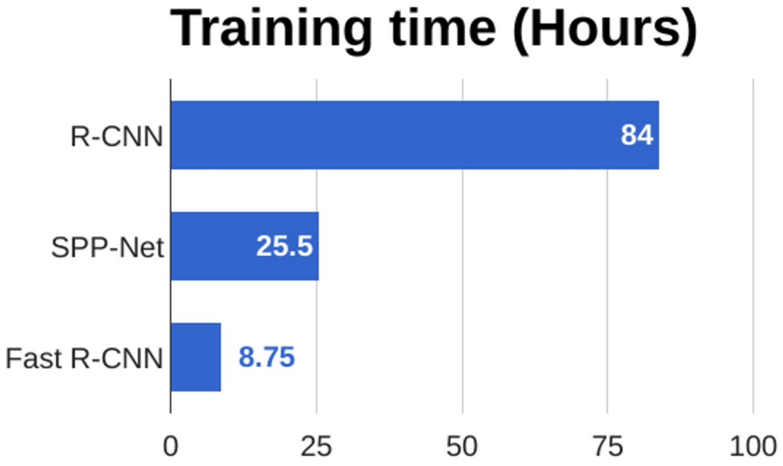
R-CNN vs Fast R-CNN

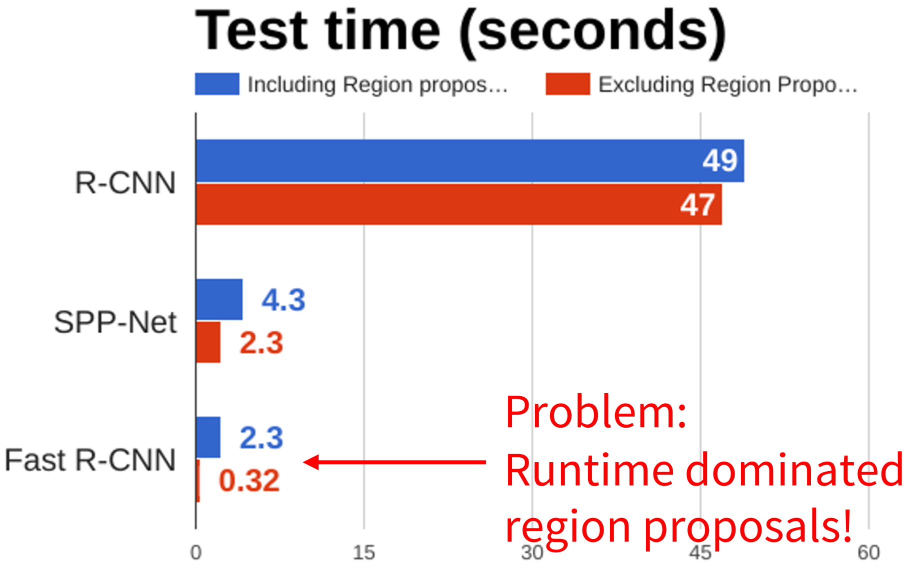




Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

R-CNN vs Fast R-CNN





Problem:
Runtime dominated by region proposals!

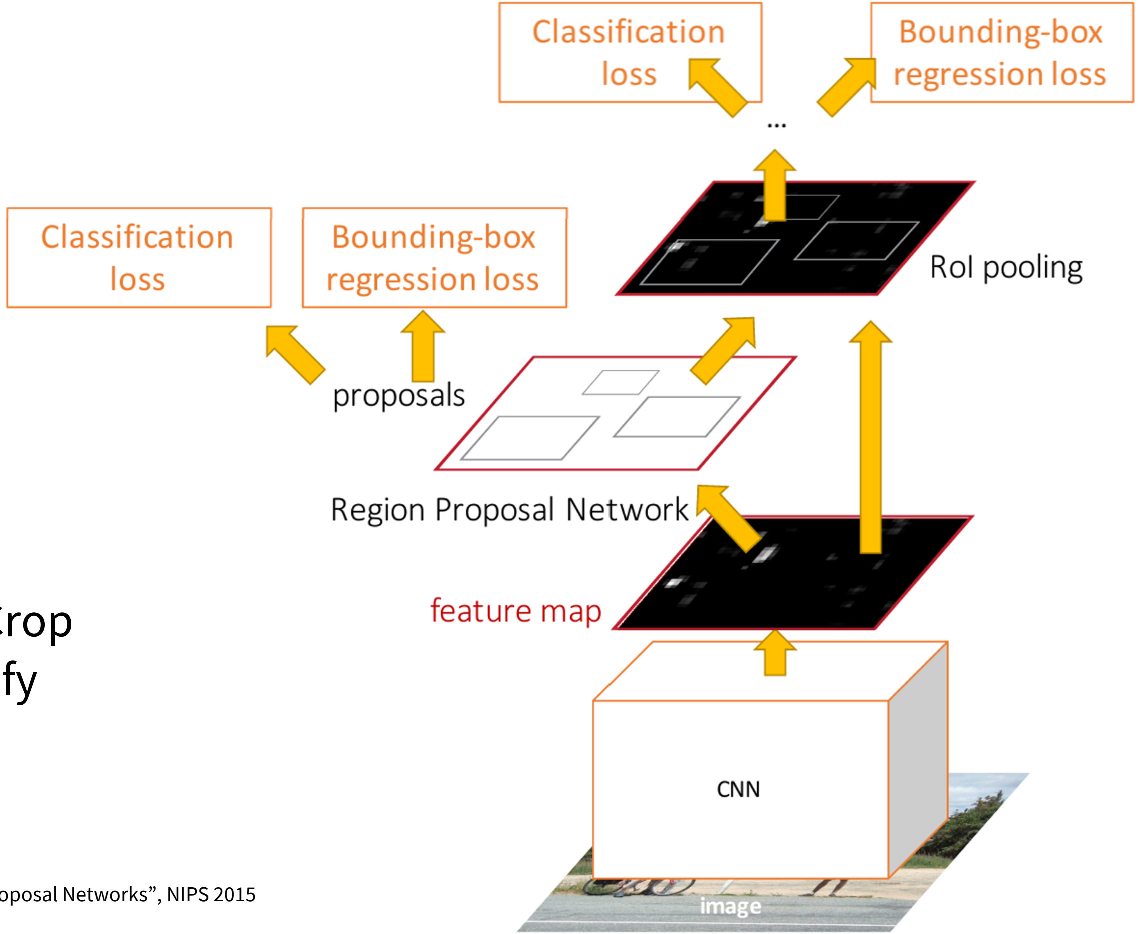
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

Faster R-CNN:

Make CNN do proposals!

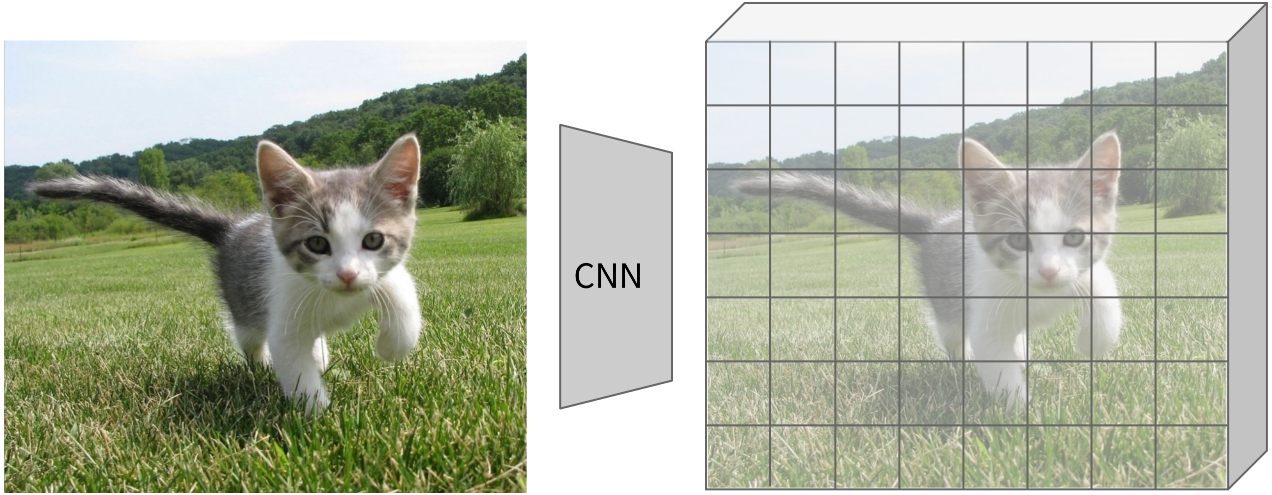
Insert Region Proposal Network (RPN) to predict proposals from features

Otherwise same as Fast R-CNN: Crop features for each proposal, classify each one



Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

Region Proposal Network



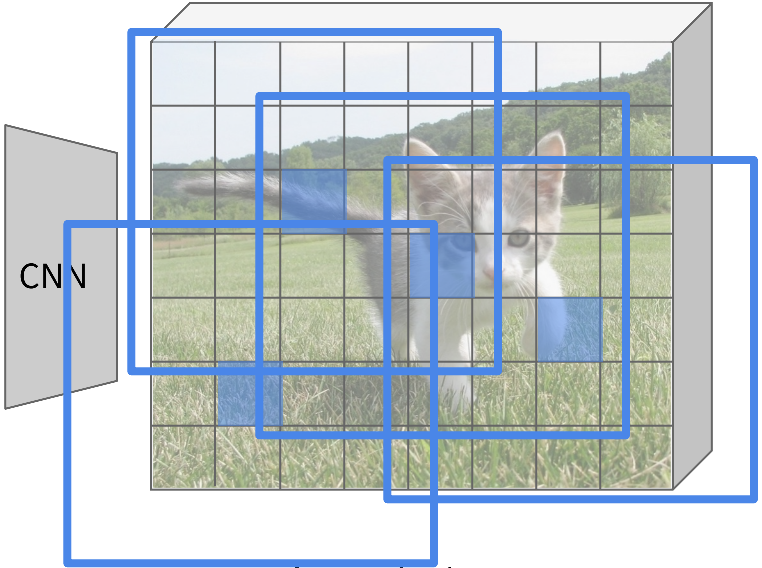
Input Image
(e.g. 3 x 640 x 480)

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

Region Proposal Network

Imagine an anchor box of fixed size at each point in the feature map

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



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Region Proposal Network

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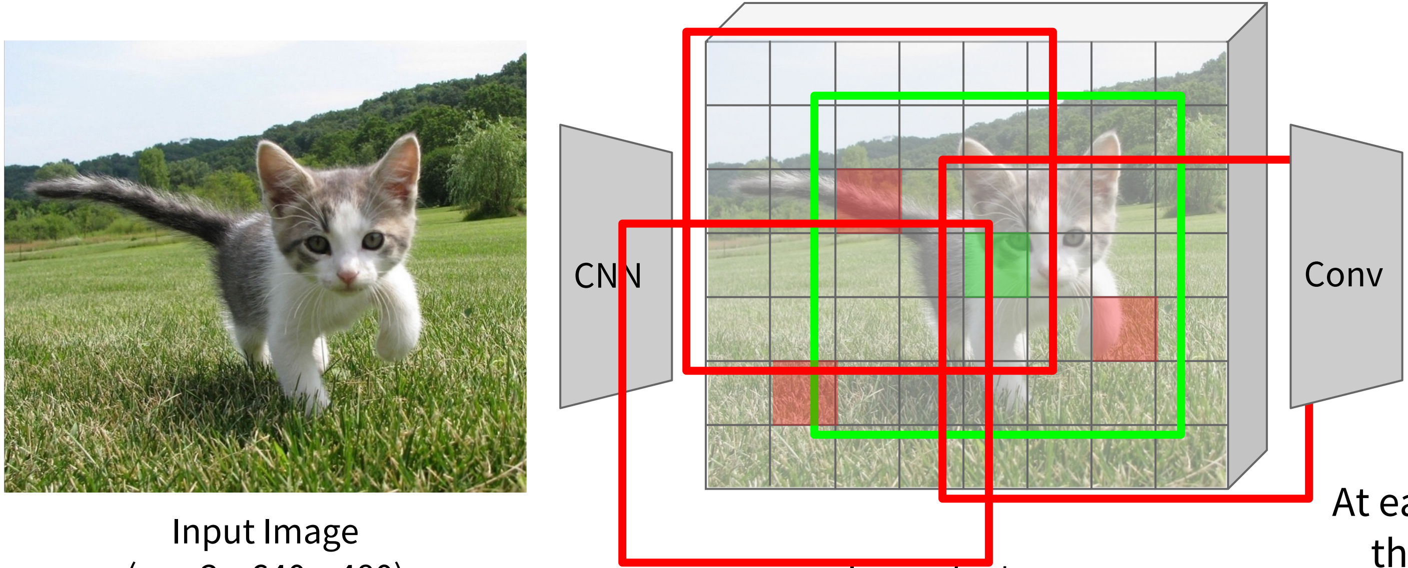


Anchor is an object?
1 x 20 x 15

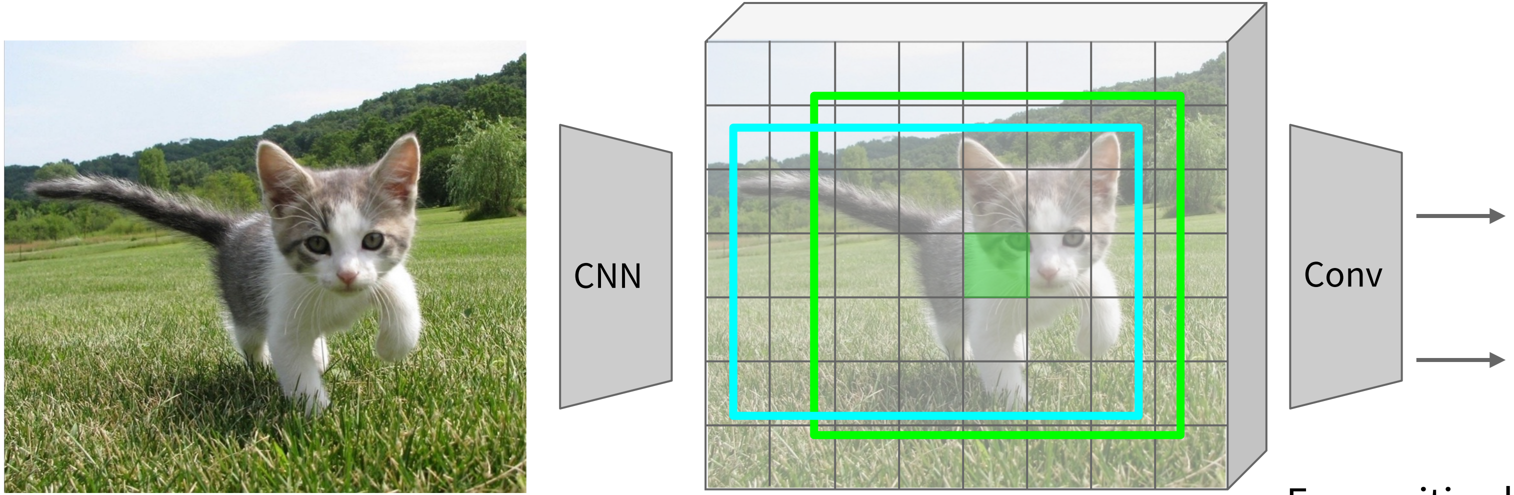
Input Image
(e.g. 3 x 640 x 480)

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

At each point, predict whether the corresponding anchor contains an object (binary classification)

Region Proposal Network

Imagine an anchor box of fixed size at each point in the feature map



Anchor is an object?
1 x 20 x 15

Box corrections
4 x 20 x 15

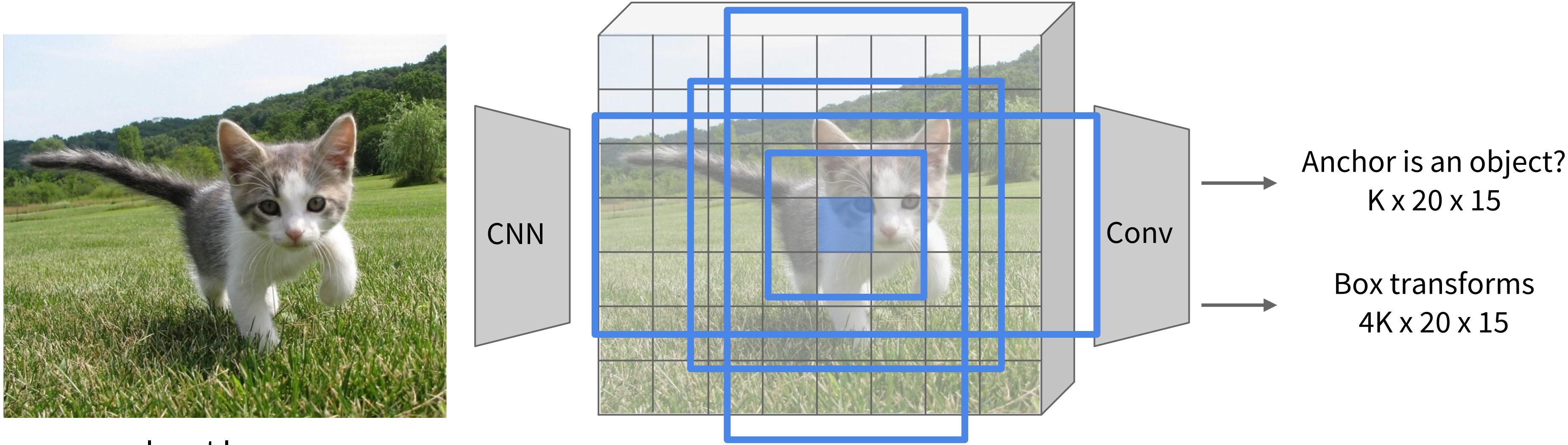
Input Image
(e.g. 3 x 640 x 480)

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

For positive boxes, also predict a corrections from the anchor to the ground-truth box (regress 4 numbers per pixel)

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point

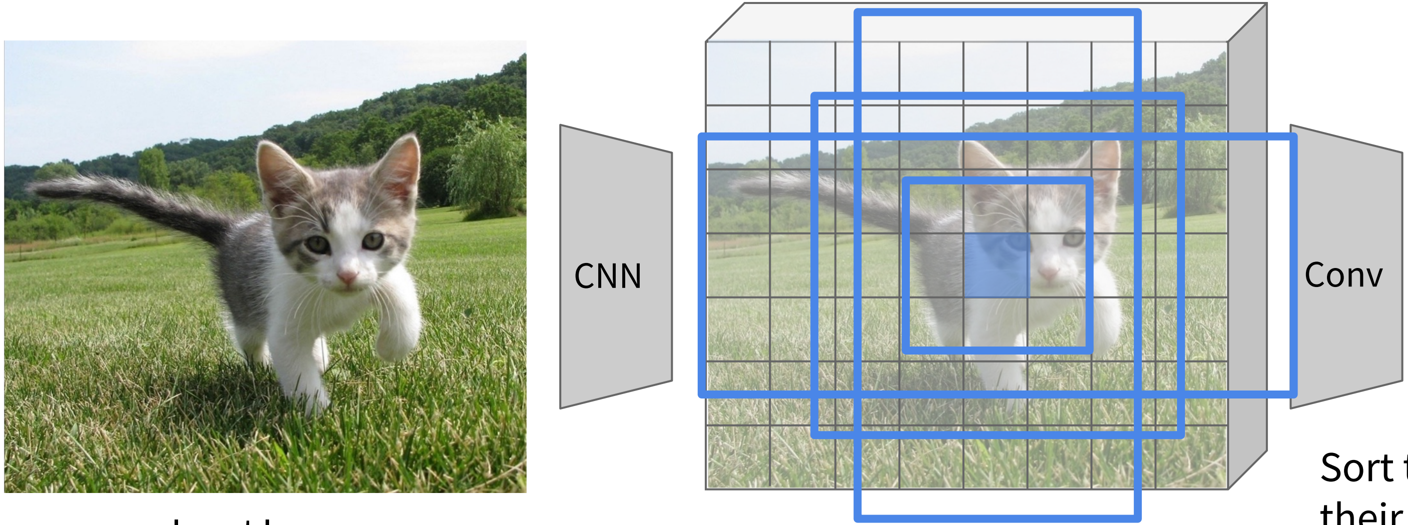


Input Image
(e.g. 3 x 640 x 480)

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

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point



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

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

Anchor is an object?
K x 20 x 15

Box transforms
4K x 20 x 15

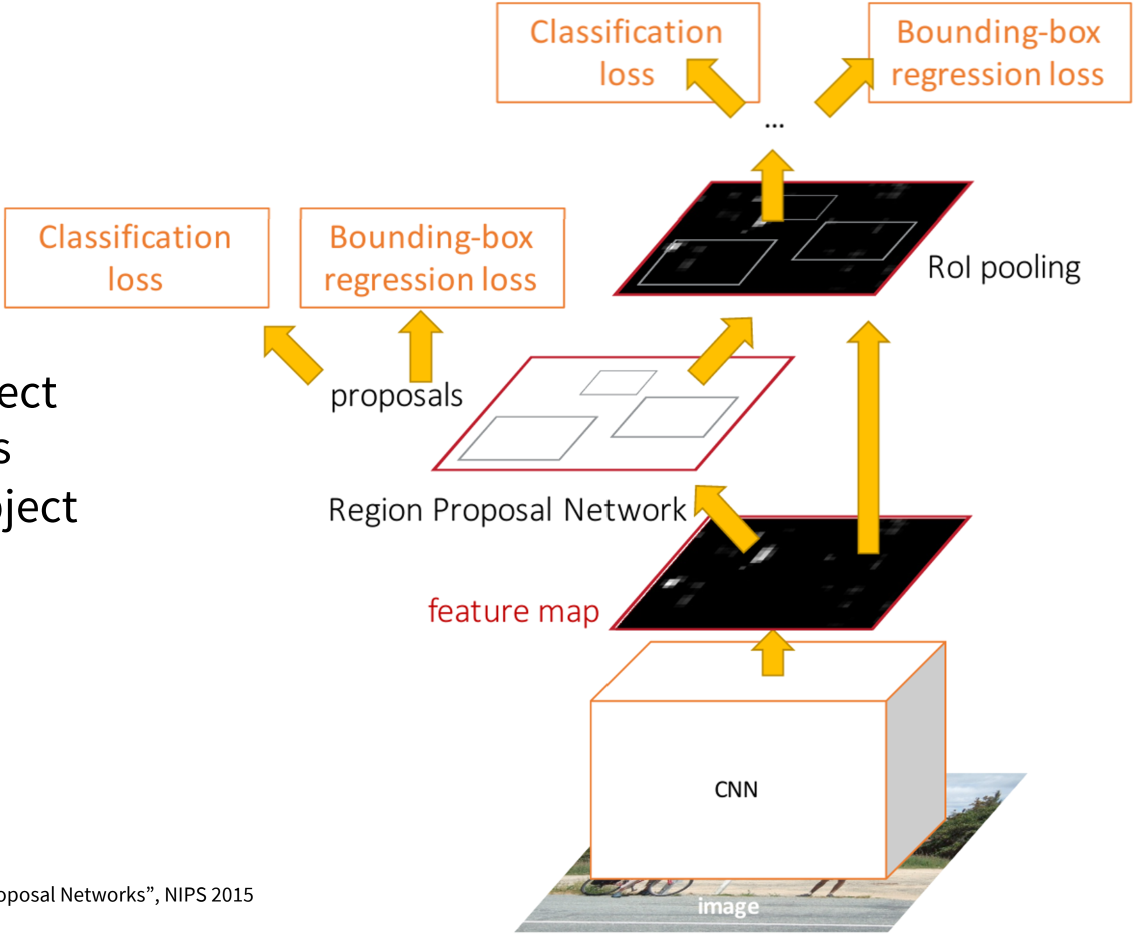
Sort the K*20*15 boxes by their “objectness” score, take top ~300 as our proposals

Faster R-CNN:

Make CNN do proposals!

Jointly train with 4 losses:

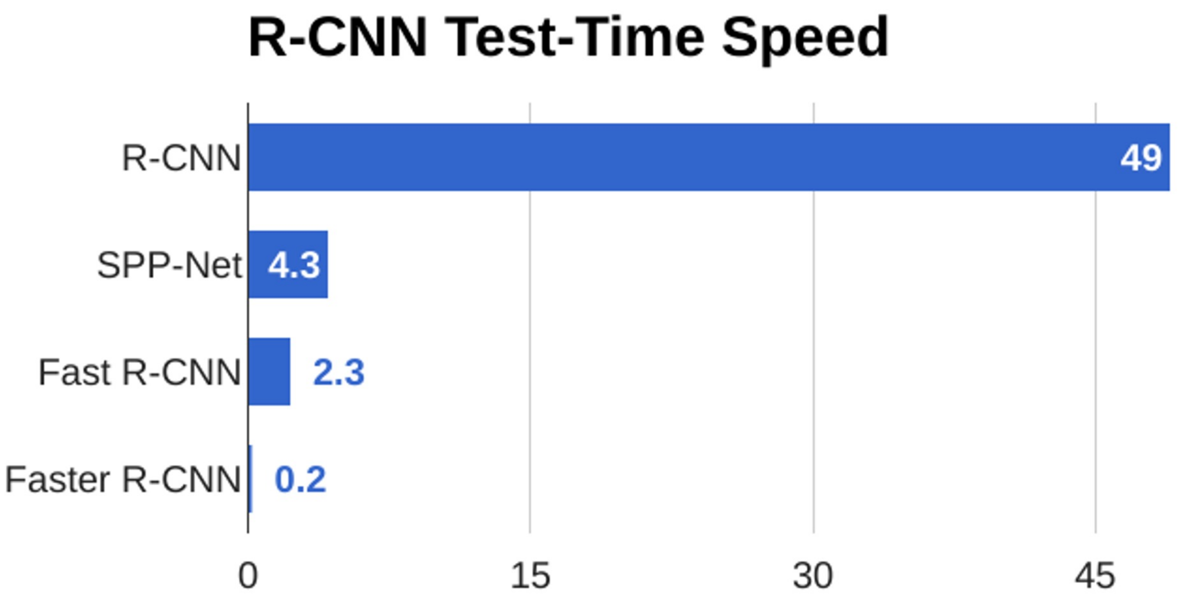
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



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

Faster R-CNN:

Make CNN do proposals!

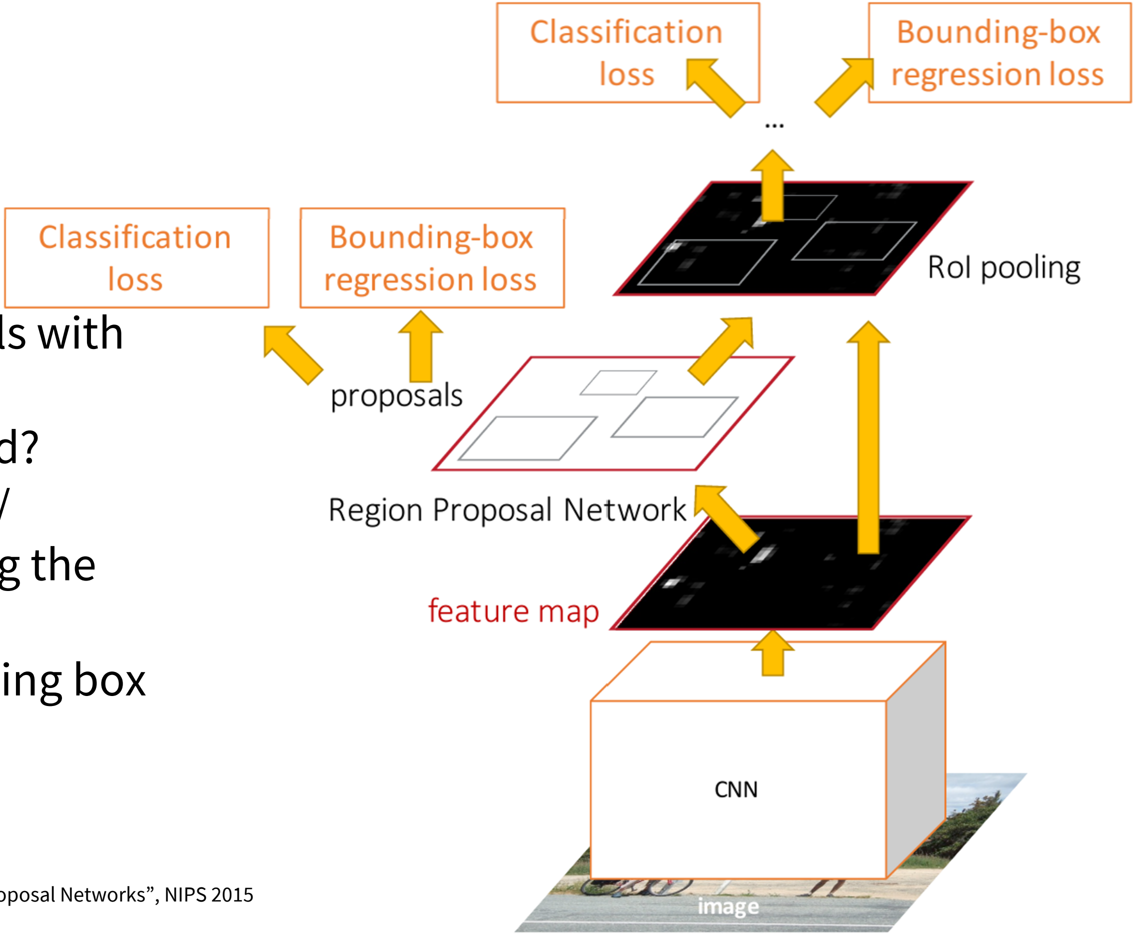


Faster R-CNN:

Make CNN do proposals!

Glossing over many details:

- Ignore overlapping proposals with non-max suppression
- How are anchors determined?
- How do we sample positive / negative samples for training the RPN?
- How to parameterize bounding box regression?



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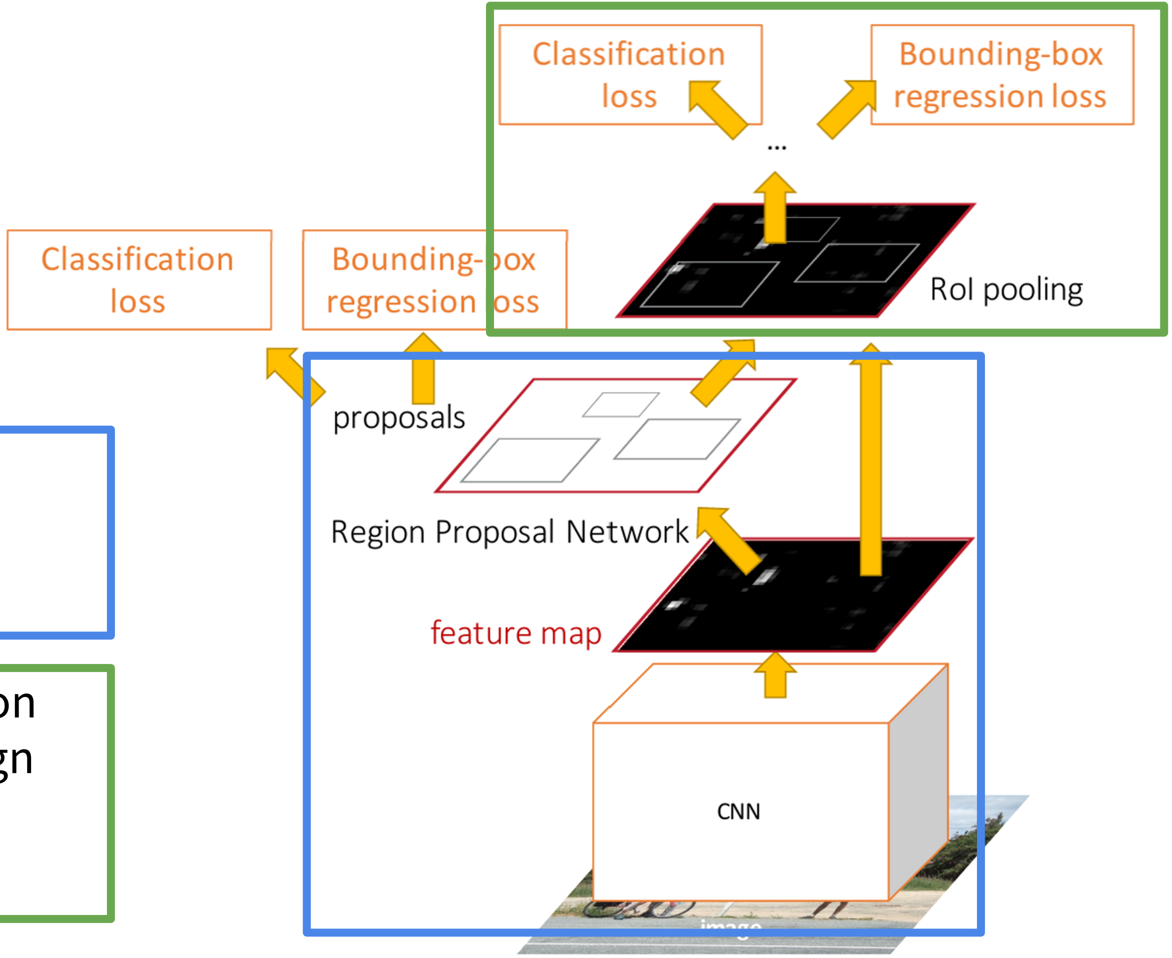
Faster R-CNN:

Make CNN do proposals!

Faster R-CNN is a
Two-stage object detector

First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Faster R-CNN:

Make CNN do proposals!

Do we really need the second stage?

Faster R-CNN is a
Two-stage object detector

First stage: Run once per image
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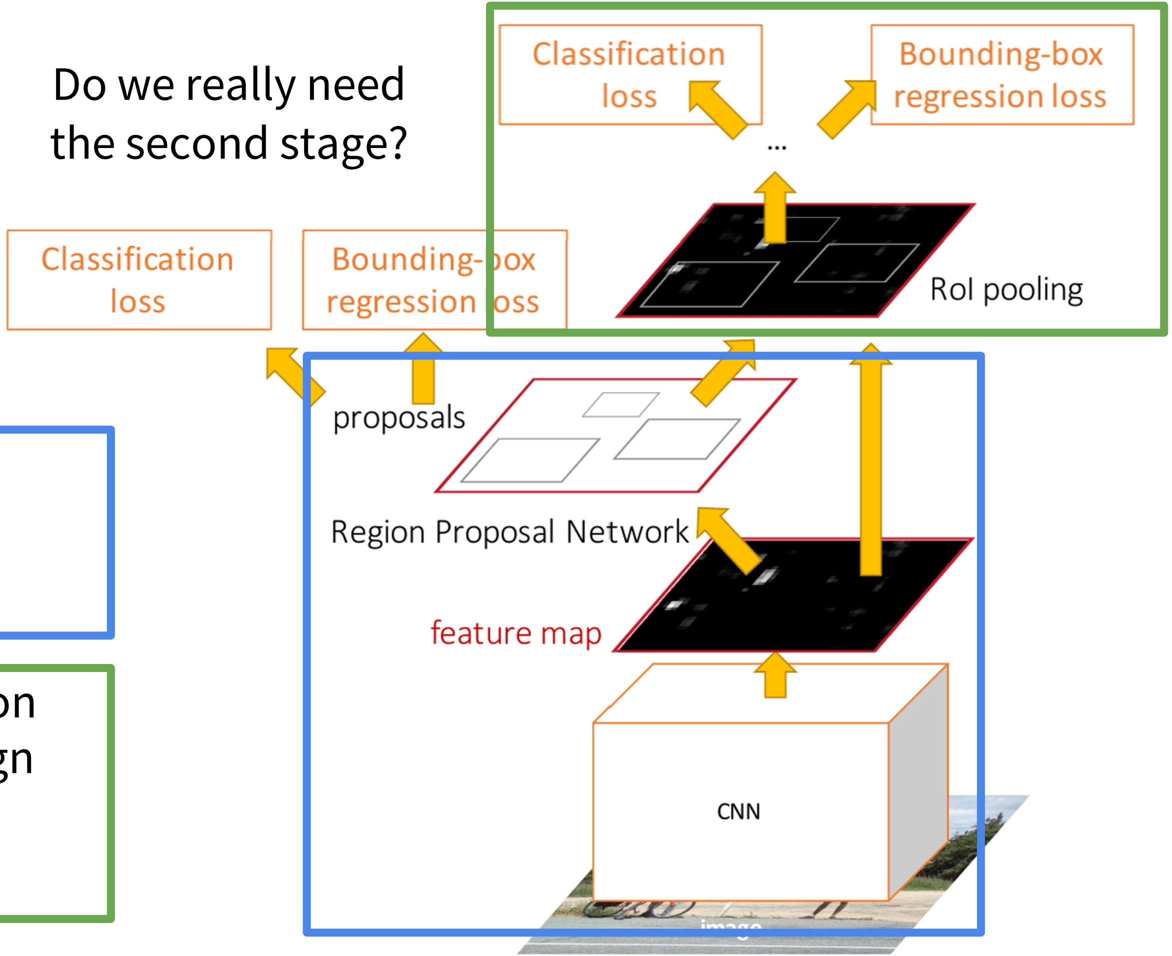
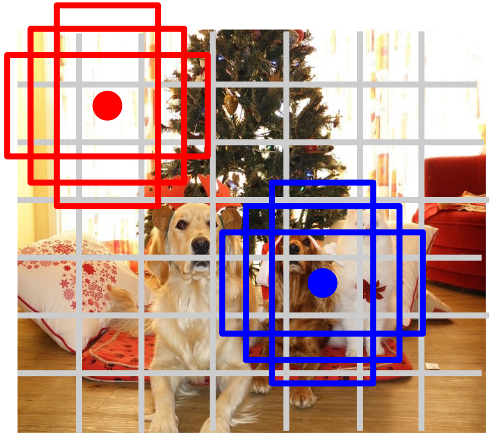


Single-Stage Object Detectors: YOLO / SSD / RetinaNet

Input image
3 x H x W



Divide image into grid
7 x 7

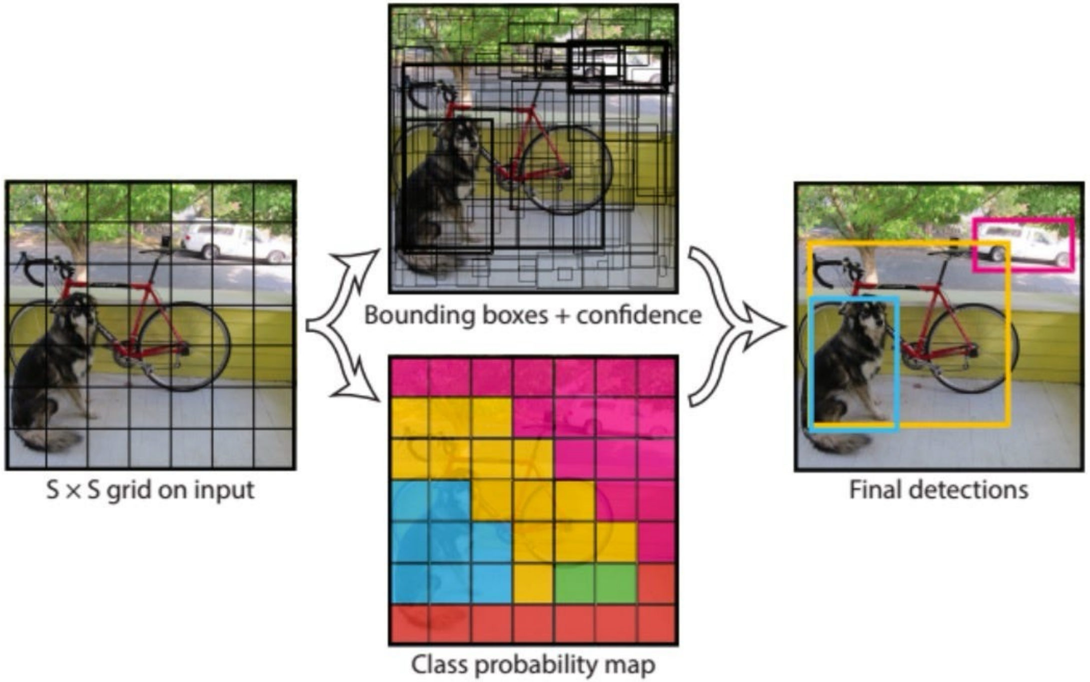
Image a set of base boxes
centered at each grid cell
Here B = 3

Within each grid cell:
- Regress from each of the B base boxes to a final box with 5 numbers:
(dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)
- Looks a lot like RPN, but category-specific!

Output:
7 x 7 x (5 * B + C)

Redmon et al, “You Only Look Once:
Unified, Real-Time Object Detection”, CVPR 2016
Liu et al, “SSD: Single-Shot MultiBox Detector”, ECCV 2016
Lin et al, “Focal Loss for Dense Object Detection”, ICCV 2017

YOLO– real-time object detection



Redmon et al. "You only look once: unified, real-time object detection (2015)."

Object Detection: Lots of variables ...

Backbone Network
VGG16
ResNet-101
Inception V2
Inception V3
Inception ResNet
MobileNet

"Meta-Architecture"
Two-stage: Faster R-CNN
Single-stage: YOLO / SSD
Hybrid: R-FCN

Image Size
Region Proposals
…

Takeaways
Faster R-CNN is slower but more accurate

SSD is much faster but not as accurate

Bigger / Deeper backbones work better

Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017

R-FCN: Dai et al, "R-FCN: Object Detection via Region-based Fully Convolutional Networks", NIPS 2016
Inception-V2: Ioffe and Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015
Inception V3: Szegedy et al, "Rethinking the Inception Architecture for Computer Vision", arXiv 2016
Inception ResNet: Szegedy et al, "Inception-V4, Inception-ResNet and the Impact of Residual Connections on Learning", arXiv 2016
MobileNet: Howard et al, "Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv 2017

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Zou et al, "Object Detection in 20 Years: A Survey", arXiv 2019

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Instance Segmentation

Classification

CAT

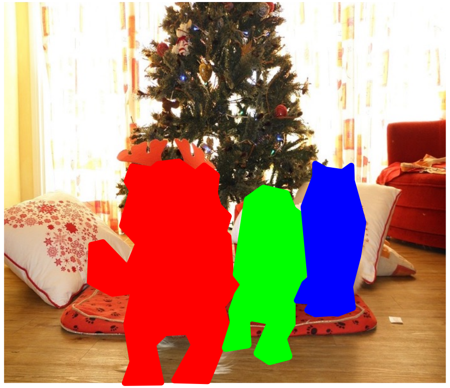
Semantic Segmentation

GRASS, CAT, TREE, SKY

Object Detection

DOG, DOG, CAT

Instance Segmentation



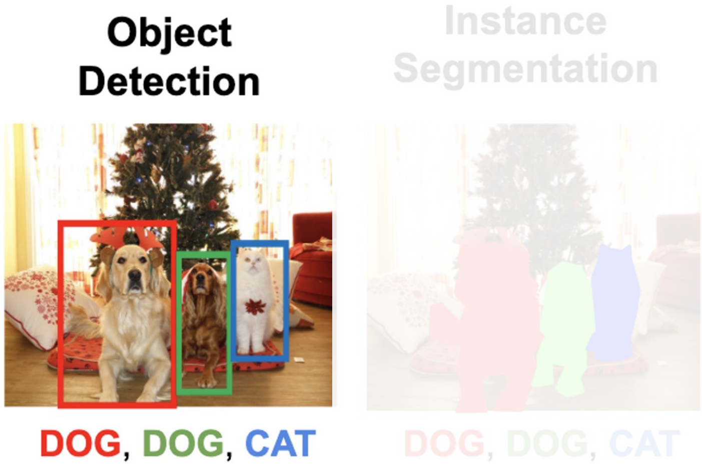
DOG, DOG, CAT

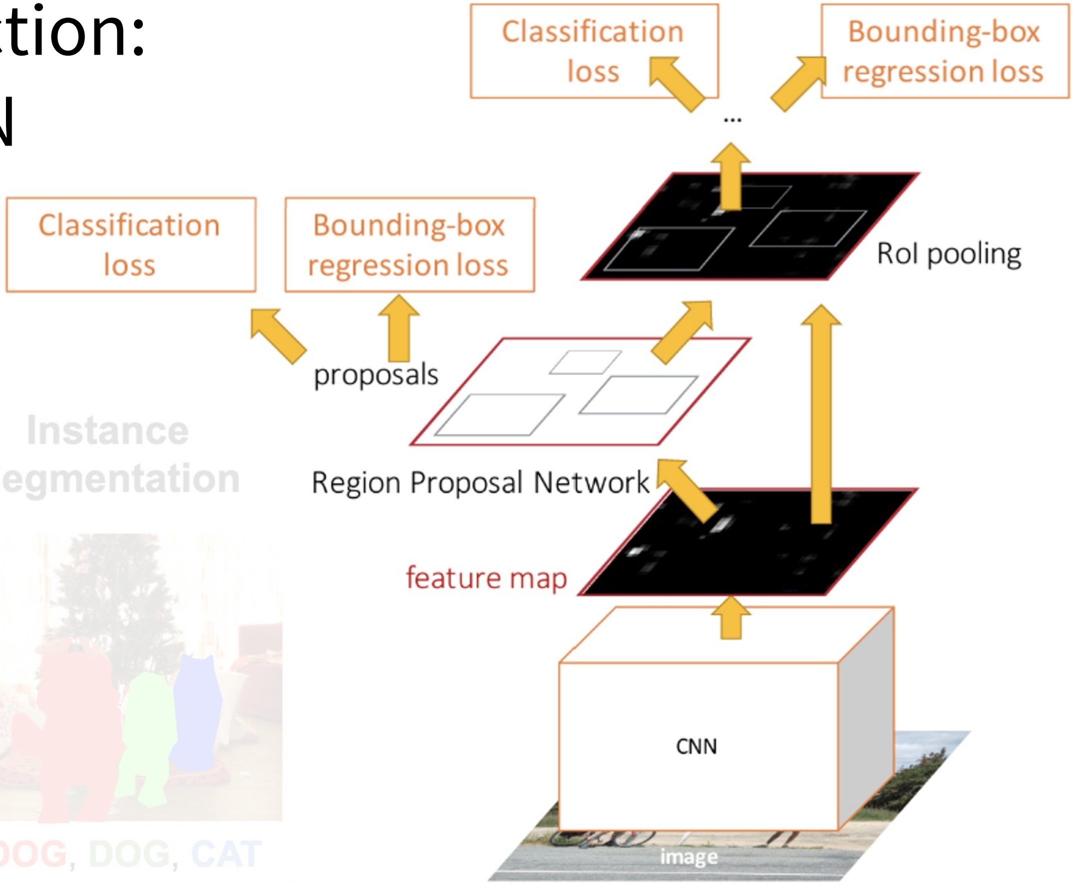
No spatial extent

No objects, just pixels

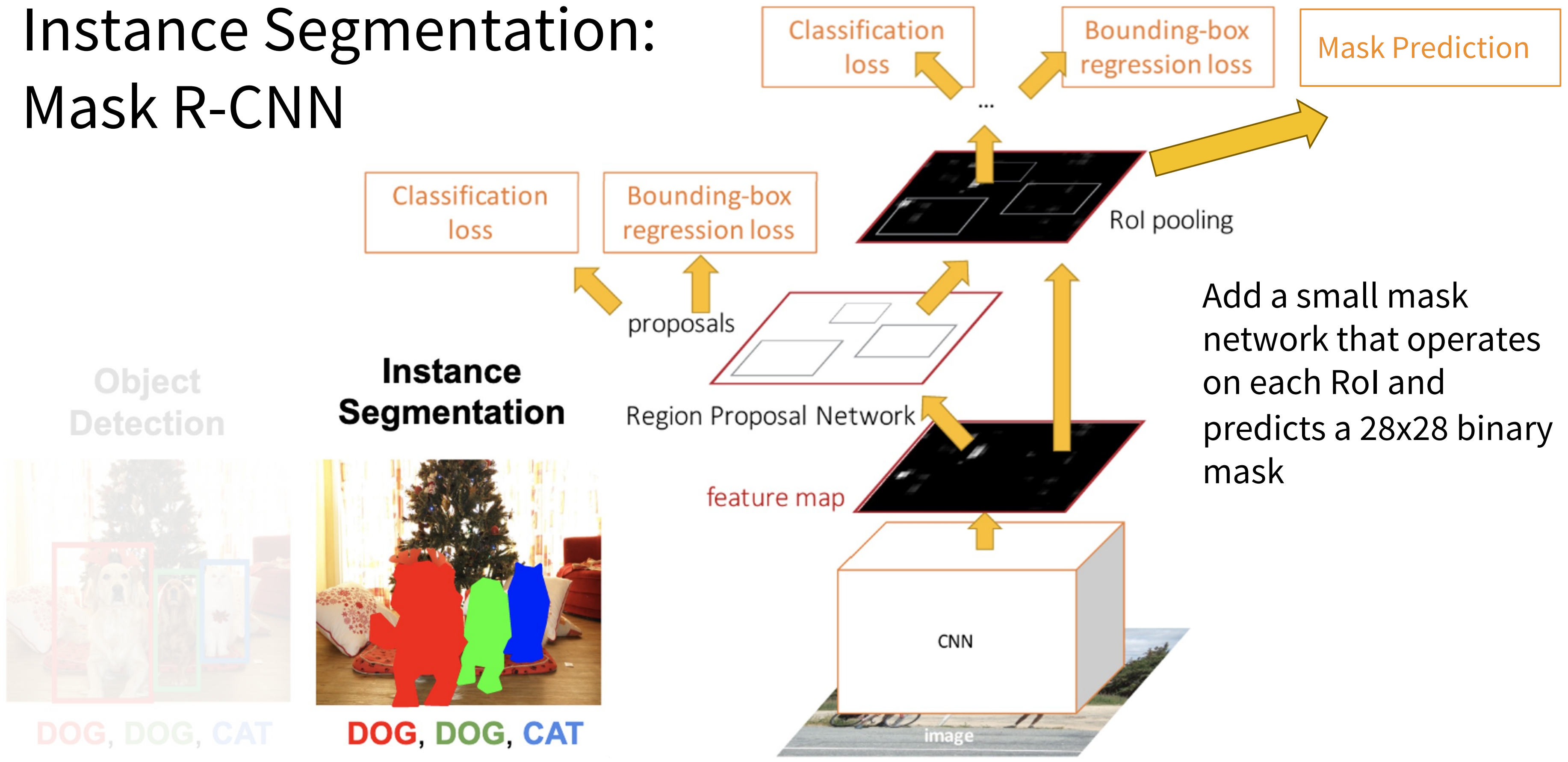
Multiple Object

Object Detection: Faster R-CNN





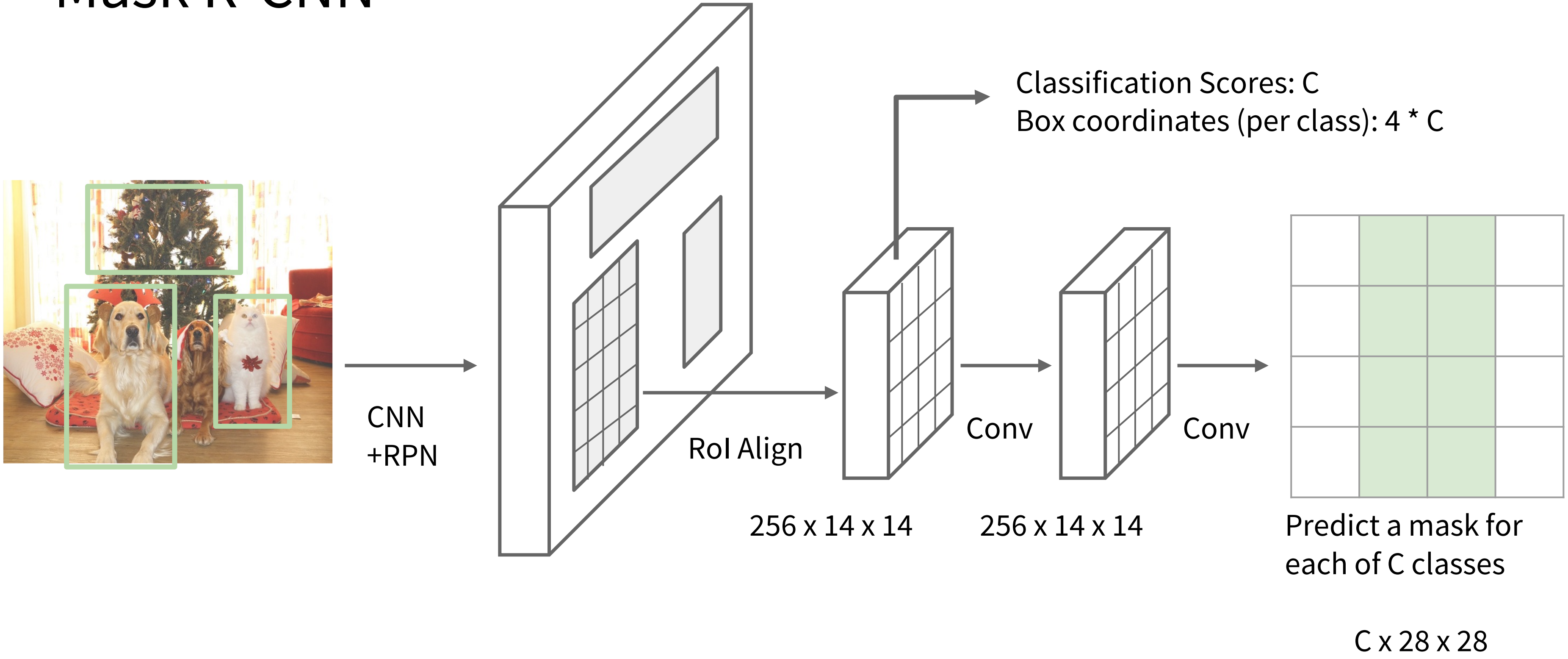
Instance Segmentation: Mask R-CNN



Add a small mask network that operates on each RoI and predicts a 28x28 binary mask

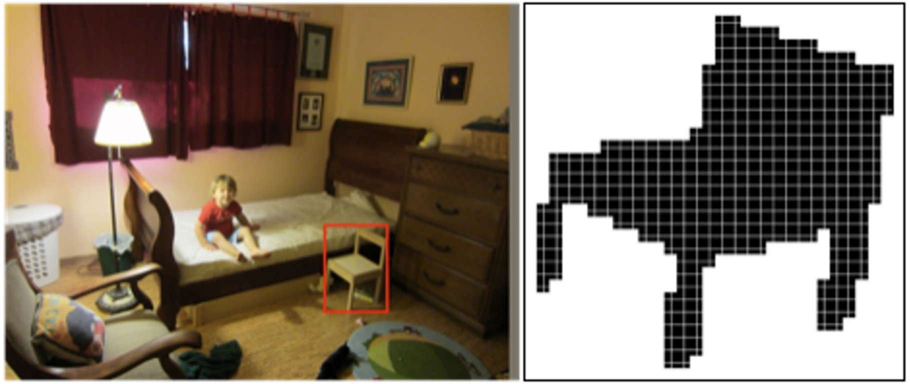
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN

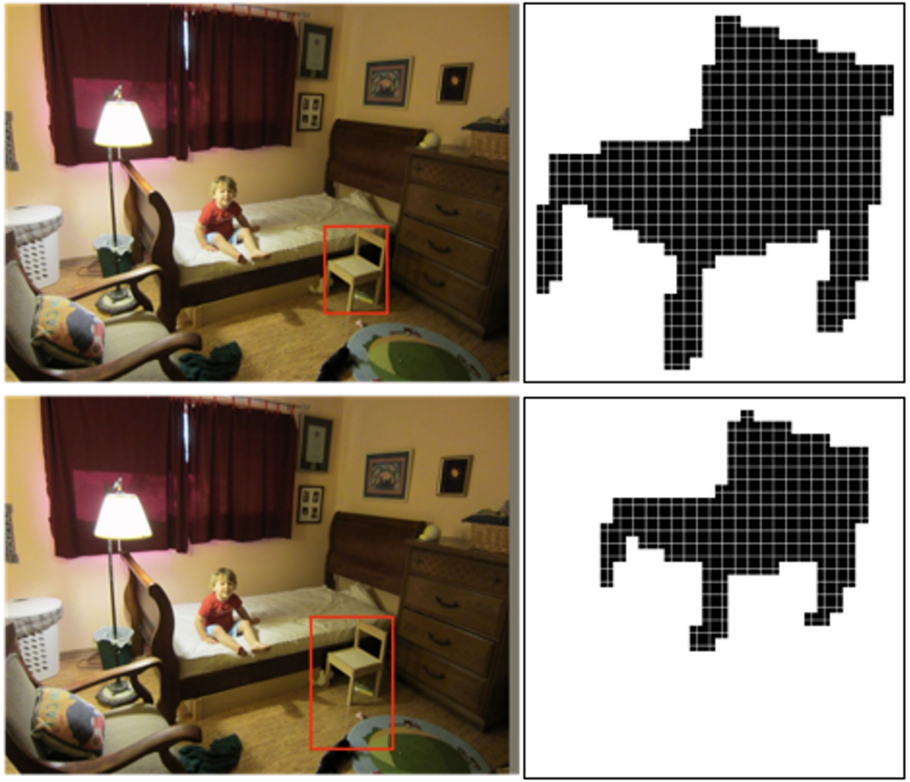


He et al, "Mask R-CNN", arXiv 2017

Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Example Mask Training Targets



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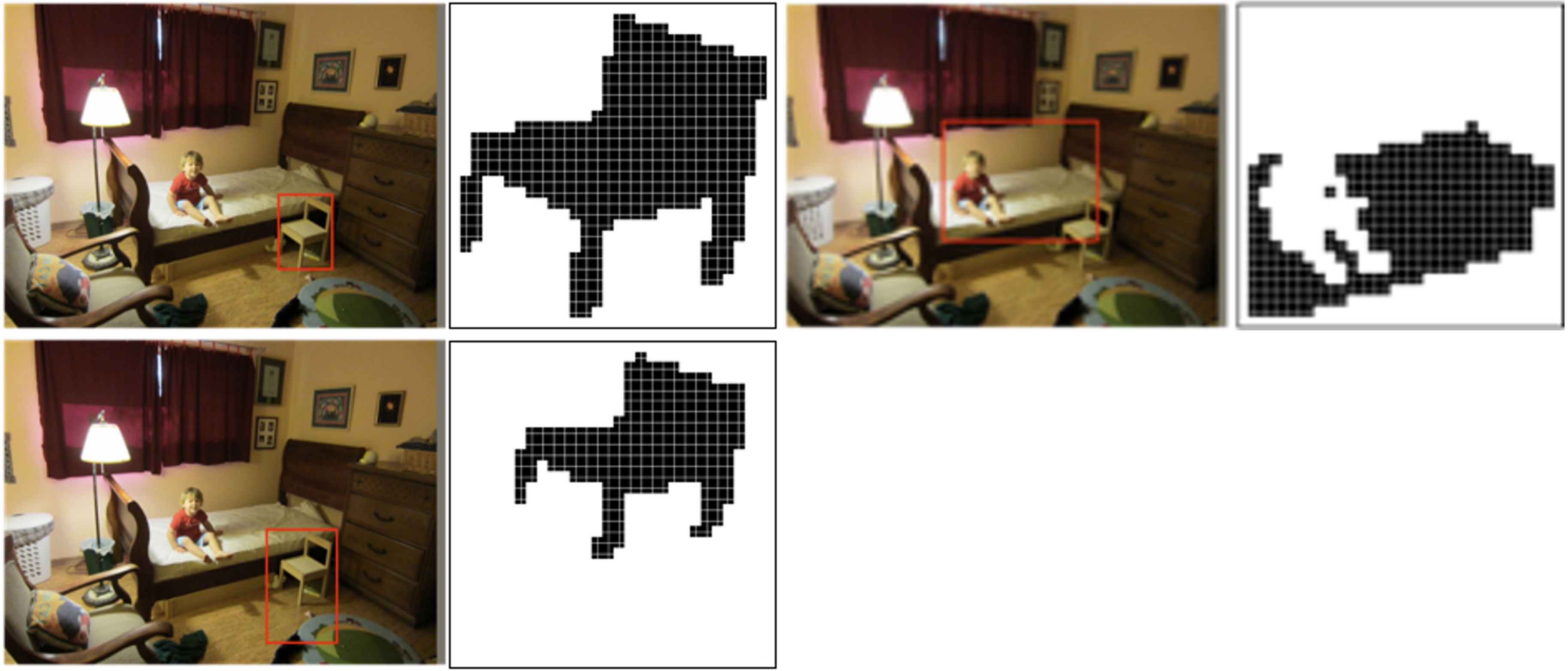

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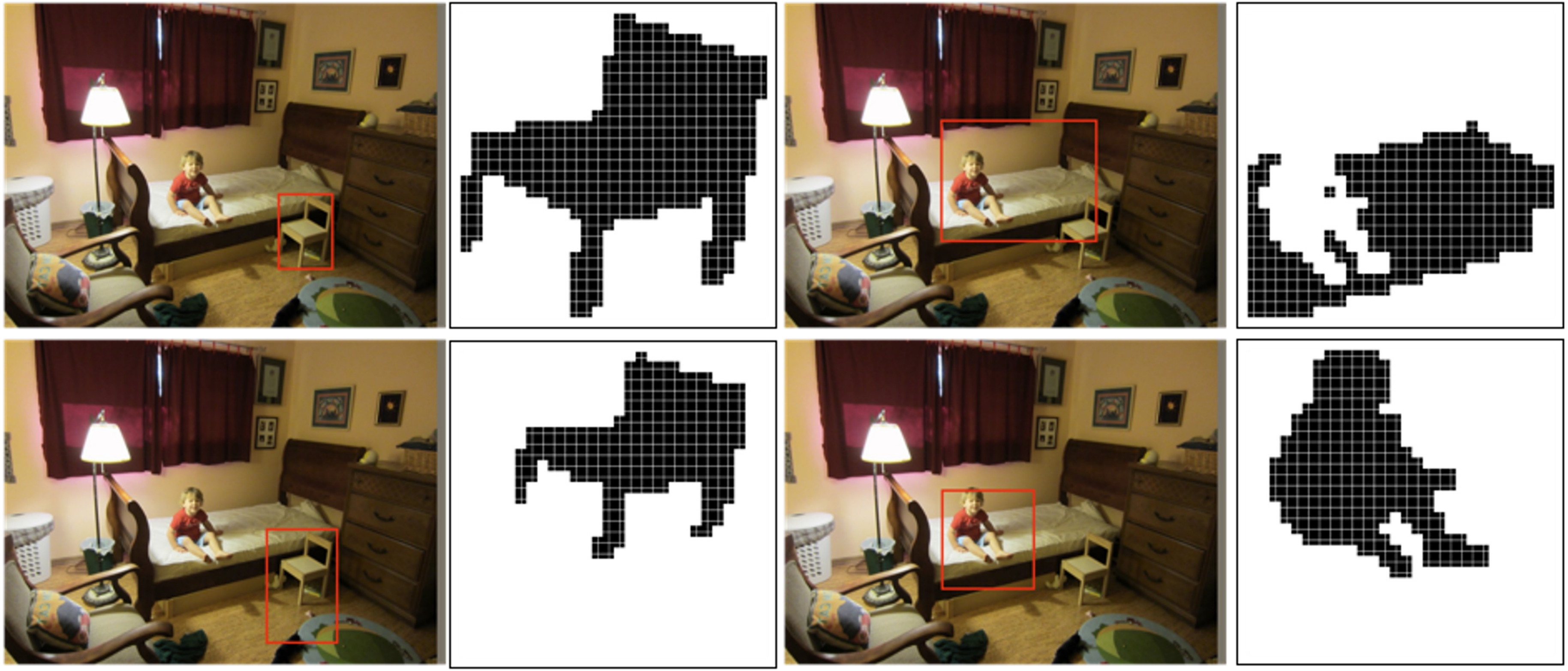
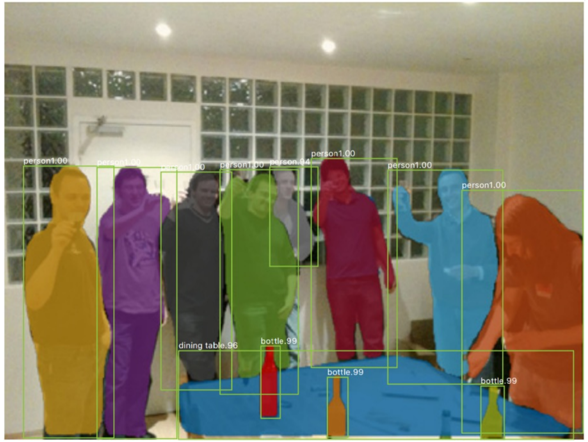


Mask R-CNN: Very Good Results!





He et al, “Mask R-CNN”, ICCV 2017

Mask R-CNN
Also does pose

He et al, “Mask R-CNN”, ICCV 2017

Open Source Frameworks

Lots of good implementations on GitHub!

TensorFlow Detection API:

https://github.com/tensorflow/models/tree/master/research/object_detection

Faster RCNN, SSD, RFCN, Mask R-CNN, ...

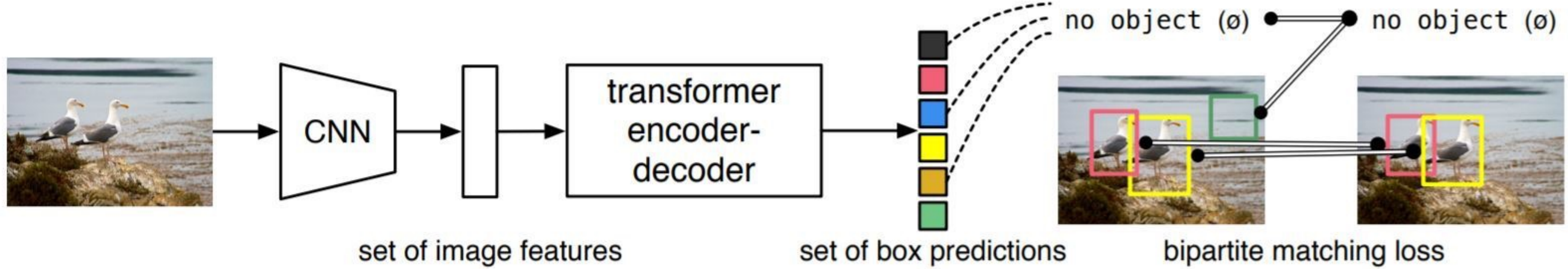
Detectron2 (PyTorch)

https://github.com/facebookresearch/detectron2

Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, R-FCN, ...

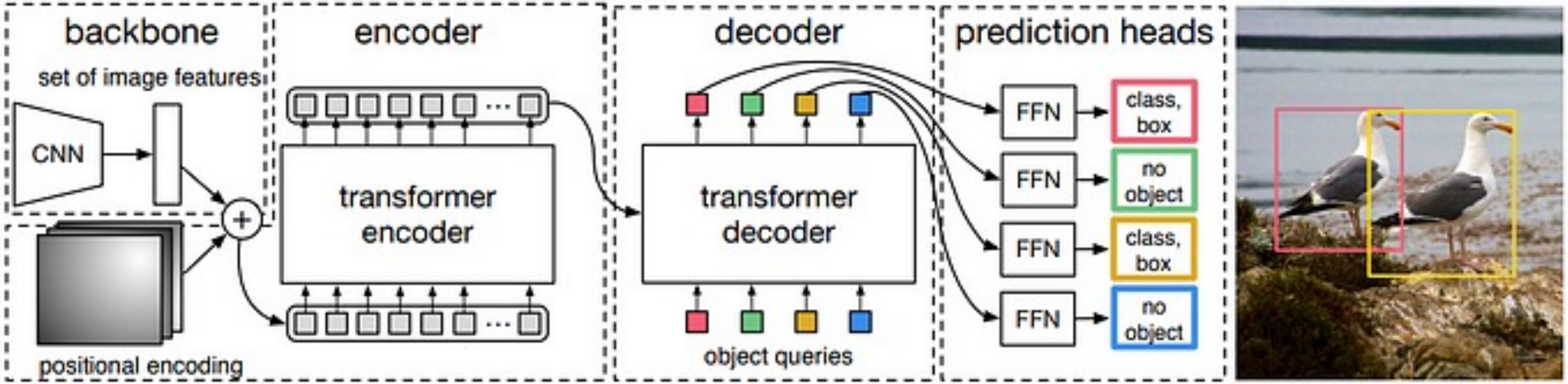
Finetune on your own dataset with pre-trained models

DETR (DEtection TRansformer)



Carion et al. "End-to-End Object Detection with Transformers" ECCV 2020

DETR (DEtection TRansformer)



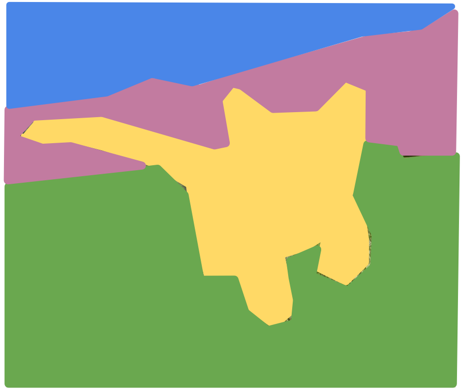
Carion et al. “End-to-End Object Detection with Transformers” ECCV 2020

Recap: Lots of computer vision tasks!

Classification

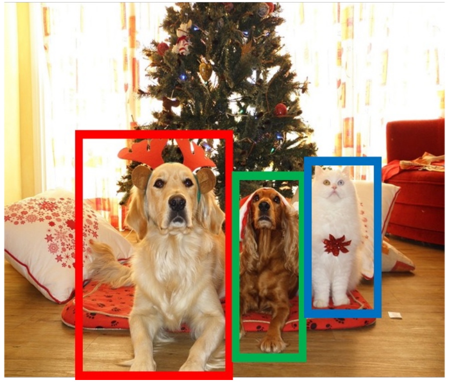
CAT

Semantic Segmentation



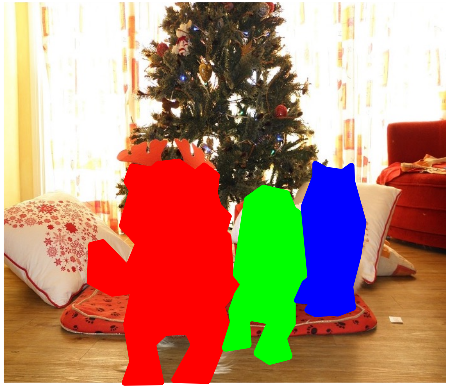
GRASS, CAT, TREE, SKY

Object Detection



DOG, DOG, CAT

Instance Segmentation



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Next time: Video Understanding