CS 4644-DL / 7643-A: LECTURE 20
DANFEI XU

Deep Learning Application to Computer Vision

- Semantic Segmentation
- Object Detection
- Instance Segmentation

Image Classification: A core task in Computer Vision

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

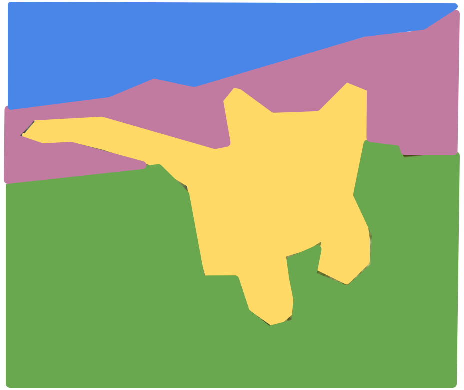
→ cat

Computer Vision Tasks

Classification

CAT

Semantic Segmentation

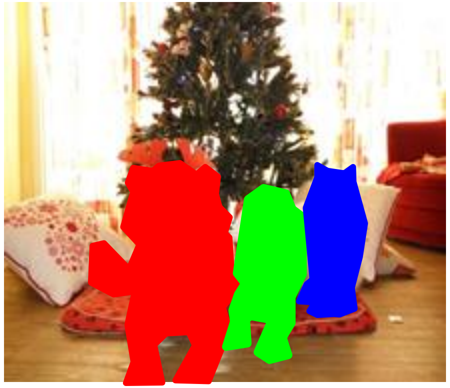


GRASS, CAT, TREE, SKY

Object Detection

DOG, DOG, CAT

Instance Segmentation



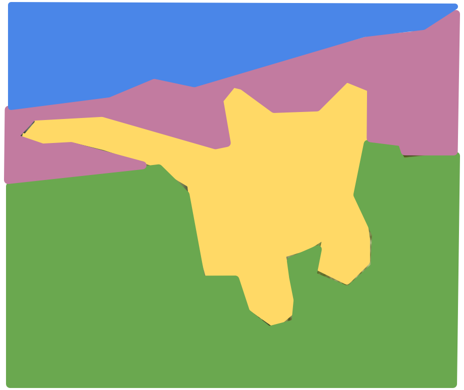
DOG, DOG, CAT

No spatial extent

No objects, just pixels

Multiple Object

Semantic Segmentation

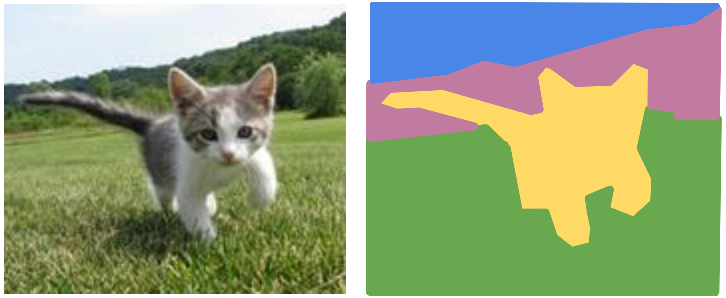
Classification	**Semantic Segmentation**	Object Detection	Instance Segmentation
			
CAT	GRASS, CAT, TREE, SKY	DOG, DOG, CAT	DOG, DOG, CAT

No spatial extent

No objects, just pixels

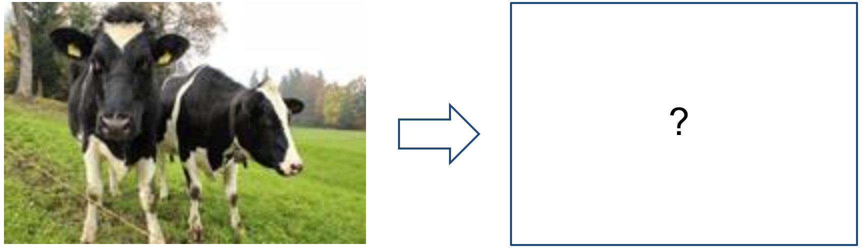
Multiple Object

Semantic Segmentation: The Problem



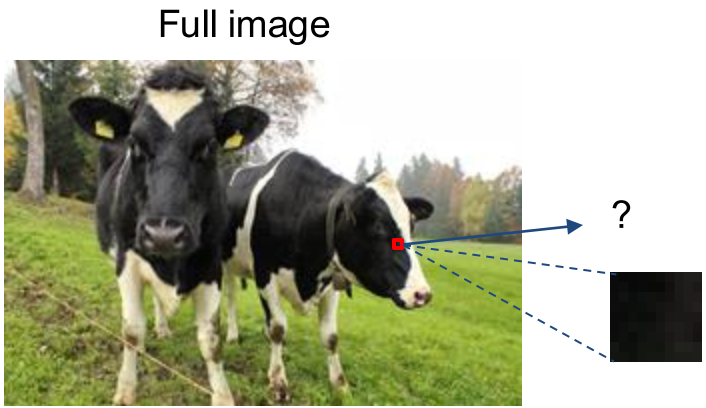
GRASS, **CAT**,
TREE, **SKY**, **...**

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



Semantic Segmentation Idea: Sliding Window

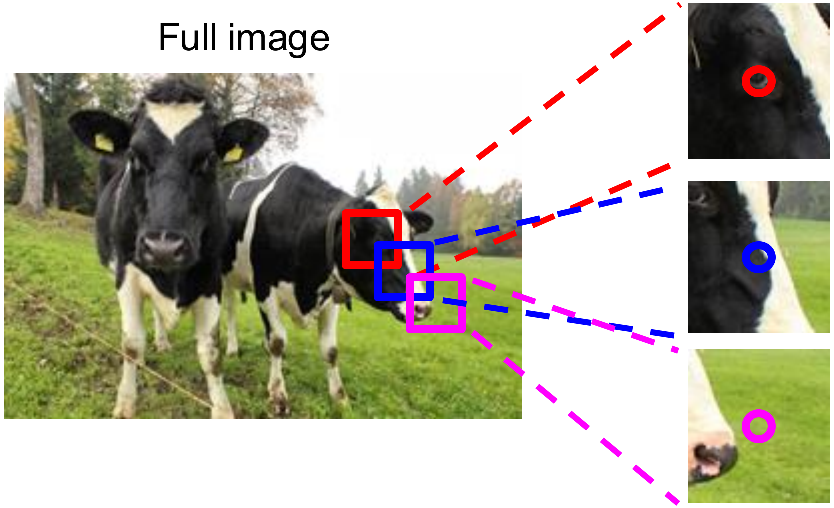
Full image

Impossible to classify without context

Q: how do we include context?

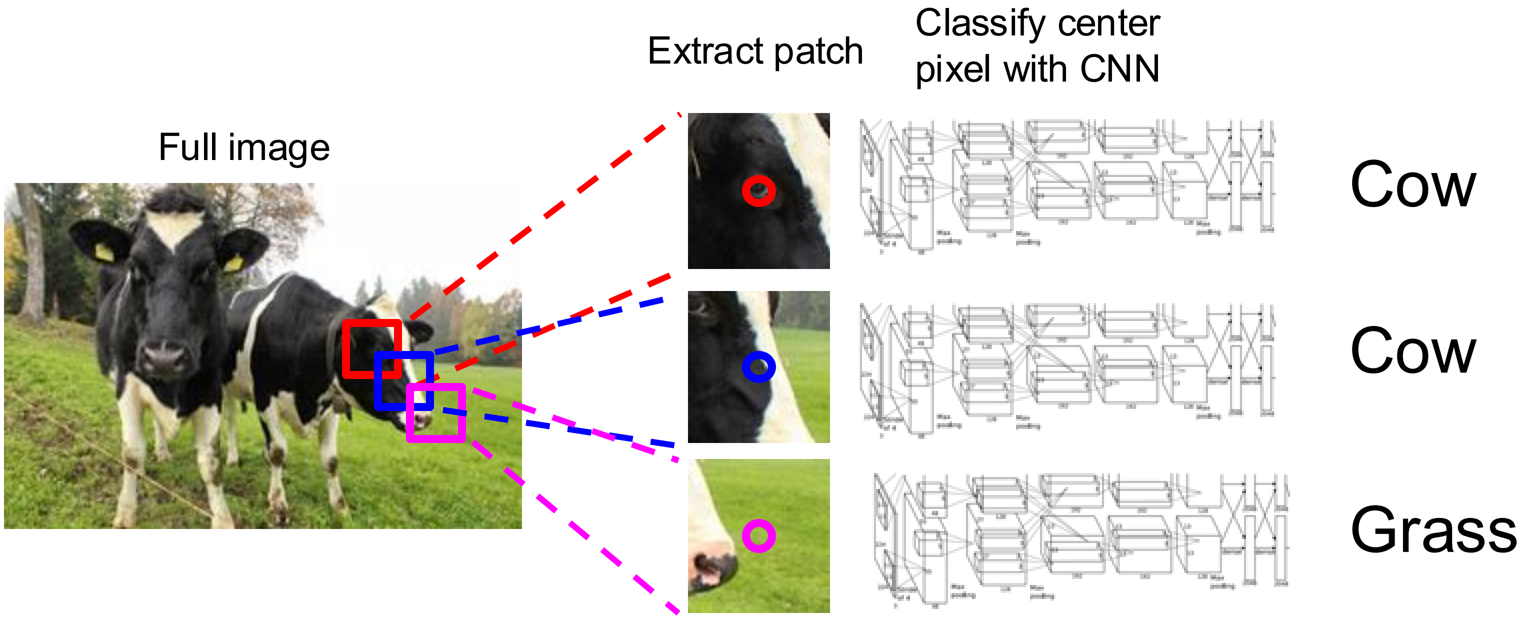
Semantic Segmentation Idea: Sliding Window

Full image



Q: how do we model this?

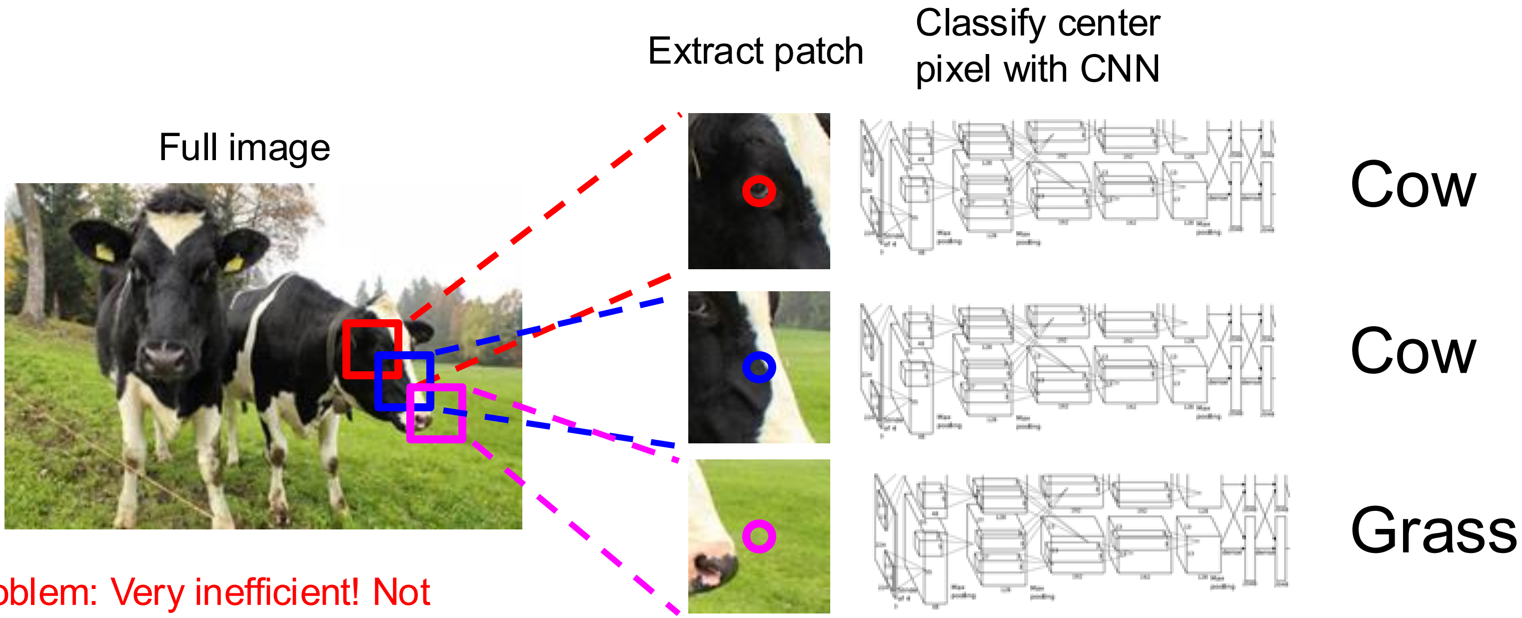
Semantic Segmentation Idea: Sliding Window



The "sliding window" approach

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



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

The “sliding window” approach

Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
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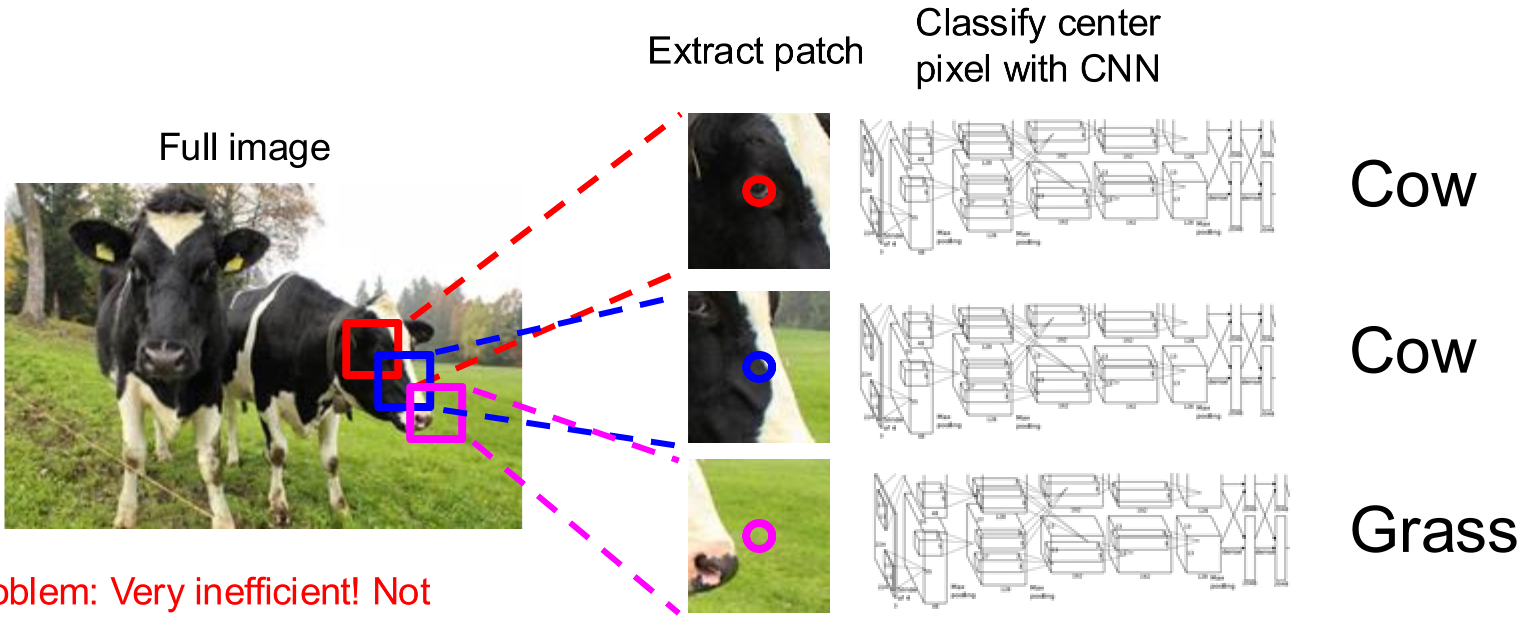
Semantic Segmentation Idea: Sliding Window



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

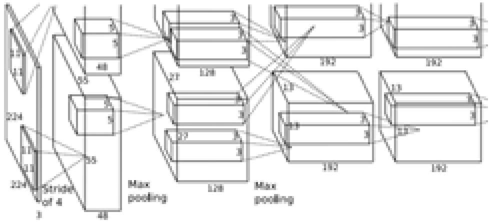
Observation: lots of duplicate computation in nearby pixels

The "sliding window" approach

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

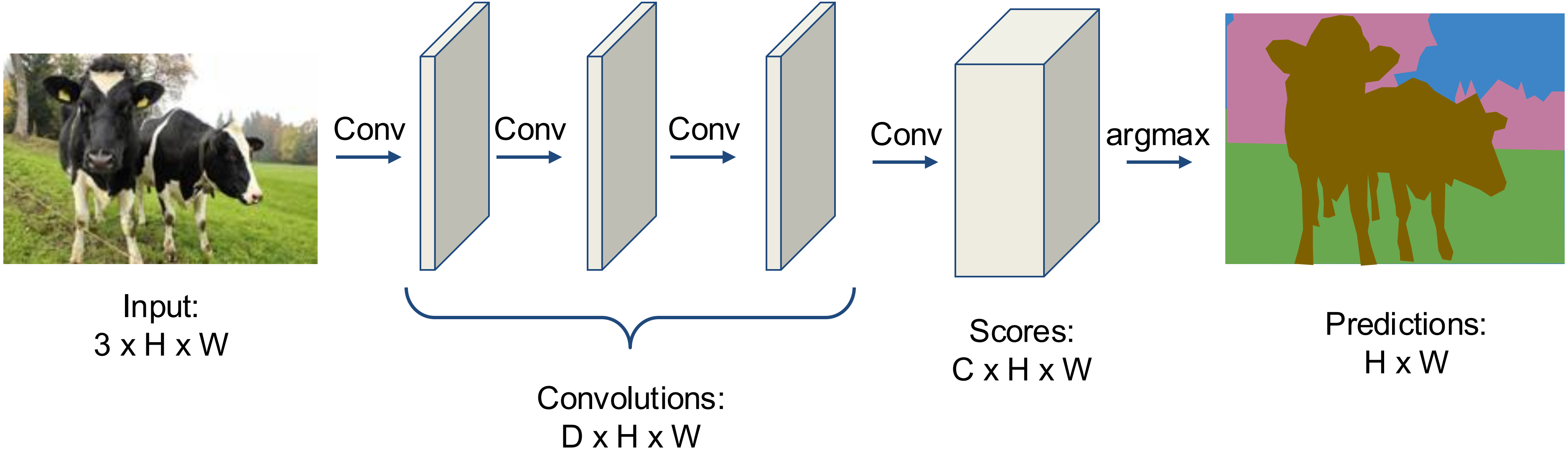


An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

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

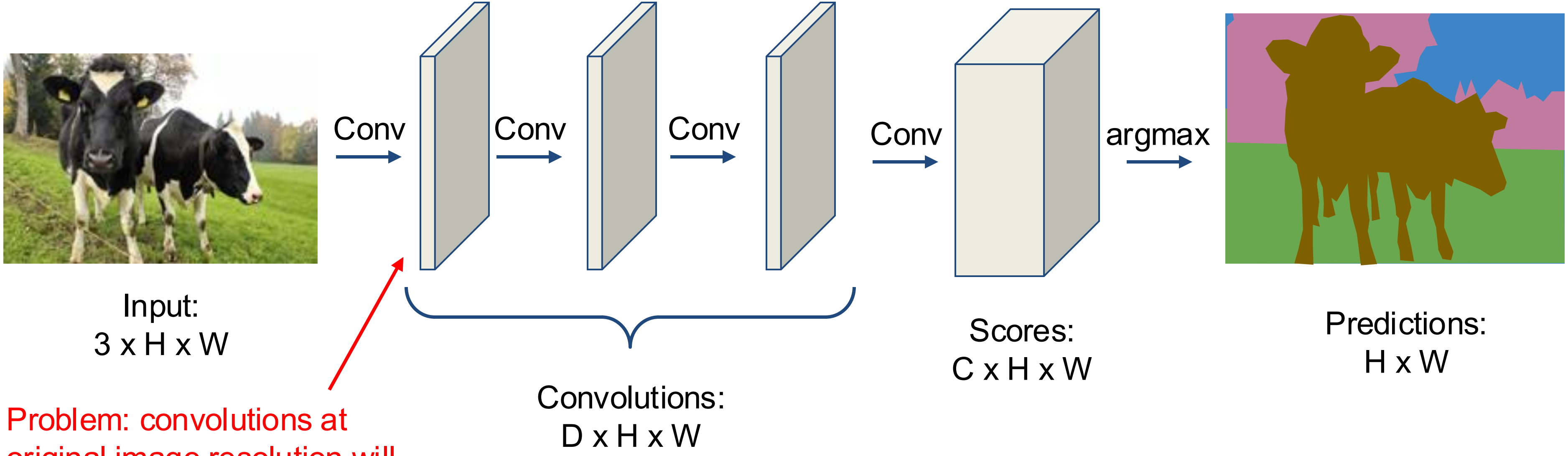
Design a network with only convolutional layers without downsampling operators to make predictions for pixels all at once!



Loss: Pixel-wise cross entropy!

Semantic Segmentation Idea: Fully Convolutional

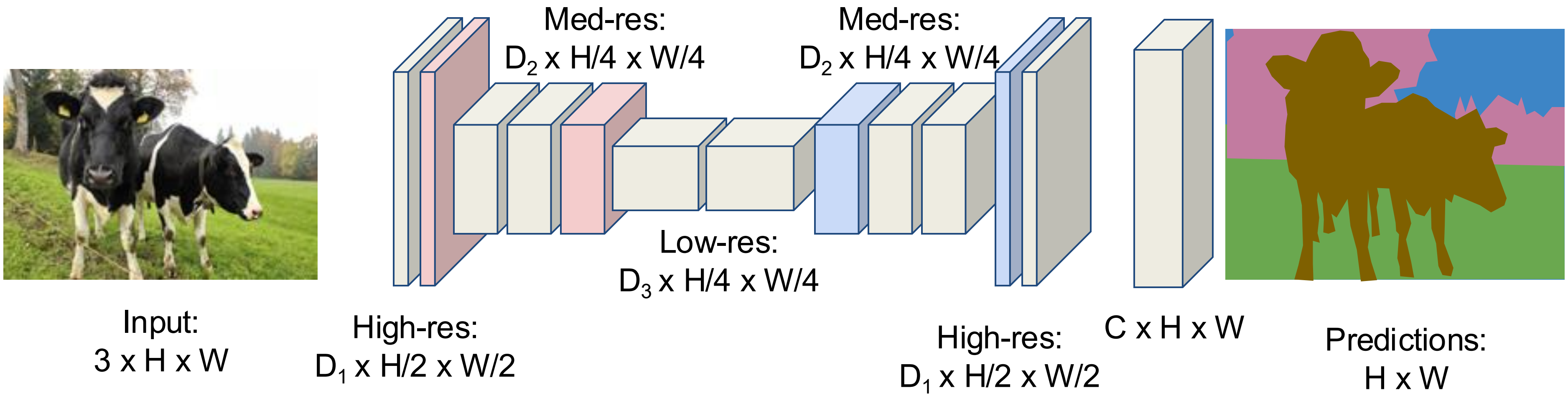
Design a network with only convolutional layers
without downsampling operators to make predictions
for pixels all at once!



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!



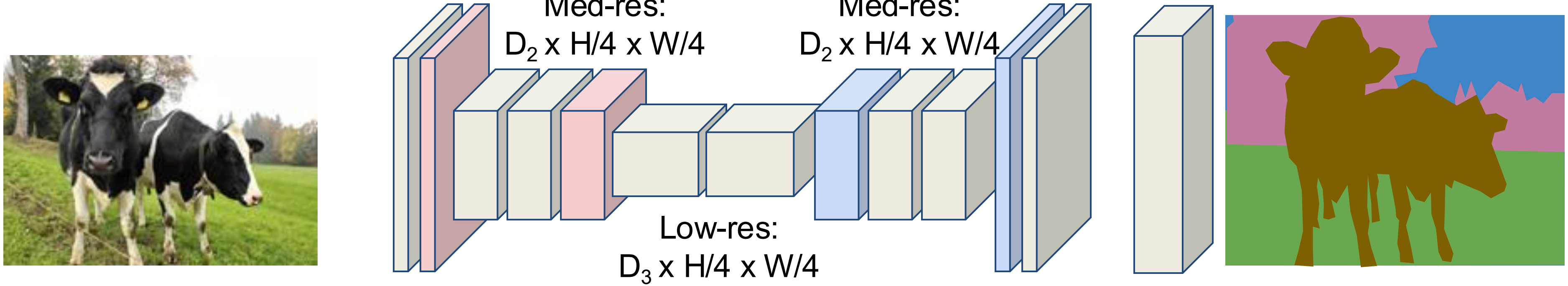
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

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

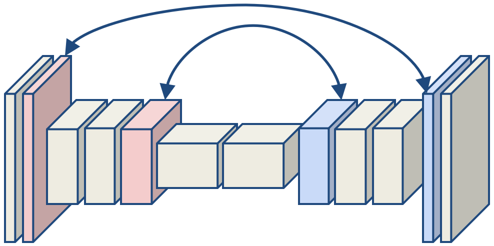
1	2
3	4

Input: 2 x 2

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

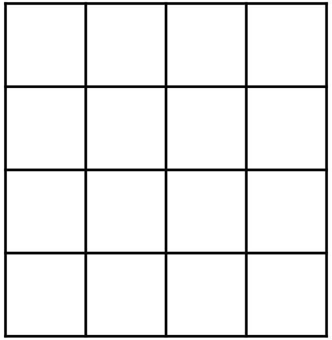
Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

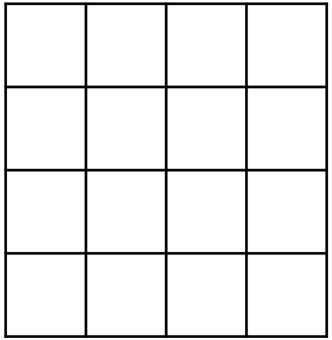


Learnable Upsampling

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



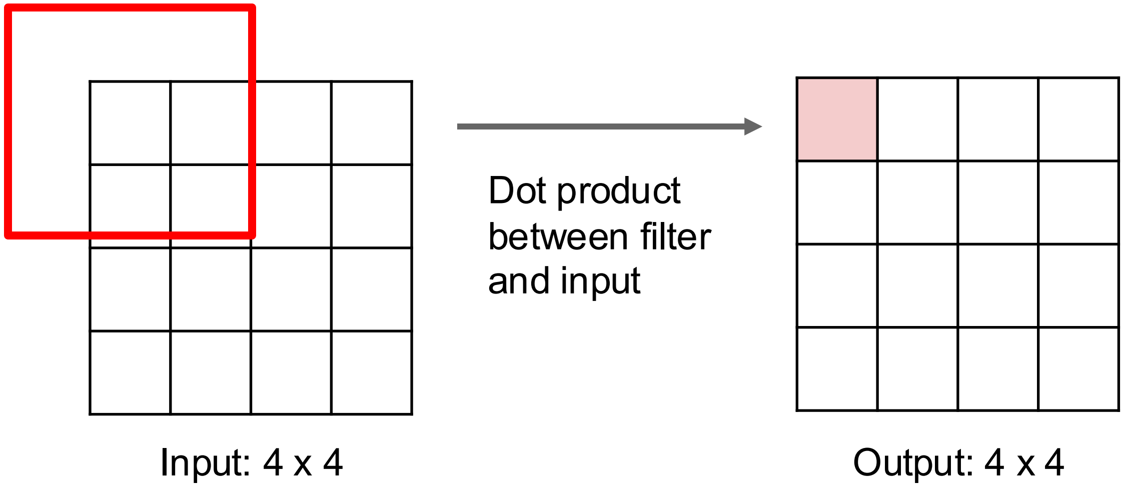
Input: 4 x 4



Output: 4 x 4

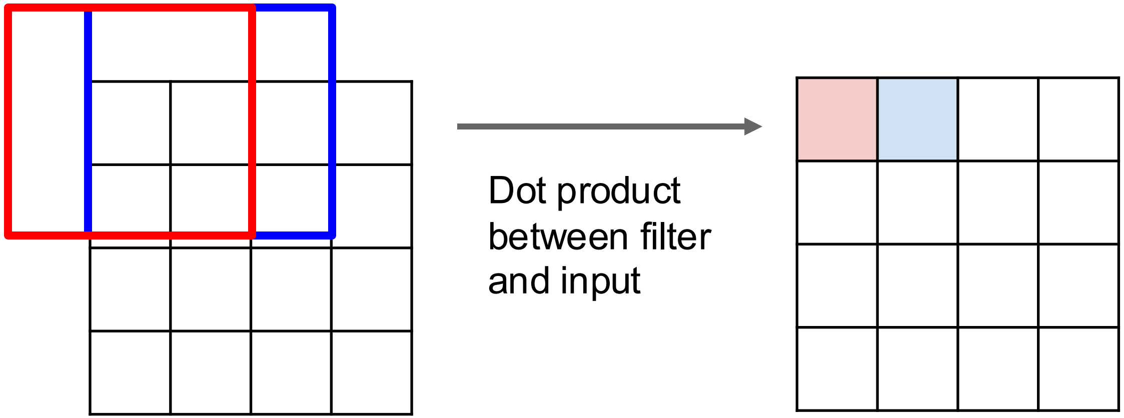
Learnable Upsampling

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



Learnable Upsampling

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

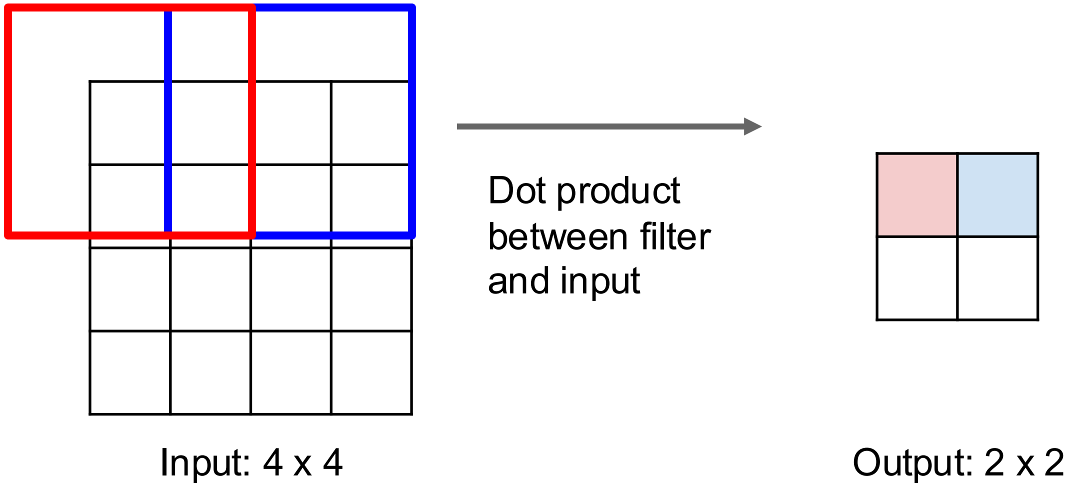


Input: 4 x 4

Output: 4 x 4

Learnable Upsampling

Recall: Normal 3 x 3 convolution, <u>stride 2</u> pad 1

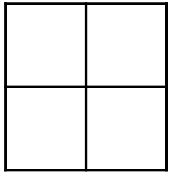


Filter moves 2 pixels in the input for every one pixel in the output

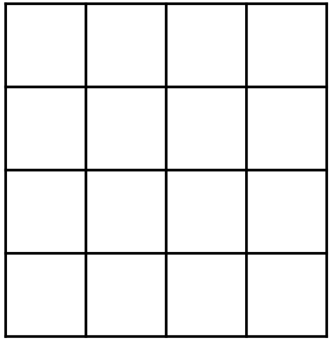
Stride gives ratio between movement in input and output

Learnable Upsampling: Transposed Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



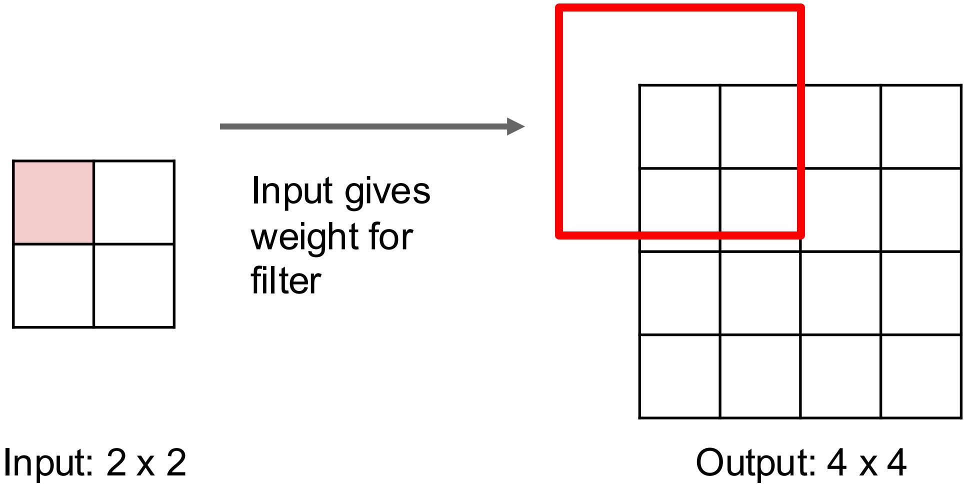
Input: 2 x 2



Output: 4 x 4

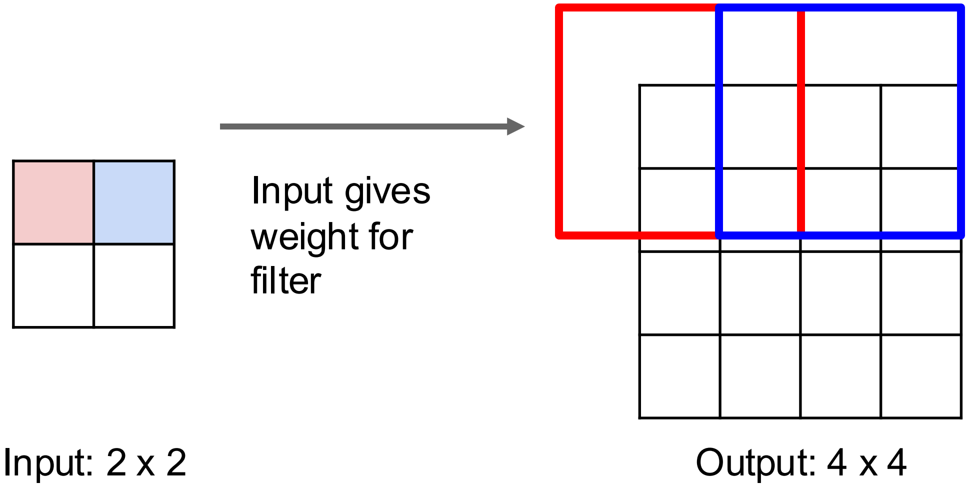
Learnable Upsampling: Transposed Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



Learnable Upsampling: Transposed Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



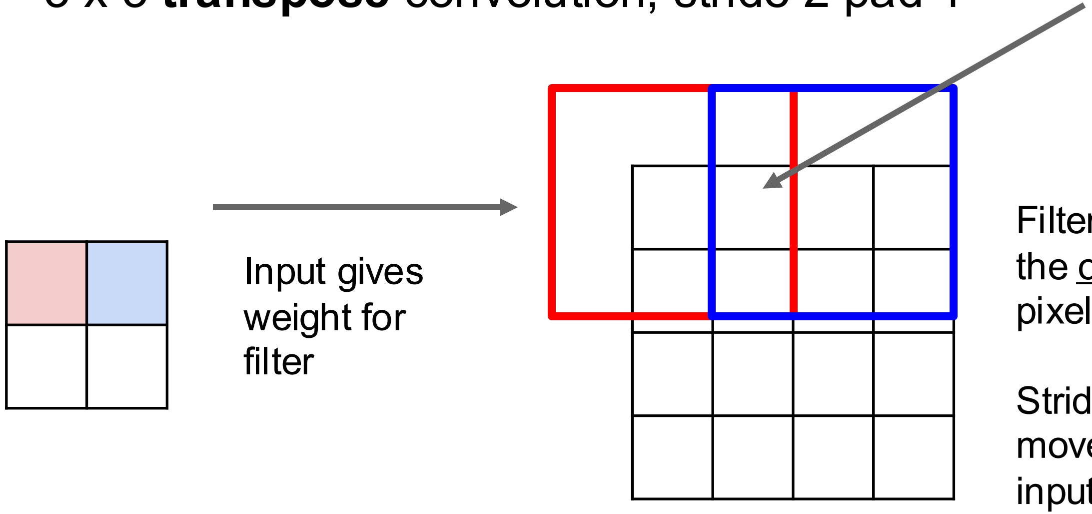
Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: Transposed Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

Sum where output overlaps



Input: 2 x 2

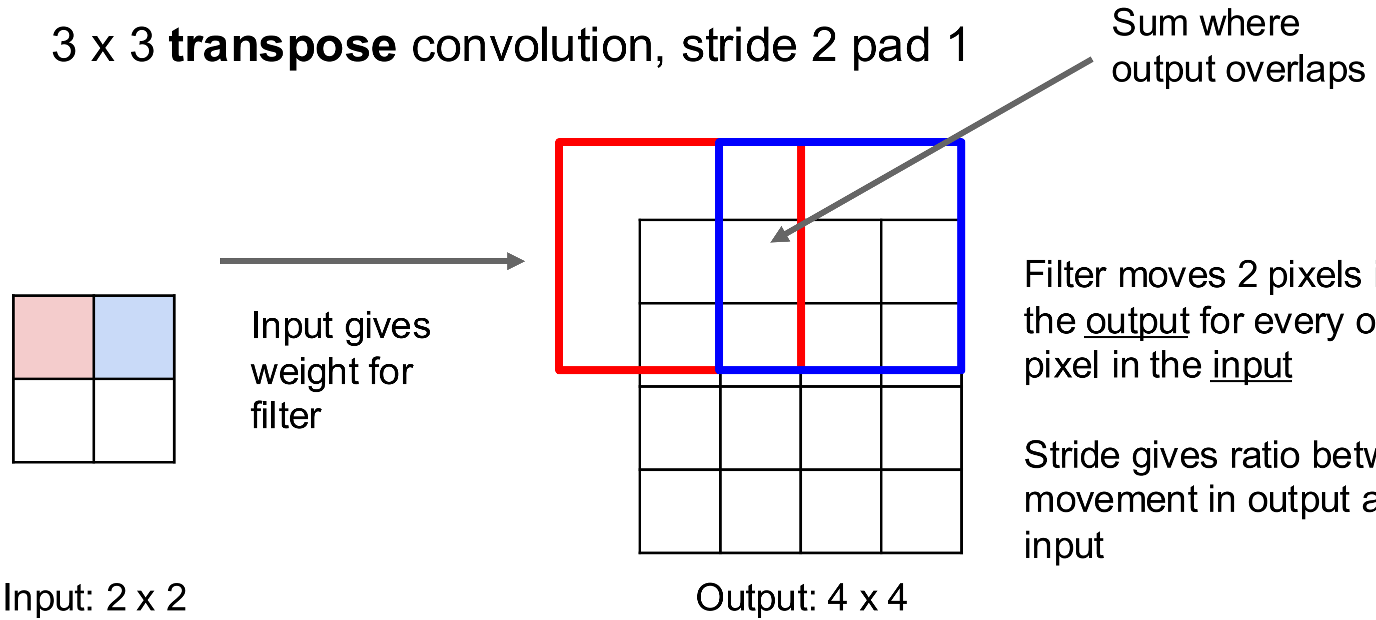
Output: 4 x 4

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

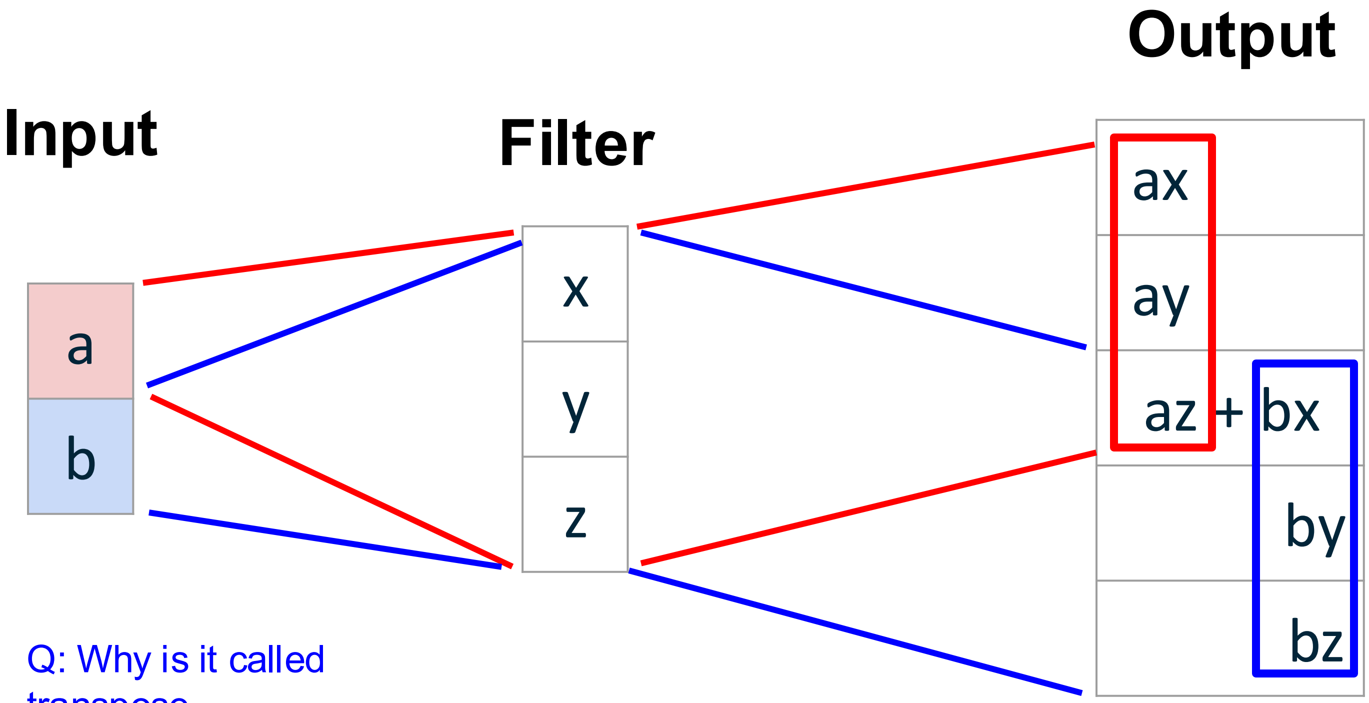
3 x 3 **transpose** convolution, stride 2 pad 1



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: 1D Example



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

Q: Why is it called transpose convolution?

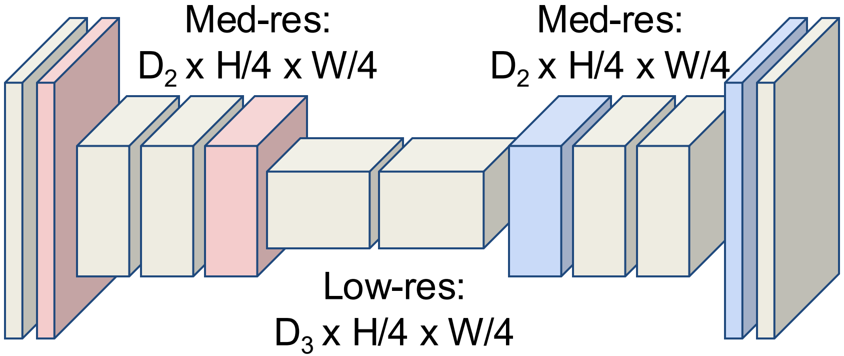
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

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

Upsampling: Unpooling or strided transpose convolution

Input: 3 x H x W



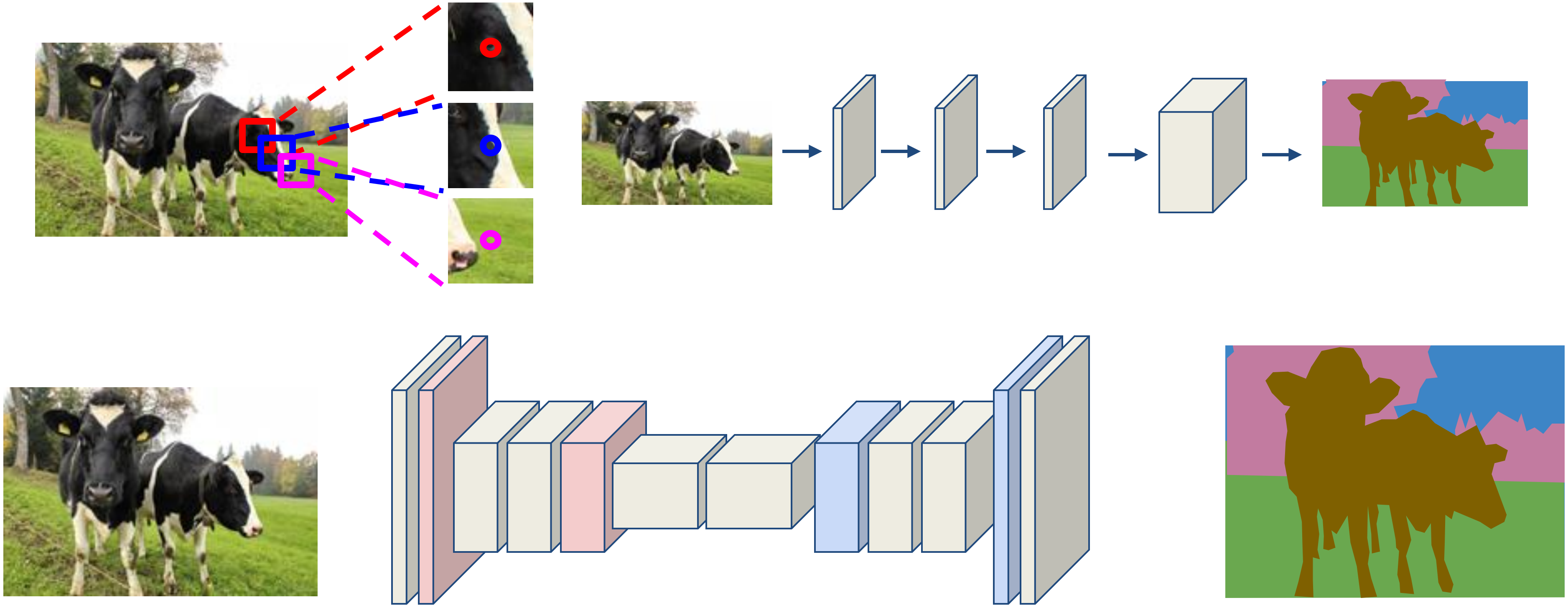
High-res: D_1 x H/2 x W/2

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

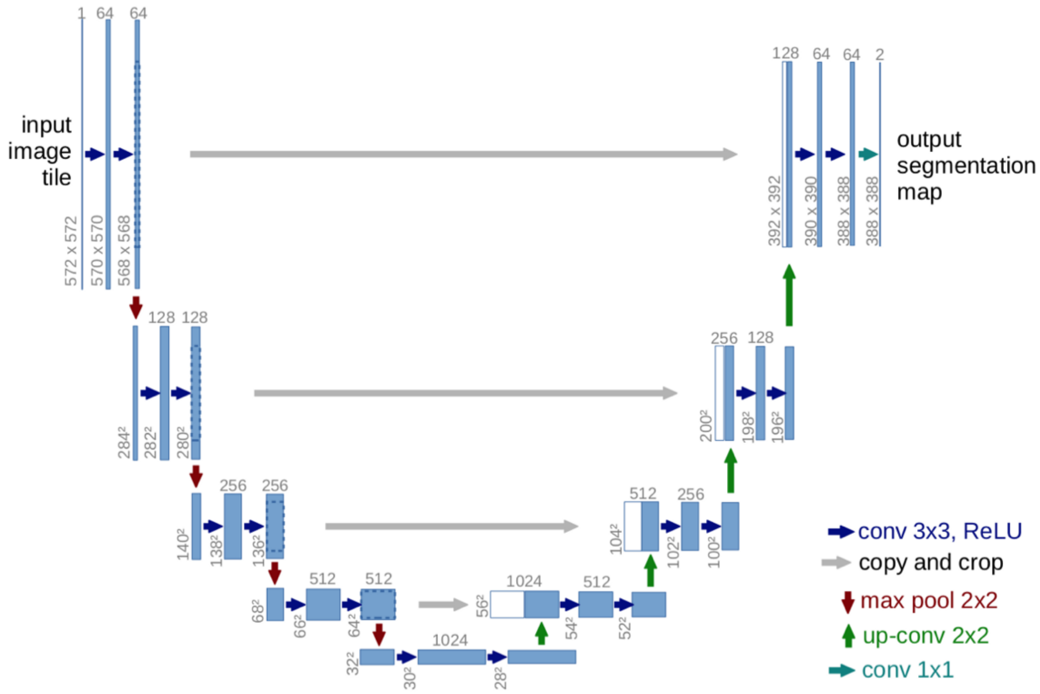
Predictions: H x W

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: Summary



Semantic Segmentation: U-Net



Idea: Concatenate feature maps from the downsampling stage with the features in the upsampling stage.

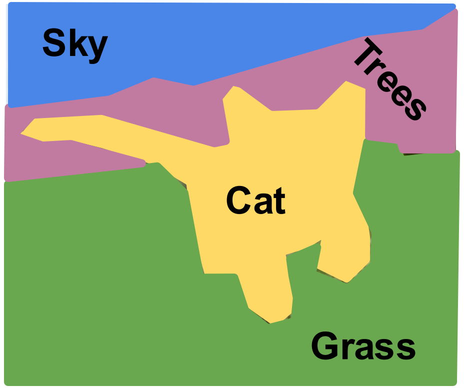
Very commonly used today!

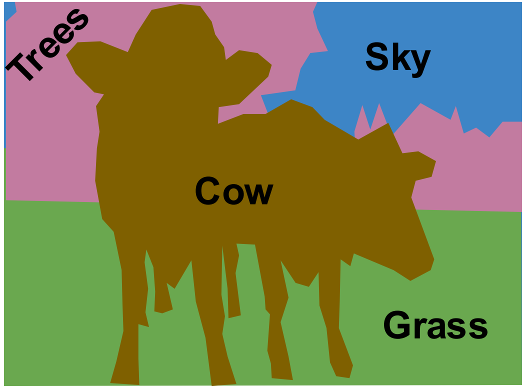
Ronneberger O, Fischer P, Brox T, 2015

Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels





Object Detection

Classification

CAT

No spatial extent

Semantic Segmentation

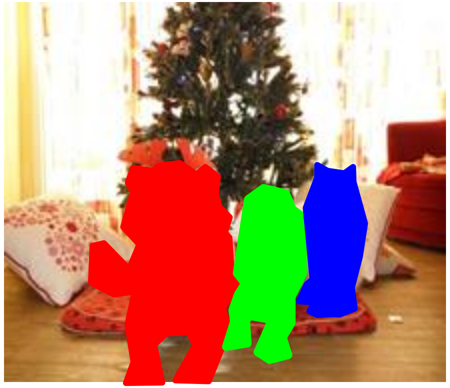
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Object Detection

Classification

CAT

No spatial extent

Semantic Segmentation

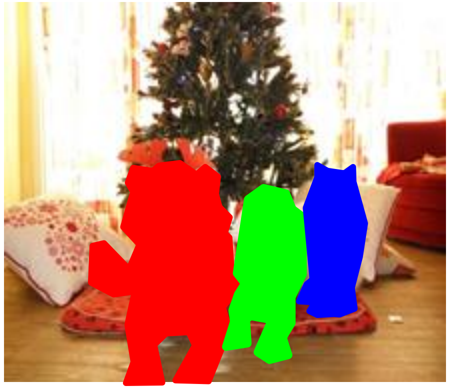
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

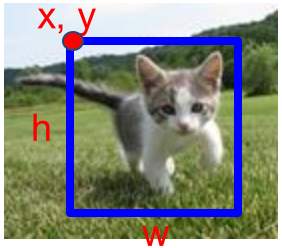
Instance Segmentation



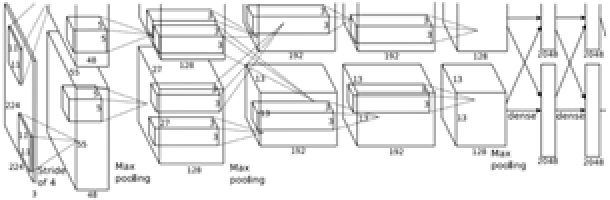
DOG, DOG, CAT

Multiple Object

Object Detection: Single Object
(Classification + Localization)



This image is CC0 public domain



Vector: 4096

Fully Connected: 4096 to 1000

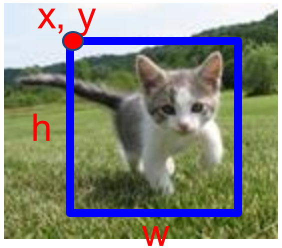
Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

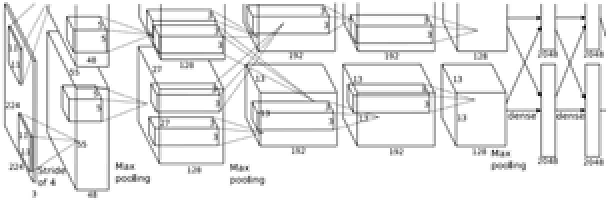
Fully Connected: 4096 to 4

Box Coordinates
(x, y, w, h)

Object Detection: Single Object

(Classification + Localization)





Vector: 4096

Fully Connected: 4096 to 1000

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

Correct label: Cat

Softmax Loss

Fully Connected: 4096 to 4

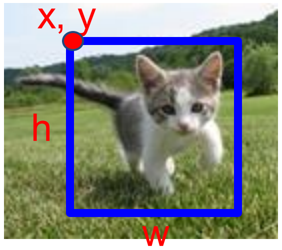
Box Coordinates (x, y, w, h)

L2 Loss

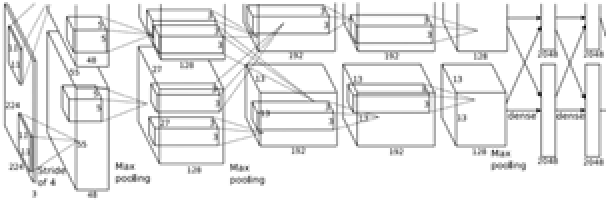
Correct box: (x', y', w', h')

Treat localization as a regression problem!

Object Detection: 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

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

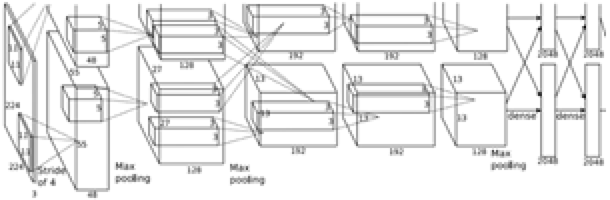
Correct box:
(x', y', w', h')

Multitask Loss

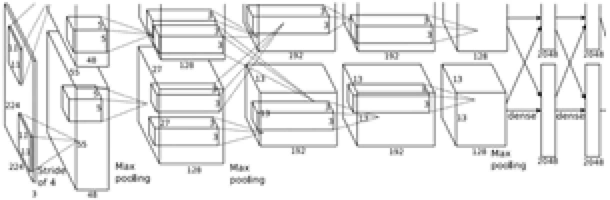
\+ → **Loss**

Treat localization as a regression problem!

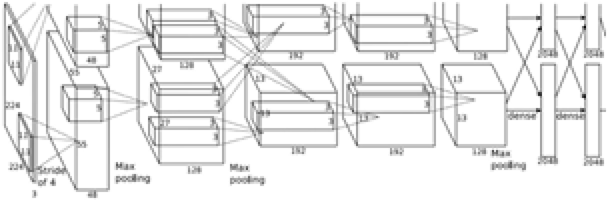
Object Detection: Multiple Objects



CAT: (x, y, w, h)



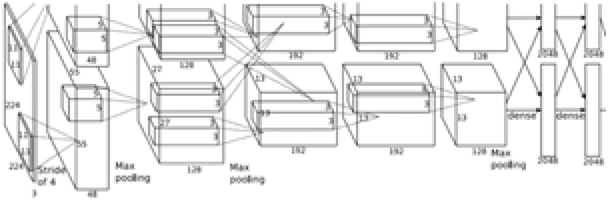
DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)



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

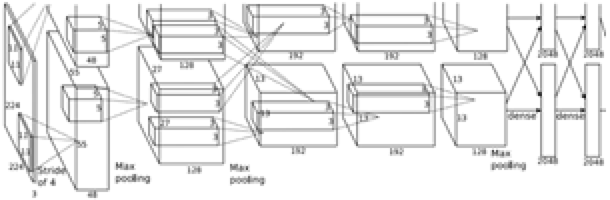
Object Detection: Multiple Objects

Each image needs a different number of outputs!

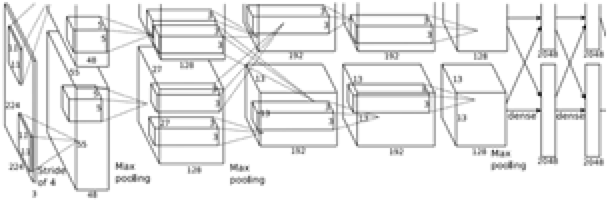
CAT: (x, y, w, h)

4 numbers

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

12 numbers

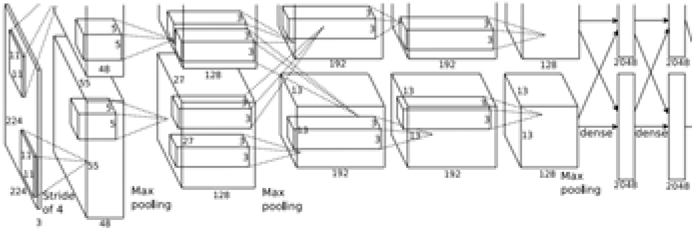



DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Many numbers!

Object Detection: Multiple Objects

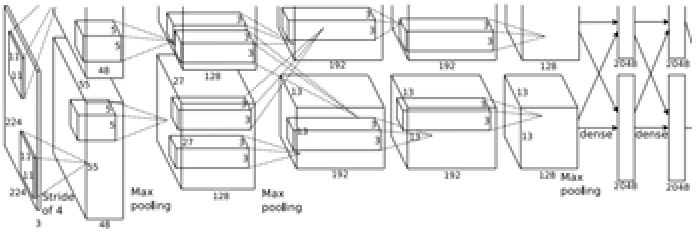
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

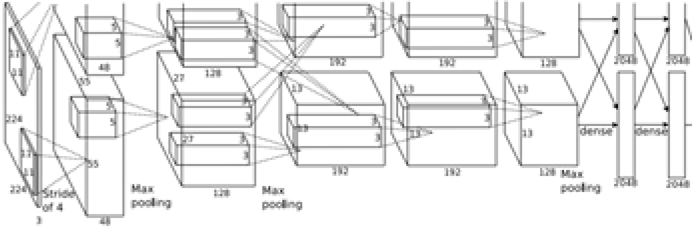
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

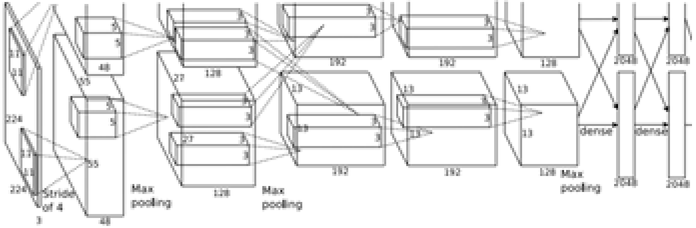
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

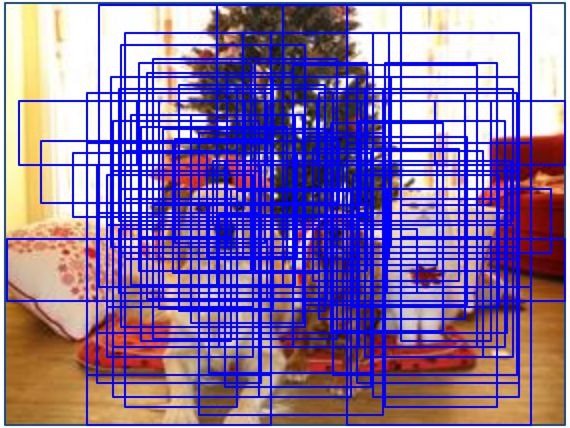
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



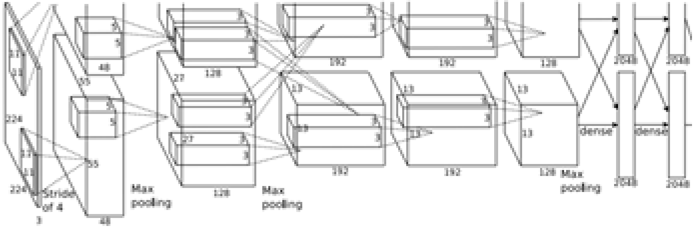
Dog? NO
Cat? YES
Background? NO

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



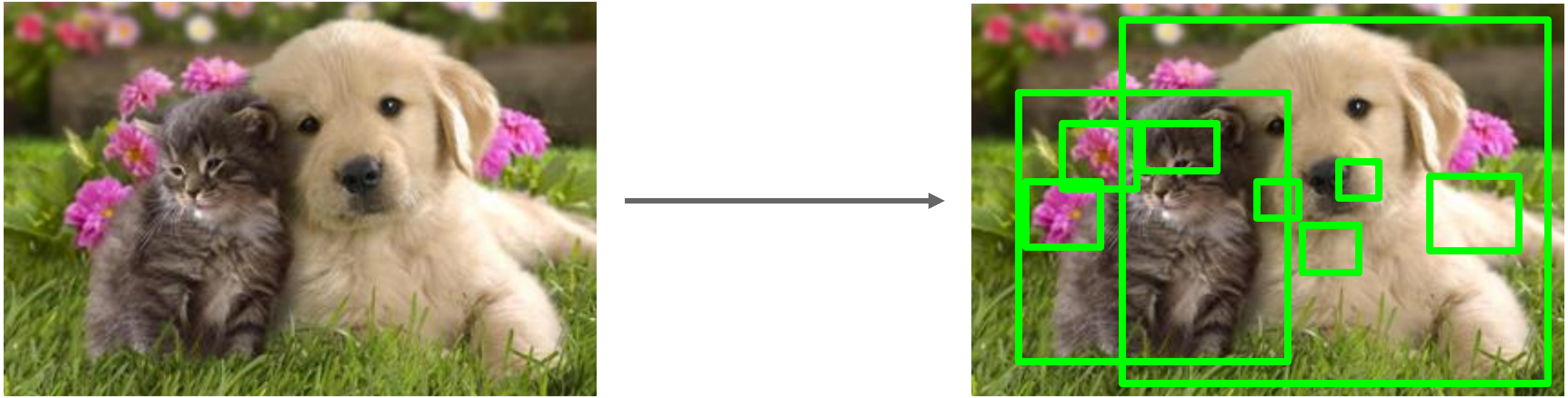
Dog? NO
Cat? YES
Background? NO

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

Need to find **promising regions**

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



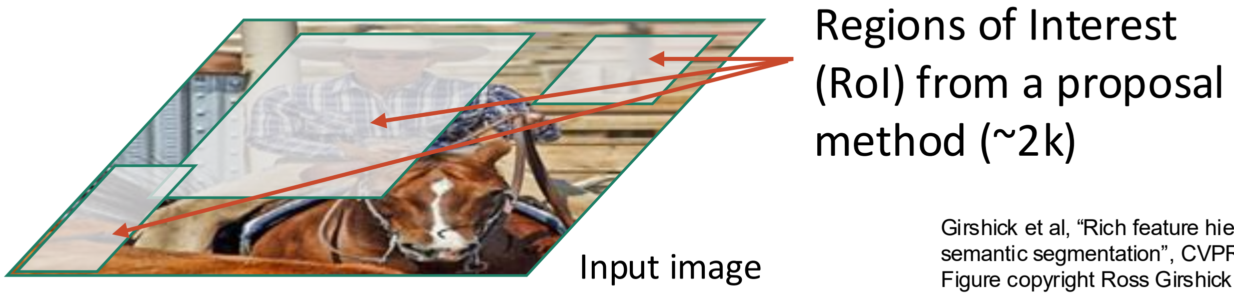
Alexe et al, “Measuring the objectness of image windows”, TPAMI 2012
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013
Cheng et al, “BING: Binarized normed gradients for objectness estimation at 300fps”, CVPR 2014
Zitnick and Dollar, “Edge boxes: Locating object proposals from edges”,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

R-CNN

Input image

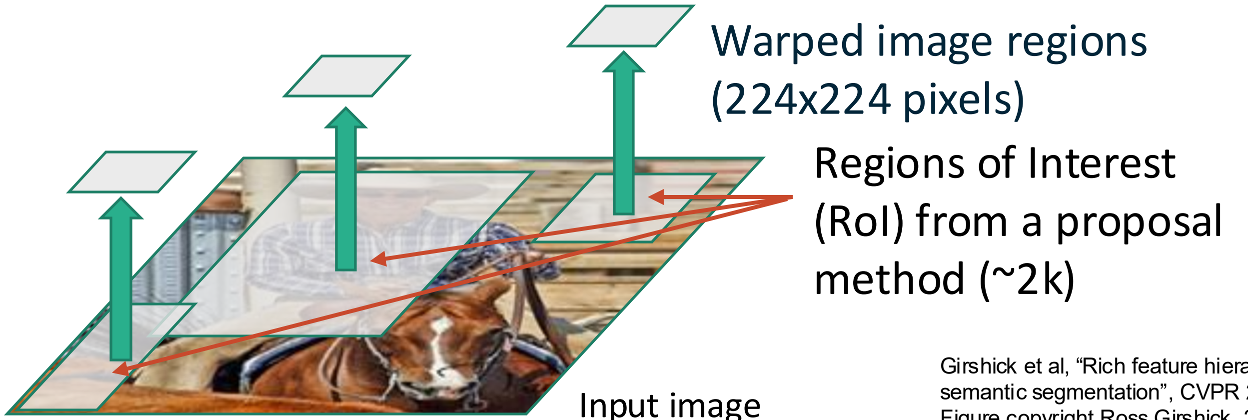
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN



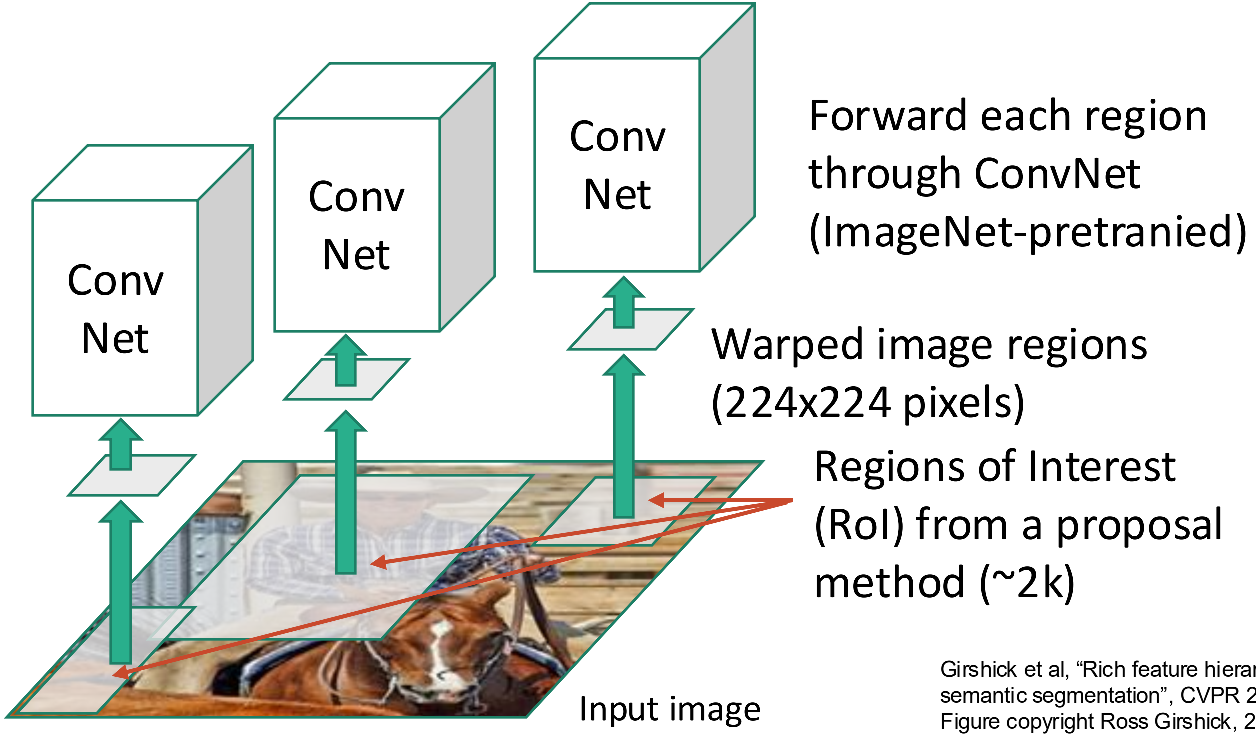
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN



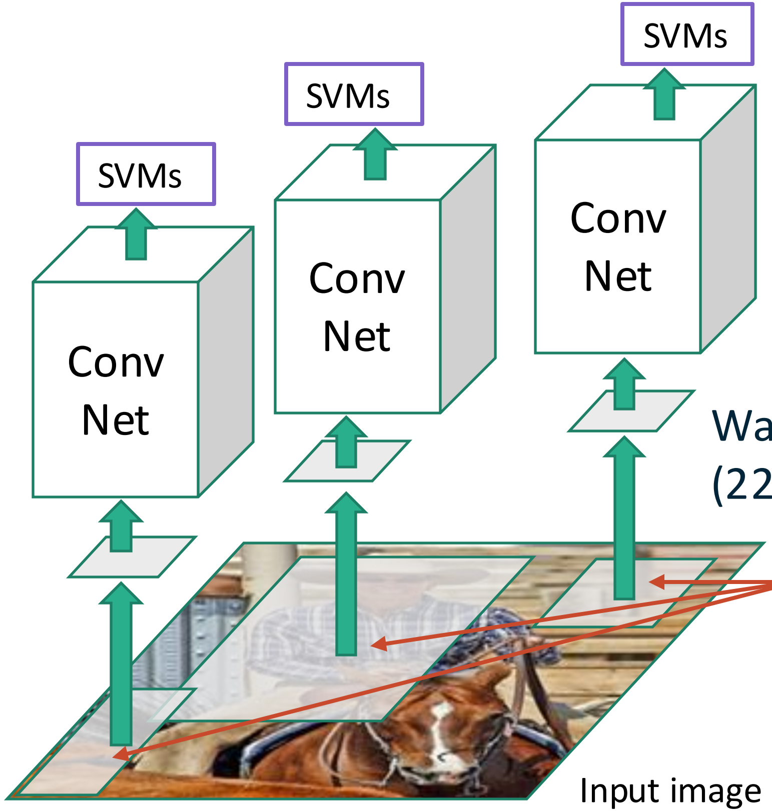
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN



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

R-CNN



Classify regions with SVMs

Forward each region through ConvNet (ImageNet-pretranied)

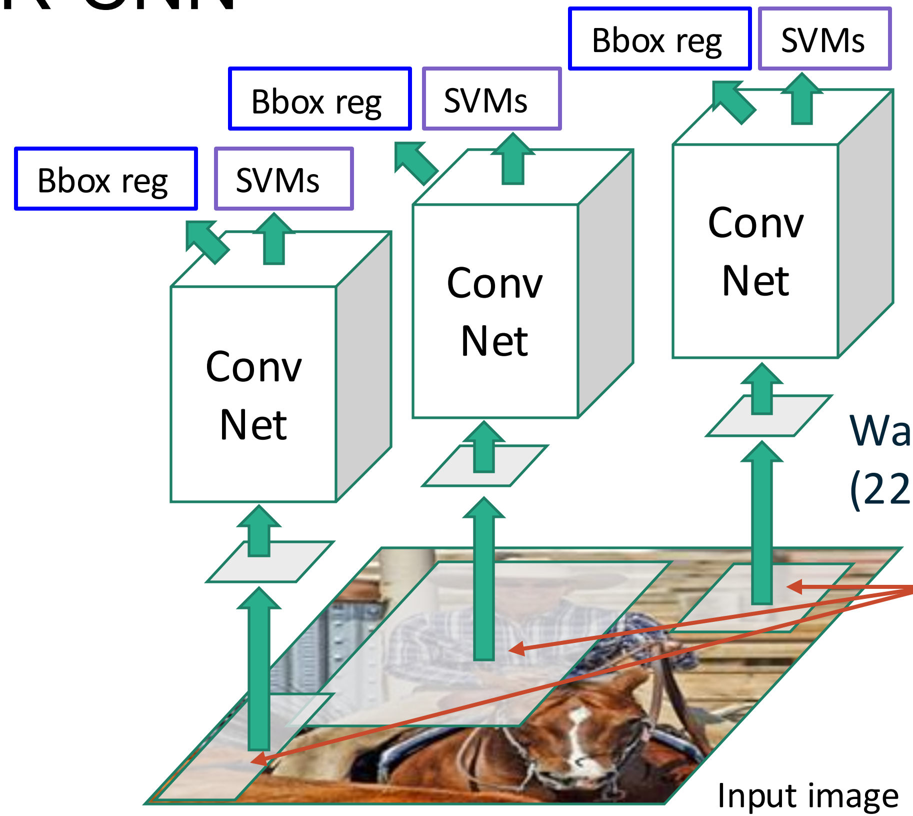
Warped image regions (224x224 pixels)

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

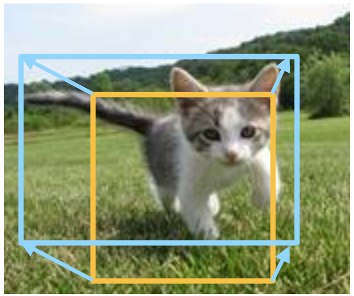
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN

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



Classify regions with SVMs



Forward each region through ConvNet (ImageNet-pretranied)

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

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R-CNN

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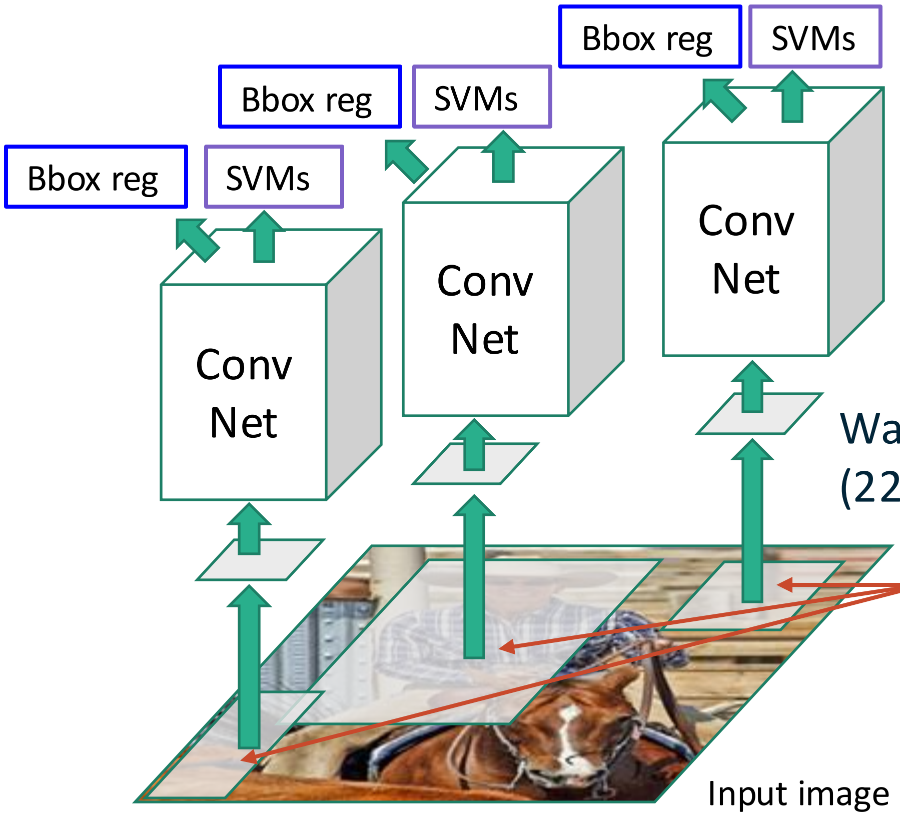


Classify regions with SVMs

Forward each region through ConvNet

Warped image regions (224x224 pixels)

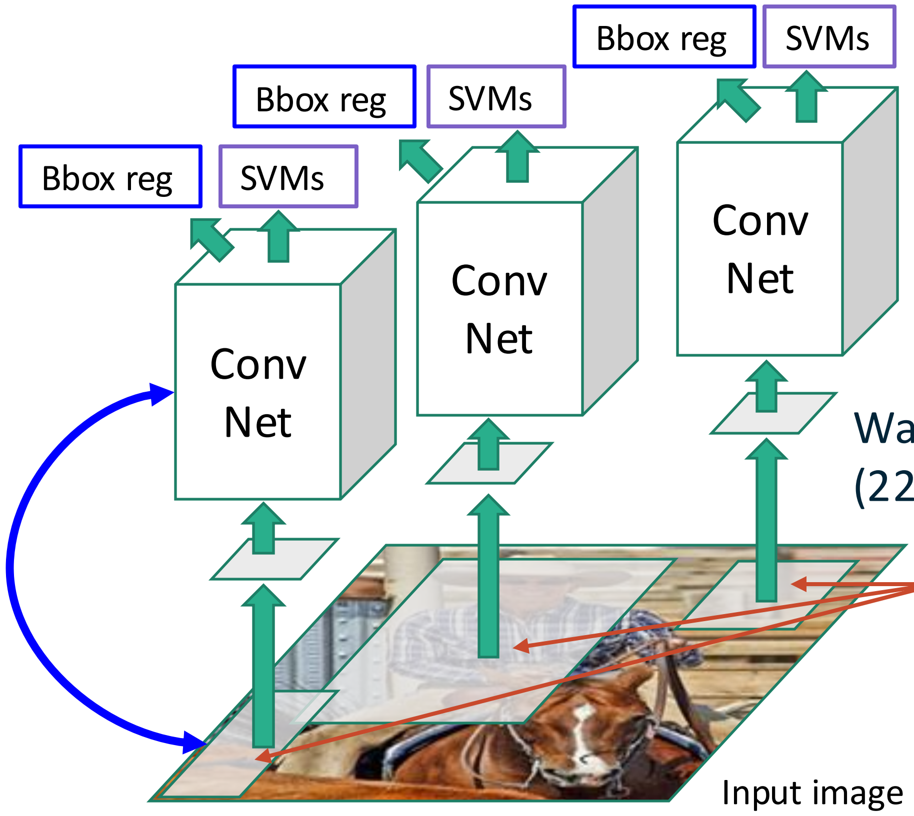
Regions of Interest (RoI) from a proposal method (~2k)

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.

"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!

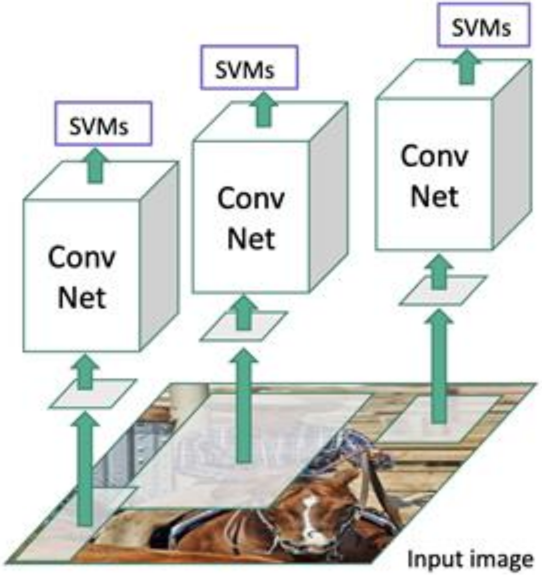
Idea: Pass the image through convnet before cropping! Crop the conv feature instead!

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

Fast R-CNN

Input image

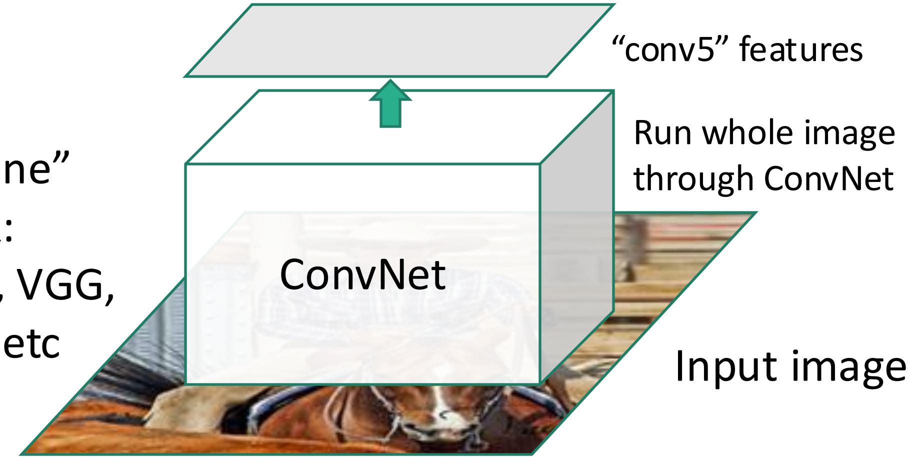
“Slow” R-CNN



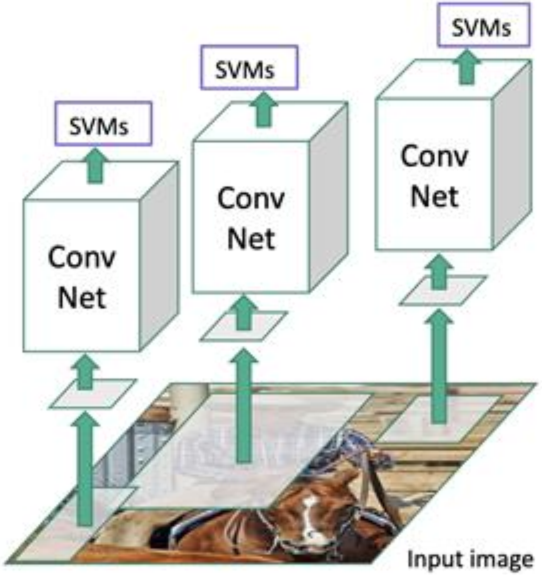
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

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



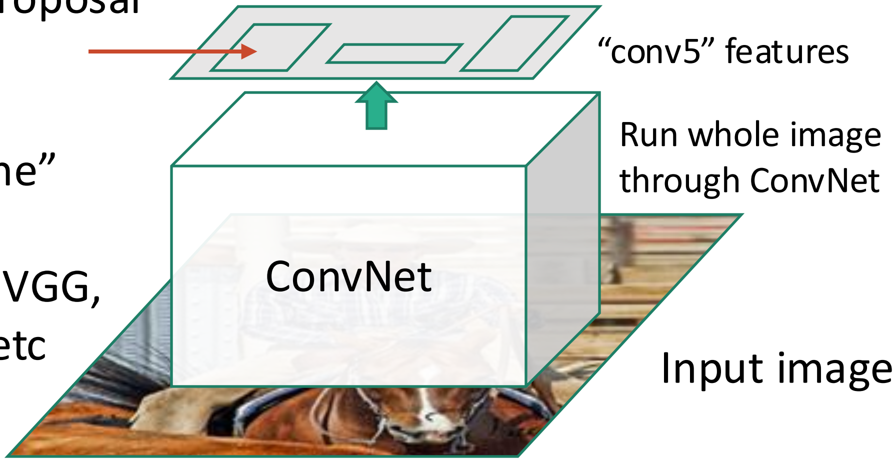
“Slow” R-CNN



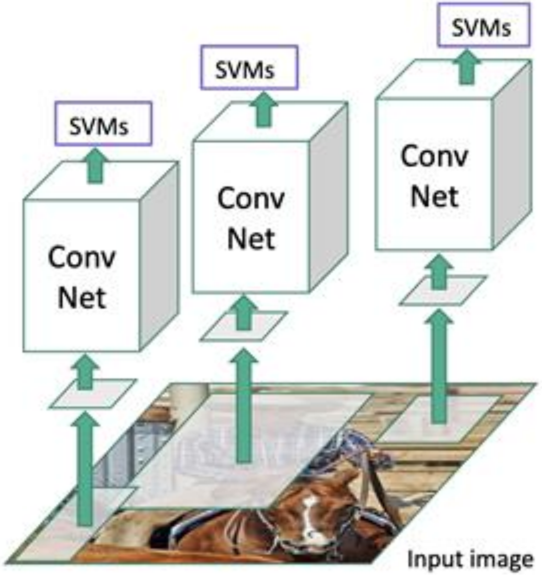
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



“Slow” R-CNN

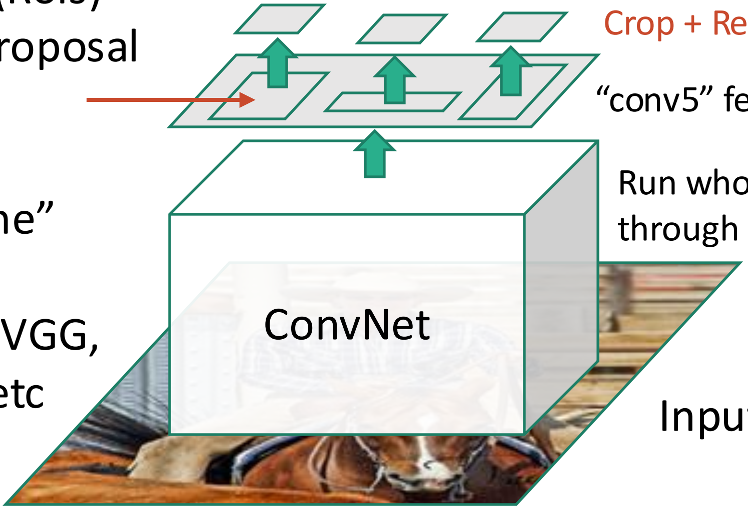


Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



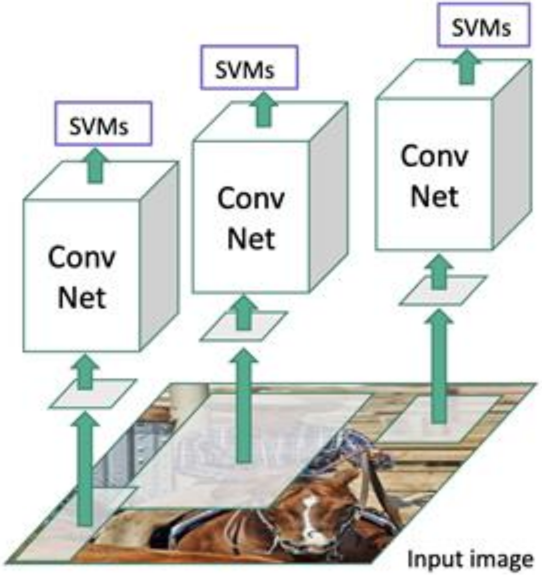
Crop + Resize features

"conv5" features

Run whole image through ConvNet

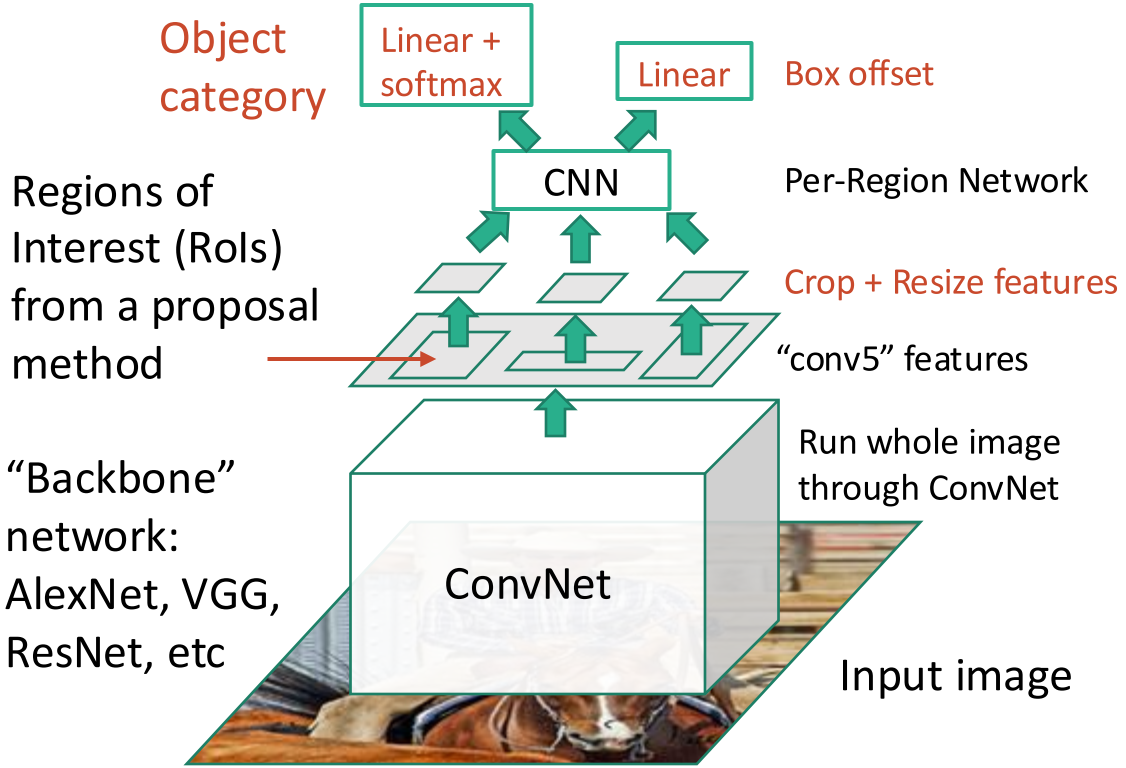
Input image

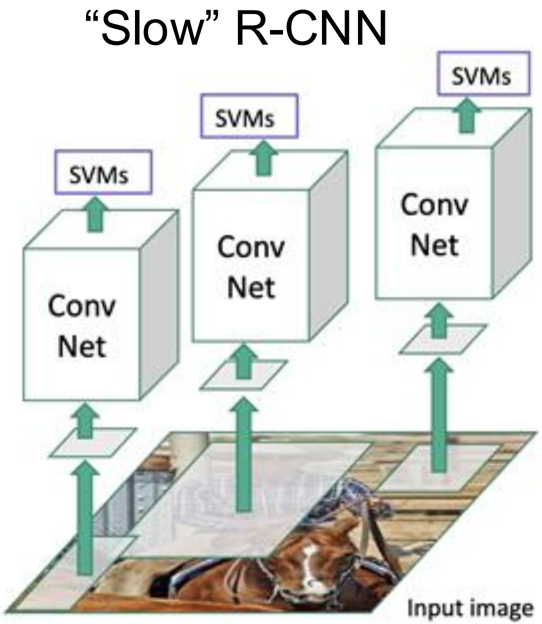
"Slow" R-CNN



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

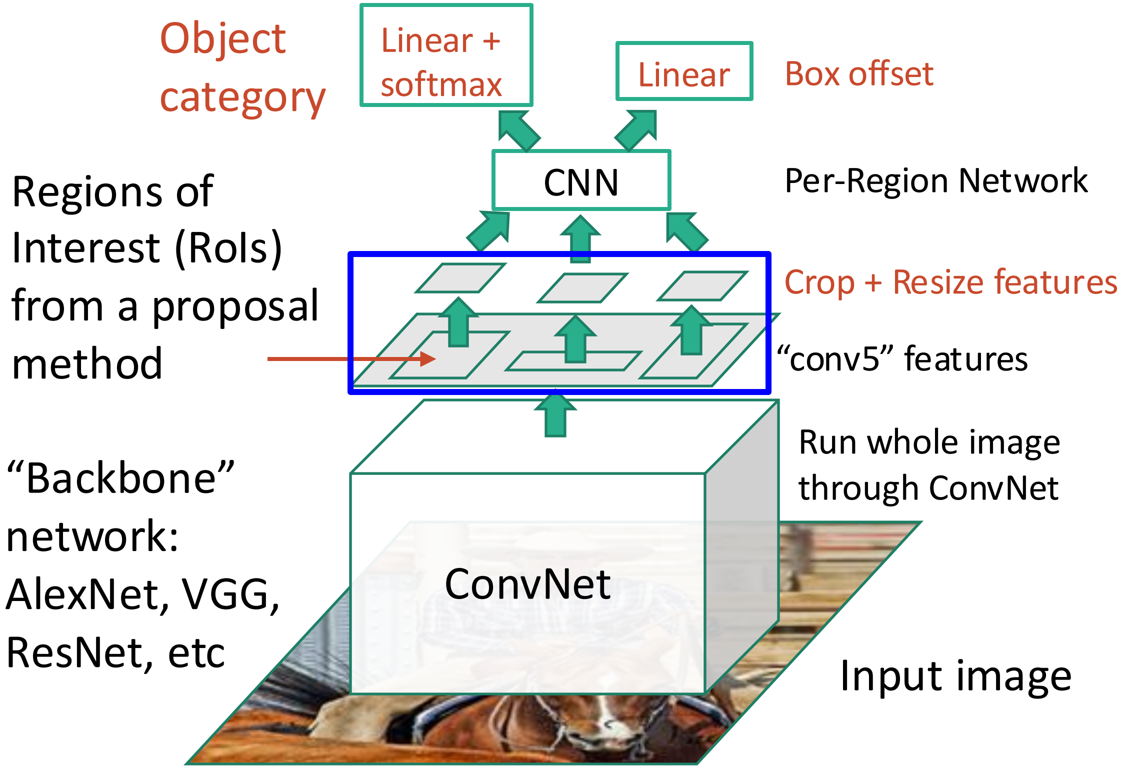
Fast R-CNN

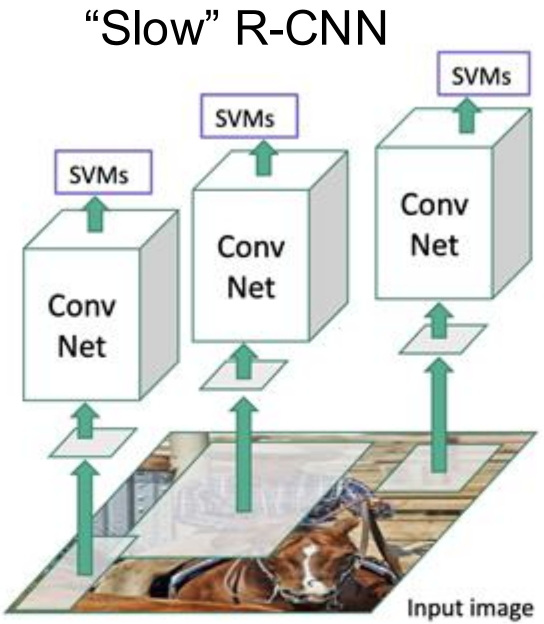




Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

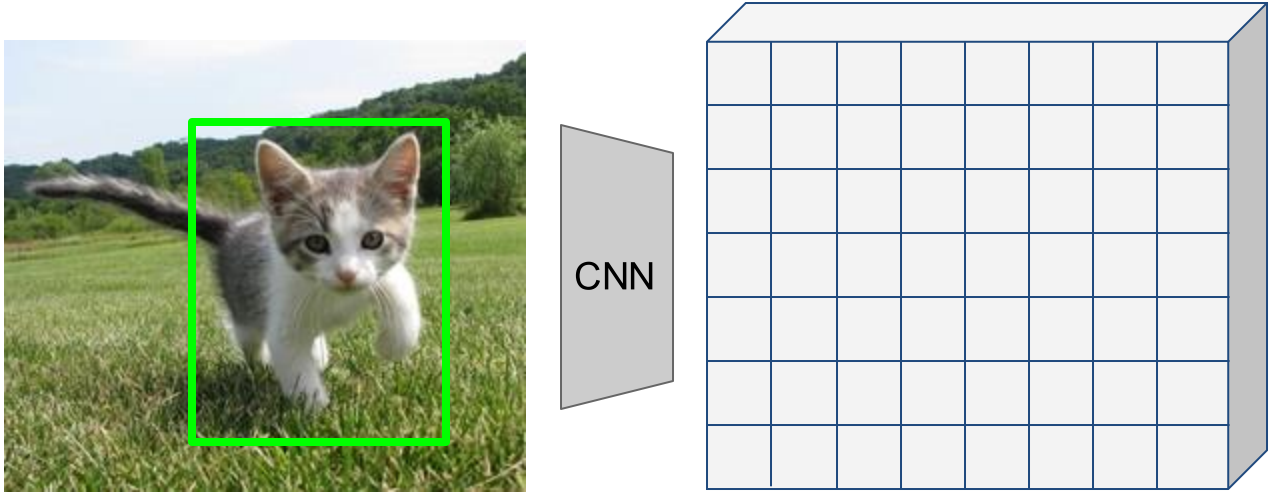
Fast R-CNN





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

Cropping Features: RoI Pool



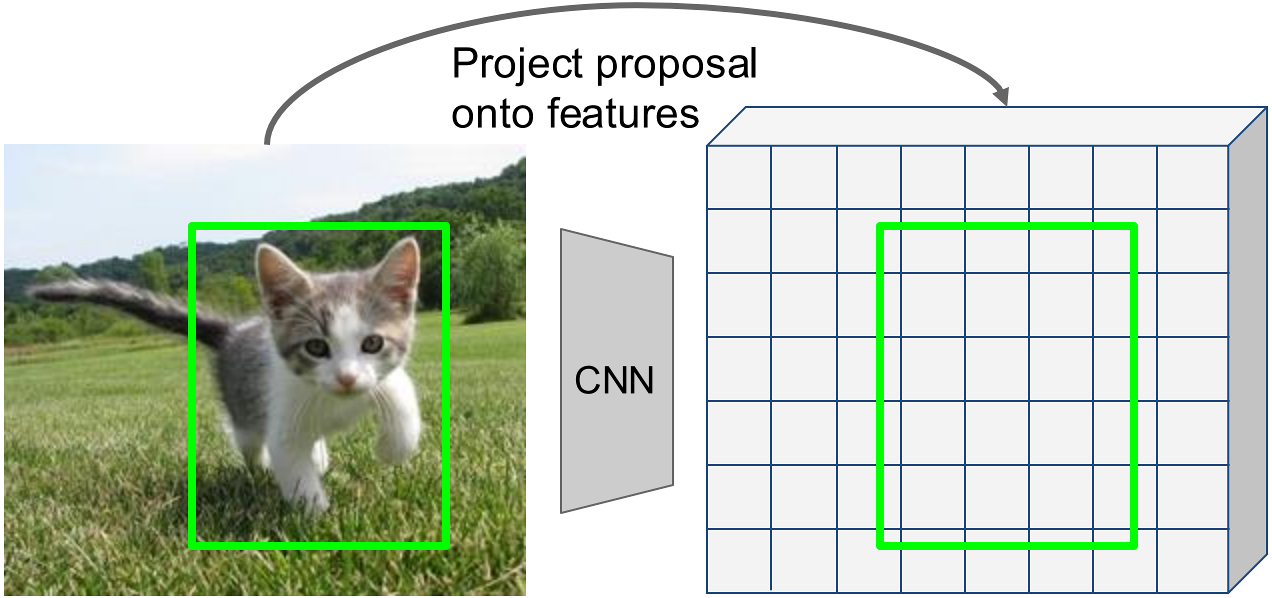
Input Image
(e.g. 3 x 640 x 480)

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



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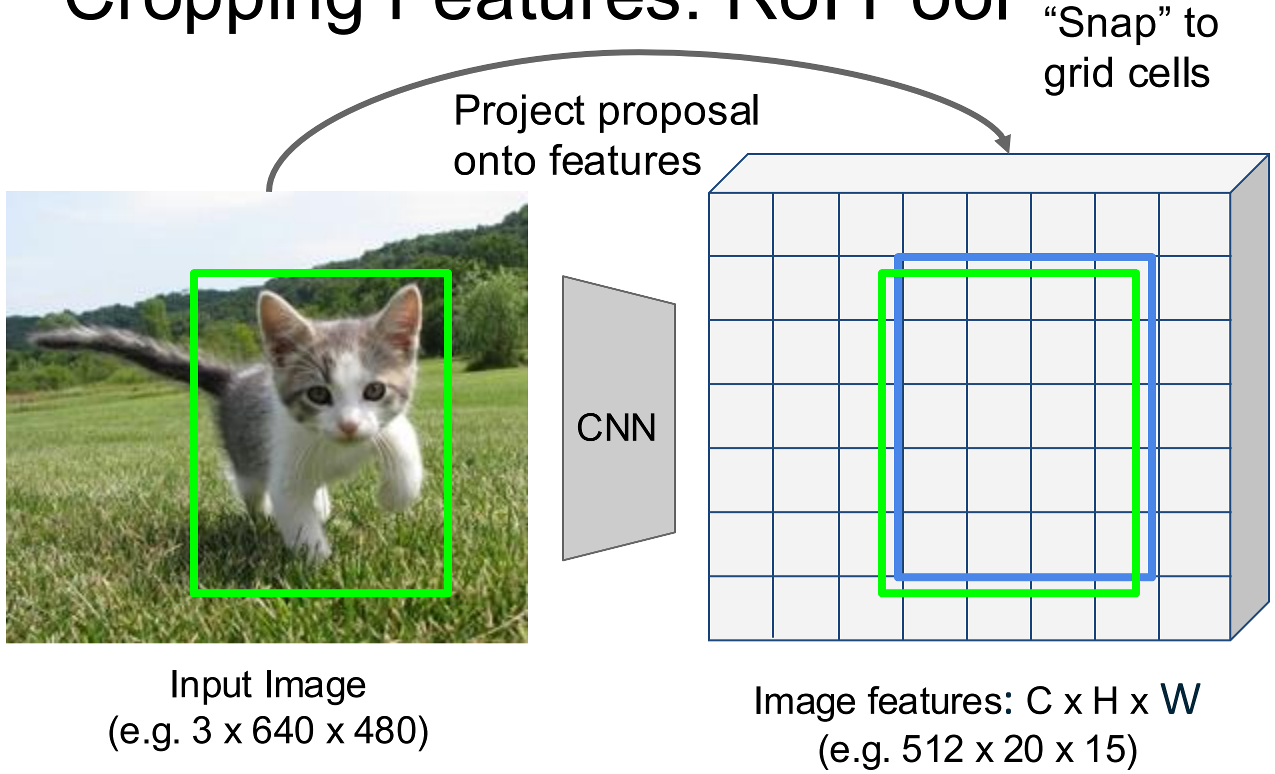
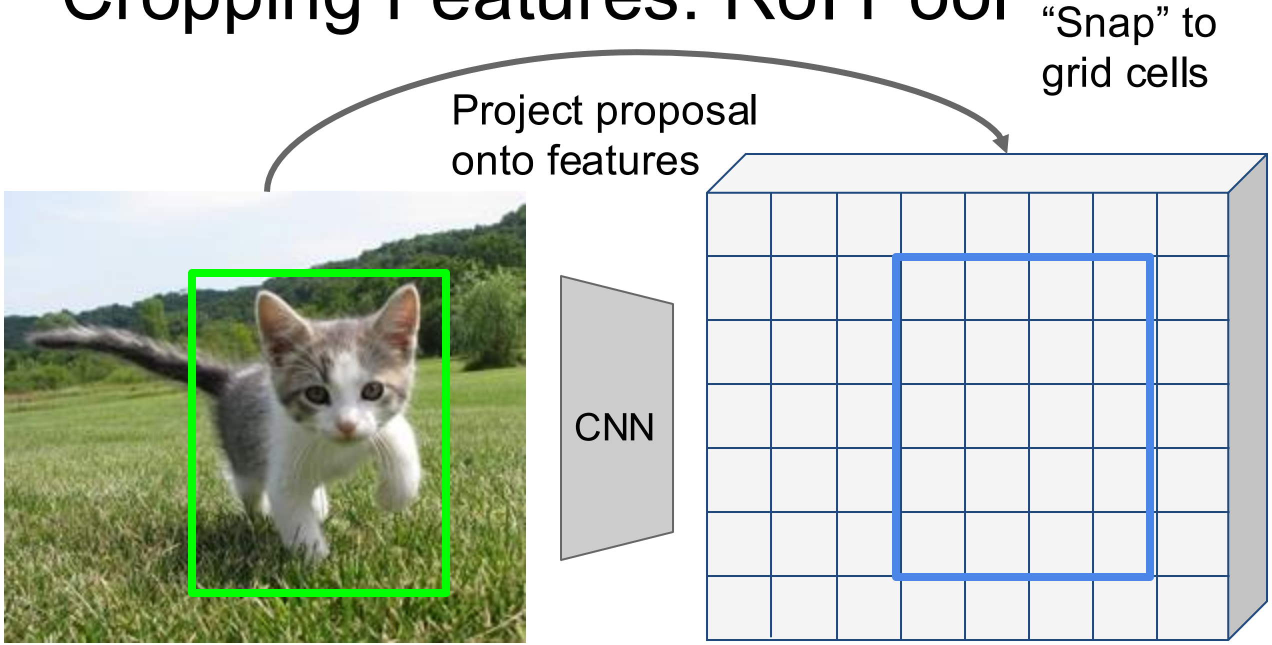


Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool



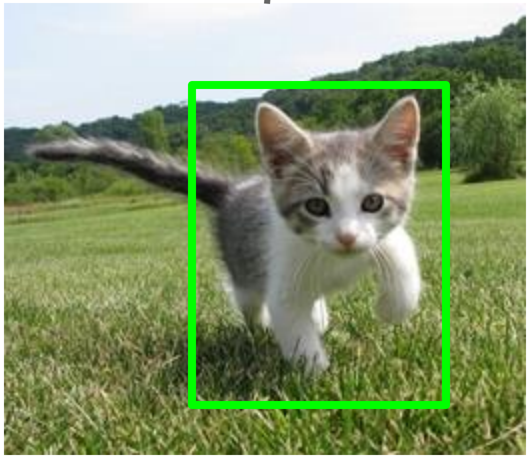
Input Image
(e.g. 3 x 640 x 480)

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

Q: how do we resize the 512 x 20 x 15 region to, e.g., a 512 x 2 x 2 tensor?.

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

Cropping Features: RoI Pool



Input Image
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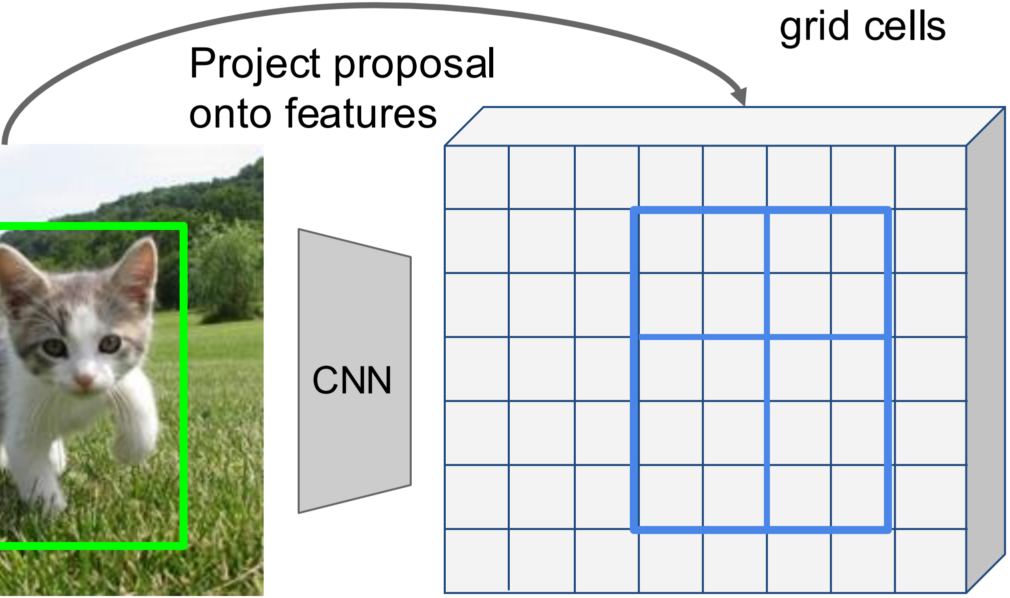


"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

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

Q: how do we resize the 512 x 20 x 15 region to, e.g., a 512 x 2 x 2 tensor?.

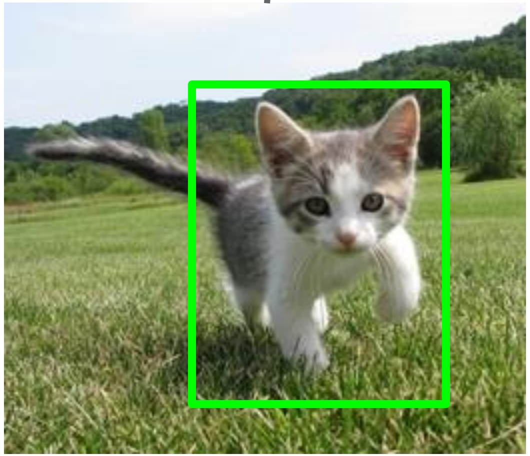
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool

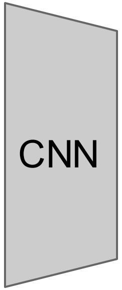
Project proposal onto features

"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions



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



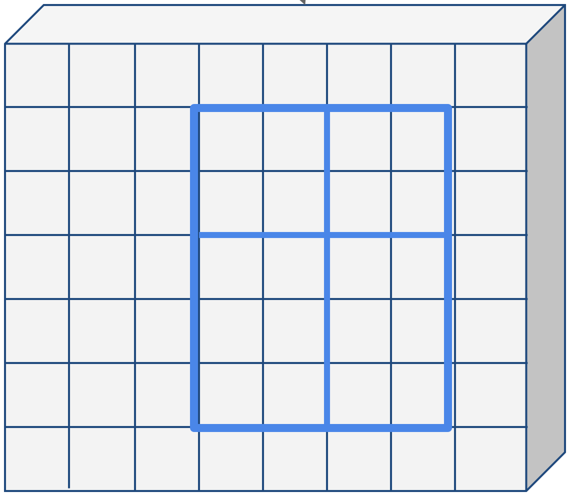
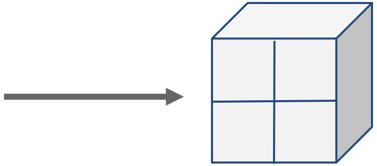


Image features: C x H x W
(e.g. 512 x 20 x 15)

Max-pool within each subregion



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

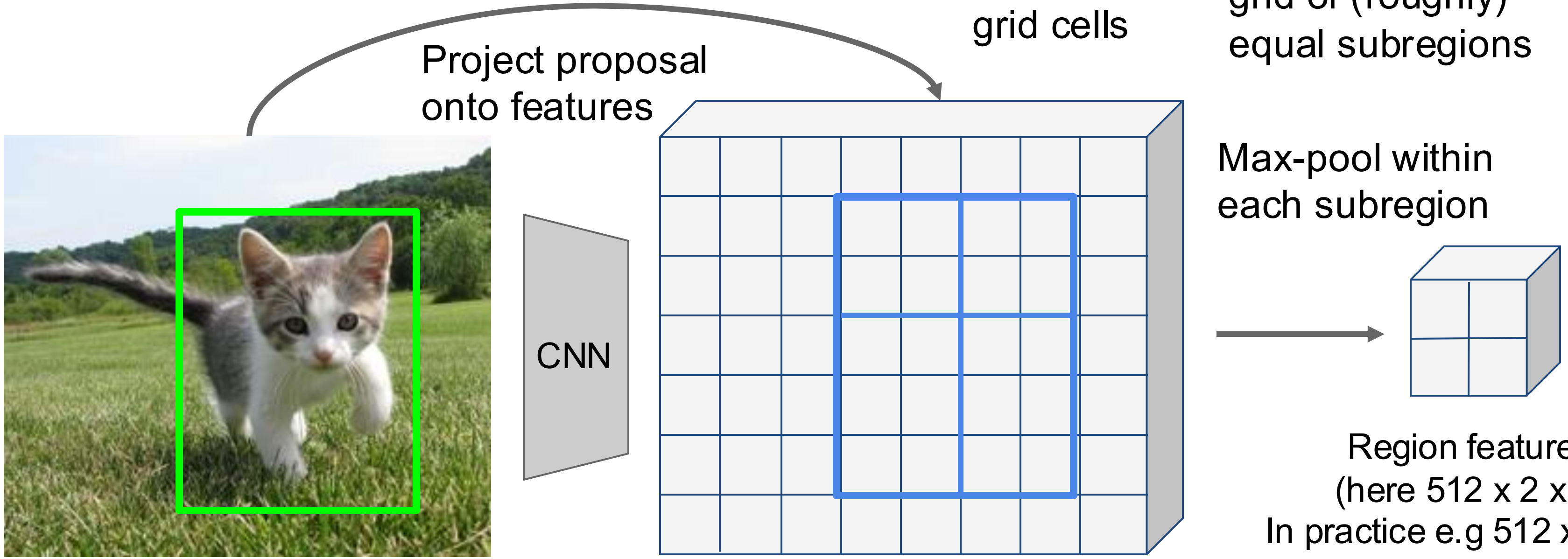
Region features always the same size even if input regions have different sizes!

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

Cropping Features: RoI Pool

“Snap” to grid cells

Divide into 2x2 grid of (roughly) equal subregions



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

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

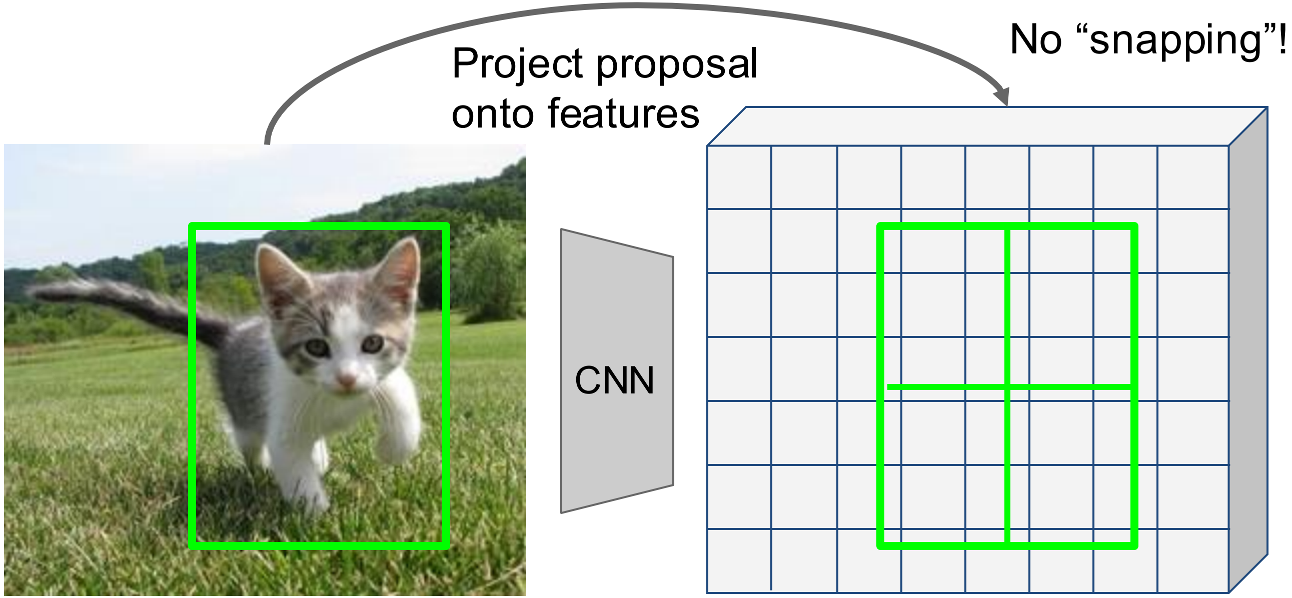
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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

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)

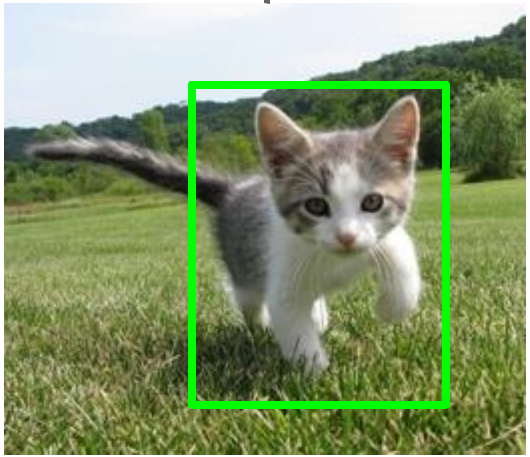
He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation

Project proposal onto features

No "snapping"!



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

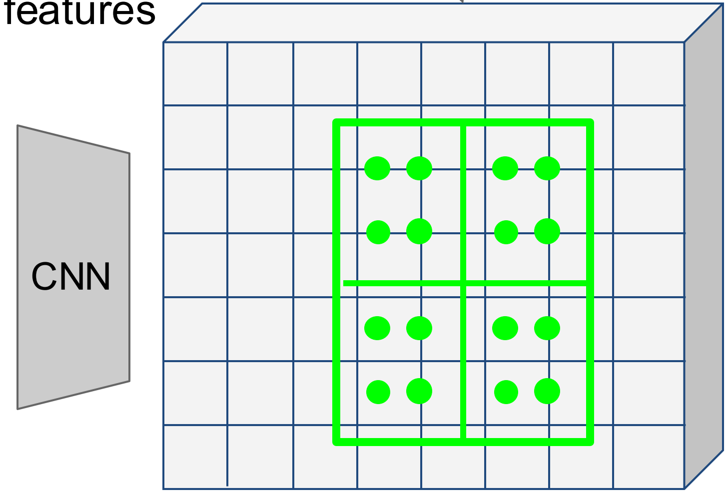
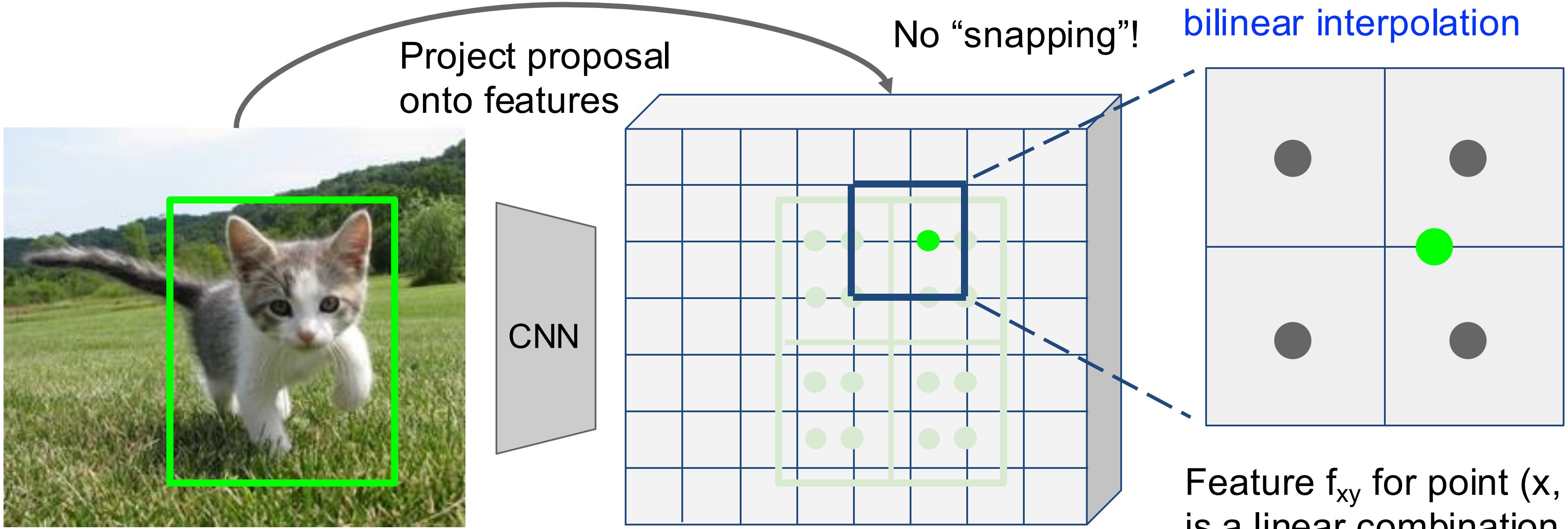


Image features: C x H x W
(e.g. 512 x 20 x 15)

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

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



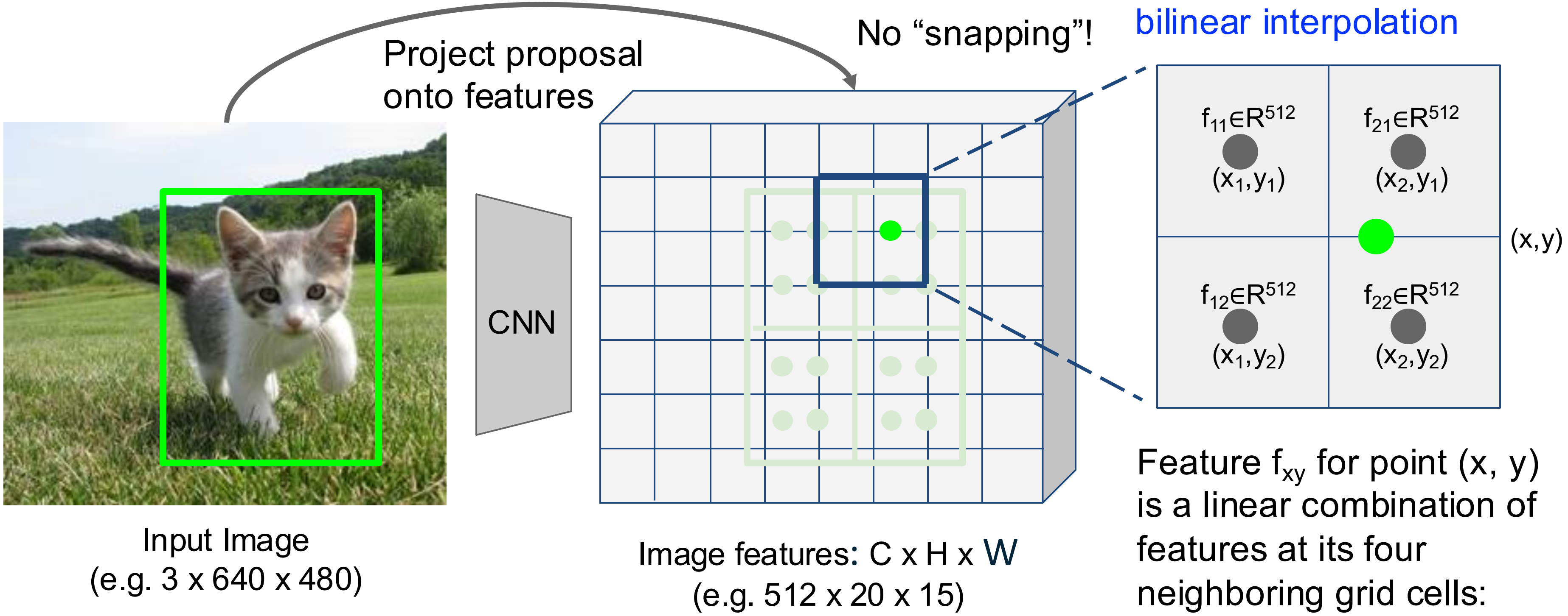
Input Image
(e.g. 3 x 640 x 480)

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



Sample at regular points in each subregion using bilinear interpolation

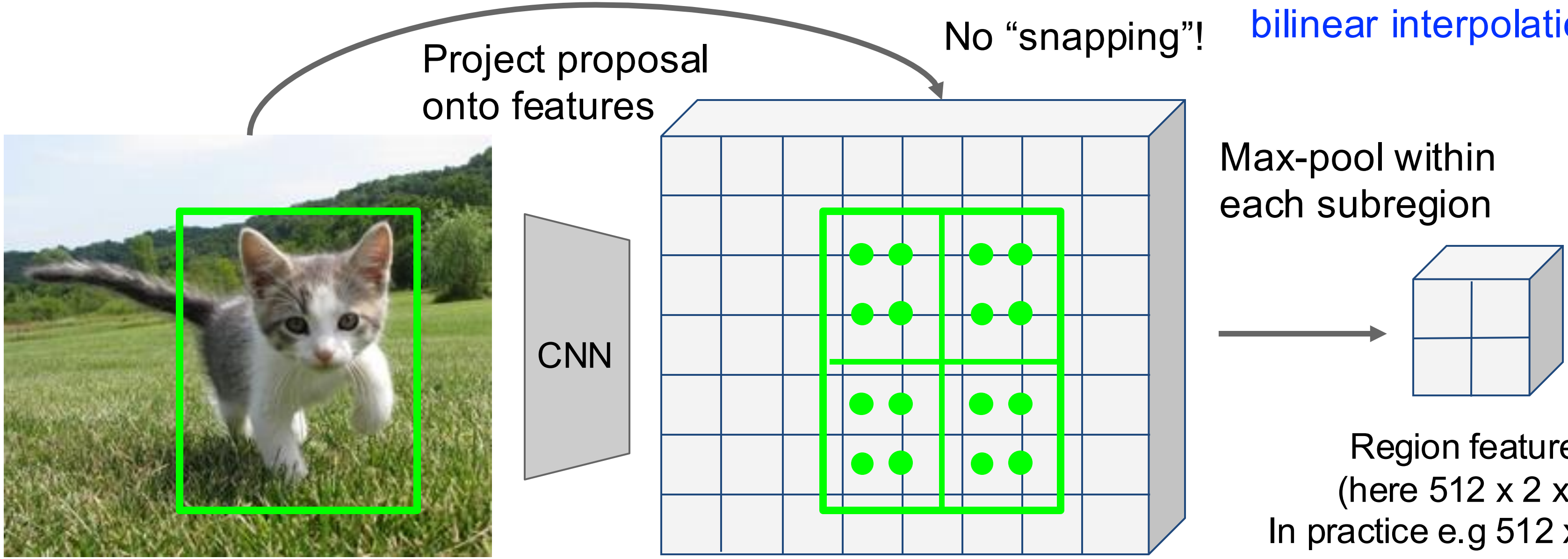
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

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

He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



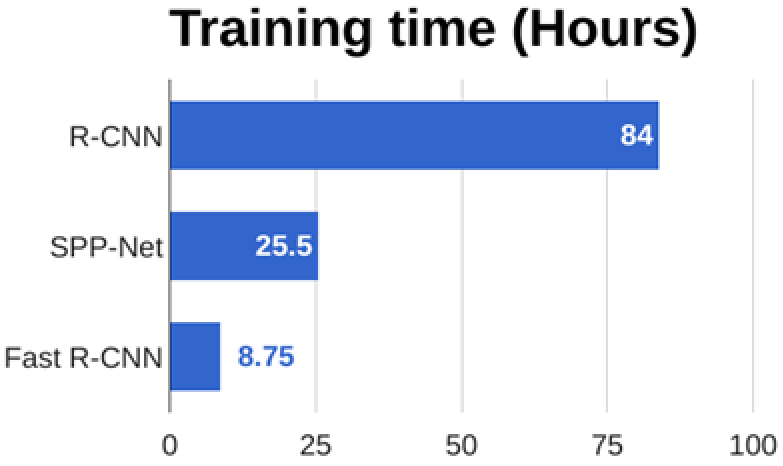
Input Image
(e.g. 3 x 640 x 480)

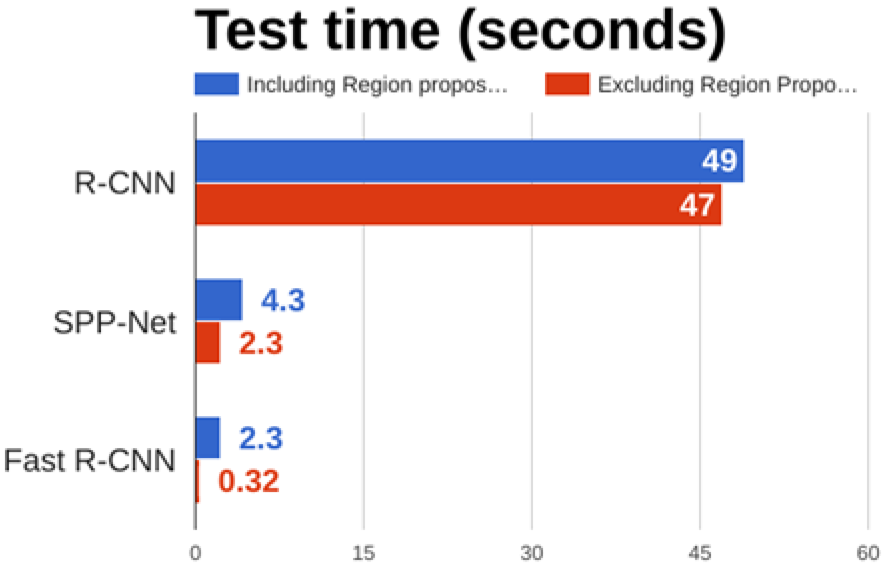
Image features: C x H x W
(e.g. 512 x 20 x 15)

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

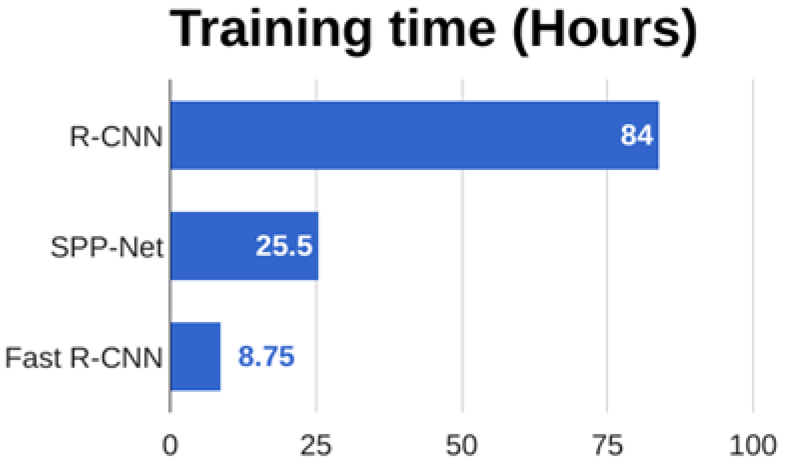
R-CNN vs Fast R-CNN

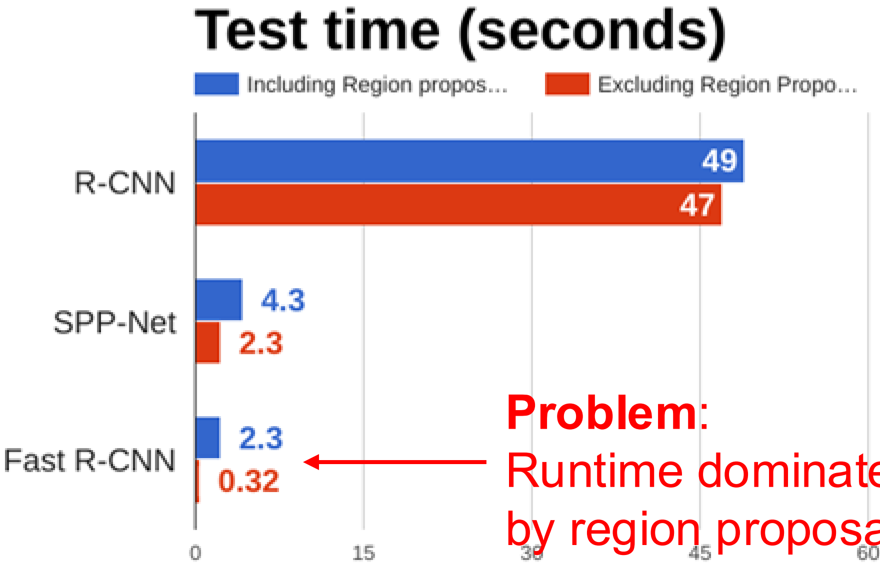




Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

R-CNN vs Fast R-CNN





Problem:
Runtime dominated by region proposals!

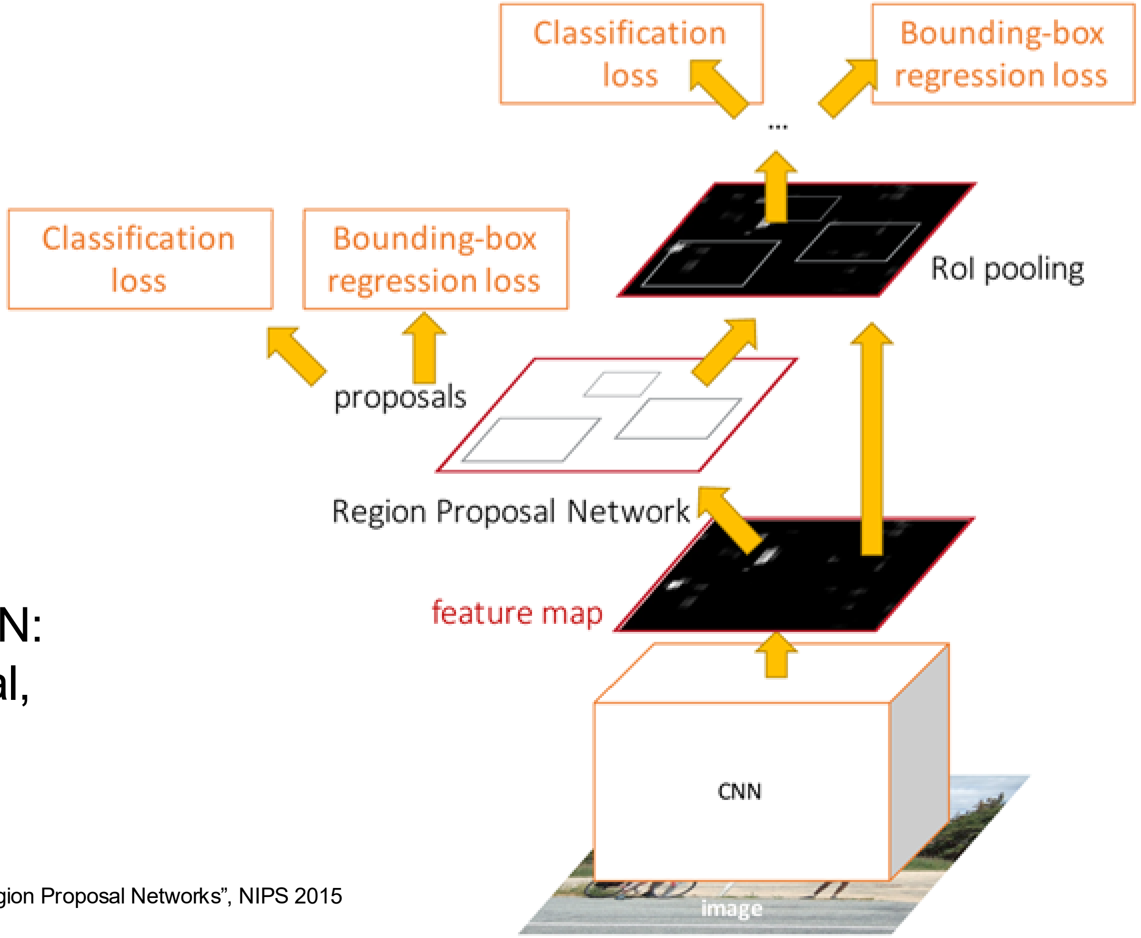
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

Faster R-CNN:

Make CNN do proposals!

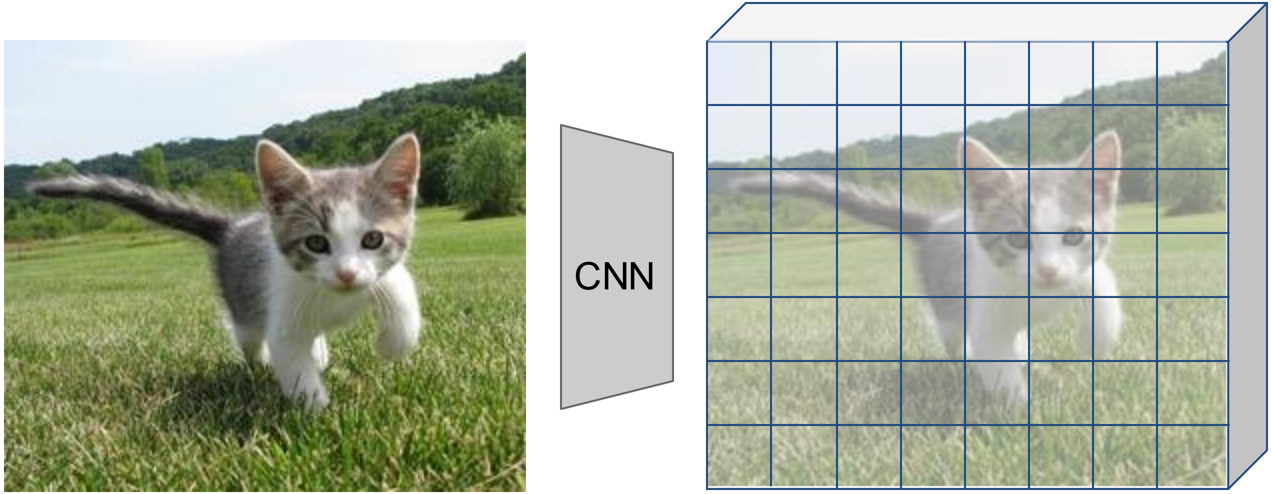
Insert **Region Proposal Network (RPN)** to predict proposals from features

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

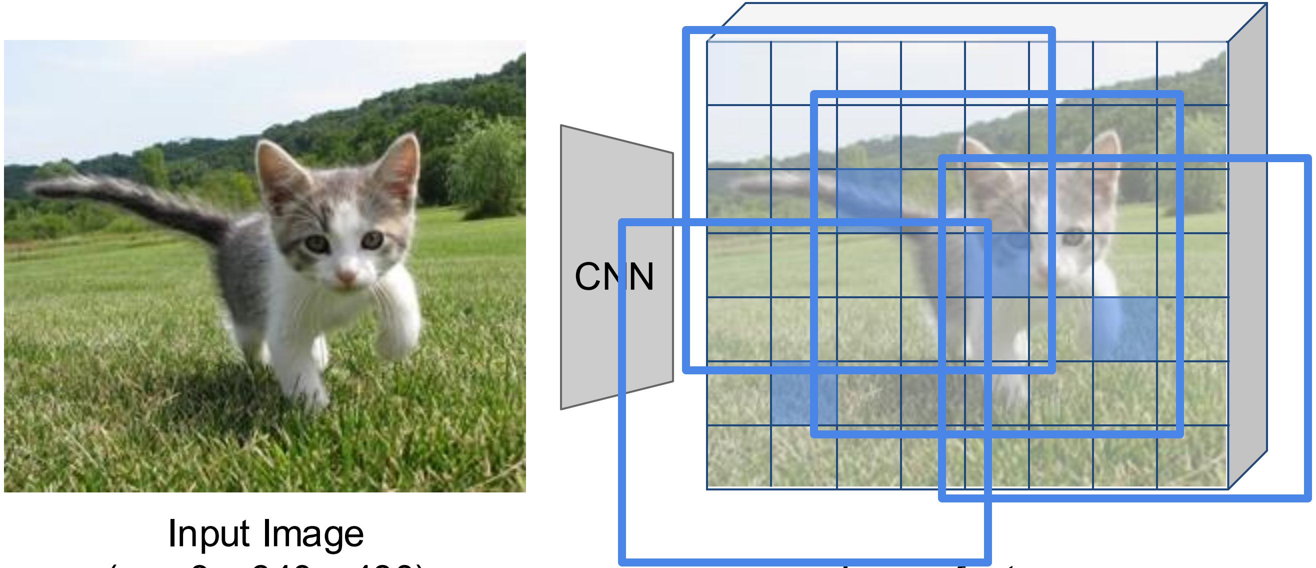


Input Image
(e.g. 3 x 640 x 480)

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

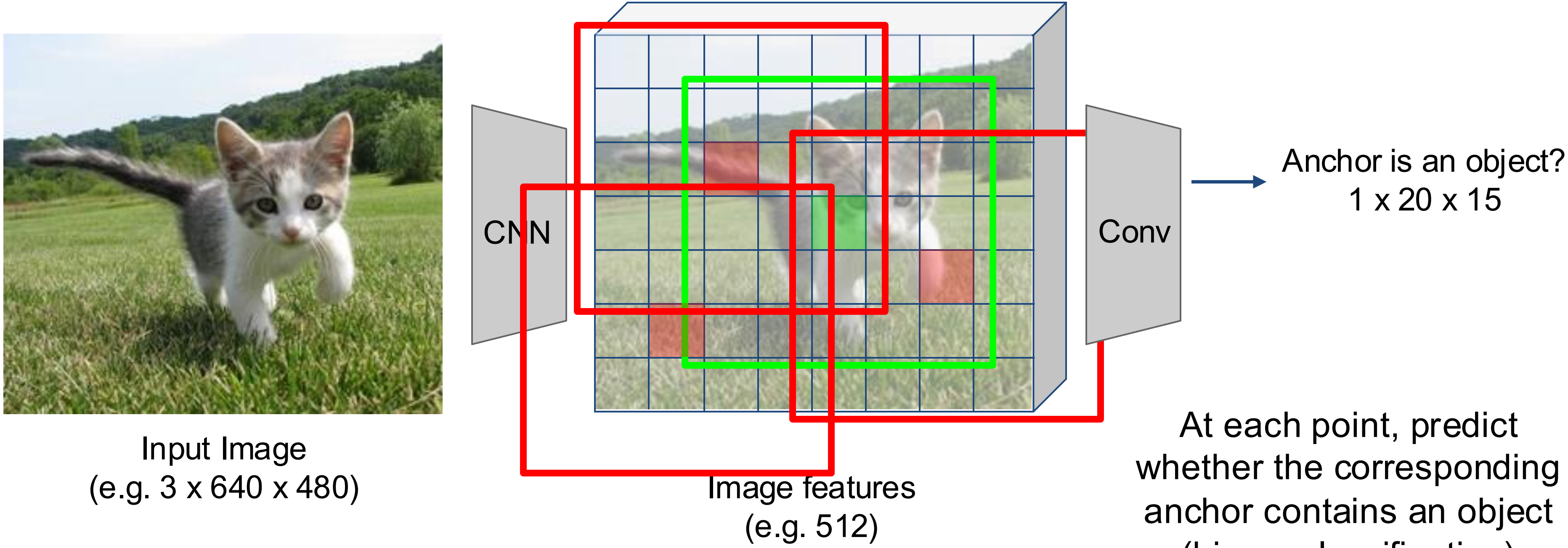


Input Image
(e.g. 3 x 640 x 480)

Image features
(e.g. 512)

Region Proposal Network

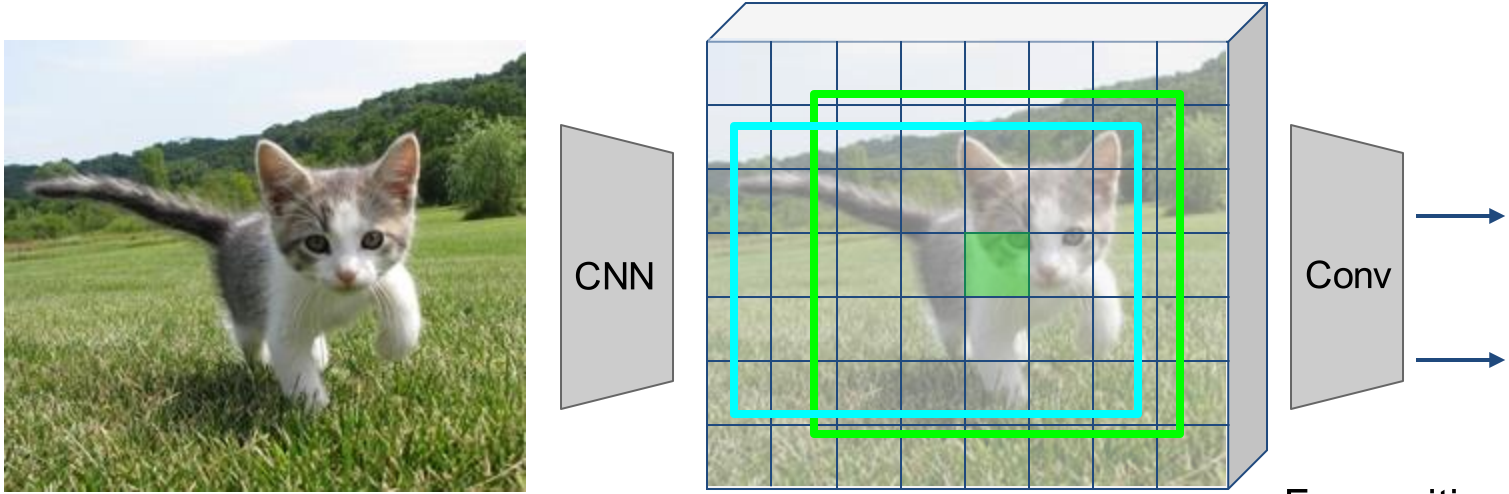
Example: 20 x 15 **anchor box** uniformly sampled on the feature map



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

Region Proposal Network

Example: 20 x 15 **anchor box** uniformly sampled on the feature map



Anchor is an object?
1 x 20 x 15

Box corrections
4 x 20 x 15

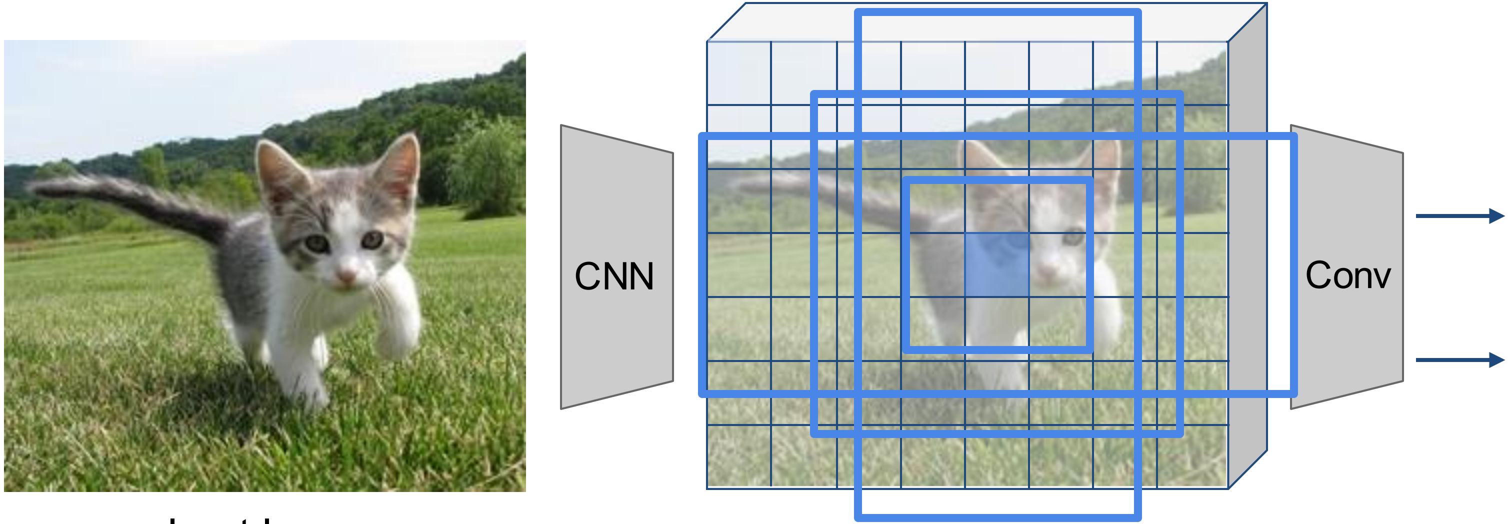
Input Image
(e.g. 3 x 640 x 480)

Image features
(e.g. 512)

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)

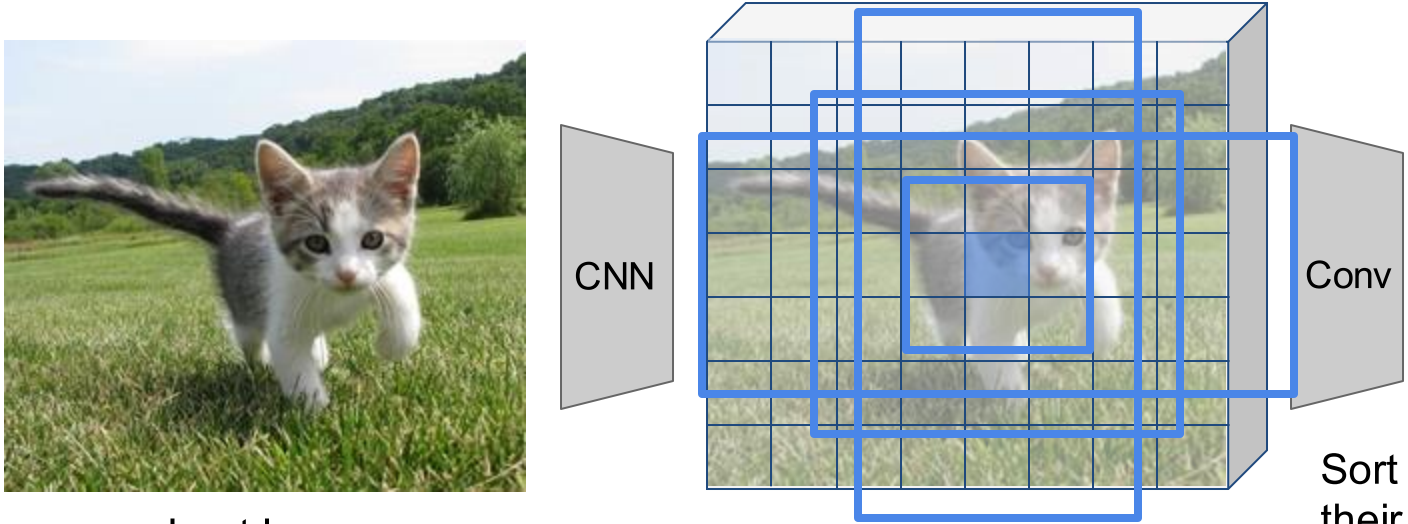
Image features
(e.g. 512)

Anchor is an object?
K x 20 x 15

Box transforms
4K 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)

Anchor is an object?
K x 20 x 15

Box transforms
4K x 20 x 15

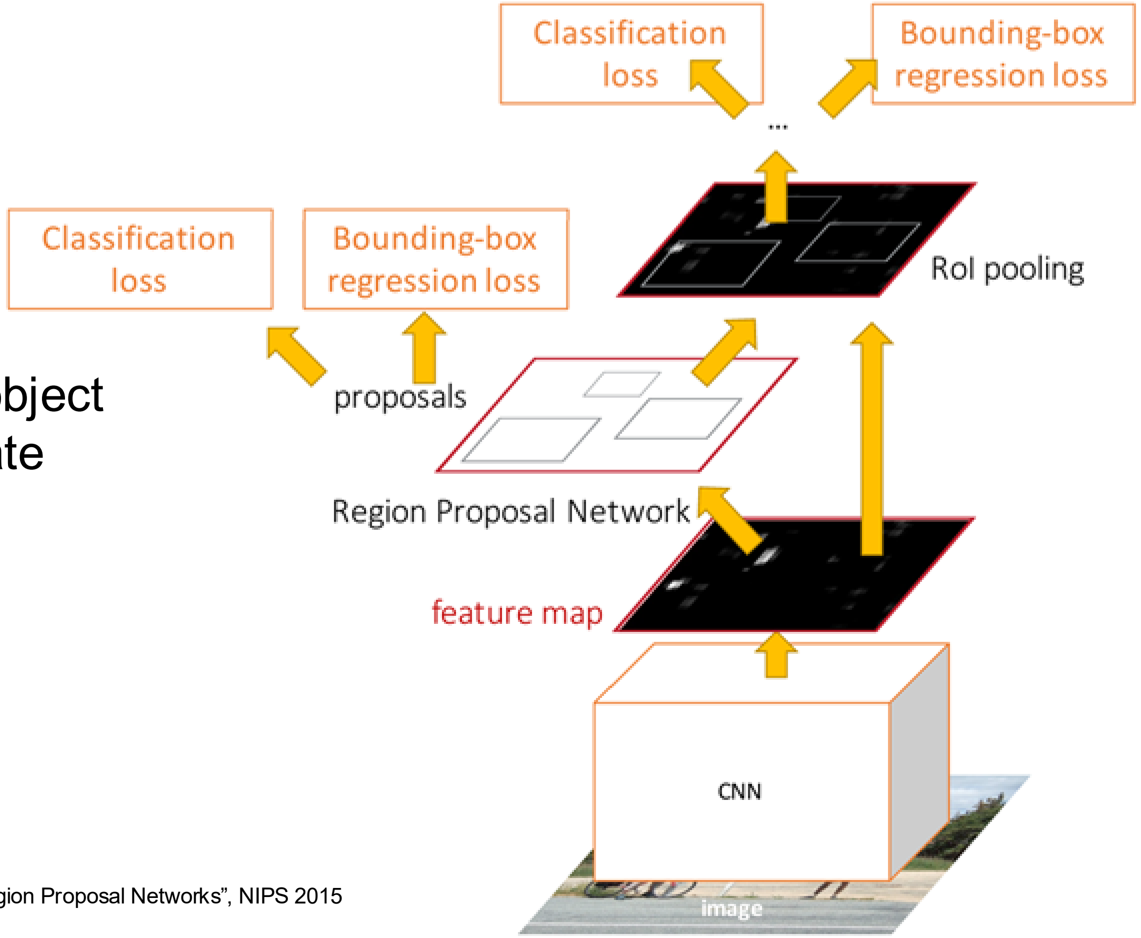
Sort the K*20*15 boxes by their “objectness” score, take top ~300 as our proposals

Faster R-CNN:

Make CNN do proposals!

Jointly train with 4 losses:

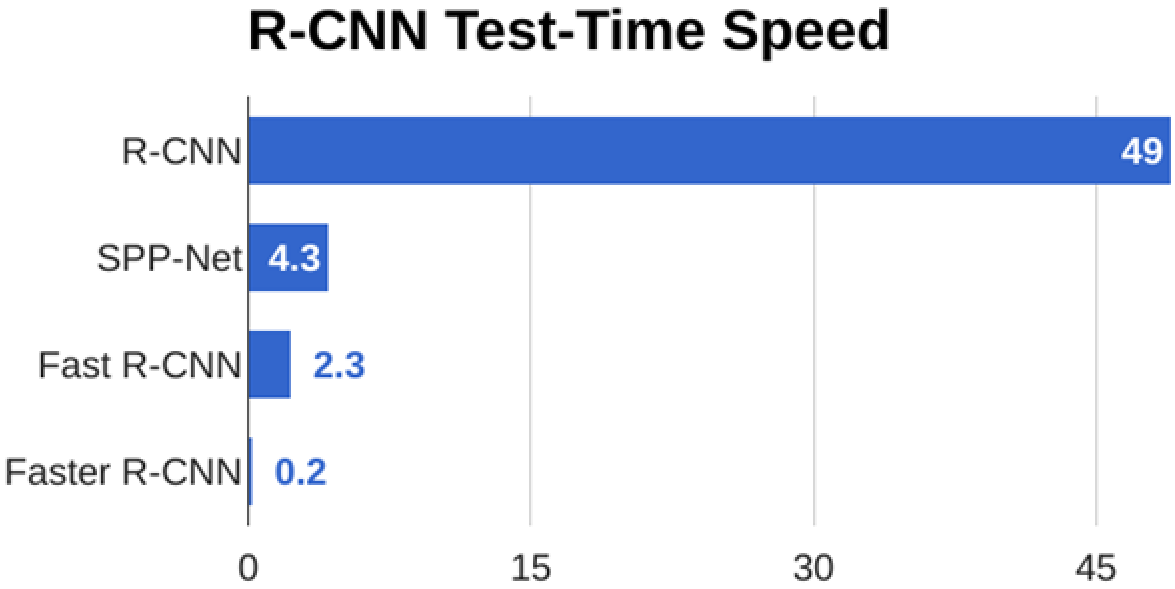
1. RPN classify object / not object
2. RPN regress box coordinate residuals
3. Final classification score (object classes)
4. Final box coordinates



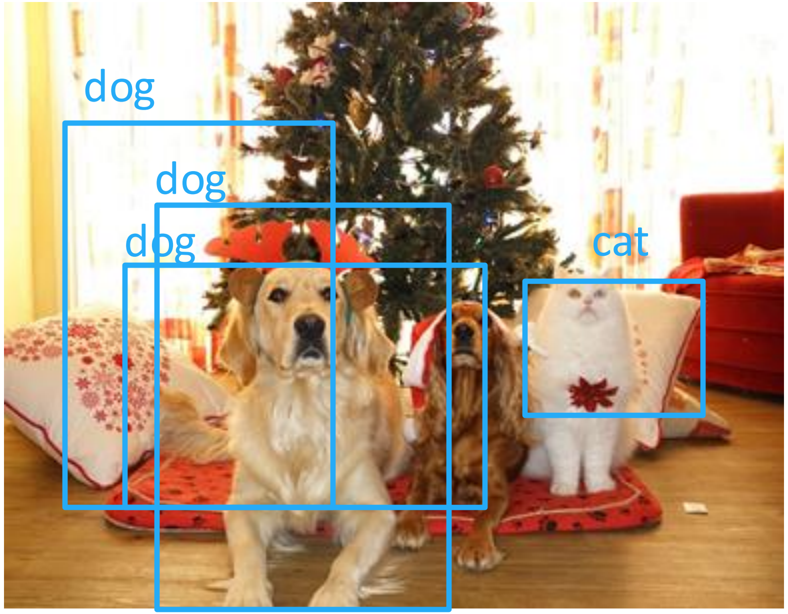
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Fast**er** R-CNN:

Make CNN do proposals!



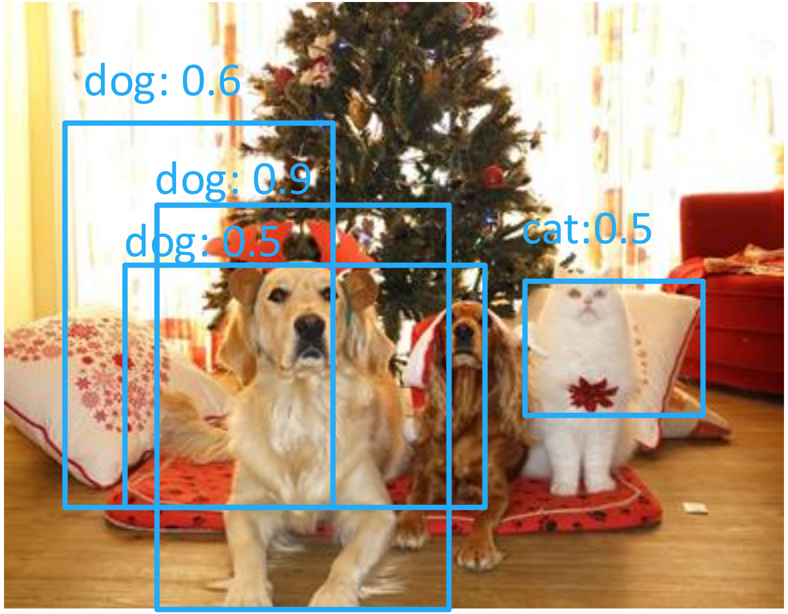
Which prediction to pick?



Problem: Detectors almost always generate more box predictions than the number of objects in the image!
E.g., 300 is an upper bound how many objects we wish to detect.

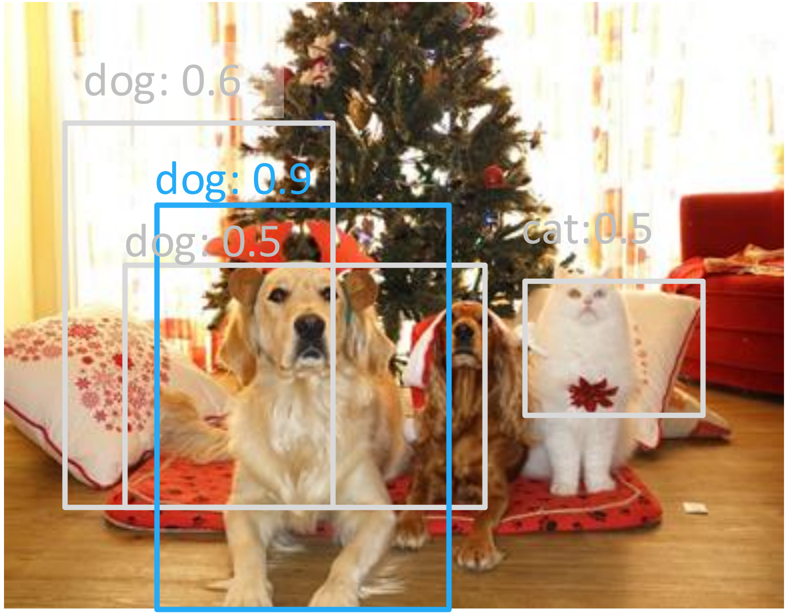
We need to remove the **redundant predictions!**

Non-Max Suppression (NMS)



Intuitively: locally pick the box that has the highest "objectless" or class score and suppress other boxes that have significant overlap with the chosen box

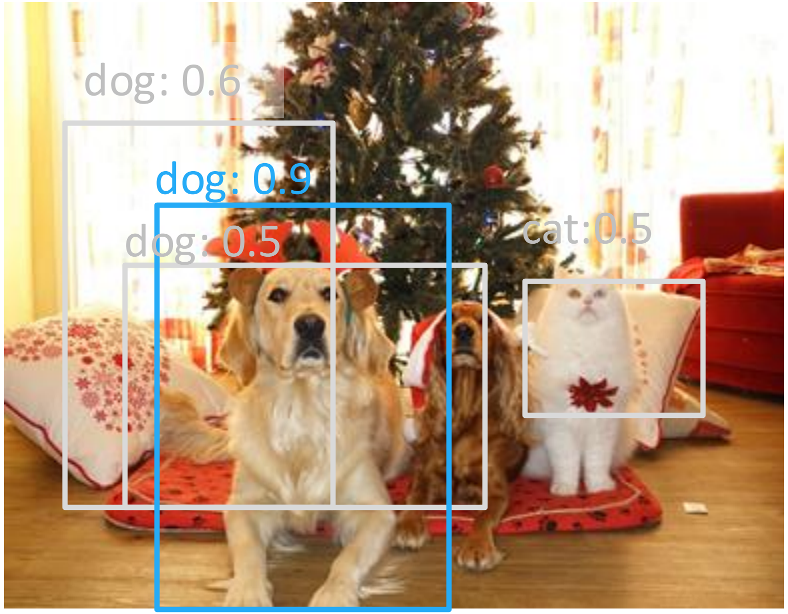
Non-Max Suppression (NMS)



Intuitively: locally pick the box that has the highest "objectless" or class score and suppress other boxes that have significant overlap with the chosen box

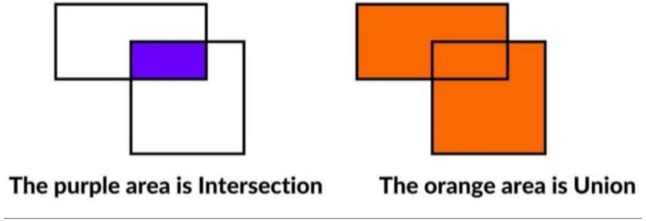
Step 1: Pick highest-score prediction box

Non-Max Suppression (NMS)

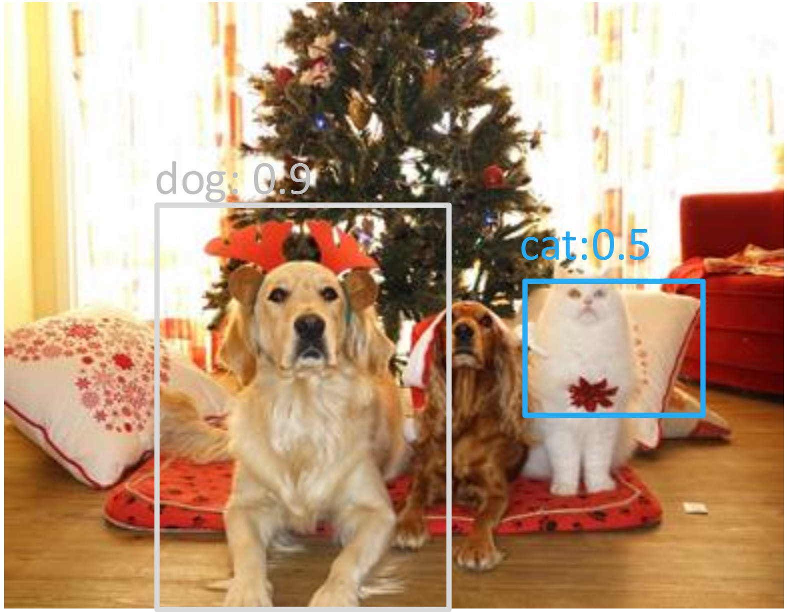


Intuitively: locally pick the box that has the highest "objectless" or class score and suppress other boxes that have significant overlap with the chosen box

Step 1: Pick highest-score prediction box
Step 2: Remove bounding boxes with **Intersection over Union (IoU) scores** higher than certain threshold (e.g., 0.5)



Non-Max Suppression (NMS)



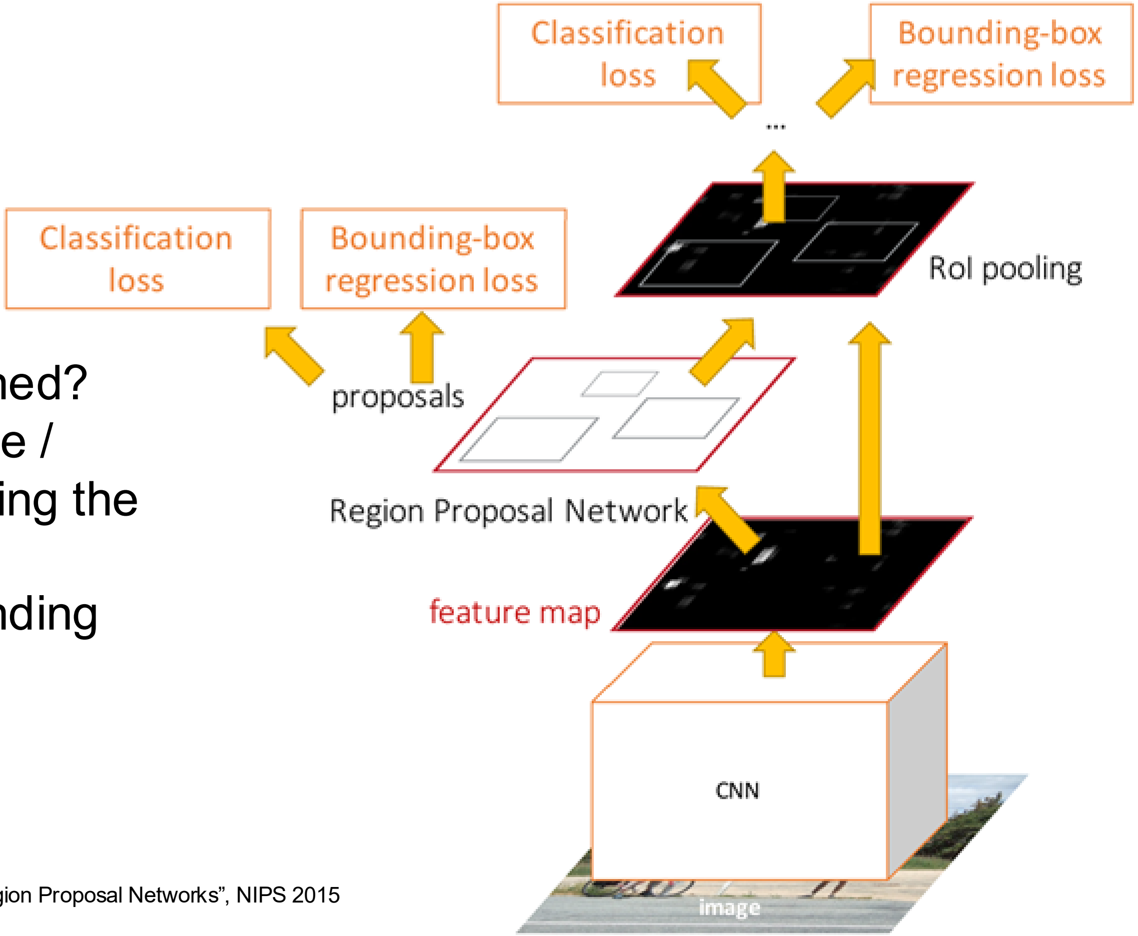
Intuitively: locally pick the box that has the highest "objectless" or class score and suppress other boxes that have significant overlap with the chosen box

Step 1: Pick highest-score prediction box
Step 2: Remove bounding boxes with **Intersection over Union (IoU) scores** higher than certain threshold (e.g., 0.5)

Go back to step 1

Faster R-CNN:
Make CNN do proposals!

Glossing over many details:
- How are anchors determined?
- How do we sample positive / negative samples for training the RPN?
- How to parameterize bounding box regression?



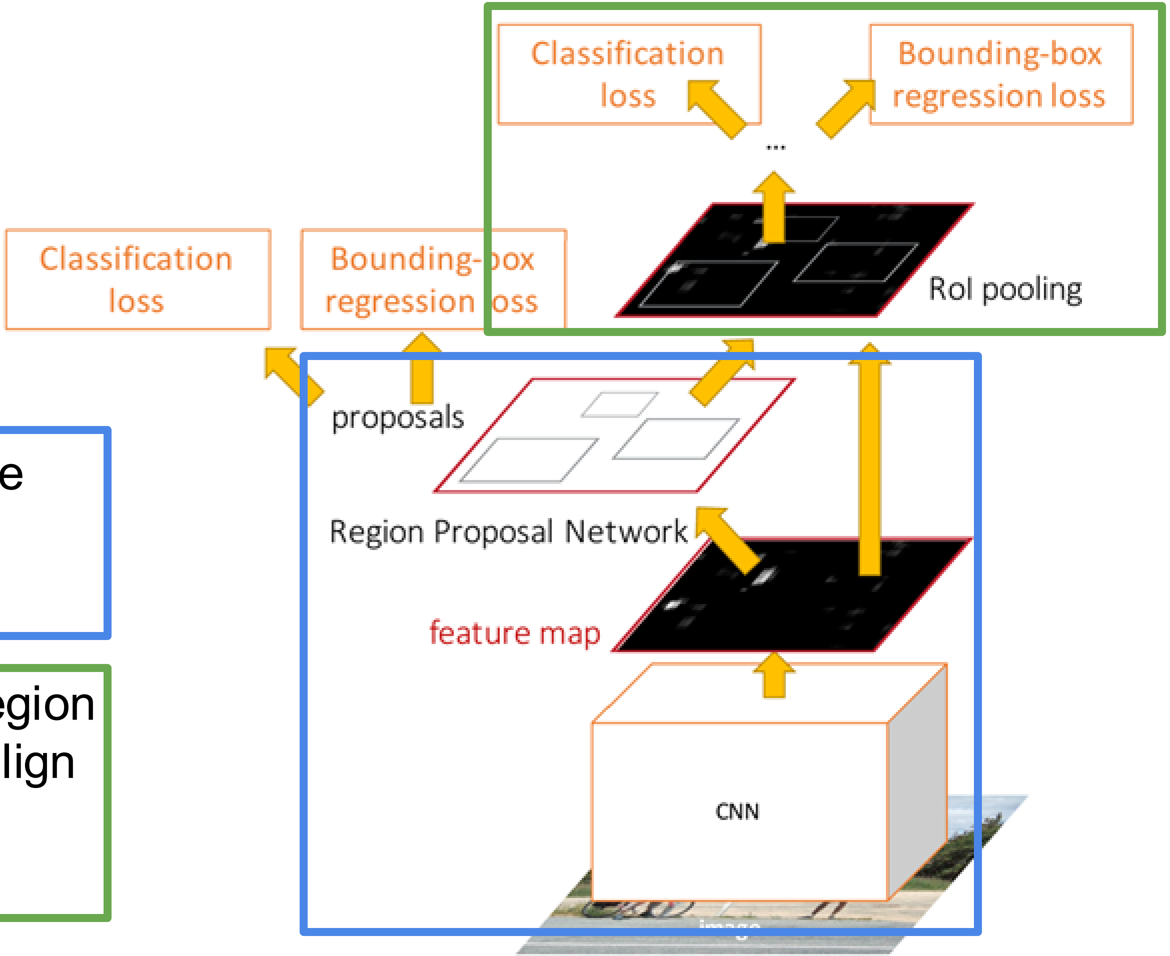
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Faster R-CNN:
Make CNN do proposals!

Faster R-CNN 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:

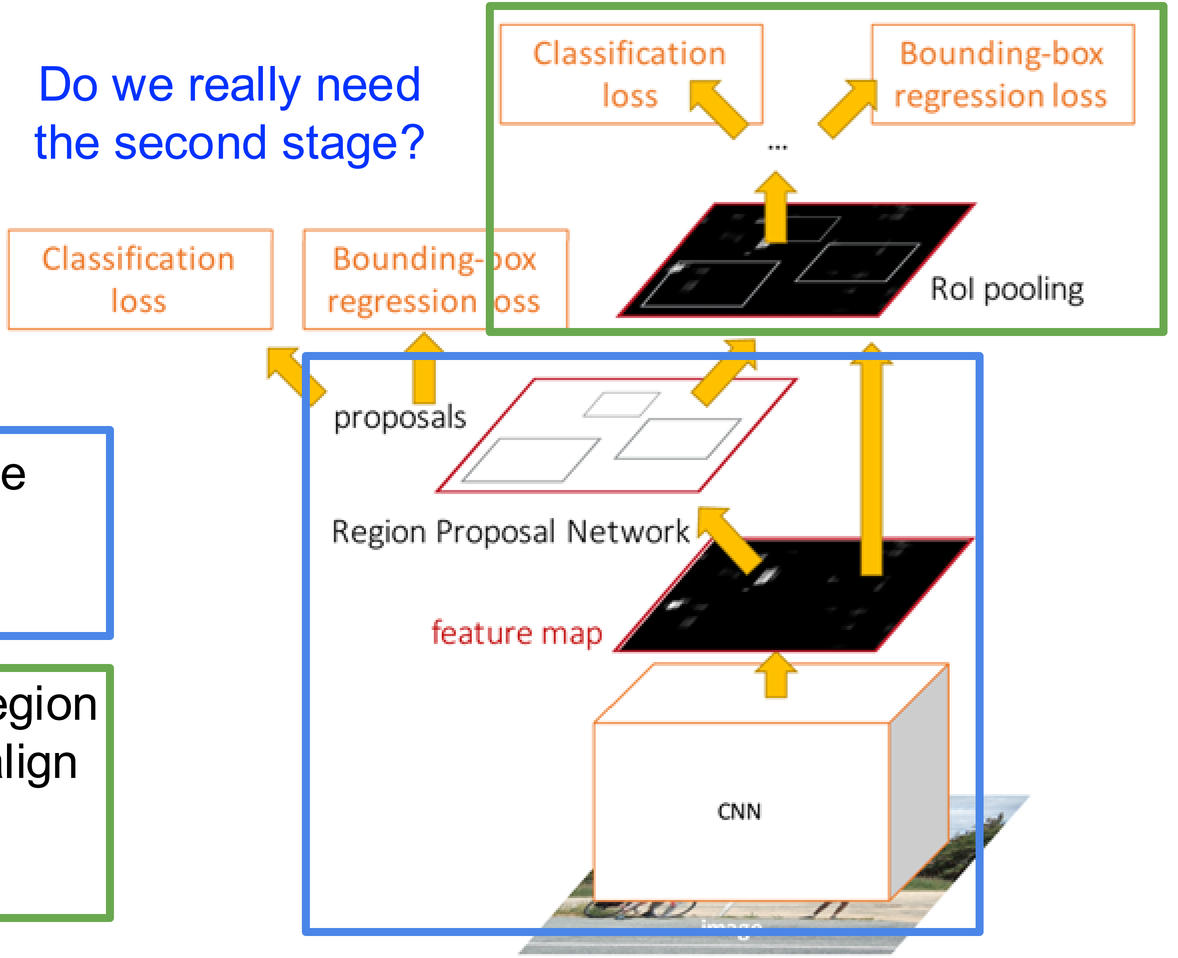
Make CNN do proposals!

Do we really need the second stage?

Faster R-CNN is a
Two-stage object detector

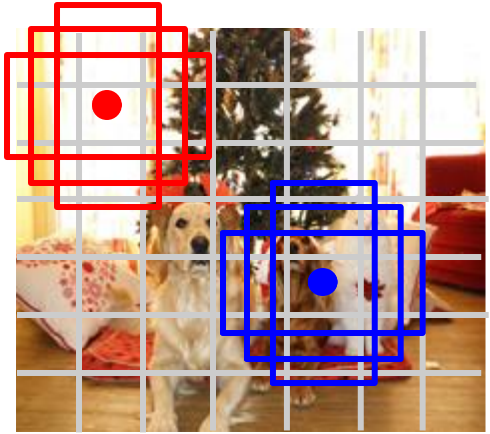
First stage: Run once per image
- Backbone network
- Region proposal network

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



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

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

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

Instance Segmentation

Classification

CAT

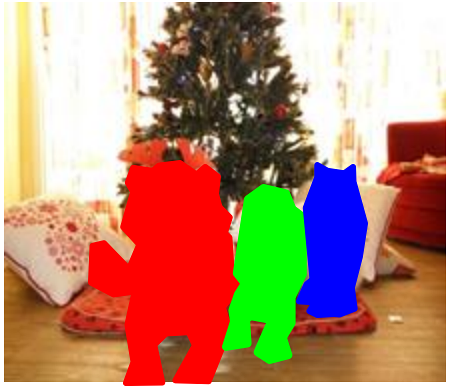
Semantic Segmentation

GRASS, CAT, TREE, SKY

Object Detection

DOG, DOG, CAT

Instance Segmentation



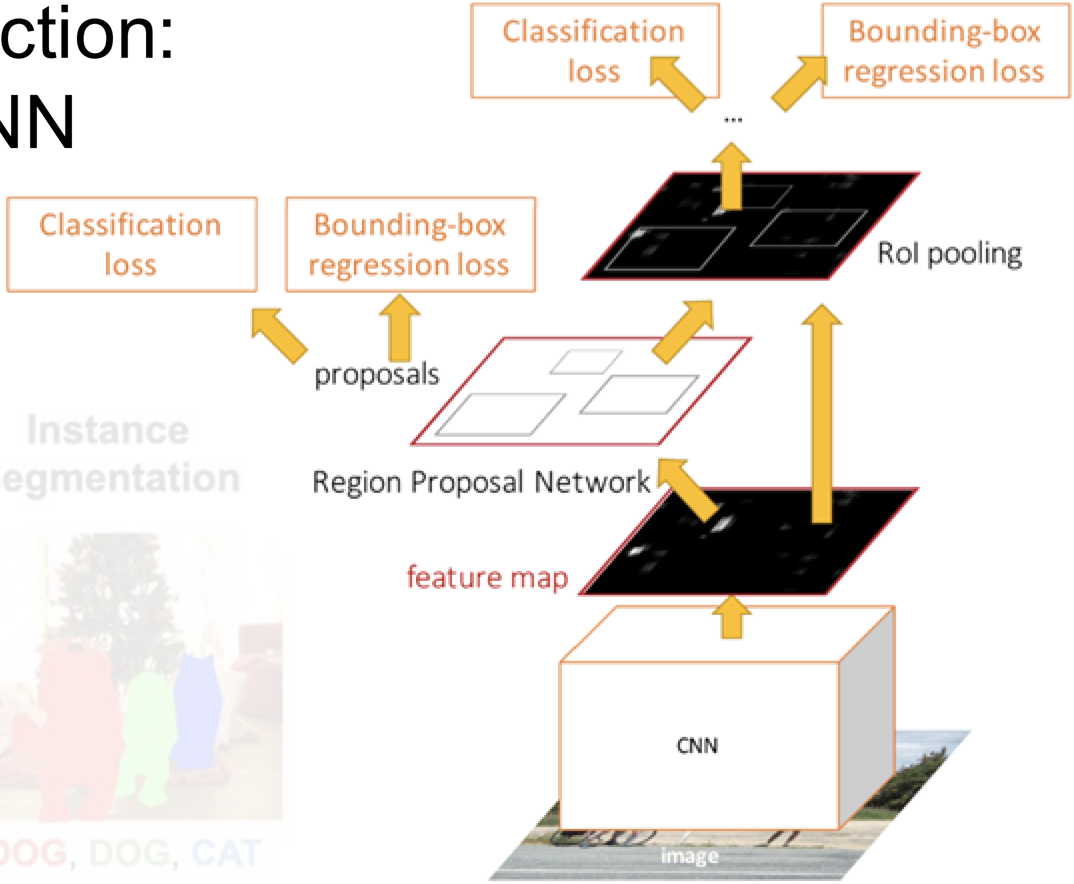
DOG, DOG, CAT

No spatial extent

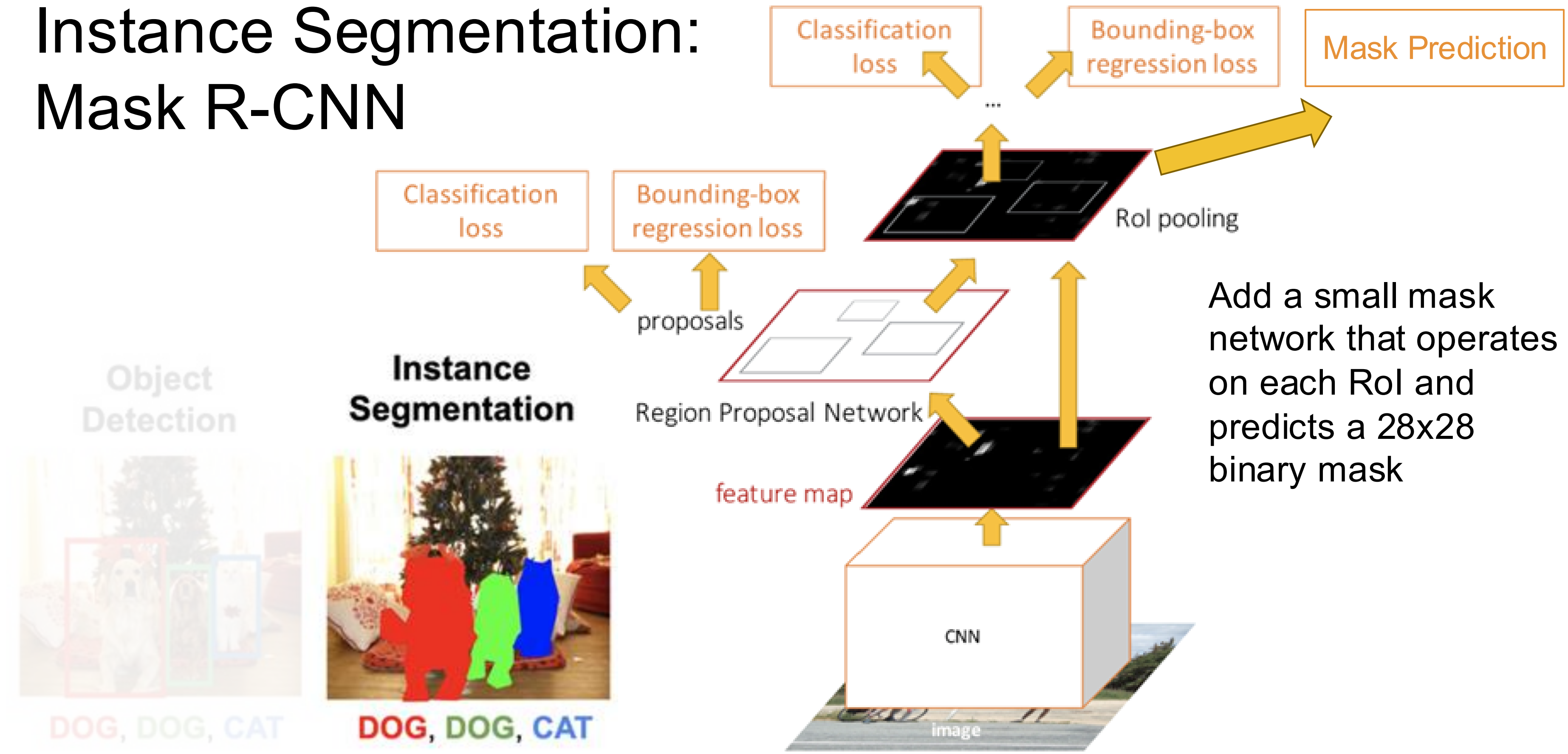
No objects, just pixels

Multiple Object

Object Detection: Faster R-CNN



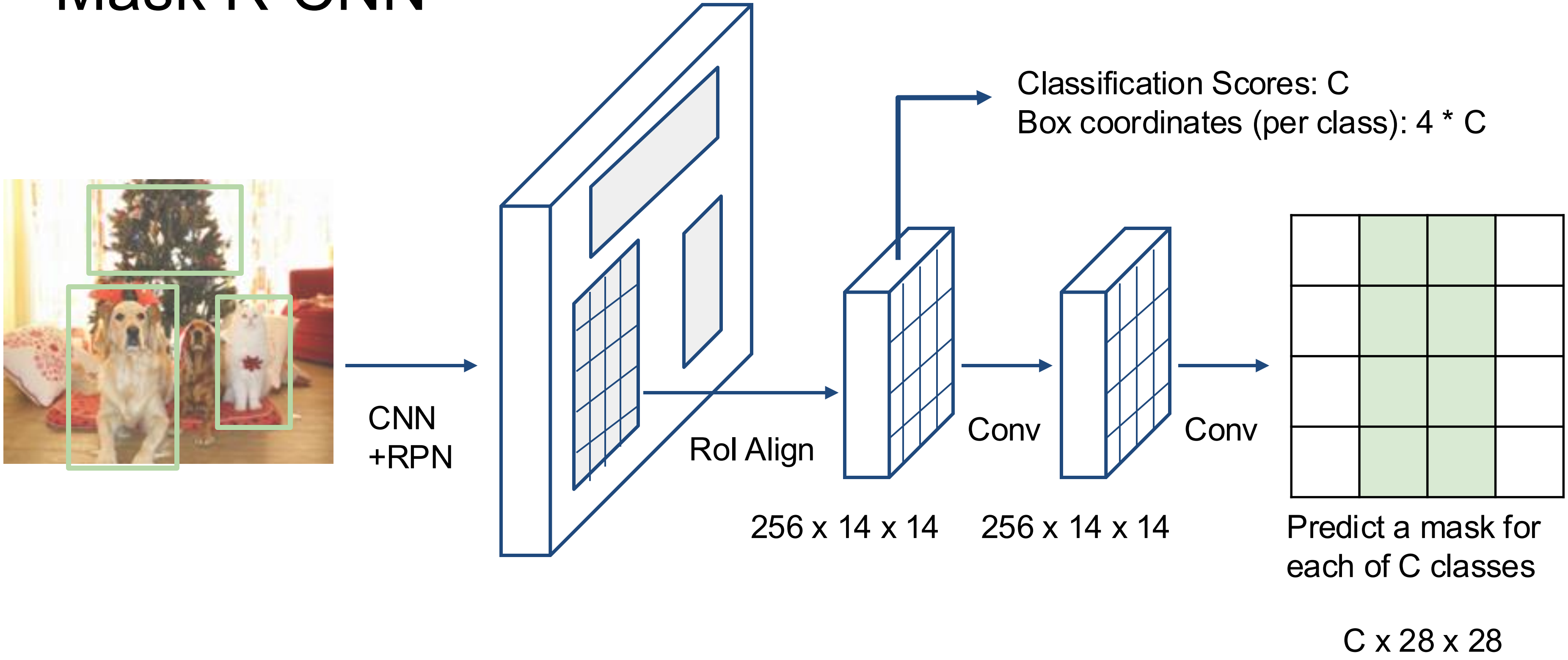
Instance Segmentation: Mask R-CNN



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

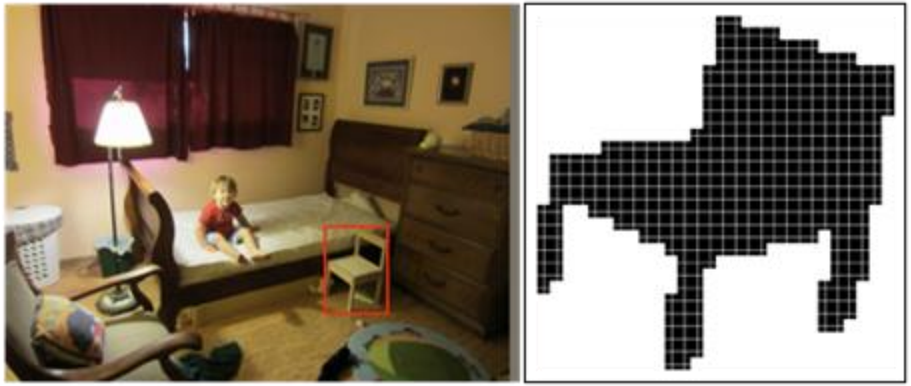
He et al, “Mask R-CNN”, ICCV 2017

Mask R-CNN

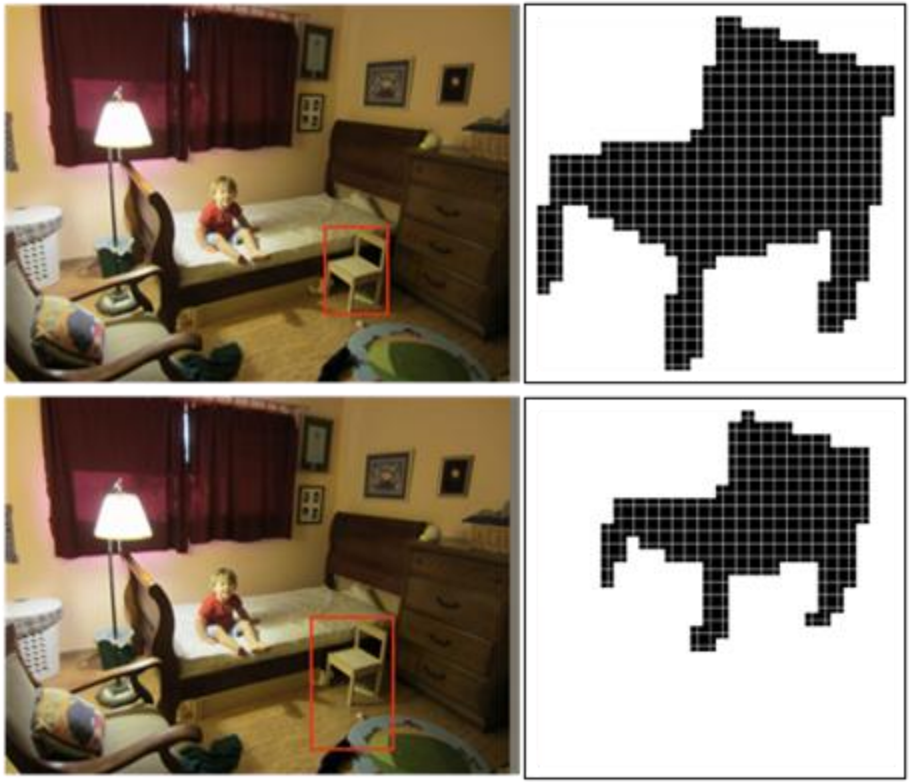


He et al, “Mask R-CNN”, arXiv 2017

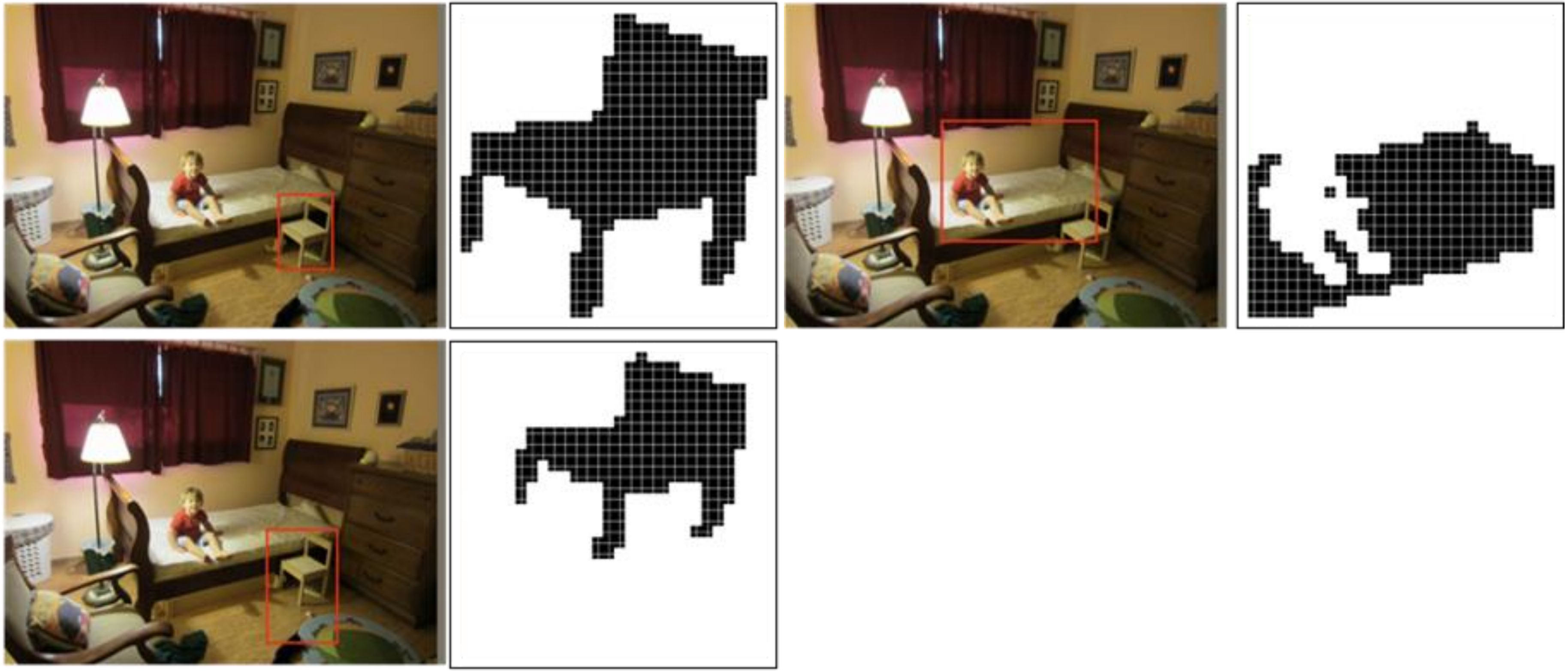
Mask R-CNN: Example Mask Training Targets



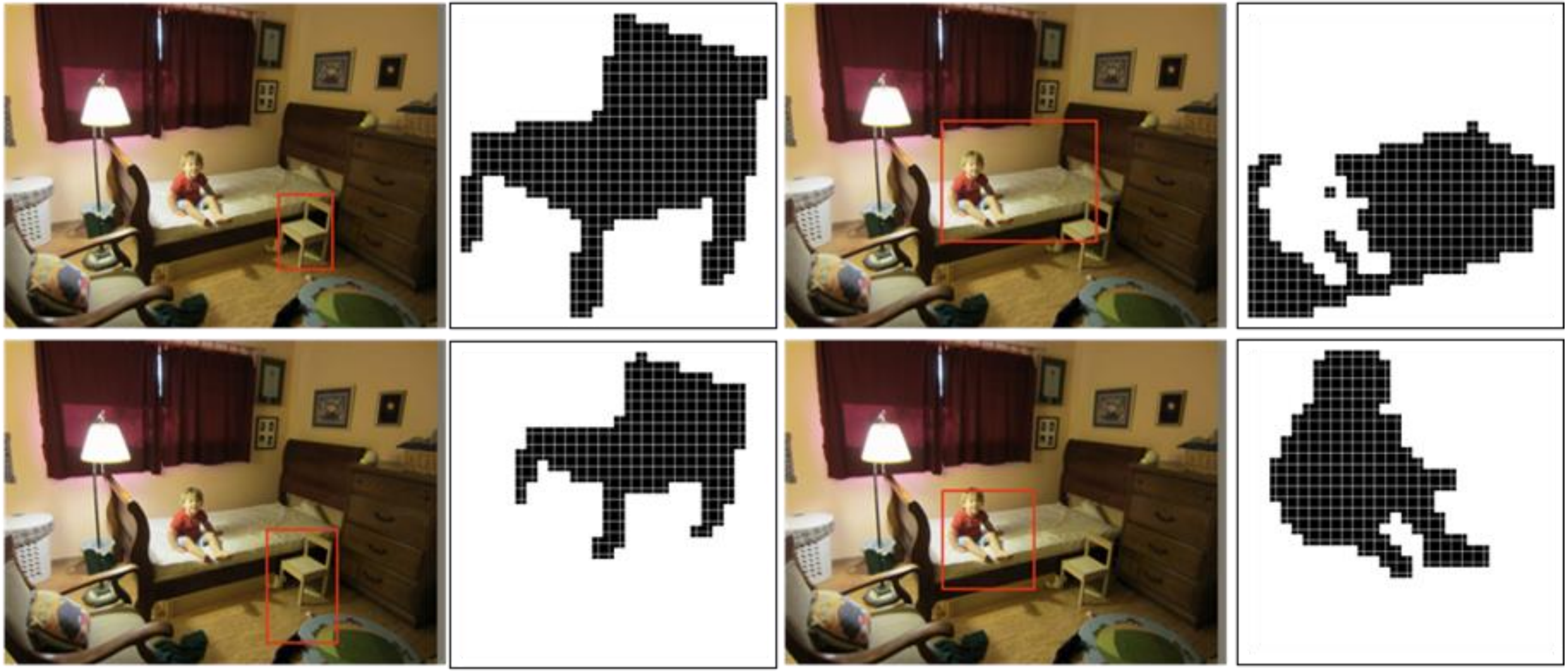
Mask R-CNN: Example Mask Training Targets



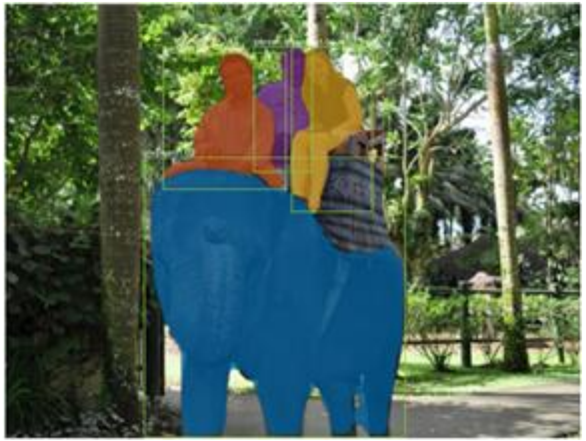
Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Very Good Results!

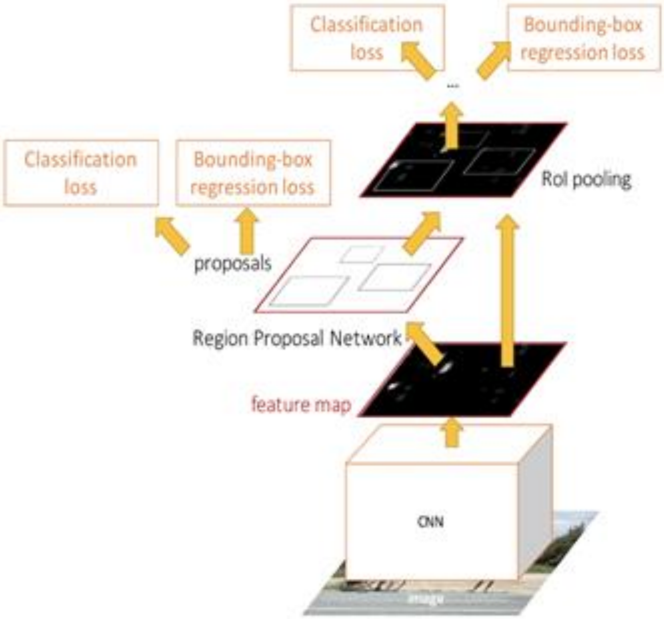
He et al, “Mask R-CNN”, ICCV 2017

Mask R-CNN
Also does pose

He et al, “Mask R-CNN”, ICCV 2017

RCNN Series

- **R-CNN**: Per-region detection, hand-crafted region proposal
- **Fast R-CNN**: Shared feature extraction, RoI Pooling, Anchors
- **Faster R-CNN**: Region Proposal Networks, RoI Align
- **Mask R-CNN**: Instance Segmentation



Detectors are becoming more complex!
Many hyperparameters to tune for each components …
Can we simplify it?

End-to-End Object Detection with Transformers

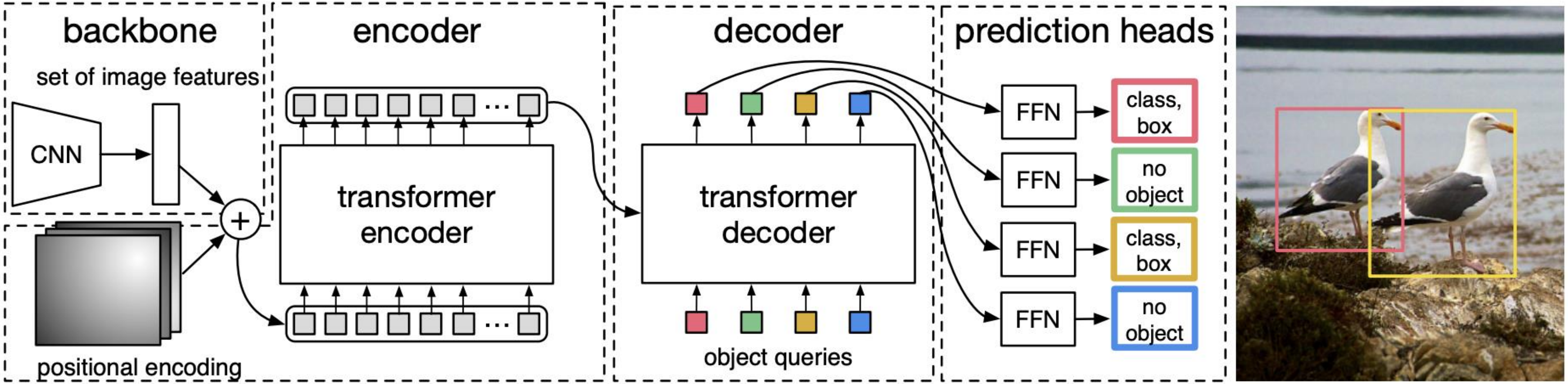
Nicolas Carion*, Francisco Massa*, Gabriel Synnaeve, Nicolas Usunier,
Alexander Kirillov, and Sergey Zagoruyko

Facebook AI

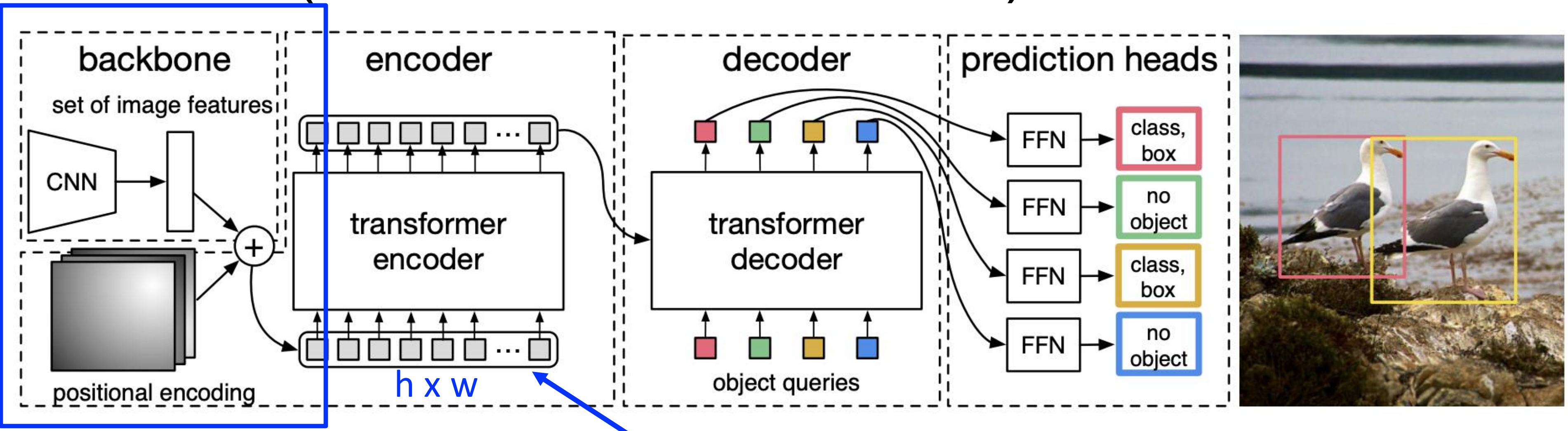
Key ideas:

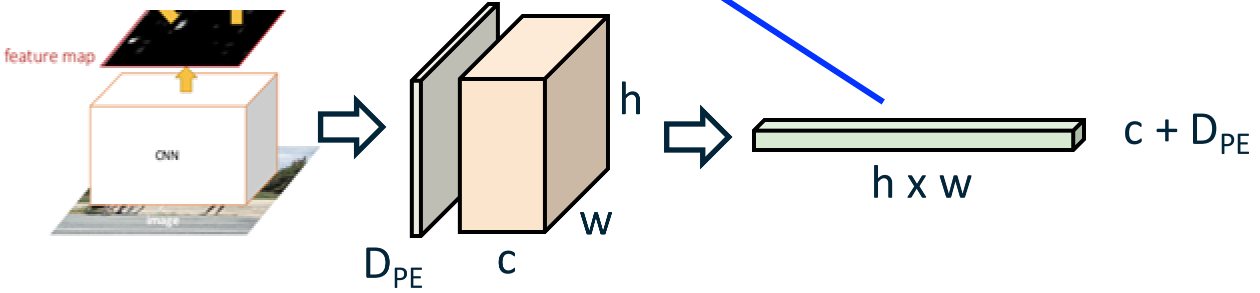
- Detection as a **set-to-set prediction** problem
- Use Transformer to model the detection problem

DETR (DEtection TRansformer)



DETR (DEtection TRansformer)





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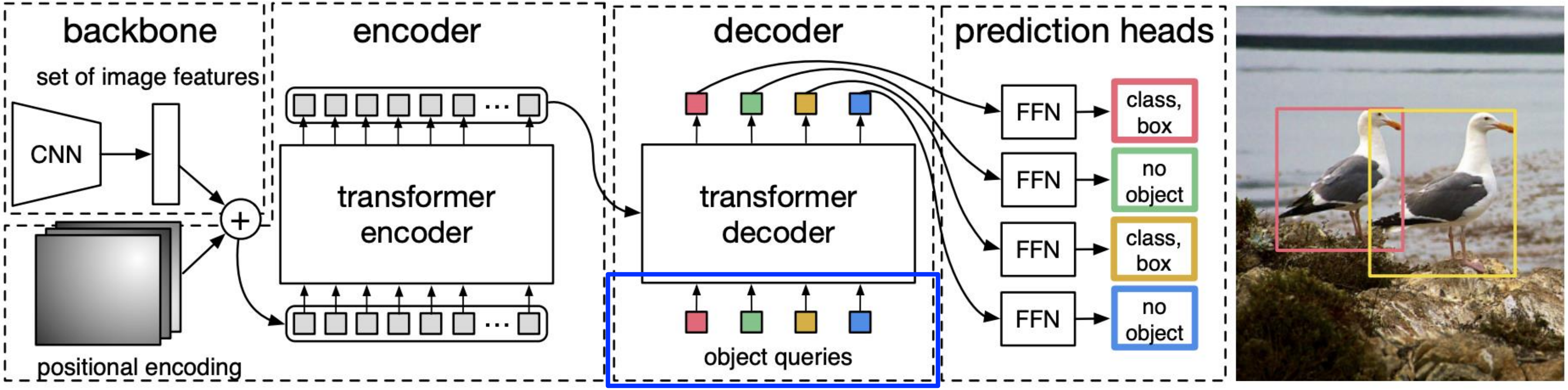
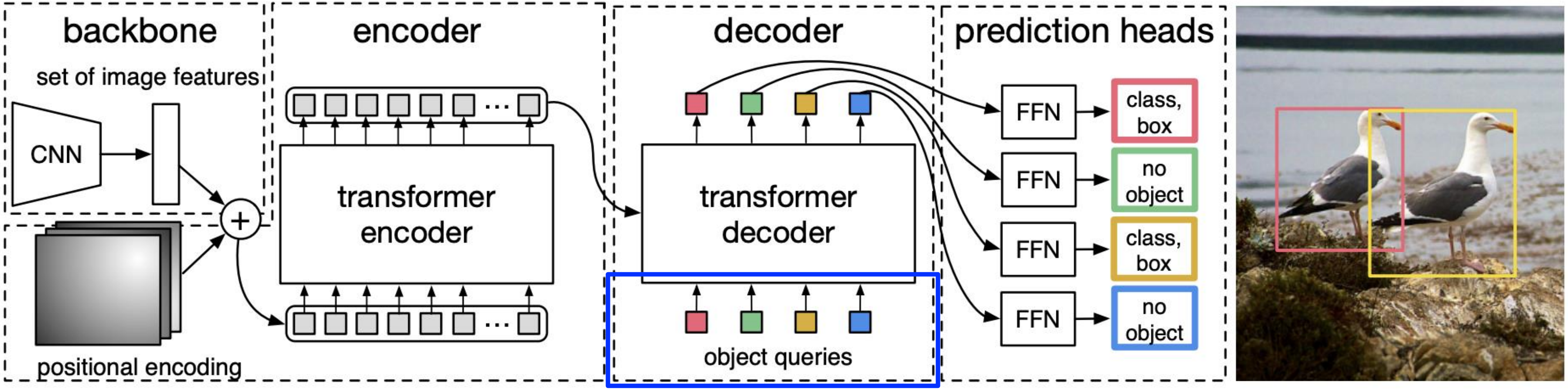
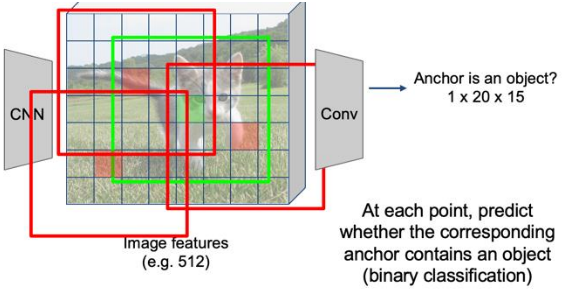


A fixed set of learnable embeddings,
e.g., 300 size-N vectors
Q: Why?

DETR (DEtection TRansformer)





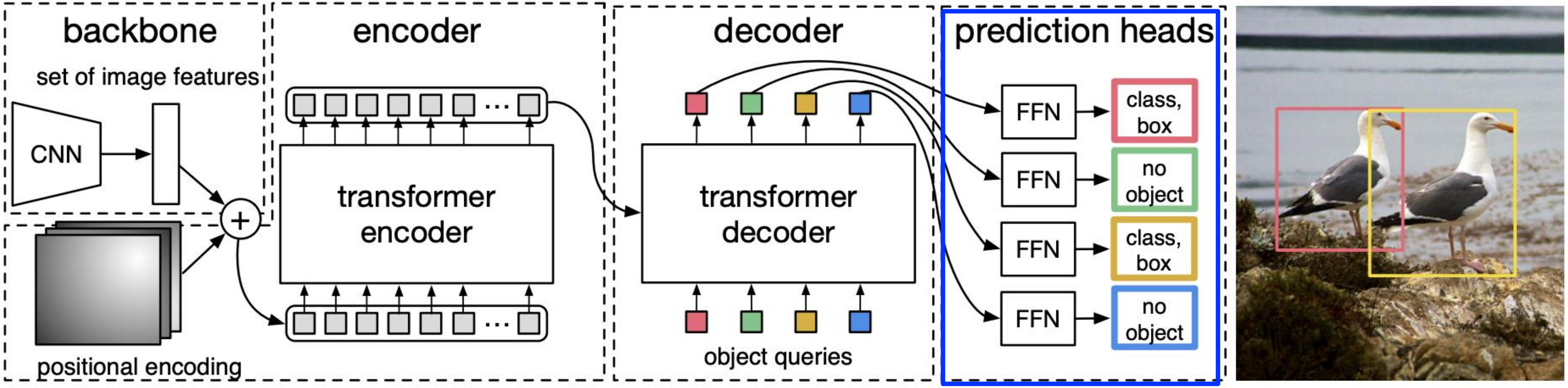
A fixed set of learnable embeddings, e.g., 300 size-N vectors

Q: Why?

A: Break the symmetry of predictions, so that each prediction is different.

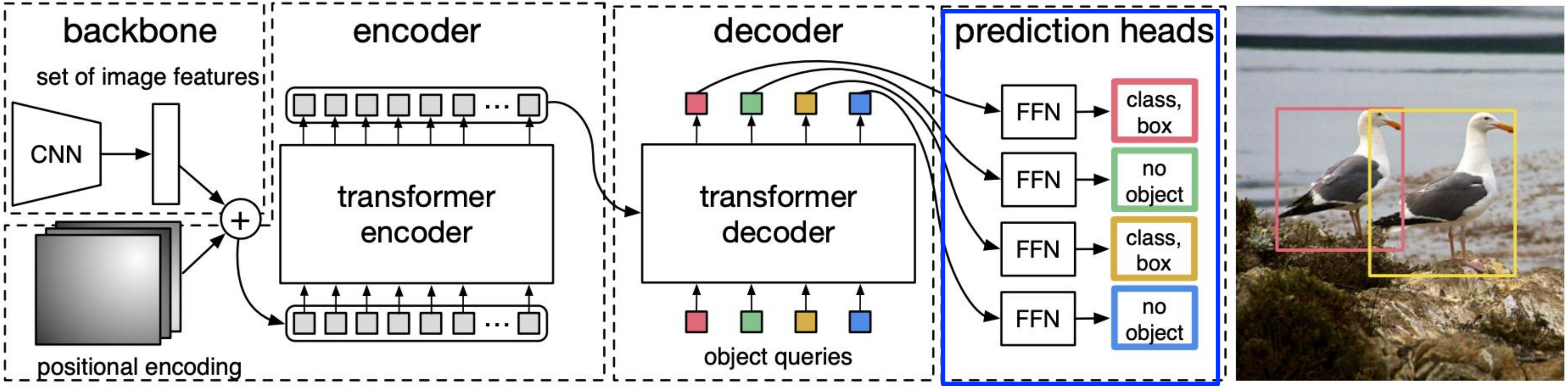
Analogous to anchors in *R-CNN, but **no spatial location**

DETR (DEtection TRansformer)



Problem: We don’t know which query corresponds to which ground truth during training! We can’t predetermine a fixed order like in sequence decoding.

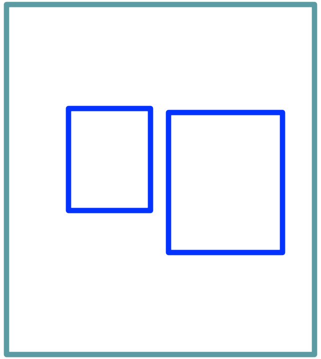
DETR (DEtection TRansformer)



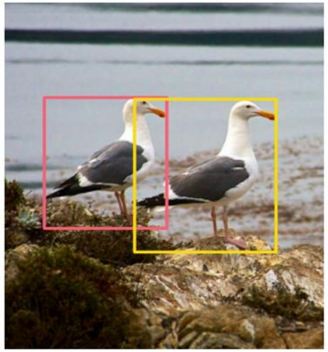
Problem: We don't know which query corresponds to which ground truth during training! We can't predetermine a fixed order like in sequence decoding.

Solution: Set matching loss --- train your model to generate a set of predictions that matches ground truth regardless of its order.

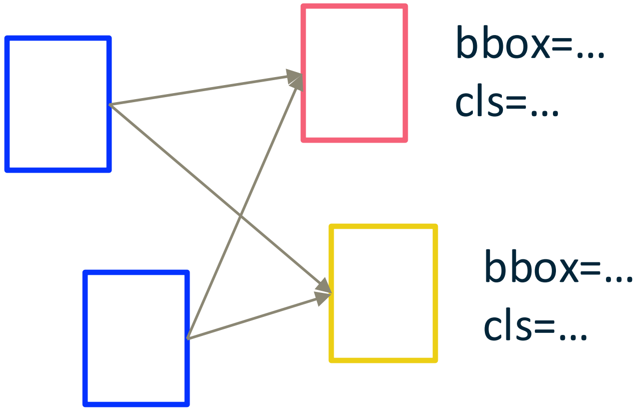
Hangarian Loss (Set Matching Loss)



Prediction



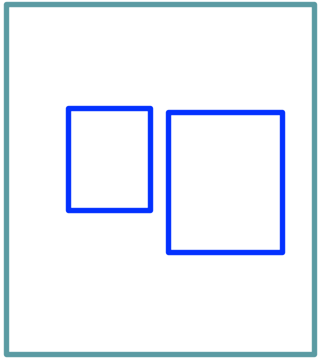
Ground Truth



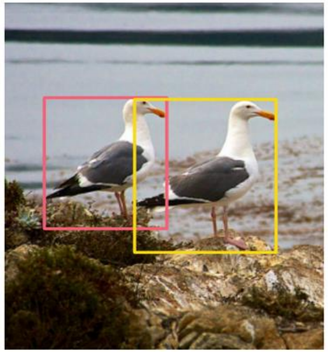
Goal: minimize bipartite distance

Problem: each query should be trained to match one ground truth. We don’t know the matching!

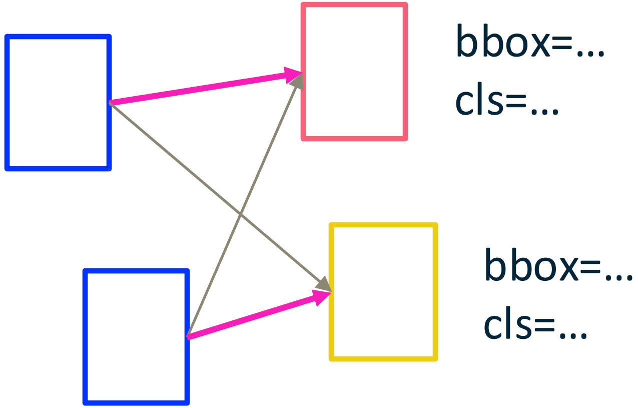
Hangarian Loss (Set Matching Loss)



Prediction



Ground Truth



Goal: minimize bipartite distance

1. **Hungarian matching:** find the minimum-loss bipartite matching between prediction and ground truth given the current prediction.
2. **Minimize matched loss:** Given the matched prediction and ground truth, minimize the detection loss (bounding box distance and classification CE loss)

Comparison with FasterRCNN

Model	GFLOPS/FPS	#params	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Faster RCNN-DC5	320/16	166M	39.0	60.5	42.3	21.4	43.5	52.5
Faster RCNN-FPN	180/26	42M	40.2	61.0	43.8	24.2	43.5	52.0
Faster RCNN-R101-FPN	246/20	60M	42.0	62.5	45.9	25.2	45.6	54.6
Faster RCNN-DC5+	320/16	166M	41.1	61.4	44.3	22.9	45.9	55.0
Faster RCNN-FPN+	180/26	42M	42.0	62.1	45.5	26.6	45.4	53.4
Faster RCNN-R101-FPN+	246/20	60M	44.0	63.9	**47.8**	**27.2**	48.1	56.0
DETR	86/28	41M	42.0	62.4	44.2	20.5	45.8	61.1
DETR-DC5	187/12	41M	43.3	63.1	45.9	22.5	47.3	61.1
DETR-R101	152/20	60M	43.5	63.8	46.4	21.9	48.0	61.8
DETR-DC5-R101	253/10	60M	**44.9**	**64.7**	47.7	23.7	**49.5**	**62.3**

Similar size, simpler, and (mostly) better!

We are still detecting a fixed number of object with finite vocabulary …

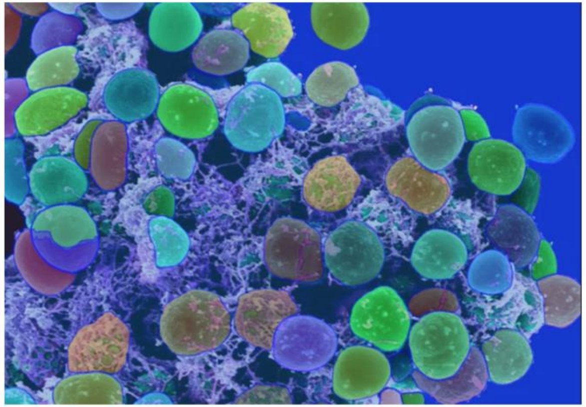
Segment Anything

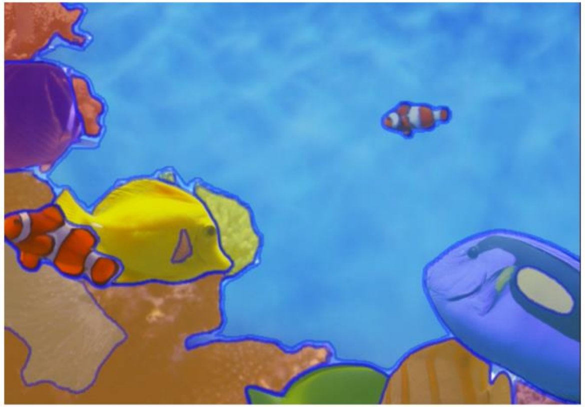
Alexander Kirillov[1,2,4] Eric Mintun[2] Nikhila Ravi[1,2] Hanzi Mao[2] Chloe Rolland[3] Laura Gustafson[3]
Tete Xiao[3] Spencer Whitehead Alexander C. Berg Wan-Yen Lo Piotr Dollár[4] Ross Girshick[4]
[1]project lead [2]joint first author [3]equal contribution [4]directional lead
Meta AI Research, FAIR

Key ideas:

- Query-based prediction instead of fixed set-to-set prediction
- Large-scale training data with auto-labeling

Foundation Image Segmentation Models





SegmentAnything (Meta AI, 2023)

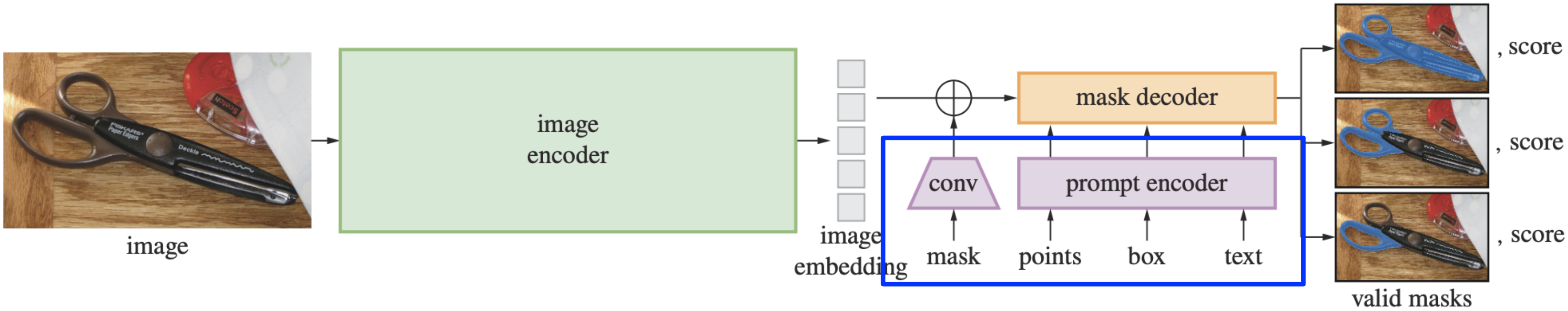
Try it yourself! https://segment-anything.com/demo#

Foundation Image Segmentation Models

SegmentAnything (Meta AI, 2023)

Try it yourself! https://segment-anything.com/demo#

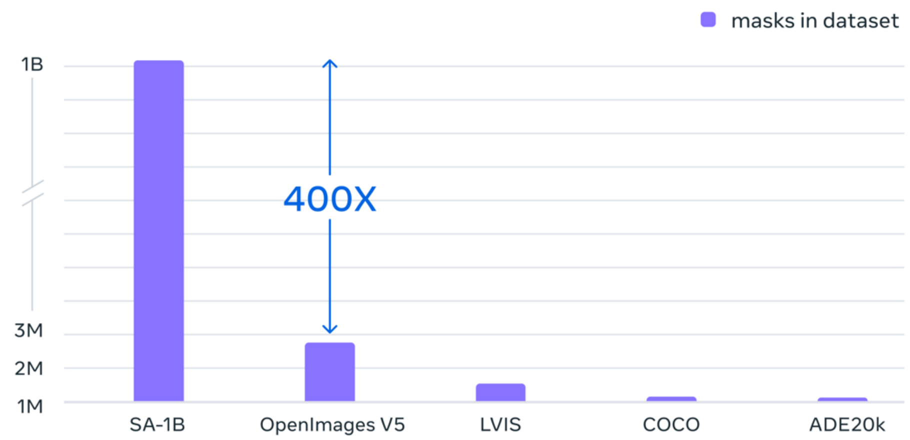
Foundation Image Segmentation Models

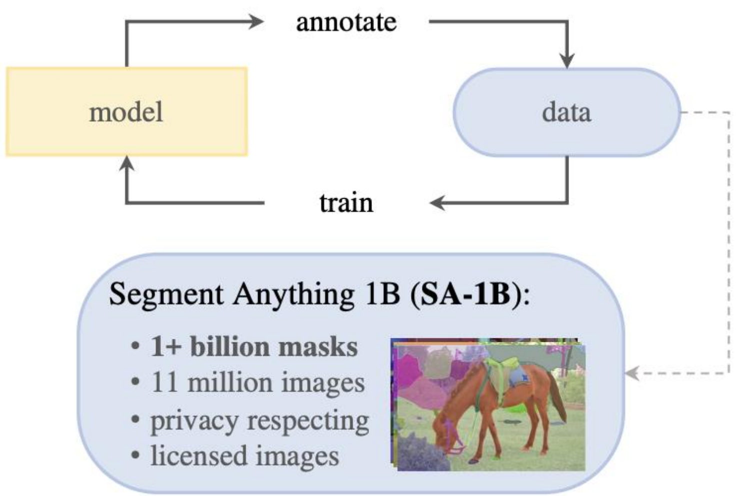


No more learned embeddings. Query anything you want!

SegmentAnything (Meta AI, 2023)

Foundation Image Segmentation Models

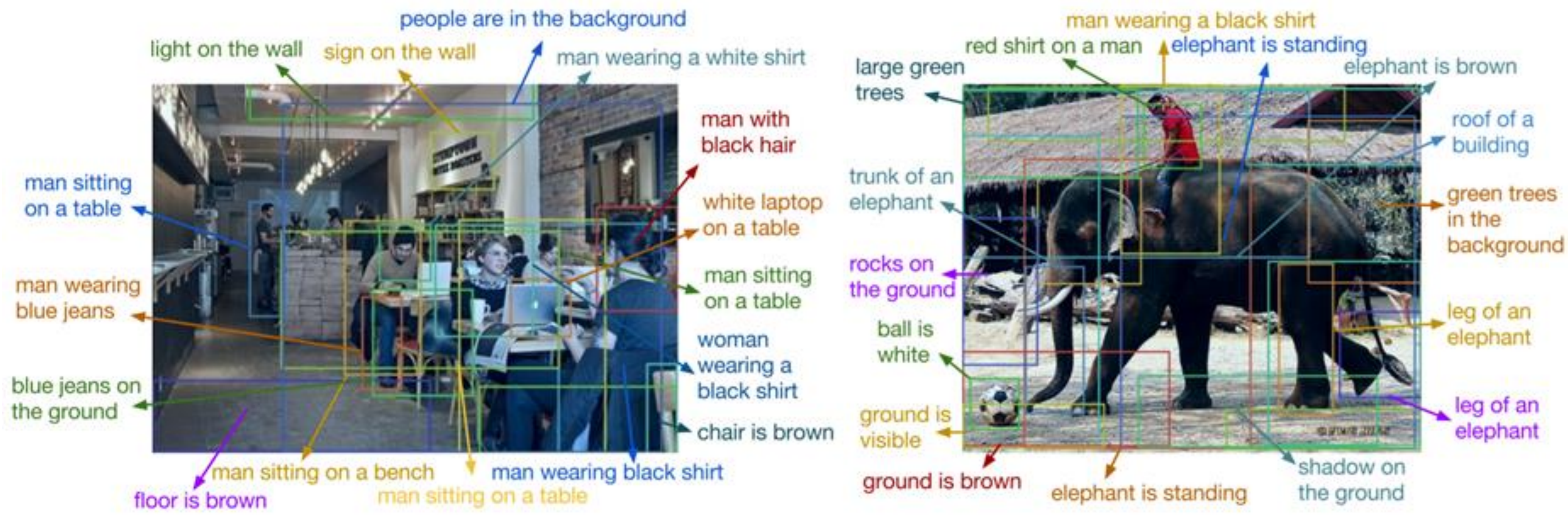




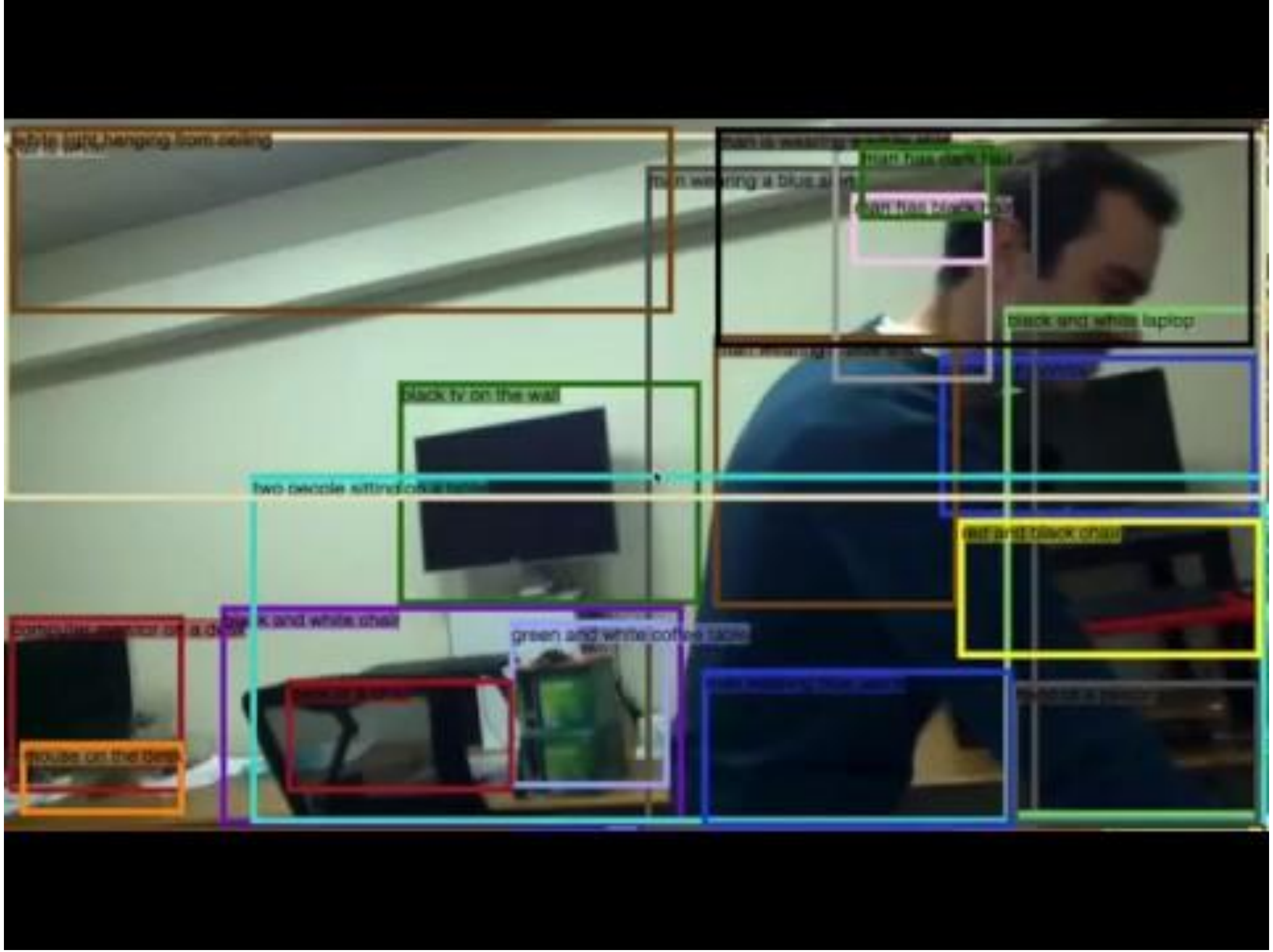
SegmentAnything (Meta AI, 2023)

Beyond 2D Object Detection...

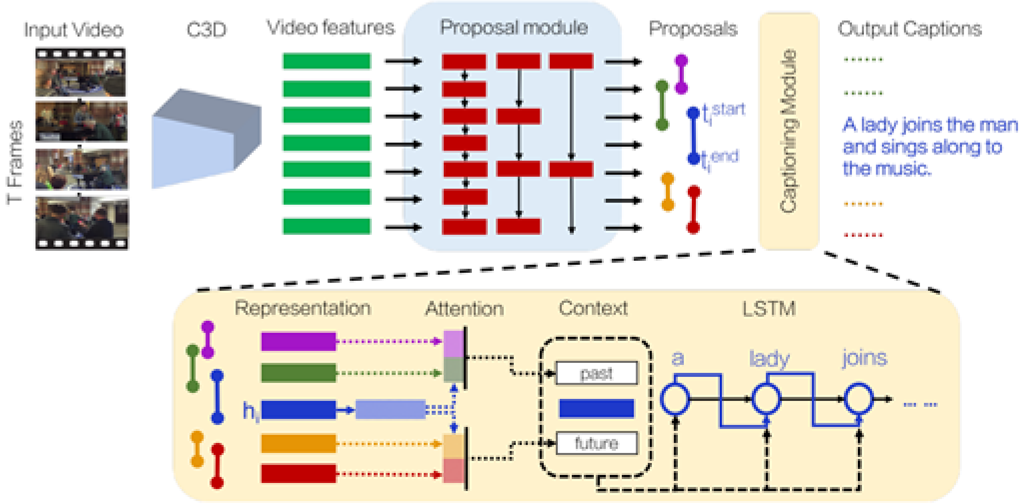
Object Detection + Captioning = Dense Captioning

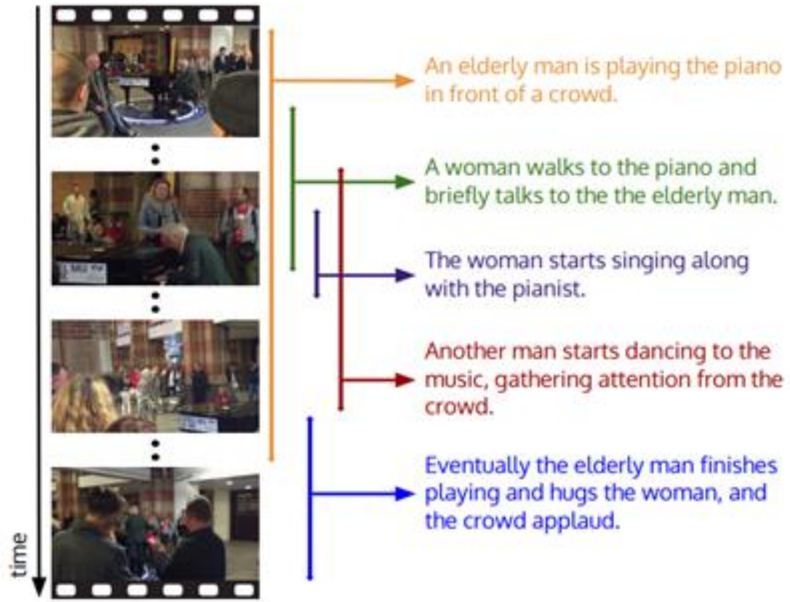


Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016


white light hanging from ceiling
man has dark hair
black and white laptop
black tv on the wall
red and black chair
black and white chair
green and white coffee table
mouse on the desk

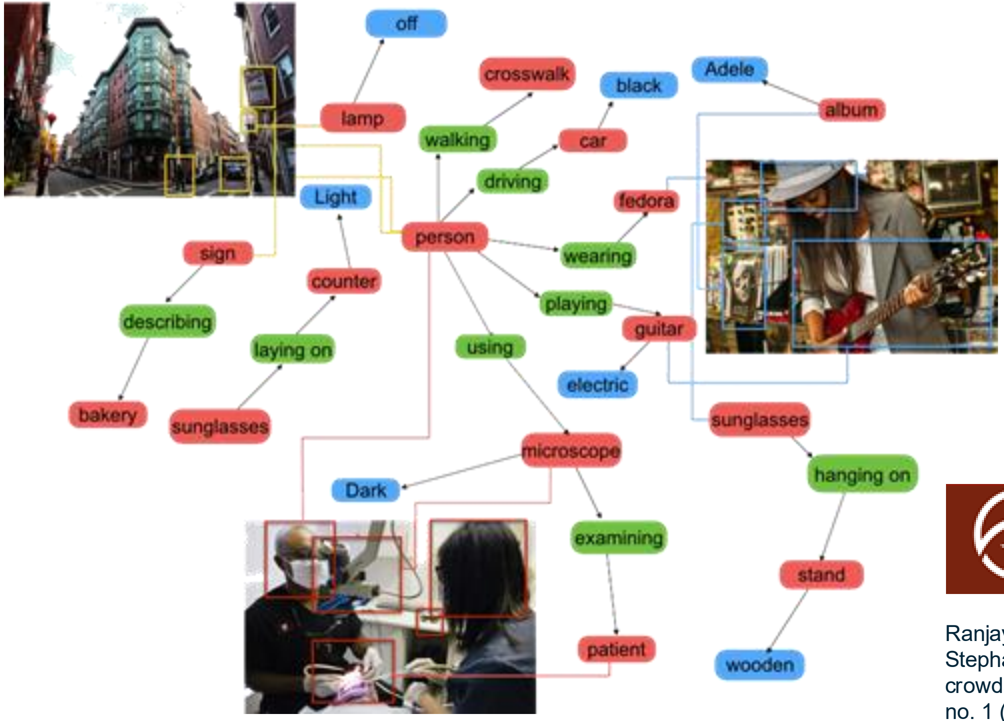
Dense Video Captioning





Ranjay Krishna et al., "Dense-Captioning Events in Videos", ICCV 2017

Objects + Relationships = Scene Graphs

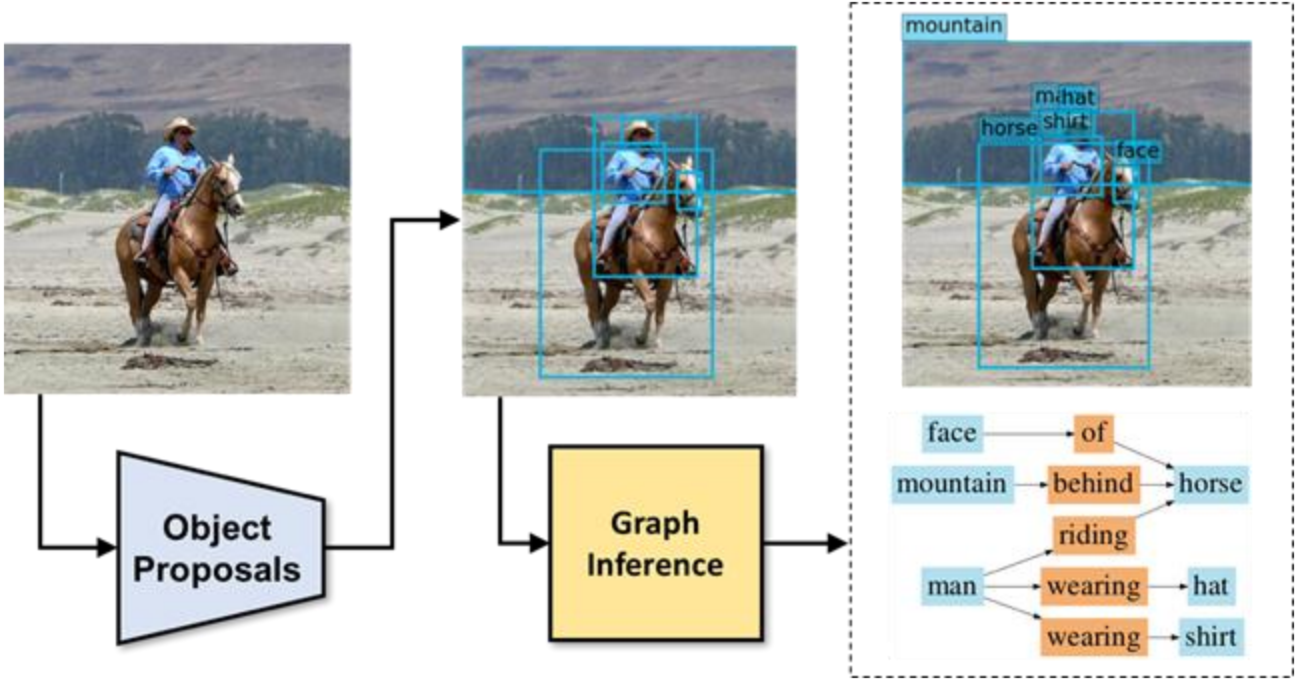


108,077 Images
5.4 Million Region Descriptions
1.7 Million Visual Question Answers
3.8 Million Object Instances
2.8 Million Attributes
2.3 Million Relationships
Everything Mapped to Wordnet Synsets

VISUALGENOME

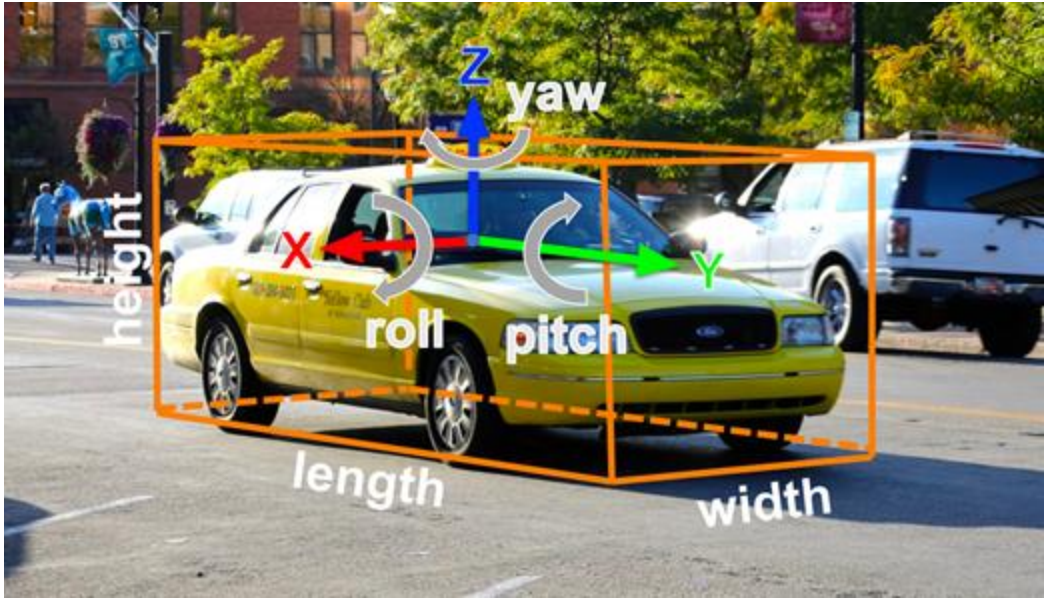
Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." International Journal of Computer Vision 123, no. 1 (2017): 32-73.

Scene Graph Prediction



Xu, Zhu, Choy, and Fei-Fei, “Scene Graph Generation by Iterative Message Passing”, CVPR 2017

3D Object Detection



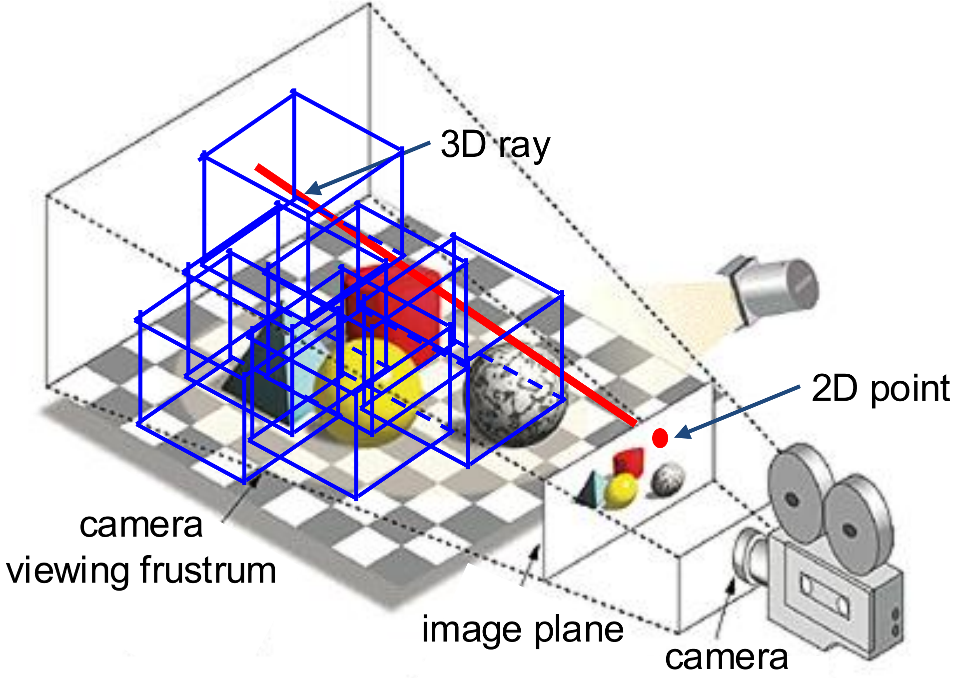
2D Object Detection:
2D bounding box
(x, y, w, h)

3D Object Detection:
3D oriented bounding box
(x, y, z, w, h, l, r, p, y)

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

3D Object Detection: Simple Camera Model



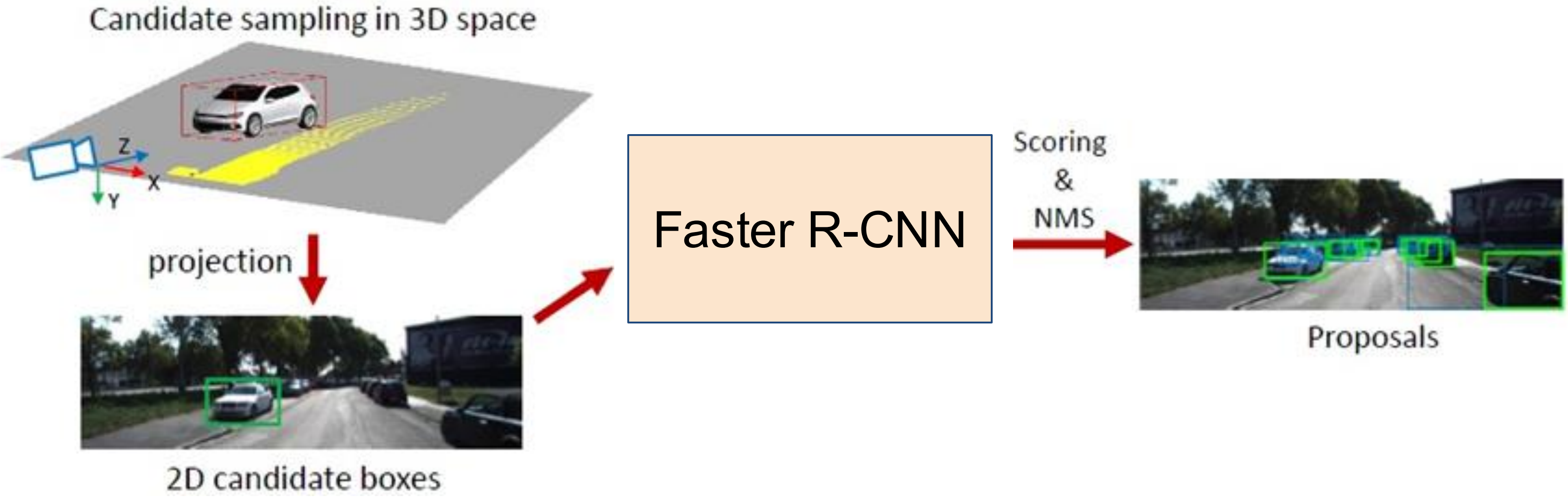
A point on the image plane corresponds to a **ray** in the 3D space

A 2D bounding box on an image is a **frustrum** in the 3D space

Localize an object in 3D:
The object can be anywhere in the **camera viewing frustrum**!

Image source: https://www.pcmag.com/encyclopedia_images/_FRUSTUM.GIF

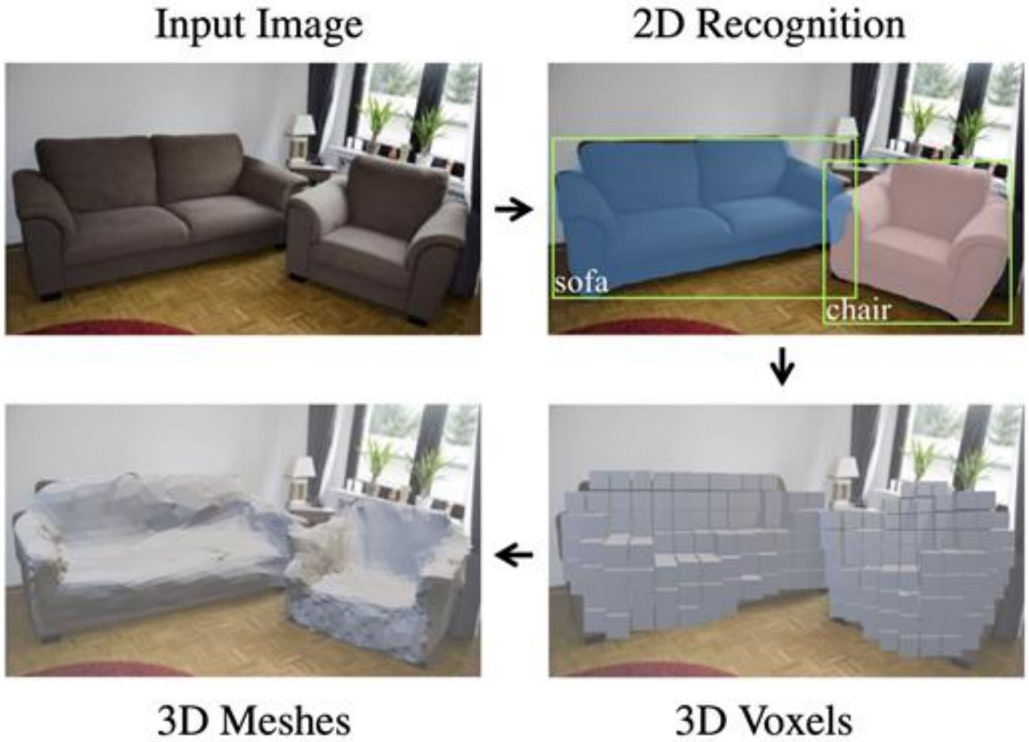
3D Object Detection: Monocular Camera



- Same idea as Faster RCNN, but proposals are in 3D
- 3D bounding box proposal, regress 3D box parameters + class score

Chen, Xiaozhi, Kaustav Kundu, Ziyu Zhang, Huimin Ma, Sanja Fidler, and Raquel Urtasun. "Monocular 3d object detection for autonomous driving." CVPR 2016.

3D Shape Prediction: Mesh R-CNN



Gkioxari et al., Mesh RCNN, ICCV 2019