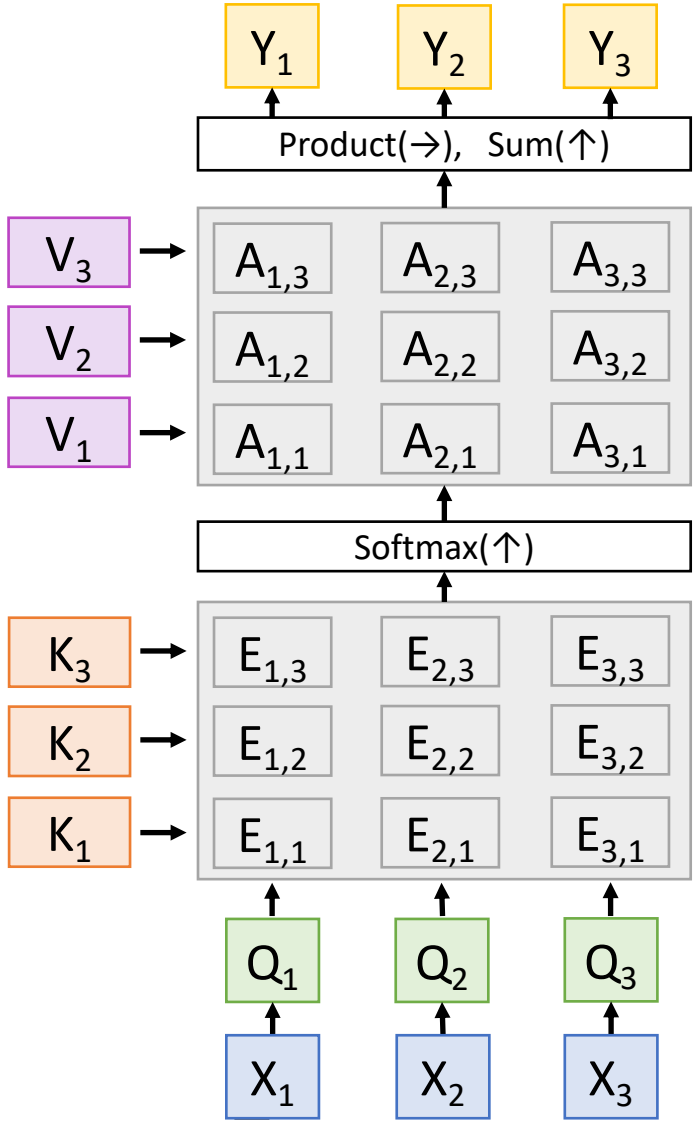
CS163: Deep Learning for Computer Vision

Lecture 13: Object Detection

Last Time: Self-Attention Layer

Inputs:
Input vectors: X (Shape: N_X x D_X)
Key matrix: W_K (Shape: D_X x D_Q)
Value matrix: W_V (Shape: D_X x D_V)
Query matrix: W_Q (Shape: D_X x D_Q)

Computation:
Query vectors: $Q = XW_Q$
Key vectors: $K = XW_K$ (Shape: N_X x D_Q)
Value Vectors: $V = XW_V$ (Shape: N_X x D_V)
Similarities: $E = QK^T / \sqrt{D_Q}$ (Shape: N_X x N_X) $E_{i,j} = (Q_i \cdot K_j) / \sqrt{D_Q}$
Attention weights: A = softmax(E, dim=1) (Shape: N_X x N_X)
Output vectors: $Y = AV$ (Shape: N_X x D_V) $Y_i = \sum_j A_{i,j} V_j$



Last Time: The Transformer

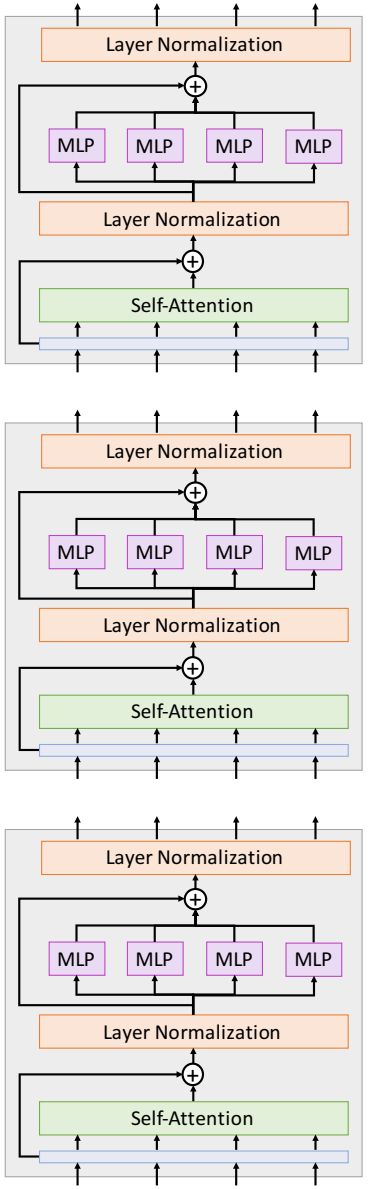
<u>Transformer Block:</u>
Input: Set of vectors x
Output: Set of vectors y

Self-attention is the only interaction between vectors!

Layer norm and MLP work independently per vector

Highly scalable, highly parallelizable

A **Transformer** is a sequence of transformer blocks



Vaswani et al, "Attention is all you need", NeurIPS 2017

Join the **UCLA Vision Seminar Mail list** to receive announcement of future CV seminars or research opportunities:
https://groups.google.com/a/lists.ucla.edu/g/vision-seminar
or send an email to vision-seminar+subscribe@lists.ucla.edu

So far: Image Classification

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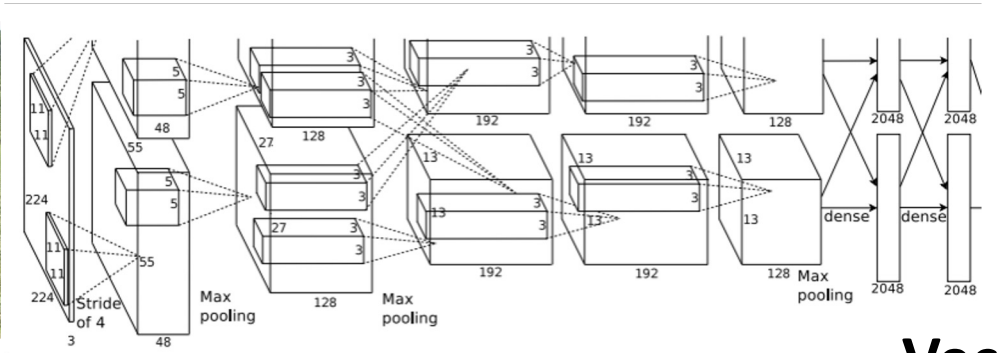


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Vector:
4096

Fully-Connected:
4096 to 1000

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

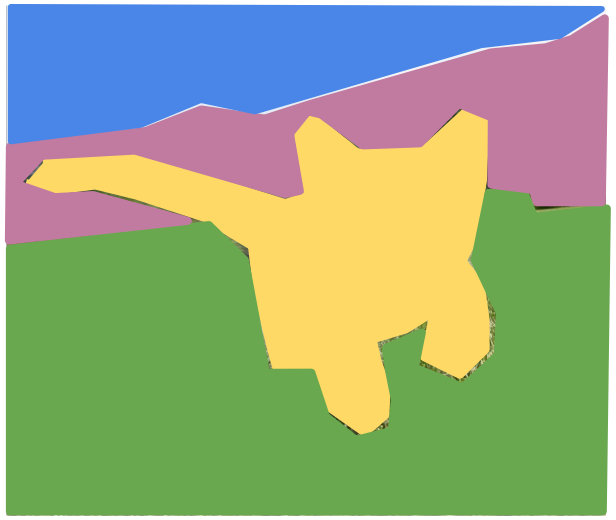
Computer Vision Tasks

Classification

CAT

No spatial extent

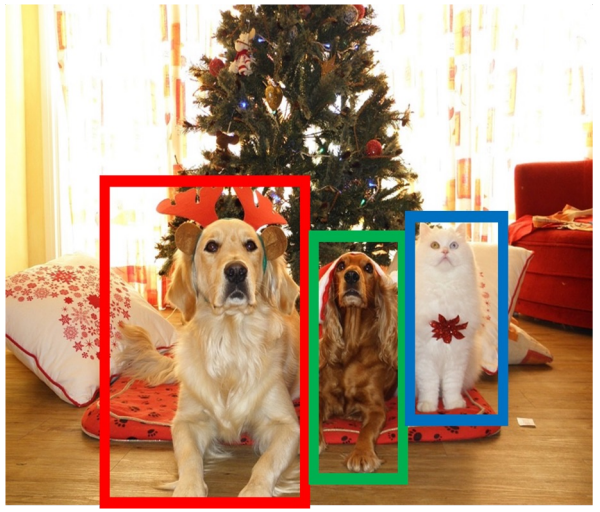
Semantic Segmentation



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

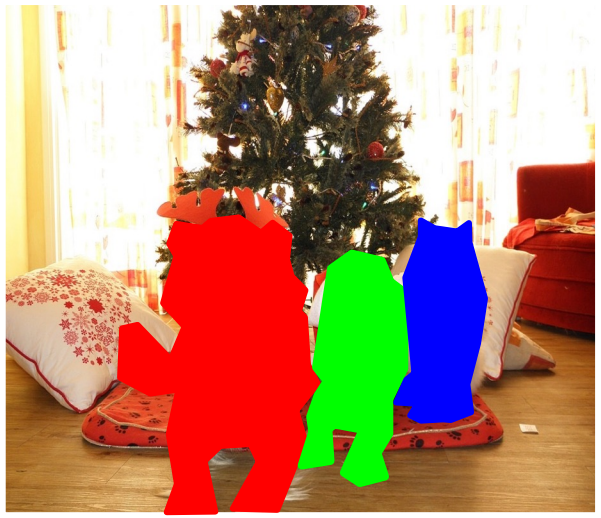
No objects, just pixels

Object Detection



DOG, **DOG**, **CAT**

Instance Segmentation



DOG, **DOG**, **CAT**

Multiple Objects

Today: Object Detection

Classification

CAT

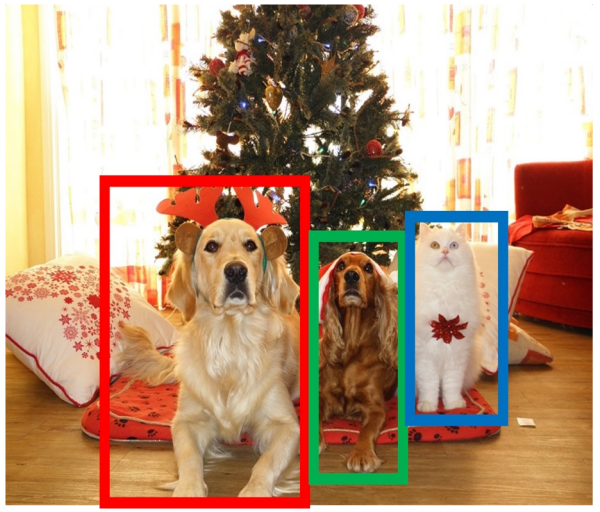
No spatial extent

Semantic Segmentation

GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

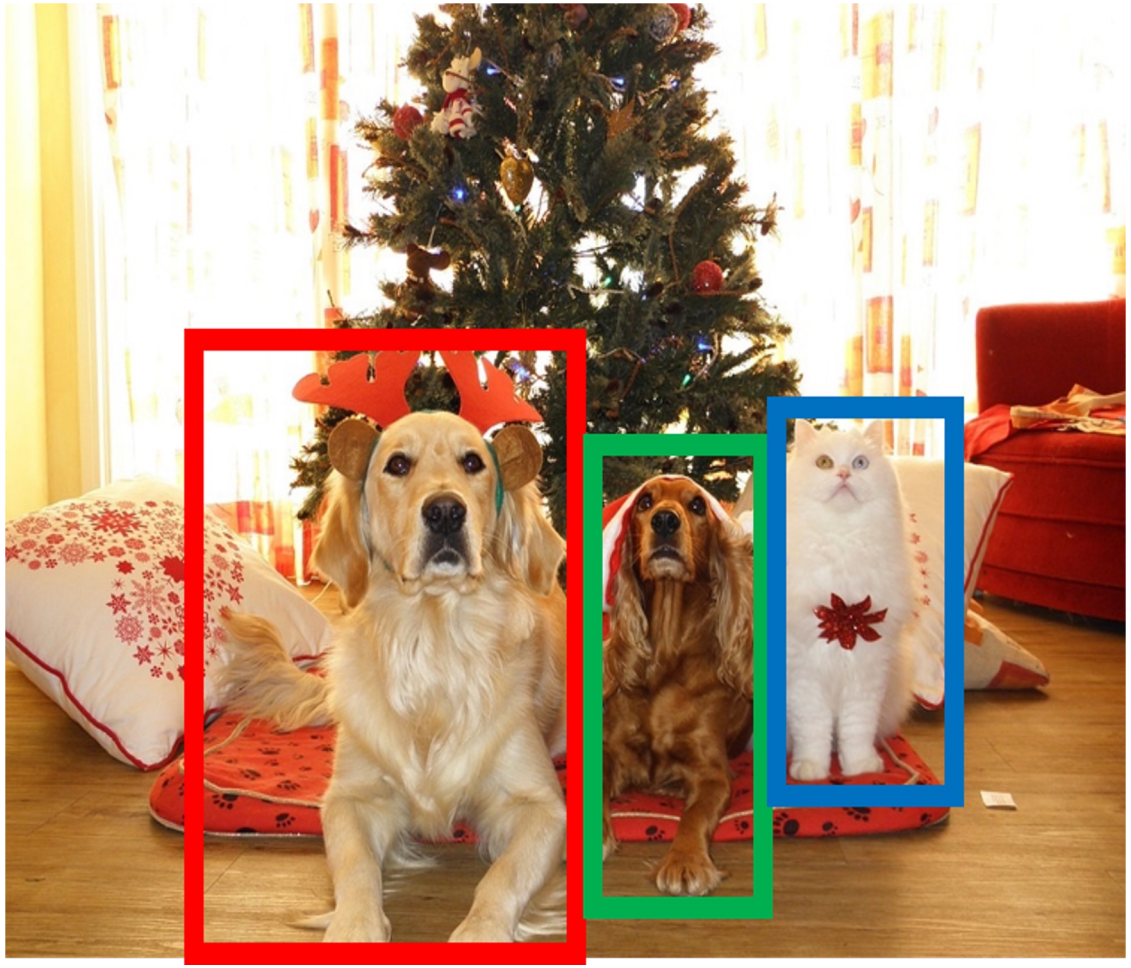
Multiple Objects

Object Detection: Task Definition

Input: Single RGB Image

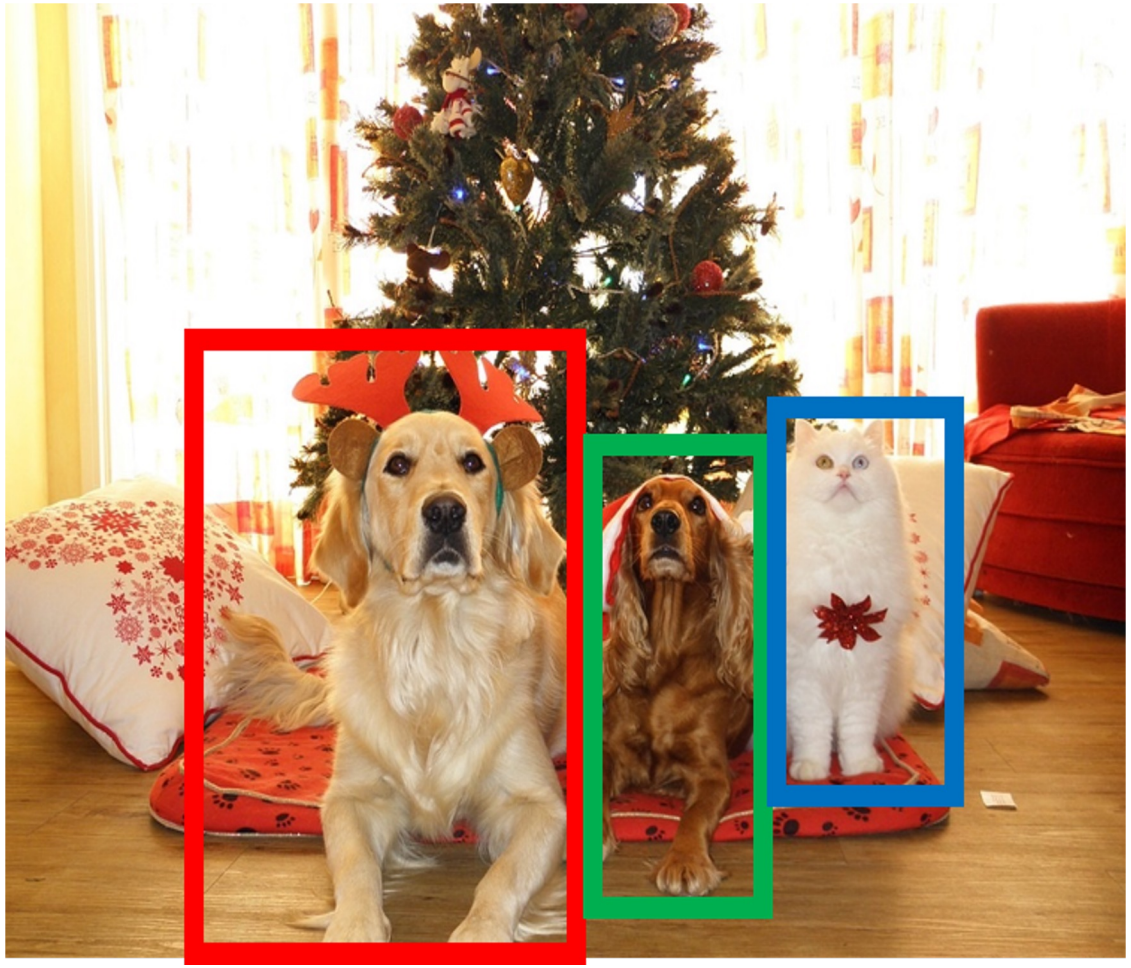
Output: A set of detected objects;
For each object predict:

1. Category label (from fixed, known set of categories)
2. Bounding box (four numbers: x, y, width, height)



Object Detection: Challenges

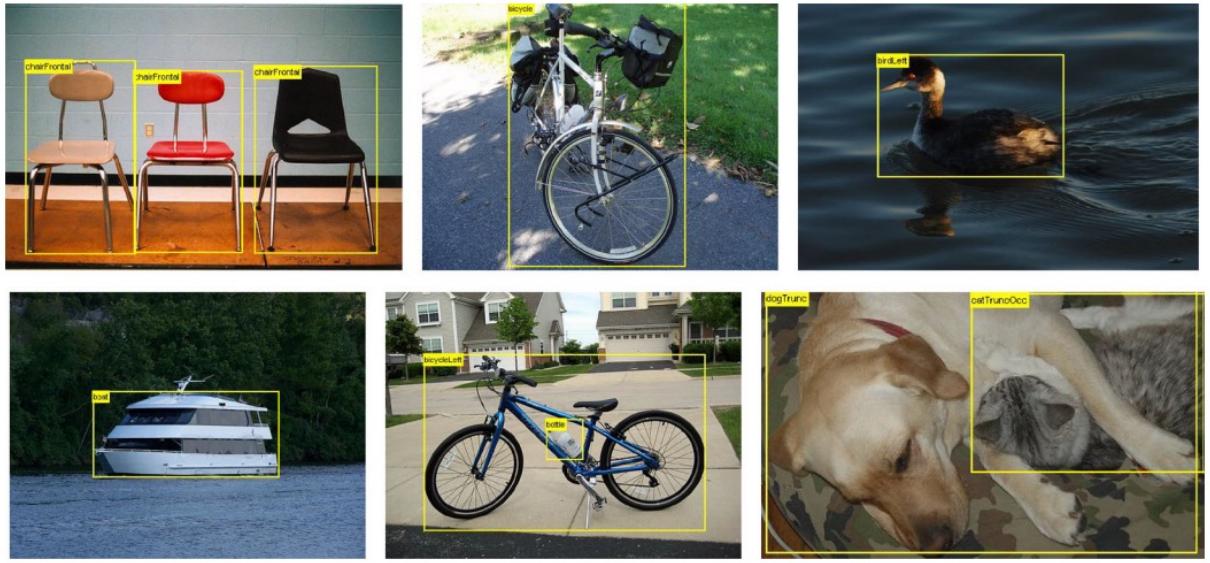
- **Multiple outputs**: Need to output variable numbers of objects per image
- **Multiple types of output**: Need to predict ”what” (category label) as well as “where” (bounding box)
- **Large images**: Classification works at 224x224; need higher resolution for detection, often ~800x600



Object Detection Datasets

Pascal VOC object detection (20 classes, ~ 10 K images) 2005-2012

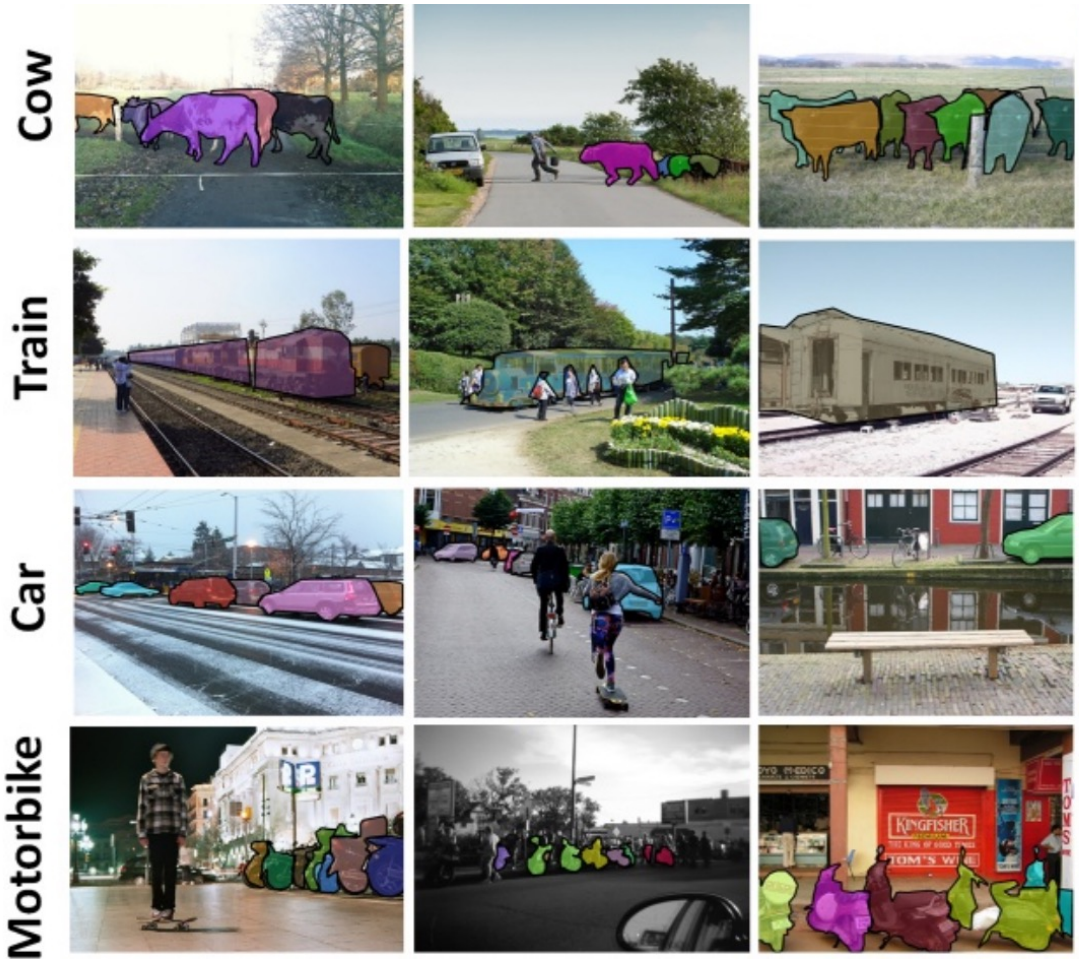
Vehicles	Household	Animals	Other
Aeroplane	Bottle	Bird	Person
Bicycle	Chair	Cat	
Boat	Dining table	Cow	
Bus	Potted plant	Dog	
Car	Sofa	Horse	
Motorbike	TV/Monitor	Sheep	
Train			



http://host.robots.ox.ac.uk/pascal/VOC/index.html

COCO Dataset (80 classes, 120K training images)

Annotations come with polygon masks



https://cocodataset.org/

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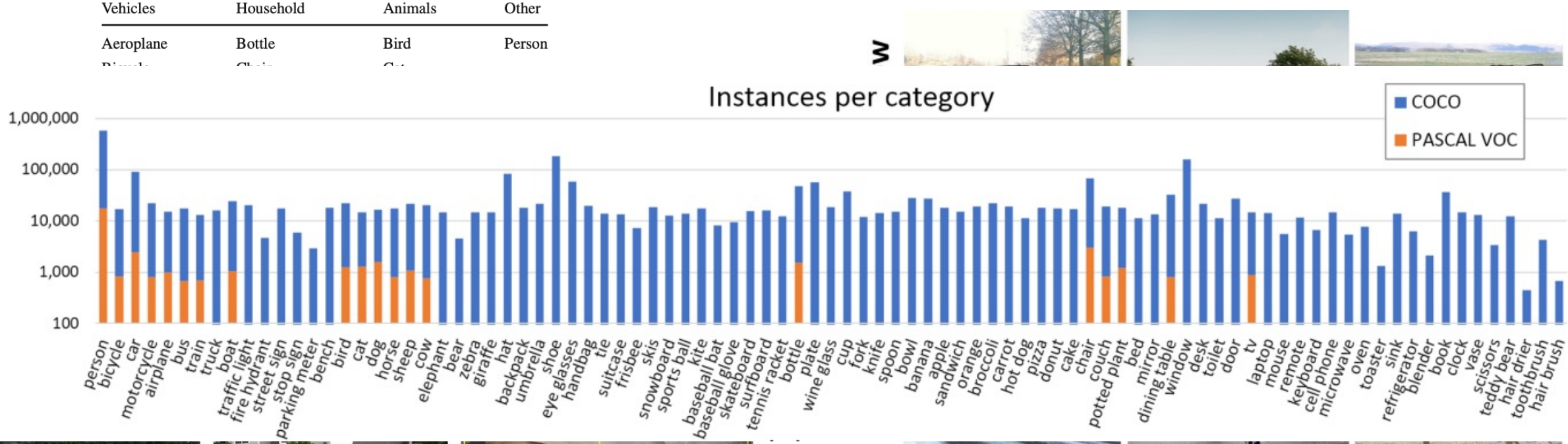
Aeroplane	Bottle	Bird	Person



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COCO Dataset (80 classes, 120K training images)

Annotations come with polygon masks

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Detecting a single object

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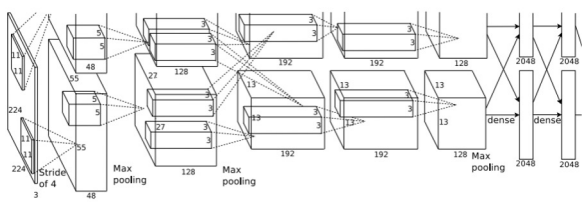


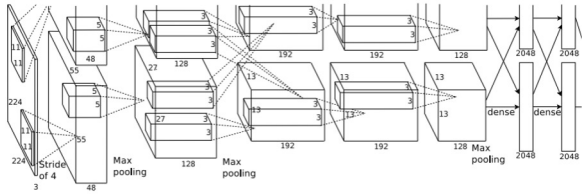
Vector:
4096

Detecting a single object

"What"

Correct label:
Cat

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

Detecting a single object

"What"

Correct label:
Cat

Fully Connected:
4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
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...

Softmax Loss

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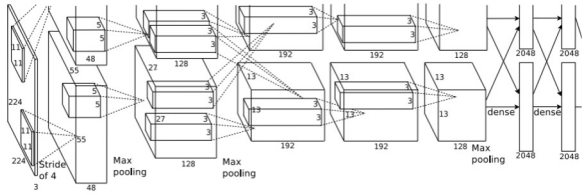

Vector:
4096

Treat localization as a regression problem!

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

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

"Where"

Detecting a single object

"What"

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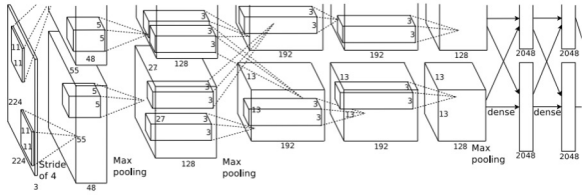


Vector: 4096

Fully Connected: 4096 to 1000

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

Correct label:
Cat

Softmax Loss

Weighted Sum

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!

"Where"

Detecting a single object

"What"

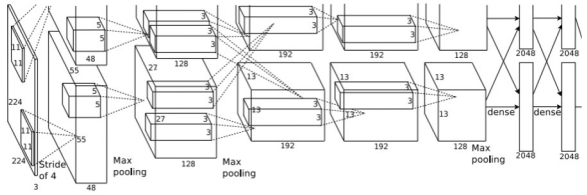
Correct label:
Cat

Fully Connected:
4096 to 1000

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

Softmax Loss

Multitask Loss



Vector:
4096

Weighted Sum

Loss

Treat localization as a regression problem!

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

"Where"

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

Detecting a single object

"What"

Correct label:
Cat

Often pretrained on ImageNet (Transfer learning)

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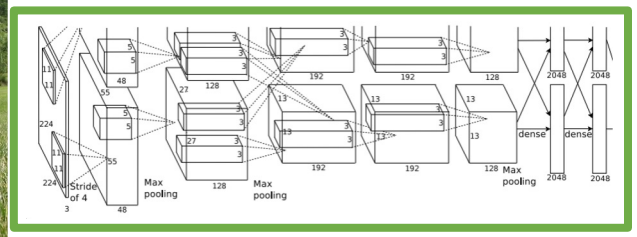

Fully Connected: 4096 to 1000

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

Softmax Loss

Multitask Loss

Weighted Sum

Loss

Vector: 4096

Treat localization as a regression problem!

Fully Connected: 4096 to 4

Box Coordinates (x, y, w, h)

L2 Loss

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

"Where"

Detecting a single object

"What"

Correct label:
Cat

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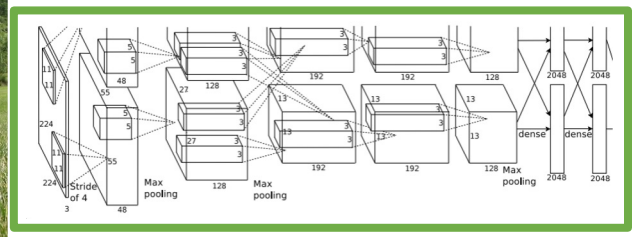


Fully Connected: 4096 to 1000

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

Softmax Loss

Multitask Loss

Weighted Sum

Loss

Vector: 4096

Fully Connected: 4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

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

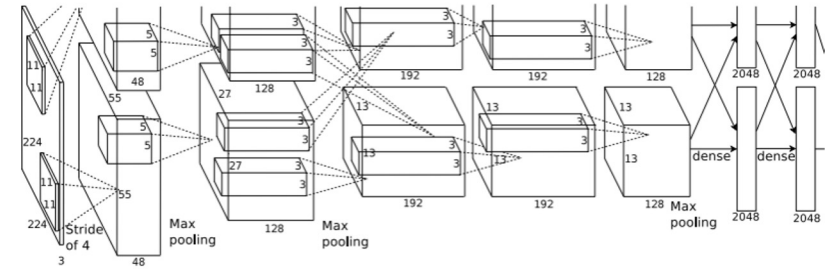
Treat localization as a regression problem!

Problem: Images can have more than one object!

"Where"

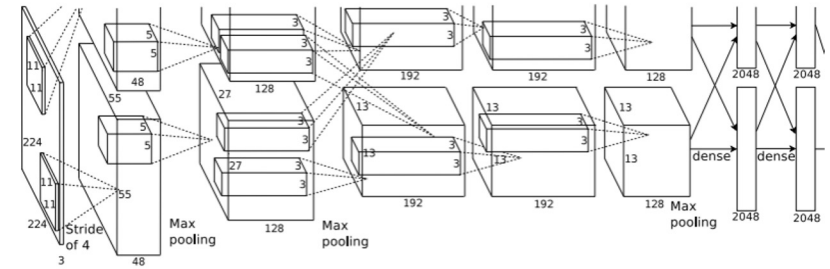
Detecting Multiple Objects

Need different numbers of outputs per image



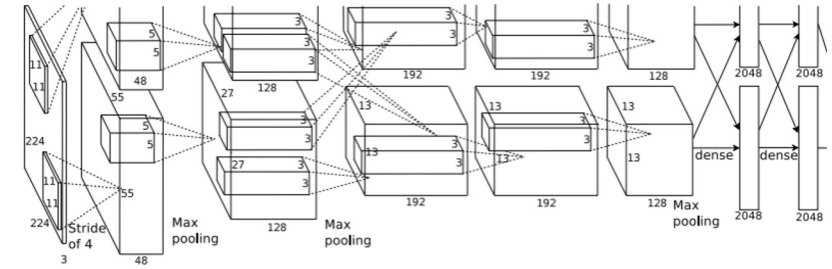
CAT: (x, y, w, h)

4 numbers



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

16 numbers

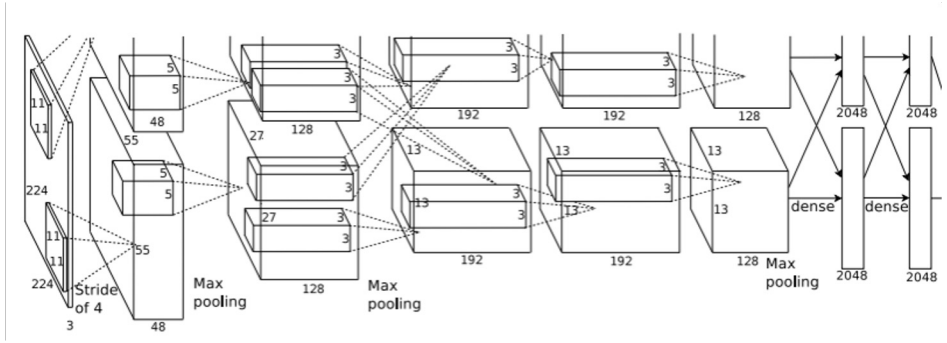


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
....

Many numbers!

Detecting Multiple Objects: **Sliding Window**

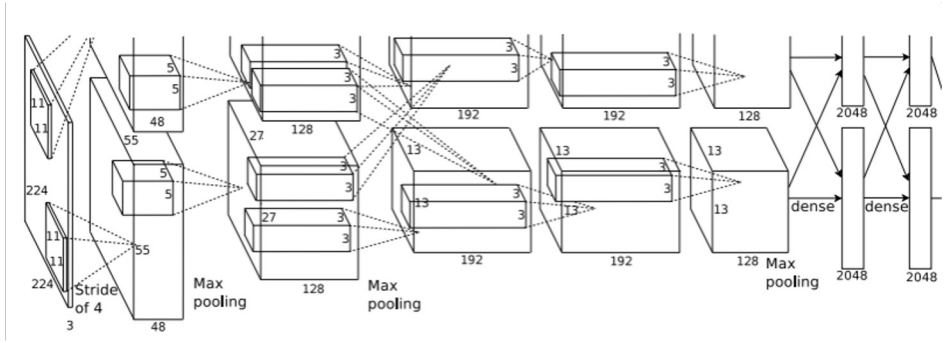
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Detecting Multiple Objects: **Sliding Window**

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



Dog? YES
Cat? NO
Background? NO

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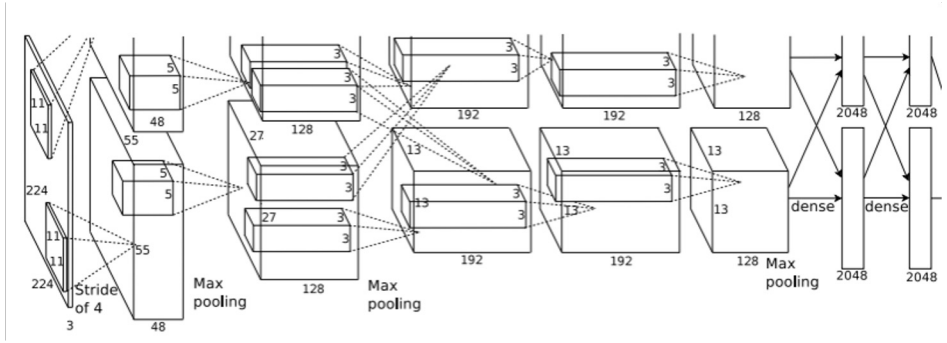
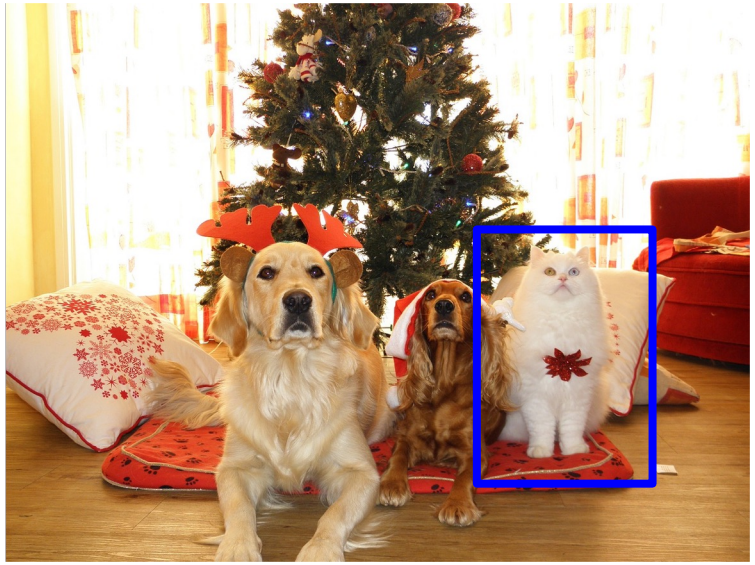
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

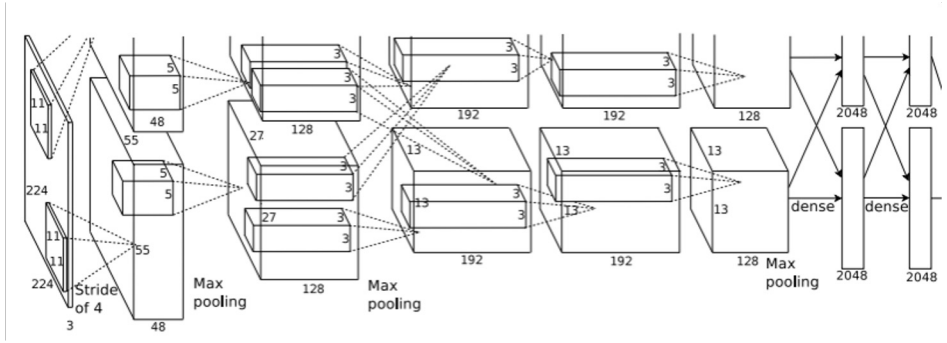


Dog? YES
Cat? NO
Background? NO

Detecting Multiple Objects: **Sliding Window**

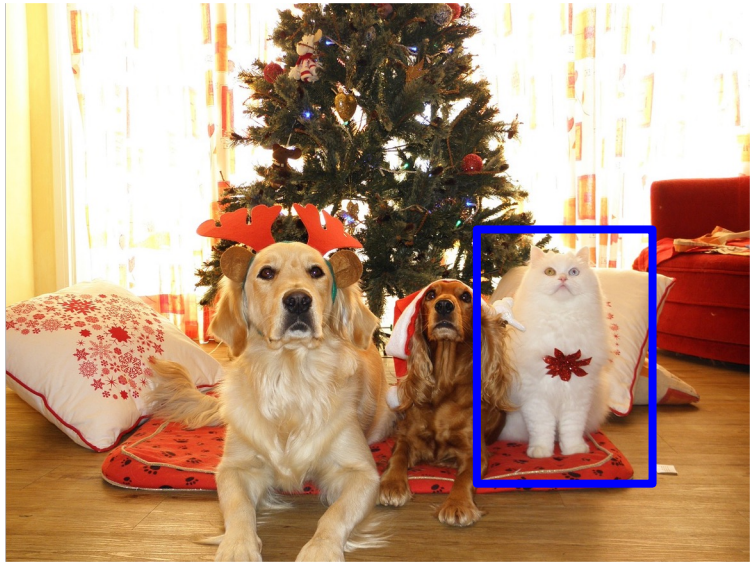


Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? YES
Background? NO

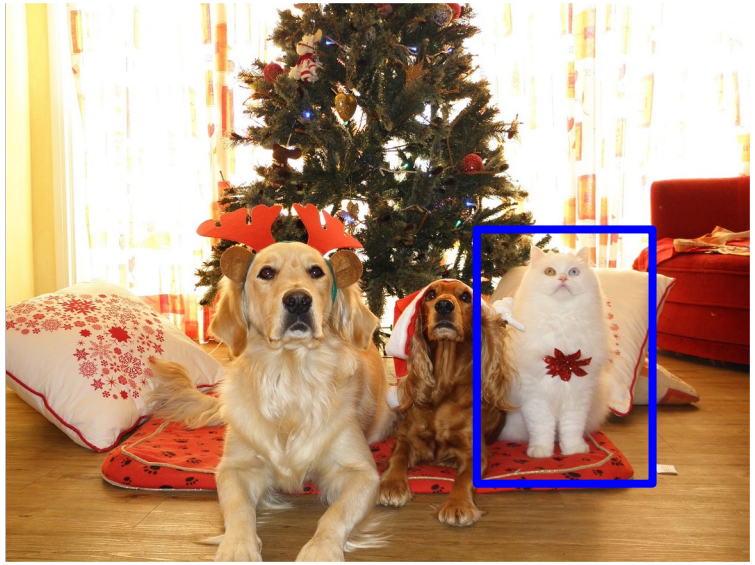
Detecting Multiple Objects: **Sliding Window**



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

Question: How many possible boxes are there in an image of size H x W?

Detecting Multiple Objects: **Sliding Window**

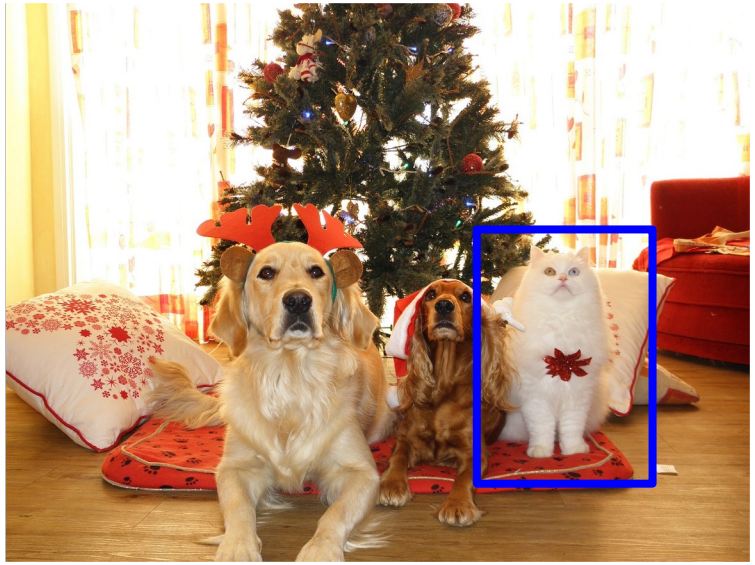


Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

Question: How many possible boxes are there in an image of size H x W?

Consider a box of size h x w:
Possible x positions: W – w + 1
Possible y positions: H – h + 1
Possible positions:
(W – w + 1) * (H – h + 1)

Detecting Multiple Objects: **Sliding Window**



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

Question: How many possible boxes are there in an image of size H x W?

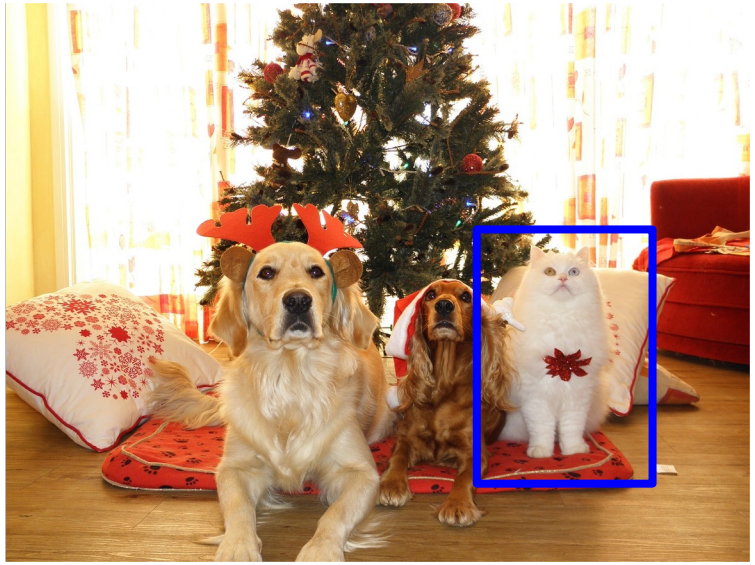
Consider a box of size h x w:
Possible x positions: W – w + 1
Possible y positions: H – h + 1
Possible positions:
(W – w + 1) * (H – h + 1)

Total possible boxes:

$$\sum_{h=1}^{H}\sum_{w=1}^{W}(W-w+1)(H-h+1)$$

$$=\frac{H(H+1)}{2}\frac{W(W+1)}{2}$$

Detecting Multiple Objects: **Sliding Window**



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

800 x 600 image has ~58M boxes! No way we can evaluate them all

Question: How many possible boxes are there in an image of size H x W?

Consider a box of size h x w:
Possible x positions: W – w + 1
Possible y positions: H – h + 1
Possible positions:
(W – w + 1) * (H – h + 1)

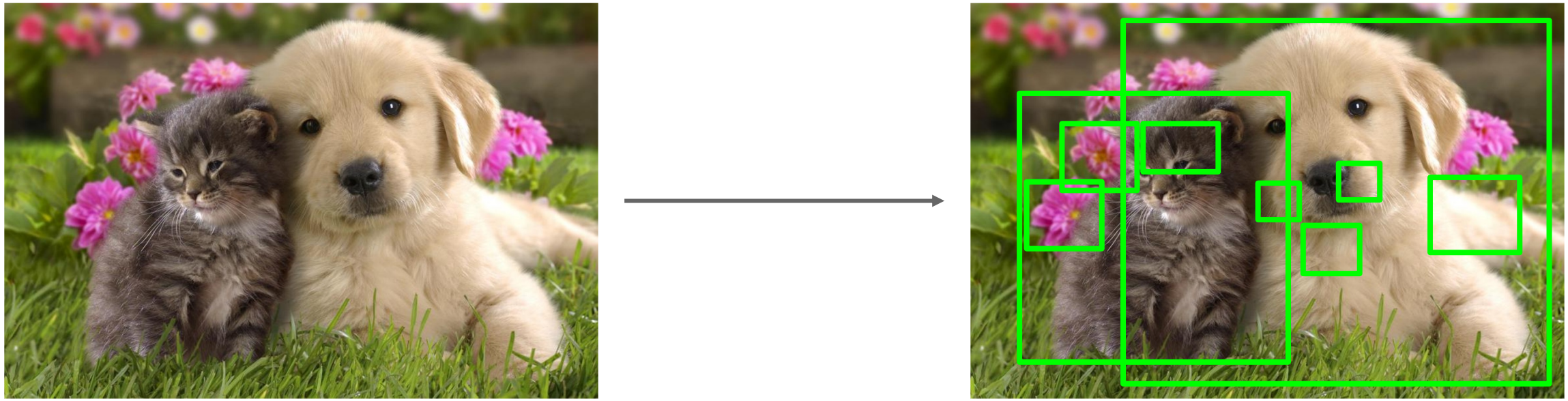
Total possible boxes:

$$\sum_{h=1}^{H}\sum_{w=1}^{W}(W-w+1)(H-h+1)$$

$$=\frac{H(H+1)}{2}\frac{W(W+1)}{2}$$

Region Proposals

- Find a small set of boxes that are likely to cover all objects
- Often based on heuristics: e.g. look for “blob-like” image regions
- 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: Region-Based CNN

Input image

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

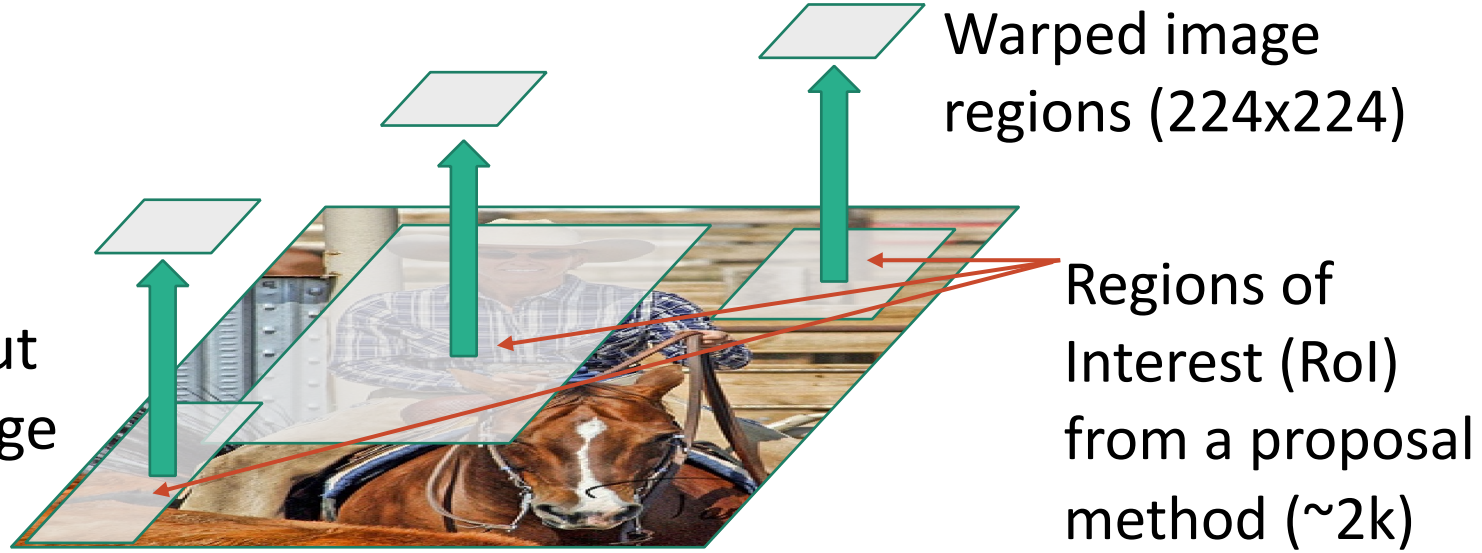
R-CNN: Region-Based CNN

Input image

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

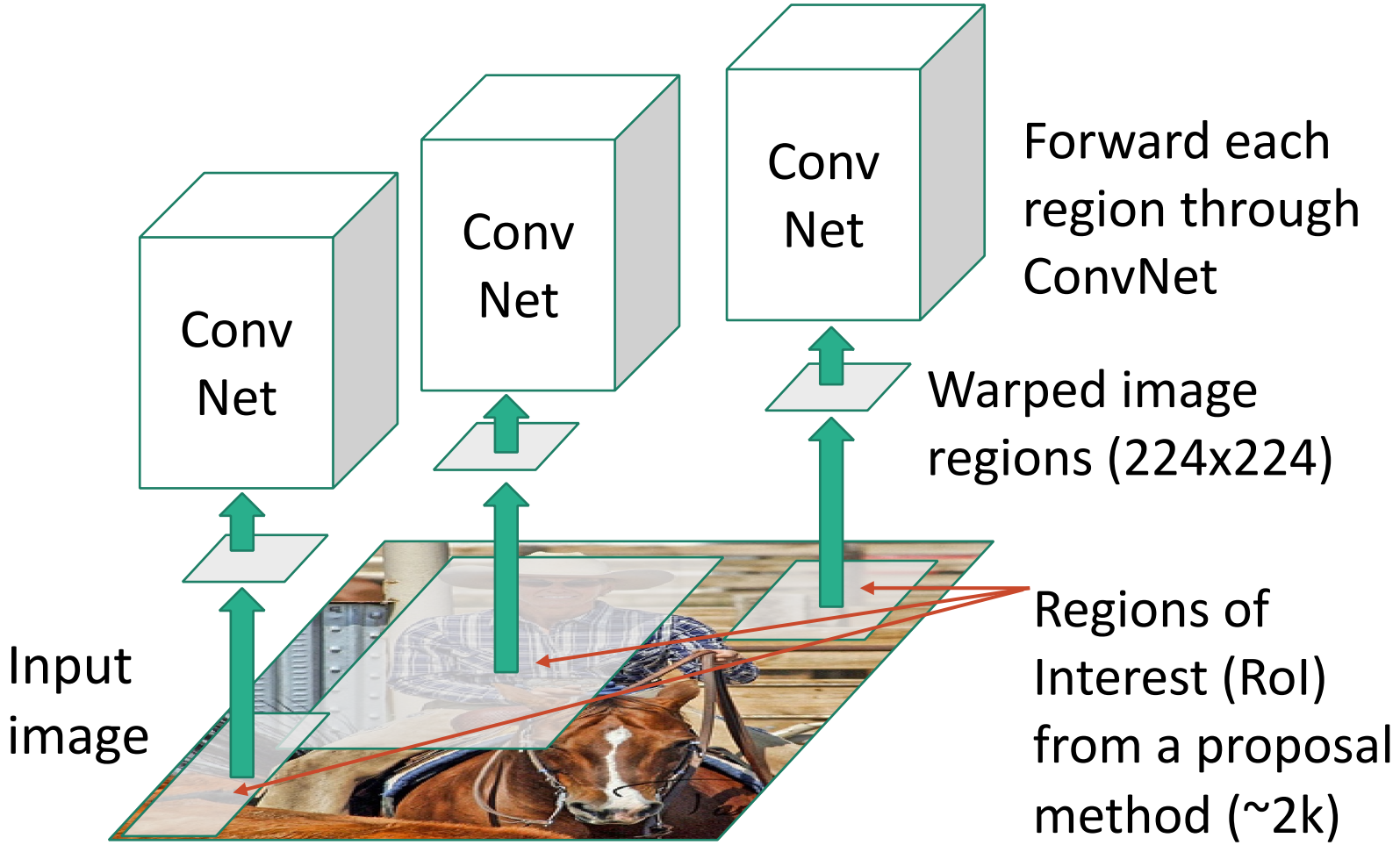
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN: Region-Based 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.

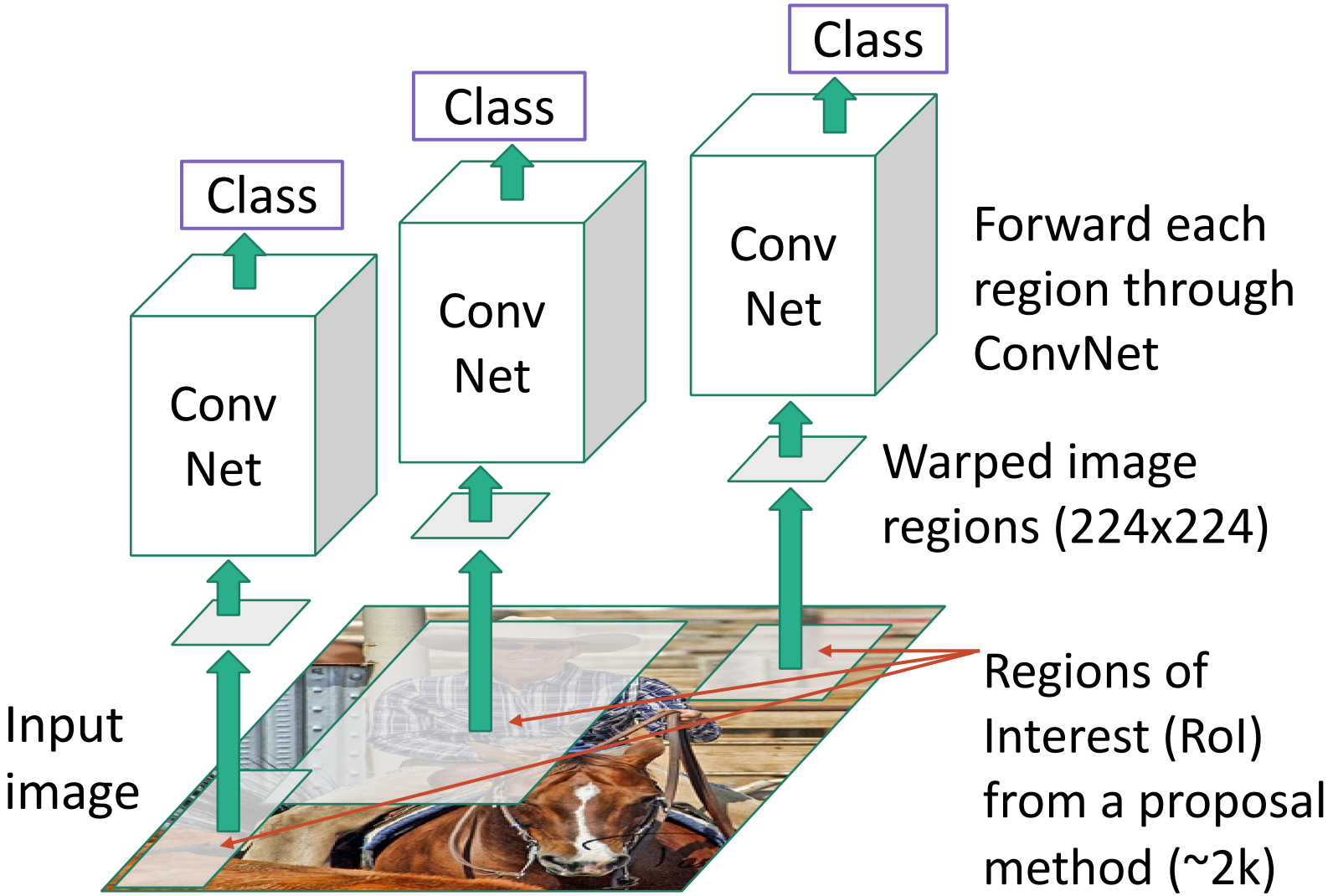
R-CNN: Region-Based CNN



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

R-CNN: Region-Based CNN

Classify each region



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
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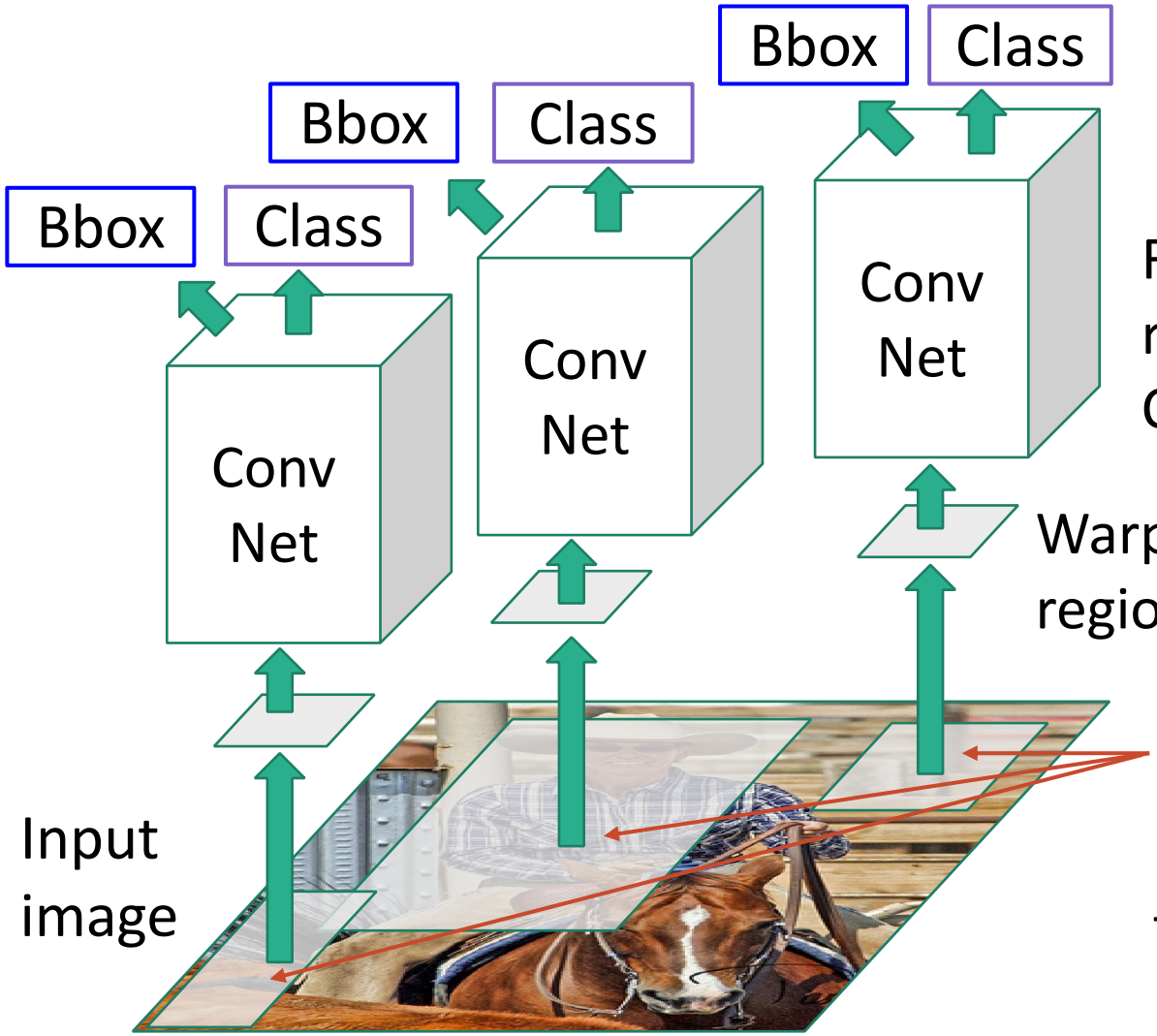
R-CNN: Region-Based CNN

Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)



Forward each region through ConvNet

Warped image regions (224x224)

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

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
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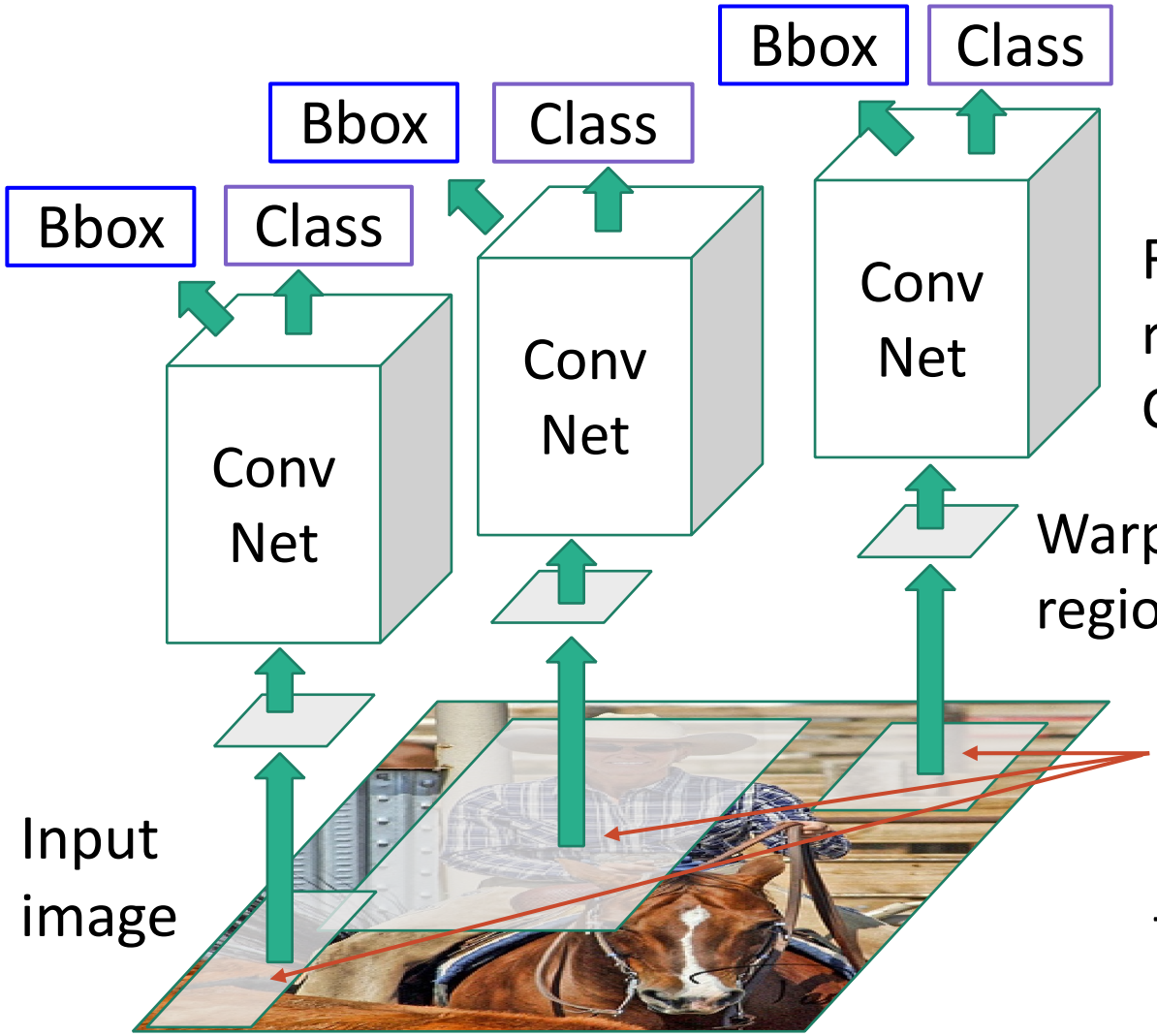
R-CNN: Region-Based CNN



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Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)

Region proposal: (p_x, p_y, p_h, p_w)
Transform: (t_x, t_y, t_h, t_w)
Output box: (b_x, b_y, b_h, b_w)

Translate relative to box size:
$b_x = p_x + p_w t_x$ $\quad b_y = p_y + p_h t_y$

Log-space scale transform:
$b_w = p_w \exp(t_w)$ $\quad b_h = p_h \exp(t_h)$

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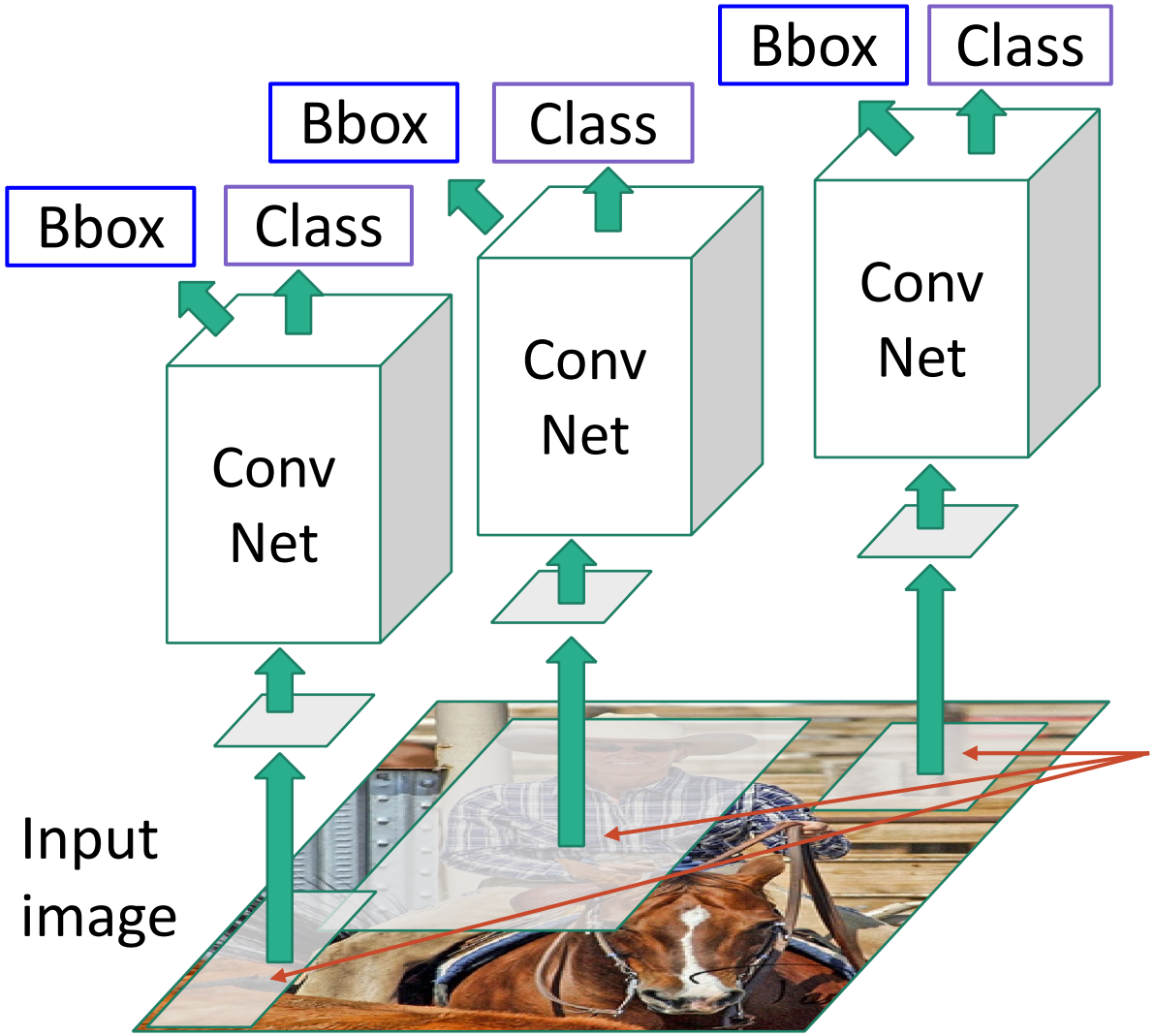
R-CNN: Test-time



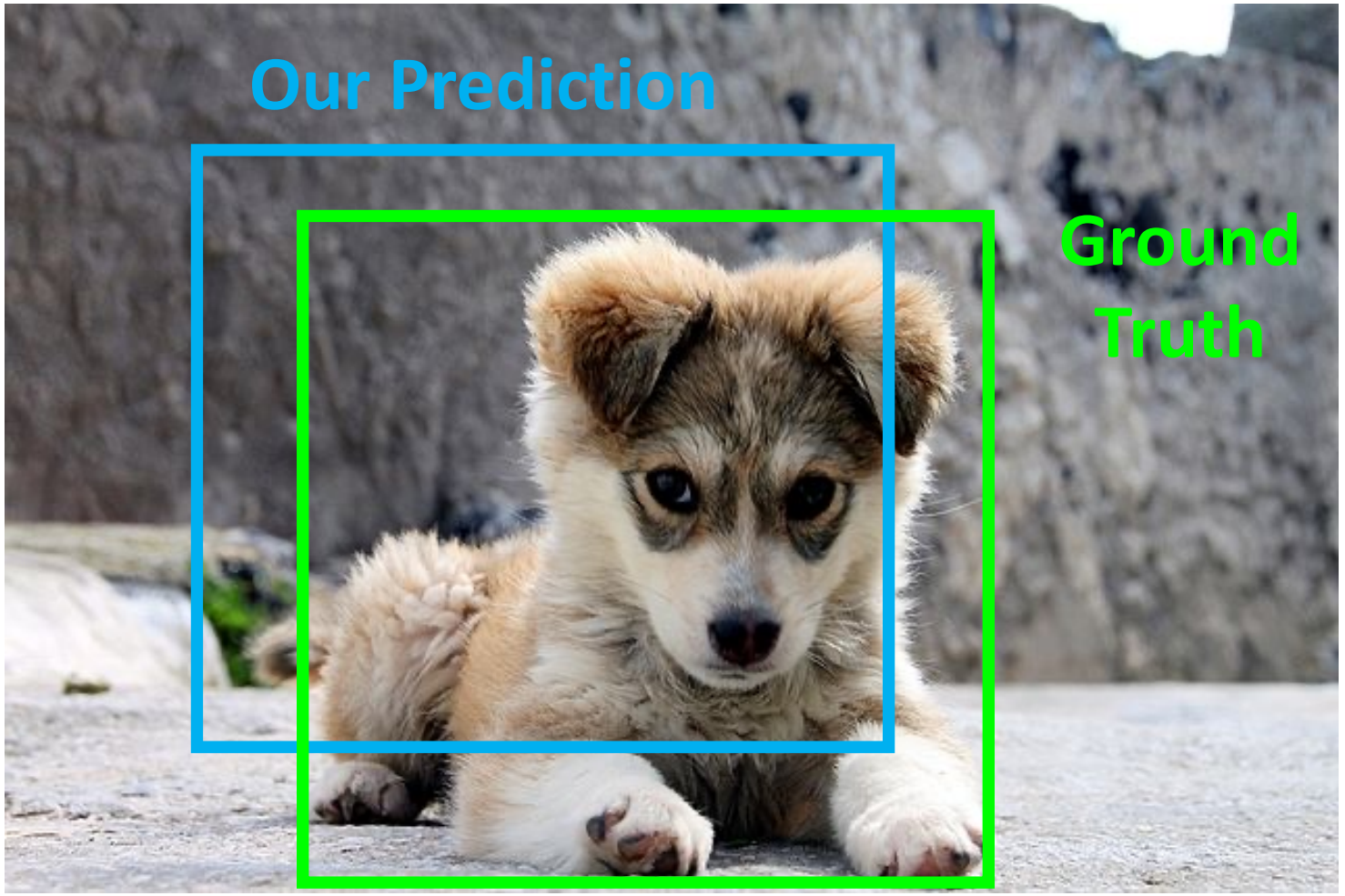
Input: Single RGB Image

1. Run region proposal method to compute ~2000 region proposals
2. Resize each region to 224x224 and run independently through CNN to predict class scores and bbox transform
3. Use scores to select a subset of region proposals to output
   (Many choices here: threshold on background, or per-category? Or take top K proposals per image?)
4. Compare with ground-truth boxes

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

Comparing Boxes: Intersection over Union (IoU)

How can we compare our prediction to the ground-truth box?



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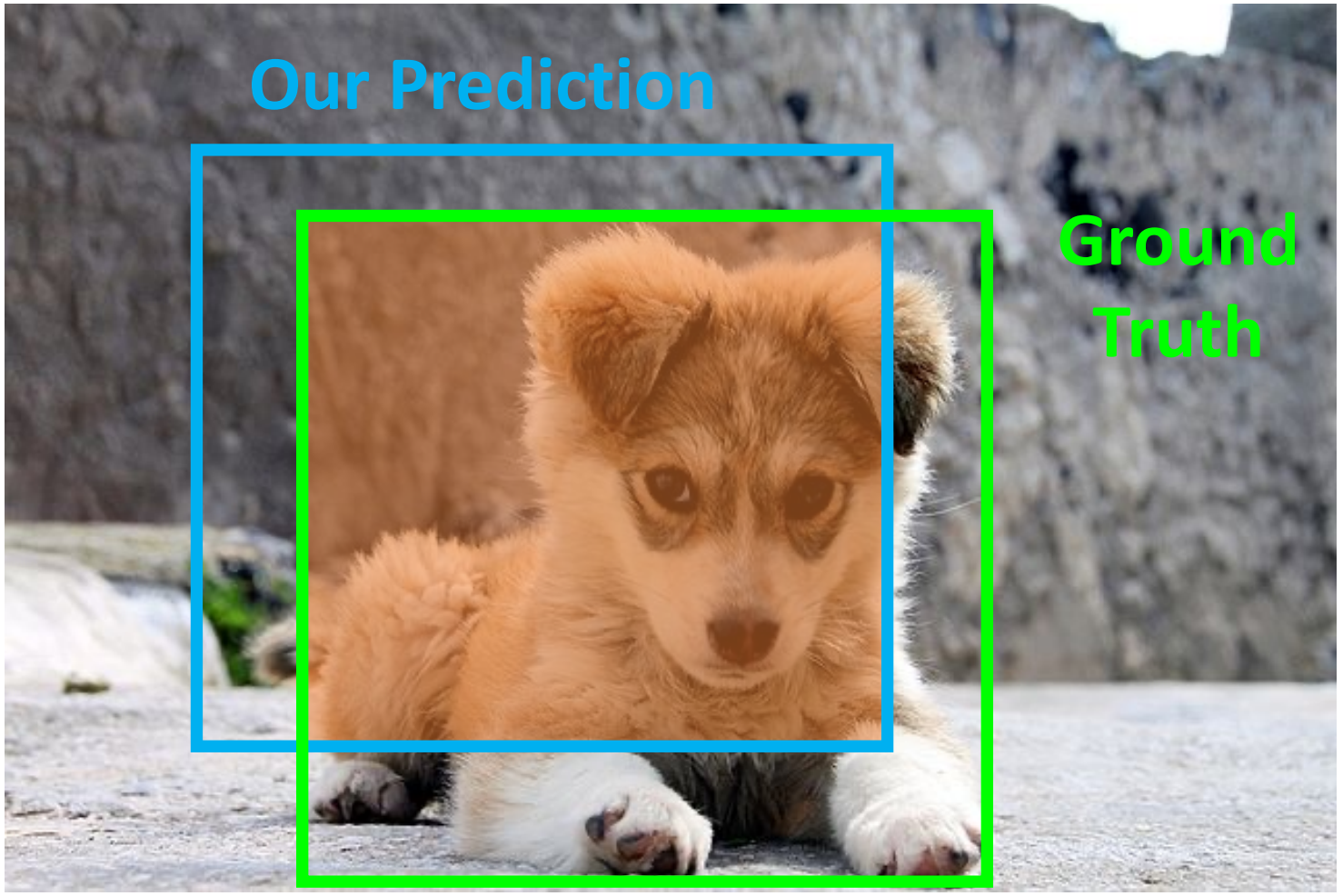
(Also called “Jaccard similarity” or “Jaccard index”):

$$\frac{Area\ of\ Intersection}{Area\ of\ Union}$$



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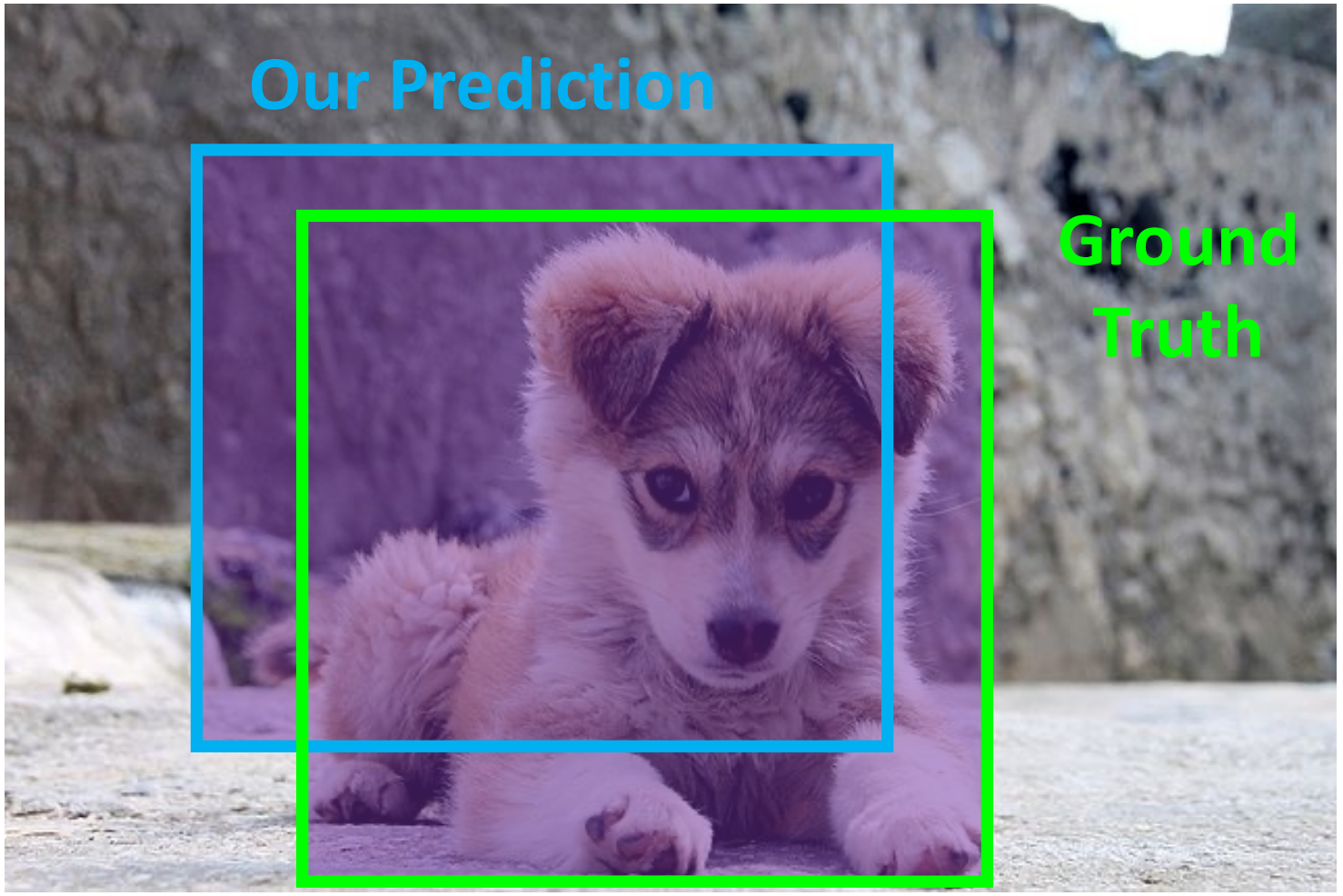

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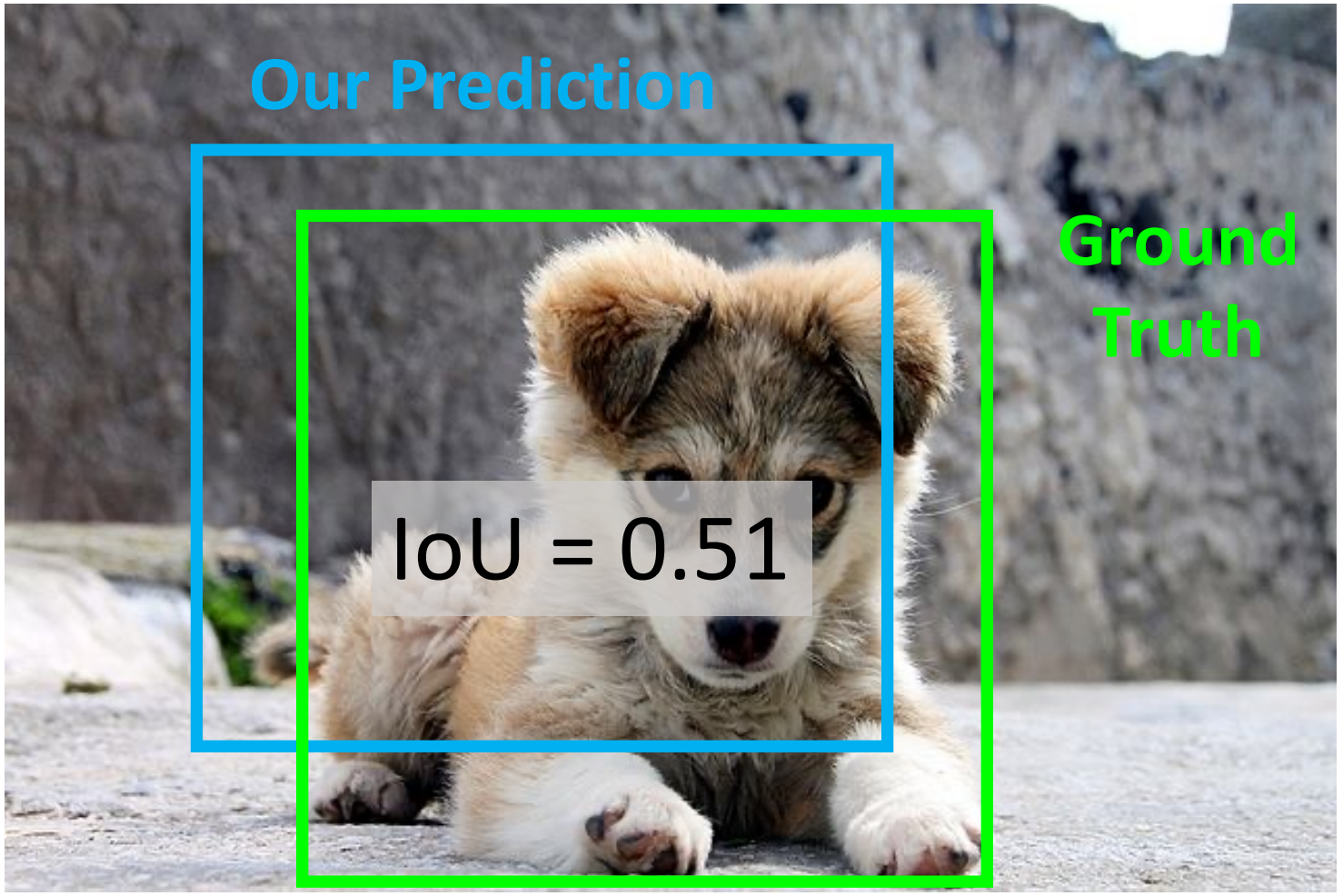
IoU > 0.5 is “decent”



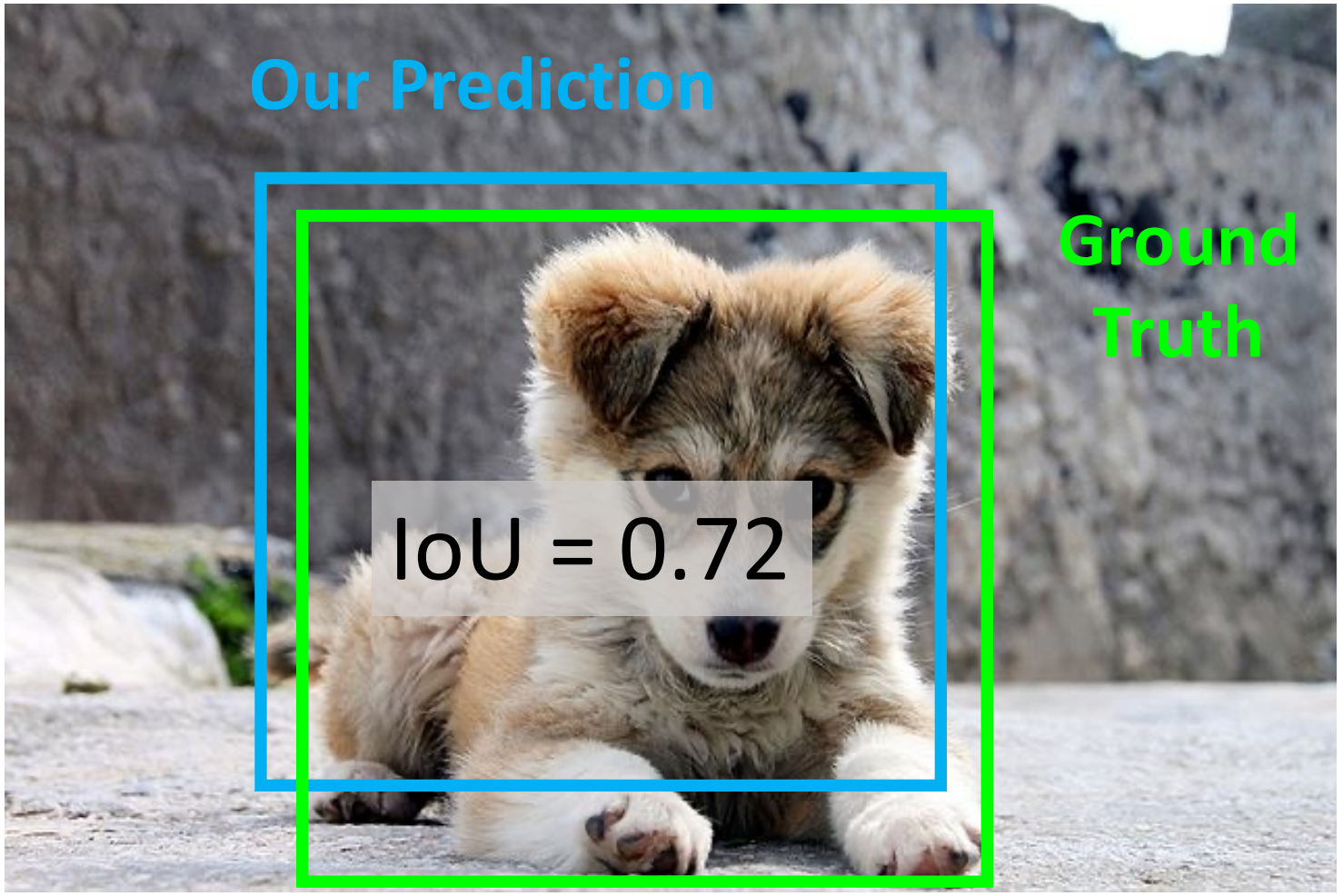
Comparing Boxes: Intersection over Union (IoU)

How can we compare our prediction to the ground-truth box?

Intersection over Union (IoU)
(Also called “Jaccard similarity” or “Jaccard index”):

$$\frac{\textit{Area of Intersection}}{\textit{Area of Union}}$$

IoU > 0.5 is “decent”,
IoU > 0.7 is “pretty good”,



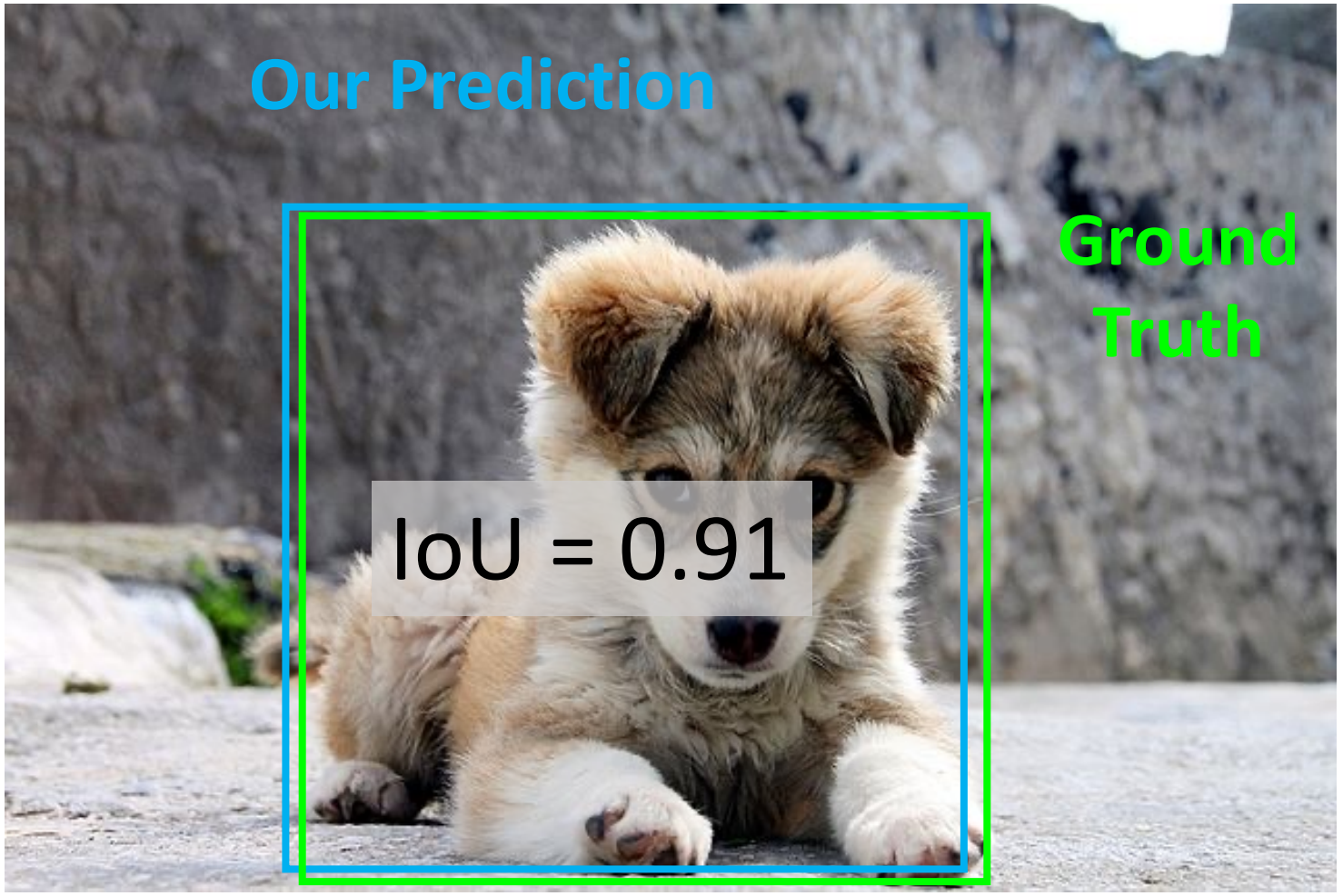
Comparing Boxes: Intersection over Union (IoU)

How can we compare our prediction to the ground-truth box?

Intersection over Union (IoU)
(Also called “Jaccard similarity” or “Jaccard index”):

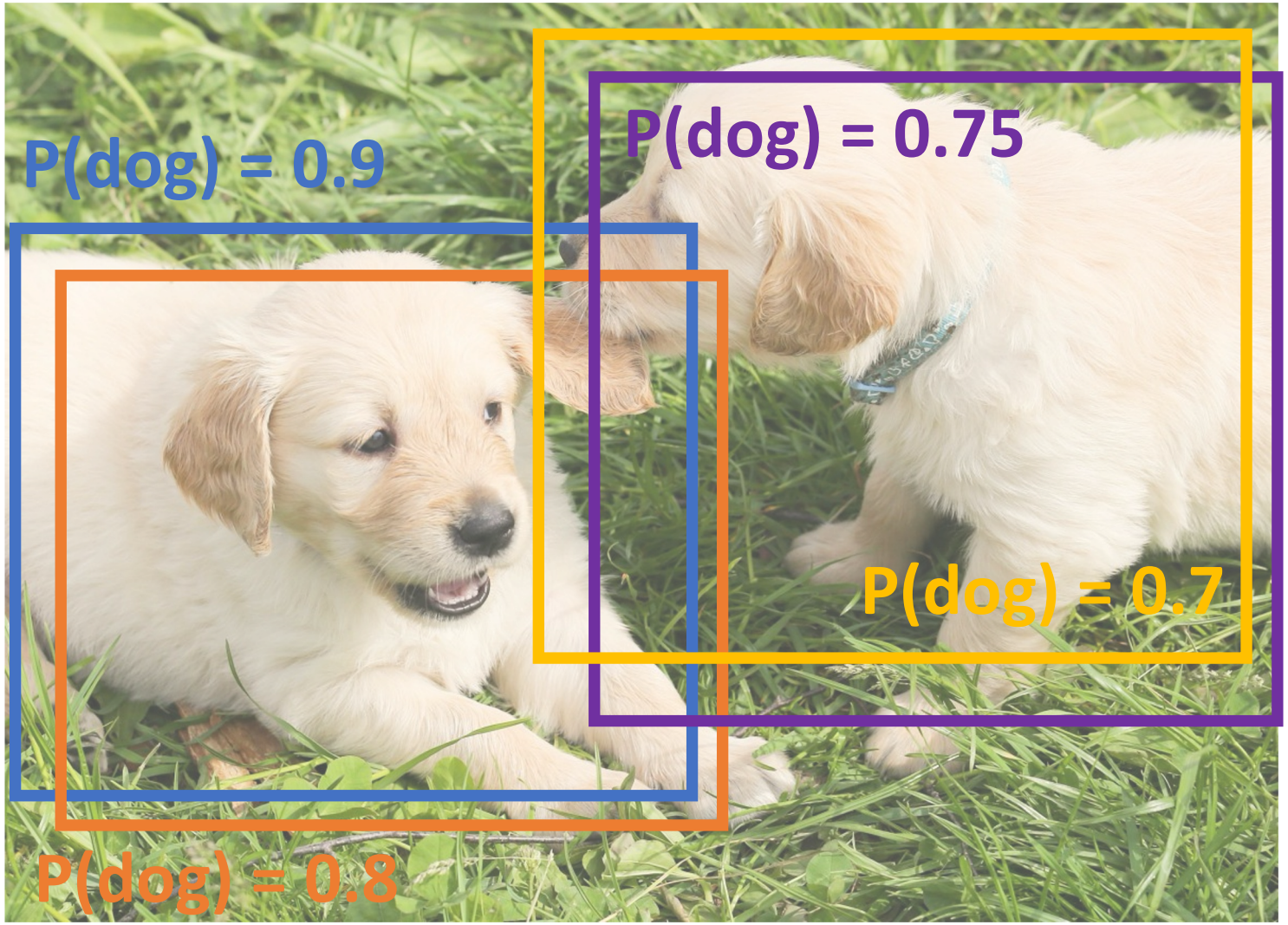
$$\frac{\textit{Area of Intersection}}{\textit{Area of Union}}$$

IoU > 0.5 is “decent”,
IoU > 0.7 is “pretty good”,
IoU > 0.9 is “almost perfect”



Overlapping Boxes

Problem: Object detectors often output many overlapping detections:



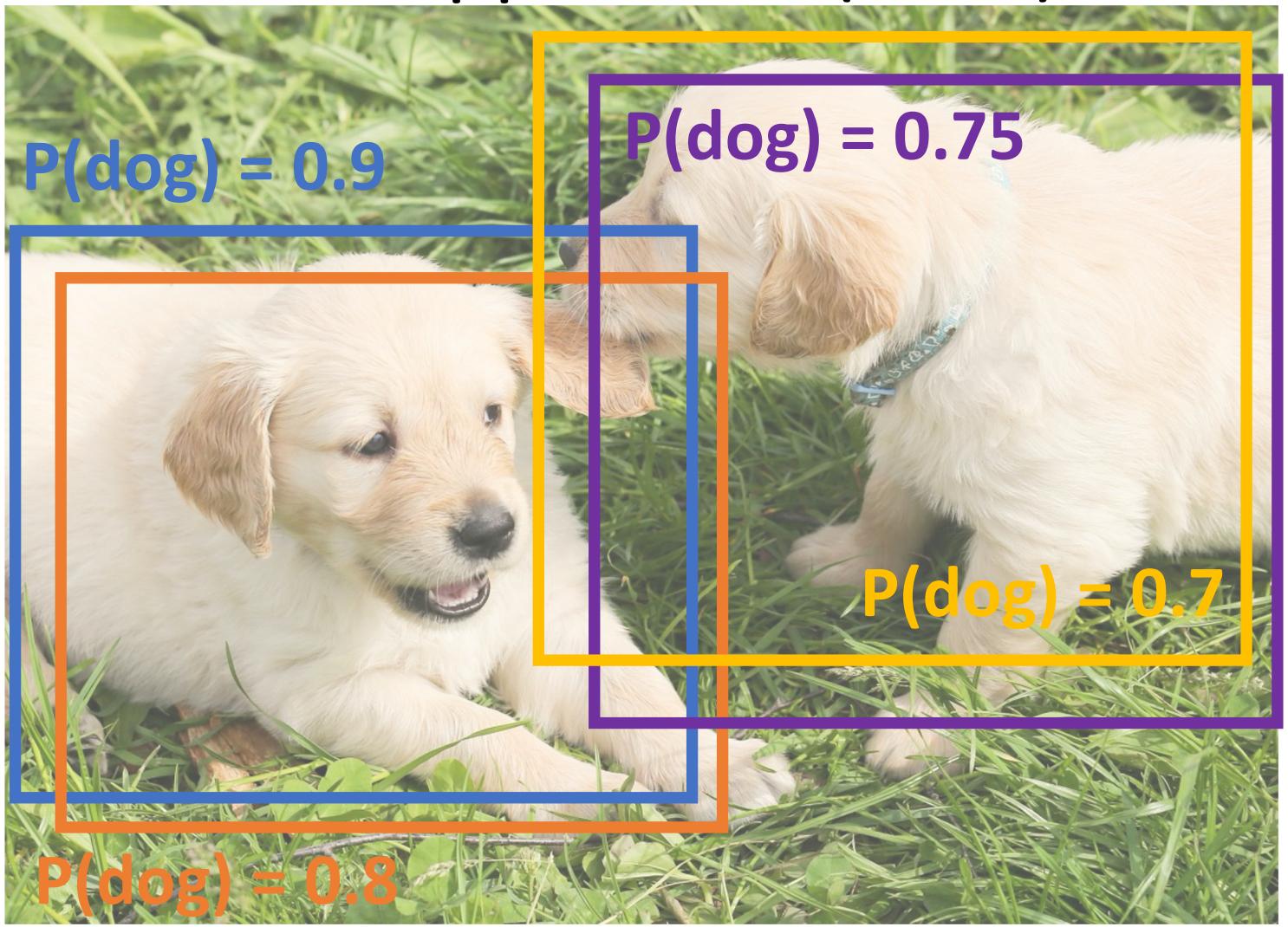
Puppy image is CC0 Public Domain

Overlapping Boxes: Non-Max Suppression (NMS)

Problem: Object detectors often output many overlapping detections:

Solution: Post-process raw detections using **Non-Max Suppression (NMS)**

1. Select next highest-scoring box
2. Eliminate lower-scoring boxes with IoU > threshold (e.g. 0.7)
3. If any boxes remain, GOTO 1



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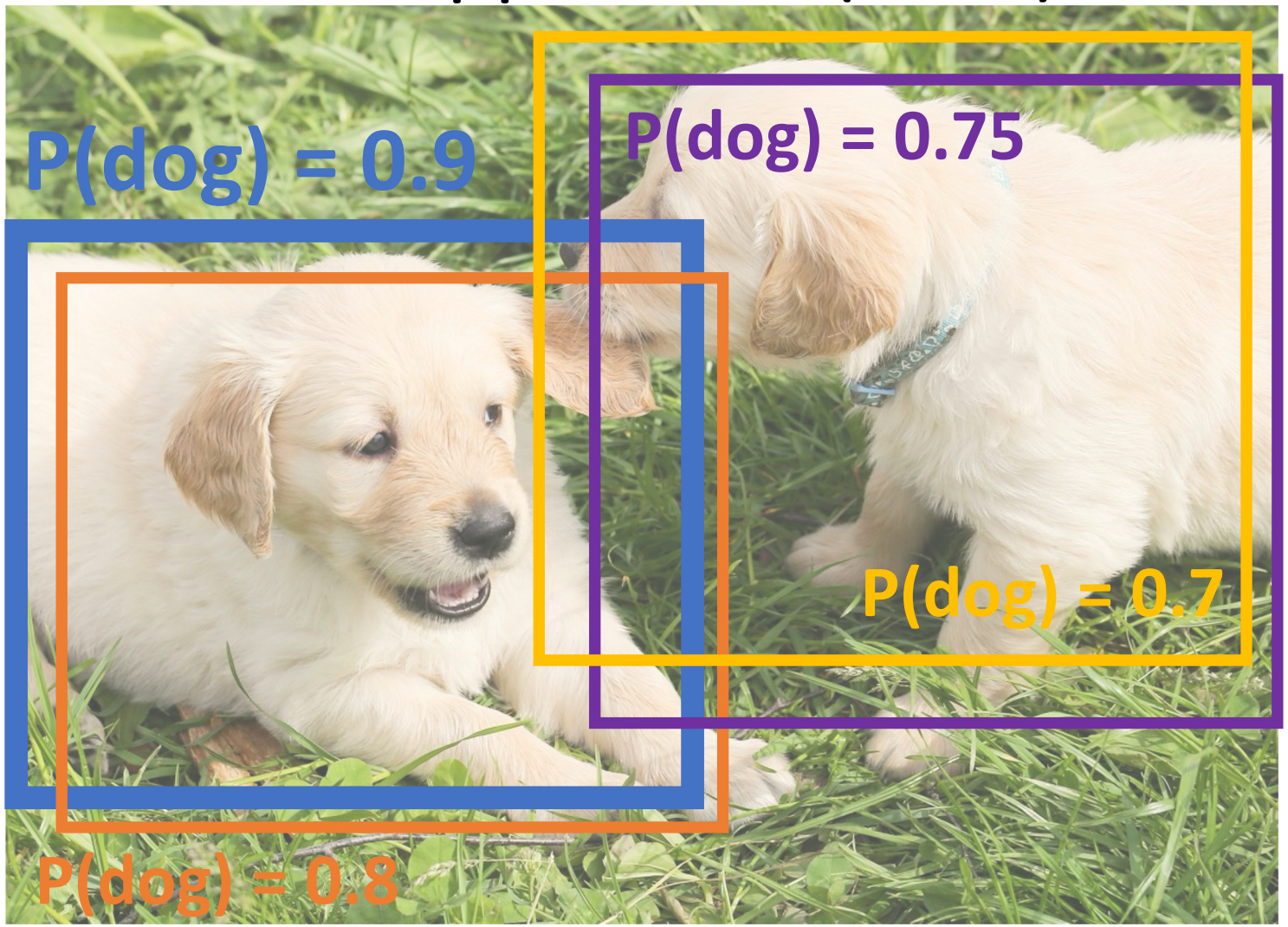
IoU(■, ■) = **0.78**
IoU(■, ■) = 0.05
IoU(■, ■) = 0.07



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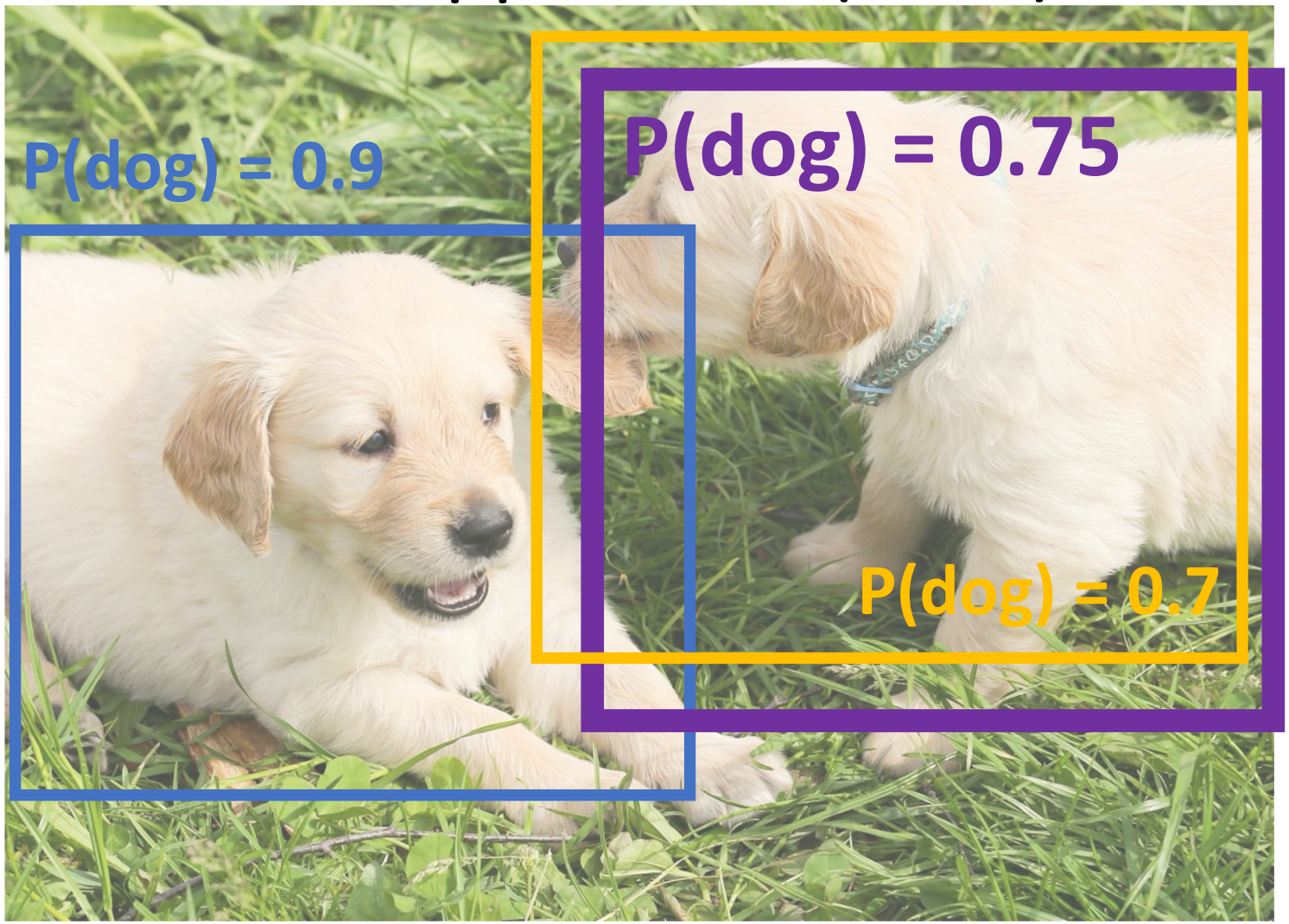
IoU(■, ■) = **0.74**



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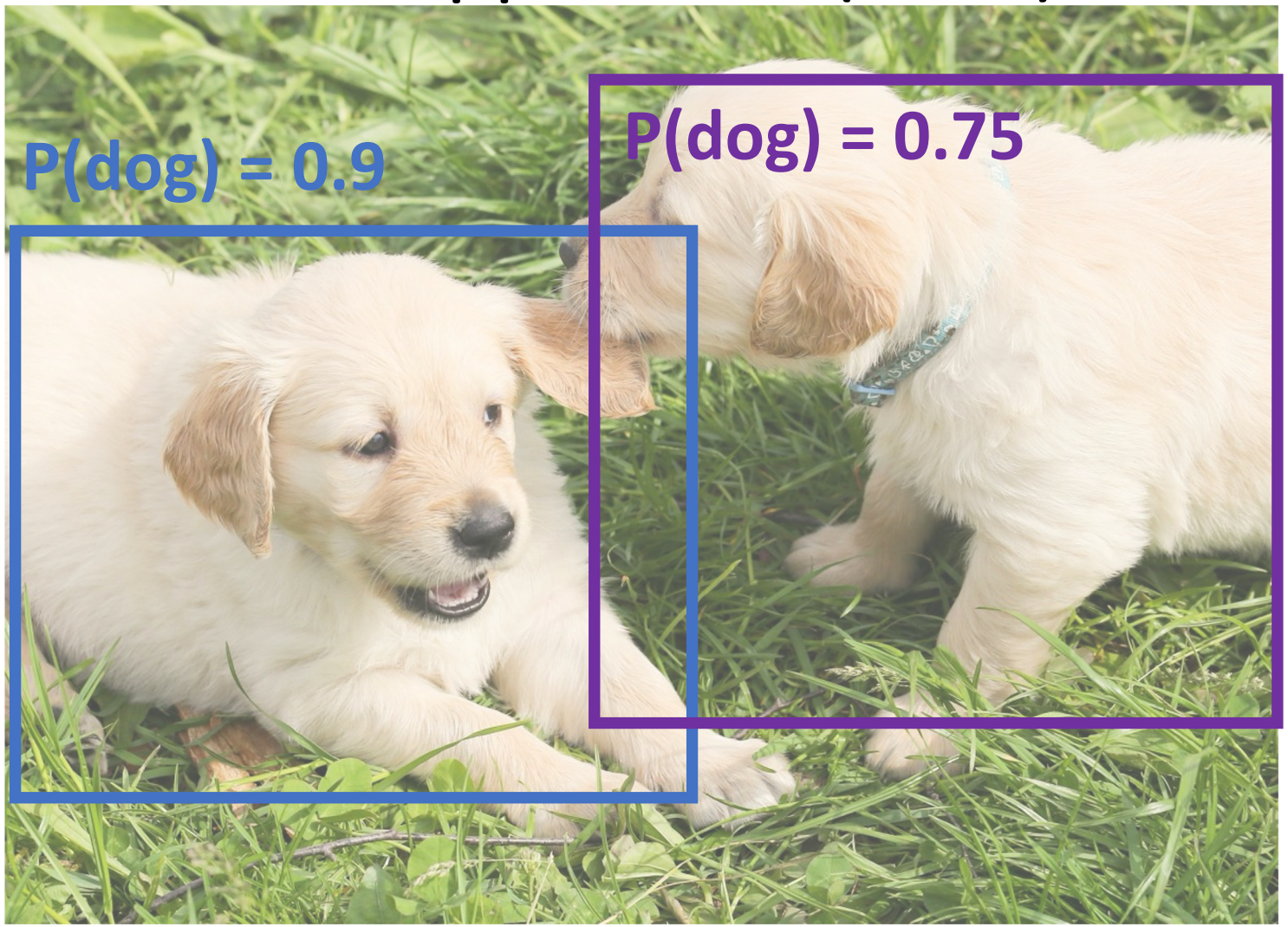

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Problem: NMS may eliminate ”good” boxes when objects are highly overlapping… no good solution =(

Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve

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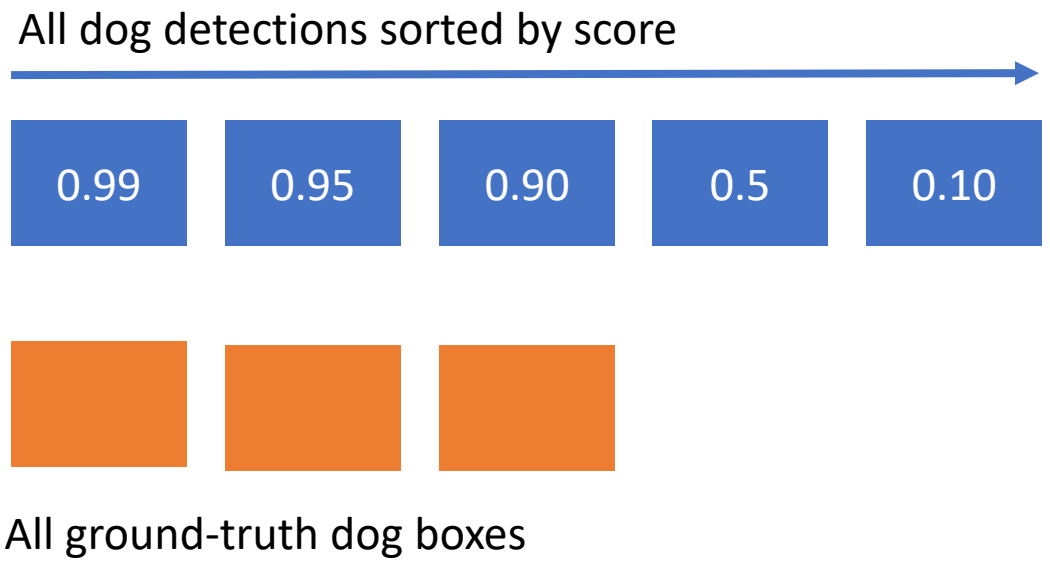

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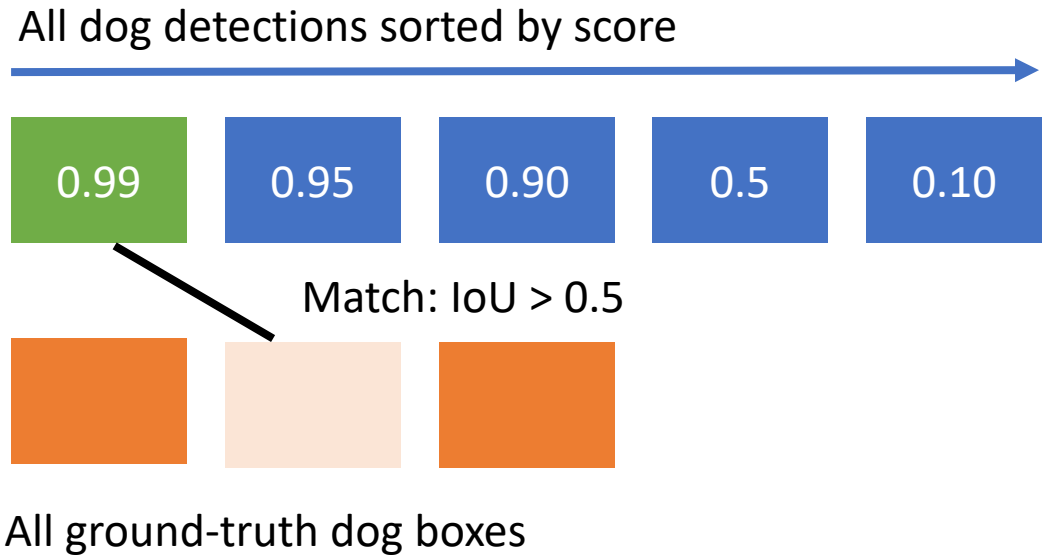

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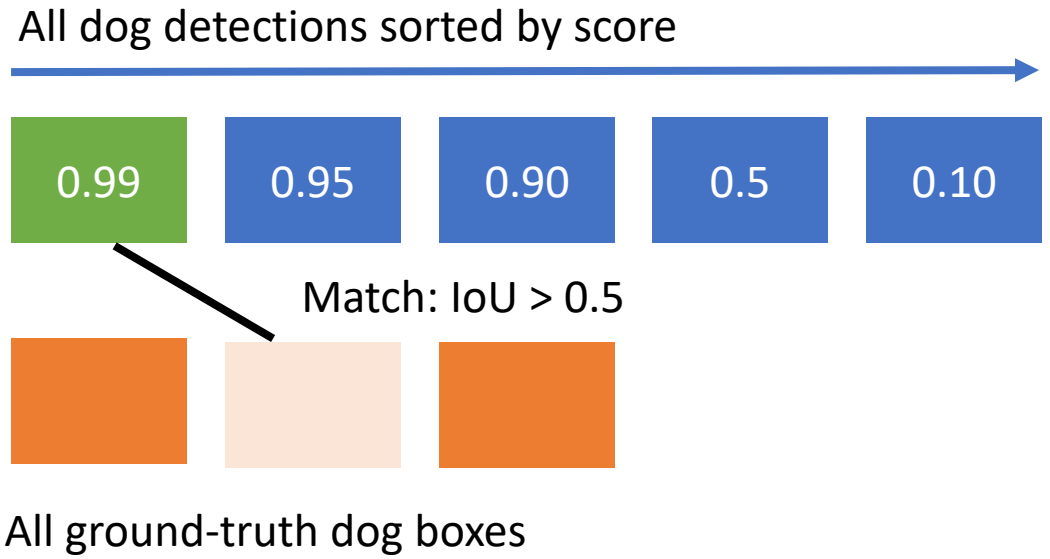
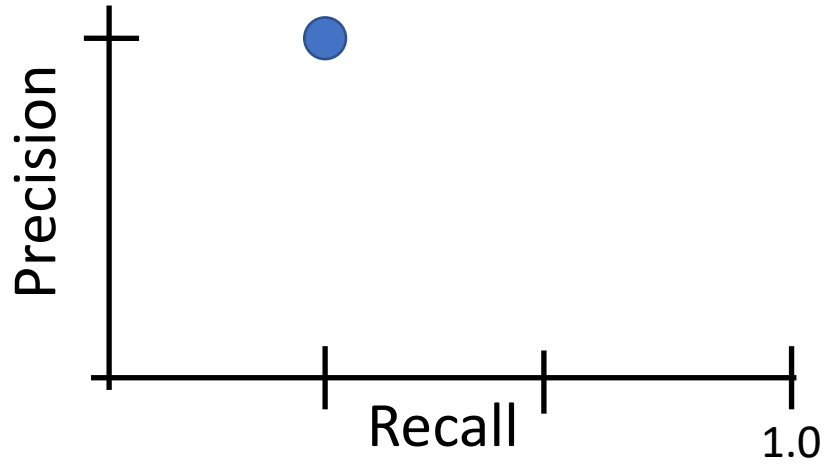


Precision = 1/1 = 1.0
Recall = 1/3 = 0.33



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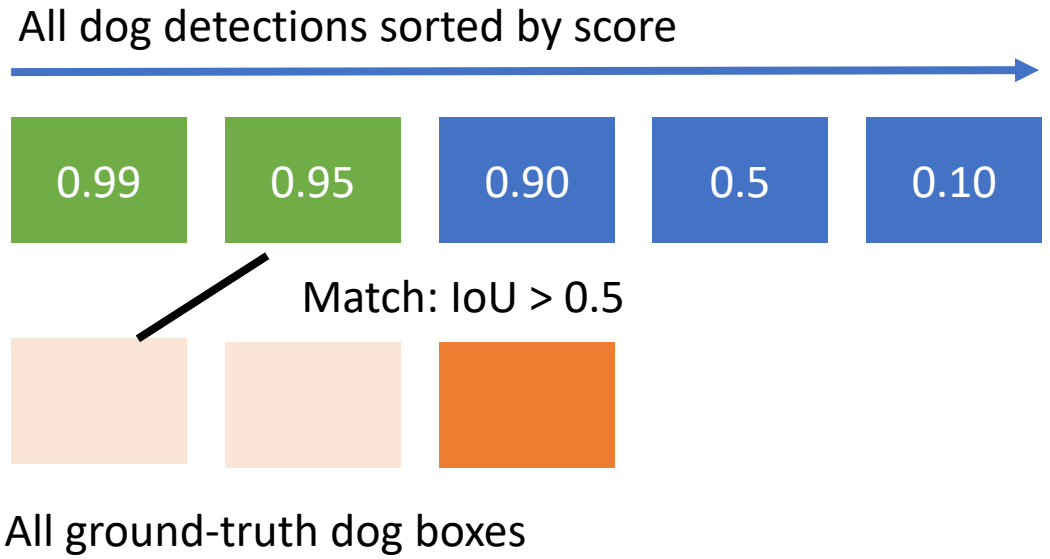
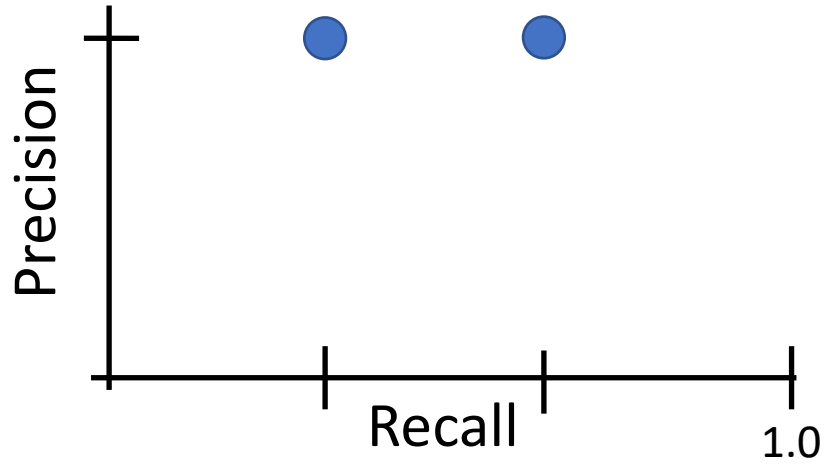


Precision = 2/2 = 1.0
Recall = 2/3 = 0.67



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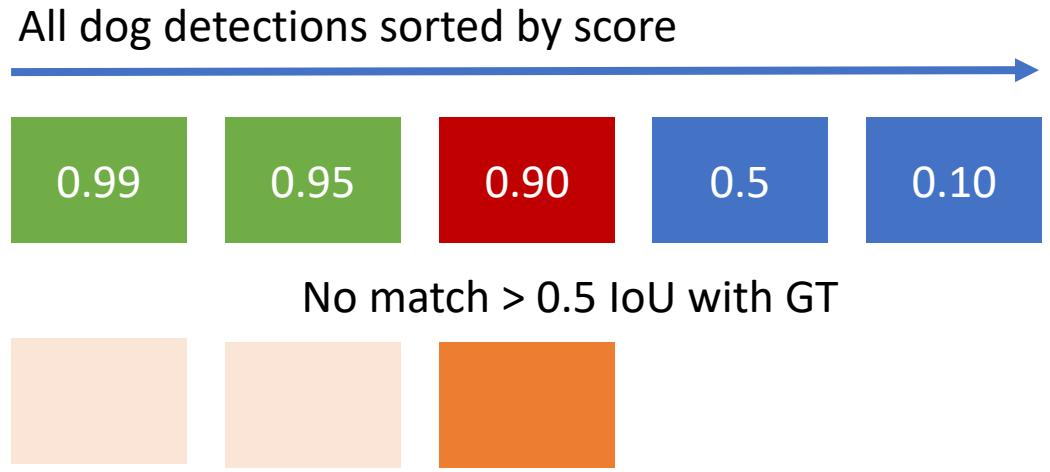

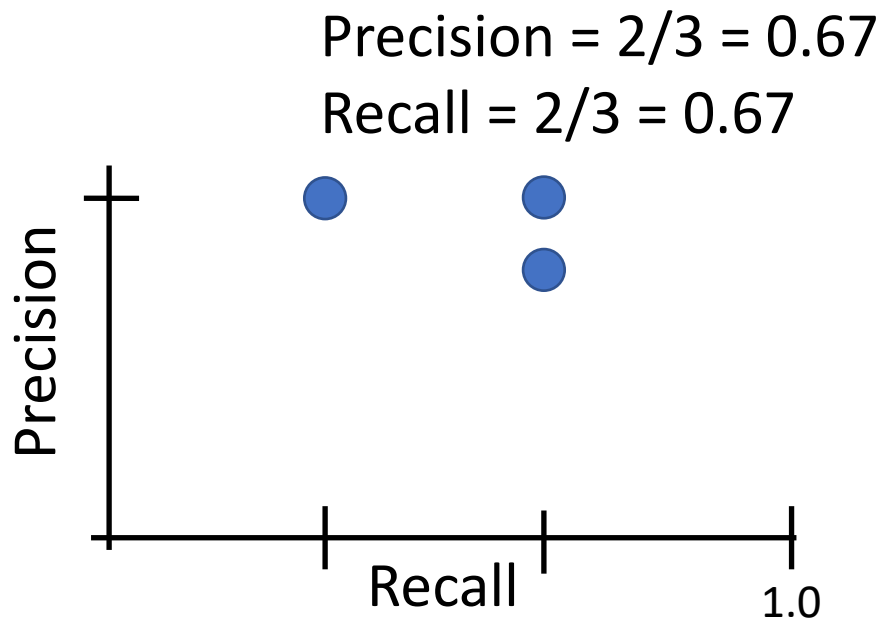

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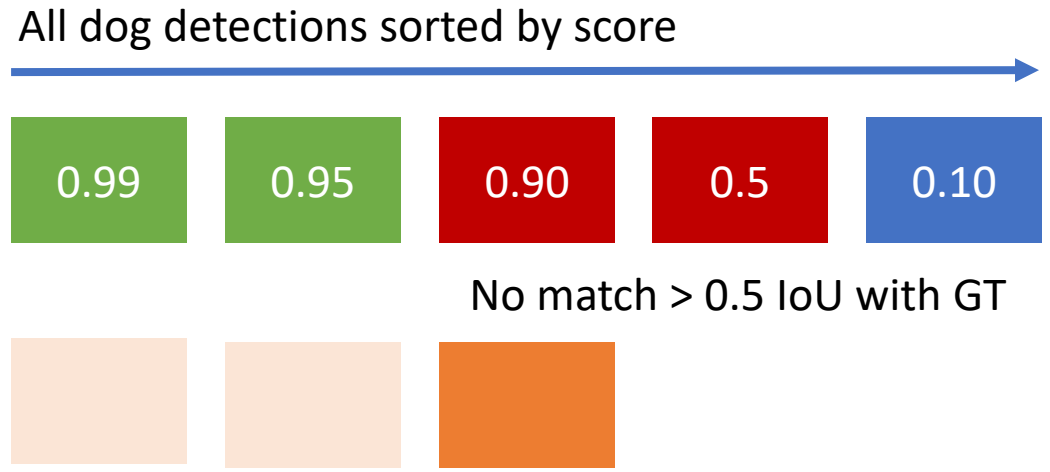

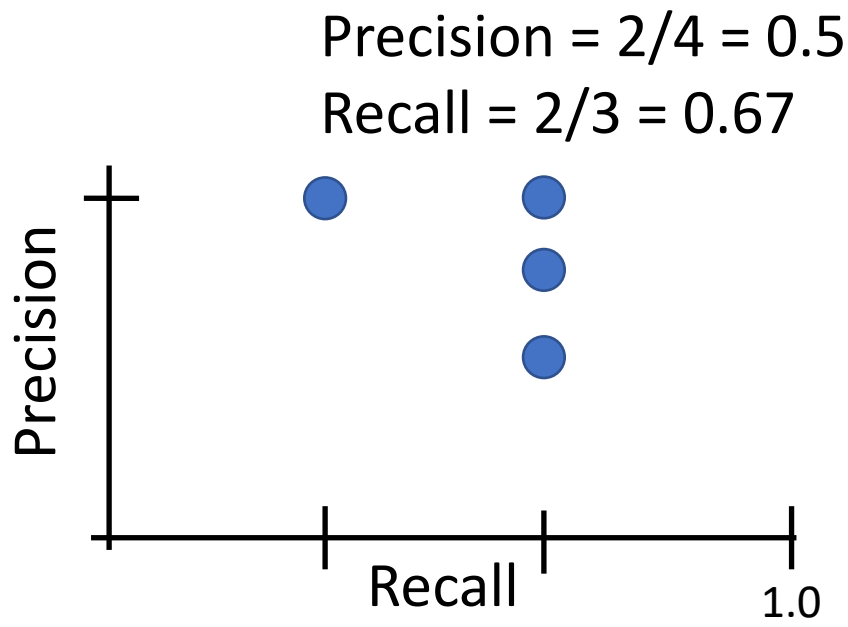

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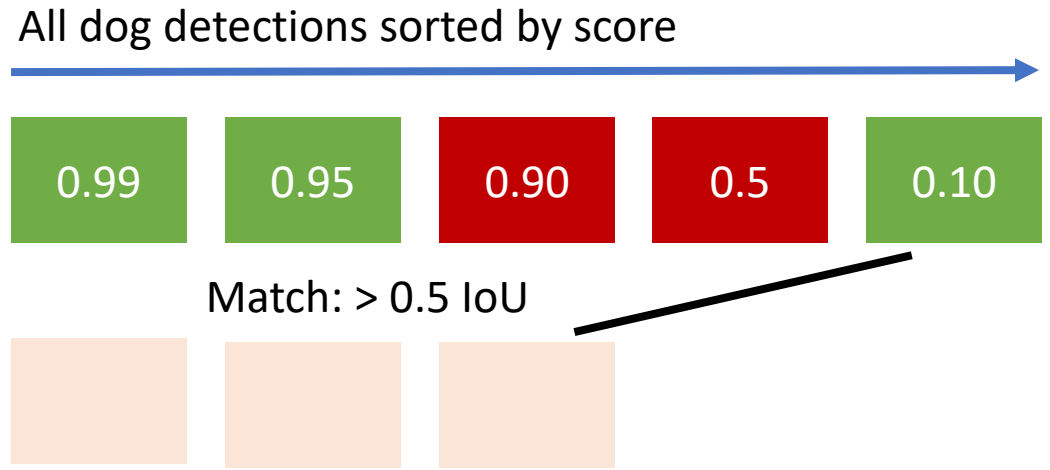
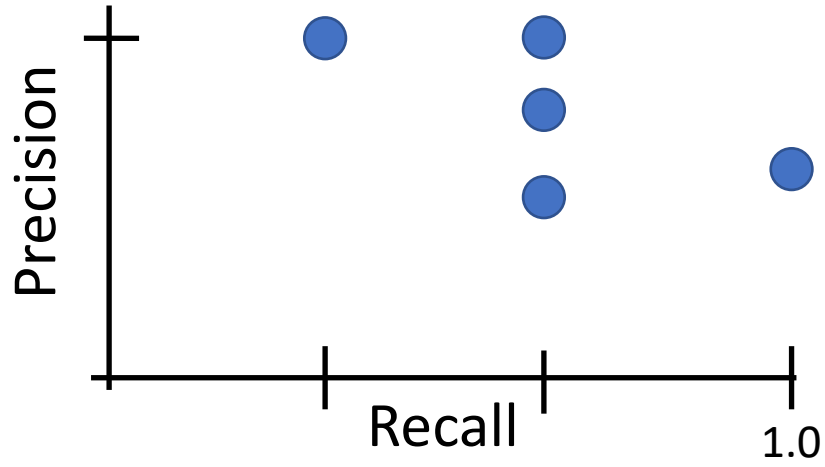


Precision = 3/5 = 0.6
Recall = 3/3 = 1.0



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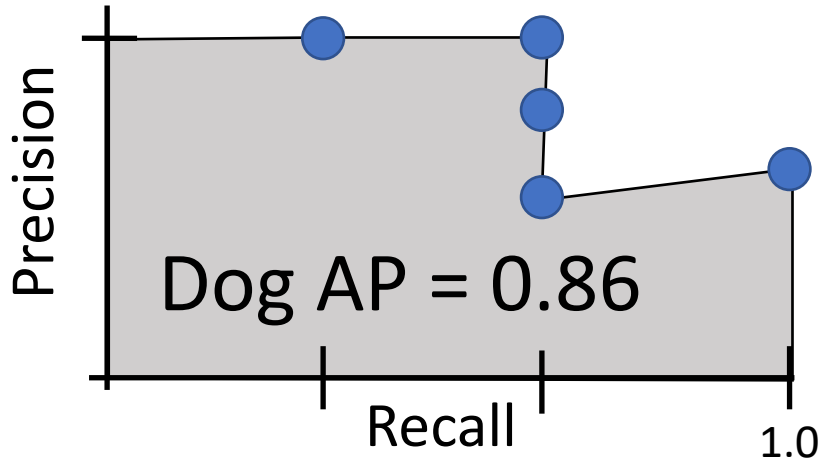
        3. Plot a point on PR Curve
    2. Average Precision (AP) = area under PR curve



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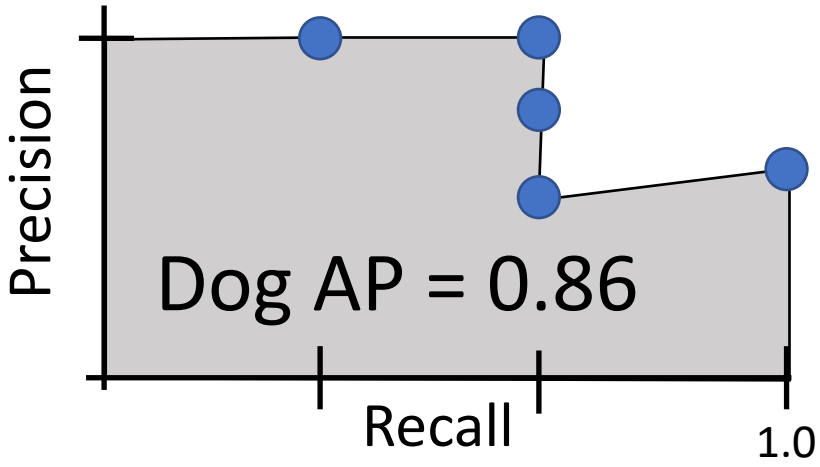
How to get AP = 1.0: Hit all GT boxes with IoU > 0.5, and have no "false positive" detections ranked above any "true positives"



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        3. Plot a point on PR Curve
    2. Average Precision (AP) = area under PR curve
3. Mean Average Precision (mAP) = average of AP for each category

Car AP = 0.65

Cat AP = 0.80

Dog AP = 0.86

mAP@0.5 = 0.77

Evaluating Object Detectors: Mean Average Precision (mAP)

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        3. Plot a point on PR Curve
    2. Average Precision (AP) = area under PR curve
3. Mean Average Precision (mAP) = average of AP for each category
4. For "COCO mAP": Compute mAP@thresh for **each IoU threshold** (0.5, 0.55, 0.6, …, 0.95) and take average

mAP@0.5 = 0.77

mAP@0.55 = 0.71

mAP@0.60 = 0.65

…

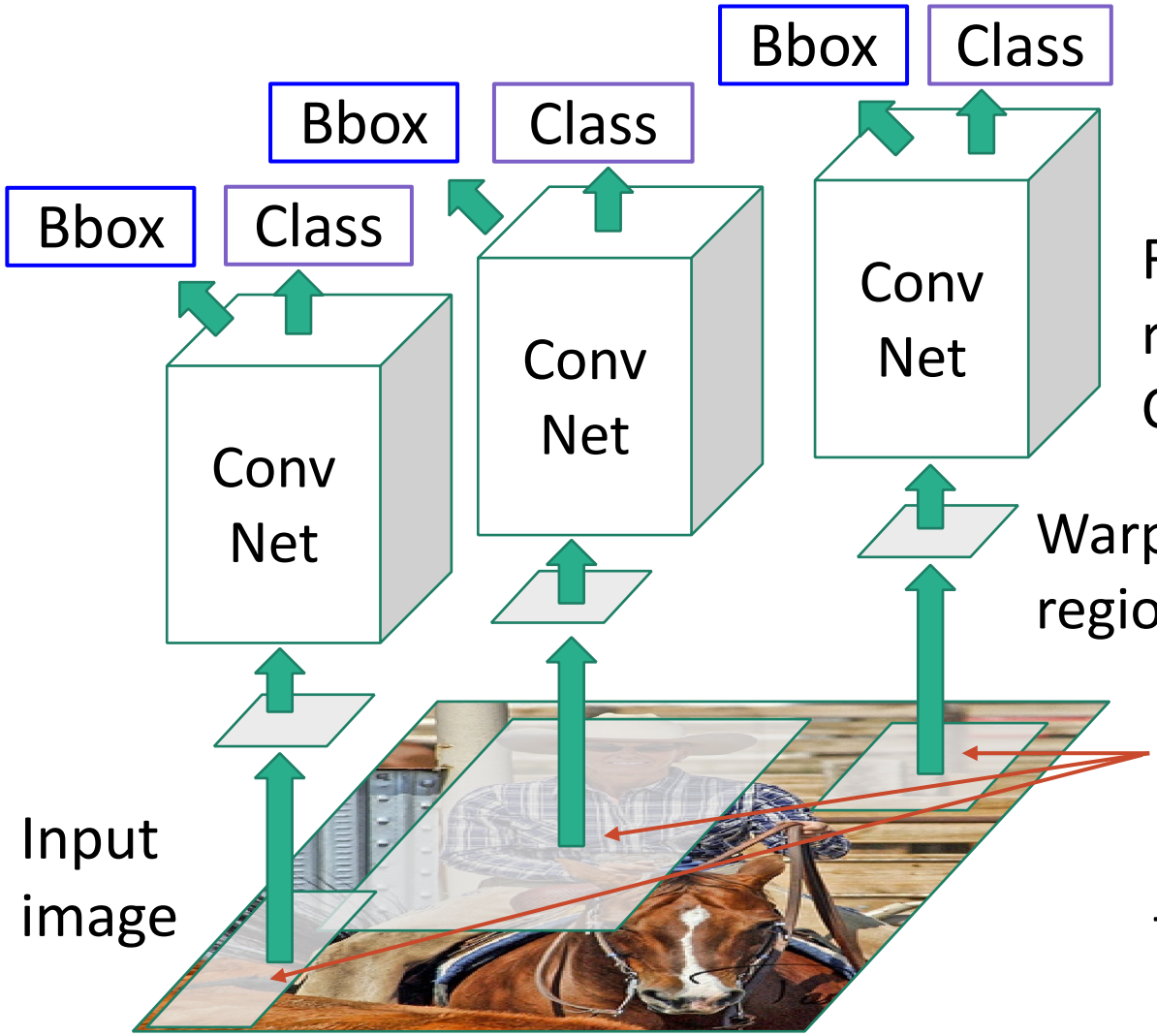
mAP@0.95 = 0.2

COCO mAP = 0.4

R-CNN: Region-Based CNN

Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)



Forward each region through ConvNet

Warped image regions (224x224)

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

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
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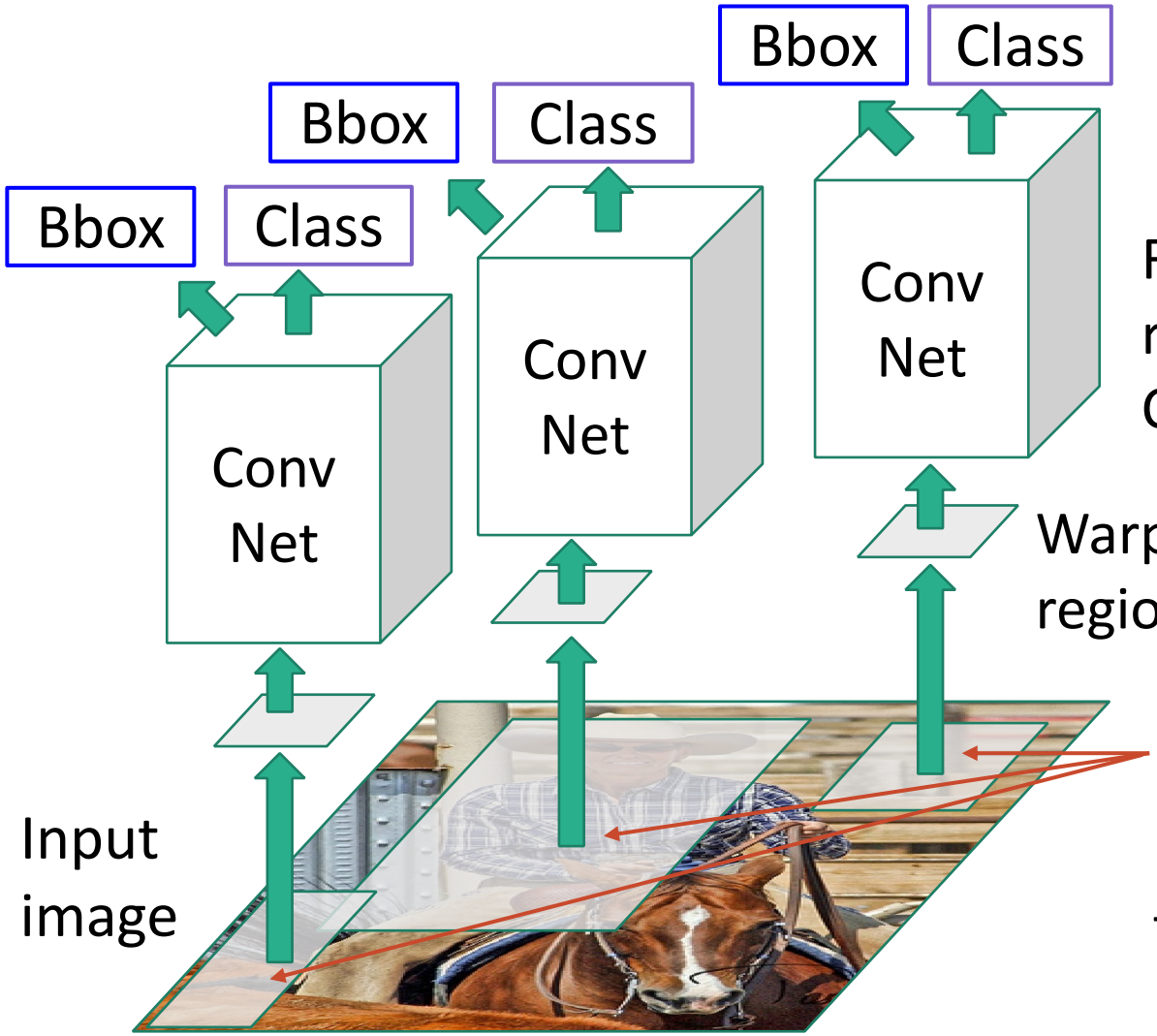
R-CNN: Region-Based CNN

Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)



Forward each region through ConvNet

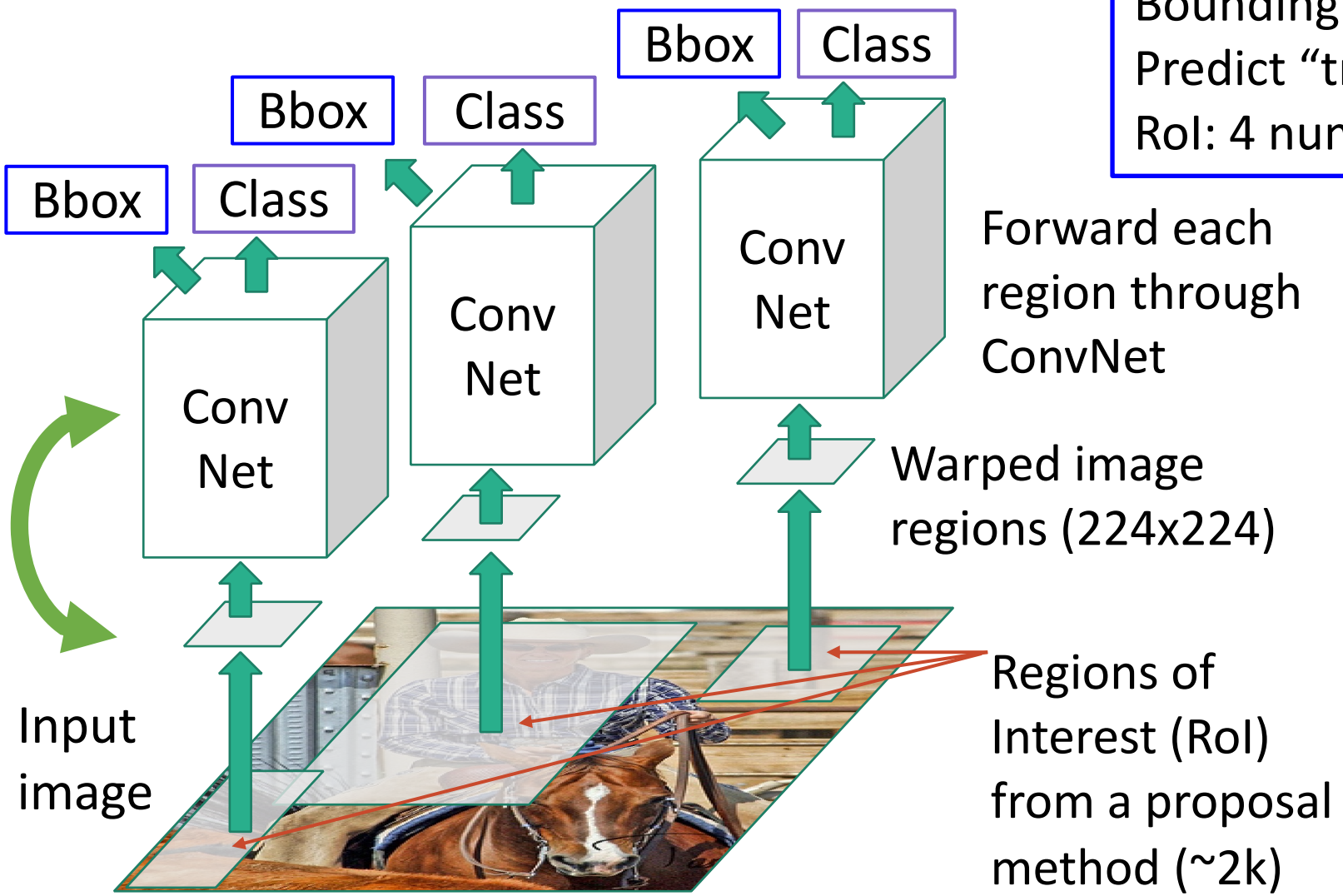
Warped image regions (224x224)

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

Problem: Very slow!
Need to do ~2k 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.

R-CNN: Region-Based CNN



Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)

Forward each region through ConvNet

Warped image regions (224x224)

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

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

Solution: Run CNN *before* warping!

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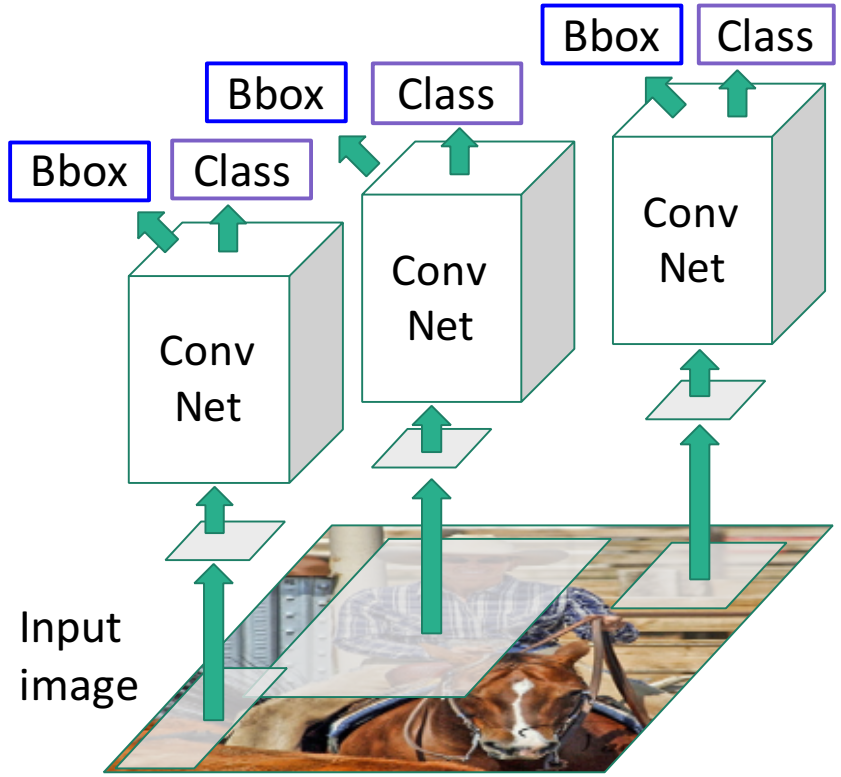
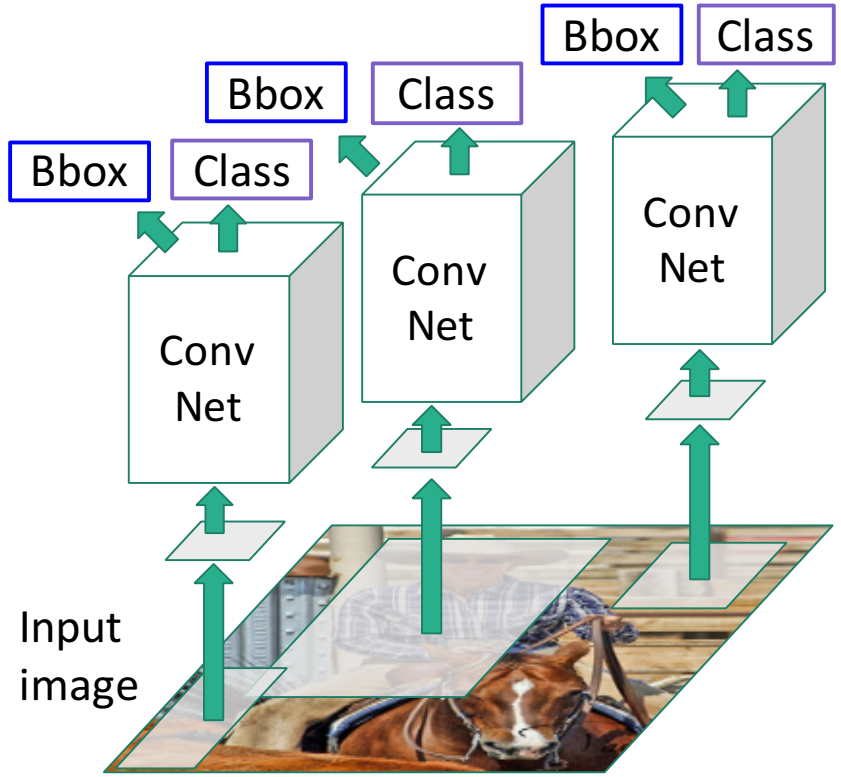
"Slow" R-CNN

Process each region independently



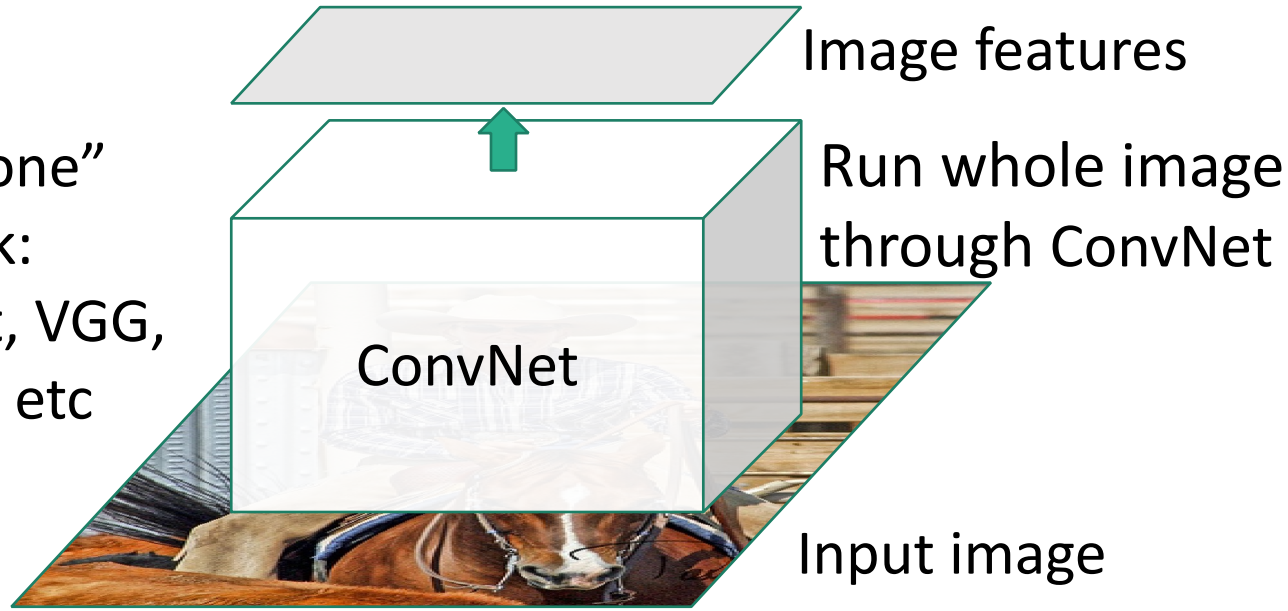
Fast R-CNN

Input image



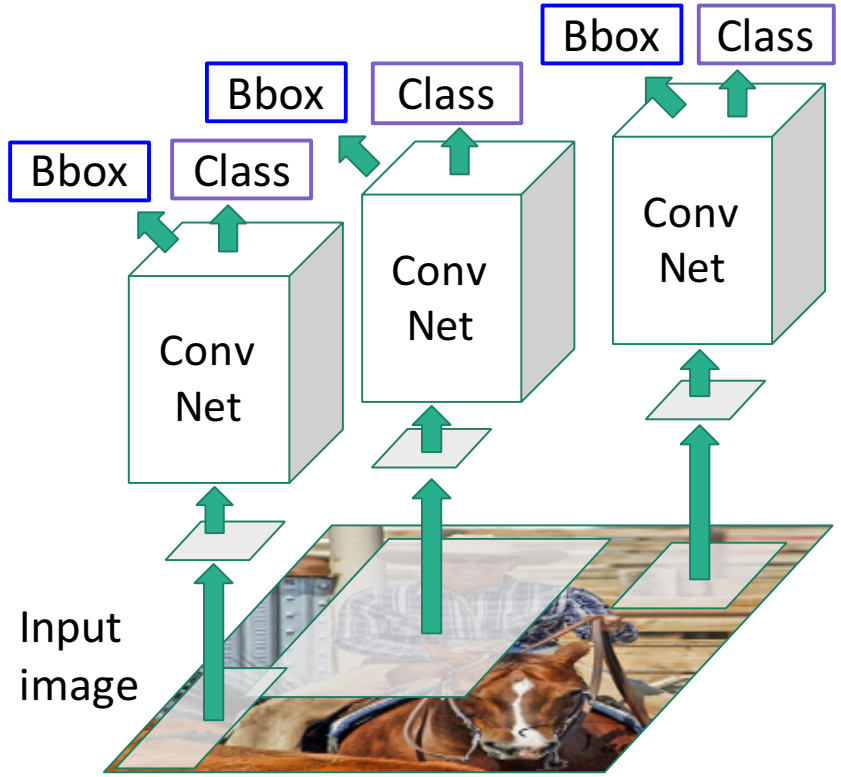
Fast R-CNN

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



"Slow" R-CNN

Process each region independently

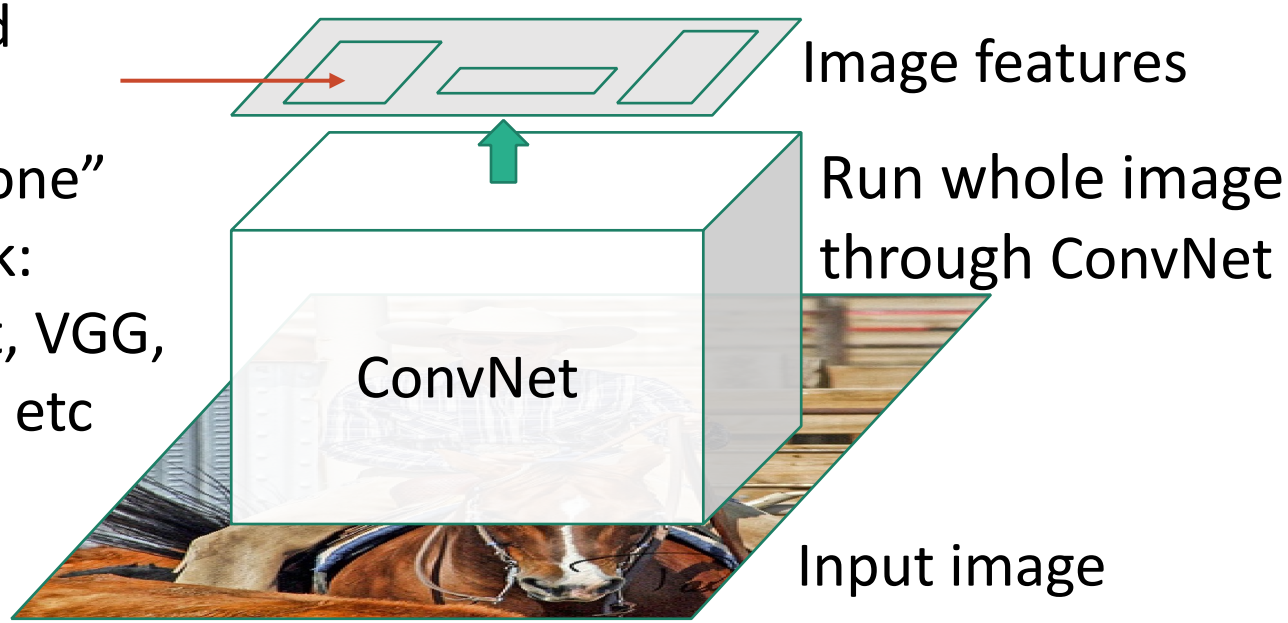


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

Regions of Interest (RoIs) from a proposal method

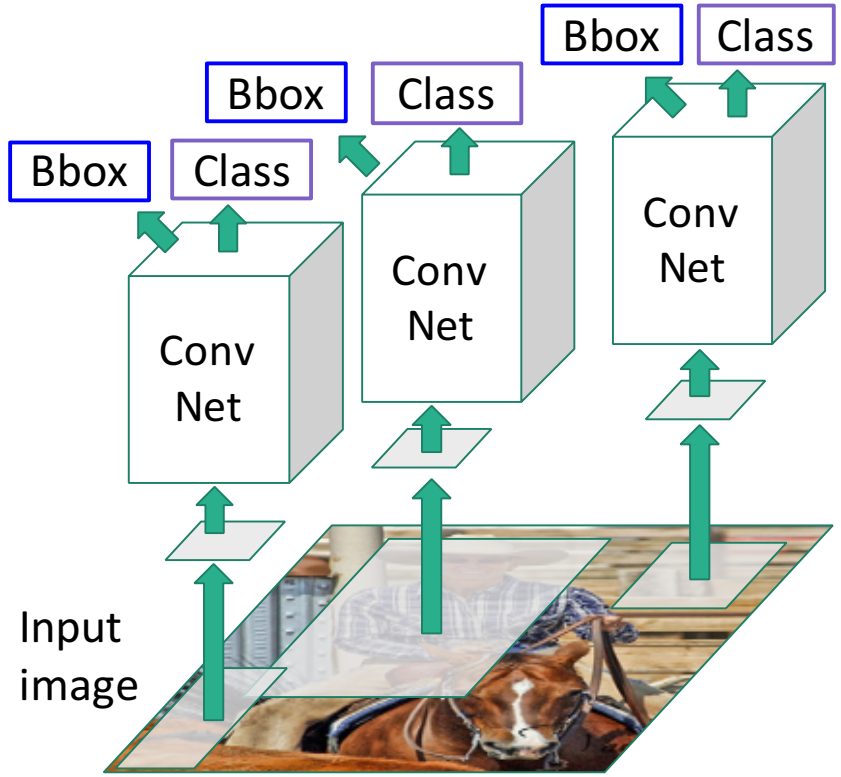
"Backbone" network: AlexNet, VGG, ResNet, etc



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

"Slow" R-CNN

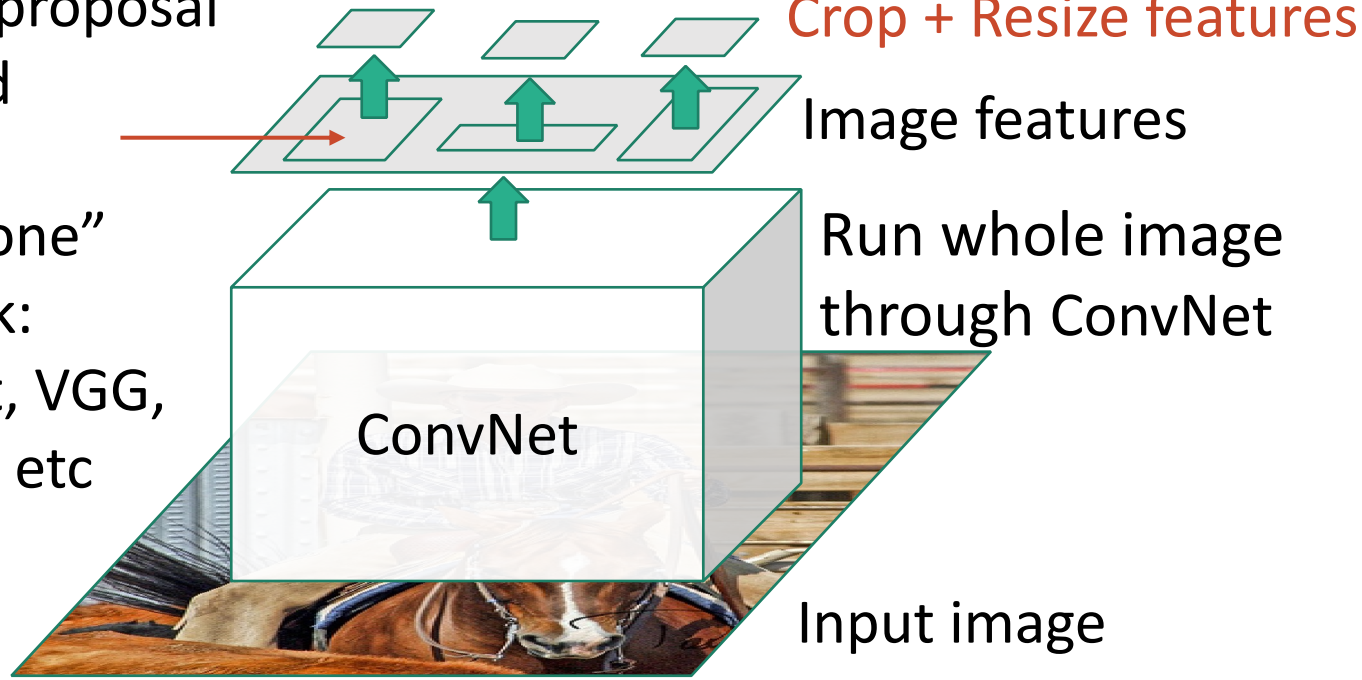
Process each region independently



Fast R-CNN

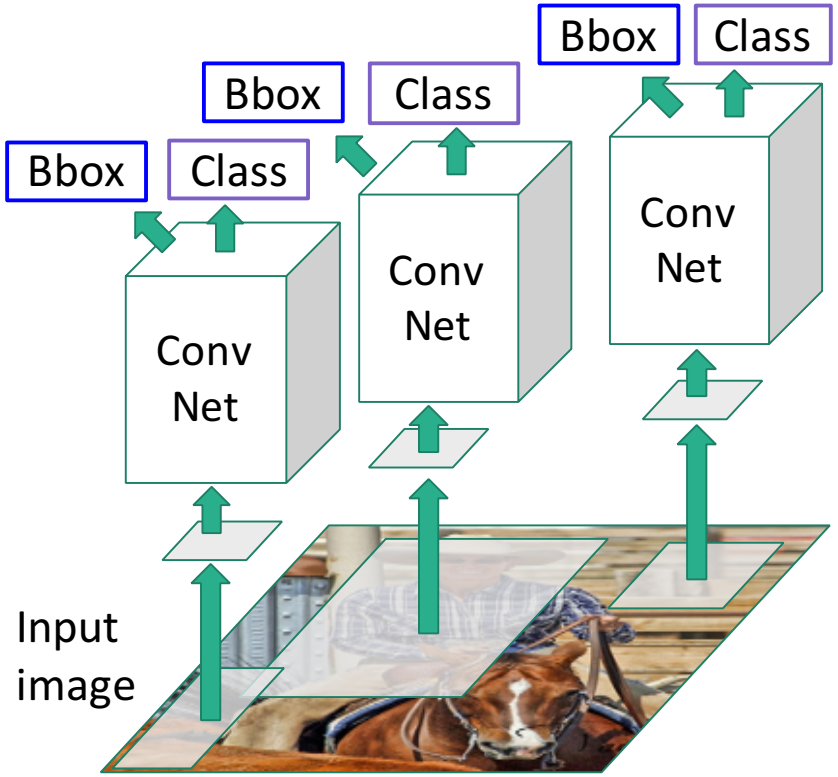
Regions of Interest (RoIs) from a proposal method

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



"Slow" R-CNN

Process each region independently

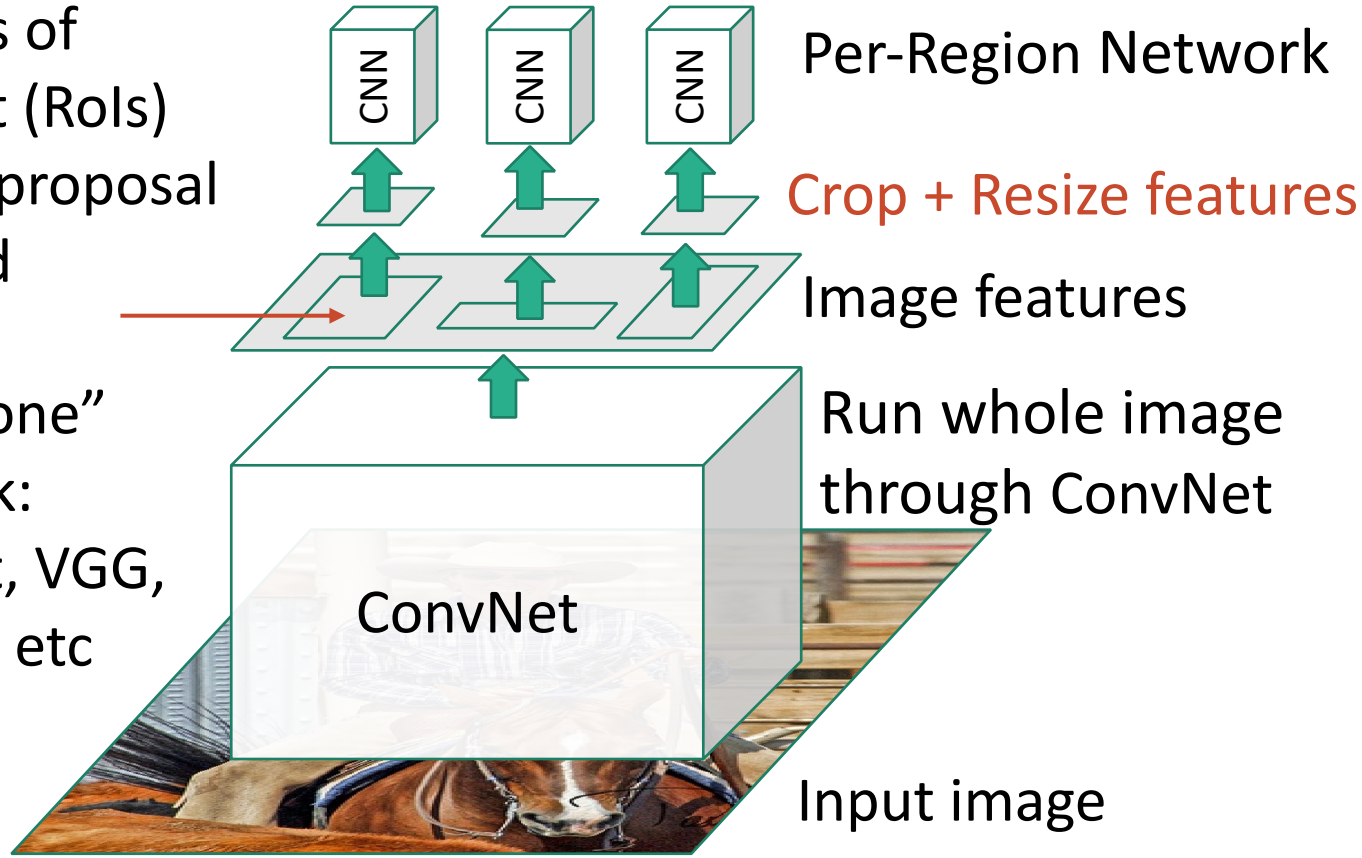


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

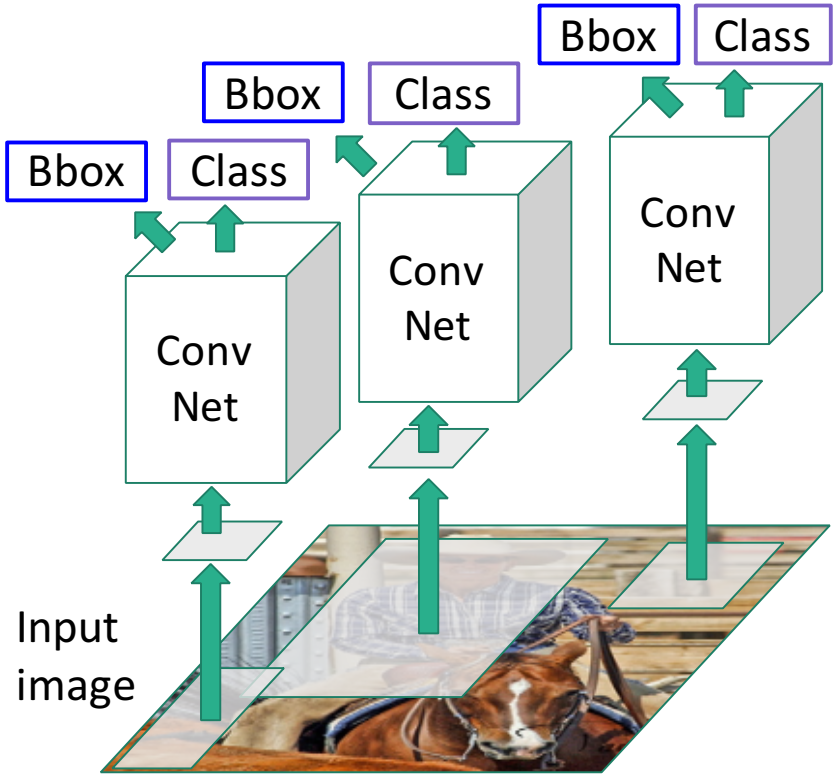
Regions of Interest (RoIs) from a proposal method

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



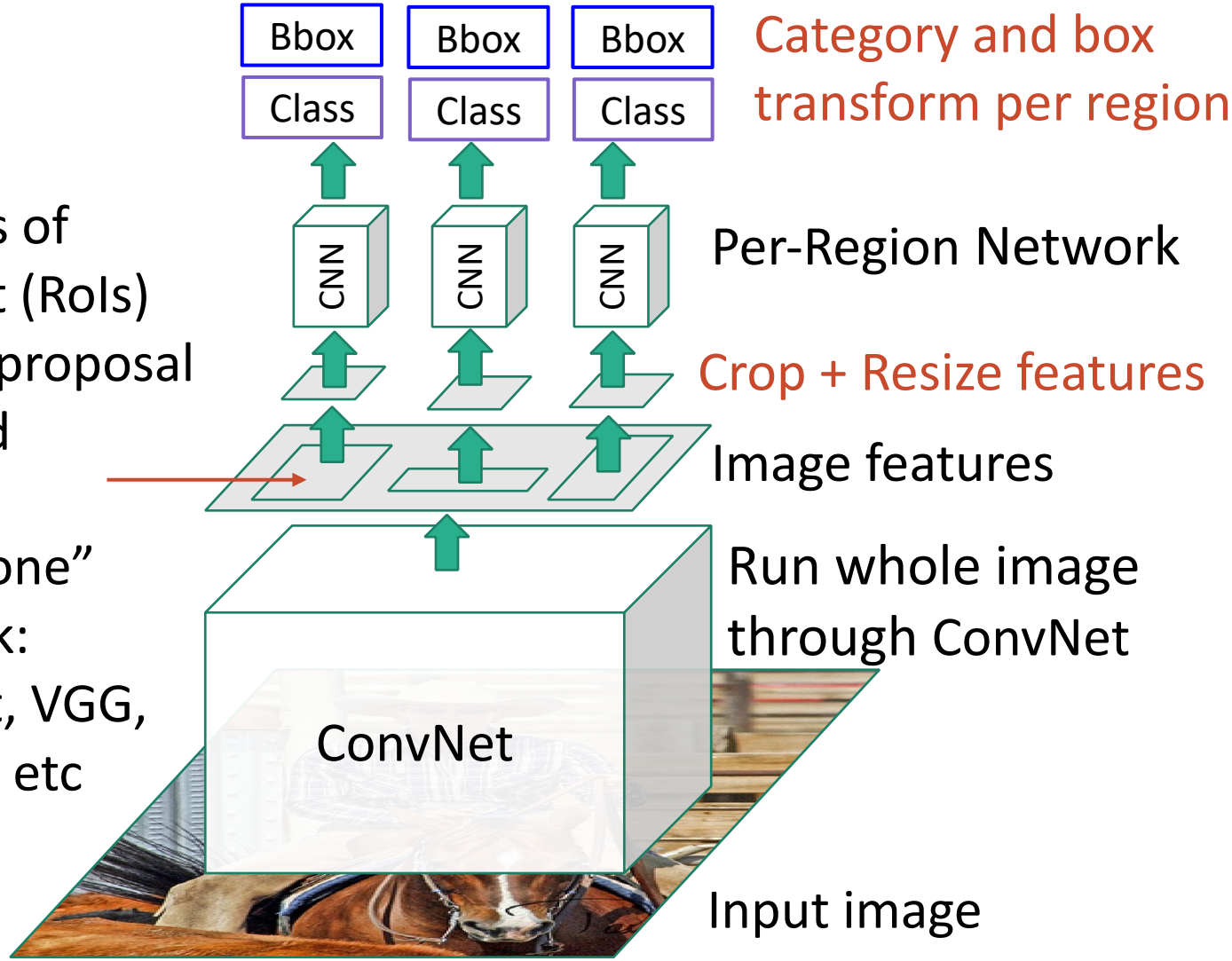
"Slow" R-CNN

Process each region independently



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

Fast R-CNN

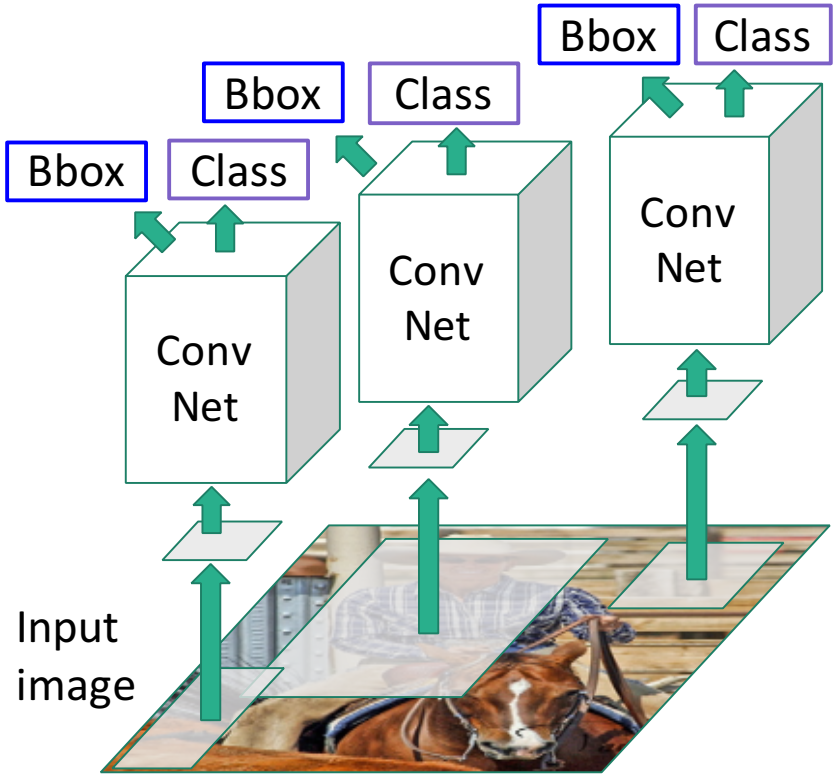


Regions of Interest (RoIs) from a proposal method

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

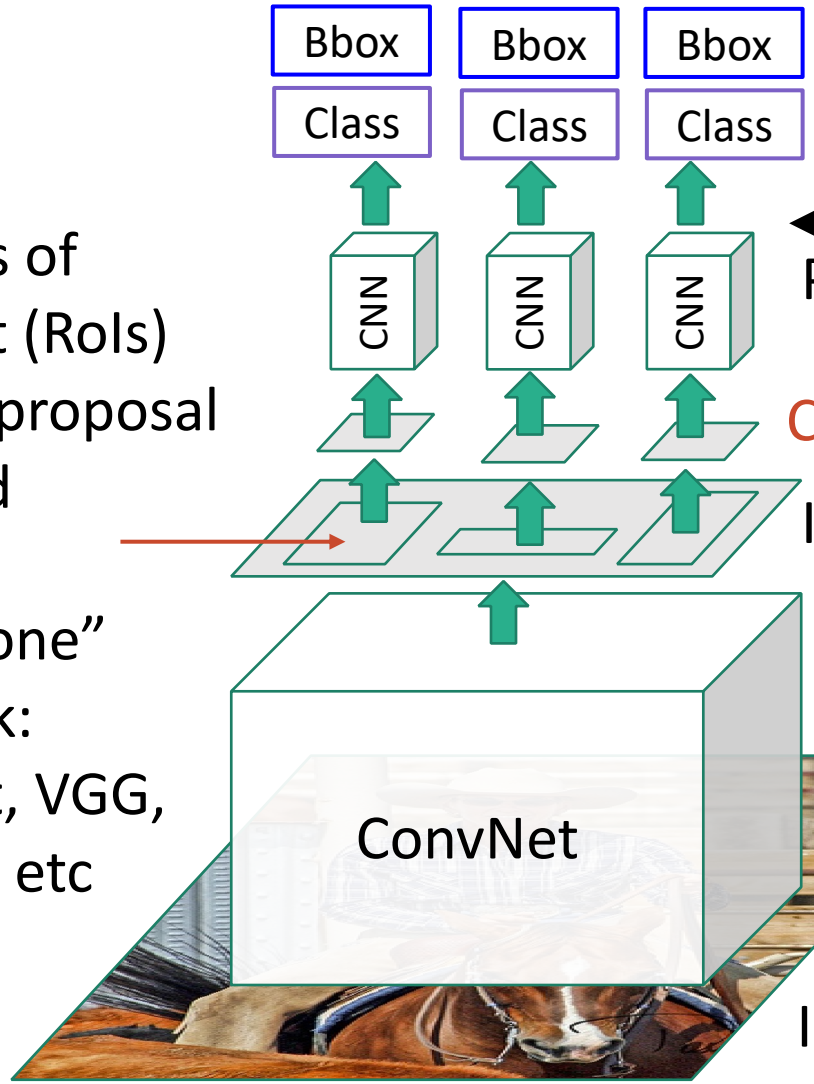
"Slow" R-CNN

Process each region independently



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

Fast R-CNN



Category and box transform per region

Per-Region network is relatively lightweight

Per-Region Network

Regions of Interest (RoIs) from a proposal method

Crop + Resize features

Image features

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

Run whole image through ConvNet

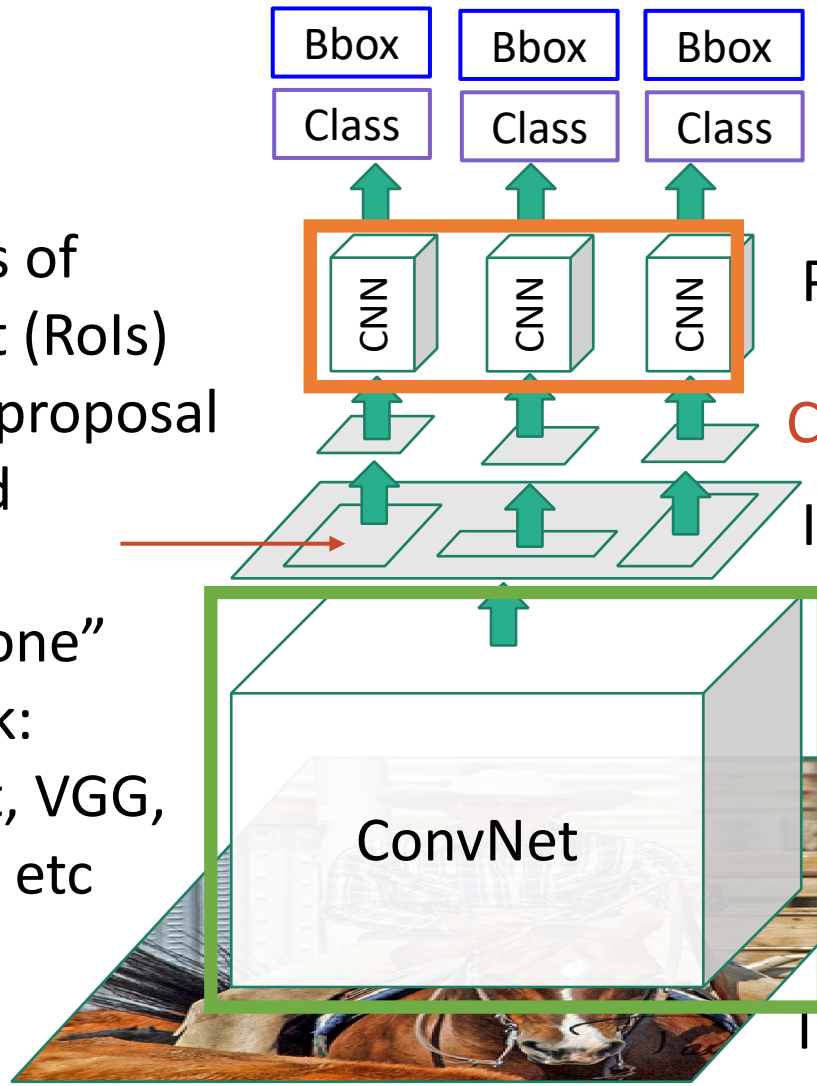
ConvNet

Most of the computation happens in backbone network; this saves work for overlapping region proposals

Input image

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

Fast R-CNN



Category and box transform per region

Per-Region Network

Crop + Resize features

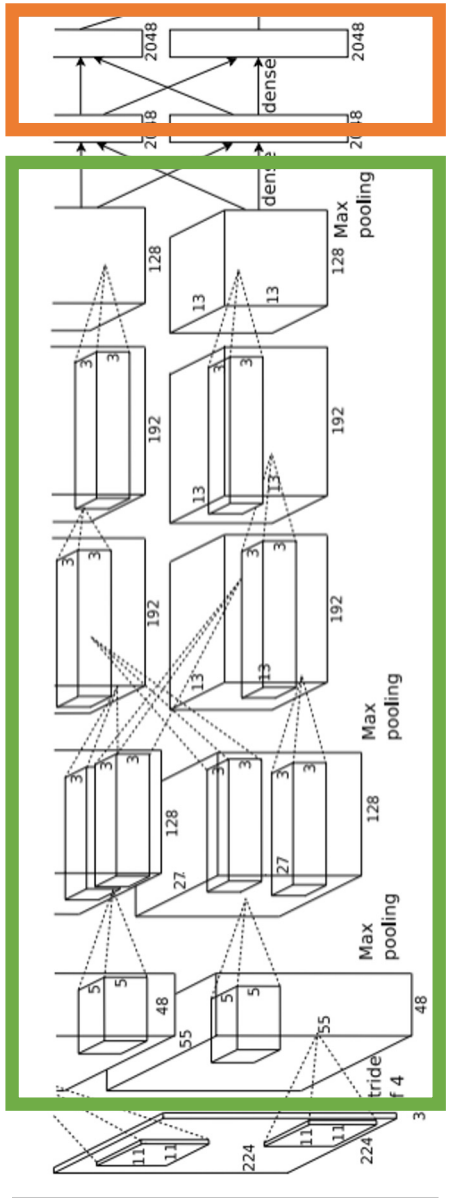
Image features

Run whole image through ConvNet

Input image

Regions of Interest (RoIs) from a proposal method

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



Example: When using AlexNet for detection, five conv layers are used for backbone and two FC layers are used for per-region network

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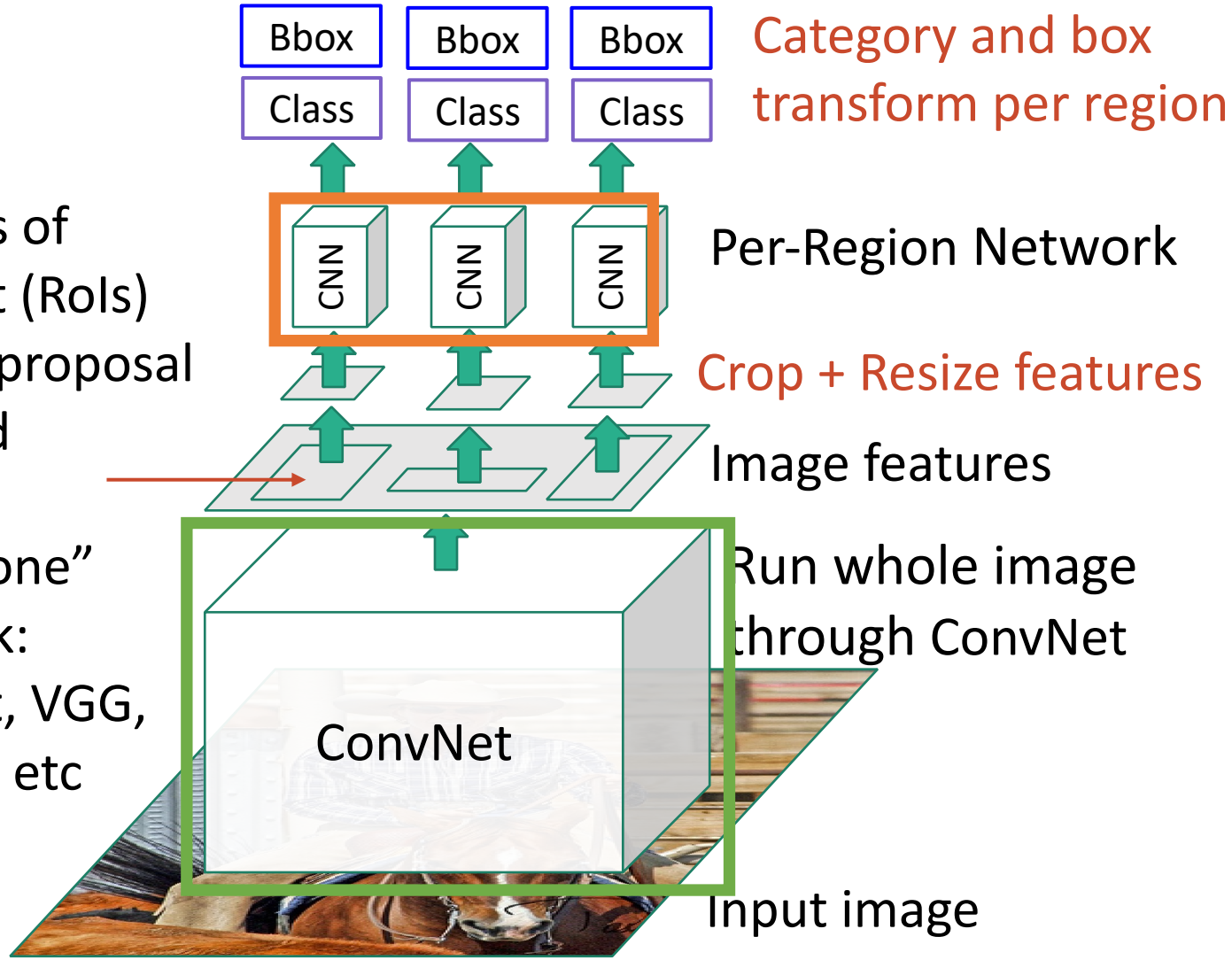
Fast R-CNN



Category and box transform per region

Regions of Interest (RoIs) from a proposal method

Per-Region Network

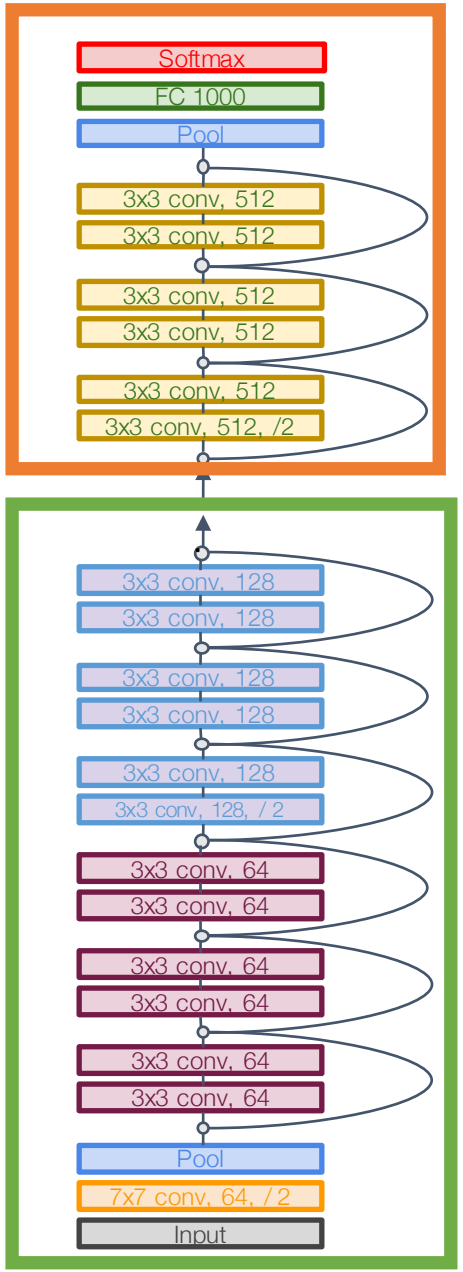
Crop + Resize features

Image features

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

Run whole image through ConvNet

Input image



Example:
For ResNet, last stage is used as per-region network; the rest of the network is used as backbone

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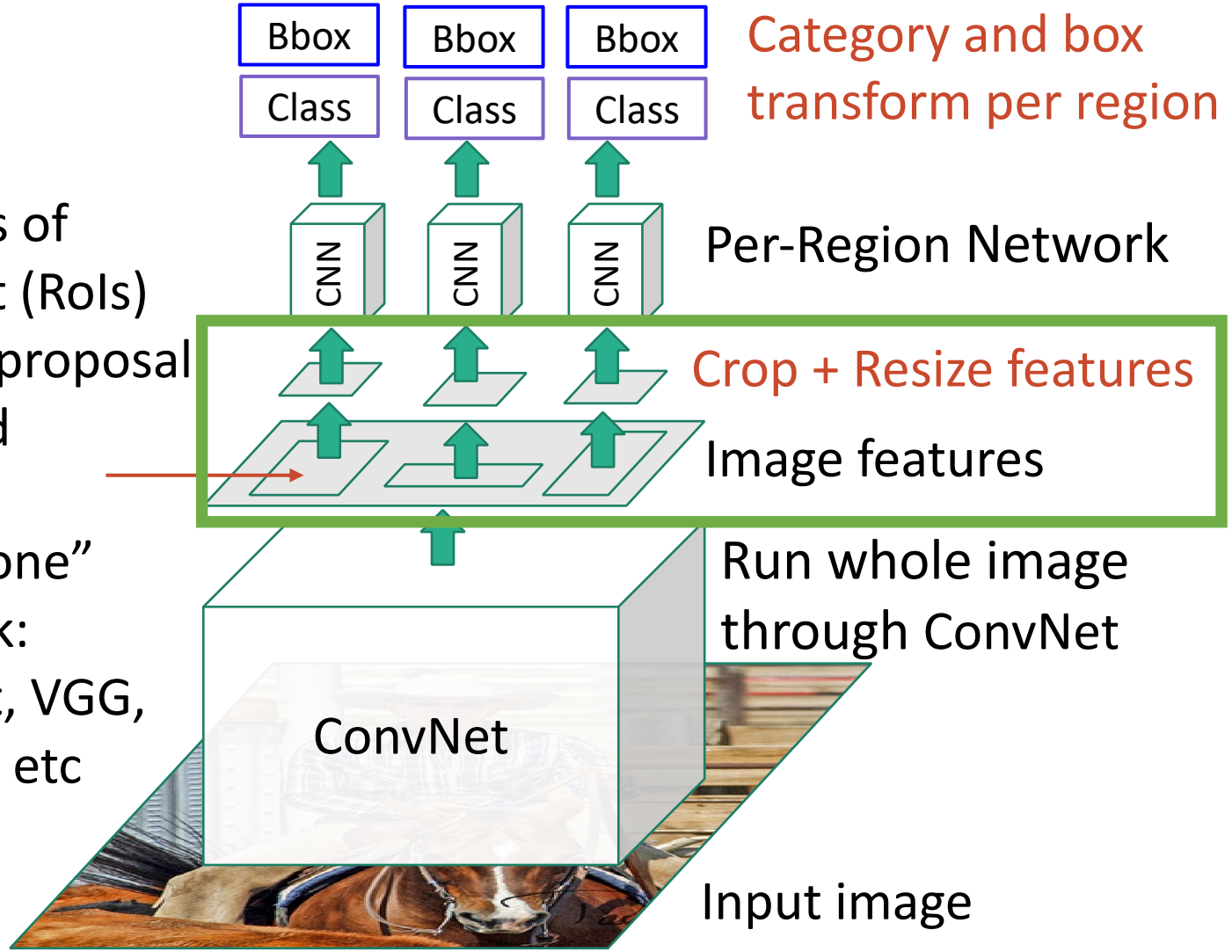
Fast R-CNN



Regions of Interest (RoIs) from a proposal method

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

How to crop features?

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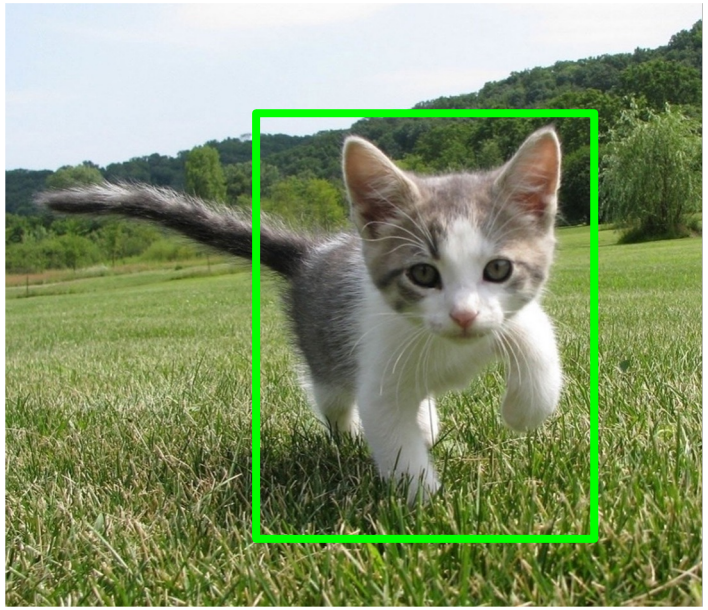
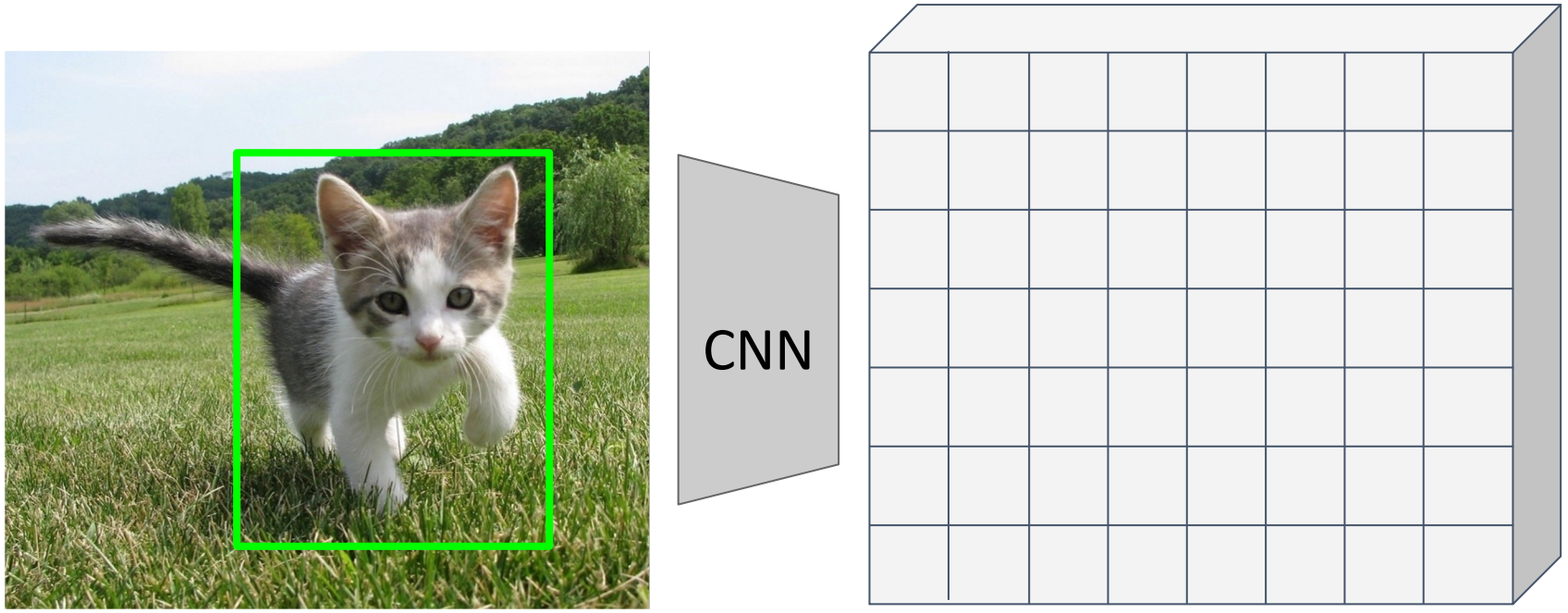
Cropping Features: RoI Pool



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

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool

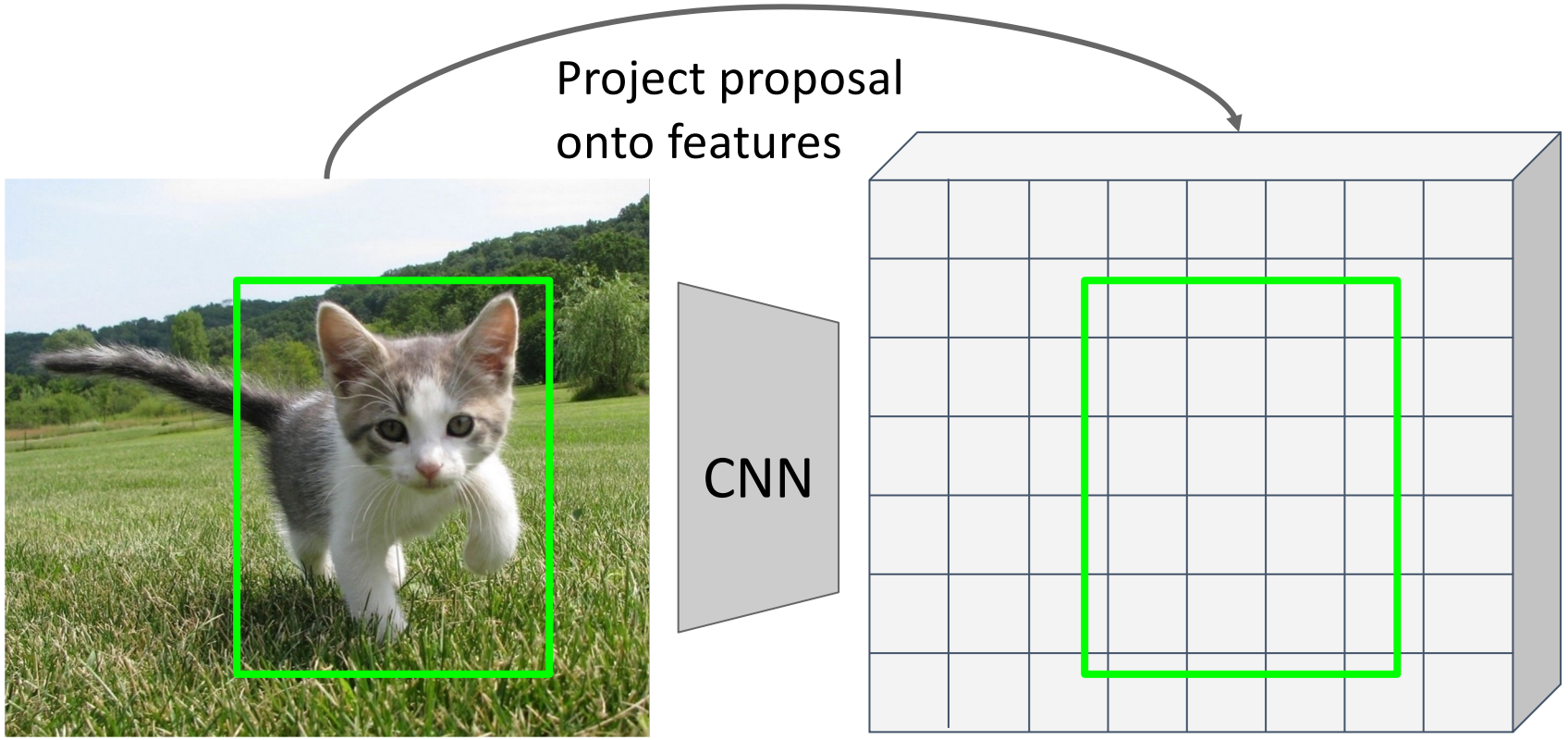


Input Image
(e.g. 3 x 640 x 480)

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

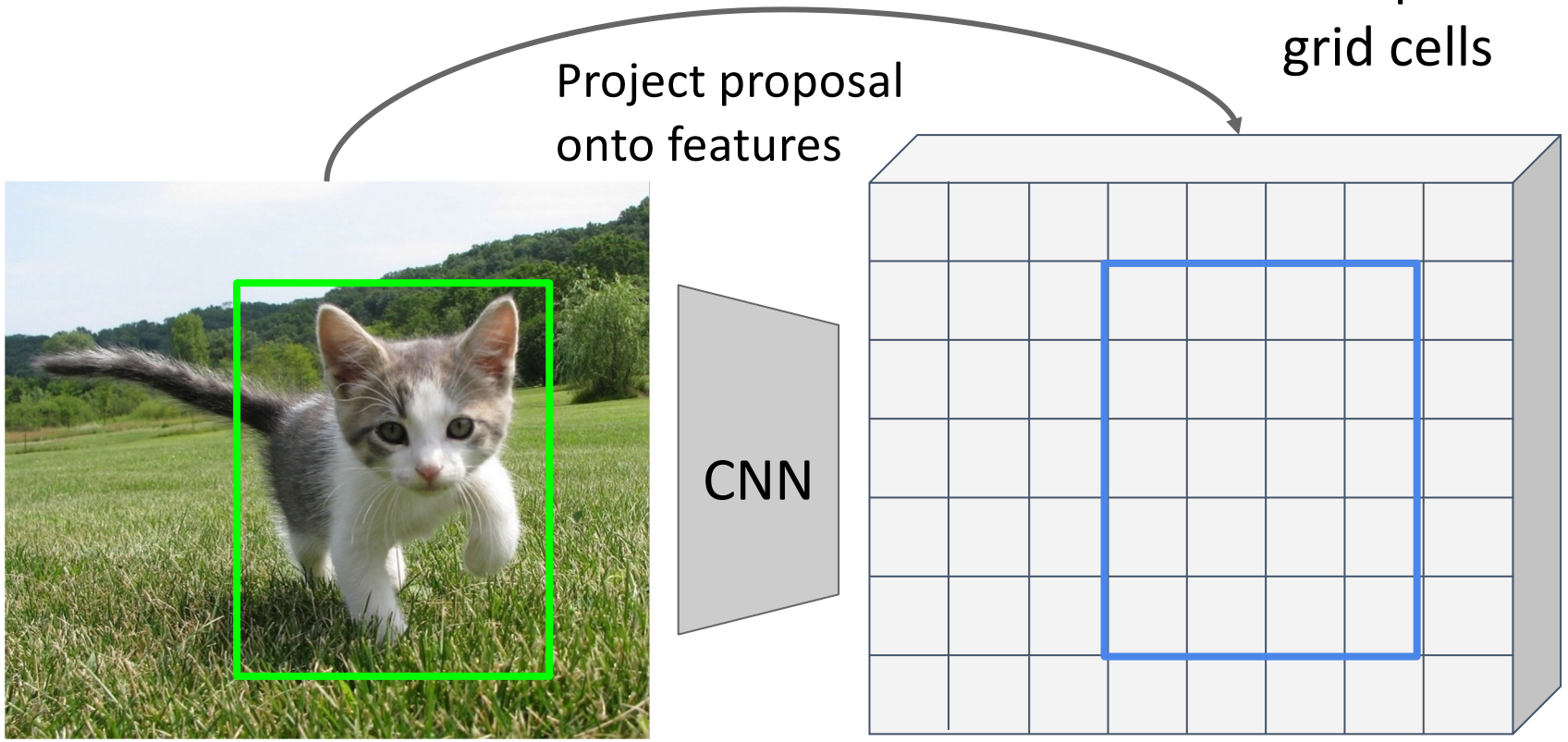
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool



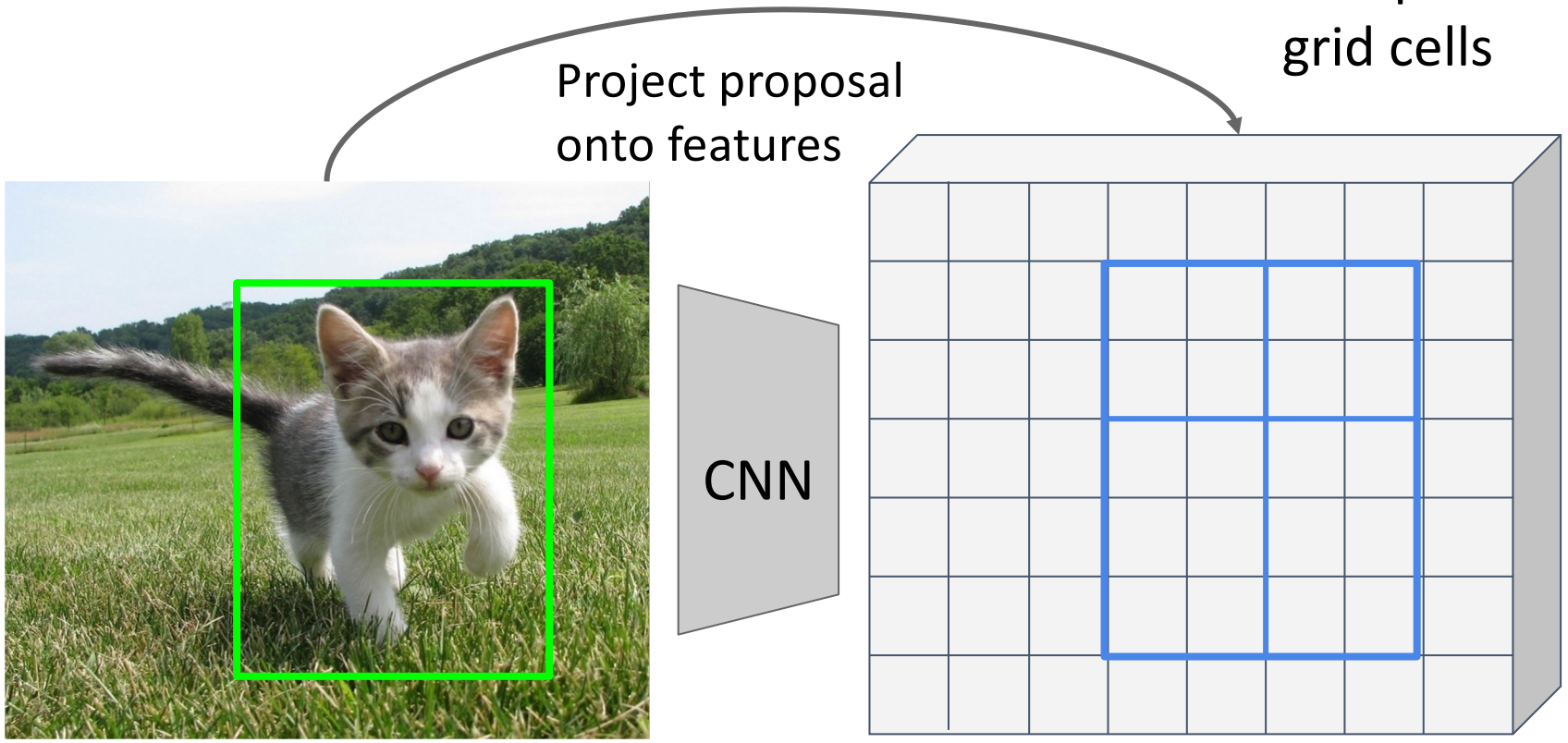
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool



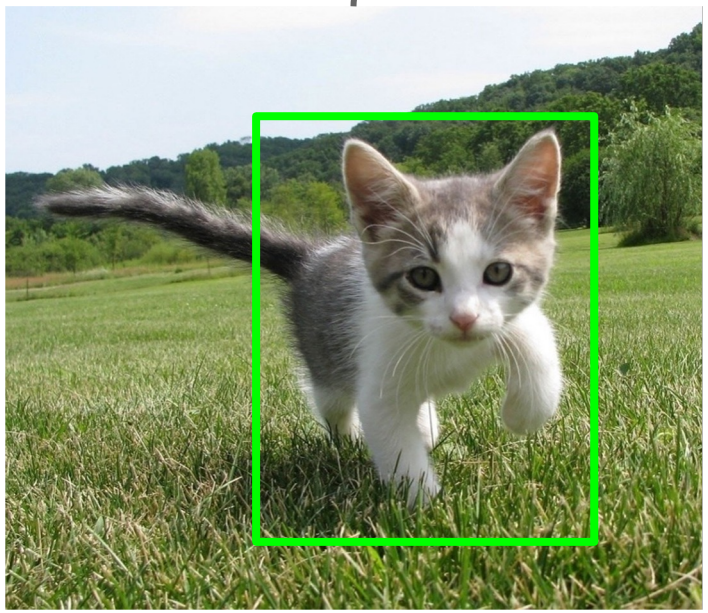
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool



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

Cropping Features: RoI Pool



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

Project proposal onto features

CNN

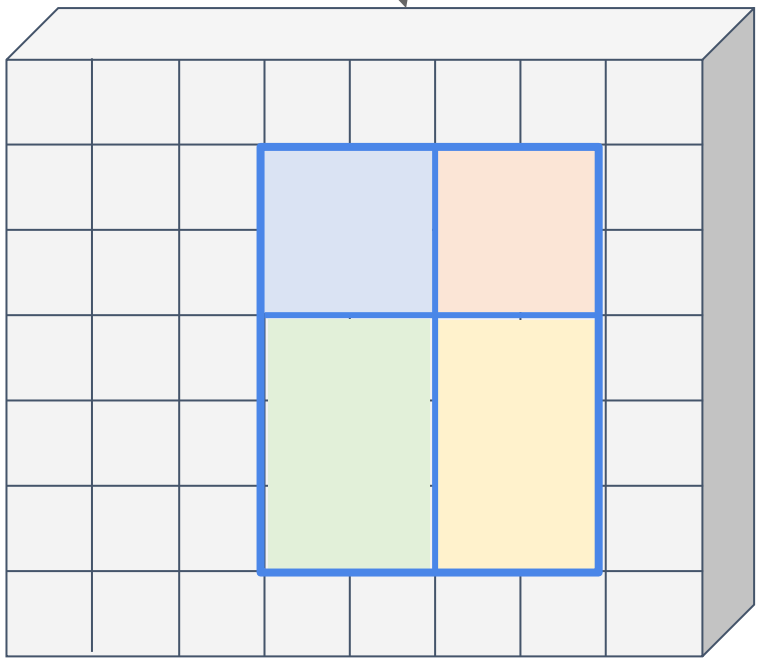
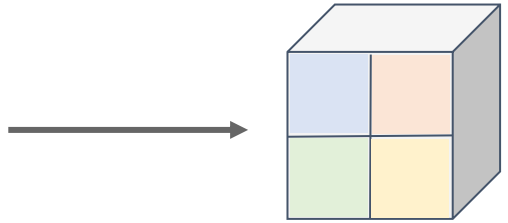


Image features
(e.g. 512 x 20 x 15)

"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion

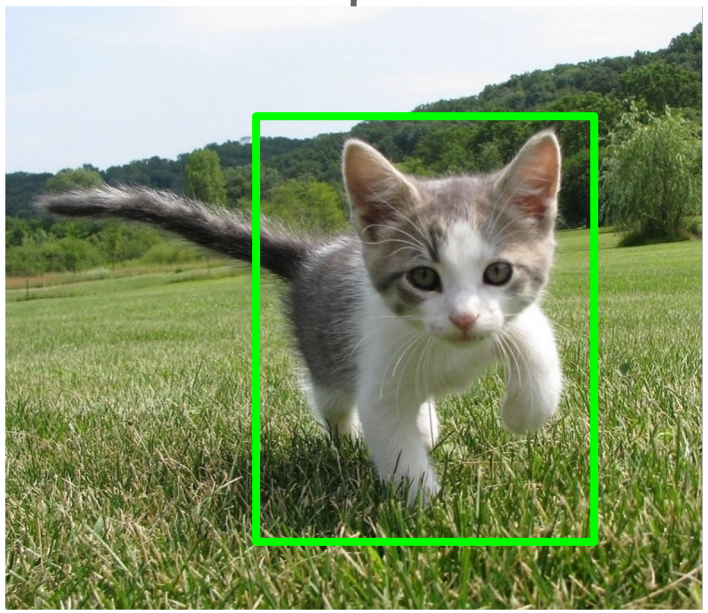


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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

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

Cropping Features: RoI Pool



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

Project proposal onto features

CNN

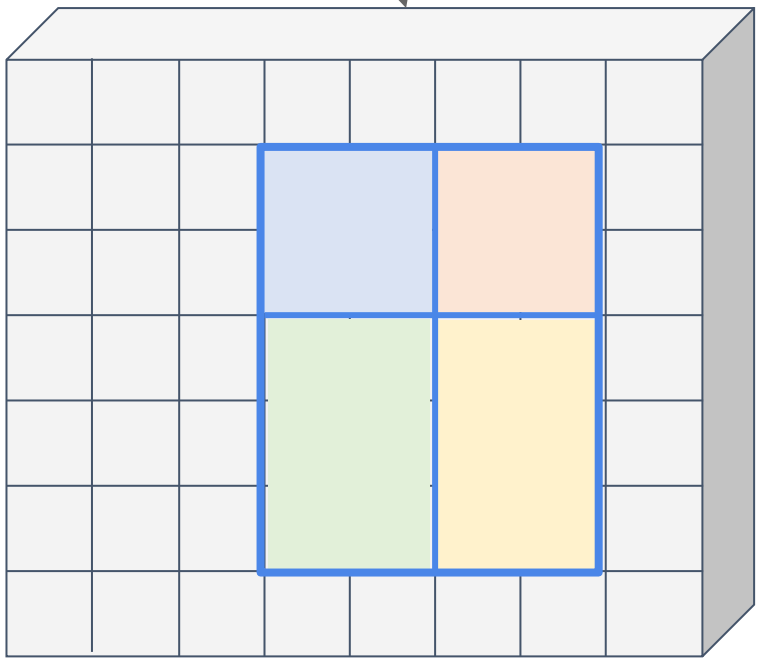


Image features
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"Snap" to grid cells

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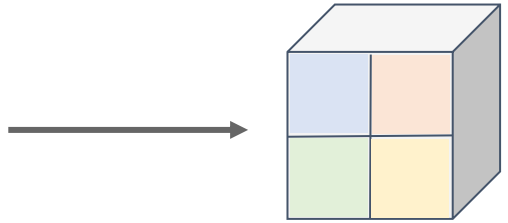
Max-pool within each subregion



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!

Problem: Slight misalignment due to snapping; different-sized subregions is weird

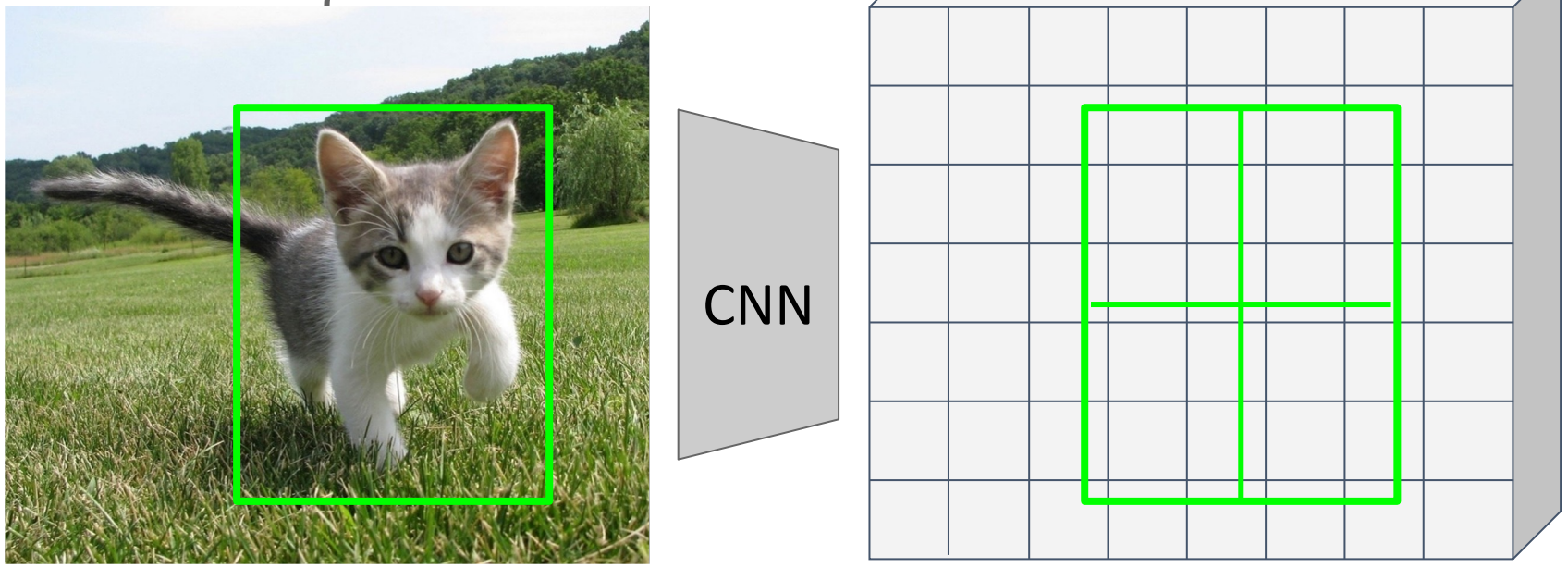
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Align

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

No “snapping”!

Project proposal
onto features



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

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

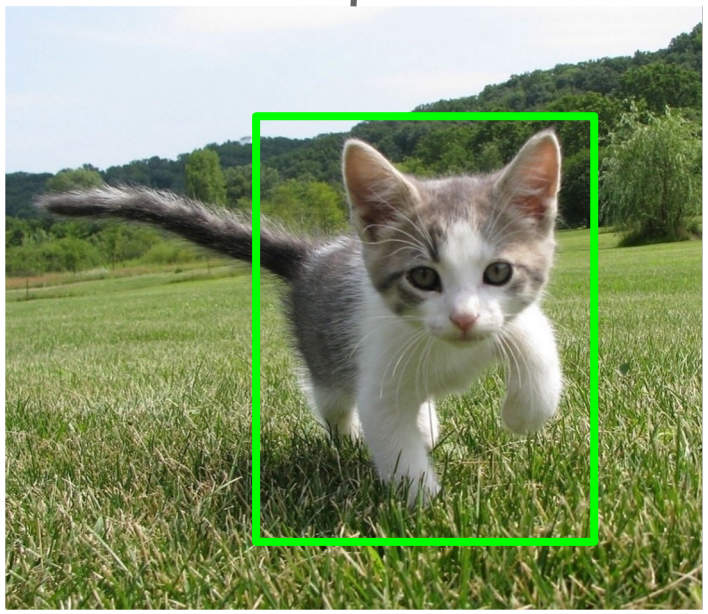
He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

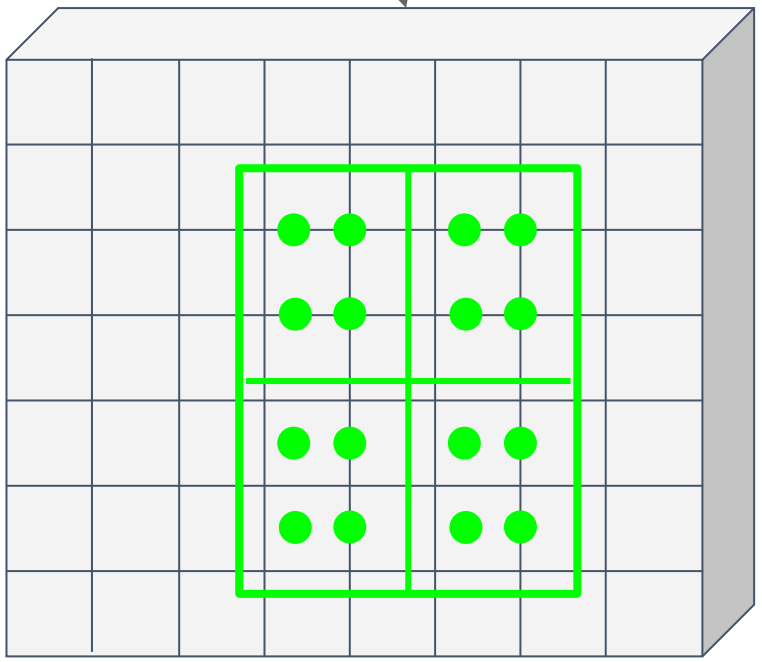
Divide into equal-sized subregions
(may not be aligned to grid!)

No “snapping”!

Project proposal
onto features



CNN



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

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

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

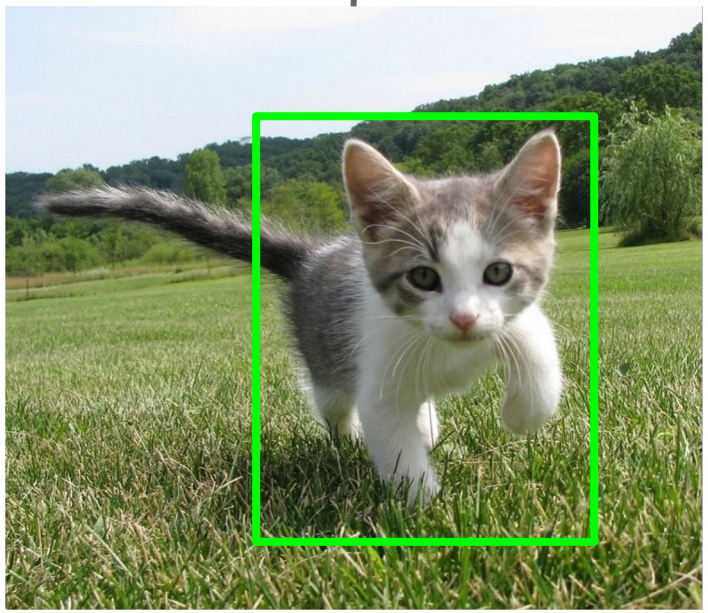
He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

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

No “snapping”!

Project proposal
onto features



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

CNN

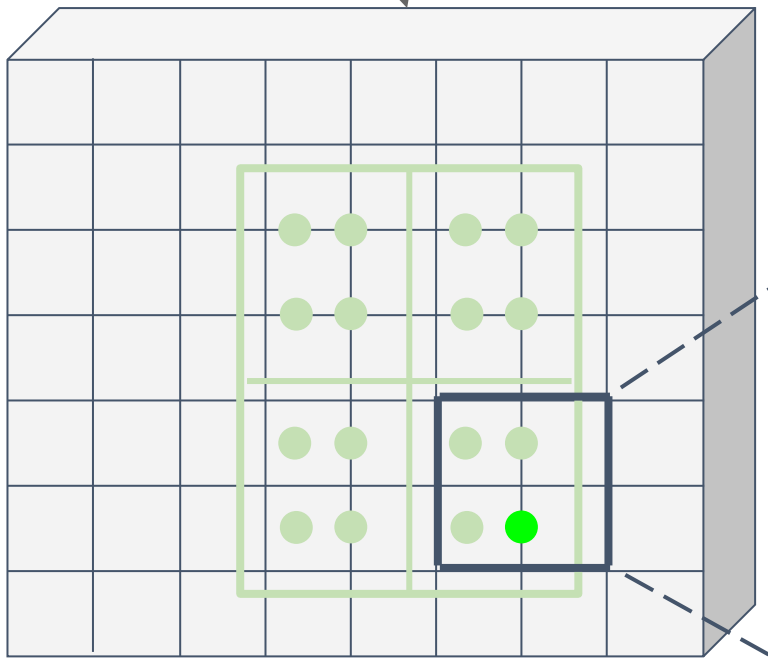
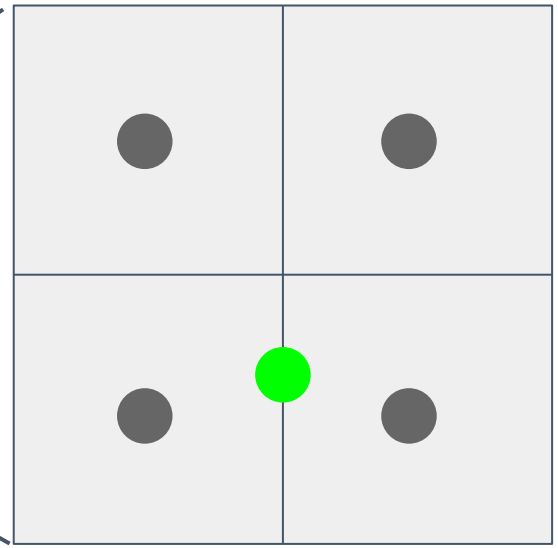


Image features
(e.g. 512 x 20 x 15)

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



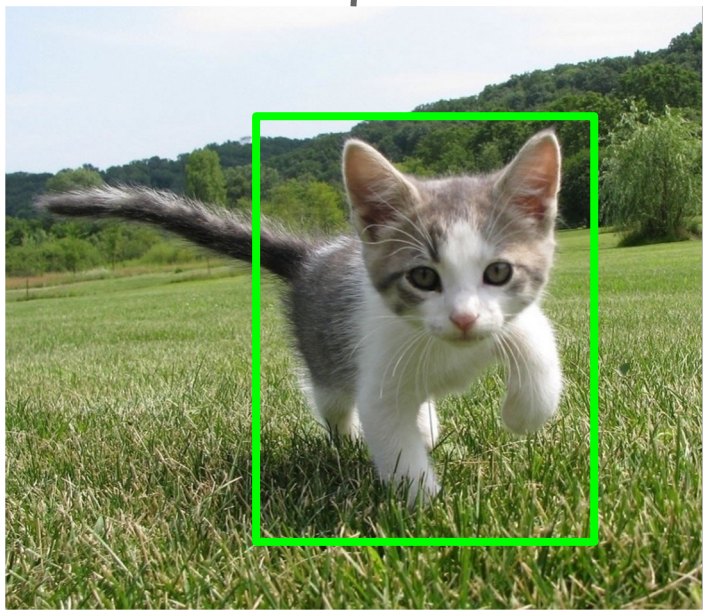
Feature f_{xy} for point (x, y) is a
linear combination of features
at its four neighboring grid cells:

Cropping Features: RoI Align

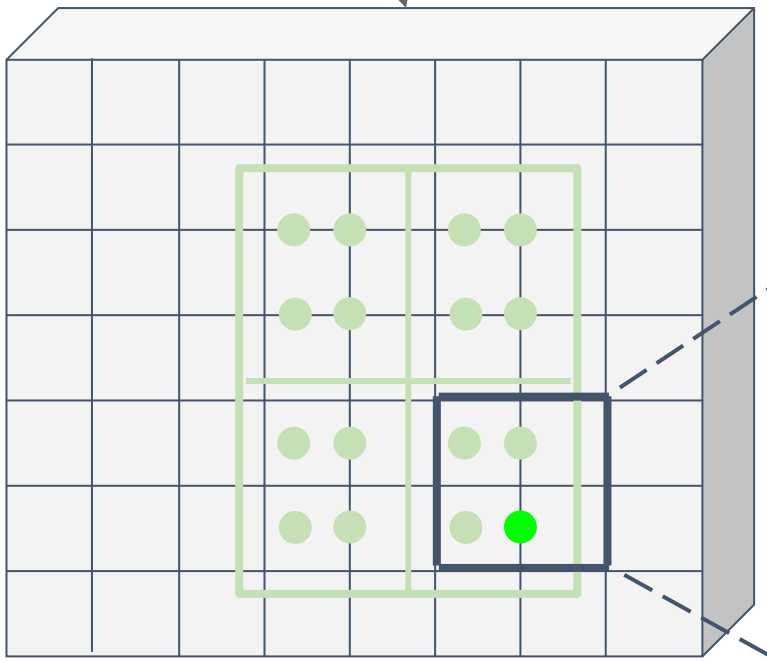
Divide into equal-sized subregions (may not be aligned to grid!)

No "snapping"!

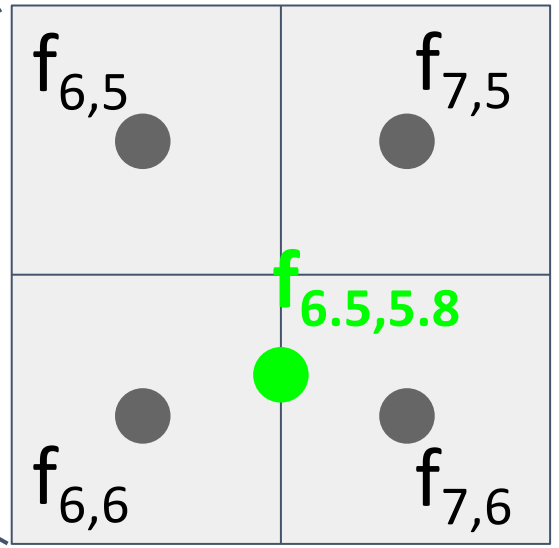
Project proposal onto features



CNN



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



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

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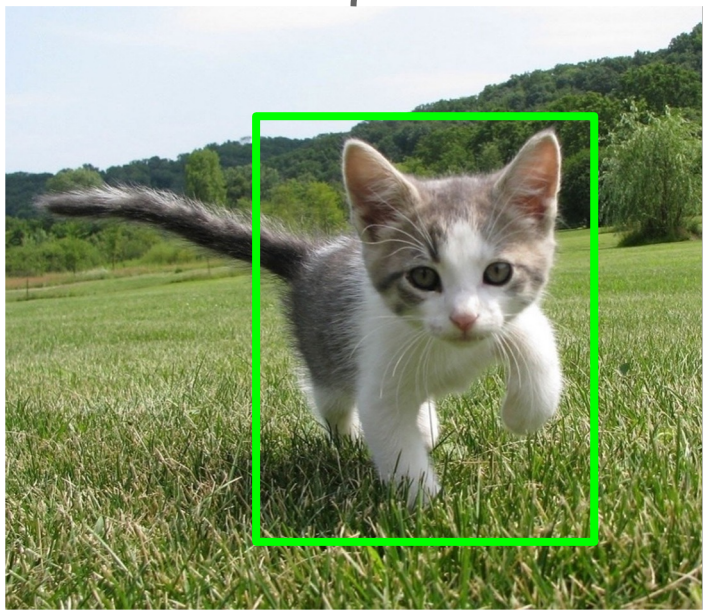
Cropping Features: RoI Align

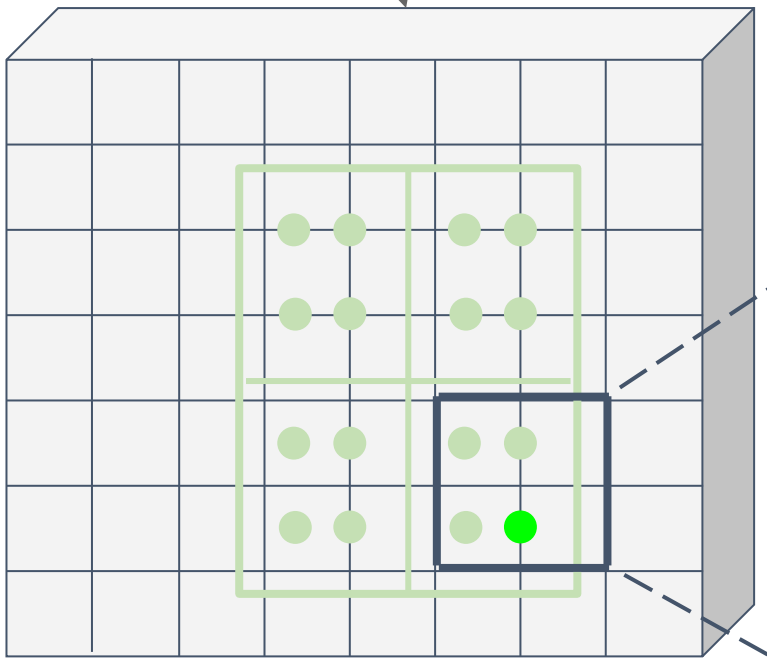
Divide into equal-sized subregions (may not be aligned to grid!)

No "snapping"!

Project proposal onto features



CNN



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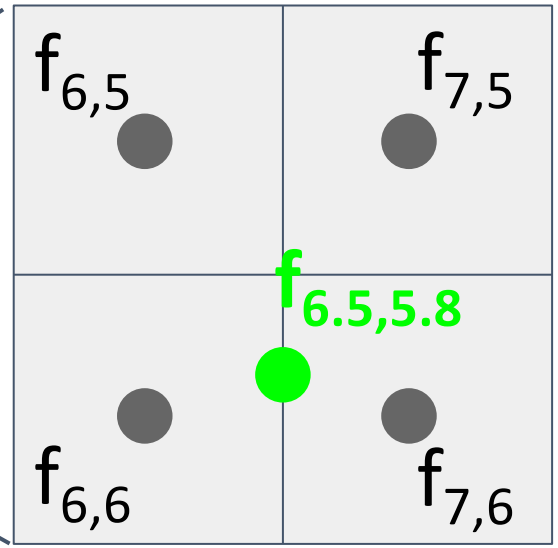

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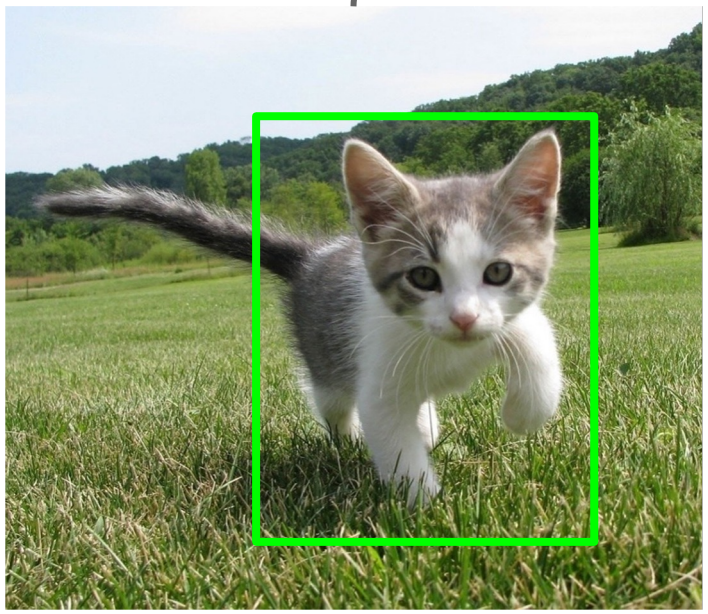
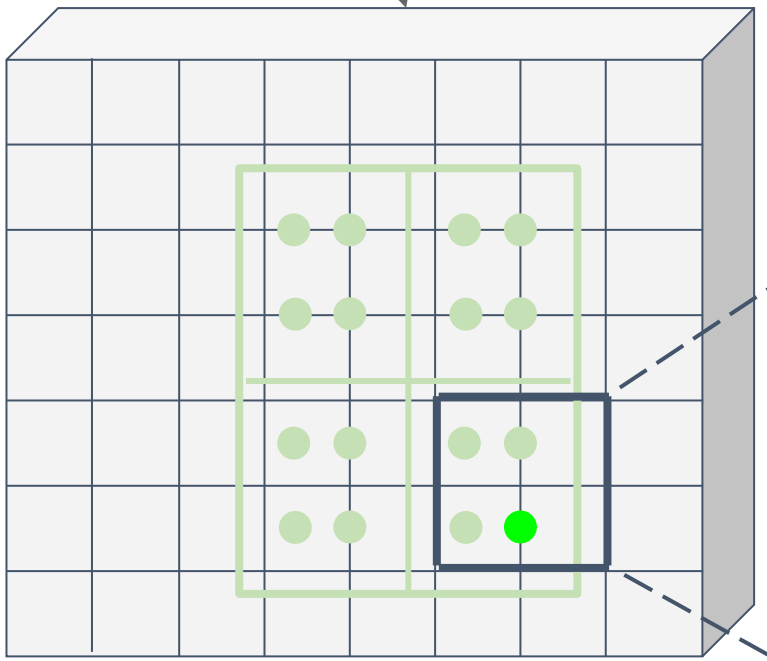
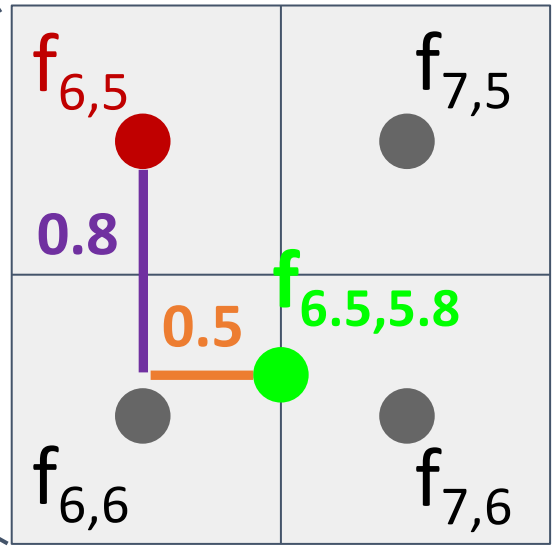


CNN



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



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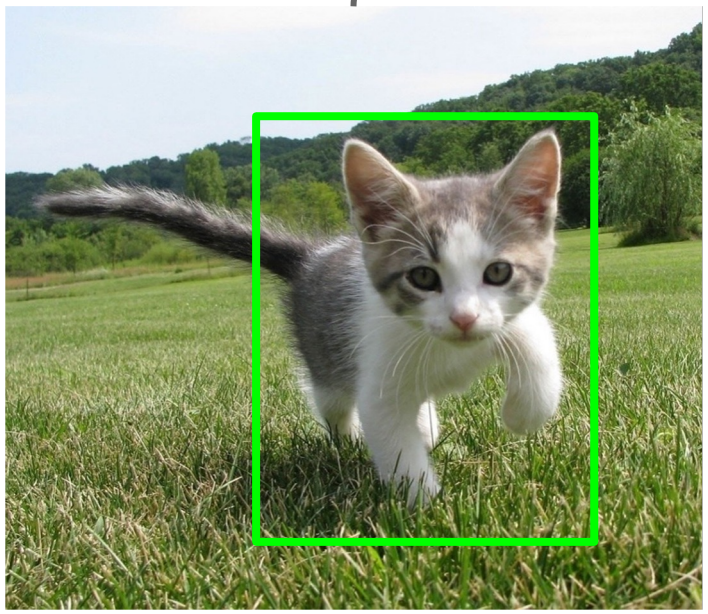
Project proposal onto features



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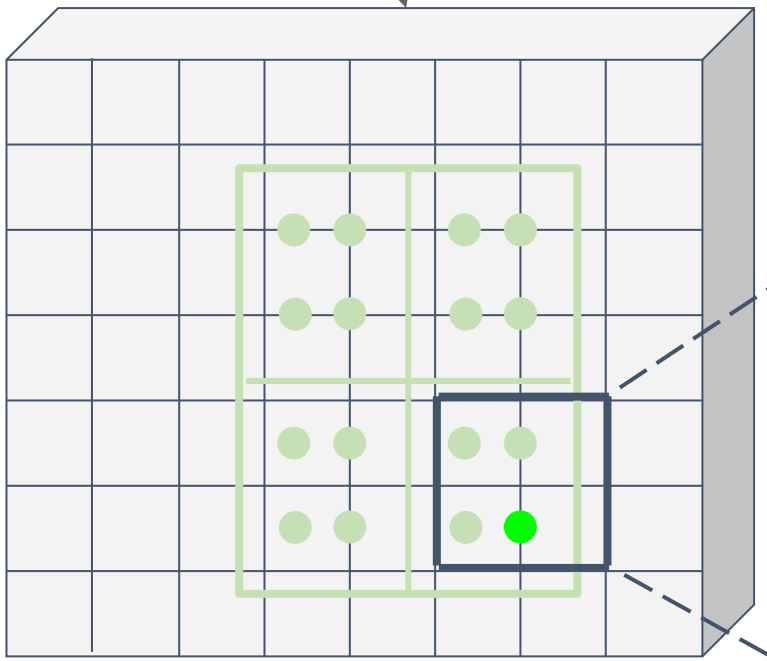
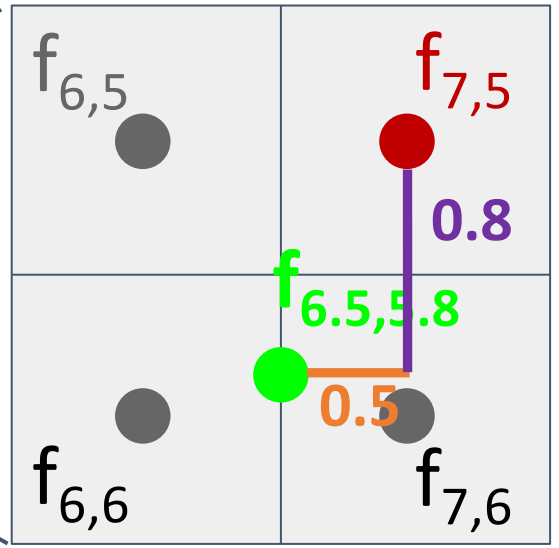


Sample features at regularly-spaced points in each subregion using **bilinear interpolation**



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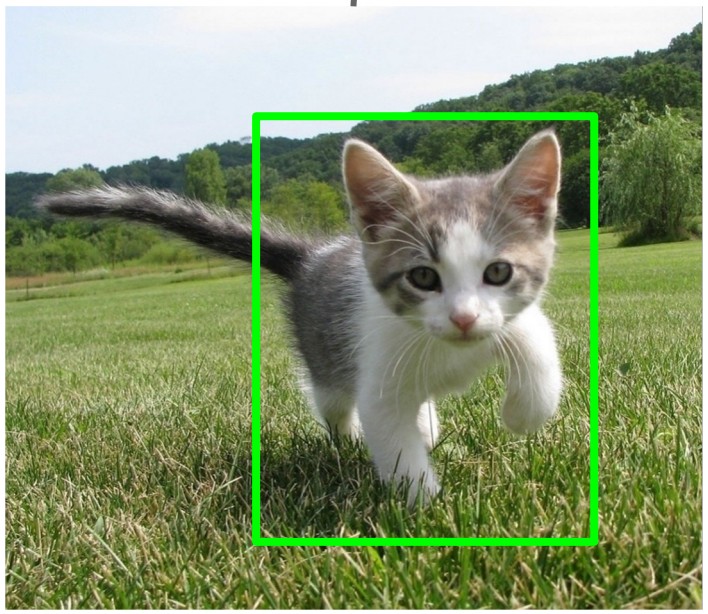
Divide into equal-sized subregions (may not be aligned to grid!)

No "snapping"!

Project proposal onto features



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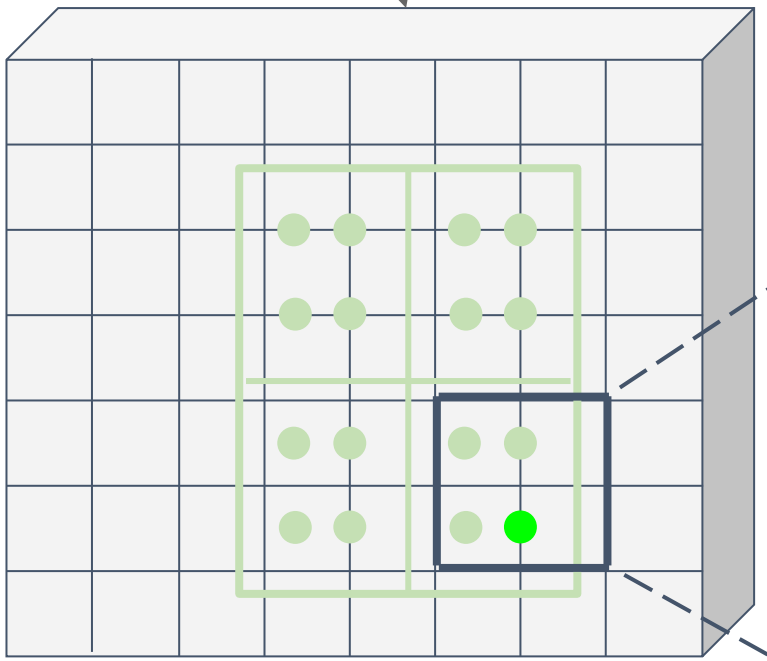

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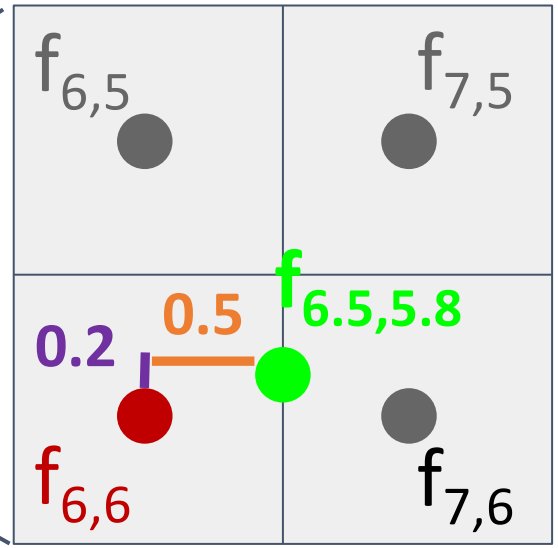

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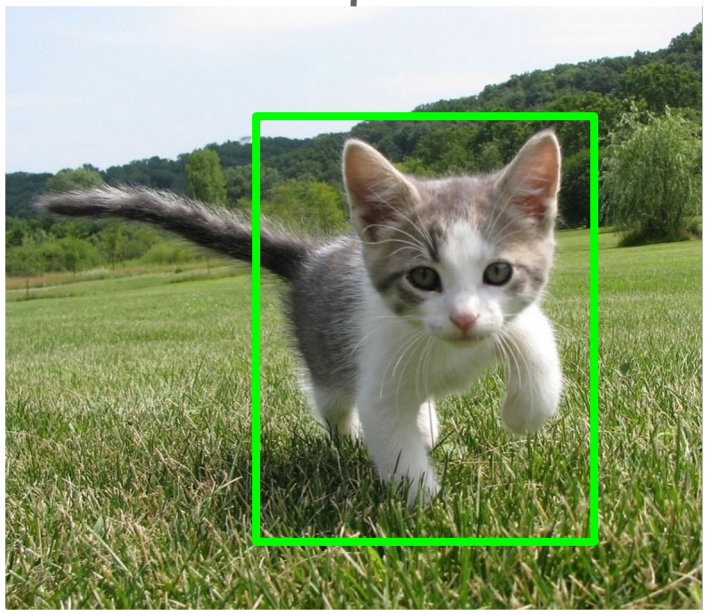
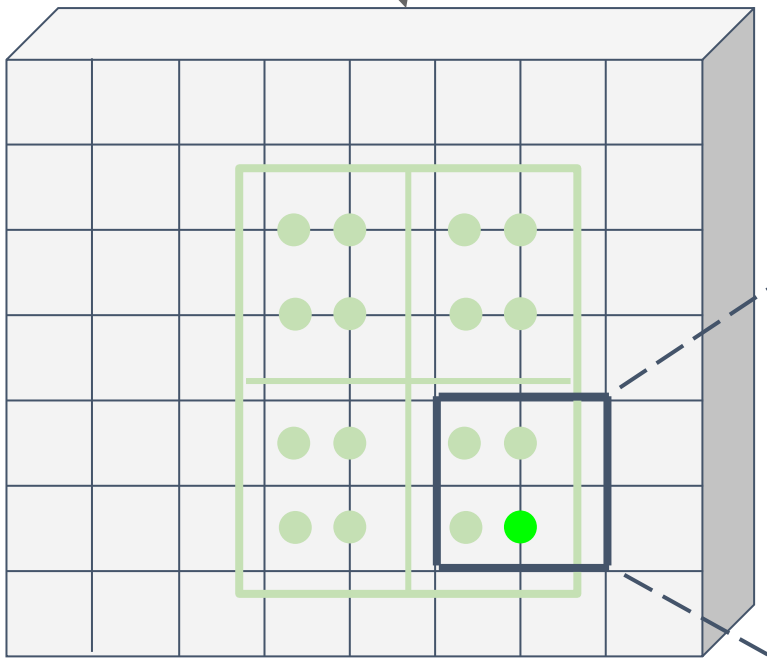
No "snapping"!

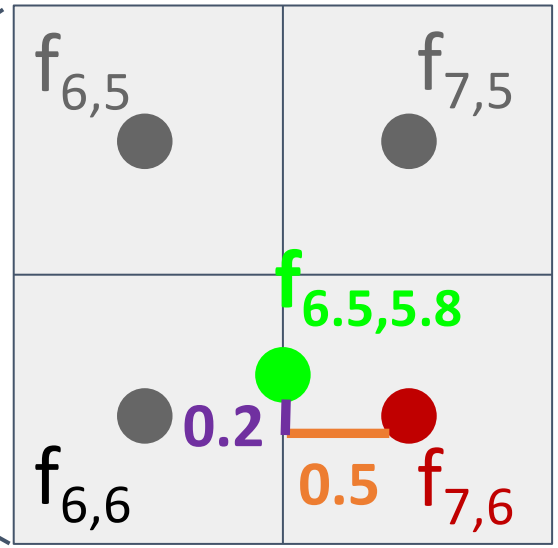
Project proposal onto features



CNN



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



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$+ (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$

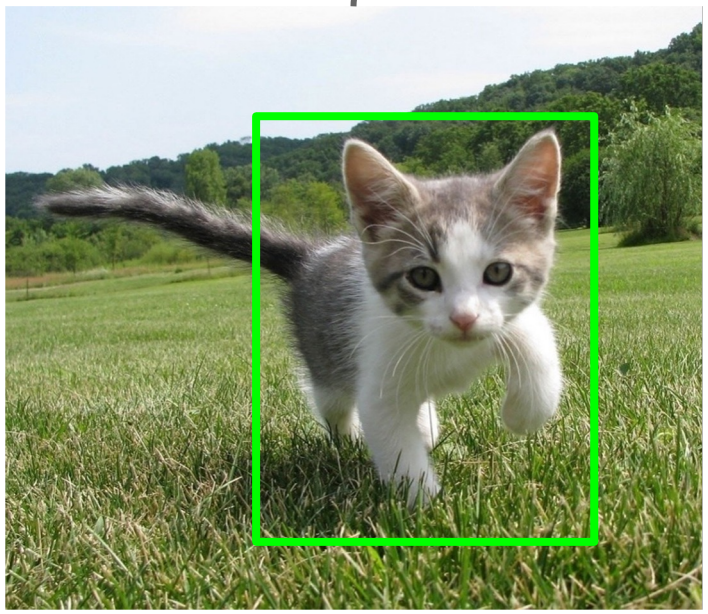
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align

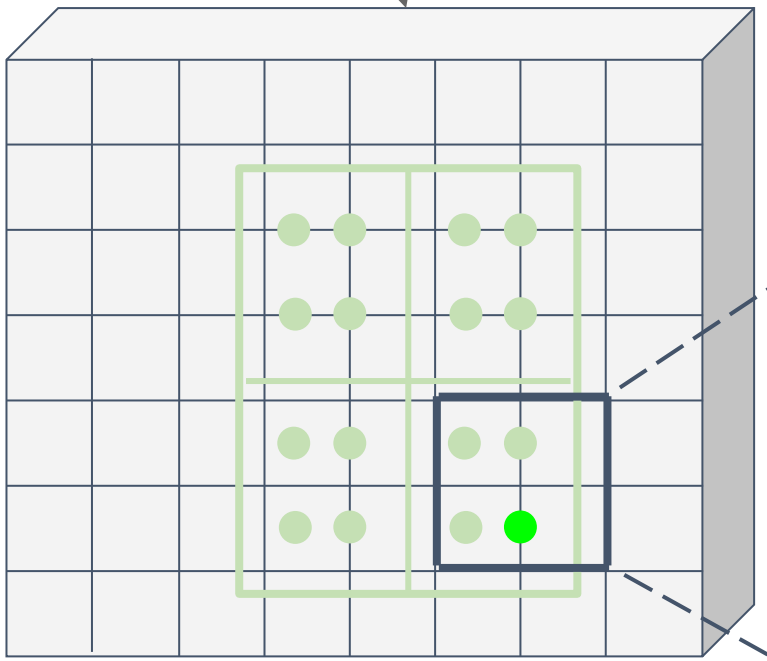
Divide into equal-sized subregions (may not be aligned to grid!)

No "snapping"!

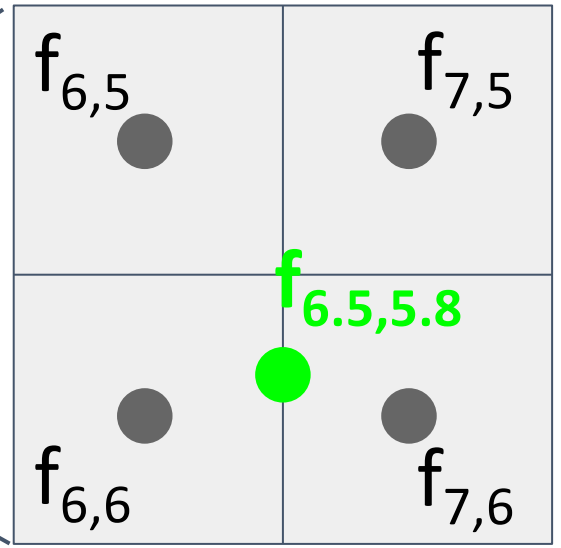
Project proposal onto features



CNN



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



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

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

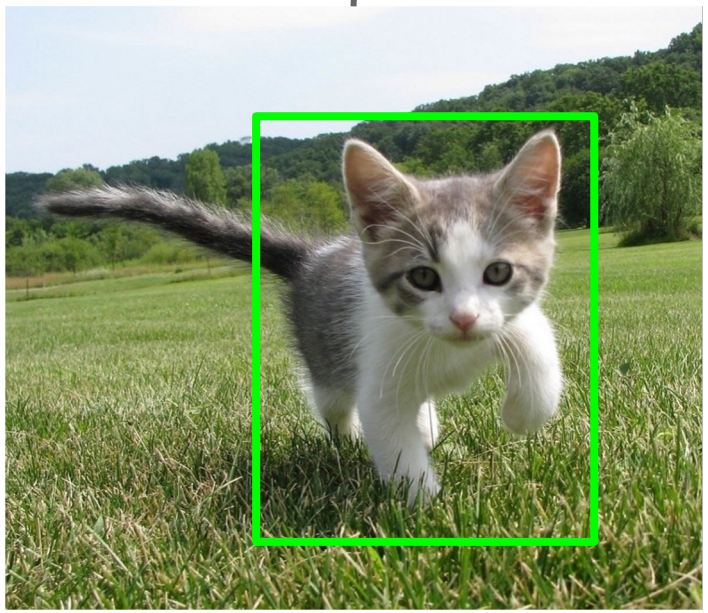
This is differentiable! Upstream gradient for sampled feature will flow backward into each of the four nearest-neighbor gridpoints

Cropping Features: RoI Align

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

No “snapping”!

Project proposal
onto features



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

CNN

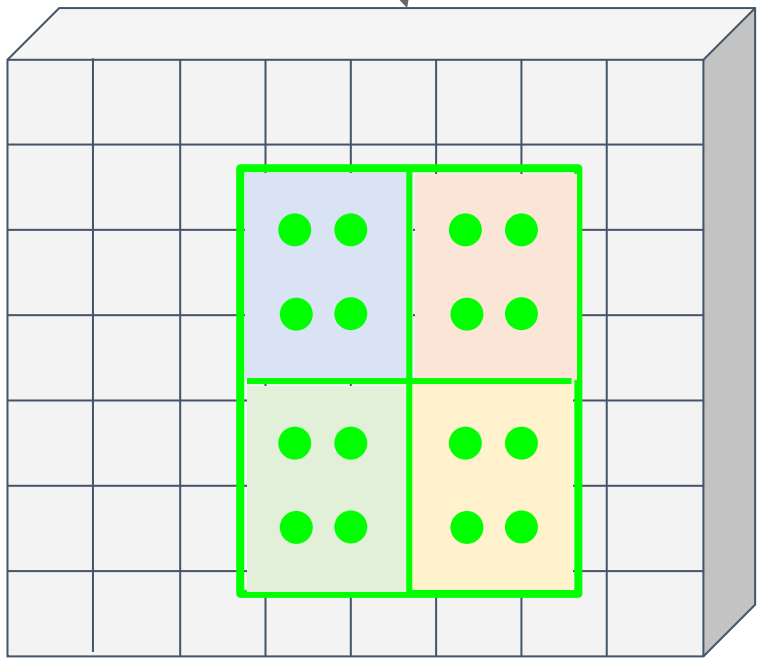
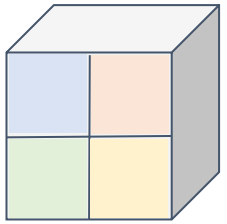


Image features
(e.g. 512 x 20 x 15)

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

After sampling, max-
pool in each subregion

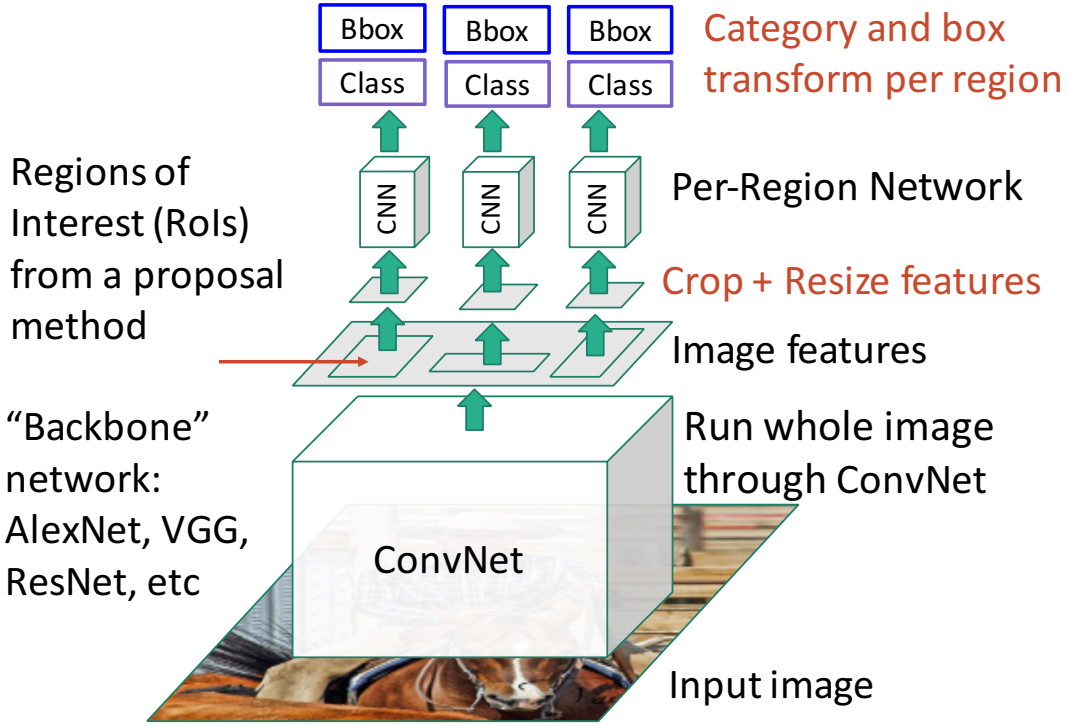


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

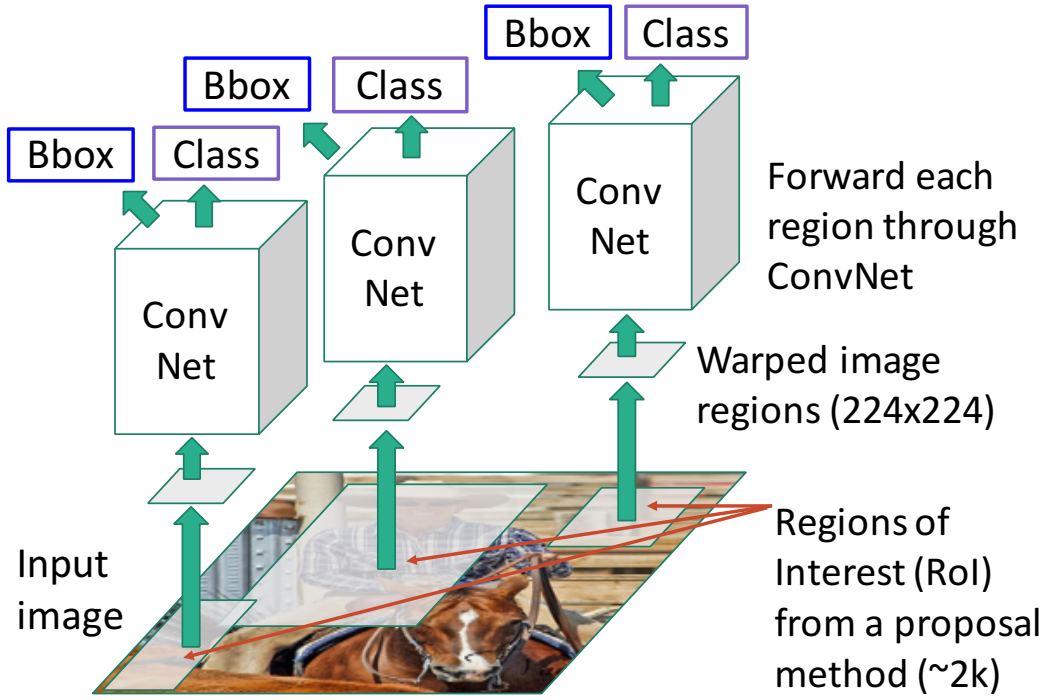
He et al, “Mask R-CNN”, ICCV 2017

Fast R-CNN vs “Slow” R-CNN

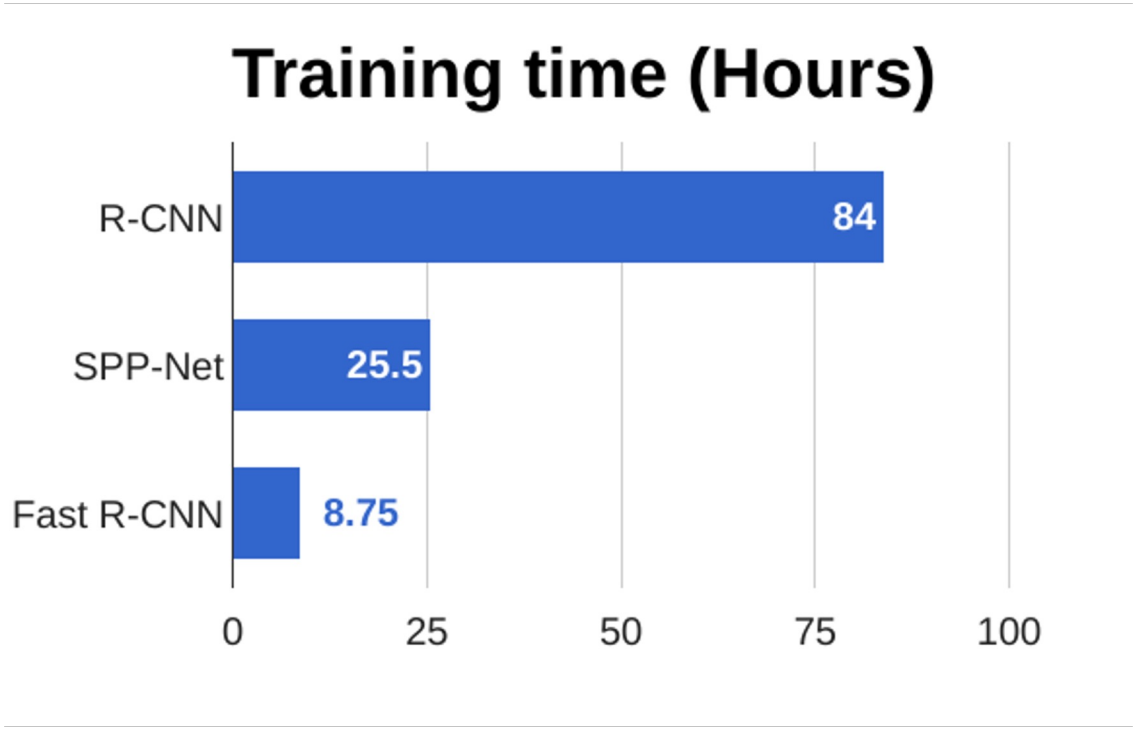
Fast R-CNN: Apply differentiable cropping to shared image features

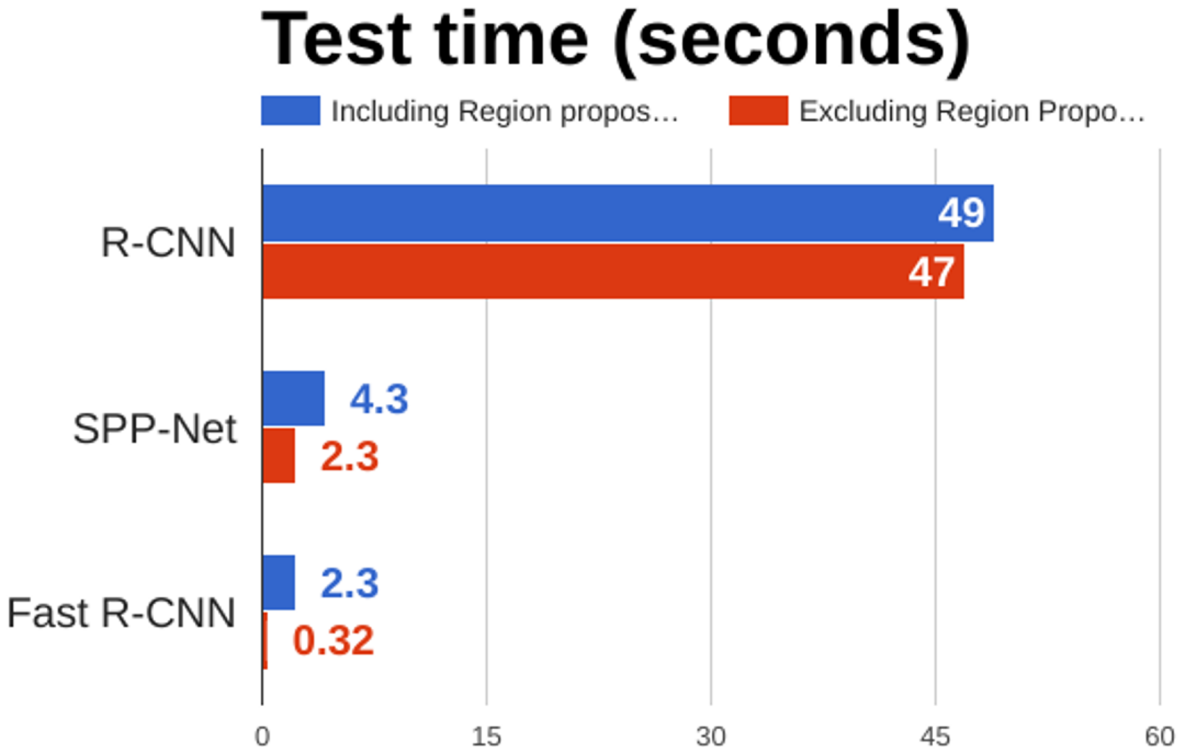


“Slow” R-CNN: Apply differentiable cropping to shared image features



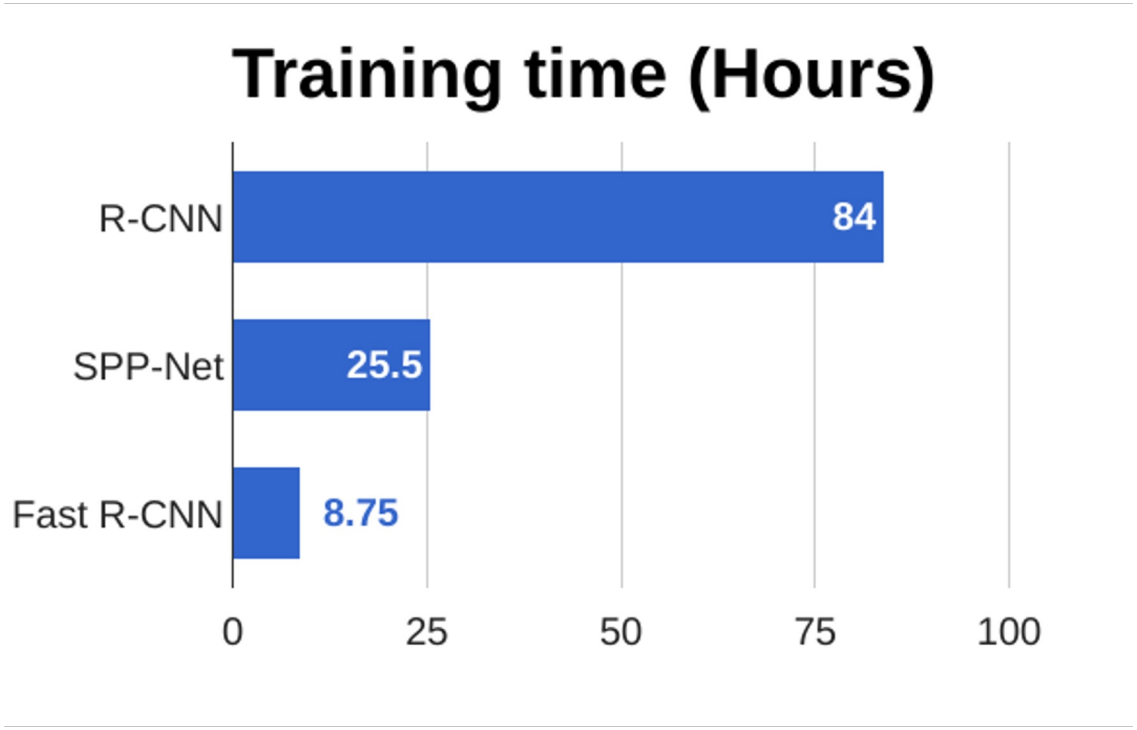
Fast R-CNN vs “Slow” R-CNN

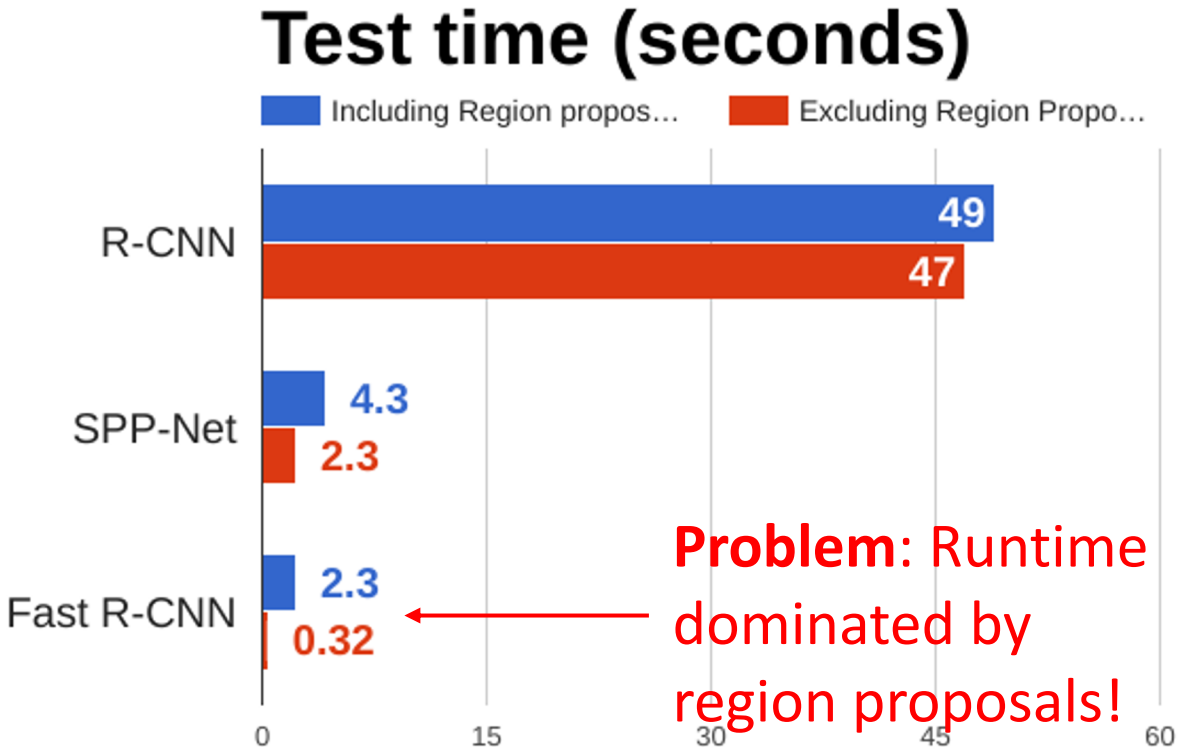




Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

Fast R-CNN vs “Slow” R-CNN





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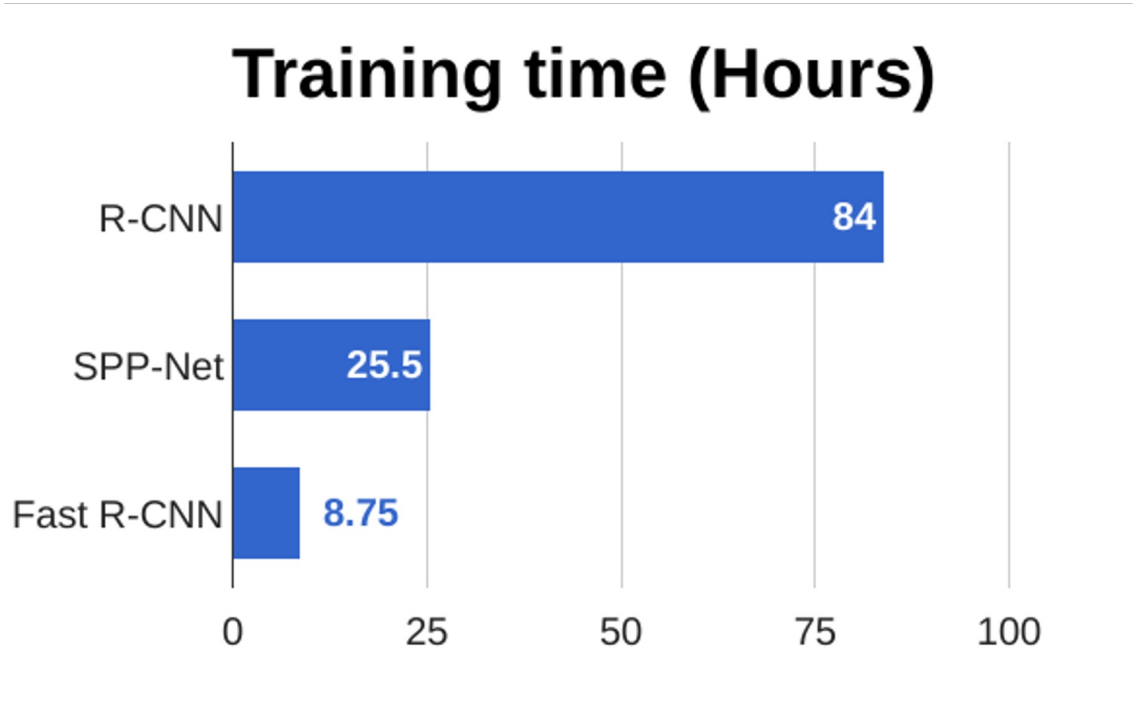

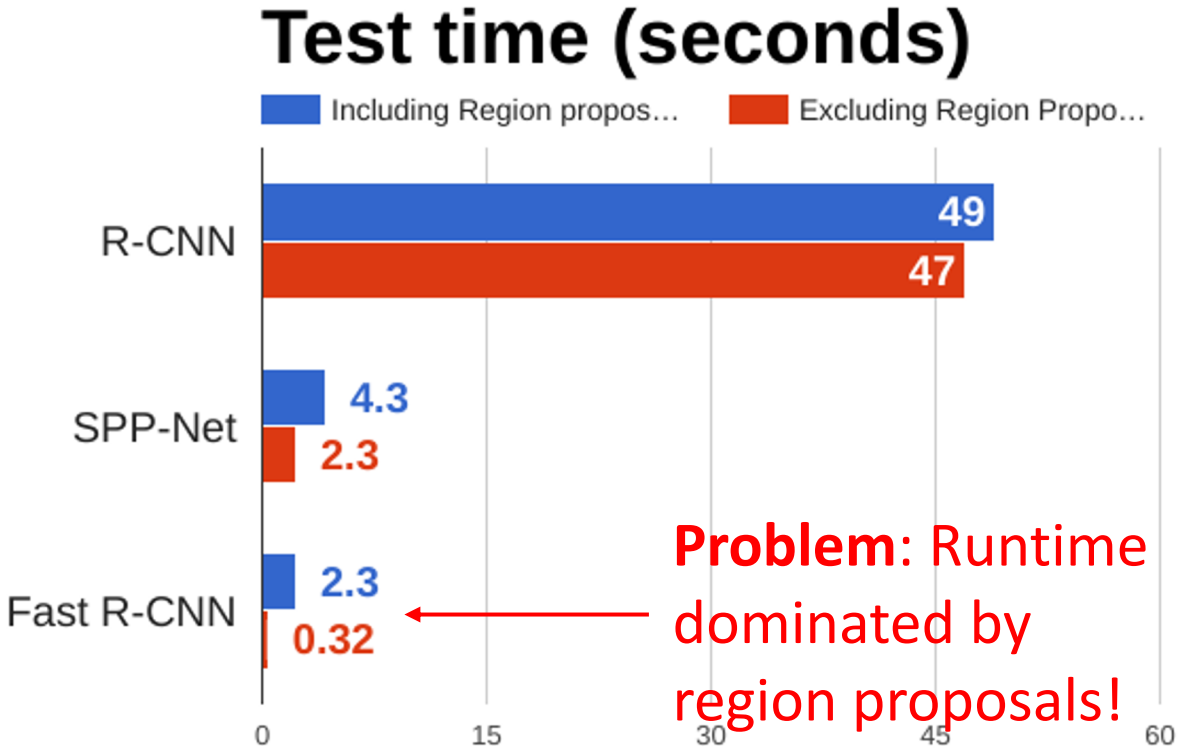

Problem: Runtime dominated by region proposals!

Recall: Region proposals computed by heuristic ”Selective Search” algorithm on CPU -- let’s learn them with a CNN instead!

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
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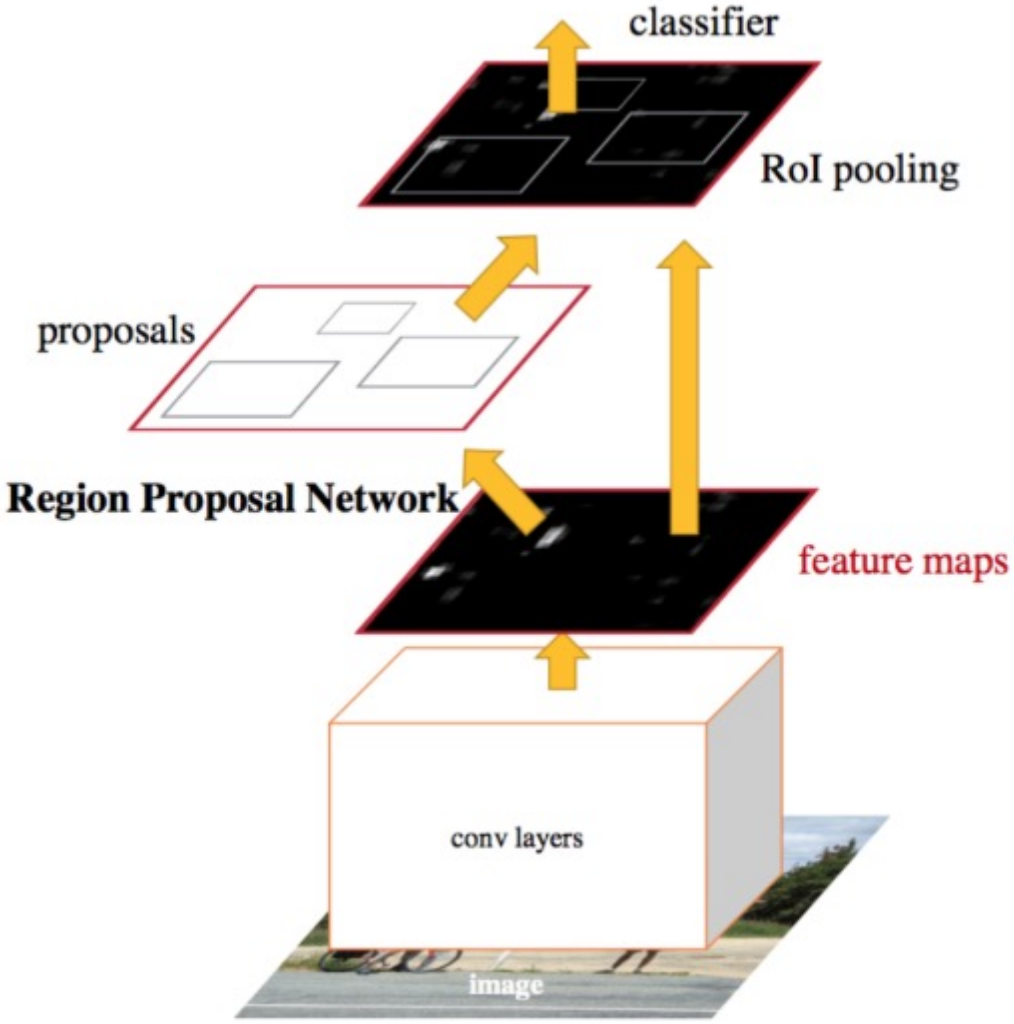
Faster R-CNN: Learnable Region Proposals

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
Figure copyright 2015, Ross Girshick; reproduced with permission

Region Proposal Network (RPN)

Run backbone CNN to get
features aligned to input image

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

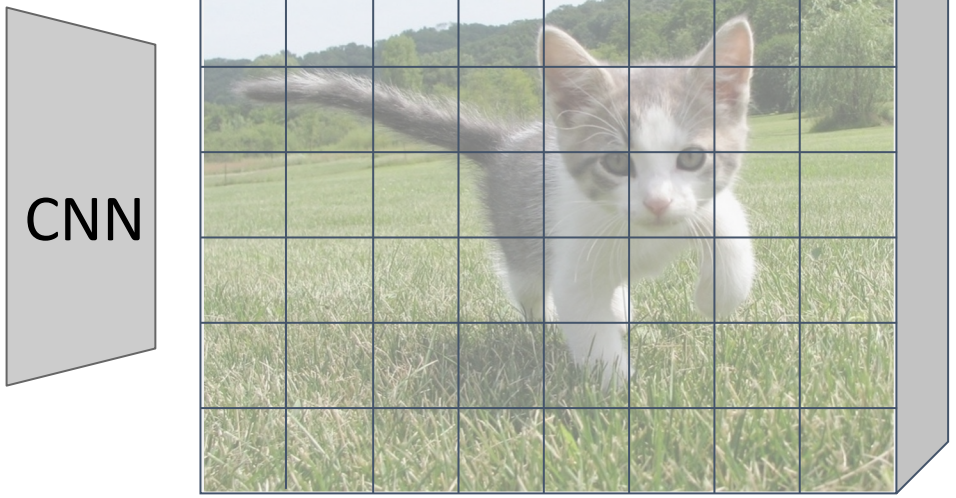


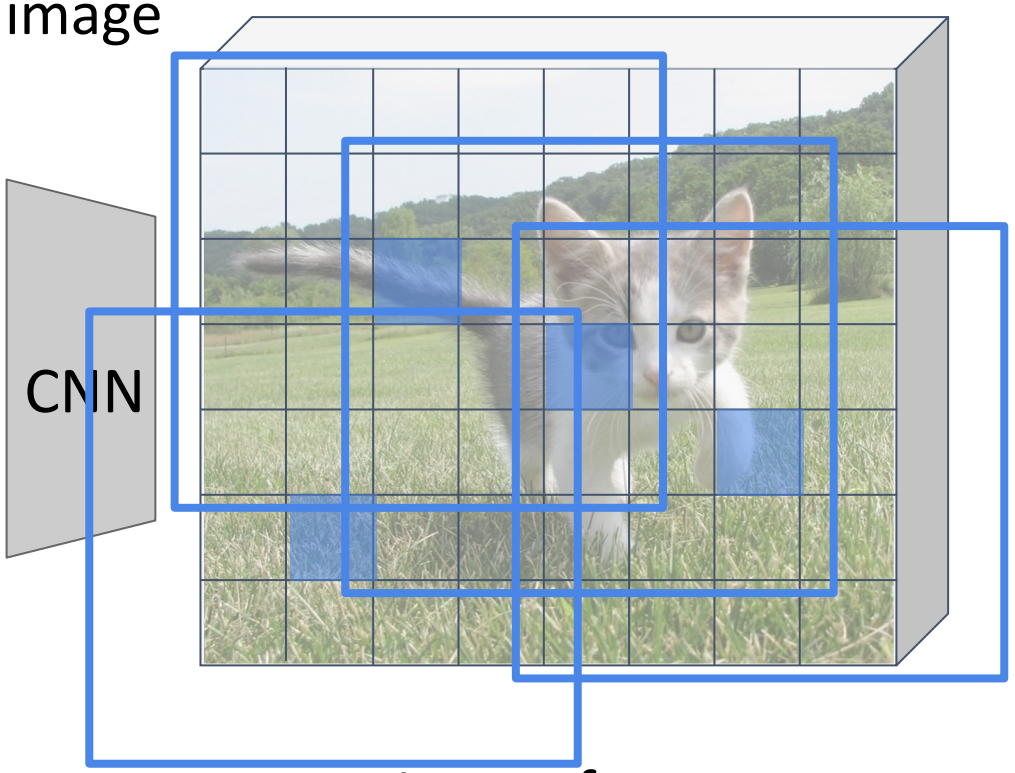
Image features
(e.g. 512 x 20 x 15)

Region Proposal Network (RPN)

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

Run backbone CNN to get features aligned to input image

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



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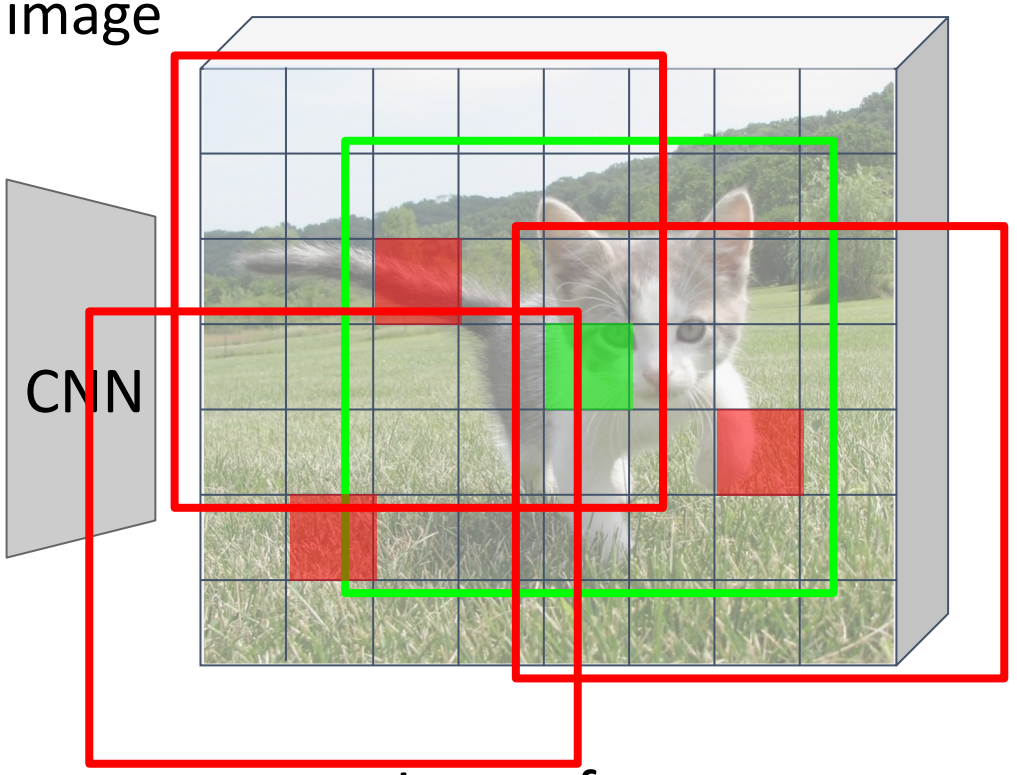

Image features
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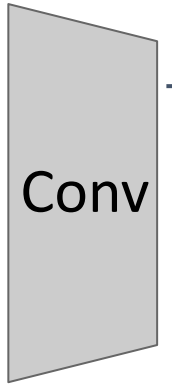


Anchor is an object?
1 x 20 x 15

At each point, predict whether the corresponding anchor contains an object (per-cell logistic regression, predict scores with conv layer)

Region Proposal Network (RPN)

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

Run backbone CNN to get features aligned to input image

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

CNN

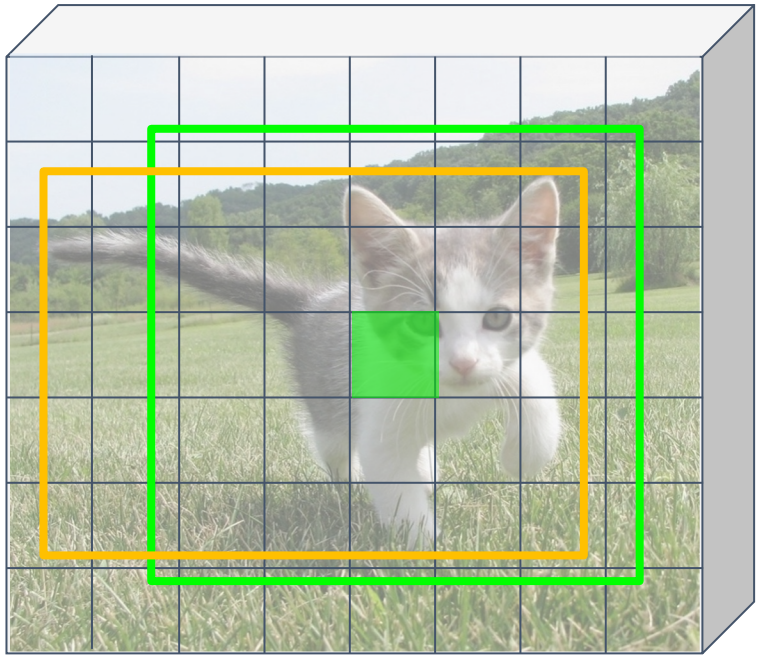


Image features
(e.g. 512 x 20 x 15)

Conv

Anchor is an object?
1 x 20 x 15

Box transforms
4 x 20 x 15

For positive boxes, also predict a box transform to regress from **anchor box** to **object box**

Region Proposal Network (RPN)

Problem: Anchor box may have the wrong size / shape

Solution: Use **K** different anchor boxes at each point!

Run backbone CNN to get features aligned to input image

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

CNN

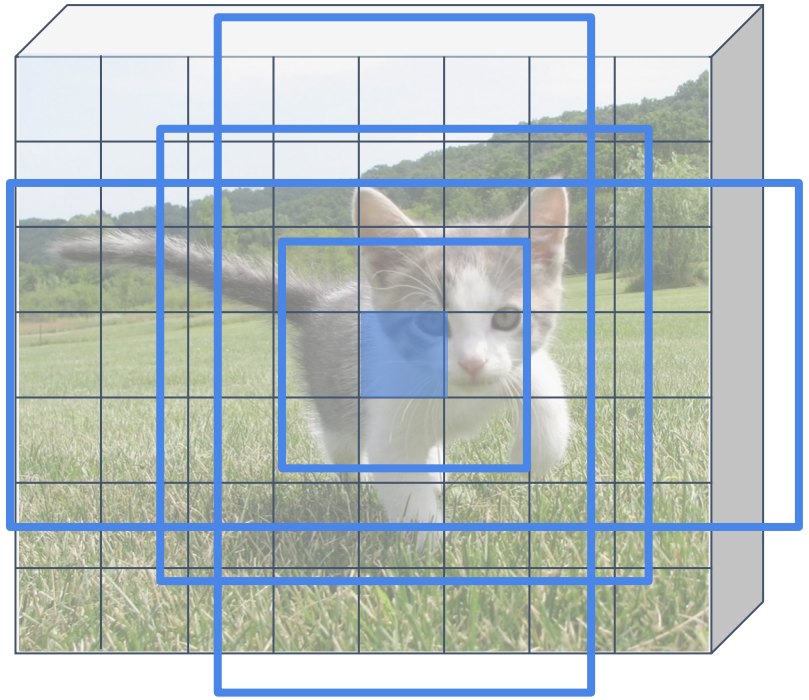


Image features
(e.g. 512 x 20 x 15)

Conv

Anchor is an object?
K x 20 x 15

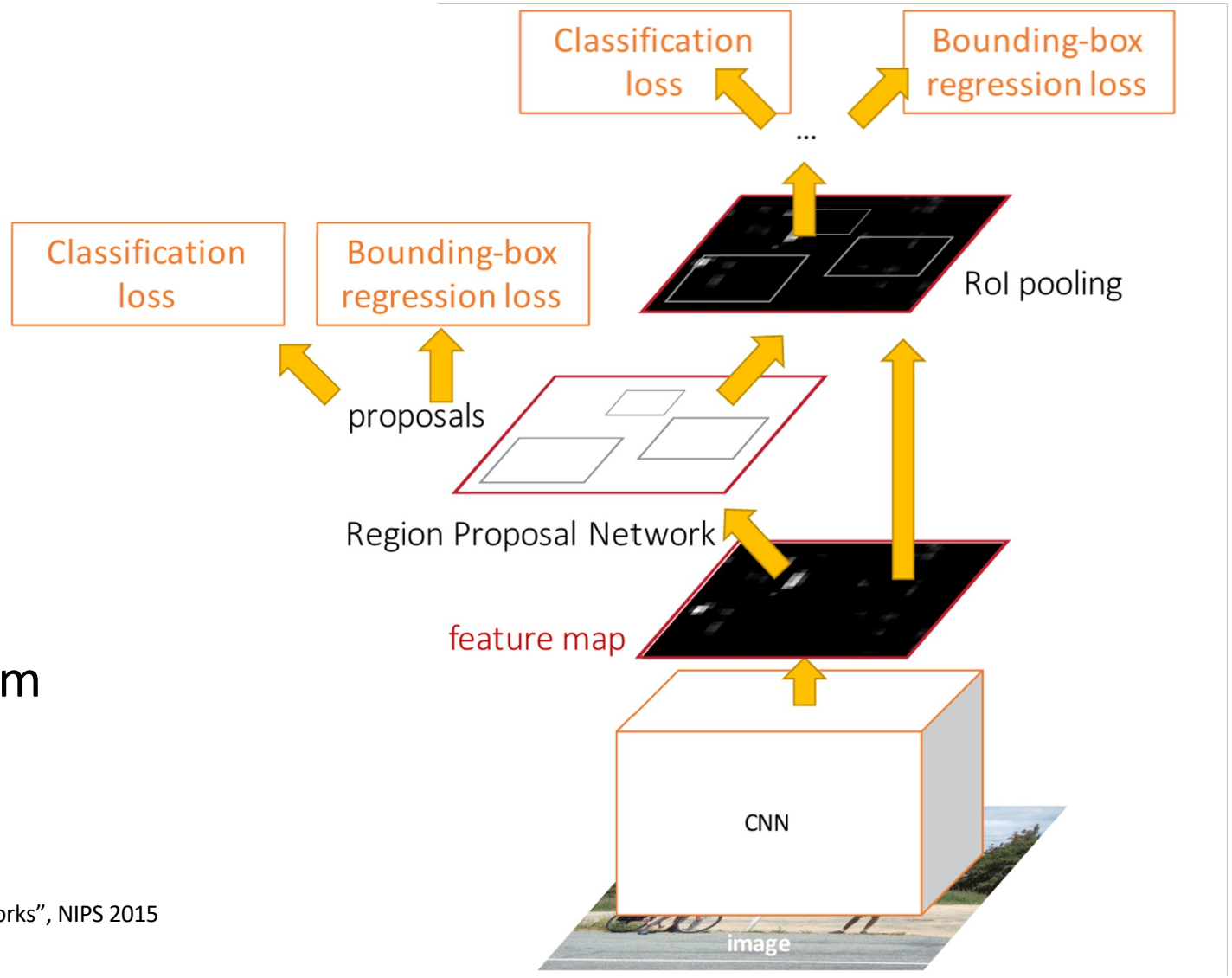
Box transforms
4K x 20 x 15

At test time: sort all K*20*15 boxes by their score, and take the top ~300 as our region proposals

Faster R-CNN: Learnable Region Proposals

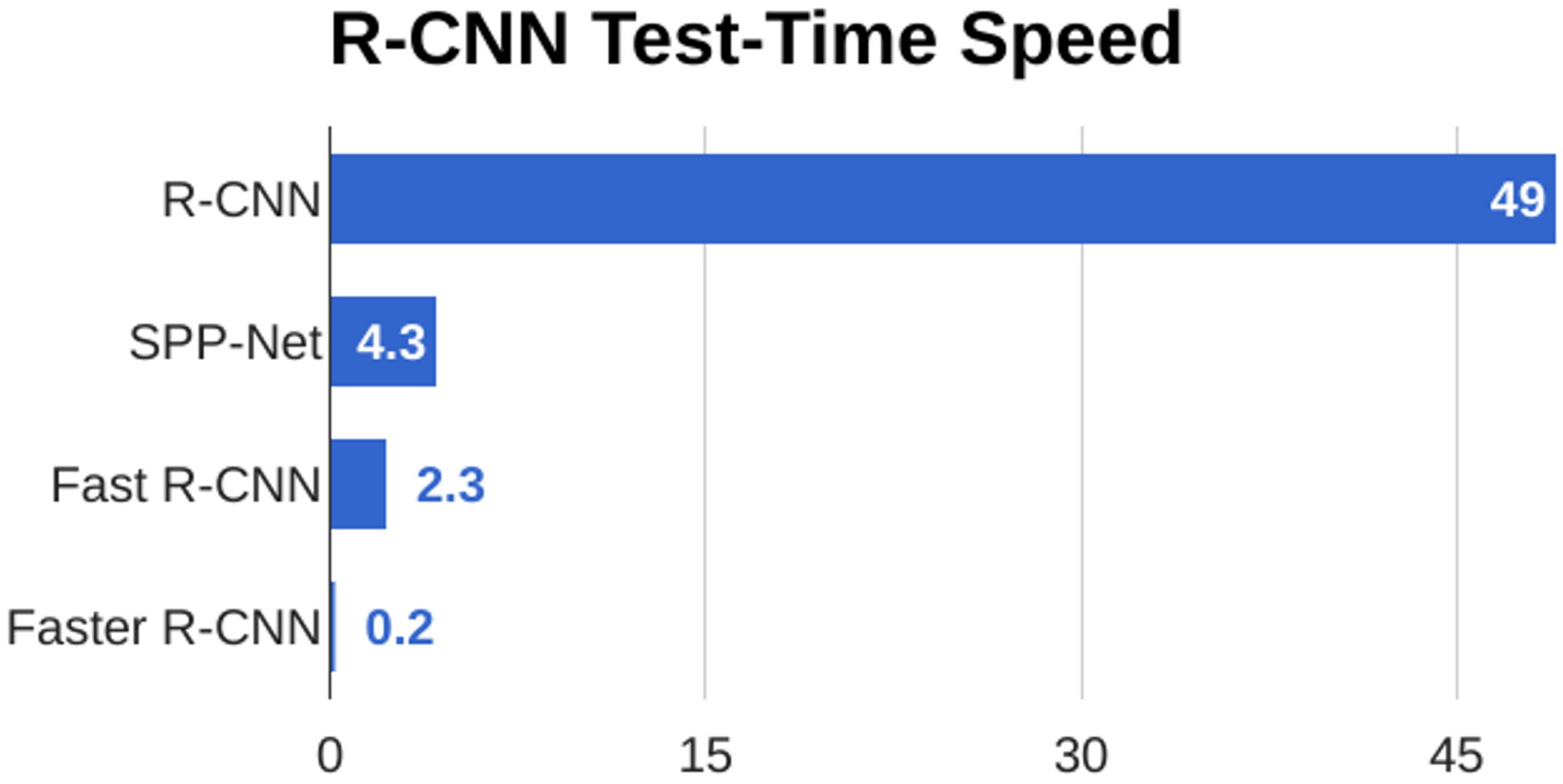
Jointly train with 4 losses:

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



Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Faster R-CNN: Learnable Region Proposals

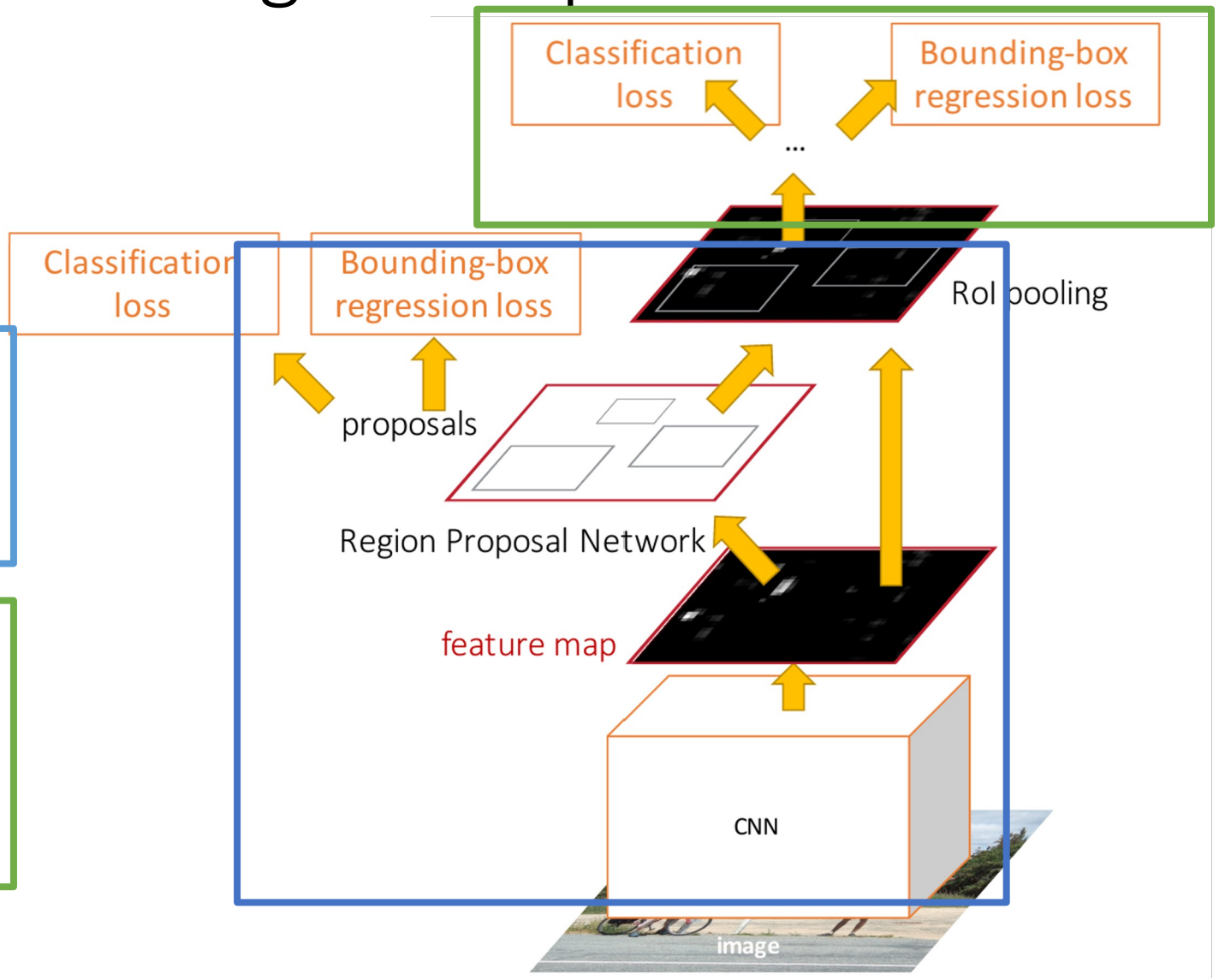


Faster R-CNN: Learnable Region Proposals

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



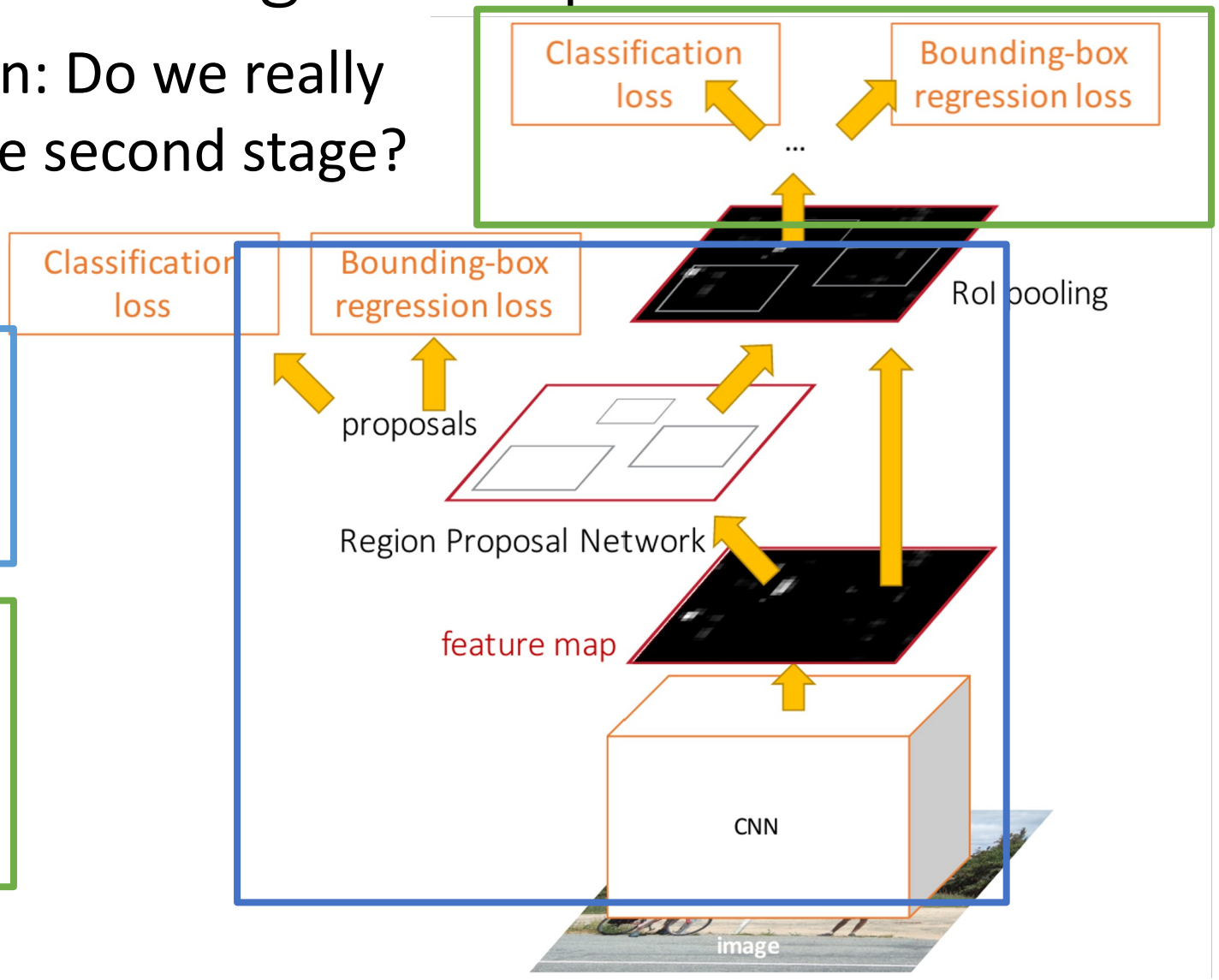
Faster R-CNN: Learnable Region Proposals

Question: 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 Detection

RPN: Classify each anchor as object / not object

Single-Stage Detector: Classify each object as one of C categories (or background)

Run backbone CNN to get features aligned to input image

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

CNN

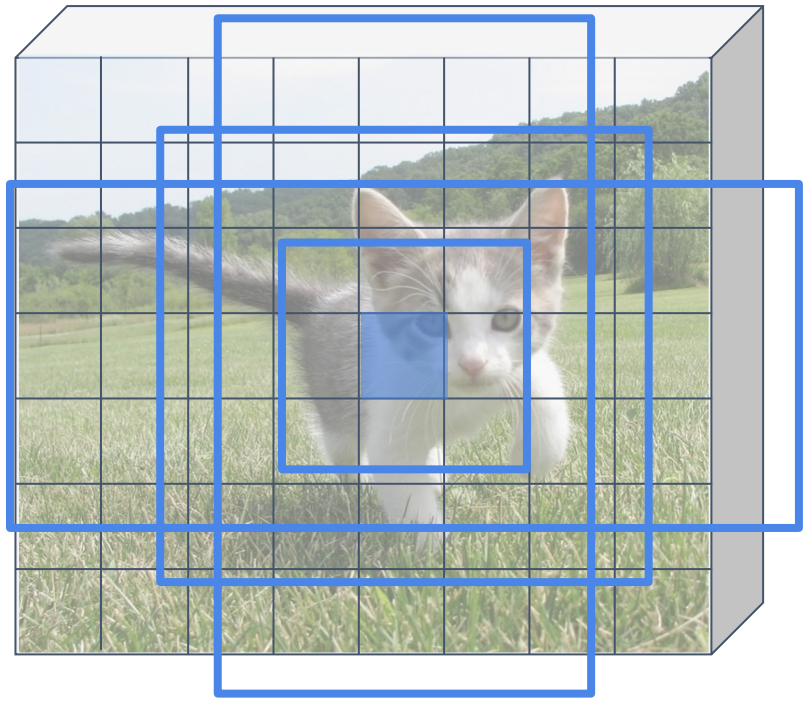


Image features
(e.g. 512 x 20 x 15)

Conv

Anchor category
(C+1) x K x 20 x 15

Box transforms
4K x 20 x 15

Remember: K anchors at each position in image feature map

Single-Stage Object Detection: YOLO and SSD

RPN: Classify each anchor as object / not object

Single-Stage Detector: Classify each object as one of C categories (or background)

Run backbone CNN to get features aligned to input image

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

CNN

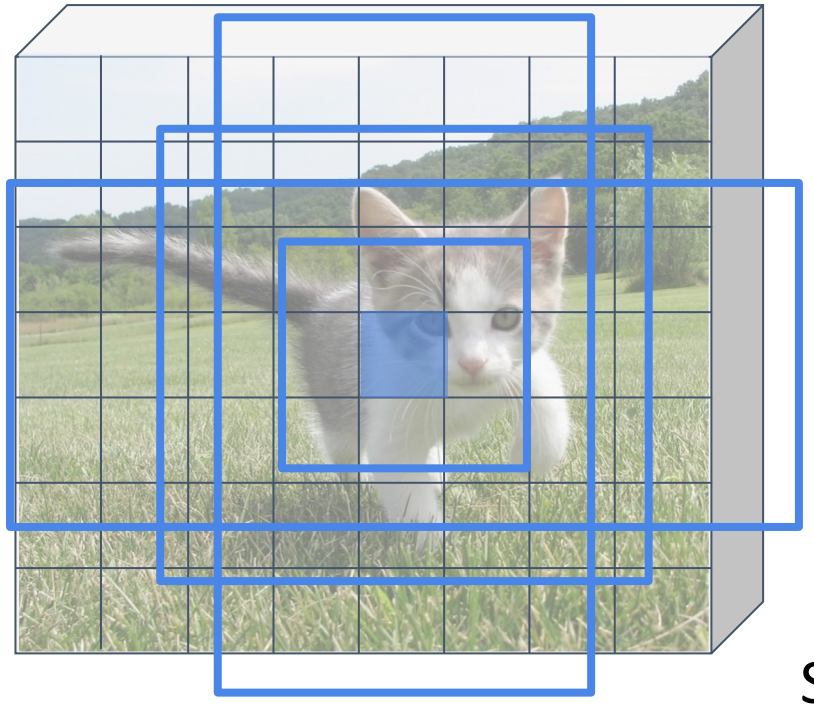


Image features
(e.g. 512 x 20 x 15)

Conv

Anchor category
(C+1) x K x 20 x 15

Box transforms
C x 4K x 20 x 15

Sometimes use **category-specific regression**: Predict different box transforms for each category

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

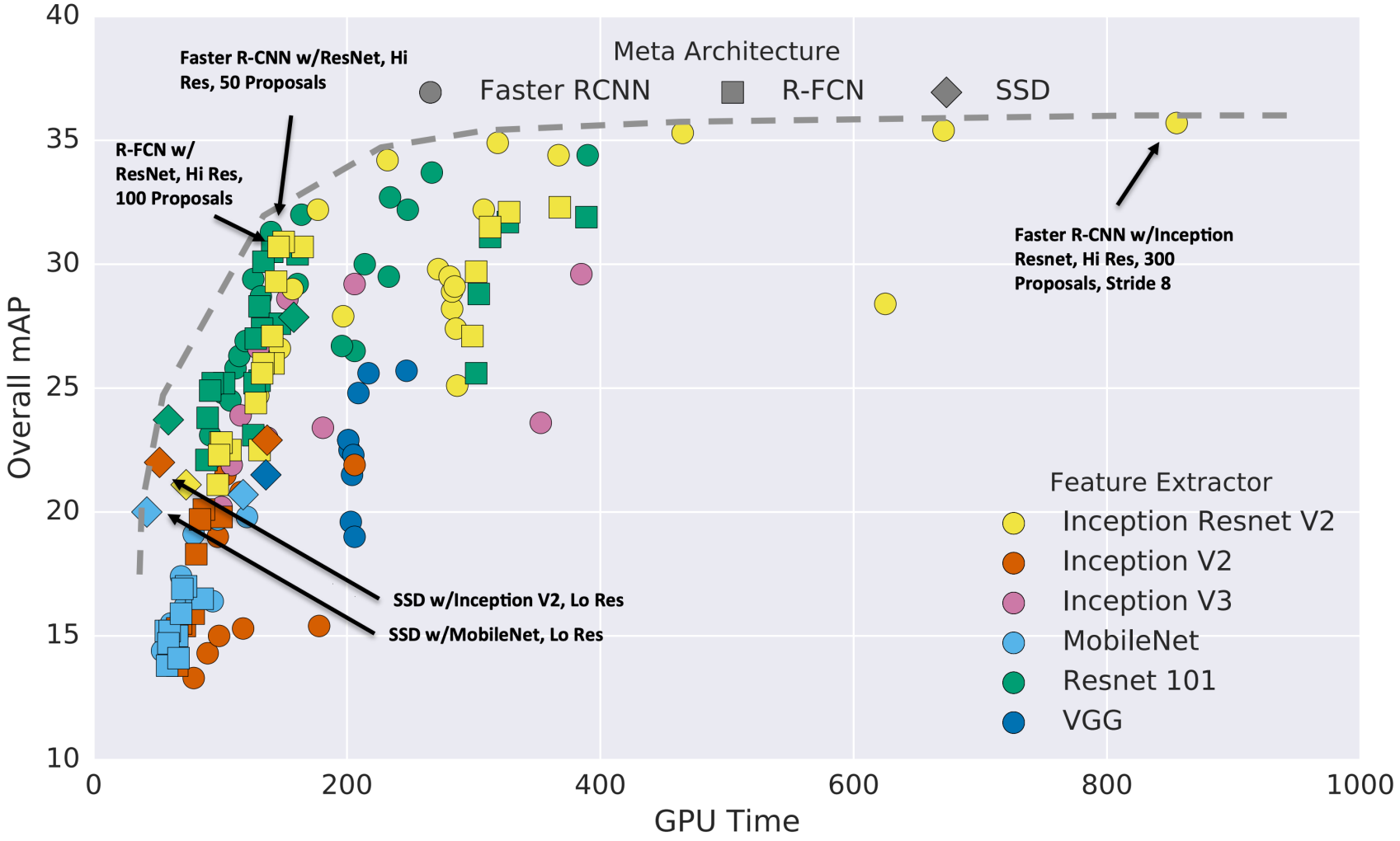
YOLO series

YOLO detection demo (YOLO, YOLOv2, YOLOv3, tinyYOLO…)

You Only Look Once: Unified, Real-Time Object Detection

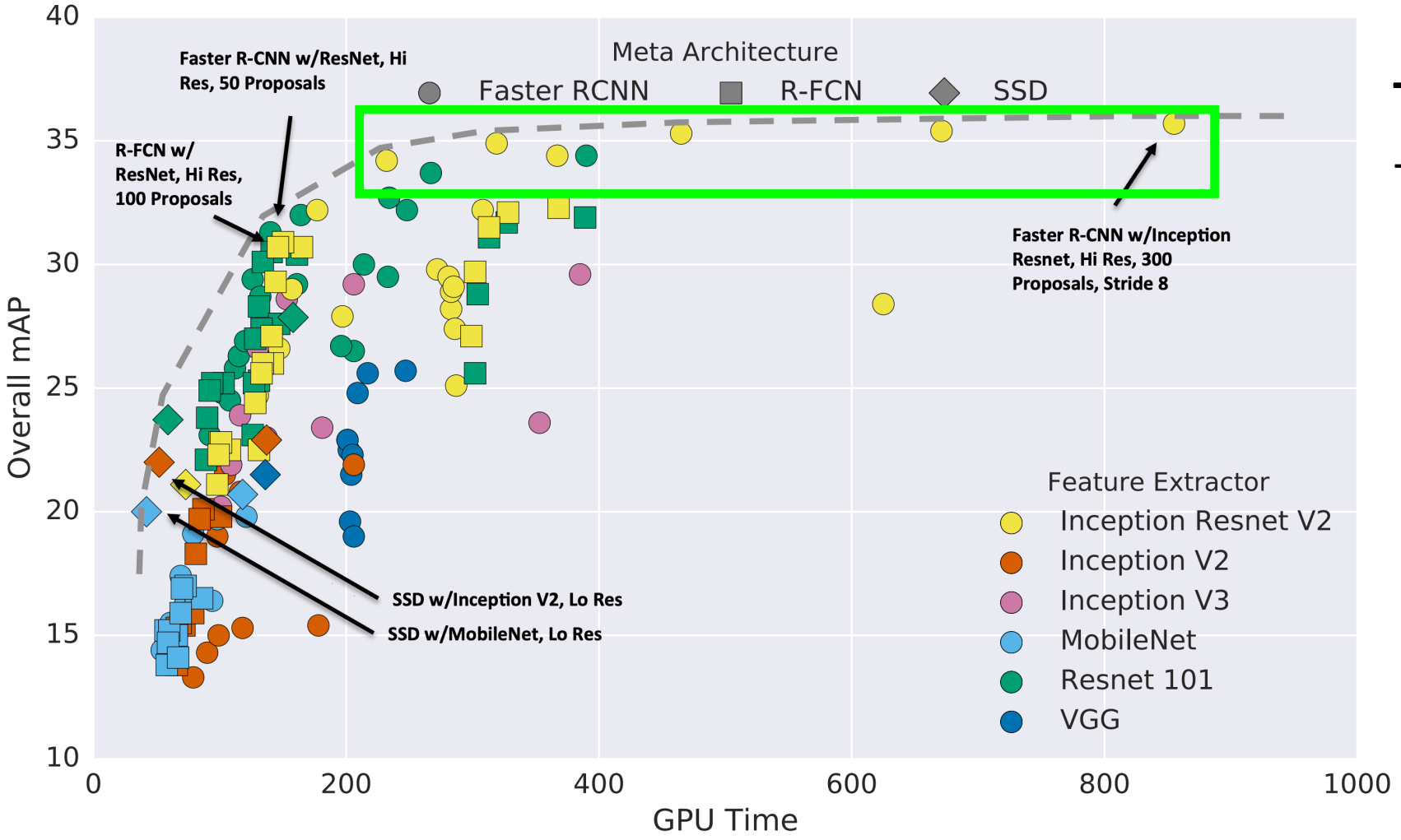
https://www.youtube.com/watch?v=VOC3huqHrss

Object Detection: Lots of variables!



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

Object Detection: Lots of variables!

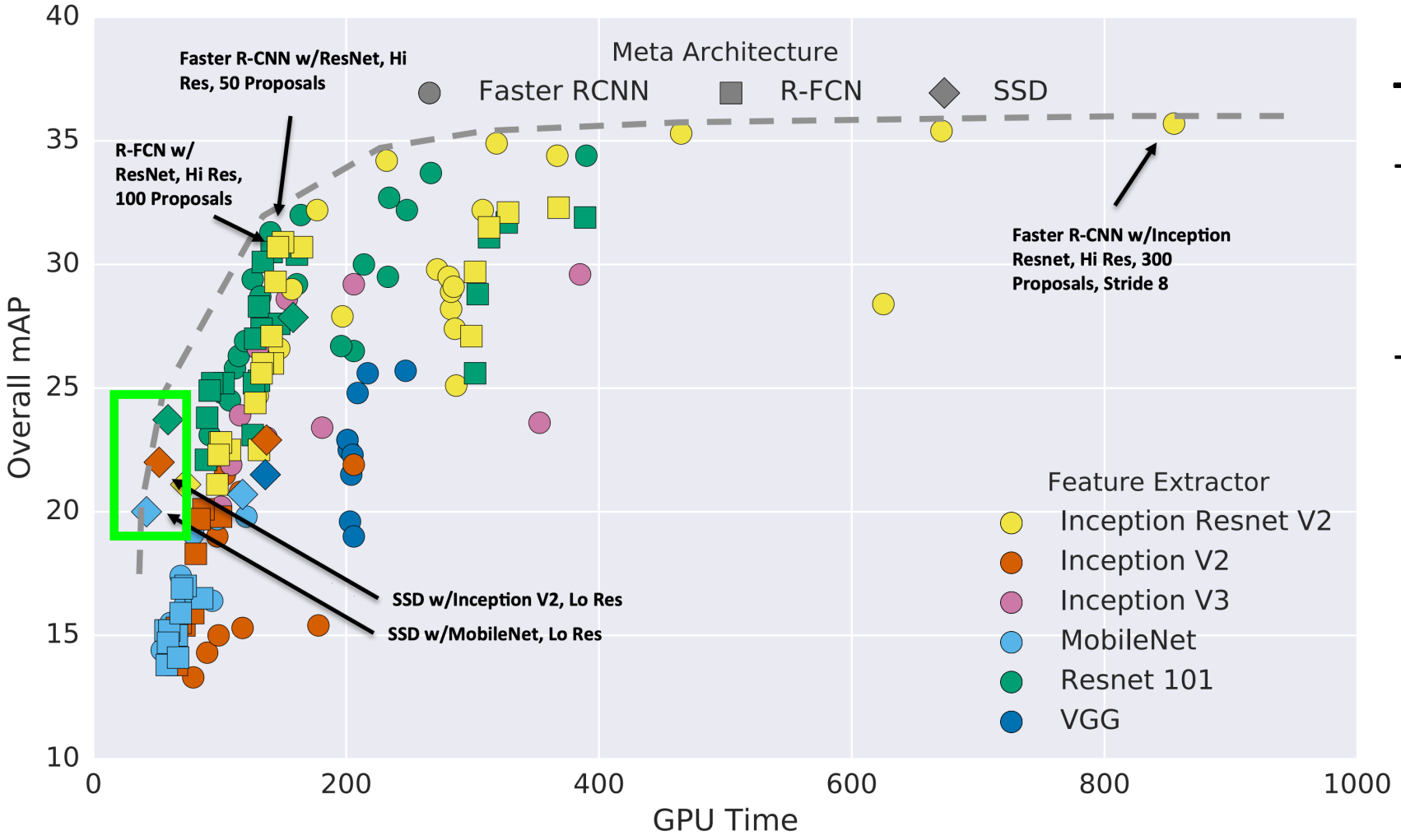


Takeaways:

- Two stage method (Faster R-CNN) get the best accuracy, but are slower

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

Object Detection: Lots of variables!

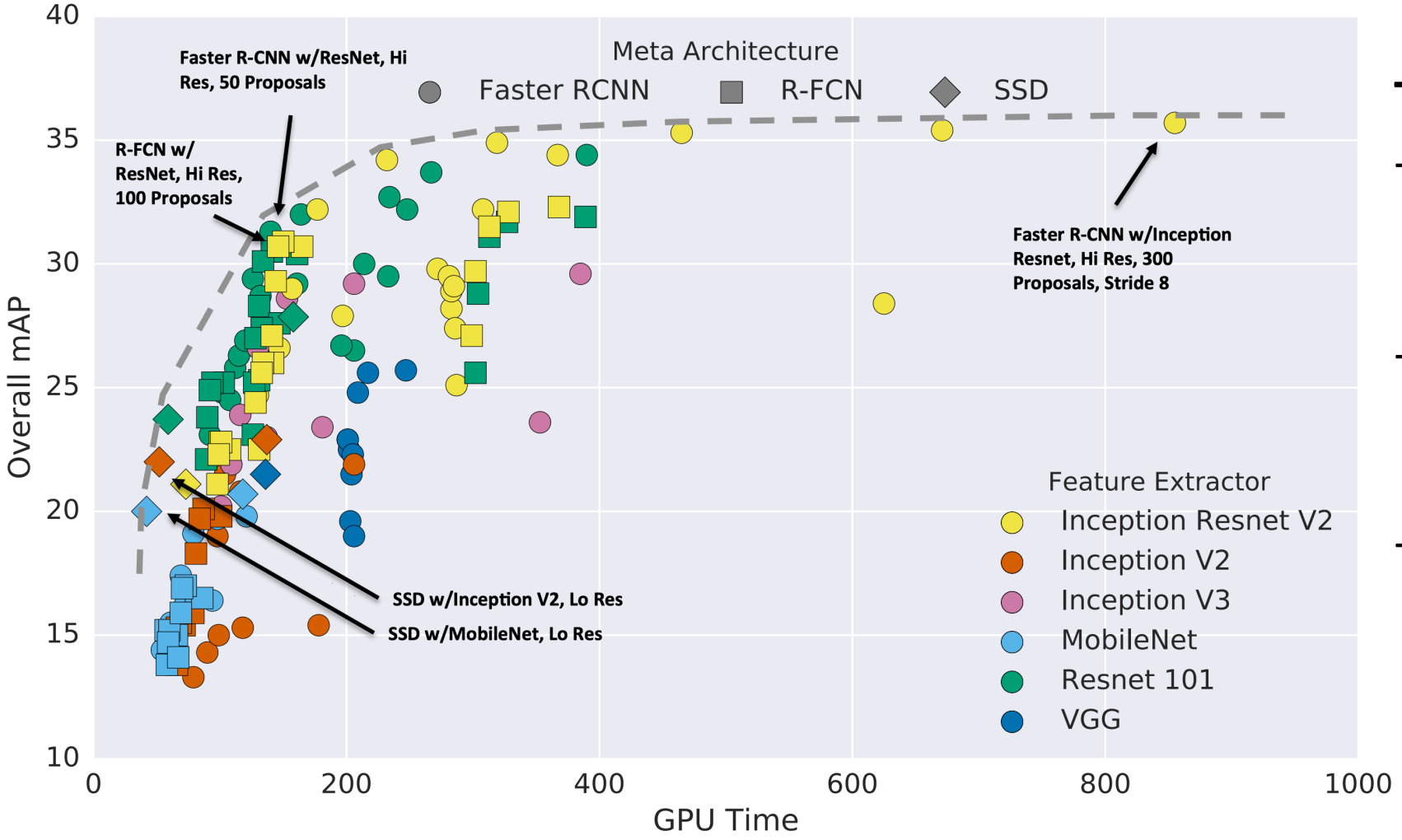


Takeaways:

- Two stage method (Faster R-CNN) get the best accuracy, but are slower
- Single-stage methods (SSD) are much faster, but don't perform as well

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

Object Detection: Lots of variables!

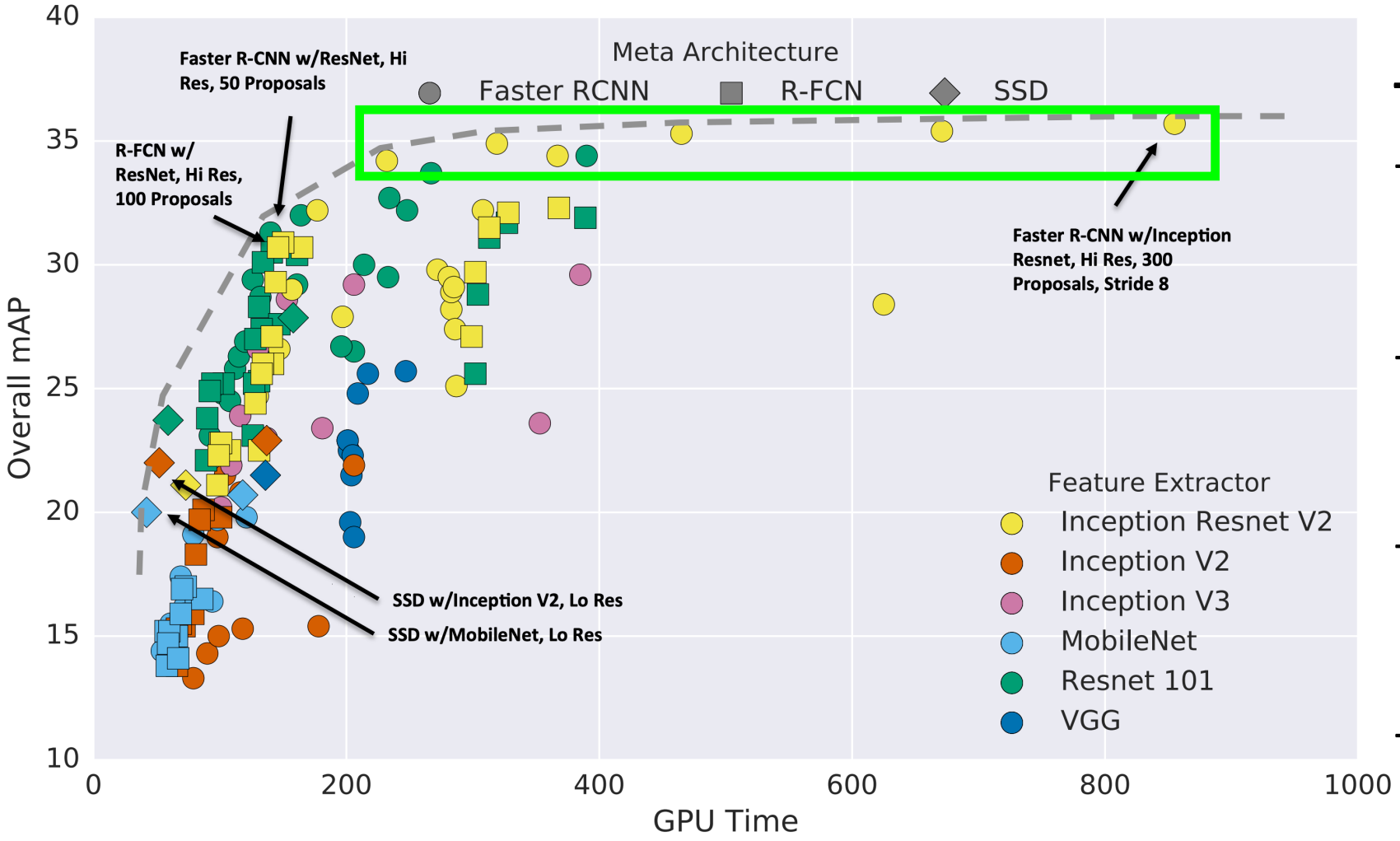


Takeaways:

- Two stage method (Faster R-CNN) get the best accuracy, but are slower
- Single-stage methods (SSD) are much faster, but don't perform as well
- Bigger backbones improve performance, but are slower

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

Object Detection: Lots of variables!

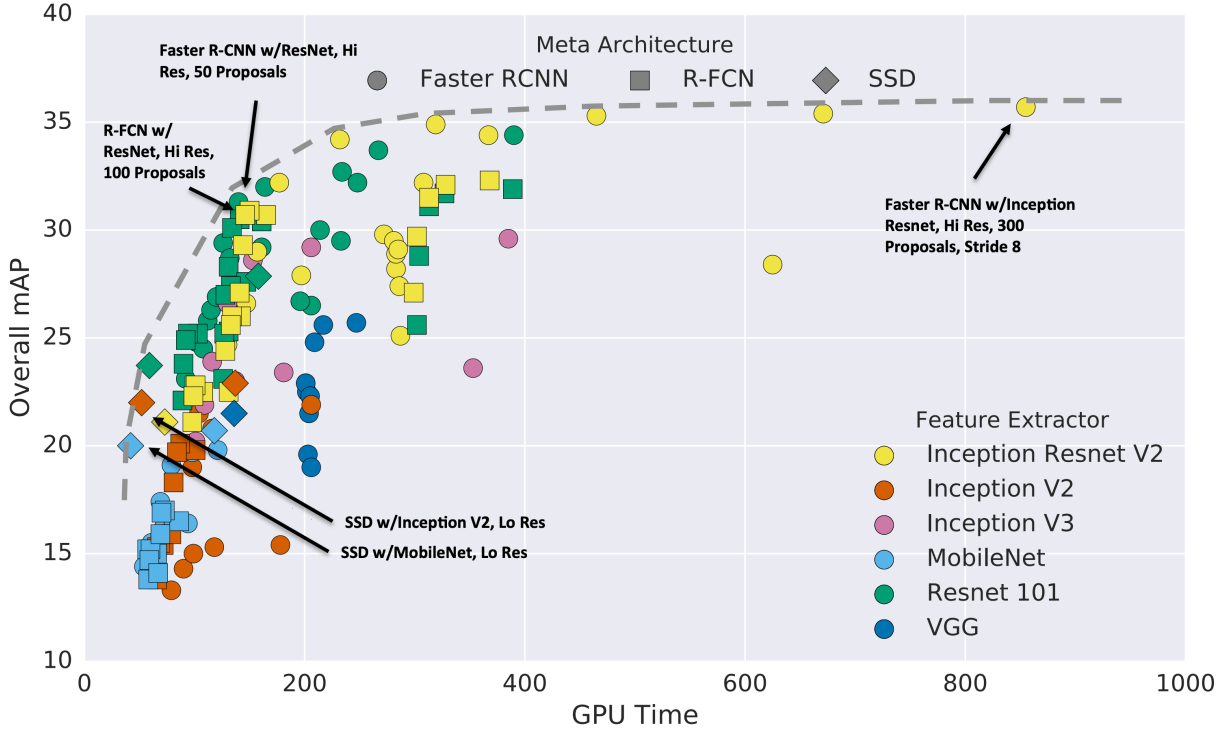


Takeaways:

- Two stage method (Faster R-CNN) get the best accuracy, but are slower
- Single-stage methods (SSD) are much faster, but don't perform as well
- Bigger backbones improve performance, but are slower
- Diminishing returns for slower methods

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

Object Detection: Lots of variables!



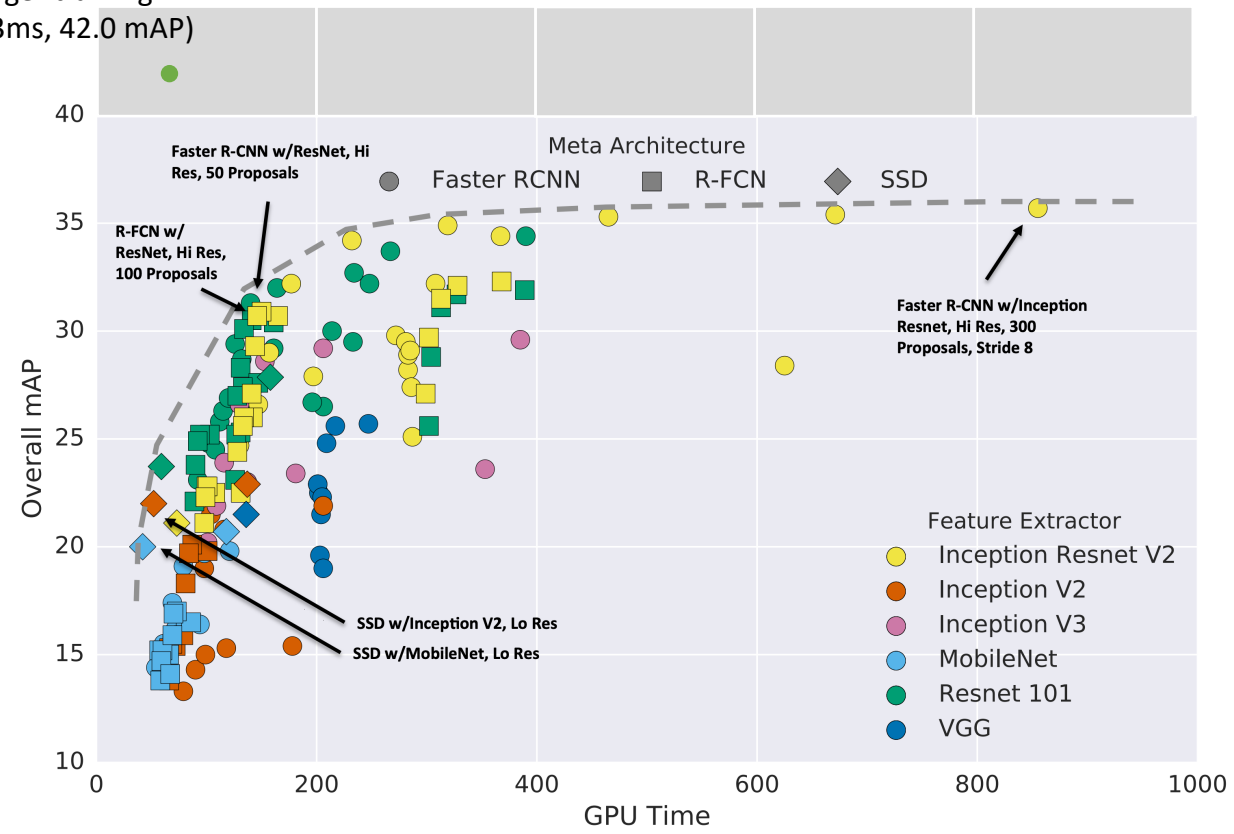
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

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

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!

Faster R-CNN w/ResNet-101-FPN, longer training (63ms, 42.0 mAP)



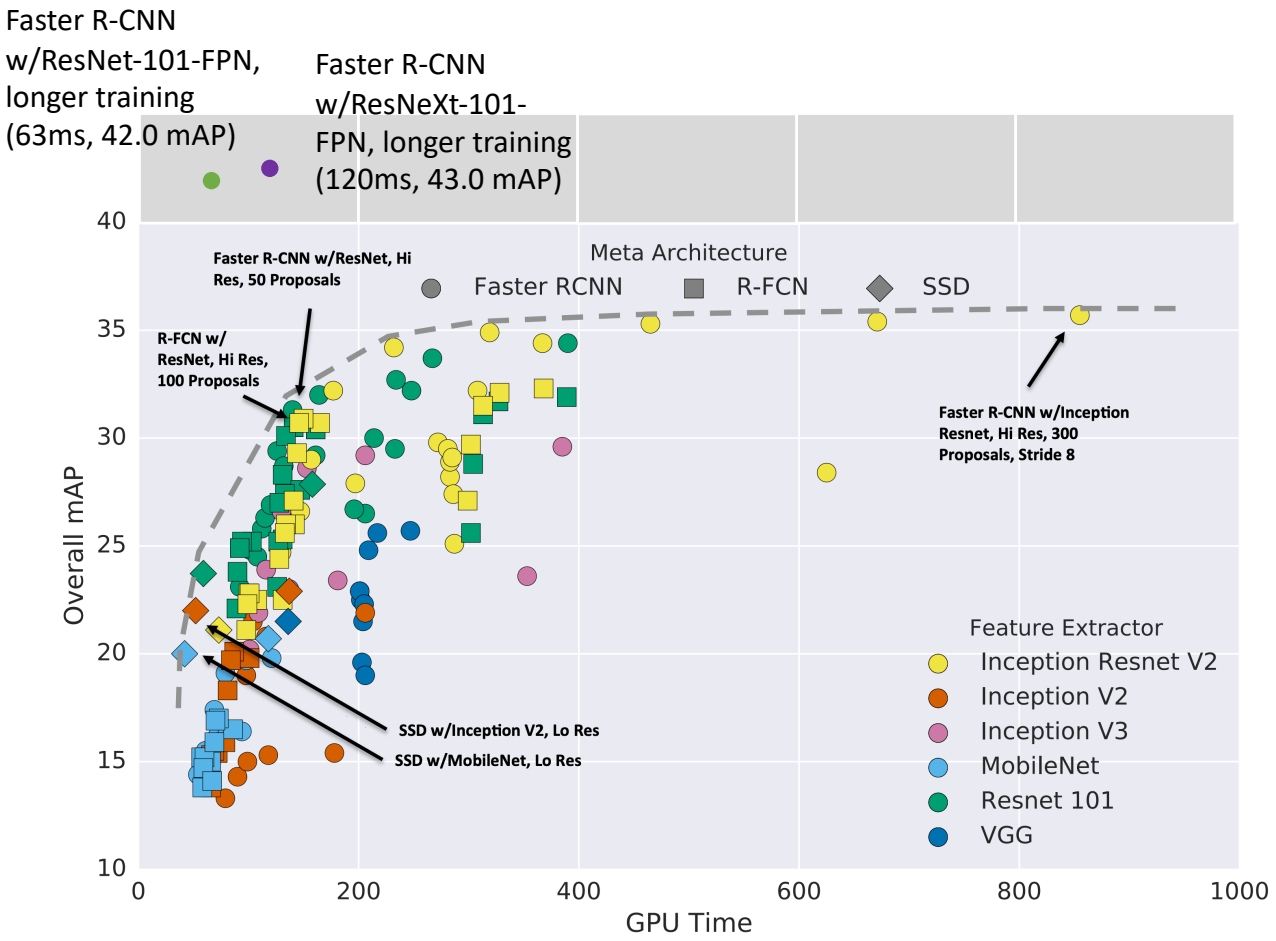
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- Train longer!
- Multiscale backbone: Feature Pyramid Networks

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

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!



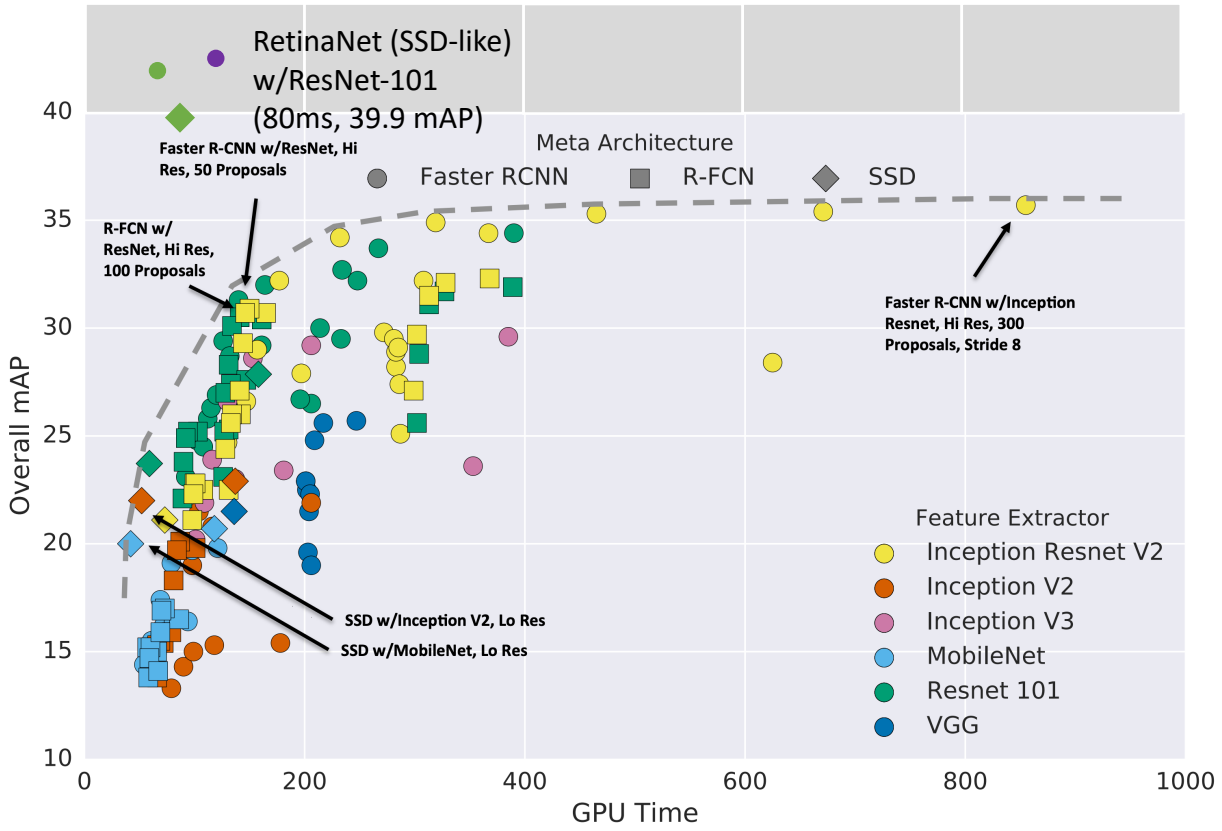
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- Train longer!
- Multiscale backbone: Feature Pyramid Networks
- Better backbone: ResNeXt

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

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!



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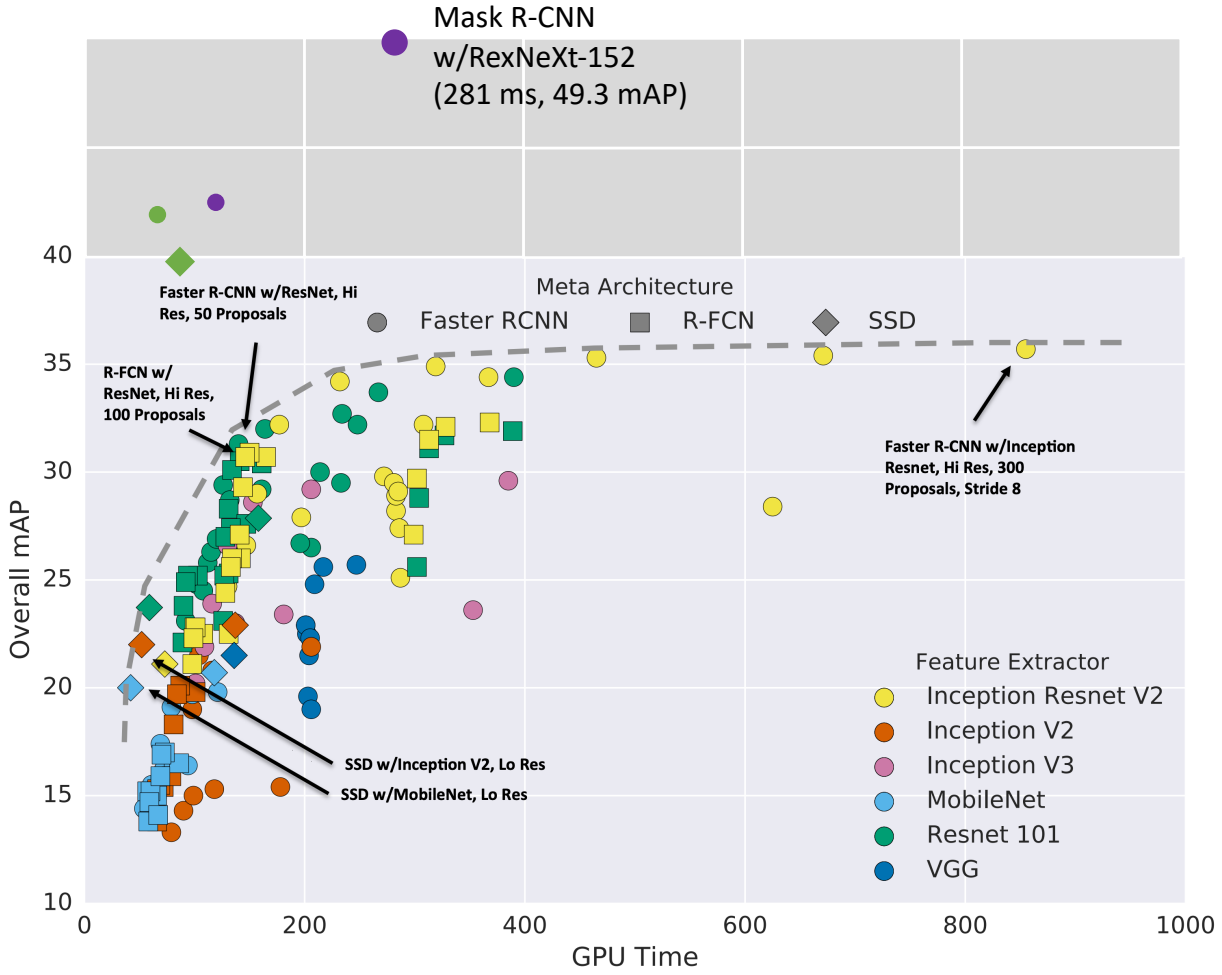
- Train longer!
- Multiscale backbone: Feature Pyramid Networks
- Better backbone: ResNeXt
- Single-Stage methods have improved

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

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!



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- Train longer!
- Multiscale backbone: Feature Pyramid Networks
- Better backbone: ResNeXt
- Single-Stage methods have improved
- Very big models work better

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

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!

These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- Train longer!
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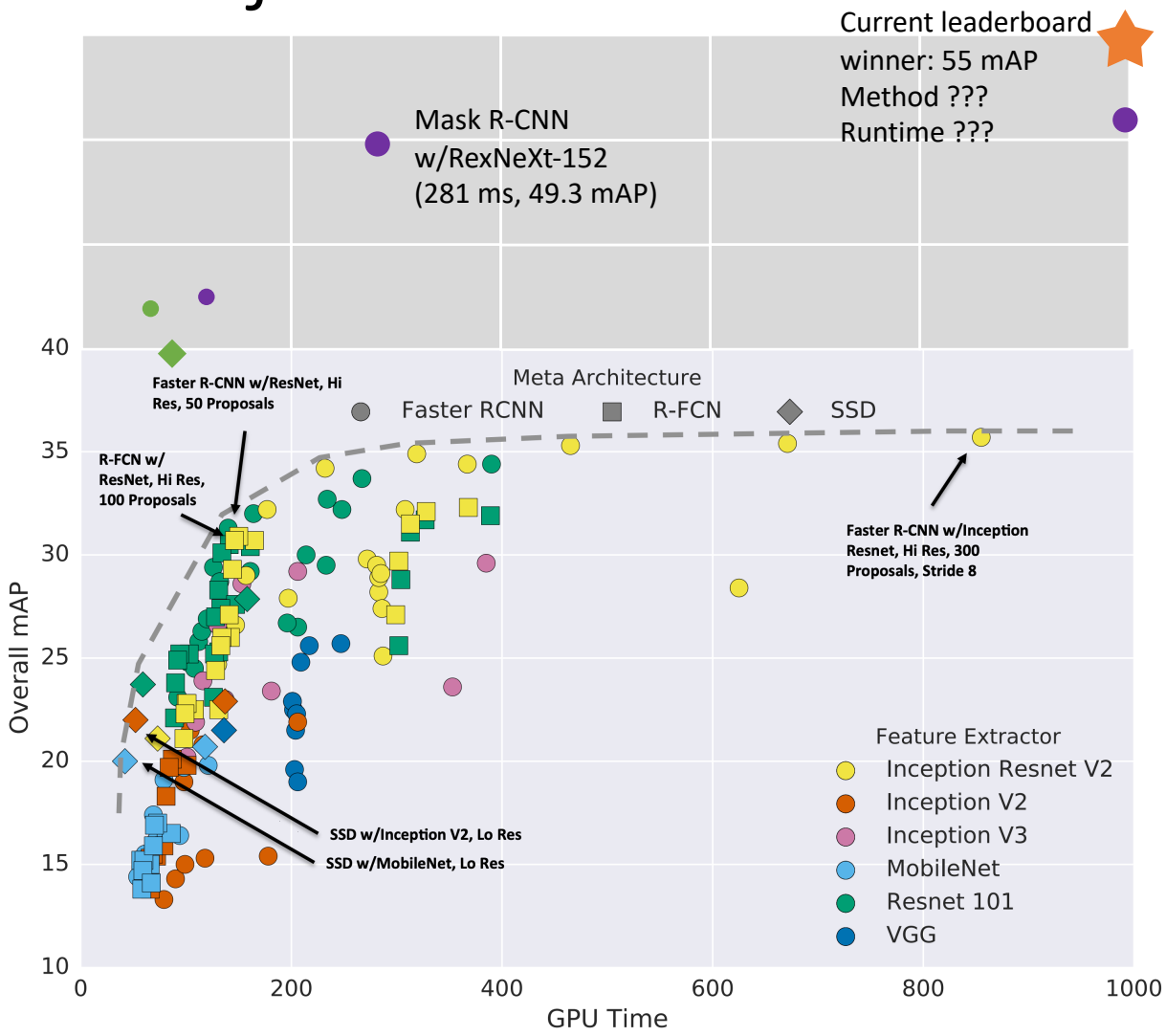
- Single-Stage methods have improved
- Very big models work better
- Test-time augmentation pushes numbers up

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

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!



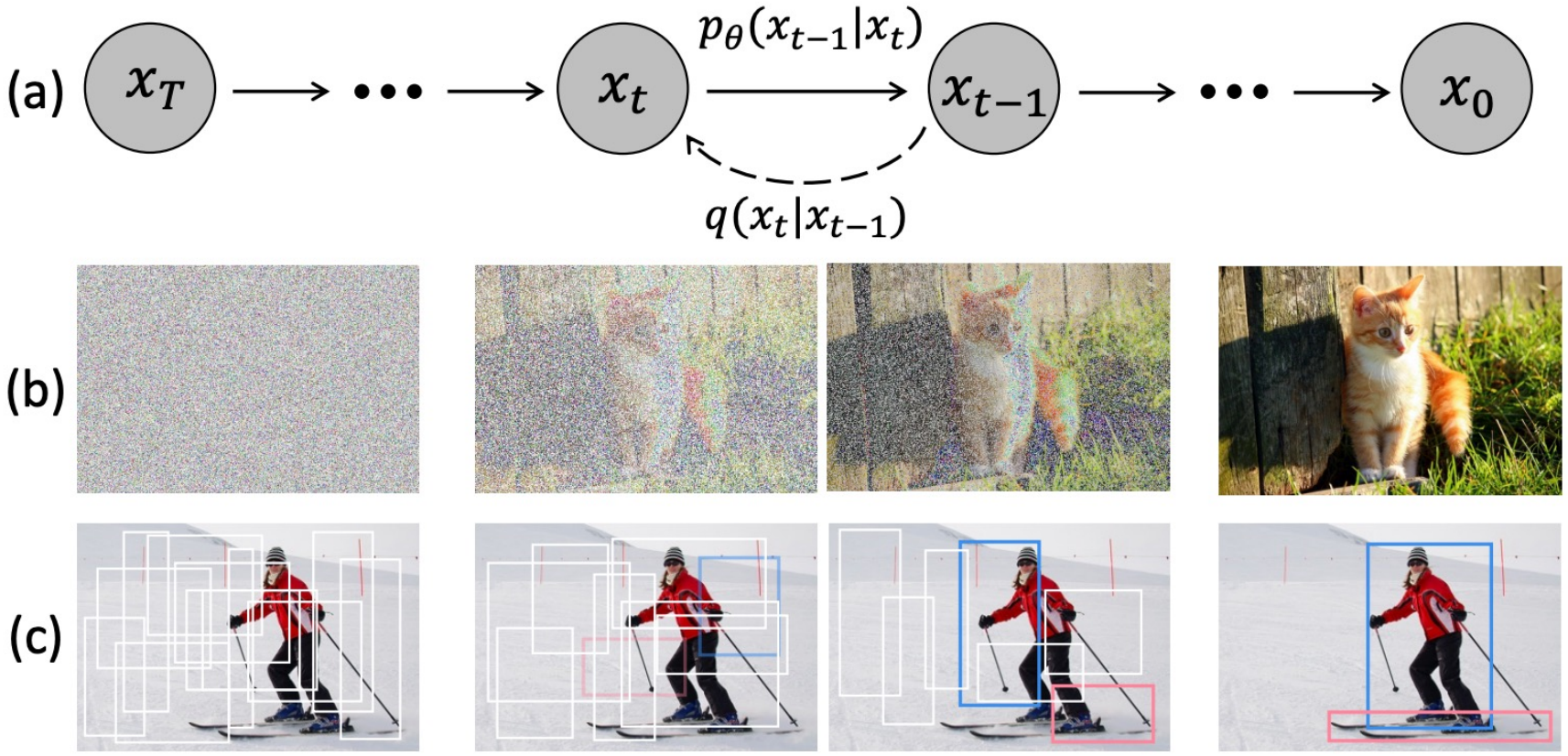
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- Train longer!
- Multiscale backbone: Feature Pyramid Networks
- Better backbone: ResNeXt
- Single-Stage methods have improved
- Very big models work better
- Test-time augmentation pushes numbers up
- Big ensembles, more data, etc

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

https://competitions.codalab.org/competitions/20794#results

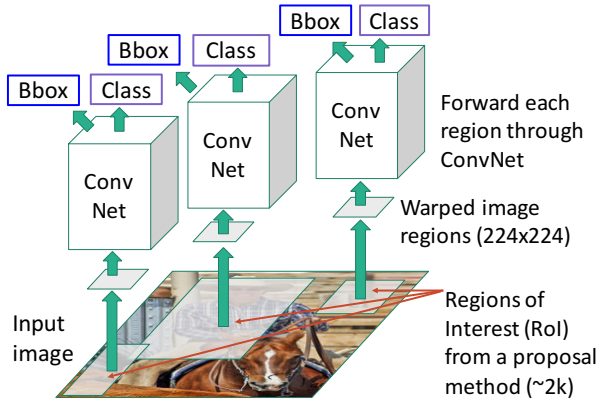
ICCV'23: Object Detection as Diffusion Process



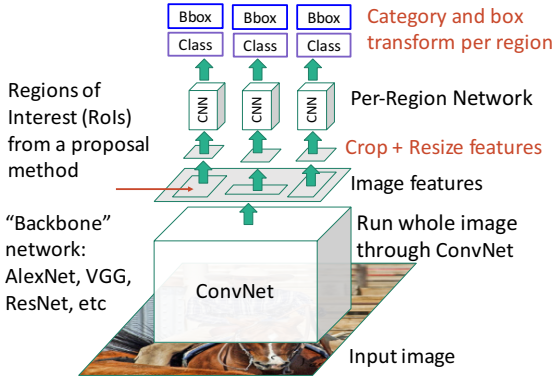
https://openaccess.thecvf.com/content/ICCV2023/papers/Chen_DiffusionDet_Diffusion_Model_for_Object_Detection_ICCV_2023_paper.pdf

Summary

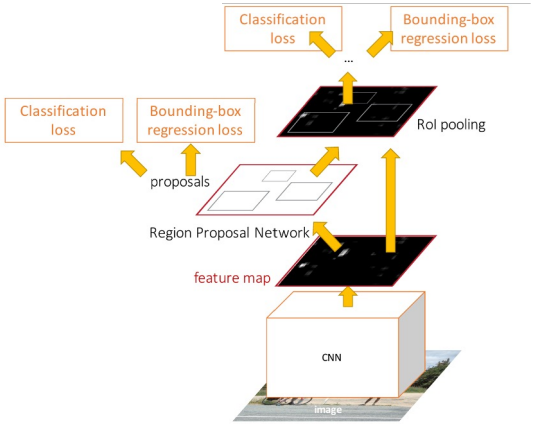
“Slow” R-CNN: Run CNN independently for each region



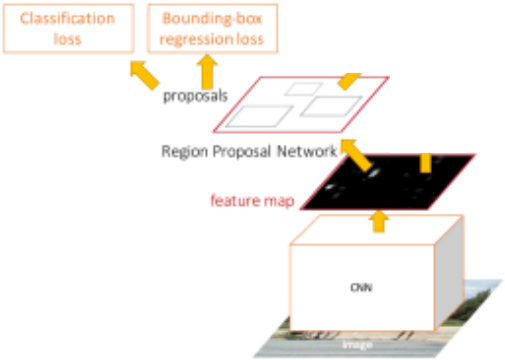
Fast R-CNN: Apply differentiable cropping to shared image features



Faster R-CNN: Compute proposals with CNN



Single-Stage: Fully convolutional detector

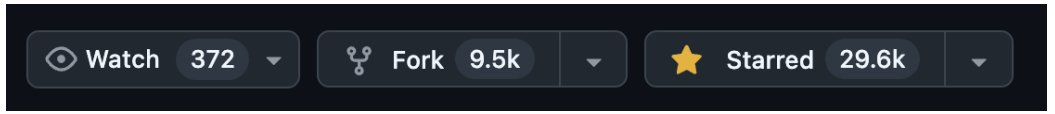


Object Detection: Open-Source Code

Object detection is very widely applicable.

Use existing library in your applications: **mmDetection (PyTorch):**

https://github.com/open-mmlab/mmdetection



Architectures

Object Detection	Instance Segmentation	Panoptic Segmentation	Other

• Foveabox (TIP'2020)
• Double-Head R-CNN (CVPR'2020)
• ATSS (CVPR'2020)
• NAS-FCOS (CVPR'2020)
• AutoAssign (ArXiv'2020)
• Side-Aware Boundary Localization (ECCV'2020)
• Dynamic R-CNN (ECCV'2020)
• DETR (ECCV'2020)
• PAA (ECCV'2020)
• VarifocalNet (CVPR'2021)
• Sparse R-CNN (CVPR'2021)
• YOLOF (CVPR'2021)
• YOLOX (CVPR'2021)
• Deformable DETR (ICLR'2021)
• TOOD (ICCV'2021)
	• Fast R-CNN (ICCV'2015)
	• Faster R-CNN (NeurIPS'2015)
	• RPN (NeurIPS'2015)
	• SSD (ECCV'2016)
	• RetinaNet (ICCV'2017)
	• Cascade R-CNN (CVPR'2018)
	• YOLOv3 (ArXiv'2018)
	• CornerNet (ECCV'2018)
	• Grid R-CNN (CVPR'2019)
	• Guided Anchoring (CVPR'2019)
	• FSAF (CVPR'2019)
	• CenterNet (CVPR'2019)
	• Libra R-CNN (CVPR'2019)
	• TridentNet (ICCV'2019)
	• FCOS (ICCV'2019)
	• RepPoints (ICCV'2019)
		• Mask R-CNN (ICCV'2017)
		• Cascade Mask R-CNN (CVPR'2018)
		• Mask Scoring R-CNN (CVPR'2019)
		• Hybrid Task Cascade (CVPR'2019)
		• YOLACT (ICCV'2019)
		• InstaBoost (ICCV'2019)
		• SOLO (ECCV'2020)
		• PointRend (CVPR'2020)
		• DetectoRS (ArXiv'2020)
		• SCNet (AAAI'2021)
		• QueryInst (ICCV'2021)
			• Panoptic FPN (CVPR'2019)	• Contrastive Learning
				  ◦ SwAV (NeurIPS'2020)
				  ◦ MoCo (CVPR'2020)
				  ◦ MoCov2 (ArXiv'2020)
				• Distillation
				  ◦ Localization Distillation (ArXiv'2021)
				  ◦ Label Assignment Distillation (WACV'2022)

Components

Backbones	Necks	Loss	Common
• VGG (ICLR'2015) • ResNet (CVPR'2016) • ResNeXt (CVPR'2017) • MobileNetV2 (CVPR'2018) • HRNet (CVPR'2019) • Generalized Attention (ICCV'2019) • GCNet (ICCVW'2019) • Res2Net (TPAMI'2020) • RegNet (CVPR'2020) • ResNeSt (ArXiv'2020) • PVT (ICCV'2021) • Swin (CVPR'2021) • PVTv2 (ArXiv'2021)	• PAFPN (CVPR'2018) • NAS-FPN (CVPR'2019) • CARAFE (ICCV'2019) • FPG (ArXiv'2020) • GRoIE (ICPR'2020)	• GHM (AAAI'2019) • Generalized Focal Loss (NeurIPS'2020) • Seasaw Loss (CVPR'2021)	• OHEM (CVPR'2016) • Group Normalization (ECCV'2018) • DCN (ICCV'2017) • DCNv2 (CVPR'2019) • Weight Standardization (ArXiv'2019) • Prime Sample Attention (CVPR'2020) • Strong Baselines (CVPR'2021)

Reading and Practice

D2L textbook: Chapter 13.3 – 13.8

Next Time:
More localization methods:
Segmentation, Keypoint Estimation