Lecture 15: Object Detection

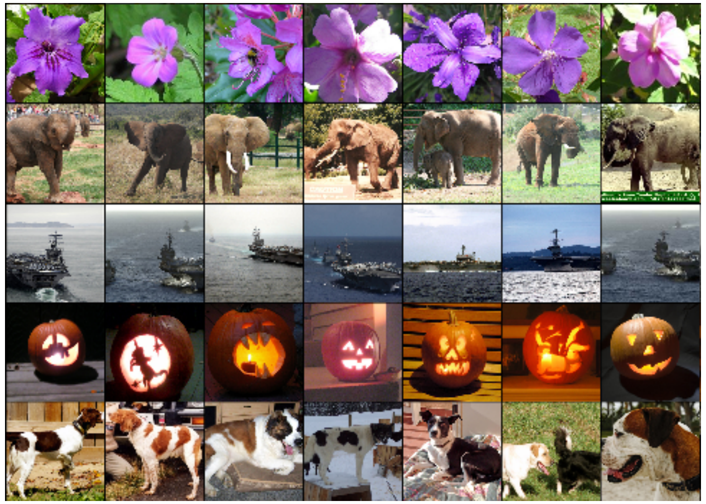
Reminder: A4

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

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

Last Time: Visualizing and Understanding CNNs

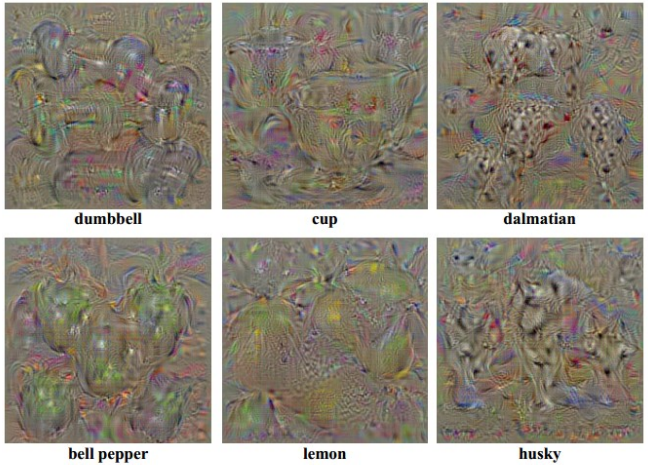
Nearest Neighbor

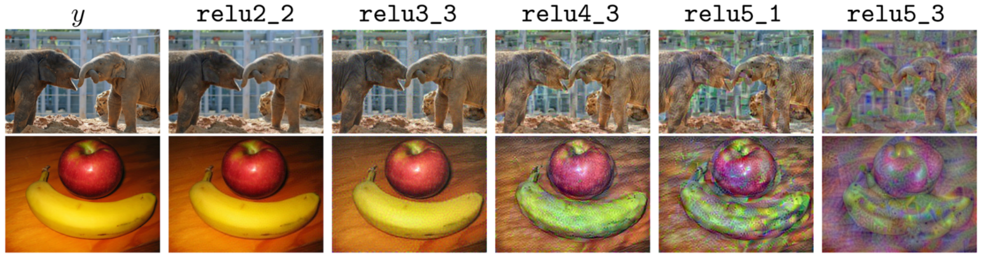


Maximally Activating Patches

(Guided) Backprop

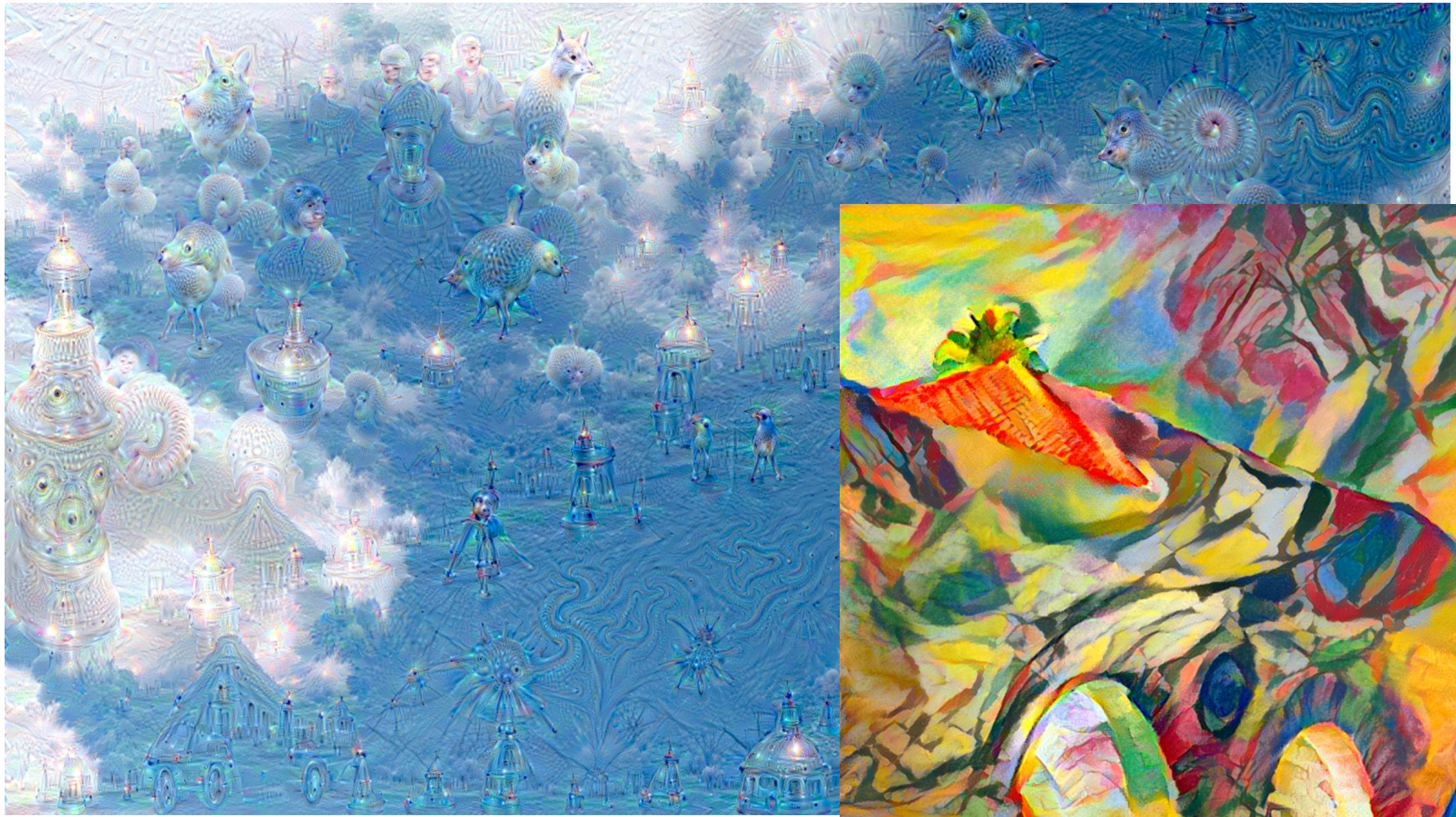
Synthetic Images via Gradient Ascent





Feature Inversion

Last Time: Making art with CNNs

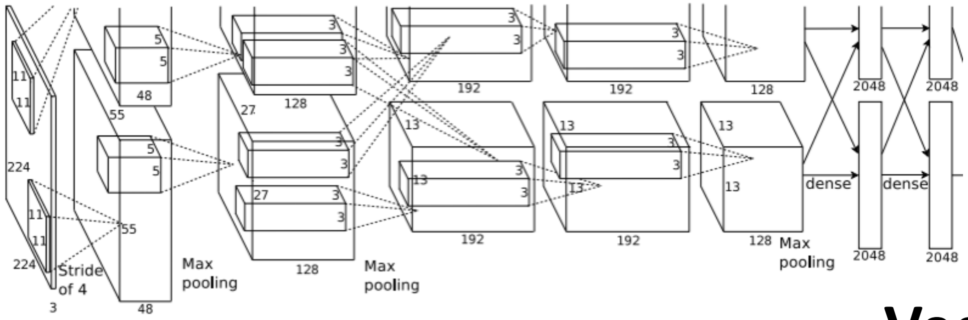


DeepDream

Style Transfer

So far: Image Classification

This image is CC0 public domain



Vector: 4096

Fully-Connected: 4096 to 1000

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

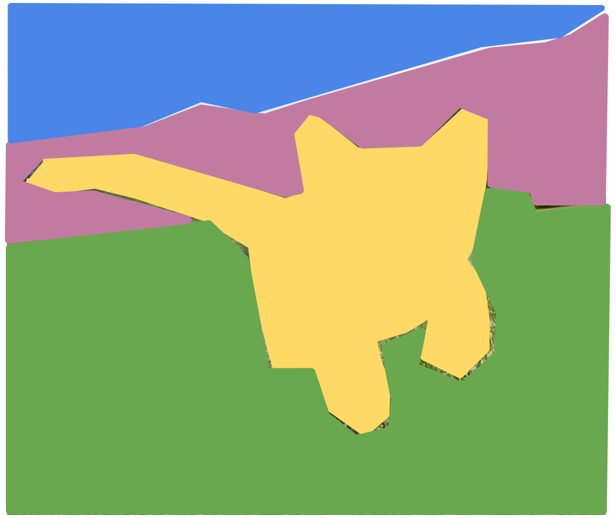
Computer Vision Tasks

Classification

CAT

No spatial extent

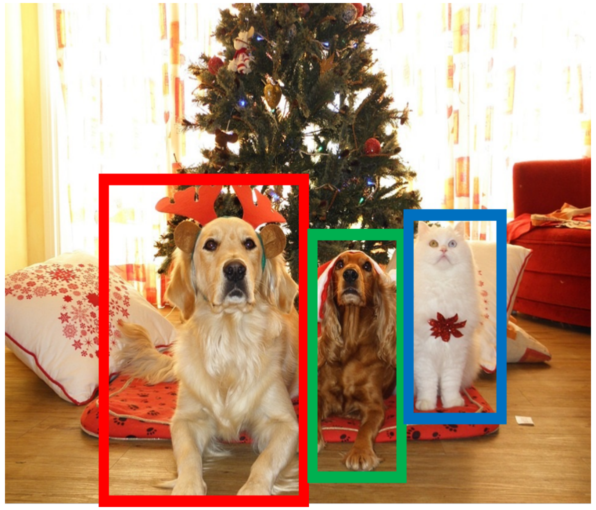
Semantic Segmentation



GRASS, CAT, TREE, SKY

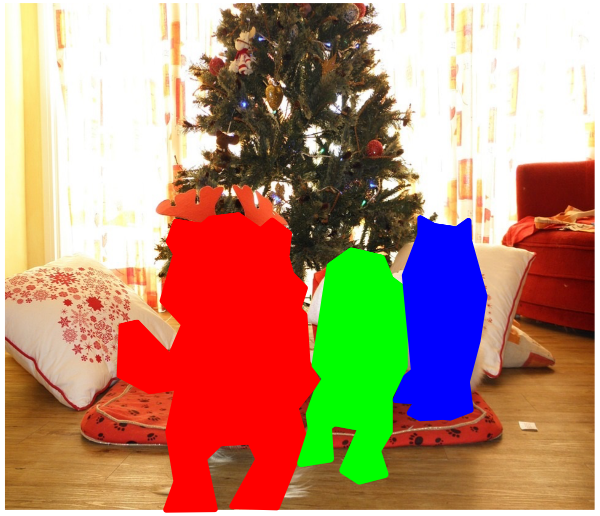
No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Objects

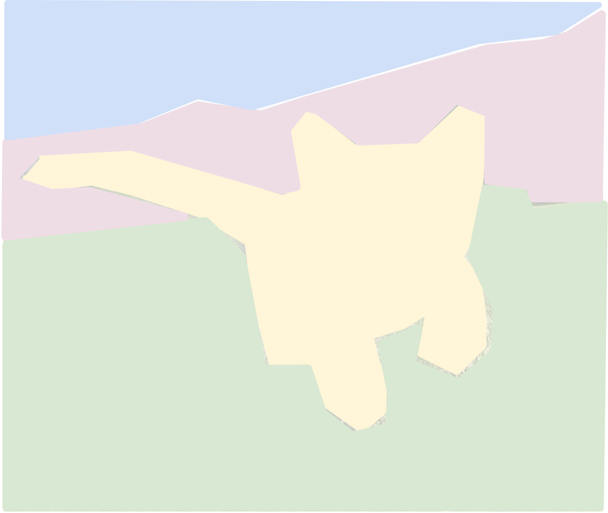
Today: Object Detection

Classification

CAT

No spatial extent

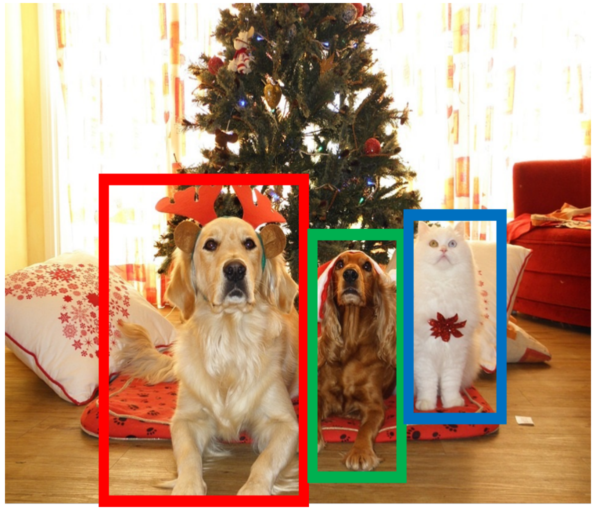
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

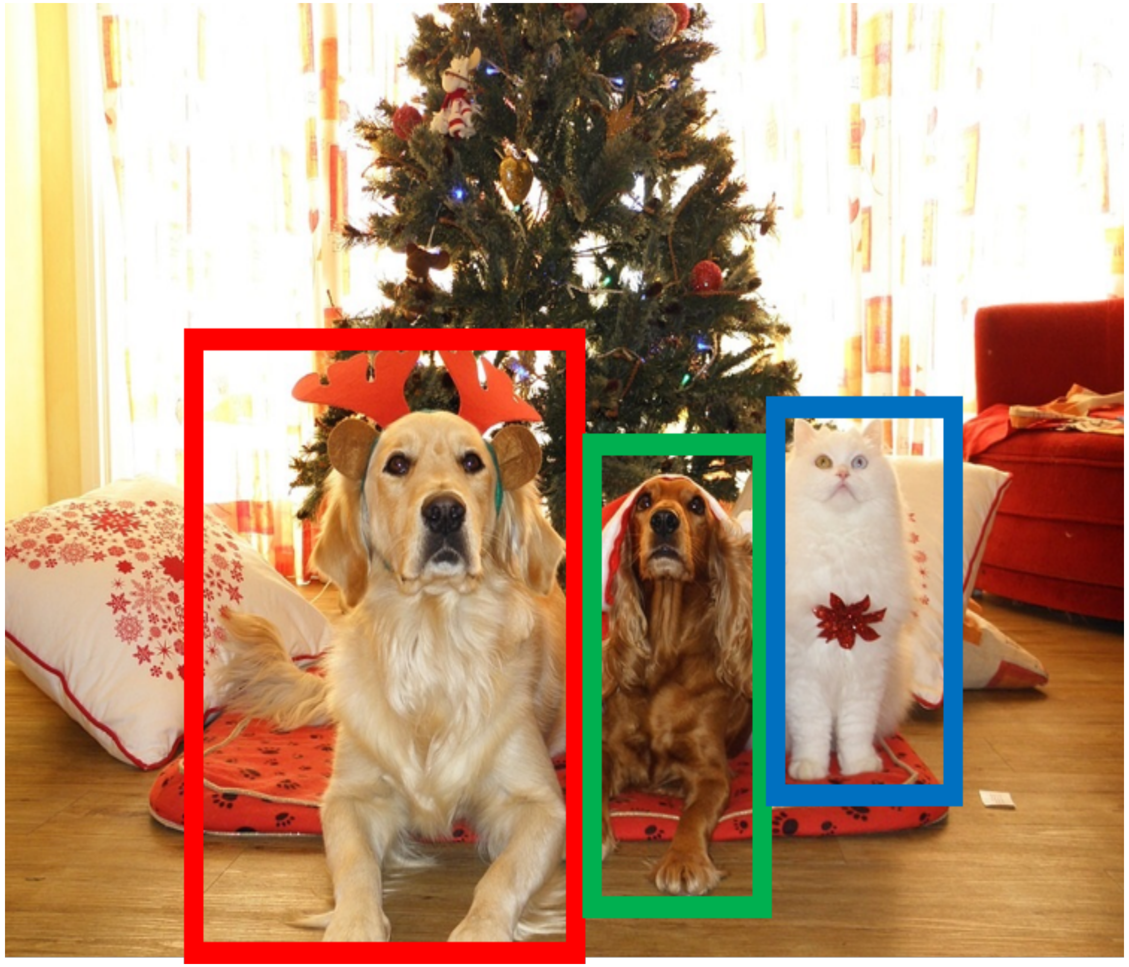
Multiple Objects

Object Detection: Task Definition

Input: Single RGB Image

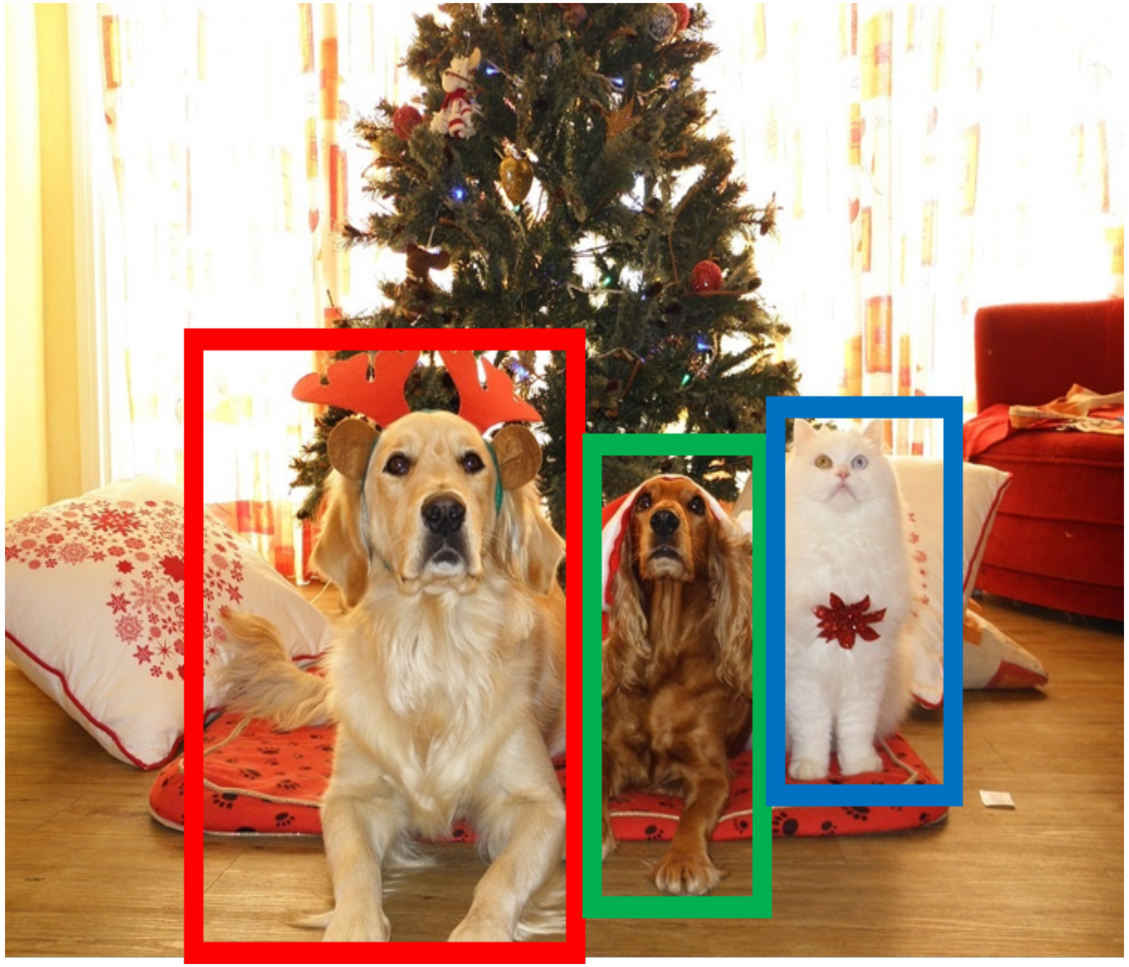
Output: A set of detected objects;
For each object predict:

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



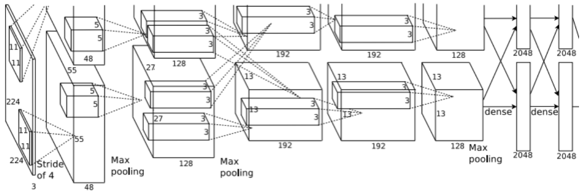
Object Detection: Challenges

- **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



Detecting a single object

This image is CC0 public domain



Vector:
4096

Detecting a single object

"What"

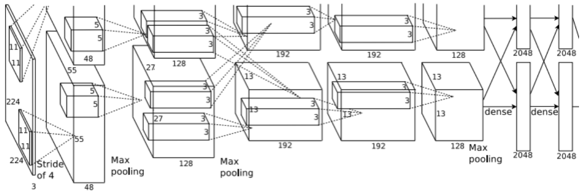
Correct label:
Cat

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

Softmax Loss

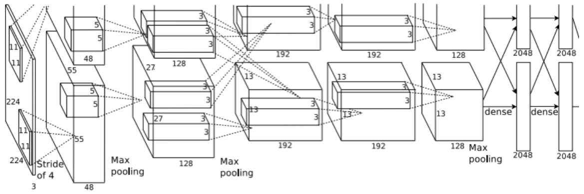
Fully Connected:
4096 to 1000

This image is CC0 public domain



Vector:
4096

Detecting a single object



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

Treat localization as a regression problem!

Vector:
4096

“What”

Fully Connected:
4096 to 1000

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

Correct label:
Cat

Softmax Loss

“Where”

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

Correct box:
(x’, y’, w’, h’)

Detecting a single object

“What”

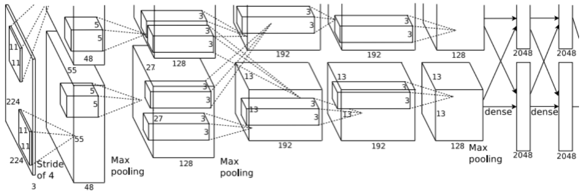
Correct label:
Cat

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

Softmax Loss

Fully Connected:
4096 to 1000

This image is CC0 public domain



Vector:
4096

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

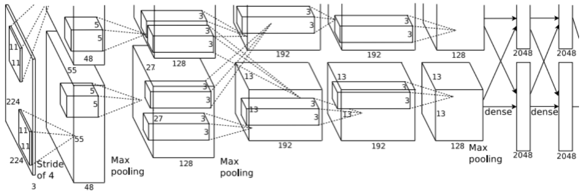
Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Fully Connected:
4096 to 1000

Softmax Loss

Multitask Loss

This image is CC0 public domain



Vector:
4096

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”

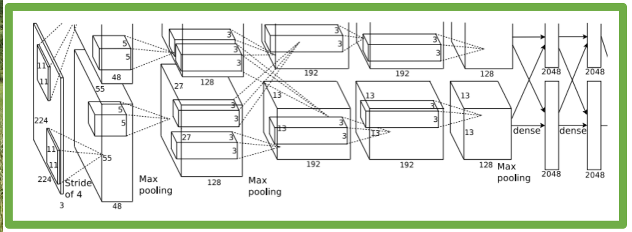
Detecting a single object

"What"

Correct label:
Cat

Often pretrained on ImageNet (Transfer learning)

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

Multitask 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

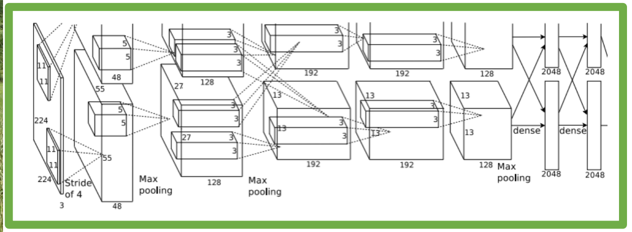
Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Multitask Loss

Weighted Sum → **Loss**

Often pretrained on ImageNet (Transfer learning)



This image is CC0 public domain

Fully Connected: 4096 to 1000

Vector: 4096

Fully Connected: 4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

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

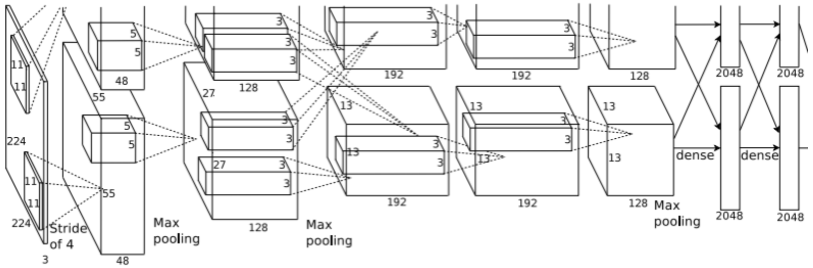
Treat localization as a regression problem!

Problem: Images can have more than one object!

"Where"

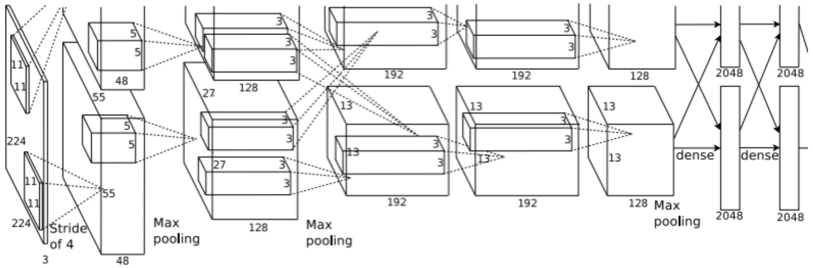
Detecting Multiple Objects

Need different numbers of outputs per image



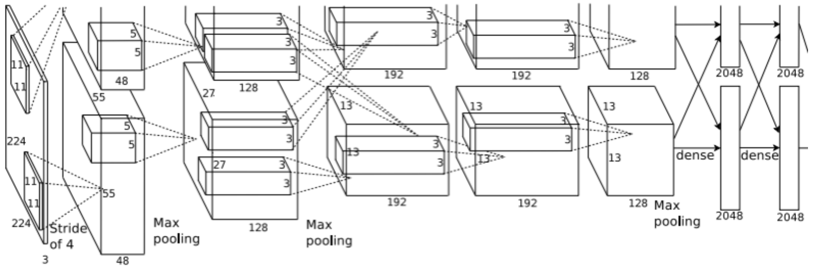
CAT: (x, y, w, h)

4 numbers



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

16 numbers

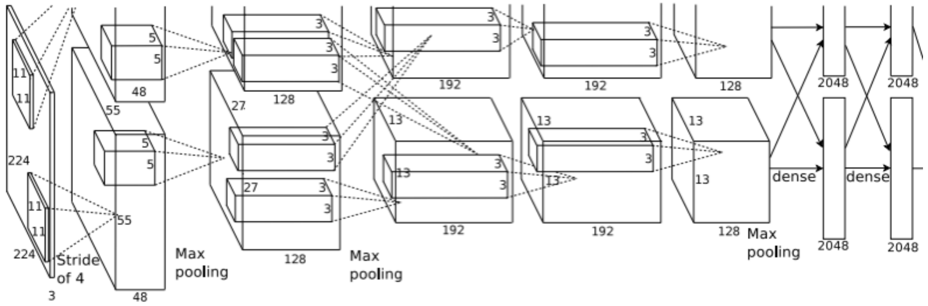


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
....

Many numbers!

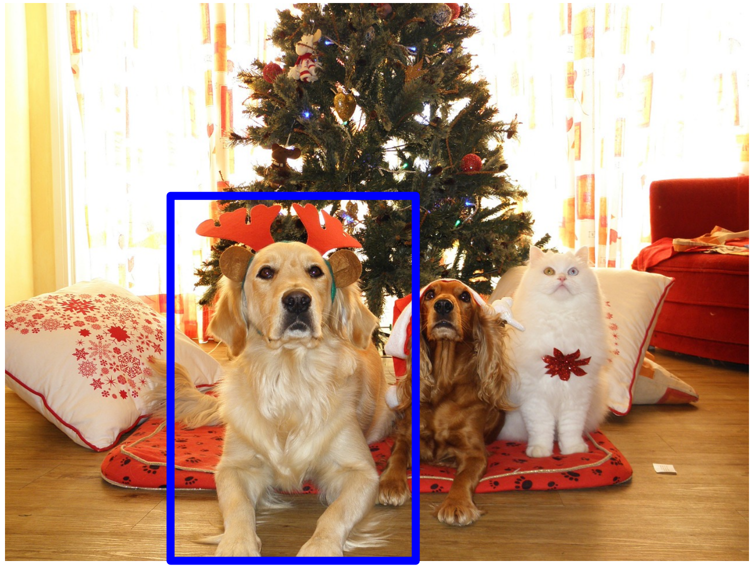
Detecting Multiple Objects: **Sliding Window**

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

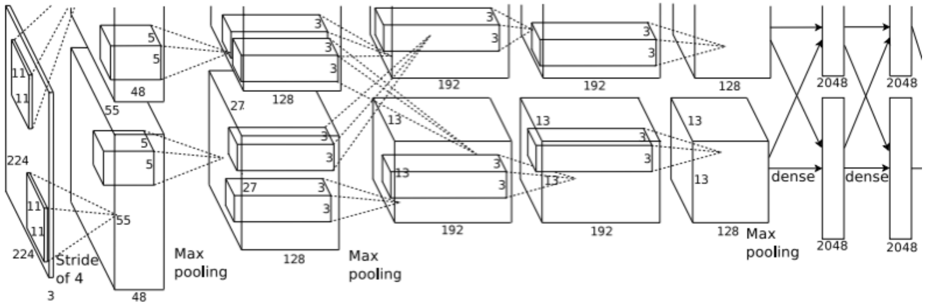


Dog? NO
Cat? NO
Background? YES

Detecting Multiple Objects: **Sliding Window**



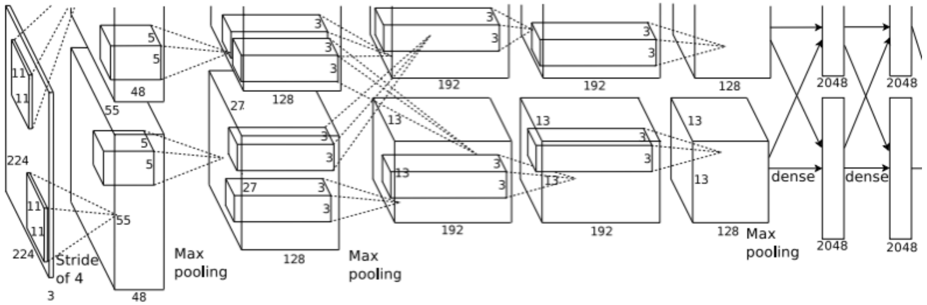
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Detecting Multiple Objects: **Sliding Window**

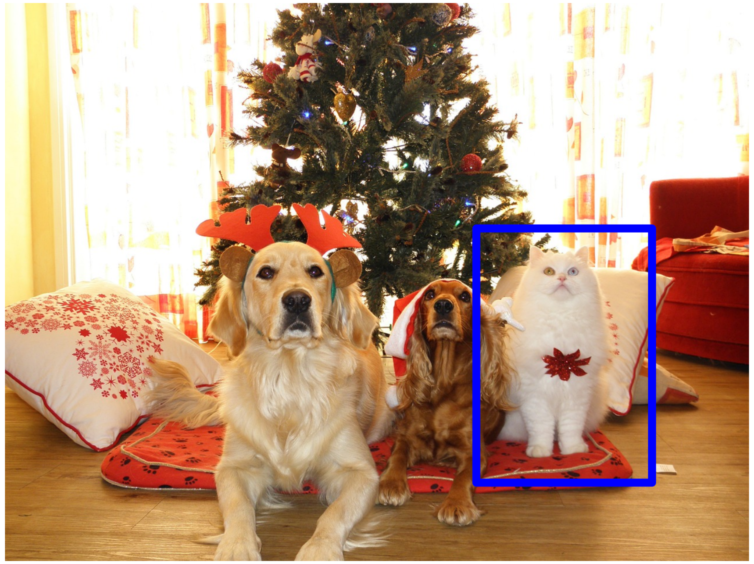
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

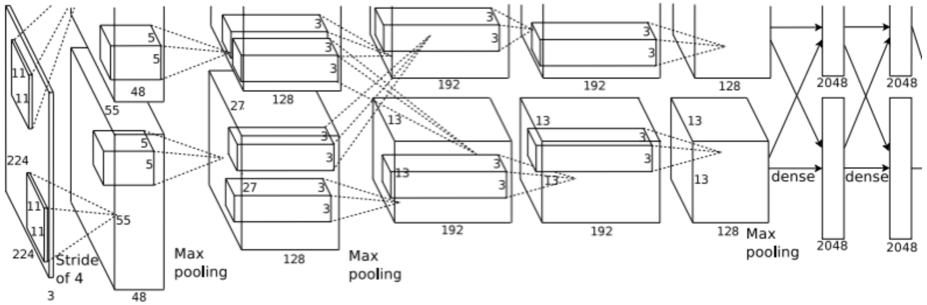


Dog? YES
Cat? NO
Background? NO

Detecting Multiple Objects: **Sliding Window**

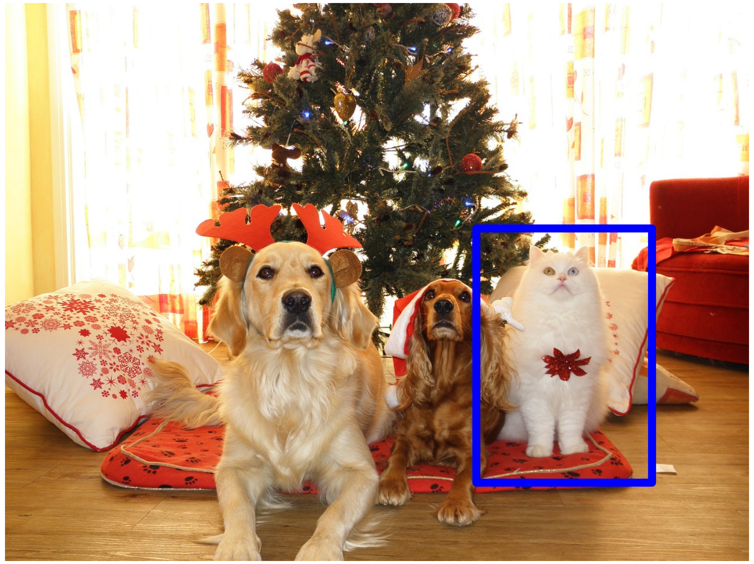
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background





Dog? NO
Cat? YES
Background? NO

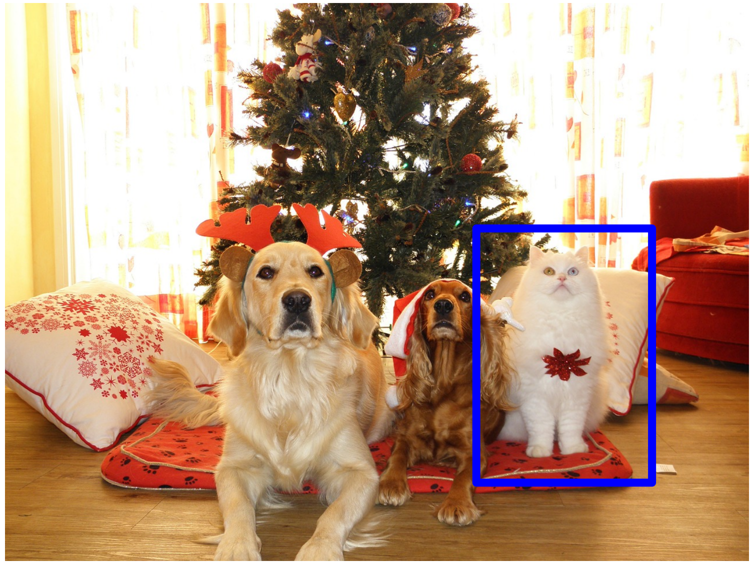
Detecting Multiple Objects: **Sliding Window**



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**

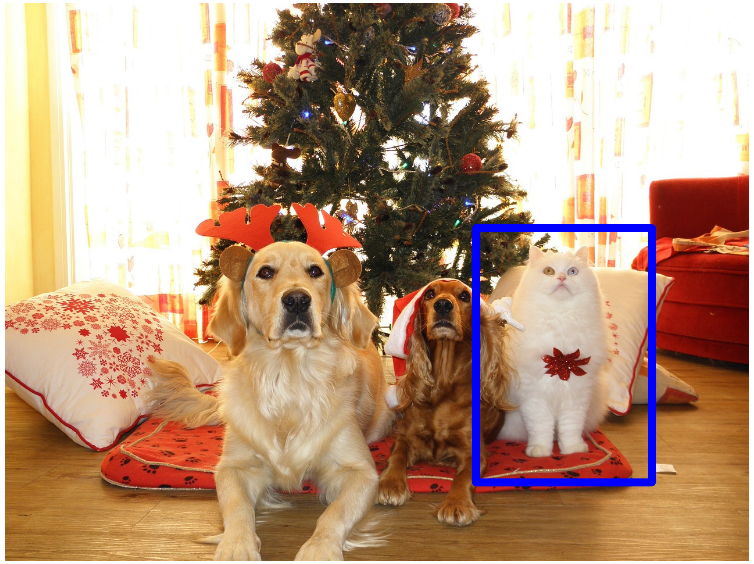


Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

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?

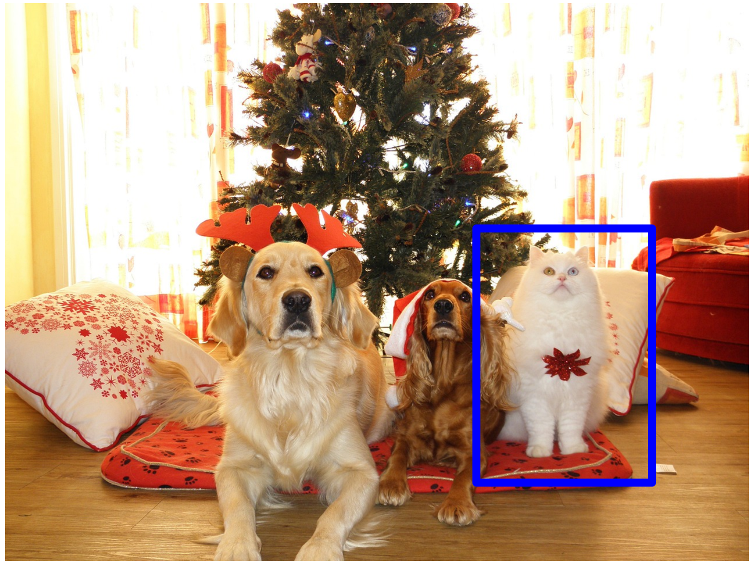
Consider a box of size h x w:
Possible x positions: W – w + 1
Possible y positions: H – h + 1
Possible positions:
(W – w + 1) * (H – h + 1)

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)

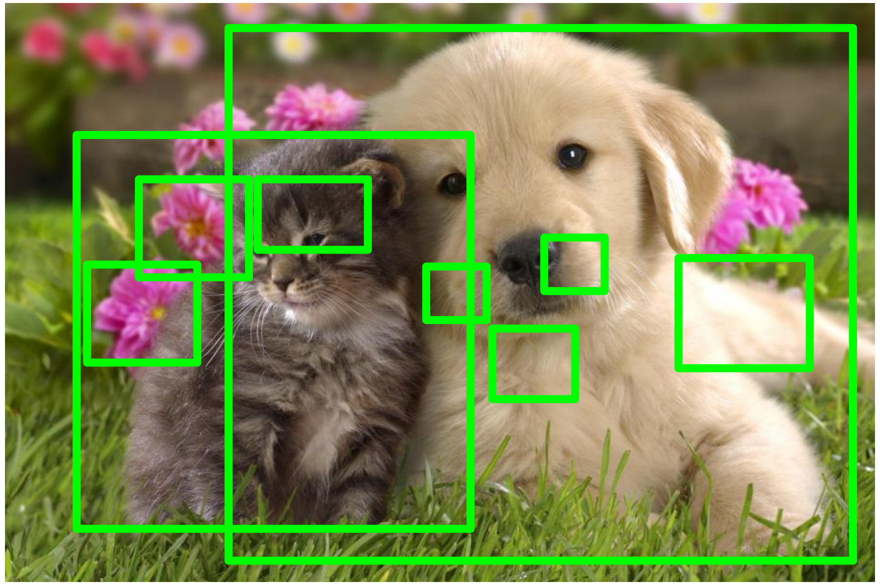
Total possible boxes:

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

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

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.

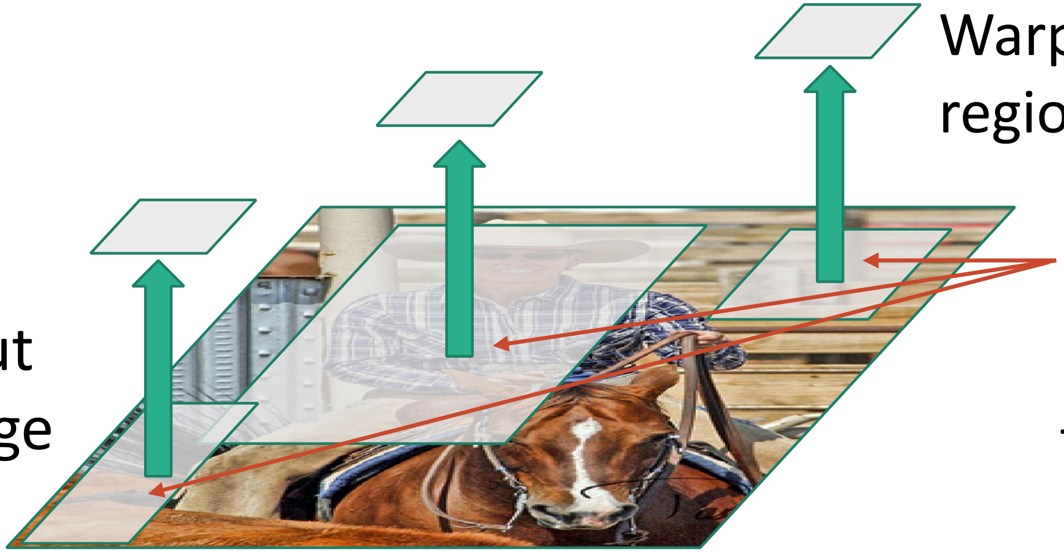
R-CNN: Region-Based CNN

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



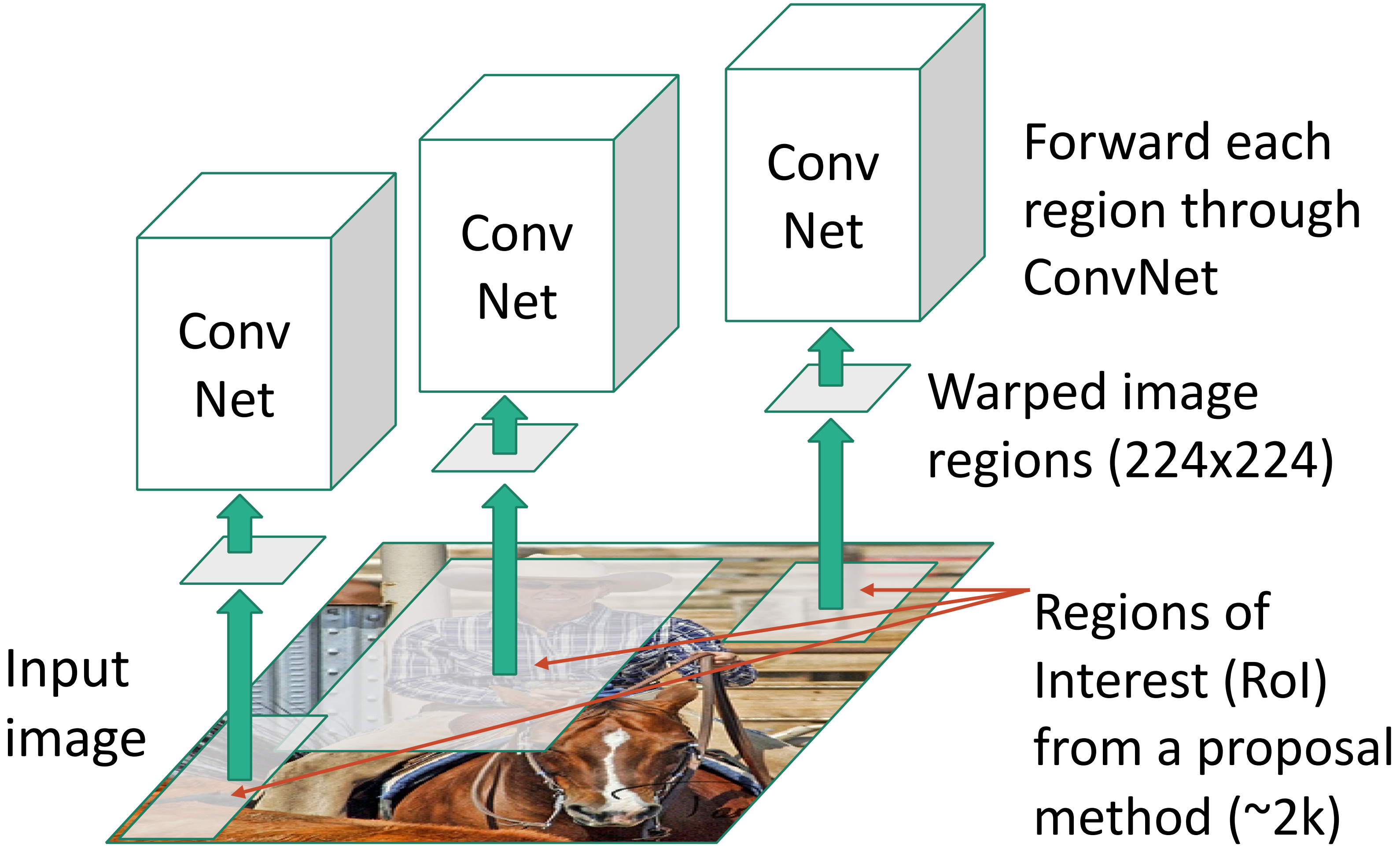
Input image

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.

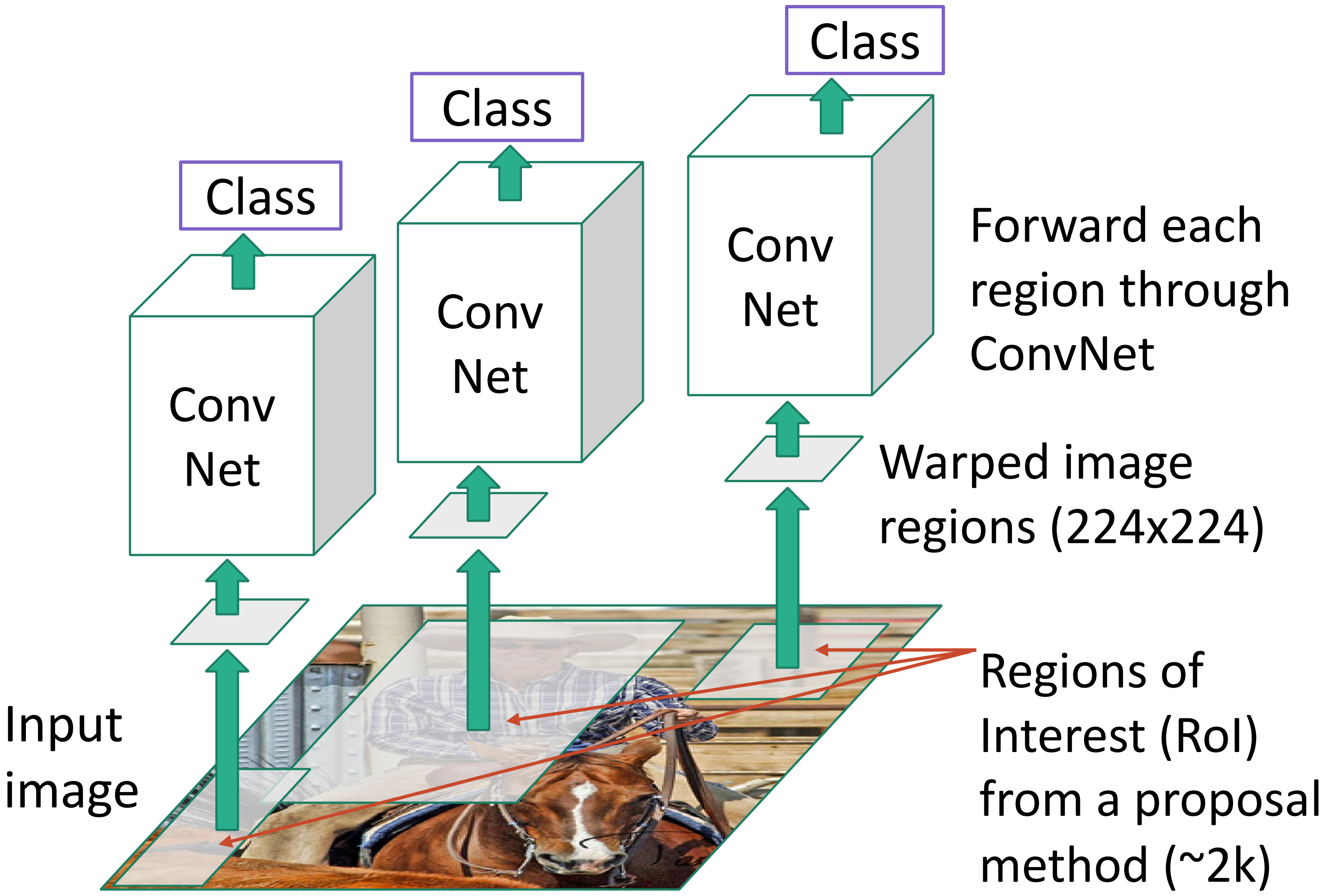
R-CNN: Region-Based CNN



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

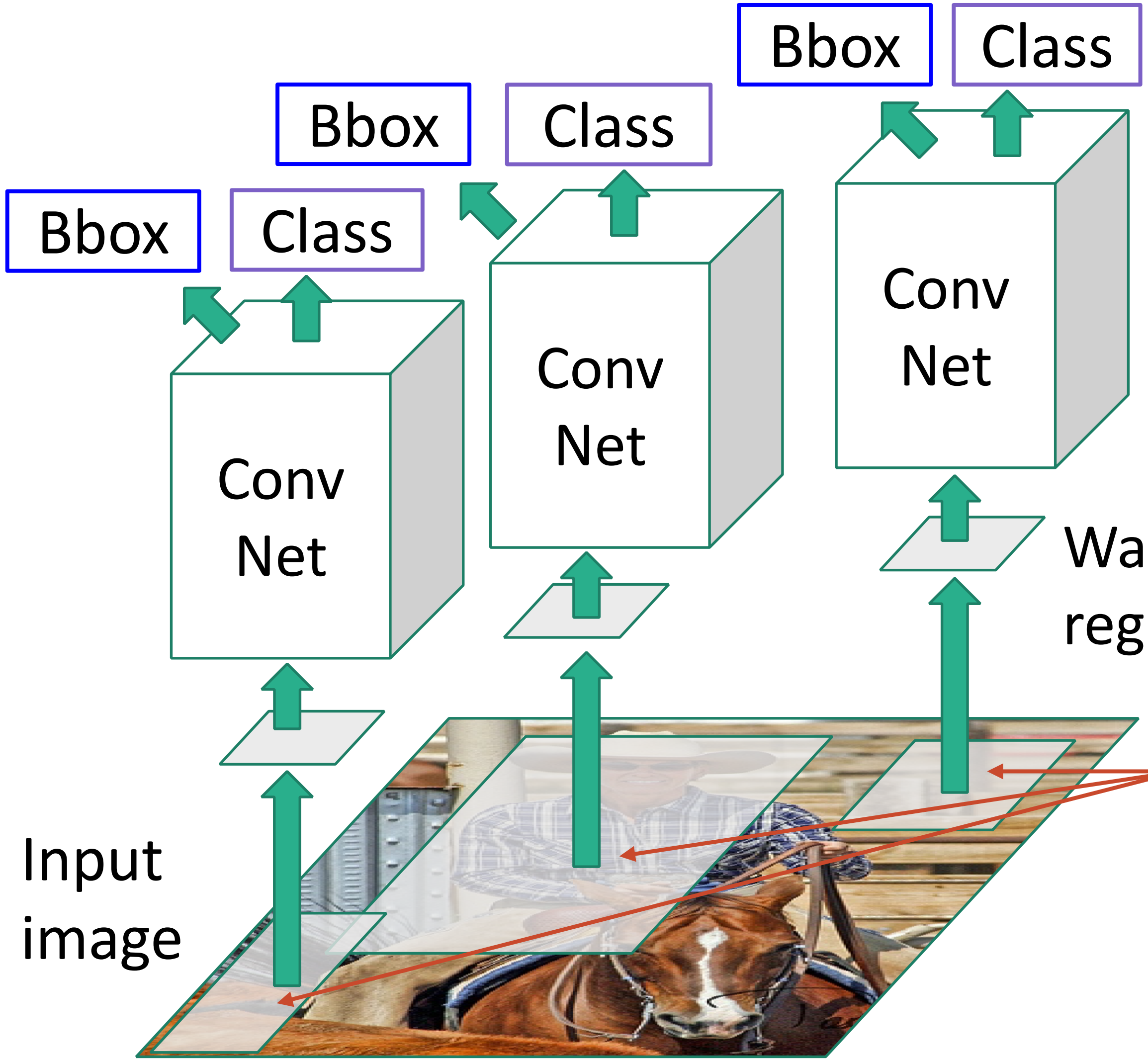
R-CNN: Region-Based CNN

Classify each region



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

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)

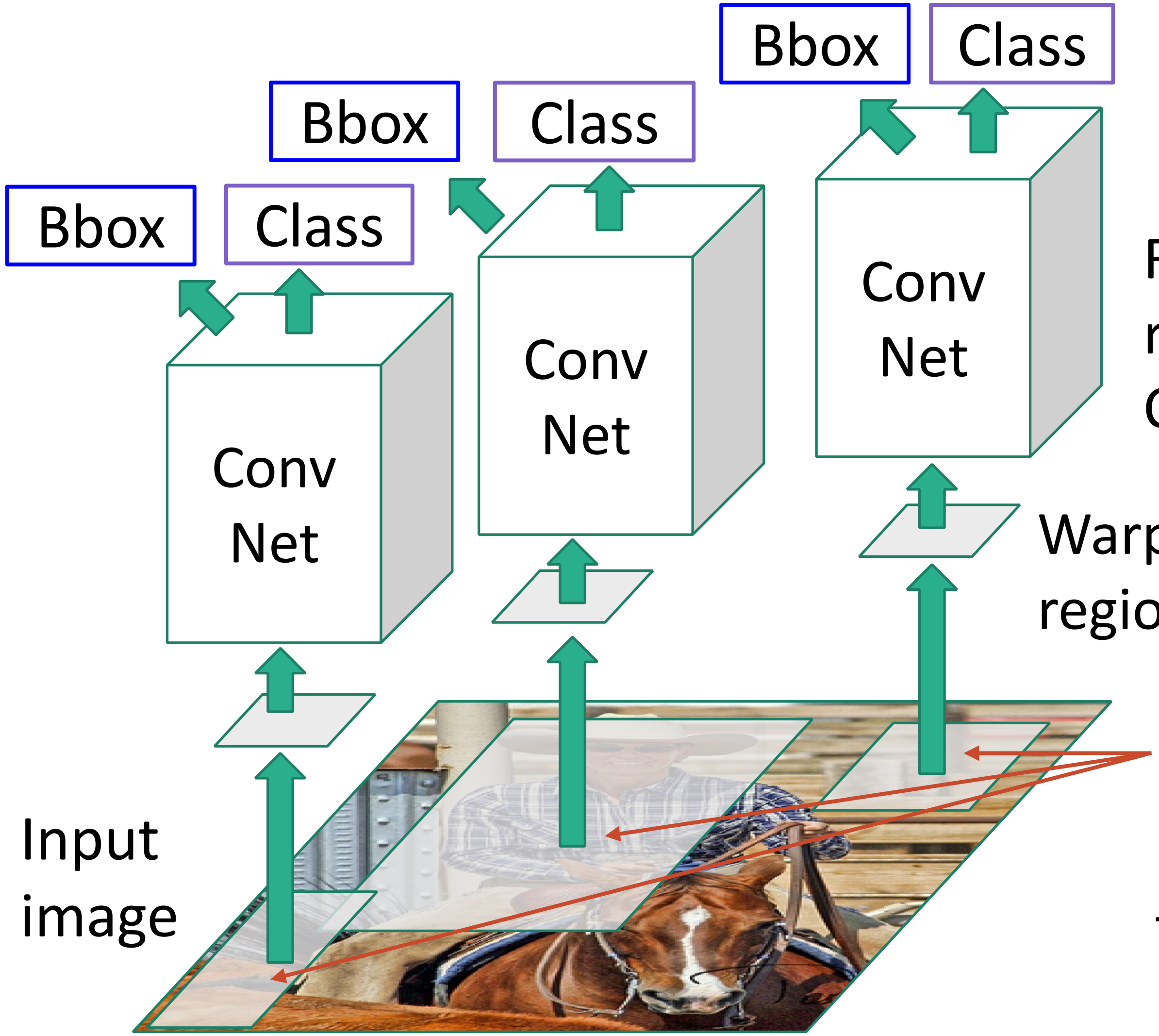
Regions of Interest (RoI) from a proposal method (~2k)

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

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)

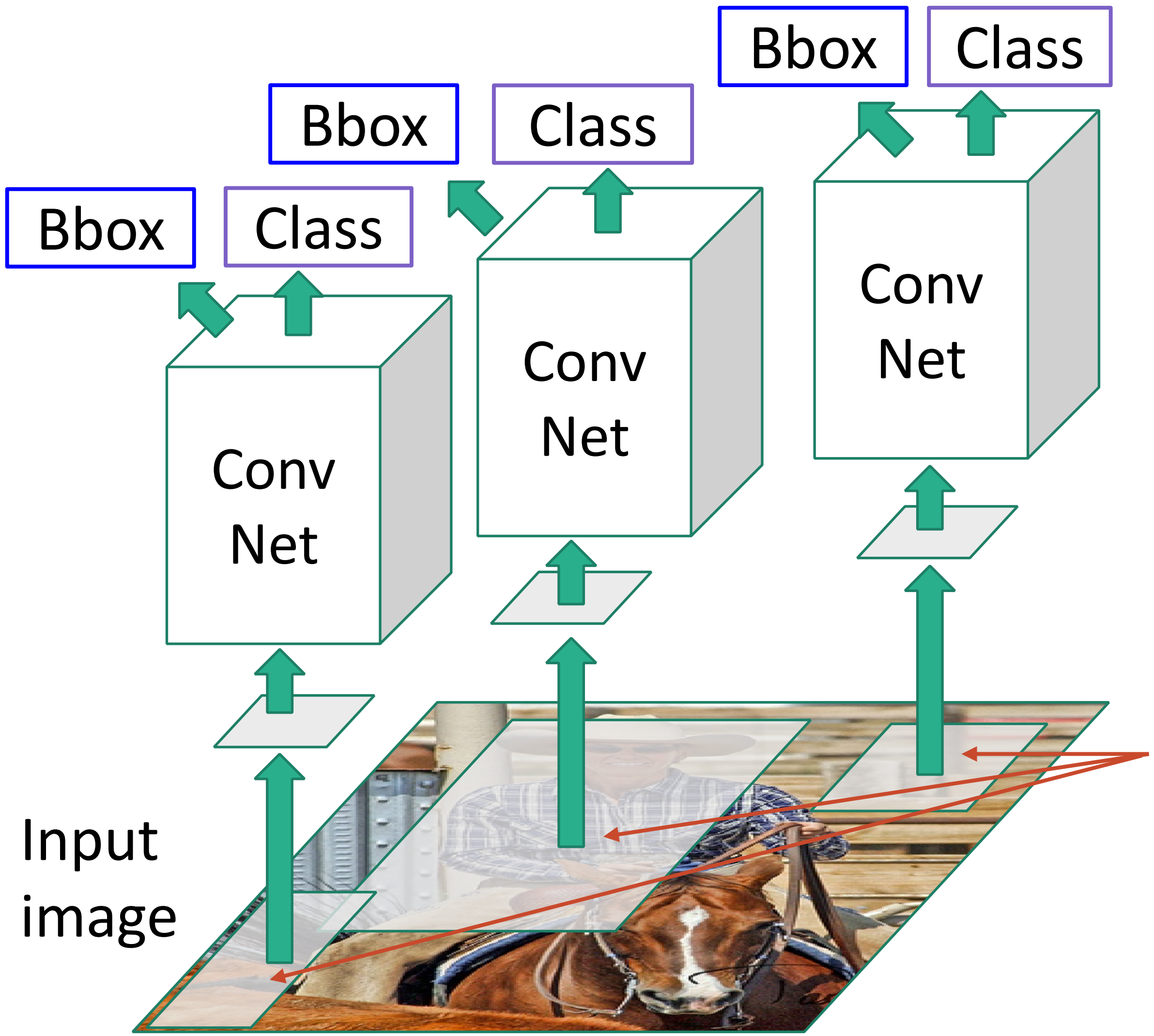
Region proposal: (p_x, p_y, p_h, p_w)
Transform: (t_x, t_y, t_h, t_w)
Output box: (b_x, b_y, b_h, b_w)

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:
$b_w = p_w \exp(t_w)$ $\quad$ $b_h = p_h \exp(t_h)$

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

R-CNN: Test-time



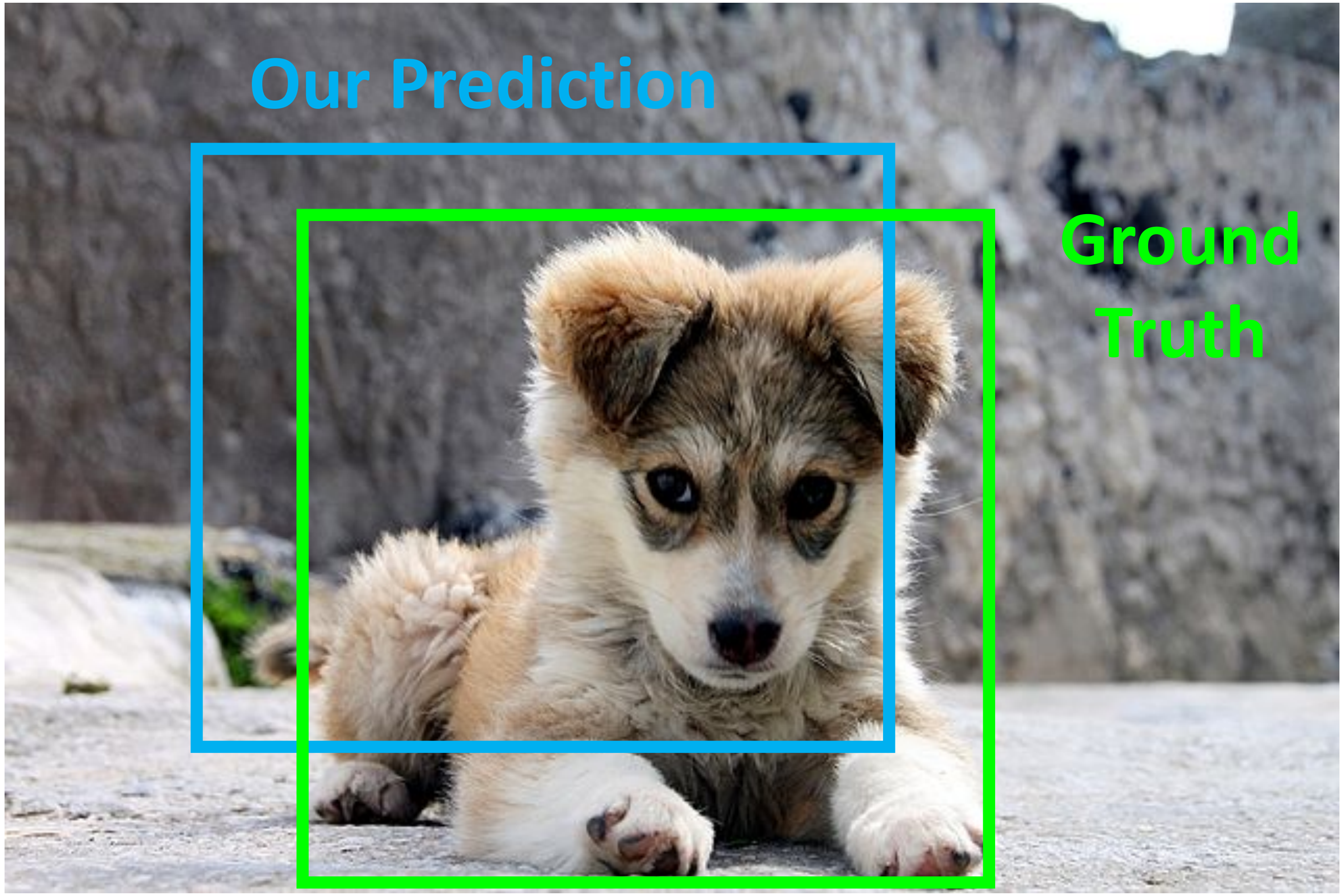
Input: Single RGB Image

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?

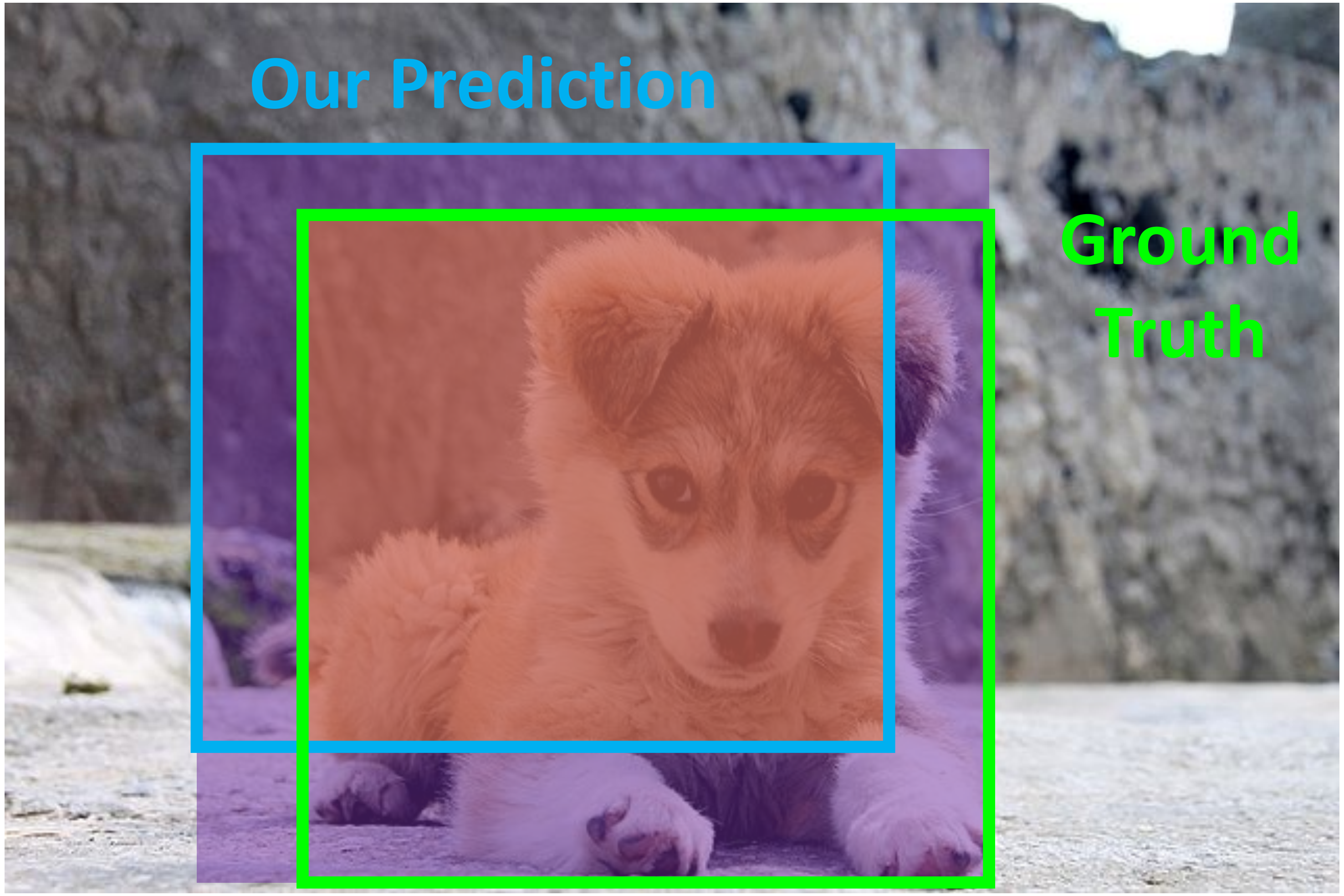


Comparing Boxes: Intersection over Union (IoU)

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

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

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



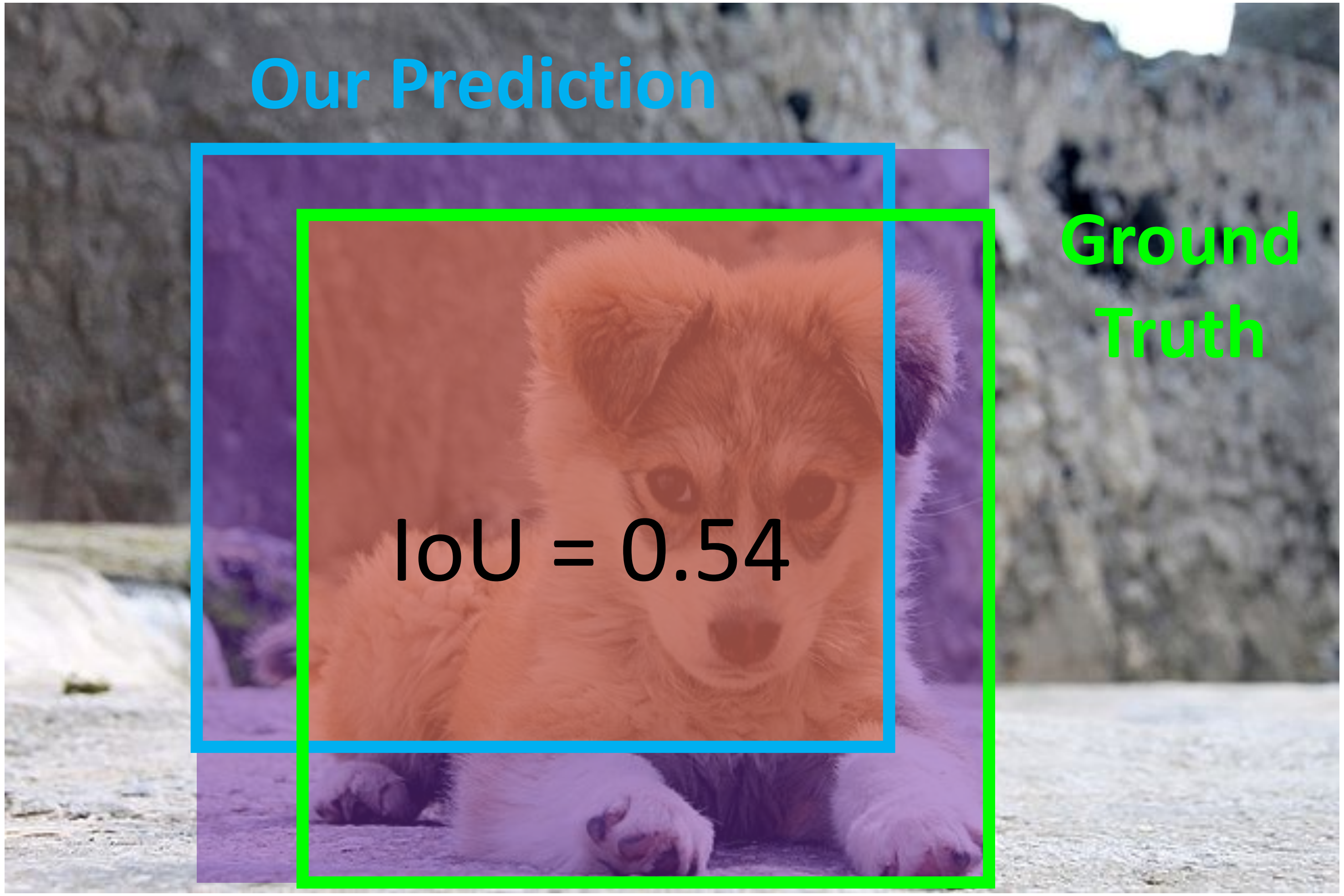
Comparing Boxes: Intersection over Union (IoU)

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"



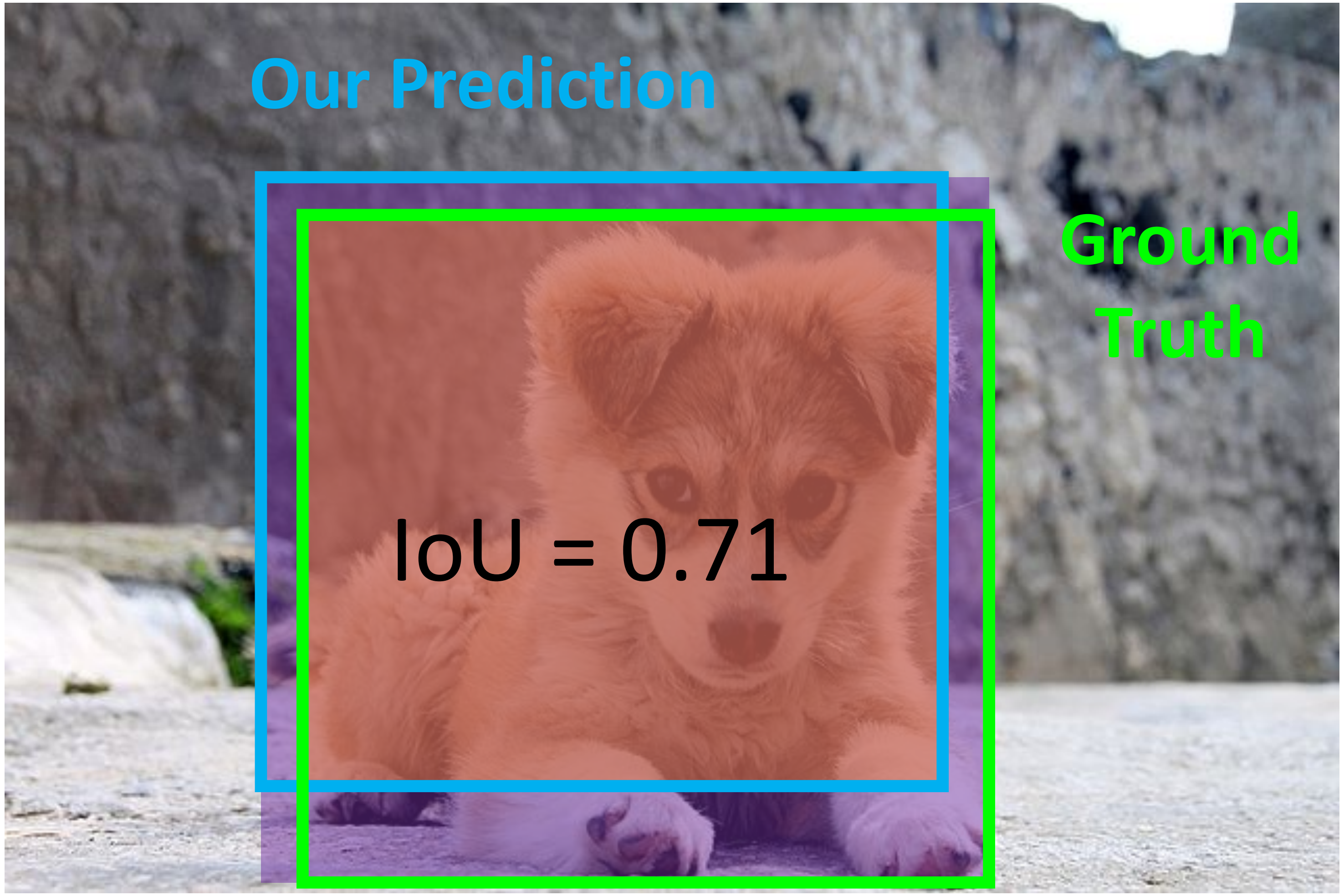
Comparing Boxes: Intersection over Union (IoU)

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?

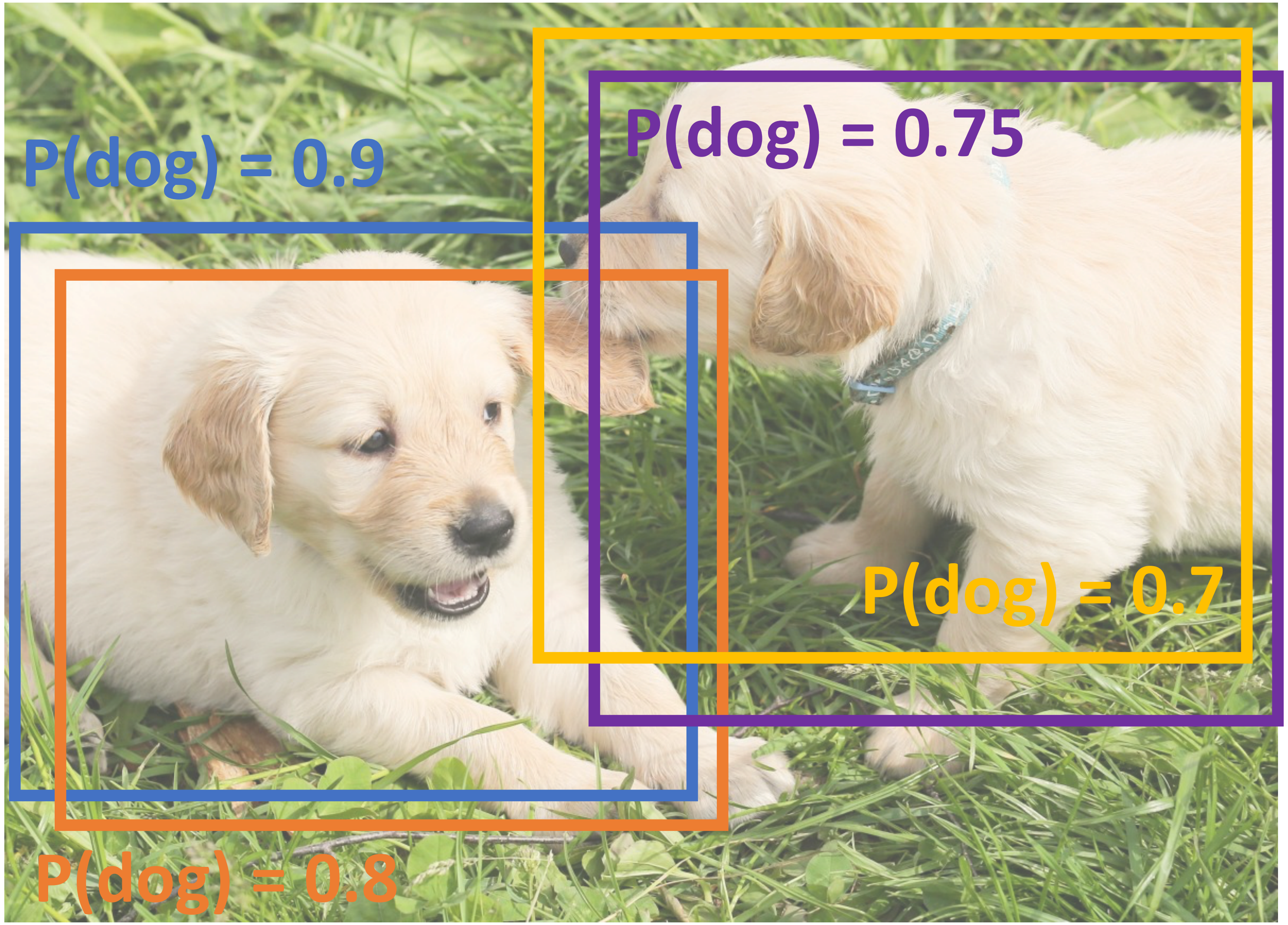
Intersection over Union (IoU)
(Also called "Jaccard similarity" or "Jaccard index"):

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

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:



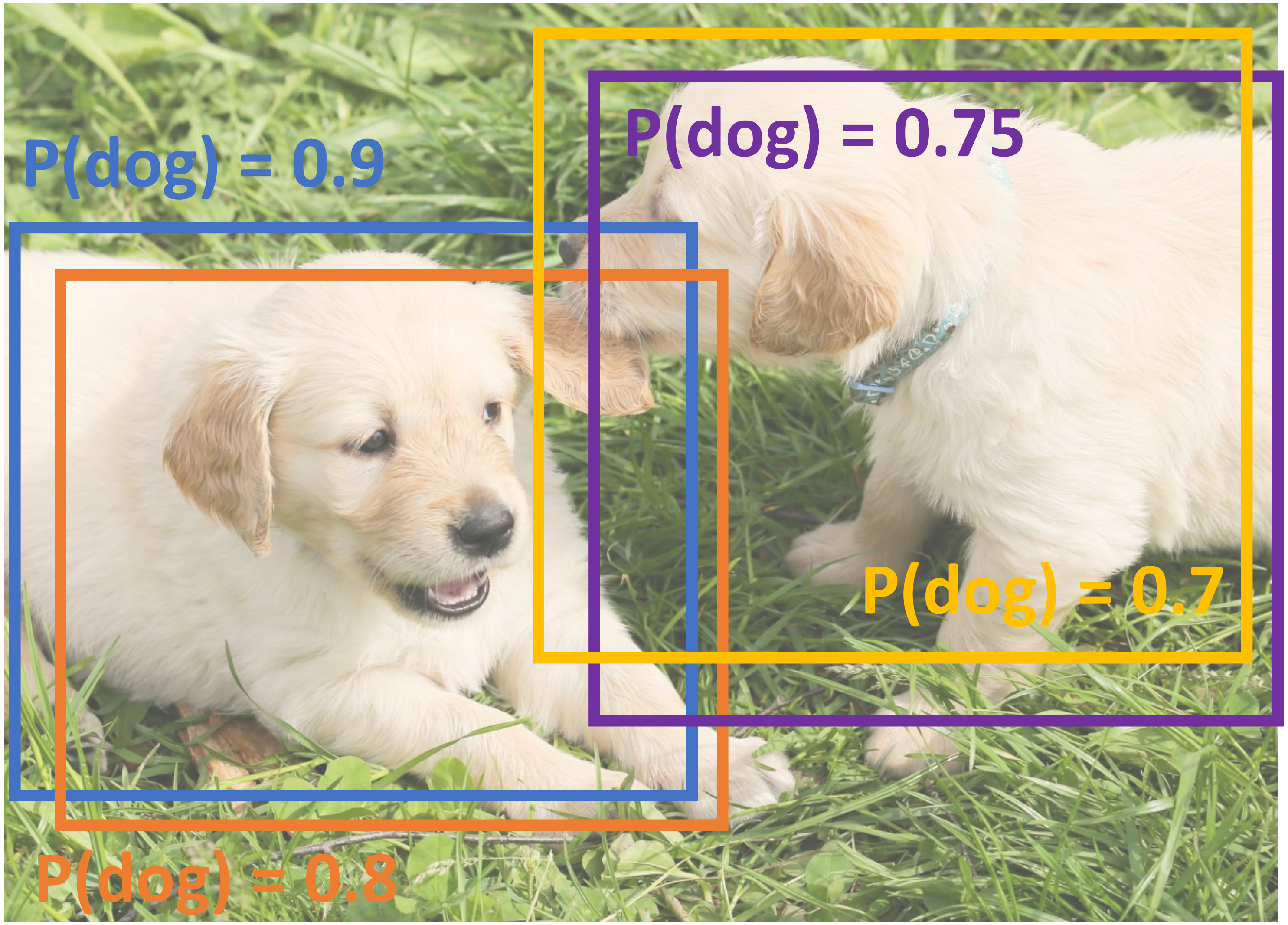
Puppy image is CC0 Public Domain

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



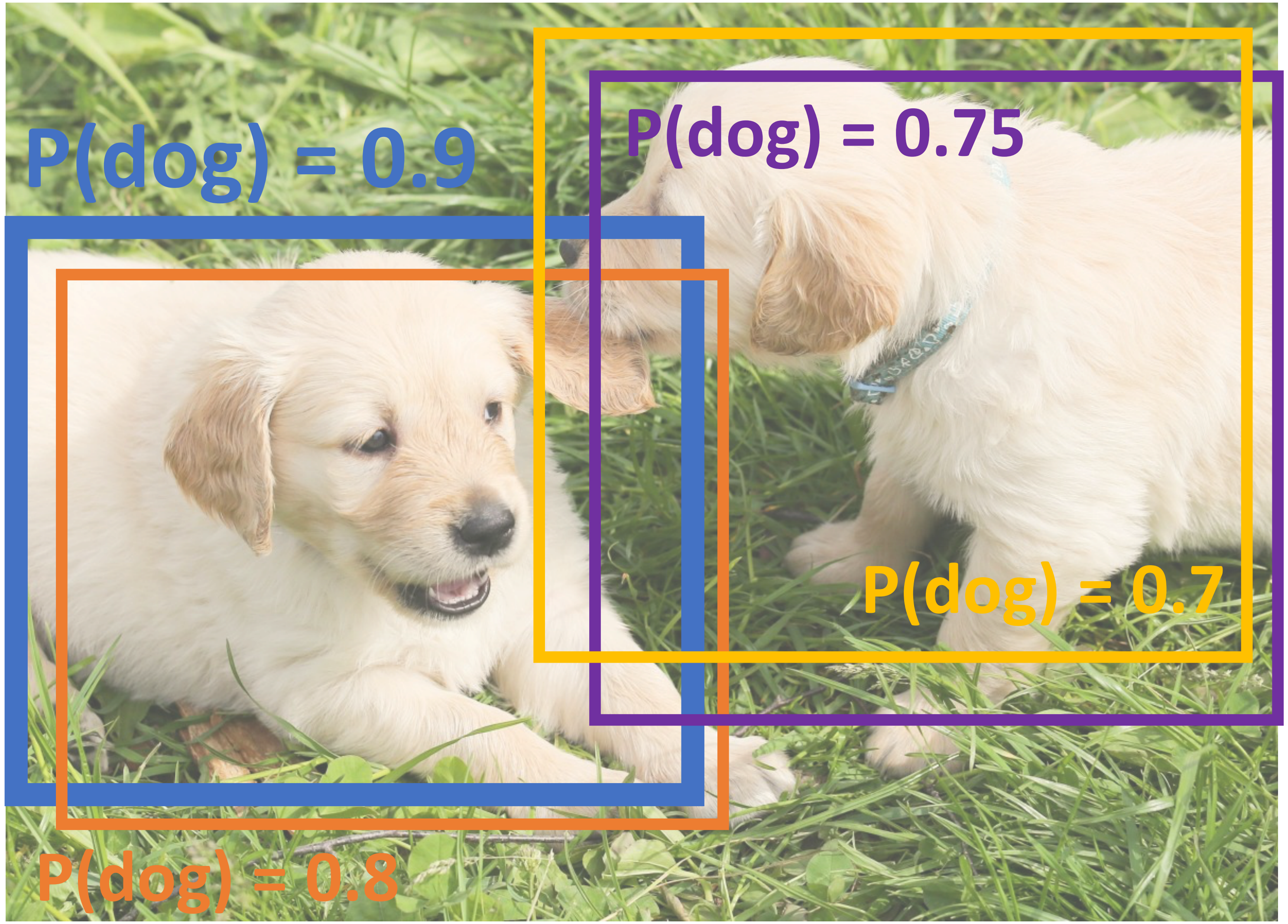
Overlapping Boxes: **Non-Max Suppression (NMS)**

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

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



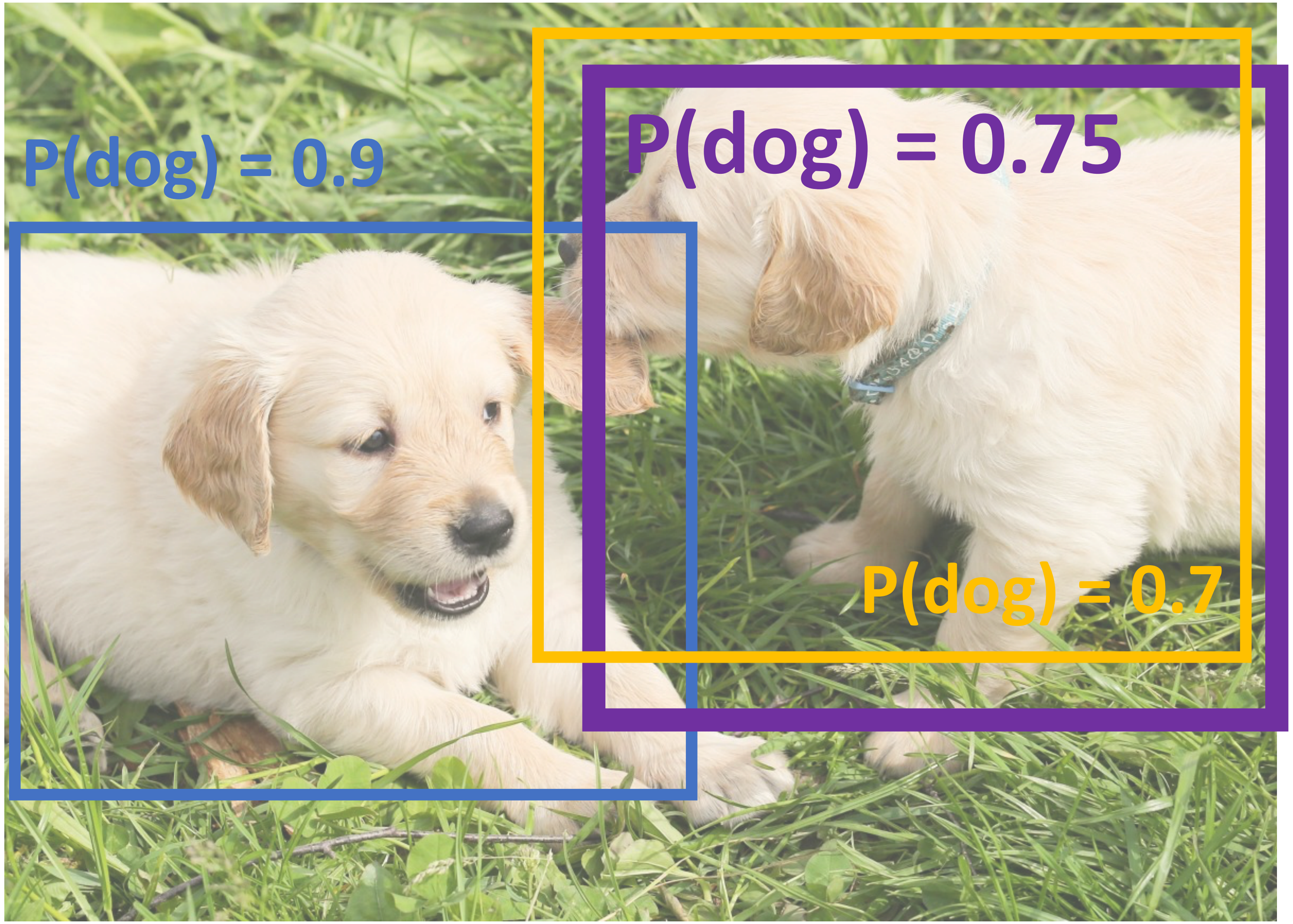
Overlapping Boxes: **Non-Max Suppression (NMS)**

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

IoU(■, ■) = **0.74**



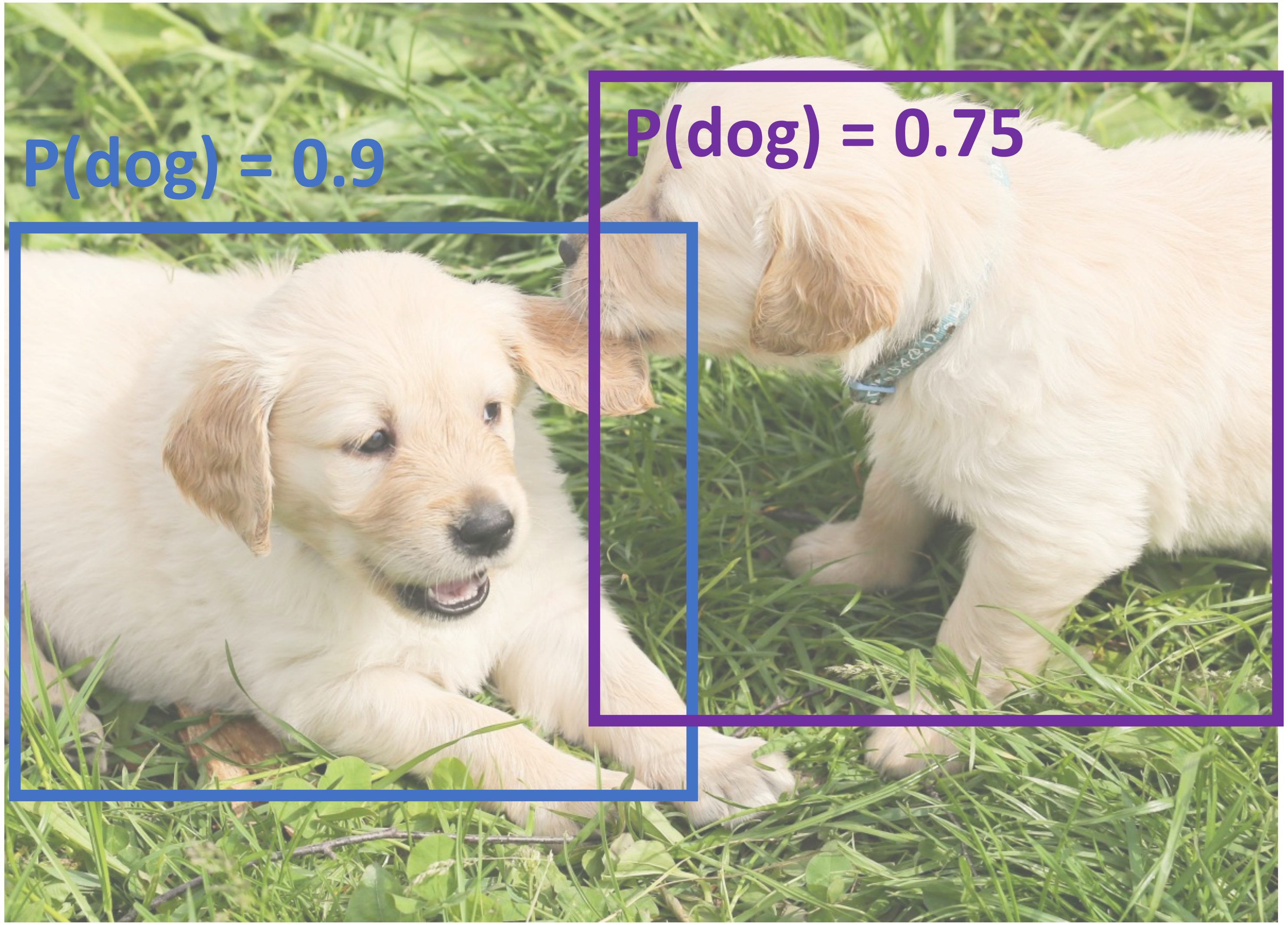
Puppy image is CC0 Public Domain

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



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

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

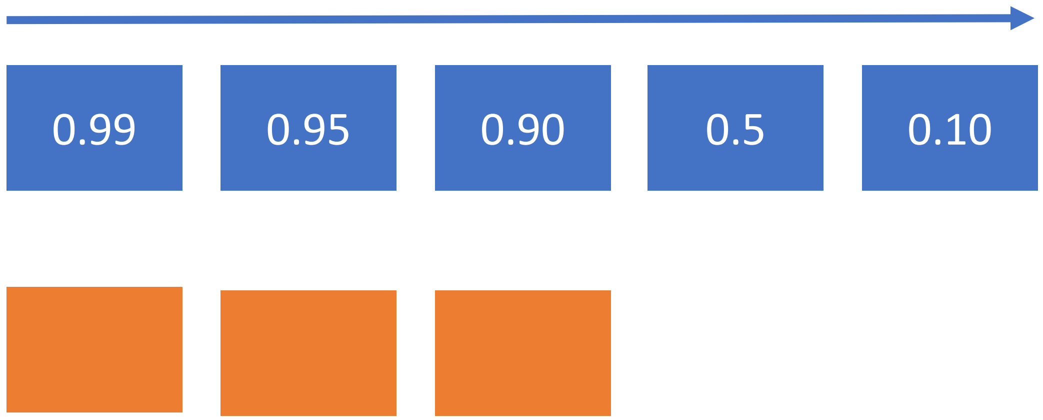
Evaluating Object Detectors: Mean Average Precision (mAP)

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

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
    1. For each detection (highest score to lowest score)

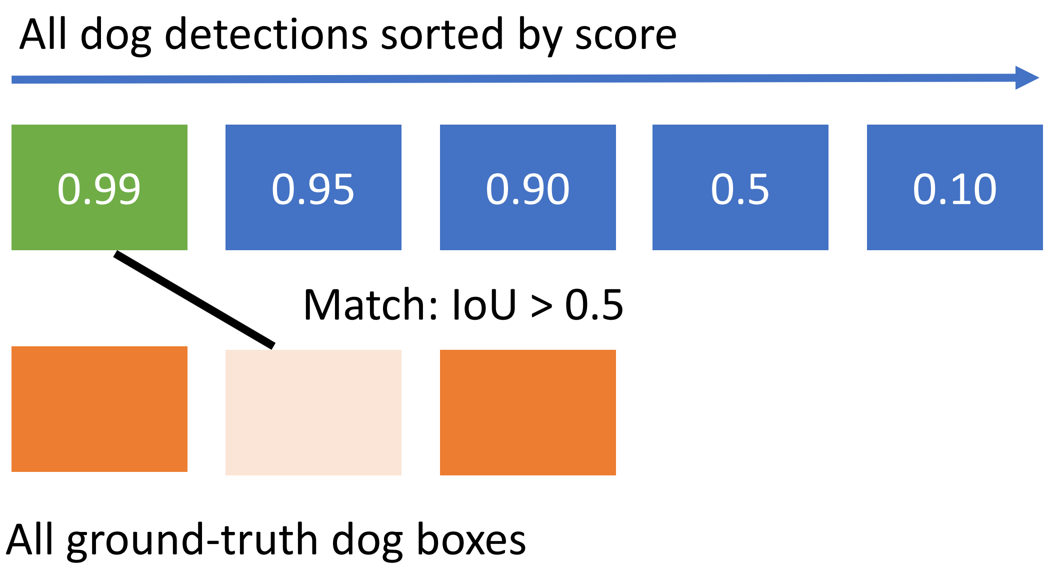
All dog detections sorted by score



All ground-truth dog boxes

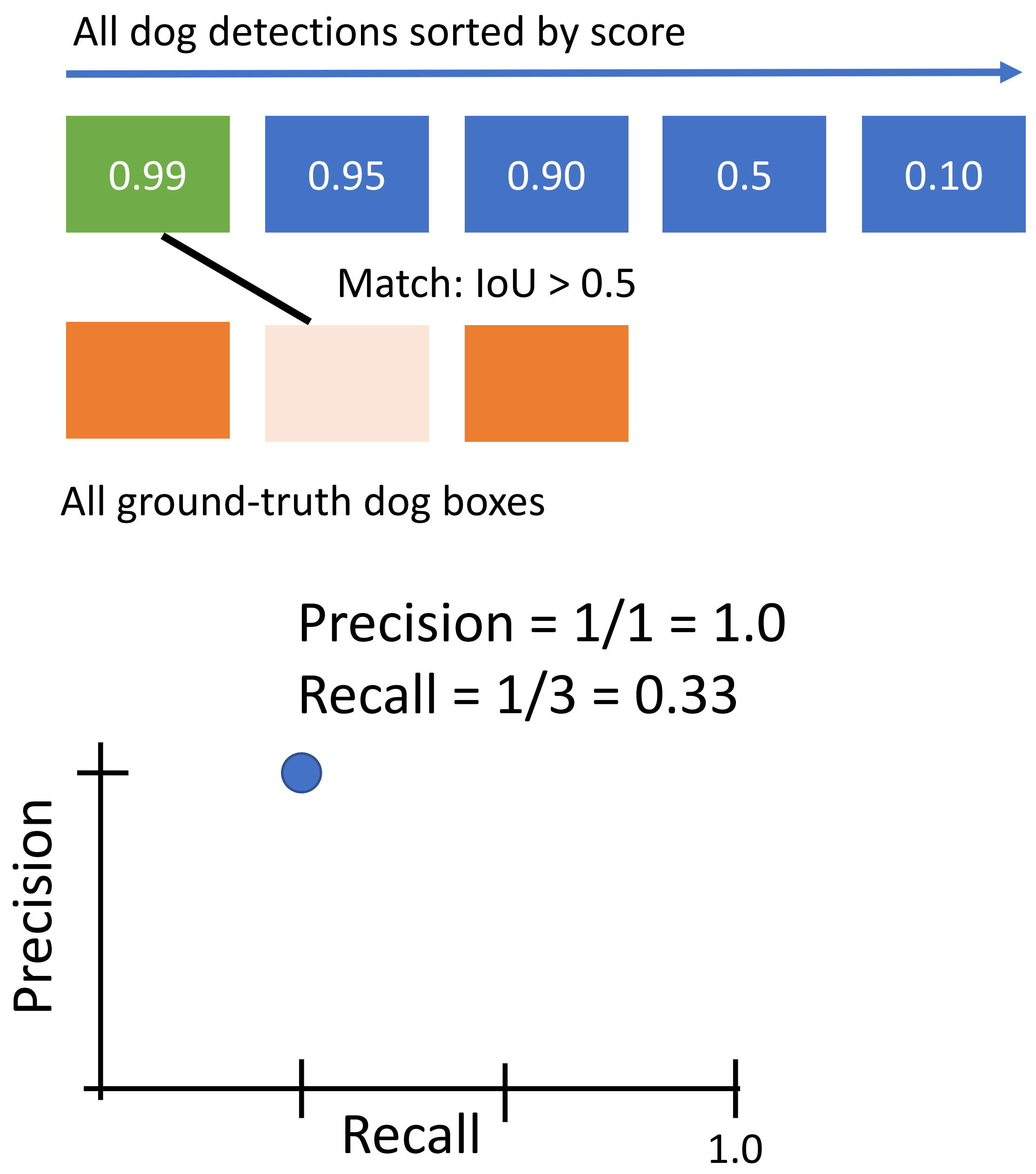
Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
   1. For each detection (highest score to lowest score)
      1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
      2. Otherwise mark it as negative



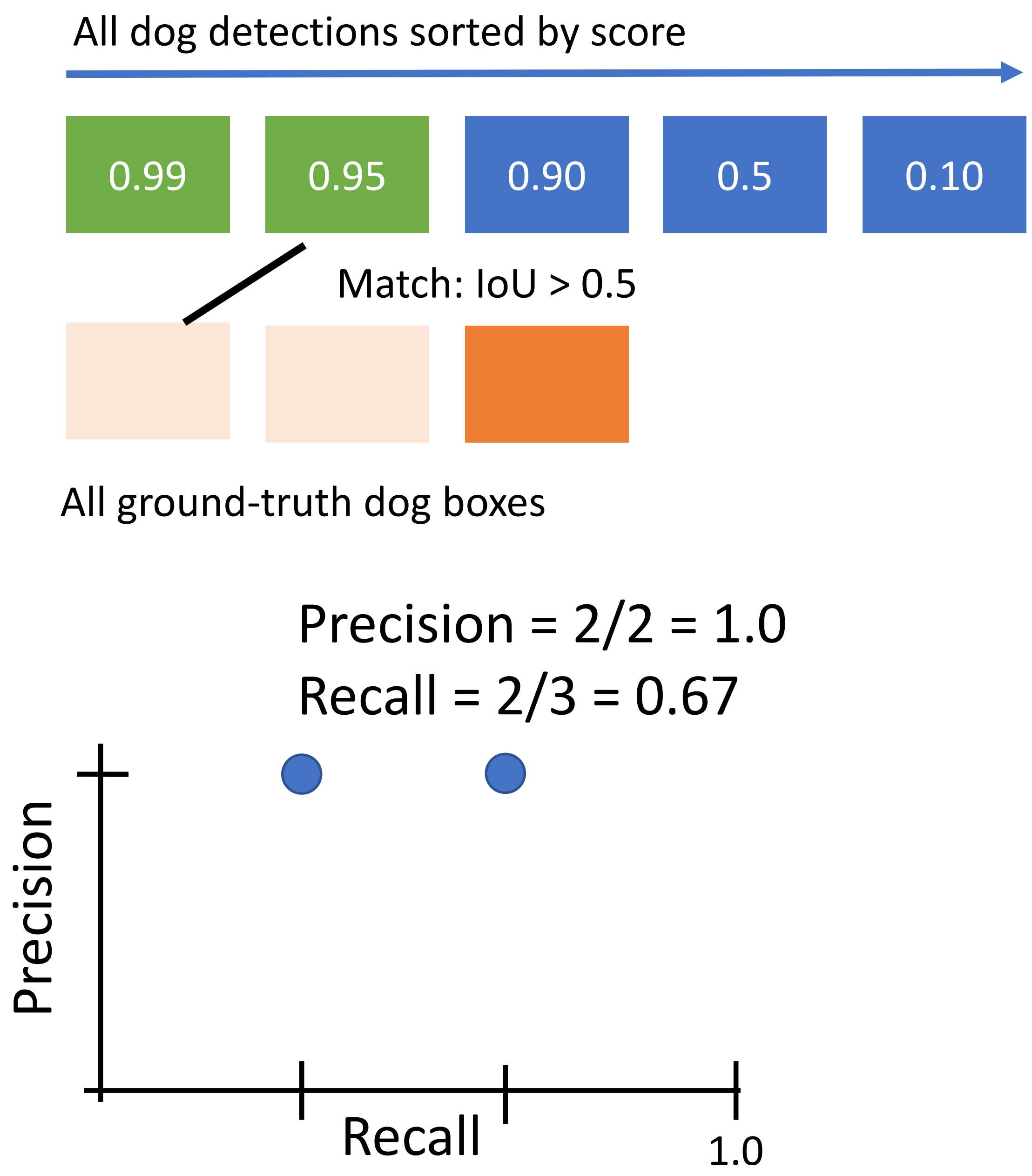
Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
   1. For each detection (highest score to lowest score)
      1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
      2. Otherwise mark it as negative
      3. Plot a point on PR Curve



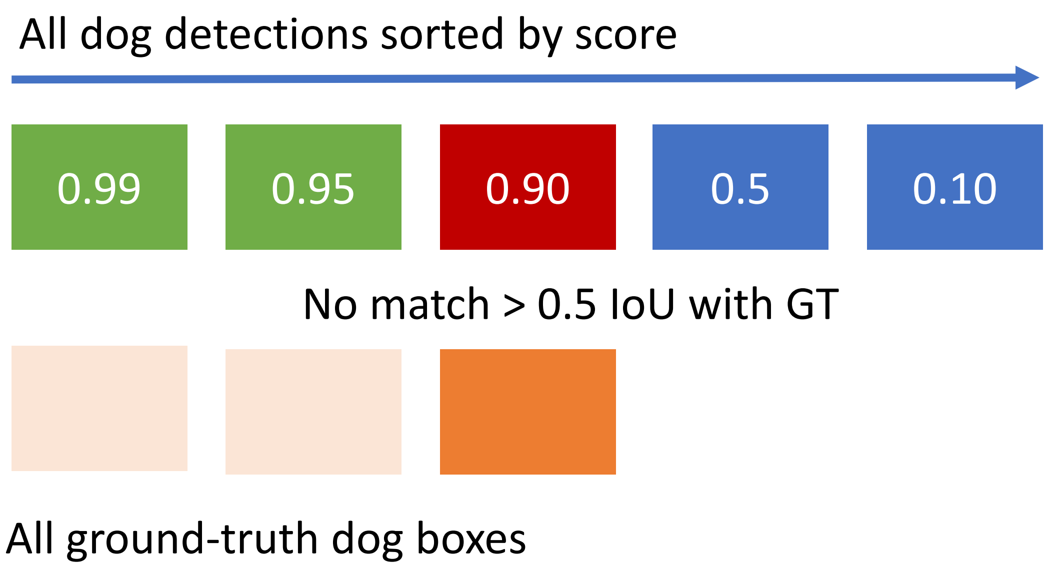
Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
    1. For each detection (highest score to lowest score)
        1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
        2. Otherwise mark it as negative
        3. Plot a point on PR Curve

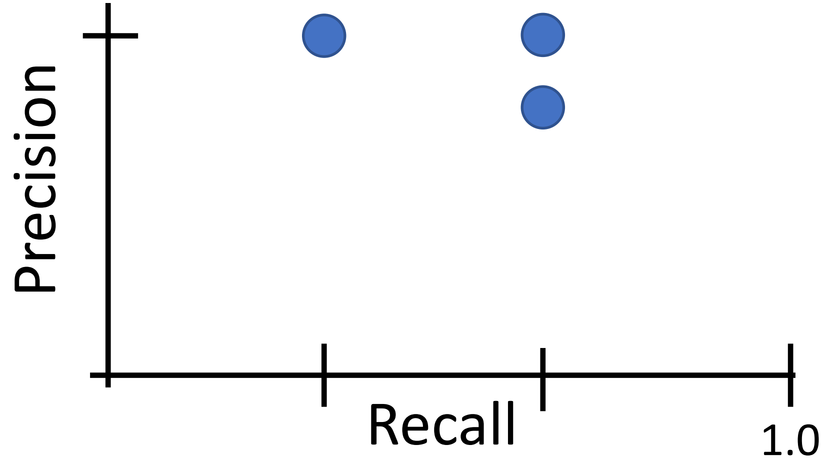


Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
    1. For each detection (highest score to lowest score)
        1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
        2. Otherwise mark it as negative
        3. Plot a point on PR Curve

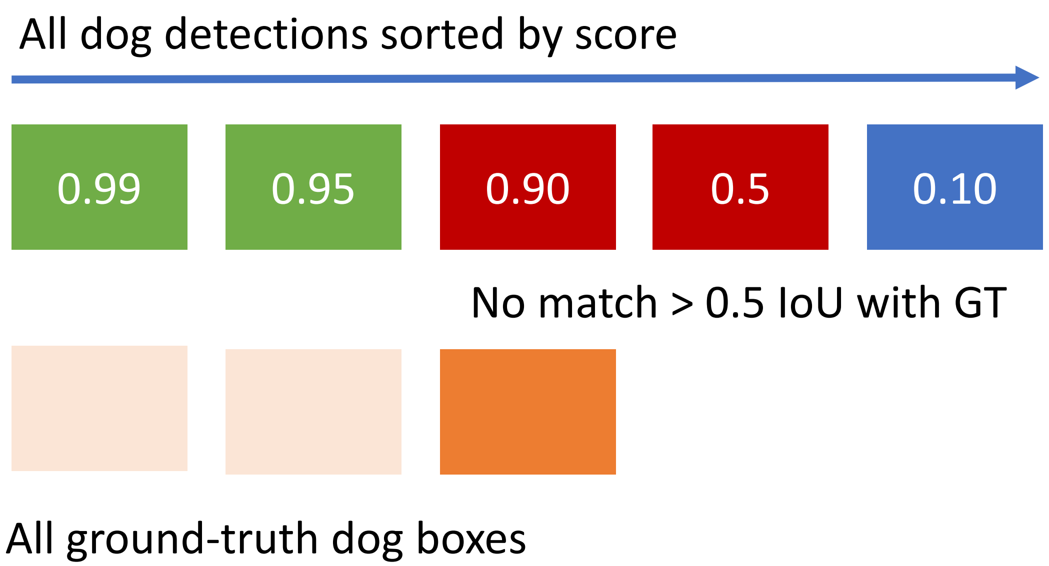


Precision = 2/3 = 0.67
Recall = 2/3 = 0.67

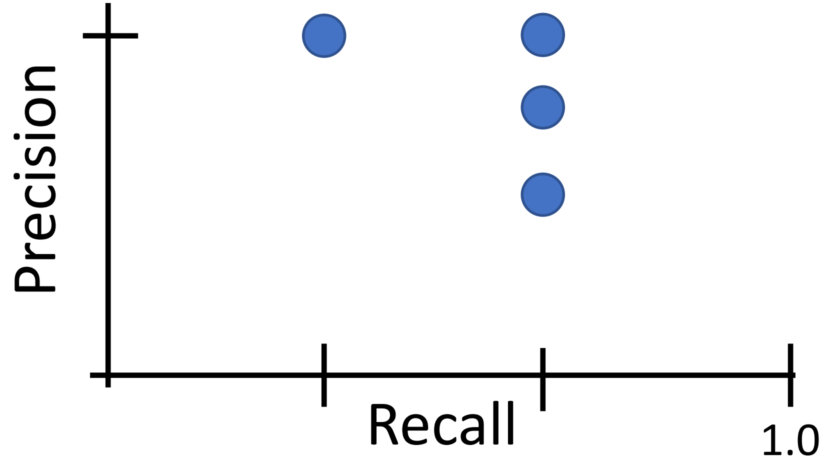


Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
   1. For each detection (highest score to lowest score)
      1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
      2. Otherwise mark it as negative
      3. Plot a point on PR Curve

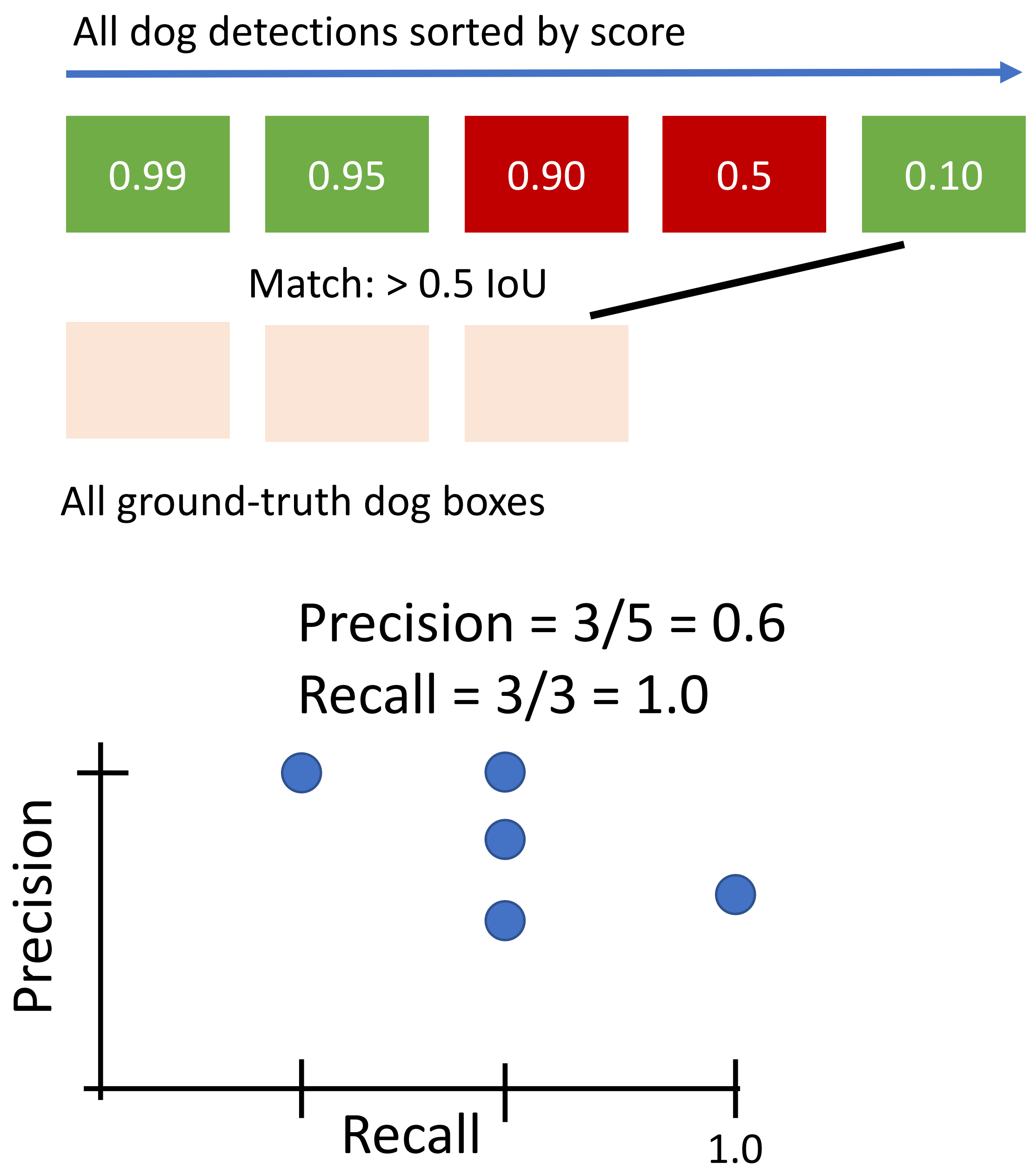


Precision = 2/4 = 0.5
Recall = 2/3 = 0.67



Evaluating Object Detectors: Mean Average Precision (mAP)

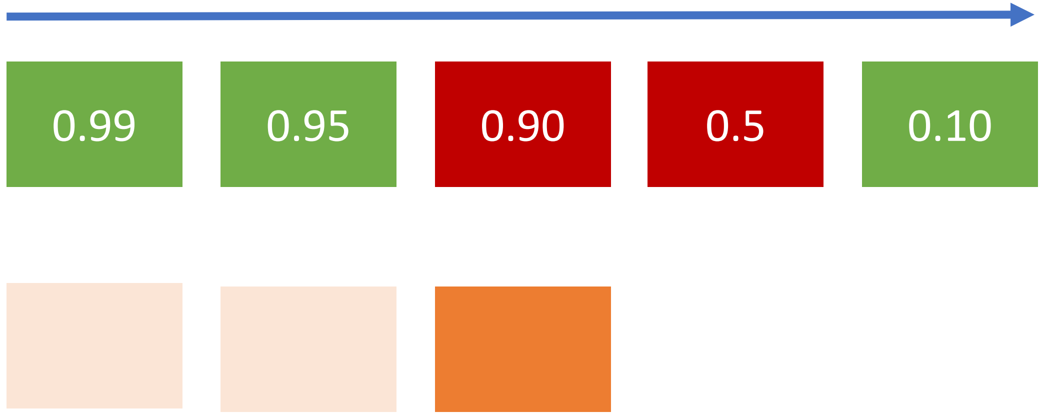
1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
   1. For each detection (highest score to lowest score)
      1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
      2. Otherwise mark it as negative
      3. Plot a point on PR Curve



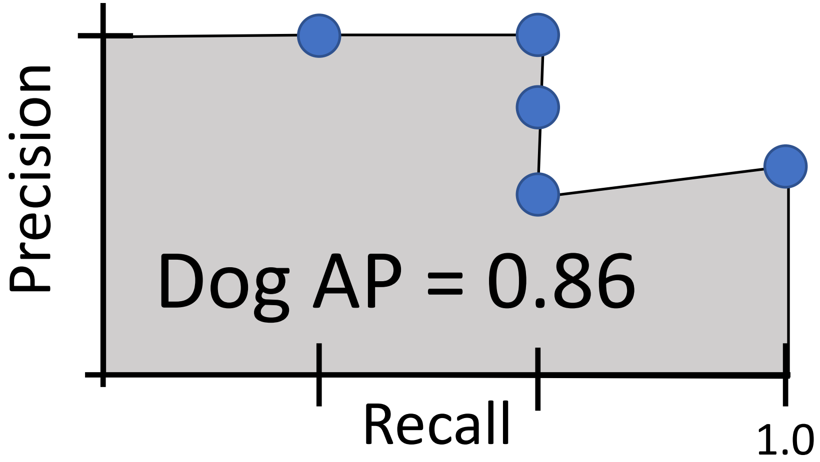
Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
    1. For each detection (highest score to lowest score)
        1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
        2. Otherwise mark it as negative
        3. Plot a point on PR Curve
    2. Average Precision (AP) = area under PR curve

All dog detections sorted by score



All ground-truth dog boxes

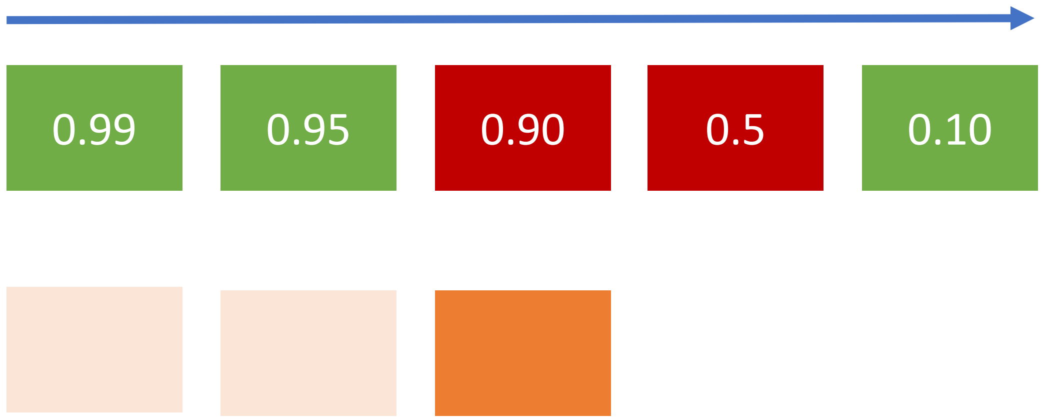


Evaluating Object Detectors: Mean Average Precision (mAP)

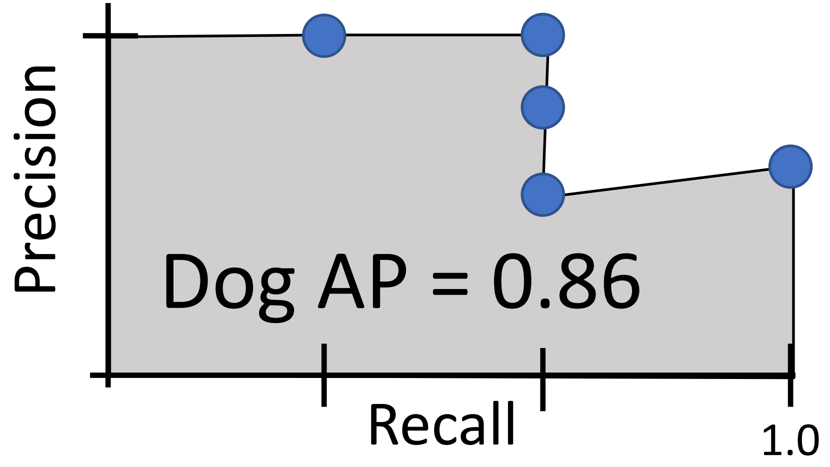
1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
   1. For each detection (highest score to lowest score)
      1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
      2. Otherwise mark it as negative
      3. Plot a point on PR Curve
   2. Average Precision (AP) = area under PR curve

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"

All dog detections sorted by score



All ground-truth dog boxes



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
    1. For each detection (highest score to lowest score)
        1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
        2. Otherwise mark it as negative
        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)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
    1. For each detection (highest score to lowest score)
        1. If it matches some GT box with IoU > 0.5, mark it as positive and eliminate the GT
        2. Otherwise mark it as negative
        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

…

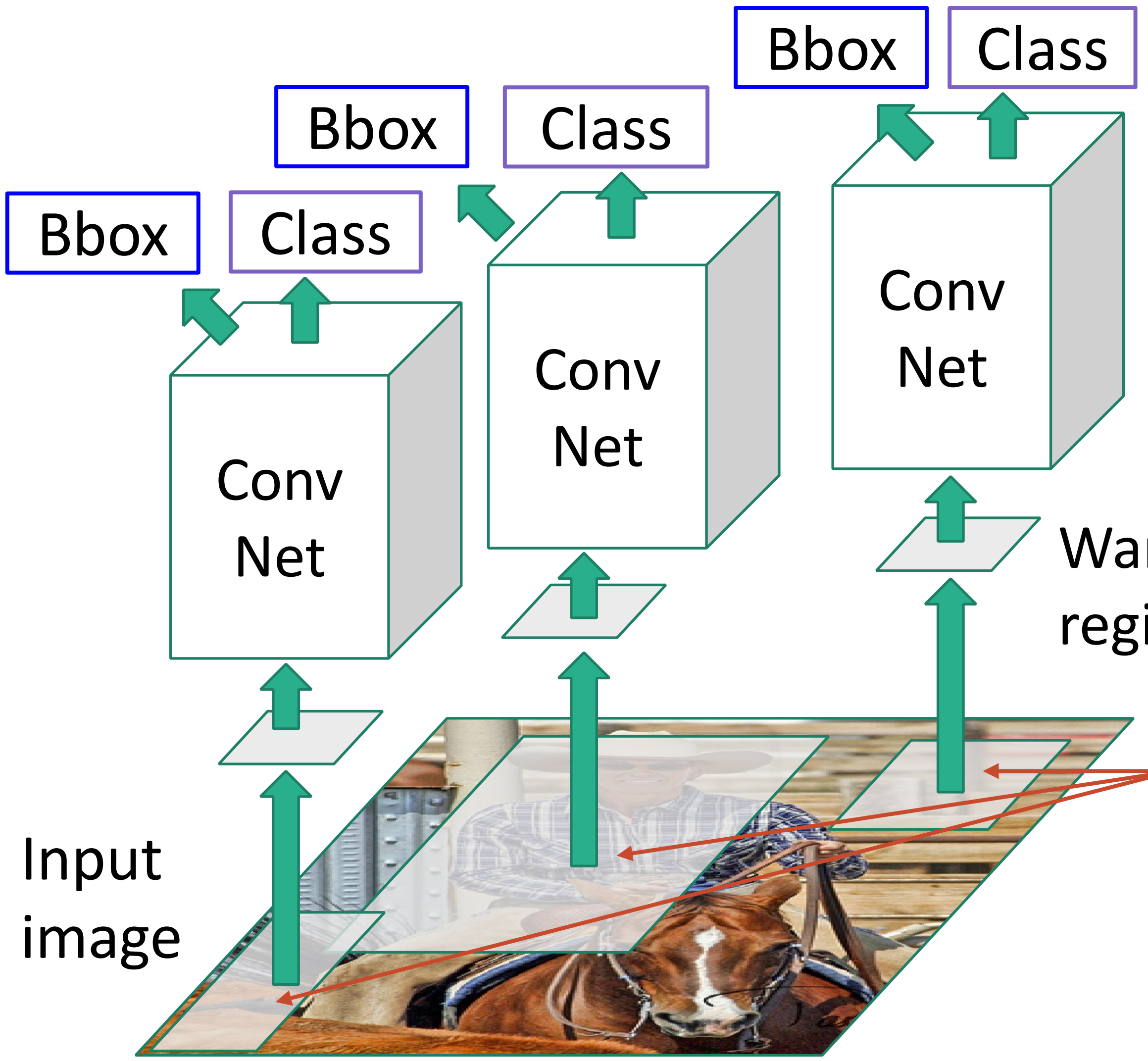
mAP@0.95 = 0.2

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)

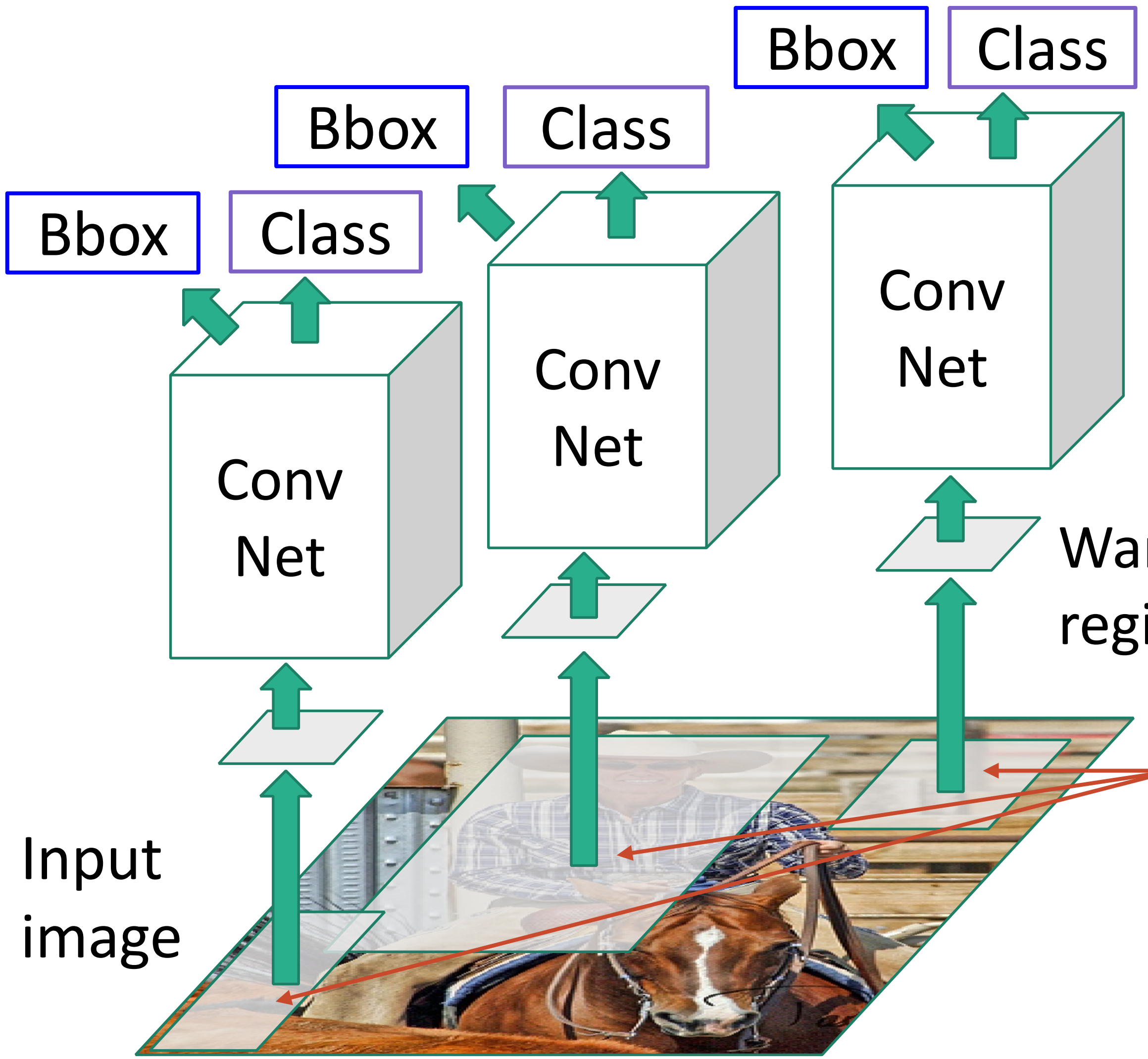
Regions of Interest (RoI) from a proposal method (~2k)

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

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)

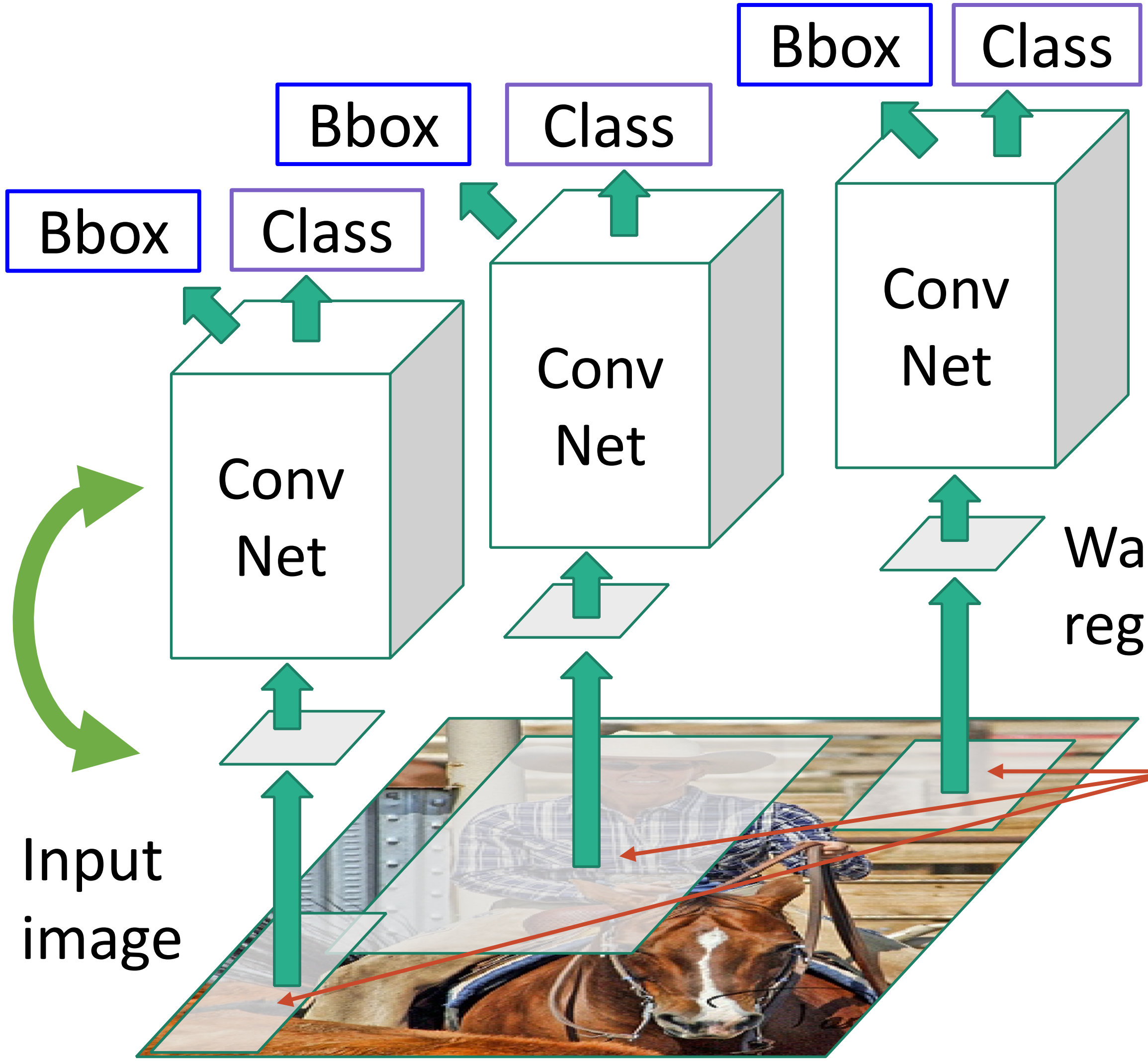
Regions of Interest (RoI) from a proposal method (~2k)

Input image

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.

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)

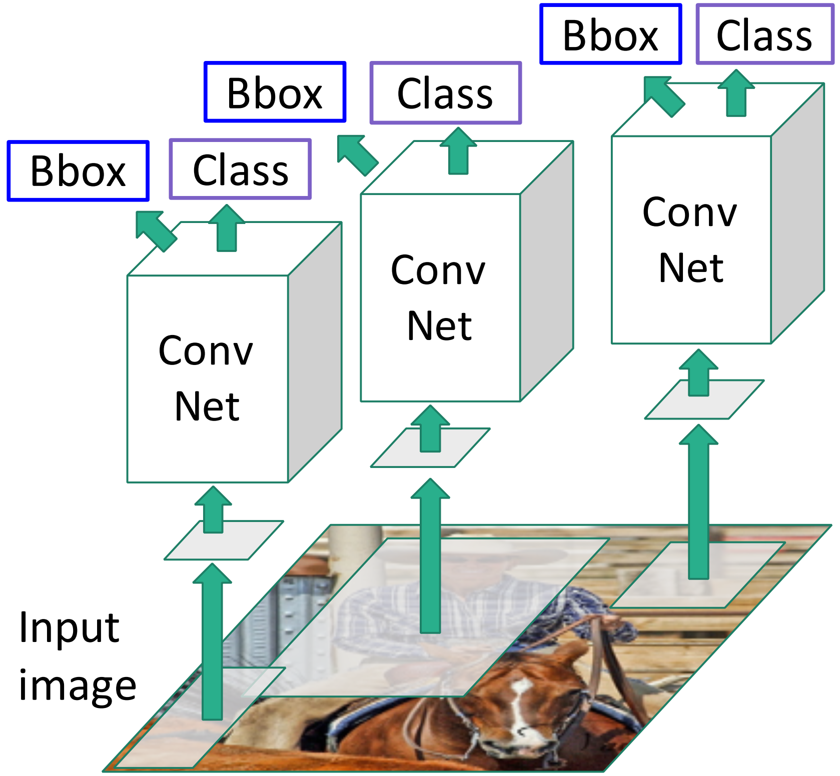
Problem: Very slow! Need to do ~2k forward passes for each image!

Solution: Run CNN *before* warping!

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

“Slow” R-CNN

Process each region independently

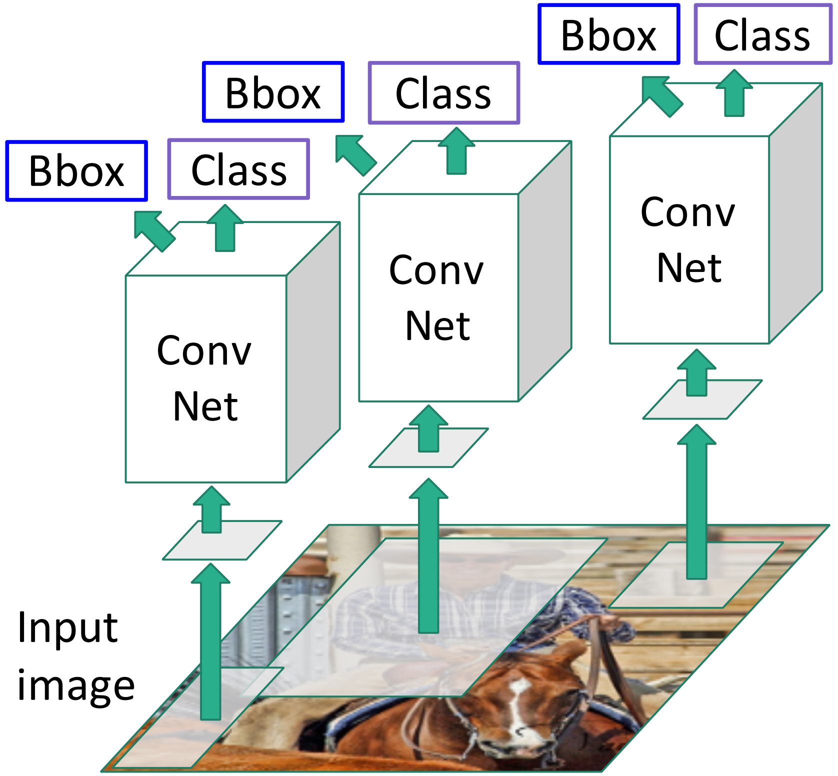


Fast R-CNN

Input image

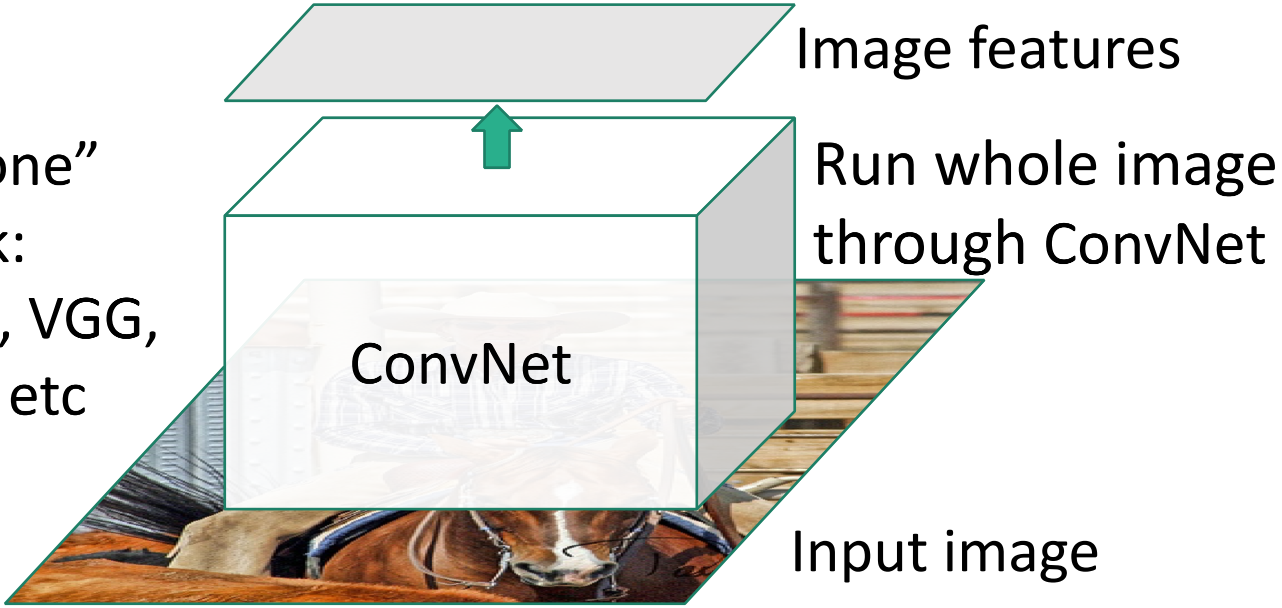
<u>"Slow" R-CNN</u>

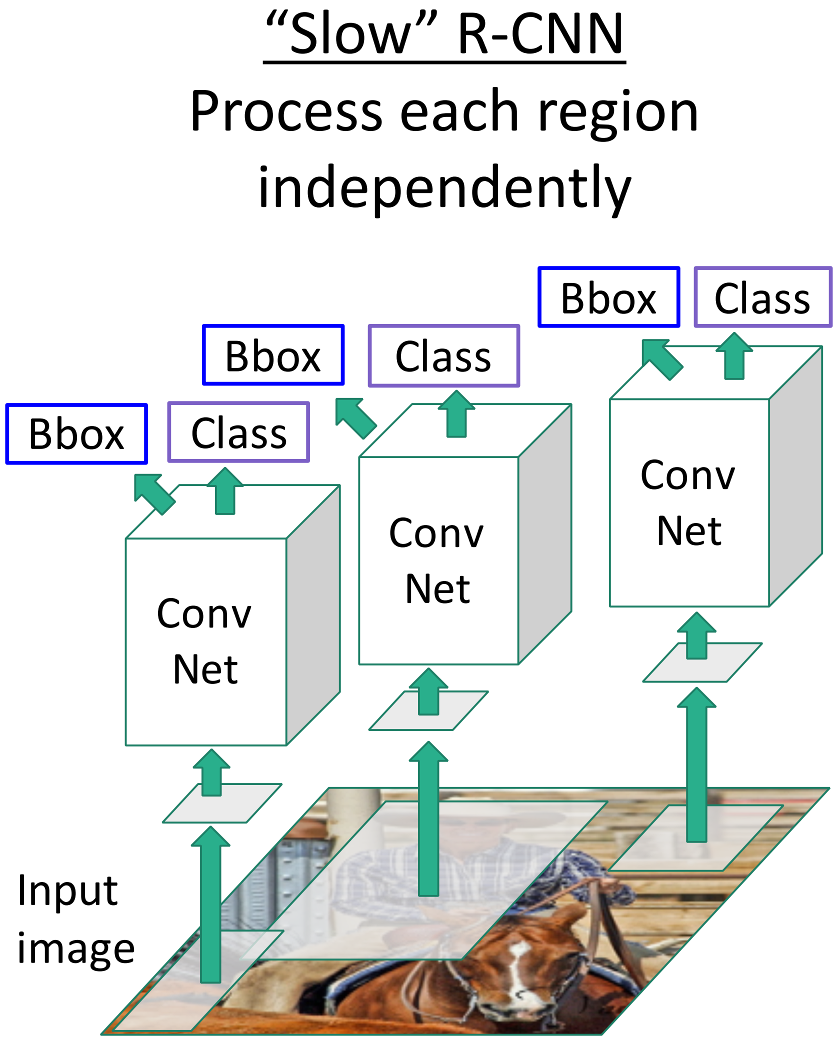
Process each region independently



Fast R-CNN

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



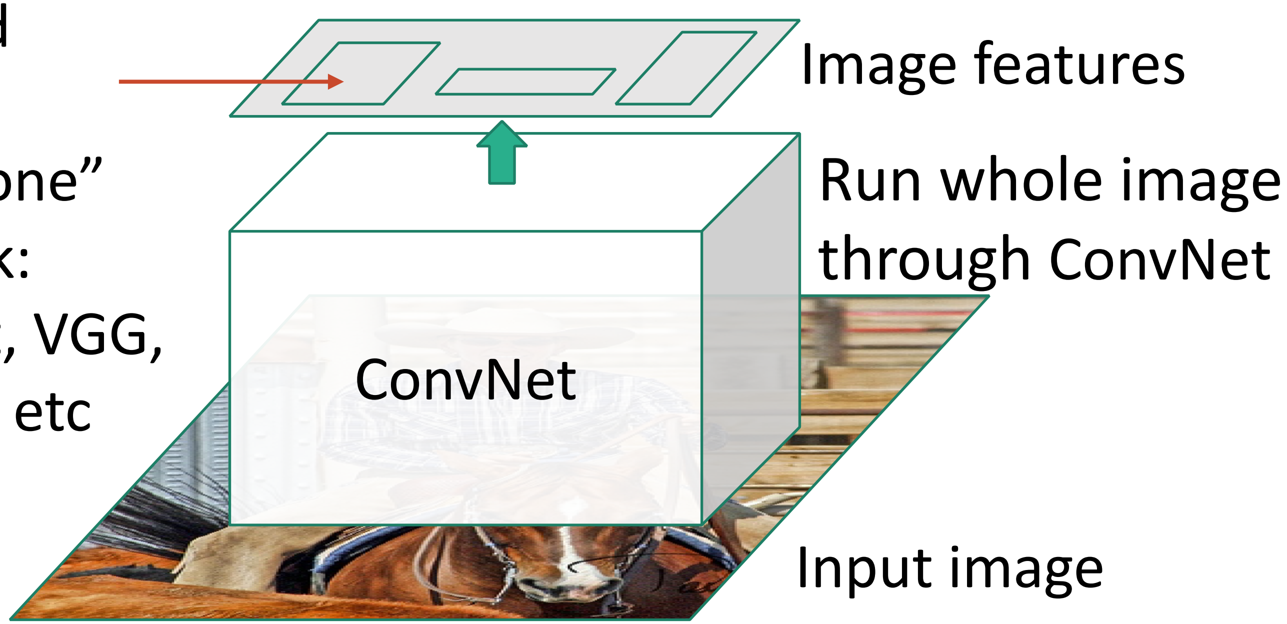


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

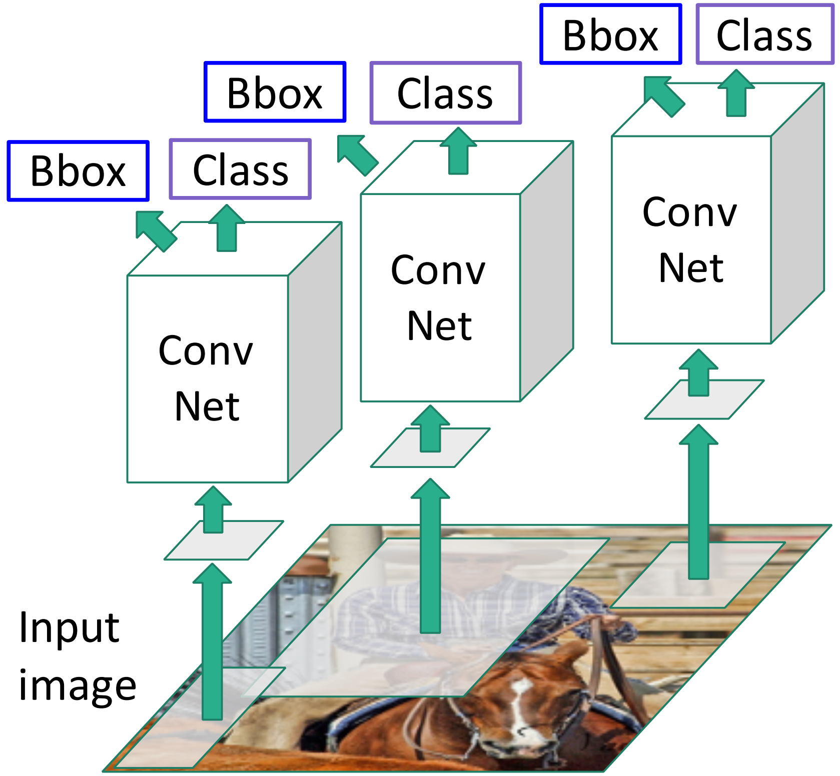
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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

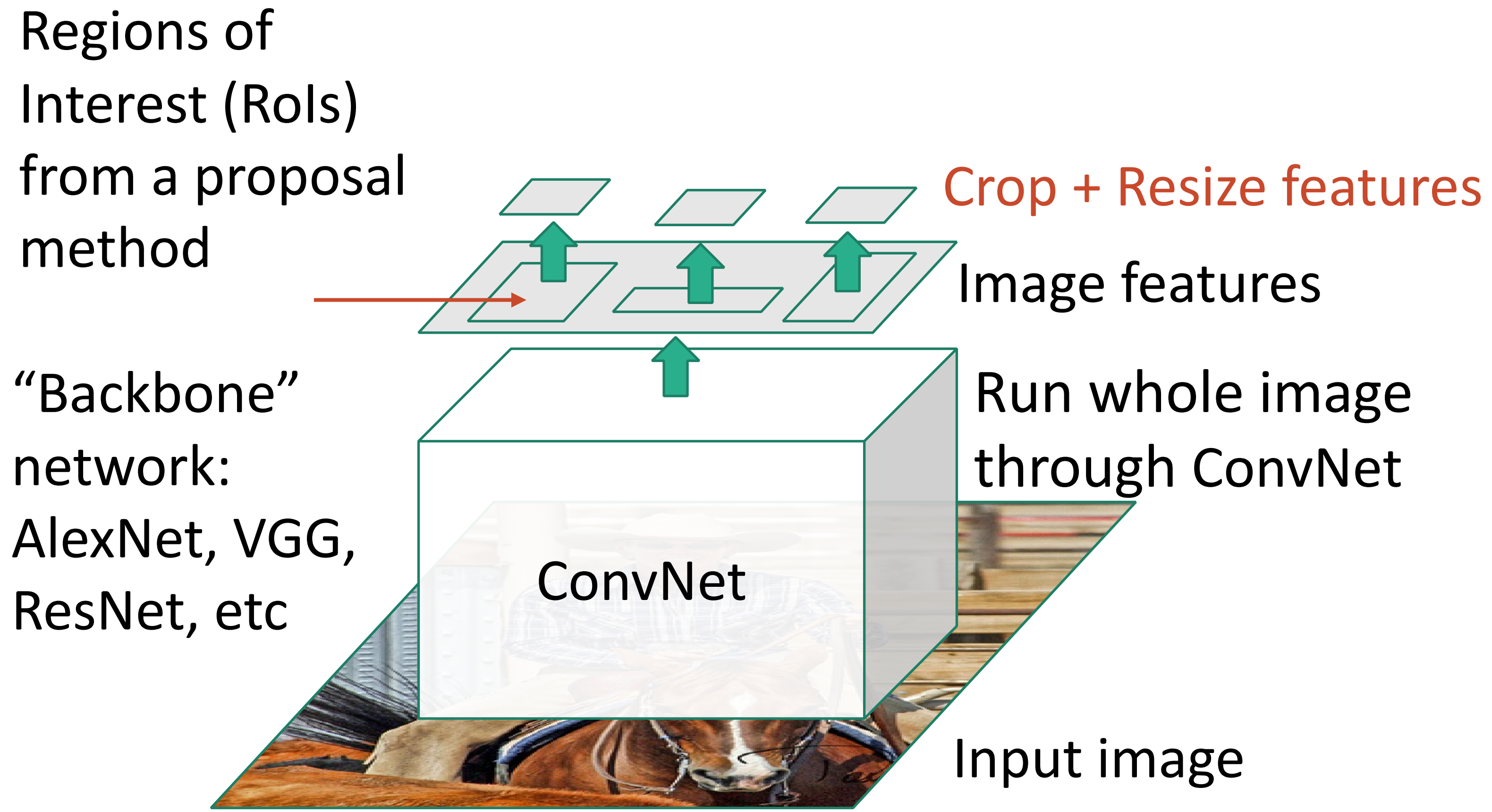


"Slow" R-CNN
Process each region independently

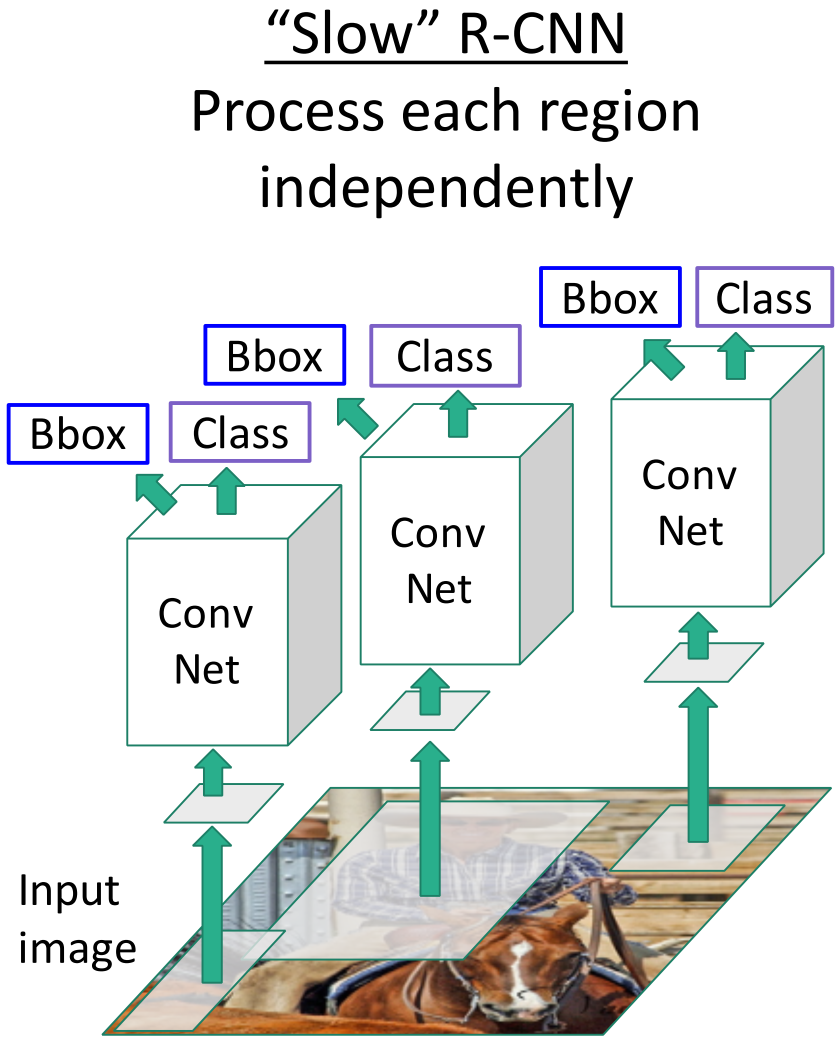


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

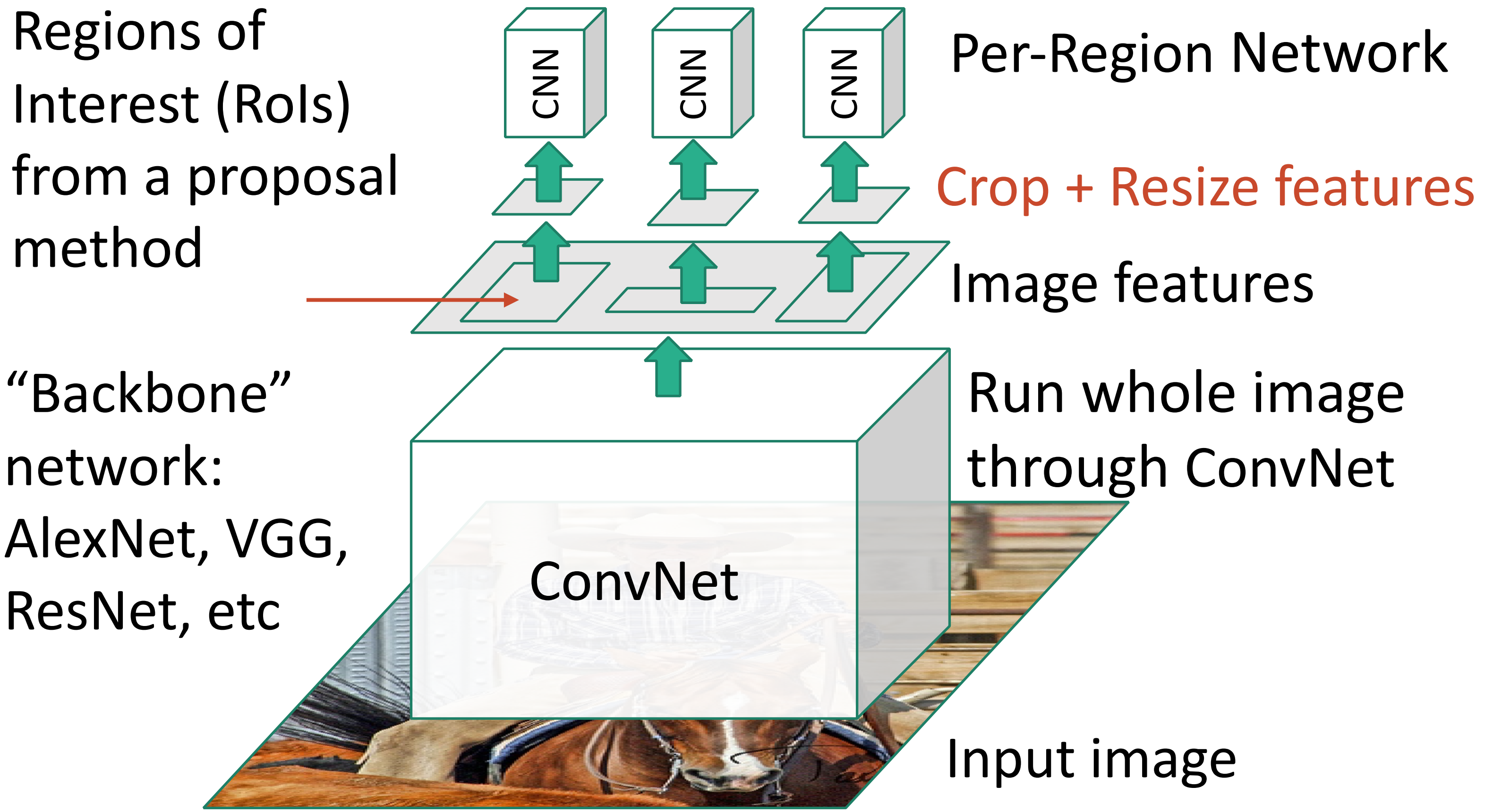


Regions of Interest (RoIs) from a proposal method
Crop + Resize features
Image features
"Backbone" network: AlexNet, VGG, ResNet, etc
ConvNet
Run whole image through ConvNet
Input image

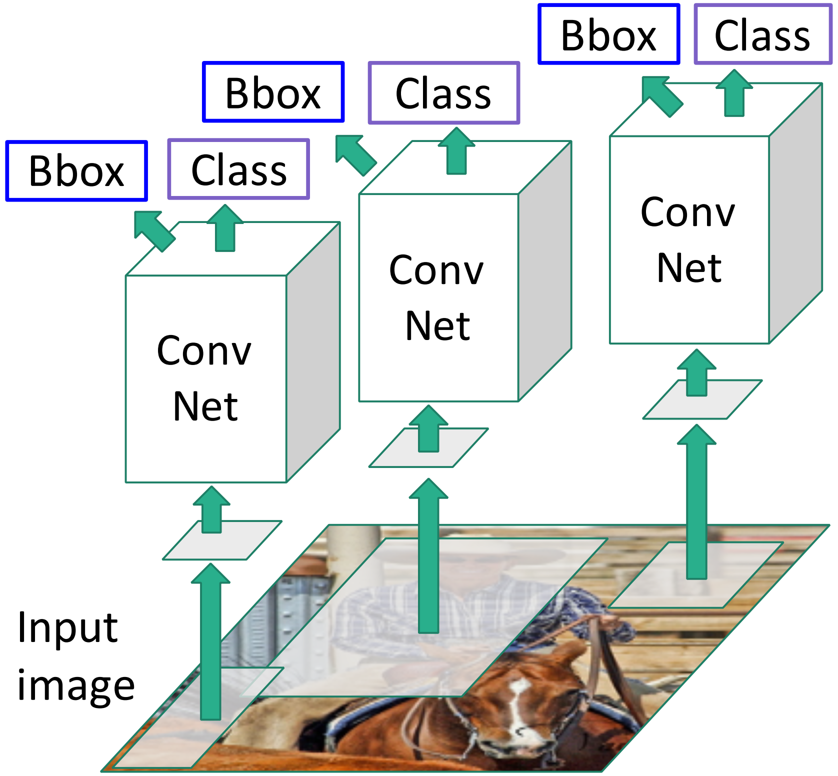


"Slow" R-CNN
Process each region independently
Bbox
Class
Bbox
Class
Bbox
Class
Conv Net
Conv Net
Conv Net
Input image

Fast R-CNN



"Slow" R-CNN
Process each region independently

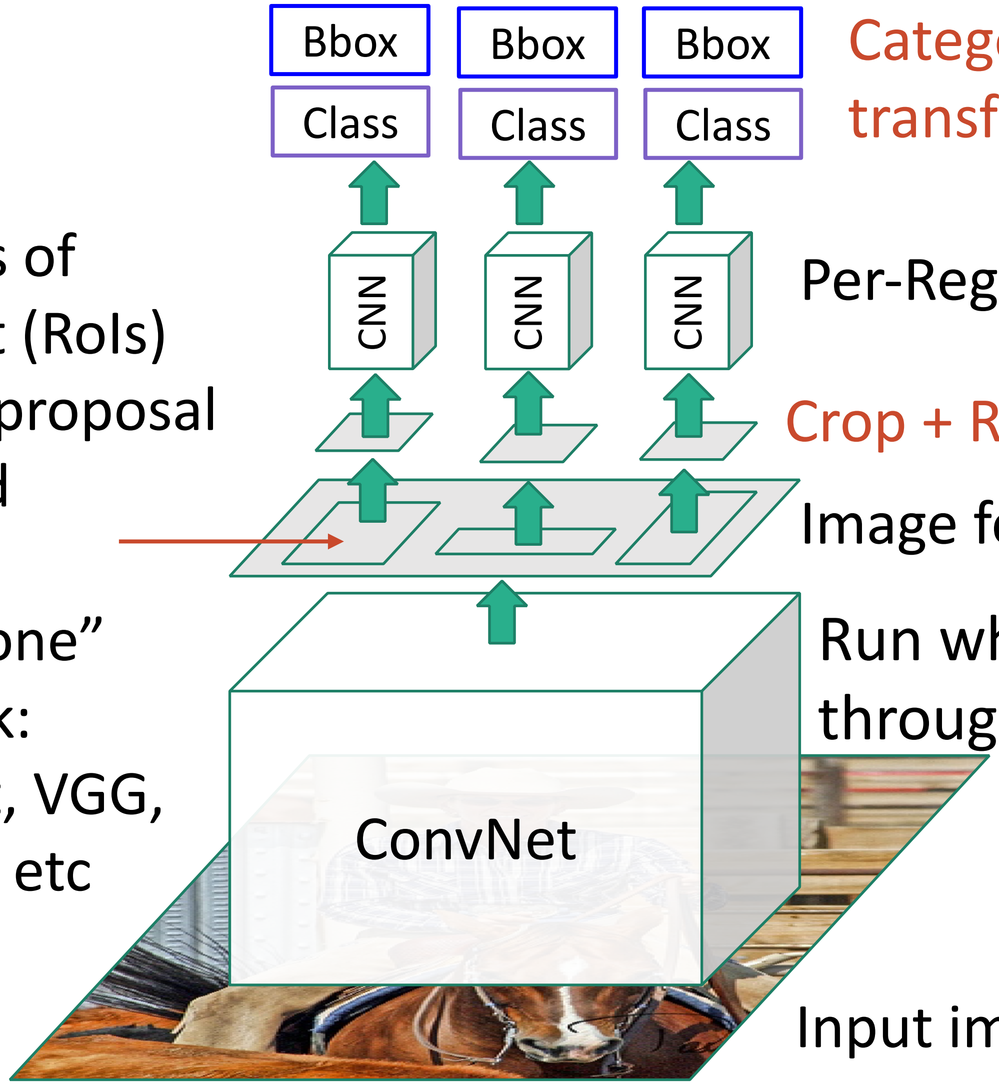


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



Category and box transform per region

Per-Region Network

Crop + Resize features

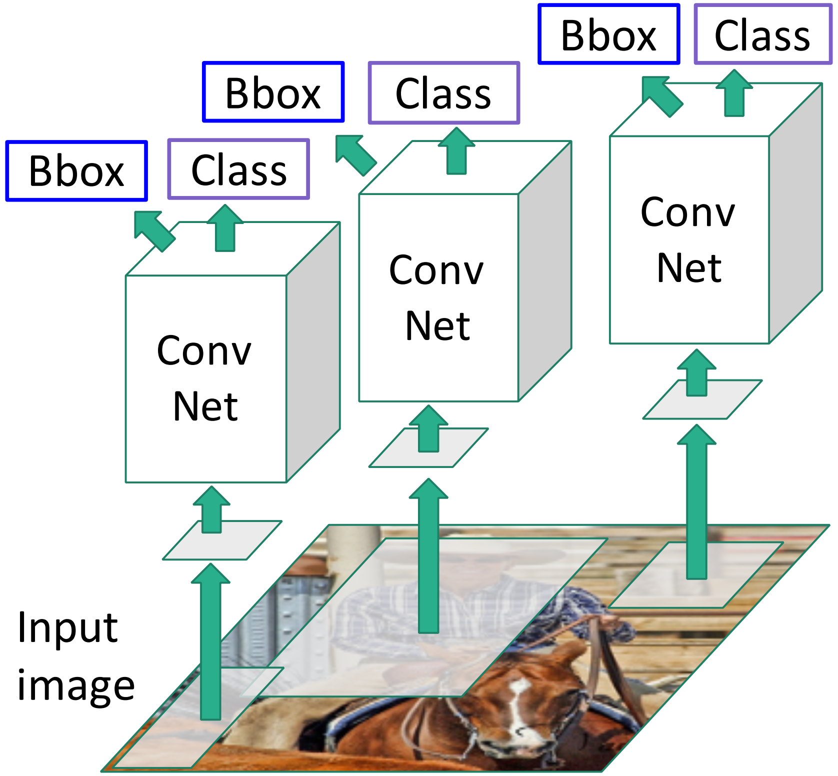
Image features

Run whole image through ConvNet

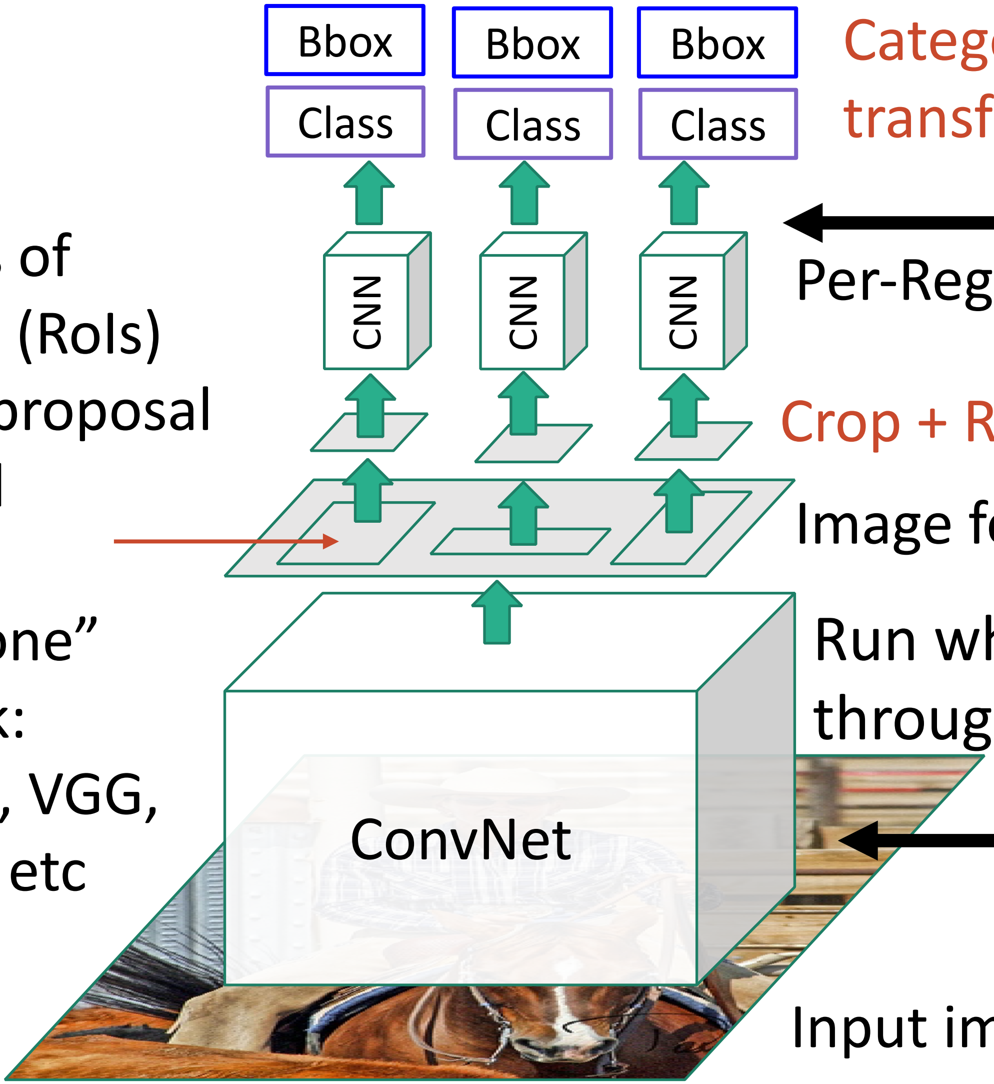
Input image

"Slow" R-CNN

Process each region independently



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

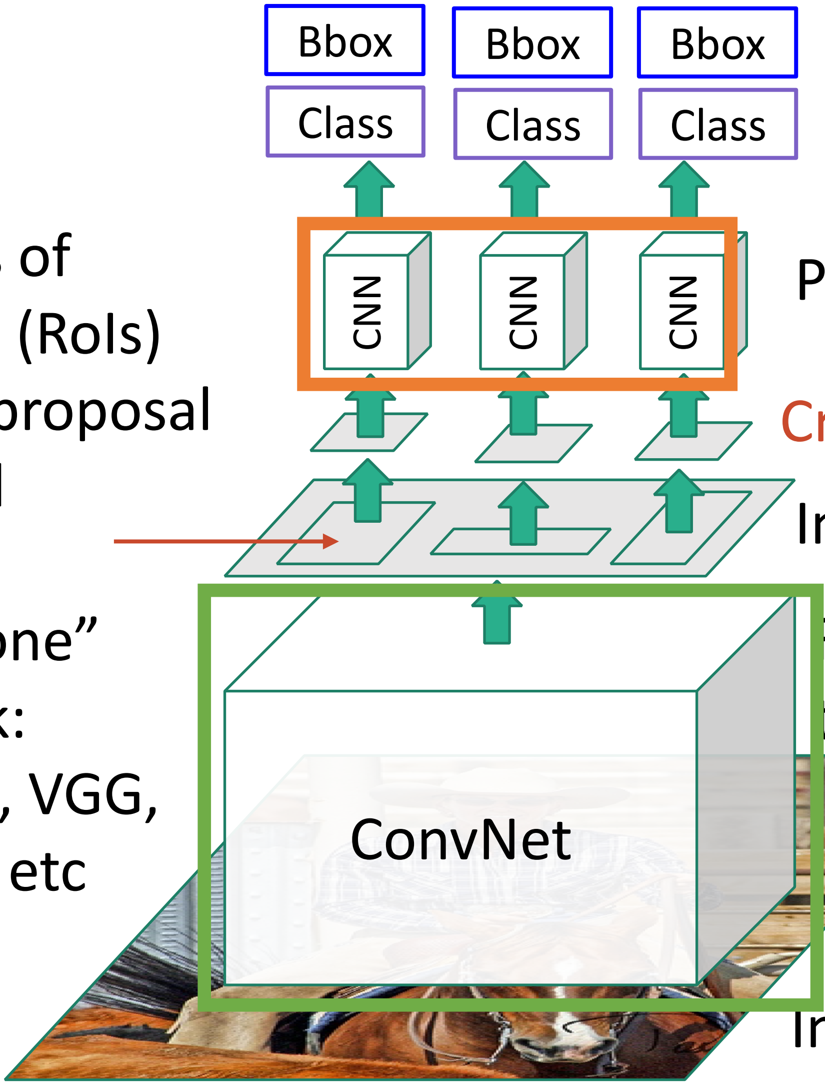
Run whole image through ConvNet

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

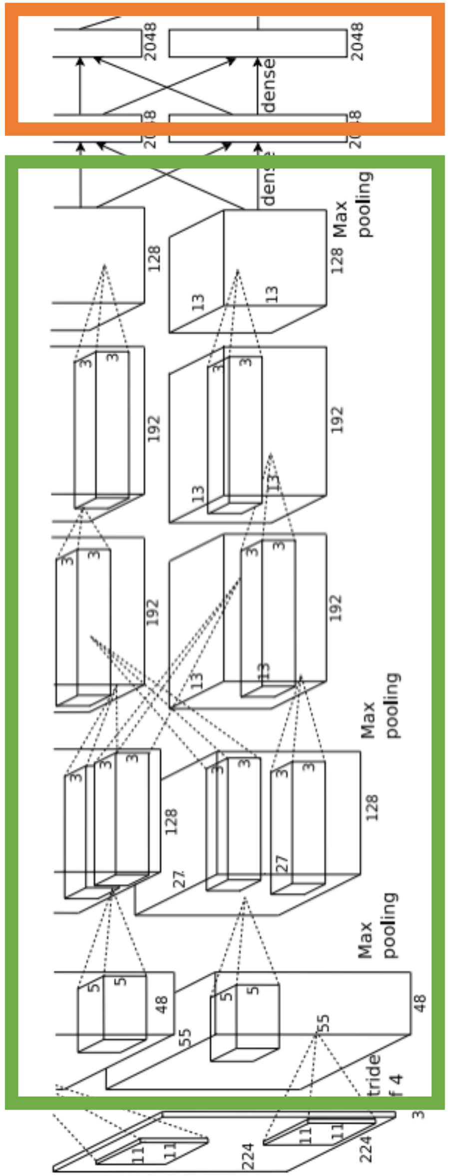
Image features

Run whole image through ConvNet

Input image

Regions of Interest (RoIs) from a proposal method

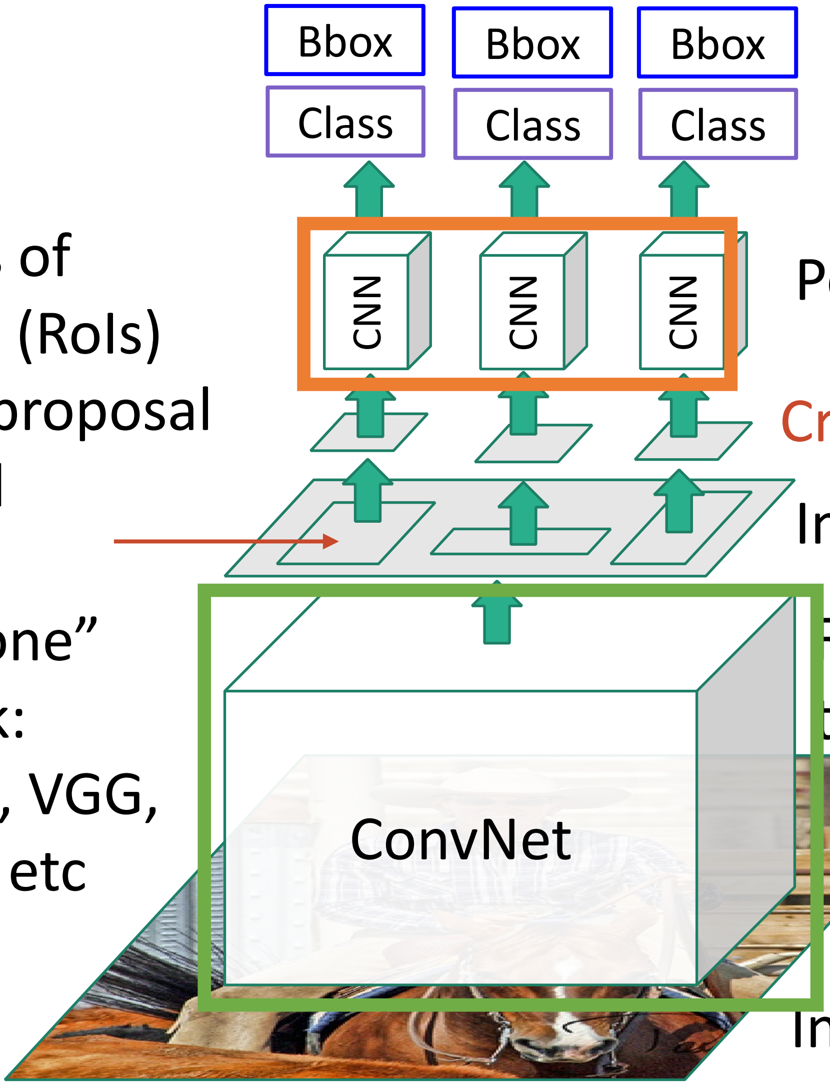
"Backbone" network: AlexNet, VGG, ResNet, etc



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

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

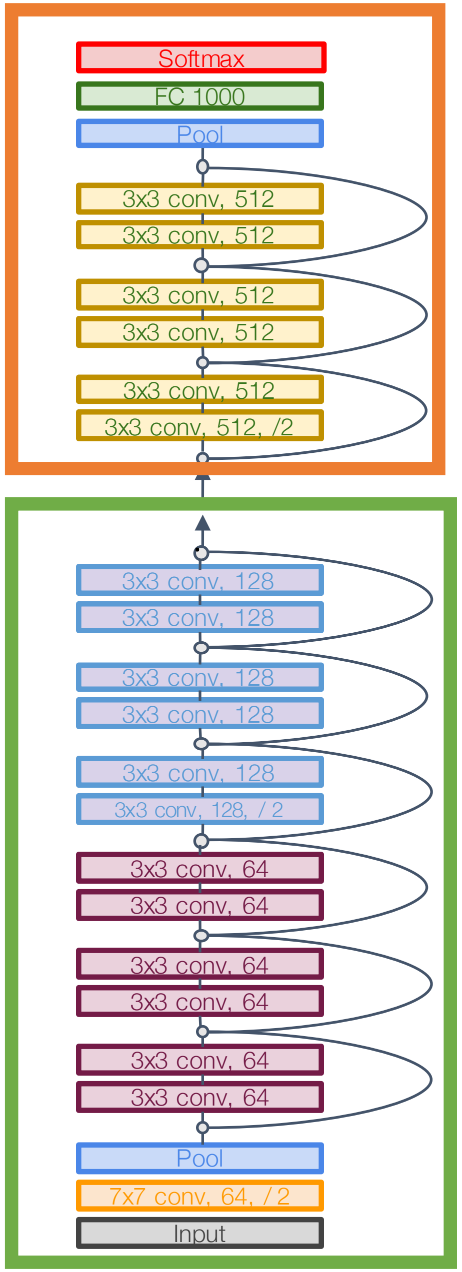
Image features

Run whole image through ConvNet

Input image

Regions of Interest (RoIs) from a proposal method

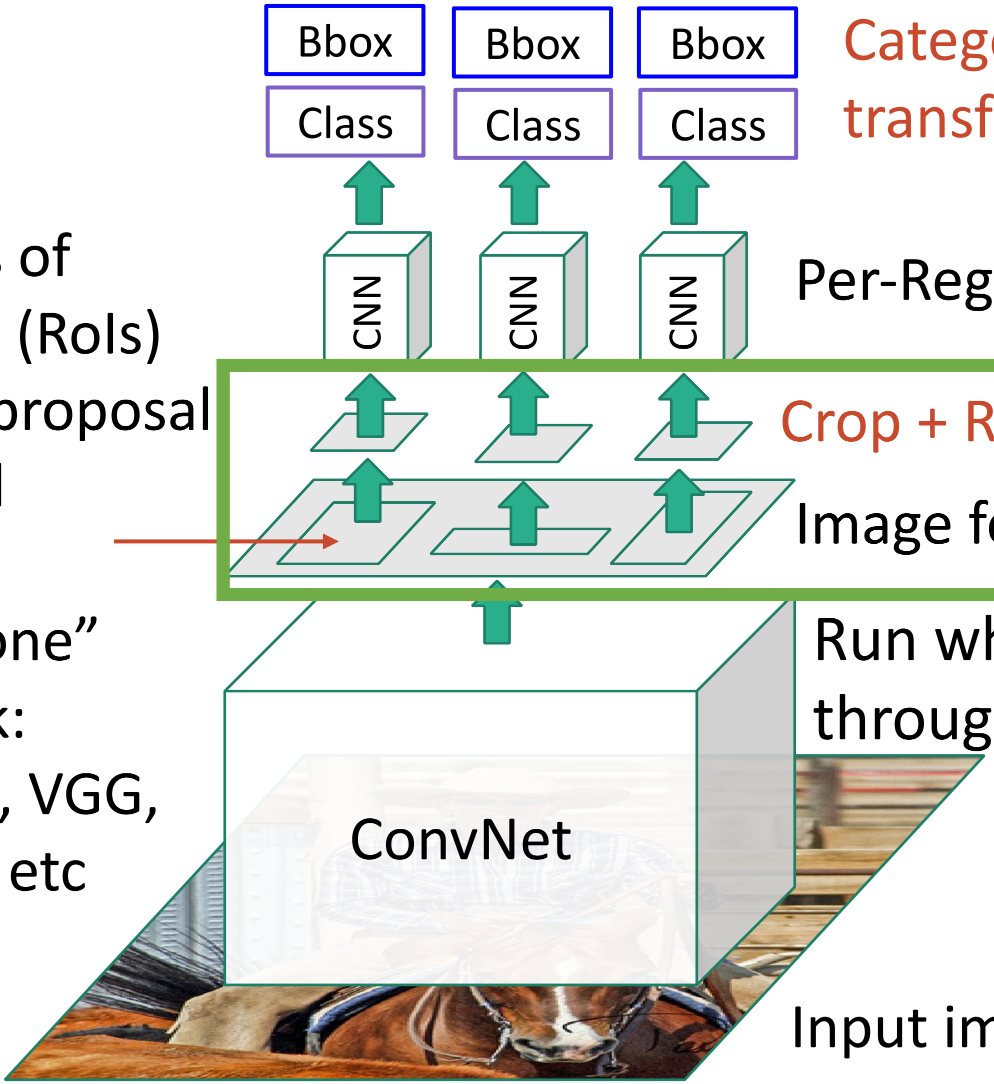
“Backbone” network: AlexNet, VGG, ResNet, etc



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

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

Regions of Interest (RoIs) from a proposal method

Crop + Resize features

Image features

How to crop features?

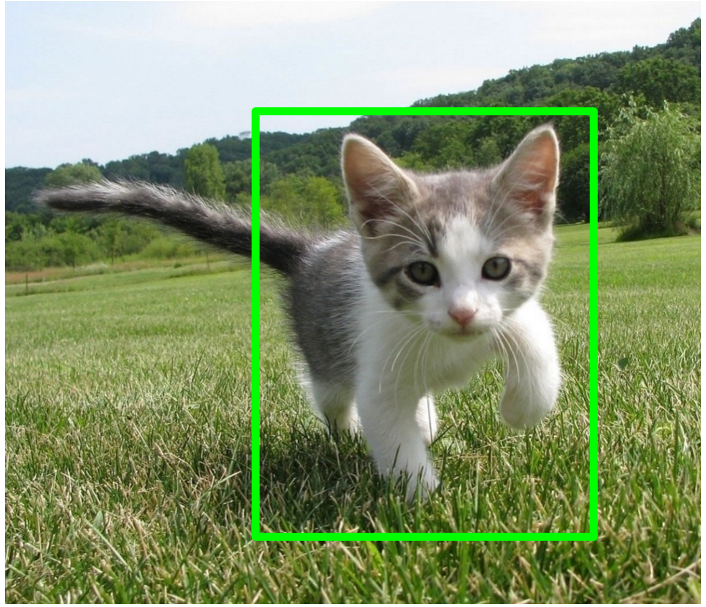
"Backbone" network: AlexNet, VGG, ResNet, etc

Run whole image through ConvNet

Input image

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

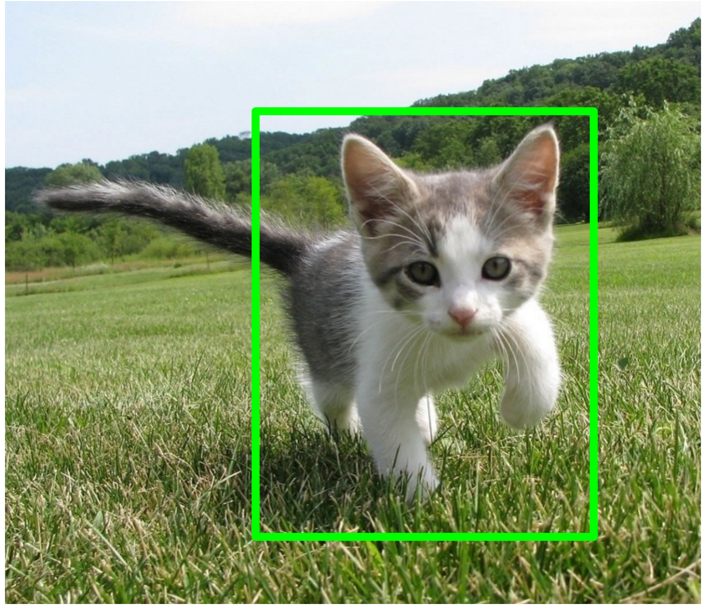
Cropping Features: RoI Pool



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

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

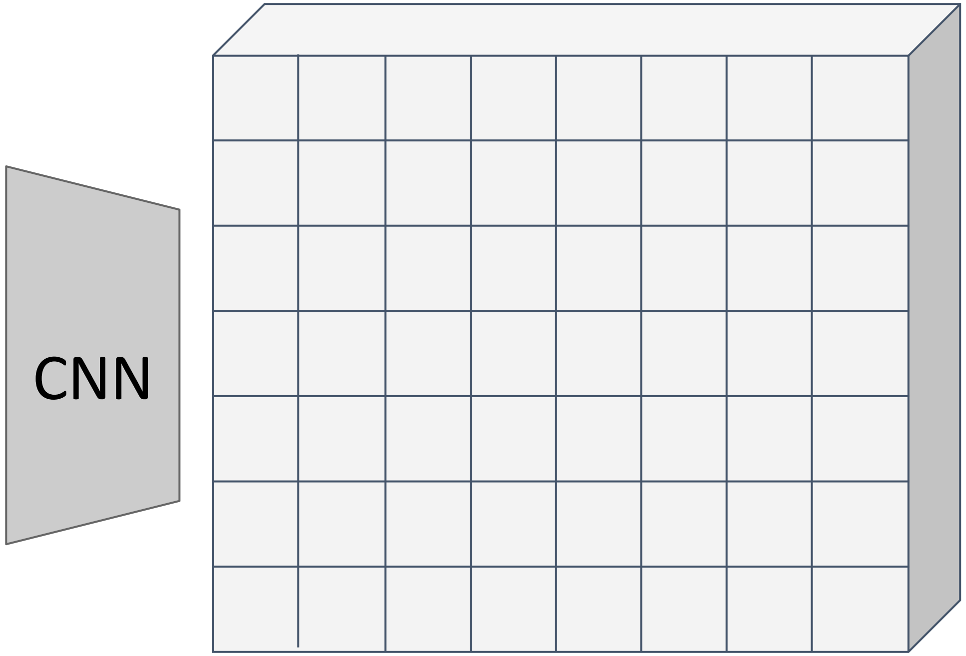
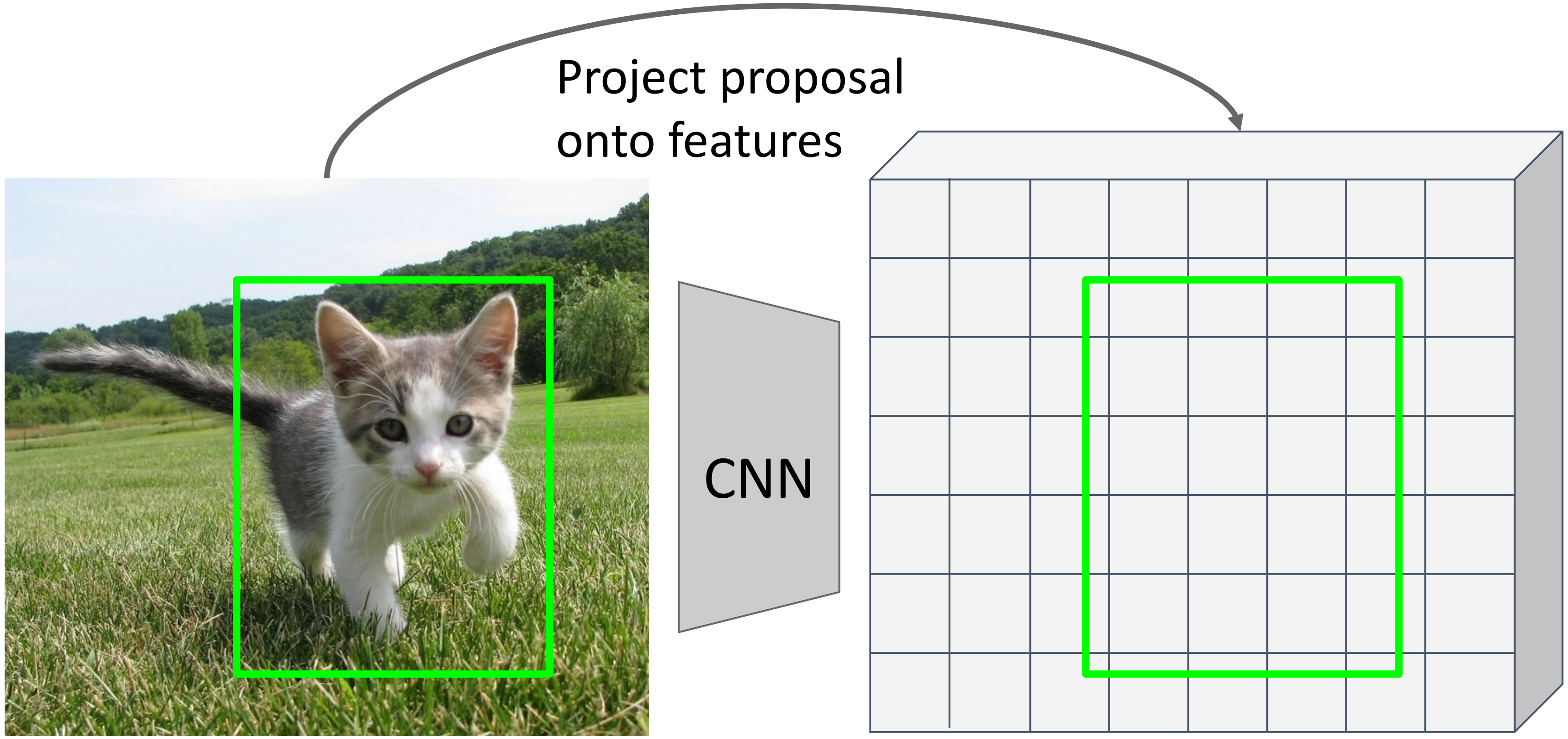


Image features
(e.g. 512 x 20 x 15)

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

Cropping Features: RoI Pool

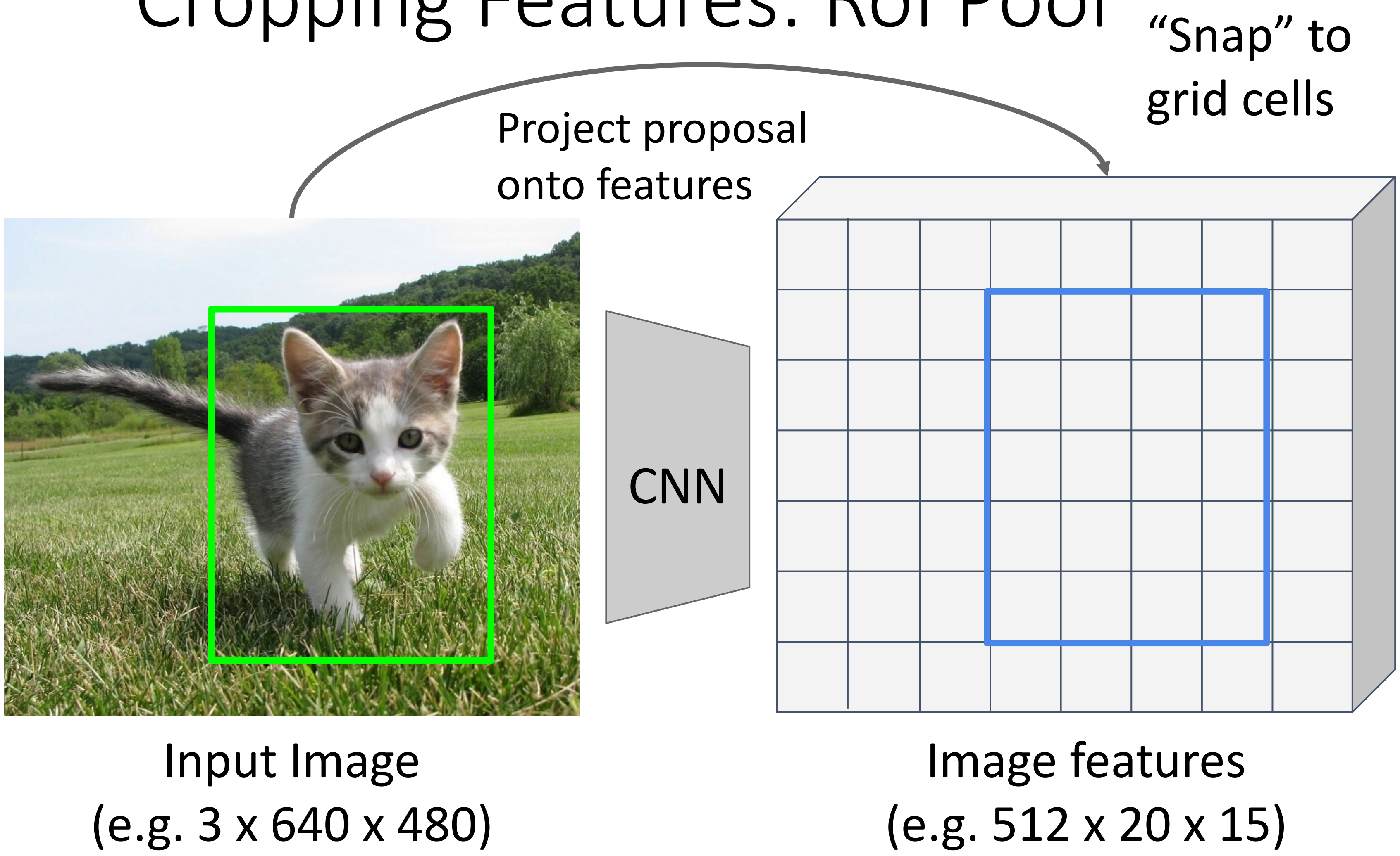


Input Image
(e.g. 3 x 640 x 480)

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

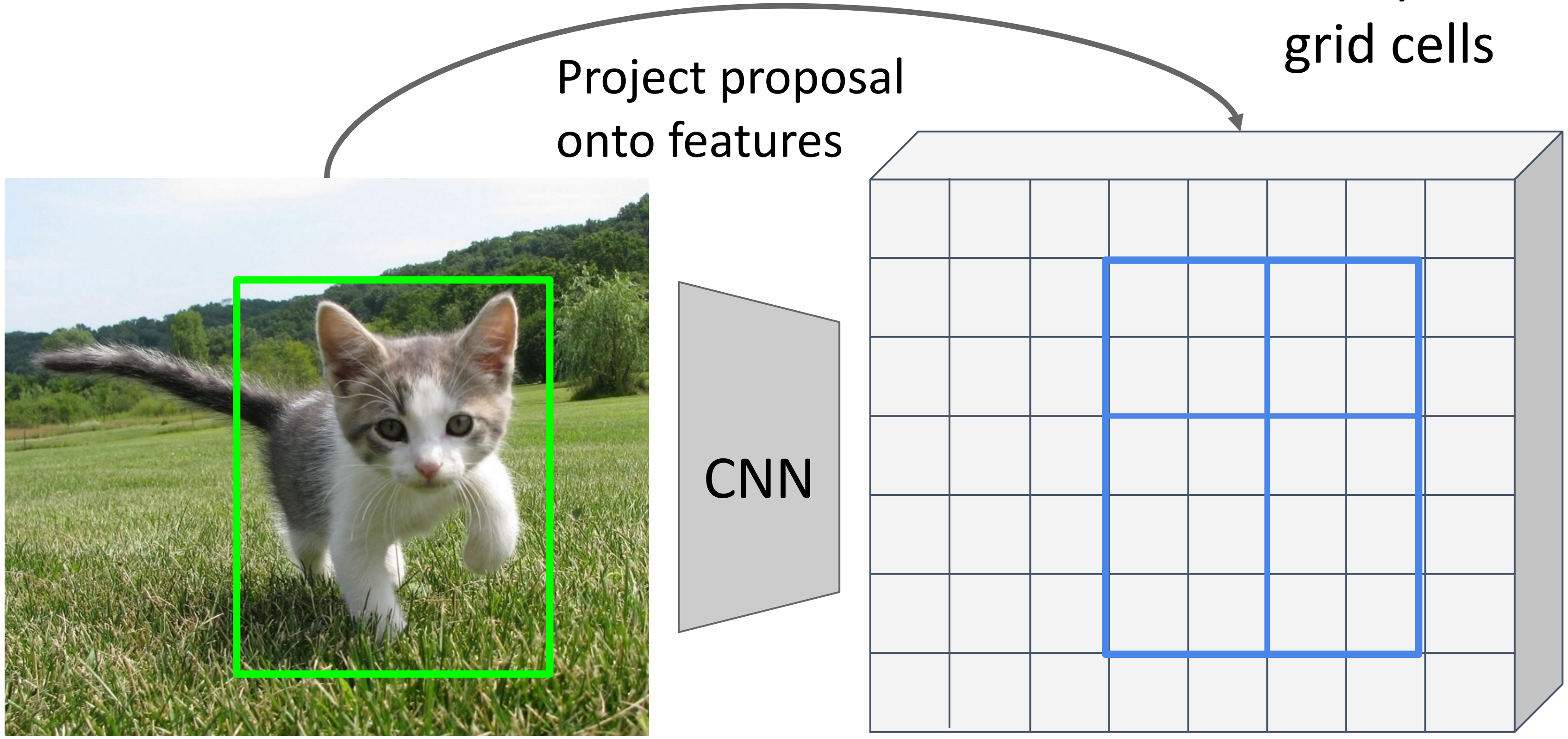
Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

Cropping Features: RoI Pool



"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

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

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

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

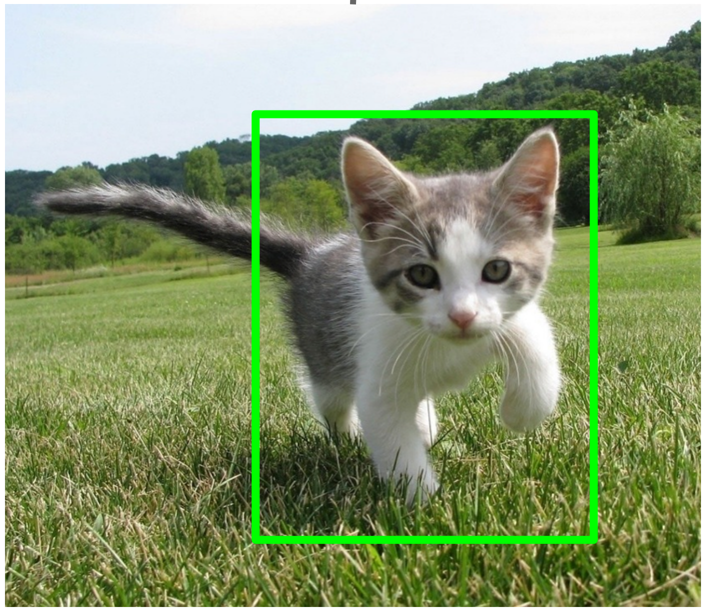
Cropping Features: RoI Pool

Project proposal
onto features

"Snap" to
grid cells

Divide into 2x2
grid of (roughly)
equal subregions

Max-pool within
each subregion



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

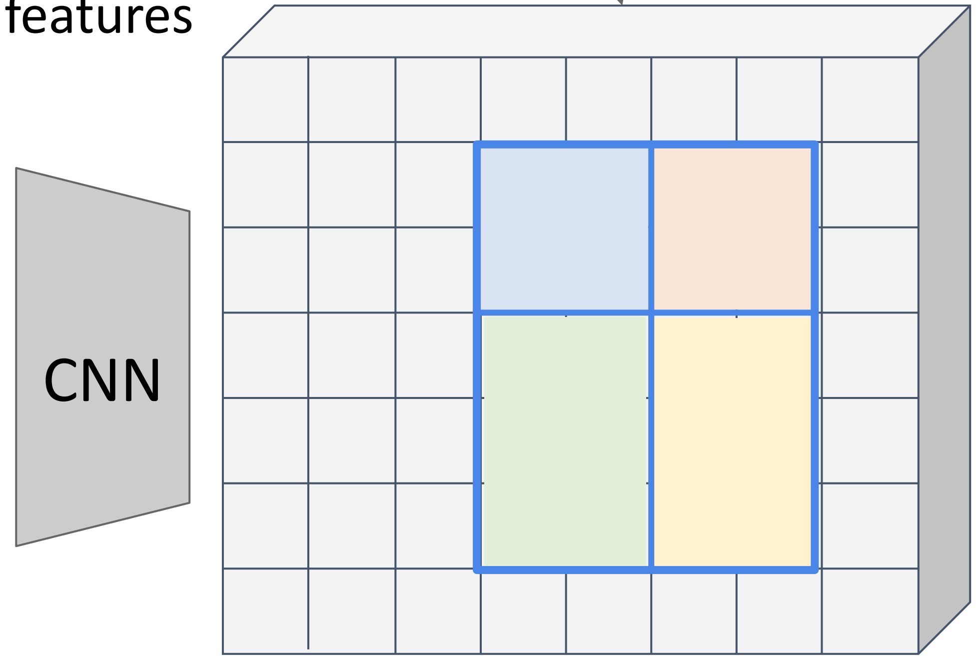
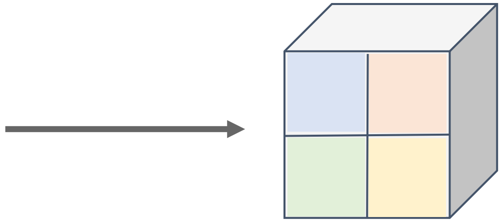


Image features
(e.g. 512 x 20 x 15)

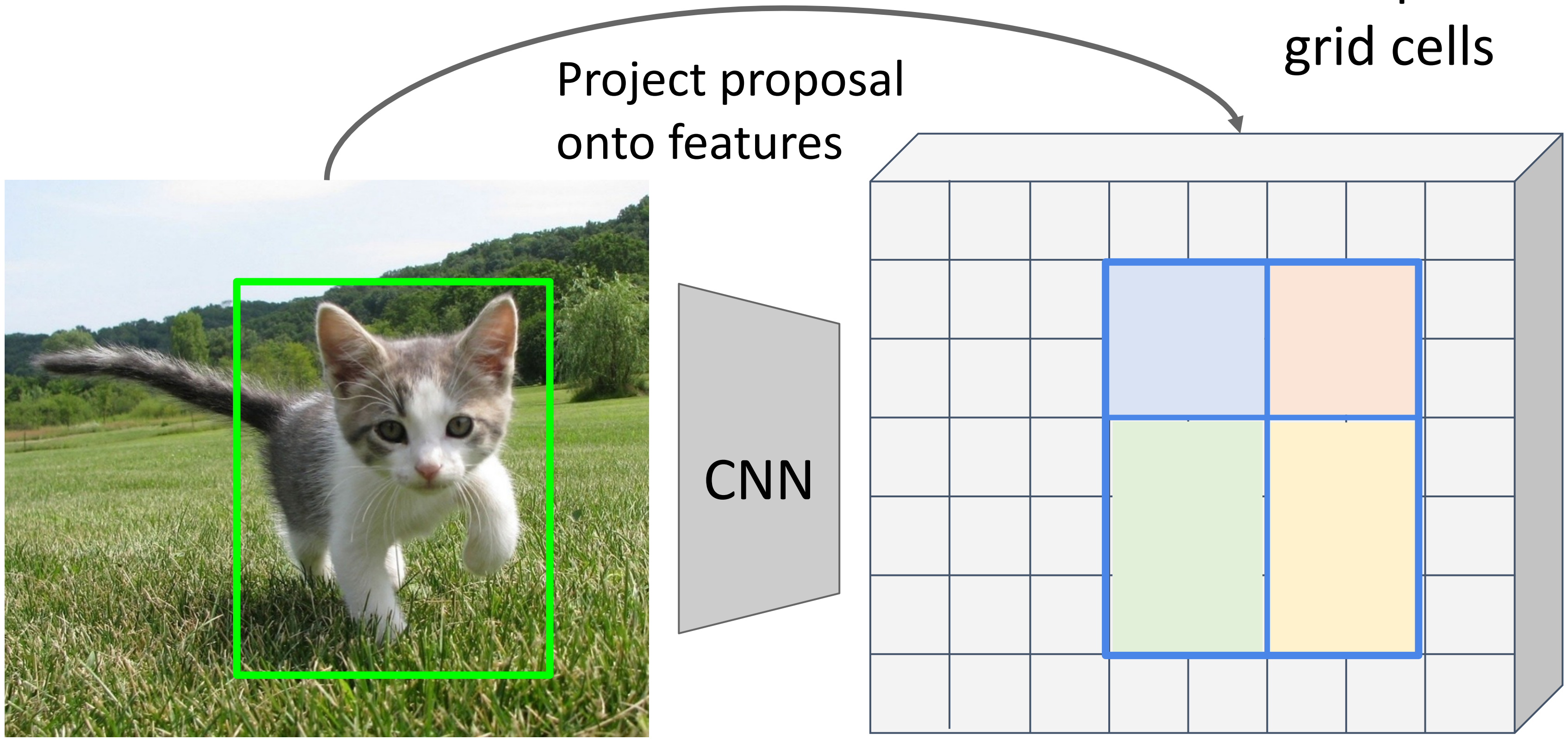


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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

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

Cropping Features: RoI Pool

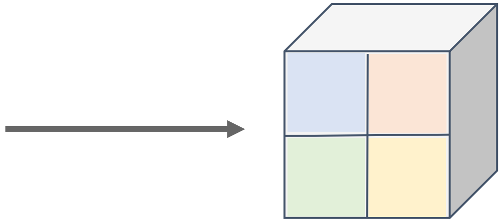


Input Image
(e.g. 3 x 640 x 480)

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

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion

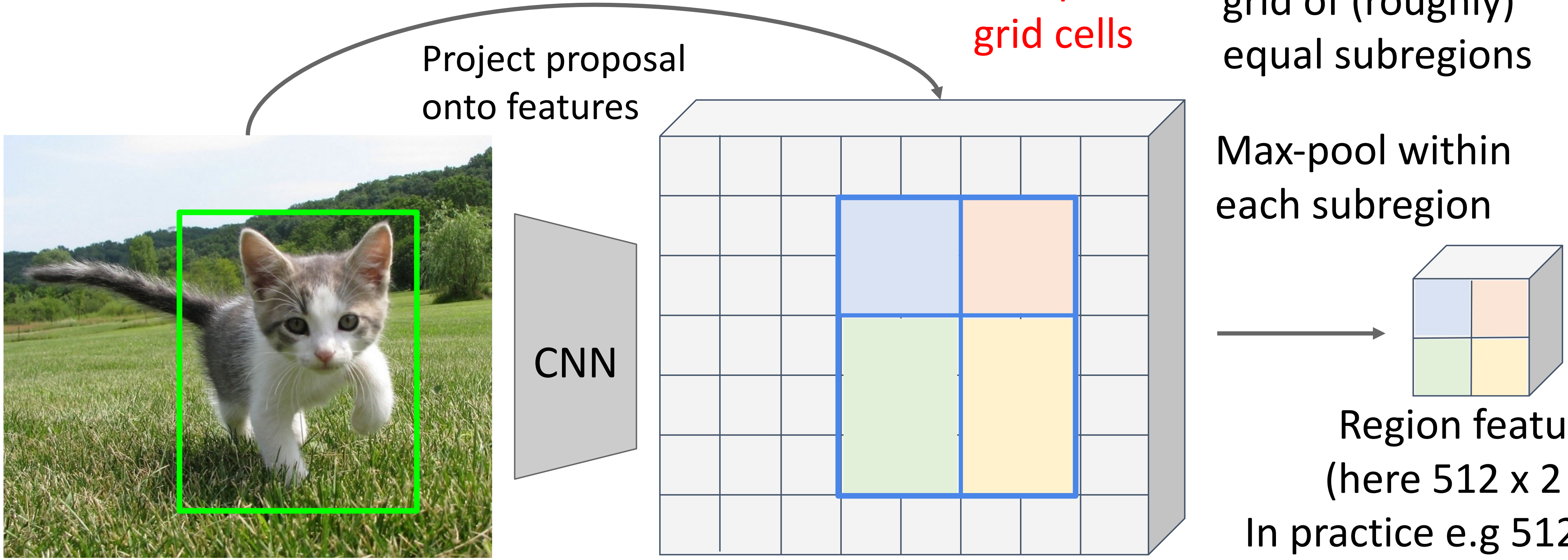


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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

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

Cropping Features: RoI Pool



"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion

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

Image features
(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: Slight misalignment due to snapping; different-sized subregions is weird

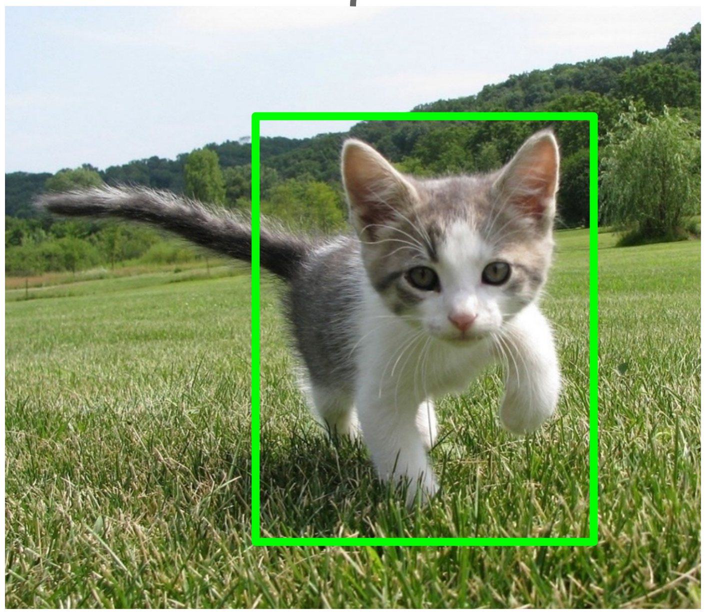
Girshick, "Fast R-CNN", ICCV 2015.

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)

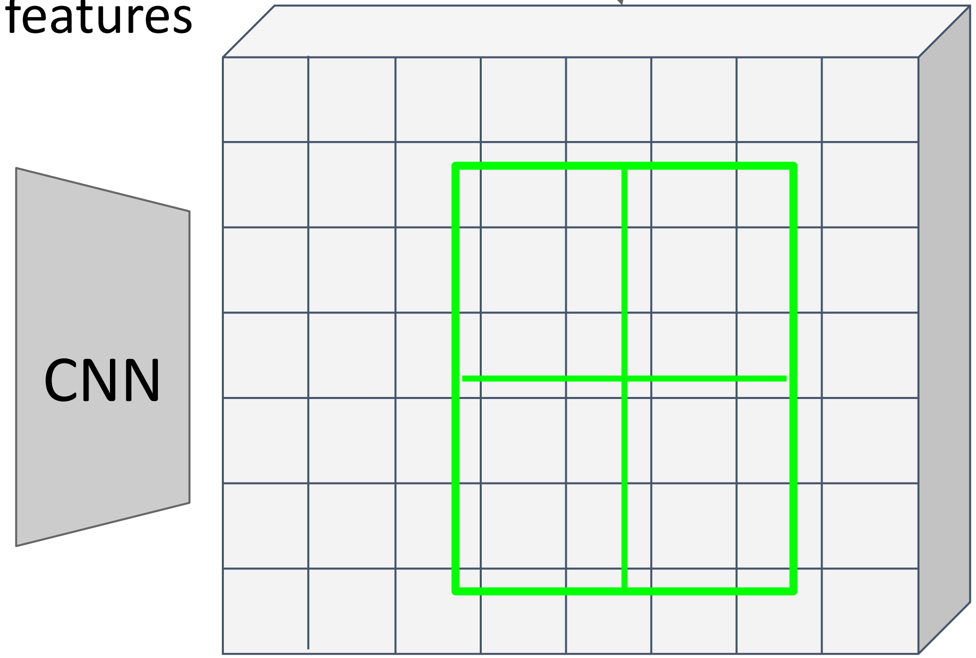


Image features
(e.g. 512 x 20 x 15)

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

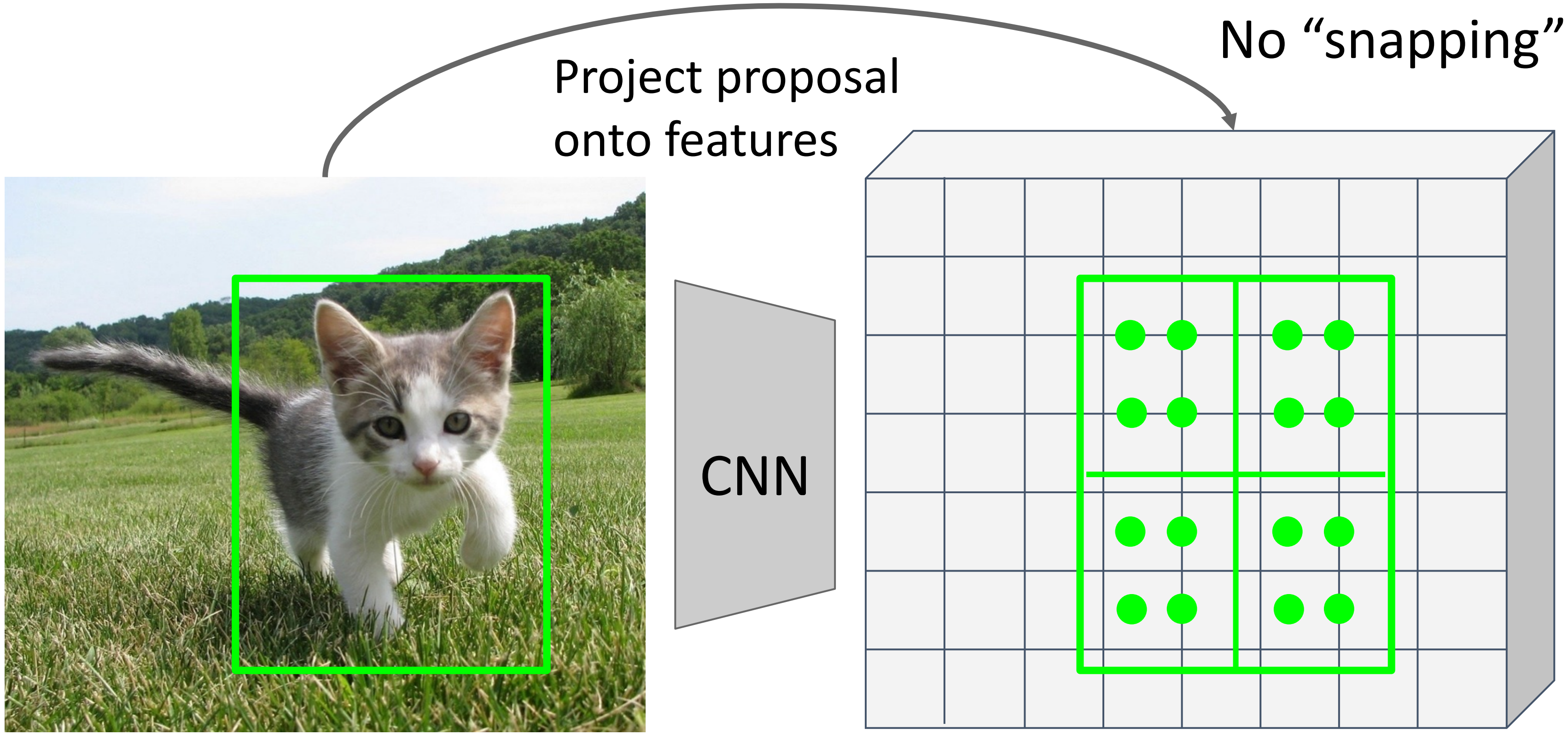
Cropping Features: RoI Align

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

Project proposal onto features

No "snapping"!

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



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

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

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

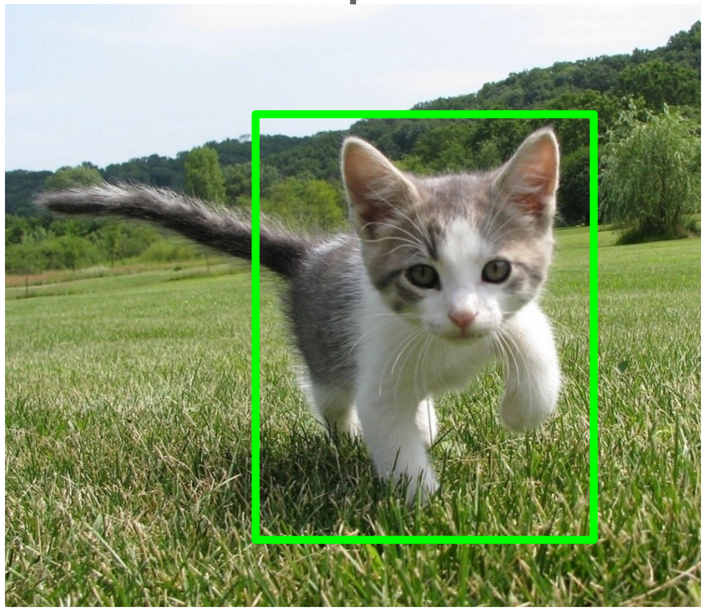
Cropping Features: RoI Align

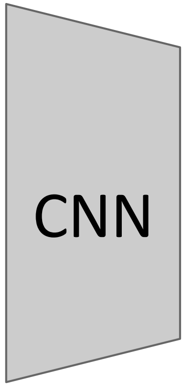
Divide into equal-sized subregions (may not be aligned to grid!)

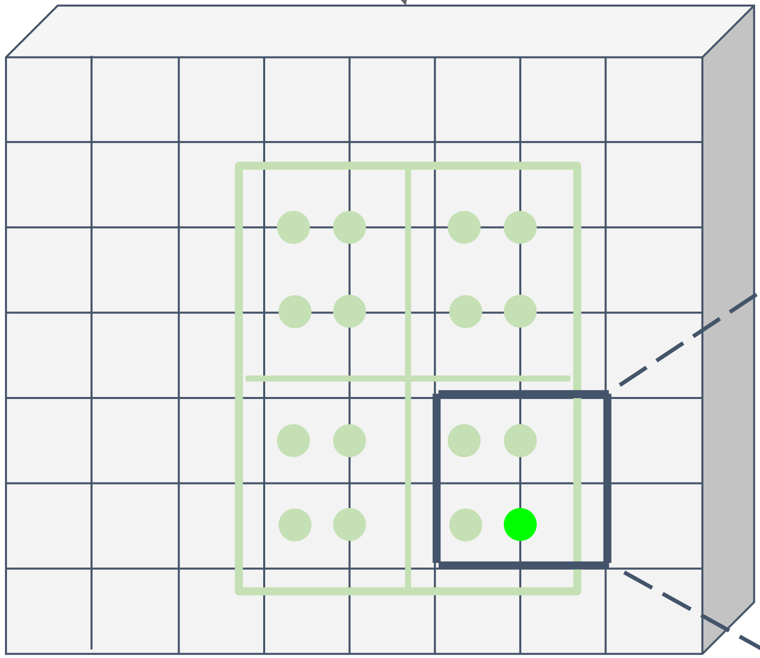
Project proposal onto features

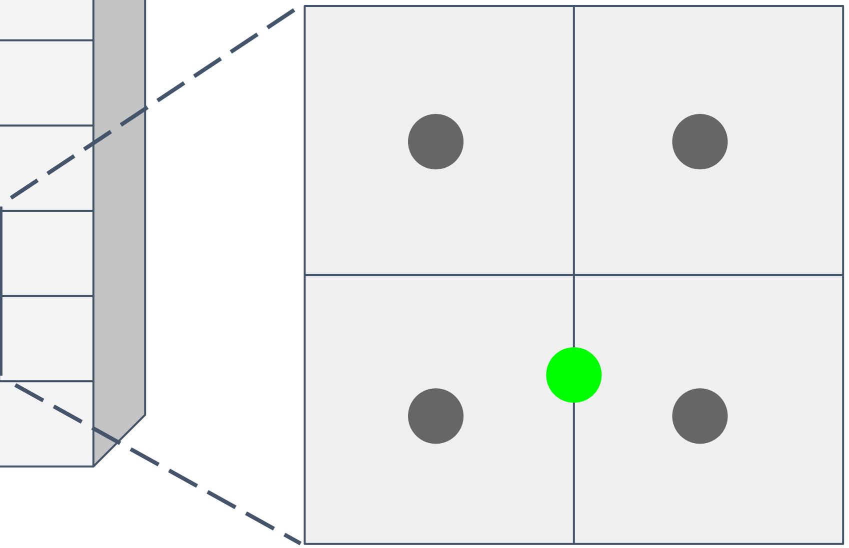
No “snapping”!

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









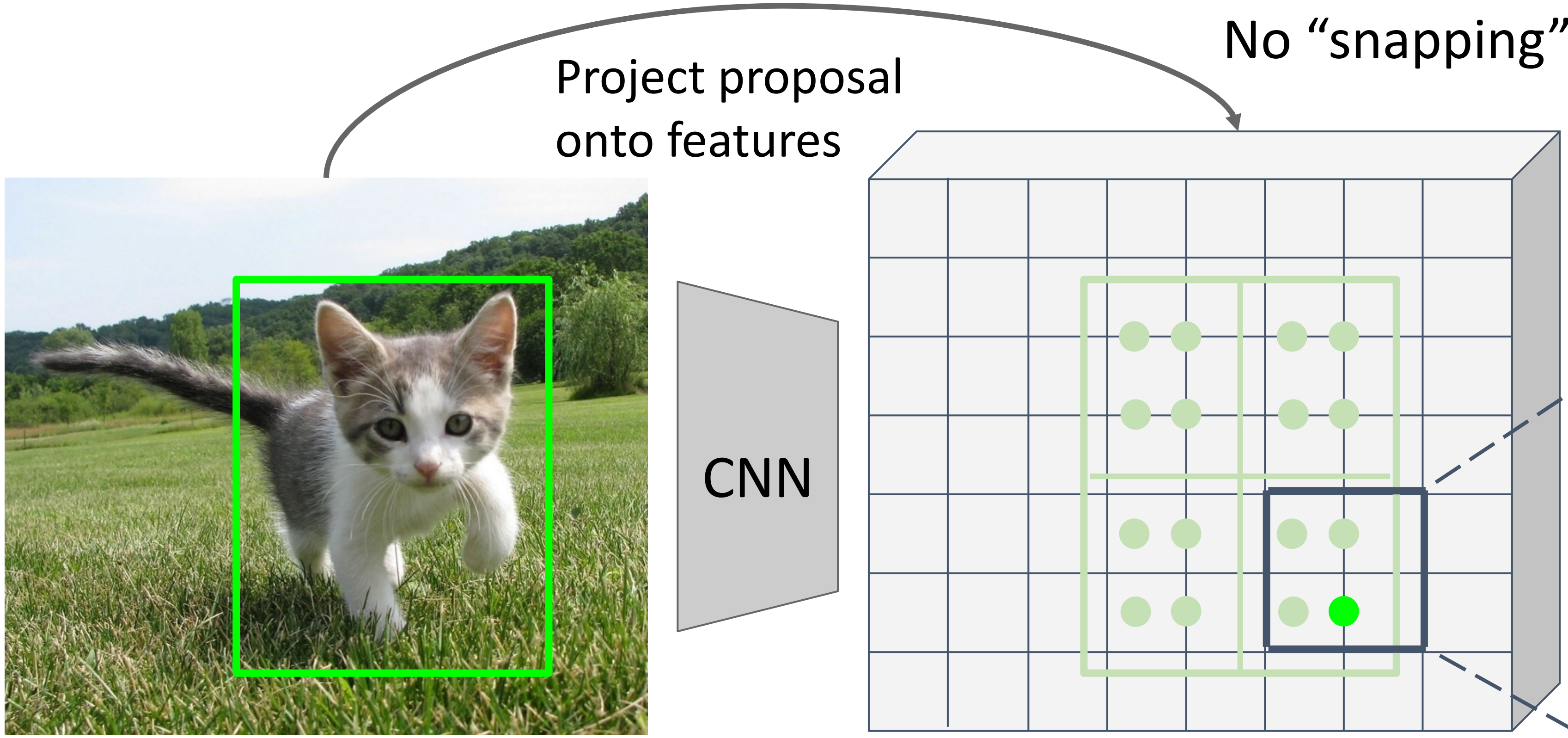
Input Image
(e.g. 3 x 640 x 480)

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

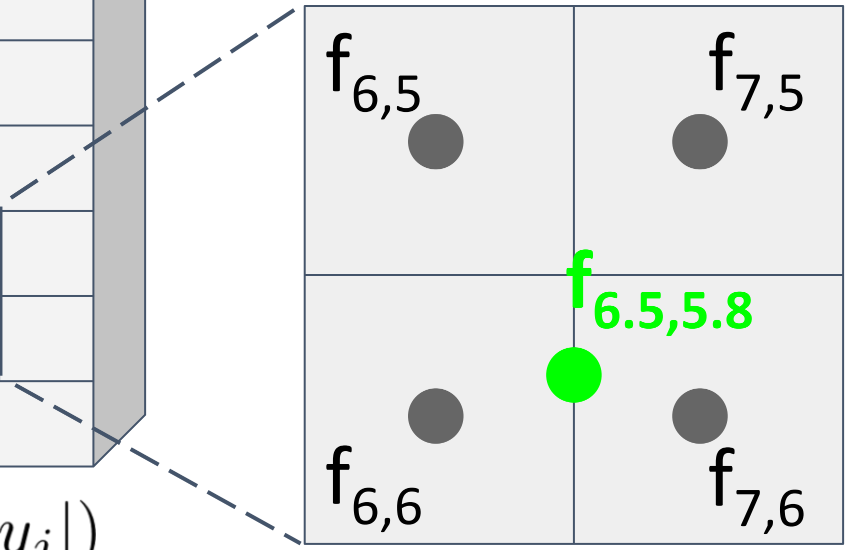
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align

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



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

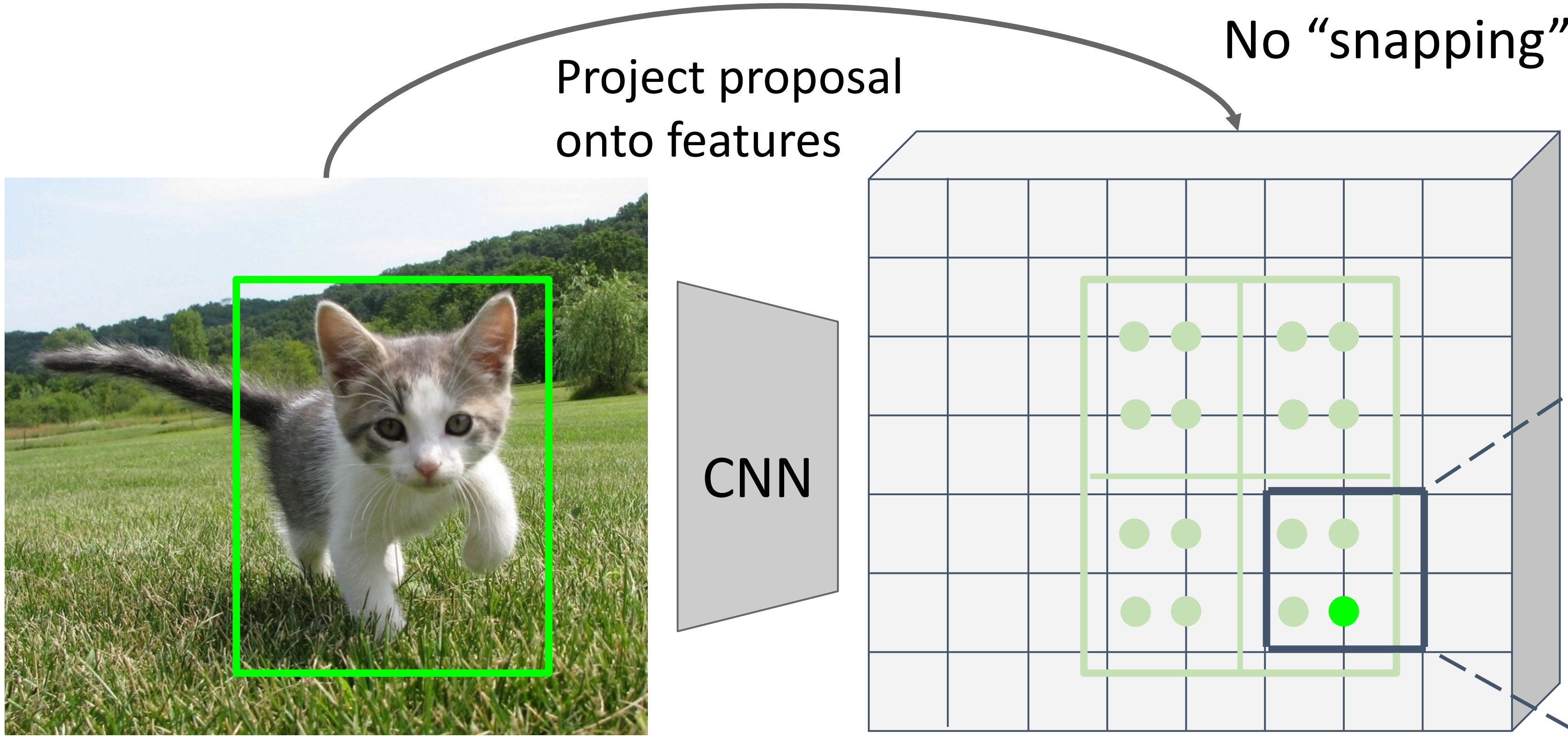


$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

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

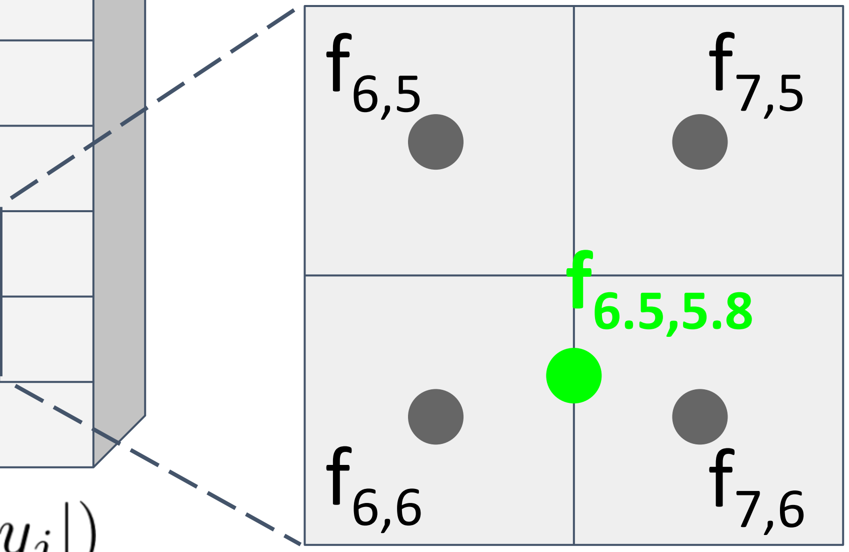
Cropping Features: RoI Align

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



No "snapping"!

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



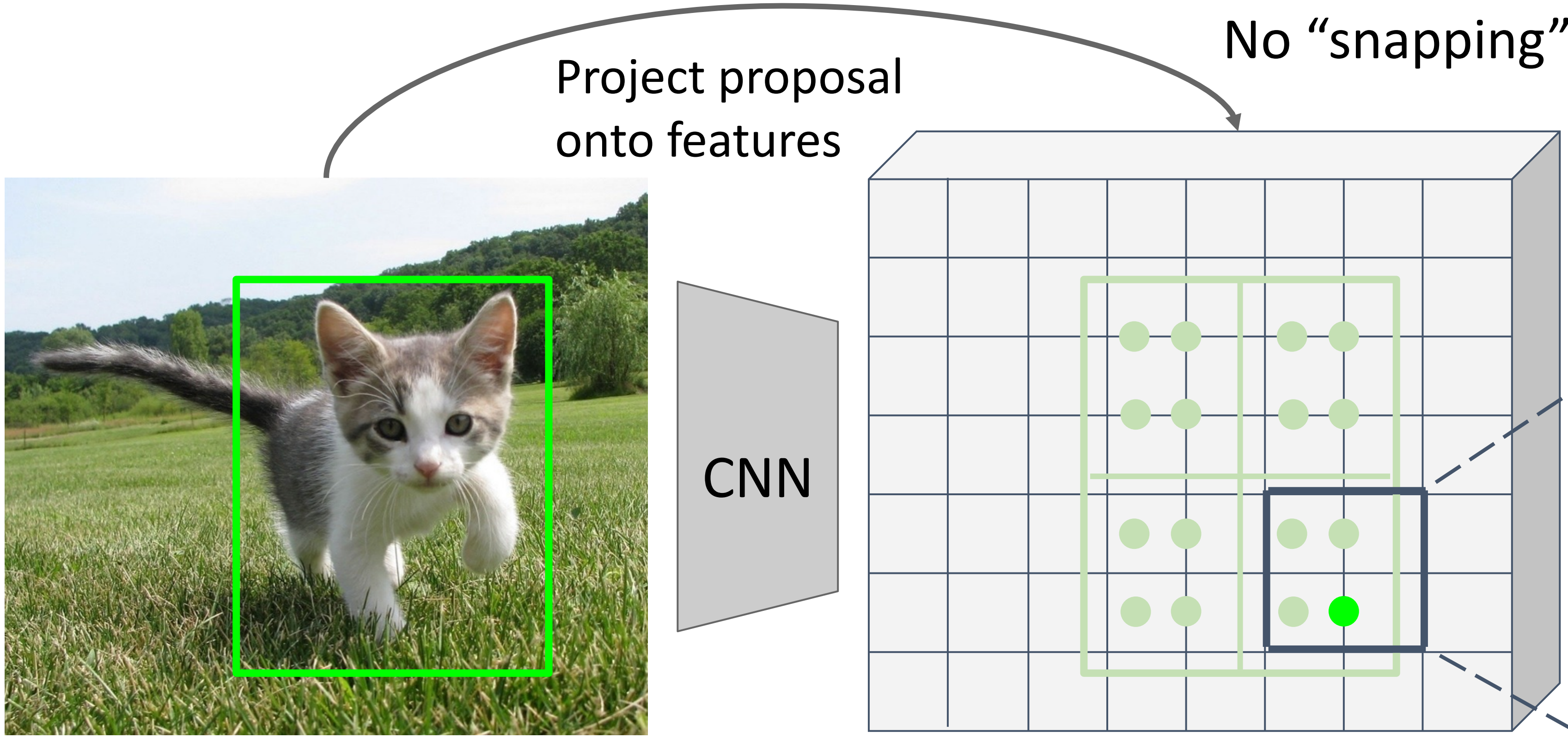
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

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

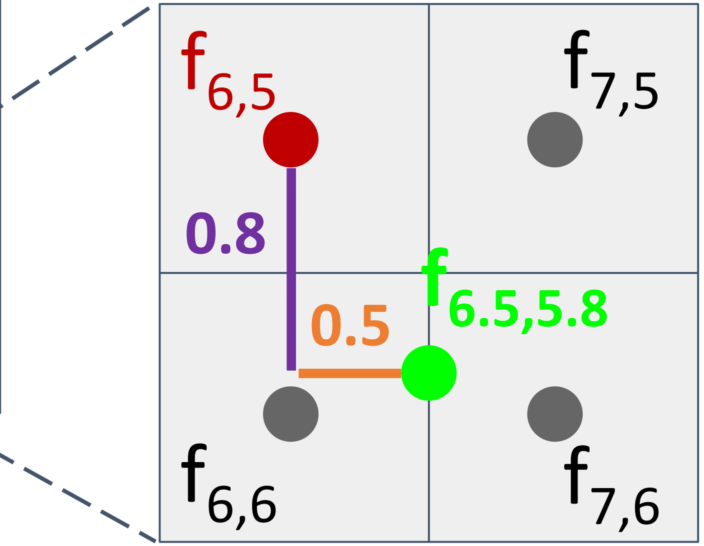
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

Cropping Features: RoI Align

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



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



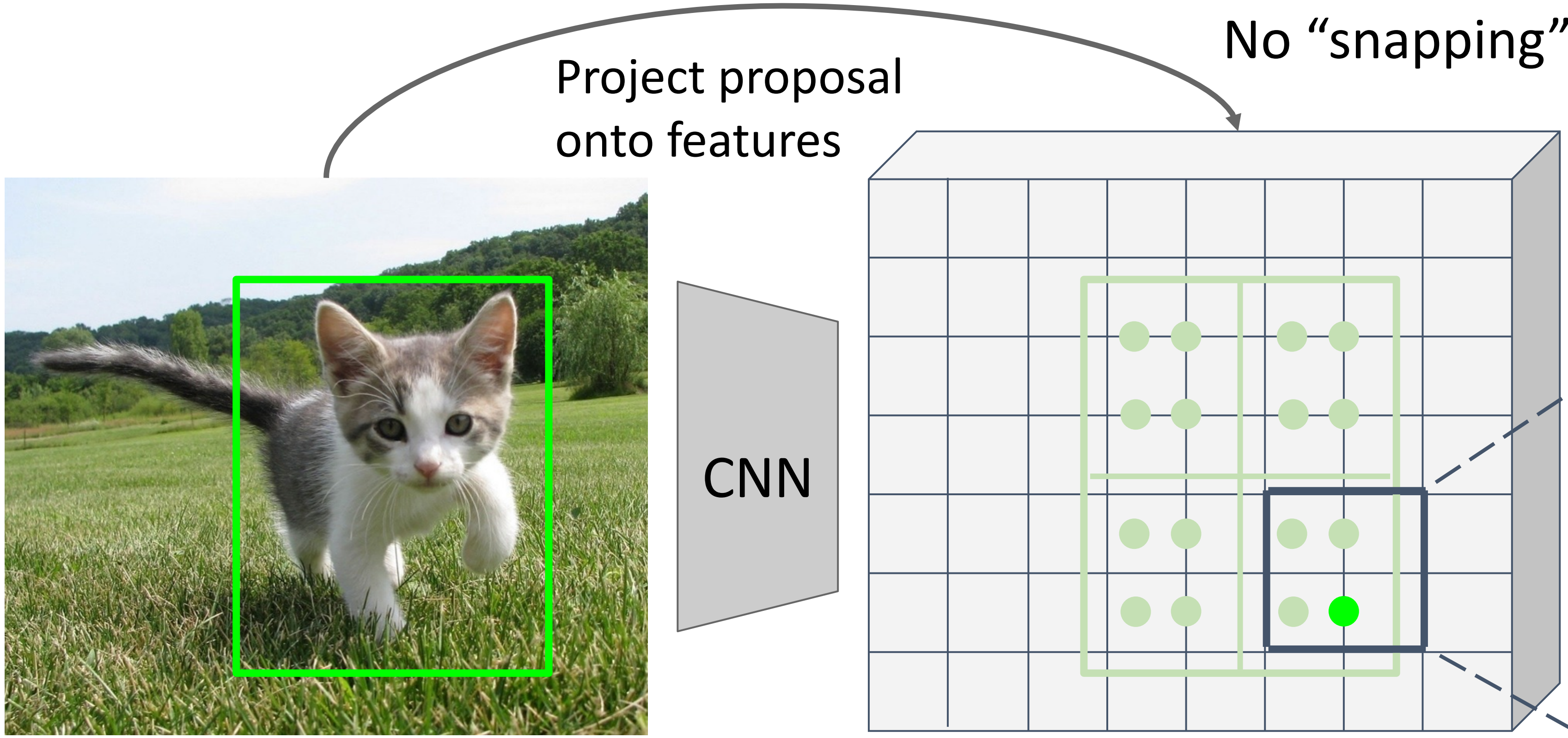
$$f_{xy} = \sum_{i,j=1}^{2} \boxed{f_{i,j}} \boxed{\max(0, 1 - |x - x_i|)} \boxed{\max(0, 1 - |y - y_j|)}$$

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

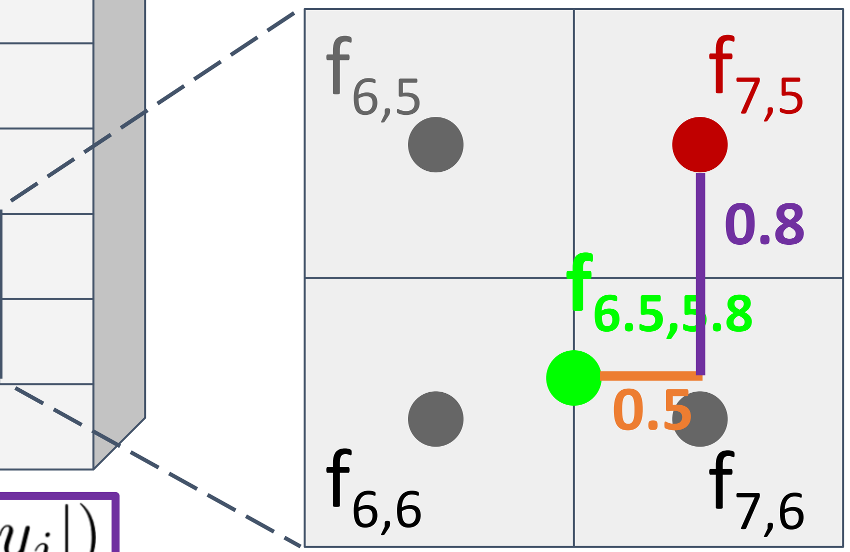
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align

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



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



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

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

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

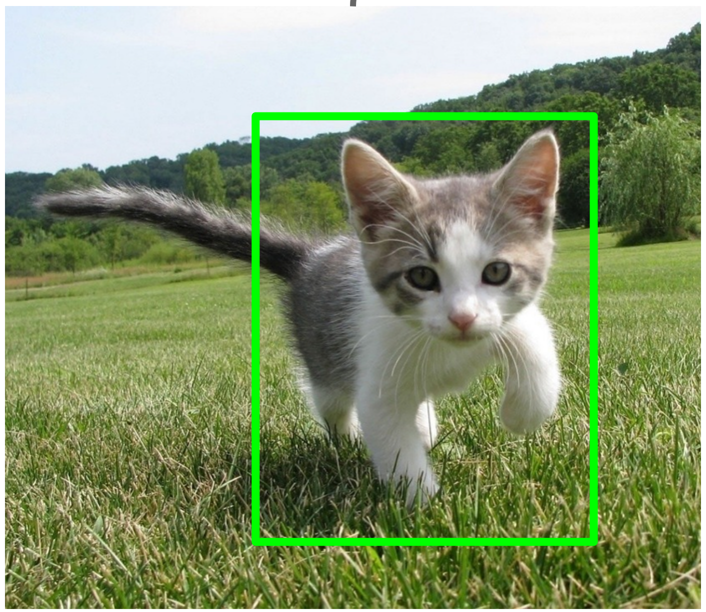
Cropping Features: RoI Align

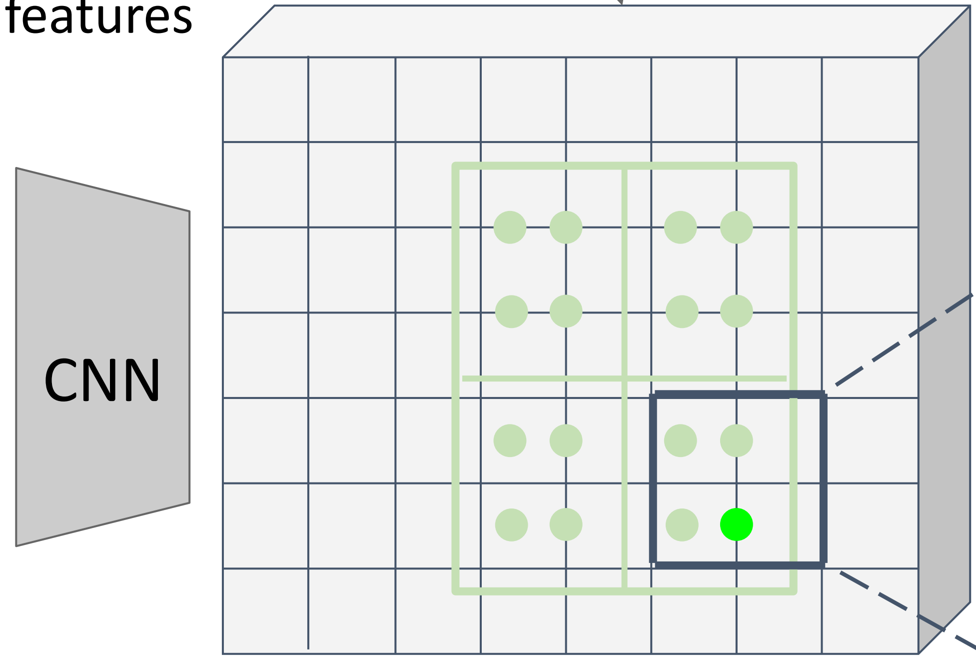
Divide into equal-sized subregions (may not be aligned to grid!)

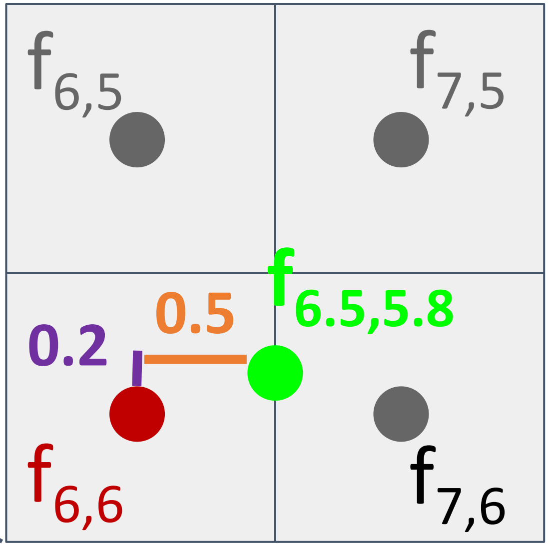
No "snapping"!

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

Project proposal onto features







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

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

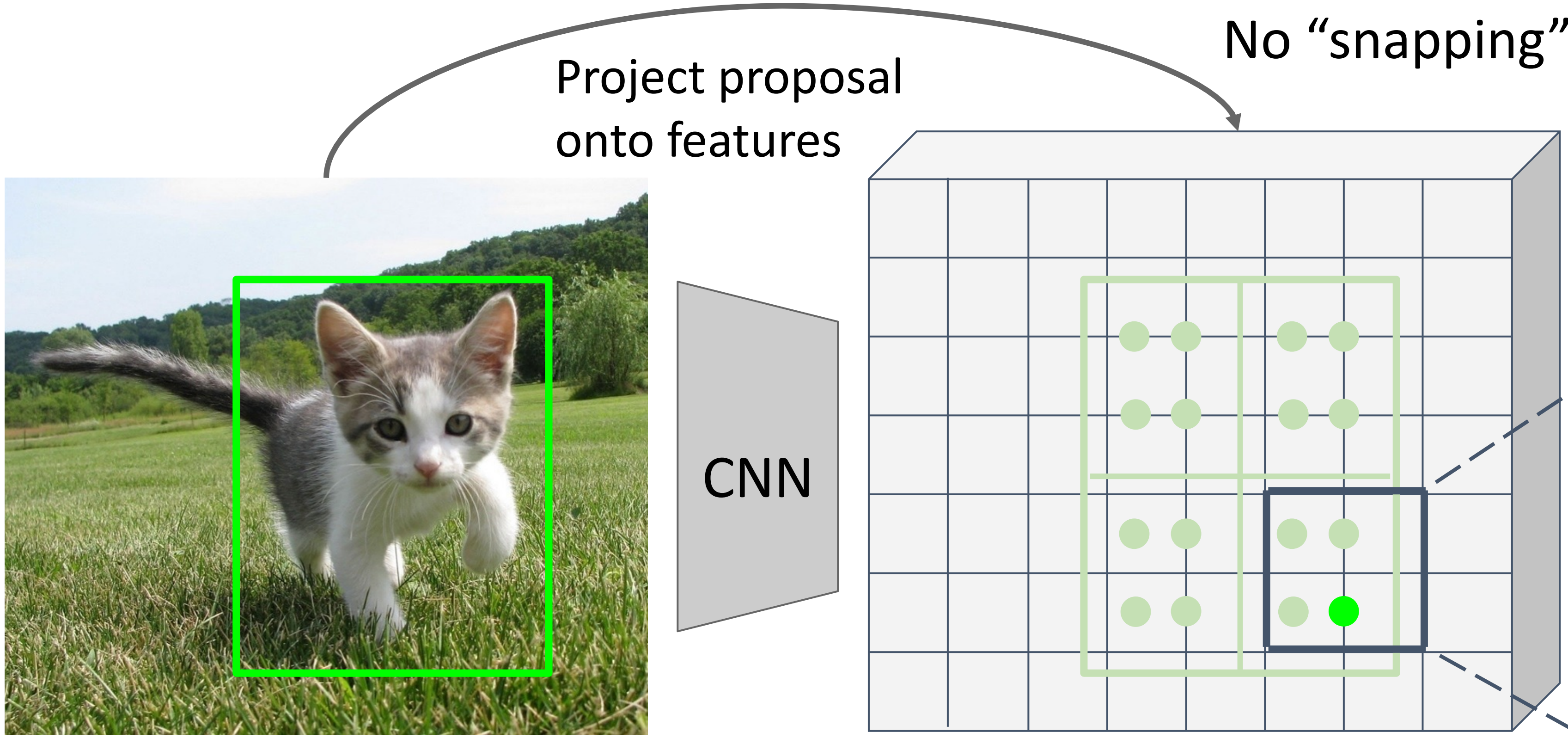
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

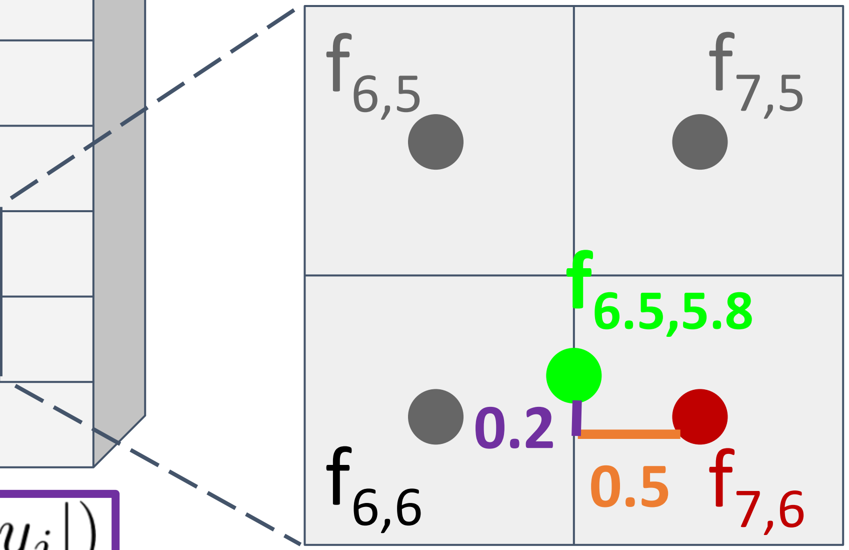
Cropping Features: RoI <u>Align</u>

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

No “snapping”!

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





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

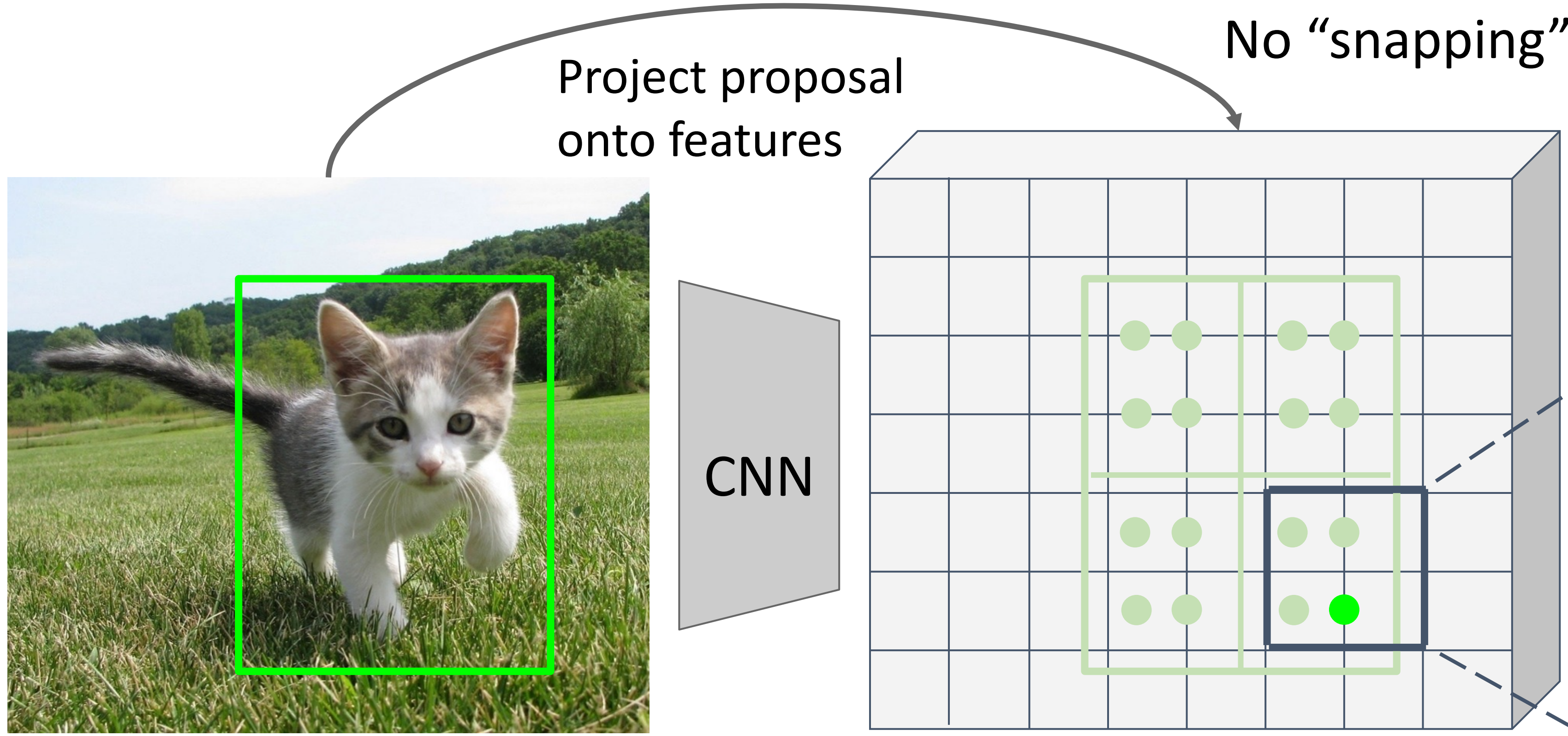
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

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

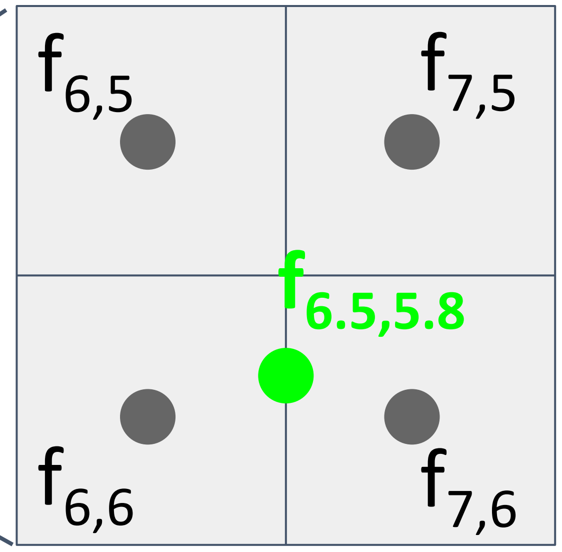
Cropping Features: RoI Align

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

No “snapping”!



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



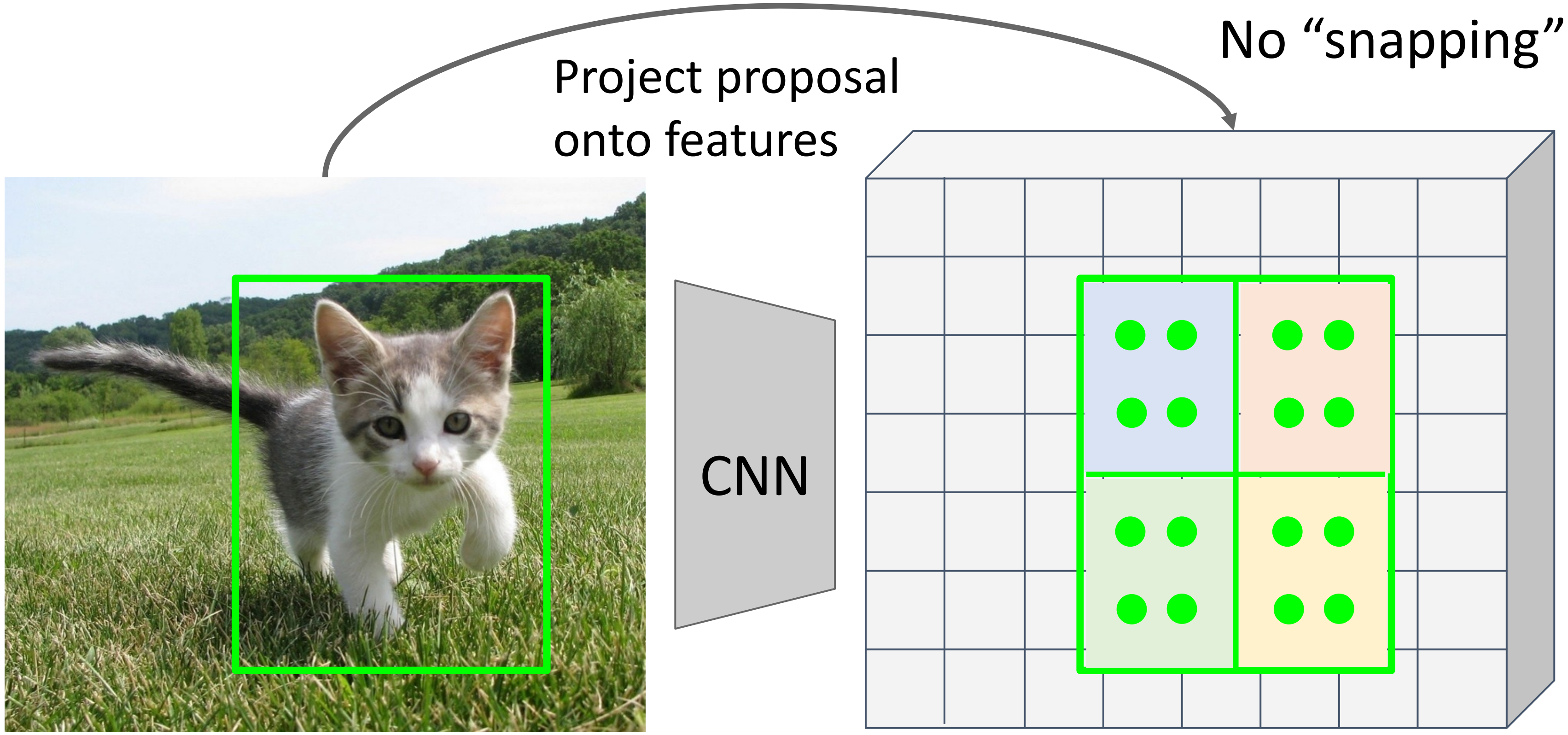
$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

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

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

Cropping Features: RoI Align

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

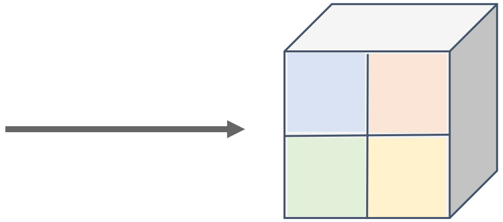


Input Image
(e.g. 3 x 640 x 480)

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

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

After sampling, max-pool in each subregion

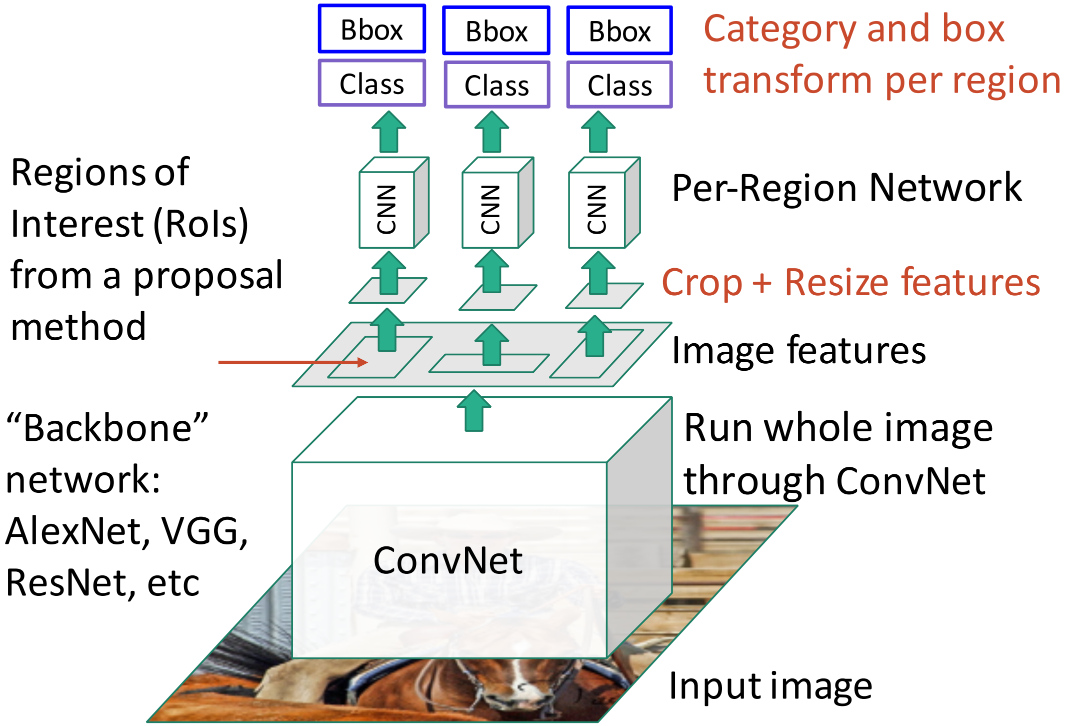


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

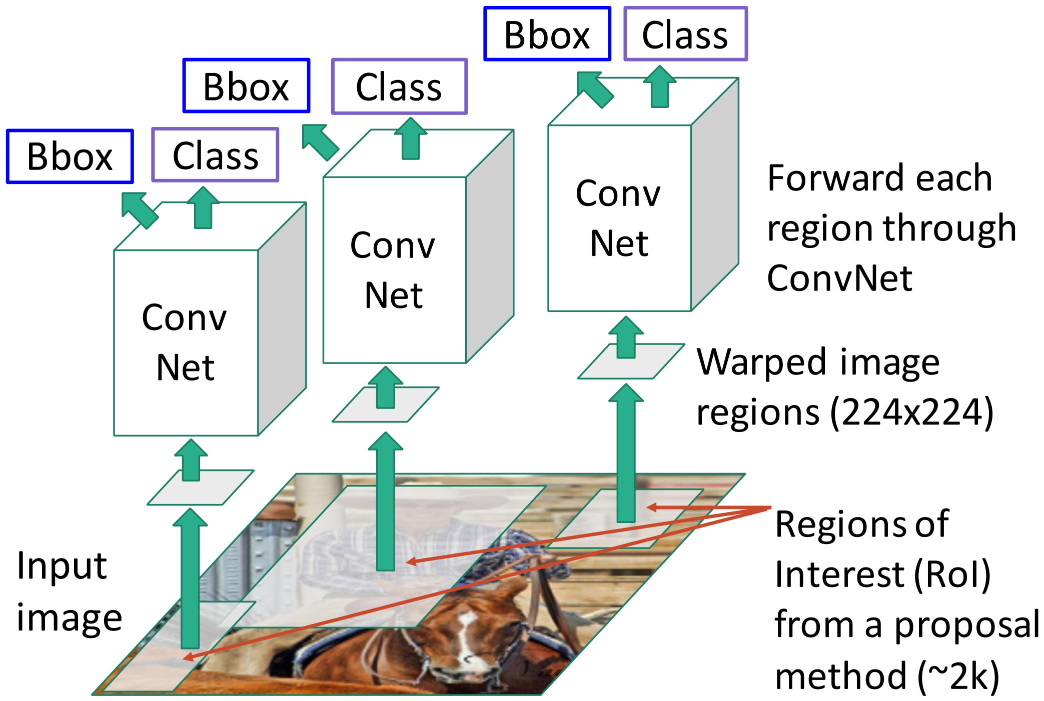
He et al, “Mask R-CNN”, ICCV 2017

Fast R-CNN vs "Slow" R-CNN

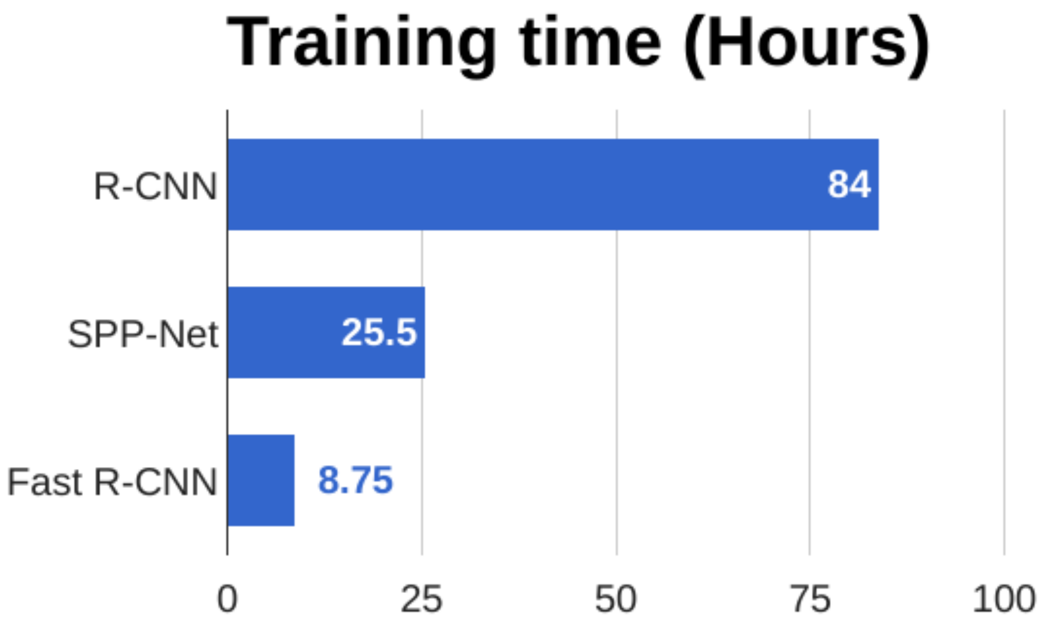
Fast R-CNN: Apply differentiable cropping to shared image features

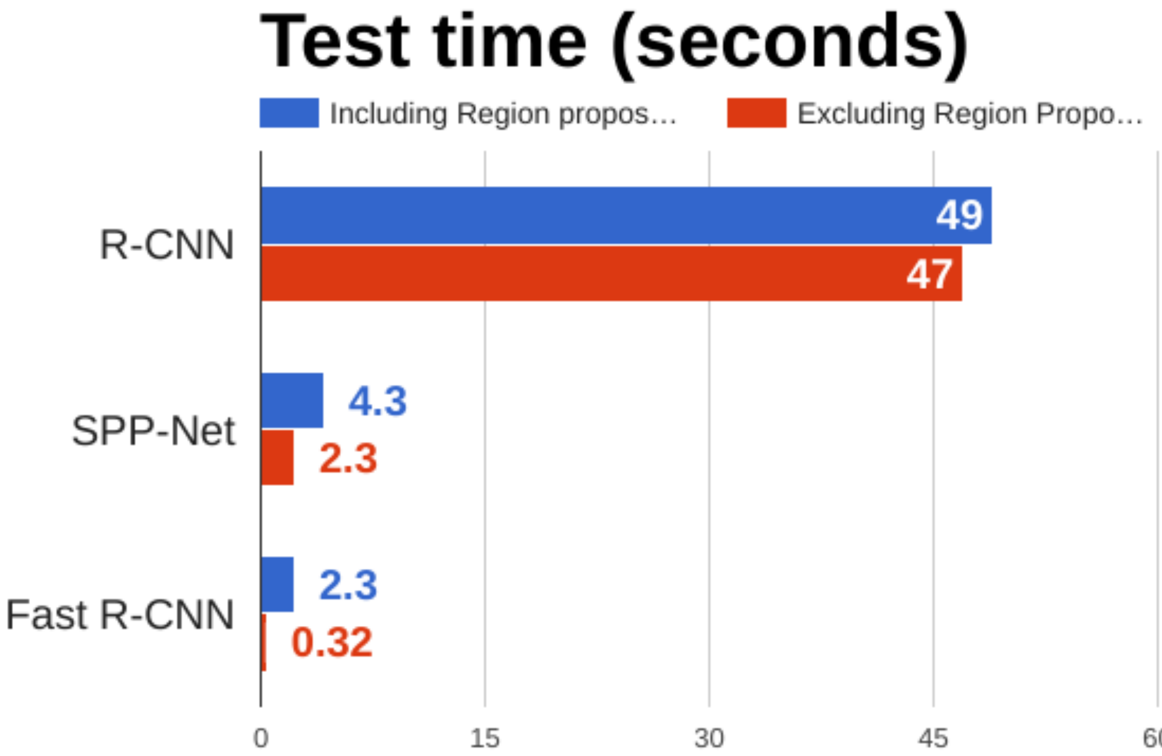


"Slow" R-CNN: Apply differentiable cropping to shared image features



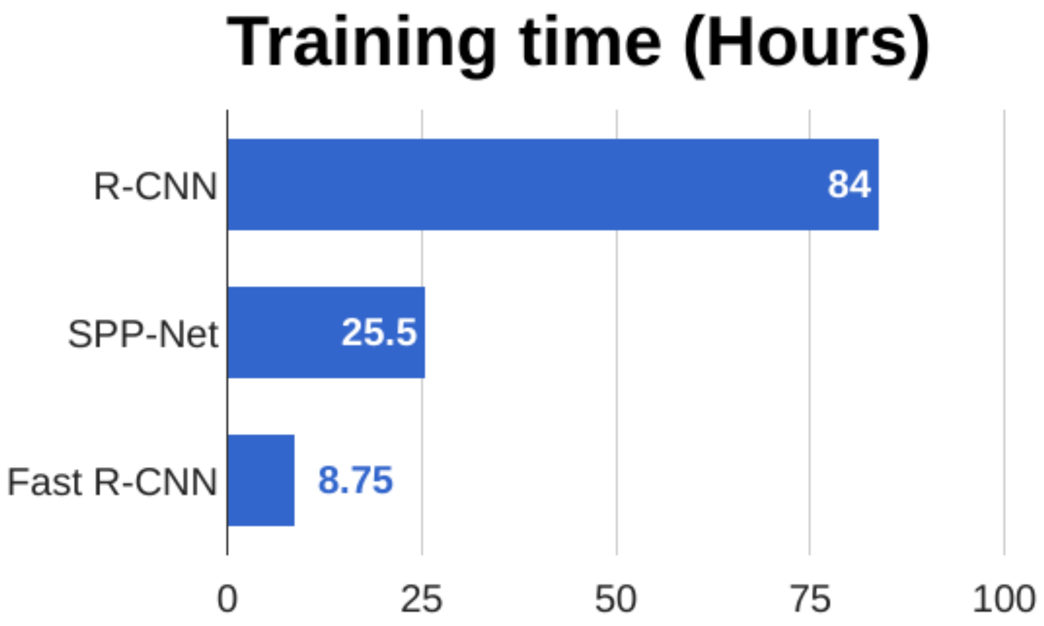
Fast R-CNN vs “Slow” R-CNN

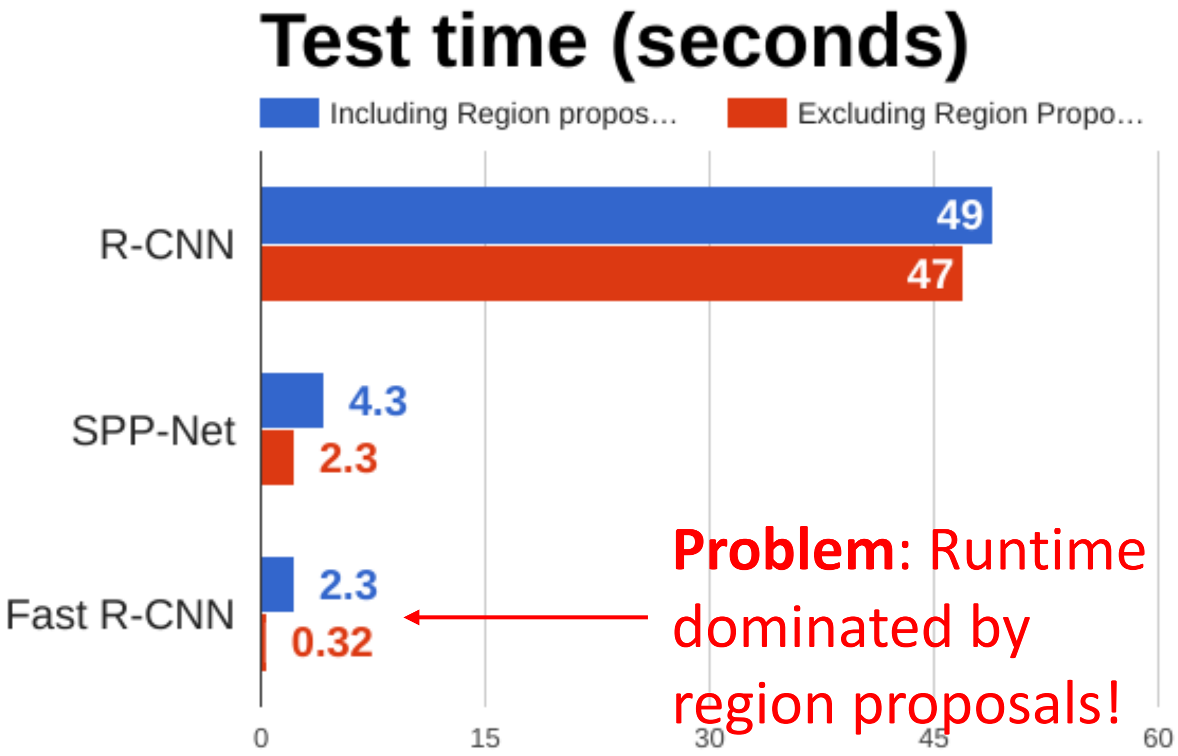




Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

Fast R-CNN vs "Slow" R-CNN

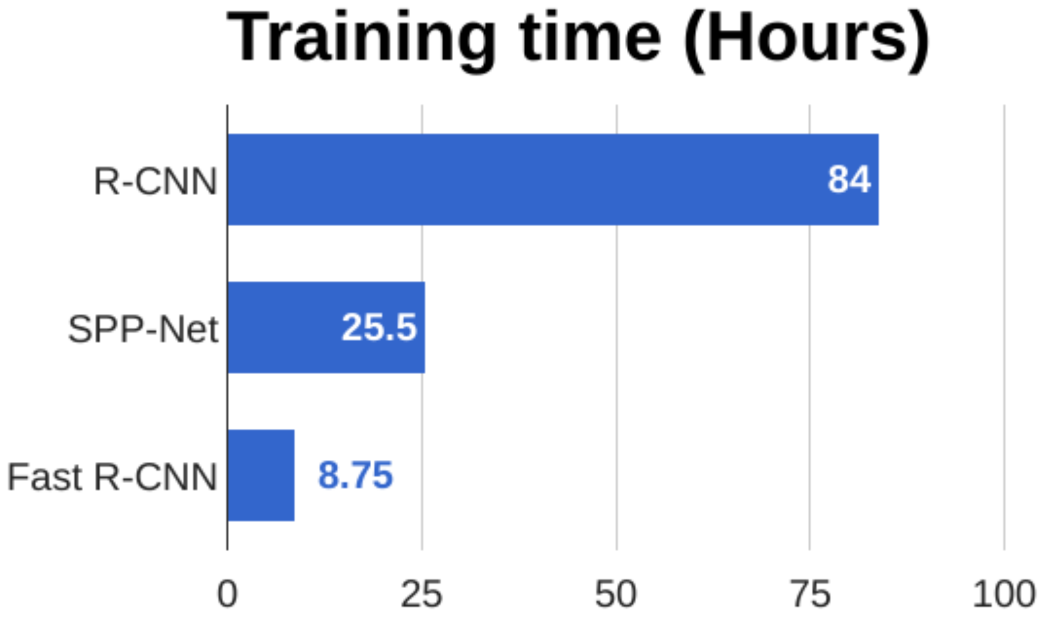


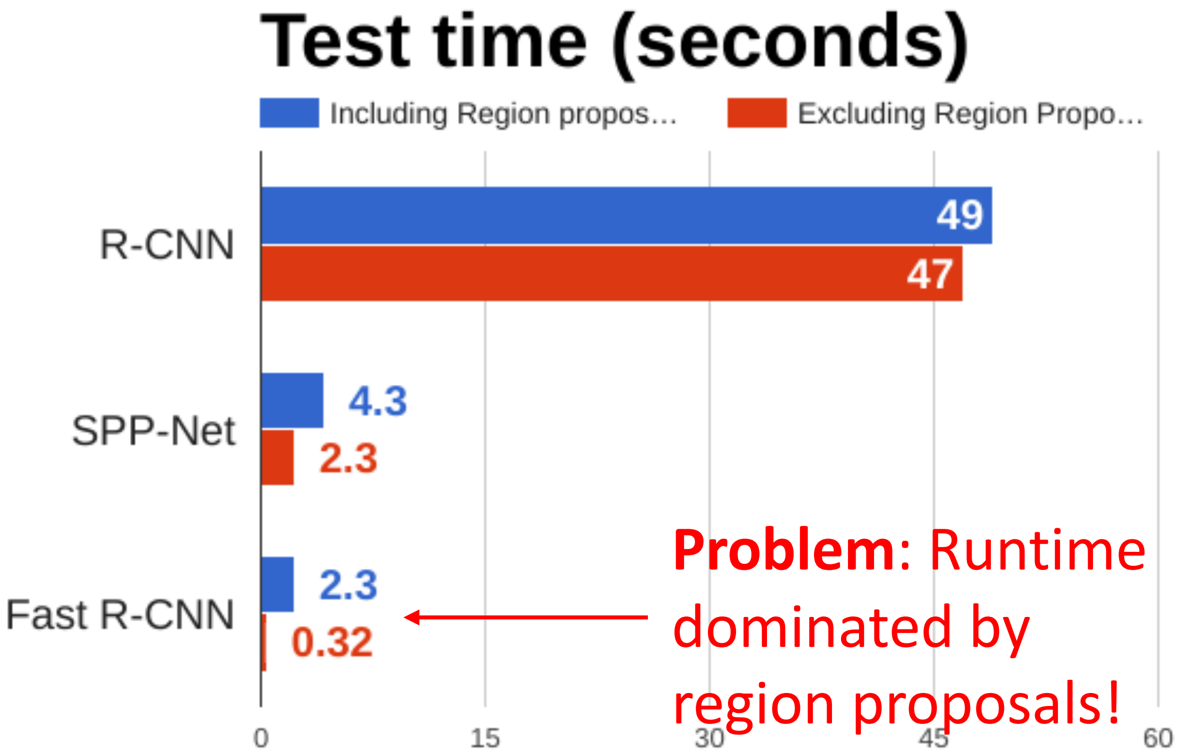


Problem: Runtime dominated by region proposals!

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

Fast R-CNN vs "Slow" R-CNN





Problem: Runtime dominated by region proposals!

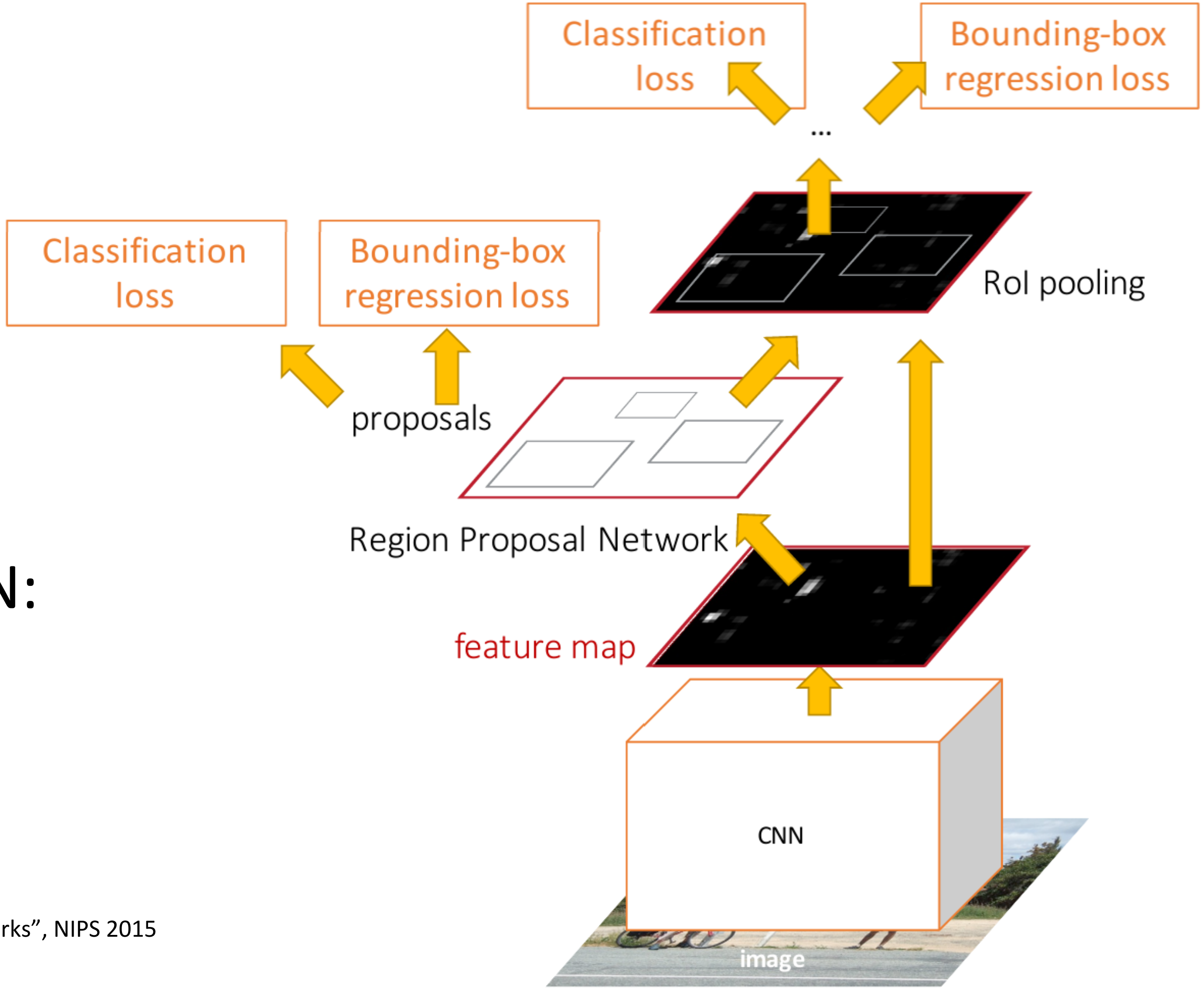
Recall: Region proposals computed by heuristic "Selective Search" algorithm on CPU -- let's learn them with a CNN instead!

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

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

Region Proposal Network (RPN)

Run backbone CNN to get
features aligned to input image

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

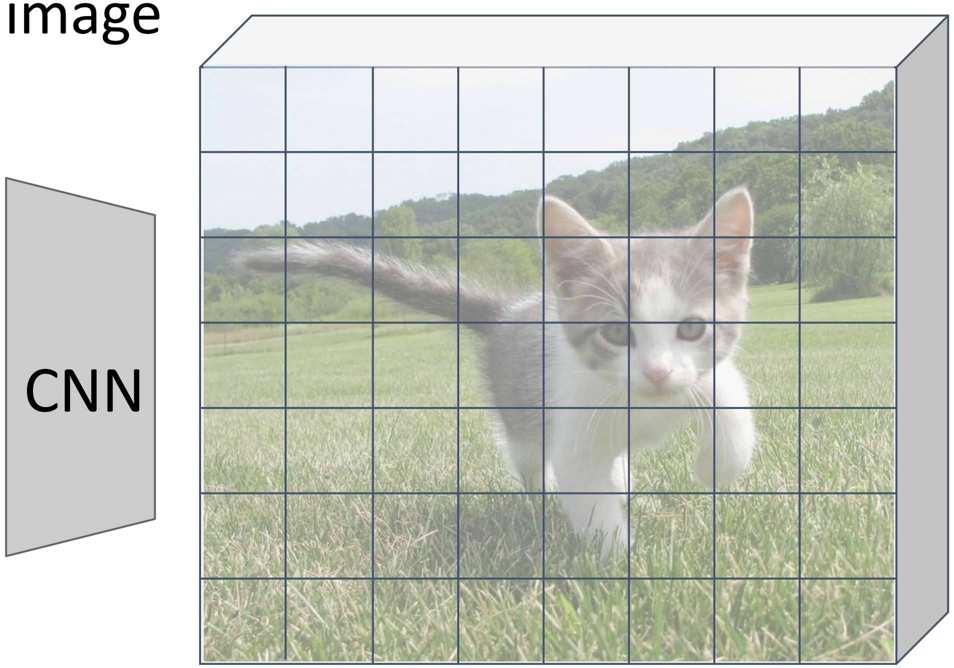


Image features
(e.g. 512 x 20 x 15)

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)

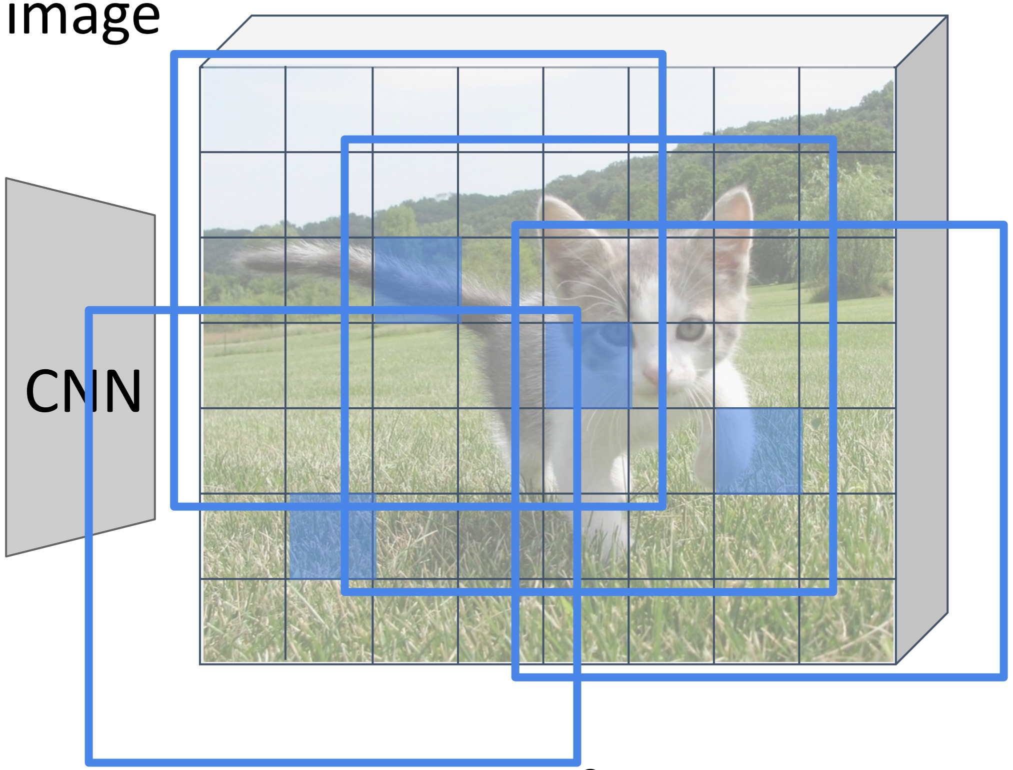
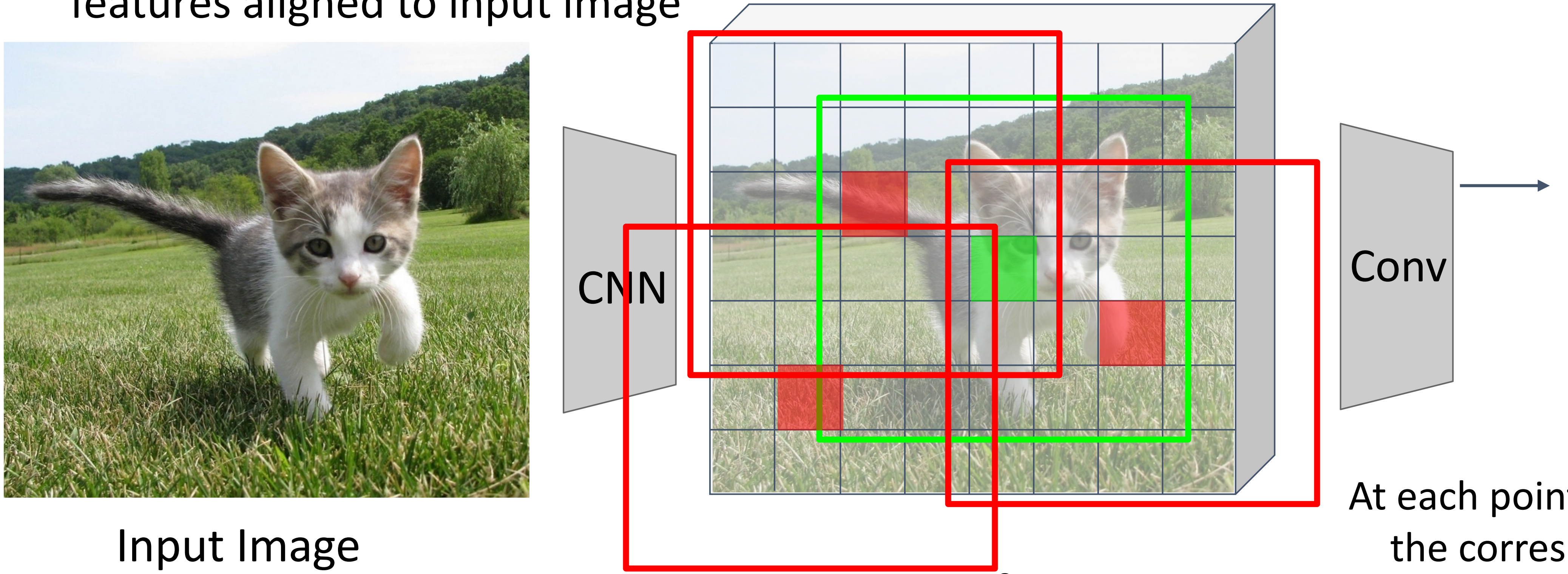


Image features
(e.g. 512 x 20 x 15)

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)

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

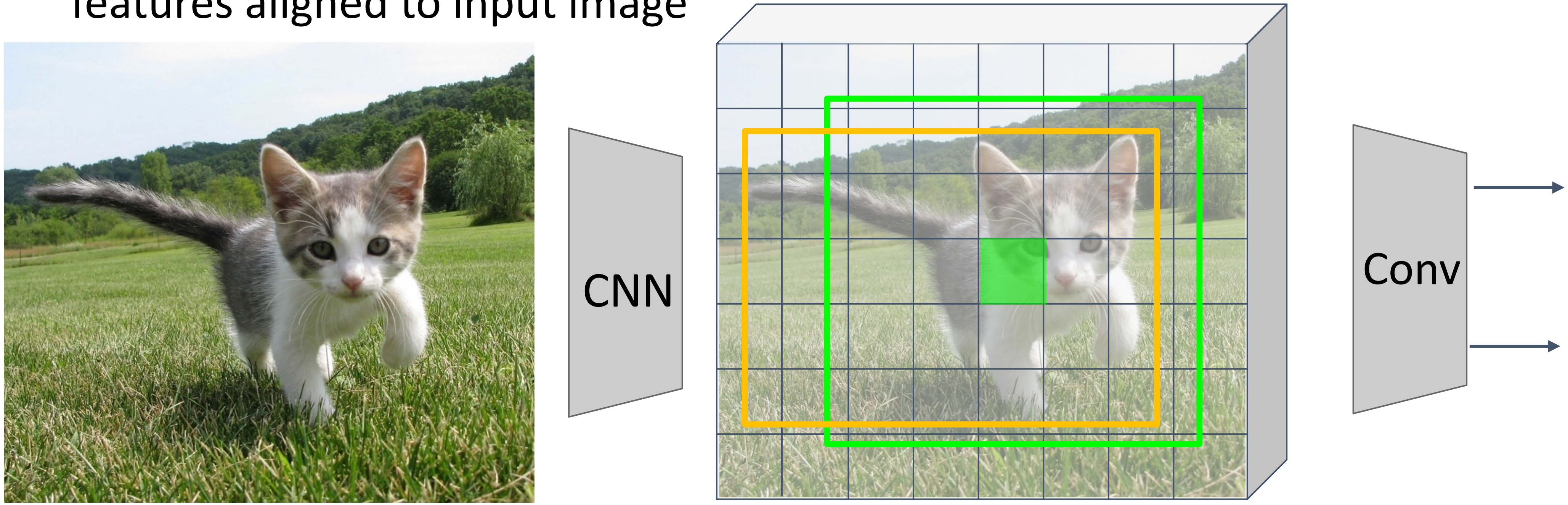
Anchor is an object?
1 x 20 x 15

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



Anchor is an object?
1 x 20 x 15

Box transforms
4 x 20 x 15

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

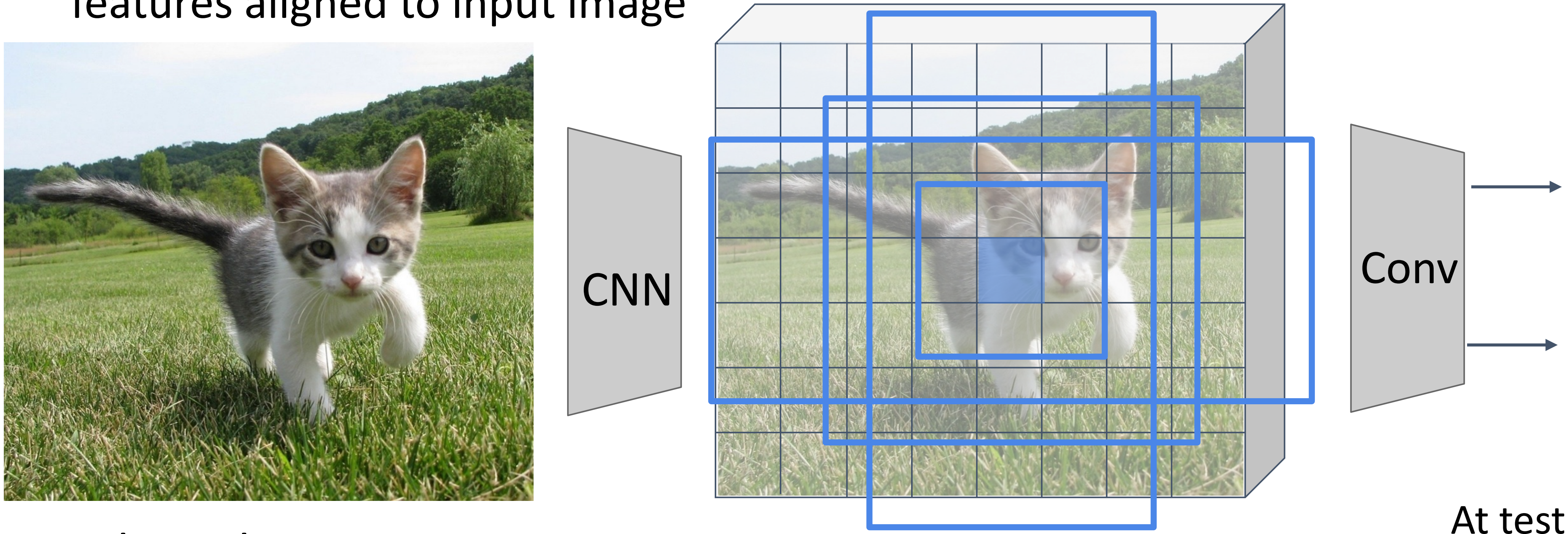
Image features
(e.g. 512 x 20 x 15)

For positive boxes, also predict a 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)

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

Anchor is an object?
K x 20 x 15

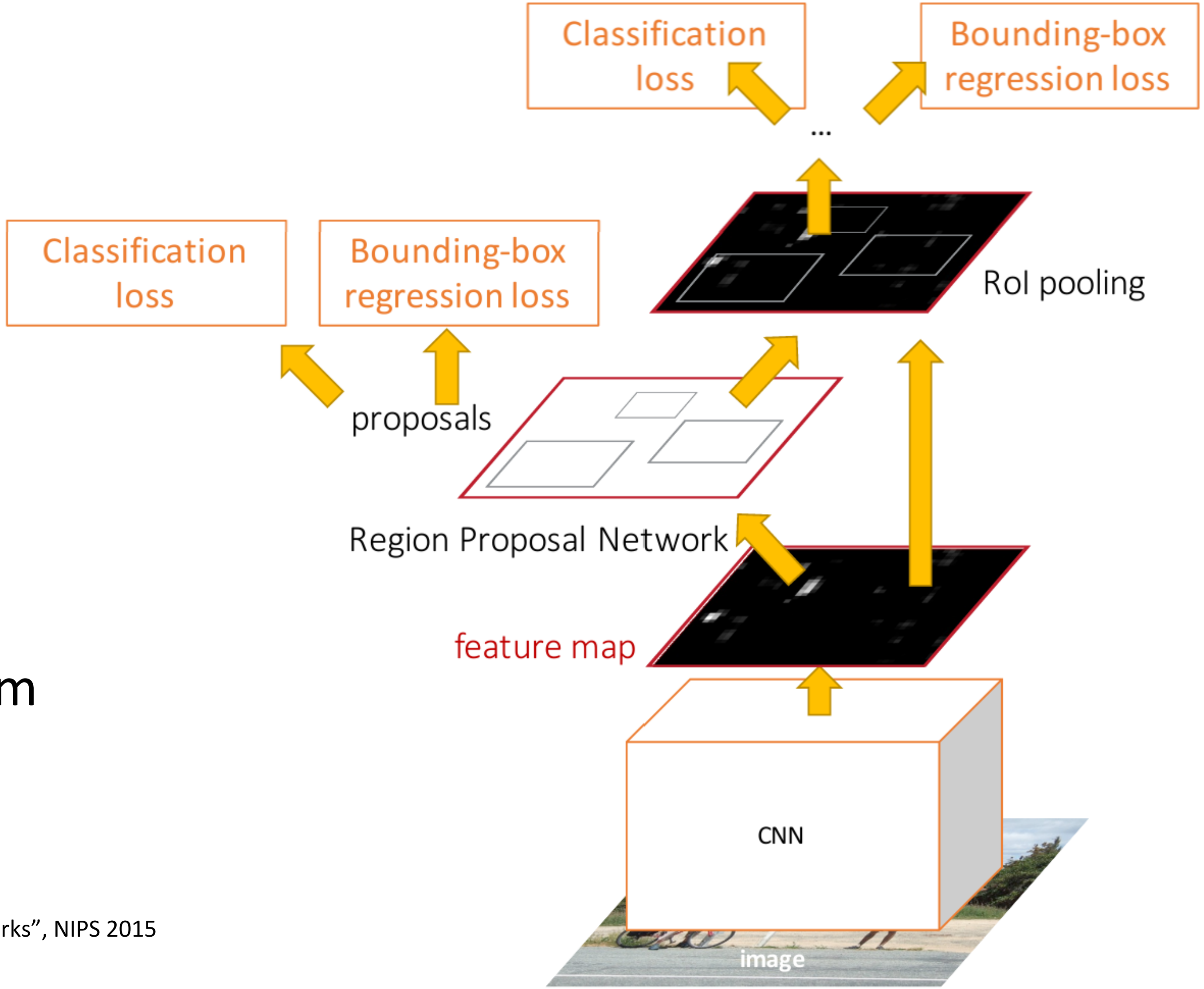
Box transforms
4K x 20 x 15

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

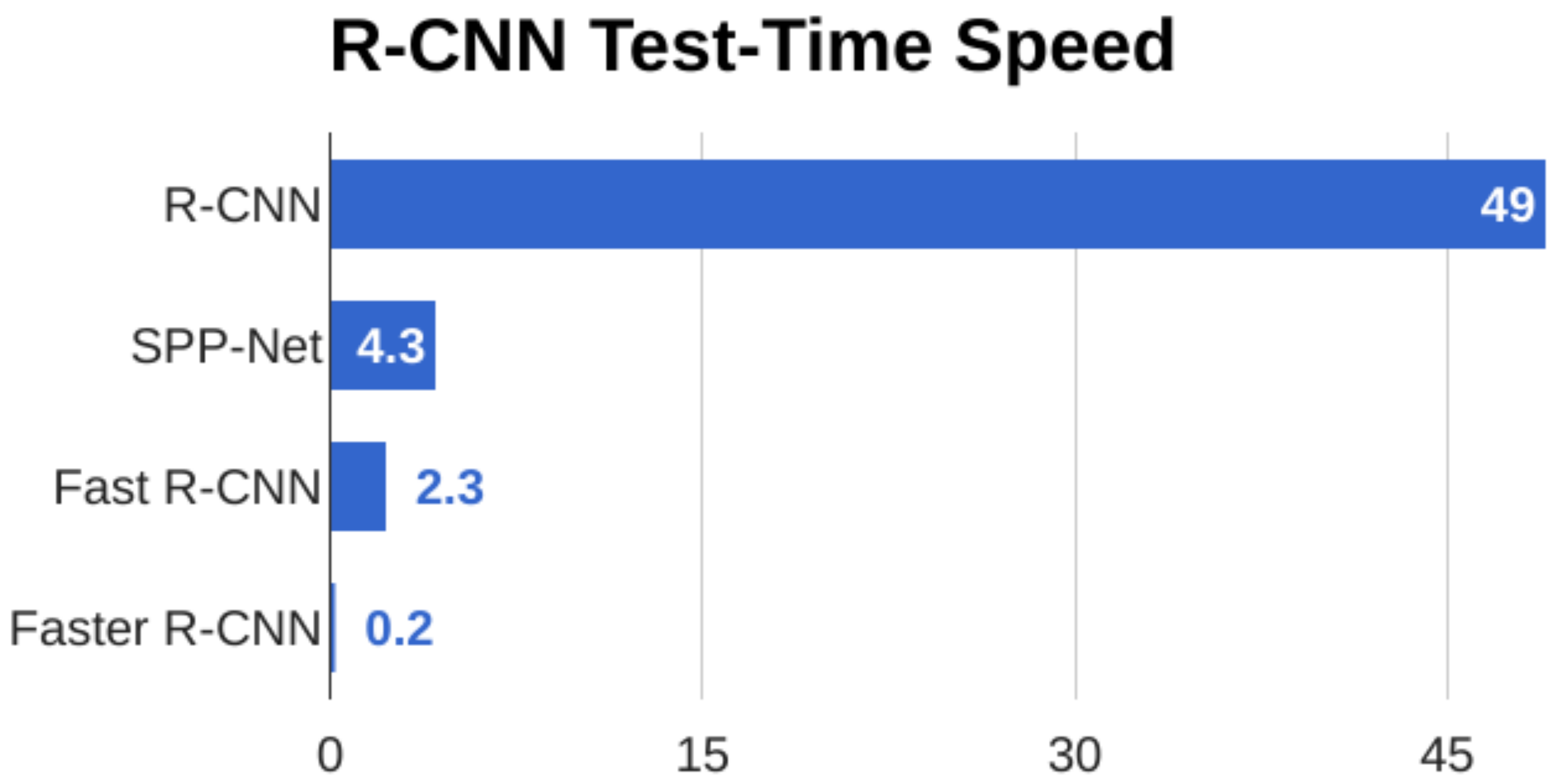
Jointly train with 4 losses:

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

Faster R-CNN: Learnable Region Proposals

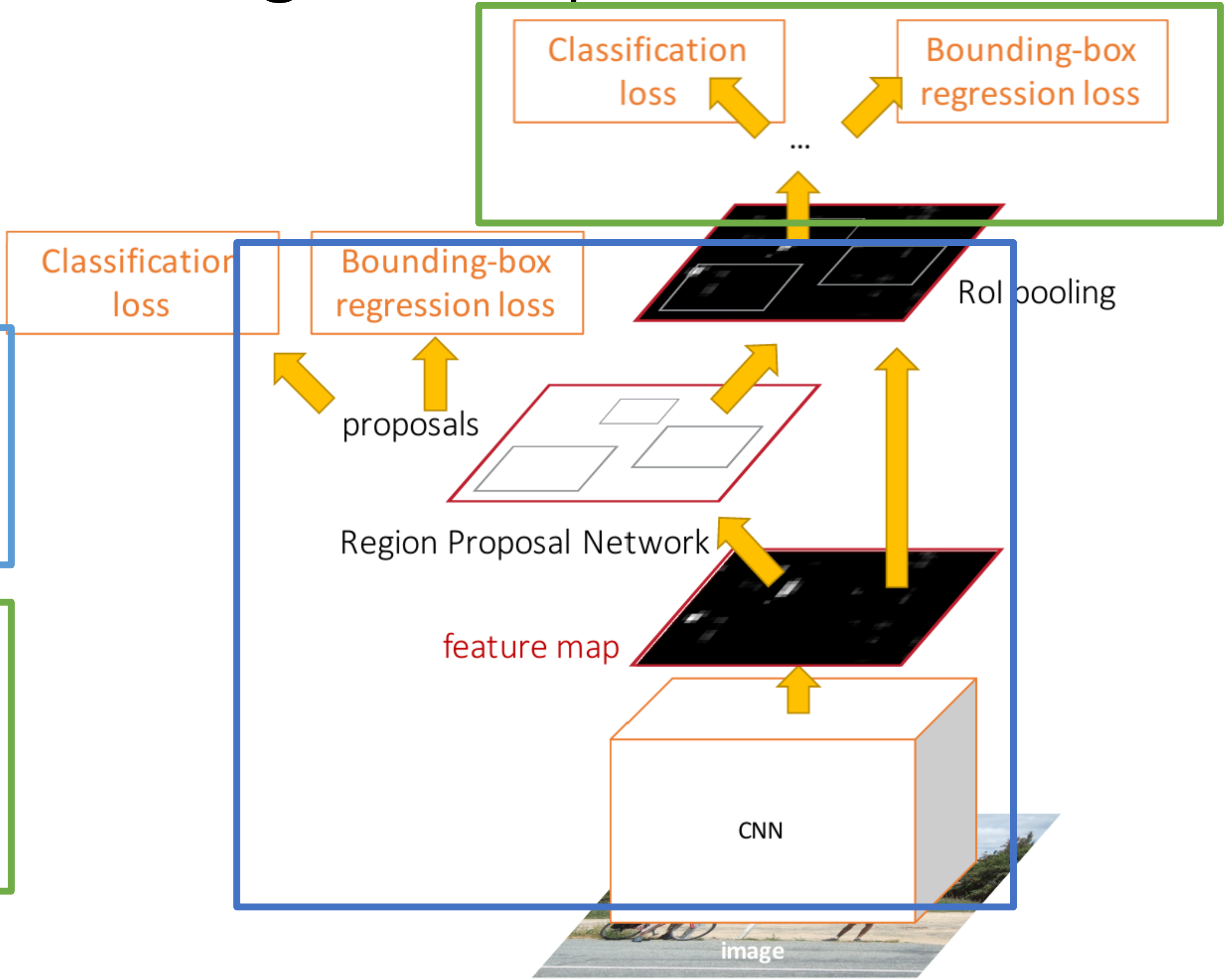


Faster R-CNN: Learnable Region Proposals

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



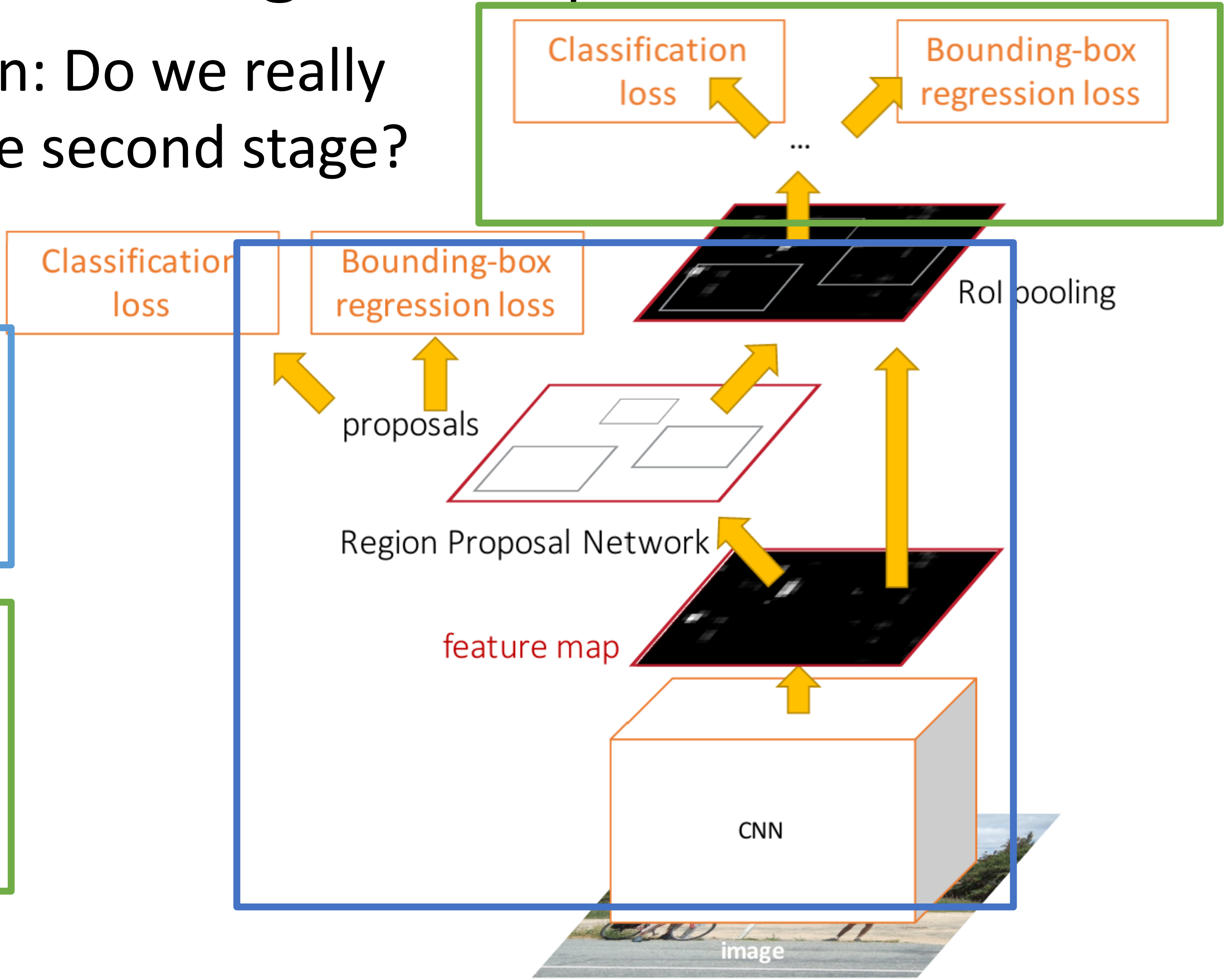
Faster R-CNN: Learnable Region Proposals

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)

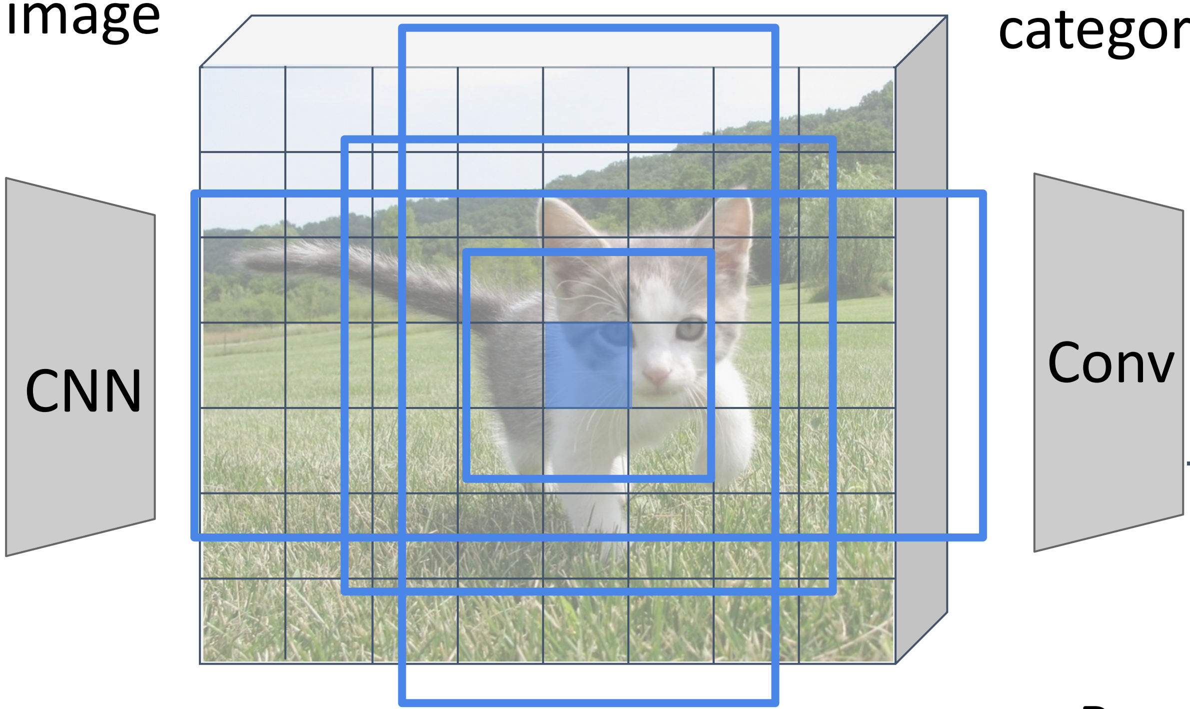


Image features
(e.g. 512 x 20 x 15)

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

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)

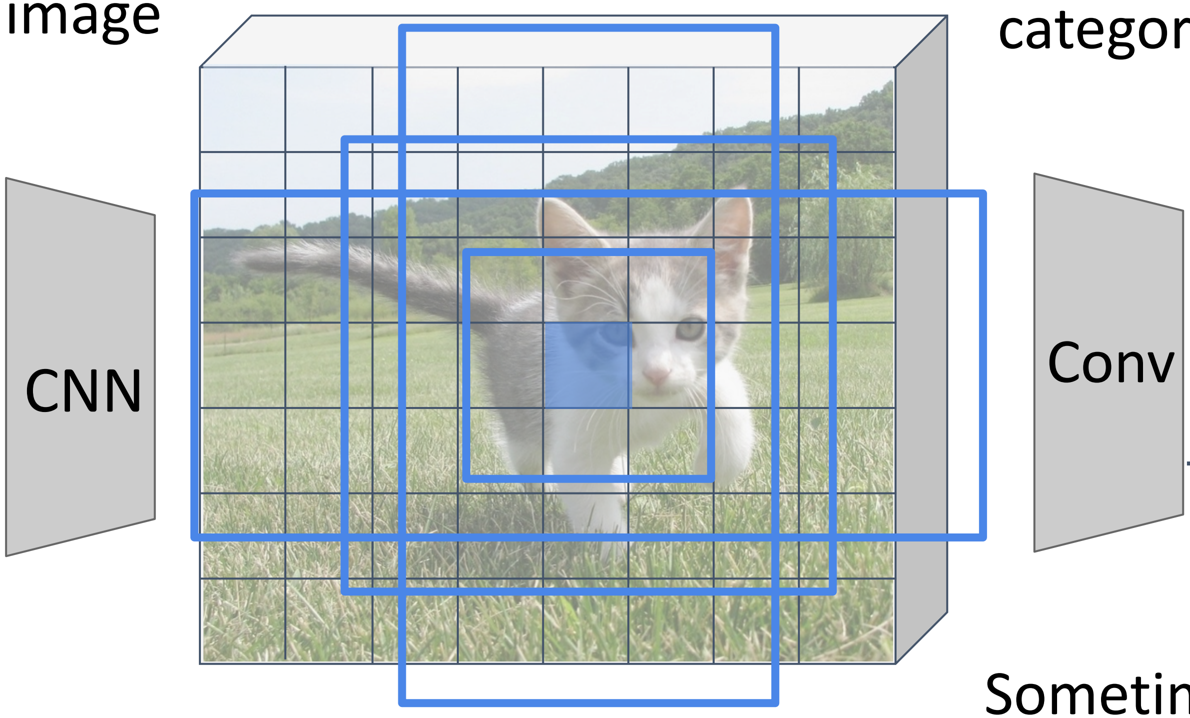


Image features
(e.g. 512 x 20 x 15)

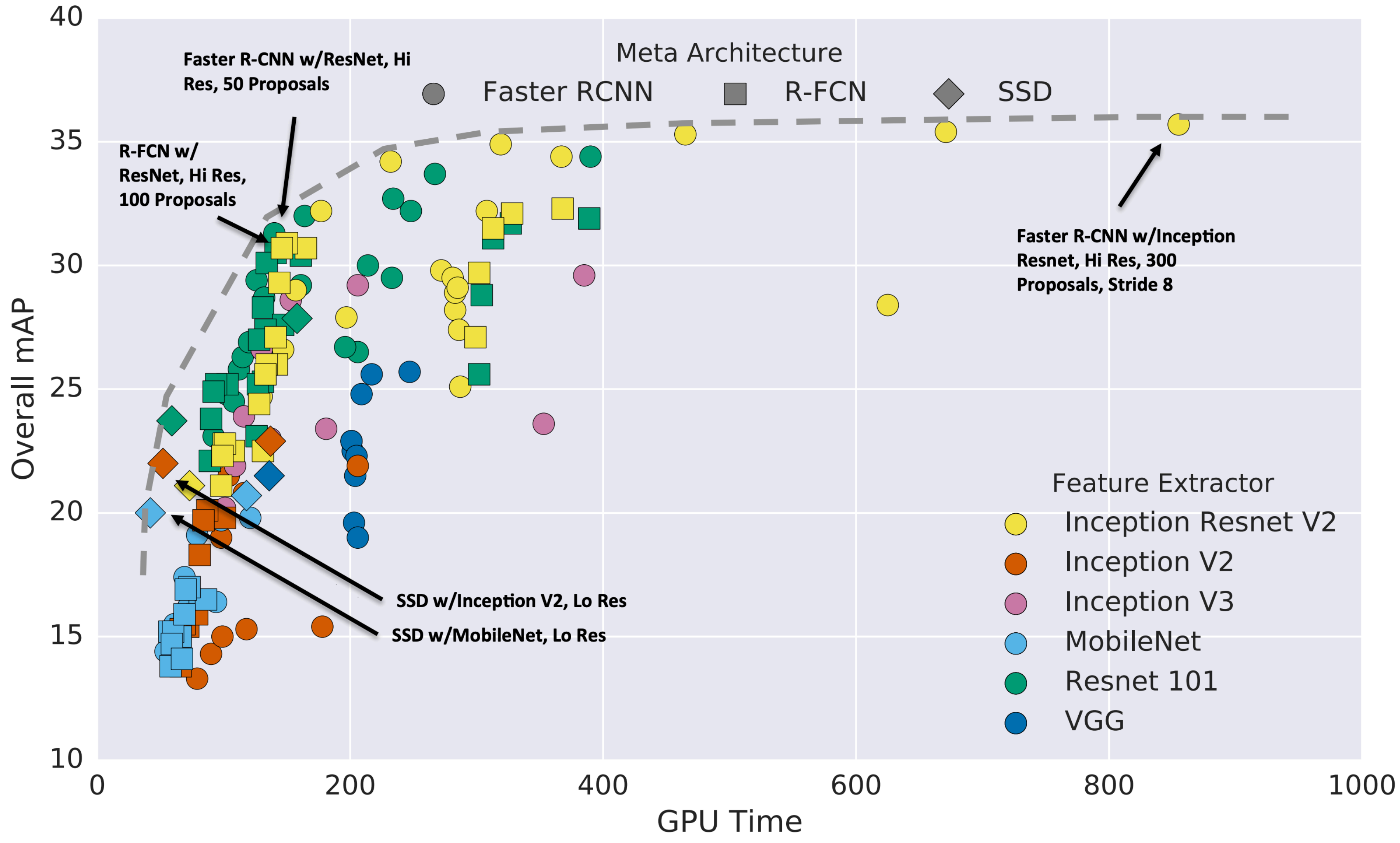
Anchor category
→ (C+1) x K x 20 x 15

→ Box transforms
C x 4K x 20 x 15

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

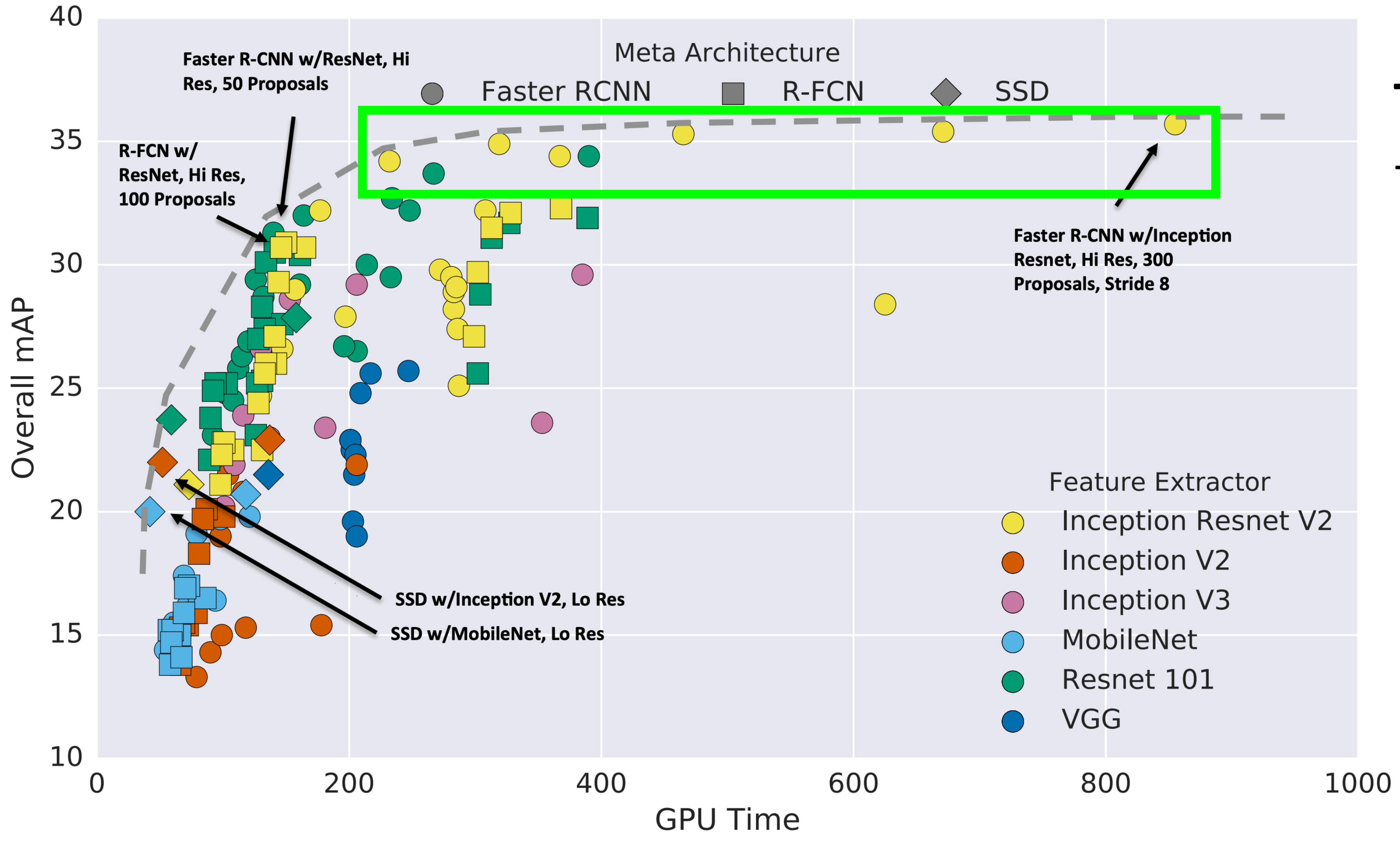
Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Object Detection: Lots of variables!



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

Object Detection: Lots of variables!

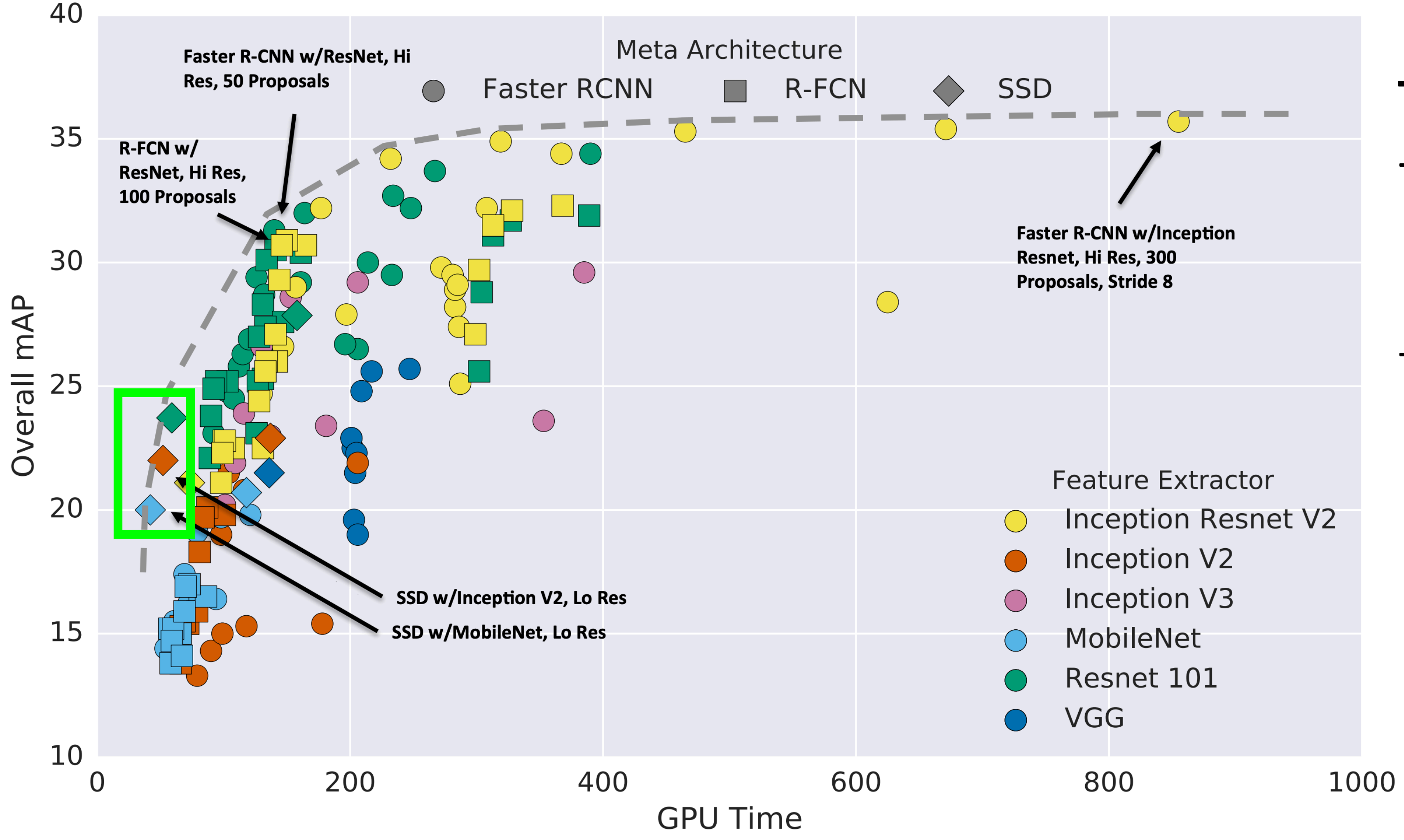


Takeaways:

- 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!

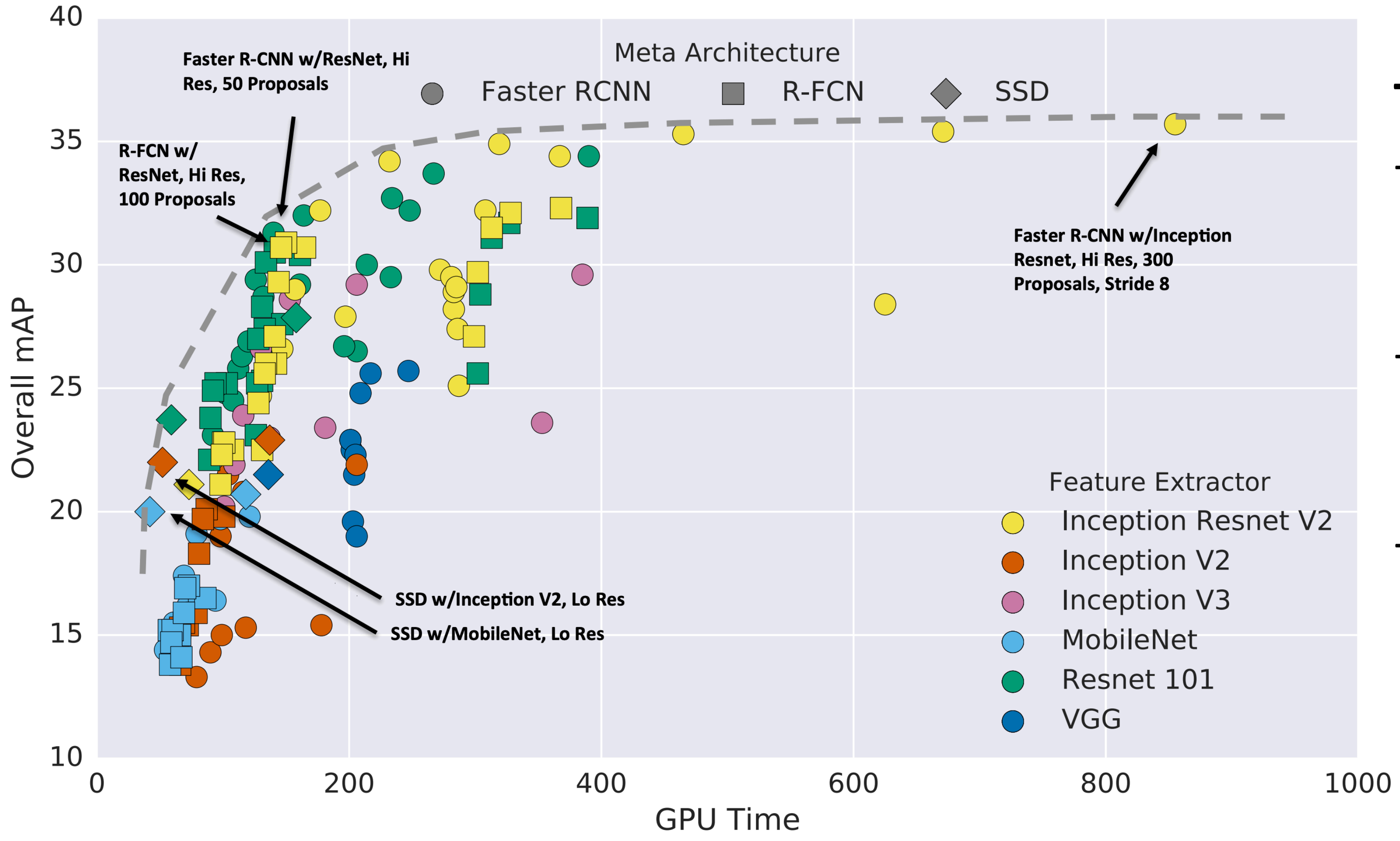


Takeaways:

- 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!

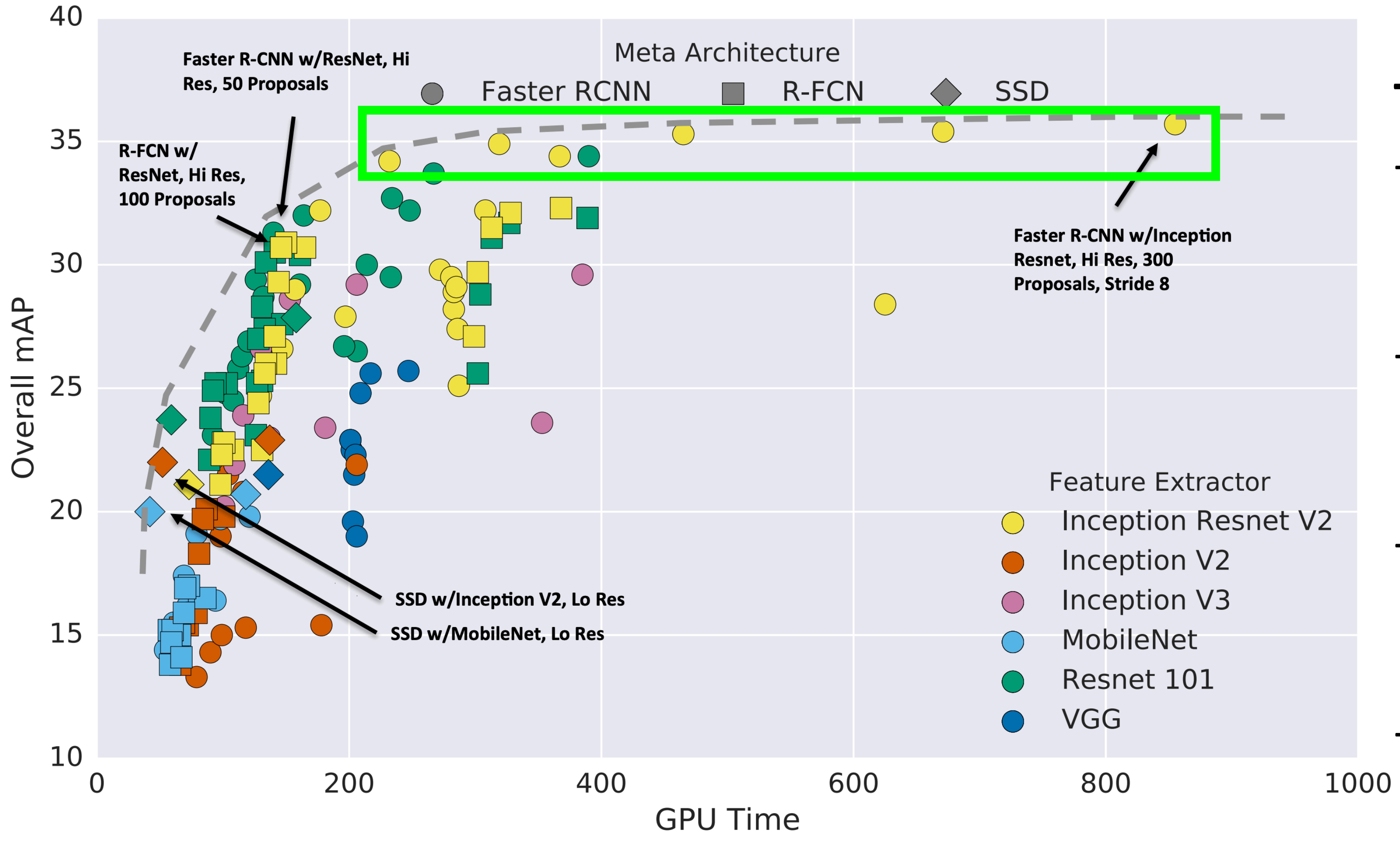


Takeaways:

- 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!



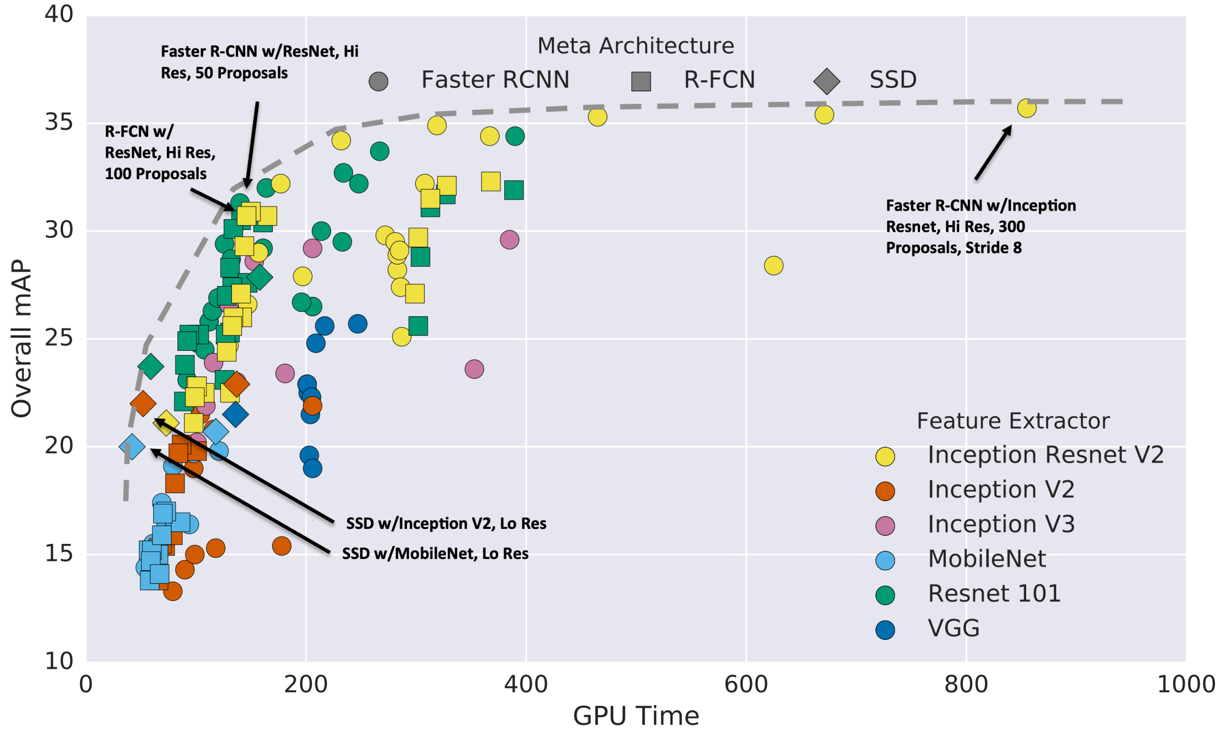
Takeaways:

- 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:

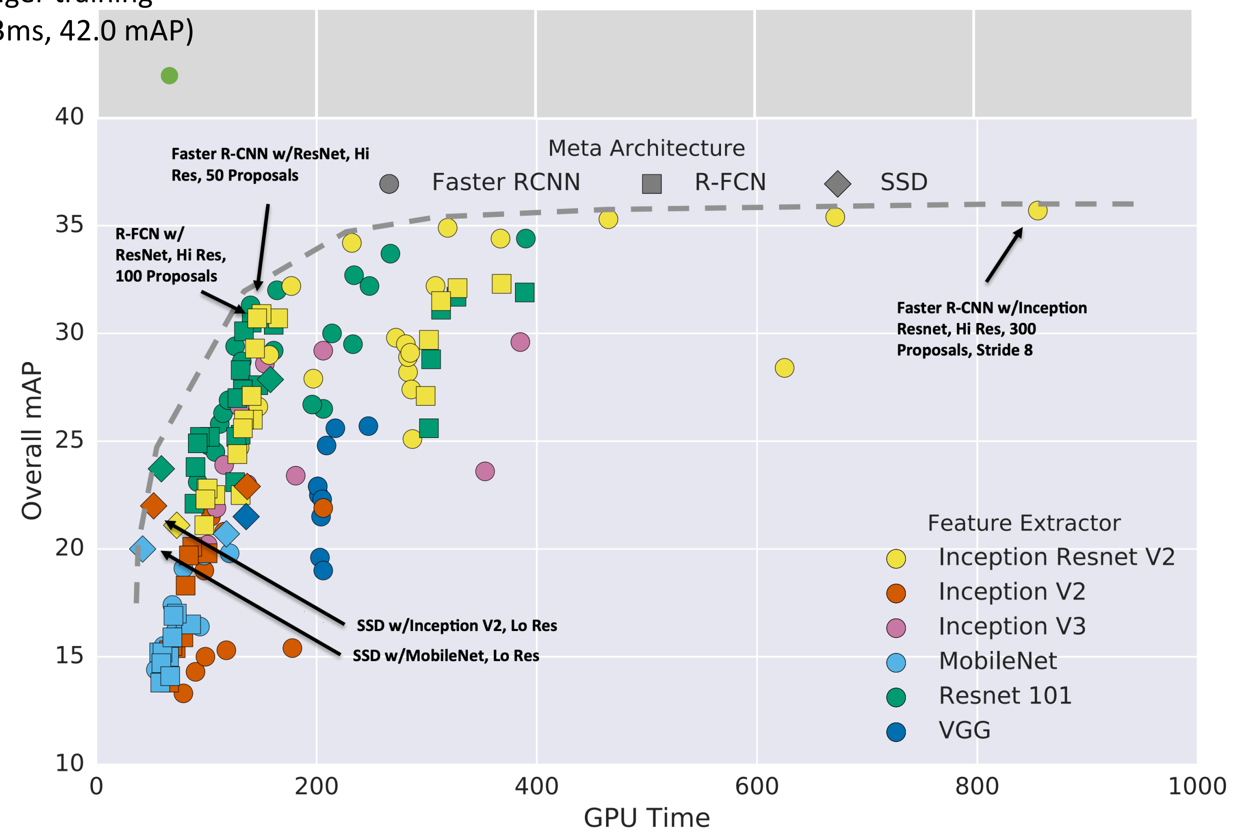


Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017

Wu et al, Detectron2, GitHub 2019

Object Detection: Lots of variables!

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



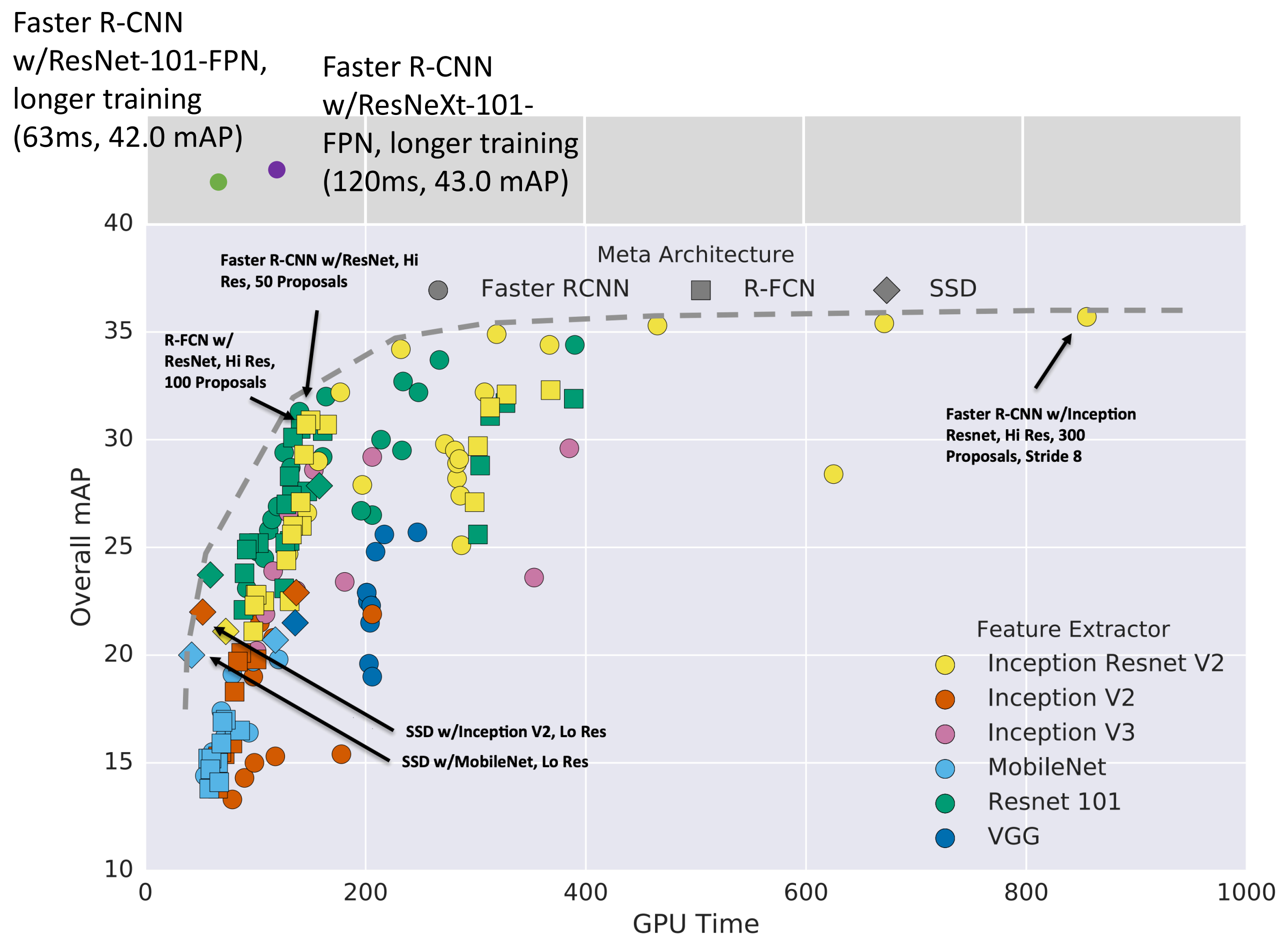
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- 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!



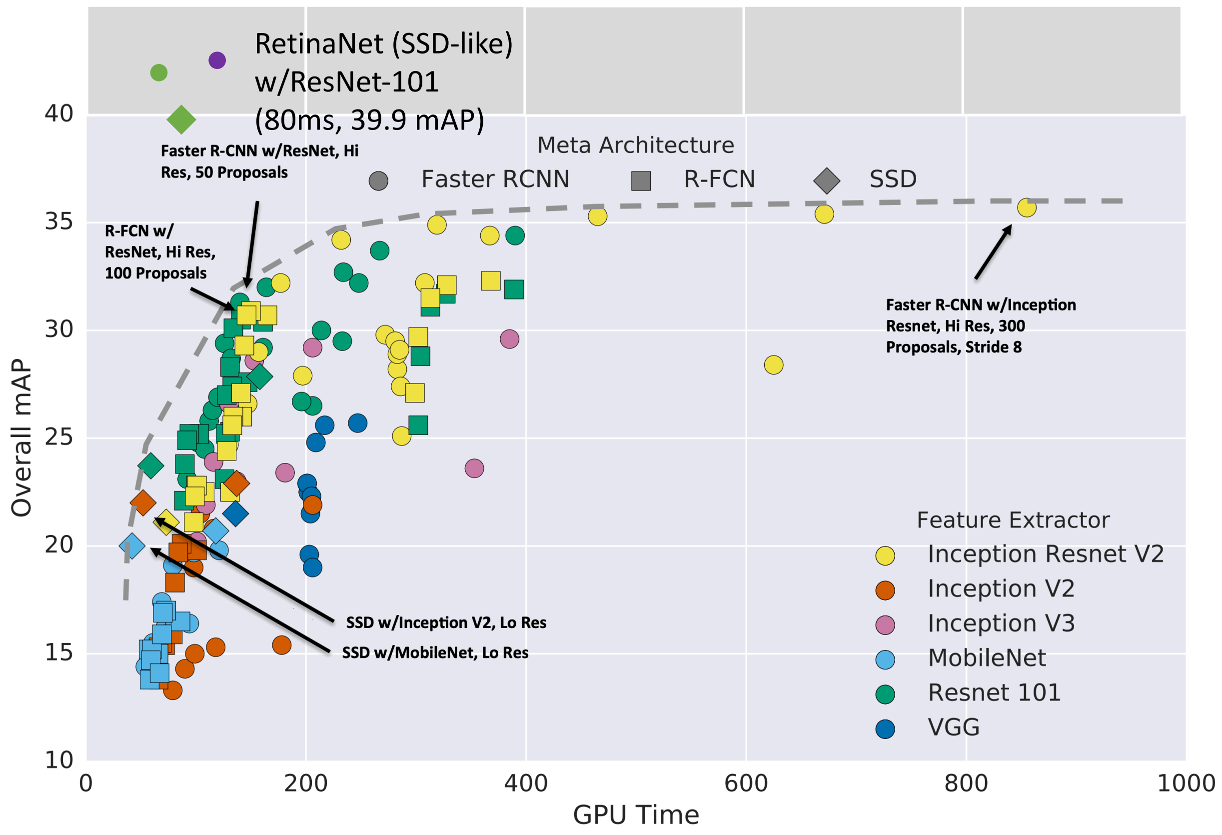
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- 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!



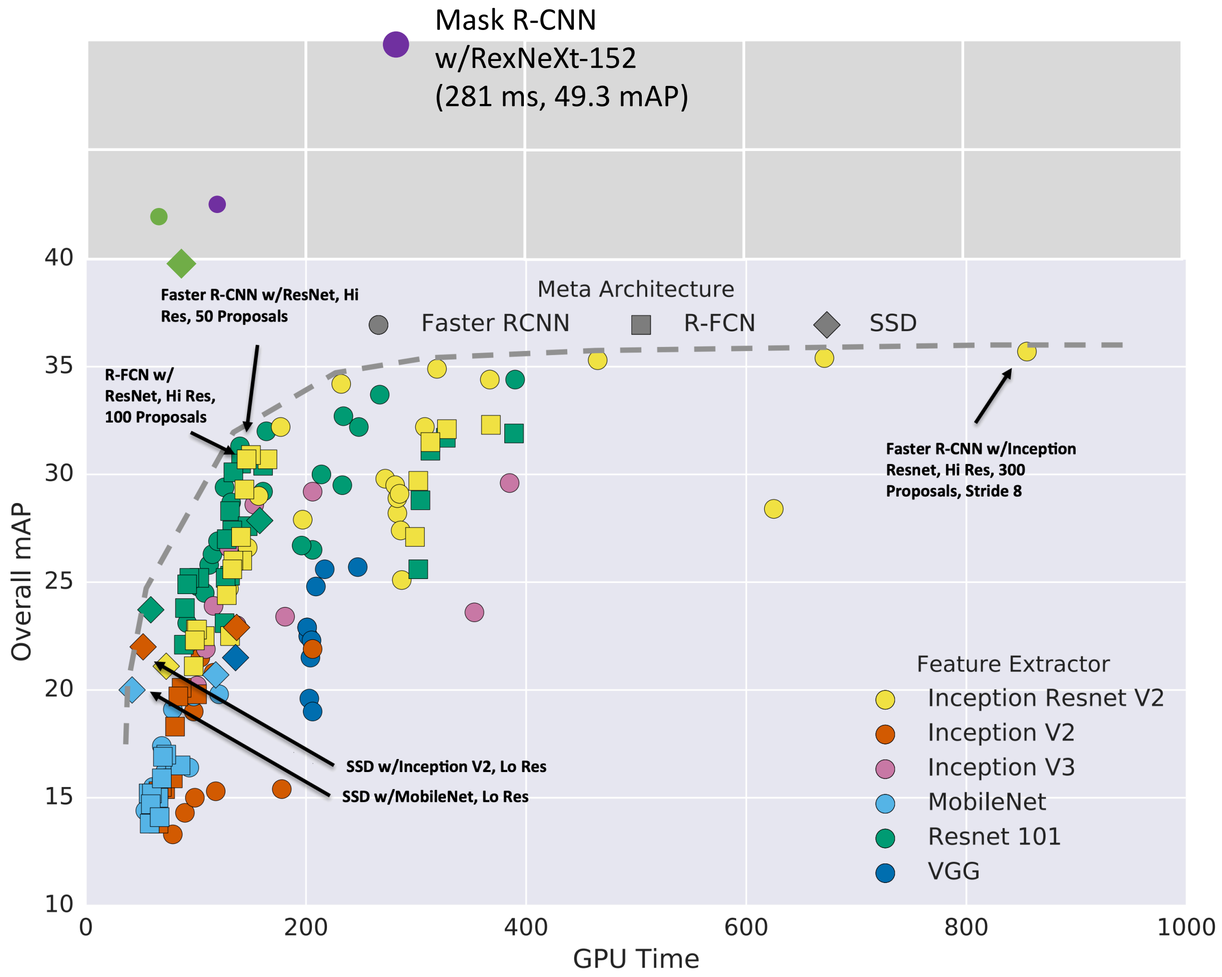
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

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

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

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!

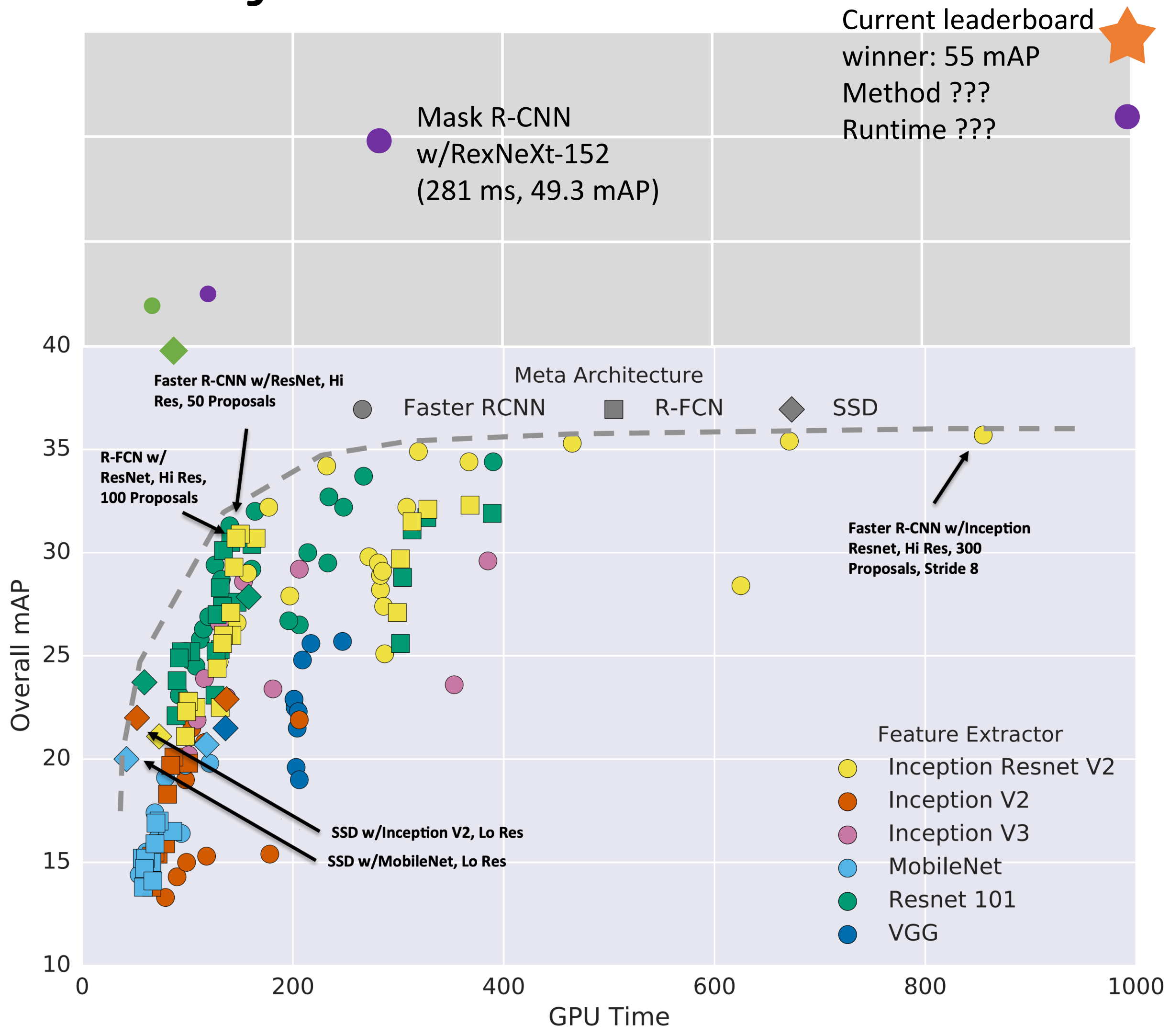
These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- 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

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

Object Detection: Open-Source Code

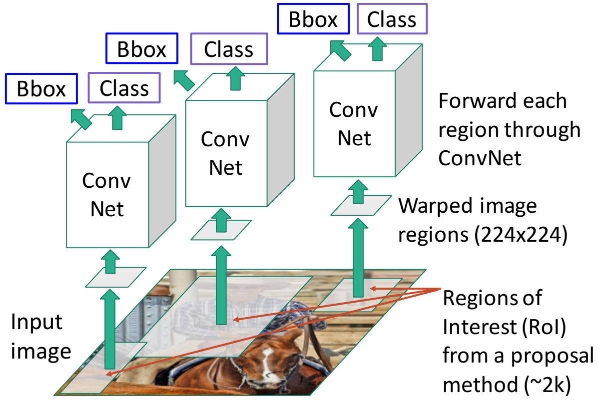
Object detection is hard! Don't implement it yourself
(Unless you are working on A5…)

TensorFlow Detection API:
https://github.com/tensorflow/models/tree/master/research/object_detection
Faster R-CNN, SSD, RFCN, Mask R-CNN

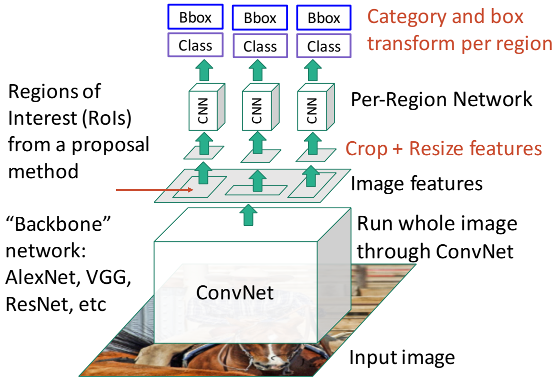
Detectron2 (PyTorch):
https://github.com/facebookresearch/detectron2
Fast / Faster / Mask R-CNN, RetinaNet

Summary

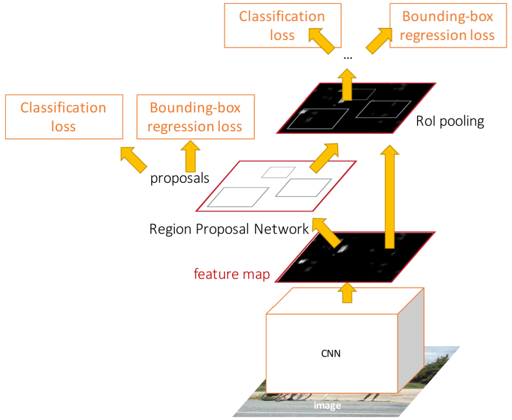
"Slow" R-CNN: Run CNN independently for each region



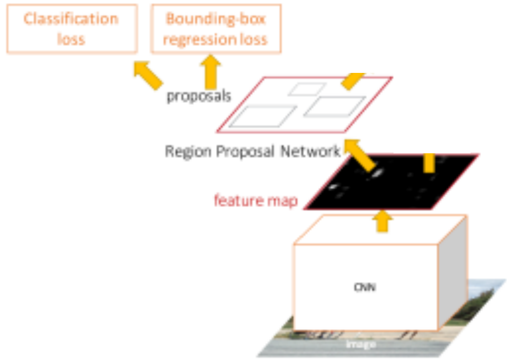
Fast R-CNN: Apply differentiable cropping to shared image features



Faster R-CNN: Compute proposals with CNN



Single-Stage: Fully convolutional detector



Next Time:
More localization methods:
Segmentation, Keypoint Estimation