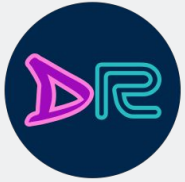
ROB 498/599: Deep Learning for Robot Perception (DeepRob)

Lecture 12: Object Detection - part 2

02/18/2026



https://deeprob.org/w26/

ROBOTICS

Today

- Feedback and Recap (5min)
- Object Detection (part 2)
  - Fast R-CNN (25min)
    - Receptive Fields
    - ROI Align
    - ROI Pool
  - Faster R-CNN (25min)
    - Region Proposal Network
  - Mask R-CNN (6min)
  - YOLO (6min)
  - Mesh R-CNN (6min)
- Summary and Takeaways (5min)

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Recap: Object Detection

- P3 released, Due March 8, 2026
Start NOW!!!
- Also, Object Detection Quiz due Feb 22

Classification

"Chocolate Pretzels"

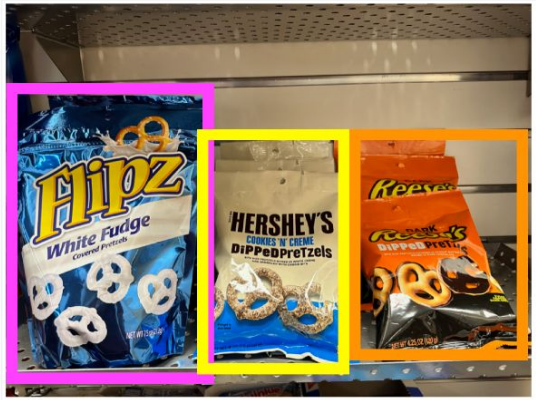
No spatial extent

Semantic Segmentation

Chocolate Pretzels, Shelf

No objects, just pixels

Object Detection



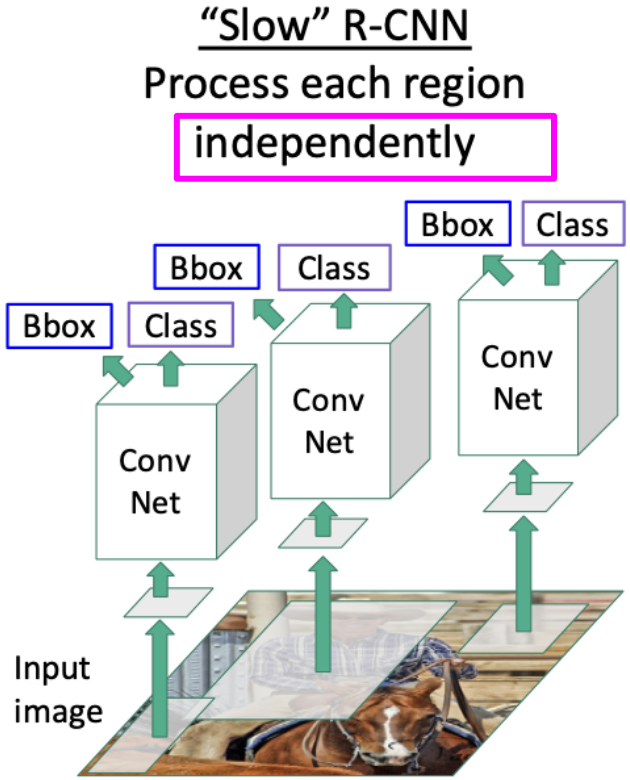
Flipz, Hershey's, Keese's

Multiple objects

Instance Segmentation

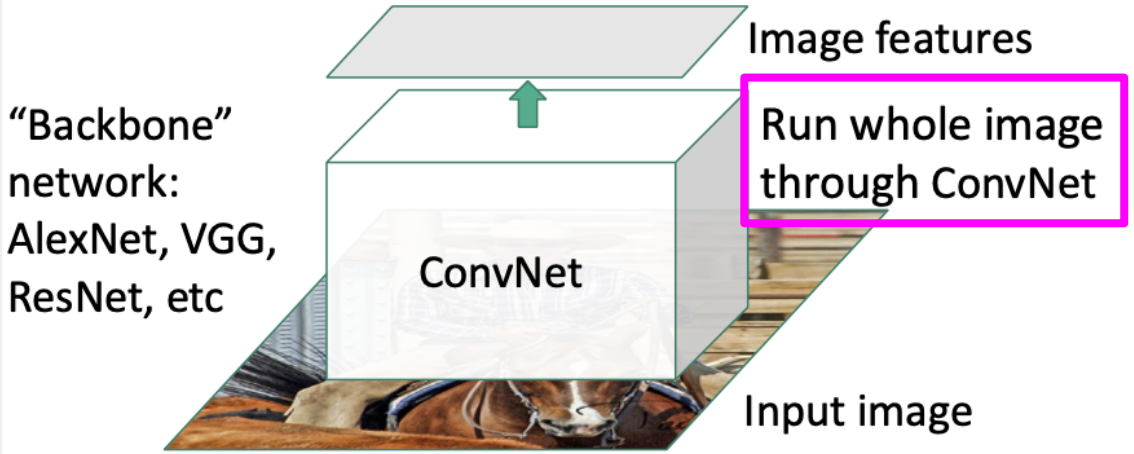
Recap: Slow vs. Fast R-CNN

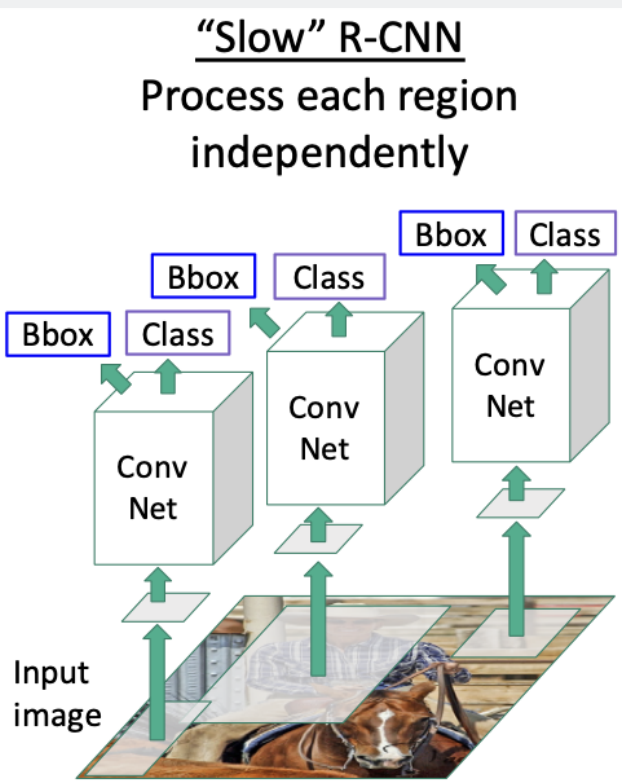
Input image



Fast R-CNN

"Heavy duty backbone"

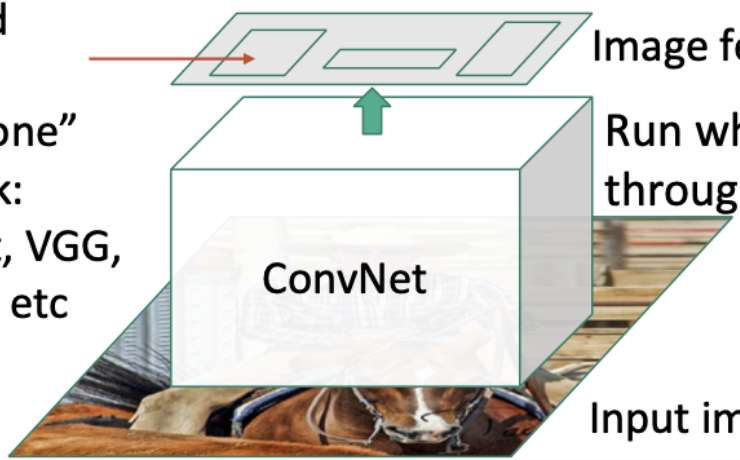




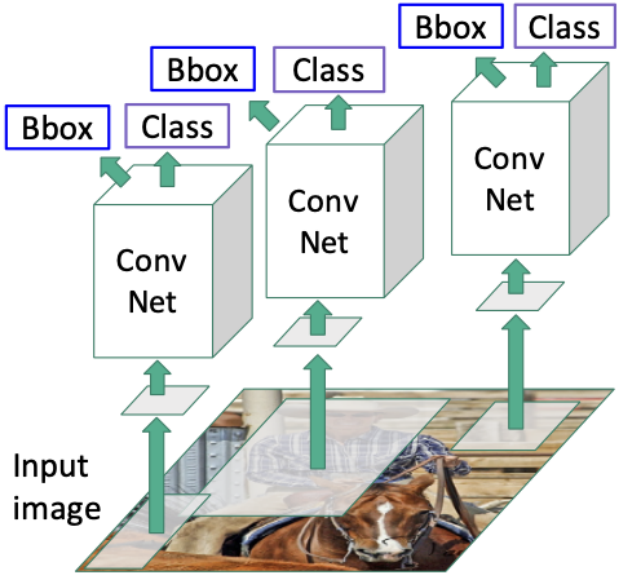
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



"Slow" R-CNN
Process each region independently



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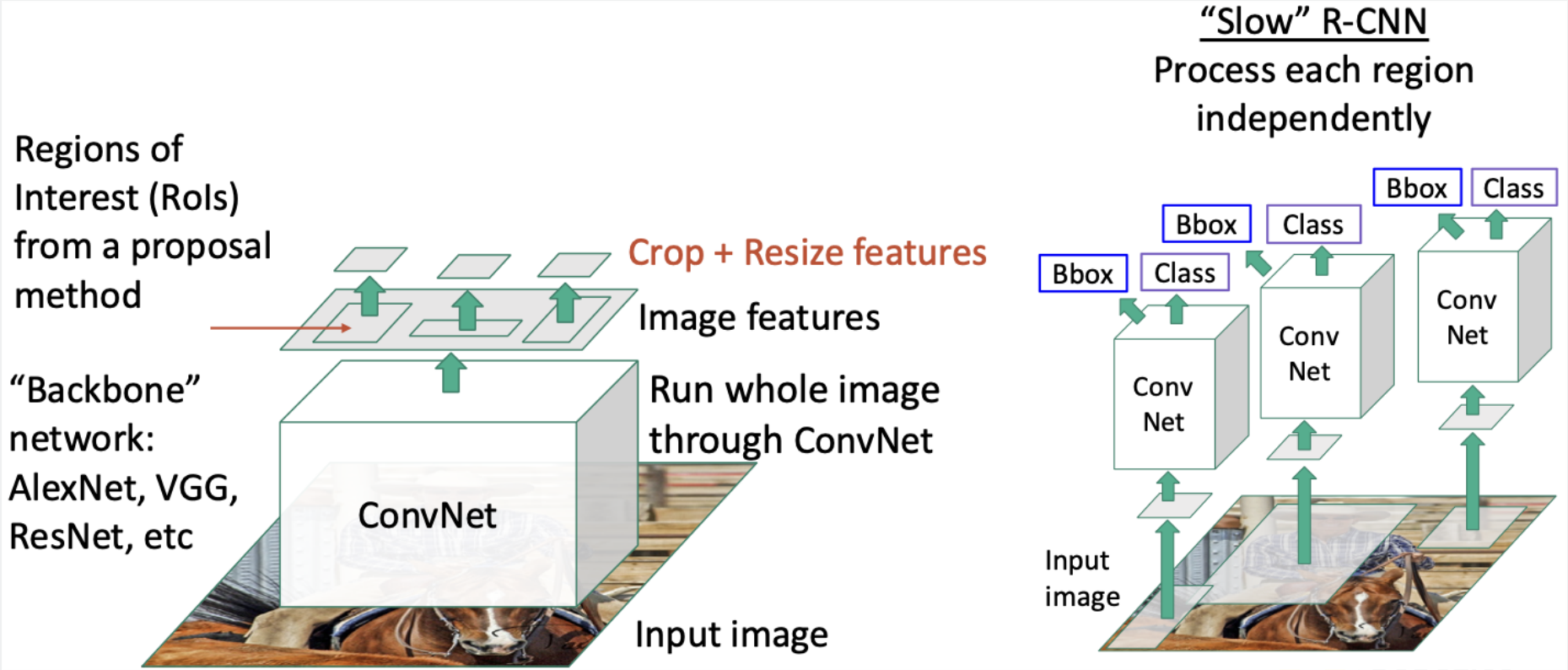
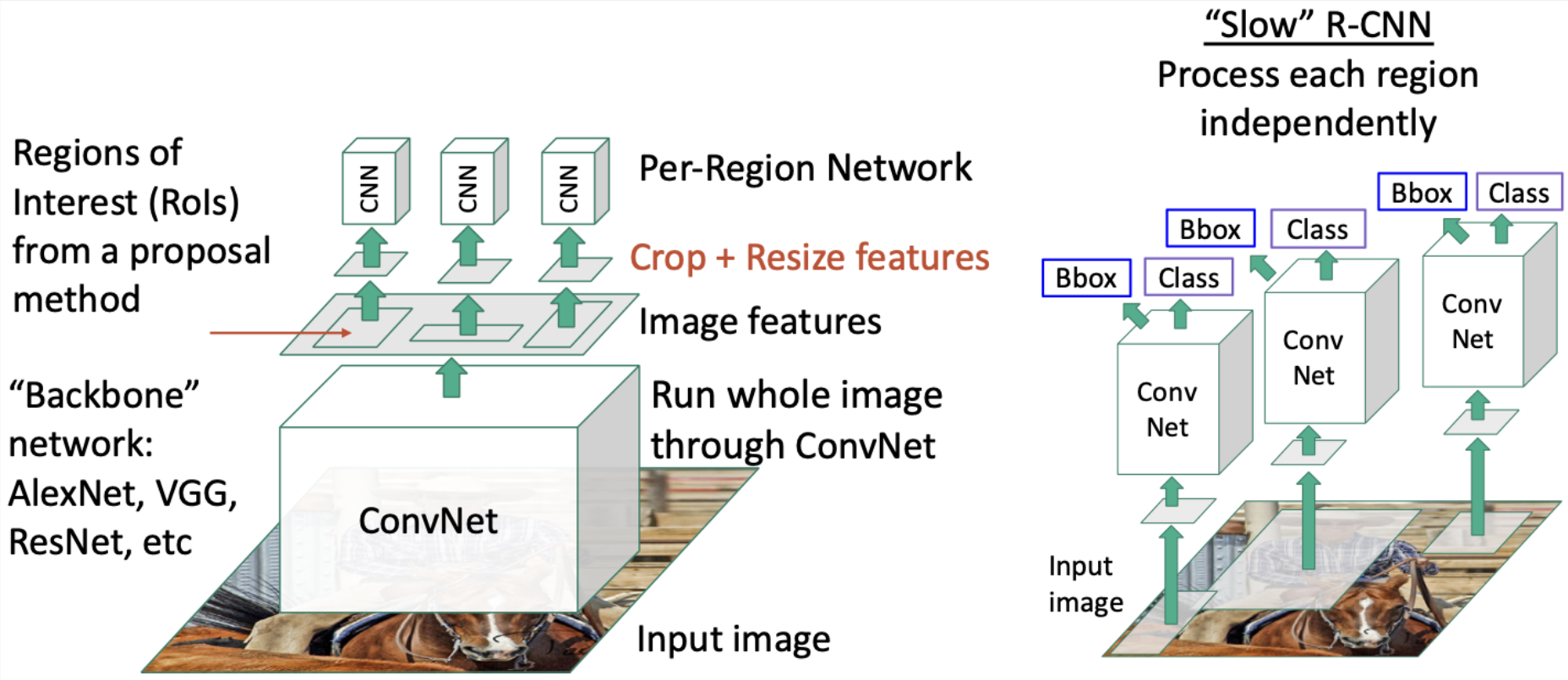
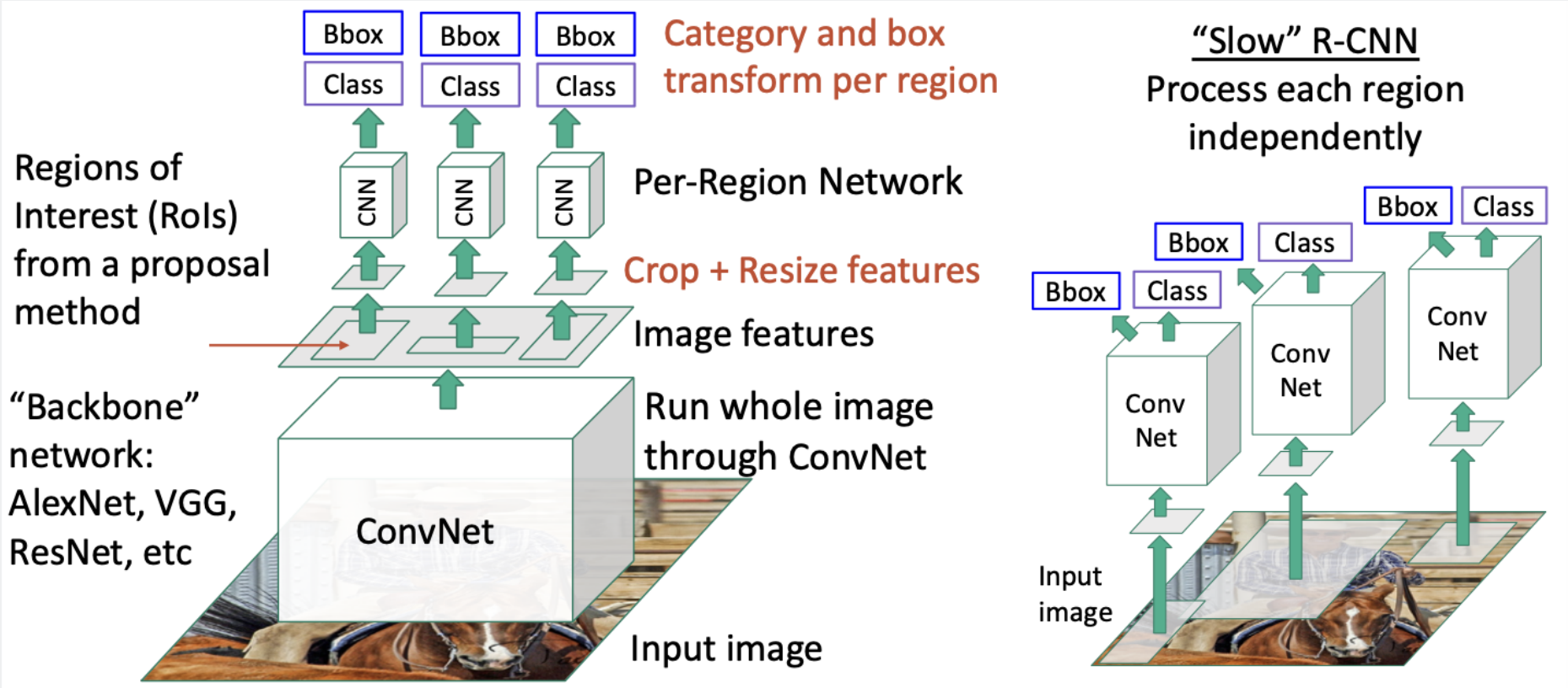
Fast R-CNN


Regions of Interest (RoIs) from a proposal method
"Backbone" network: AlexNet, VGG, ResNet, etc
Crop + Resize features
Image features
Run whole image through ConvNet
ConvNet
Input image
"Slow" R-CNN
Process each region independently
Bbox
Class
Conv Net
Input image

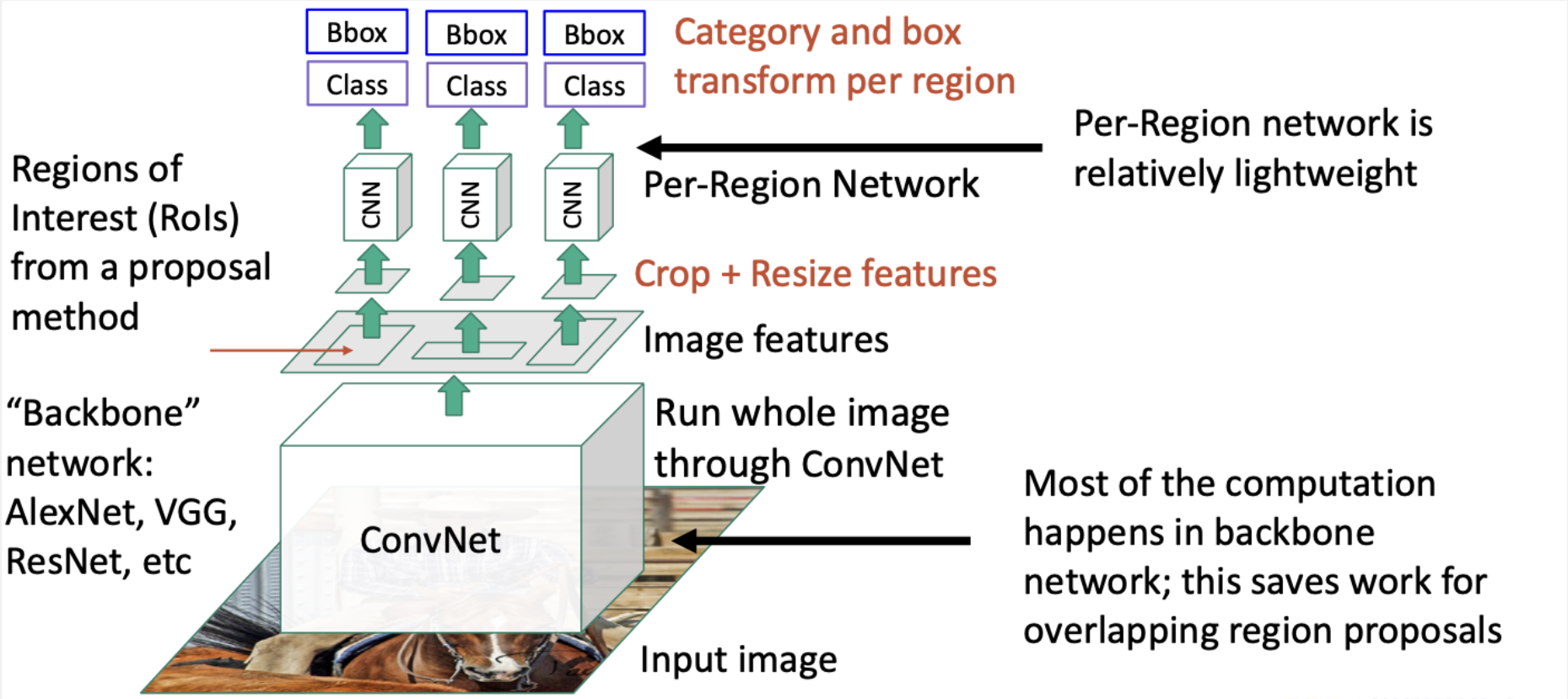
Fast R-CNN


Regions of Interest (RoIs) from a proposal method
"Backbone" network: AlexNet, VGG, ResNet, etc
CNN
CNN
CNN
Per-Region Network
Crop + Resize features
Image features
Run whole image through ConvNet
ConvNet
Input image
"Slow" R-CNN
Process each region independently
Bbox
Class
Conv Net
Input image

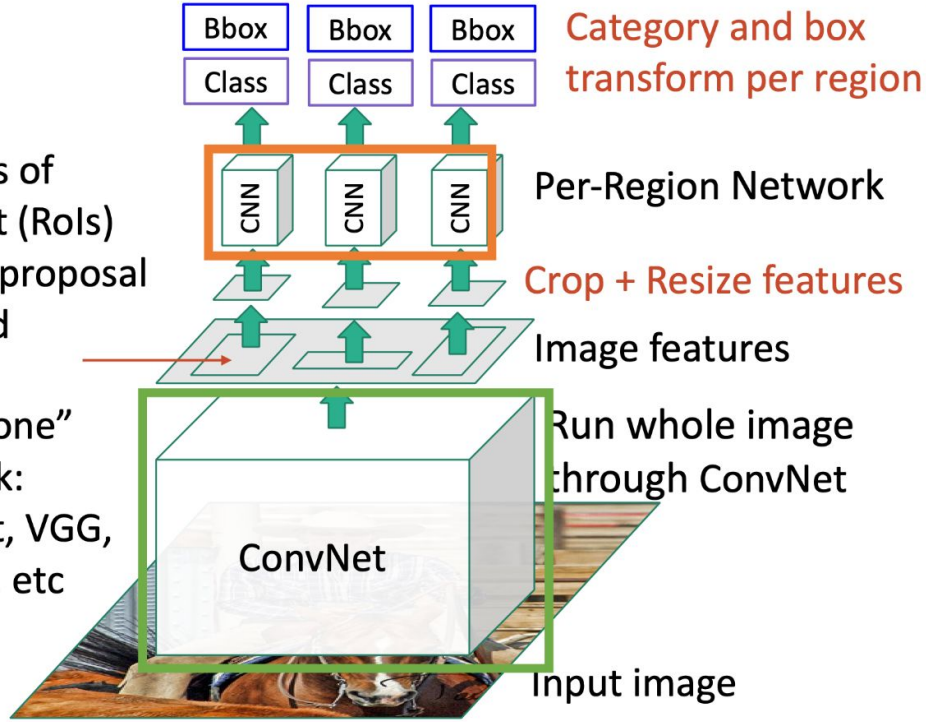
Fast R-CNN

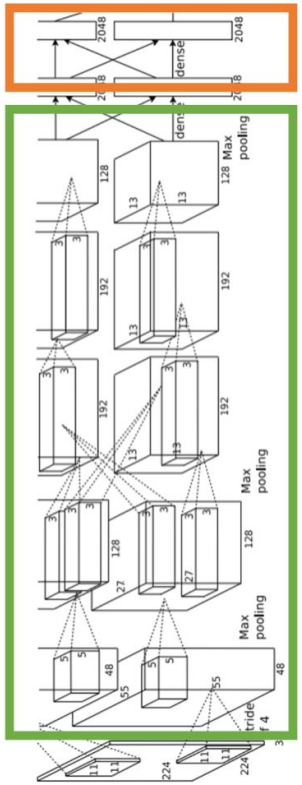

Bbox
Bbox
Bbox
Class
Class
Class
Category and box transform per region
Regions of Interest (RoIs) from a proposal method
CNN
CNN
CNN
Per-Region Network
Crop + Resize features
Image features
"Backbone" network: AlexNet, VGG, ResNet, etc
Run whole image through ConvNet
ConvNet
Input image
"Slow" R-CNN
Process each region independently
Bbox
Class
Conv Net
Input image

Fast R-CNN


Bbox
Bbox
Bbox
Class
Class
Class
Category and box transform per region
Per-Region network is relatively lightweight
Regions of Interest (RoIs) from a proposal method
CNN
CNN
CNN
Per-Region Network
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

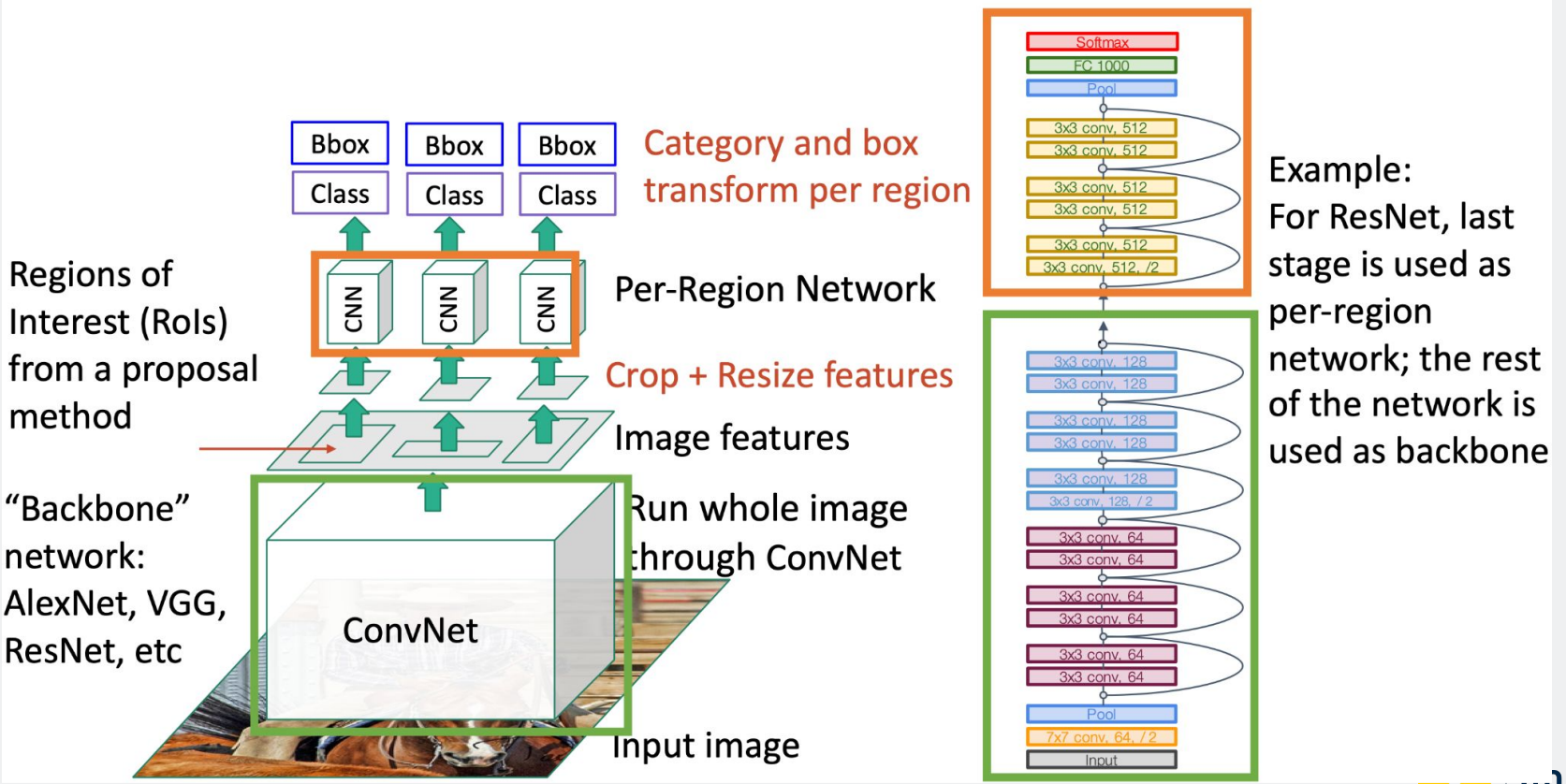
Fast R-CNN



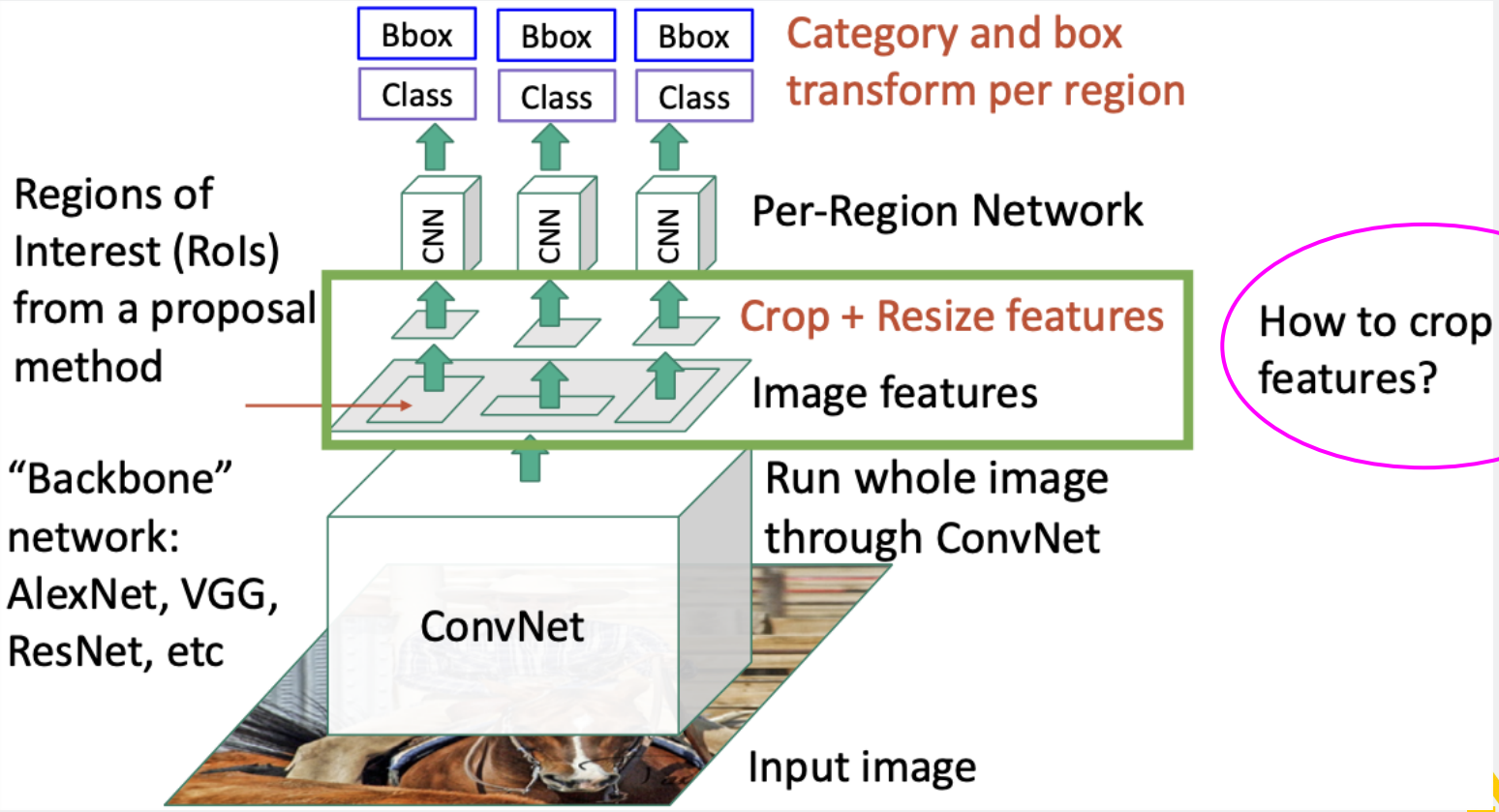


Example: When using AlexNet for detection, five conv layers are used for backbone and two FC layers are used for per-region network

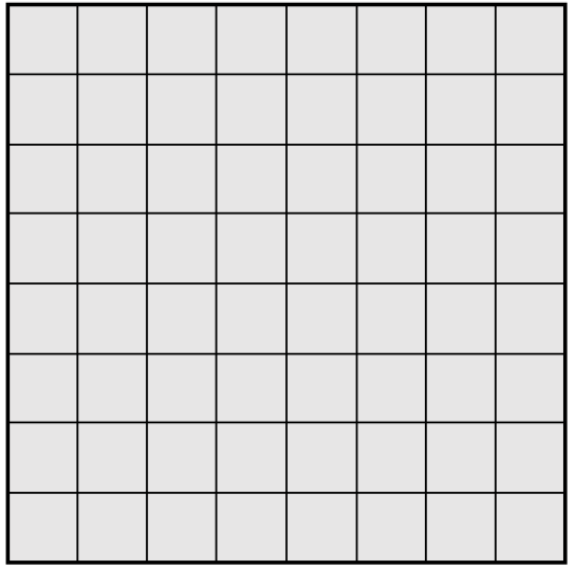
Fast R-CNN



Fast R-CNN



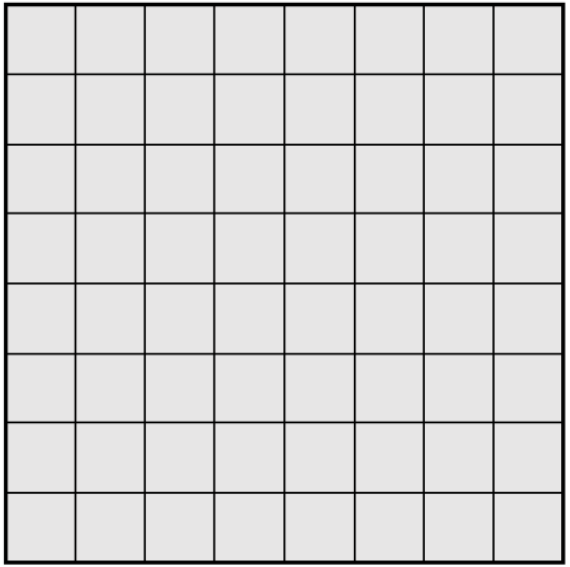
Recall: Receptive Fields



Input Image: 8 x 8

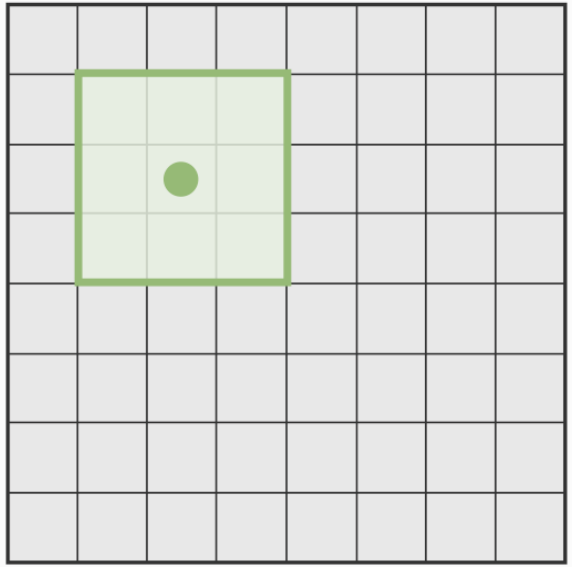
Every position in the output feature map depends on a ??? receptive field in the input

3x3 Conv
Stride 1, pad 1



Output Image: 8 x 8

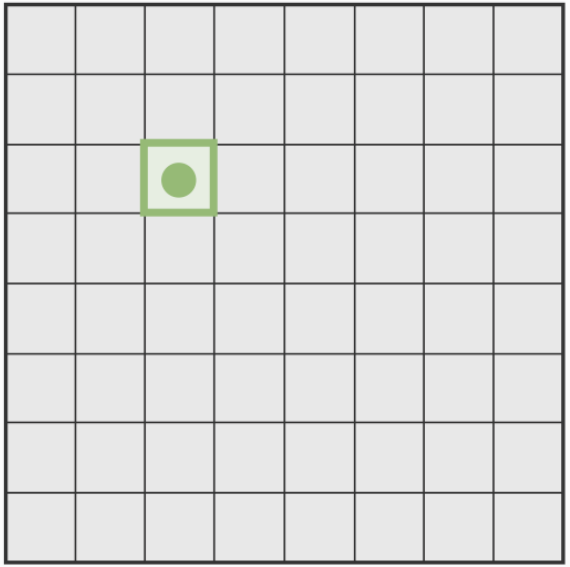
Recall: Receptive Fields



Input Image: 8 x 8

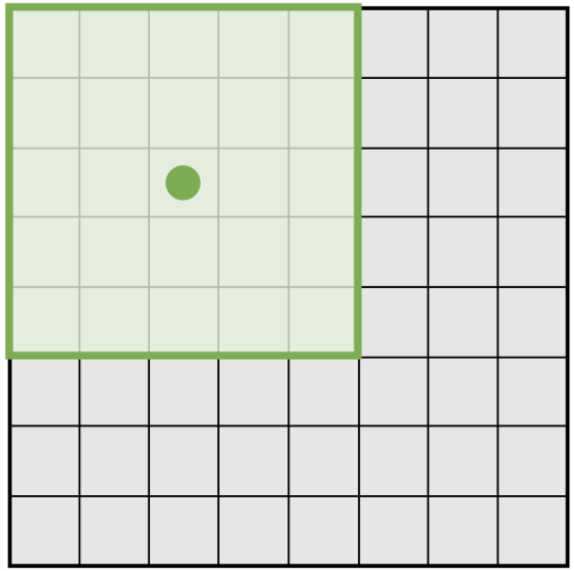
Every position in the output feature map depends on a 3x3 receptive field in the input

3x3 Conv
Stride 1, pad 1



Output Image: 8 x 8

Recall: Receptive Fields

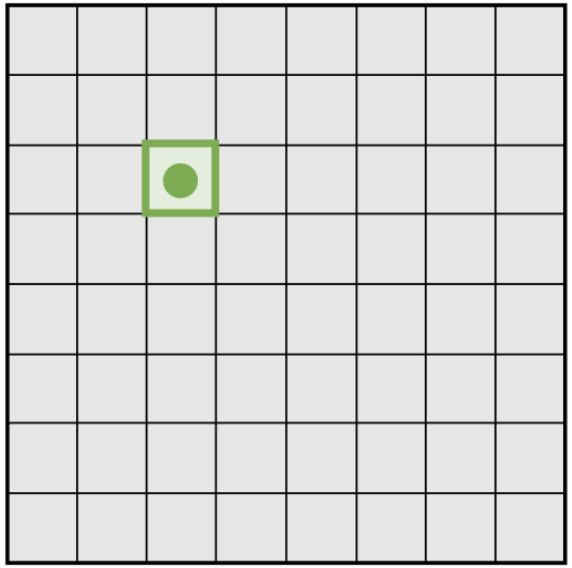


Input Image: 8 x 8

Every position in the output feature map depends on a 5x5 receptive field in the input

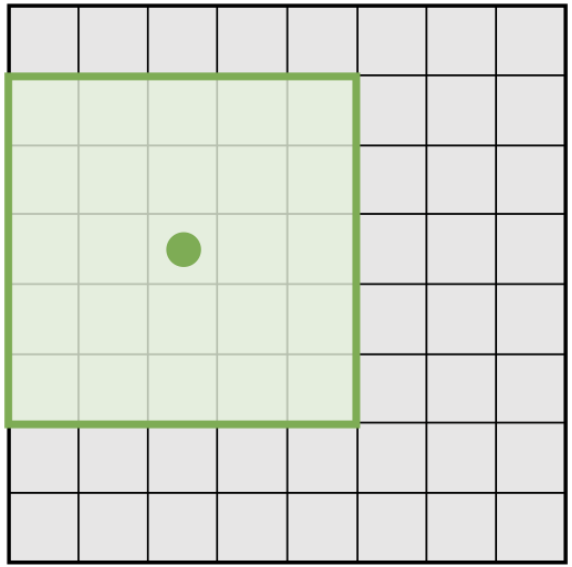
3x3 Conv
Stride 1, pad 1

3x3 Conv
Stride 1, pad 1



Output Image: 8 x 8

Recall: Receptive Fields

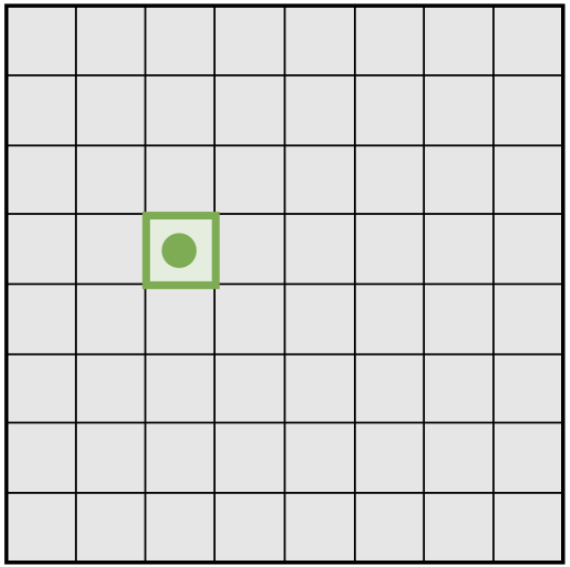


Input Image: 8 x 8

Moving one unit in the output space also moves the receptive field by one

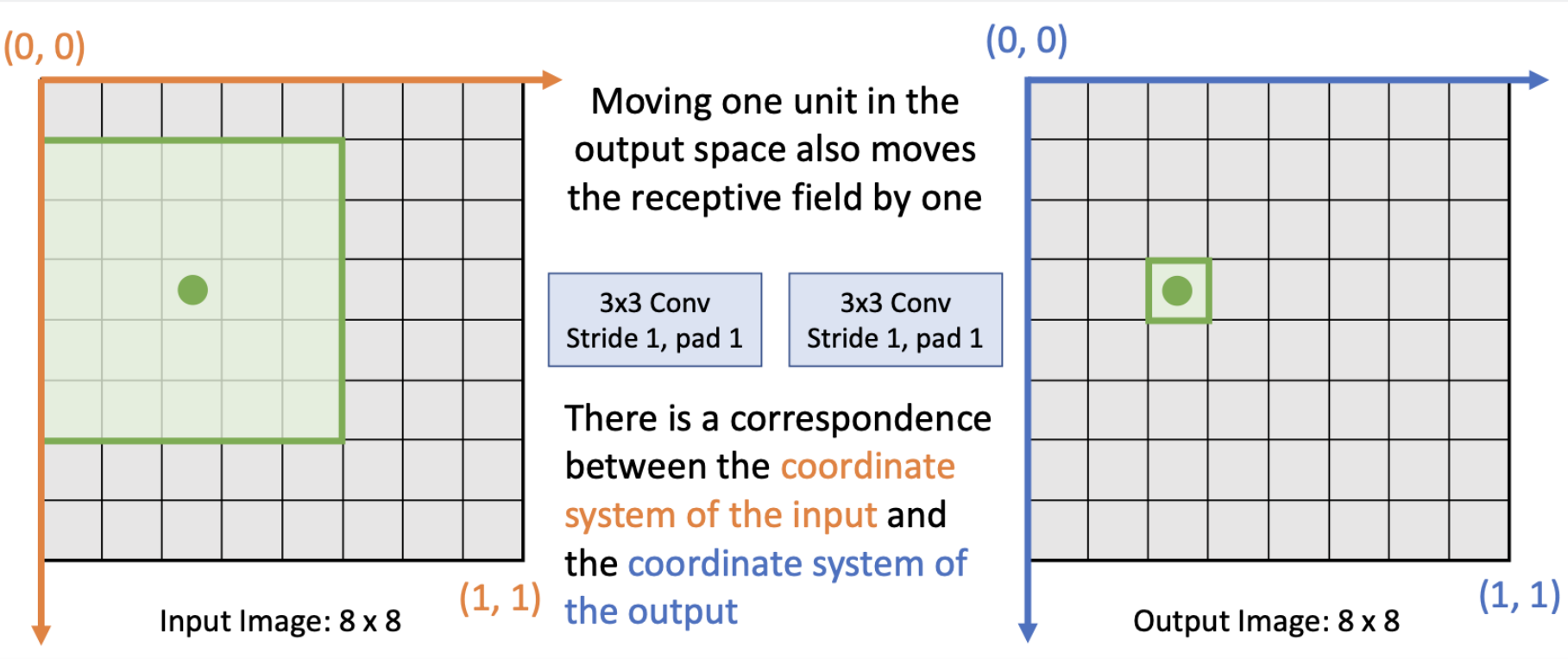
3x3 Conv
Stride 1, pad 1

3x3 Conv
Stride 1, pad 1



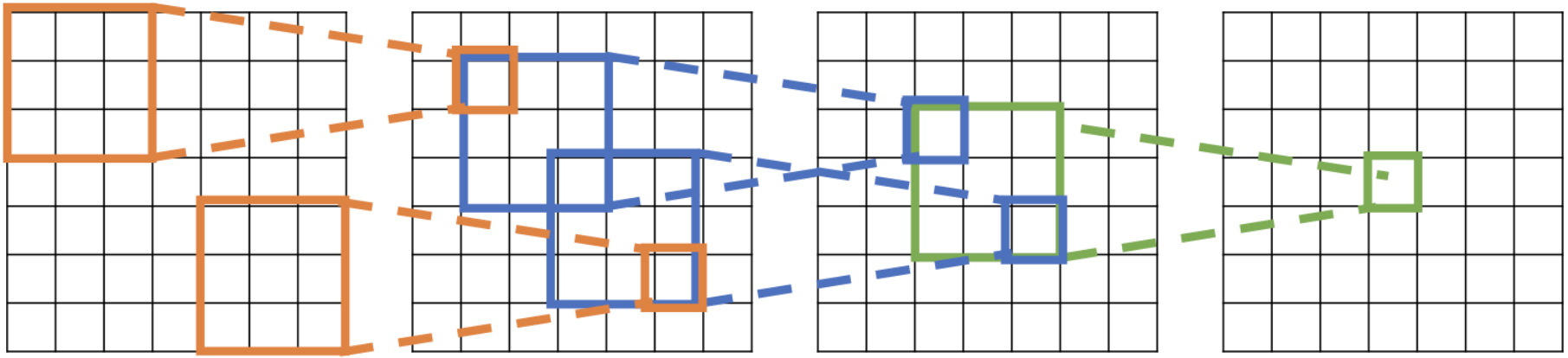
Output Image: 8 x 8

Recall: Receptive Fields



Recall: Receptive Fields

Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)



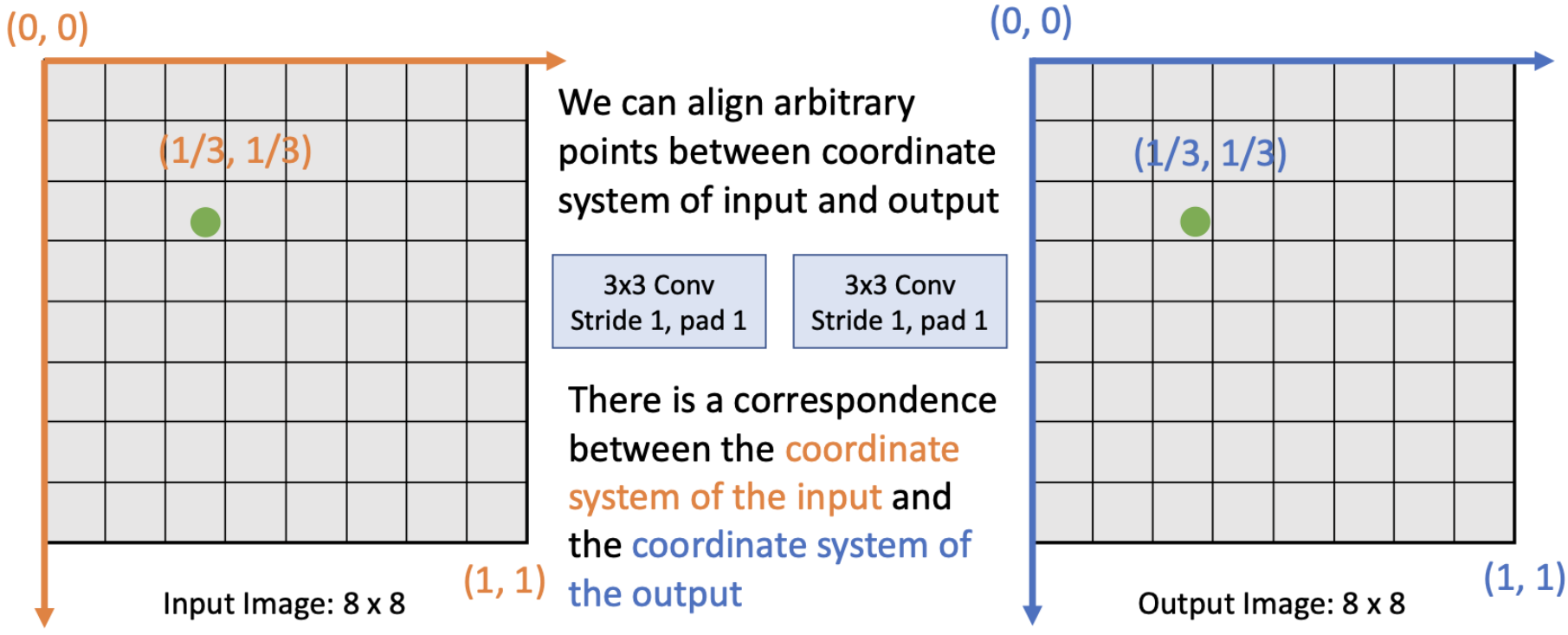
Input

Output

Problem: For large images we need many layers for each output to "see" the whole image image

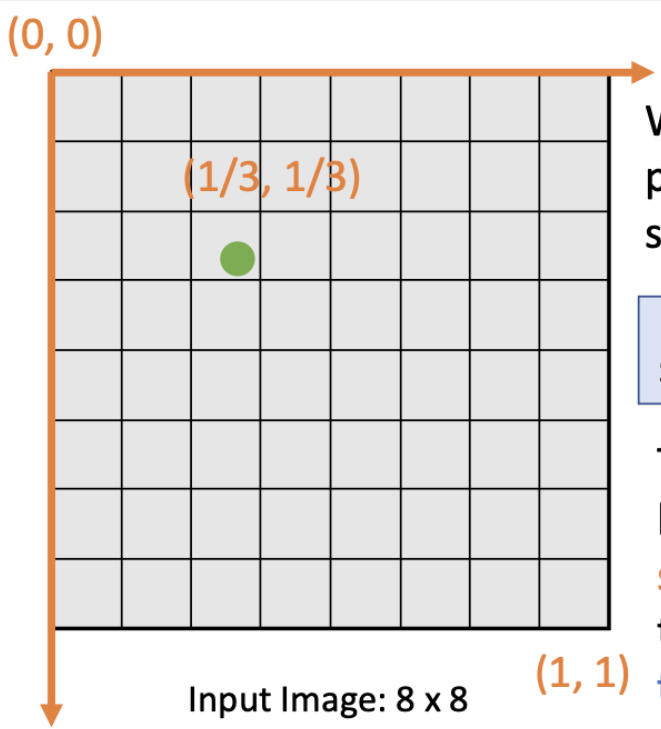
Solution: Downsample inside the network

Projecting Points



Projecting Points

Same logic holds for more complicated CNNs, even if spatial resolution of input and output are different

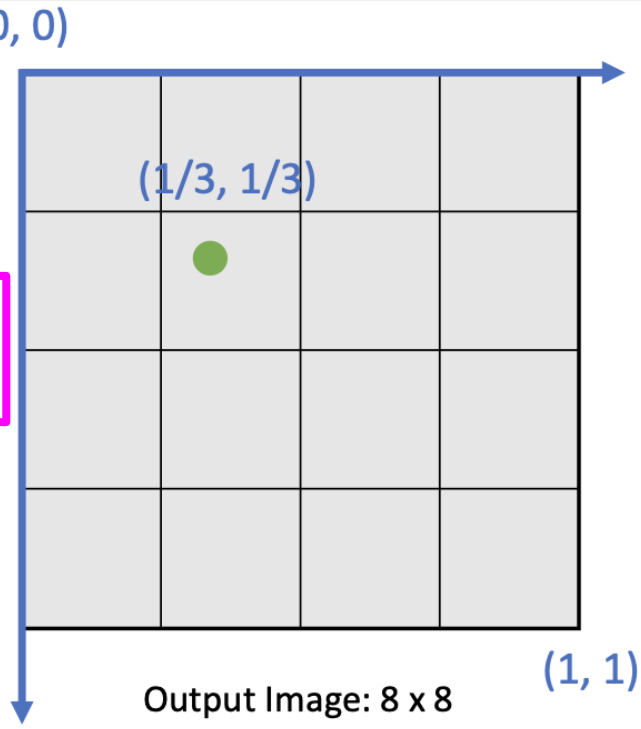


We can align arbitrary points between coordinate system of input and output

3x3 Conv
Stride 1, pad 1

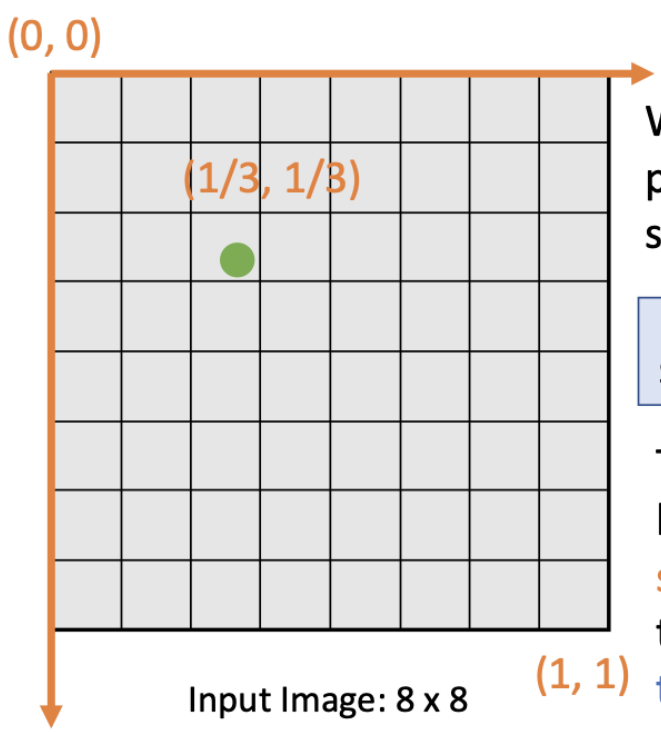
2x2 MaxPool
Stride 2

There is a correspondence between the coordinate system of the input and the coordinate system of the output



Projecting Points

Same logic holds for more complicated CNNs, even if spatial resolution of input and output are different

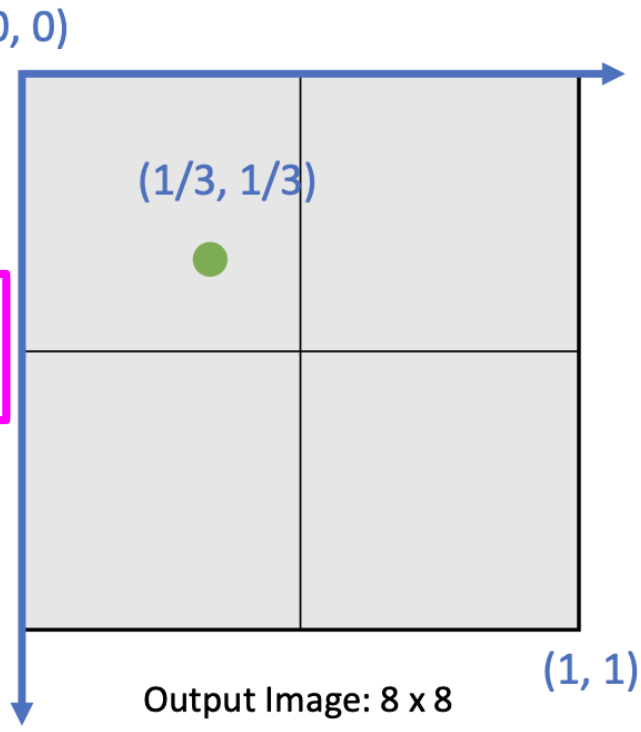


We can align arbitrary points between coordinate system of input and output

3x3 Conv
Stride 1, pad 1

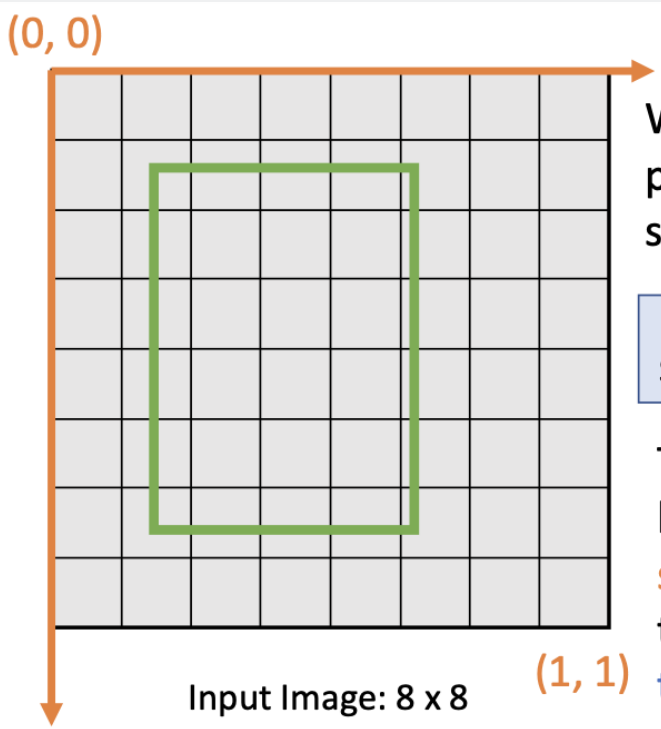
4x4 MaxPool
Stride 4

There is a correspondence between the coordinate system of the input and the coordinate system of the output



Projecting Points

We can use this idea to project **bounding boxes** between an input image and a feature map

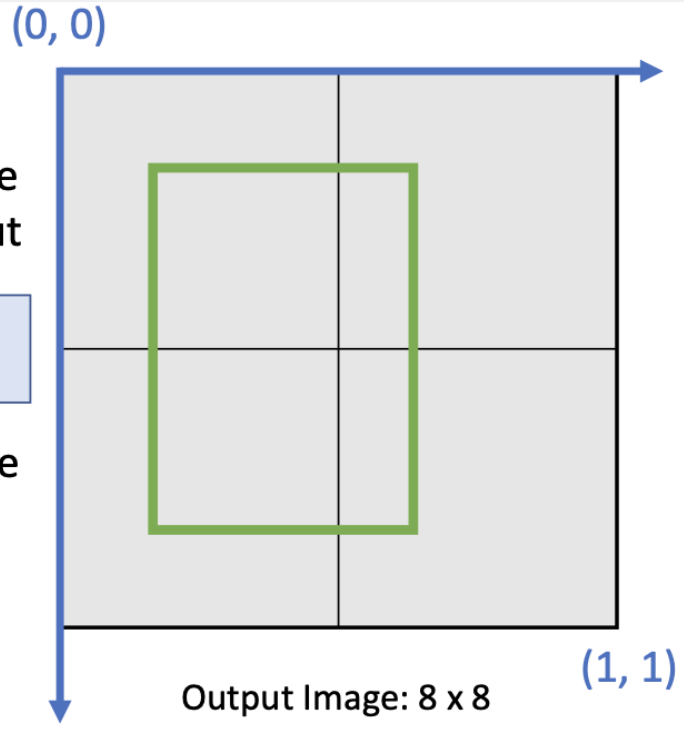


We can align arbitrary points between coordinate system of input and output

3x3 Conv
Stride 1, pad 1

4x4 MaxPool
Stride 4

There is a correspondence between the coordinate system of the input and the coordinate system of the output



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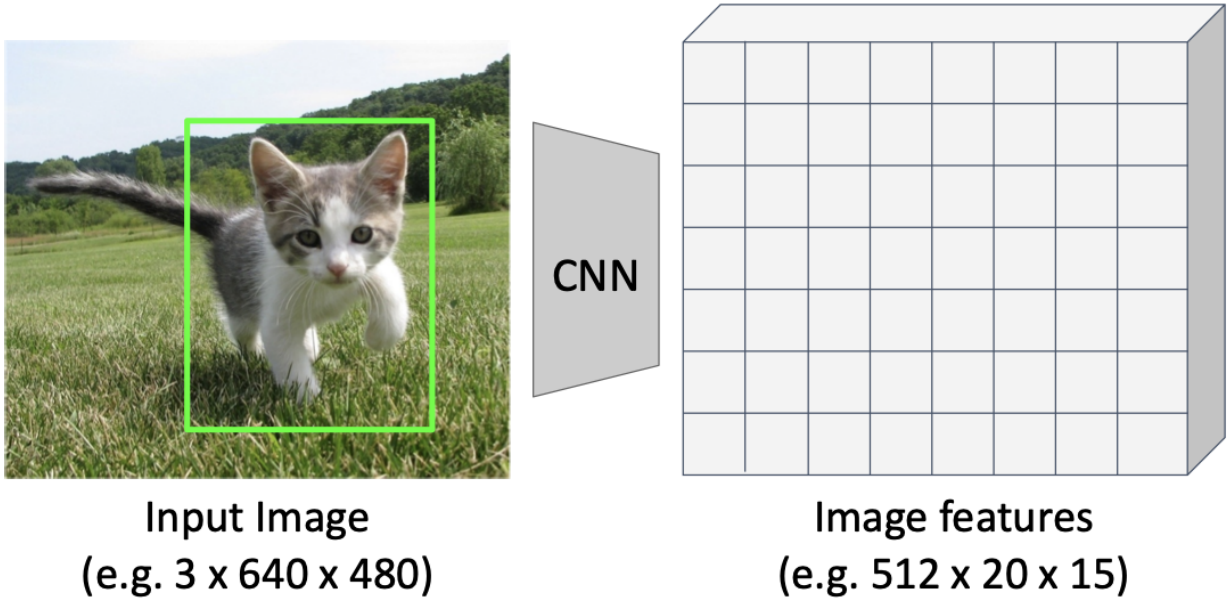
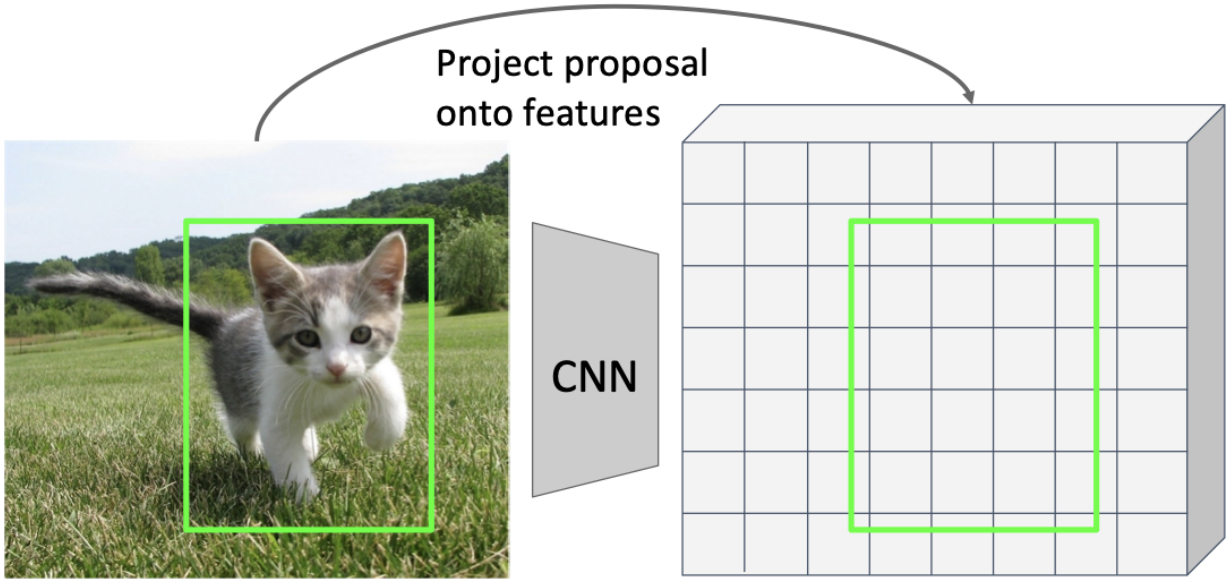
Cropping Features: RoI Pool



Want features for the box of a fixed size (2x2 in this example, 7x7 or 14x14 in practice)

Girshick, “Fast R-CNN”, ICCV 2015.
https://openaccess.thecvf.com/content_iccv_2015/papers/Girshick_Fast_R-CNN_ICCV_2015_paper.pdf

Cropping Features: RoI Pool



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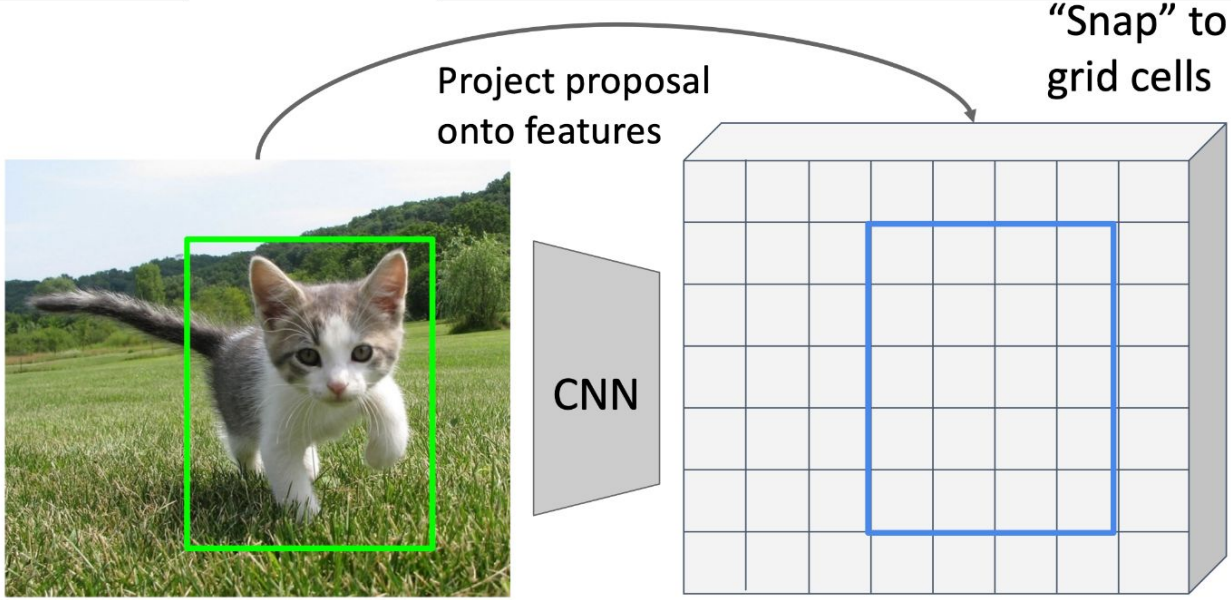
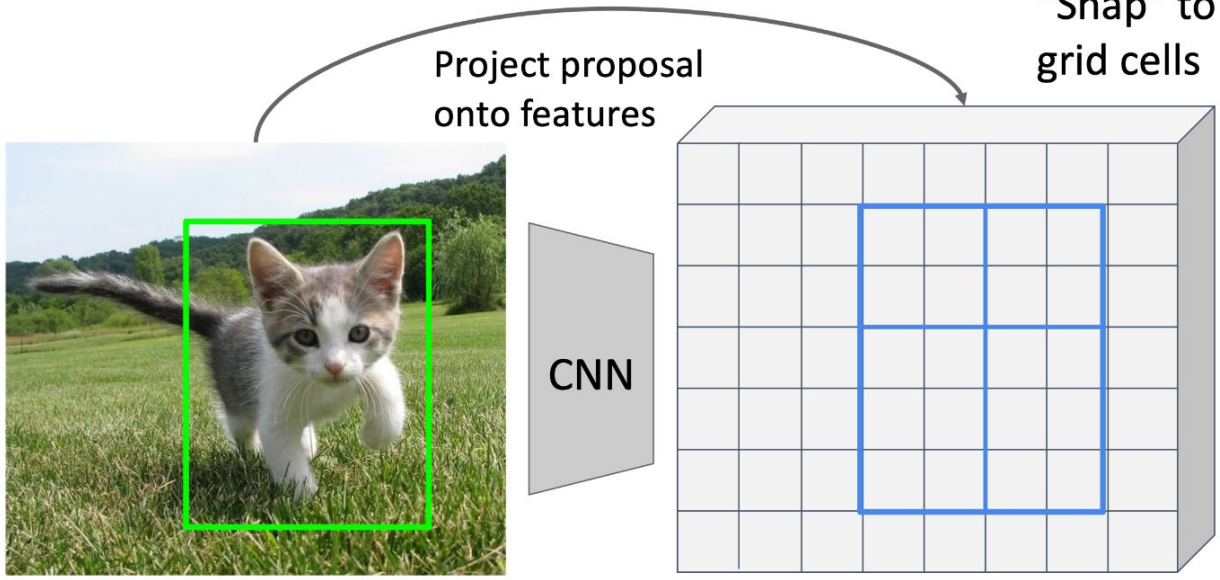
Cropping Features: RoI Pool



Want features for the box of a fixed size (2x2 in this example, 7x7 or 14x14 in practice)

Cropping Features: RoI Pool



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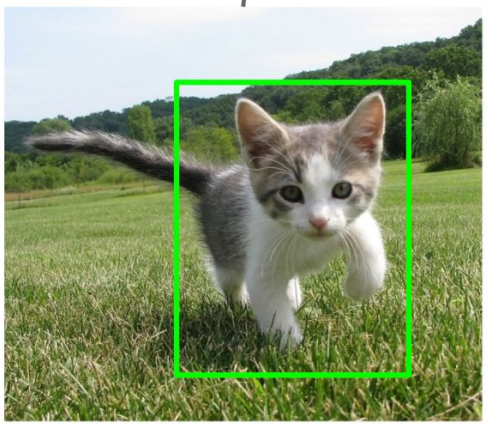
Cropping Features: RoI Pool



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

Project proposal onto features

CNN

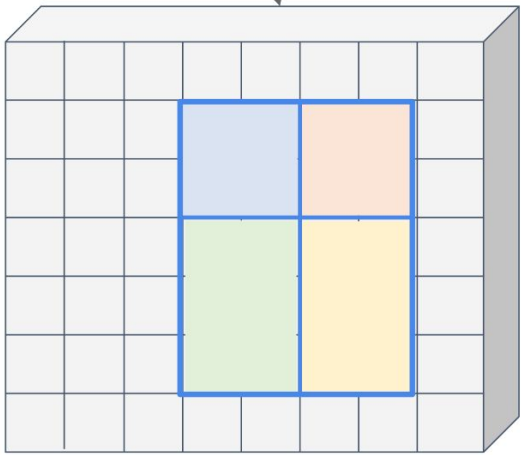
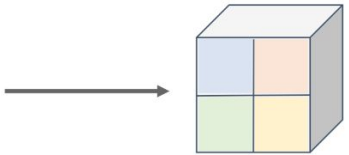


Image features
(e.g. 512 x 20 x 15)

"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion

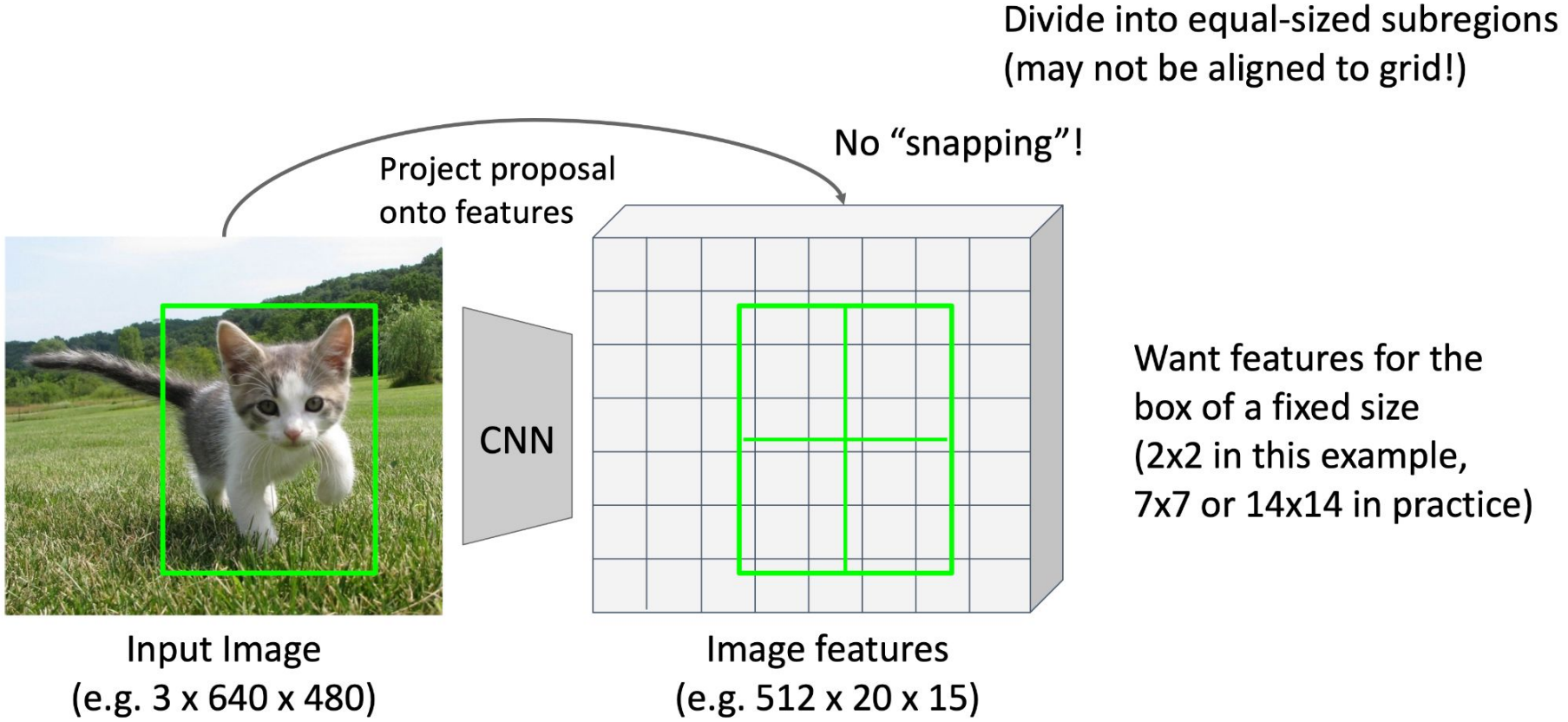


Region features
(here 512 x 2 x 2;
In practice 512x7x7)

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

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

Cropping Features: RoI Align

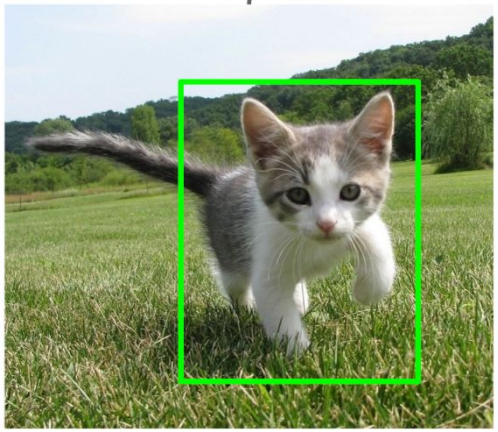


Cropping Features: RoI Align

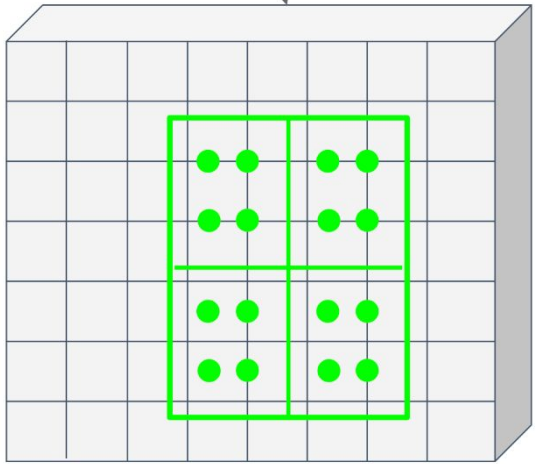
Divide into equal-sized subregions
(may not be aligned to grid!)

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)

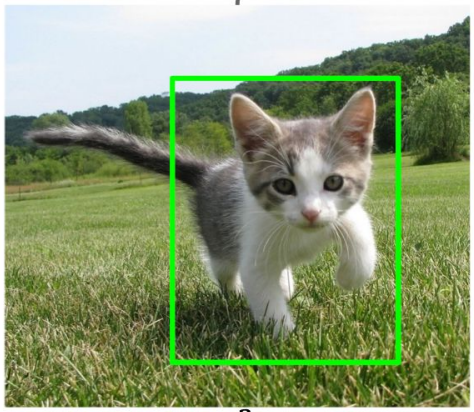
Image features
(e.g. 512 x 20 x 15)

Cropping Features: RoI Align

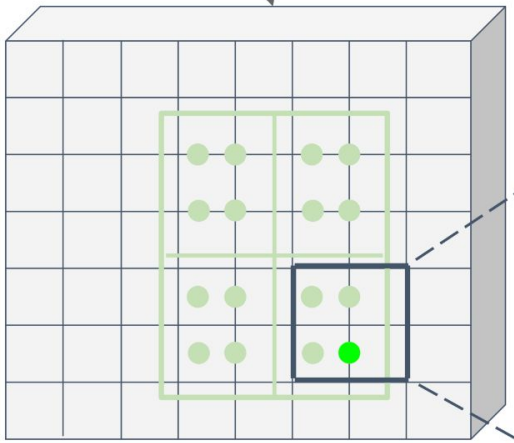
Divide into equal-sized subregions
(may not be aligned to grid!)

No “snapping”!

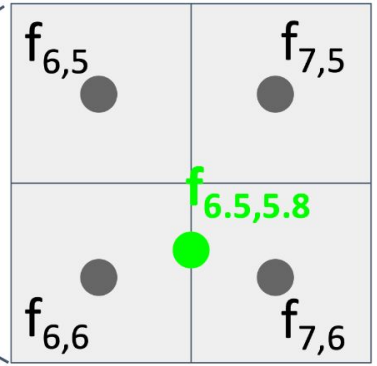
Project proposal
onto features



CNN



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



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

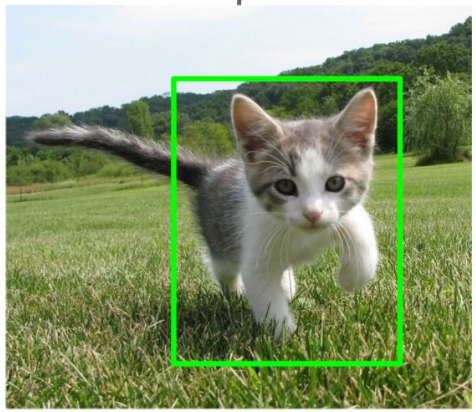
Feature f_{xy} for point (x, y) is a
linear combination of features
at its four neighboring grid cells:

Cropping Features: RoI Align

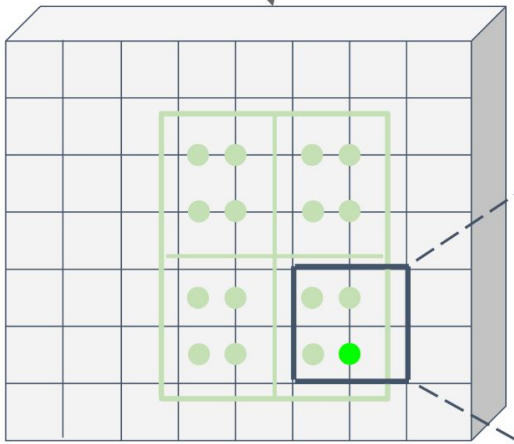
Divide into equal-sized subregions
(may not be aligned to grid!)

No “snapping”!

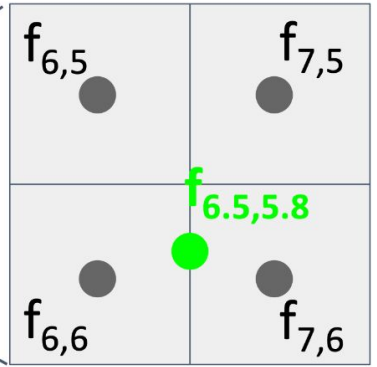
Project proposal
onto features



CNN



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

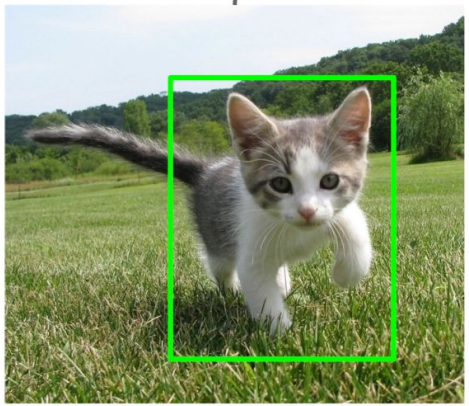


$$f_{xy} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_i|)$$

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

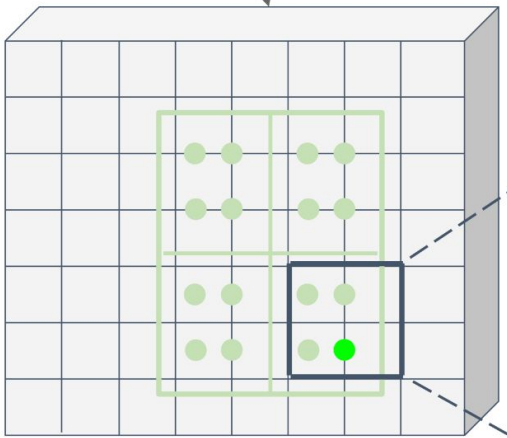
Feature f_{xy} for point (x, y) is a
linear combination of features
at its four neighboring grid cells:

Cropping Features: RoI Align



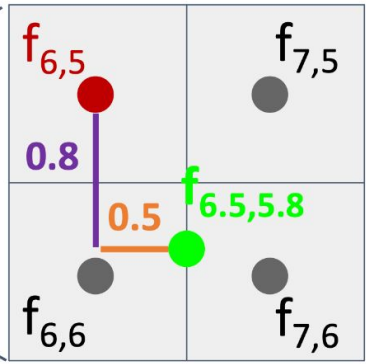
Project proposal onto features

CNN



No “snapping”!

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



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

$f_{6.5,5.8}$ = ($f_{6,5}$ * **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:

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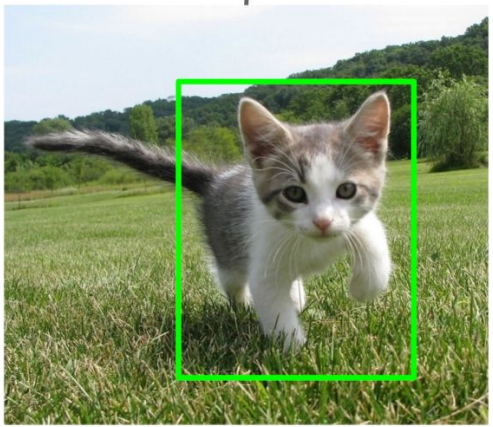
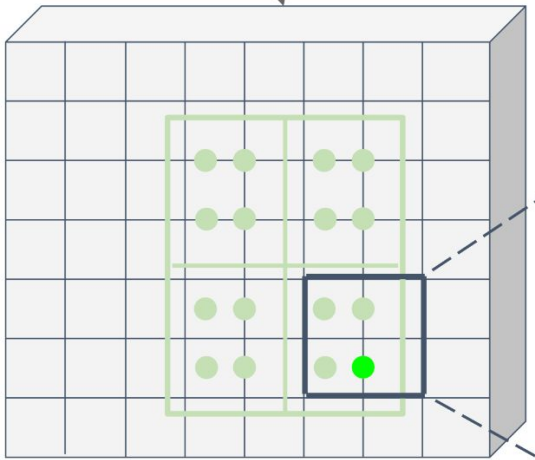
Cropping Features: RoI Align



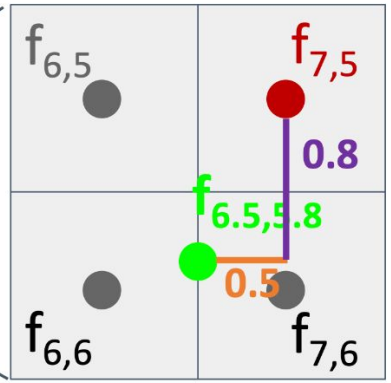
Project proposal onto features

CNN



No “snapping”!

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



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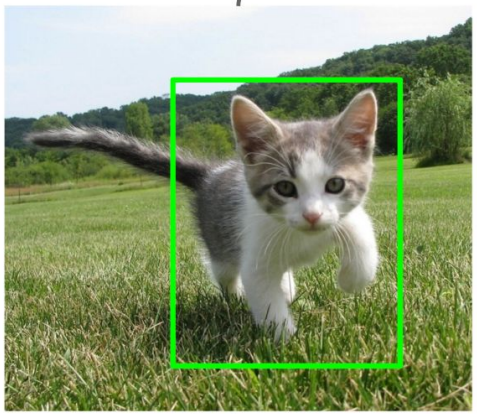
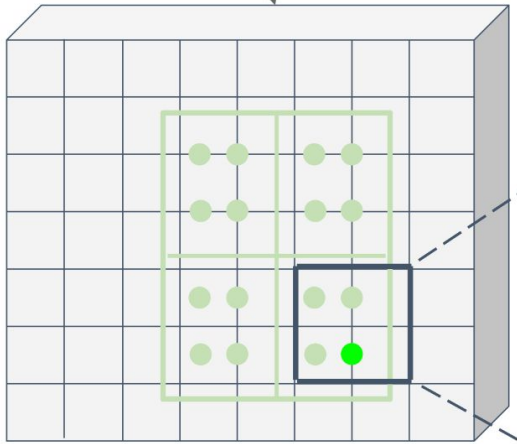
Cropping Features: RoI Align



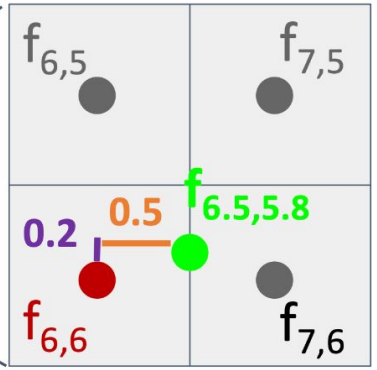
Project proposal onto features

No “snapping”!

CNN



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



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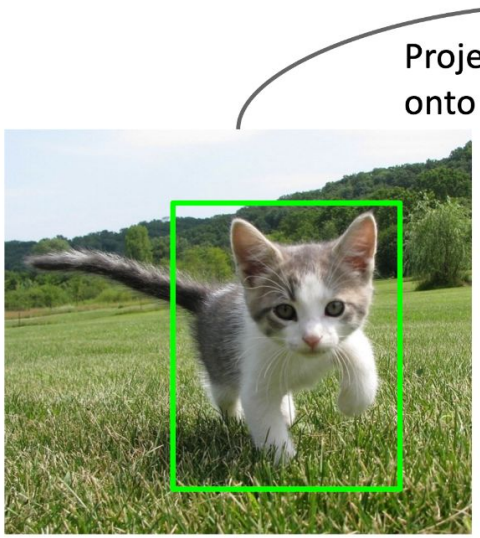
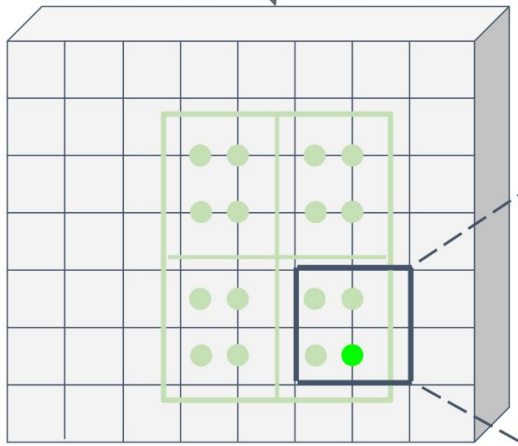


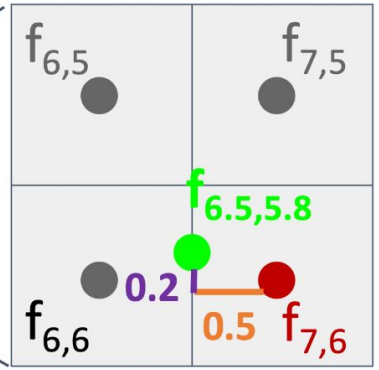
Project proposal onto features

No “snapping”!

CNN



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



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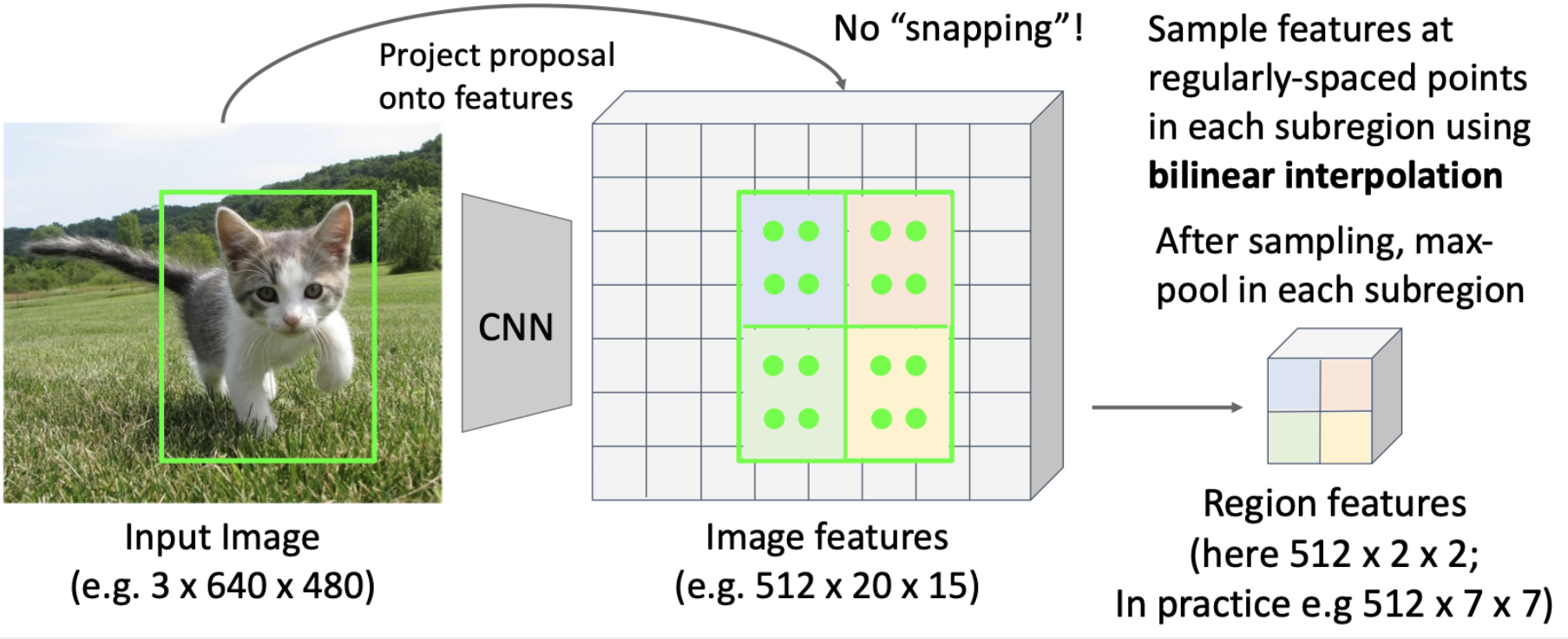
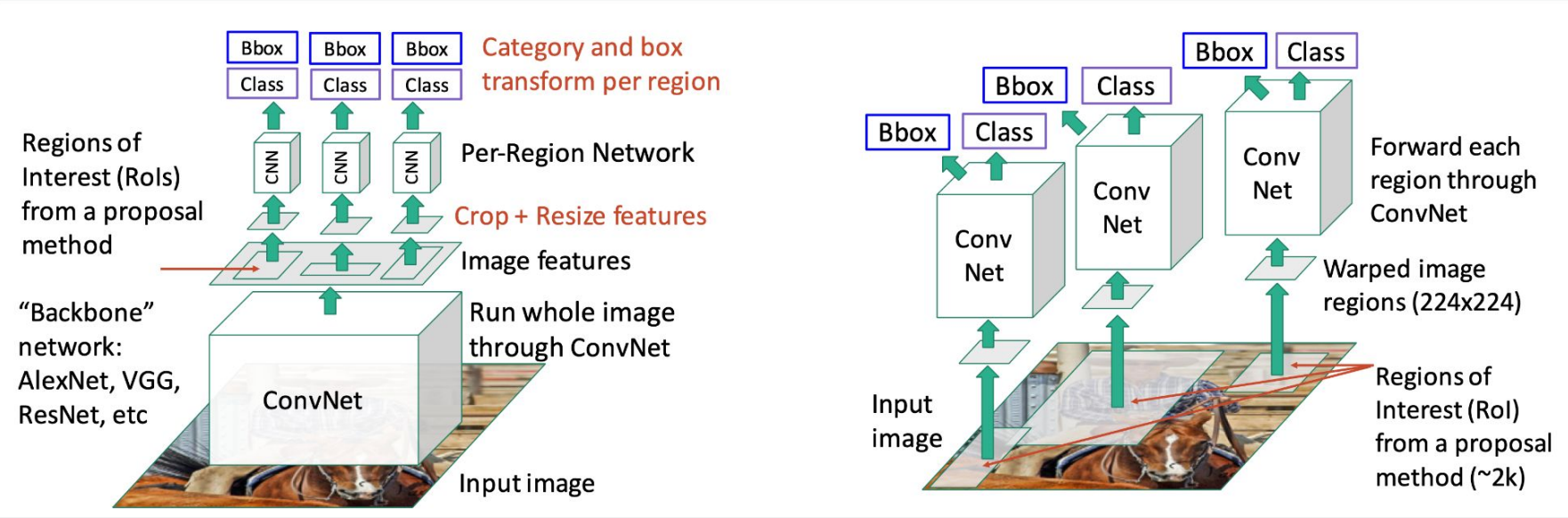
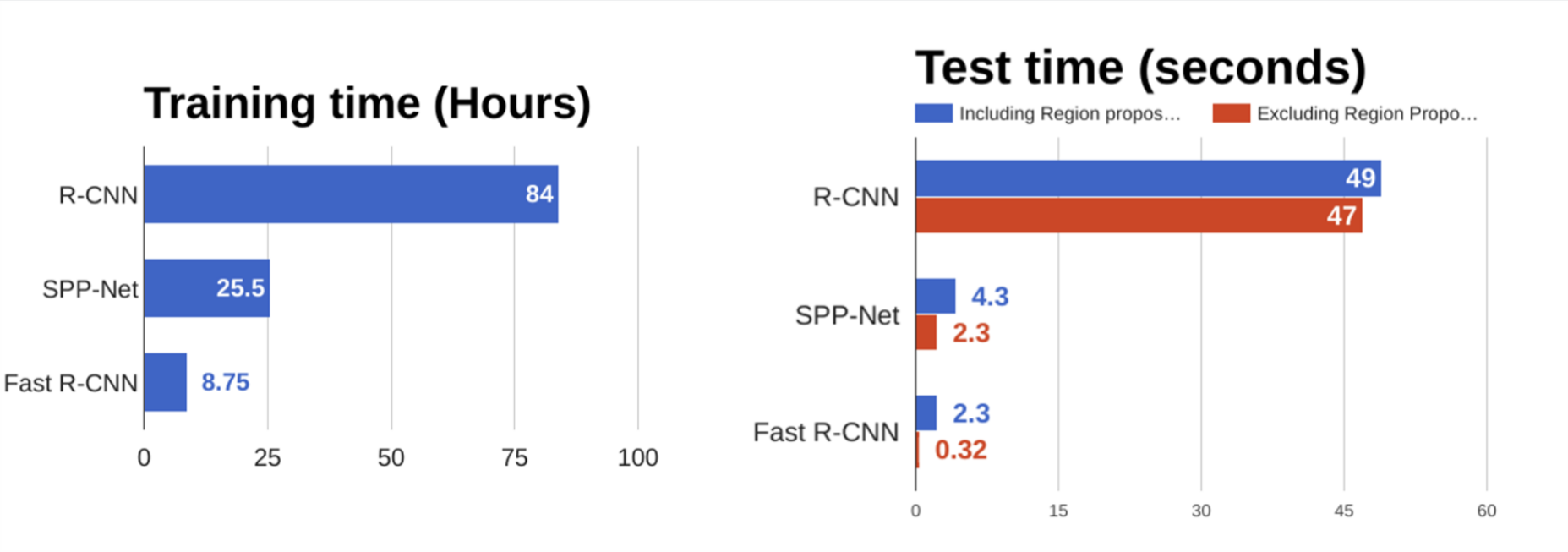


Fast R-CNN vs “Slow” R-CNN

Fast 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

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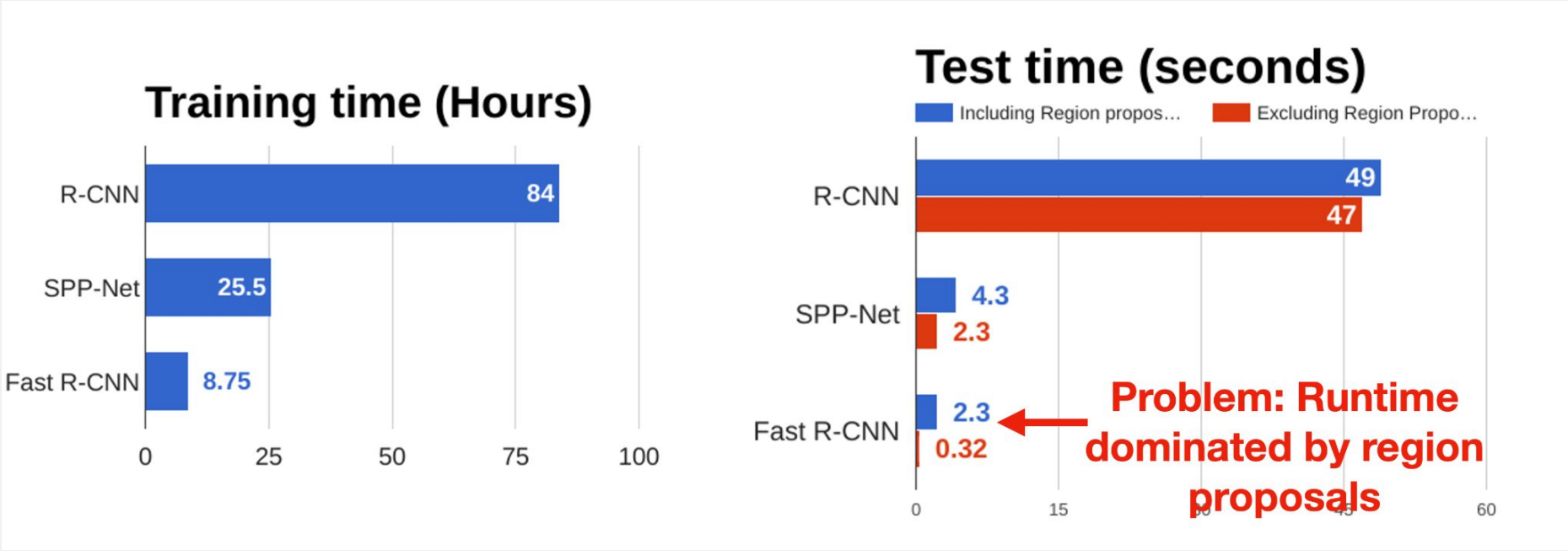
Fast R-CNN vs “Slow” R-CNN



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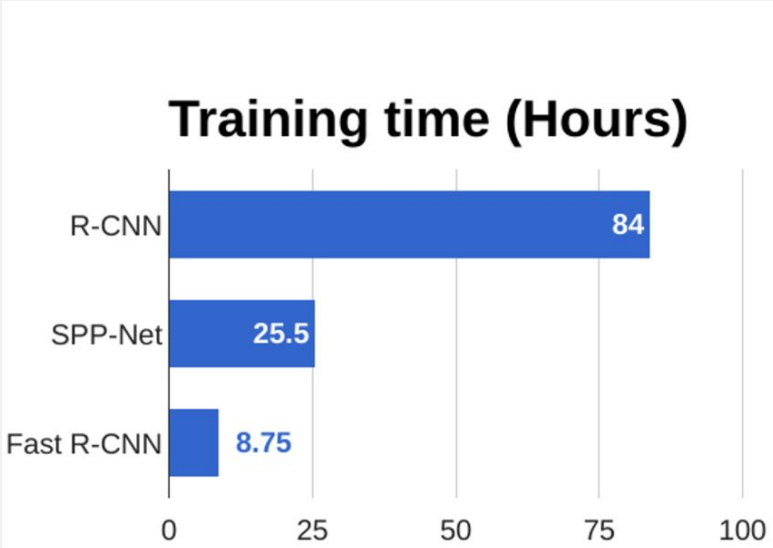
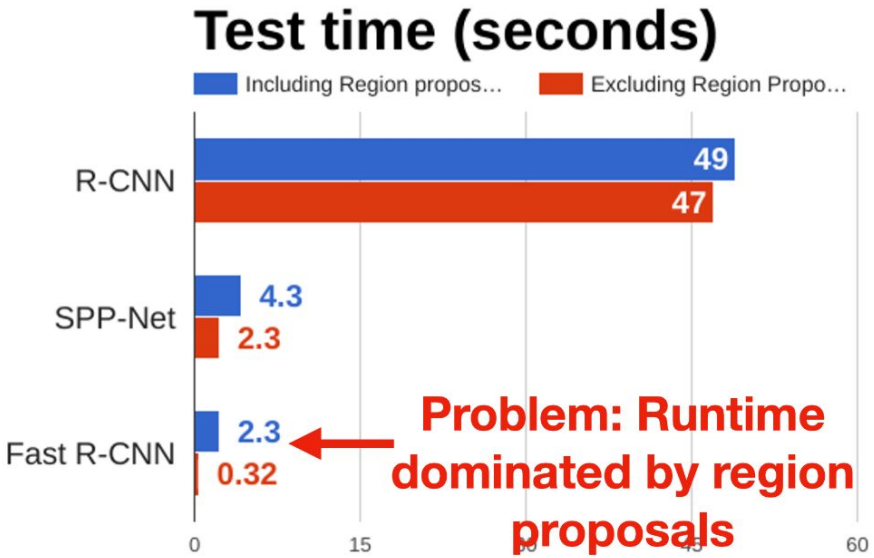
Fast R-CNN vs “Slow” R-CNN





Recall: Region proposals computed by heuristic “Selective search” algorithm on CPU — let’s learn them with a CNN

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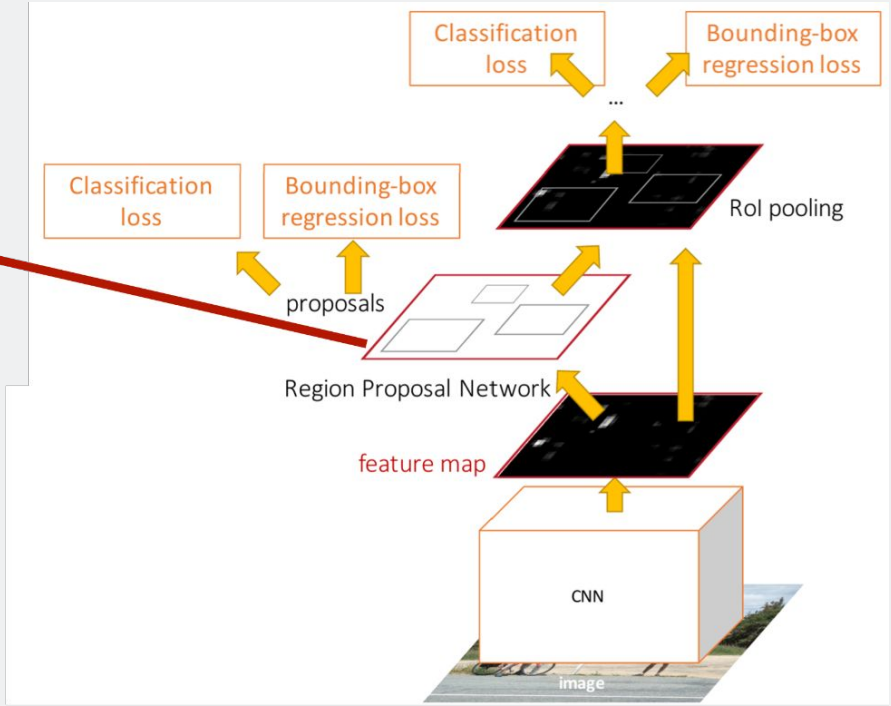
Faster R-CNN: Learnable Region Proposals

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

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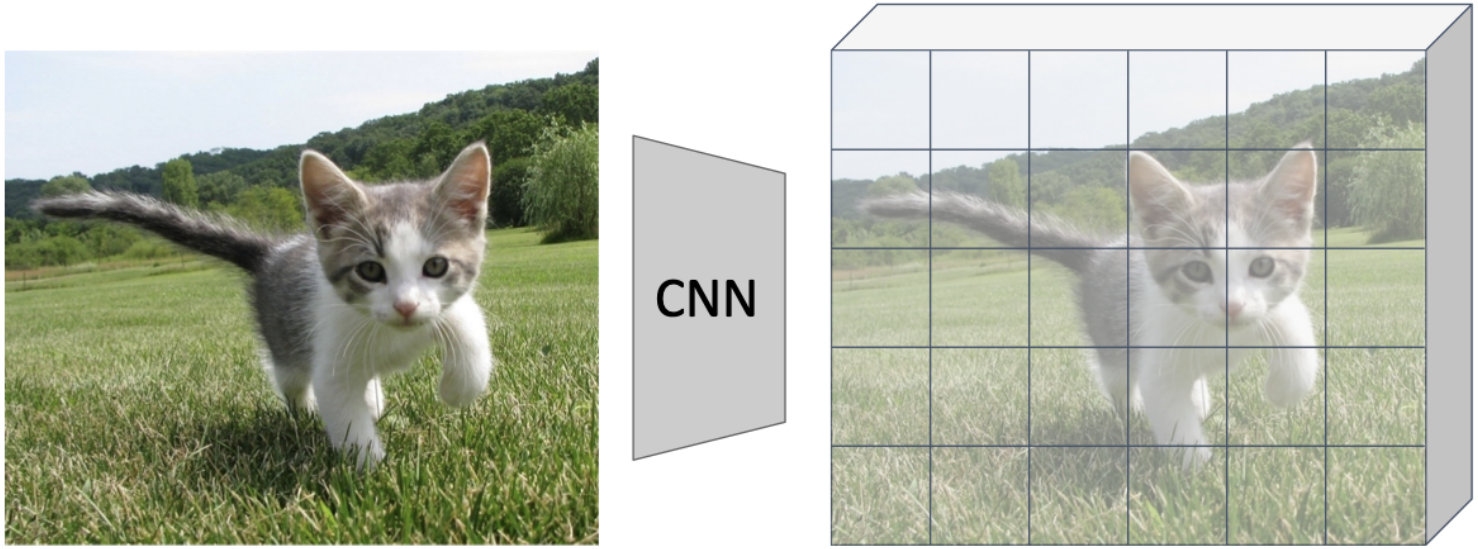
Region Proposal Network (RPN)

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 5 x 6)

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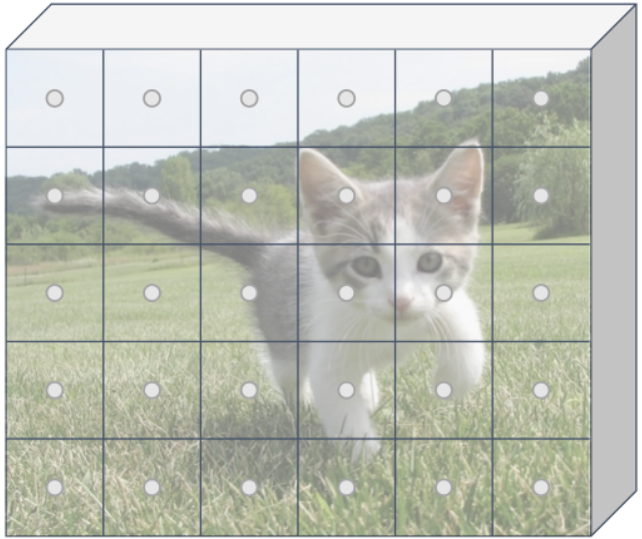
Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input

CNN



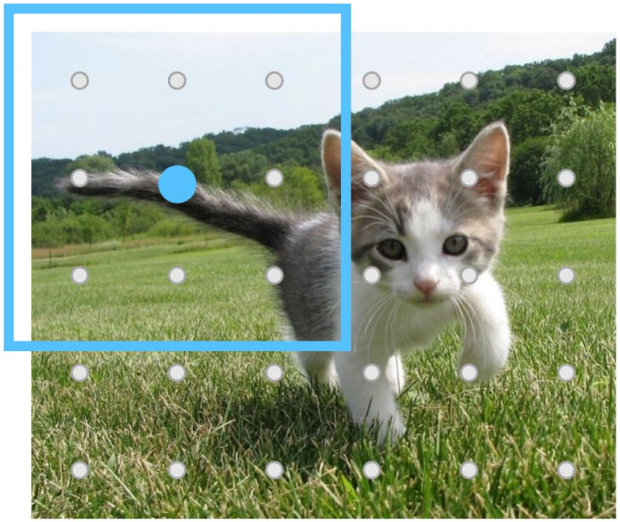
Input Image
(e.g. 3 x 640 x 480)

Image features
(e.g. 512 x 5 x 6)

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

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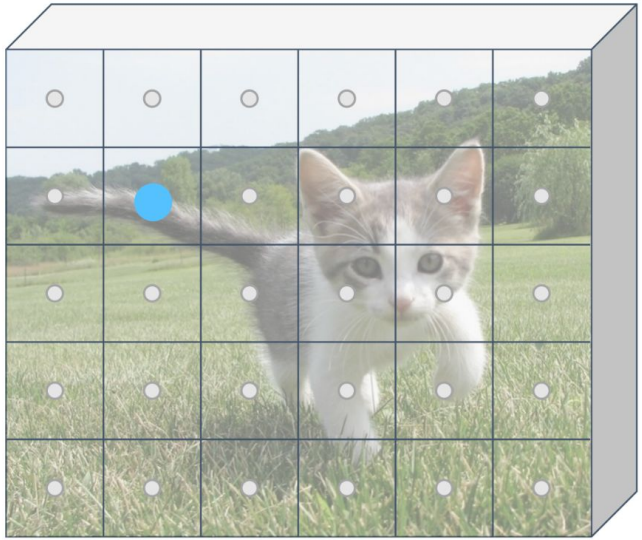

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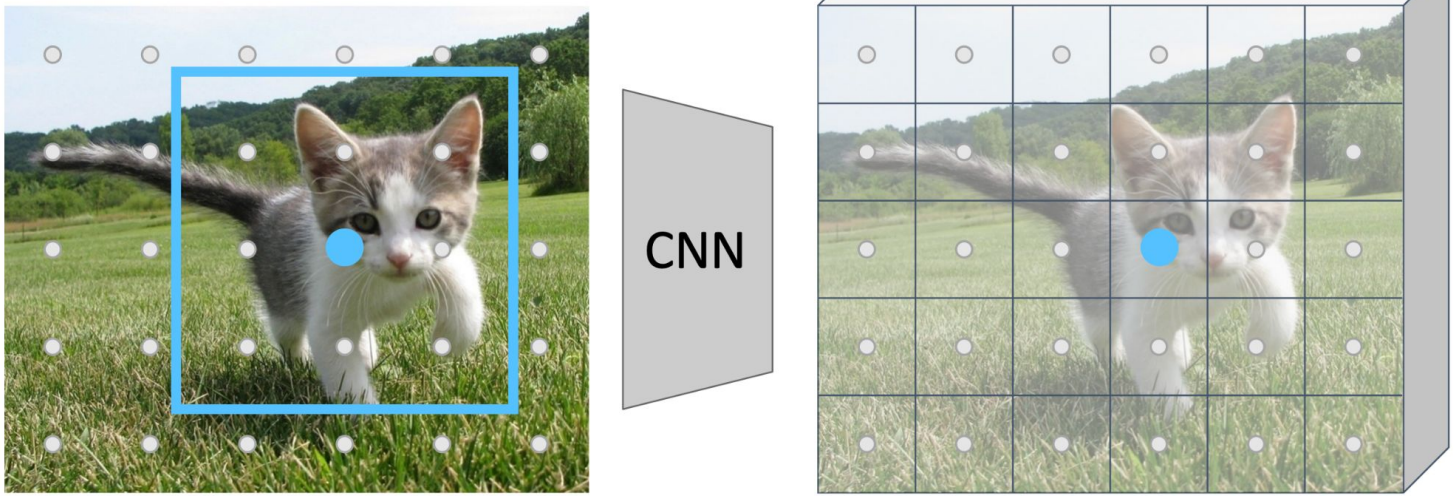

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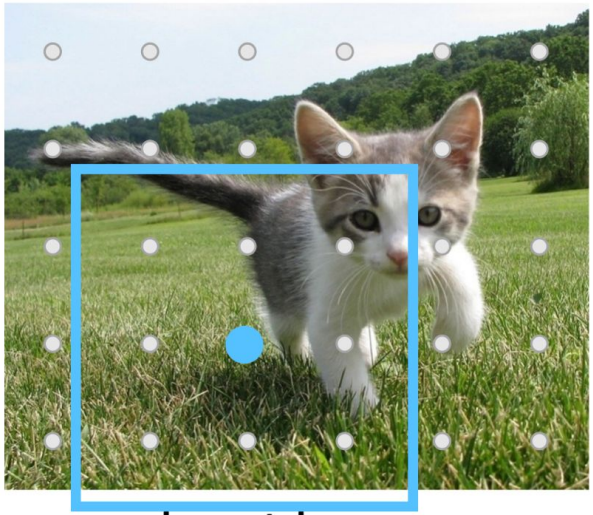

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CNN

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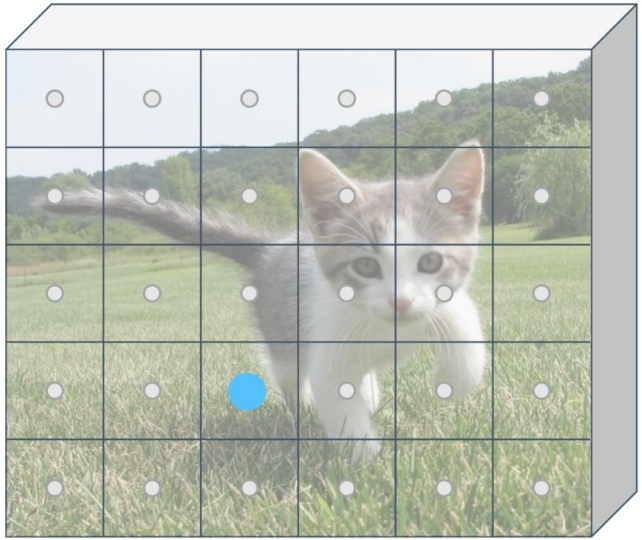

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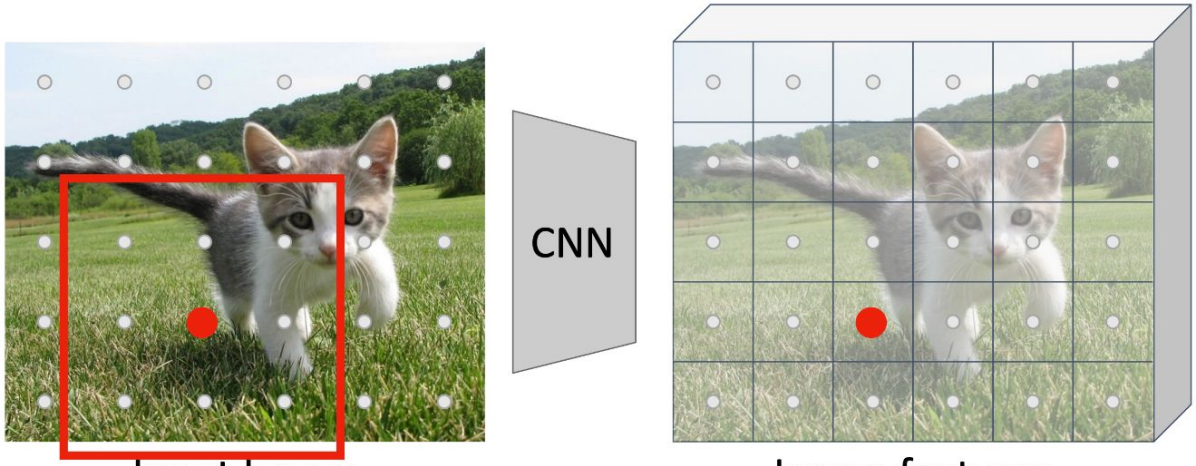


Input Image
(e.g. 3 x 640 x 480)

Image features
(e.g. 512 x 5 x 6)

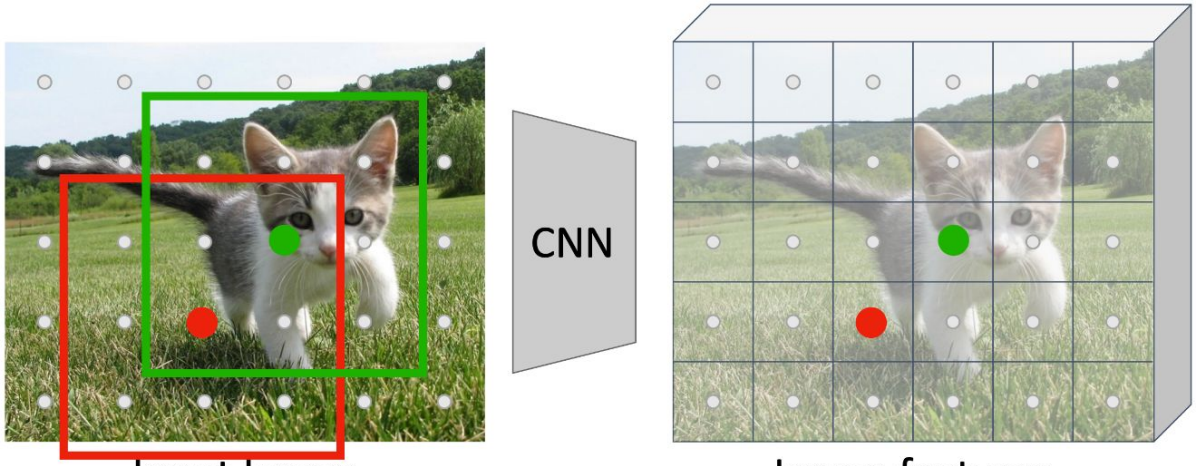
Classify each anchor as positive (object) or negative (no object)

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

Each feature corresponds to a point in the input



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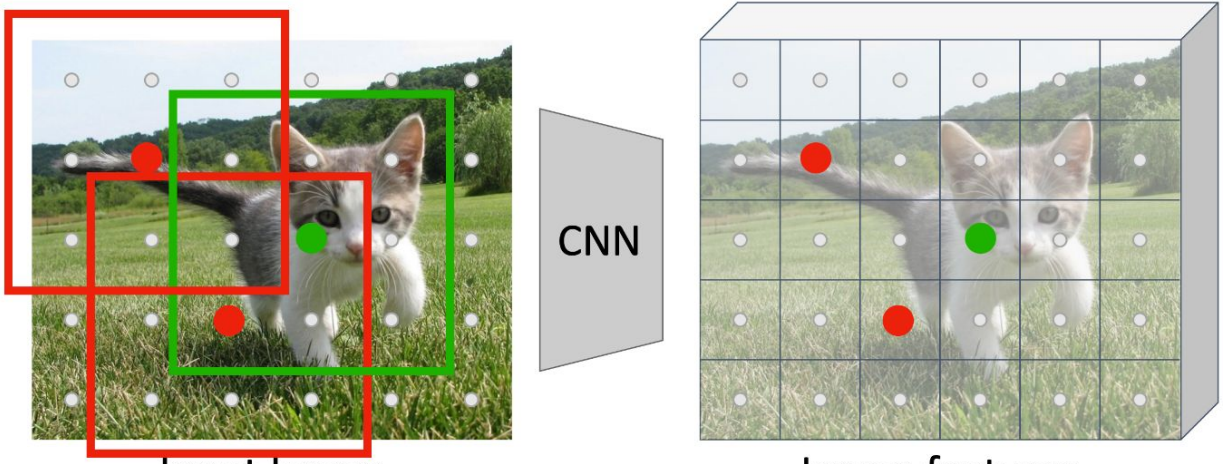

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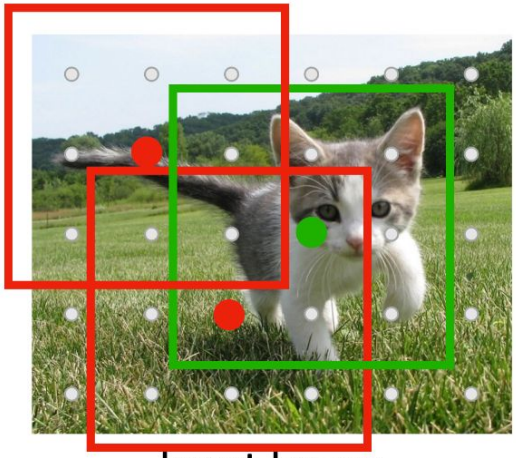


Input Image
(e.g. 3 x 640 x 480)

CNN

Each feature corresponds to a point in the input

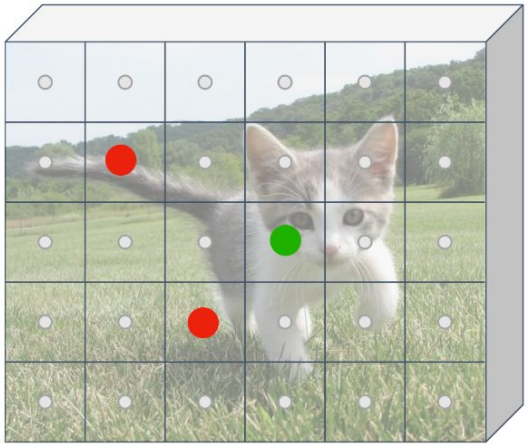
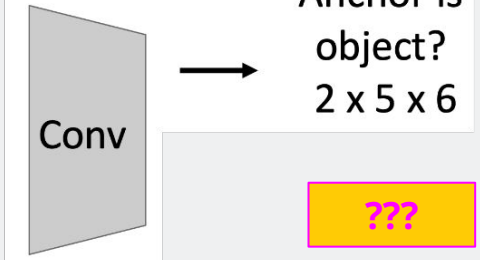


Image features
(e.g. 512 x 5 x 6)

Predict object vs not object scores for all anchors with a conv layer (512 input filters, 2 output filters)



Classify each anchor as positive (object) or negative (no object)

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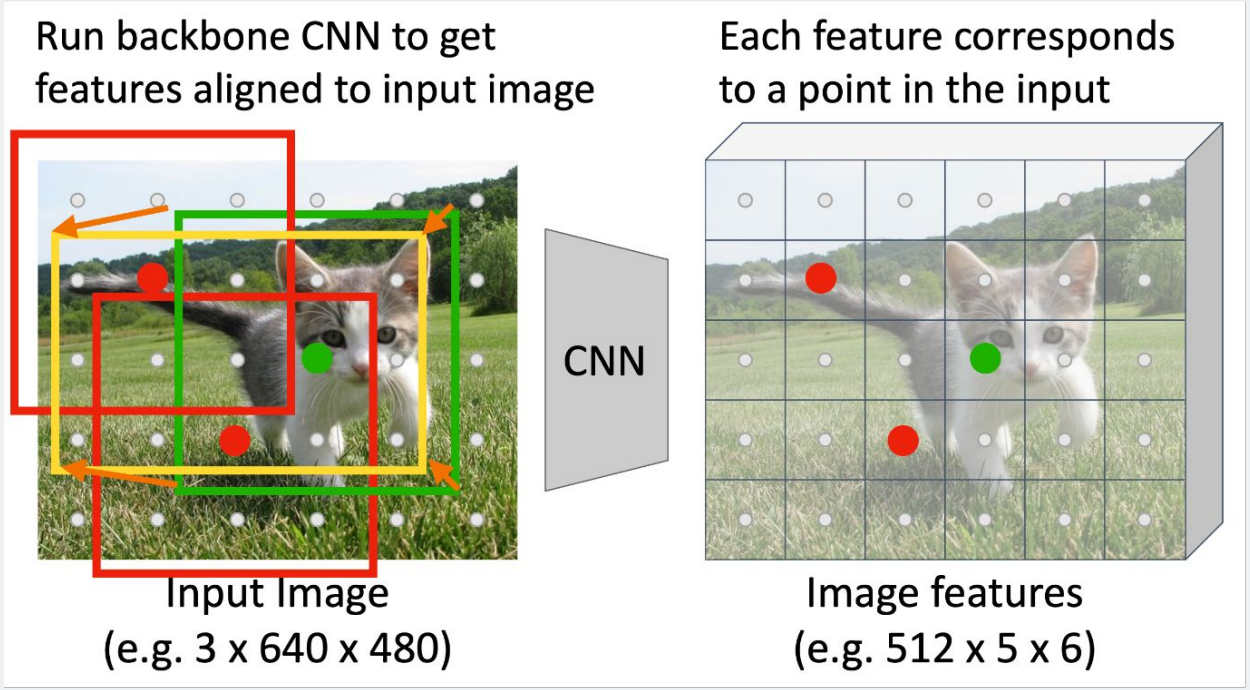
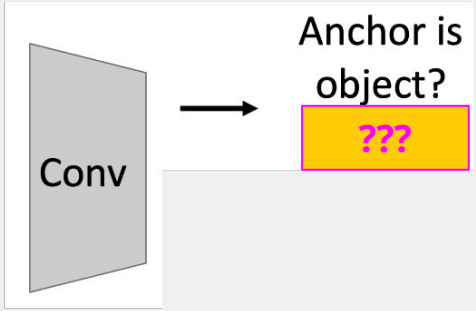
Region Proposal Network (RPN)



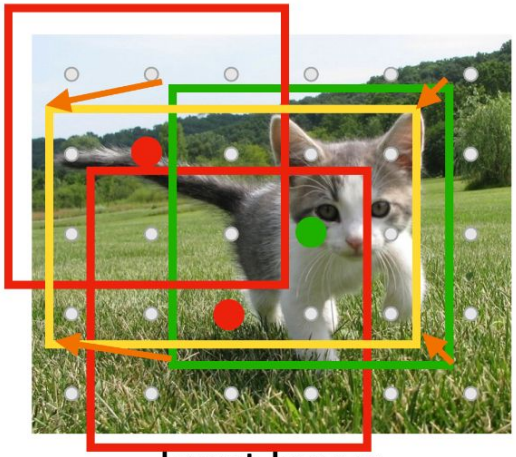
For positive anchors, also predict a transform that converting the anchor to the GT box (like R-CNN)



Classify each anchor as positive (object) or negative (no object)

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image



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

CNN

Each feature corresponds to a point in the input

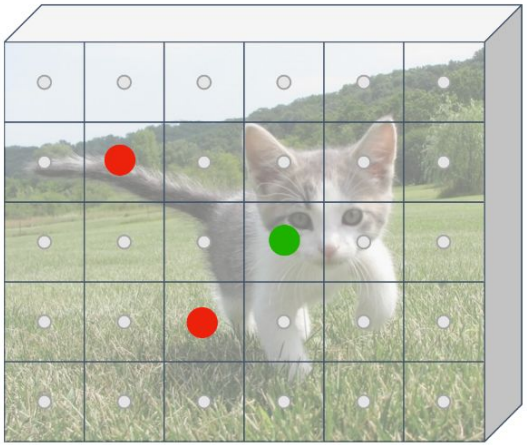


Image features
(e.g. 512 x 5 x 6)

For positive anchors, also predict a transform that converting the anchor to the GT box (like R-CNN)

Conv

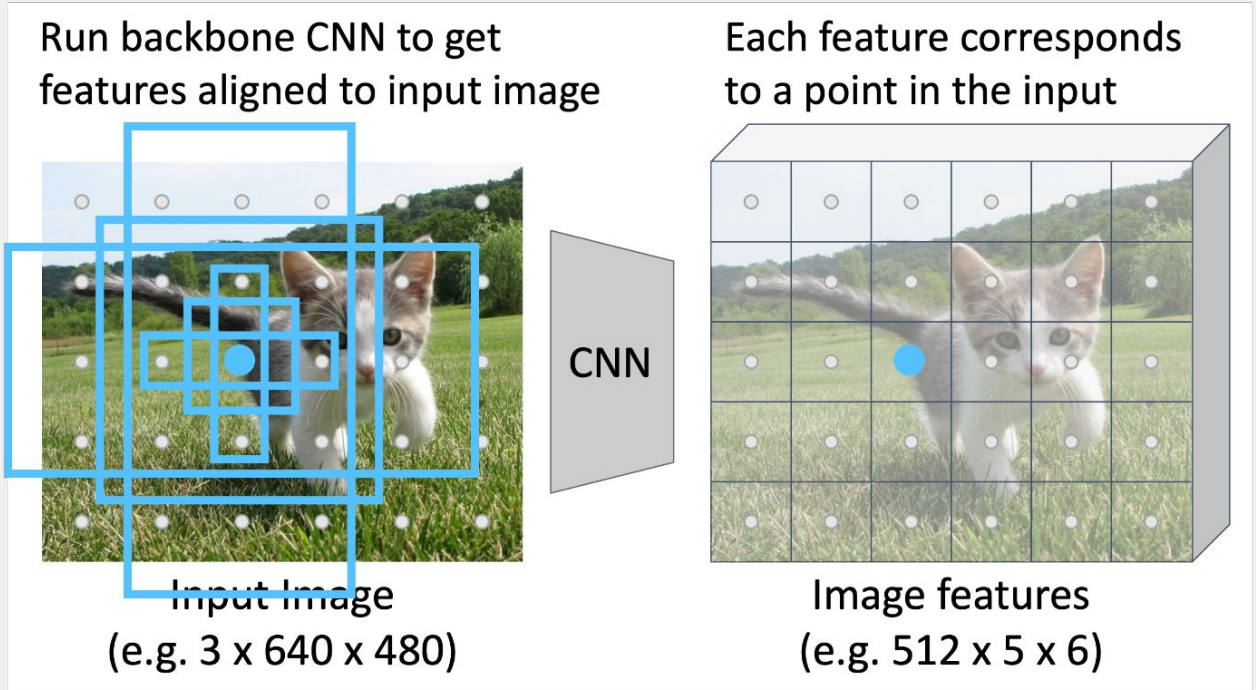
Anchor is object?

???

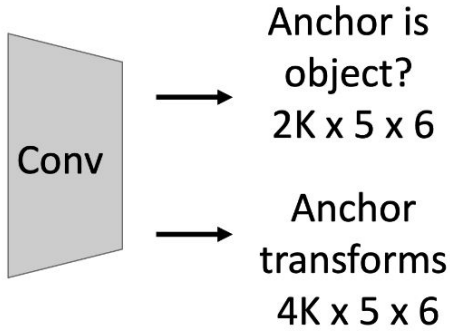
Anchor transforms
4 x 5 x 6

Classify each anchor as positive (object) or negative (no object)

Region Proposal Network (RPN)

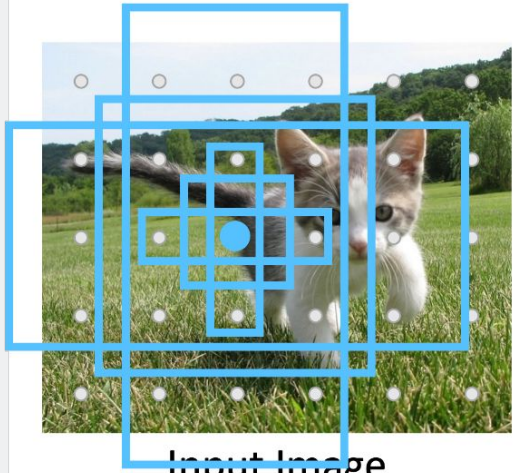


In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)



Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image



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

CNN

Each feature corresponds to a point in the input

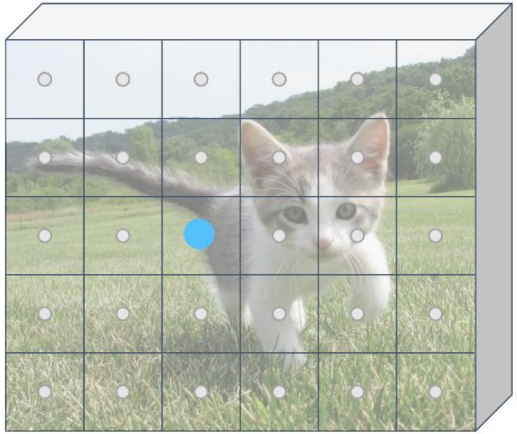
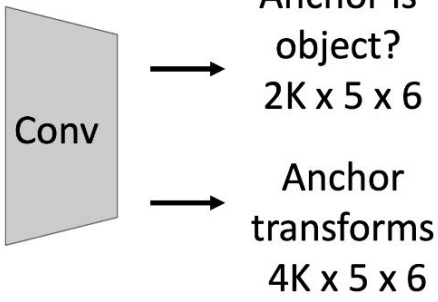


Image features
(e.g. 512 x 5 x 6)

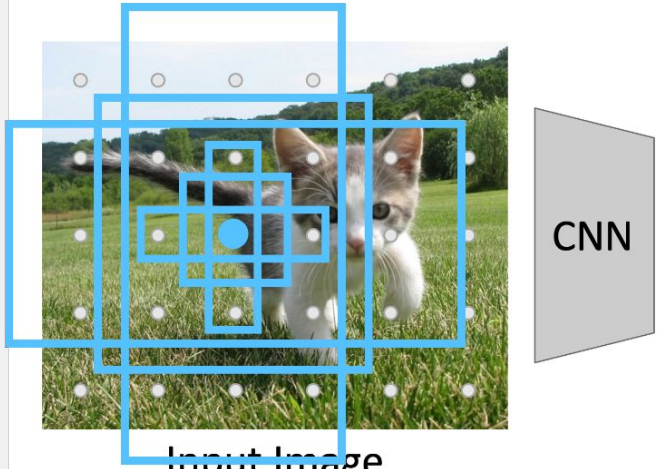
In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)



During training, supervised positive / negative anchors and box transforms like R-CNN

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image



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

CNN

Each feature corresponds to a point in the input

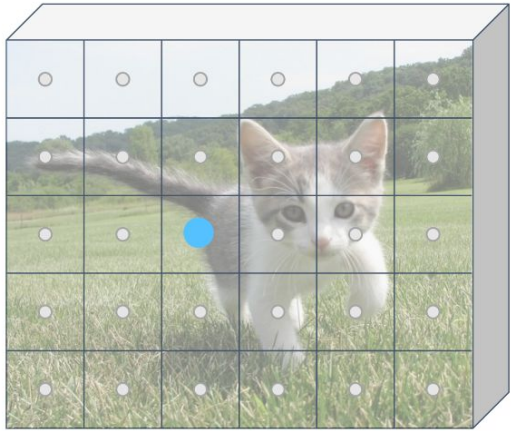
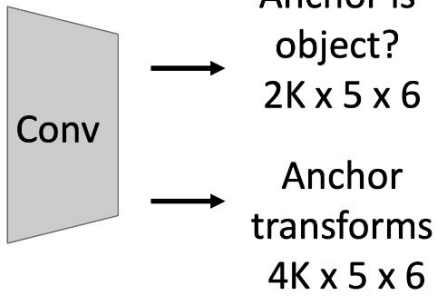


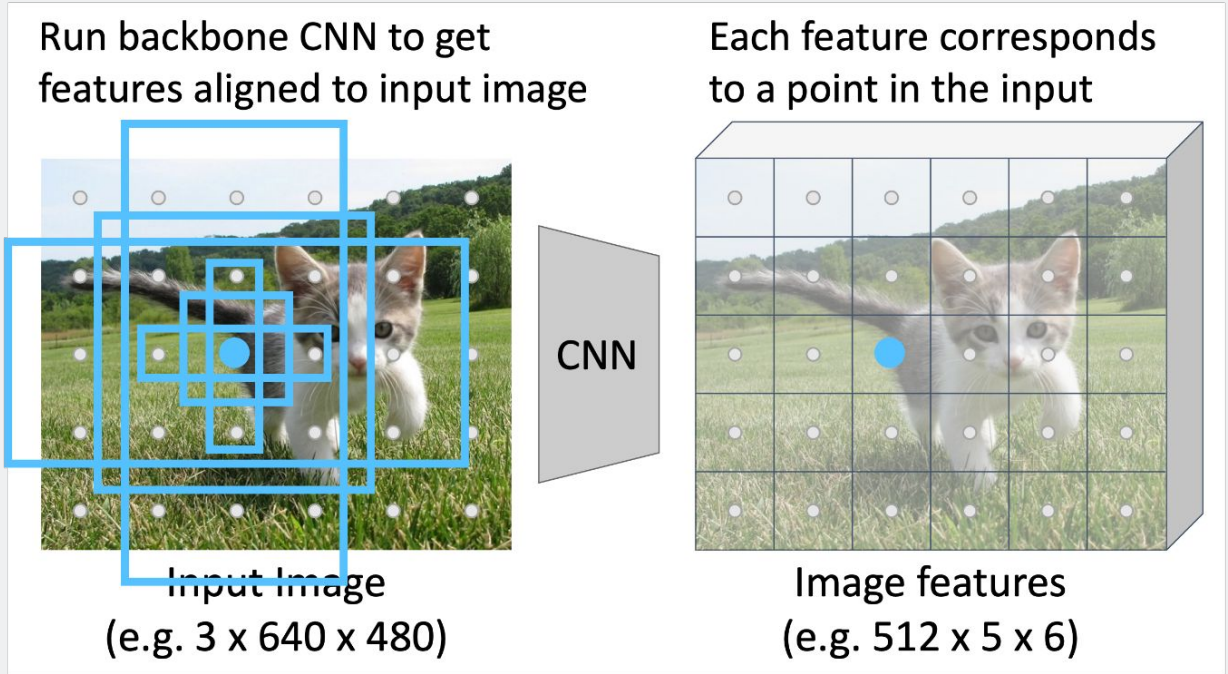
Image features
(e.g. 512 x 5 x 6)

In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)

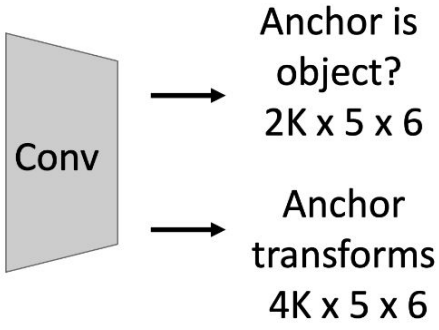


Positive anchors: >= 0.7 IoU with some GT box (plus highest IoU to each GT)

Region Proposal Network (RPN)



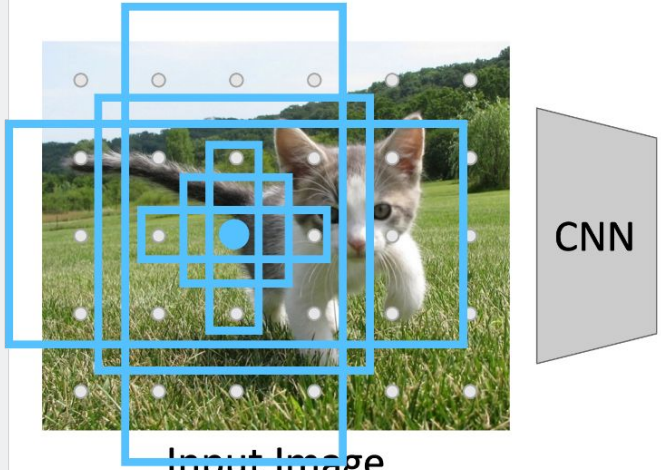
In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)



Negative anchors: < 0.3 IoU with all GT boxes. Don't supervised transforms for negative boxes.

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image



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

CNN

Each feature corresponds to a point in the input

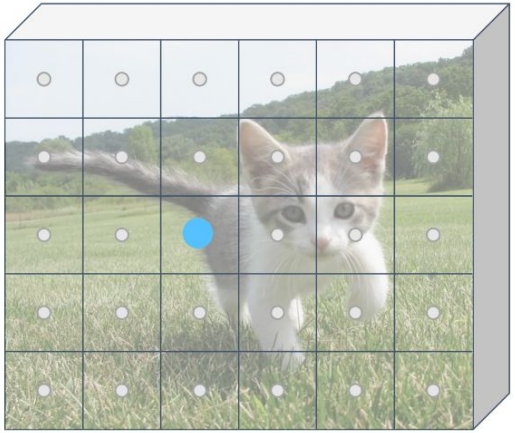
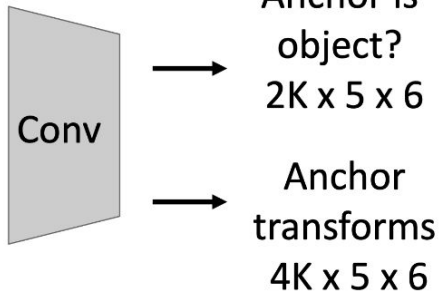


Image features
(e.g. 512 x 5 x 6)

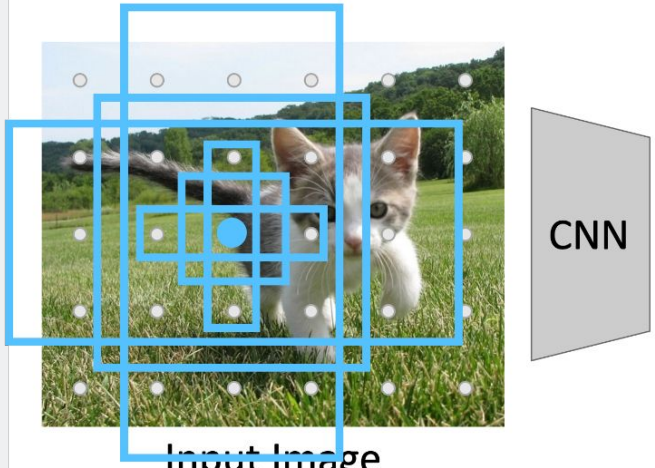
In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)



Neutral anchors: between 0.3 and 0.7 IoU with all GT boxes; ignored during training

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image



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

CNN

Each feature corresponds to a point in the input

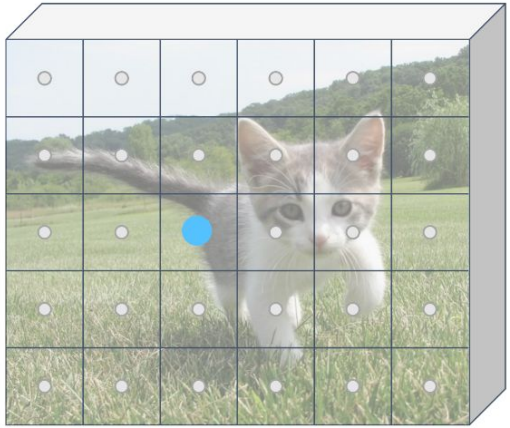
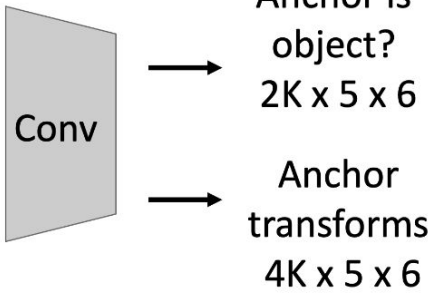


Image features
(e.g. 512 x 5 x 6)

In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)



At test-time, sort all K*5*6 boxes by their positive score, take top 300 as our region proposals

Faster R-CNN: Learnable Region Proposals

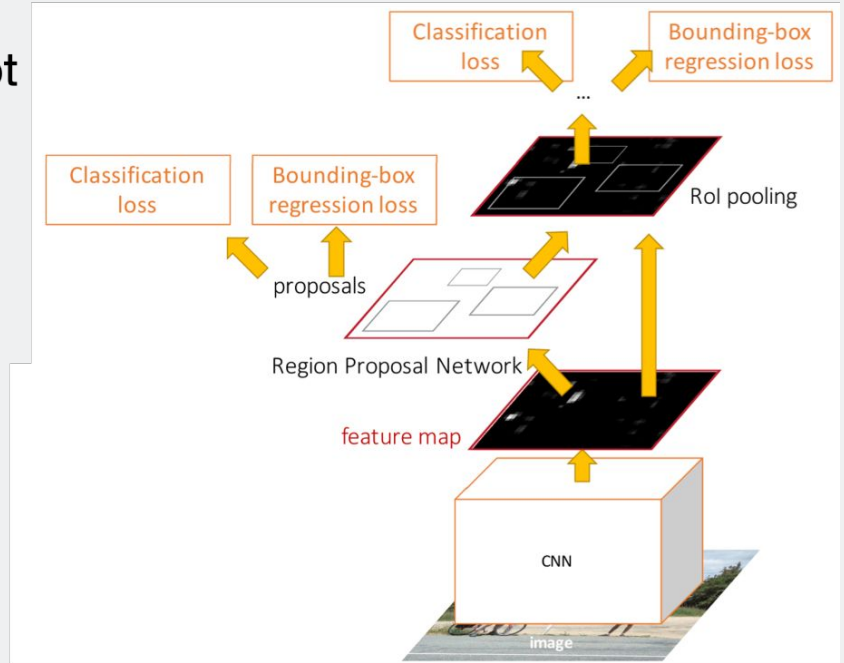
Jointly train four losses:

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



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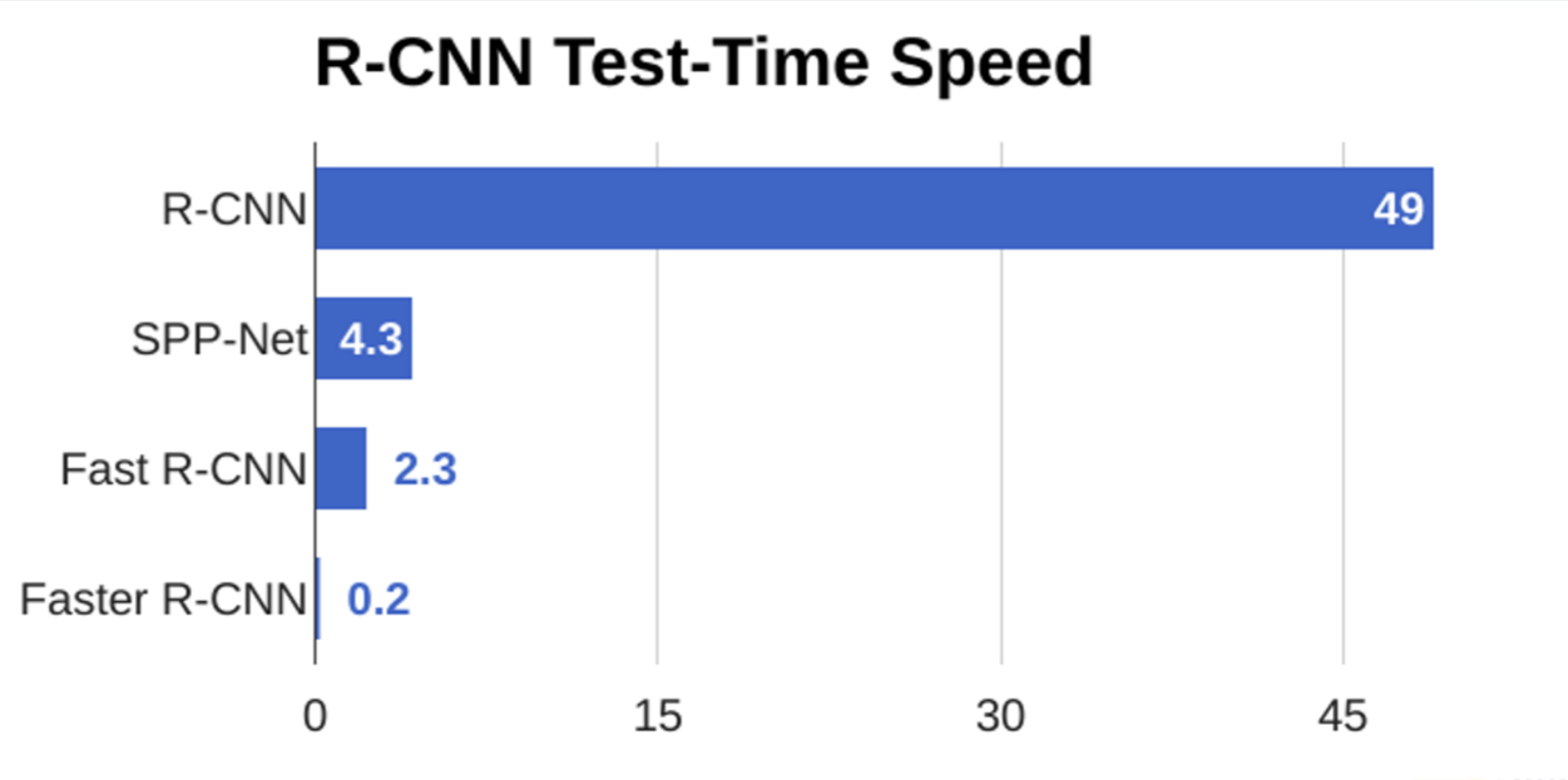
Faster R-CNN: Learnable Region Proposals



Extend Faster R-CNN to Image Segmentation: Mask R-CNN

Classification

"Chocolate Pretzels"

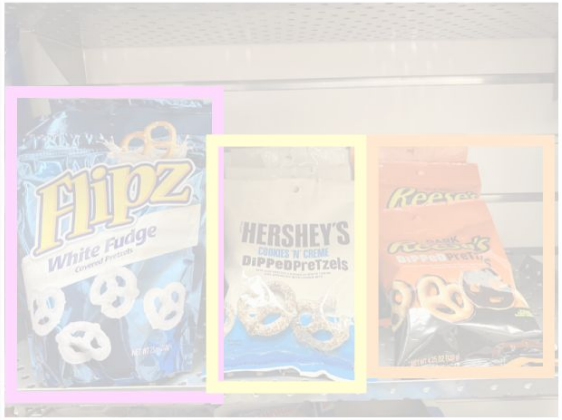
No spatial extent

Semantic Segmentation

Chocolate Pretzels, Shelf

No objects, just pixels

Object Detection



Flipz, Hershey's, Keese's

Multiple objects

Instance Segmentation

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Extend Faster R-CNN to Image Segmentation: Mask R-CNN

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

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

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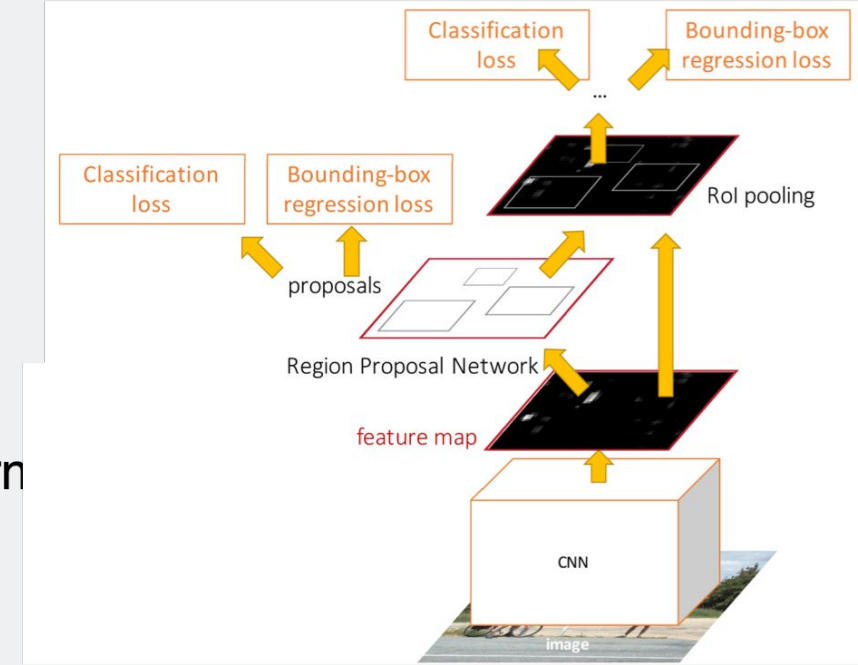
Extend Faster R-CNN to Mask R-CNN

Faster R-CNN

1. **Feature Extraction** at the image-level
2. **Regions of Interest** proposal from feature map
3. **In Parallel**
   1. **Object classification:** classify proposals
   2. **Object regression:** predict transform from proposal box to object box



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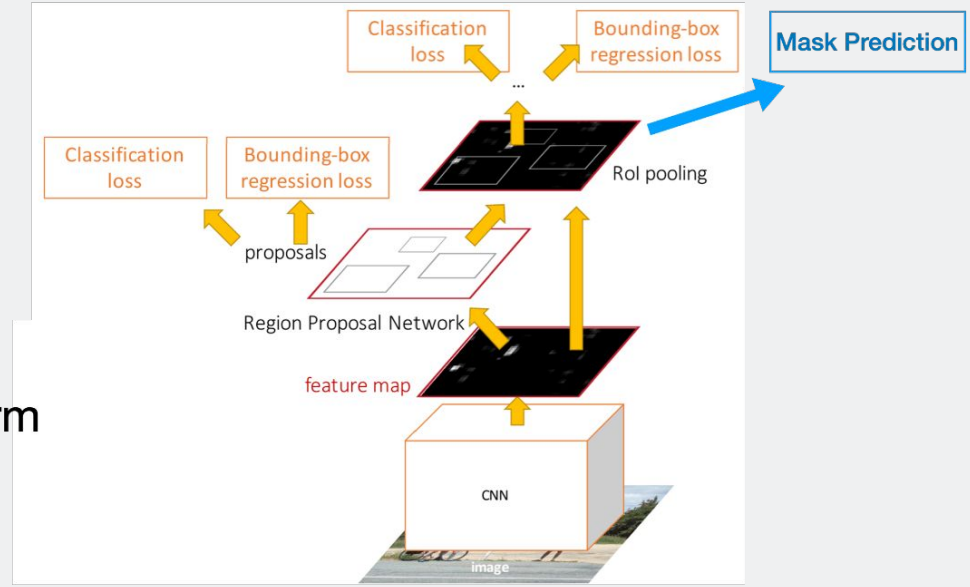
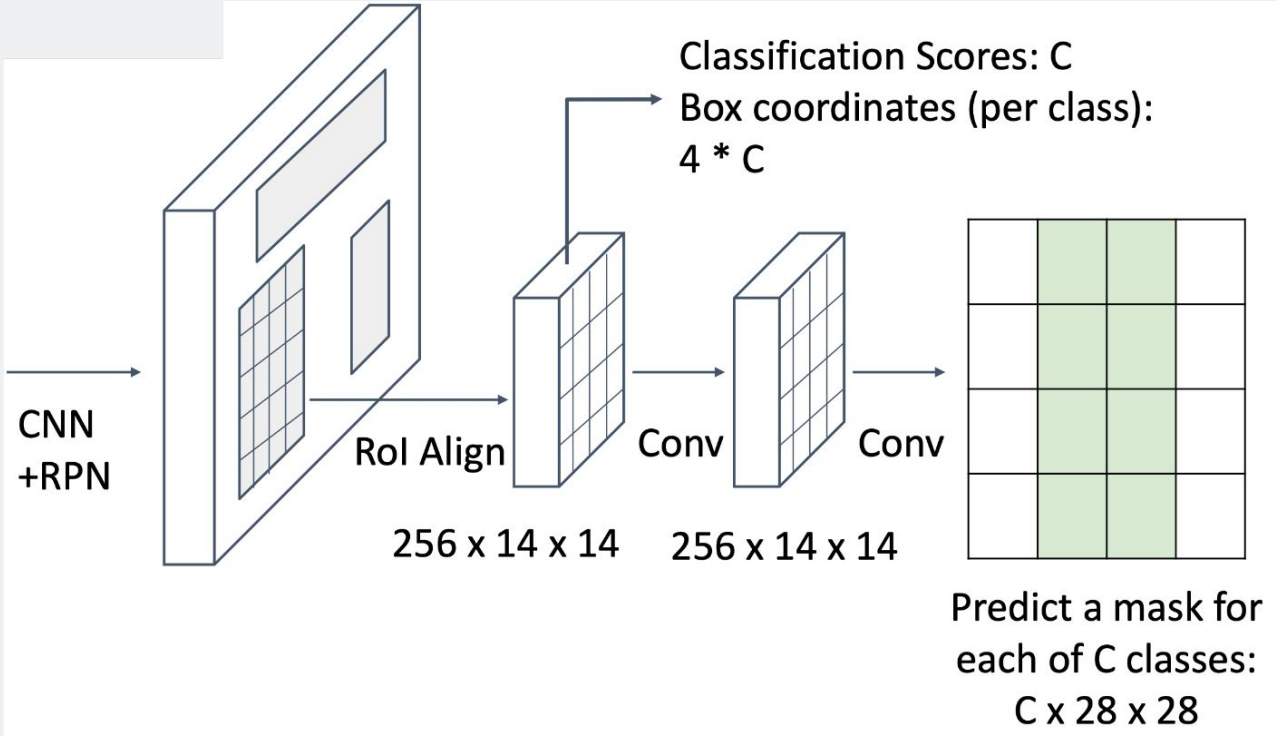
Extend Faster R-CNN to Mask R-CNN

Mask R-CNN

1. **Feature Extraction** at the image-level
2. **Regions of Interest** proposal from feature map
3. **In Parallel**
   a. **Object Classification:** classify proposals
   b. **Object Regression:** predict transform from proposal box to object box
   c. **Mask Prediction:** predict a binary mask for every region



Mask R-CNN



He et al., “Mask R-CNN”, ICCV 2017
https://openaccess.thecvf.com/content_ICCV_2017/papers/He_Mask_R-CNN_ICCV_2017_paper.pdf

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Mask R-CNN

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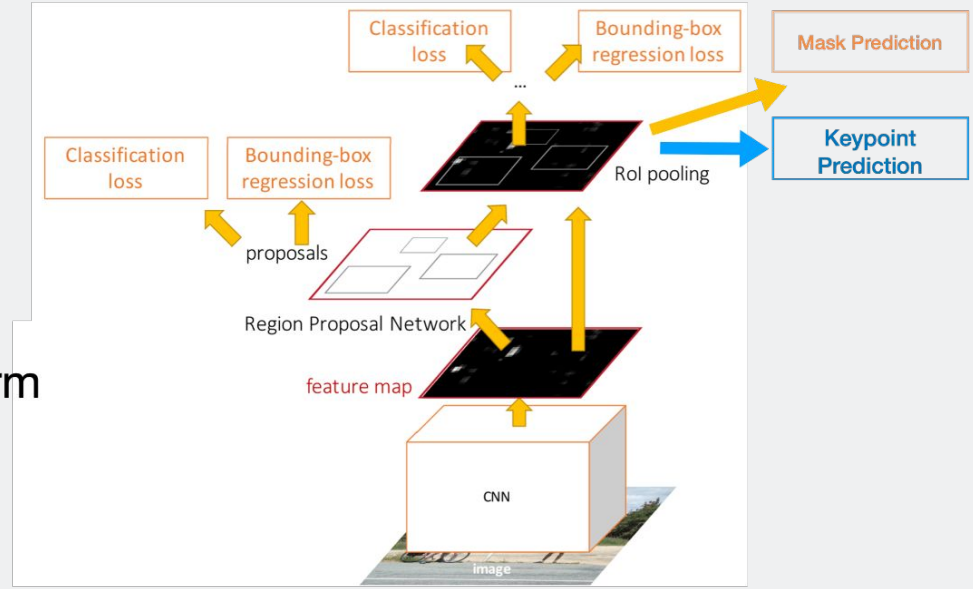
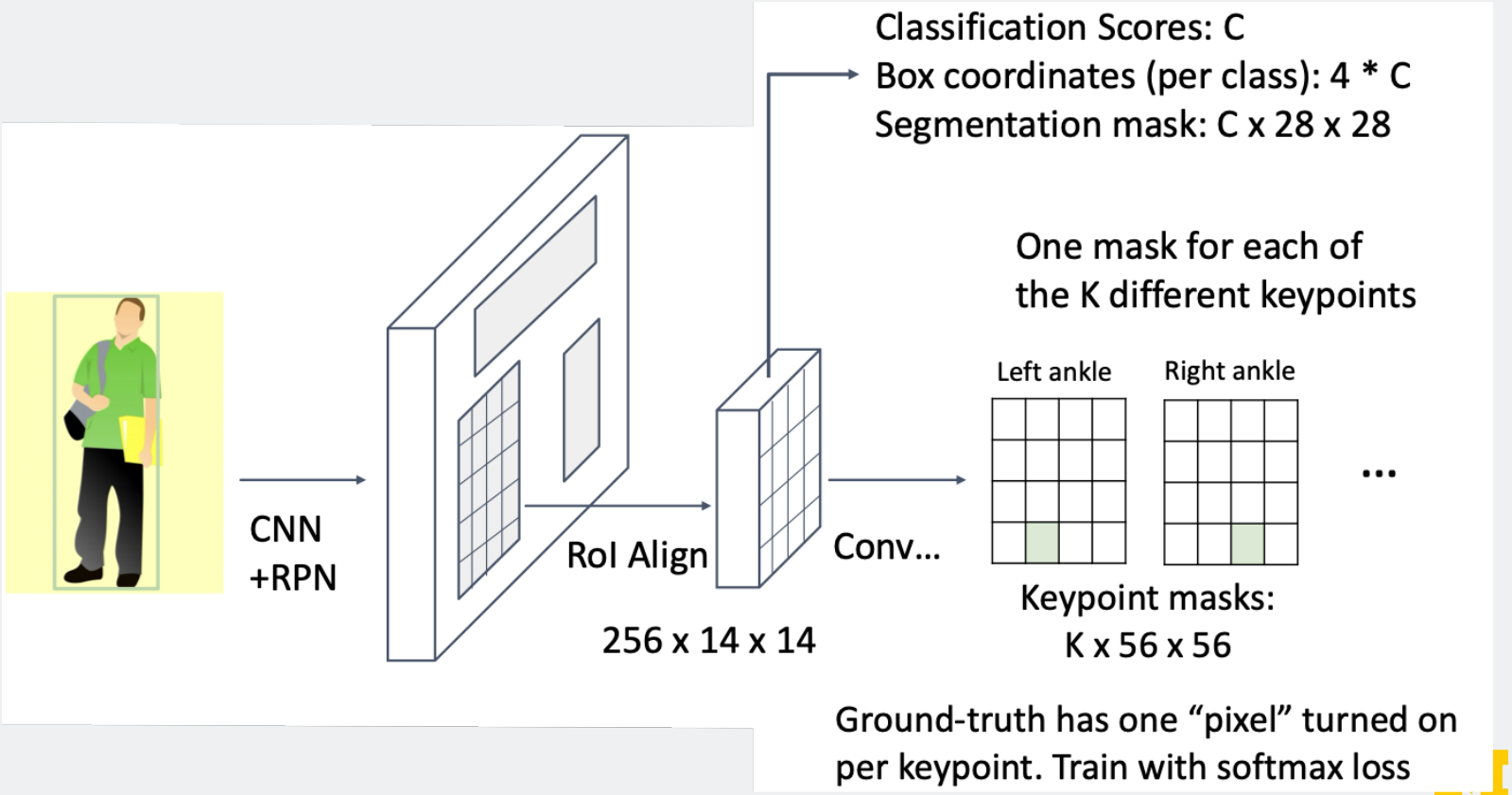
Mask R-CNN for Human Pose Estimation

Mask R-CNN

1. **Feature Extraction** at the image-level
2. **Regions of Interest** proposal from feature map
3. **In Parallel**
   a. **Object Classification:** classify proposals
   b. **Object Regression:** predict transform from proposal box to object box
   c. **Mask Prediction:** predict a binary mask for every region
   d. **Keypoint Prediction:** predict binary mask for human key points



Mask R-CNN for Human Pose Estimation



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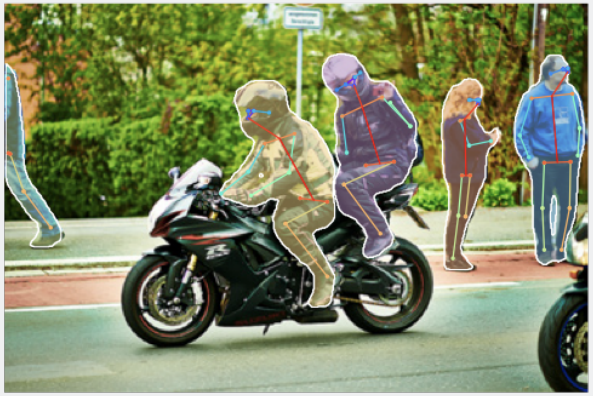
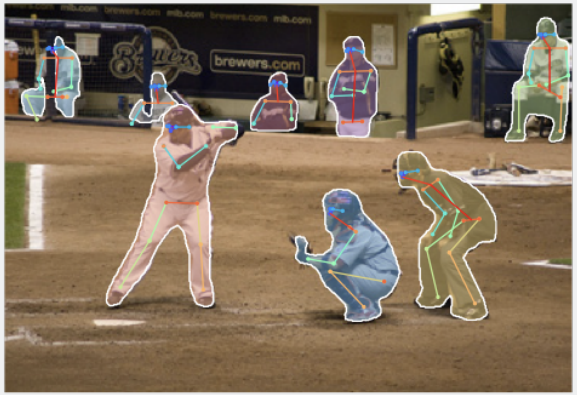
Mask R-CNN for Human Pose Estimation





Detection without Anchors - Transformers

(more details later)

+ No RPN
+ No Anchors
+ No NMS

- Slow to train
- Worse than Faster R-CNN for smaller objects

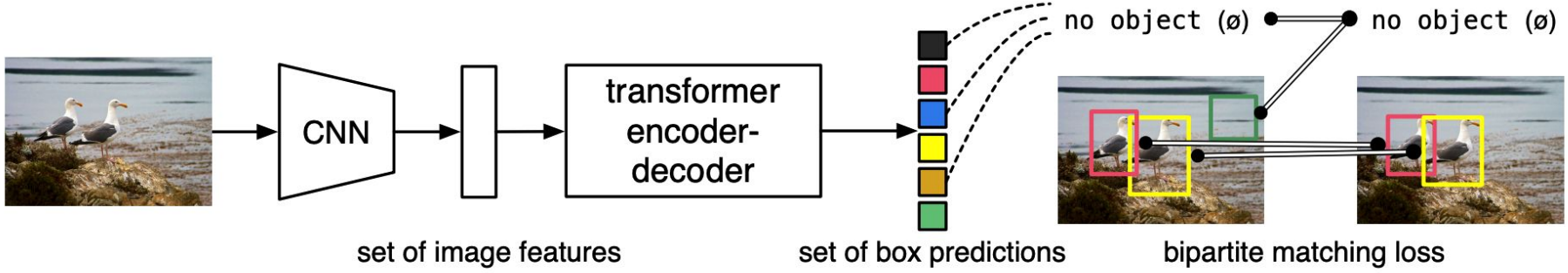


Fig. 1: DETR directly predicts (in parallel) the final set of detections by combining a common CNN with a transformer architecture. During training, bipartite matching uniquely assigns predictions with ground truth boxes. Prediction with no match should yield a "`no object`" (∅) class prediction.

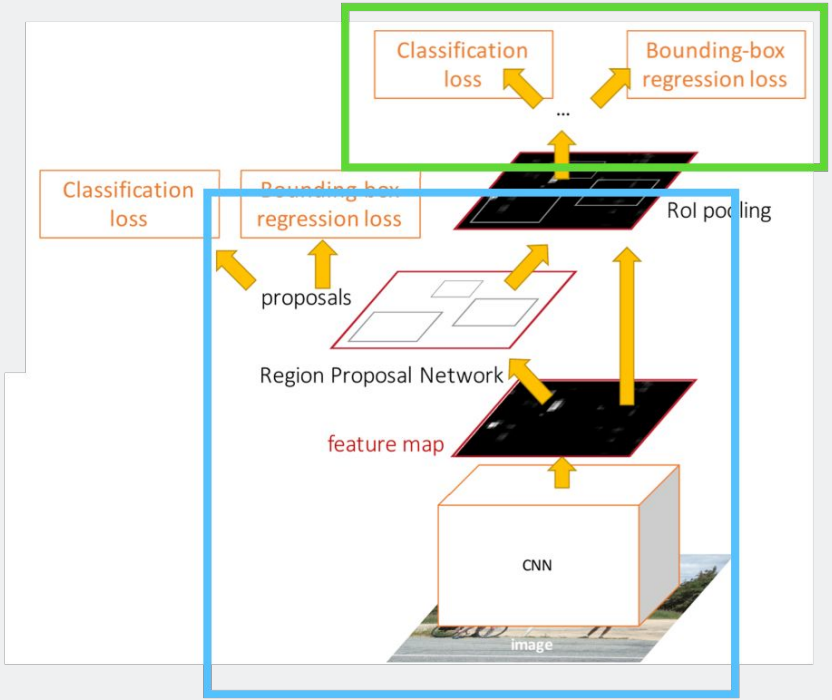
https://arxiv.org/abs/2005.12872

Two Stage vs One Stage Detectors

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



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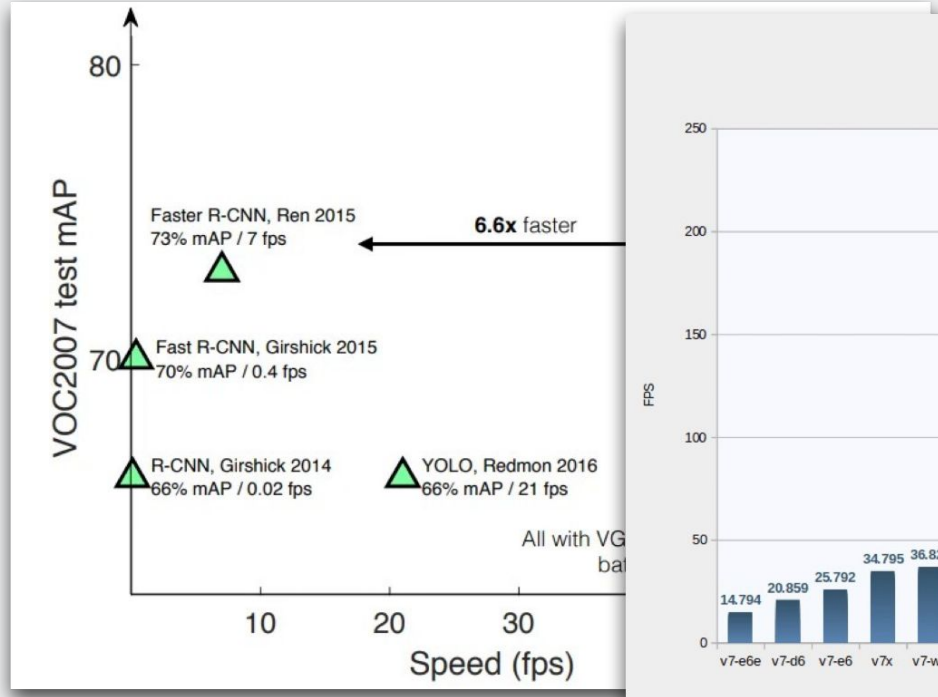
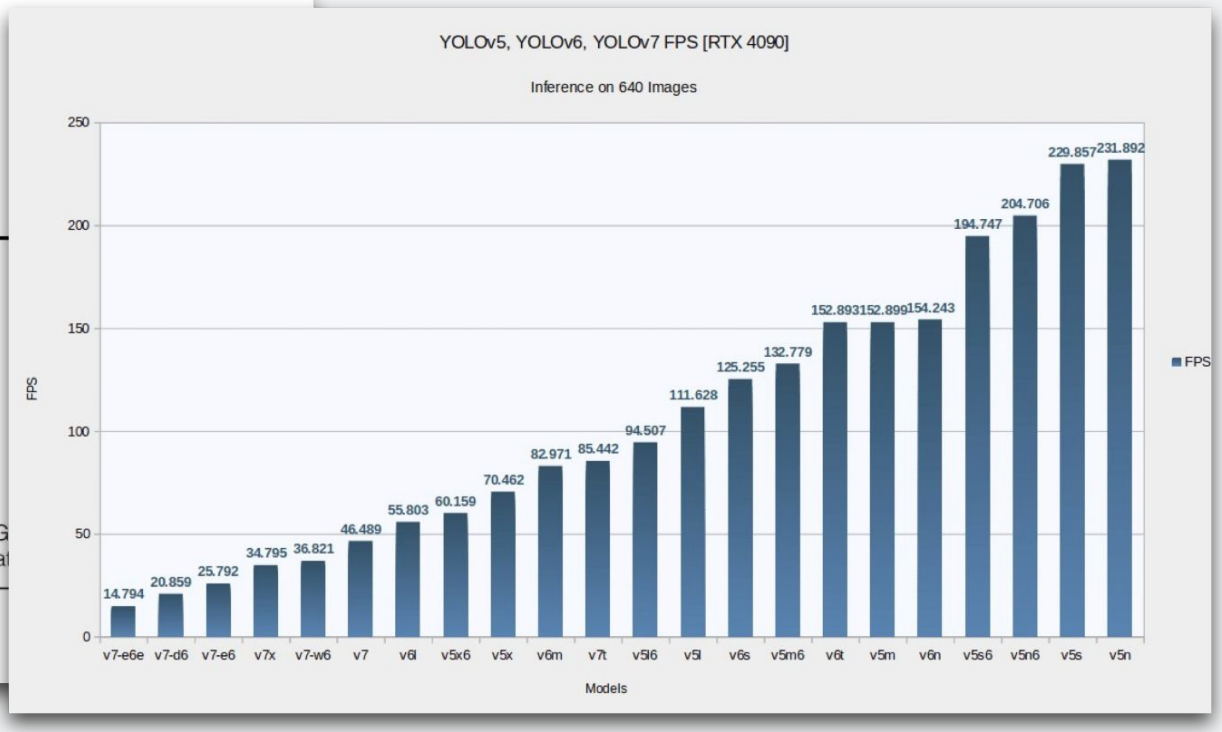
Two Stage vs One Stage Detectors





https://pjreddie.com/yolo/

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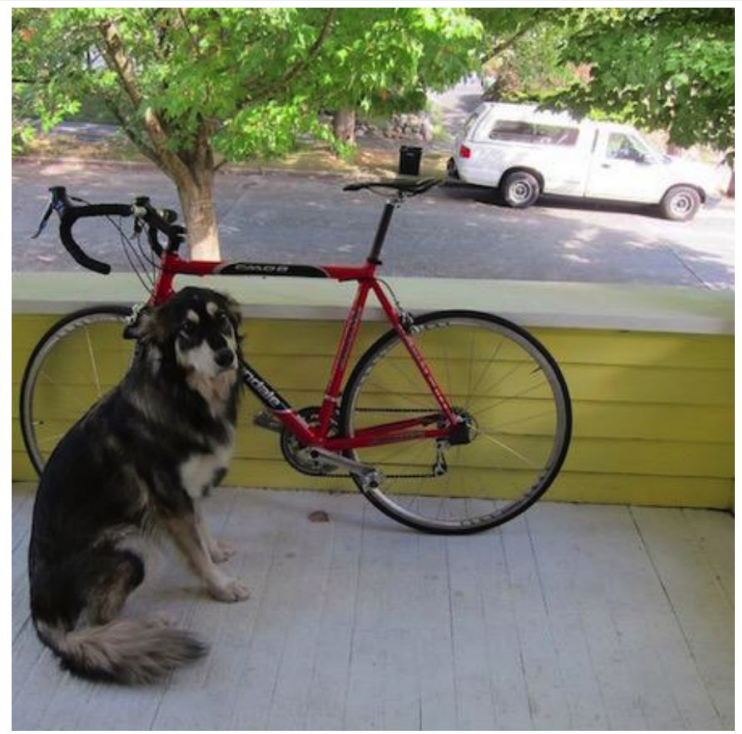
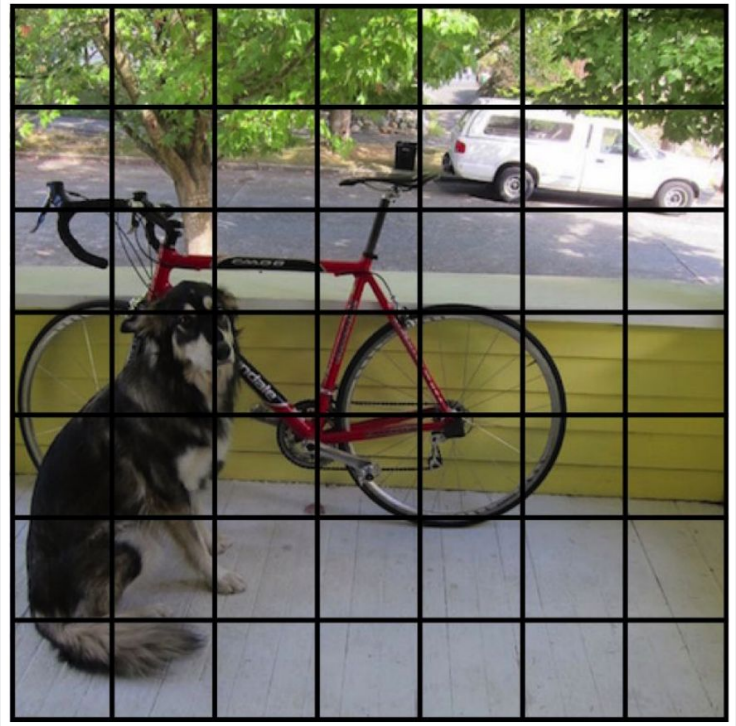
YOLO: You Only Look Once

Split into SxS grid





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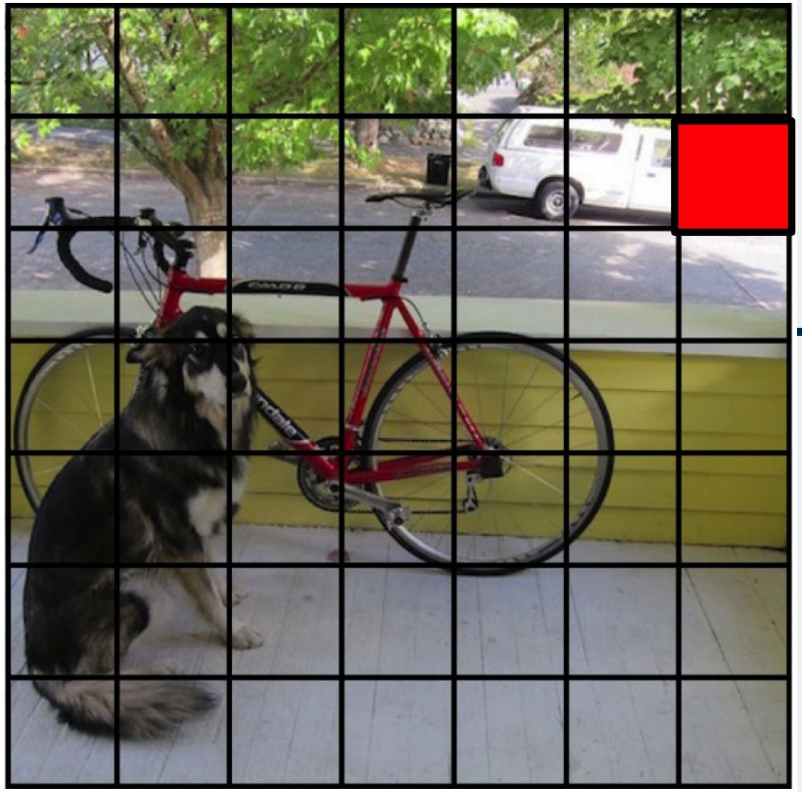
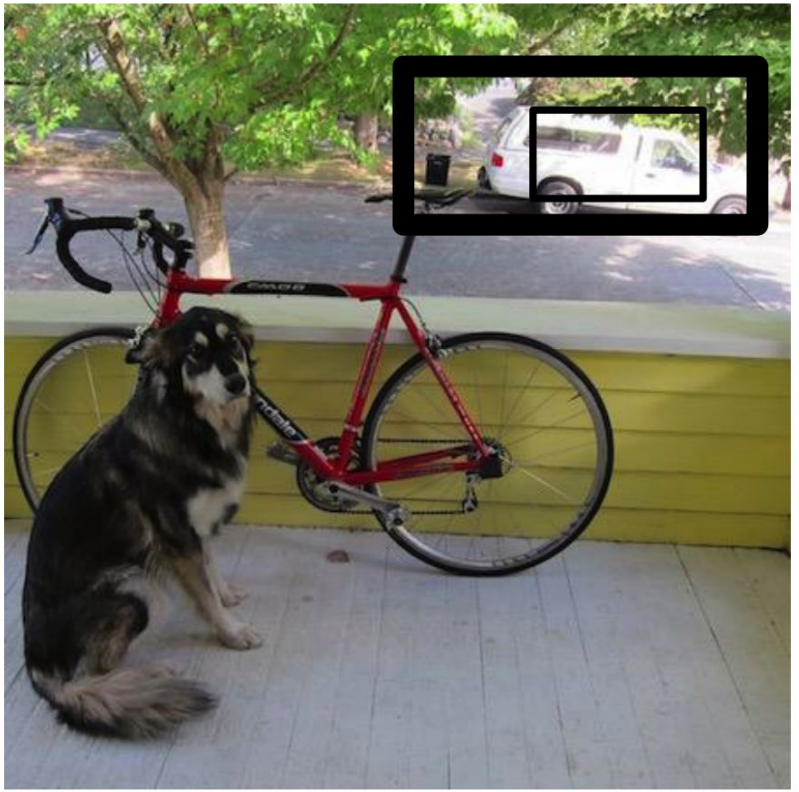
YOLO

Each cell predicts B boxes(x,y,w,h) and confidences of each box: P(Object)





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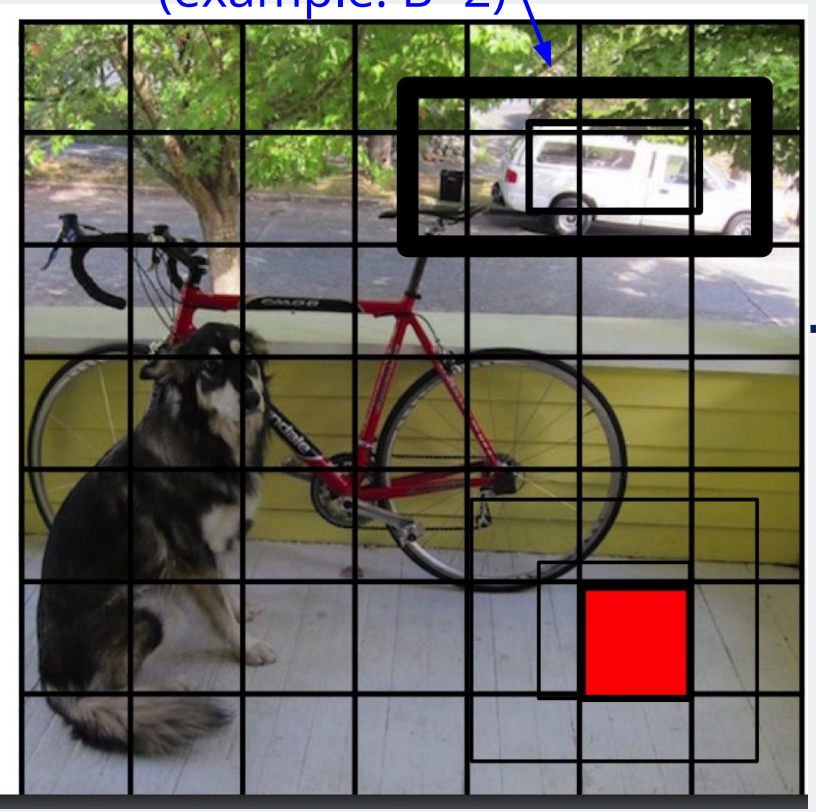
YOLO

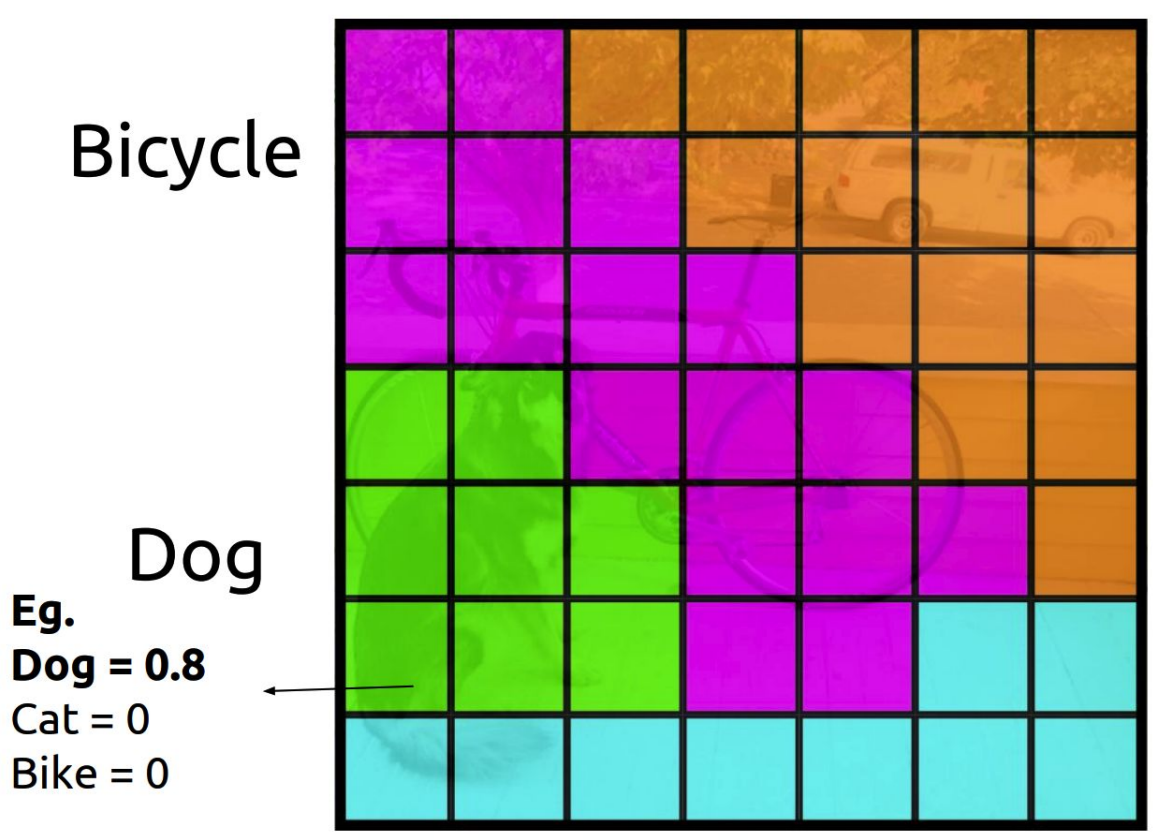
Each cell predicts boxes and confidences

(example: B=2)



YOLO

Each cell also predicts a class probability
Conditioned on object: P(Class | Object)



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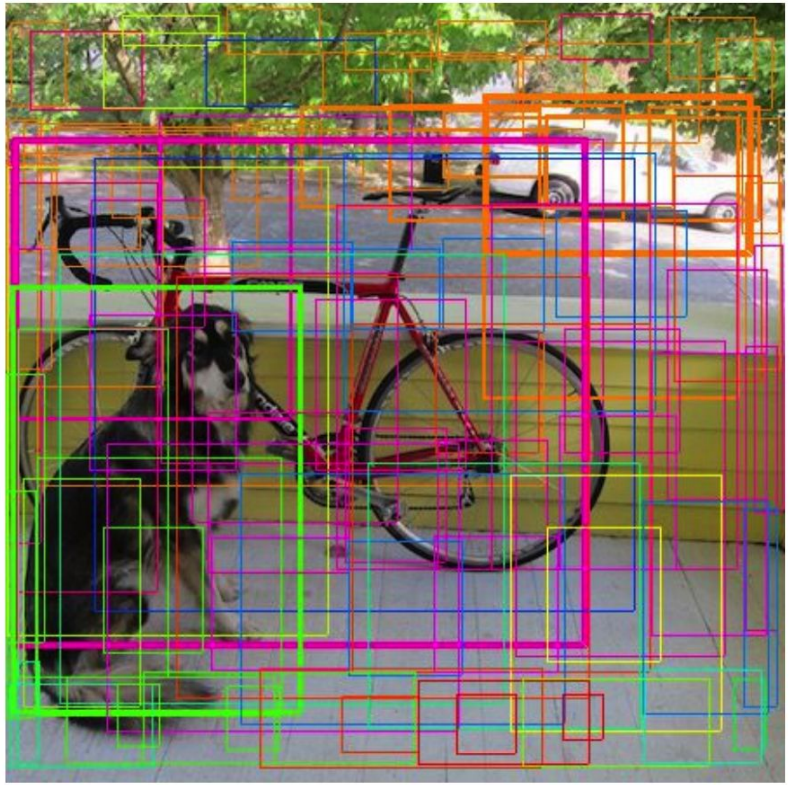
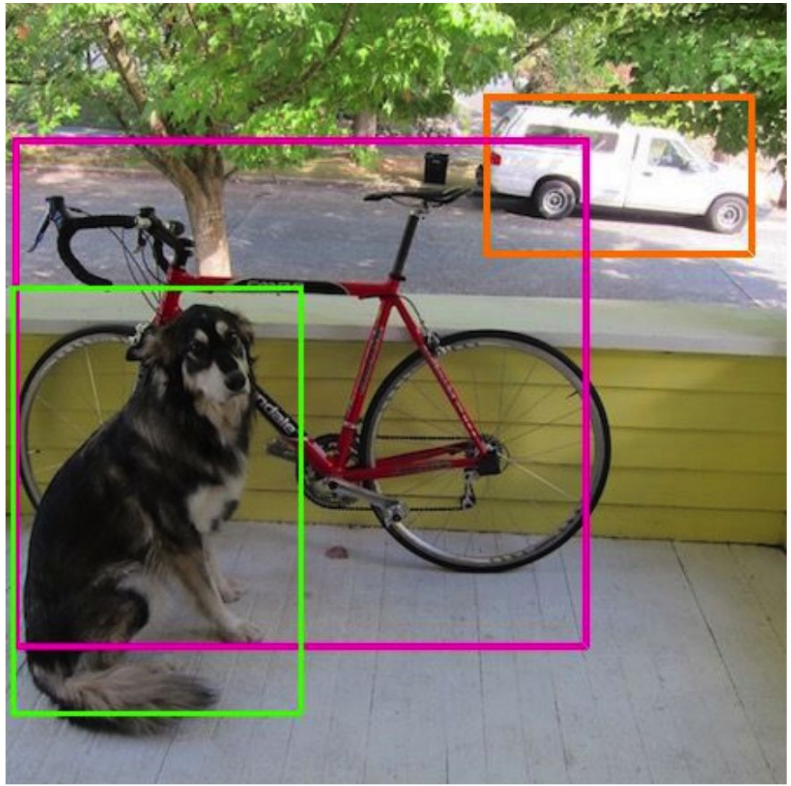
YOLO

Combine boxes and class probabilities
Apply NMS

P(class|Object) * P(Object)
=P(class)



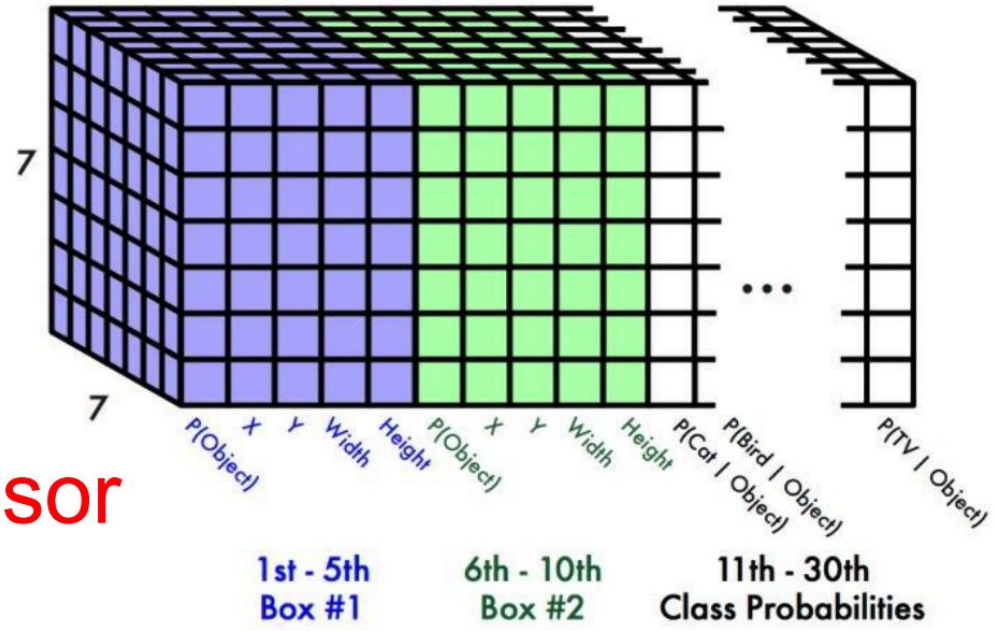
NMS



YOLO

Each cell predicts:

- For each bounding box:
  - 4 coordinates (x, y, w, h)
  - 1 confidence value
- Some number of class probabilities



S * S * (B * 5 + C) tensor

What's the size of the YOLO output

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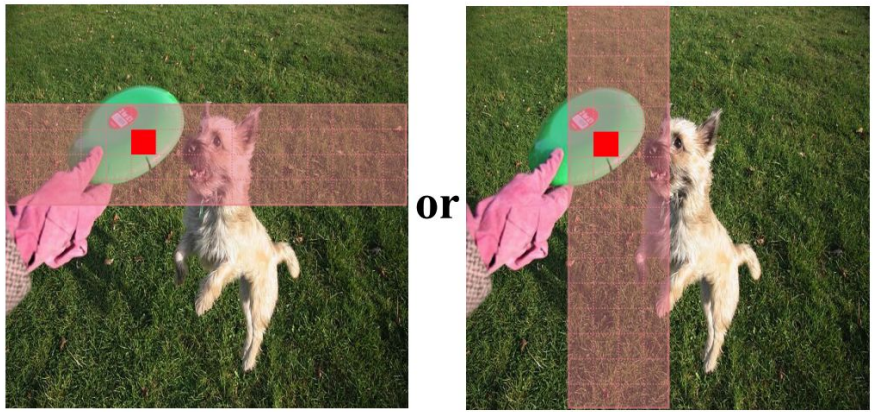
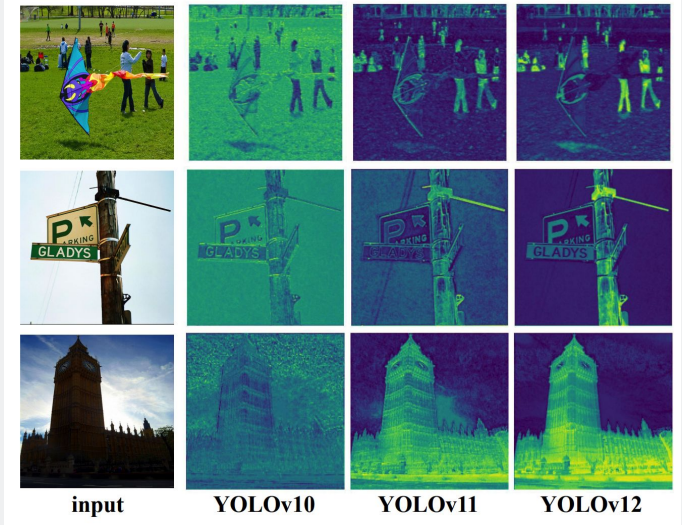
YOLO Variants

https://arxiv.org/abs/1506.02640 (original YOLO paper, 2015)
https://arxiv.org/abs/2304.00501 (from YOLOv1 to YOLOv8 and YOLO-NAS, 2023)
https://arxiv.org/abs/2402.13616 (YOLOv9, Feb. 2024)
https://arxiv.org/abs/2405.14458 (YOLOv10, May 2024)
https://arxiv.org/abs/2410.17725 (YOLOv11, Oct. 2024)
https://www.arxiv.org/abs/2502.12524 (YOLOv12, Feb.18, 2025)
https://github.com/sunsmarterjie/yolov12 (YOLOv12 pytorch, Attention-centric YOLO)





heatmap comparison

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3D Shape Prediction: Mesh R-CNN

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

Mesh R-CNN:
2D image -> 3D triangle meshes

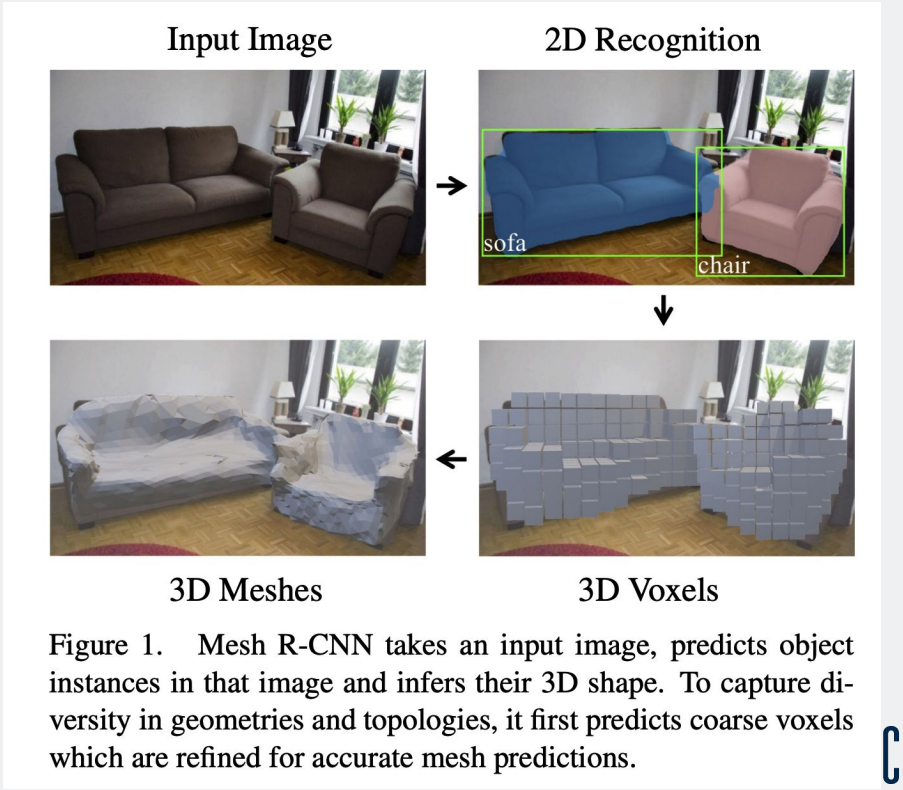


Figure 1. Mesh R-CNN takes an input image, predicts object instances in that image and infers their 3D shape. To capture diversity in geometries and topologies, it first predicts coarse voxels which are refined for accurate mesh predictions.

https://arxiv.org/abs/1906.02739

3D Shape Prediction: Mesh R-CNN

Input: Single RGB image

Output:

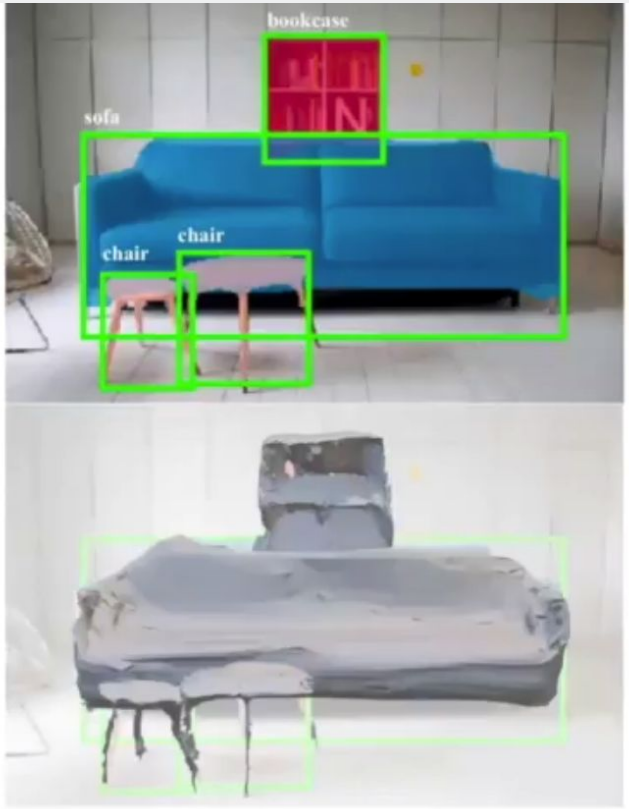
A set of detected objects

For each object:

- Bounding box
- Category label
- Instance segmentation
- 3D triangle mesh

Mask R-CNN

Mesh head



Attach a customized head that operates on each RoI coming out of Mask R-CNN

3D Shape Prediction: Mesh R-CNN

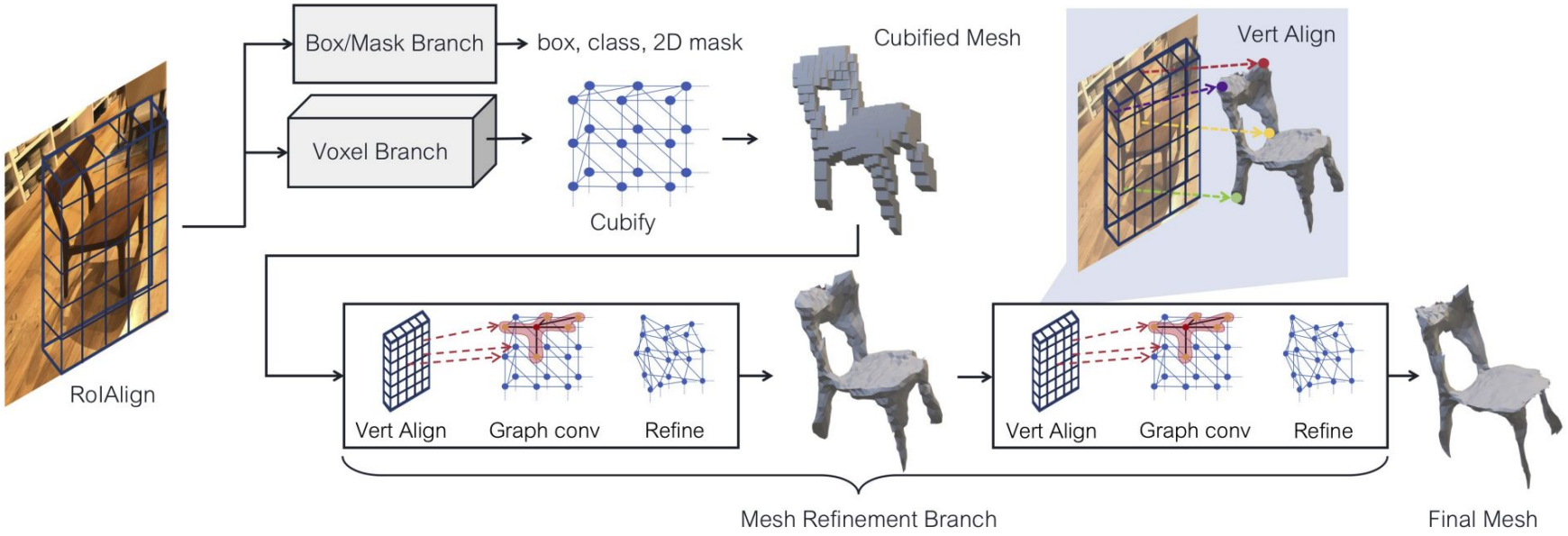


Figure 3. System overview of Mesh R-CNN. We augment Mask R-CNN with 3D shape inference. The *voxel branch* predicts a coarse shape for each detected object which is further deformed with a sequence of refinement stages in the *mesh refinement branch*.

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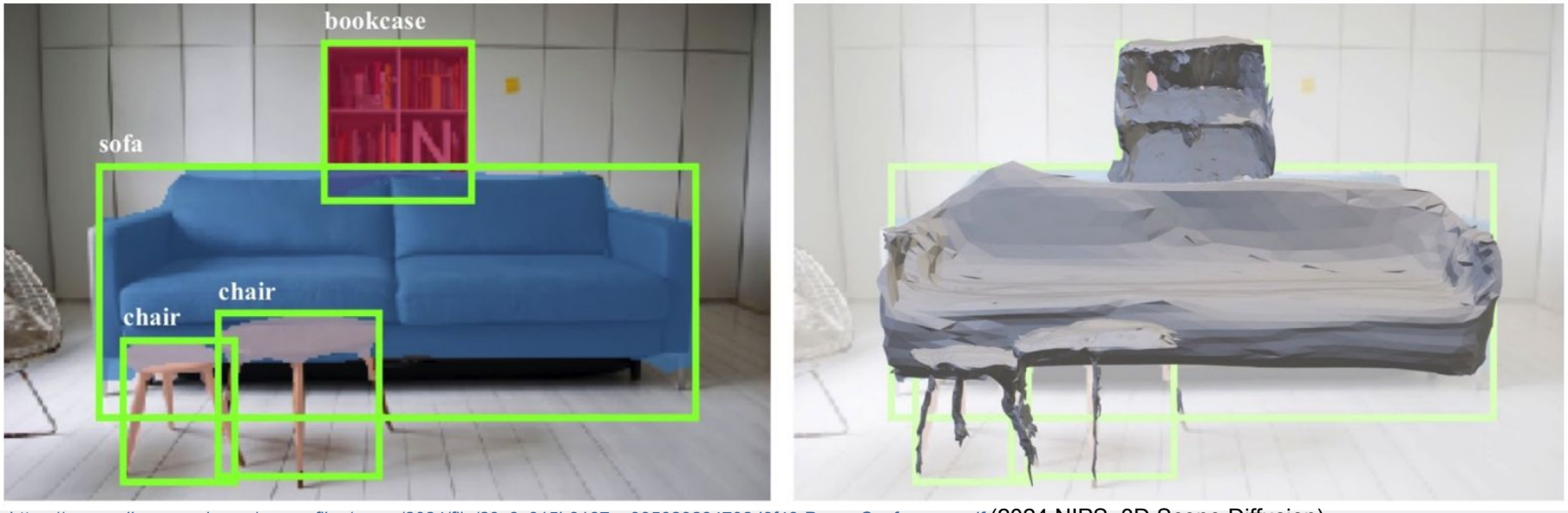
3D Shape Prediction: 2024



https://proceedings.neurips.cc/paper_files/paper/2024/file/29c8c615b3187ee995029284702d3f43-Paper-Conference.pdf (2024 NIPS, 3D Scene Diffusion)

3D Shape Prediction: 2025

https://github.com/facebookresearch/sam-3d-objects (SAM 3D: 3Dfy Anything in Images, Nov 2025)

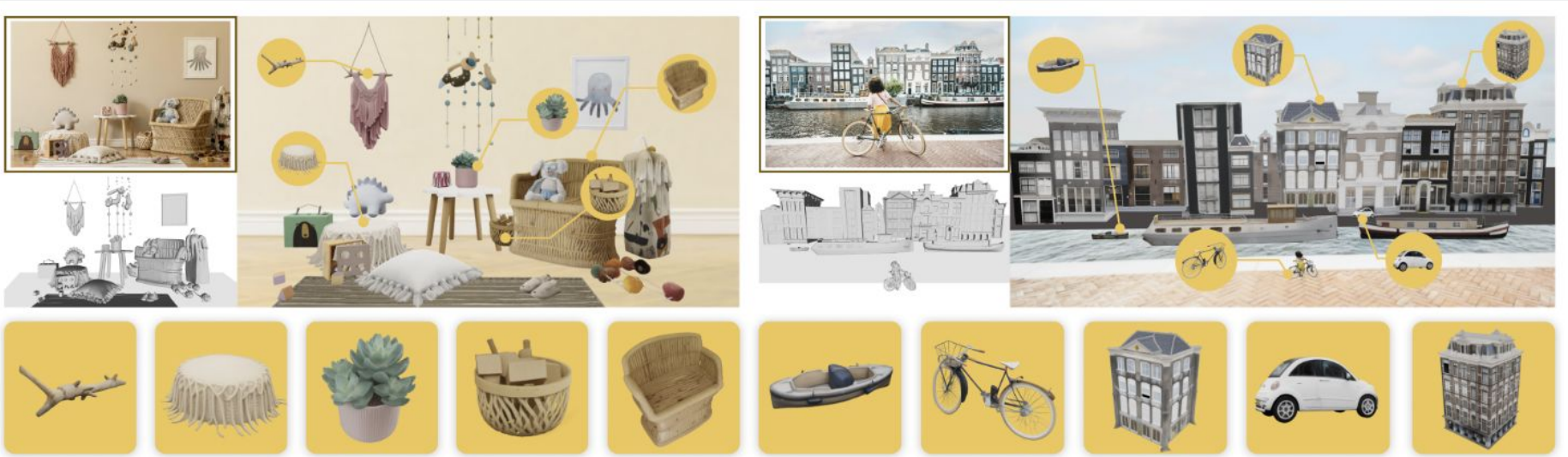


Figure 1 SAM 3D converts a single image into a composable 3D scene made of individual objects: Our method predicts per-object geometry, texture, and layout, enabling full scene reconstruction. Bottom: high-quality 3D assets recovered for each object.

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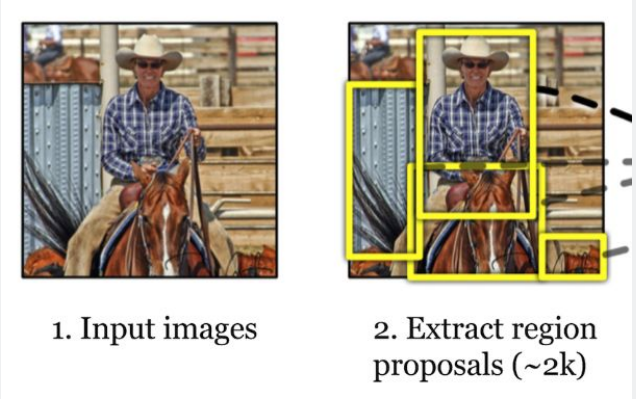
Summary

- **P3 released, Due March 8, 2026**

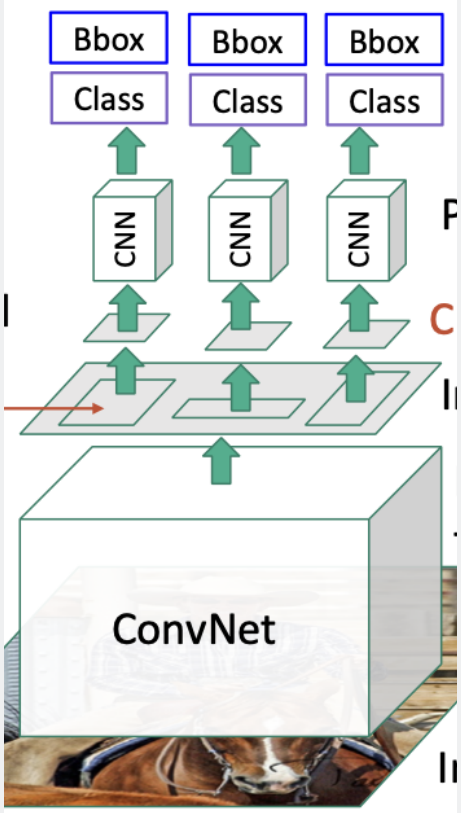
Start NOW!!!

- **Also, Canvas Quizzes**

"R-CNN Family"



Region proposals



ROI Pool
ROI Align

RPNs

Instance Segmentation

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