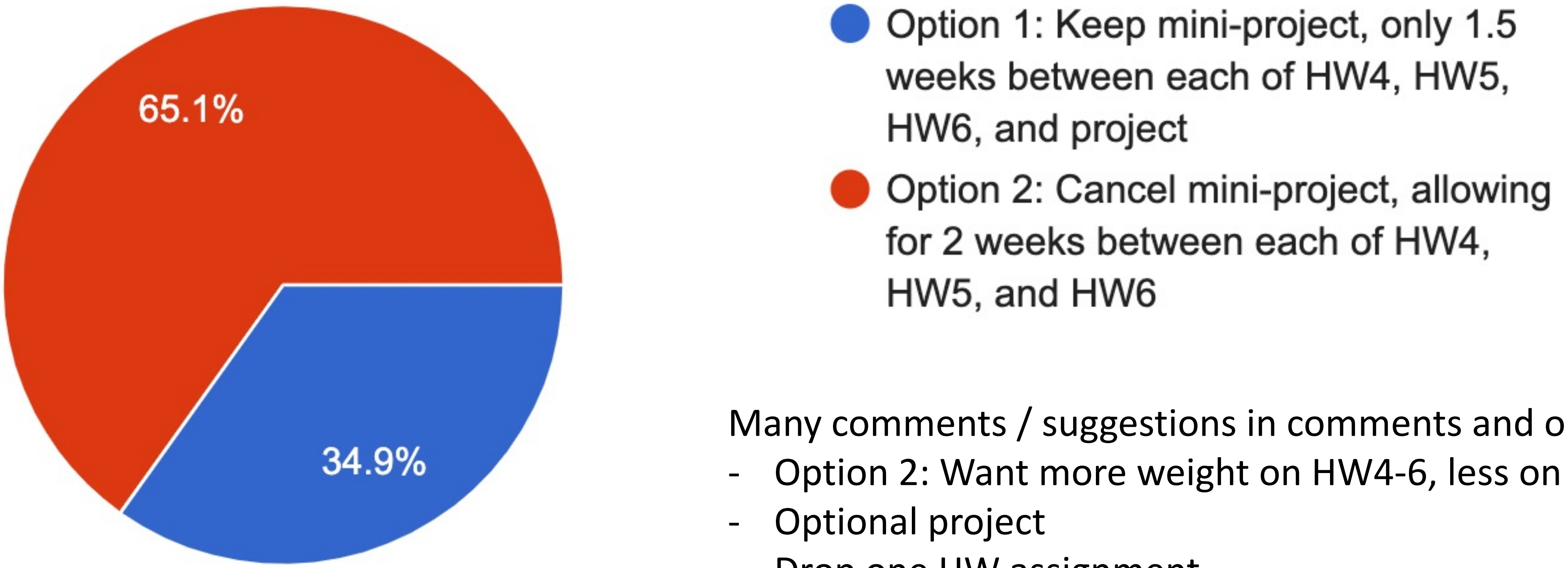
Lecture 14:
Object Detectors

Poll Results



Many comments / suggestions in comments and on Piazza:

- Option 2: Want more weight on HW4-6, less on midterm
- Optional project
- Drop one HW assignment
- Extra late days

Decision

- We will keep 2-week gap between each of HW4-6
- Students can also complete a project if they wish (spec out next week)
- Each student can choose one of the following options:

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Option A:
Do all assignments,
Do not do project.

Grading scheme:
HW1-3: 12%
Midterm: 22%
HW4-6: 14%

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Option B:
Do 5 or 6 assignments
Do project

Grading scheme (whichever gives you better grade):
HW1-3: 12%
Midterm: 22%
HW4-6: 14%
Project: Replaces lowest HW

Original grading scheme:
HW1-6: 10%
Midterm: 20%
Project: 20%

In addition: Everyone gets +3 late days (cannot be applied to A6 or project)

Decision

- We will keep 2-week gap between each of HW4-6
- Students can also complete a project if they wish (spec out next week)
- Each student can choose one of the following options:

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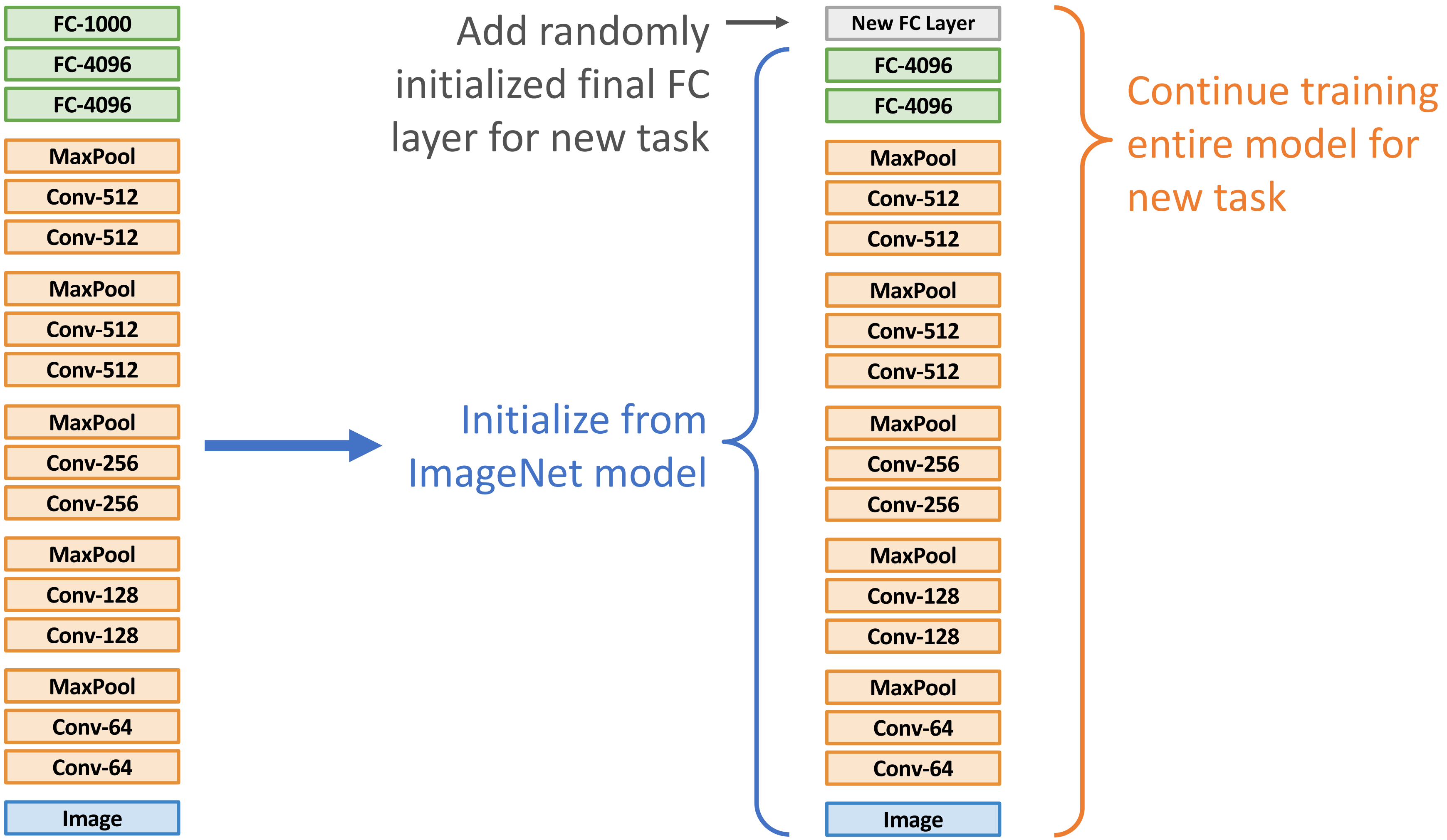
Project: Replaces lowest HW

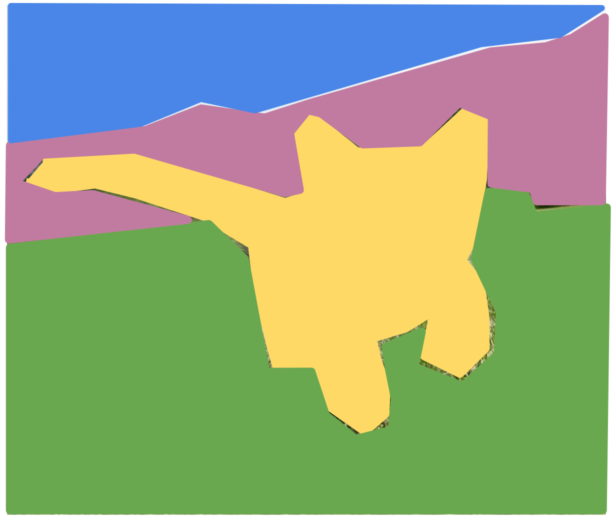
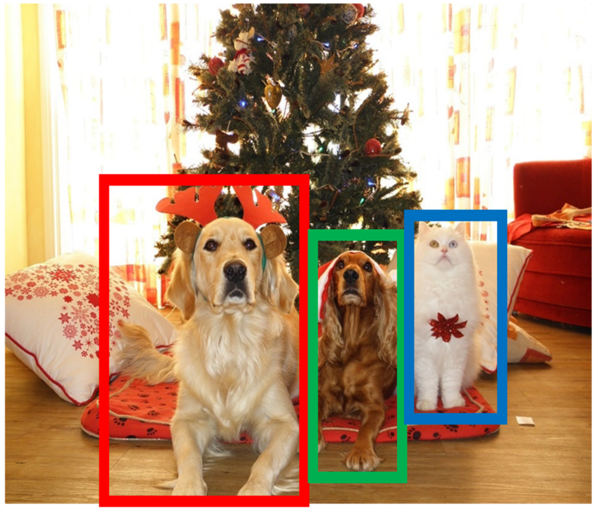
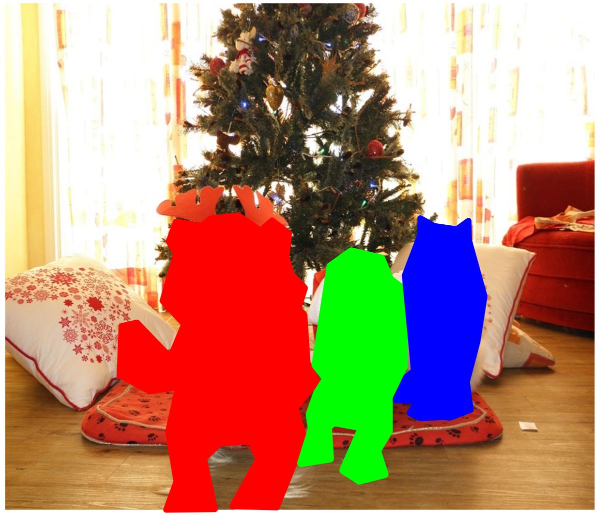
Original grading scheme:
HW1-6: 10%
Midterm: 20%
Project: 20%

Last Time: Transfer Learning

1. Train on ImageNet



Last Time: Localization Tasks

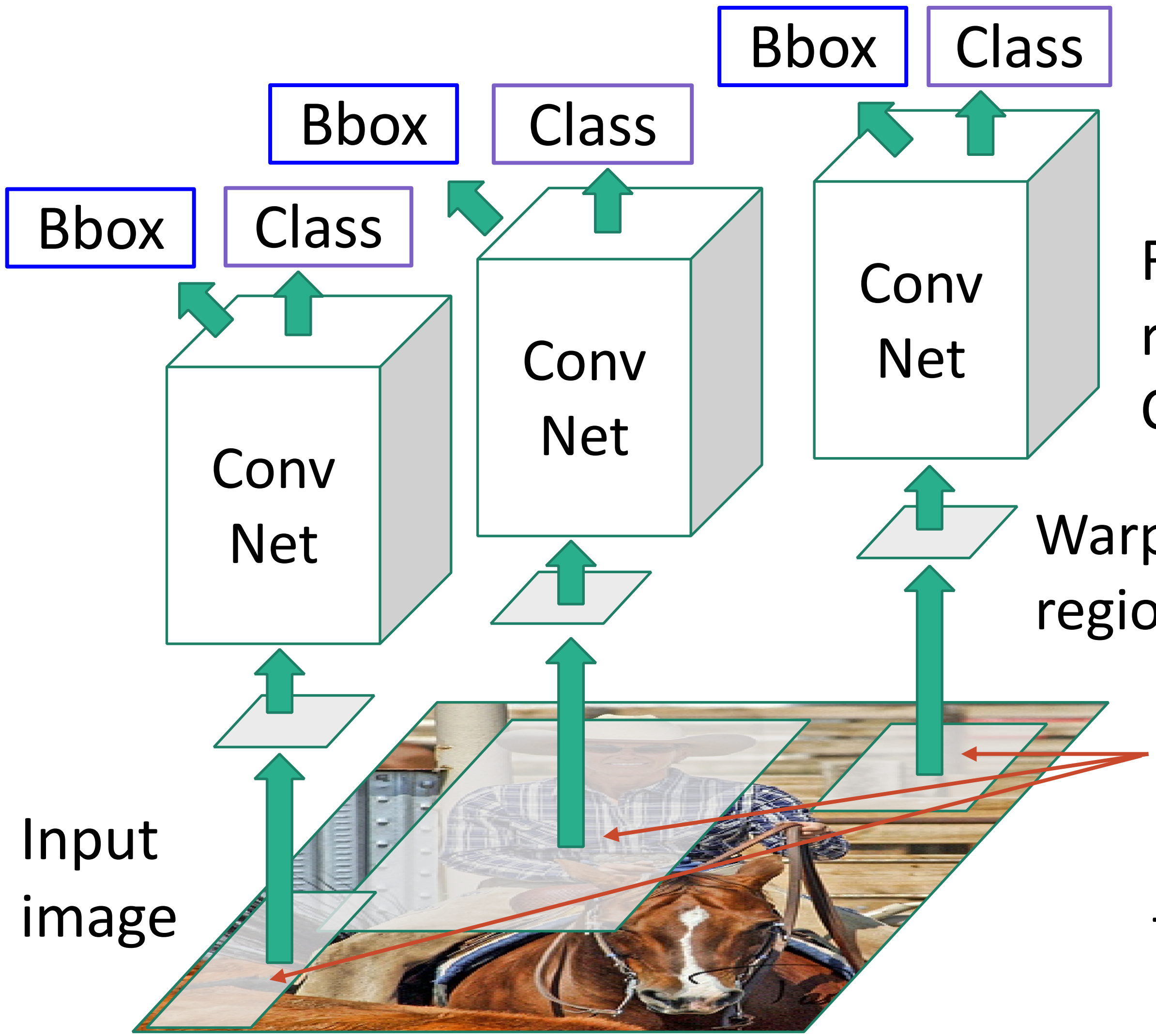
Classification	Semantic Segmentation	Object Detection	Instance Segmentation
			
CAT	**GRASS, CAT, TREE, SKY**	**DOG, DOG, CAT**	**DOG, DOG, CAT**
No spatial extent	No objects, just pixels	Multiple Objects	

This image is CC0 public domain

Last Time: R-CNN

Classify each region

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



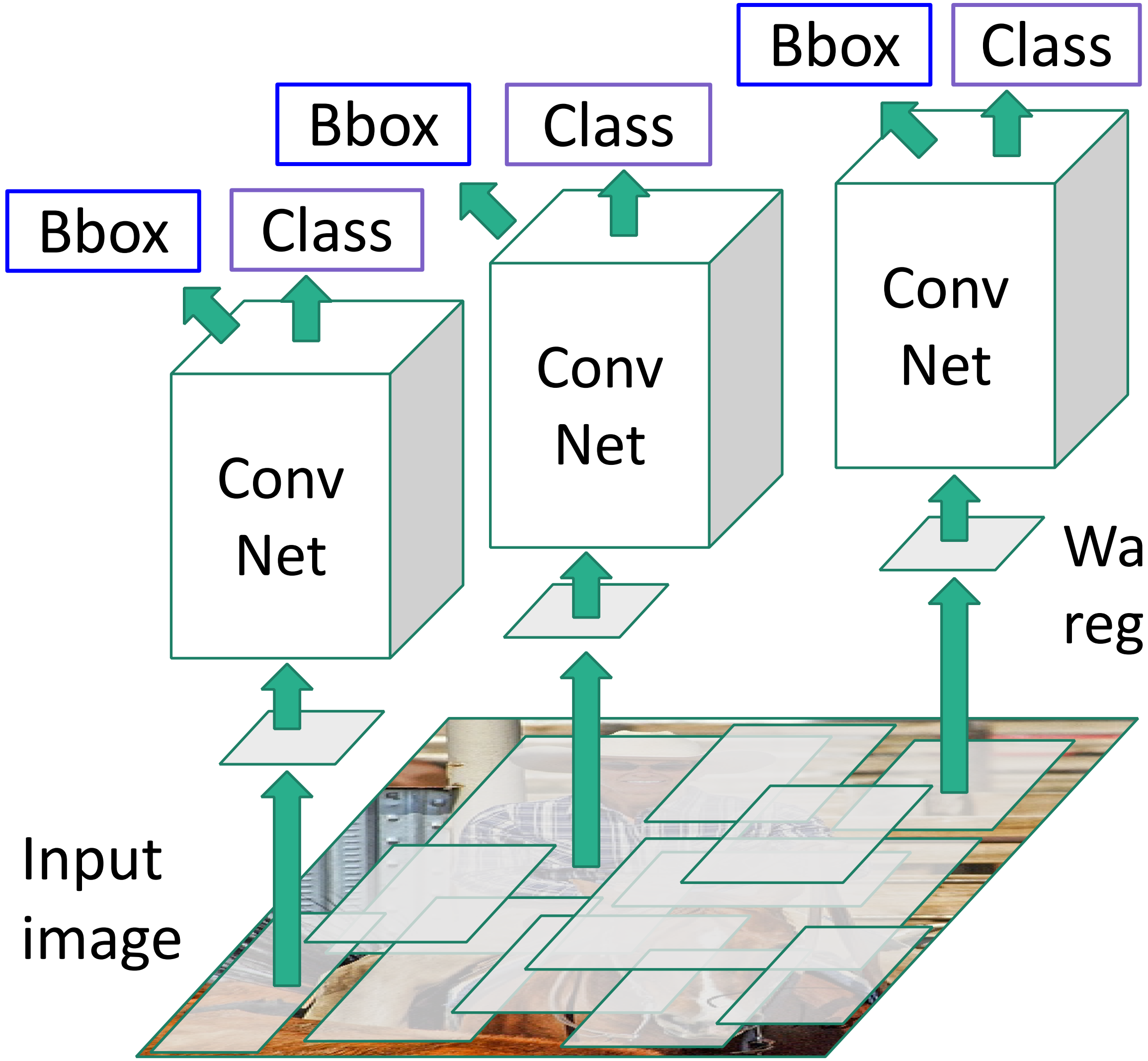
Forward each region through ConvNet

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.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Last Time: R-CNN



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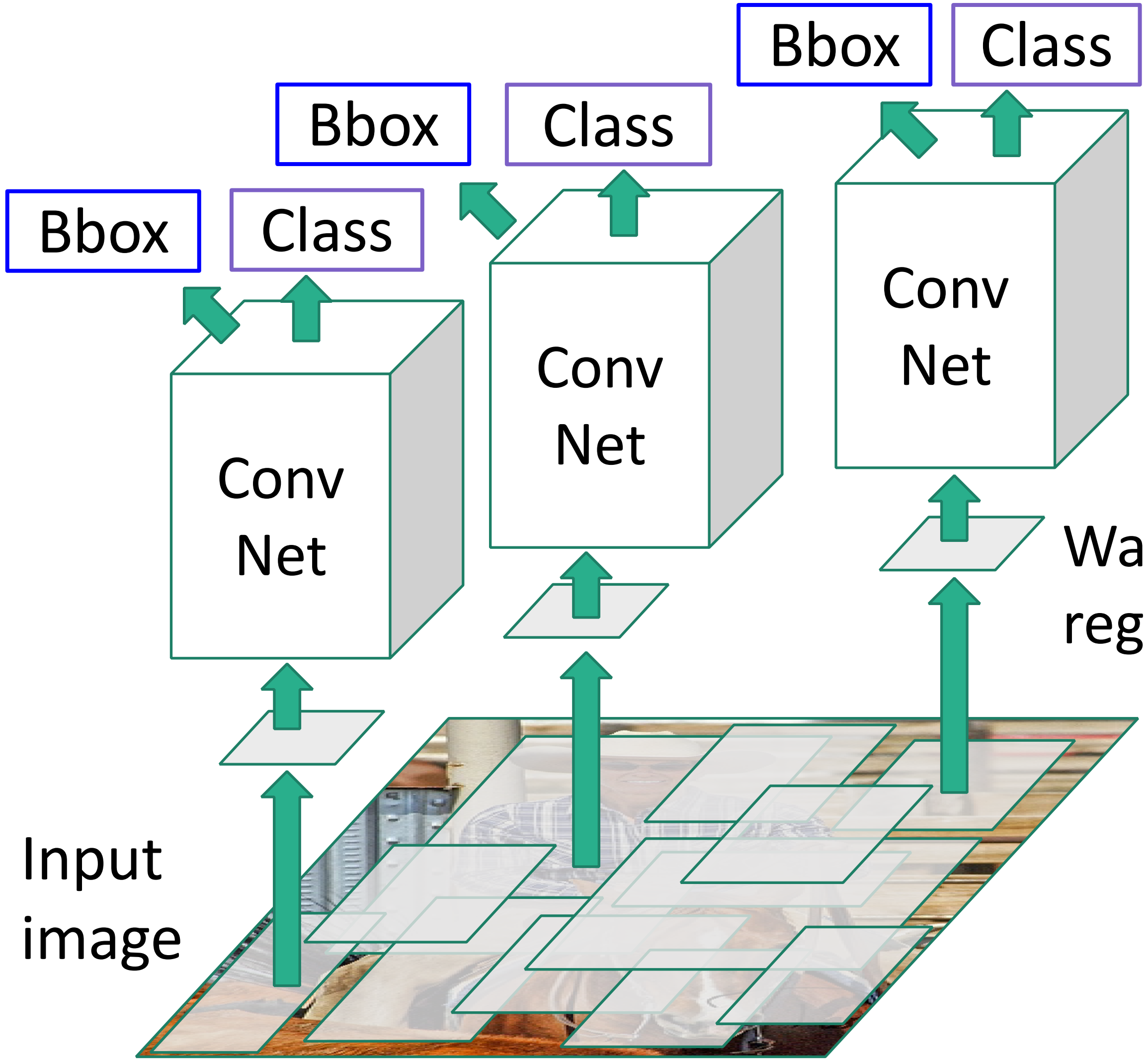
Problem: Very slow! Need to do 2000 forward passes through CNN per image

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

Last Time: R-CNN



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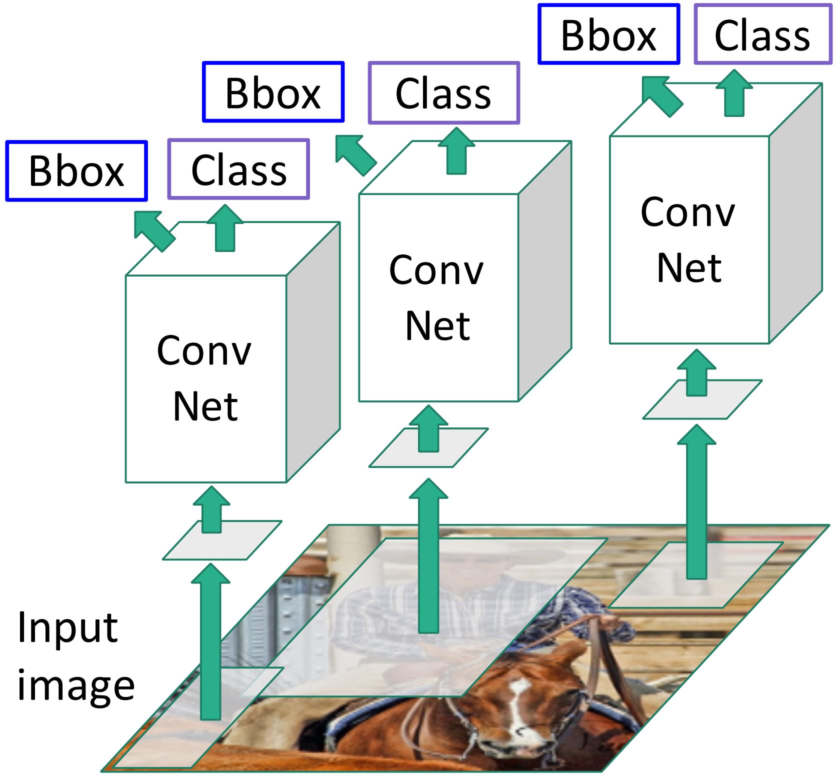
Problem: Very slow! Need to do 2000 forward passes through CNN per image

Idea: Overlapping proposals cause a lot of repeated work: same pixels processed many times. Can we avoid this?

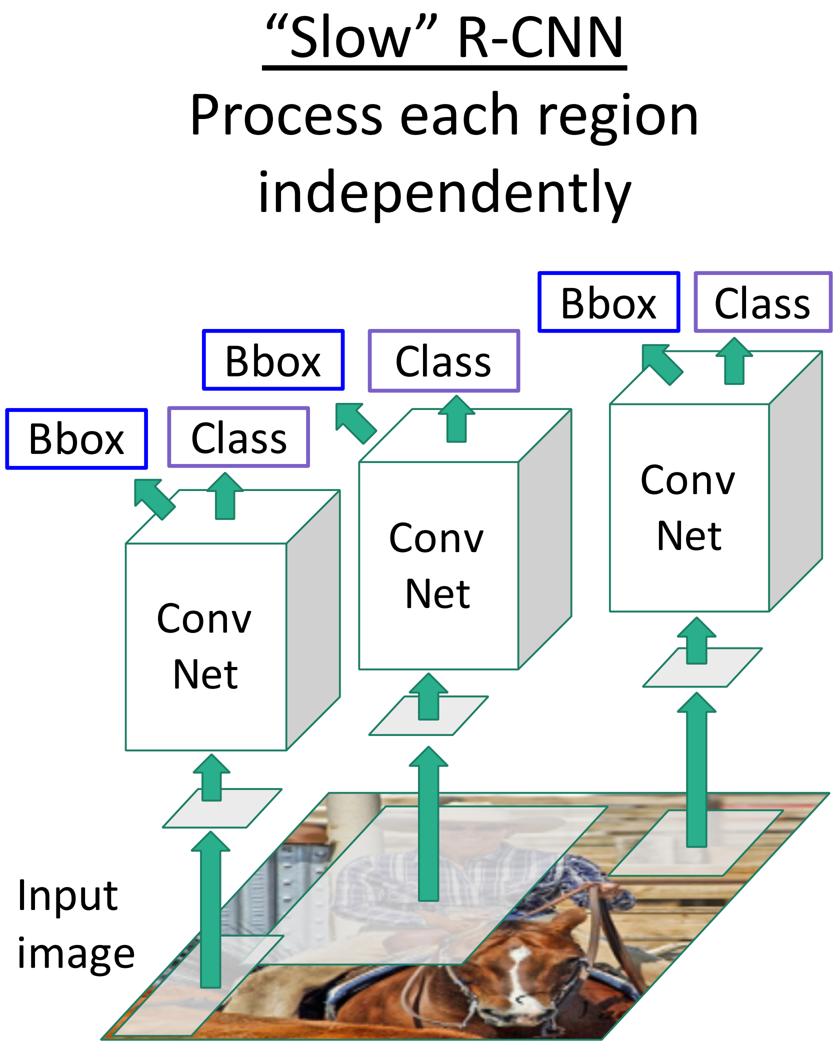
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

“Slow” R-CNN
Process each region independently



Fast R-CNN

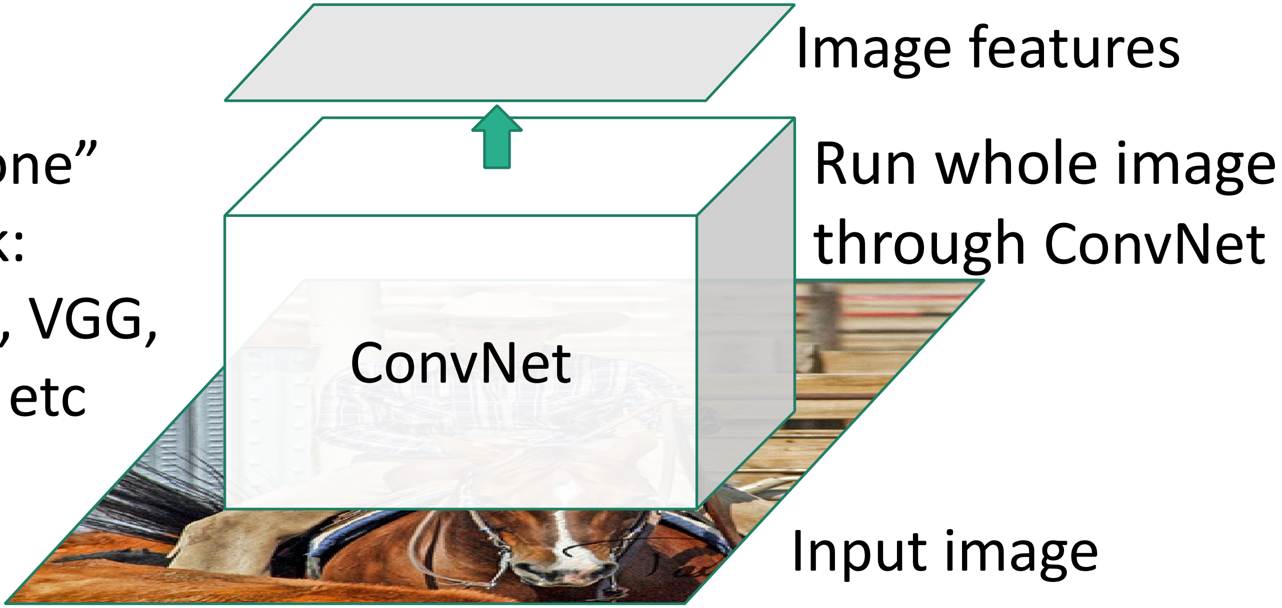
Input image



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

Fast R-CNN

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



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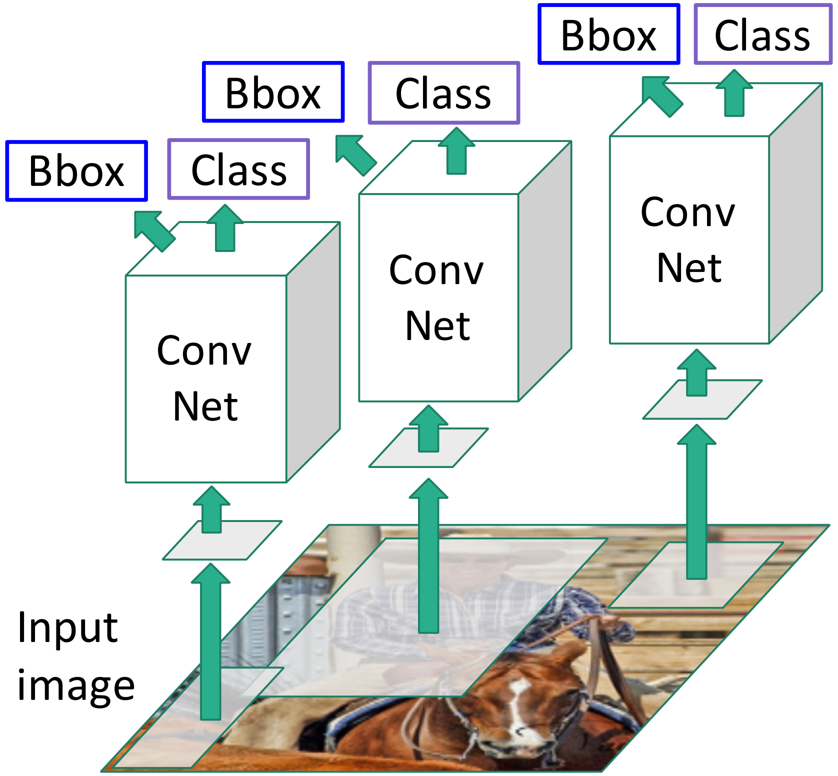

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Fast R-CNN

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Regions of Interest (RoIs) from a proposal method

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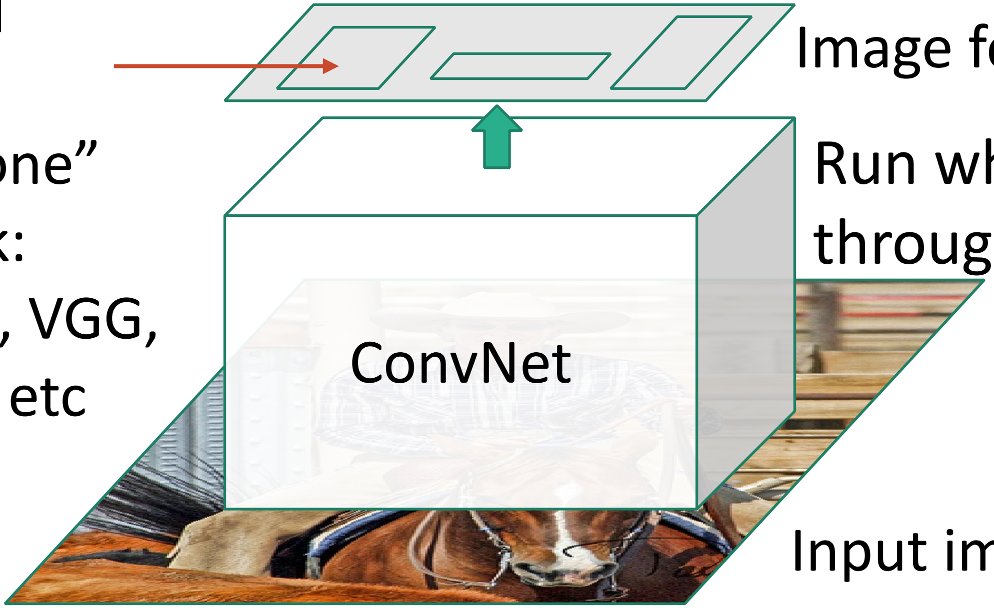
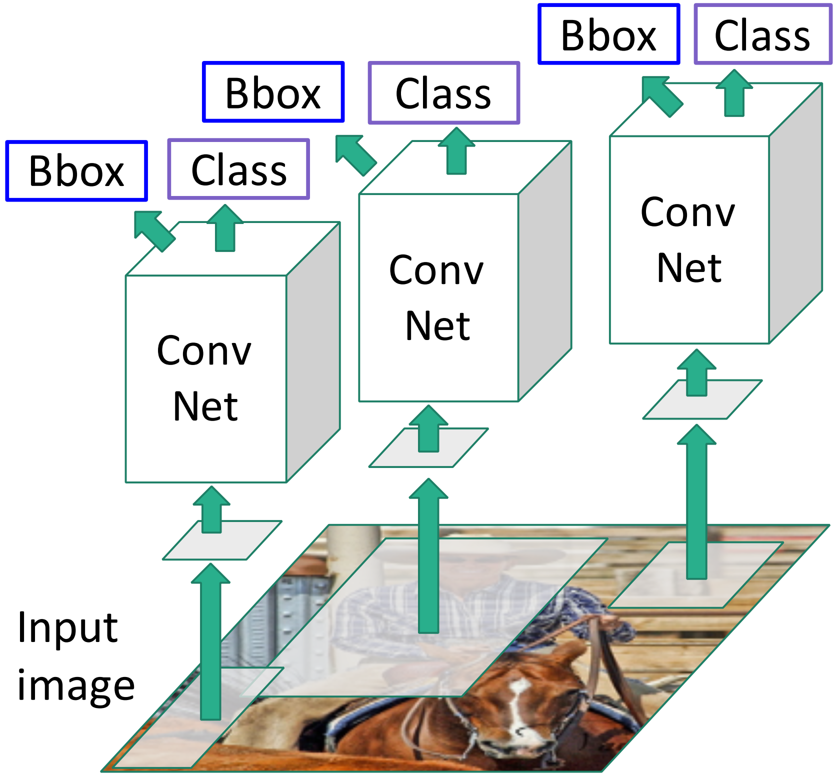


Image features

Run whole image through ConvNet

Input image



Fast R-CNN

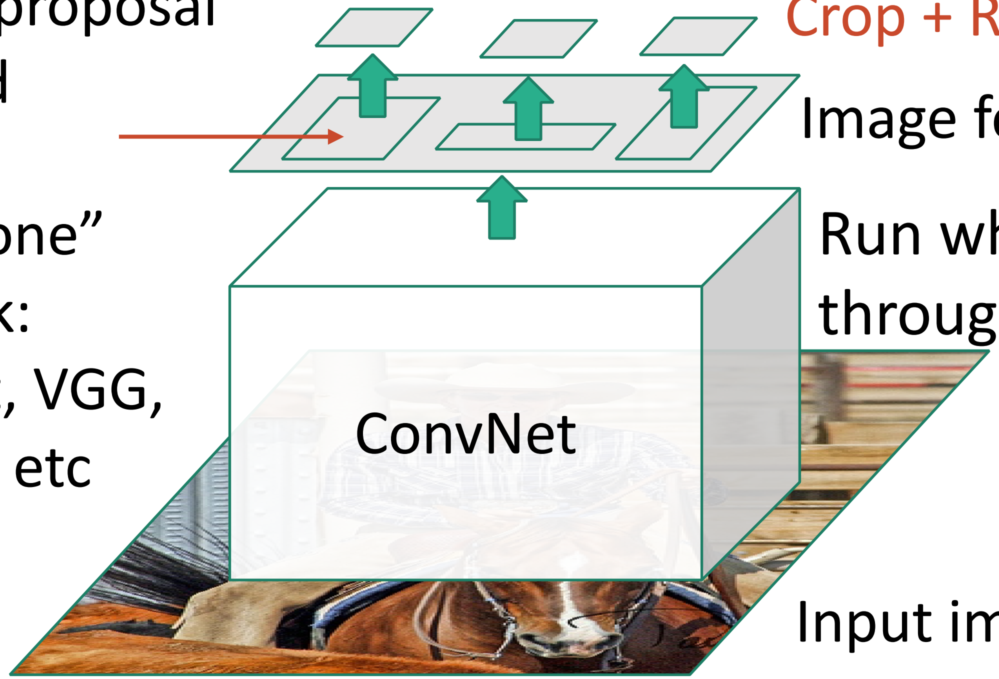
Regions of Interest (RoIs) from a proposal method

Crop + Resize features

Image features

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

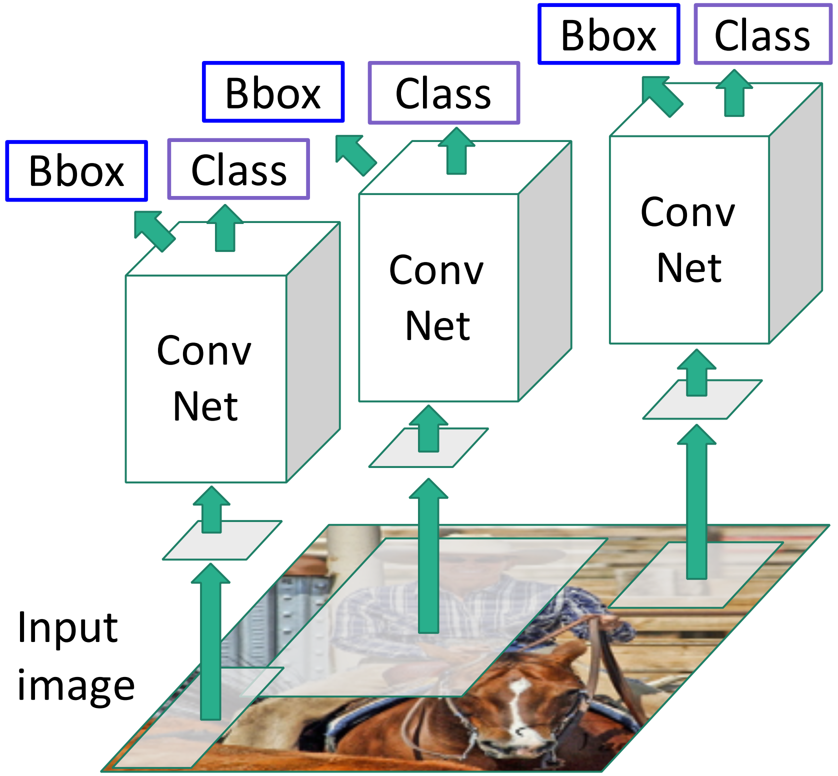
Run whole image through ConvNet



Input image

"Slow" R-CNN

Process each region independently



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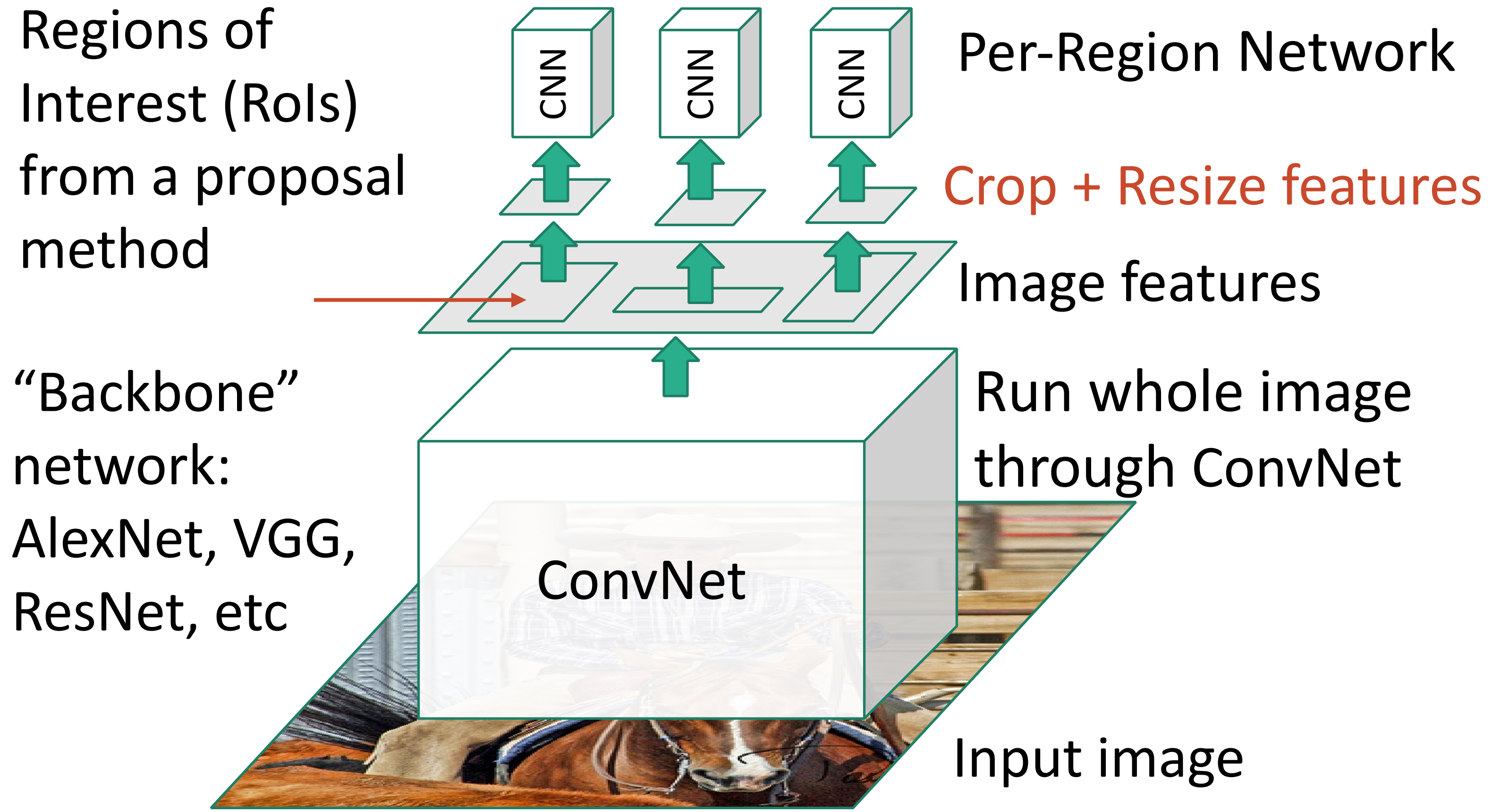
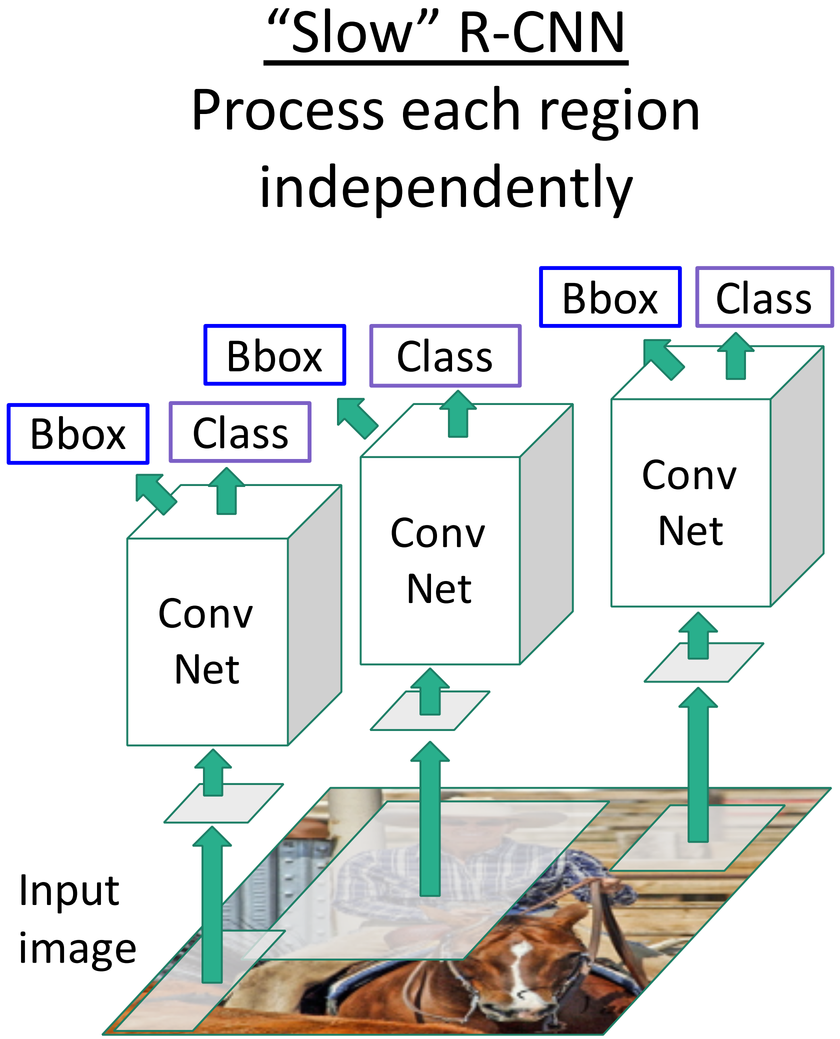
Fast R-CNN





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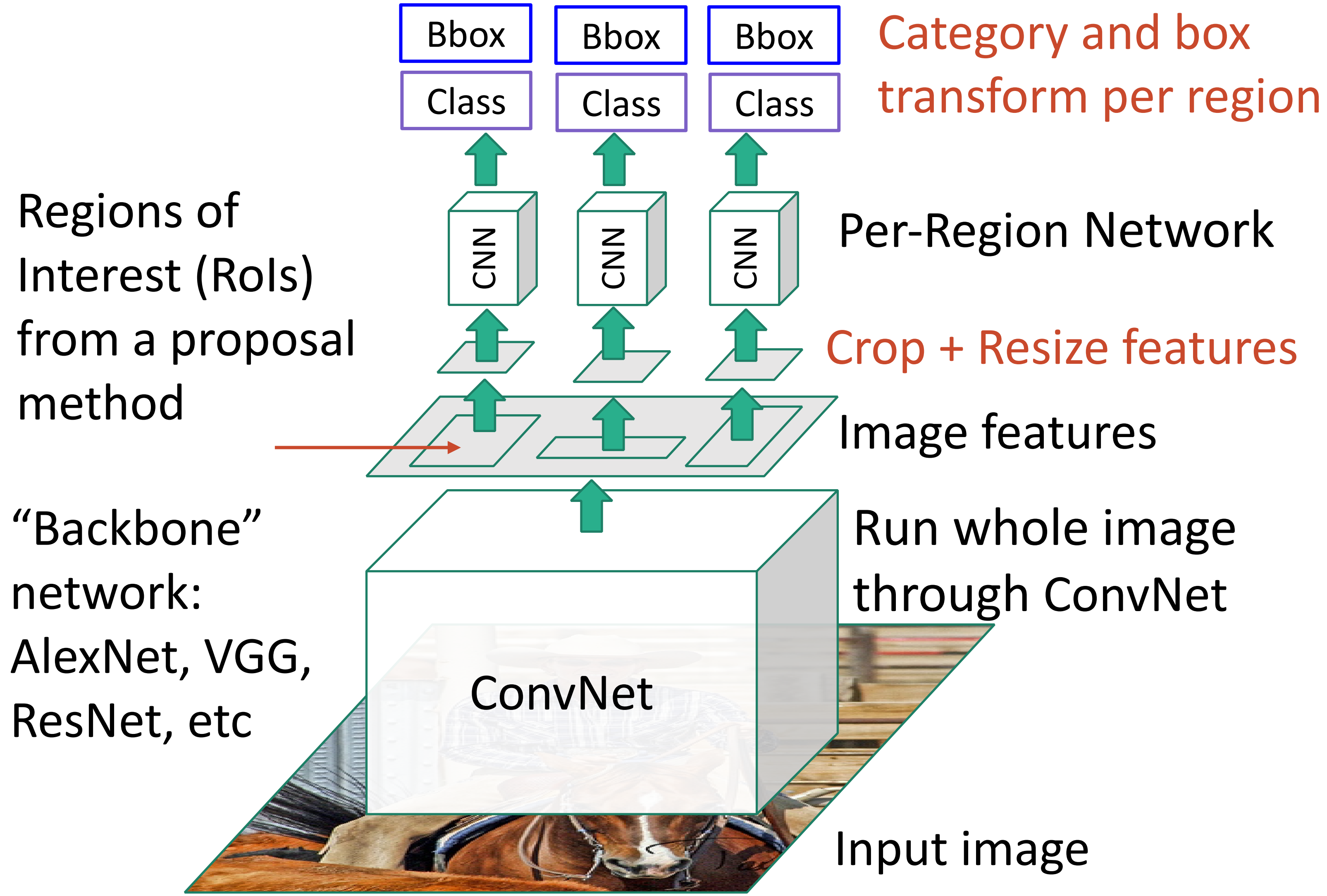
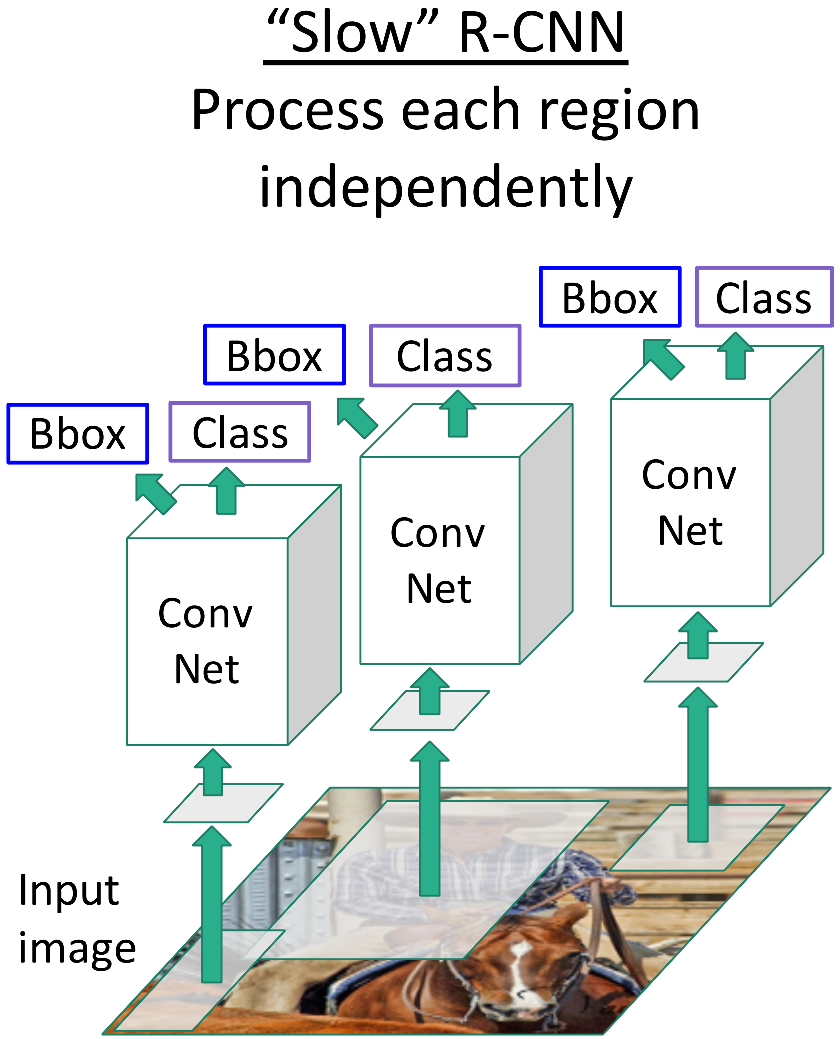
Fast R-CNN





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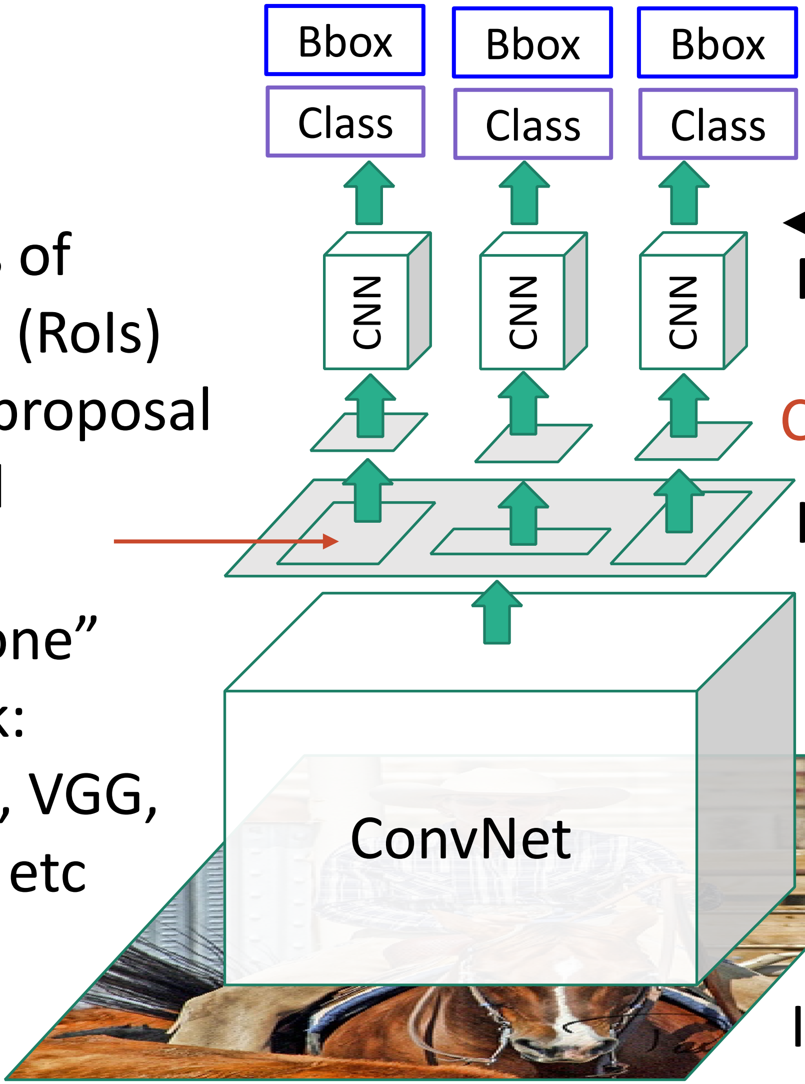
Fast R-CNN



Category and box transform per region

Per-Region network is relatively lightweight

Regions of Interest (RoIs) from a proposal method

Per-Region Network

Crop + Resize features

Image features

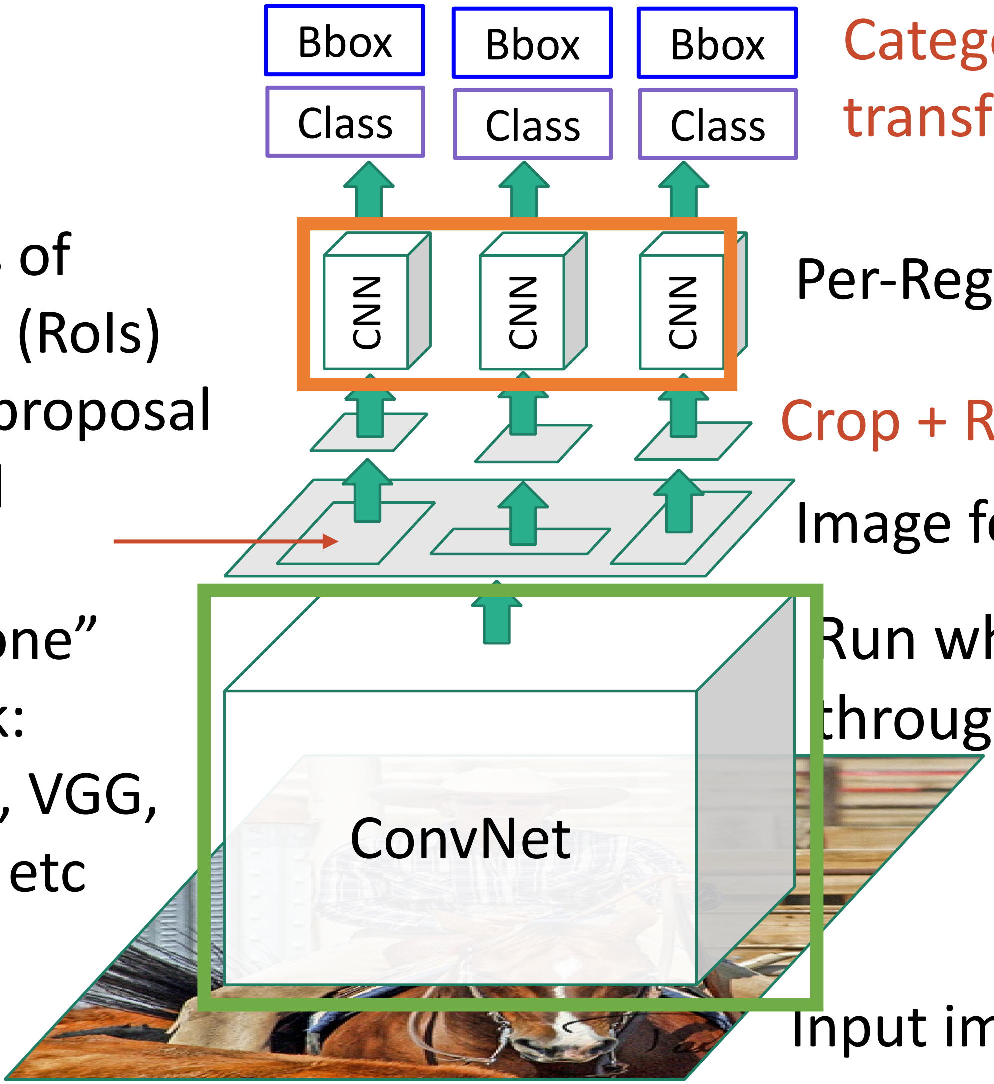
"Backbone" network: AlexNet, VGG, ResNet, etc

Run whole image through ConvNet

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

Input image

Fast R-CNN



Category and box transform per region

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Input image

Regions of Interest (RoIs) from a proposal method

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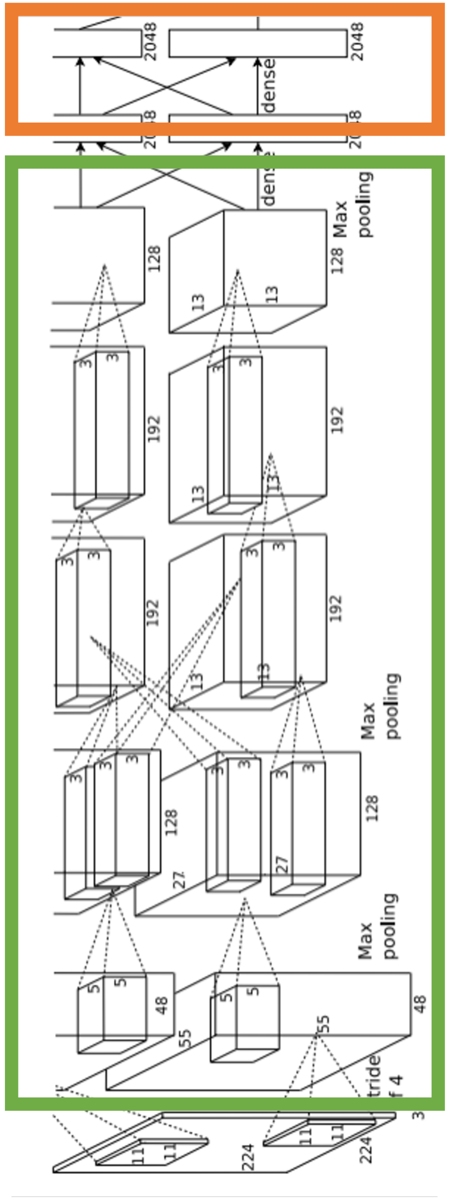

Example: When using AlexNet for detection, five conv layers are used for backbone and two FC layers are used for per-region network

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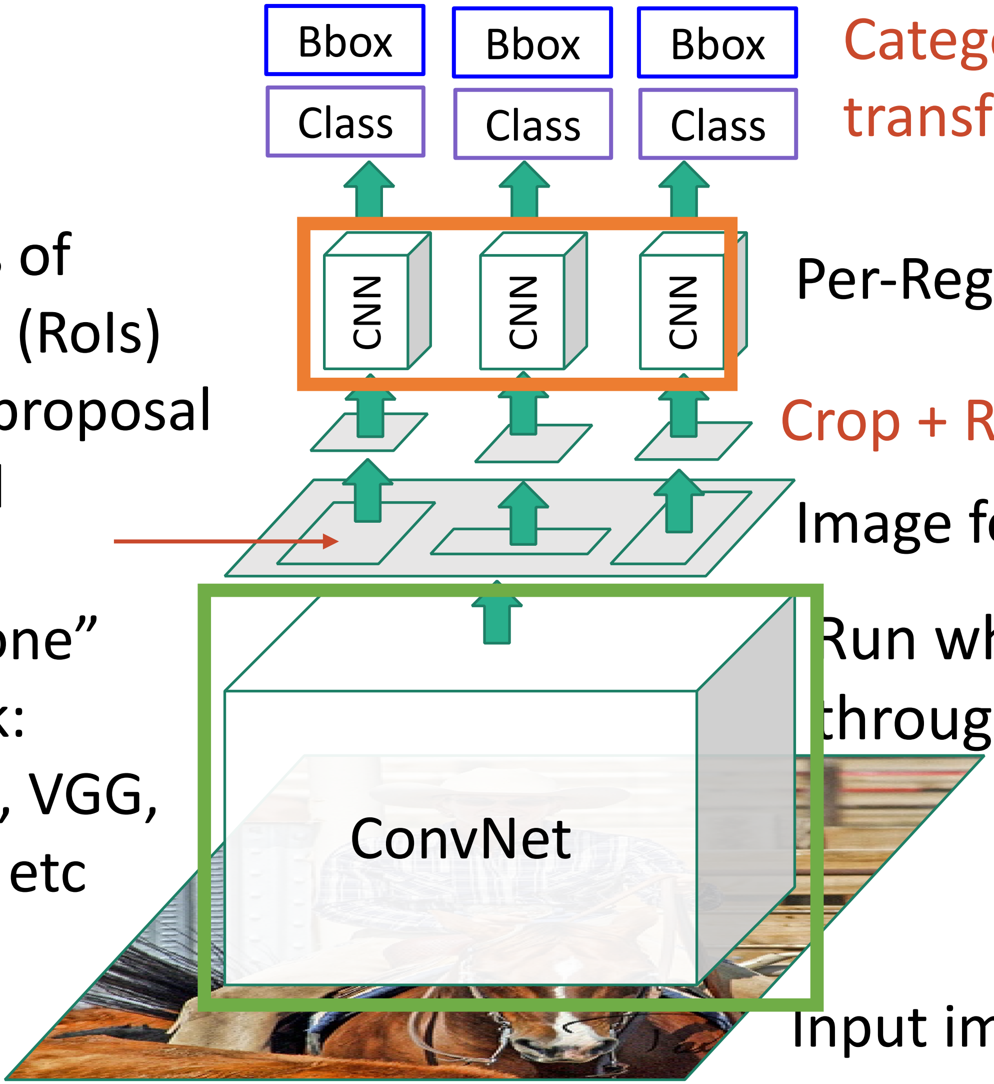
Fast R-CNN



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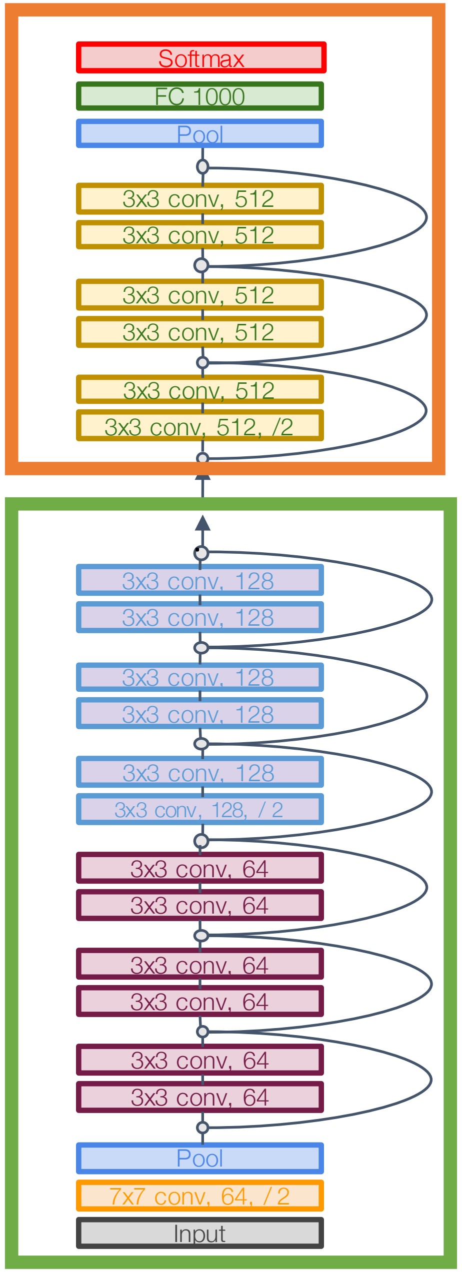
Input image



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

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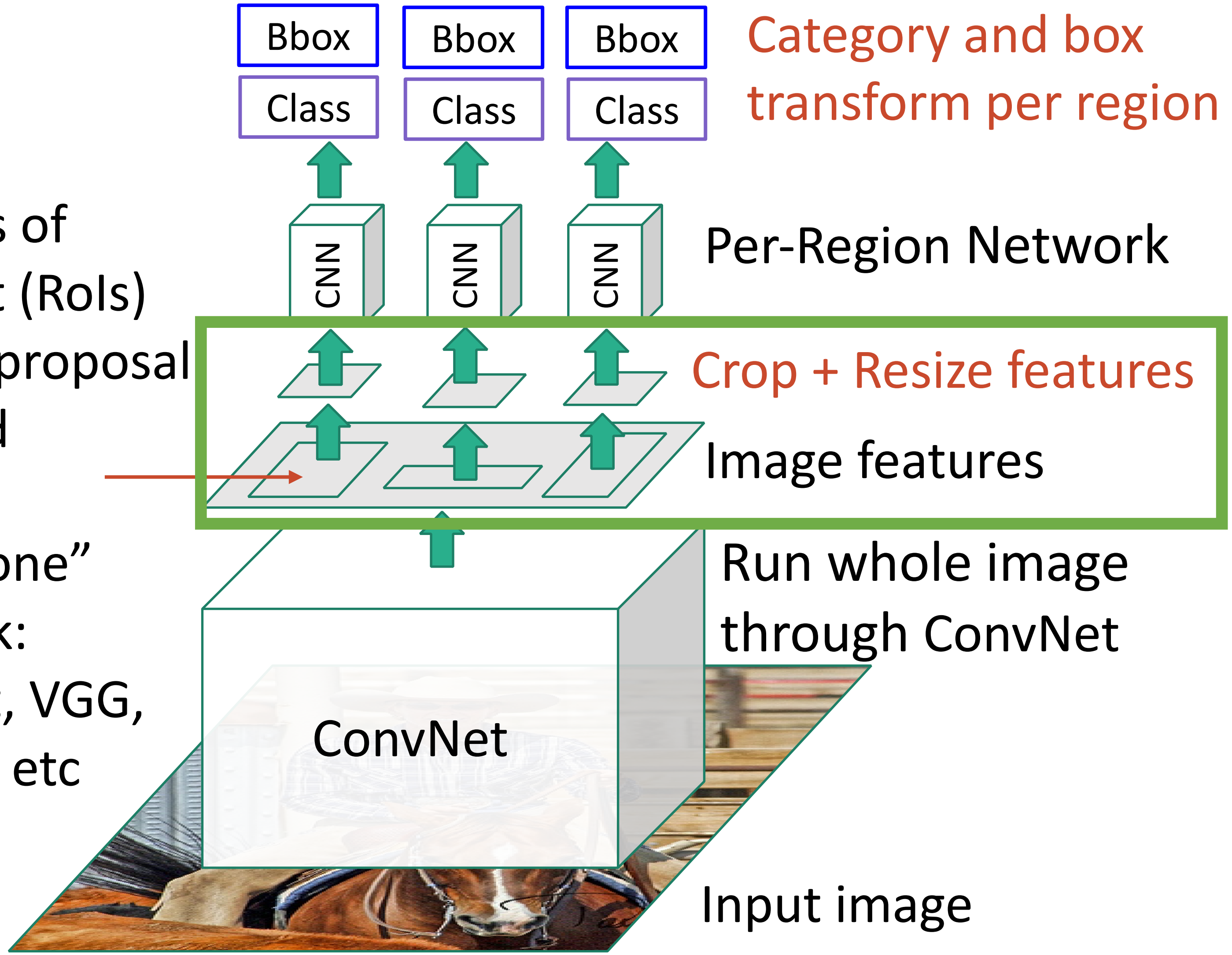
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



How to crop features?

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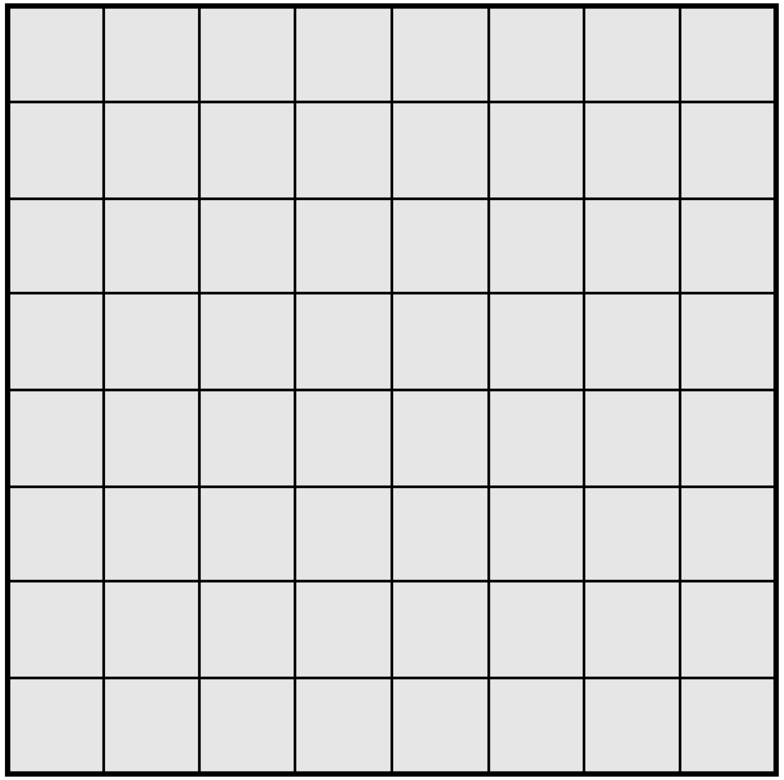
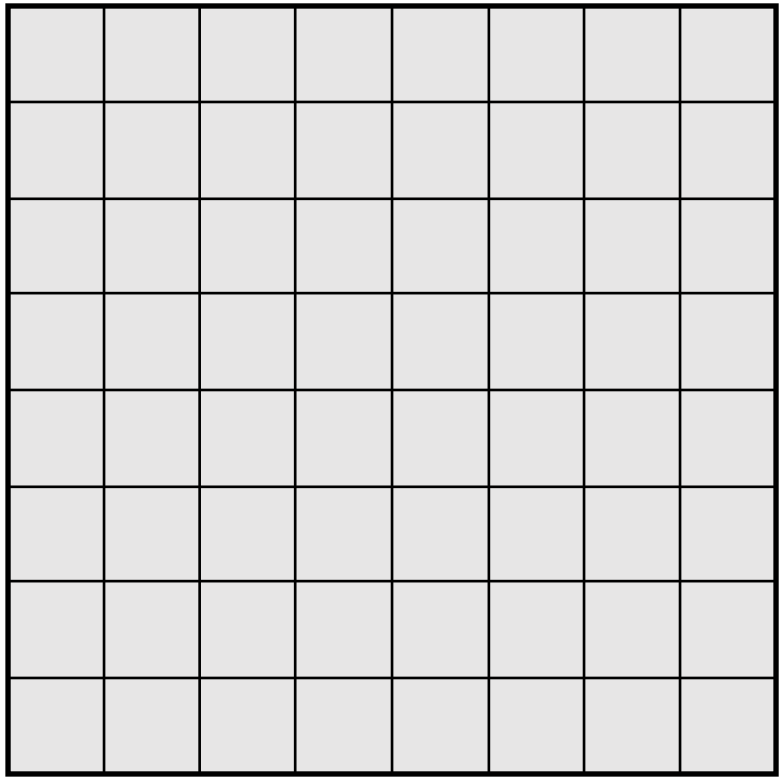
Recall: Receptive Fields

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



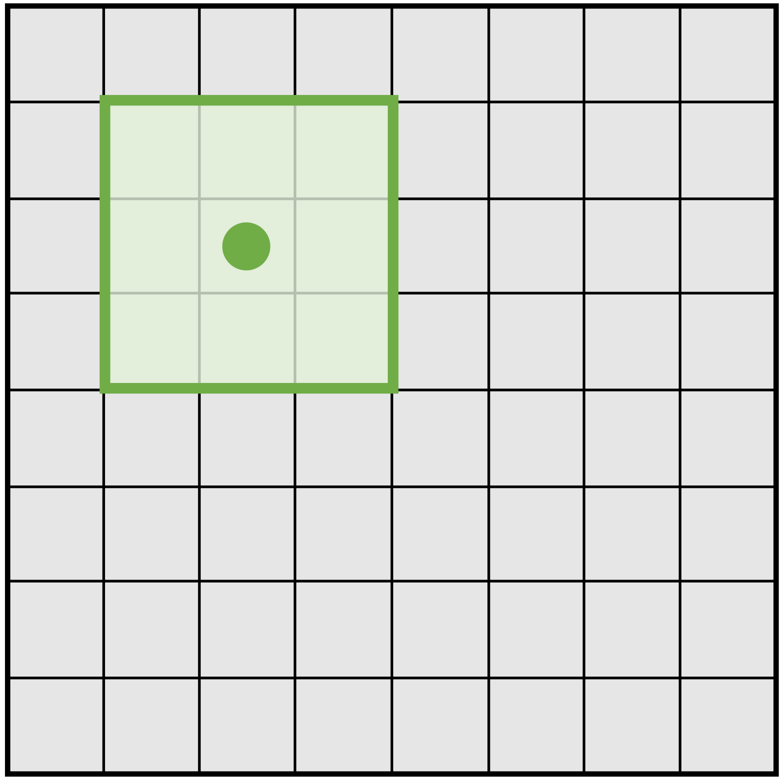
3x3 Conv
Stride 1, pad 1



Input Image: 8 x 8

Output Image: 8 x 8

Recall: Receptive Fields



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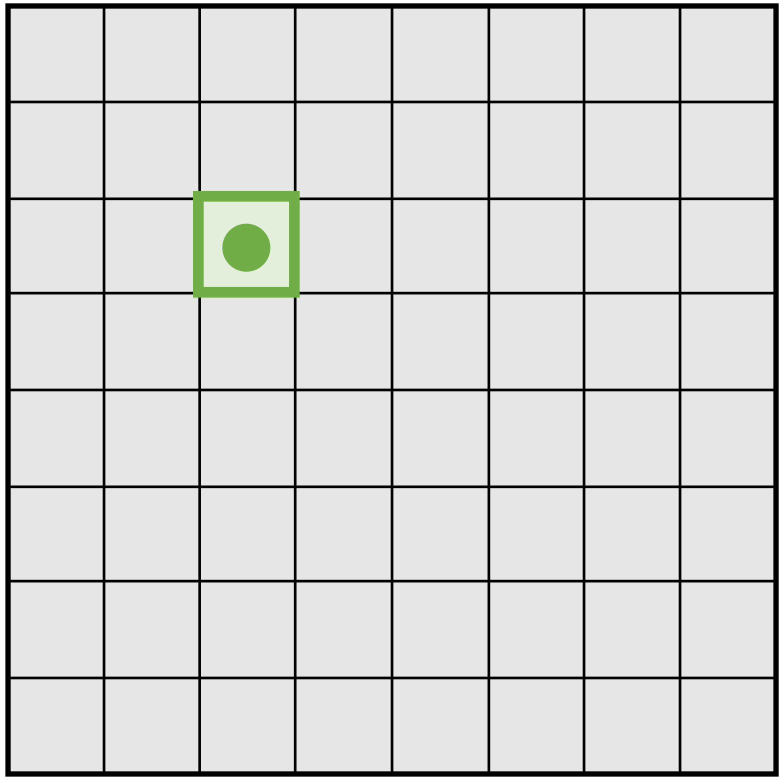
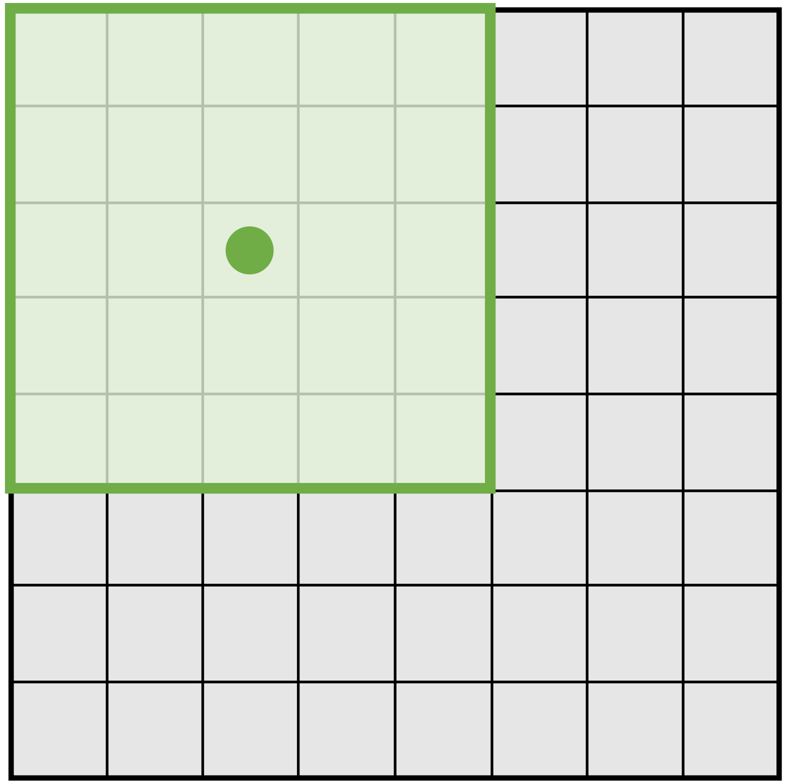
3x3 Conv
Stride 1, pad 1



Input Image: 8 x 8

Output Image: 8 x 8

Recall: Receptive Fields

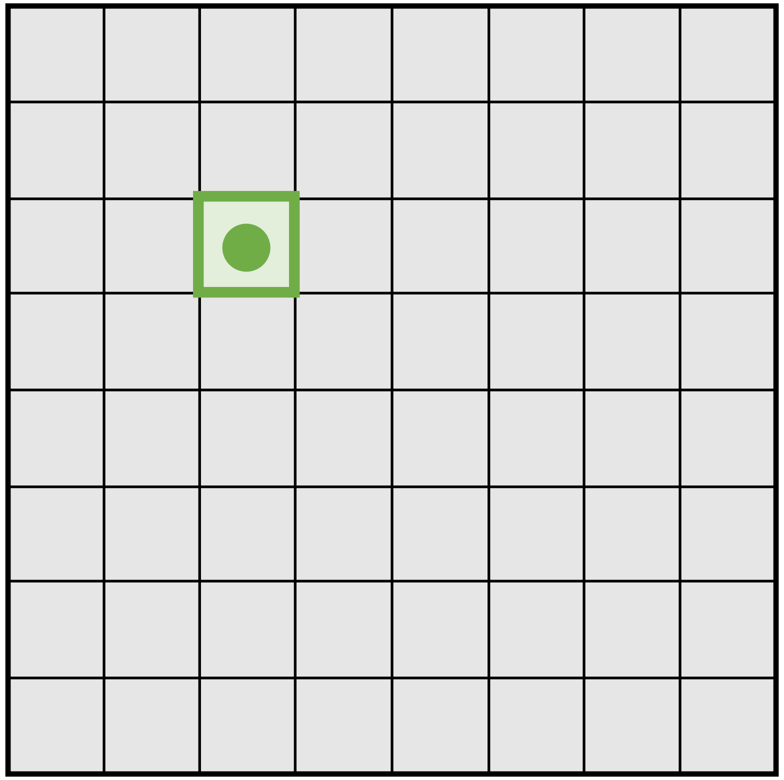


Input Image: 8 x 8

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

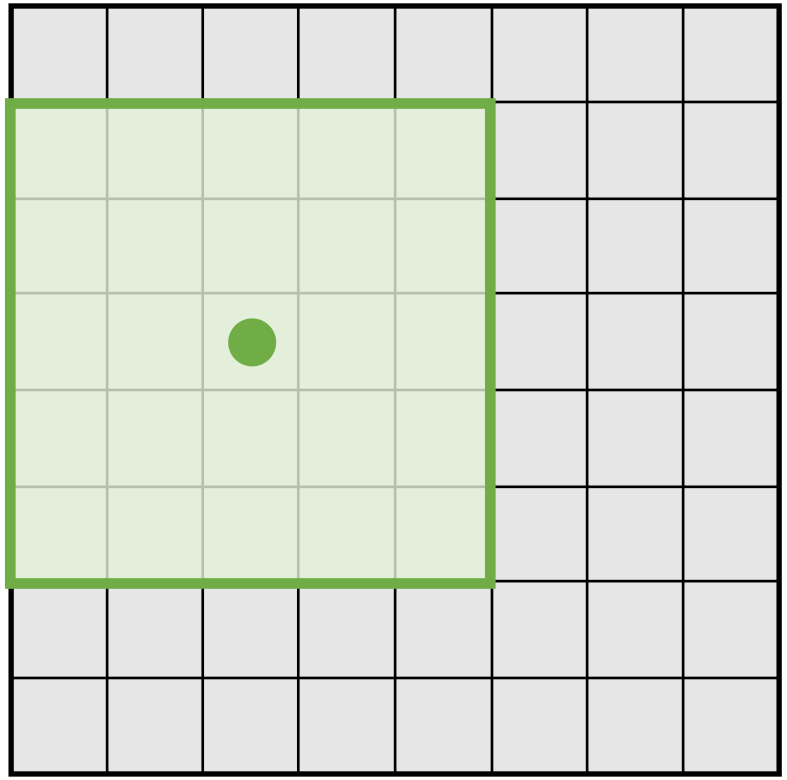
3x3 Conv
Stride 1, pad 1

3x3 Conv
Stride 1, pad 1



Output Image: 8 x 8

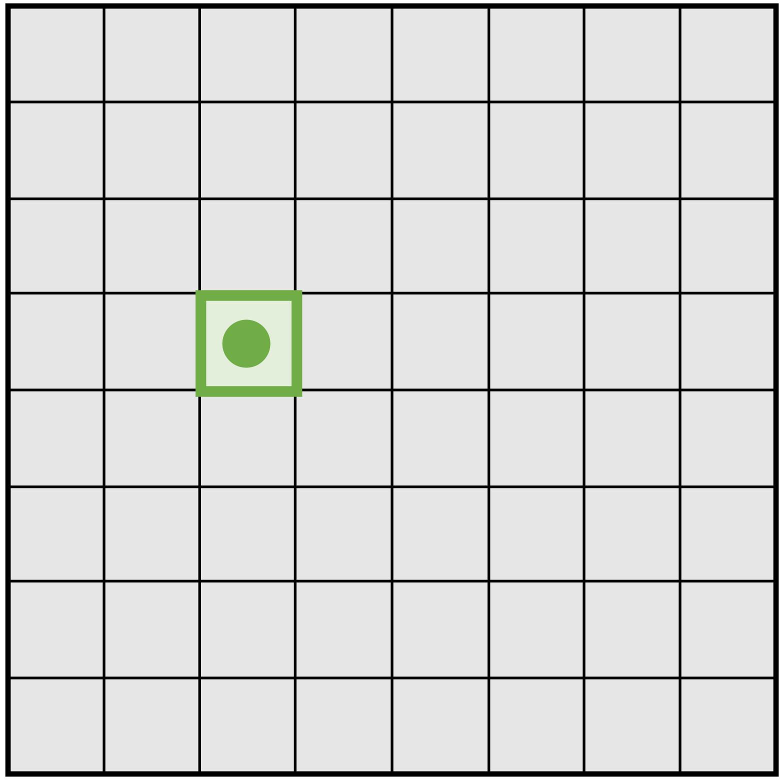
Recall: Receptive Fields



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

3x3 Conv
Stride 1, pad 1

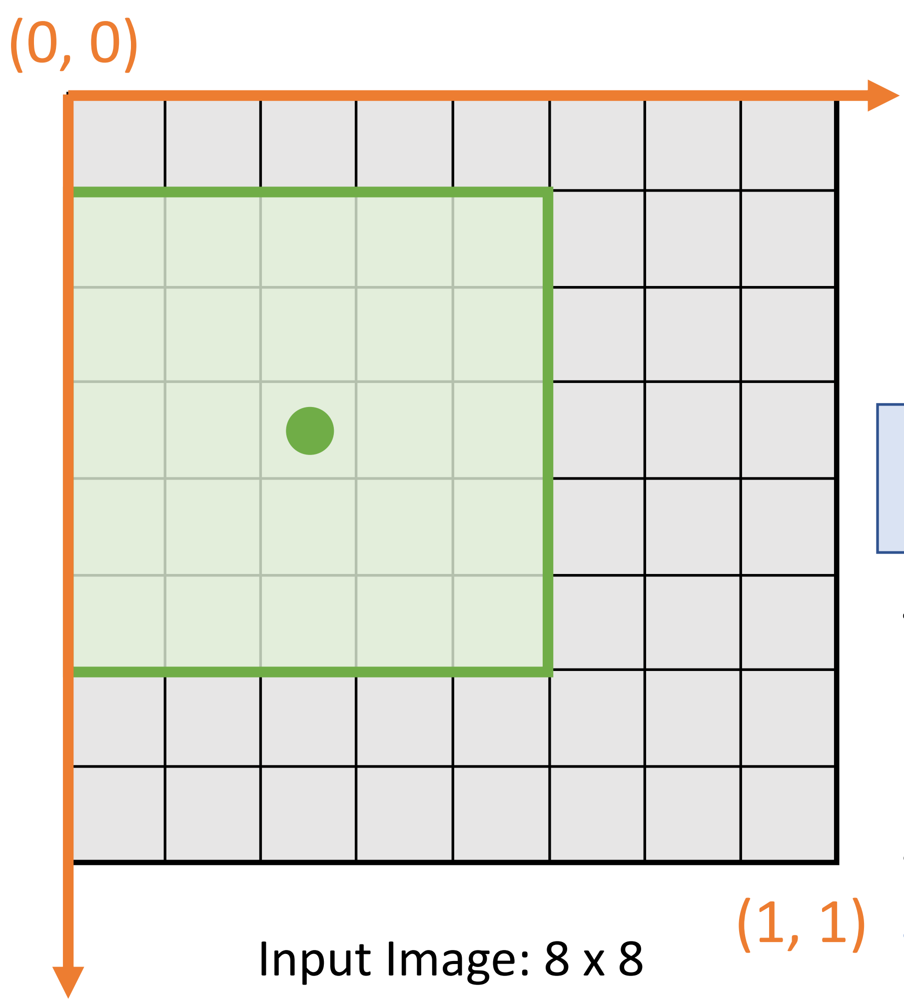
3x3 Conv
Stride 1, pad 1



Input Image: 8 x 8

Output Image: 8 x 8

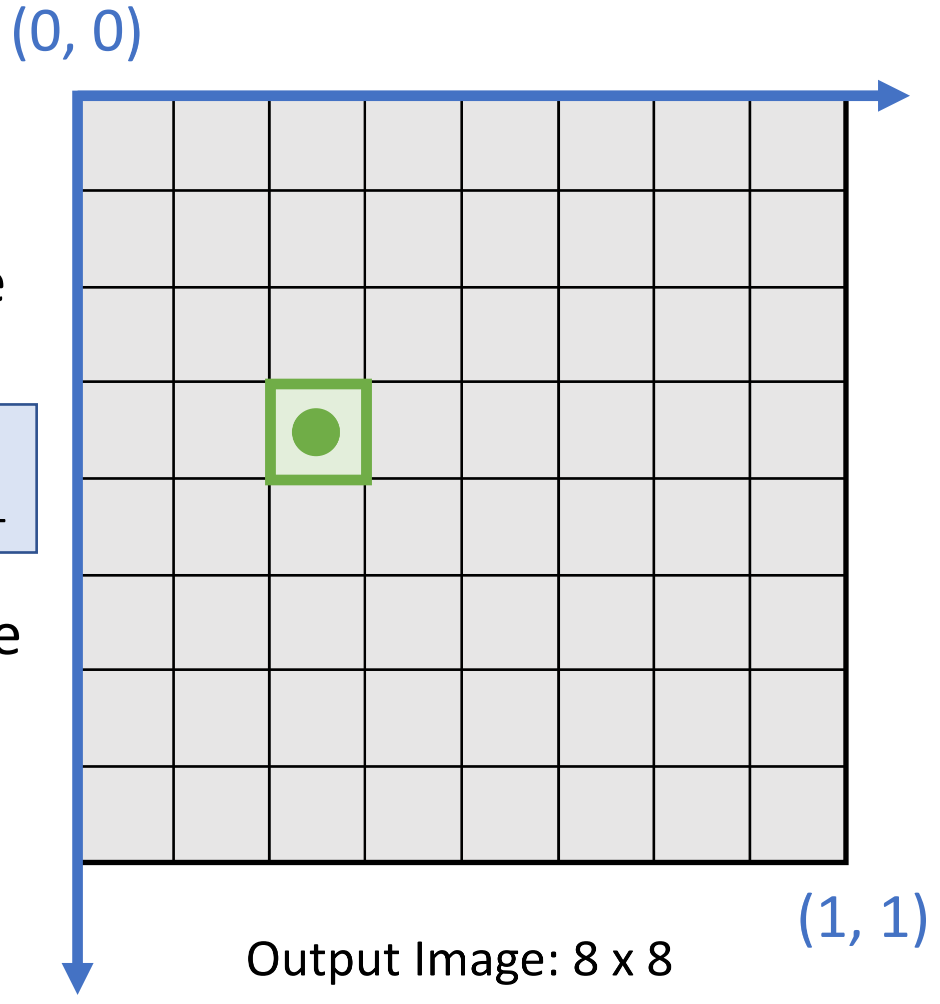
Recall: Receptive Fields



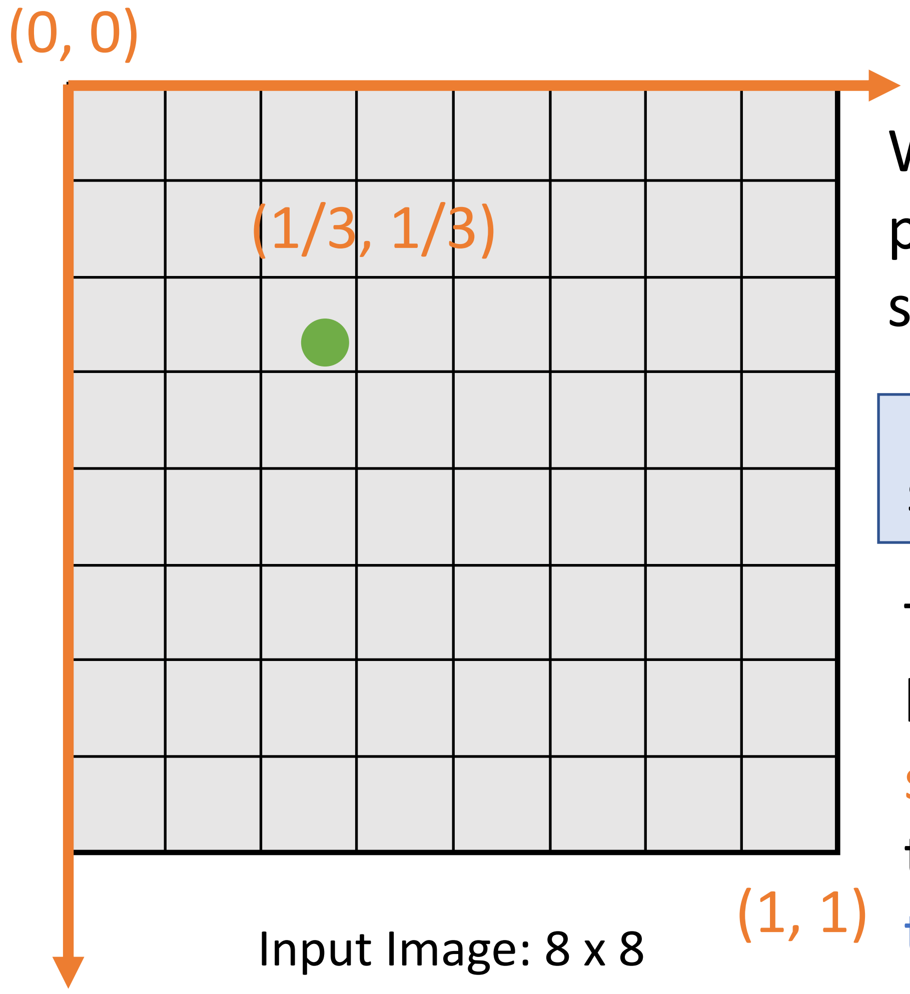
Moving one unit in the output space also moves the receptive field by one

3x3 Conv Stride 1, pad 1	3x3 Conv Stride 1, pad 1

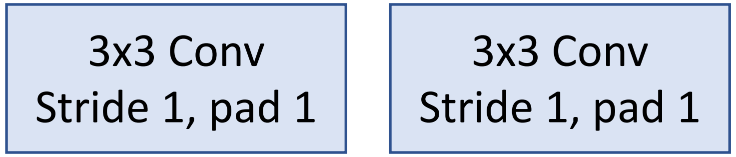
There is a correspondence between the coordinate system of the input and the coordinate system of the output



Projecting Points



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



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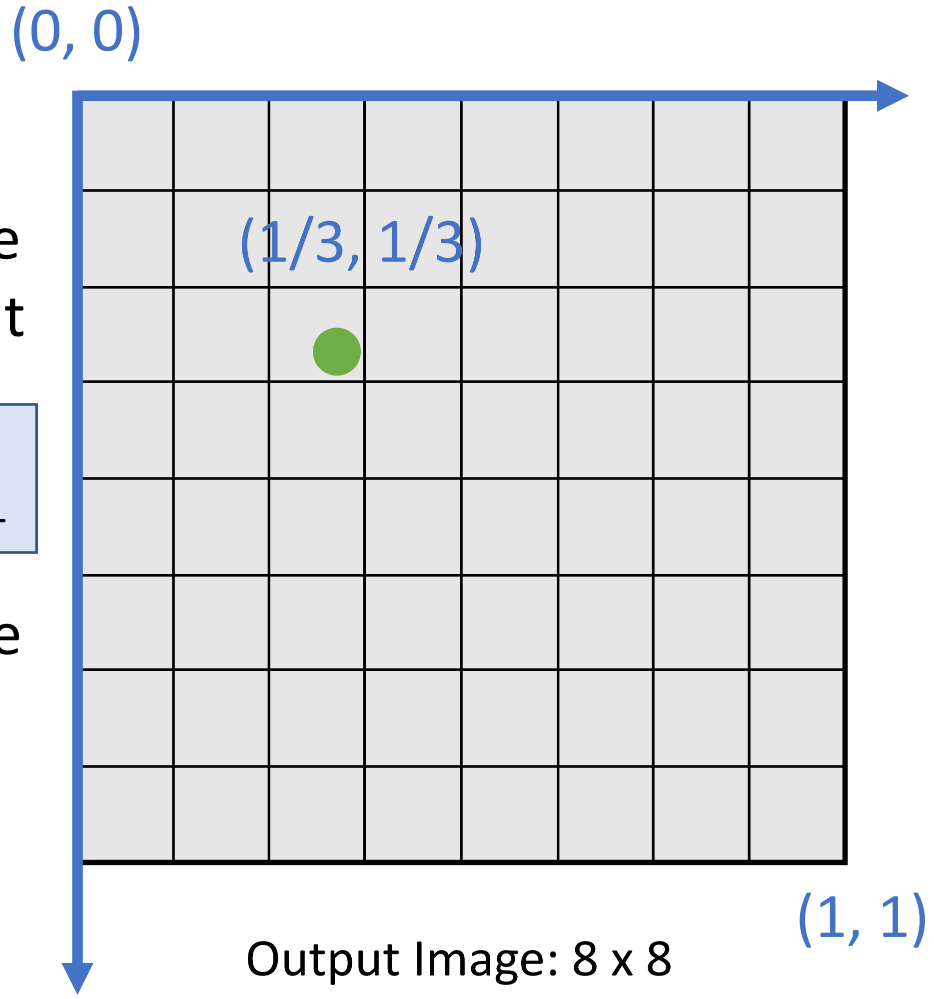
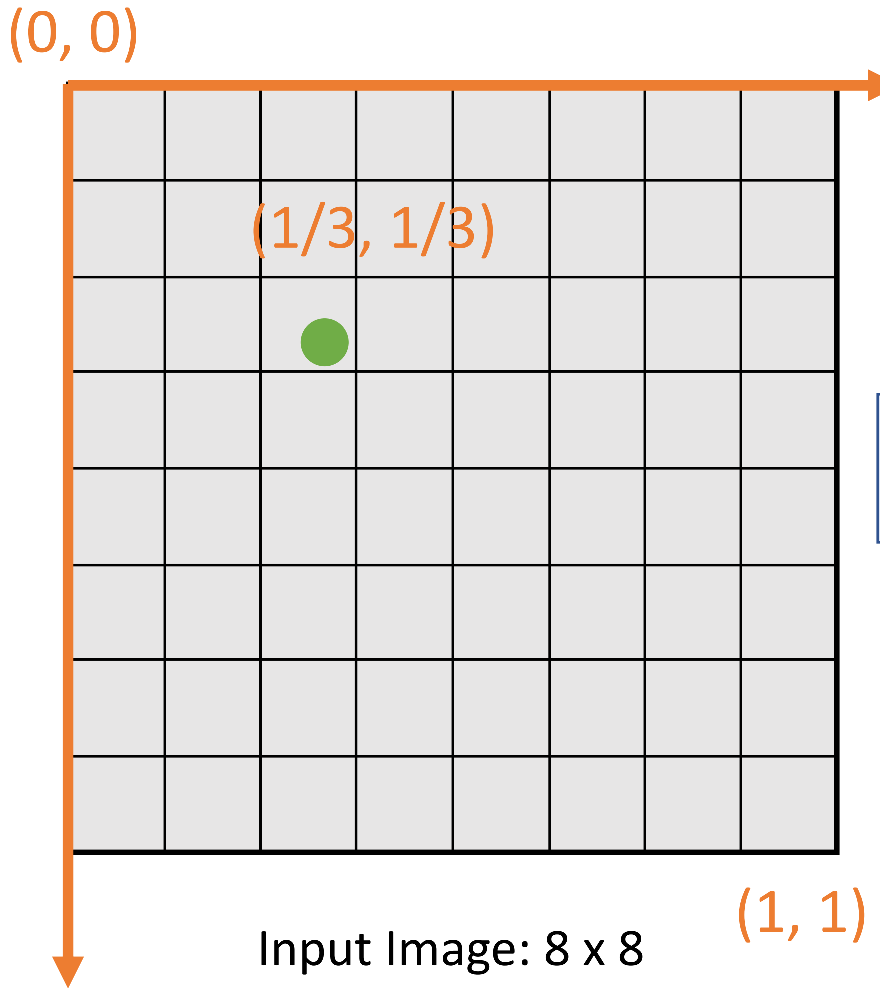


Projecting Points

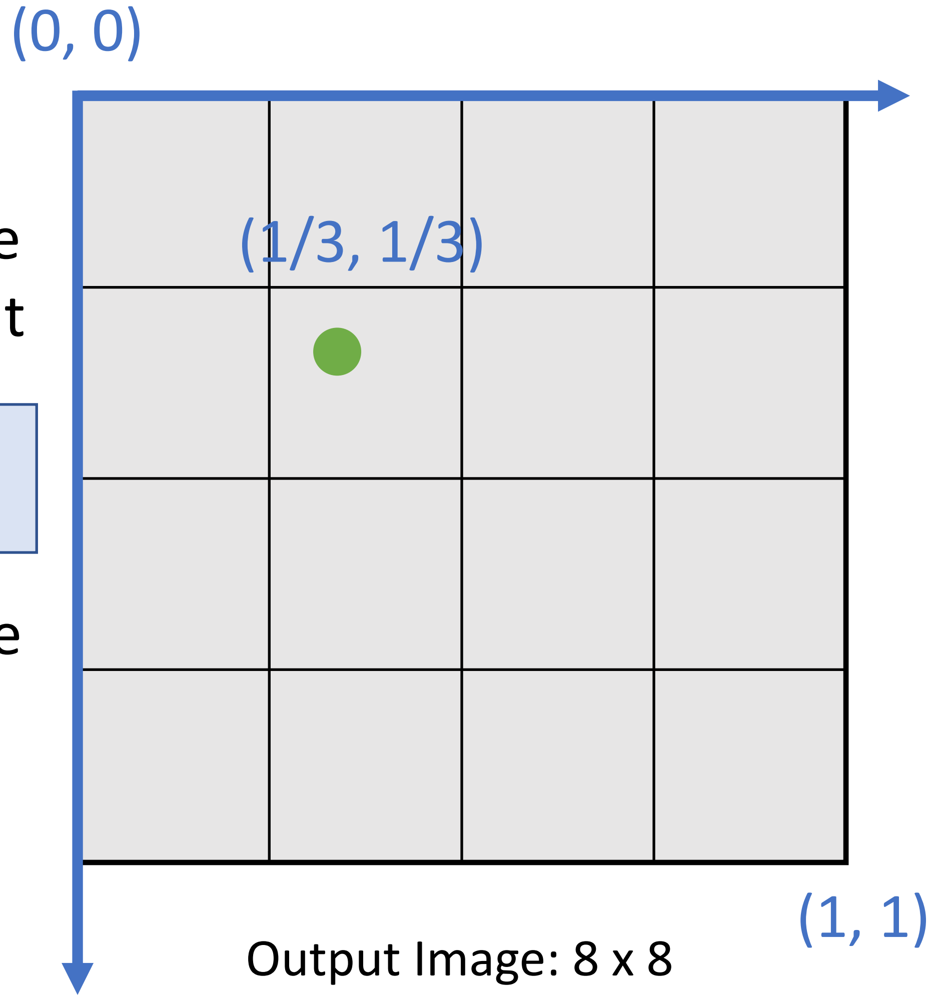
Same logic holds for more complicated CNNs, even if spatial resolution of input and output are different



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



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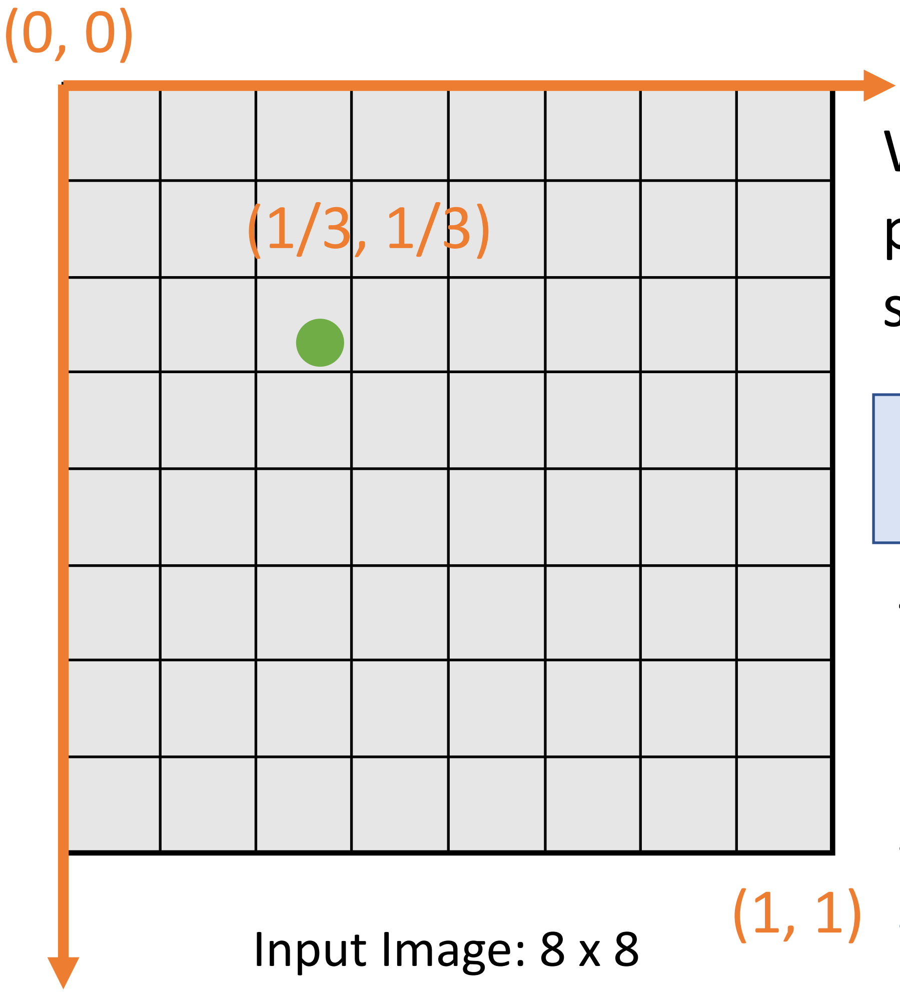
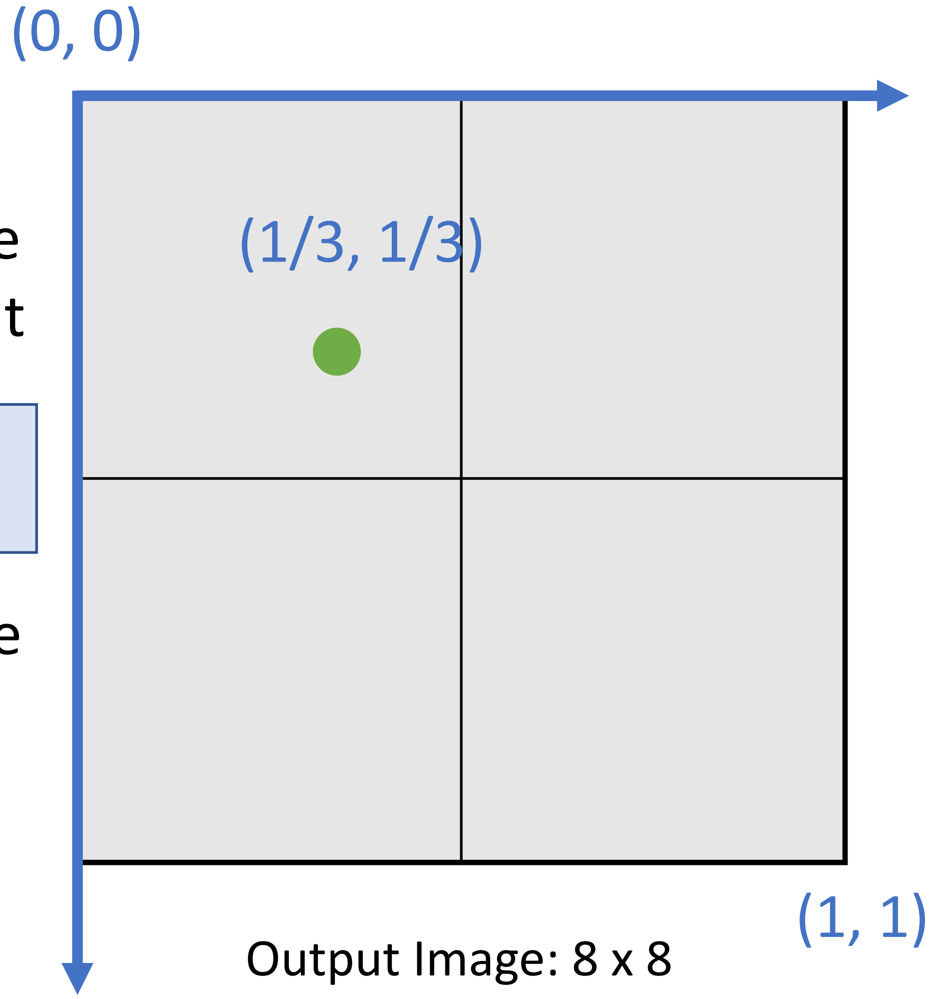


Input Image: 8 x 8

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

3x3 Conv Stride 1, pad 1	4x4 MaxPool Stride 4

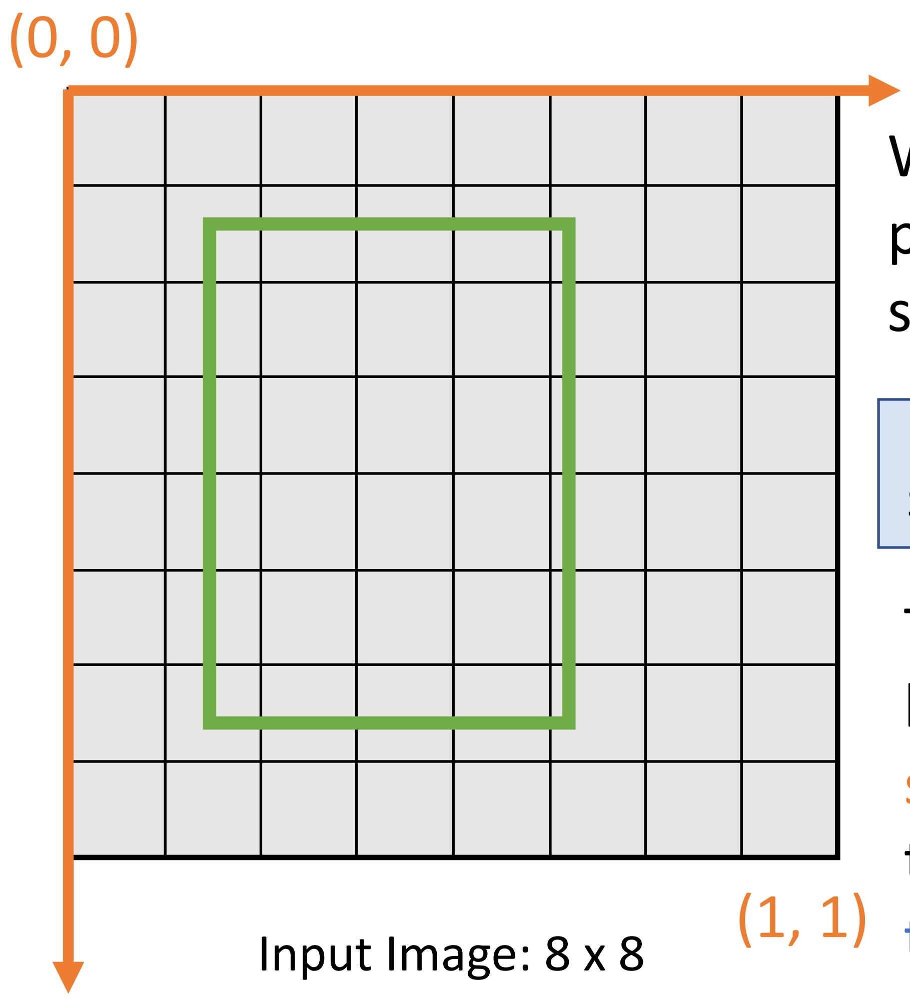
There is a correspondence between the coordinate system of the input and the coordinate system of the output



Output Image: 8 x 8

Projecting Boxes

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



Input Image: 8 x 8

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

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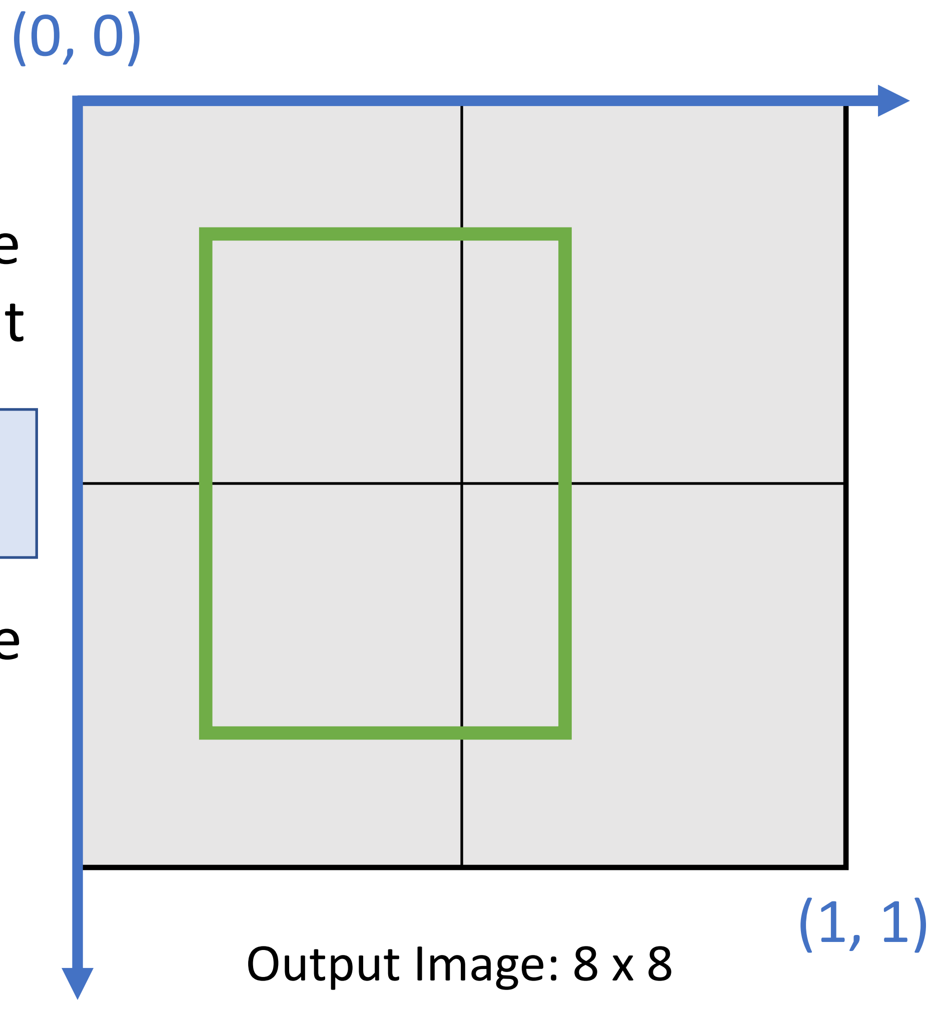
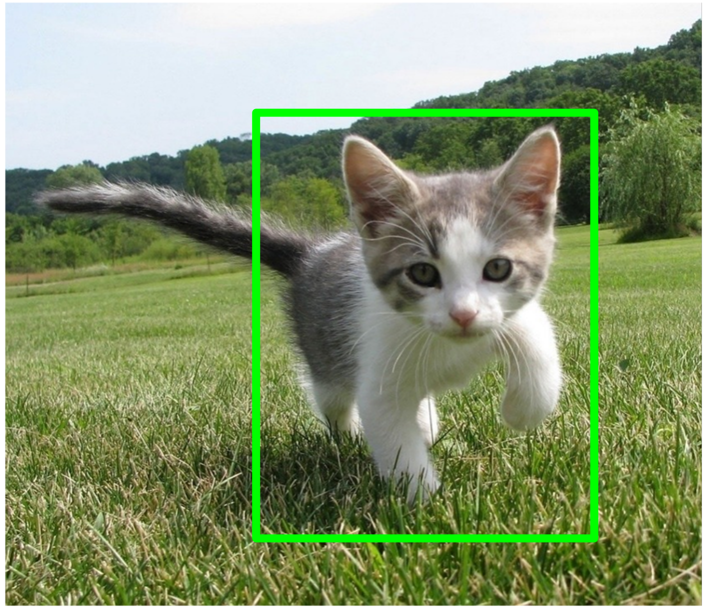


Output Image: 8 x 8

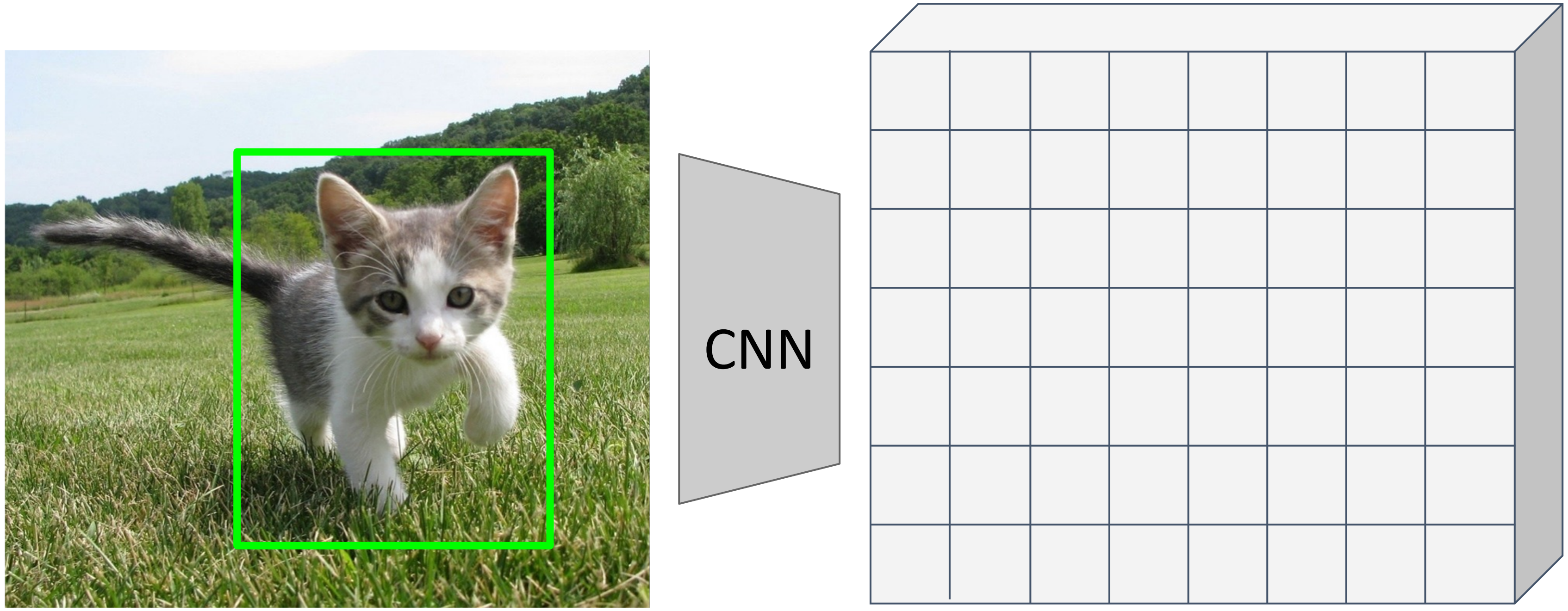
Cropping Features: RoI Pool



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

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



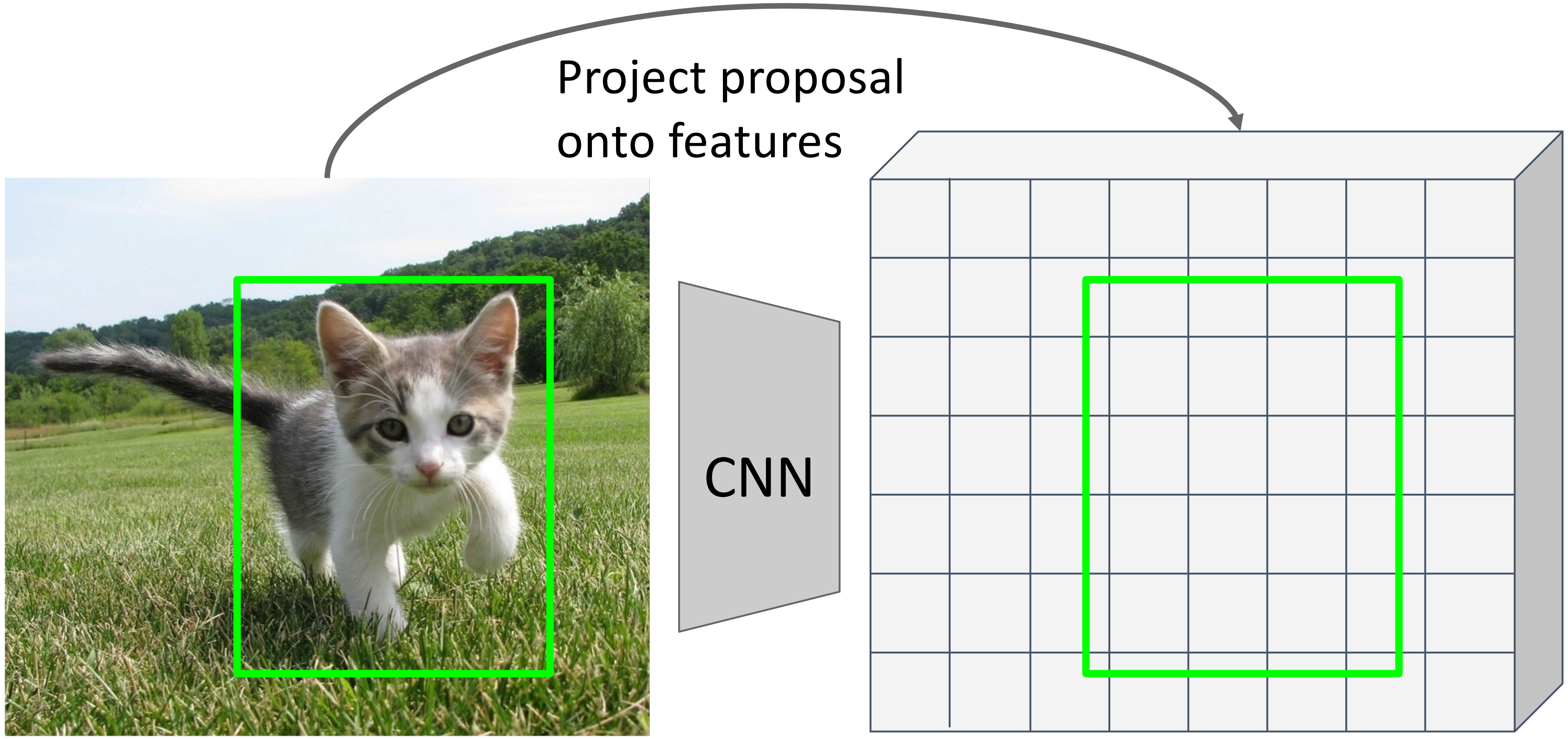
Input Image
(e.g. 3 x 640 x 480)

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

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

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

Cropping Features: RoI Pool



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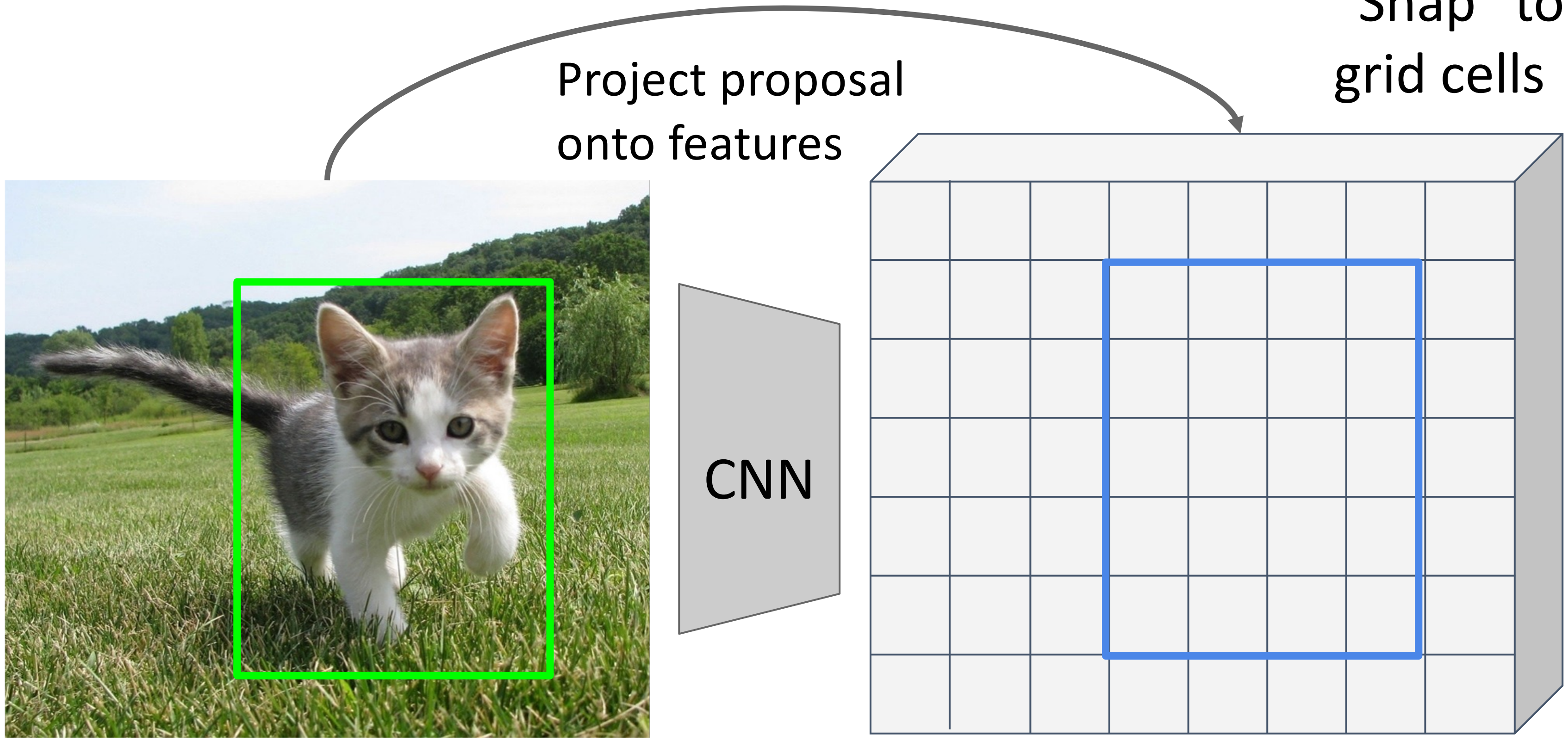

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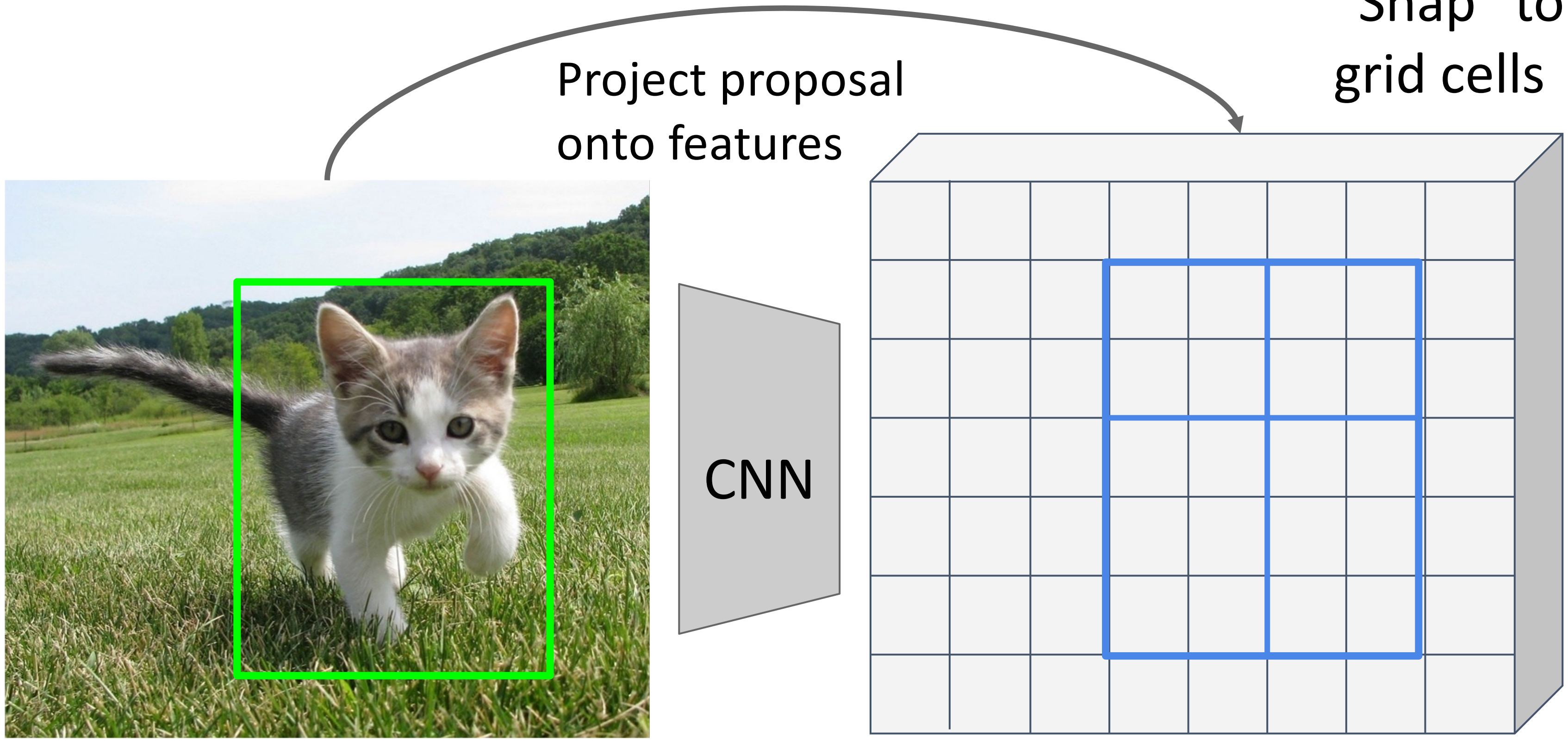


Divide into 2x2 grid of (roughly) equal subregions

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

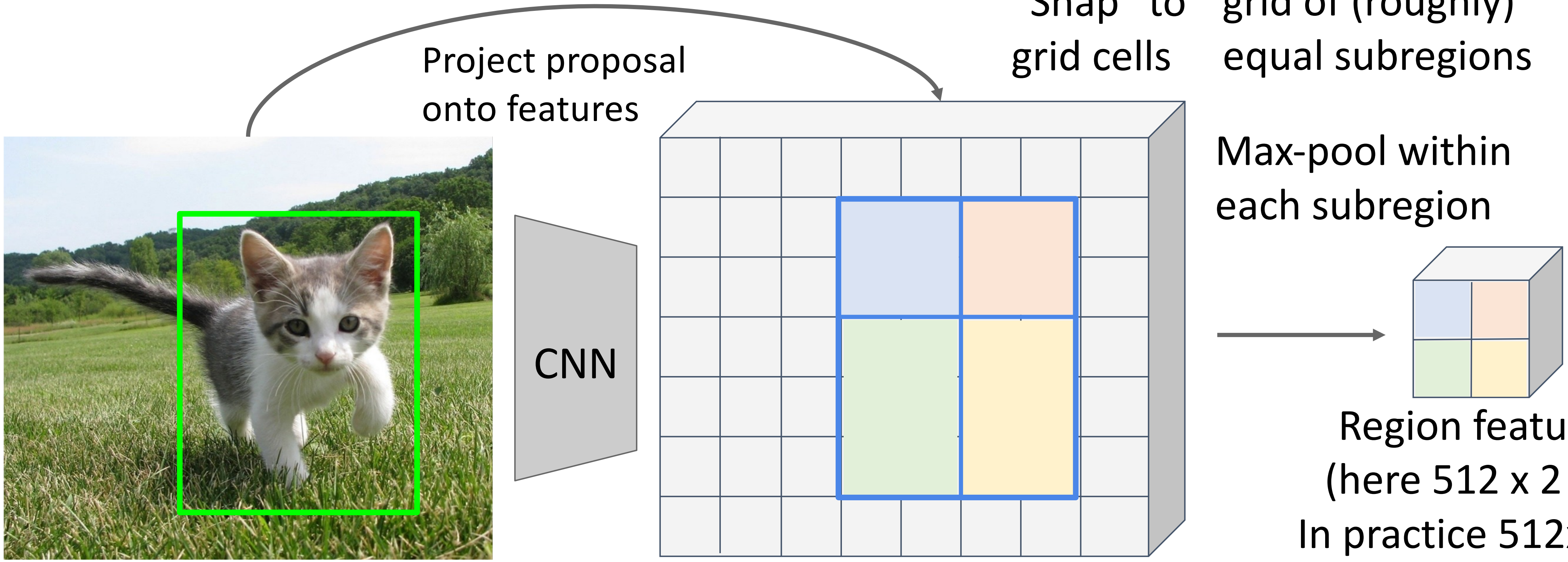
Image features
(e.g. 512 x 20 x 15)

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

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

Cropping Features: RoI Pool

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)

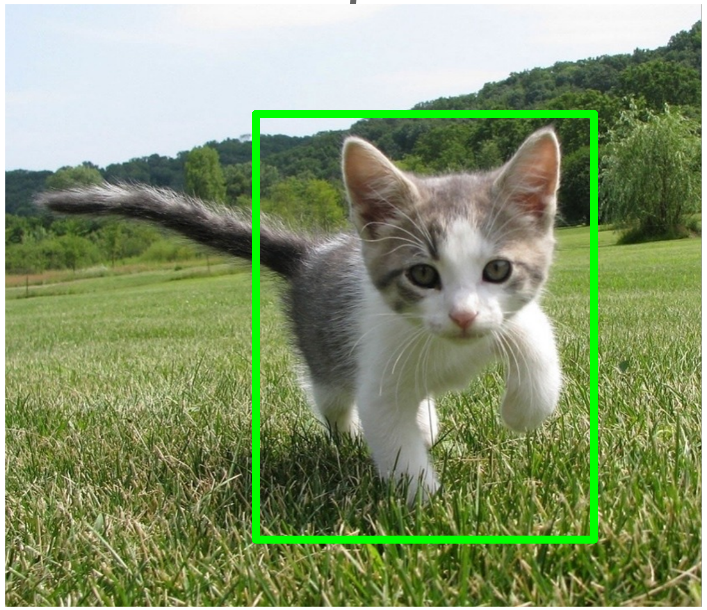
Region features
(here 512 x 2 x 2;
In practice 512x7x7)

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

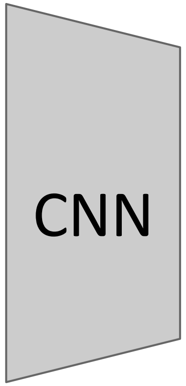
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool

Project proposal
onto features



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



"Snap" to
grid cells

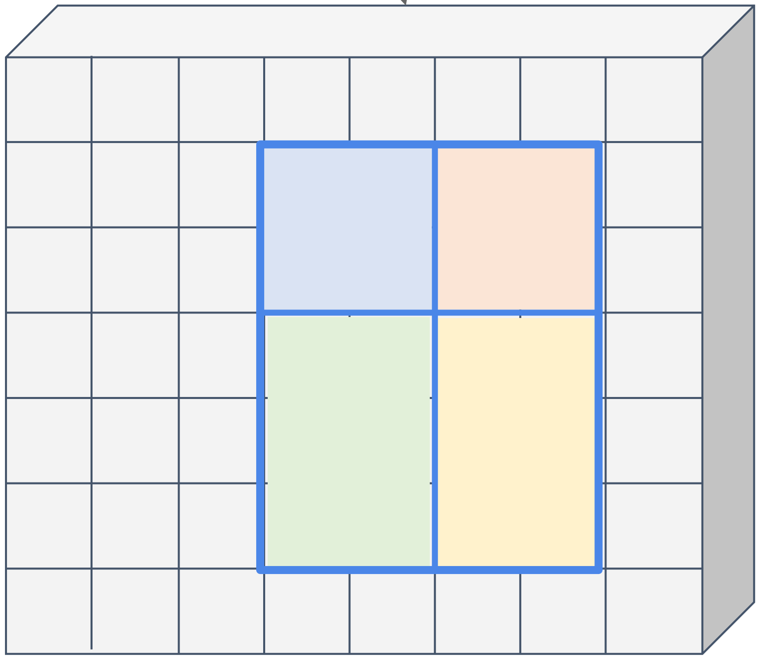
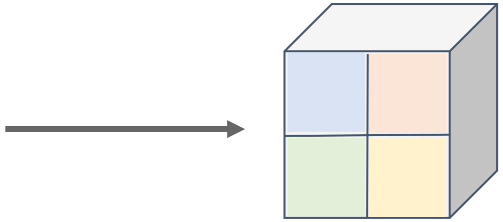


Image features
(e.g. 512 x 20 x 15)

Divide into 2x2
grid of (roughly)
equal subregions

Max-pool within
each subregion



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

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

Cropping Features: RoI Align

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

No “snapping”!

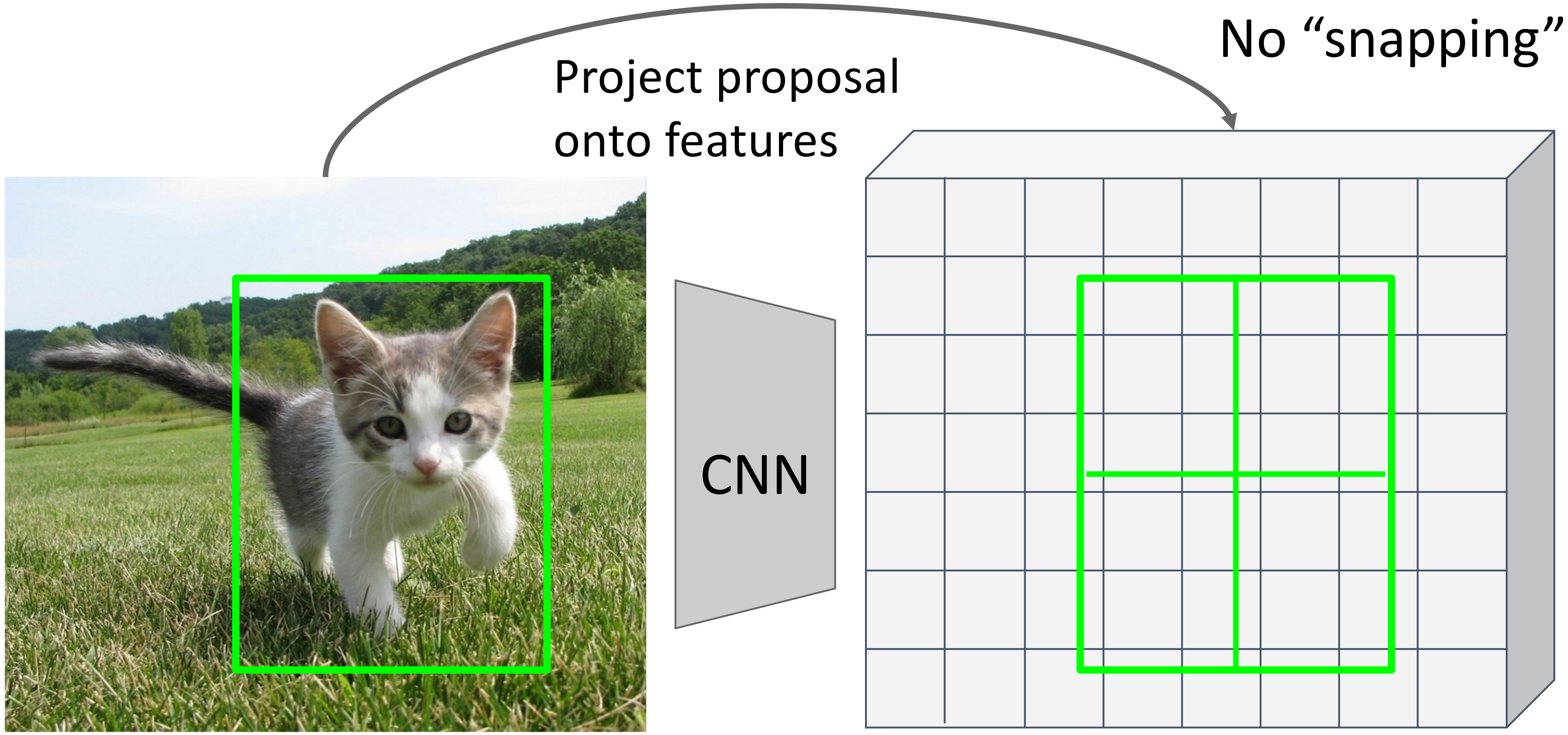


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Image features
(e.g. 512 x 20 x 15)

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

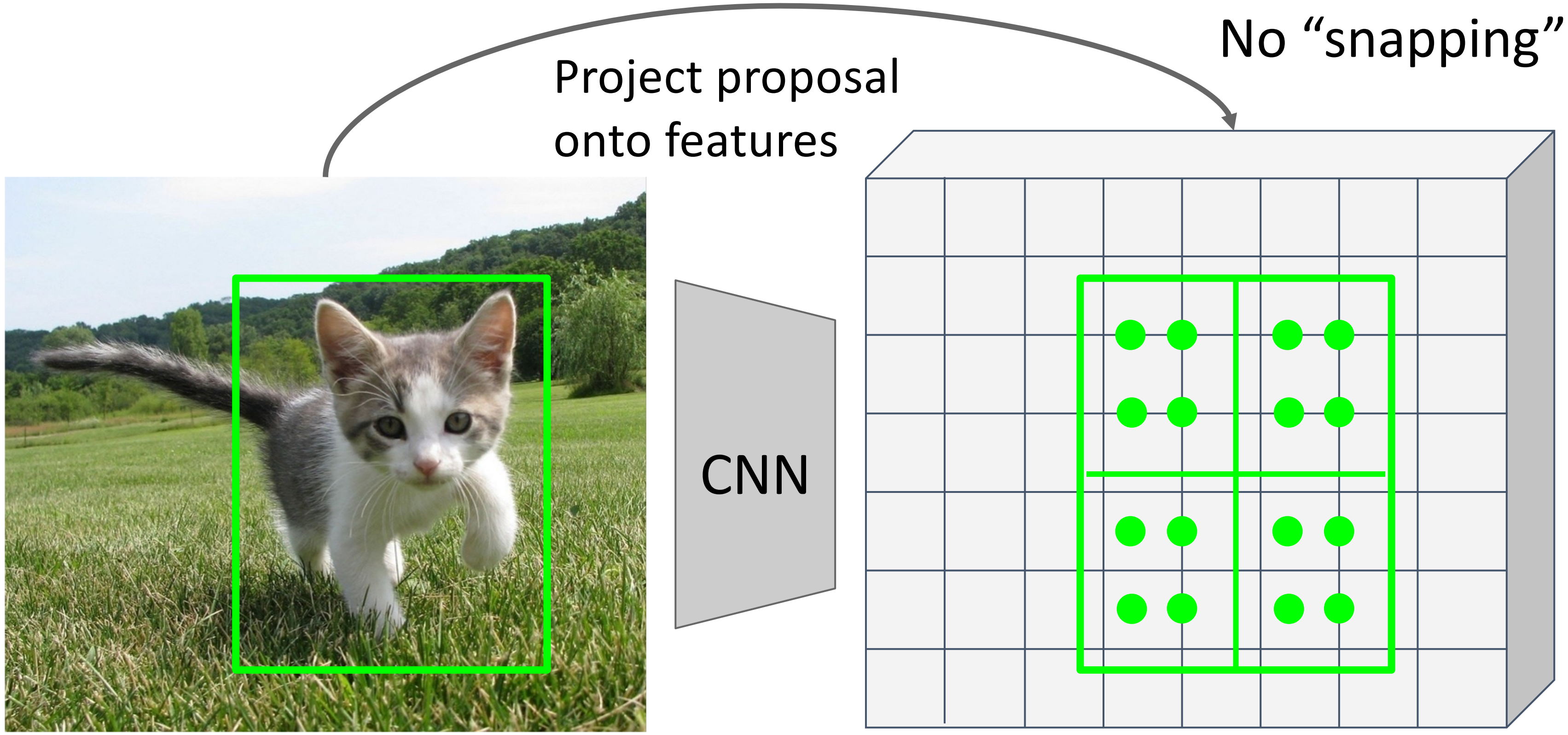
He et al, “Mask R-CNN”, ICCV 2017.

Cropping Features: RoI Align

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

No “snapping”!

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



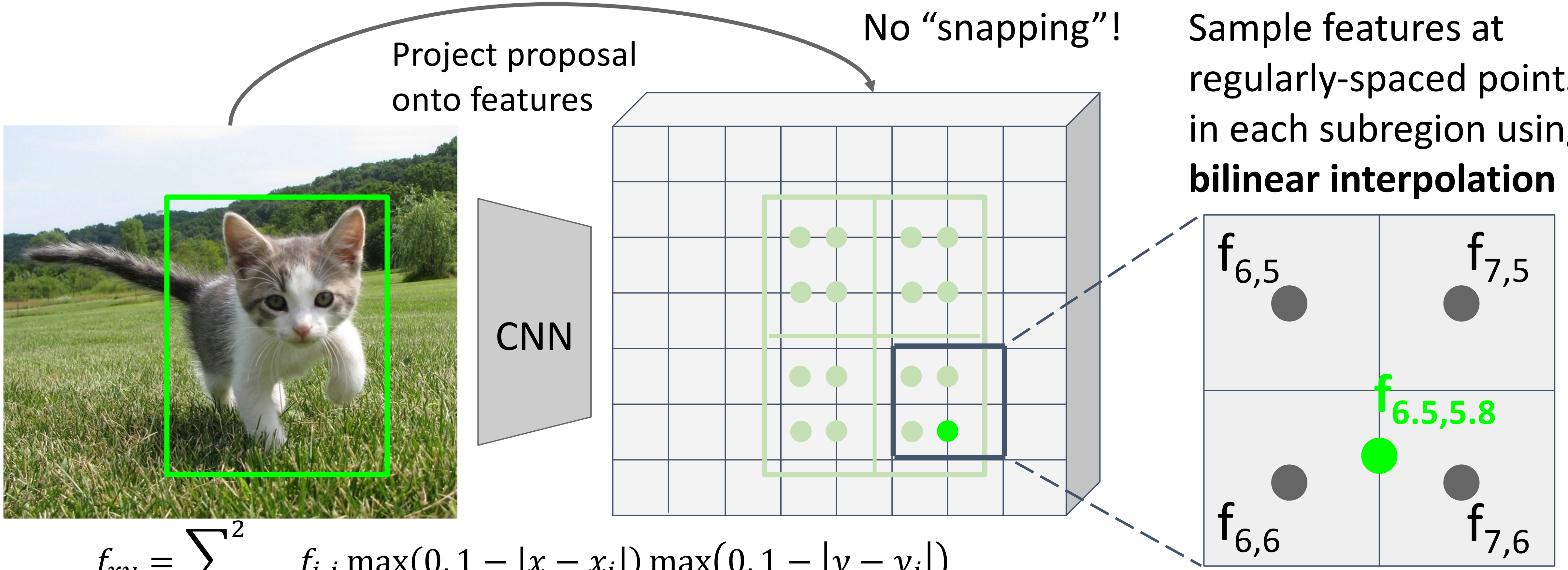
Input Image
(e.g. 3 x 640 x 480)

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!)



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:

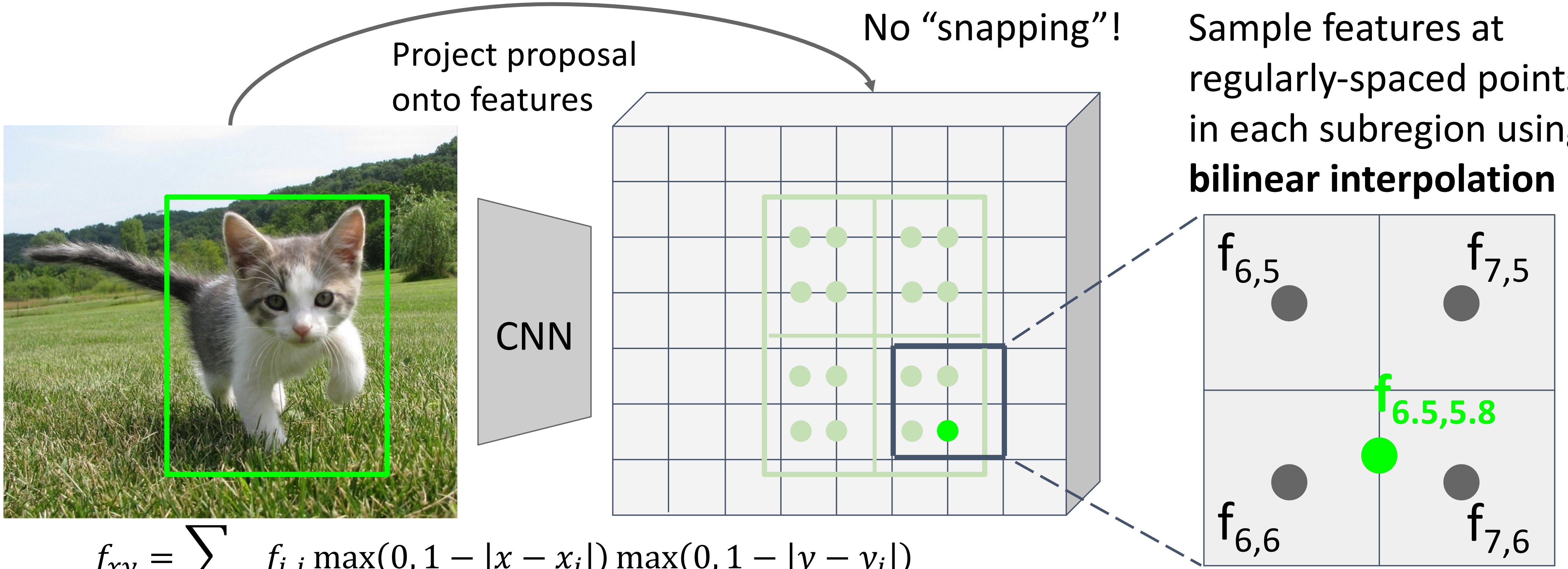
$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

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**

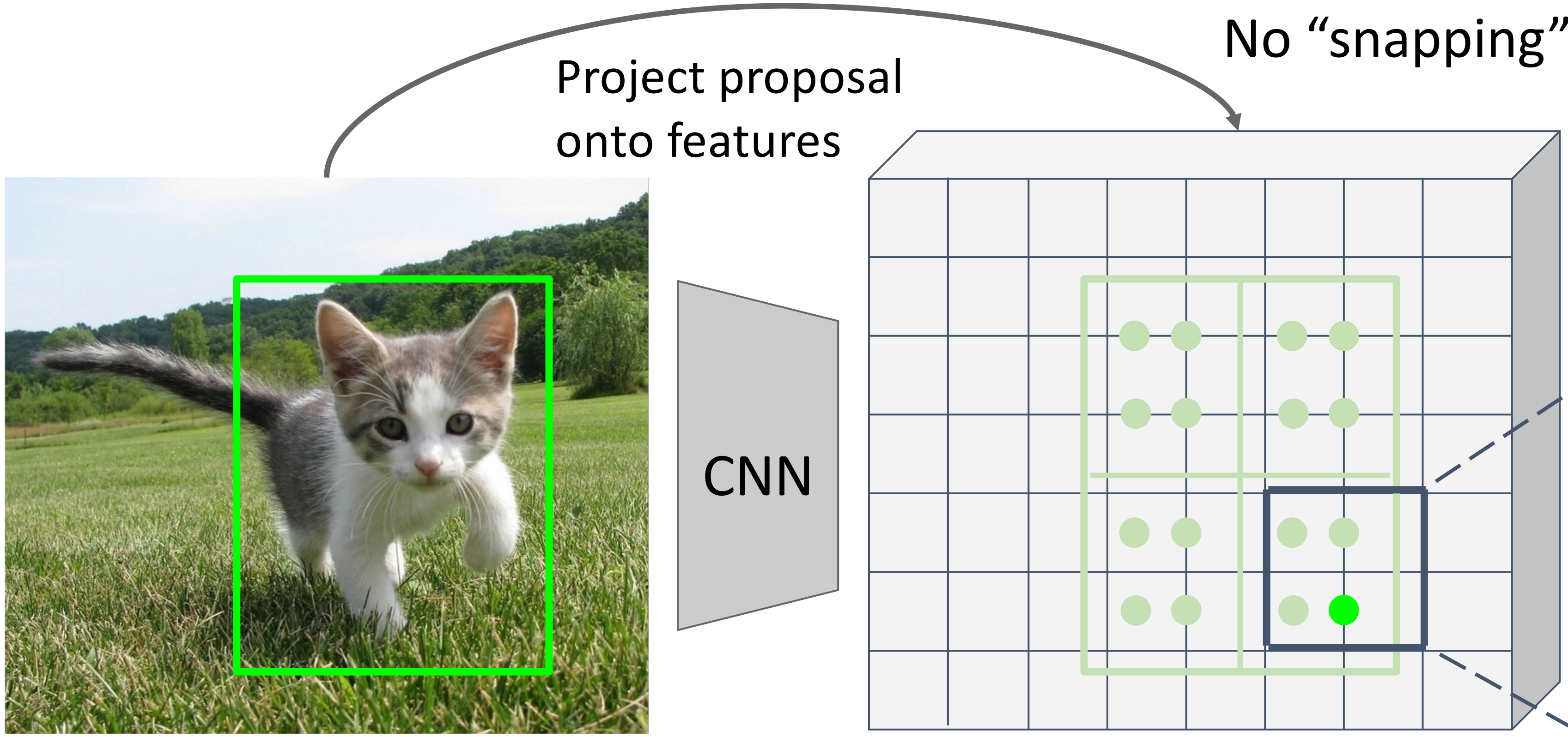


$$f_{xy} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_i|)$$

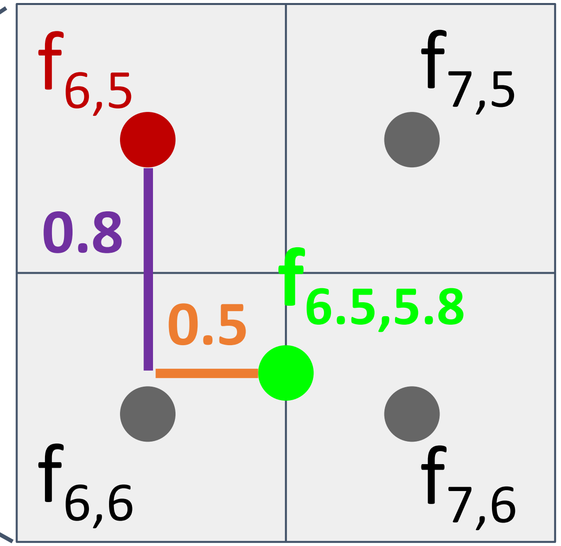
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

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

Cropping Features: RoI Align



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



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

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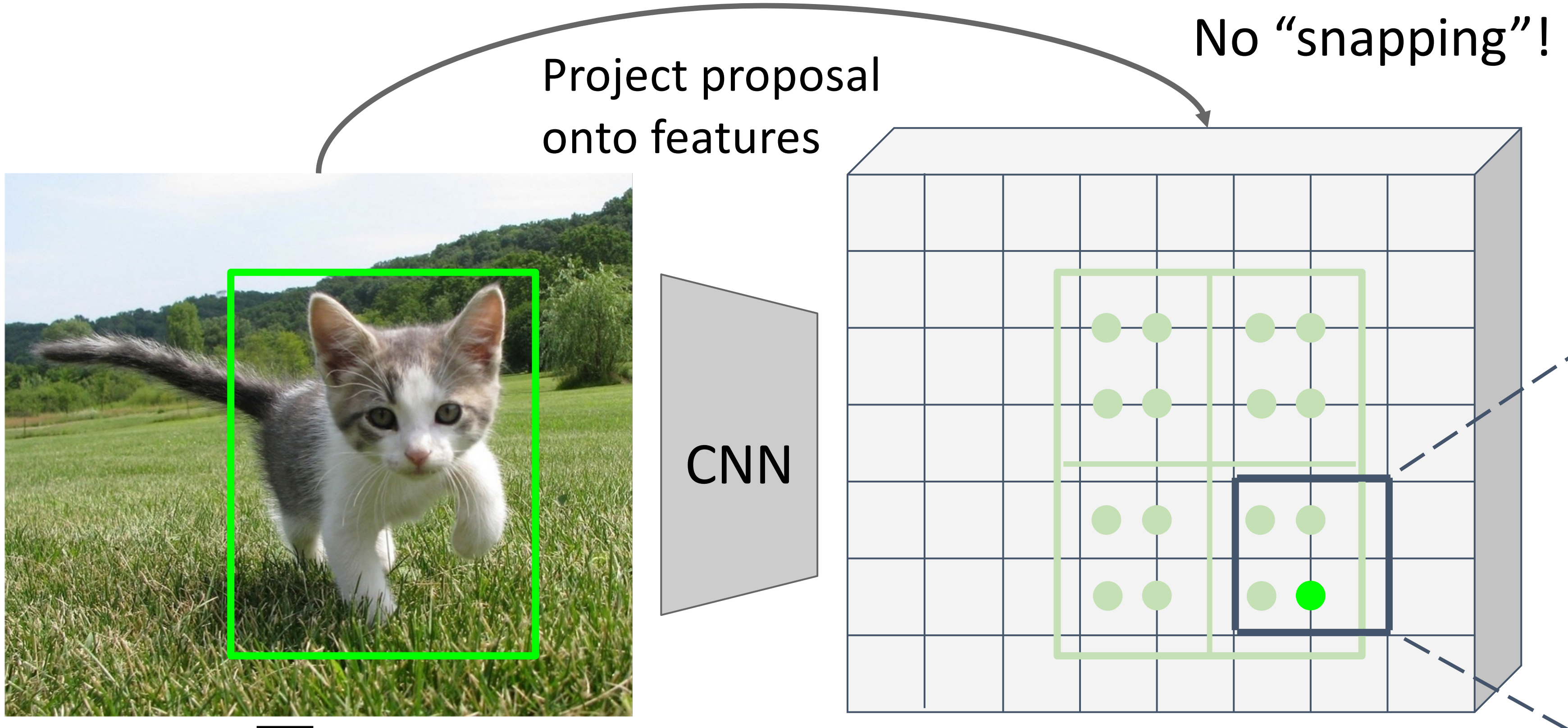
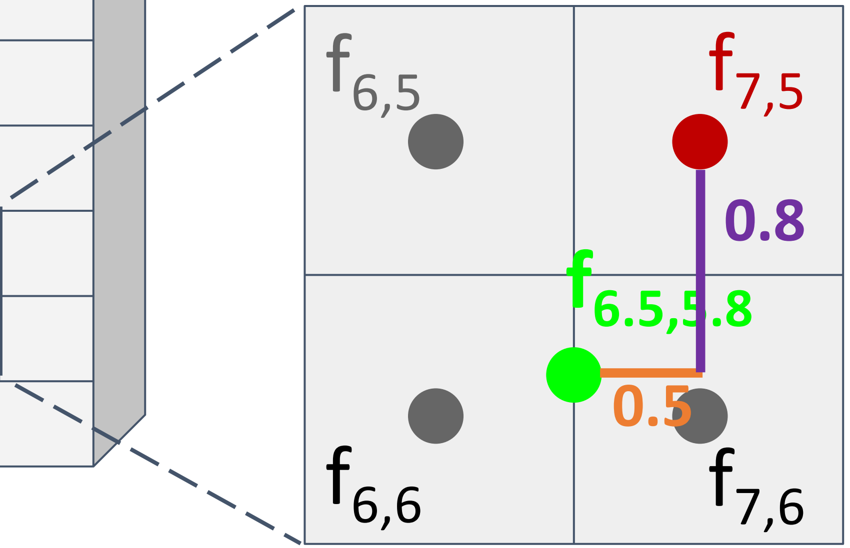
Cropping Features: RoI Align



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



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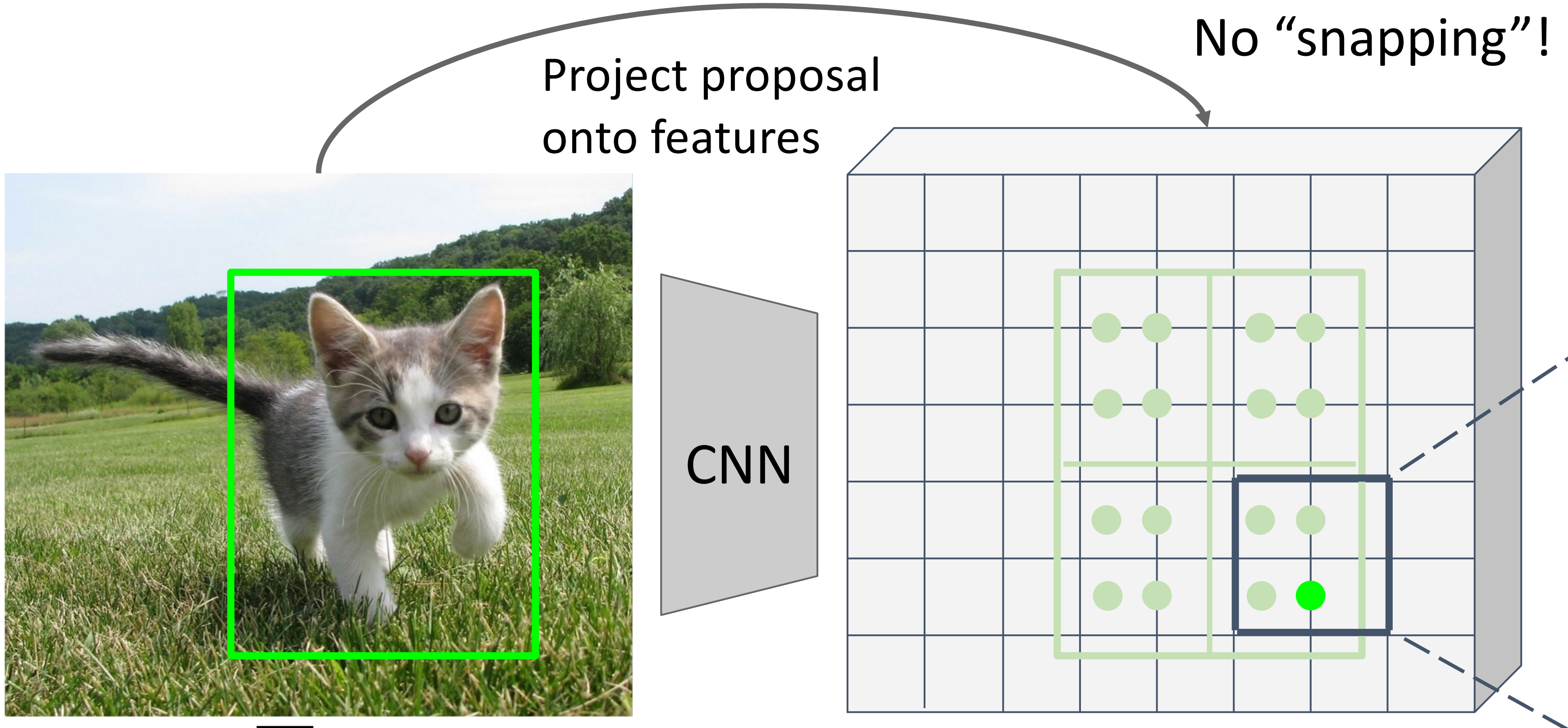
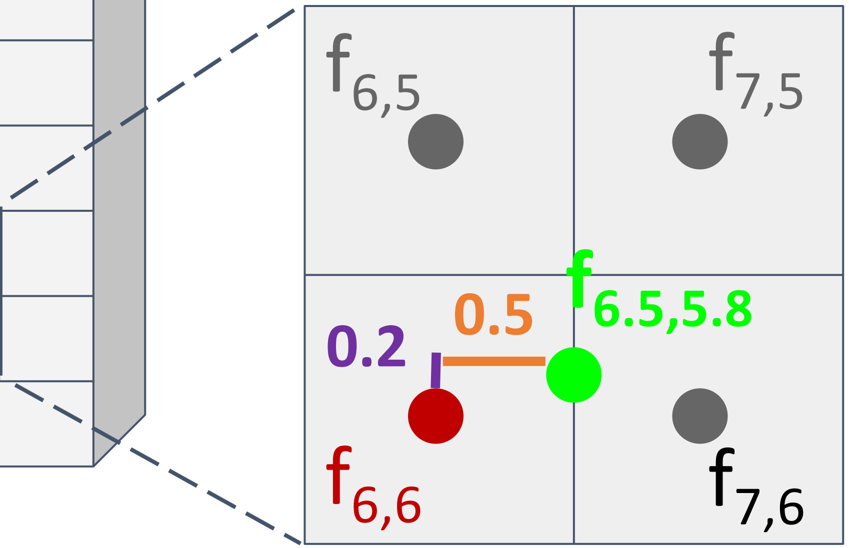
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align



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



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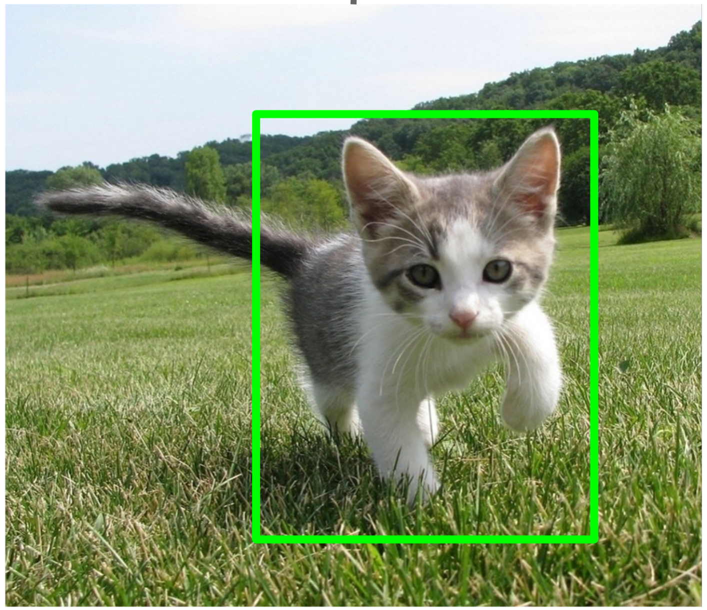
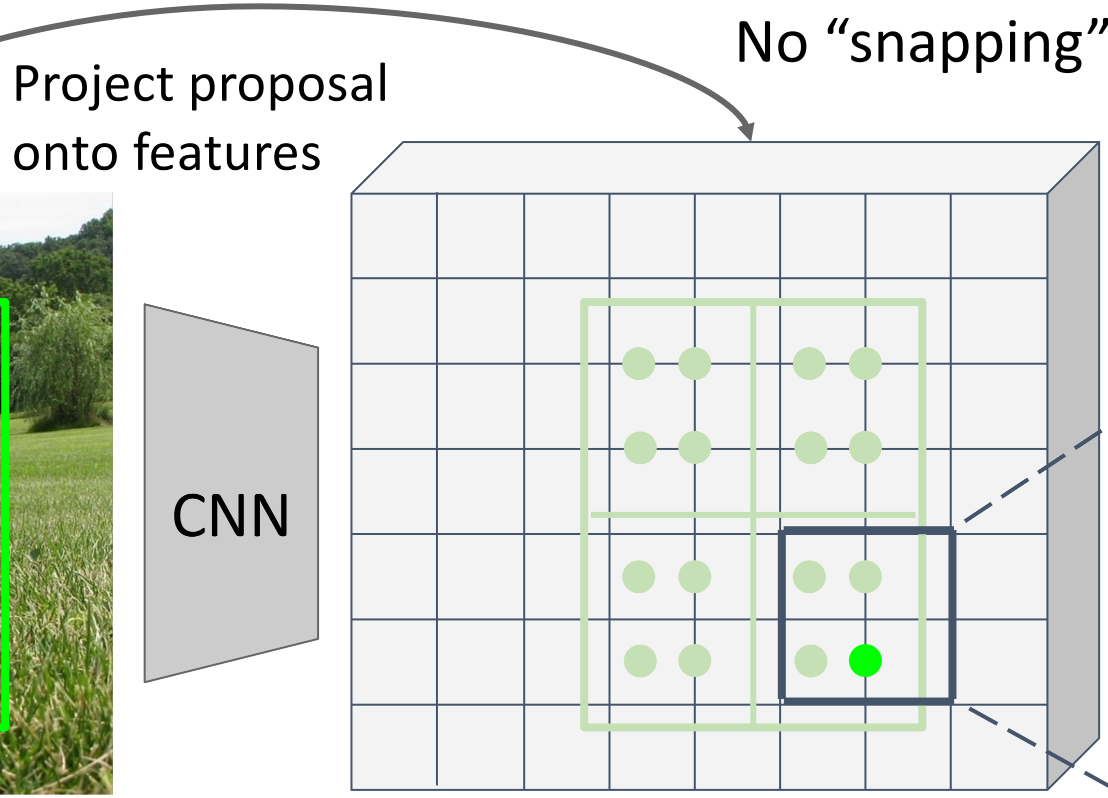
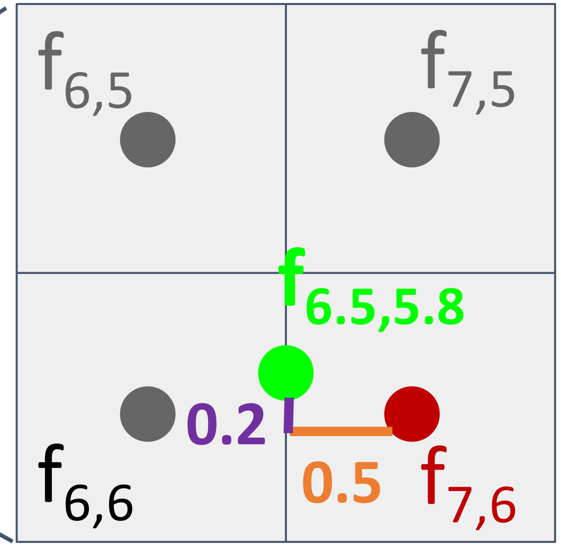
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

Cropping Features: RoI Align





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



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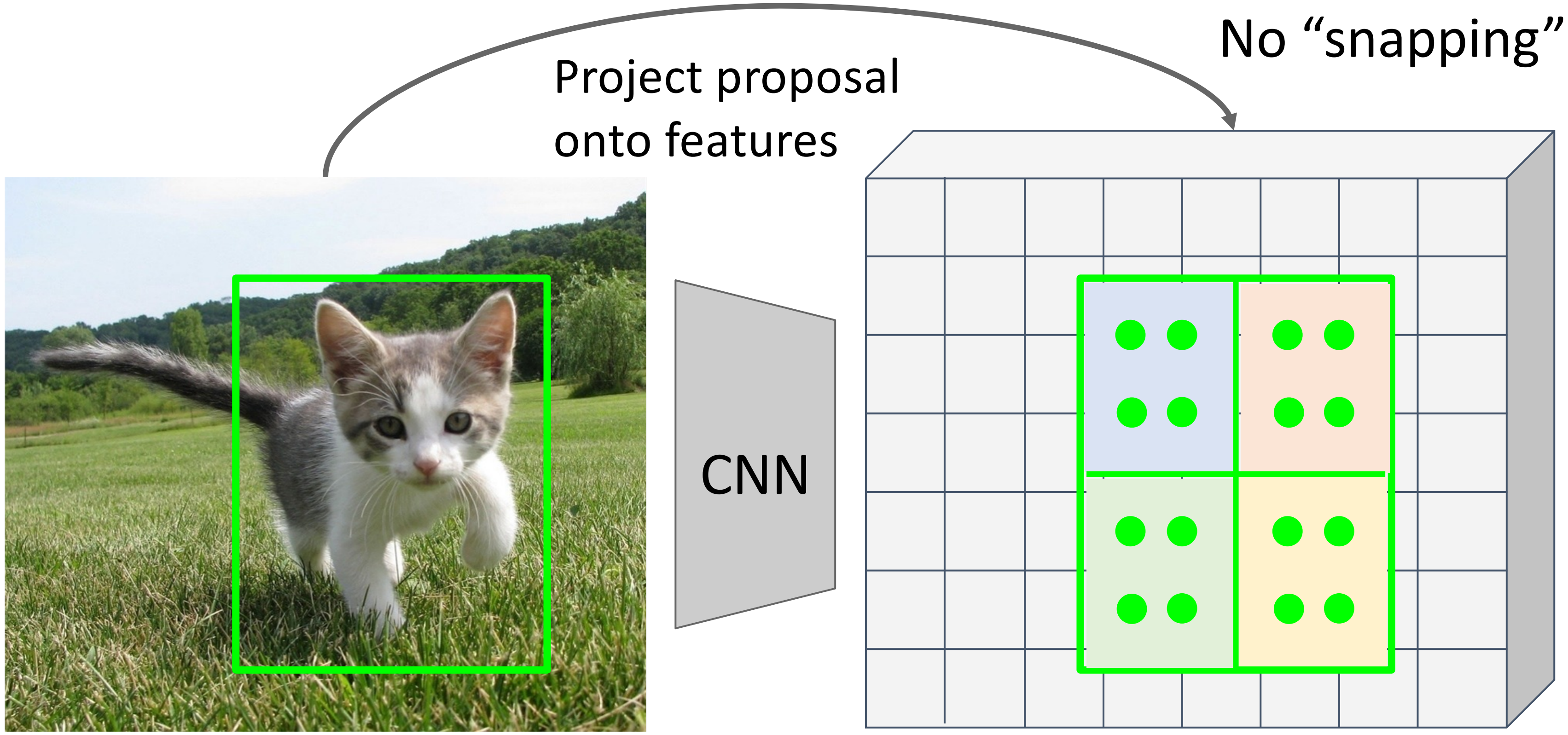
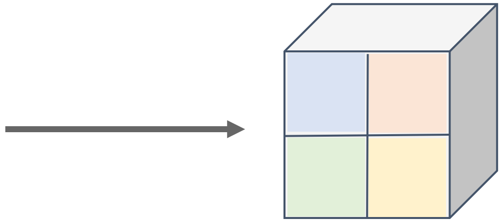


No "snapping"!

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

After sampling, max-pool in each subregion



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

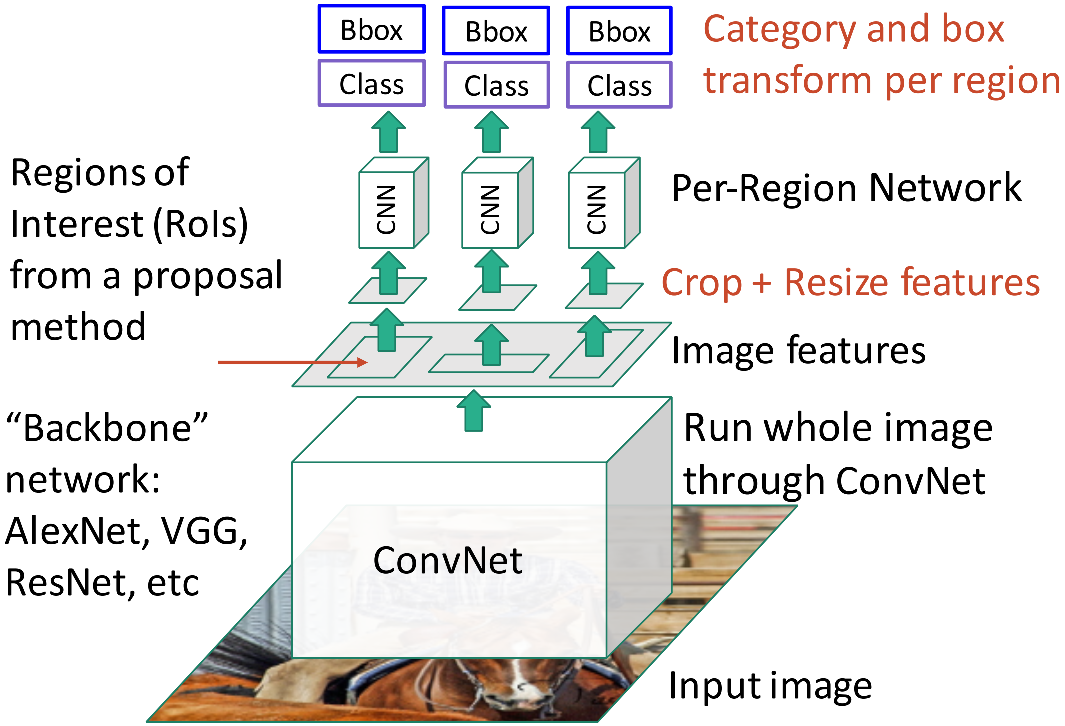
Image features
(e.g. 512 x 20 x 15)

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

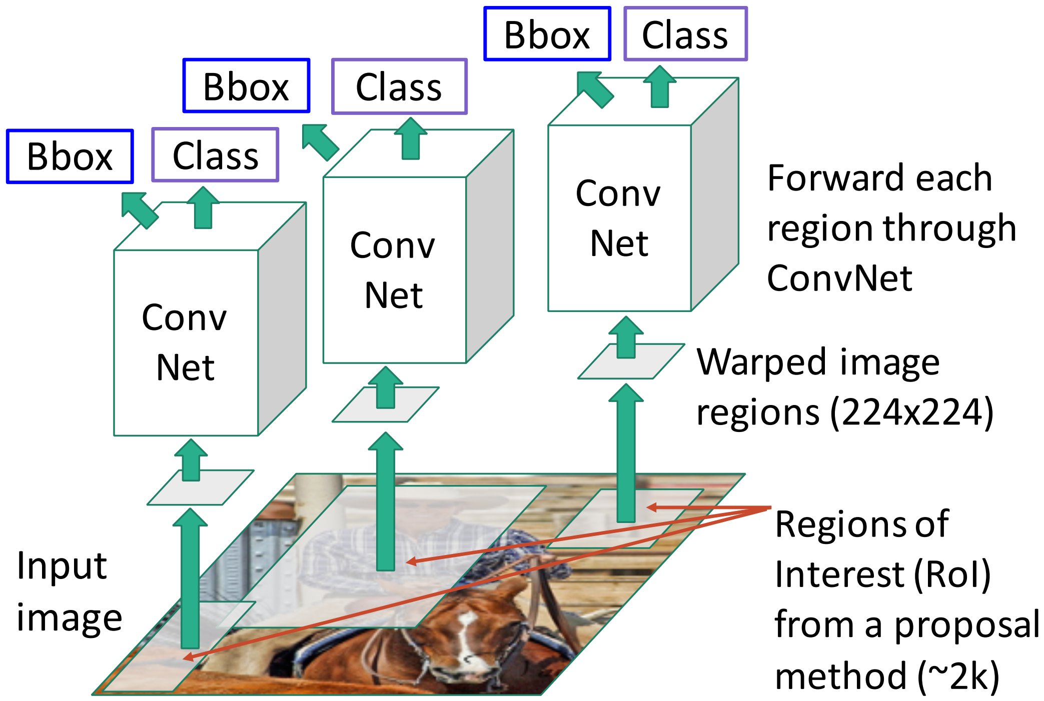
He et al, "Mask R-CNN", ICCV 2017

Fast R-CNN vs “Slow” R-CNN

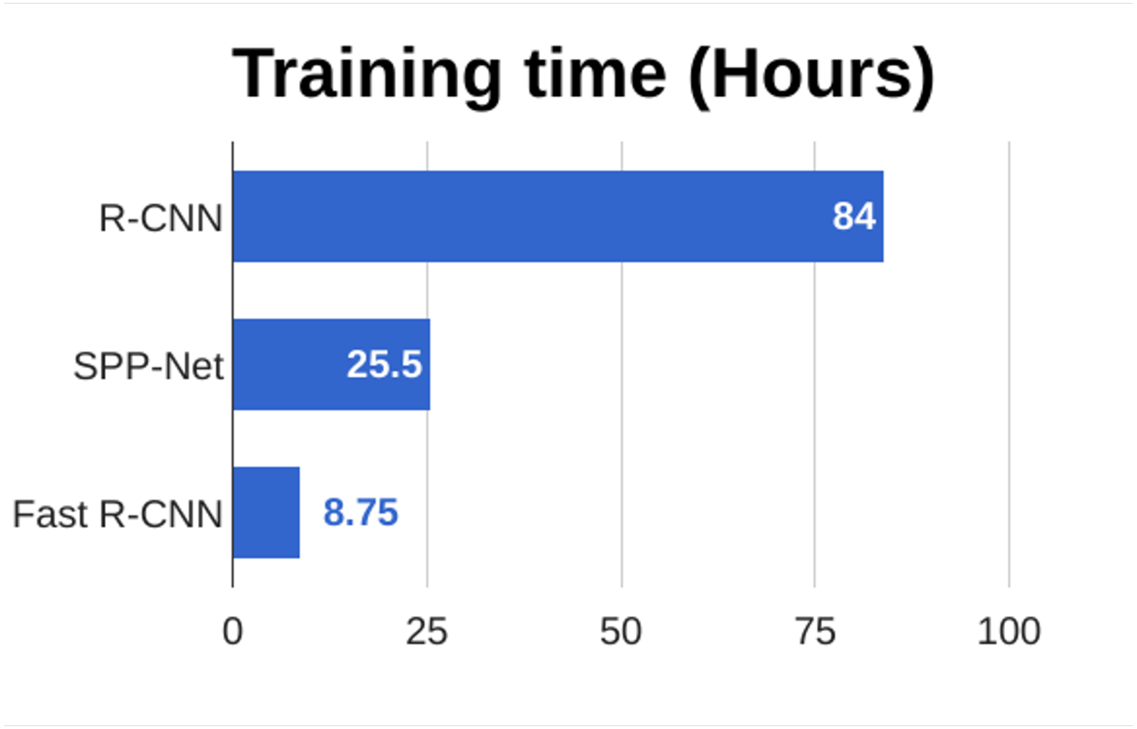
Fast R-CNN: Apply differentiable cropping to shared image features

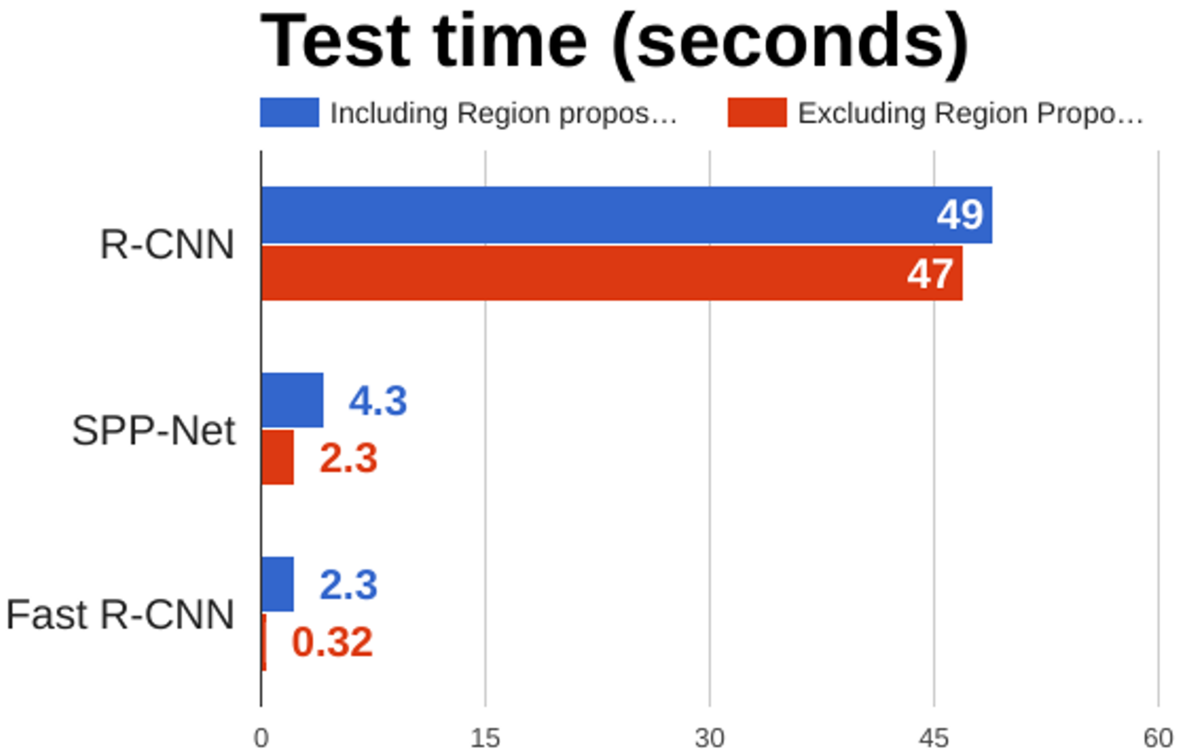


“Slow” R-CNN: Apply differentiable cropping to shared image features



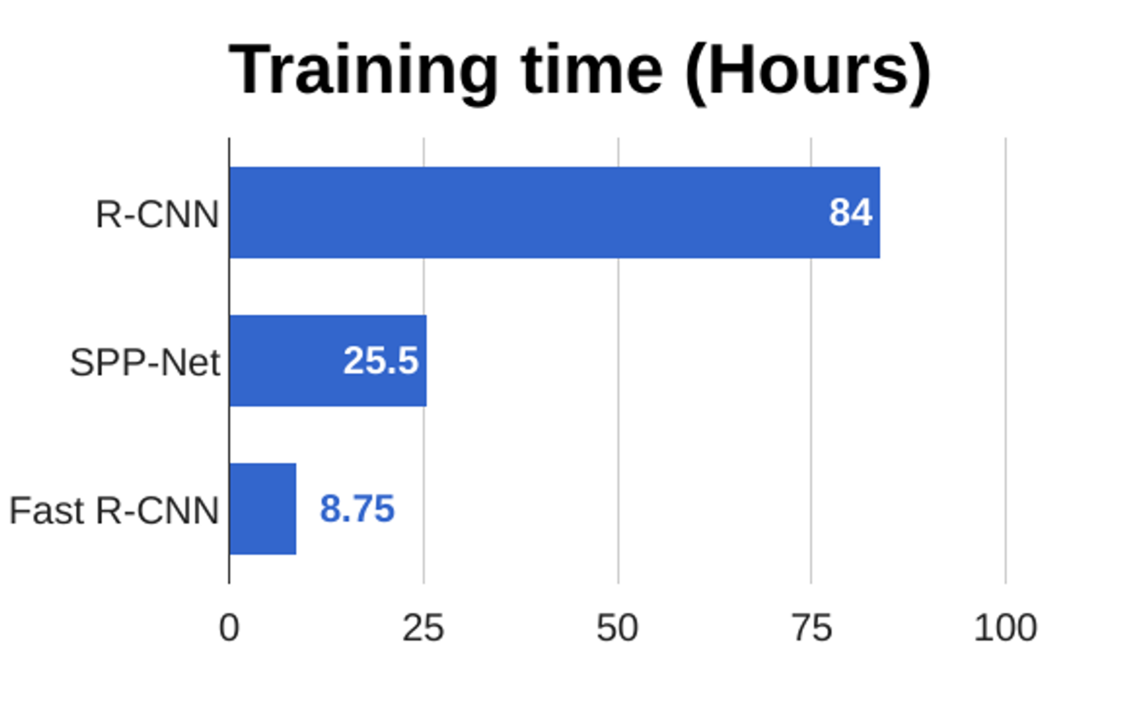
Fast R-CNN vs "Slow" R-CNN

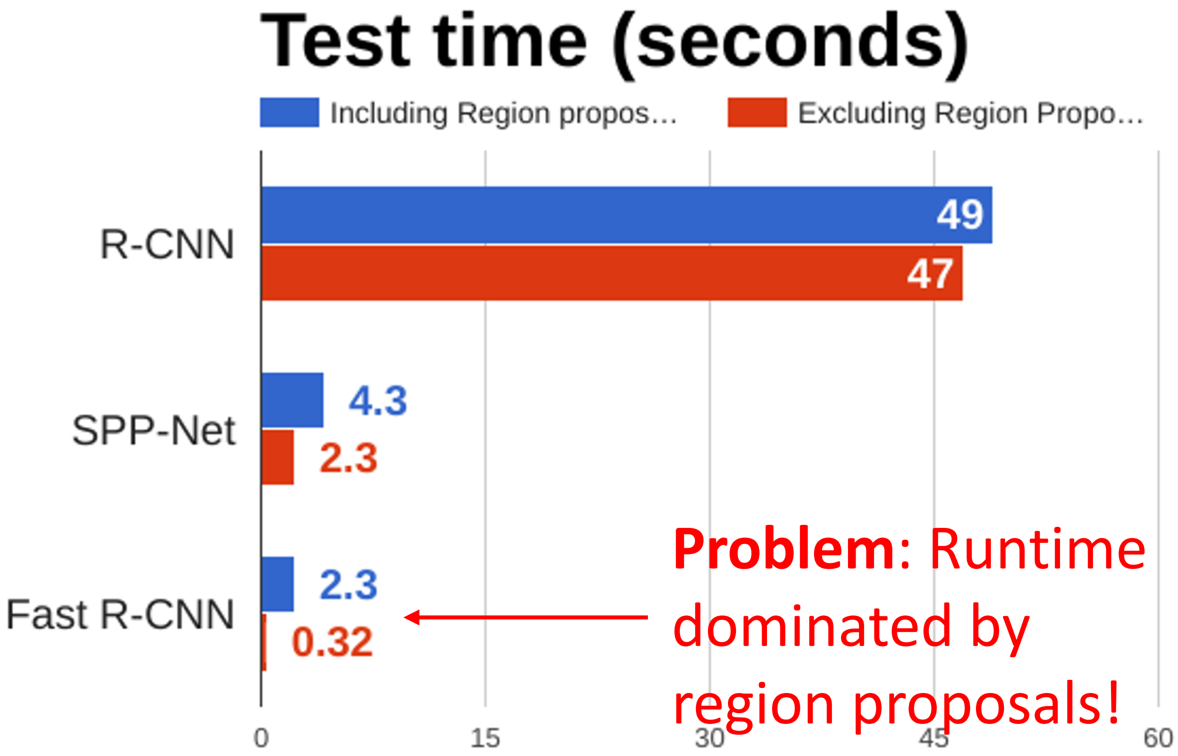




Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

Fast R-CNN vs "Slow" R-CNN





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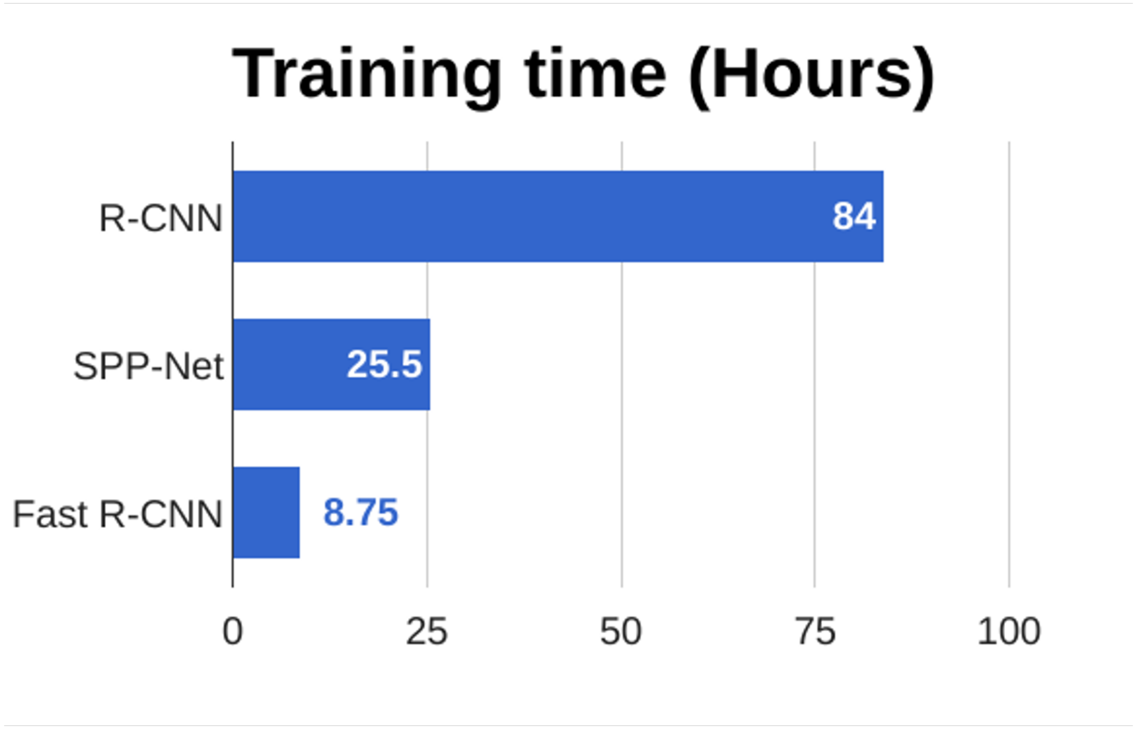
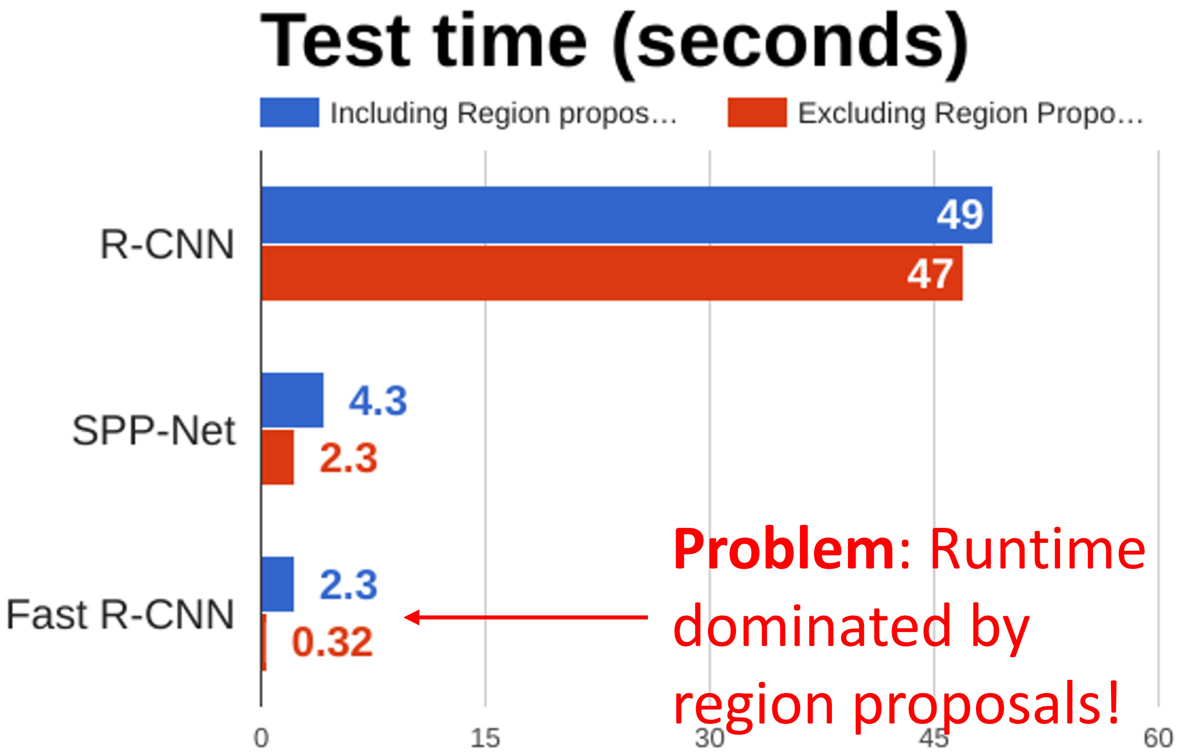




Problem: Runtime dominated by region proposals!

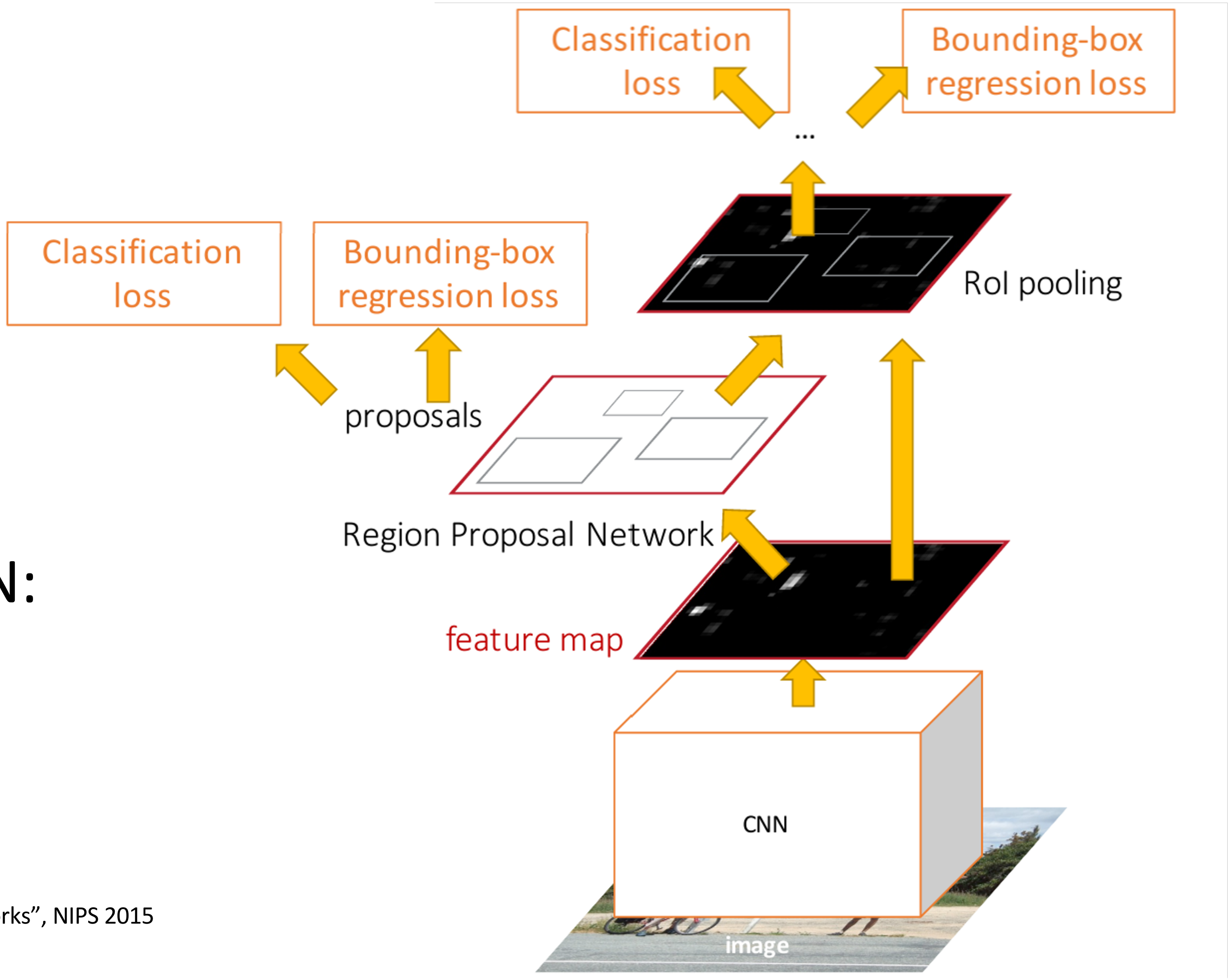
Recall: Region proposals computed by heuristic "Selective Search" algorithm on CPU -- let's learn them with a CNN instead!

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

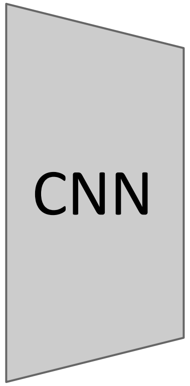


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

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



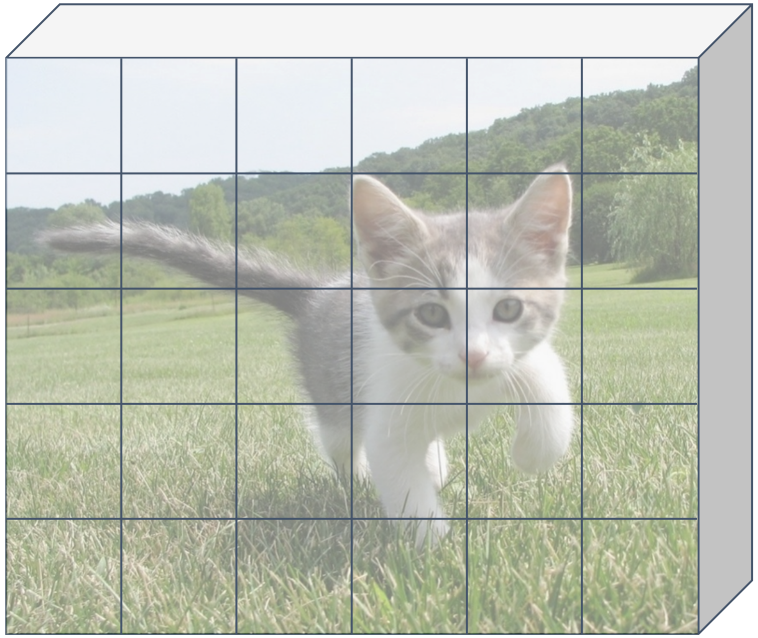


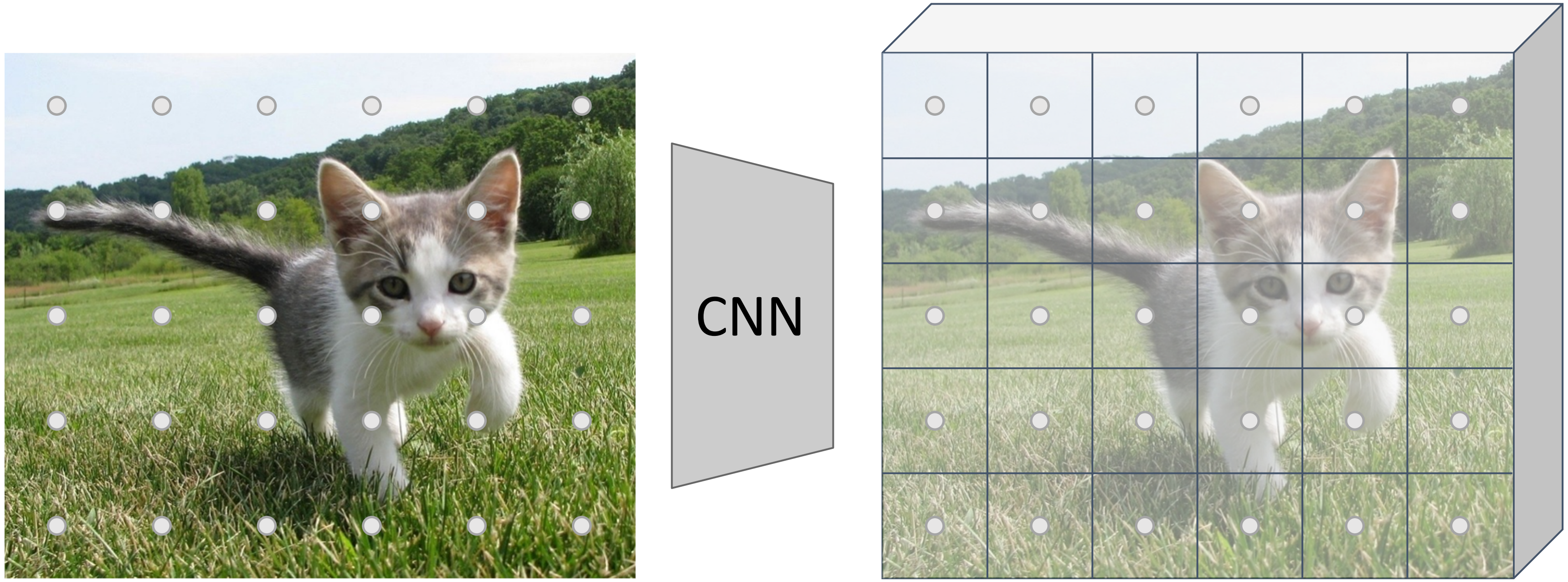
Image features
(e.g. 512 x 5 x 6)

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

Each feature corresponds to a point in the input



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

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

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

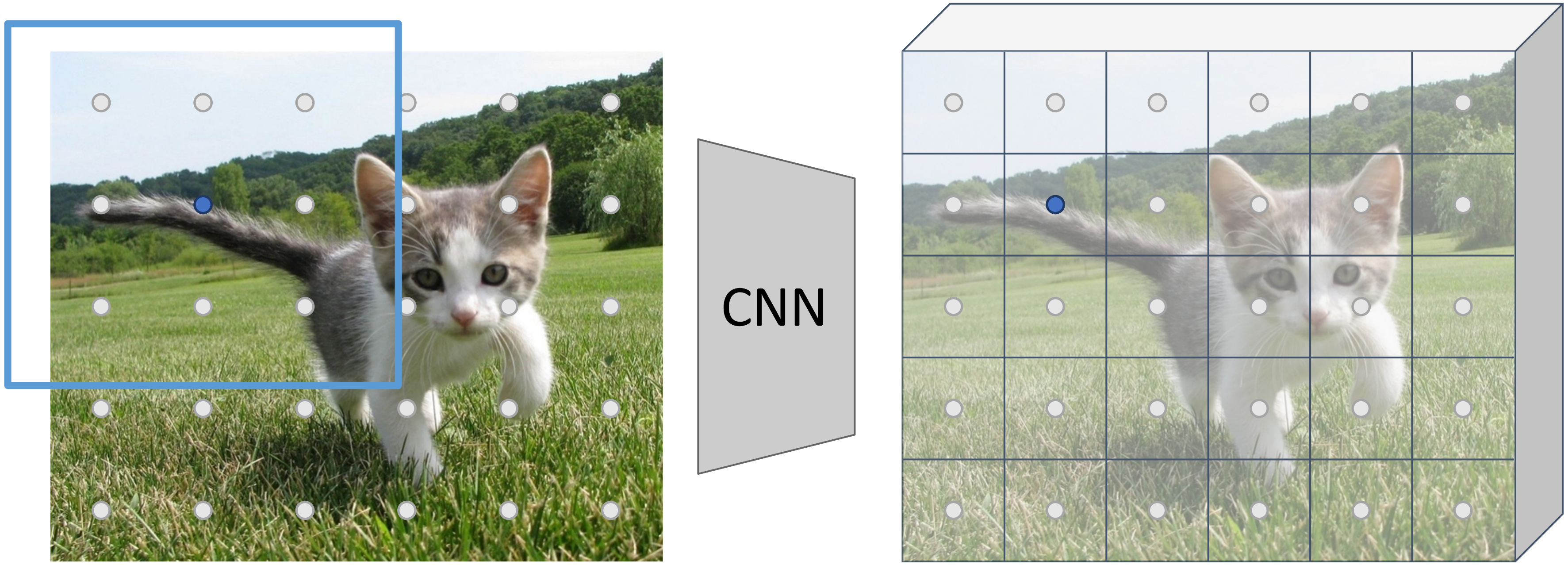

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Image features
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Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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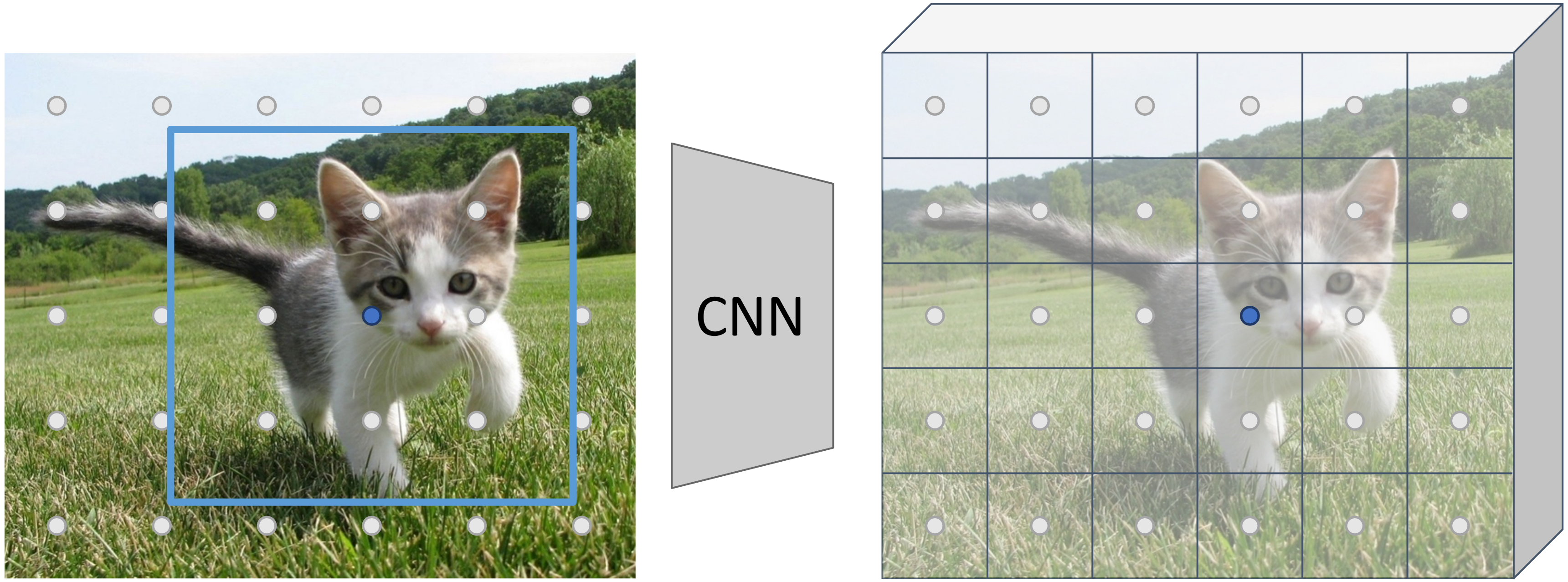

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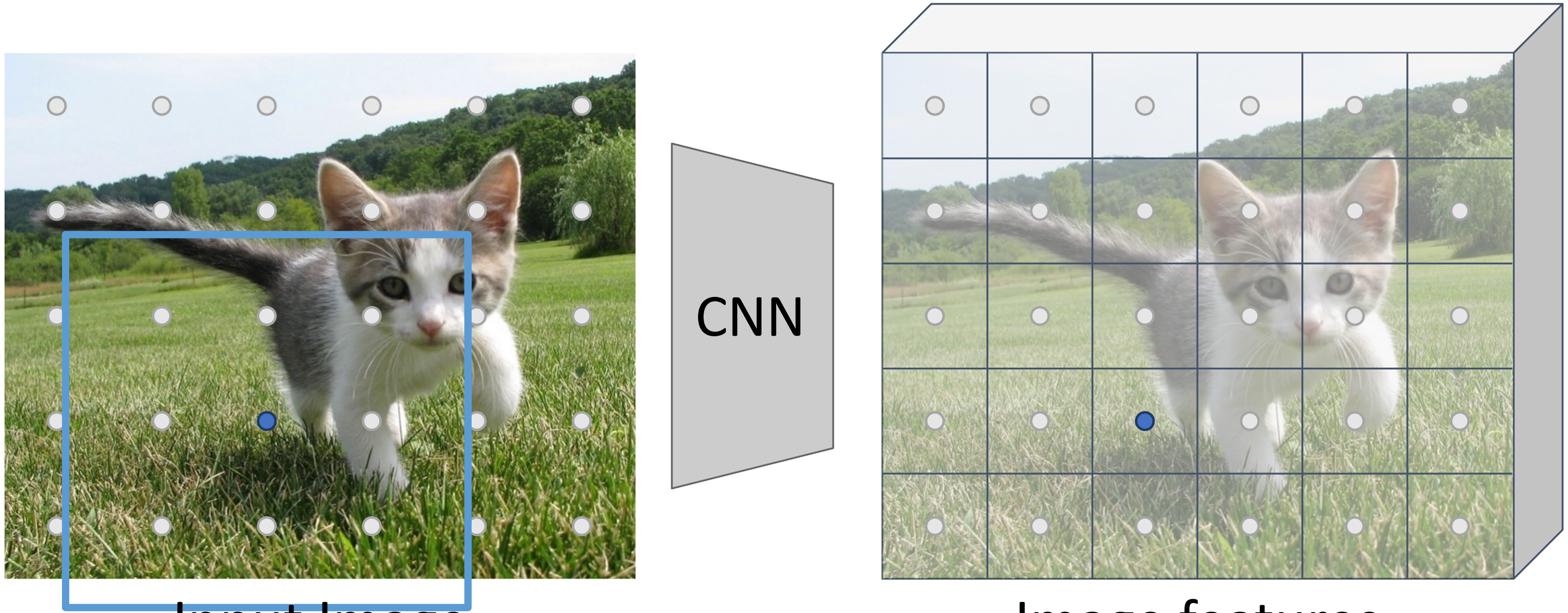

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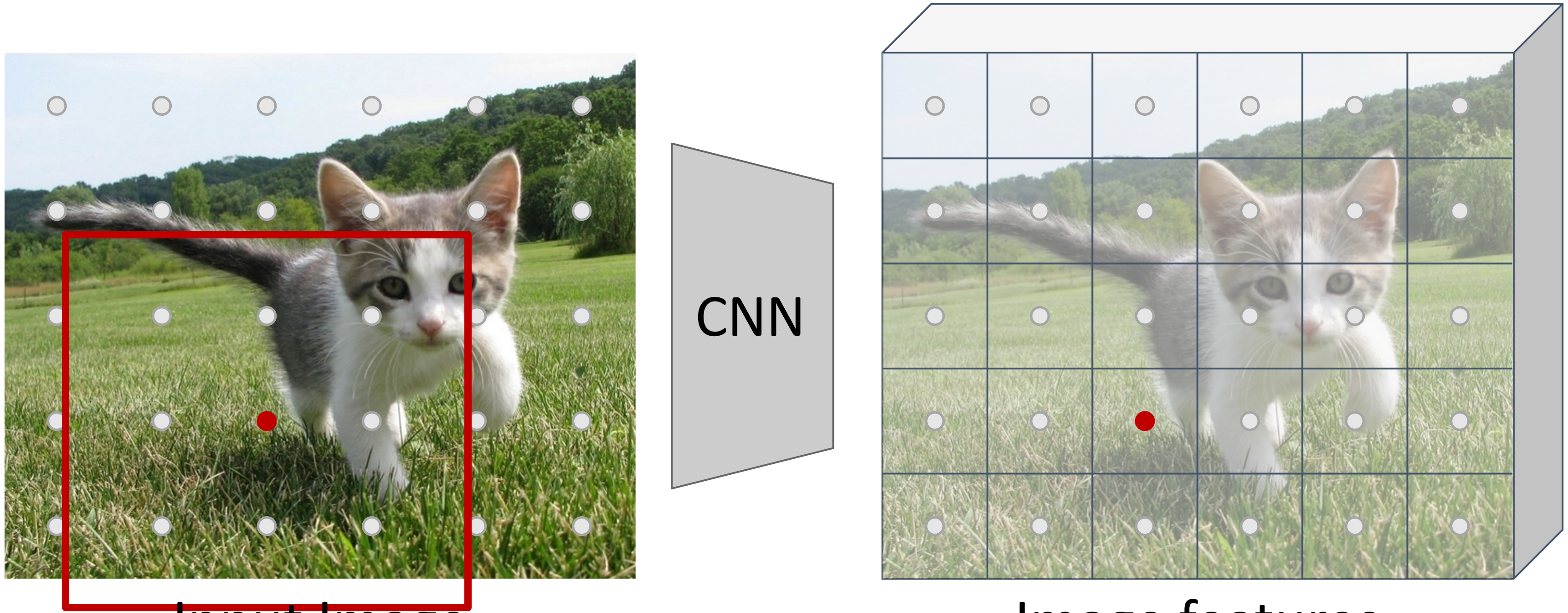

Input Image
(e.g. 3 x 640 x 480)

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

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

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

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

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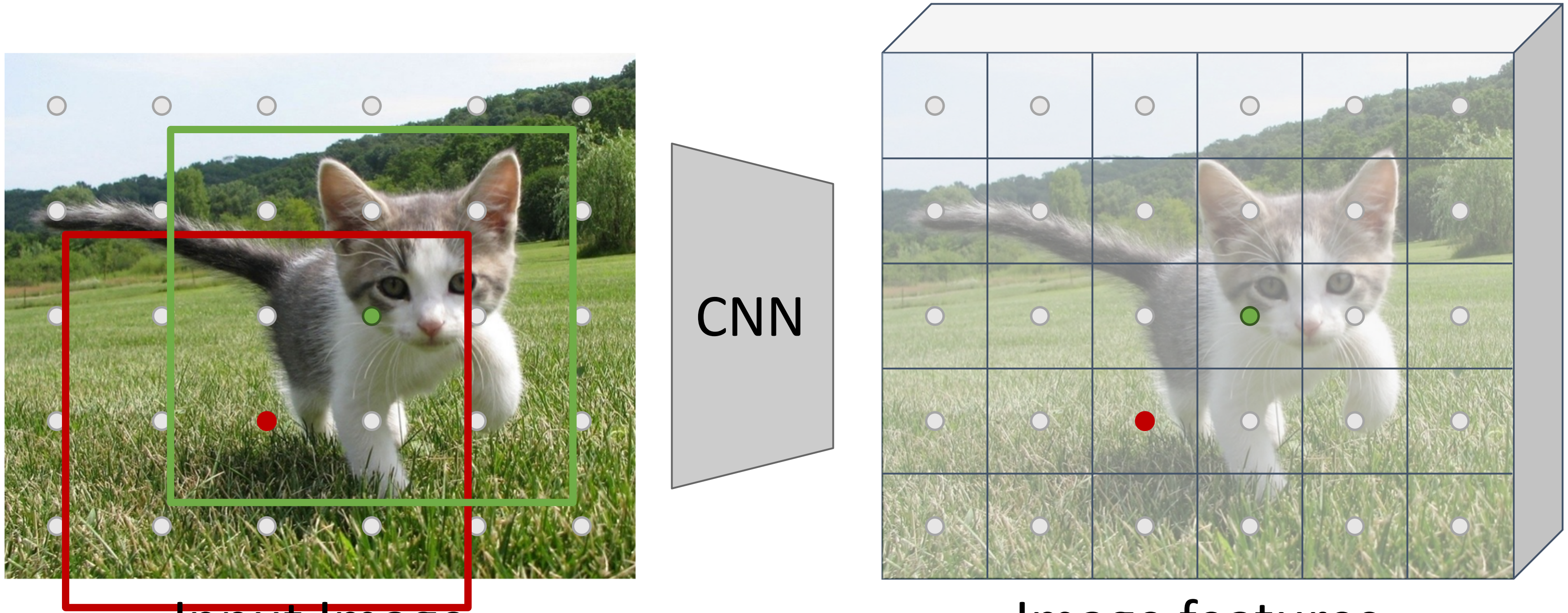

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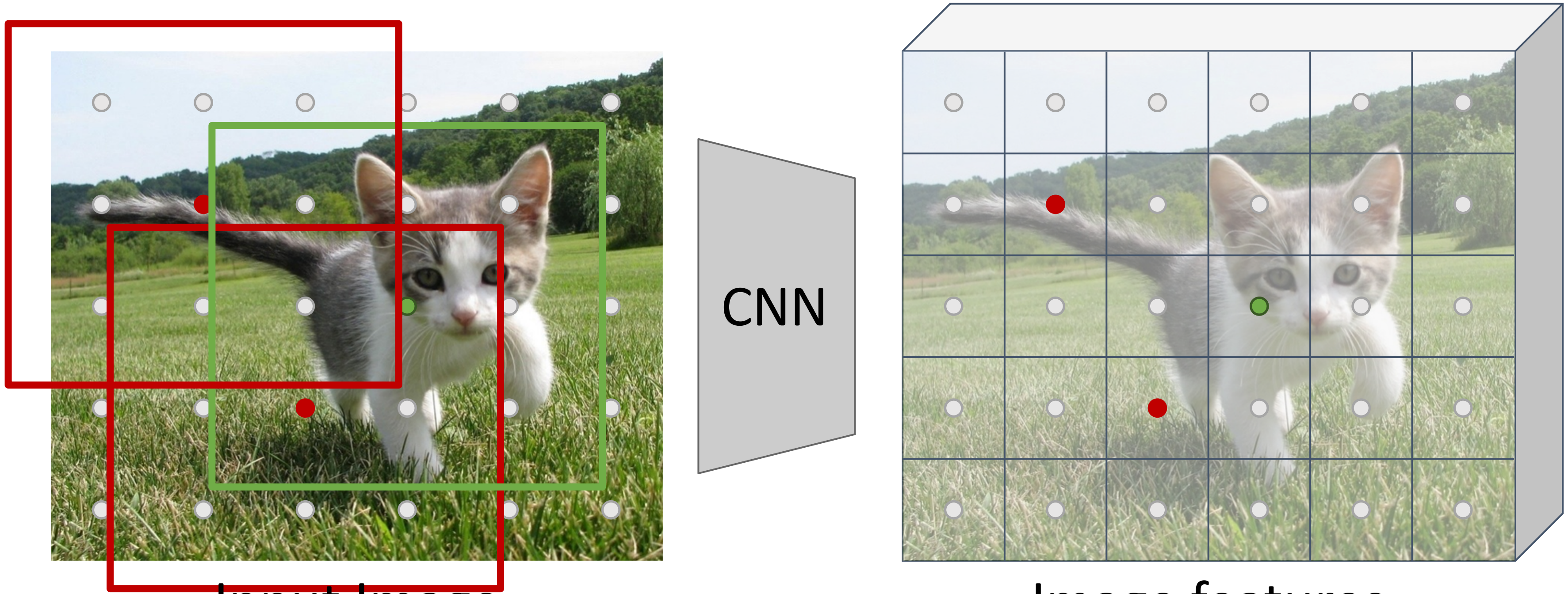


Input Image
(e.g. 3 x 640 x 480)

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

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

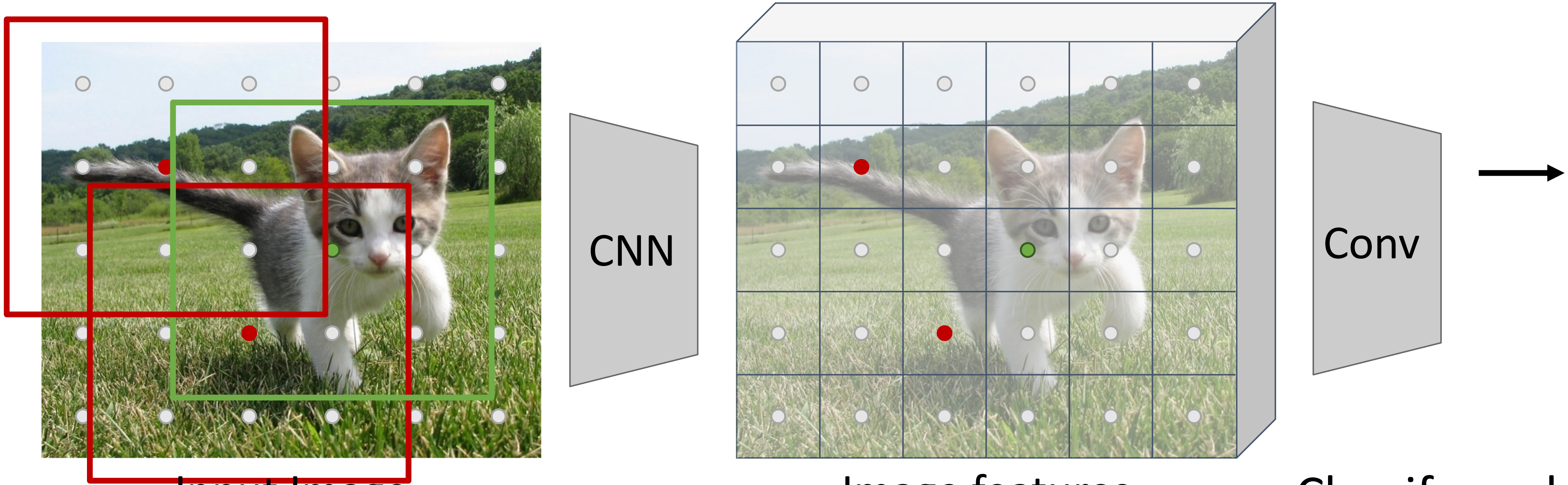
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input

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



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

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

Anchor is object?
2 x 5 x 6

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

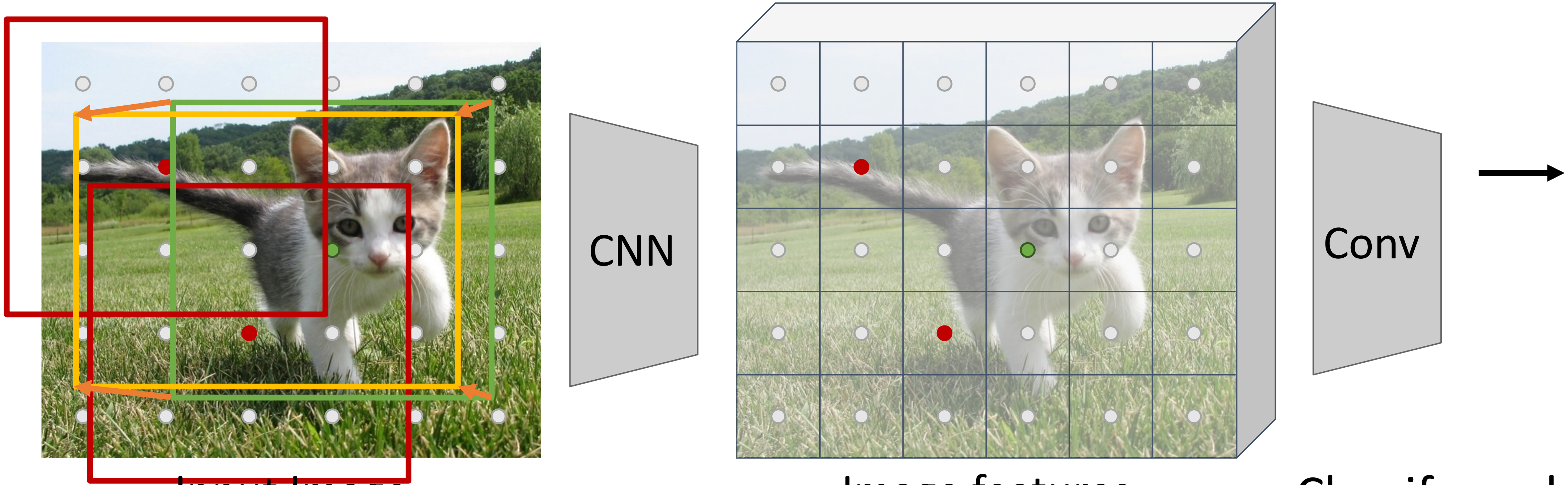
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network (RPN)

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

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



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

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

Anchor is object?
2 x 5 x 6

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

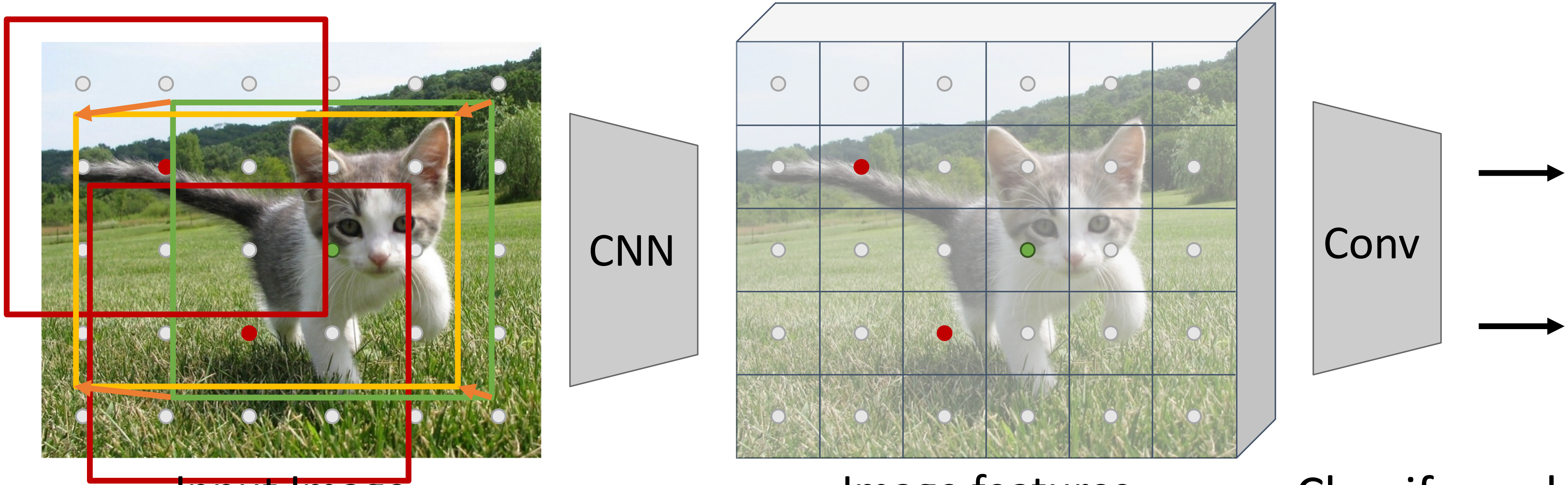
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network (RPN)

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

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



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

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

Anchor is object?
2 x 5 x 6

Anchor transforms
4 x 5 x 6

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

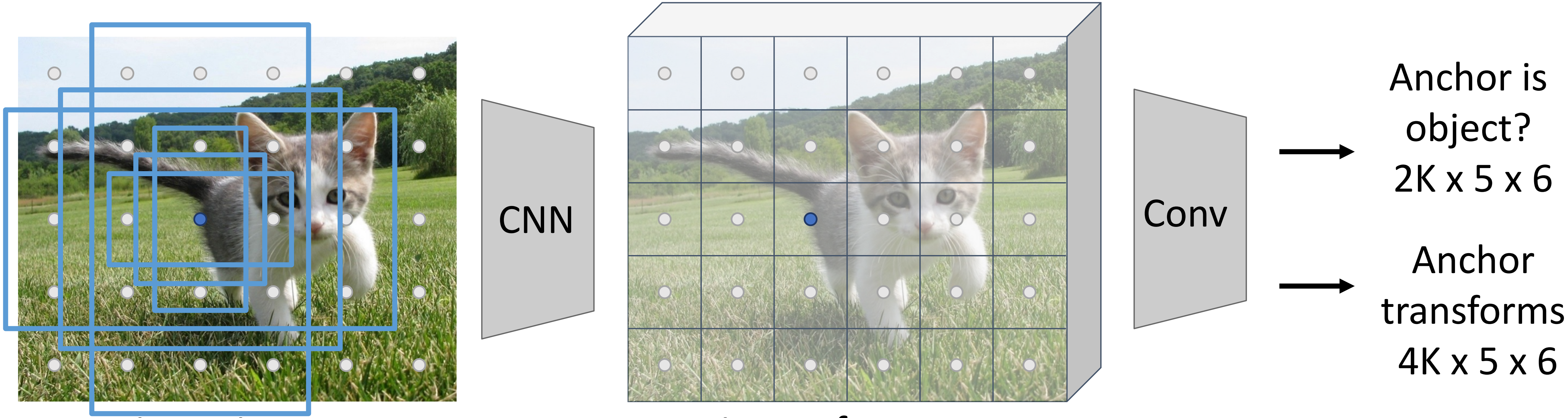
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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)

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



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

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

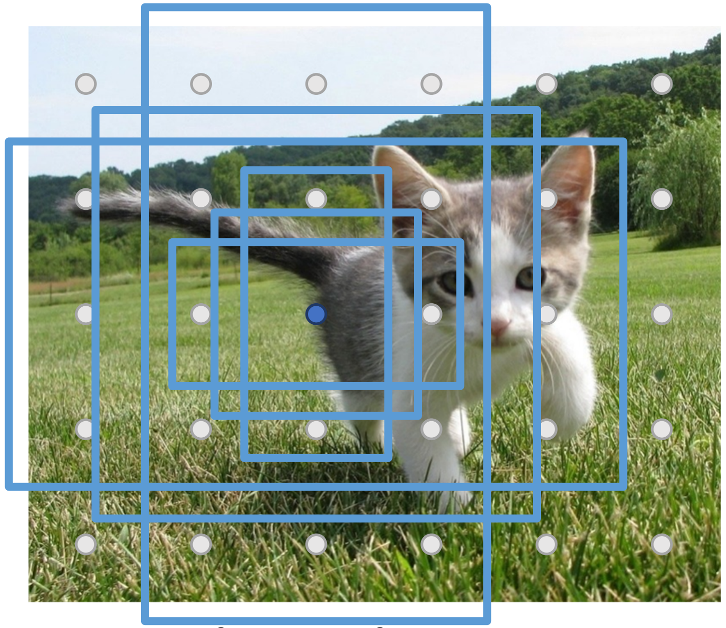
Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

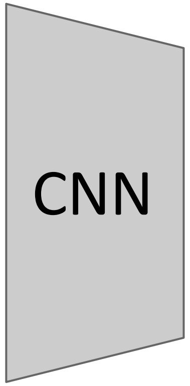
Region Proposal Network (RPN)

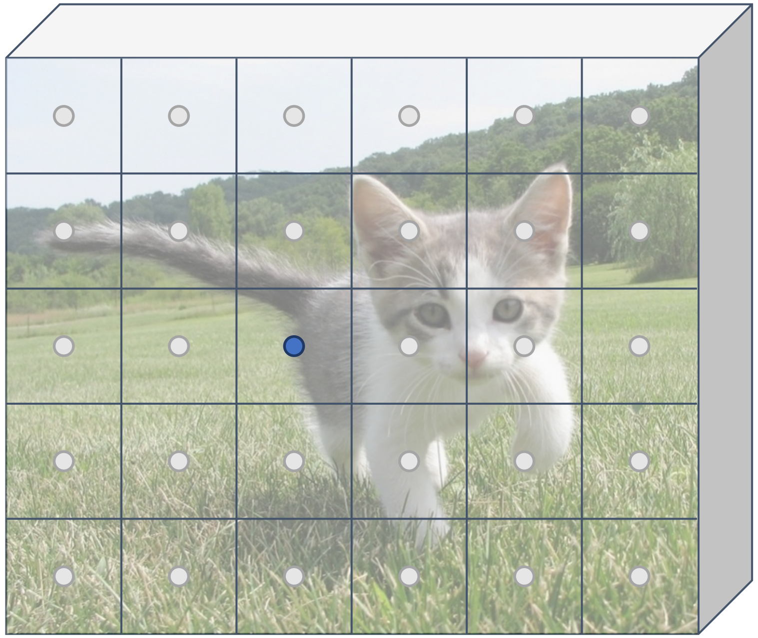
In practice: Rather than using one anchor per point, instead consider K different anchors with different size and scale (here K = 6)

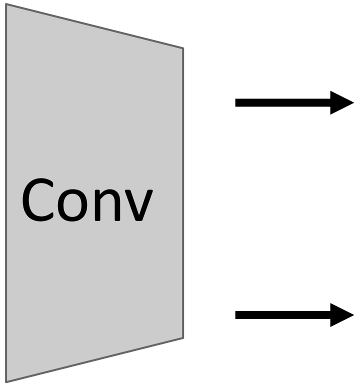
Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input









Anchor is object?
2K x 5 x 6

Anchor transforms
4K x 5 x 6

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

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

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

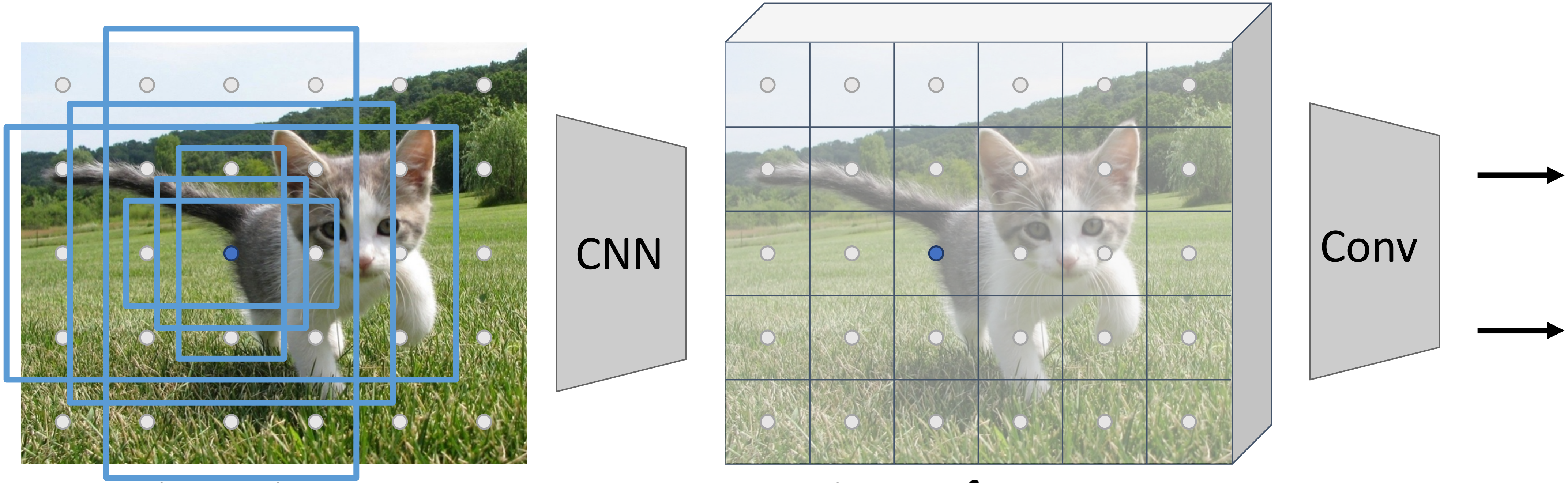
Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

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)

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



Anchor is object?
2K x 5 x 6

Anchor transforms
4K x 5 x 6

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

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

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

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

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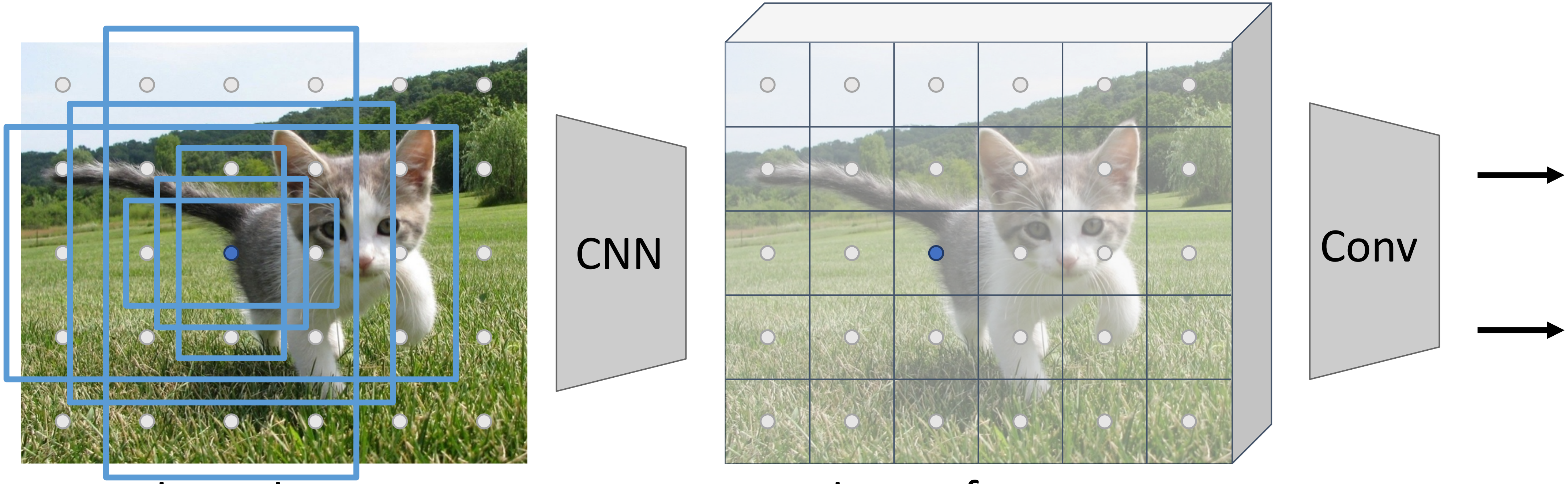

Anchor is object?
2K x 5 x 6

Anchor transforms
4K x 5 x 6

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

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

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

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

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)

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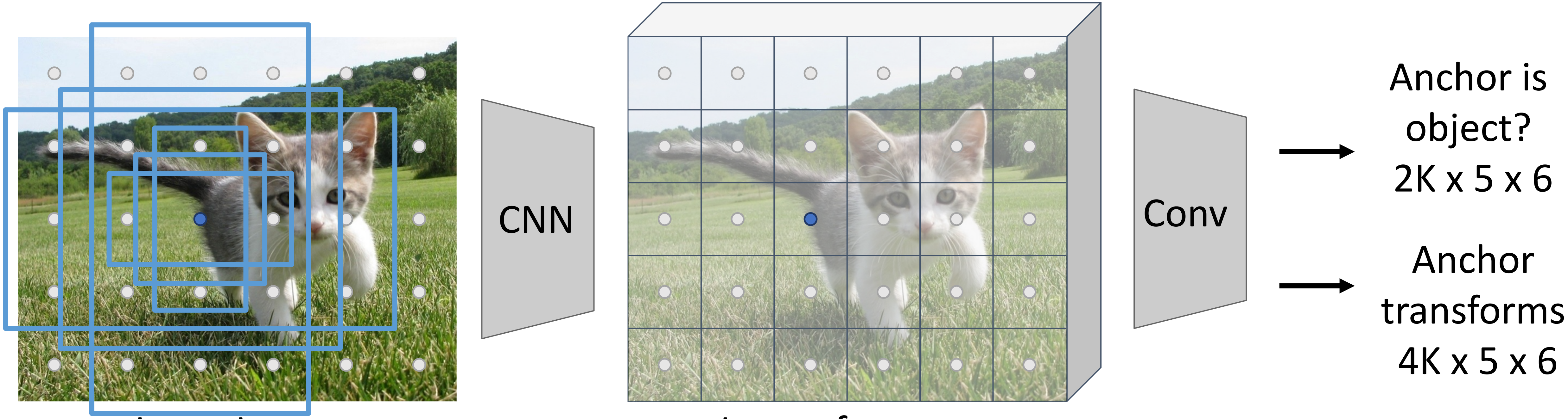

Input Image
(e.g. 3 x 640 x 480)

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

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

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

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)

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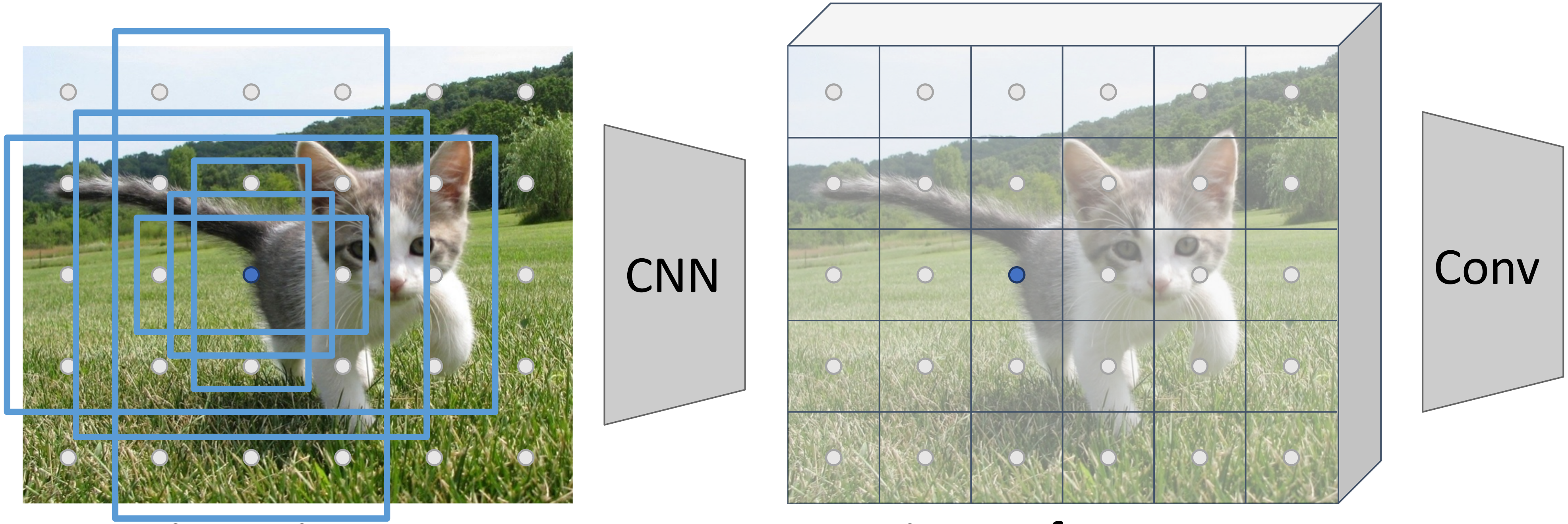


Input Image
(e.g. 3 x 640 x 480)

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

→ Anchor is object?
2K x 5 x 6

→ Anchor transforms
4K x 5 x 6

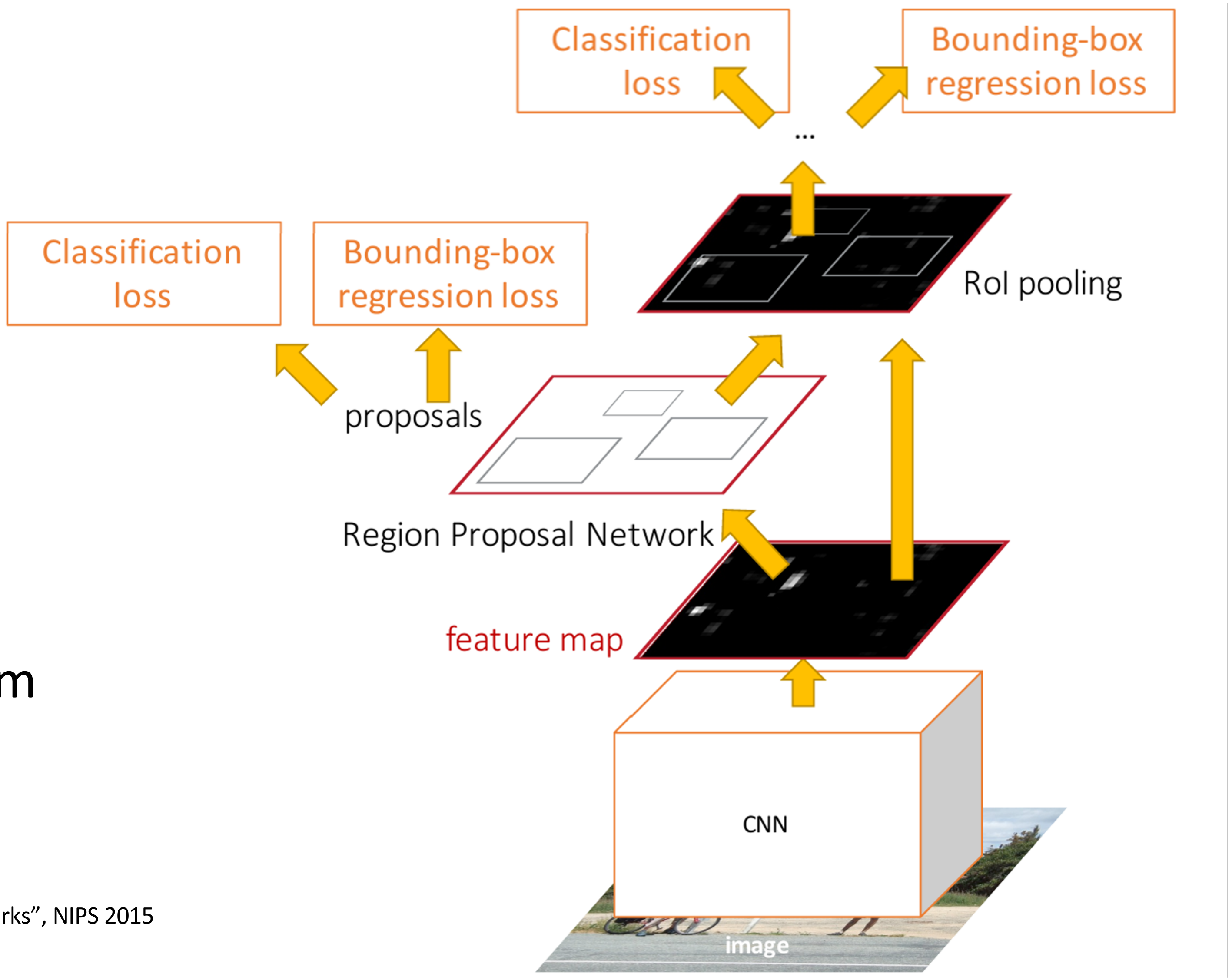
At test-time, sort all K*5*6 boxes by their positive score, take top 300 as our region proposals

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

Faster R-CNN: Learnable Region Proposals

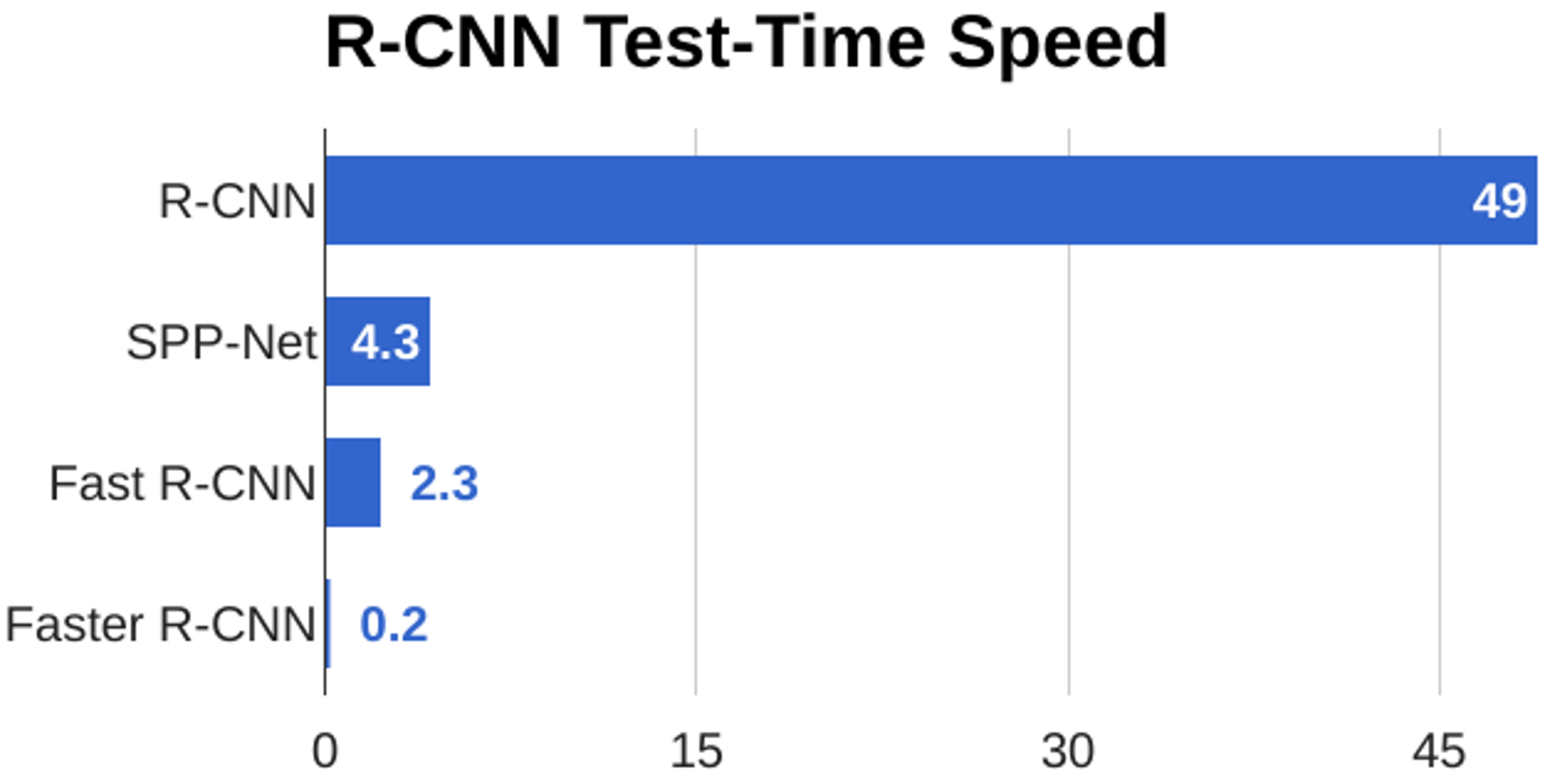
Jointly train with 4 losses:

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

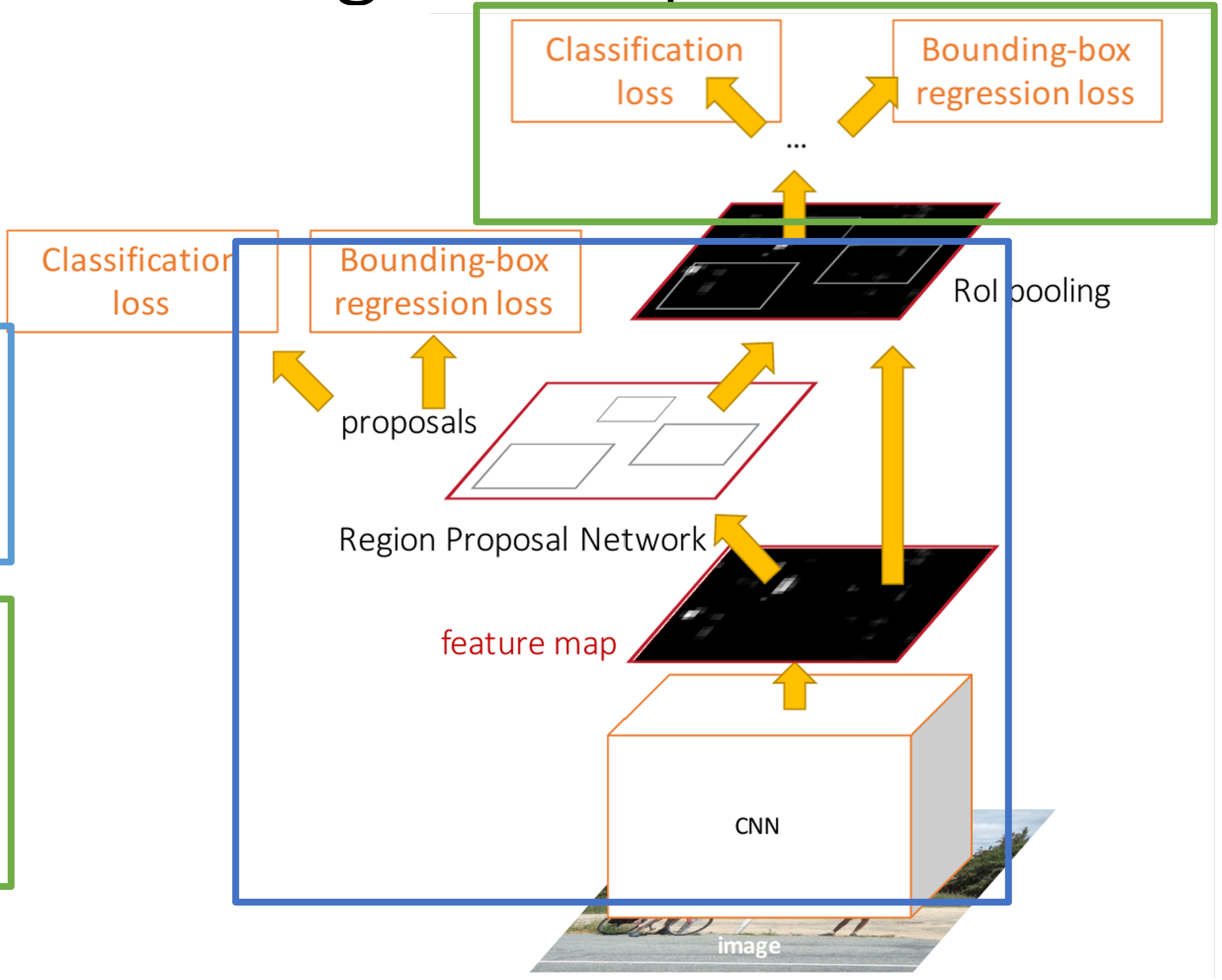


Faster R-CNN: Learnable Region Proposals

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

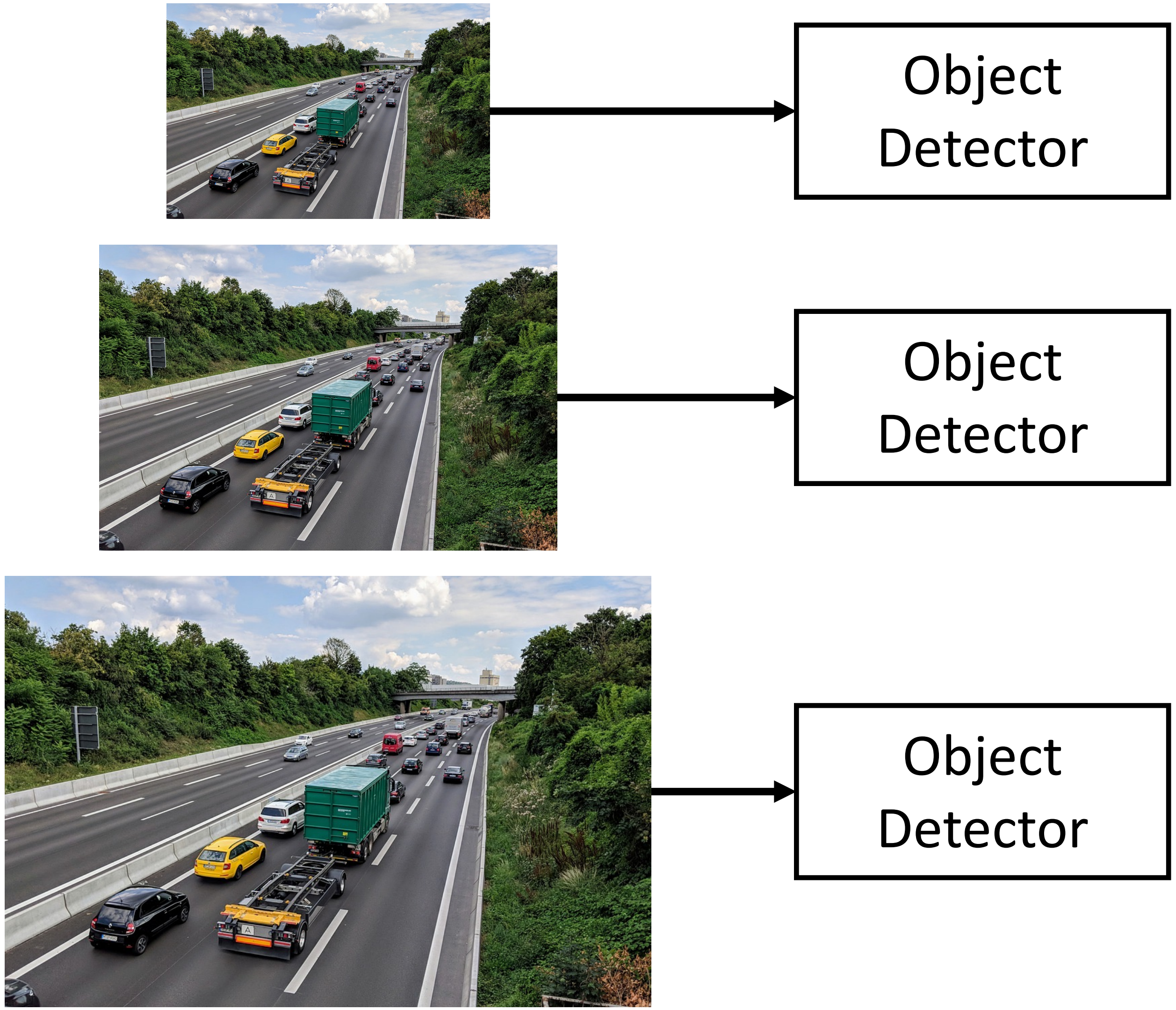


Dealing with Scale

We need to detect objects of many different scales.
How to improve *scale invariance* of the detector?

Dealing with Scale: Image Pyramid

Classic idea: build an *image pyramid* by resizing the image to different scales, then process each image scale independently.

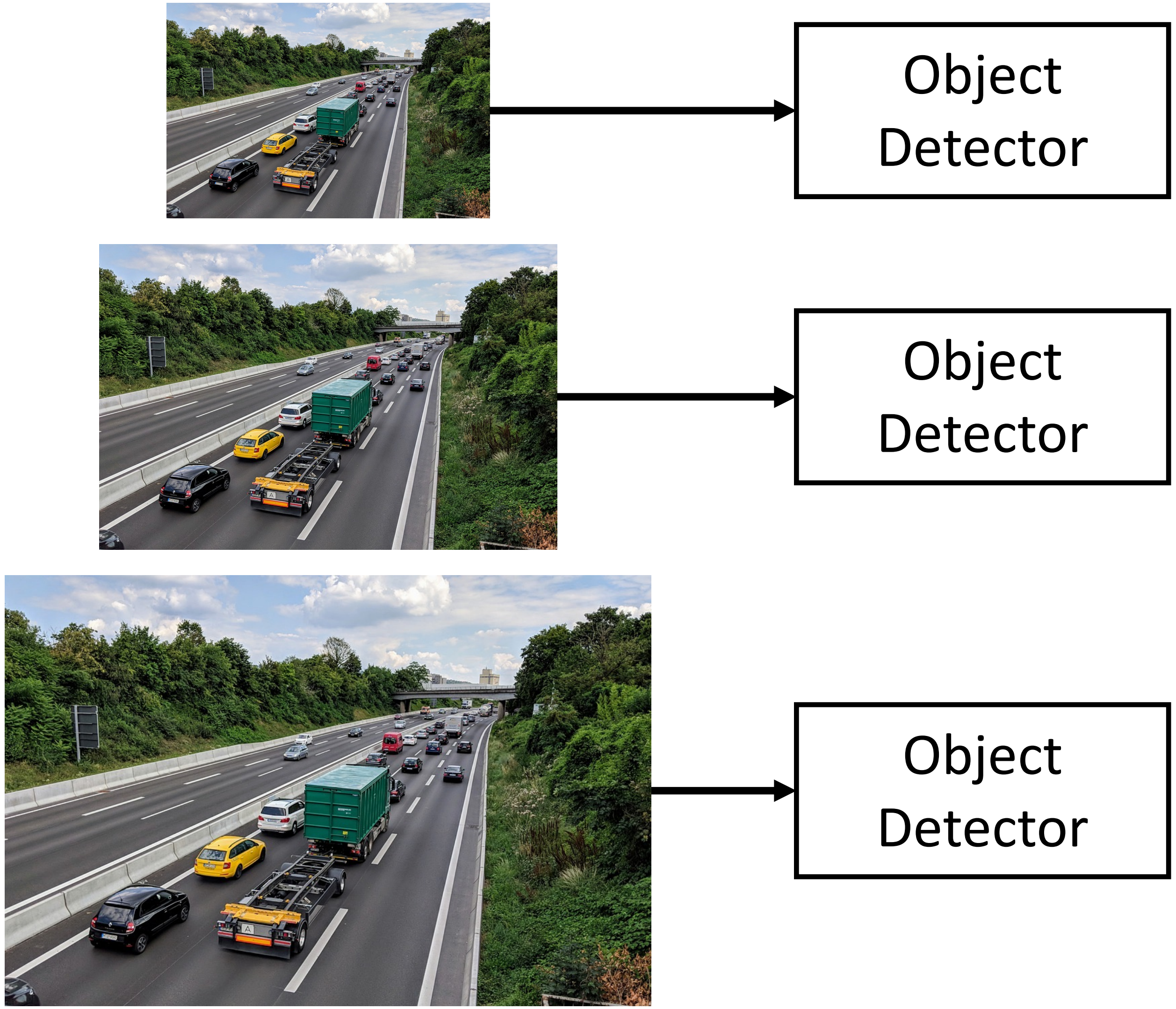


Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

Dealing with Scale: Image Pyramid

Classic idea: build an *image pyramid* by resizing the image to different scales, then process each image scale independently.

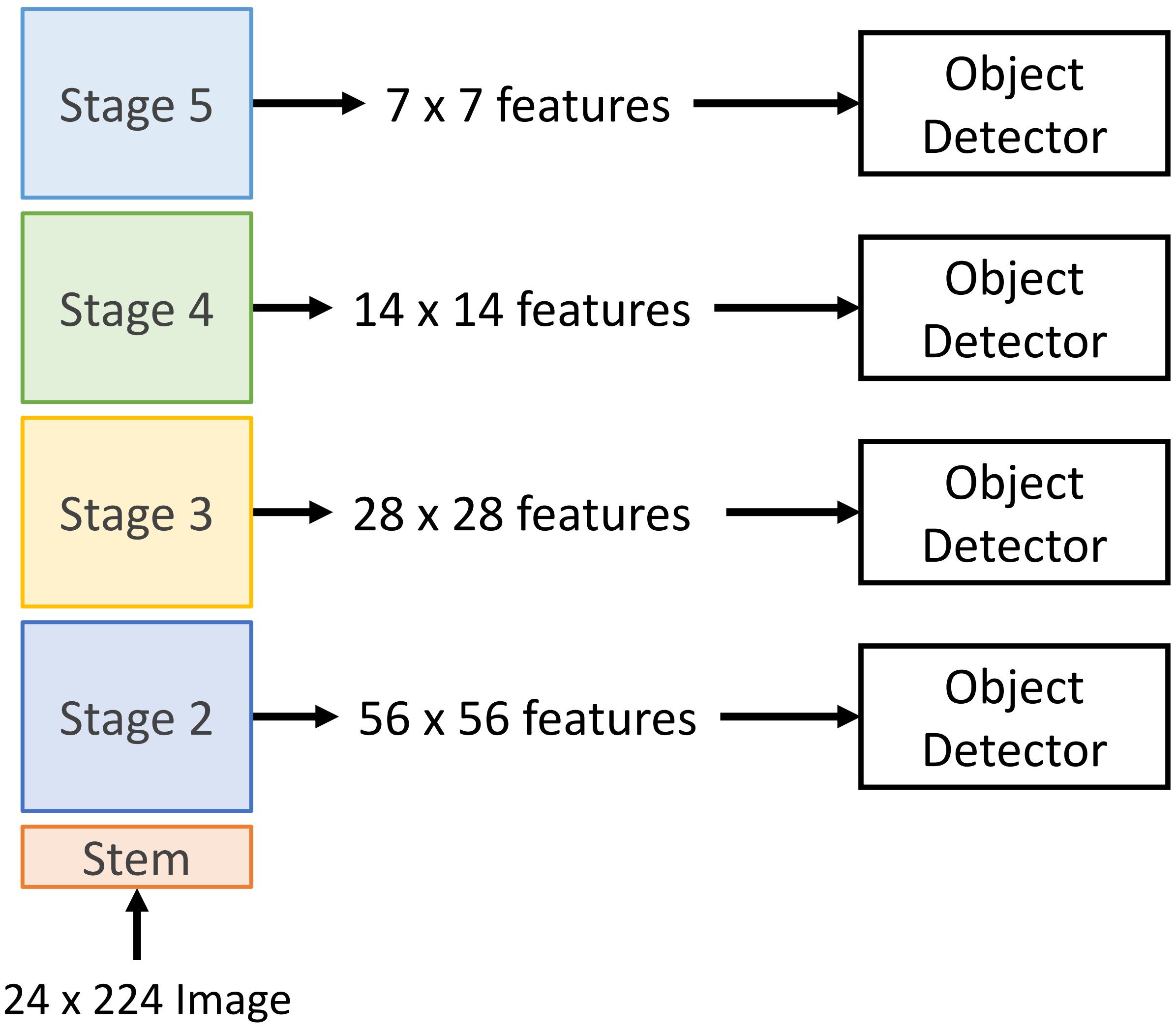
Problem: Expensive! Don't share any computation between scales



Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

Dealing with Scale: Multiscale Features

CNNs have multiple *stages* that operate at different resolutions. Attach an independent detector to the features at each level

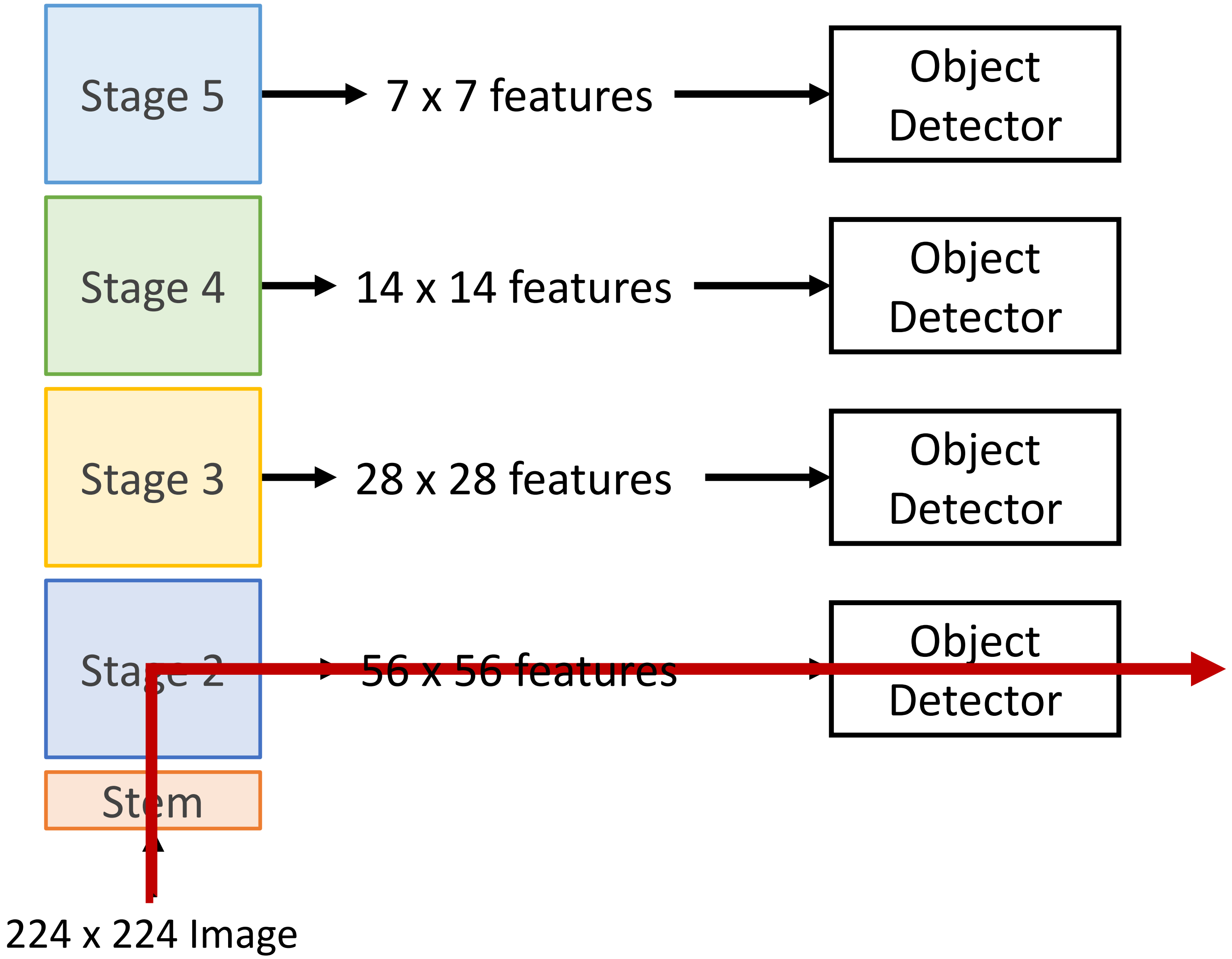


Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

Dealing with Scale: Multiscale Features

CNNs have multiple *stages* that operate at different resolutions. Attach an independent detector to the features at each level

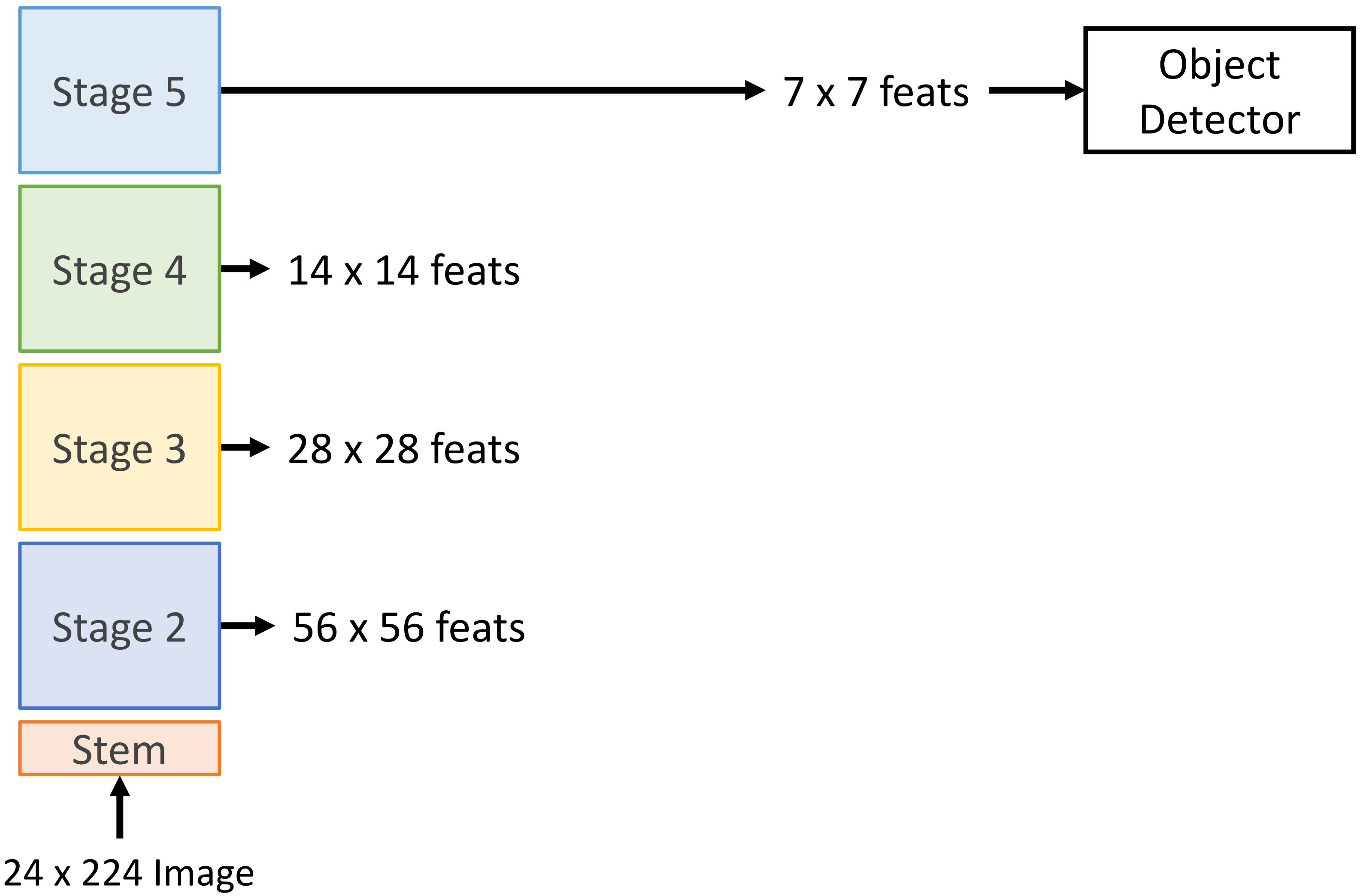
Problem: detector on early features doesn't make use of the entire backbone; doesn't get access to high-level features



Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

Dealing with Scale: Feature Pyramid Network

Add *top down connections* that feed information from high level features back down to lower level features



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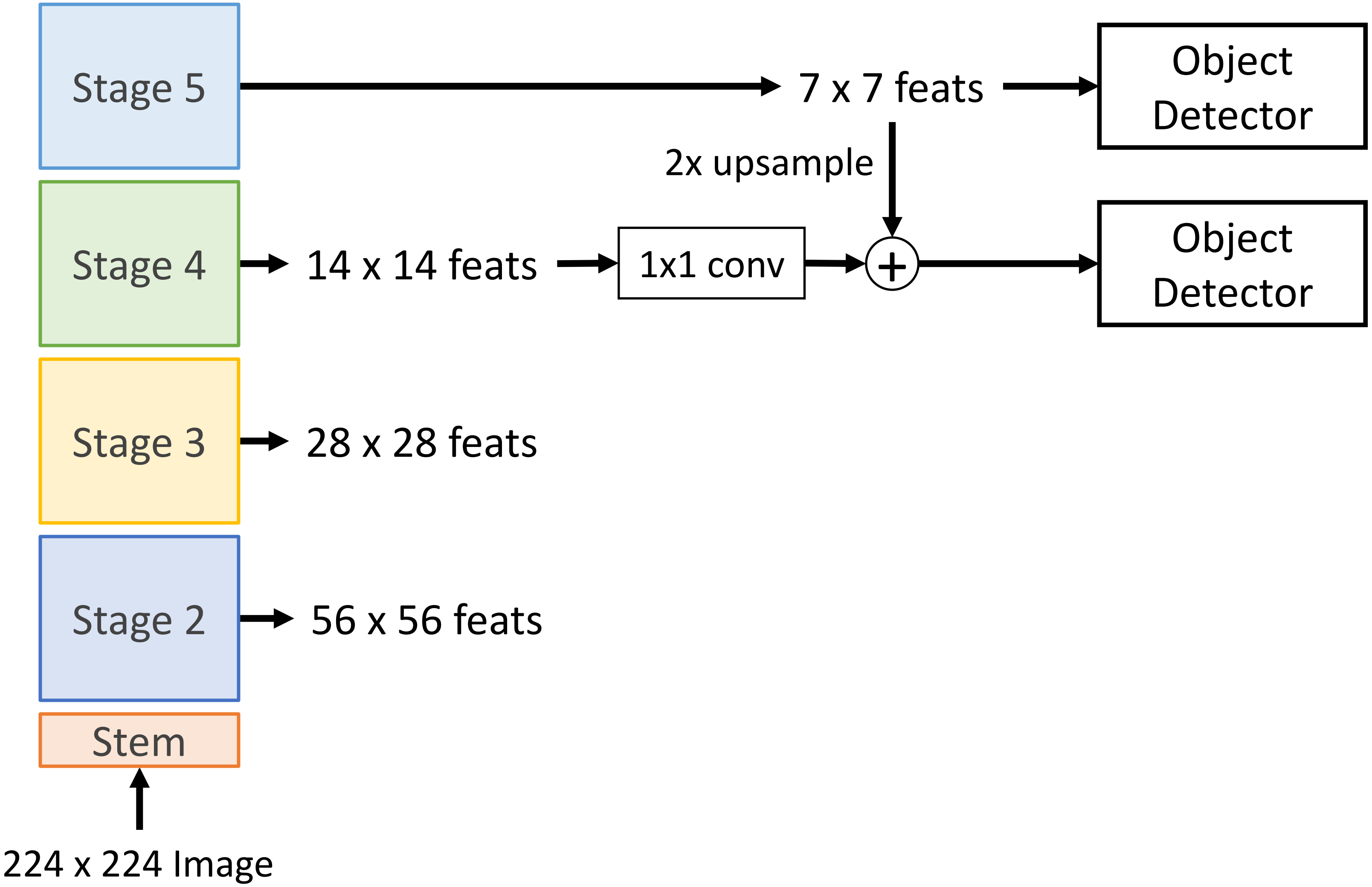

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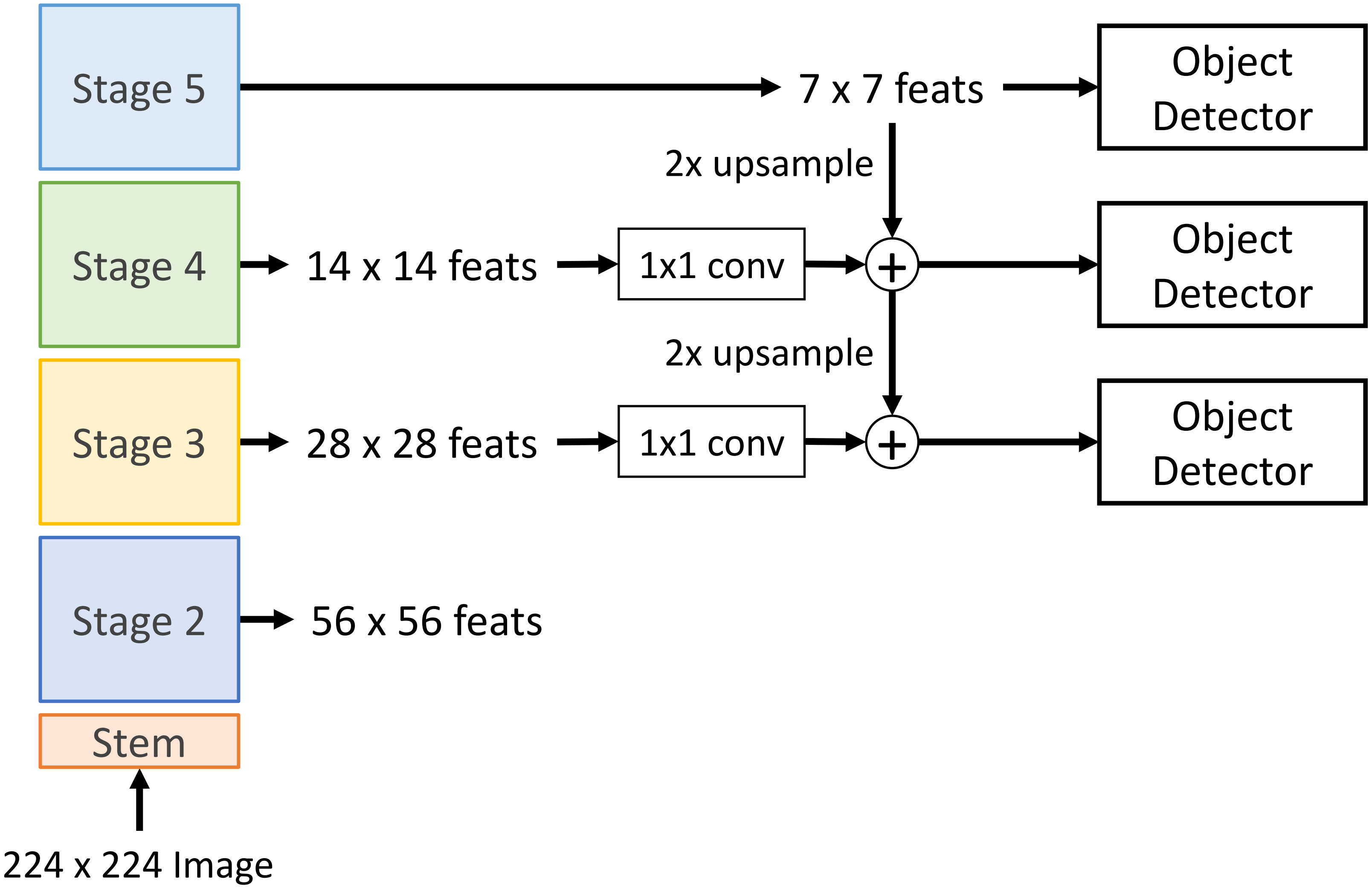

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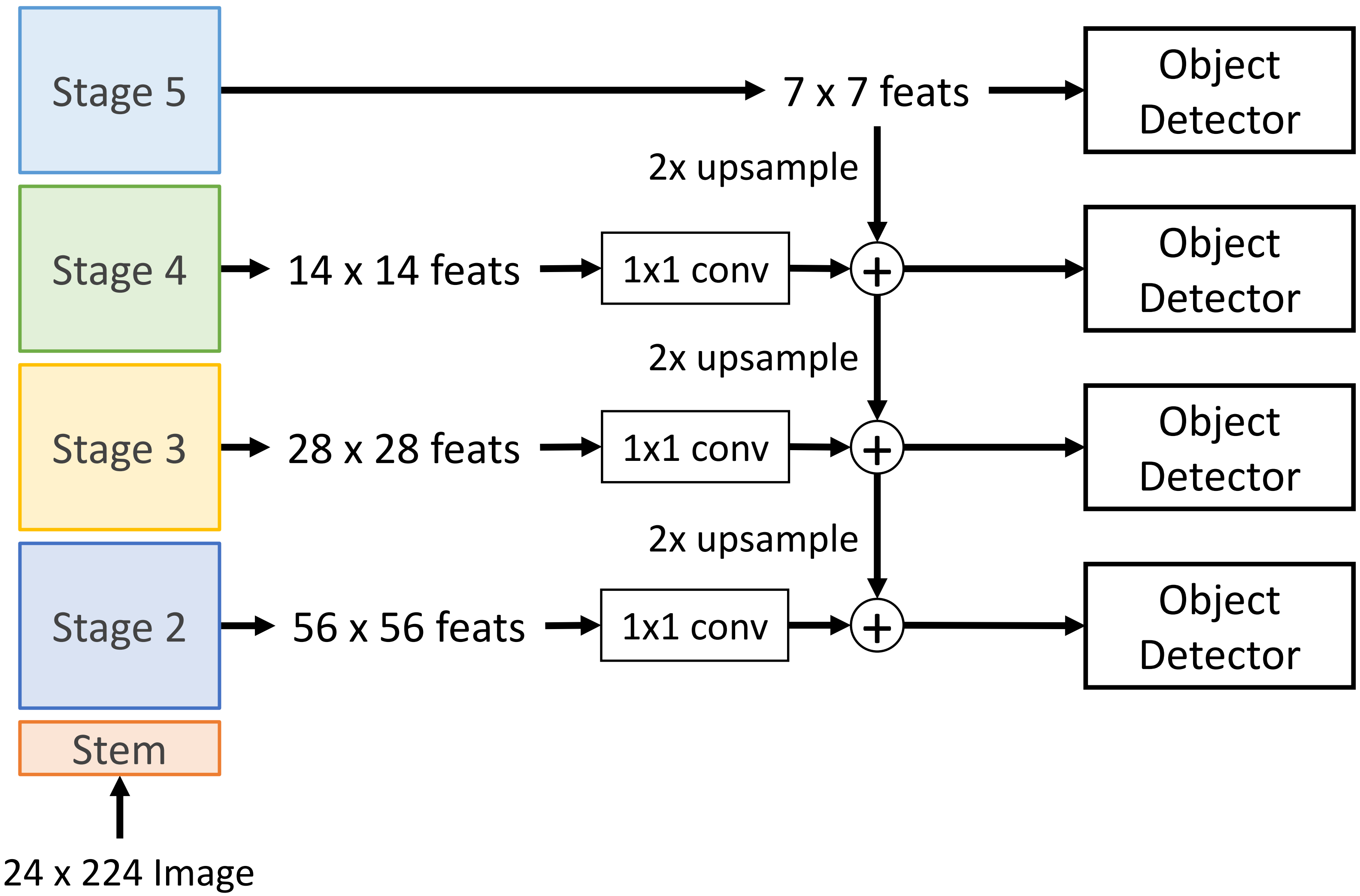

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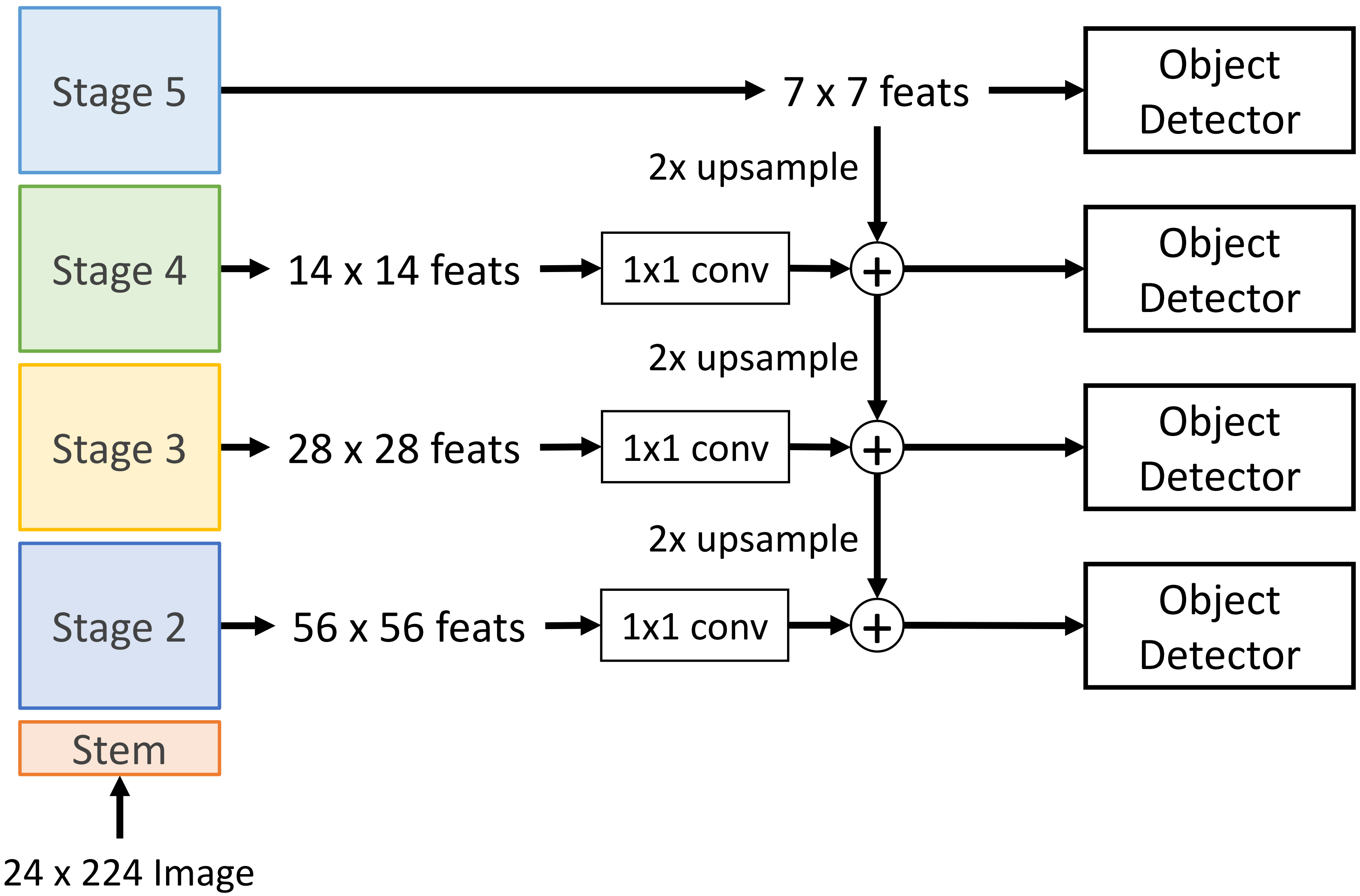
Dealing with Scale: Feature Pyramid Network

Add *top down connections* that feed information from high level features back down to lower level features

Efficient multiscale features where all levels benefit from the whole backbone! Widely used in practice



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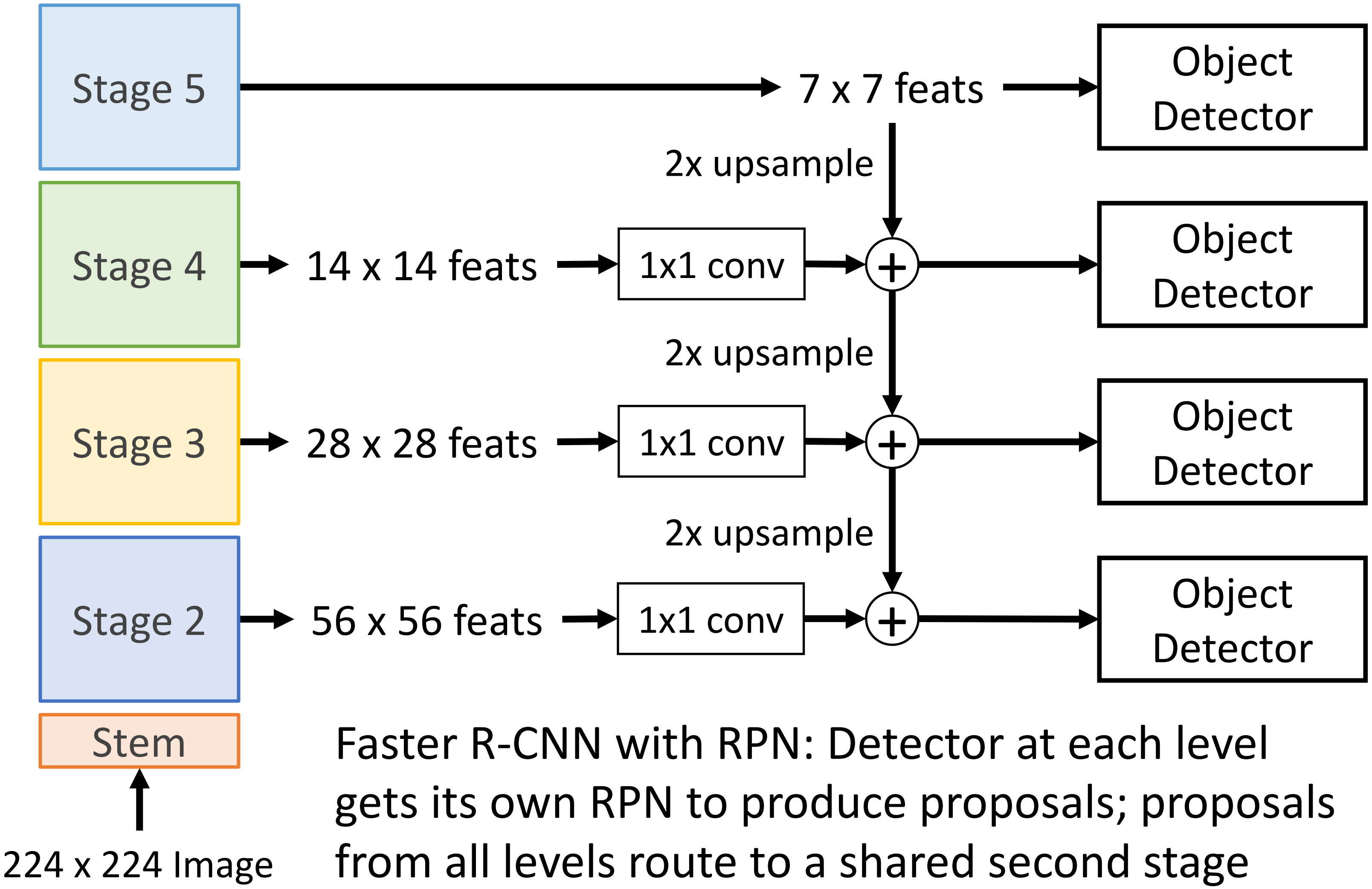


Faster R-CNN with RPN: Detector at each level gets its own RPN to produce proposals; proposals from all levels route to a shared second stage

Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

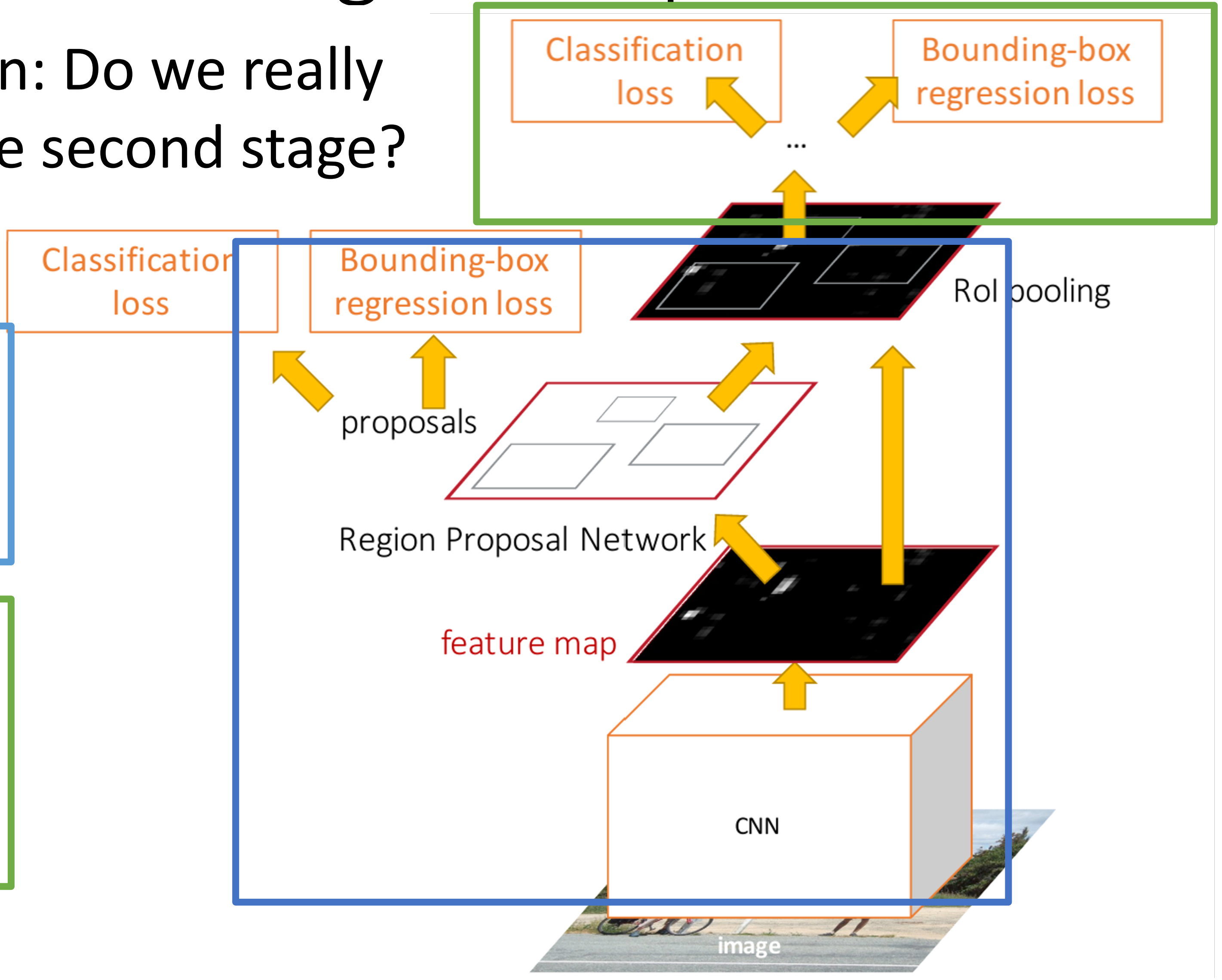
Faster R-CNN: Learnable Region Proposals

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

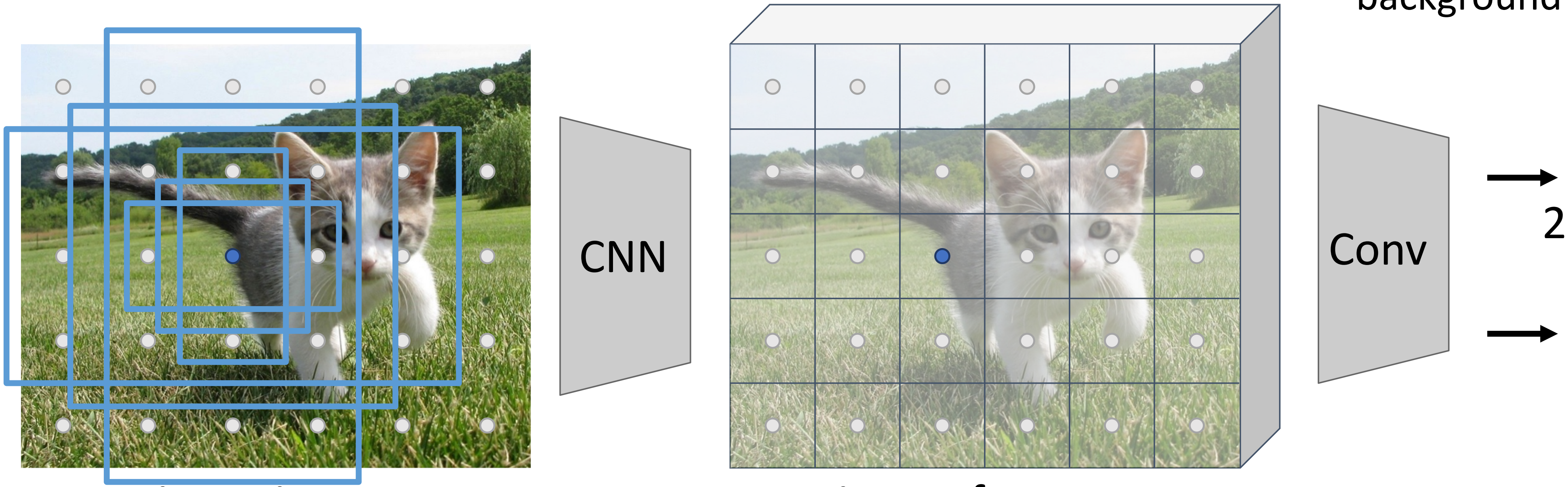


Single-Stage Detectors: RetinaNet

Similar to RPN – but rather than classify anchors as object/no object, directly predict object category (among C categories) or background

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



Anchor classification
2K*(C+1) x 5 x 6

Anchor transforms
4K x 5 x 6

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

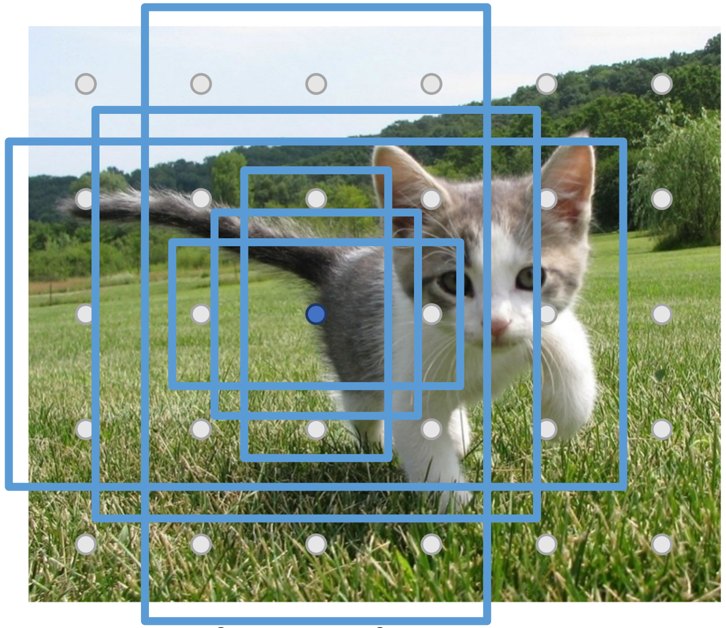
Image features
(e.g. 512 x 5 x 6)

Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Single-Stage Detectors: RetinaNet

Problem: class imbalance – many more background anchors vs non-background

Run backbone CNN to get features aligned to input image



Input Image
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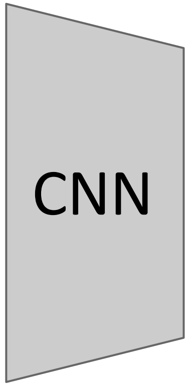

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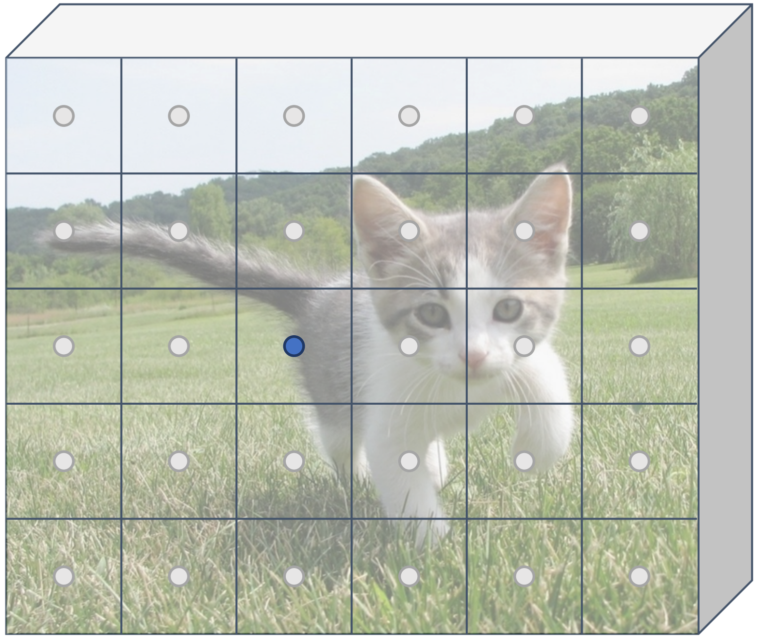
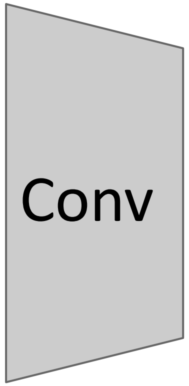


Image features
(e.g. 512 x 5 x 6)



Anchor classification
2K*(C+1) x 5 x 6

Anchor transforms
4K x 5 x 6

Lin et al, “Focal Loss for Dense Object Detection”, ICCV 2017

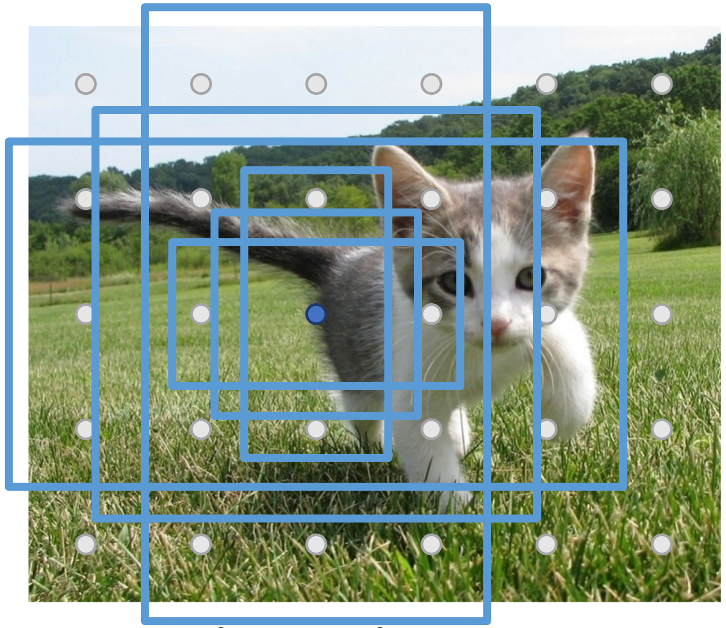
Single-Stage Detectors: RetinaNet

Problem: class imbalance – many more background anchors vs non-background

Solution: new loss function (Focal Loss); see paper

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



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

CNN

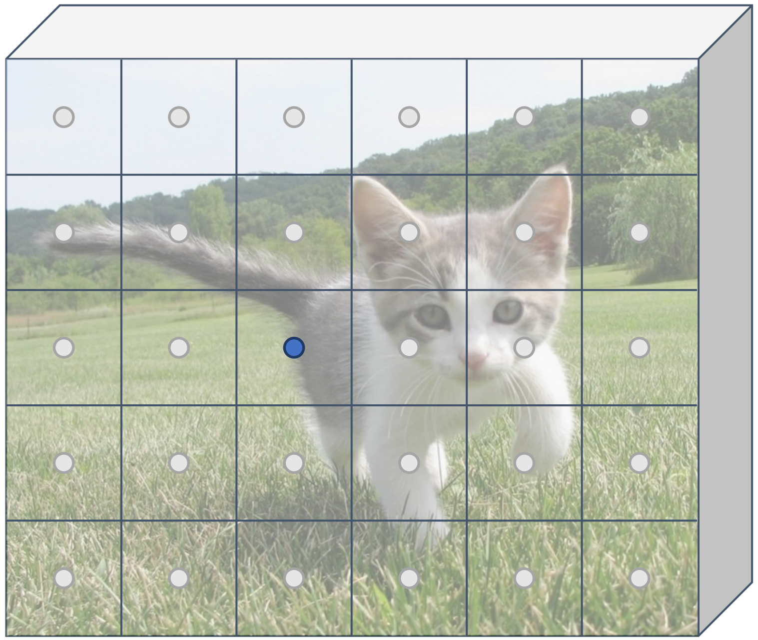


Image features
(e.g. 512 x 5 x 6)

Conv

Anchor classification
2K*(C+1) x 5 x 6

Anchor transforms
4K x 5 x 6

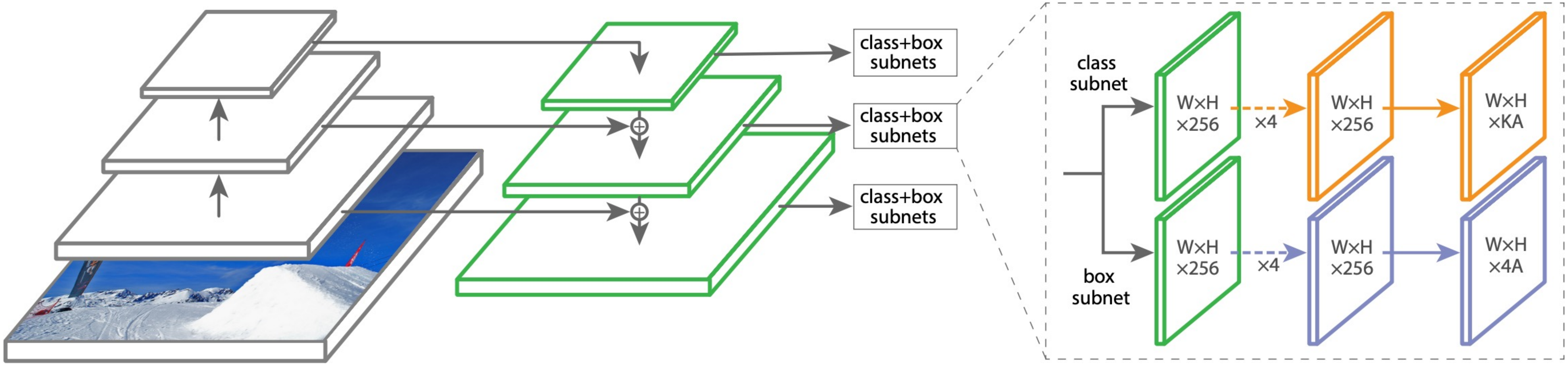
$$\mathrm{CE}(p_t) = -\log(p_t)$$

$$\mathrm{FL}(p_t) = -(1-p_t)^{\gamma}\log(p_t)$$

Lin et al, “Focal Loss for Dense Object Detection”, ICCV 2017

Single-Stage Detectors: RetinaNet

In practice, RetinaNet also uses Feature Pyramid Network to handle multiscale



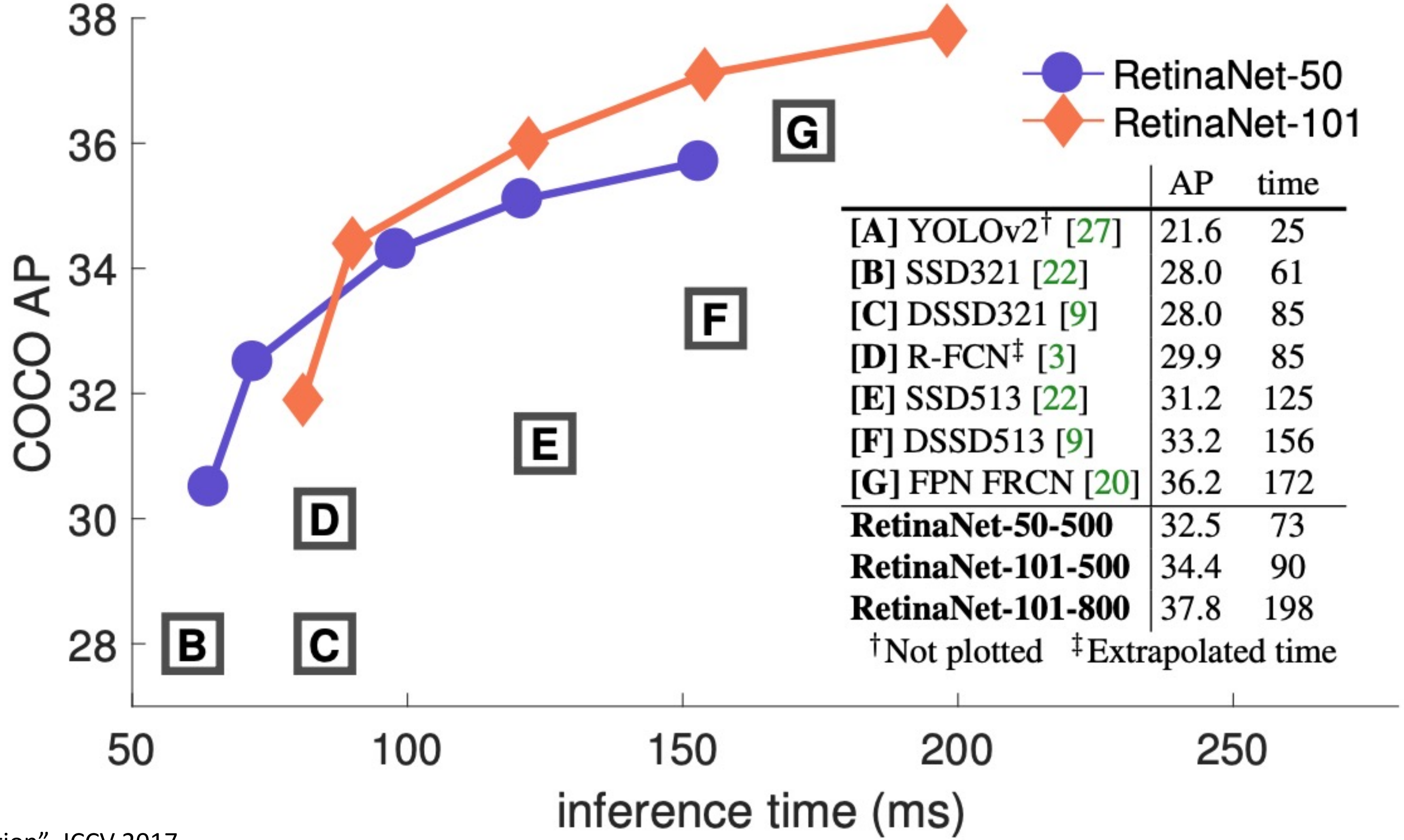
(a) ResNet (b) feature pyramid net (c) class subnet (top) (d) box subnet (bottom)

Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Figure credit: Lin et al, ICCV 2017

Single-Stage Detectors: RetinaNet

Single-Stage detectors can be much faster than two-stage detectors



	AP	time
[A] YOLOv2† [27]	21.6	25
[B] SSD321 [22]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [22]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [20]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Figure credit: Lin et al, ICCV 2017

Single-Stage Detectors: RetinaNet

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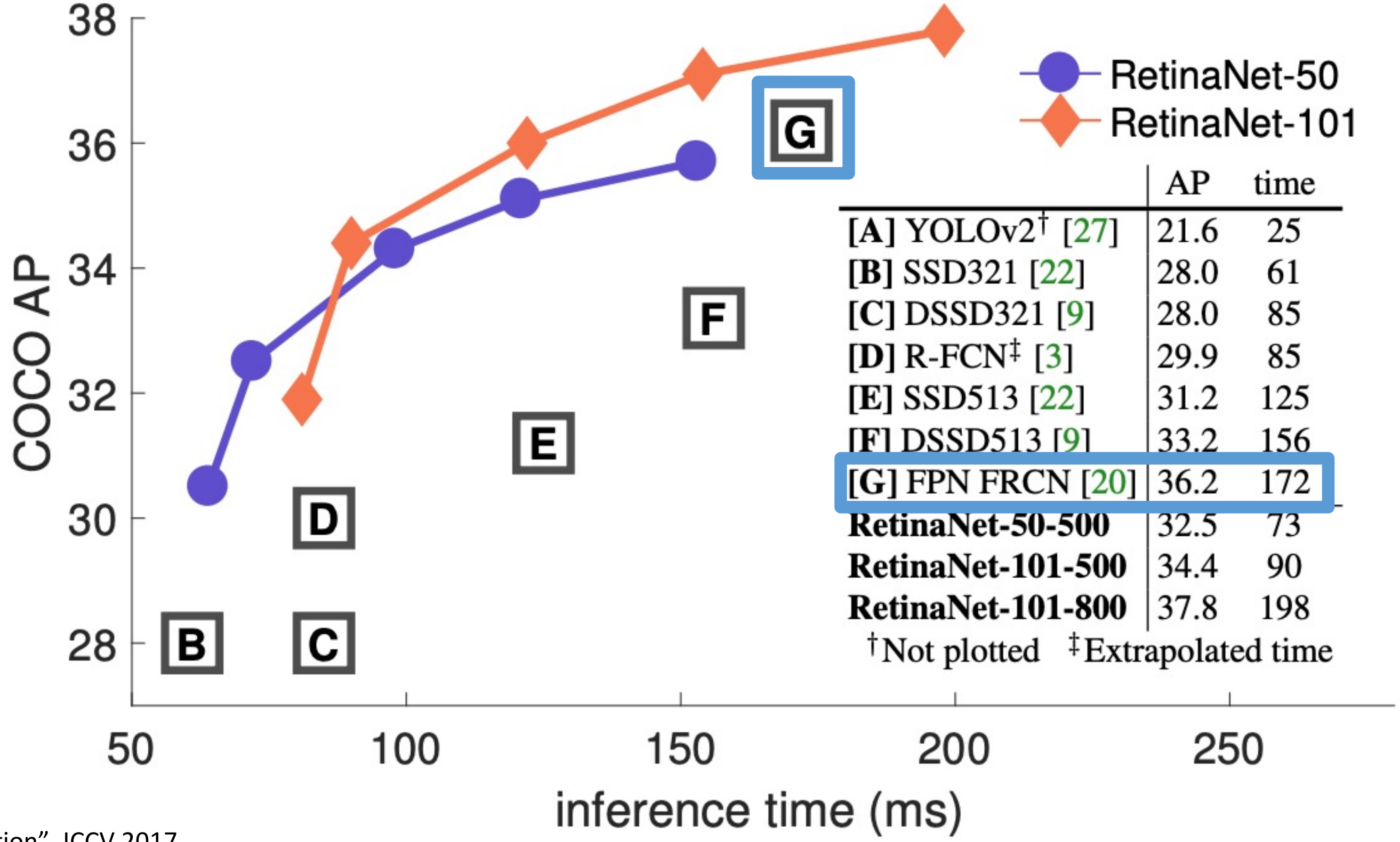

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Faster R-CNN with Feature Pyramid Network

Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

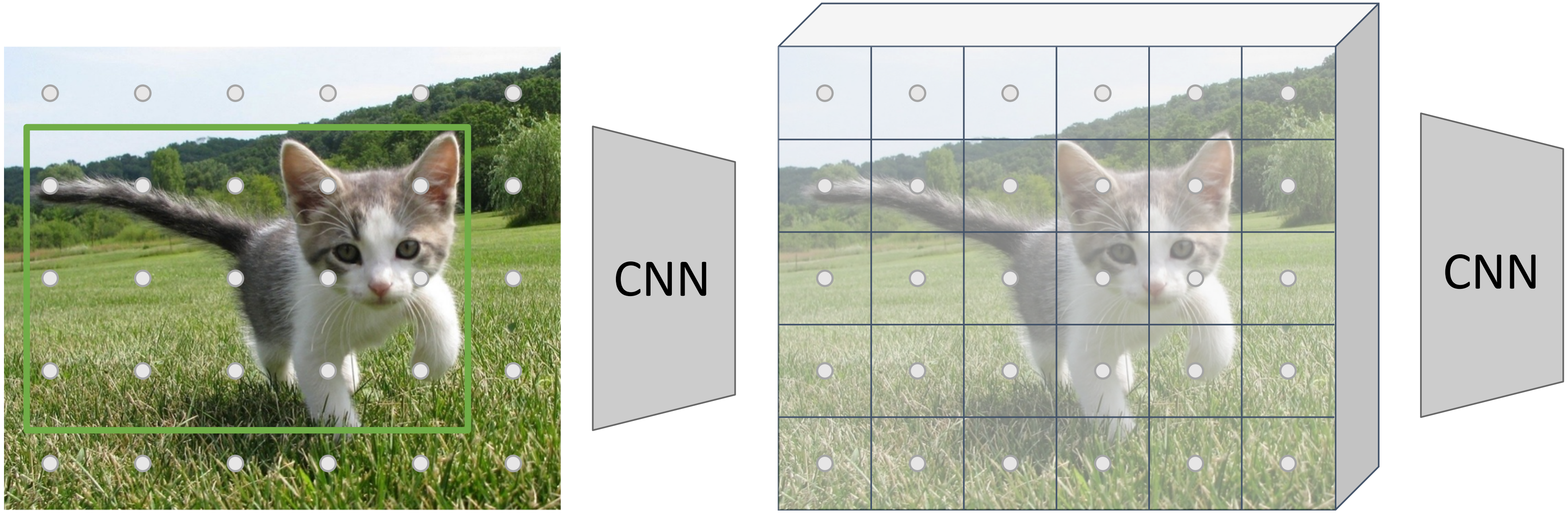
Figure credit: Lin et al, ICCV 2017

Single-Stage Detectors: FCOS

"Anchor-free" detector

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



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

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

Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

Single-Stage Detectors: FCOS

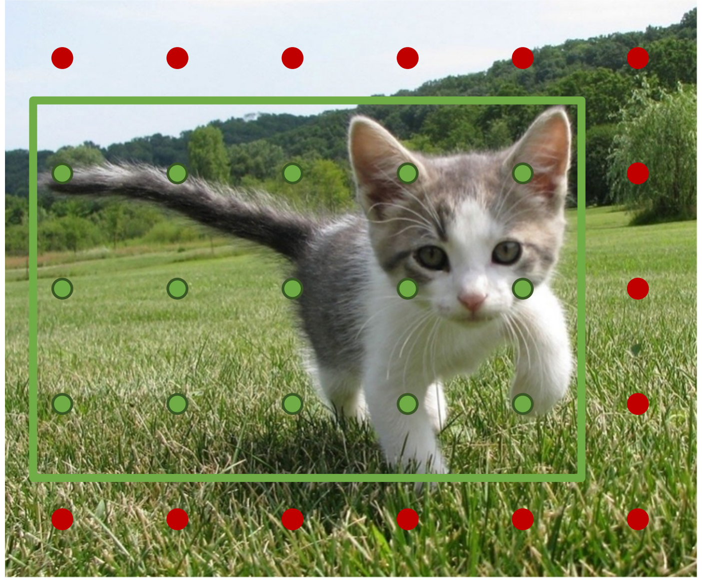
"Anchor-free" detector

Classify points as positive if they fall into a GT box, or negative if they don't

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input

Train independent per-category logistic regressors



Input Image
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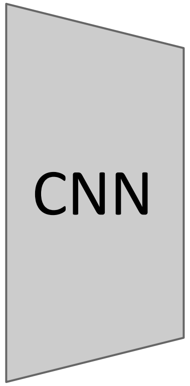


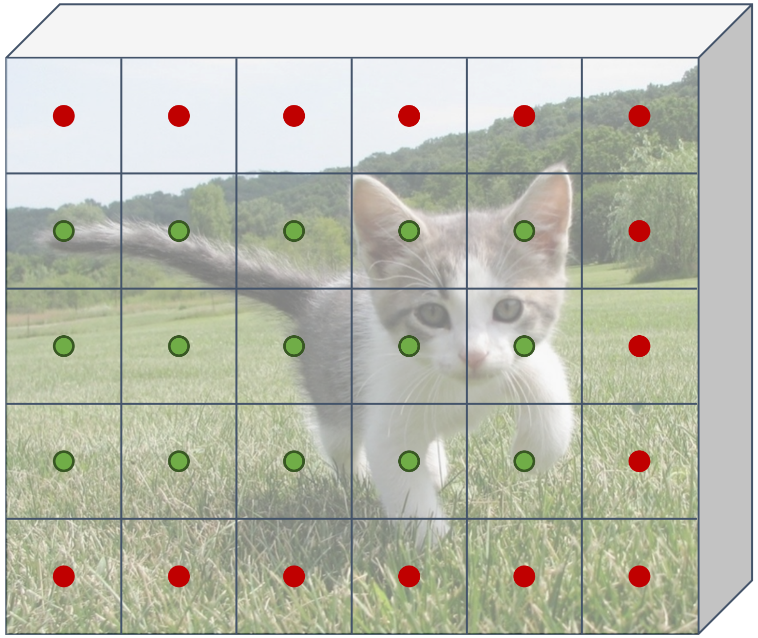
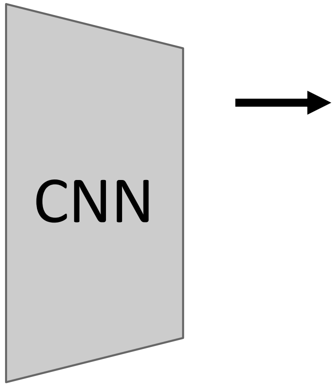


Image features
(e.g. 512 x 5 x 6)



Class scores
C x 5 x 6

Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

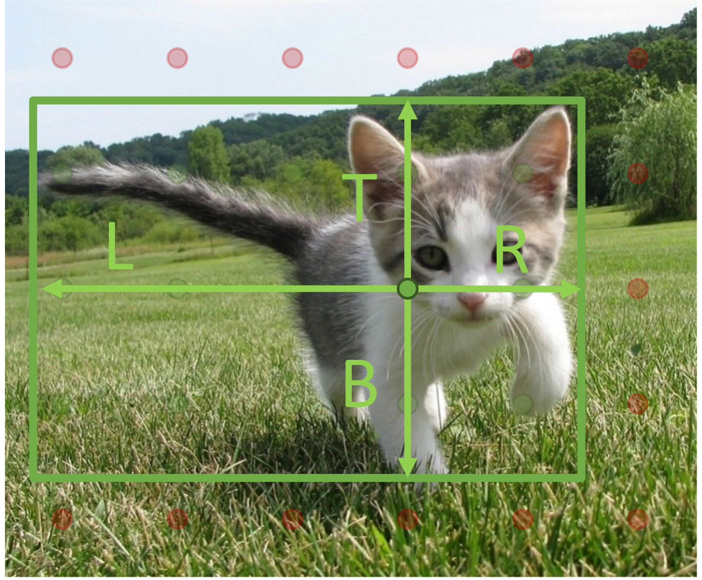
Single-Stage Detectors: FCOS

"Anchor-free" detector

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input

For positive points, also regress distance to left, right, top, and bottom of ground-truth box (with L2 loss)



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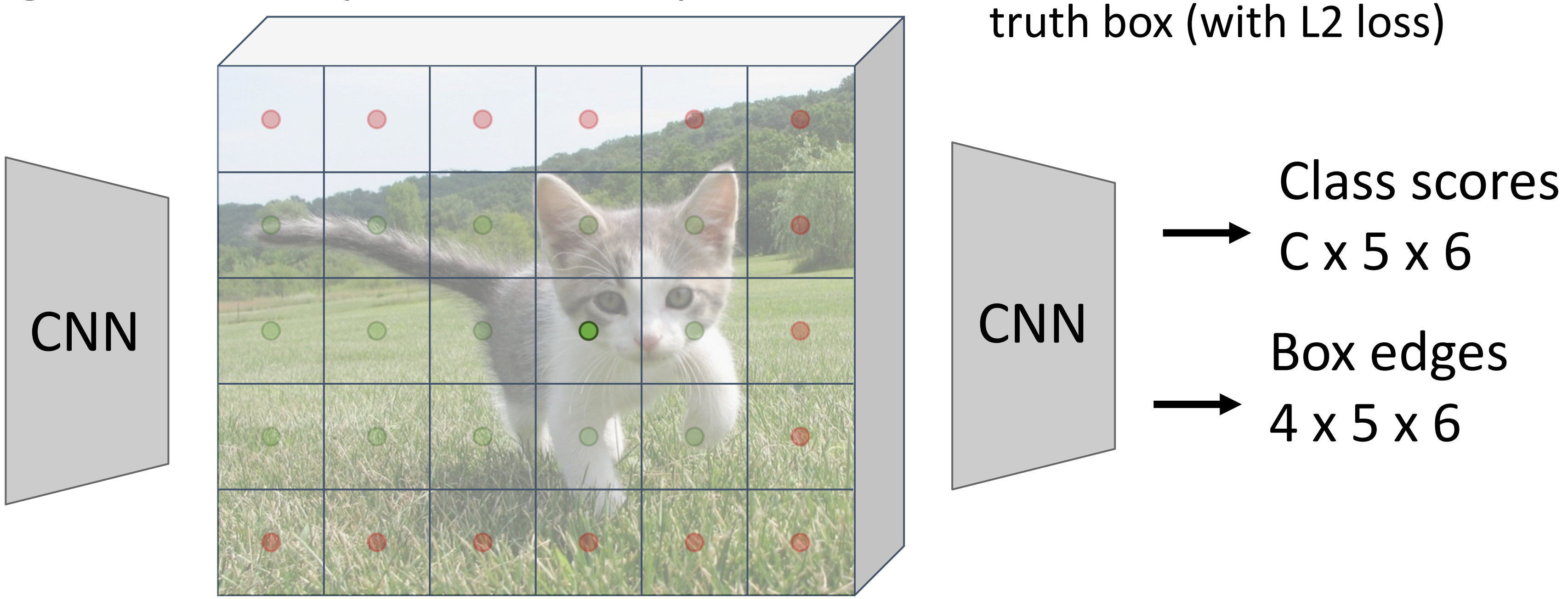

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Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

Single-Stage Detectors: FCOS

"Anchor-free" detector

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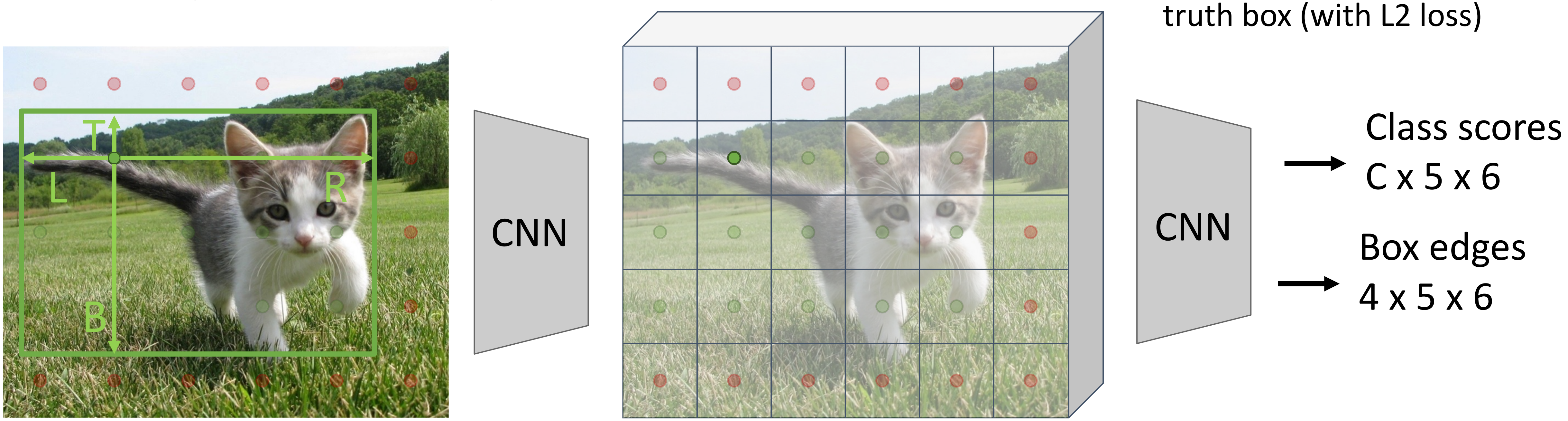


Input Image
(e.g. 3 x 640 x 480)

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

Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

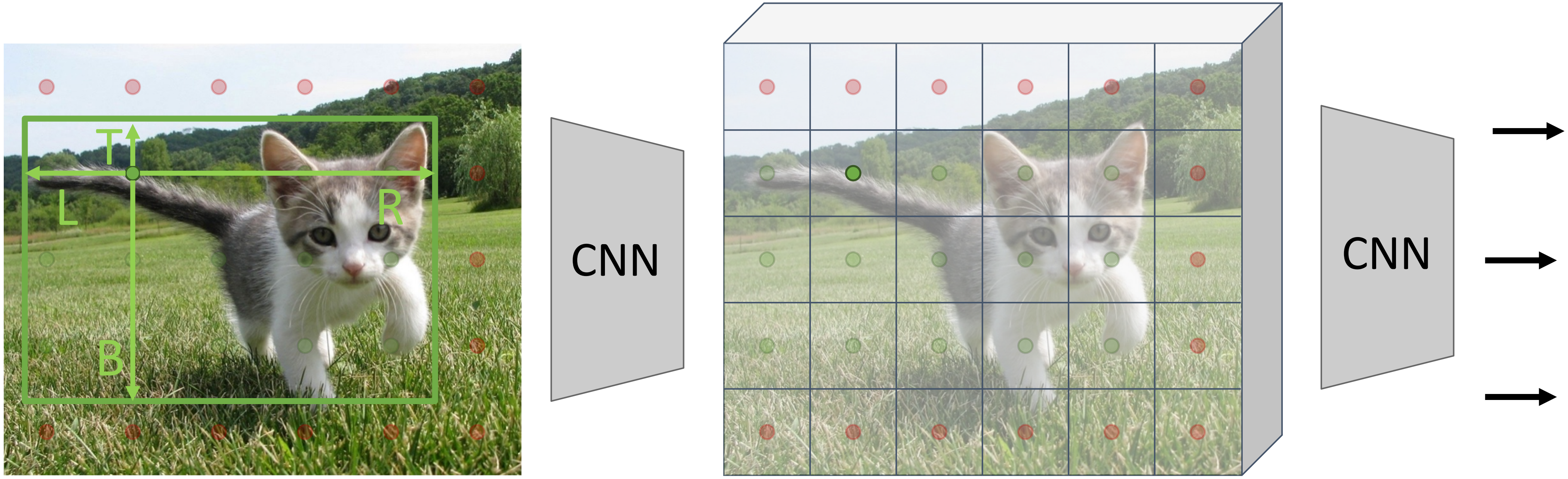
Single-Stage Detectors: FCOS

"Anchor-free" detector

Finally, predict "centerness" for all positive points (using logistic regression loss)

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



Class scores
C x 5 x 6

Box edges
4 x 5 x 6

Centerness
1 x 5 x 6

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

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

$$centerness = \sqrt{\frac{\min(L,R)}{\max(L,R)} \cdot \frac{\min(T,B)}{\max(T,B)}}$$

Ranges from 1 at box center to 0 at box edge

Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

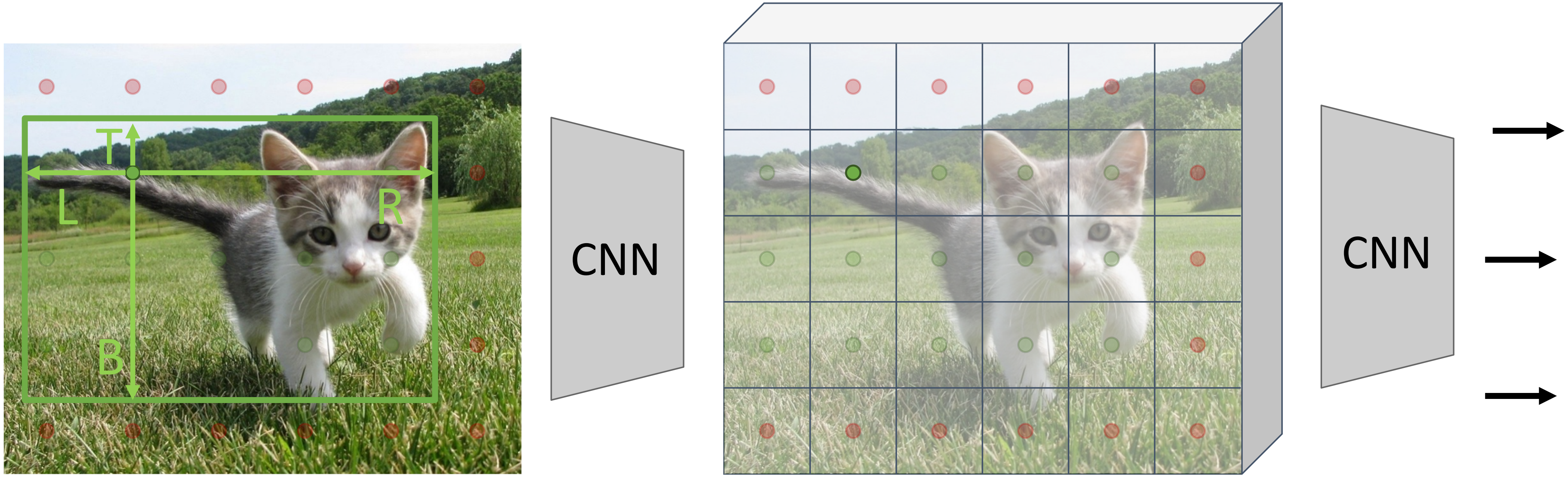
Single-Stage Detectors: FCOS

"Anchor-free" detector

Test-time: predicted "confidence" for the box from each point is product of its class score and centerness

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



Class scores
C x 5 x 6

Box edges
4 x 5 x 6

Centerness
1 x 5 x 6

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

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

$$centerness = \sqrt{\frac{\min(L,R)}{\max(L,R)} \cdot \frac{\min(T,B)}{\max(T,B)}}$$

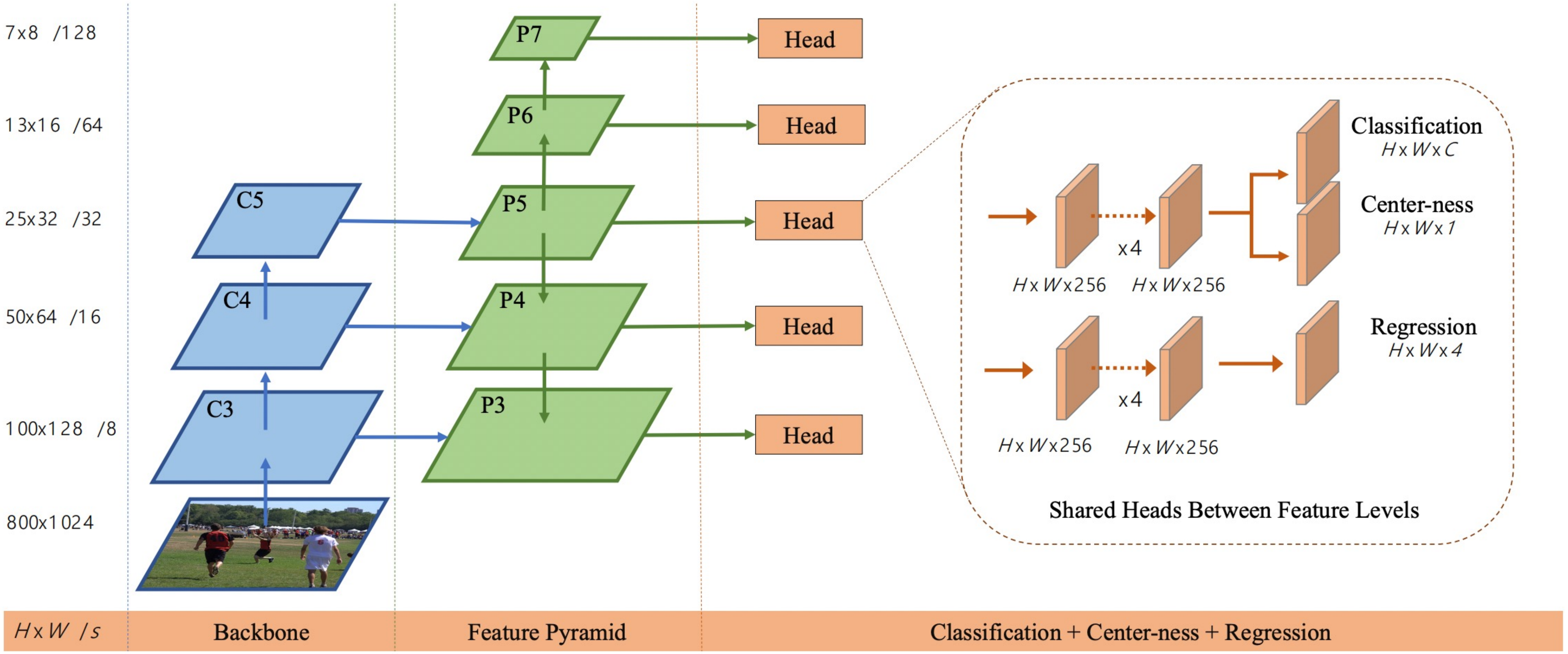
Ranges from 1 at box center to 0 at box edge

Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

Single-Stage Detectors: FCOS

"Anchor-free" detector

FCOS also uses a Feature Pyramid Network with heads shared across stages



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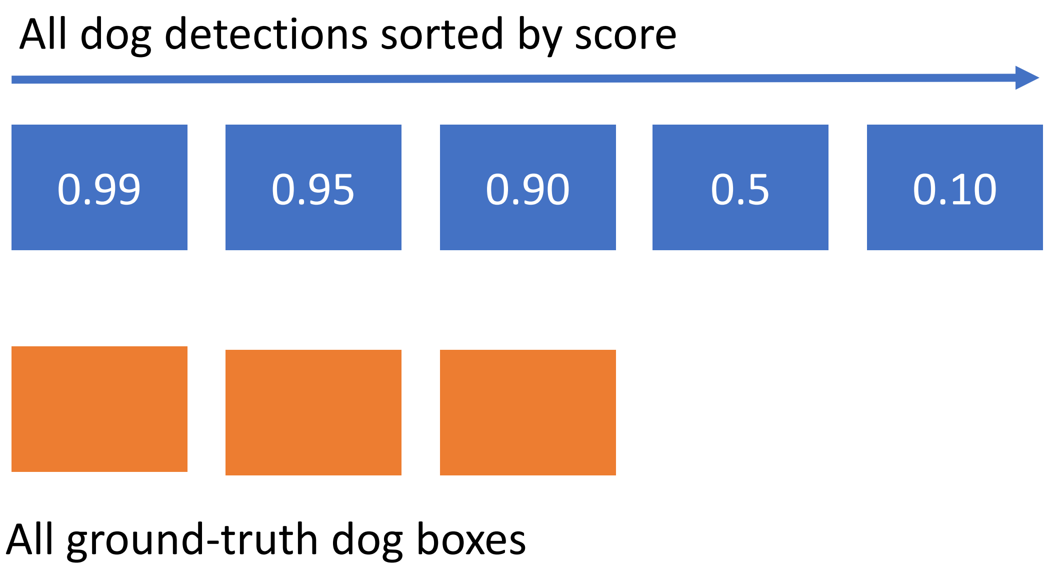
Evaluating Object Detectors: Mean Average Precision (mAP)

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)



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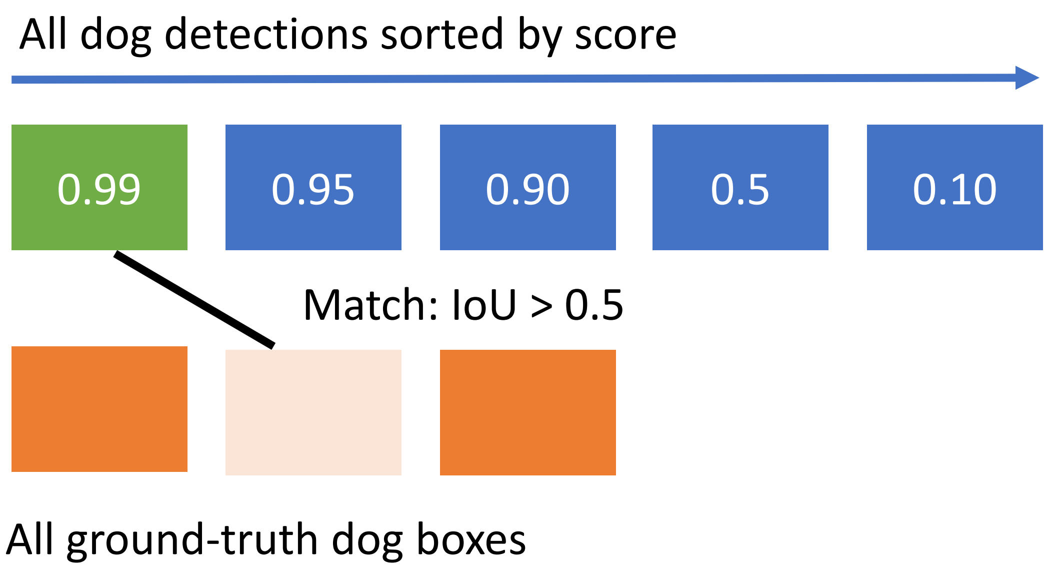

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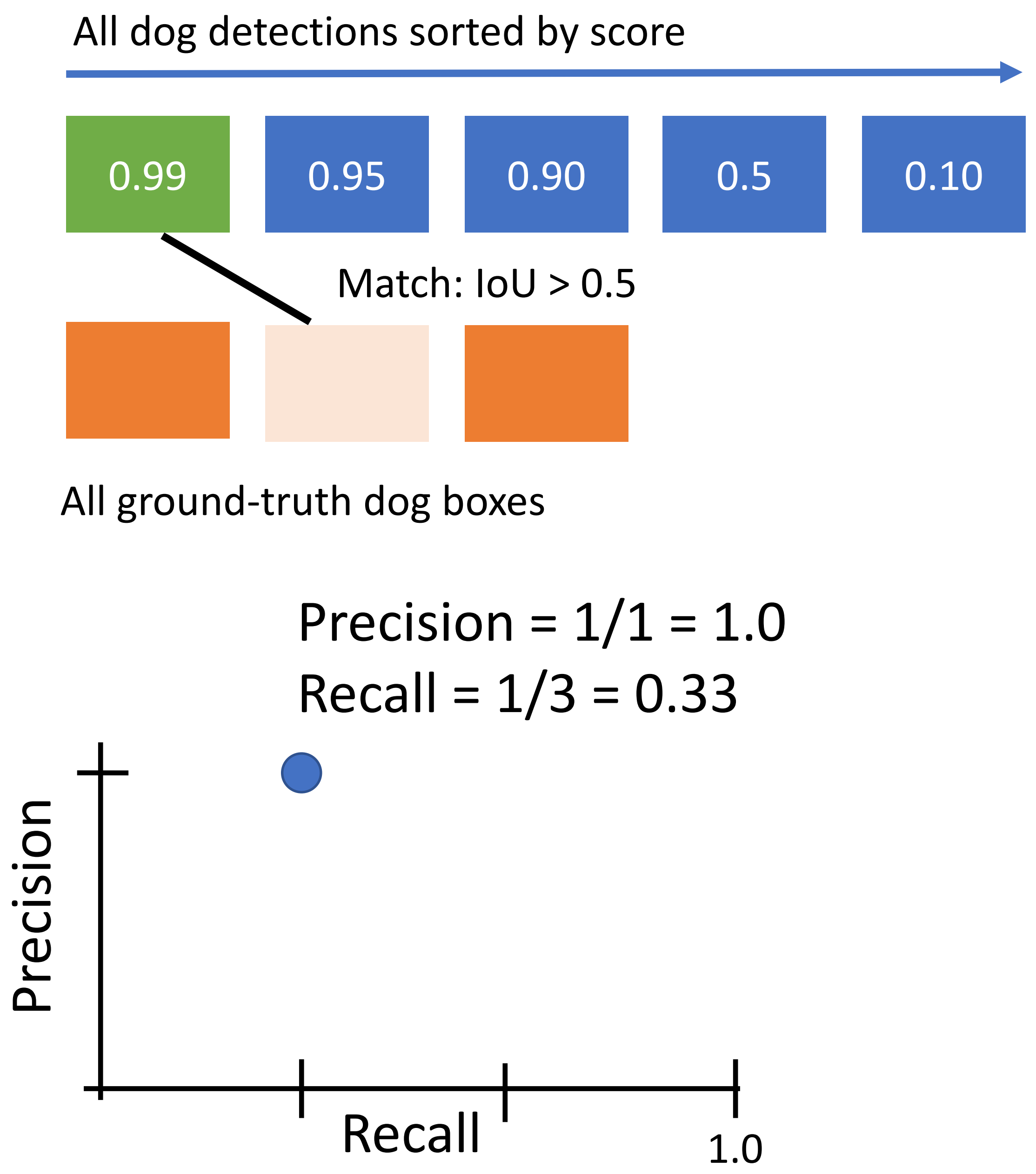

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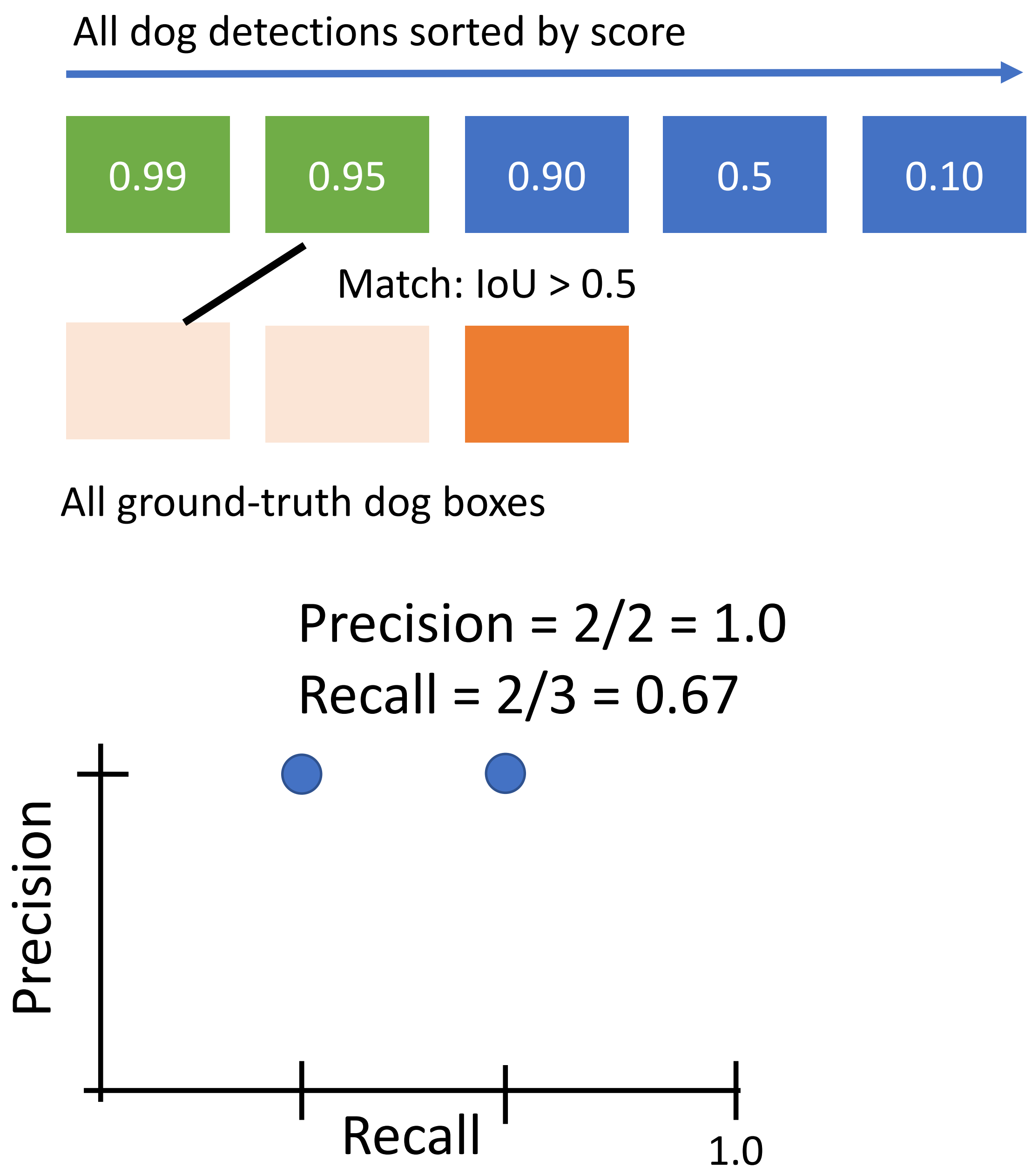

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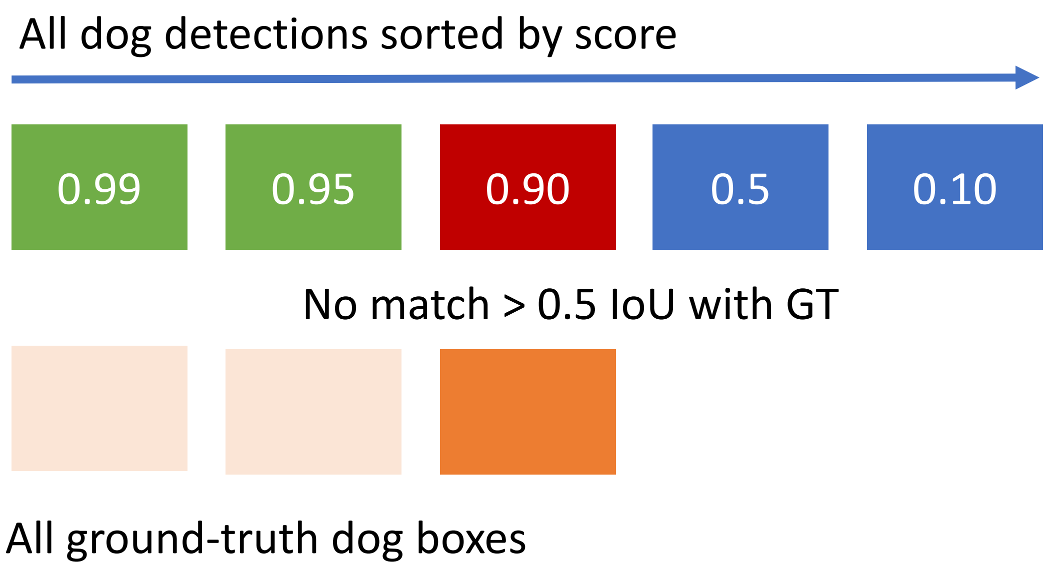

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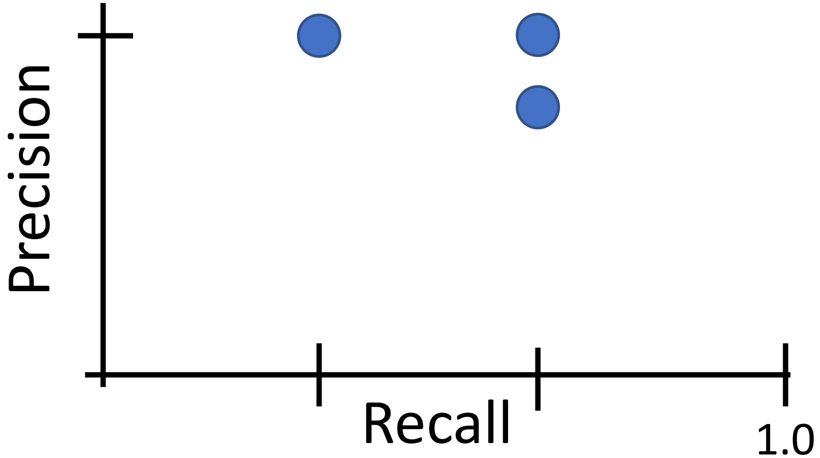
Precision = 2/3 = 0.67
Recall = 2/3 = 0.67



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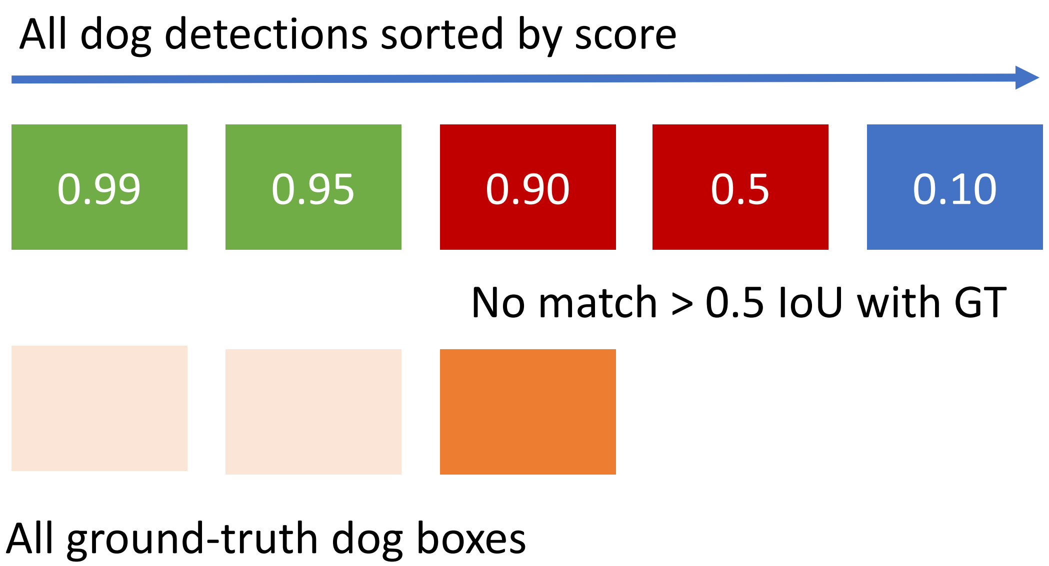
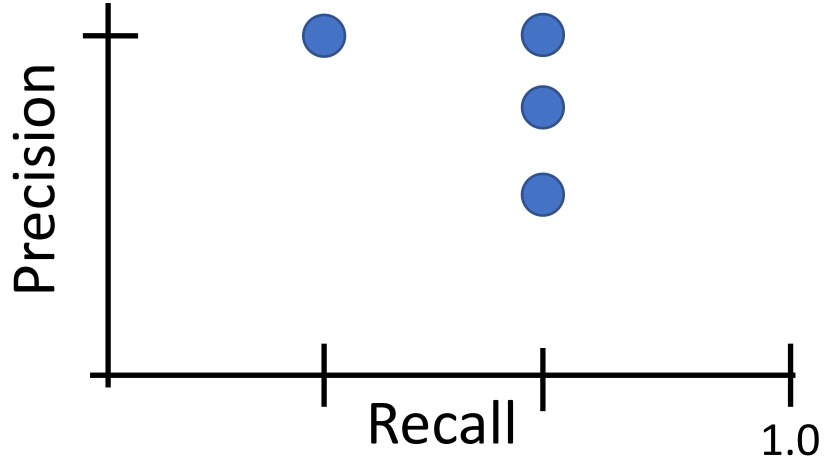


Precision = 2/4 = 0.5
Recall = 2/3 = 0.67



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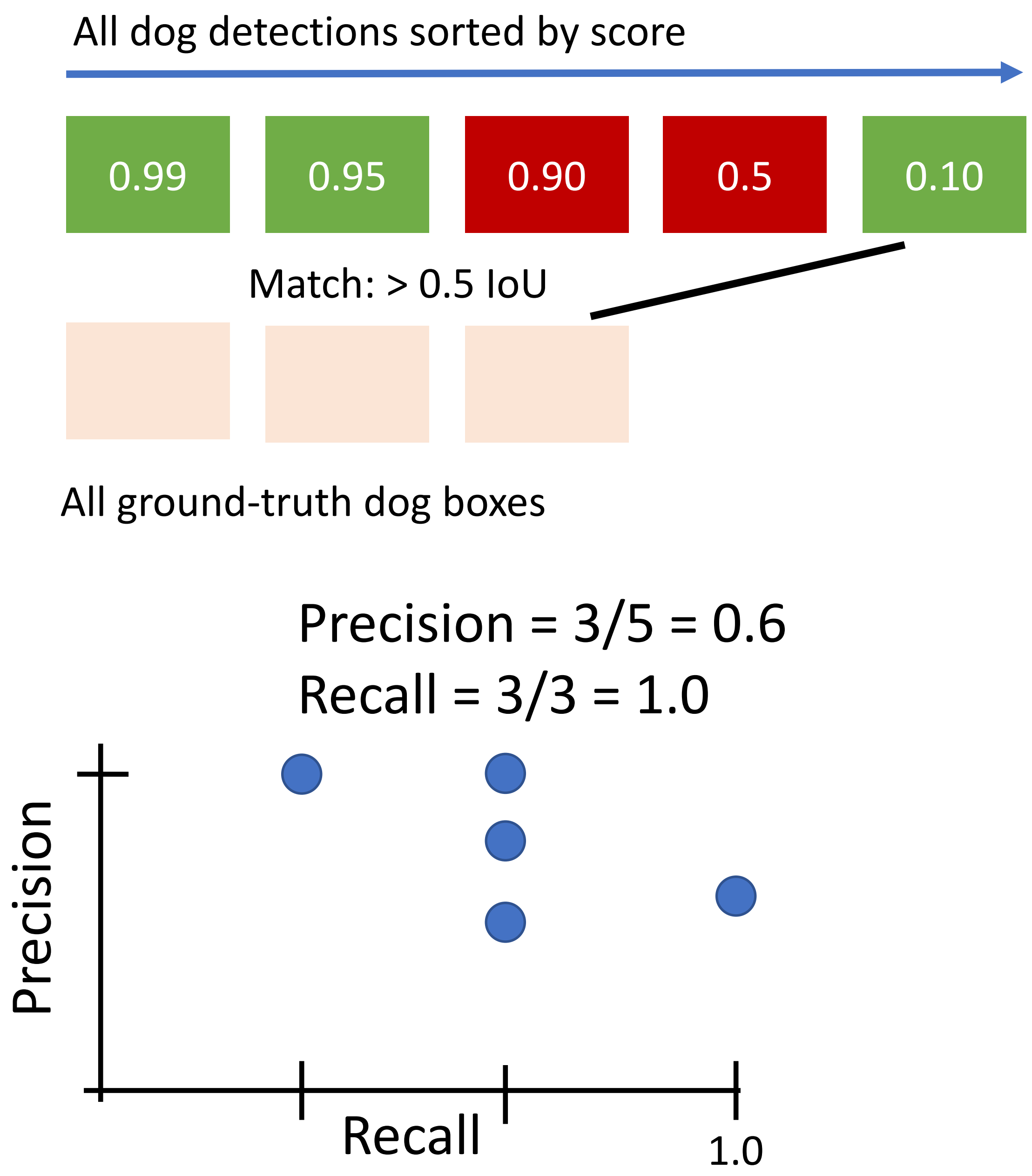

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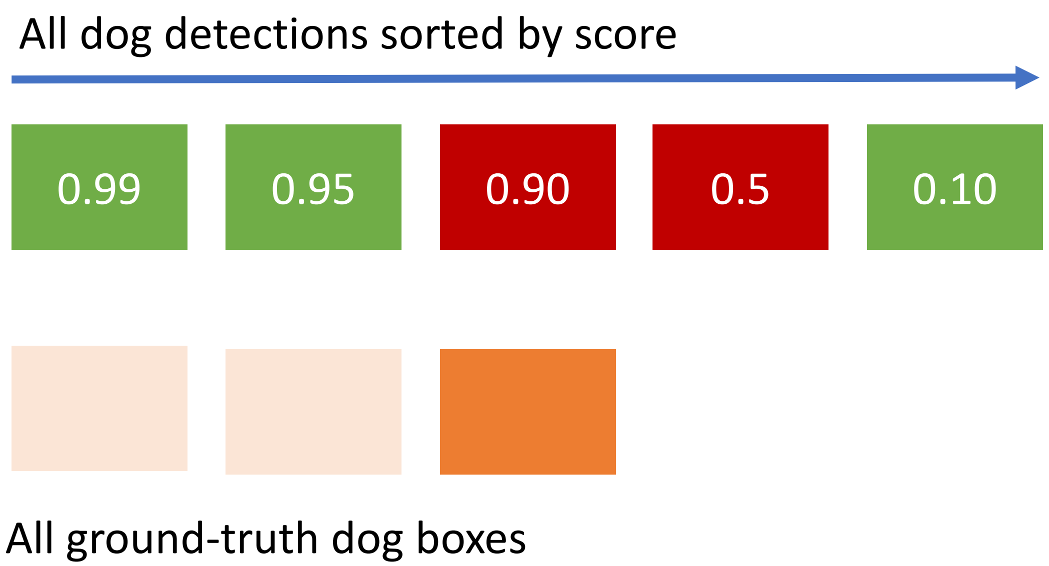
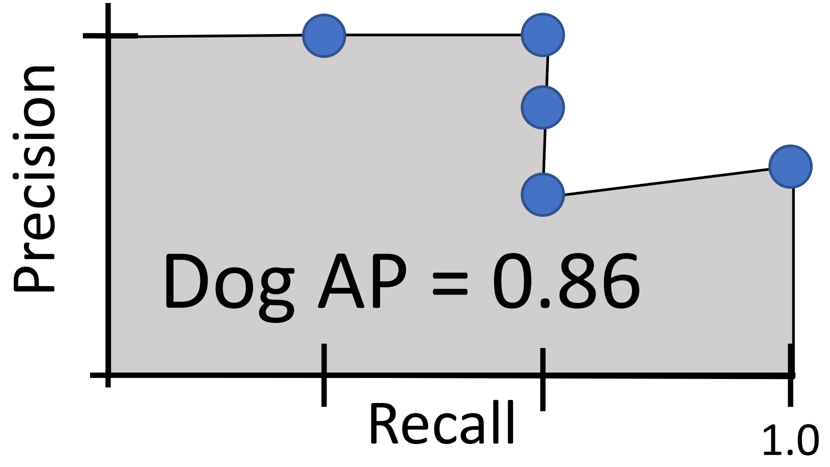
      3. Plot a point on PR Curve
   2. Average Precision (AP) = area under PR curve





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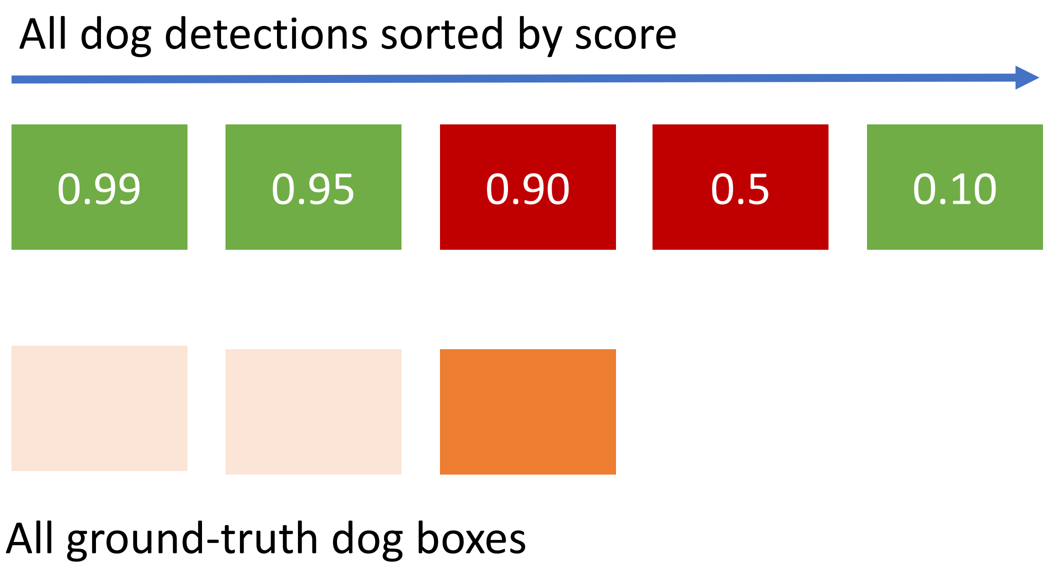
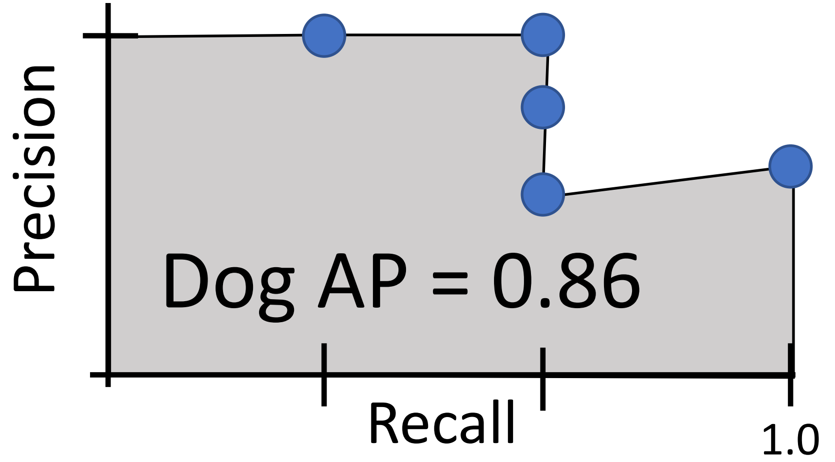
      3. Plot a point on PR Curve
   2. Average Precision (AP) = area under PR curve

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"





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

Car AP = 0.65

Cat AP = 0.80

Dog AP = 0.86

mAP@0.5 = 0.77

Evaluating Object Detectors: Mean Average Precision (mAP)

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

mAP@0.5 = 0.77
mAP@0.55 = 0.71
mAP@0.60 = 0.65
…
mAP@0.95 = 0.2

COCO mAP = 0.4

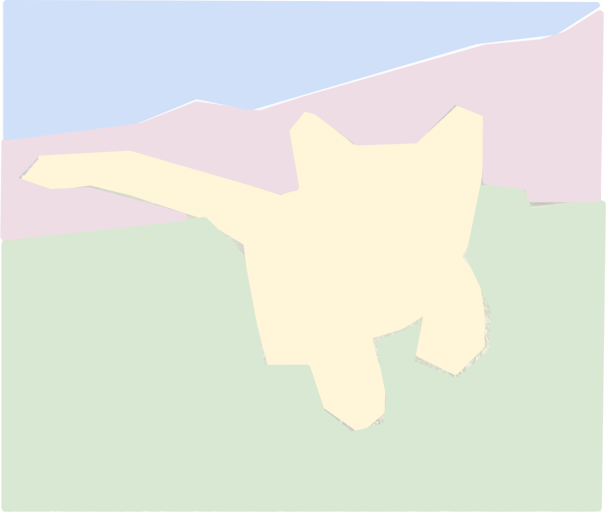
Summary: Beyond Image Classification

Classification

CAT

No spatial extent

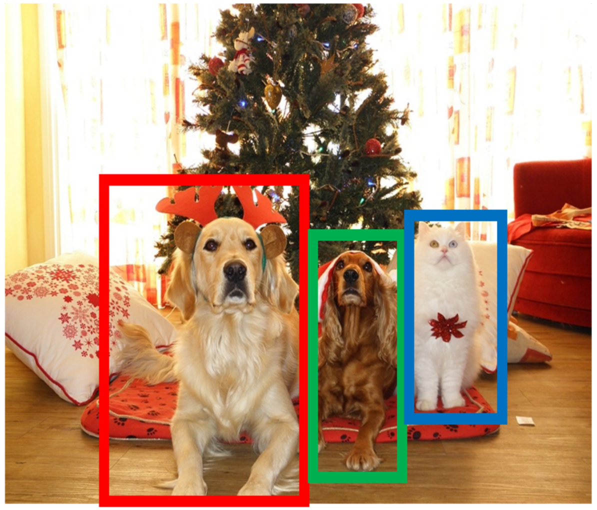
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

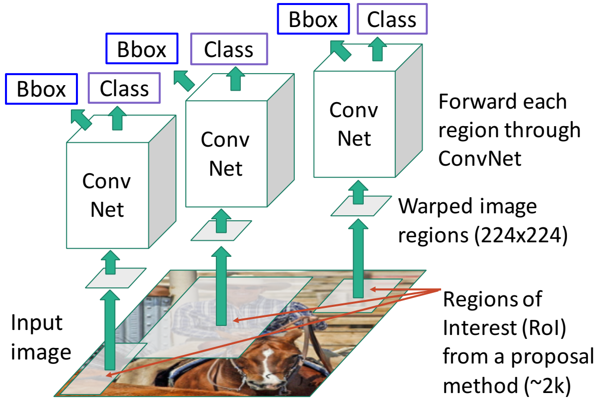
Instance Segmentation

DOG, DOG, CAT

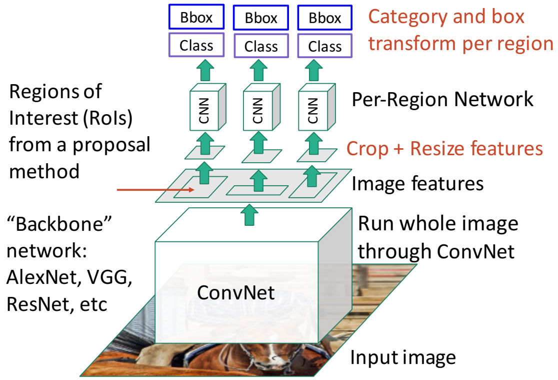
Multiple Objects

Summary

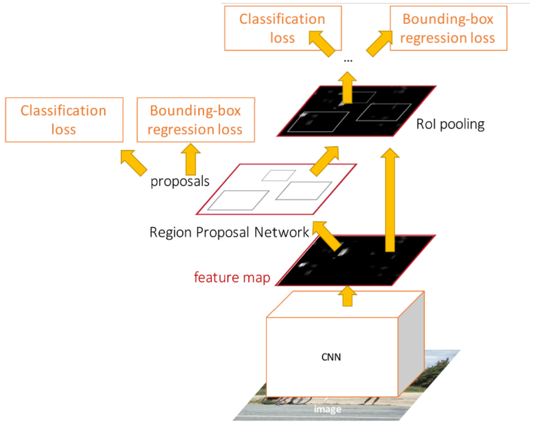
"Slow" R-CNN: Run CNN independently for each region



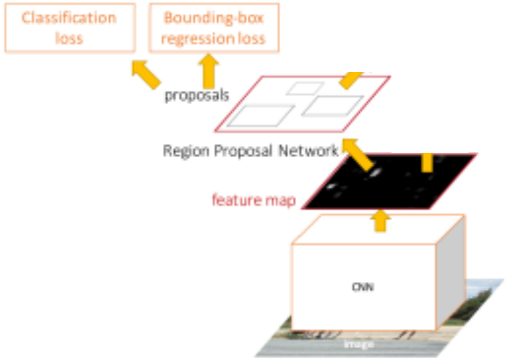
Fast R-CNN: Apply differentiable cropping to shared image features



Faster R-CNN: Compute proposals with CNN



Single-Stage: Fully convolutional detector



With anchors: RetinaNet
Anchor-Free: FCOS

Next time:
Image and Instance Segmentation