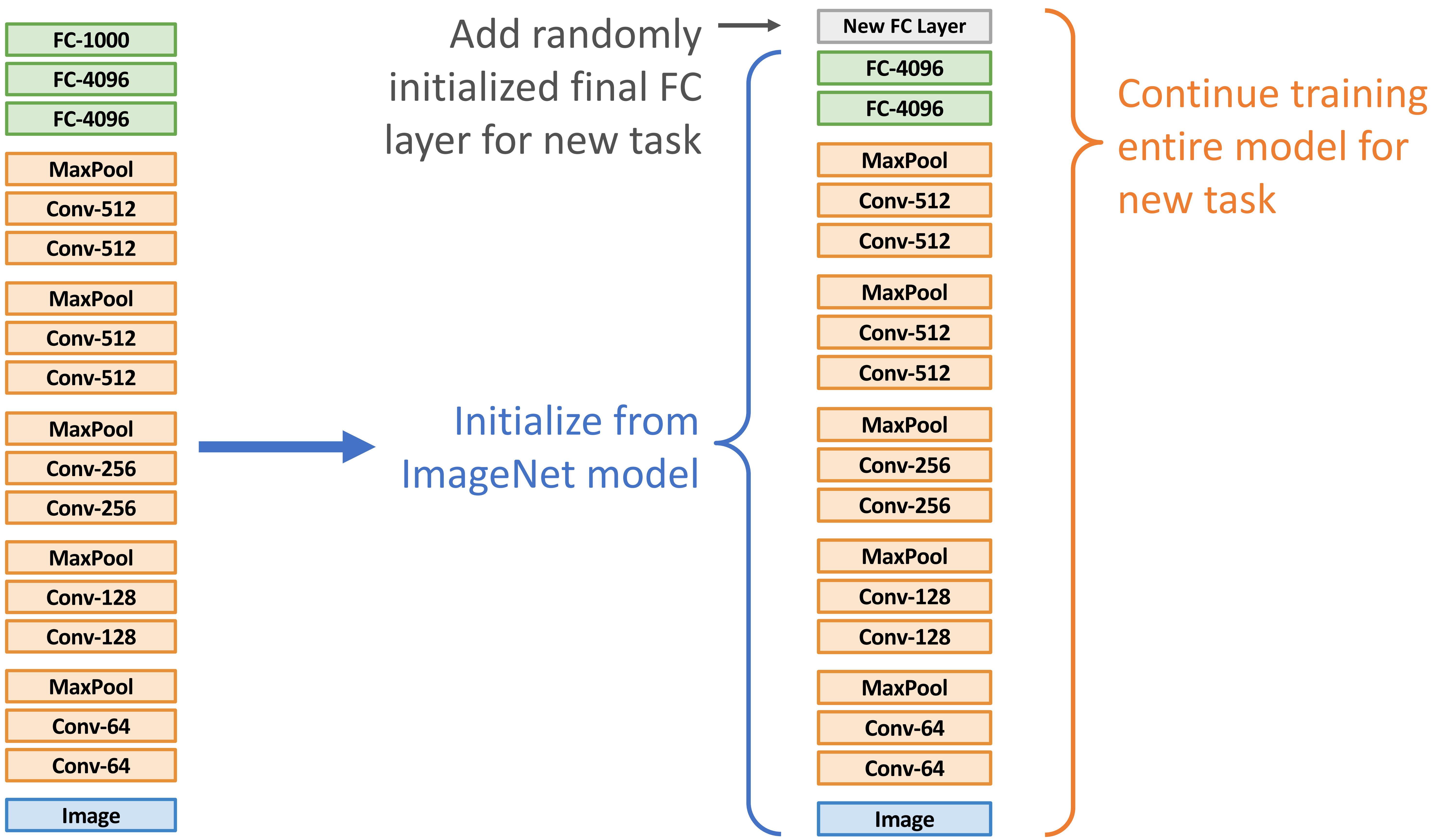
DeepRob

Lecture 13
Object Detectors and Segmentation
University of Michigan and University of Minnesota

Last time: Transfer Learning

1. Train on ImageNet



Last time: Localization Tasks

Classification

"Chocolate Pretzels"

No spatial extent

Semantic Segmentation

Chocolate Pretzels, Shelf

No objects, just pixels

Object Detection

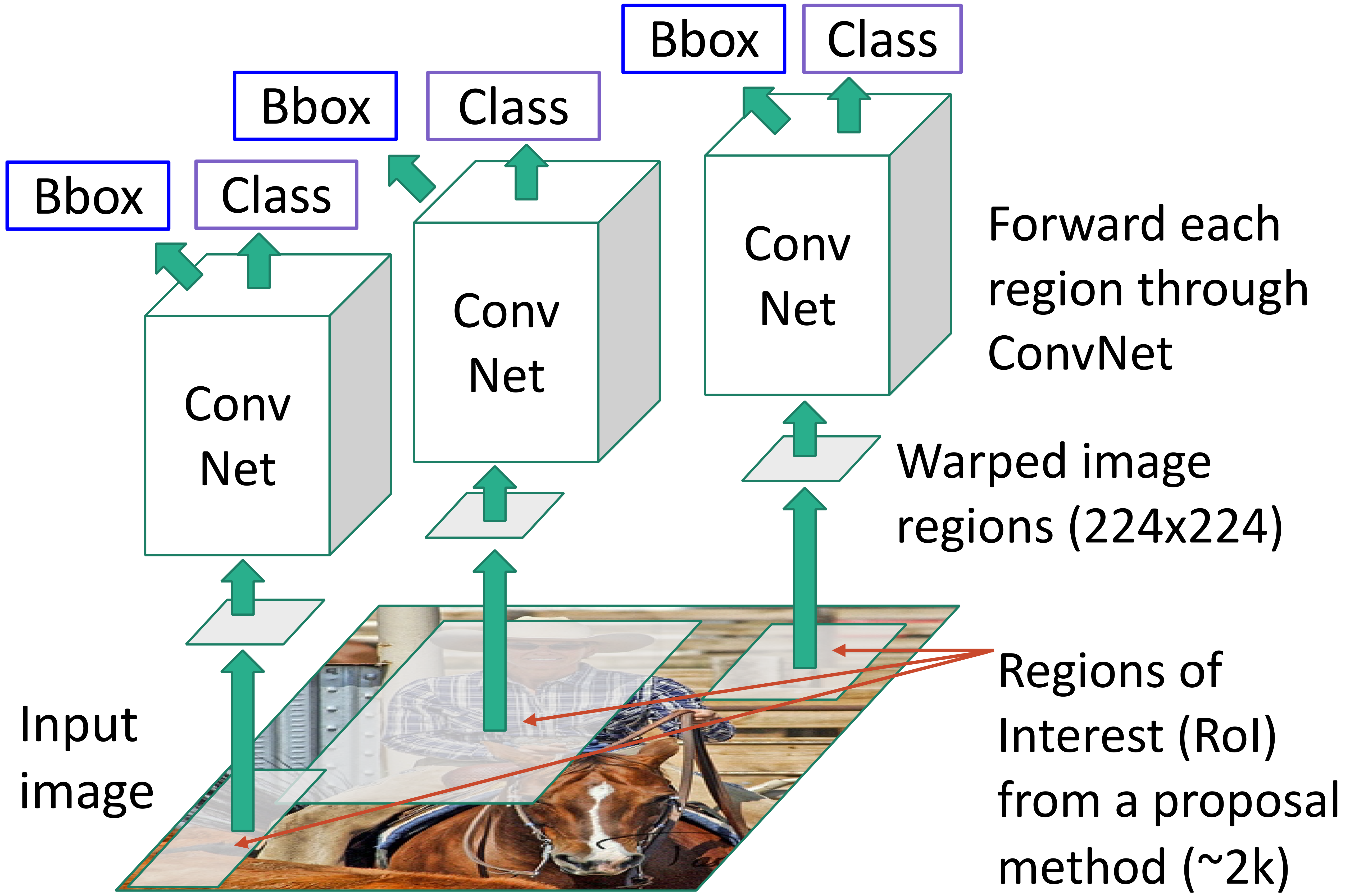
Instance Segmentation

Flipz, Hershey's, Keese's

Multiple objects

Last time: R-CNN

R-CNN: Region-Based CNN

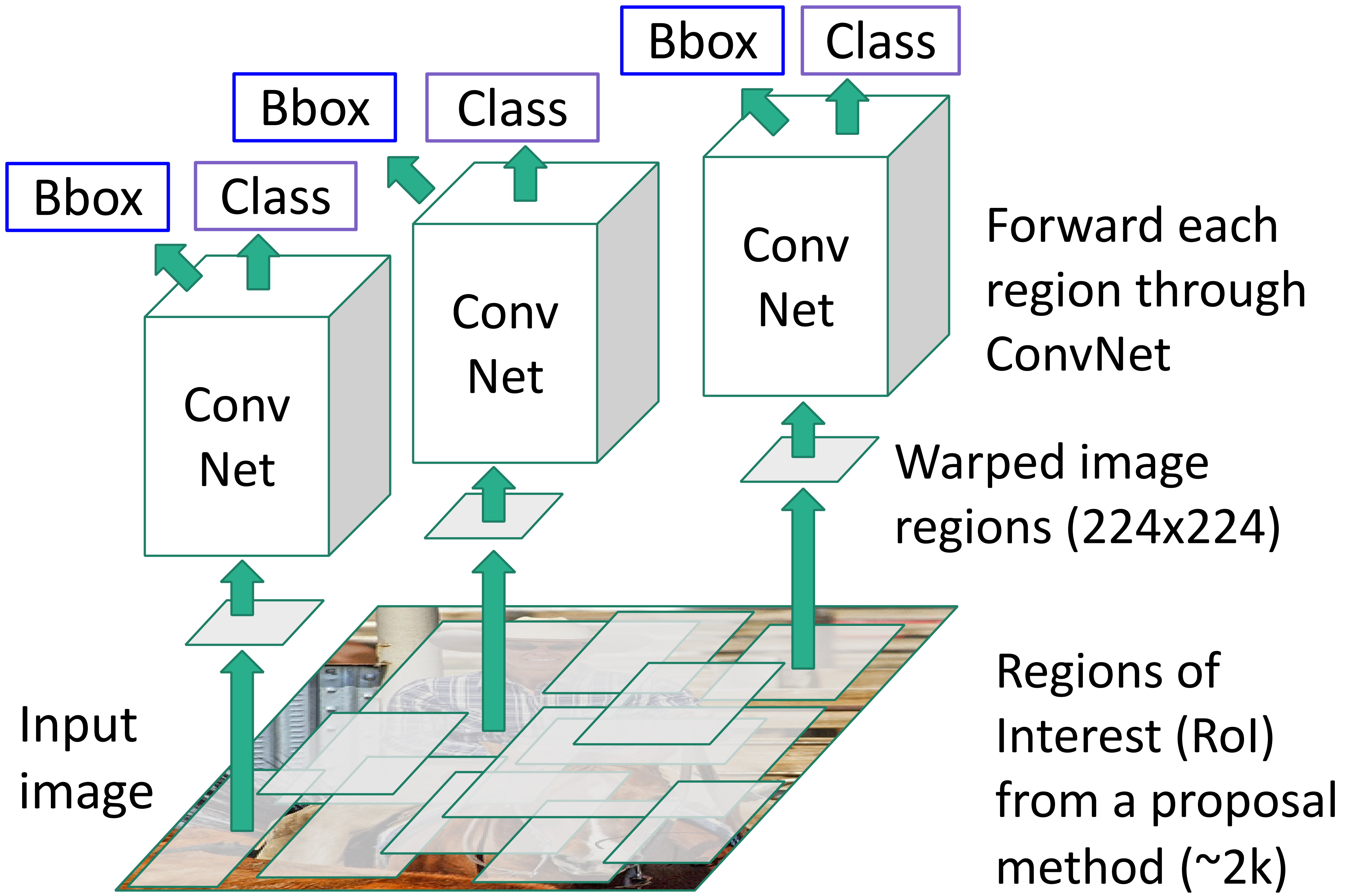


Classify each region

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

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

Last time: R-CNN



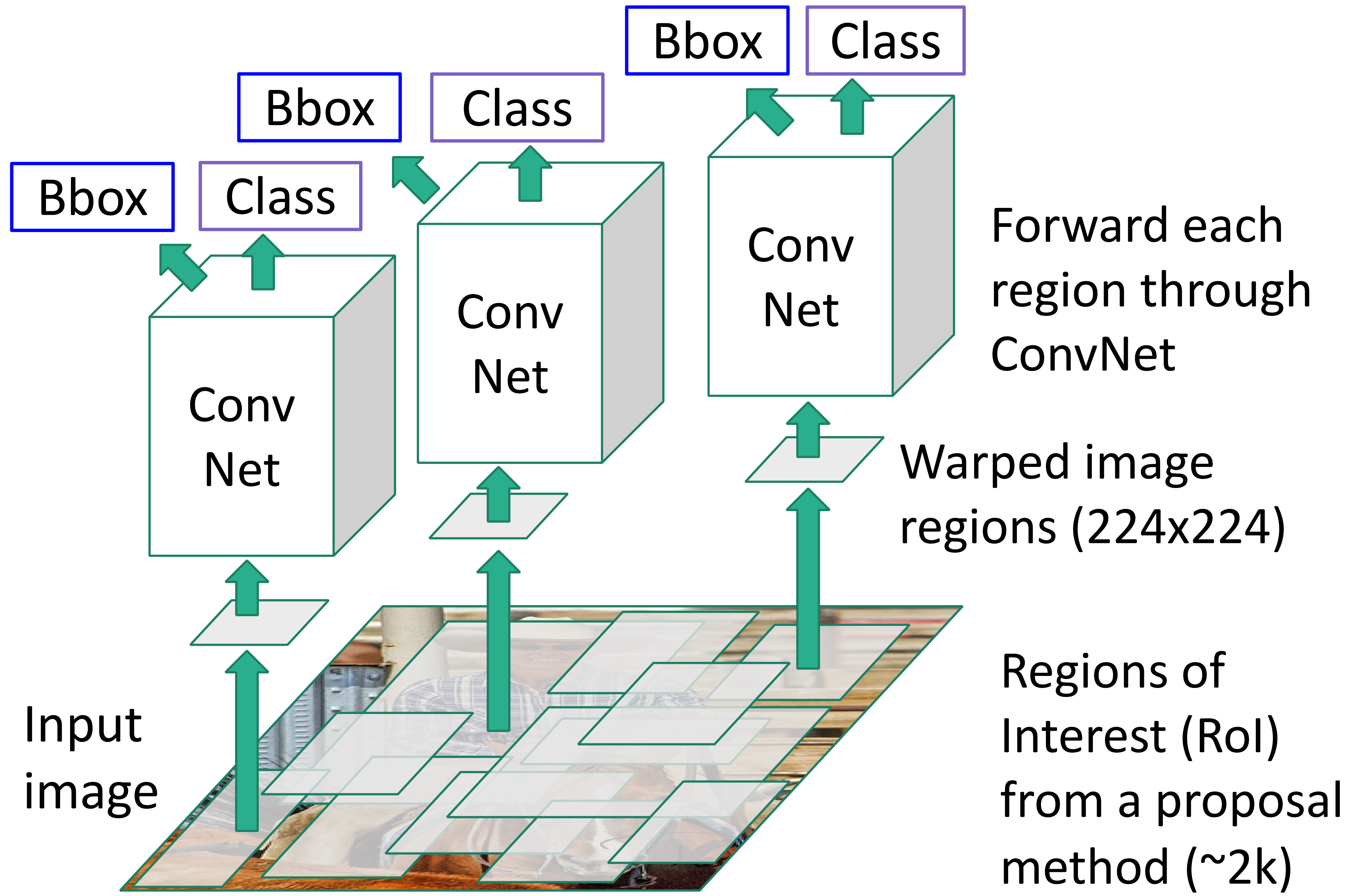
Classify each region

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

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



Classify each region

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

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

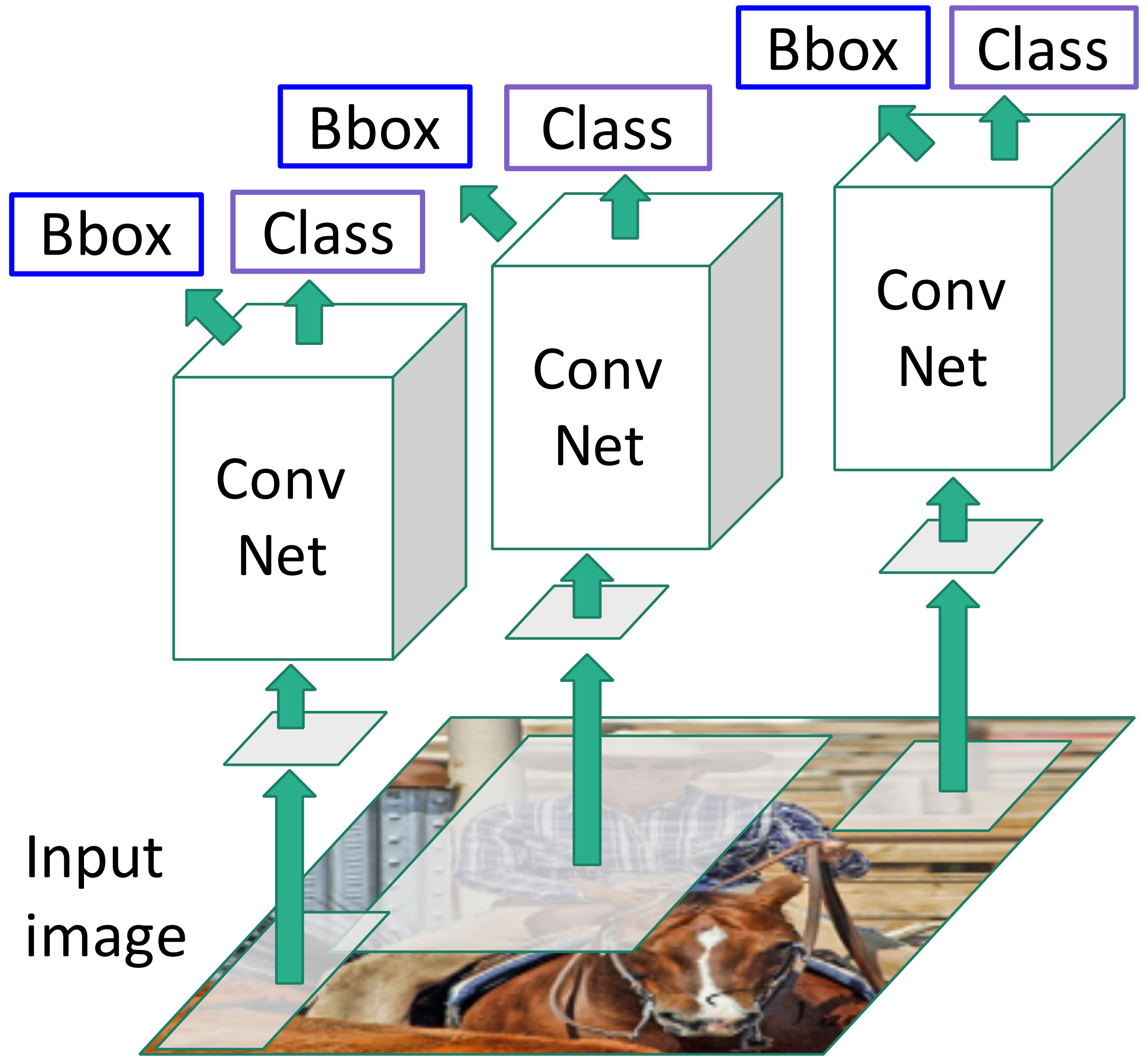
Idea: Overlapping proposals cause a lot of repeated work; same pixels processed many times. Can we avoid this?

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

Fast R-CNN

Input image

"Slow" R-CNN
Process each region independently



Fast R-CNN

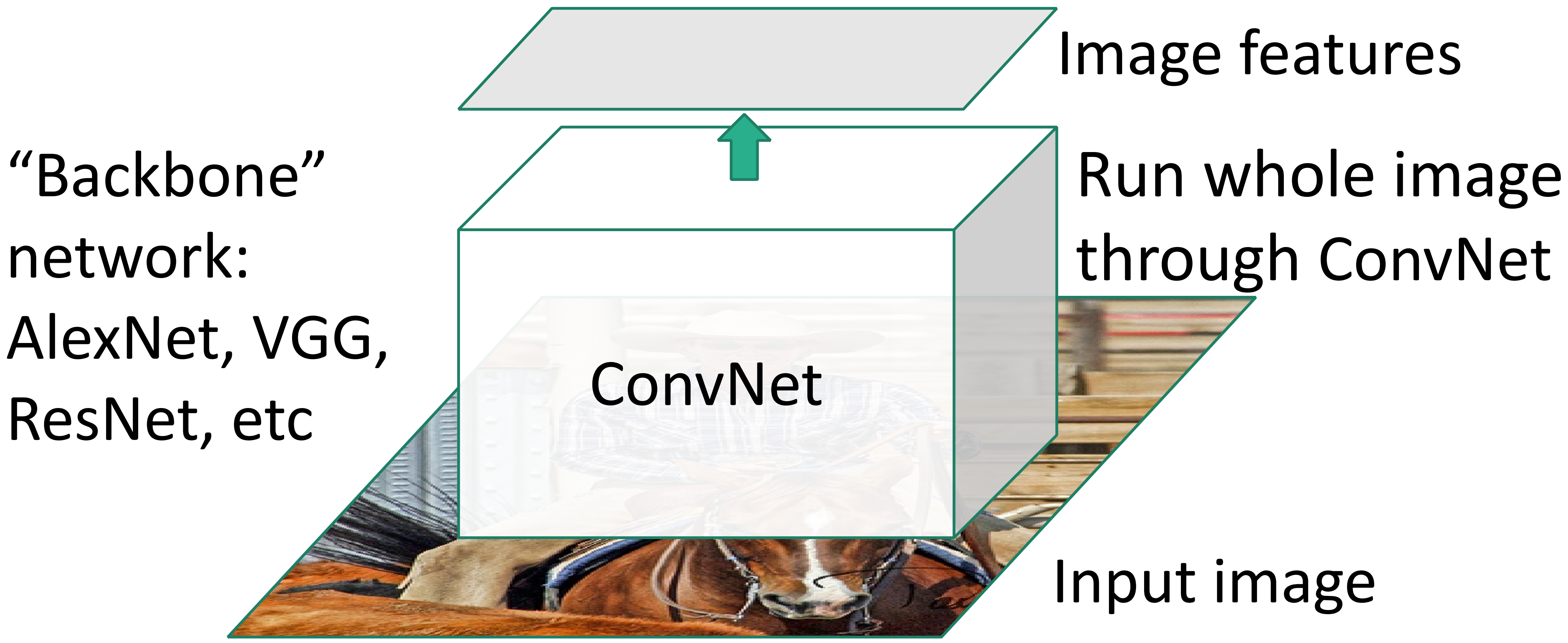
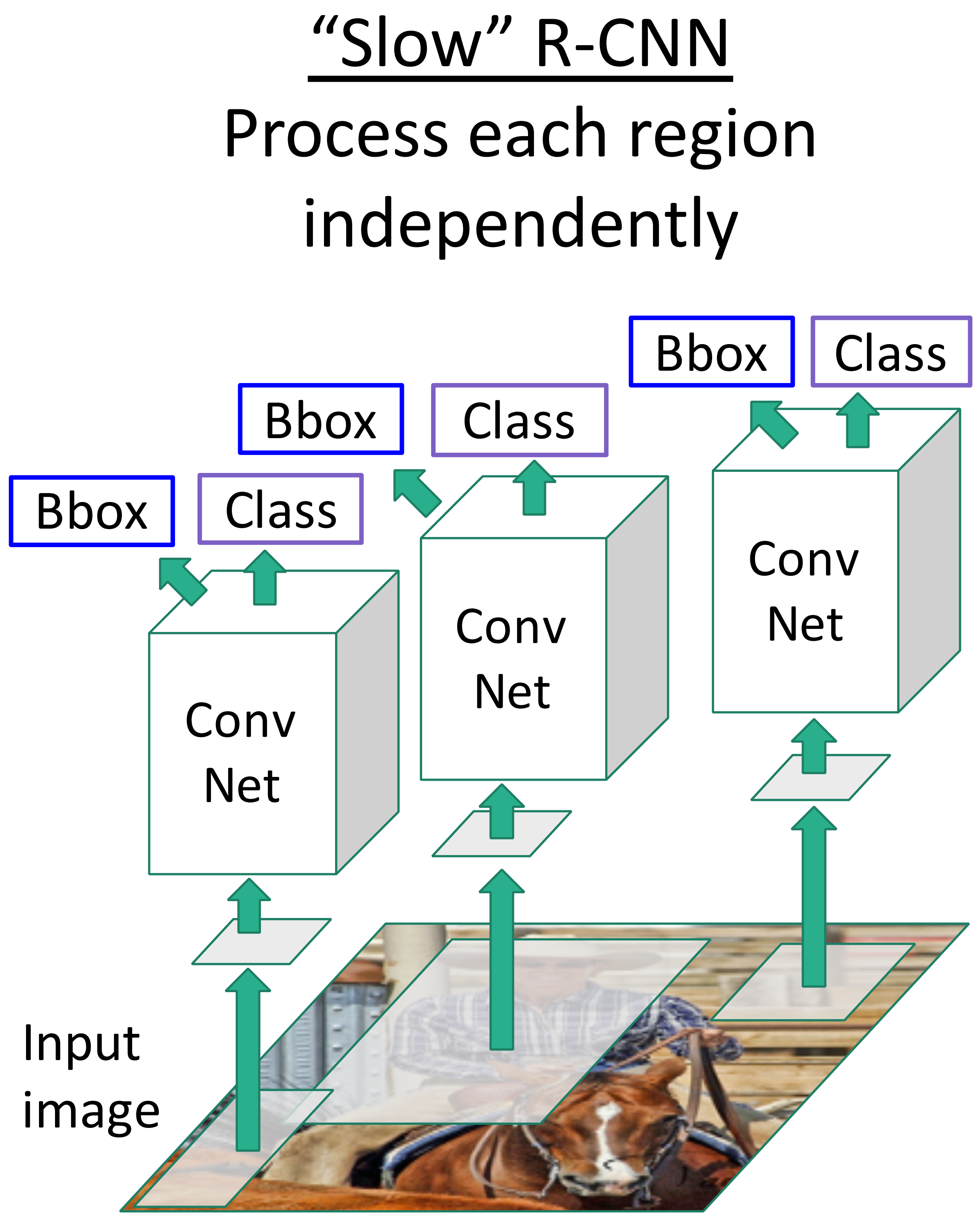


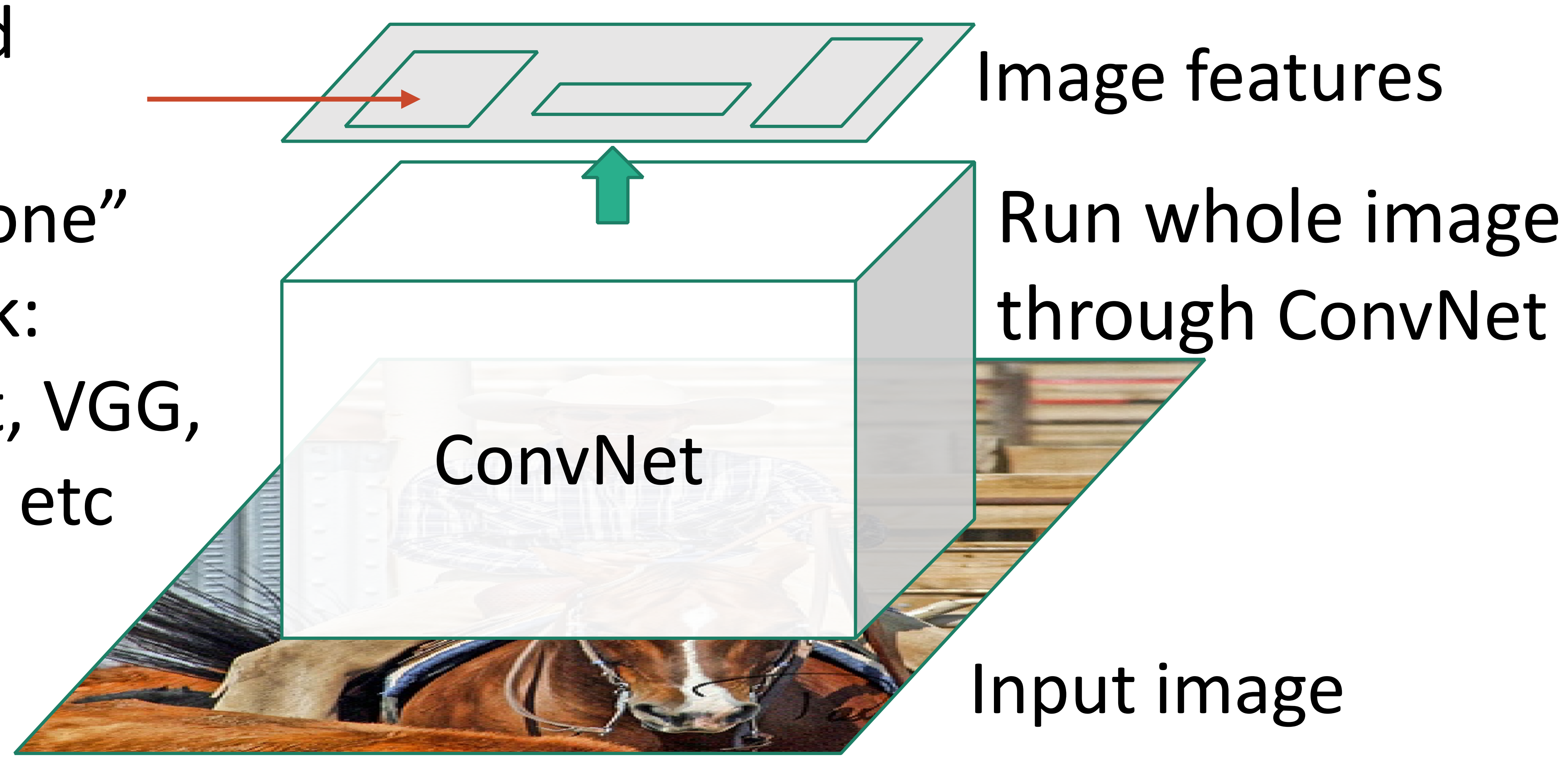
Image features
Run whole image
through ConvNet
"Backbone"
network:
AlexNet, VGG,
ResNet, etc
ConvNet
Input image


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

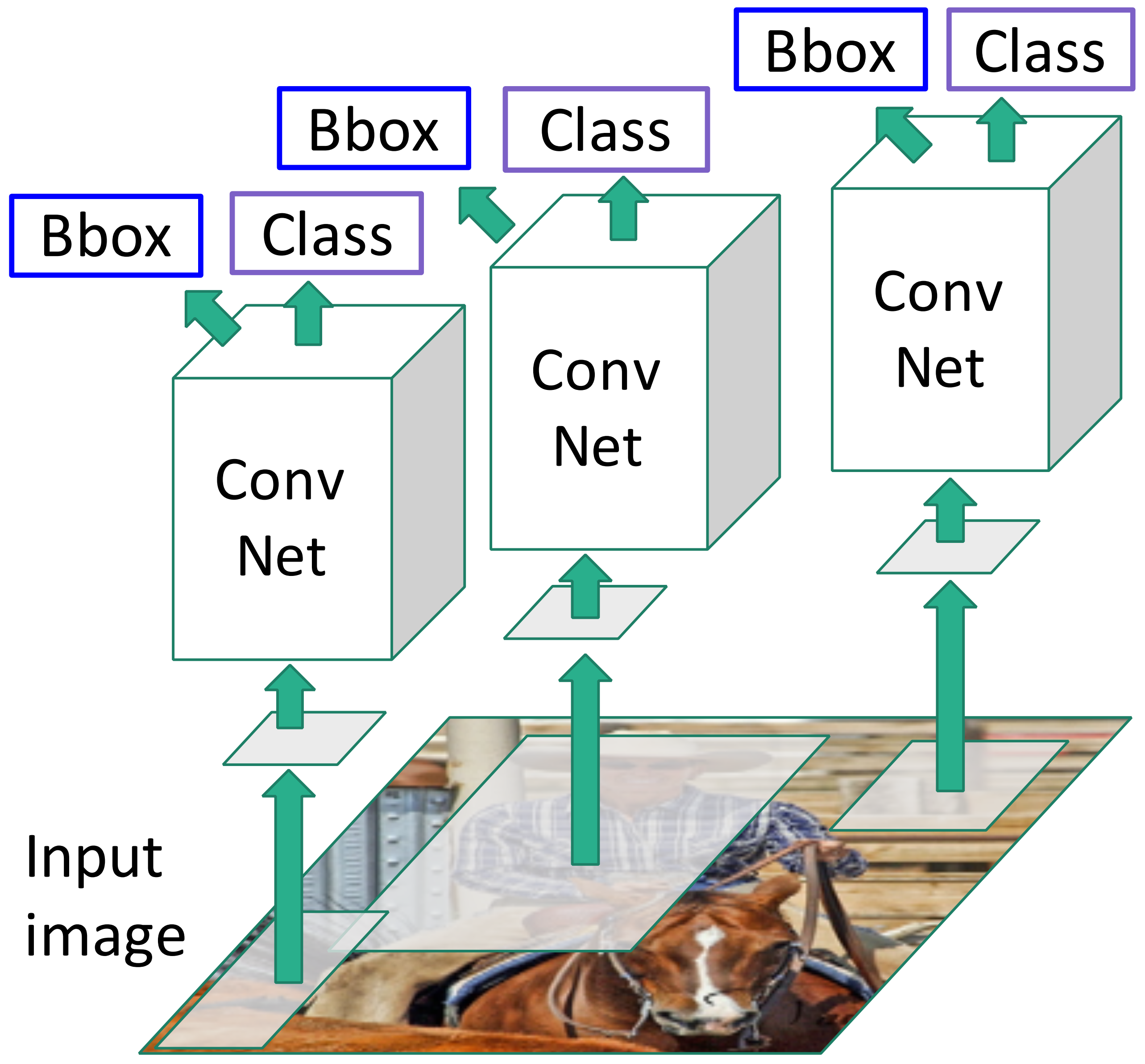
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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

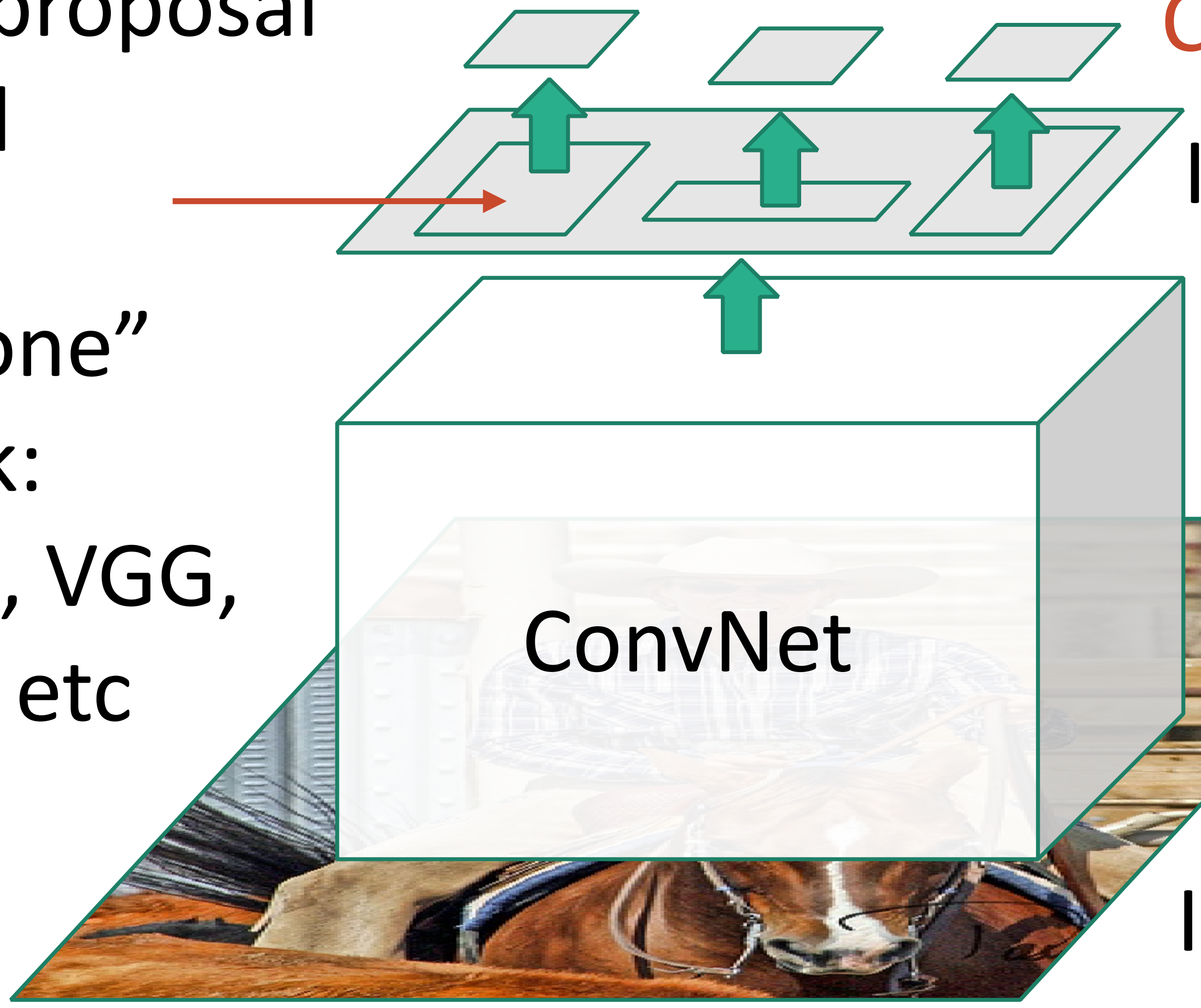


"Slow" R-CNN
Process each region independently



Fast R-CNN

Regions of Interest (RoIs) from a proposal method



Crop + Resize features

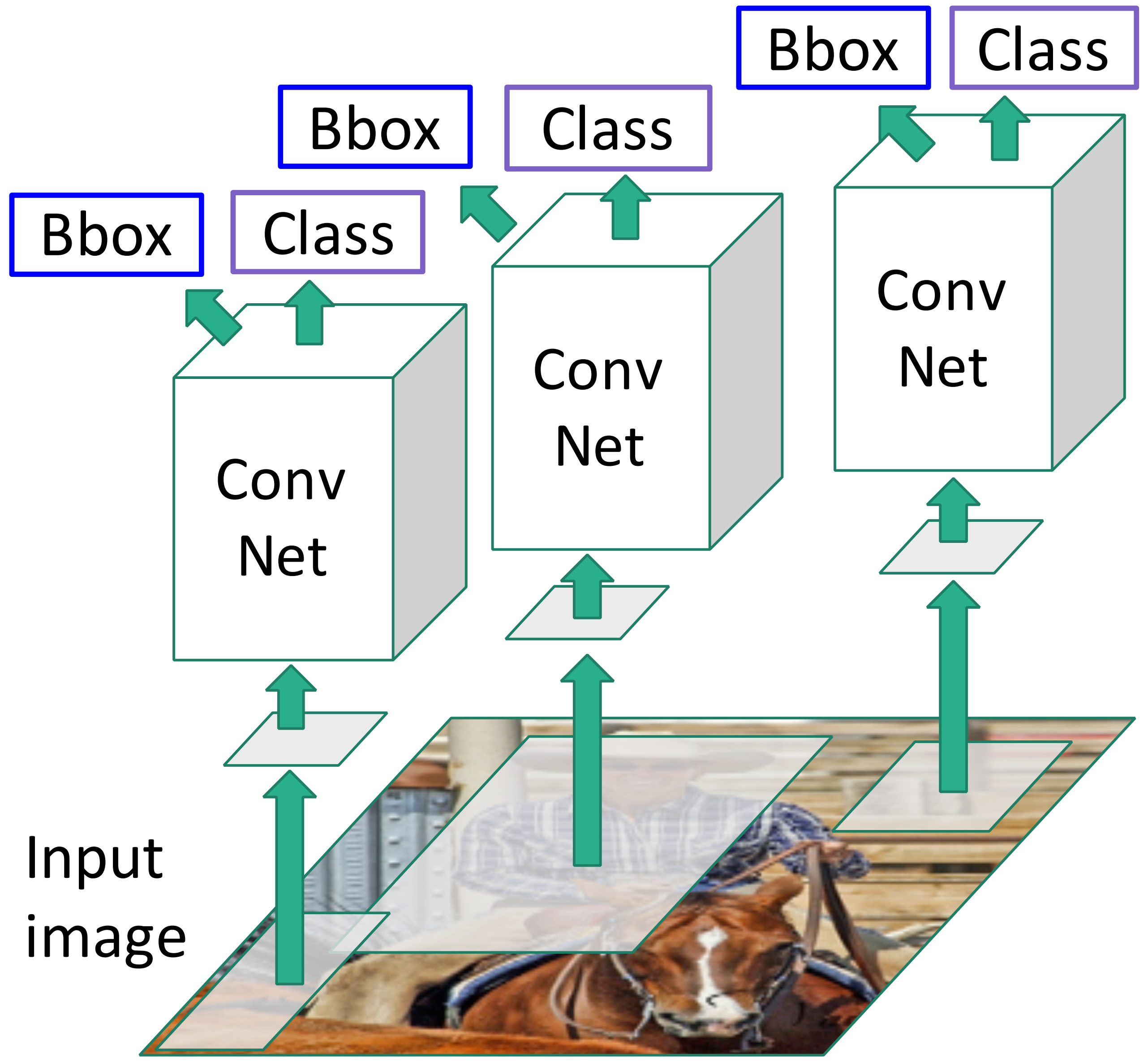
Image features

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

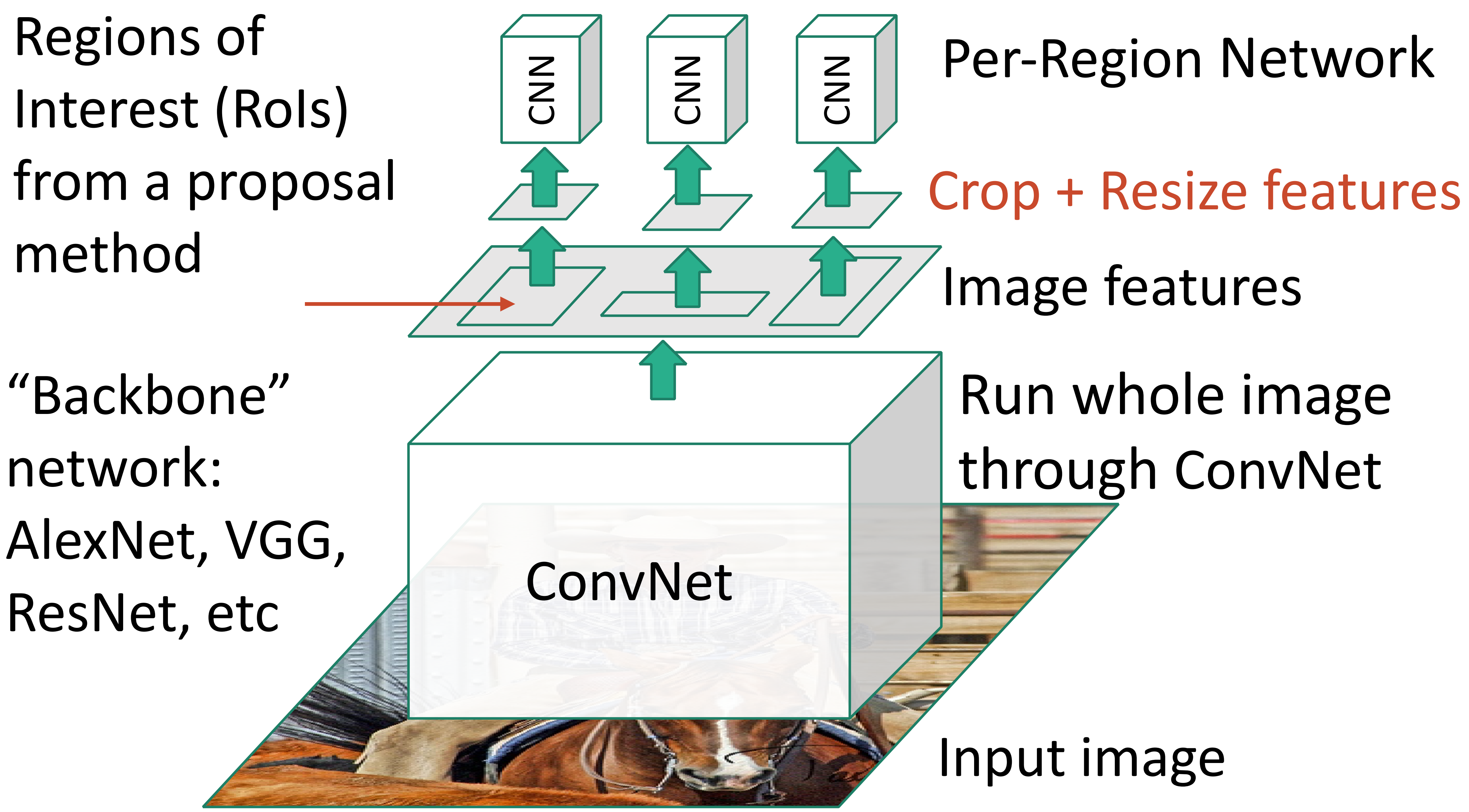
Run whole image through ConvNet

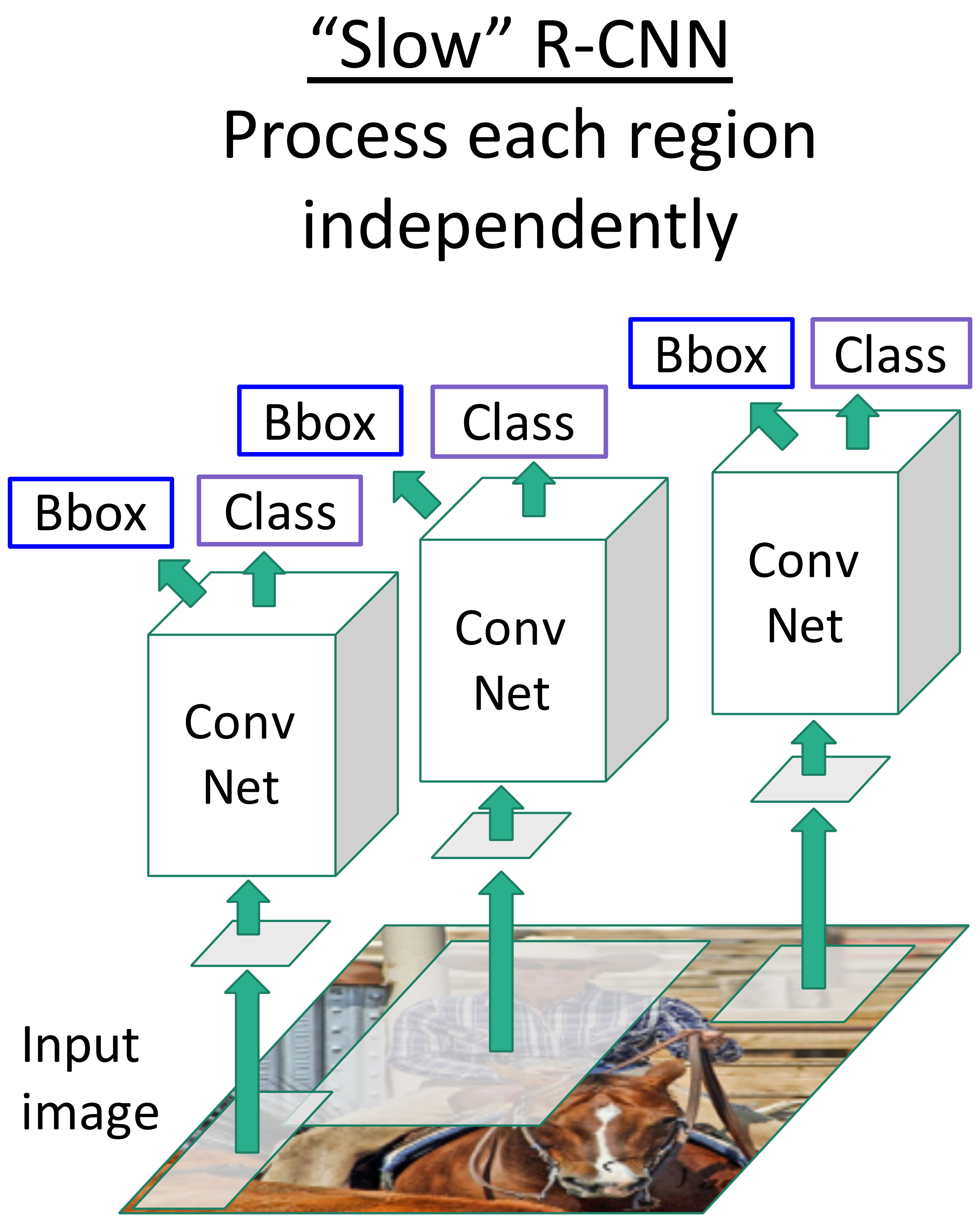
Input image

"Slow" R-CNN
Process each region independently

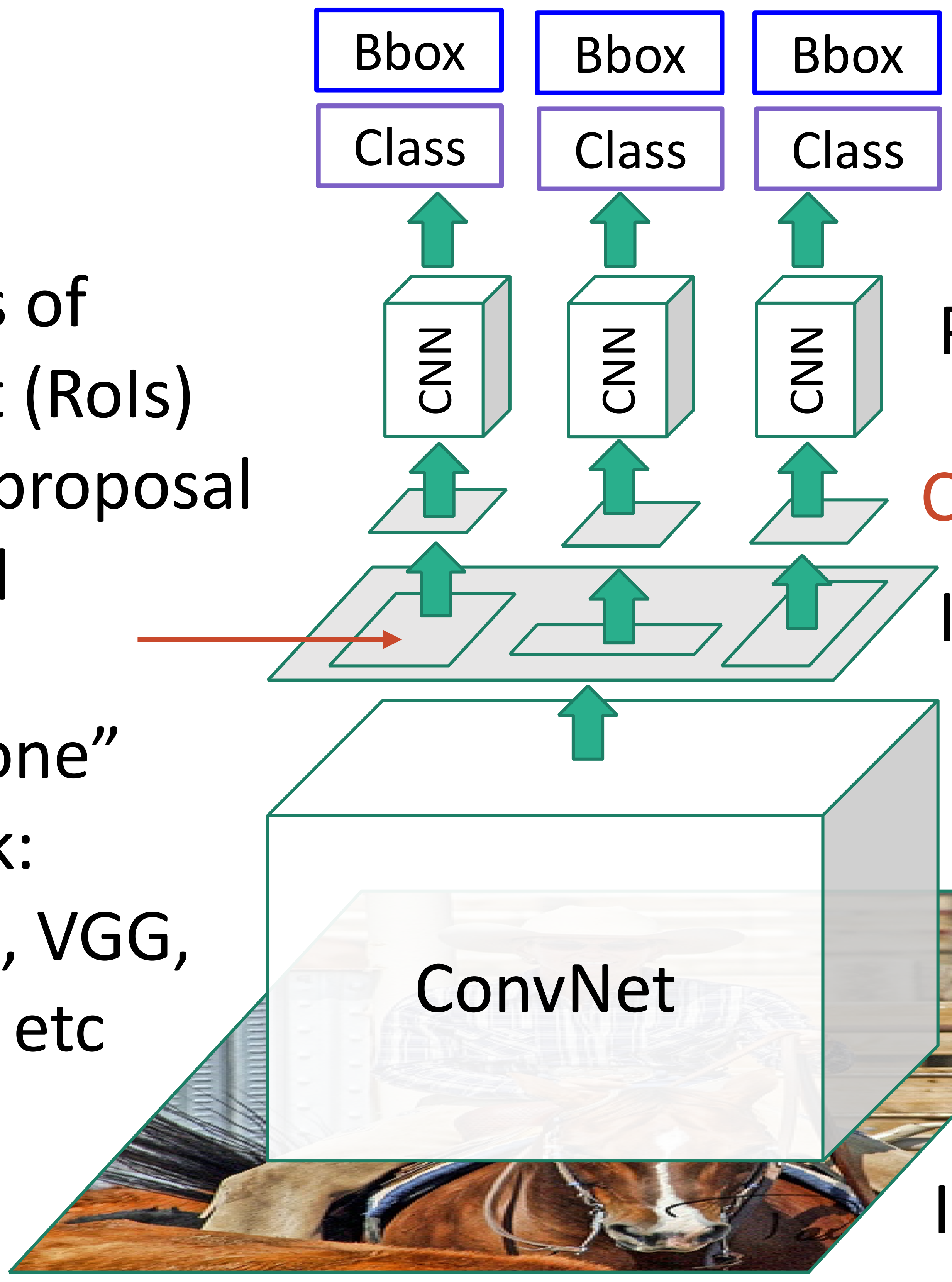


Fast R-CNN

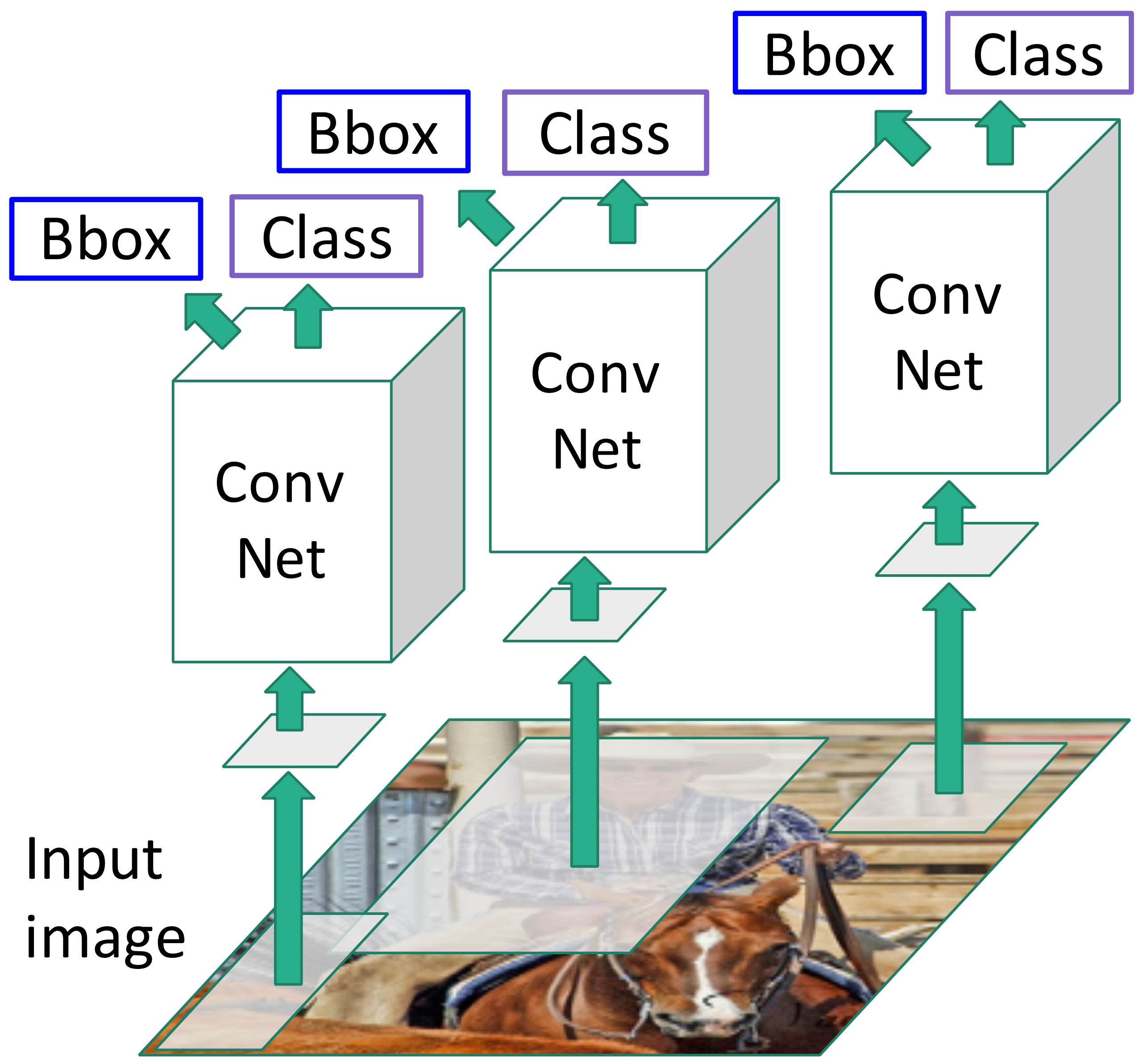

Regions of Interest (RoIs) from a proposal method
CNN
CNN
CNN
Per-Region Network
Crop + Resize features
Image features
"Backbone" network: AlexNet, VGG, ResNet, etc
ConvNet
Run whole image through ConvNet
Input image


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

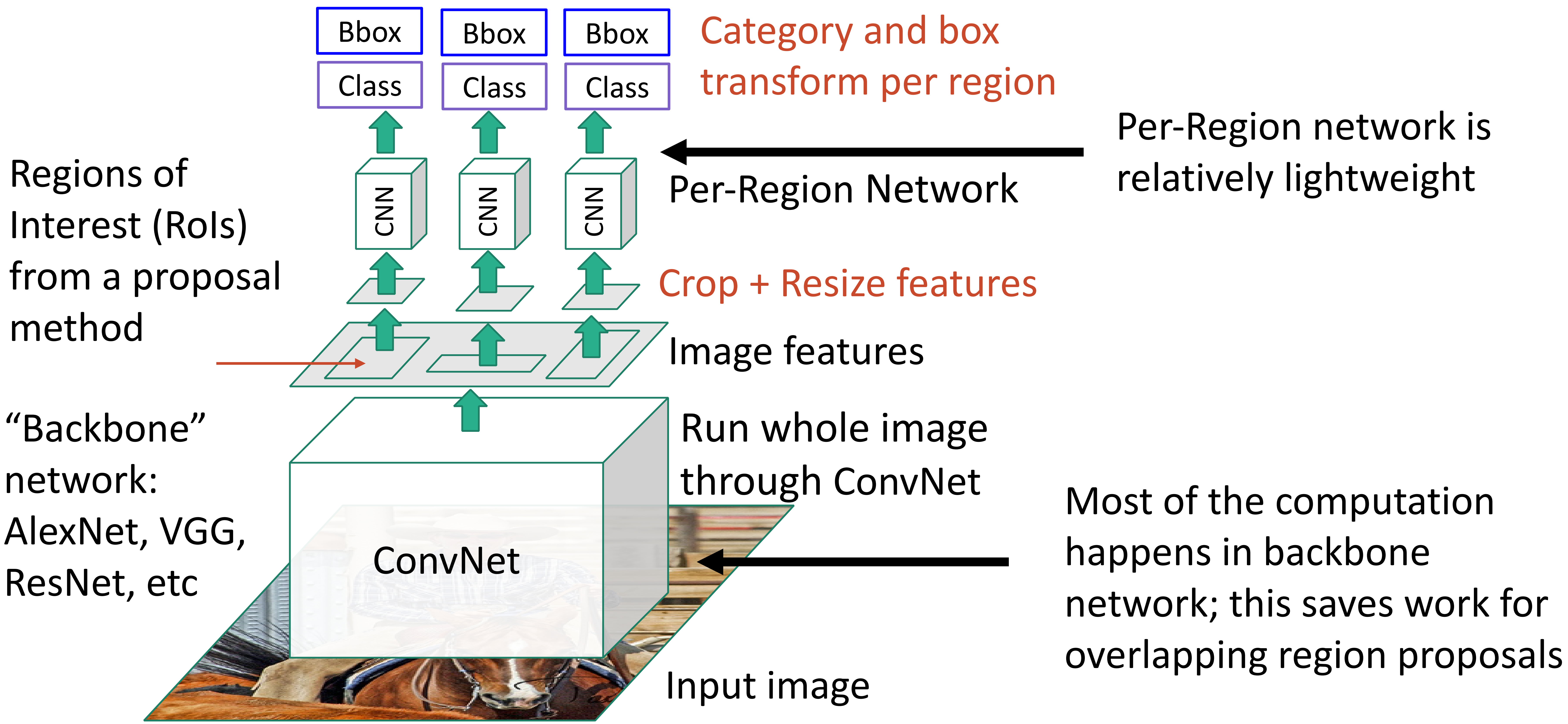
Fast R-CNN



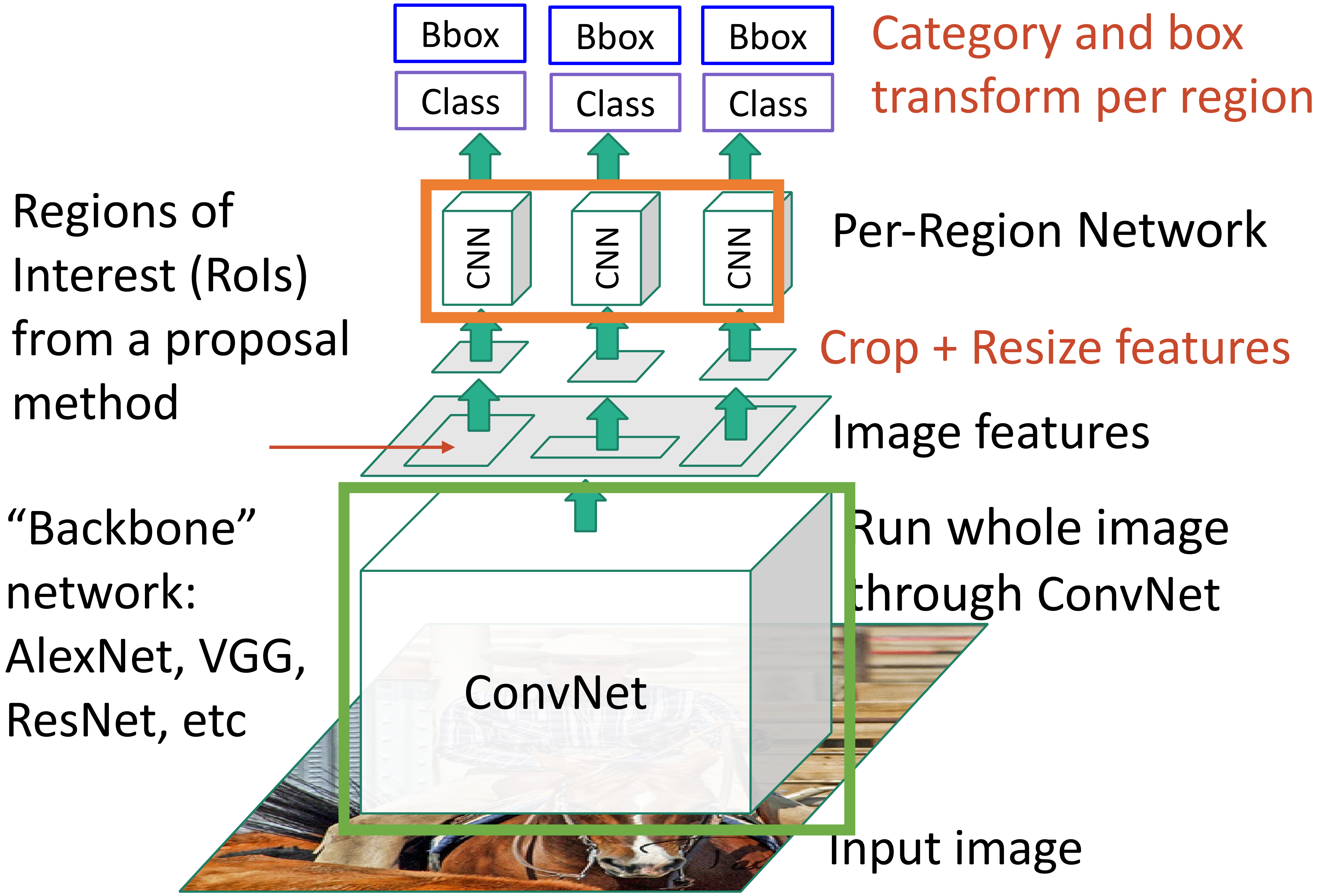
"Slow" R-CNN
Process each region independently

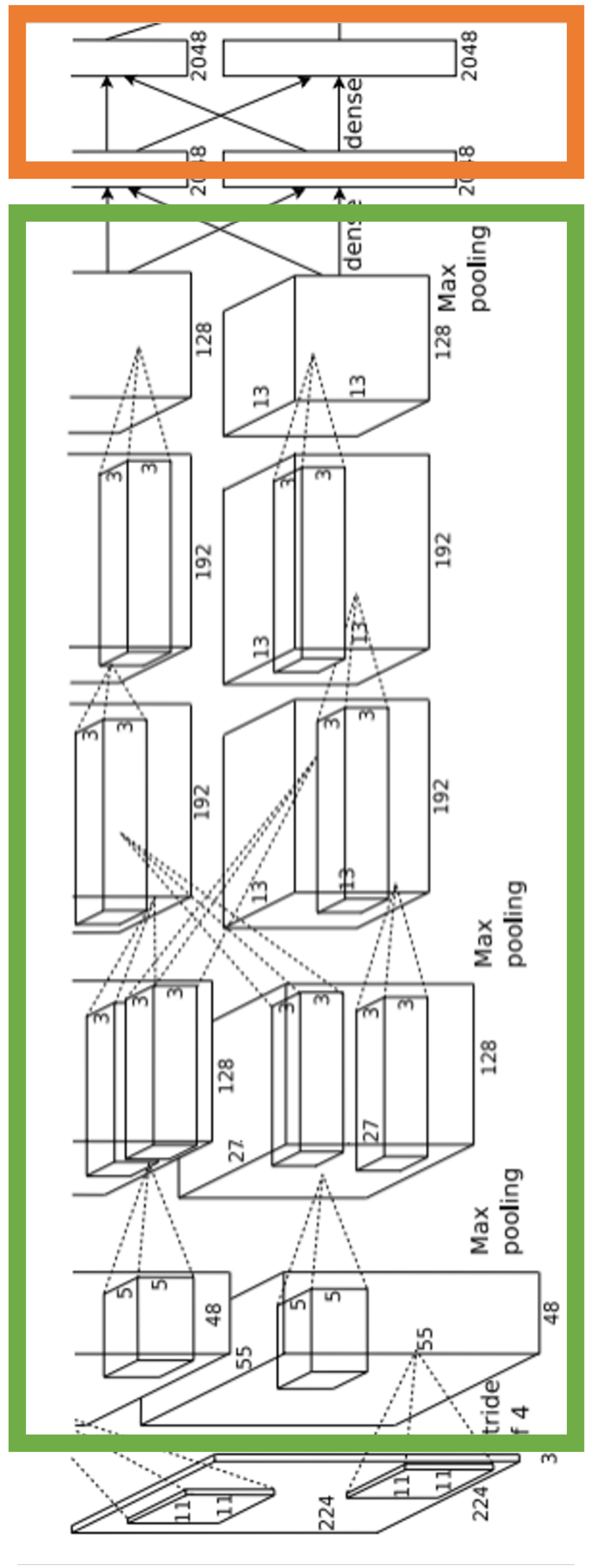


Fast R-CNN


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



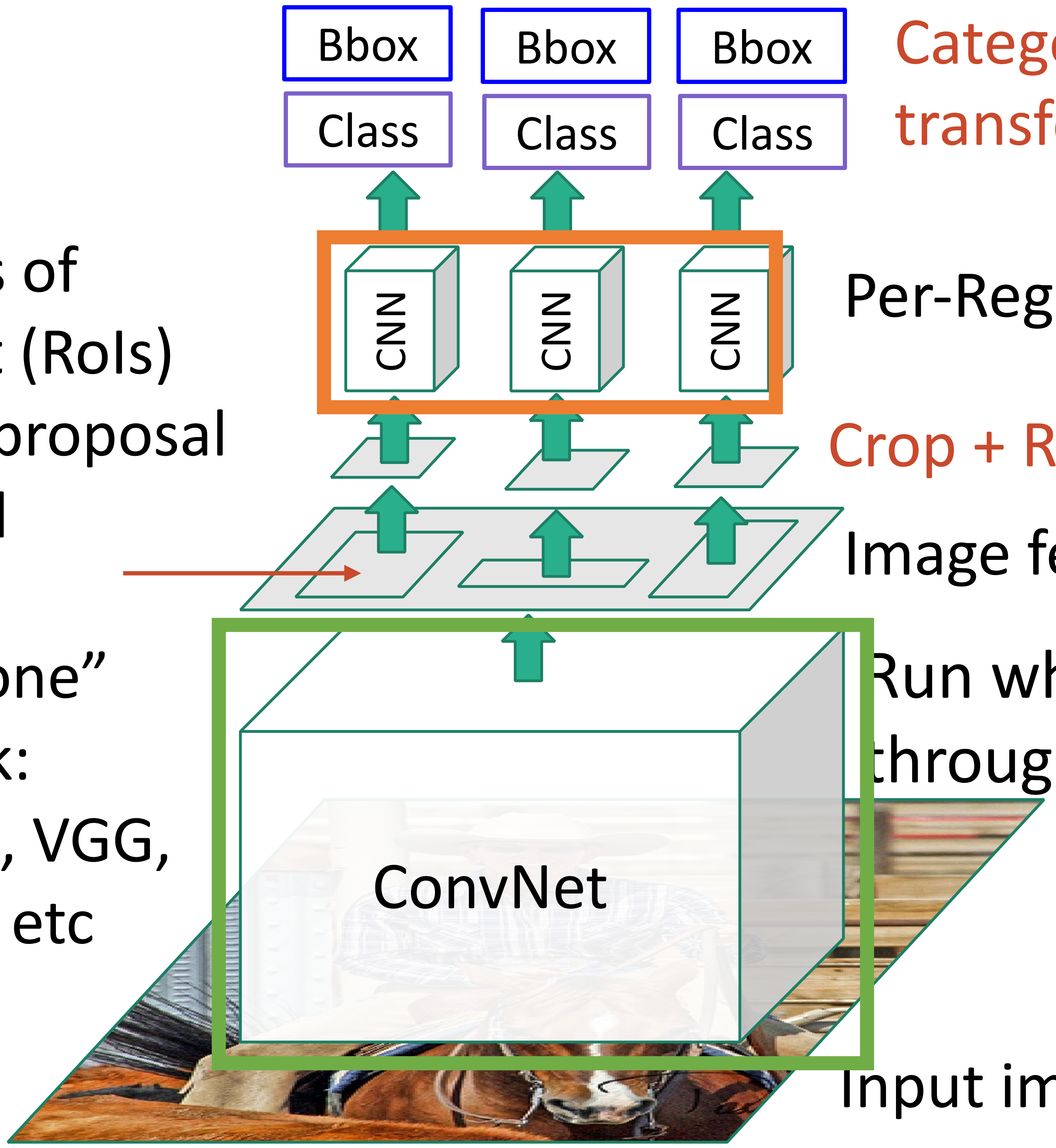


Example: When using AlexNet for detection, five conv layers are used for backbone and two FC layers are used for per-region network

Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



Category and box transform per region

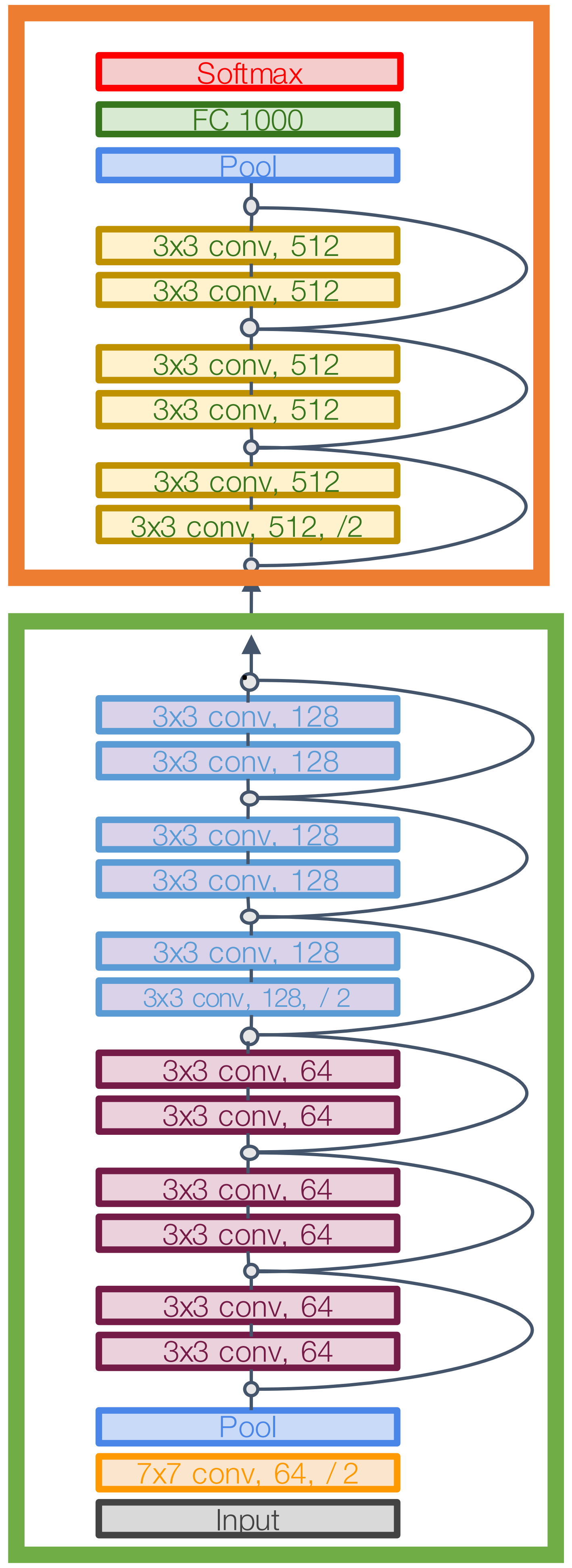
Per-Region Network

Crop + Resize features

Image features

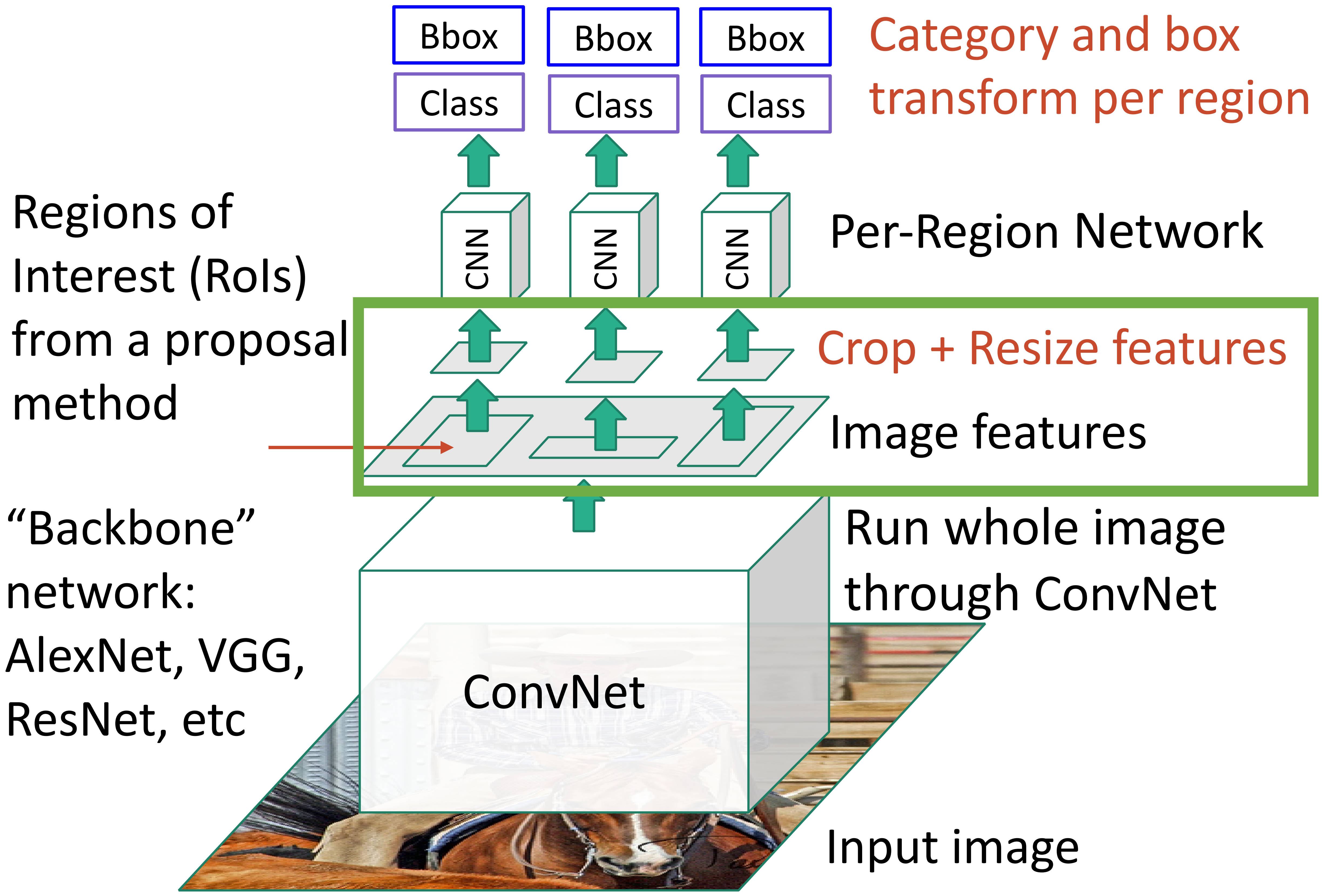
Run whole image through ConvNet

Input image



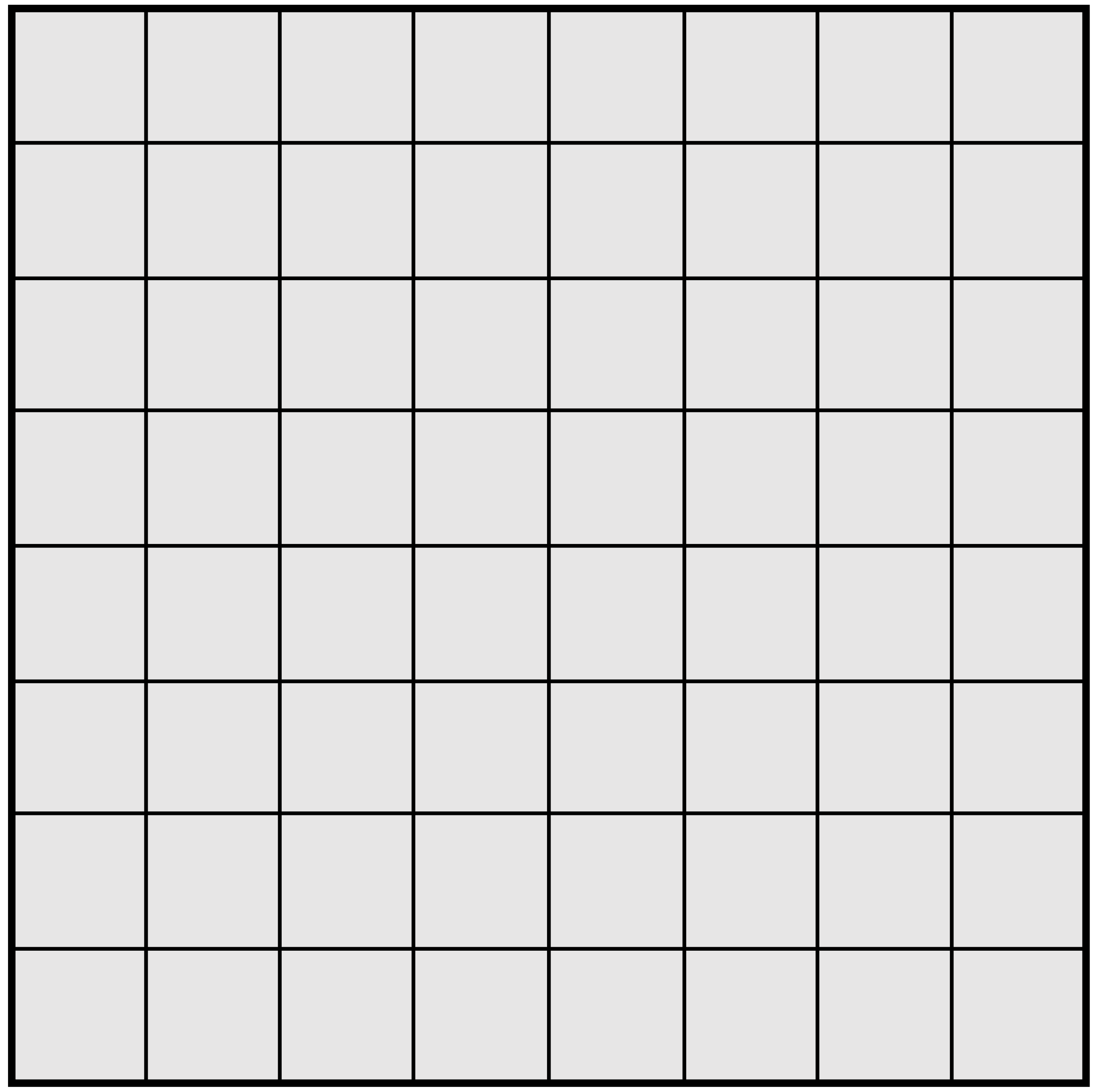
Example: For ResNet, last stage is used as per-region network; the rest of the network is used as backbone

Fast R-CNN



How to crop features?

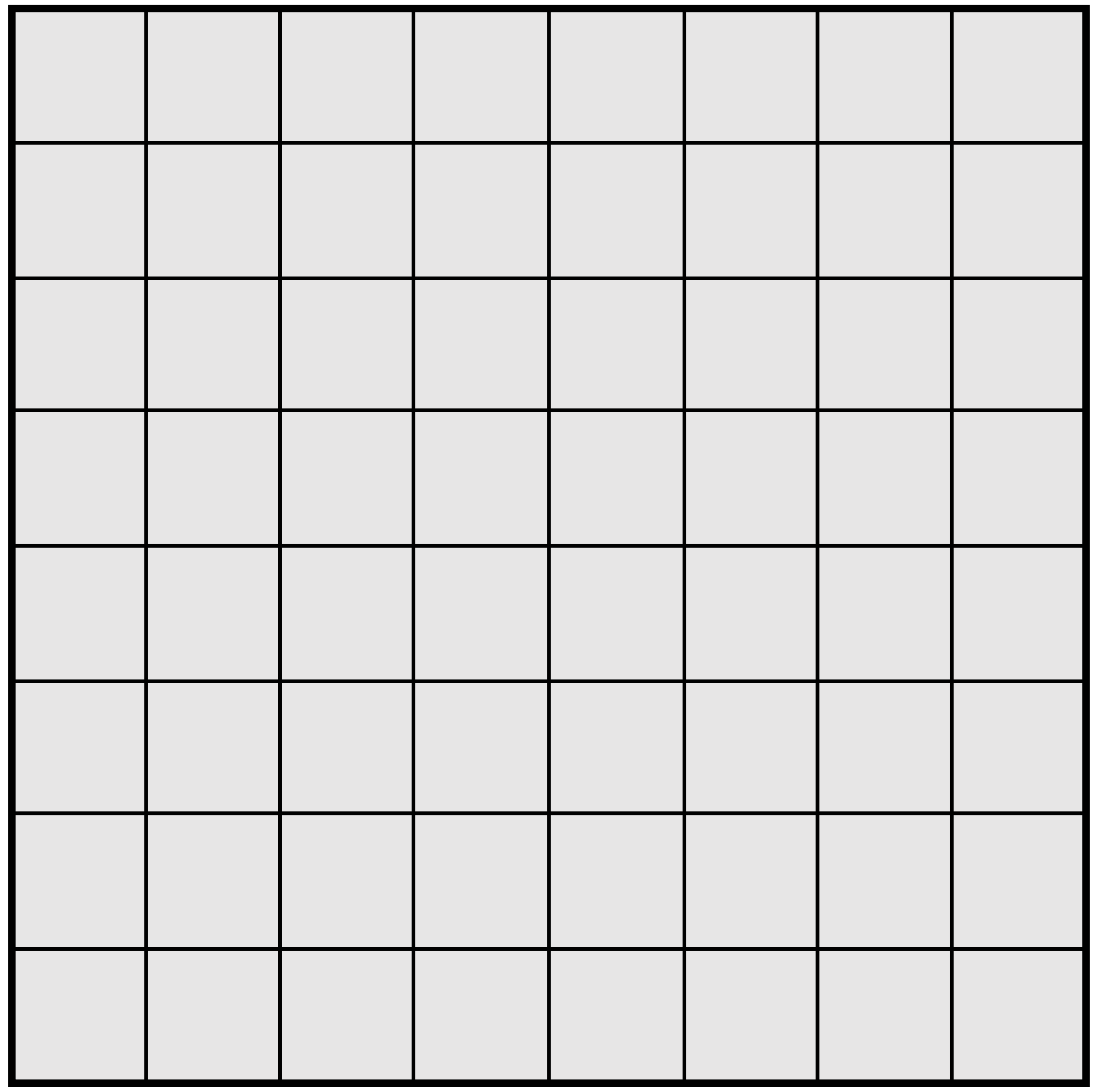
Recall: Receptive Fields



Input Image: 8 x 8

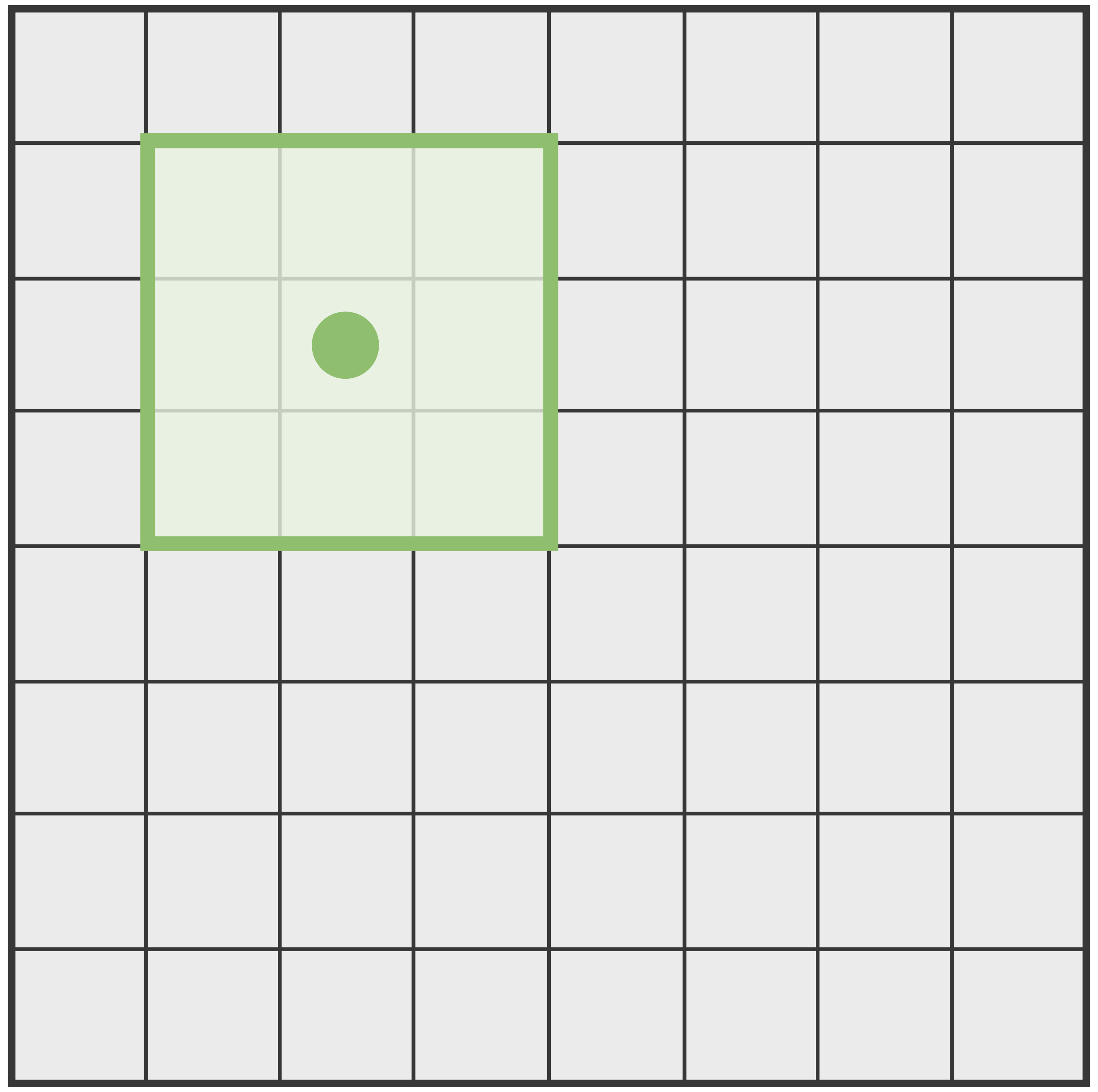
Every position in the output feature map depends on a 3x3 receptive field in the input

3x3 Conv
Stride 1, pad 1

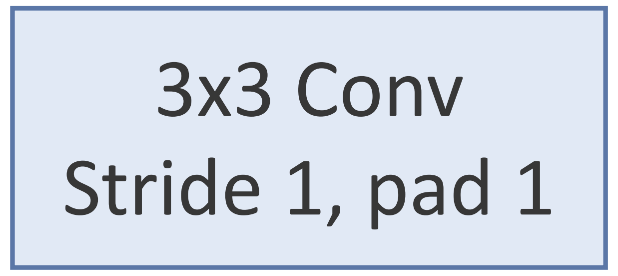


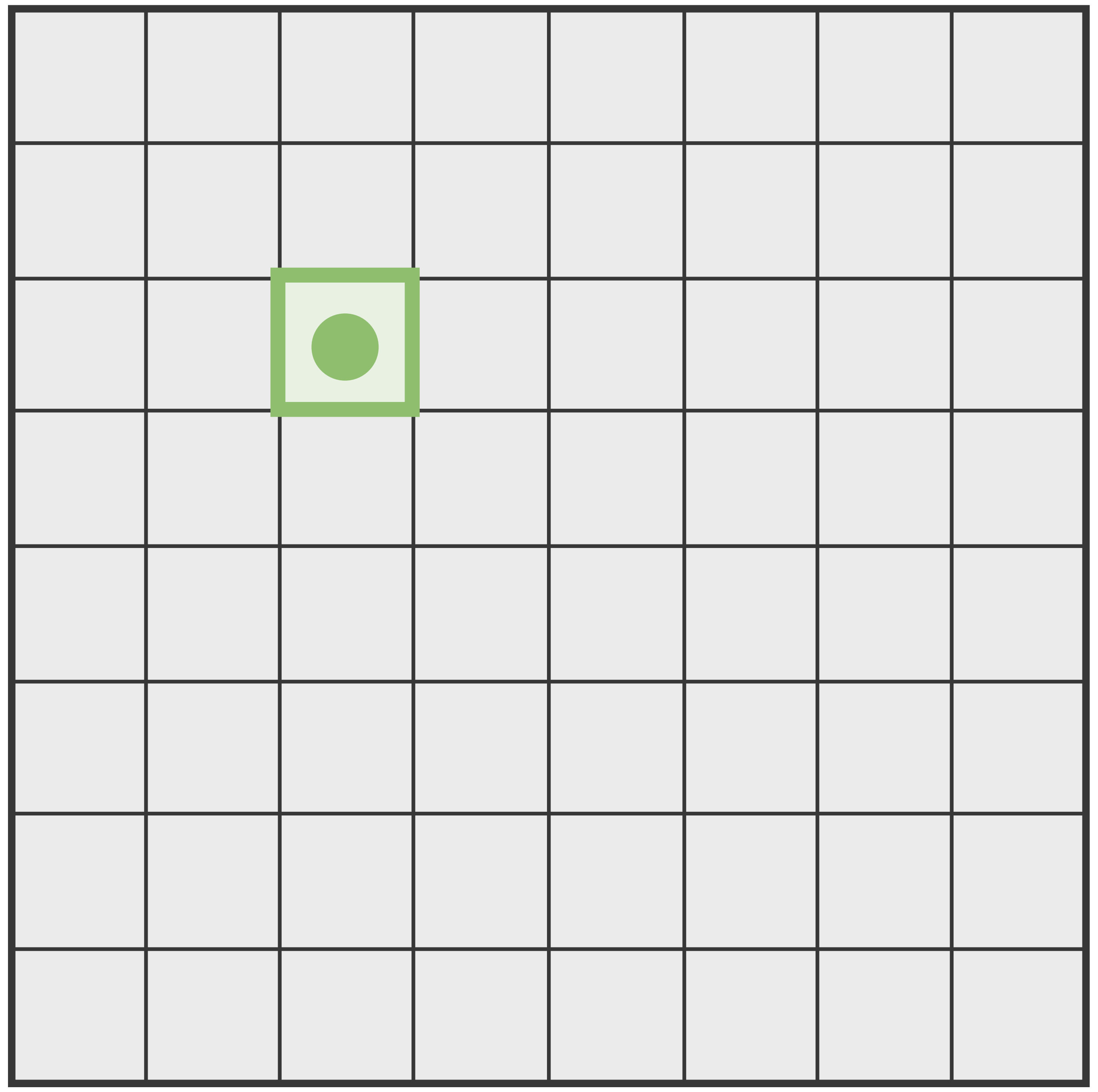
Output Image: 8 x 8

Recall: Receptive Fields



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



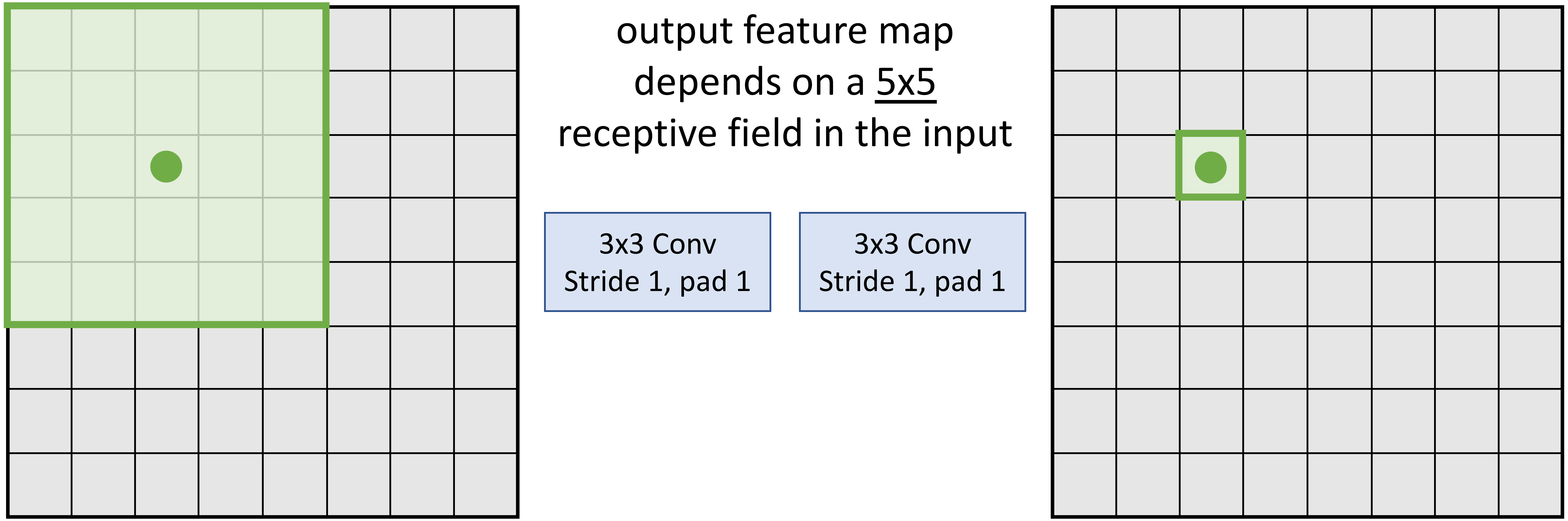


Input Image: 8 x 8

Output Image: 8 x 8

Recall: Receptive Fields

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

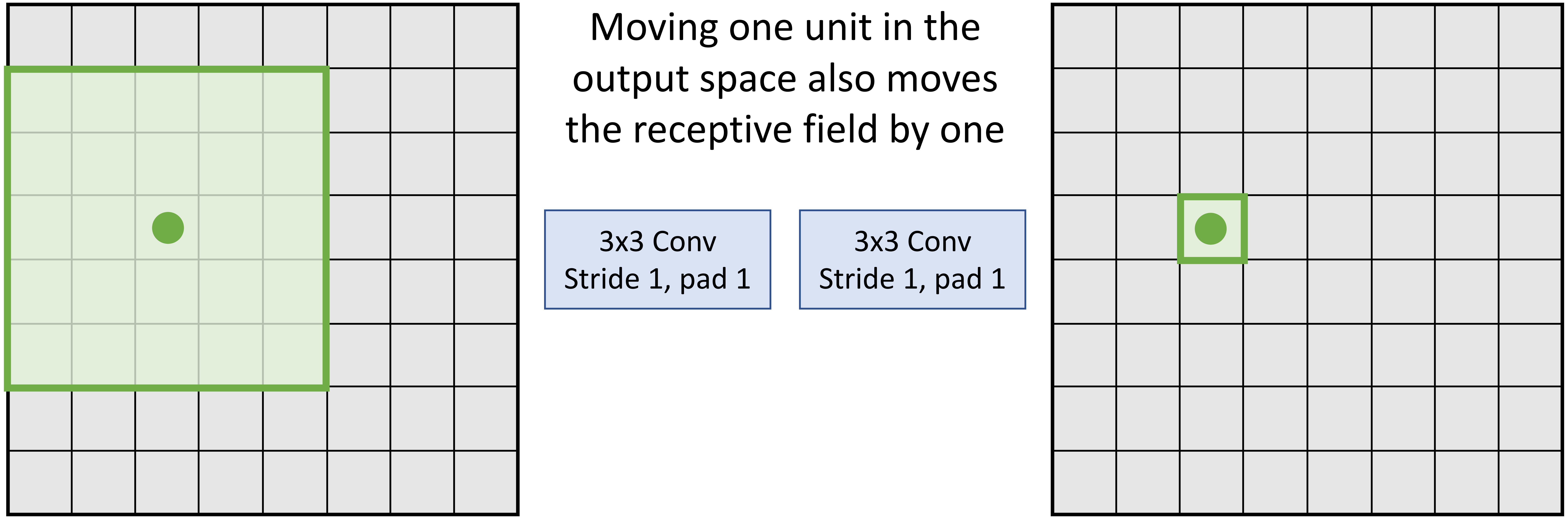


Input Image: 8 x 8

Output Image: 8 x 8

Recall: Receptive Fields

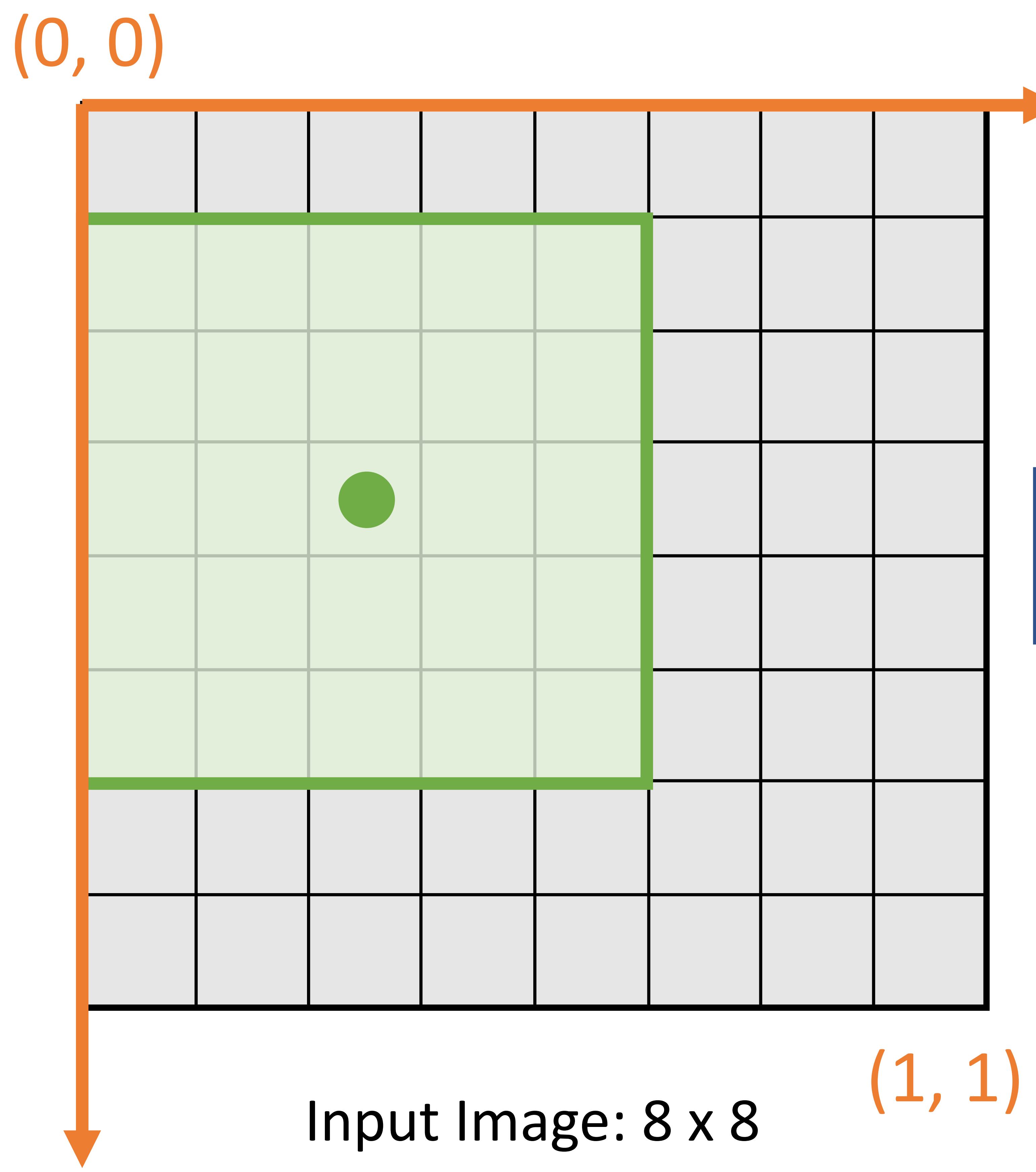
Moving one unit in the output space also moves the receptive field by one



Input Image: 8 x 8

Output Image: 8 x 8

Recall: Receptive Fields

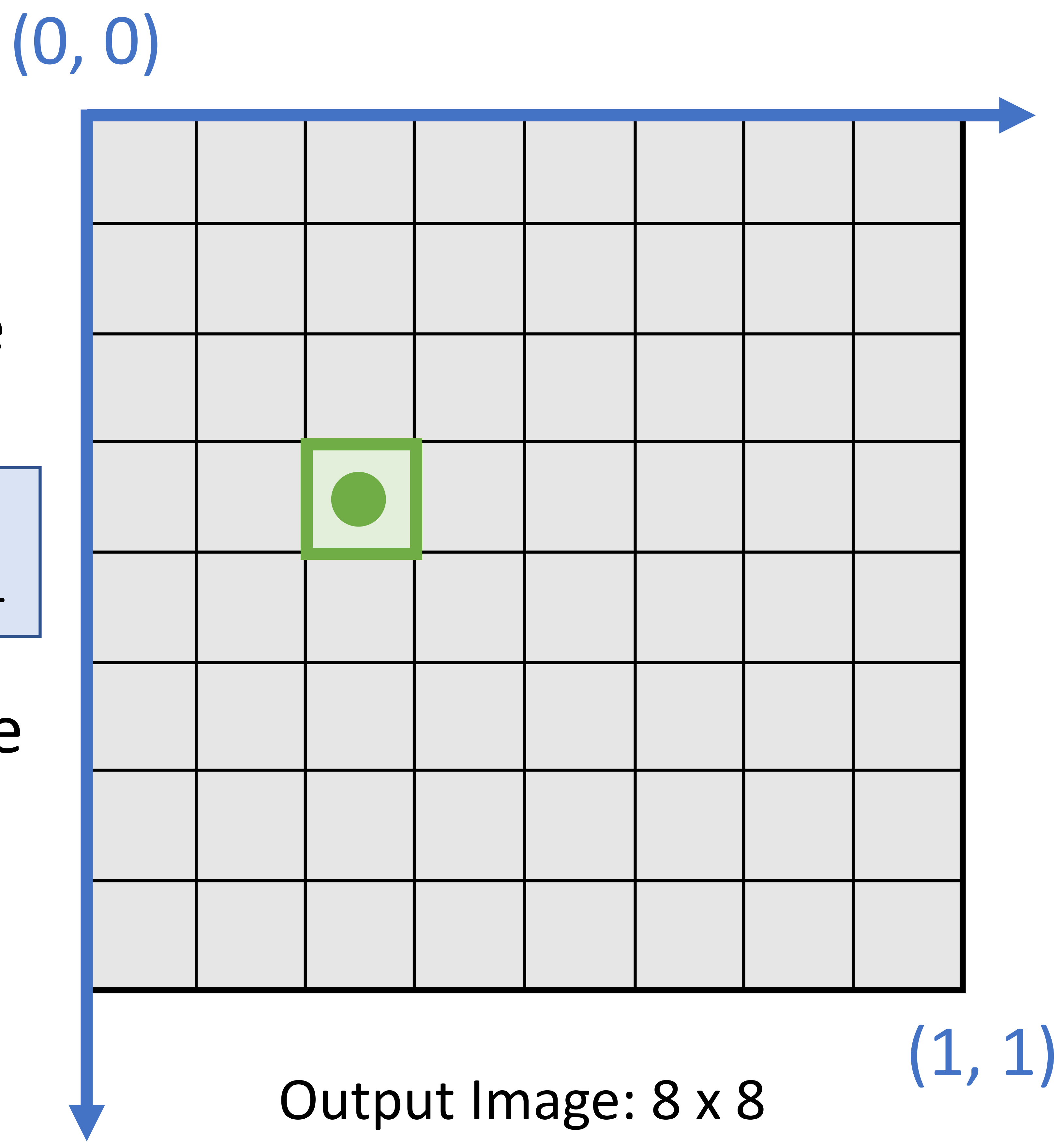


Moving one unit in the output space also moves the receptive field by one

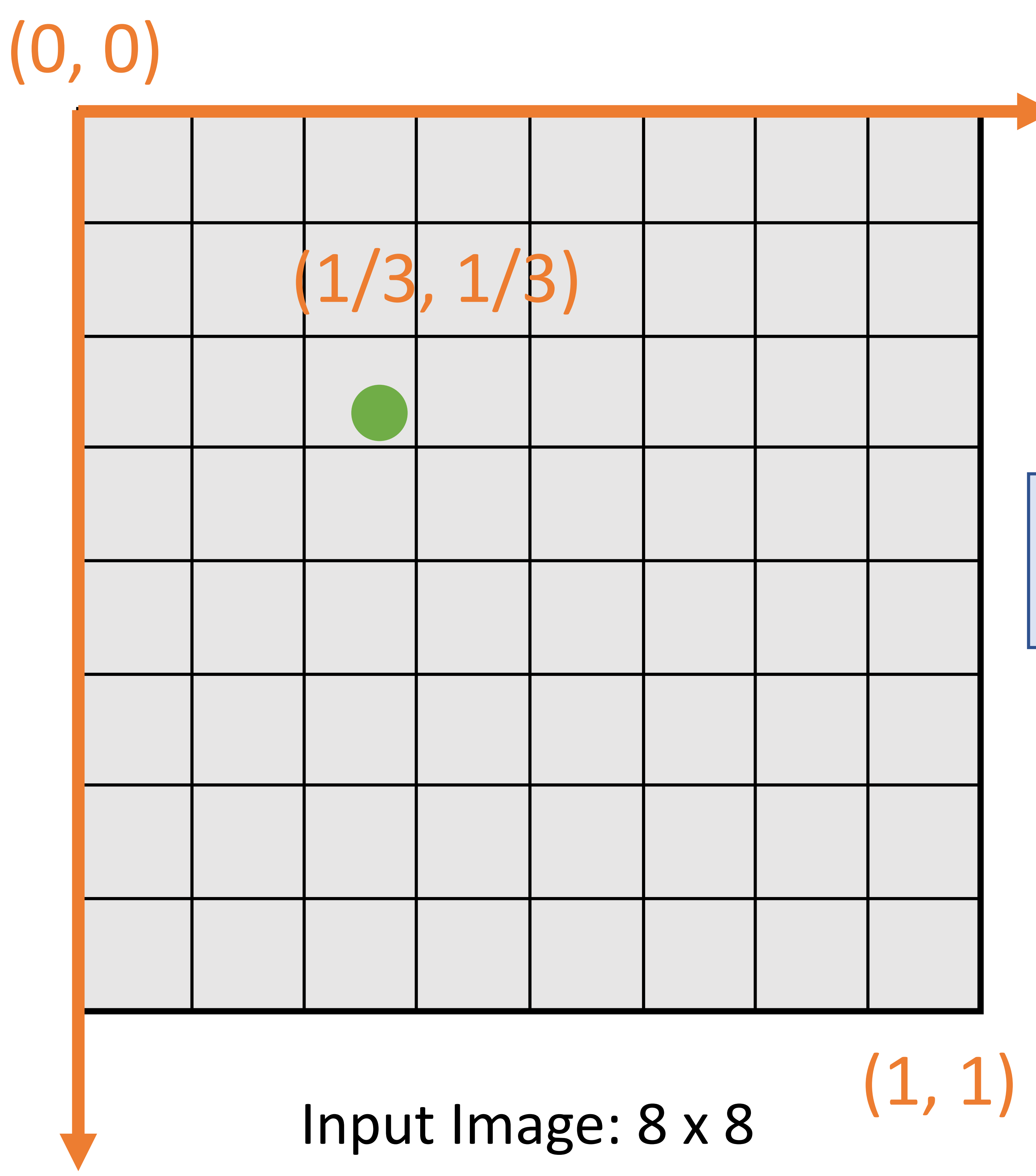
3x3 Conv
Stride 1, pad 1

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

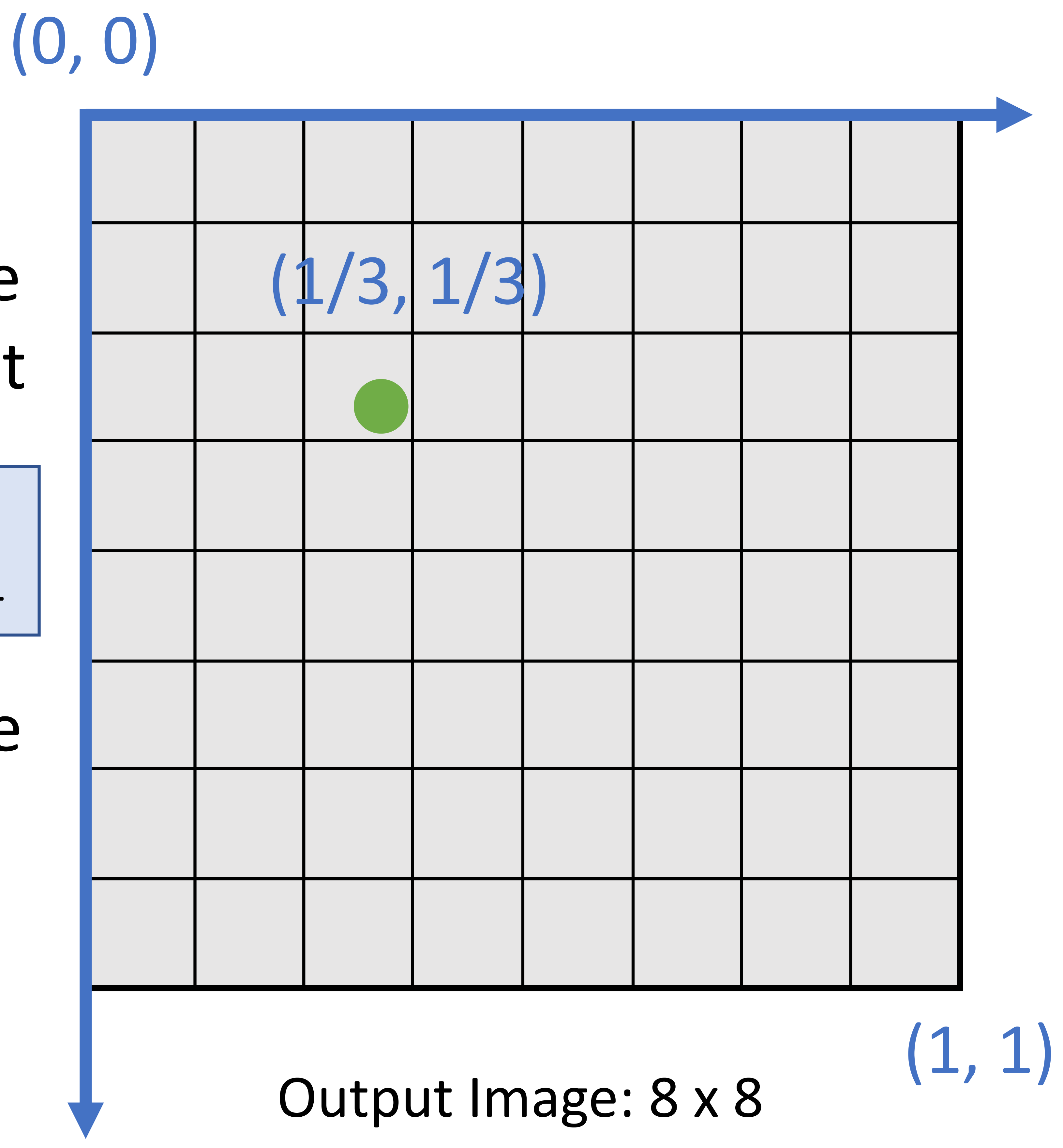


We can align arbitrary points between coordinate system of input and output

3x3 Conv
Stride 1, pad 1

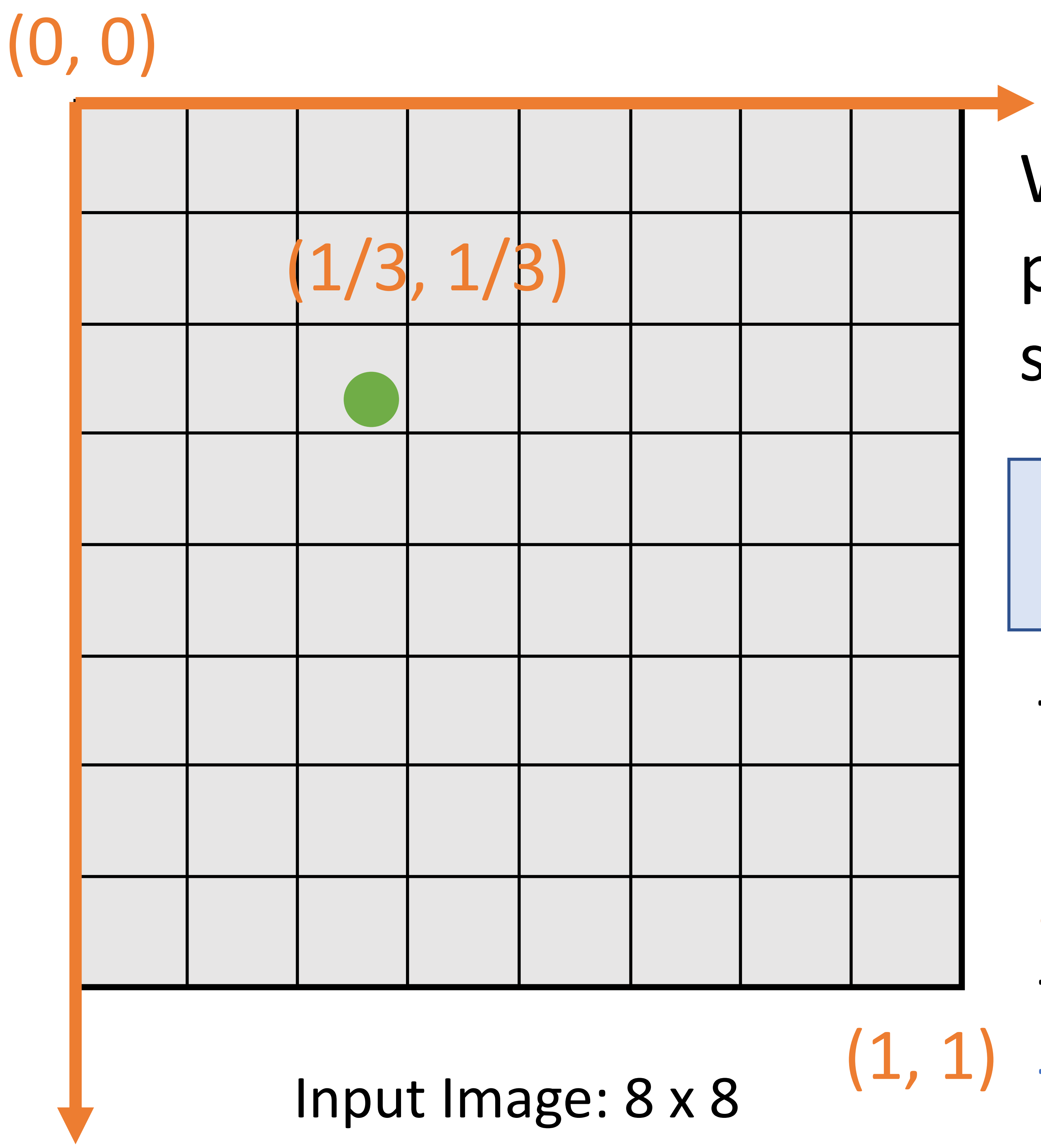
3x3 Conv
Stride 1, pad 1

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



Projecting Points

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

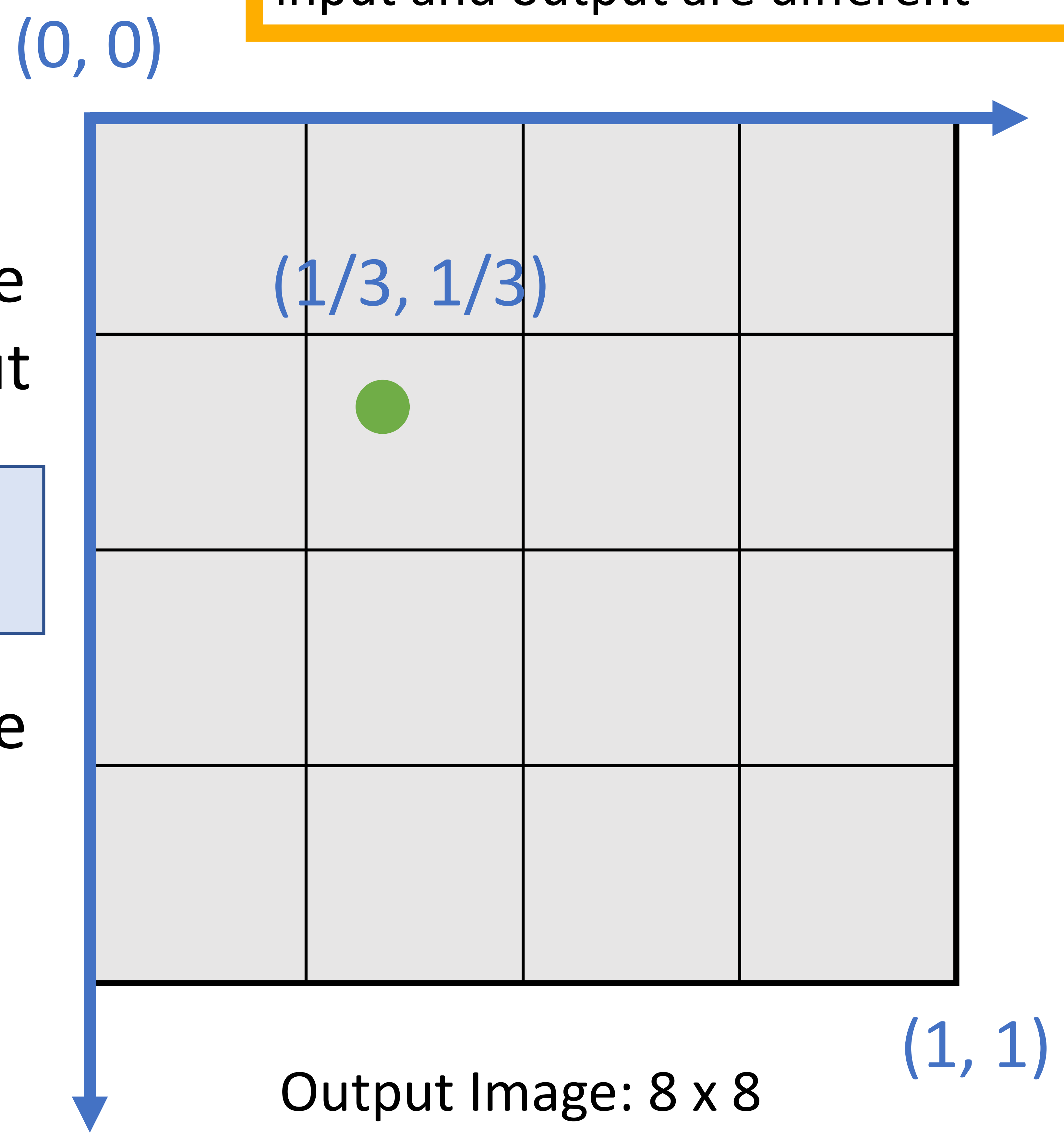


Input Image: 8 x 8

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

3x3 Conv Stride 1, pad 1	2x2 MaxPool Stride 2

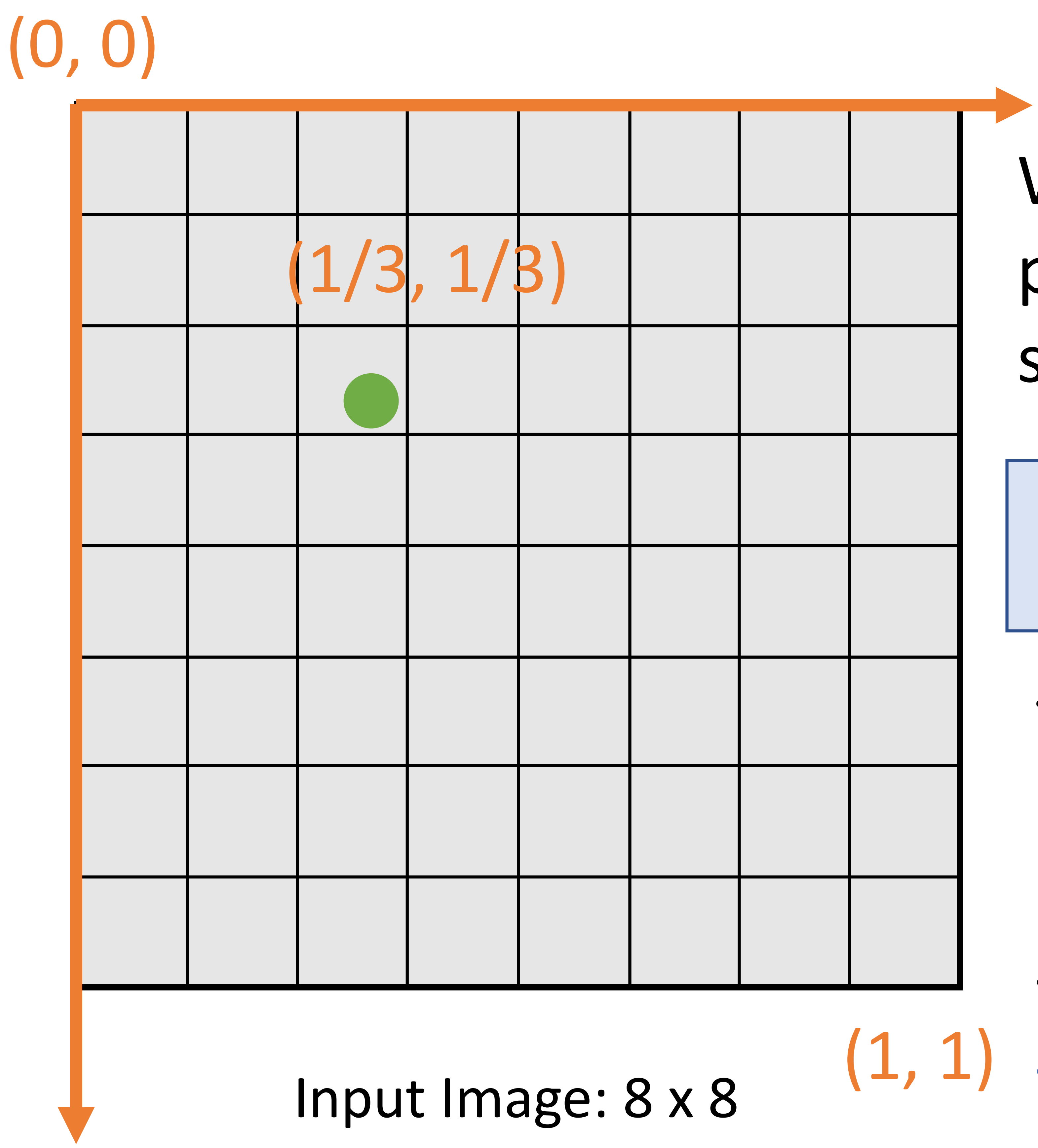
There is a correspondence between the coordinate system of the input and the coordinate system of the output



Output Image: 8 x 8

Projecting Points

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



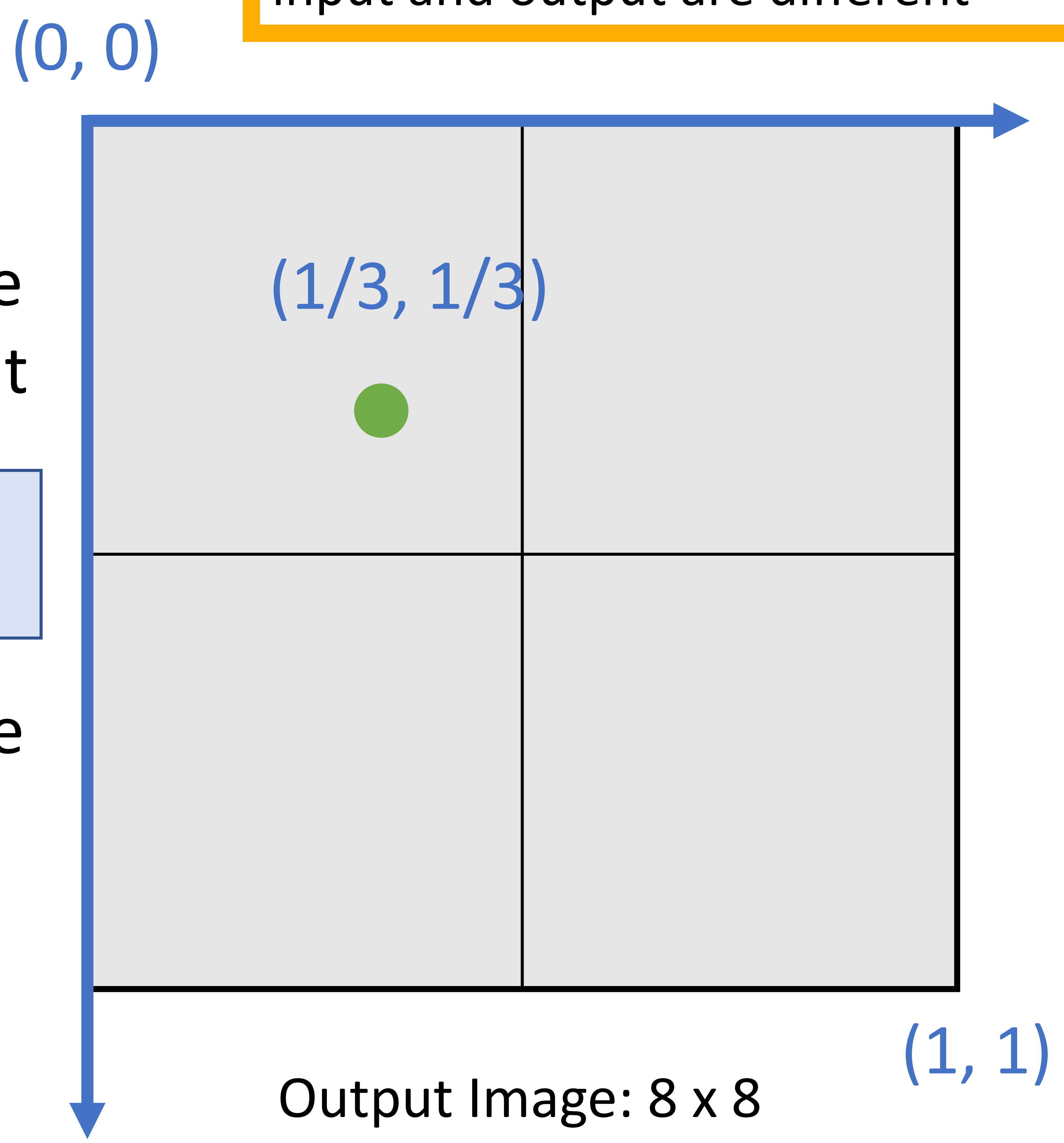
Input Image: 8 x 8

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

3x3 Conv
Stride 1, pad 1

4x4 MaxPool
Stride 4

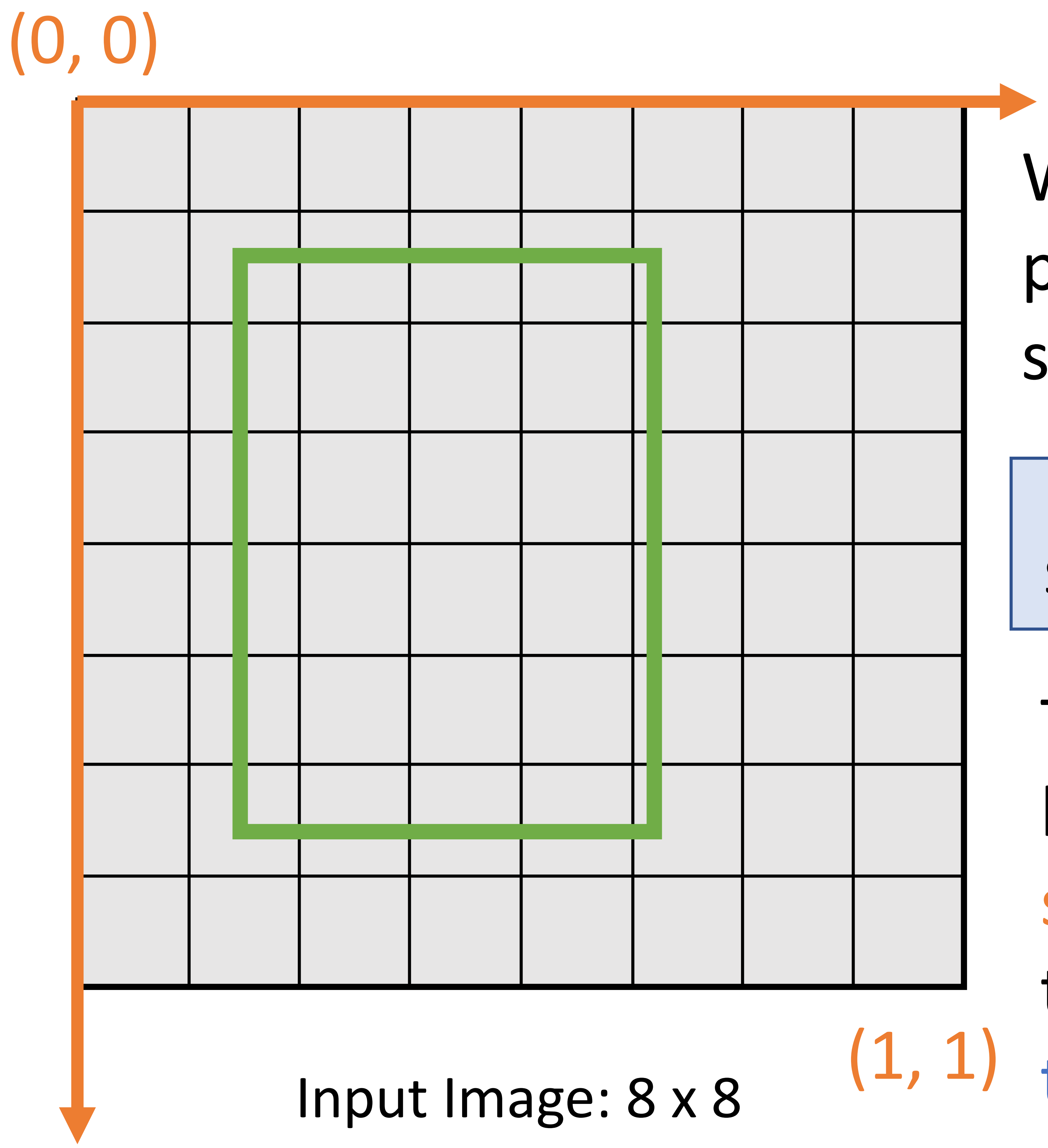
There is a correspondence between the coordinate system of the input and the coordinate system of the output



Output Image: 8 x 8

Projecting Points

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



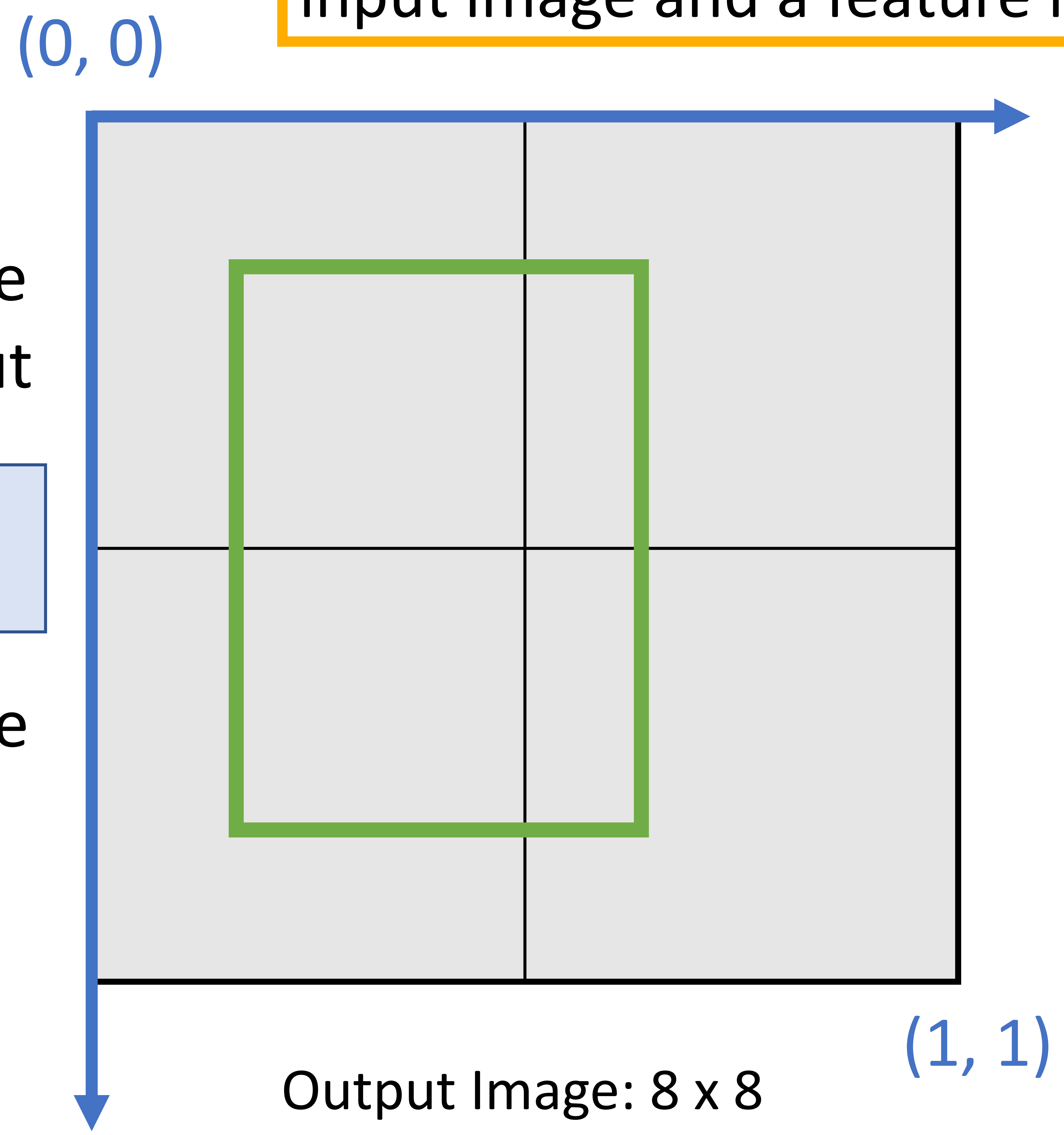
Input Image: 8 x 8

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

3x3 Conv
Stride 1, pad 1

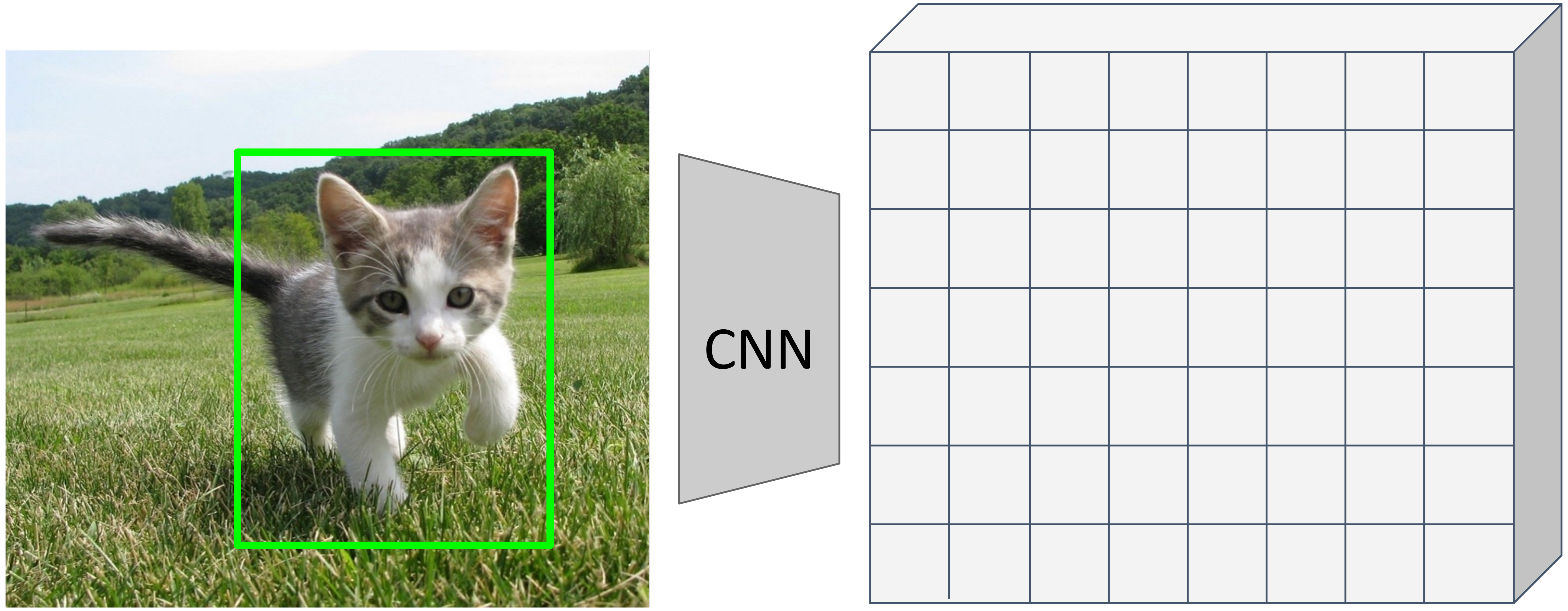
4x4 MaxPool
Stride 4

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



Output Image: 8 x 8

Cropping Features: RoI Pool



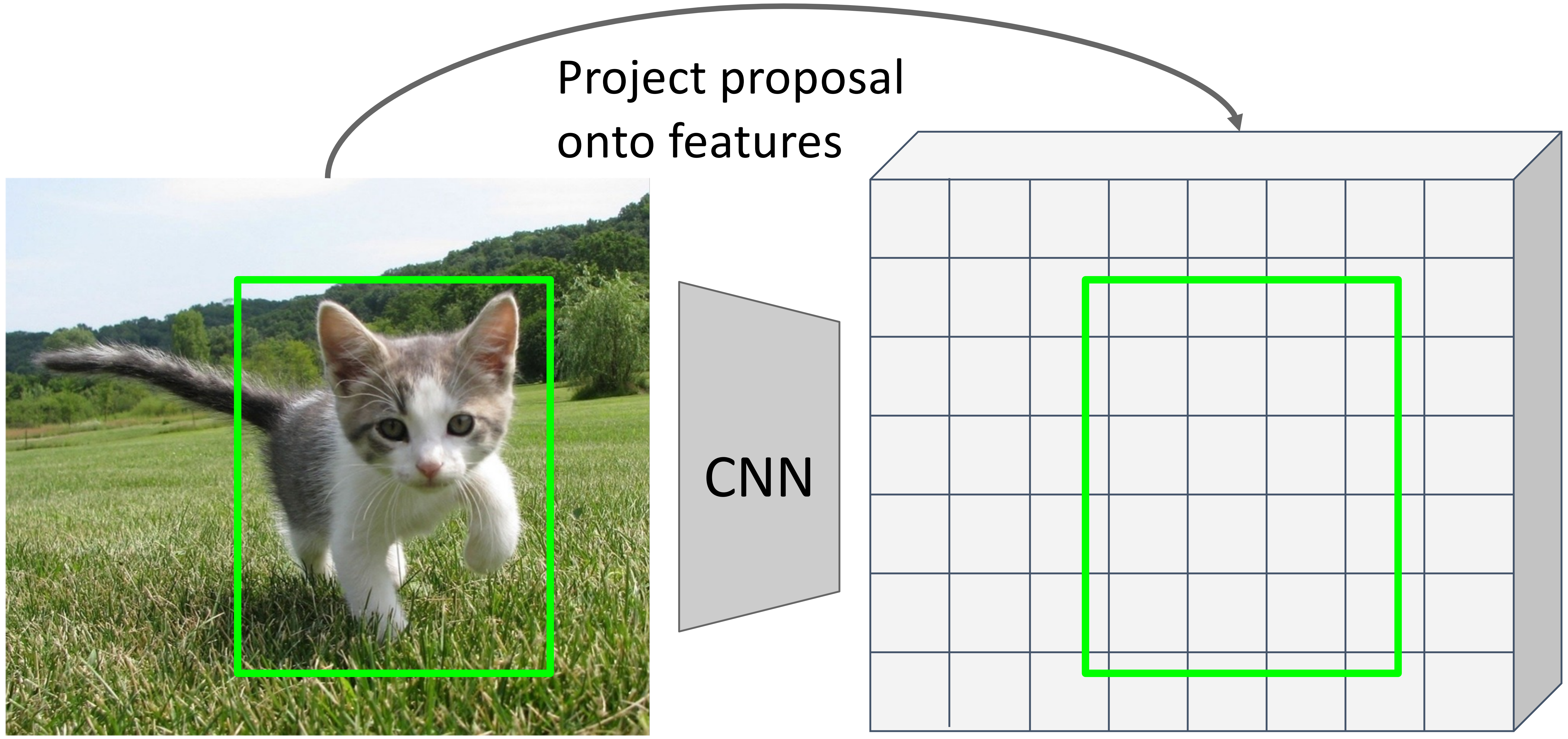
Input Image
(e.g. 3 x 640 x 480)

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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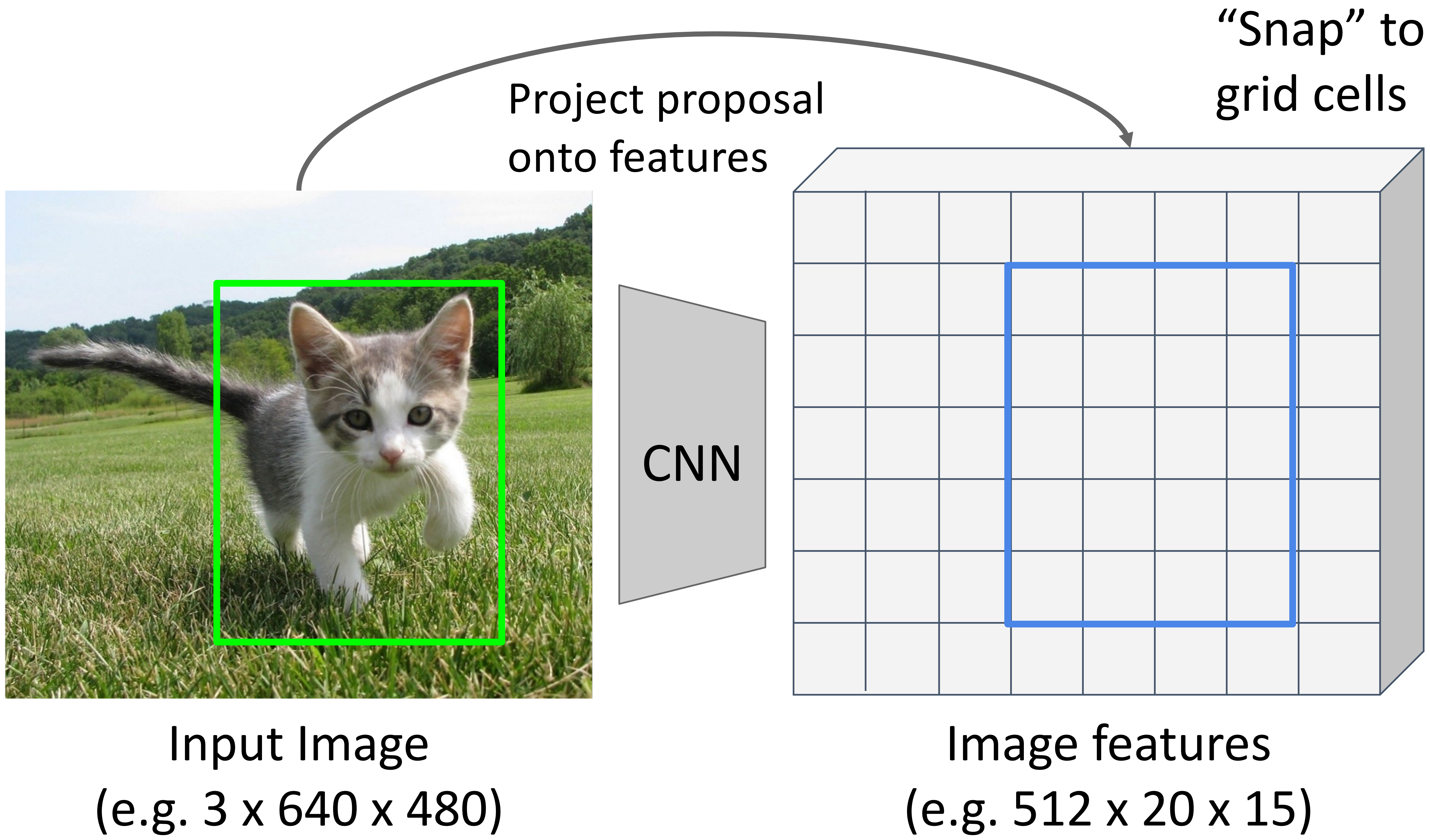

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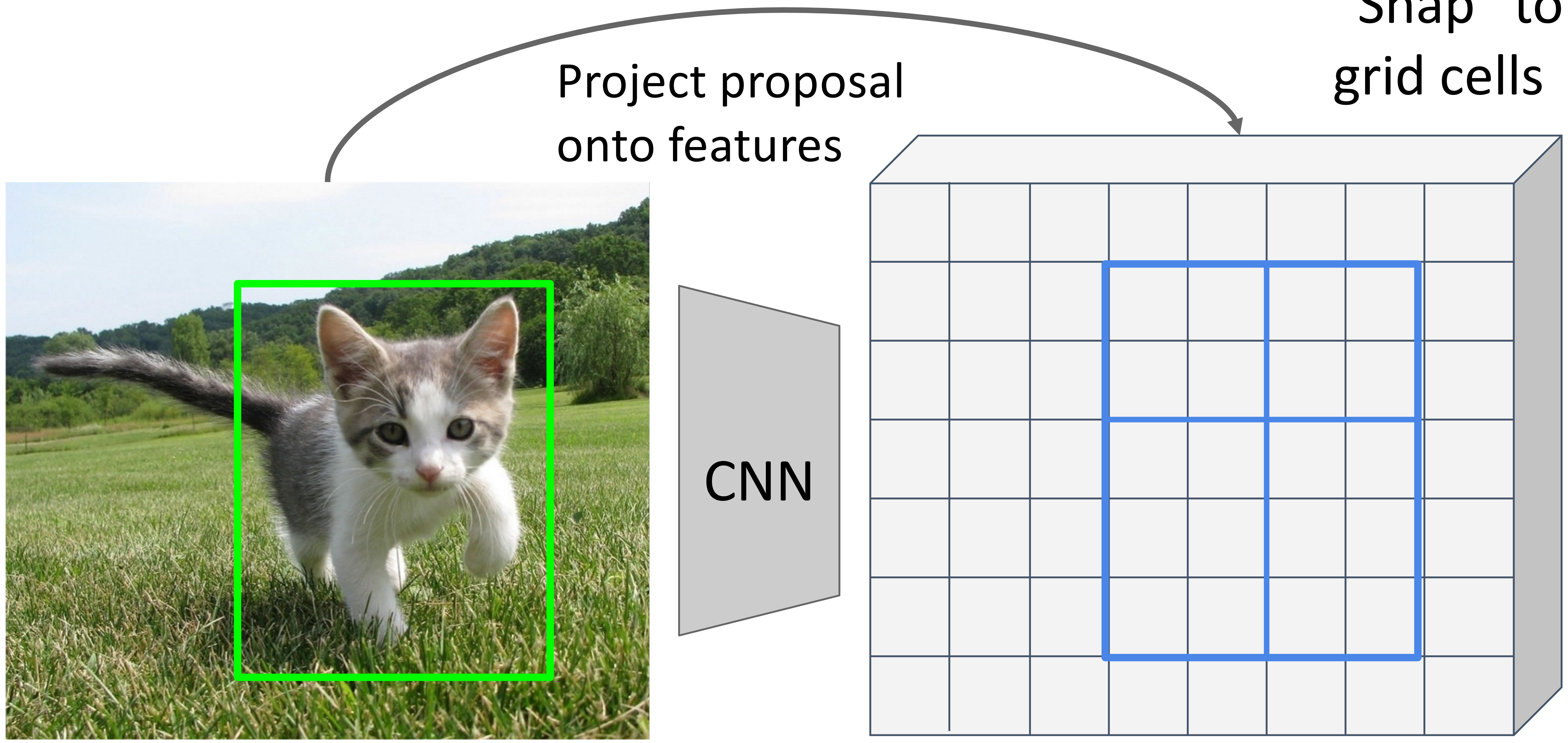


Input Image
(e.g. 3 x 640 x 480)

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

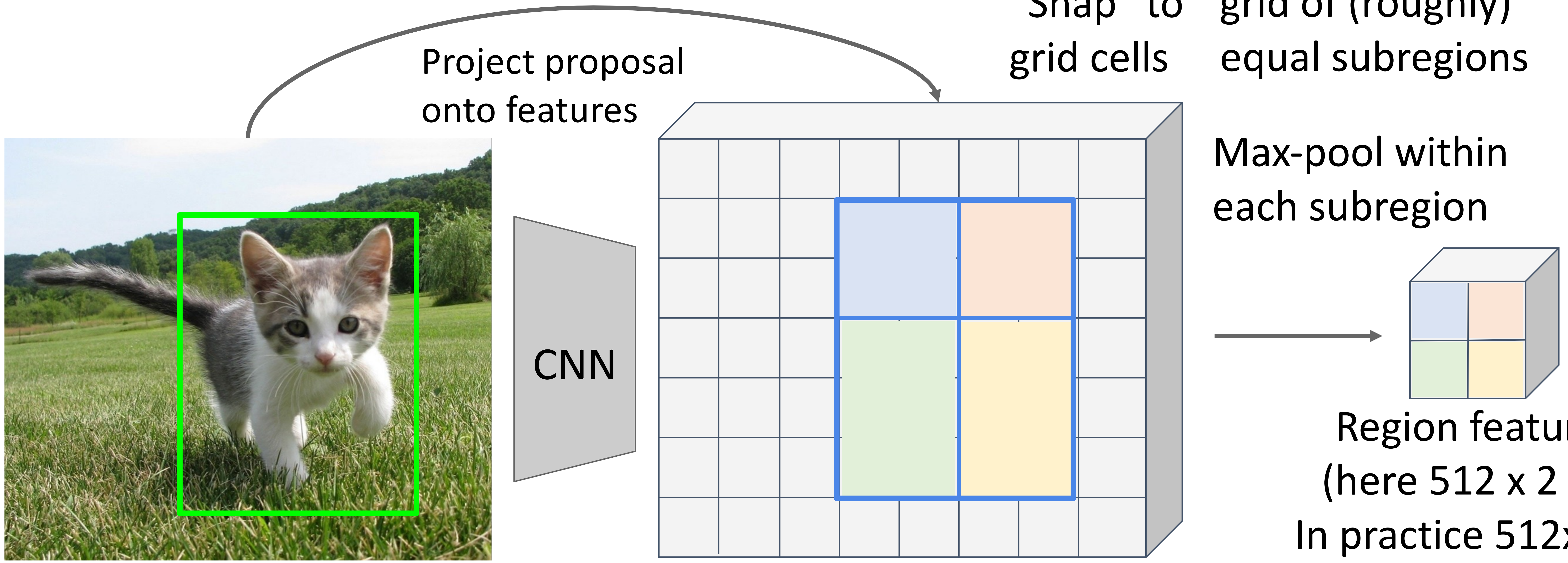
"Snap" to grid cells

Divide into 2x2 grid of (roughly) equal subregions

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



“Snap” to grid cells

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion

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

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

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

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

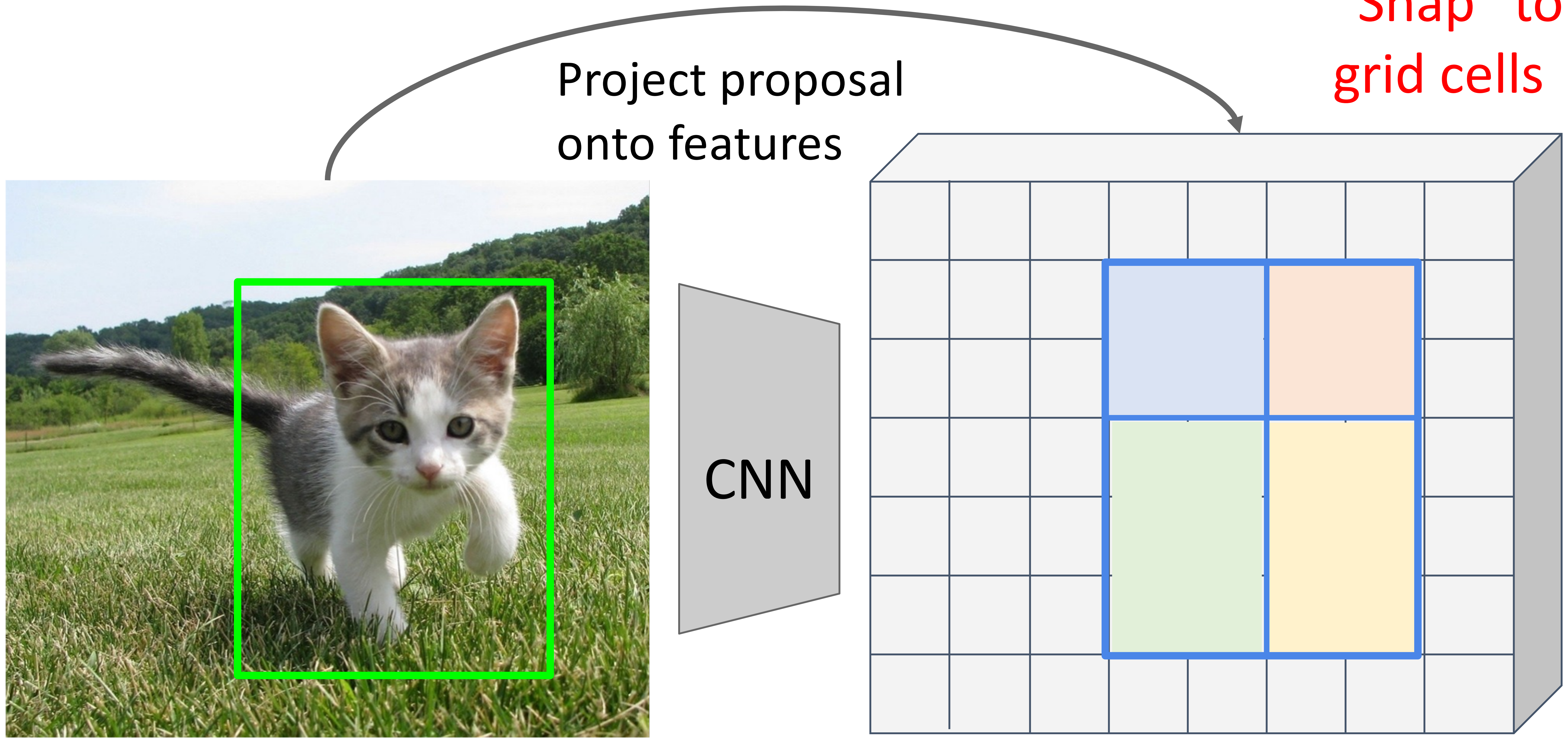
Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool

"Snap" to grid cells

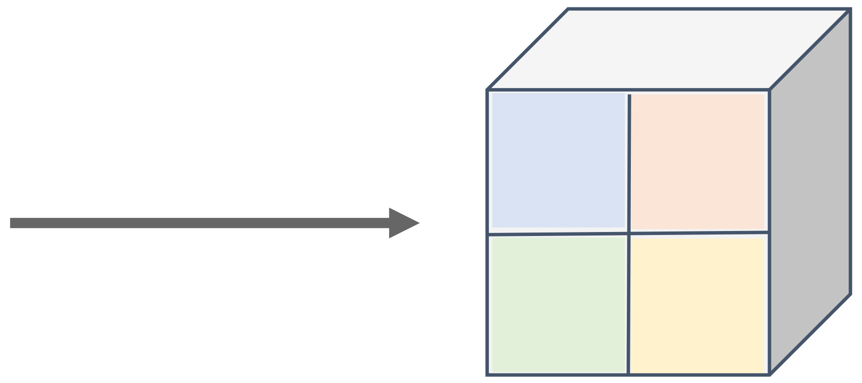
Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion



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

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



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

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

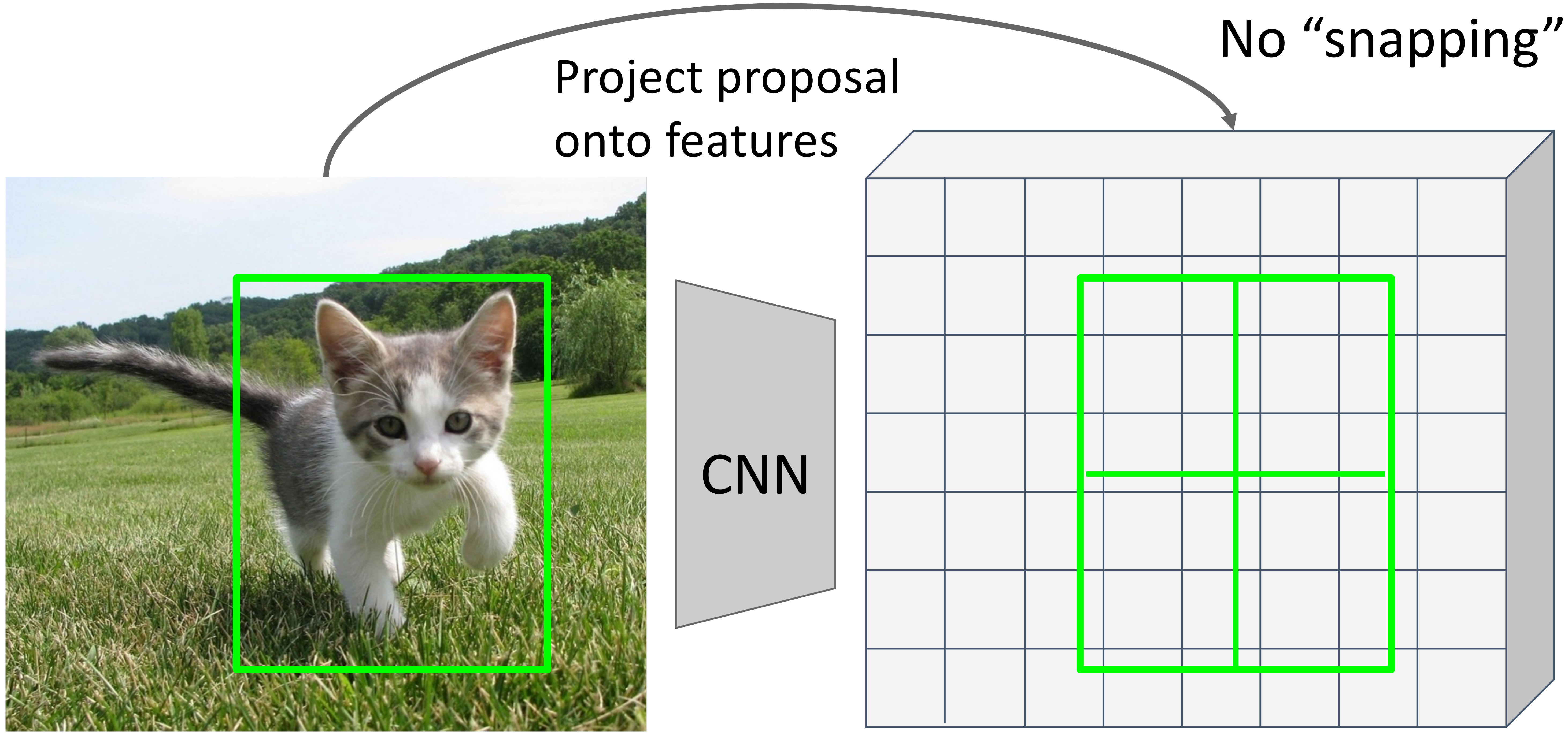
Problem: Slight misalignment due to snapping; different-sized subregions is weird

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

Cropping Features: RoI Align

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

No “snapping”!



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

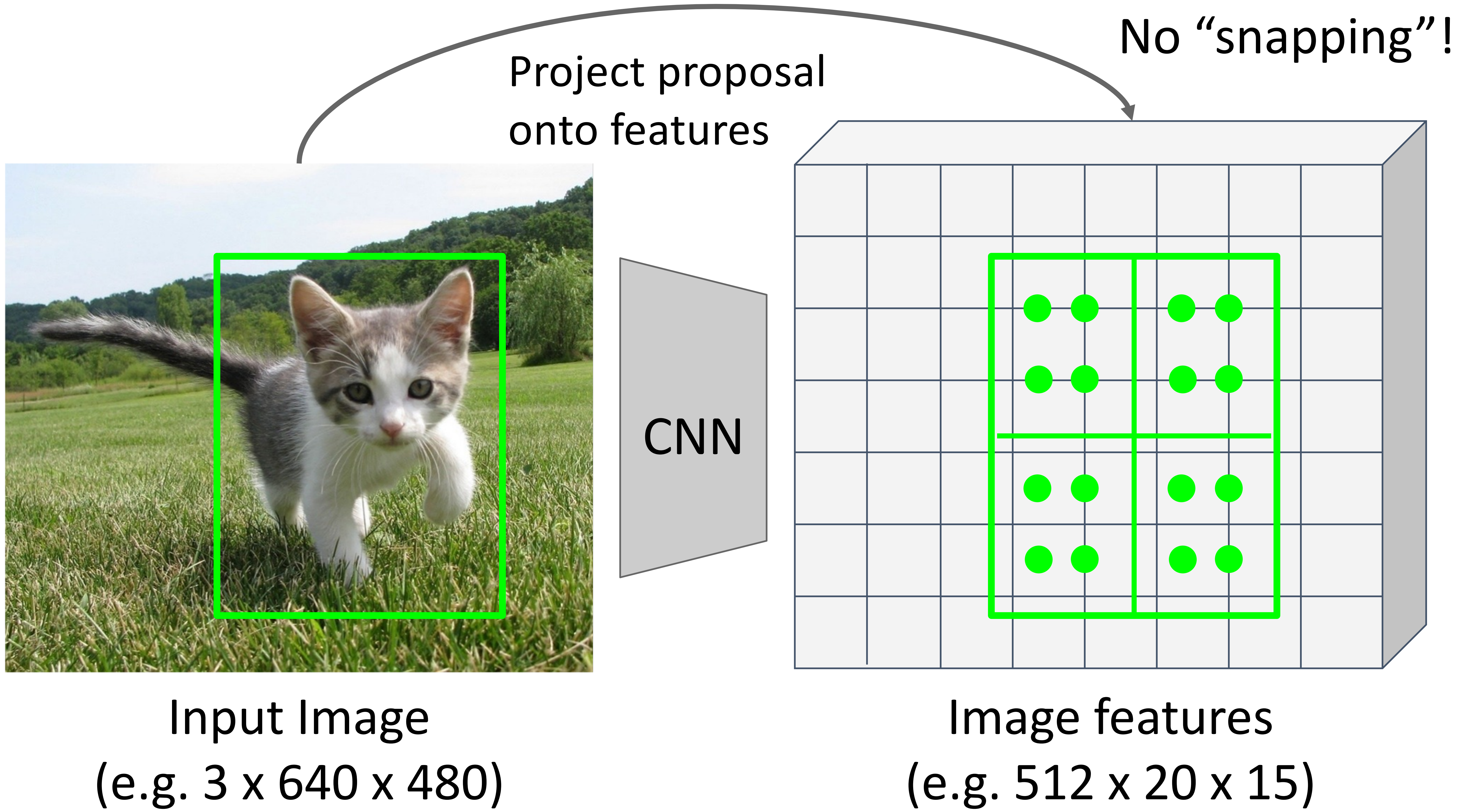
Image features
(e.g. 512 x 20 x 15)

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 Align

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



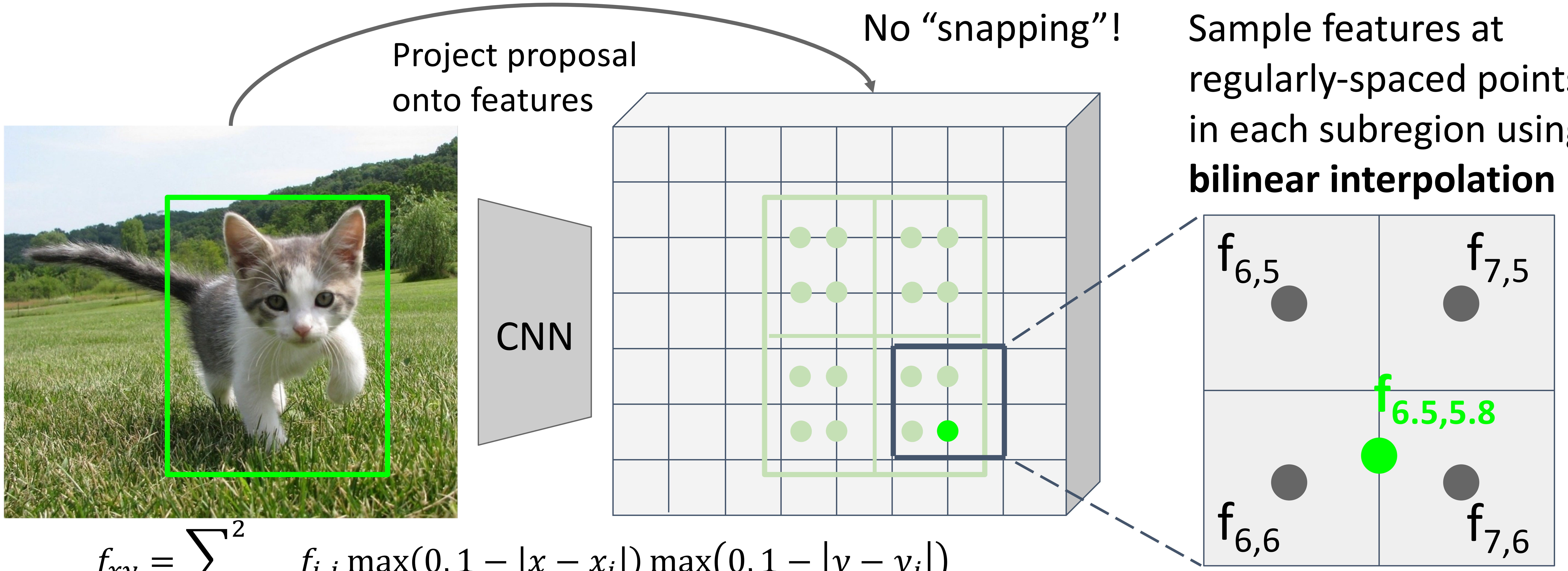
Sample features at regularly-spaced points in each subregion using **bilinear interpolation**

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**



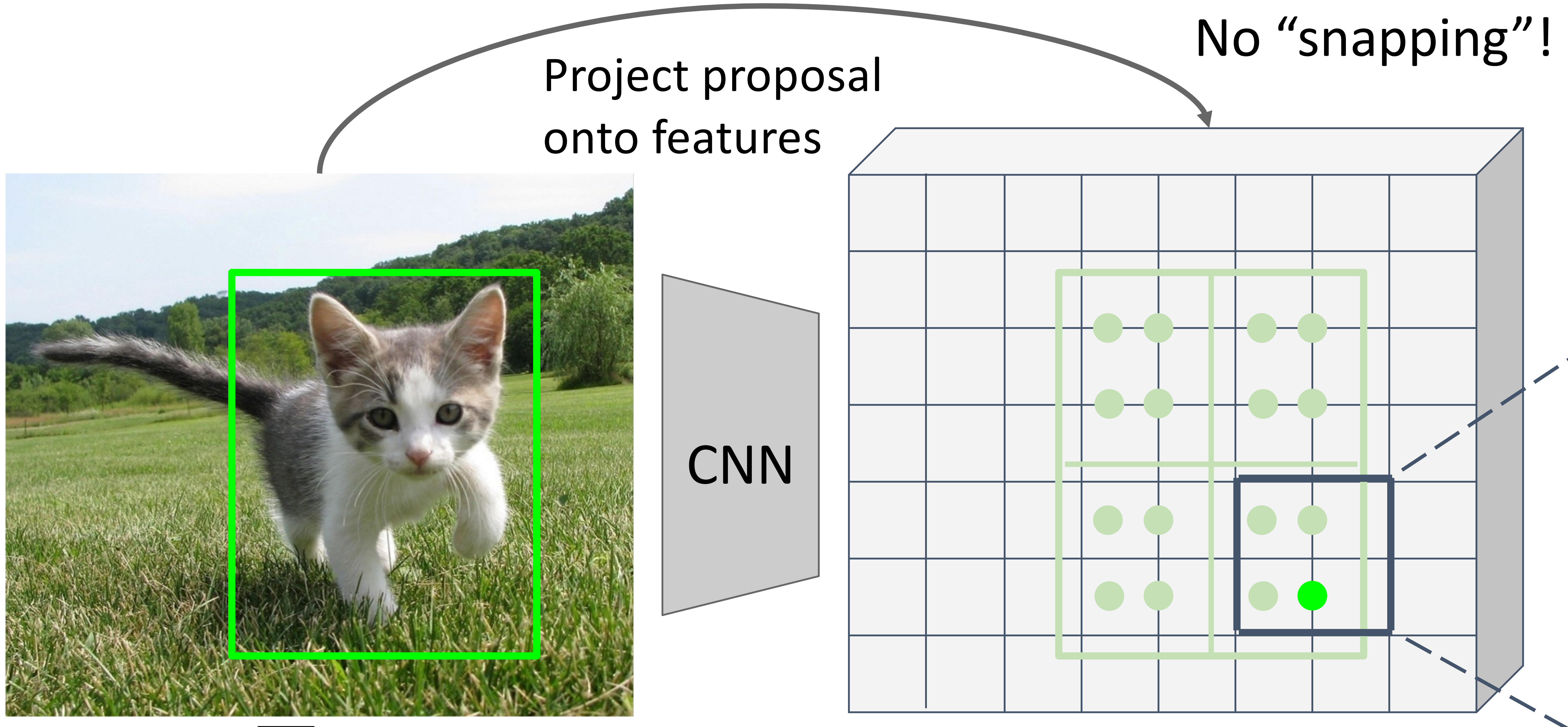
$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

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

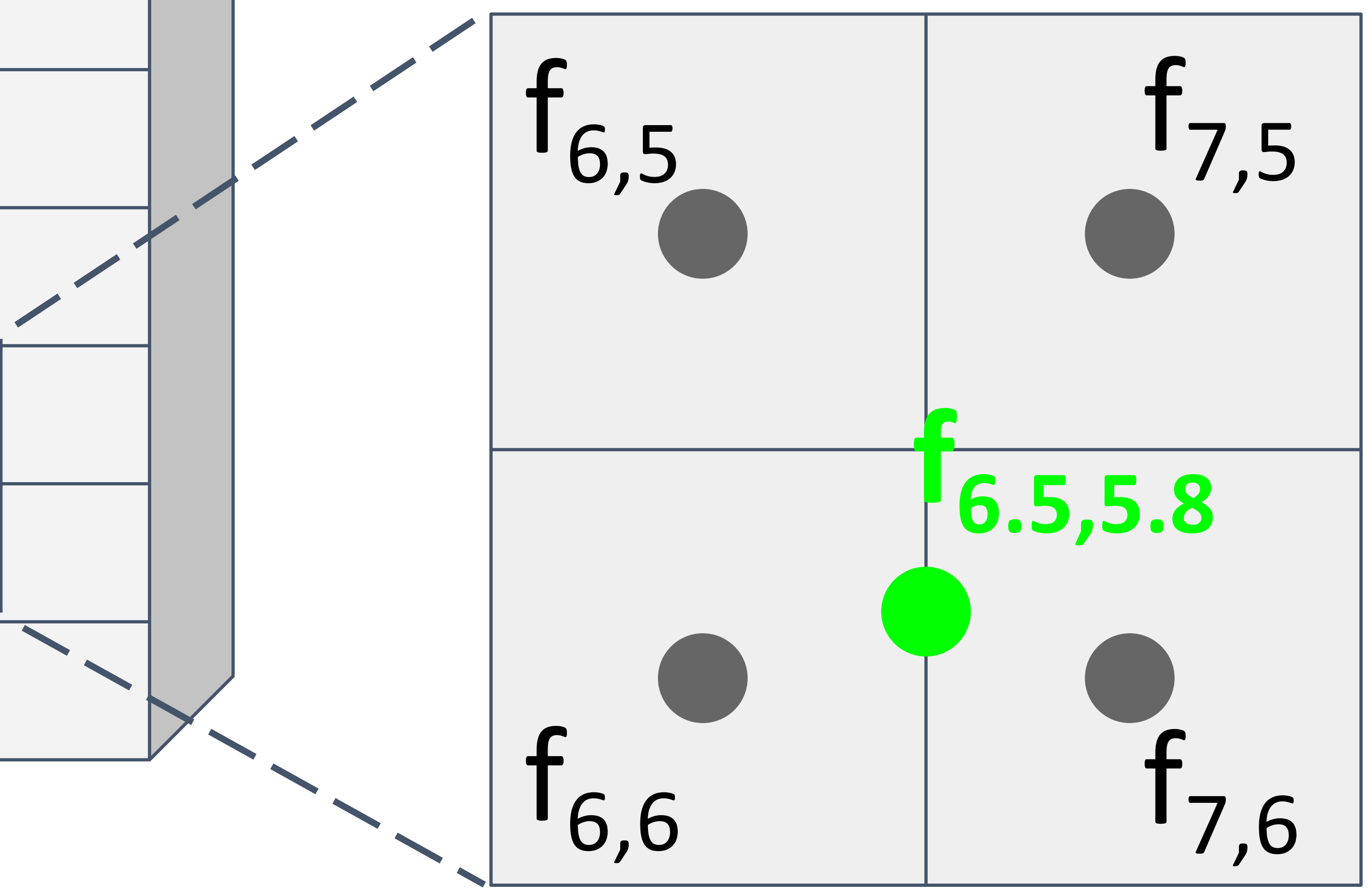
He et al, "Mask R-CNN", ICCV 2017

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**



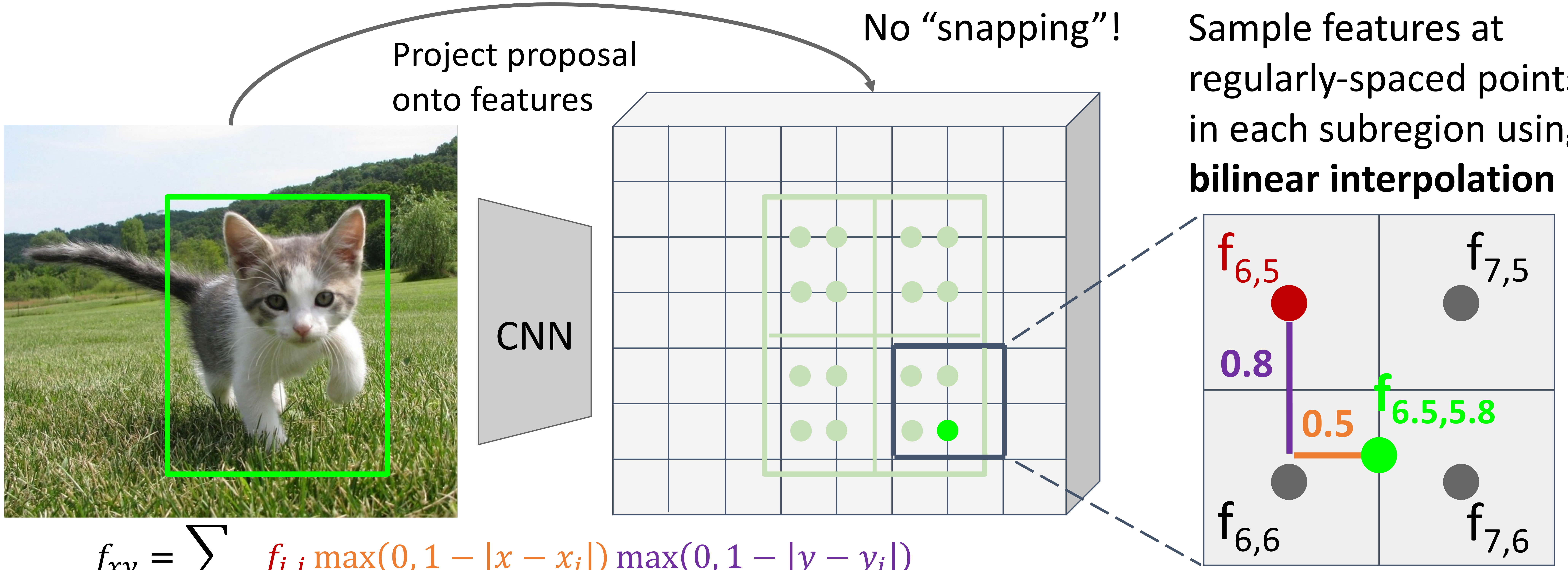
$$f_{xy} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_i|)$$

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

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

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

Cropping Features: RoI Align



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

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

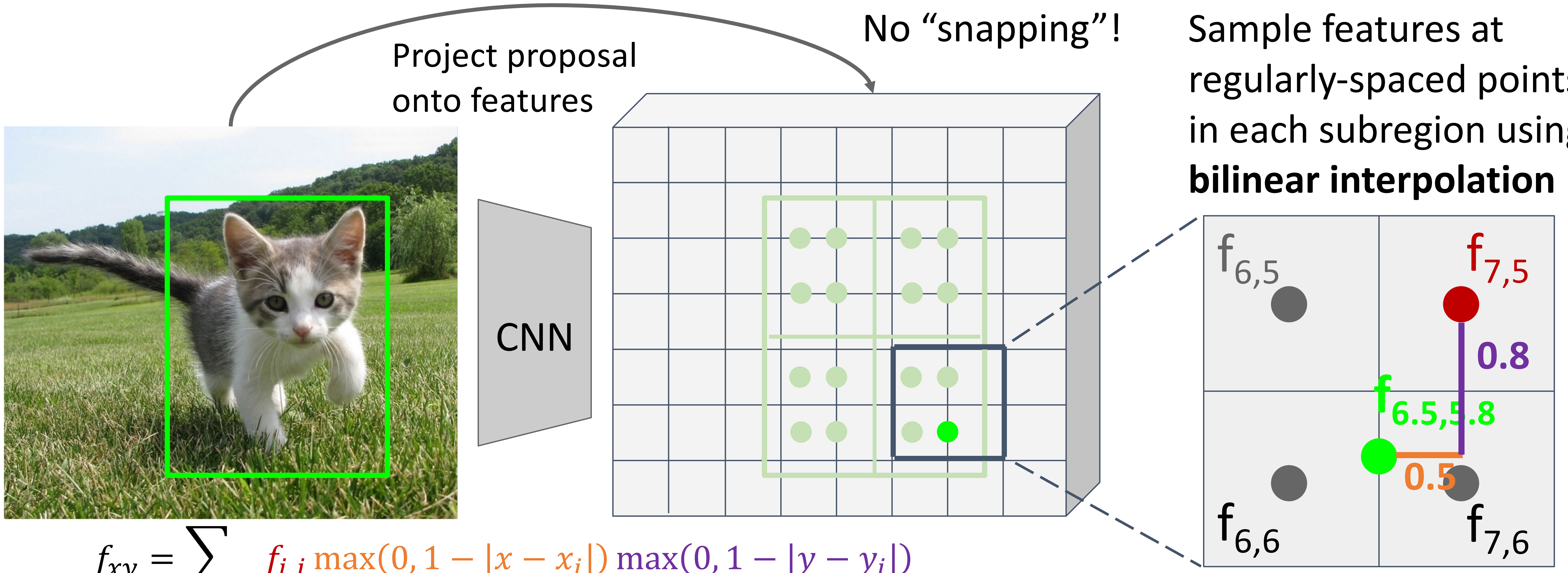
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

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

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

Cropping Features: RoI Align

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



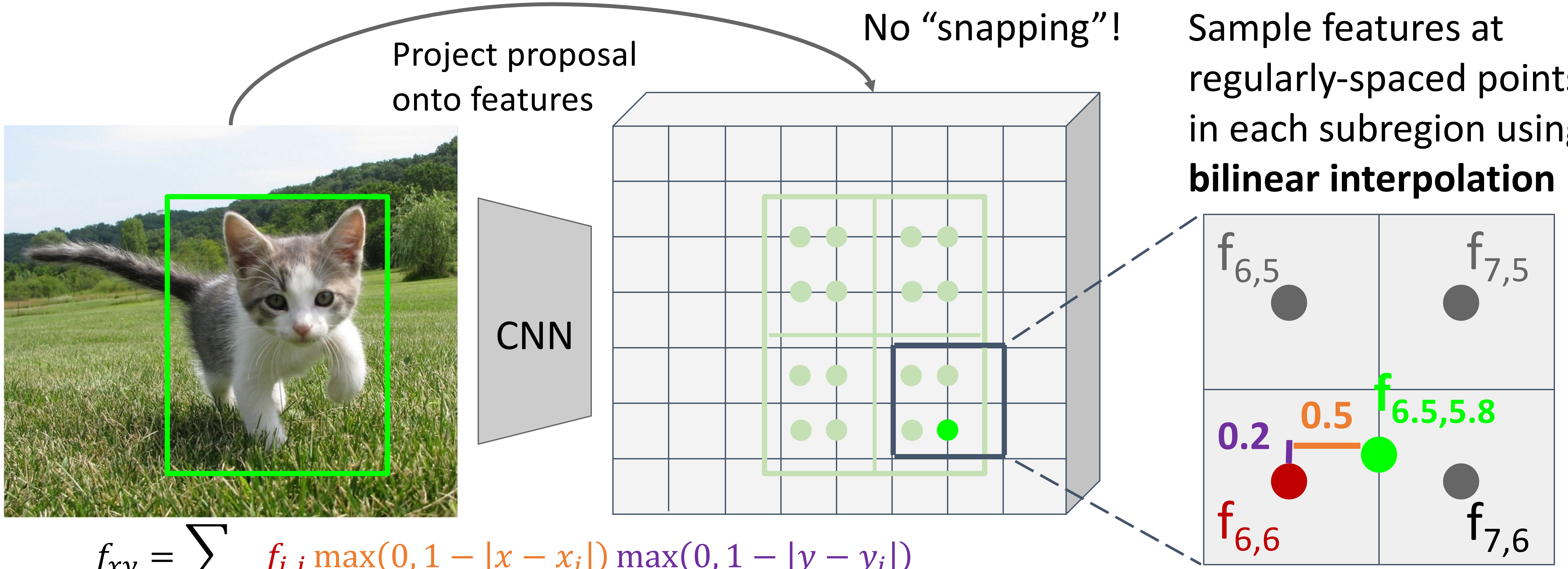
$$f_{xy} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_i|)$$

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

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

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

Cropping Features: RoI Align



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

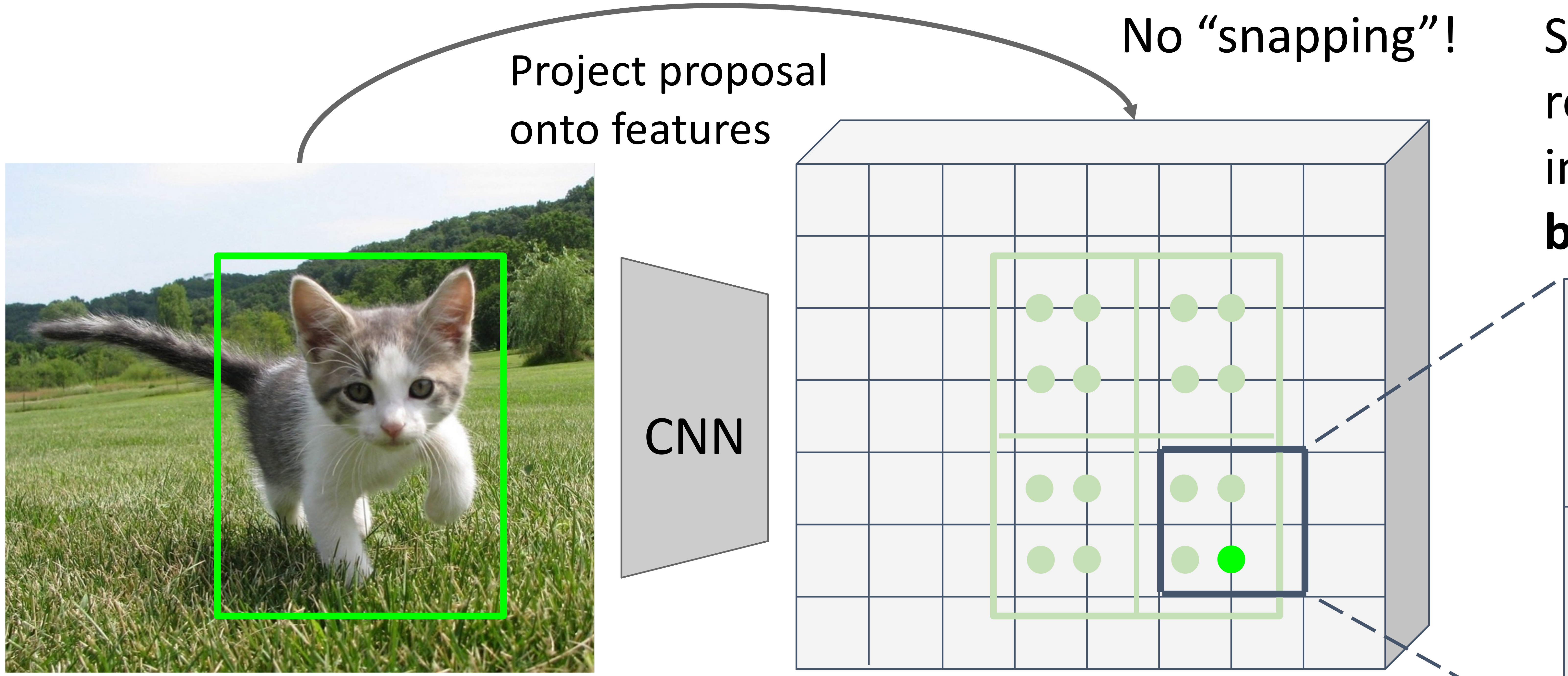
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

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

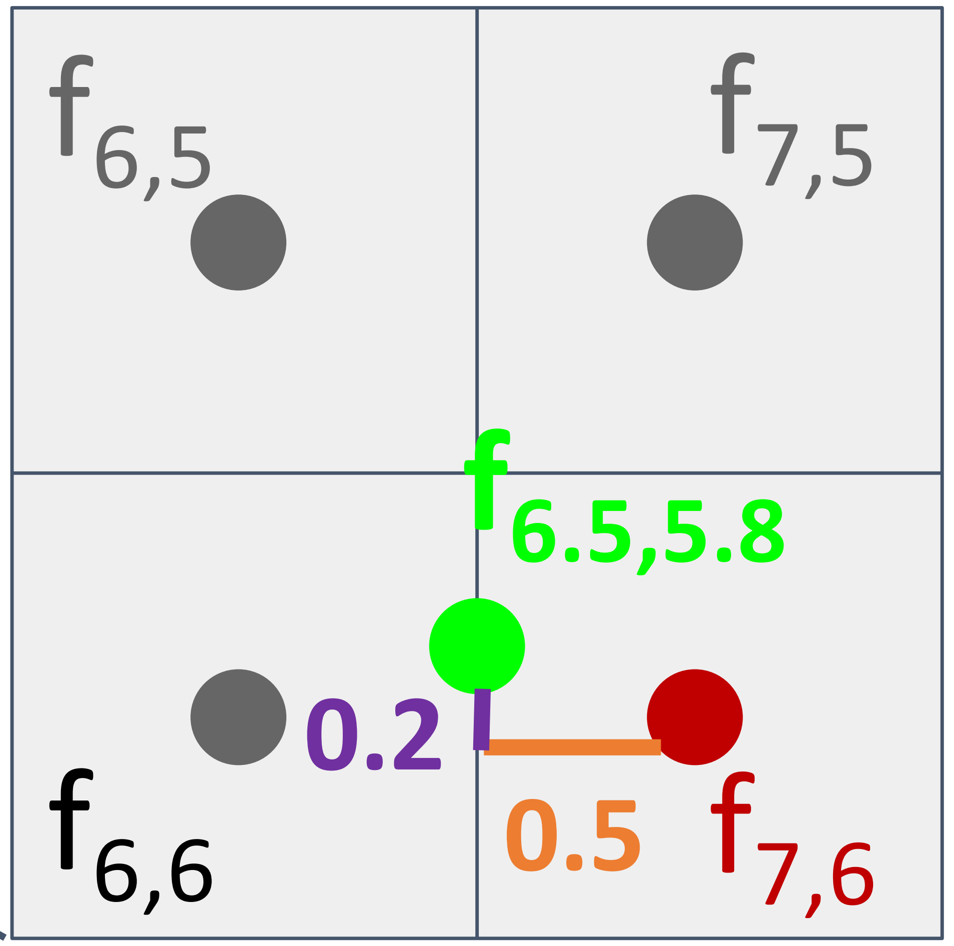
$$f_{6.5,5.8} = (f_{6,5} * 0.5 * 0.2) + (f_{7,5} * 0.5 * 0.2) + (f_{6,6} * 0.5 * 0.8) + (f_{7,6} * 0.5 * 0.8)$$

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

Cropping Features: RoI Align



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



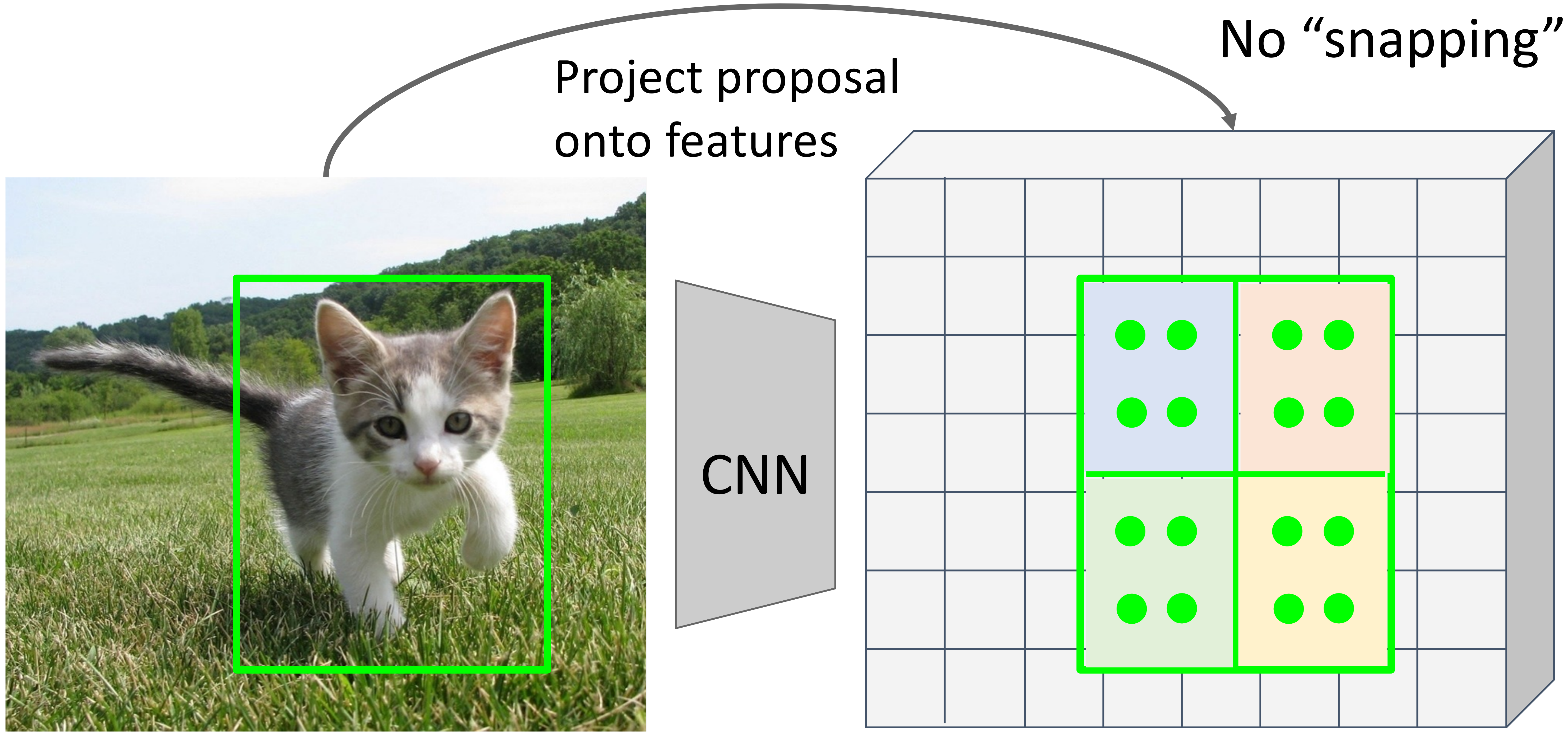
$$f_{xy} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_i|)$$

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

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

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

Cropping Features: RoI Align

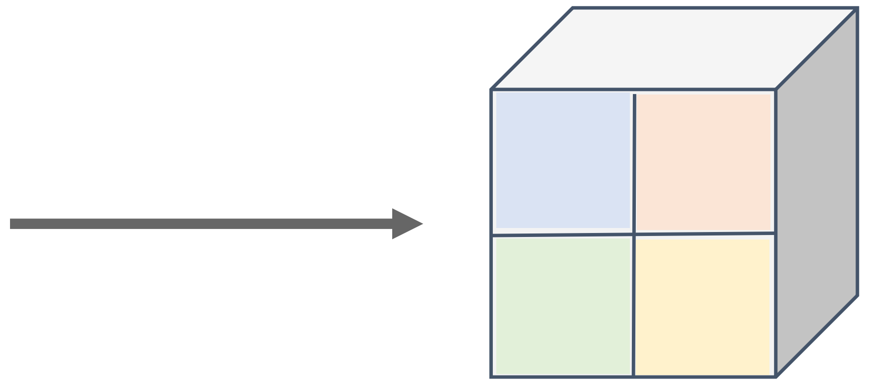


Input Image
(e.g. 3 x 640 x 480)

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

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

After sampling, max-pool in each subregion

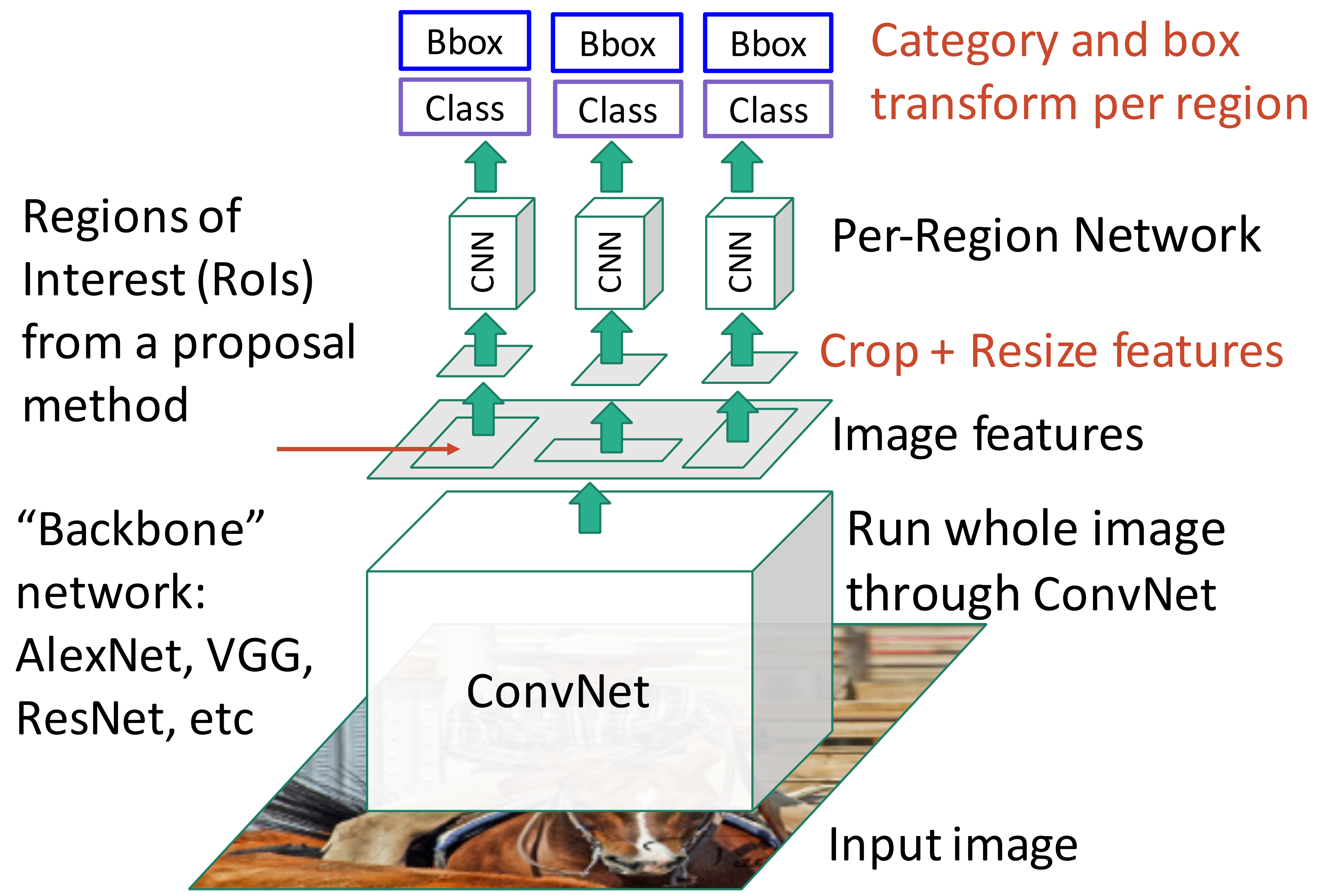


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

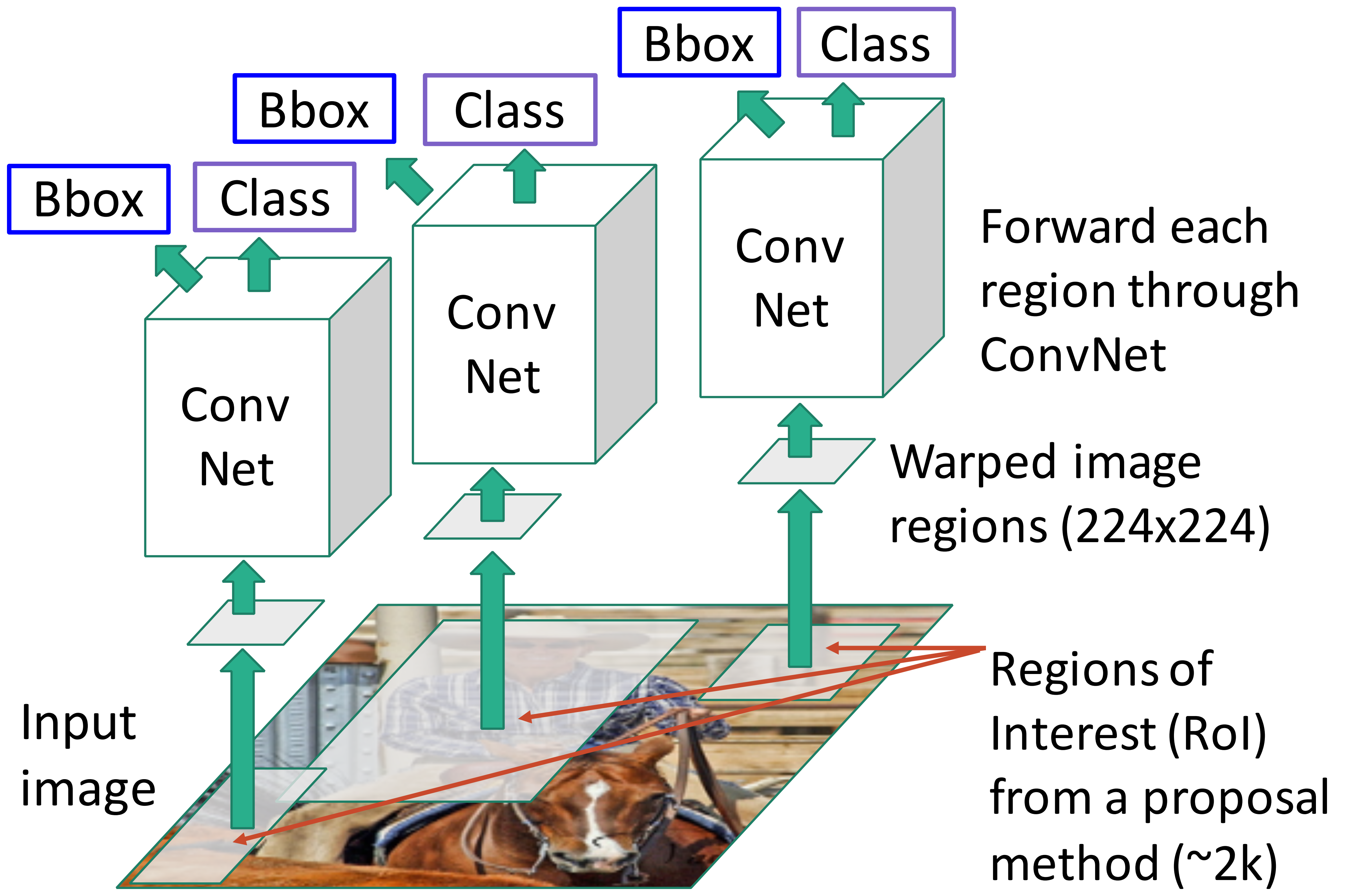
He et al, "Mask R-CNN", ICCV 2017

Fast R-CNN vs "Slow" R-CNN

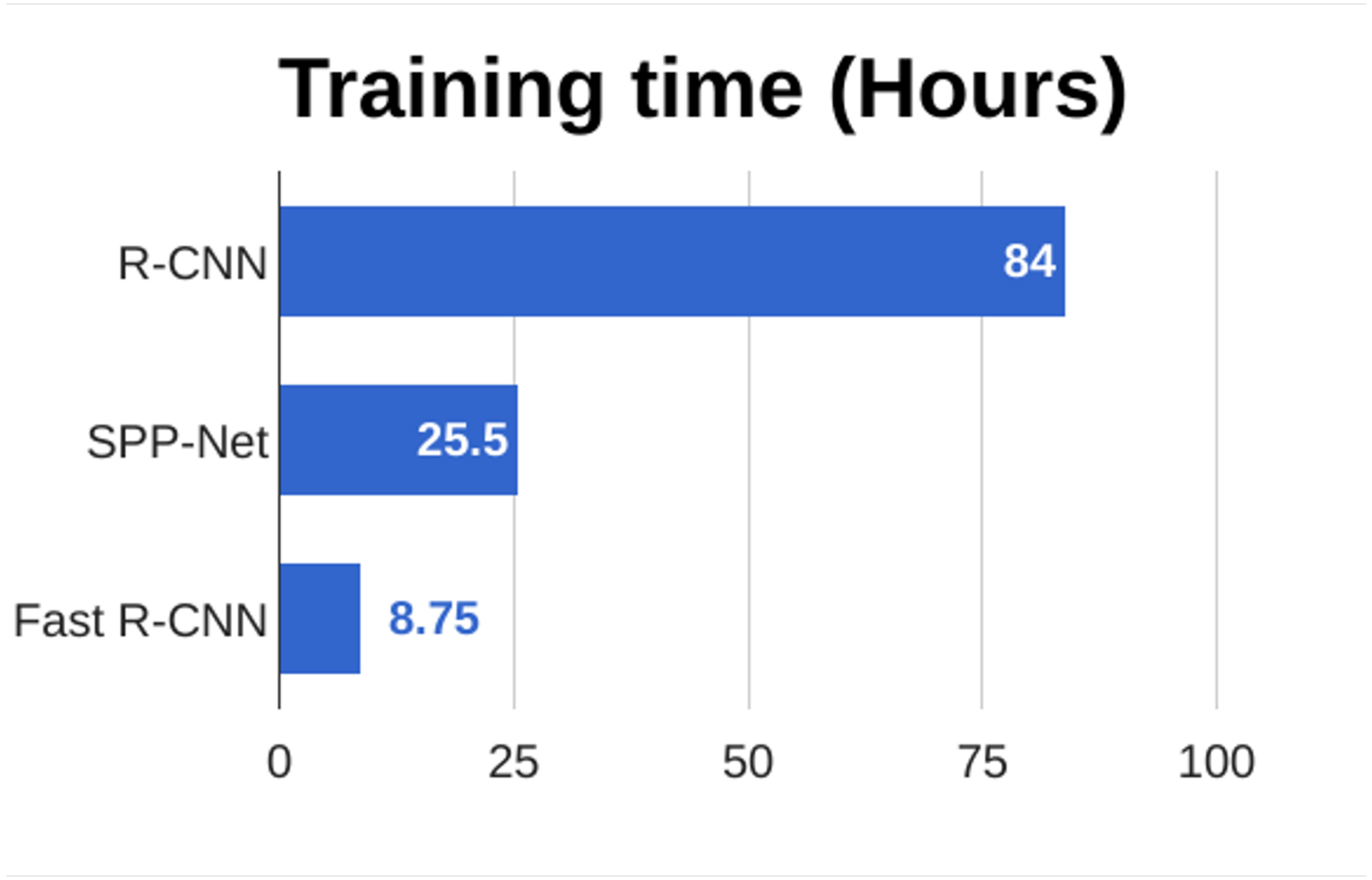
Fast R-CNN: Apply differentiable cropping to shared image features

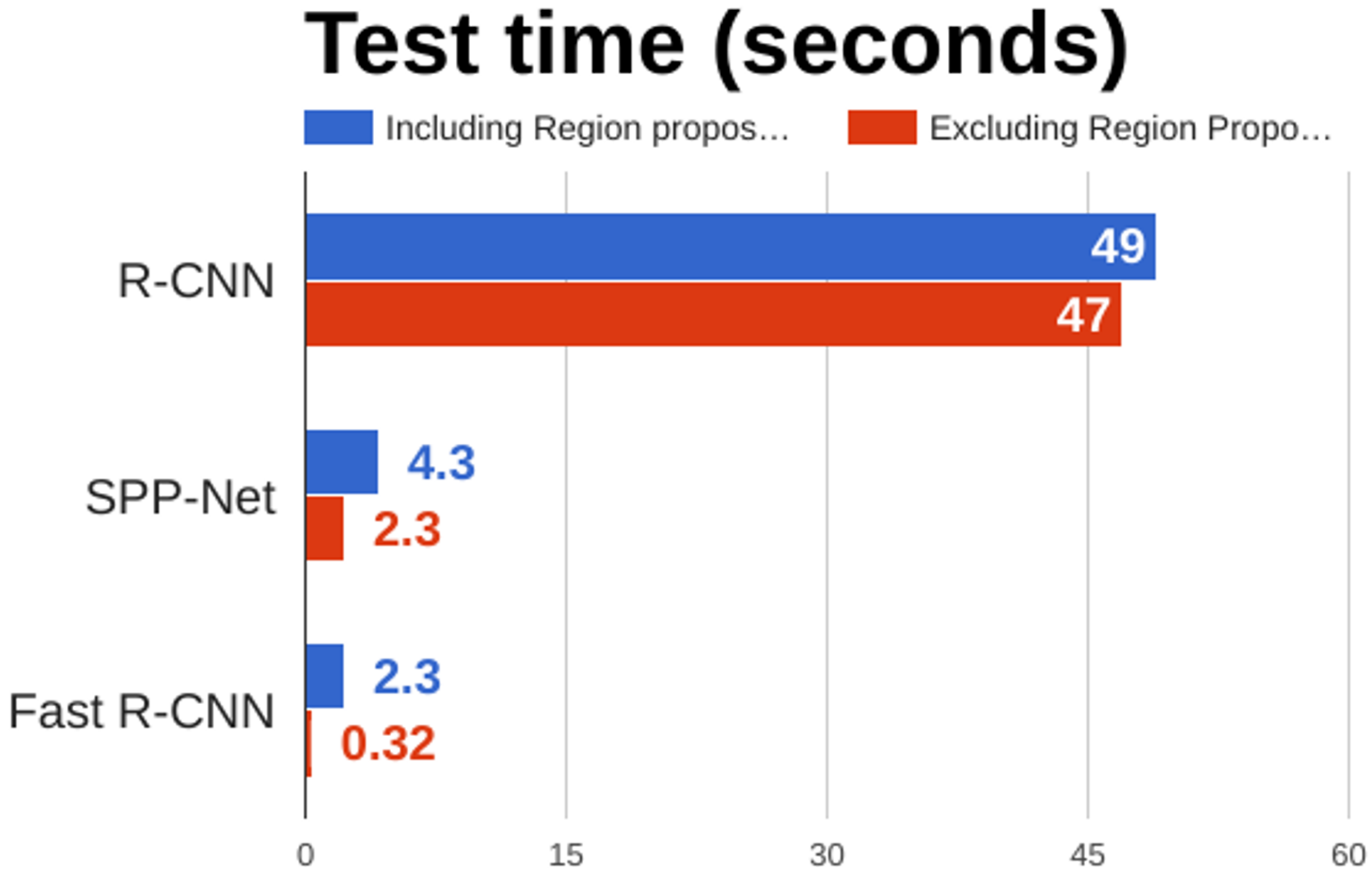


"Slow" R-CNN: Apply differentiable cropping to shared image features



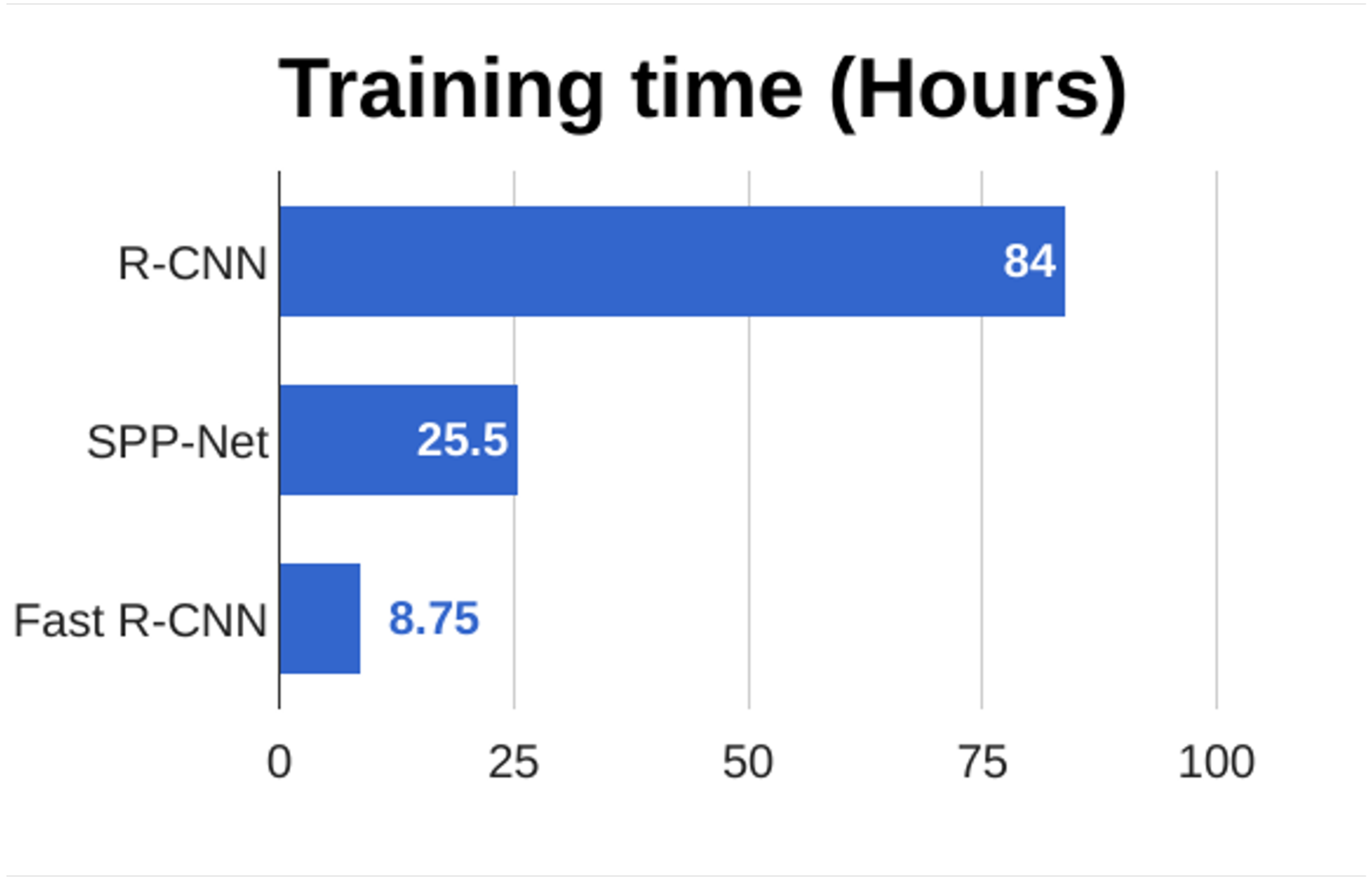
Fast R-CNN vs “Slow” R-CNN

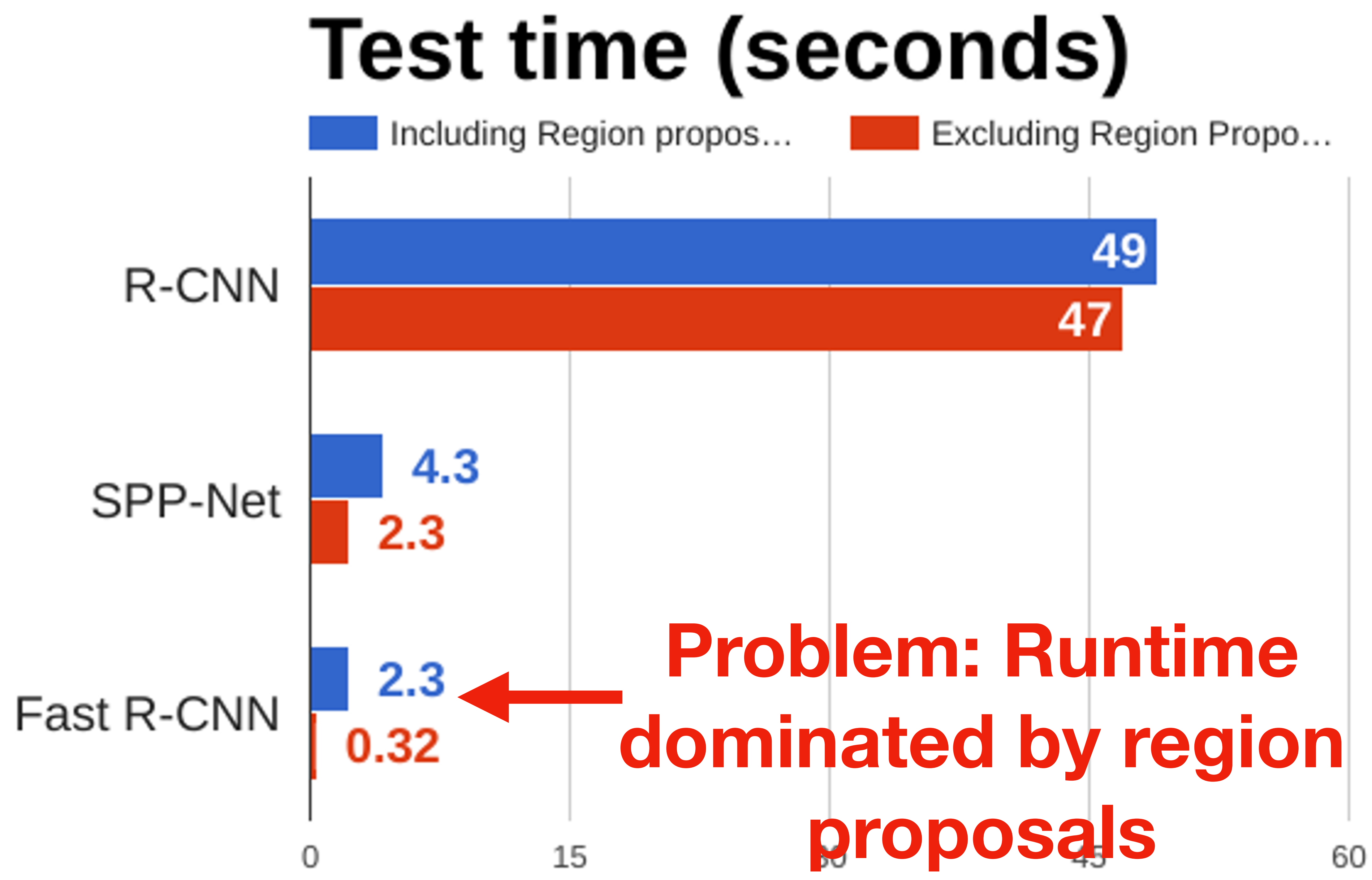




Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

Fast R-CNN vs “Slow” R-CNN

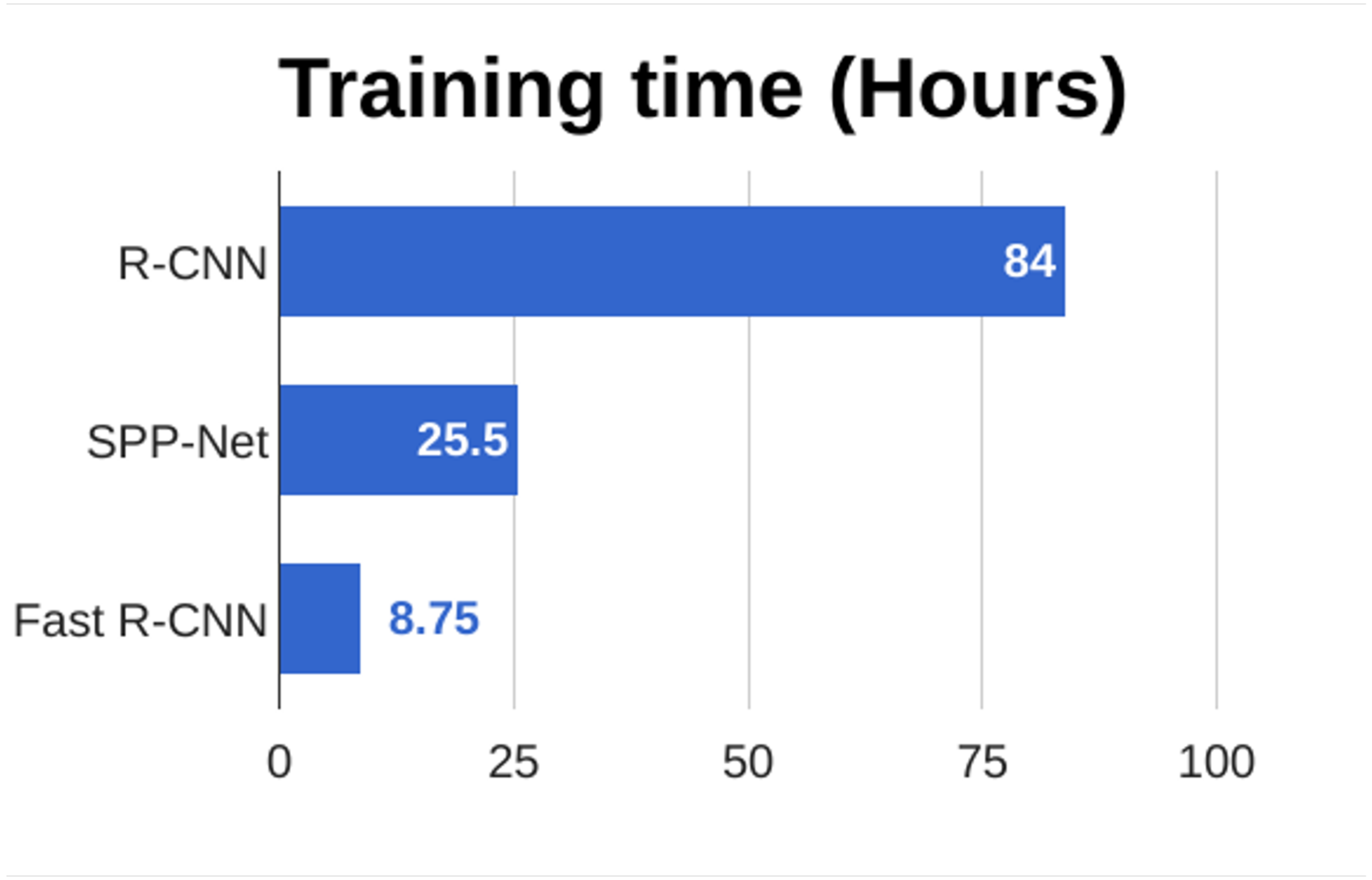


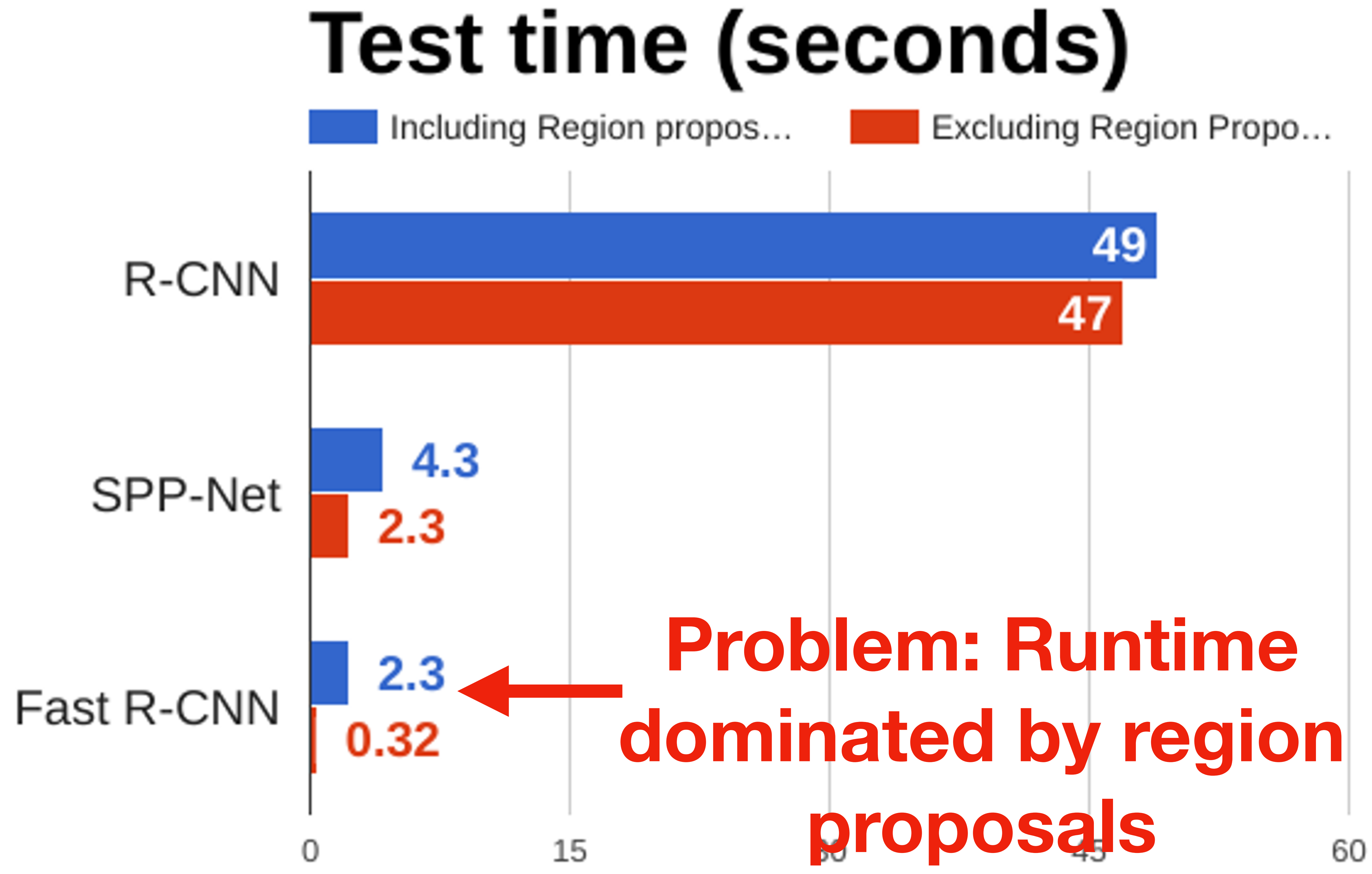


Problem: Runtime dominated by region proposals

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

Fast R-CNN vs "Slow" R-CNN





Problem: Runtime dominated by region proposals

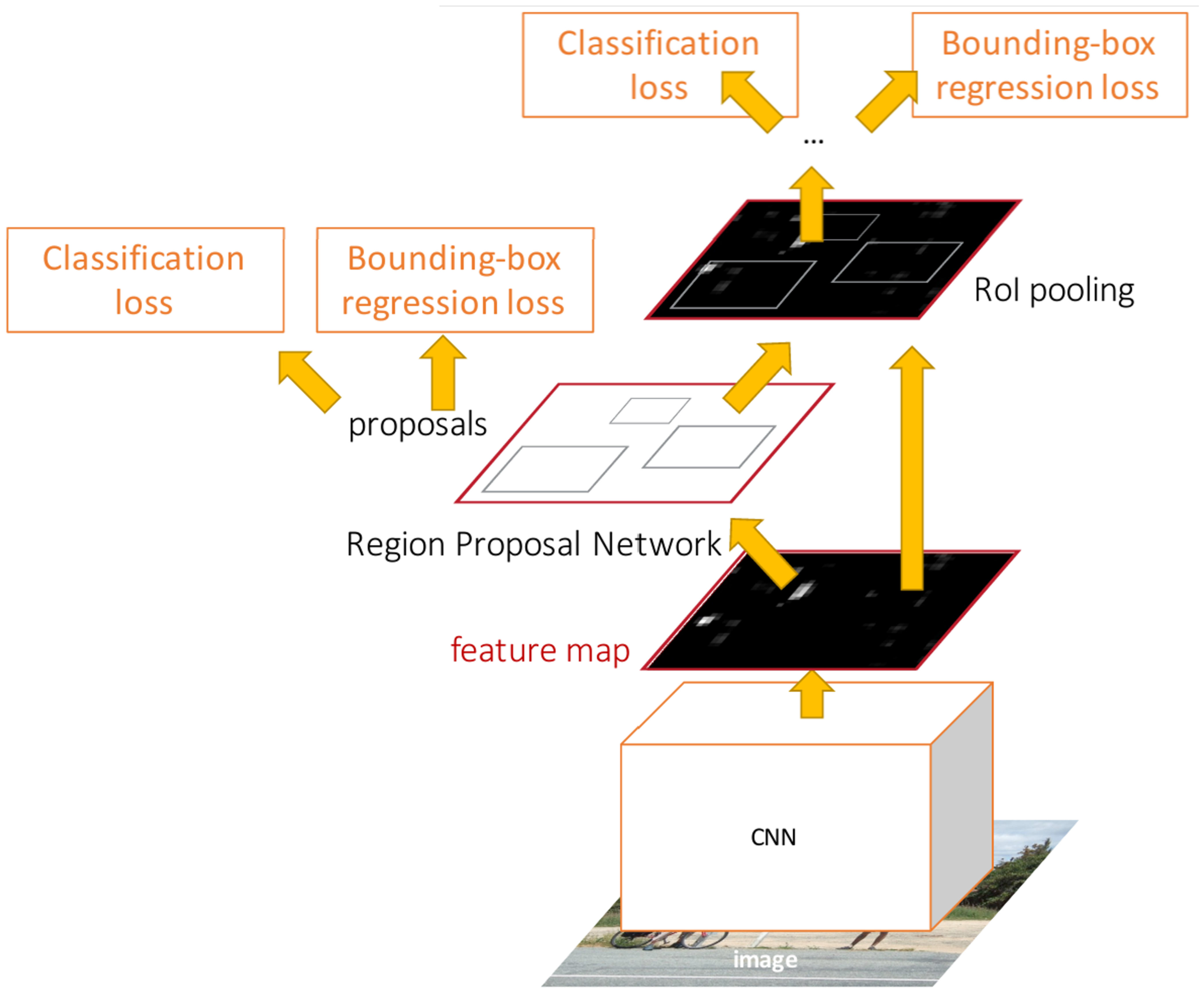
Recall: Region proposals computed by heuristic "Selective search" algorithm on CPU — let's learn them with a CNN

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

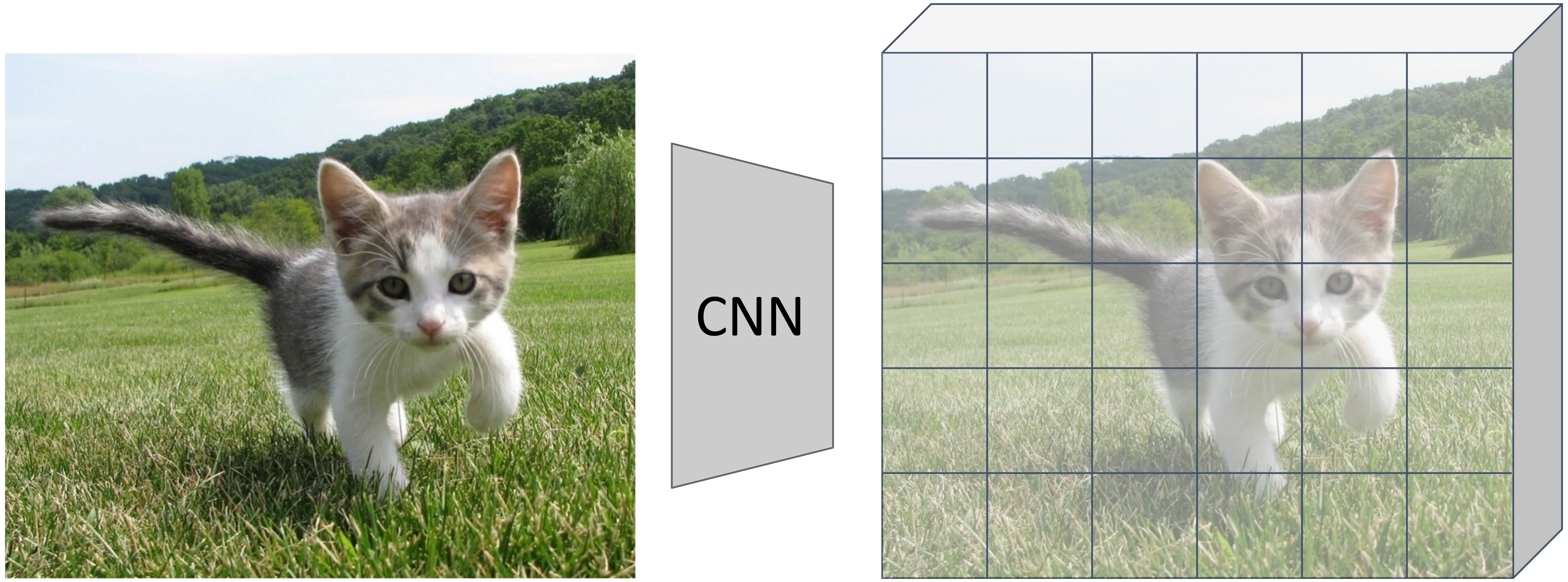
Otherwise same as Fast R-CNN: Crop features for each proposal, classify each one



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



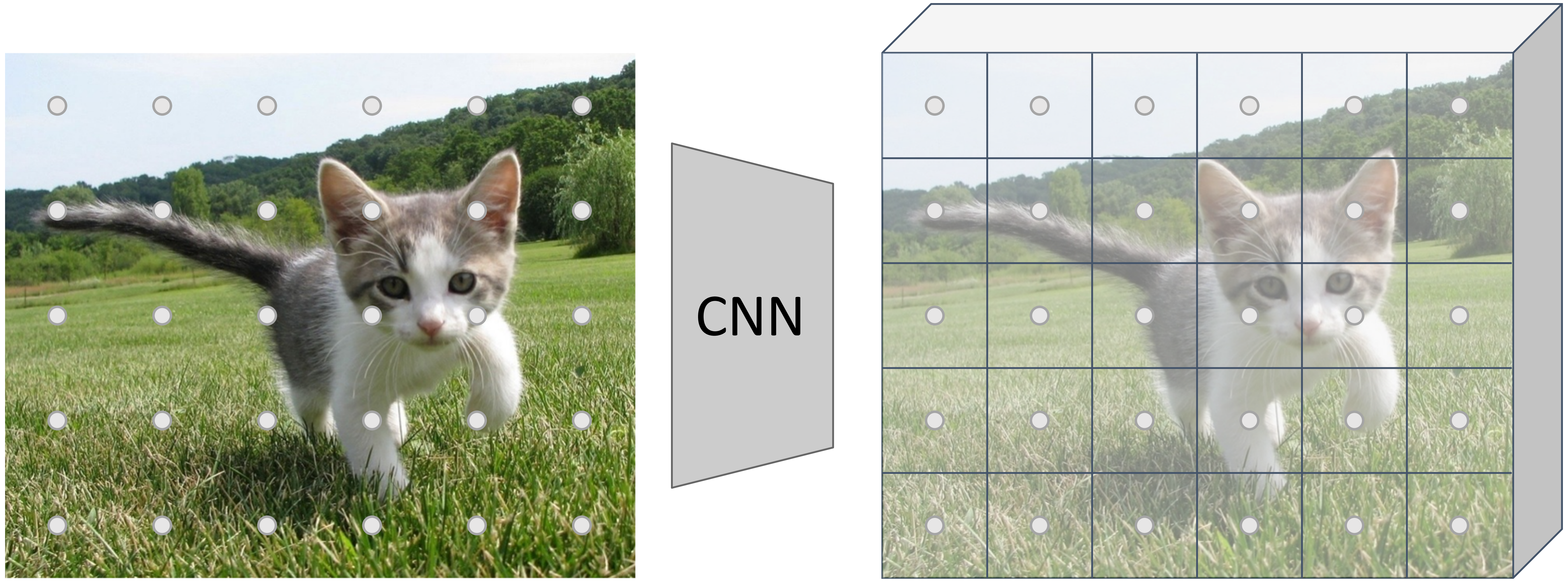
Input Image
(e.g. 3 x 640 x 480)

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

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
(e.g. 3 x 640 x 480)

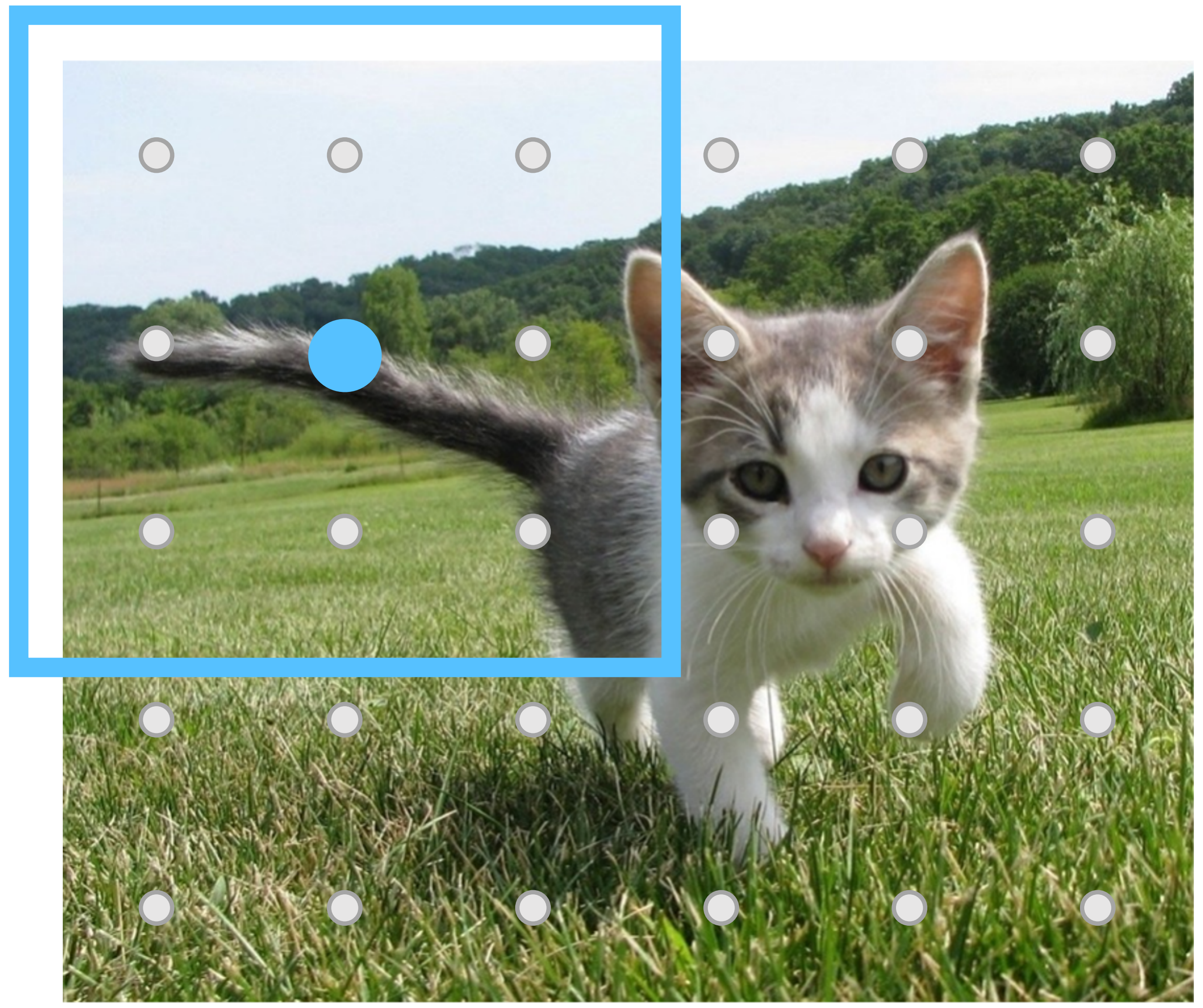
Image features
(e.g. 512 x 5 x 6)

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

Each feature corresponds to a point in the input



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

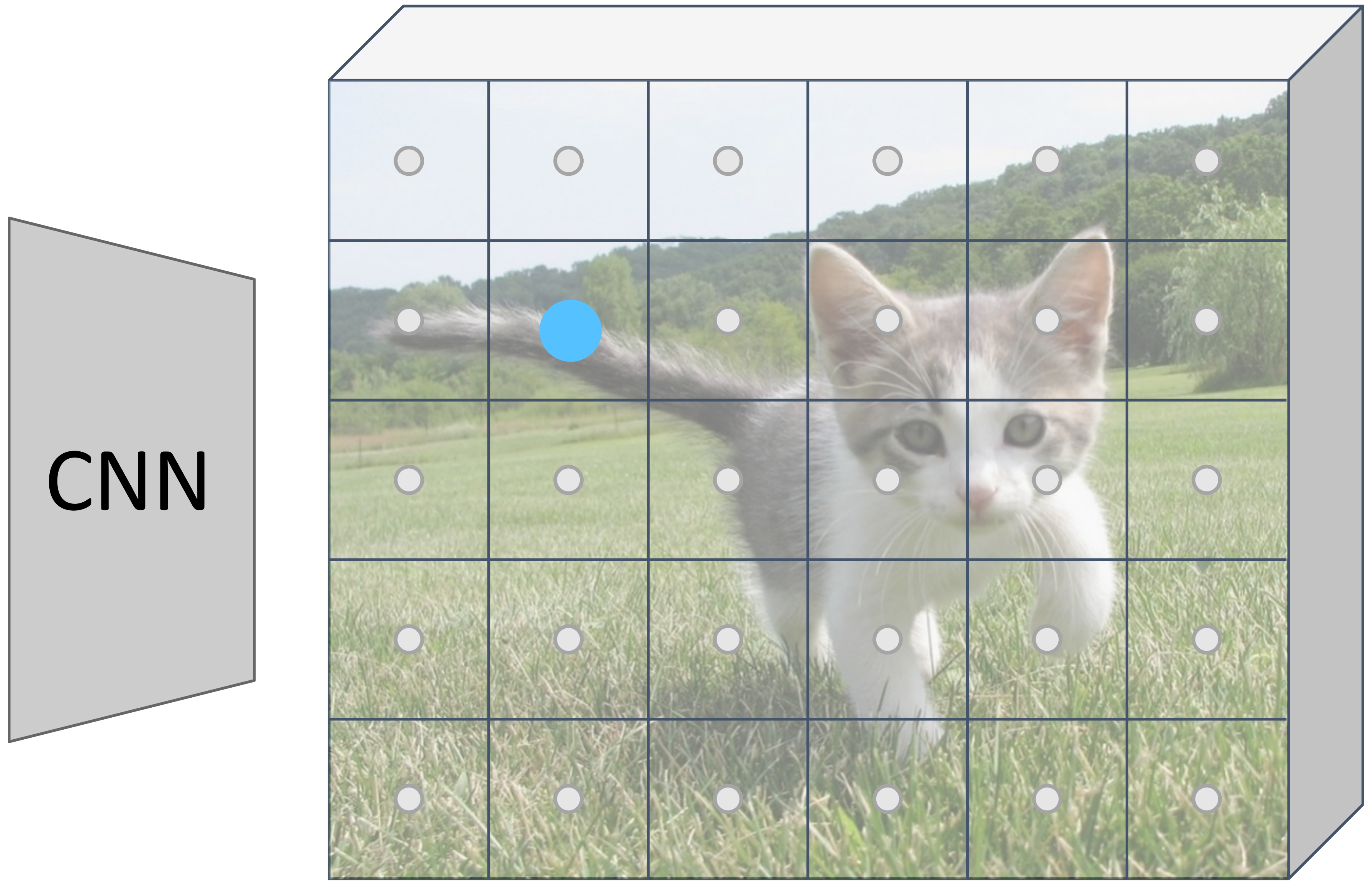


Image features
(e.g. 512 x 5 x 6)

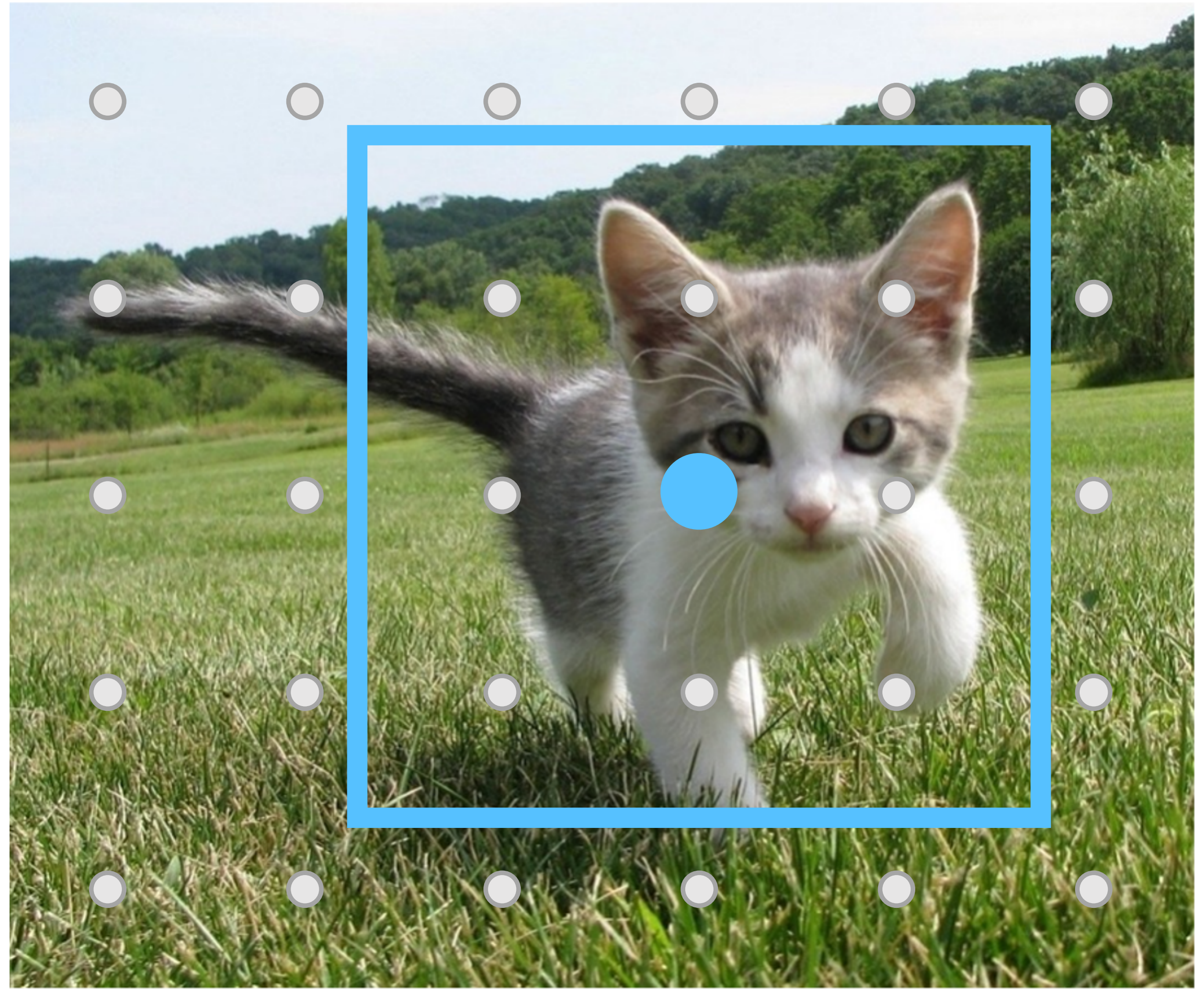
Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

Region Proposal Network (RPN)

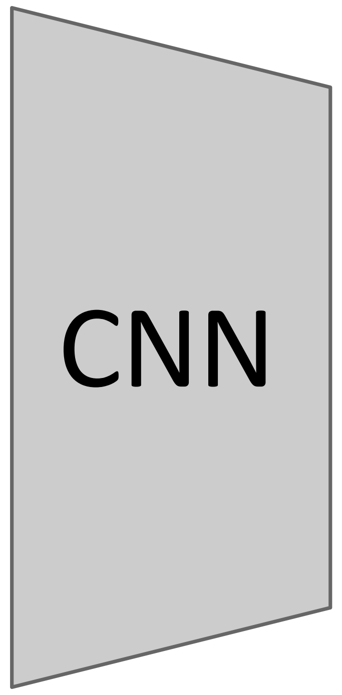
Imagine an **anchor box** of fixed size at each point in the feature map

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input



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



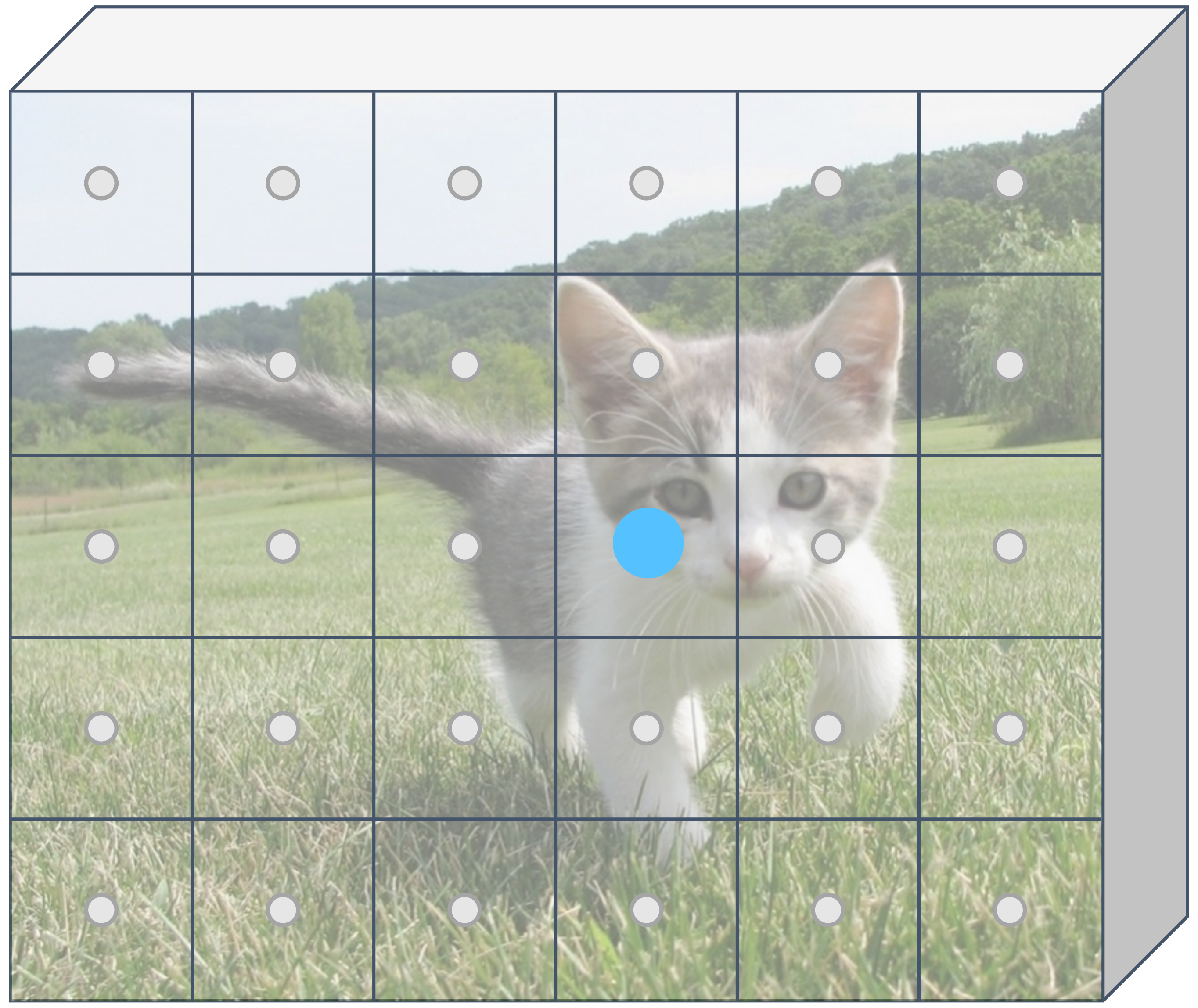


Image features
(e.g. 512 x 5 x 6)

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

Region Proposal Network (RPN)

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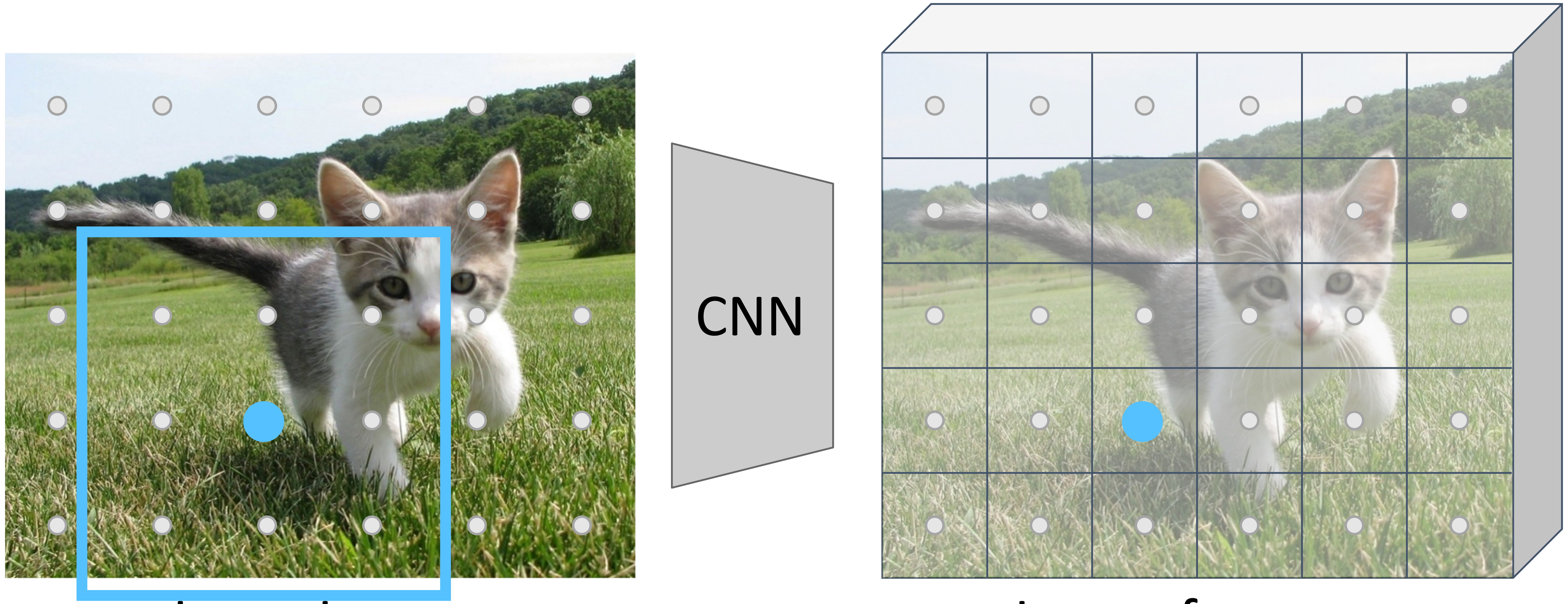

Input Image
(e.g. 3 x 640 x 480)

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)

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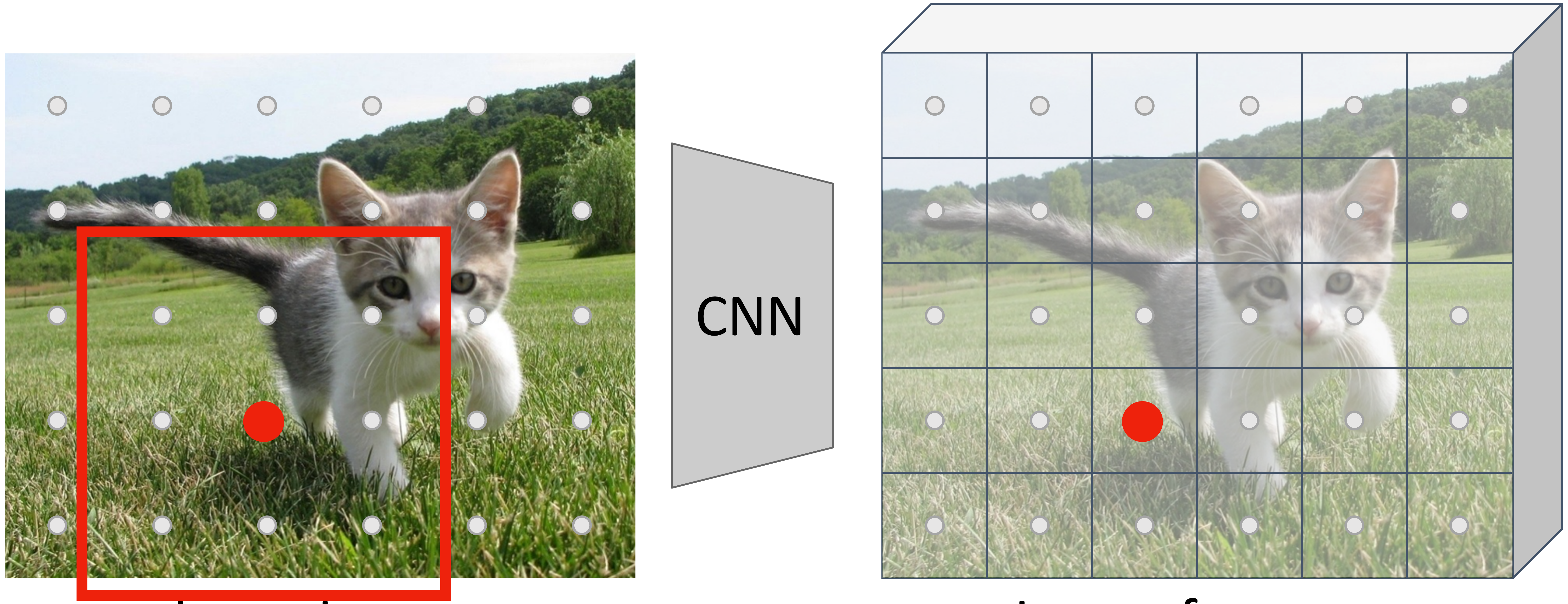


Input Image
(e.g. 3 x 640 x 480)

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

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

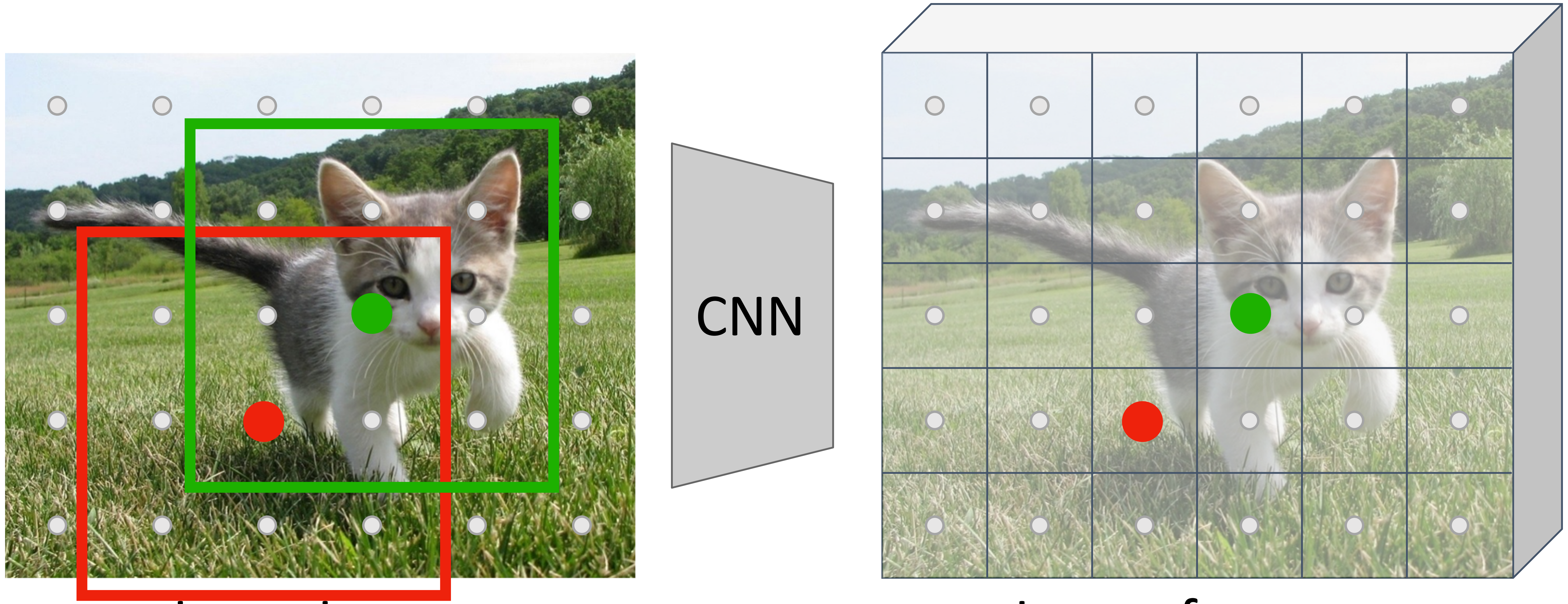
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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

Each feature corresponds to a point in the input



Input Image
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Image features
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Classify each anchor as positive (object) or negative (no object)

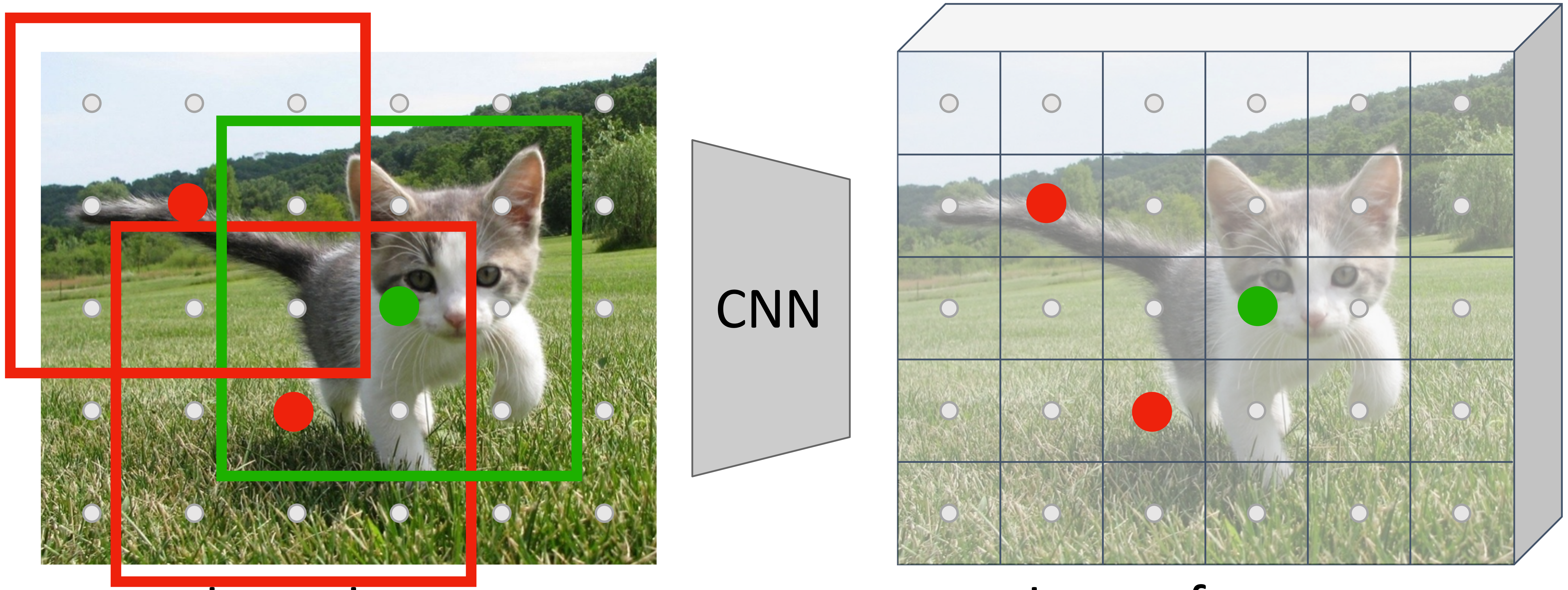
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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

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)

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

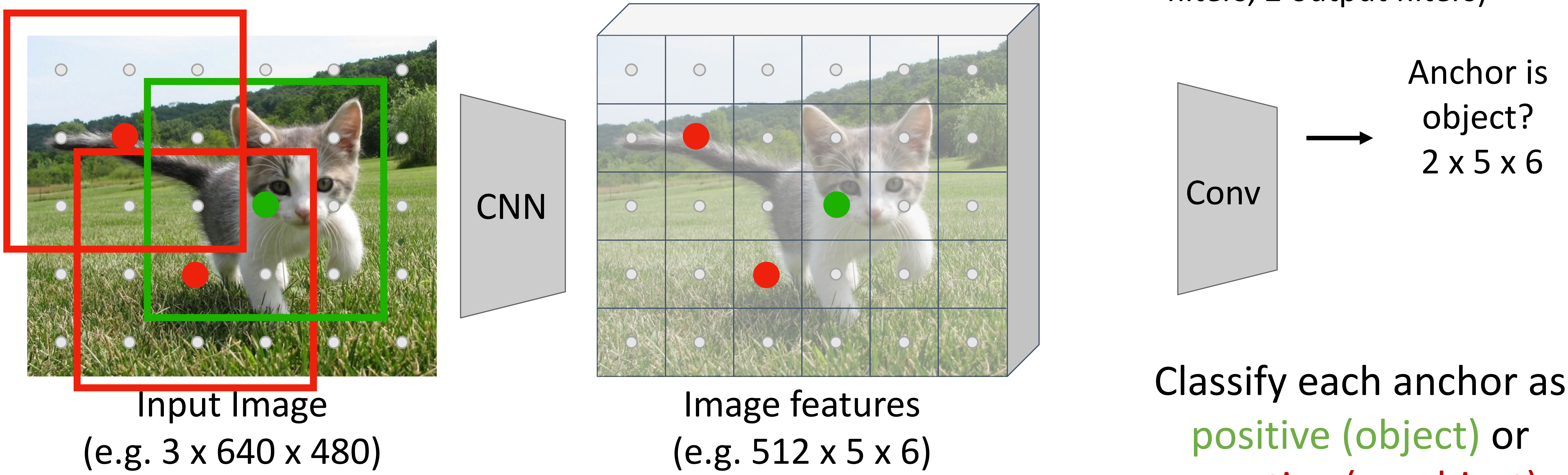
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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)



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

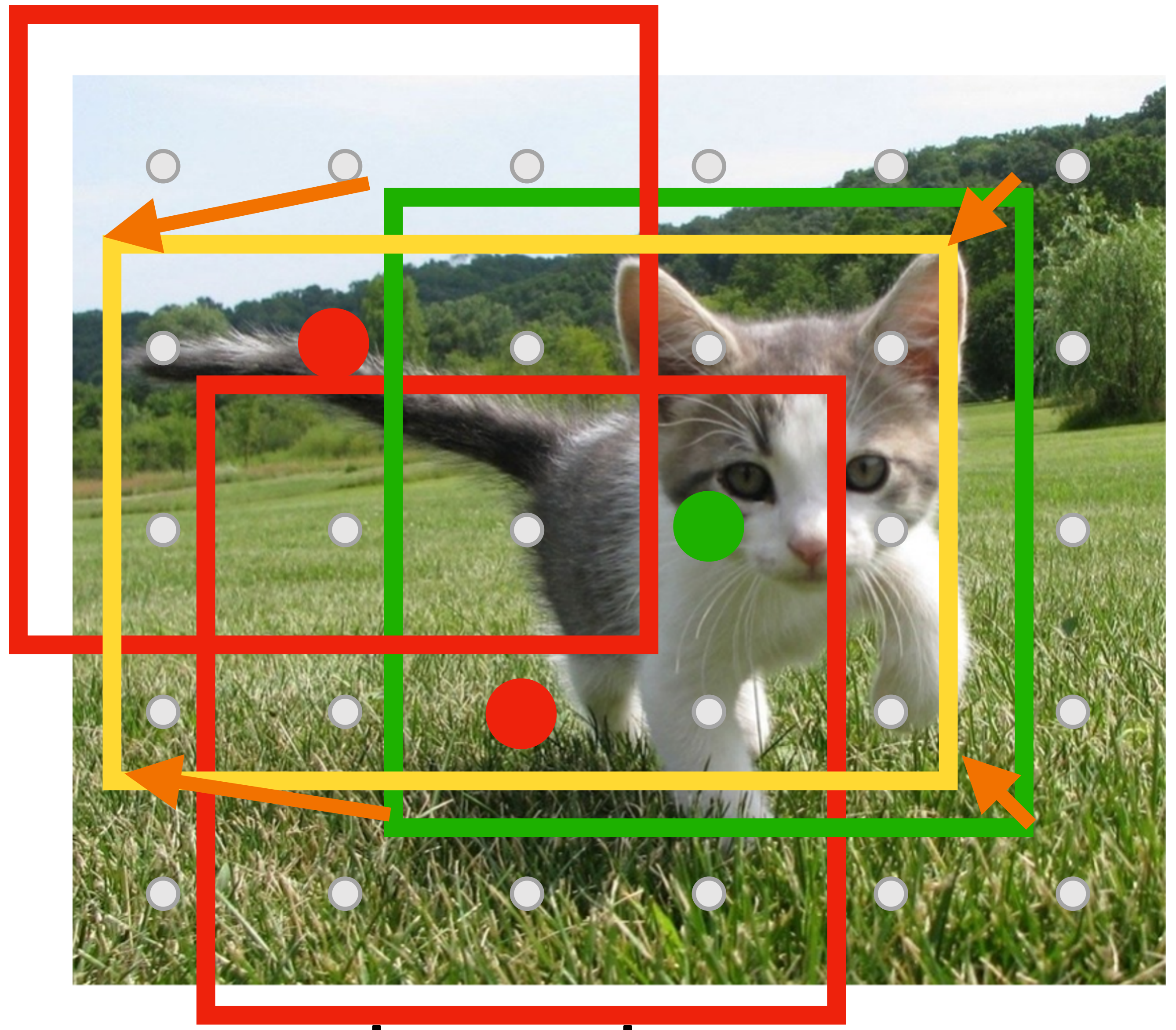
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network (RPN)

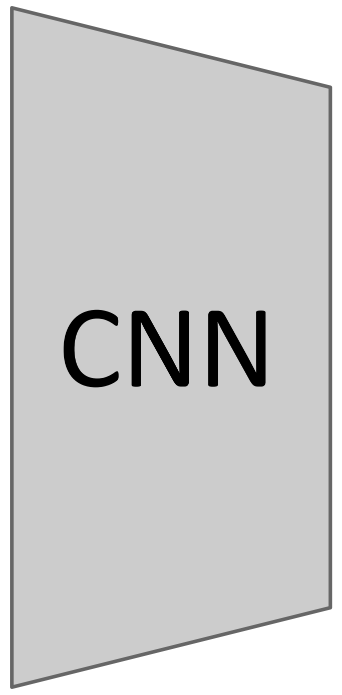
For positive anchors, also predict a transform that converting the anchor to the GT box (like R-CNN)

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)



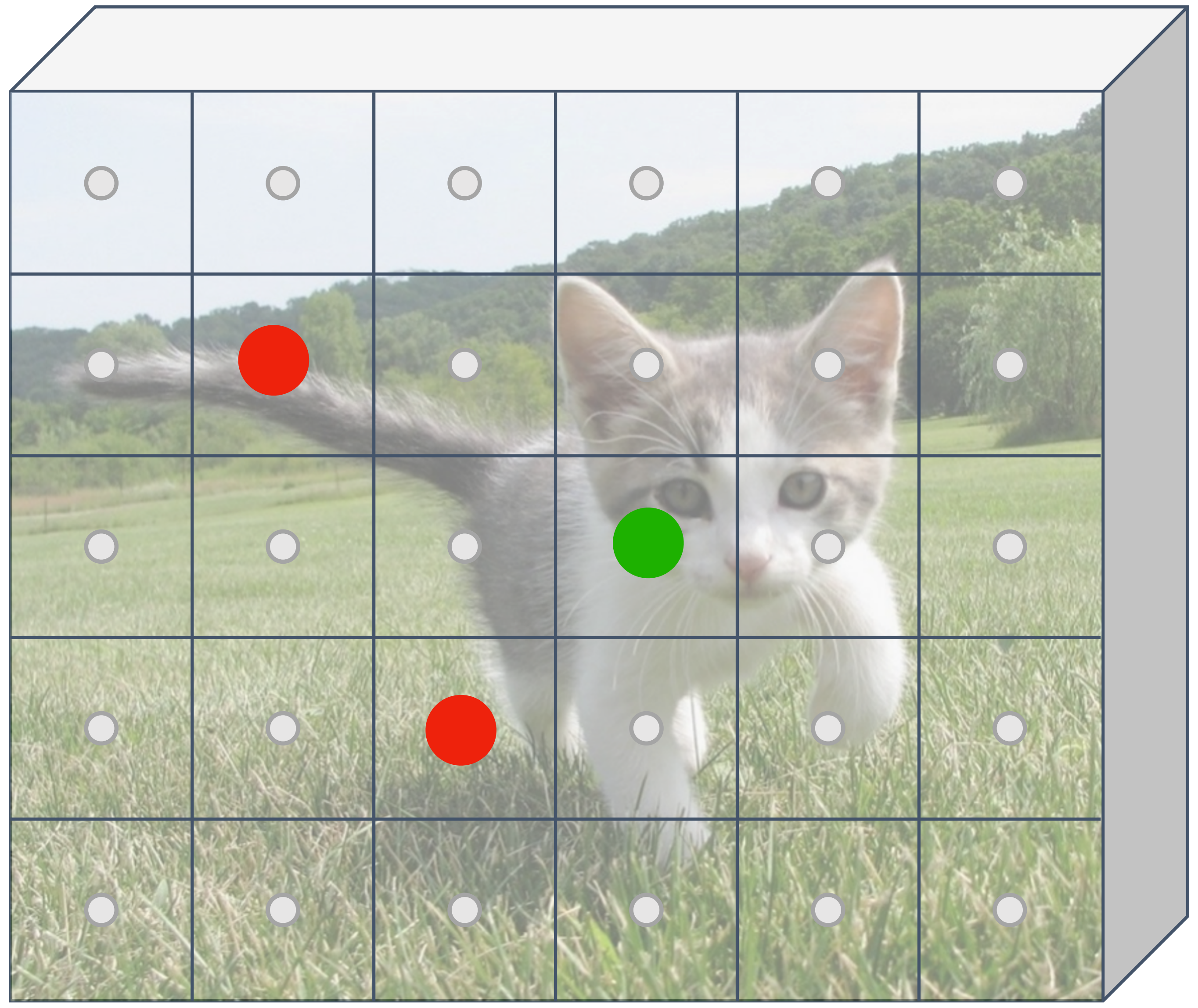
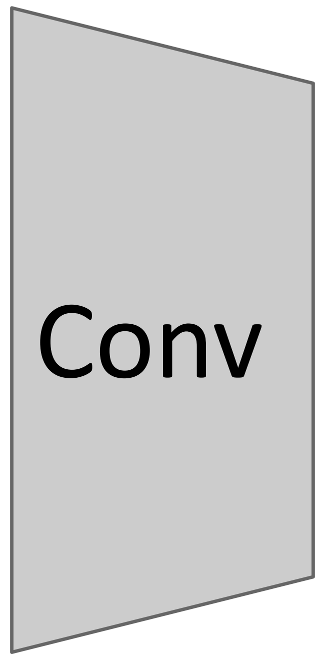


Image features
(e.g. 512 x 5 x 6)



Anchor is object?
2 x 5 x 6

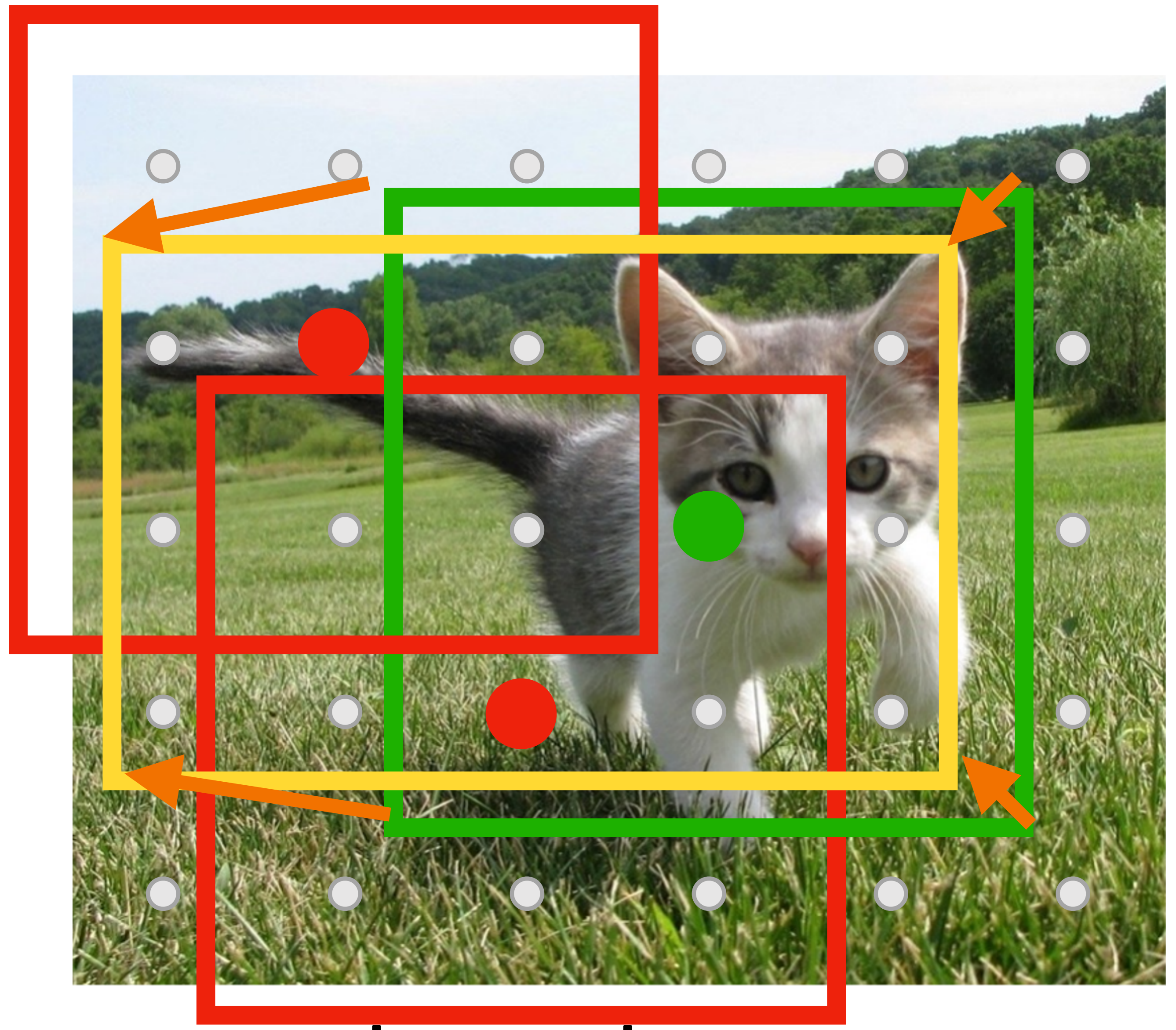
Classify each anchor as positive (object) or negative (no object)

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

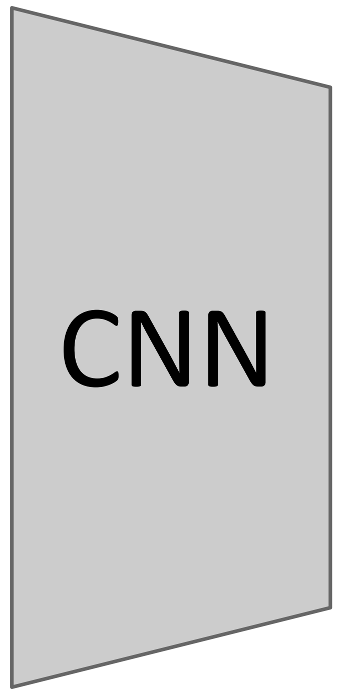
Region Proposal Network (RPN)

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

Run backbone CNN to get features aligned to input image



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



Each feature corresponds to a point in the input

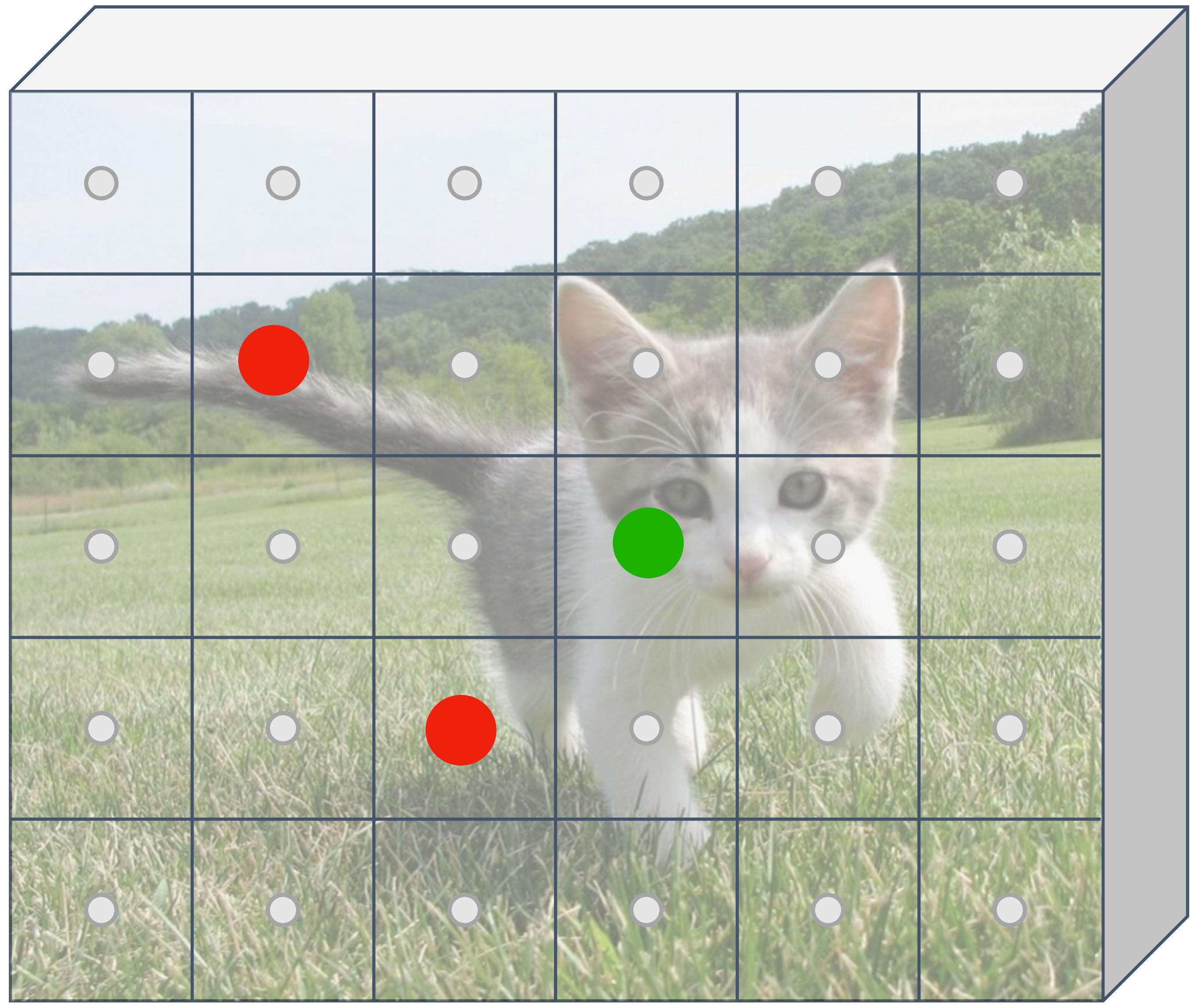
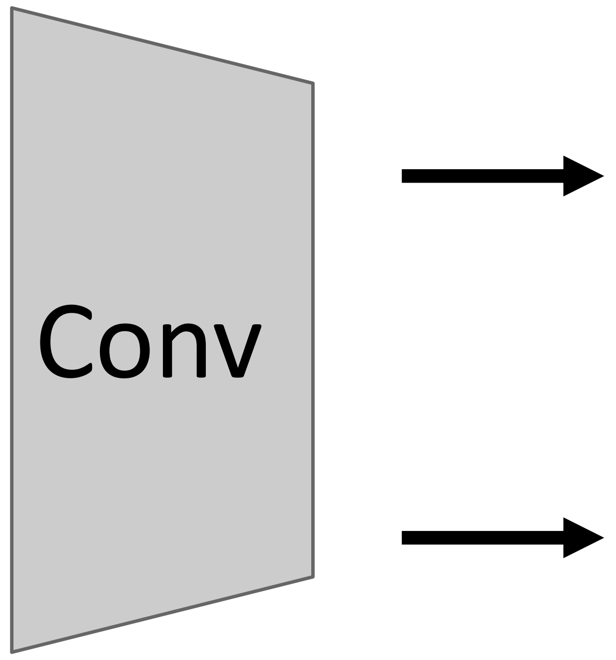


Image features
(e.g. 512 x 5 x 6)



Anchor is object?
2 x 5 x 6

Anchor transforms
4 x 5 x 6

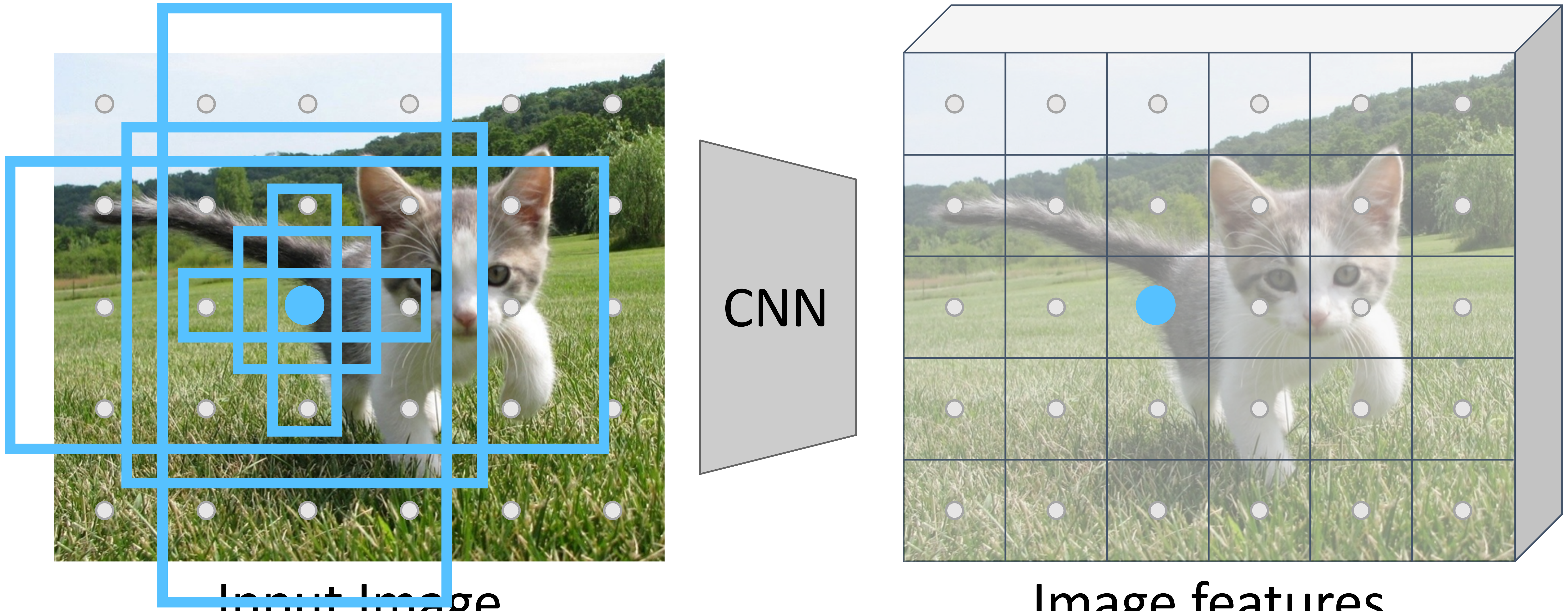
Classify each anchor as positive (object) or negative (no object)

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

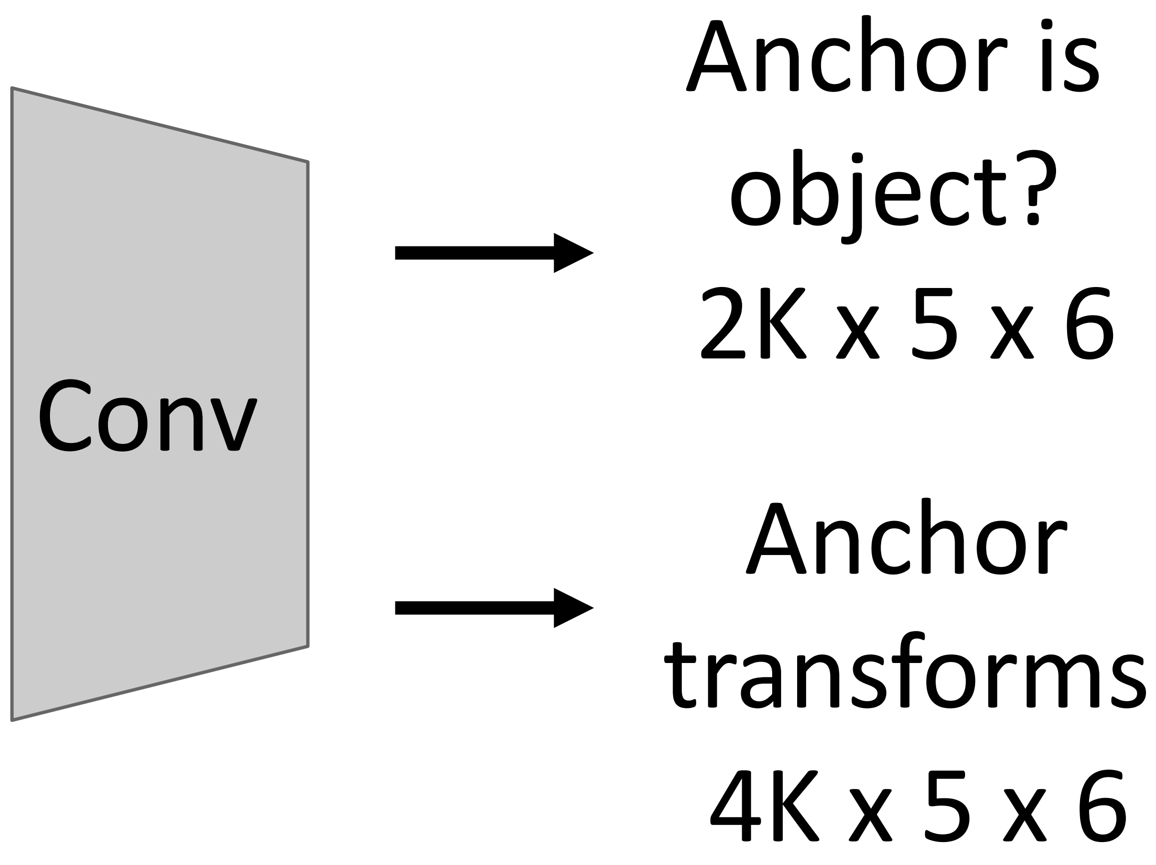
Each feature corresponds to a point in the input

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



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

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

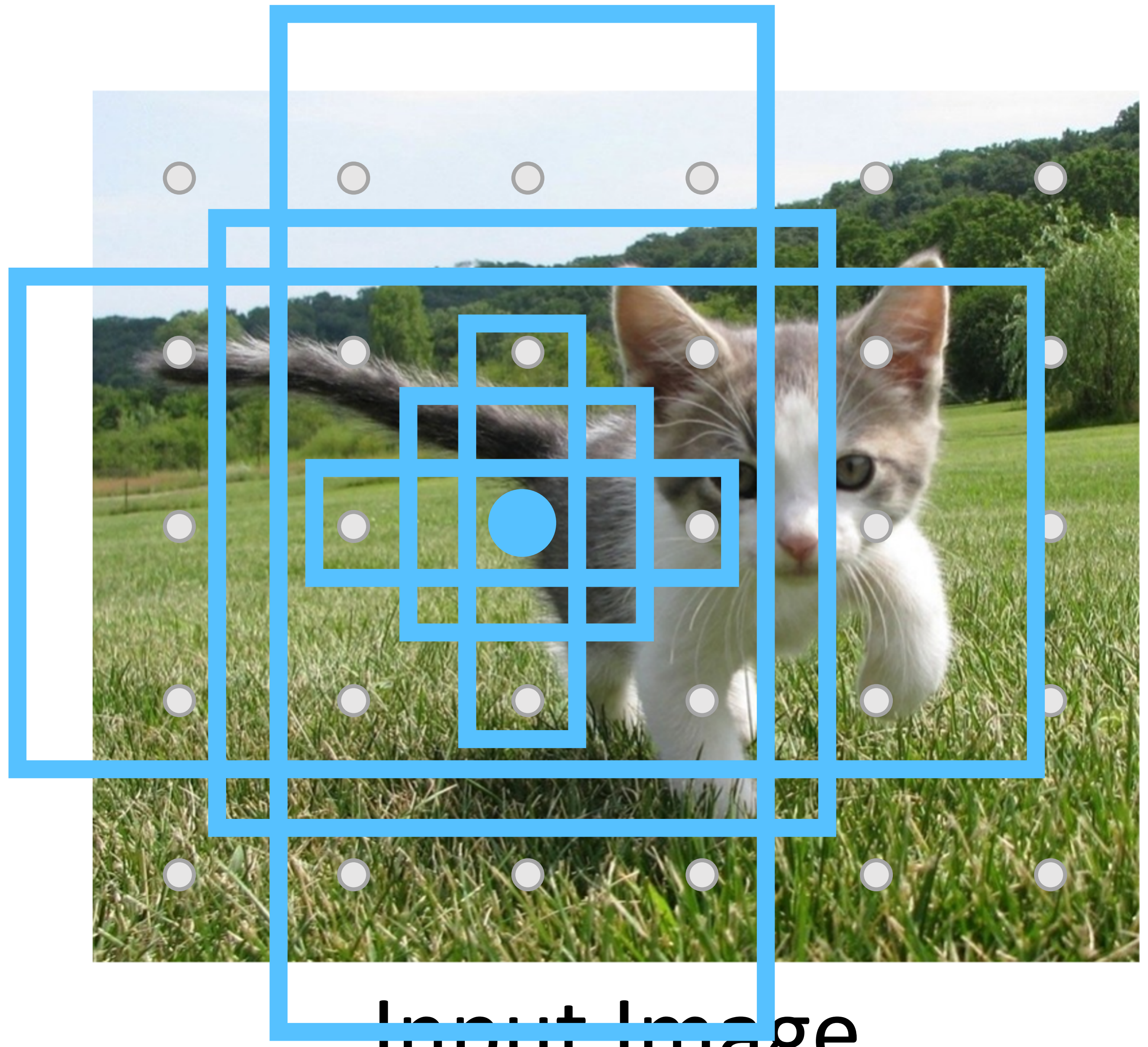


Region Proposal Network (RPN)

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
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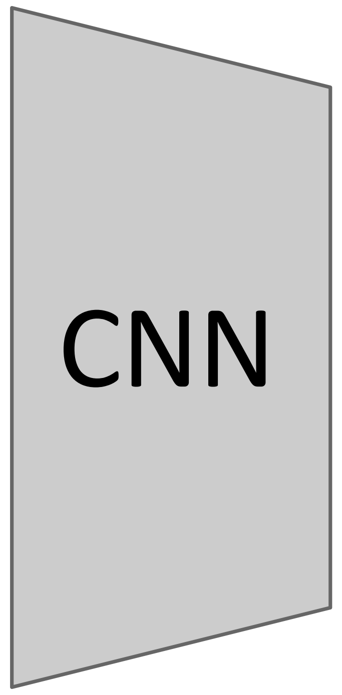
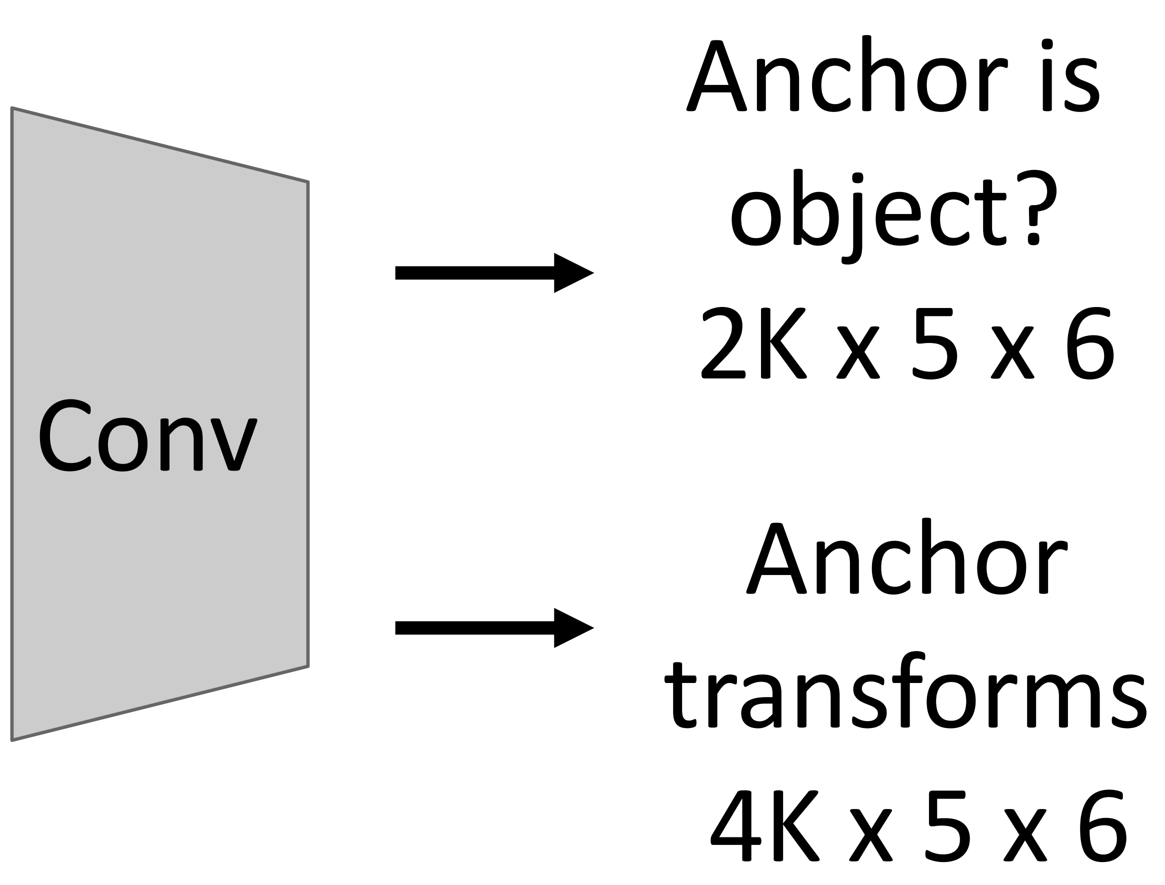


Image features
(e.g. 512 x 5 x 6)



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

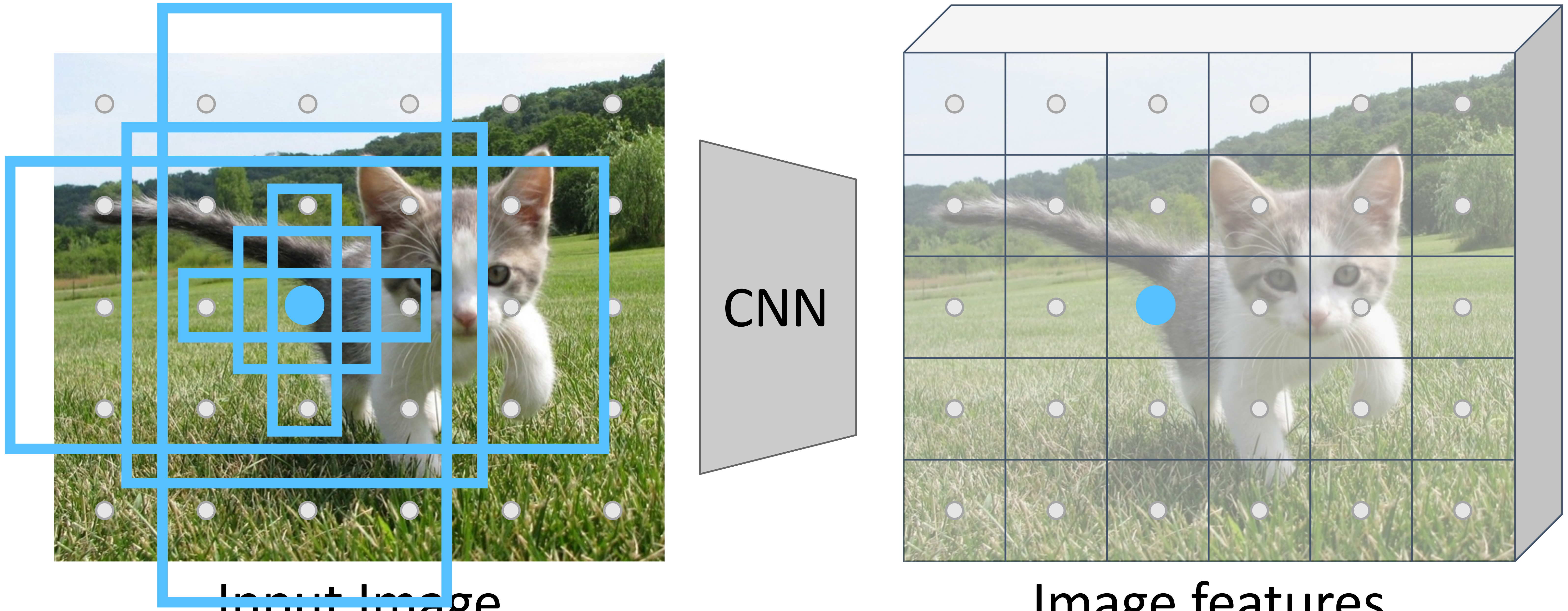
Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

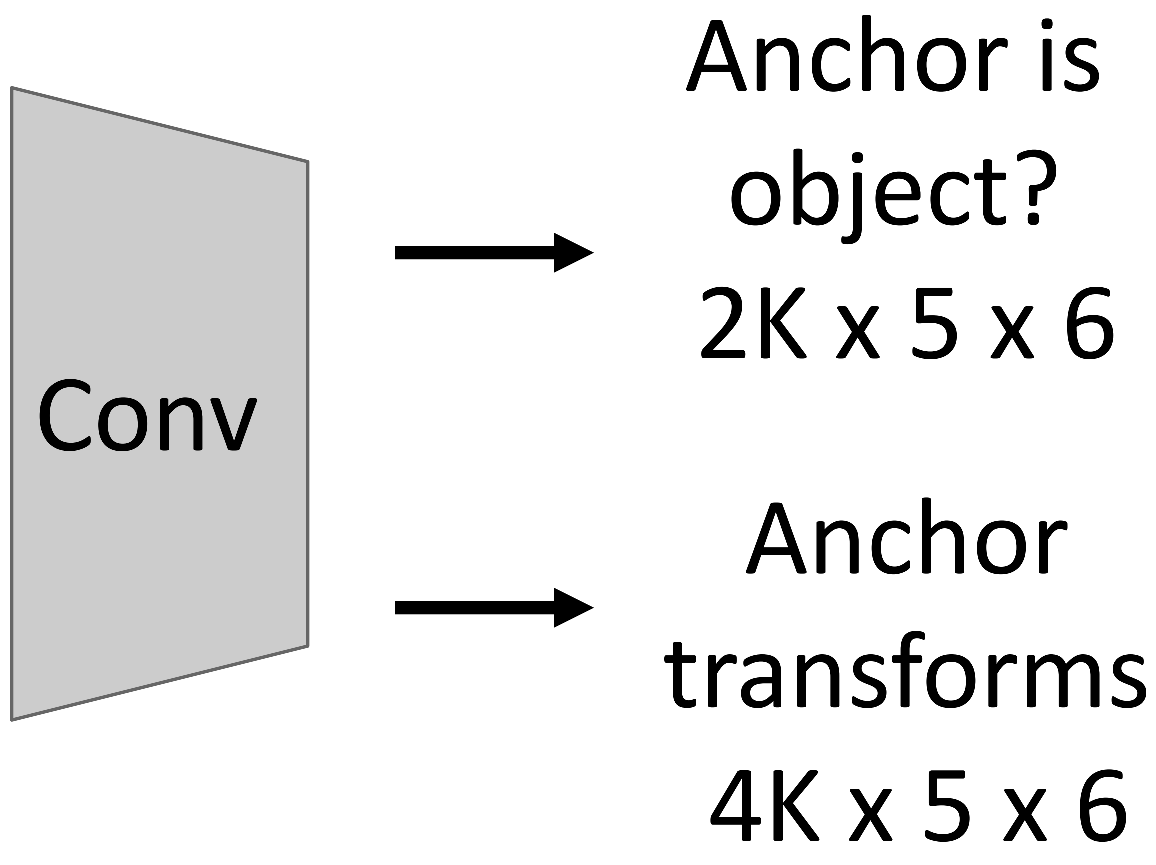
Each feature corresponds to a point in the input

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

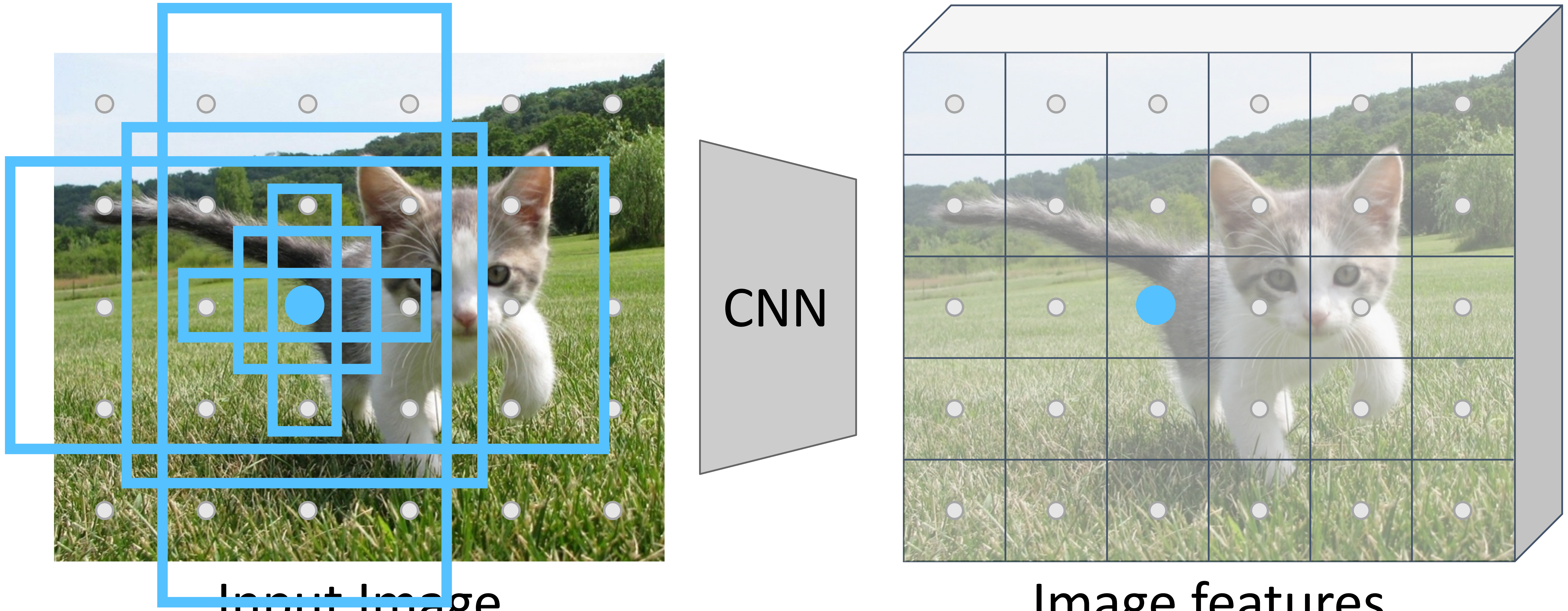
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

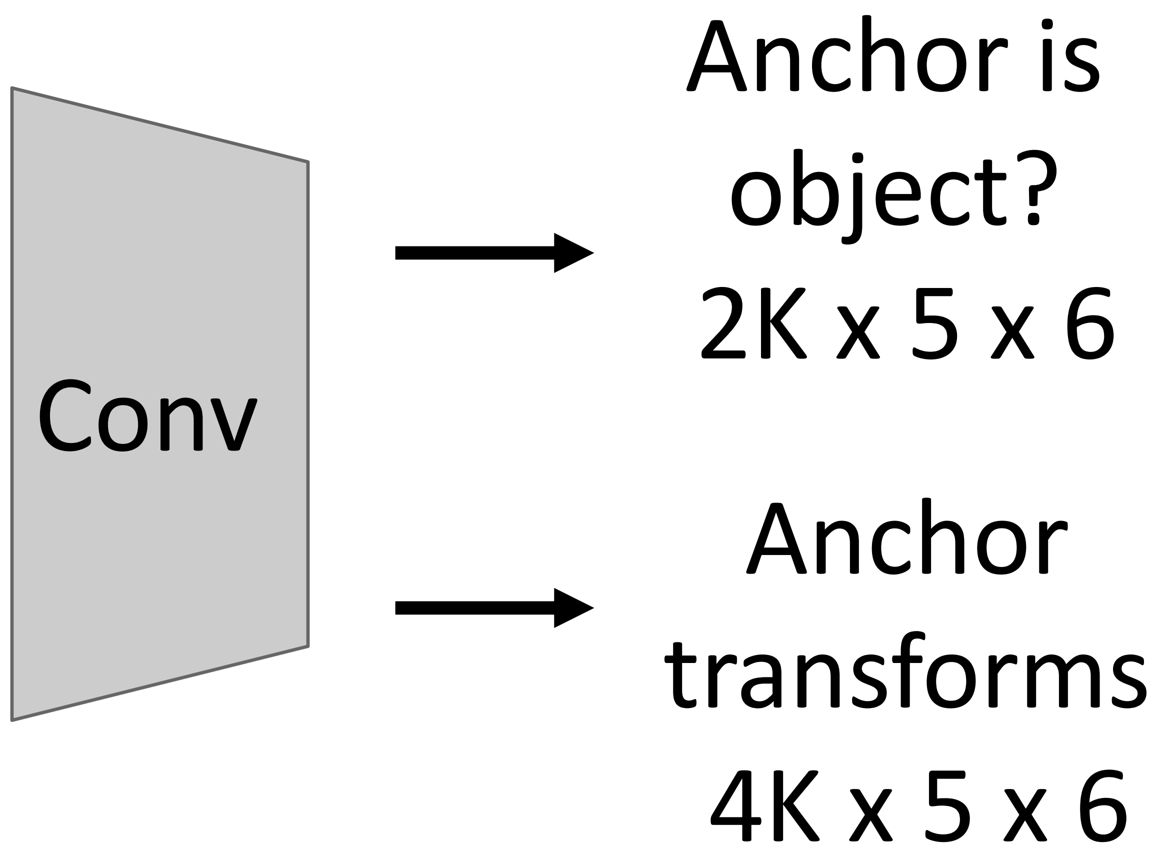
Each feature corresponds to a point in the input

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

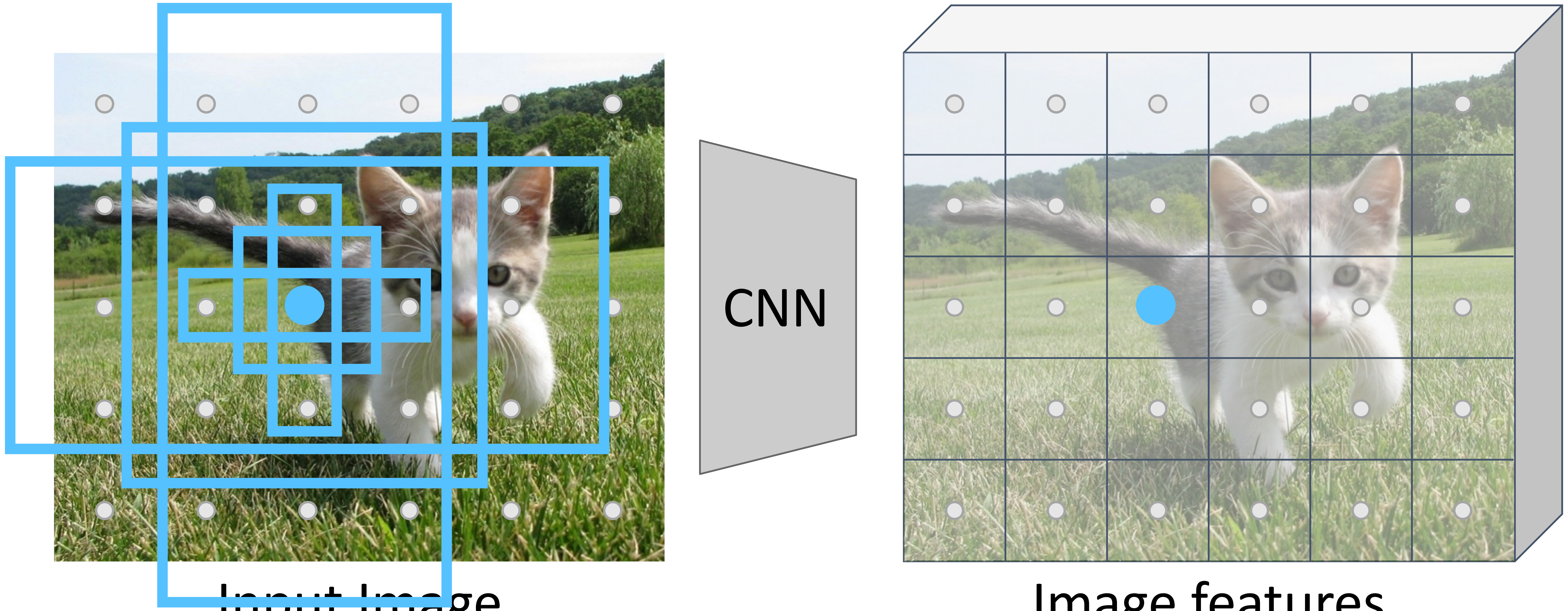
Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

Region Proposal Network (RPN)

Run backbone CNN to get features aligned to input image

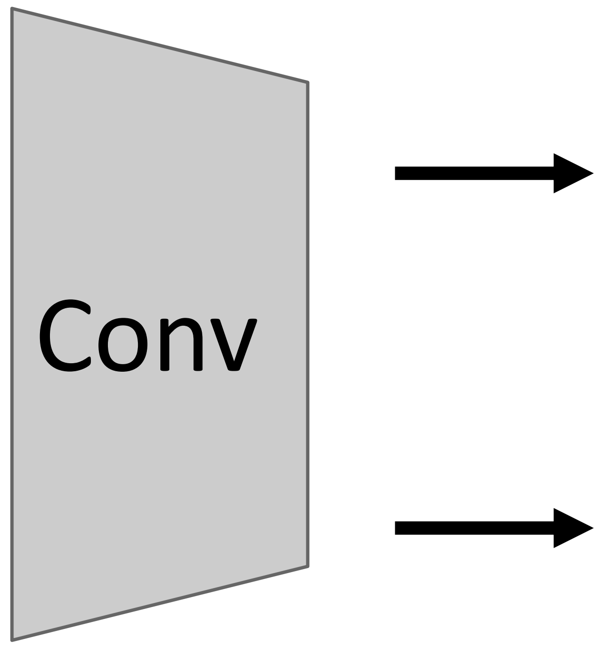
Each feature corresponds to a point in the input

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



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

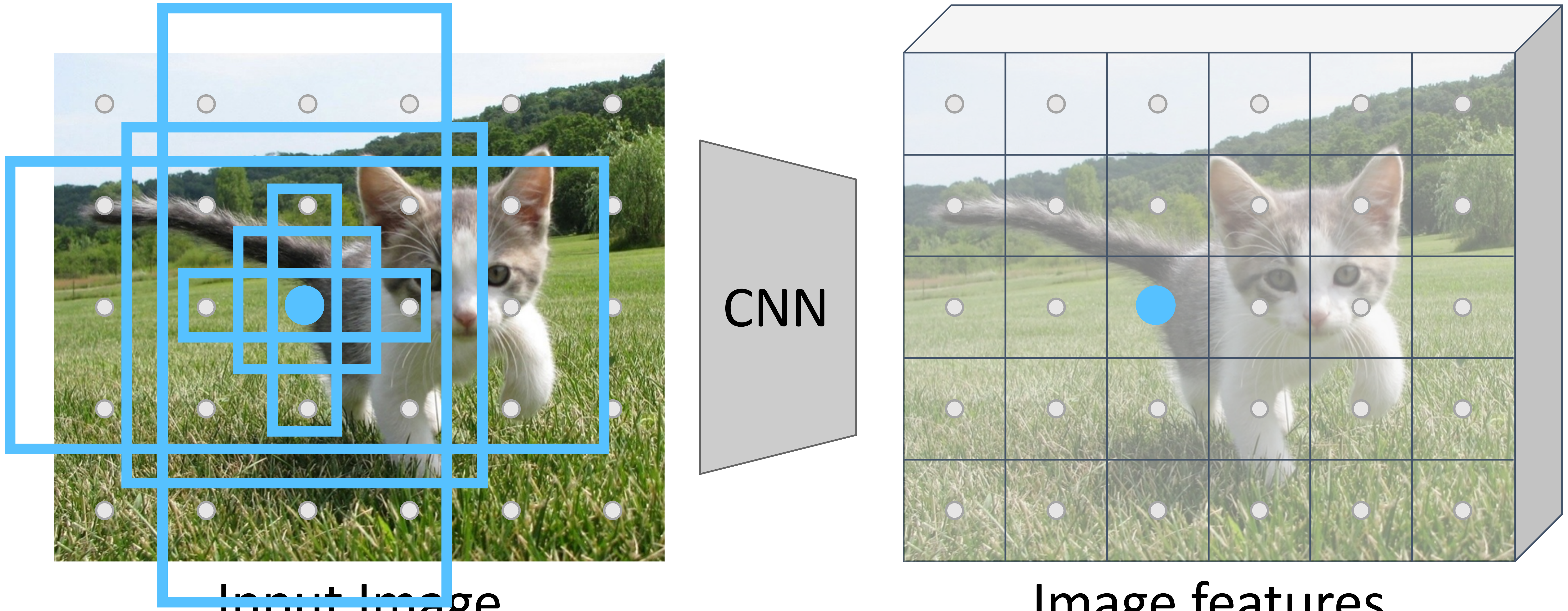
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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)

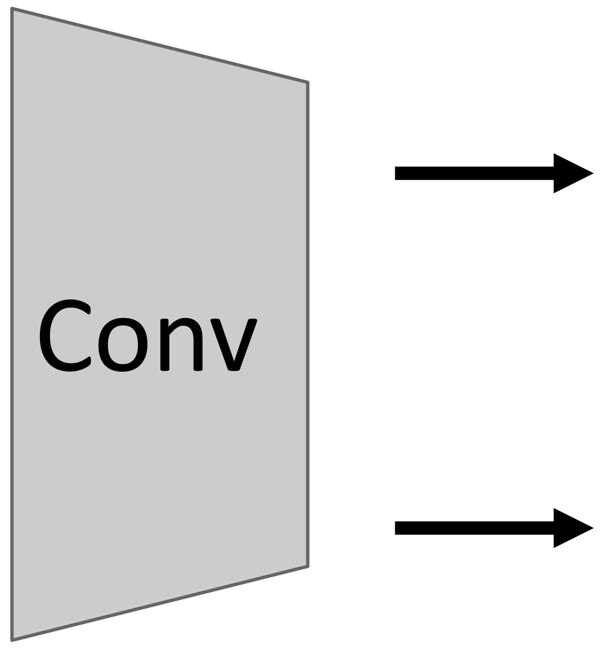
Run backbone CNN to get features aligned to input image

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)



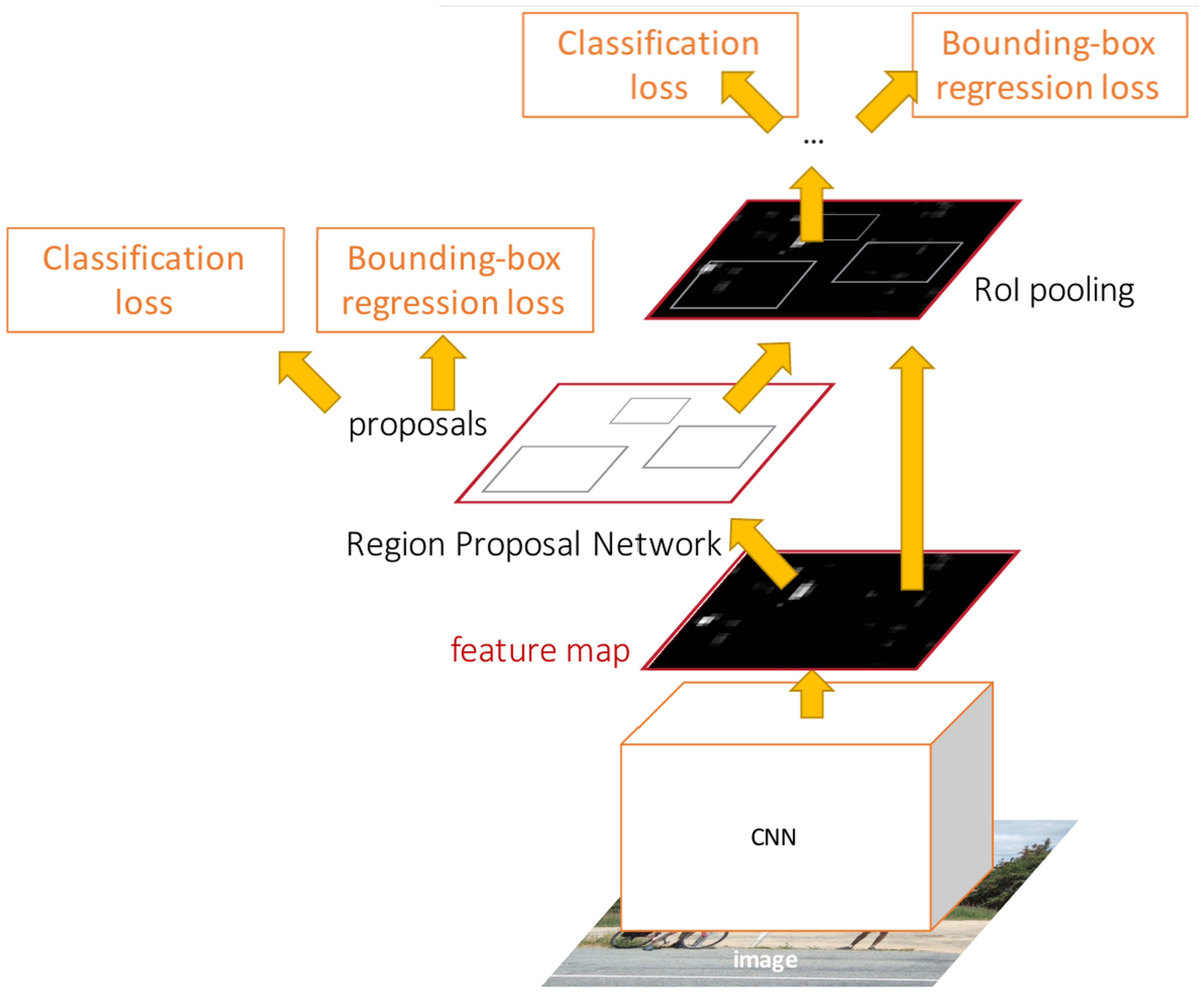
At test-time, sort all K*5*6 boxes by their positive score, take top 300 as our region proposals

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

Faster R-CNN: Learnable Region Proposals

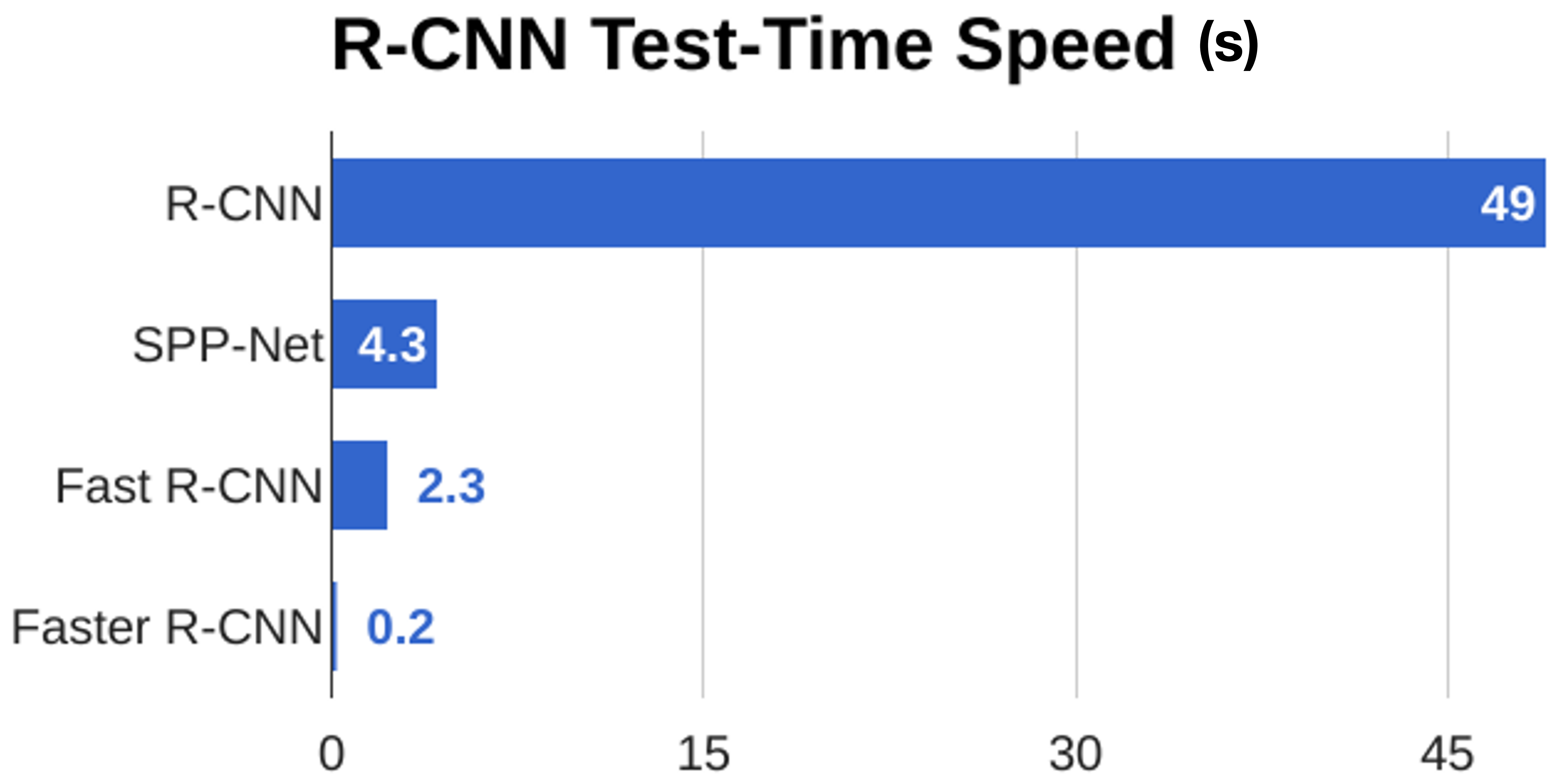
Jointly train four losses:

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



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

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

Instance Segmentation

Flipz, Hershey's, Keese's

Multiple objects

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

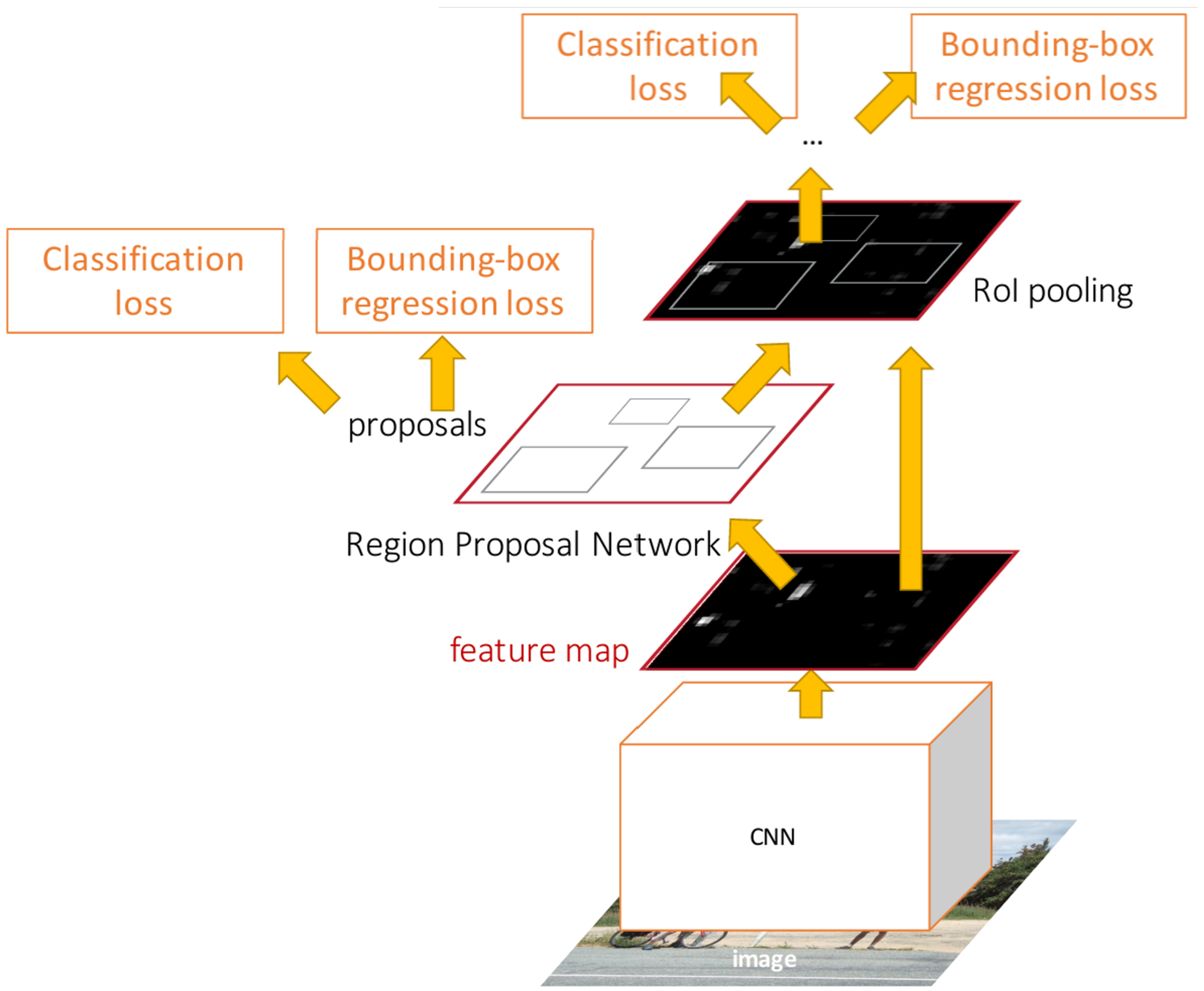
Instance Segmentation
Detect all objects in the image and identify the pixels that belong to each object (Only things!)

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

Extend Faster R-CNN into 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

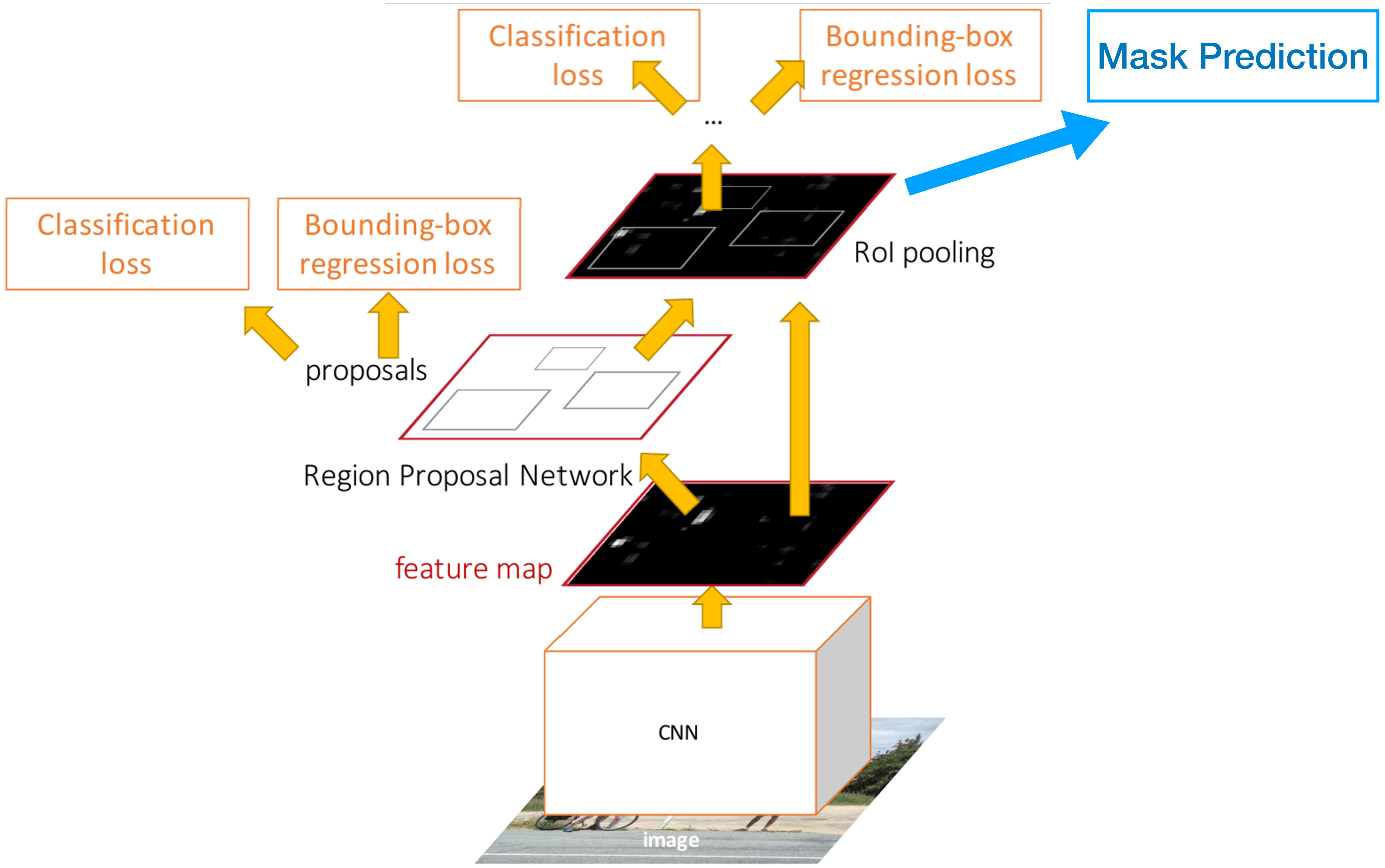


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick.

Extend Faster R-CNN into Mask R-CNN

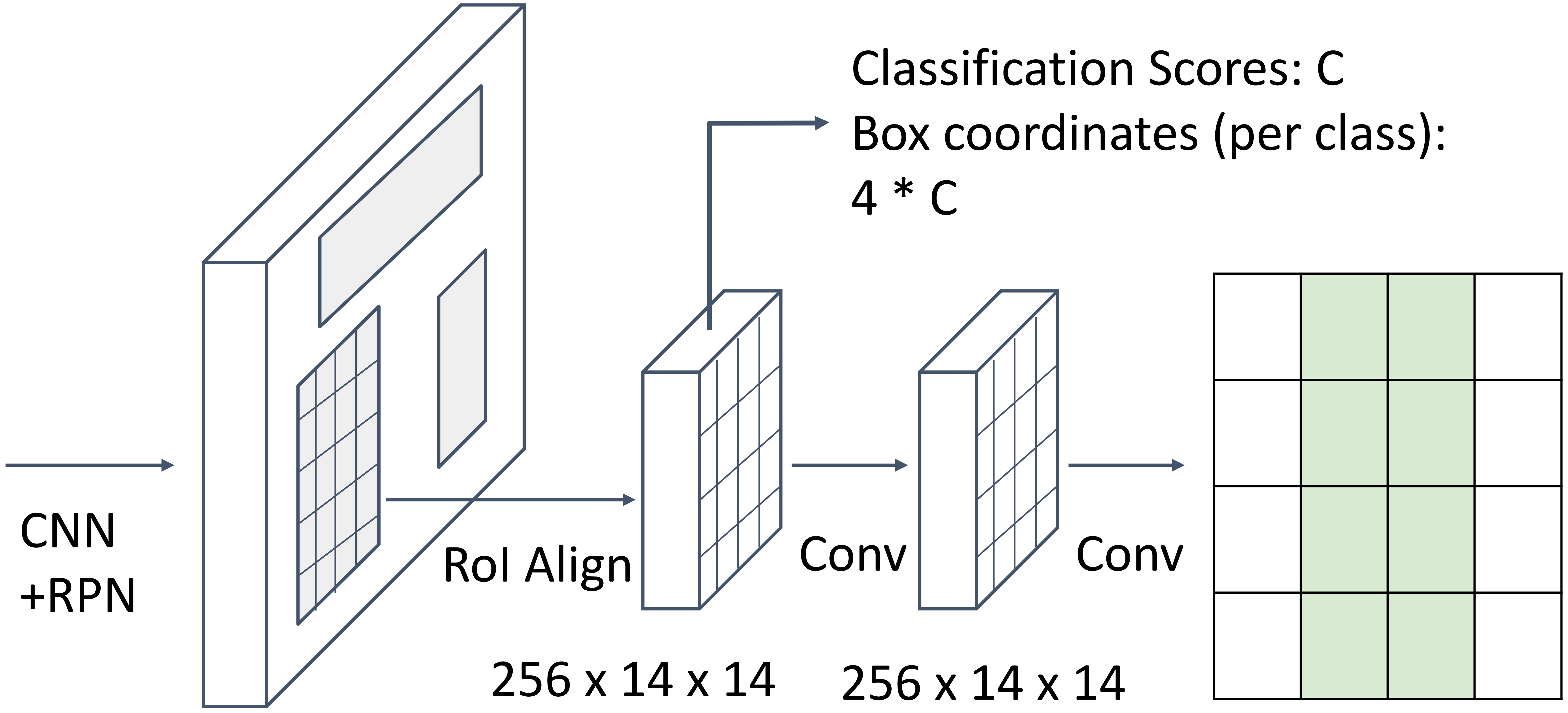
Mask R-CNN

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



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

Mask R-CNN



He et al., “Mask R-CNN”, ICCV 2017

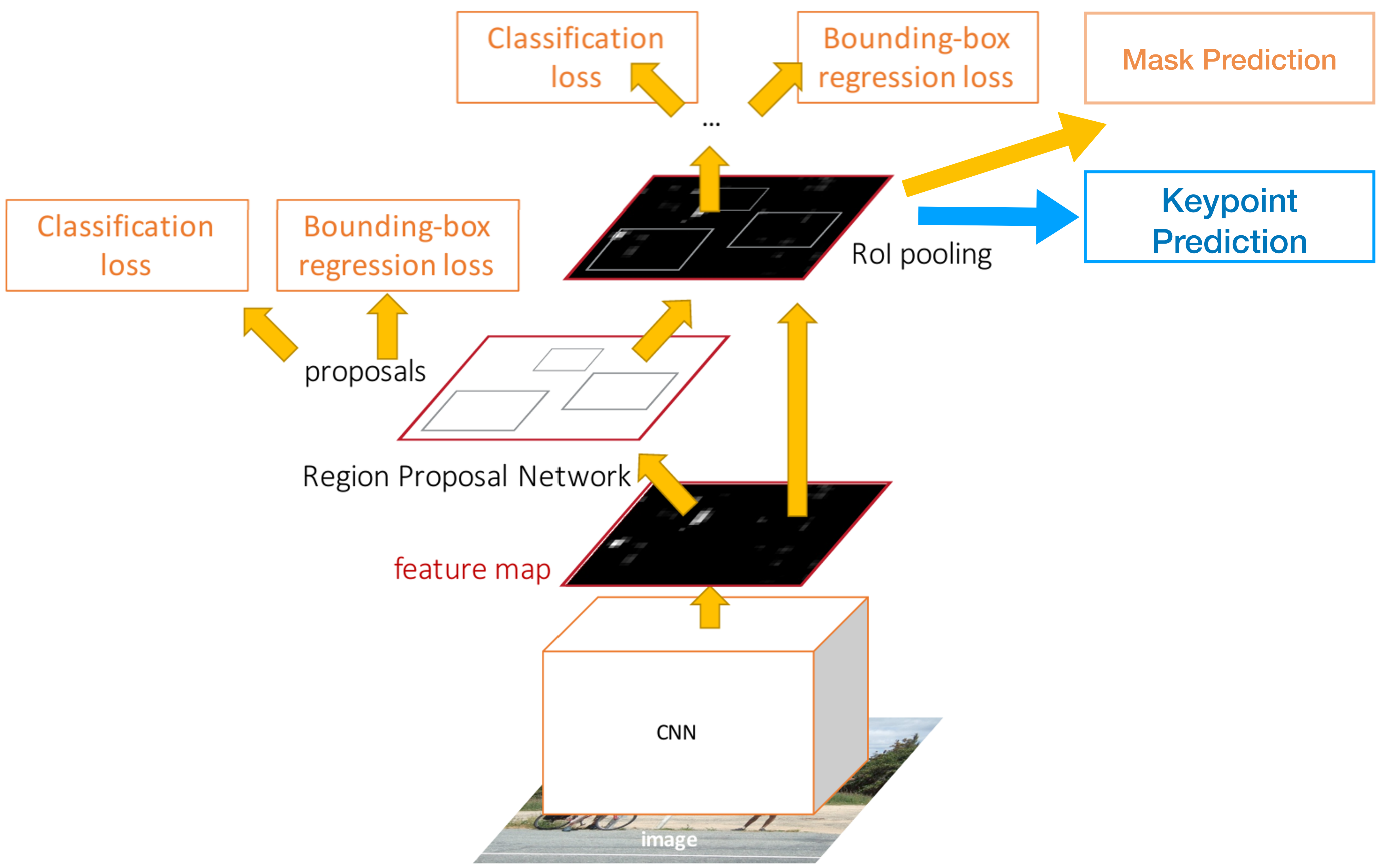
Mask R-CNN: Very Good Results!

He et al., “Mask R-CNN”, ICCV 2017

Mask R-CNN for Human Pose Estimation

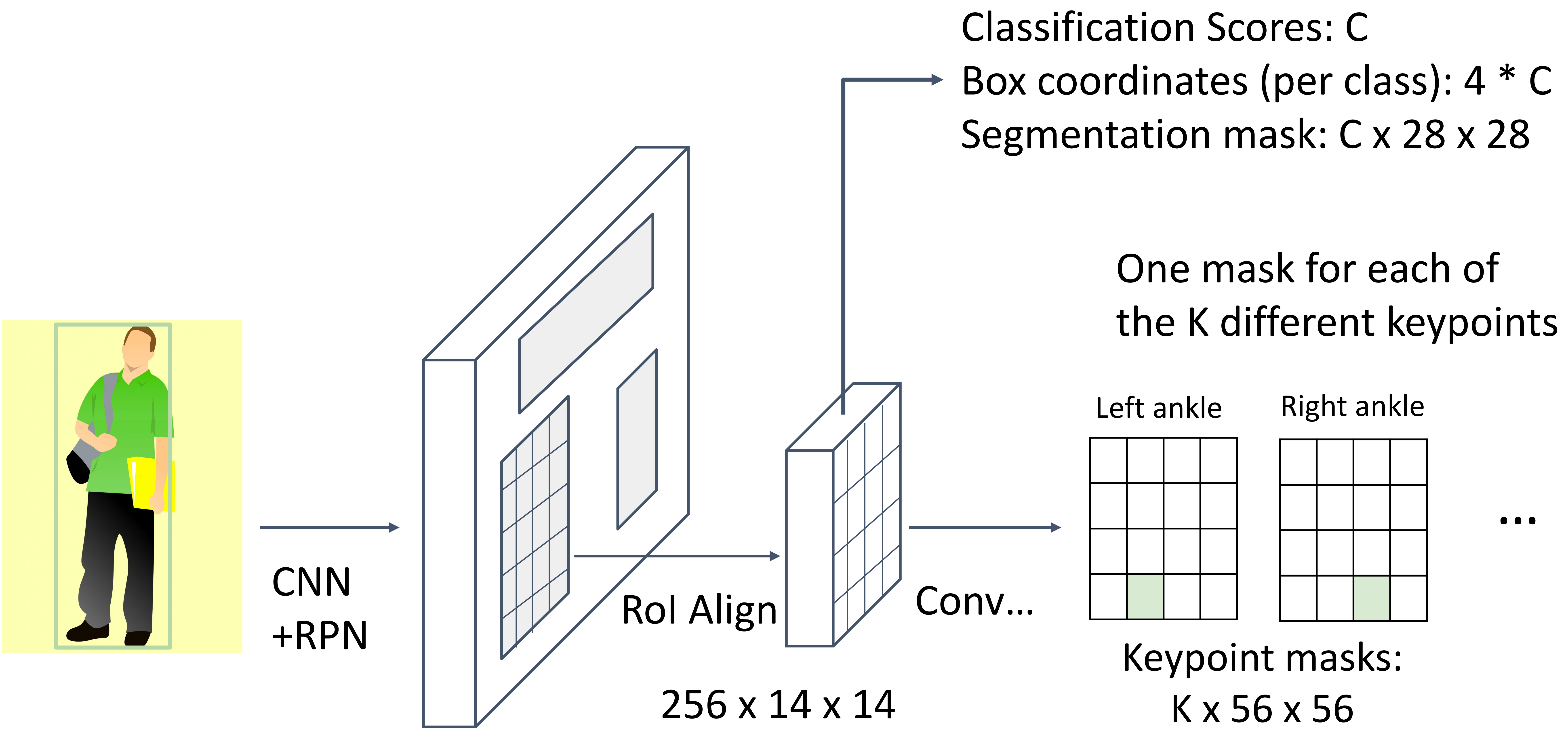
Mask R-CNN

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



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

Mask R-CNN for Human Pose Estimation



Ground-truth has one "pixel" turned on per keypoint. Train with softmax loss

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

Mask R-CNN for Human Pose Estimation

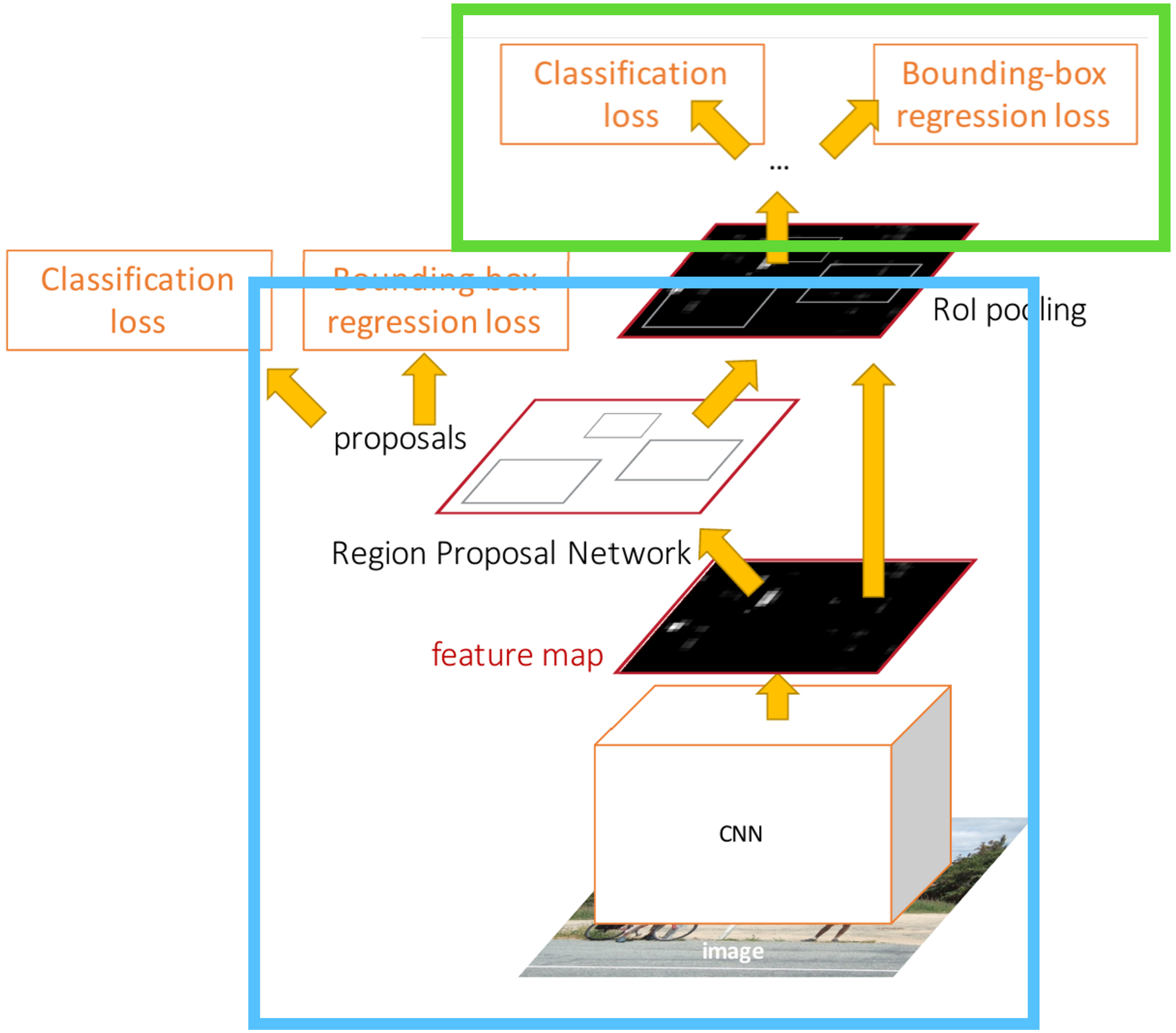
He et al., "Mask R-CNN", ICCV 2017

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



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

DeepRob

Lecture 13
Object Detectors and Segmentation
University of Michigan and University of Minnesota