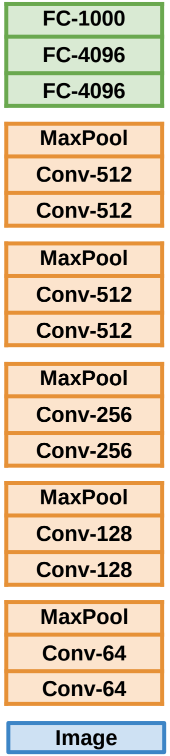
Week 15: Object Detection

Justin Johnson 2023

Transfer Learning with CNNs

Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

1. Train on Imagenet



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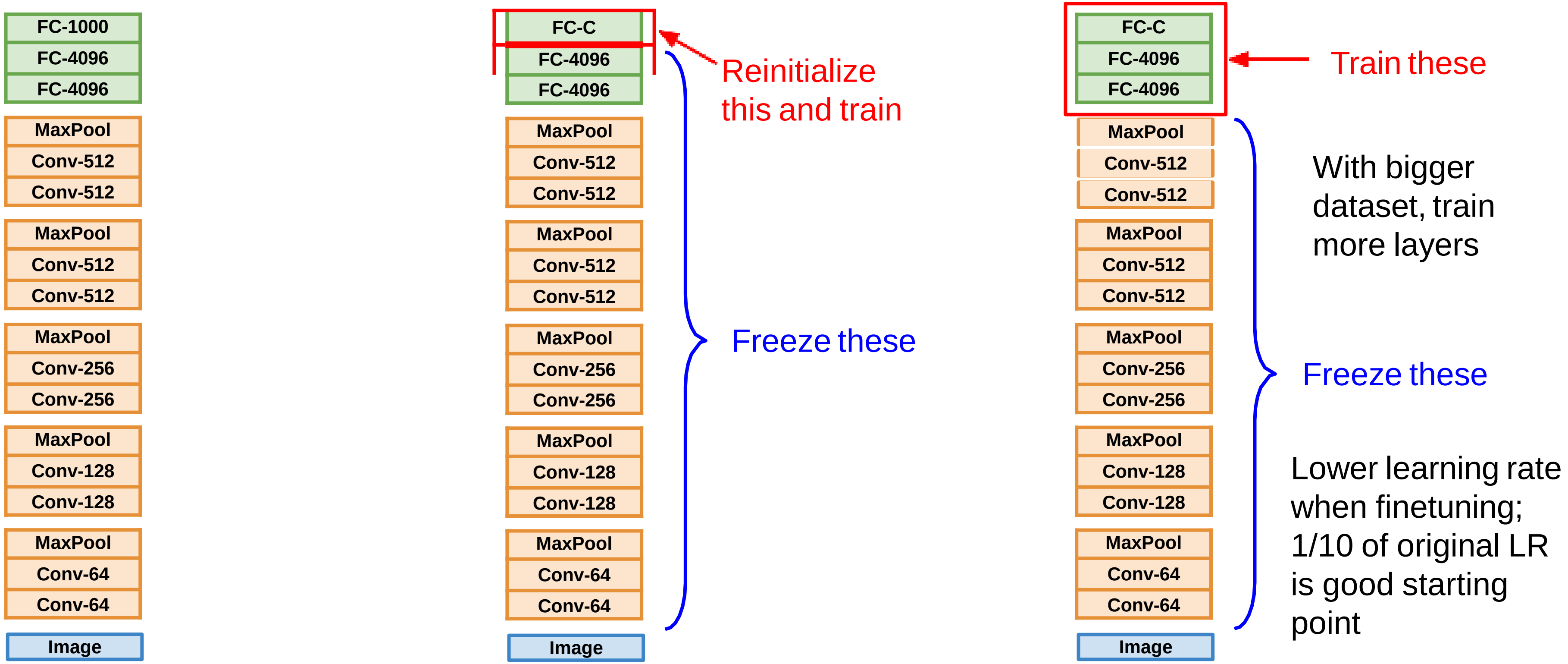
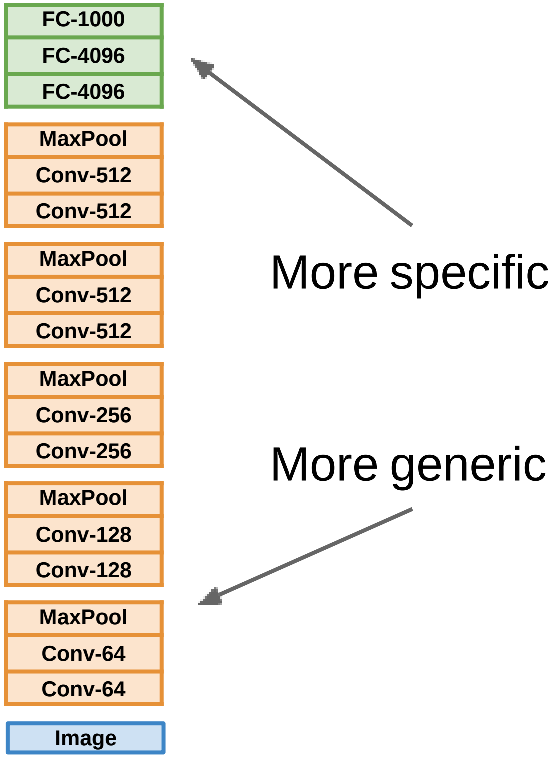
1. Train on Imagenet

2. Small Dataset (C classes)

3. Bigger dataset

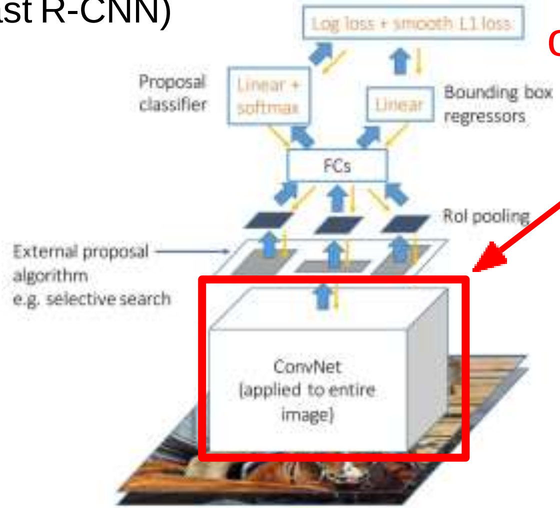




	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

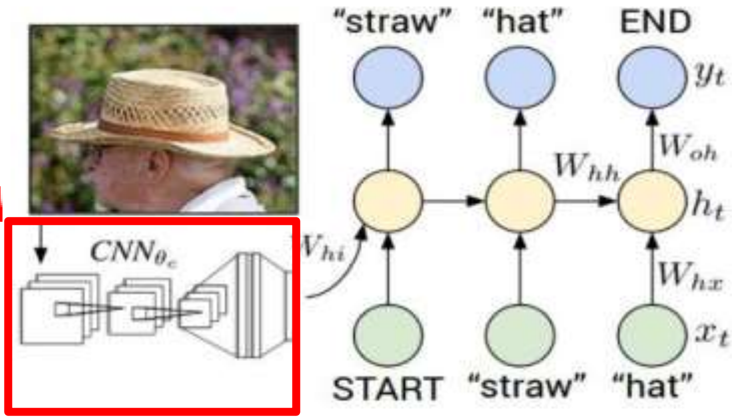
Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Object Detection
(Fast R-CNN)



CNN pretrained on ImageNet

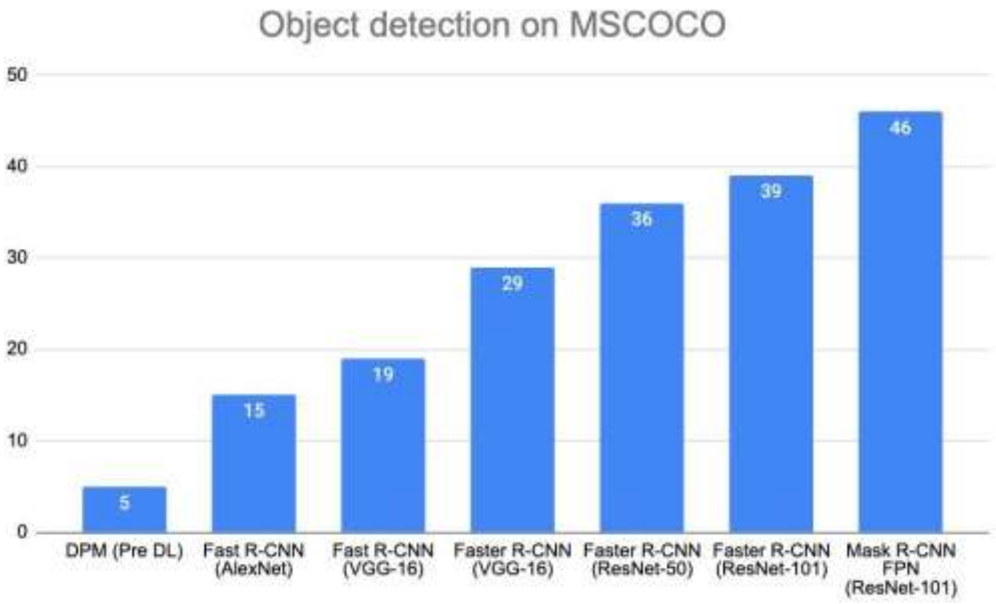
Image Captioning: CNN + RNN



Girshick, "Fast R-CNN", ICCV 2015

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

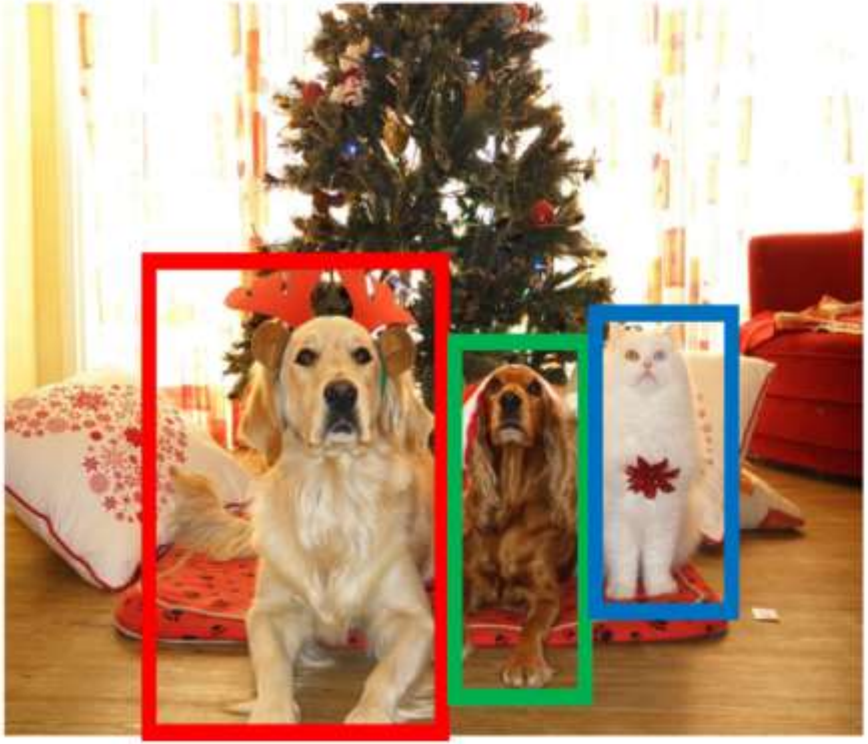
Transfer learning with CNNs - Architecture matters



Girshick, "The Generalized R-CNN Framework for Object Detection", ICCV 2017 Tutorial on Instance-Level Visual Recognition

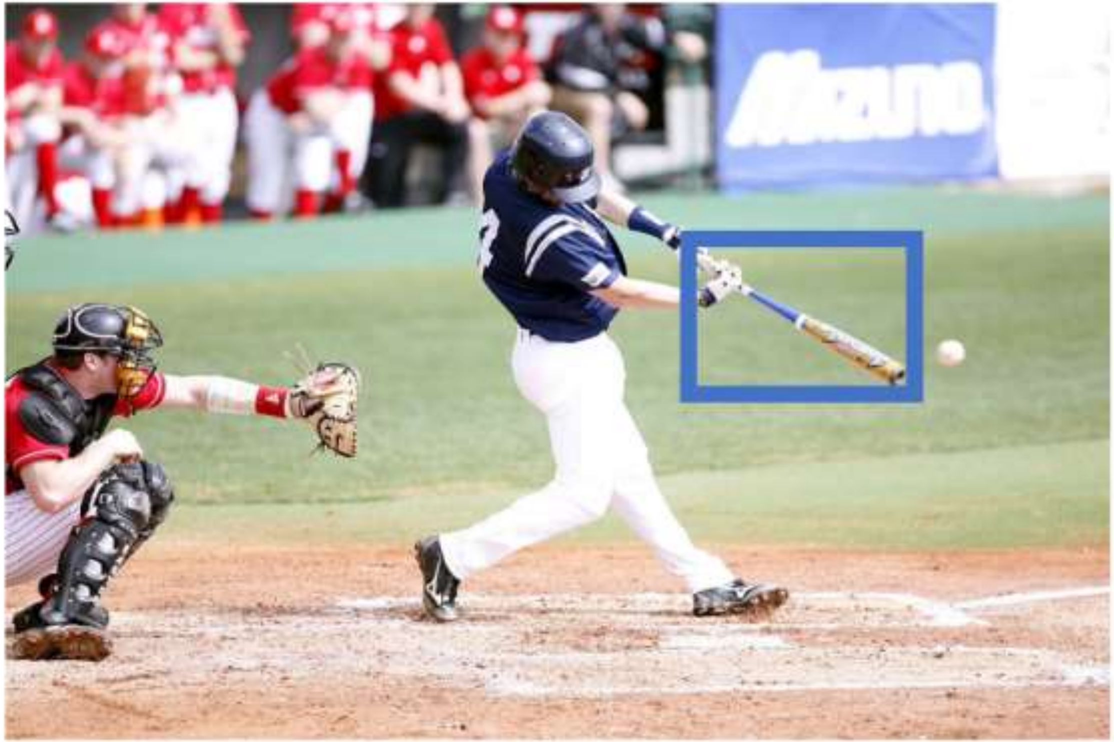
Object Detection: Challenges

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



Bounding Boxes

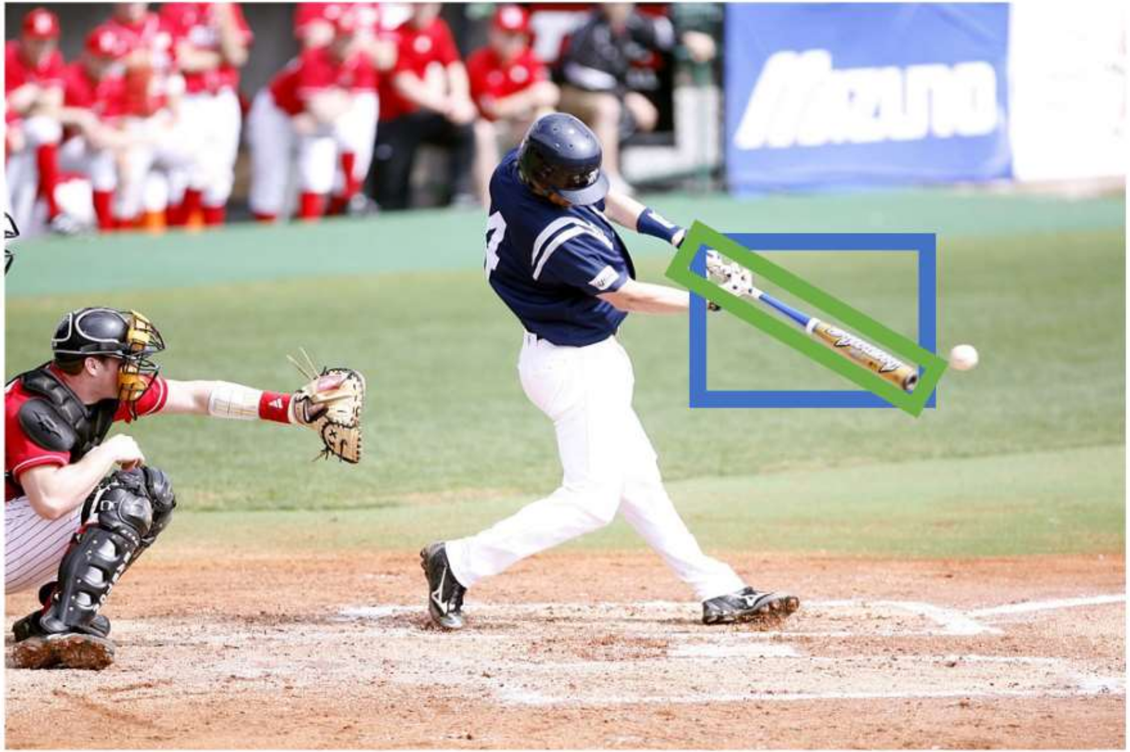
Bounding boxes are typically *axis-aligned*



Bounding Boxes

Bounding boxes are typically *axis-aligned*

Oriented boxes are much less common



Object Detection: Modal vs Amodal Boxes

Bounding boxes (usually) cover only the visible portion of the object

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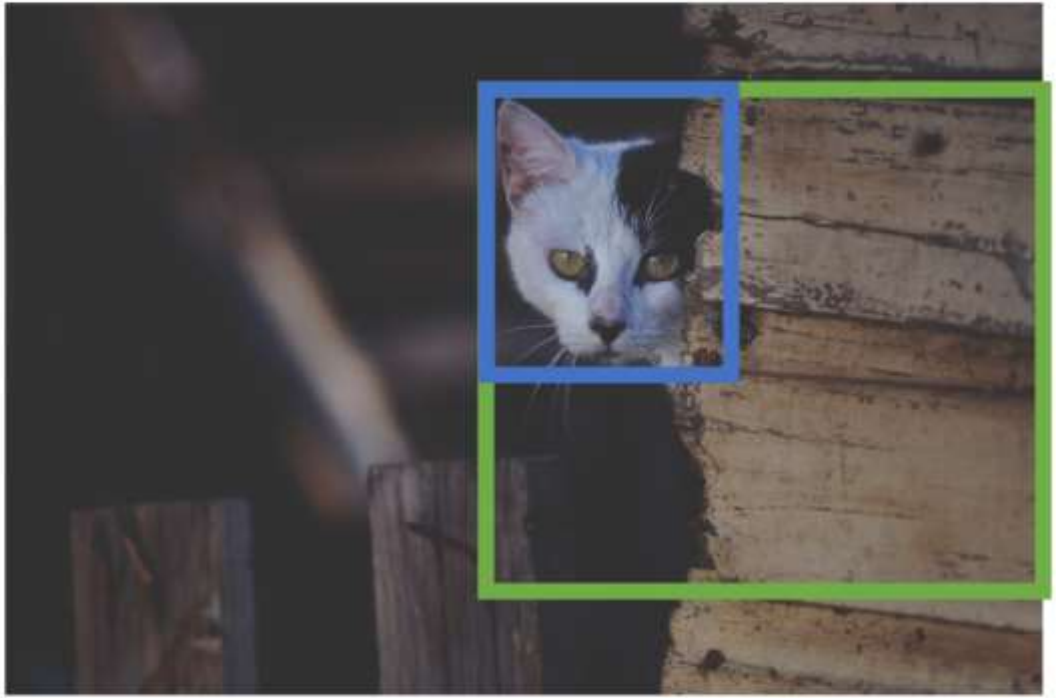
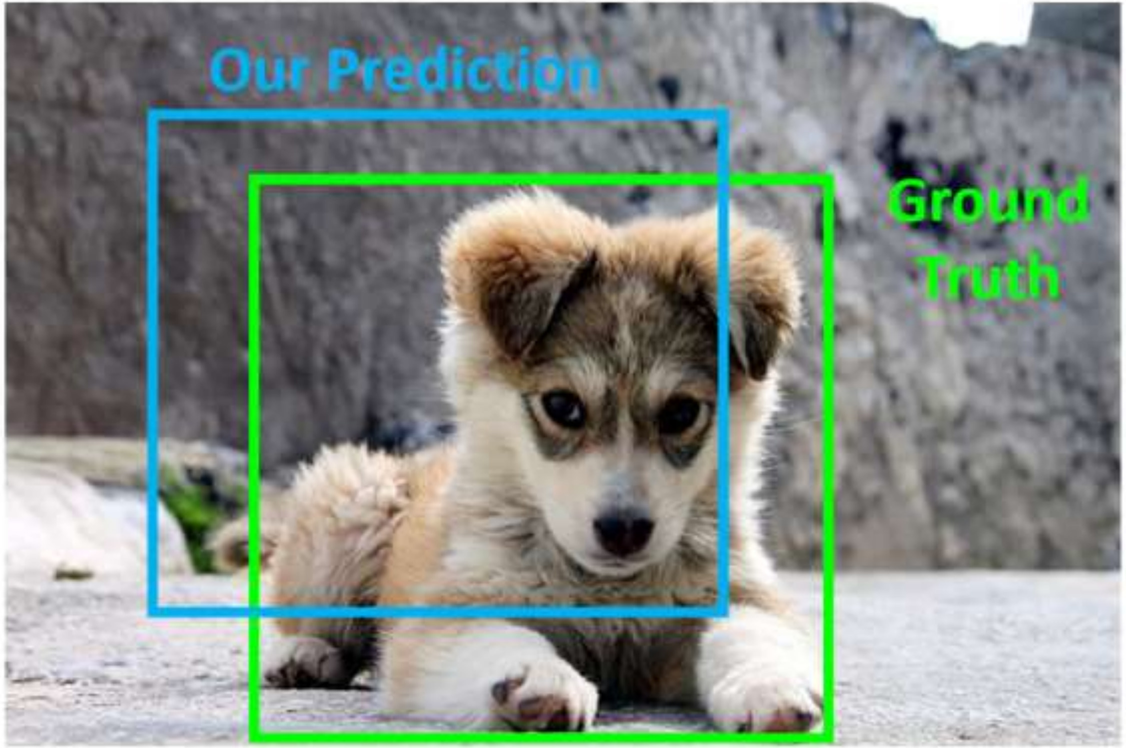
<u>Amodal detection</u>: box covers the entire extent of the object, even occluded parts



Comparing Boxes: Intersection over Union (IoU)

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



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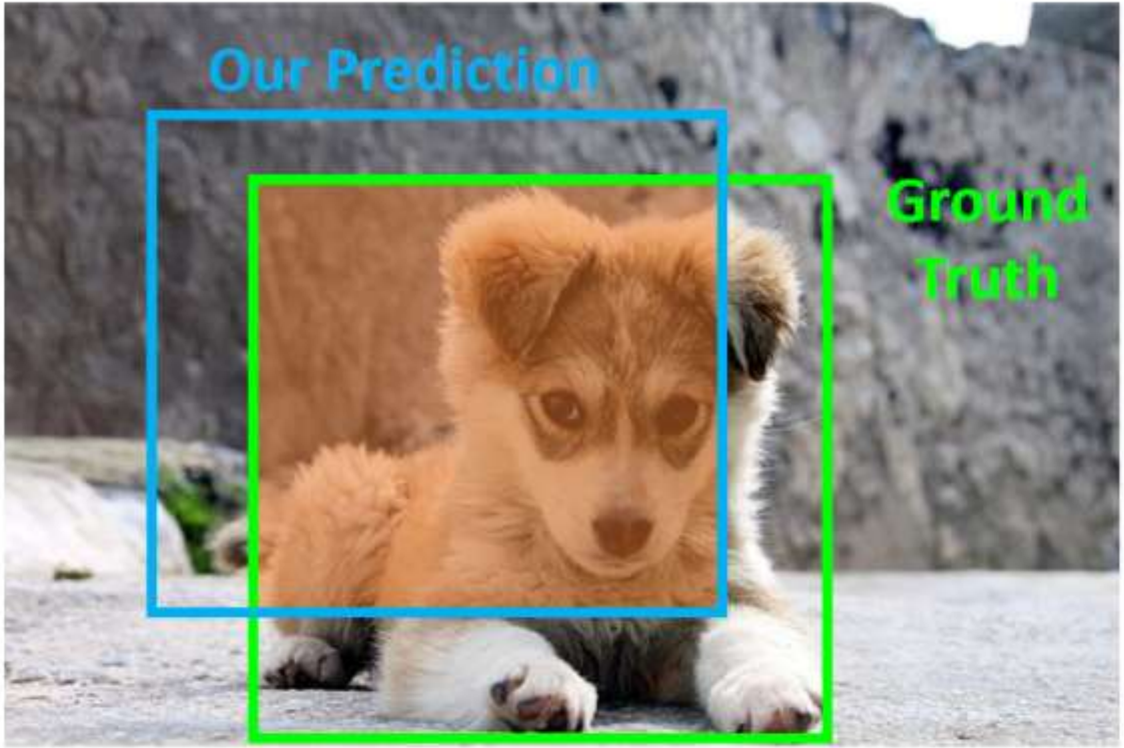
Intersection over Union (IoU)
(Also called "Jaccard similarity" or "Jaccard index"):

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



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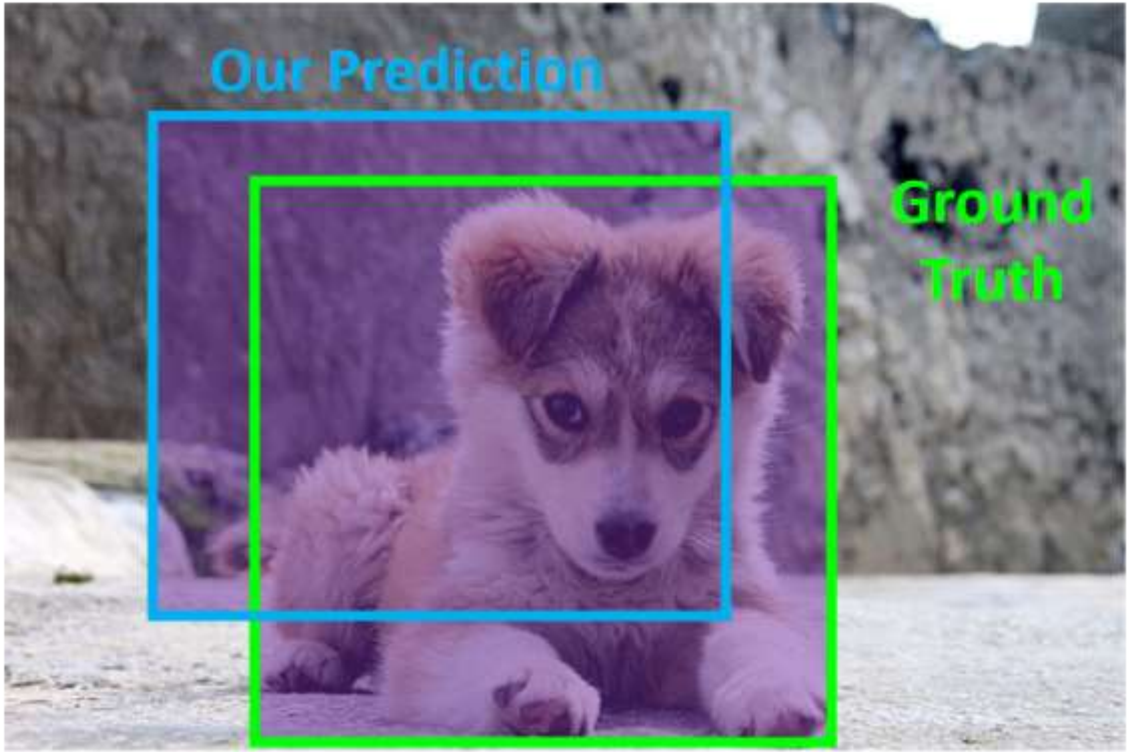

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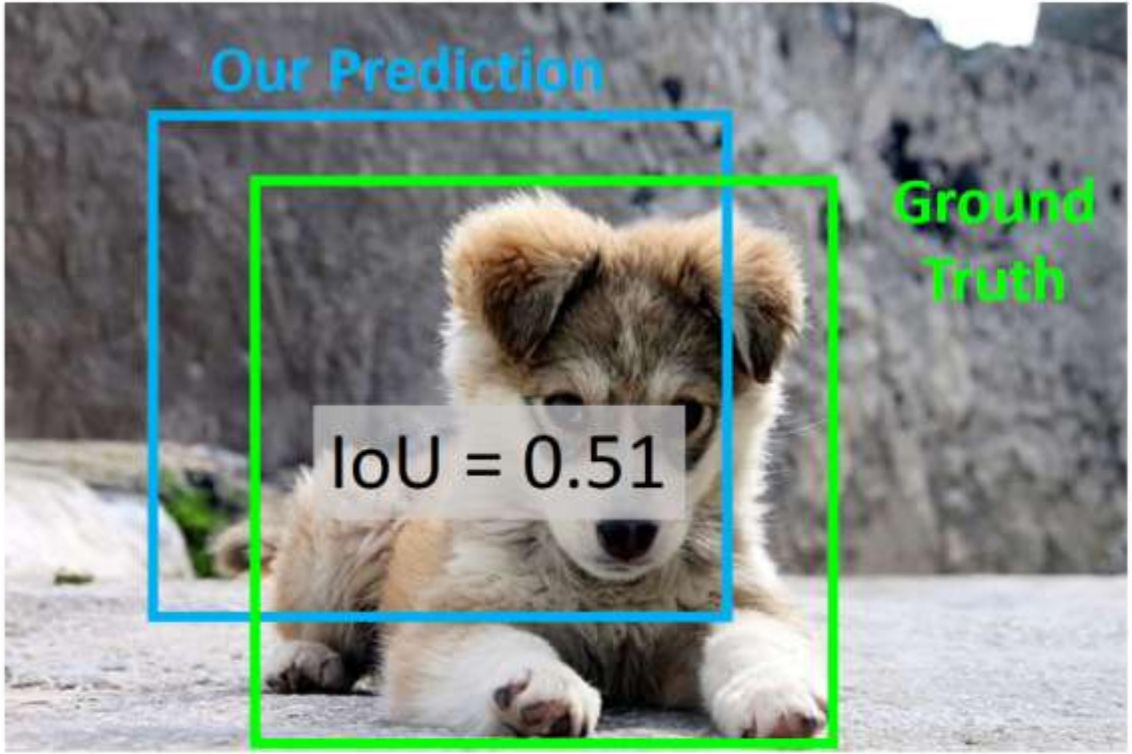

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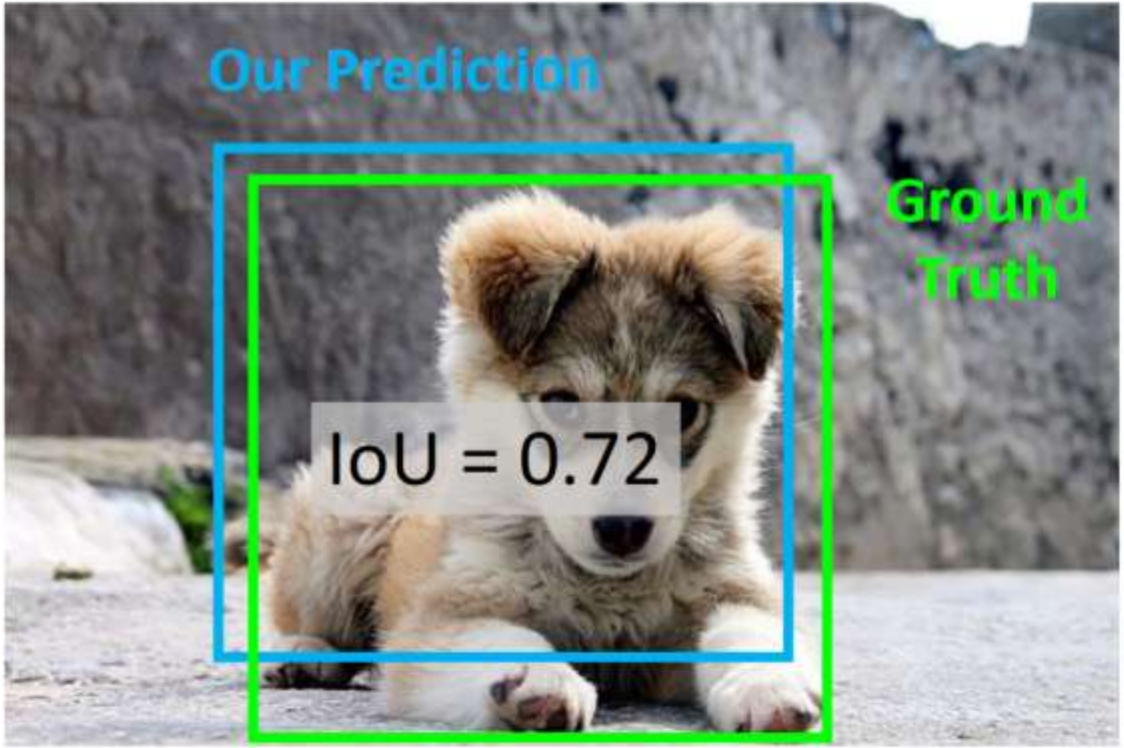

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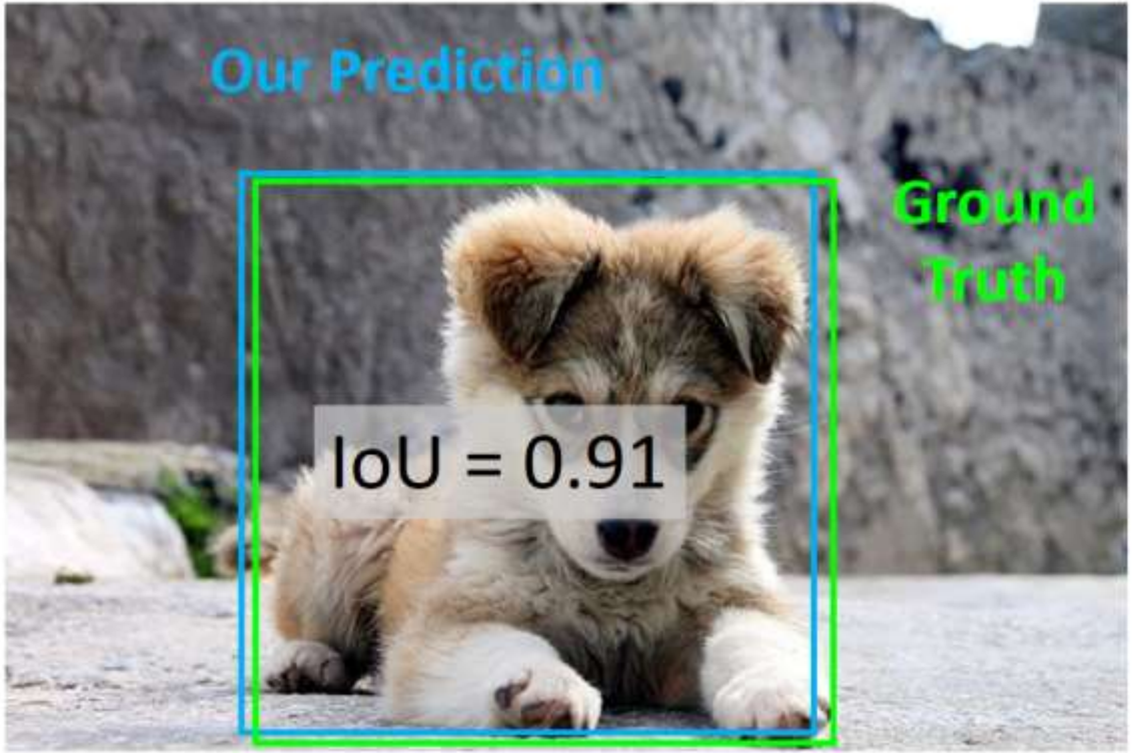
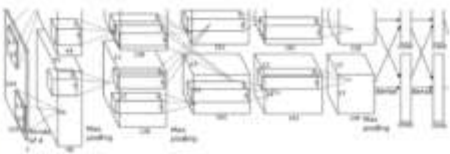
IoU > 0.5 is "decent",
IoU > 0.7 is "pretty good",
IoU > 0.9 is "almost perfect"



Detecting a single object



Vector:
4096

Treat localization as a regression problem!

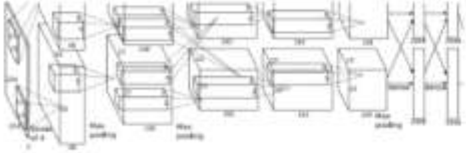
Detecting a single object "What"

Correct label:
Cat

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

Softmax Loss

Fully Connected:
4096 to 1000



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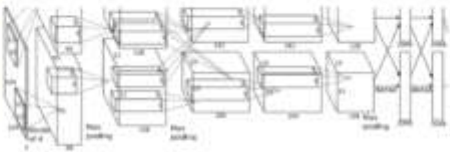


Vector:
4096

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

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

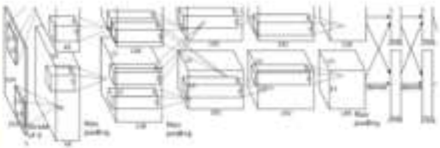
Treat localization as a regression problem!

"Where"

Detecting a single object "What"

Correct label:
Cat

This image is CC0 public domain



Vector:
4096

Fully Connected:
4096 to 1000

Class Scores
Cat: 0.9
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...

Softmax Loss

Multitask Loss

Weighted Sum → Loss

$L = L_{cls} + \lambda L_{reg}$

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

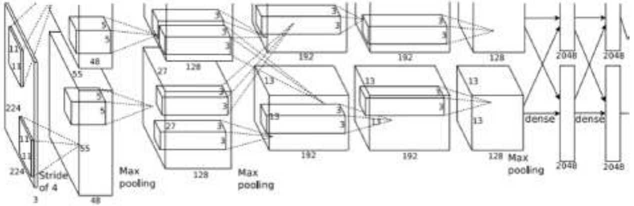
Correct box:
(x', y', w', h')

"Where"

Treat localization as a regression problem!

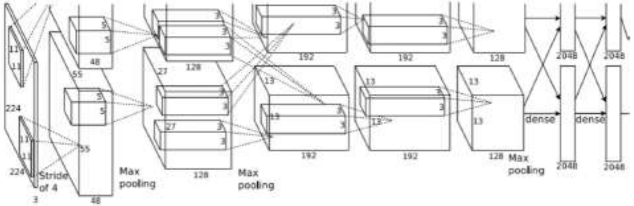
Detecting Multiple Objects

Need different numbers of outputs per image



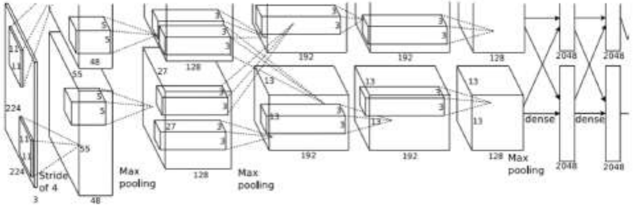
CAT: (x, y, w, h)

4 numbers



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

12 numbers

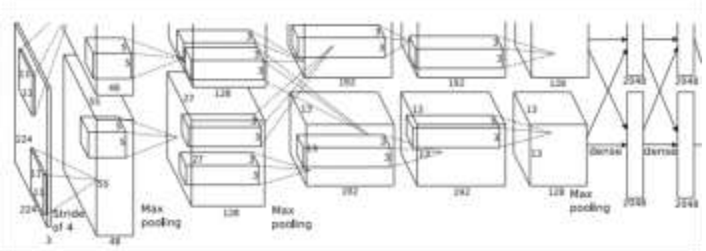


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
....

Many numbers!

Detecting Multiple Objects: Sliding Window

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



Dog? NO
Cat? NO
Background? YES

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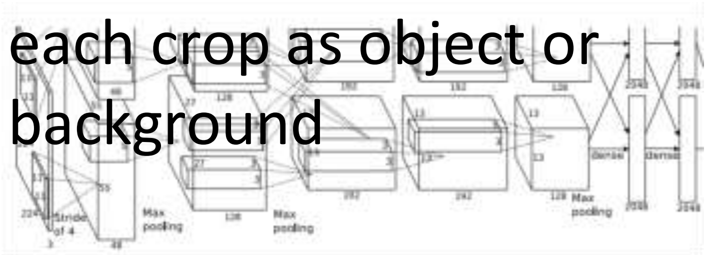

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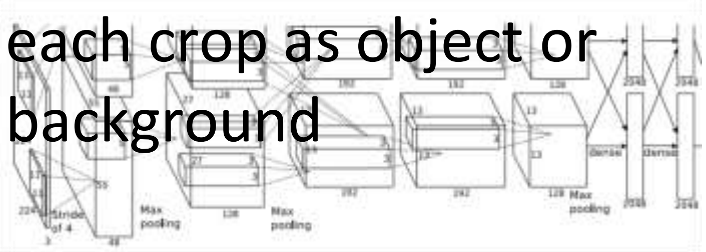

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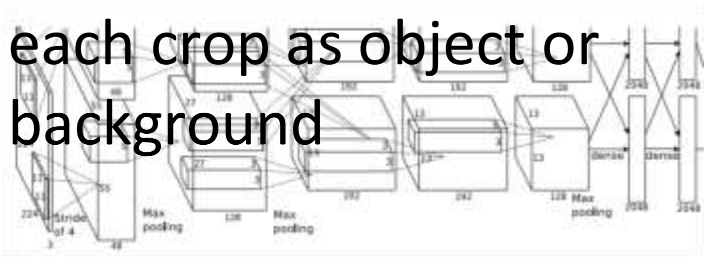

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Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

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

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

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Possible positions:
(W – w + 1) * (H – h + 1)

Total possible boxes:

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

Detecting Multiple Objects: Sliding Window

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

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

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

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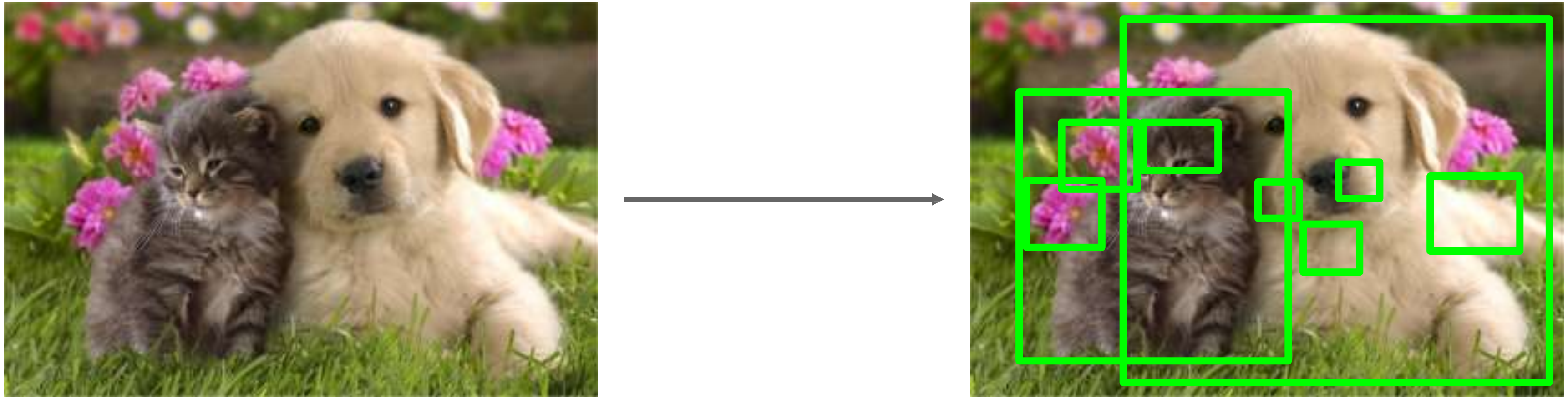
Possible x positions: W – w + 1
Possible y positions: H – h + 1
Possible positions:
(W – w + 1) * (H – h + 1)

Total possible boxes:

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

Region Proposals

- Find a small set of boxes that are likely to cover all objects
- Often based on heuristics: e.g. look for "blob-like" image regions
- Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



Alexe et al, "Measuring the objectness of image windows", TPAMI 2012
Uijlings et al, "Selective Search for Object Recognition", IJCV 2013
Cheng et al, "BING: Binarized normed gradients for objectness estimation at 300fps", CVPR 2014
Zitnick and Dollar, "Edge boxes: Locating object proposals from edges", ECCV 2014

R-CNN: Region-Based CNN

Input image

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

R-CNN: Region-Based CNN

Input image

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

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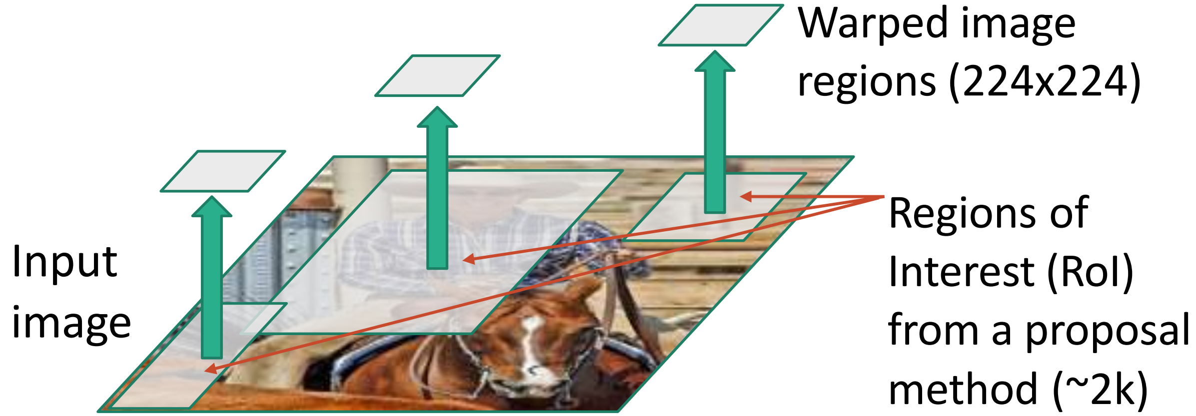

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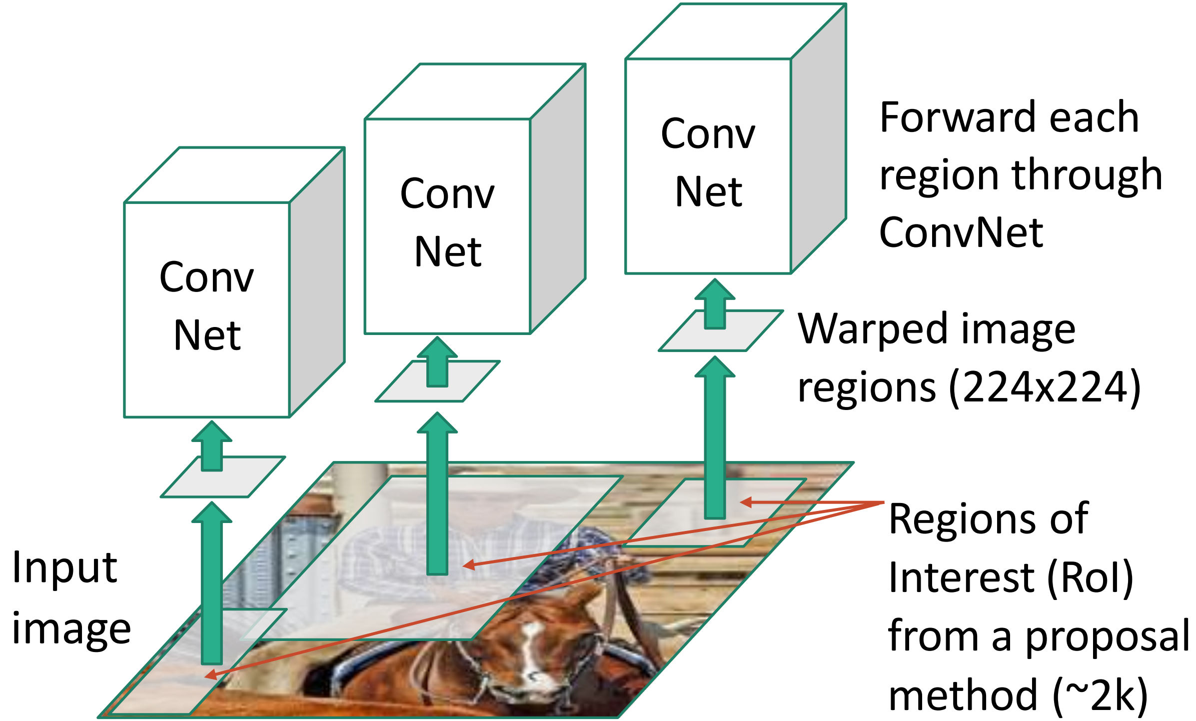

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
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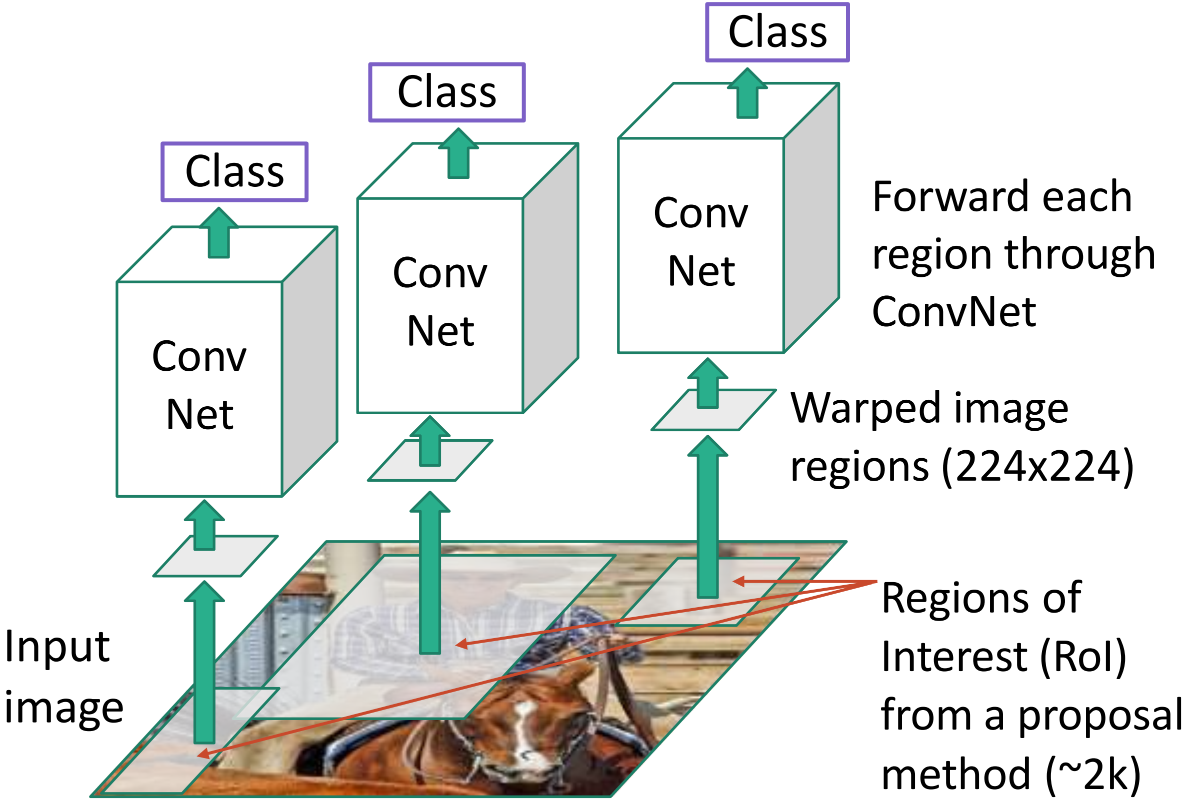
R-CNN: Region-Based CNN

Classify each region



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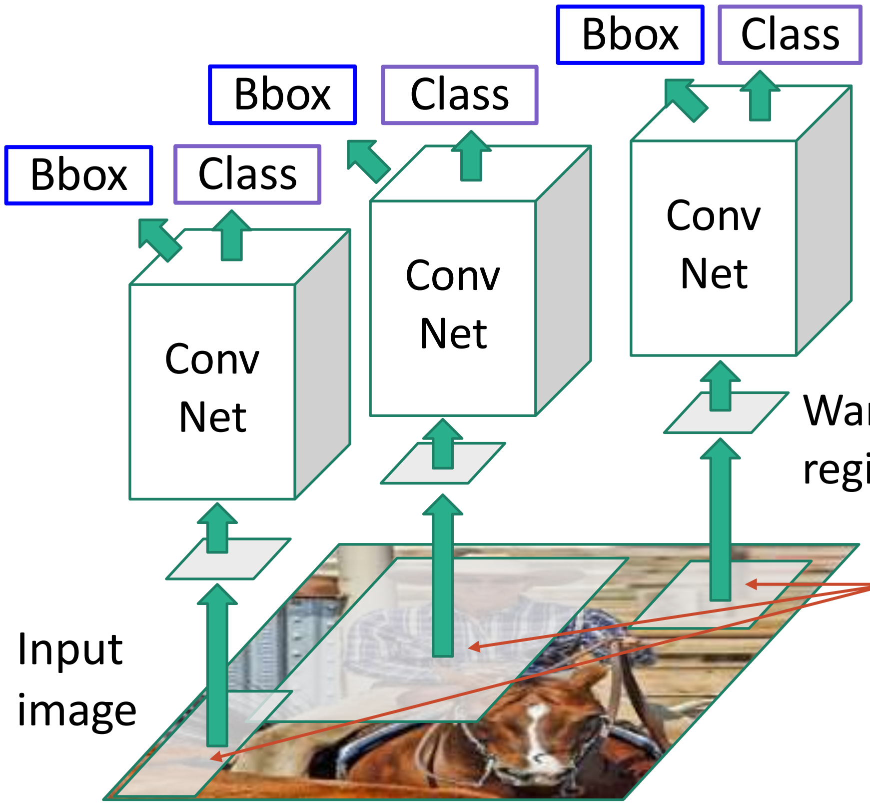

Classify each region

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

Forward each region through ConvNet

Warped image regions (224x224)

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Input image

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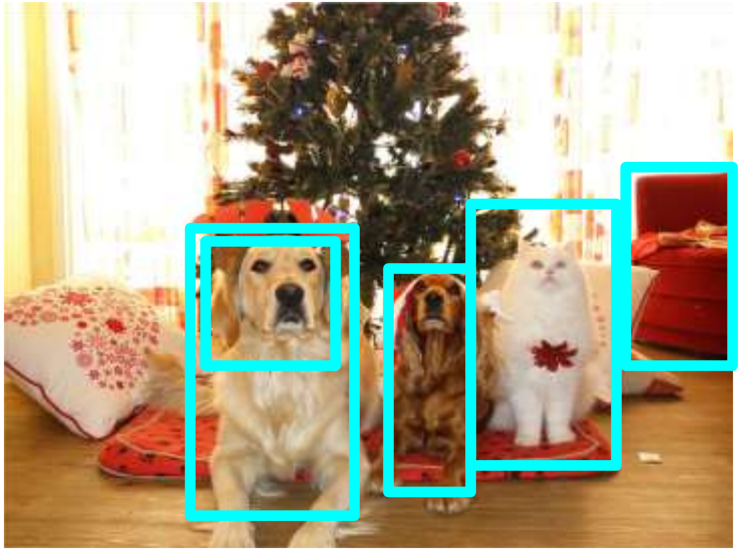
R-CNN Test-Time

Input Image



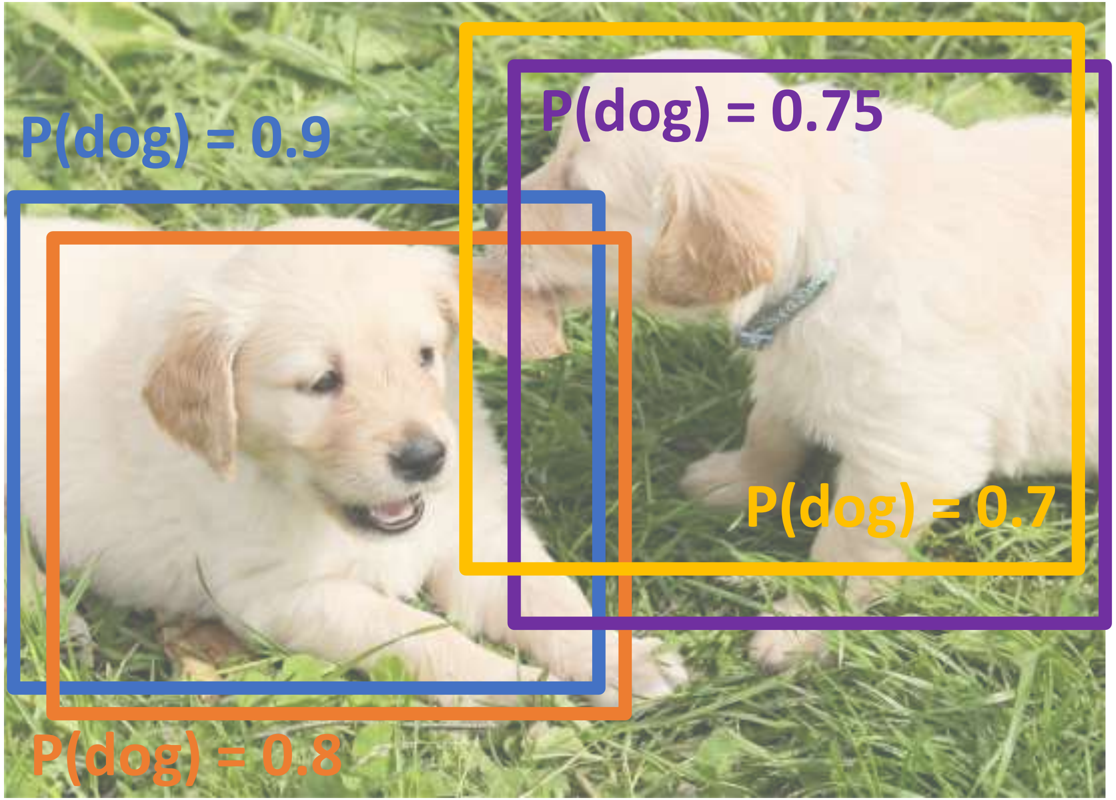
Region Proposals

1. Run proposal method
2. Run CNN on each proposal to get class scores, transforms
3. Threshold class scores to get a set of detections

2 problems:
- CNN often outputs overlapping boxes
- How to set thresholds?

Overlapping Boxes

Problem: Object detectors often output many overlapping detections:



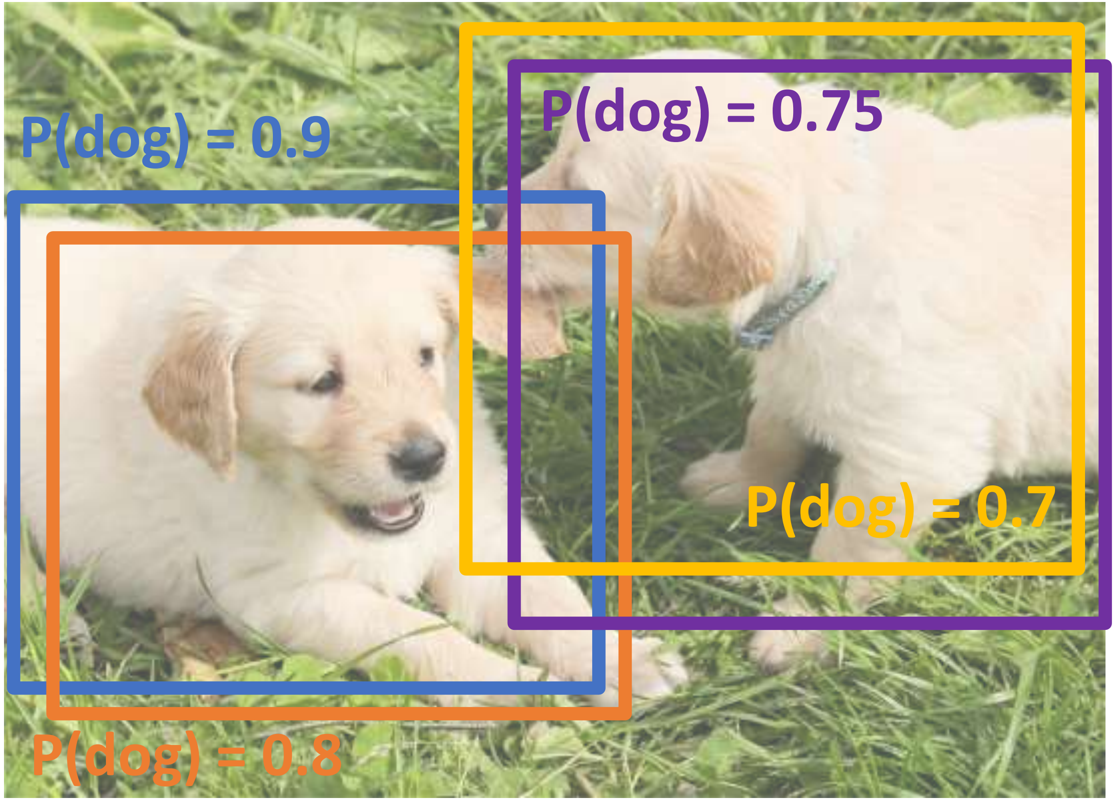
Puppy image is CC0 Public Domain

Overlapping Boxes: Non-Max Suppression (NMS)

Problem: Object detectors often output many overlapping detections:

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

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



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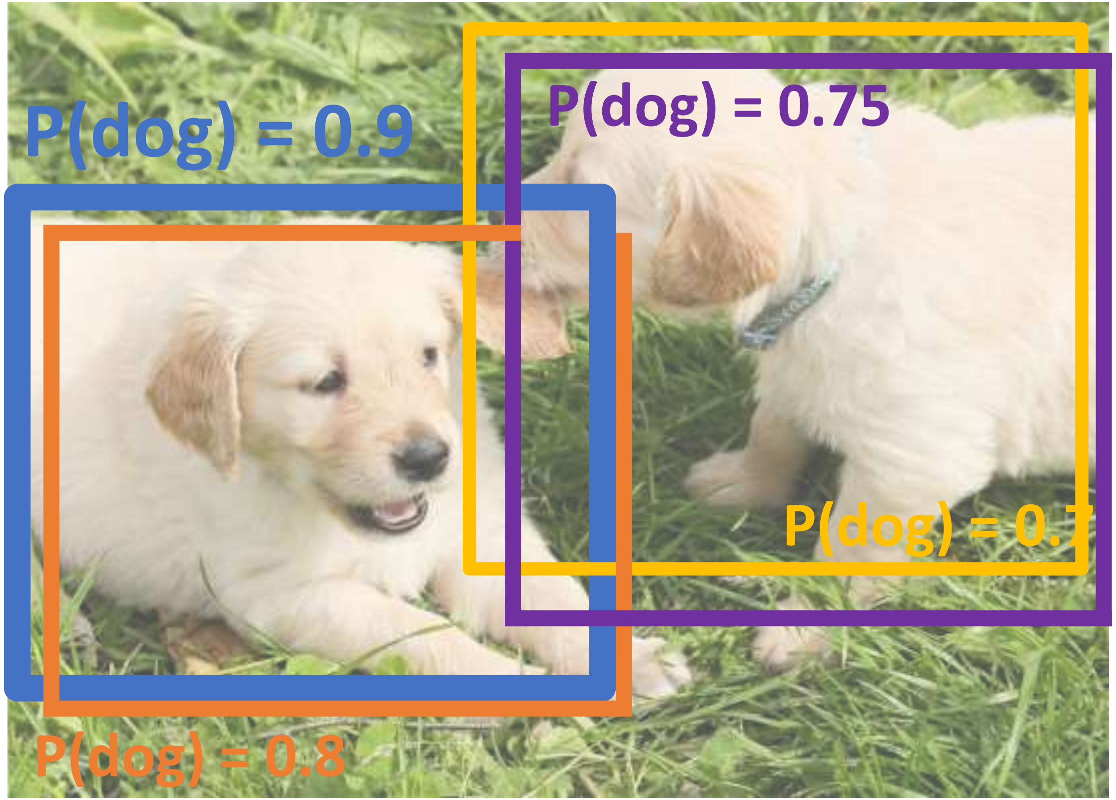
IoU(■, ■) = **0.78**
IoU(■, ■) = 0.05
IoU(■, ■) = 0.07



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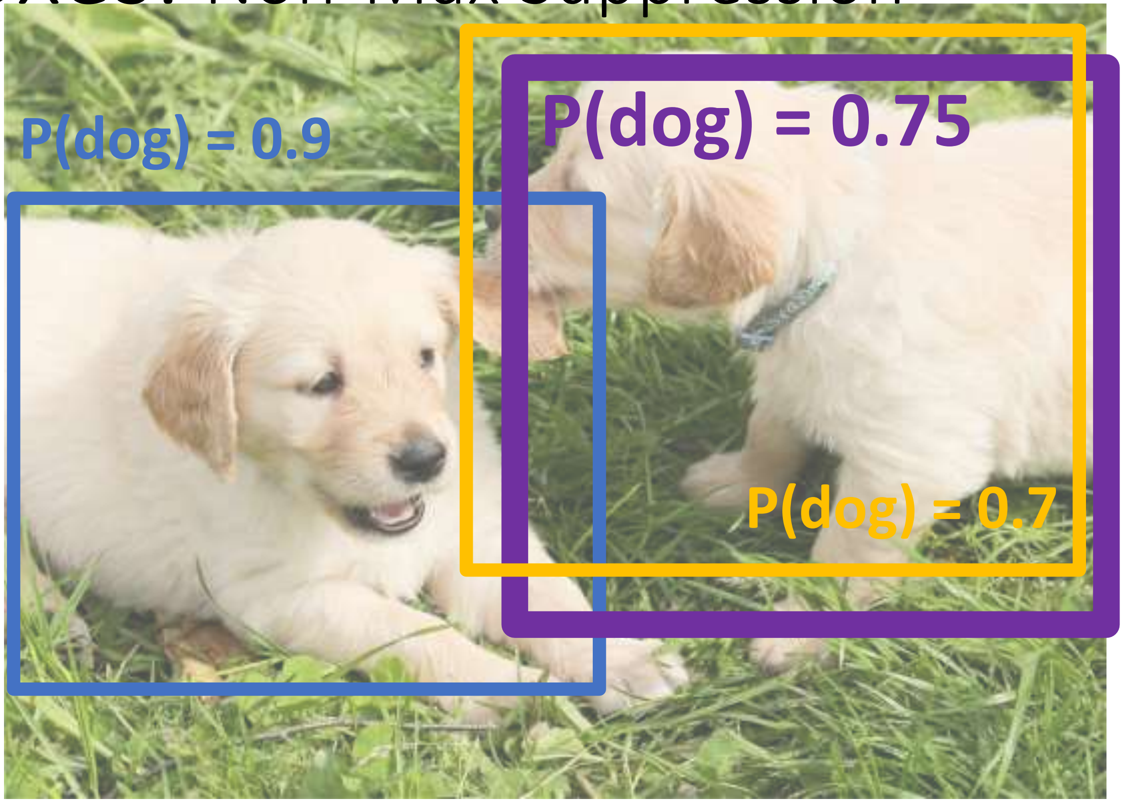
IoU(■, ■) = **0.74**



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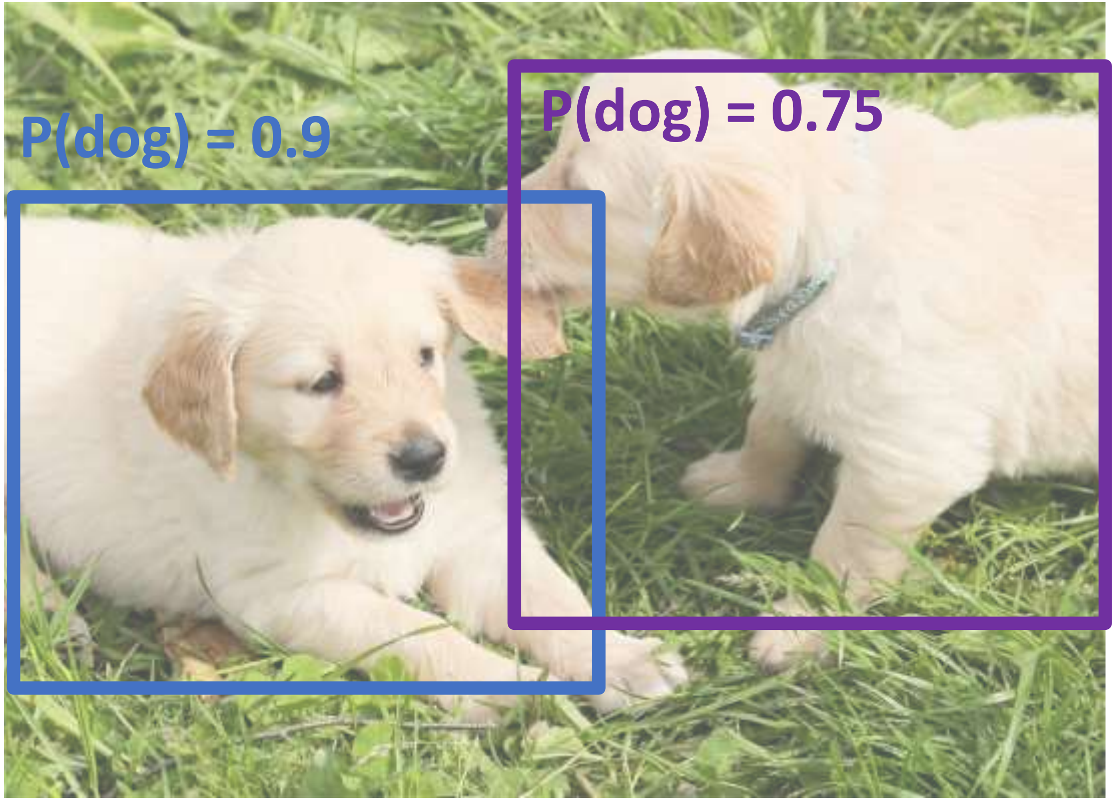

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Problem: NMS may eliminate "good" boxes when objects are highly overlapping... no good solution =(

Summary

Transfer learning allows us to re-use a trained network for new tasks

Object detection is the task of localizing objects with bounding boxes

Intersection over Union (IoU) quantifies differences between bounding boxes

The **R-CNN** object detector processes **region proposals** with a CNN

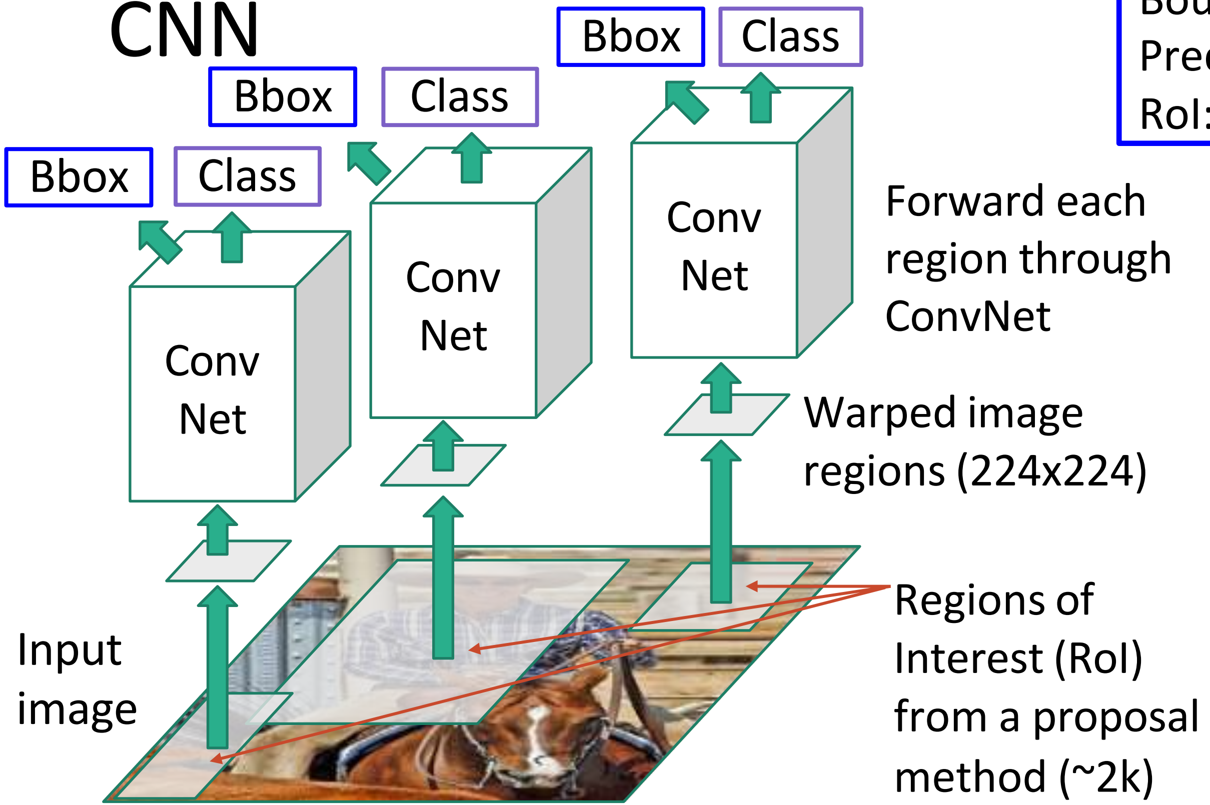
At test-time, eliminate overlapping detections using **non-max suppression (NMS)**

Evaluate object detectors using **mean average precision (mAP)**

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)



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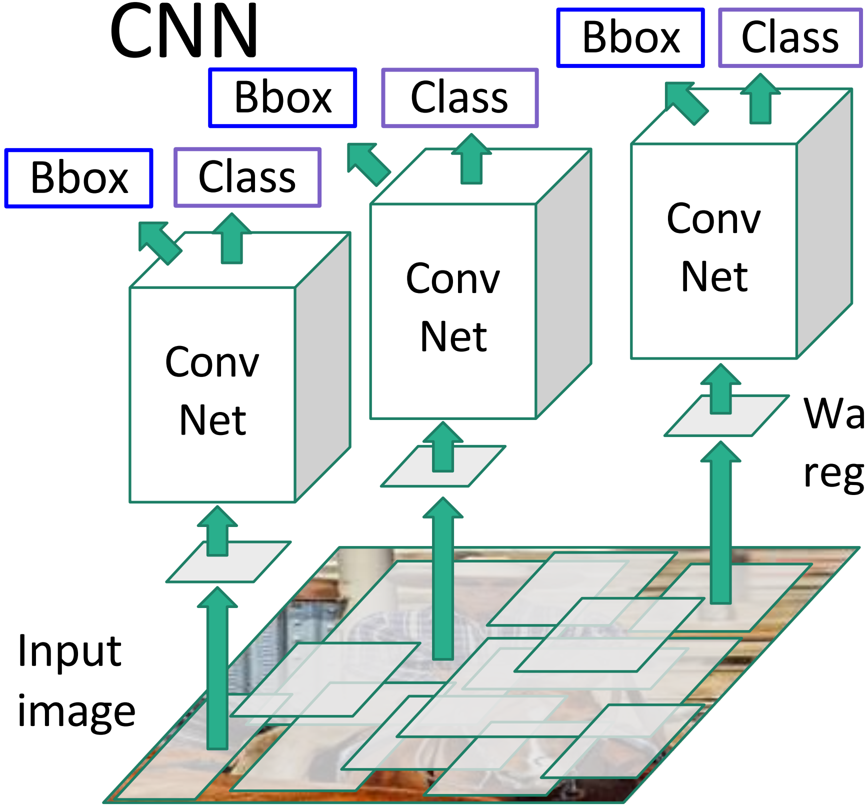

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Forward each region through ConvNet

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

Warped image regions (224x224)

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

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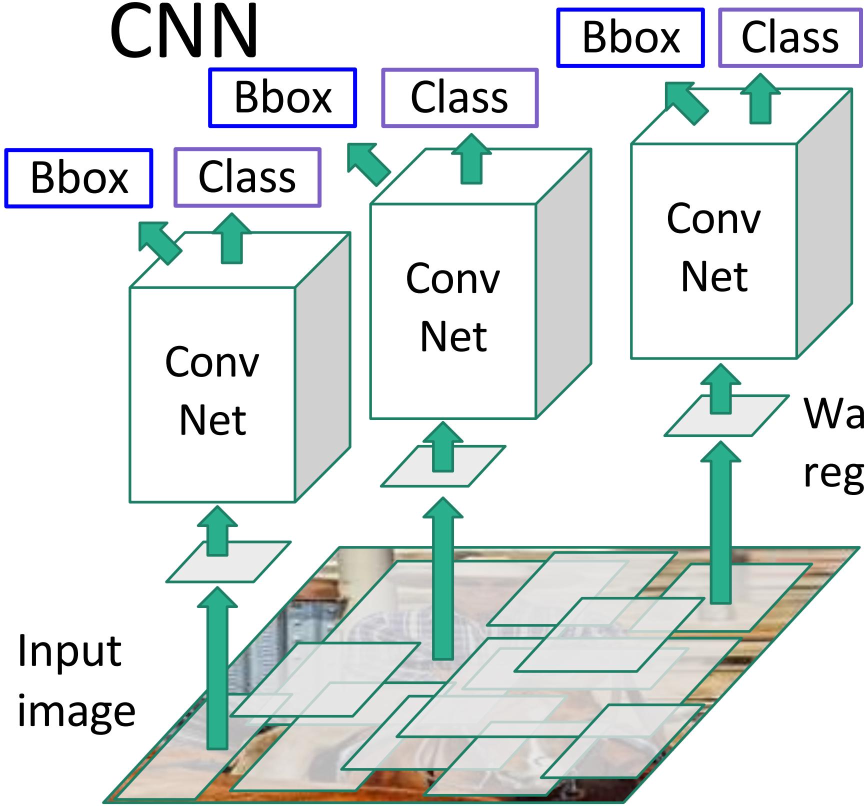

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Regions of Interest (RoI) from a proposal method (~2k)

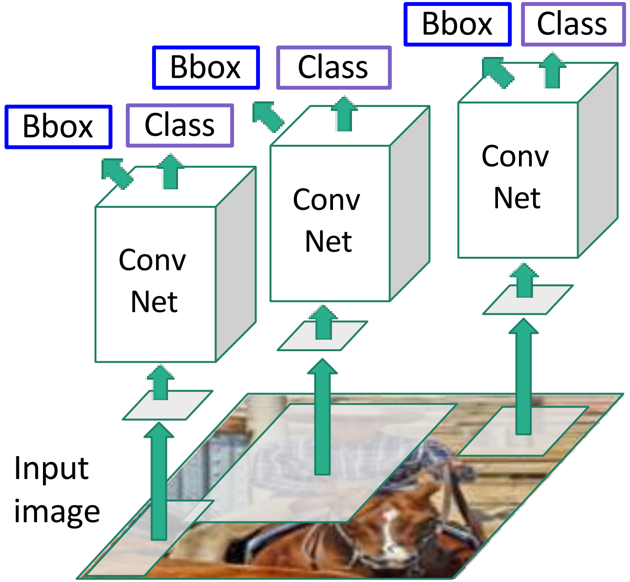
Problem: Very slow! Need to do 2000 forward passes through CNN per image

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

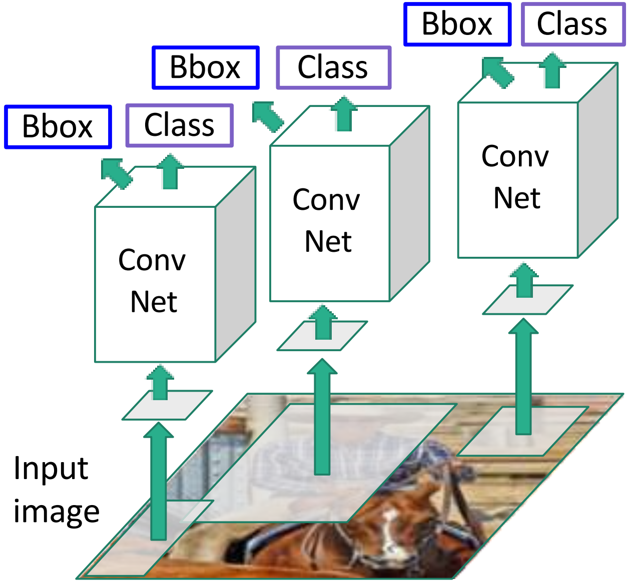
Process each region independently



Fast R-CNN

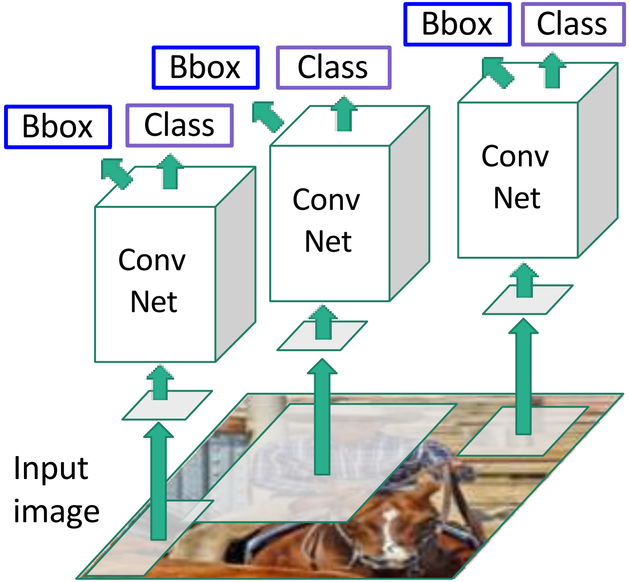
Input image

"Slow" R-CNN
Process each region independently

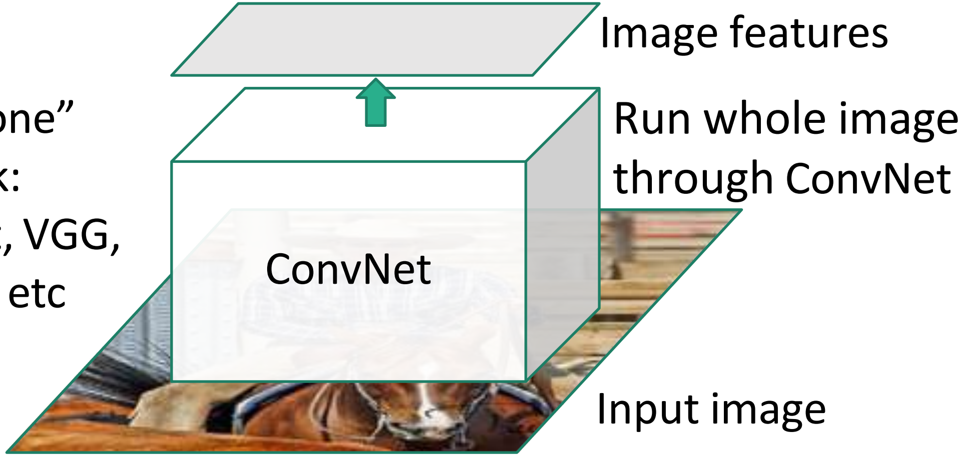


Fast R-CNN

"Slow" R-CNN
Process each region independently



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

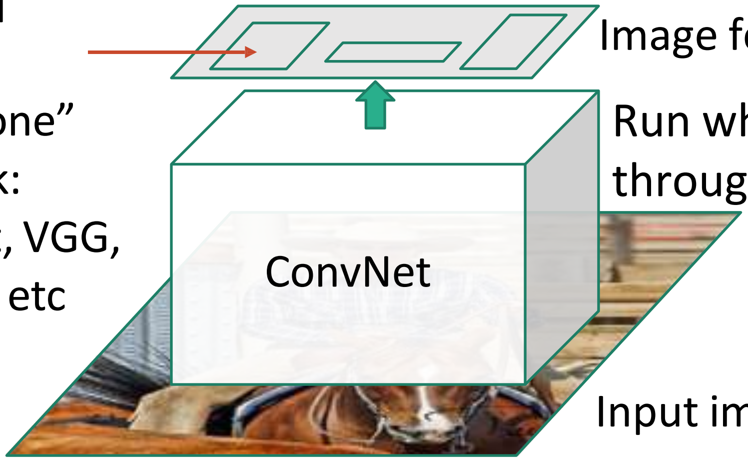


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

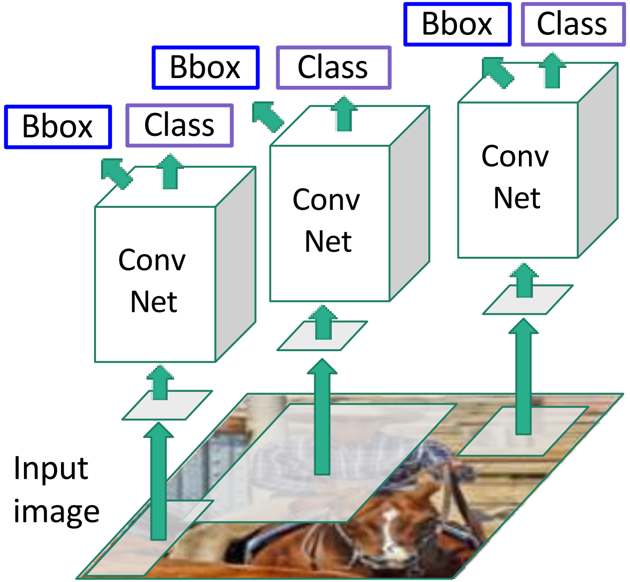
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



"Slow" R-CNN
Process each region independently



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Fast R-CNN

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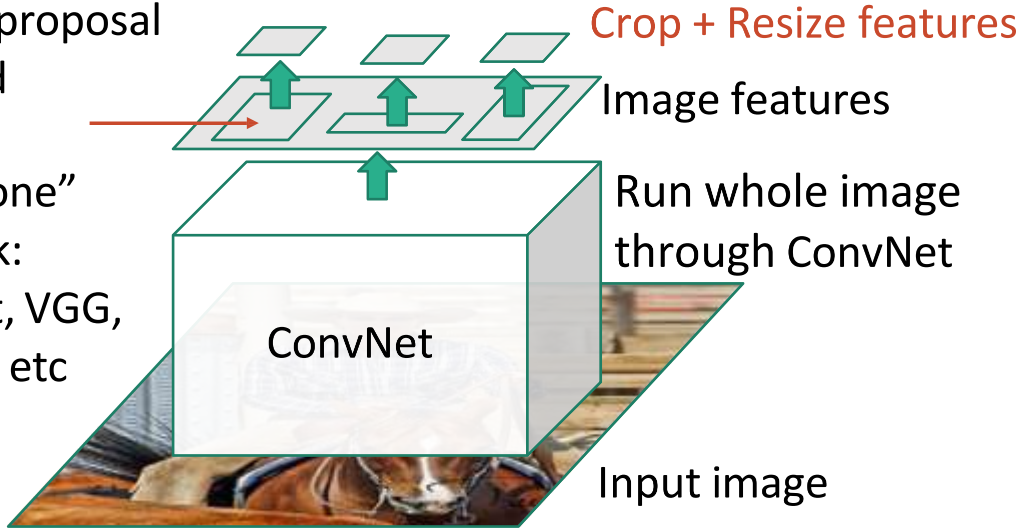
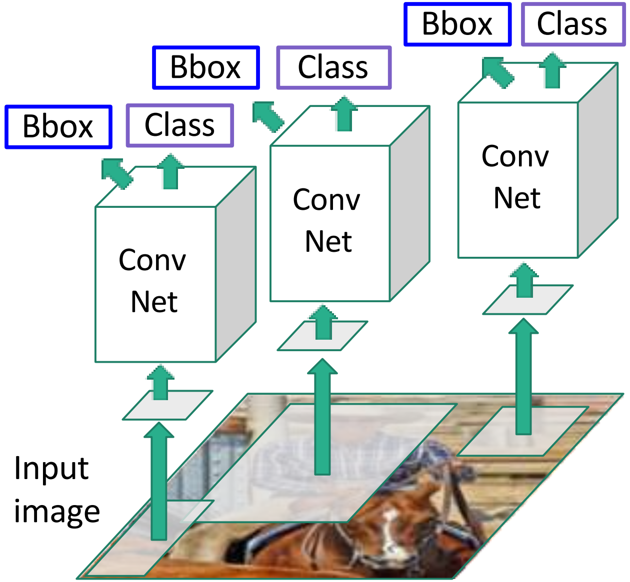


"Slow" R-CNN
Process each region independently



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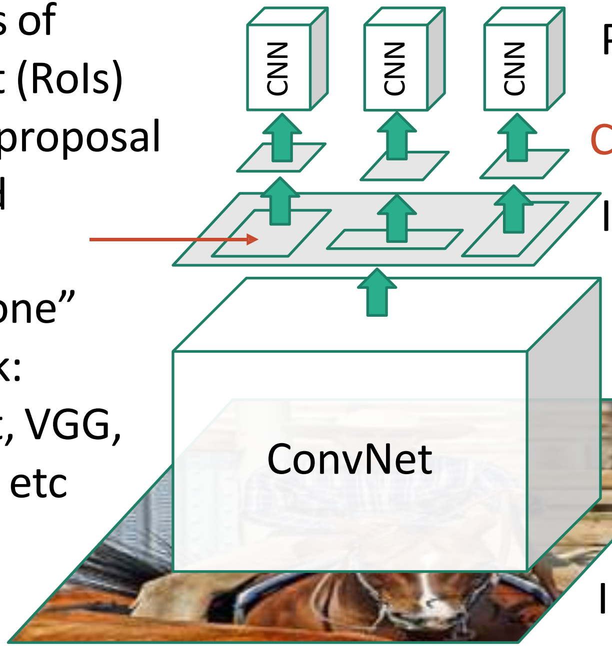
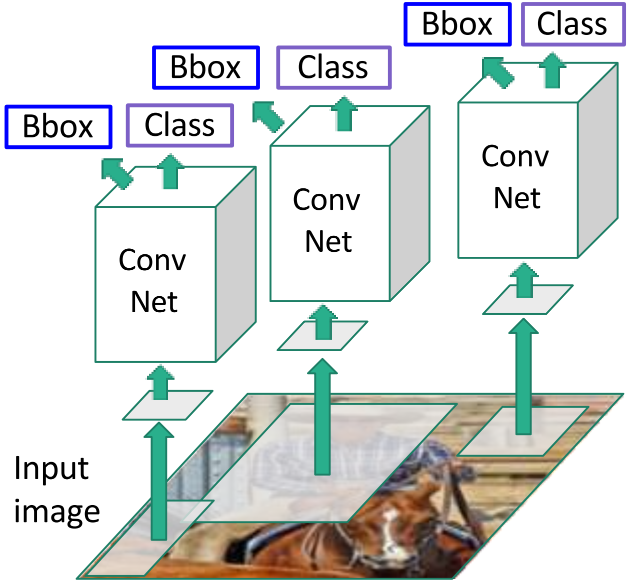
Fast R-CNN





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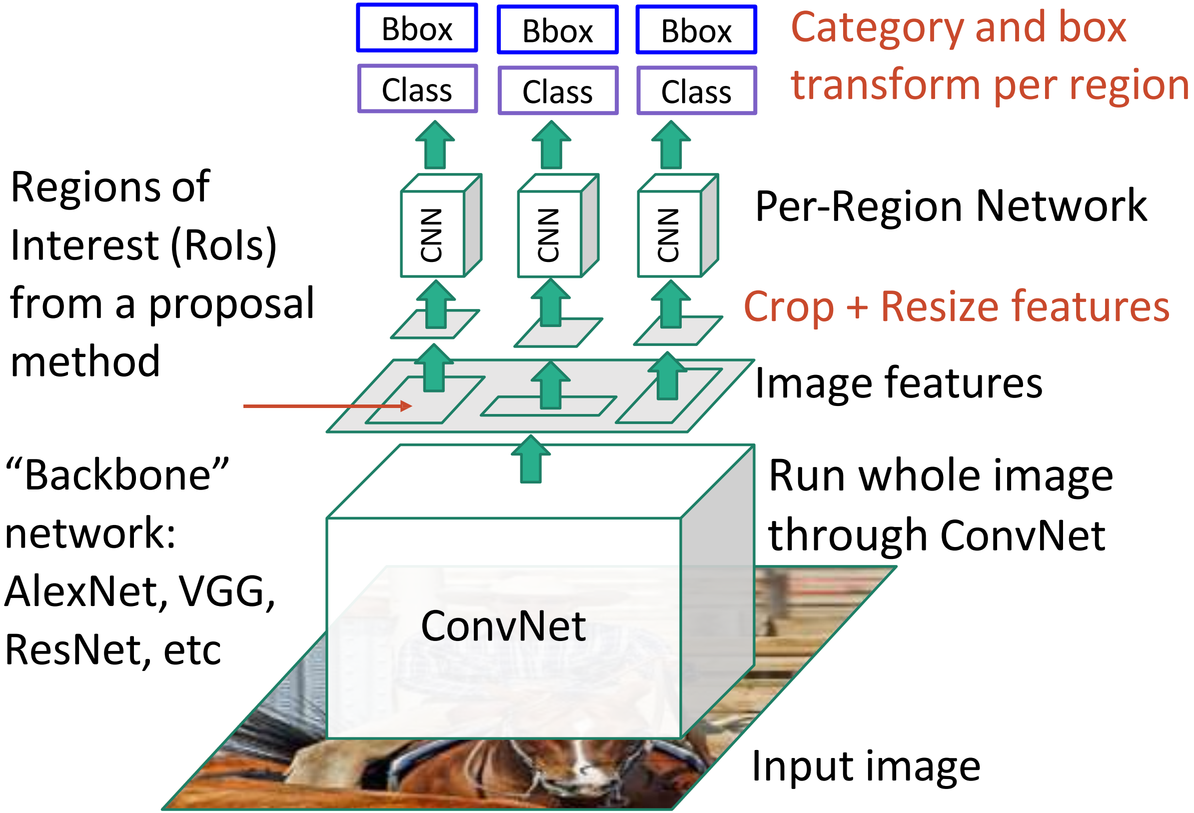
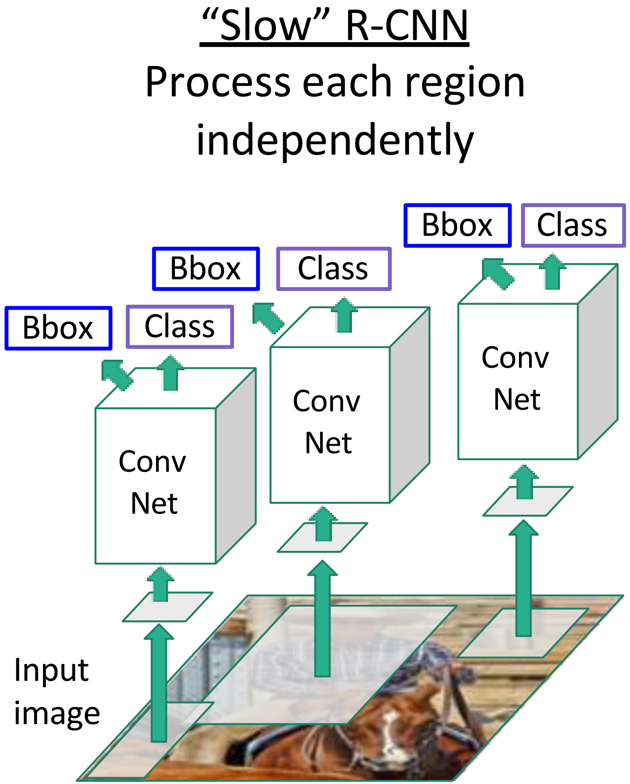
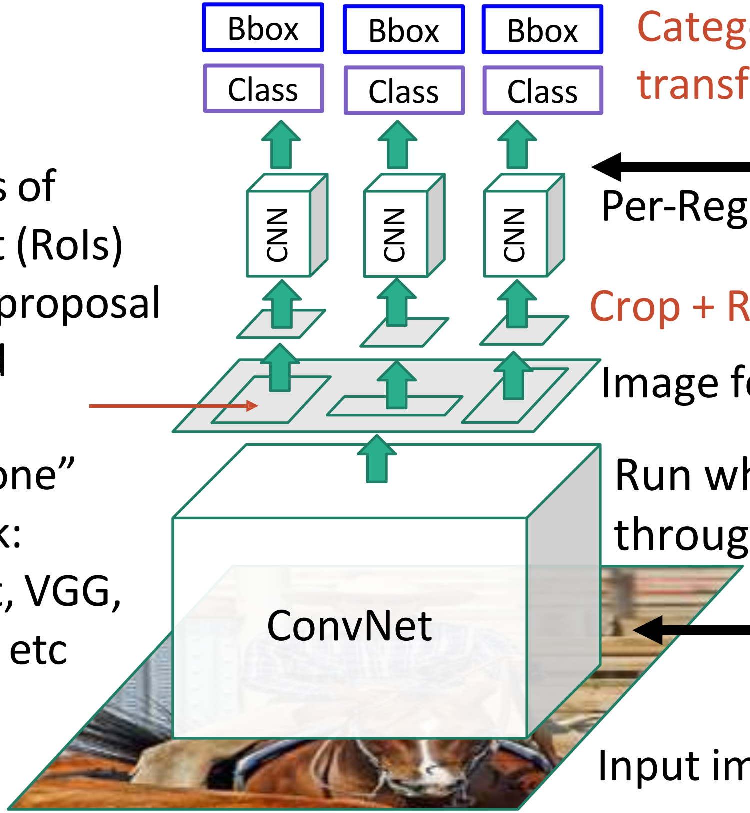
Fast R-CNN





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

Fast R-CNN



Category and box transform per region

Per-Region network is relatively lightweight

Per-Region Network

Regions of Interest (RoIs) from a proposal method

Crop + Resize features

Image features

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

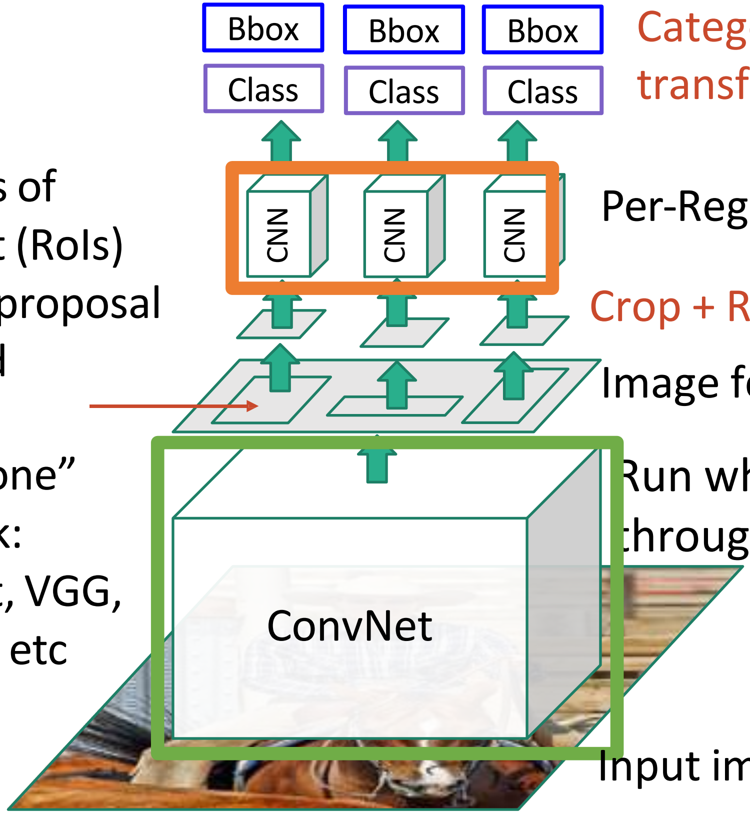
Run whole image through ConvNet

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

Input image

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

Fast R-CNN



Category and box transform per region

Per-Region Network

Crop + Resize features

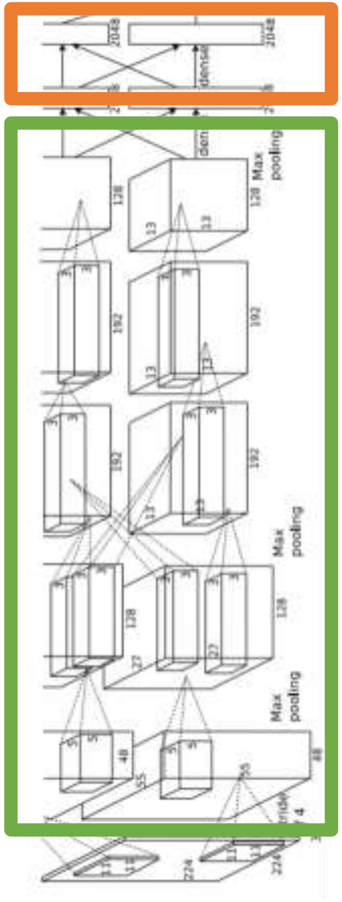
Image features

Run whole image through ConvNet

Input image

Regions of Interest (RoIs) from a proposal method

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



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

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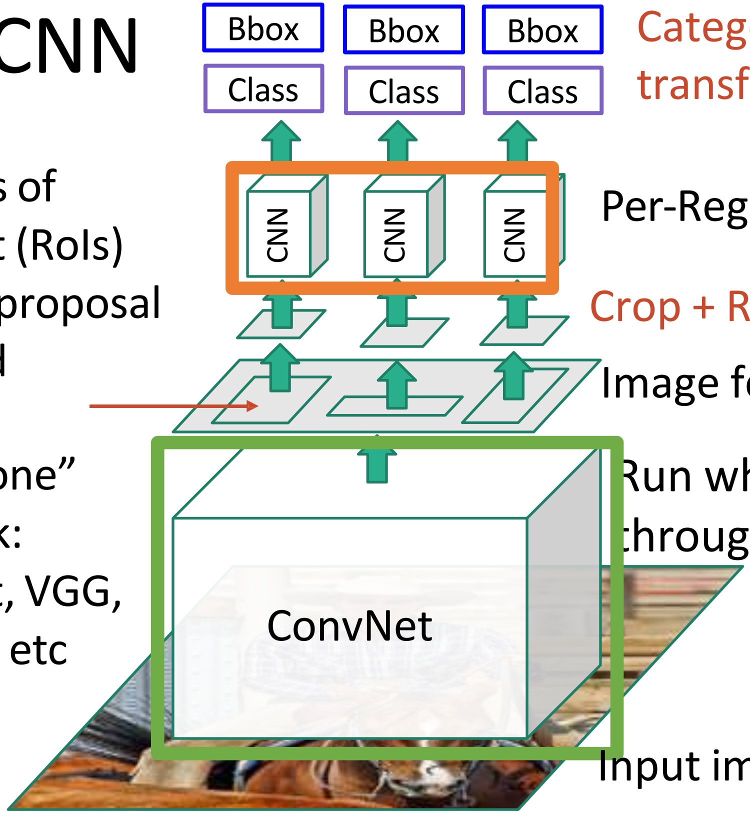
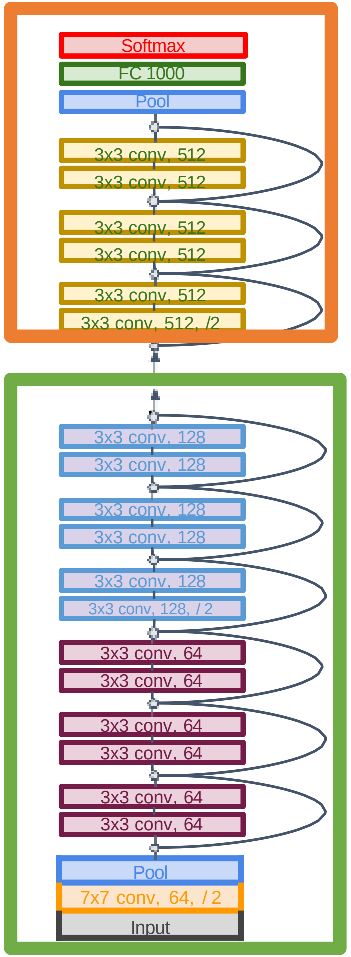
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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





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

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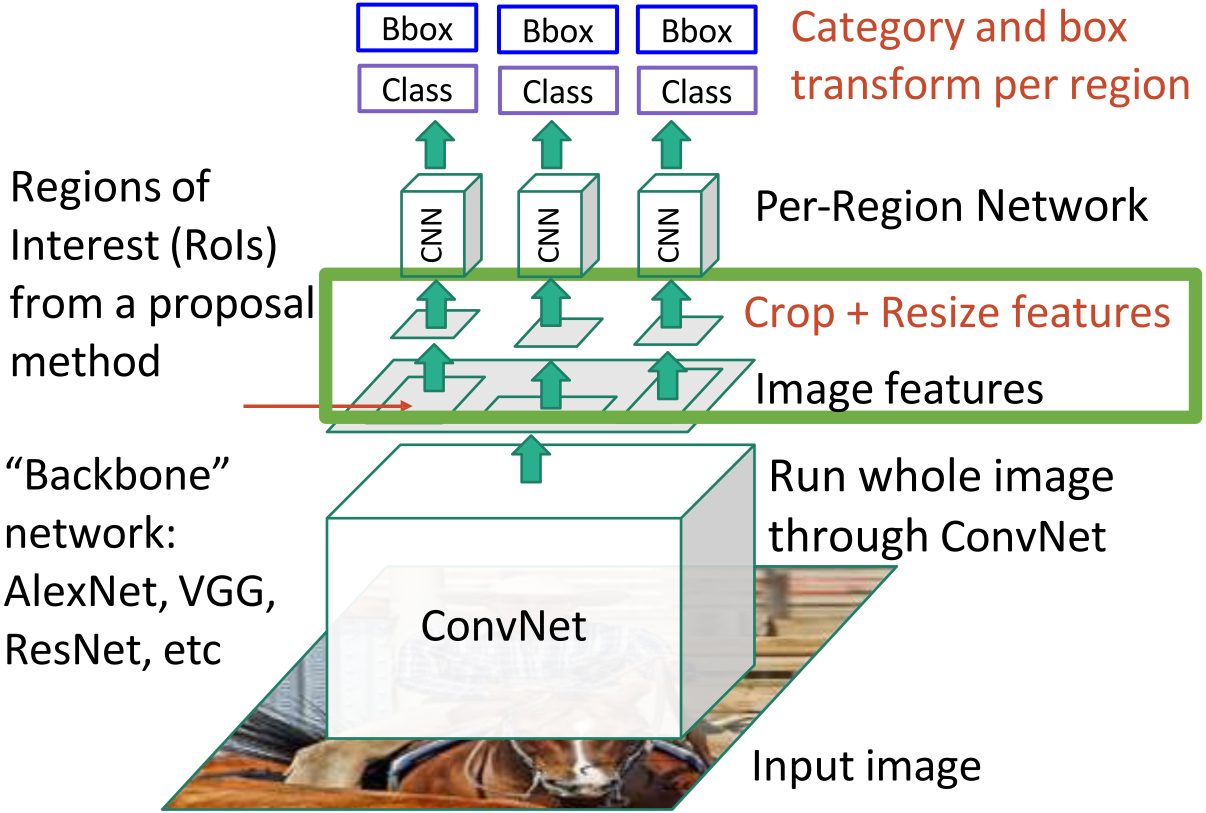
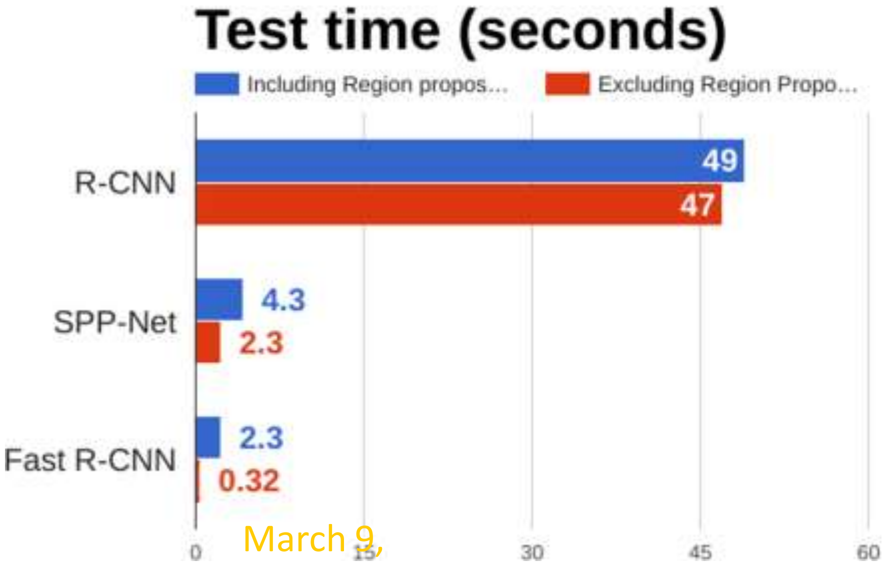
Fast R-CNN



How to crop features?

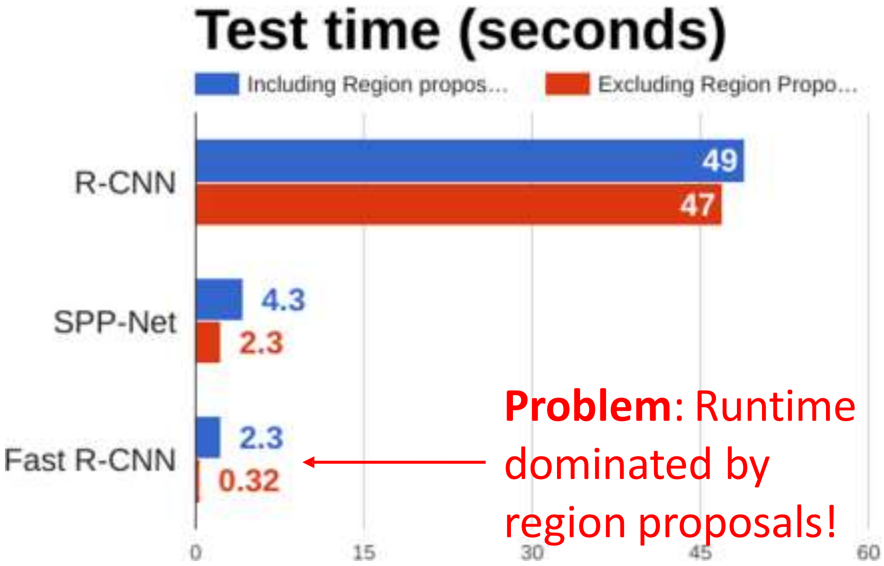
Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; [source](). Reproduced with permission.

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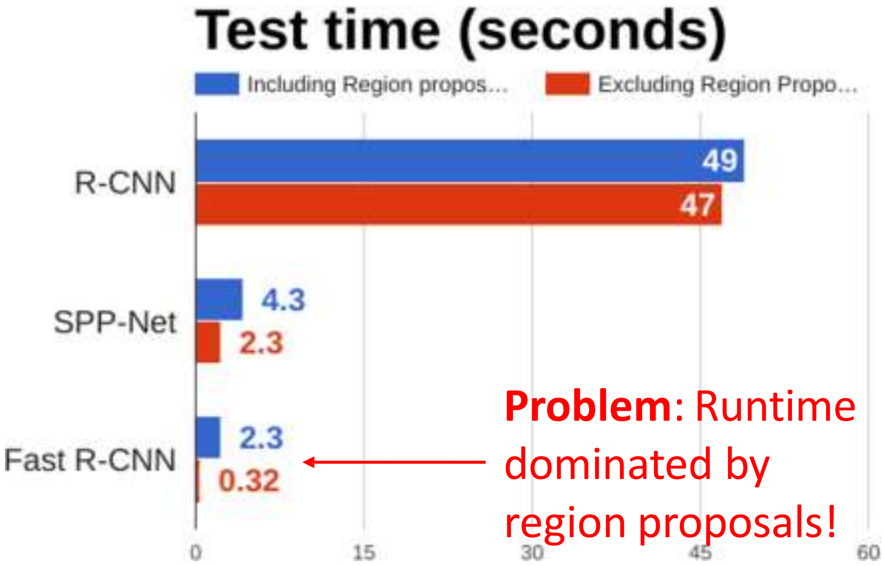
Girshick, "Fast R-CNN", ICCV 2015

Fast R-CNN vs “Slow” R-CNN



Problem: Runtime dominated by region proposals!

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

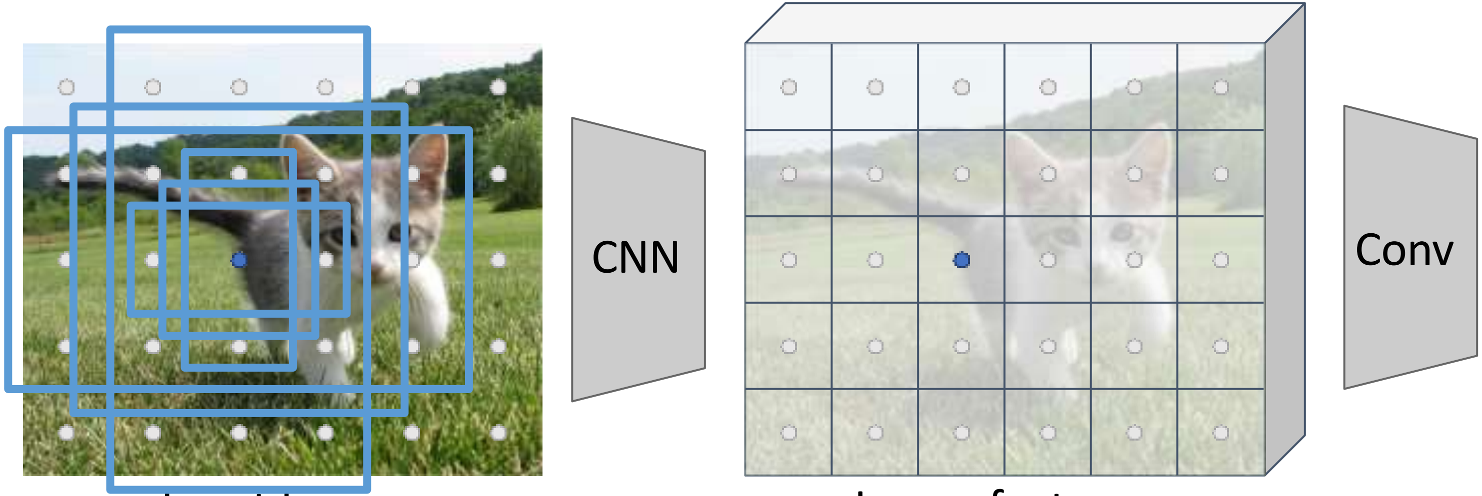
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

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)

Anchor is object?
2K x 5 x 6

Anchor transforms
4K x 5 x 6

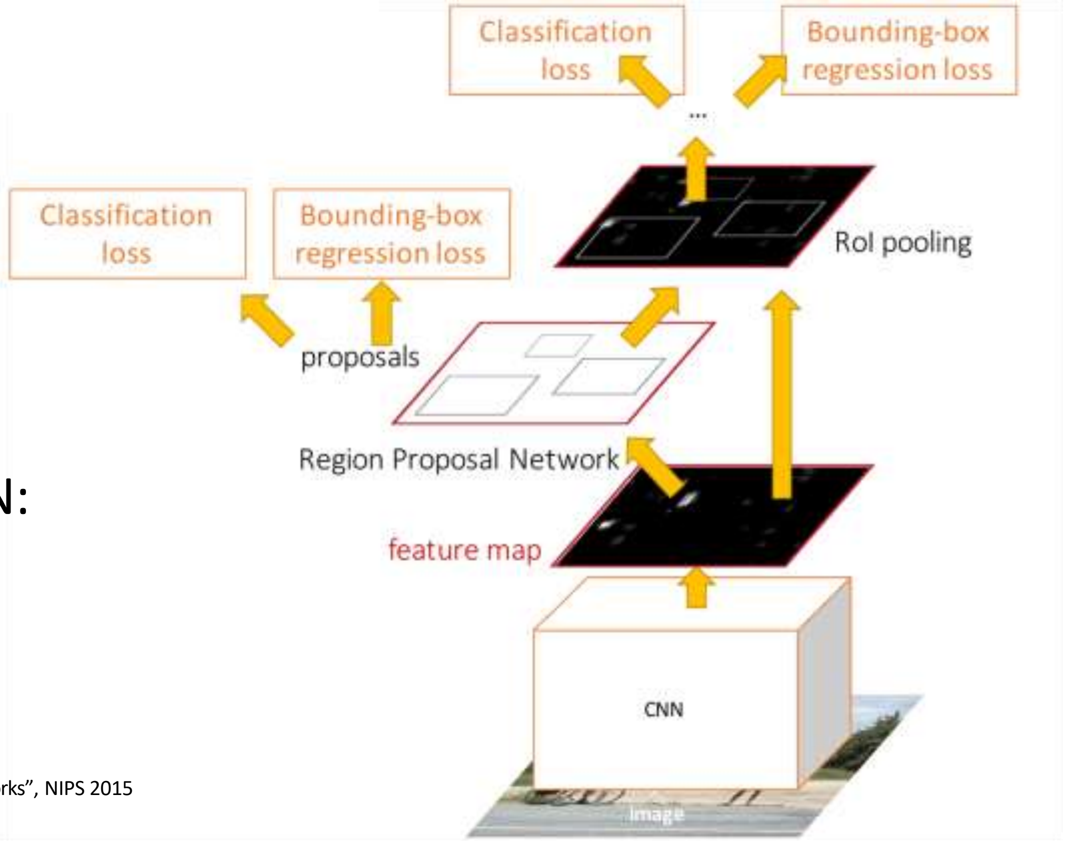
At test-time, sort all K*5*6 boxes by their positive score, take top 300 as our region proposals

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

Faster R-CNN: Learnable Region Proposals

Insert **Region Proposal Network (RPN)** to predict proposals from features

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

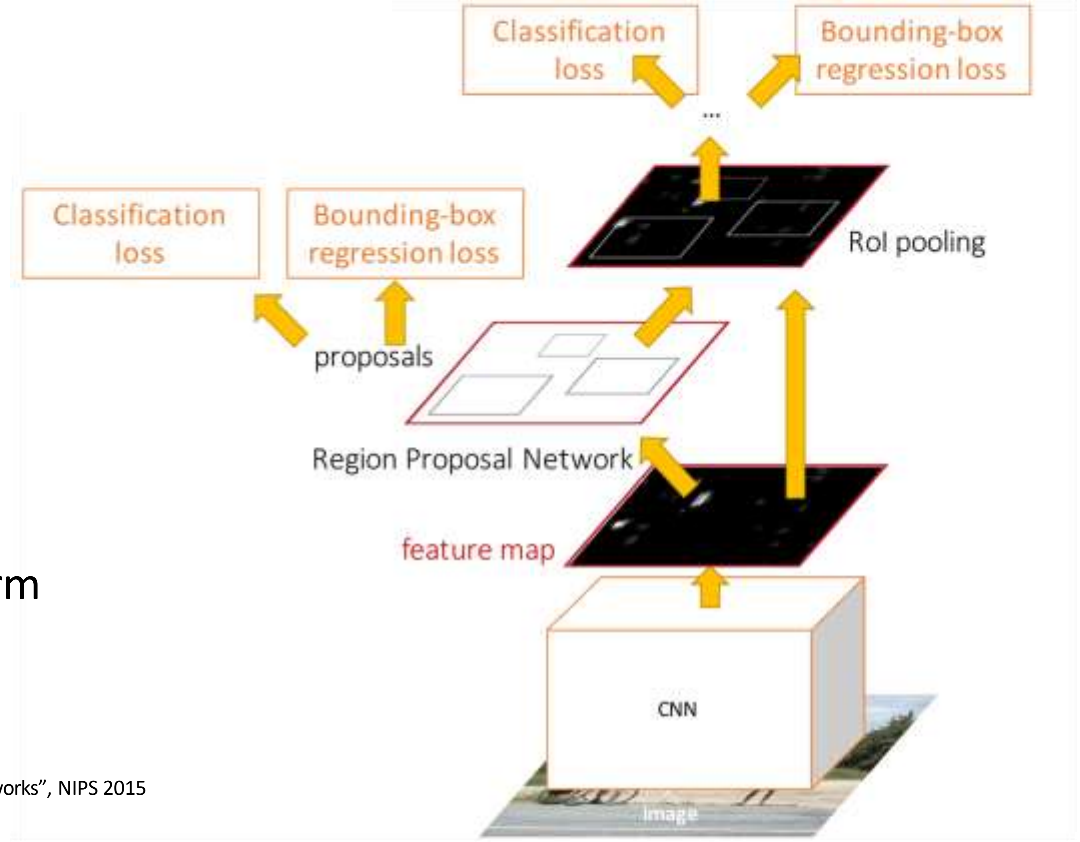


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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



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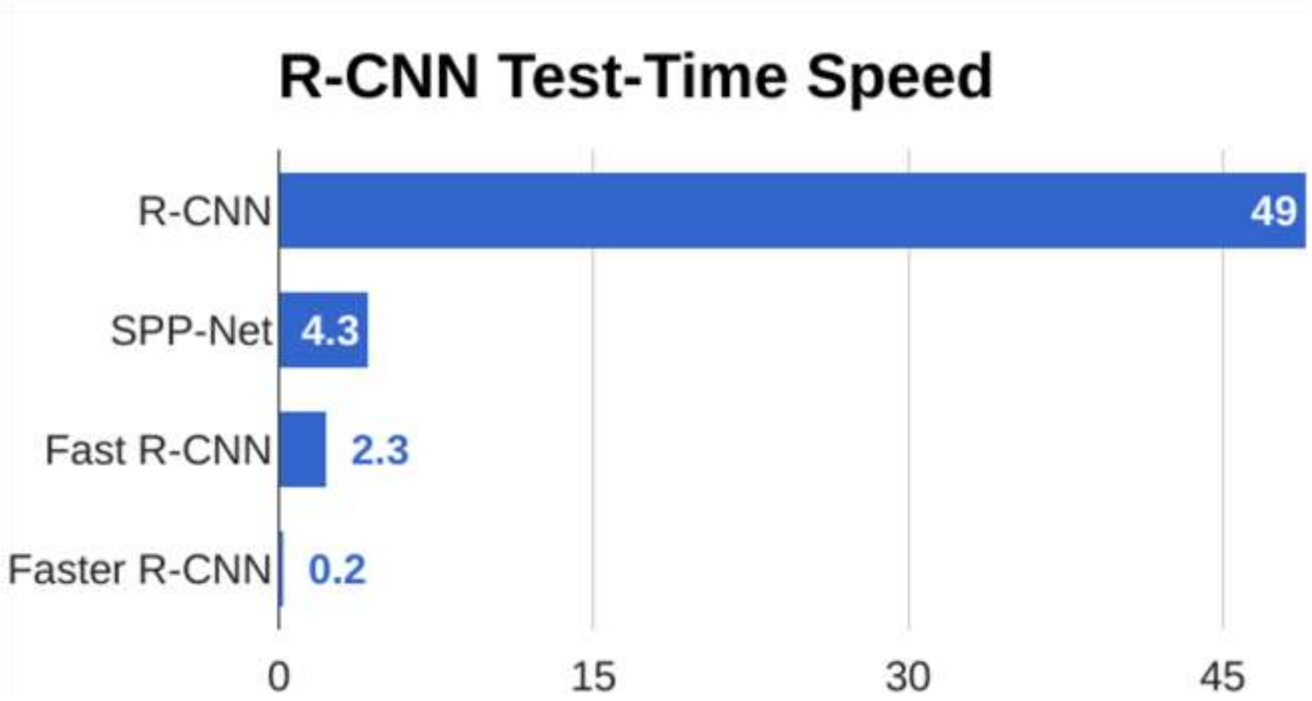
Faster R-CNN: Learnable Region Proposals

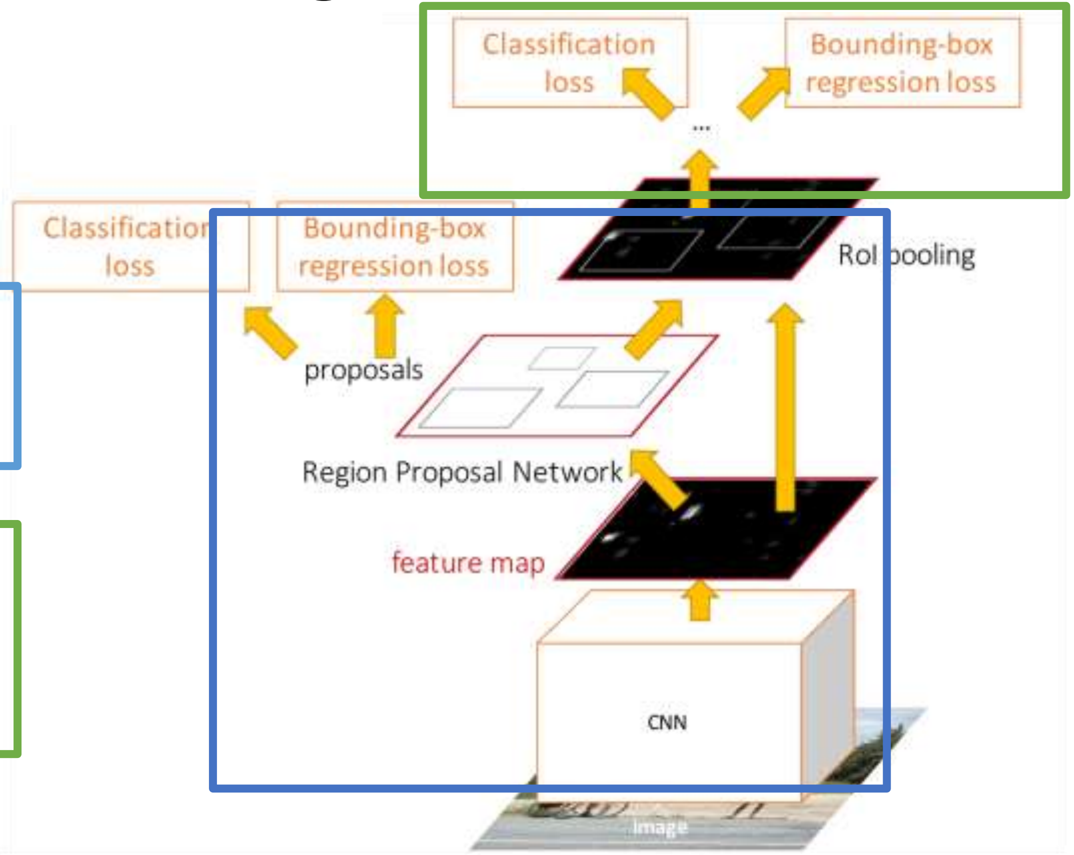


Faster R-CNN: Learnable Region Proposals

Faster R-CNN is a
Two-stage object detector

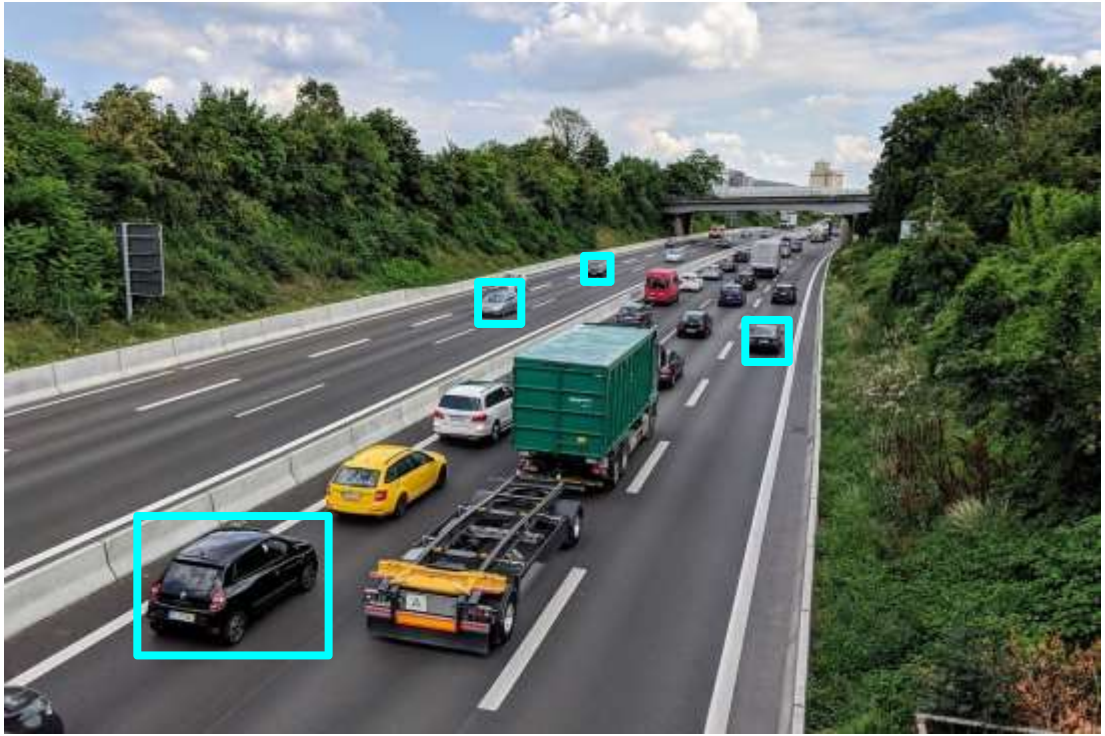
First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



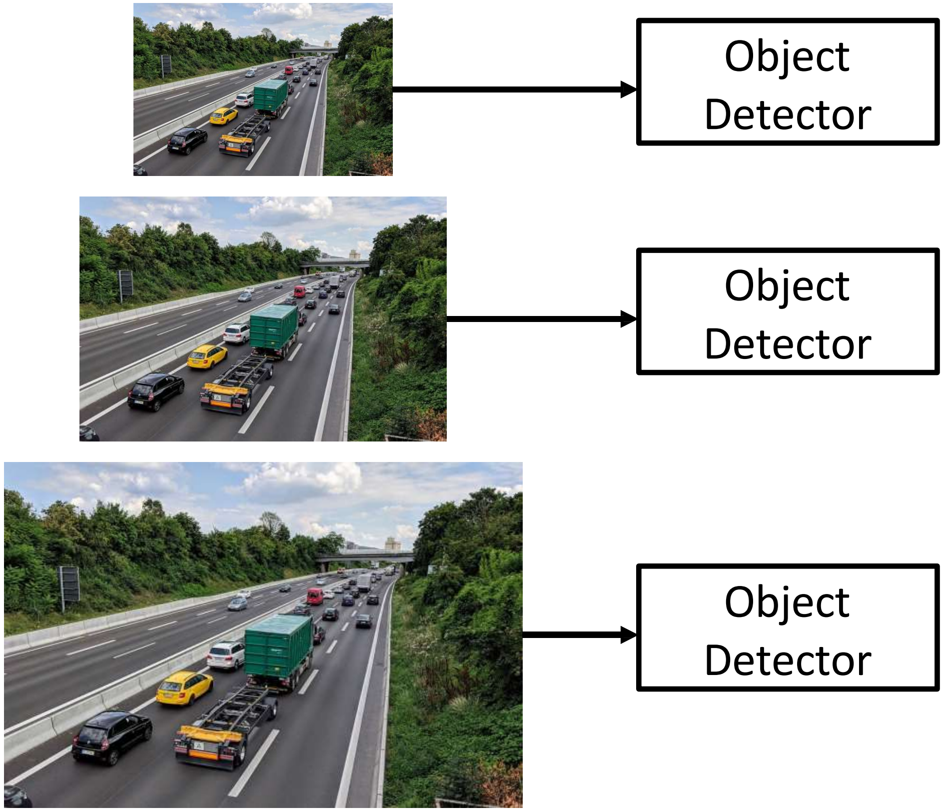
Dealing with Scale

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



Dealing with Scale: Image Pyramid

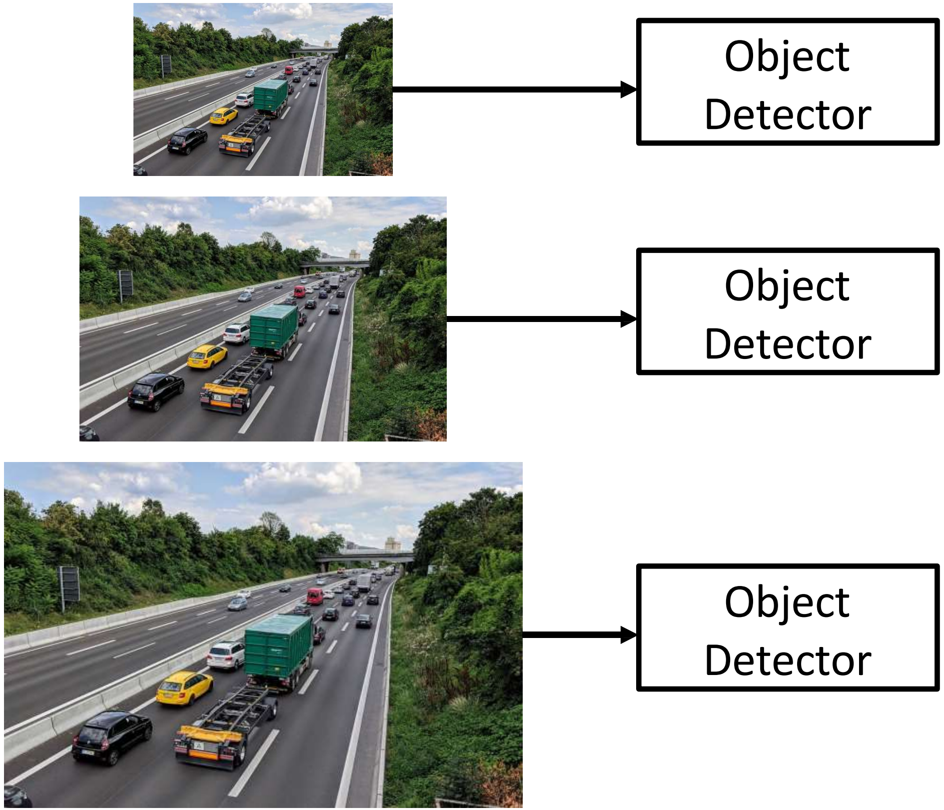
Classic idea: build an *image pyramid* by resizing the image to different scales, then process each image scale independently.



Dealing with Scale: Image Pyramid

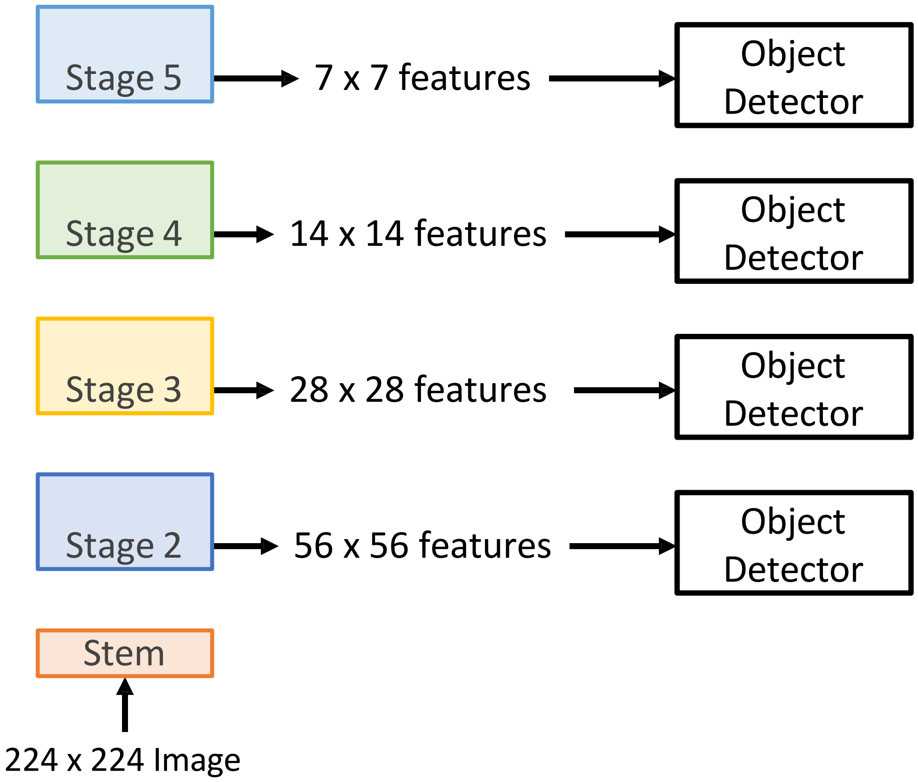
Classic idea: build an *image pyramid* by resizing the image to different scales, then process each image scale independently.

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



Dealing with Scale: Multiscale Features

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

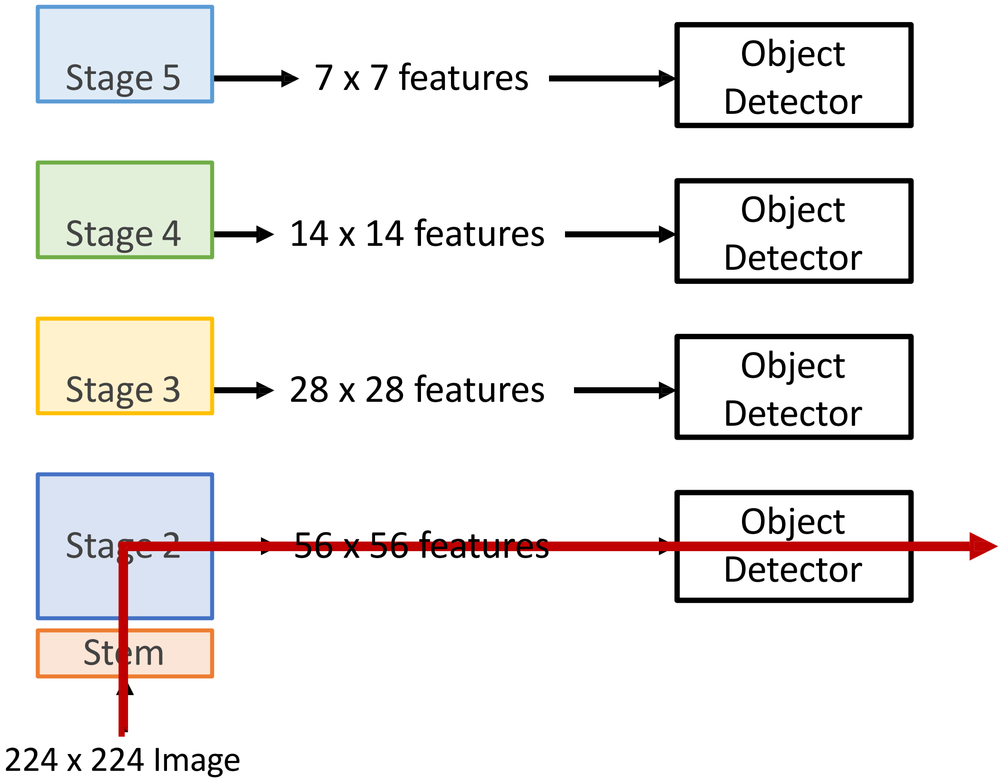


Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

Dealing with Scale: Multiscale Features

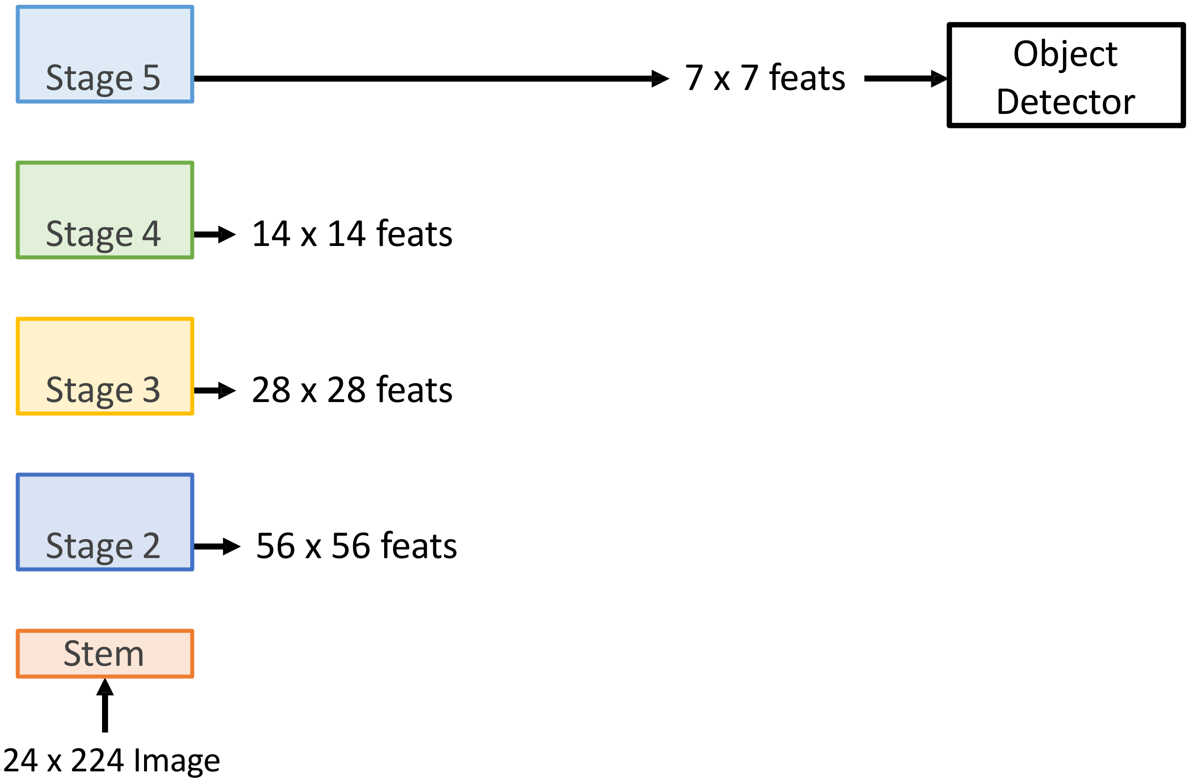
CNNs have multiple *stages* that operate at different resolutions. Attach an independent detector to the features at each level

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



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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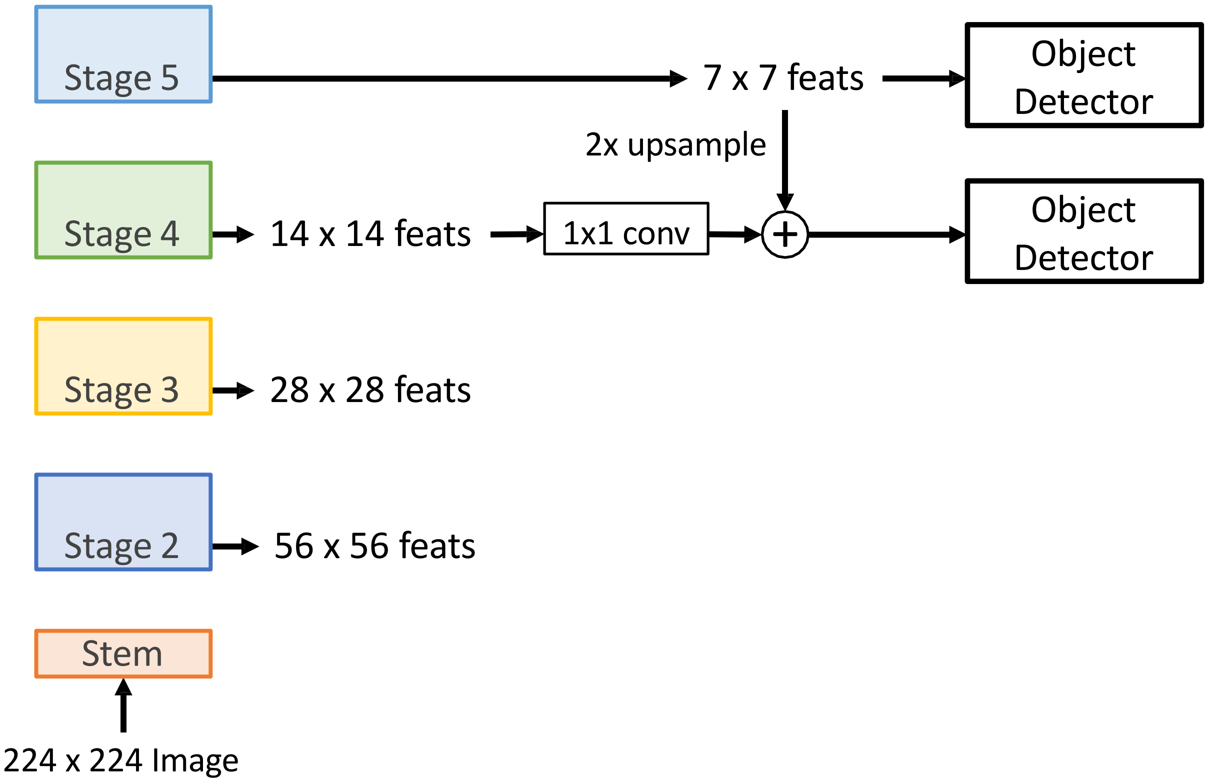

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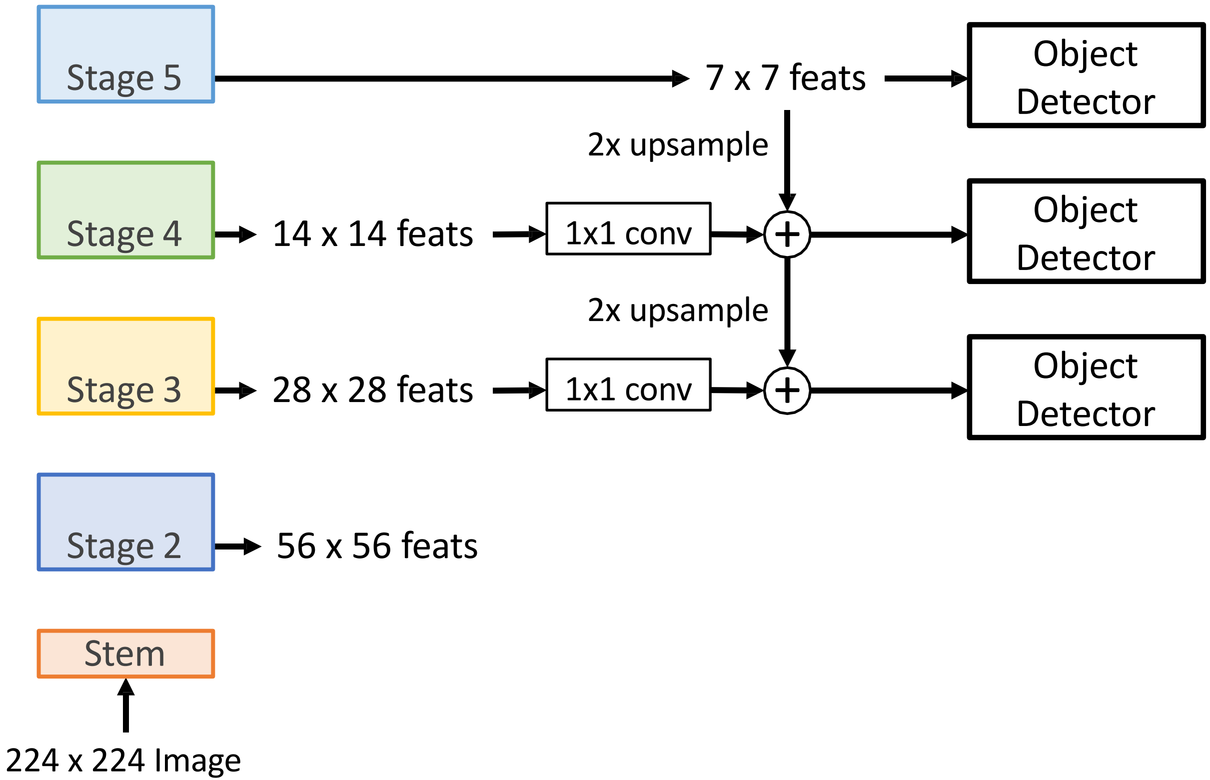

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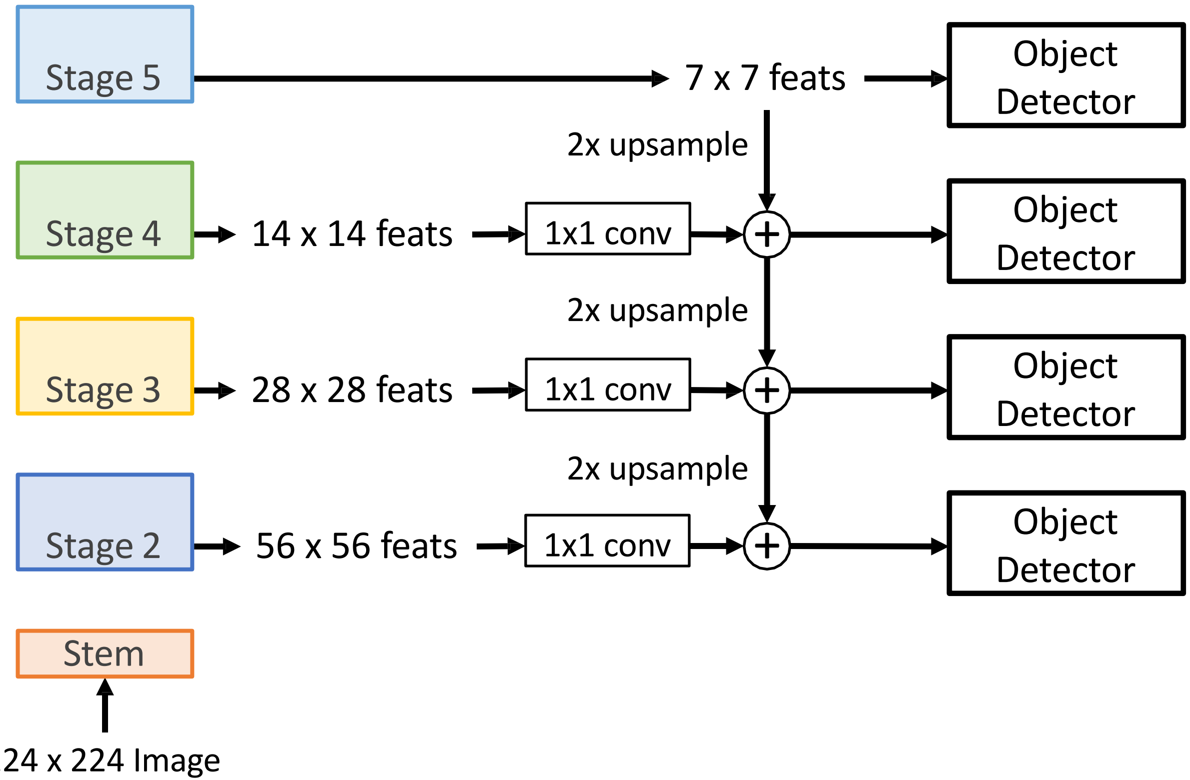
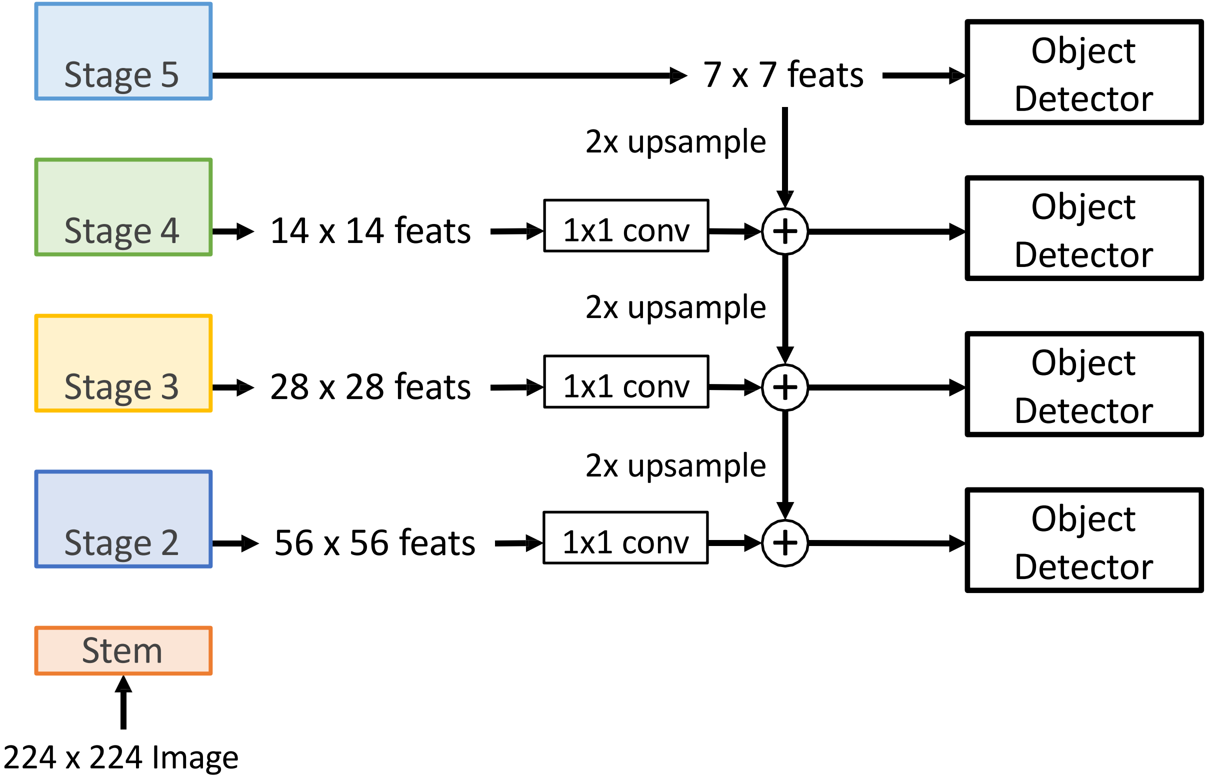


Lin et al, "Feature Pyramid Networks for Object Detection", ICCV 2017

Dealing with Scale: Feature Pyramid Network

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

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



Dealing with Scale: Feature Pyramid Network

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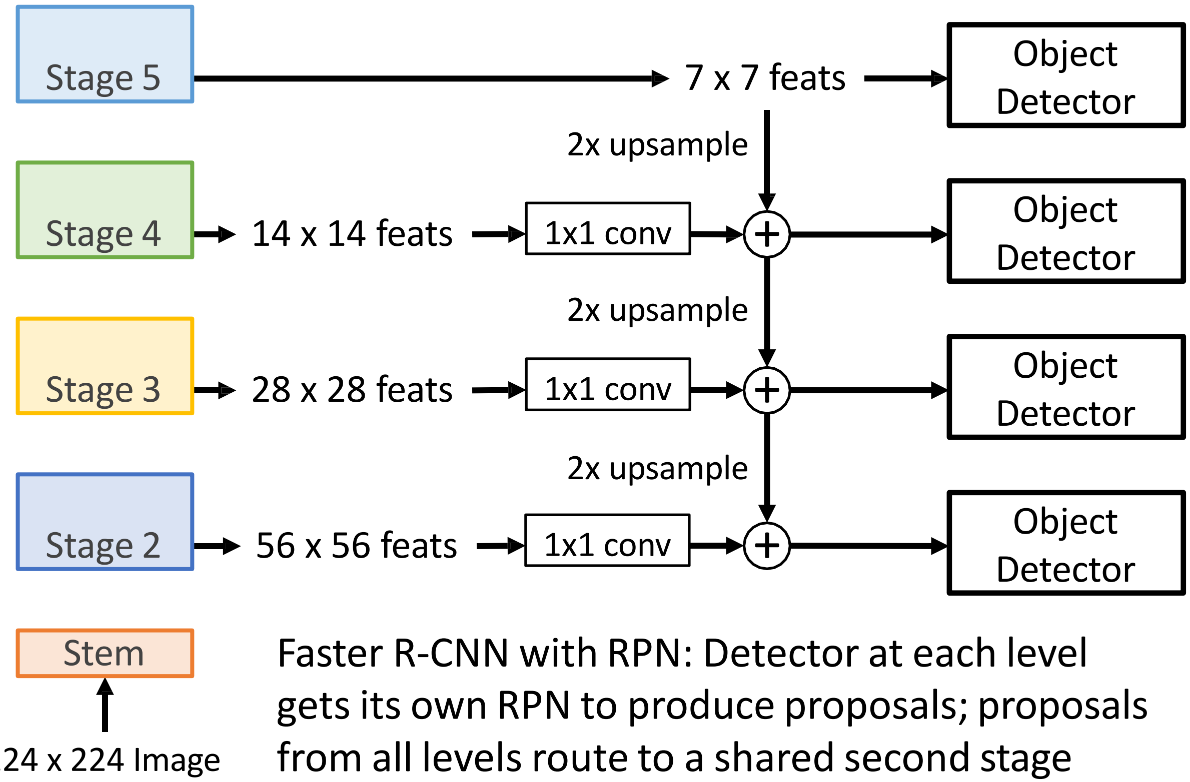


Faster R-CNN with RPN: Detector at each level gets its own RPN to produce proposals; proposals from all levels route to a shared second stage

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

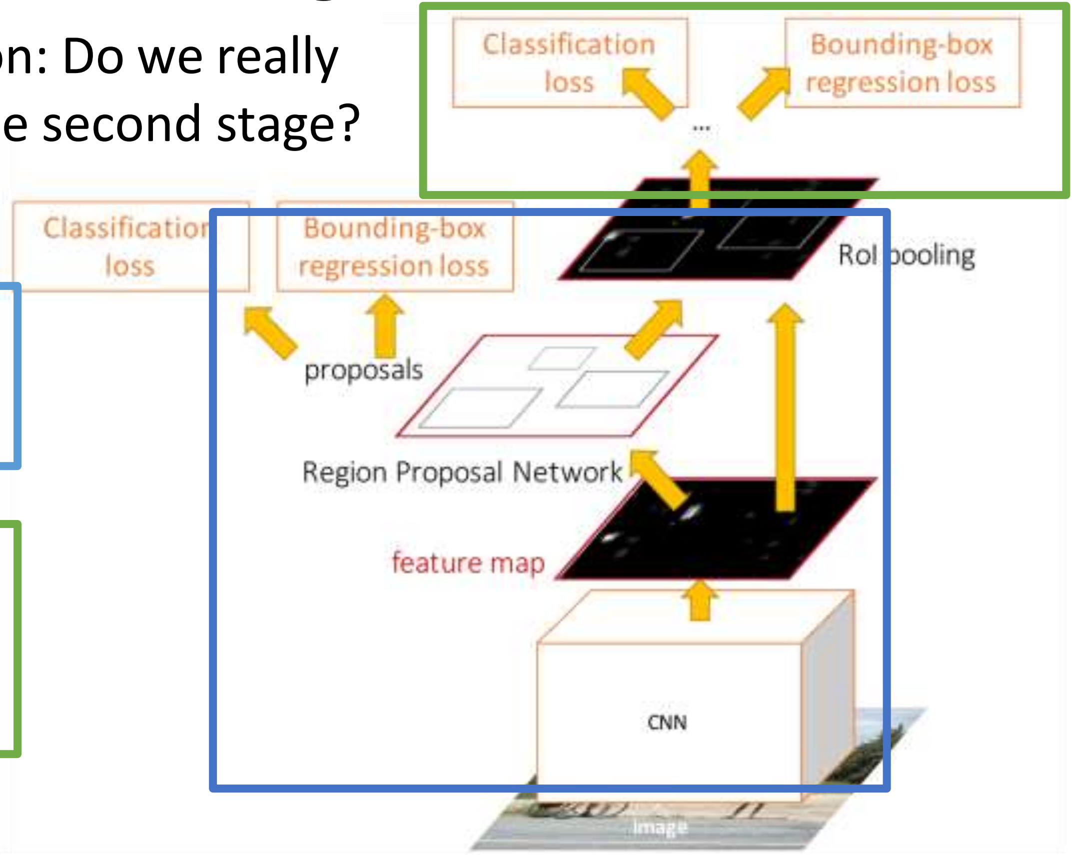
Faster R-CNN: Learnable Region Proposals

Question: Do we really need the second stage?

Faster R-CNN is a
Two-stage object detector

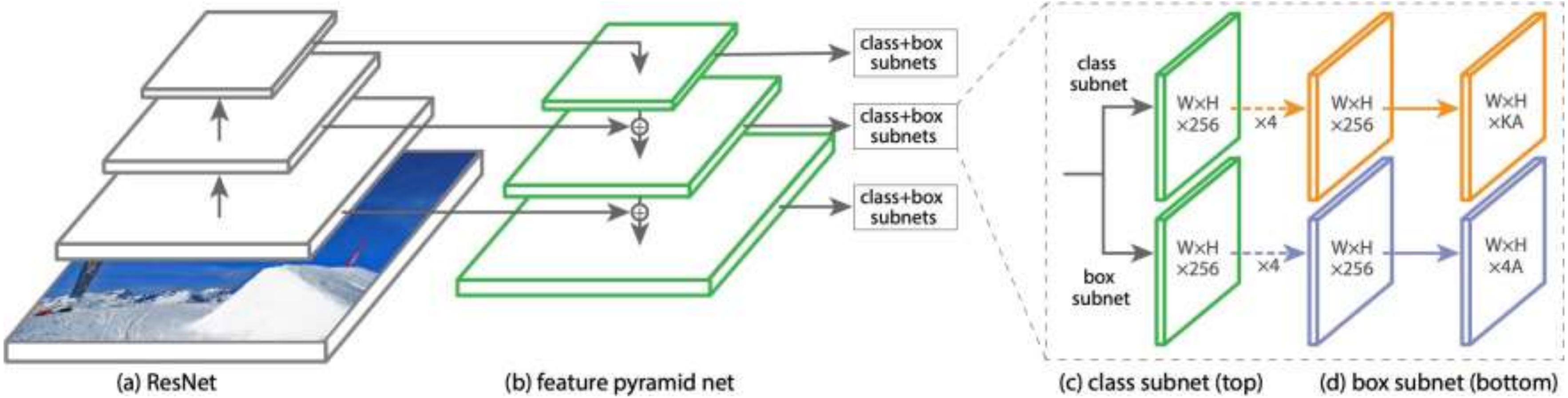
First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Single-Stage Detectors: RetinaNet

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

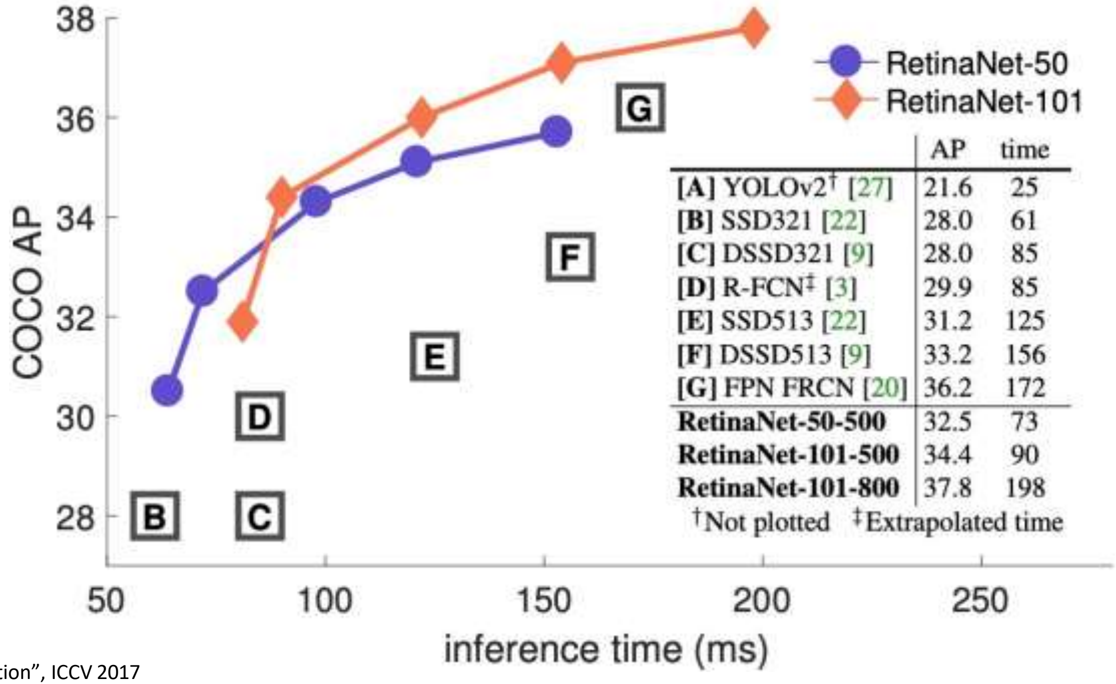


Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

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

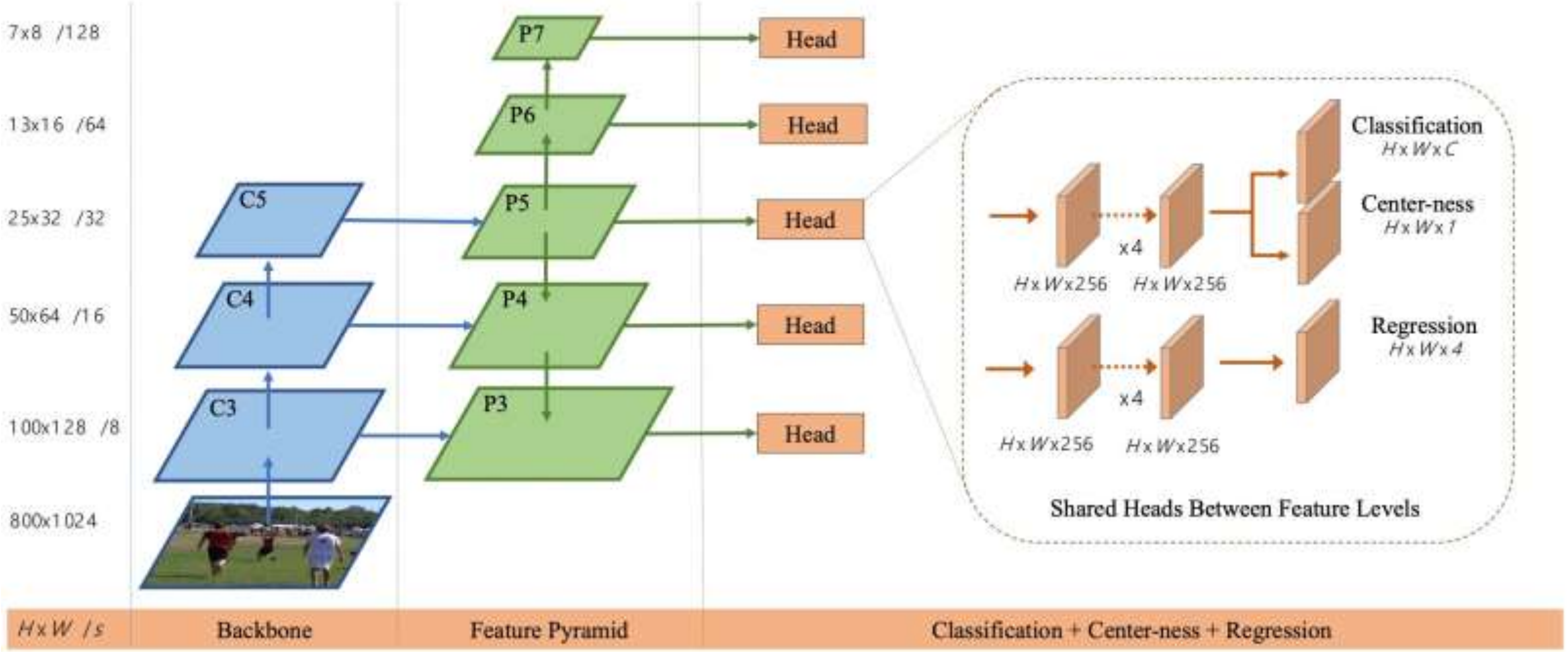
Lin et al, “Focal Loss for Dense Object Detection”, ICCV 2017

Figure credit: Lin et al, ICCV 2017

Single-Stage Detectors: FCOS

"Anchor-free" detector

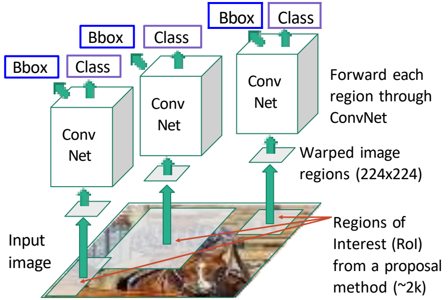
FCOS also uses a Feature Pyramid Network with heads shared across stages



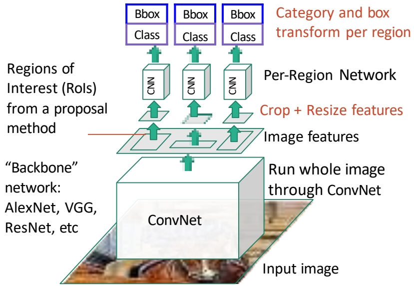
Tian et al, "FCOS: Fully Convolutional One-Stage Object Detection", ICCV 2019

Summary

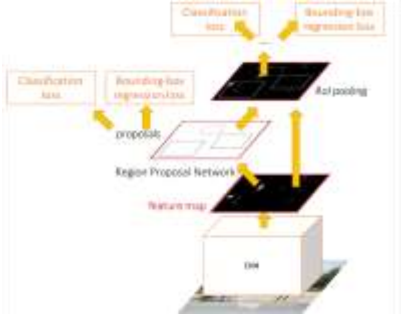
“Slow” R-CNN: Run CNN independently for each region



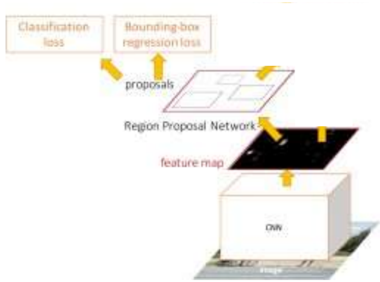
Fast R-CNN: Apply differentiable cropping to shared image features



Faster R-CNN: Compute proposals with CNN



Single-Stage: Fully convolutional detector



With anchors: RetinaNet
Anchor-Free: FCOS