Lecture 08: Spatial Localization and Detection

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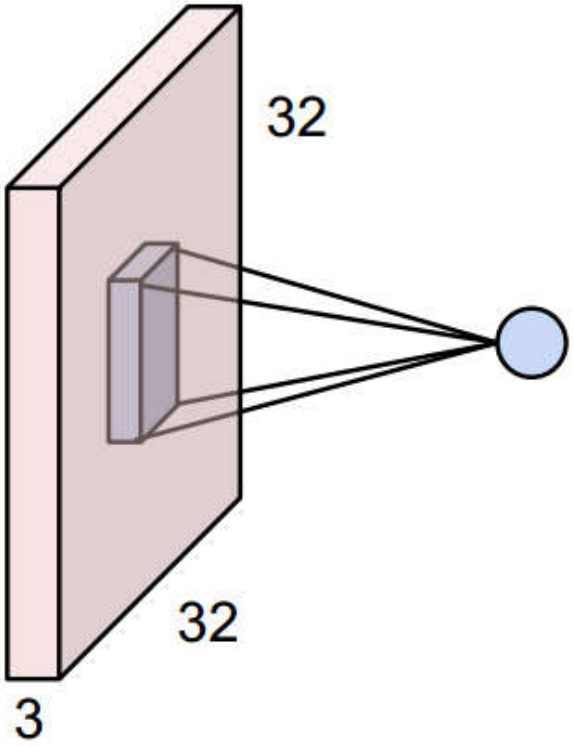
인하대학교 컴퓨터비전 연구실

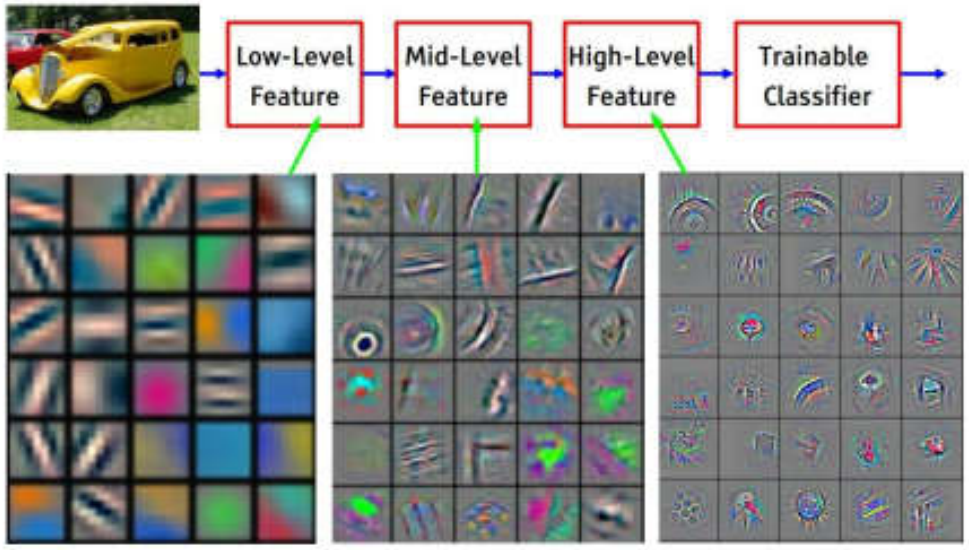
Recap From Last Class

Convolution



Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

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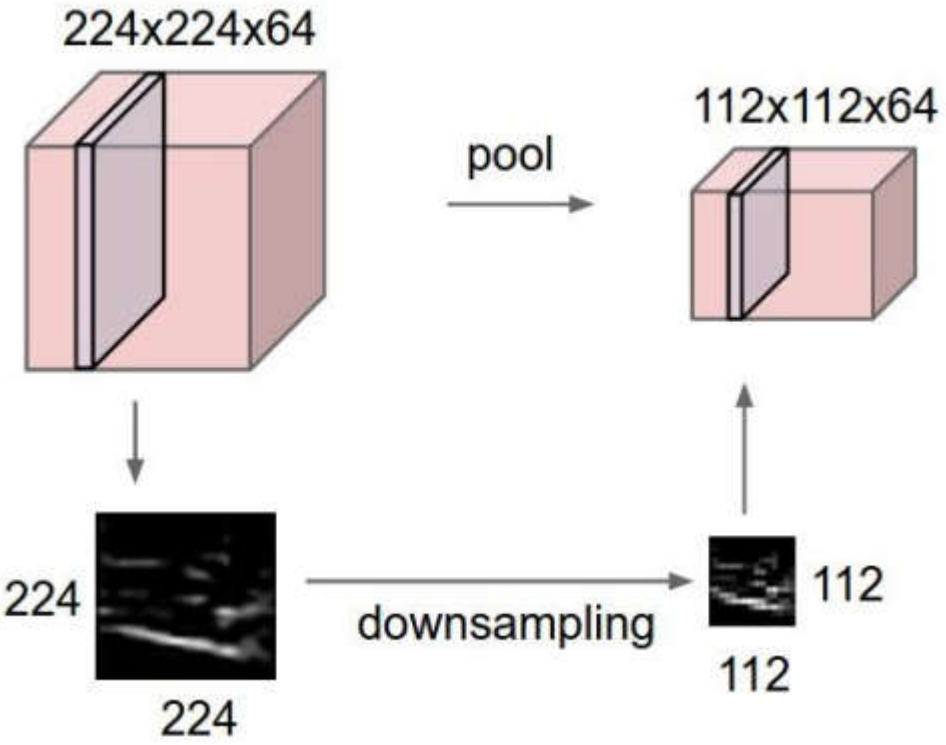
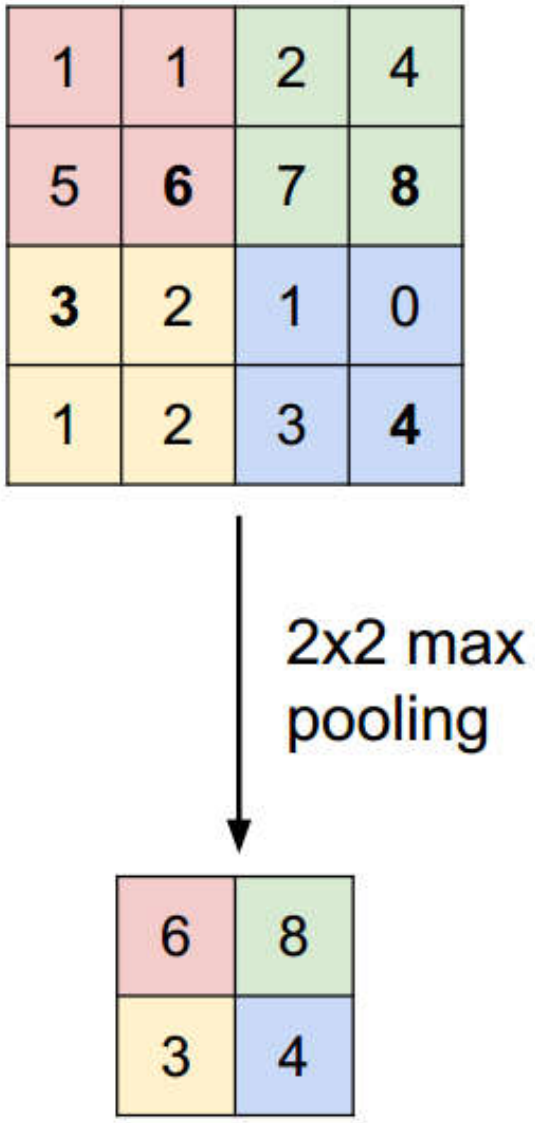
Recap From Last Class

Pooling





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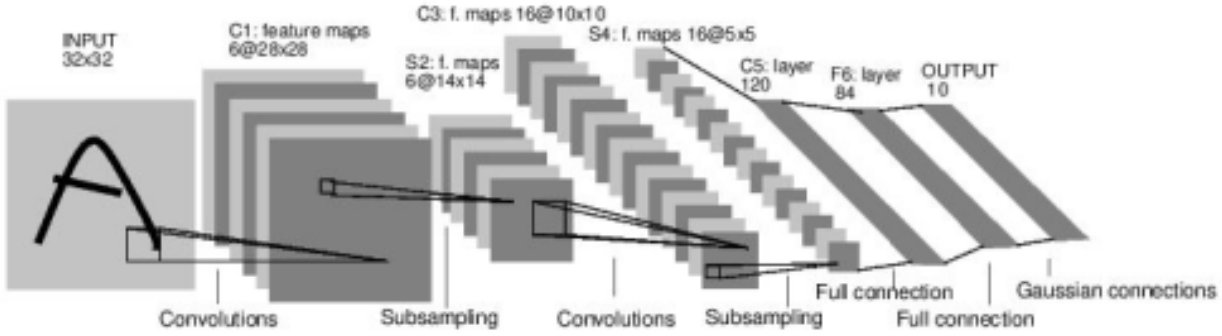
Recap From Last Class

Case Studies

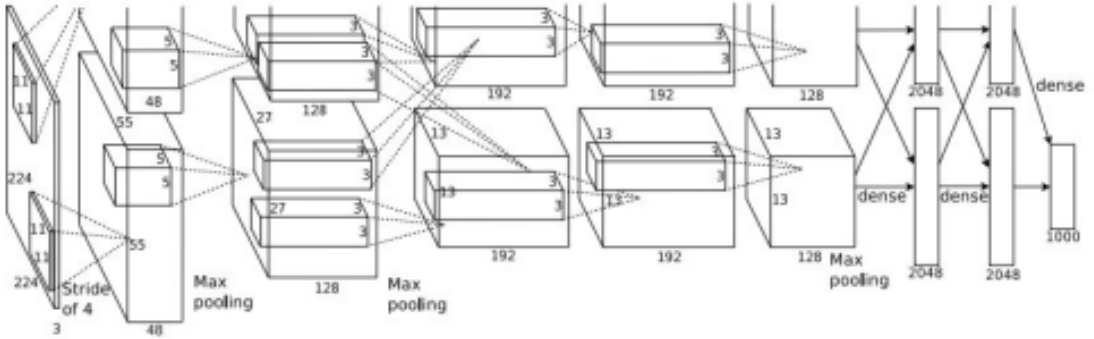
LeNet

(1998)



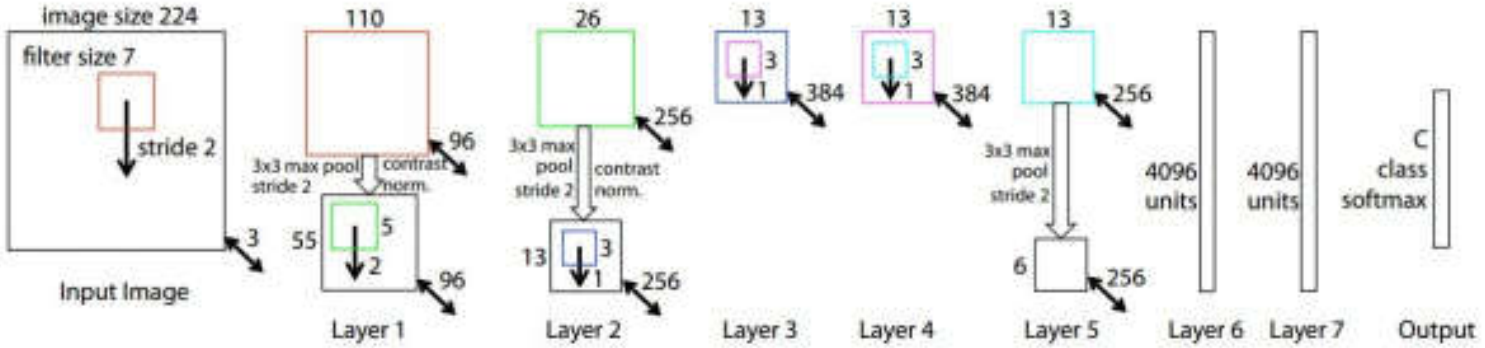
AlexNet

(2012)



ZFNet

(2012)



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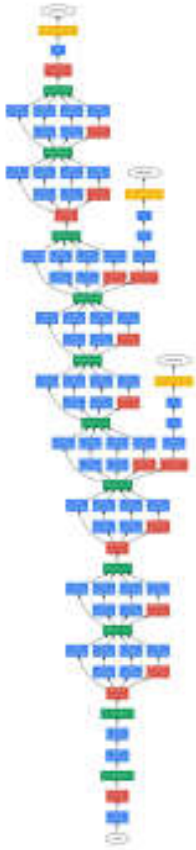
Recap From Last Class

Case Studies

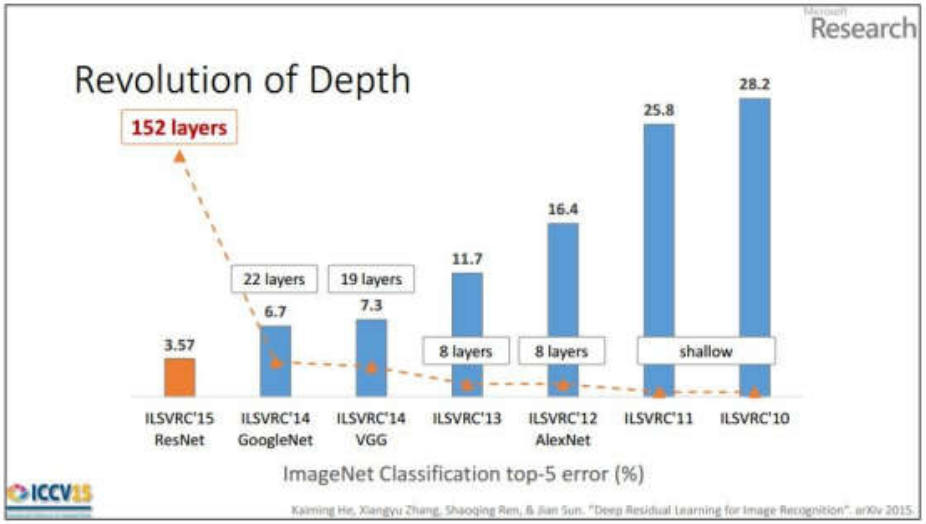
D	E
16 weight layers	19 weight layers
ge)	
conv3-64 conv3-64	conv3-64 conv3-64
conv3-128 conv3-128	conv3-128 conv3-128
conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool	
FC-4096	
FC-4096	
FC-1000	
soft-max	

VGG
(2014)



GoogLeNet
(2014)

ResNet
(2014)



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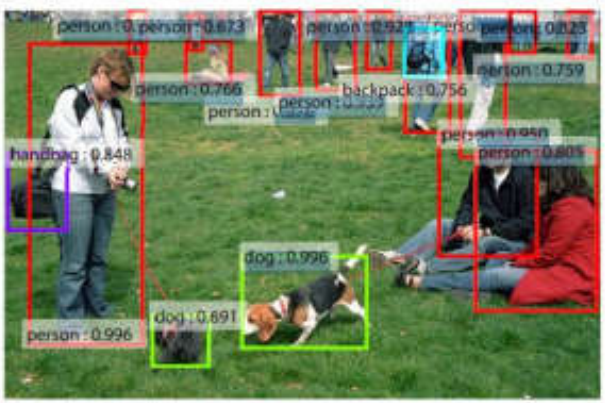
Localization and Detection

Localization and Detection



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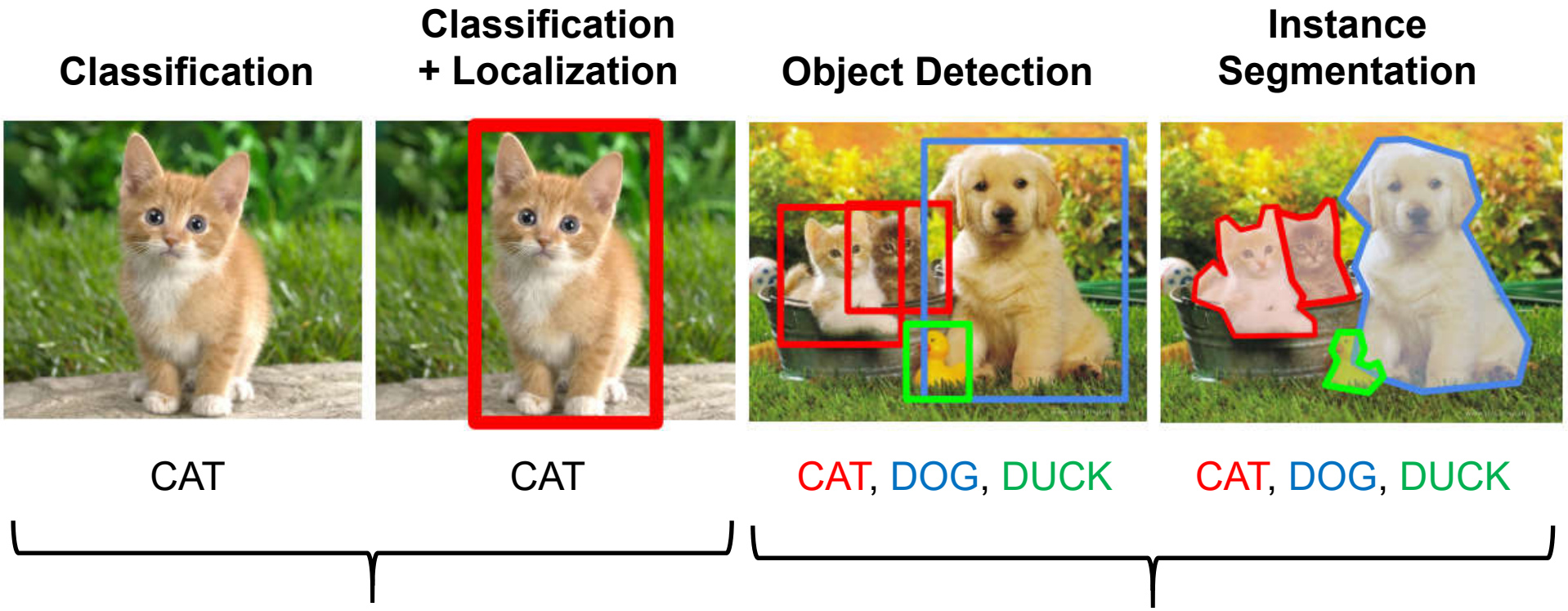
Computer Vision Tasks



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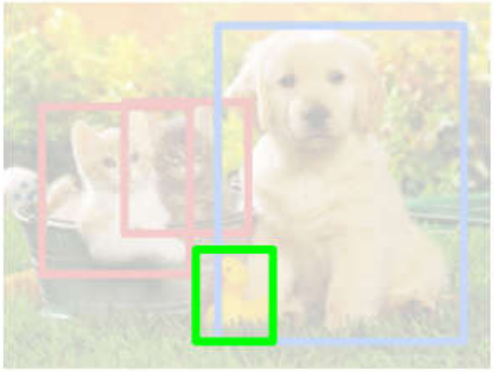
Computer Vision Tasks

Classification

Classification + Localization

Object Detection



Instance Segmentation

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Classification + Localization: Task

Classification: C classes
Input: Image
Output: Class label
Evaluation metrics: Accuracy

CAT

Localization:
Input: Image
Output: Box in the image (x, y, w, h)
Evaluation metric: Intersection over Union (IoU)

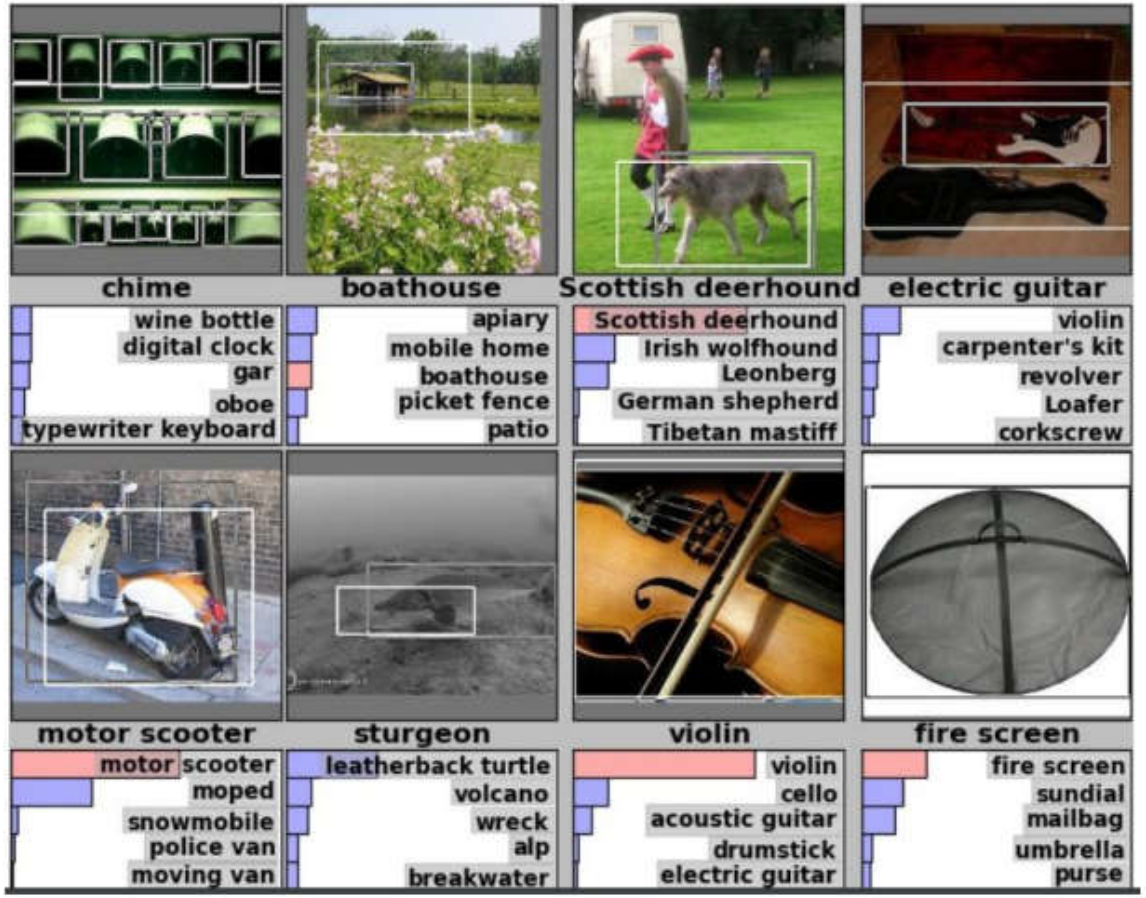
(x, y, w, h)

Classification + Localization: Do both

Slide from CS231n

Classification + Localization: ImageNet

- 1000 classes (same as classification)
- Each image has 1 class, at least one bounding box
- ~800 training images per class
- Algorithm produces 5 (class, box) guesses
- Example is correct if at least one guess has correct class AND bounding box at least 0.5 IoU



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Idea #1: Localization as Regression

Idea #1: Localization as Regression

Only one object, simpler than detection

Input: image

Neural Net

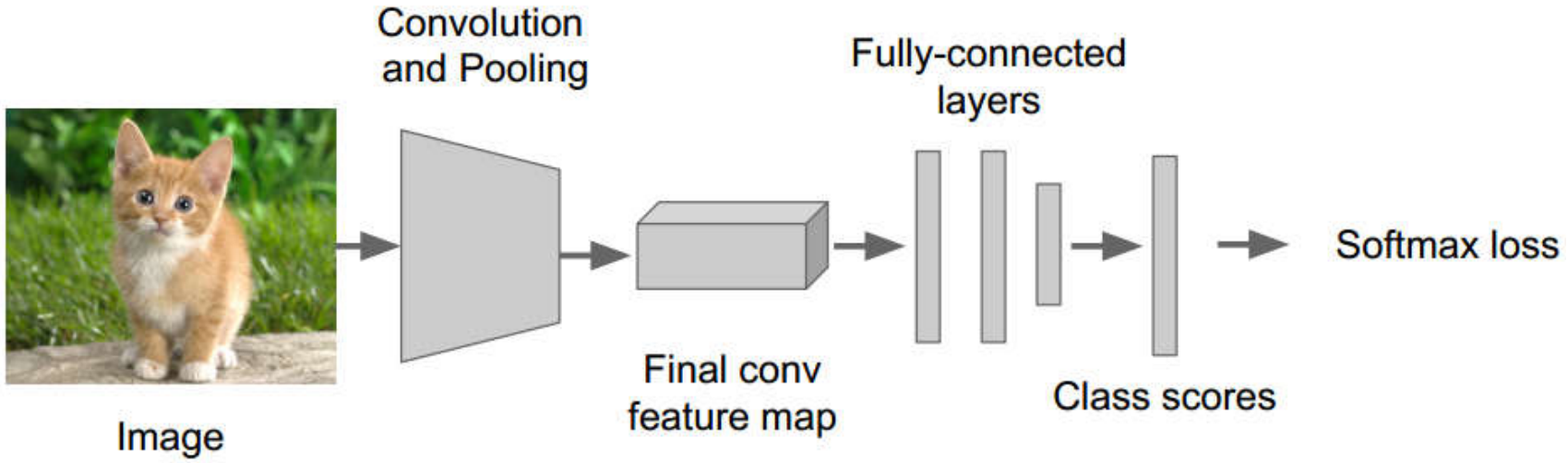
Output:
Box coordinates
(4 numbers)

Correct output:
Box coordinates
(4 numbers)

Loss:
L2 distance

Simple Recipe for Classification + Localization

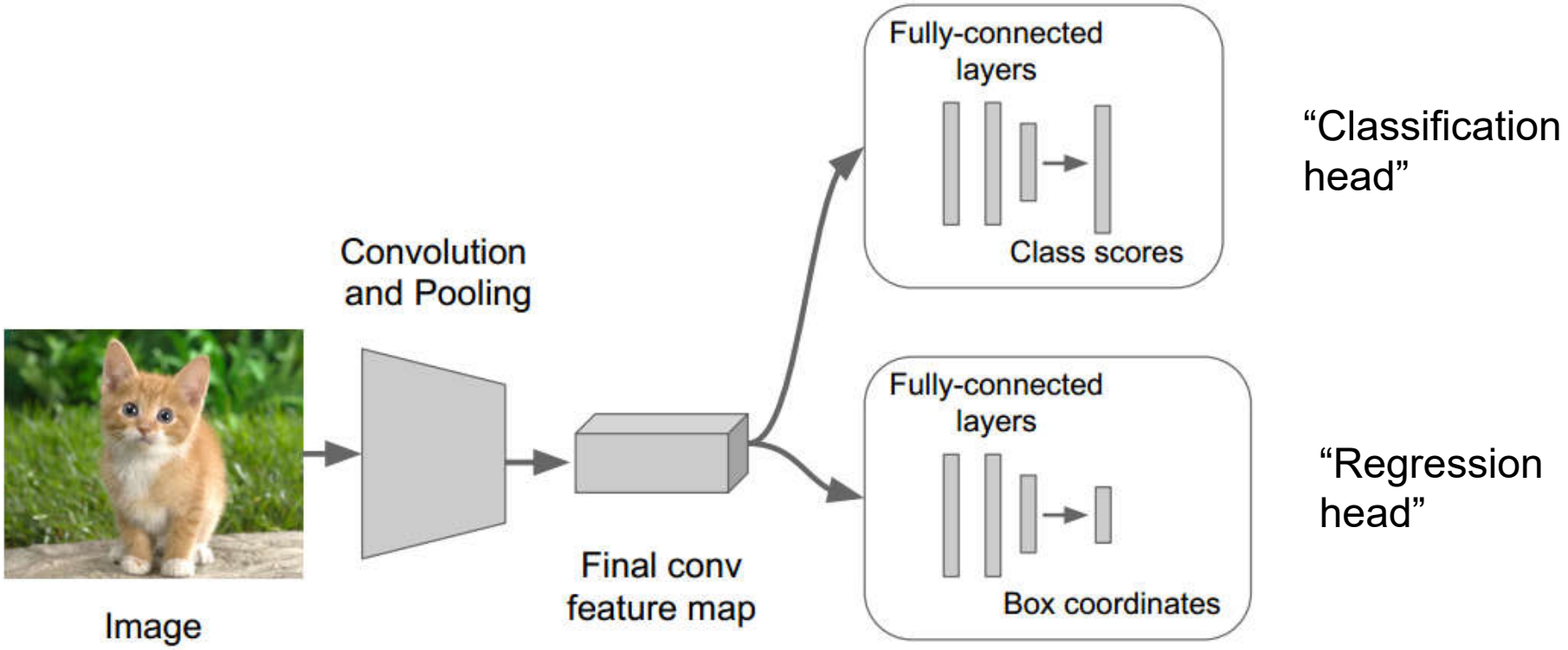
Step 1: Train (or download) a classification model (AlexNet, VGG, GoogLeNet)



Slide from CS231n

Simple Recipe for Classification + Localization

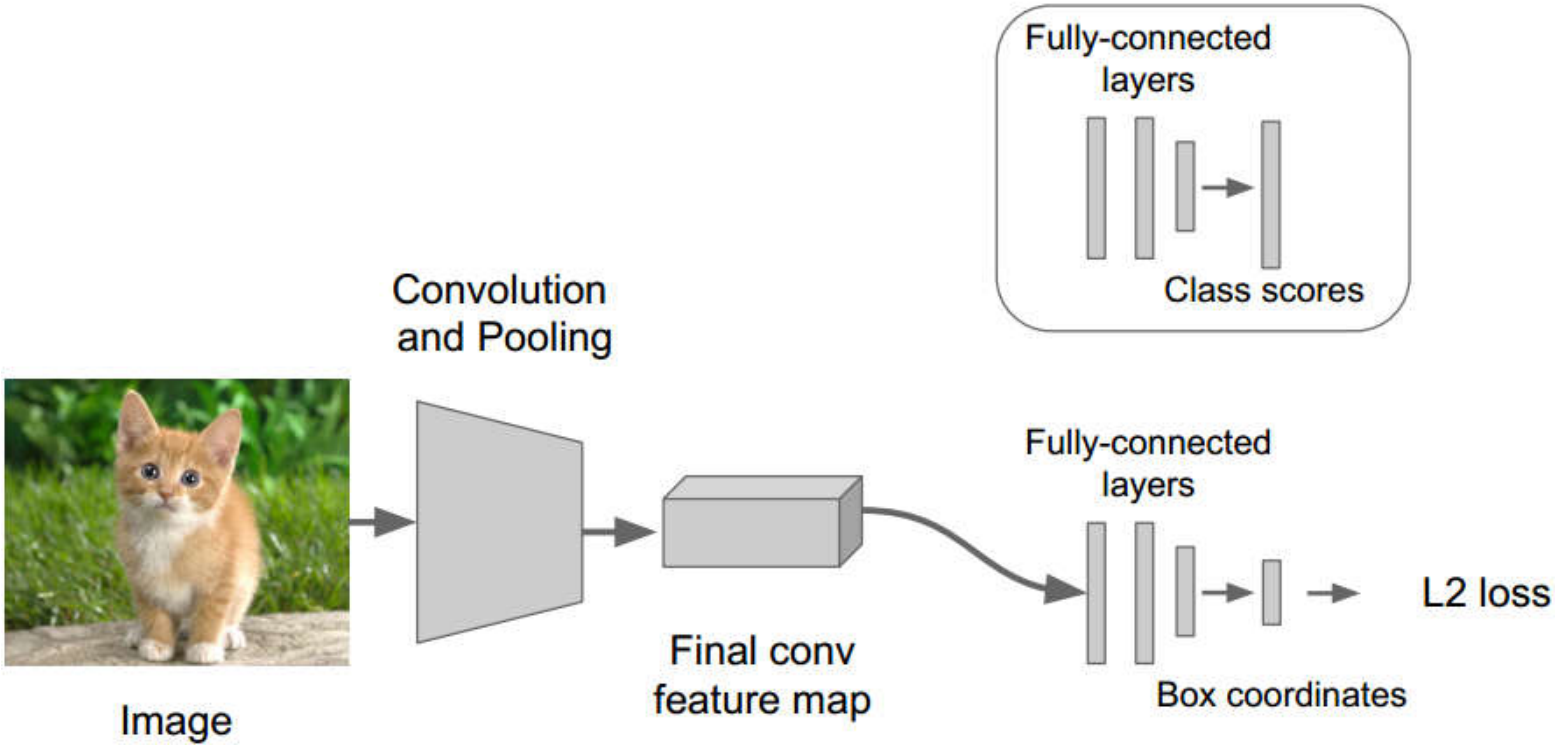
Step 2: Attach new fully-connected “regression head” to the network



Slide from CS231n

Simple Recipe for Classification + Localization

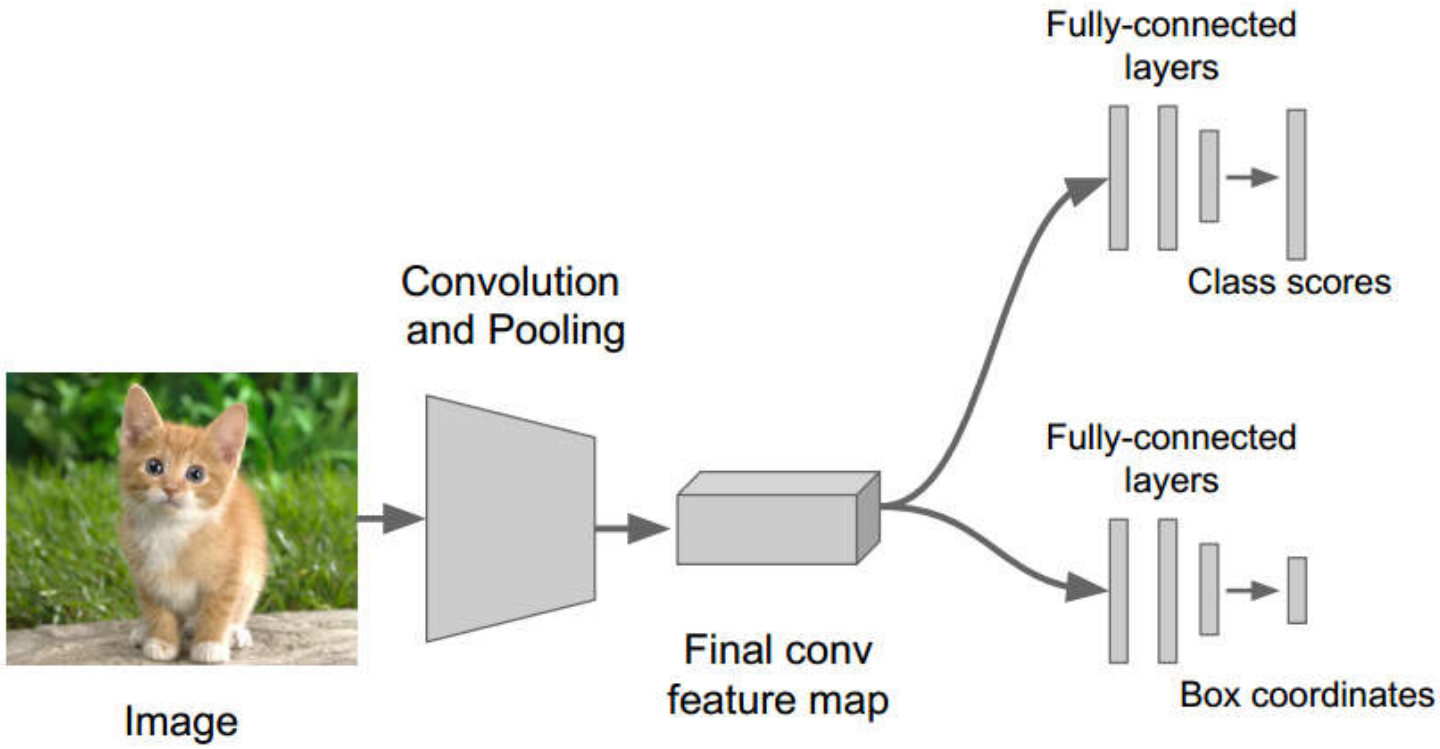
Step 3: Train the regression head only with SGD and L2 loss



Slide from CS231n

Simple Recipe for Classification + Localization

Step 4: At test time use both heads



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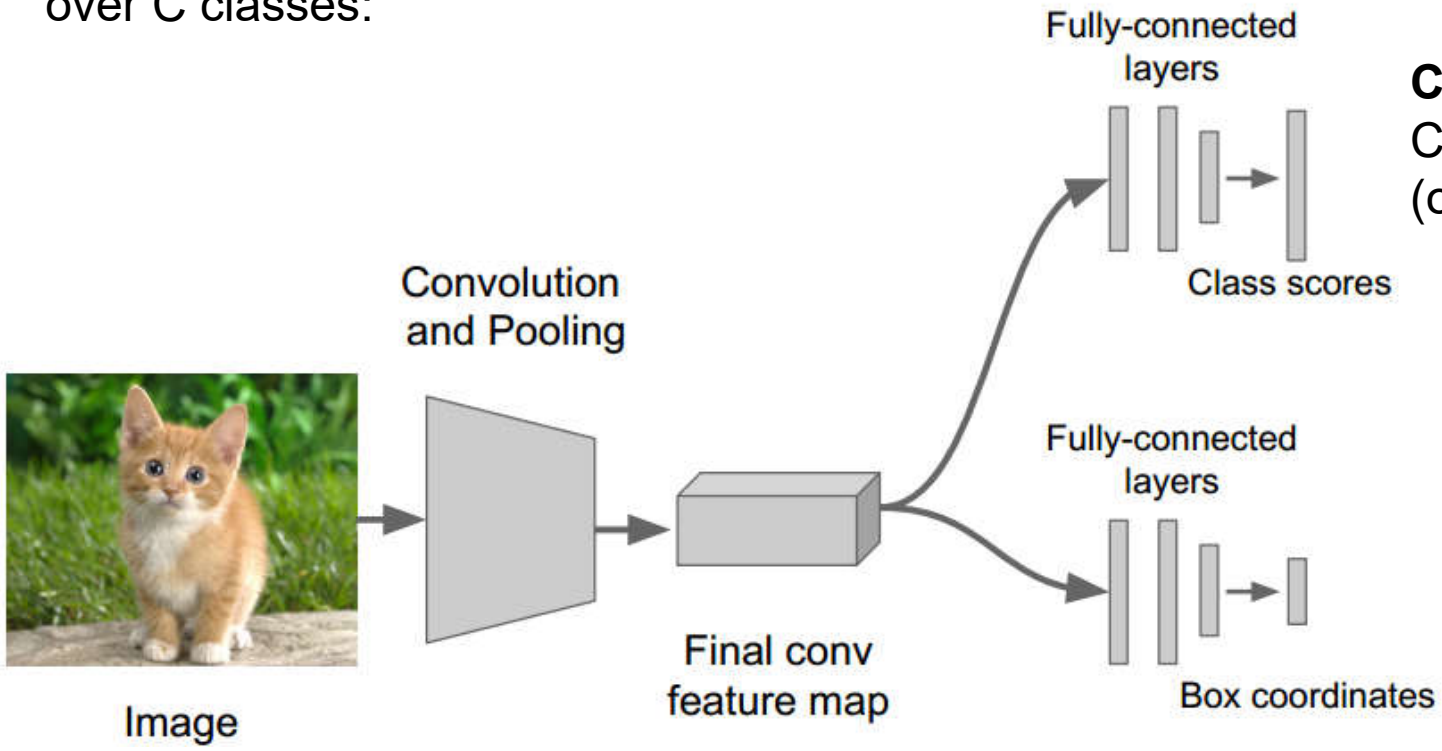
Simple Recipe for Classification + Localization

Assume classification over C classes:



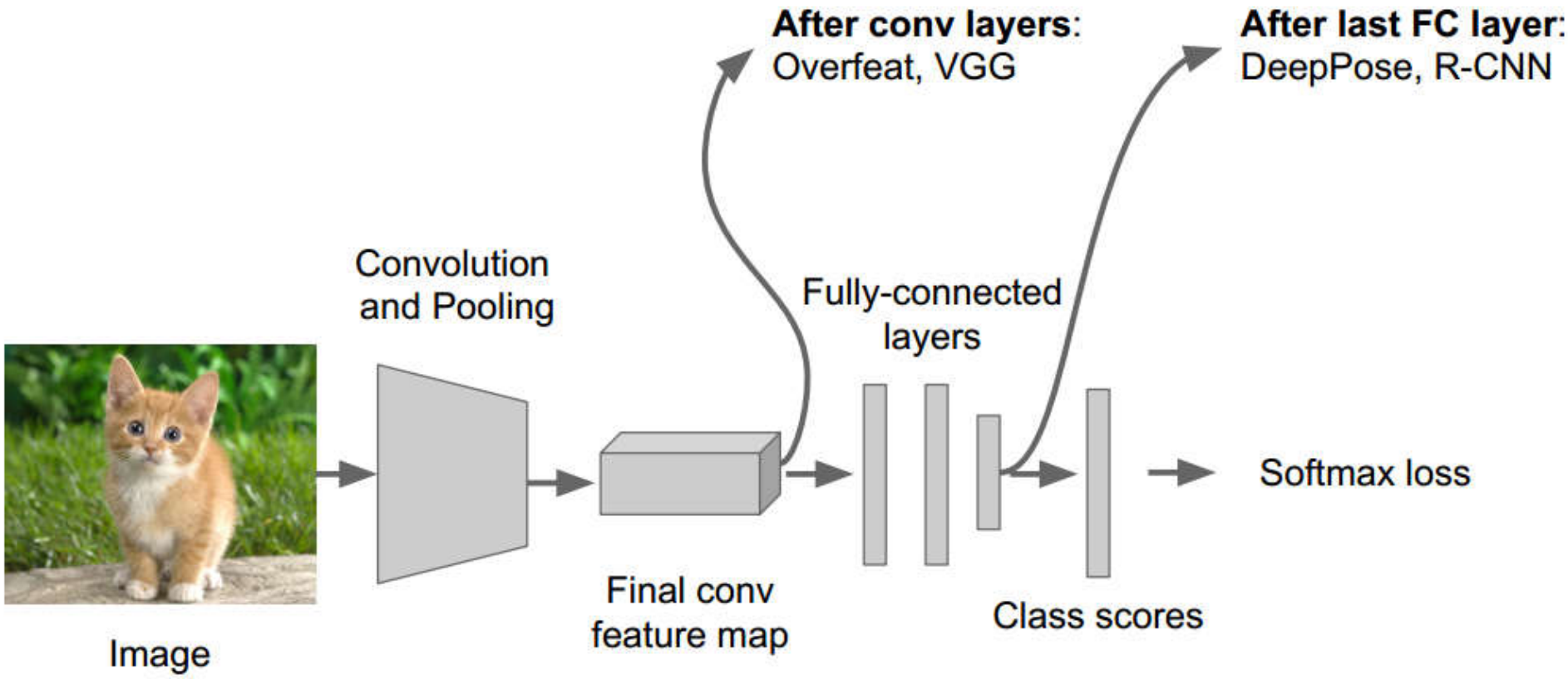
Classification head:
C numbers
(one per class)

Class agnostic:
4 numbers
(one box)

Class specific:
C x 4 numbers
(one box per class)

Slide from CS231n

Where to Attach the Regression Head?



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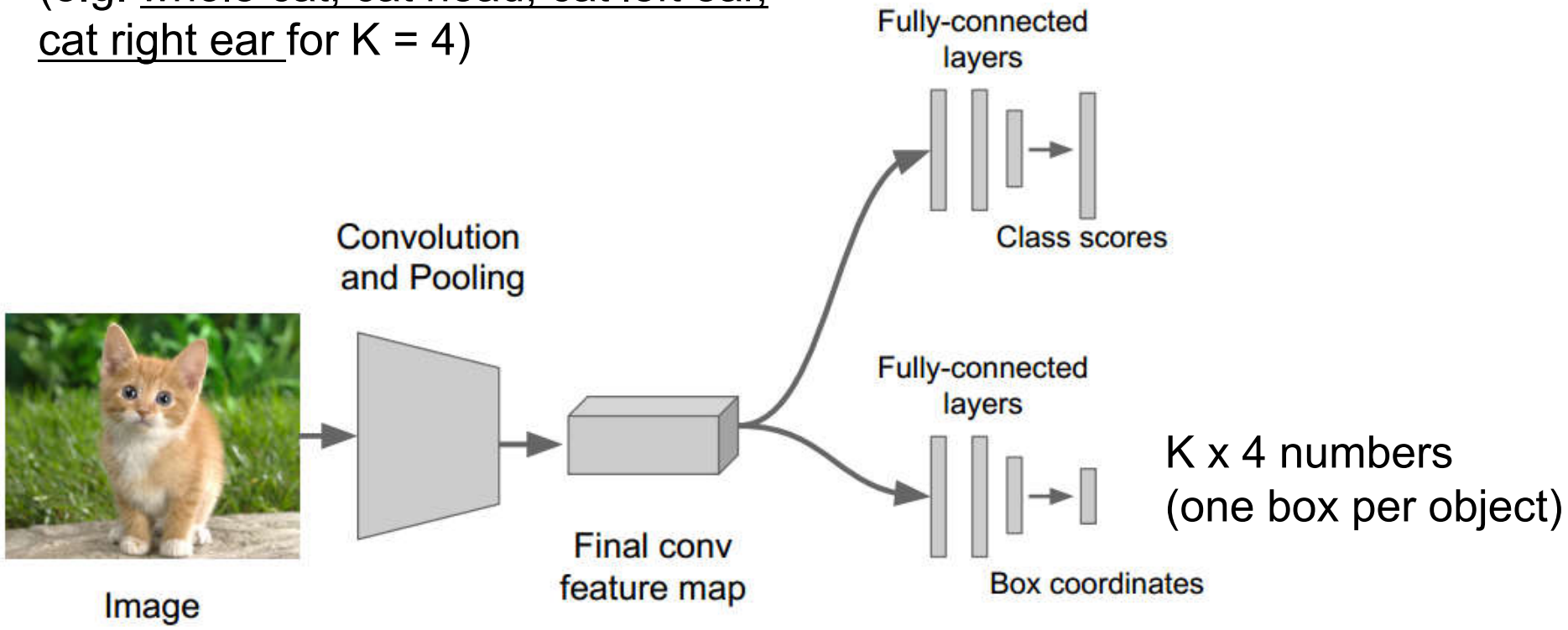
Aside: Localizing Multiple Objects

Want to localize **exactly** K objects in each image

(e.g. whole cat, cat head, cat left ear, cat right ear for K = 4)



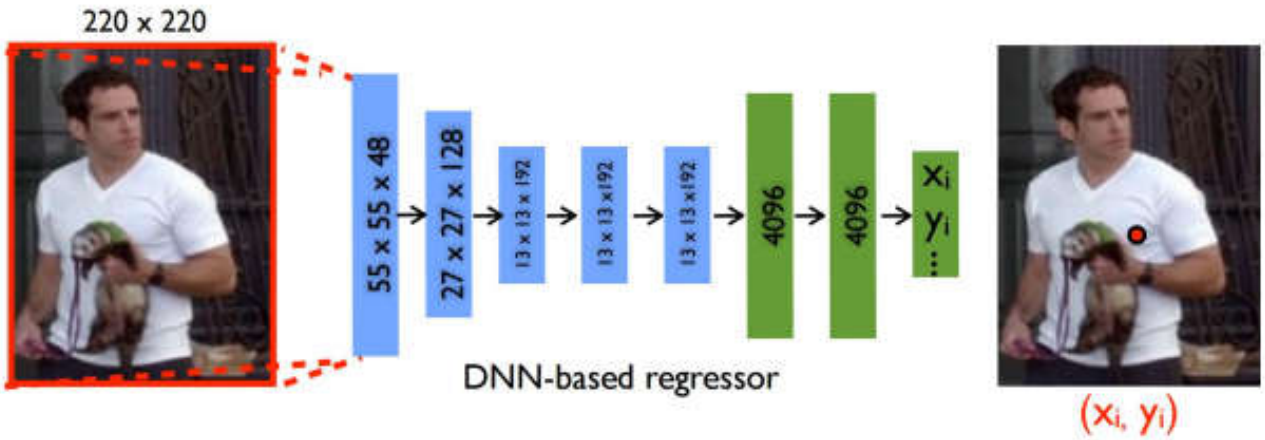
Fixed number of objects

Slide from CS231n

Aside: Human Pose Estimation

- Represent a person by K joints
- Regress (x, y) for each joint from last full-connected layer of **AlexNet**

(Details: Normalized coordinates, iterative refinement)



Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks," CVPR2014

Idea #2: Sliding Window

Idea #2: Sliding Window

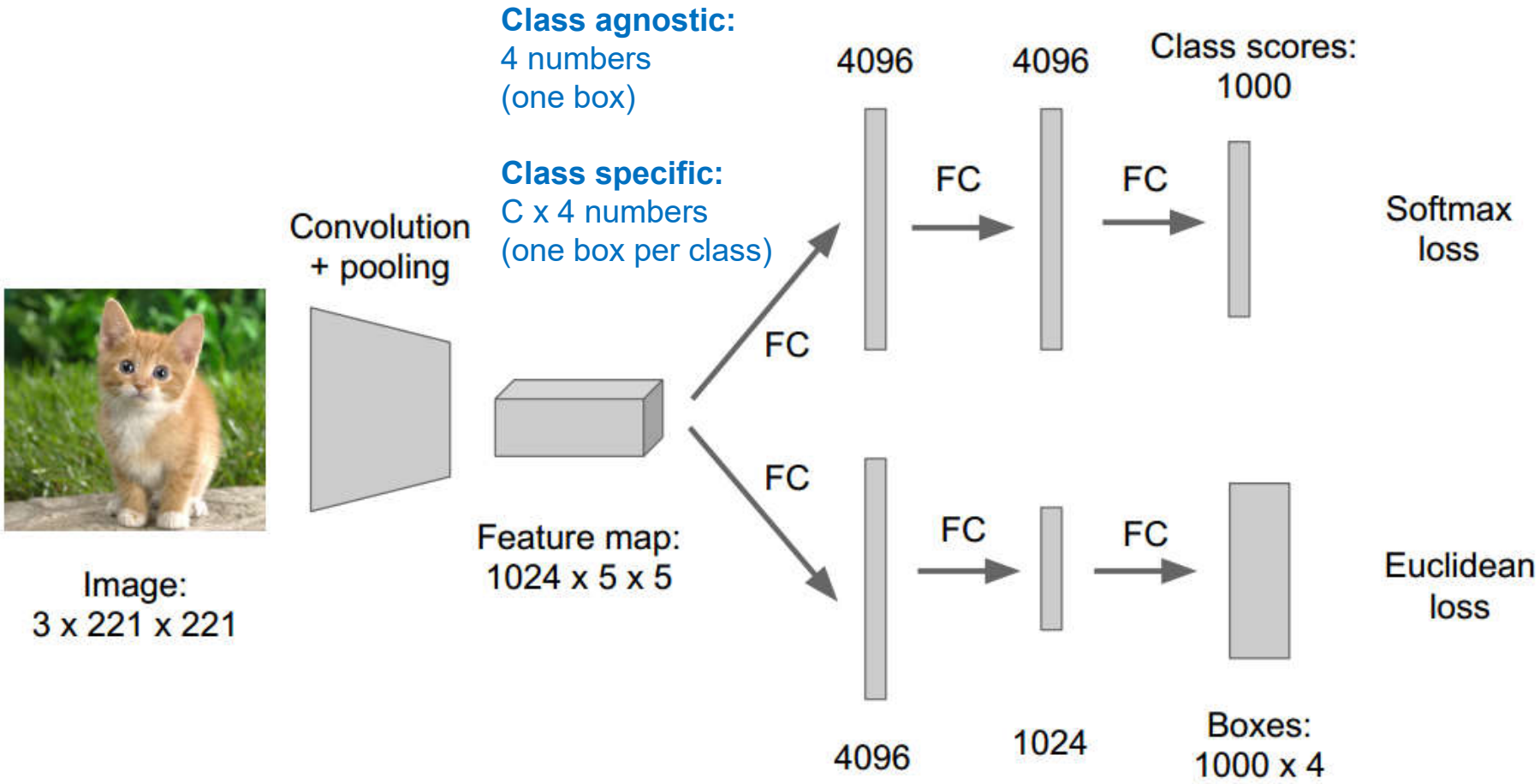
- Run classification + regression network at multiple locations on a high-resolution image

- Convert full-connected layers into convolutional layers for efficient computation

- Combine classifier and regressor predictions across all scales for final prediction

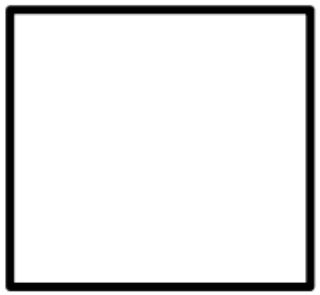
Sliding Window: Overfeat

- Winner of ILSVRC 2013 localization challenge



Sermanet et al. “Integrated Recognition, Localization and Detection using Convolutional networks,” ICLR2014

Sliding Window: Overfeat

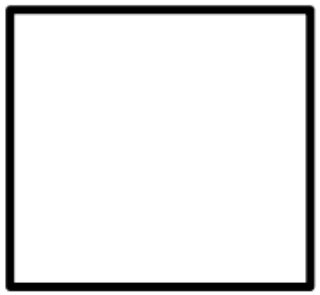


Network input:
3 x 221 x 221

Larger image
3 x 257 x 257

Slide from CS231n

Sliding Window: Overfeat



Network input:
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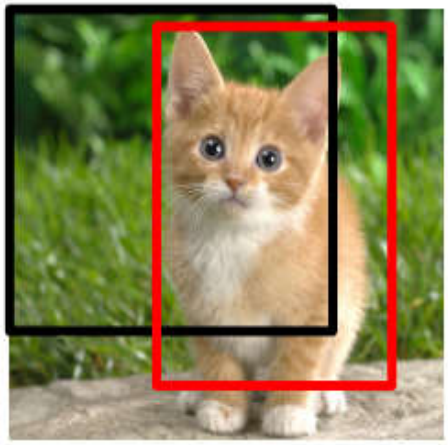
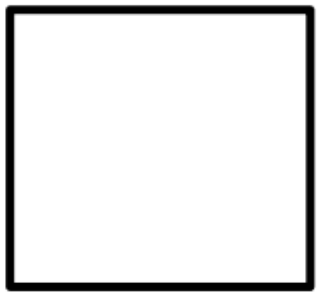


Larger image
3 x 257 x 257

Classification scores
P(cat)

Slide from CS231n

Sliding Window: Overfeat



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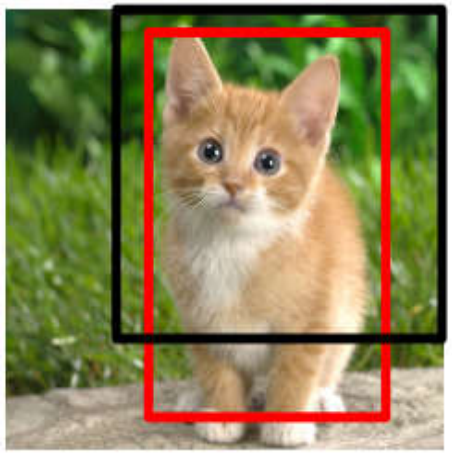
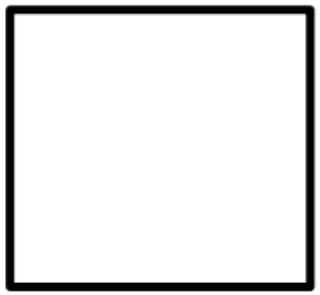


Larger image
3 x 257 x 257

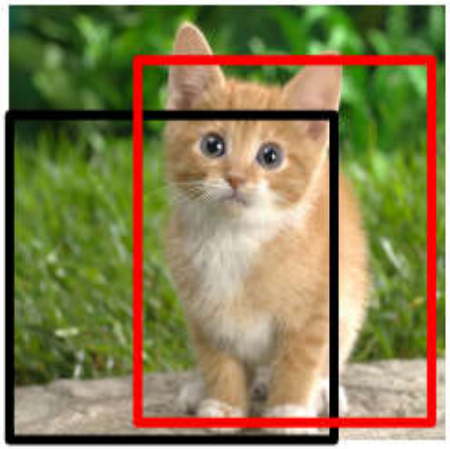
Classification scores
P(cat)

Slide from CS231n

Sliding Window: Overfeat



Network input:
3 x 221 x 221



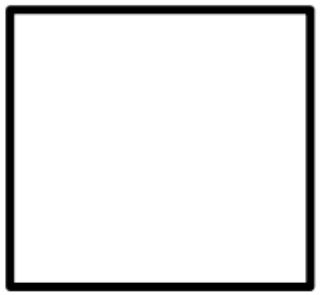
Larger image
3 x 257 x 257

0.5	0.75
0.6	

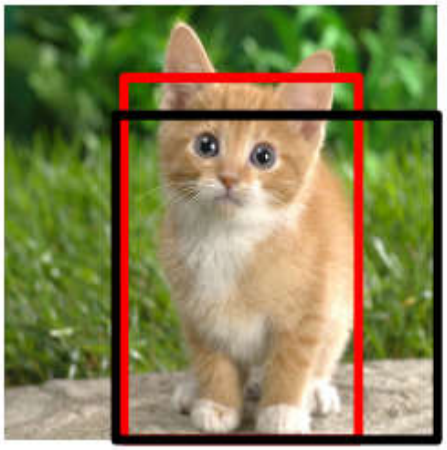
Classification scores
P(cat)

Slide from CS231n

Sliding Window: Overfeat



Network input:
3 x 221 x 221



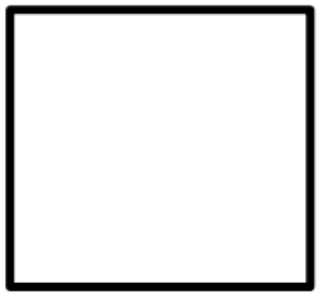
Larger image
3 x 257 x 257

0.5	0.75
0.6	0.8

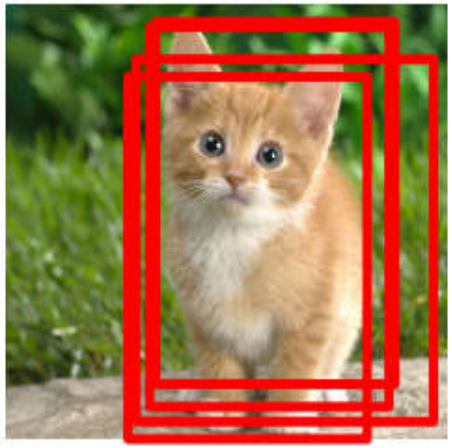
Classification scores
P(cat)

Slide from CS231n

Sliding Window: Overfeat



Network input:
3 x 221 x 221



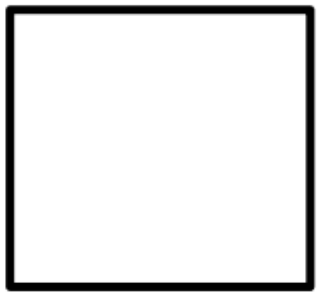
Larger image
3 x 257 x 257

0.5	0.75
0.6	0.8

Classification scores
P(cat)

Sliding Window: Overfeat

Greedily merge boxes and scores (details in paper)



Network input:
3 x 221 x 221

Larger image
3 x 257 x 257

0.8

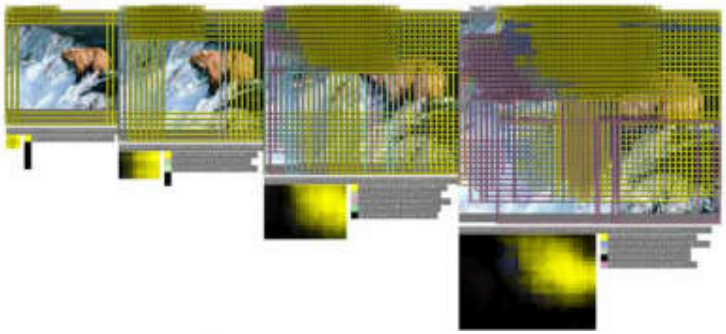
Classification scores
P(cat)

Slide from CS231n

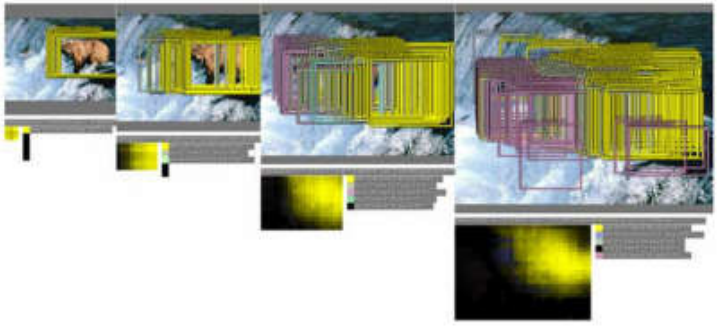
Sliding Window: Overfeat

In practice use many sliding window locations and multiple scales

Window positions + score maps



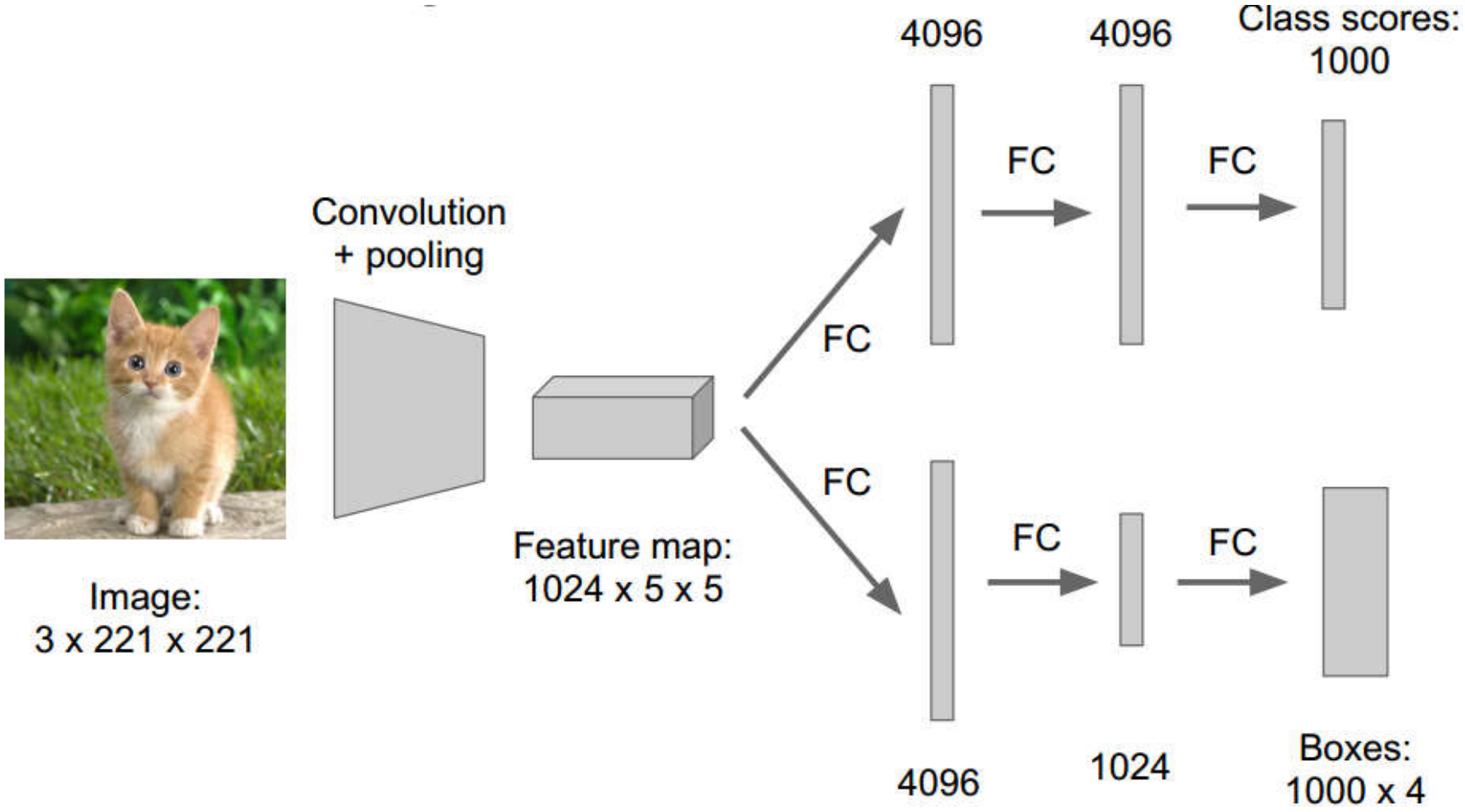
Box regression outputs



Final predictions

Sermanet et al., “Integrated Recognition, Localization and Detection using Convolutional Networks,” ICLR 2014

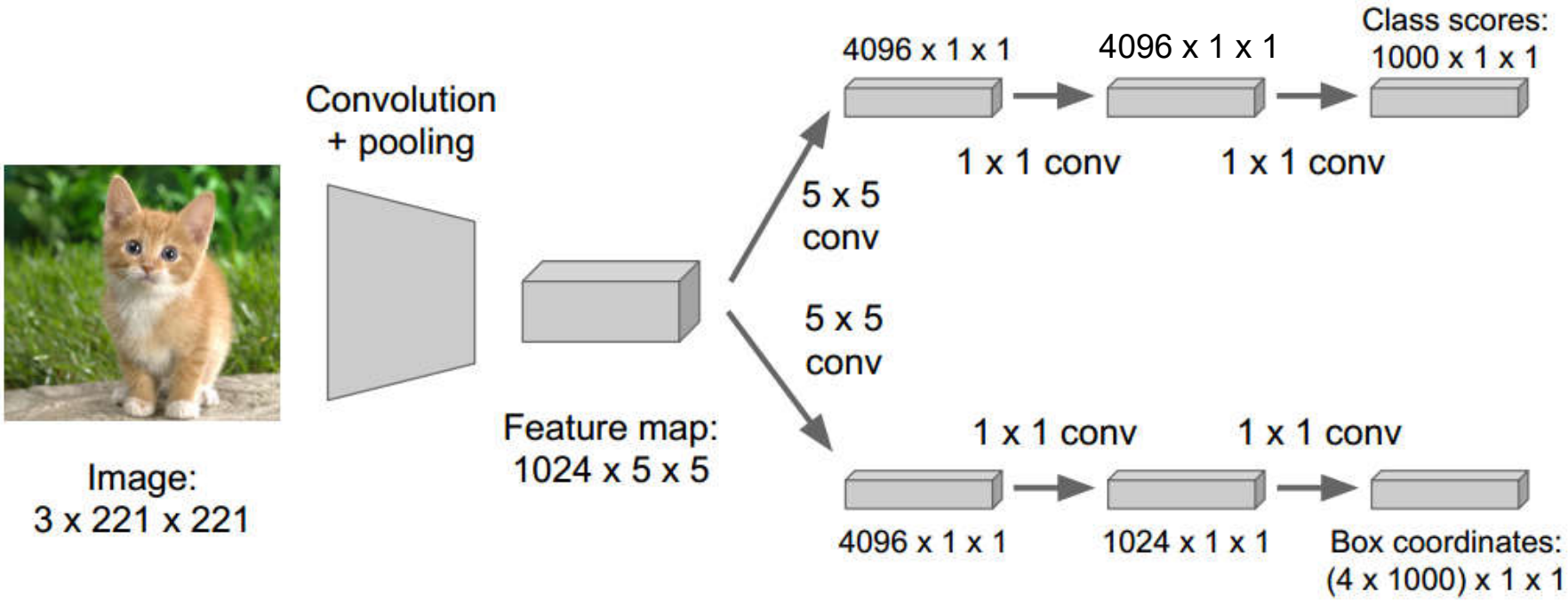
Efficient Sliding Window: Overfeat



Slide from CS231n

Efficient Sliding Window: Overfeat

- Efficient sliding window by converting fully-connected layers into convolutions

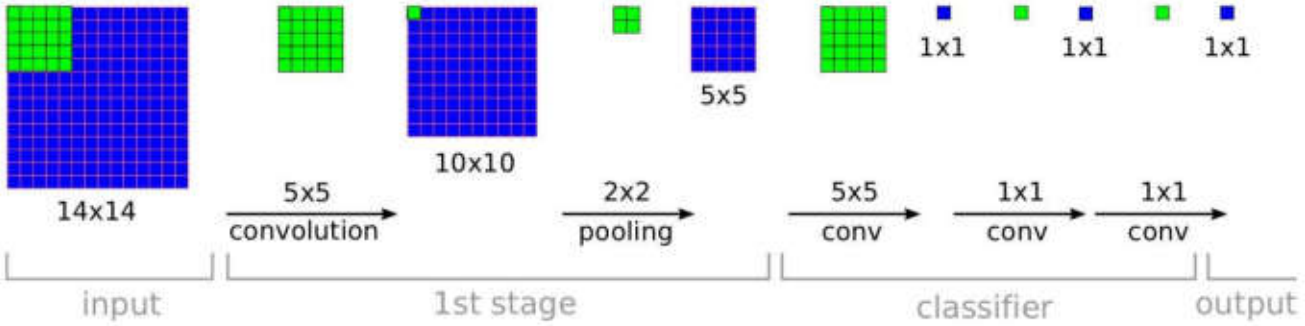


- Now we can run images at different sizes

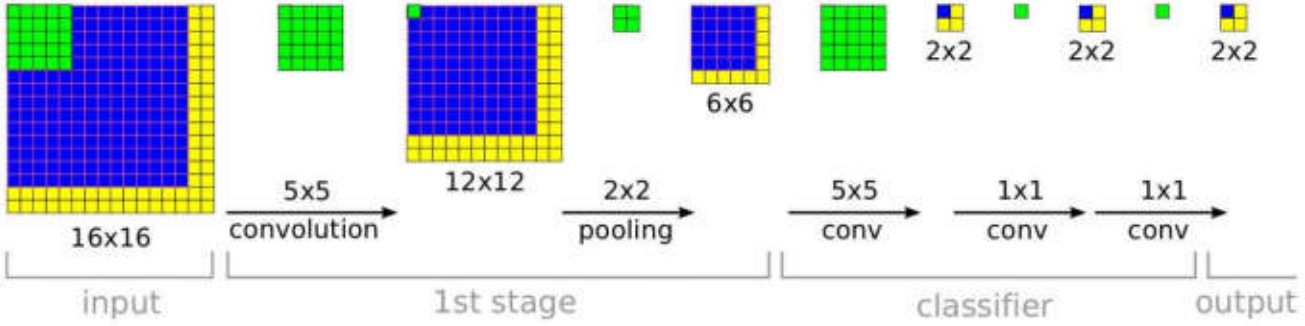
Slide from CS231n

Efficient Sliding Window: Overfeat

Training time: Small image, 1 x 1 classifier output



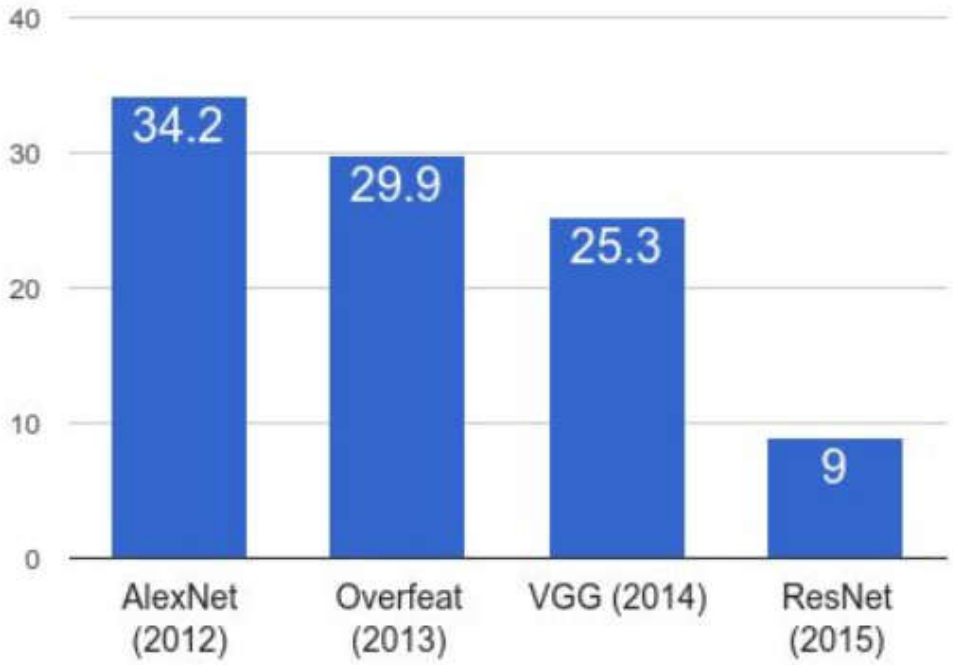
Test time: Larger image, 2 x 2 classifier output, only extra compute at yellow regions



Sermanet et al., “Integrated Recognition, Localization and Detection using Convolutional Networks,” ICLR 2014

ImageNet Classification + Localization

Localization Error (Top 5)



AlexNet: Localization method not published

Overfeat: Multiscale convolutional regression with box merging

VGG: Same as Overfeat, but fewer scales and locations; simpler method, gains all due to deeper features

ResNet: Different localization method (RPN) and much deeper features

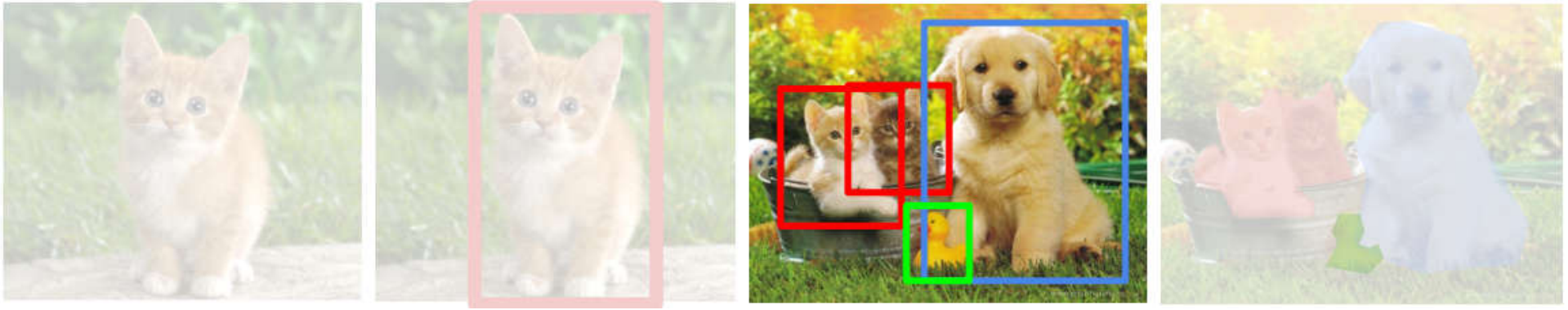
Computer Vision Tasks

Classification

Classification
+ Localization

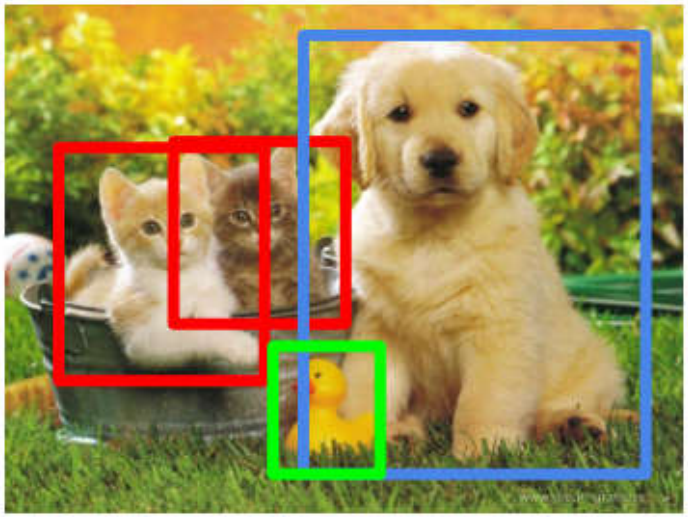
Object Detection

Instance
Segmentation



Slide from CS231n

Detection as Regression?



Dog (x, y, w, h)

Cat (x, y, w, h)

Cat (x, y, w, h)

Duck (x, y, w, h)

= 4 x 4 = **16 numbers**

Slide from CS231n

Detection as Regression?

DOG, (x, y, w, h)

CAT, (x, y, w, h)

= 8 numbers

Slide from CS231n

Detection as Regression?

CAT, (x, y, w, h)

CAT, (x, y, w, h)

…

CAT, (x, y, w, h)

= many numbers

Need variable sized outputs

Slide from CS231n

Detection as Classification

CAT? No

DOG? No

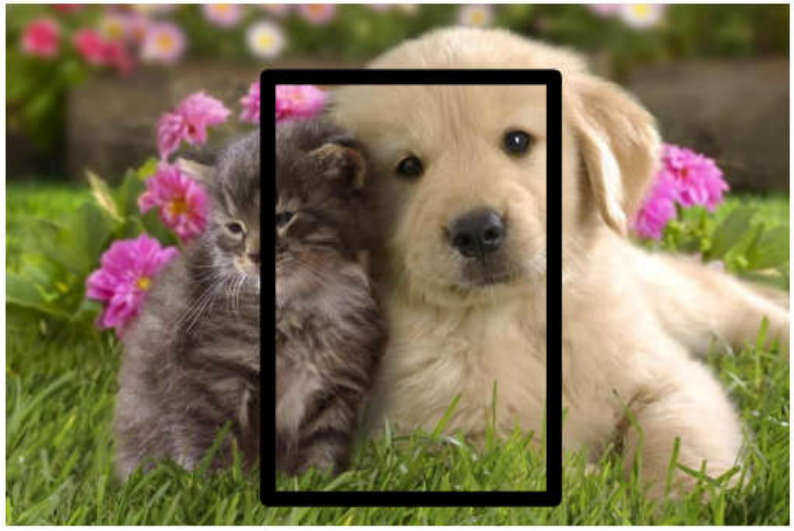
Detection as Classification

CAT? YES!

DOG? No

Slide from CS231n

Detection as Classification



CAT? No

DOG? No

Detection as Classification

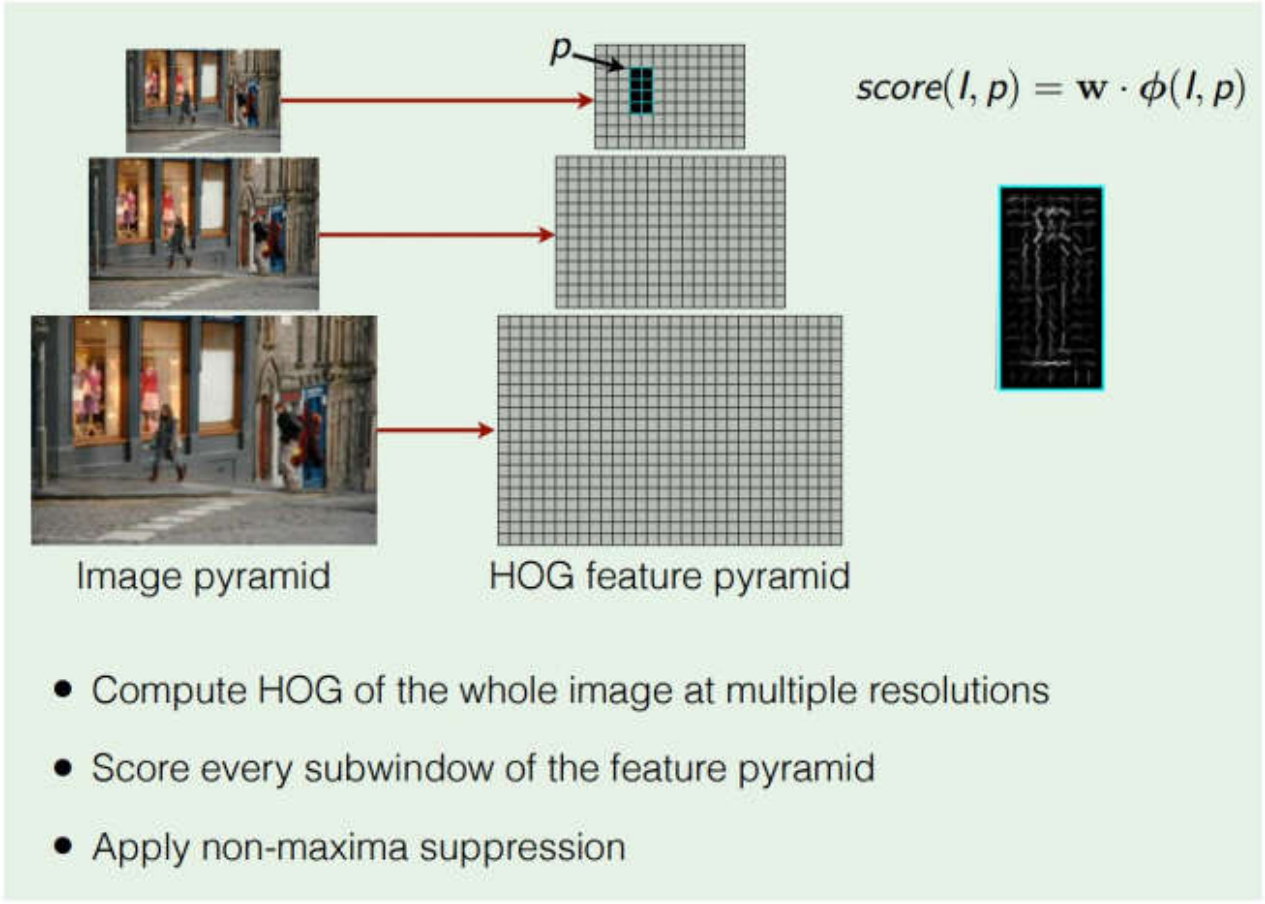
Problem: Need to test many positions and scales

Solution: If your classifier is fast enough, just do it

Slide from CS231n

Object Detection: A Bit of History

Histogram of Oriented Gradients (HOG)



Dalal and Triggs, “Histograms of Oriented Gradients for Human Detection”, CVPR 2005

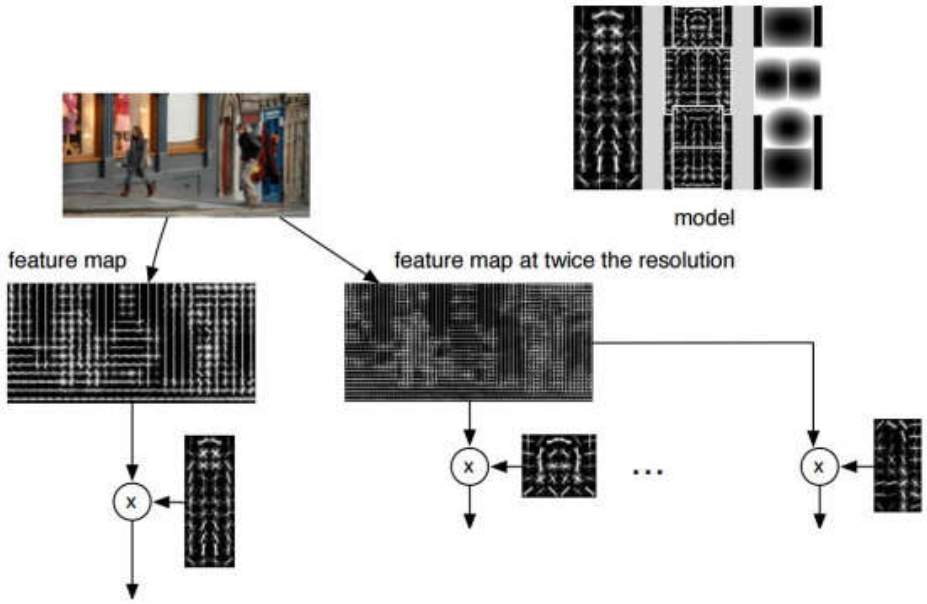
Object Detection: A Bit of History

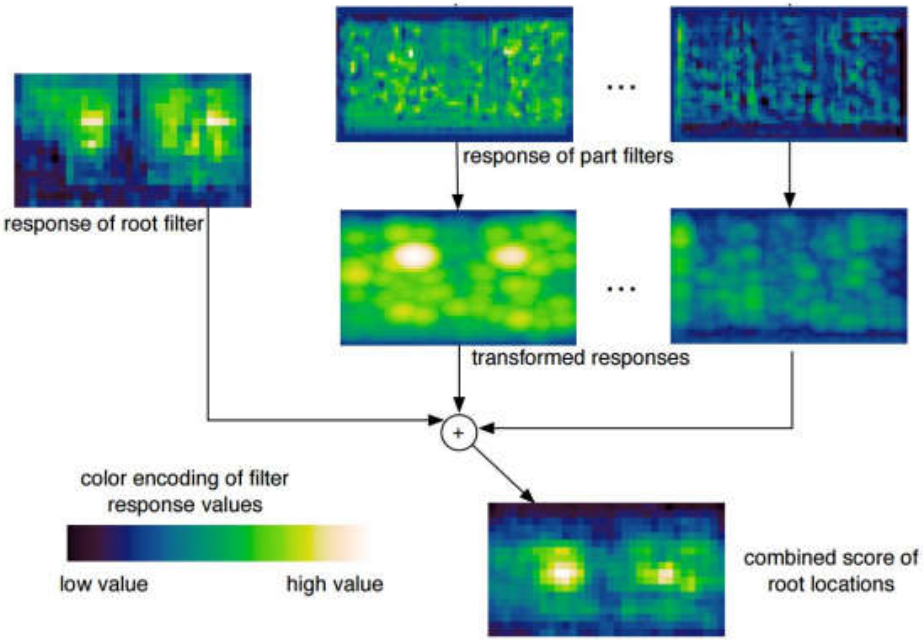
- Template model
- Latent SVM
- Dynamic programing

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 32, NO. 9, SEPTEMBER 2010 1627

Object Detection with Discriminatively Trained Part-Based Models

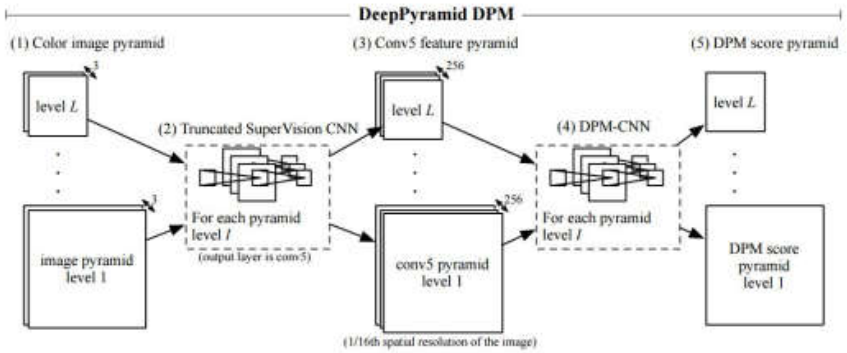
Pedro F. Felzenszwalb, *Member, IEEE Computer Society*, Ross B. Girshick, *Student Member, IEEE*, David McAllester, and Deva Ramanan, *Member, IEEE*

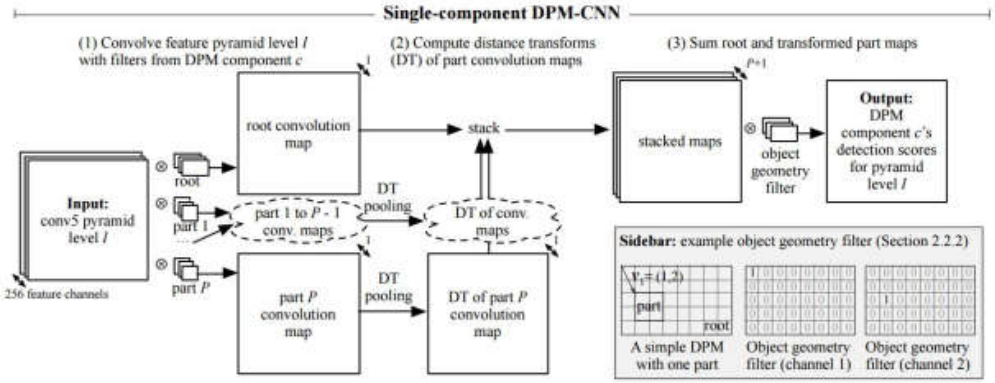




Felzenszwalb et al., “Object Detection with Discriminatively Trained Part Based Models”, PAMI 2010

Aside: Deformable Parts Models are CNNs?





Girshick et al., "Deformable Part Models are Convolutional Neural Networks", CVPR 2015

Detection as Classification

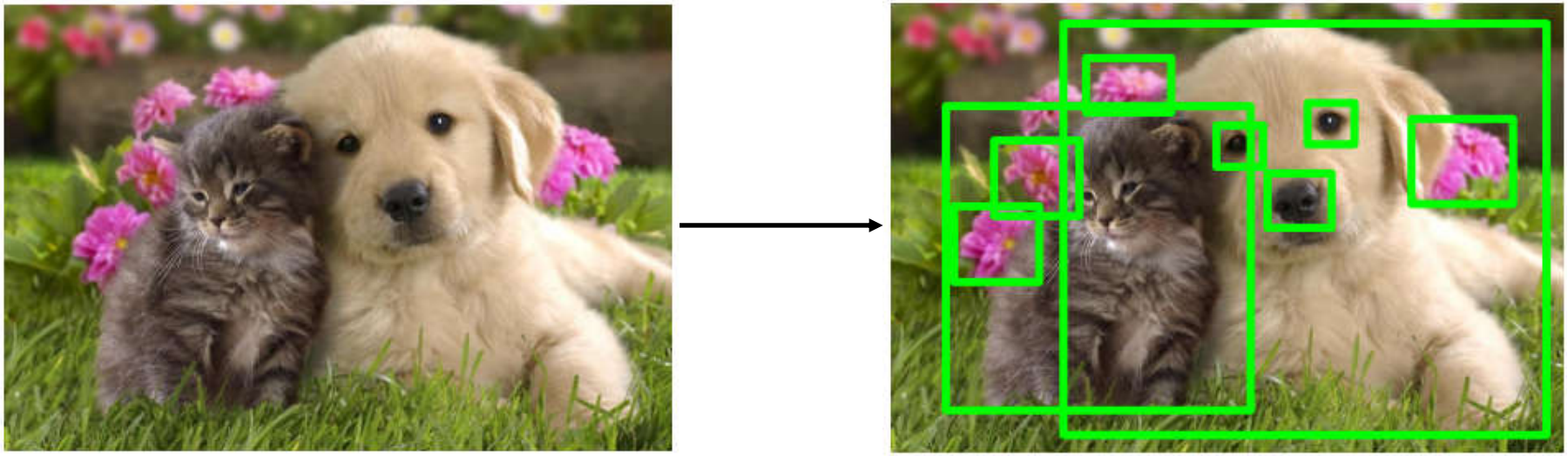
Problem: Need to test many positions and scales, and use a computationally demanding classifier (CNN)

Solution: Only look at a tiny subset of possible positions

Slide from CS231n

Region Proposals

- Find “blobby” image regions that are likely to contain objects
- “Class-agnostic” object detector
- Look for “blob-like” regions

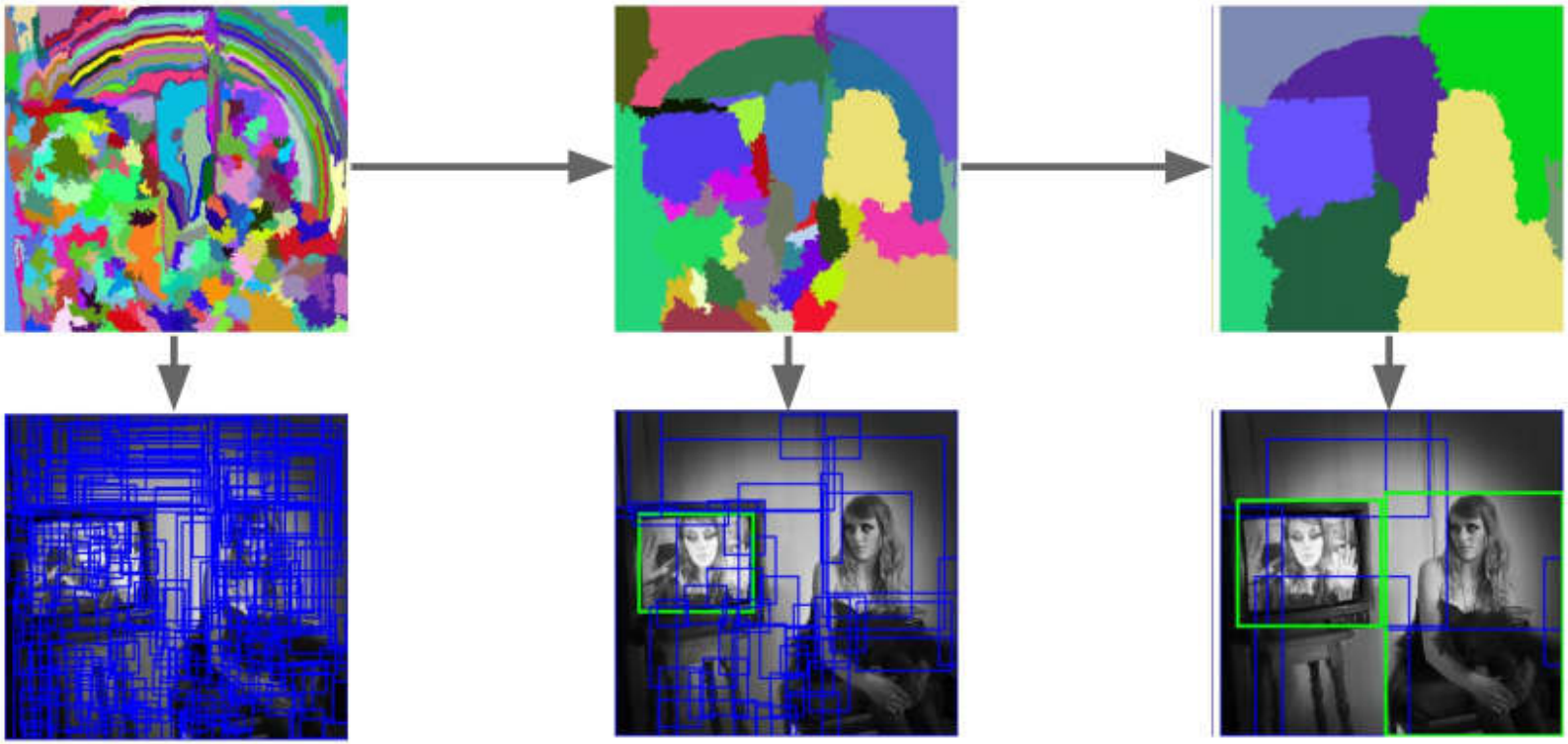


Slide from CS231n

Region Proposals: Selective Search

Bottom-up segmentation, merging regions at multiple scales

Convert regions to boxes



Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013

Region Proposals: Many Other choices

Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec.)	Repea-tability	Recall Results	Detection Results
Bing [18]	Window scoring		✓	✓	0.2	⋆⋆⋆	⋆	·
CPMC [19]	Grouping	✓	✓	✓	250	-	⋆⋆	⋆
EdgeBoxes [20]	Window scoring		✓	✓	0.3	⋆⋆	⋆⋆⋆	⋆⋆⋆
Endres [21]	Grouping	✓	✓	✓	100	-	⋆⋆⋆	⋆⋆
Geodesic [22]	Grouping	✓		✓	1	⋆	⋆⋆⋆	⋆⋆
MCG [23]	Grouping	✓	✓	✓	30	⋆	⋆⋆⋆	⋆⋆⋆
Objectness [24]	Window scoring		✓	✓	3	·	⋆	·
Rahtu [25]	Window scoring		✓	✓	3	·	·	⋆
RandomizedPrim's [26]	Grouping	✓		✓	1	⋆	⋆	⋆⋆
Rantalankila [27]	Grouping	✓		✓	10	⋆⋆	·	⋆⋆
Rigor [28]	Grouping	✓		✓	10	⋆	⋆⋆	⋆⋆
SelectiveSearch [29]	Grouping	✓	✓	✓	10	⋆⋆	⋆⋆⋆	⋆⋆⋆
Gaussian				✓	0	·	·	⋆
SlidingWindow				✓	0	⋆⋆⋆	·	·
Superpixels		✓			1	⋆	·	·
Uniform				✓	0	·	·	·

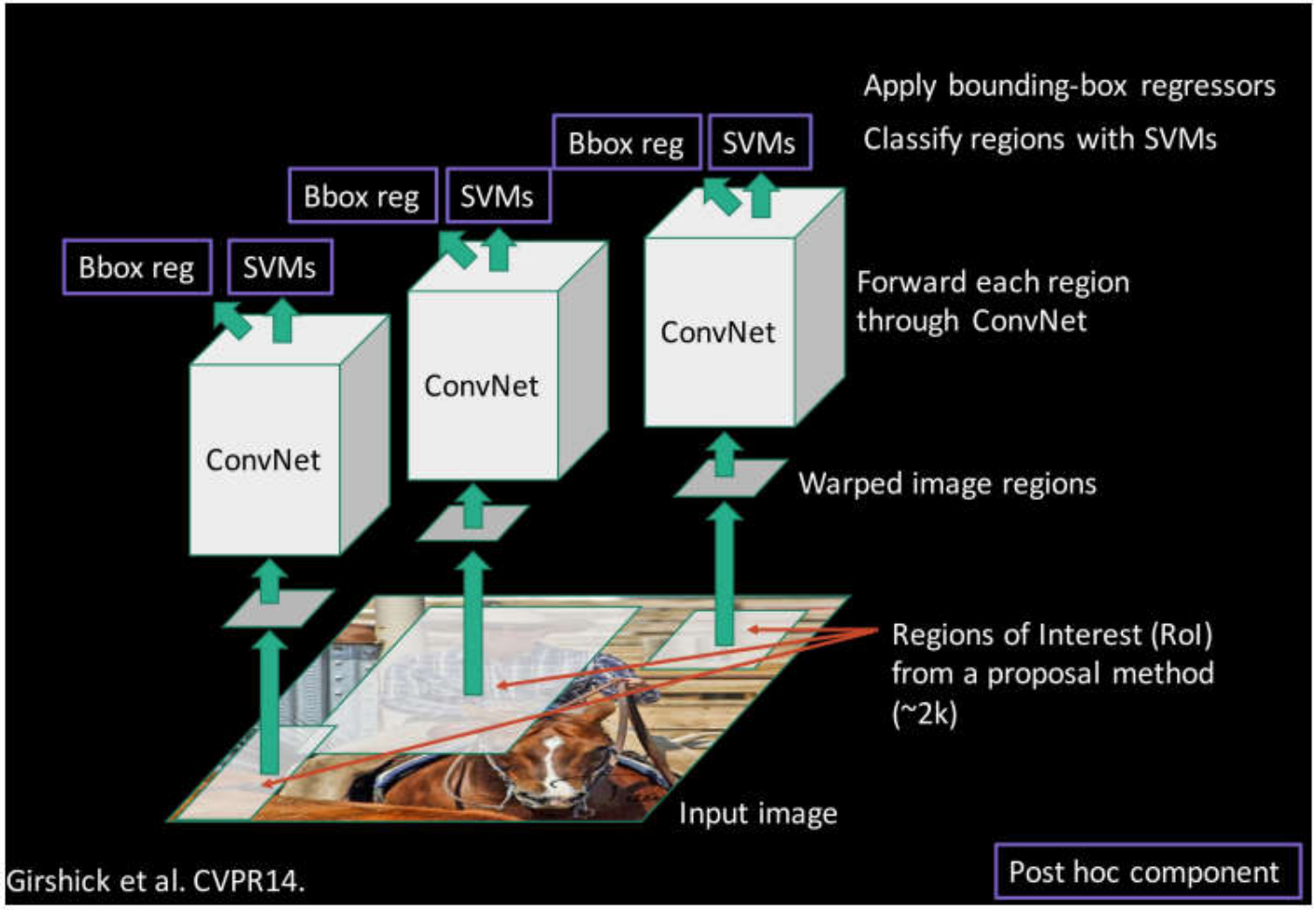
Hosang et al, “What makes for effective detection proposals?”, PAMI 2015

Region Proposals: Many Other choices

Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec.)	Repea-tability	Recall Results	Detection Results
Bing [18]	Window scoring		✓	✓	0.2	★★★	★	·
CPMC [19]	Grouping	✓	✓	✓	250	-	★★	★
EdgeBoxes [20]	Window scoring		✓	✓	0.3	★★	★★★	★★★
Endres [21]	Grouping	✓	✓	✓	100	-	★★★	★★
Geodesic [22]	Grouping	✓		✓	1	★	★★★	★★
MCG [23]	Grouping	✓	✓	✓	30	★	★★★	★★★
Objectness [24]	Window scoring		✓	✓	3	·	★	·
Rahtu [25]	Window scoring		✓	✓	3	·	·	★
RandomizedPrim's [26]	Grouping	✓		✓	1	★	★	★★
Rantalankila [27]	Grouping	✓		✓	10	★★	·	★★
Rigor [28]	Grouping	✓		✓	10	★	★★	★★
SelectiveSearch [29]	Grouping	✓	✓	✓	10	★★	★★★	★★★
Gaussian				✓	0	·	·	★
SlidingWindow				✓	0	★★★	·	·
Superpixels		✓			1	★	·	·
Uniform				✓	0	·	·	·

Hosang et al, “What makes for effective detection proposals?”, PAMI 2015

Putting it Together: R-CNN

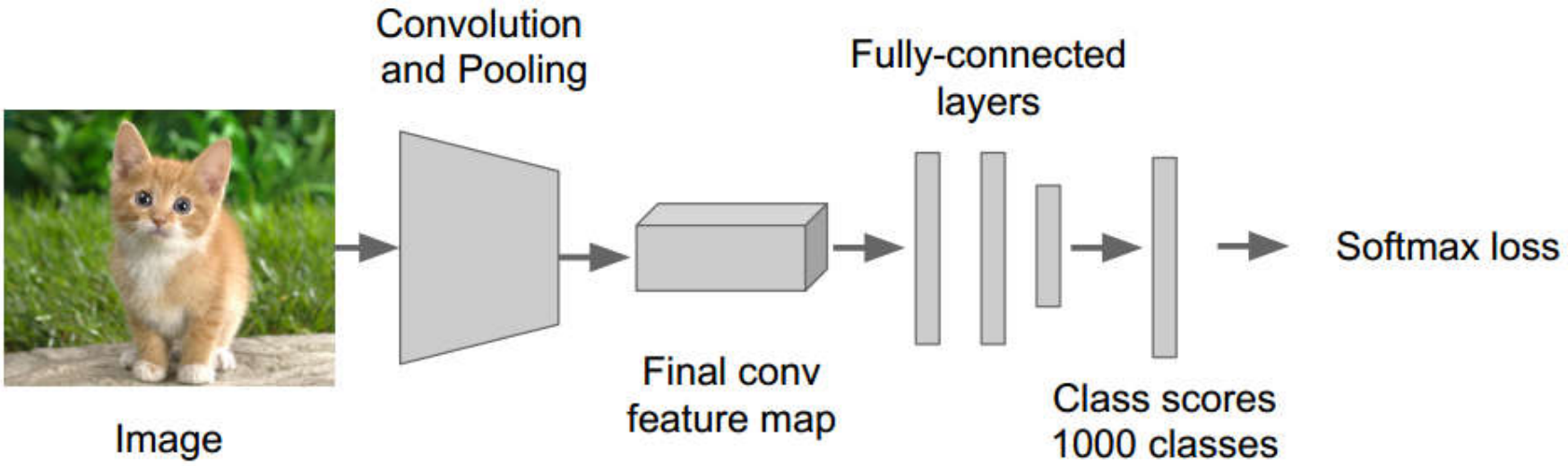


Girchick et al. “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR2014

Slide credit: Ross Girschick

R-CNN Training

Step 1: Train (or download) a classification model for ImageNet (ALexNet)

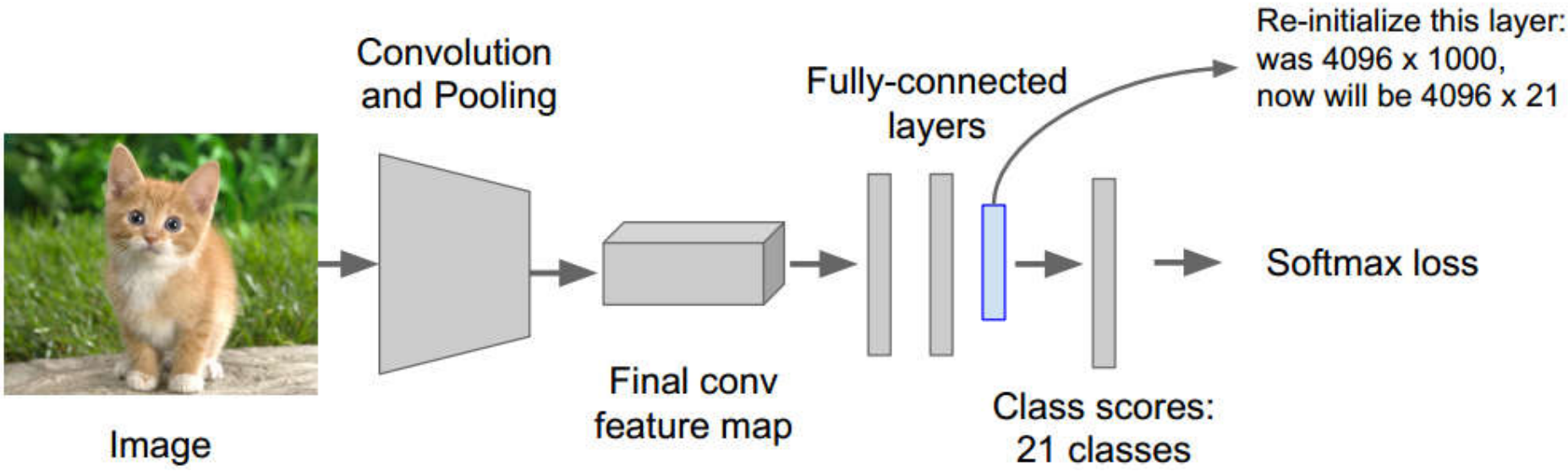


Slide from CS231n

R-CNN Training

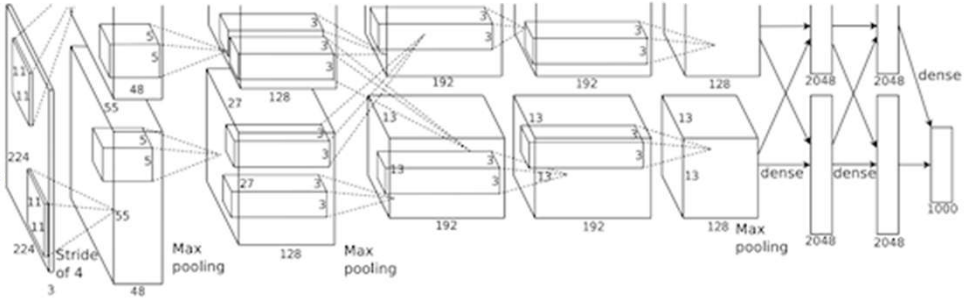
Step 2: Fine-tune model for detection

- Instead of 1000 ImageNet classes, want 20 object classes + background
- Throw away final fully-connected layer, reinitialize from scratch
- Keep training model using positive / negative regions from detection images



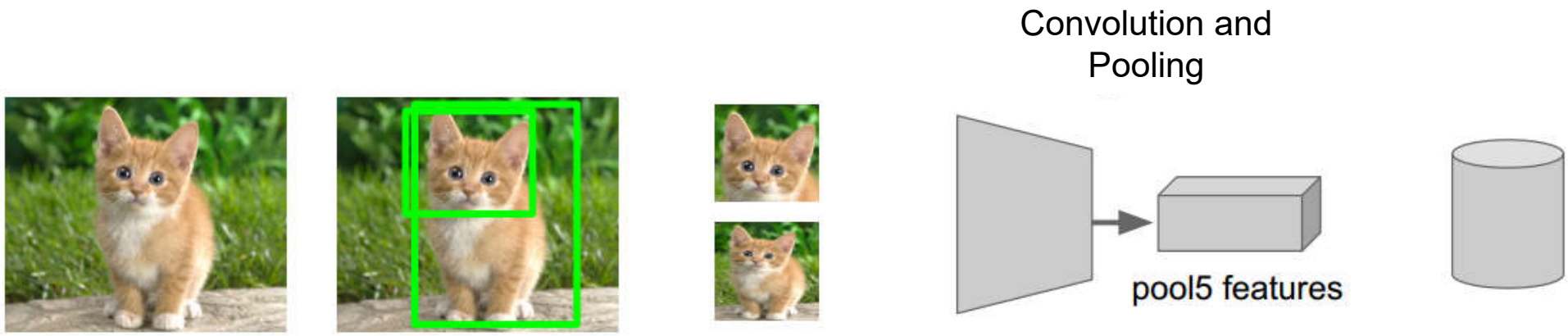
Slide from CS231n

R-CNN Training



Step 3: Extract features

- Extract region proposals for all images
- For each region: warp to CNN input size, run forward through CNN, save pool5 features to disk
- Have a big hard drive: features are ~200GB for PASCAL dataset!

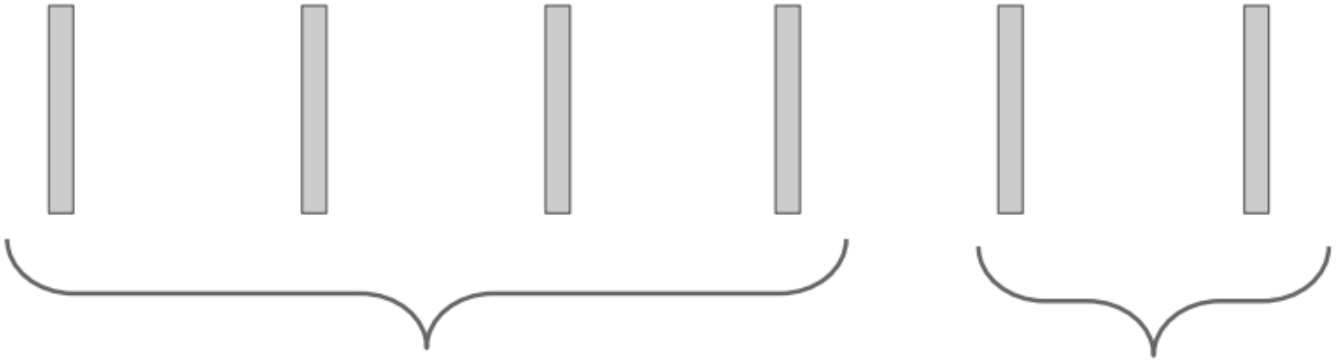


R-CNN Training

Step 4: Train one binary SVM per class to classify region features

Training image regions

Cached region features



Positive samples for cat SVM

Negative samples for cat SVM

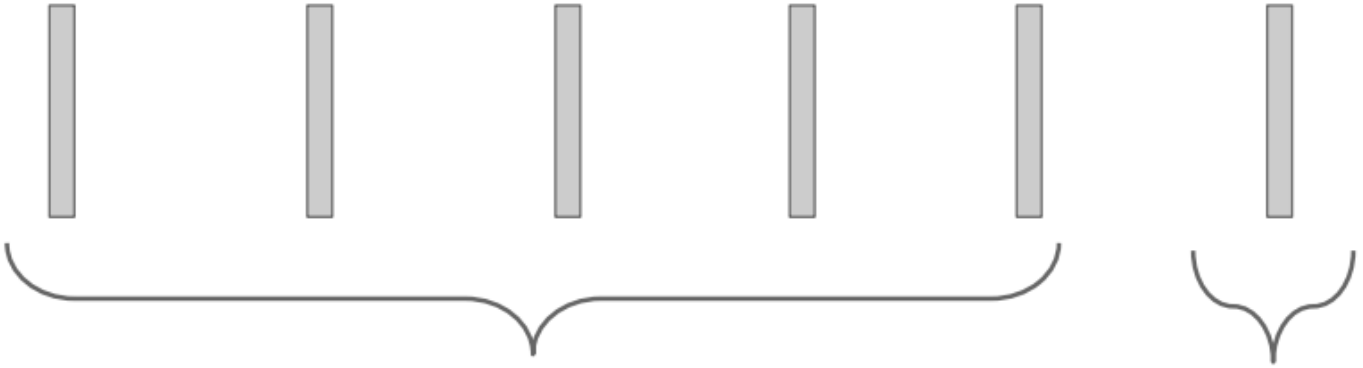
Slide from CS231n

R-CNN Training

Step 4: Train one binary SVM per class to classify region features

Training image regions

Cached region features



Negative samples for dog SVM

Positive samples for dog SVM

Slide from CS231n

R-CNN Training

Step 5 (bbox regression): For each class, **train a linear regression model** to map from cached features to offsets to GT boxes to make up for "slightly wrong" proposals

Training image regions			
Cached region features			
Regression targets (dx, dy, dw, dh) Normalized coordinates	(0, 0, 0, 0) Proposal is good	(.25, 0, 0, 0) Proposal too far to left	(0, 0, -0.125, 0) Proposal too wide

Slide from CS231n

Object Detection: Datasets

	PASCAL VOC (2010)	ImageNet Detection (ILSVRC 2014)	MS-COCO (2014)
Number of classes	20	**200**	80
Number of images (train + val)	~20k	**~470k**	~120k
Mean objects per image	2.4	1.1	**7.2**

Slide from CS231n

Object Detection: Evaluation

- We use a metric called "mean average precision" (**mAP**)
- Compute average precision (AP) separately for each class, then average over classes
- A detection is a true positive if it has IoU with a ground-truth box greater than some threshold (usually 0.5) (mAP@0.5)
- Combine all detections from all test images to draw precision /recall curve for each class; AP is area under curve

TL;DR mAP is a number from 0 to 100; high is good

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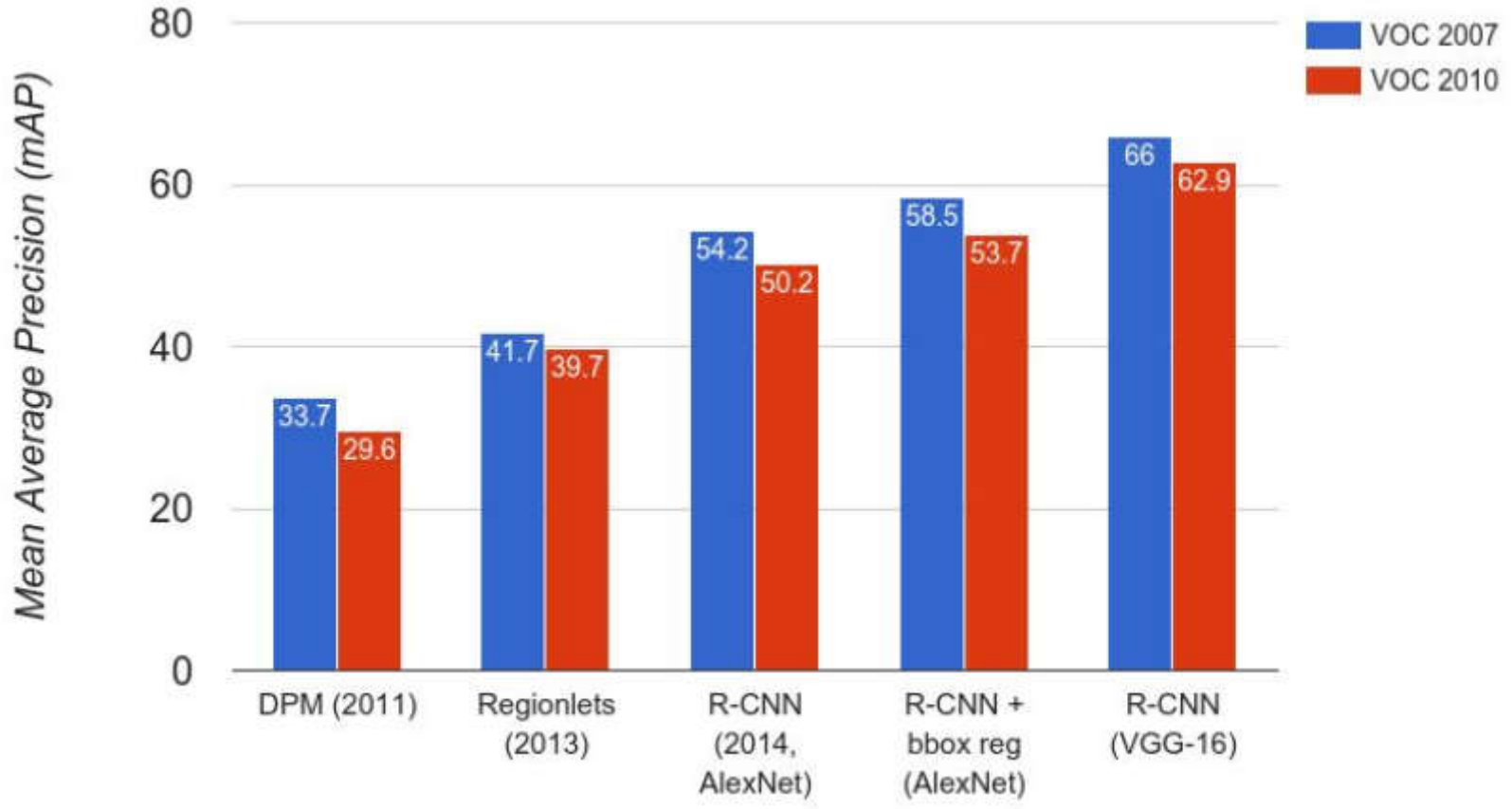
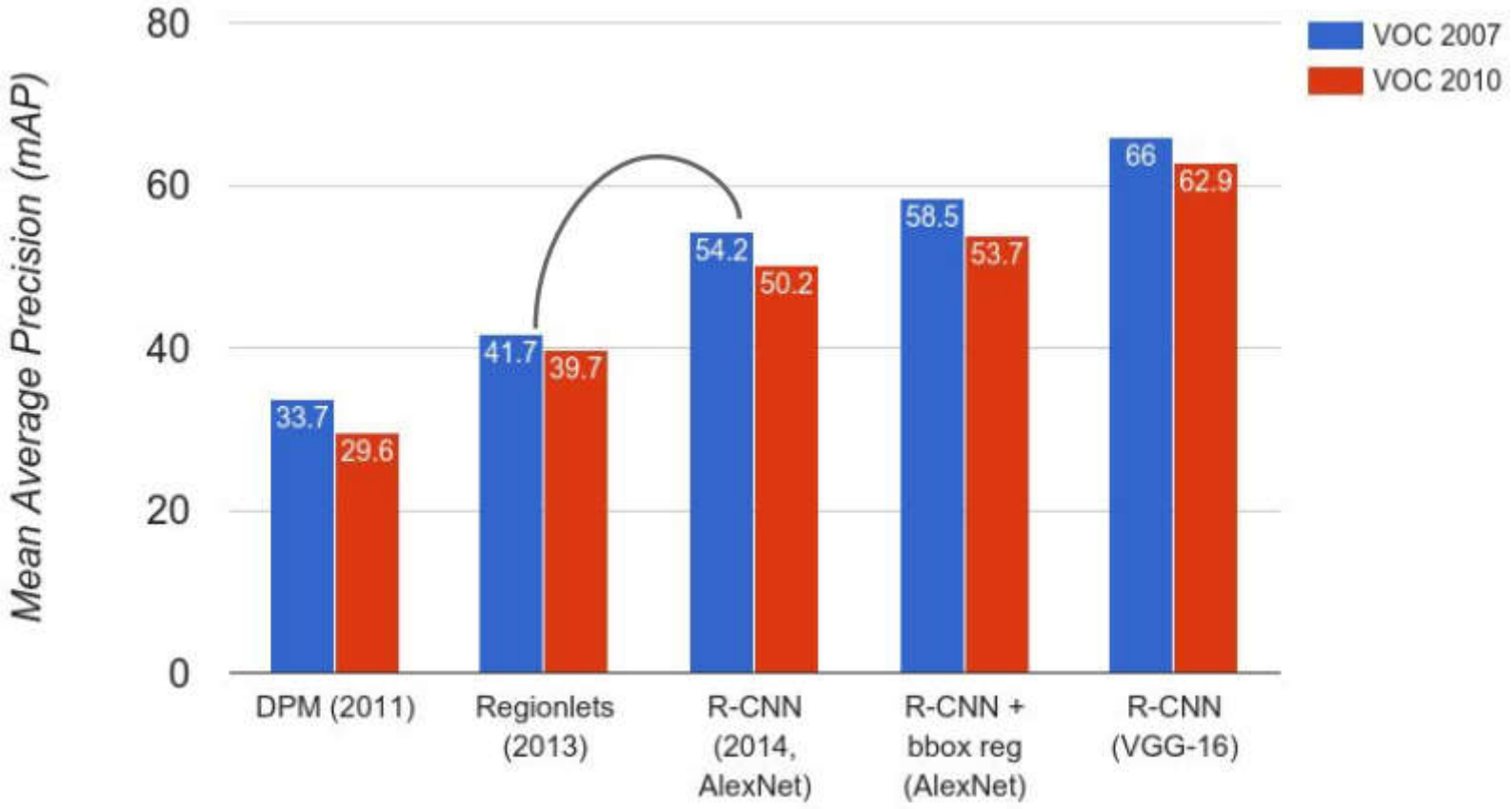
R-CNN Results



Wang et al, “Regionlets for Generic Object Detection”, ICCV 2013

R-CNN Results

Big improvement compared
to pre-CNN methods



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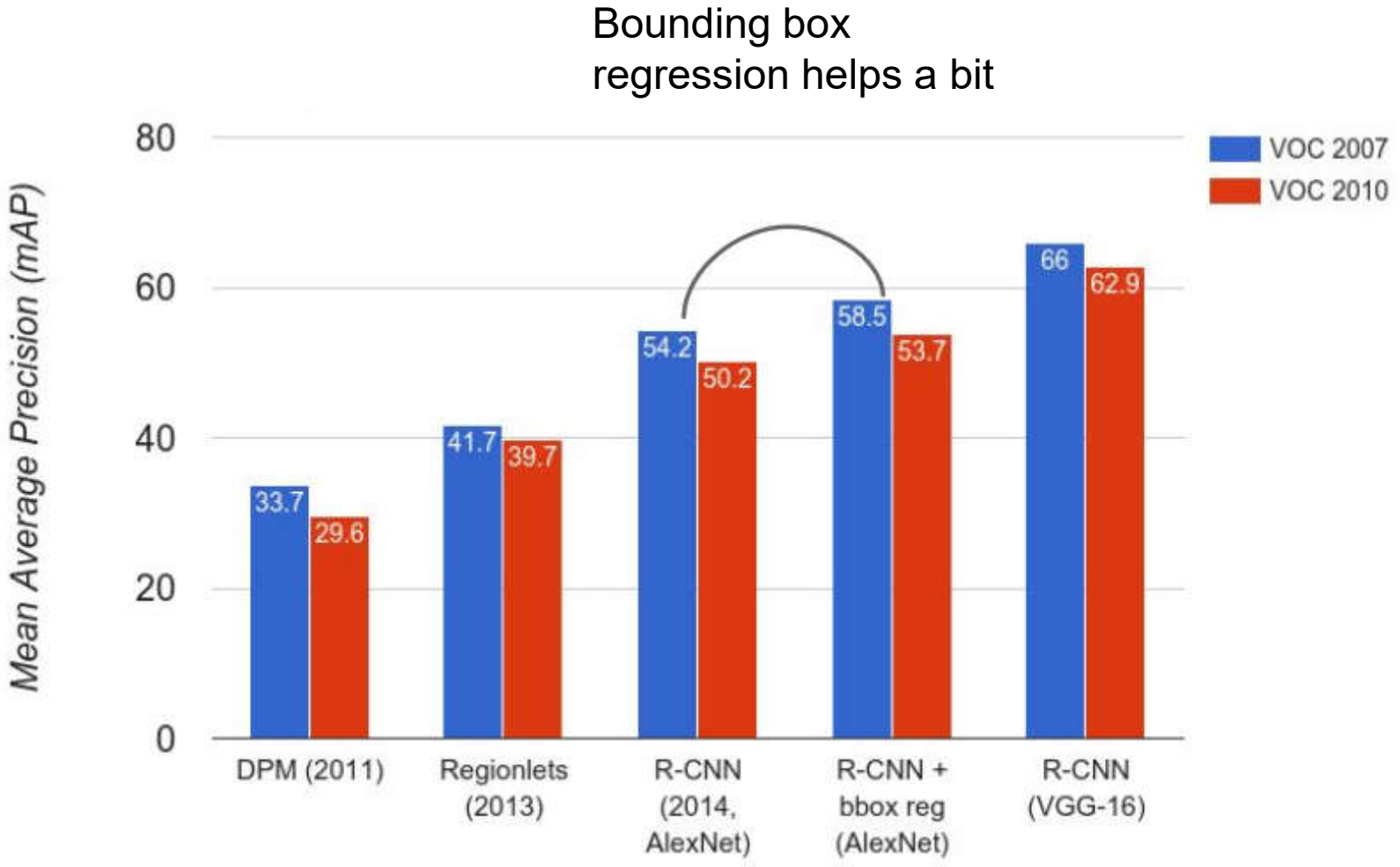
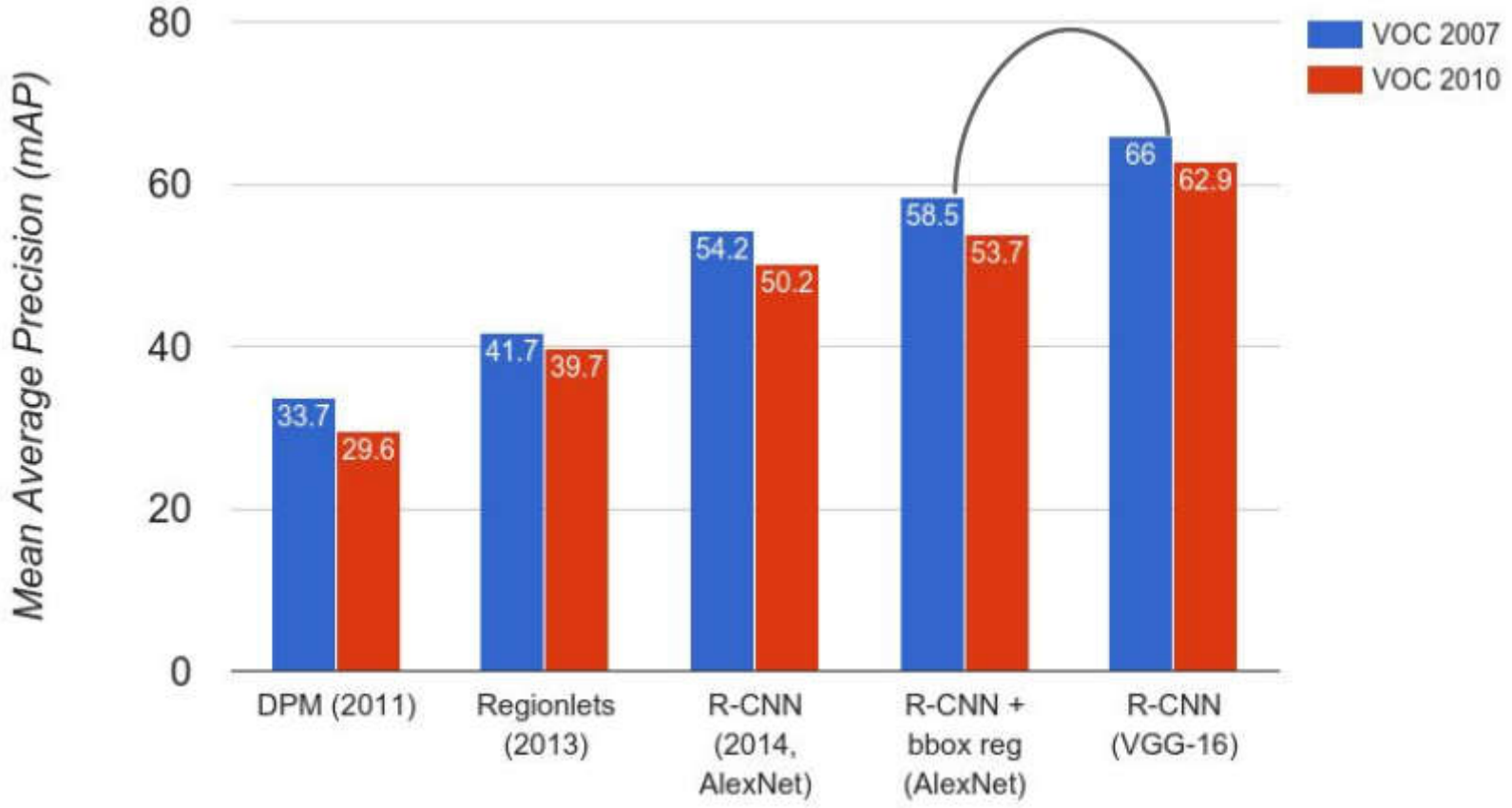
R-CNN Results



Slide from CS231n

R-CNN Results

Features from a deeper network help a lot



Slide from CS231n

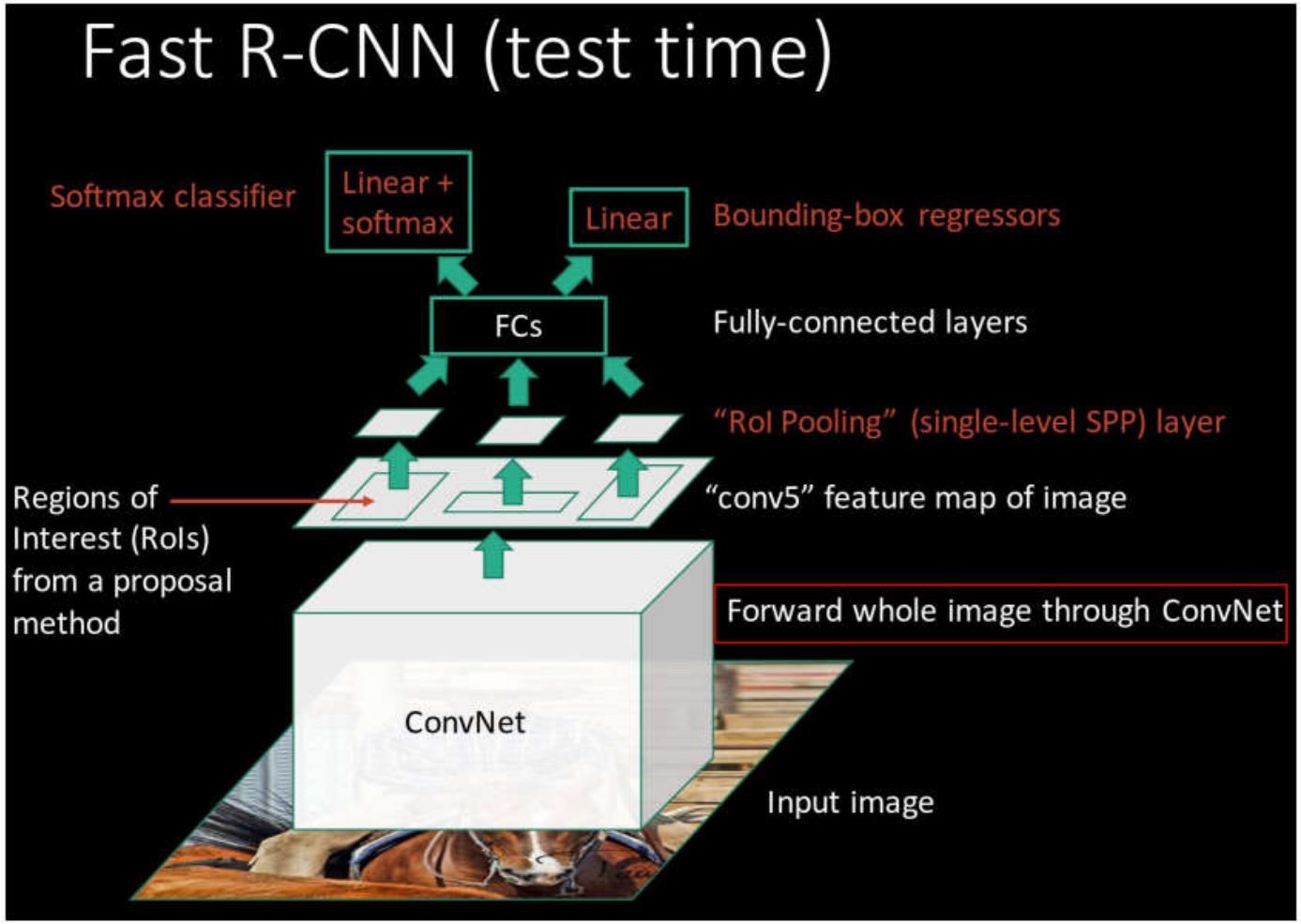
R-CNN Problems

1. Slow at test-time: need to run full forward pass of CNN for each region proposal

2. SVMs and regressors are post-hoc: CNN features not updated in response to SVMs and regressors

3. Complex multistage training pipeline

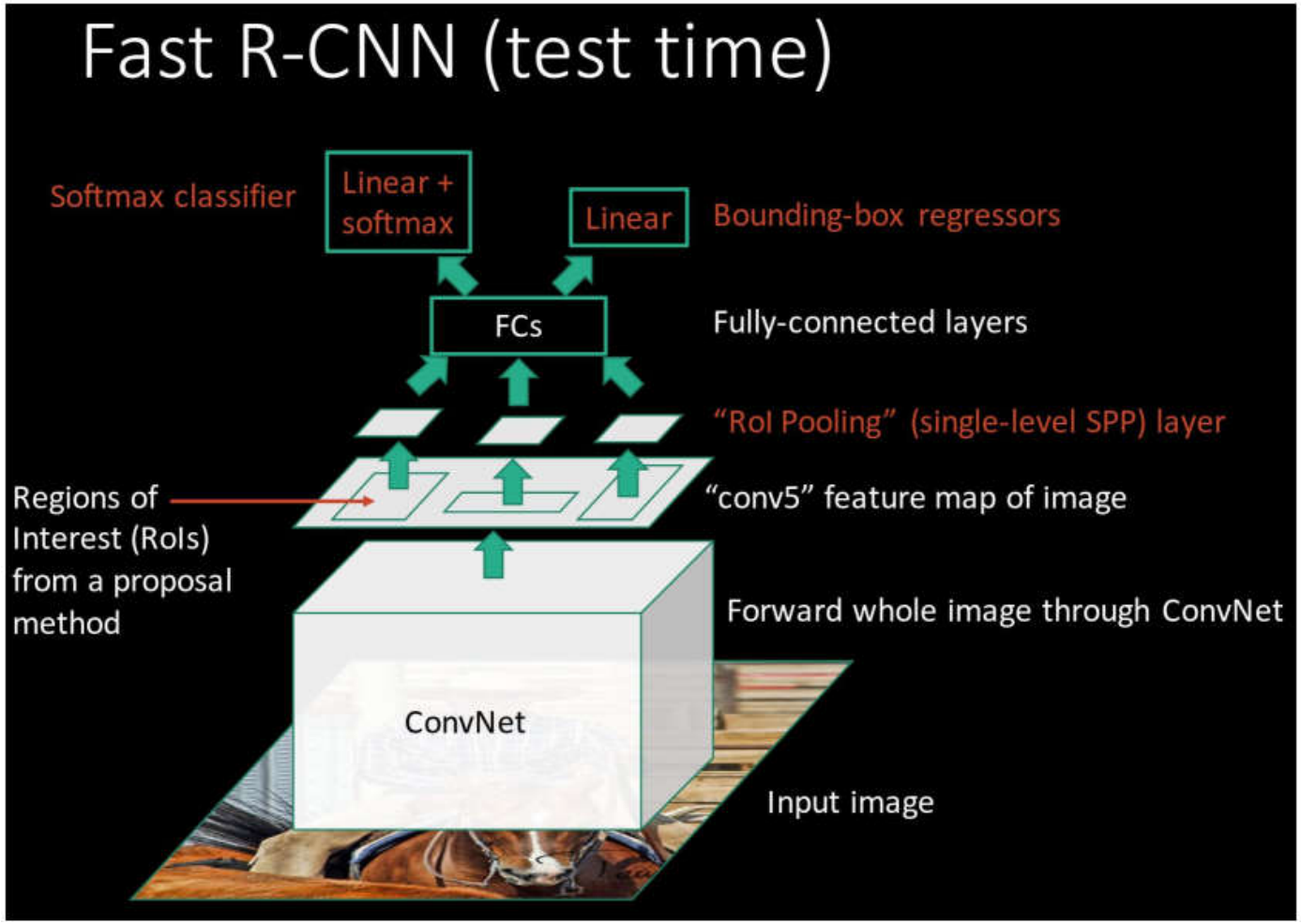
Fast R-CNN



Girschick, "Fast R-CNN", ICCV 2015

Slide credit: Ross Girschick

Fast R-CNN



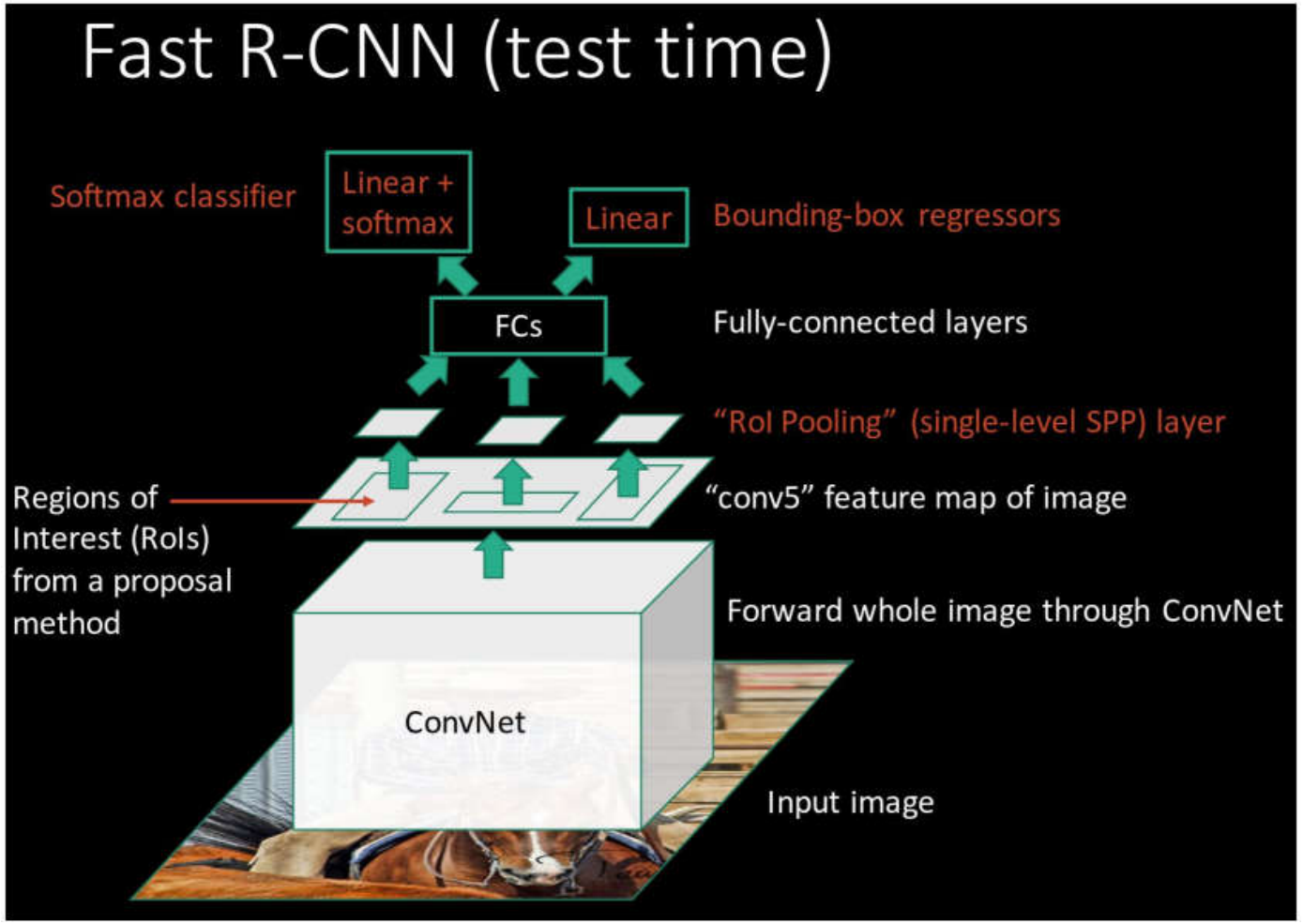
R-CNN Problem #1:
Slow at test-time due to independent forward passes of the CNN

Solution:
Share computation of convolutional layers between proposals for an image

Girschick, "Fast R-CNN", ICCV 2015

Slide credit: Ross Girschick

Fast R-CNN



R-CNN Problem #2:
Post-hoc training: CNN not updated in response to final classifiers and regressors

R-CNN Problem #3:
Complex training pipeline

Solution:
Just train the whole system end-to-end all at once!

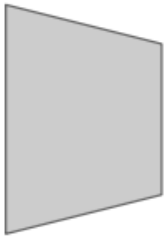
Girschick, "Fast R-CNN", ICCV 2015

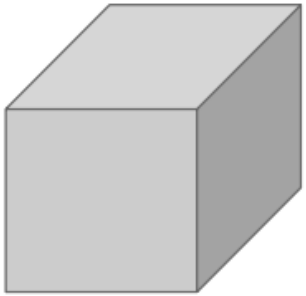
Slide credit: Ross Girschick

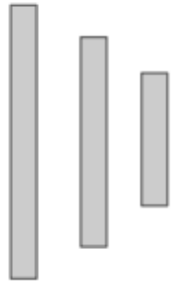
Fast R-CNN: Region of Interest Pooling

Convolution and Pooling

Fully-connected layers







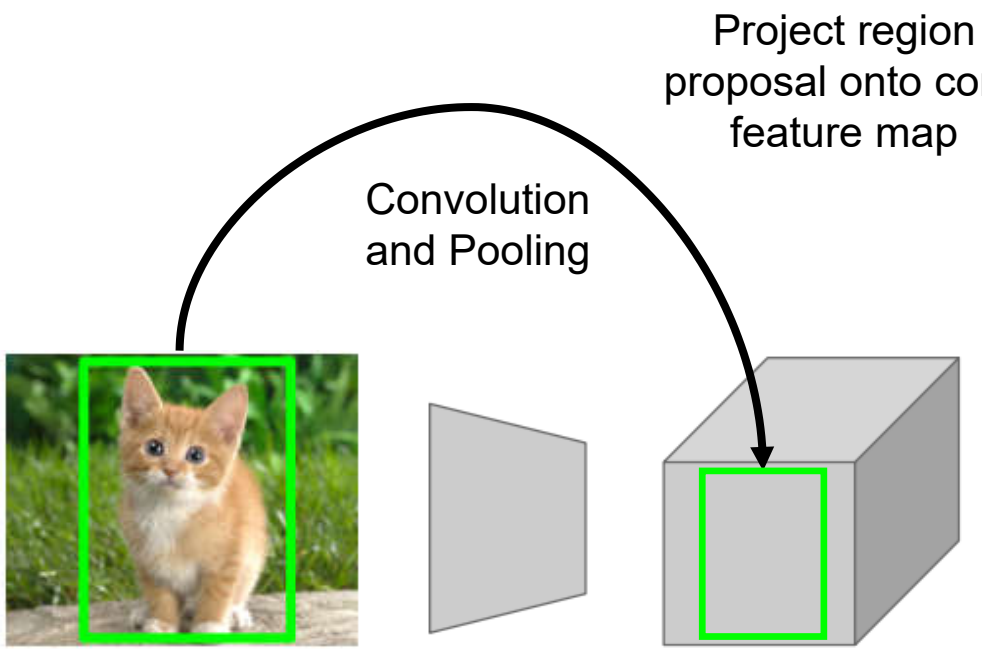
Hi-res input image: 3 x 800 x 600 with region proposal

Hi-res features: C x H x W with region proposal

Problem: Fully-connected layers expect low-res conv features: C x h x w

Slide from CS231n

Fast R-CNN: Region of Interest Pooling



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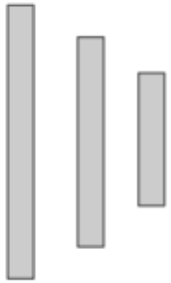
Hi-res features: C x H x W with region proposal

Fully-connected layers



Problem: Fully-connected layers expect low-res conv features: C x h x w

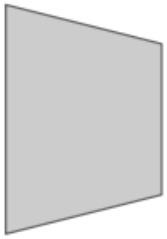
Slide from CS231n

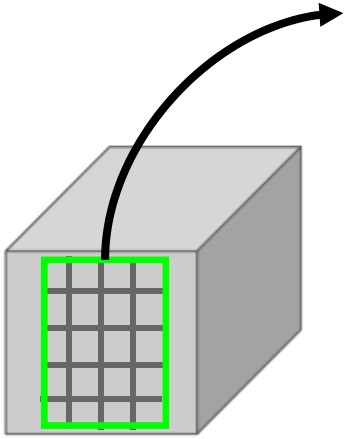
Fast R-CNN: Region of Interest Pooling

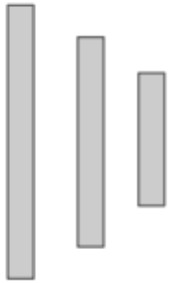
Convolution and Pooling

Divide projected region into h x w grid

Fully-connected layers







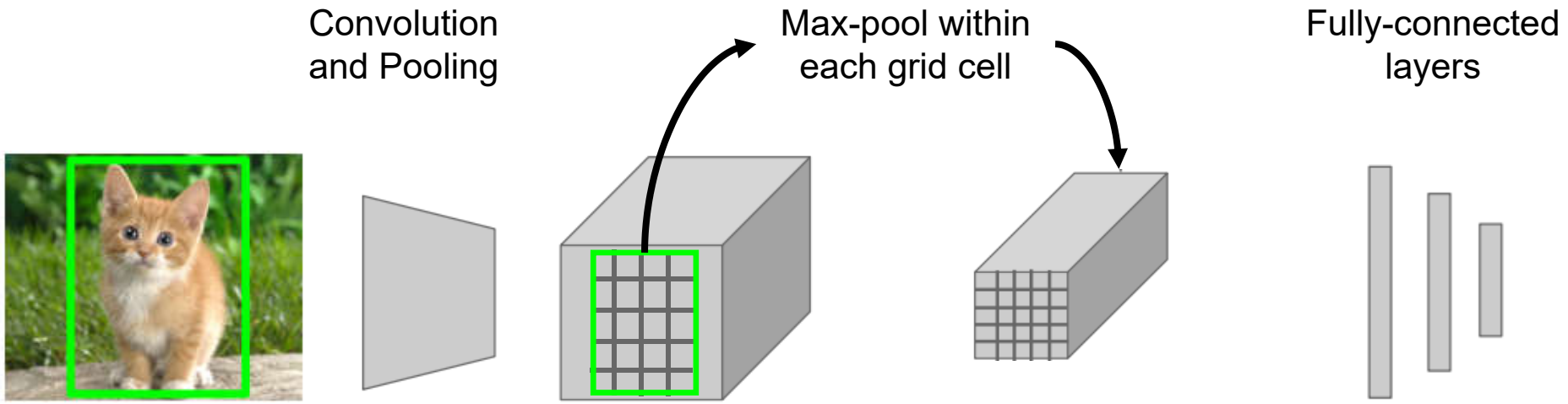
Hi-res input image: 3 x 800 x 600 with region proposal

Hi-res features: C x H x W with region proposal

Problem: Fully-connected layers expect low-res conv features: C x h x w

Slide from CS231n

Fast R-CNN: Region of Interest Pooling



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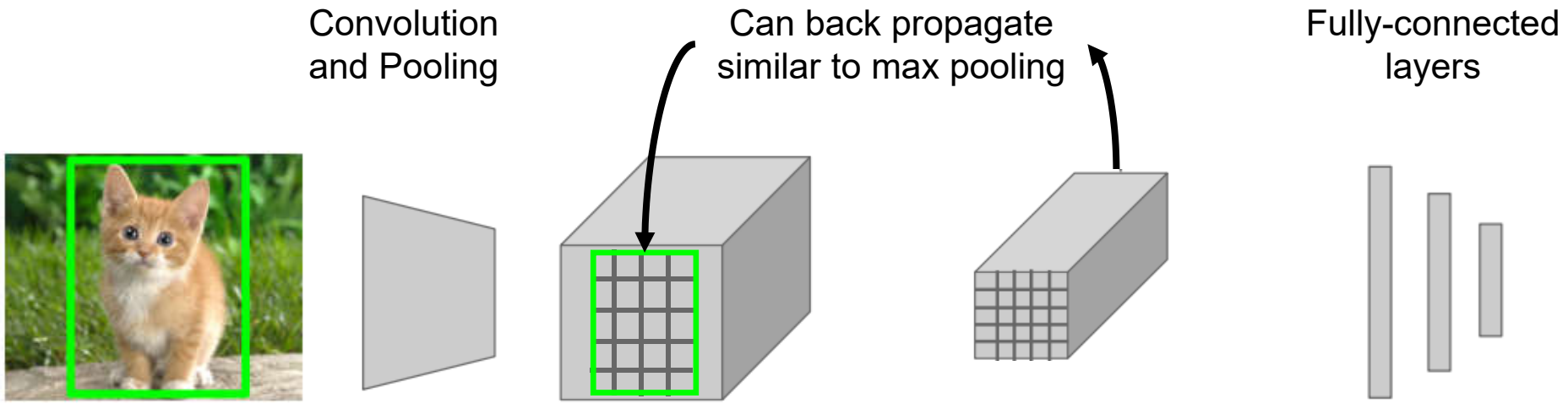
Fast R-CNN: Region of Interest Pooling



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Fast R-CNN Results

Faster!

	R-CNN	Fast R-CNN
Training Time:	84 hours	**9.5 hours**
(Speedup)	1x	**8.8x**

Using VGG-16 CNN on Pascal VOC 2007 dataset

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Fast R-CNN Results

Faster!

FASTER!

	R-CNN	Fast R-CNN
Training Time:	84 hours	**9.5 hours**
(Speedup)	1x	**8.8x**
Test time per image	47 seconds	**0.32 seconds**
(Speedup)	1x	**146x**

Using VGG-16 CNN on Pascal VOC 2007 dataset

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Fast R-CNN Results

	R-CNN	Fast R-CNN
Faster! Training Time:	84 hours	**9.5 hours**
(Speedup)	1x	**8.8x**
FASTER! Test time per image	47 seconds	**0.32 seconds**
(Speedup)	1x	**146x**
Better! mAP (VOC 2007)	66.0	**66.9**

Using VGG-16 CNN on Pascal VOC 2007 dataset

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Fast R-CNN Problem:

- Test-time speeds don't include **region proposals**

	R-CNN	Fast R-CNN
Test time per image	47 seconds	**0.32 seconds**
(Speedup)	1x	**146x**
Test time per image with Selective Search	50 seconds	**2 seconds**
(Speedup)	1x	**25x**

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Fast R-CNN Solution:

- Test-time speeds don't include region proposals
- Just make the CNN do region proposals too!

	R-CNN	Fast R-CNN
Test time per image	47 seconds	**0.32 seconds**
(Speedup)	1x	**146x**
Test time per image with Selective Search	50 seconds	**2 seconds**
(Speedup)	1x	**25x**

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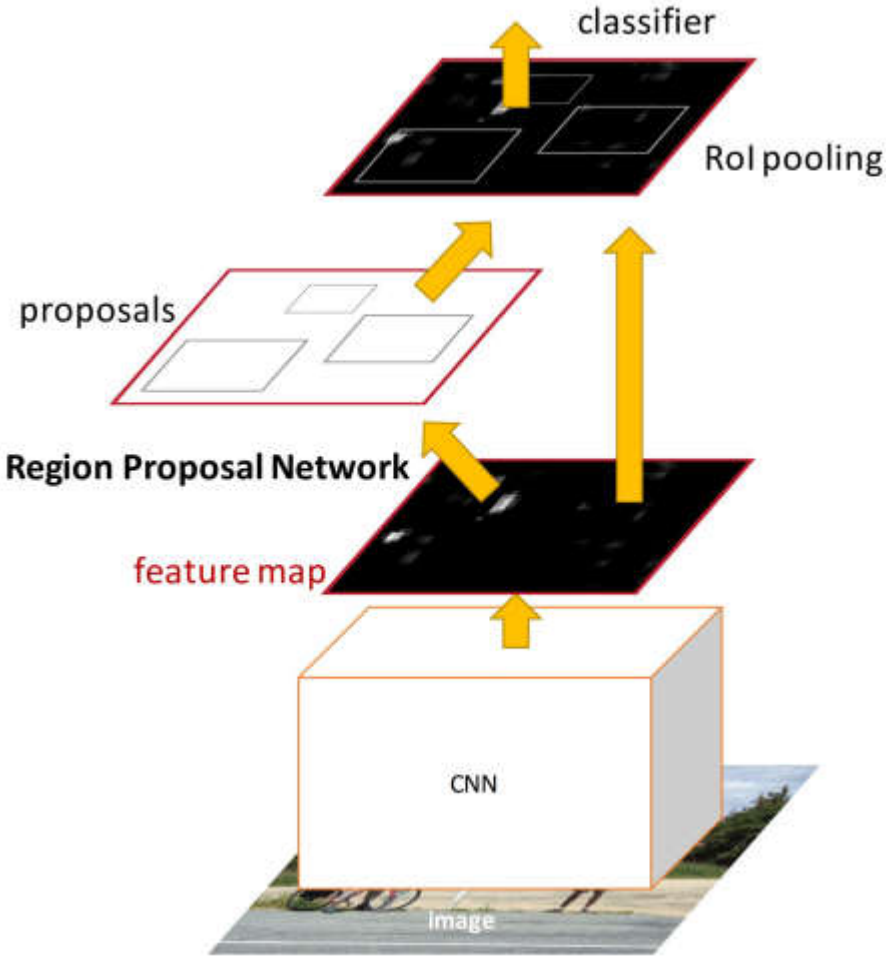
Faster R-CNN:



Insert a **Region Proposal Network (RPN)** after the last convolutional layer

RPN trained to produce region proposals directly; no need for external region proposals!

After RPN, use RoI Pooling and an upstream classifier and bbox regressor just like Fast R-CNN

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

Slide credit: Ross Girschick

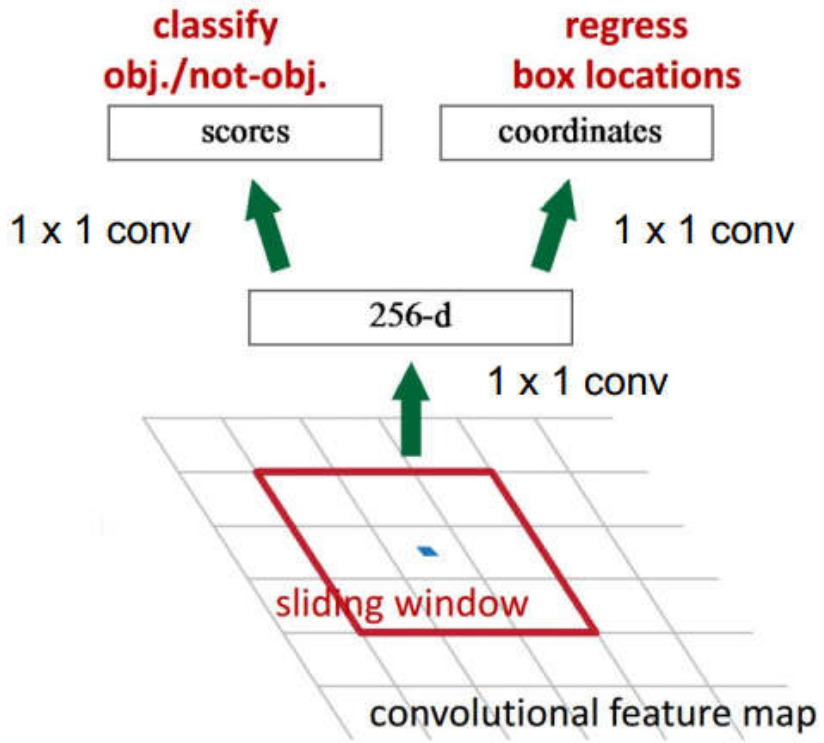
Faster R-CNN: Region Proposal Network

Slide a small window on the feature map

Build a small network for:
- Classifying object or not-object, and
- Regressing bbox locations

Position of the sliding window provides localization information with reference to the image

Box regression provides finer localization information with reference to this sliding window



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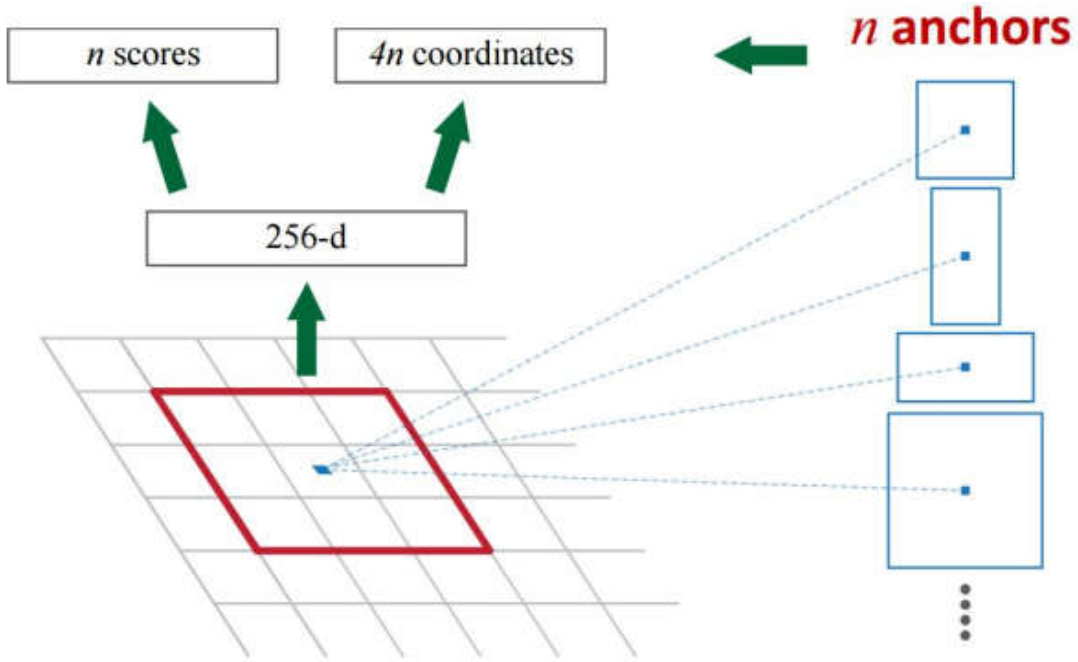
Faster R-CNN: Region Proposal Network

Use **N anchor boxes** at each location

Anchors are **translation invariant:** use the same ones at every location

Regression gives offsets from anchor boxes

Classification gives the probability that each (regressed) anchor shows an object



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Faster R-CNN: Training

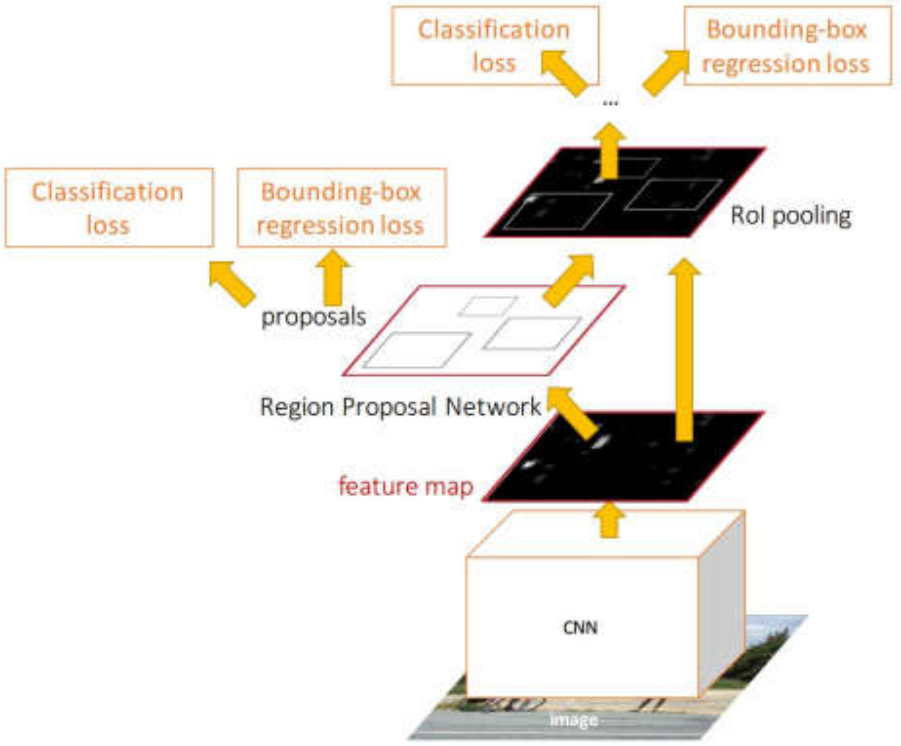
In the paper: Ugly pipeline

- Use alternating optimization to train RPN, then Fast R-CNN with RPN proposals, etc.
- More complex than it has to be

Since publication: Joint training!

One network, four losses

- RPN classification (anchor good / bad)
- RPN regression (anchor -> proposal)
- Fast R-CNN classification (over classes)
- Fast R-CNN regression (proposal -> box)



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Faster R-CNN: Results

	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image (with proposals)	50 seconds	2 seconds	**0.2 seconds**
(Speedup)	1x	25x	**250x**
mAP (VOC 2007)	66.0	**66.9**	**66.9**

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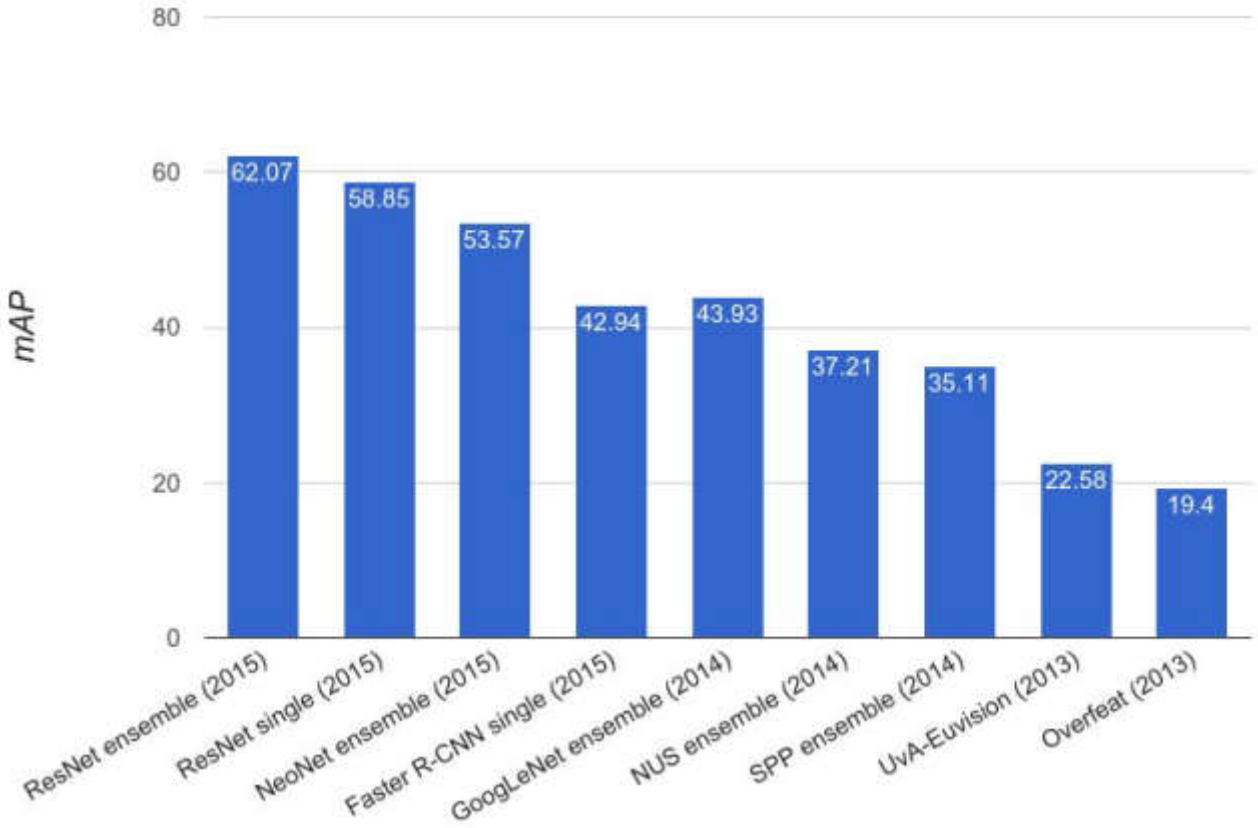
Object Detection State-of-the-art: ResNet 101 + Faster R-CNN + some extras

training data	COCO train		COCO trainval	
test data	COCO val		COCO test-dev	
mAP	@.5	@[.5, .95]	@.5	@[.5, .95]
baseline Faster R-CNN (VGG-16)	41.5	21.2		
baseline Faster R-CNN (ResNet-101)	48.4	27.2		
+box refinement	49.9	29.9		
+context	51.1	30.0	53.3	32.2
+multi-scale testing	53.8	32.5	**55.7**	**34.9**
ensemble			**59.0**	**37.4**

He et. al, “Deep Residual Learning for Image Recognition”, arXiv2015

ImageNet Detection 2013-2015



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Mask R-CNN, ICCV2017

Kaiming He, Georgia Gkioxari, Pior Dollar, Ross Girshick, “Mask R-CNN,” **ICCV2017**

Focal Loss for Dense Object Detection, ICCV2017

Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, Piotr Dollar, et al., “Focal loss for dense object detection”, ICCV2017

YOLO: You Only Look Once Detection as Regression

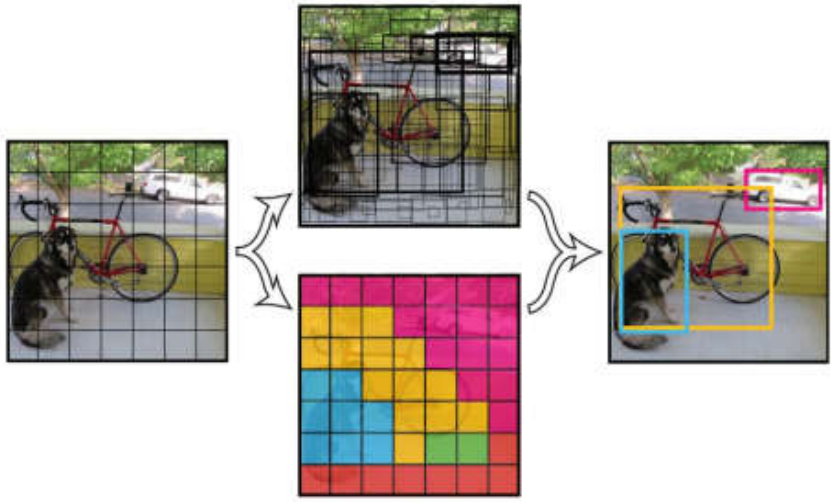
Divide image into S x S grid

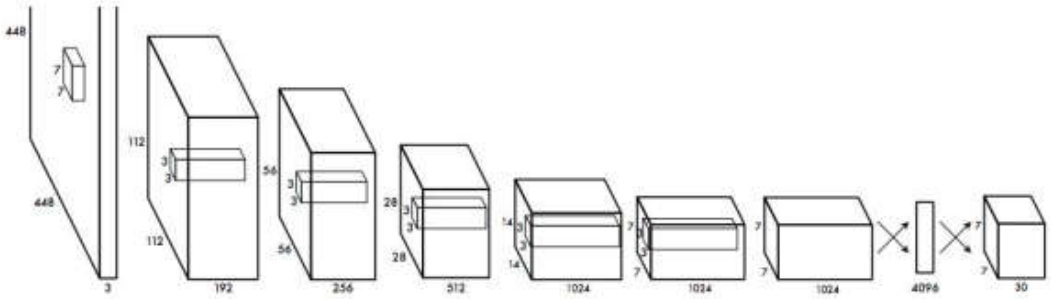
Within each grid cell predict:

- B Boxes: 4 coordinates + confidence
- Class scores: C numbers

Regression from image to 7 x 7 x (5 * B + C) tensor

Direct prediction using a CNN





J. Redmon, et al., You Only Look Once: Unified, Real-Time Object Detection, CVPR2016

YOLO: You Only Look Once Detection as Regression

Faster than Faster R-CNN, but not as good

Real-Time Detectors	Train	mAP	FPS
100Hz DPM [30]	2007	16.0	100
30Hz DPM [30]	2007	26.1	30
Fast YOLO	2007+2012	52.7	**155**
YOLO	2007+2012	**63.4**	45
Less Than Real-Time			
Fastest DPM [37]	2007	30.4	15
R-CNN Minus R [20]	2007	53.5	6
Fast R-CNN [14]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[27]	2007+2012	73.2	7
Faster R-CNN ZF [27]	2007+2012	62.1	18
YOLO VGG-16	2007+2012	66.4	21

J. Redmon, et al., You Only Look Once: Unified, Real-Time Object Detection, CVPR2016

Summary

Classification with Localization:

- Find a fixed number of objects (one or many)
- L2 regression from CNN features to box coordinates
- Much simpler than detection
- Overfeat: Regression + efficient sliding window with FC -> conv conversion
- Deeper networks do better

Object Detection:

- Find a variable number of objects by classifying image regions
- Before CNNs: *dense multiscale sliding window* (HoG, DPM)
- Avoid dense sliding window with region proposals
- R-CNN: Selective Search + CNN classification / regression
- Fast R-CNN: Swap order of convolutions and region extraction
- Faster R-CNN: Compute region proposals within the network
- Deeper networks do better

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Thank you for your attention!