

# Localization & Detection

---

2016.11.10

SCHOOL OF MATHEMATICAL SCIENCE, PEKING UNIVERSITY

# Preview

---

Lecture 7: Introduction to CNN

**Lecture 8: Spatial Localization and Detection (Today!!)**

Lecture 9: Understanding and Visualizing CNN

Lecture 11: CNNs in Practice

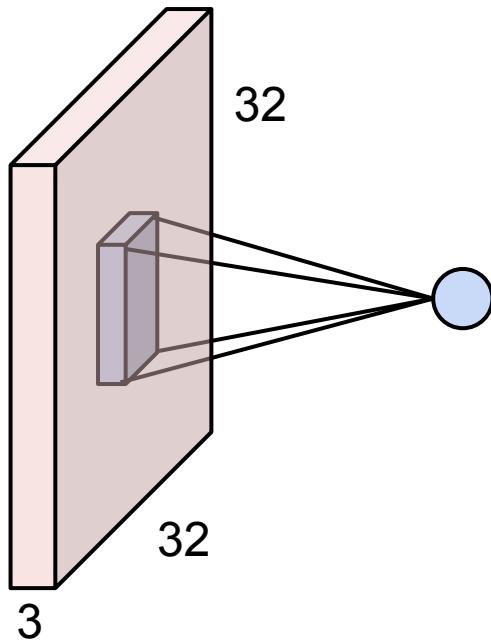
# Lecture 8:

# Spatial Localization and Detection

# Administrative

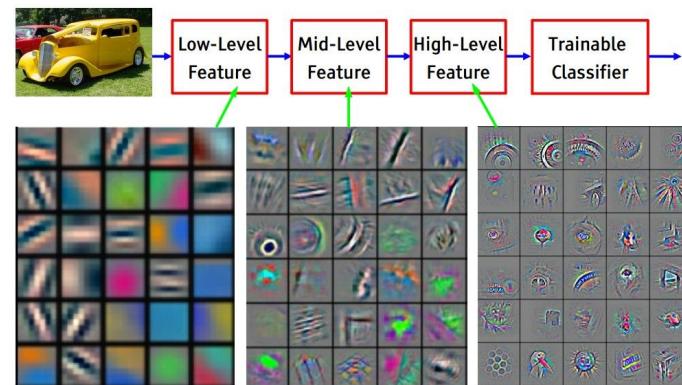
- Project Proposals were due on Saturday
- Homework 2 due Friday 2/5
- Homework 1 grades out this week
- Midterm will be in-class on Wednesday 2/10

# Convolution



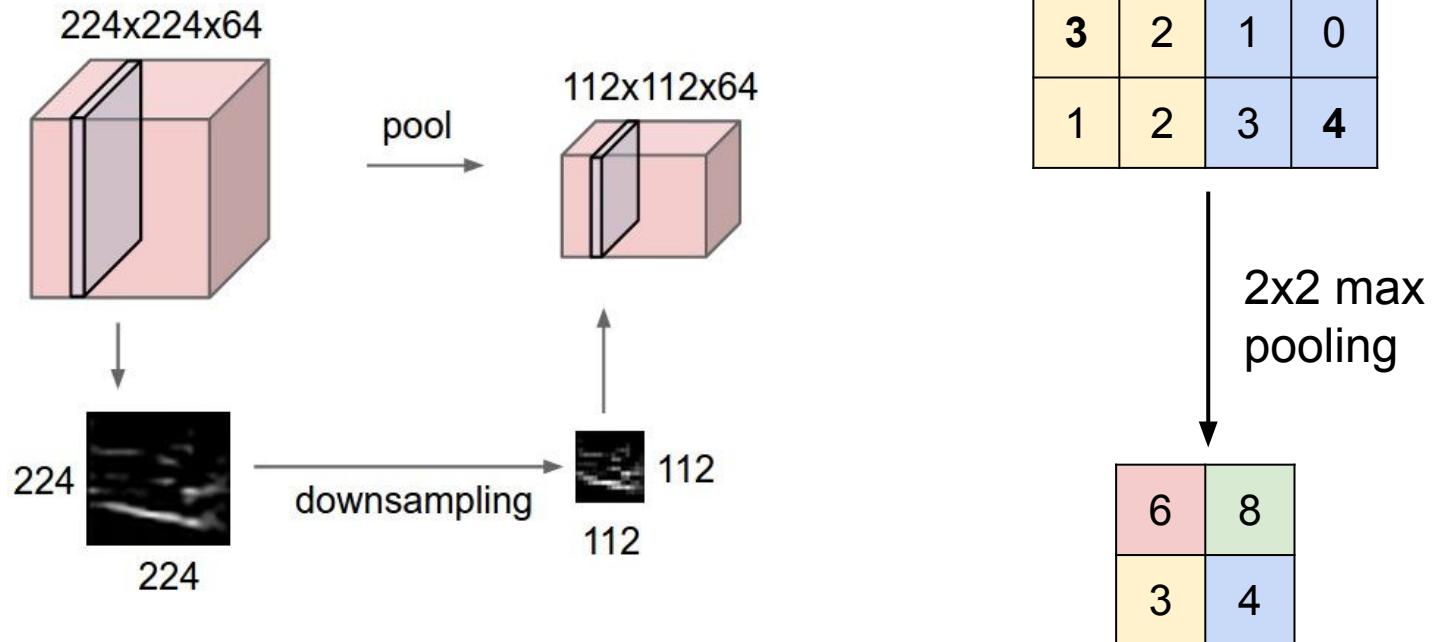
**Summary.** To summarize, the Conv Layer:

- 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  $P$ .



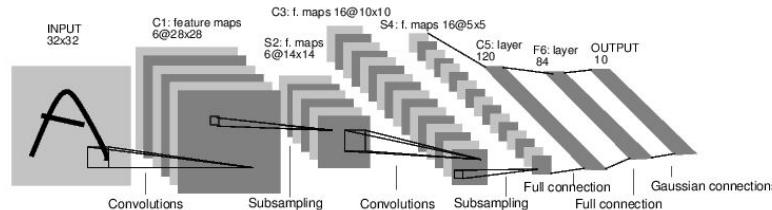
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

# Pooling

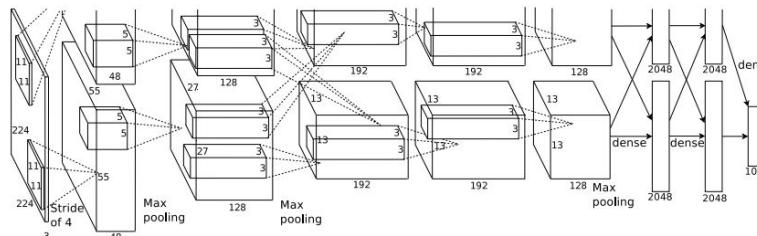


# Case Studies

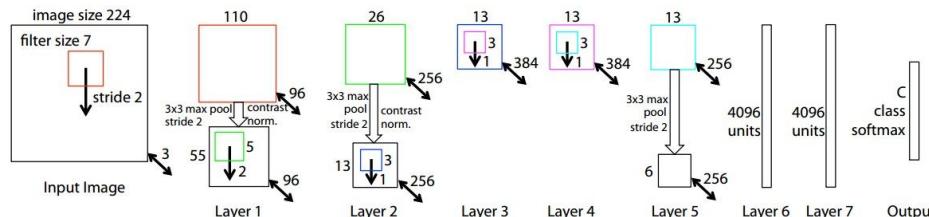
LeNet  
(1998)



AlexNet  
(2012)



ZFNet  
(2013)



# Case Studies

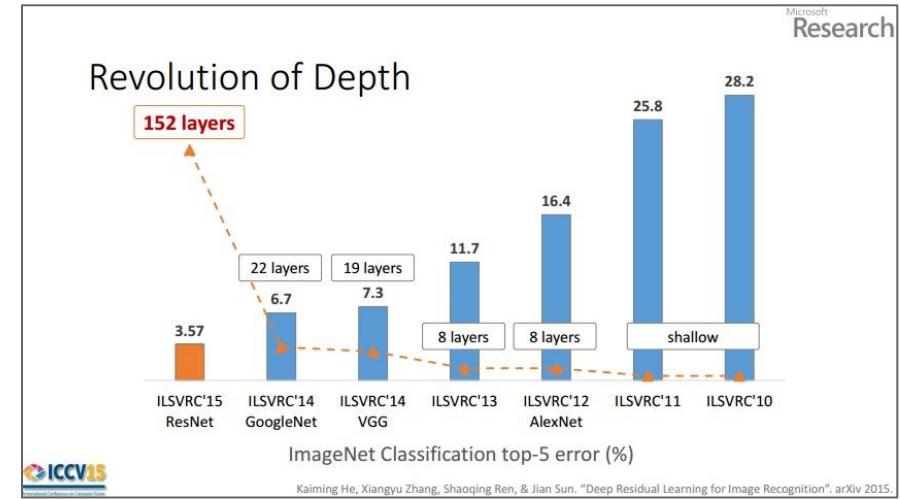
D	E
16 weight layers	19 weight layers
conv3-64 conv3-64	conv3-64 conv3-64
conv3-128 conv3-128	conv3-128 conv3-128
conv3-256 conv3-256 <b>conv3-256</b>	conv3-256 conv3-256 <b>conv3-256</b>
conv3-512 conv3-512 <b>conv3-512</b>	conv3-512 conv3-512 <b>conv3-512</b>
conv3-512 conv3-512 <b>conv3-512</b>	conv3-512 conv3-512 <b>conv3-512</b>
maxpool	
FC-4096	
FC-4096	
FC-1000	
soft-max	



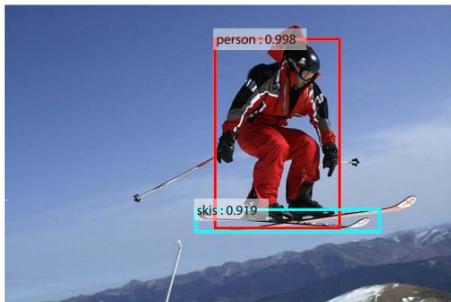
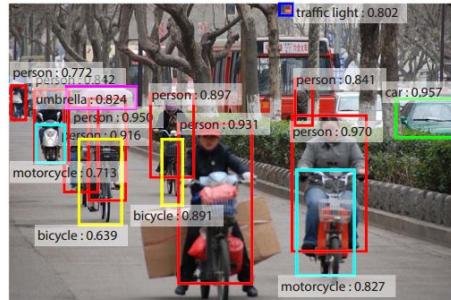
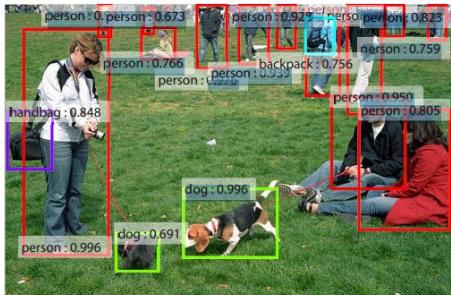
VGG  
(2014)



ResNet  
(2015)



# Localization and Detection



Results from Faster R-CNN, Ren et al 2015

# Computer Vision Tasks

Classification



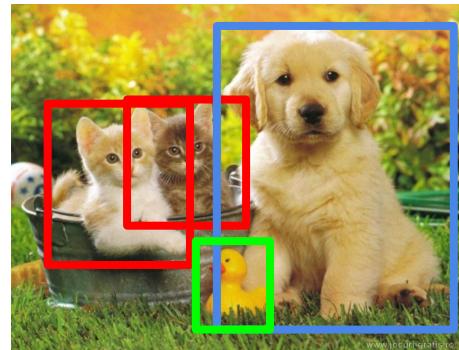
CAT

Classification + Localization



CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation



CAT, DOG, DUCK

Single object

Multiple objects

# ImageNet中的几个任务

## Classification

- 给图片中的主要物体分类

## Localization

- 给出图片中一个物体的分类和位置

## Detection

- 给出图片中所有物体的分类和位置  
(物体个数未知)

Easy



Hard

# 评价标准

---

**Classification Top 5 Error:** 给出5个预测分类，任一个正确则认为正确（考虑到一张图上可能有多个物体）

**Localization** 同时给出分类和物体位置，当分类正确且  $IoU \geq 50\%$  时认为正确。其中，IoU（Intersection over Union）：

$$IOU = \frac{DetectionResult \cap GroundTruth}{DetectionResult \cup GroundTruth}$$

**Detection** 给出能够检测到的分类和物体位置，取平均后得到准确度的分数，错例会惩罚

# Computer Vision Tasks

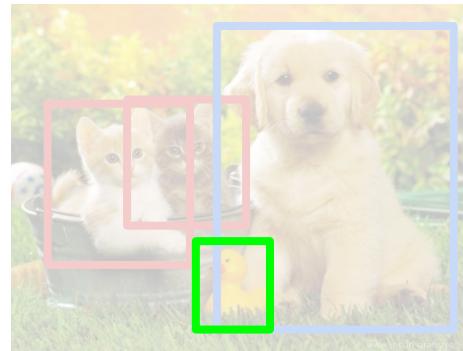
Classification



**Classification  
+ Localization**



Object Detection



Instance  
Segmentation



# Classification + Localization: Task

**Classification:** C classes

**Input:** Image

**Output:** Class label

**Evaluation metric:** Accuracy



**Localization:**

**Input:** Image

**Output:** Box in the image ( $x, y, w, h$ )

**Evaluation metric:** Intersection over Union



**Classification + Localization:** Do both

# Classification + Localization: ImageNet

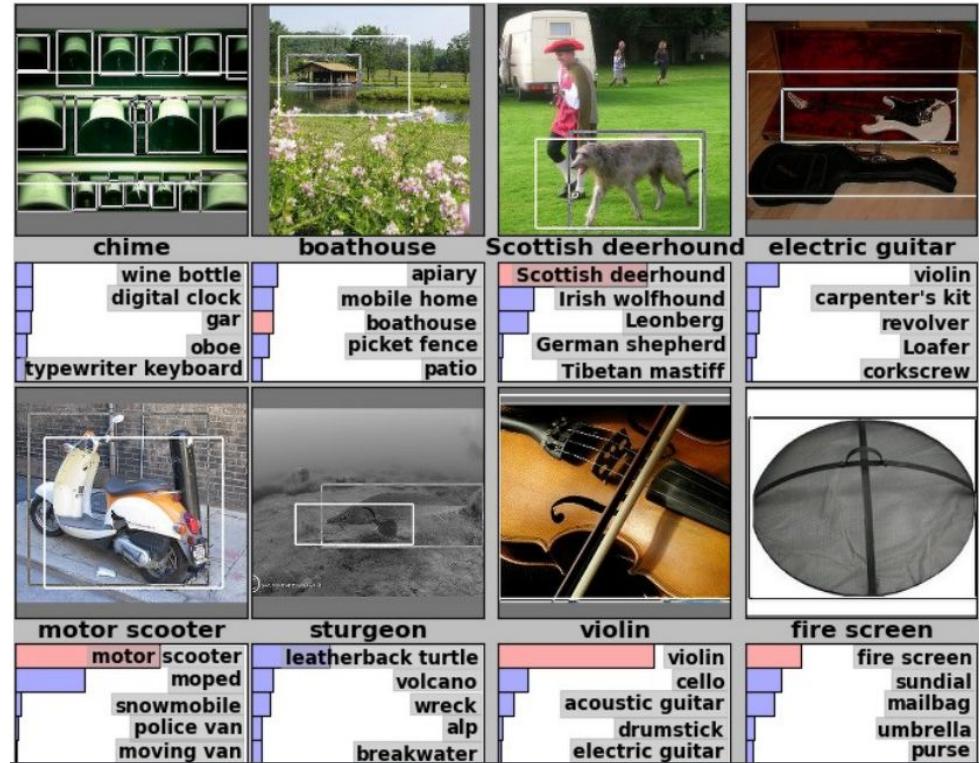
1000 classes (same as classification)

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 intersection over union (IoU)



Krizhevsky et. al. 2012

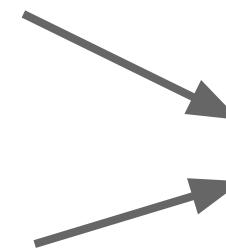
# Idea #1: Localization as Regression

**Input:** image



Neural Net  
→

**Output:**  
Box coordinates  
(4 numbers)

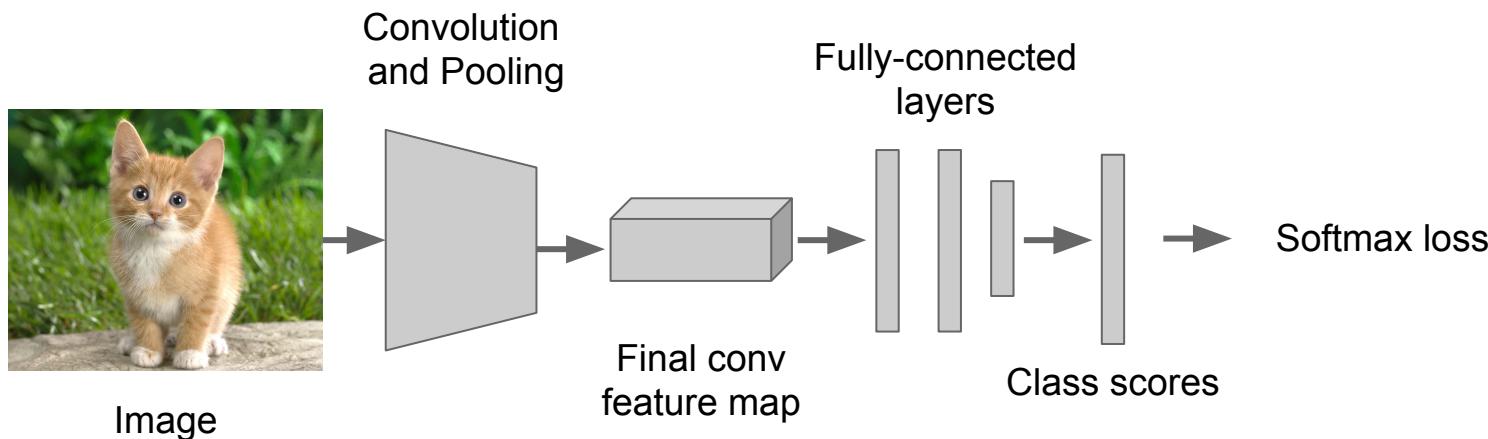


**Loss:**  
L2 distance

Only one object,  
simpler than detection

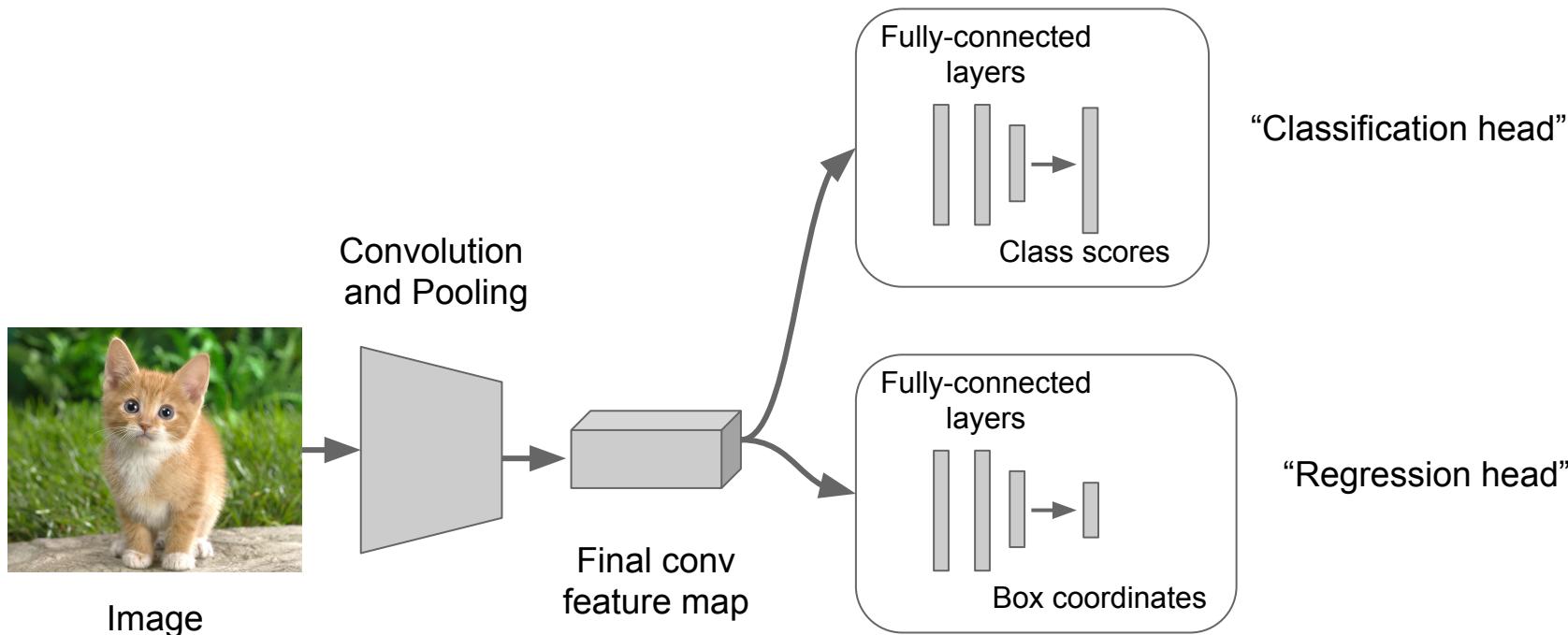
# Simple Recipe for Classification + Localization

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



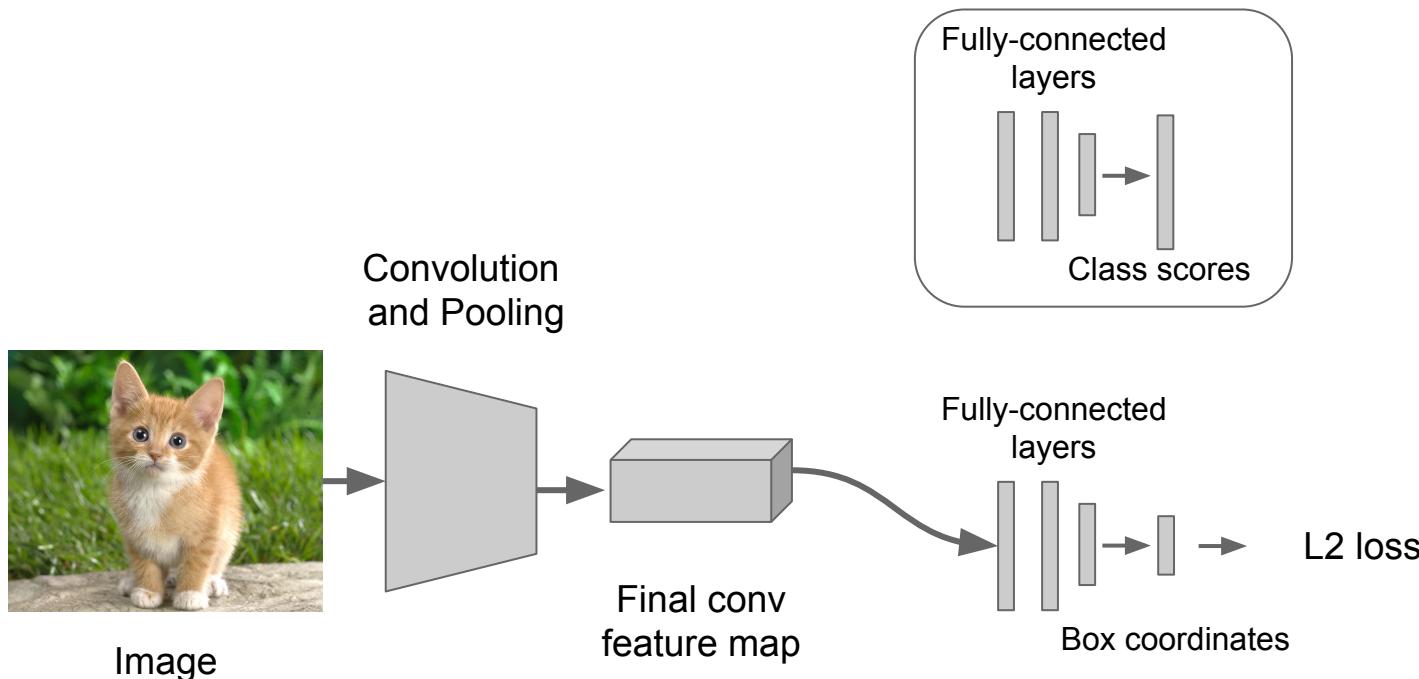
# Simple Recipe for Classification + Localization

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



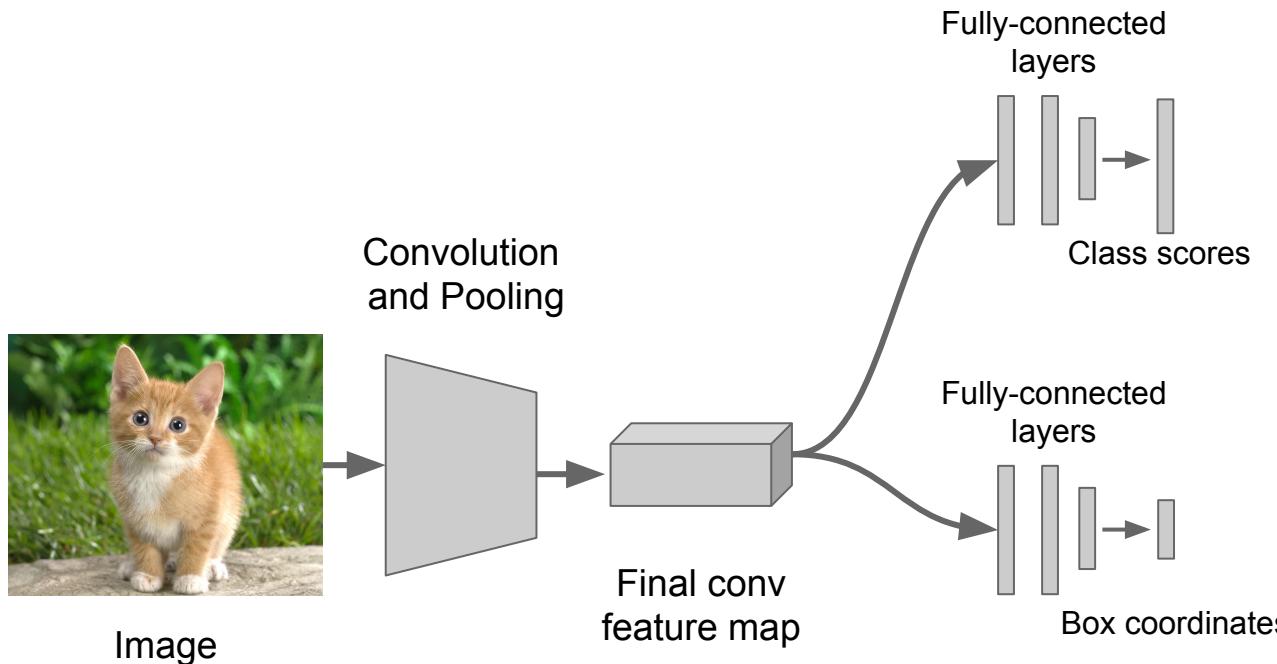
# Simple Recipe for Classification + Localization

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



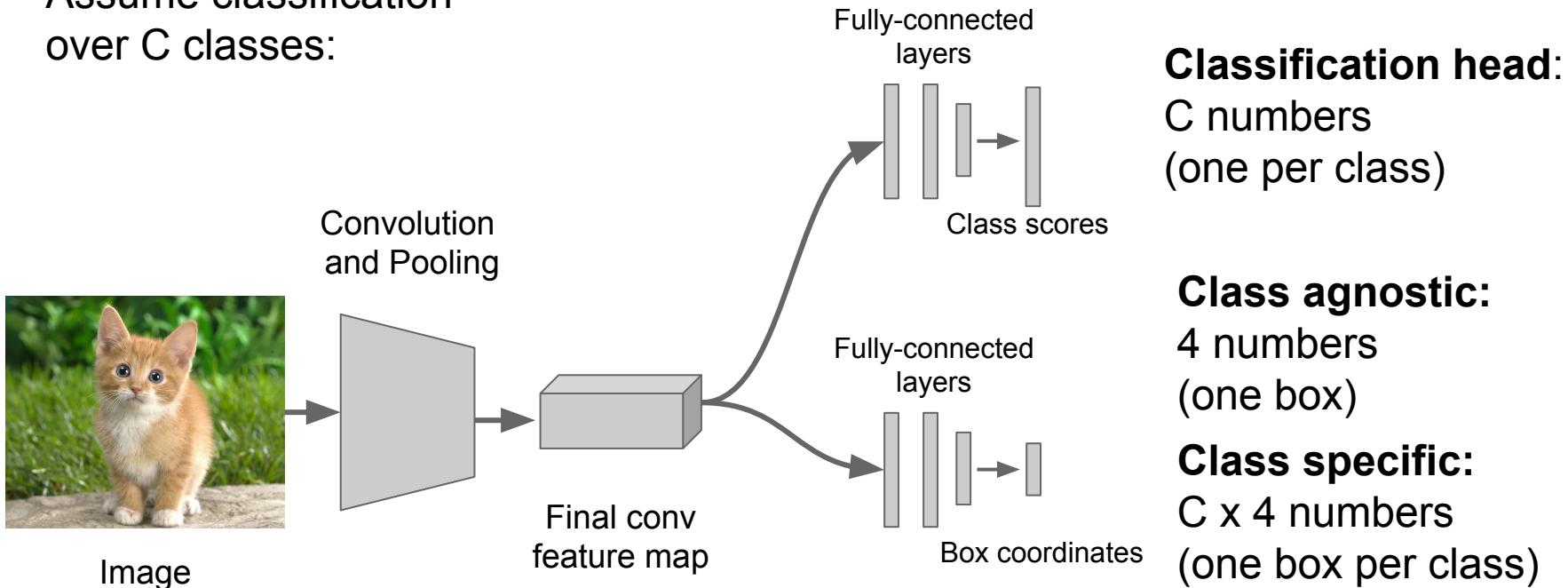
# Simple Recipe for Classification + Localization

**Step 4:** At test time use both heads

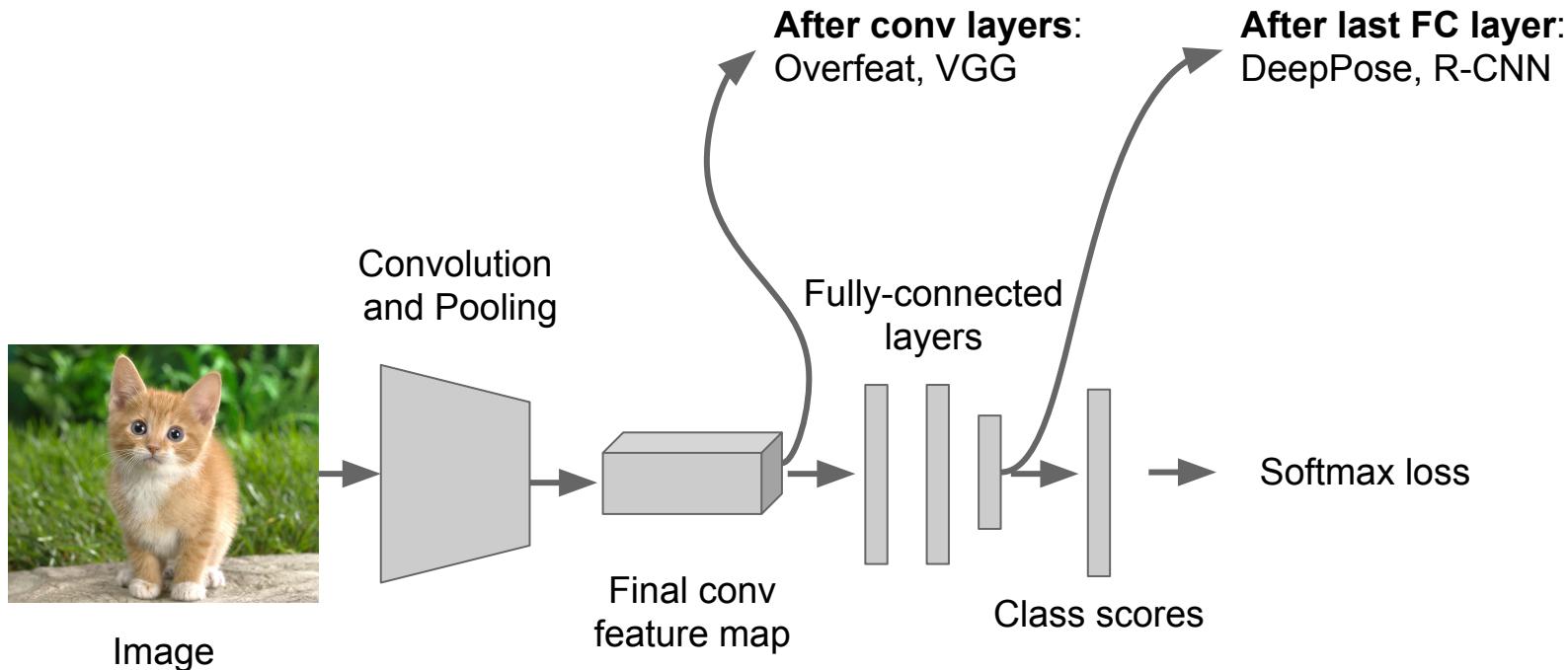


# Per-class vs class agnostic regression

Assume classification over C classes:



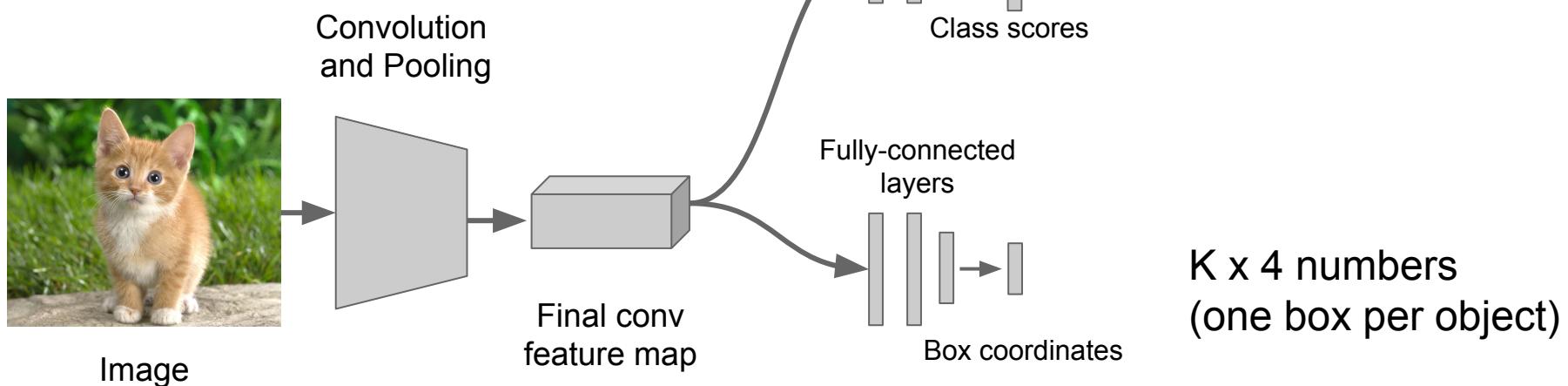
# Where to attach the regression head?



# 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)

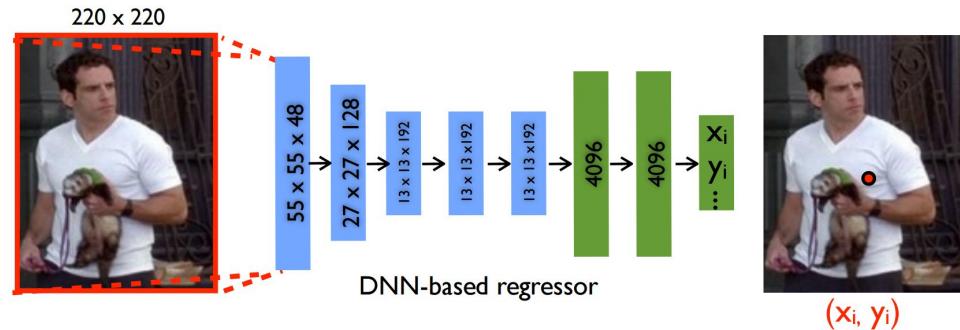


# Aside: Human Pose Estimation

Represent a person by K joints

Regress  $(x, y)$  for each joint from last fully-connected layer of AlexNet

(Details: Normalized coordinates, iterative refinement)



Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

# Localization as Regression

Very simple

Think if you can use this for projects

# Idea #2: Sliding Window

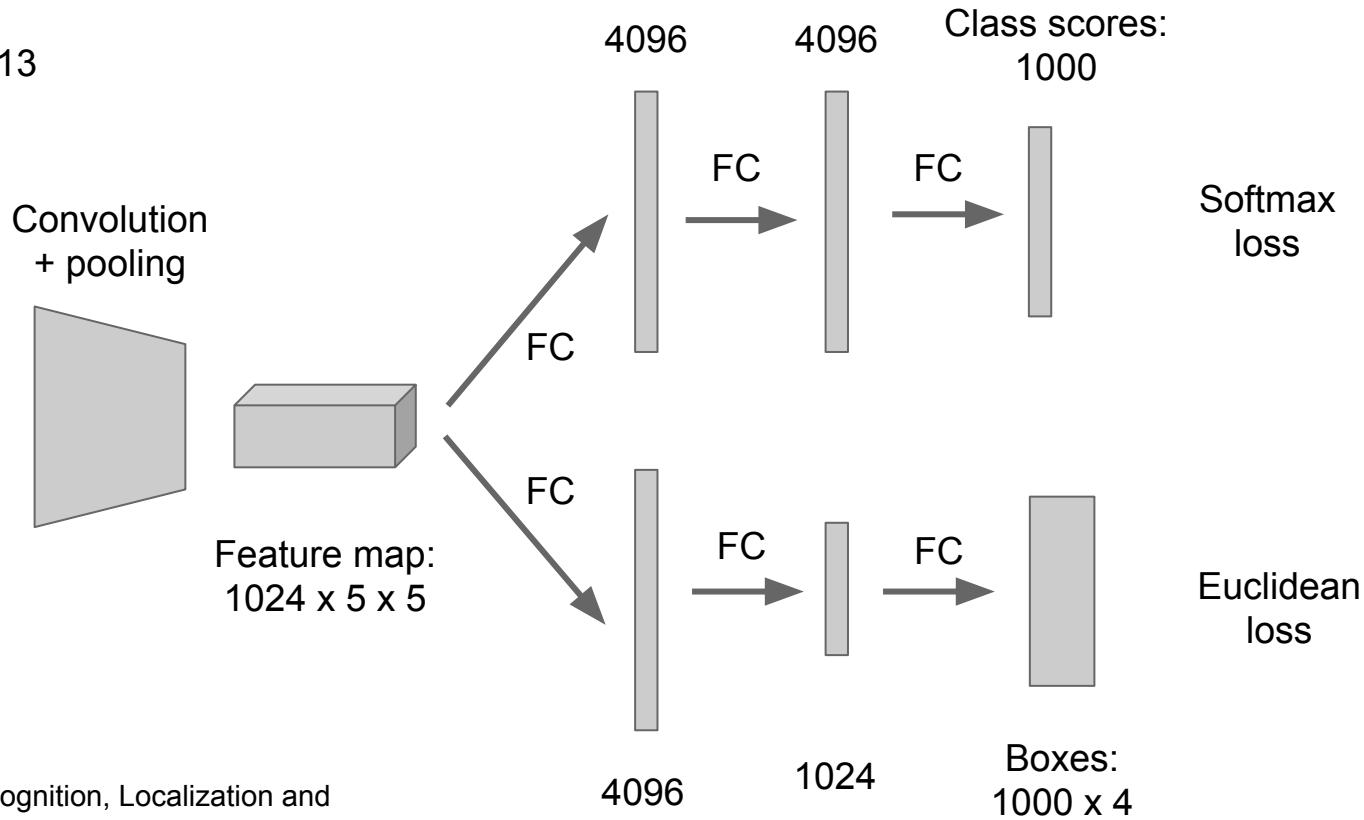
- Run classification + regression network at multiple locations on a high-resolution image
- Convert fully-connected layers into convolutional layers for efficient computation
- Combine classifier and regressor predictions across all scales for final prediction

# Sliding Window: Overfeat

Winner of ILSVRC 2013  
localization challenge

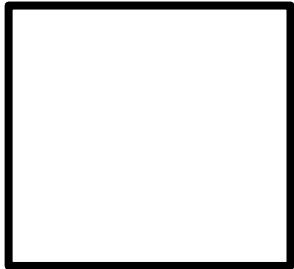


Image:  
 $3 \times 221 \times 221$



Sermanet et al, "Integrated Recognition, Localization and Detection using Convolutional Networks", ICLR 2014

# Sliding Window: Overfeat

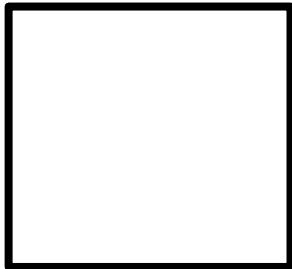


Network input:  
 $3 \times 221 \times 221$

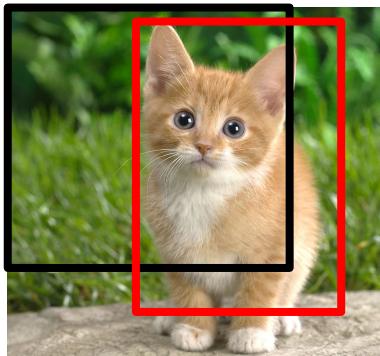


Larger image:  
 $3 \times 257 \times 257$

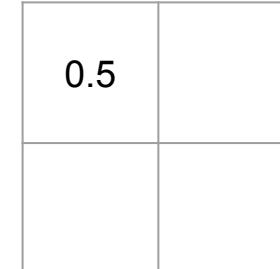
# Sliding Window: Overfeat



Network input:  
 $3 \times 221 \times 221$

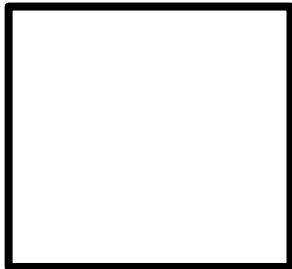


Larger image:  
 $3 \times 257 \times 257$

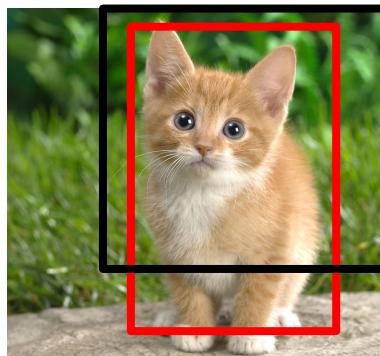


Classification scores:  
 $P(\text{cat})$

# Sliding Window: Overfeat



Network input:  
 $3 \times 221 \times 221$

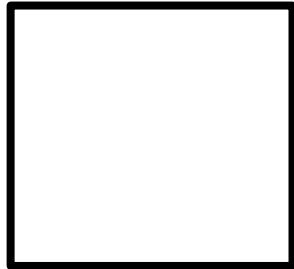


Larger image:  
 $3 \times 257 \times 257$

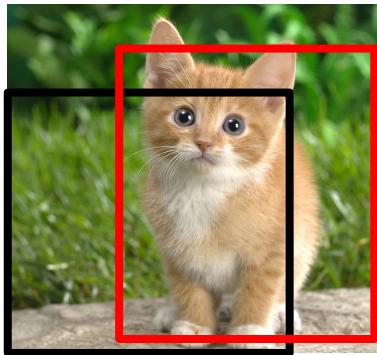
0.5	0.75

Classification scores:  
 $P(\text{cat})$

# Sliding Window: Overfeat



Network input:  
 $3 \times 221 \times 221$

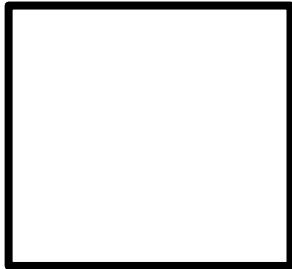


Larger image:  
 $3 \times 257 \times 257$

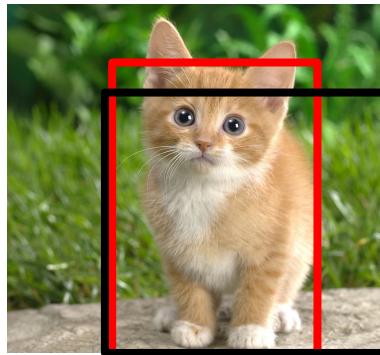
0.5	0.75
0.6	

Classification scores:  
 $P(\text{cat})$

# Sliding Window: Overfeat



Network input:  
 $3 \times 221 \times 221$

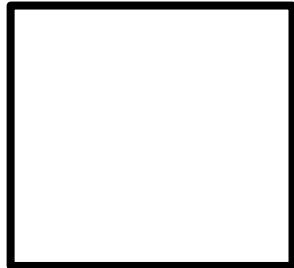


Larger image:  
 $3 \times 257 \times 257$

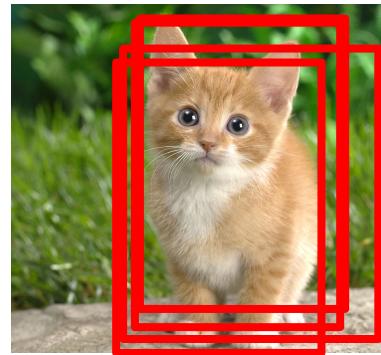
0.5	0.75
0.6	0.8

Classification scores:  
 $P(\text{cat})$

# Sliding Window: Overfeat



Network input:  
 $3 \times 221 \times 221$

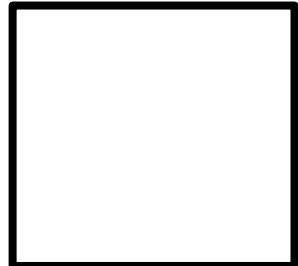


Larger image:  
 $3 \times 257 \times 257$

0.5	0.75
0.6	0.8

Classification scores:  
 $P(\text{cat})$

# Sliding Window: Overfeat



Network input:  
 $3 \times 221 \times 221$



Larger image:  
 $3 \times 257 \times 257$

Greedily merge boxes and  
scores (details in paper)

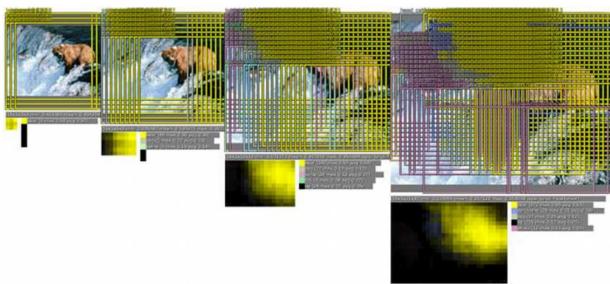
0.8

Classification score: P  
(cat)

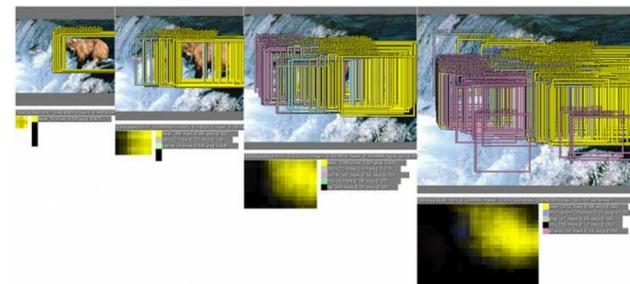
# Sliding Window: Overfeat

In practice use many sliding window locations and multiple scales

Window positions + score maps



Box regression outputs



Final Predictions

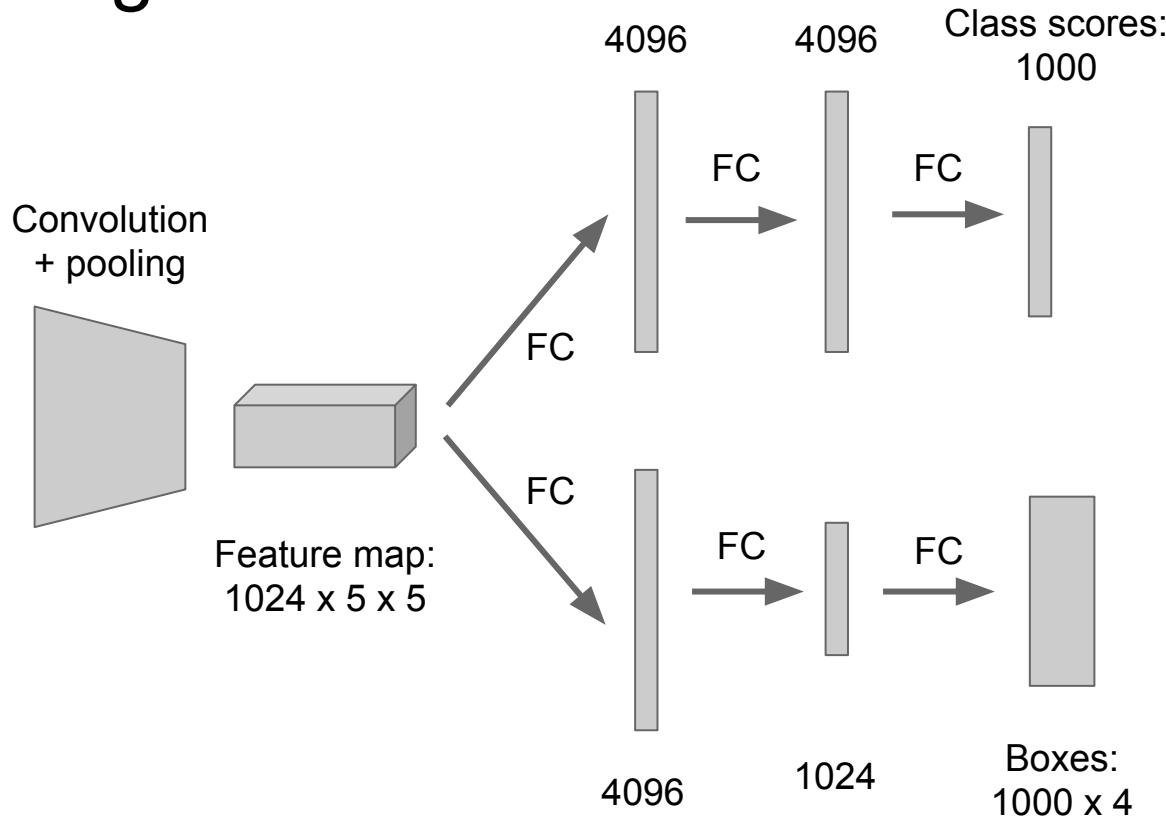


Sermanet et al, "Integrated Recognition, Localization and Detection using Convolutional Networks", ICLR 2014

# Efficient Sliding Window: Overfeat



Image:  
 $3 \times 221 \times 221$



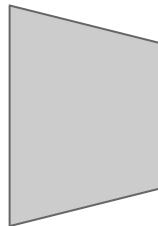
# Efficient Sliding Window: Overfeat

Efficient sliding window by converting fully-connected layers into convolutions

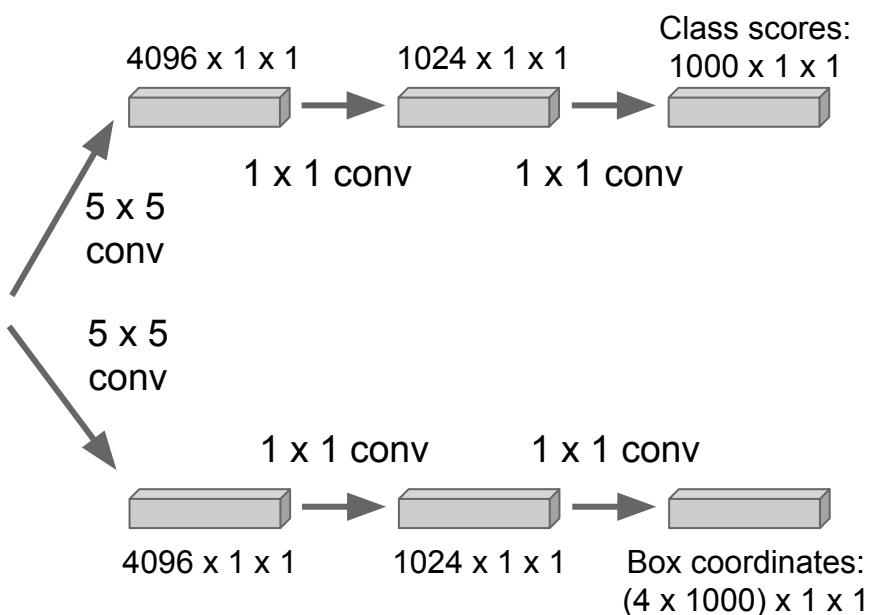
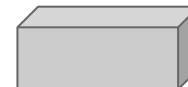


Image:  
 $3 \times 221 \times 221$

Convolution  
+ pooling

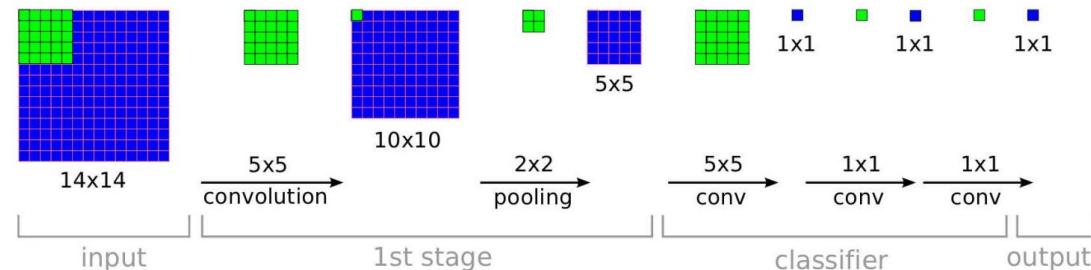


Feature map:  
 $1024 \times 5 \times 5$

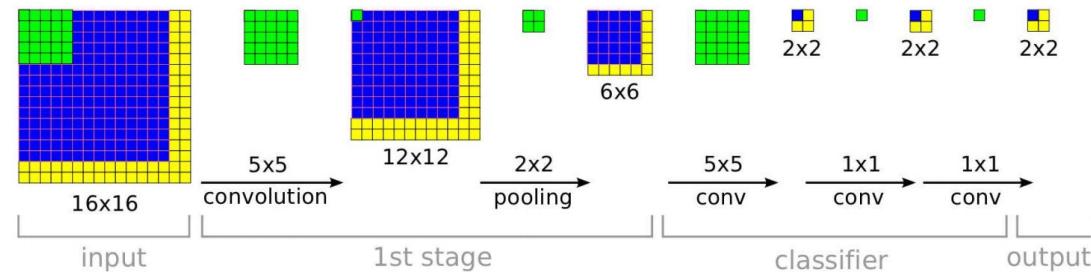


# Efficient Sliding Window: Overfeat

**Training time:** Small image, 1 x 1 classifier output

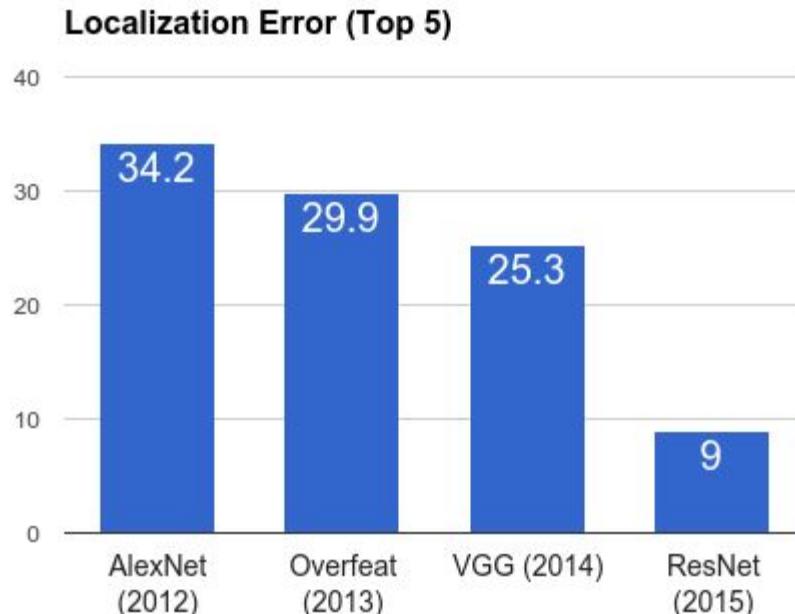


**Test time:** Larger image, 2 x 2 classifier output, only extra compute at yellow regions



Sermanet et al, "Integrated Recognition, Localization and Detection using Convolutional Networks", ICLR 2014

# ImageNet Classification + Localization



**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

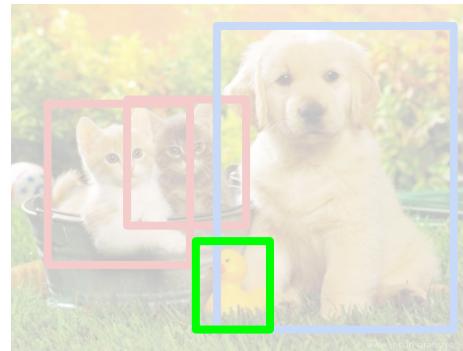
Classification



**Classification  
+ Localization**



Object Detection



Instance  
Segmentation



# Computer Vision Tasks

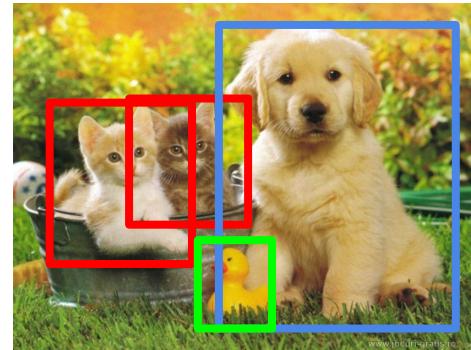
Classification



Classification  
+ Localization



Object Detection



Instance  
Segmentation



# Detection as Regression?



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

= 16 numbers

# Detection as Regression?



DOG, (x, y, w, h)

CAT, (x, y, w, h)

= 8 numbers

# Detection as Regression?



CAT, (x, y, w, h)

CAT, (x, y, w, h)

....

CAT (x, y, w, h)

= many numbers

Need variable sized outputs

# Detection as Classification



**CAT? NO**

**DOG? NO**

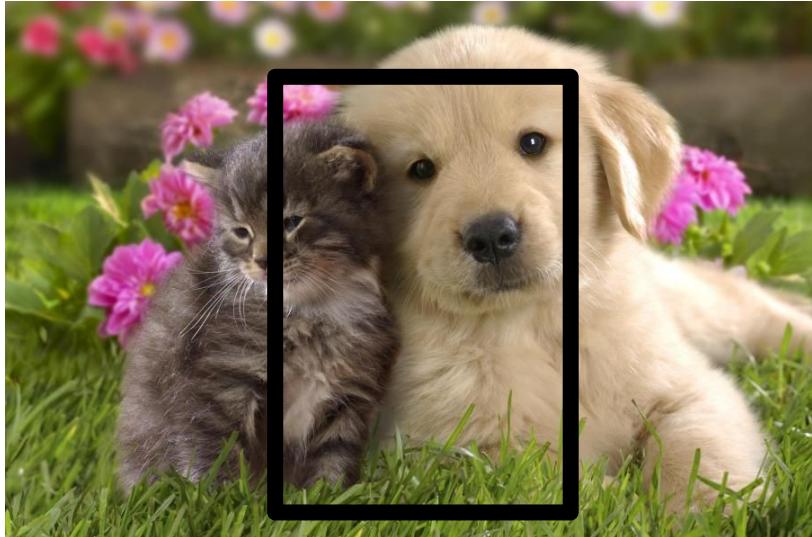
# Detection as Classification



CAT? YES!

DOG? NO

# Detection as Classification



**CAT? NO**

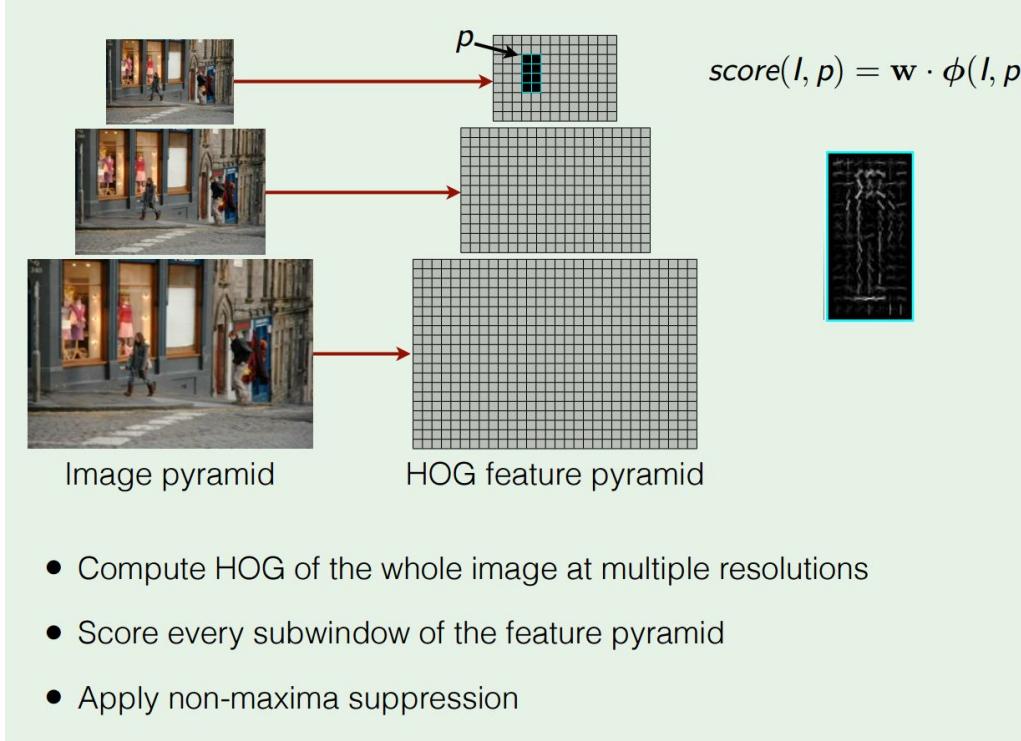
**DOG? NO**

# Detection as Classification

**Problem:** Need to test many positions and scales

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

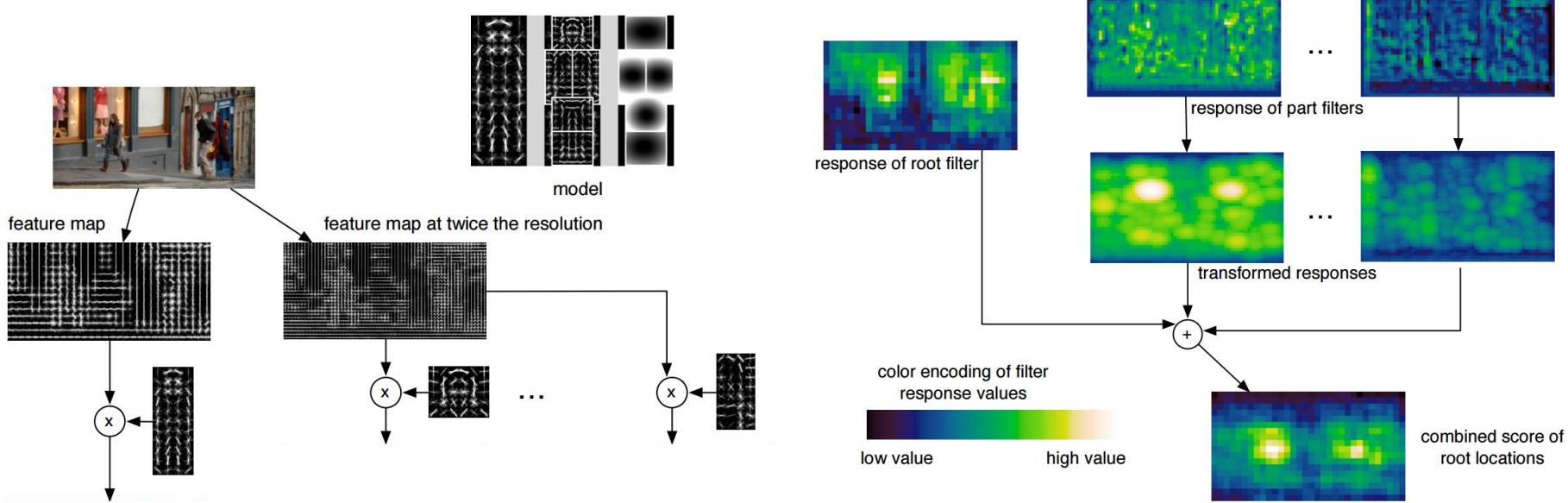
# Histogram of Oriented Gradients



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

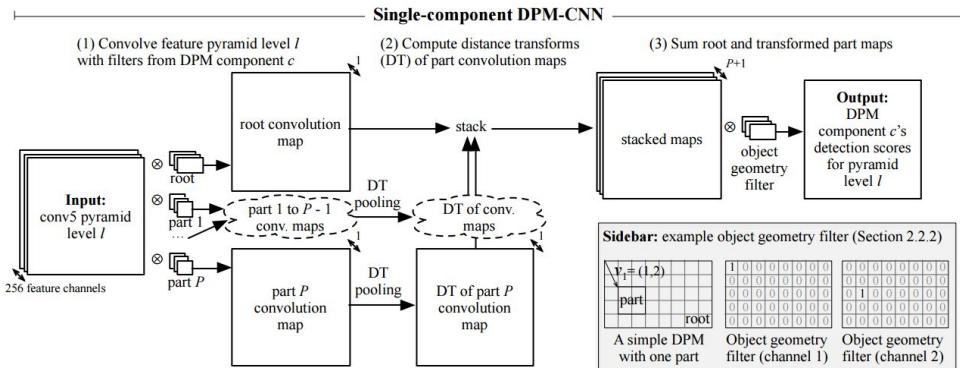
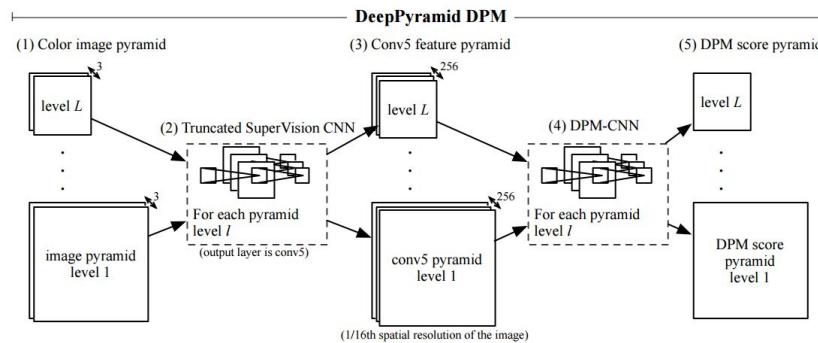
Slide credit: Ross Girshick

# Deformable Parts Model (DPM)



Felzenszwalb et al, "Object Detection with Discriminatively Trained Part Based Models", PAMI 2010

# Aside: Deformable Parts Models are CNNs?



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

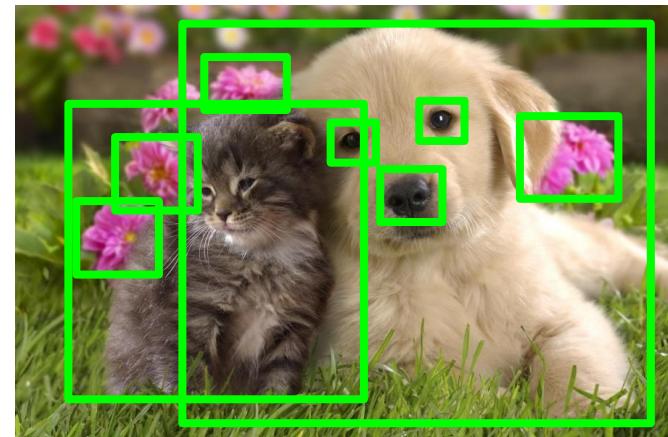
# Detection as Classification

**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

# Region Proposals

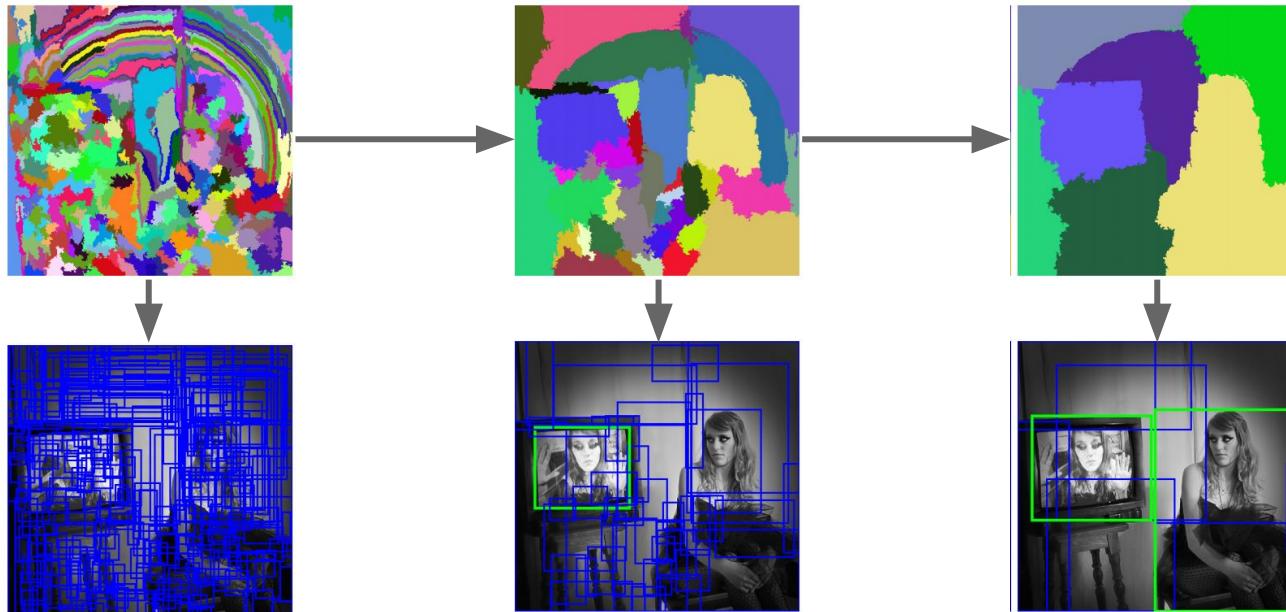
- Find “blobby” image regions that are likely to contain objects
- “Class-agnostic” object detector
- Look for “blob-like” regions



# 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.)	Repeatability	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	*	*	**
Rantalaankila [27]	Grouping	✓		✓	10	**	.	**
Rigor [28]	Grouping	✓		✓	10	*	**	**
SelectiveSearch [29]	Grouping	✓	✓	✓	10	**	***	***
Gaussian				✓	0	.	.	*
SlidingWindow				✓	0	***	.	.
Superpixels		✓			1	*	.	.
Uniform				✓	0	.	.	.

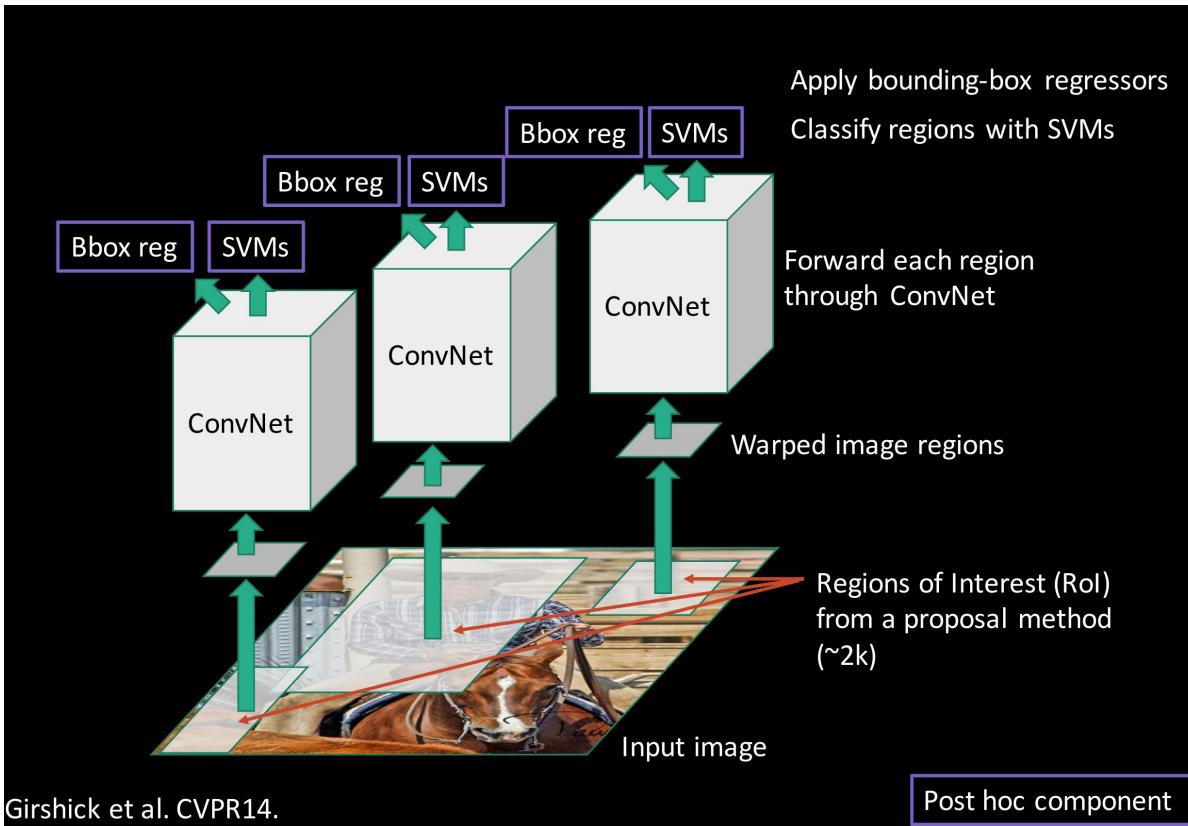
Hosang et al, "What makes for effective detection proposals?", PAMI 2015

# Region Proposals: Many other choices

Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec.)	Repeatability	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	*	*	**
Rantalaankila [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

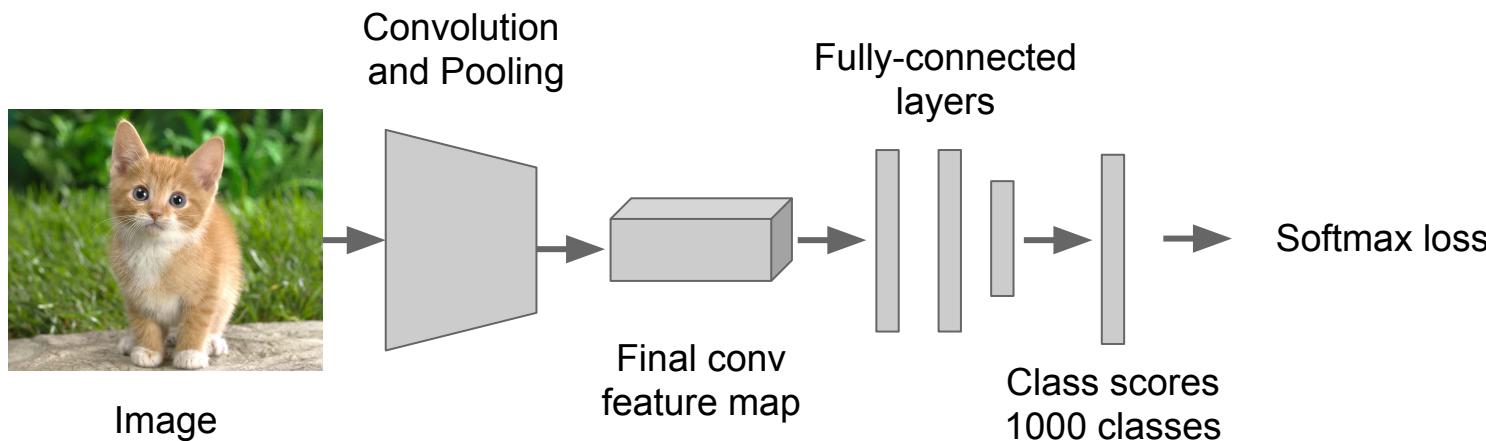


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014

Slide credit: Ross Girshick

# R-CNN Training

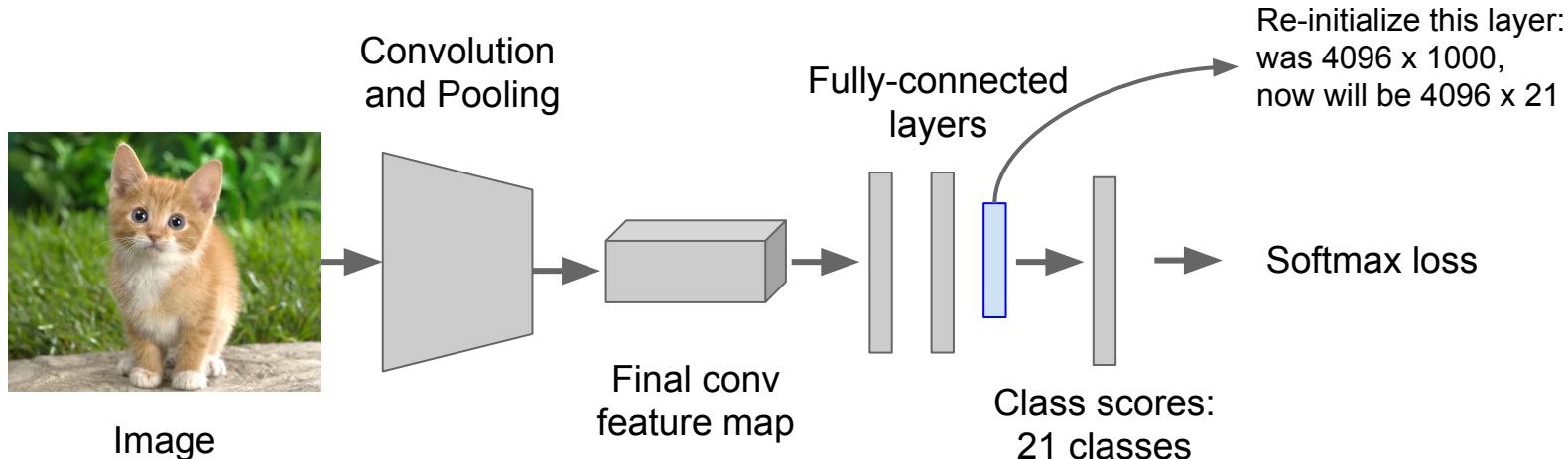
**Step 1:** Train (or download) a classification model for ImageNet (AlexNet)



# 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



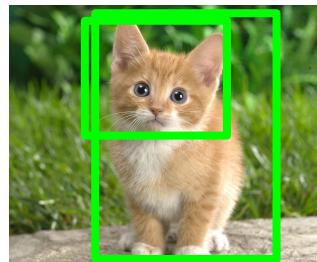
# R-CNN Training

## 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!



Image

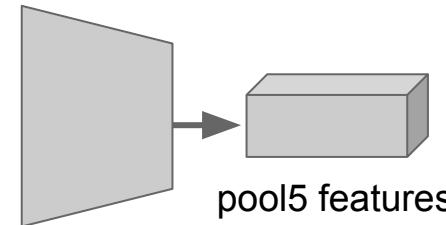


Region Proposals

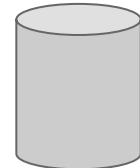


Crop + Warp

Convolution  
and Pooling



Forward pass



Save to disk

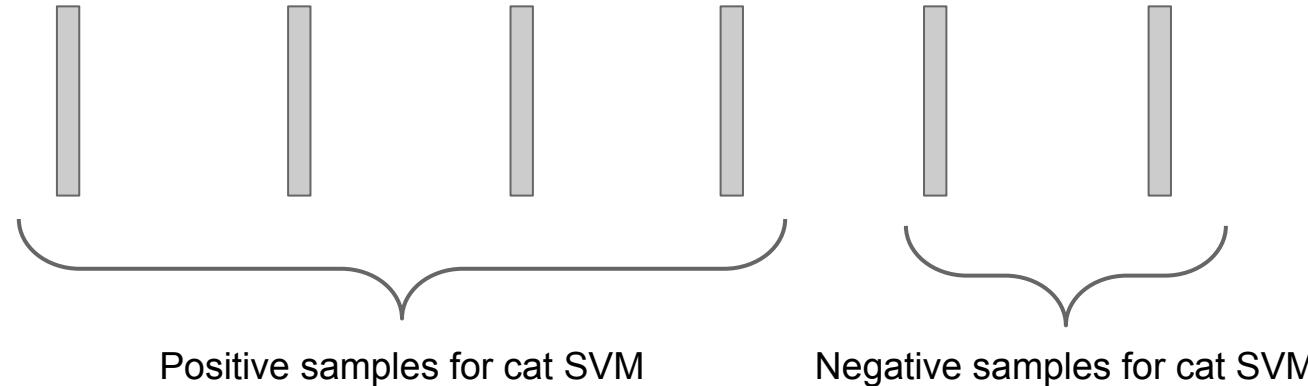
# R-CNN Training

**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

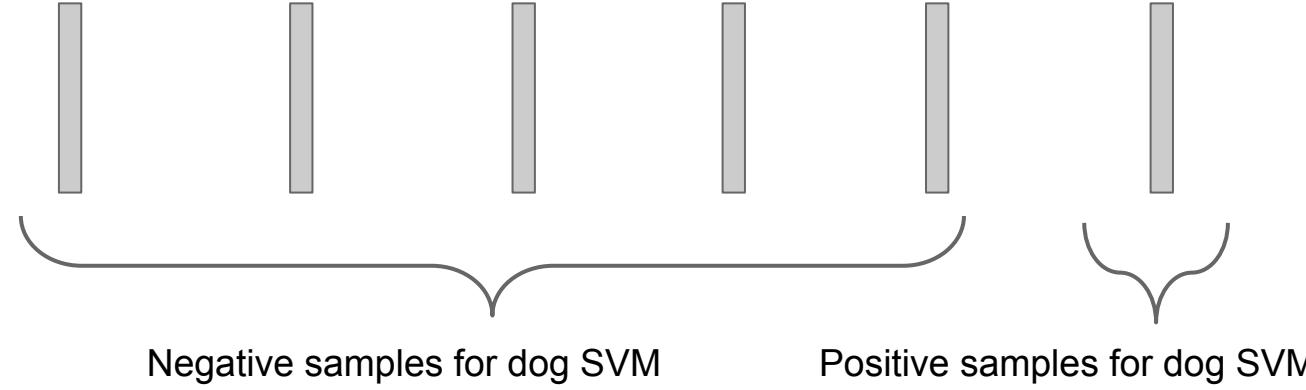
# R-CNN Training

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

Training image regions



Cached region features



# 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

# Object Detection: Datasets

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

# Object Detection: Evaluation

We use a metric called “mean average precision” (mAP)

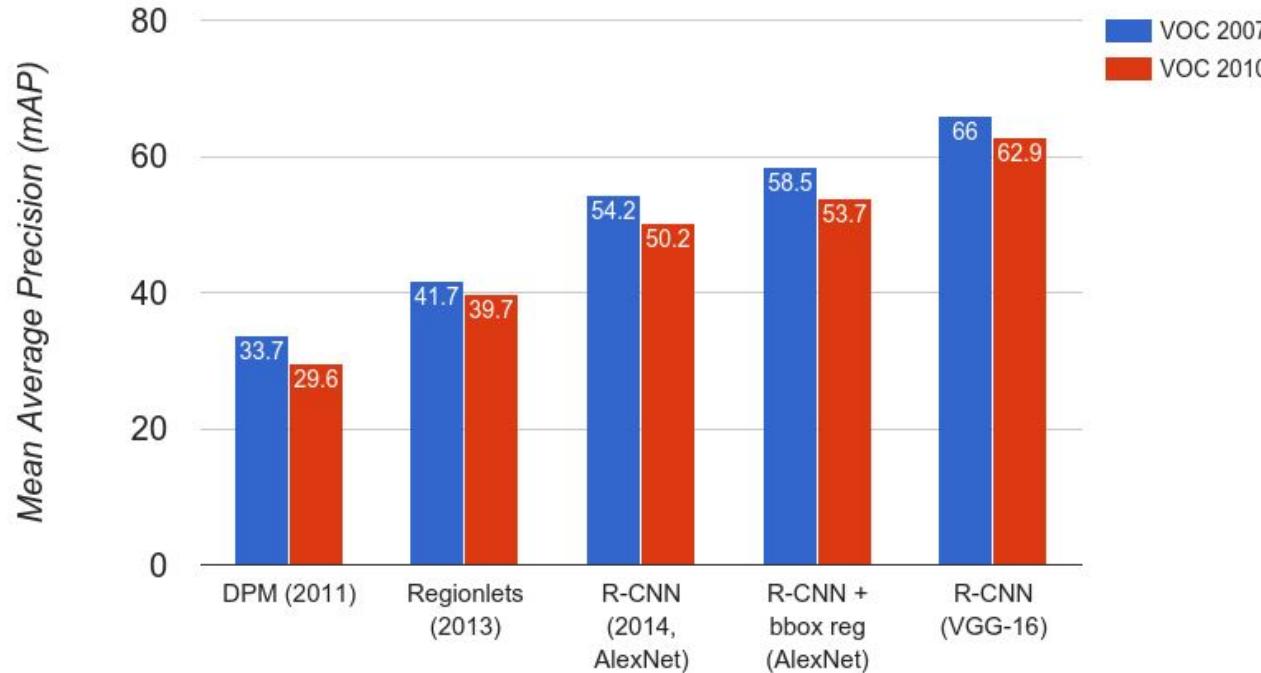
Compute average precision (AP) separately for each class, then average over classes

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 a precision / recall curve for each class; AP is area under the curve

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

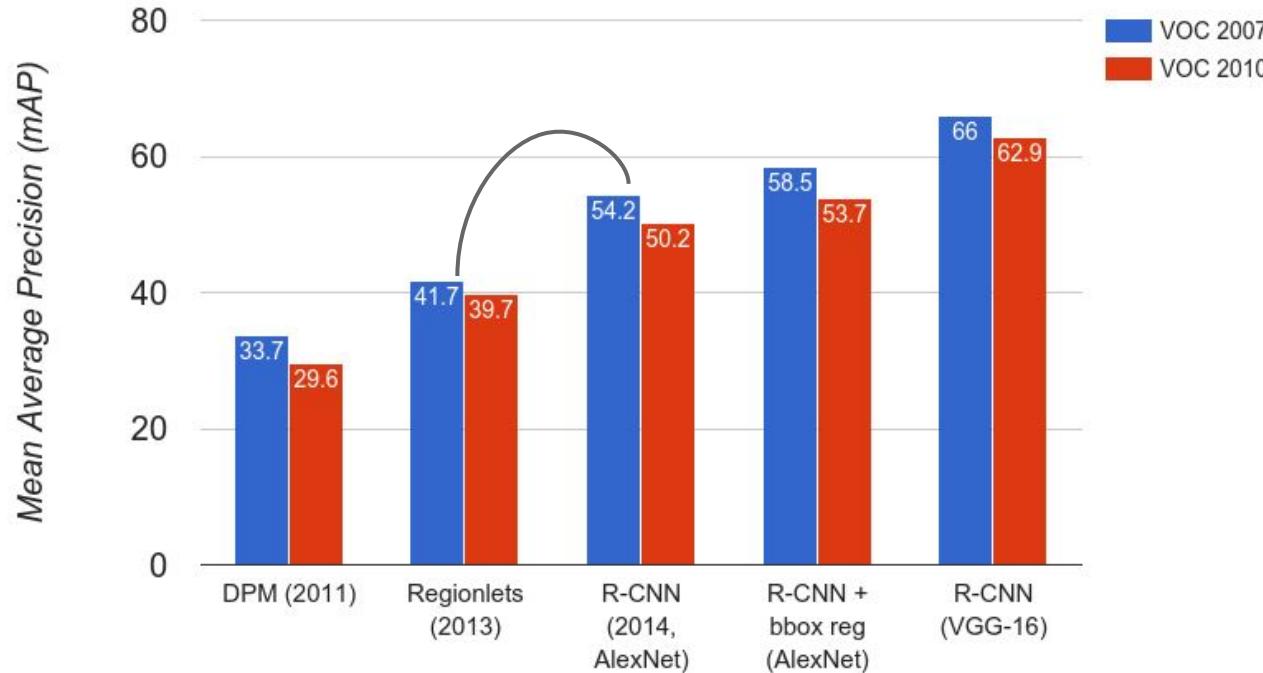
# R-CNN Results



Wang et al, "Regionlets for Generic Object Detection", ICCV 2013

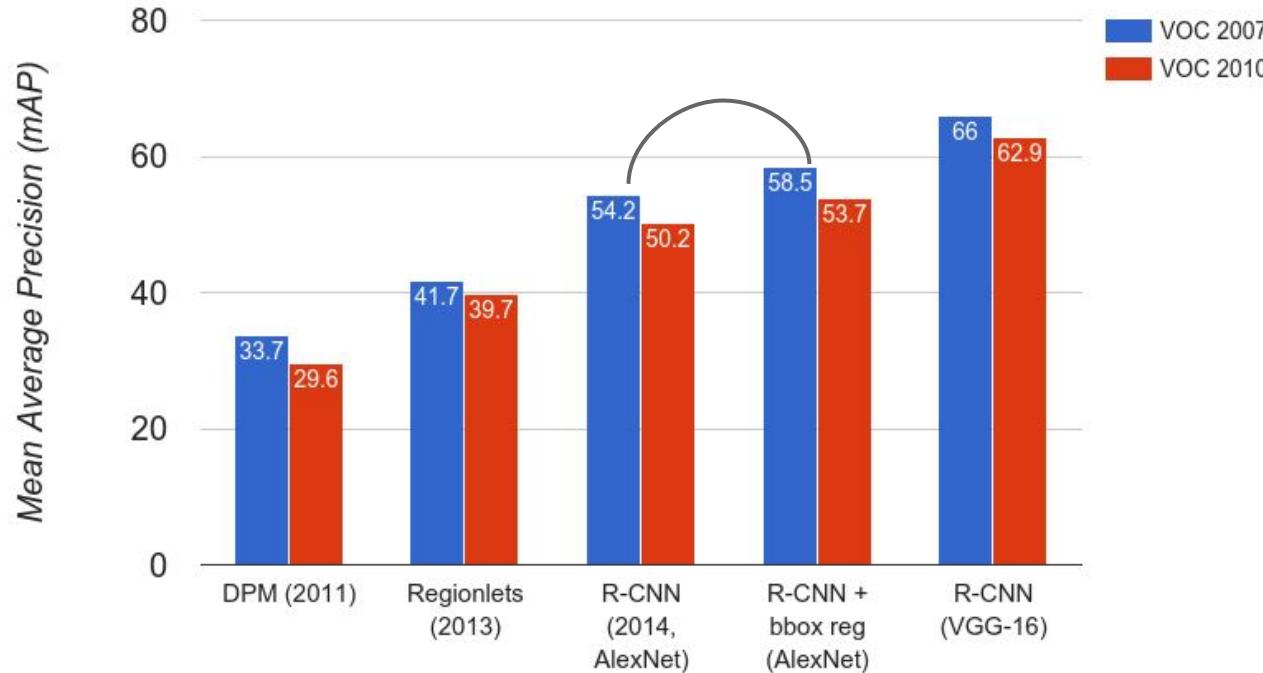
# R-CNN Results

Big improvement compared  
to pre-CNN methods



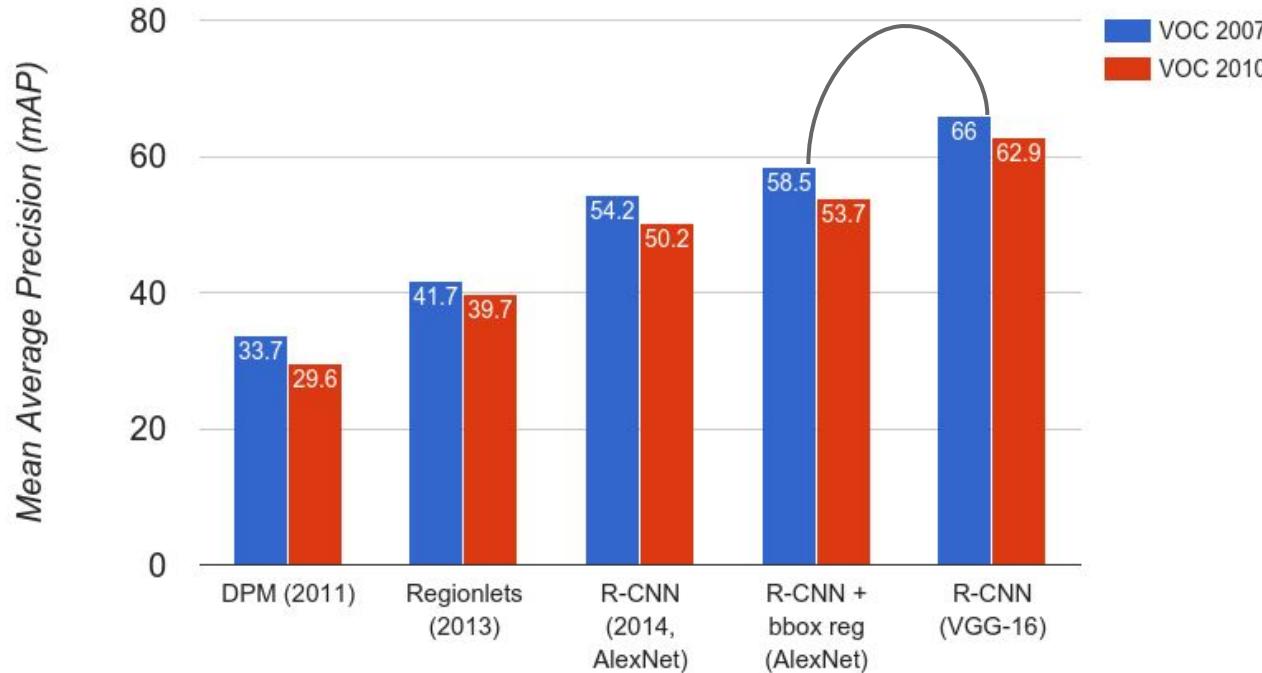
# R-CNN Results

Bounding box regression  
helps a bit



# R-CNN Results

Features from a deeper  
network help a lot

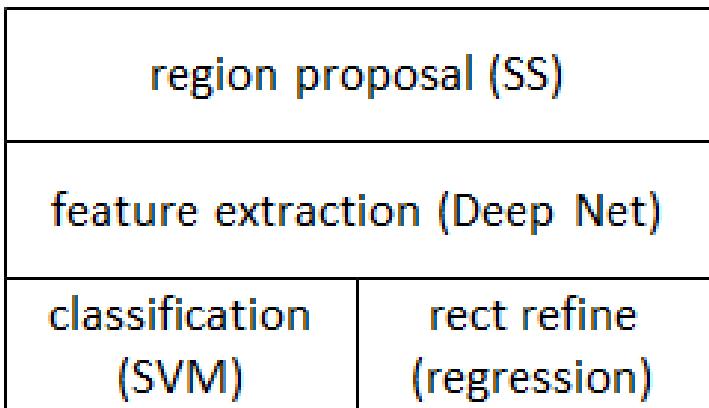


# R-CNN Problems

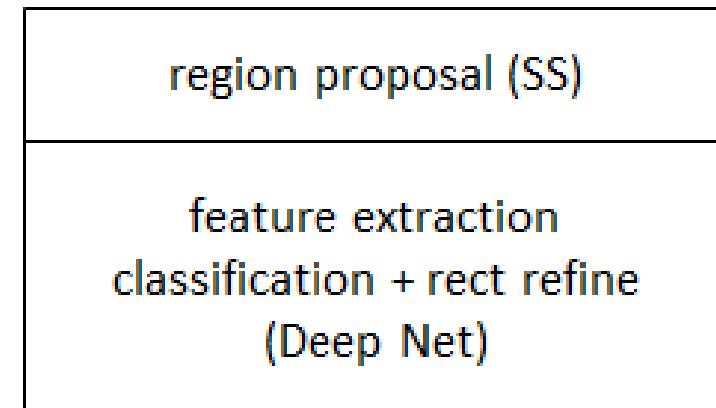
1. Slow at test-time: need to run full forward pass of CNN for each region proposal
2. SVMs and regressors are post-hoc: CNN features not updated in response to SVMs and regressors
3. Complex multistage training pipeline

# R-CNN → Fast R-CNN

---

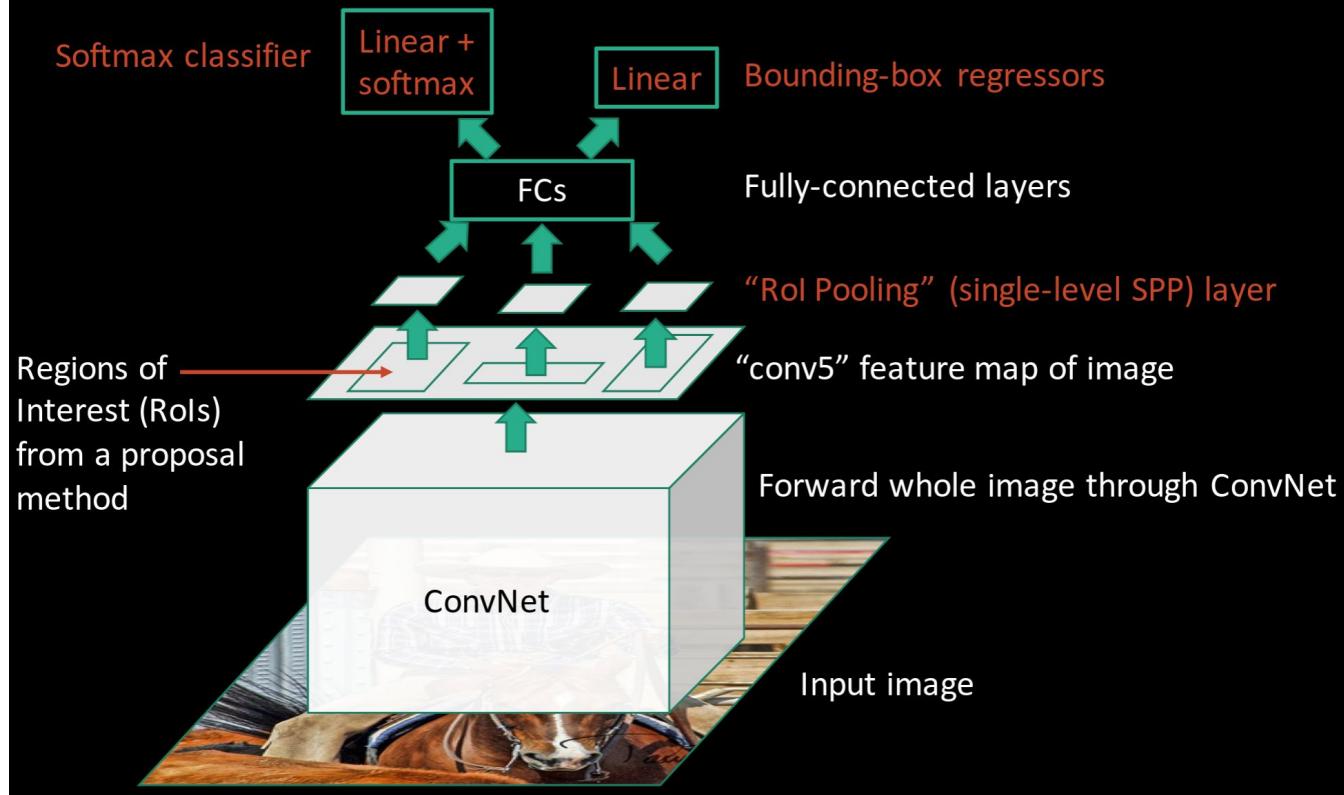


RCNN



fast RCNN

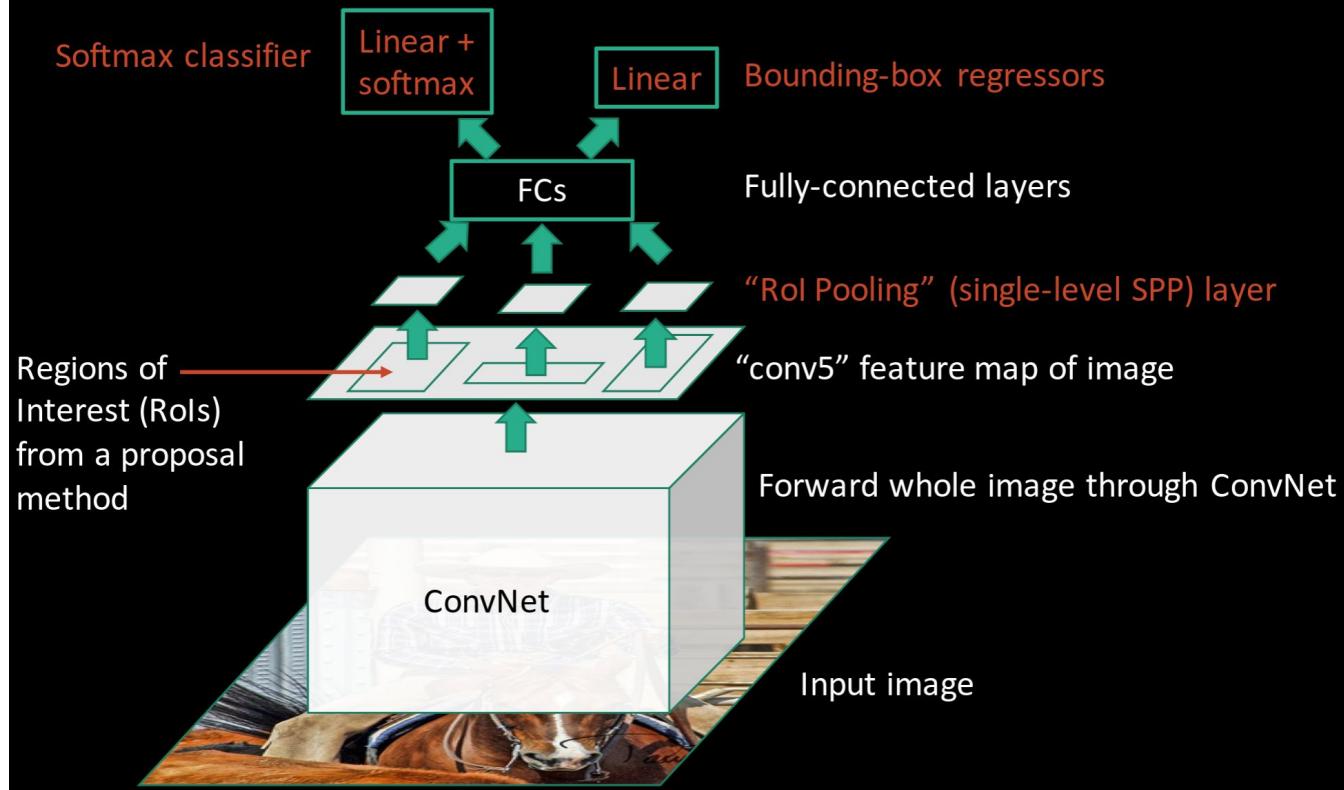
# Fast R-CNN (test time)



Girschick, "Fast R-CNN", ICCV 2015

Slide credit: Ross Girschick

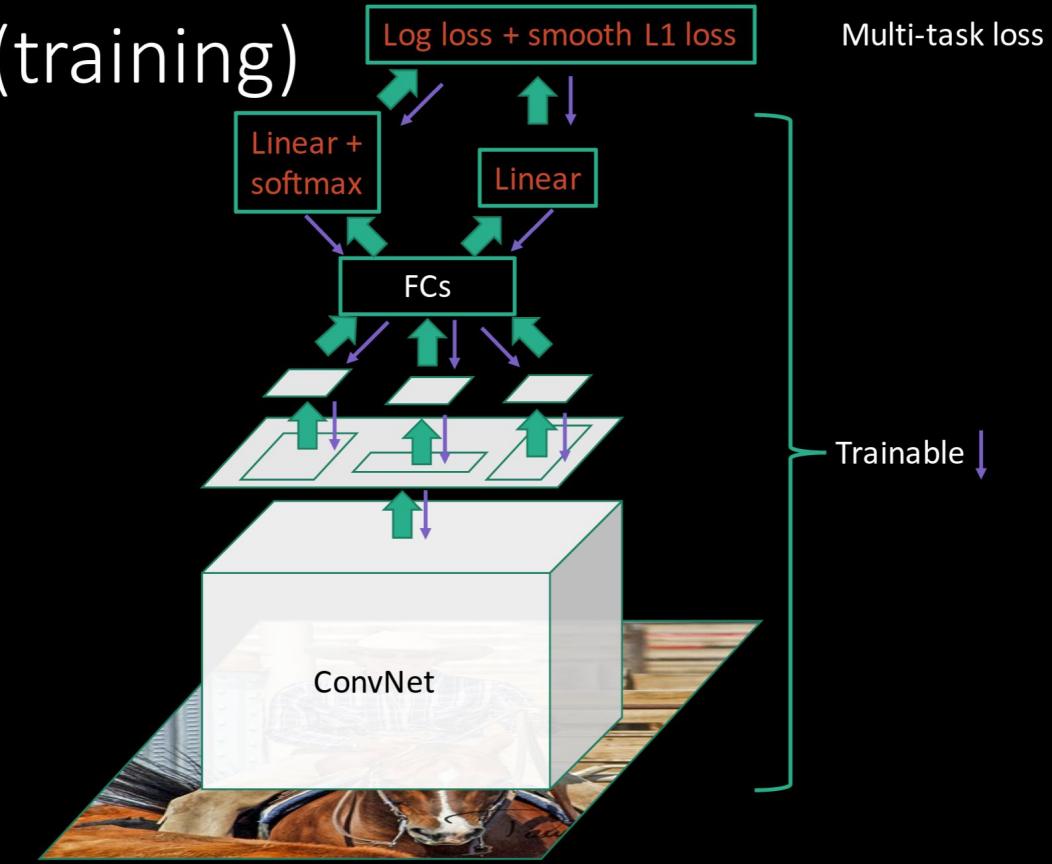
# Fast R-CNN (test time)



**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

# Fast R-CNN (training)



## R-CNN Problem #2:

Post-hoc training: CNN not updated in response to final classifiers and regressors

## R-CNN Problem #3:

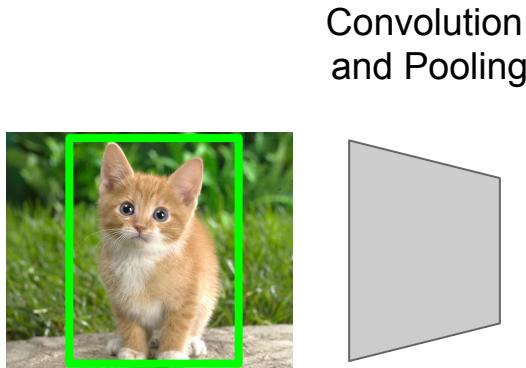
Complex training pipeline

## Solution:

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

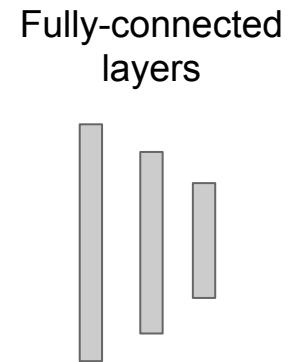
Slide credit: Ross Girshick

# Fast R-CNN: Region of Interest Pooling



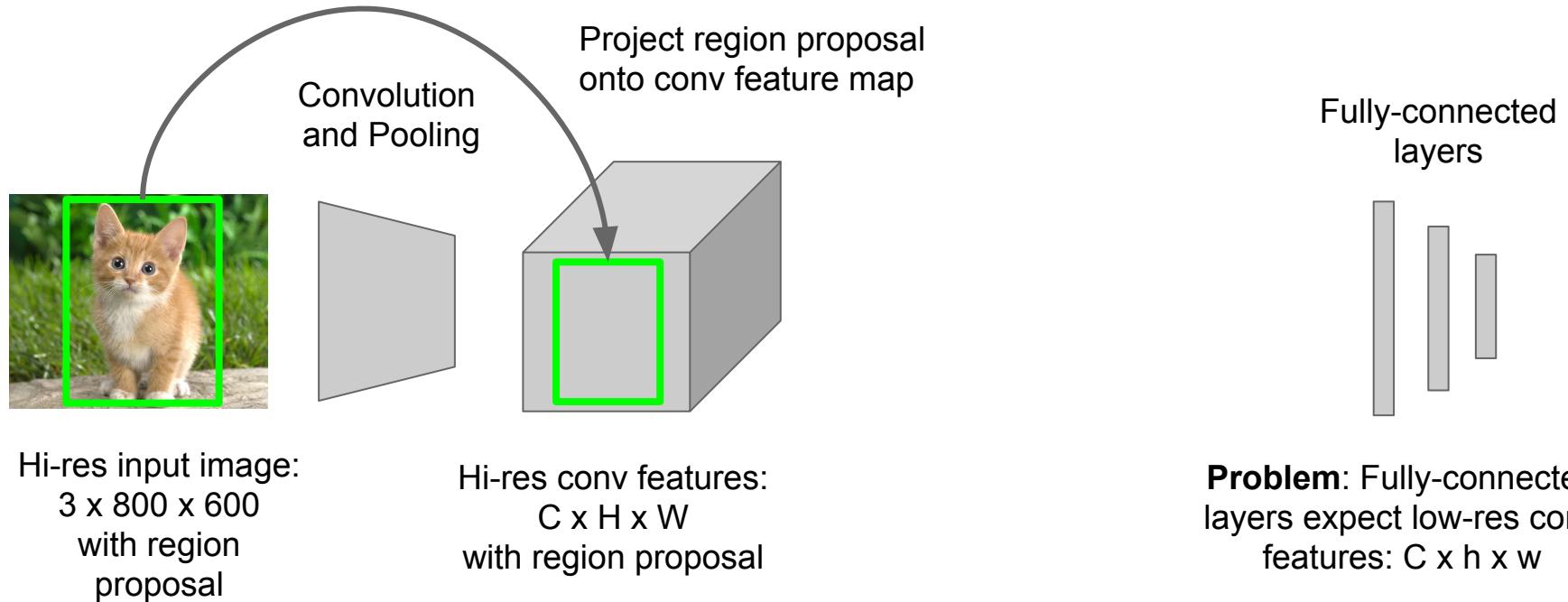
Hi-res input image:  
 $3 \times 800 \times 600$   
with region  
proposal

Hi-res conv features:  
 $C \times H \times W$   
with region proposal

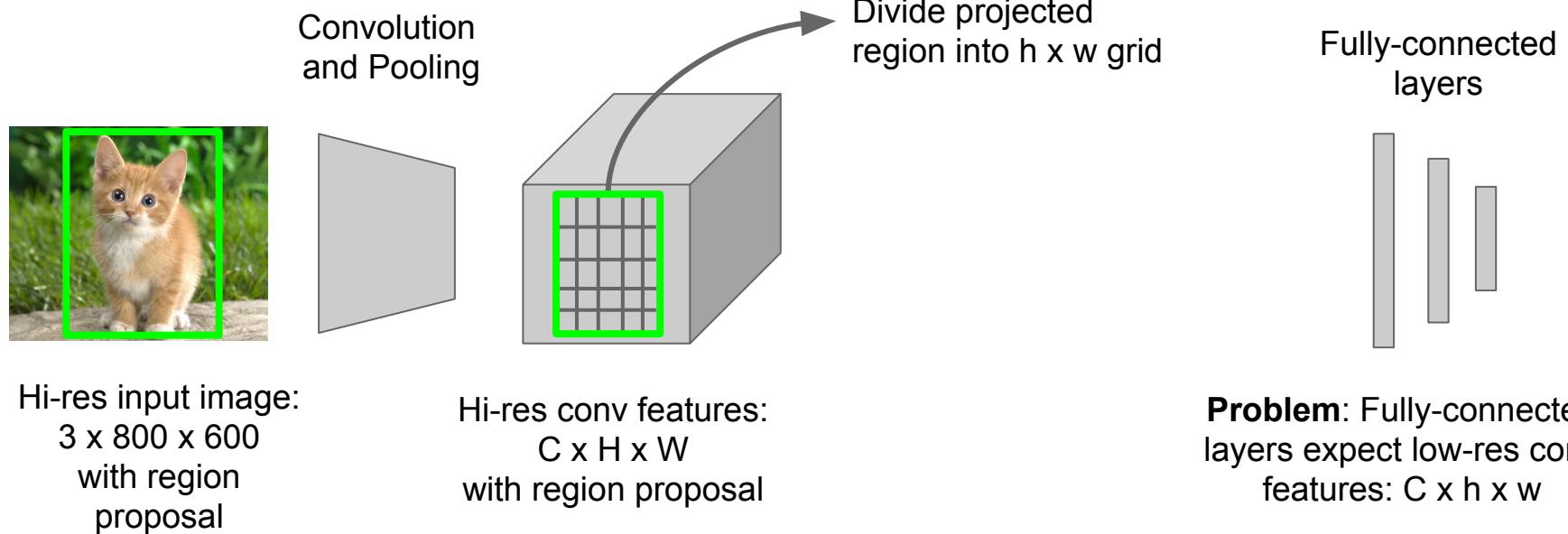


**Problem:** Fully-connected  
layers expect low-res conv  
features:  $C \times h \times w$

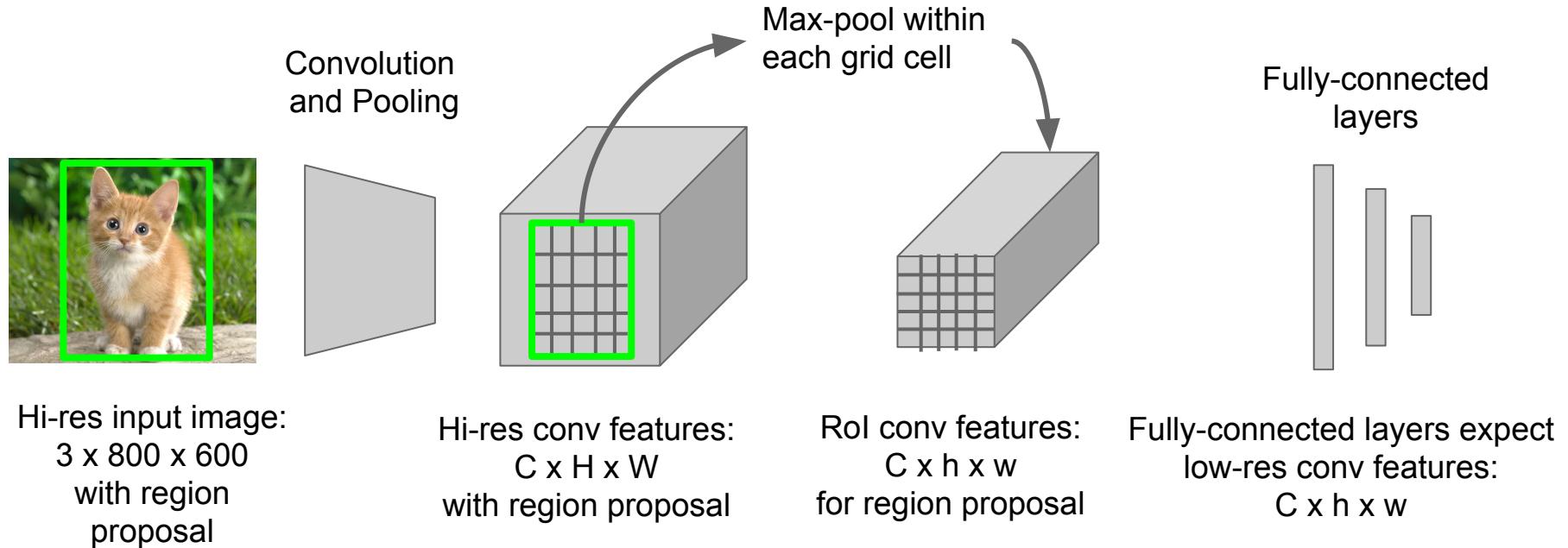
# Fast R-CNN: Region of Interest Pooling



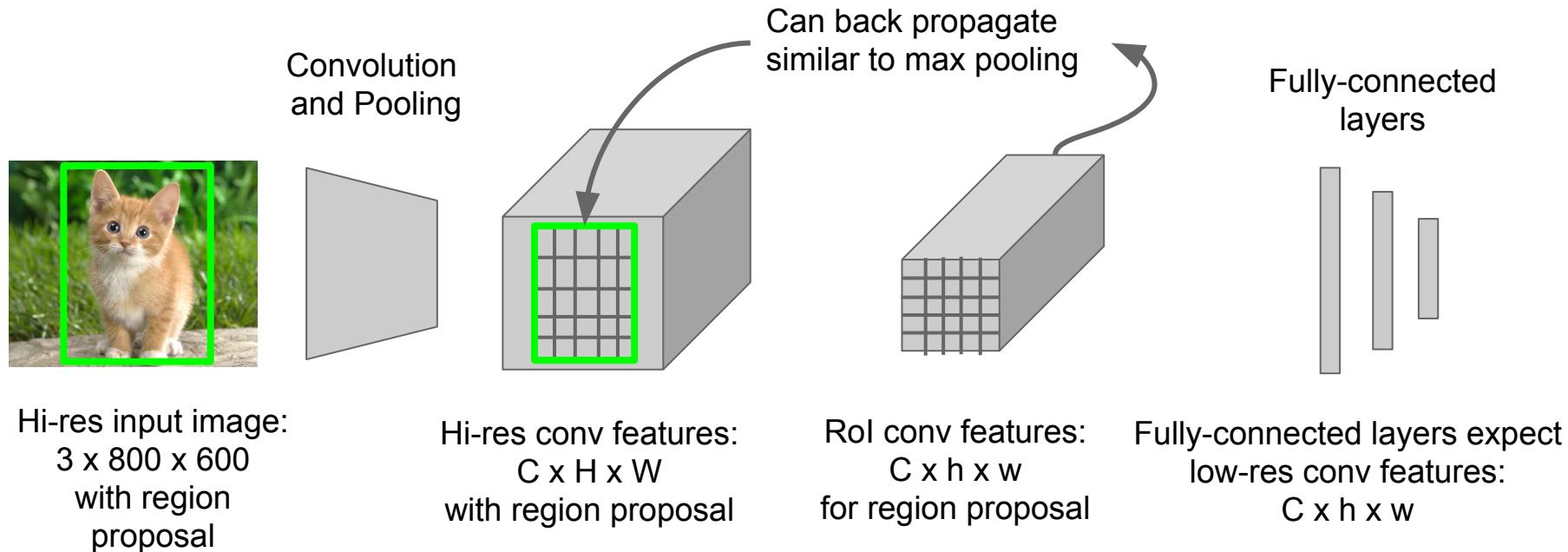
# Fast R-CNN: Region of Interest Pooling



# Fast R-CNN: Region of Interest Pooling



# Fast R-CNN: Region of Interest Pooling



# Fast R-CNN Results

Faster!

	<b>R-CNN</b>	<b>Fast R-CNN</b>
Training Time:	84 hours	<b>9.5 hours</b>
(Speedup)	1x	<b>8.8x</b>

Using VGG-16 CNN on Pascal VOC 2007 dataset

# Fast R-CNN Results

Faster!

FASTER!

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

Using VGG-16 CNN on Pascal VOC 2007 dataset

# Fast R-CNN Results

Faster!

FASTER!

Better!

	R-CNN	Fast R-CNN
Training Time:	84 hours	<b>9.5 hours</b>
(Speedup)	1x	<b>8.8x</b>
Test time per image	47 seconds	<b>0.32 seconds</b>
(Speedup)	1x	<b>146x</b>
mAP (VOC 2007)	66.0	<b>66.9</b>

Using VGG-16 CNN on Pascal VOC 2007 dataset

# Fast R-CNN Problem:

Test-time speeds don't include region proposals

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

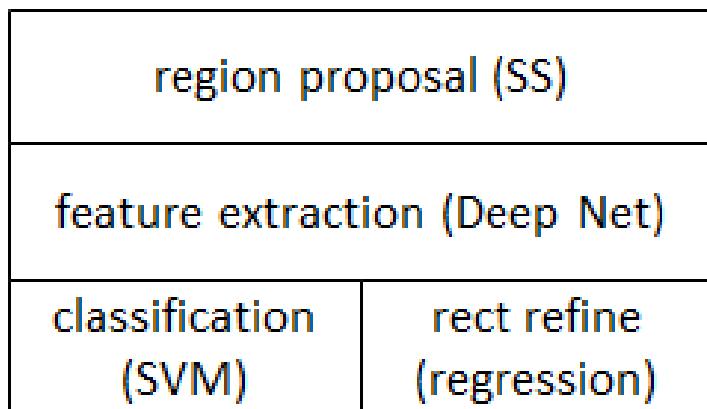
# Fast R-CNN Problem Solution:

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

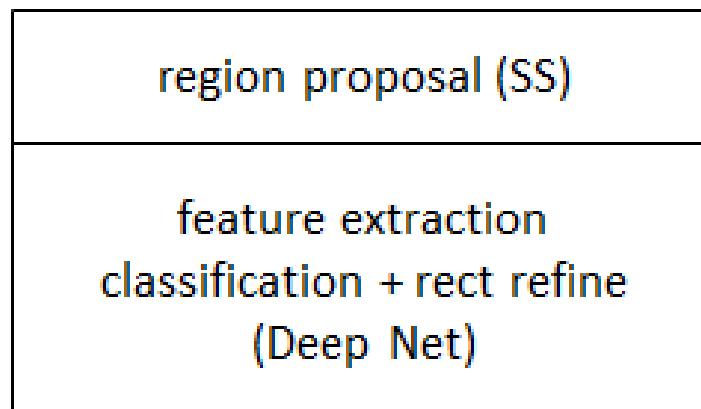
	R-CNN	Fast R-CNN
Test time per image	47 seconds	<b>0.32 seconds</b>
(Speedup)	1x	<b>146x</b>
Test time per image with Selective Search	50 seconds	<b>2 seconds</b>
(Speedup)	1x	<b>25x</b>

# R-CNN → Fast R-CNN → Faster R-CNN

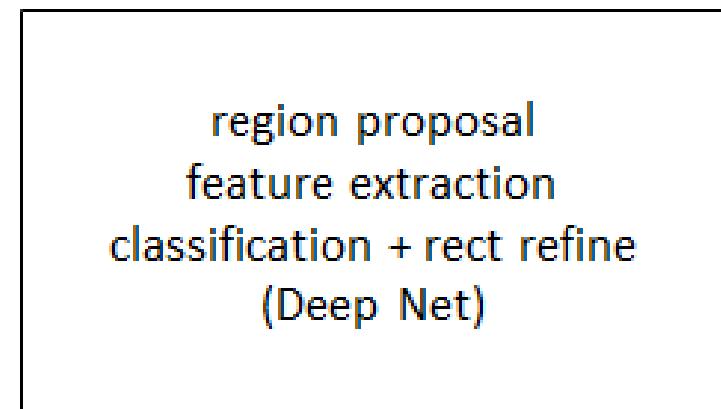
---



RCNN

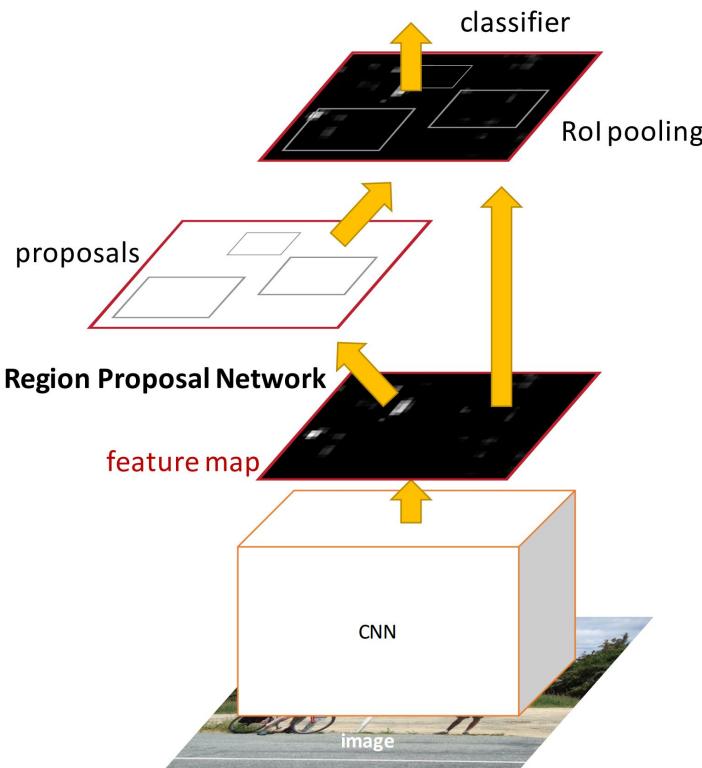


fast RCNN



faster RCNN

# 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 Girshick

# Faster R-CNN: Region Proposal Network

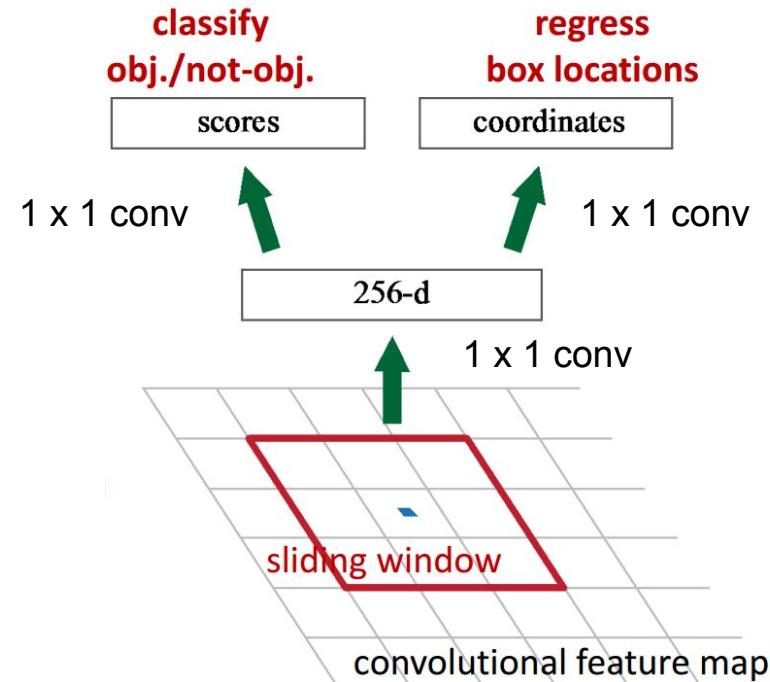
Slide a small window on the feature map

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



Slide credit: Kaiming He

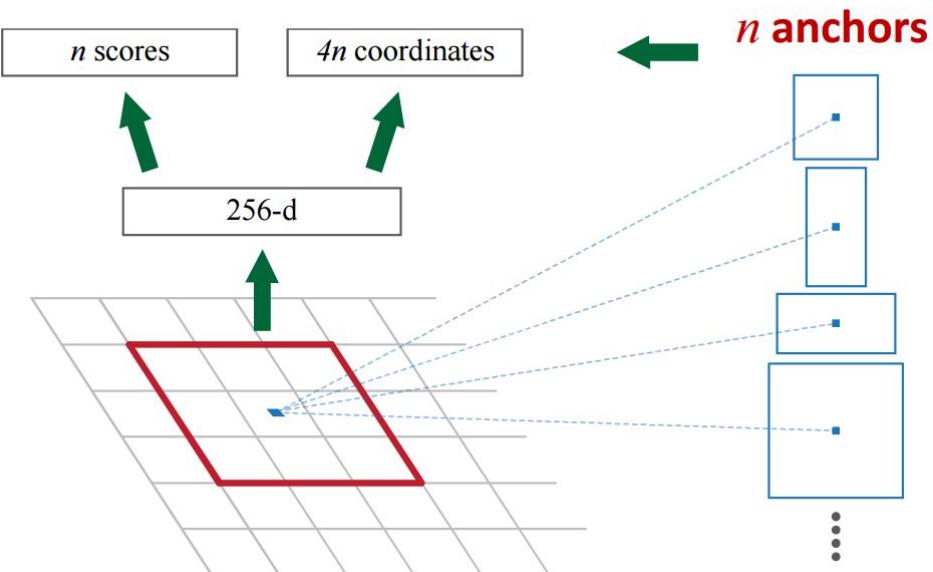
# Faster R-CNN: Region Proposal Network

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



# Faster R-CNN: Training

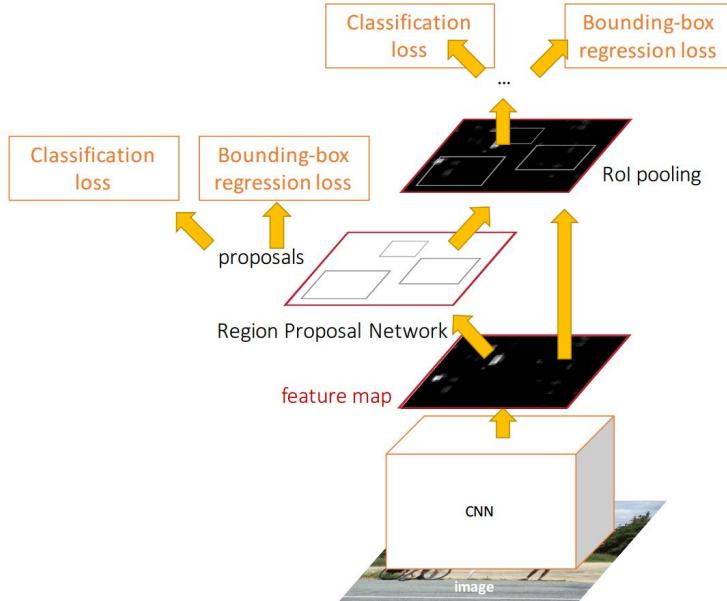
In the paper: Ugly pipeline

- 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  $\rightarrow$  proposal)
- Fast R-CNN classification (over classes)
- Fast R-CNN regression (proposal  $\rightarrow$  box)



Slide credit: Ross Girshick

# Faster R-CNN: Results

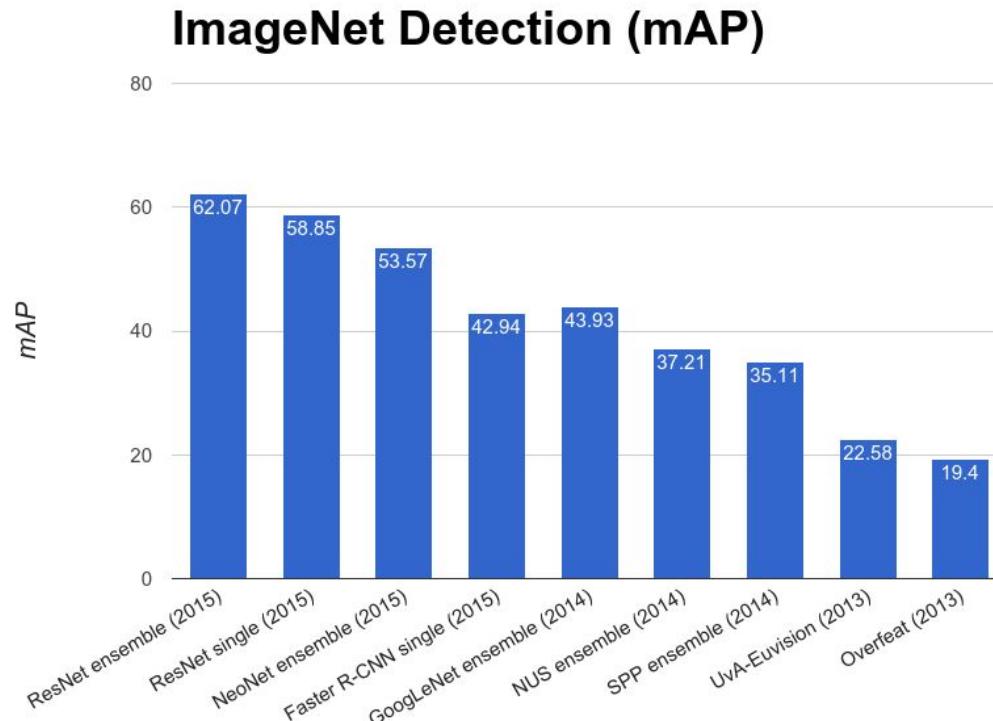
	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image (with proposals)	50 seconds	2 seconds	<b>0.2 seconds</b>
(Speedup)	1x	25x	<b>250x</b>
mAP (VOC 2007)	66.0	<b>66.9</b>	<b>66.9</b>

# 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	<b>55.7</b>	<b>34.9</b>
ensemble			<b>59.0</b>	<b>37.4</b>

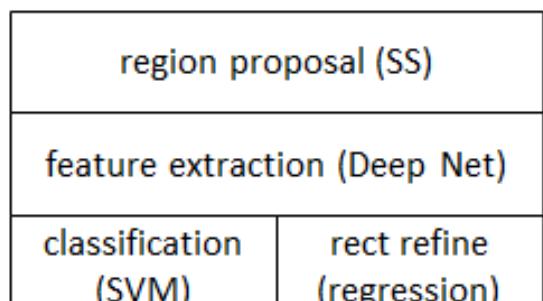
He et. al, "Deep Residual Learning for Image Recognition", arXiv 2015

# ImageNet Detection 2013 - 2015

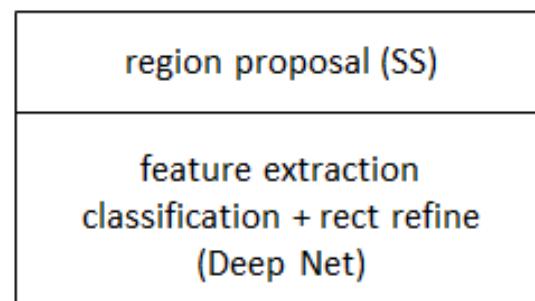


# R-CNN → Fast R-CNN → Faster R-CNN → YOLO

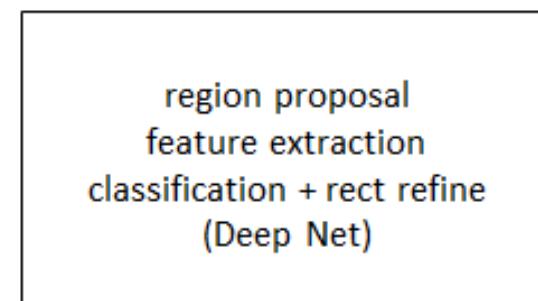
---



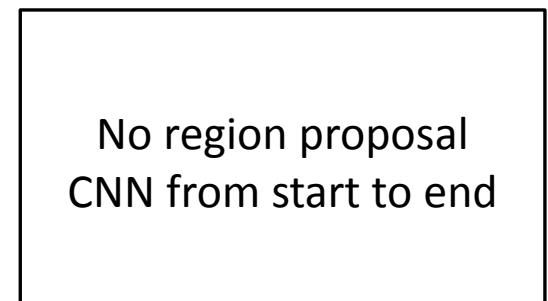
RCNN



fast RCNN



faster RCNN



YOLO

# YOLO: You Only Look Once Detection as Regression

Divide image into  $S \times S$  grid

Within each grid cell predict:

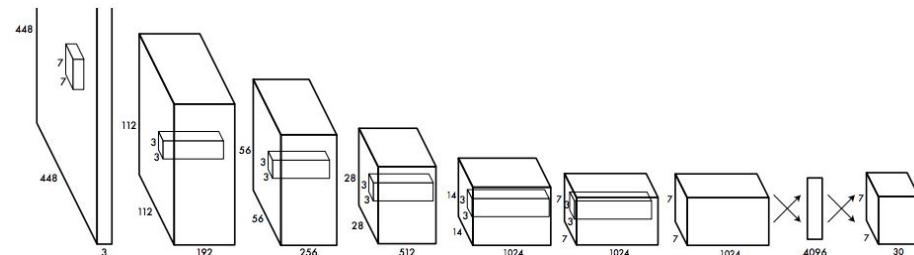
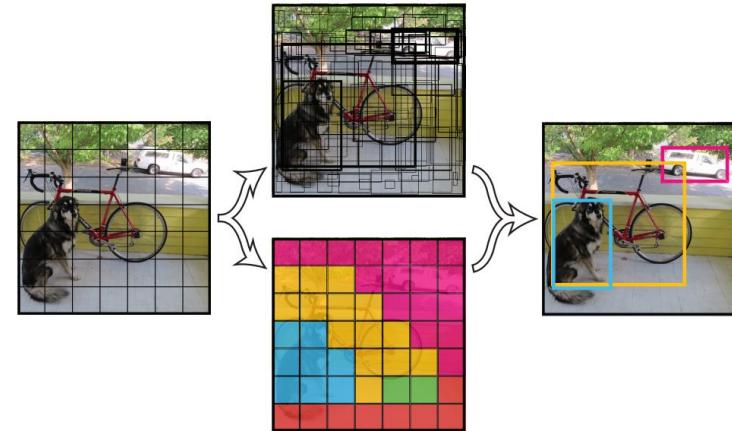
B Boxes: 4 coordinates + confidence

Class scores: C numbers

Regression from image to  
 $7 \times 7 \times (5 * B + C)$  tensor

Direct prediction using a CNN

Redmon et al, "You Only Look Once:  
Unified, Real-Time Object Detection", arXiv 2015



# YOLO: You Only Look Once

## Detection as Regression

Faster than Faster R-CNN, but not  
as good

Redmon et al, "You Only Look Once:  
Unified, Real-Time Object Detection", arXiv 2015

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	<b>155</b>
YOLO	2007+2012	<b>63.4</b>	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

# Object Detection code links:

## R-CNN

(Caffe + MATLAB): <https://github.com/rbgirshick/rcnn>

Probably don't use this; too slow

## Fast R-CNN

(Caffe + MATLAB): <https://github.com/rbgirshick/fast-rcnn>

## Faster R-CNN

(Caffe + MATLAB): [https://github.com/ShaoqingRen/faster\\_rcnn](https://github.com/ShaoqingRen/faster_rcnn)

(Caffe + Python): <https://github.com/rbgirshick/py-faster-rcnn>

## YOLO

<http://pjreddie.com/darknet/yolo/>

Maybe try this for projects?

# Recap

## Localization:

- Find a fixed number of objects (one or many)
- L2 regression from CNN features to box coordinates
- Much simpler than detection; consider it for your projects!
- 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