

DEEP LEARNING FOR COMPUTER VISION

Summer Seminar UPC TelecomBCN, 4 - 8 July 2016



Instructors



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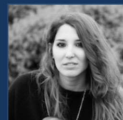
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UNIVERSITAT POLITÈCNICA
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**Barcelona
Supercomputing
Center**
Centro Nacional de Supercomputación



Dublin City University
Oileici Chathair Bhaile Átha Cliath



Centre for Data Analytics



GPU
CENTER OF
EXCELLENCE

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of the European Union

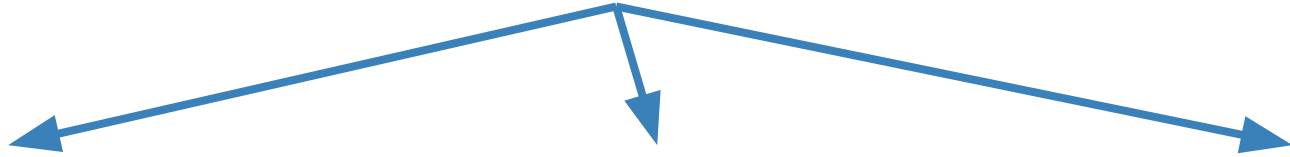


+ info: TelecomBCN.DeepLearning.Barcelona

Day 3 Lecture 4

Object Detection

Deep ConvNets for Recognition for...



Images (global)



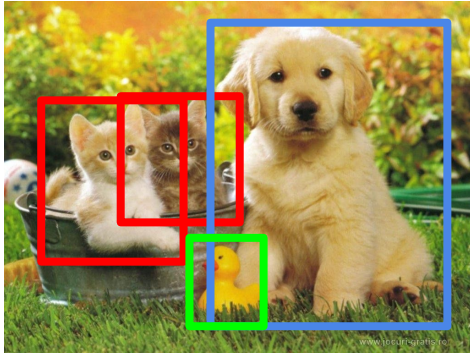
Objects (local)



Video (2D+T)



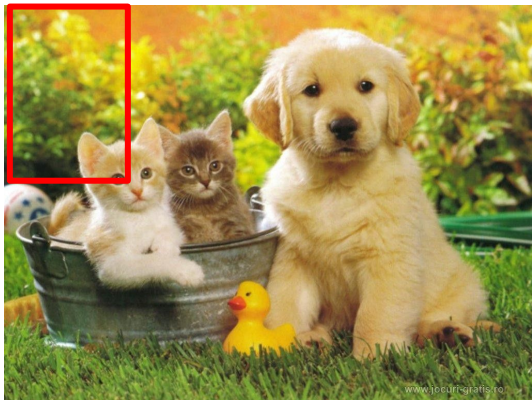
Object Detection



CAT, DOG, DUCK

The task of assigning a **label** and a **bounding box** to all objects in the image

Object Detection as Classification



Classes = [cat, dog, duck]

Cat ? NO

Dog ? NO

Duck? NO

Object Detection as Classification

Classes = [cat, dog, duck]



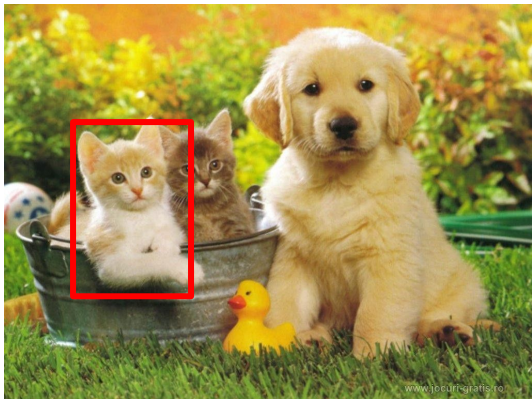
Cat ? NO

Dog ? NO

Duck? NO

Object Detection as Classification

Classes = [cat, dog, duck]

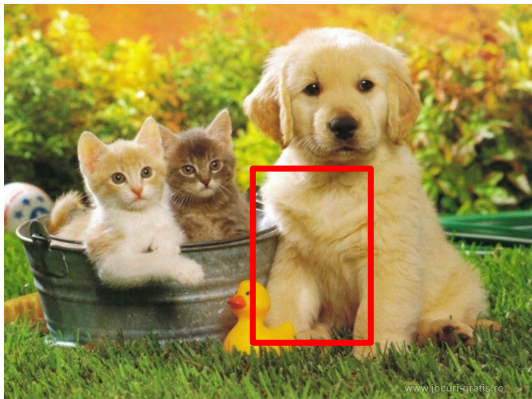


Cat ? YES

Dog ? NO

Duck? NO

Object Detection as Classification



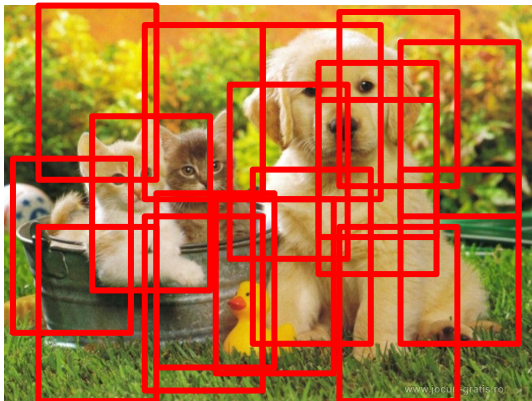
Classes = [cat, dog, duck]

Cat ? NO

Dog ? NO

Duck? NO

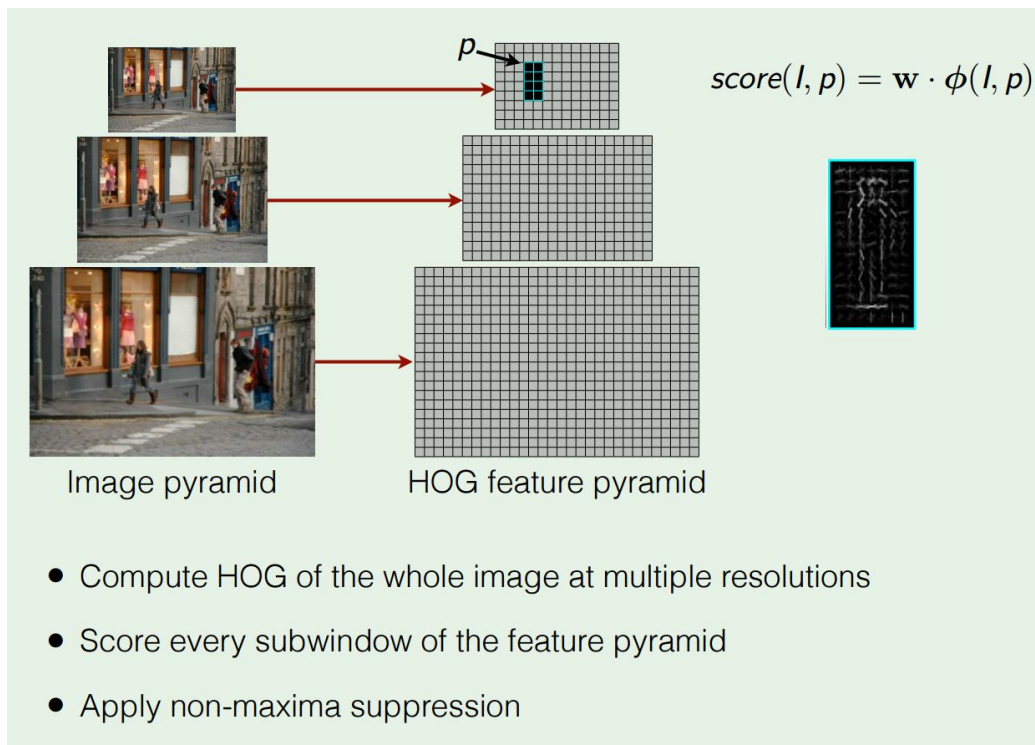
Object Detection as Classification



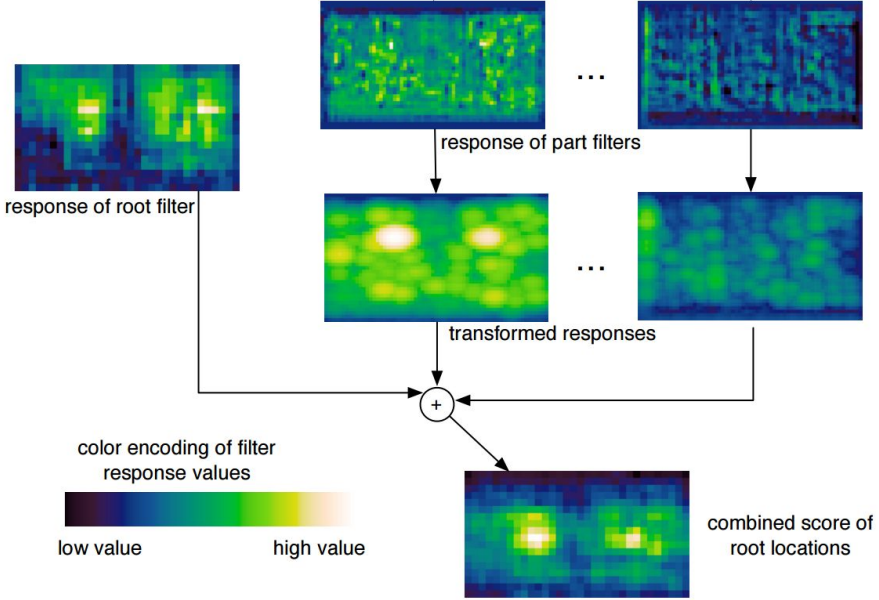
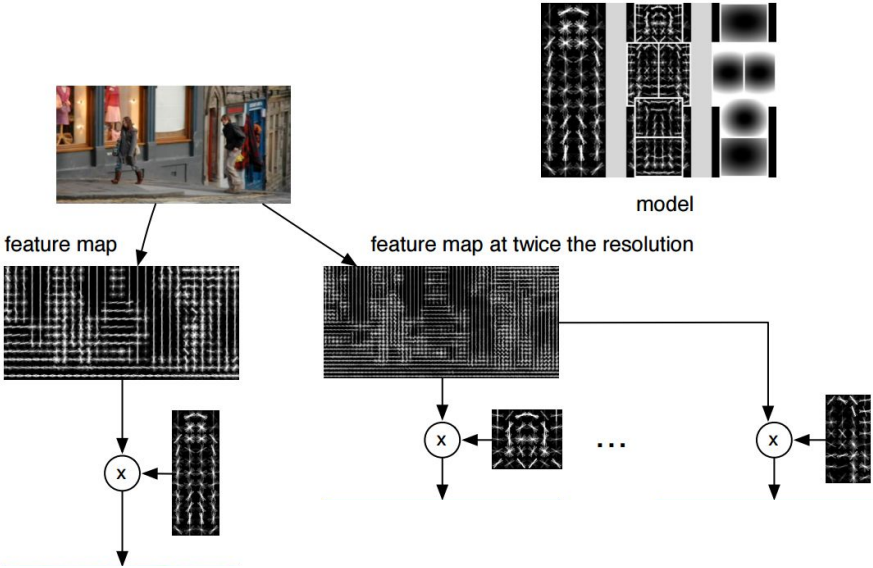
Problem:
Too many positions & scales to test

Solution: If your classifier is fast enough, go for it

HOG

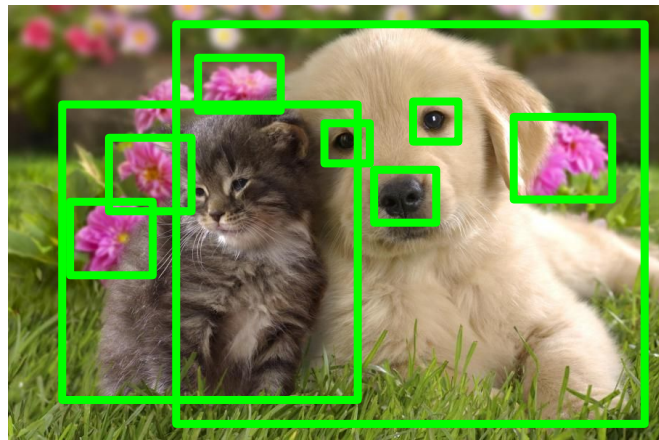


Deformable Part Model

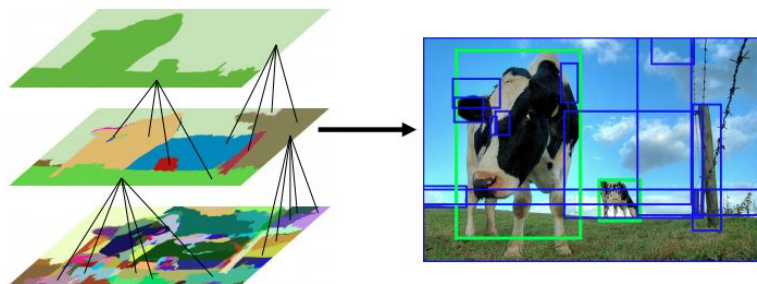


Region Proposals

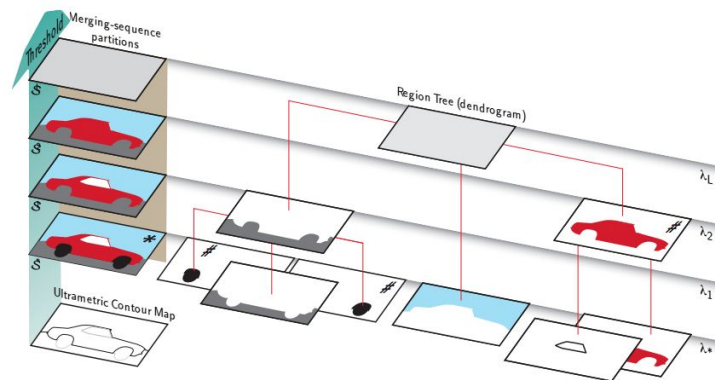
- Find “blobby” image regions that are likely to contain objects
- “Class-agnostic” object detector
- Look for “blob-like” regions



Region Proposals



Selective Search (SS)

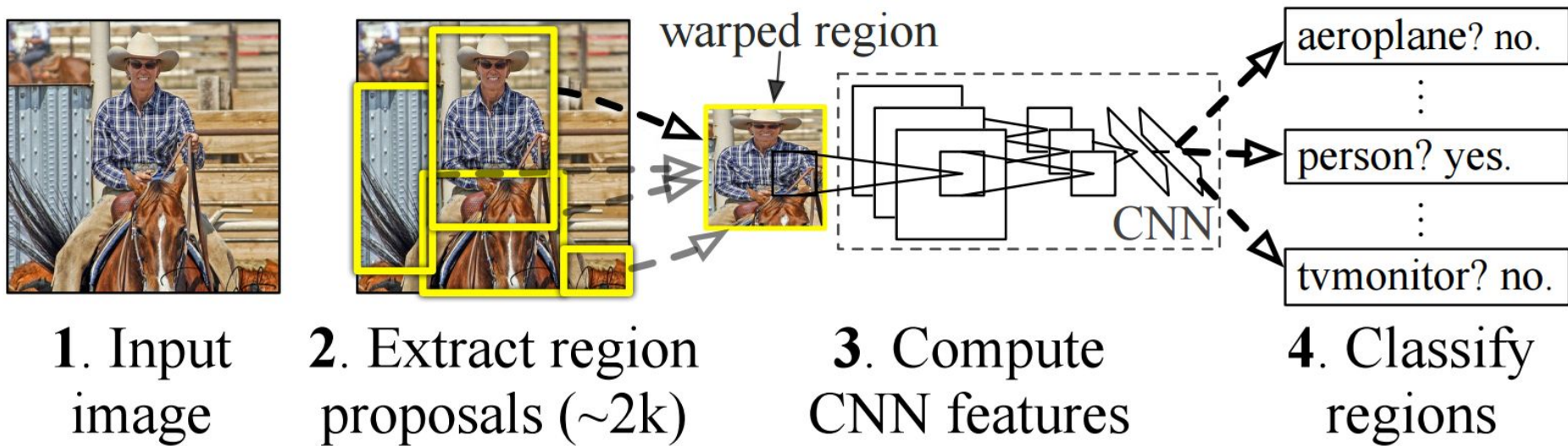


Multiscale Combinatorial Grouping (MCG)

[SS] Uijlings et al. [Selective search for object recognition](#). IJCV 2013

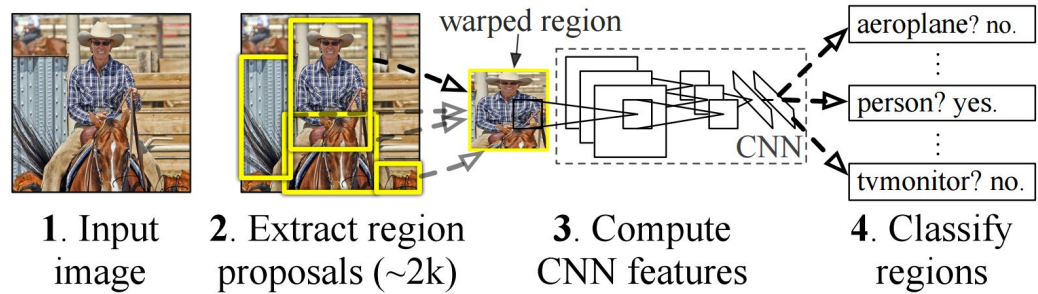
[MCG] Arbeláez, Pont-Tuset et al. [Multiscale combinatorial grouping](#). CVPR 2014

Object Detection with CNNs: R-CNN



R-CNN

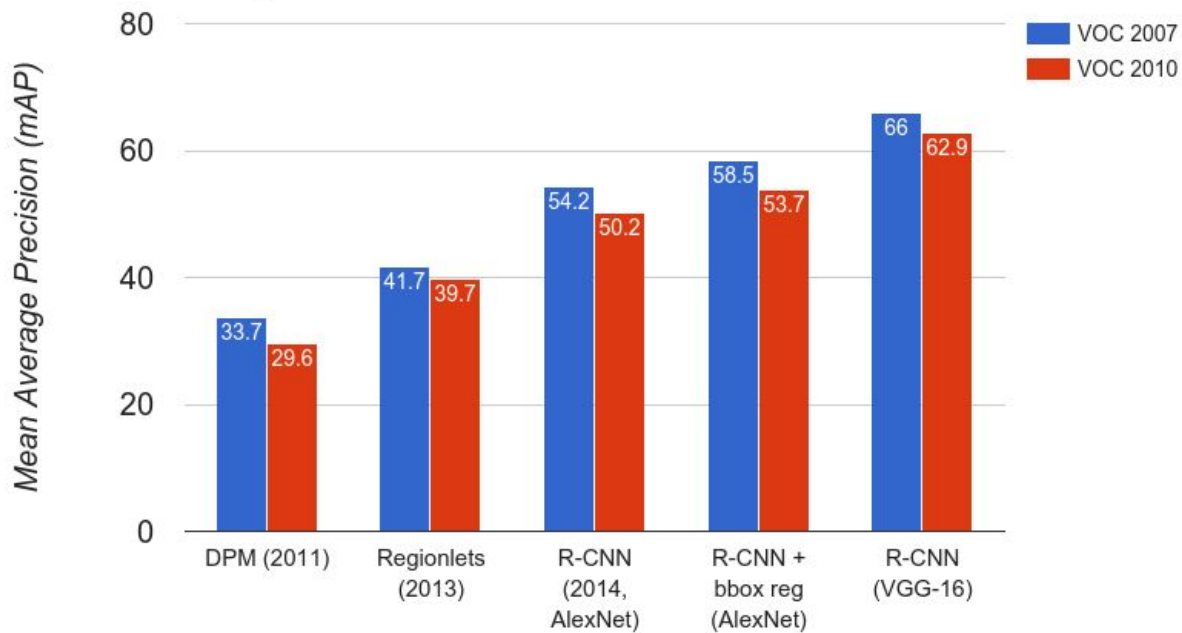
1. Train network on proposals



2. Post-hoc training of SVMs & Box regressors on fc7 features

Girshick et al. [Rich feature hierarchies for accurate object detection and semantic segmentation](#). CVPR 2014

R-CNN



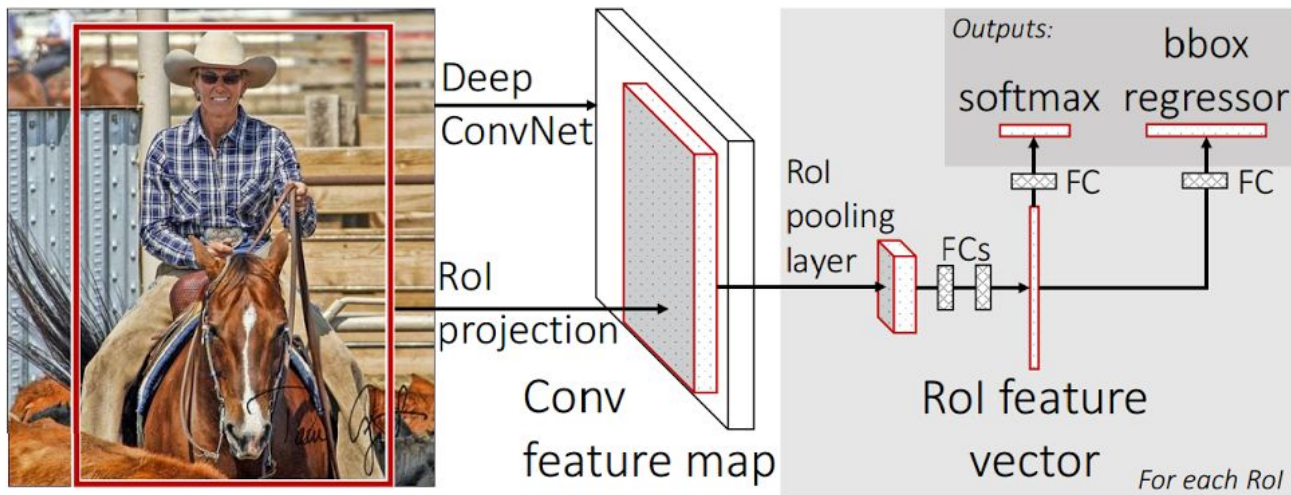
Girshick et al. [Rich feature hierarchies for accurate object detection and semantic segmentation](#). CVPR 2014

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

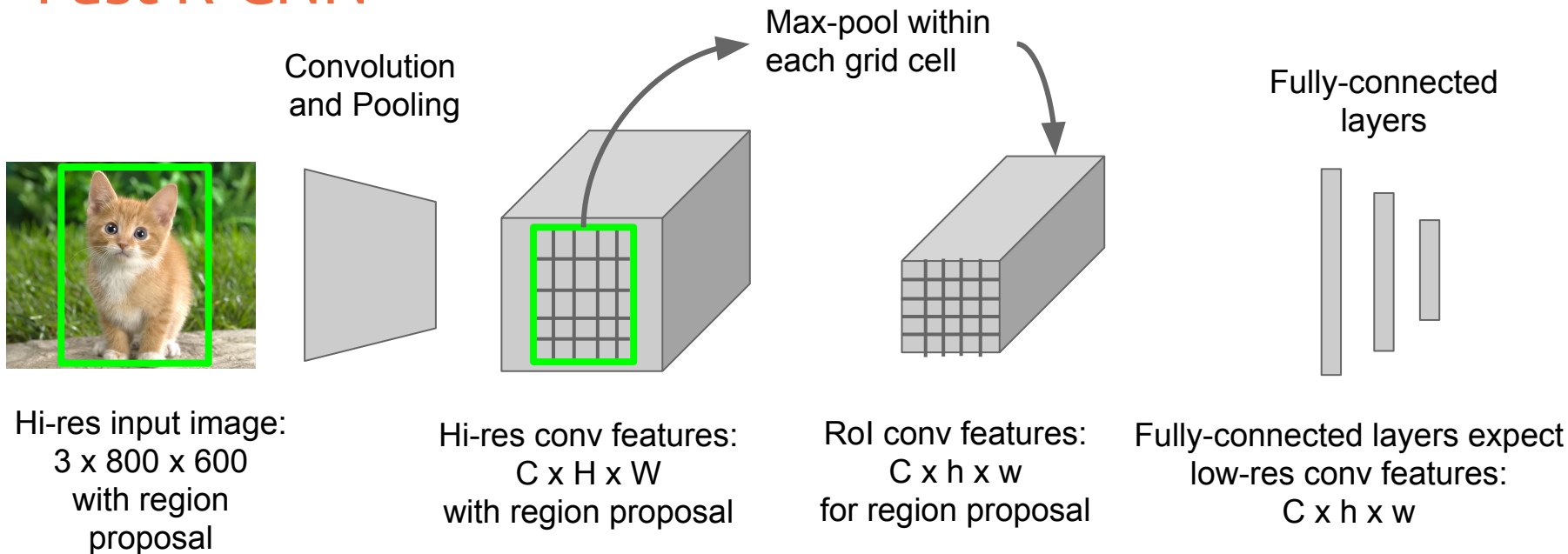
Fast R-CNN

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



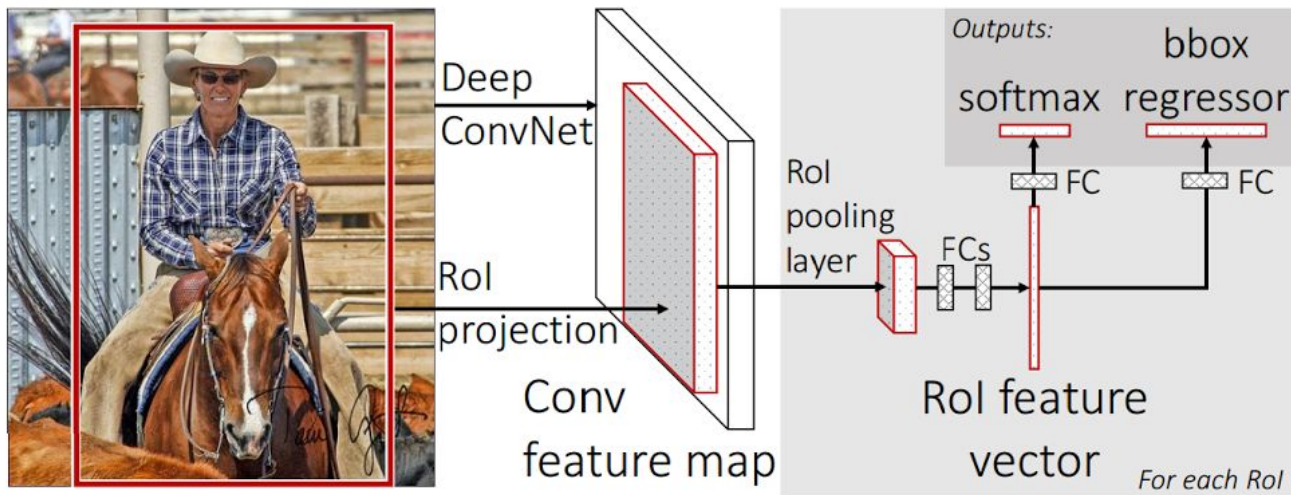
Solution: Share computation of convolutional layers between region proposals for an image

Fast R-CNN



Fast R-CNN

R-CNN Problem #2&3: SVMs and regressors are post-hoc. Complex training.



Solution: Train it all at together E2E

Fast R-CNN

	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

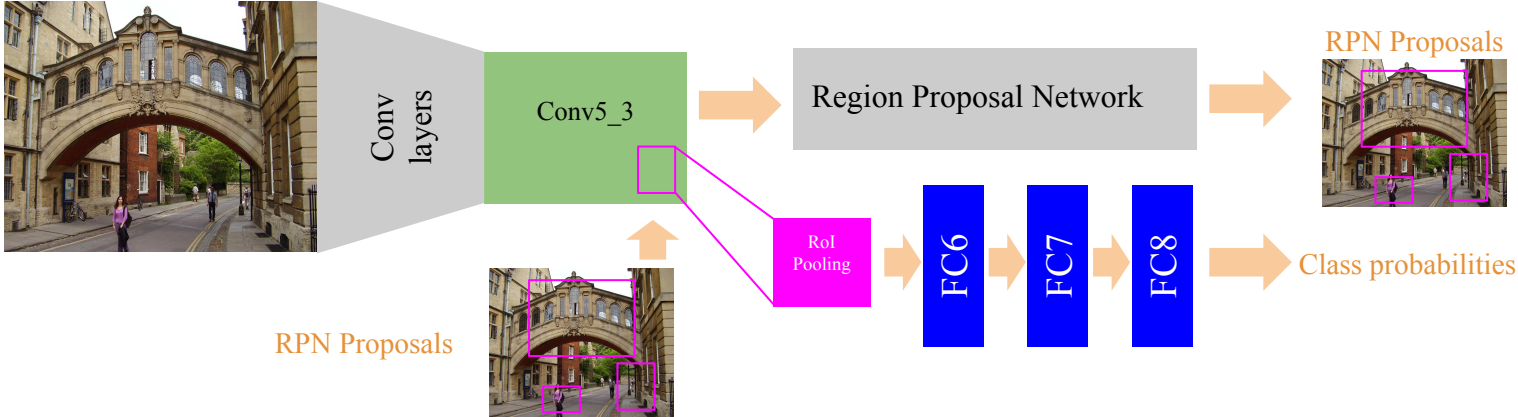
Using VGG-16 CNN on Pascal VOC 2007 dataset

Fast R-CNN: Problem

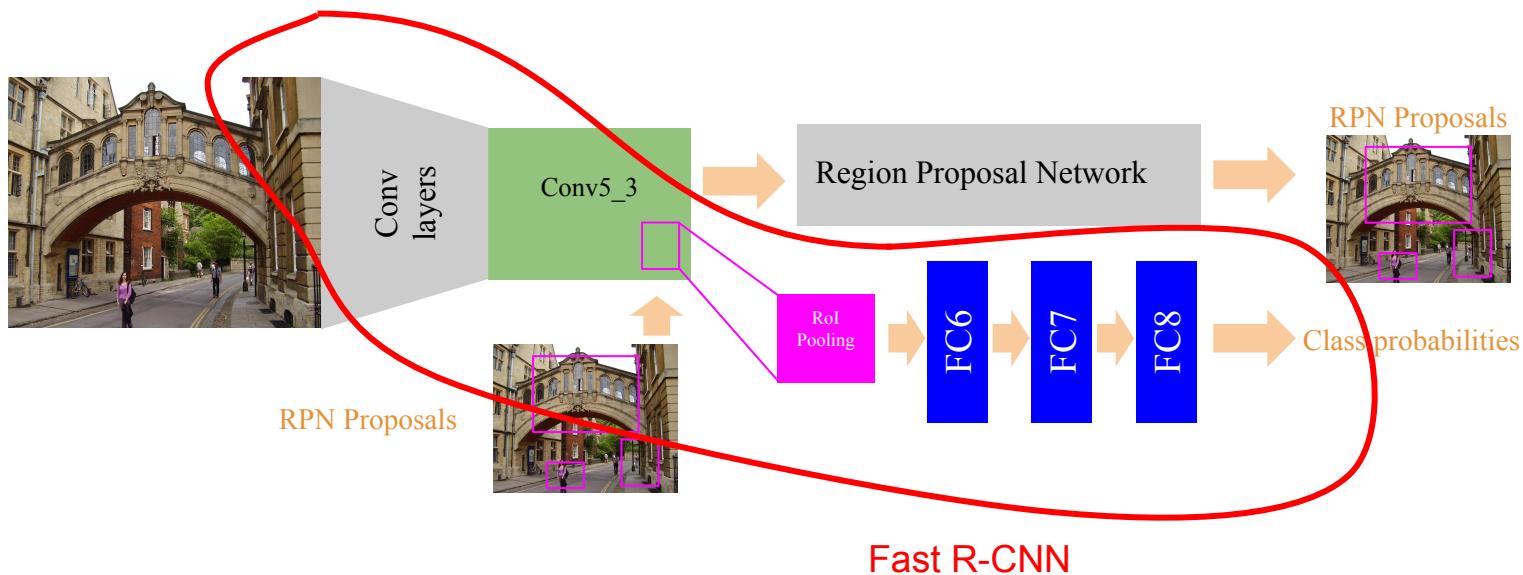
Test-time speeds don't include region proposals

	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

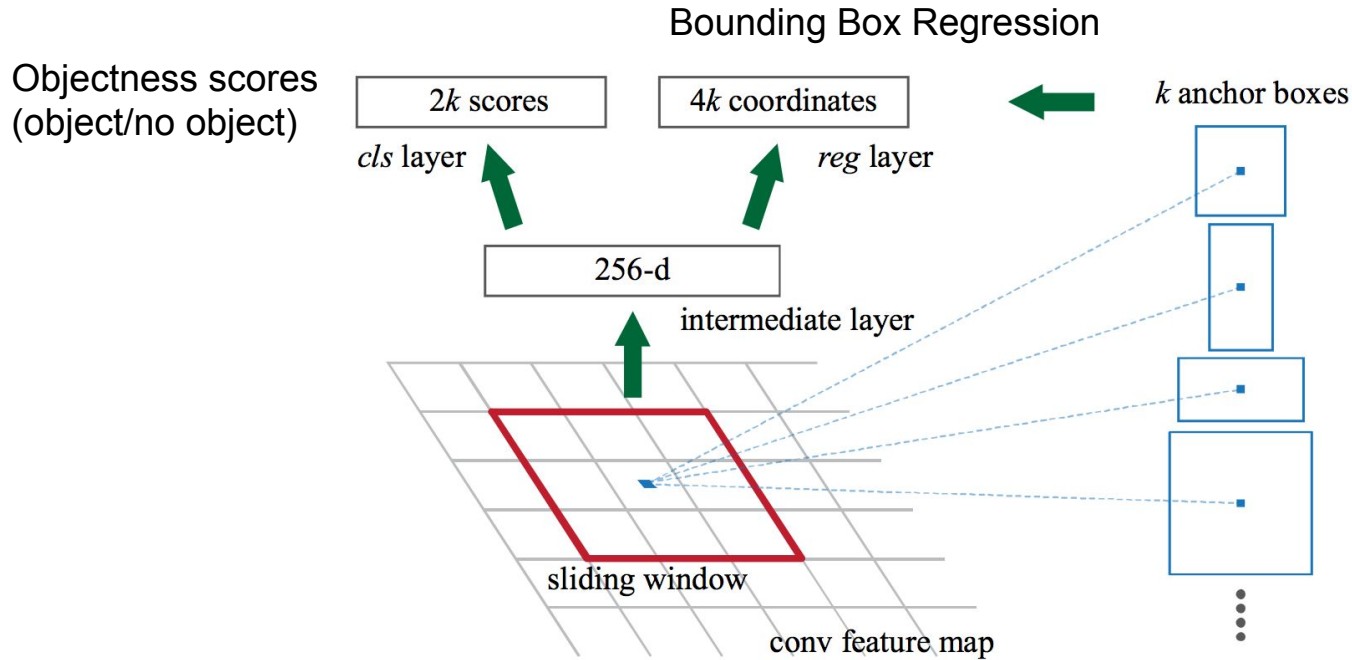
Faster R-CNN



Faster R-CNN



Region Proposal Network



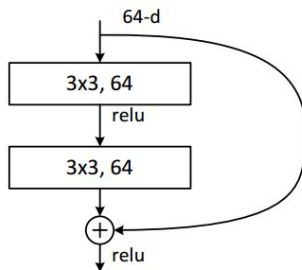
In practice, $k = 9$ (3 different scales and 3 aspect ratios)

Faster R-CNN

	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

Faster R-CNN

- Faster R-CNN is the basis of the winners of COCO and ILSVRC 2015 object detection competitions.



He et al. [Deep residual learning for image recognition](#). arXiv 2015

YOLO: You Only Look Once

Divide image into $S \times S$ grid

Within each grid cell predict:

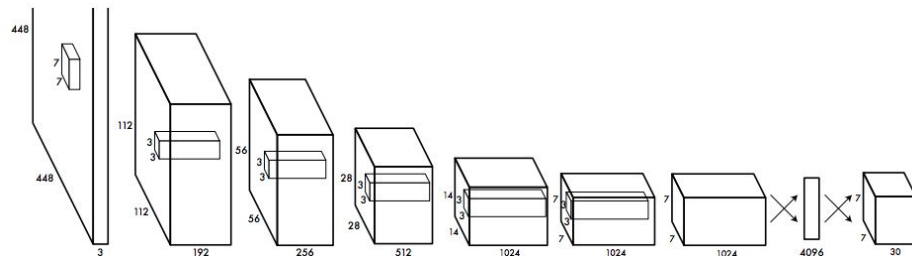
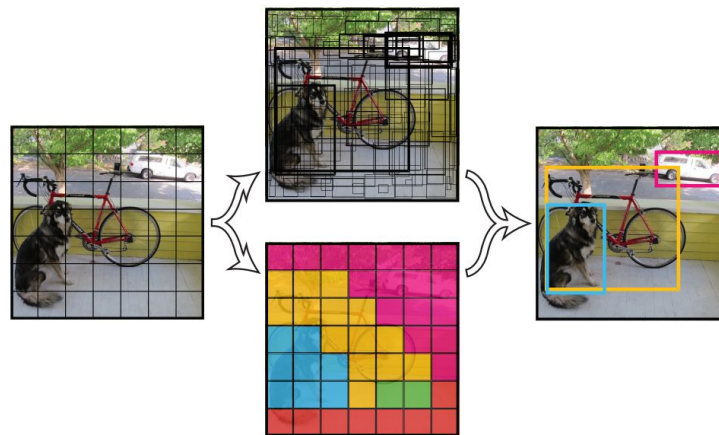
B Boxes: 4 coordinates + confidence

Class scores: C numbers

Regression from image to

$7 \times 7 \times (5 * B + C)$ tensor

Direct prediction using a CNN



SSD: Single Shot MultiBox Detector

System	VOC2007 test <i>mAP</i>	FPS (Titan X)	Number of Boxes
Faster R-CNN (VGG16)	73.2	7	300
Faster R-CNN (ZF)	62.1	17	300
YOLO	63.4	45	98
Fast YOLO	52.7	155	98
SSD300 (VGG)	72.1	58	7308
SSD300 (VGG, cuDNN v5)	72.1	72	7308
SSD500 (VGG16)	75.1	23	20097

Training with Pascal VOC 07+12

Resources

- Related Lecture from CS231n @ Stanford [[slides](#)][[video](#)]
- Caffe Code for:
 - [R-CNN](#)
 - [Fast R-CNN](#)
 - Faster R-CNN [[matlab](#)][[python](#)]
- YOLO
 - [Original \(Darknet\)](#)
 - [Tensorflow](#)
 - [Keras](#)
- [SSD](#) (Caffe)