Object Detection: A Recap

- Classify each window in an image
  - Too many windows: Need speed and accuracy

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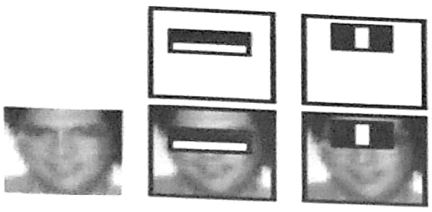
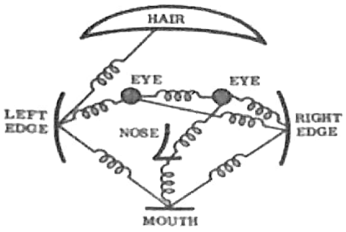
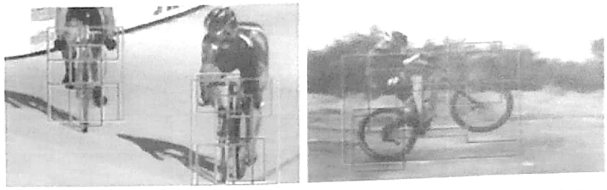
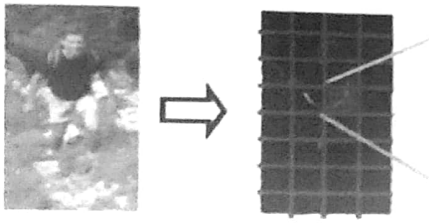
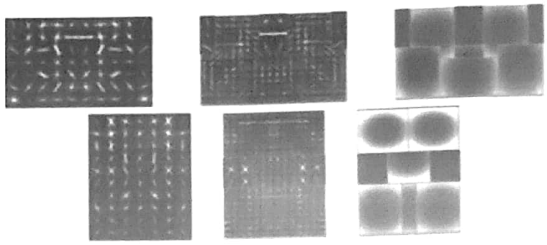






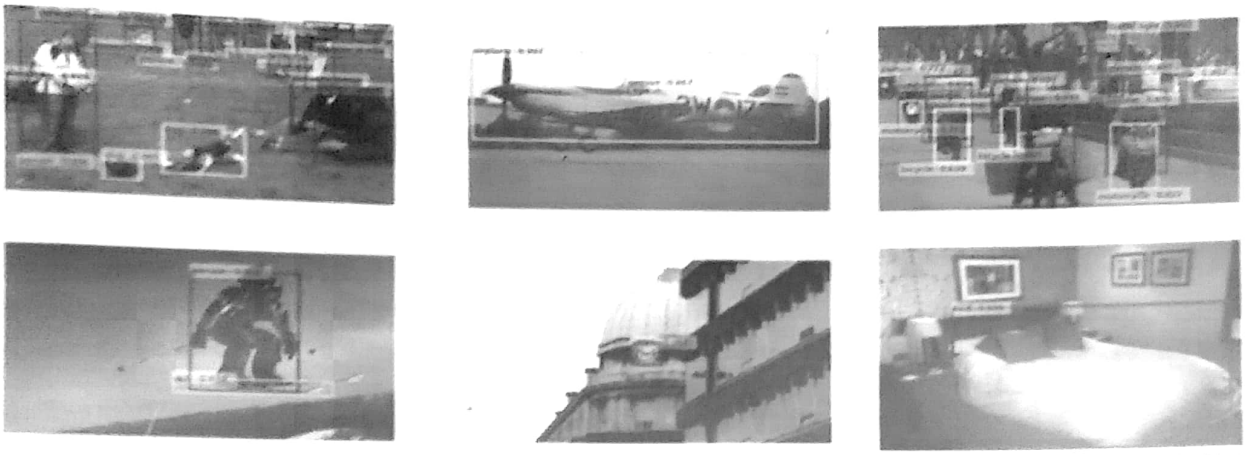




Deep Learning based Detection

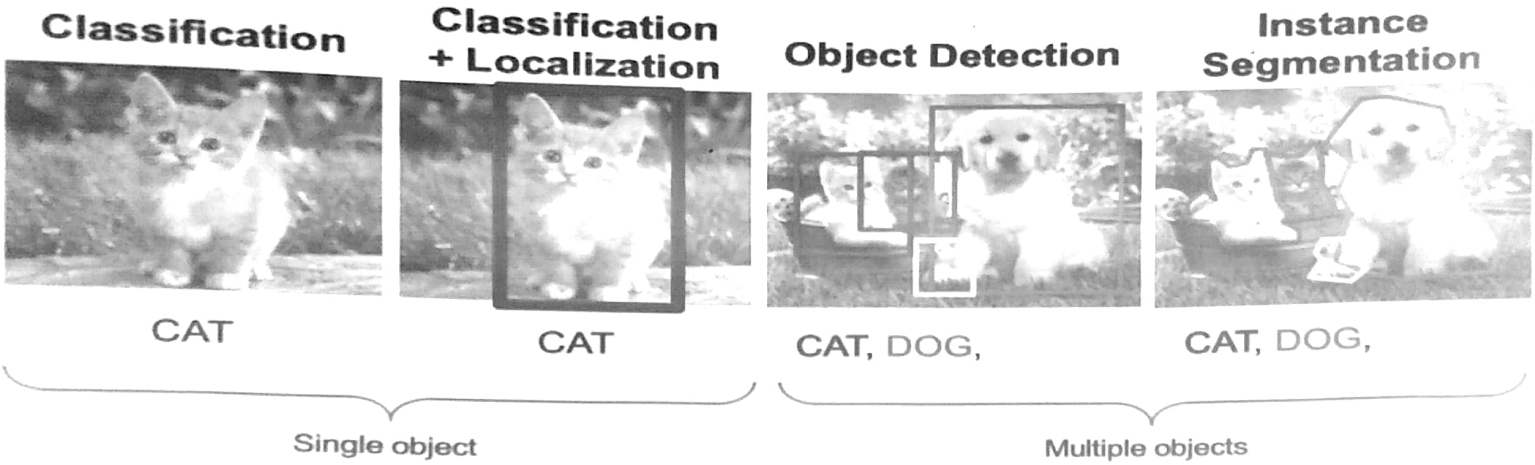
- Use deep Learnt features for detection
  - Cannot afford to do for every window
- Classify select windows (Region Proposals)
  - RCNN, Fast RCNN, Faster RCNN, Mask RCNN
- Directly predict bounding boxes
  - YOLO V1, V2, V3
- Deeplab V3, Xception
- Dialated Residual Networks

Localization / Detection



Results from Faster R-CNN, Ren et al 2015

Computer Vision Tasks



Classification + Localization: Task

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

→ CAT

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

→ (x, y, w, h)

Classification + Localization: Do both

Classification + Localization: ImageNet

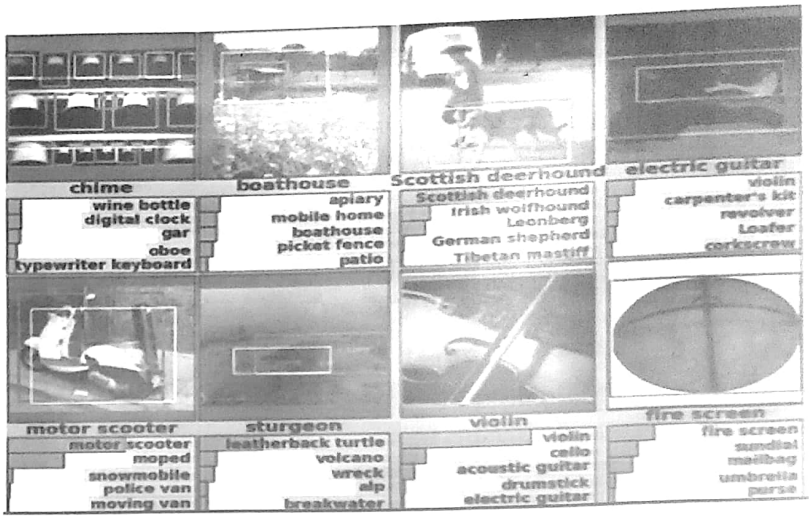
1000 classes (same as classification)

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 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

Only one object,
simpler than detection

Neural Net

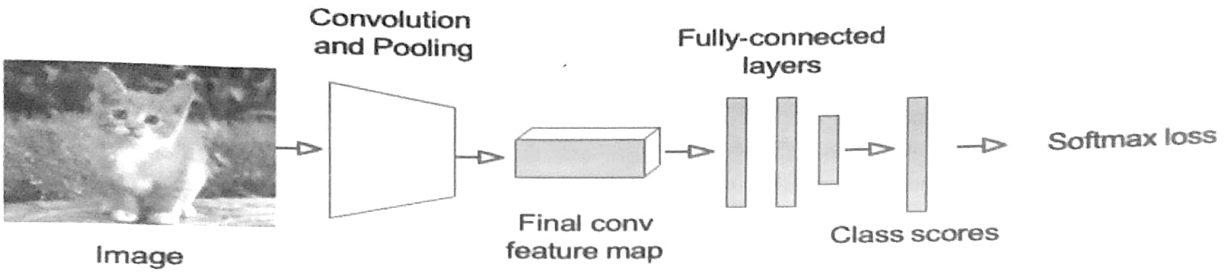
Output:
Box coordinates
(4 numbers)

Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

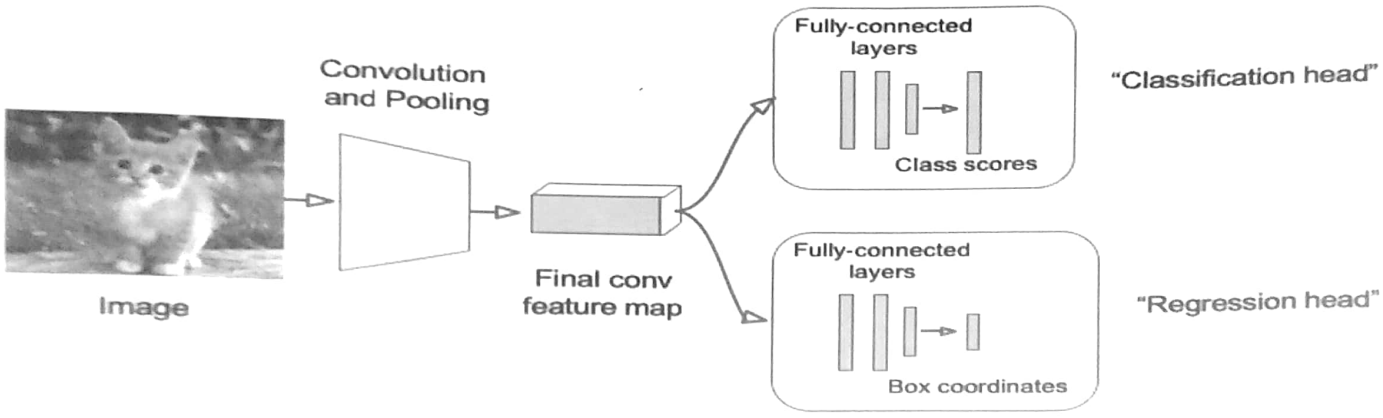
Simple Recipe for Classification + Localization

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



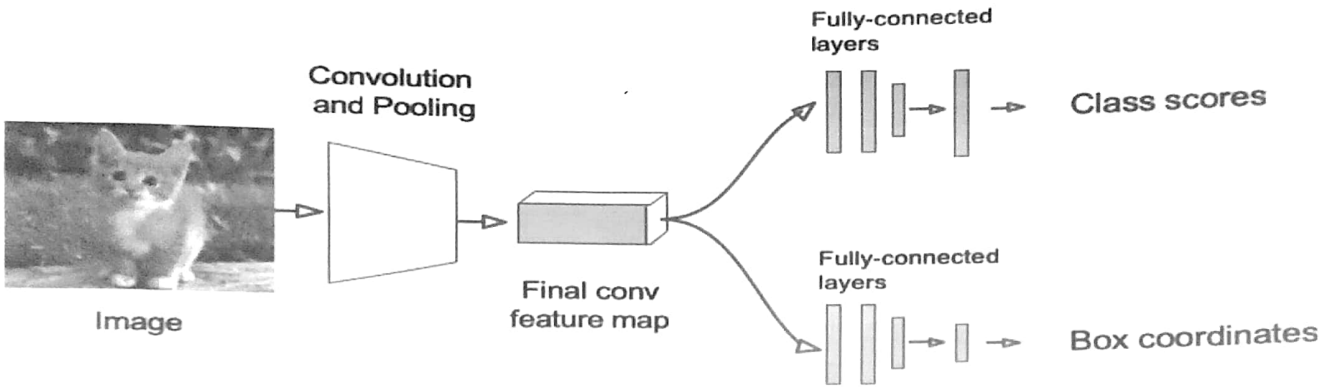
Simple Recipe for Classification + Localization

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



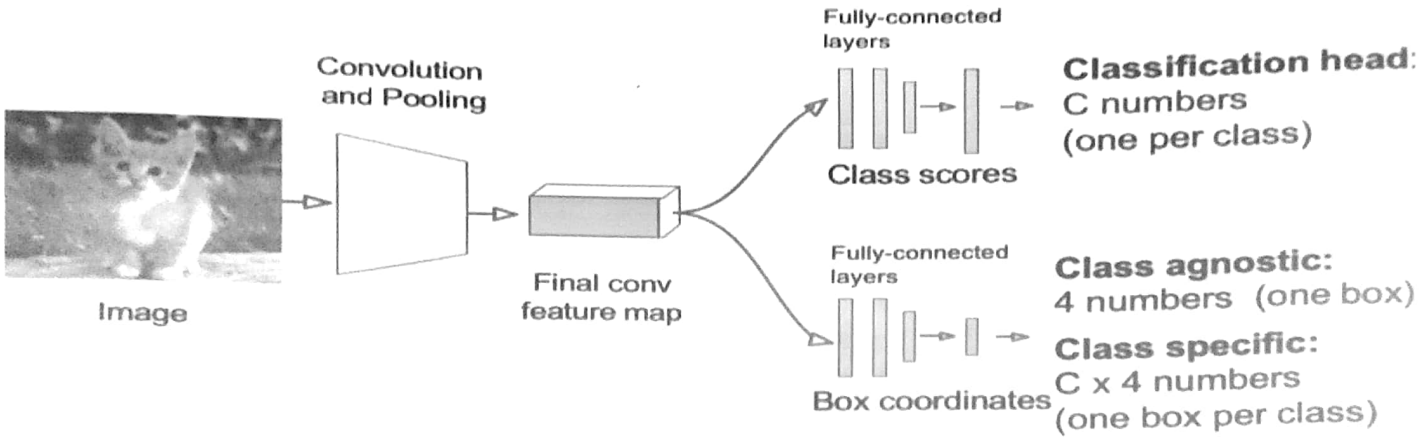
Simple Recipe for Classification + Localization

Step 4: At test time, use both scores



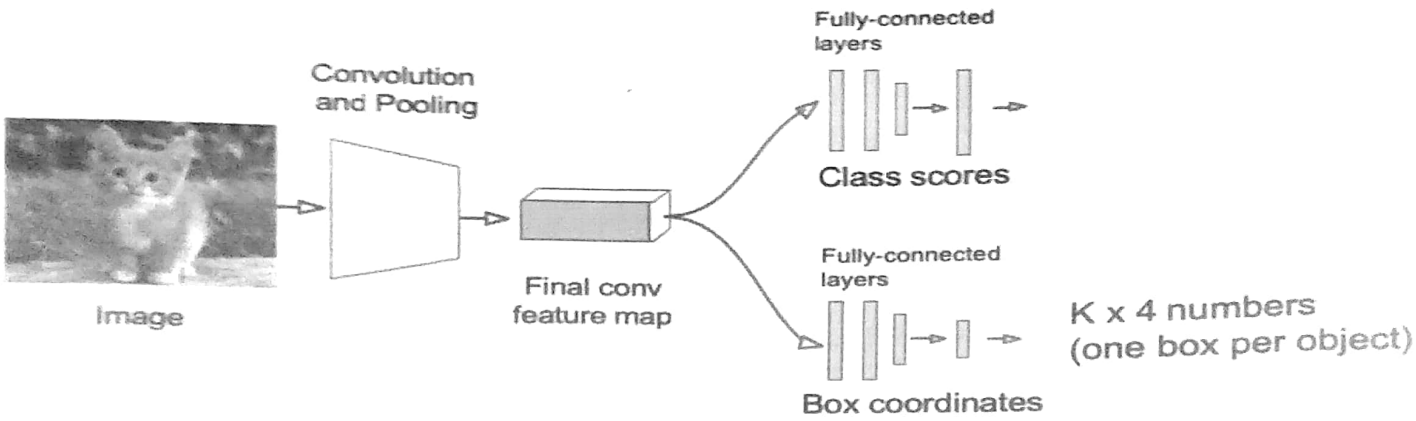
Per-class vs Class-Agnostic Regression

Assume classification over C classes



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)



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 x 221 x 221

Convolution
+ pooling

Feature map:
1024 x 5 x 5

FC

FC

4096

FC

4096

FC

Class scores:
1000

Softmax
loss

FC

FC

4096

FC

1024

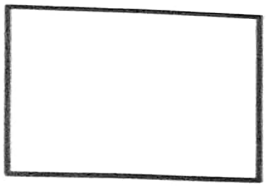
FC

Boxes:
1000 x 4

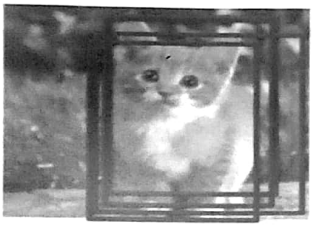
Euclidean
loss

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

Sliding Window: Overfeat



Network input:
3 x 221 x 221



Larger image:
3 x 257 x 257

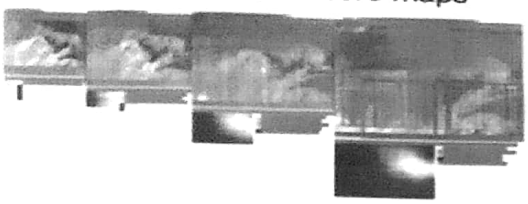
0.5	0.75
0.6	0.8

Classification scores:
P(cat)

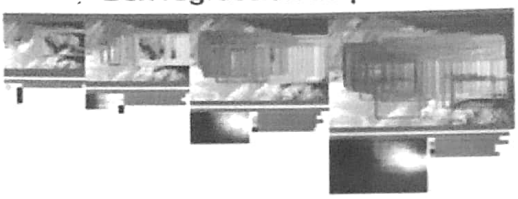
Sliding Window: Overfeat

In practice use many sliding window locations and multiple scales

Window positions + score maps



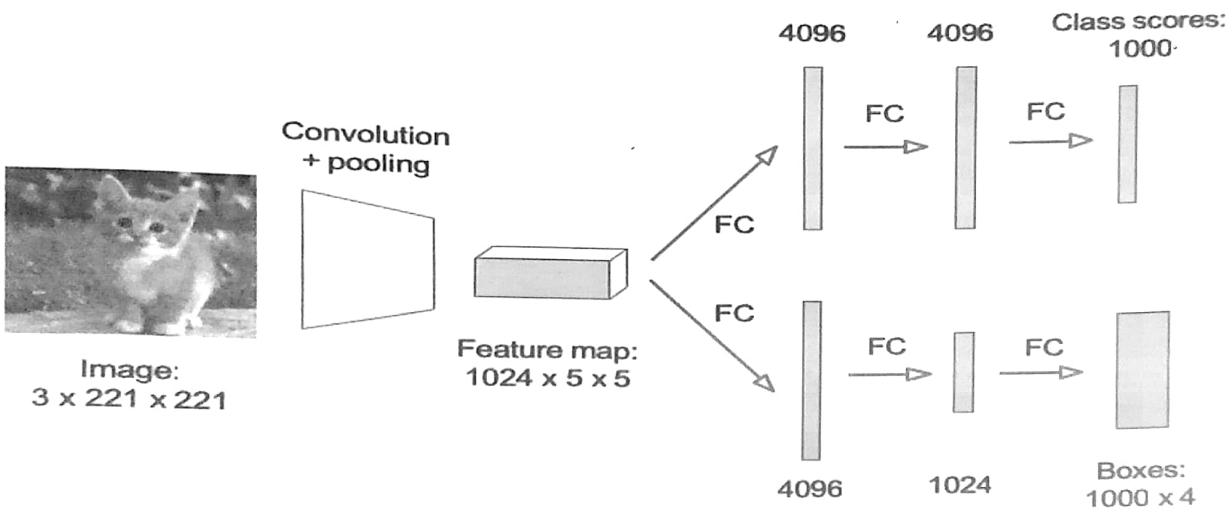
Box regression outputs



Final Predictions

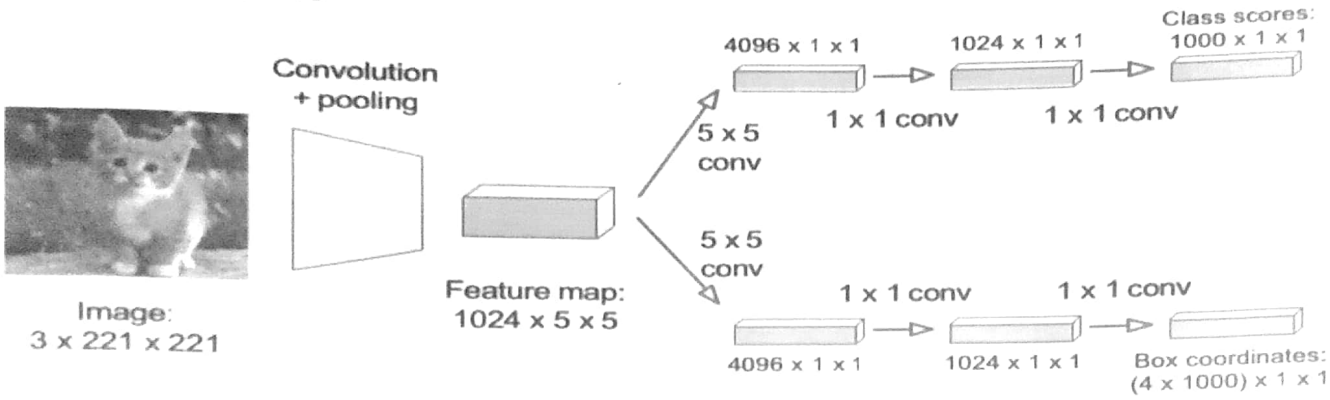
Sermanet et al, "Integrated Recognition, Localization and Detection using Convolutional Networks", ICLR 2014

Efficient Sliding Window: Overfeat



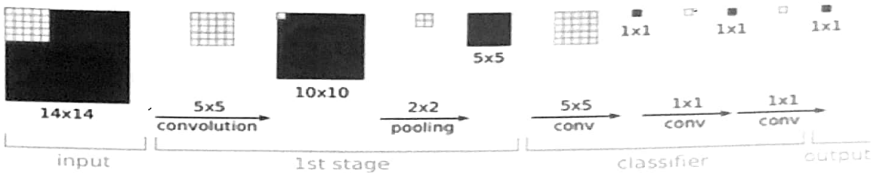
Efficient Sliding Window: Overfeat

Efficient sliding window by converting fully-connected layers into convolutions

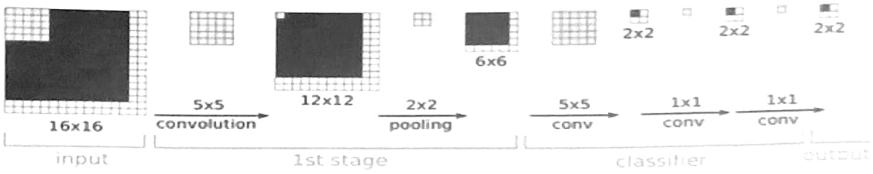


Efficient Sliding Window: Overfeat

Training time: Small image, 1 x 1 classifier output

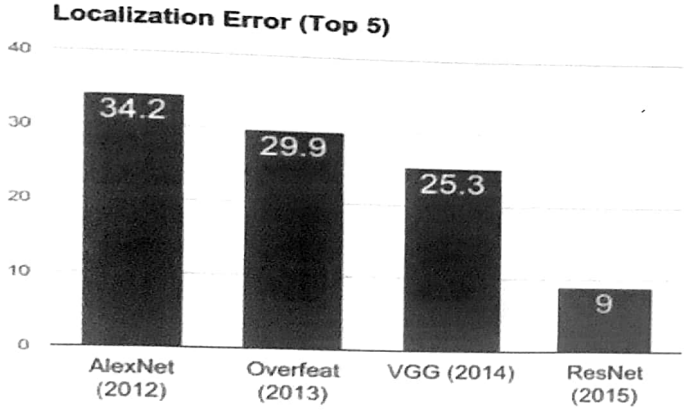


Test time: Larger image, 2 x 2 classifier output, only extra compute at yellow regions



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 + Localization

Object Detection

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

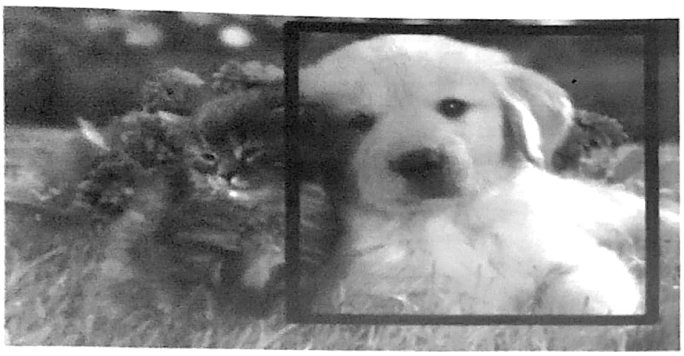
Need variable sized outputs

Detection as Classification

CAT? NO

DOG? NO

Detection as Classification



CAT? NO

DOG? YES!

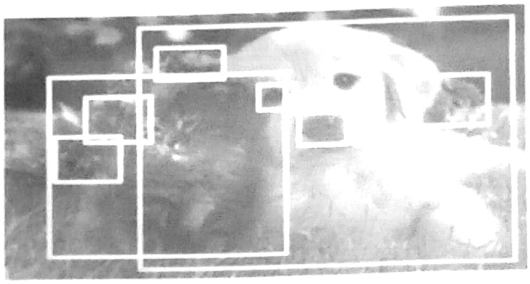
Detection as Classification

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

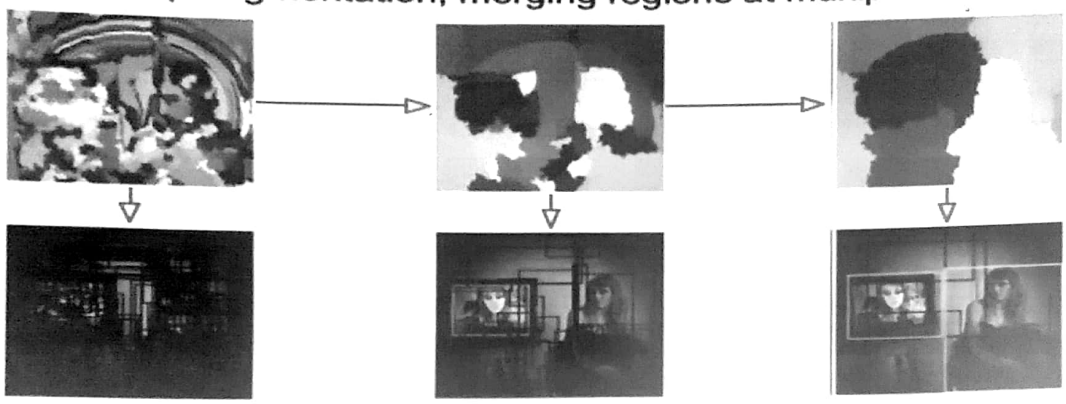
- Find "blobby" image regions that are likely to contain objects
- "Class-agnostic" object detector
- Look for "blob-like" regions



Region Proposals: Selective Search

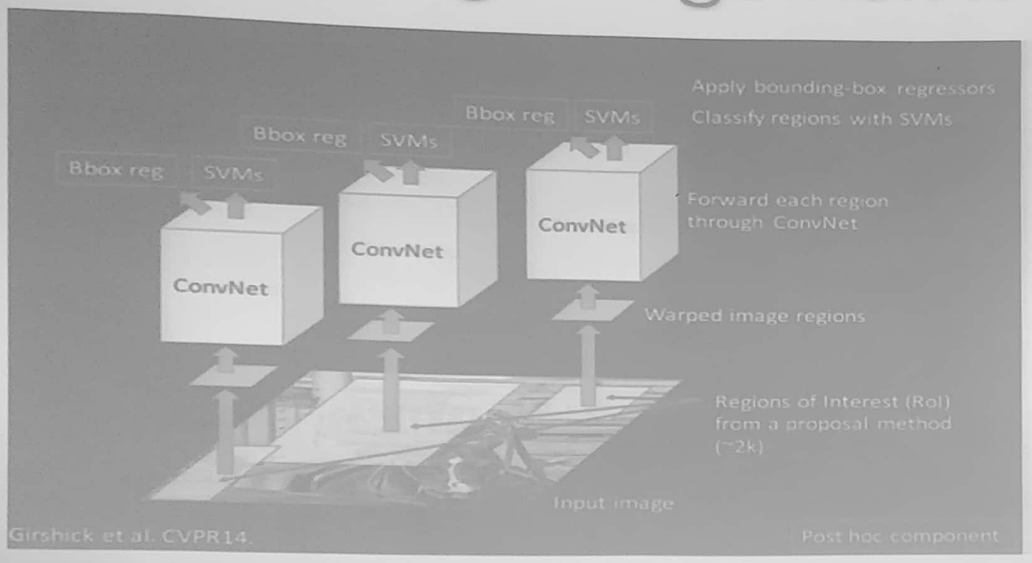
Bottom-up segmentation, merging regions at multiple scales

Convert regions to boxes



Uijlings et al, "Selective Search for Object Recognition", IJCV 2013

Putting it Together: R-CNN

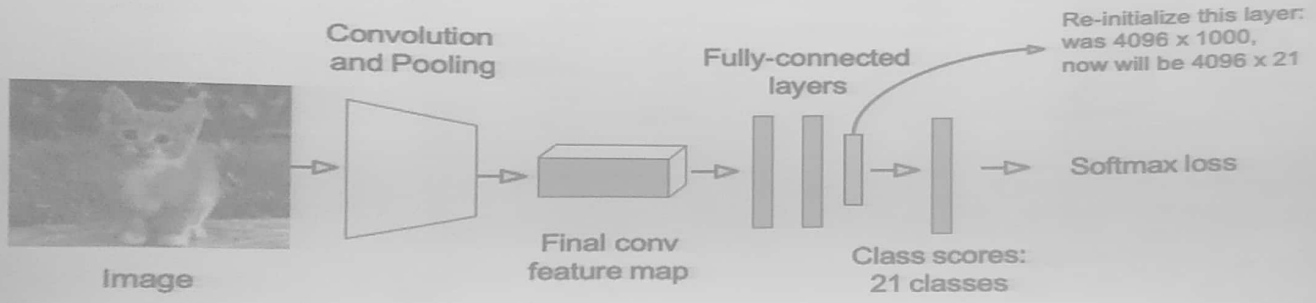


Girschick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014

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
- In hard drive? Features are ~200GB for PASCAL dataset!

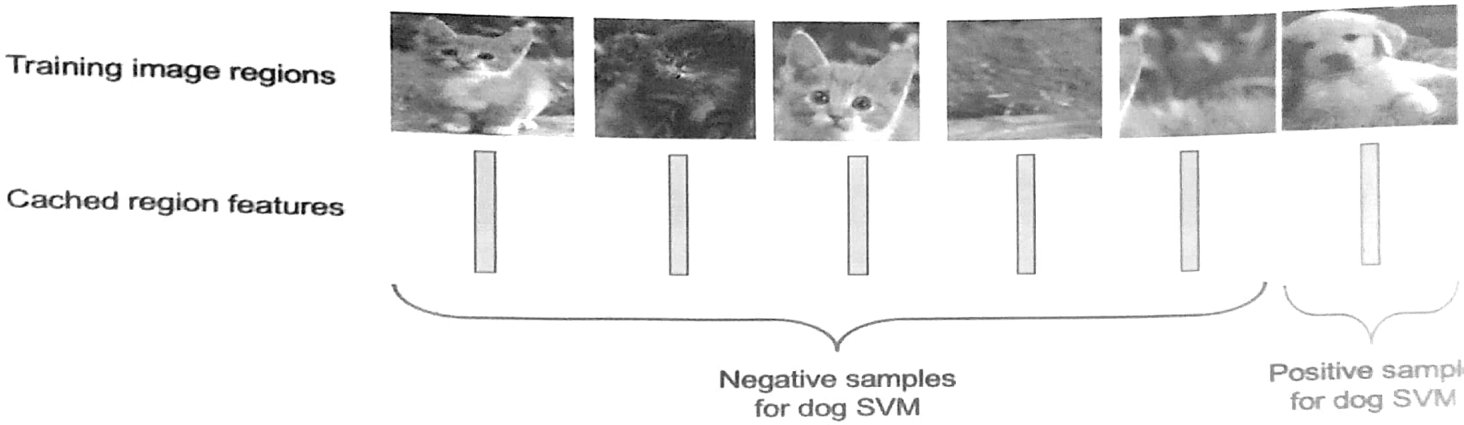
R-CNN Training

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
- In hard drive? Features are ~200GB for PASCAL dataset!

R-CNN Training

Step 4: Train one binary SVM per class to classify 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

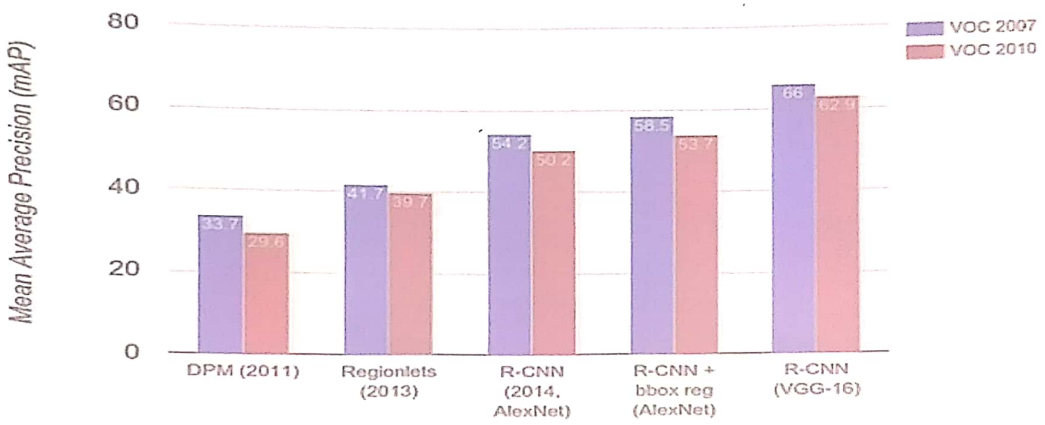
Object Detection: Datasets

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

Object Detection: Evaluation

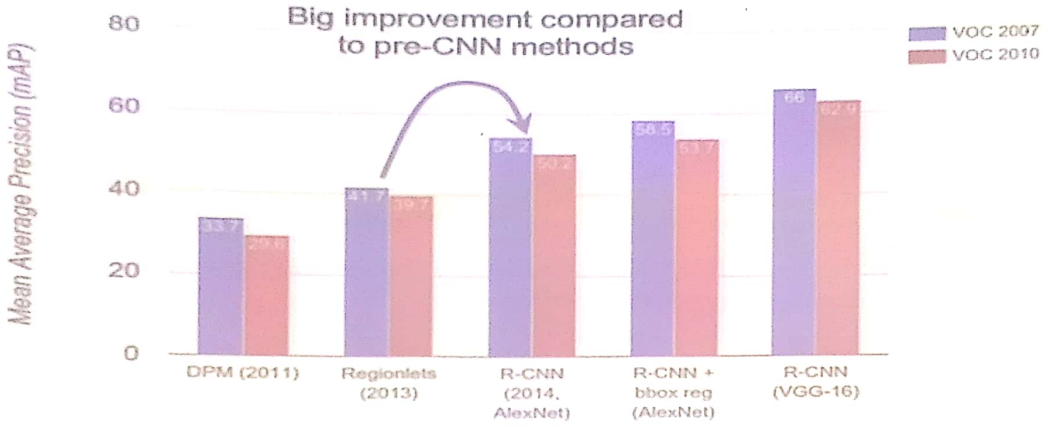
- Popular metric: "mean average precision" (mAP)
- Precision: # Correct detections / # Detections
- Combine all detections from all test images to draw a P-R curve for each class; AP is the area under the curve
- Compute the average precision (AP) separately for each class. Its mean over classes gives mAP
- 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)
- mAP is a number from 0 to 100; high is good

R-CNN Results

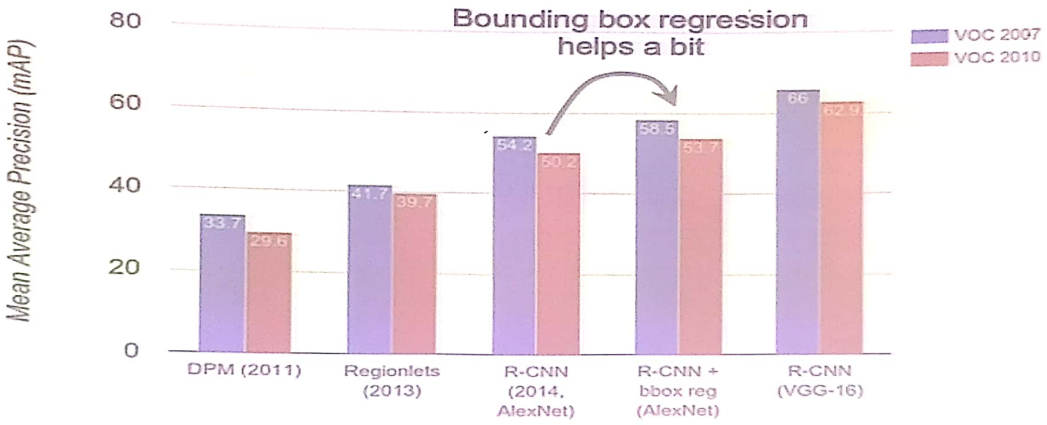


Wang et al, "Regionlets for Generic Object Detection", ICCV 2013

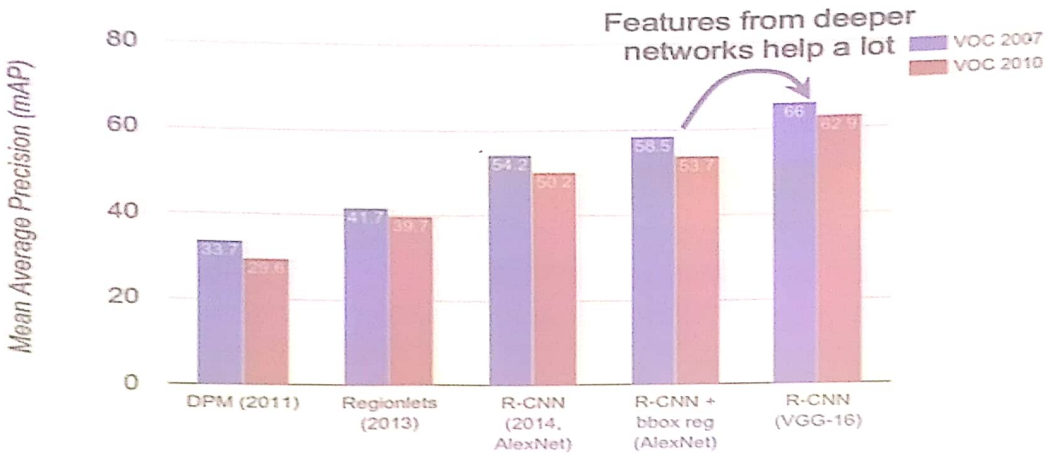
R-CNN Results



R-CNN Results

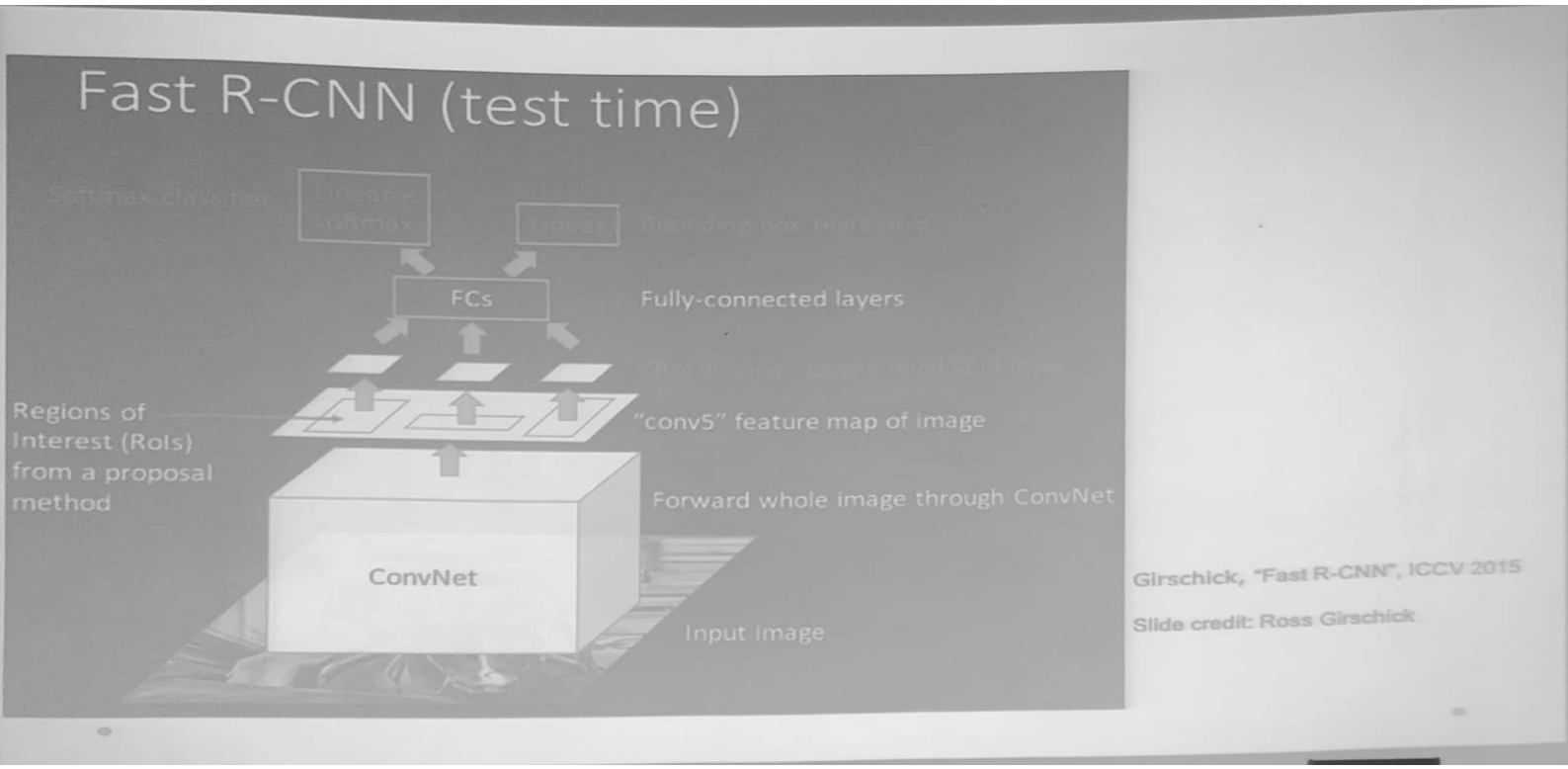


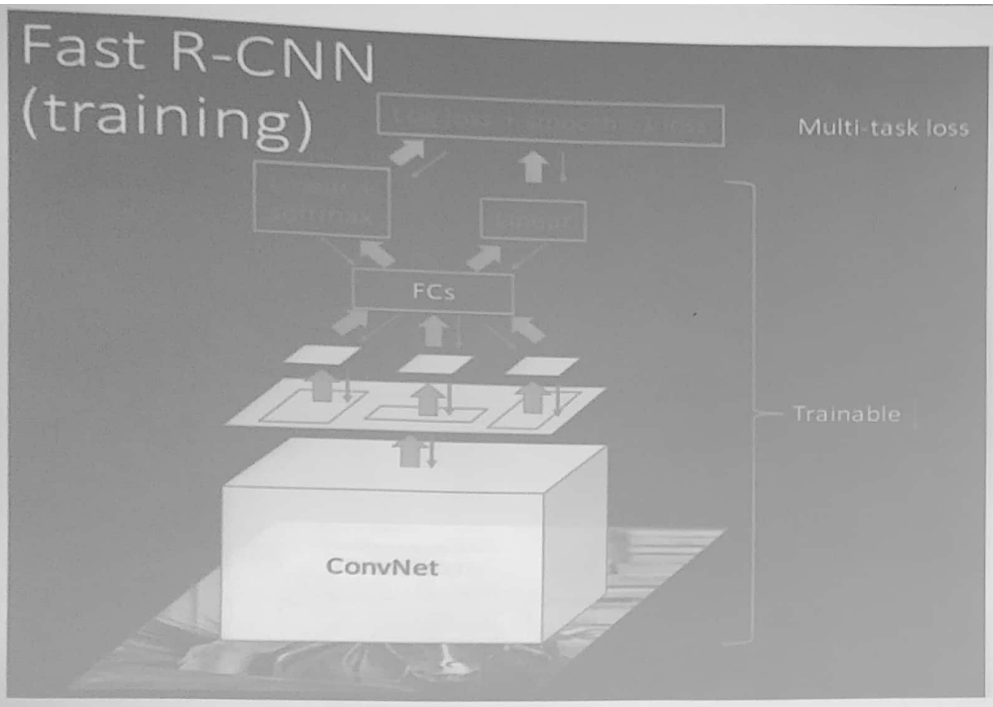
R-CNN Results



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 are not updated in response to SVMs and regressors
3. Complex multistage training pipeline





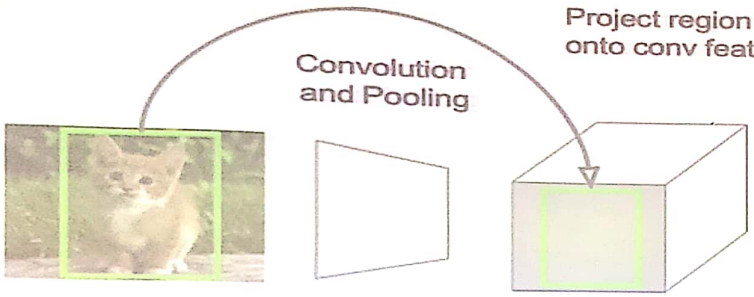
R-CNN Problem #2:
Post-hoc training: CNN not updated in response to final classifiers and regressors

R-CNN Problem #3:
Complex training pipeline

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

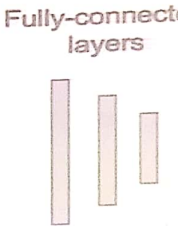
Slide credit: Ross Girschick

Fast R-CNN: Region of Interest Pooling



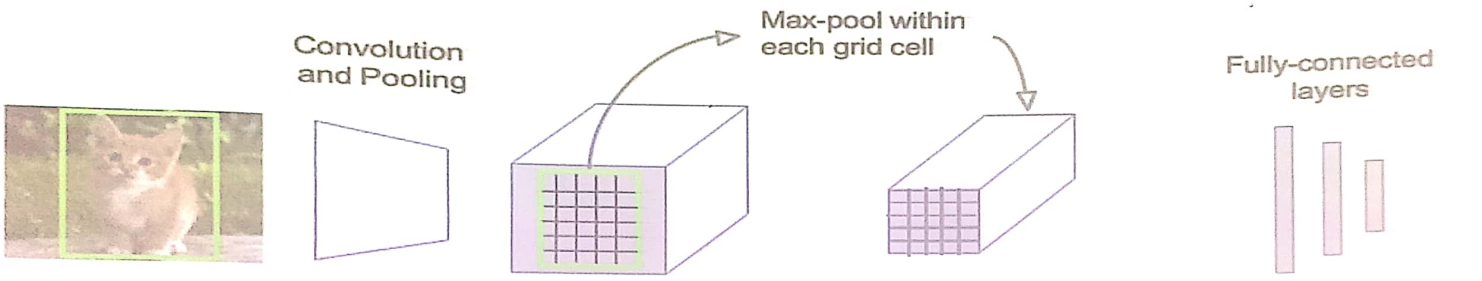
Hi-res input image:
3 x 800 x 600
with region
proposal

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



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

Fast R-CNN: Region of Interest Pooling



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

Fast R-CNN Results

	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**

Faster!

FASTER!

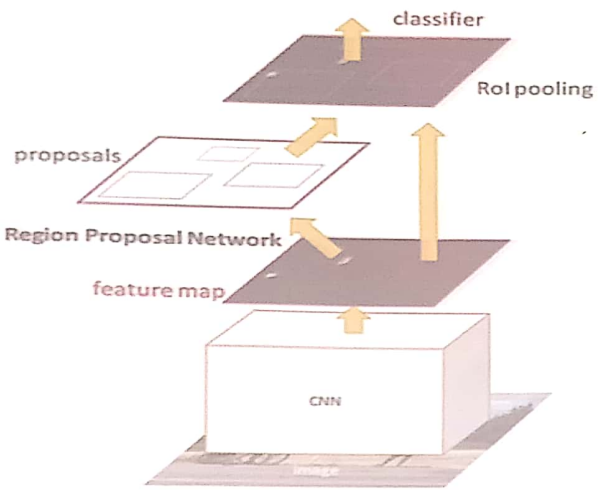
Using VGG-16 CNN on Pascal VOC 2007 dataset

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:



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

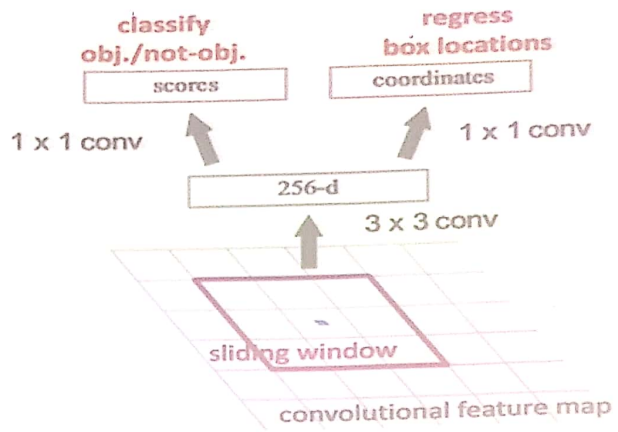
Faster R-CNN: Region Proposal Network

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



Slide credit: Kaiming He

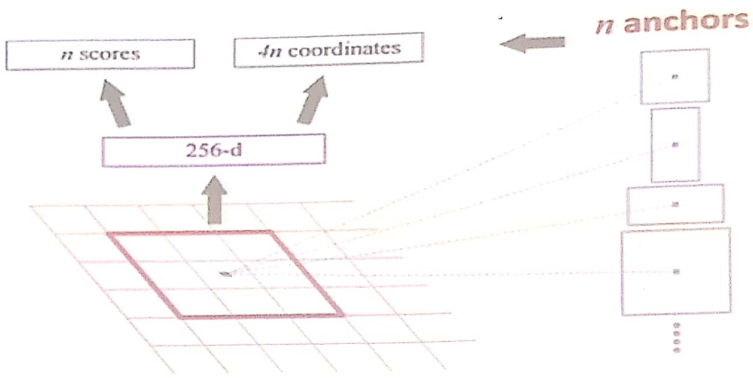
Faster R-CNN: Region Proposal Network

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: 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**

ResNet 101 + Faster R-CNN + 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", arXiv 2015

Deep Learning based Detection

- Use deep Learnt features for detection
  - Cannot afford to do for every window
- Classify select windows (Region Proposals)
  - RCNN, Fast RCNN, Faster RCNN, Mask RCNN
- Directly predict bounding boxes
  - YOLO V1, V2, V3
- Deeplab V3, Xception
- Dialated Residual Networks