CV overview and R-CNN

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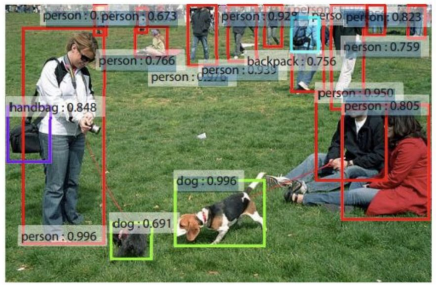
Outline

- Computer Vision tasks
  - Classification
  - Localisation
  - Detection
  - Semantic Segmentation
  - Instance Segmentation
- Metrics
- Datasets
- R-CNN
- Fast R-CNN
- Faster R-CNN

Computer Vision tasks

Computer Vision tasks



- Classification
- Localisation
- Detection

- Semantic Segmentation
- Instance Segmentation

- Human Pose Estimation
- Person Reidentification
- Object Tracking
- Style Transfer
- Adversarial Attacks
- .....

Classification

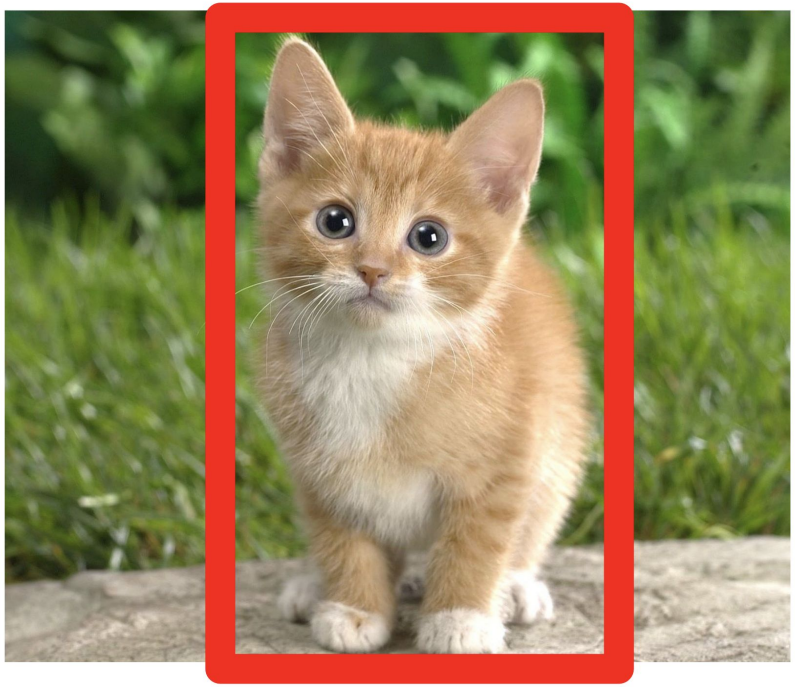
Cat

Input image (C x H x W)

Output

class label (int)

Localisation



Cat

Input image (C x H x W)

Output

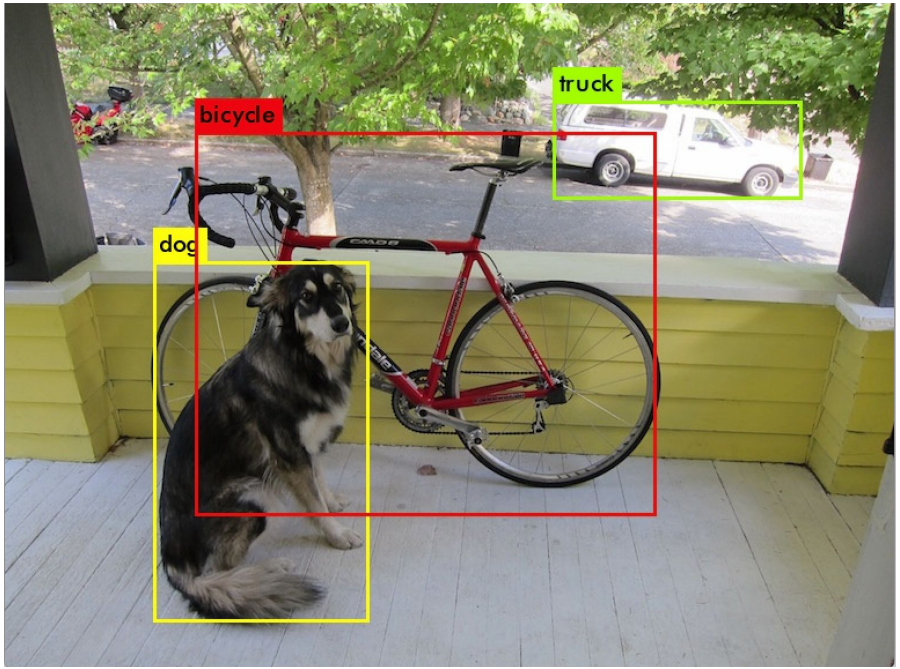
class label (int), BB* coordinates (4 ints)

Assumption

one object per image

* BB - bounding box

Detection



Input image (C x H x W)

Output

class label (int), confidence (0-1 float), BB (4 ints)

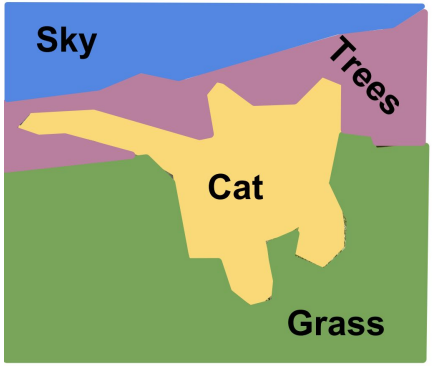
……

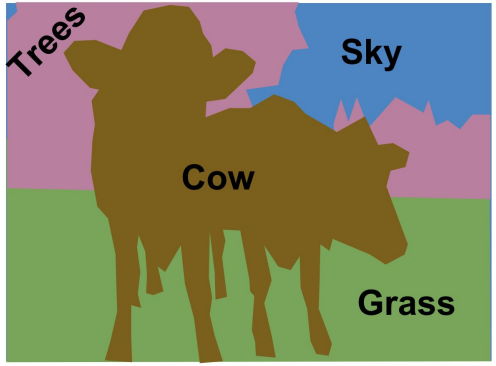
class label (int), confidence (0-1 float), BB (4 ints)

Assumption

multiple objects per image

Semantic Segmentation





Input image (C x H x W)

Output

mask of classes (1 x H x W)

Assumption

just class label for each pixel

Instance Segmentation

Input image (C x H x W)

Output

mask of class instances (detection + 1 x H x W)

Assumption

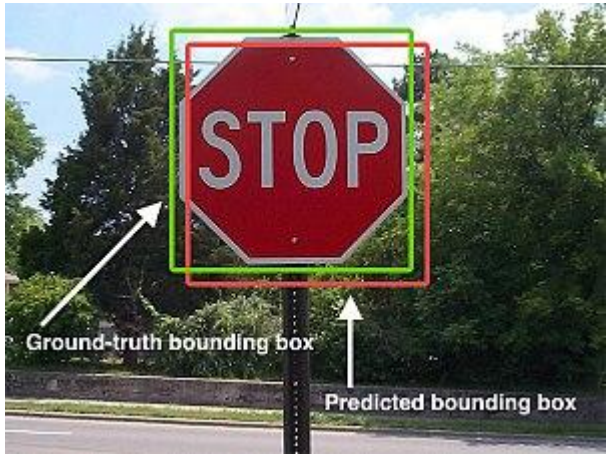
separated masks for each distinct object

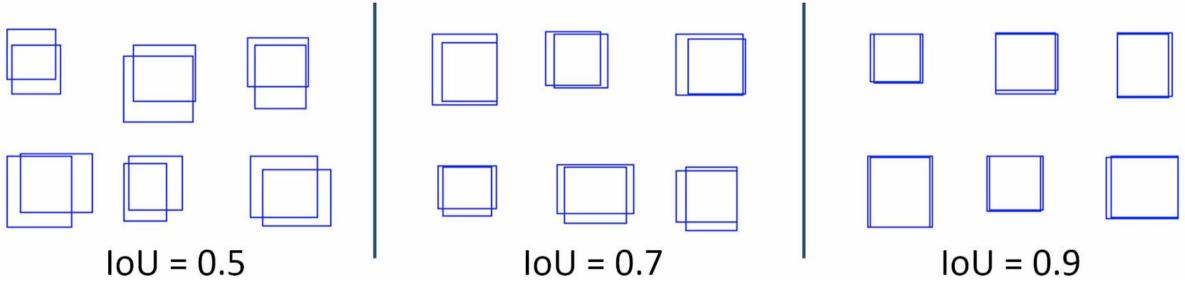
Metrics in CV

Intersection over Union (IoU)

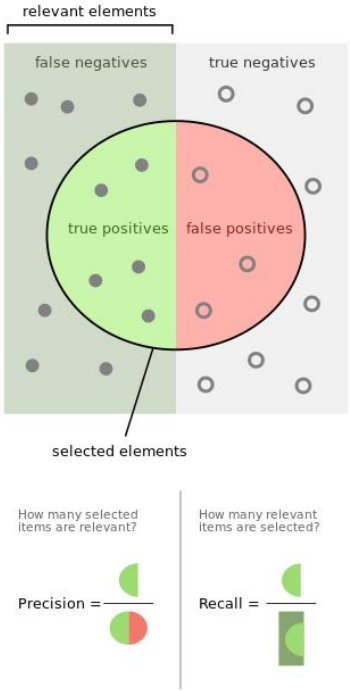
aka Jaccard index

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$





mean Average Precision (mAP)

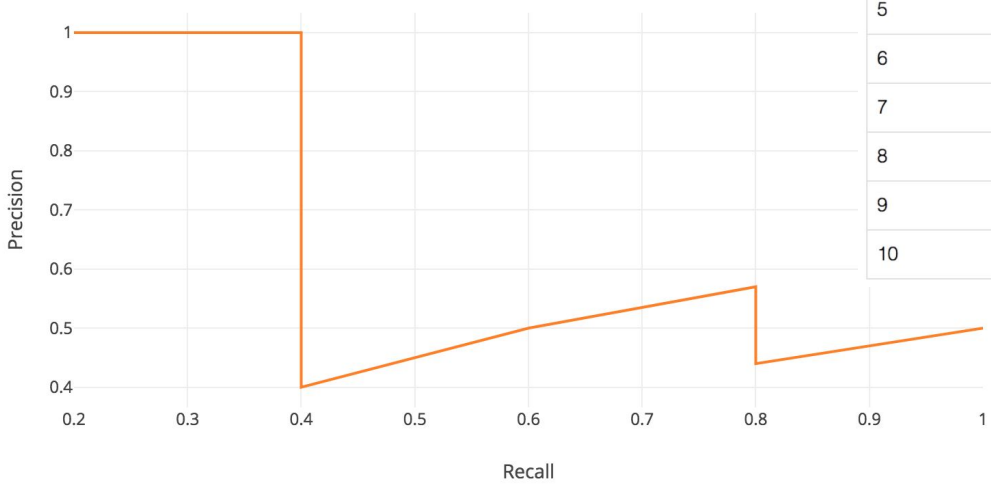


Consider 5 objects and 10 detections

Rank	Correct?	Precision	Recall
1	True	1.0	0.2
2	True	1.0	0.4
3	False	0.67	0.4
4	False	0.5	0.4
5	False	0.4	0.4
6	True	0.5	0.6
7	True	0.57	0.8
8	False	0.5	0.8
9	False	0.44	0.8
10	True	0.5	1.0

mean Average Precision (mAP)

The intention in interpolating the precision/recall curve in this way is to reduce the impact of the “wiggles” in the precision/recall curve, caused by small variations in the ranking of examples.



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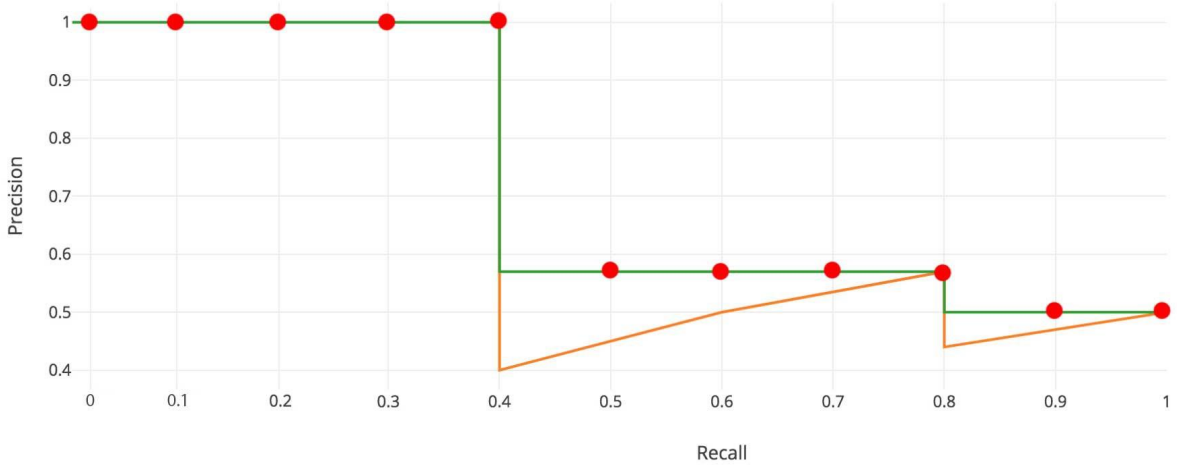
mean Average Precision (mAP)

mAP is mean of AP over all classes

$$AP = \frac{1}{11} \times \left(AP_r(0) + AP_r(0.1) + \ldots + AP_r(1.0) \right)$$

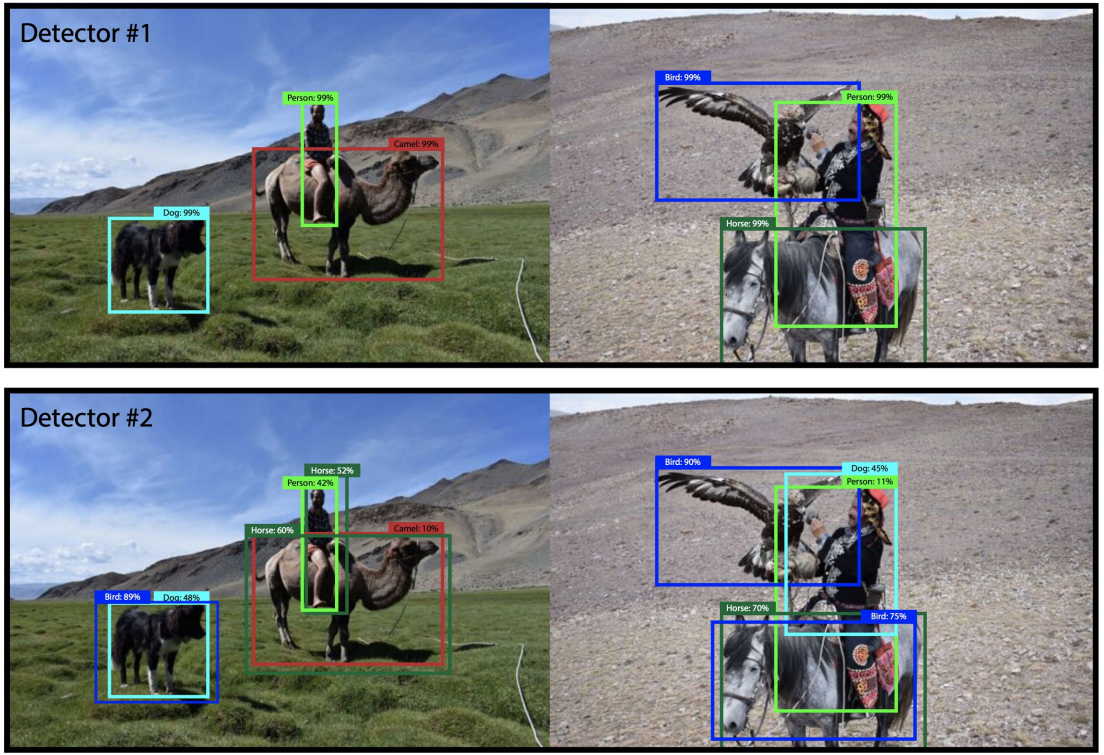


mean Average Precision (mAP)

Problems

These two hypothetical detectors are perfect according to mAP over these two images. They are both perfect. Totally equal

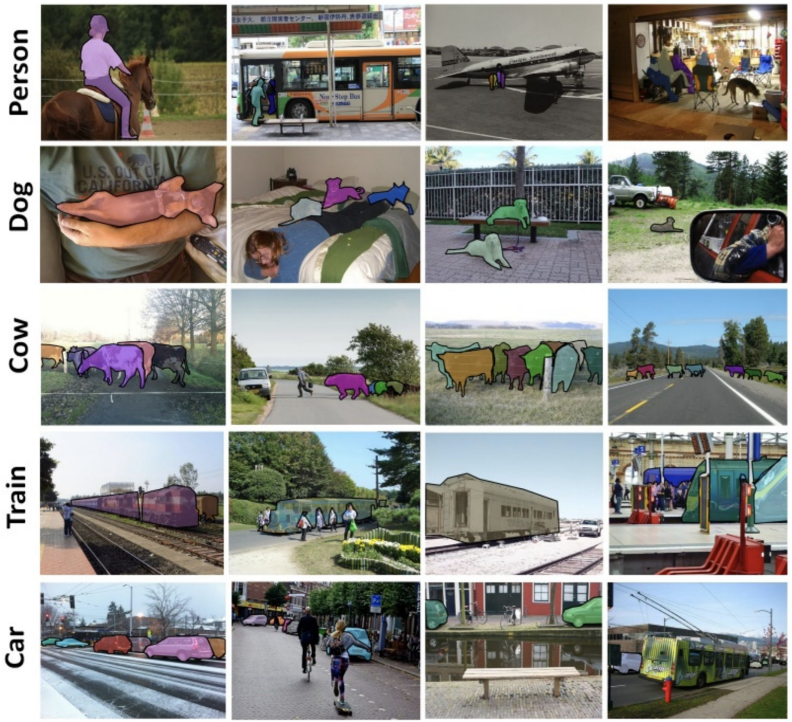
(from YOLOv3 article)

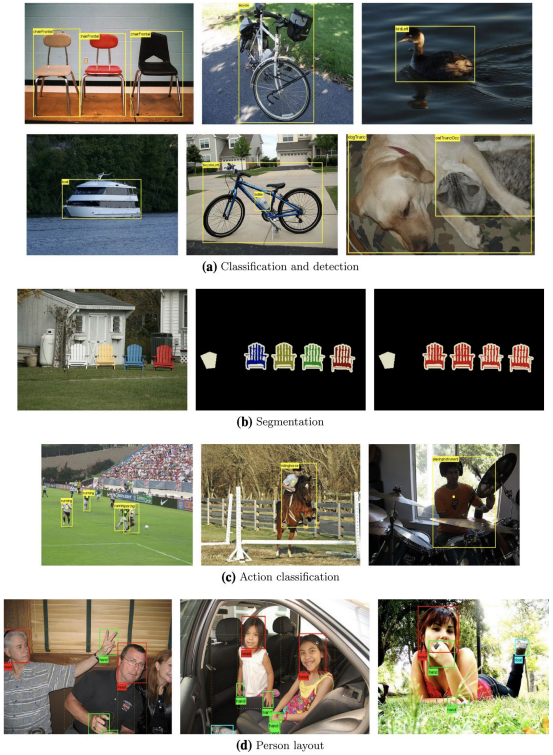


Datasets

Detection datasets

1. PASCAL VOC 2012
2. ImageNet
3. MS COCO 2017
4. Google Open Images v4




(a) Classification and detection

(b) Segmentation

(c) Action classification

(d) Person layout

Thanks to Ilya Zakharkin
for materials

PASCAL VOC 2012

Table 1 The VOC classes

Vehicles	Household	Animals	Other
Aeroplane	Bottle	Bird	Person
Bicycle	Chair	Cat	
Boat	Dining table	Cow	
Bus	Potted plant	Dog	
Car	Sofa	Horse	
Motorbike	TV/Monitor	Sheep	
Train			

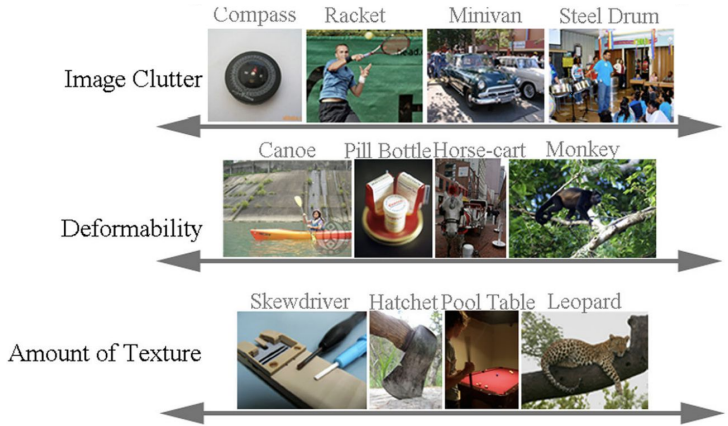
The classes can be considered in a notional taxonomy

Relevant dataset overview:
http://host.robots.ox.ac.uk/pascal/VOC/pubs/everingham15.pdf

- PASCAL Visual Object Classes
- developed since 2005 and 4 classes
- 11,5k images
- 20 classes
- 31,5k detections
- 7k segmentations
- Images came from flickr.com

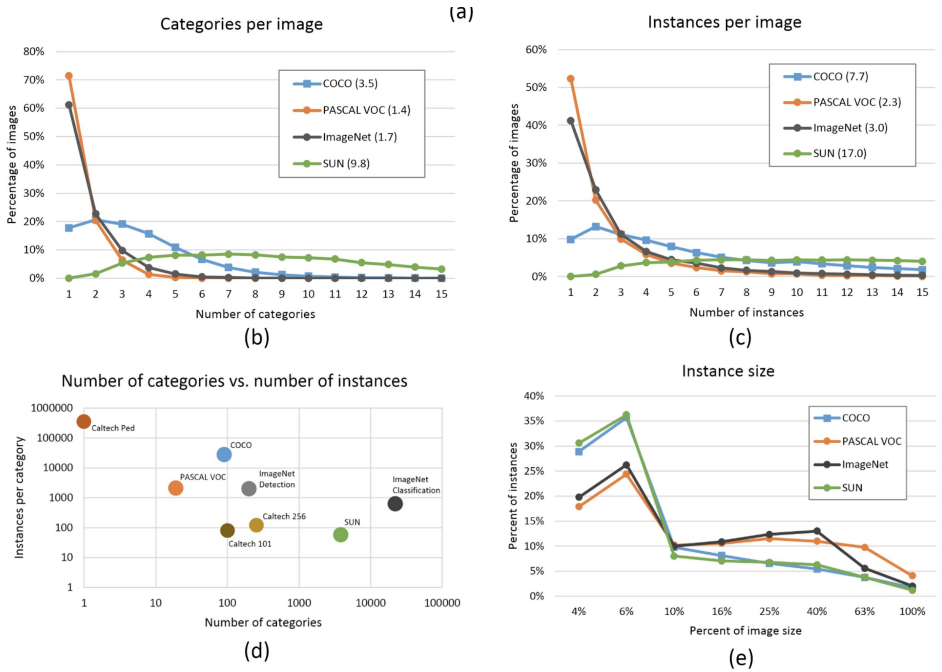
ImageNet

- organized according to the WordNet hierarchy
- 14.2m images
- 1000 classes
- 1m images with BBs
- more fine graded classes than PASCAL
- more diverse objects properties



http://image-net.org/explore

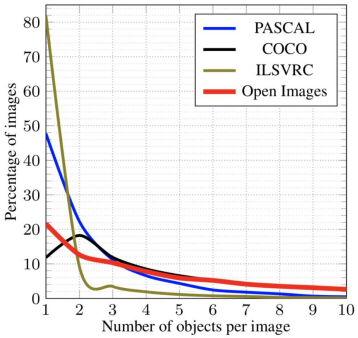
MS COCO 2017

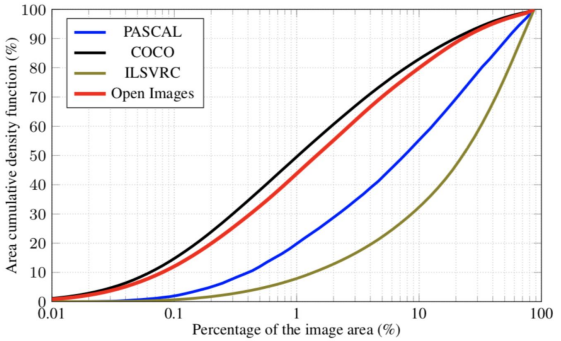


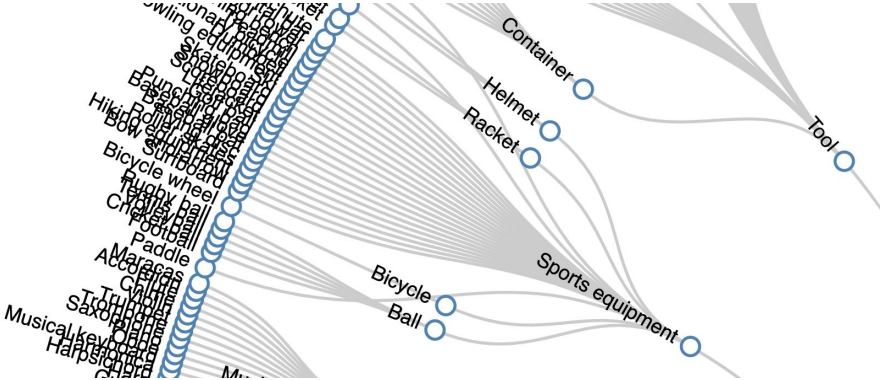
- MicroSoft Common Objects in COntext
- 328k images
- 91 object categories
- 82 having more than 5,000 labeled instances
- 2,5m labeled instances in total
- 250k people with keypoints
- online exploration tool http://cocodataset.org/#explore
- overview https://arxiv.org/pdf/1405.0312.pdf

Open Images

- Currently relevant challenge
- 15m boxes on 600 categories
- 2,8m instance segmentations on 350 categories
- 36,5m image-level labels on 20k categories
- 391k relationship annotations of 329 relationships
- Extension - 478k crowdsourced images with 6k+ categories







https://storage.googleapis.com/openimages/web/factsfigures.html

R-CNN

Detection as Classification

CAT? NO

DOG? NO

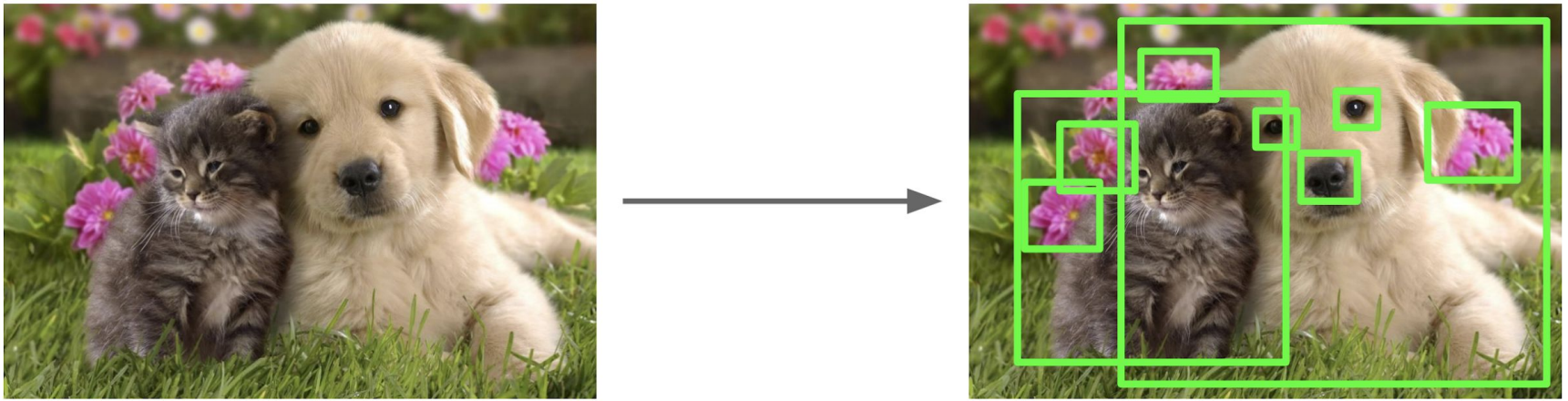
Detection as Classification

CAT? YES!

DOG? NO

Region Proposals

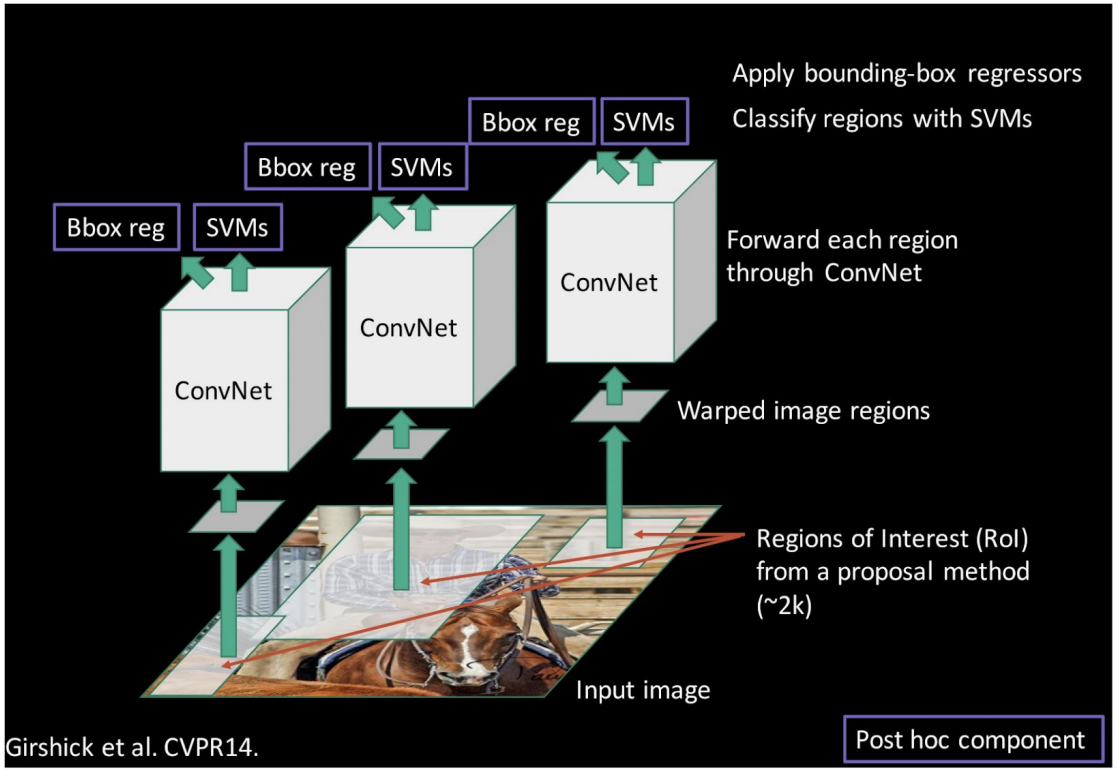
- Find “blobby” image regions that are likely to contain objects
- “Class-agnostic” object detector
- Look for “blob-like” regions



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	·	·	·

Putting it together: R-CNN

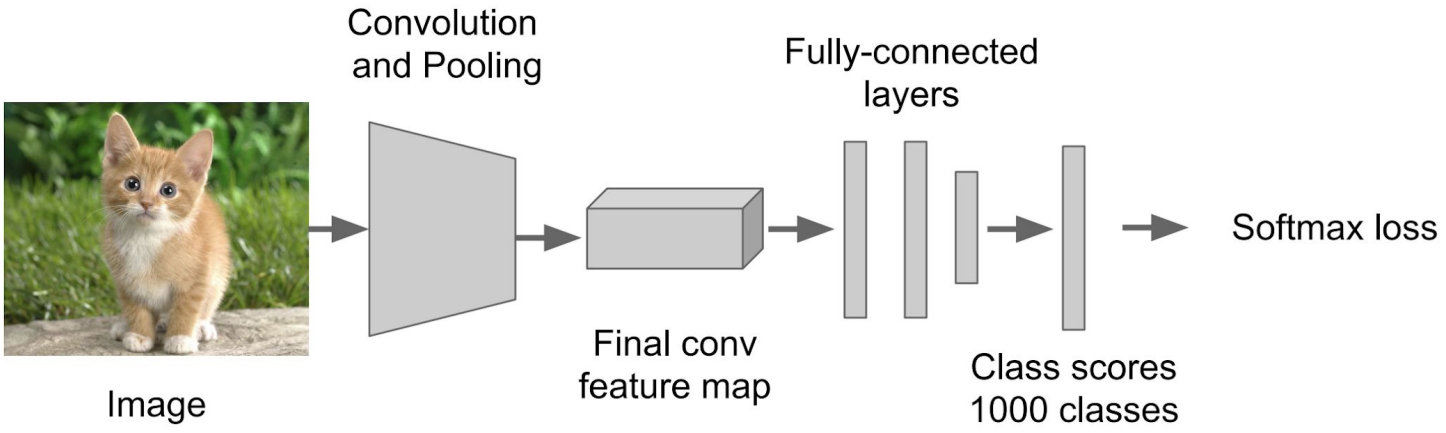


Girschick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014

Slide credit: Ross Girschick

R-CNN Training

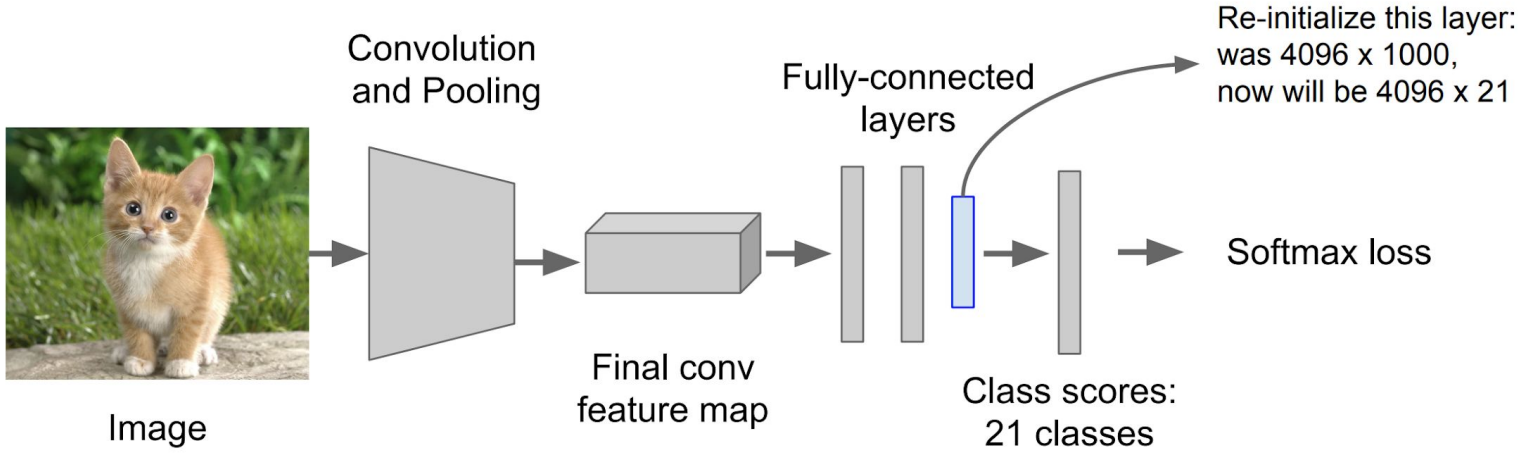
Step 1: Train (or download) a classification model for ImageNet (AlexNet)



R-CNN Training

Step 2: Fine-tune model for detection

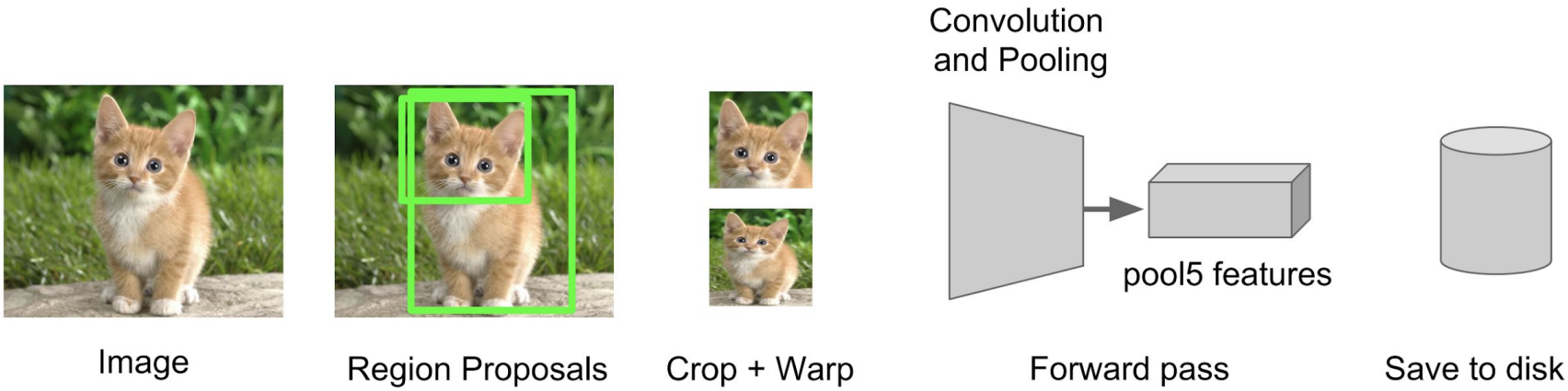
- Instead of 1000 ImageNet classes, want 20 object classes + background
- Throw away final fully-connected layer, reinitialize from scratch
- Keep training model using positive / negative regions from detection images



R-CNN Training

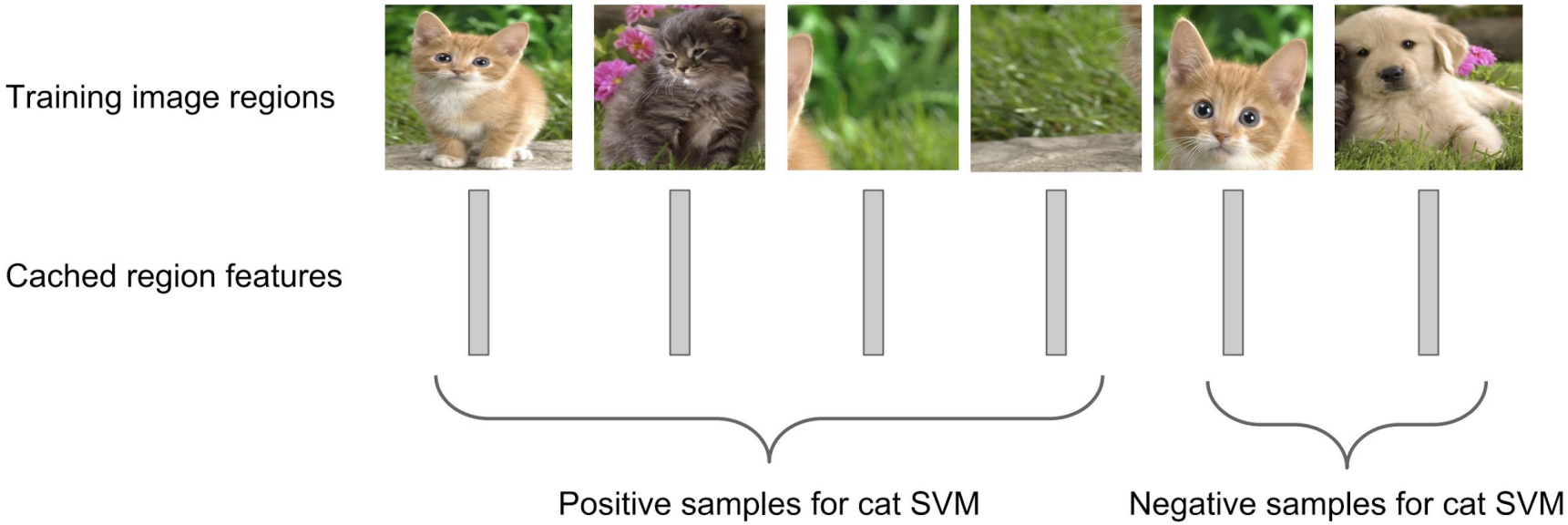
Step 3: Extract features

- 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!



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

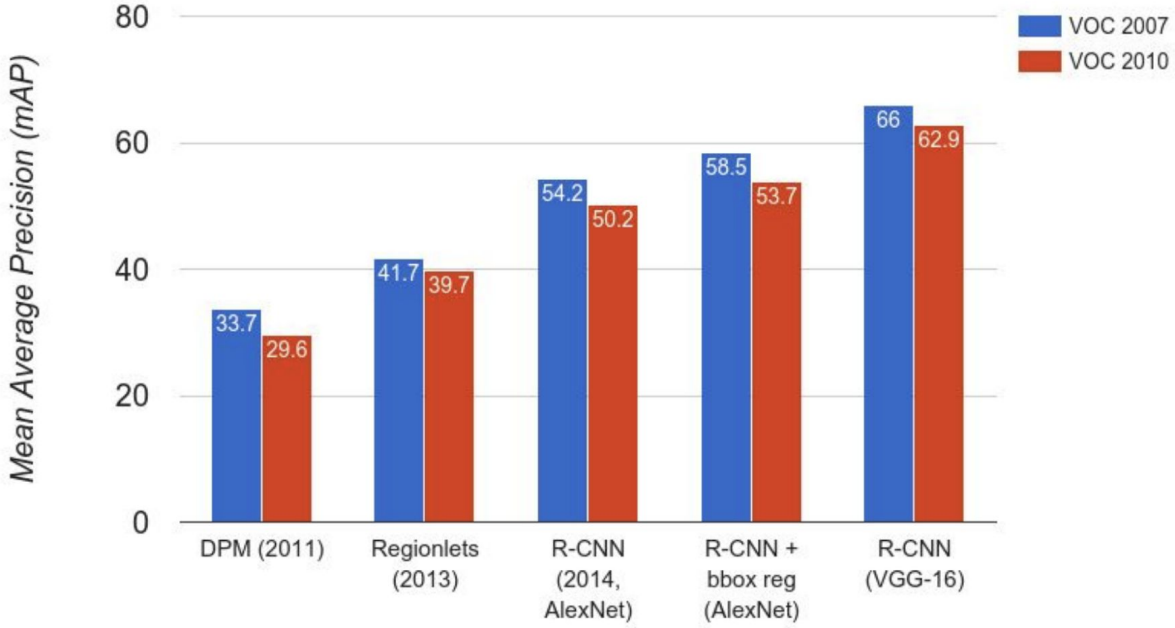
Regression targets
(dx, dy, dw, dh)
Normalized coordinates

(0, 0, 0, 0)
Proposal is good

(.25, 0, 0, 0)
Proposal too far to left

(0, 0, -0.125, 0)
Proposal too wide

R-CNN Results



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

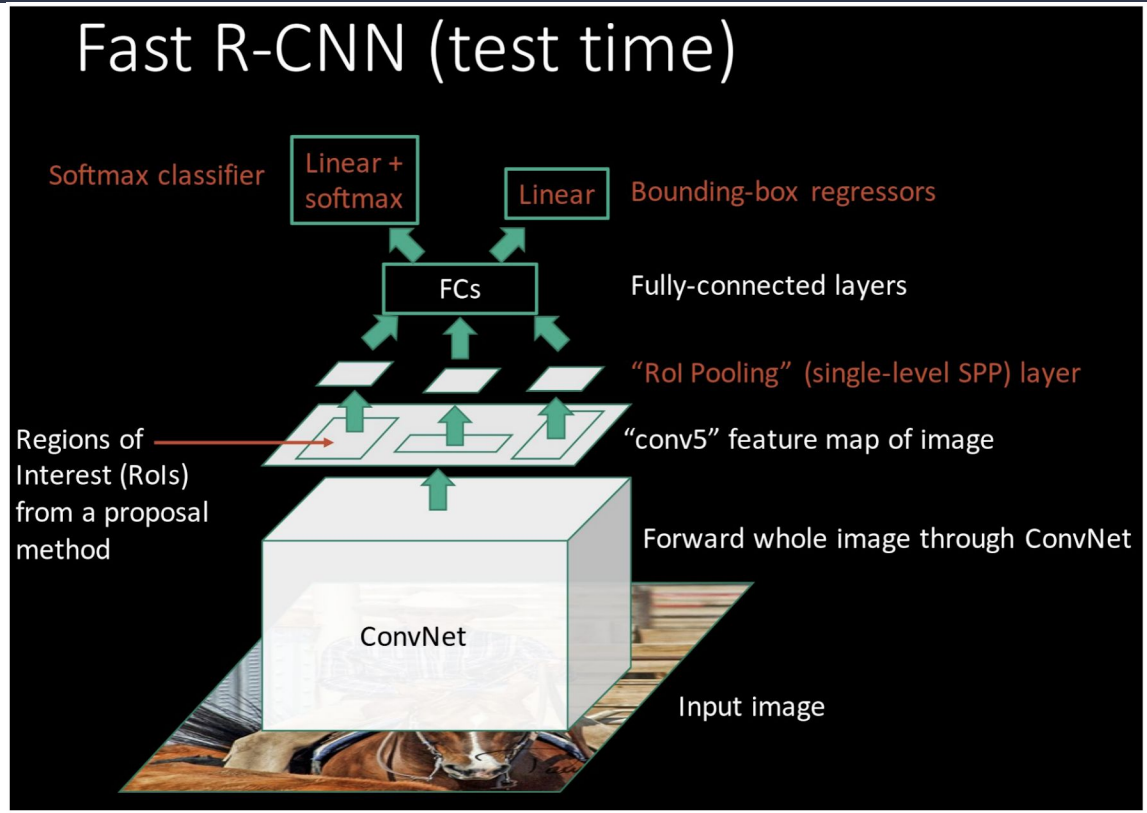
R-CNN Problems

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

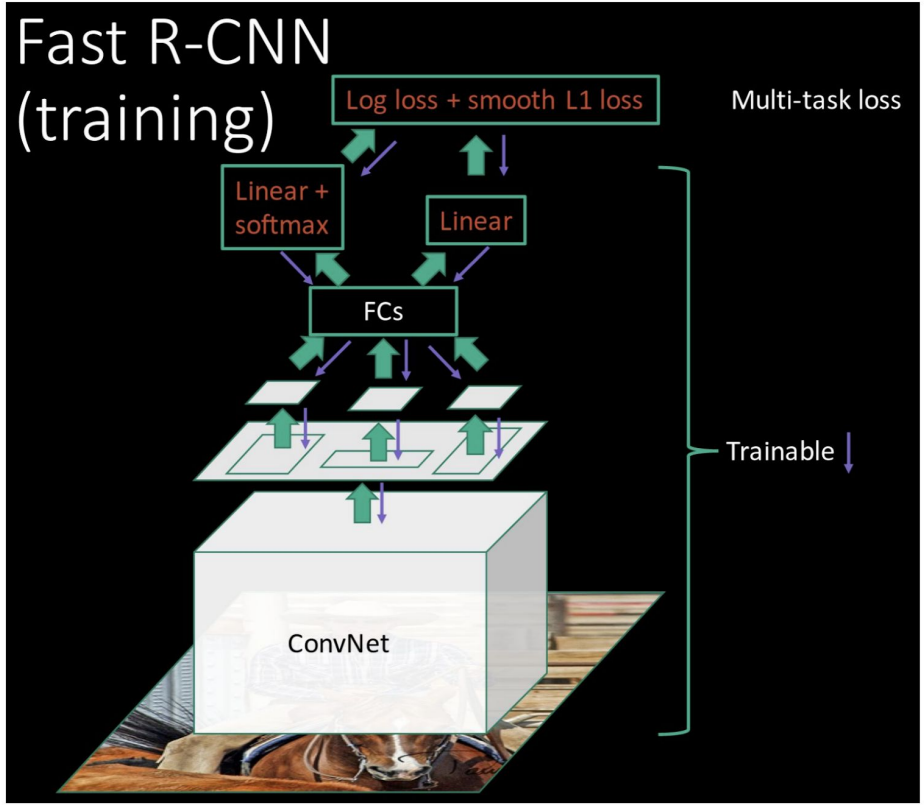
Fast R-CNN



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

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

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

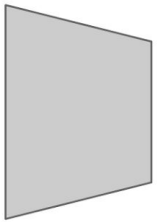
Solution:
Just train the whole system end-to-end all at once!

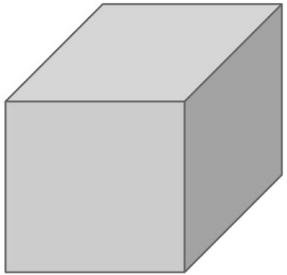
Slide credit: Ross Girschick

Fast R-CNN: Region of Interest Pooling

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

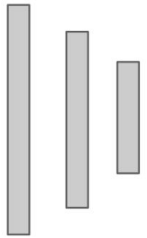
Convolution
and Pooling





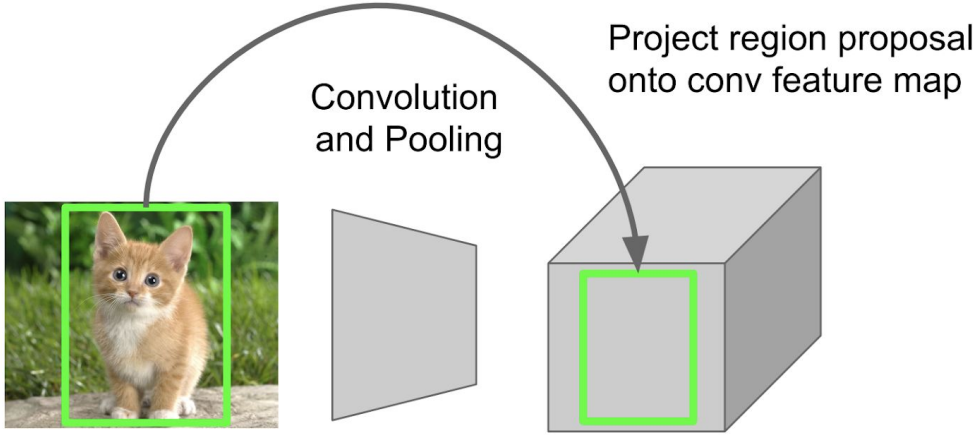
Hi-res conv features:
C x H x W
with region proposal

Fully-connected
layers



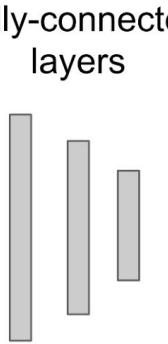
Problem: Fully-connected
layers expect low-res conv
features: C x h x w

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

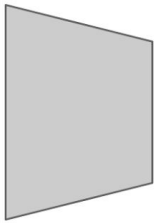


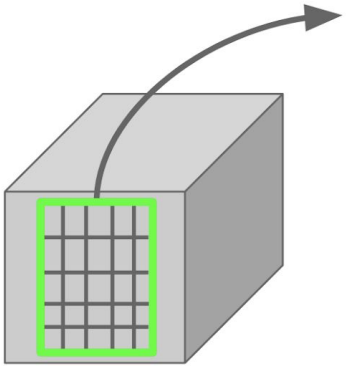
Problem: Fully-connected layers expect low-res conv features: C x h x w

Fast R-CNN: Region of Interest Pooling

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

Convolution
and Pooling

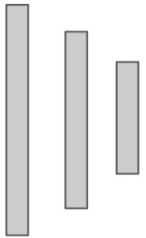




Divide projected
region into h x w grid

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

Fully-connected
layers

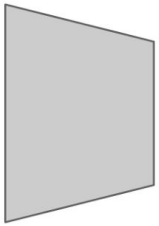


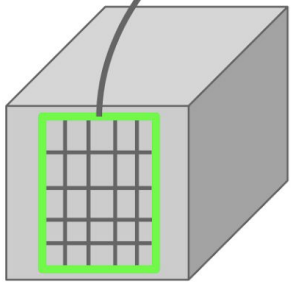
Problem: Fully-connected
layers expect low-res conv
features: C x h x w

Fast R-CNN: Region of Interest Pooling

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

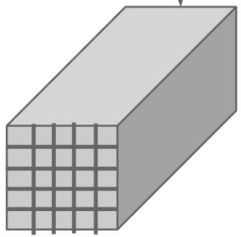
Convolution
and Pooling





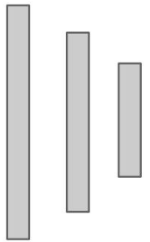
Hi-res conv features:
C x H x W
with region proposal

Max-pool within
each grid cell



RoI conv features:
C x h x w
for region proposal

Fully-connected
layers

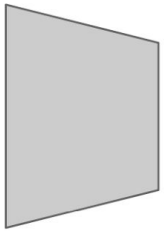


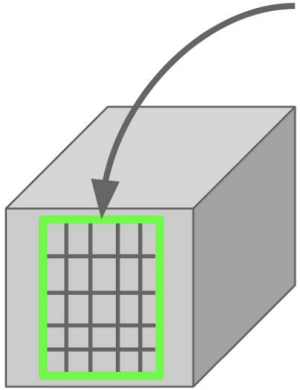
Fully-connected layers expect
low-res conv features:
C x h x w

Fast R-CNN: Region of Interest Pooling

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

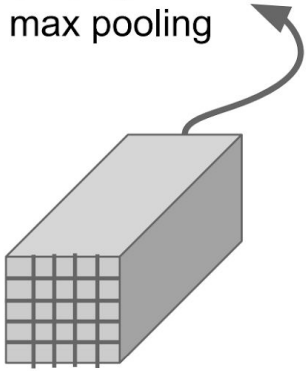
Convolution
and Pooling





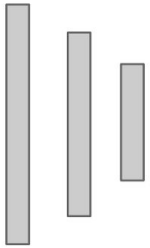
Hi-res conv features:
C x H x W
with region proposal

Can back propagate
similar to max pooling



RoI conv features:
C x h x w
for region proposal

Fully-connected
layers



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

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**
mAP (VOC 2007)	66.0	**66.9**

Faster!

FASTER!

Better!

Using VGG-16 CNN on Pascal VOC 2007 dataset

Fast R-CNN Problem

Test-time speeds don't include region proposals

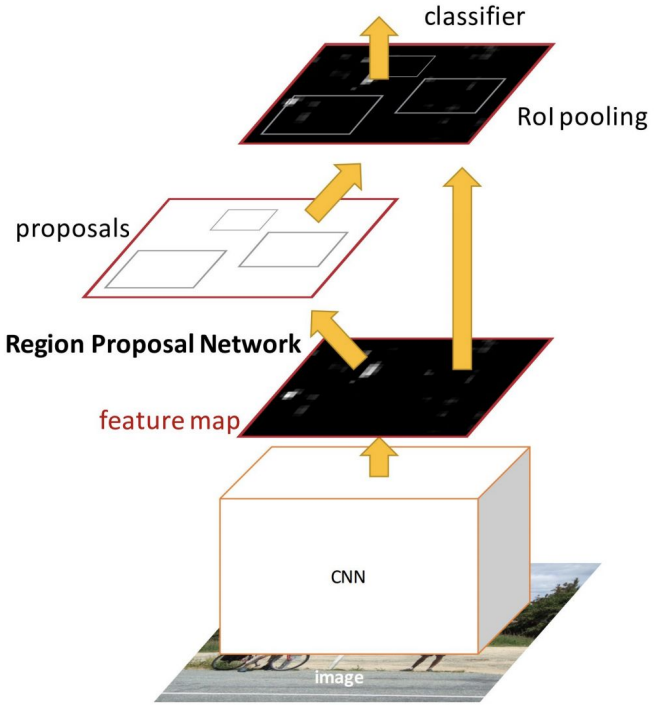
	R-CNN	**Fast R-CNN**
Test time per image	47 seconds	**0.32 seconds**
(Speedup)	1x	**146x**
Test time per image with Selective Search	50 seconds	**2 seconds**
(Speedup)	1x	**25x**

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	**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

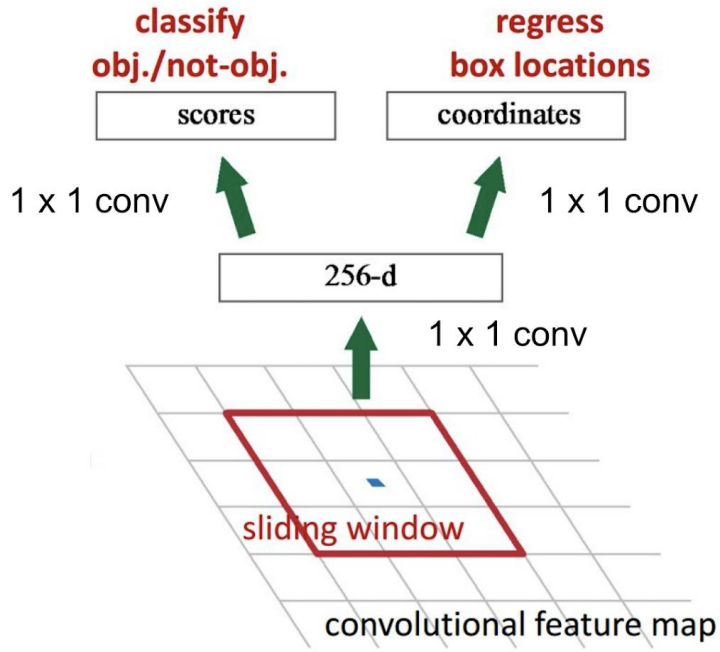
Faster R-CNN: Region Proposal Network

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

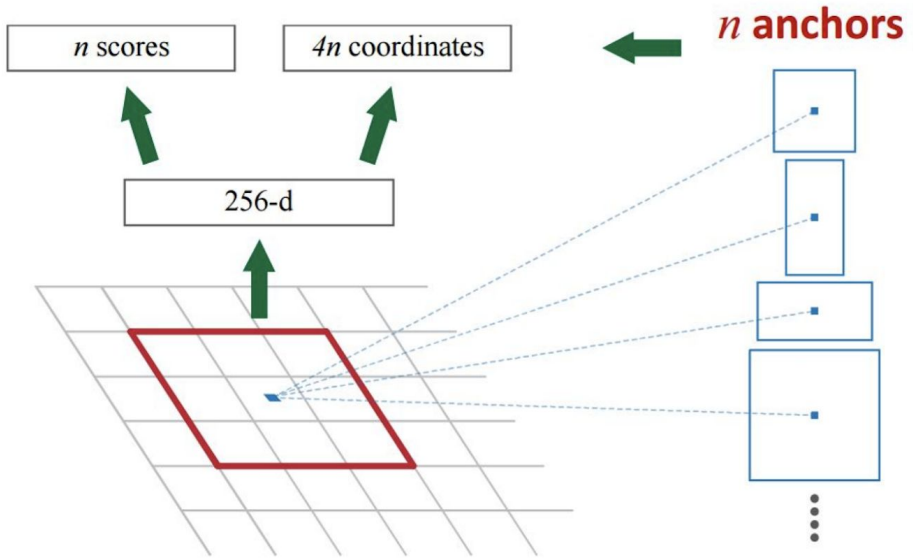
Faster R-CNN: Region Proposal Network

Use **N anchor boxes** at each location

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

Regression gives offsets from anchor boxes

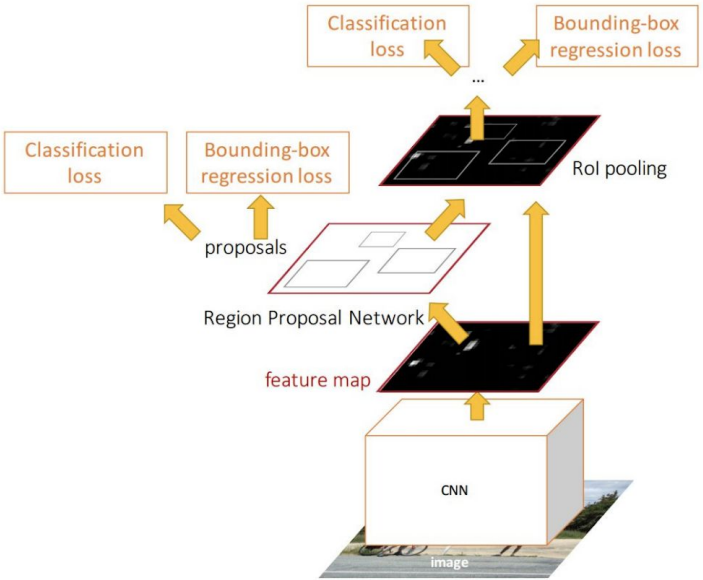
Classification gives the probability that each (regressed) anchor shows an object



Faster R-CNN: 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)

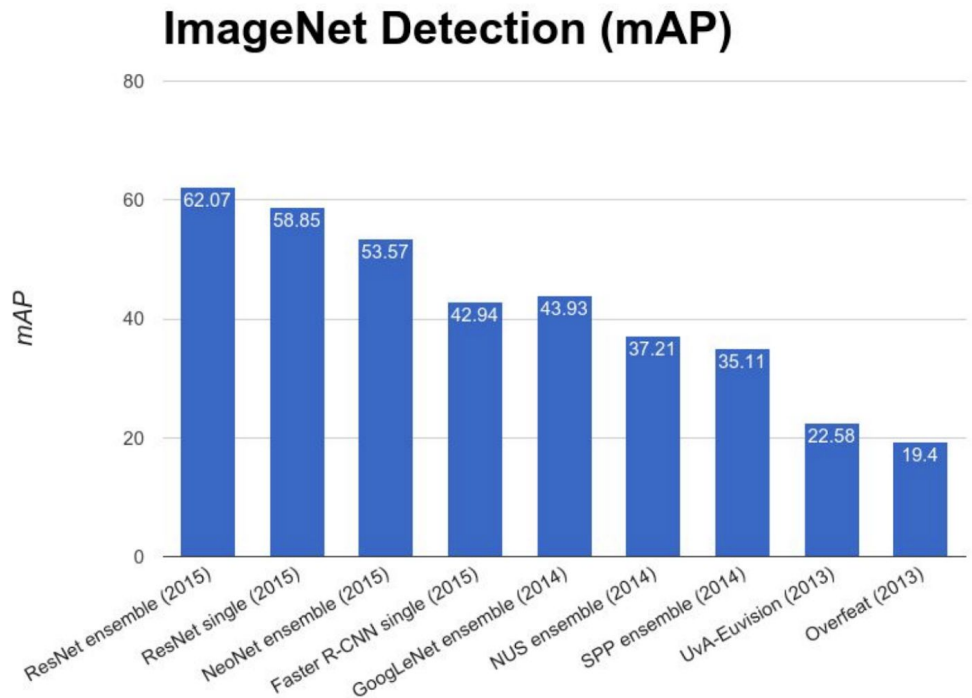


Slide credit: Ross Girschick

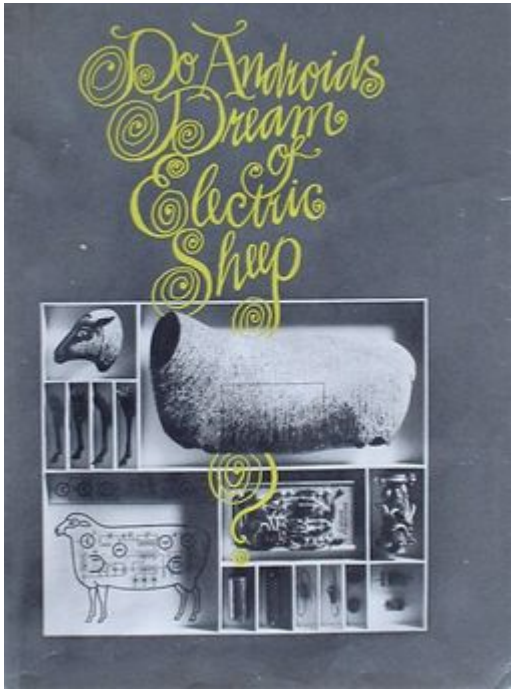
Faster R-CNN: Results

	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**

ImageNet Detection 2013 - 2015



More CV to come...



Next time will:

- try to Only Look Once at an image
- know Do Androids Dream of Electric Sheep?