CSE428: Image Processing

Lecture 15

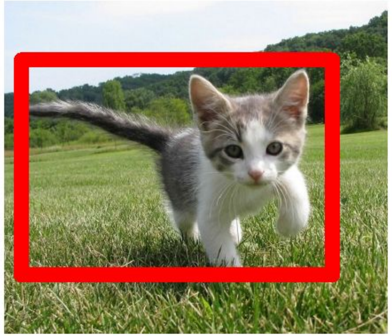
Object Detection

Image Recognition Problems

Classification

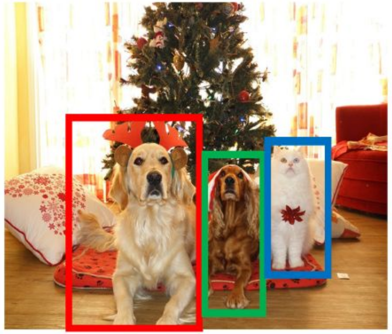
[{CAT}]

Classification + Localization



[{CAT, (x, y, h, w)}]

Object Detection



[{DOG, (x, y, h, w)},
{DOG, (x, y, h, w)},
{CAT, (x, y, h, w)}]

Object Detection Methods

Methods for object detection generally fall into either neural network-based or non-neural approaches.

1. Non-neural approaches:
   - Viola–Jones object detection framework based on Haar features
   - Scale-invariant feature transform (SIFT)
   - Histogram of oriented gradients (HOG) features
2. Neural network approaches:
   - Region Proposals (R-CNN, Fast R-CNN, Faster R-CNN)
   - Single Shot MultiBox Detector (SSD)
   - You Only Look Once (YOLO)

https://en.wikipedia.org/wiki/Object_detection

Non-neural Object Detection Methods

Non-neural approaches:

- Viola–Jones object detection framework based on Haar features
- Scale-invariant feature transform (SIFT)
- Histogram of oriented gradients (HOG) features

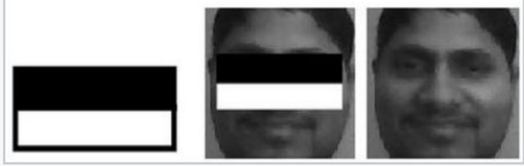
For non-neural approaches, it becomes necessary to first define **features** (which are preferably: **scale, position, rotation & lighting invariant**) using one of the methods above, then using a technique such as support vector machine (SVM) to do the classification.

Viola-Jones Algorithm (Face Detection)

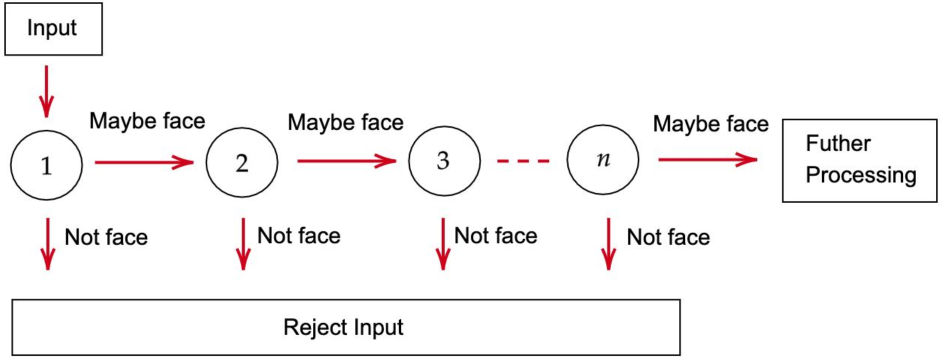
The algorithm has four stages:

1. Haar Feature Selection
2. Creating an Integral Image
3. Adaboost Training
4. Cascading Classifiers

Haar Feature that looks similar to the bridge of the nose is applied onto the face



Haar Feature that looks similar to the eye region which is darker than the upper cheeks is applied onto a face



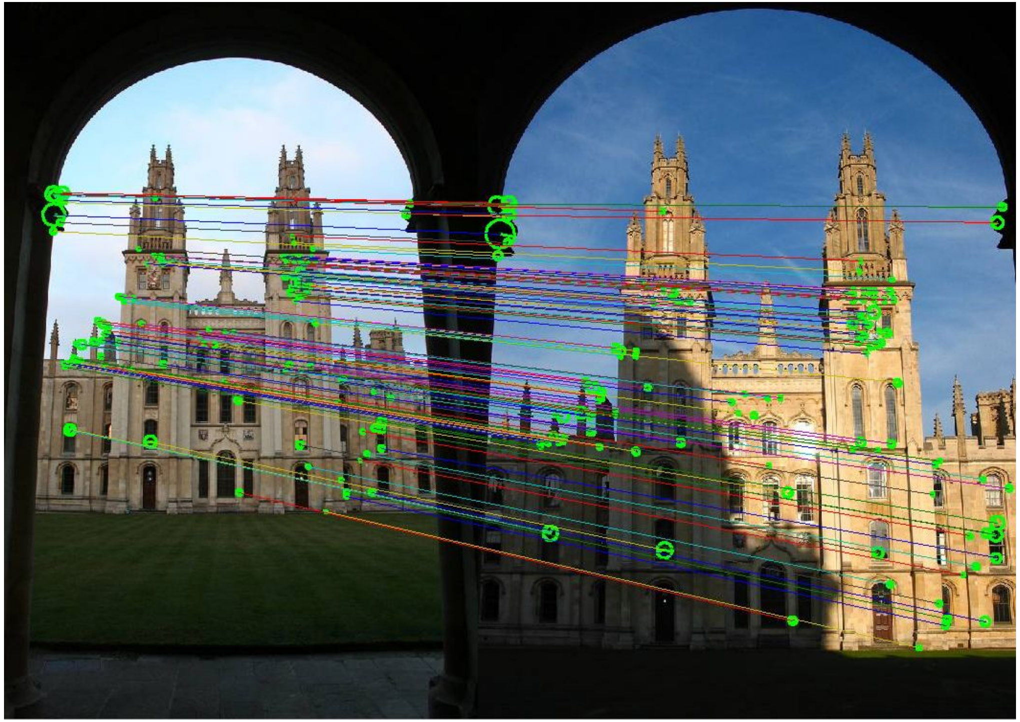
Scale invariant: zoom in/out in your selfie camera?
Rotation invariant: ?
Lighting: ?
Position: ?

https://en.wikipedia.org/wiki/Viola%E2%80%93Jones_object_detection_framework

Scale-invariant feature transform (SIFT)

SIFT **keypoints** of objects are first extracted from a set of reference images and stored in a database.

An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their **feature vectors**.

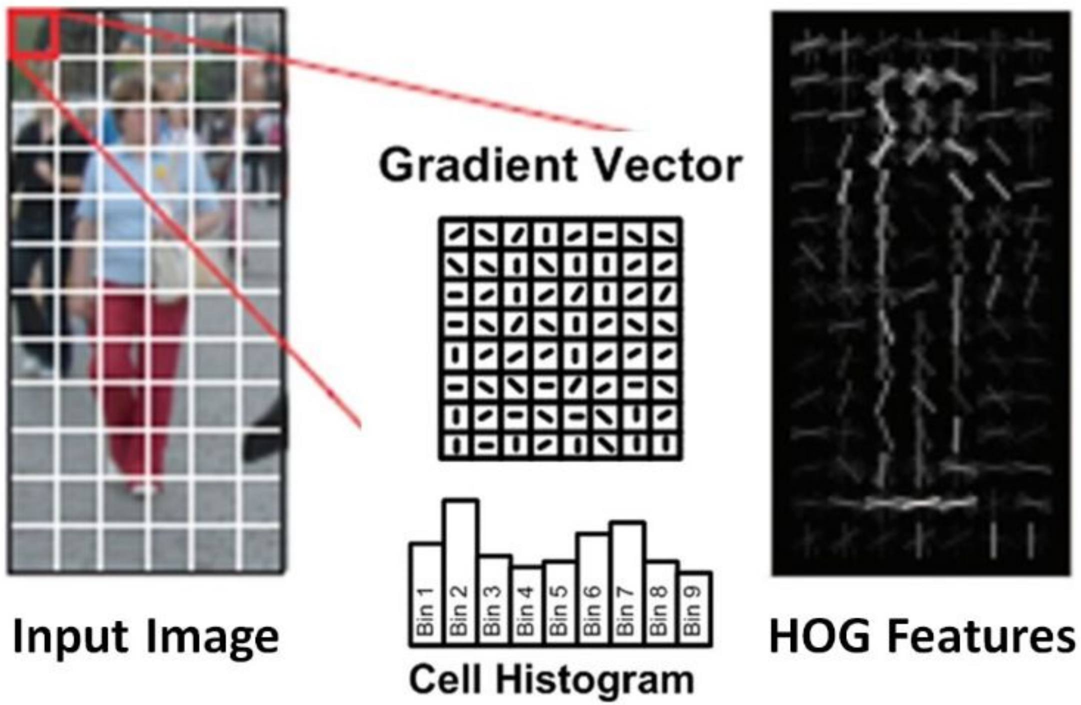


https://en.wikipedia.org/wiki/Scale-invariant_feature_transform

Histogram of oriented gradients (HOG)

Local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions.

The image is divided into small connected regions called cells, and for the pixels within each cell, a histogram of gradient directions is compiled. The descriptor is the concatenation of these histograms.



https://en.wikipedia.org/wiki/Histogram_of_oriented_gradients

Deep Learning Based Object Detection Methods

Neural network approaches:

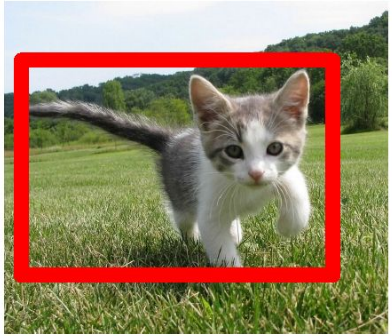
- Region Proposals (R-CNN, Fast R-CNN, Faster R-CNN)
- Single Shot MultiBox Detector (SSD)
- You Only Look Once (YOLO)

neural techniques are able to do end-to-end object detection without specifically defining features, and are typically based on convolutional neural networks (CNN).

Classification + Localization

Only applicable when there is **one object/image**!

Classification + Localization



[{CAT, (x, y, h, w)}]

Classification + Localization

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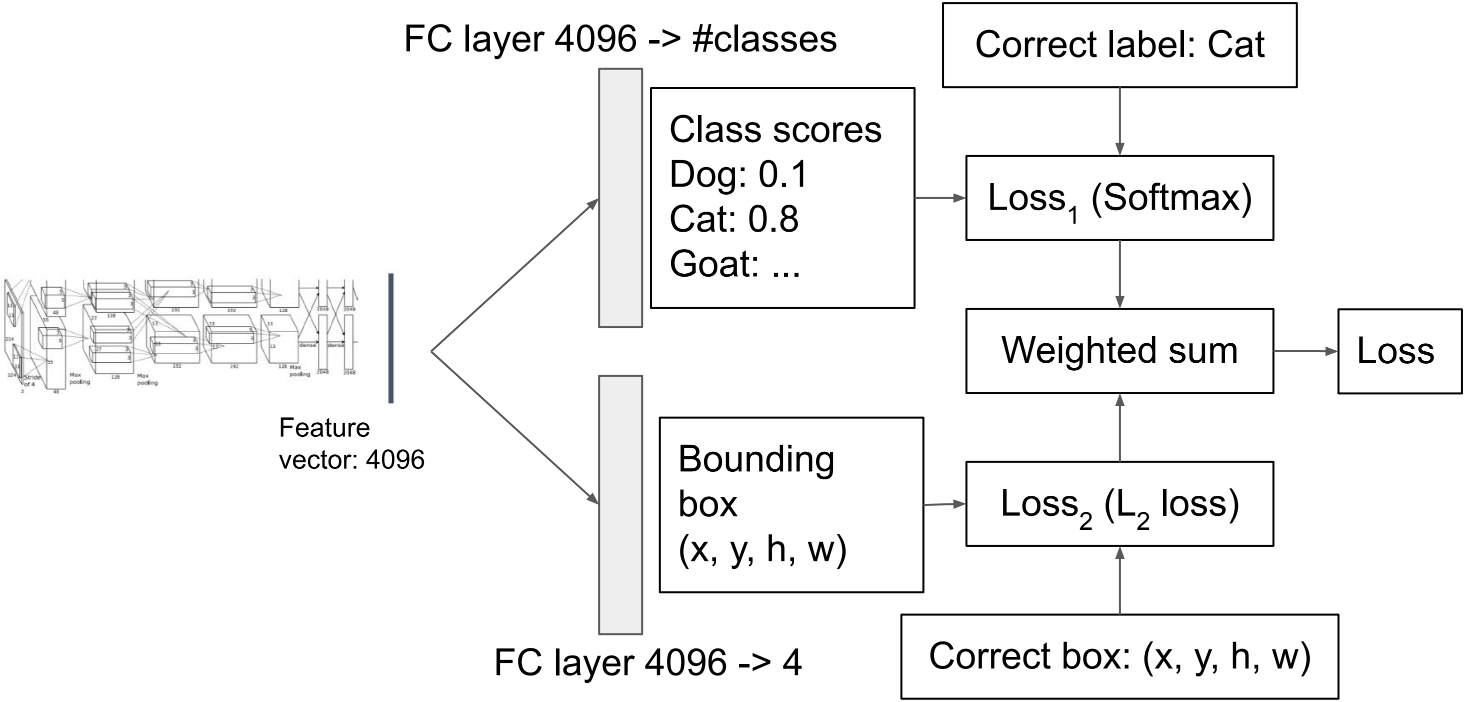

Classification + Localization

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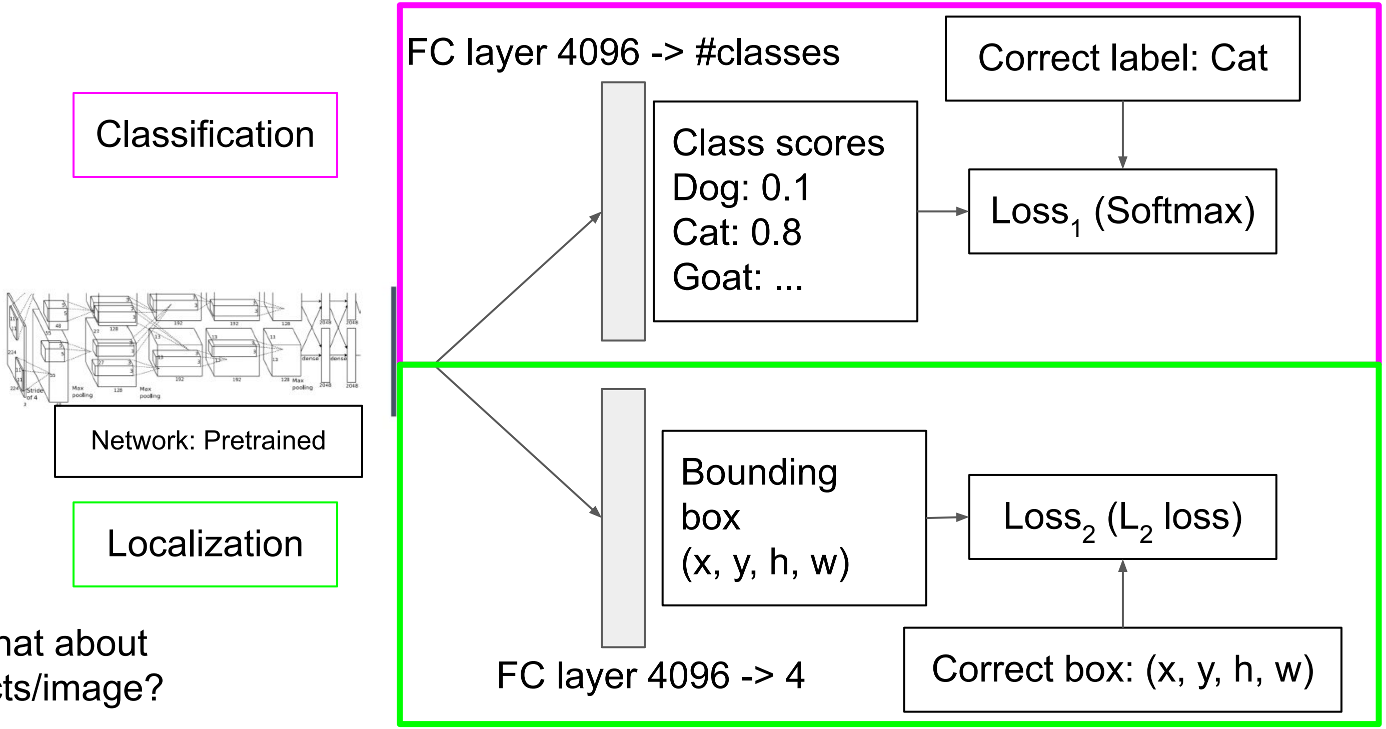


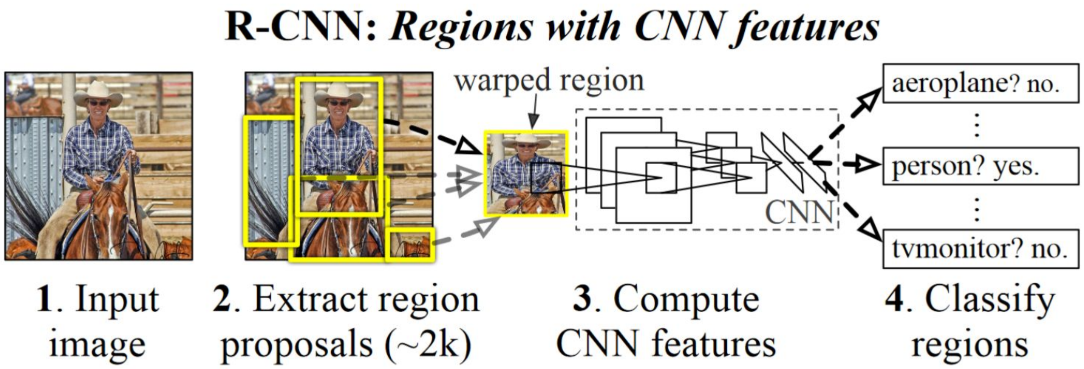
Question: What about multiple objects/image?

For multiple objects/image this algorithm would be highly inefficient!

Region-based CNN (R-CNN)

Region-based CNN

1. takes an input image
2. extracts around 2000 bottom-up region proposals
3. computes features for each proposal using a large CNN
4. classifies each region using class-specific linear SVMs

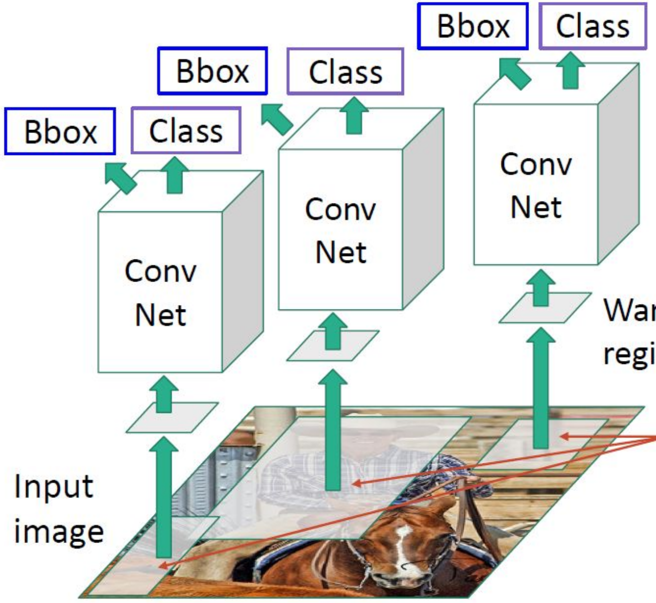


- R-CNN achieves a mean average precision (mAP) of 53.7% on PASCAL VOC 2010.
- On the 200-class ILSVRC 2013 detection dataset, R-CNN's mAP is 31.4%

https://arxiv.org/abs/1311.2524

R-CNN

Bounding box regression



Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)

Region proposal: (p_x, p_y, p_h, p_w)
Transform: (t_x, t_y, t_h, t_w)
Output box: (b_x, b_y, b_h, b_w)

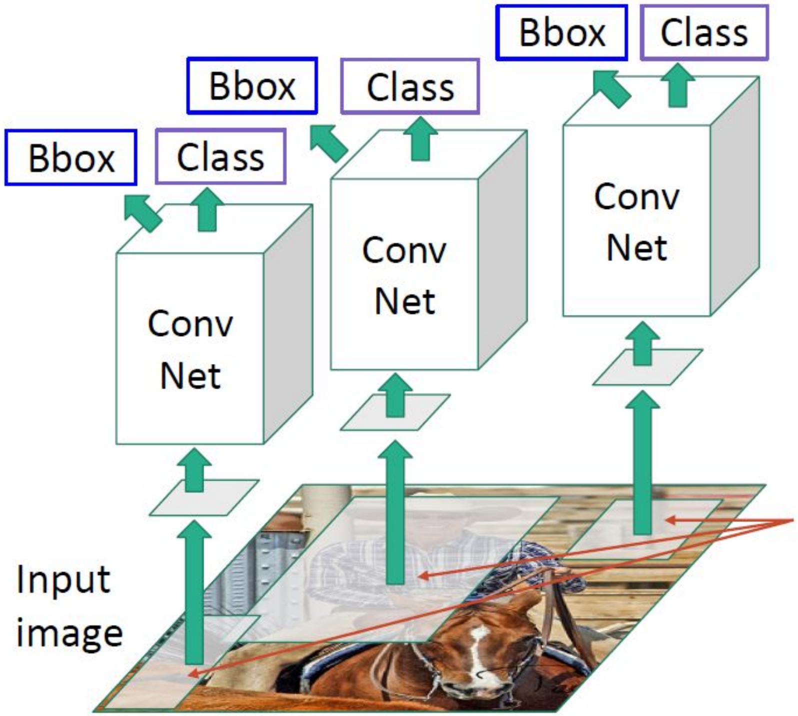
Translate relative to box size:
$b_x = p_x + p_w t_x$ $\quad$ $b_y = p_y + p_h t_y$

Log-space scale transform:
$b_w = p_w \exp(t_w)$ $\quad$ $b_h = p_h \exp(t_h)$

R-CNN

Inference time: for an RGB input image

1. Run region proposal method to compute ~2000 region proposals
2. Resize each region to 224x224 and run independently through CNN to predict **class scores** and **bbox transform**
3. Use scores to **filter** a subset of region proposals to output
4. *Compare* with ground-truth boxes

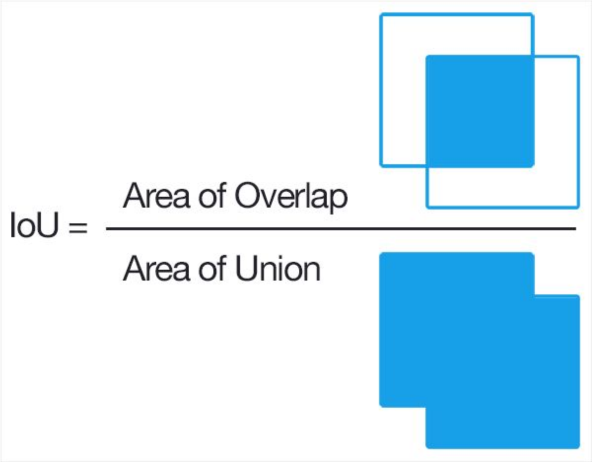


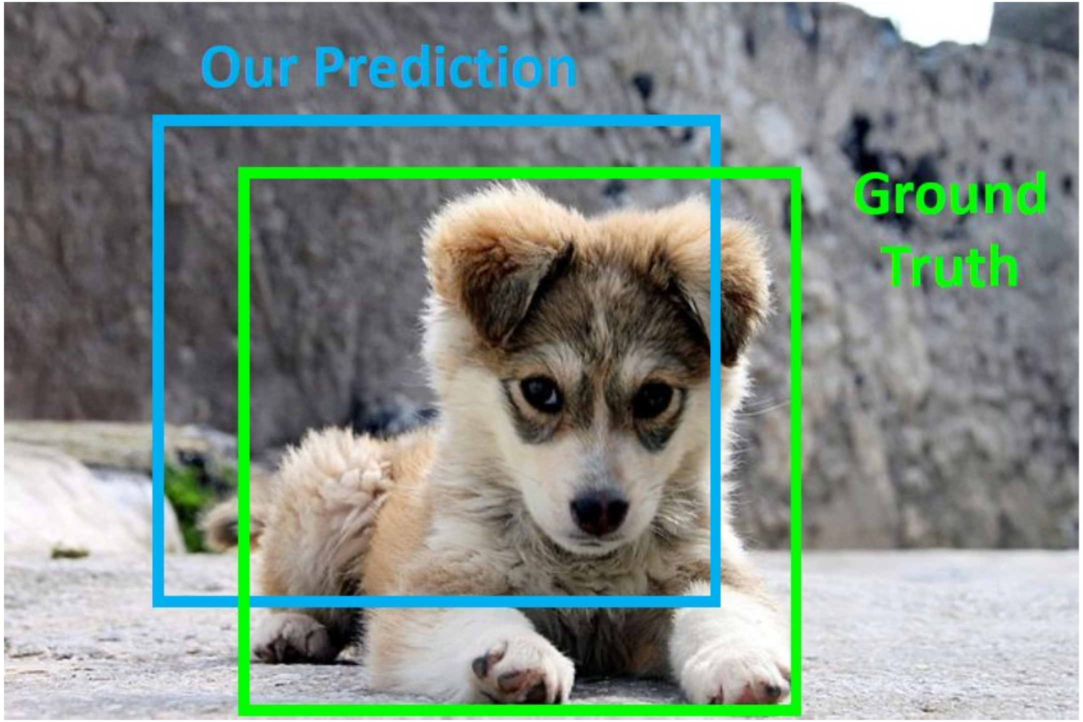
How to evaluate predictions for object detection?

Concept: IoU

How to compare the quality of bounding box prediction?

Intersection over Union (IoU)

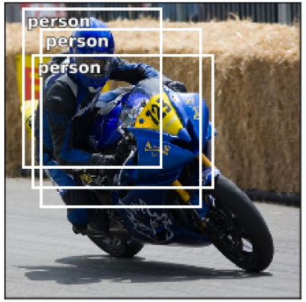




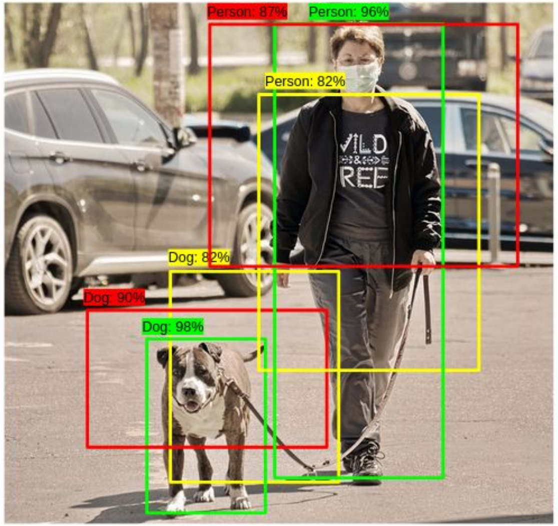
Concept: Non Max Suppression (NMS)

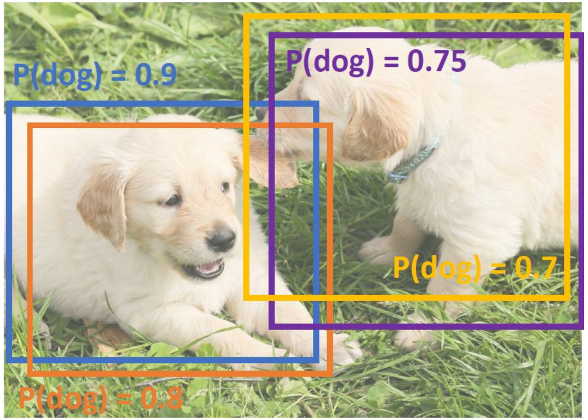
Model usually outputs multiple redundant boxes per object

For each class...



After filtering out low confidence predictions, we may still be left with ***redundant*** **detections**



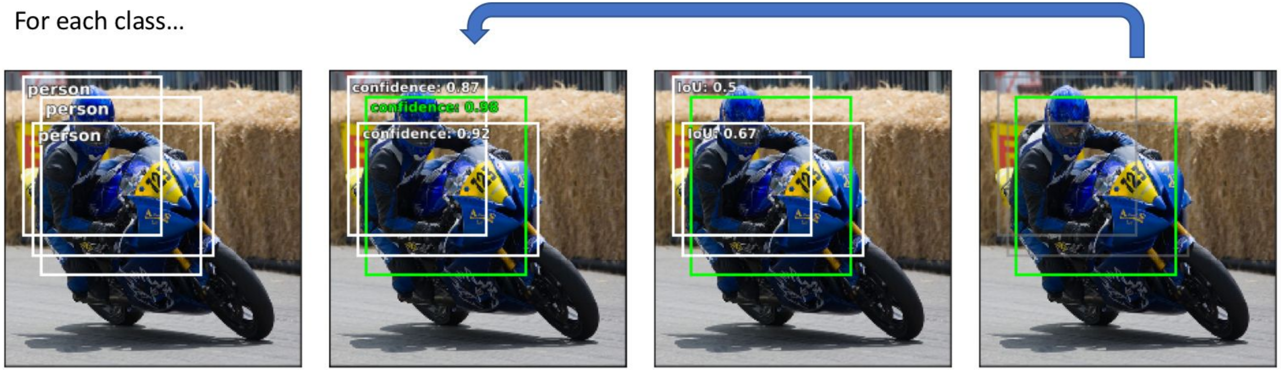


Concept: Non Max Suppression (NMS)

Apply NMS

Repeat with next highest confidence prediction until no more boxes are being suppressed

For each class...



After filtering out low confidence predictions, we may still be left with ***redundant* detections**

Select the bounding box prediction with the **highest confidence**

Calculate the IoU between the **selected box** and all remaining predictions

Remove any boxes which have an IoU score above some defined threshold

Concept: Non Max Suppression (NMS)

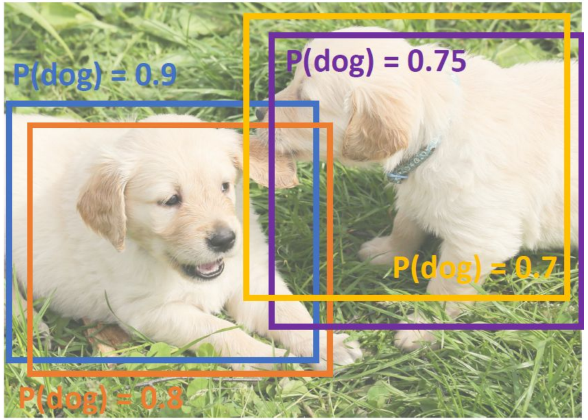
NMS Algorithm

Pseudocode

```
sorted_boxes = sort_boxes_by_confidence(boxes)
ids_to_suppress = []

for maximum_box in sorted_boxes:
    for idx, box in enumerate(boxes):
        iou = compute_iou(maximum_box, box)
        if iou > iou_threshold:
            ids_to_suppress.append(idx)

processed_boxes = np.delete(boxes, ids_to_suppress)
```



Concept: TP, FP, FN, P, R

True positive (TP): A correct detection. Detection with IoU ≥ threshold

False positive (FP): An incorrect detection of a nonexistent object or a misplaced detection of an existing object. Detection with IoU < threshold

False negative (FN): An undetected ground-truth bounding box

Precision (P): TP / (TP + FP) = TP / All detections

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} = \frac{\mathrm{TP}}{\text{all detections}},$$

Recall (R): TP / (TP + TN) = TP / All ground truths

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} = \frac{\mathrm{TP}}{\text{all ground truths}}.$$

Concept: AP

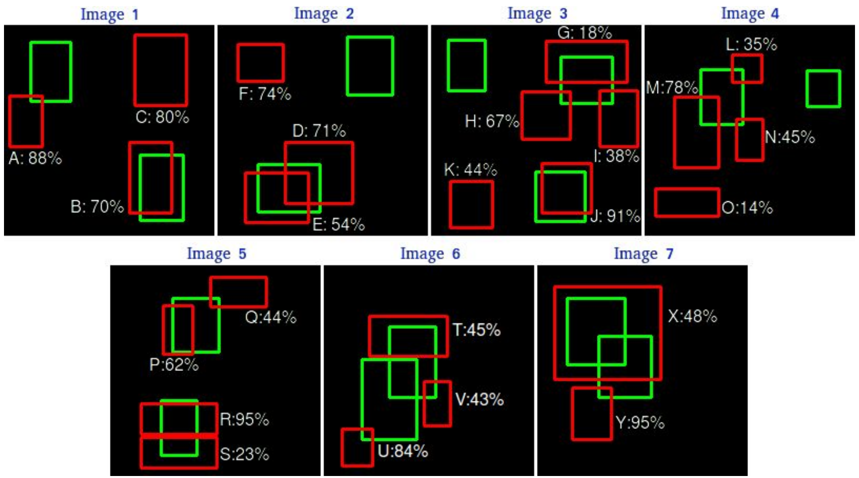
Average Precision (AP):

For *each* detection of a **single category** (highest score to lowest score)

1. If it matches some GT box with IoU > **0.5**, mark it as true positive (TP) and eliminate the GT
2. Otherwise mark it as negative (FP)
3. Plot a point on PR Curve
4. Average Precision (AP) = area under PR curve

Concept: AP

There are 7 images with 15 ground truth objects represented by the green bounding boxes and 24 detected objects represented by the red bounding boxes. Each detected object has a confidence level and is identified by a letter (A,B,...,Y).



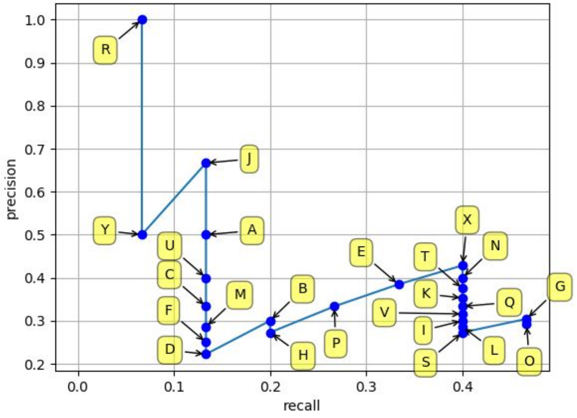
Images	Detections	Confidences	TP or FP
Image 1	A	88%	FP
Image 1	B	70%	TP
Image 1	C	80%	FP
Image 2	D	71%	FP
Image 2	E	54%	TP
Image 2	F	74%	FP
Image 3	G	18%	TP
Image 3	H	67%	FP
Image 3	I	38%	FP
Image 3	J	91%	TP
Image 3	K	44%	FP
Image 4	L	35%	FP
Image 4	M	78%	FP
Image 4	N	45%	FP
Image 4	O	14%	FP
Image 5	P	62%	TP
Image 5	Q	44%	FP
Image 5	R	95%	TP
Image 5	S	23%	FP
Image 6	T	45%	FP
Image 6	U	84%	FP
Image 6	V	43%	FP
Image 7	X	48%	TP
Image 7	Y	95%	FP

The following table shows the bounding boxes with their corresponding confidences. The last column identifies the detections as TP or FP. In this example a TP is considered if IoU 30%, otherwise it is a FP.

https://github.com/rafaelpadilla/Object-Detection-Metrics

Concept: AP

- First we need to order the detections by their confidences, then we calculate the precision and recall for each accumulated detection.
- Plotting the precision and recall values we have the following Precision vs. Recall curve



Images	Detections	Confidences	TP	FP	Acc TP	Acc FP	Precision	Recall
Image 5	R	95%	1	0	1	0	1	0.0666
Image 7	Y	95%	0	1	1	1	0.5	0.0666
Image 3	J	91%	1	0	2	1	0.6666	0.1333
Image 1	A	88%	0	1	2	2	0.5	0.1333
Image 6	U	84%	0	1	2	3	0.4	0.1333
Image 1	C	80%	0	1	2	4	0.3333	0.1333
Image 4	M	78%	0	1	2	5	0.2857	0.1333
Image 2	F	74%	0	1	2	6	0.25	0.1333
Image 2	D	71%	0	1	2	7	0.2222	0.1333
Image 1	B	70%	1	0	3	7	0.3	0.2
Image 3	H	67%	0	1	3	8	0.2727	0.2
Image 5	P	62%	1	0	4	8	0.3333	0.2666
Image 2	E	54%	1	0	5	8	0.3846	0.3333
Image 7	X	48%	1	0	6	8	0.4285	0.4
Image 4	N	45%	0	1	6	9	0.4	0.4
Image 6	T	45%	0	1	6	10	0.375	0.4
Image 3	K	44%	0	1	6	11	0.3529	0.4
Image 5	Q	44%	0	1	6	12	0.3333	0.4
Image 6	V	43%	0	1	6	13	0.3157	0.4
Image 3	I	38%	0	1	6	14	0.3	0.4
Image 4	L	35%	0	1	6	15	0.2857	0.4
Image 5	S	23%	0	1	6	16	0.2727	0.4
Image 3	G	18%	1	0	7	16	0.3043	0.4666
Image 4	O	14%	0	1	7	17	0.2916	0.4666

https://github.com/rafaelpadilla/Object-Detection-Metrics

Concept: mAP

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve
3. Mean Average Precision (mAP) = average of AP for each category

Car AP = 0.65

Cat AP = 0.80

Dog AP = 0.86

mAP@**0.5** = 0.77

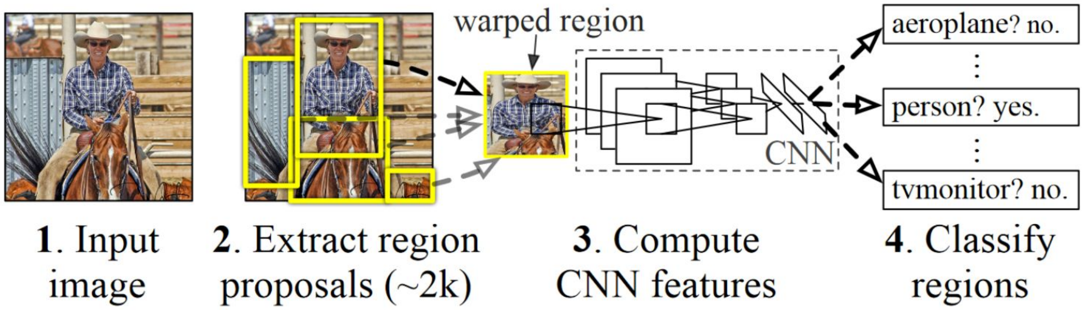
If a prediction matches some GT box with IoU > **0.5**, mark it as true positive (TP) and eliminate the GT

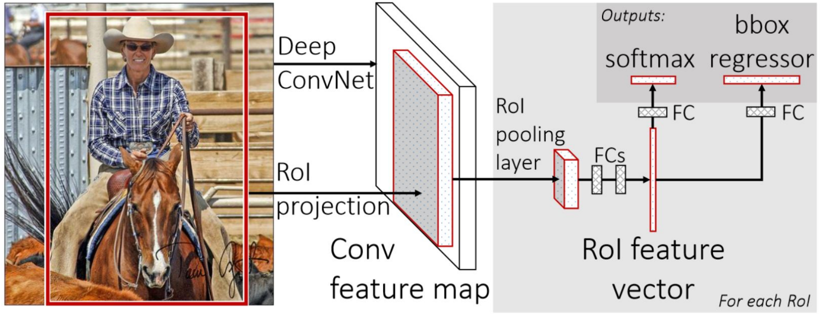
Region-based CNN (R-CNN)

Problem

Very slow because computing CNN feature maps for ~2k region proposals

Workaround: what if instead of passing each region proposals through a CNN, we first compute the feature map for the whole image and use projected region proposals onto the feature map?

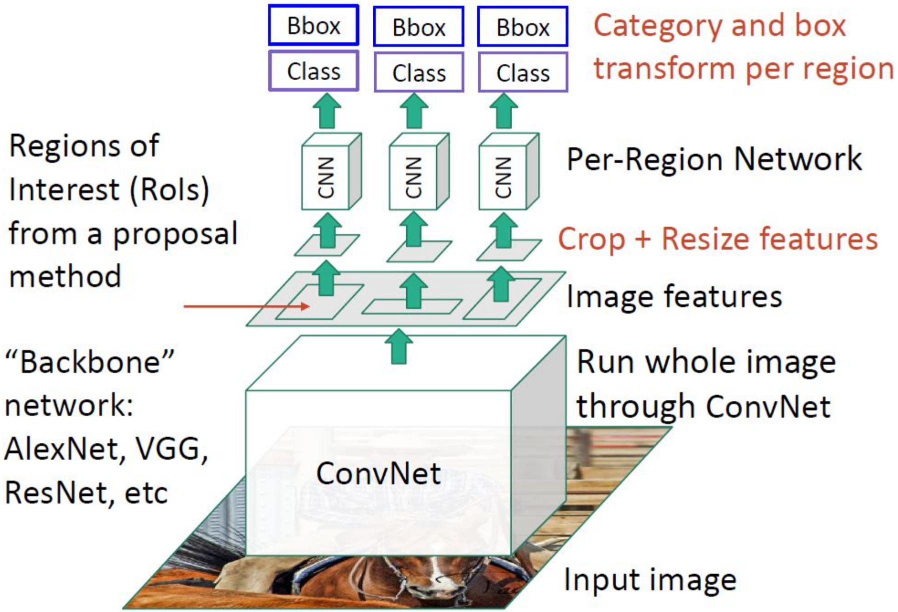




Fast R-CNN

Fast R-CNN

- An input image and multiple regions of interest (RoIs) are input into a fully convolutional network.
- Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs).
- The network has two output vectors per RoI: softmax probabilities and per-class bounding-box regression offsets.
- The architecture is trained end-to-end with a multi-task loss.



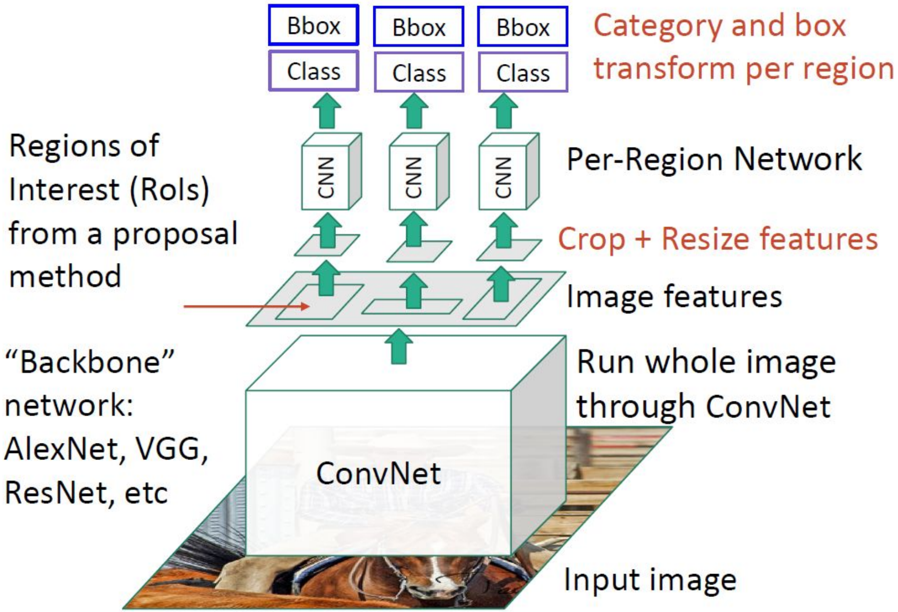
https://arxiv.org/abs/1504.08083

Fast R-CNN

Performance

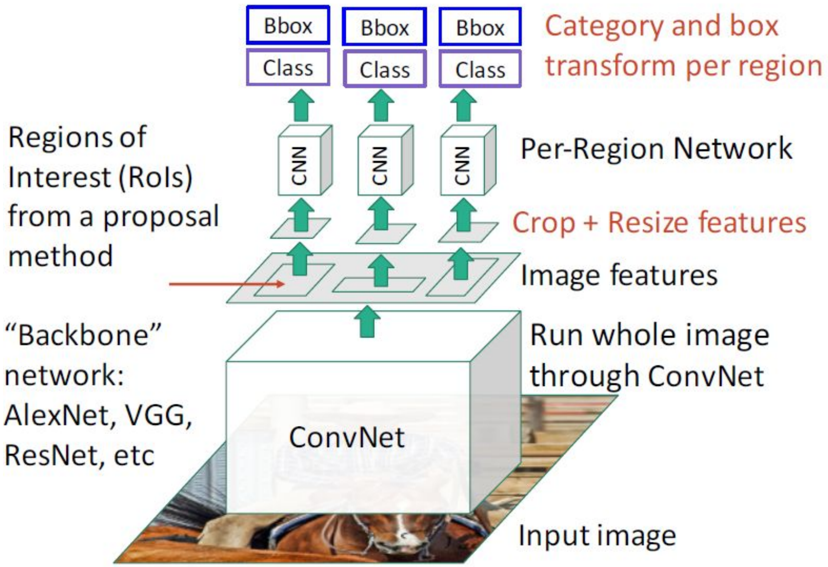
Fast R-CNN achieves the top result on VOC12 with a mAP of 65.7%

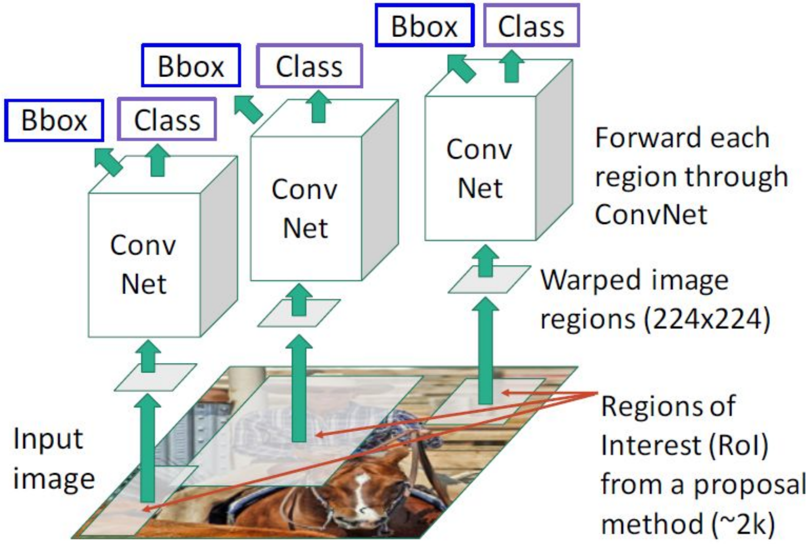
R-CNN achieves a mAP of 66.0% on the MS COCO dataset.



Fast R-CNN Vs R-CNN

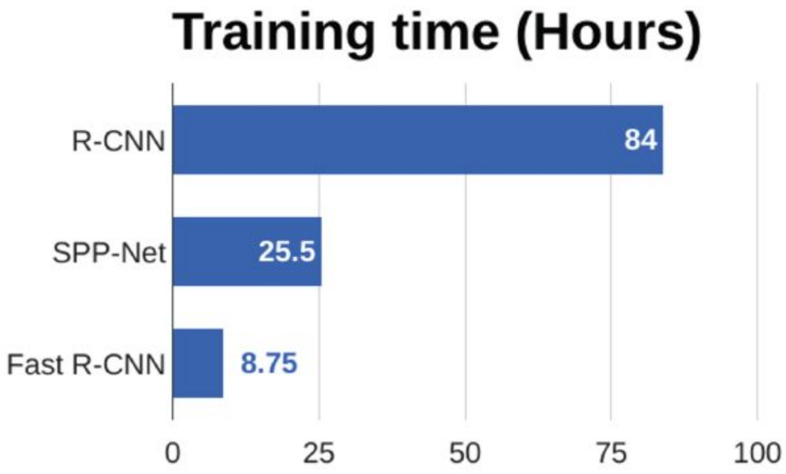
Architecture comparison

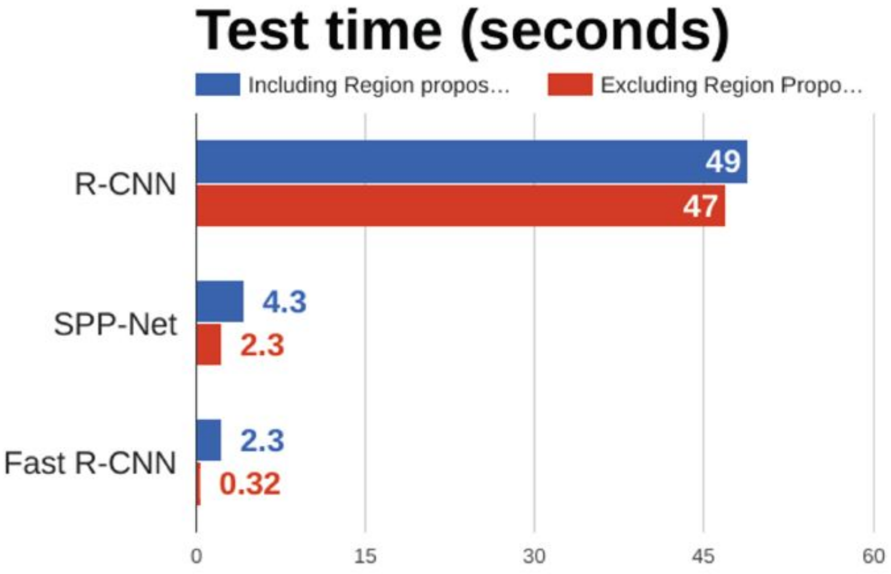




Fast R-CNN Vs R-CNN

Performance comparison

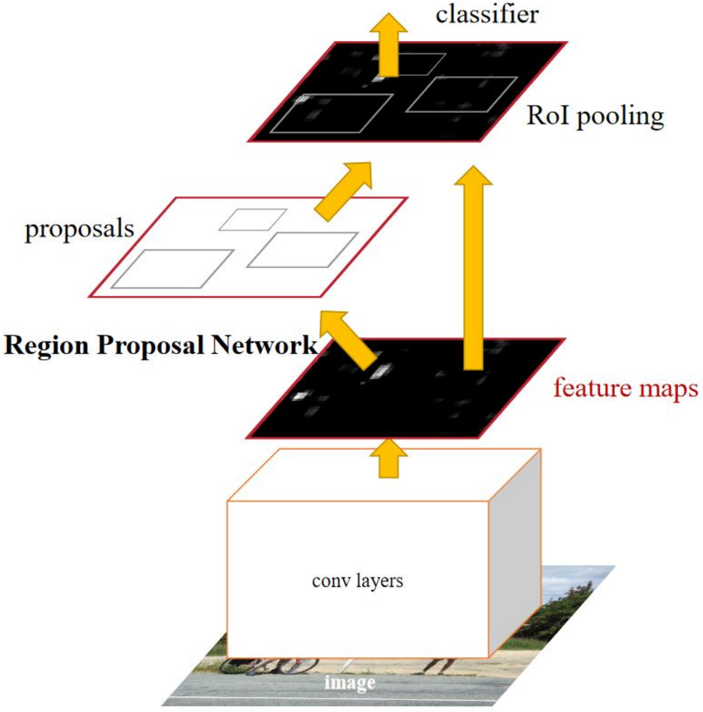




Faster R-CNN

Faster R-CNN

1. Regions of interest are generated using the region proposal network (RPN). To generate RoIs, the RPN uses convolutional layers.
2. The second part of Faster R-CNN is classification. It outputs the final bounding boxes and accepts two inputs—the list of RoIs from the previous step (RPN), and a feature volume computed from the input image.



https://arxiv.org/abs/1506.01497

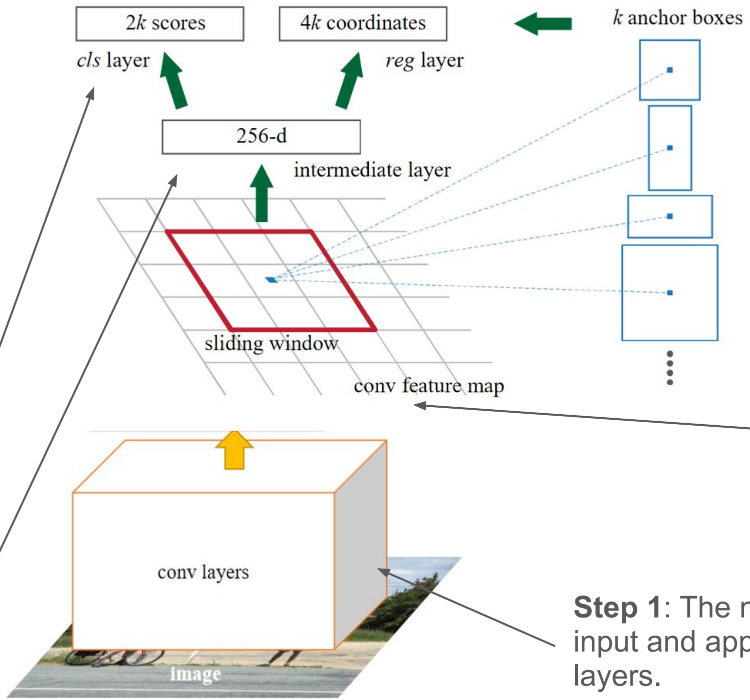
Faster R-CNN

RPN Stage

- **Input**: RGB Image
- **Output**: list of RoIs

Step 4: Two sibling 1 × 1 convolutional layers compute the objectness scores and the bounding box coordinates. There are two objectness scores for each of the k bounding boxes.

Step 3: At each position in the feature volume, each sliding window is mapped to a lower-dimensional feature vector (256-d for ZF and 512-d for VGG) for k anchor boxes



Step 5: Postprocessing to keep only regions with highest confidence (~300)

Step 2: It outputs a feature volume. A convolutional filter is applied over the feature volume.

Step 1: The network accepts an image as input and applies several convolutional layers.

https://arxiv.org/abs/1506.01497

Faster R-CNN

Classification Stage

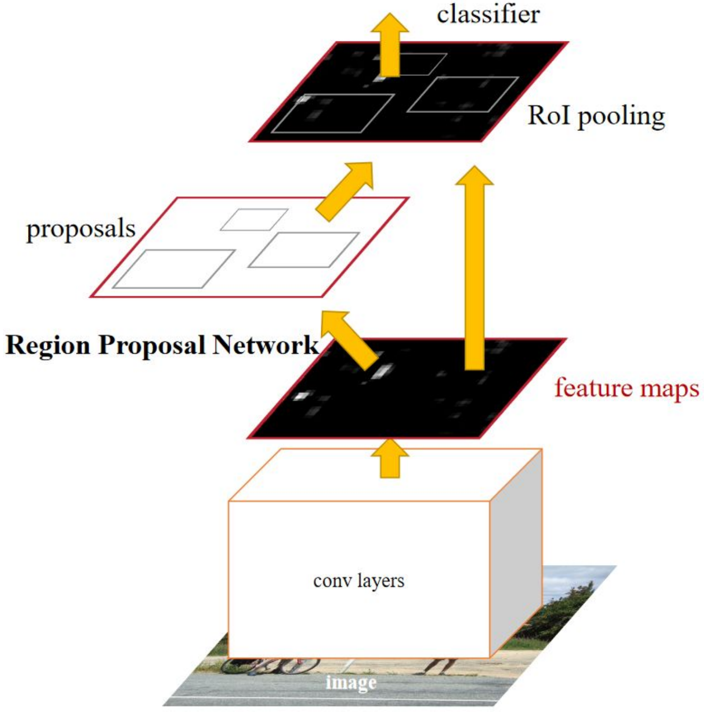
- **Input**: list of RoIs + Conv feature map
- **Output**: Class score + bbox refinement

1. Accept the feature maps and the RoIs from the RPN step.

2. Resize each RoI to make it fit the input of the fully connected layers.

3. Apply the fully connected layer. It is very similar to the final layers of any convolutional network. We obtain a feature vector.

4. Apply two different convolutional layers. One handles the classification (called cls) and the other handles the refinement of the RoI (called rgs).



https://arxiv.org/abs/1506.01497

Faster R-CNN

Training

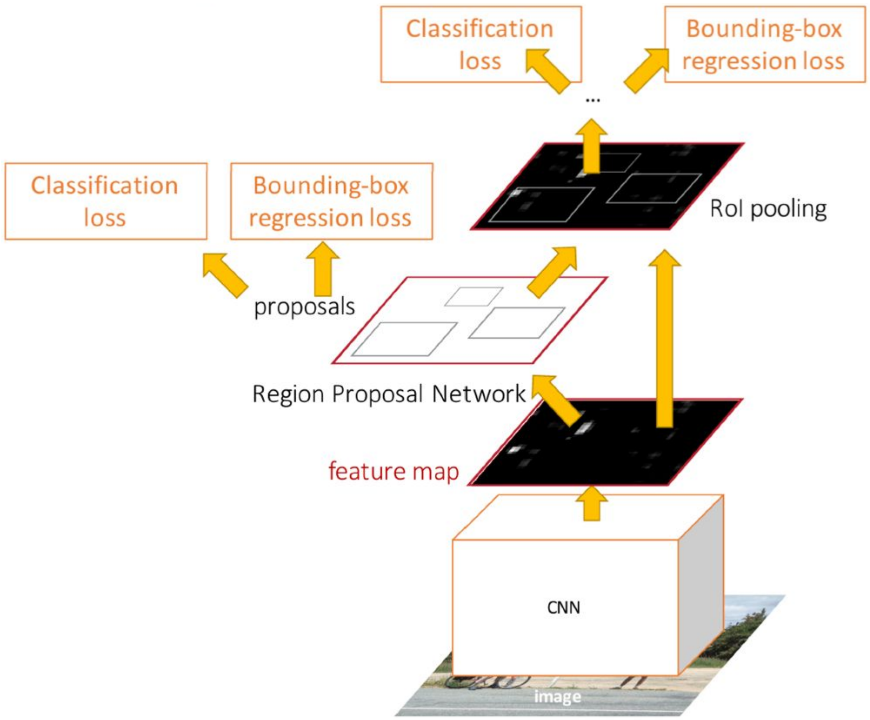
Jointly train with 4 losses:

1. RPN classification: anchor box is object / not an object

2. RPN regression: predict transform from anchor box to proposal box

3. Object classification: classify proposals as background / object class

4. Object regression: predict transform from proposal box to object box



https://arxiv.org/abs/1506.01497

R-CNN, Fast R-CNN & Faster R-CNN

Algorithm	Features	Prediction time / image	Limitations
CNN	Divides the image into multiple regions and then classify each region into various classes.	–	Needs a lot of regions to predict accurately and hence high computation time.
RCNN	Uses selective search to generate regions. Extracts around 2000 regions from each image.	40-50 seconds	High computation time as each region is passed to the CNN separately also it uses three different model for making predictions.
Fast RCNN	Each image is passed only once to the CNN and feature maps are extracted. Selective search is used on these maps to generate predictions. Combines all the three models used in RCNN together.	2 seconds	Selective search is slow and hence computation time is still high.
Faster RCNN	Replaces the selective search method with region proposal network which made the algorithm much faster.	0.2 seconds	Object proposal takes time and as there are different systems working one after the other, the performance of systems depends on how the previous system has performed.

https://www.analyticsvidhya.com/blog/2018/10/a-step-by-step-introduction-to-the-basic-object-detection-algorithms-part-1/

Resources

1. https://cs231n.github.io/convolutional-networks/
2. https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/
3. https://www.tensorflow.org/api_docs/python/tf/keras
4. Deep Learning with Python Book by François Chollet
5. https://www.deeplearningbook.org/
6. **Hands-on Computer Vision with TensorFlow 2 by Eliot Andres & Benjamin Planche (Packt Pub.)**