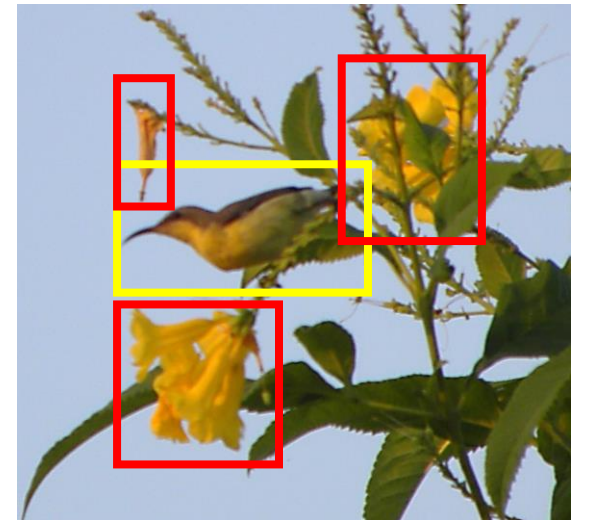




# Object Detection

## State-of-the-Art-Algorithms

CS8004: Deep Learning and Applications



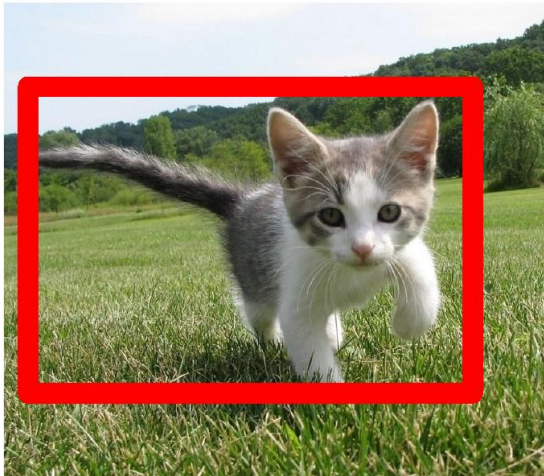
# Object Detection

- What all objects are in the scene?
- Can you locate them ?
- How did you locate them ?



# Object Classification, Object Detection and Segmentation

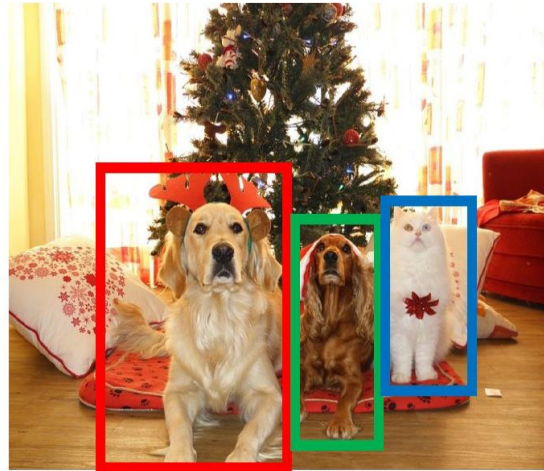
**Classification  
+ Localization**



**CAT**

Single Object

**Object  
Detection**



**DOG, DOG, CAT**

Multiple Object

**Instance  
Segmentation**



**DOG, DOG, CAT**

[This image is CC0 public domain](#)



# Classification and Localization

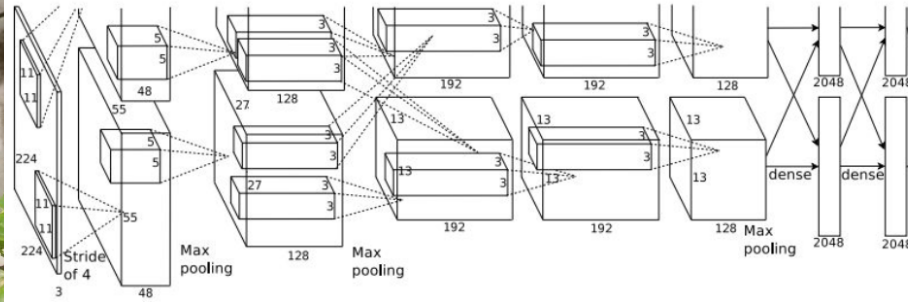
## Classification with localization



Flower with bounding box

- Suppose there are five categories of objects with their corresponding labels.
  - Flower ( 1: [1,0,0,0,0])
  - Fruit (2: [0, 1,0,0,0,])
  - Bird (3: [0, 0, 1,0,0])
  - Insect (4: [0,0,0,1,0])
  - Background only ( none of the above)  
(5: [0,0,0,0,1])
- CNN output would be 'flower' with bounding box:
  - centre, height and width.

# Classification and Localization



Fully connected  
4096 to 5

## Class Scores

Flower: 0.92  
Fruit : 0.023  
Bird: 0.02  
Insect: 0.07  
Background: 0.32

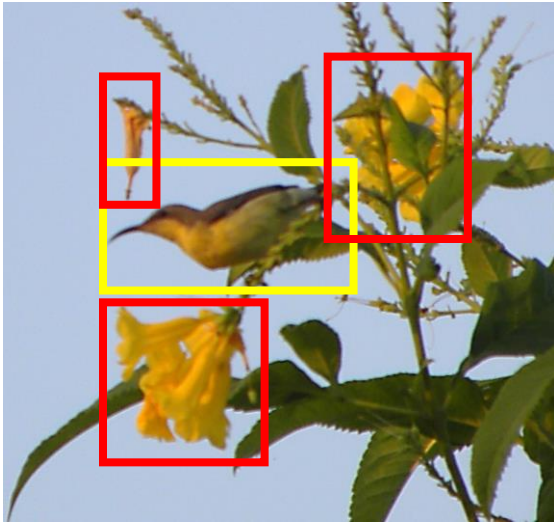
Vector:  
4096

Fully  
Connected:  
4096 to 4

**Box  
Coordinates**  
(x, y, w, h)

Localisation is a regression problem !

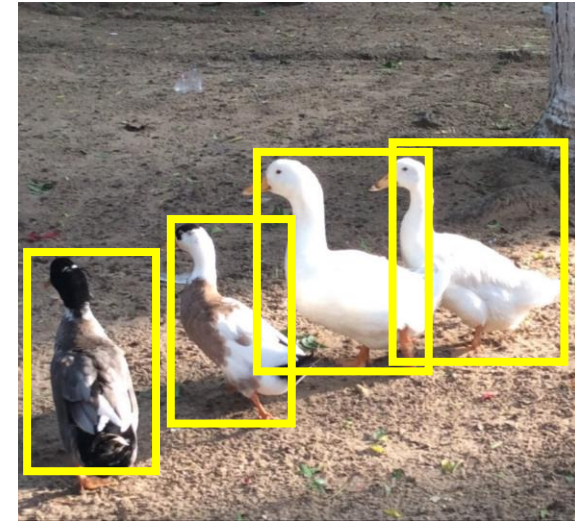
# Detection as a Regression Problem



2 classes  
4 boxes



1 class  
1 box

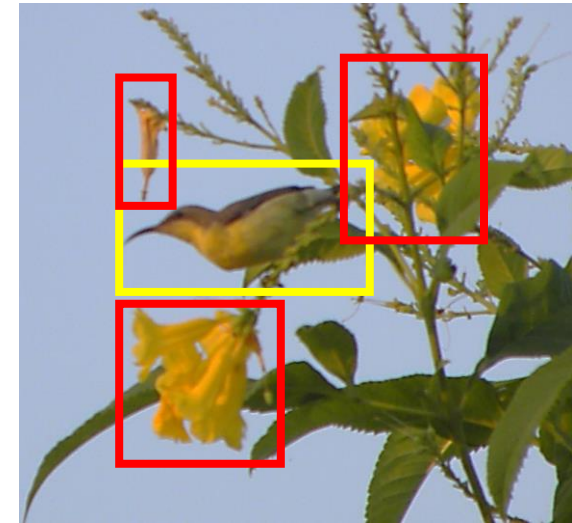


1 class  
4 boxes

Each image can give different number of outputs !

# Object Detection: Data Labels

- Two classes, four instances.
- How will you label?
- Five classes dataset:



( [1,0,0,0,0], bounding box of flower location 1,  
[0,0,1,0,0], bounding box of bird,  
[ 1,0,0,0,0], bounding box of flower location 2,  
[1,0,0,0,0], bounding box of flower location 3)

# Object Detection Methods using CNN

- Two types of methods
  - Two stage methods : Initial feature extraction locally and then classification of each segmented \local region.
  - Single stage methods : both object localisation and their classification by a single pass through CNN.



# Region Based CNN (R-CNN): Two Stage Method

- **Region proposal** : Propose category-independent regions of interest by selective search ( ~ 2000 per image)
- **Classification of regions** : Use CNN for feature extraction and SVM for classification

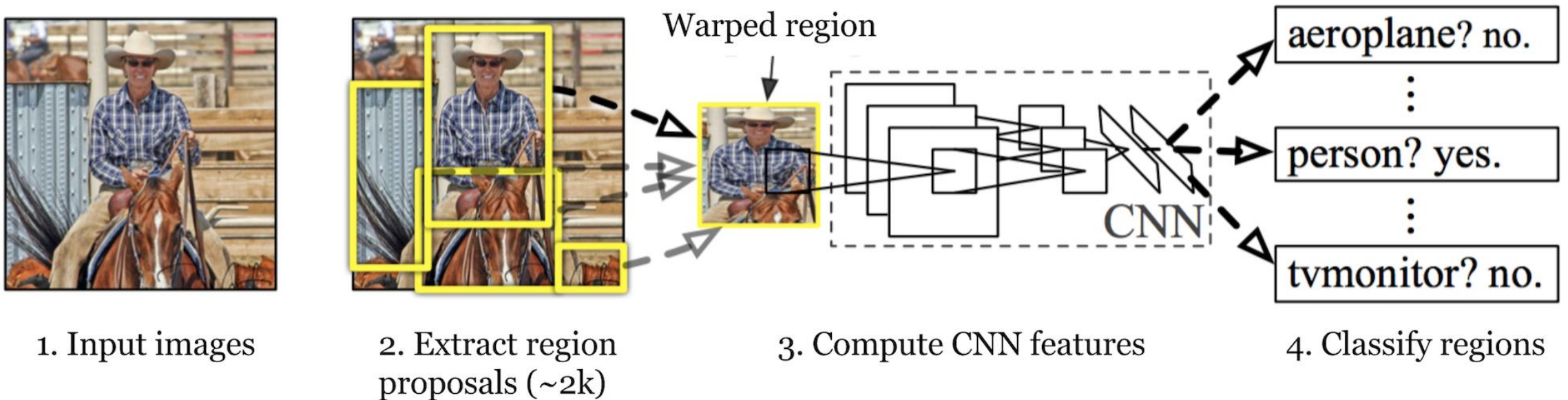


Image source: Girshick et al., 2014

# Region Based CNN (R-CNN)...

- Category-independent region proposals:
  - Defines the set of candidate detections for the detector.
- A large convolutional neural network:
  - Extracts a fixed-length feature vector from each region.
- A set of class specific linear SVMs: provides binary classification for each proposal.

# Region Based CNN (R-CNN)...

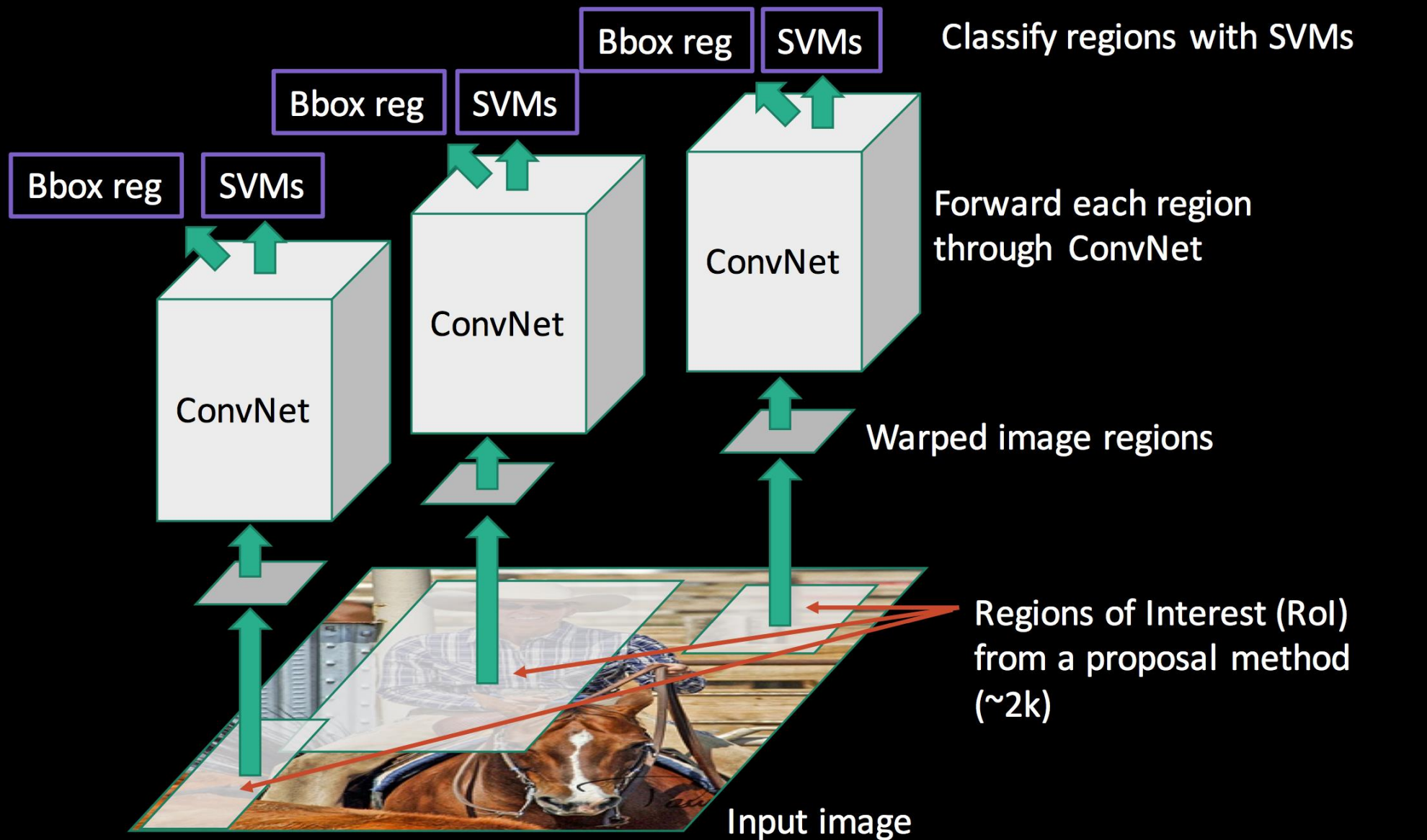
- Selective search for region proposals
  - Start with thousands of tiny initial regions. ( divide the image into a grid and process the grid cells for extracting information )
  - Use a greedy algorithm to grow a region. Similar regions are merged with a similarity measure  $S$  between regions  $a$  and  $b$  defined as:

$$S(a, b) = S_{size}(a, b) + S_{texture}(a, b)$$

# Selective search for region proposals





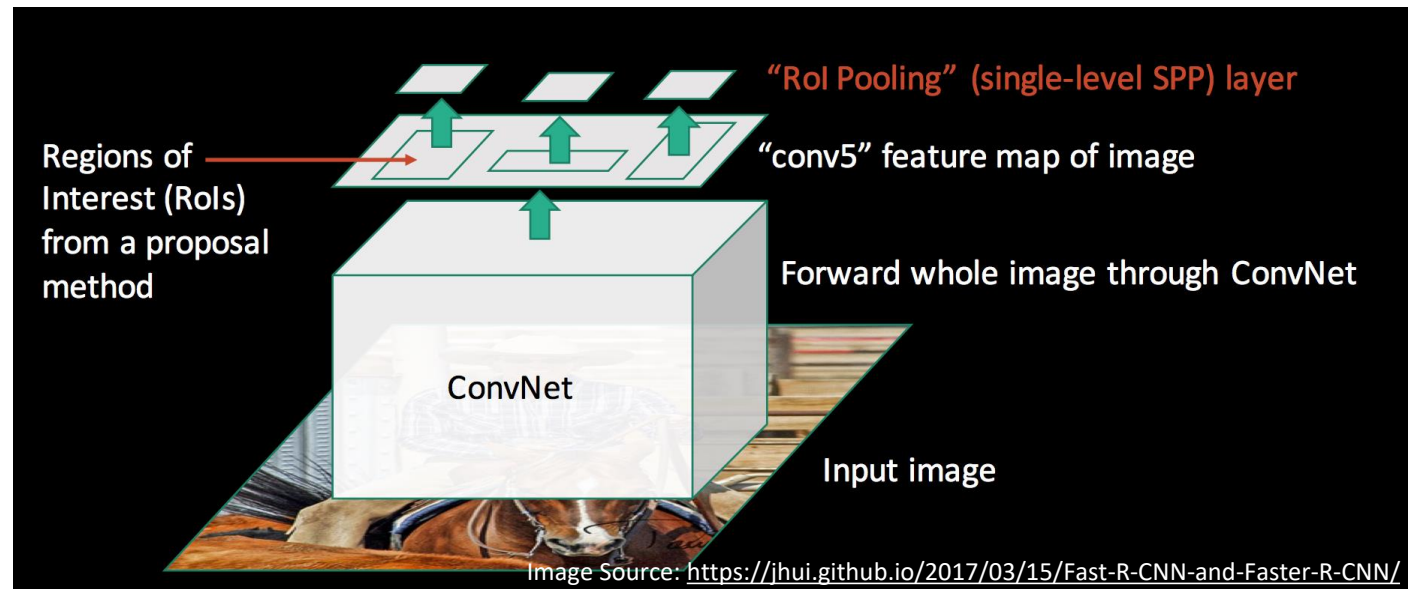


Girshick et al. CVPR14.

Image Source: <https://jhui.github.io/2017/03/15/Fast-R-CNN-and-Faster-R-CNN/>

# Main Drawback of R-CNN & Fast R-CNN as an Improvement

- Very slow in training and inference.
- Nearly 2,000 region proposals are needed to be processed by a CNN to extract features.
- Therefore R-CNN repeats the CNN feature extraction process approx. 2,000 times.
- Fast R-CNN was introduced by Girshik et al, (2015) to overcome this processing issue.

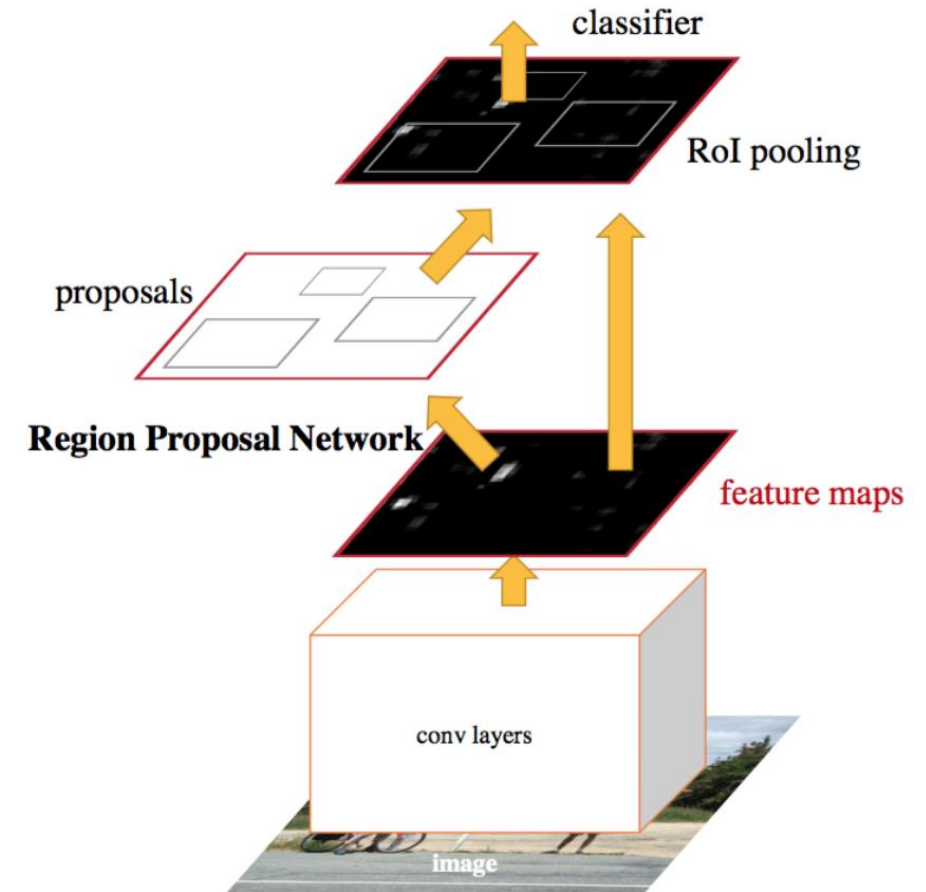


# Faster RCNN

- Faster R-CNN does not use a special region proposal method to create region proposals.

A region proposal network is trained to extract region proposals from the feature maps.

These proposals are then fed into the Region of interest ( RoI) pooling layer in the Fast R-CNN type network.



Ren et al, {2015)

# Region Proposal Network

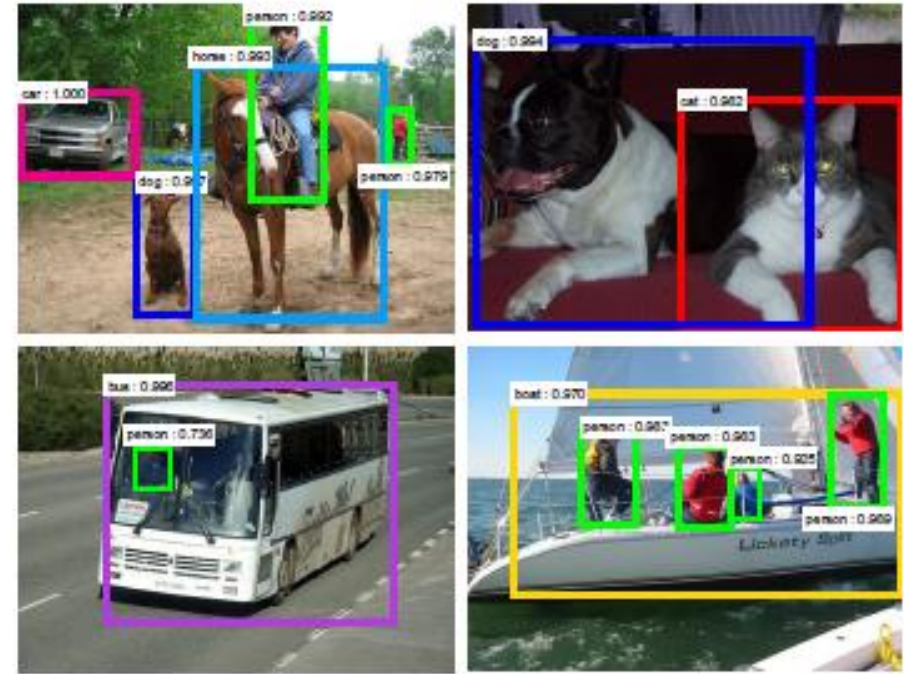
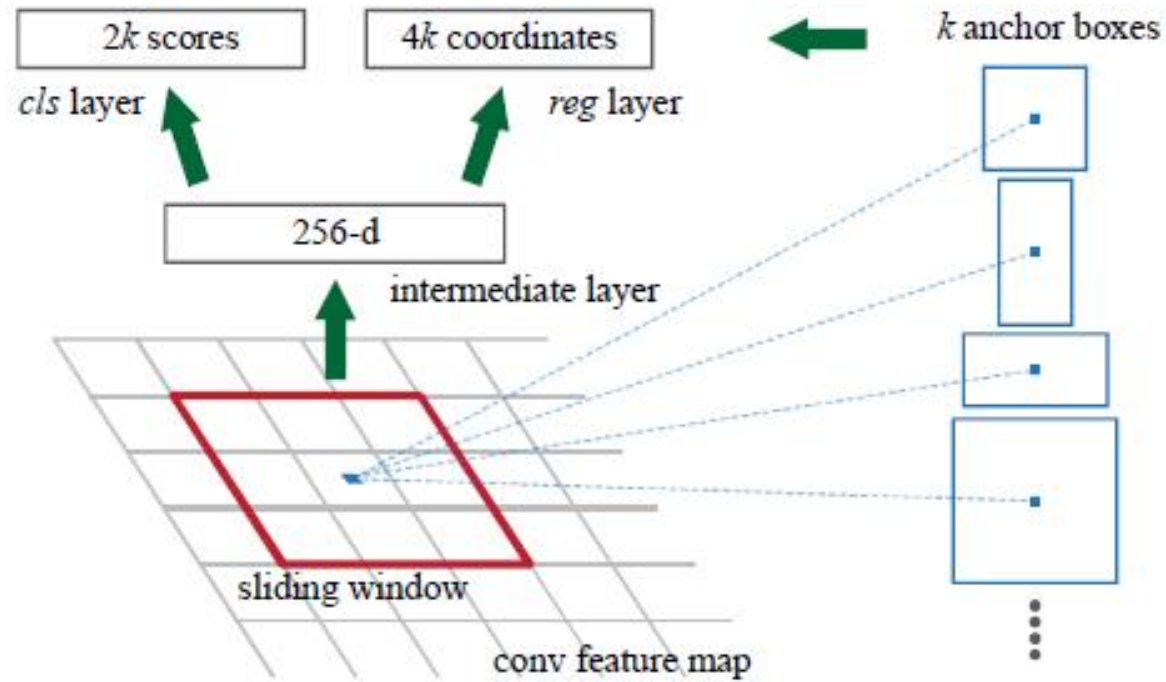


Image source: Ren et al, {2015}

Exhibited a good performance of upto 17 frames per second fps processing and 70% mAP 9 mean average precision.

Yet not suitable for real time applications.



# Next

- Single Shot Object Detection

# References

- Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2015). Region-based convolutional networks for accurate object detection and segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 38(1), 142-158. ( first appeared in 2014).
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