

# **AI in Built Environment**

## **DCP4300**

### **Lec10: Computer Vision**

**Object detection/ Segmentation**

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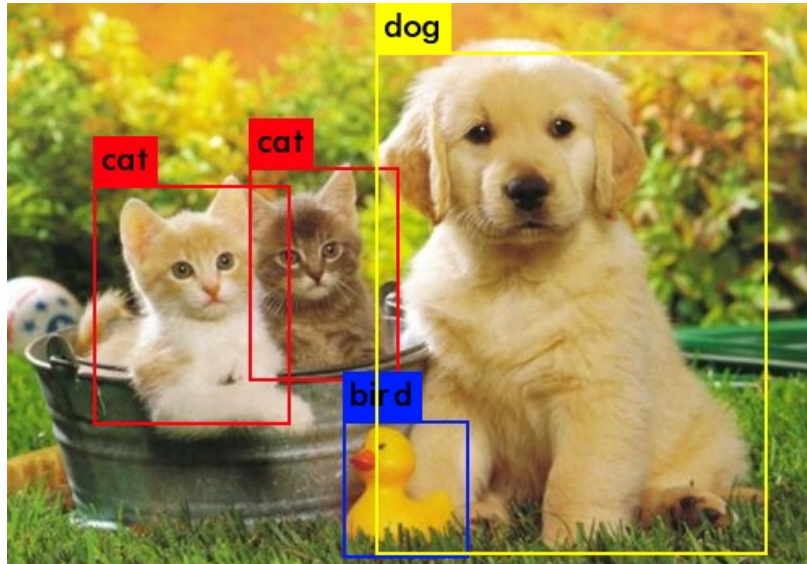
University of Florida  
College of Design Construction and Planning

# Major Tasks of Computer Vision

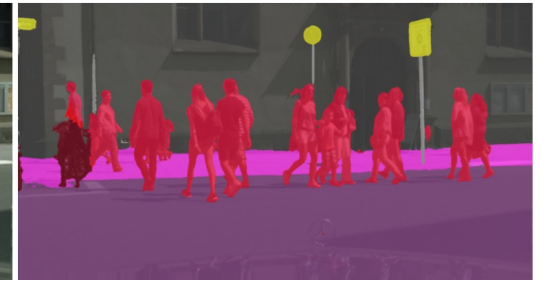
## Classification



## Object detection



## Segmentation

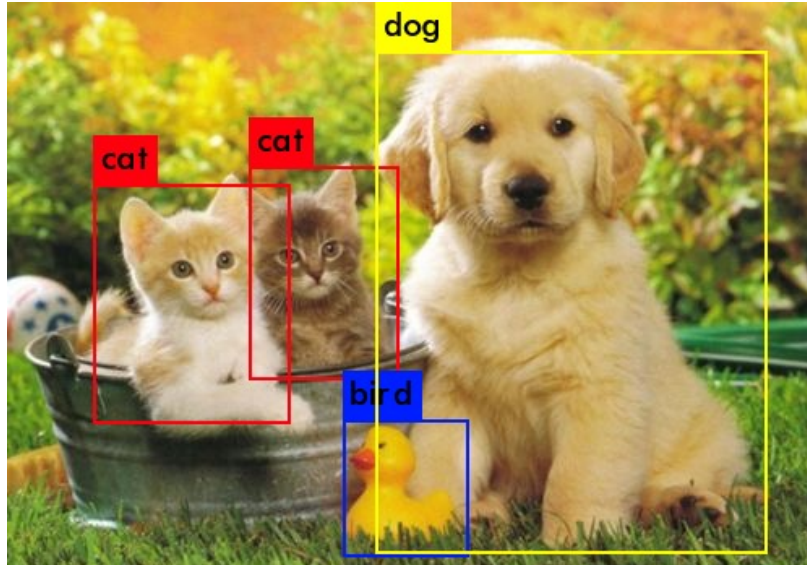


# Major Tasks of Computer Vision

## Classification



## Object detection



Localization + Classification (sub-image)

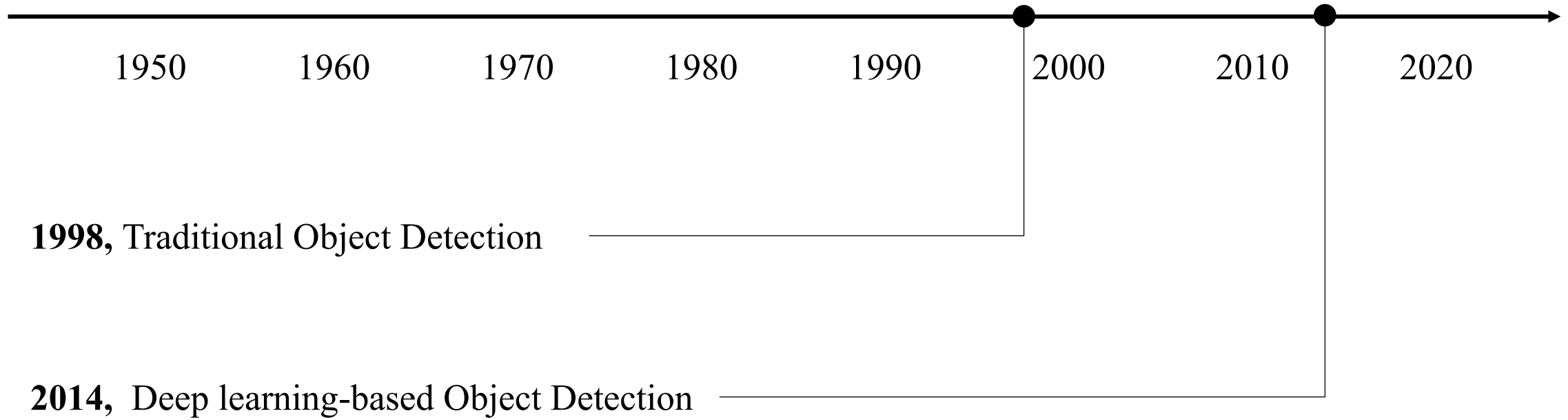
## Scenarios to use object detection

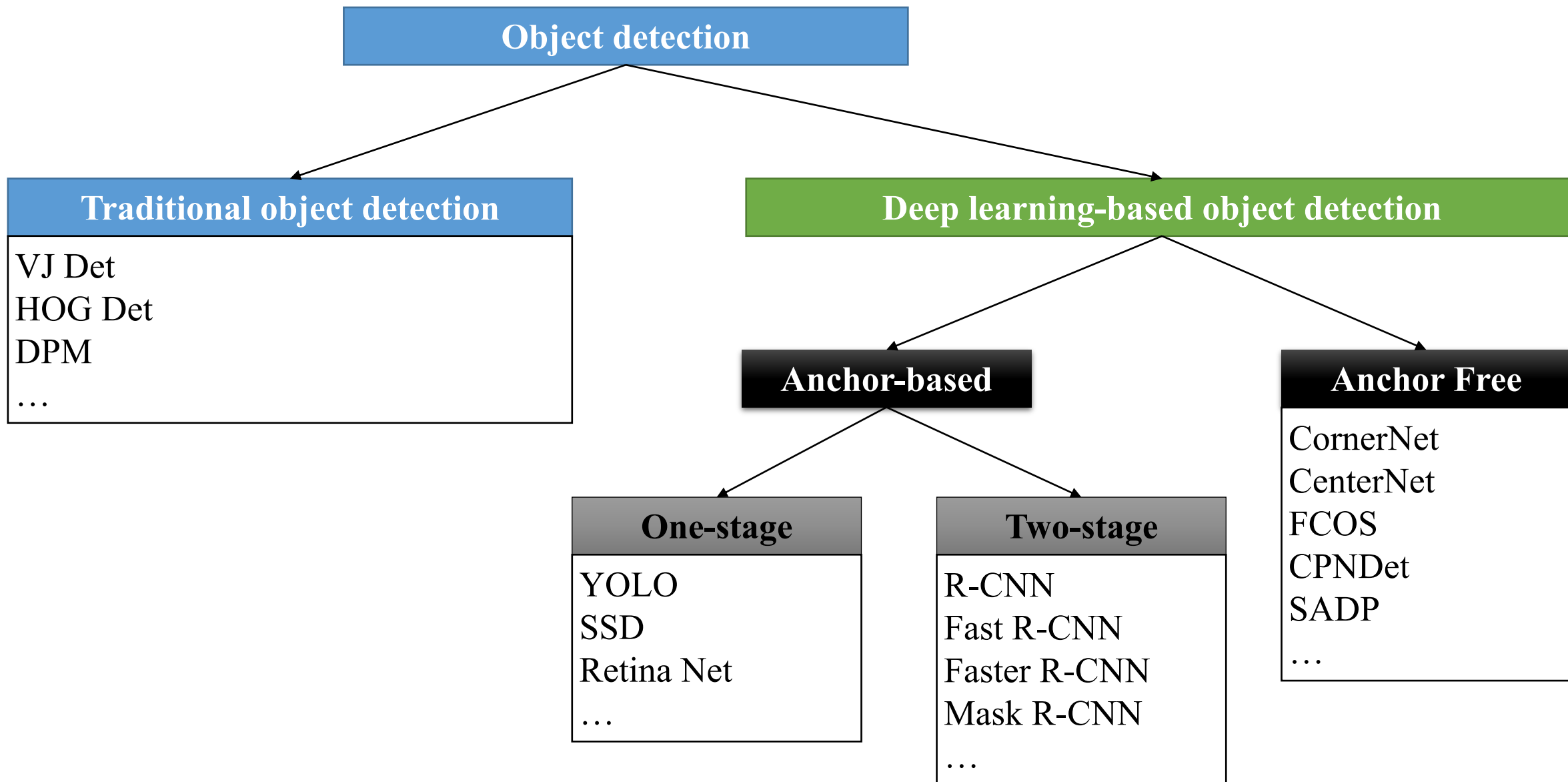
Multiple objects of interest in the image

Need to know the location of objects

The objects of interest are not predominant

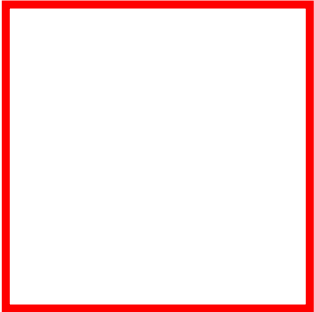
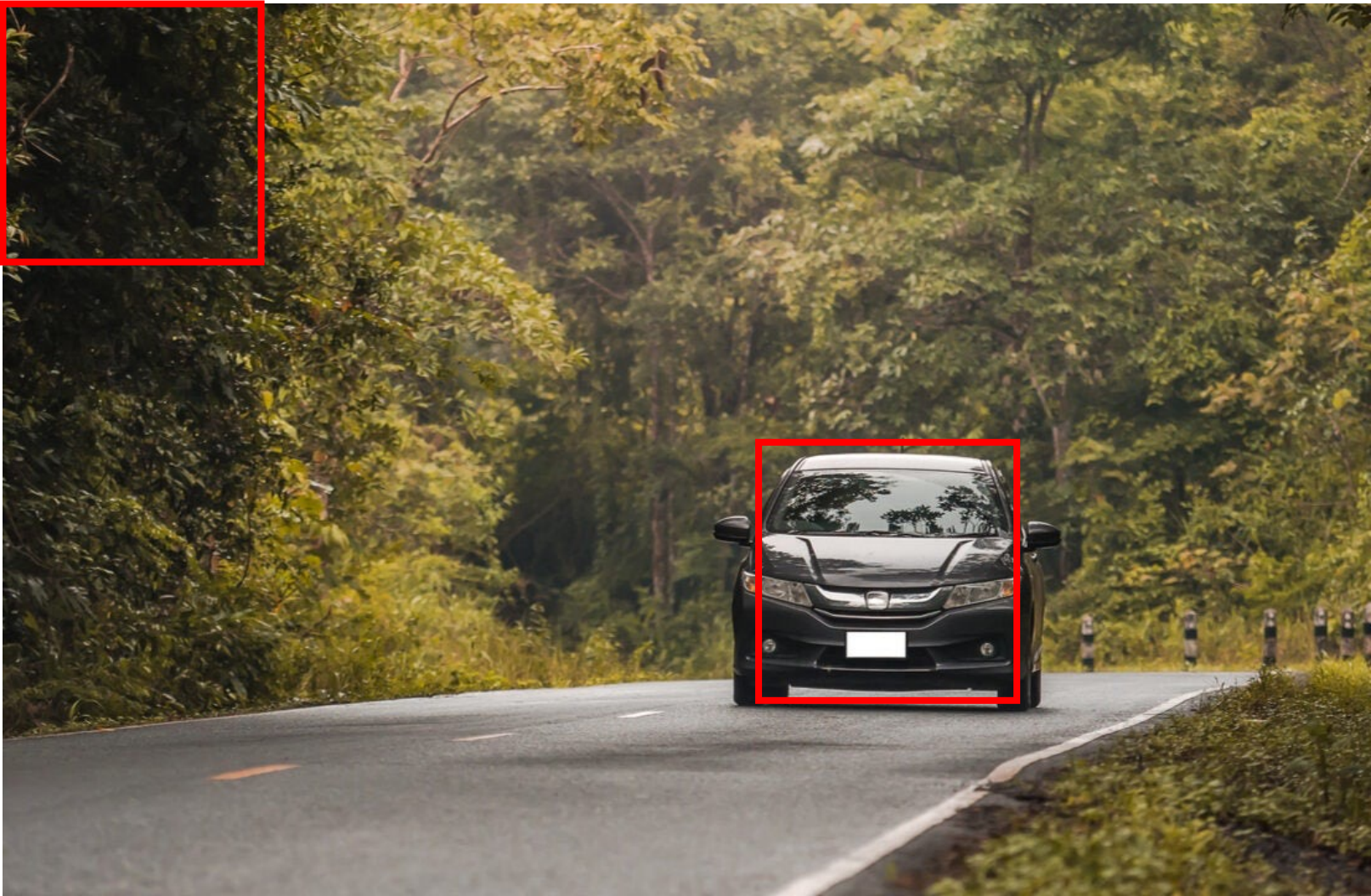
## Key points in the history of object detection





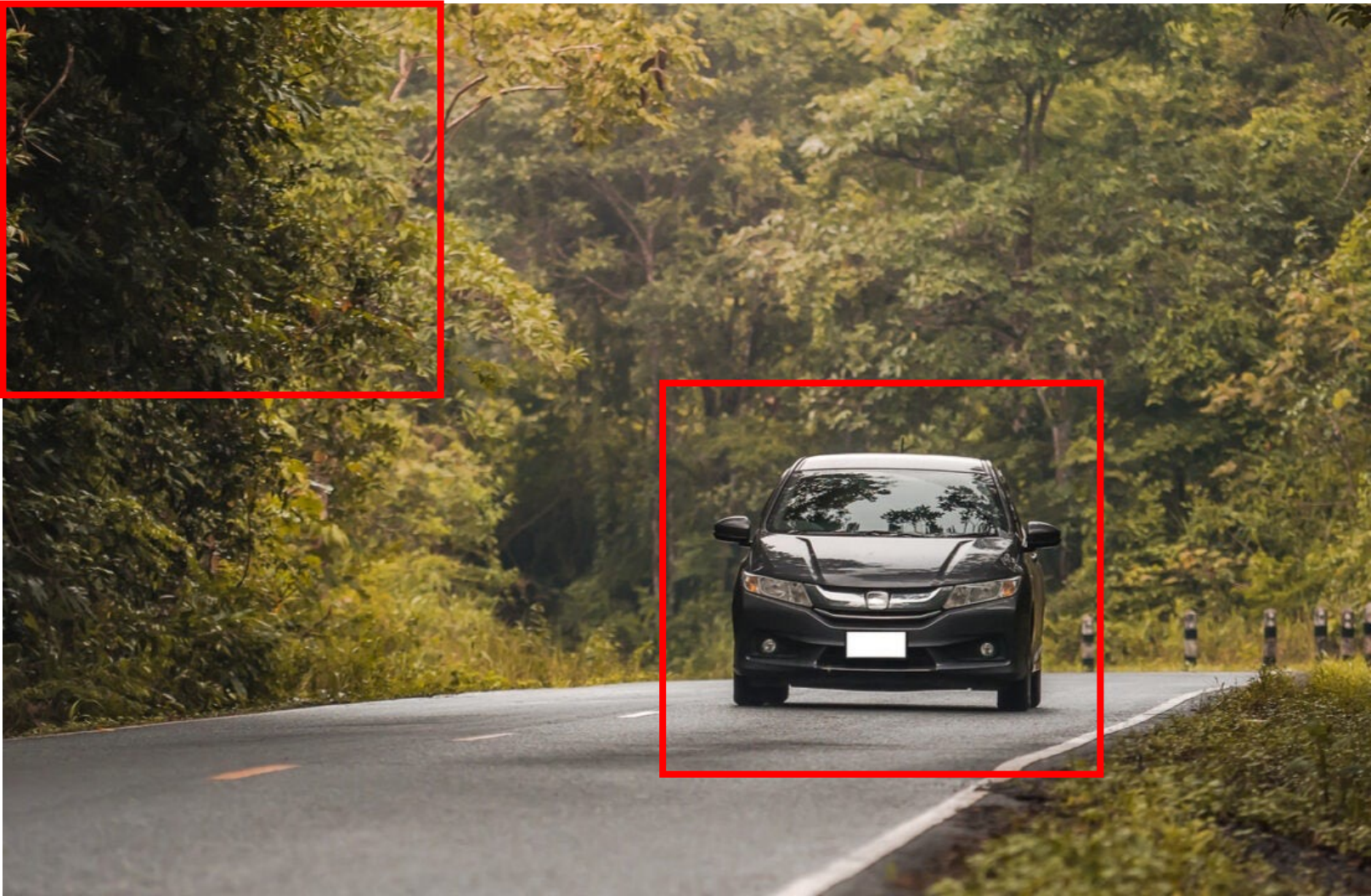


Sliding windows





Sliding windows



Change window size

## Sliding windows

Early stage: Hand-engineered features + Simple classifiers



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



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

## Viola–Jones method

Viola, P., & Jones, M. (2001). Robust real-time object detection. *International journal of computer vision*, 4(34-47), 4.



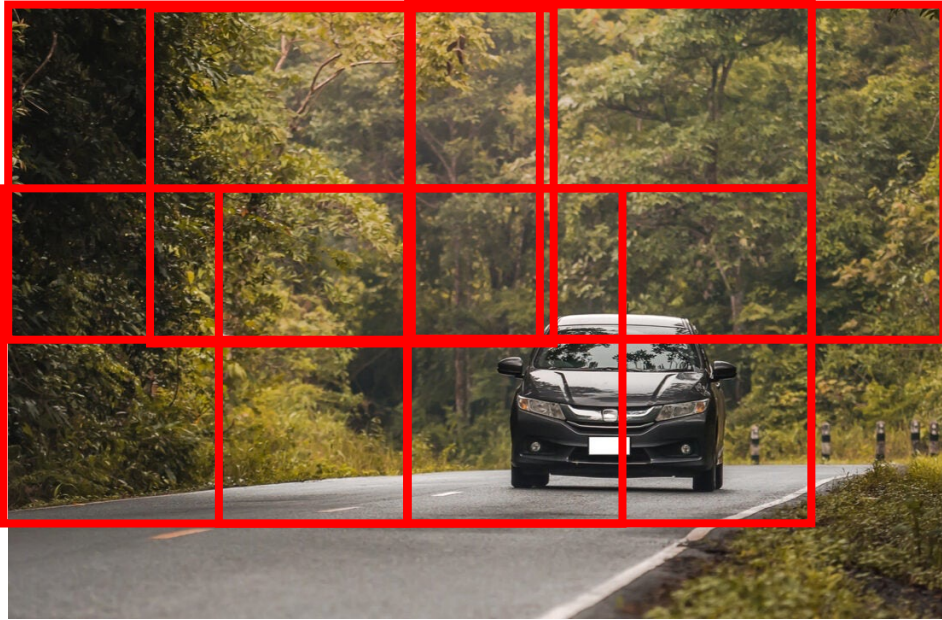
## Sliding windows

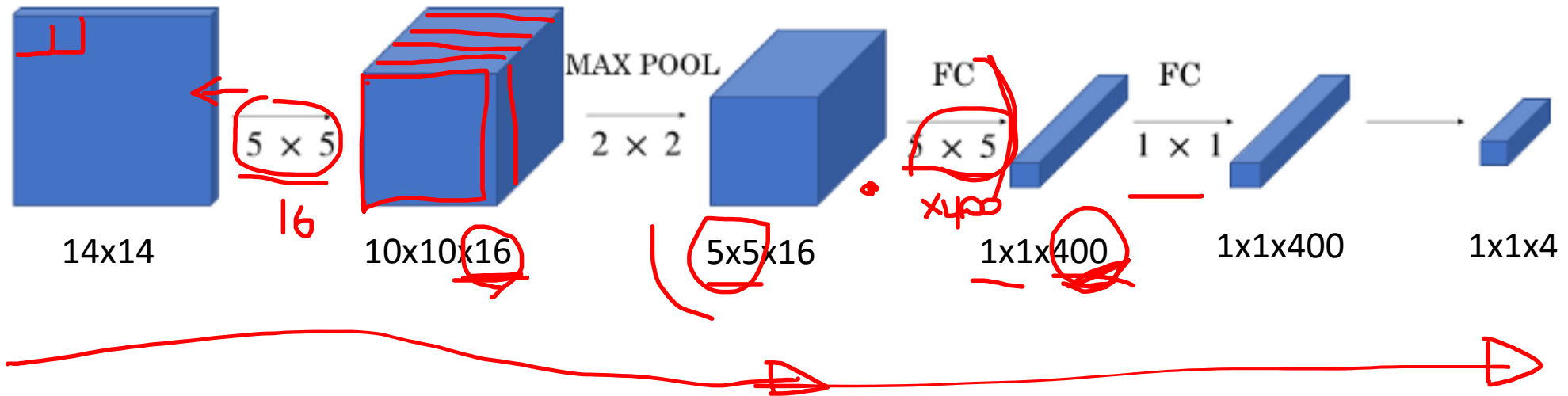
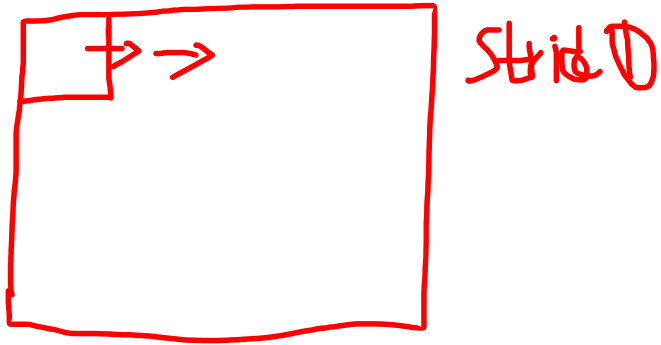
Sliding windows + Simple linear classifiers

Speed is ok, but performance is not good

Sliding windows + Neural networks

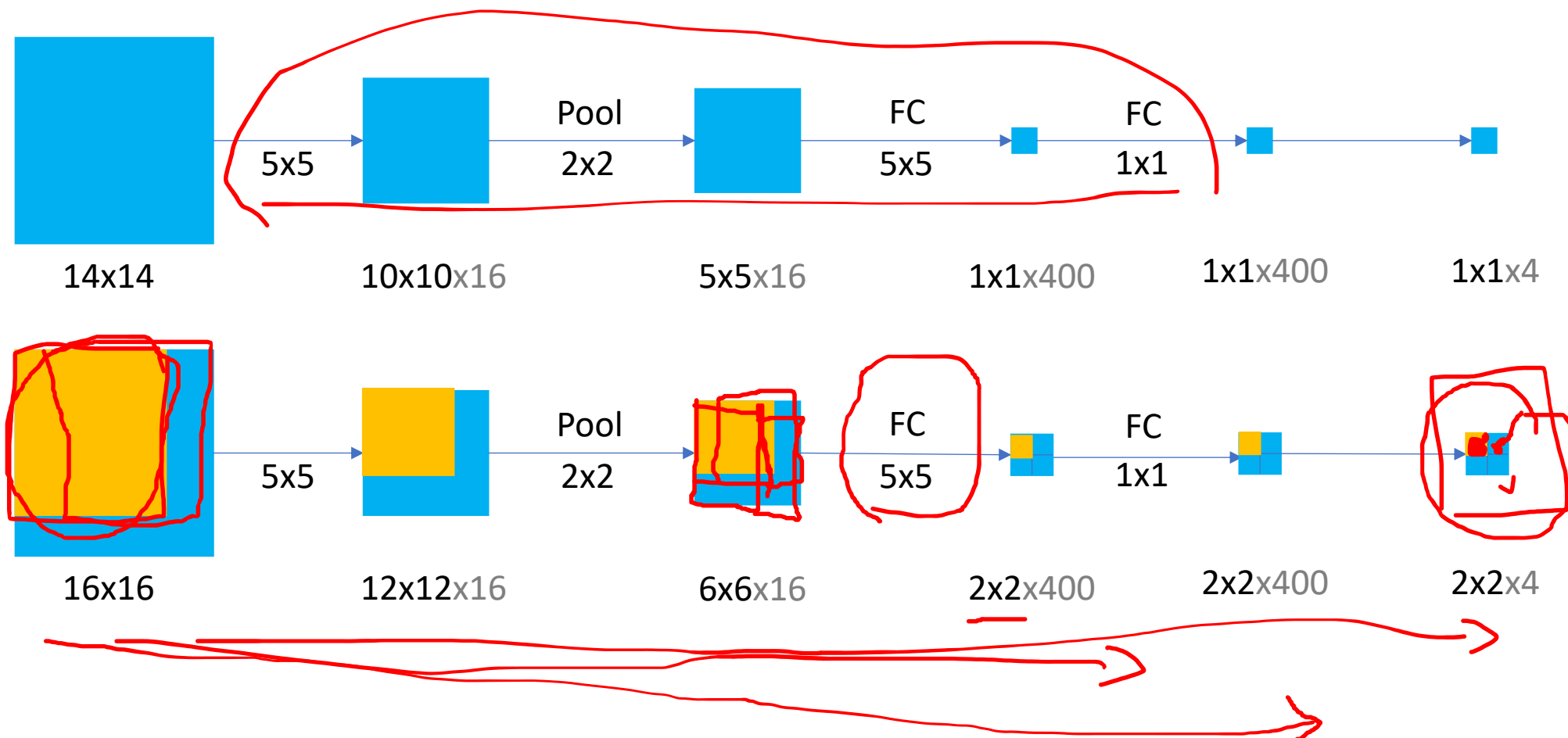
Performance is higher but slower





Example of a convolutional neural network classifier

## Convolutional Implementation of Sliding Windows



Sermanet, P., Eigen, D., Zhang, X., Mathieu, M., Fergus, R., & LeCun, Y. (2013). Overfeat: Integrated recognition, localization and detection using convolutional networks. arXiv preprint arXiv:1312.6229. <https://arxiv.org/abs/1312.6229>

# Convolutional Implementation of Sliding Windows

## Disadvantages:

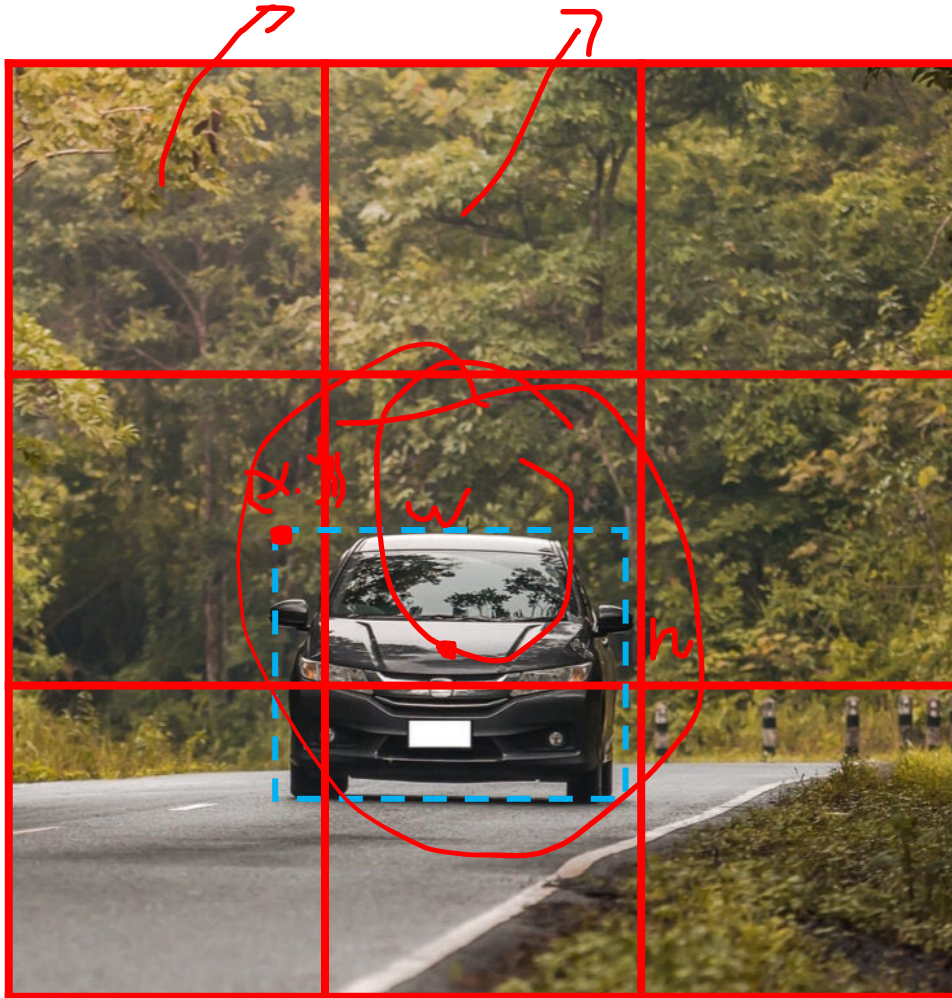
1. Computationally expensive, slow
2. Bounding box prediction not accurate

Sermanet, P., Eigen, D., Zhang, X., Mathieu, M., Fergus, R., & LeCun, Y. (2013). Overfeat: Integrated recognition, localization and detection using convolutional networks. arXiv preprint arXiv:1312.6229. <https://arxiv.org/abs/1312.6229>



# Anchor-based One-stage algorithm

## YOLO



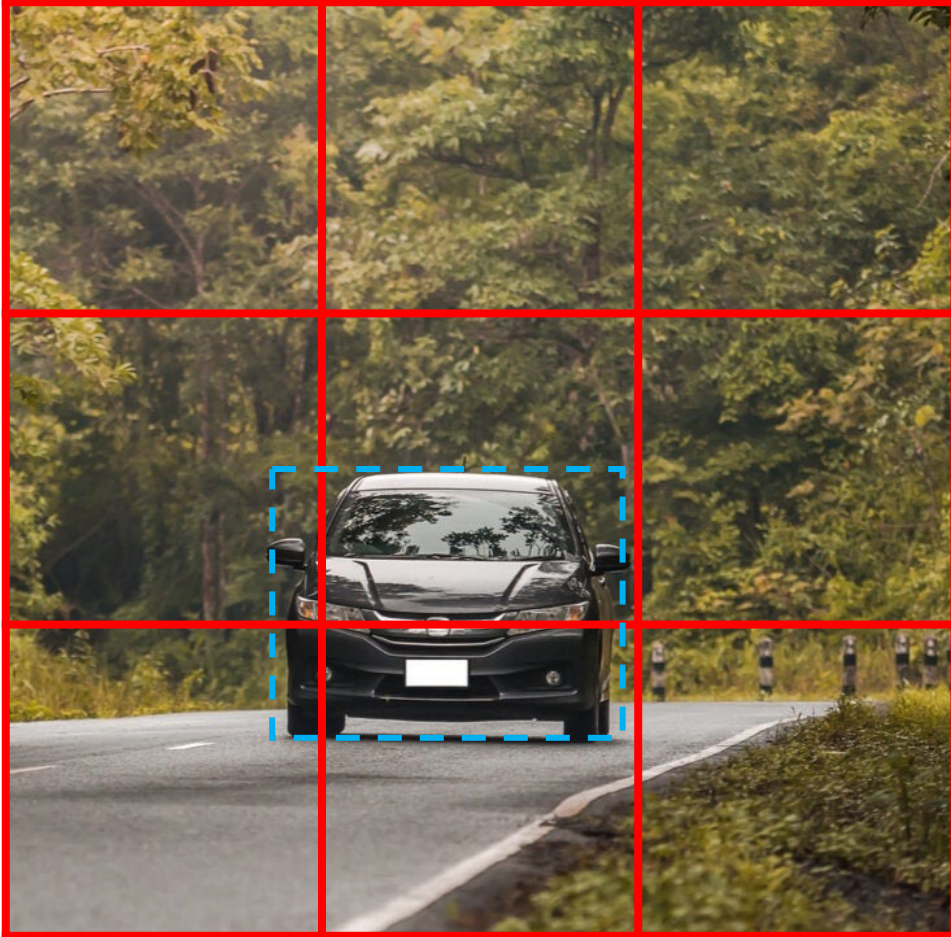
$$Y = 3 \times 3 \times 8$$

$$y = \begin{bmatrix} p \\ x \\ y \\ w \\ h \\ C_1 = 1 \\ C_2 = 0 \end{bmatrix} \quad y = \begin{bmatrix} p \\ . \\ . \end{bmatrix}$$

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788). [https://www.cv-foundation.org/openaccess/content\\_cvpr\\_2016/papers/Redmon\\_You\\_Only\\_Look\\_CVPR\\_2016\\_paper.pdf](https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf)

# Anchor-based One-stage algorithm

## YOLO

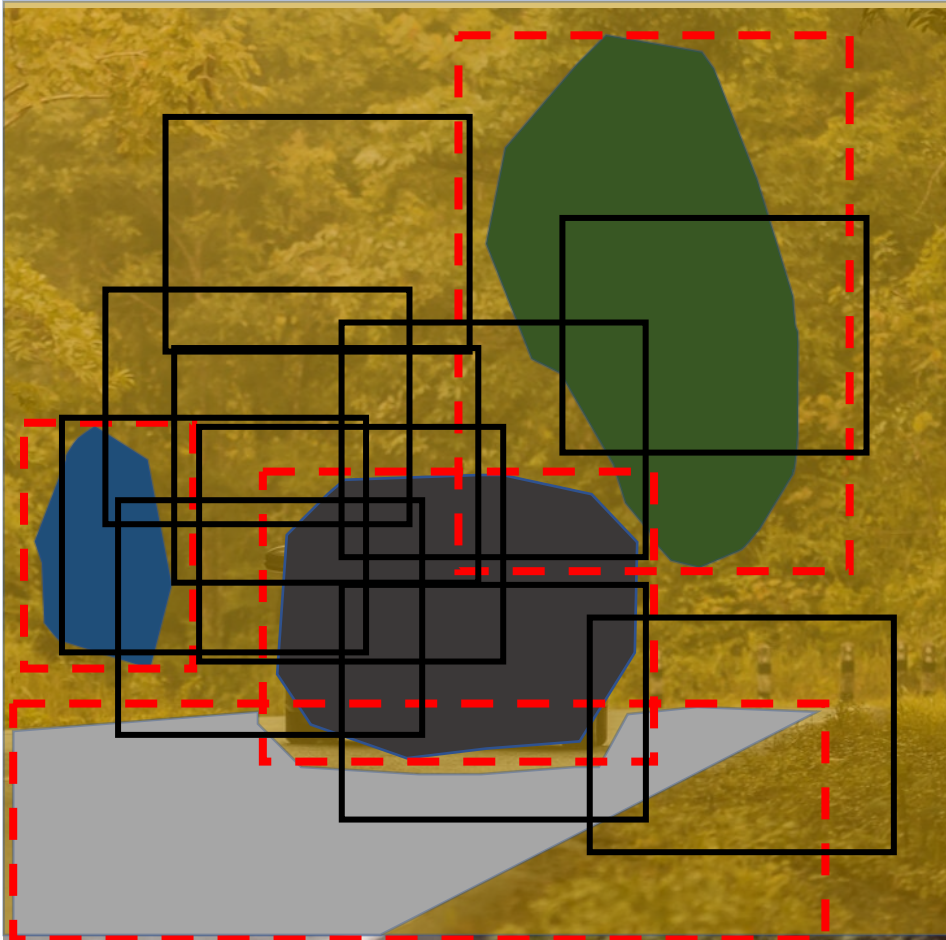


Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788). [https://www.cv-foundation.org/openaccess/content\\_cvpr\\_2016/papers/Redmon\\_You\\_Only\\_Look\\_CVPR\\_2016\\_paper.pdf](https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf)

## Traditional CV: Segmentation

## Anchor-based Two-stage algorithm

### Region Proposals (R-CNN)

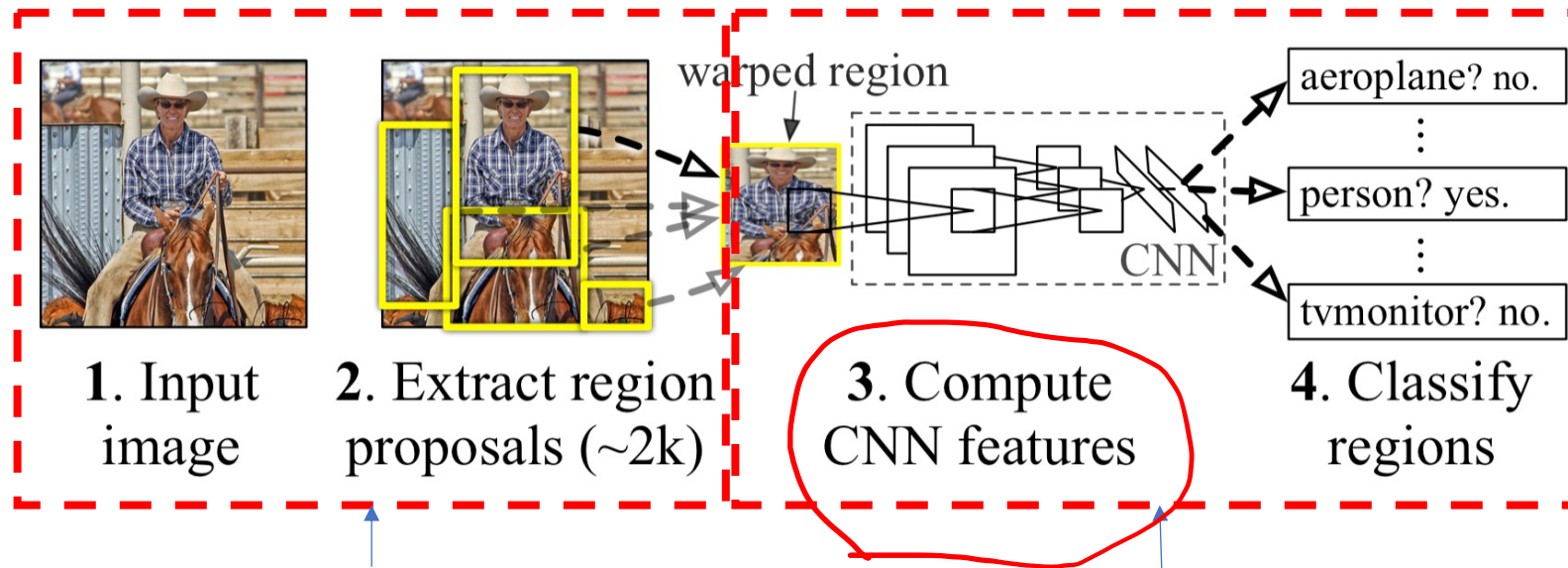


Stage-1: Generate region proposals from image

Stage-2: Predict bounding boxes from region proposals



## R-CNN



Generate region proposals: method agnostic

The author chose the selective search method:

A greedy algorithm to recursively combine similar regions into larger ones

A CNN-based classifier

Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 580-587).

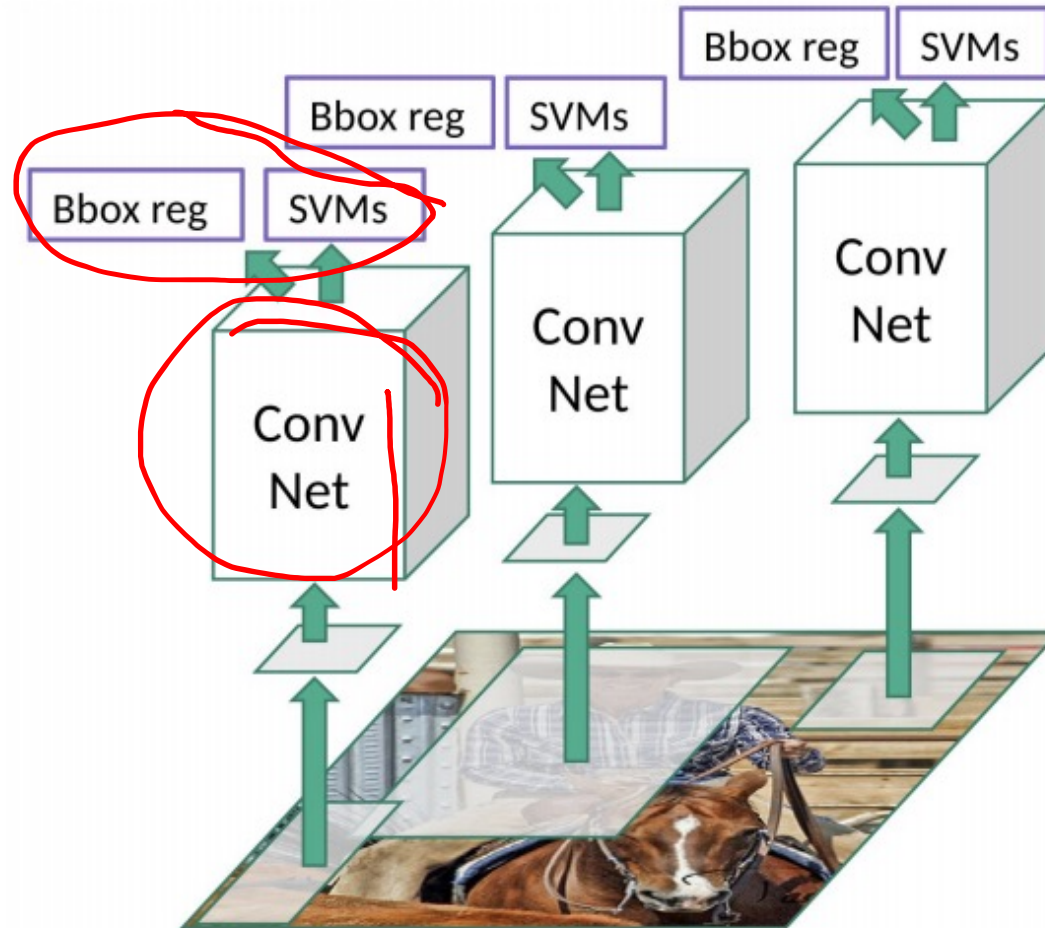
[https://openaccess.thecvf.com/content\\_cvpr\\_2014/papers/Girshick\\_Rich\\_Feature\\_Hierarchies\\_2014\\_CVPR\\_paper.pdf](https://openaccess.thecvf.com/content_cvpr_2014/papers/Girshick_Rich_Feature_Hierarchies_2014_CVPR_paper.pdf)

Selective search: J.Uijlings, K.vandeSande, T.Gevers, and A.Smeulders. Selective search for object recognition. *IJCV*, 2013.

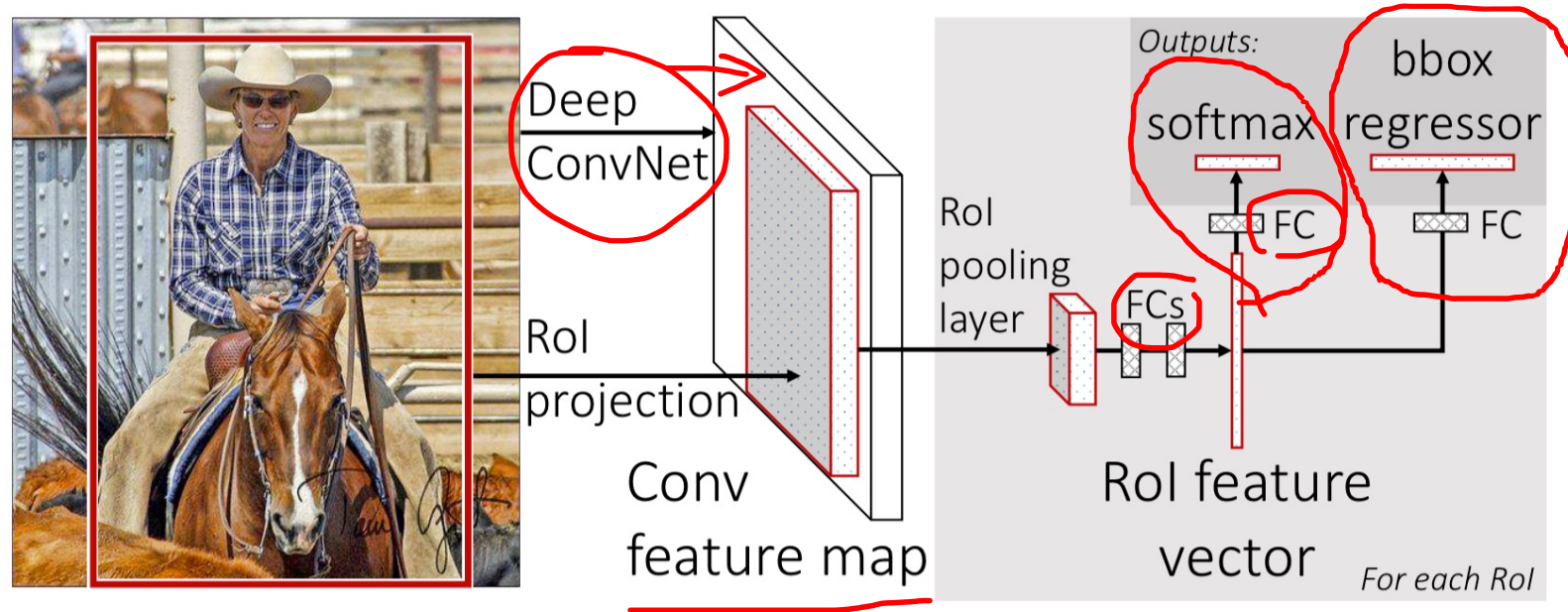
<https://staff.fnwi.uva.nl/th.gevers/pub/GeversIJCV2013.pdf>

## R-CNN

It's very slow:  
Too much proposals;  
Each needs to be classified, independently.



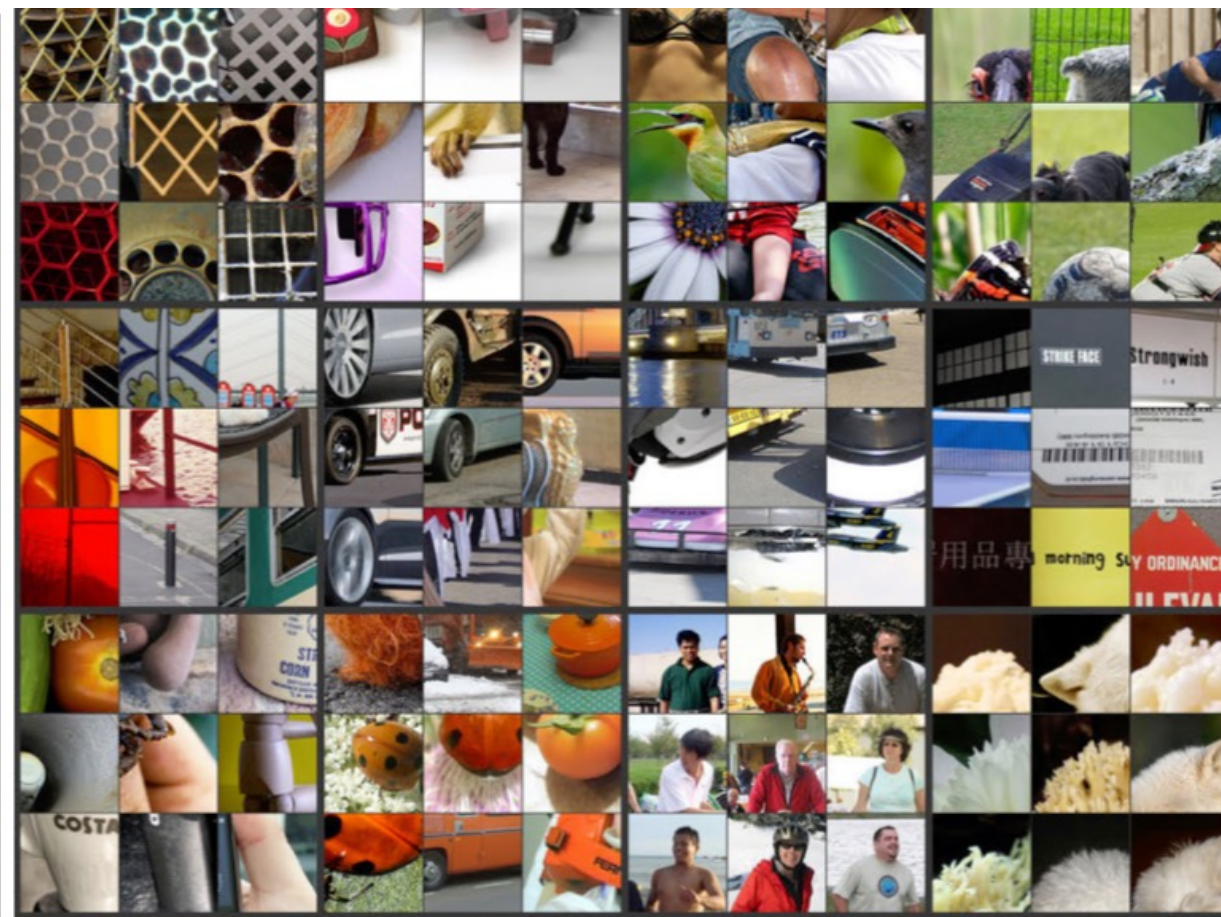
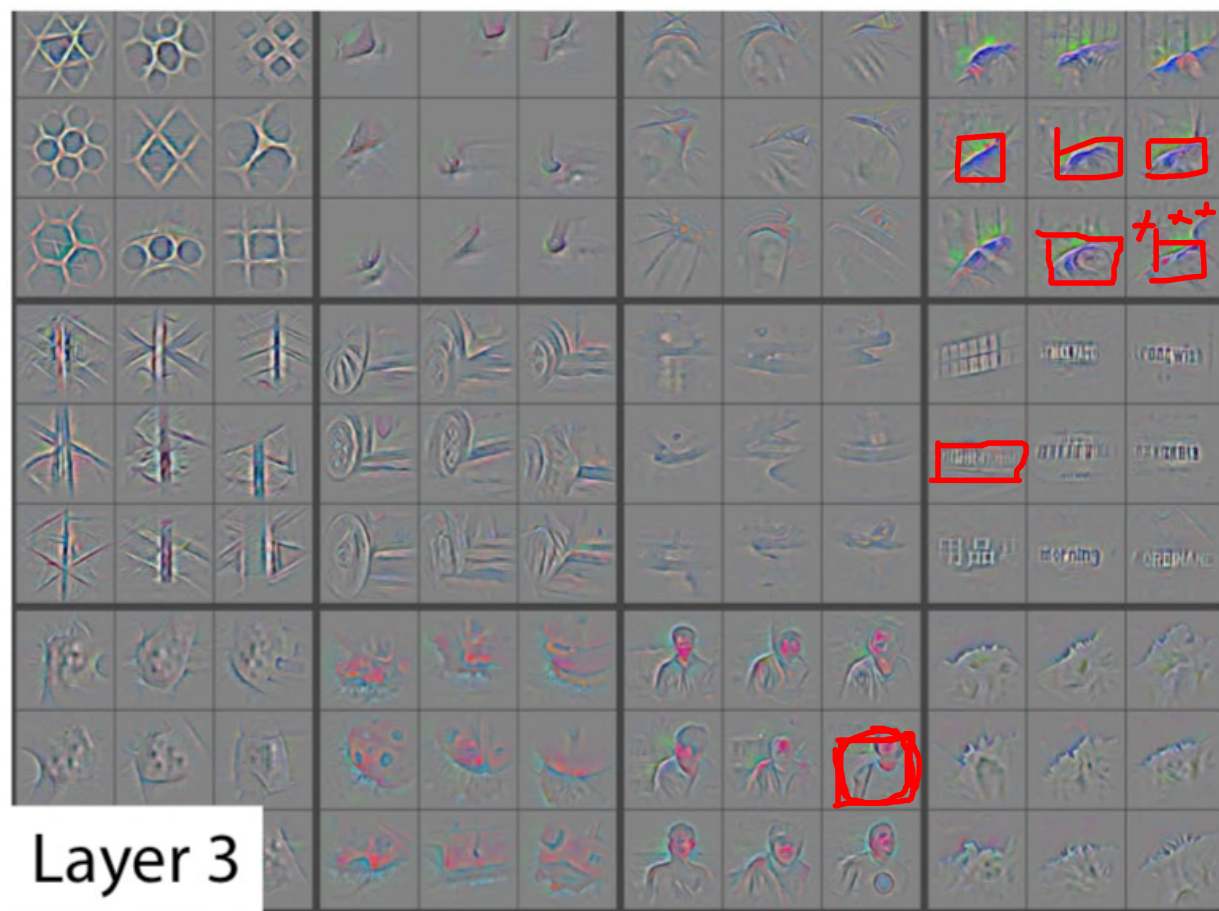
## Fast R-CNN



Input image-> ConvNet->Conv feature map->proposals->FCs...



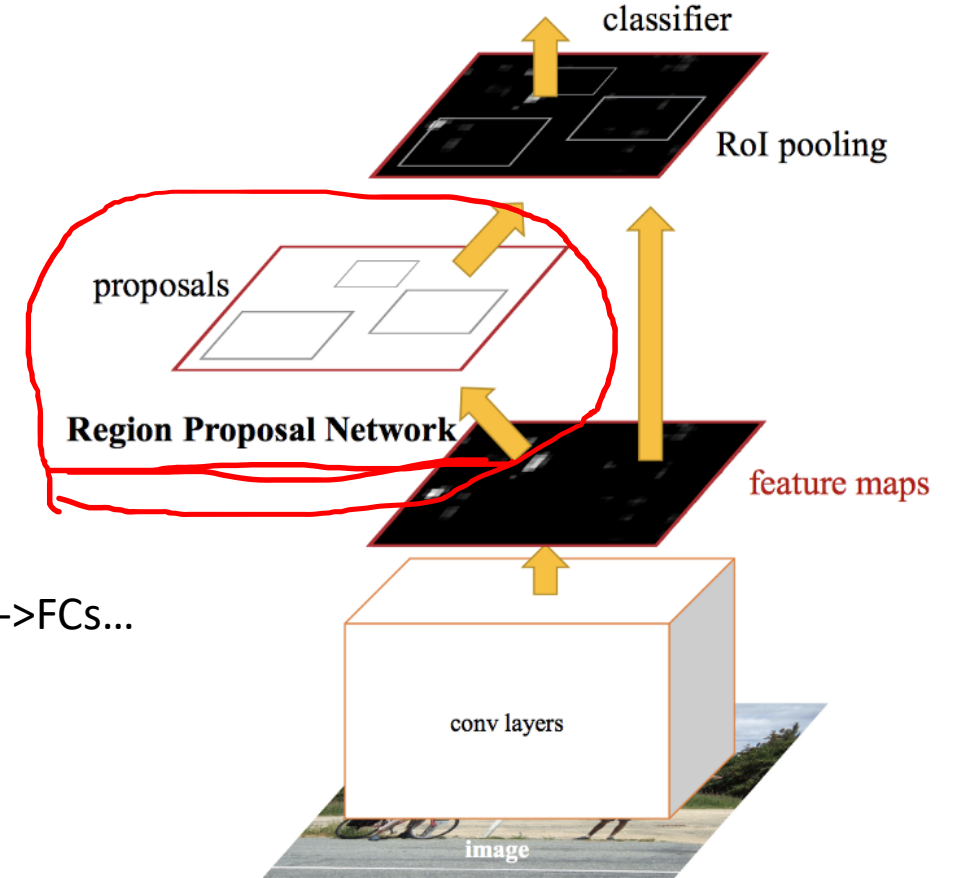
# Conv feature map





## Faster R-CNN

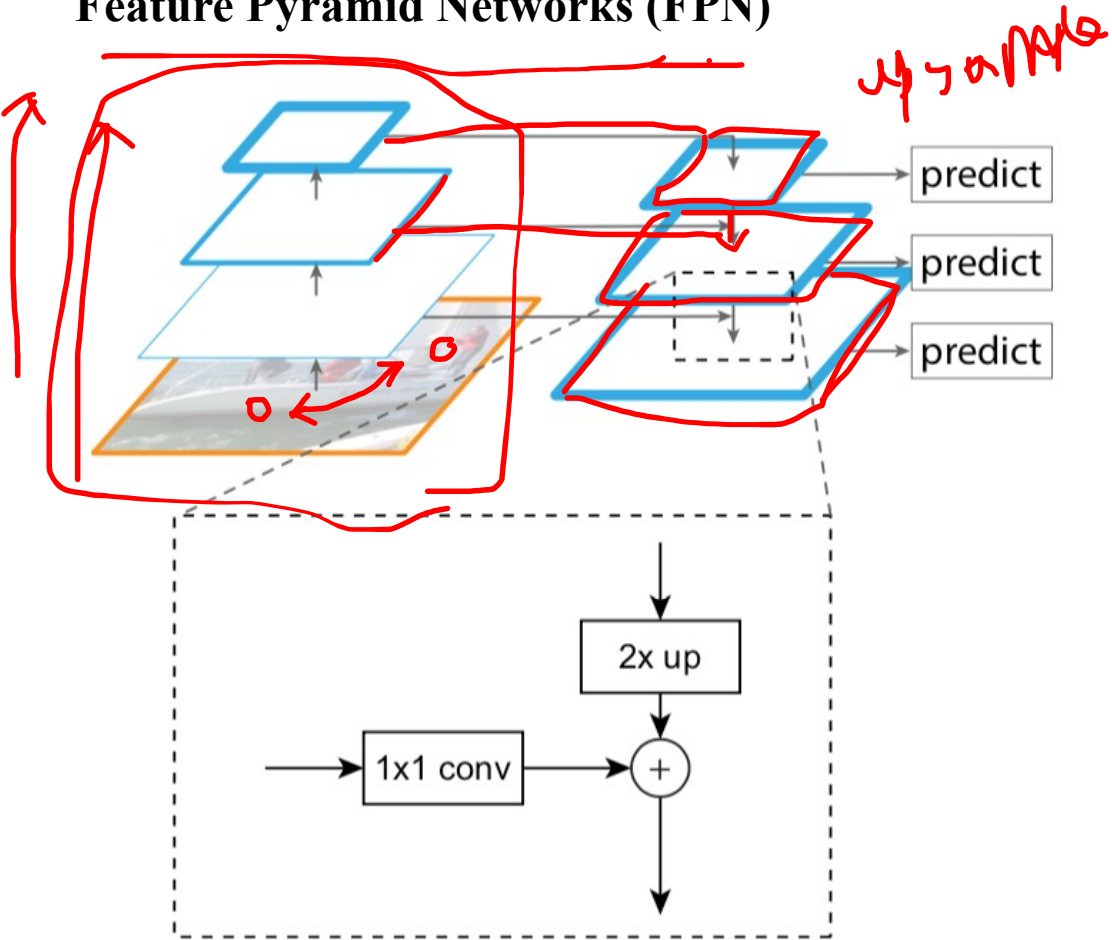
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Input image-> ConvNet->Conv feature map **by a network**->proposals->FCs...

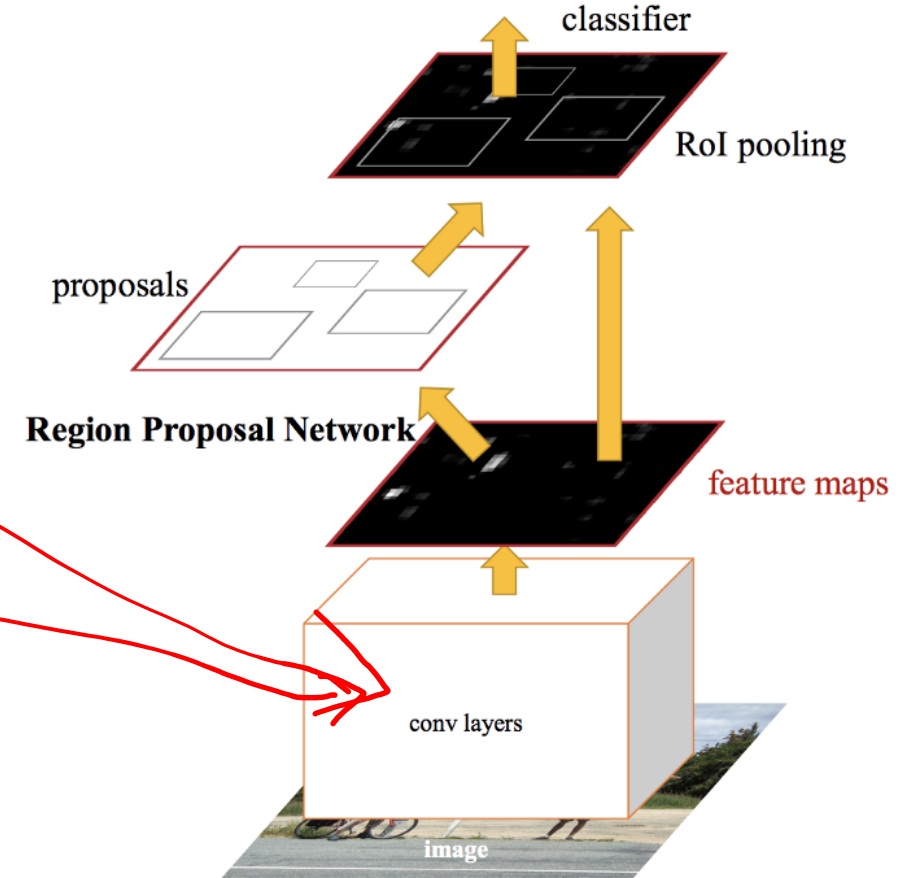
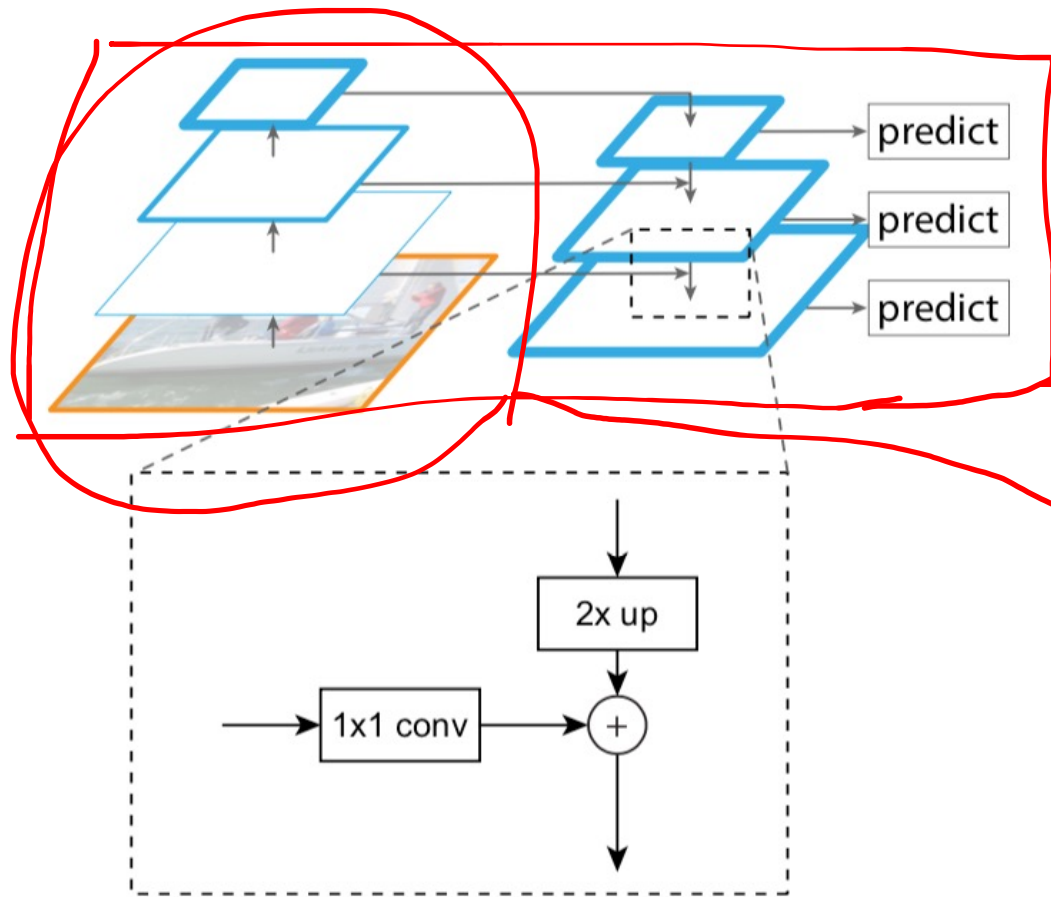
Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems, 28, 91-99. <https://proceedings.neurips.cc/paper/5638-faster-r-cnn-towards-real-time-object-detection-with-region-proposal-networks.pdf>

## Feature Pyramid Networks (FPN)



Lin, T. Y., Dollár, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). Feature pyramid networks for object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2117-2125). [http://openaccess.thecvf.com/content\\_cvpr\\_2017/papers/Lin\\_Feature\\_Pyramid\\_Networks\\_CVPR\\_2017\\_paper.pdf](http://openaccess.thecvf.com/content_cvpr_2017/papers/Lin_Feature_Pyramid_Networks_CVPR_2017_paper.pdf)

## Feature Pyramid Networks (FPN) in Faster R-CNN



Lin, T. Y., Dollár, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). Feature pyramid networks for object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2117-2125). [http://openaccess.thecvf.com/content\\_cvpr\\_2017/papers/Lin\\_Feature\\_Pyramid\\_Networks\\_CVPR\\_2017\\_paper.pdf](http://openaccess.thecvf.com/content_cvpr_2017/papers/Lin_Feature_Pyramid_Networks_CVPR_2017_paper.pdf)

## One-stage vs. Two-stage

### One-stage detectors:

Computational demand is relatively low

Generally faster than two-stage methods

Suitable for real-time detections

Not good at recognizing irregularly shaped objects or a group of small objects.

Popular one-stage detectors include the YOLO, SSD, and RetinaNet.

### Two-stage detectors:

Demand more computational resources

Generally slower than one-stage methods

Two-stage methods achieve the highest detection accuracy

Various two-stage detectors include region convolutional neural network (RCNN), with evolutions

Faster R-CNN or Mask R-CNN. The latest evolution is the granulated RCNN (G-RCNN).

Two-stage object detectors first find a region of interest and use this cropped region for classification.

However, such multi-stage detectors are usually not end-to-end trainable because cropping is a non-differentiable operation.



## Anchor free methods

### CornerNet

[http://openaccess.thecvf.com/content\\_ECCV\\_2018/papers/Hei\\_Law\\_CornerNet\\_Detecting\\_Objects\\_ECCV\\_2018\\_paper.pdf](http://openaccess.thecvf.com/content_ECCV_2018/papers/Hei_Law_CornerNet_Detecting_Objects_ECCV_2018_paper.pdf)

### CenterNet

[https://openaccess.thecvf.com/content\\_ICCV\\_2019/papers/Duan\\_CenterNet\\_Keypoint\\_Triplets\\_for\\_Object\\_Detection\\_ICCV\\_2019\\_paper.pdf](https://openaccess.thecvf.com/content_ICCV_2019/papers/Duan_CenterNet_Keypoint_Triplets_for_Object_Detection_ICCV_2019_paper.pdf)

### FSAF

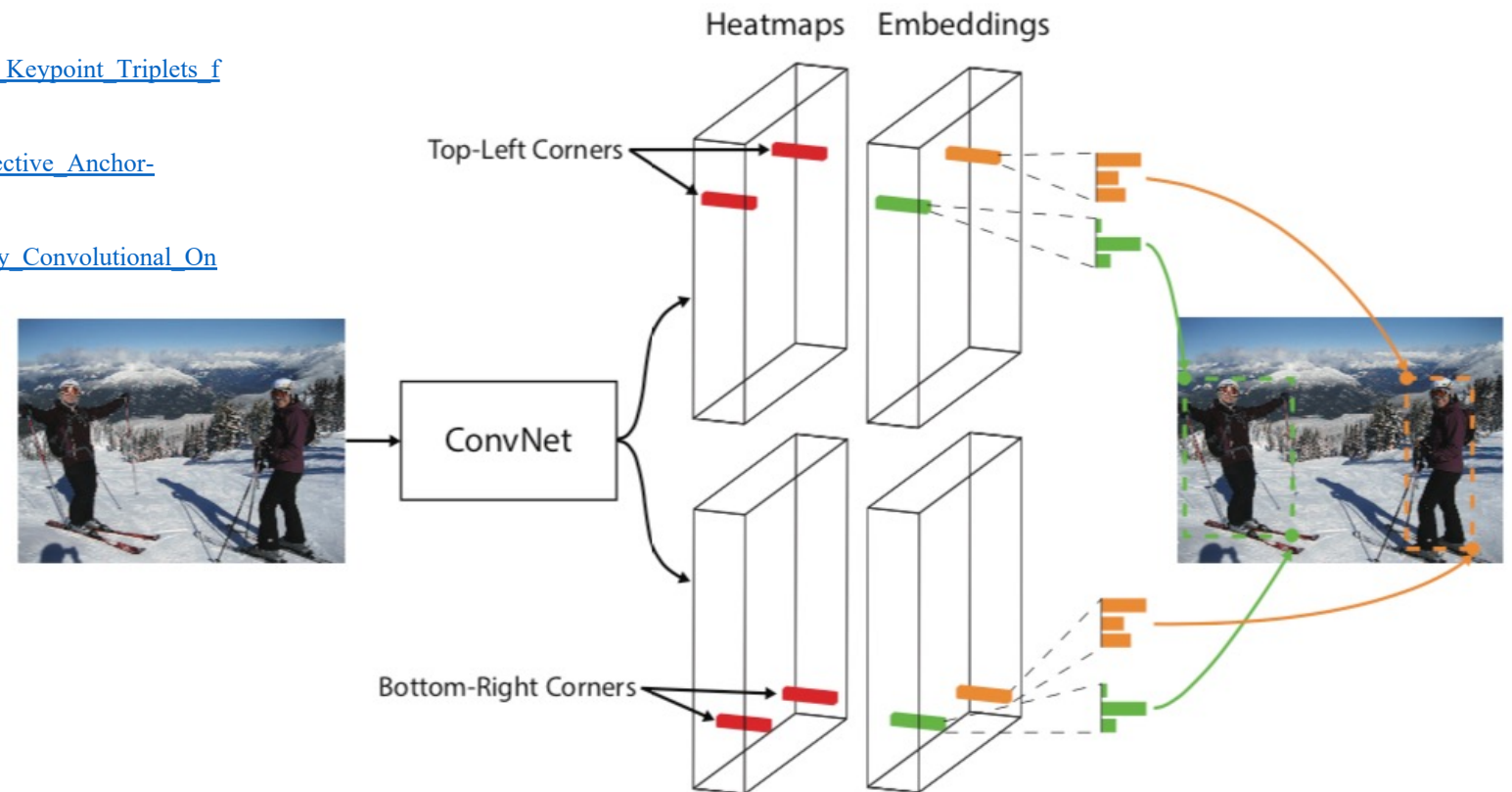
[http://openaccess.thecvf.com/content\\_CVPR\\_2019/papers/Zhu\\_Feature\\_Selective\\_Anchor-Free\\_Module\\_for\\_Single-Shot\\_Object\\_Detection\\_CVPR\\_2019\\_paper.pdf](http://openaccess.thecvf.com/content_CVPR_2019/papers/Zhu_Feature_Selective_Anchor-Free_Module_for_Single-Shot_Object_Detection_CVPR_2019_paper.pdf)

### FCOS

[https://openaccess.thecvf.com/content\\_ICCV\\_2019/papers/Tian\\_FCOS\\_Fully\\_Convolutional\\_One-Stage\\_Object\\_Detection\\_ICCV\\_2019\\_paper.pdf](https://openaccess.thecvf.com/content_ICCV_2019/papers/Tian_FCOS_Fully_Convolutional_One-Stage_Object_Detection_ICCV_2019_paper.pdf)

### SAPD

<https://arxiv.org/pdf/1911.12448>




## CornerNet

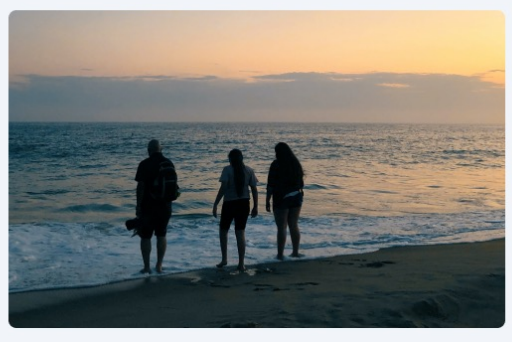
Proceedings of the European conference on computer vision (ECCV) (pp. 734-750). [http://openaccess.thecvf.com/content\\_ECCV\\_2018/papers/Hei\\_Law\\_CornerNet\\_Detecting\\_Objects\\_ECCV\\_2018\\_paper.pdf](http://openaccess.thecvf.com/content_ECCV_2018/papers/Hei_Law_CornerNet_Detecting_Objects_ECCV_2018_paper.pdf)

## Metrics

Intersection Over Union (IOU):

The ratio of intersection of ground truth and predicted bounding box or segmentation outputs over their union.

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




Image



Semantic Segmentation



Instance Segmentation

**Popular algorithms:**

U-Net

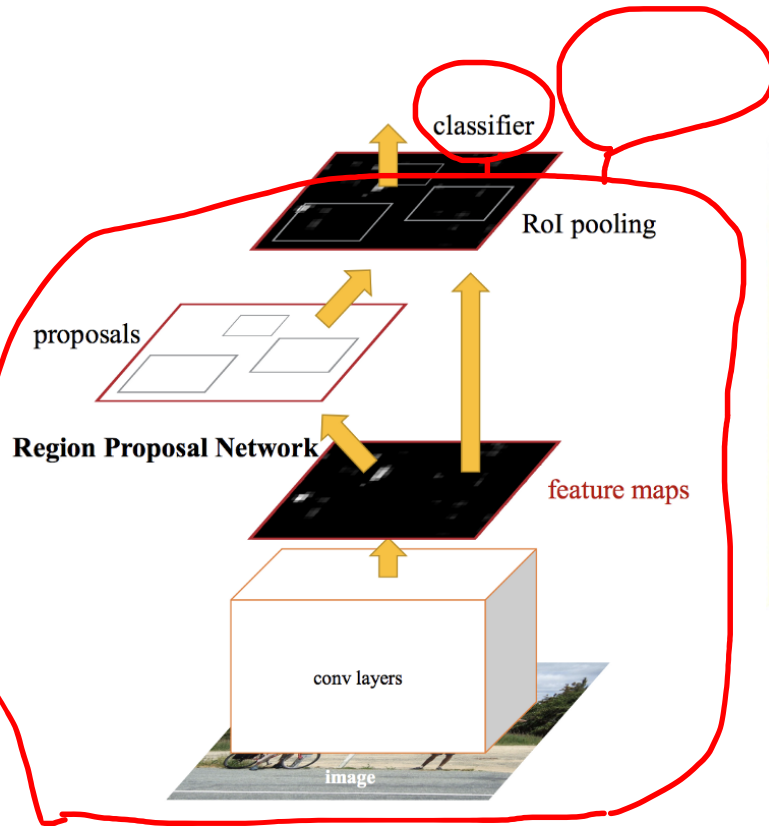
Fast Fully Convolutional Network (FastFCN)

DeepLab

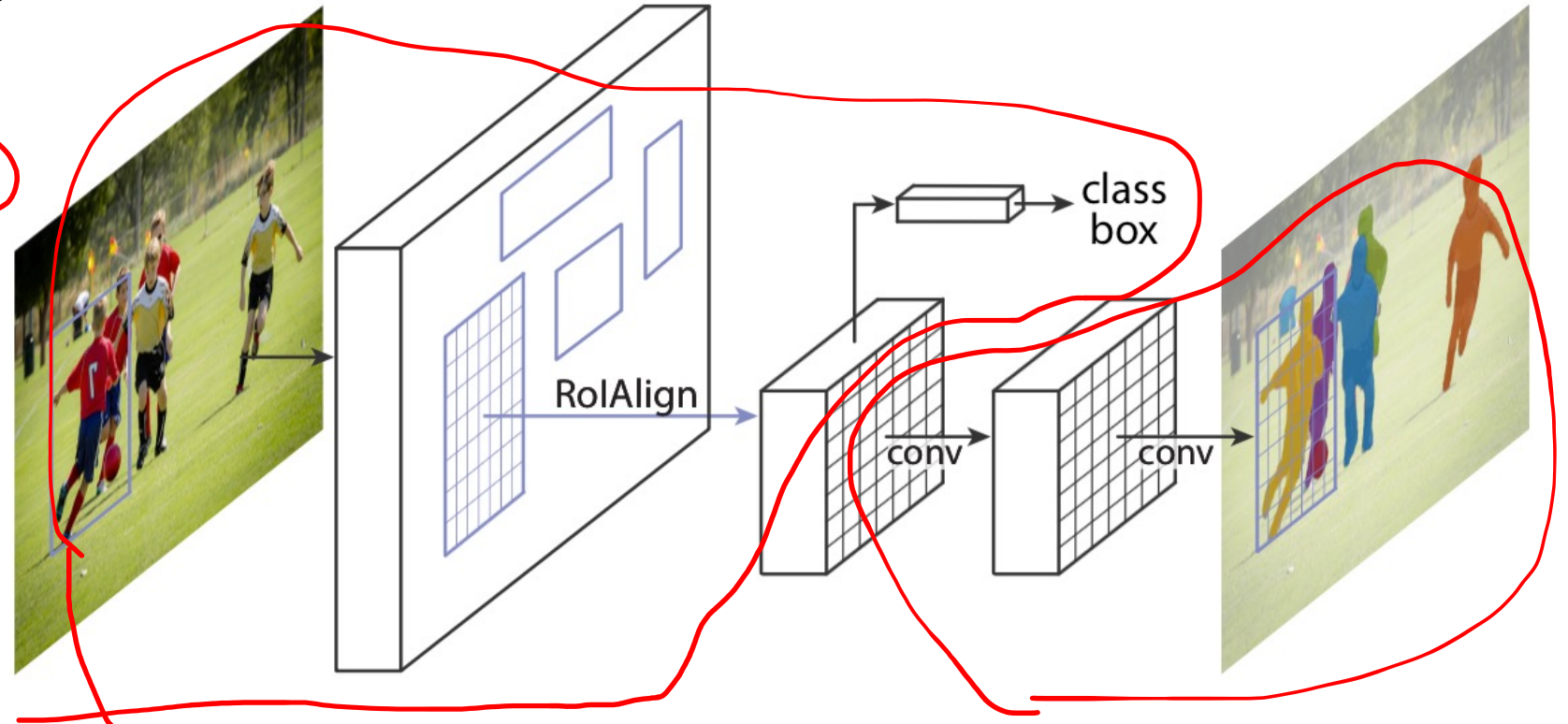
Mask R-CNN

...

## Mask R-CNN For Detection + Segmentation



Faster R-CNN



Extends Faster R-CNN: adding a branch in the head for predicting segmentation masks on each Region of Interest

Mask R-CNN



## Demo: Object detection and instance segmentation

Will run this demo in a Jupyter notebook on Google Colab:

[https://colab.research.google.com/drive/1\\_FT8Izry\\_7uYRQ-jXF0Rg75H5vKB\\_oy2?usp=sharing](https://colab.research.google.com/drive/1_FT8Izry_7uYRQ-jXF0Rg75H5vKB_oy2?usp=sharing)