

# Deep Object Detection summary

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Version 3.8



## Object Detection for UAV sports (VML cinematography

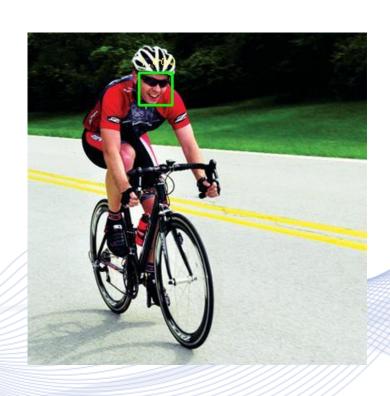






## Object Detection for UAV sports (VML cinematography







Target/object examples: athletes, boats, bicycles.







- Object detection = classification + localization:
- Find what is in a picture as well as where it is.

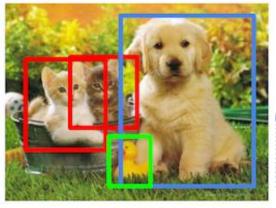
Classification

Classification + Localization

**Object Detection** 











CAT, DOG, DUCK



## Object Detection with CNNs





Object detection: CNN pipeline for bounding box regression.







#### Region proposal-based detectors

- R-CNN, Fast R-CNN, Faster R-CNN
- R-FCN

#### Single Stage Detectors

- YOLO
- SSD
- YOLO v2, v3, v4
- RetinaNet, RBFnet
- CornerNet, CenterNet
- DETR.







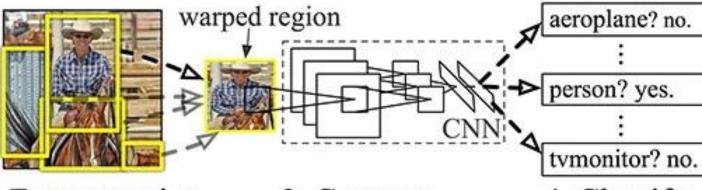
#### R-CNN: Regions with CNN features



1. Input image



2. Extract region proposals (~2k)



3. Compute CNN features

4. Classify regions

[GIR2014]





#### **R-CNN**

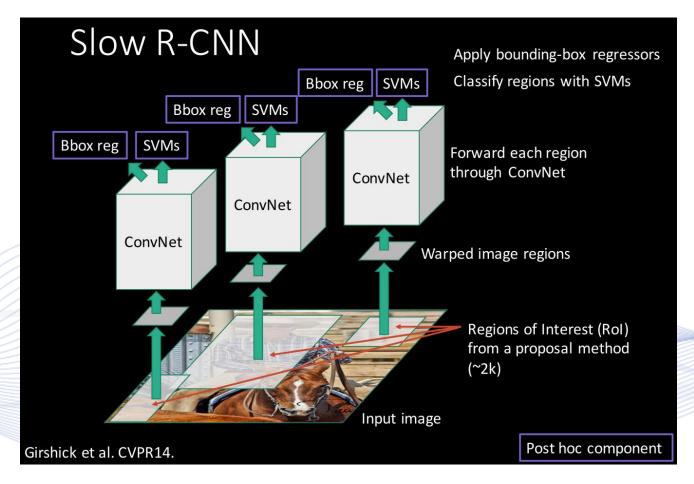






#### **R-CNN**

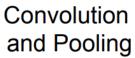






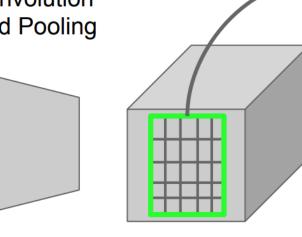


#### **Fast R-CNN**

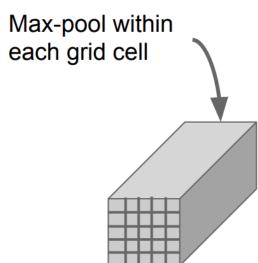




Hi-res input image: 3 x 800 x 600 with region proposal



Hi-res conv features: CxHxWwith region proposal



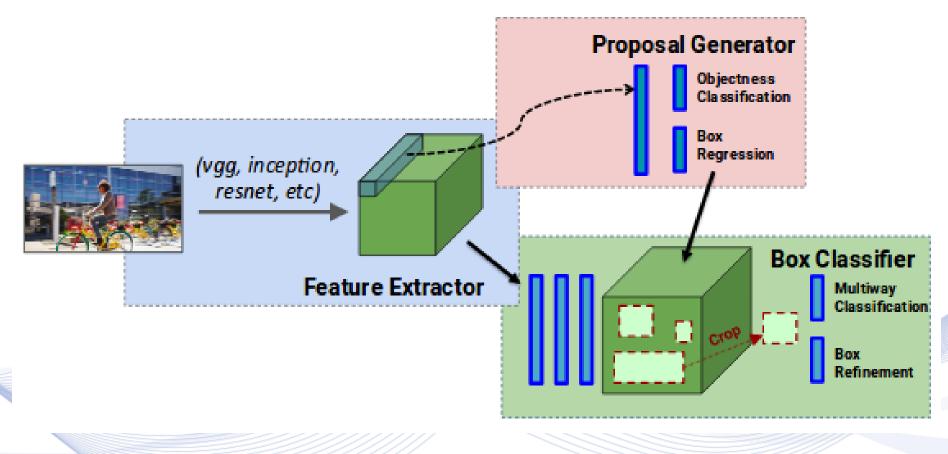
Rol conv features: Cxhxwfor region proposal

ROI pooling.





#### **R-FCN**

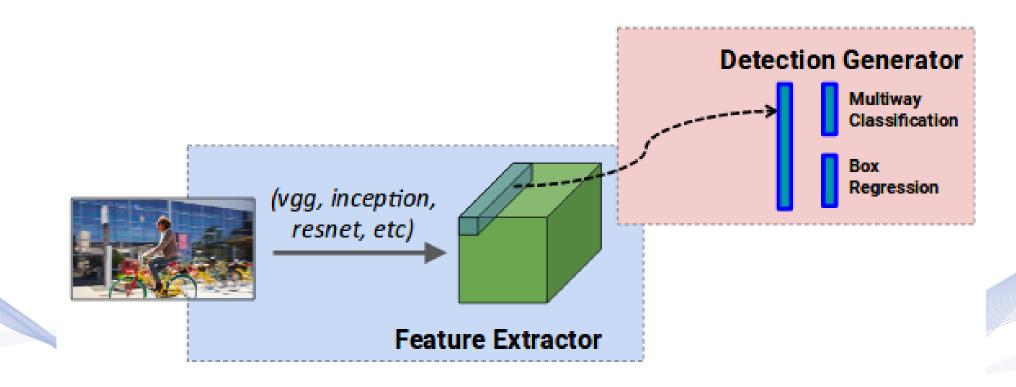


[HUA2017]



### SSD



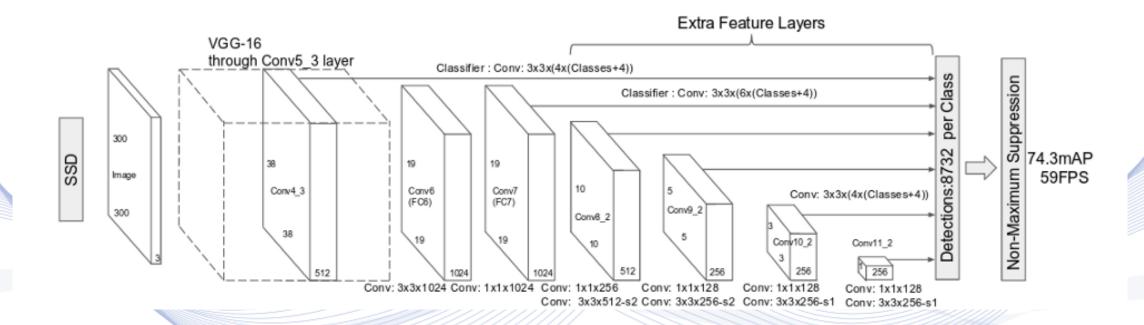


SSD architecture [HUA2017].





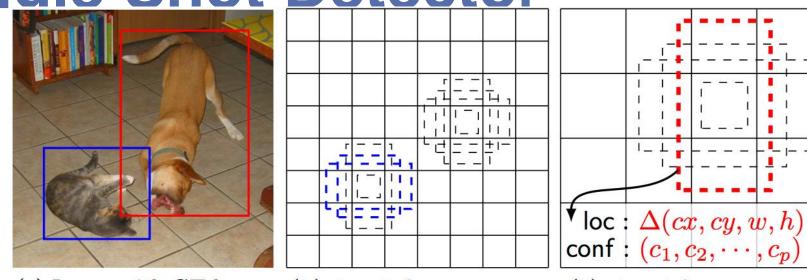
### Single Shot Detector







Sinale Shot Detector



- (a) Image with GT boxes
- (b)  $8 \times 8$  feature map (c)  $4 \times 4$  feature map
- Example: The cat has 2 anchors (ROIs) that match on the  $8 \times 8$  feature map, but none match the dog.
- On the  $4 \times 4$  feature map there is one anchor that matches the dog and it is refined.

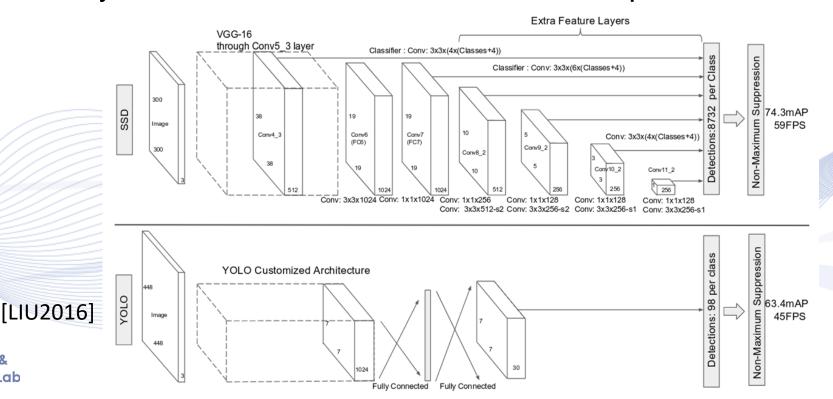






#### YOLO (You Only Look Once) architecture:

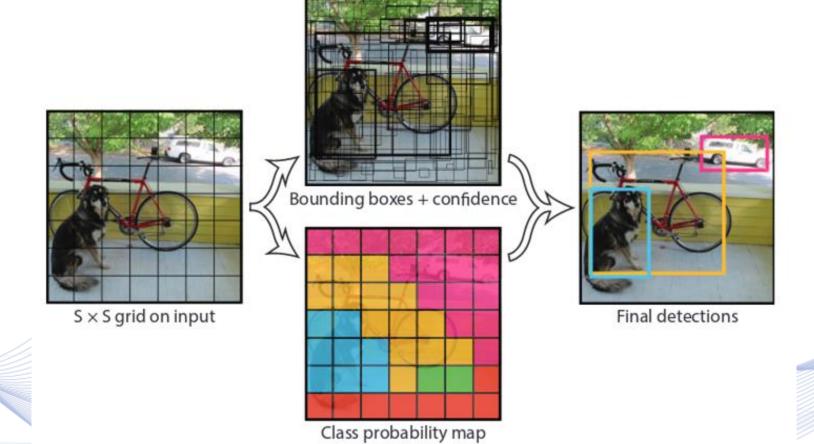
- Darkenet19 convolutional network plus FC layer.
- Prediction only at the final convolutional feature map.











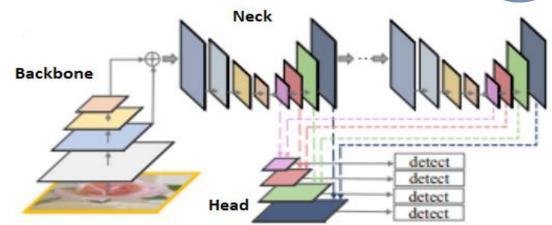


[RED2016]

#### YOLO v4



YOLO v4 design:



• Backbone: CSPDarknet53.

[BOC2020]

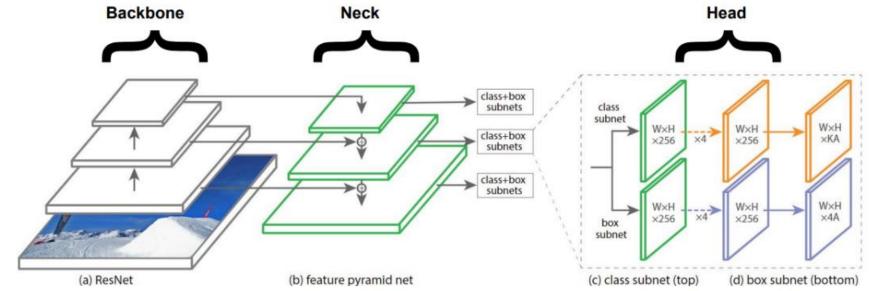
- Neck: Spatial pyramid pooling (SPP) and Path Aggregation
  - Network (PAN).
- Head: Same as YOLO v3.





#### RetinaNet

- ResNet is used as a backbone for feature extraction.
- Feature Pyramid Network (FPN) is used as a neck on top of ResNet for constructing a rich multi-scale feature pyramid from one single resolution image.





#### **RFBNet**



Spatial Array

3x3 conv

rate=1

1x1 conv

• It inspired by the structure of receptive fields in human visual system [LIU2018].

 Use of multiple dilated convolutions with different kernel sizes in each convolutional layer.

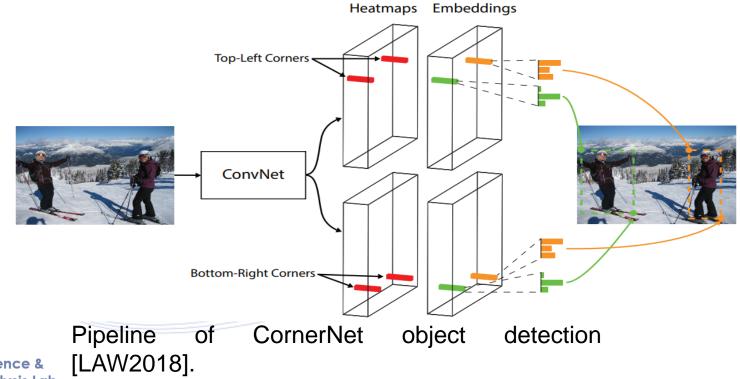
State-of-the-art results and fast inference time.





#### CornerNet

- Each set of heatmaps has C channels and is of size h × w pixels:
  - *C*: number of categories to detect.

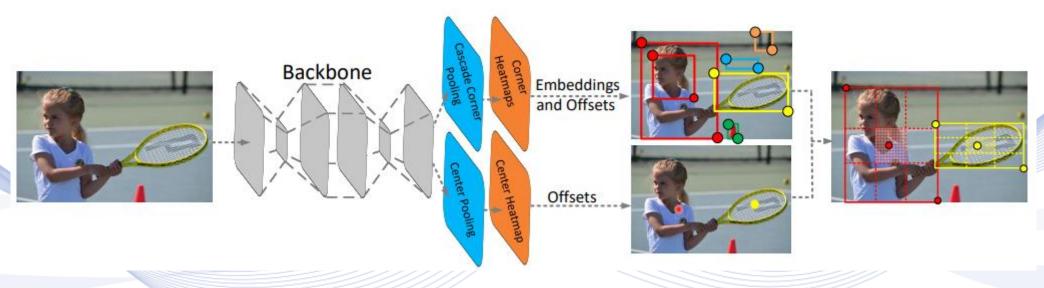






#### CenterNet

 A CNN backbone applies cascade cornel pooling and center pooling in order to output two corner heatmaps and a center keypoint heatmap, respectively.

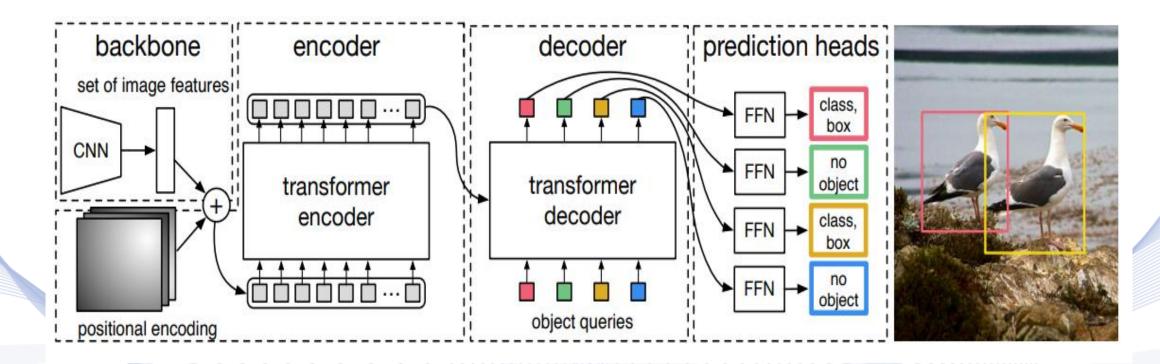


Architecture of CenterNet. [DUA2019].





#### **DETR**



DETR architecture [CAR2020].



## Using object detectors for drone-based shooting



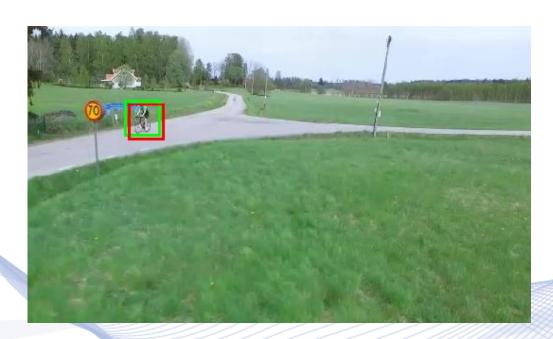
- Reducing the input image size can also increase the detection speed
  - However, this can significantly impact the accuracy when detecting very small objects (which is the case for drone shooting)

Model	Input Size	Pascal 2007 test mAP*
YOLO v.2	544x544	77.44
YOLO v.2	416x416	74.60
YOLO v.2	288x288	67.12
YOLO v.2	160x160	48.72
YOLO v.2	128x128	40.68



## Object Localization Performance Metrics







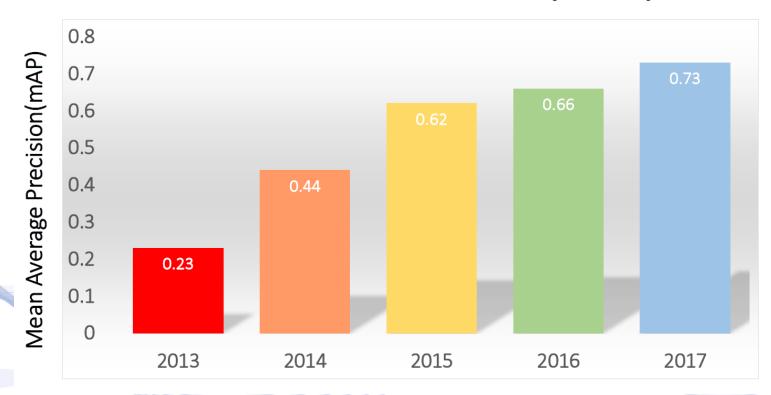
Object detection: a)  $J(\mathcal{A}, \mathcal{B}) = 0.67$ ; b)  $J(\mathcal{A}, \mathcal{B}) = 0.27$ .



## **Object Detection Performance Metrics**



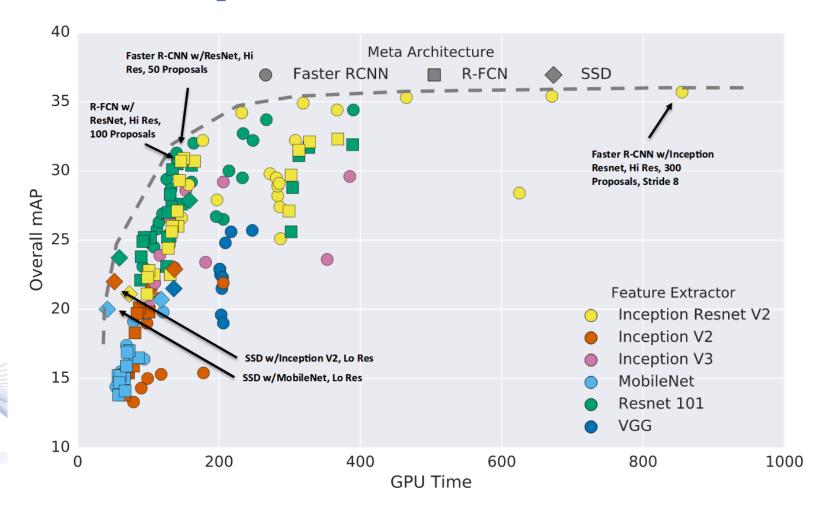
Detection Results (DET)







### **CNN** comparison

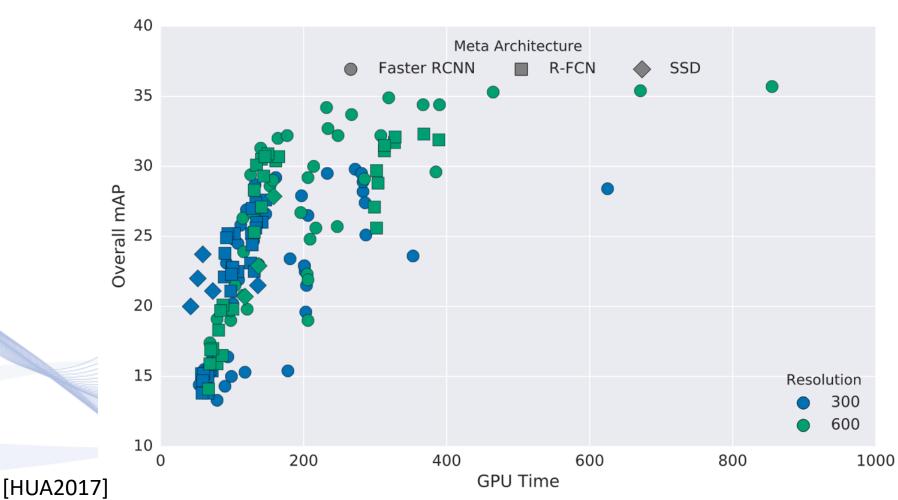




[HUA2017]

## VML

### Input Size NxN









- Faster R-CNN is more accurate but slower.
- YOLO, SSD are much faster but not as accurate.
- YOLO, SSD make more mistakes when objects are small and have trouble correctly predicting the exact location of such objects.



## Object detection acceleration



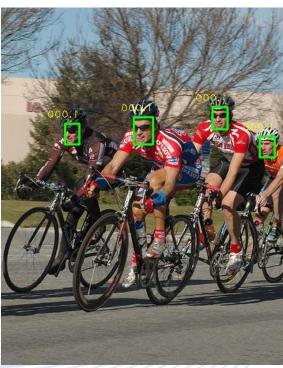
- Examples of acceleration techniques:
  - Input size reduction.
  - Specific object detection instead of multi-object detection.
  - Parameter reduction.
  - Post-training optimizations with TensorRT (NVIDIA), including FP16 (floating point 16 bit) computations.

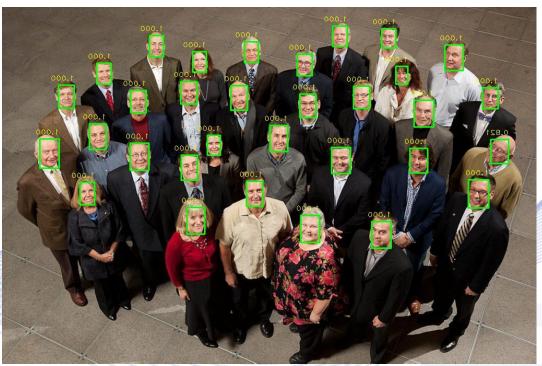




### Face detection examples









### Object Detection for UAV powerline (VML inspection









#### Q & A

Thank you very much for your attention!

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