# Lecture 08 – Image Detection and Segmentation

Prof. André Gustavo Hochuli

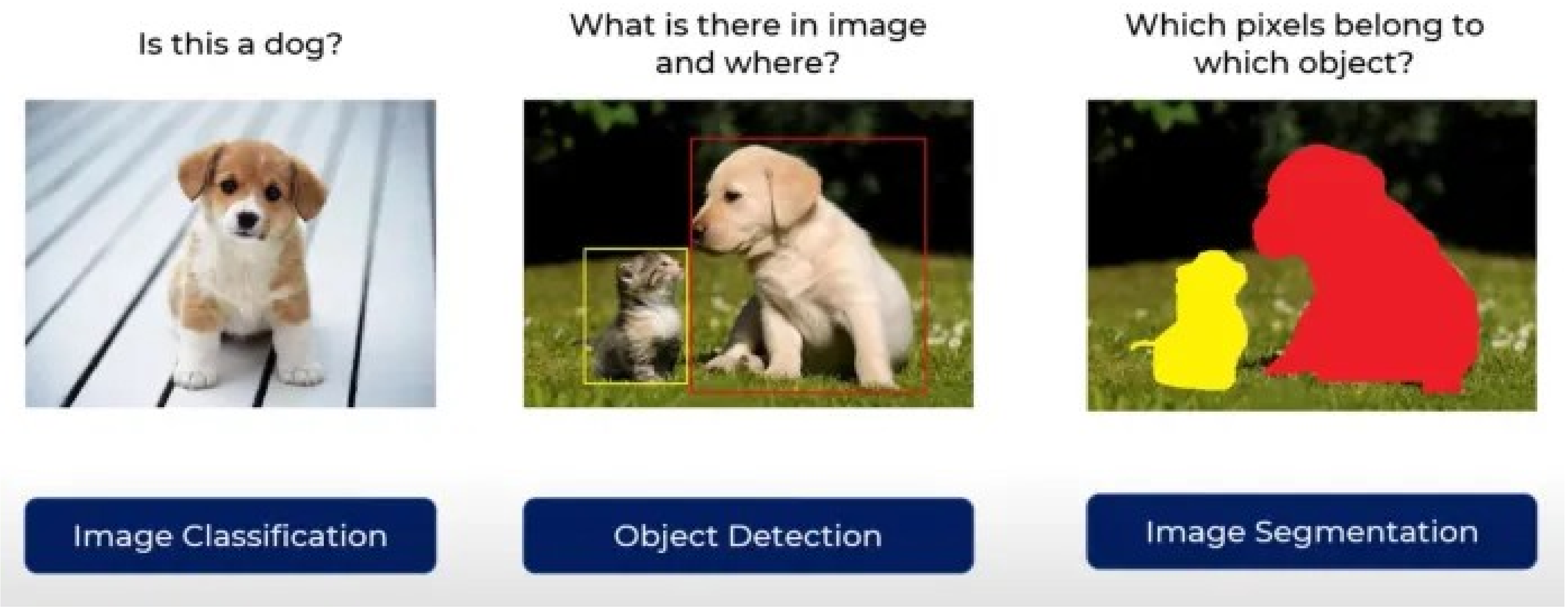
gustavo.hochuli@pucpr.br
aghochuli@ppgia.pucpr.br

# Topics

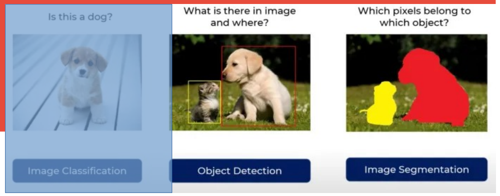
- Review of Lecture 10 – CNN Applications and Tricks

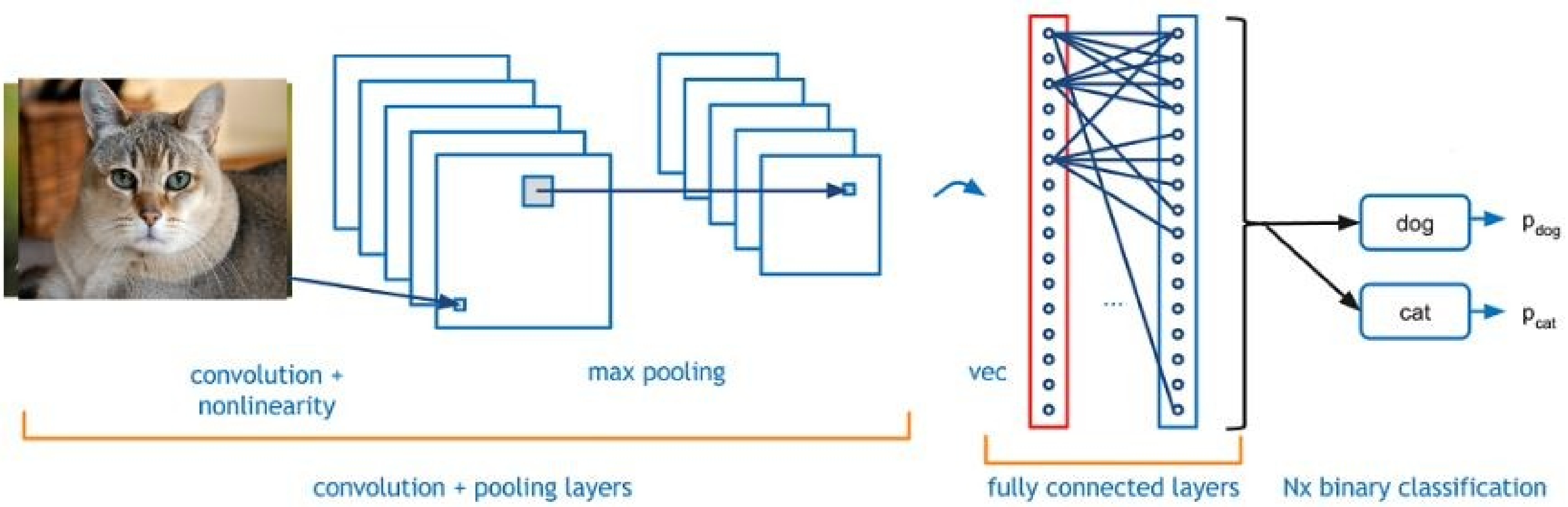
- Classification vs Segmentation
  - Classification
  - Object Detection
  - Segmentation
- Practice

# Classification vs Segmentation



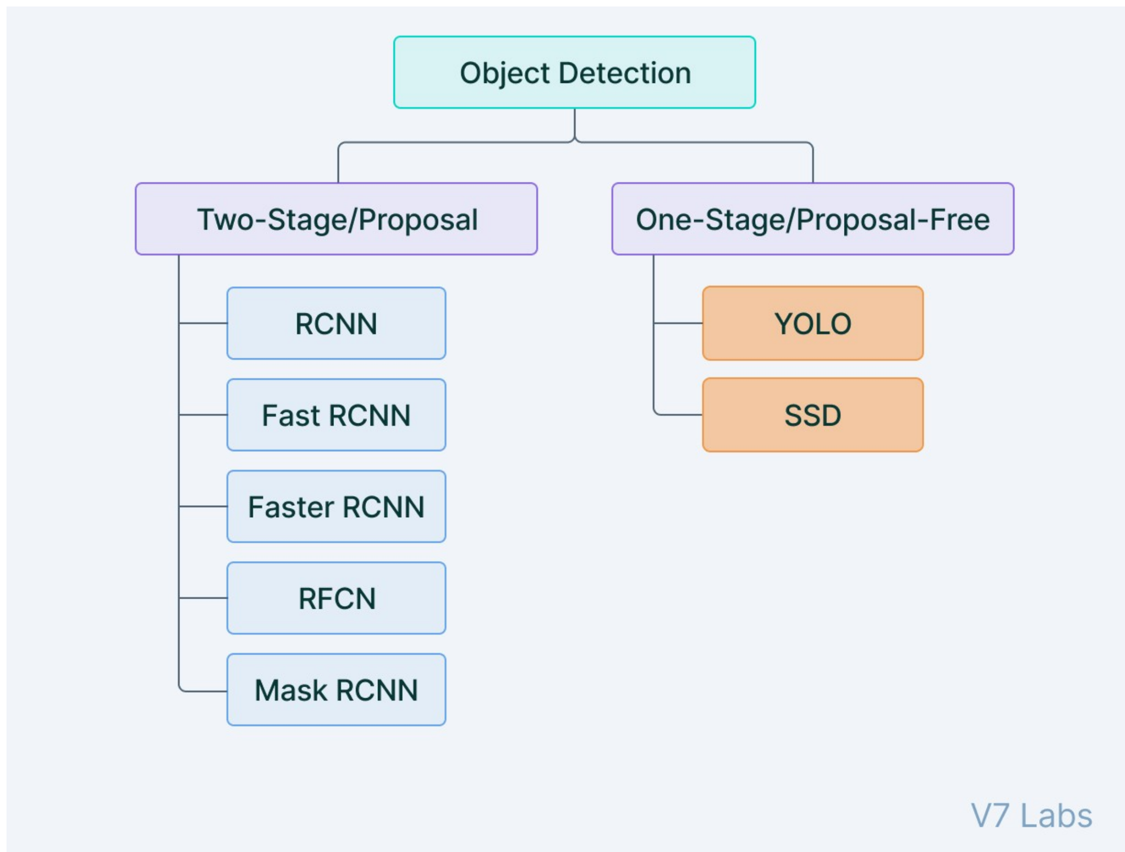
# Classification



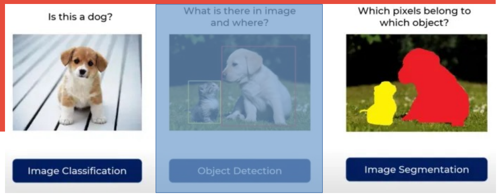



# Object Detection

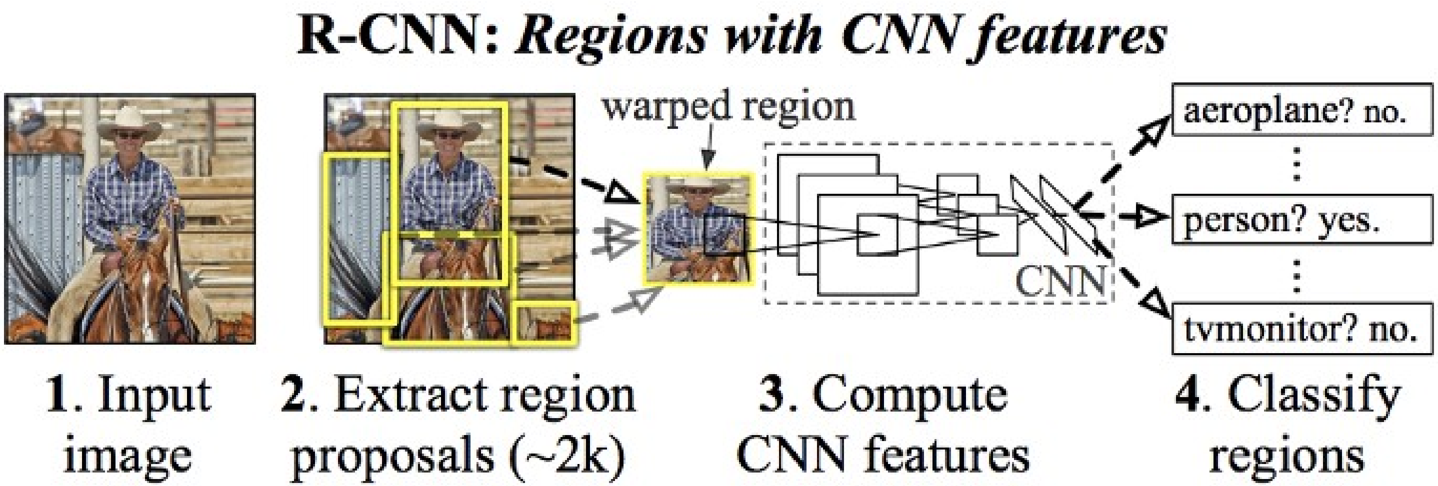
# Object Detection

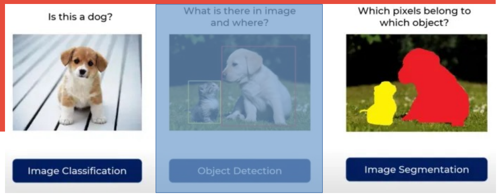
# Object Detection - RCNN



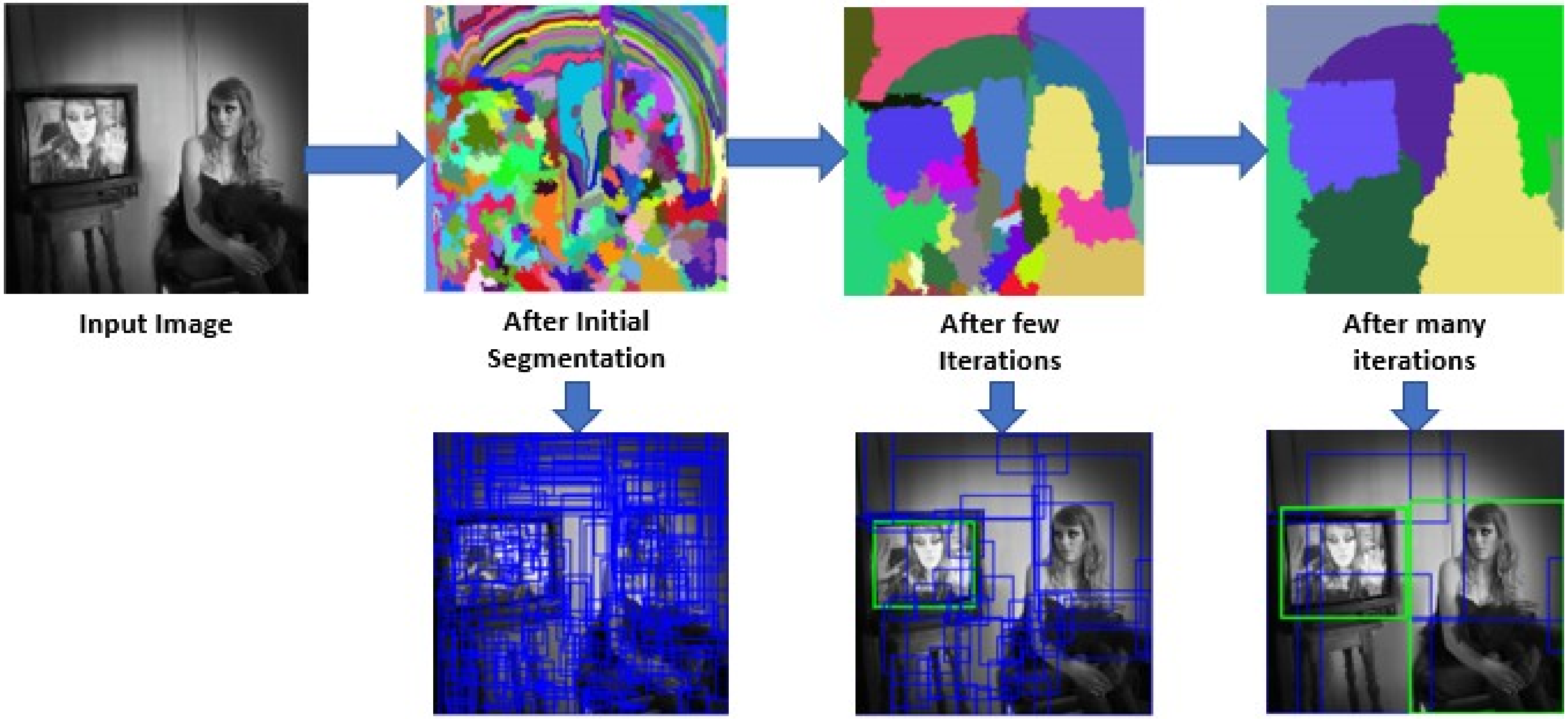

- Region Based Convolutional Neural Network (2014) - Ross Girshick
- Selective Search Algorithm (Region Proposal)
- CNN (Classification)



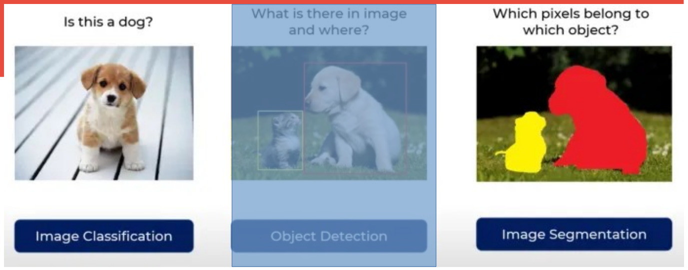
# Object Detection - RCNN



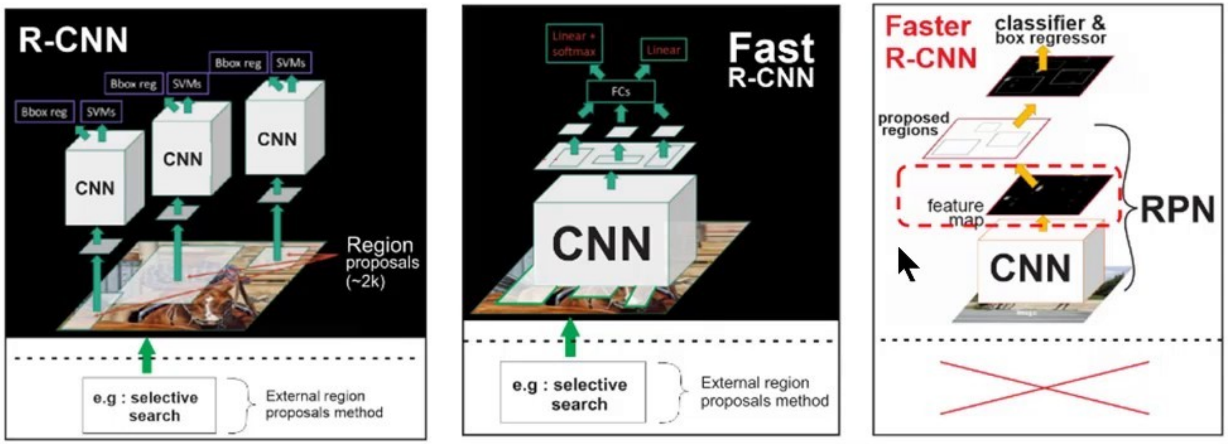

- Selective Search Algorithm (Region Proposal)



# Object Detection - RCNN



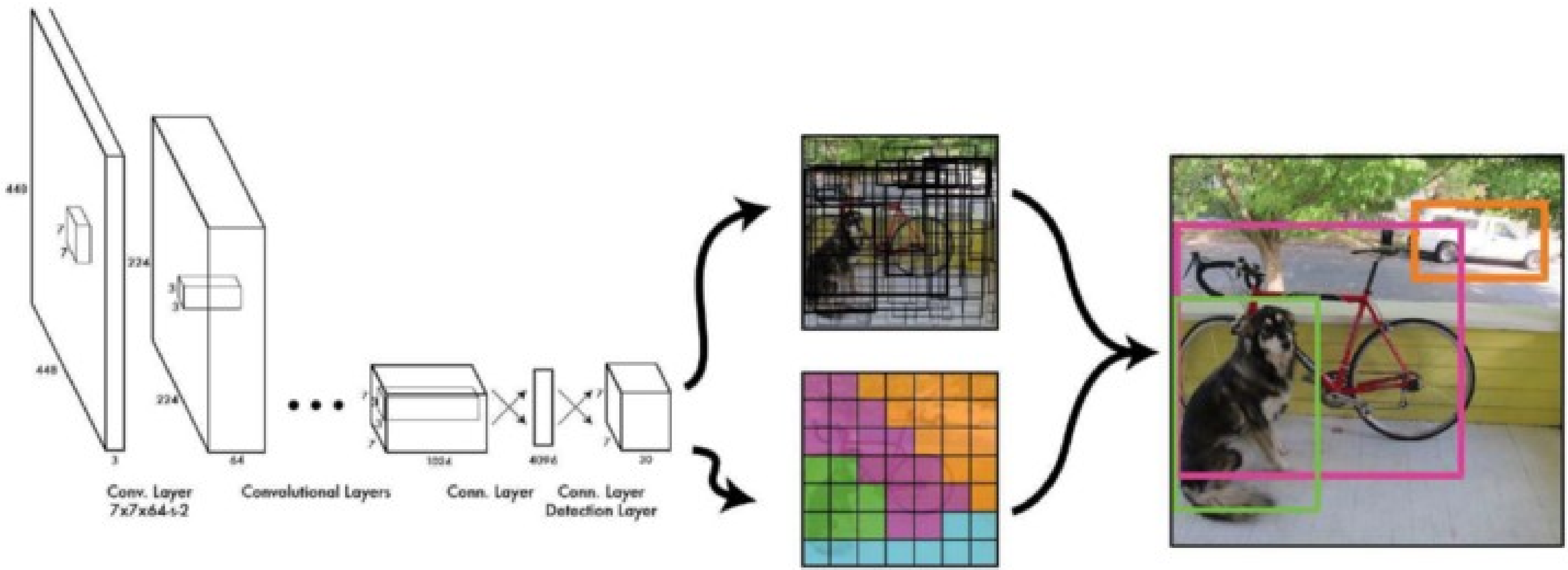

- R-CNN: Selective Search->CNN
- Fast: End-to-end (Sel. Search->ROI Pooling→FC)
- Faster: Region Proposal Network (RPN)



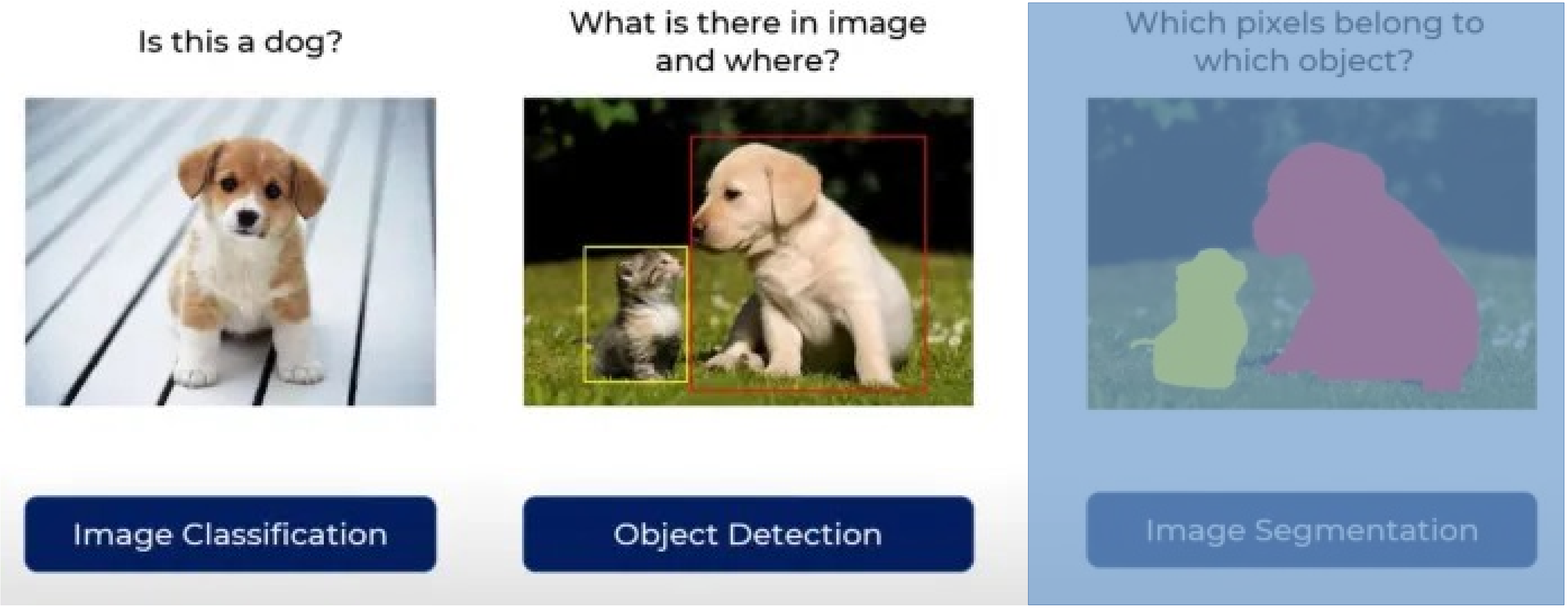

| | R-CNN | Fast R-CNN | Faster R-CNN |
|---|---|---|---|
| Test time per image | 50 seconds | 2 seconds | 0.2 seconds |
| Speed-up | 1x | 25x | 250x |
| mAP (VOC 2007) | 66.0% | 66.9% | 66.9% |

# Object Detection - Yolo

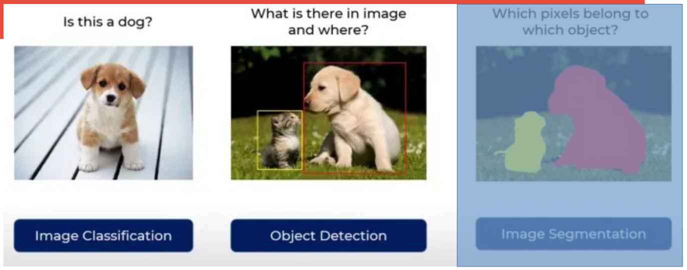

- You Look Once (YoLo - 2015 - now)
  - Joseph Redmon / Ross Girshick
- Fast End-to-End Architecture



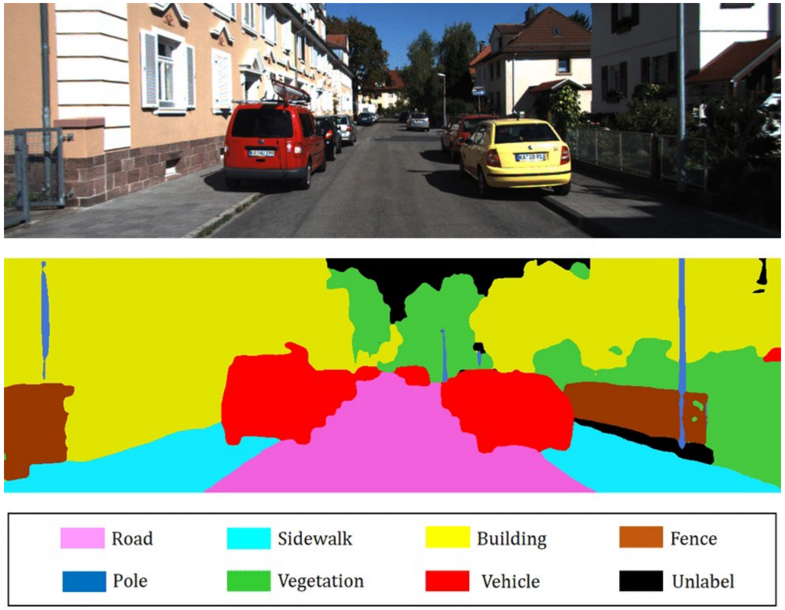
# Segmentation

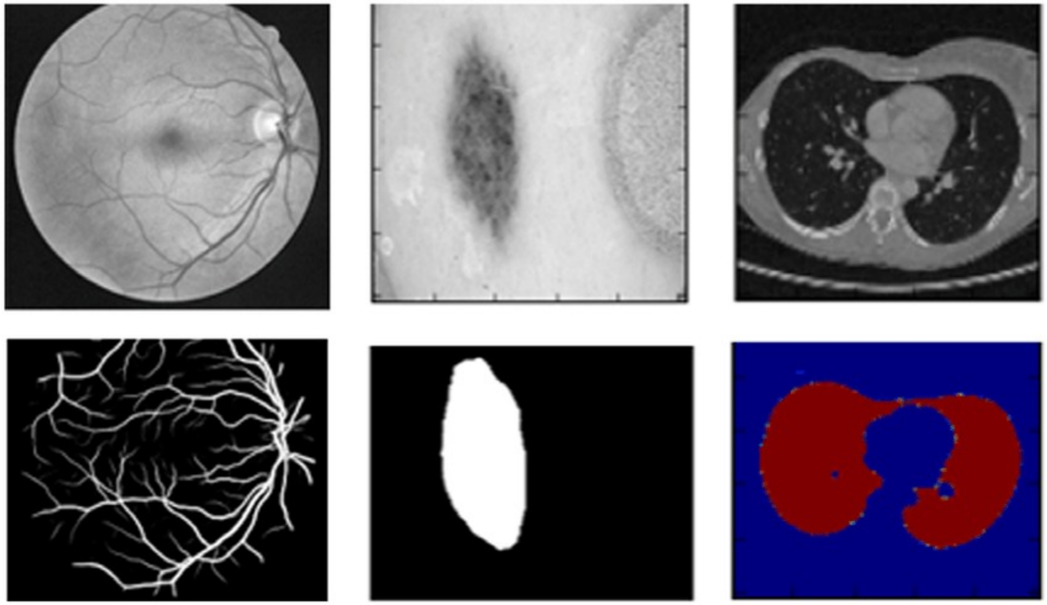


# Segmentation

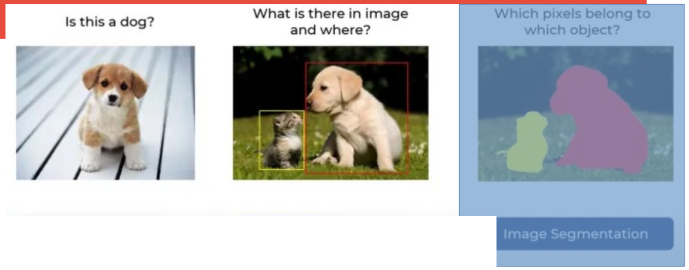



- Classification at pixel level

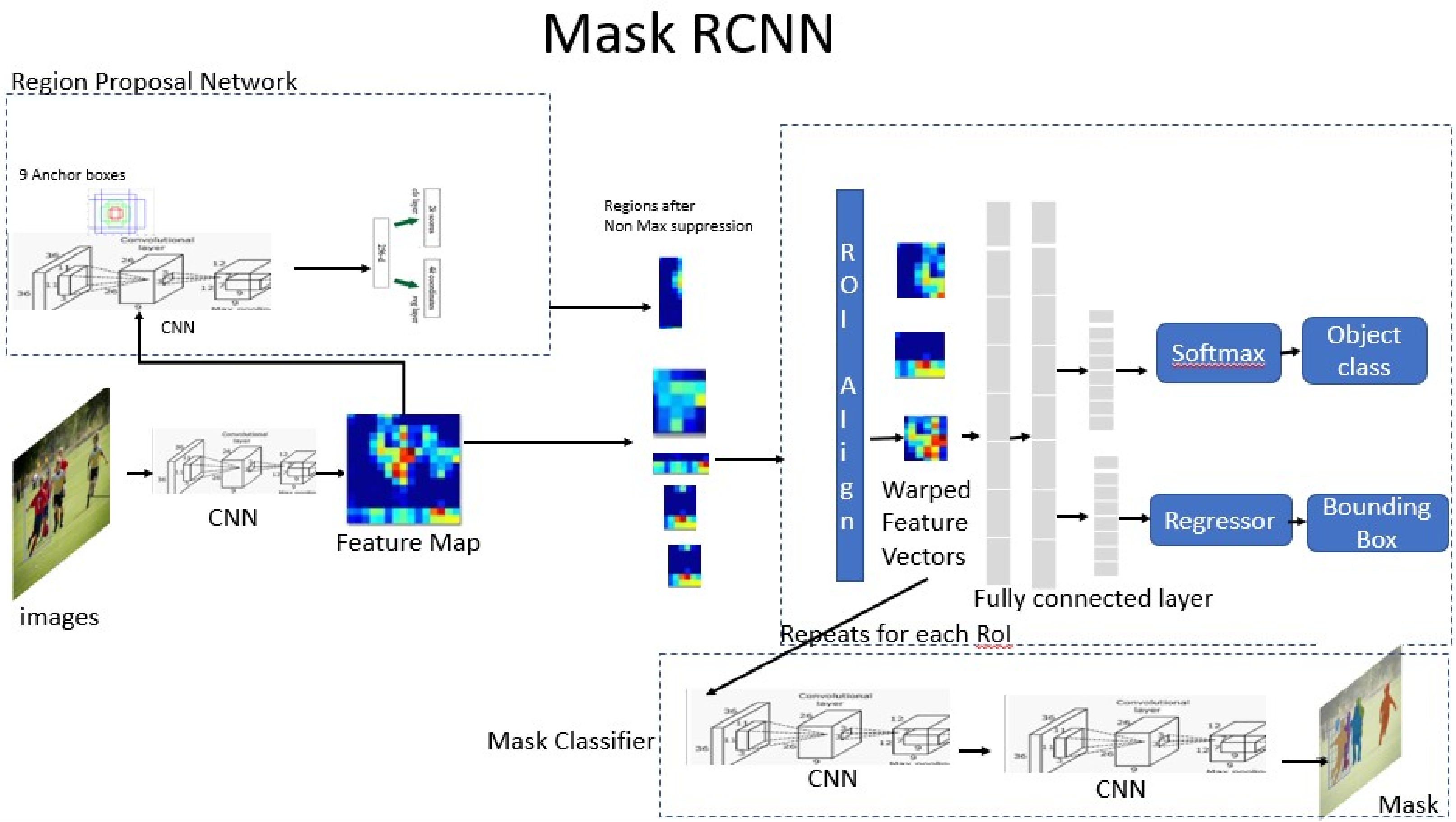


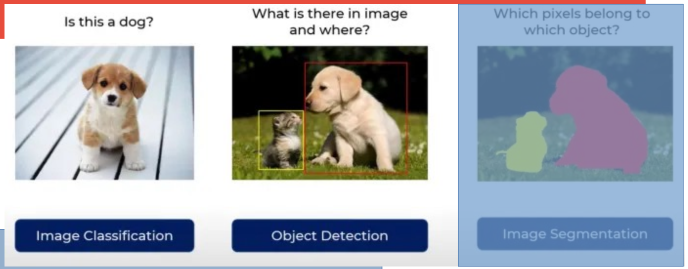
# Segmentation – Mask RCNN



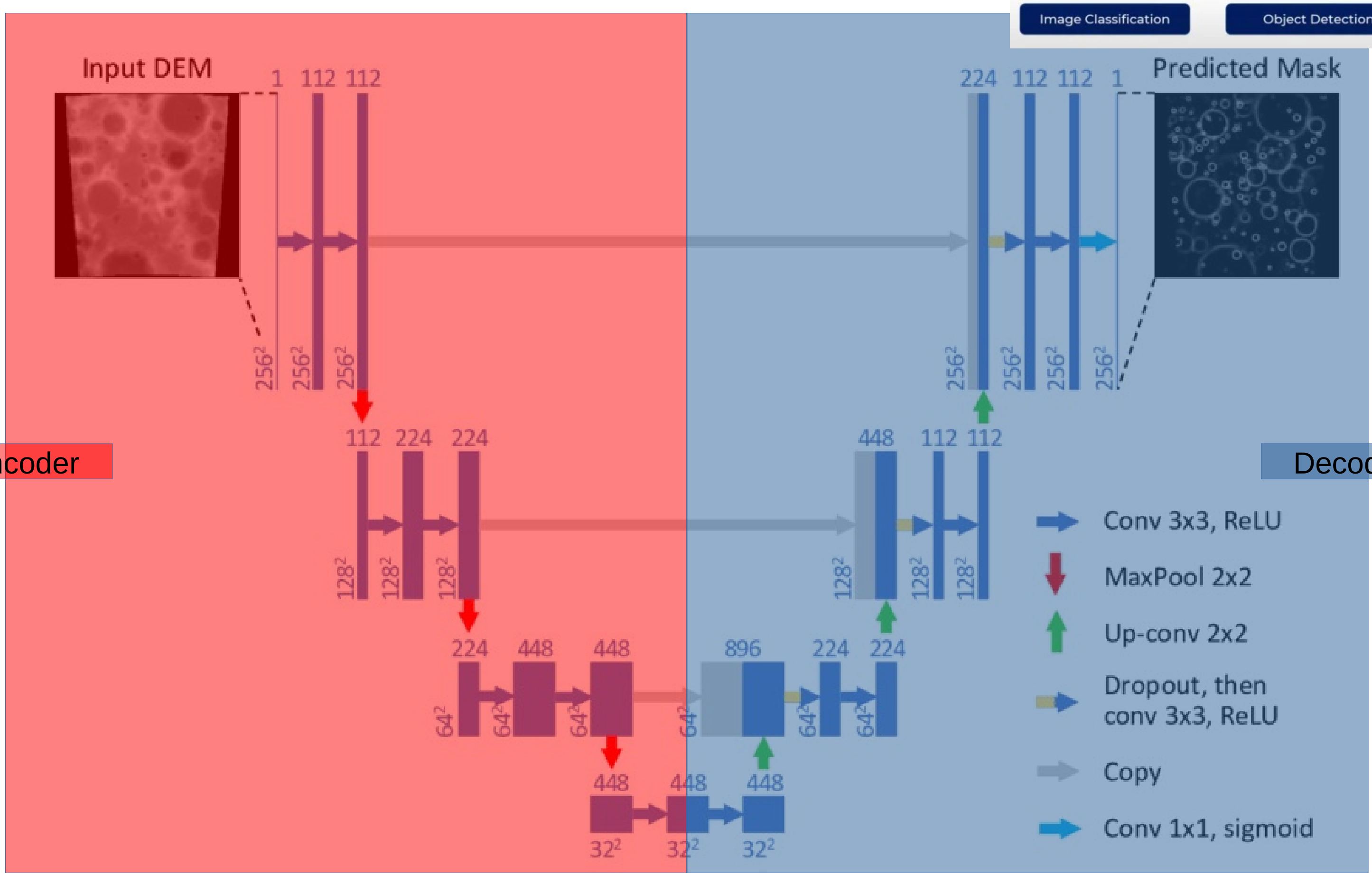

- Faster R-CNN with Binary Mask (2017)



# Segmentation - UNET




- U-Net (Encoder and Decoder)

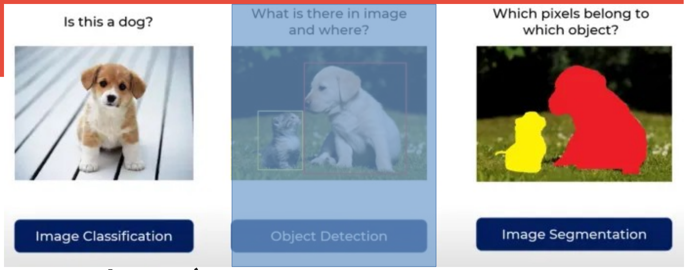



Encoder

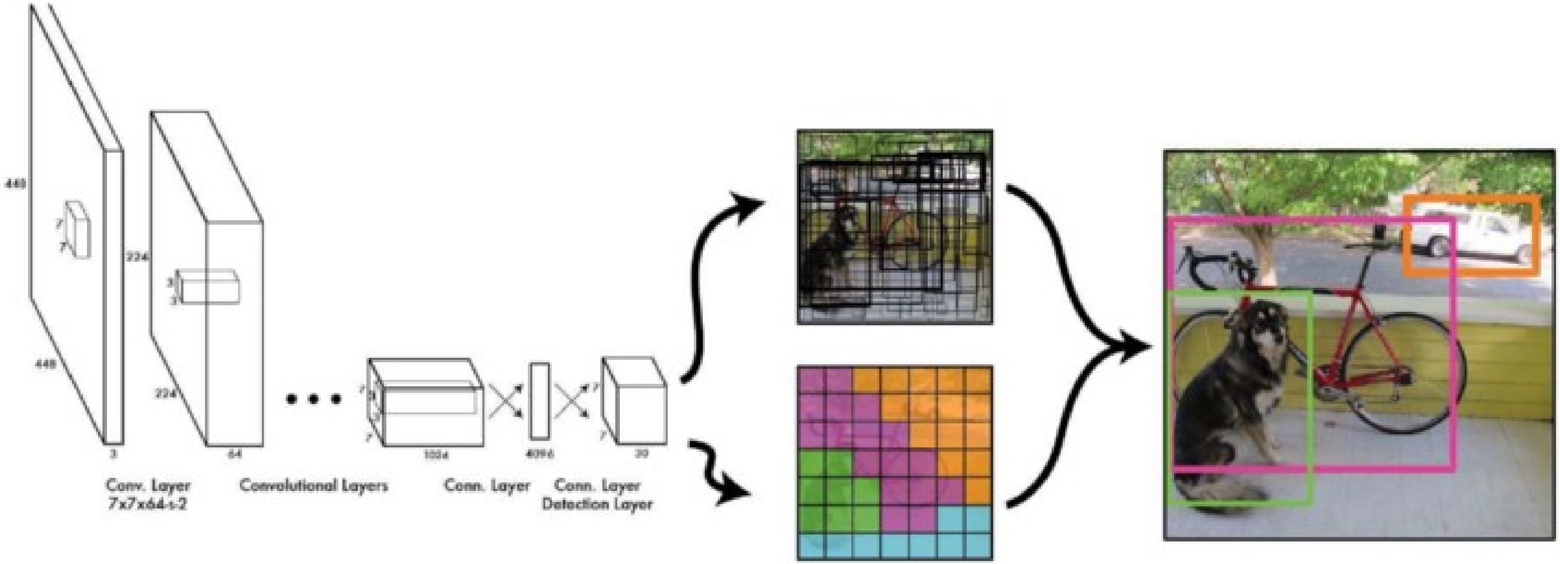
Decoder

# YoLo – You Look Once

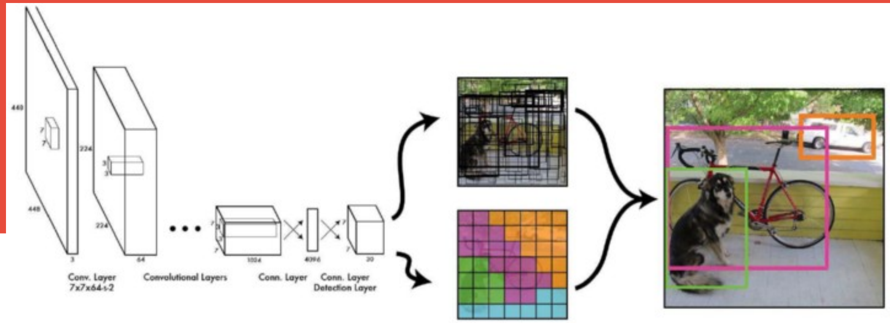
# Object Detection - Yolo



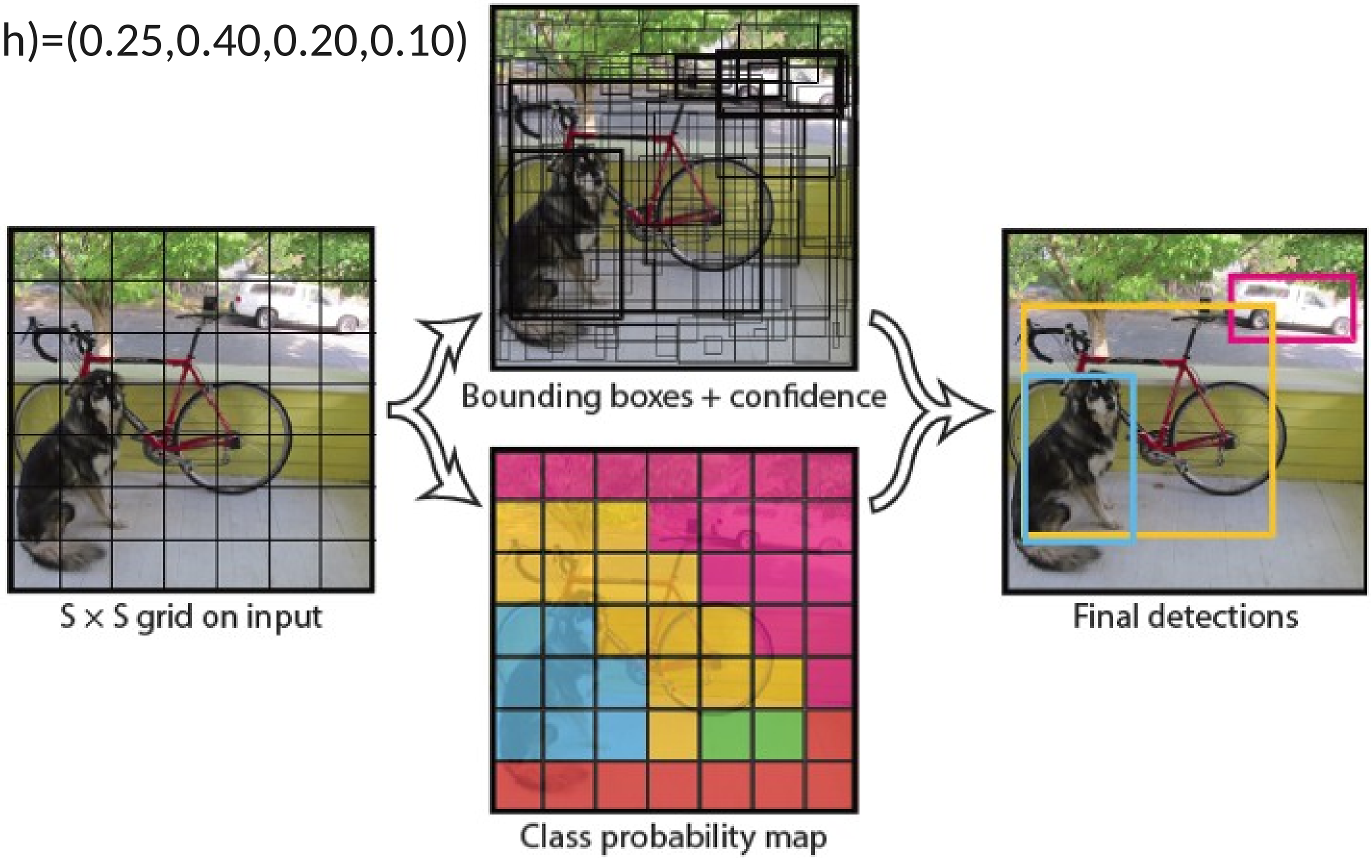

- You Look Once (YoLo - 2015 - now)
  - The input image  passes through convolutional backbone (e.g., Darknet)
  - The output is a feature map of lower spatial resolution (e.g for instance, 80×80, 20x20 )
  - The split is applied on the latent (feature map), not the raw input. Each feature cell corresponds to a specific spatial region (receptive field) of the input image.



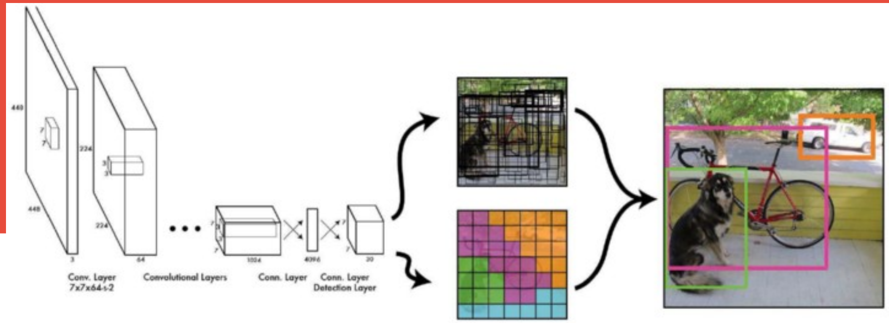
# Object Detection - Yolo



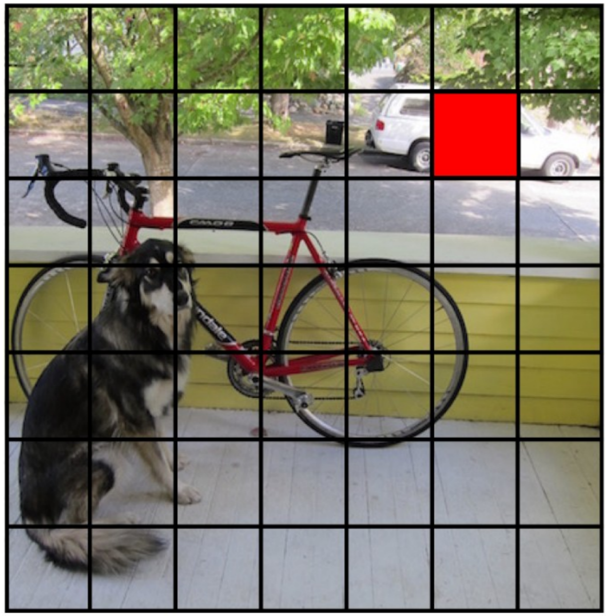
- Regression is the key!
  - Bounding boxes are treated as continuous variablesin normalized image coordinates.
    - (x,y,w,h)=(0.25,0.40,0.20,0.10)



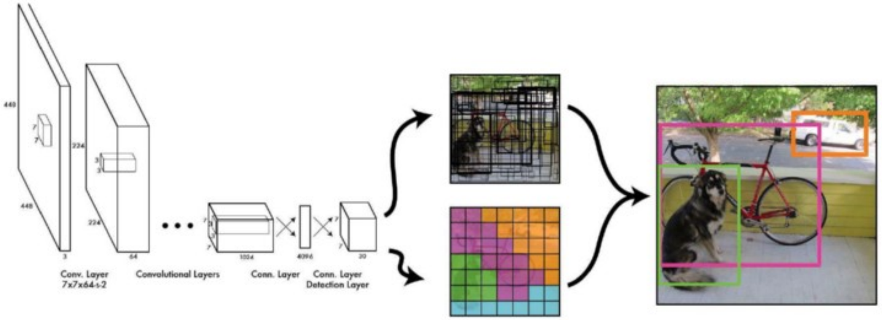
# Object Detection - Yolo




- Each cell predicts  bounding boxes and confidences
  - P(object): [0,1]  quantifies the confidence that any object occupies this box (not background)



# Object Detection - Yolo

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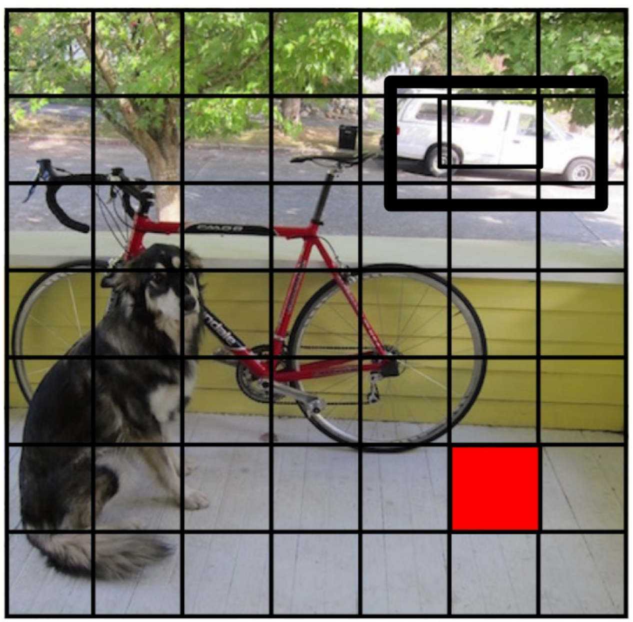
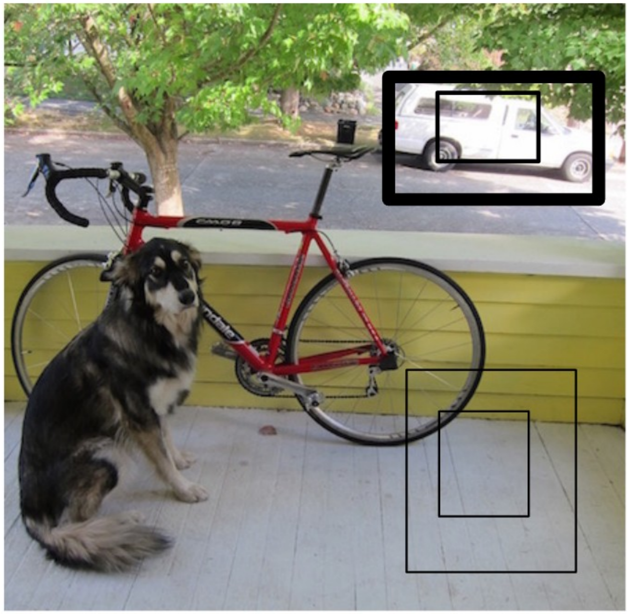
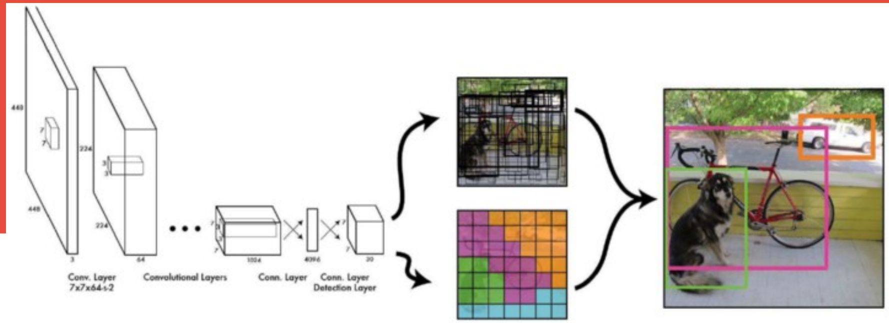
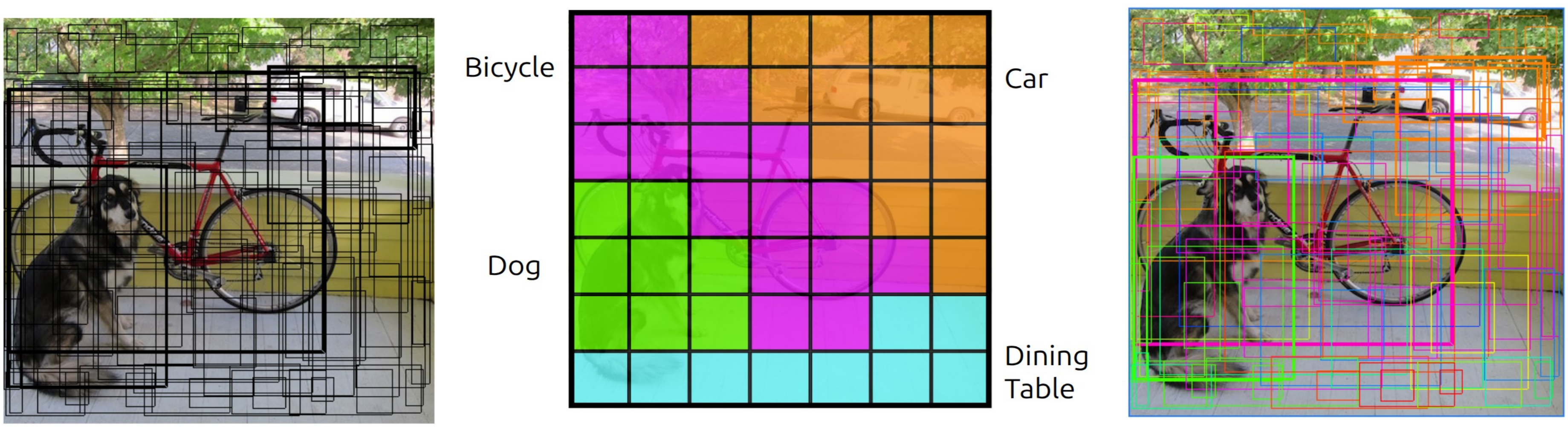




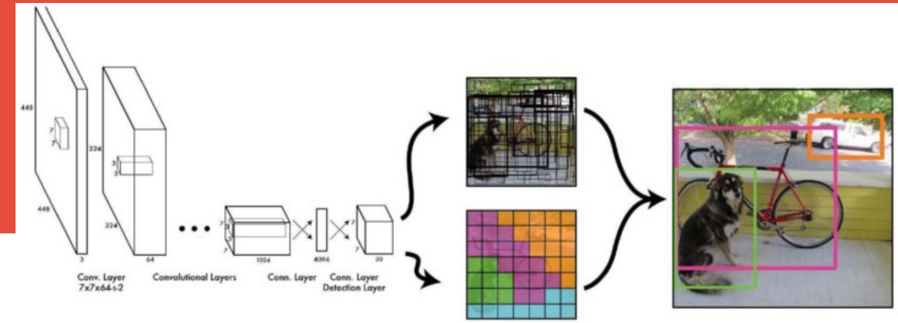
# Object Detection - Yolo



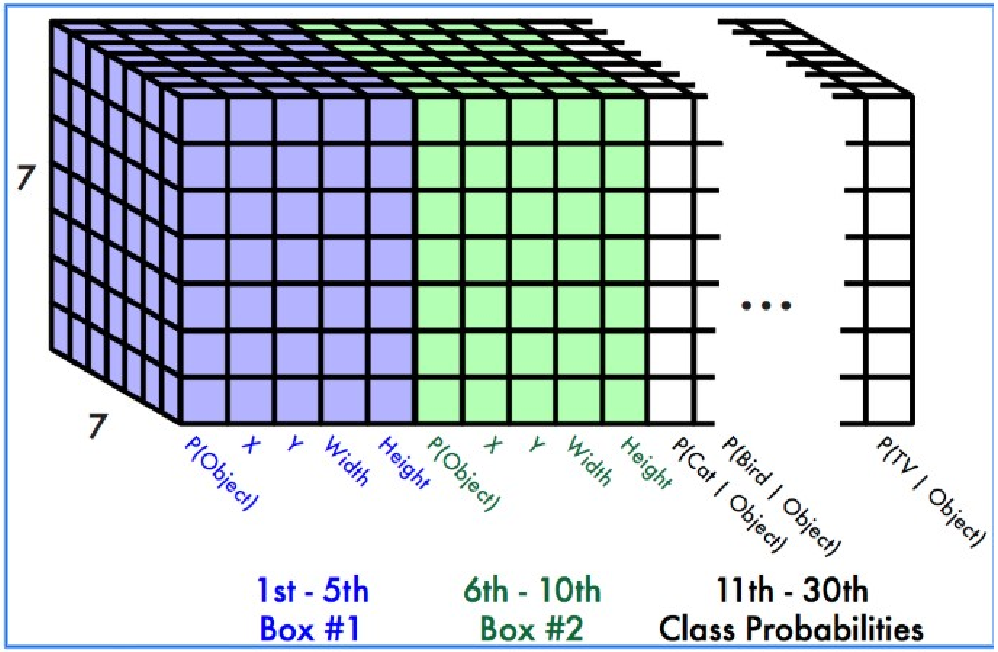
- Class Prob = P(class) => P(car) = 0.8
- Conditionated Prob: e.g P(class | object) => P(car) = 0.9
- Confidence:
  - P(Object) * P (Car | Object)   = 0.72



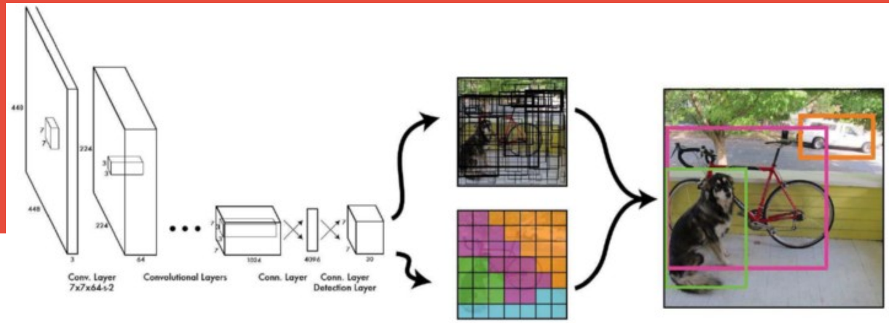
# Object Detection - Yolo



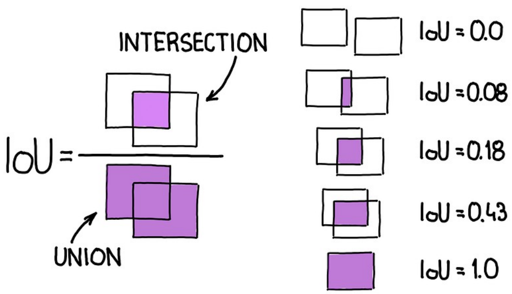

- Each cell predicts:
  - Bounding Boxes:
    - 4 Coordinates (X,Y,W,H)
    - 1 Confidence
  - I.E PASCAL VOC
    - 7x7 Grid
    - 2 Bounding Box / Cell
    - 20 Classes
    - 7 * 7 * (2 * 5 + 20) = 7x7*30 tensors per cell => 1470 predictions per image

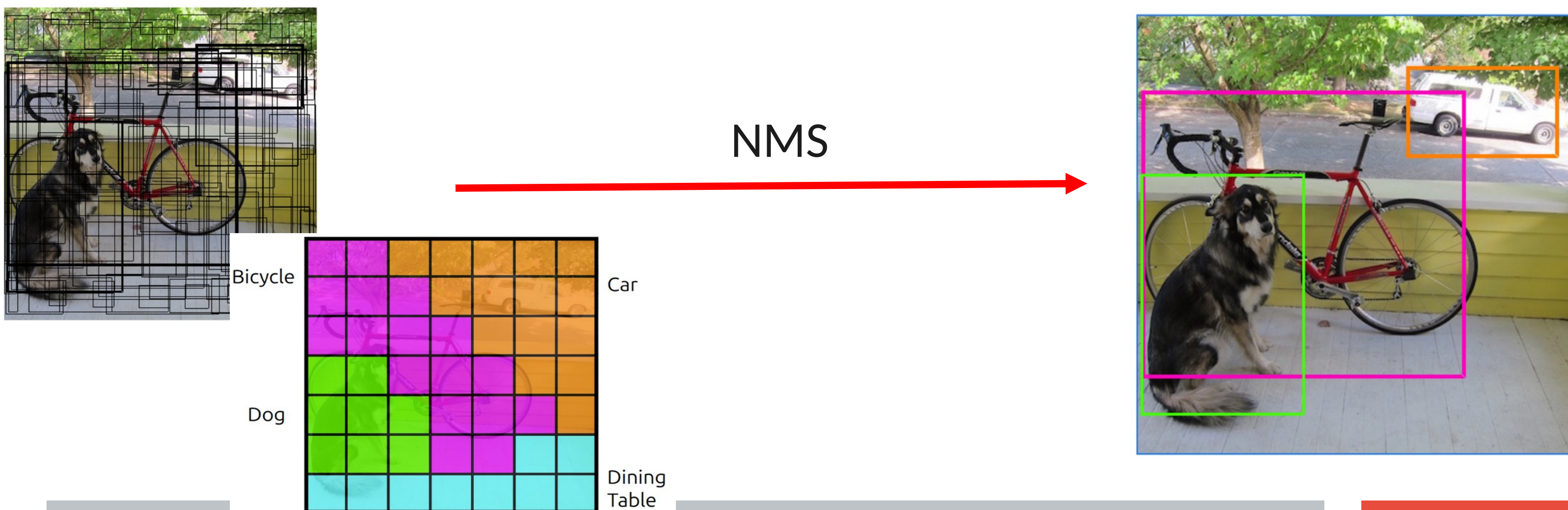


# Object Detection - Yolo

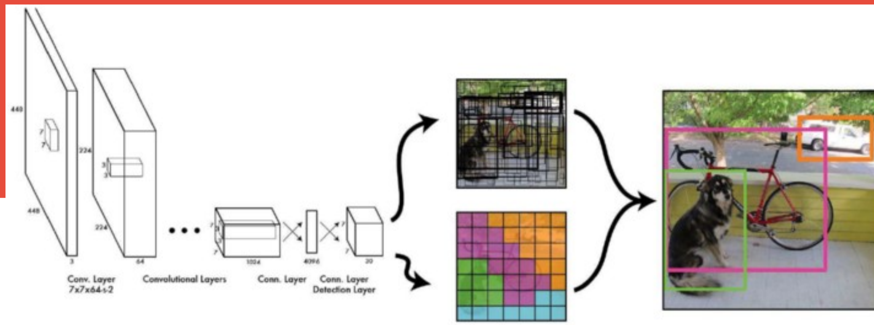



- Non-Maximum Supression (NMS)
  - Sort all boxes by confidence score (P(object)×P(class)).
  - Pick the box with the highest score → keep it as the best detection.
    - Compute IoU between this box and all others
    - Remove all boxes with IoU above the suppression threshold (e.g., 0.5)
    - Repeat until all boxes are processed

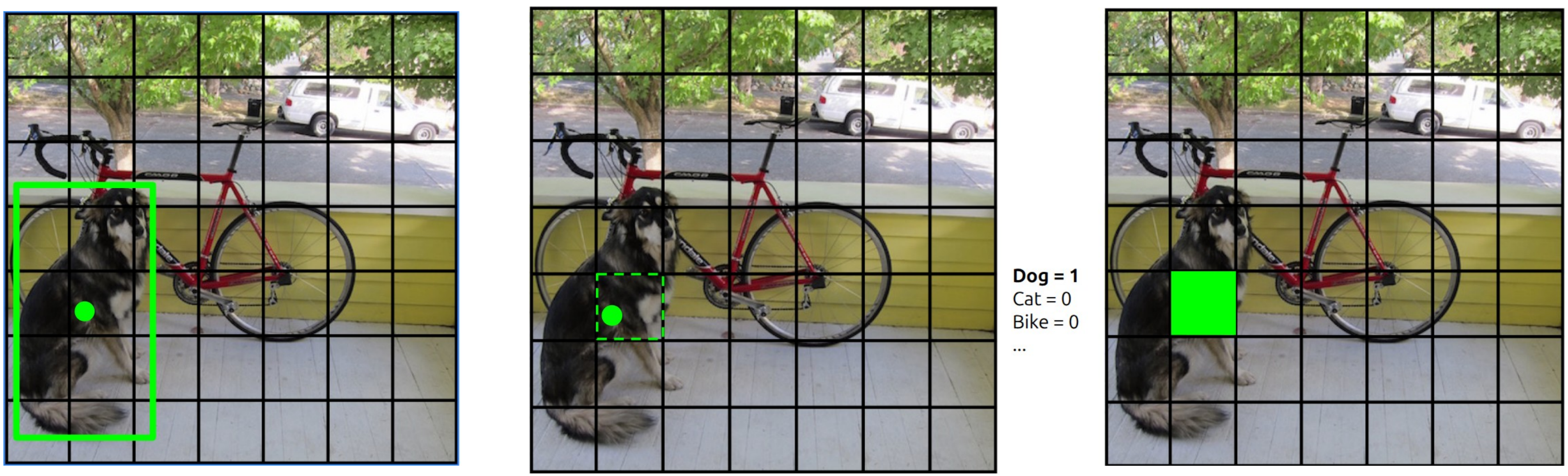


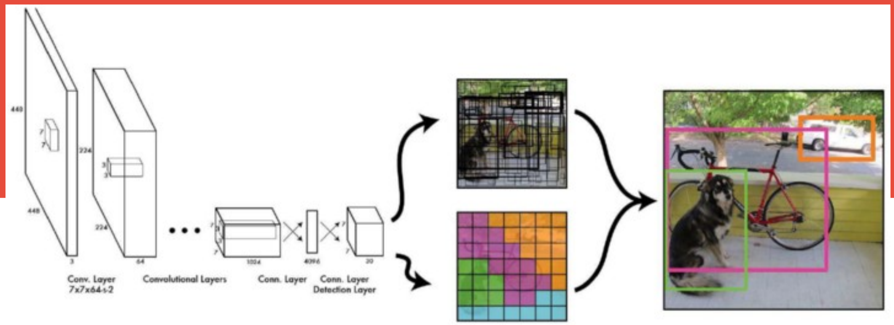
# Object Detection - Yolo



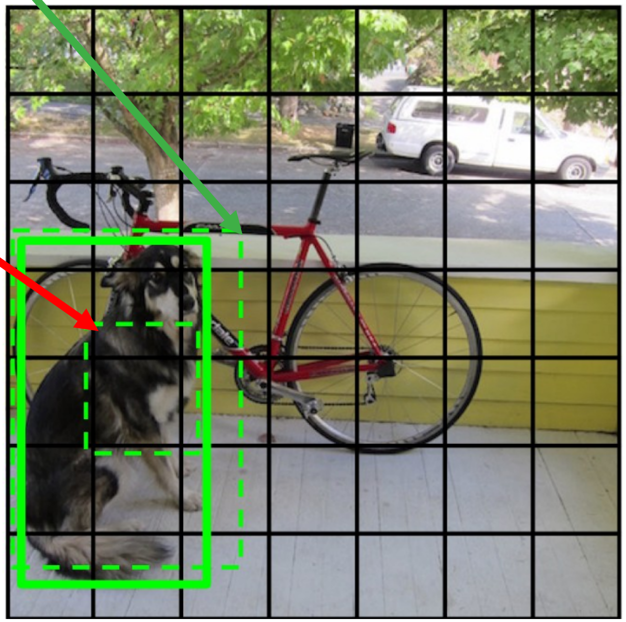
- Training
  - Match example to the right cell (ground-truth)



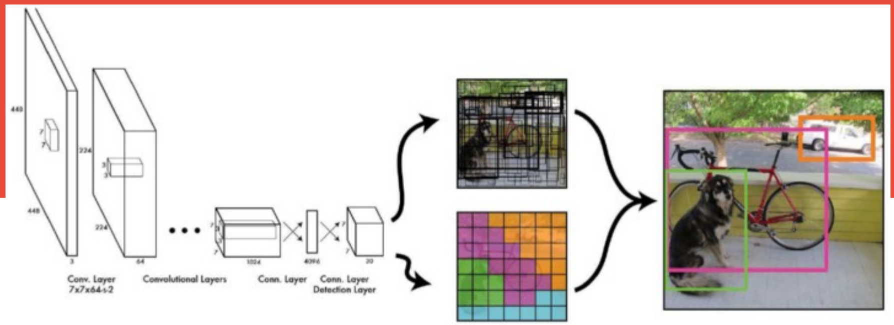
# Object Detection - Yolo



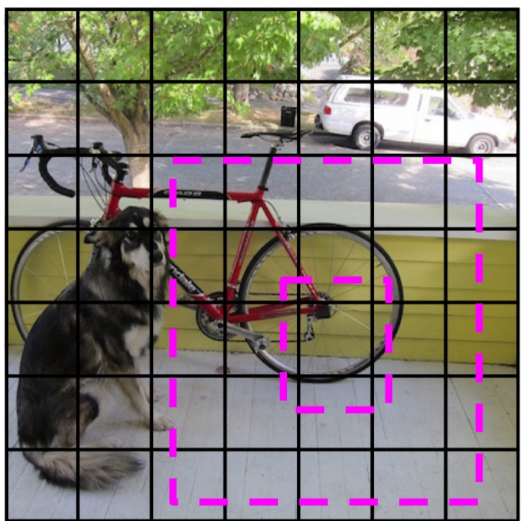
- Training
  - Predict Bounding-Boxes
    - Selects the best fit and increases its confidence
    - Penalizes all other predictions

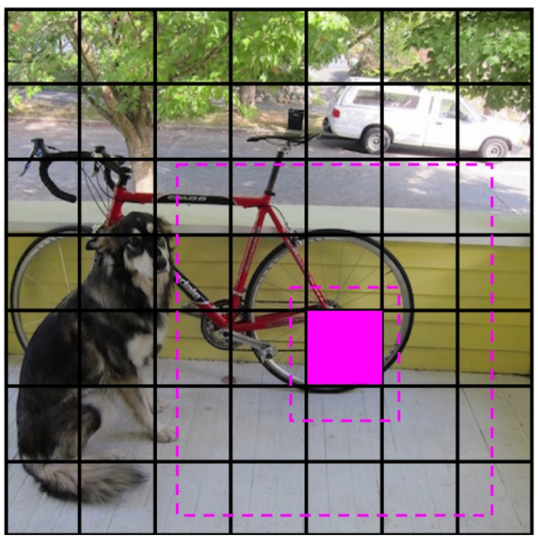


# Object Detection - Yolo

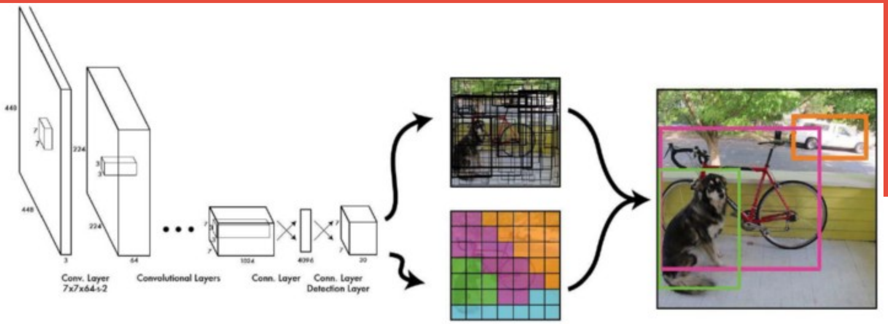


- Training
  - Penalizes when the prediction does not match any class (i.e., background).





# Object Detection - Yolo



loss function:

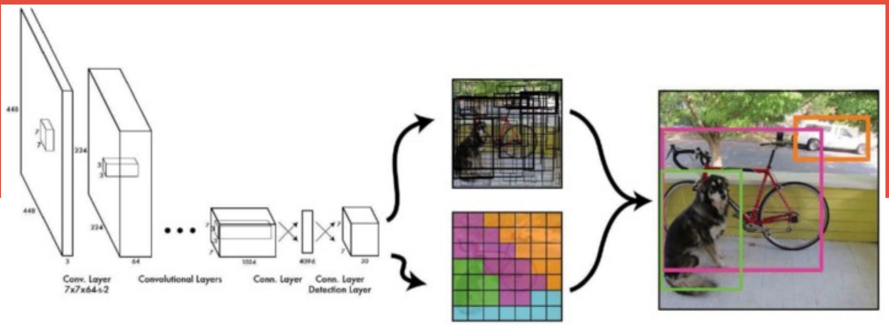
$$\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[ (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$
$$+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[ \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$
$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left( C_i - \hat{C}_i \right)^2$$
$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left( C_i - \hat{C}_i \right)^2$$
$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \qquad (3)$$

model. We use sum-squared error because it is easy to optimize, however it does not perfectly align with our goal of maximizing average precision. It weights localization error equally with classification error which may not be ideal. Also, in every image many grid cells do not contain any object. This pushes the “confidence” scores of those cells towards zero, often overpowering the gradient from cells that do contain objects. This can lead to model instability, causing training to diverge early on.

To remedy this, we increase the loss from bounding box coordinate predictions and decrease the loss from confidence predictions for boxes that don’t contain objects. We use two parameters, $\lambda_{\text{coord}}$ and $\lambda_{\text{noobj}}$ to accomplish this. We set $\lambda_{\text{coord}} = 5$ and $\lambda_{\text{noobj}} = .5$.

$$\lambda_{\text{coord}}=5, \ \lambda_{\text{noobj}}=0.5$$

# Object Detection - Yolo



loss function:

$$
\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \boxed{\mathbb{1}_{ij}^{\text{obj}}} \left[ (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]
$$
$$
+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \boxed{\mathbb{1}_{ij}^{\text{obj}}} \left[ \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]
$$
$$
+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \boxed{\mathbb{1}_{ij}^{\text{obj}}} \left( C_i - \hat{C}_i \right)^2
$$
$$
+ \lambda_{\textrm{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \boxed{\mathbb{1}_{ij}^{\text{noobj}}} \left( C_i - \hat{C}_i \right)^2
$$
$$
+ \sum_{i=0}^{S^2} \boxed{\mathbb{1}_{i}^{\text{obj}}} \sum_{c \in \textrm{classes}} (p_i(c) - \hat{p}_i(c))^2 \qquad (3)
$$

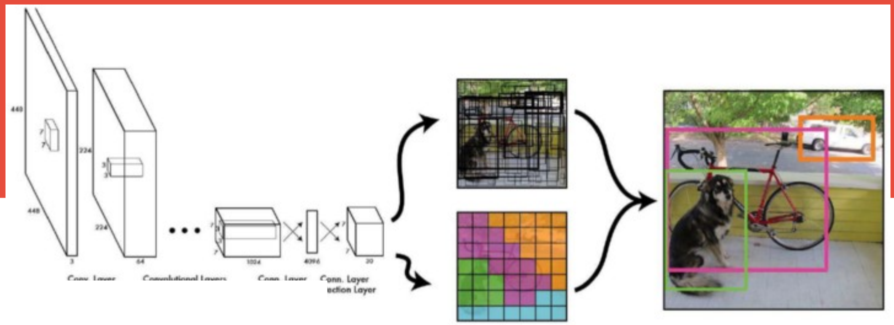
$\boxed{\mathbb{1}_{ij}^{obj}}$ The *j*th bbox predictor in ***cell i*** is "responsible" for that prediction

$\boxed{\mathbb{1}_{ij}^{noobj}}$

$\boxed{\mathbb{1}_{i}^{obj}}$ If object appears in ***cell i***

Note that the loss function only penalizes classification error if an object is present in that grid cell (hence the conditional class probability discussed earlier). It also only penalizes bounding box coordinate error if that predictor is "responsible" for the ground truth box (i.e. has the highest IOU of any predictor in that grid cell).

# Object Detection - Yolo



- Datasets
- PASCAL VOC 2007 & VOC 2012

[2007](#)

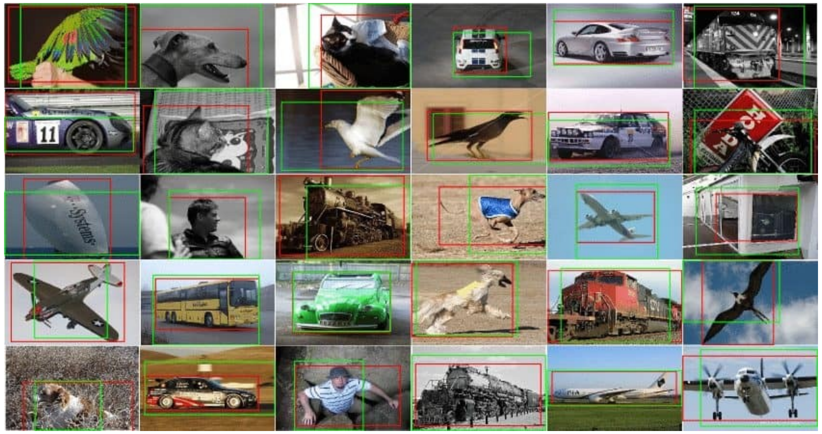
20 classes:

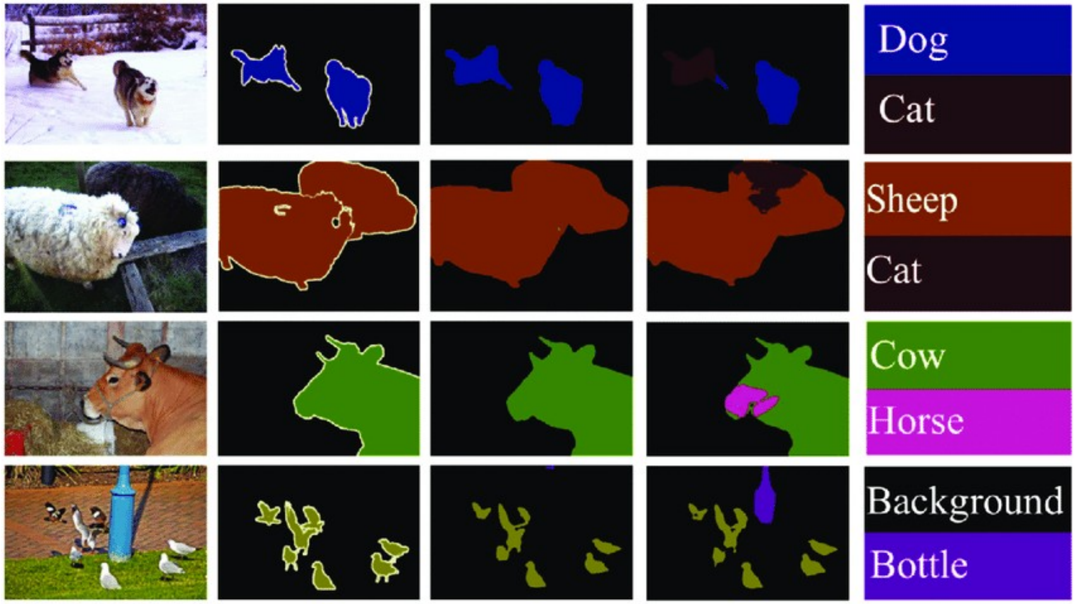
- *Person:* person
- *Animal:* bird, cat, cow, dog, horse, sheep
- *Vehicle:* aeroplane, bicycle, boat, bus, car, motorbike, train
- *Indoor:* bottle, chair, dining table, potted plant, sofa, tv/monitor

Train/validation/test: 9,963 images containing 24,640 annotated objects.

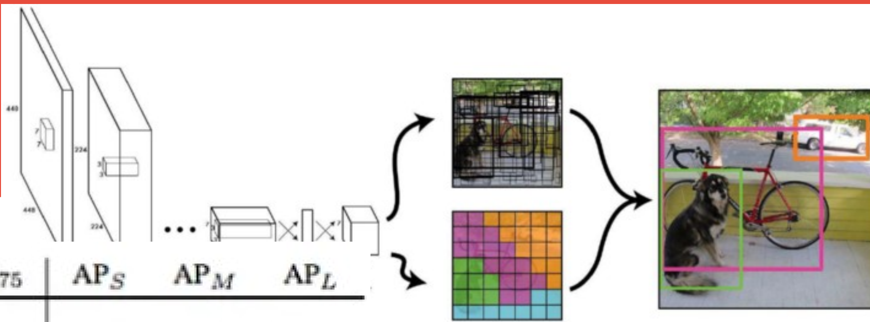
[2012](#)

20 classes. The train/val data has 11,530 images containing 27,450 ROI annotated objects and 6,929 segmentations.





# Object Detection - Yolo



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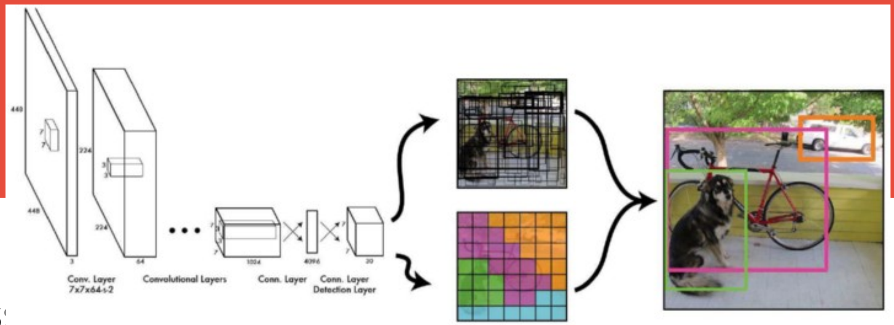
| | backbone | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ |
|---|---|---|---|---|---|---|---|
| *Two-stage methods* | | | | | | | |
| Faster R-CNN+++ [3] | ResNet-101-C4 | 34.9 | 55.7 | 37.4 | 15.6 | 38.7 | 50.9 |
| Faster R-CNN w FPN [6] | ResNet-101-FPN | 36.2 | 59.1 | 39.0 | 18.2 | 39.0 | 48.2 |
| Faster R-CNN by G-RMI [4] | Inception-ResNet-v2 [19] | 34.7 | 55.5 | 36.7 | 13.5 | 38.1 | 52.0 |
| Faster R-CNN w TDM [18] | Inception-ResNet-v2-TDM | 36.8 | 57.7 | 39.2 | 16.2 | 39.8 | **52.1** |
| *One-stage methods* | | | | | | | |
| YOLOv2 [13] | DarkNet-19 [13] | 21.6 | 44.0 | 19.2 | 5.0 | 22.4 | 35.5 |
| SSD513 [9, 2] | ResNet-101-SSD | 31.2 | 50.4 | 33.3 | 10.2 | 34.5 | 49.8 |
| DSSD513 [2] | ResNet-101-DSSD | 33.2 | 53.3 | 35.2 | 13.0 | 35.4 | 51.1 |
| RetinaNet [7] | ResNet-101-FPN | 39.1 | 59.1 | 42.3 | 21.8 | 42.7 | 50.2 |
| RetinaNet [7] | ResNeXt-101-FPN | **40.8** | **61.1** | **44.1** | **24.1** | **44.2** | 51.2 |
| YOLOv3 608 × 608 | Darknet-53 | 33.0 | 57.9 | 34.4 | 18.3 | 35.4 | 41.9 |

| | **Pascal 2007 mAP** | **Speed** | |
|---|---|---|---|
| DPM v5 | 33.7 | .07 FPS | 14 s/img |
| R-CNN | 66.0 | .05 FPS | 20 s/img |
| Fast R-CNN | 70.0 | .5 FPS | 2 s/img |
| Faster R-CNN | 73.2 | 7 FPS | 140 ms/img |
| YOLO | ~~63.4~~ 69.0 | 45 FPS | 22 ms/img |

# Object Detection - Yolo



- mAP measures a detector’s average precision acros

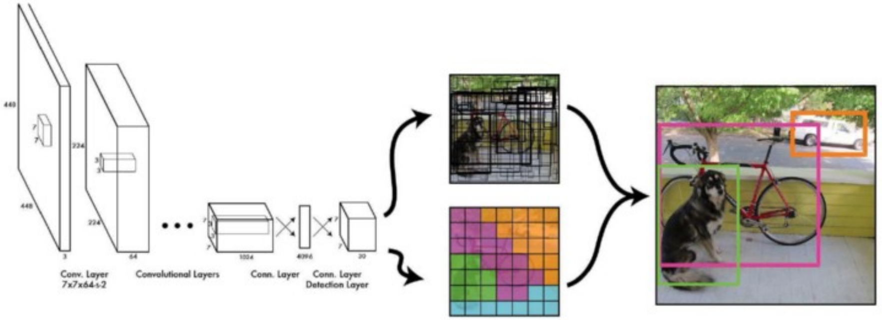
- 

| | backbone | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ |
|---|---|---|---|---|---|---|---|
| *Two-stage methods* | | | | | | | |
| Faster R-CNN+++ [3] | ResNet-101-C4 | 34.9 | 55.7 | 37.4 | 15.6 | 38.7 | 50.9 |
| Faster R-CNN w FPN [6] | ResNet-101-FPN | 36.2 | 59.1 | 39.0 | 18.2 | 39.0 | 48.2 |
| Faster R-CNN by G-RMI [4] | Inception-ResNet-v2 [19] | 34.7 | 55.5 | 36.7 | 13.5 | 38.1 | 52.0 |
| Faster R-CNN w TDM [18] | Inception-ResNet-v2-TDM | 36.8 | 57.7 | 39.2 | 16.2 | 39.8 | **52.1** |
| *One-stage methods* | | | | | | | |
| YOLOv2 [13] | DarkNet-19 [13] | 21.6 | 44.0 | 19.2 | 5.0 | 22.4 | 35.5 |
| SSD513 [9, 2] | ResNet-101-SSD | 31.2 | 50.4 | 33.3 | 10.2 | 34.5 | 49.8 |
| DSSD513 [2] | ResNet-101-DSSD | 33.2 | 53.3 | 35.2 | 13.0 | 35.4 | 51.1 |
| RetinaNet [7] | ResNet-101-FPN | 39.1 | 59.1 | 42.3 | 21.8 | 42.7 | 50.2 |
| RetinaNet [7] | ResNeXt-101-FPN | **40.8** | **61.1** | **44.1** | **24.1** | **44.2** | 51.2 |
| YOLOv3 608 × 608 | Darknet-53 | 33.0 | 57.9 | 34.4 | 18.3 | 35.4 | 41.9 |

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

| | **Pascal 2007 mAP** | **Speed** | |
|---|---|---|---|
| DPM v5 | 33.7 | .07 FPS | 14 s/img |
| R-CNN | 66.0 | .05 FPS | 20 s/img |
| Fast R-CNN | 70.0 | .5 FPS | 2 s/img |
| Faster R-CNN | 73.2 | 7 FPS | 140 ms/img |
| YOLO | ~~63.4~~ 69.0 | 45 FPS | 22 ms/img |

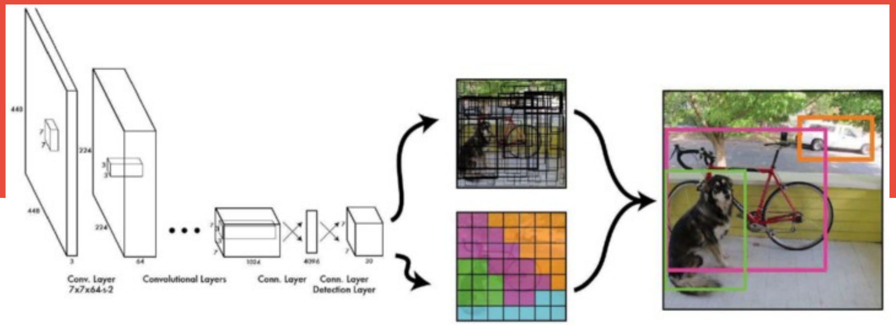
# Object Detection - Yolo



- Let's Code!
  - This exercise will utilize Ultralytics (www.ultralytics.com) as the framework.
    - Single Image
    - Frame by Frame (Video / Camera)
  - Check out the GitHub repository, specifically the yolo-ultralytics folder.

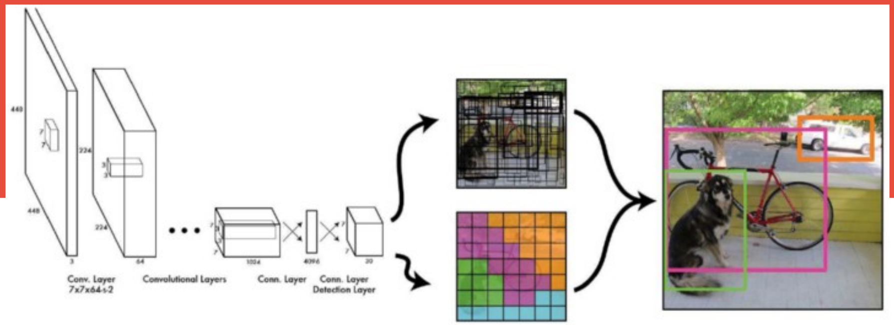
# YoLo – Training and Annotation

# Yolo Training



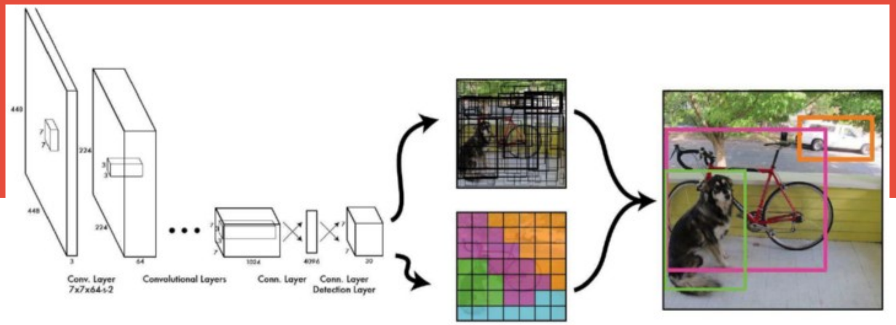
- Each image must include:
  - Bounding box coordinates (4 points) and the corresponding class label
  - Bounding boxes should be relative (normalized), not absolute pixel coordinates
- Avaliable annotation tools:
  - LabelImg (simple and lightweight)
  - LabelMe (browser-based)
  - CVAT (advanced, collaborative)
  - Roboflow Annotate

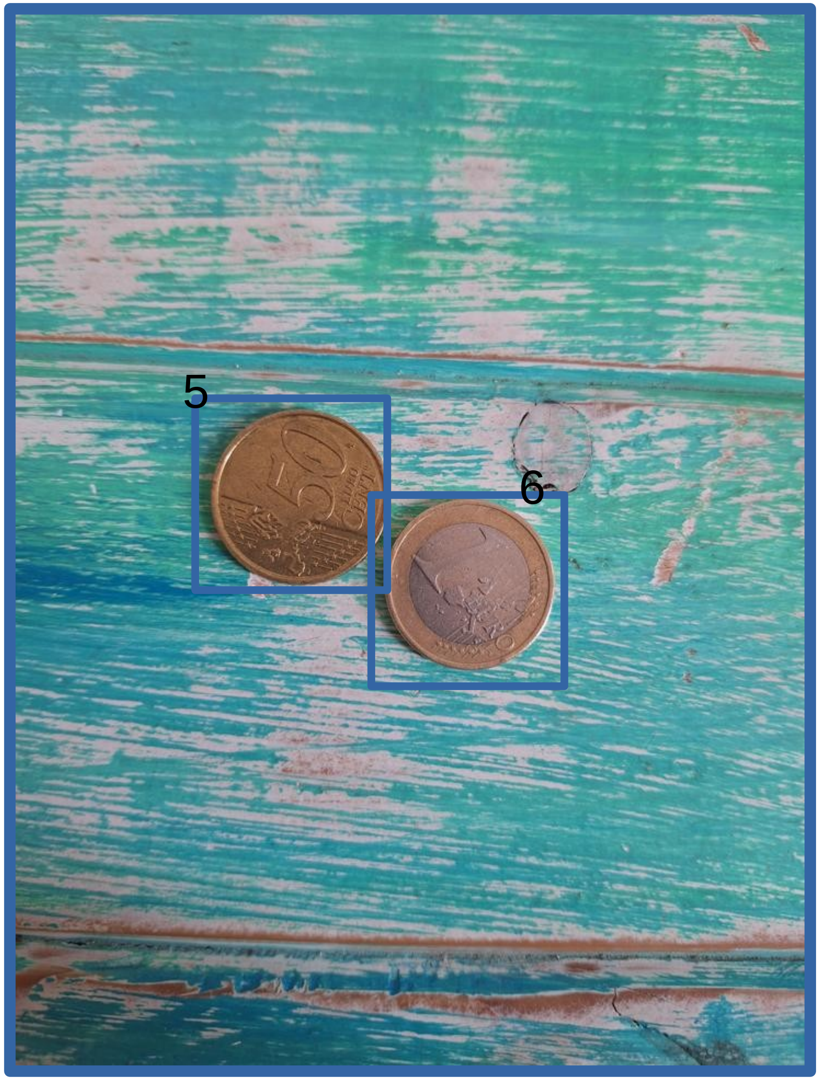
# Yolo Training



5 0.360417 0.459375 0.229167 0.165625
6 0.575000 0.543750 0.216667 0.162500

# Yolo Training

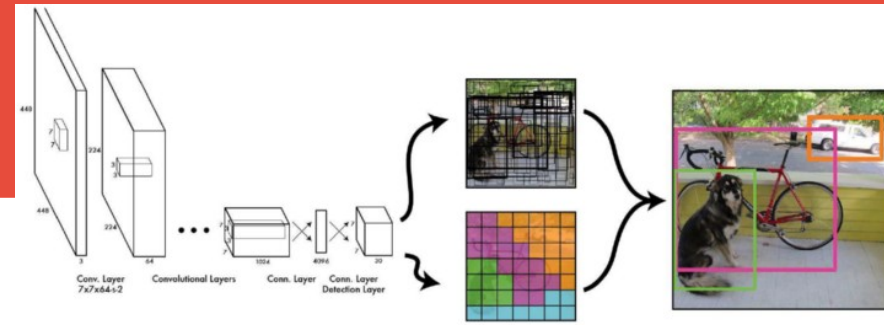


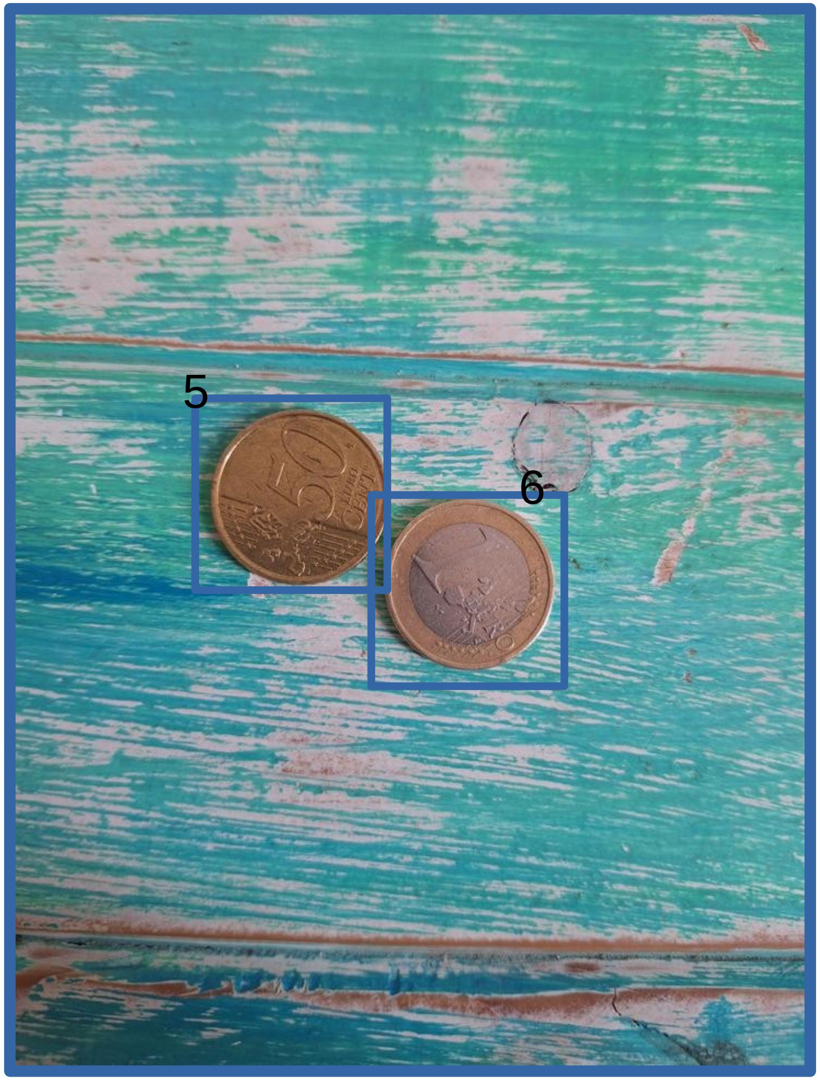



5 0.360417 0.459375 0.229167 0.165625
6 0.575000 0.543750 0.216667 0.162500

```
class_names = [
        '1C', #0
        '2C', #1
        '5C', #2
        '10C', #3
        '20C', #4
        '50C', #5
        '1Eu', #6
        '2Eu' #7
]
```

# Yolo Training






data.yaml

```yaml
path: /content/dataset
train: images/train
val: images/val
test: images/test
nc: 8
names:
- 1C
- 2C
- 5C
- 10C
- 20C
- 50C
- 1Eu
- 2Eu
```

- dataset
  - images
    - test
    - train
    - val
  - labels
    - test
    - train
    - val
  - data.yaml

Let's Code!