



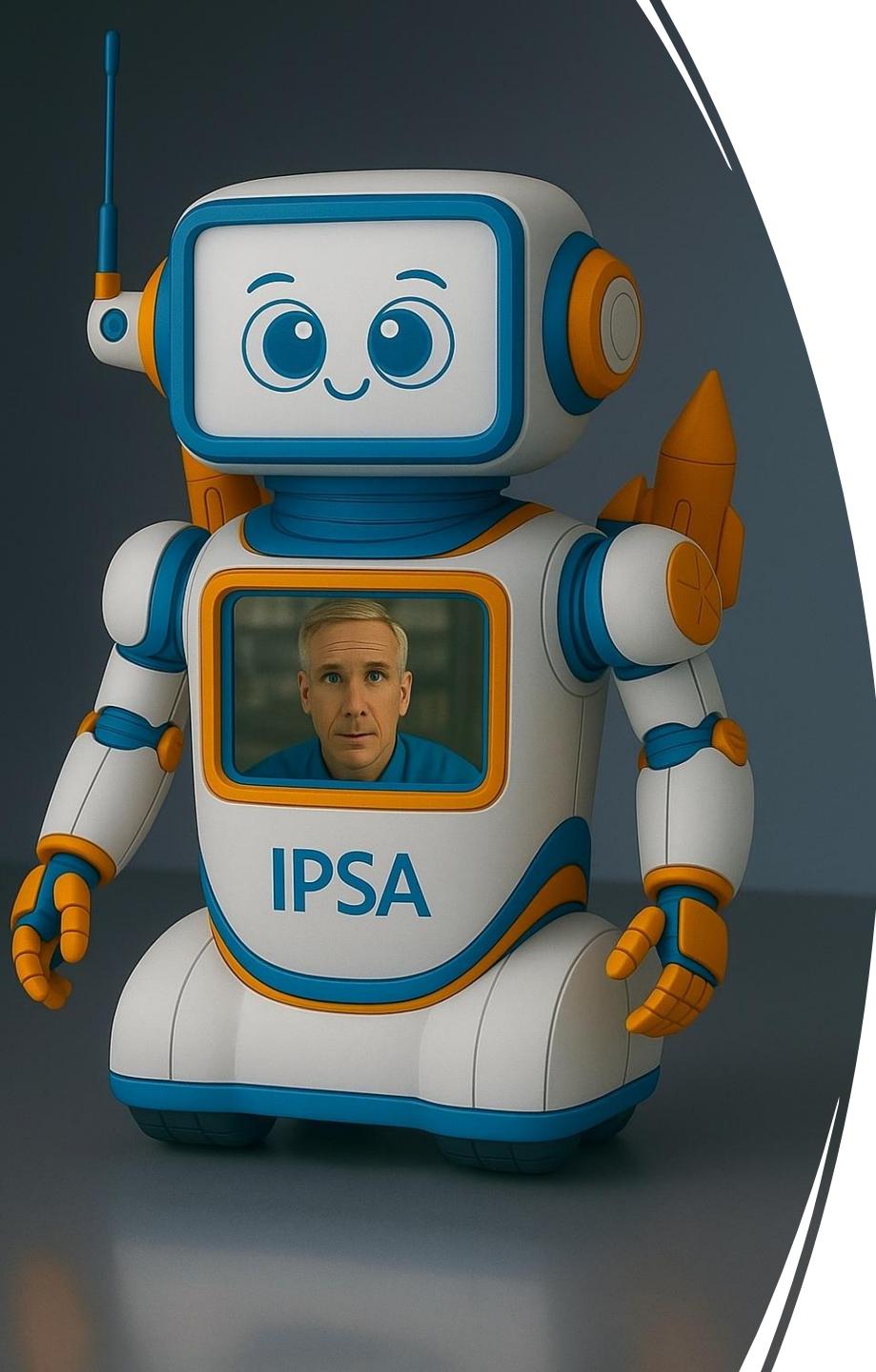
# In511 Commandes Intelligentes

**The second part of the course, October 2025**

**by Aybüke ÖZTÜRK SURI**

# The objective of the second part of the course

How to do object detection by training your own datasets and show the object on the camera by using vocal commands.



# An ongoing project: Robot Voya

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- Autonomous Movement
  - Ability to navigate environments using sensors (LIDAR, cameras).
  - Path planning and obstacle avoidance
- Perception System
  - AI-based vision for object classification
- Manipulation
  - Pick and place objects
- Human interaction
  - Human-tracking system with vision or sensors
  - Gesture recognition to interpret simple commands (e.g., waving to stop or follow)

# Data Collection & Preparation

104 object to use in your experiments



# Voice-Activated Real-Time Object Detection Using Custom Datasets

## Model

Input



“Show me Laptop”



Voice  
model



Dataset Preparation

Model Training



Output



highlighted only the  
requested object

# Data Collection & Preparation

- Create the data folder

## In511/custom\_dataset

Name	Type
! data	Fichier source Yaml
images	File folder
labels	File folder

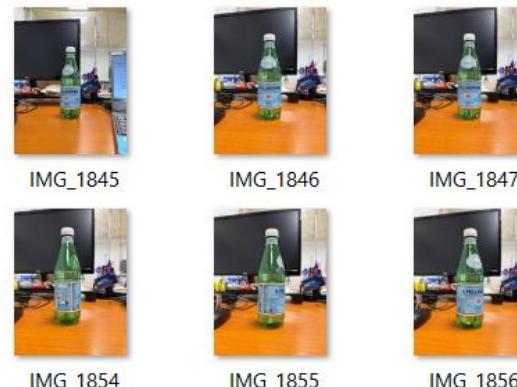
```
# data.yaml
path: ./custom_office_dataset # dataset root dir
train: images/train # train images (relative to path)
val: images/val # val images (relative to path)

# Classes
nc: 3 # number of classes
names: ['Bottle', 'Bee', 'Stapler']
```

## In511/custom\_dataset/images

Name	Date modified
train	7/18/2025 11:31 AM
val	7/18/2025 12:02 PM

## In511/custom\_dataset/images/train & In511/custom\_dataset/images/val



your custom images

# Data Collection & Preparation

- Create the data folder

## In511/custom\_dataset

Name	Type
data	Fichier source Yaml
images	File folder
labels	File folder

## In511/custom\_dataset/label

Name	Date modified
train	7/18/2025 11:31 AM
val	7/18/2025 12:02 PM

## In511/custom\_dataset/labels/train

Name	Type
classes	Document texte
IMG_1845	Document texte
IMG_1846	Document texte
IMG_1847	Document texte
IMG_1848	Document texte
IMG_1849	Document texte

## classes.txt

Fichier	Modifier	Affichage
Bottle		
Bee		
Stapler		

your custom object names

# Data Collection & Preparation

- Create the data folder

## In511/custom\_dataset

Name	Type
data	Fichier source Yaml
images	File folder
labels	File folder

## In511/custom\_dataset/label

Name	Date modified
train	7/18/2025 11:31 AM
val	7/18/2025 12:02 PM

## In511/custom\_dataset/labels/train

Name	Type
classes	Document texte
IMG_1845	Document texte
IMG_1846	Document texte
IMG_1847	Document texte
IMG_1848	Document texte
IMG_1849	Document texte

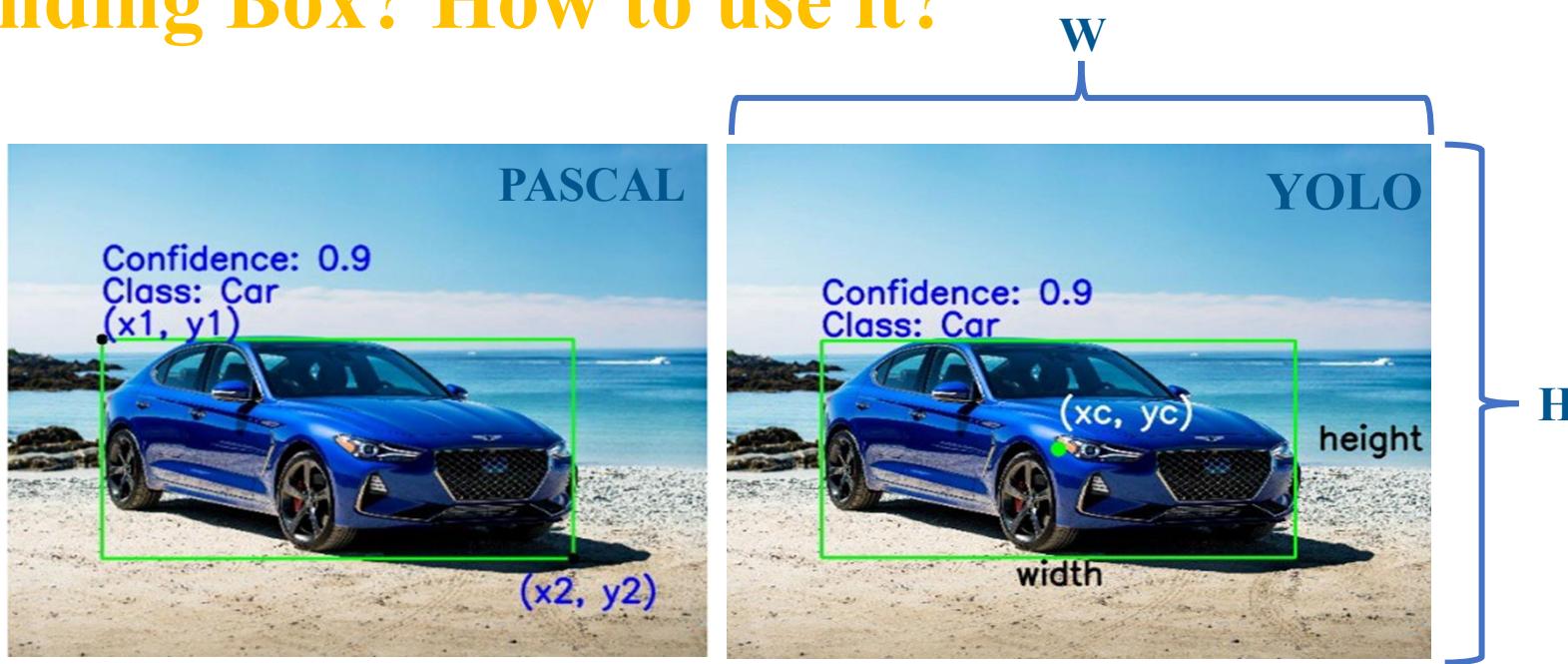
## IMG\_1845.txt

Fichier	Modifier	Affichage
0	0.502801 0.512430 0.188142 0.500000	

Class ID

Bounding Box  
Values

# What is Bounding Box? How to use it?



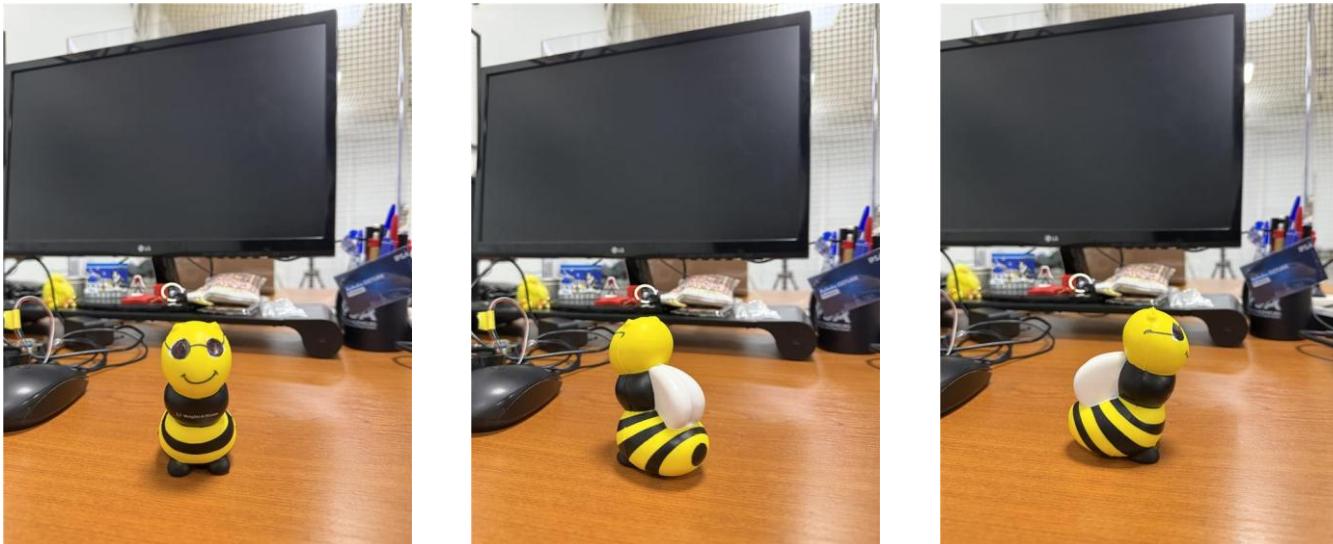
<https://nanonets.com/blog/image-processing-and-bounding-boxes-for-ocr/>

Format	Coordinates	Storage	Normalization	the center of the bounding box in pixels:	the normalized center coordinates:
PASCAL VOC	xmin, ymin, xmax, ymax	XML	No (pixels)	$X_{center} = \frac{X_1 + X_2}{2}$ $Y_{center} = \frac{Y_1 + Y_2}{2}$	$x_c = \frac{X_{center}}{W}$ $y_c = \frac{Y_{center}}{H}$
COCO	x, y, width, height	JSON	No (pixels)	W x H: the size of the Image, width: the width of the bounding box, height: the height of the bounding box.	
YOLO	x_center, y_center, width, height	TXT	Yes (0–1)	$(X_1, Y_1)$ : the X and Y coordinates of the top left corner of the rectangle. $(X_2, Y_2)$ : the X and Y coordinates of the bottom right corner of the rectangle. $(X_c, Y_c)$ : the normalized coordinates of the center of the bounding box.	

# Data Collection & Preparation

Capture **100 images** of the custom object using your phone.

- **75 images** will be used for training.
- **25 images** will be used for validation.
- Make sure to capture the object from **different angles** and at **various distances** to improve dataset diversity.

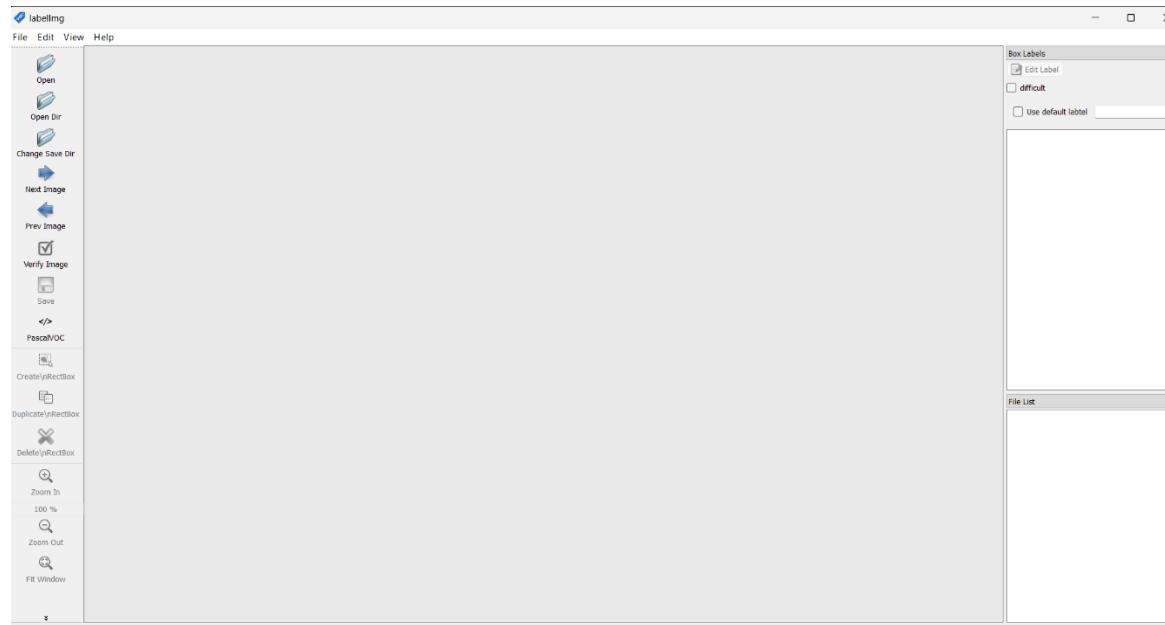


Example images of a custom object

# Data Collection & Preparation

- If your images are in **HEIC format**, convert them to **PNG format** using the provided example code on Moodle: **heicToPngConverter.py** or you can find a heicToJpeg code online.
- Create labels for your dataset  
You can download the desktop version of the labeling tool **LabelImg** from the following link:  
<https://github.com/HumanSignal/labelImg/releases>

**LabelImg**  
Application

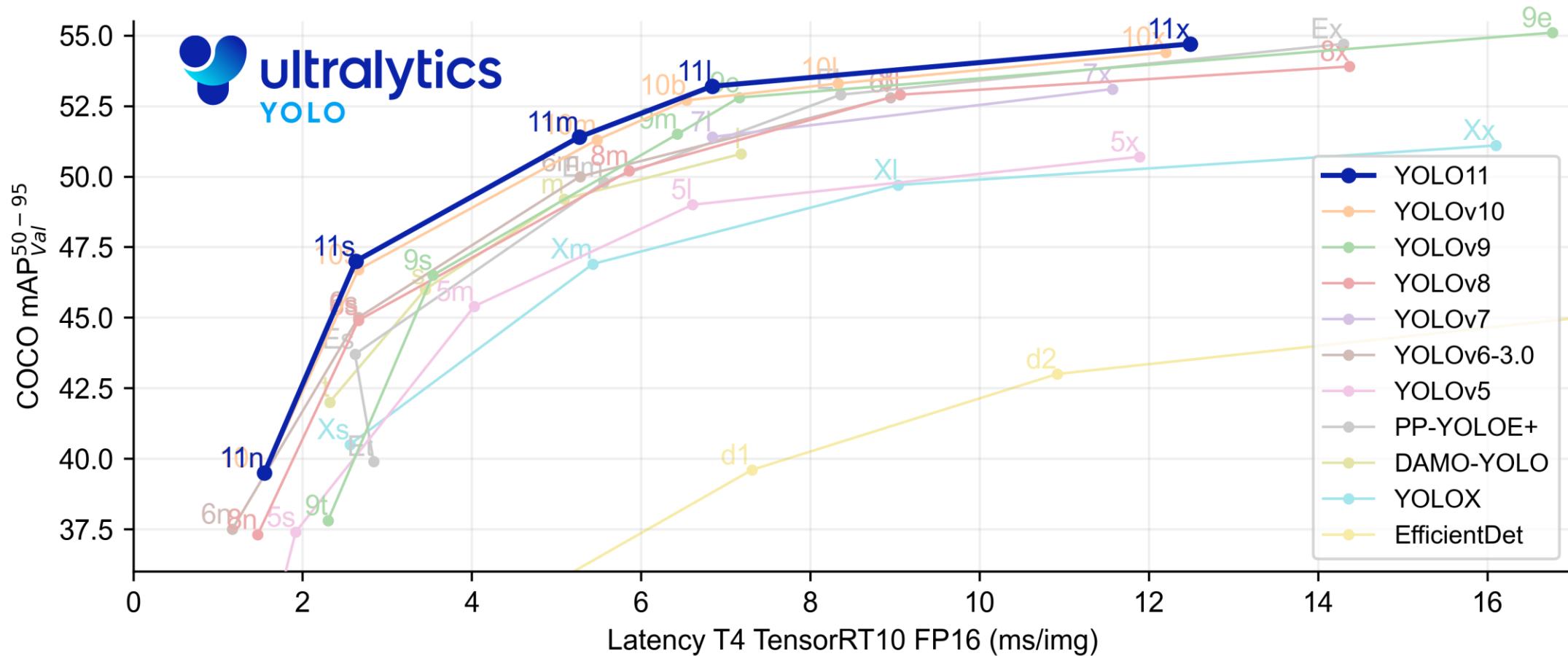


# Model Training - History of YOLO

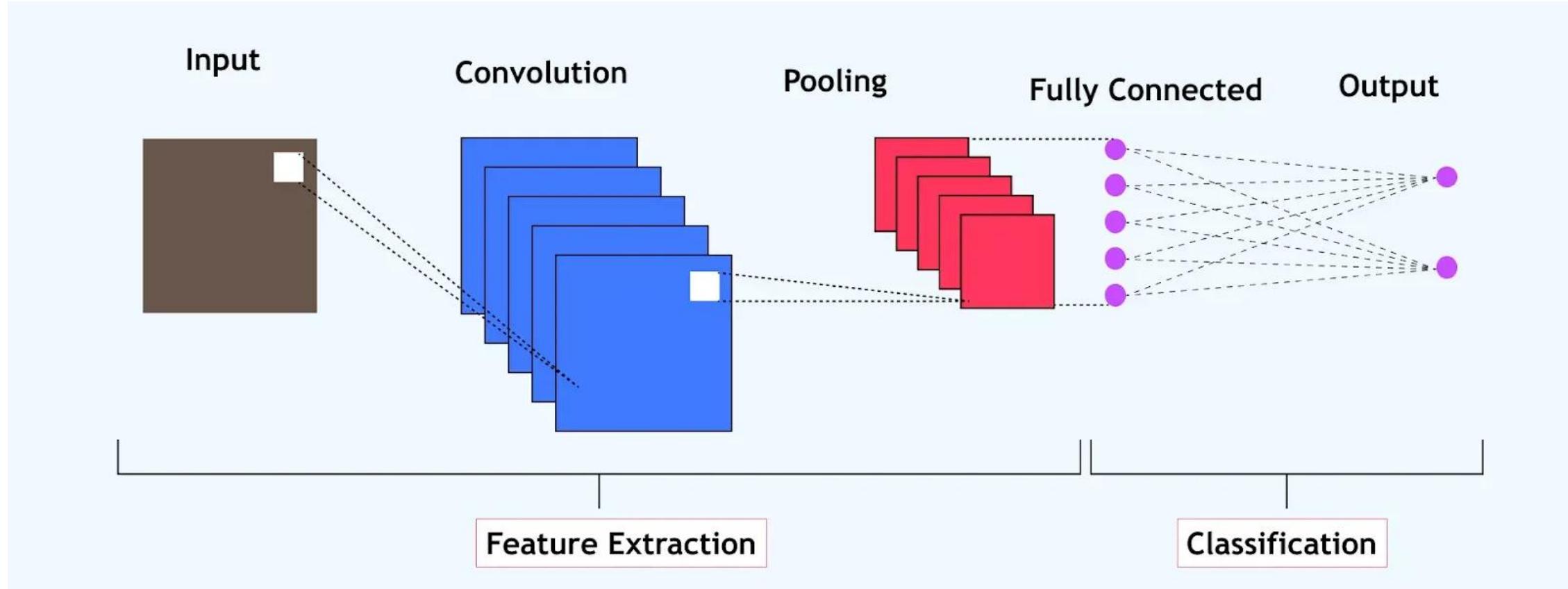
Year	Version	Highlights
2016	YOLOv1 – Redmon <i>et al.</i>	Introduced YOLO in “ <b>You Only Look Once: Unified, Real-Time Object Detection</b> ” ( <b>CVPR 2016</b> ), establishing the foundation of single-pass object detection.
2017	YOLOv2 / YOLO9000	Added anchor boxes, batch normalization, and real-time detection of 9,000 classes.
2018	YOLOv3	Adopted Darknet-53 backbone, multi-scale detection, and improvements in accuracy.
2020–2023	YOLOv4, v5, v6, v7, v8	Continuous improvements in speed and accuracy. e.g., YOLOv7 set new state-of-the-art (SOTA) results.
2024	YOLOv10	Introduced NMS-free training, dual-assignment strategy, and holistic efficiency improvements.
September 2024	YOLO11	Released by Ultralytics at YOLO Vision 2024 (YV24); features architectural refinements (C3k2, C2PSA blocks), fewer parameters, improved speed, and multi-task support.
February 18, 2025	YOLOv12 – Tian <i>et al.</i>	Attention-centric architecture (Area Attention, R-ELAN, FlashAttention). Achieves SOTA mAP with very low latency—e.g., YOLOv12-N hits 40.6% mAP in <b>1.64 ms</b> , outperforming prior versions.

Reference for ULTRALYTICS: <https://docs.ultralytics.com/models/yolo11/>

# Performance of YOLO Versions

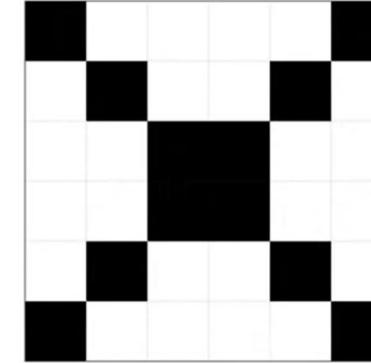
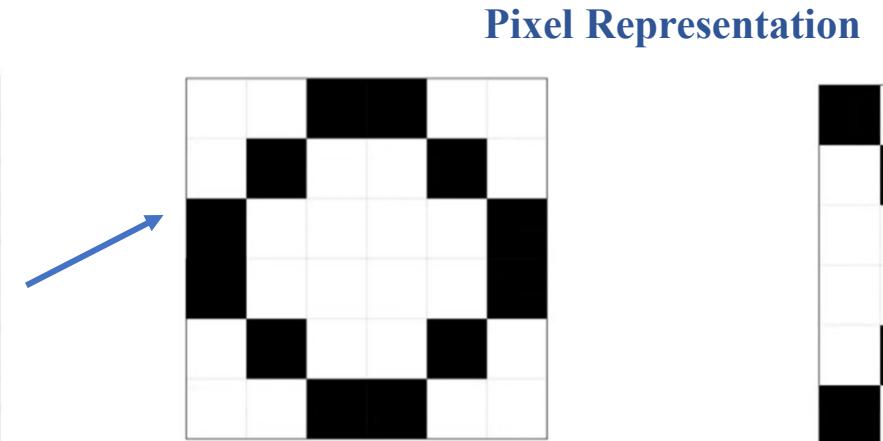
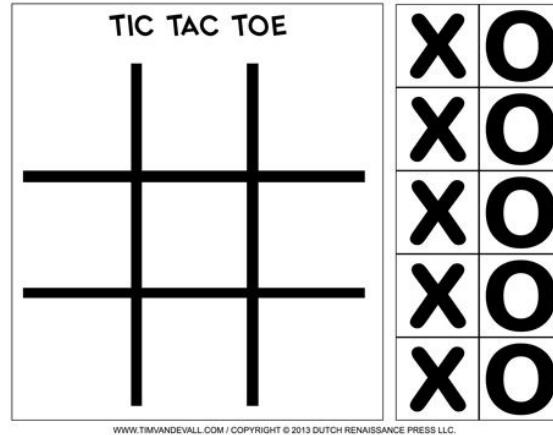


# Basic Architecture of Convolutional Neural Networks (CNNs)



# How does Convolutional Neural Networks (CNNs) work?

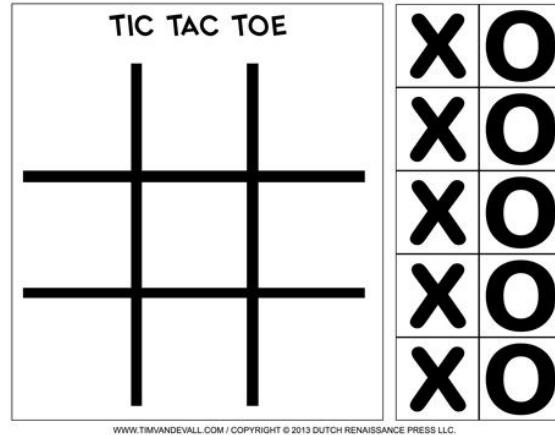
## Example



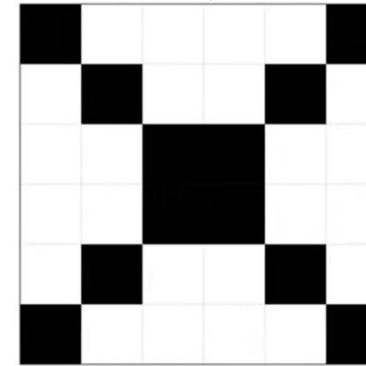
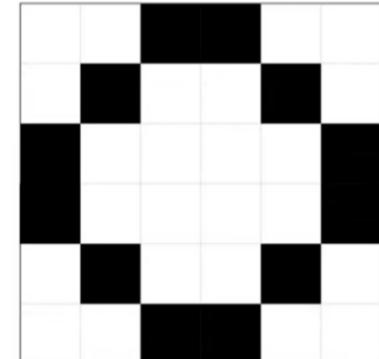
<https://www.youtube.com/watch?v=HGwBXDKFk9I>

# How does Convolutional Neural Networks (CNNs) work?

## Example



Pixel Representation



0 for white, 1 for black pixels

0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

<https://www.youtube.com/watch?v=HGwBXDKFk9I>

# How does Convolutional Neural Networks (CNNs) work?

## Example

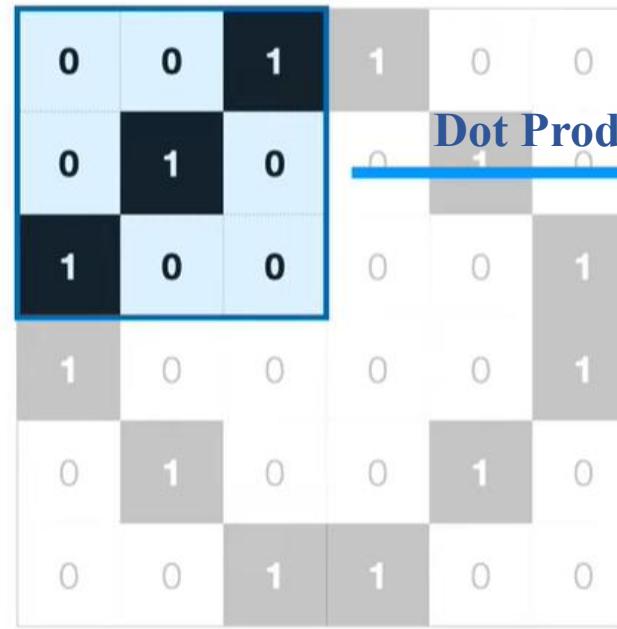
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0



## (3x3) Kernel Matrices (Filters)

0	0	1
0	1	0
1	0	0

1	0	1
0	0	1
1	1	0



Filter

Dot Product

0	0	1
0	1	0
1	0	0

$$(0 \times 0) + (0 \times 0) + (1 \times 1)$$

$$+ (0 \times 0) + (1 \times 1) + (0 \times 0)$$

$$+ (1 \times 1) + (0 \times 0) + (0 \times 0)$$

$$= 3$$

Convolutional Layer

In Python, for example;

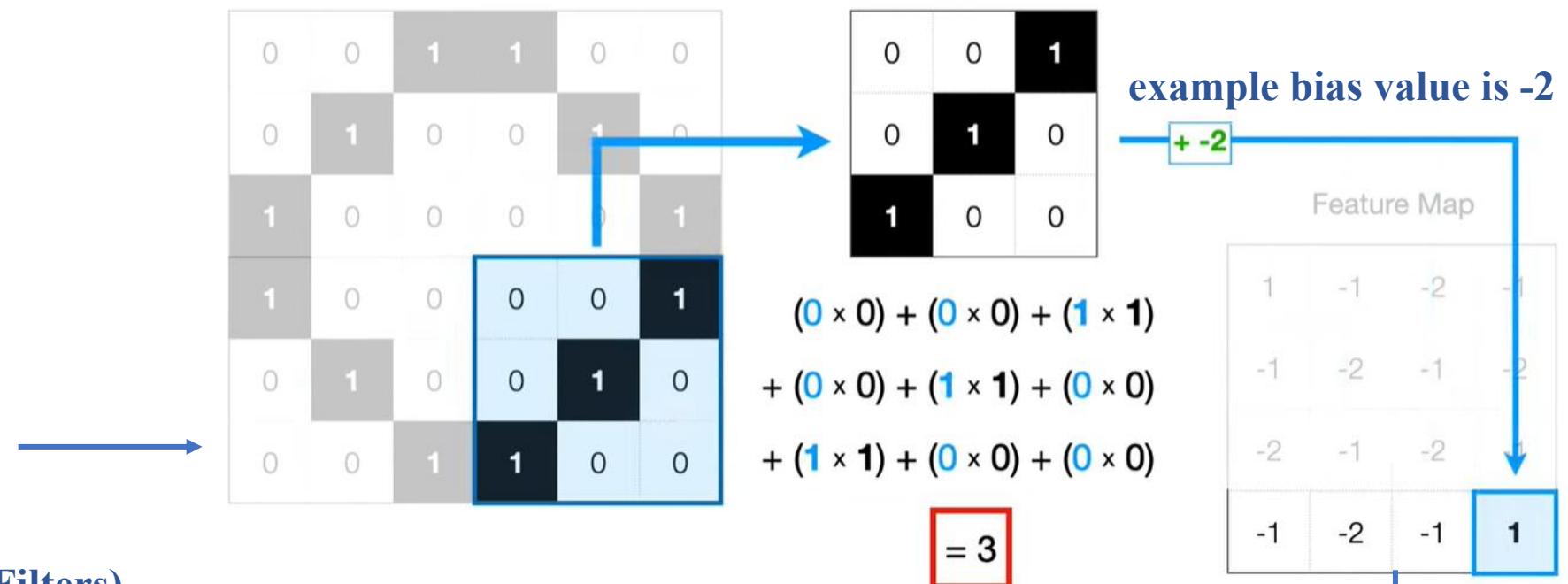
```
nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3)
```

<https://www.youtube.com/watch?v=HGwBXDKFk9I>

# How does Convolutional Neural Networks (CNNs) work?

## Example

0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0



## (3x3) Kernel Matrices (Filters)

0	0	1
0	1	0
1	0	0

1	0	1
0	0	1
1	1	0

## Convolutional Layer

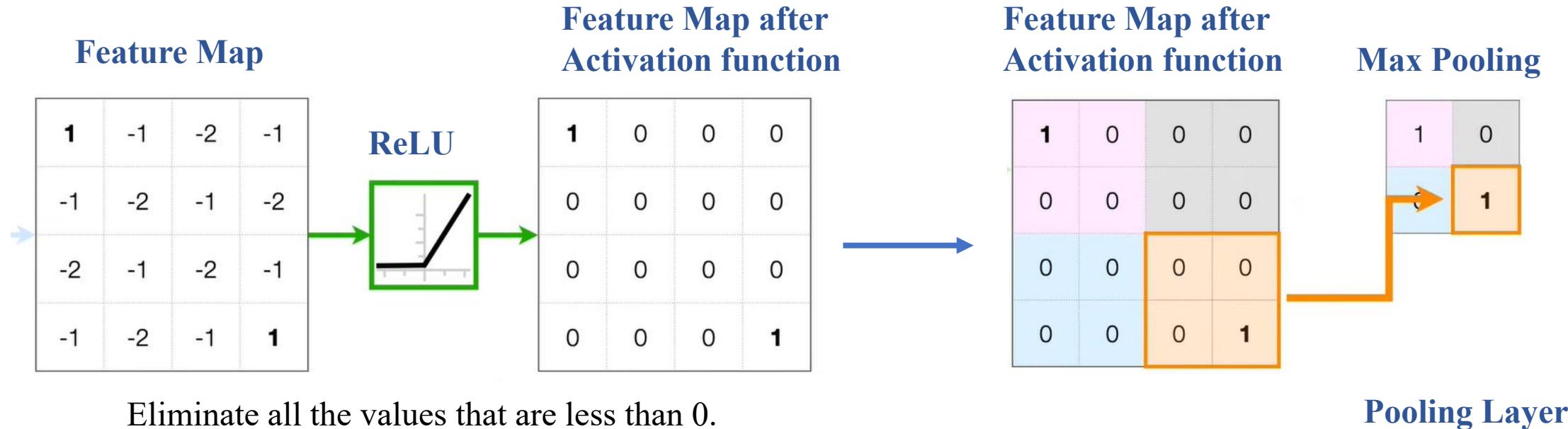
## Feature Map

1	-1	-2	-1
-1	-2	-1	-2
-2	-1	-2	-1
-1	-2	-1	1

<https://www.youtube.com/watch?v=HGwBXDKFk9I>

# How does Convolutional Neural Networks (CNNs) work?

## Example

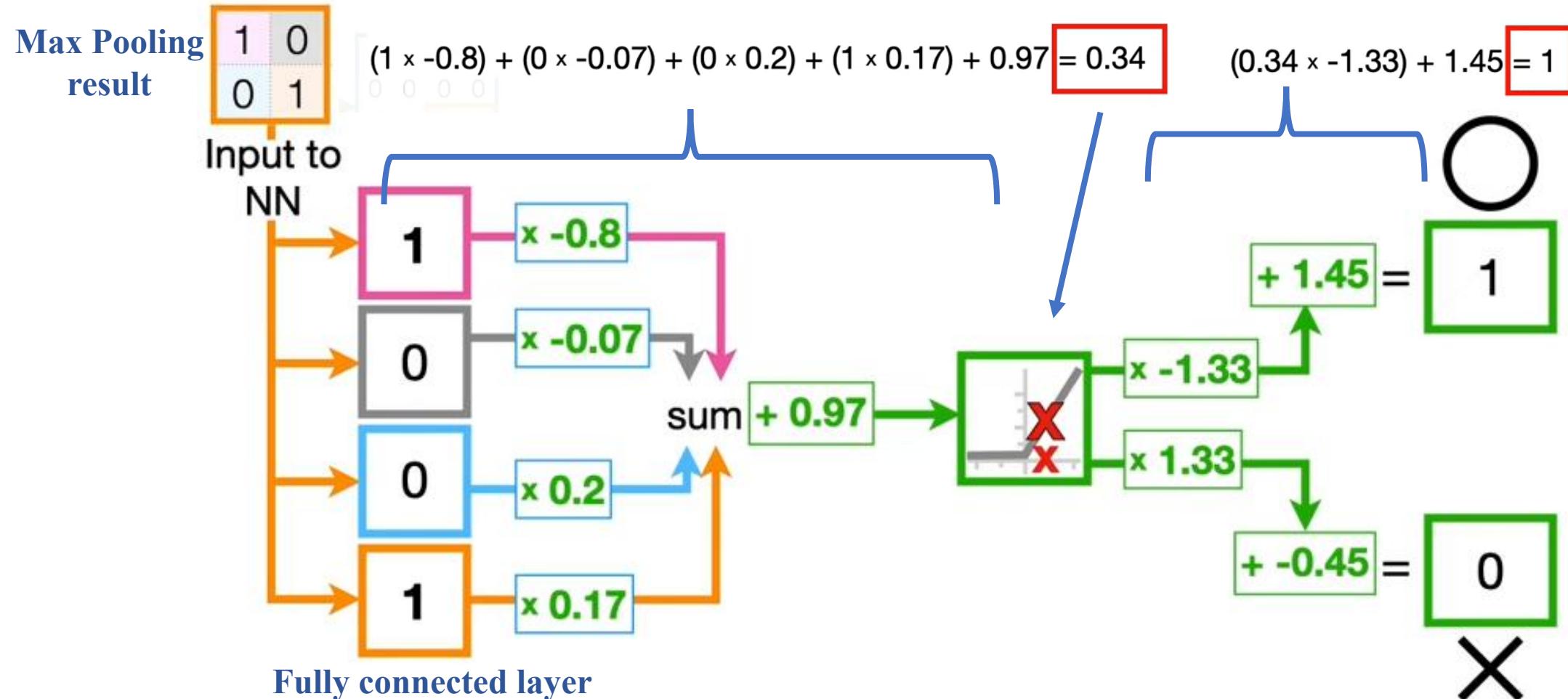


ReLU - Rectified linear unit

<https://www.youtube.com/watch?v=HGwBXDKFk9I>

# How does Convolutional Neural Networks (CNNs) work?

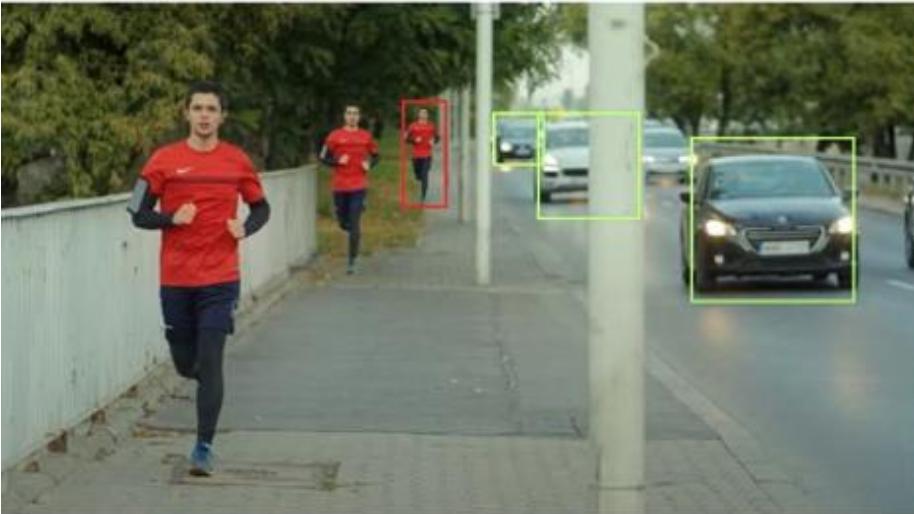
## Example



<https://www.youtube.com/watch?v=HGwBXDKFk9I>

# How does Region-based CNN (R-CNN) work?

## Example Image



Crops of different size



How to handle the same object with different sizes?

Crops of downscale version of the image



<https://arxiv.org/pdf/1311.2524>

<https://www.youtube.com/watch?v=nJzQDpppFj0&t=1s>

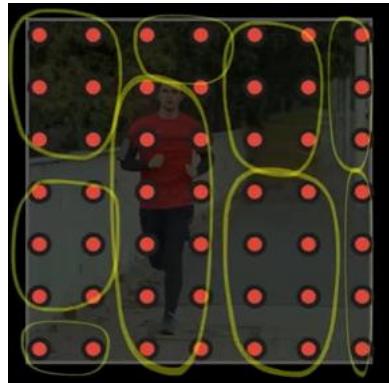
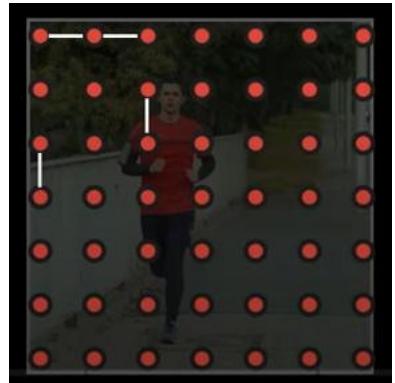
<https://www.youtube.com/watch?v=5DvljLV4S1E>

# How does Region-based CNN (R-CNN) work?

## Example Image



**Step 1**  
check distance between pixels



**How to choose regions to pass through the CNN?**

**Selective Search**

**Step 1:** segment image into regions

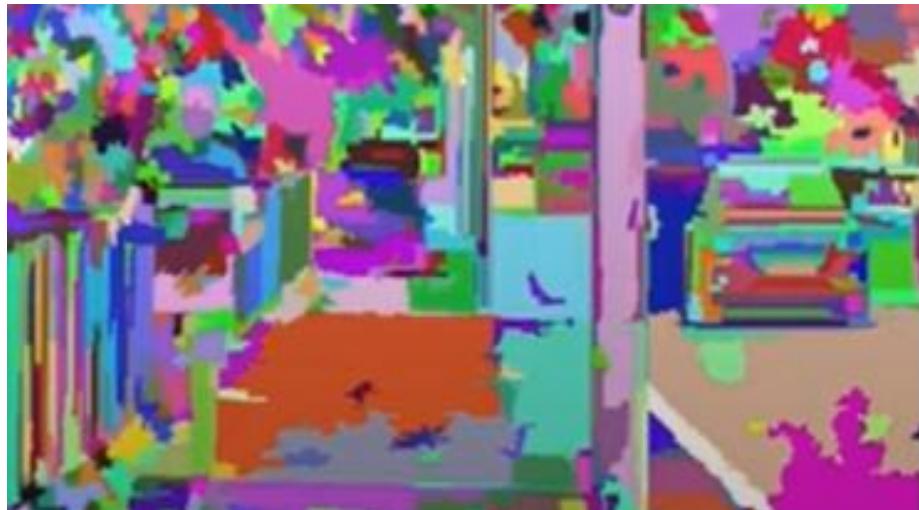
**Step 2:** merge similar regions to create larger regions

# How does Region-based CNN (R-CNN) work?

## Example Image



**Step 2**  
check similarity based on color, texture, size, shape



**How to choose regions to pass through the CNN?**

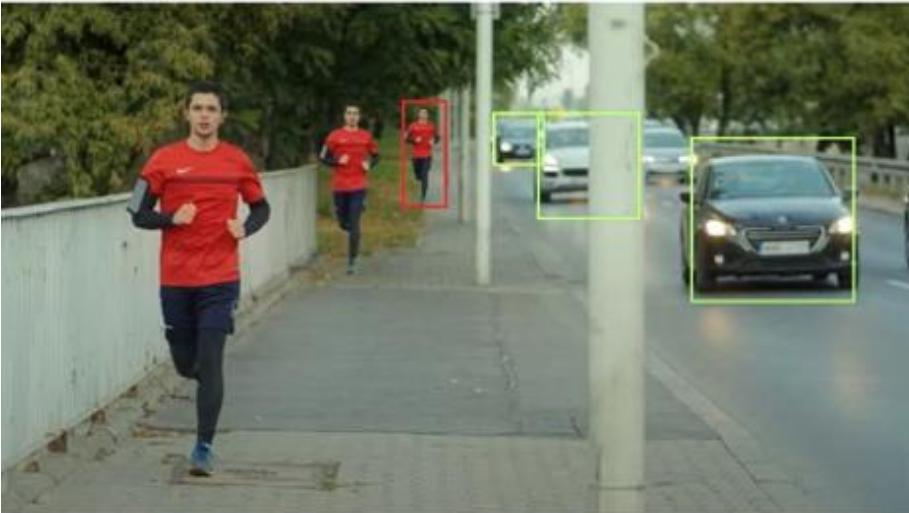
**Selective Search**

**Step 1:** segment image into regions

**Step 2:** merge similar regions to create larger regions

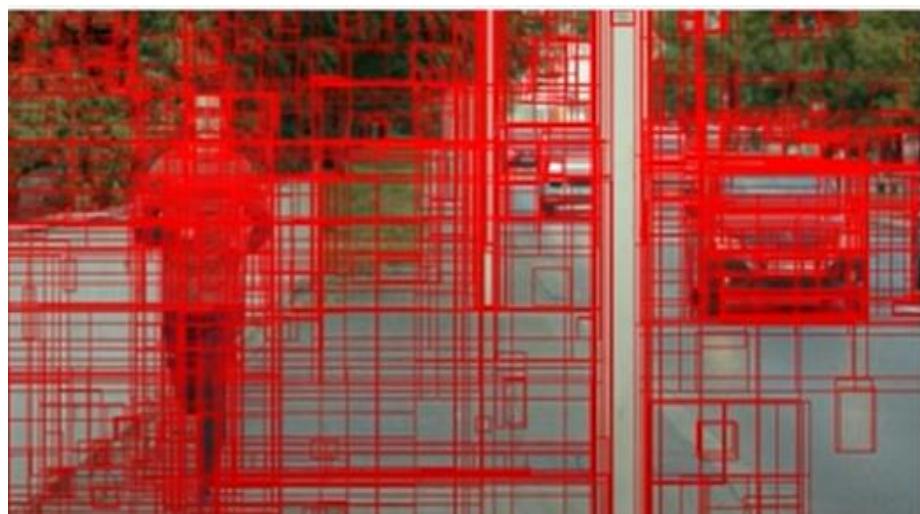
# How does Region-based CNN (R-CNN) work?

## Example Image



Any arbitrary shape proposed regions, how to pass them through the CNN?

Fix size region should be given as an input  
Label for every chosen regions

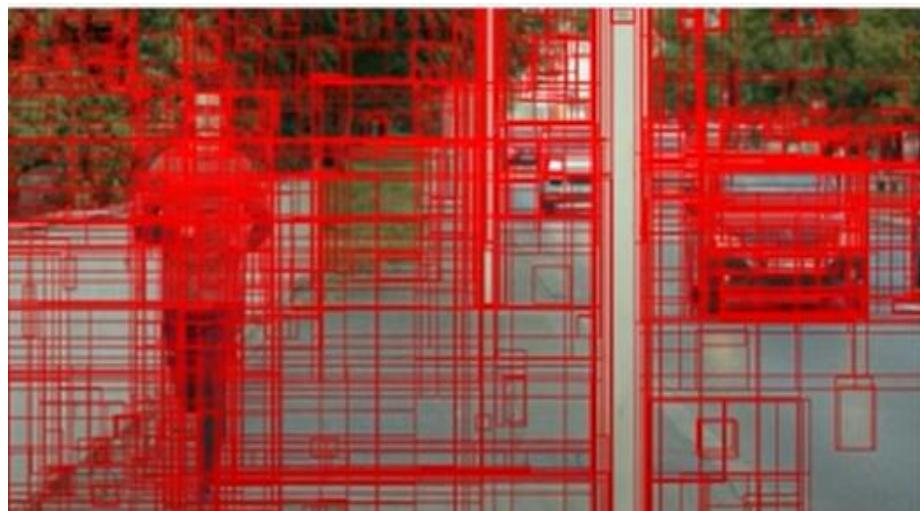


1600 region proposals



# How does Region-based CNN (R-CNN) work?

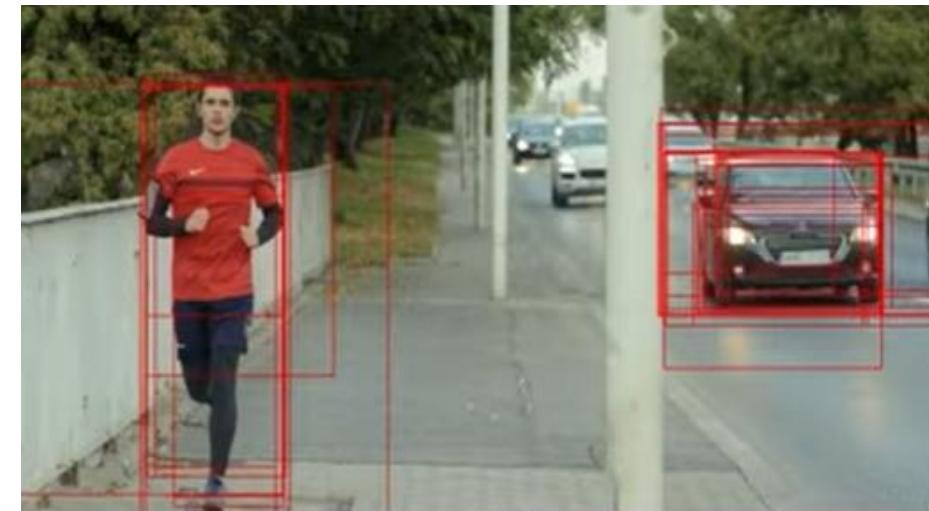
## Example Image



1600 region proposals

## Intersection over Union

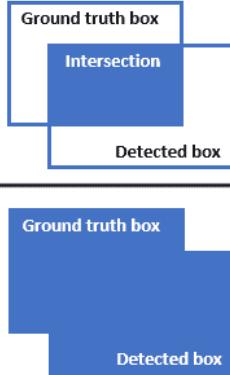
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{\text{Intersection}}{\text{Ground truth box} + \text{Detected box} - \text{Intersection}}$$



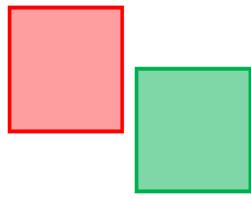
Solution: Non-maximum suppression

# Intersection over Union (IoU)

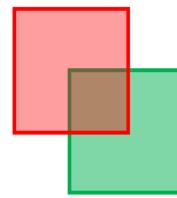
IoU measures the accuracy of the detections

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


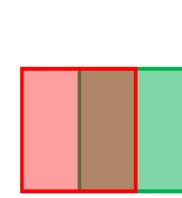
## Examples of different IoU values



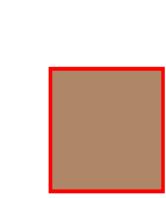
IoU = 0



IoU = 0.142



IoU = 0.333



IoU = 1

<https://www.baeldung.com/cs/object-detection-intersection-vs-union>

## The IoU-based loss functions

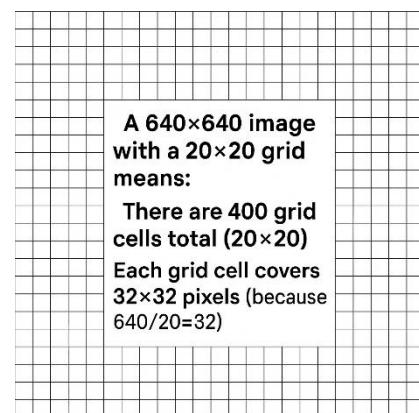
GIoU (Generalized IoU)

DIoU (Distance IoU)

**CIoU (Complete IoU)**

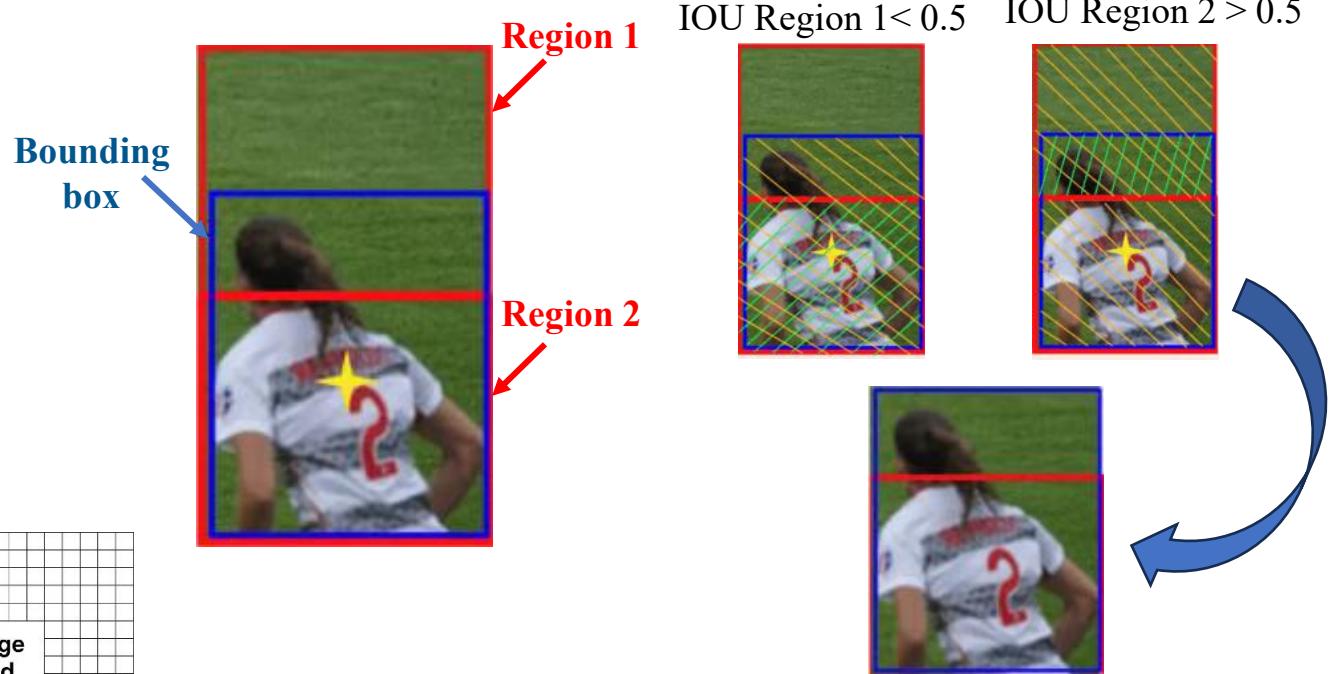
**SIoU (Scalable IoU)**

} YOLOv8



## Example

- The user can define an IOU selection threshold, for instance, 0.5.
- YOLO computes the IOU of each grid cell with the formula on the left side.
- It considers only  $\text{IOU} > \text{threshold}$ .

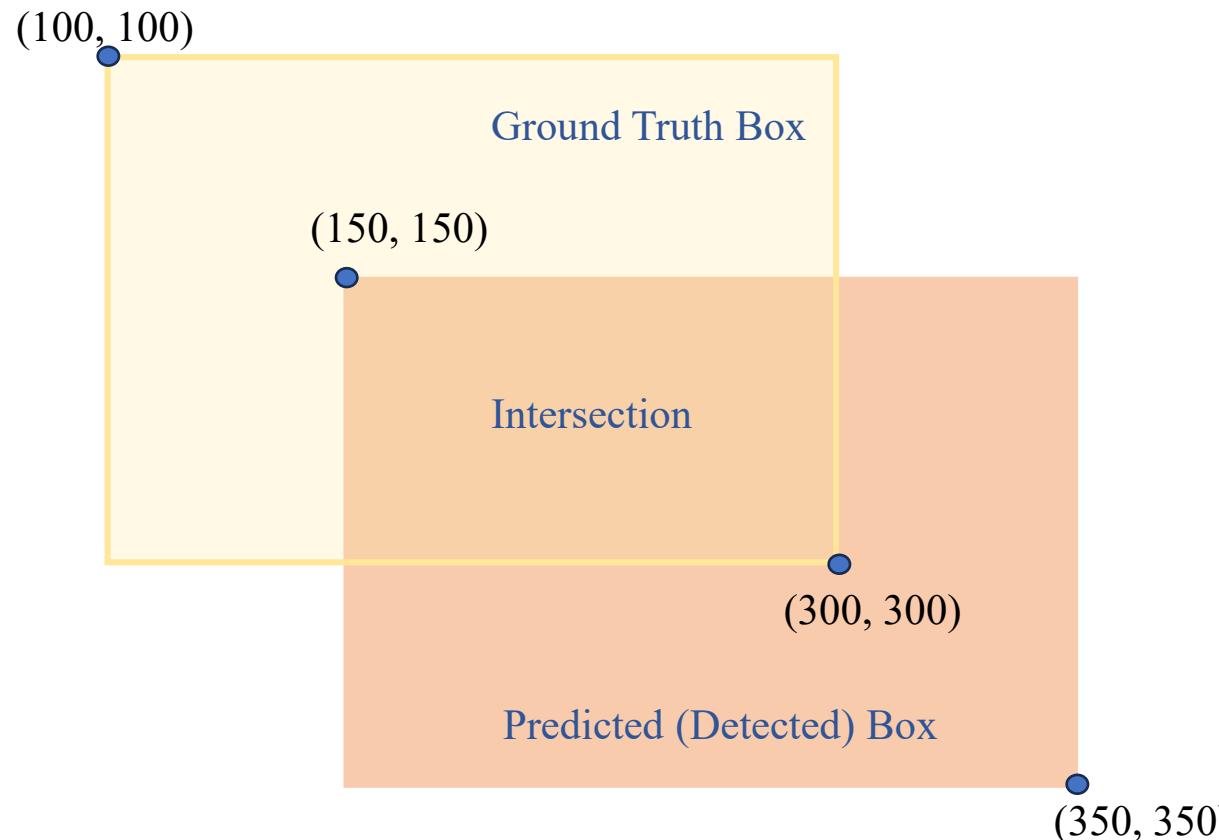


<https://www.datacamp.com/blog/yolo-object-detection-explained>

# Intersection over Union (IoU)

IoU measures the accuracy of the detections

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



$$\text{Area of Ground Truth Box} = 200 \times 200 = 40,000 \text{ pixels}^2$$

$$\text{Area of Predicted Box} = 200 \times 200 = 40,000 \text{ pixels}^2$$

$$\text{Area of Intersection} = 150 \times 150 = 22,500 \text{ pixels}^2$$

$$\text{Union} = \text{Area(GT)} + \text{Area(P)} - \text{Intersection}$$

$$\text{Union} = 40,000 + 40,000 - 22,500 = 57,500$$

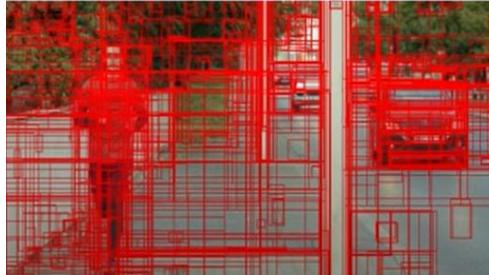
$$\text{IoU} = \text{Intersection over Union} = \frac{22,500}{57,500} \approx 0.391$$

# How does Region-based CNN (R-CNN) work?

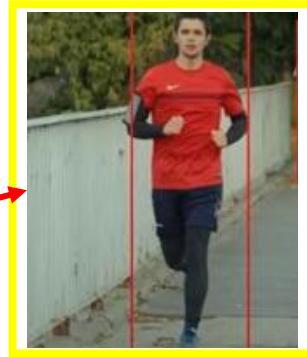
## Example Image



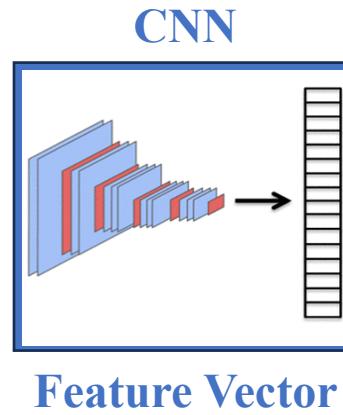
Input



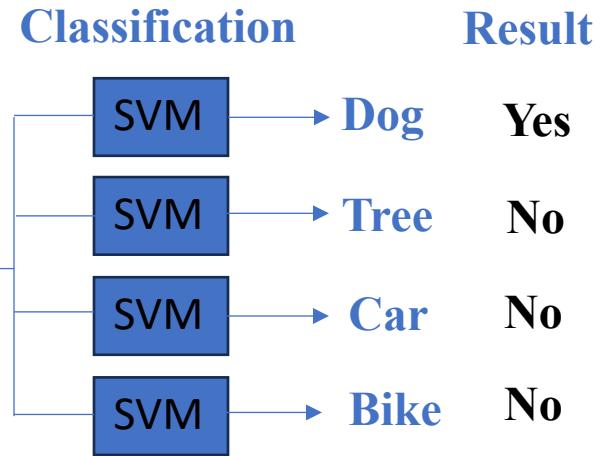
Region Proposals



Resized  
Region  
Image



Feature Vector



Train with  $\text{IoU} \geq 0.5$   
with ground truth  
boxes of that class

SVM – Support vector machine – classification method

Girshick et. al (2014) “Rich feature hierarchies for accurate object detection and semantic segmentation”

<https://arxiv.org/pdf/1311.2524>

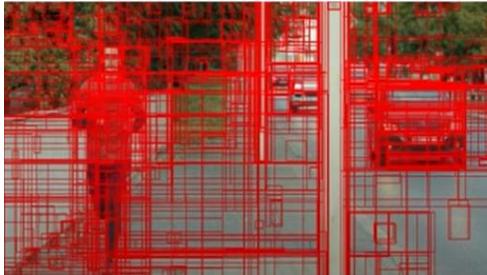
Source: Redmon and <https://www.youtube.com/watch?v=svn9-xV7wjk&t=170s>

# How does Region-based CNN (R-CNN) work?

## Example Image



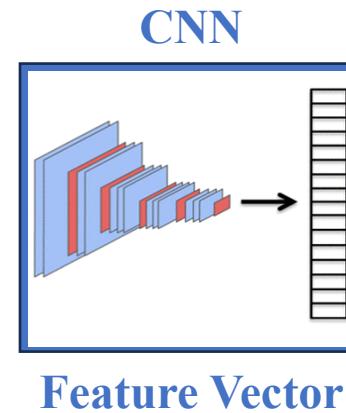
Input



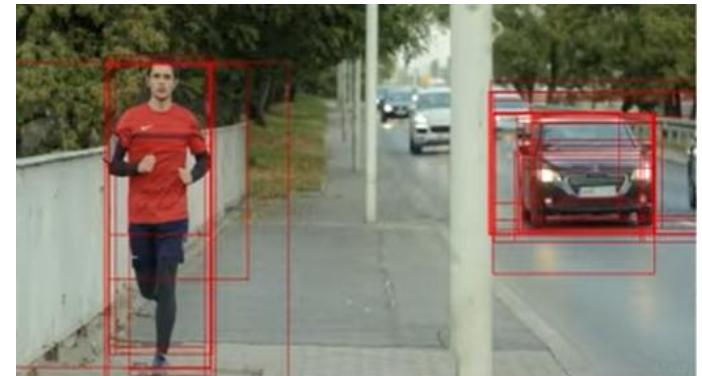
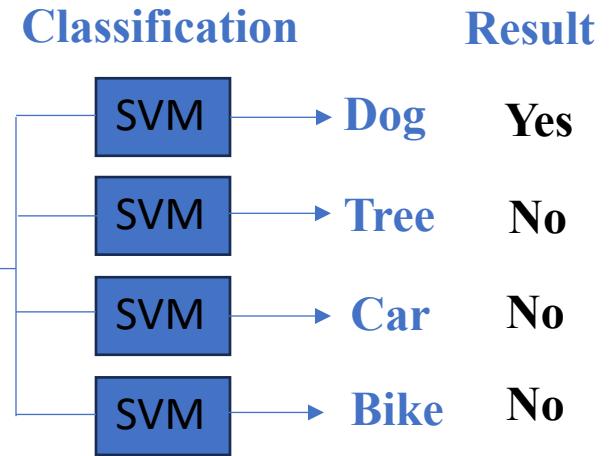
Region Proposals



Resized  
Region  
Image



Feature Vector



## How to evaluate the model R-CNN?

- apply **Non-Maximum Suppression (NMS)** to remove duplicate detections. → If  $IoU(P_1, P_2) > \text{Threshold}$ :
- evaluate predictions using **Average Precision (AP)** per class and **Mean Average Precision (mAP)** across classes.

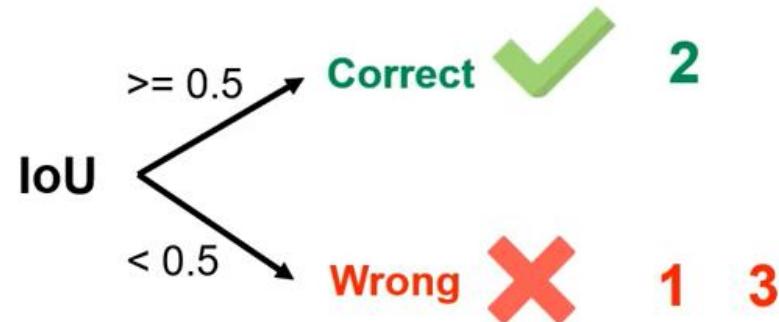
$$P = \operatorname{argmax}(C(P_1), C(P_2))$$

# How does Region-based CNN (R-CNN) work?

## Example Image

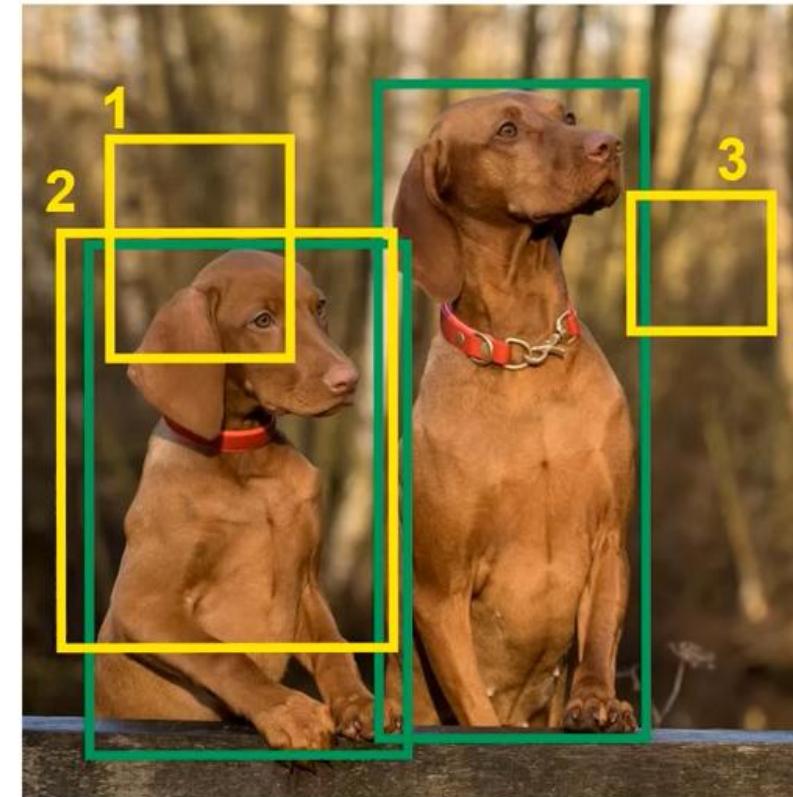
### Mean Average Precision (mAP)

Which predicted bounding boxes are correct?



Precision  $\frac{1}{3}$

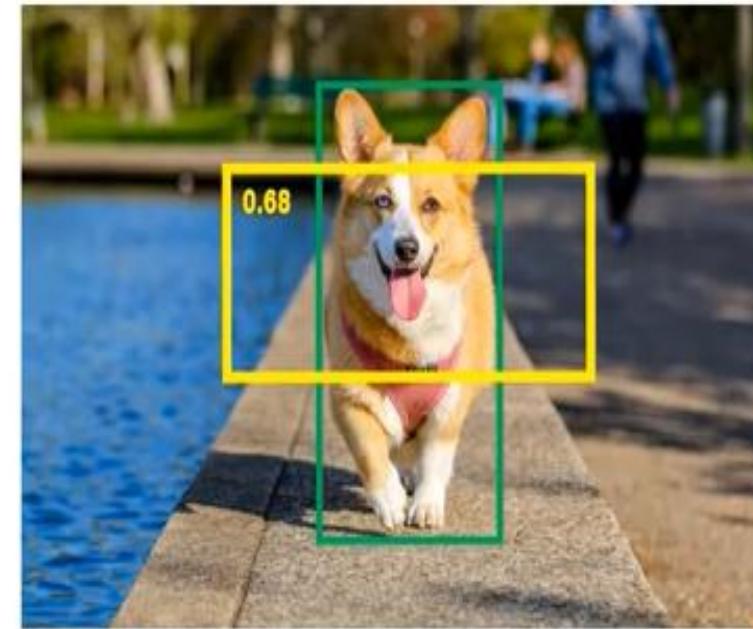
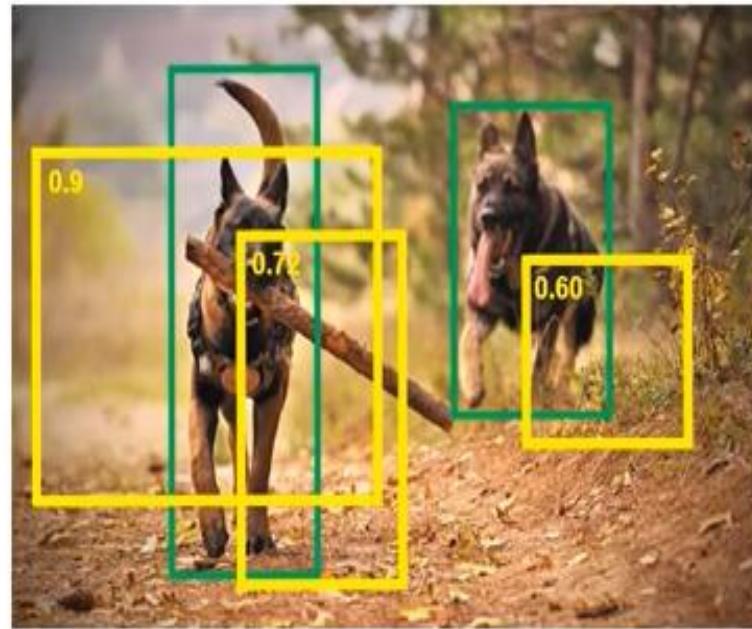
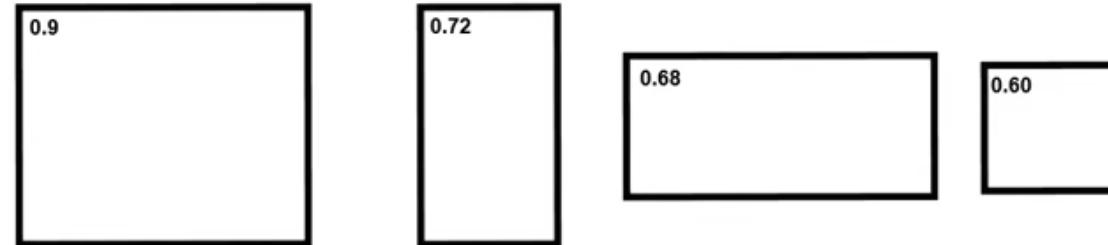
Recall  $\frac{1}{2}$



# How does Region-based CNN (R-CNN) work?

## Example Image

### Mean Average Precision (mAP)

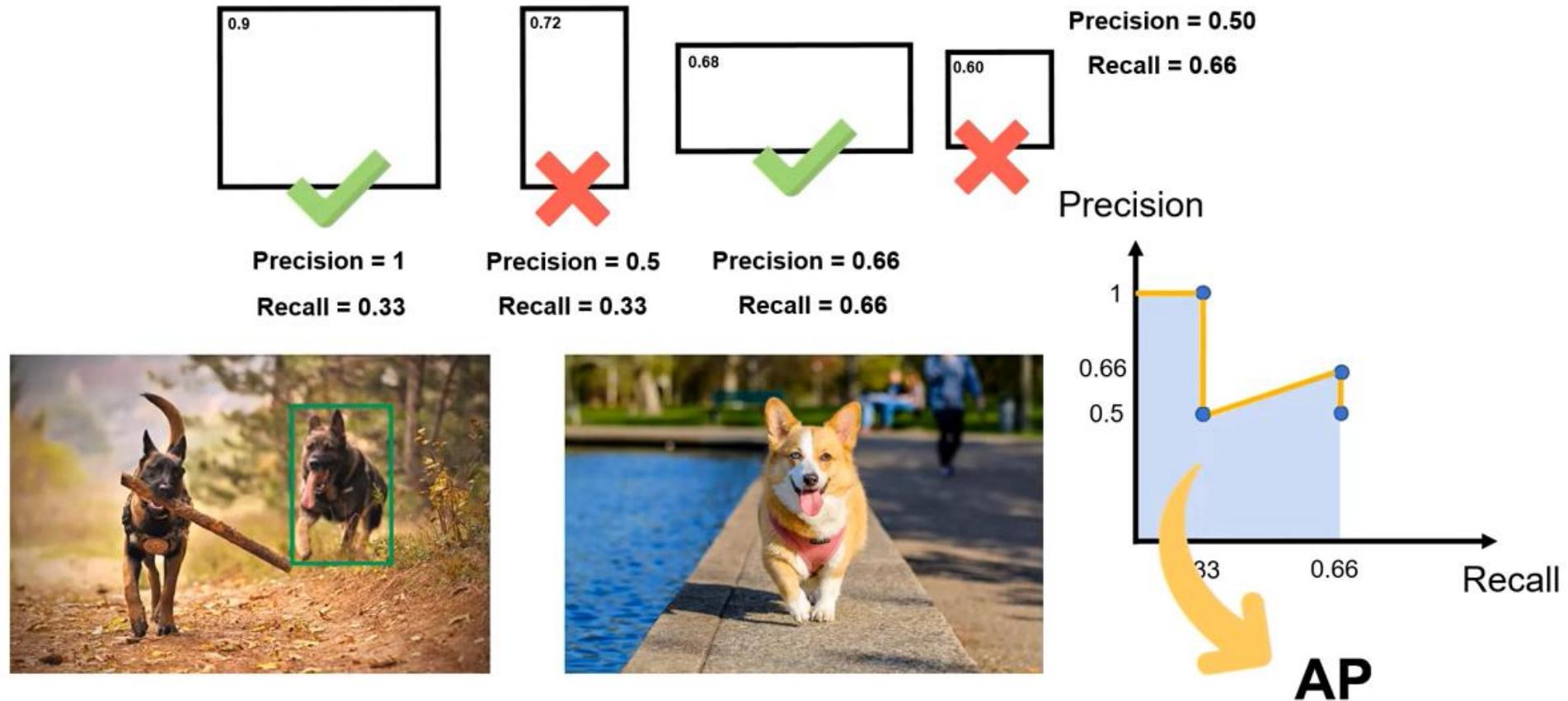


<https://www.youtube.com/watch?v=nJzQDpppFj0&t=1s>

# How does Region-based CNN (R-CNN) work?

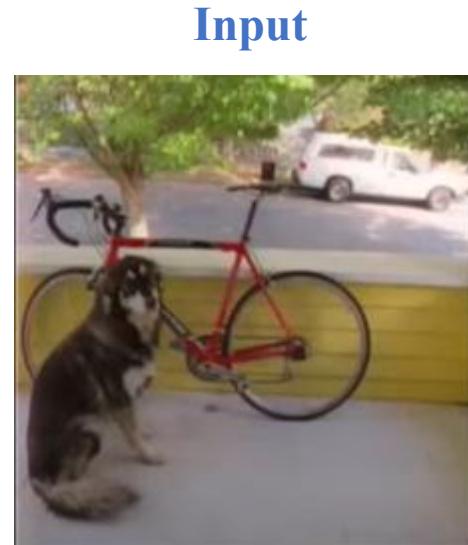
## Example Image

### Mean Average Precision (mAP)

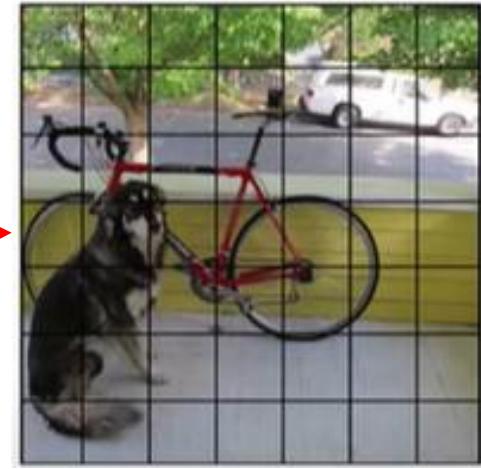


<https://www.youtube.com/watch?v=nJzQDpppFj0&t=1s>

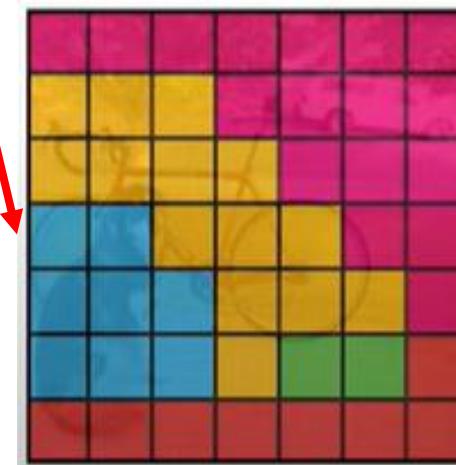
# How does YOLO Work?



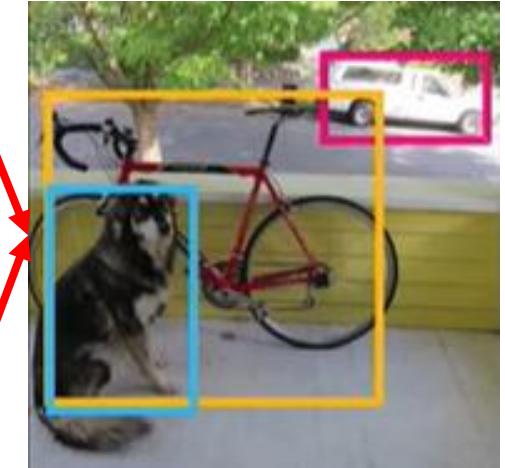
$S \times S$  grid



Bounding boxes  
+ Confidence score



Class probability map



Detections

	Bicycle
	Car
	Desk
	Dog
	Dining Table

In YOLO, each grid cell directly predicts:

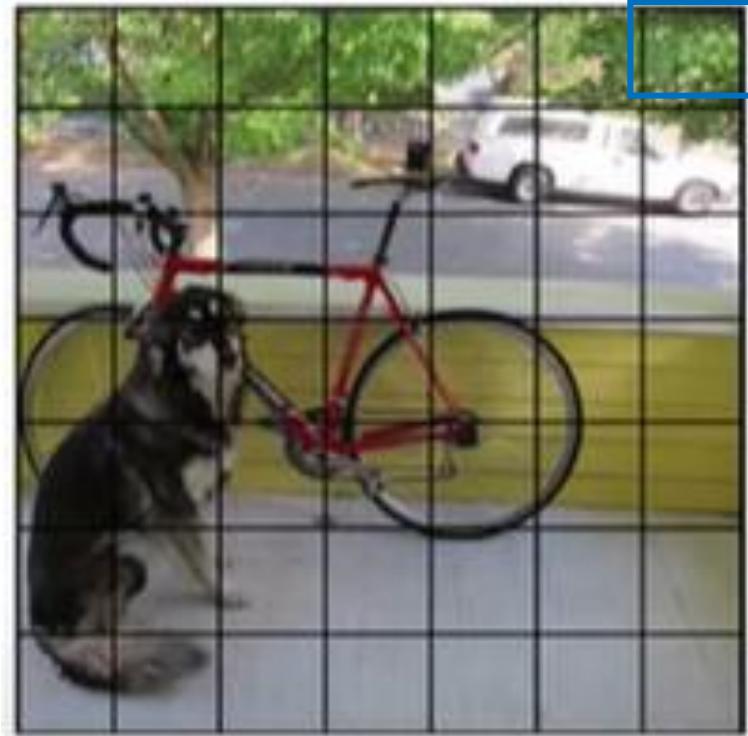
- A fixed number of **bounding boxes**
- Each box's ( $x$ ,  $y$ ,  $w$ ,  $h$ ) coordinates
- A **confidence score & class probabilities**

Redmon et. al (2016) “you Only Look Once: Unified, Real-Time Detection”

[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)

Source: <https://www.youtube.com/watch?v=svn9-xV7wjk&t=170s>

# How does YOLO Work?



**S x S grid**

**Output Vector Length**

$$B \times 7 + n$$

**Class probabilities**

$$[p(c_1), p(c_2), \dots, p(c_n)]$$

**Bounding box predictions**

$$[x_1, y_1, \sqrt{w_1}, \sqrt{h_1}, C_1]$$

$$[x_2, y_2, \sqrt{w_2}, \sqrt{h_2}, C_2]$$

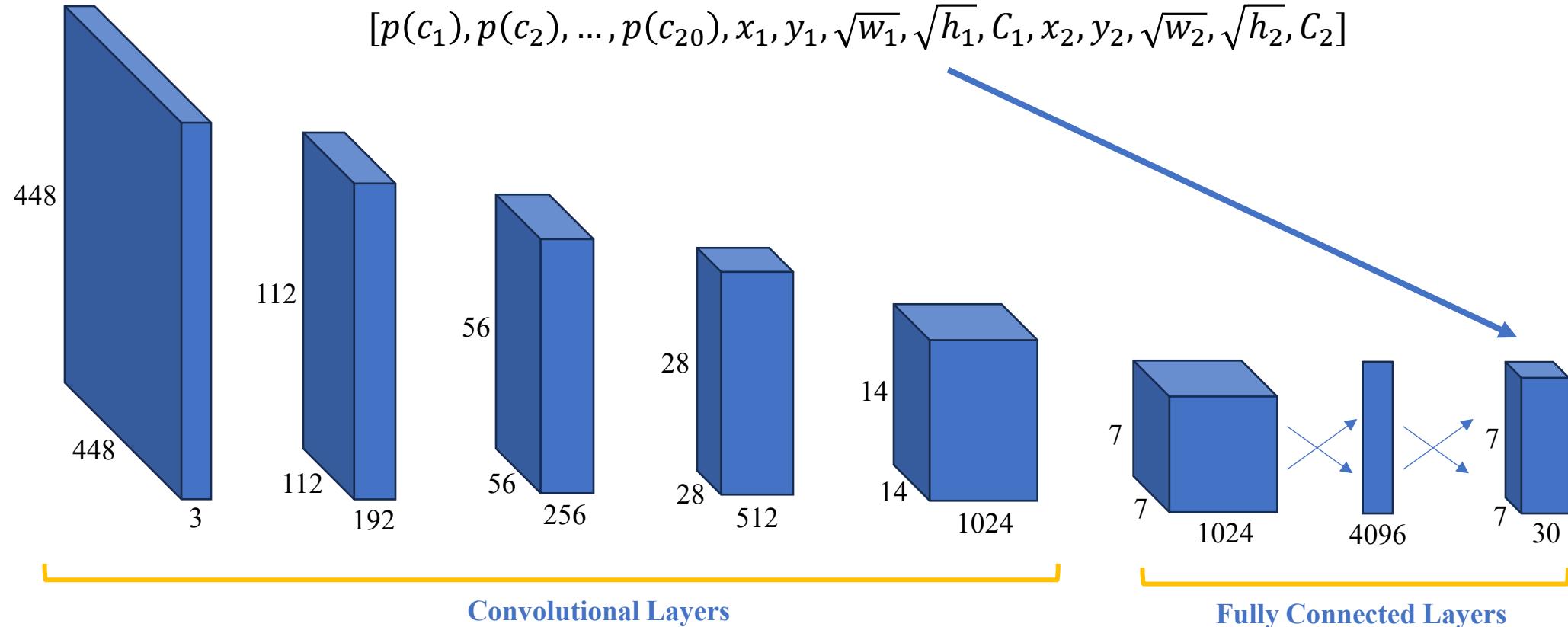
...

$$[x_B, y_B, \sqrt{w_B}, \sqrt{h_B}, C_B]$$

n is the number of object classes

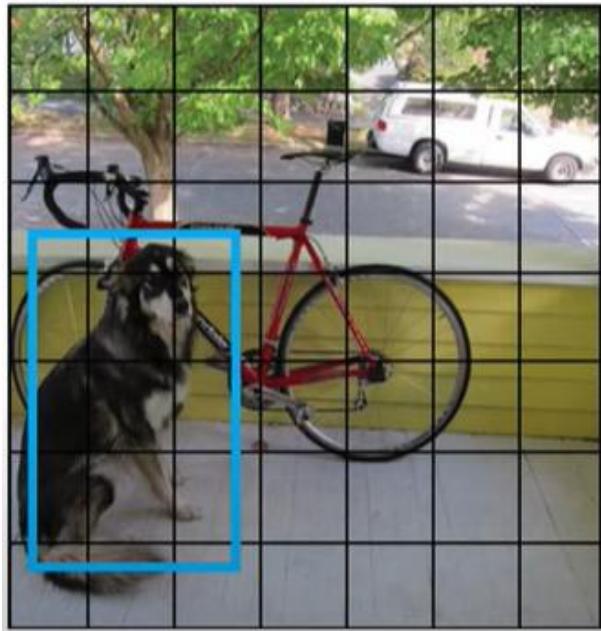
B is the number of bounding boxes

# How does YOLO Work?

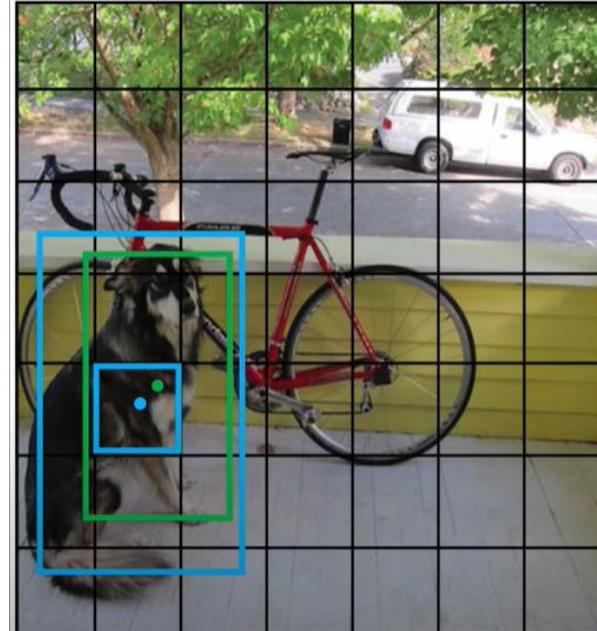


# How does YOLO Work?

## Ground truth (class probabilities)

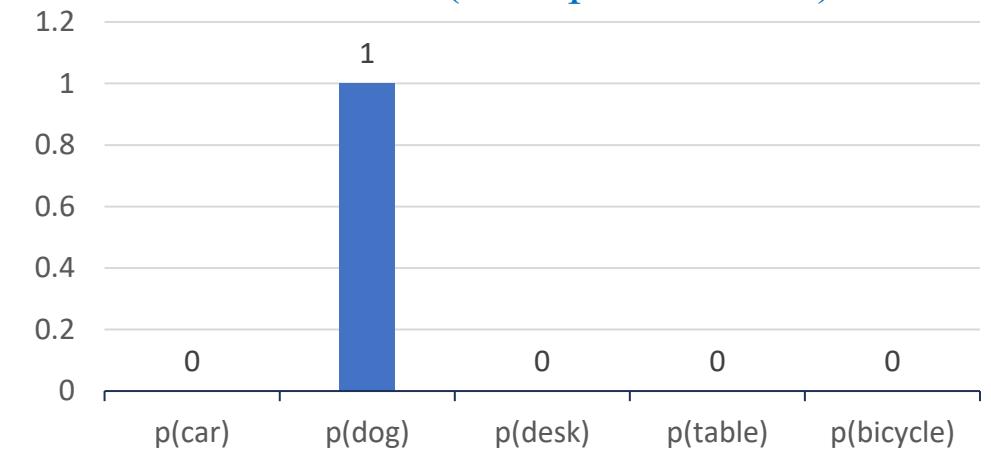


Let's predict this bounding box



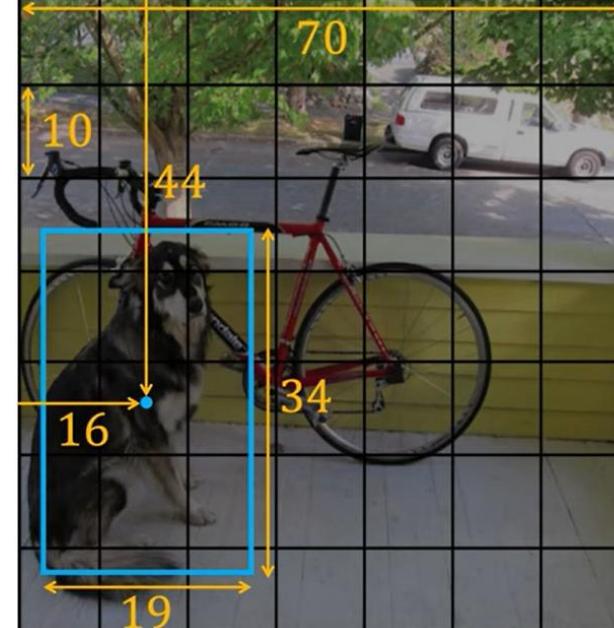
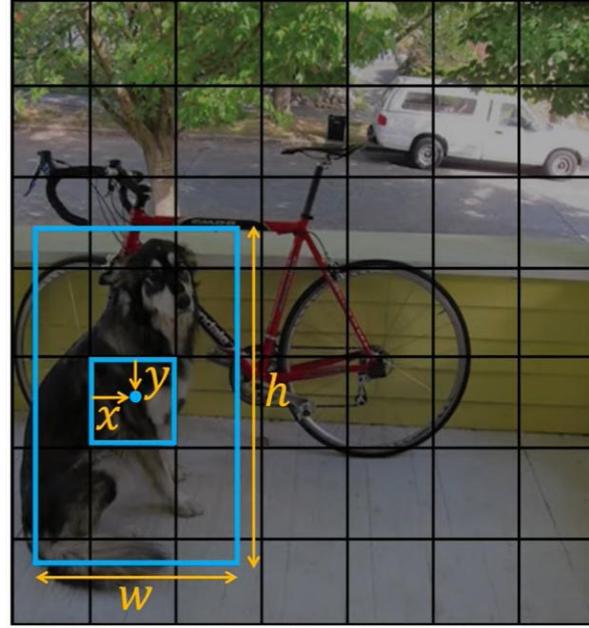
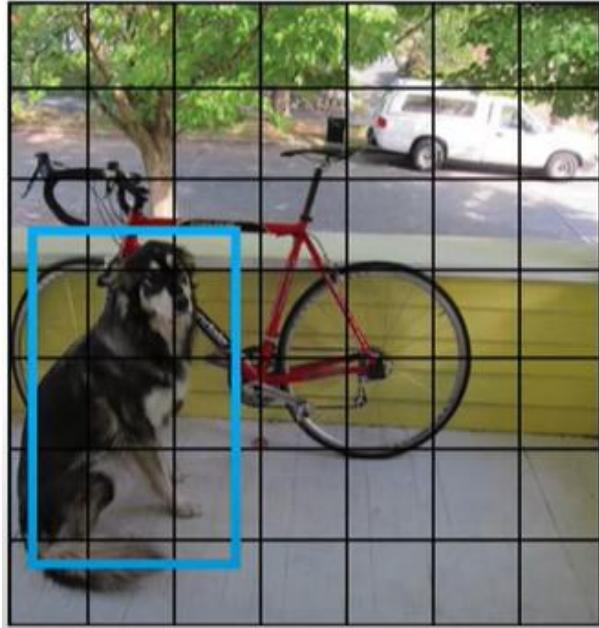
Green box is our prediction

## Ground truth (class probabilities)



# How does YOLO Work?

## Ground truth (box coordinates)



Let's predict this bounding box

Calculate the ground truth and predicted boxes by using the coordinates

$$x = \frac{16\%10}{10} = 0.60$$

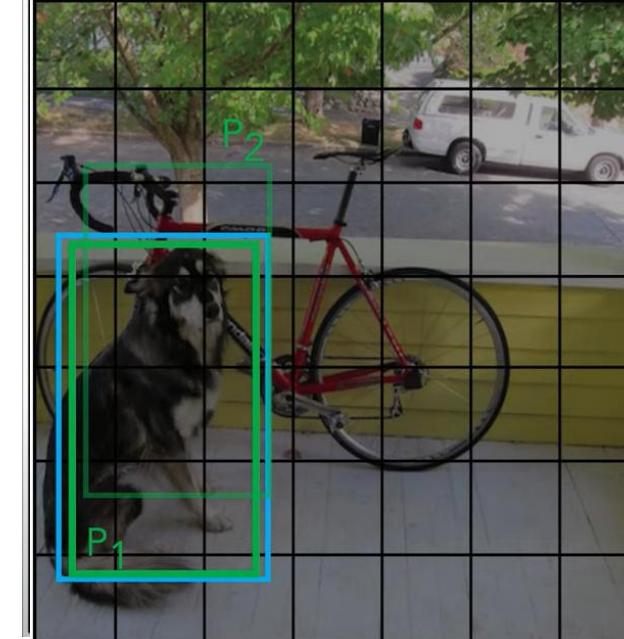
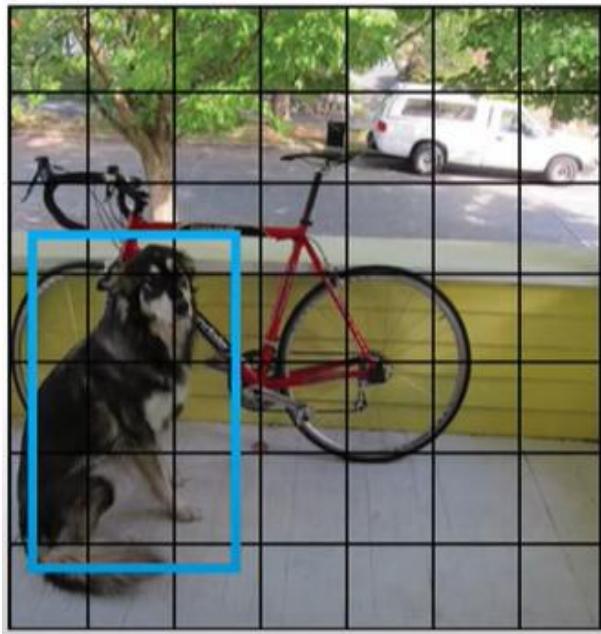
$$y = \frac{44\%10}{10} = 0.40$$

$$w = \frac{19}{70} = 0.27$$

$$h = \frac{34}{70} = 0.49$$

# How does YOLO Work?

## Ground truth (confidence)



Let's predict this bounding box

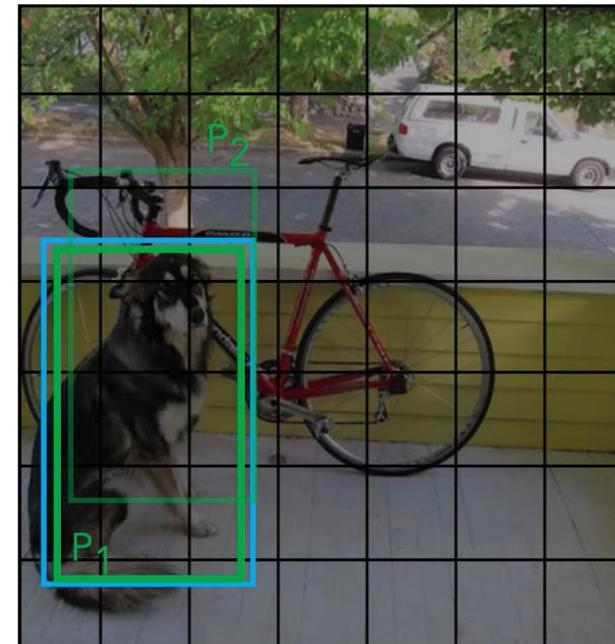
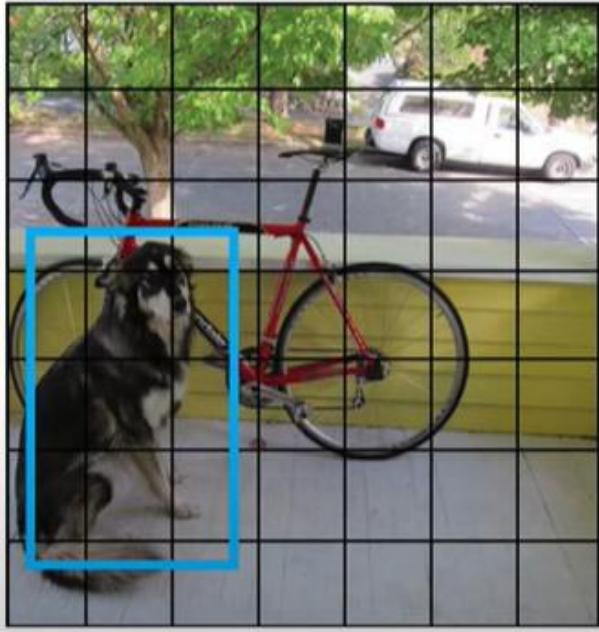
$$\textcolor{red}{\square} = 0$$

$$C = IoU (\textcolor{green}{pred}, \textcolor{blue}{true})$$

$$\textcolor{green}{\square} = IoU (pred, true)$$

# How does YOLO Work?

## Box selection (Inference)



Let's predict this bounding box

*If  $IoU(P_1, P_2) > \text{Threshold}$ :*

$$P = \text{argmax}(C(P_1), C(P_2))$$

# How does YOLO Work?

Helps to put more weight to  
box coordinates

Bounding box coordinate loss (Coordinate regression loss)

$$L = \lambda_{coord} \times \sum_{i=1}^{S^2} 1_i^{obj} \times \left( (\Delta x_i^* - \Delta \hat{x}_i)^2 + (\Delta y_i^* - \Delta \hat{y}_i)^2 + \left( \sqrt{\Delta w_i^*} - \sqrt{\Delta \hat{w}_i} \right)^2 + \left( \sqrt{\Delta h_i^*} - \sqrt{\Delta \hat{h}_i} \right)^2 \right)$$

For training part,  
Loss function

$$+ \sum_{i=1}^{S^2} 1_i^{obj} \times (c_i^* - \hat{c}_i)^2 + \sum_{i=1}^{S^2} 1_i^{obj} \times \sum_{c=1}^{20} (p_{i,c} - \hat{p}_{i,c})^2$$

Confidence score loss

Class probability loss

$$+ \lambda_{no\_obj} \sum_{i=1}^{S^2} 1_i^{no\_obj} \times \sum_{j=1}^B (c_{i,j} - \hat{c}_{i,j})^2$$

If there is an object,  
it is evaluated

If there is no object,  
it is evaluated