

# Object Detection Basics

Deep Learning for Computer Vision

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*Teaching computers to see and locate objects*

# Why Object Detection?

Imagine you're driving...

[Car] <-- Your car sees this scene

[Ped] pedestrian

↓  
STOP!

[Car] car

↓  
SLOW DOWN

[Bike] cyclist

↓  
CAREFUL!

Your car needs to know:

- WHAT is there? (classification)
- WHERE is it? (localization)
- HOW MANY? (counting)

Classification alone says "there's a person somewhere" — **not enough!**

# What You Will Learn Today

Part 1: The Core Problem

Classification → Detection → Segmentation

Part 2: Bounding Boxes

How we represent "WHERE is the object?"

Part 3: IoU (Intersection over Union)

How we measure "Is this box correct?"

Part 4: NMS (Non-Maximum Suppression)

How we handle "Too many boxes!"

Part 5: YOLO Architecture

How real detectors work

Part 6: Training & Metrics

How we train and evaluate detectors

# Part 1: The Core Problem

**What IS Object Detection?**

# The Vision Task Hierarchy

## Level 1: CLASSIFICATION

"What is in this image?"

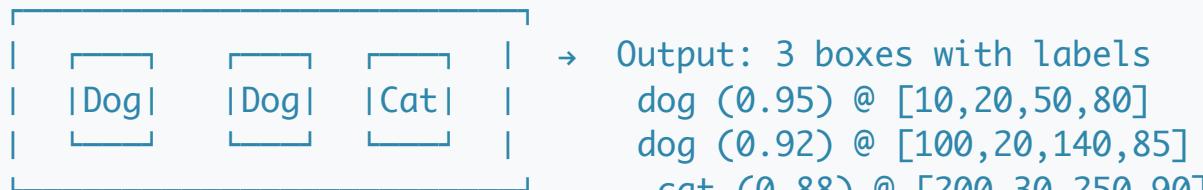


-> Output: "dog" (or "cat")

Just ONE label for the whole image

## Level 2: OBJECT DETECTION

"What + Where?"



→ Output: 3 boxes with labels  
dog (0.95) @ [10,20,50,80]  
dog (0.92) @ [100,20,140,85]  
cat (0.88) @ [200,30,250,90]

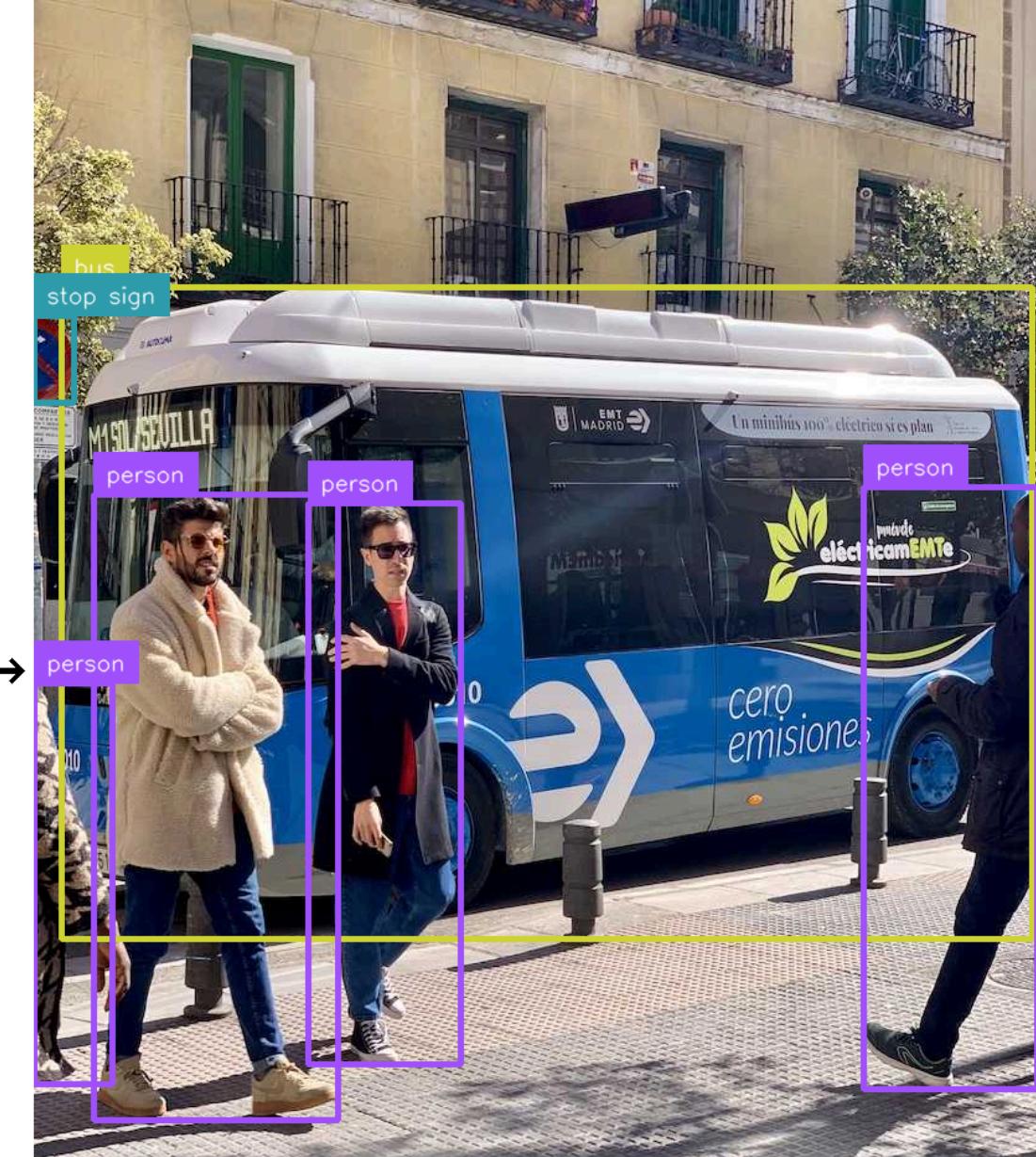
## Level 3: INSTANCE SEGMENTATION

"Exact shape of each object"



→ Pixel-perfect mask for each individual object

# Classification vs Detection: Key Difference



# A More Detailed Comparison

Aspect	Classification	Detection	Segmentation
Output	Single label	Boxes + labels	Pixel masks
Multiple objects?	No (or multi-label)	Yes ✓	Yes ✓
Location?	No	Box ✓	Exact shape ✓
Typical use	"What is this?"	"Where are things?"	"Precise boundaries"
Difficulty	Easier	Medium	Harder
Speed	Fastest	Fast	Slower

**Real applications:** • Classification: "Is this X-ray normal?" • Detection: "Where are the tumors?" • Segmentation: "Exact tumor boundary for surgery planning"

# Real-World Detection Applications

## OBJECT DETECTION IN THE WILD

### AUTONOMOUS DRIVING

- Pedestrians, cars, signs
- Traffic lights, lanes
- Cyclist detection

### SMARTPHONE CAMERAS

- Face detection for focus
- Scene understanding
- AR filters positioning

### RETAIL & INVENTORY

- Shelf stock monitoring
- Checkout-free stores (Amazon Go)
- Customer flow analysis

### MEDICAL IMAGING

- Tumor detection
- Cell counting
- Organ localization

### SECURITY & SURVEILLANCE

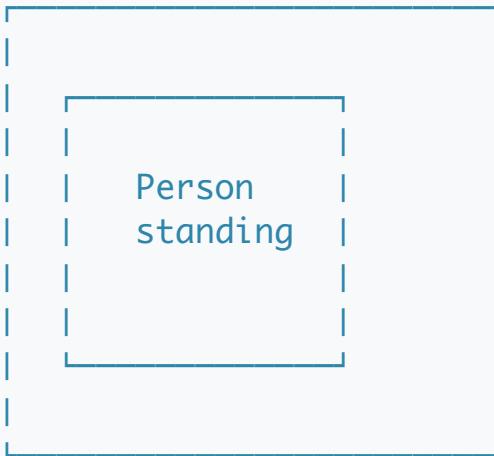
- Intrusion detection
- Crowd monitoring
- License plate recognition

### MANUFACTURING

- Defect detection
- Quality control
- Safety compliance

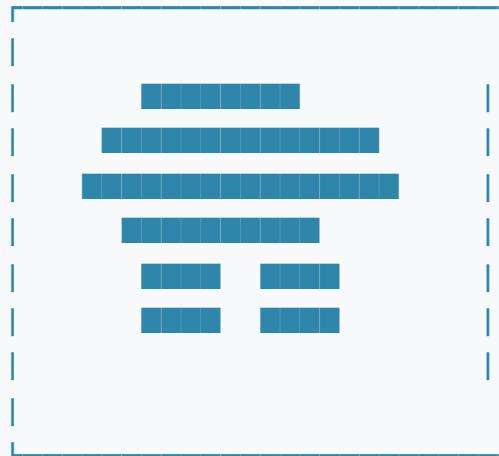
# Instance Segmentation: Beyond Boxes

DETECTION gives you BOXES:



Box includes background!

SEGMENTATION gives you MASKS:



Every pixel classified!

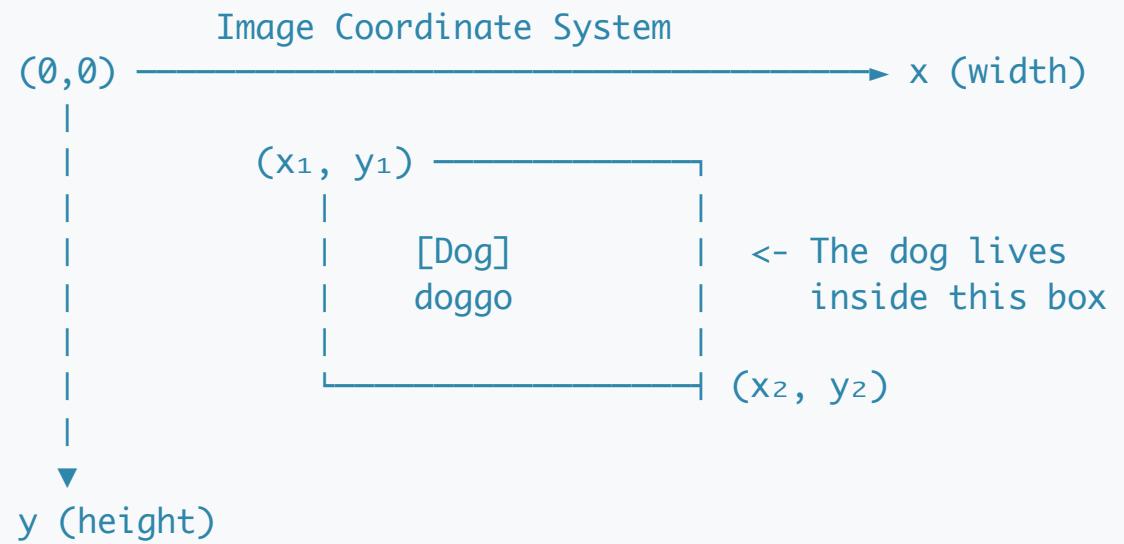
Segmentation is needed for: video editing backgrounds, medical boundaries, precise robotics

## Part 2: Bounding Boxes

How We Represent "WHERE"

# What IS a Bounding Box?

A bounding box is a RECTANGLE that tightly contains an object.



The box is defined by 4 numbers. But WHICH 4?

Different systems use different conventions — this causes many bugs!

# The Three Main Formats

## Format 1: CORNER FORMAT ( $x_1, y_1, x_2, y_2$ )

- Top-left and bottom-right corners
- Used by: PyTorch, many APIs
- Easy for: drawing, IoU calculation

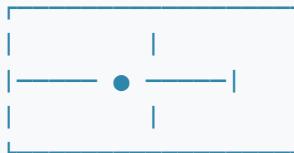


Box = [100, 50, 300, 200]  
Width = 300 - 100 = 200  
Height = 200 - 50 = 150

# The Three Main Formats (continued)

## Format 2: CENTER FORMAT ( $cx$ , $cy$ , $w$ , $h$ )

- Center point + width + height
- Used by: YOLO, many papers
- Easy for: predicting from grid cells



● = center (200, 125)  
 $w = 200, h = 150$

Box = [200, 125, 200, 150]  
 $x_1 = 200 - 200/2 = 100$   
 $y_1 = 125 - 150/2 = 50$

## Format 3: CORNER + SIZE ( $x$ , $y$ , $w$ , $h$ )

- Top-left corner + width + height
- Used by: COCO dataset format
- Easy for: drawing ( $x, y$  is start point)



Box = [100, 50, 200, 150]

# Format Conversion Cheat Sheet

```
# Corner (x1,y1,x2,y2) → Center (cx,cy,w,h)
```

```
cx = (x1 + x2) / 2
```

```
cy = (y1 + y2) / 2
```

```
w = x2 - x1
```

```
h = y2 - y1
```

```
# Center (cx,cy,w,h) → Corner (x1,y1,x2,y2)
```

```
x1 = cx - w/2
```

```
y1 = cy - h/2
```

```
x2 = cx + w/2
```

```
y2 = cy + h/2
```

```
# Corner+Size (x,y,w,h) → Corner (x1,y1,x2,y2)
```

```
x1 = x
```

```
y1 = y
```

```
x2 = x + w
```

```
y2 = y + h
```

**Common bug alert!** Always check your dataset's format before training. COCO uses [x,y,w,h], PASCAL VOC uses [x1,y1,x2,y2], YOLO uses normalized [cx,cy,w,h]

# Absolute vs Normalized Coordinates

## ABSOLUTE COORDINATES (Pixels):

Image size:  $640 \times 480$  pixels  
Box: [100, 50, 300, 200] ← pixel values

Problem: What if image is resized to  $320 \times 240$ ?  
Box values become invalid!

## NORMALIZED COORDINATES (0 to 1):

Image size: ANY  
Box: [0.156, 0.104, 0.469, 0.417] ← proportions

Conversion:  
 $x_{norm} = x_{pixel} / image\_width$   
 $y_{norm} = y_{pixel} / image\_height$

Same box works for ANY image size!

YOLO uses normalized center format:  $[cx/W, cy/H, w/W, h/H]$  — all values between 0 and 1

# Quick Format Quiz

Image: 640 × 480 pixels

Object is at: top-left (100, 50), bottom-right (300, 200)

What is the box in each format?

Format	Values
Corner (xyxy)	[100, 50, 300, 200]
Corner+Size (xywh)	[100, 50, 200, 150]
Center (cxcywh)	[200, 125, 200, 150]
Normalized xyxy	[0.156, 0.104, 0.469, 0.417]
Normalized cxcywh	[0.312, 0.260, 0.312, 0.312]

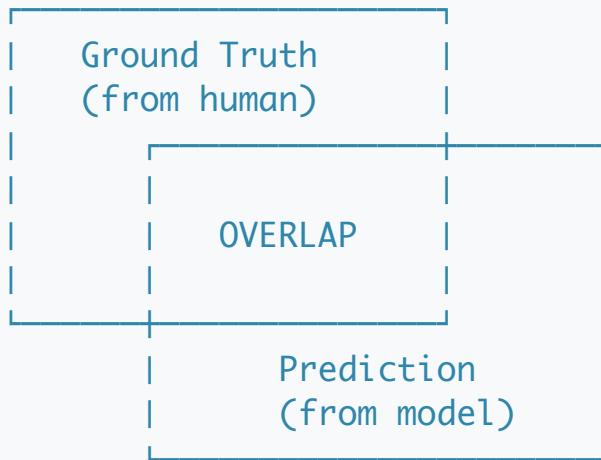
Always verify which format your framework expects!

## Part 3: Intersection over Union (IoU)

How Good Is a Detection?

# The Core Question

Your model predicted a box. Ground truth is another box.  
Is your prediction "correct"?

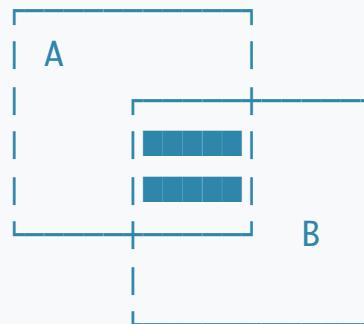


Question: How do we measure if prediction is "close enough"?

Answer: IoU = Intersection / Union

# IoU: The Formula

$$\text{IoU} = \frac{\text{Area of OVERLAP}}{\text{Area of BOTH boxes (counted once)}}$$

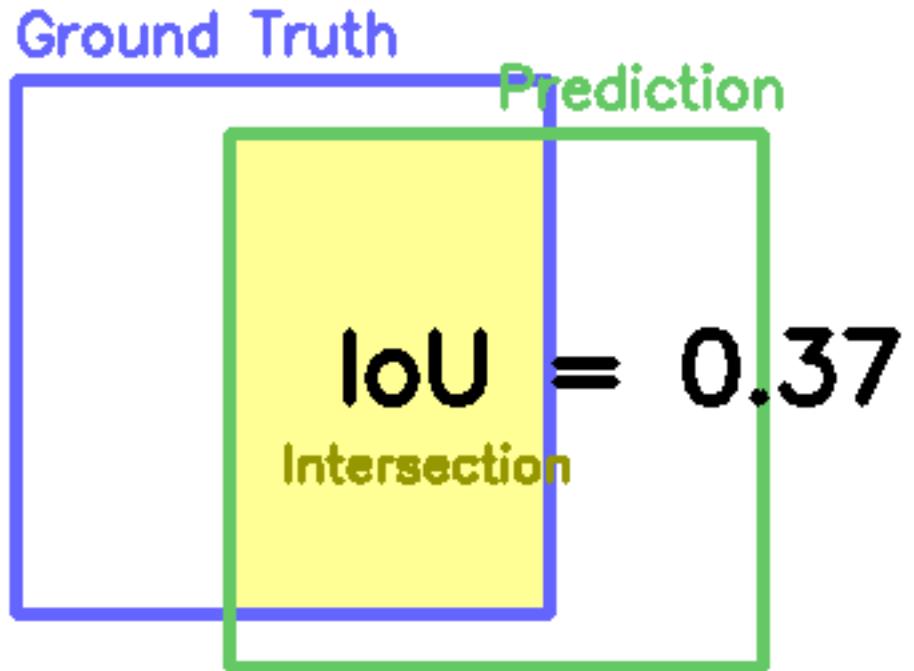


INTERSECTION = shaded area  
UNION = A + B - Intersection

$$\text{IoU} = \frac{\text{Intersection}}{\text{Union}}$$

$$\text{IoU} = \frac{\text{Intersection}}{\text{A} + \text{B} - \text{Intersection}}$$

# IoU: Visual Example



IoU is between 0 and 1. Higher is better. Think of it as "percent overlap."

# Computing IoU: Step by Step

```
def compute_iou(box1, box2):
    """
    Boxes in format: [x1, y1, x2, y2]
    """

    # Step 1: Find intersection rectangle
    x1_inter = max(box1[0], box2[0]) # leftmost right edge
    y1_inter = max(box1[1], box2[1]) # topmost bottom edge
    x2_inter = min(box1[2], box2[2]) # rightmost left edge
    y2_inter = min(box1[3], box2[3]) # bottommost top edge

    # Step 2: Compute intersection area
    inter_width = max(0, x2_inter - x1_inter)
    inter_height = max(0, y2_inter - y1_inter)
    intersection = inter_width * inter_height

    # Step 3: Compute union area
    area1 = (box1[2] - box1[0]) * (box1[3] - box1[1])
    area2 = (box2[2] - box2[0]) * (box2[3] - box2[1])
    union = area1 + area2 - intersection

    # Step 4: IoU = intersection / union
    return intersection / union if union > 0 else 0
```

# IoU Thresholds in Practice

IoU THRESHOLD GUIDE	
IoU Value	What it means
1.0	Perfect match (never happens in practice)
0.9+	Excellent – boxes nearly identical
0.75	Very good – used in strict evaluation
0.50	Standard threshold – "correct" in most benchmarks
0.25	Loose – used in some older benchmarks
0.0	No overlap at all – completely wrong

The RULE in most systems:

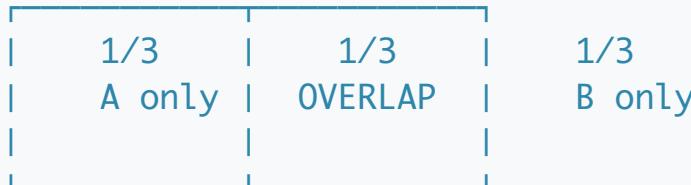
$\text{IoU} \geq 0.5 \rightarrow \text{TRUE POSITIVE (TP)} \checkmark \text{ "You found the object!"}$

$\text{IoU} < 0.5 \rightarrow \text{FALSE POSITIVE (FP)} \times \text{ "Wrong detection"}$

# Why 0.5 Is the Magic Number

Think about it visually:

$\text{IoU} = 0.5$  means: Intersection is  $1/3$  of each box's area



$$\text{Union} = 1/3 + 1/3 + 1/3 = 1$$

$$\text{Intersection} = 1/3$$

$$\text{IoU} = 1/3 \div 1 = 0.33? \text{ No wait...}$$

Actually for  $\text{IoU} = 0.5$ :

If  $\text{Intersection} = I$ ,  $\text{Union} = 2I$

Because:  $A + B - I = 2I$  means  $A + B = 3I$

So each box is  $\sim 2I$ , overlapping by  $I$

Roughly: boxes overlap by about half their area

$\text{IoU} = 0.5$  is when the overlap is "significant enough" to say "yes, you found it"

# Different Benchmarks, Different Thresholds

PASCAL VOC (older, easier):

- Single threshold:  $\text{IoU} \geq 0.5$
- One number:  $\text{mAP}@0.5$
- 20 object classes

MS COCO (modern, stricter):

- Multiple thresholds: 0.50, 0.55, 0.60, ..., 0.95
- Reports:  $\text{mAP}@0.5$ ,  $\text{mAP}@0.75$ ,  $\text{mAP}@[.5:.95]$
- 80 object classes
- Also evaluates different object sizes (small/medium/large)

Why COCO is harder:

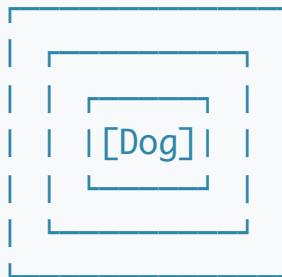
- Must be accurate at multiple thresholds
- Average over 10 thresholds penalizes sloppy boxes
- Same model might get 60% on VOC but only 40% on COCO

## Part 4: Non-Maximum Suppression (NMS)

Cleaning Up Duplicate Detections

# The Problem: Too Many Boxes!

What the detector sees:



<- Same dog, but 5 different boxes!  
All have high confidence!

Boxes with confidences:

- Box 1: dog (0.95)
- Box 2: dog (0.93)
- Box 3: dog (0.91)
- Box 4: dog (0.87)
- Box 5: dog (0.85)

Problem: We want ONE box per object, not five!

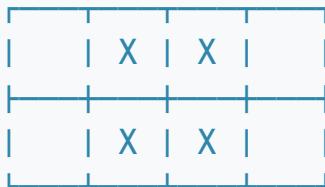
# Why Does This Happen?

Detectors check MANY locations:

YOLO divides image into  $7 \times 7 = 49$  cells  
Each cell predicts 2 boxes  
= 98 boxes per class

Modern YOLO has  $3$  scales  $\times$   $(13^2 + 26^2 + 52^2)$   $\times$   $3$  anchors  
= ~10,000+ candidate boxes!

Many of these will fire on the same object:



X = cells that detect the dog  
Each X outputs a box  
All boxes are similar, all correct  
But we only want ONE

# NMS: The Intuition

Non-Maximum Suppression = "Keep the best, remove the rest"

Like choosing the best photo from burst mode:



Algorithm intuition:

1. Sort all boxes by confidence (best first)
2. Pick the best box → definitely keep it
3. Remove all boxes that overlap too much with it  
(they're probably detecting the same object)
4. Repeat with remaining boxes

[0.95] ← Keep this (highest confidence)

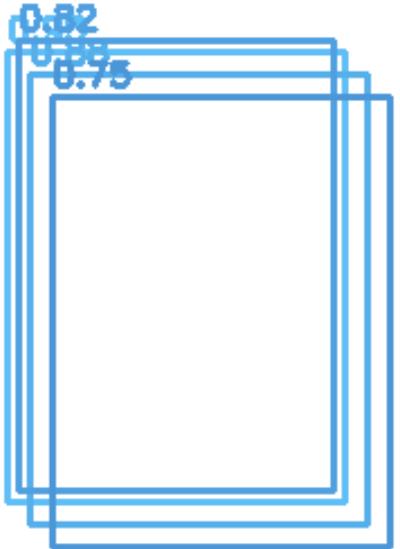


Remove these if IoU > threshold:

[0.93, 0.91, 0.87, 0.85] ← All overlapping, all removed

## NMS: Before and After

Before NMS



4 overlapping boxes

After NMS



1 best box kept

NMS  
→

### The Algorithm:

1. **Sort** all boxes by confidence (descending)
2. **Take** the best box, add to "keep" list
3. **Remove** all boxes with  $\text{IoU} >$  threshold (default 0.5) from queue

# NMS: The Code

```
def nms(boxes, scores, iou_threshold=0.5):
    """
    boxes: List of [x1, y1, x2, y2]
    scores: Confidence for each box
    Returns: Indices of boxes to keep
    """
    # Sort by score (descending)
    order = scores.argsort()[:-1]

    keep = []

    while len(order) > 0:
        # Take the best remaining box
        best_idx = order[0]
        keep.append(best_idx)

        # Compute IoU with all remaining boxes
        remaining = order[1:]
        ious = compute_iou_batch(boxes[best_idx], boxes[remaining])

        # Keep only boxes with low overlap (different objects)
        mask = ious <= iou_threshold
        order = remaining[mask]

    return keep
```

# NMS Parameters

IoU THRESHOLD controls how aggressive NMS is:

threshold = 0.3 (aggressive)

---

- Removes boxes even with small overlap
- Might accidentally merge two close objects into one
- Use when objects are far apart

threshold = 0.5 (standard)

---

- Good balance for most cases
- Default in most frameworks

threshold = 0.7 (lenient)

---

- Keeps more boxes
- Better when objects overlap (crowded scenes)
- Might keep some duplicates

Rule of thumb: Start with 0.5, adjust based on your data

# NMS Variants

## STANDARD NMS:

- Apply separately per class
- Simple, fast, widely used

## SOFT-NMS:

- Instead of removing, reduce confidence of overlapping boxes
- Better for crowded scenes
- $\text{score} = \text{score} \times (1 - \text{IoU})$  or  $\text{score} \times \exp(-\text{IoU}^2/\sigma)$

## CLASS-AGNOSTIC NMS:

- Apply across all classes
- Prevents same location detecting "dog" AND "cat"

## BATCHED NMS:

- Optimized for GPU
- Process all classes in parallel

## DIoU-NMS:

- Uses Distance-IoU instead of IoU
- Considers center distance, not just overlap
- Better for overlapping objects

## Part 5: How Detectors Work

### The YOLO Architecture

# Two Families of Detectors

## TWO-STAGE DETECTORS (Accurate but slower)

Stage 1: "Where might  
objects be?"  
Stage 2: "What are they?"



↓  
~2000 boxes  
↓  
Classify each

### Examples:

- R-CNN, Fast R-CNN
- Faster R-CNN
- Mask R-CNN

~5-10 FPS

## ONE-STAGE DETECTORS (Fast, good enough)

Single pass:  
"Here are all objects  
with their locations"



↓  
Direct output  
↓  
Boxes + Classes

### Examples:

- YOLO (v1-v8)
- SSD
- RetinaNet

~30-100+ FPS

# YOLO: You Only Look Once

The revolutionary idea (2015):

BEFORE YOLO:

Run classifier 1000s of times  
at different locations/scales

| → Is there object here?  
| → Is there object here?  
| IMG | → Is there object here?  
| → Is there object here?  
| → ... (repeat 1000x)

Very slow (seconds per image)

YOLO:

Run CNN ONCE  
Output everything directly

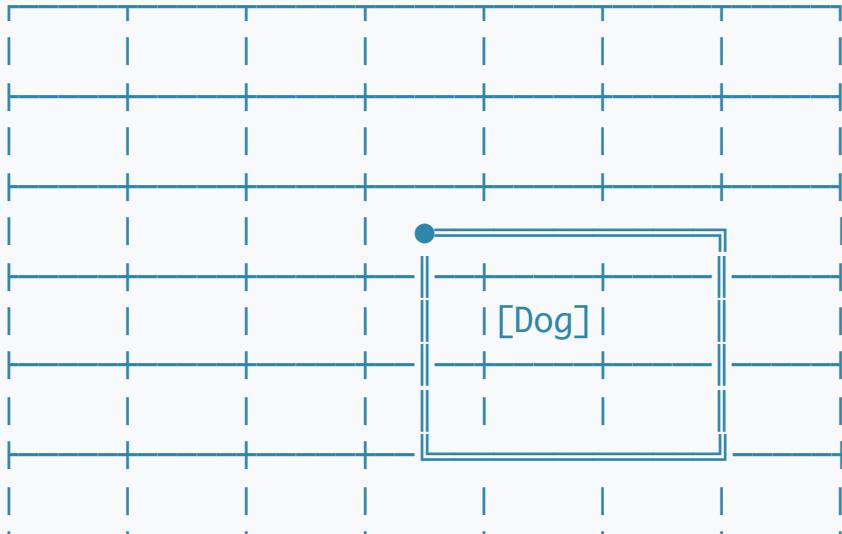
| → All boxes +  
| IMG | All classes +  
| → All confidences  
| (ONE forward pass)

Very fast (milliseconds)

YOLO = "You Only Look Once" — the entire detection in a single neural network pass

# YOLO Core Idea: Grid Division

YOLO divides the image into an  $S \times S$  grid (e.g.,  $7 \times 7$ ):



↑  
The cell containing the CENTER of the dog  
is "responsible" for detecting that dog

# What Each Cell Predicts

Each grid cell outputs:

For EACH BOUNDING BOX (B boxes per cell):

- $x, y$  = center offset (relative to cell)
- $w, h$  = width, height (relative to image)
- conf =  $P(\text{object}) \times \text{IoU}$  with ground truth

For the CELL (shared across boxes):

- $P(\text{class}_1), P(\text{class}_2), \dots, P(\text{class}_C)$

OUTPUT SHAPE:

$$S \times S \times (B \times 5 + C)$$

$$\begin{aligned} \text{Example: } 7 \times 7 \times (2 \times 5 + 20) &= 7 \times 7 \times 30 \\ &= 1470 \text{ numbers describing all detections} \end{aligned}$$

# YOLO Prediction Visualization

One cell's prediction (2 boxes, 20 classes):

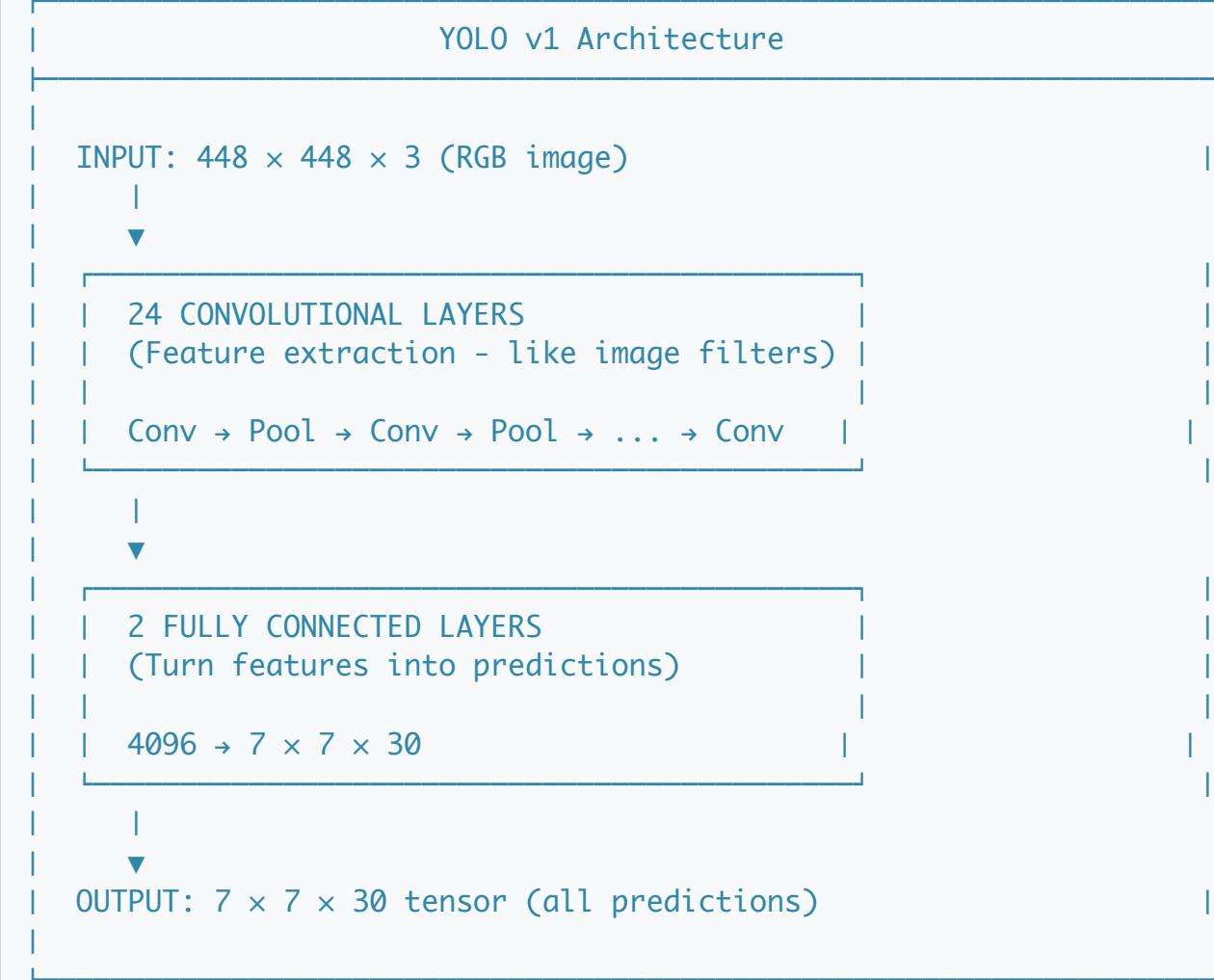
Box 1	Box 2	Classes
x: 0.3	x: 0.6	P(person): 0.01
y: 0.4	y: 0.5	P(car): 0.02
w: 0.5	w: 0.3	P(dog): 0.92
h: 0.7	h: 0.4	P(cat): 0.03
conf: 0.85	conf: 0.12	...

↓                    ↓                    ↓

High conf!  
This is the  
main detection      Low conf,  
ignore      Most likely: DOG

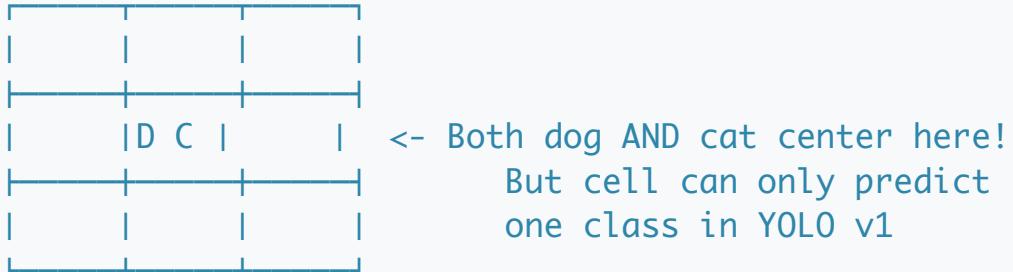
Final: Box 1 predicts "dog" with confidence  $0.85 \times 0.92 = 0.78$

# The YOLO Network Architecture (v1)



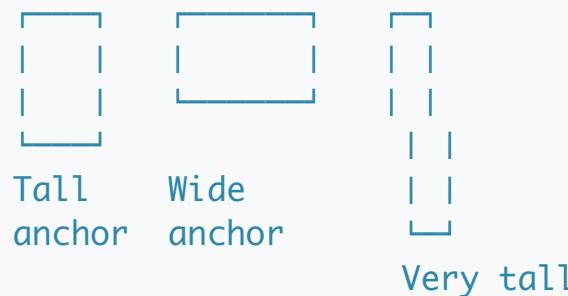
# Anchor Boxes: Handling Multiple Objects Per Cell

PROBLEM: What if TWO objects have centers in the SAME cell?



SOLUTION: Anchor boxes (YOLO v2+)

Pre-define box SHAPES (anchors):



Each anchor predicts separately!  
Now cell can detect person (tall) AND car (wide)

# Anchor Boxes: How They Work

Each cell has K anchor boxes (e.g., K=5 in YOLOv2, K=9 in YOLOv3)

ANCHOR SHAPES (Learned from data using K-means clustering):

Anchor 1 (small)	Anchor 2 (tall)	Anchor 3 (wide)	Anchor 4 (medium)	Anchor 5 (large)
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PREDICTION: Instead of predicting raw  $(x, y, w, h)$ ,  
predict OFFSETS from anchor:

$$\begin{aligned} \text{predicted}_w &= \text{anchor}_w \times \exp(t_w) \\ \text{predicted}_h &= \text{anchor}_h \times \exp(t_h) \end{aligned}$$

This makes learning easier! Network just learns adjustments.

# YOLO Evolution: v1 → v8

YOLOv1 (2015): Original breakthrough

- 7×7 grid, 2 boxes/cell, 45 FPS
- Simple but limited

YOLOv2 (2016): Better and faster

- Anchor boxes, batch normalization
- Multi-scale training

YOLOv3 (2018): Big improvement

- 3 scales (13×13, 26×26, 52×52)
- Better small object detection
- Darknet-53 backbone

YOLOv4 (2020): Bag of tricks

- Many augmentations (Mosaic, CutMix)
- CSPDarknet backbone

YOLOv5-v8 (2020-2023): Ultralytics versions

- PyTorch native
- Easy to use API
- State-of-the-art speed/accuracy

# Modern YOLO (v5/v8): Key Features

## YOLO v5/v8 INNOVATIONS

### 1. MULTI-SCALE DETECTION

- Small objects:  $52 \times 52$  grid (detailed)
- Medium objects:  $26 \times 26$  grid
- Large objects:  $13 \times 13$  grid (coarse)

### 2. FEATURE PYRAMID NETWORK (FPN)

- Combines low-level (edges) and high-level (semantics)
- Better detection at all sizes

### 3. PATH AGGREGATION NETWORK (PAN)

- Bottom-up path for better localization

### 4. MOSAIC AUGMENTATION

- Combine 4 images → more objects per batch
- Better generalization

### 5. AUTO-ANCHOR

- Automatically compute best anchors for your data

# YOLO Model Sizes

YOLOv8 Model Variants				
Model	Parameters	Size	mAP (COCO)	Speed (GPU)
v8n	3.2M	6 MB	37.3	~1.0 ms
v8s	11.2M	22 MB	44.9	~1.5 ms
v8m	25.9M	52 MB	50.2	~2.5 ms
v8l	43.7M	87 MB	52.9	~4.0 ms
v8x	68.2M	136 MB	53.9	~6.0 ms

n = nano (edge devices, phones)

s = small (good balance)

m = medium

l = large

x = extra large (best accuracy)

Start with YOLOv8n for prototyping, move to larger models if needed.

## **Part 6: Training & Evaluation**

**How We Train and Measure Detectors**

# The Detection Loss Function

Detection models optimize MULTIPLE objectives simultaneously:

$$\text{TOTAL LOSS} = \lambda_1 \cdot L_{\text{box}} + \lambda_2 \cdot L_{\text{obj}} + \lambda_3 \cdot L_{\text{class}}$$

|  $L_{\text{box}}$  (Localization Loss)

| "Is the box in the right place?"

- Mean squared error on (x, y, w, h)
- Or IoU-based loss (GIoU, DIoU, CIoU)

|  $L_{\text{obj}}$  (Objectness Loss)

| "Is there an object here?"

- Binary cross-entropy
- Confidence should match IoU with ground truth

|  $L_{\text{class}}$  (Classification Loss)

| "What class is it?"

- Cross-entropy for each class

# Understanding the Box Loss

ORIGINAL YOLO (MSE Loss):

---

$$L_{\text{box}} = (x - \hat{x})^2 + (y - \hat{y})^2 + (\sqrt{w} - \sqrt{\hat{w}})^2 + (\sqrt{h} - \sqrt{\hat{h}})^2$$

Why square root of w,h?

- Large boxes shouldn't dominate
- Error of 10px matters more for 20px box than 200px box
- $\sqrt{\cdot}$  compresses the range

MODERN YOLO (IoU-based Loss):

---

$$L_{\text{box}} = 1 - \text{IoU}(\text{predicted}, \text{ground\_truth})$$

Or better variants:

- GIoU: Adds penalty for gap between boxes
- DIoU: Adds penalty for center distance
- CIoU: DIoU + aspect ratio penalty

These directly optimize what we care about: overlap!

# Precision and Recall: Detection Version

For DETECTION, we need to define TP/FP/FN differently:

TRUE POSITIVE (TP):

- Detection exists
- Matches a ground truth box with  $\text{IoU} \geq \text{threshold}$
- Correct class

FALSE POSITIVE (FP):

- Detection exists BUT:
  - Doesn't match any ground truth (IoU too low)
  - OR correct box but wrong class
  - OR duplicate detection (already matched)

FALSE NEGATIVE (FN):

- Ground truth box exists
- No detection matched it

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

"Of my detections,  
how many are correct?"

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

"Of the actual objects,  
how many did I find?"

# Precision vs Recall Trade-off

As we lower the CONFIDENCE THRESHOLD:

High threshold (0.9):

- Only very confident detections
- Might miss some objects
- HIGH PRECISION, LOW RECALL

Low threshold (0.3):

- Many detections (even uncertain)
- Might include wrong detections
- LOW PRECISION, HIGH RECALL

Example on 10 real dogs:

Threshold=0.9:

- Found: 4 dogs (all correct)
- Precision =  $4/4 = 100\%$
- Recall =  $4/10 = 40\%$

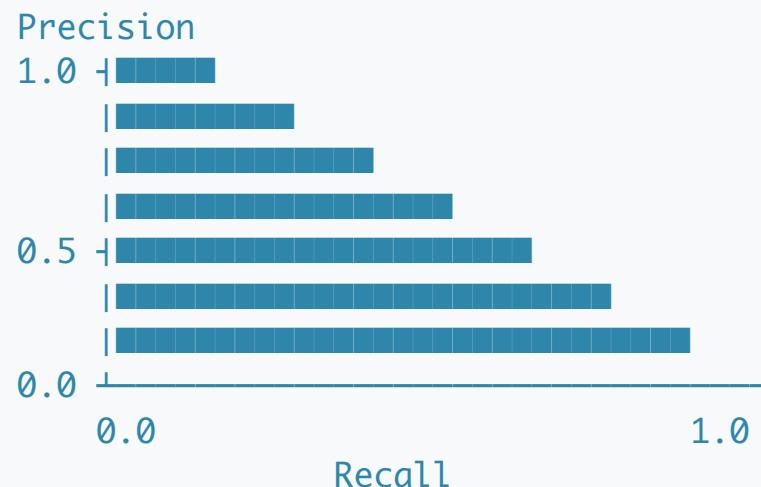
Threshold=0.3:

- Found: 12 "dogs" (9 correct, 3 wrong)
- Precision =  $9/12 = 75\%$
- Recall =  $9/10 = 90\%$



# Average Precision (AP)

AP = Area under the Precision-Recall curve



AP = Area of this curve (shaded region)

Higher AP = better detector (good precision at all recall levels)

In practice, we compute AP by:

1. Sort detections by confidence
2. At each detection, compute precision and recall so far
3. Interpolate and compute area under curve

# Mean Average Precision (mAP)

mAP = Mean of AP across all classes

For each class:

AP\_person = 0.85

AP\_car = 0.92

AP\_dog = 0.78

AP\_cat = 0.71

...

AP\_class\_80 = 0.65

$$\text{mAP@0.5} = \frac{\text{AP}_1 + \text{AP}_2 + \dots + \text{AP}_C}{C \text{ (number of classes)}}$$

COCO also reports:

- mAP@0.75 (stricter IoU threshold)

- mAP@[0.5:0.95] (average over 10 thresholds: 0.5, 0.55, ..., 0.95)

# mAP Calculation Example

Let's compute mAP step by step:

Dataset: 5 images with dogs and cats

Ground truth: 3 dogs, 2 cats

Model predictions (sorted by confidence):

#	Class	Conf	Matched?	Status
1	dog	0.95	Yes	TP
2	dog	0.90	Yes	TP
3	cat	0.85	Yes	TP
4	dog	0.80	No	FP
5	cat	0.75	Yes	TP
6	dog	0.70	Yes	TP

For dogs: TP=3, FP=1, FN=0 (found all 3)

For cats: TP=2, FP=0, FN=0 (found all 2)

AP\_dog = (compute P-R curve area)

AP\_cat = (compute P-R curve area)

mAP = (AP\_dog + AP\_cat) / 2

# Data Augmentation for Detection

IMPORTANT: When transforming the image, ALSO transform the boxes!

## HORIZONTAL FLIP:

Original



Flipped

Box: [10, 20, 60, 80]

Box: [W-60, 20, W-10, 80]

## SCALE/RESIZE:

Scale factor =  $s$

New box: [ $x*s$ ,  $y*s$ ,  $w*s$ ,  $h*s$ ]

## CROP:

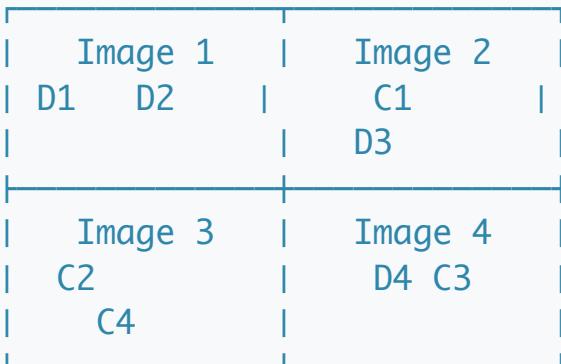
Remove boxes that fall outside crop

Clip boxes that partially overlap

Adjust coordinates relative to crop origin

# Mosaic Augmentation (YOLO v4+)

Combine 4 images into 1 training sample:



↓  
Single training image with  
4x the objects!

## BENEFITS:

- More objects per batch
- Objects in unusual contexts
- Better generalization
- Reduces need for large batch sizes

# Training Tips for Detection

## PRACTICAL TRAINING TIPS

### 1. START WITH PRETRAINED WEIGHTS

- Use COCO pretrained model
- Fine-tune on your dataset
- Much faster than training from scratch

### 2. BALANCE YOUR DATASET

- Roughly equal examples per class
- Or use focal loss to handle imbalance

### 3. ANCHOR BOX ANALYSIS

- Run k-means on your box sizes
- Use auto-anchor feature in YOLOv5/v8

### 4. IMAGE SIZE MATTERS

- Larger images = better small object detection
- But slower training/inference
- 640x640 is common default

### 5. AUGMENTATION IS KEY

- Mosaic, MixUp, color jitter
- More augmentation = better generalization

# Common Detection Benchmarks

## POPULAR DATASETS & BENCHMARKS

PASCAL VOC  
(2007, 2012)

- 20 classes, ~10K images
- Classic benchmark
- mAP@0.5 metric

MS COCO  
(2014-present)

- 80 classes, ~120K images
- Modern standard benchmark
- mAP@[0.5:0.95] metric (harder)
- Small/medium/large object splits

Open Images

- 600 classes, 1.7M images
- Largest, most diverse

Custom

- Your domain-specific data
- Label with Roboflow, CVAT, LabelImg

# State-of-the-Art Results (2024)

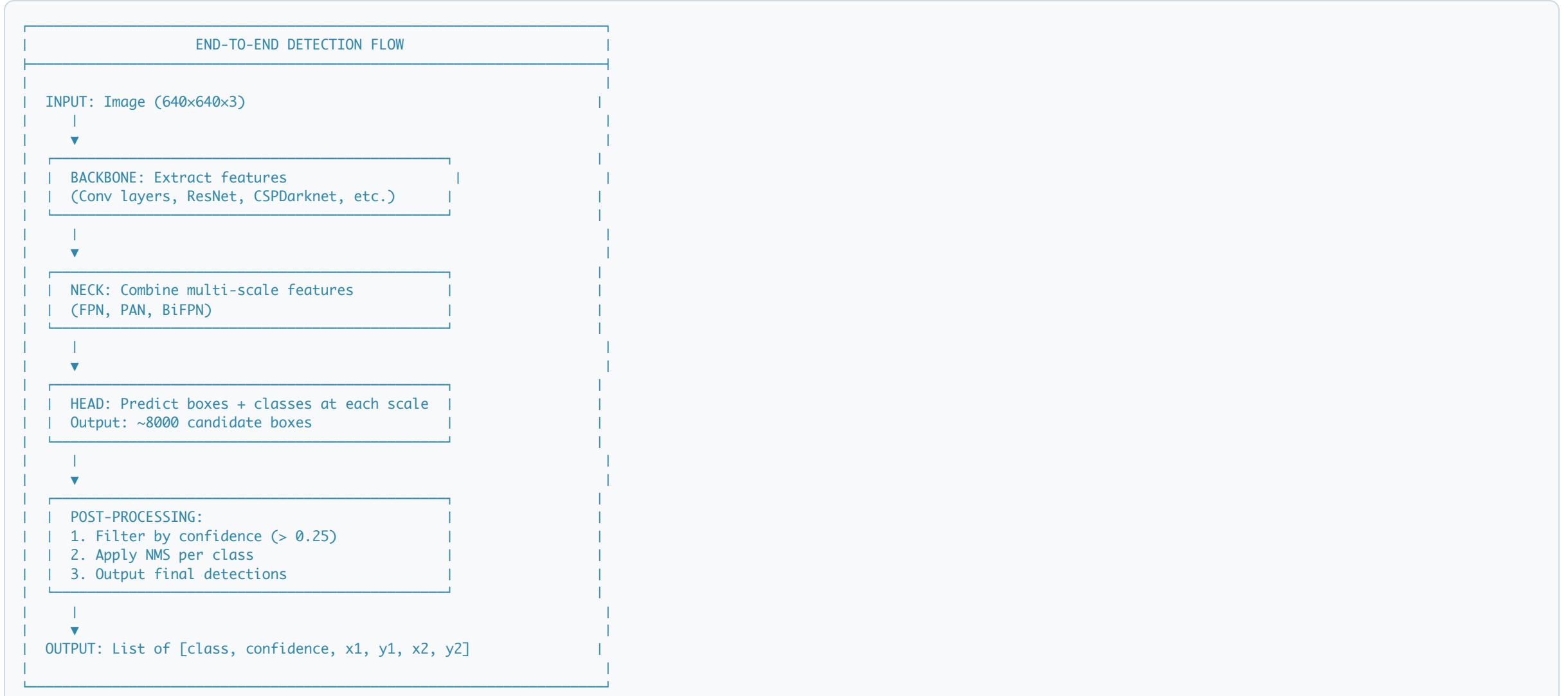
MS COCO leaderboard (mAP@[0.5:0.95]):

Model	mAP	Params	Speed
DINO (Transformer-based)	63.3	218M	Slow
Focal-DINO	58.4	-	Slow
Co-DETR	66.0	218M	Slow
YOLOv8-X	53.9	68M	Fast
YOLOv9-E	55.6	60M	Fast
YOLO-World	45.0*	46M	Fast

\* Zero-shot (no COCO training)

Key insight: Transformer detectors (DINO, DETR) now beat CNNs in accuracy  
but YOLO family still dominates real-time applications.

# Complete Detection Pipeline



# Getting Started: YOLO in 3 Lines

```
# Install: pip install ultralytics  
  
from ultralytics import YOLO  
  
# Load a pretrained model  
model = YOLO('yolov8n.pt')  
  
# Run detection on an image  
results = model('your_image.jpg')  
  
# Display results  
results[0].show()  
  
# Access detections programmatically  
for box in results[0].boxes:  
    cls = int(box.cls[0])          # Class index  
    conf = float(box.conf[0])       # Confidence  
    xyxy = box.xyxy[0].tolist()    # [x1, y1, x2, y2]  
  
    print(f"Class: {model.names[cls]}, Conf: {conf:.2f}")  
    print(f"Box: {xyxy}")
```

That's it! You now have a working object detector. Try it on your own photos!

# Training on Custom Data

```
# Step 1: Prepare your dataset (YOLO format)
# data/
#   images/
#     train/  val/
#   labels/
#     train/  val/
# Each label file: class_id cx cy w h (normalized)

# Step 2: Create data.yaml
"""
path: ./data
train: images/train
val: images/val
names:
  0: cat
  1: dog
  2: bird
"""

# Step 3: Train!
from ultralytics import YOLO

model = YOLO('yolov8n.pt') # Start from pretrained

results = model.train(
    data='data.yaml',
    epochs=50,
    imgsz=640,
    batch=16
)

# Step 4: Use your trained model
model = YOLO('runs/detect/train/weights/best.pt')
model.predict('test_image.jpg')
```

# Summary: Key Takeaways

## KEY CONCEPTS

1. DETECTION = CLASSIFICATION + LOCALIZATION  
Find WHAT objects and WHERE they are
2. BOUNDING BOX FORMATS VARY  
Always check: corner vs center, absolute vs normalized
3. IoU MEASURES OVERLAP QUALITY  
 $\text{IoU} \geq 0.5$  is standard threshold for "correct"
4. NMS REMOVES DUPLICATES  
Keep highest confidence, remove overlapping
5. YOLO IS FAST AND PRACTICAL  
One-stage detection, grid-based, real-time capable
6. mAP IS THE GOLD STANDARD METRIC  
Average precision across classes and IoU thresholds
7. START WITH PRETRAINED MODELS  
Fine-tune on your data for best results

# Resources for Learning More

## PAPERS:

- YOLO v1: "You Only Look Once" (Redmon et al., 2015)
- YOLO v3: "YOLOv3: An Incremental Improvement" (Redmon, 2018)
- Faster R-CNN: "Faster R-CNN" (Ren et al., 2015)
- DETR: "End-to-End Object Detection with Transformers" (2020)

## CODE & TUTORIALS:

- Ultralytics YOLov8: <https://github.com/ultralytics/ultralytics>
- Roboflow Blog: <https://blog.roboflow.com/>
- PyTorch Detection: <https://pytorch.org/vision/stable/models.html>

## DATASETS:

- COCO: <https://cocodataset.org/>
- Open Images: <https://storage.googleapis.com/openimages/>
- Roboflow Universe: <https://universe.roboflow.com/> (100K+ datasets)

# What's Next?

## NOW YOU CAN:

---

- ✓ Understand how object detection differs from classification
- ✓ Work with bounding boxes in different formats
- ✓ Implement and understand IoU calculation
- ✓ Apply Non-Maximum Suppression
- ✓ Use YOLO for real-time detection
- ✓ Evaluate detectors with mAP

## NEXT STEPS:

---

- Try detection on your own images/videos
- Fine-tune YOLO on a custom dataset
- Explore instance segmentation (Mask R-CNN, YOL0v8-seg)
- Learn about transformer-based detectors (DETR, DINO)
- Deploy detection models on edge devices

# Thank You!

**Object Detection opens the door to...**

- Self-driving cars
- Augmented reality
- Medical diagnosis
- Smart retail
- Security systems
- Robotics

And so much more!

**Questions?**

# Appendix: Common Pitfalls

## THINGS THAT GO WRONG

### 1. WRONG BOX FORMAT

- Model expects YOLO format, you gave COCO format
- Solution: Always verify format in documentation

### 2. FORGETTING TO NORMALIZE

- Pixel coordinates don't work for different image sizes
- Solution: Use normalized coordinates or resize consistently

### 3. NMS THRESHOLD TOO AGGRESSIVE

- Two close objects merged into one detection
- Solution: Increase NMS threshold ( $0.5 \rightarrow 0.7$ )

### 4. SMALL OBJECTS MISSED

- Default models optimized for medium/large objects
- Solution: Use larger image size, or specialized models

### 5. CLASS IMBALANCE

- 1000 cars, 10 motorcycles → model ignores motorcycles
- Solution: Oversample rare classes, use focal loss

# Appendix: IoU Loss Variants

## IoU-BASED LOSS FUNCTIONS

Standard IoU Loss:

$$L = 1 - \text{IoU}$$

Problem: No gradient when boxes don't overlap

GIoU (Generalized IoU):

$$L = 1 - \text{IoU} + |C - \text{Union}| / |C|$$

C = smallest enclosing box

Handles non-overlapping boxes!

DIoU (Distance IoU):

$$L = 1 - \text{IoU} + d^2 / c^2$$

d = center distance, c = diagonal of enclosing box

Faster convergence

CIoU (Complete IoU):

$$L = 1 - \text{IoU} + d^2 / c^2 + \alpha v$$

$\alpha, v$  = aspect ratio penalty terms

Best overall performance