Object Detection Basics

Deep Learning for Computer Vision

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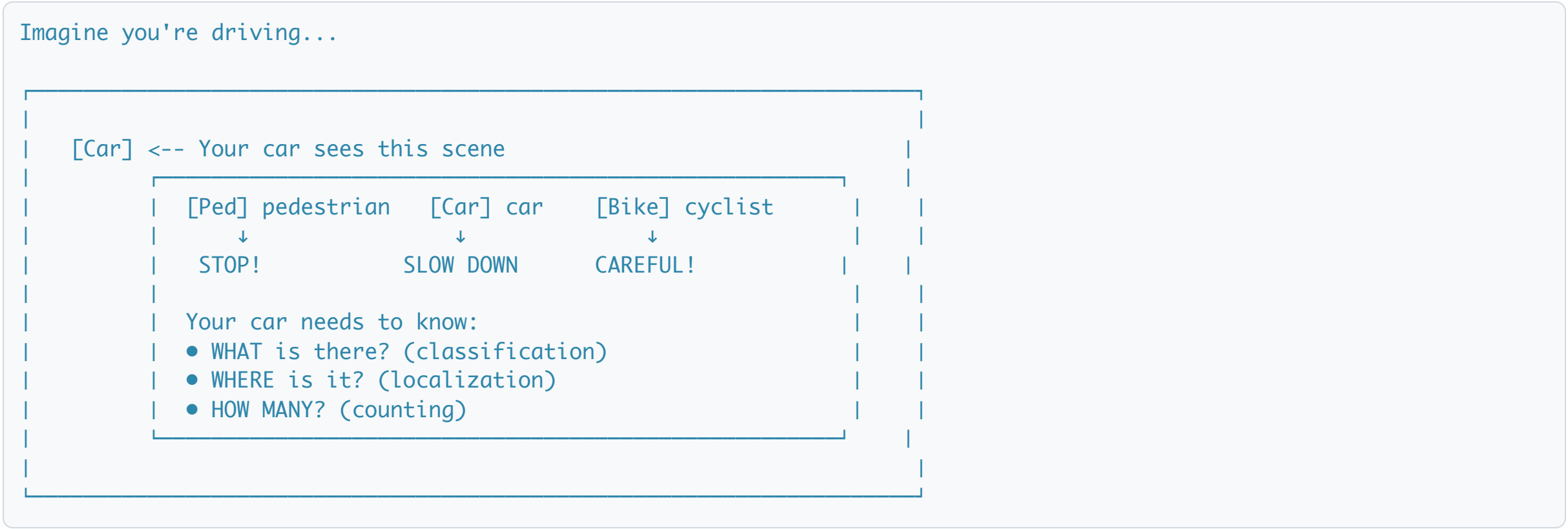
Teaching computers to see and locate objects

Why Object Detection?



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                    │
│                                                                  │
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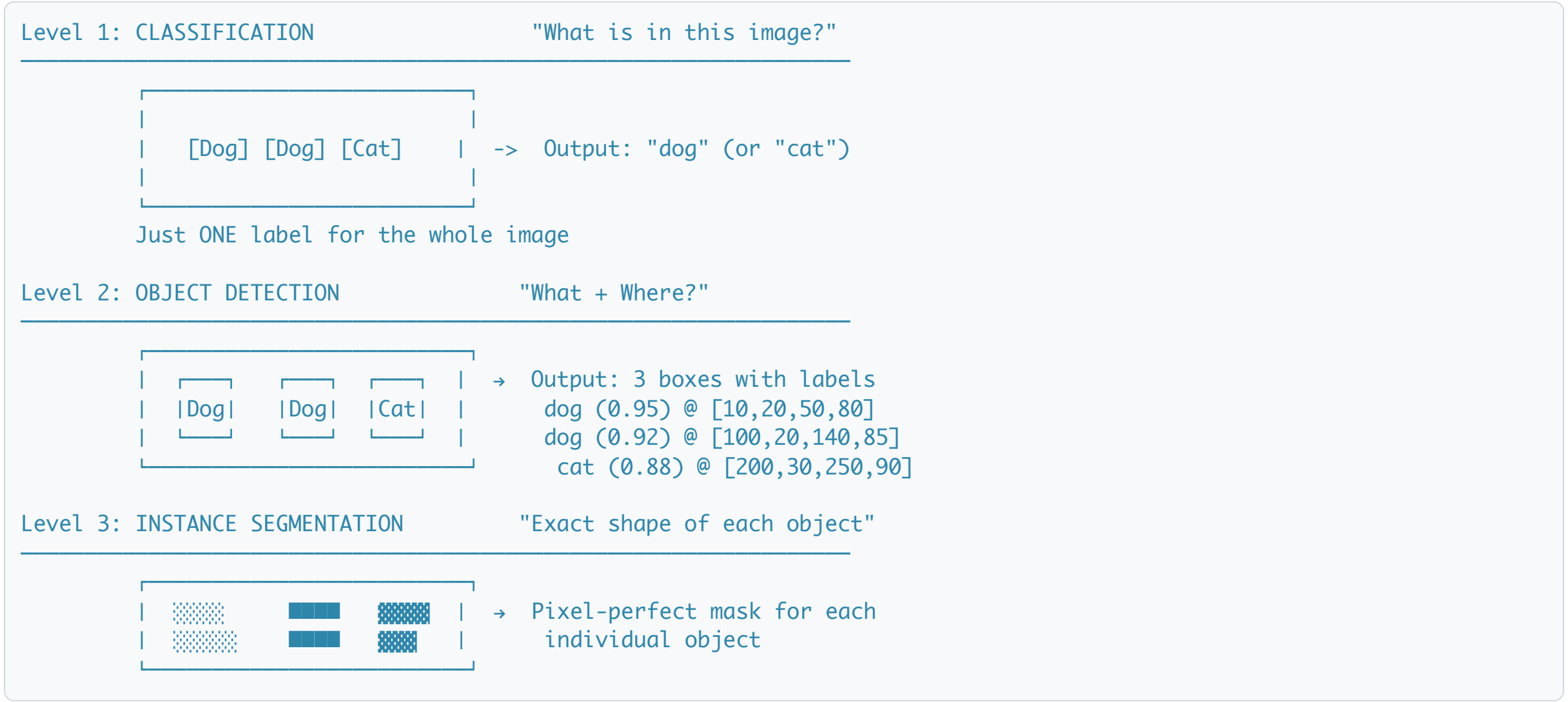
Part 1: The Core Problem

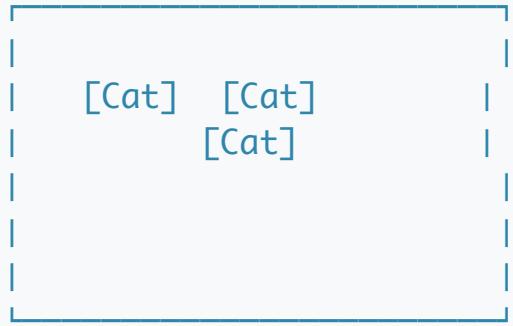
What IS Object Detection?

The Vision Task Hierarchy



Classification vs Detection: Key Difference

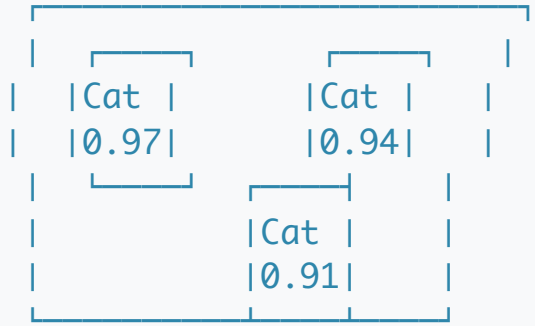
CLASSIFICATION:
"Is there a cat?"



Output: "cat" (0.99)

ONE answer for the image

DETECTION:
"Where are all the cats?"



Output: 3 detections
- cat @ box1 (0.97)
- cat @ box2 (0.94)
- cat @ box3 (0.91)

MULTIPLE answers with locations

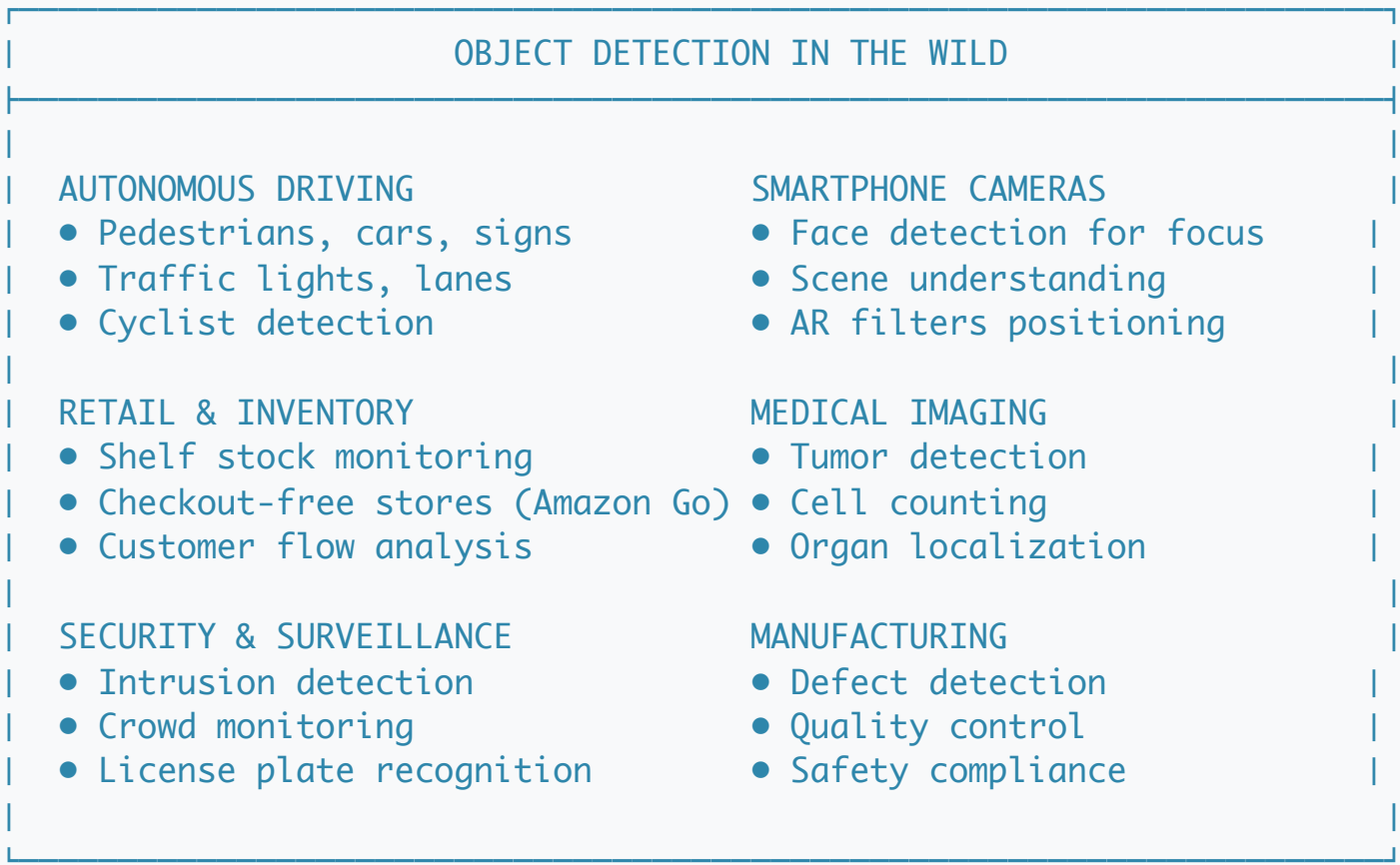
> Detection = Classification + Localization + Counting (implicitly)

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

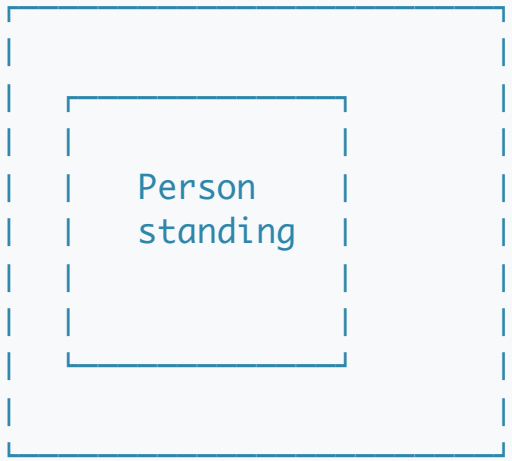
Real applications: • Classification: "Is this X-ray normal?" • Detection: "Where are the tumors?" • Segmentation: "Exact tumor boundary for surgery planning"

Real-World Detection Applications



Instance Segmentation: Beyond Boxes

DETECTION gives you BOXES:



Box includes background!

SEGMENTATION gives you MASKS:

Every pixel classified!

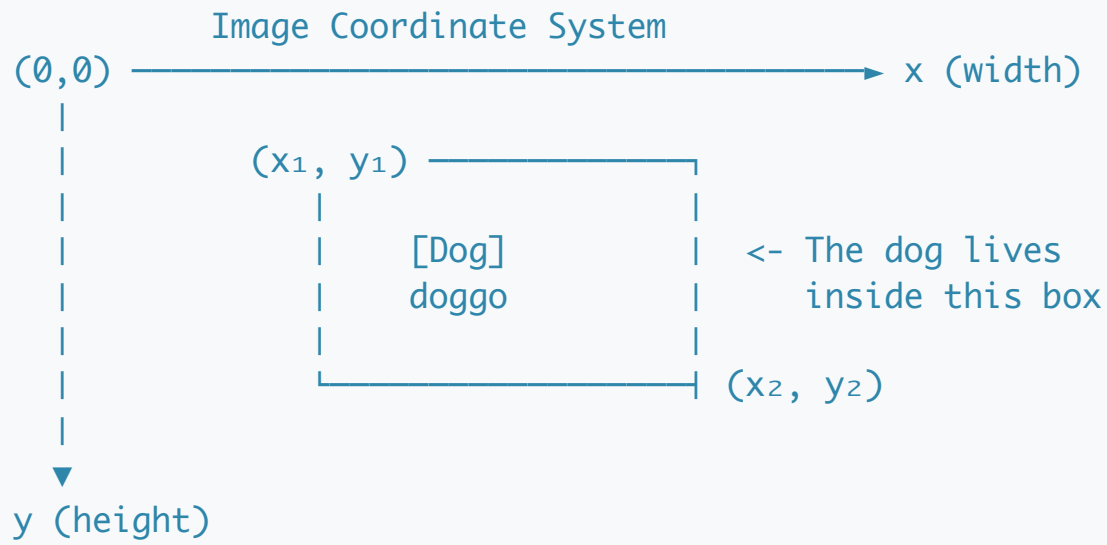
Segmentation is needed for: video editing backgrounds, medical boundaries, precise robotics

Part 2: Bounding Boxes

How We Represent "WHERE"

What IS a Bounding Box?

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



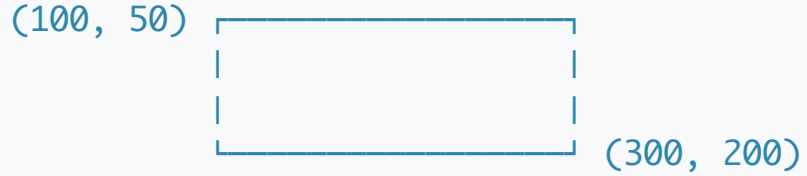
The box is defined by 4 numbers. But WHICH 4?

> 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

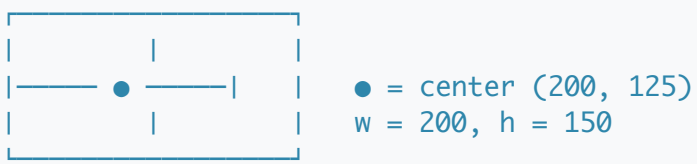



```
Box = [100, 50, 300, 200]
Width = 300 - 100 = 200
Height = 200 - 50 = 150
```

The Three Main Formats (continued)

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

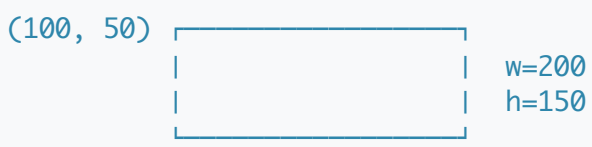
- Center point + width + height
- Used by: YOLO, many papers
- Easy for: predicting from grid cells



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 × 480 pixels
    Box: [100, 50, 300, 200]  ← pixel values

    Problem: What if image is resized to 320 × 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]

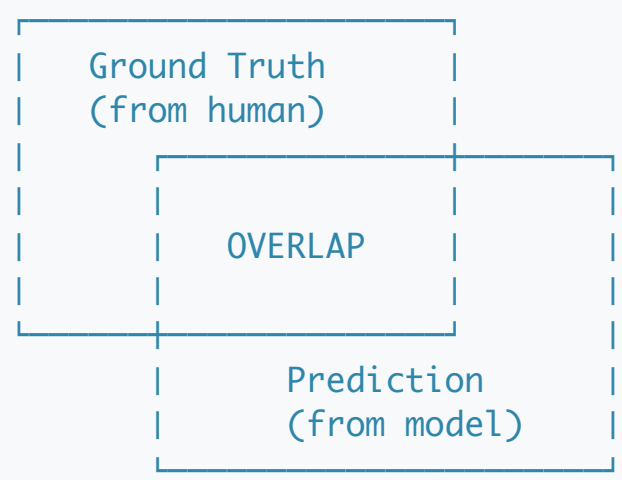
Always verify which format your framework expects!

Part 3: Intersection over Union (IoU)

How Good Is a Detection?

The Core Question

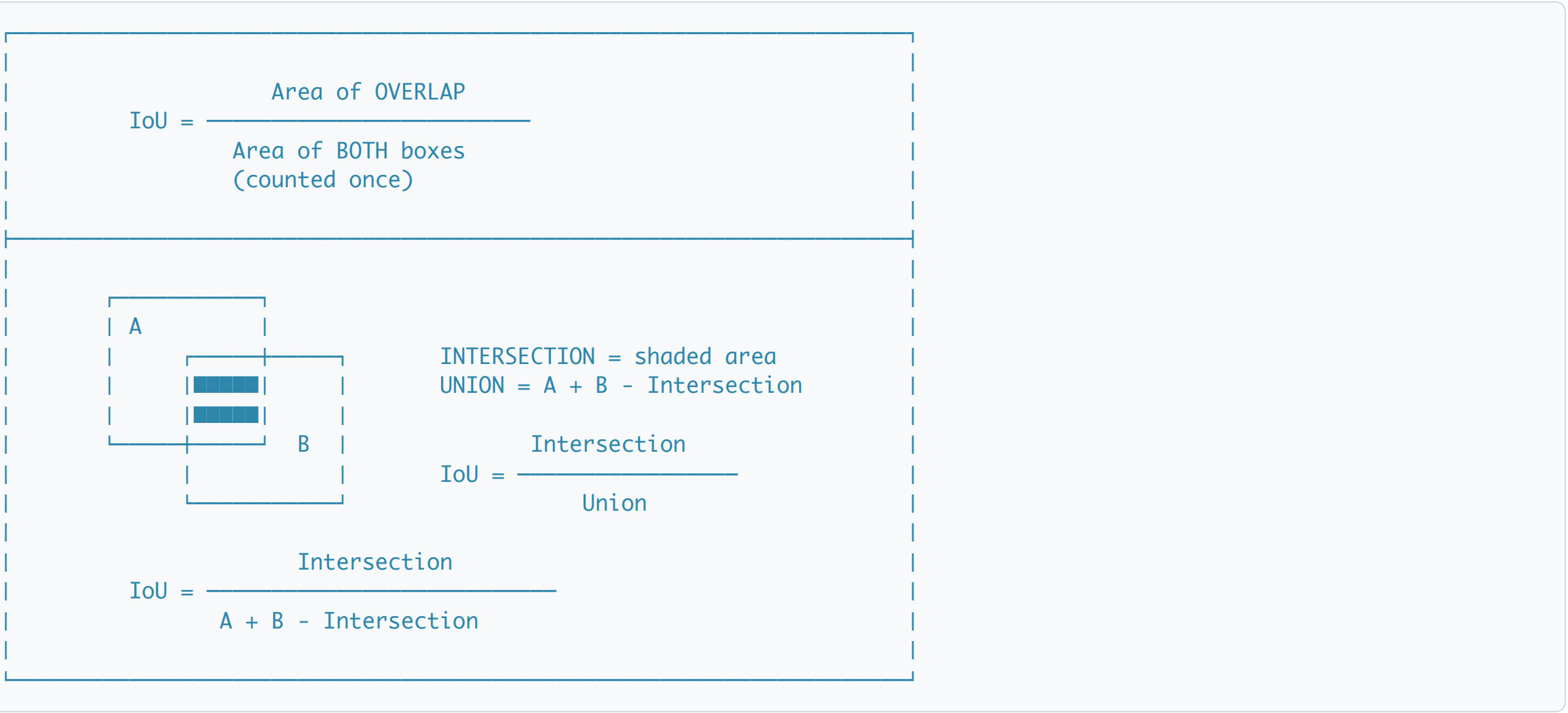
```
Your model predicted a box. Ground truth is another box.
Is your prediction "correct"?
```



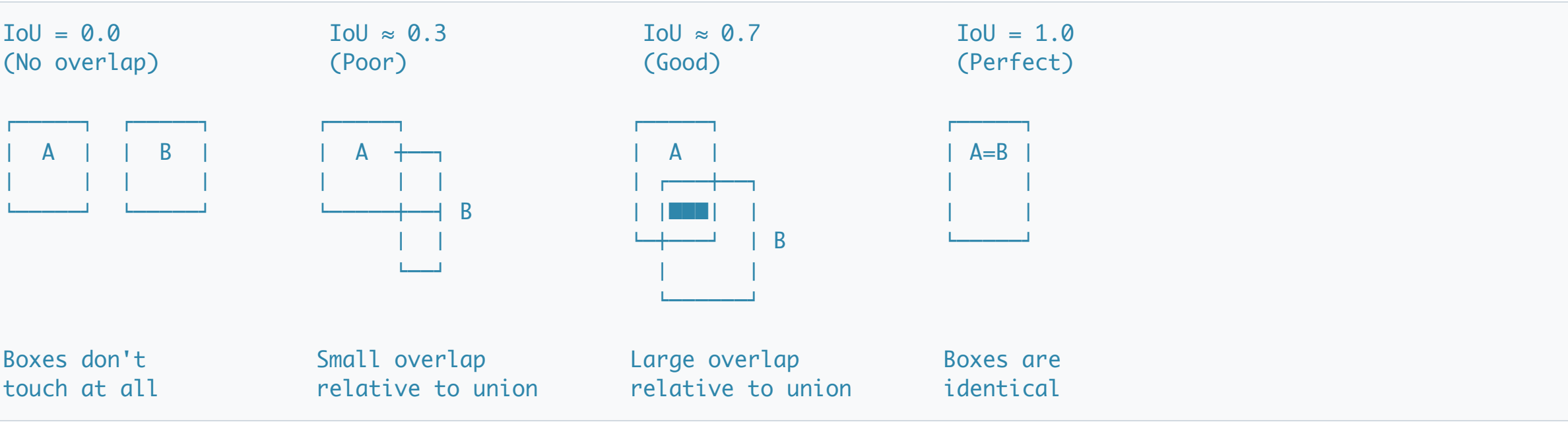

```
Question: How do we measure if prediction is "close enough"?

Answer: IoU = Intersection / Union
```

IoU: The Formula



IoU: Visual Examples



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

Computing IoU: Step by Step

```python
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:
    IoU ≥ 0.5  →  TRUE POSITIVE (TP) ✓  "You found the object!"
    IoU < 0.5  →  FALSE POSITIVE (FP) ✗  "Wrong detection"
```

Why 0.5 Is the Magic Number

```
Think about it visually:

IoU = 0.5 means: Intersection is 1/3 of each box's area

    ┌─────────────┬─────────────┐
    |    1/3      |    1/3      |    1/3
    |    A only   |  OVERLAP    |    B only
    |             |             |
    └─────────────┴─────────────┘

    Union = 1/3 + 1/3 + 1/3 = 1
    Intersection = 1/3
    IoU = 1/3 ÷ 1 = 0.33? No wait...

Actually for IoU = 0.5:
    If Intersection = I, Union = 2I
    Because: A + B - I = 2I means A + B = 3I
    So each box is ~2I, overlapping by I

    Roughly: boxes overlap by about half their area
```

> 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: IoU ≥ 0.5
- One number: mAP@0.5
- 20 object classes

MS COCO (modern, stricter):

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

Why COCO is harder:

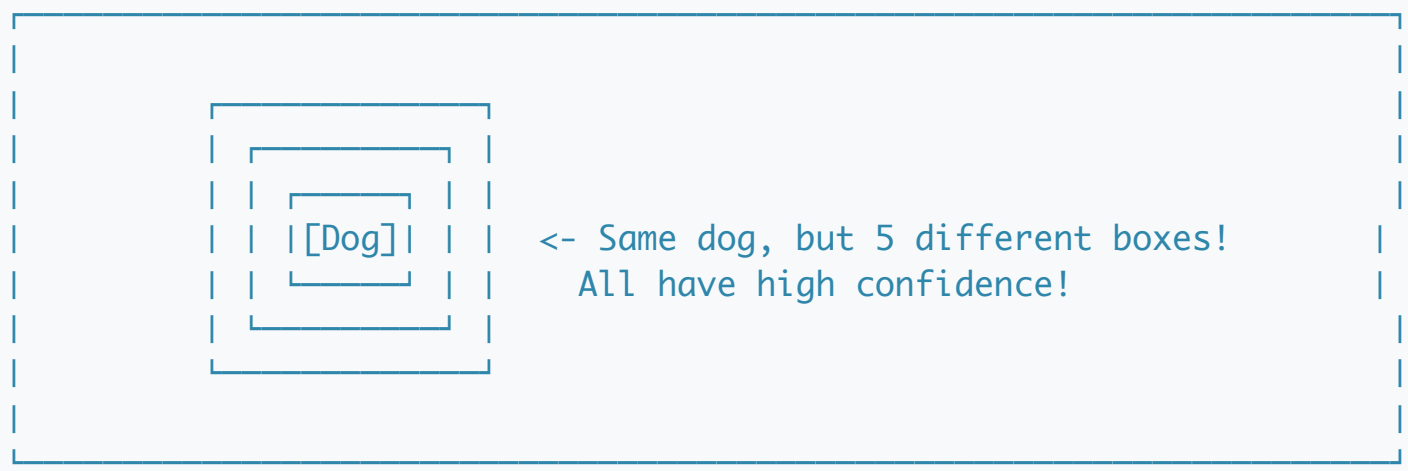
- Must be accurate at multiple thresholds
- Average over 10 thresholds penalizes sloppy boxes
- Same model might get 60% on VOC but only 40% on COCO

Part 4: Non-Maximum Suppression (NMS)

Cleaning Up Duplicate Detections

The Problem: Too Many Boxes!

What the detector sees:



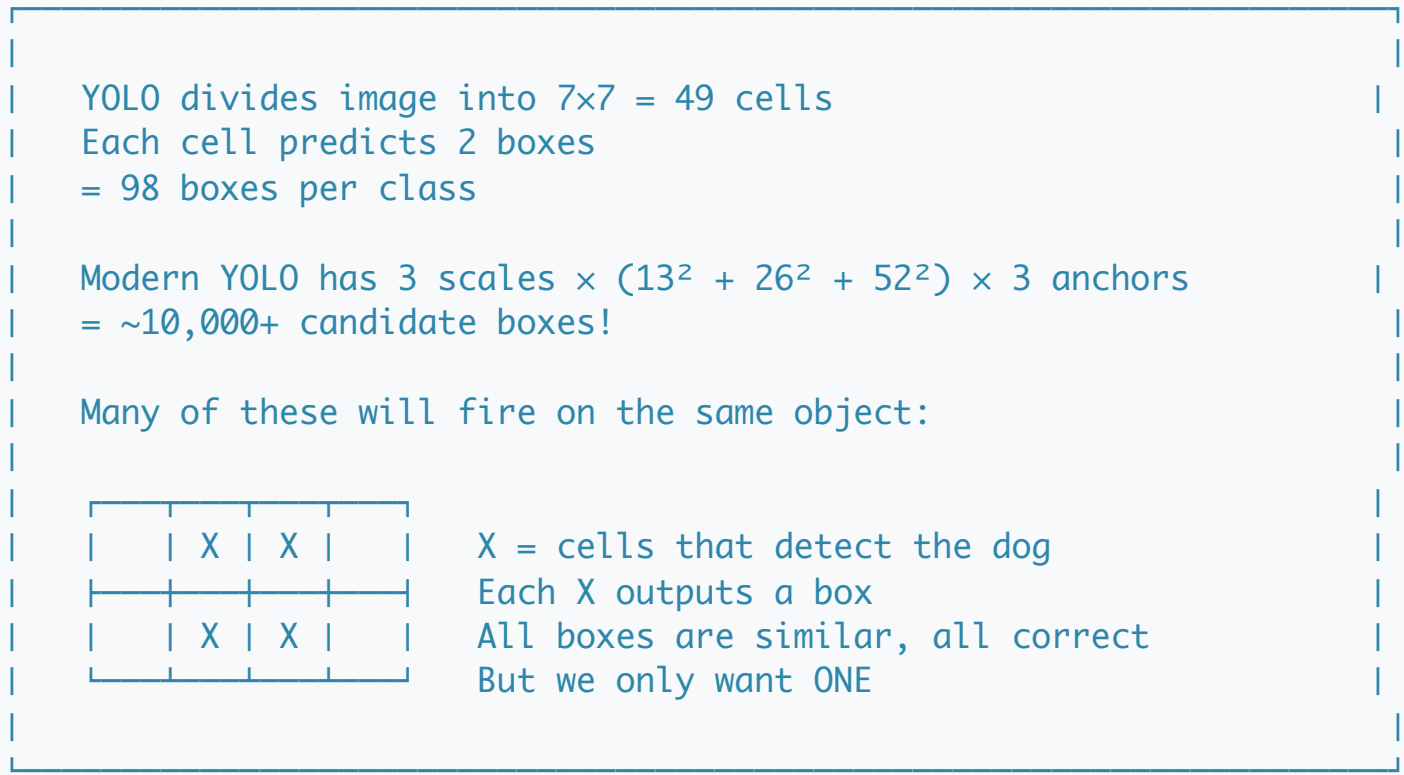
Boxes with confidences:

- 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:



NMS: The Intuition

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

Like choosing the best photo from burst mode:
    📸 📸 📸 📸 📸 → 📸 (keep best one)

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: Step-by-Step Visualization

```
Step 0: All detections (same class: "dog")
──────────────────────────────────────────────────────────────────────

Boxes:   [A: 0.95]  [B: 0.91]  [C: 0.85]  [D: 0.70]
         (all overlap with each other, except D is far away)

Step 1: Sort by confidence
──────────────────────────────────────────────────────────────────────

Queue:   A(0.95) → B(0.91) → C(0.85) → D(0.70)
Keep:    []

Step 2: Take A (best), add to keep
──────────────────────────────────────────────────────────────────────

Queue:   B(0.91) → C(0.85) → D(0.70)
Keep:    [A]
Check:   IoU(A,B)=0.8 > 0.5 → remove B
         IoU(A,C)=0.7 > 0.5 → remove C
         IoU(A,D)=0.0 < 0.5 → keep D in queue

Step 3: Take D (next best remaining), add to keep
──────────────────────────────────────────────────────────────────────

Queue:   (empty)
Keep:    [A, D]

DONE! From 4 boxes → 2 boxes (one for each actual dog)
```

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
- score = score × (1 - IoU) or score × exp(-IoU²/σ)

CLASS-AGNOSTIC NMS:
- Apply across all classes
- Prevents same location detecting "dog" AND "cat"

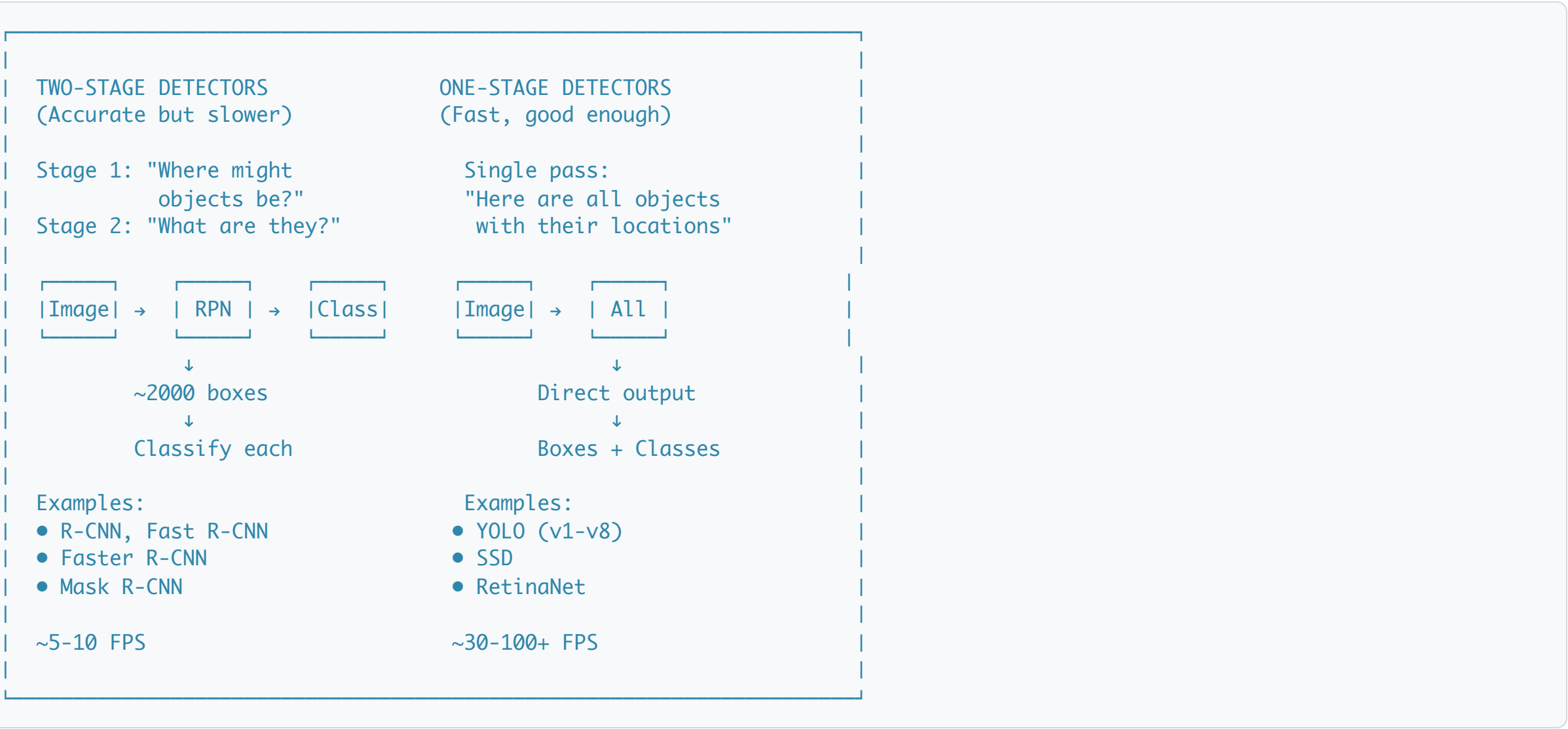
BATCHED NMS:
- Optimized for GPU
- Process all classes in parallel

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

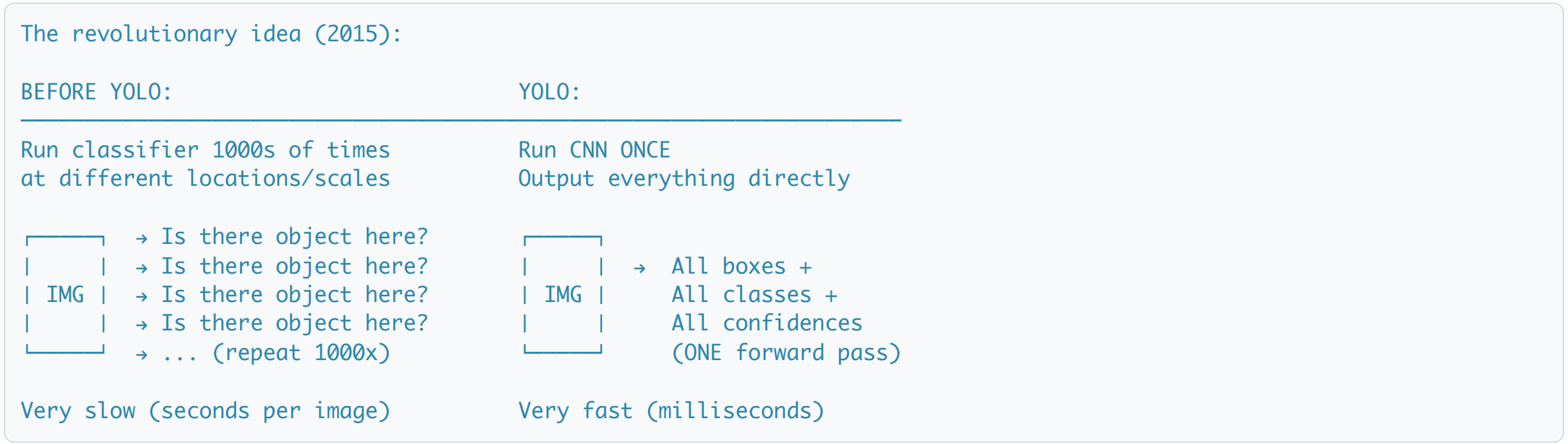
Part 5: How Detectors Work

The YOLO Architecture

Two Families of Detectors



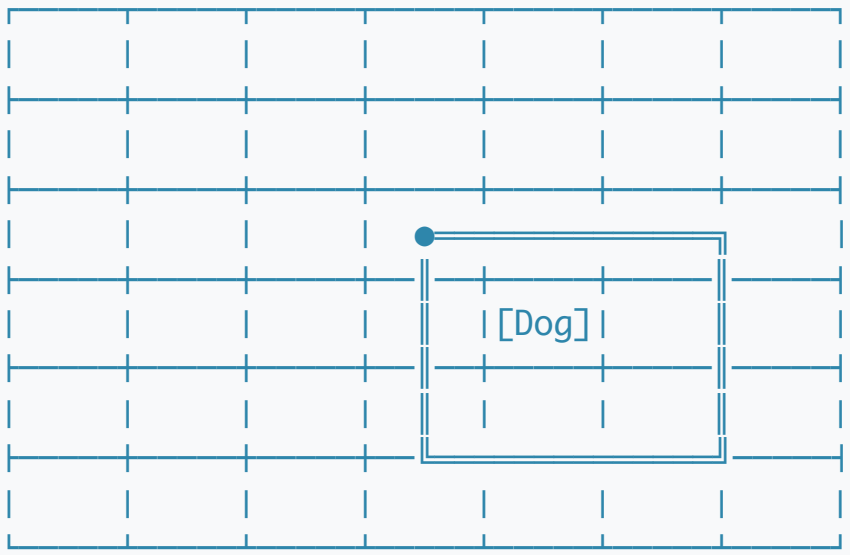
YOLO: You Only Look Once



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×S grid (e.g., 7×7):



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(object) × IoU with ground truth

For the CELL (shared across boxes):

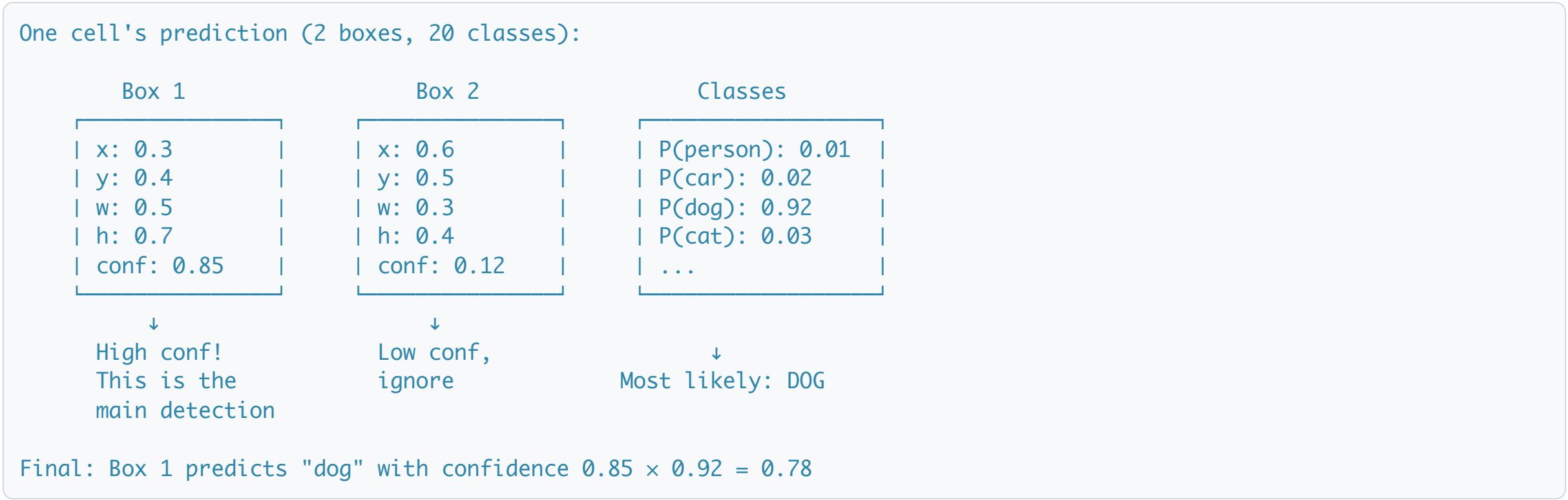
- $P(class_1), P(class_2), ..., P(classC)$

OUTPUT SHAPE:

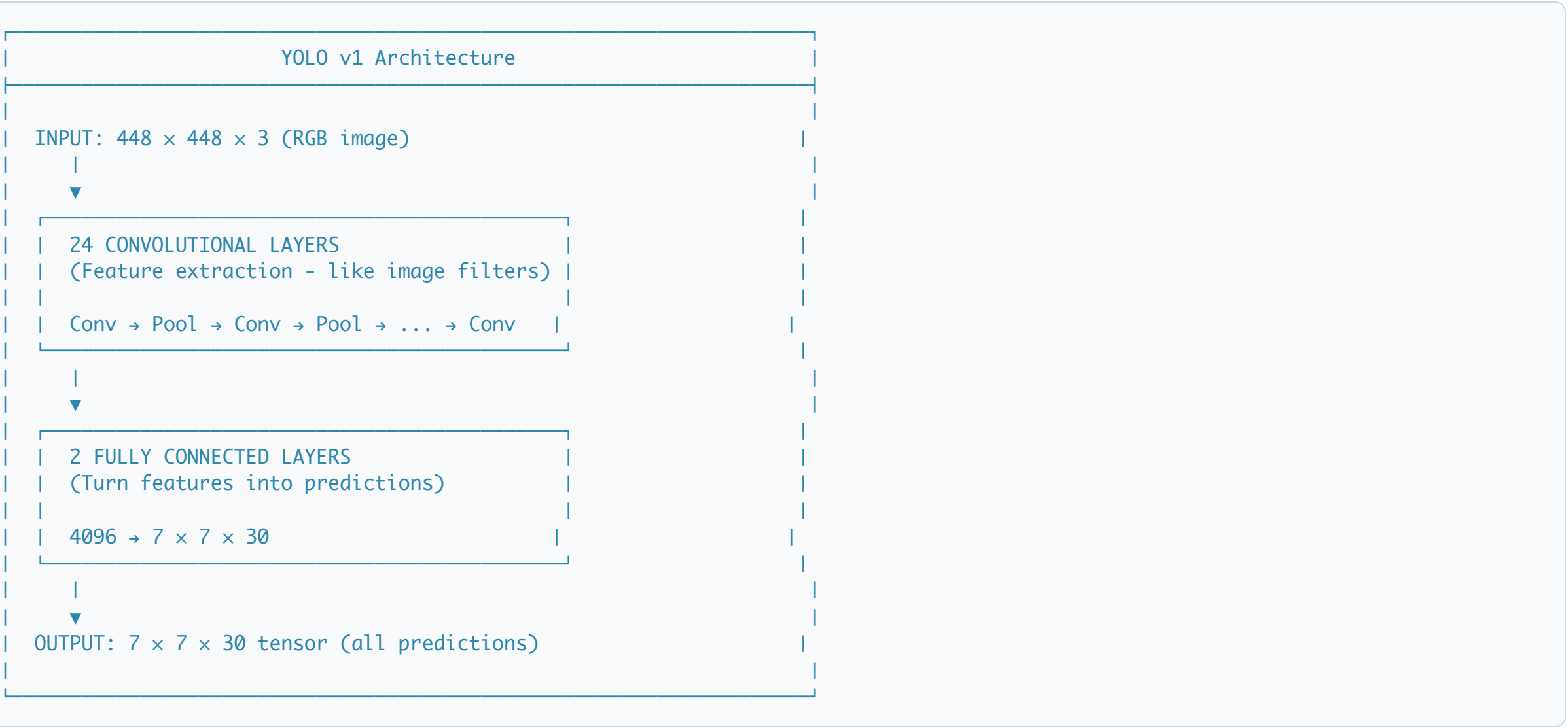
$S \times S \times (B \times 5 + C)$

Example: $7 \times 7 \times (2 \times 5 + 20) = 7 \times 7 \times 30$
= 1470 numbers describing all detections

YOLO Prediction Visualization



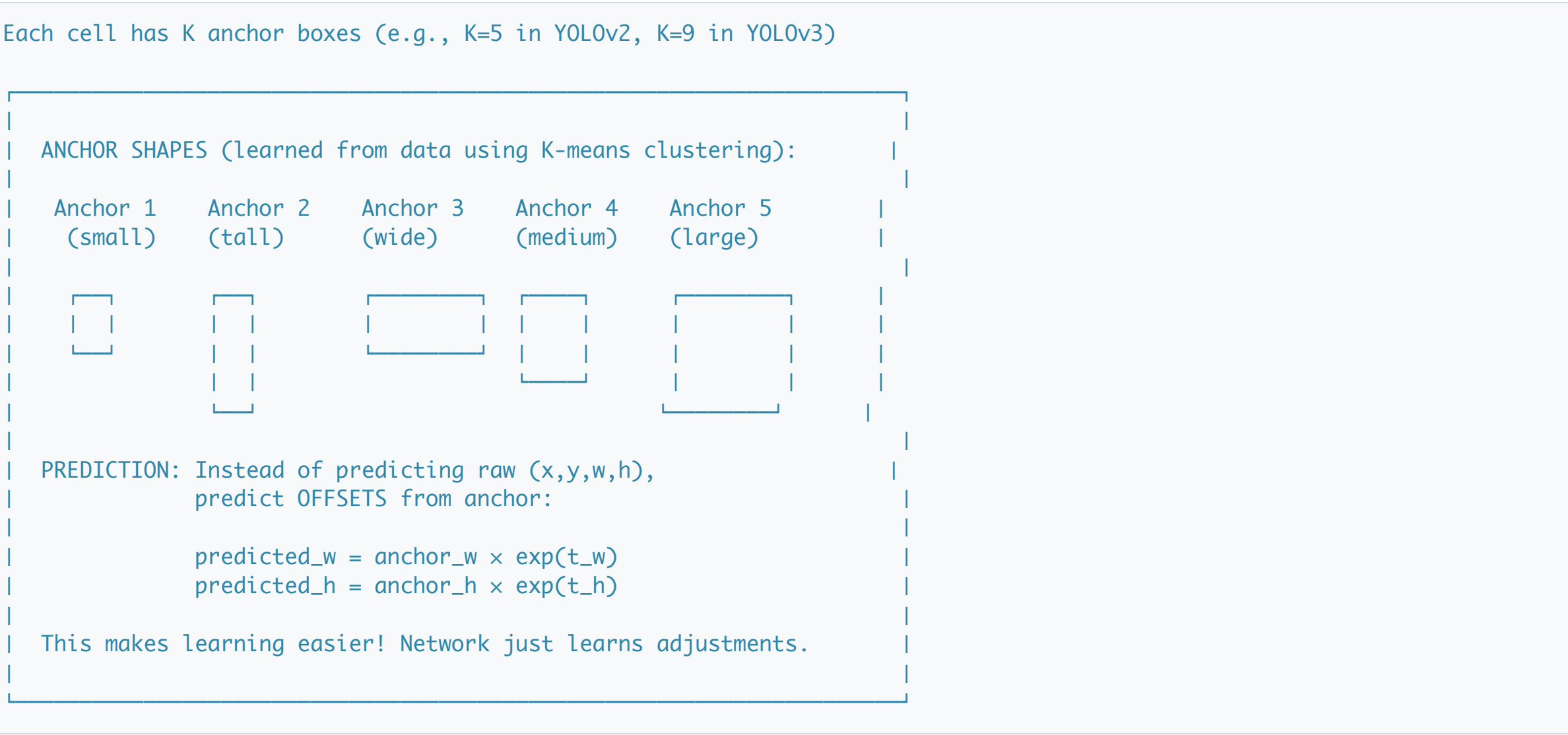
The YOLO Network Architecture (v1)



Anchor Boxes: Handling Multiple Objects Per Cell

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

    ┌─────┬─────┬─────┐
    │     │     │     │
    ├─────┼─────┼─────┤
    │     │D C  │     │  <- Both dog AND cat center here!
    ├─────┼─────┼─────┤       But cell can only predict
    │     │     │     │       one class in YOLO v1
    └─────┴─────┴─────┘

SOLUTION: Anchor boxes (YOLO v2+)

    Pre-define box SHAPES (anchors):

    ┌──┐   ┌────┐    ┌┐
    │  │   │    │    ││
    │  │   └────┘    ││
    └──┘             ││
    Tall   Wide      ││
    anchor anchor    └┘
                    Very tall

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

Anchor Boxes: How They Work



YOLO Evolution: v1 → v8

YOLOv1 (2015): Original breakthrough
- 7×7 grid, 2 boxes/cell, 45 FPS
- Simple but limited

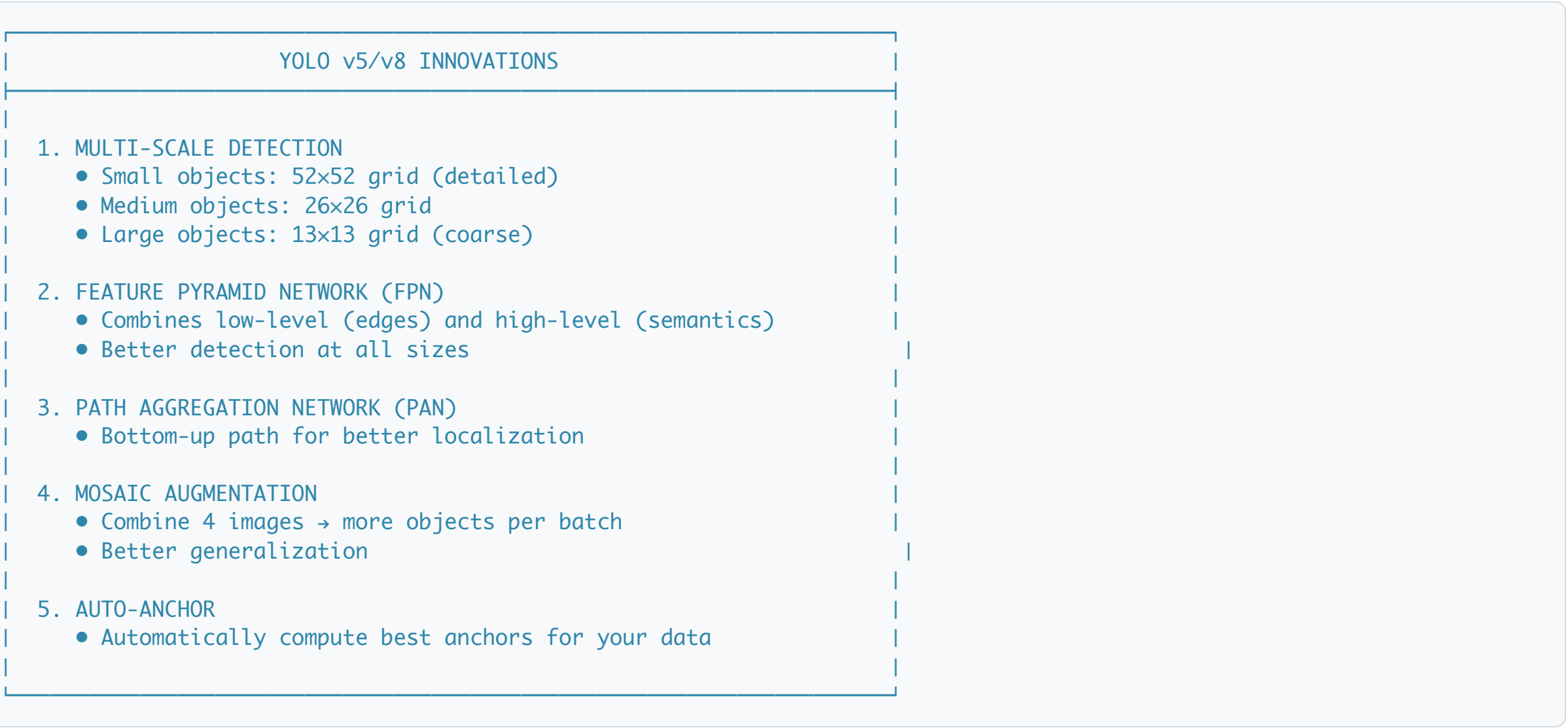
YOLOv2 (2016): Better and faster
- Anchor boxes, batch normalization
- Multi-scale training

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 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)
```

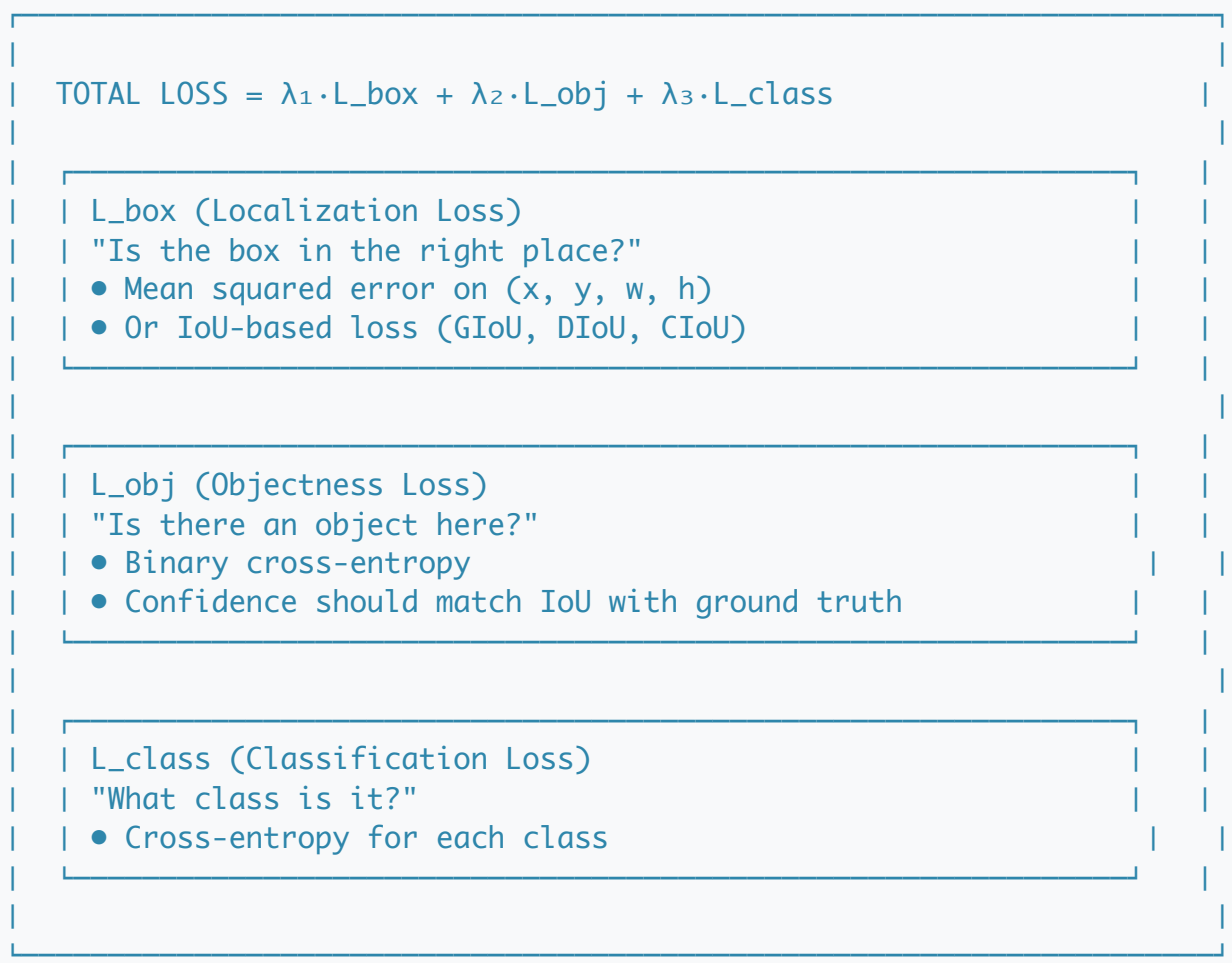
> Start with YOLOv8n for prototyping, move to larger models if needed.

Part 6: Training & Evaluation

How We Train and Measure Detectors

The Detection Loss Function

Detection models optimize MULTIPLE objectives simultaneously:



Understanding the Box Loss

ORIGINAL YOLO (MSE Loss):

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

Why square root of w,h?

- Large boxes shouldn't dominate
- Error of 10px matters more for 20px box than 200px box
- √ compresses the range

MODERN YOLO (IoU-based Loss):

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

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 IoU ≥ 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

$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

"Of my detections, how many are correct?"

"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

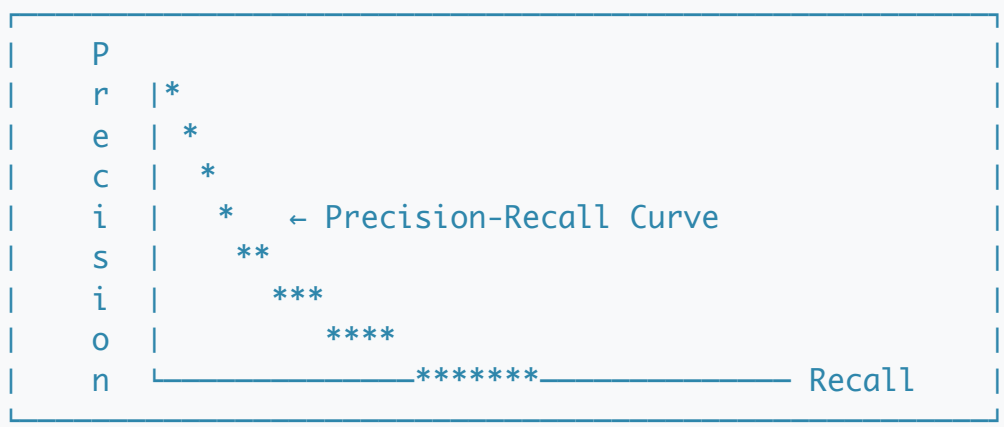
Example on 10 real dogs:

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

    Precision
    1.0 ┤▆▆▆▆▆
        │▆▆▆▆▆▆▆▆▆
        │▆▆▆▆▆▆▆▆▆▆▆▆▆
        │▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆
    0.5 ┤▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆
        │▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆
        │▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆▆
    0.0 └──────────────────────────────────
        0.0                            1.0
                    Recall

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

$$mAP@0.5 = \frac{AP_1 + AP_2 + \ldots + APc}{C \text{ (number of classes)}}$$

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):

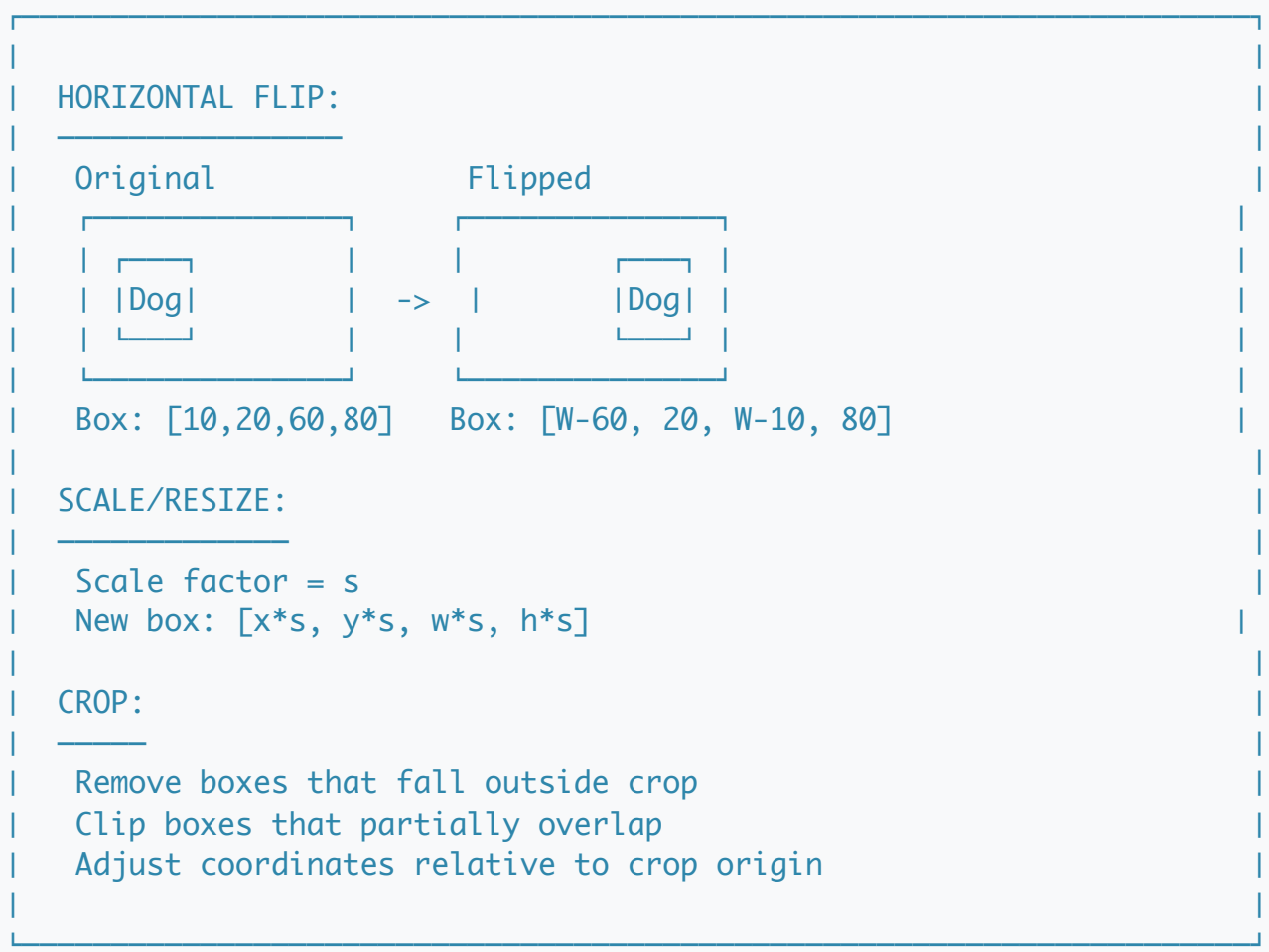
#	Class	Conf	Matched?	Status
1	dog	0.95	Yes	TP
2	dog	0.90	Yes	TP
3	cat	0.85	Yes	TP
4	dog	0.80	No	FP
5	cat	0.75	Yes	TP
6	dog	0.70	Yes	TP

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

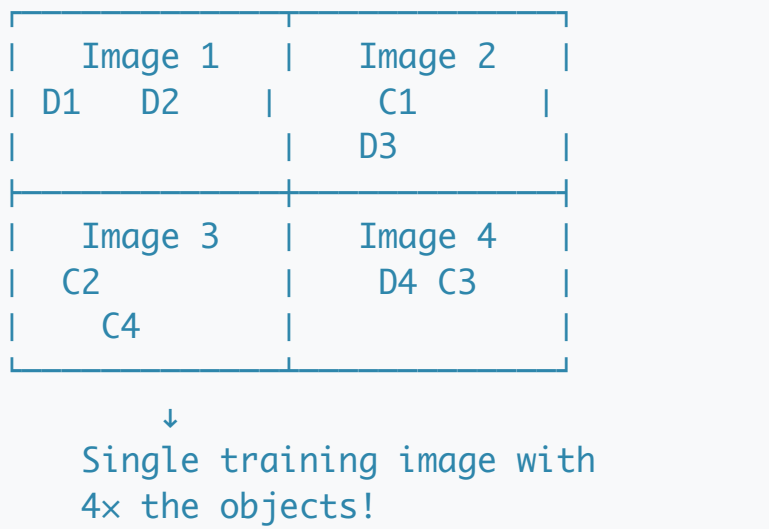
Data Augmentation for Detection

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



Mosaic Augmentation (YOLO v4+)

Combine 4 images into 1 training sample:



↓

Single training image with 4× 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                               │
│     • 640×640 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)

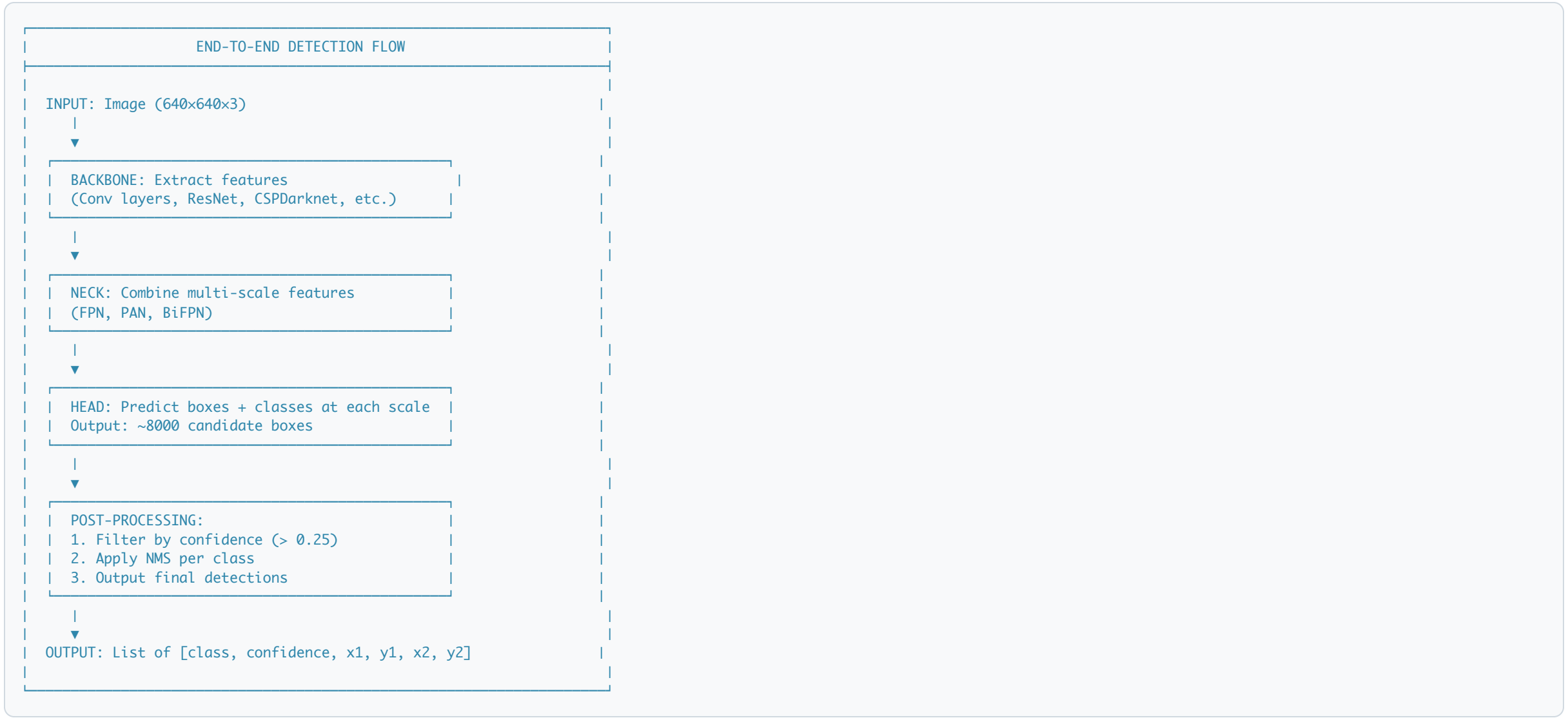
MS COCO leaderboard (mAP@[0.5:0.95]):

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                                     │
│     IoU ≥ 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, YOLOv8-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 → 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 - IoU                                                 │
│      Problem: No gradient when boxes don't overlap               │
│                                                                  │
│  GIoU (Generalized IoU):                                         │
│      L = 1 - IoU + |C - Union| / |C|                             │
│      C = smallest enclosing box                                  │
│      Handles non-overlapping boxes!                              │
│                                                                  │
│  DIoU (Distance IoU):                                            │
│      L = 1 - IoU + d² / c²                                       │
│      d = center distance, c = diagonal of enclosing box          │
│      Faster convergence                                          │
│                                                                  │
│  CIoU (Complete IoU):                                            │
│      L = 1 - IoU + d² / c² + αv                                  │
│      α, v = aspect ratio penalty terms                           │
│      Best overall performance                                    │
│                                                                  │
└──────────────────────────────────────────────────────────────────┘
```