CVPR2016, CVPR2017

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自动驾驶论文讲坛：

YOLO, YOLO9000:
Unified, Real-Time Object Detection

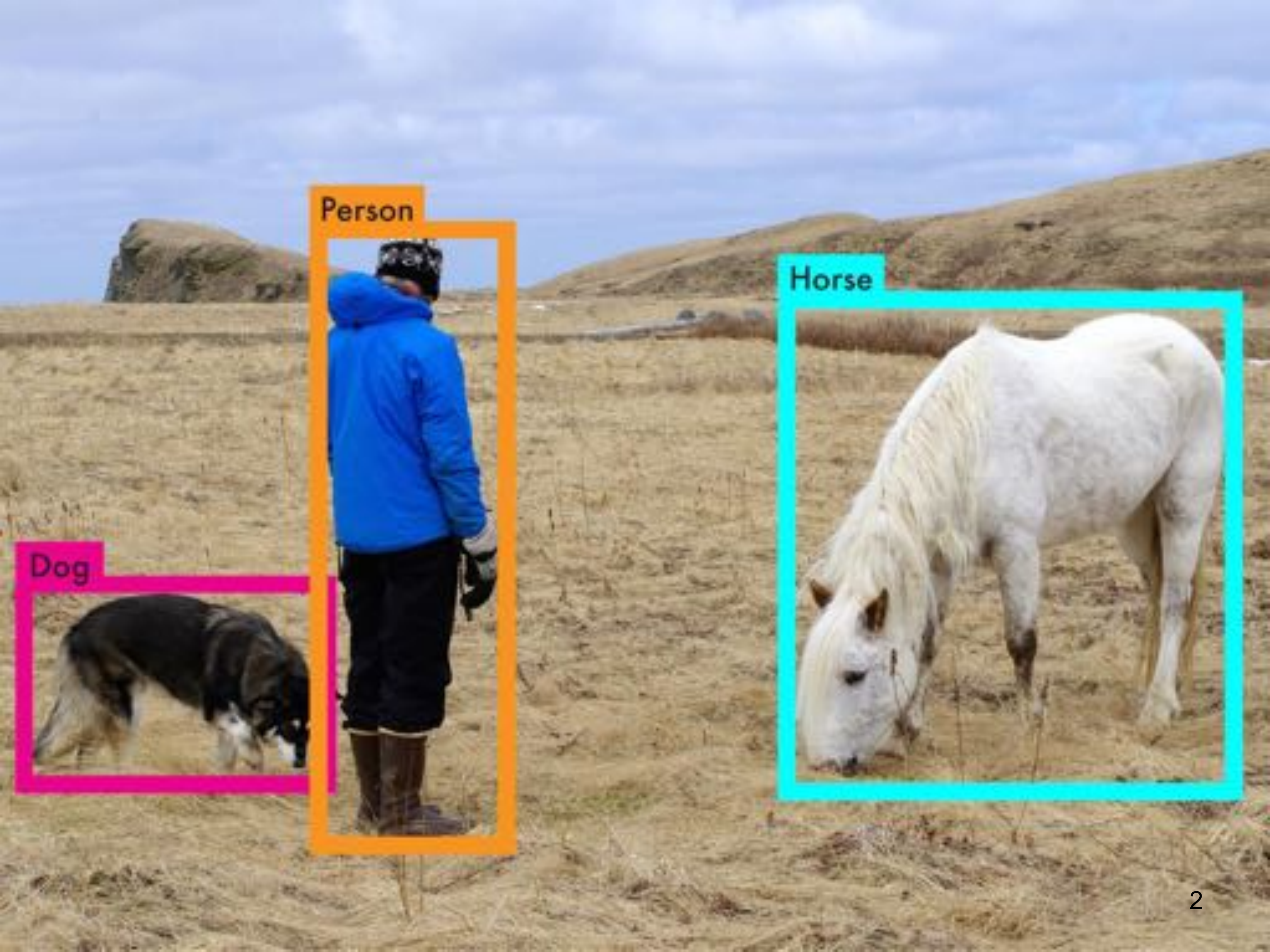
Authors: Joseph Redmon, Ali Farhadi, Santosh Divvala, Ross Girshick

Speaker: Yuehong Huang

Friday 17/11/2017

12:00 PM (GMT+8)

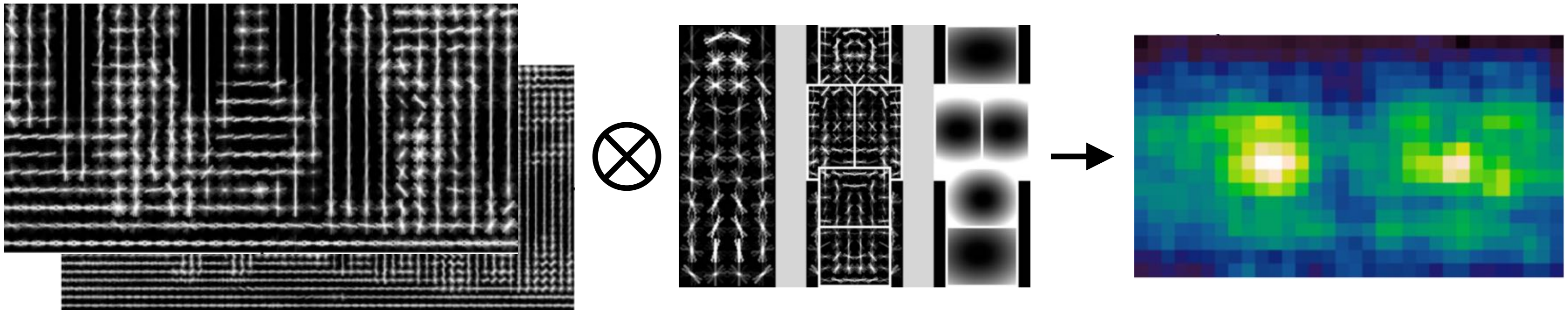
Zoom.us Webinar


Person
Horse
Dog

Comparison to Other Detection System -- Accurate object detection is slow!

	Pascal 2007 mAP	**Speed**	
DPM v5	33.7	.07 FPS	14 s/img

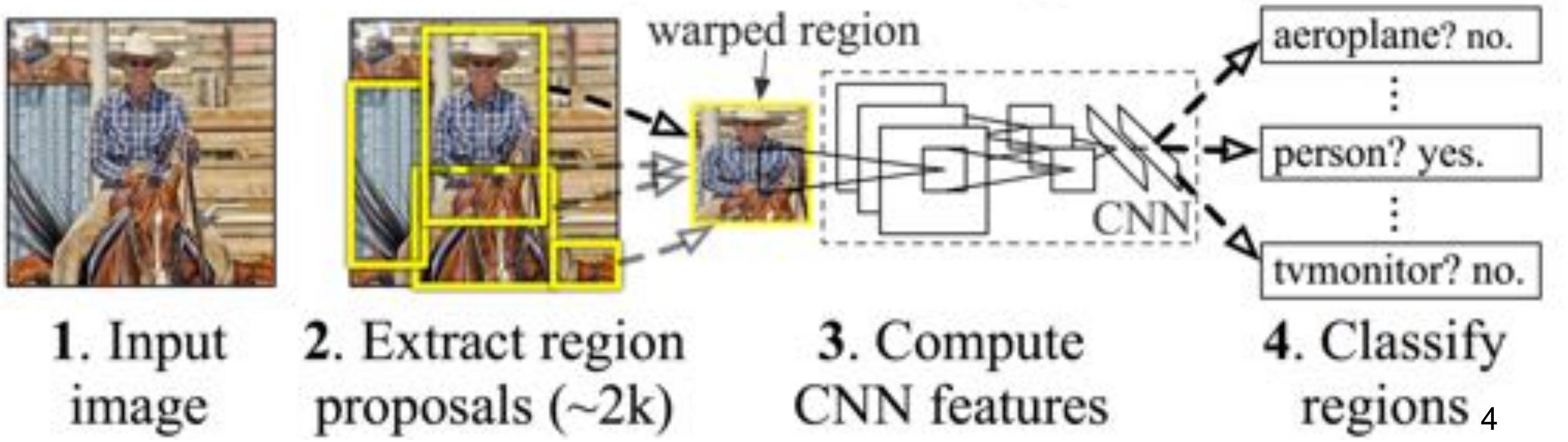
DPM: ***Deformable Part Models***



Accurate object detection is slow!

	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img
R-CNN	66.0	.05 FPS	20 s/img

R-CNN: *Regions with CNN features*



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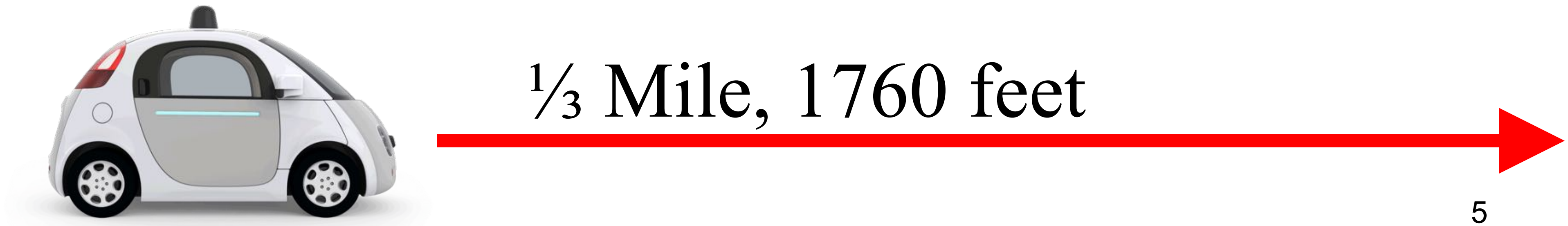
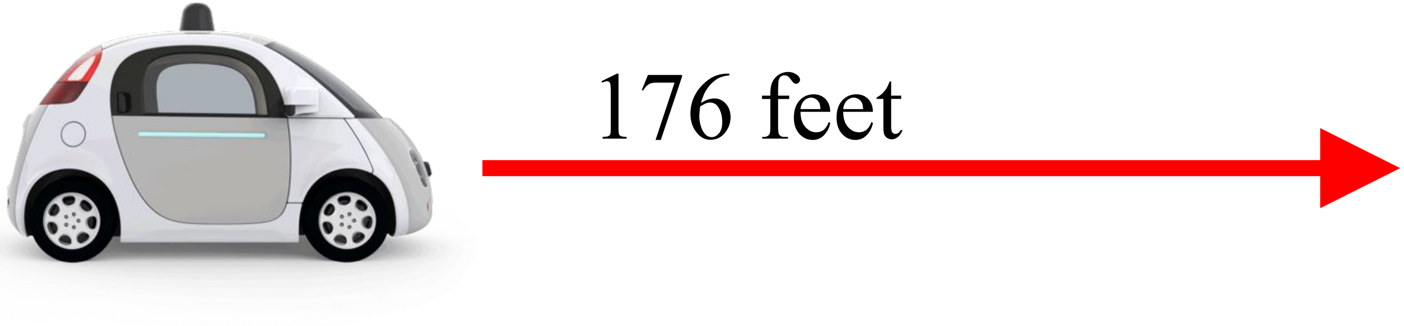


Accurate object detection is slow!

	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img
R-CNN	66.0	.05 FPS	20 s/img
Fast R-CNN	70.0	.5 FPS	2 s/img



176 feet

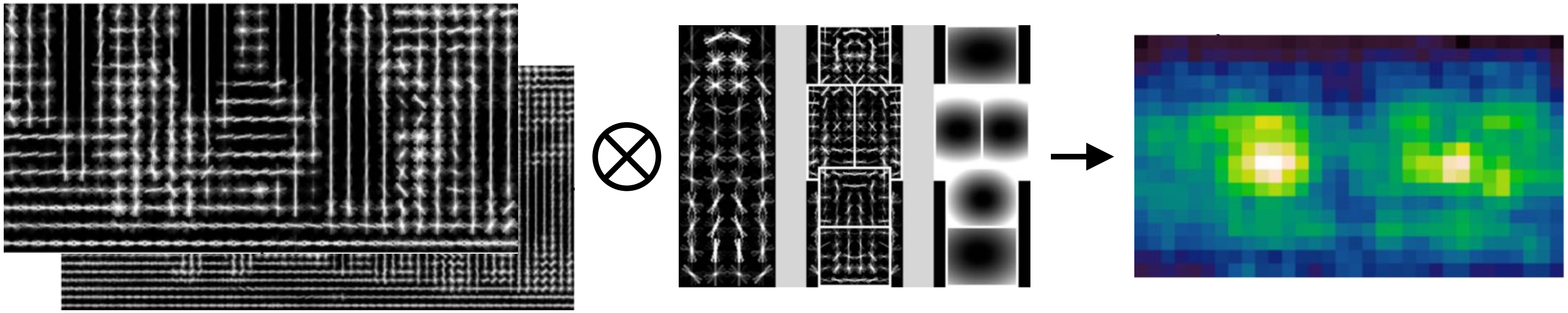
Accurate object detection is slow!

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

8 feet
12 feet

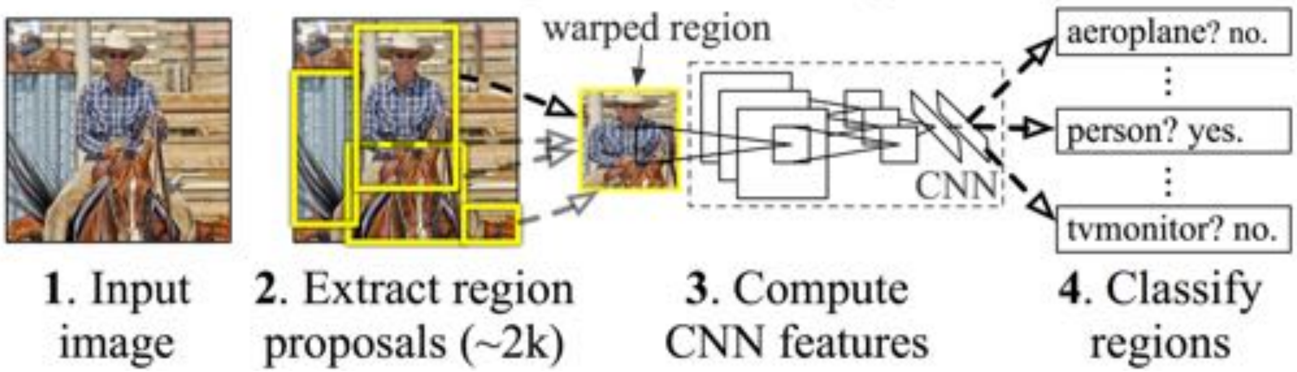
Sliding window, DPM, R-CNN all train region-based classifiers to perform detection

DPM: ***Deformable Part Models***



Complex Pipeline

R-CNN: ***Regions with CNN features***



Accurate object detection is slow!

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

2 feet

YOLO can be better!

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

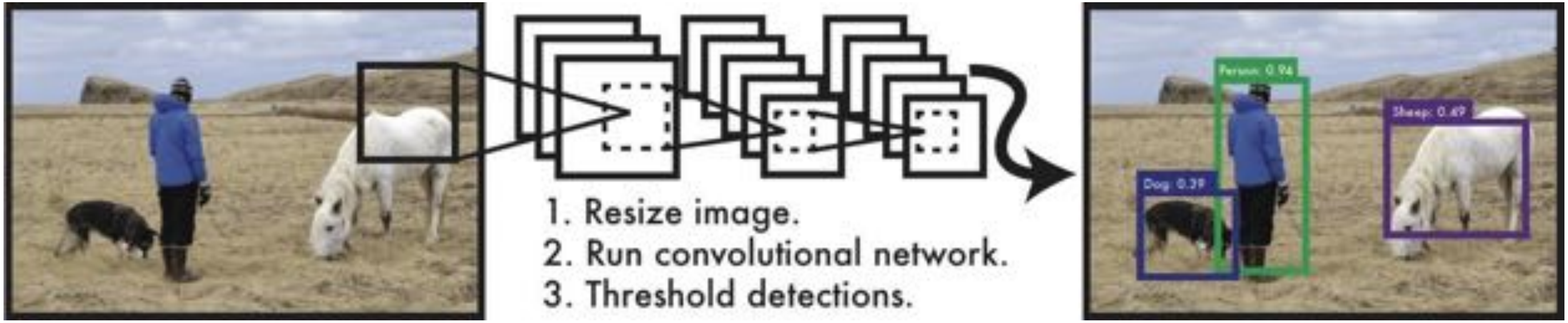
🙁 ↗

↖ 😁

YOLOv2, YOLO9000

With YOLO, you only look once at an image to perform detection

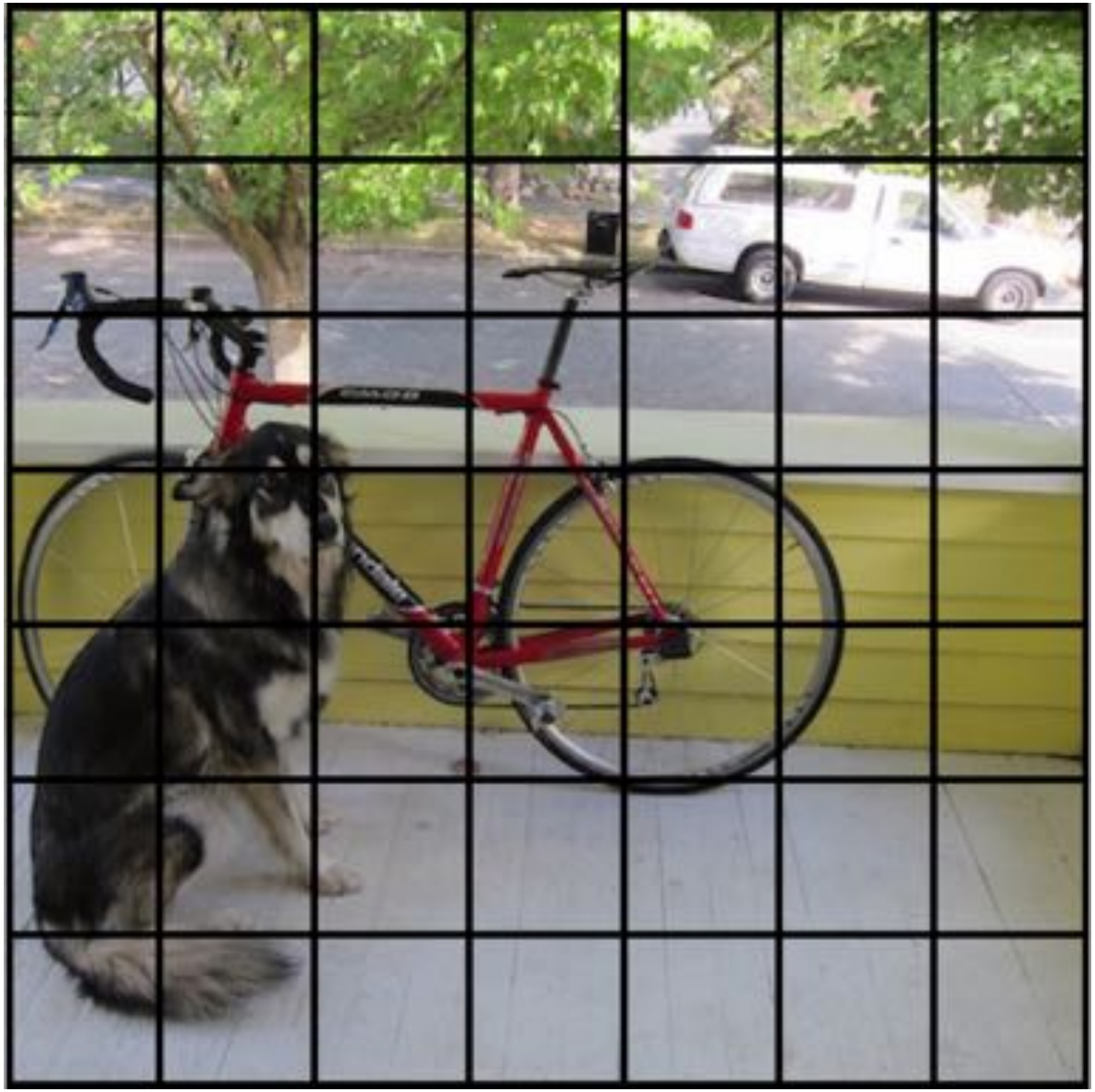
YOLO: ***You Only Look Once***



Unified Model:

1. YOLO is extremely fast -- no complex pipeline
2. Twice the mean average precision of other real-time systems
3. YOLO reasons globally about the image – less background errors
4. YOLO learns generalizable representations of objects – new domain and unexpected input (art works).

Unified Detection -- we split the image into a grid



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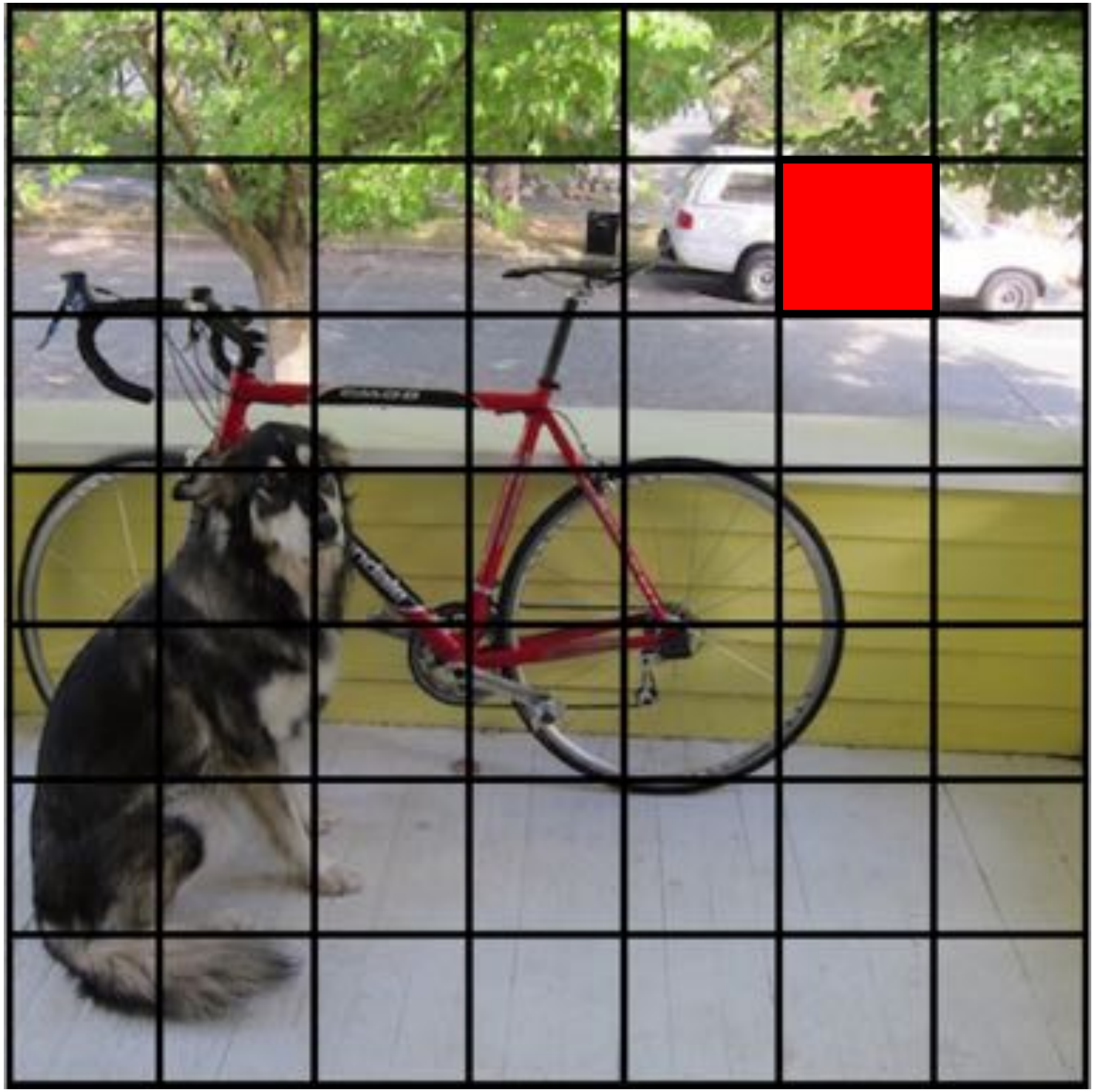
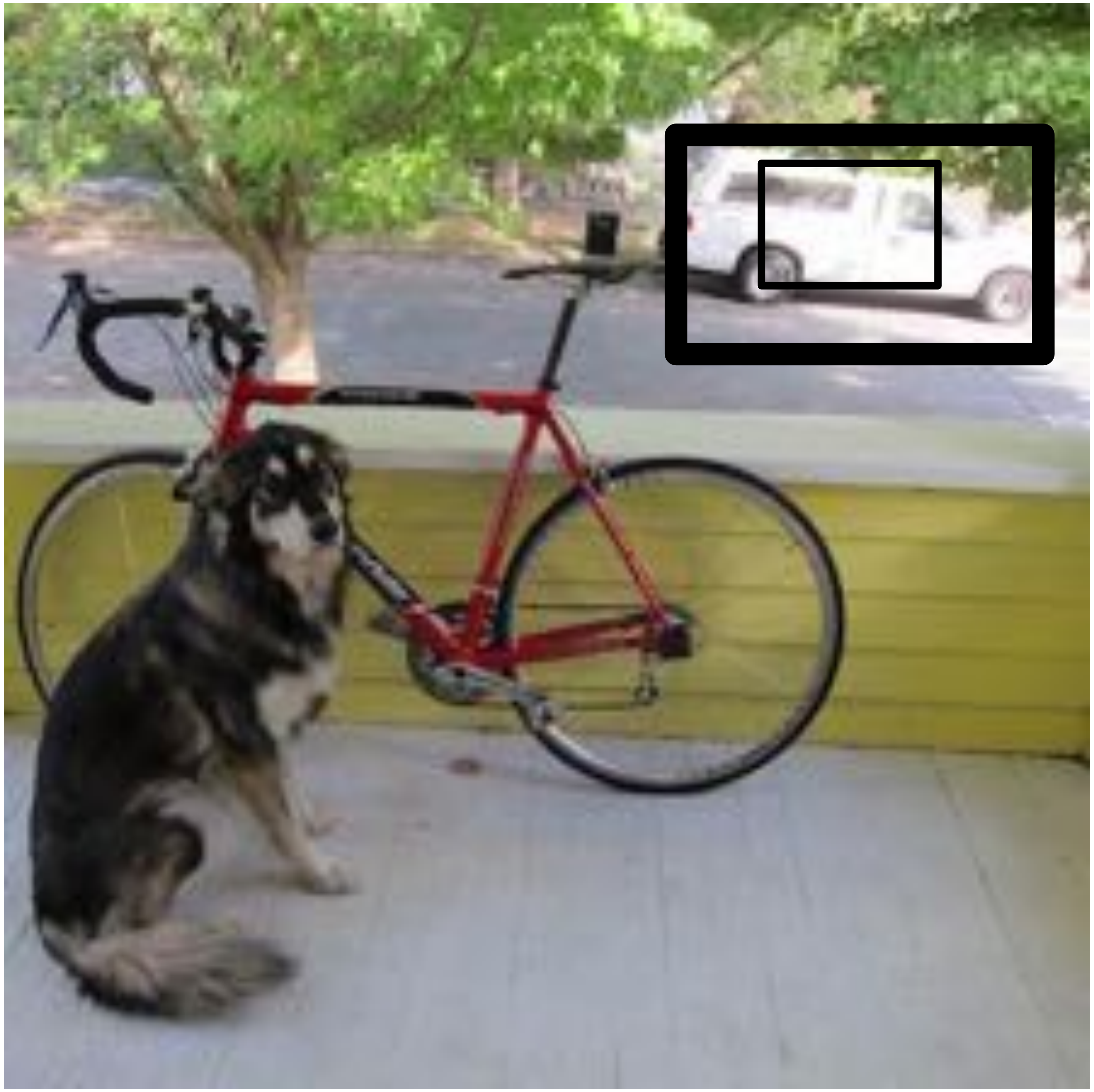
Each cell predicts boxes and confidences: P(Object)



iMorpheus

Each cell predicts boxes and confidences: P(Object)



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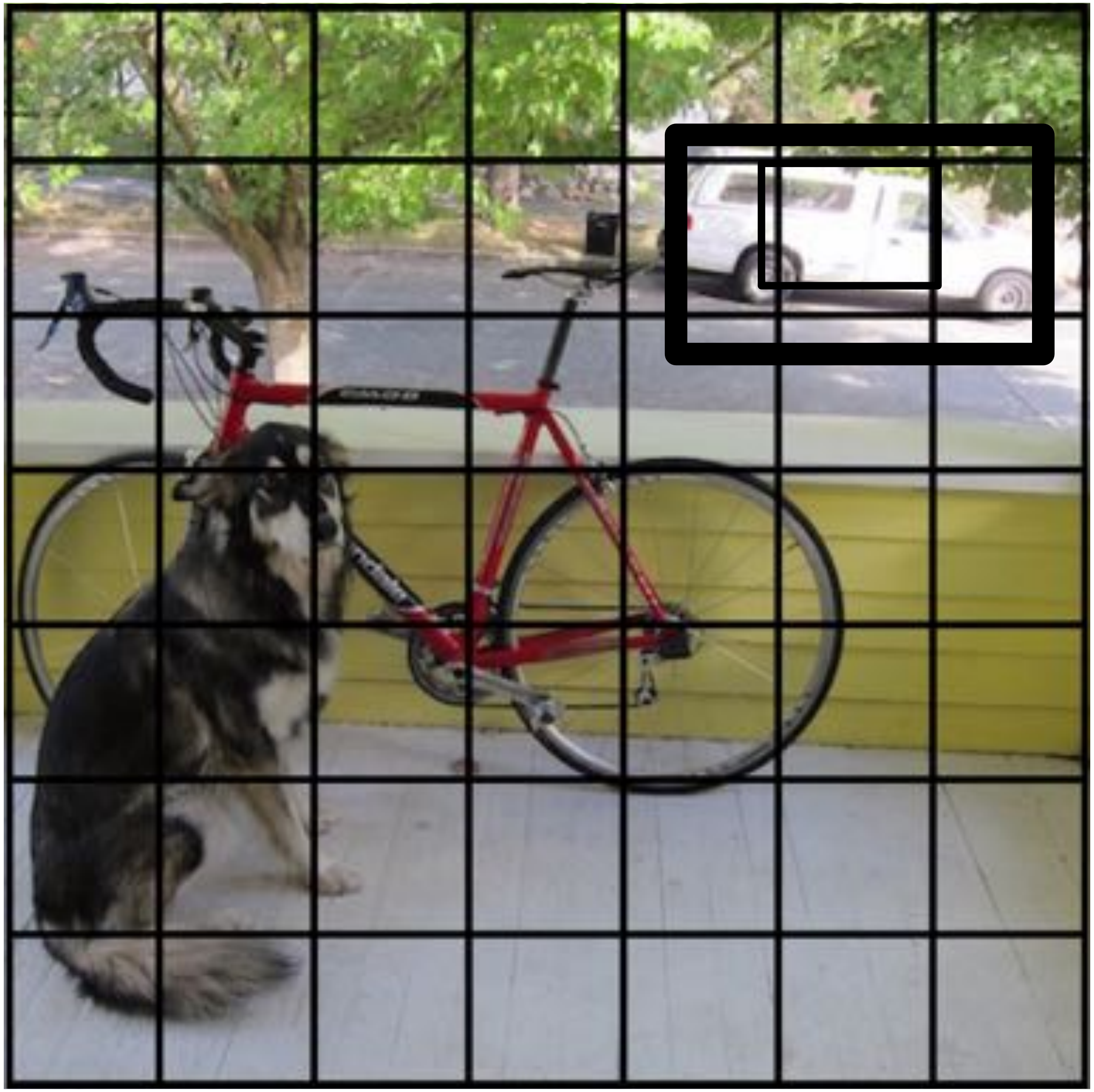
Each cell predicts boxes and confidences: P(Object)



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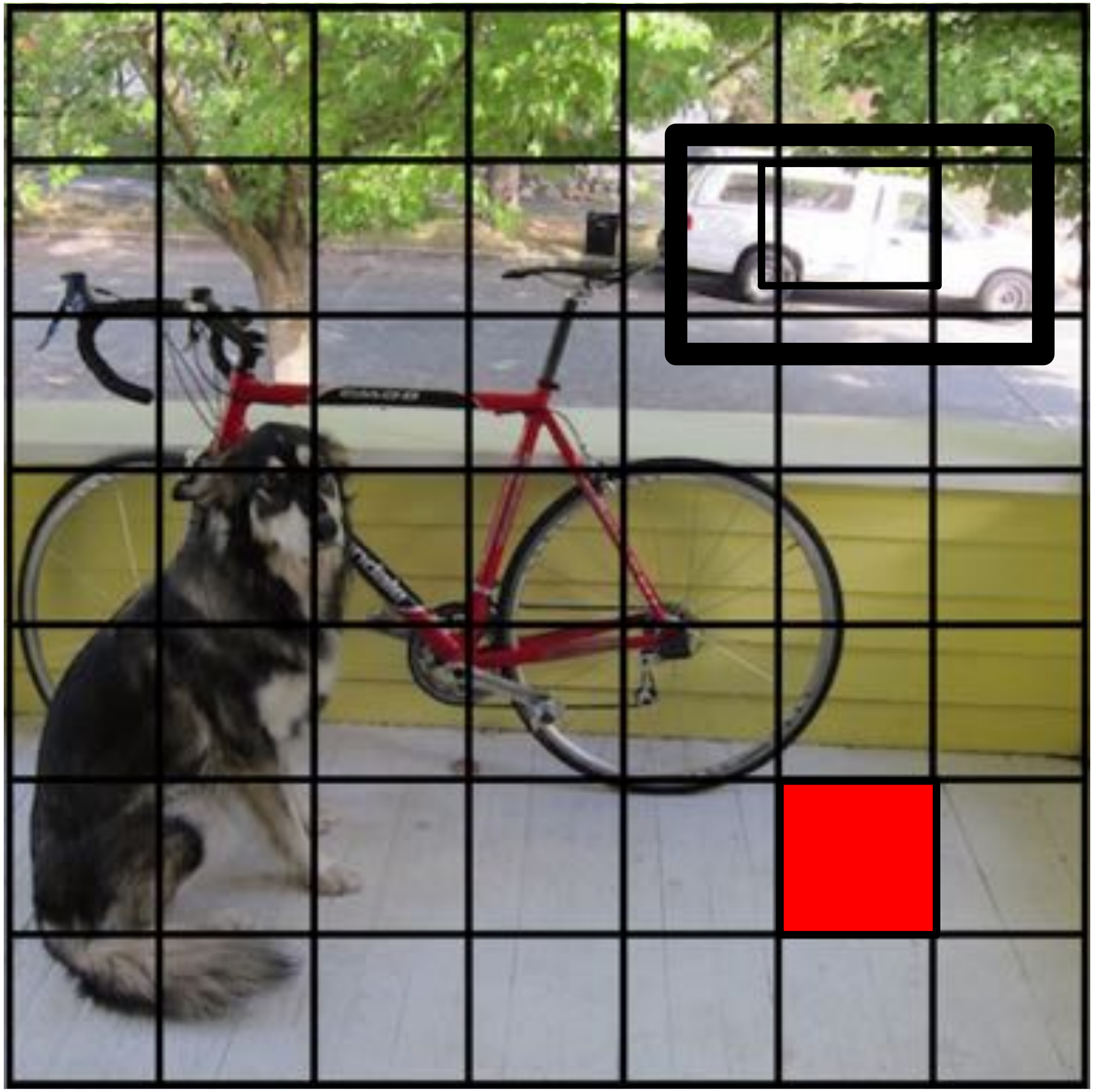
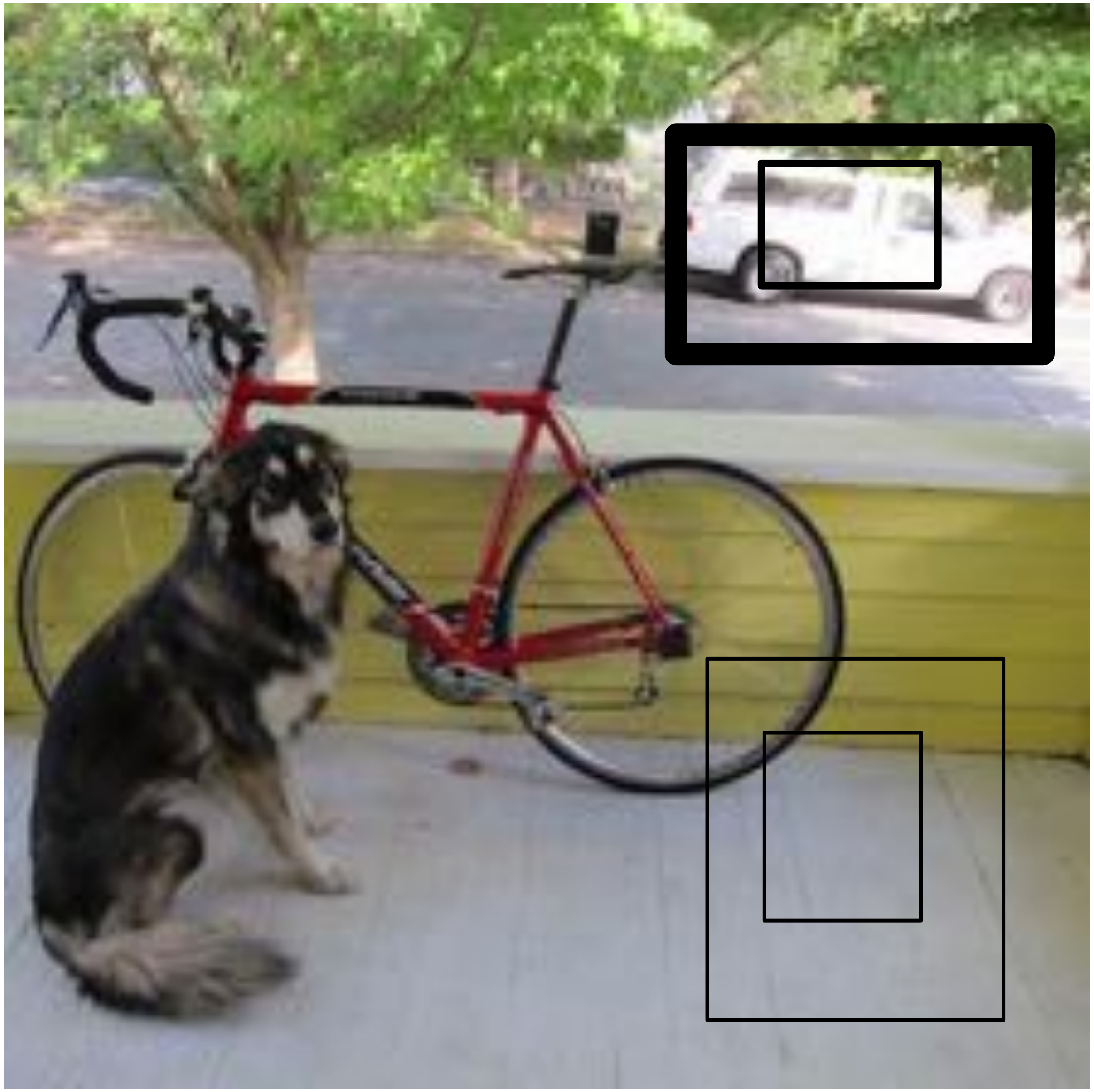
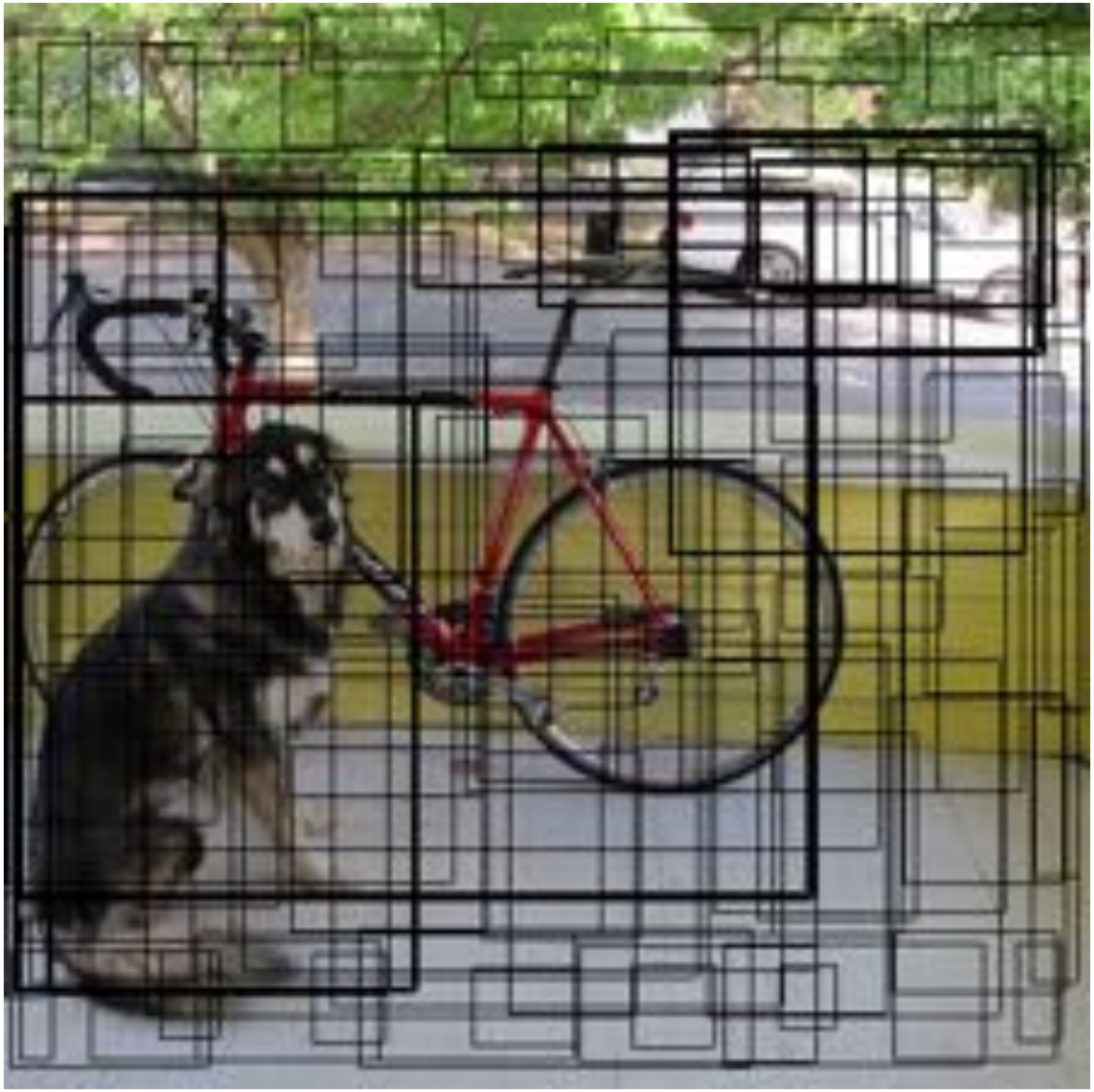
Each cell predicts boxes and confidences: P(Object)



Each cell predicts boxes and confidences: P(Object)



Each cell predicts boxes and confidences: P(Object)



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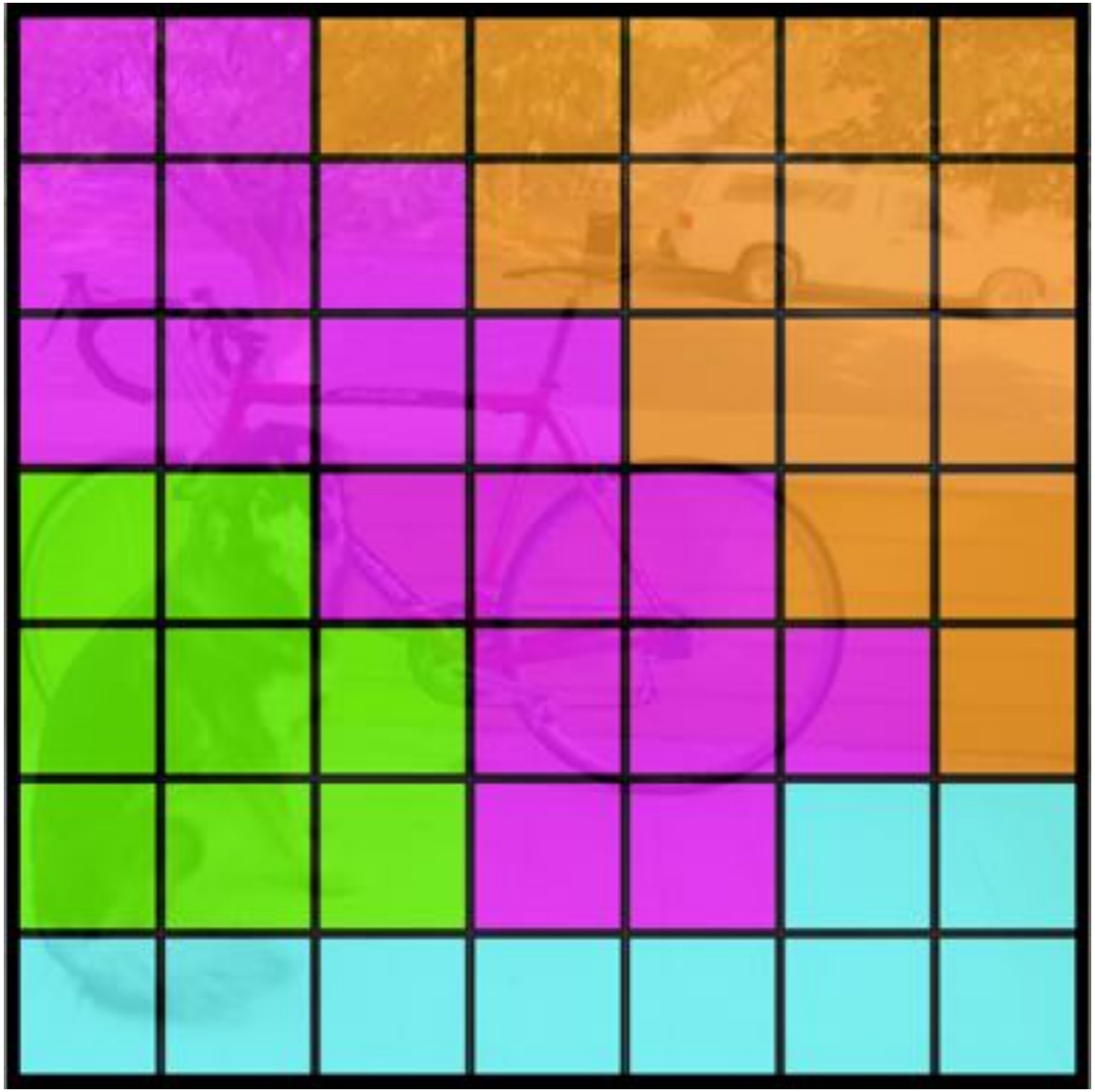
Each cell also predicts a class probability.

Conditioned on object: P(Car | Object)



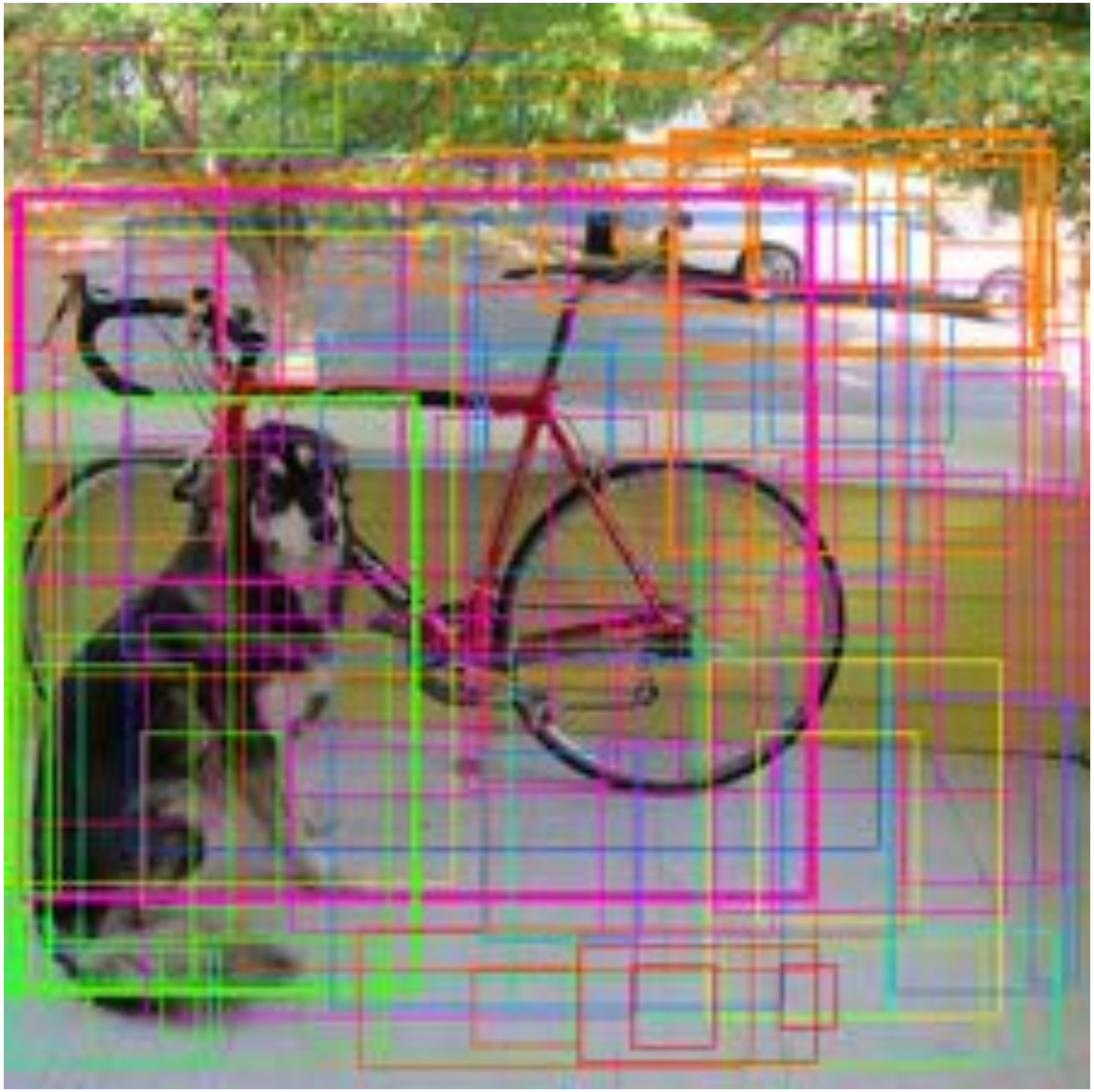
Bicycle

Car

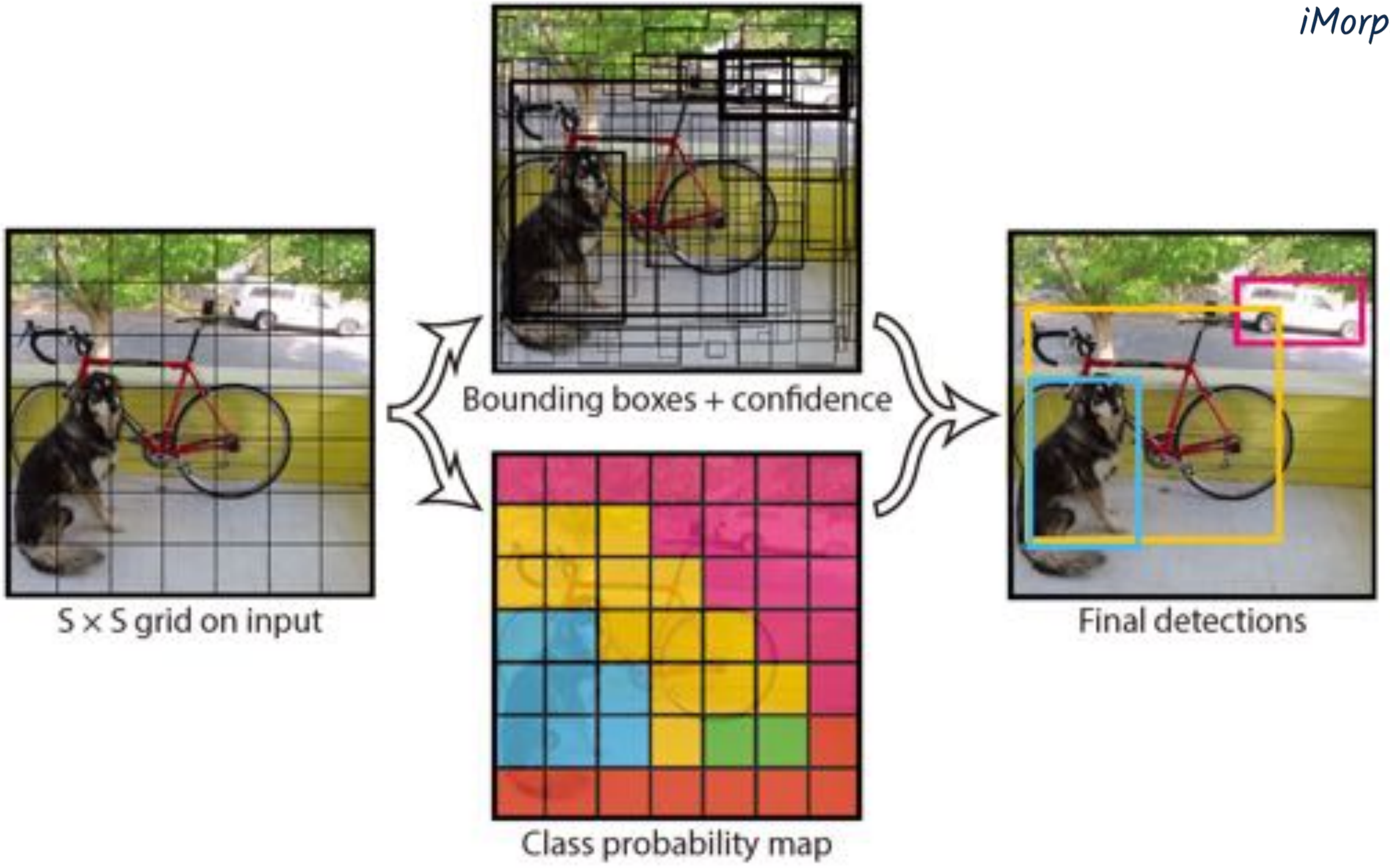
Dog

Dining Table

Then we combine the box and class predictions.



Finally we do threshold detections



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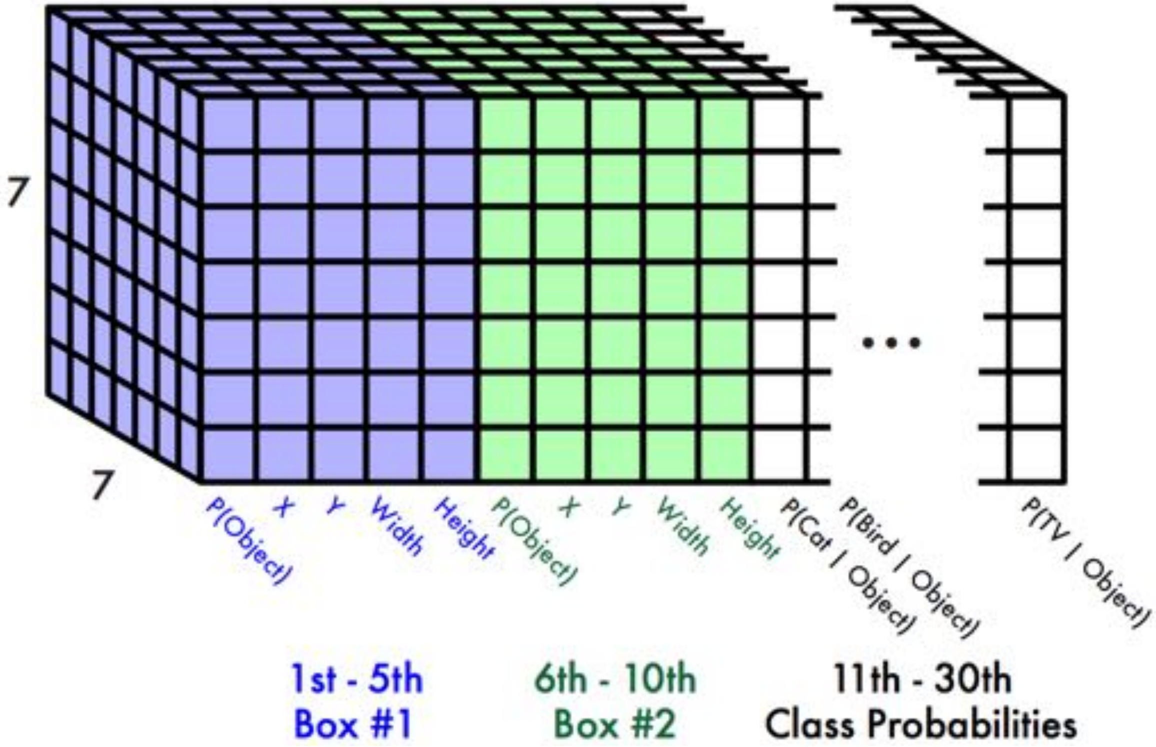
This parameterization fixes the output size

Each cell predicts:

- For each bounding box:
  - 4 coordinates (x, y, w, h)
  - 1 confidence value
- Some number of class probabilities



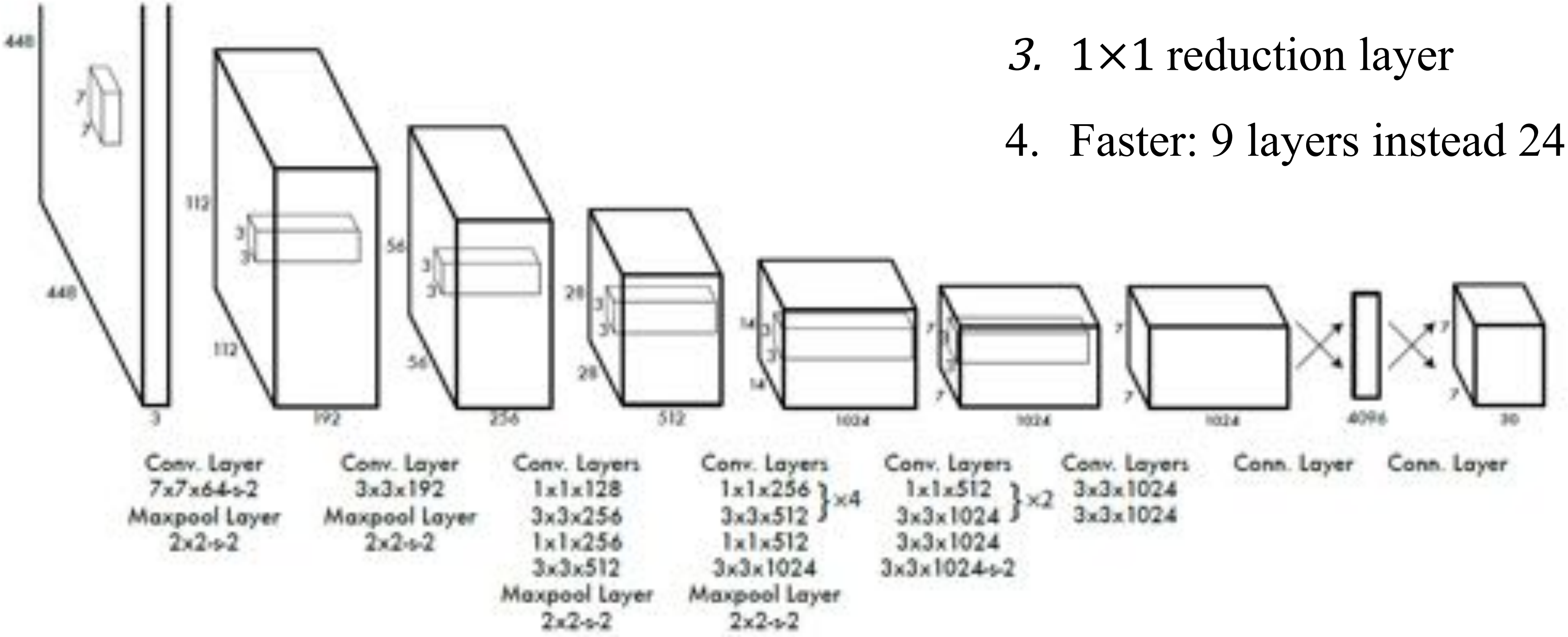
For Pascal VOC:

- 7x7 grid
- 2 bounding boxes / cell
- 20 classes

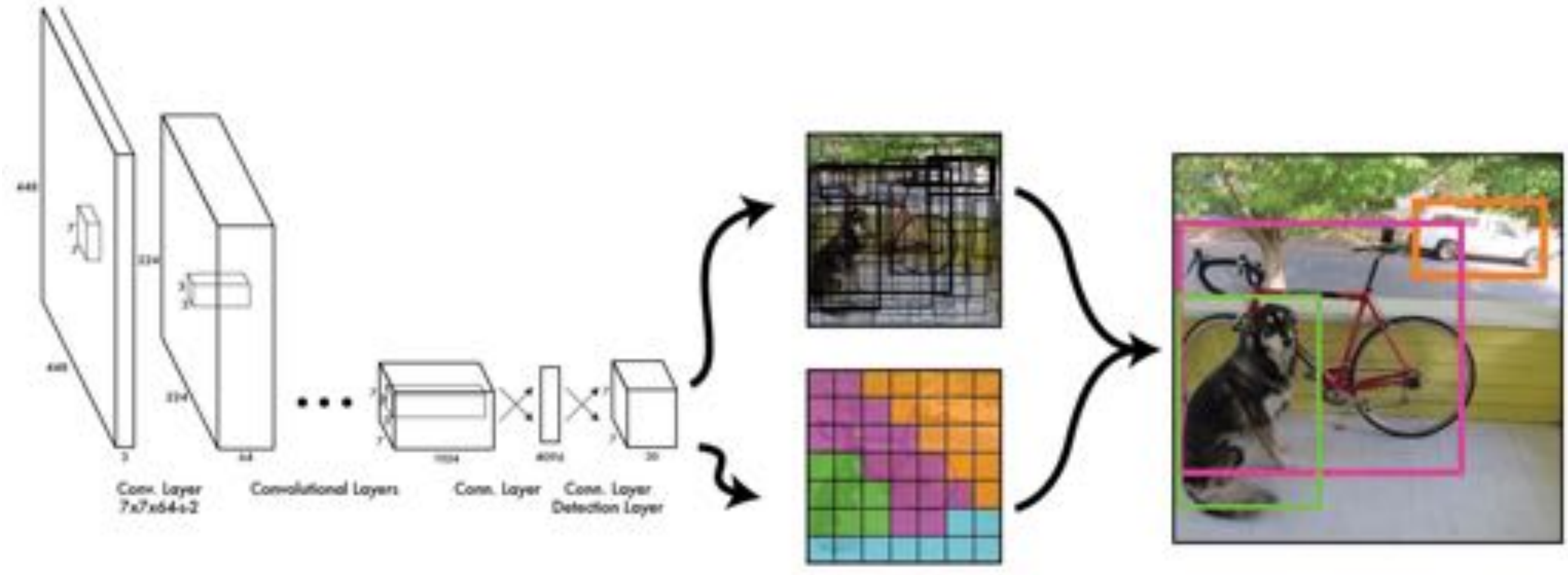
7 x 7 x (2 x 5 + 20) = 7 x 7 x 30 tensor = **1470 outputs**

The architecture of network

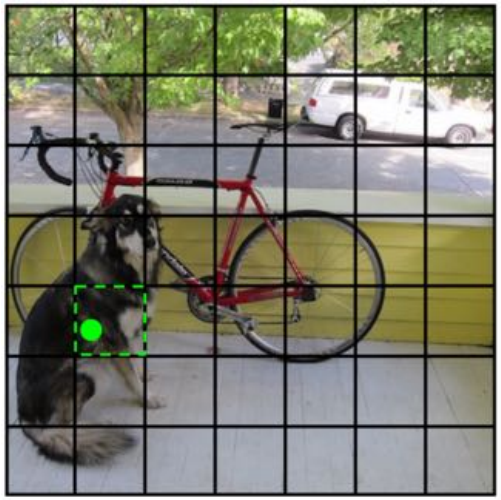
1. 24 convolutional layers
2. 2 fully connected layers
3. 1×1 reduction layer
4. Faster: 9 layers instead 24



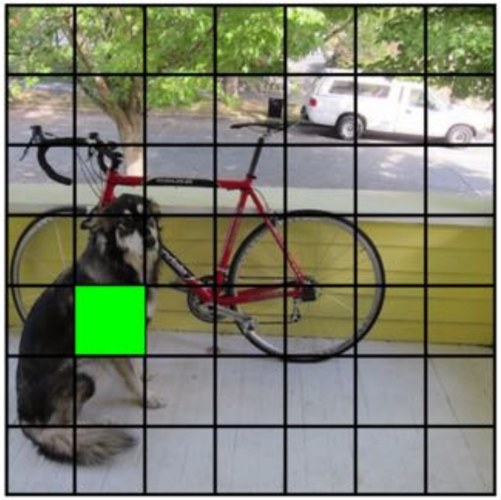
Thus we can train one neural network to be a whole detection pipeline

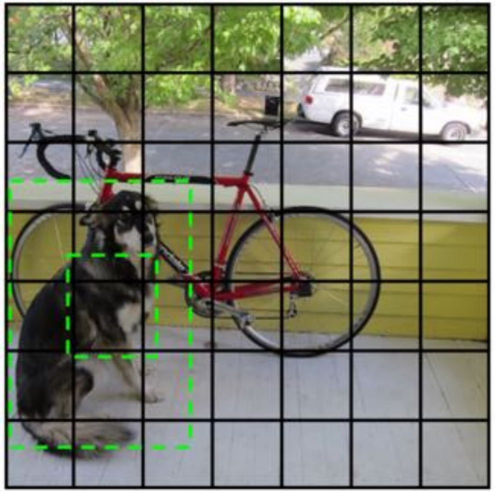


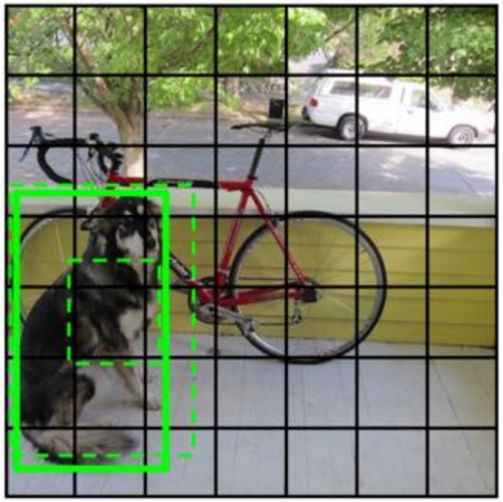
During training, match example to the right cell

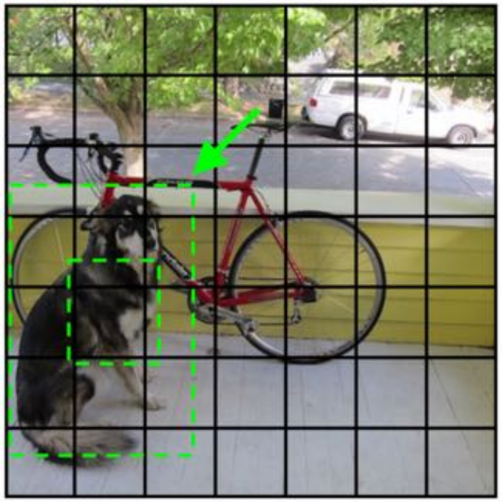


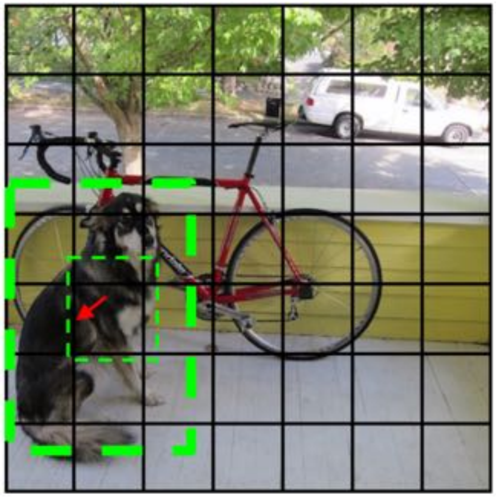
Dog = 1
Cat = 0
Bike = 0
...



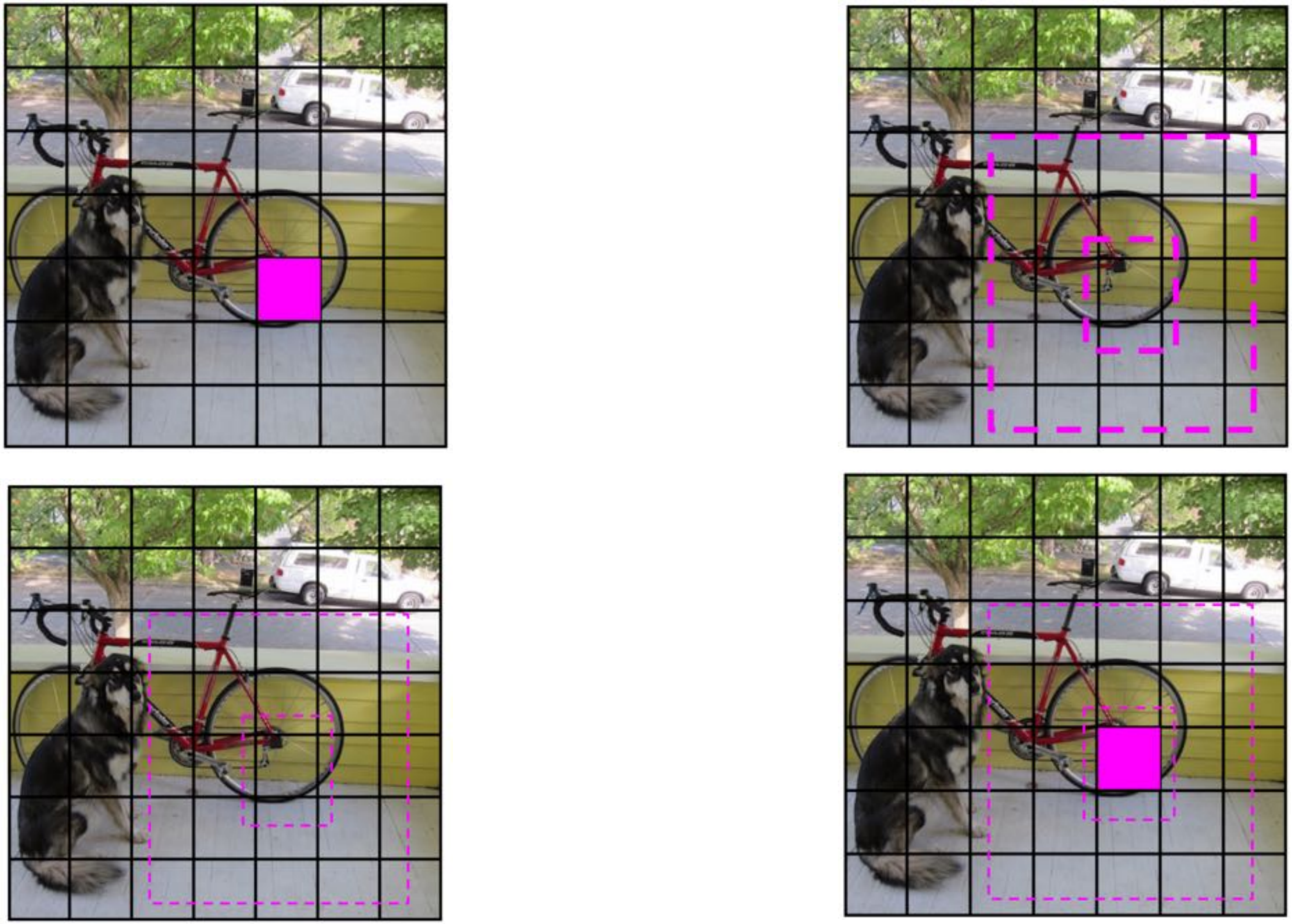






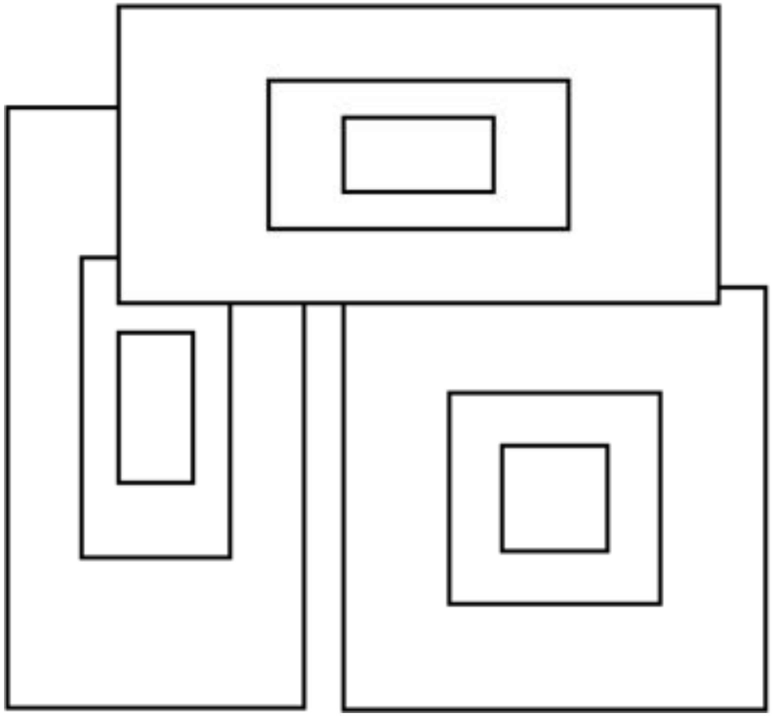


Some cells don’t have any ground truth detections!



YOLOv2, YOLO9000

Anchor boxes use static initialization



Sizes:

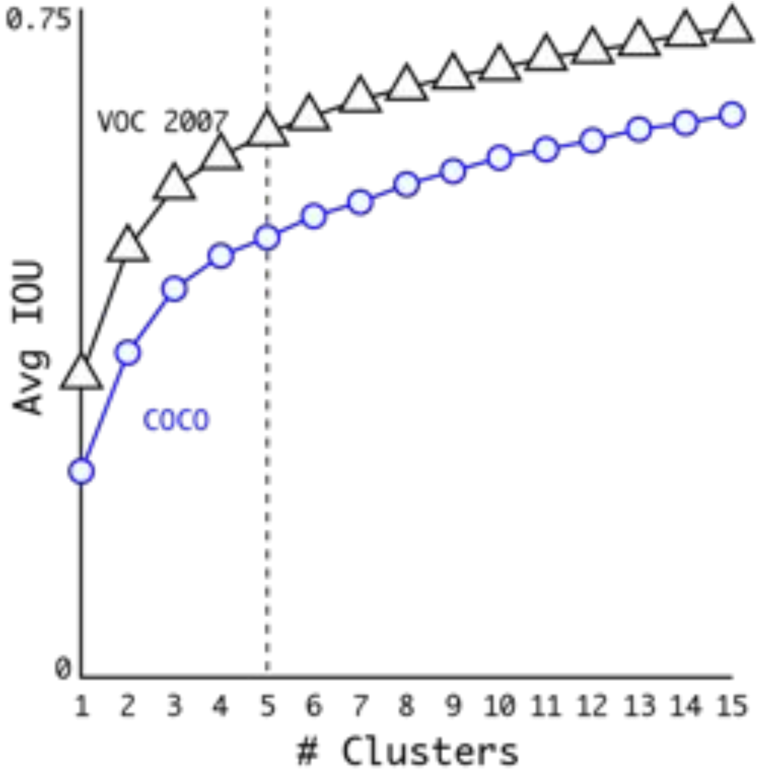
- 128
- 256
- 512

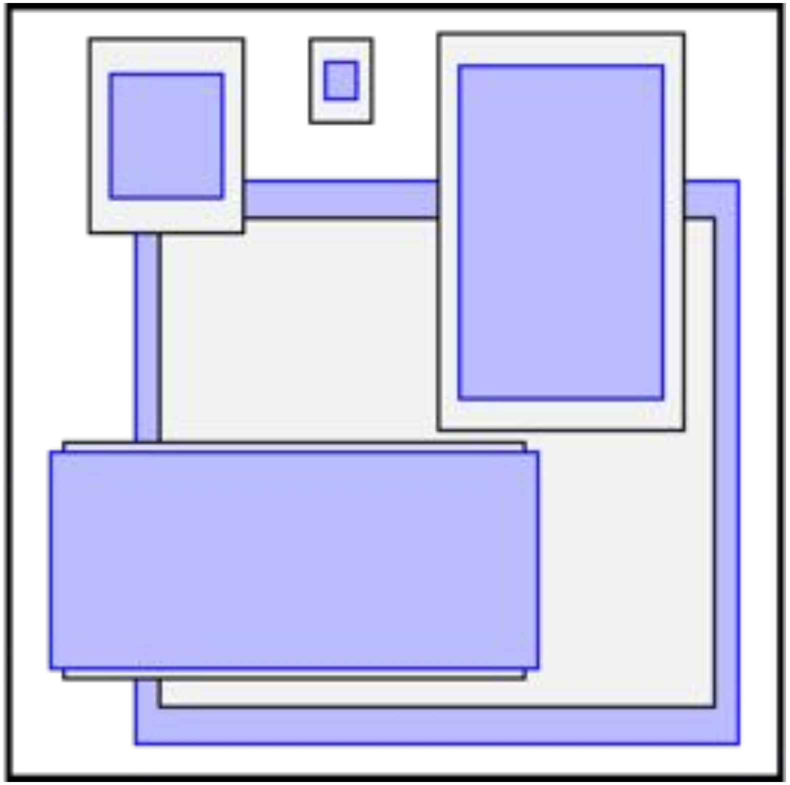
Ratios:

- 1x1
- 1x2
- 2x1

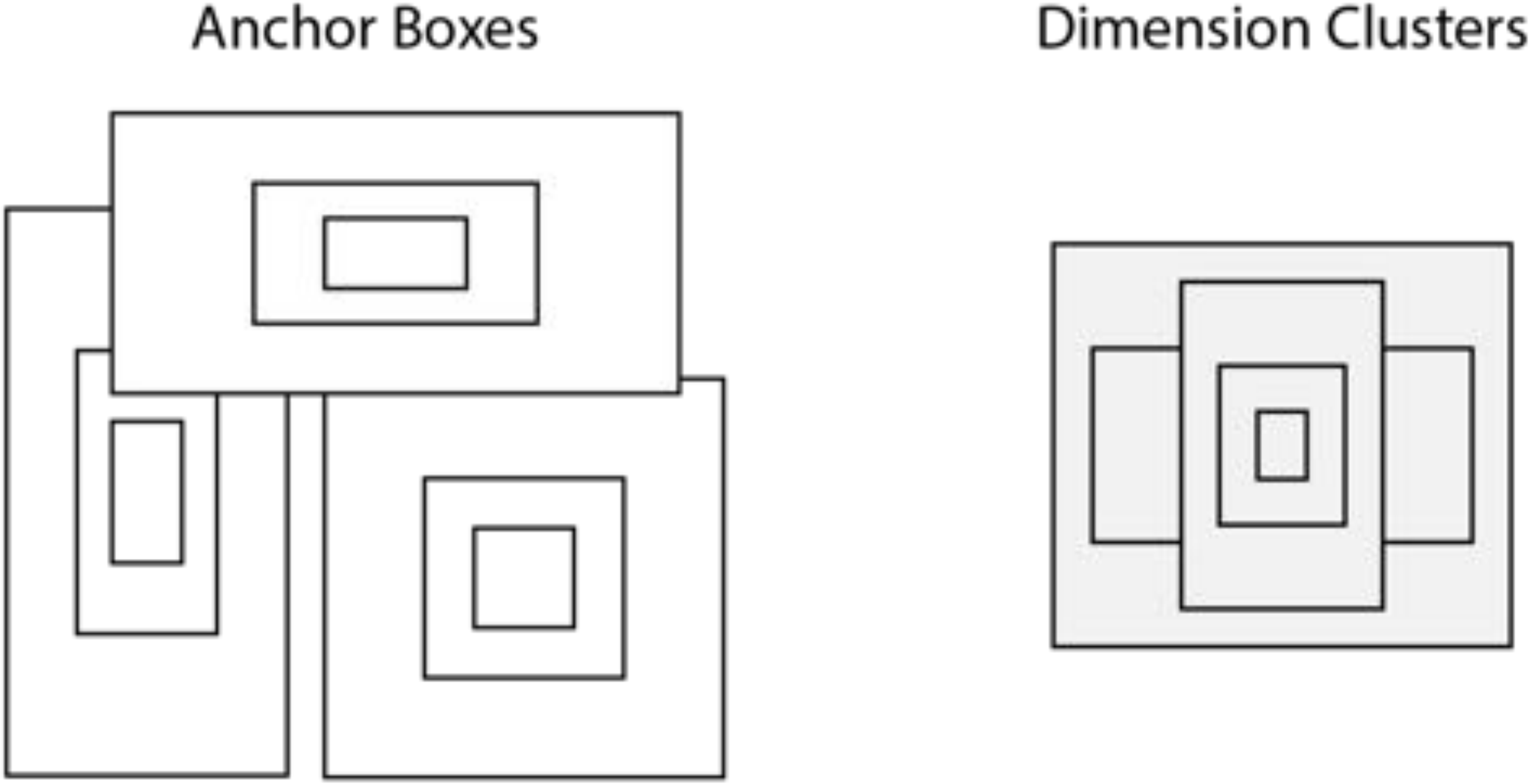
YOLOv2, YOLO9000

We use k-means to find better initializations



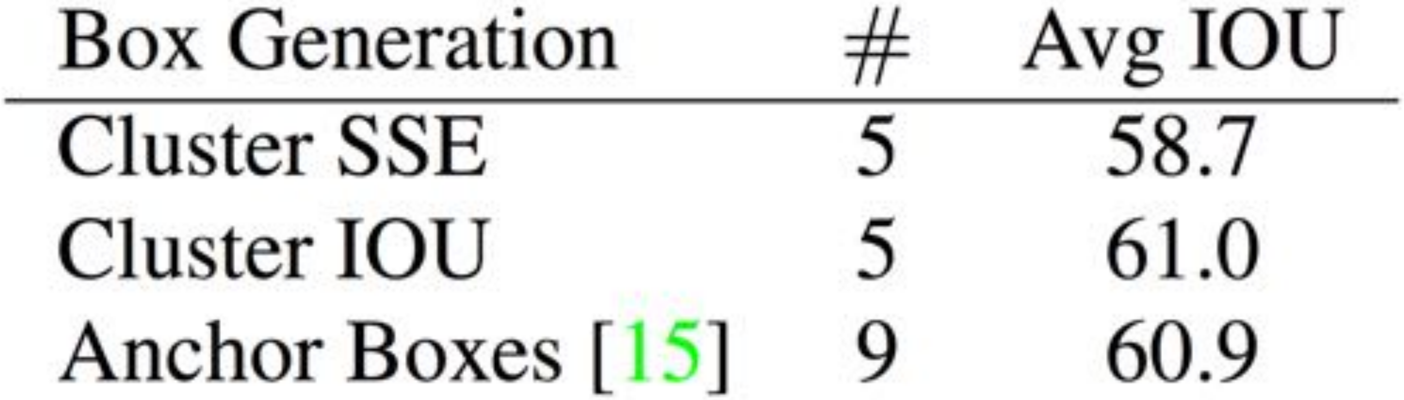


YOLOv2, YOLO9000



YOLOv2, YOLO9000

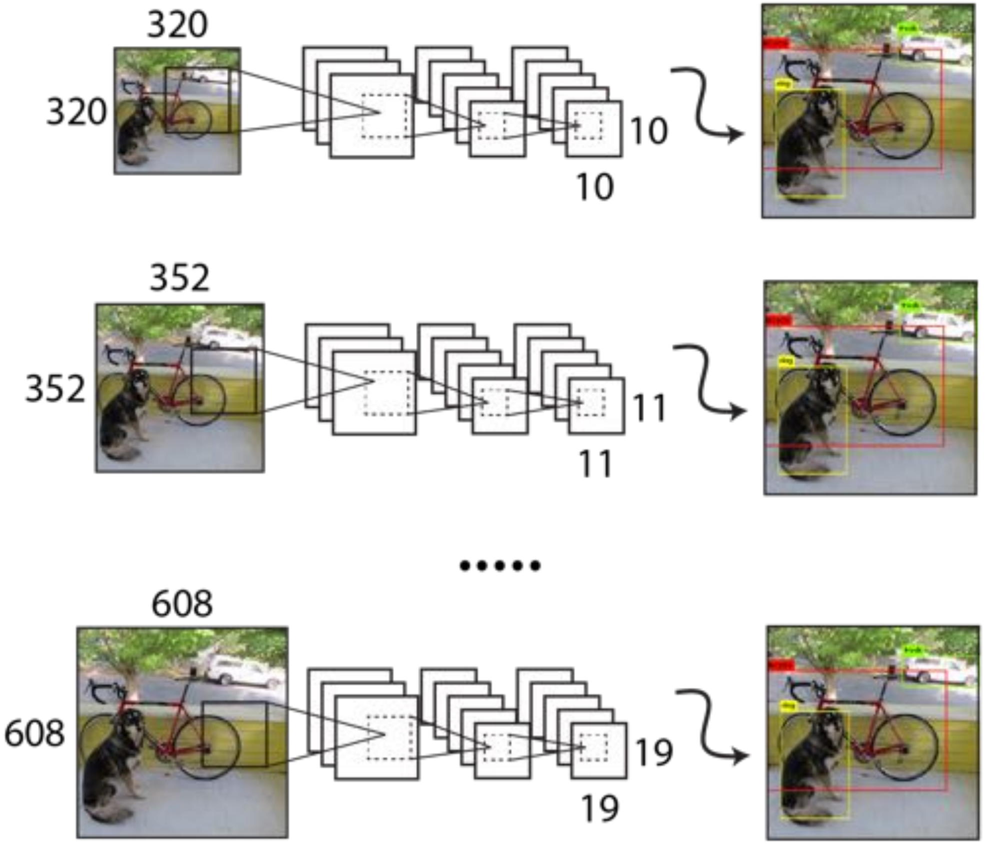
Dimension Clusters: +5% mAP



Box Generation	#	Avg IOU
Cluster SSE	5	58.7
Cluster IOU	5	61.0
Anchor Boxes [15]	9	60.9

YOLOv2, YOLO9000

Multi-scale training: +1.5% mAP



YOLOv2: Fast, Accurate Detection

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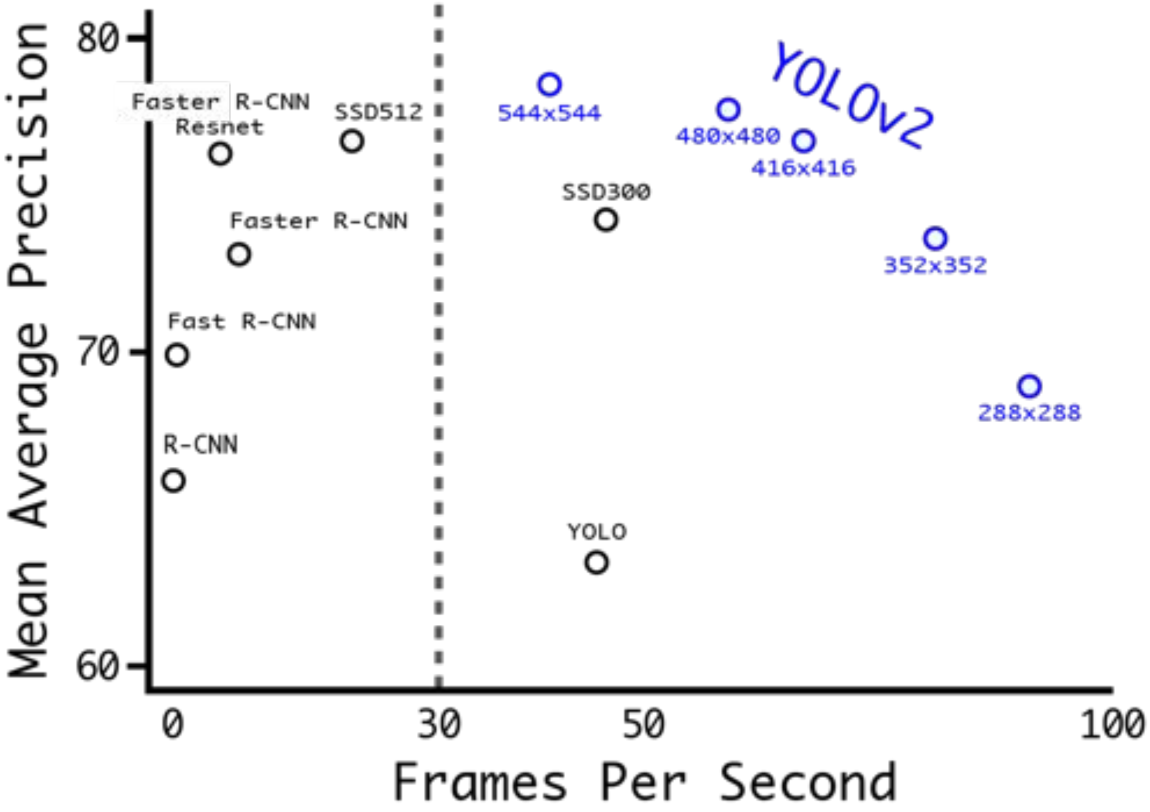
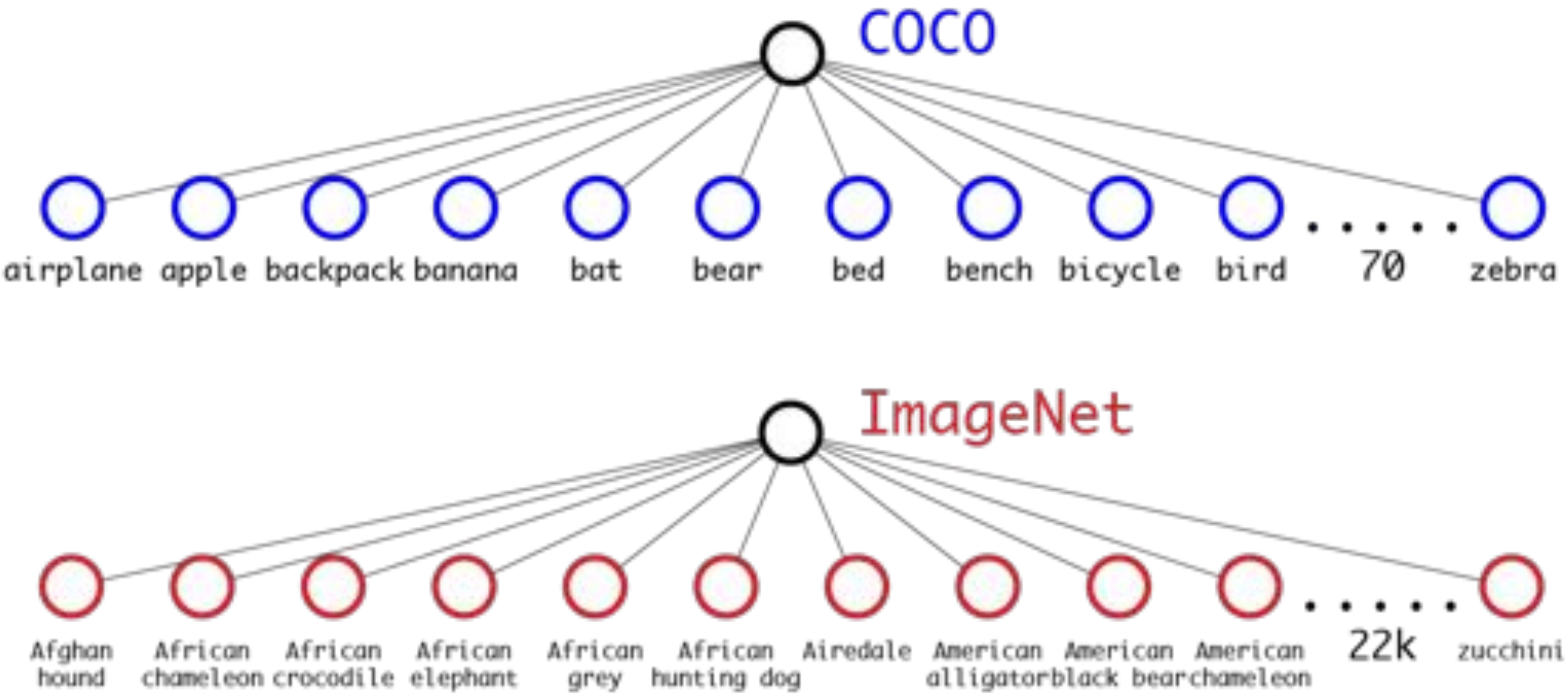


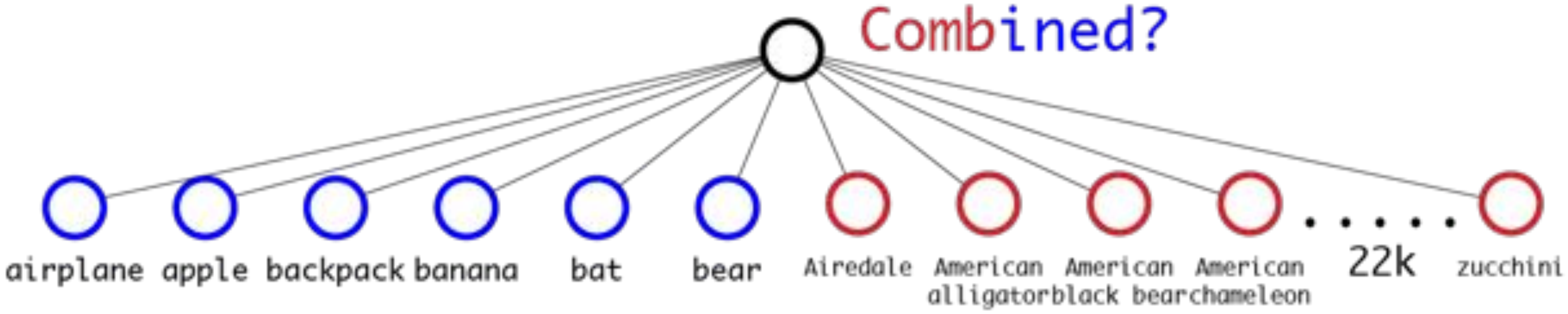
YOLOv2, YOLO9000

Typically use softmax over all classes



YOLOv2, YOLO9000

Can’t just mash classes together...



YOLOv2, YOLO9000

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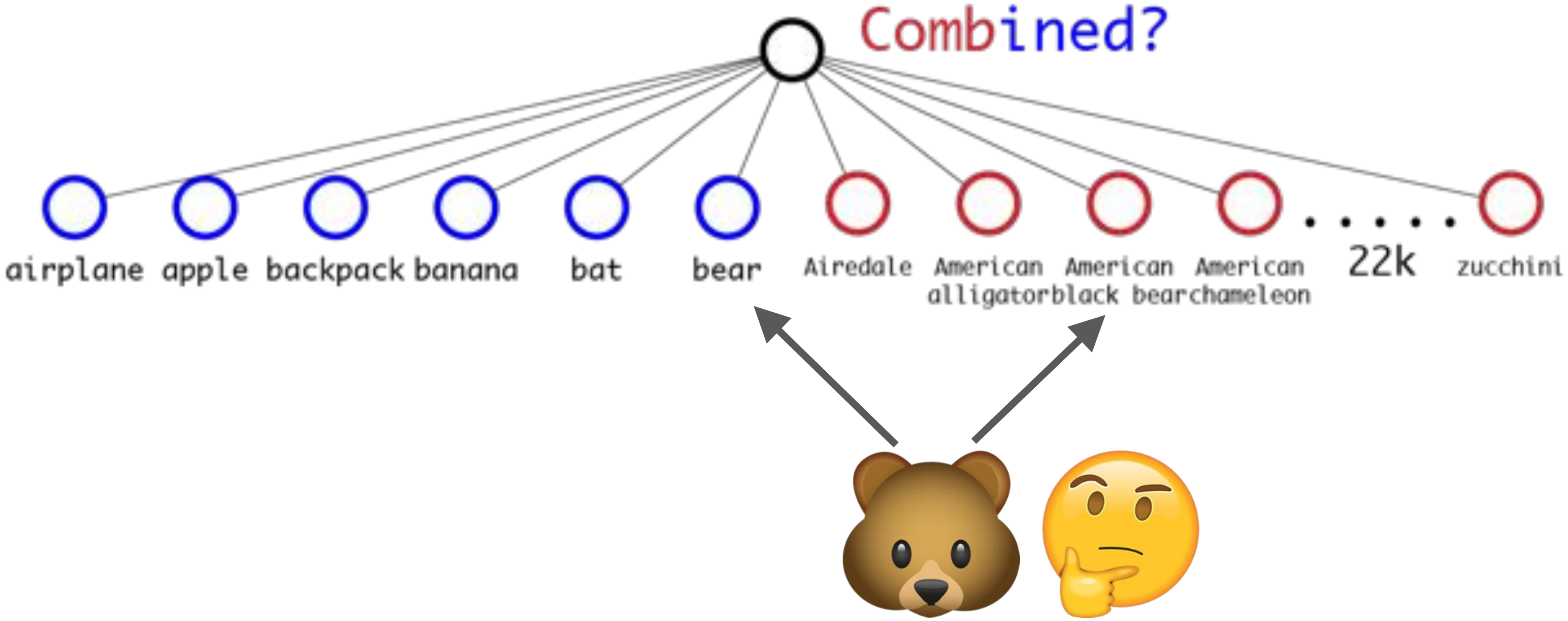
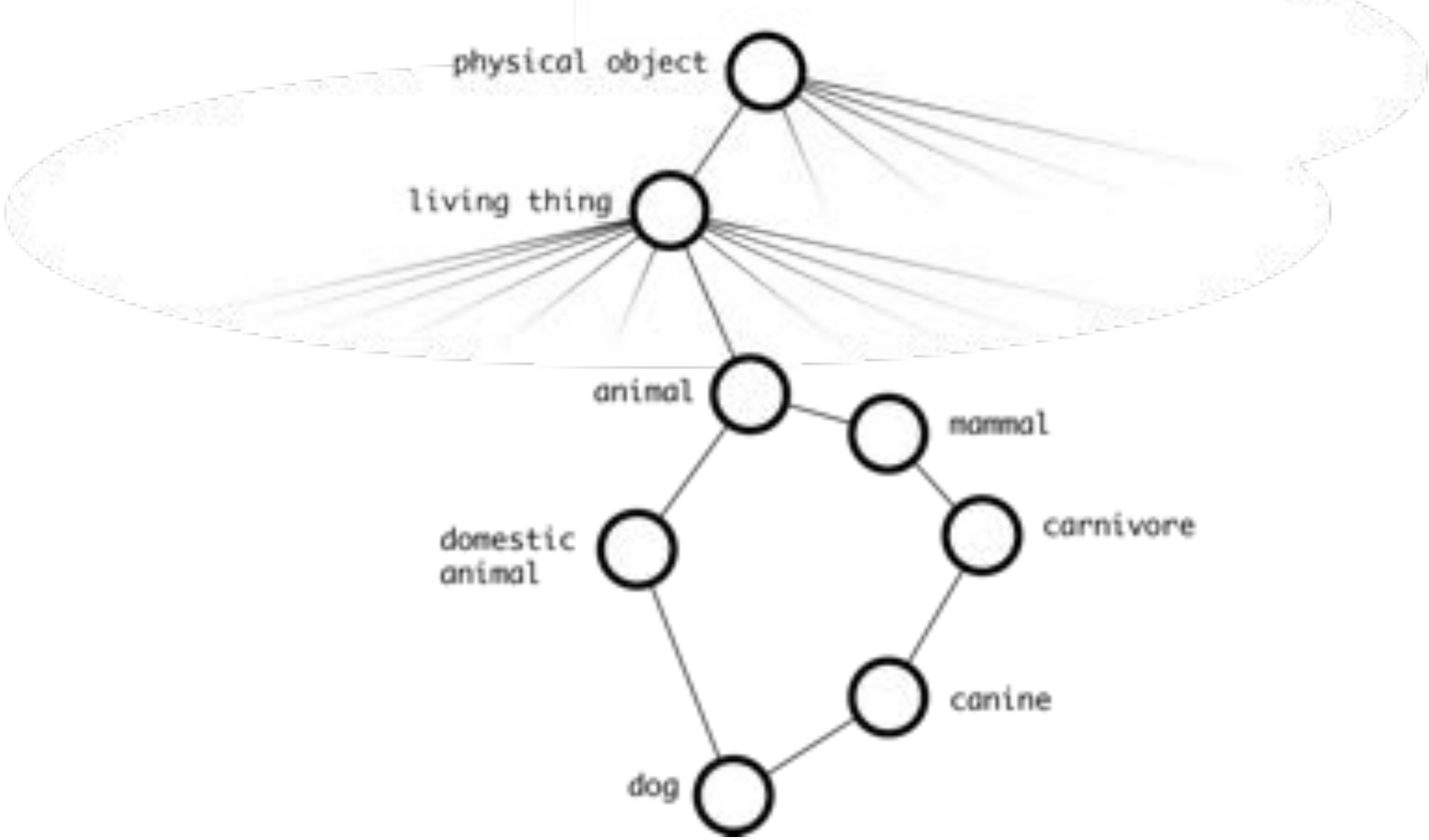
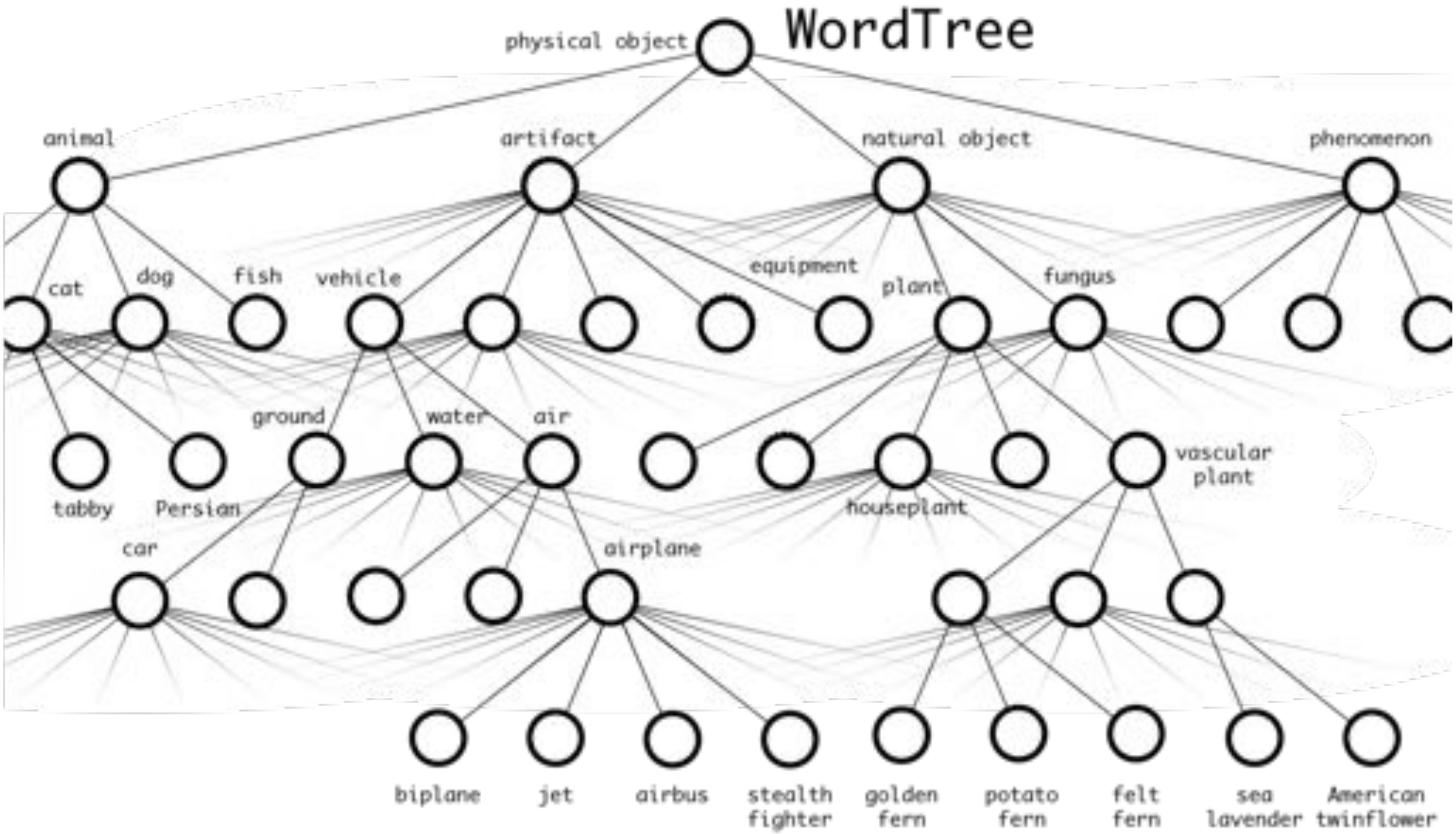


YOLOv2, YOLO9000

WordNet has structure but it's messy

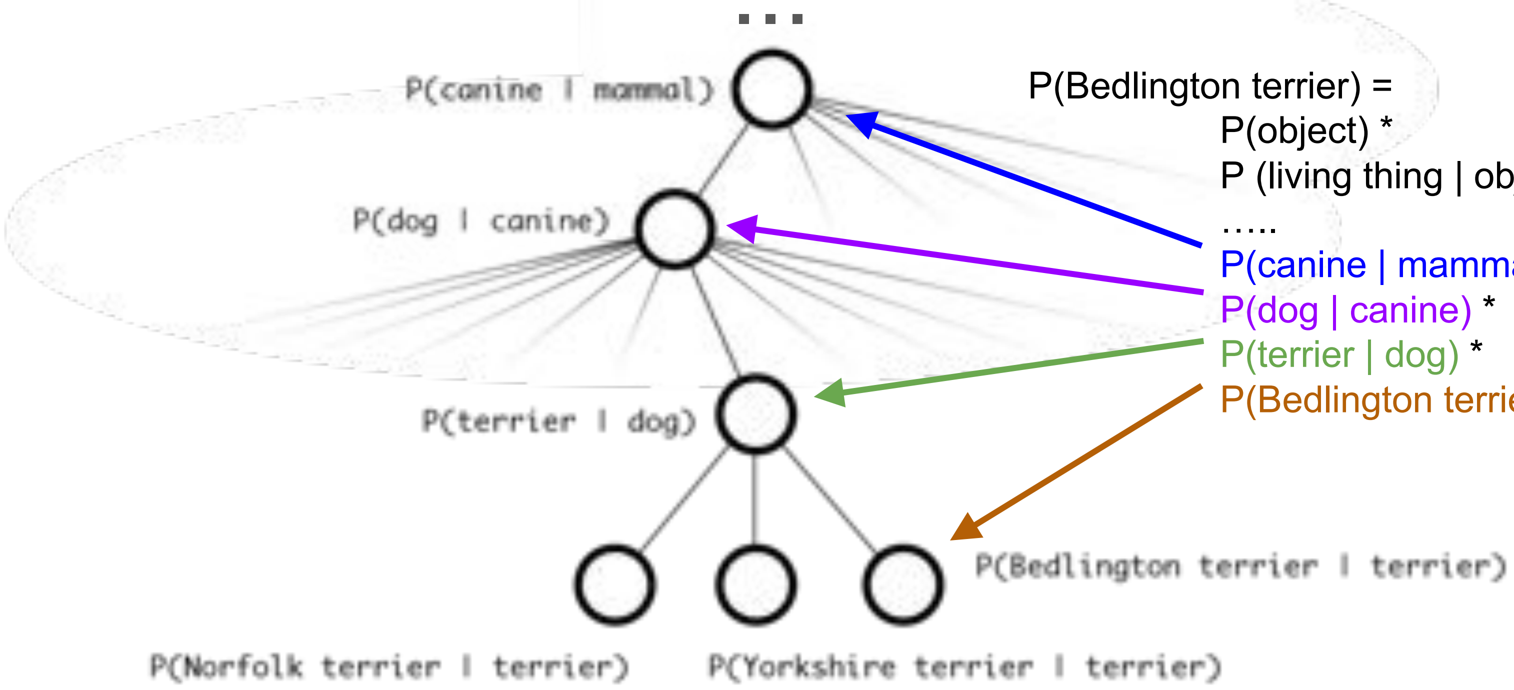


YOLOv2, YOLO9000



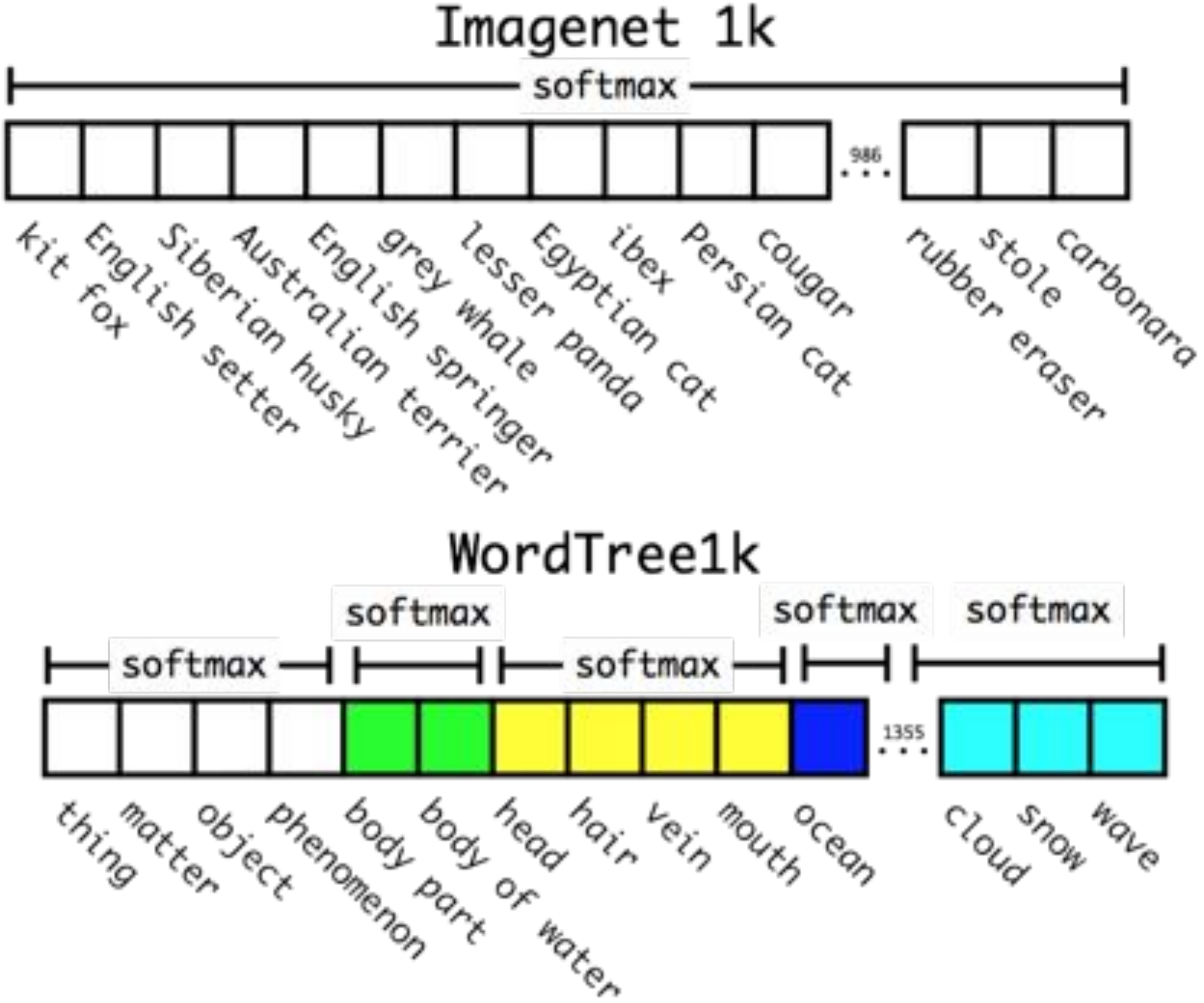
YOLOv2, YOLO9000

Each node is a conditional probability

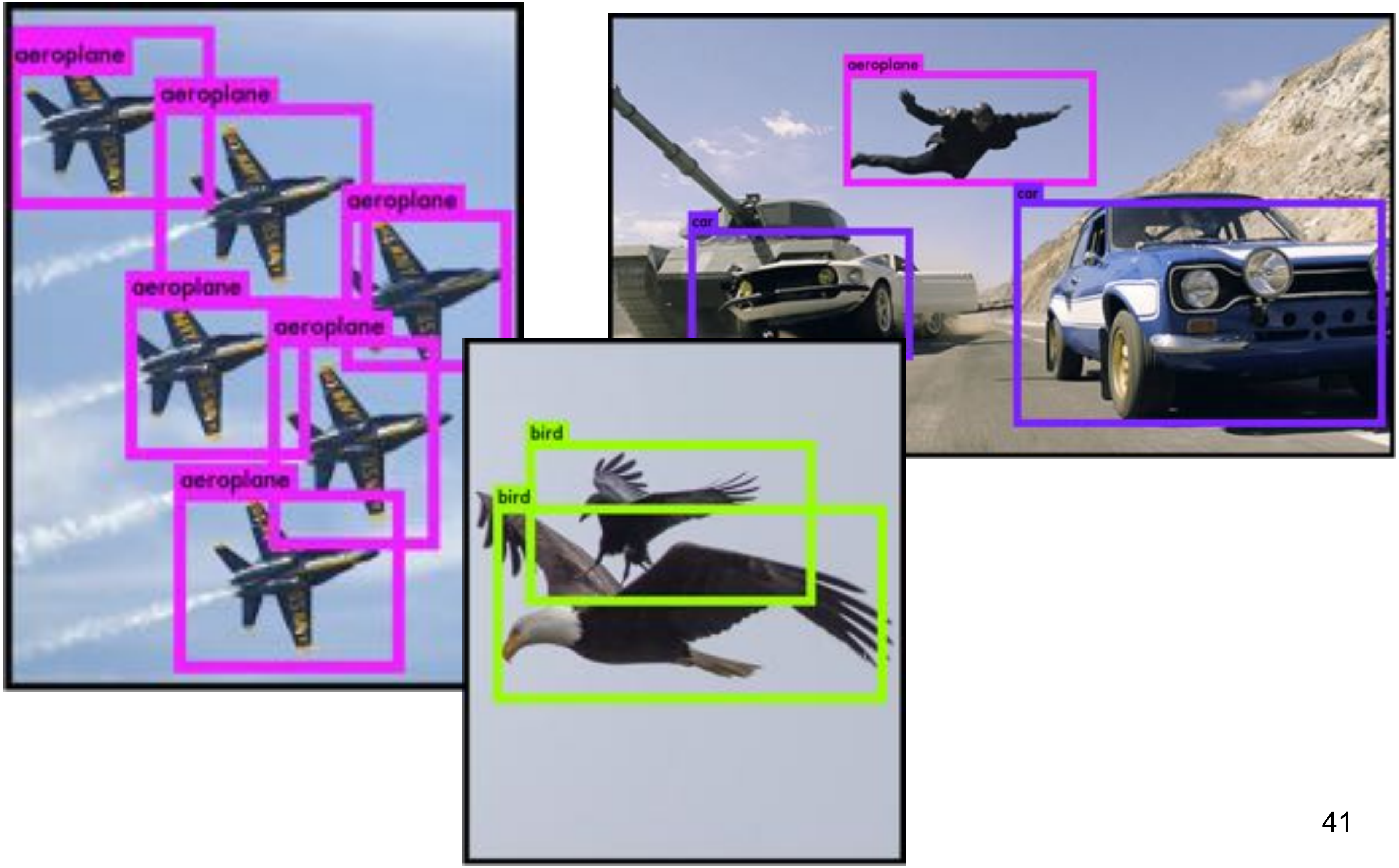

...
P(canine | mammal)
P(dog | canine)
P(terrier | dog)
P(Bedlington terrier | terrier)
P(Norfolk terrier | terrier)
P(Yorkshire terrier | terrier)

P(Bedlington terrier) =
P(object) *
P (living thing | object) *
…..
P(canine | mammal) *
P(dog | canine) *
P(terrier | dog) *
P(Bedlington terrier | terrier)

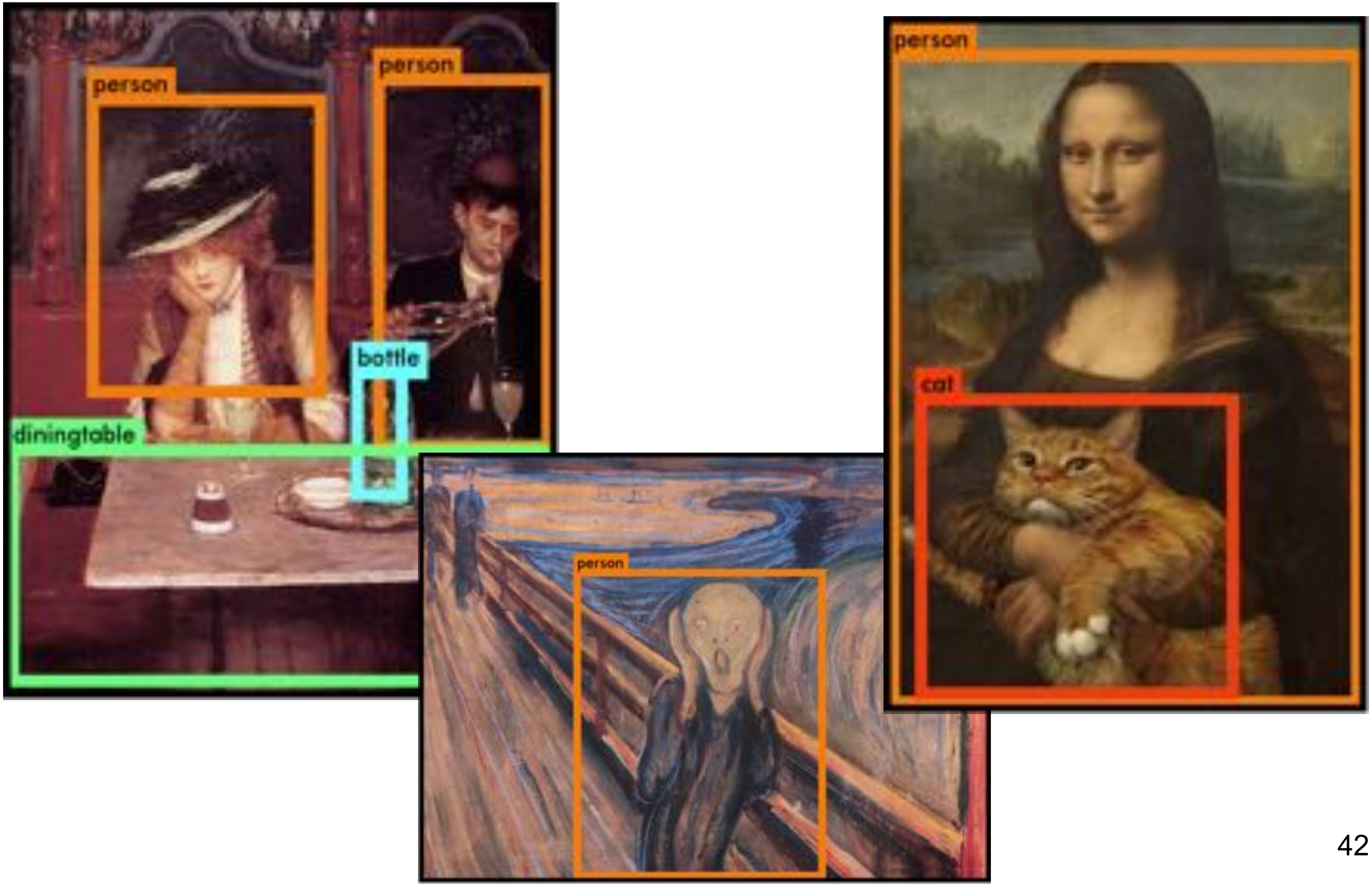
YOLOv2, YOLO9000



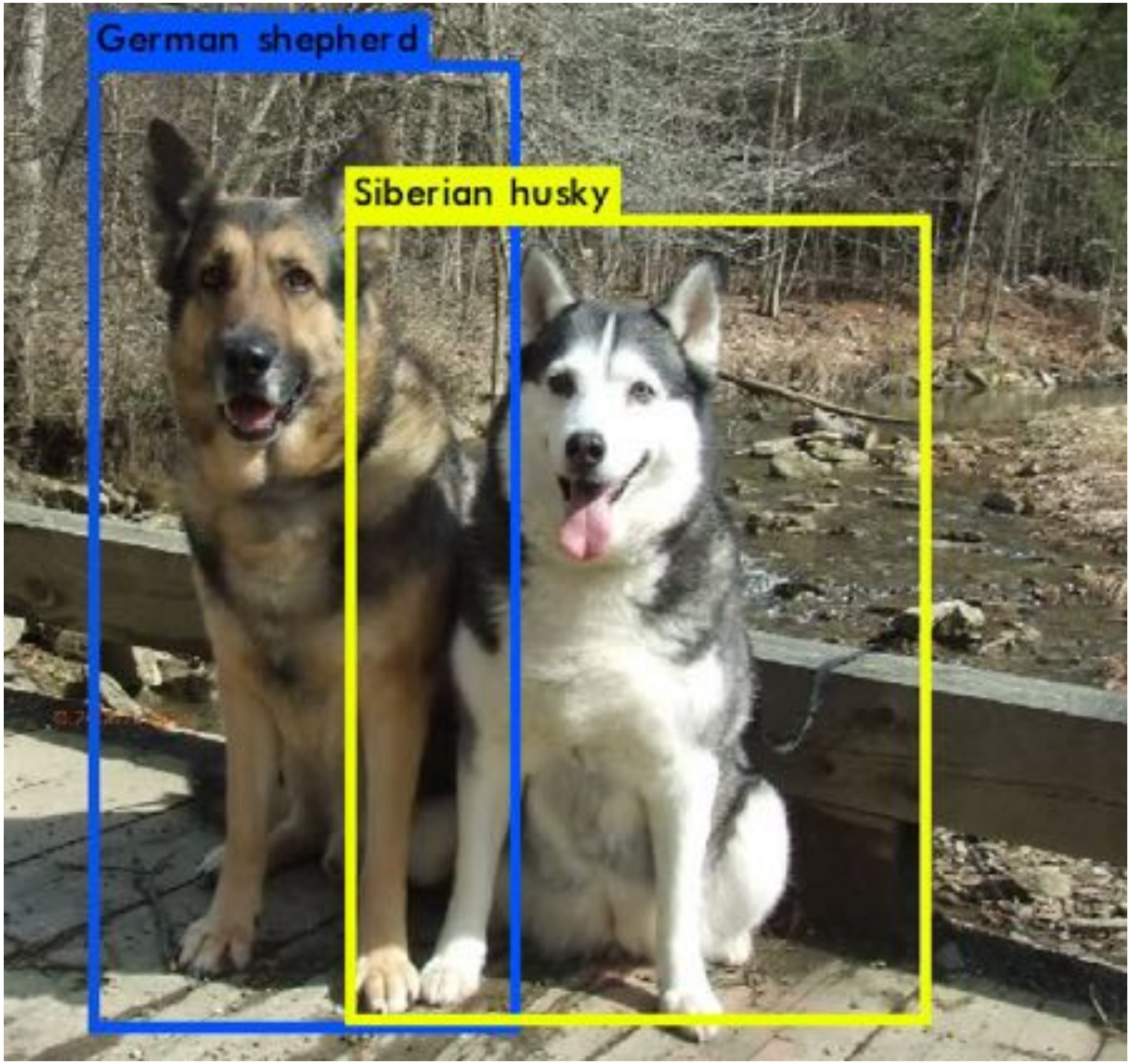
Experiments -- YOLO works across a variety of natural images

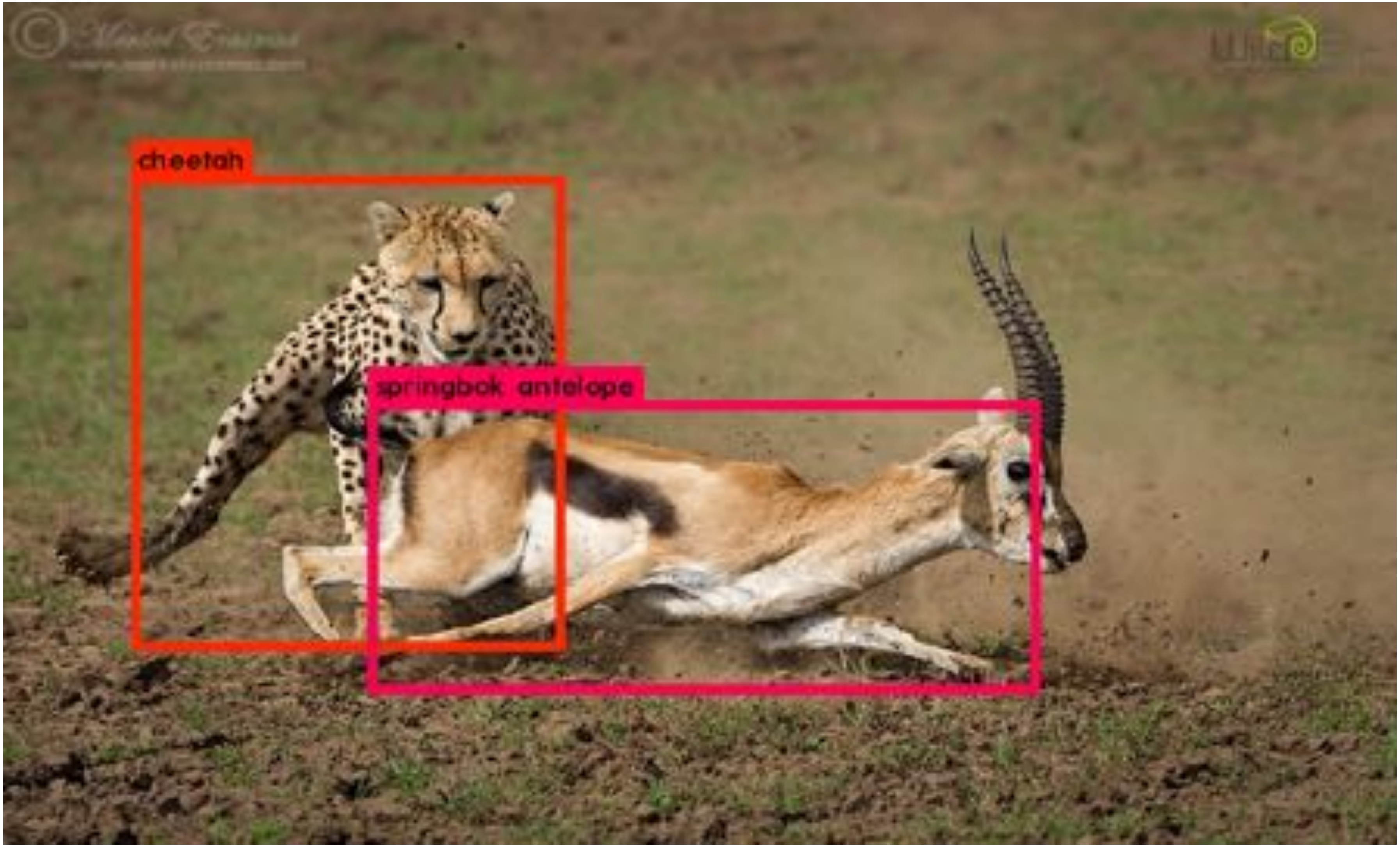


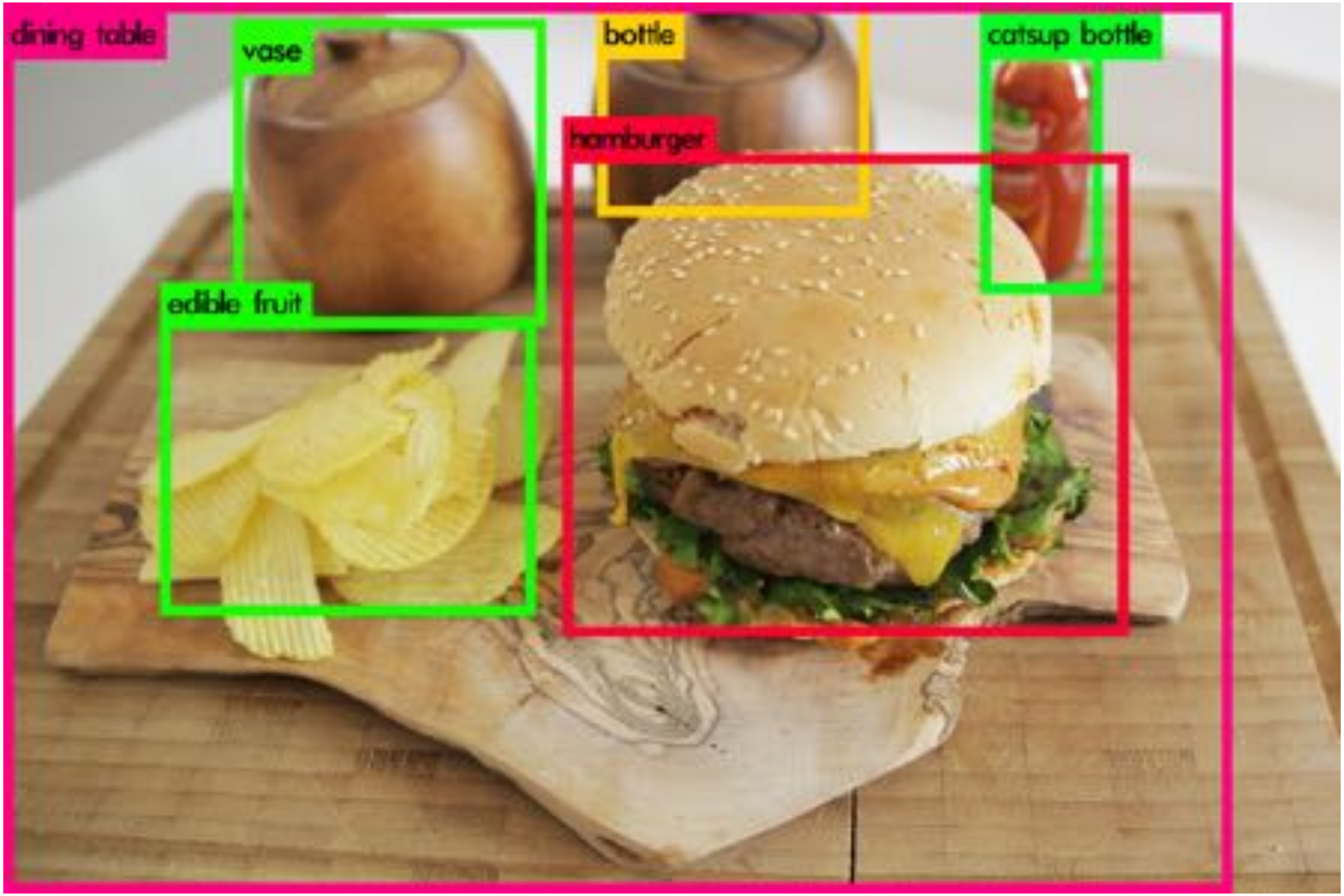
It also generalizes well to new domains (like art)

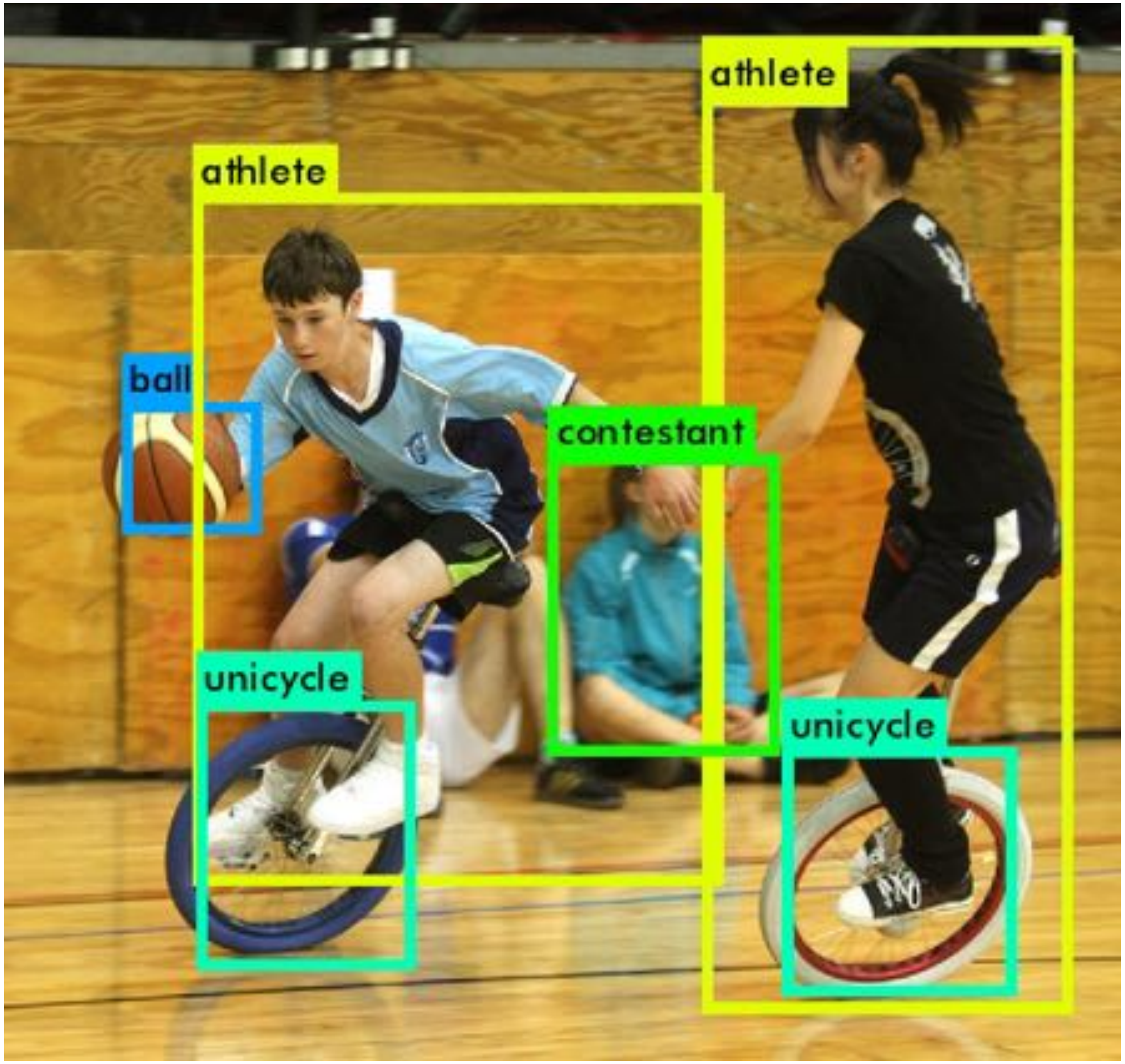


YOLOv2, YOLO9000




cheetah
springbok antelope


dining table
vase
bottle
catsup bottle
hamburger
edible fruit



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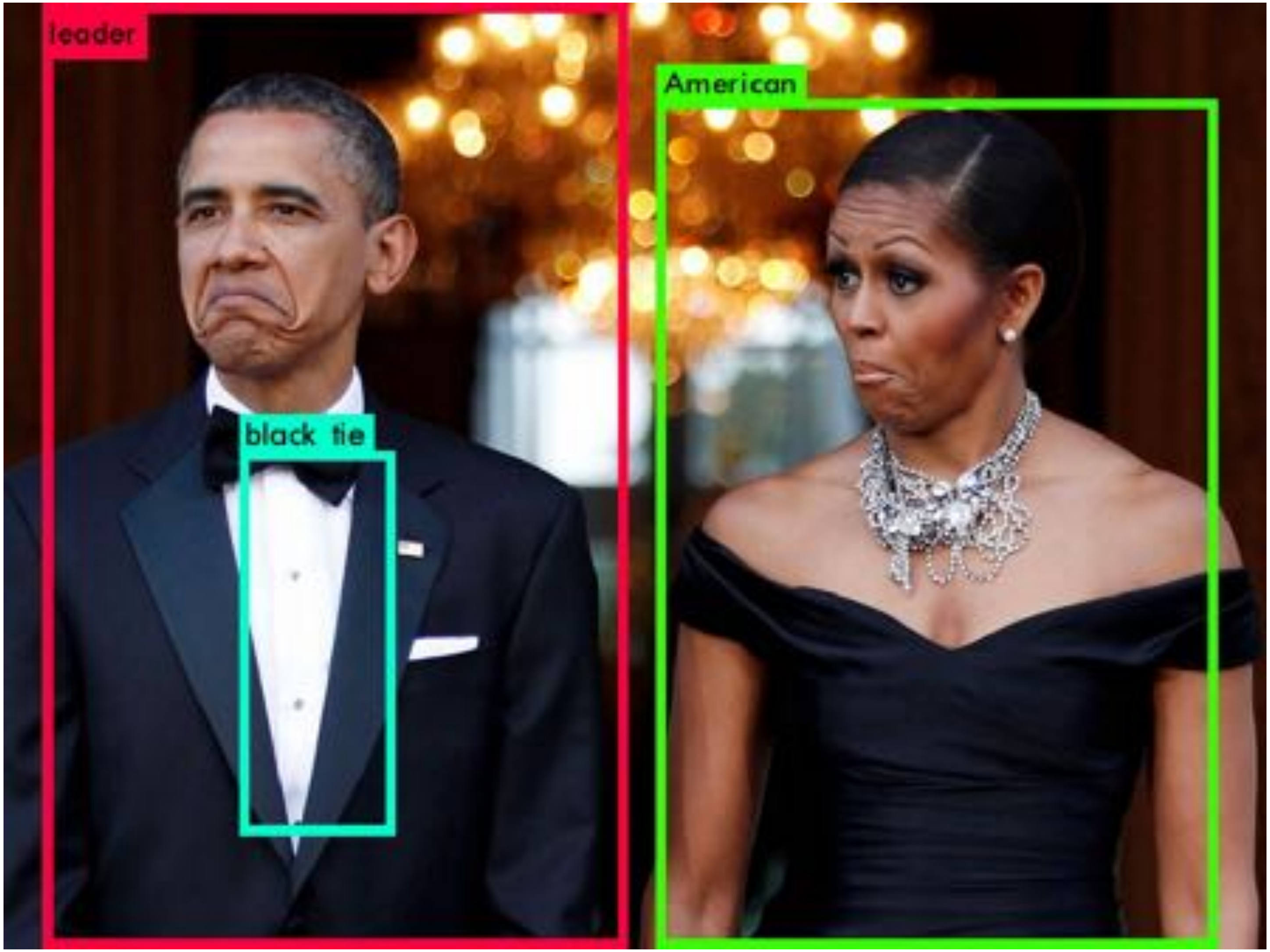
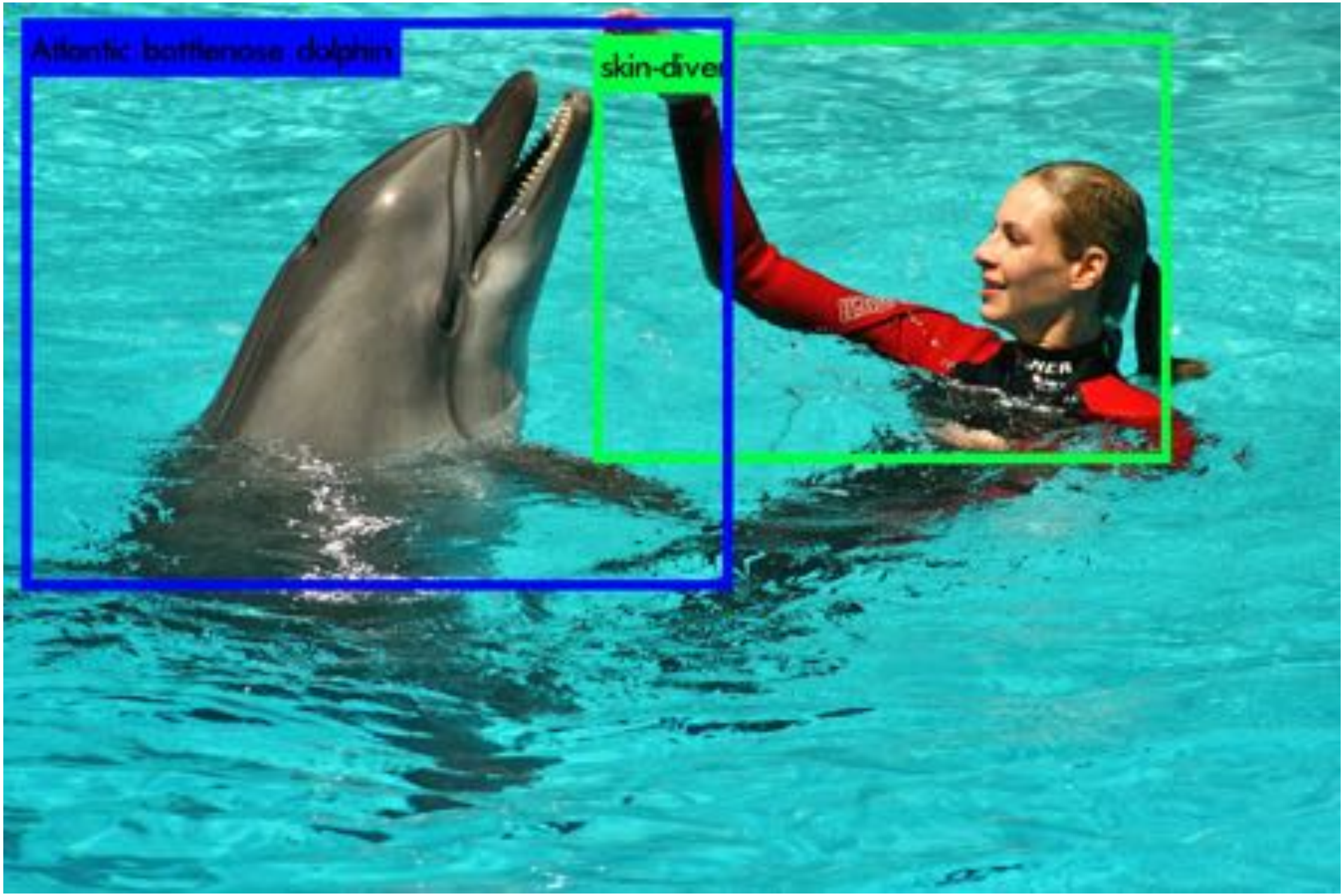
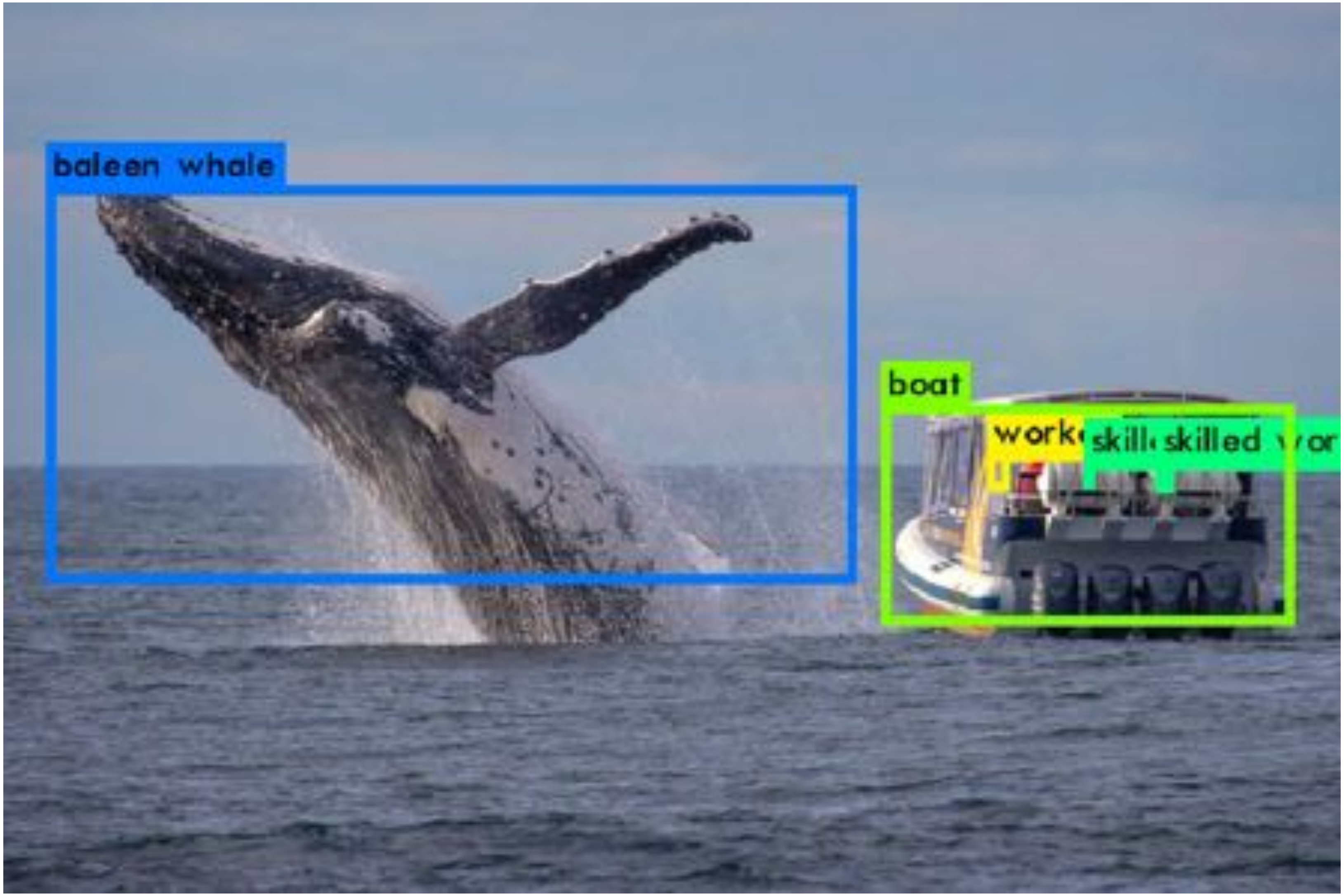
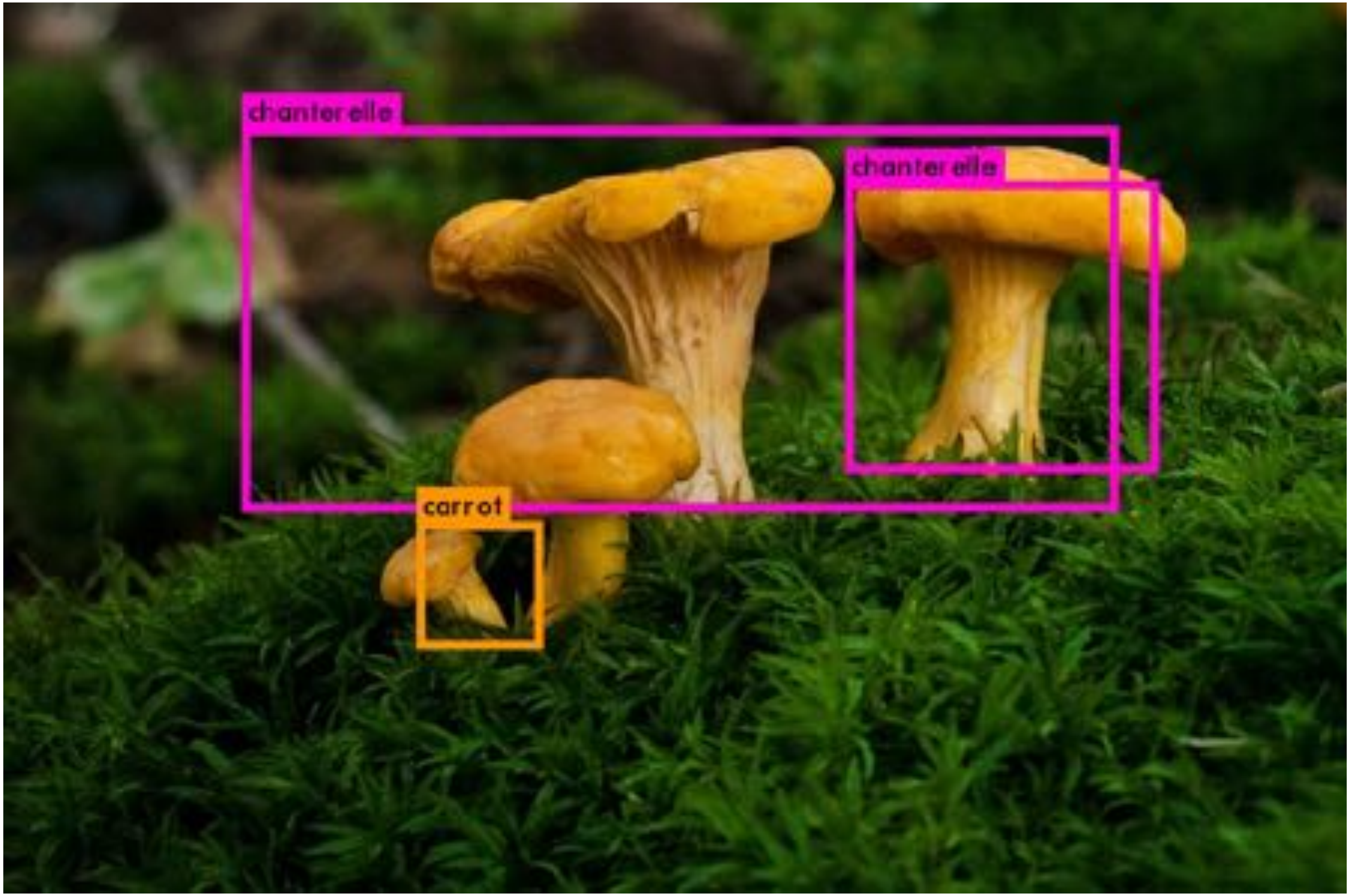

leader
American
black tie


Atlantic bottlenose dolphin
skin-diver


baleen whale
boat
work
skill
skilled wor



chanterelle
chanterelle
carrot

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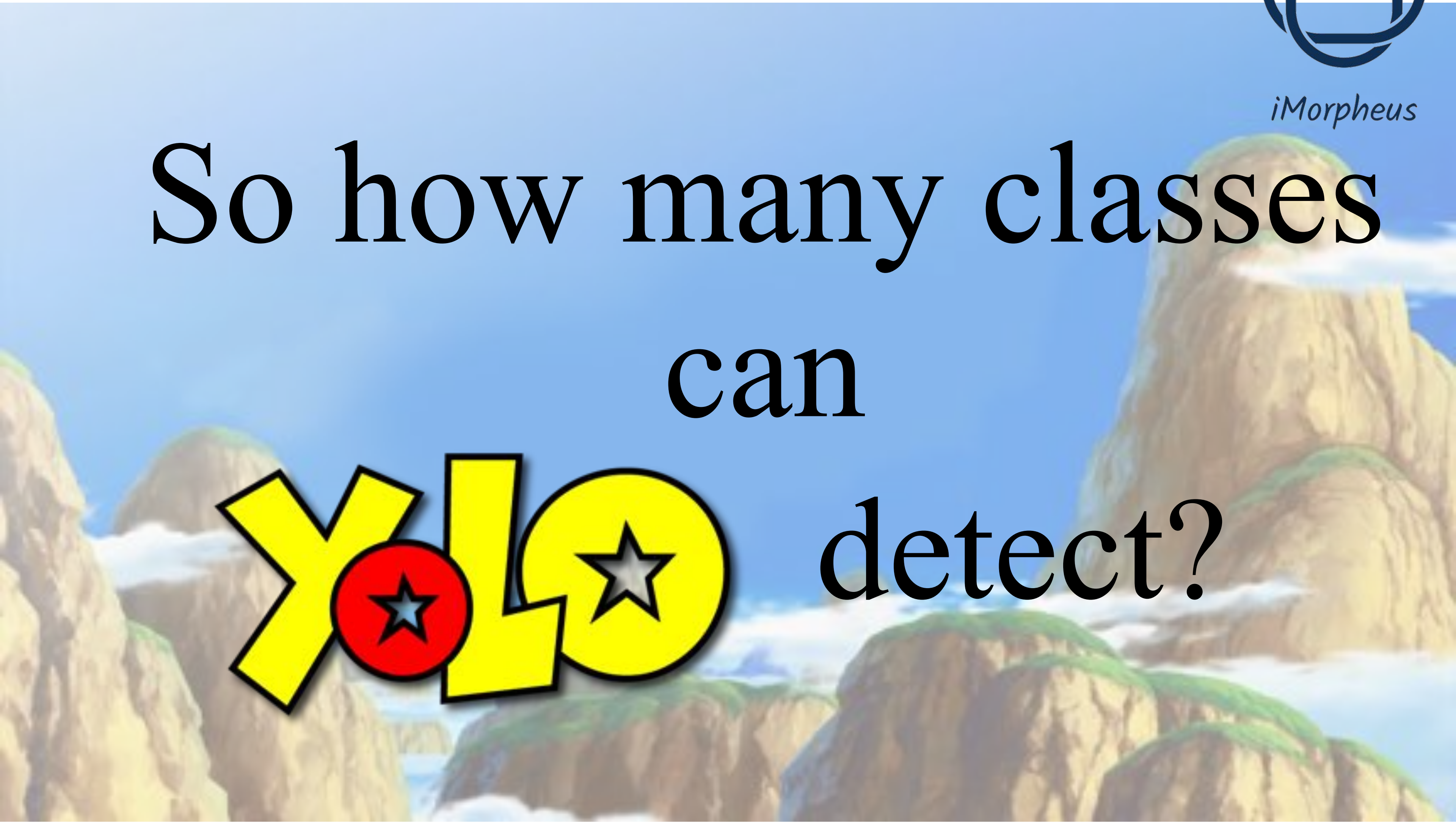

So how many classes can YOLO detect?

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Code, models, and updates:

https://pjreddie.com/yolo/

XNOR.AI

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