

Object Detection Overview

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May 30, 2025

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Object Detection: Challenges

Object detection is a complex task in computer vision that involves identifying and localizing objects within images.

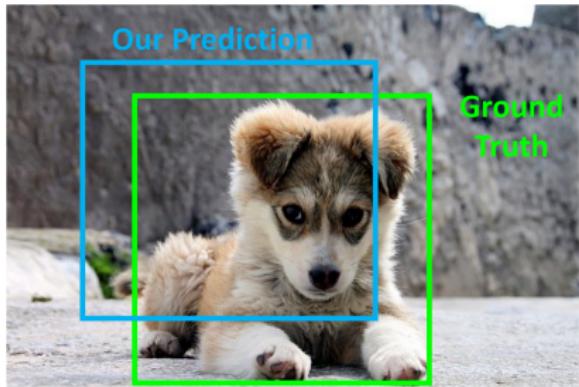
Unlike image classification, which assigns a single label to an entire image, object detection requires both identifying the objects present and determining their locations within the image.

This task presents several challenges that make it more difficult than classification:

- ▶ **Multiple outputs:** Need to output variable numbers of objects per image
- ▶ **Multiple types of output:** Need to predict "what" (category label) as well as "where" (bounding box)
- ▶ **Large images:** Classification works at 224x224; need higher resolution for detection, often $\sim 800 \times 600$

Comparing Boxes: Intersection over Union (IoU)

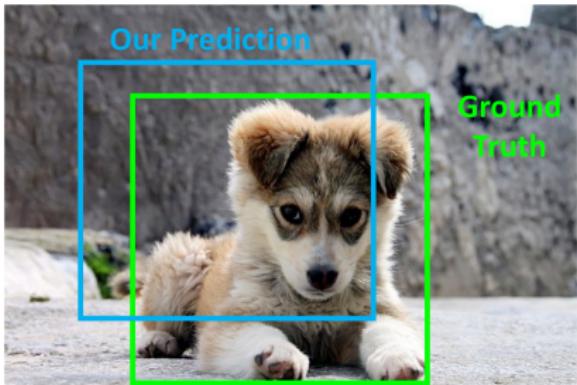
- ▶ How can we compare our prediction to the ground-truth box?



Comparing Boxes: Intersection over Union (IoU)

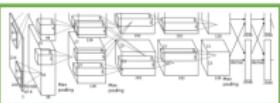
- ▶ How can we compare our prediction to the ground-truth box?
- ▶ **Intersection over Union (IoU)**
(Also called "Jaccard similarity" or "Jaccard index"):

$$\frac{\text{Area of Intersection}}{\text{Area of Union}}$$



Detecting a Single Object

Often pretrained
on ImageNet
(Transfer learning)



Vector:
4096

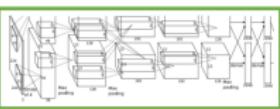
This image is CC0 public domain

Treat localization as a
regression problem!

Detecting a Single Object (cont.)



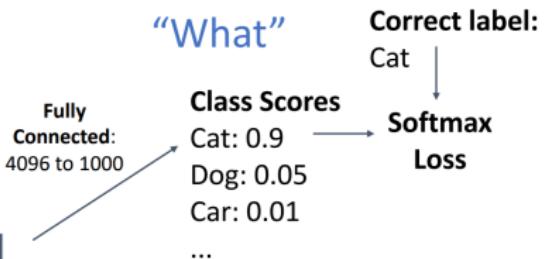
Often pretrained
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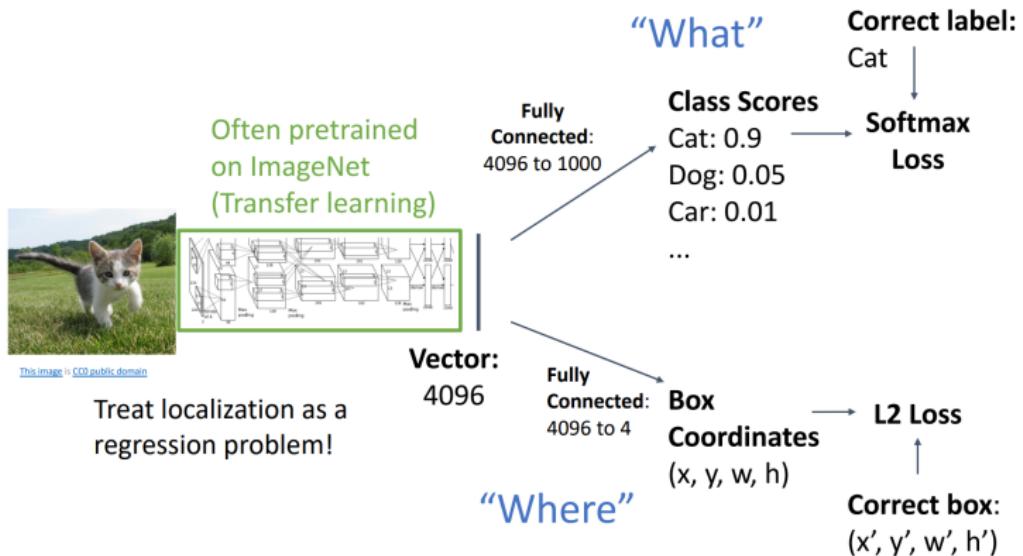
This image is CC0 public domain

Treat localization as a
regression problem!

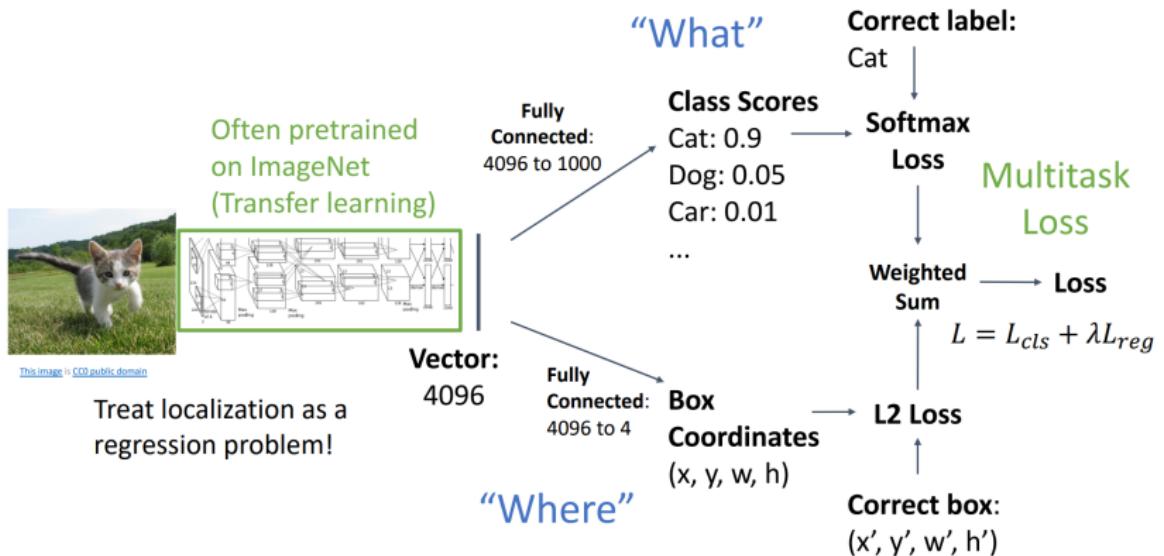
Vector:
4096



Detecting a Single Object (cont.)



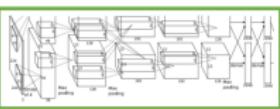
Detecting a Single Object (cont.)



Detecting a Single Object (cont.)



Often pretrained
on ImageNet
(Transfer learning)

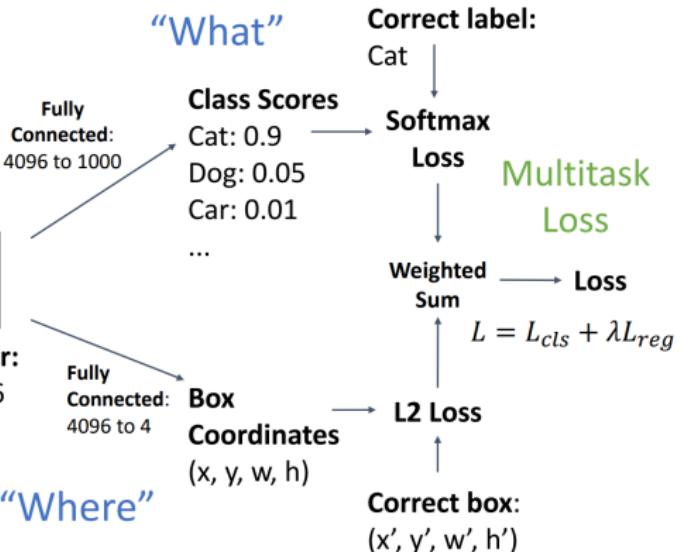


This image is CC0 public domain

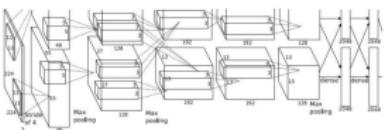
Treat localization as a
regression problem!

Problem: Images can have
more than one object!

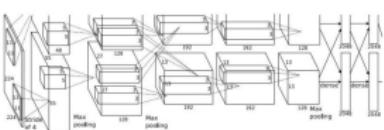
Vector:
4096



Multiple Objects



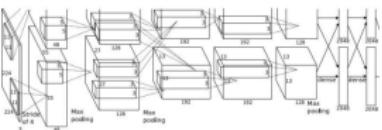
CAT: (x, y, w, h)



DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)



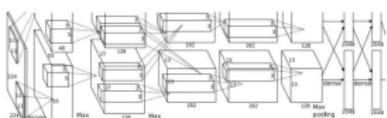
DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

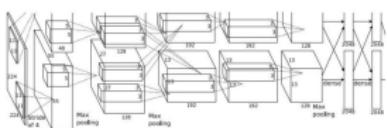
....

Multiple Objects (cont.)

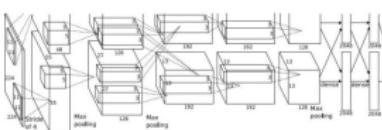
Each image needs a different number of outputs!



CAT: (x, y, w, h) **4 numbers**



DOG: (x, y, w, h)
DOG: (x, y, w, h) **12 numbers**
CAT: (x, y, w, h)



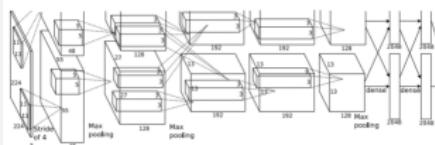
DUCK: (x, y, w, h) **Many**
DUCK: (x, y, w, h) **numbers!**

....

Detecting Multiple Objects: Sliding Window



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

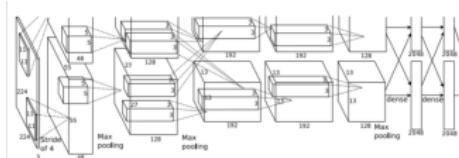


Dog? NO
Cat? NO
Background? YES

Detecting Multiple Objects: Sliding Window (cont.)



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

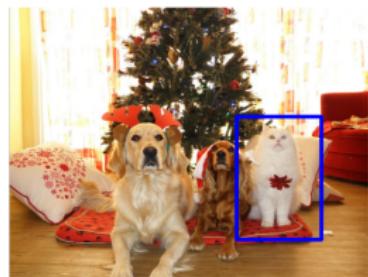


Dog? YES

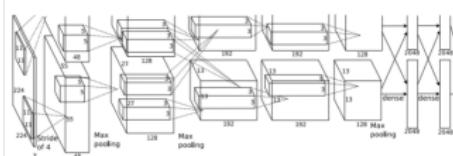
Cat? NO

Background? NO

Detecting Multiple Objects: Sliding Window (cont.)



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

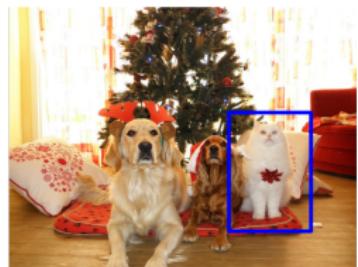


Dog? NO

Cat? YES

Background? NO

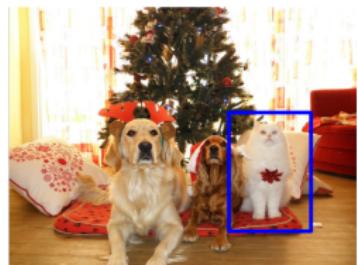
Detecting Multiple Objects: Sliding Window (cont.)



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

Question: How many possible boxes are there in an image of size $H \times W$?

Detecting Multiple Objects: Sliding Window (cont.)



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

Question: How many possible boxes are there in an image of size $H \times W$?

Consider a box of size $h \times w$:

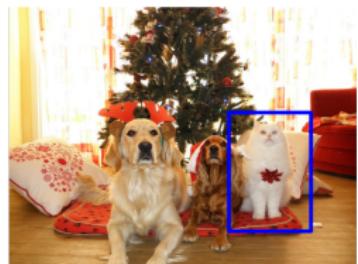
Possible x positions: $W - w + 1$

Possible y positions: $H - h + 1$

Possible positions:

$$(W - w + 1) * (H - h + 1)$$

Detecting Multiple Objects: Sliding Window (cont.)



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

Question: How many possible boxes are there in an image of size $H \times W$?

Consider a box of size $h \times w$:

Possible x positions: $W - w + 1$

Possible y positions: $H - h + 1$

Possible positions:

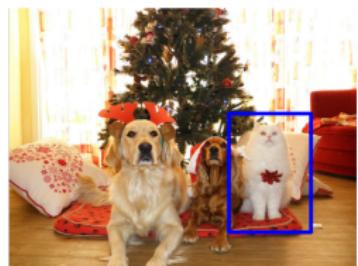
$$(W - w + 1) * (H - h + 1)$$

Total possible boxes:

$$\sum_{h=1}^H \sum_{w=1}^W (W - w + 1)(H - h + 1)$$

$$= \frac{H(H + 1)}{2} \frac{W(W + 1)}{2}$$

Detecting Multiple Objects: Sliding Window (cont.)



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

800 x 600 image
has ~58M boxes!
No way we can evaluate them all

Question: How many possible boxes are there in an image of size $H \times W$?

Consider a box of size $h \times w$:

Possible x positions: $W - w + 1$

Possible y positions: $H - h + 1$

Possible positions:

$$(W - w + 1) * (H - h + 1)$$

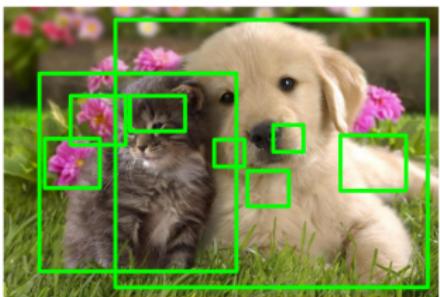
Total possible boxes:

$$\sum_{h=1}^H \sum_{w=1}^W (W - w + 1)(H - h + 1)$$

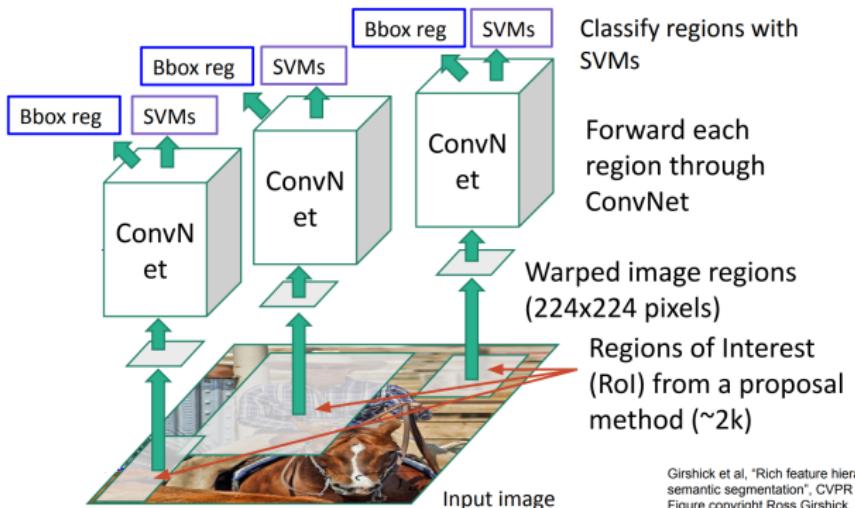
$$= \frac{H(H+1)}{2} \frac{W(W+1)}{2}$$

Region Proposal

- ▶ Find a small set of boxes that are likely to cover all objects
- ▶ Often based on heuristics: e.g. look for “blob-like” image regions
- ▶ Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



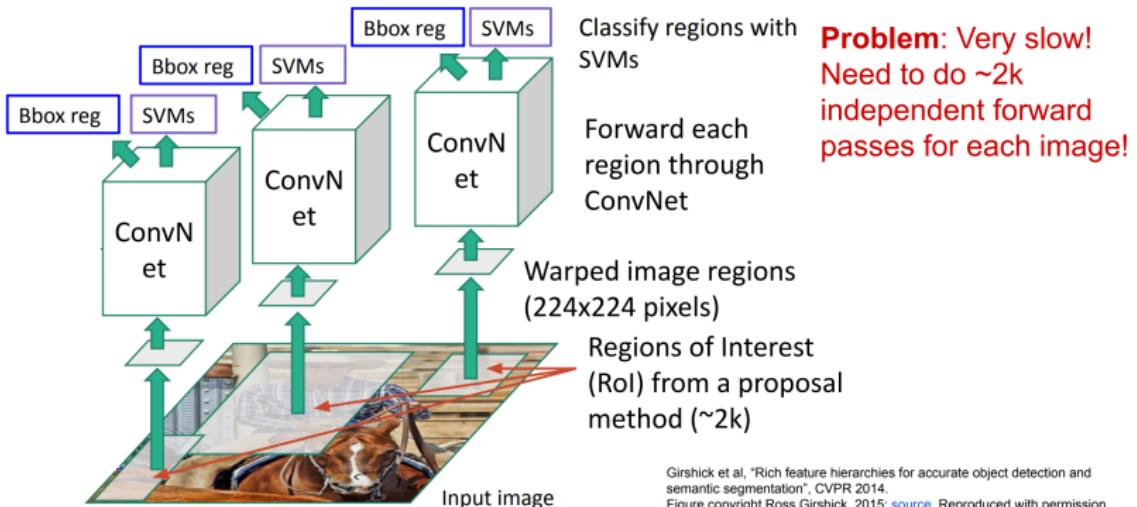
Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN (cont.)

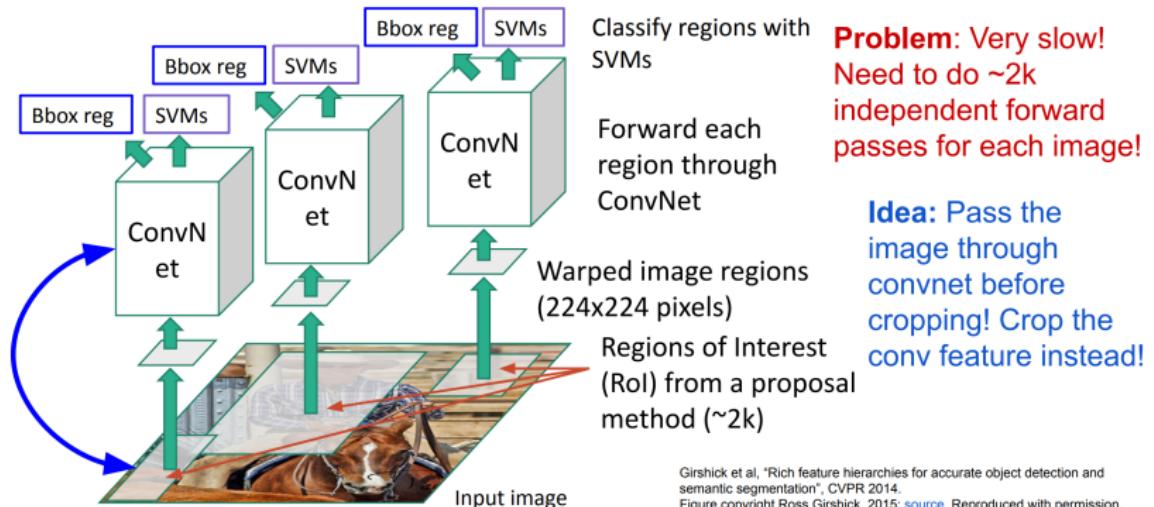
Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)



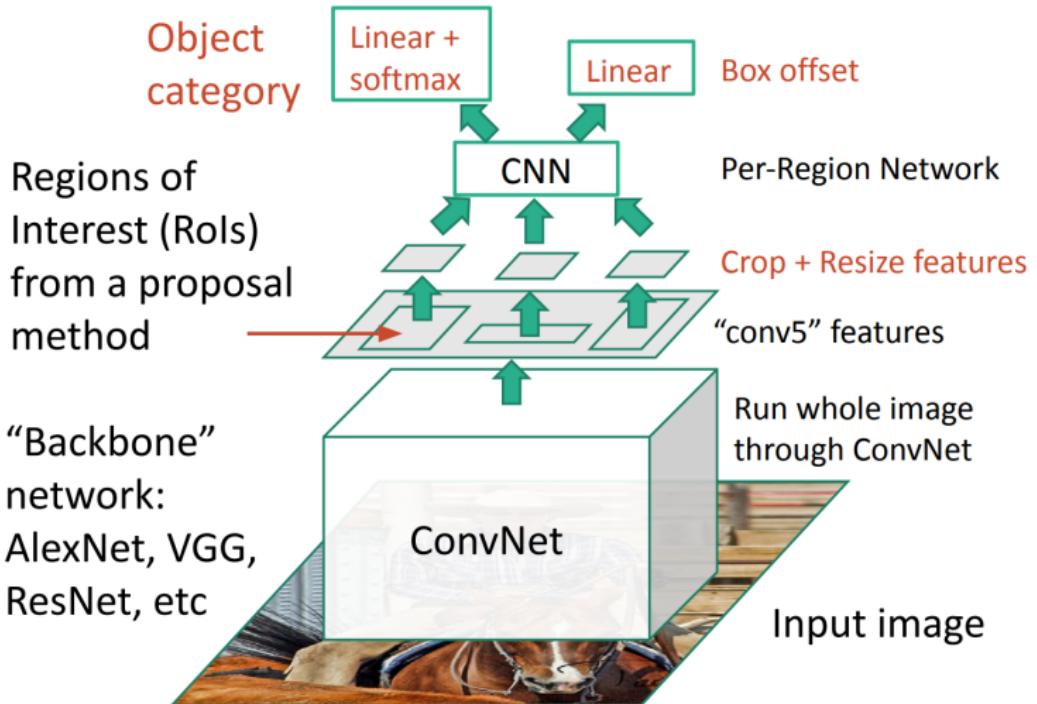
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN (cont.)

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)

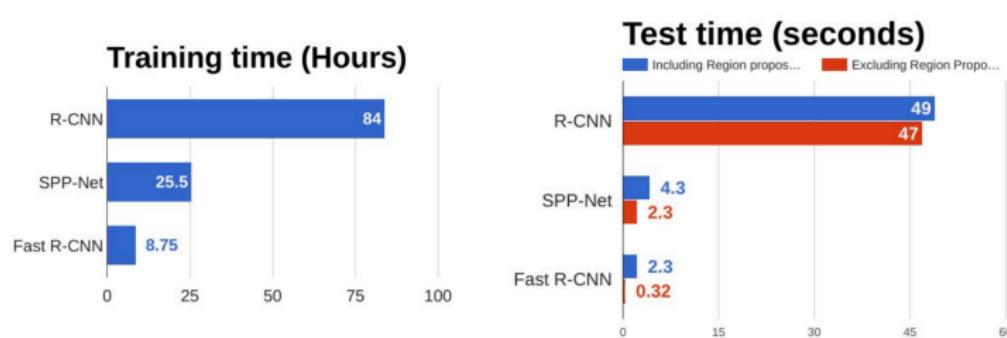


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

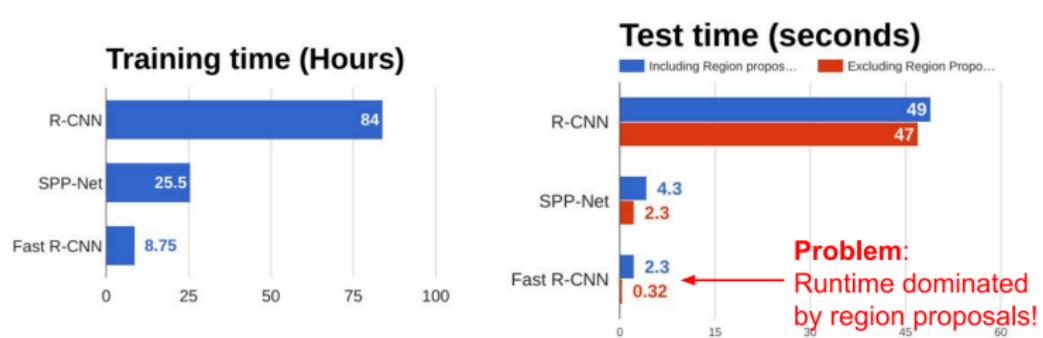


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN (cont.)



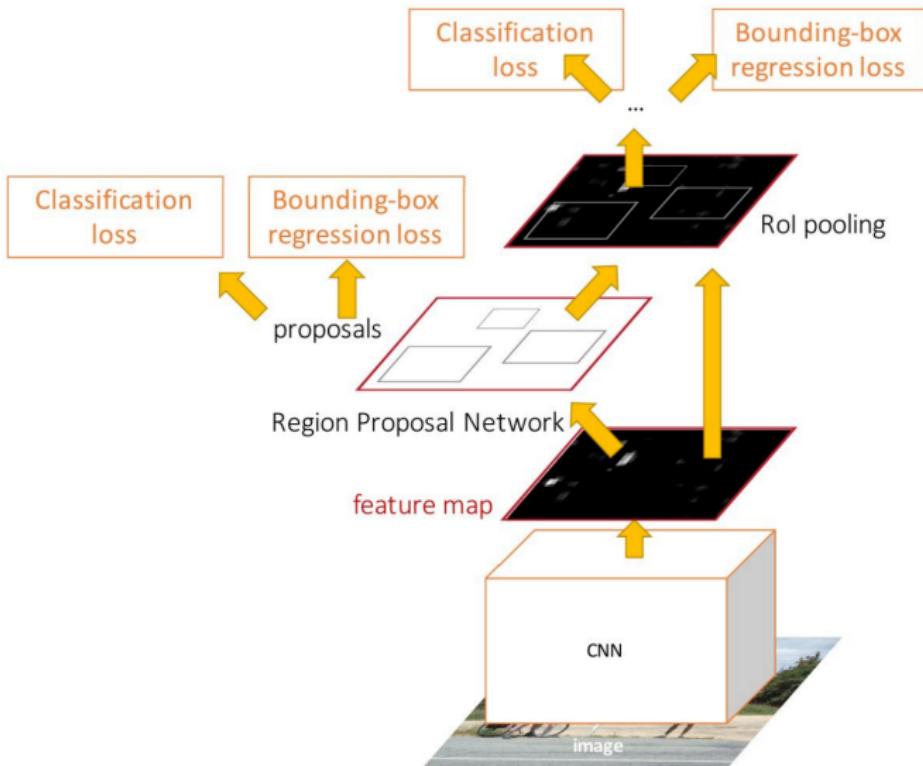
Fast R-CNN (cont.)



- ▶ Make CNN do proposals!
- ▶ Insert Region Proposal Network (RPN) to predict proposals from features

- ▶ Make CNN do proposals!
- ▶ Insert Region Proposal Network (RPN) to predict proposals from features
- ▶ Jointly train on 4 losses:
 - **RPN classification:** anchor box is object / not an object
 - **RPN regression:** predict transform from anchor box to proposal box
 - **Object classification:** classify proposals as background / object class
 - **Object regression:** predict transform from proposal box to object box

Faster R-CNN



Faster R-CNN: Make CNN do proposals!

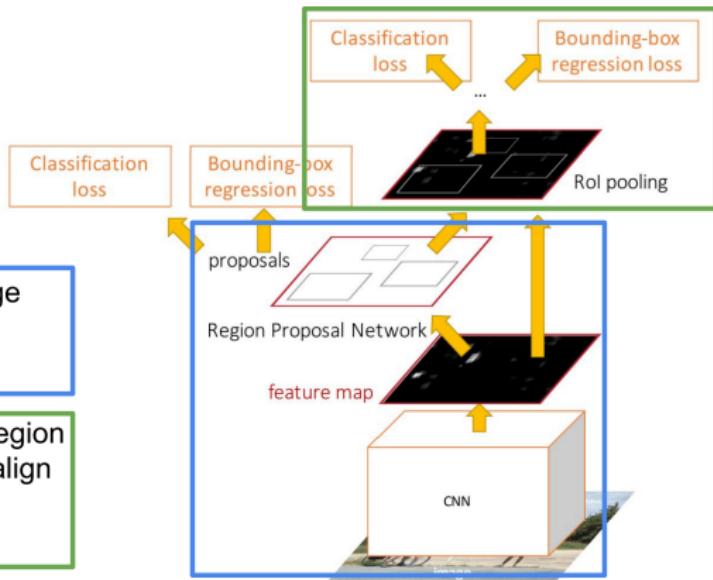
Faster R-CNN is a
Two-stage object detector

First stage: Run once per image

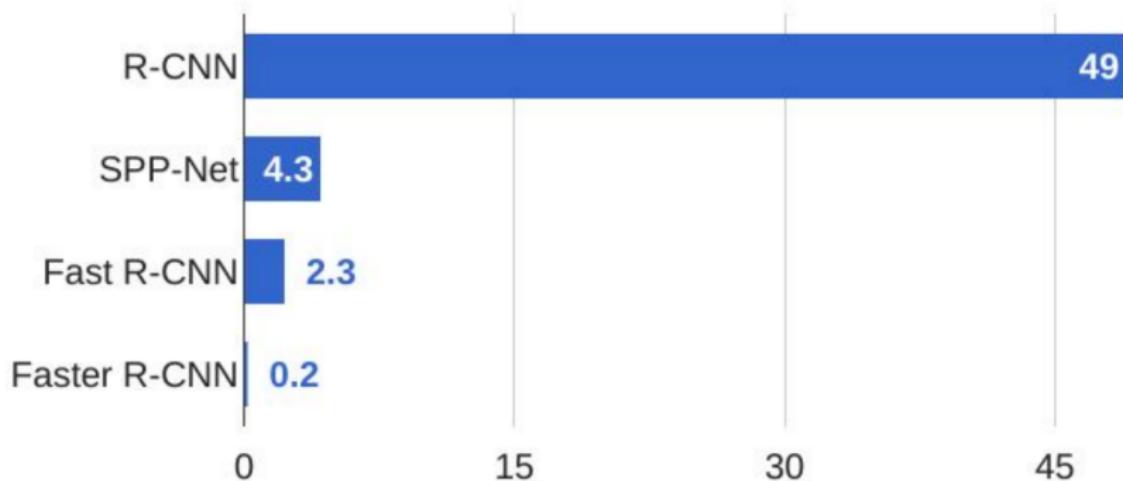
- Backbone network
- Region proposal network

Second stage: Run once per region

- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



R-CNN Test-Time Speed



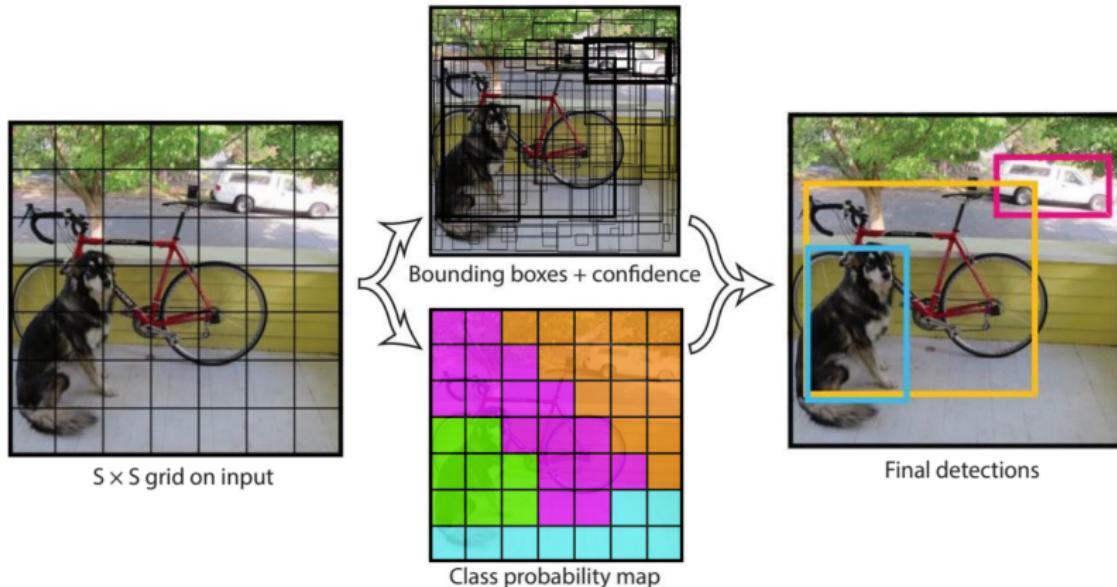
Single Shot Object Detection



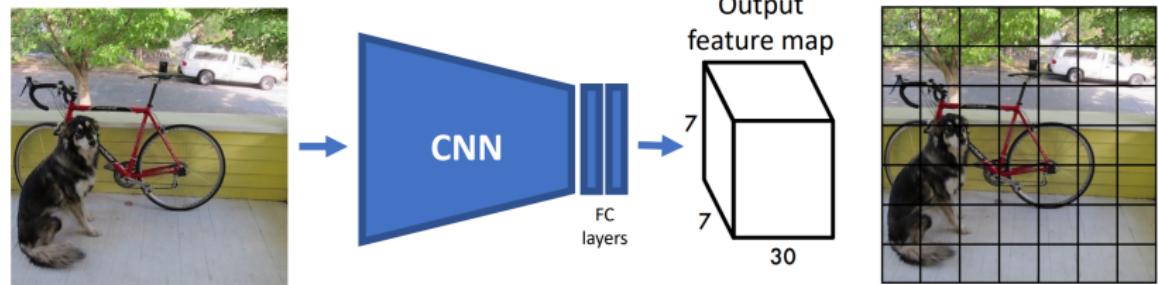
Single Shot:
SSD, YOLO ...

Fast
High false rate

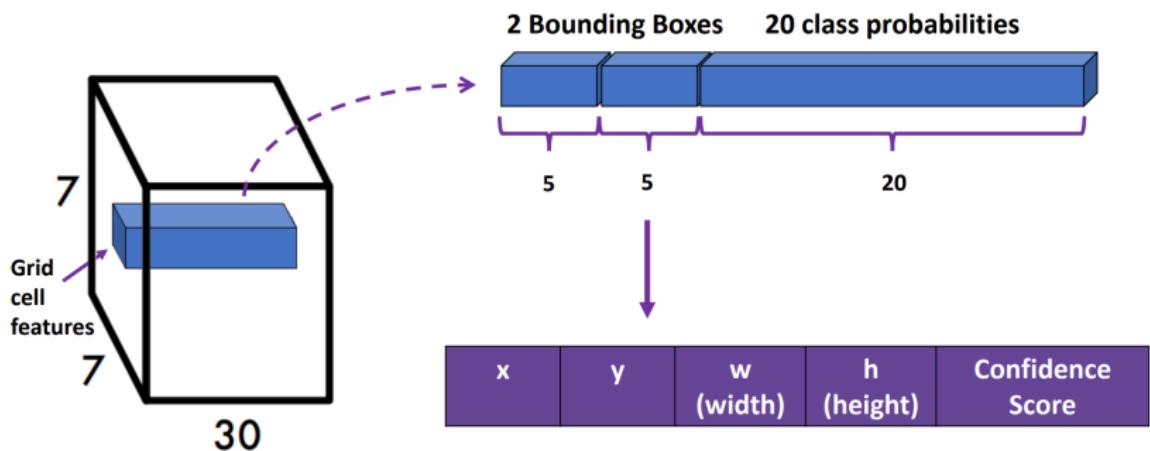
YOLO - Overview

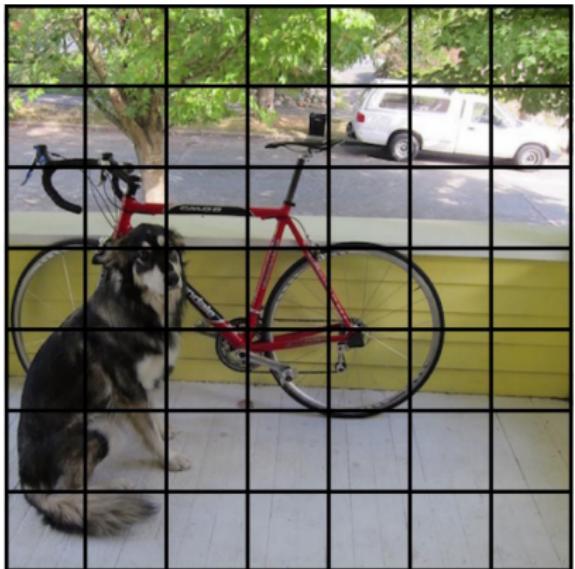


YOLO - Overview

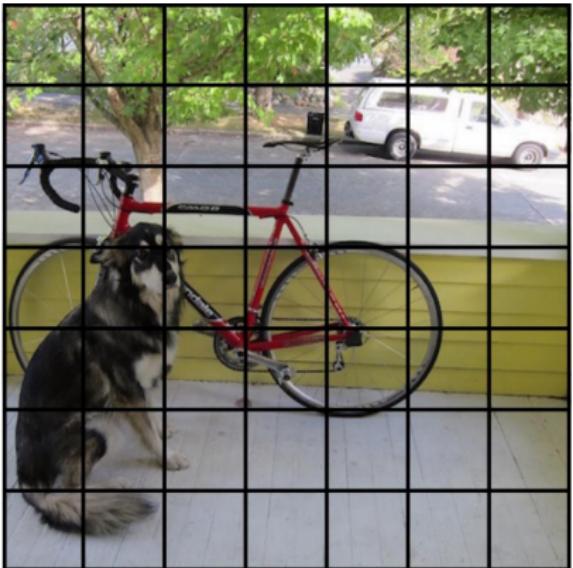


YOLO - Overview



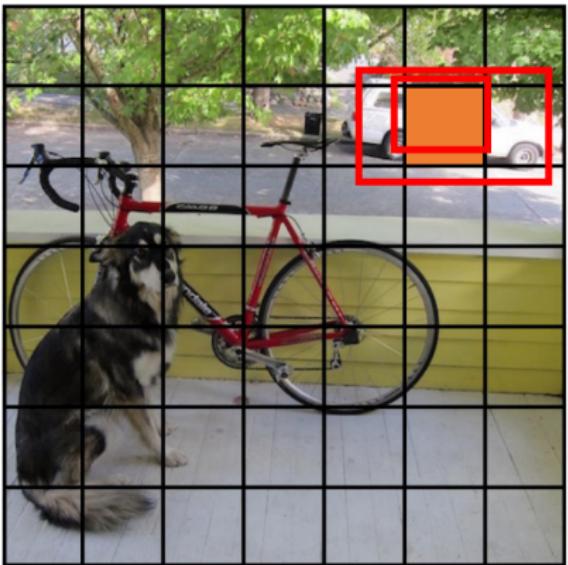


Each cell predicts



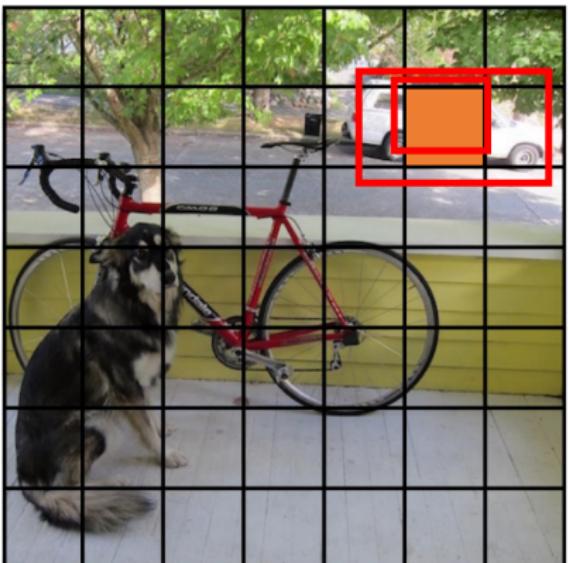
Each cell predicts

- ▶ $B = 2$ bounding boxes
 $(x, y, w, h) + \text{confidence score}$



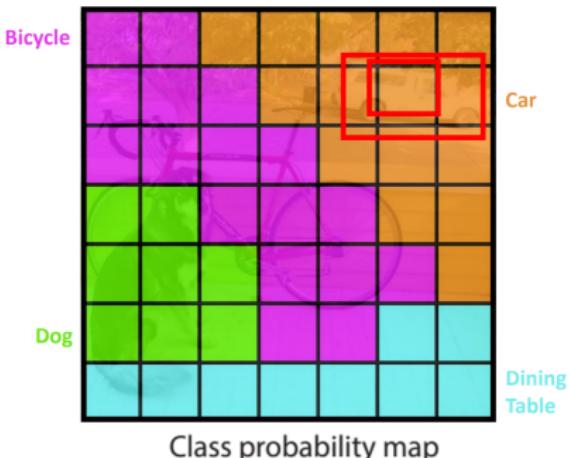
Each cell predicts

- ▶ $B = 2$ bounding boxes
 $(x, y, w, h) +$ confidence score
- ▶ $C = 20$ class probabilities



Each cell predicts

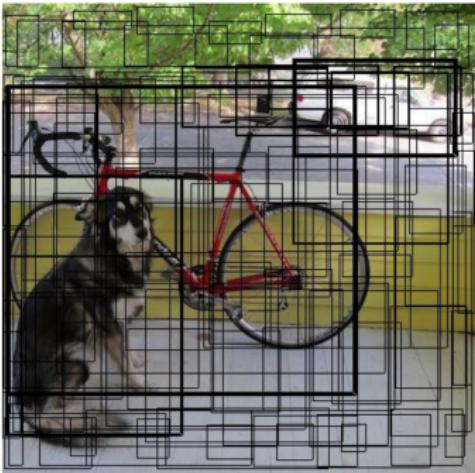
- ▶ $B = 2$ bounding boxes
 $(x, y, w, h) +$ confidence score
- ▶ $C = 20$ class probabilities



Each cell predicts

- ▶ $B = 2$ bounding boxes
 $(x, y, w, h) +$ confidence score
- ▶ $C = 20$ class probabilities

SxSxB Bounding-Boxes ($S=7, B=2 \rightarrow 96$ Bboxs)

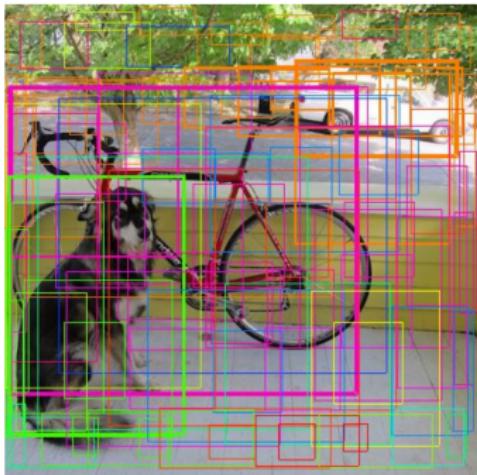


$S \times S$ grid on input

Each cell predicts

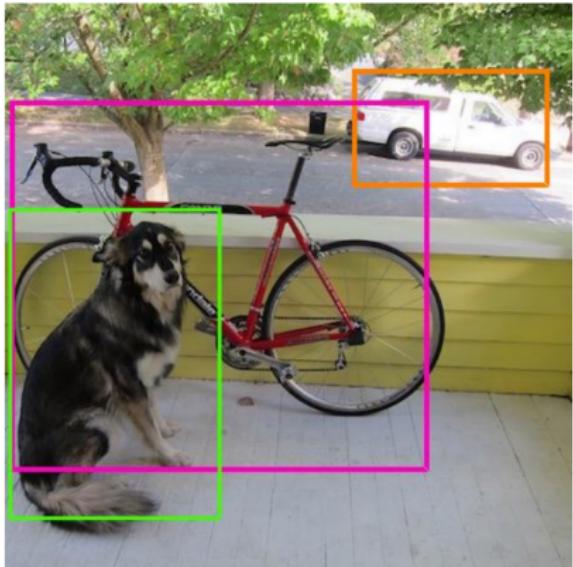
- ▶ $B = 2$ bounding boxes
 $(x, y, w, h) +$ confidence score
- ▶ $C = 20$ class probabilities

SxSxB Bounding-Boxes ($S=7, B=2 \rightarrow 96$ Bboxes)



Each cell predicts

- ▶ $B = 2$ bounding boxes
 $(x, y, w, h) +$ confidence score
- ▶ $C = 20$ class probabilities
- ▶ Apply Non-Maximum Suppression



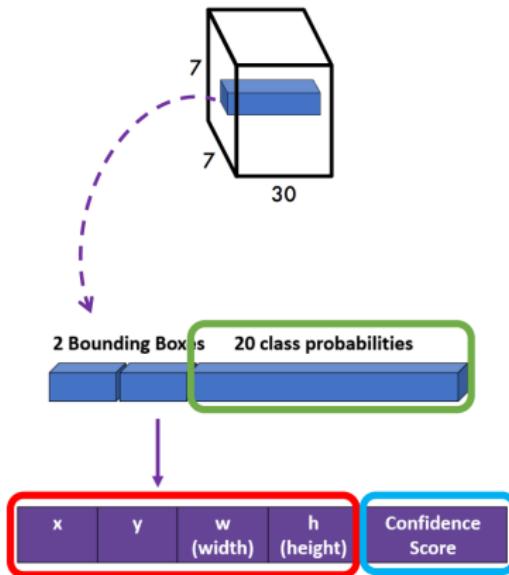
YOLO - Loss Function

YOLO – Loss function

$$\mathcal{L} = \mathcal{L}_{Localization\ Loss}$$

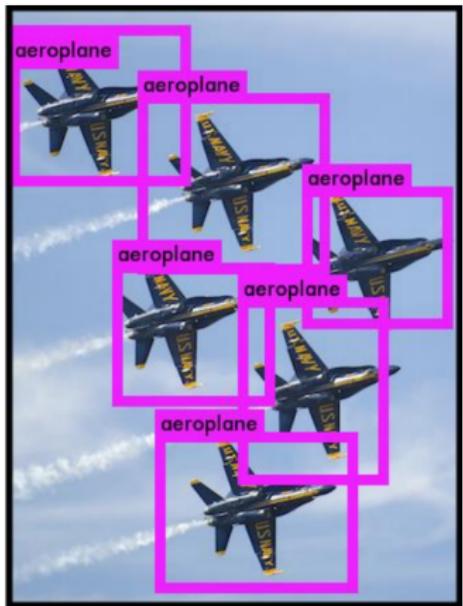
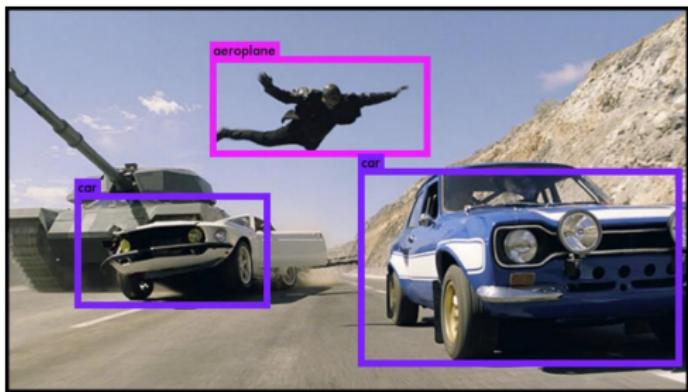
$$+ \mathcal{L}_{Confidence\ Loss}$$

$$+ \mathcal{L}_{Classification\ Loss}$$

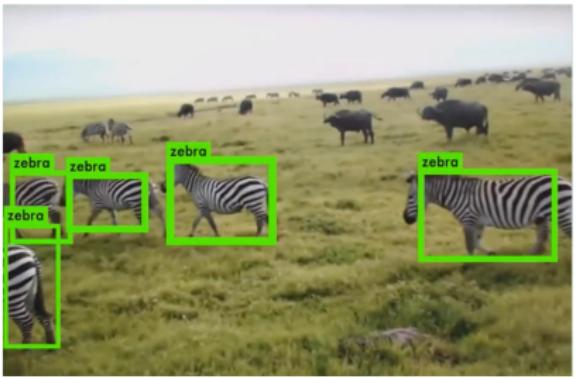


YOLO - Benefits

- ▶ Fast. Good for real-time processing
- ▶ End-to-end training

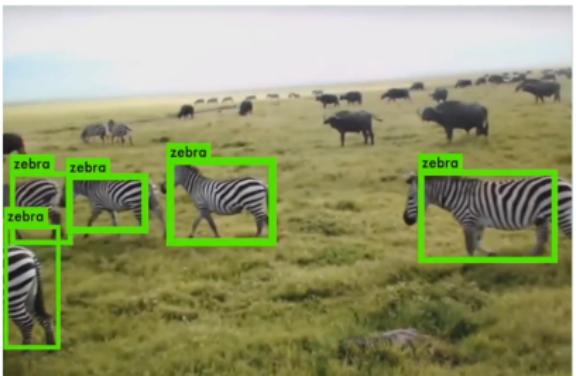


YOLO - Limitations



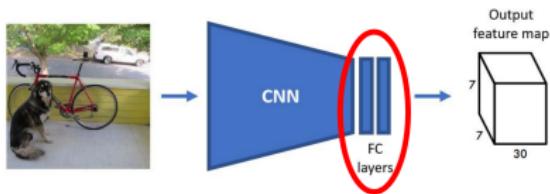
YOLO - Limitations

- ▶ Difficult to detect small objects
- ▶ Coarse predictions



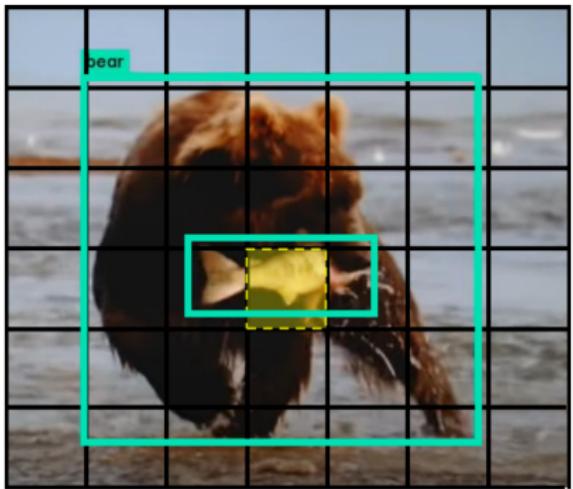
YOLO - Limitations

- ▶ Difficult to detect small objects
 - ▶ Coarse predictions
 - ▶ Fixed input size



YOLO - Limitations

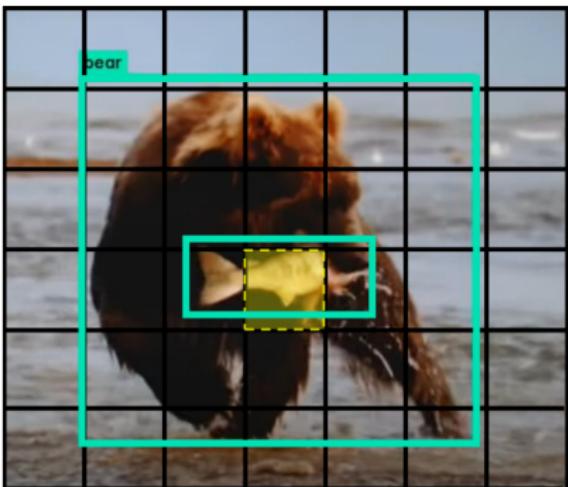
- ▶ Difficult to detect small objects
- ▶ Coarse predictions
- ▶ Fixed input size
- ▶ A grid cell can predict only one class



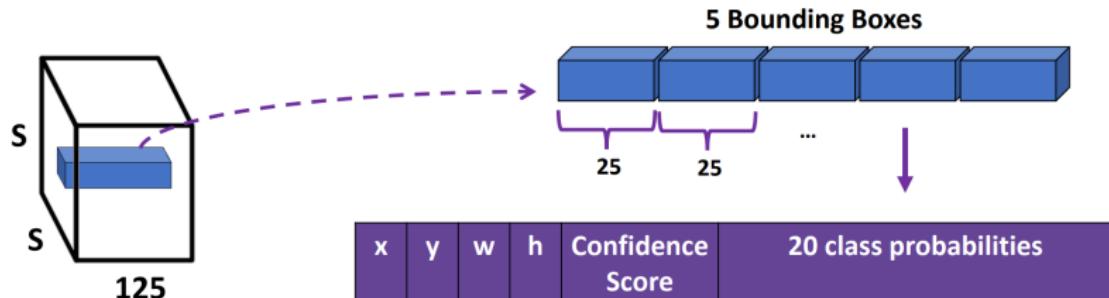
YOLO - Limitations

- ▶ Difficult to detect small objects
- ▶ Coarse predictions
- ▶ Fixed input size
- ▶ A grid cell can predict only one class

- ▶ Solutions:
 - Remove fc layers!
 - Predict class per bbox (not per cell)



- ▶ Removed fully connected layers
- ▶ A grid cell predicts class probabilities for each box



► YOLOv3

- J. Redmon, A. Farhadi. Yolov3: An incremental improvement, 2018

► YOLOv4

- A. Bochkovskiy, C. Wang, H. Liao. Yolov4: Optimal speed and accuracy of object detection (Feb. 2020)

► YOLOv5

- YOLOv5 by ultralytics (June 2020)

► PP-YOLO

- X. Long, K. Deng, G. Wang, Y. Zhang, Q. Dang, Y. Gao, H. Shen, J. Ren, S. Han, E. Ding, S. Wen. Pp-yolo: An effective and efficient implementation of object detector (June 2020)

► PP-YOLOv2 (2021)

- J. X. Huang, X. Wang, W. Lv, X. Bai, X. Long, K. Deng, Q. Dang, S. Han, Q. Liu, X. Hu, D. Yu, Y. Ma, O. Yoshie. PP-YOLOv2: A Practical Object Detector (2021)

Object Detection: Summary

- ▶ Object detection is a complex task that involves identifying and localizing objects within images.
- ▶ Key challenges include:
 - Variability in object appearance, scale, and orientation.
 - Occlusion and clutter in images.
 - Real-time processing requirements for applications like autonomous driving.
- ▶ Techniques range from traditional methods like sliding windows to advanced deep learning approaches like YOLO and Faster R-CNN.
- ▶ Intersection over Union (IoU) is a critical metric for evaluating the accuracy of object detection models.
- ▶ YOLO (You Only Look Once) is a popular real-time object detection algorithm that processes images in a single pass, making it efficient for applications requiring speed.

These slides have been adapted from

- ▶ Fei-Fei Li, Yunzhu Li & Ruohan Gao, Stanford CS231n: Deep Learning for Computer Vision
- ▶ Assaf Shocher, Shai Bagon, Meirav Galun & Tali Dekel, WAIC DL4CV Deep Learning for Computer Vision: Fundamentals and Applications
- ▶ Justin Johnson, UMich EECS 498.008/598.008: Deep Learning for Computer Vision

Credits

Dr. Prashant Aparajeya

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This project benefited from external collaboration, and we acknowledge their contribution with gratitude.