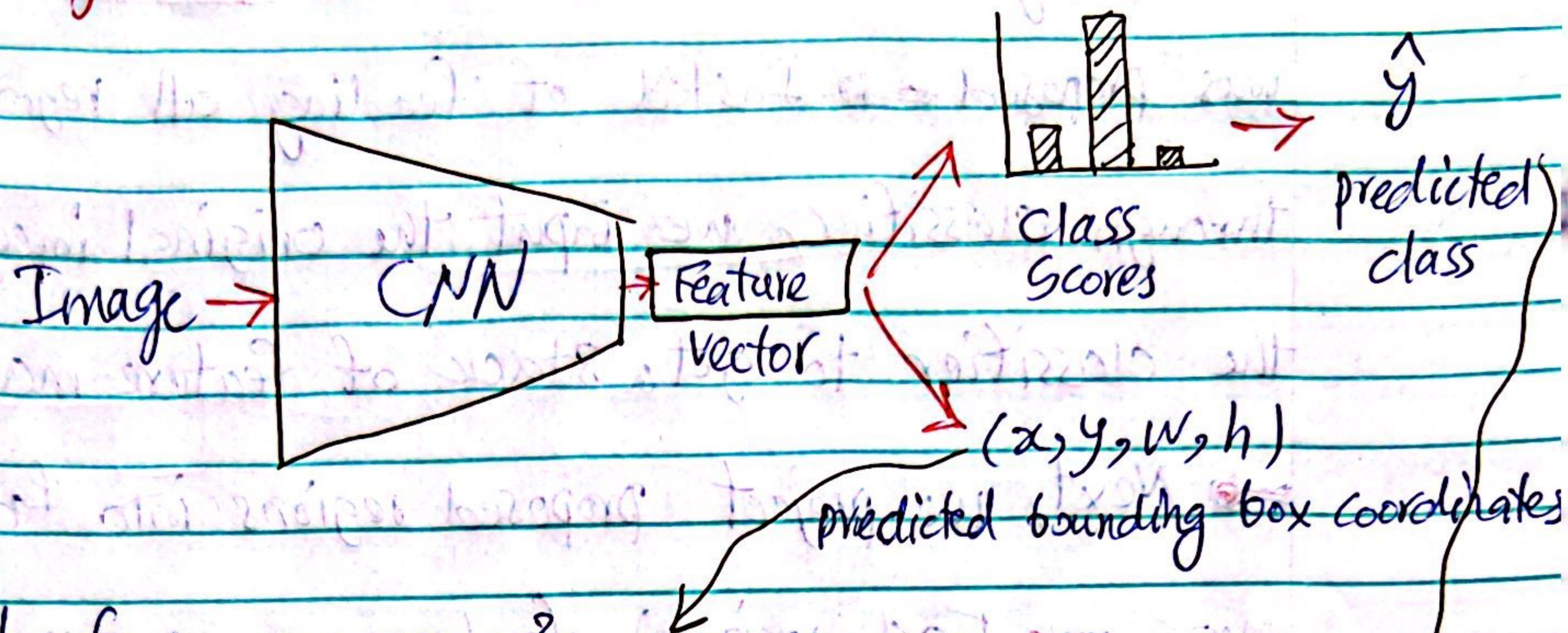


"Object Detection"



sort of α error?
regression

\hookrightarrow L1, MSE, smooth L1 loss

Cross-entropy error

? The method presented above works for one object in the image \rightarrow What if we have multiple of objects?!

\rightarrow We need region proposals! \rightarrow We can randomly generate

several cropped parts of the image with different bounding

box sizes \rightarrow feed them to CNN \rightarrow Classify them as

background or some specific objects! \Rightarrow Too SLOW!

due to huge amount of cropped images \rightarrow This is RCM

which R stands for "regional" \rightarrow We have several random

regions \rightarrow We make them standard size \rightarrow feed them

to classifier and so on!

① To remedy the slowness of RCNN, Fast RCNN was proposed \Rightarrow Instead of feeding all regions through classifier, we input the original image into the classifier to get a stack of feature maps.

\Rightarrow Next, we project proposed regions into feature maps \Rightarrow Each region in feature map corresponds to larger region in the original image \Rightarrow We can pass each small region in feature map into FC layer and evade time-consuming stage of image processing in CNN classifier.

after passing them from

Region of Interest (ROI) pooling to make sizes uniform.

\Rightarrow Fast R-CNN is faster than R-CNN, but not fast enough.
(10 times!)

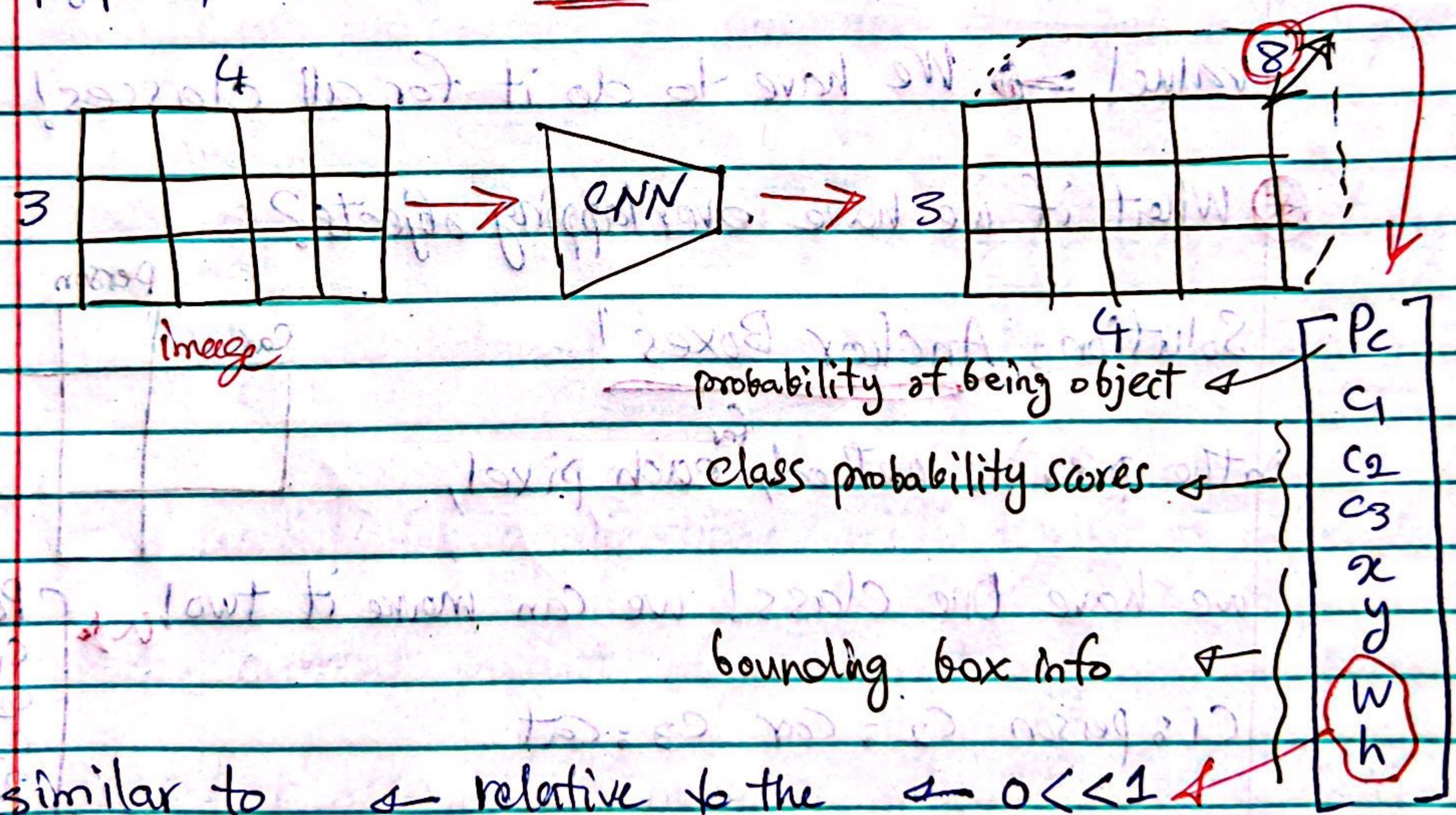
① Faster R-CNN, inputs the image into a network upto some layers (Similar to Fast RCNN) and then feeds these processed feature into the Region Proposal Network \Rightarrow If some regions in the feature map is rich in detected edges or other features, it will

be proposed as RoI. Then for each region, the network performs a quick binary identification: object or non-object. Then discards non-object regions. Rest is similar to R-CNN.

② Is it possible to perform object detection without region proposals?

Yes! E.g., YOLO and SST.

In YOLO, instead of using a sliding window for region proposal, we use a grid!



similar to relative to the entire image
normalization

→ easier to train and converge!

⊗ How to resolve too many boxes? → non-maximal suppression

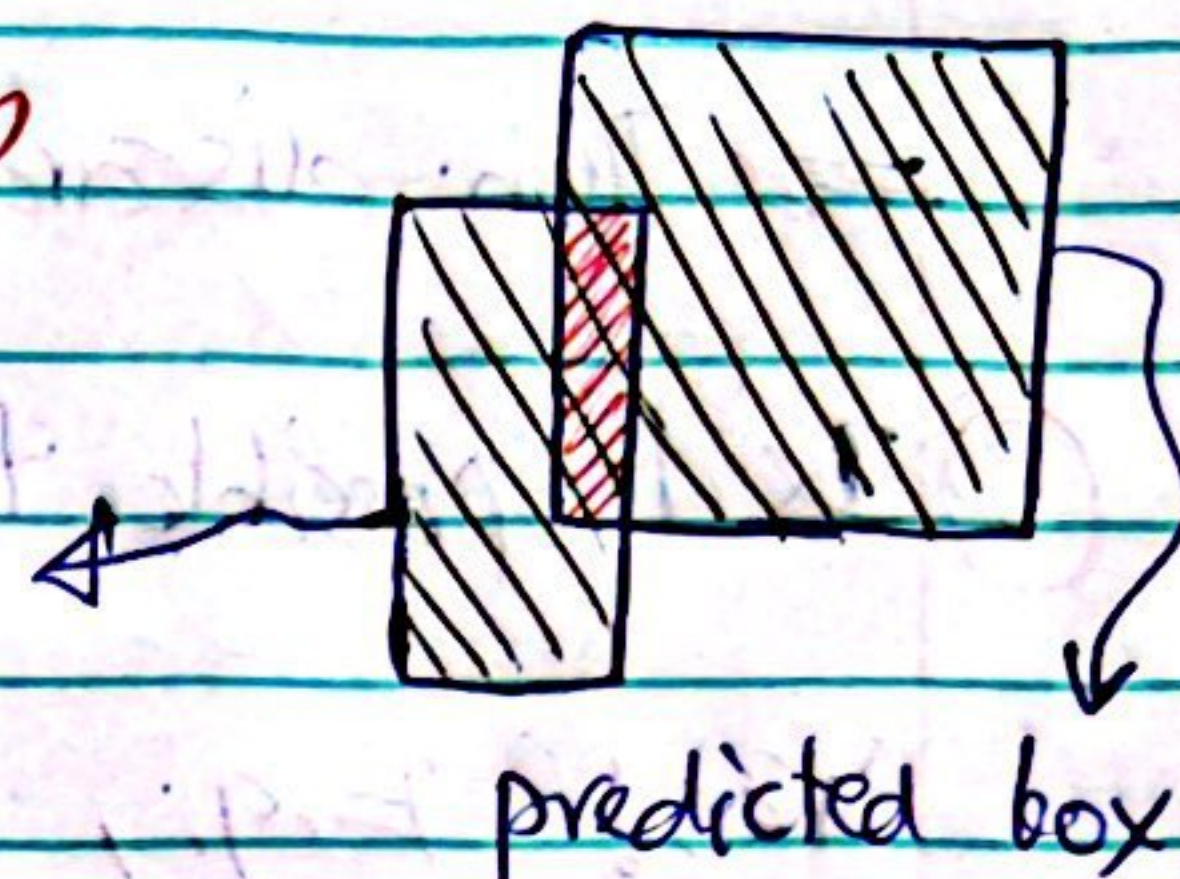
≡ finding bounding boxes that best matches an object in an image! → How we can compare two bounding boxes

in terms of being good bounding box for an object!

→ Answer: Intersection of Union (IoU)

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

ground truth box



→ Non-Maximal Suppression: removes overlapping

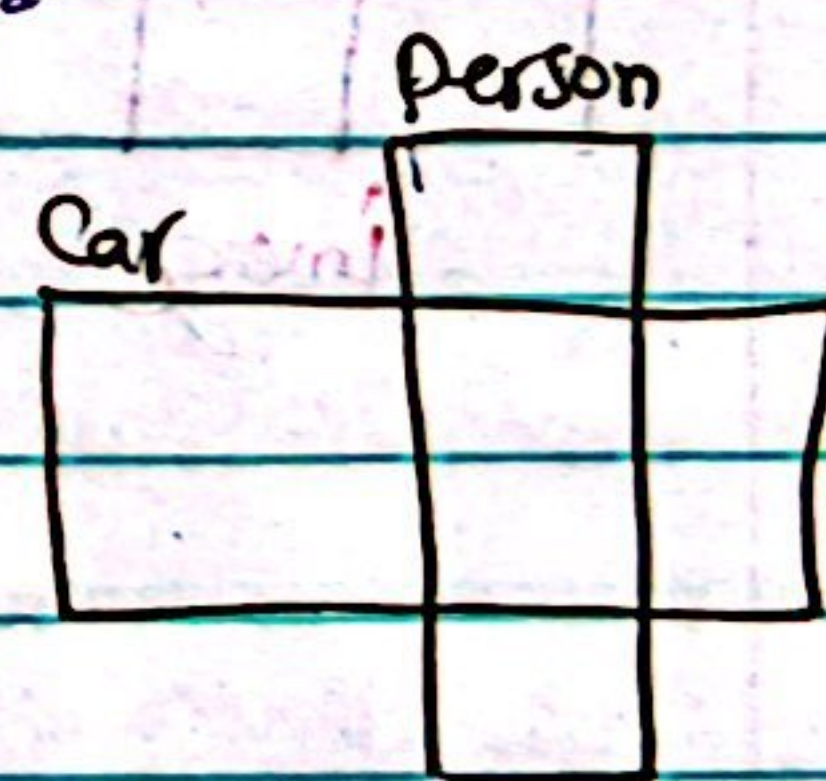
Bounding boxes and keep the box with the highest p_c

value! → We have to do it for all classes!

⊗ What if we have overlapping objects?

Solution: Anchor Boxes!

in the previous method, for each pixel,



we have one class! we can make it two!

C_1 : person C_2 : Car C_3 : cat

This algorithm fails if we have 3 or more

overlapping objects. → but it is rare!

P_c	1
C_1	0
C_2	1
C_3	0
x	x
y	y
w	w
h	h
P_c	1
C_1	1
C_2	0
C_3	0
x	x
y	y
w	w
h	h