Convolution Neural Network 2

Dr. Kelly Trinh

Housekeeping

- Data for Assessment 3
  - Data must NOT be the one already covered in Practical sessions and AWS Jupyter Lab (such as MNIST, CIFAR, dogs and cats).

Today

- Image Localisation
- Image Detection

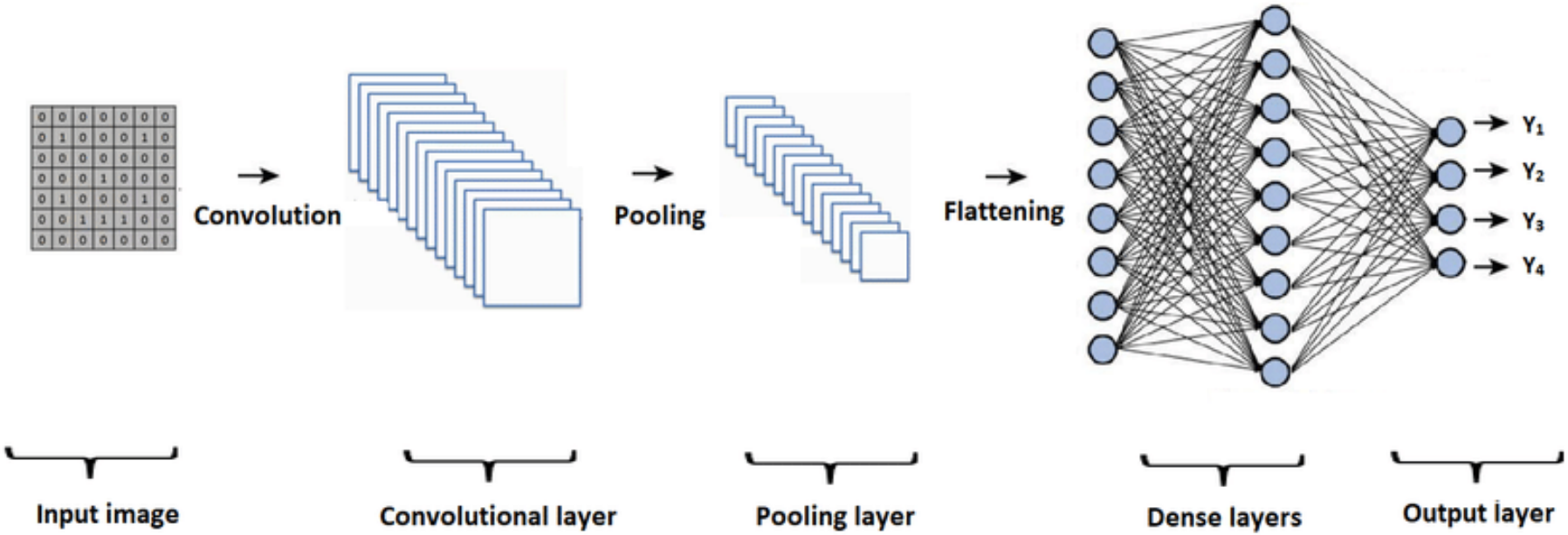
Image Classification

Image Classification (Convnet)

Input: RGB image

Output: Object class (a dog)

Object classification-CNN



In this example: output $\in \{dog, cat\}$

Object localisation

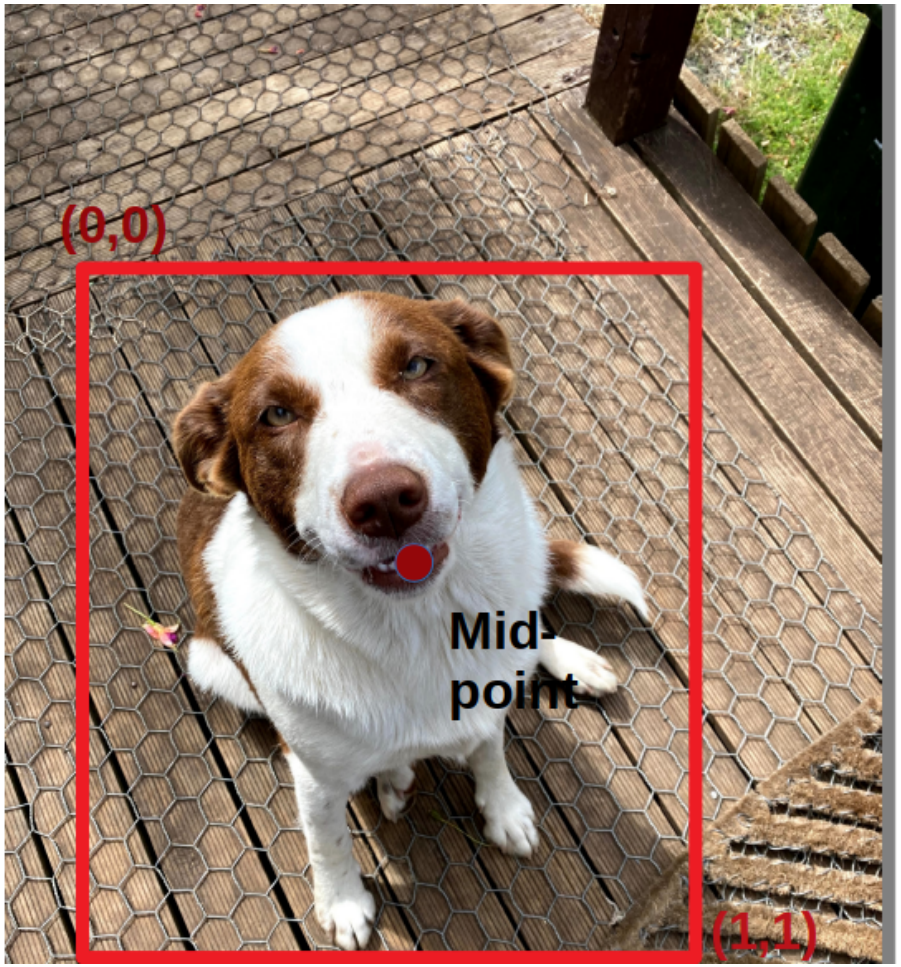
- Object localisation : identifying object and location with bounding box.

Image Localisation (Convnet)

Input: RGB image

Output:
- **P**robability if there is an object in the image
- bounding box (x,y, width, height)
- object class (a dog)

E.g:
X= 0.5
Y= 0.45
W= 0.3
H= 0.7



Object localisation

Image classification

$$o = \begin{bmatrix} p(c_1) \\ p(c_2) \end{bmatrix}$$

An example of loss function

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} c_i log(p(c_i)) + (1 - c_i) log(1 - p(c_i))$$

Image localisation

$$o = \begin{bmatrix} p_c \\ x \\ y \\ w \\ h \\ c_1 \\ c_2 \end{bmatrix} = \begin{bmatrix} \text{is the object in an image?} \\ \text{x coordinate relative to an image, } x \in [0,1] \\ \text{y coordinate relative to an image , } y \in [0,1] \\ \text{width of the image relative to an image , } w > 0 \\ \text{height of the image relative to an image , } h > 0 \\ \text{confidence level that image belongs to class 1 or not} \\ \text{confidence level image belongs to class 2 or not} \end{bmatrix}$$

An example of loss function

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

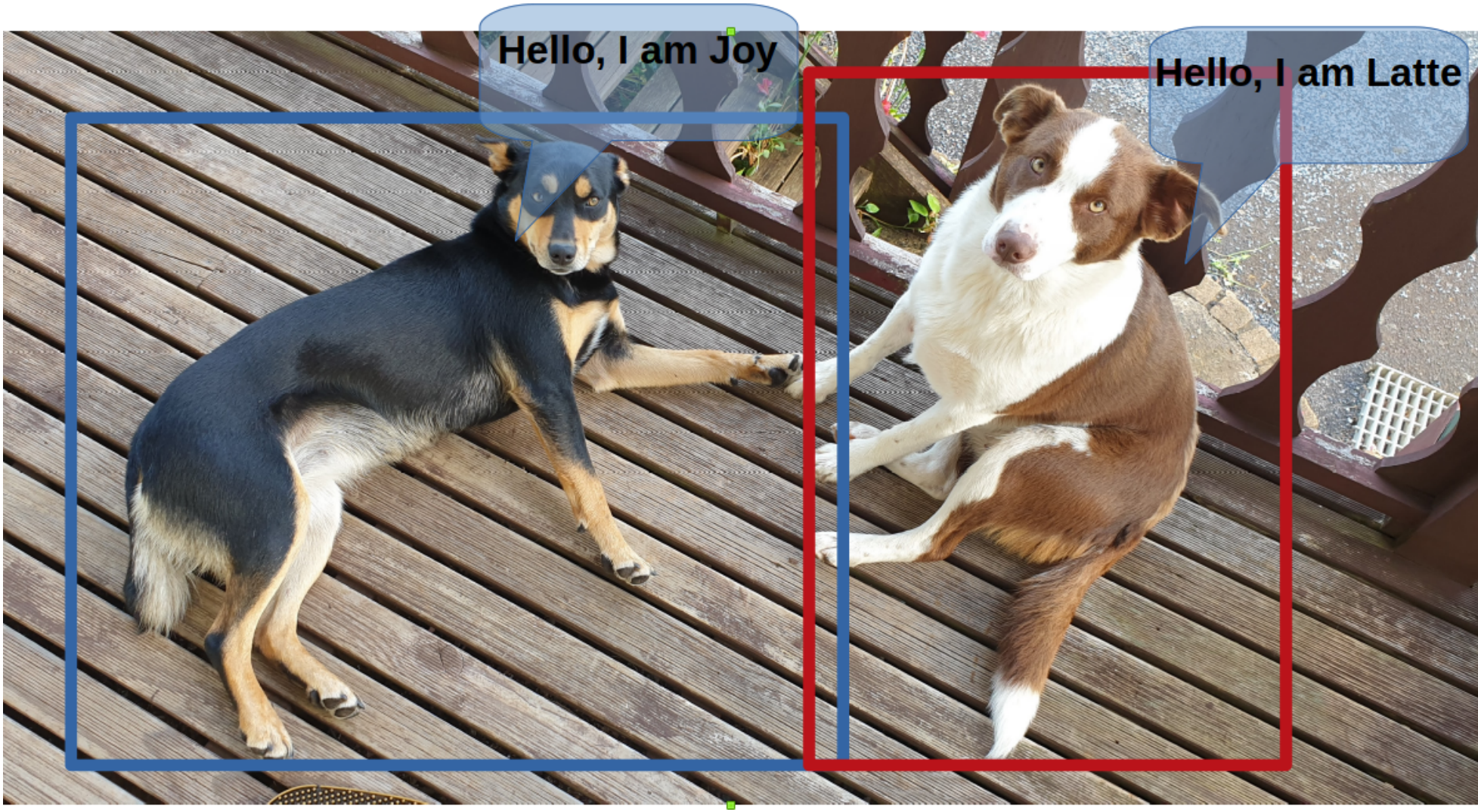
$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \quad (3)$$

Object detection

- Object detection : identifying objects and locations of each object with bounding boxes.



Object detection-Challenges

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- Large images: classification generally work with 224×224, need higher resolution for detection 800×600. Therefore, always beware of computation cost and memory when doing image detection.

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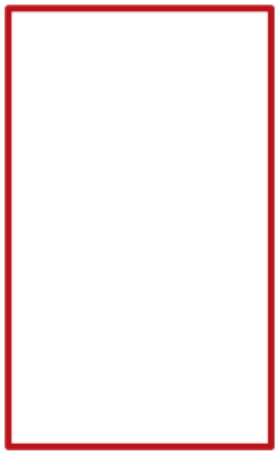
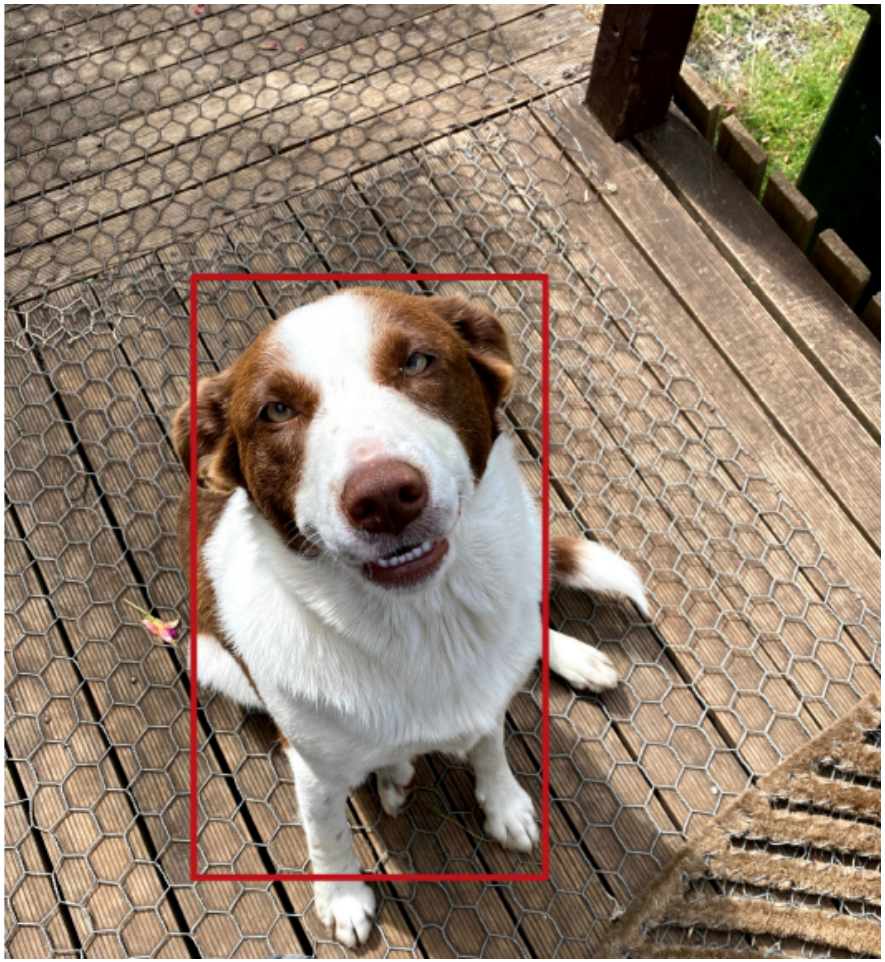
Naive approach: sliding window detection



Fixed window size

Apply a CNN to many crops of image. and CNN will classify each window as an object or a background

Naive approach: sliding window detection



How many possible boxes are there?

- An image of size $H \times W$, a box of size $h \times w$:
- Possible x positions: $W-w+1$
- Possible y positions: $H-h+1$
- Possible positions: $(W-w+1) \times (H-h+1)$
- Total possible boxes:

$$\sum_{w=1}^{W} \sum_{h=1}^{H} (W-w+1) \times (H-h+1)$$
$$= \frac{H(H+1)W(W+1)}{4}$$

- An image 600x600 will have approximately 32 million possible bounding boxes!!!

Image detection approaches

- Convolution Implementation of Sliding windows
- Regional Based CNN (R-CNN) ([Girshick et al., 2014])
- Fast regional CNN (R-CNN)([Girshick, 2015], [Ren et al., 2015])
- Mask R-CNN ([He et al., 2017])
- Single shot detector [Liu et al., 2015]
- YOLO (YOLOv1, YOLOv2, YOLOv3, YOLOv4) ([Redmon et al., 2015], [Redmon and Farhadi, 2018])

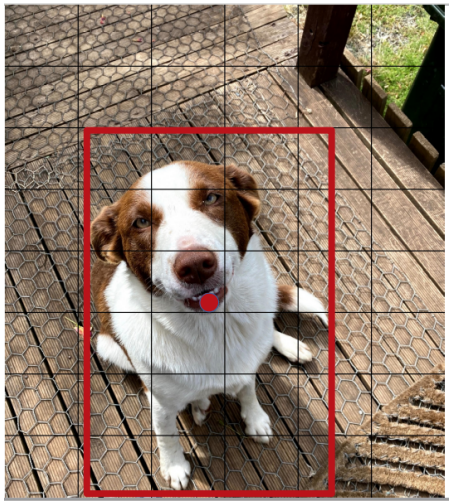
Image Detection

- Bounding boxes
- Intersection over Union
- Non-Max Suppression
- Mean Average Precision

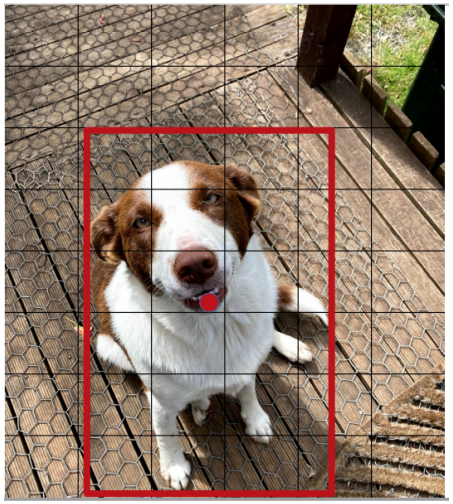
How to select a better bounding box?

YOLO algorithm-Bounding Box

- Divide an image into $s \times s$ grids (e.g. 6×6)



YOLO algorithm-Bounding Box



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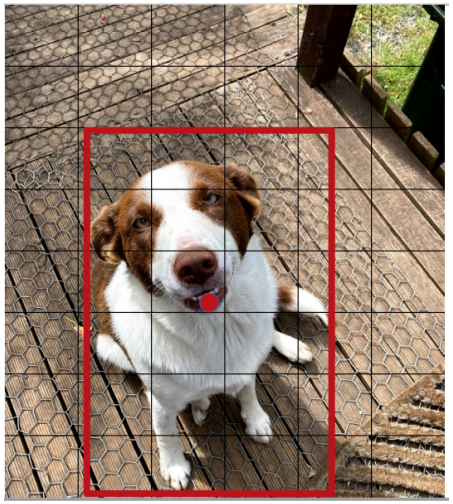
- The cell contains the mid-point of an object is responsible for detecting the object

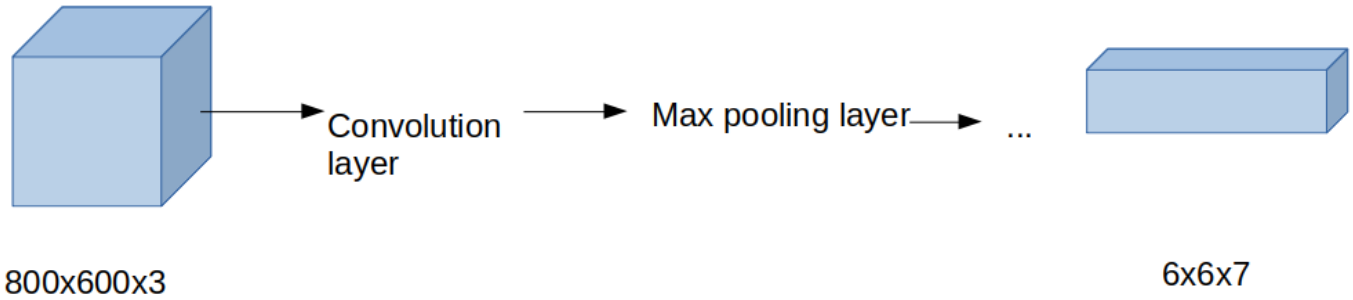
YOLO algorithm-Bounding Box

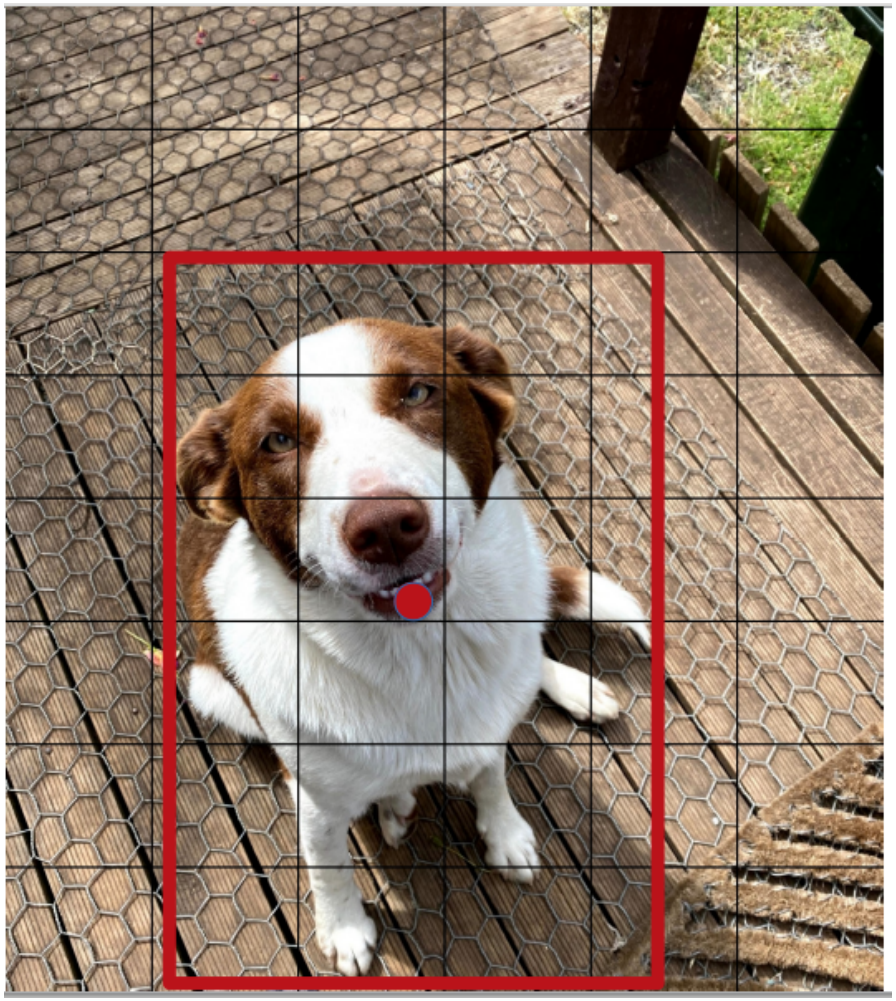


- Divide an image into $s \times s$ grids (e.g. 6×6)
- The cell contains the mid-point of an object is responsible for detecting the object
- Each grid cell provide

$$o = \begin{bmatrix} p_o \\ x \\ y \\ w \\ h \\ p_{c_1} \\ p_{c_2} \end{bmatrix} = \begin{bmatrix} \text{is the object in the grid?} \\ \text{x coordinate relative to the grid cell, } x \in [0,1] \\ \text{y coordinate relative to the grid cell, } y \in [0,1] \\ \text{width of the image relative to the grid cell, } w > 0 \\ \text{height of the image relative to the grid cell, } h > 0 \\ \text{confidence level that image belongs to class 1 or not} \\ \text{confidence image belongs to class 2 or not} \end{bmatrix}$$

- Total output dimension is $6 \times 6 \times 7$

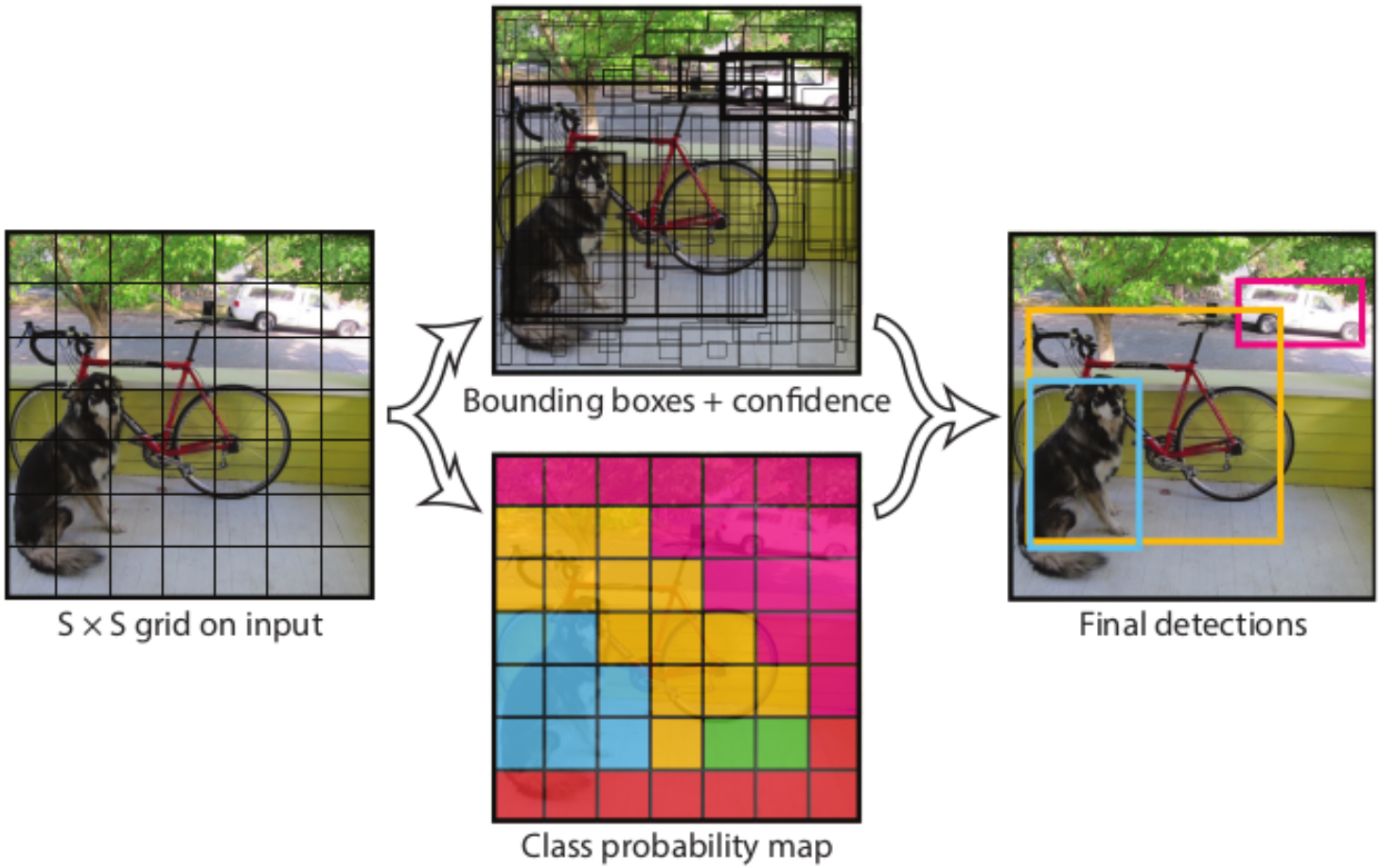




- Each grid cell provide

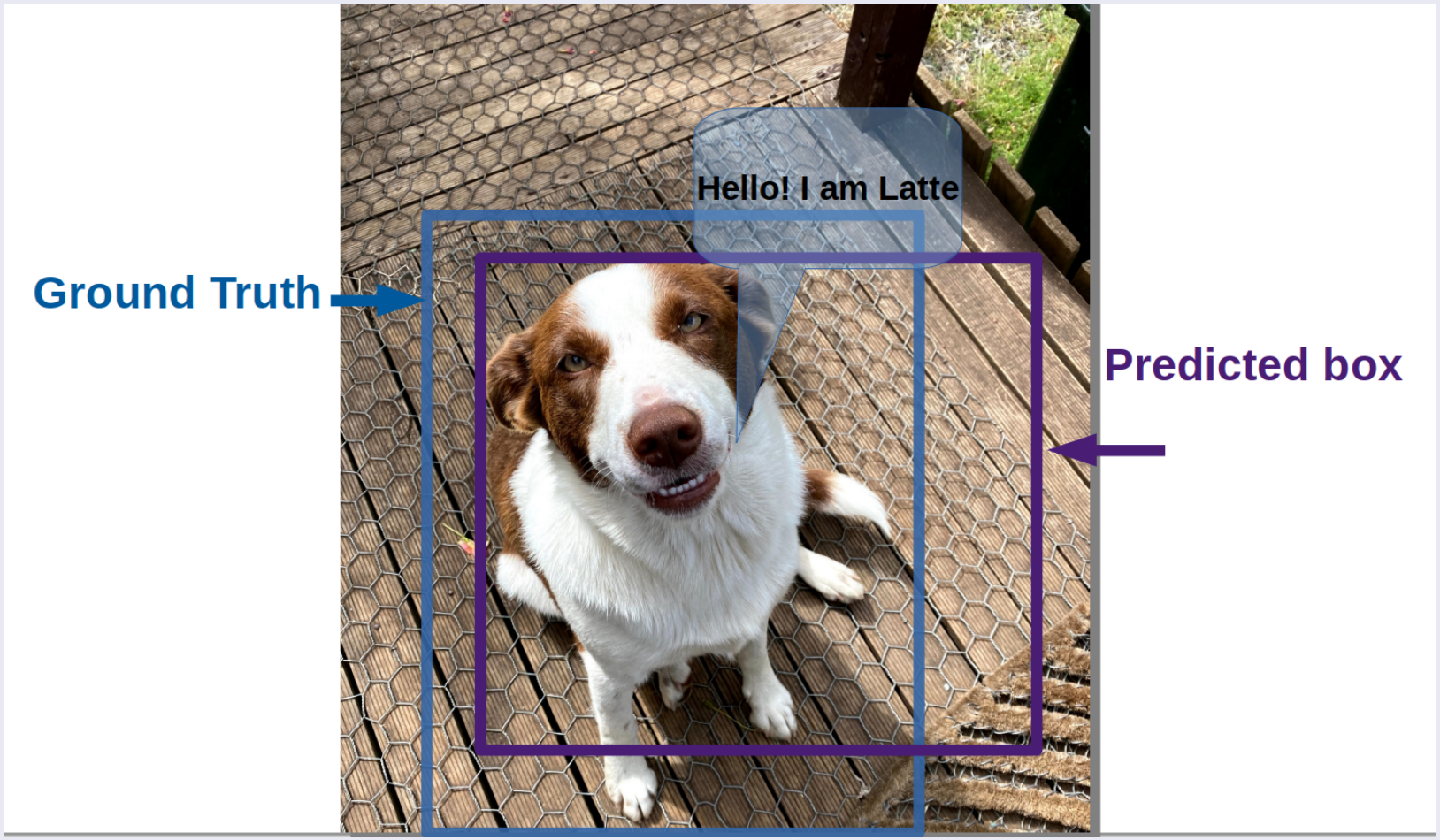
$$\text{bounding box} = \begin{bmatrix} x \\ y \\ w \\ h \end{bmatrix} = \begin{bmatrix} 0.9 \\ 0.9 \\ 3.2 \\ 6 \end{bmatrix}$$

YOLO-v1



Source:[Redmon et al., 2015]

How to determine if it is a good predicted bounding box?

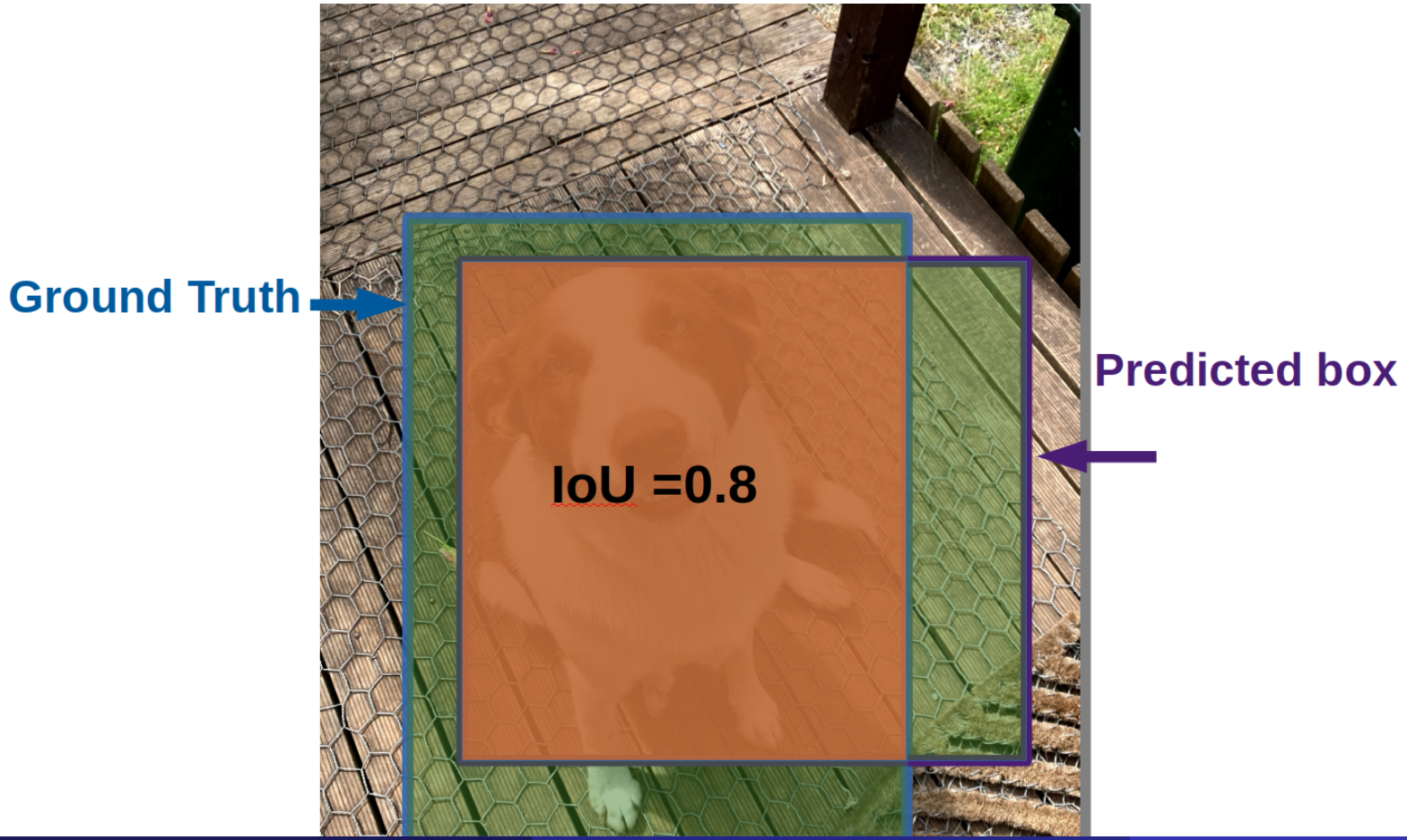


How to evaluate bounding boxes? Intersection over Union

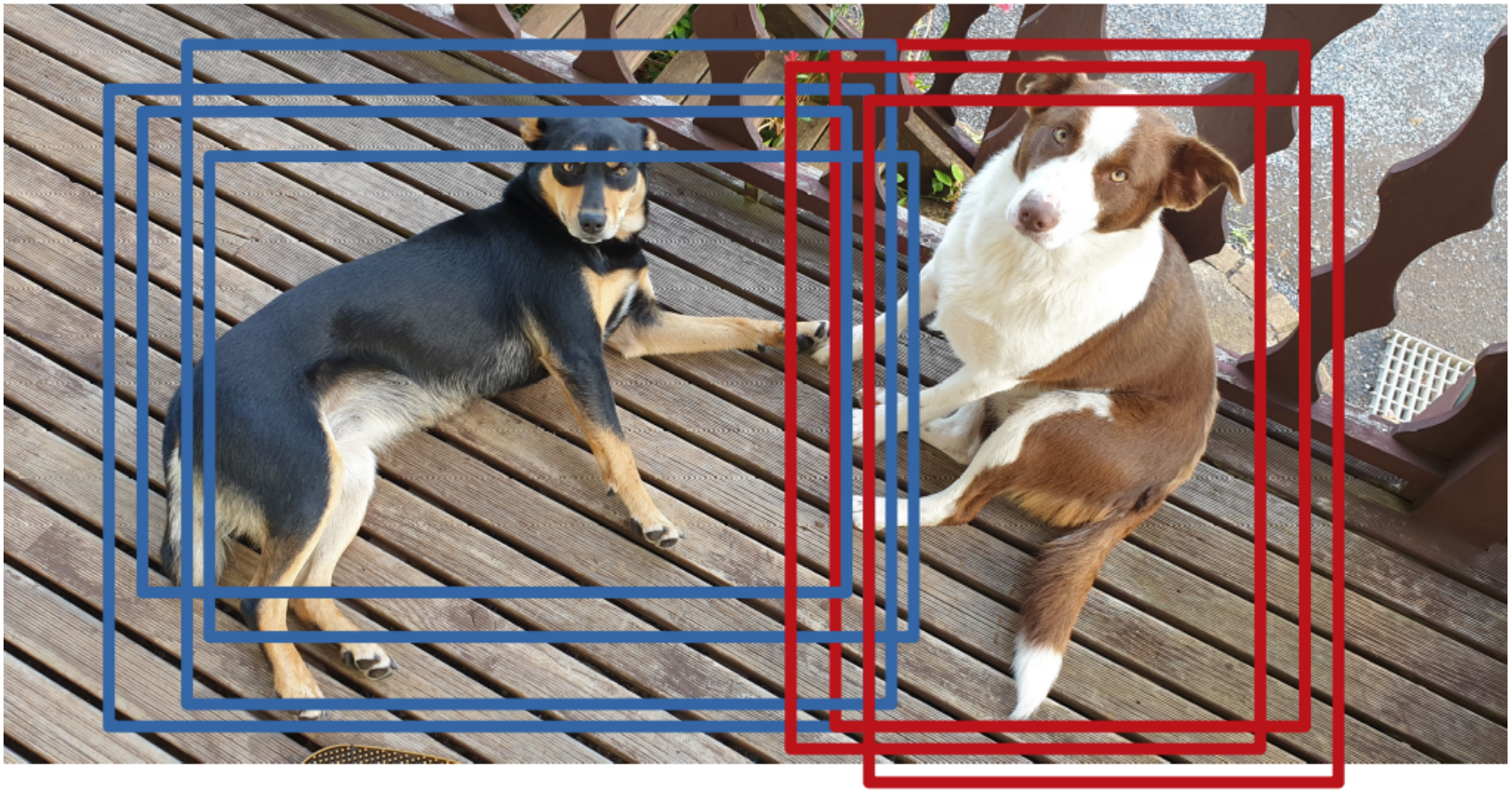
- How to compare the predicted bounding box to the ground truth box?
- Intersection over Union (IoU)

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

- $IoU > 0.5$ is okay; $IoU > 0.7$ is good, $IoU > .9$ is almost perfect

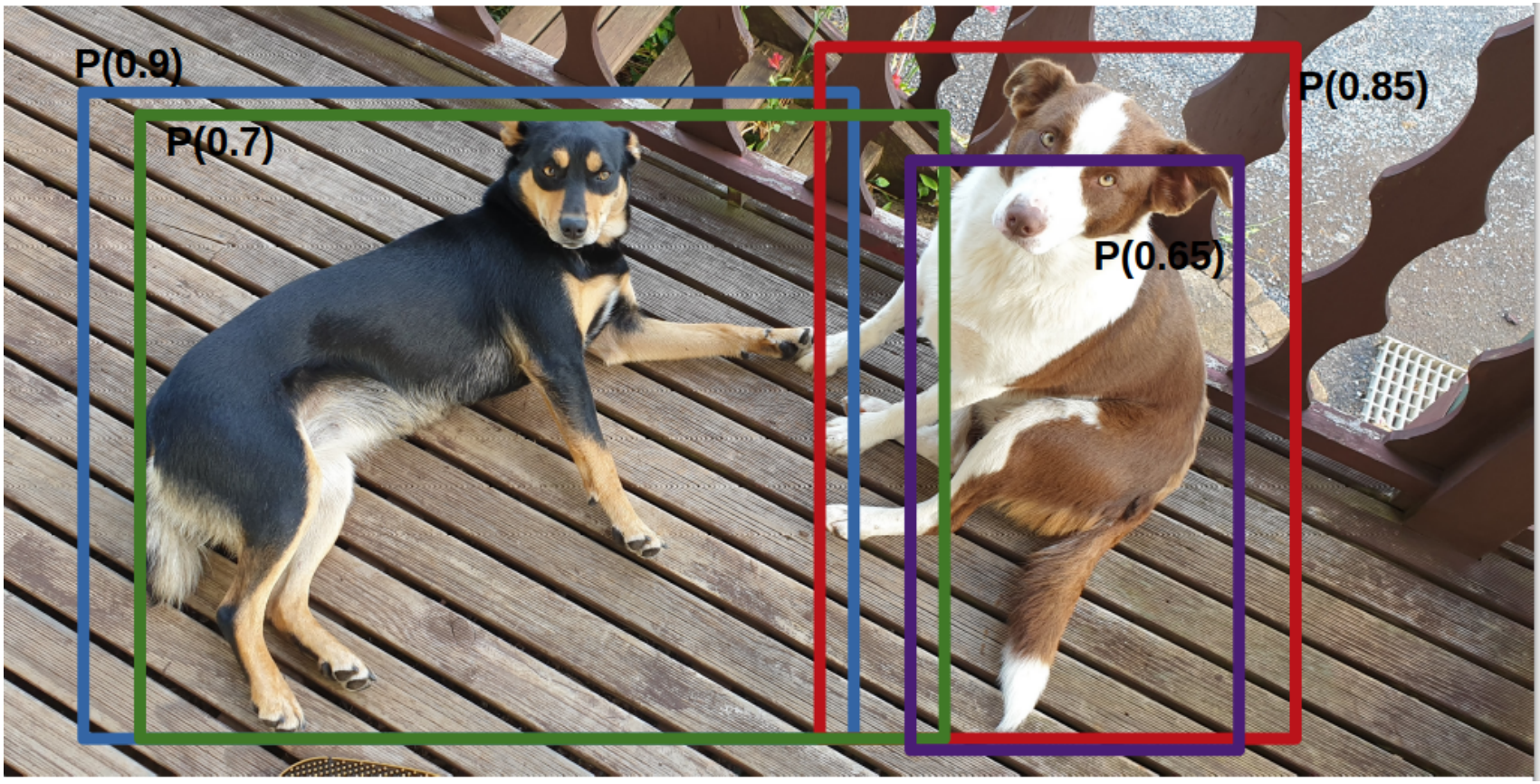


Cleaning multiple bounding boxes

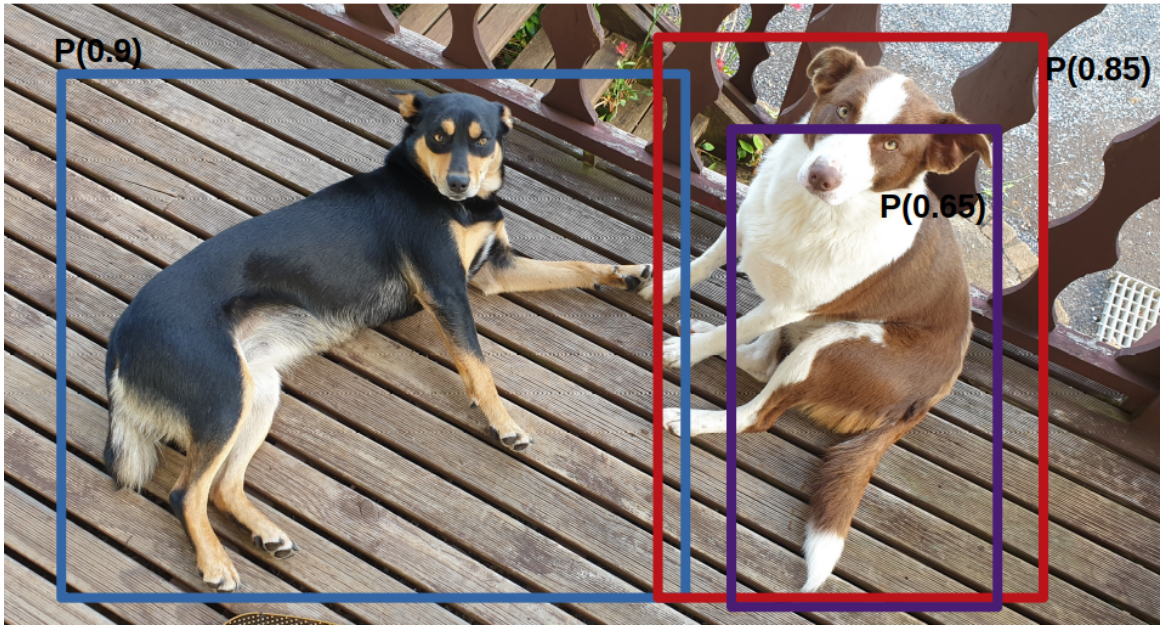


- Object detectors often produce many bounding boxes overlapping. We only need one bounding box to detect an object.

Non-max suppression



- Object detectors often produce many bounding boxes overlapping
- Solution: Non-Max Suppression (NMS)
  1. Discard all boxes with $p_c \leq$ threshold (e.g. 0.6)
  2. Select next highest-scoring box
  3. Eliminate any remaining boxes with IoU $\geq$ threshold (e.g. 0.7)
  4. If any boxes remain, return step 1

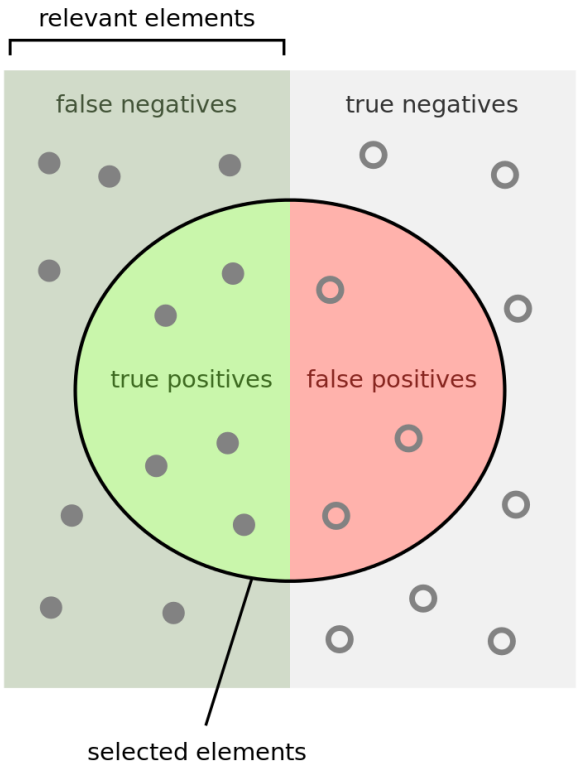

P(0.9)
P(0.85)
P(0.65)


P(0.9)
P(0.85)

How to evaluate the performance of image detection algorithm?

- Precision versus Recall
- Mean Average Precision (mAP)

Precision and Recall



How many selected items are relevant?

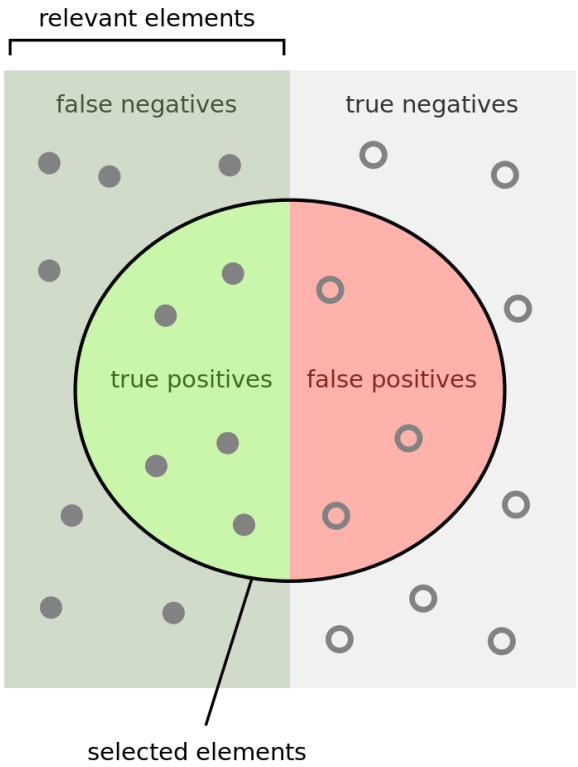
$$\text{Precision} = \frac{\text{true positives}}{\text{selected elements}}$$

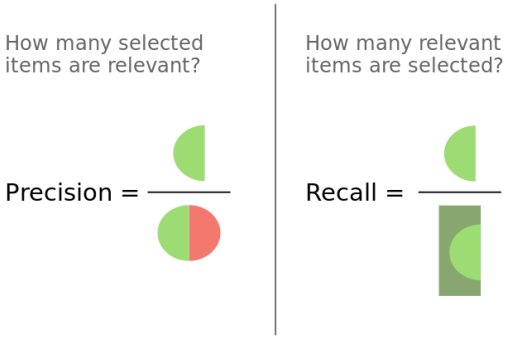
How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{relevant elements}}$$

Source: Wikipedia

Precision and Recall

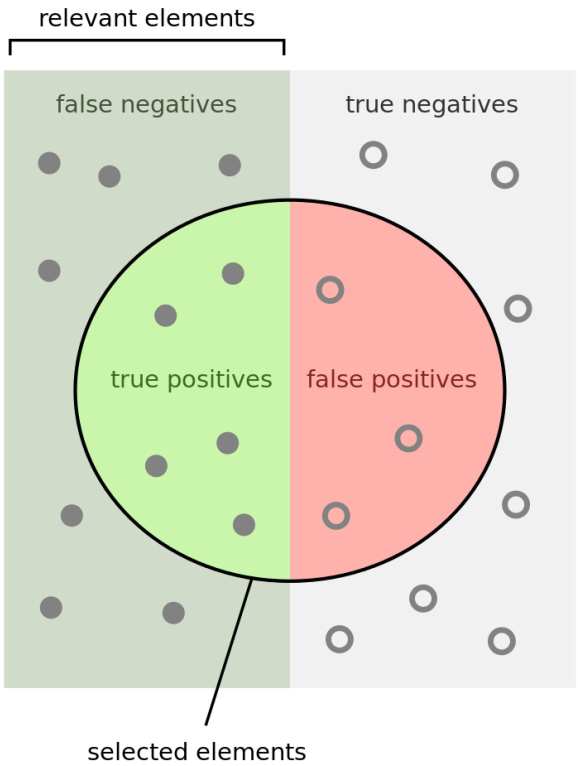


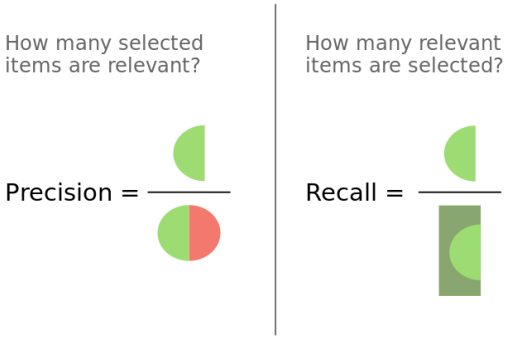


- True positive: the bounding boxes that shares $IoU > .5$ with the ground truth bounding box

Source: Wikipedia

Precision and Recall





- True positive: the bounding boxes that shares $IoU > .5$ with the ground truth bounding box
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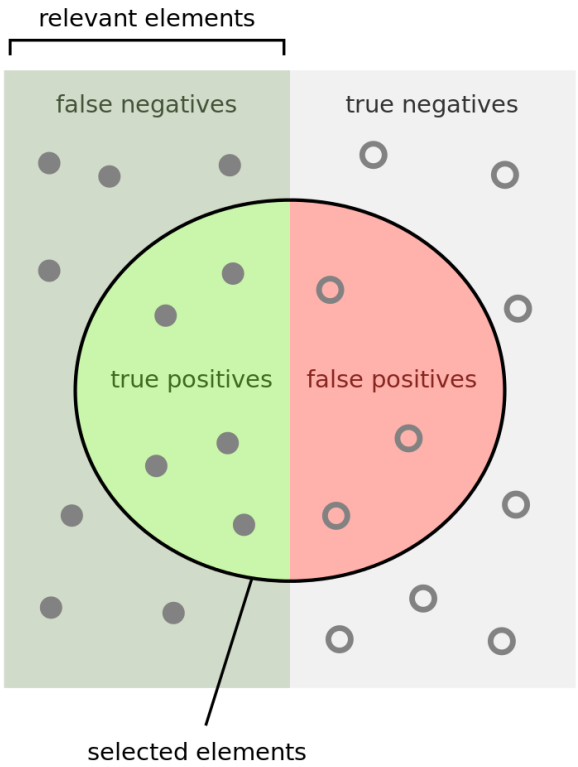

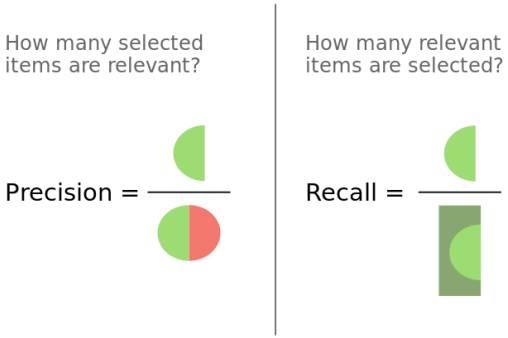

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Source: Wikipedia

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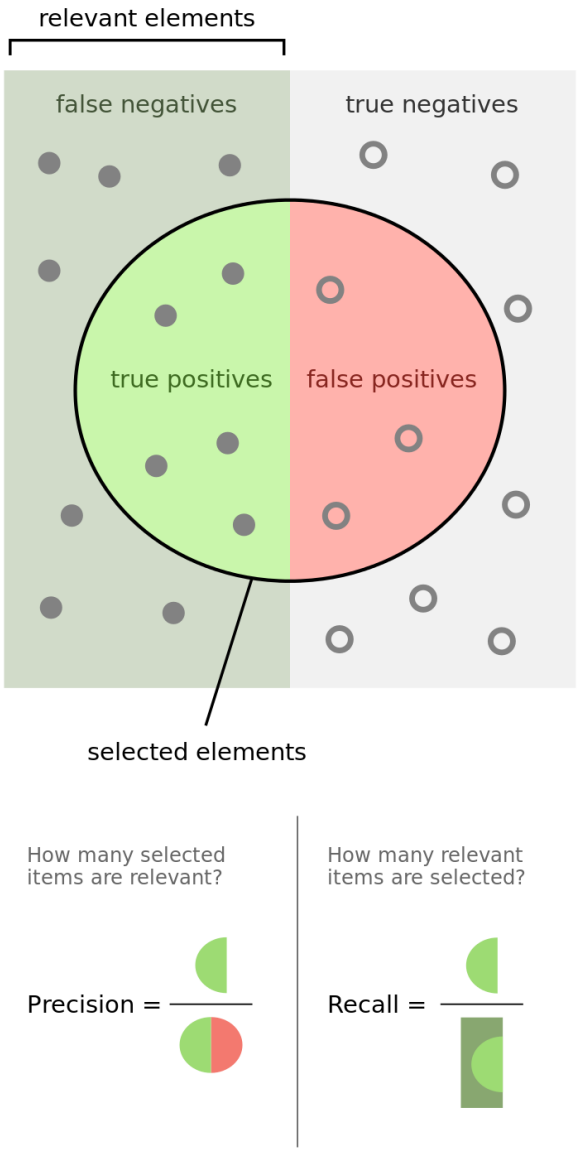

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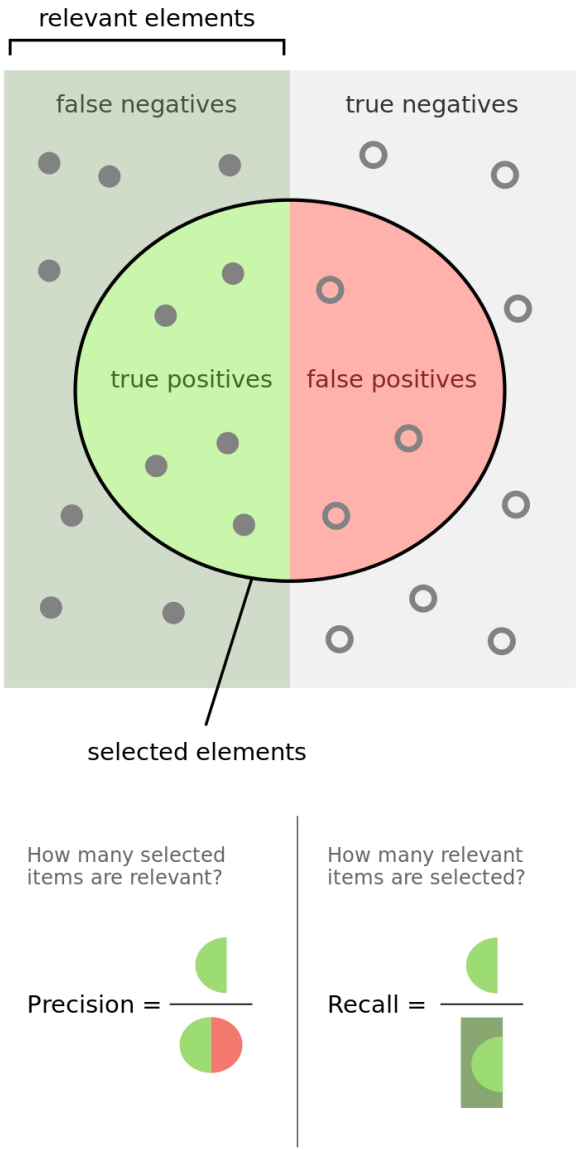
- Precision: Of all bounding box predictions, what fraction was actually correct?

Source: Wikipedia

Precision and Recall



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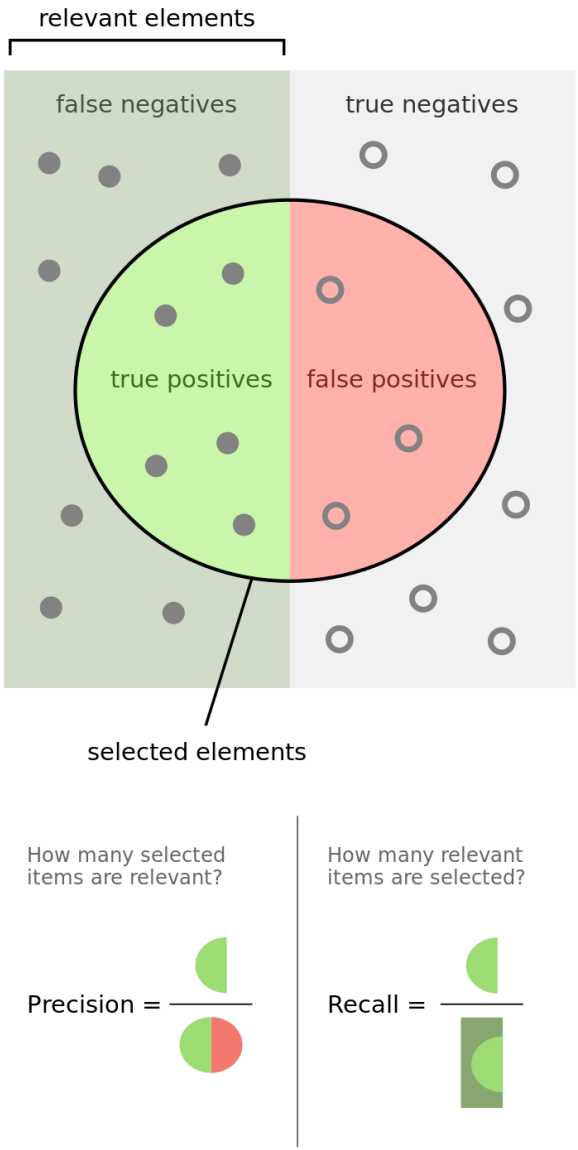
Precision and Recall



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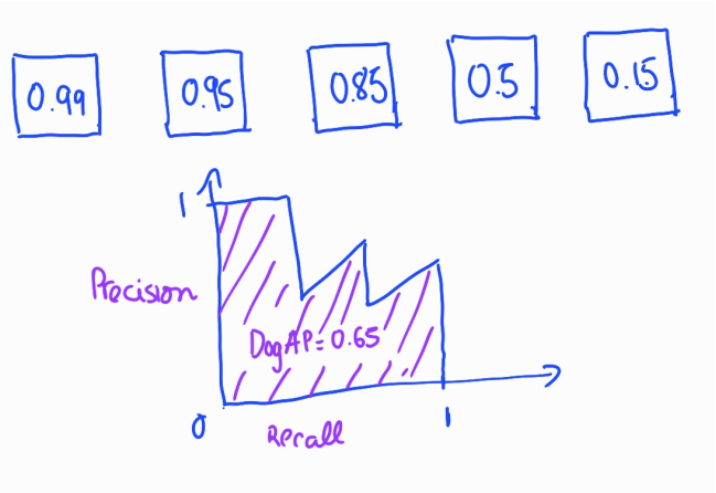
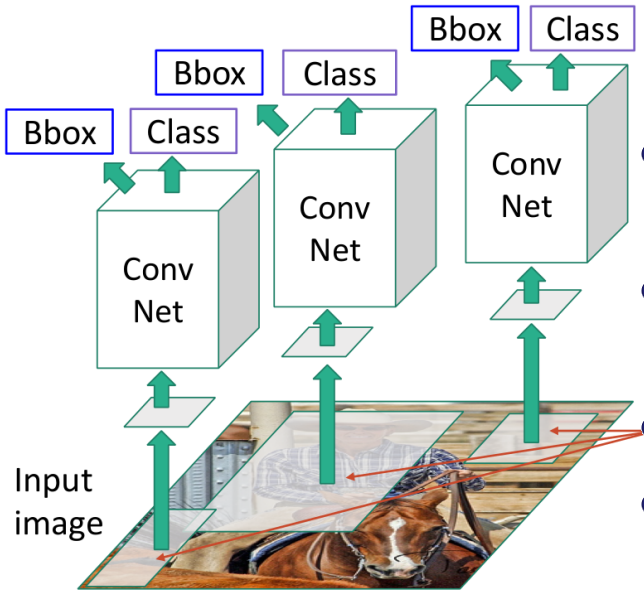
Source: Wikipedia

MAP



- The area under the PR curve is **average precision**
  - DogAP = 0.65
  - CatAP = 0.5
  - mAP = (0.55+0.6)/2.
  - The mAP is calculated at a specific IoU threshold of 0.5
- We need to redo all computation for IoU .5, 0.55, ... 0.95. and take average this and this will be for the final results.$mAP@0.5 : 0.05 : 0.95$

Regional proposals



Source: Justin Johnson

- Run region proposal method to extract around 2000 region proposals
- Resize each region to 224x224 and run independently through CNN to predict class scores and bounding boxes
- Use scores to select a subset of region proposals to output
- Compare with ground-truth boxes

Code to practice with image detection

- YOLO on SageMaker
- SSD on SageMaker
- Mask-RCNN on SageMaker

Lab session

Built-in Computer Vision in SageMaker for Image Classification

Next week

- Transfer learning
- QA session and Review A2

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