Université de Paris

Deep learning and applications – Part 2

Sylvain Lobry

11/11/2023

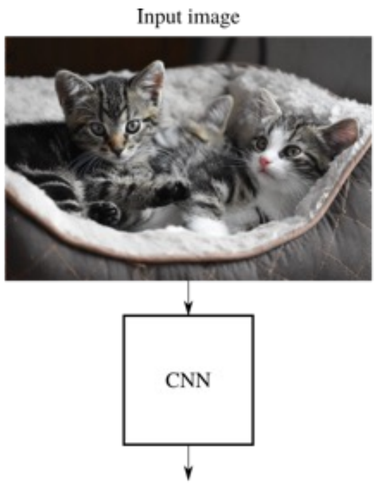
Object detection

What can you do with an image?

Input image

Object detection

What can you do with an image?



Object detection

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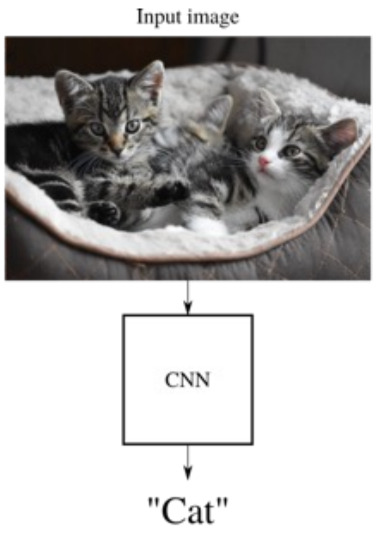

Object detection

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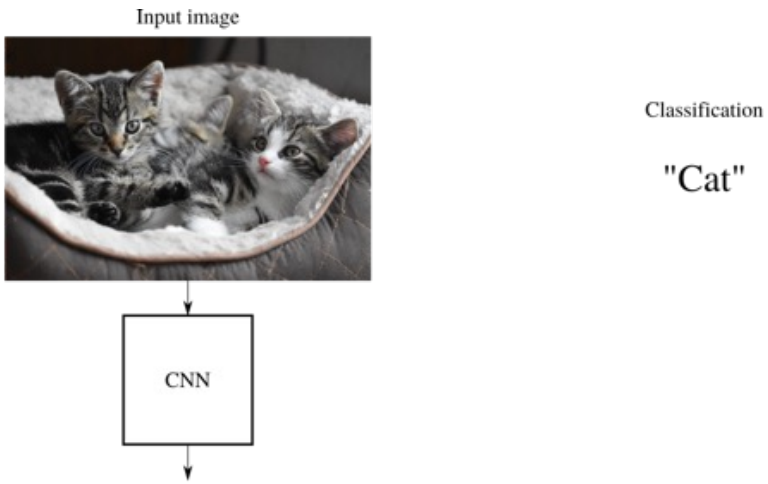

Object detection

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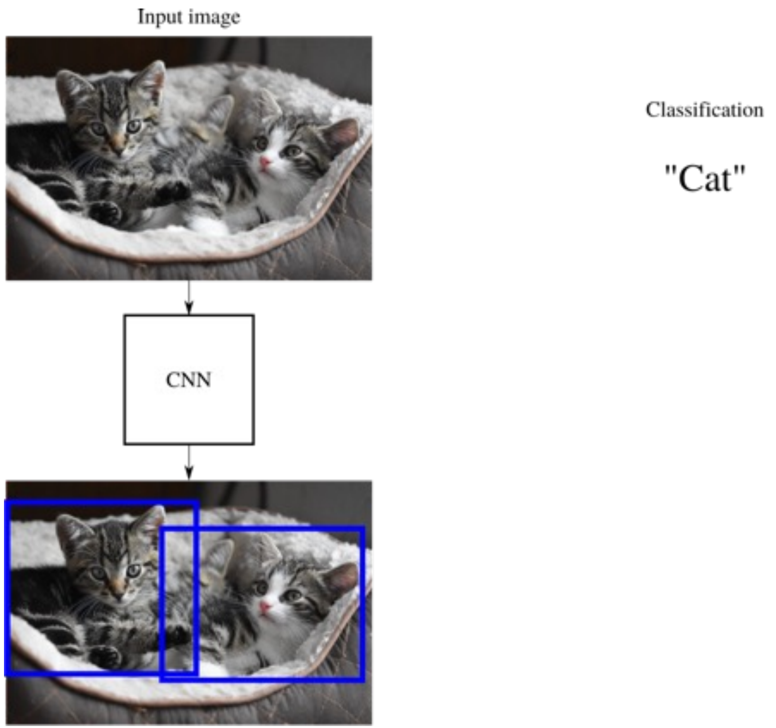

Object detection

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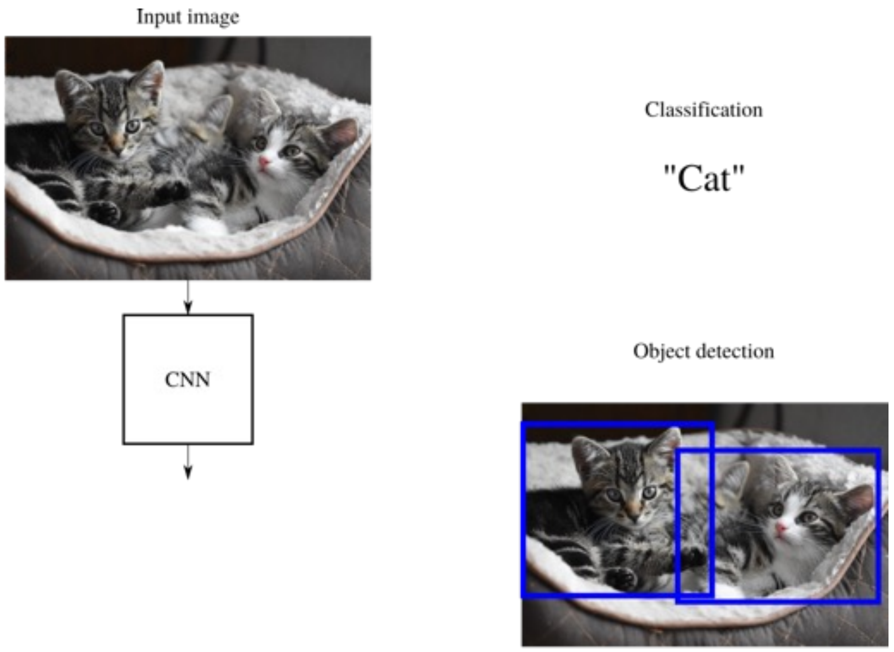

Object detection

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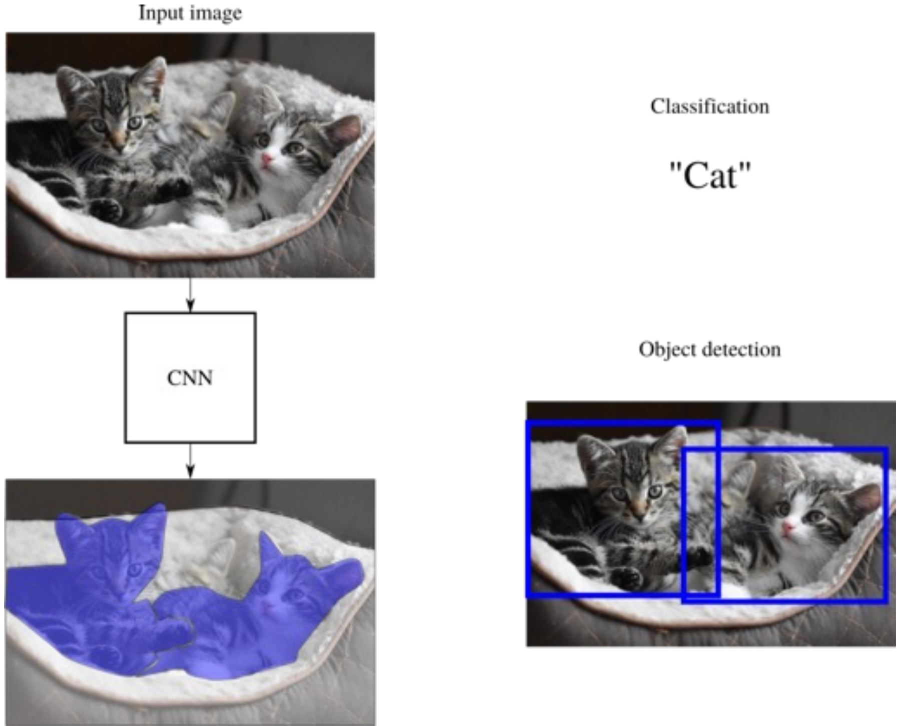
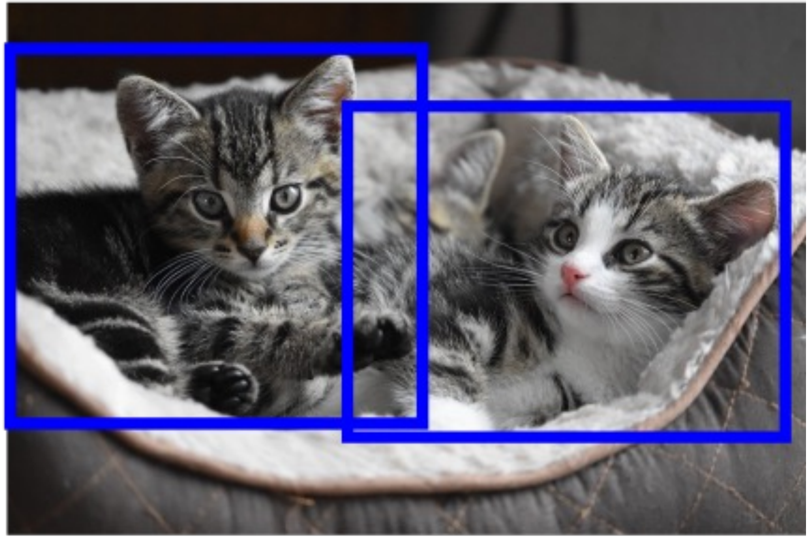


Object detection

Task of object detection

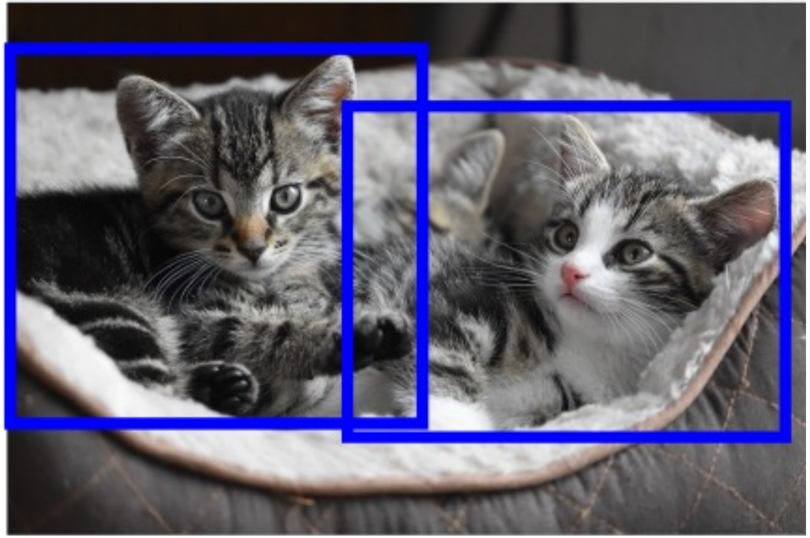


Objective:
get a set of bounding boxes associated to an objet

Output = $\{(\mathrm{Bbox}_1, class_1), \ldots (\mathrm{Bbox}_n, class_n)\}$

Object detection

Task of object detection



Compared to classification:
+ Spatial information
+ Can describe more
- More complicated

Compared to semantic segmentation:
+ Much more simple
+ Sufficient in most cases

Object detection

Why do we need it?

– Face recognition

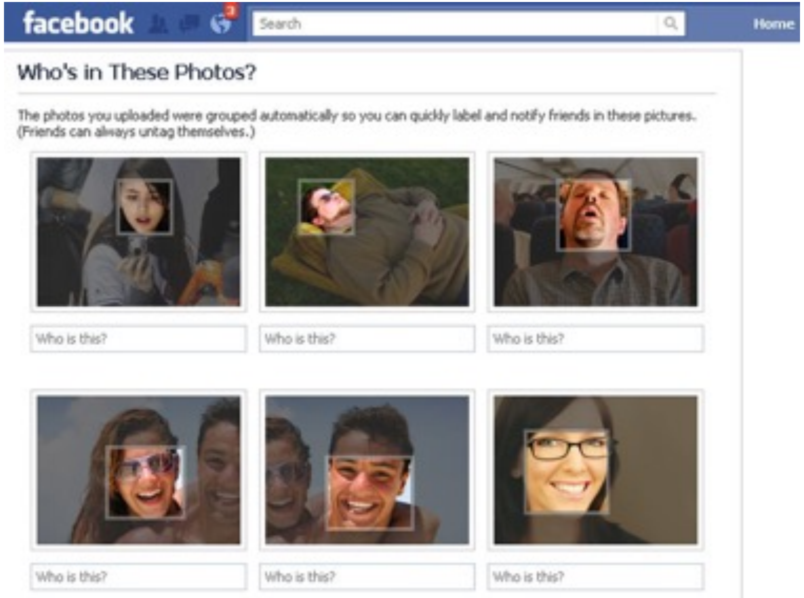
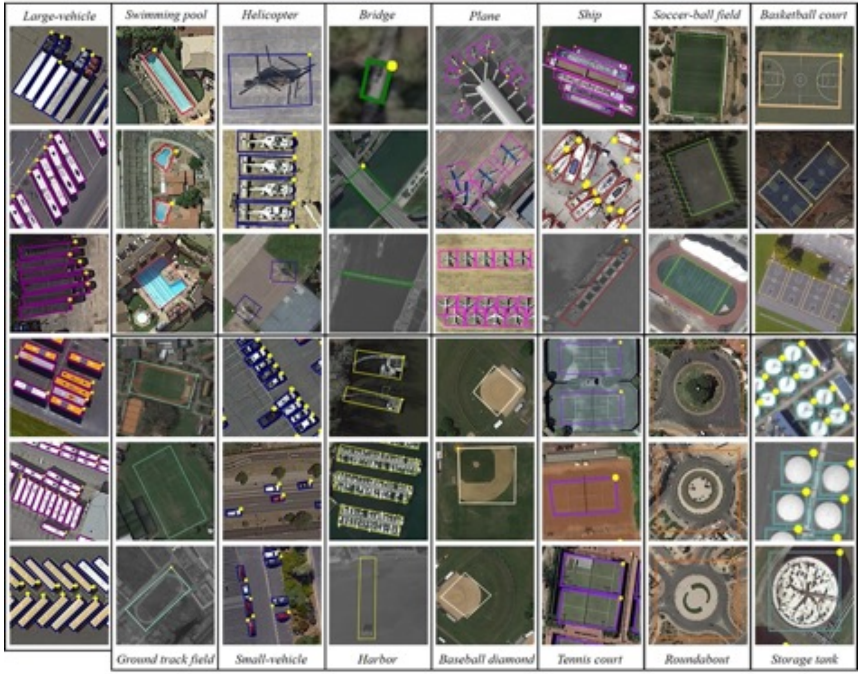


Image: CNET

Object detection

Why do we need it?

- Remote sensing

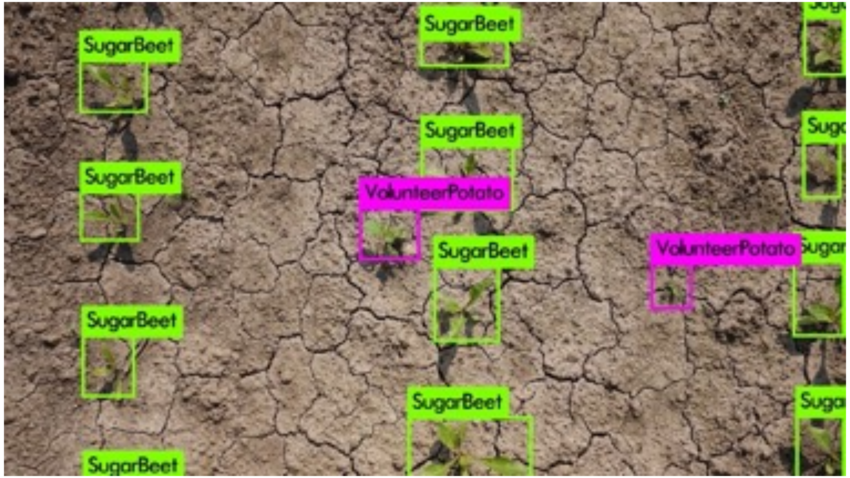


DOTA Dataset
Image source: https://captain-whu.github.io/DOTA/index.html

Object detection

Why do we need it?

- Security scans at airports
- Trash detection
- Crop monitoring
- Autonomous vehicles…



Object detection

Bounding box

Object detection

Bounding box

- Rectangle delineating the object

Object detection

Bounding box

- Rectangle delineating the object
- 3 options:
  - (x,y) of top left corner and width/height

Object detection

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- 3 options:
  - (x,y) of top left corner and width/height
  - (x,y) of the center and width/height

Object detection

Bounding box

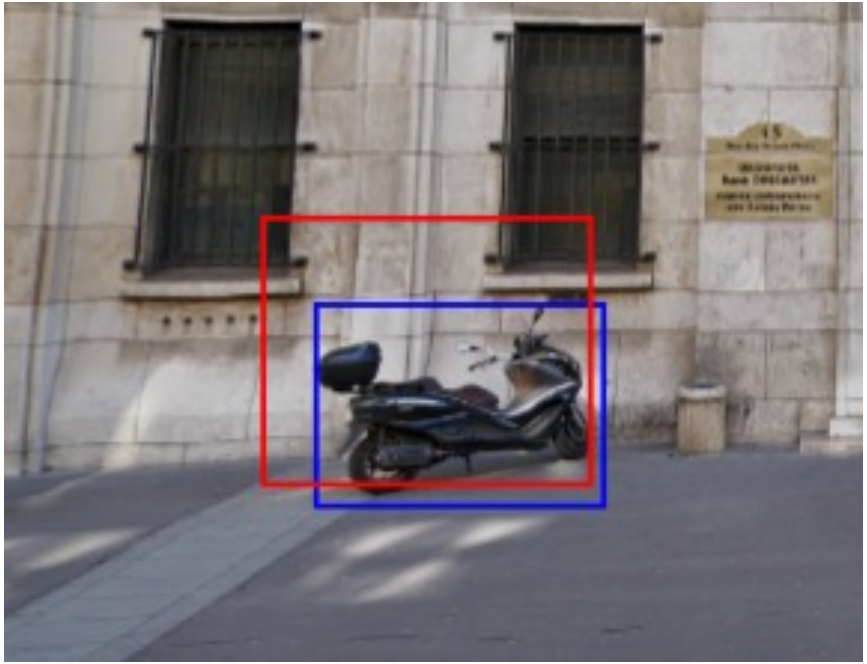
- Rectangle delineating the object
- 3 options:
  - (x,y) of top left corner and width/height
  - (x,y) of the center and width/height
  - (x,y) of top left and bottom right corners
- In any case, bounding box = 4 variables
- Coordinates and width/height are normalized by the size of the image.

Object detection

Evaluation of a bounding box

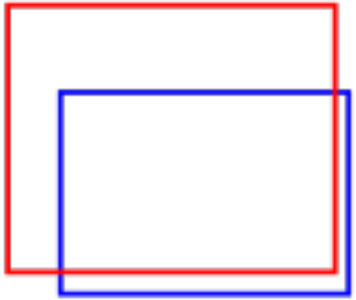
Object detection

Evaluation of a bounding box



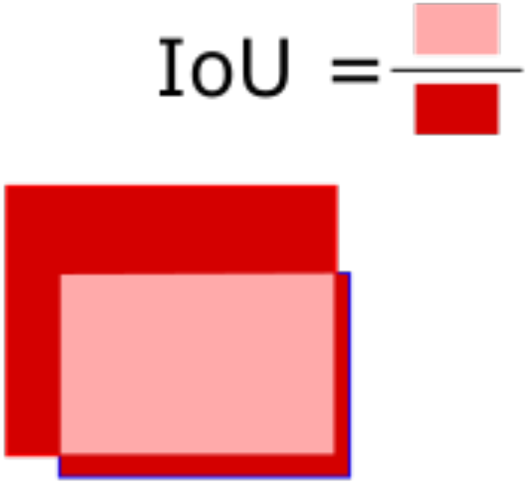
Object detection

Evaluation of a bounding box



Object detection

Evaluation of a bounding box



IoU (Intersection over Union)
a.k.a. Jaccard index

IoU is then thresholded to determine whether
The bounding box is accurate

Object detection

Naïve object detection

Idea: We know how to classify an image. Let’s classify bounding boxes (sliding window)!

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(P, x, y, w, h, c1, c2)

(0, _, _, _, _, _,

Object detection

Naïve object detection

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Object detection

Naïve object detection

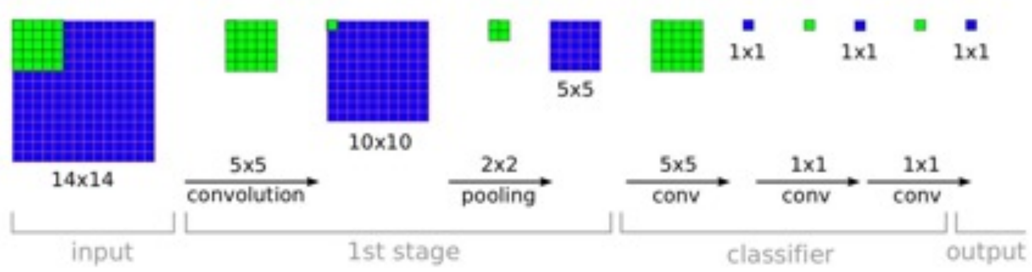
Idea: We know how to classify an image. Let’s classify bounding boxes (sliding window)!

- And you can slide a new window with a different bounding box size…
- Not efficient AT ALL…

Object detection

Naïve object detection – take 2

Previous approach does not really work as you have to make as many inference pass as the number of Bounding boxes tested…
Idea from Sermanet et. al. : sliding window can be seen as a convolution!
It could be as a Fully Convolutionnal Network (FCN).



Careful: only spatial dimensions indicated.
Multi-dimensional output!

Sermanet, P., Eigen, D., Zhang, X., Mathieu, M., Fergus, R., & LeCun, Y. (2013). Overfeat: Integrated recognition, localization and detection using convolutional networks. *arXiv preprint arXiv:1312.6229*.

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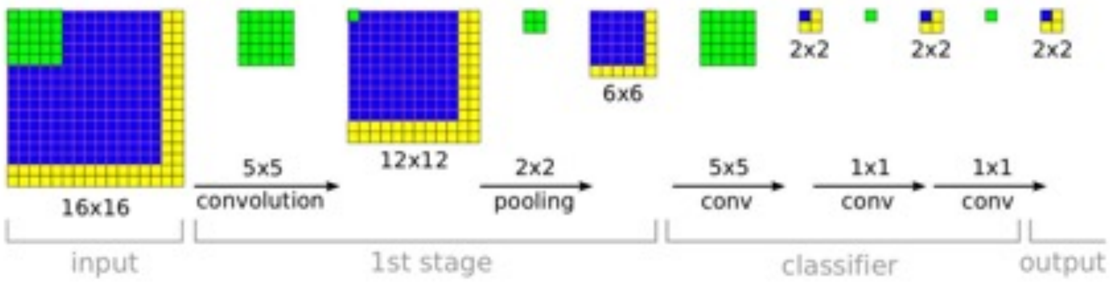

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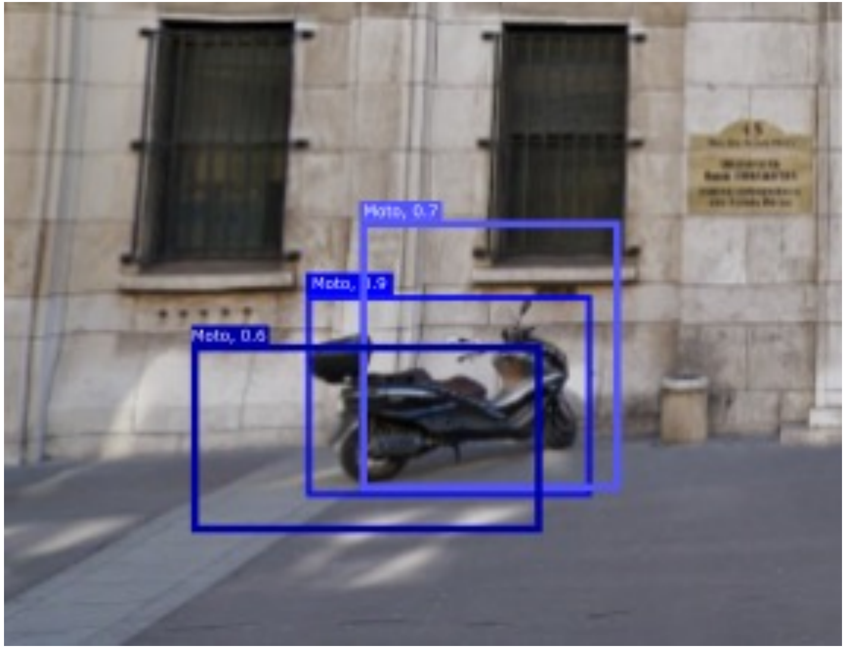
Object detection

Non-maximum suppresion



Problem: you might have more than one detection for each object…

Object detection

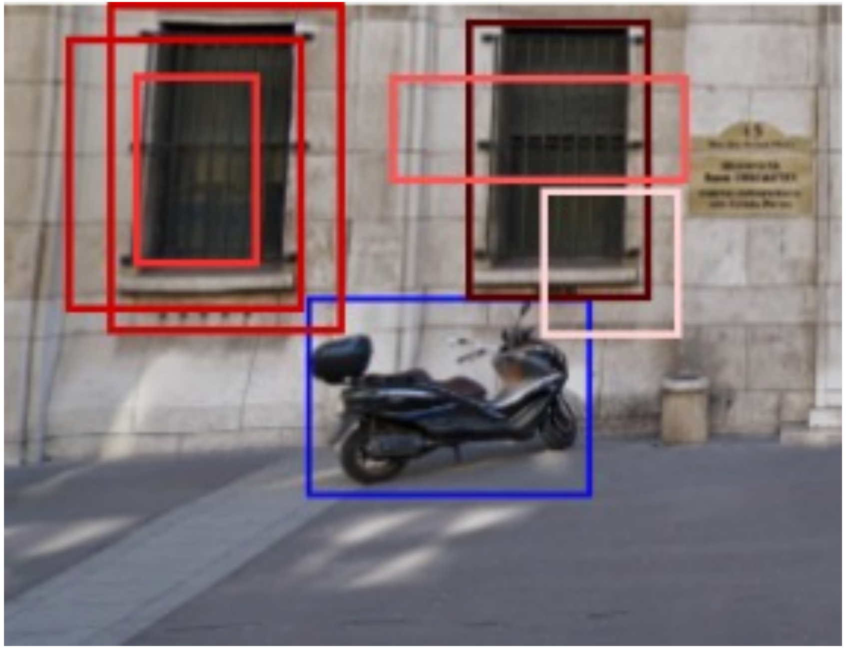
Non-maximum suppresion

Problem: you might have more than one detection for each object…

We want to remove least confident predictions: Non-maximum suppression (NMS)

Object detection

Non-maximum suppresion



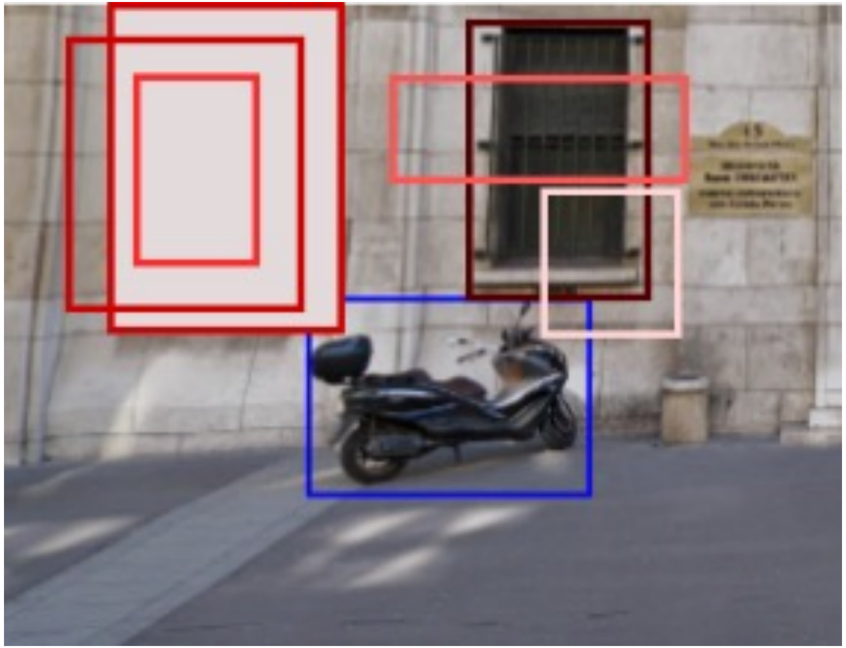
Example on windows: darker frame = better confidence on the detection.

Step1: for each class, order bounding boxes by decreasing order of confidence

Step2: select the most confident box as the reference.

Object detection

Non-maximum suppresion

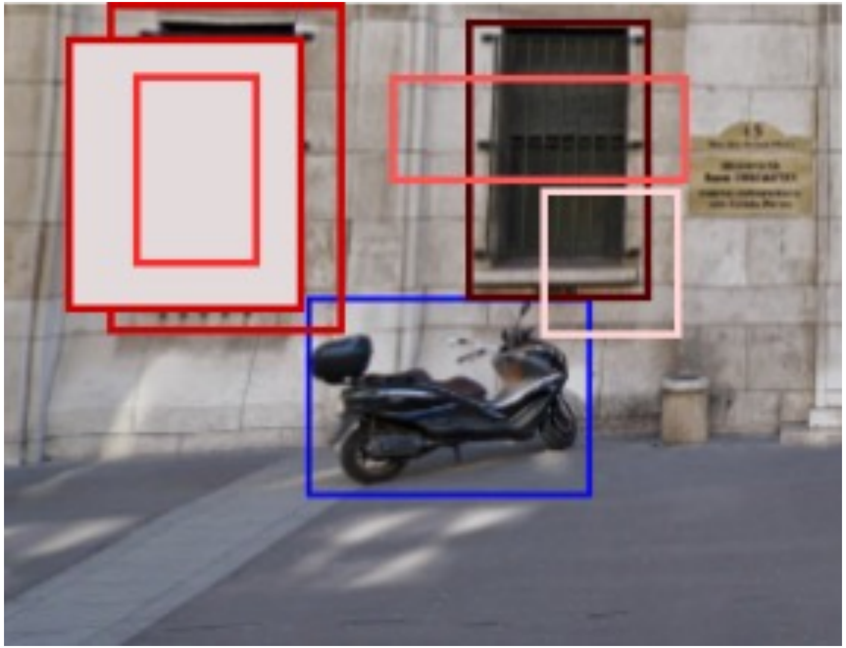


Example on windows: darker frame = better confidence on the detection.

Step1: for each class, order bounding boxes by decreasing order of confidence
Step2: select the most confident box as the reference.
Step3: select the second most confident box:
-- IoU with reference > threshold ?
--- remove
-- else
--- keep

Object detection

Non-maximum suppresion



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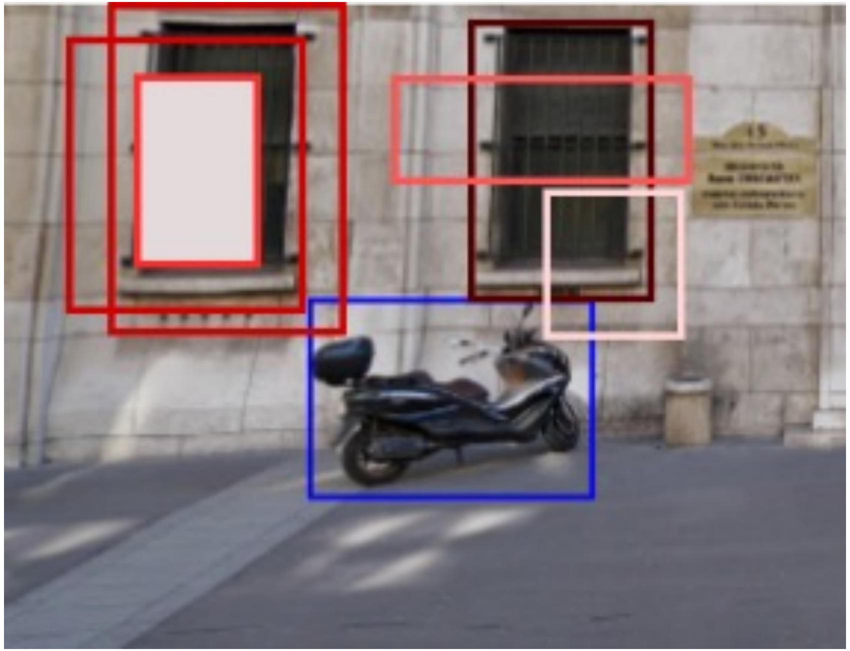

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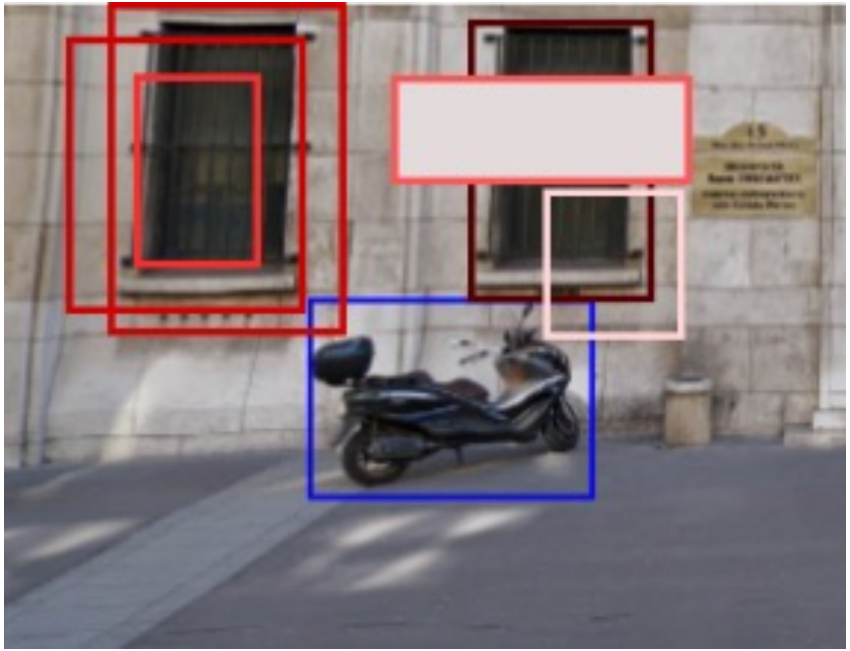

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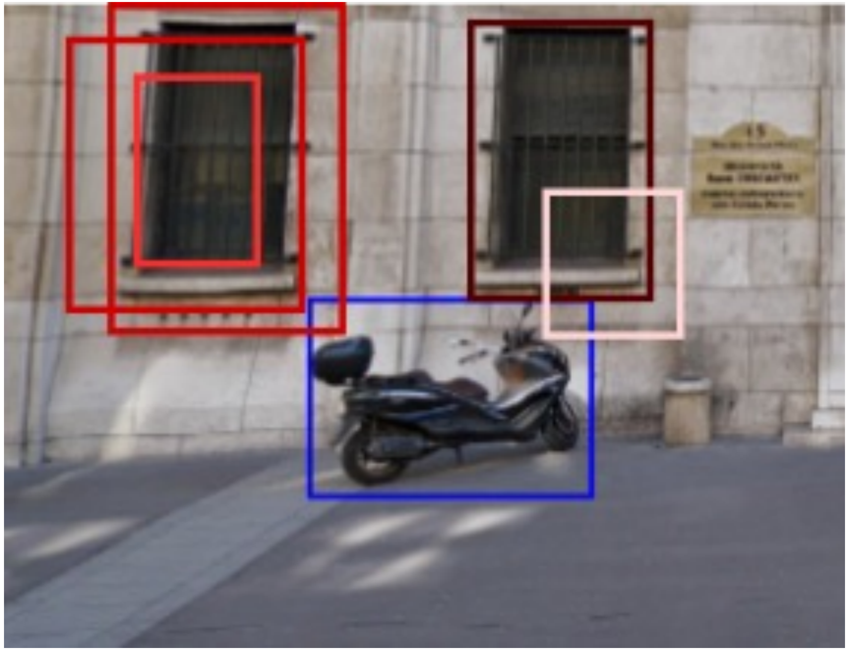

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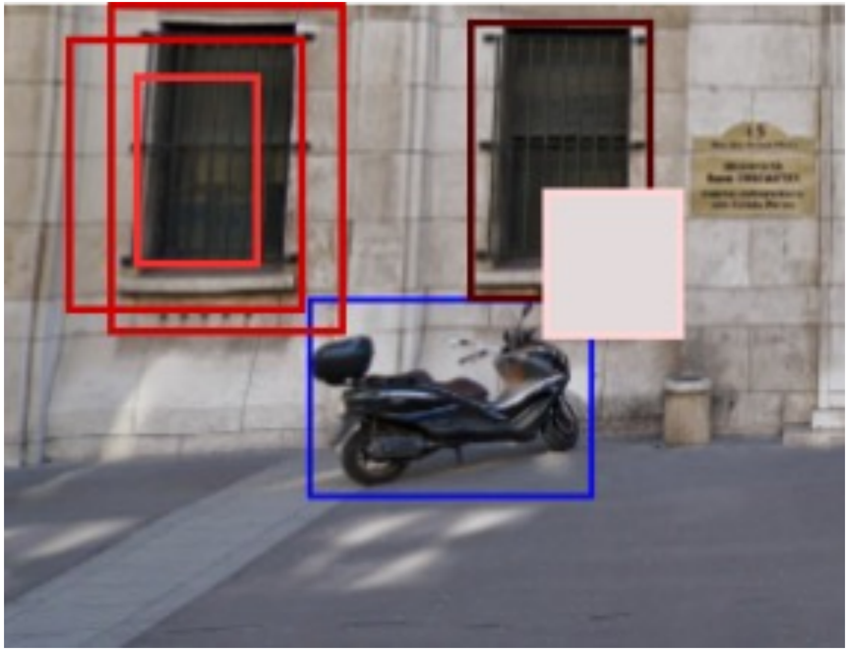

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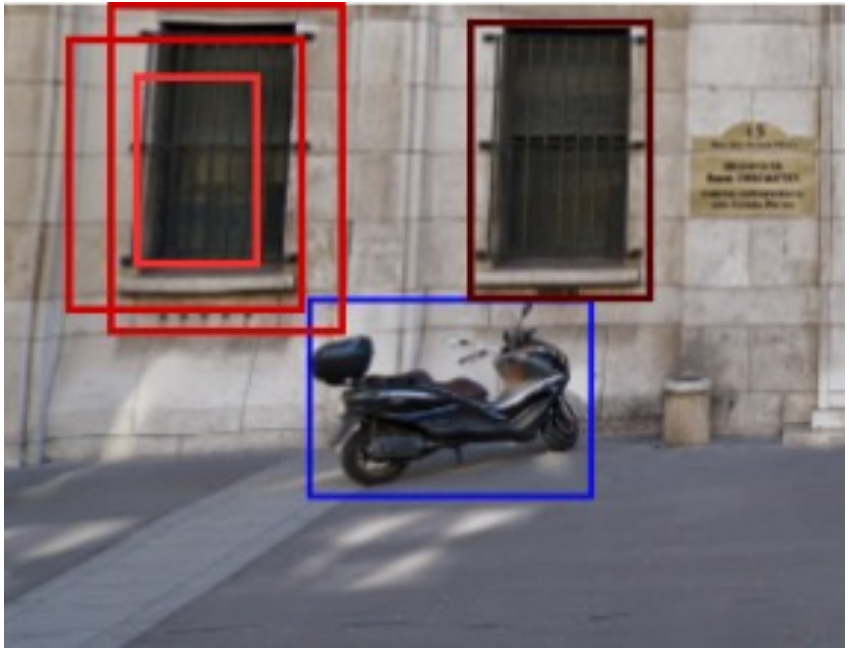

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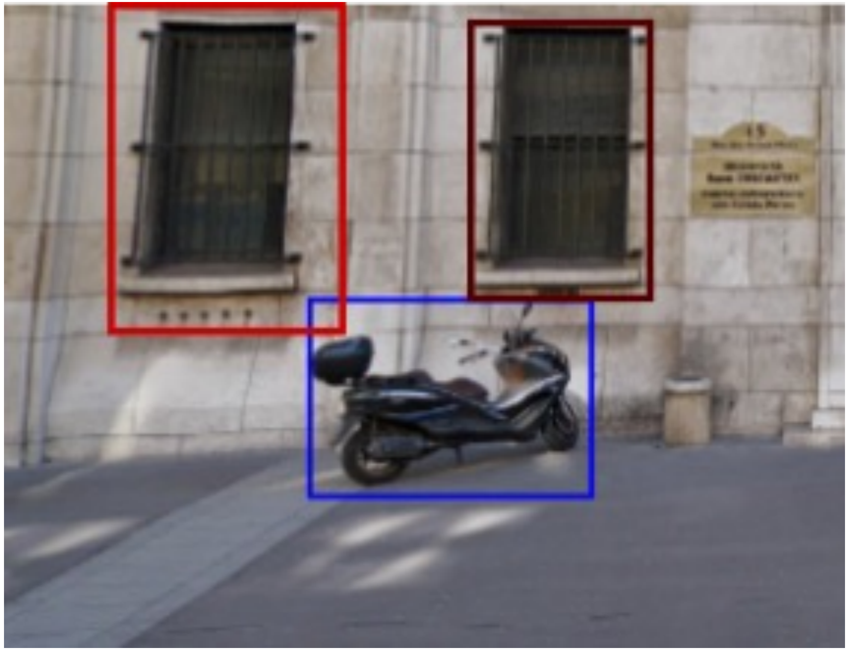

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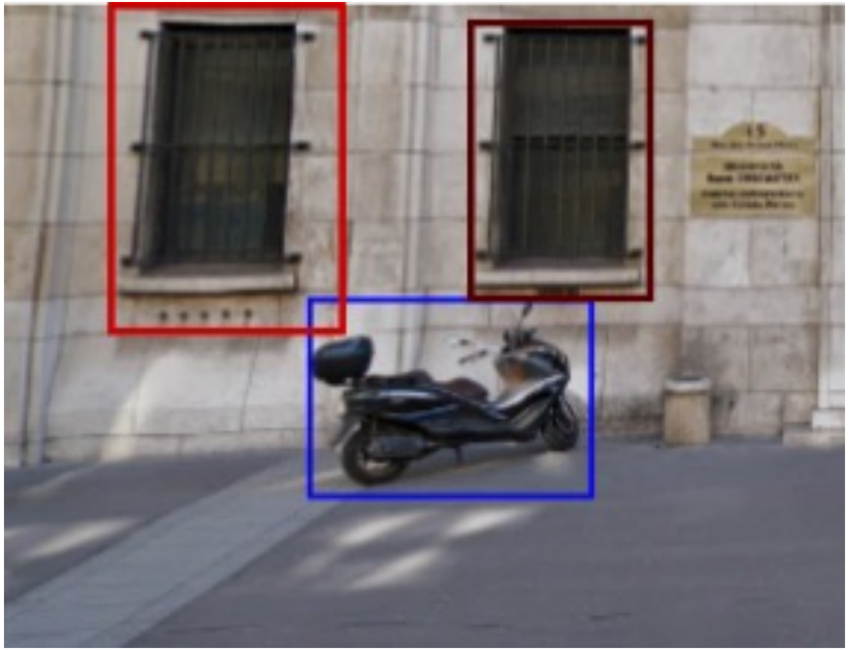


Important: to be done for each object separatly !

Object detection

Recap

We have seen:

- What is a bounding box
- How to evaluate its accuracy
- How to suppress multiple detections

Questions?

Object detection

Recap

We have seen:

- What is a bounding box
- How to evaluate its accuracy
- How to suppress multiple detections

But… How do you get the bounding boxes?
2 options:

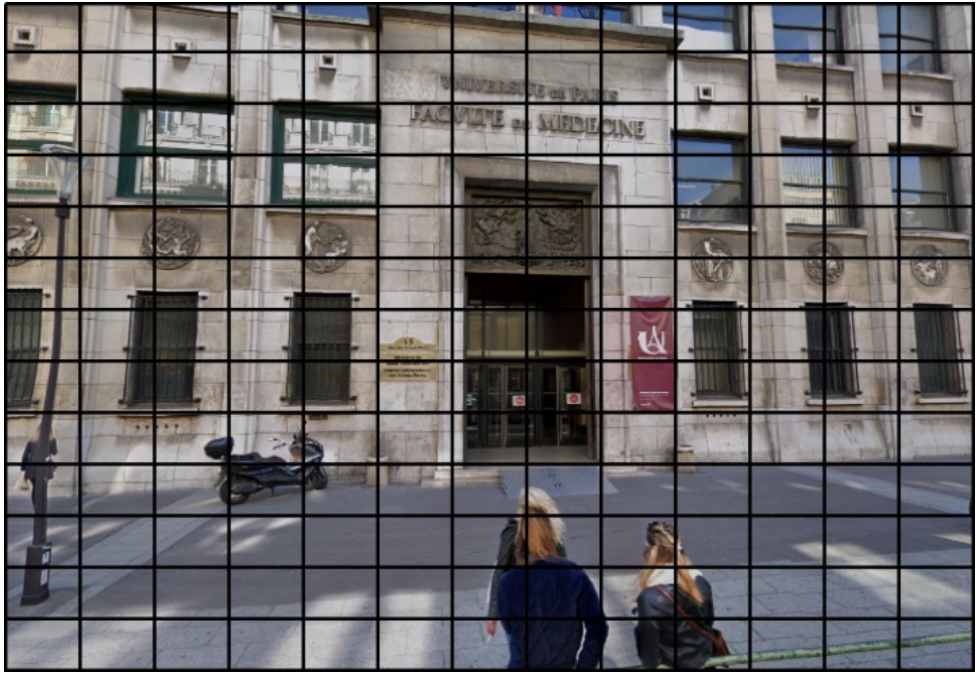
- Hardcoded bounding boxes (a.k.a. anchor boxes)
- Try to predict the bounding boxes (a.k.a. region proposal)

Object detection

Anchor box

Object detection

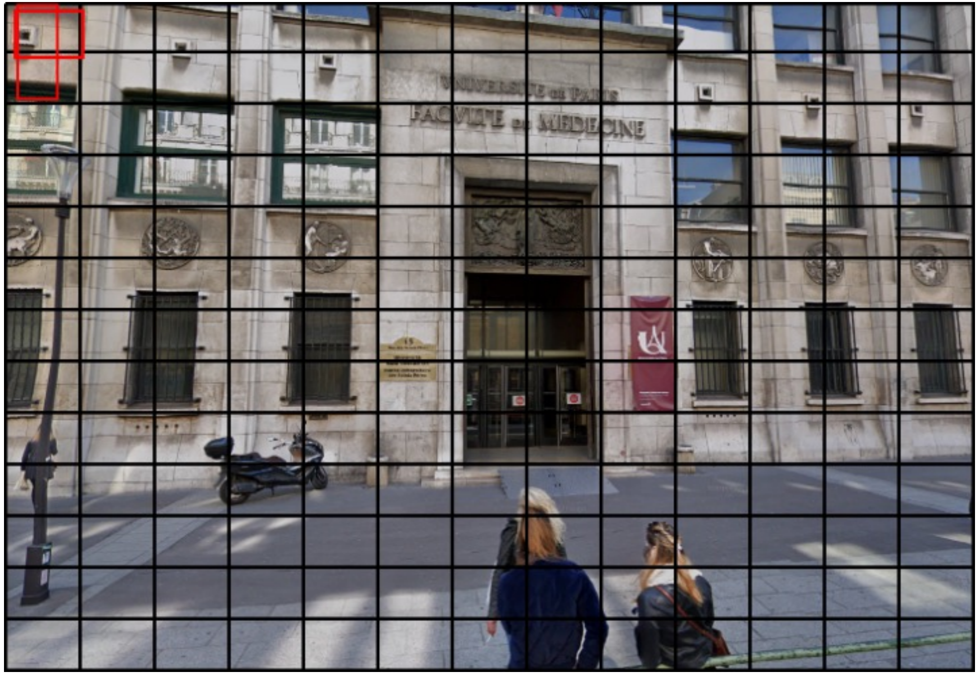
Anchor box



- Divide the image into a grid

Object detection

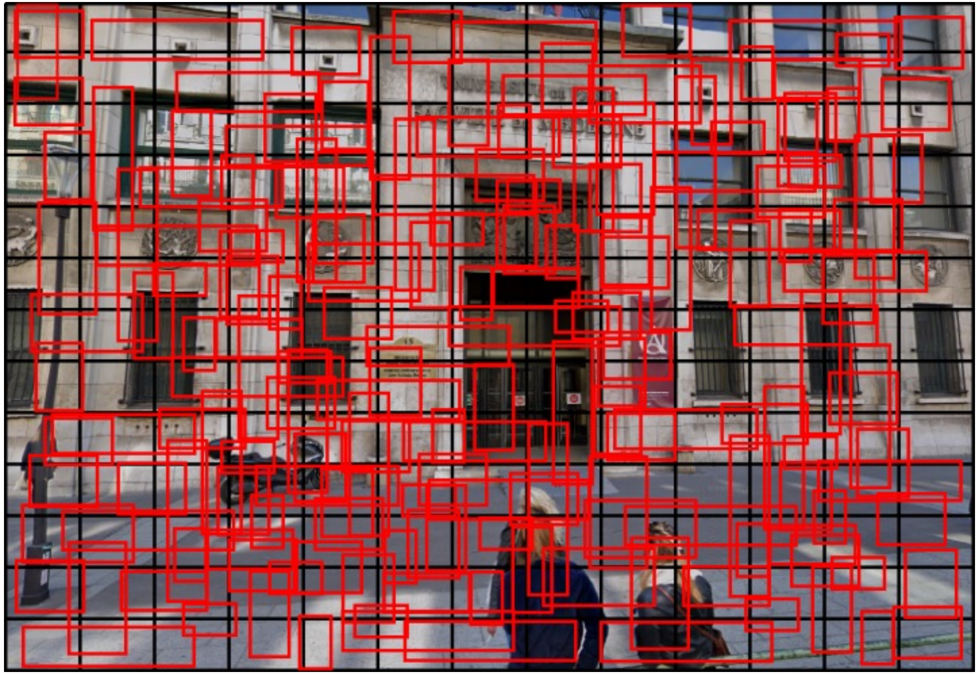
Anchor box



- Divide the image into a grid
- For each cell, define B bounding boxes (here B = 2)

Object detection

Anchor box



- Divide the image into a grid
- For each cell, define B bounding boxes (here B = 2)
- Prediction for each grid cell:

$$(\underbrace{x_1, y_1, w_1, h_1, p_1}_{\text{Box 1}}, \dots, \underbrace{x_B, y_B, h_B, w_B, p_B}_{\text{Box B}}, \underbrace{c_1, c_2}_{\text{Classes}})$$

Object detection

YOLO

Put everything we have seen until now (prediction based on anchor boxes, NMS): YOLO

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788). ISO 690

Object detection

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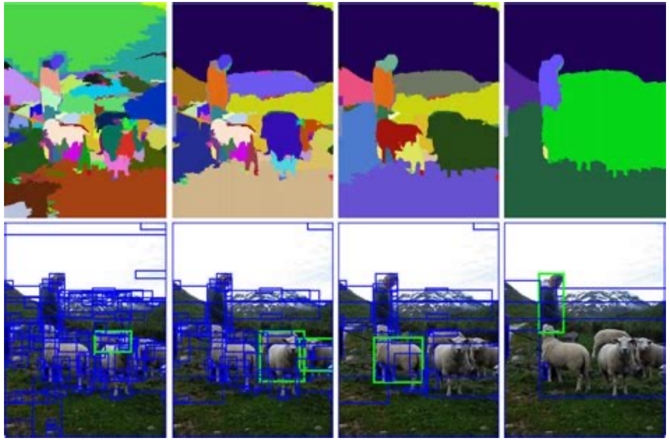
Object detection

R-CNN

1) Region proposal algorithm: selective search [1]: semantic segmentation + grouping

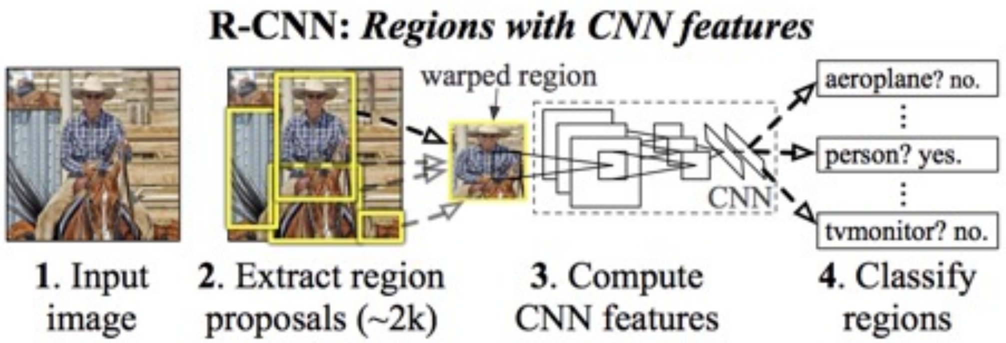


[1] J.Uijlings, K.van de Sande,T.Gevers, and A.Smeulders. Selective search for object recognition. *IJCV*, 2013
[2] Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 580-587).

Object detection

R-CNN

1) Region proposal algorithm: selective search [1]: semantic segmentation + grouping -> select ~2000 regions
2) Classification of the regions by a CNN -> R-CNN [2]



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Object detection

R-CNN vs YOLO

R-CNN: Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR
YOLO: Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. CVPR

Improvements over the two types of algorithms in the past years

[1] J.Uijlings, K.van de Sande,T.Gevers, and A.Smeulders. Selective search for object recognition. *IJCV*, 2013
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Let’s code!