Deep Learning

Big Data & Machine Learning Bootcamp - Keep Coding



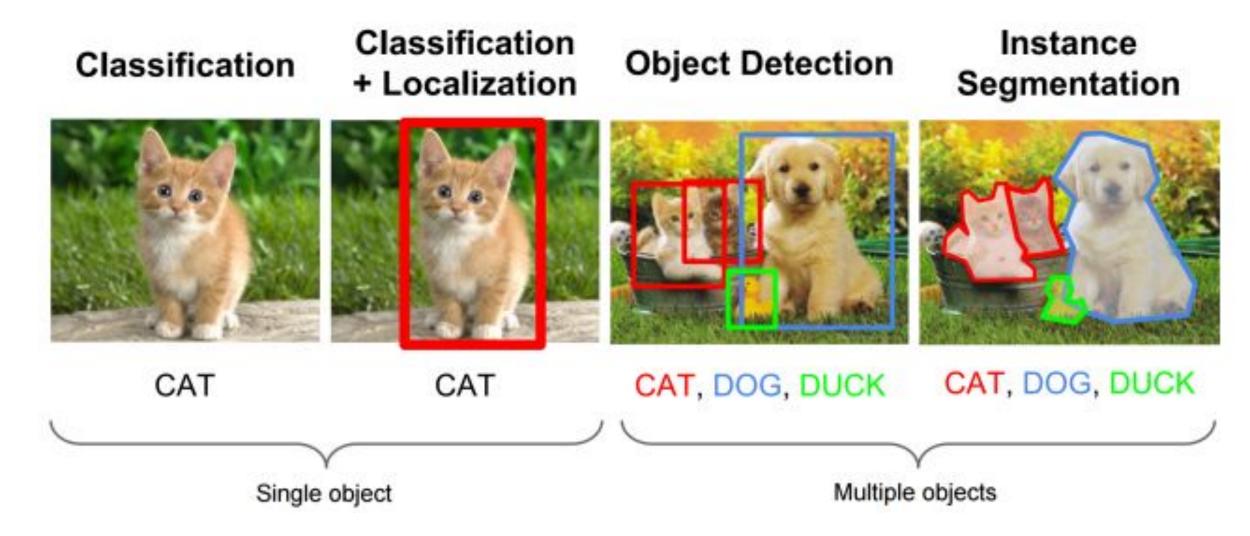
Outline

- 1. Object localization
- 2. Landmark detection
- 3. Object detection
- 4. Convolutional implementation of sliding windows
- 5. Bounding box predictions (YOLO)
- 6. Intersection over union (IoU) (YOLO)
- 7. Non-max suppression (YOLO)
- 8. Anchor boxes (YOLO)
- 9. YOLO algorithm



1. Object localization

It is important to first distinguished **the difference tasks**. What is classification, classification with localization, object detection and instance segmentation. Depending on the task, the labels will change.



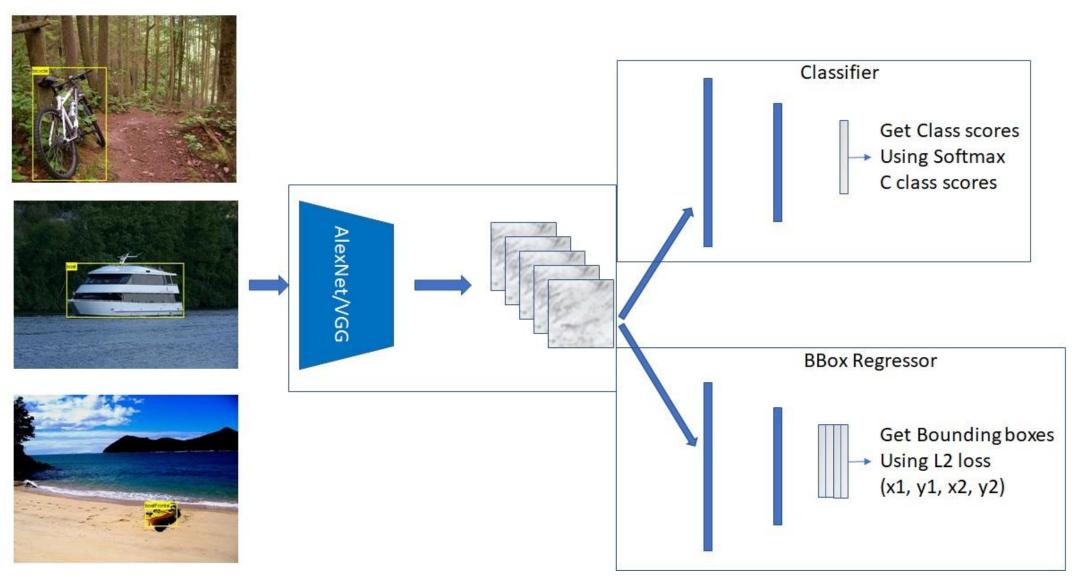


⁻ Coursera

⁻ https://towardsdatascience.com/object-localization-in-overfeat-5bb2f7328b62

1. Object localization

Classification with localization



Remember that for classification only, the output was a class for each image?

For this task, the output is the class AND also the bounding box coordinates (x1, y1, x2, y2)



- Coursera
- https://cogneethi.com/evodn/object_detection_intro/

1. Object localization

Labels for classification with localization:

Say for instance we have 4 different classes:

- 1. Pedestrian
- 2. Car
- 3. Motorcycle

Then the label "y" will be a vector of 8 numbers. The first component (p_c) will indicate if there is an object in the image, the next 4 components (b_x , b_y , b_h , b_w) will specify the bounding box and the last 3 (c_1 , c_2 , c_3) will represent the label for the detected object.

If there is no object in the image, $p_c = 0$ and the other values won't matter

$$Y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

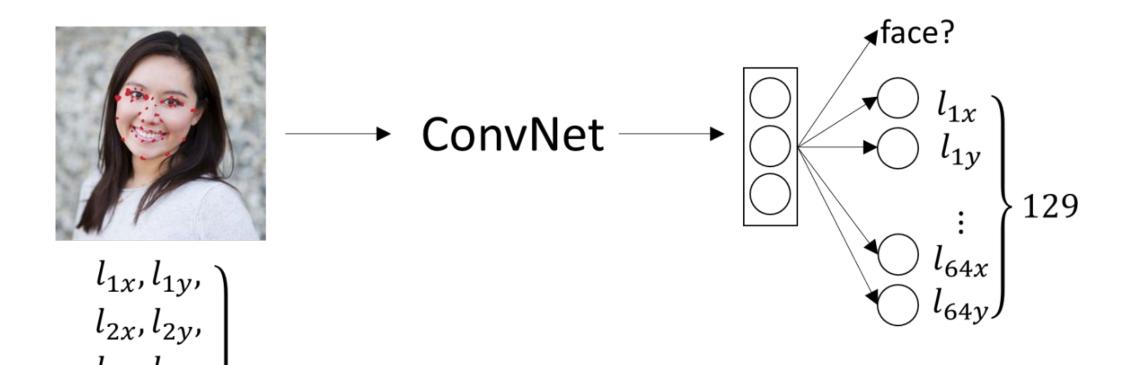


⁻ Coursera

⁻ https://medium.com/machine-learning-bites/deeplearning-series-objection-detection-and-localization-yolo-algorithm-r-cnn-71d4dfd07d5f

2. Landmark detection

The idea of having multiple numbers as labels can also be applied to landmark detection.



The first number in the vector indicate if there is a face in the image. The other numbers represent landmark in the face is represented by (x, y) coordinate.

Applications of this are emotion detection, graphic effects and virtual reality!

Have you seen the instagram effects?



- Coursera
- https://datahacker.rs/deep-learning-landmark-detection/

 l_{64x}, l_{64y}

3. Object detection

Sliding window for object detection



Basically you choose a window size and pass it through the image with a defined stride. Each time classifying whether the object is in the window. Then, Increment the window and pass it again to the image.

Huge disadvantage:

- Computation cost

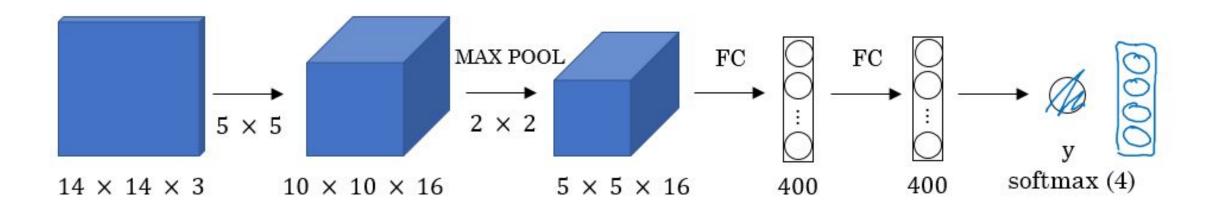


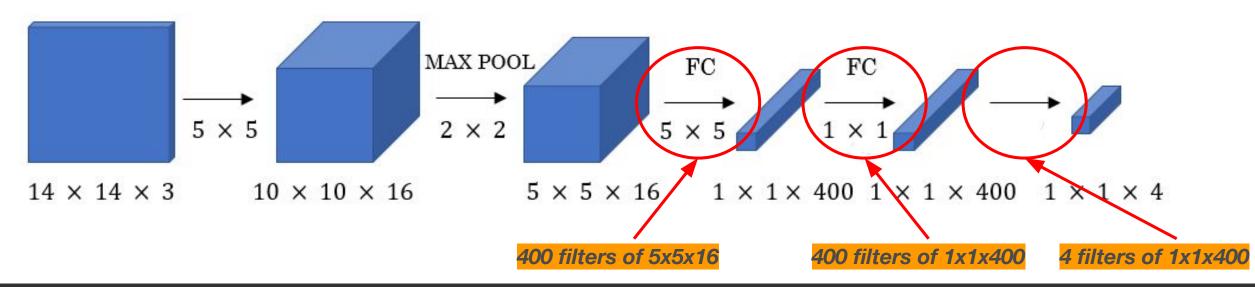
- Coursera
- http://datahacker.rs/deep-learning-object-detection/

4. Convolutional implementation of sliding windows

Sliding window implemented convolutionally.

Let's first see how we can turn a fully connected layer into a convolutional layer:







⁻ Coursera

⁻ https://zhangruochi.com/Convolutional-Neural-Networks/2019/03/27/

4. Convolutional implementation of sliding windows

Sliding window implemented convolutionally.

This is for one window 5x5 10x10 5x5 2x2 5x5 1x1 1x1 14x14 convolution pooling conv conv conv Running a pooling layer of 2x2 1st stage input classifier output corresponds to slide a window of All of these computations 14x14 with stride of 2 in the original performed at once!! 2x2 2x2 2x2 6x6 12x12 5x5 2x2 5x5 1x1 1x1 convolution' pooling conv conv conv 16x16 This is for 4 windows 1st stage input output classifier



image

Sermanet, et al. "Overfeat: Integrated recognition, localization and detection using convolutional networks." arXiv preprint arXiv:1312.6229 (2013).

- Coursera
- https://www.oreilly.com/library/view/deep-learning-for/9781788295628/e1f0c48f-e9bd-4972-b31c-a3d87a462e73.xhtml

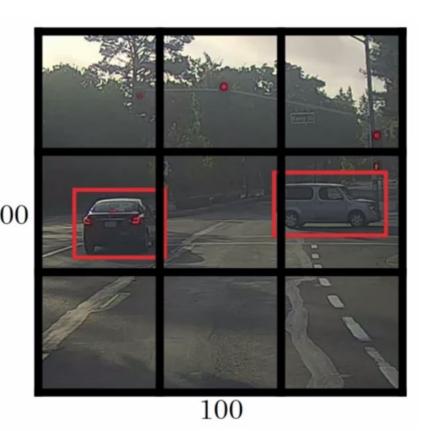
5. Bounding box predictions (YOLO)

YOLO algorithm: You only look once!

The previous approach still have the problem that the bounding box is not always the size of the object we want to detect.

YOLO algorithm first place a grid down to the image and then apply 100 the classification with localization algorithm.

Let's see how the labels "y" are for this approach

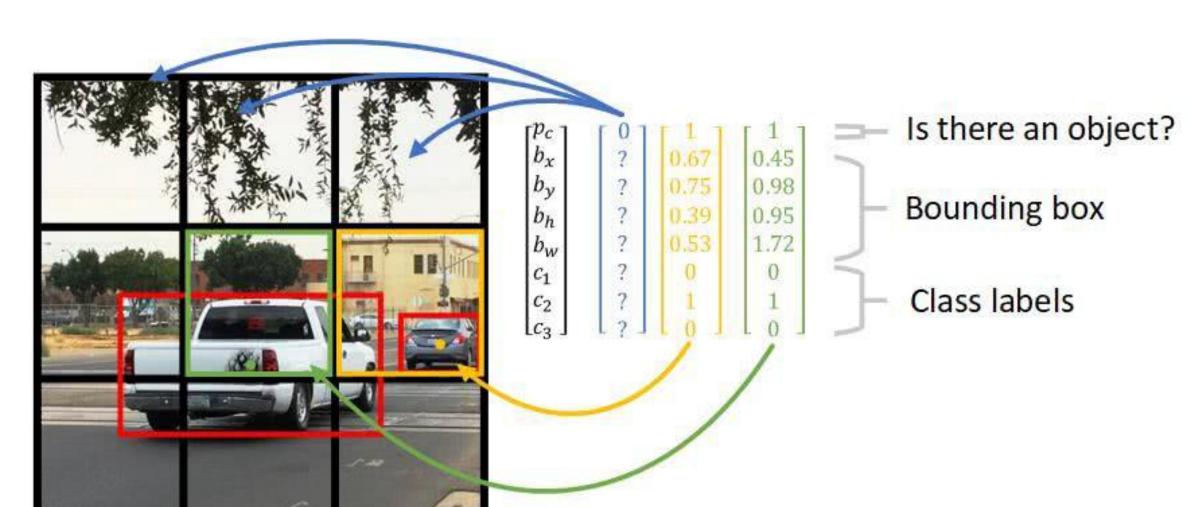




Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).

5. Bounding box predictions (YOLO)

Labels for the YOLO algorithm



In this case, in which we placed a grid of 3x3, the labels will have a size of 3x3x8.

The label will be 1 when the cell contains the centre of the bounding box.

Usually, the grid is 19x19 or even more!

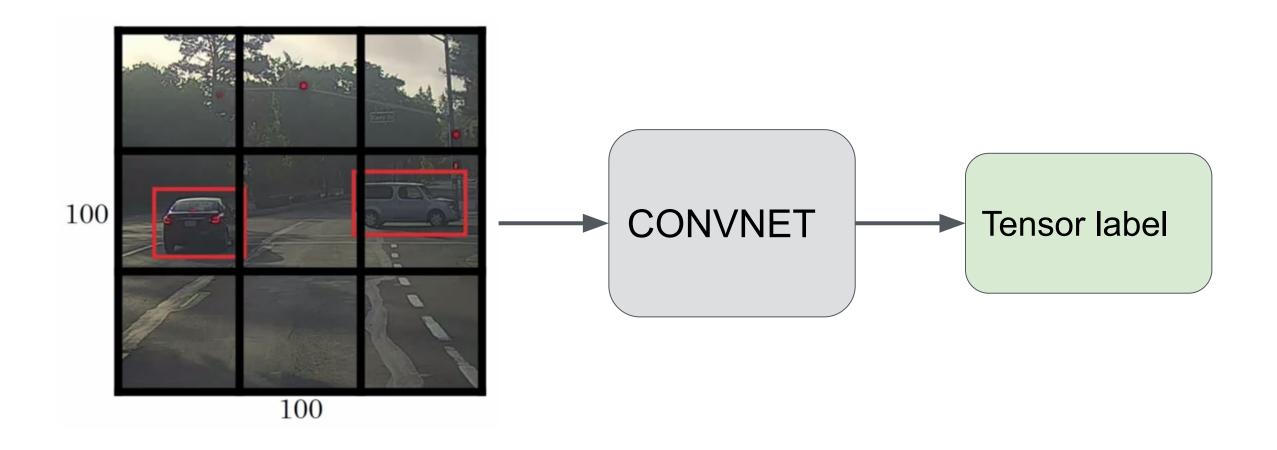


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- Coursera
- https://stackoverflow.com/questions/50575301/yolo-object-detection-how-does-the-algorithm-predict-bounding-boxes-larger-than

5. Bounding box predictions (YOLO)

YOLO architecture in general



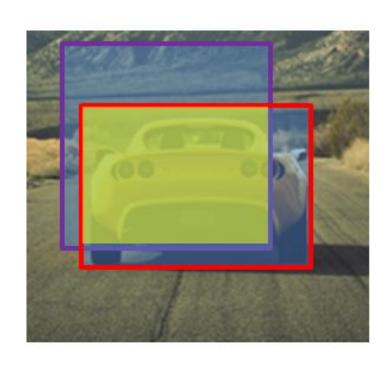


Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).

6. Intersection Over Union (YOLO)

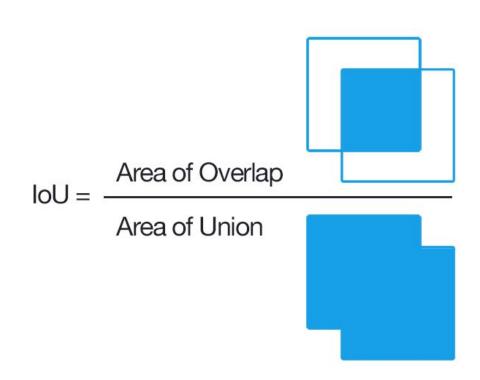
Intersection Over Union (IoU) tells us if our object detection algorithm is doing well.

In general, this is a way to tell whether two boxes are similar



Intersection over union (IoU)

"Correct" if IoU ≥ 0.5





⁻ Coursera

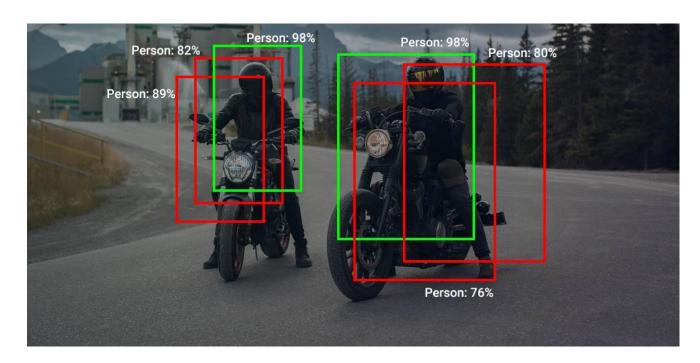
7. Non-max suppression (YOLO)

Non-max suppression helps us to remove the bounding boxes that are not similar to the ground truth/labels.

In other words, it is a way to make sure the algorithm only detects each object only once!

Here are the steps:

- Discard the bounding boxes that have $p_c \le 0.6$
- While there are any remaining boxes:
 - Pick the box with the largest p_c -> **This will be our final** prediction
 - Discard any remaining box with IoU >= 0.5 with the box output in the previous step





In this case we showed only one class, but non-max suppression should be applied for the classes

- Coursera
- https://www.analyticsvidhya.com/blog/2020/08/selecting-the-right-bounding-box-using-non-max-suppression-with-implementation/

8. Anchor boxes (YOLO)

Anchor boxes allows each grid cell to detect more than one object.

Labels for each grid cell will contain information regarding all the number of bounding boxes we have.



Anchor box 1 Anchor box 2

Anchor box 2:

Anchor box 1:

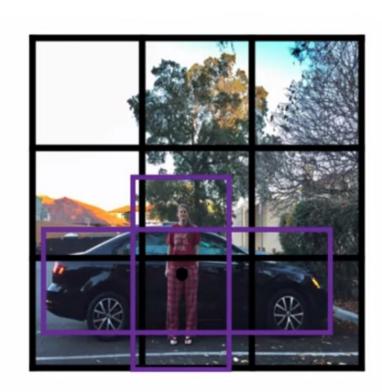
In this case we're showing only two anchor boxes, but there can be 5, 6 or 10



- Coursera
- http://datahacker.rs/deep-learning-anchor-boxes/

8. Anchor boxes (YOLO)

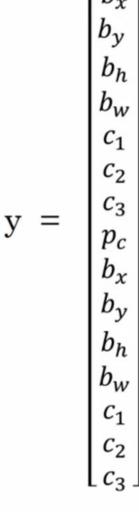
Another example of anchor boxes and the labels size



Anchor box 1: Anchor box 2:







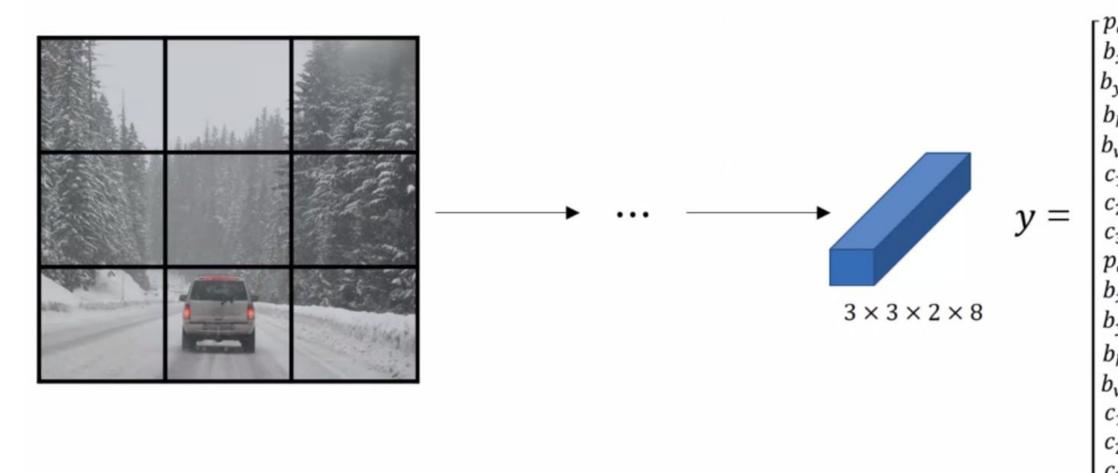
When there is a grid cell that only contains one anchor box, $p_c = 0$ for the other anchor boxes



9. YOLO Algorithm

Let's put all the components together to form the YOLO algorithm.

- For training, we first need to create the labels "y" for all our grid cells and anchor boxes



One vector like this for each grid cell.

This is when we have four objects and 2 anchor boxes.

9. YOLO Algorithm

Let's put all the components together to form the YOLO algorithm.

- Then you run non-max suppression:
 - 1. For each grid cell, get 2 predicted bounding boxes (in the example in which we have two bounding boxes of course)
 - 2. Get rid of low probability prediction
 - 3. For each class use non-max suppression to generate final predictions





Good to know (R-CNN, Fast R-CNN, Faster R-CNN)

There is another approach to detect objects that is called region proposals or R-CNN.

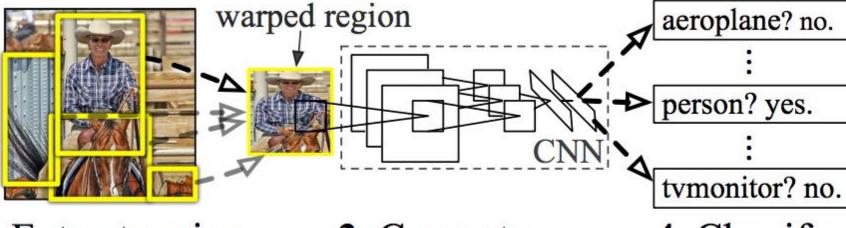
R-CNN: Regions with CNN features



1. Input image



2. Extract region proposals (~2k)



3. Compute CNN features

4. Classify regions

We first use a region proposal network and then run the convolutional sliding window on the regions!

Because it has two steps, it is a bit slower than YOLO



⁻ Coursera

⁻ https://towardsdatascience.com/step-by-step-r-cnn-implementation-from-scratch-in-python-e97101ccde55