Object localization

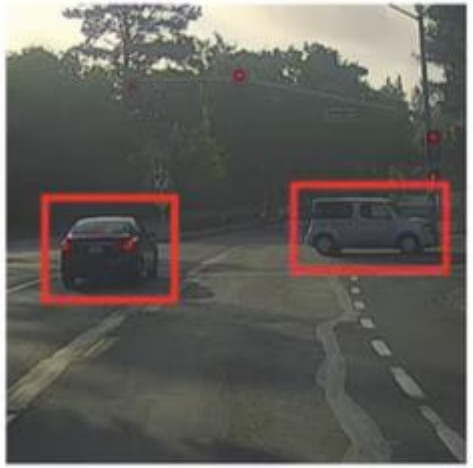
Object localization

- Q. AVG POOL / Activation function -> Sigmoid / 적은 변수 갯수

Image classification

Classification with localization

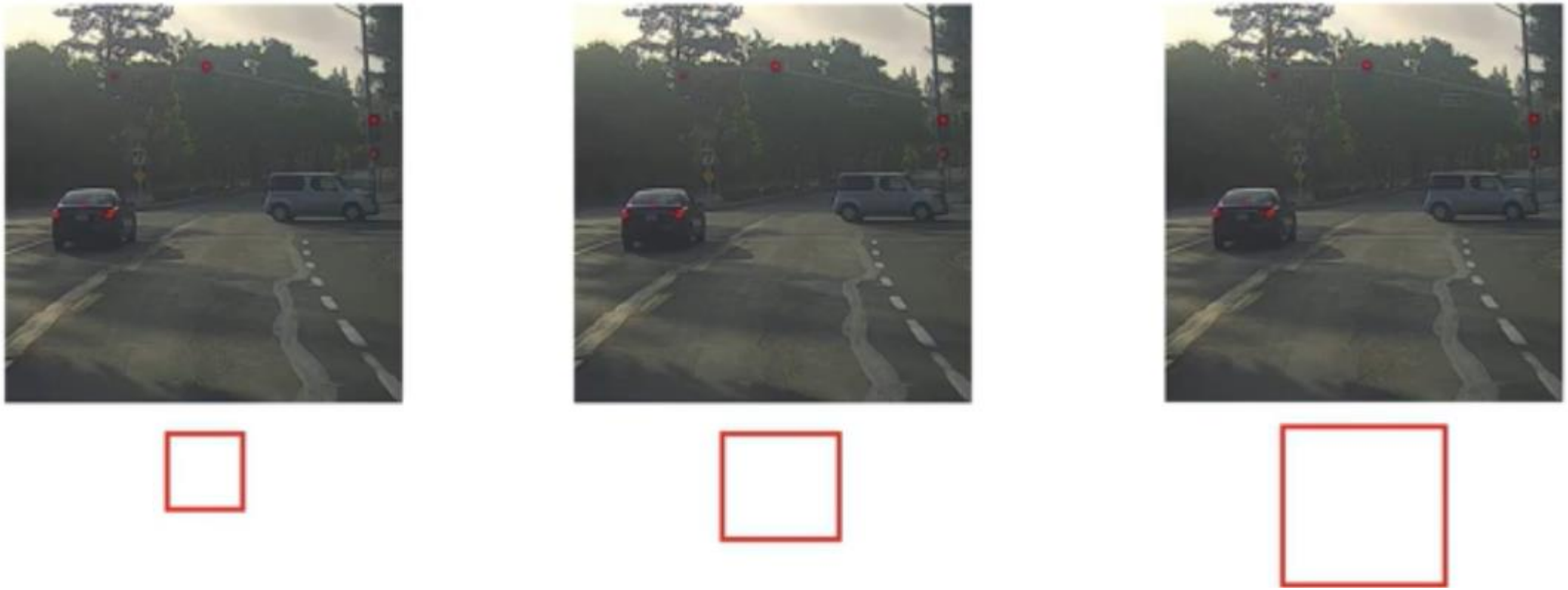
Detection



Sliding windows detection

Sliding windows detection

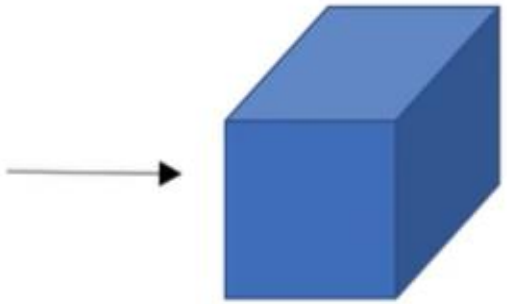
- 윈도우가 모든 영역을 지나가면서 conv 연산한다. / 계산비용이 크다./
  윈도우가 작을 경우 물체를 못 잡을 수도 있다.



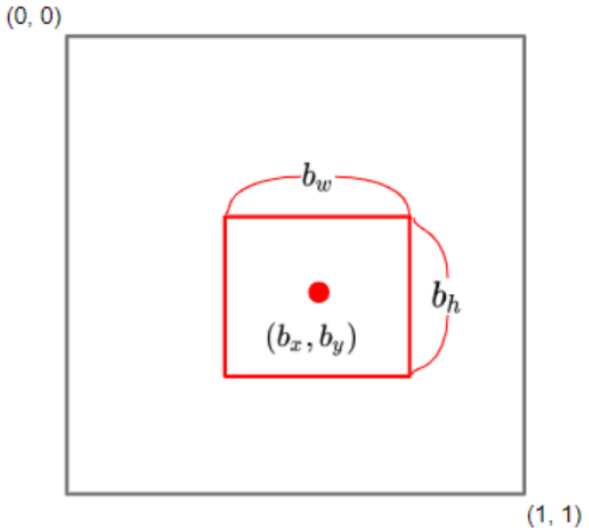
Classification with localization

(0 , 0)

(b_x, b_y)



soft max



1 - pedestrian
2 - car
3 - motorcycle
4 - background

bounding box
b_x, b_y, b_h, b_w

Defining the target label ‘y’

▶ **Q. 아래의 이미지일때, bounding box의 좌표는 b_x, b_y, b_h, b_w로 정의하고, label ‘y’를 정의**

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

p_c : object probability : 물체 존재여부의 확률

b : bounding box : 경계상자의 위치

c : classes : 0, 1로 이루어진 물체 클래스의 라벨

1 - pedestrian
2 - car
3 - motorcycle
4 - background

p_c / b_x, b_y, b_h, b_w , / 0 , 1, 0
(background는 object probabilit가 ‘0’일 때라서 class에 포함 X)

Landmark detection

Landmark detection

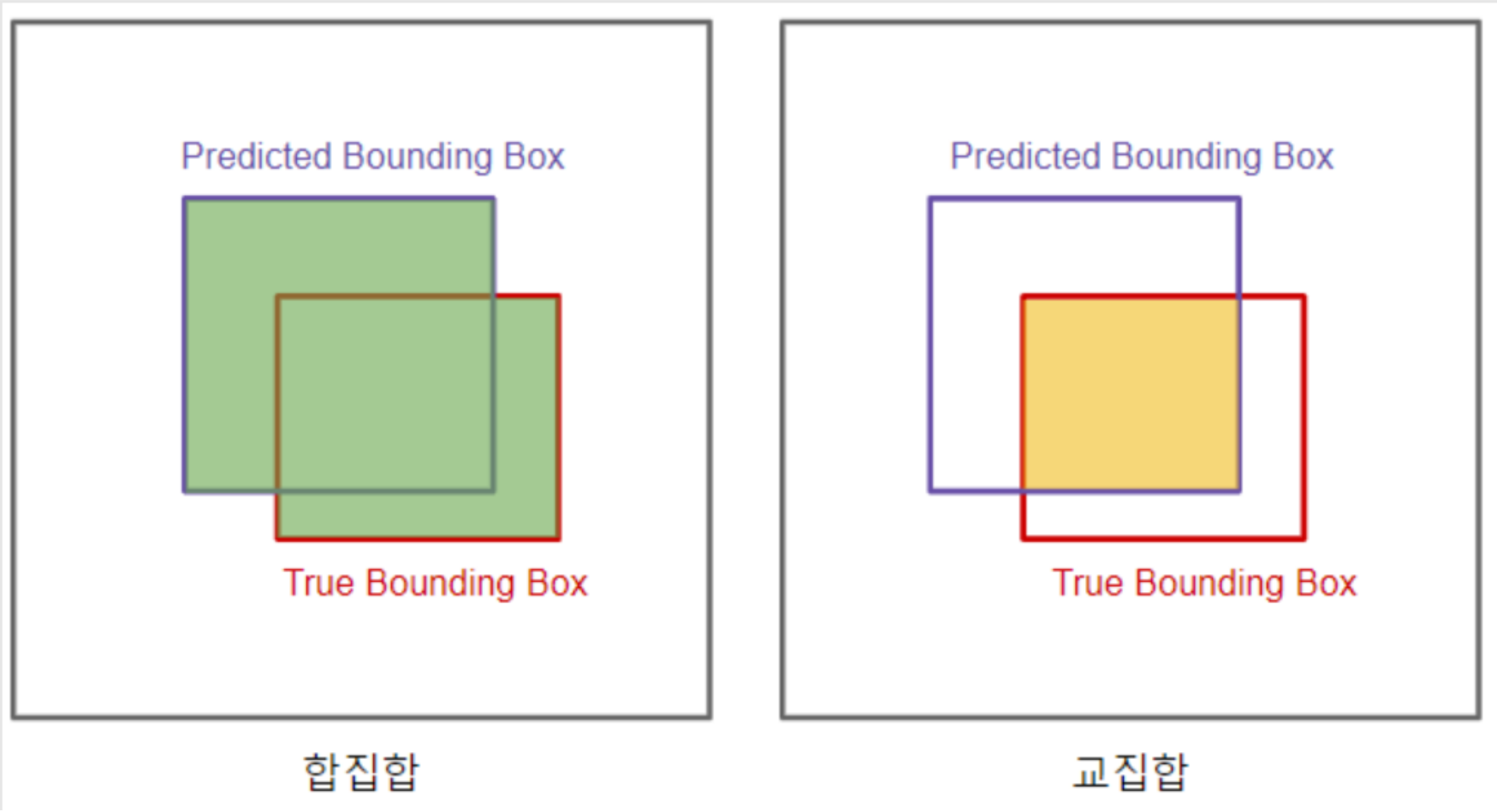
- 얼굴인식도 동일하게 얼굴유무, 인식할 좌표 로 클래스를 분류한다.

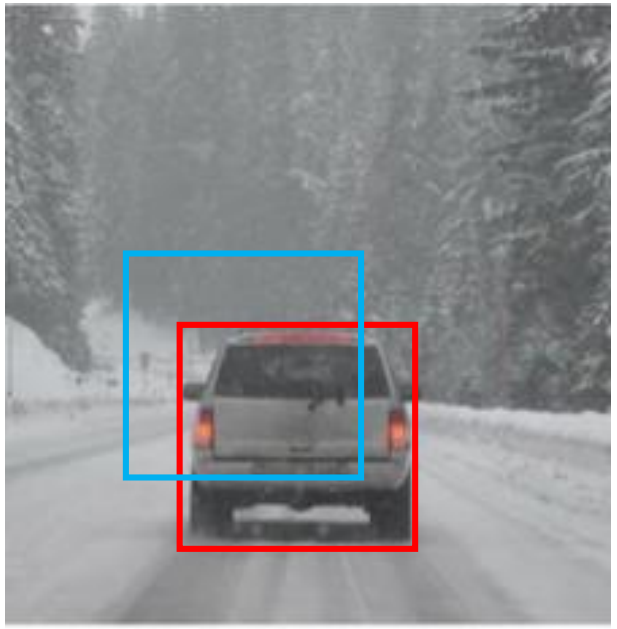
b_x, b_y, b_h, b_w

Object Detection

IOU

▶ **통상 IOU가 0.5보다 크면 맞다고 판단**





Q. 하나의 물체에 여러 개의 bounding box를 인식 할때 ?

Non-max suppression algorithm

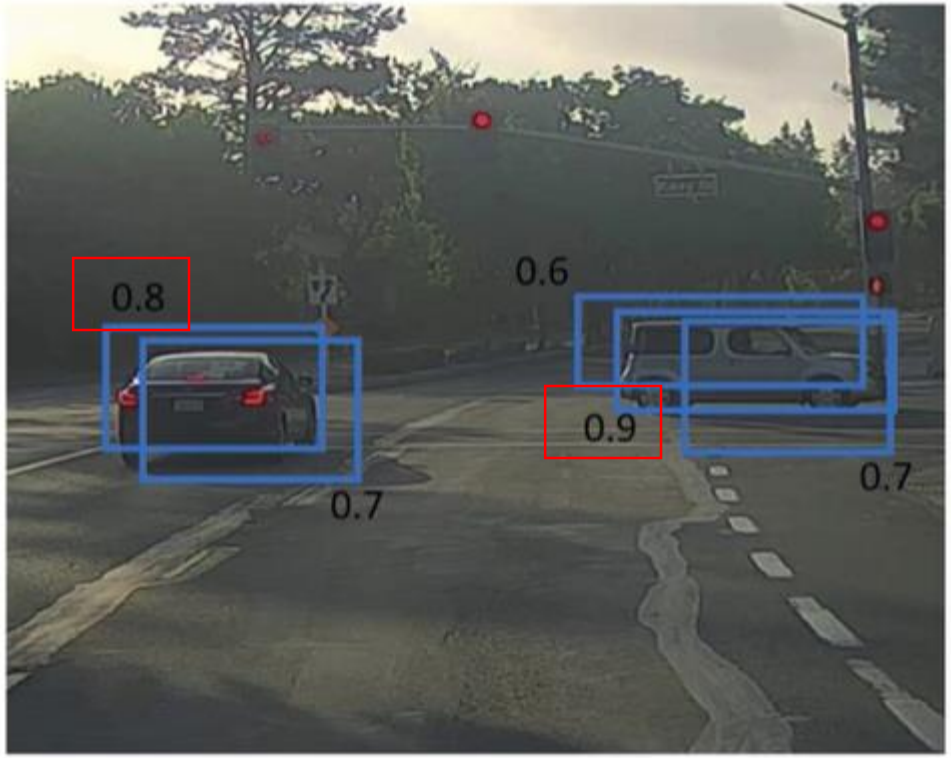
Non-max suppression algorithm

▶ 물체 감지가 여러 개 되었을때

가장 큰 확률값을 가지는 BOX 선택 (특징 임계점 이하의 확률값은 사용하지 않는다.

/ 예측값이 가장 큰 box 선택 주변 BOX 감지된 물체와의 IOU가 높은 BOX 제거한다.

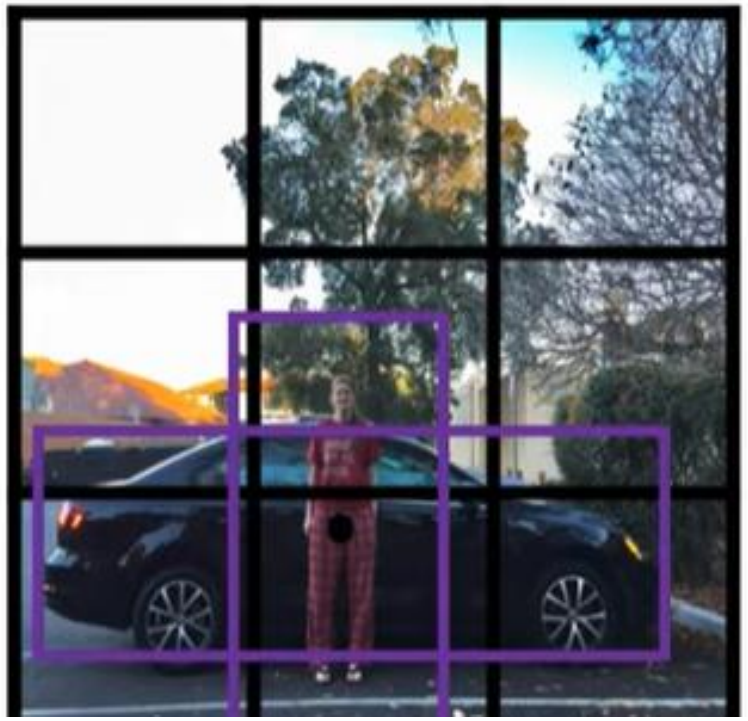
(IOU 비슷한 것 제거)



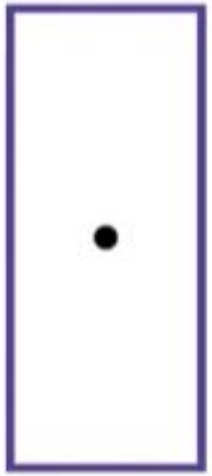
Q. 물체가 겹쳐 있을 때는?

Anchor box

Anchor box

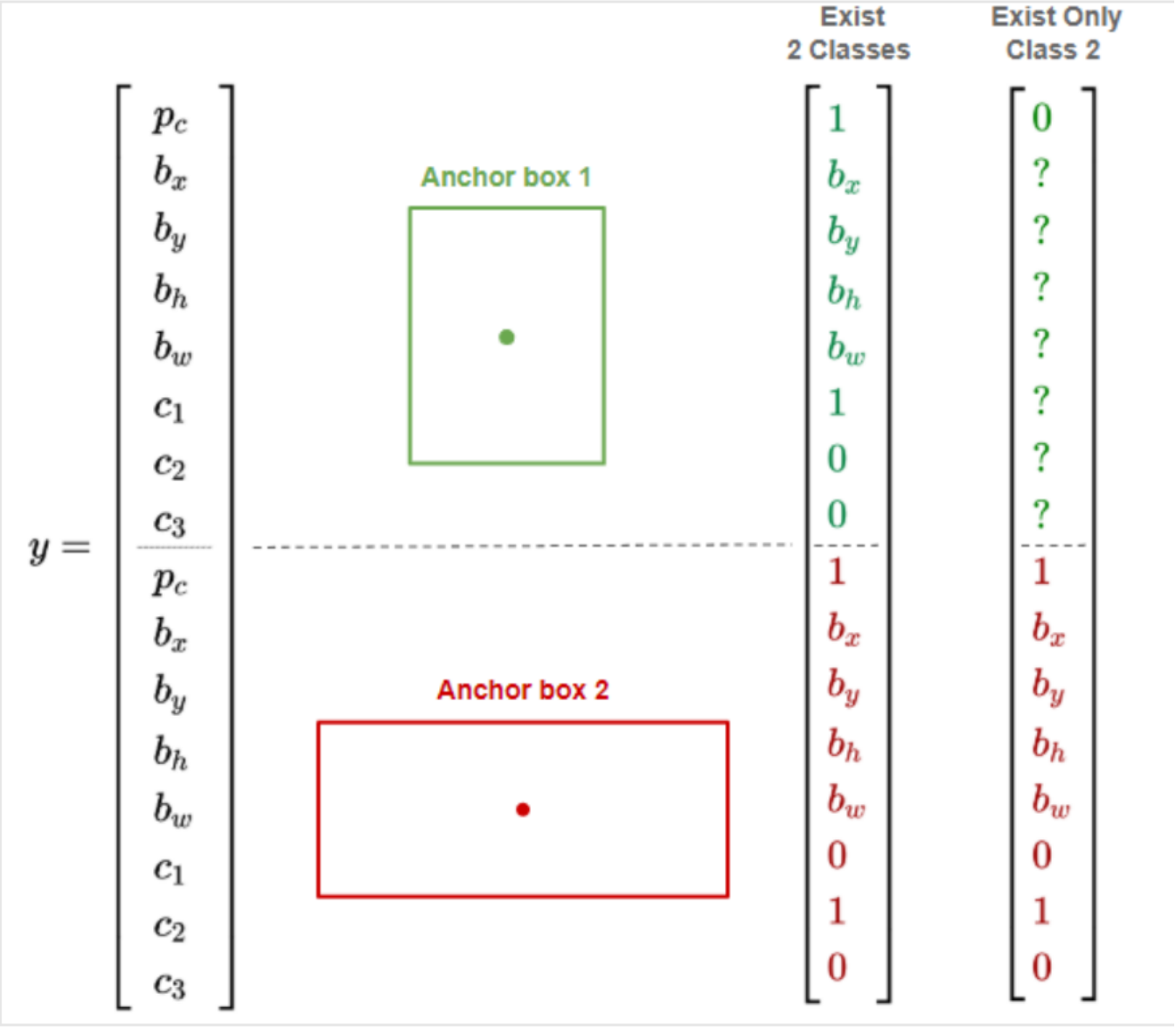


Anchor box 1:



Anchor box 2:

Anchor box


Exist
2 Classes
Exist Only
Class 2
$y =$
p_c b_x b_y b_h b_w c_1 c_2 c_3
p_c b_x b_y b_h b_w c_1 c_2 c_3
Anchor box 1
Anchor box 2
1 b_x b_y b_h b_w 1 0 0
1 b_x b_y b_h b_w 0 1 0
0 ? ? ? ? ? ? ?
1 b_x b_y b_h b_w 0 1 0

YOLO

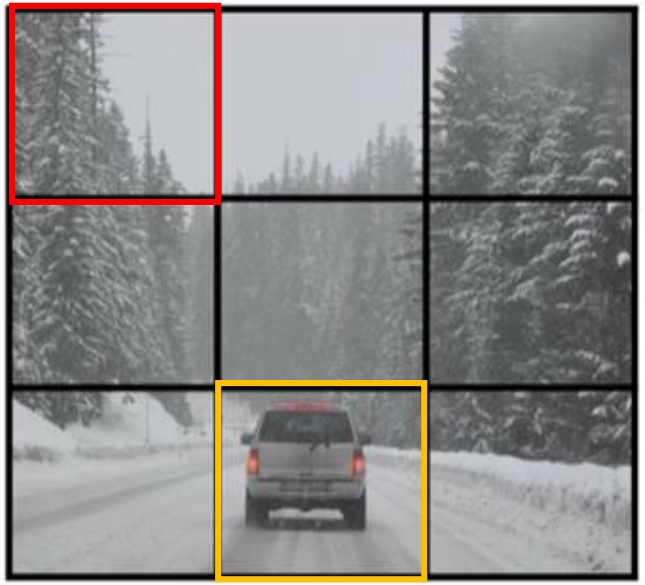
YOLO

anchor
$3 \times 3 \times 2 \times 8$

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

p_c, b_x, b_y, b_h, b_w, c1, c2, c3

YOLO



1 - pedestrian
2 - car
3 - motorcycle

$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix} \quad \begin{matrix} 0 \\ \\ \\ \\ \\ \\ \\ \\ 0 \\ \\ \\ \\ \\ \\ \\ \end{matrix} \quad \begin{matrix} 0 \\ \\ \\ \\ \\ \\ \\ \\ 1 \\ \\ \\ \\ \\ \\ \\ \end{matrix}$$

Anchor

y is $3 \times 3 \times 2 \times 8$ (3 X 3 X 16)

p_c, b_x, b_y, b_h, b_w, c1, c2, c3x

YOLO

1. 두개의 앵커박스의 예로 들면 각 셀에 2개의 Bounding Box가 생긴다.

YOLO

1. 두개의 앵커박스의 예로 들면 각 셀에 2개의 Bounding Box가 생긴다.
2. 낮은 확률의 예측을 제거한다.

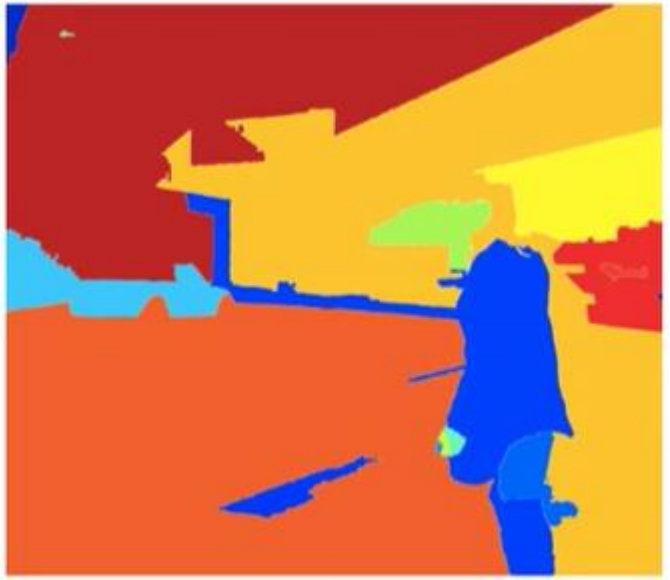
YOLO

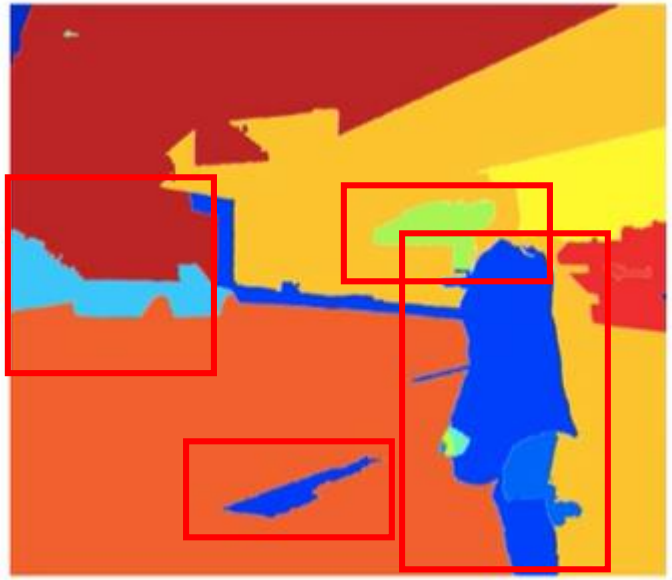
1. 두개의 앵커박스의 예로 들면 각 셀에 2개의 Bounding Box가 생긴다.
2. 낮은 확률의 예측을 제거한다.
3. 예측 하는 각 클래스에 대해서 **Non-max suppression algorithm**를 실행한다.

R-CNN

R-CNN

segmentation algorithm





Neural style transfer

Neural style transfer

▶ **Gradient desent를 사용해서 초기화된 이미지에서 부터 점점 변화한다.**

Content C

Style S

Generated image G

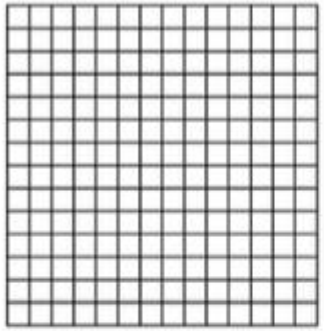
- $J(G) = \alpha J_{\text{content}}(C, G) + \beta J_{\text{style}}(S, G)$
- $J_{\text{content}}(C, G)$: 내용 비용, 생성 이미지와 내용 이미지의 내용이 비슷한 정도
- $J_{\text{style}}(S, G)$: 스타일 비용, 생성 이미지와 스타일 이미지의 비슷한 정도

Gradient Desent

초기 이미지

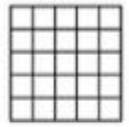
1D, 2D, 3D Data

2D, 1D Data



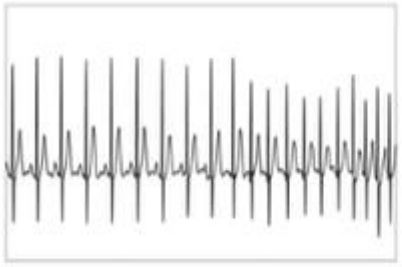
2D input image
14 × 14

*



2D filter
5 × 5

(14 X 14 X 3) * (5 X 5 X 3) / filter = 16
-> 10 X 10 X 16



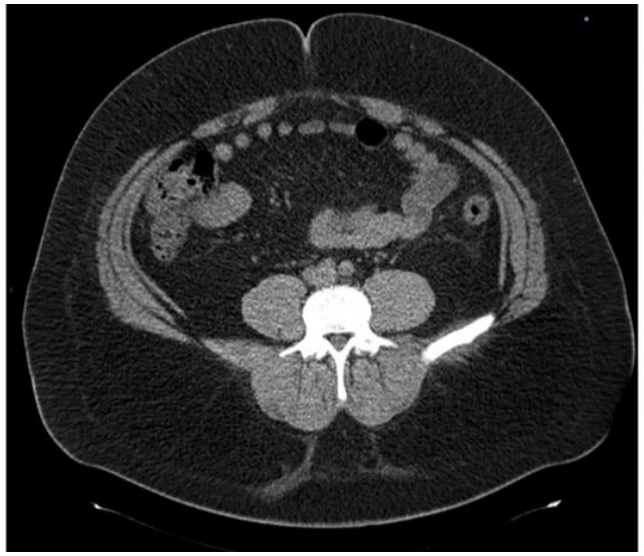
*

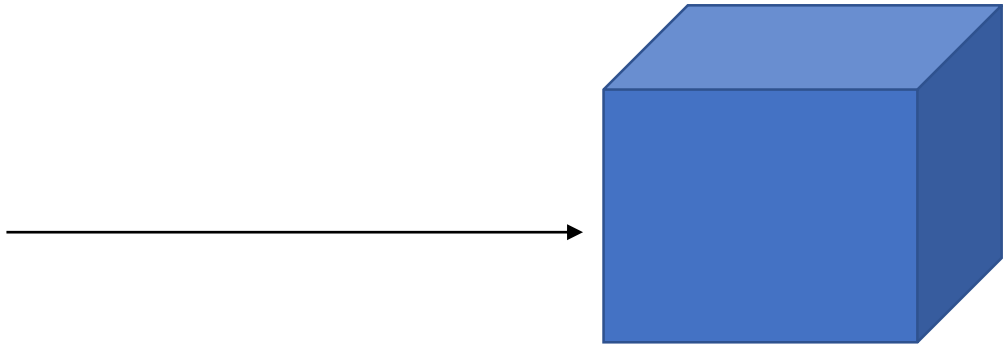
1	20	15	3	18	12	4	17

1	3	10	3	1

(14 X 1) * (5 X 1) / filter = 16
-> 10 X 16
(10 X 16) * (10 X 16) / filter = 32
-> 6 X 32

3D Data





3D data

3D volume

*

3D filter

(14 X 14 X 14 X 1) * (5 X 5 X 5 X 1) / filter = 16
-> 10 X 10 X 10 X 16
(10 X 10 X 10 X 16) * (5 X 5 X 5 X 16) / filter = 32
-> (6 X 6 X 6 X 32)

채널 수