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# Object Detection

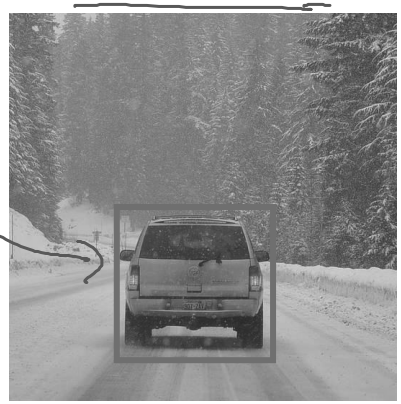
## Object localization

# What are localization and detection?

Image classification

"Car"

Classification with localization



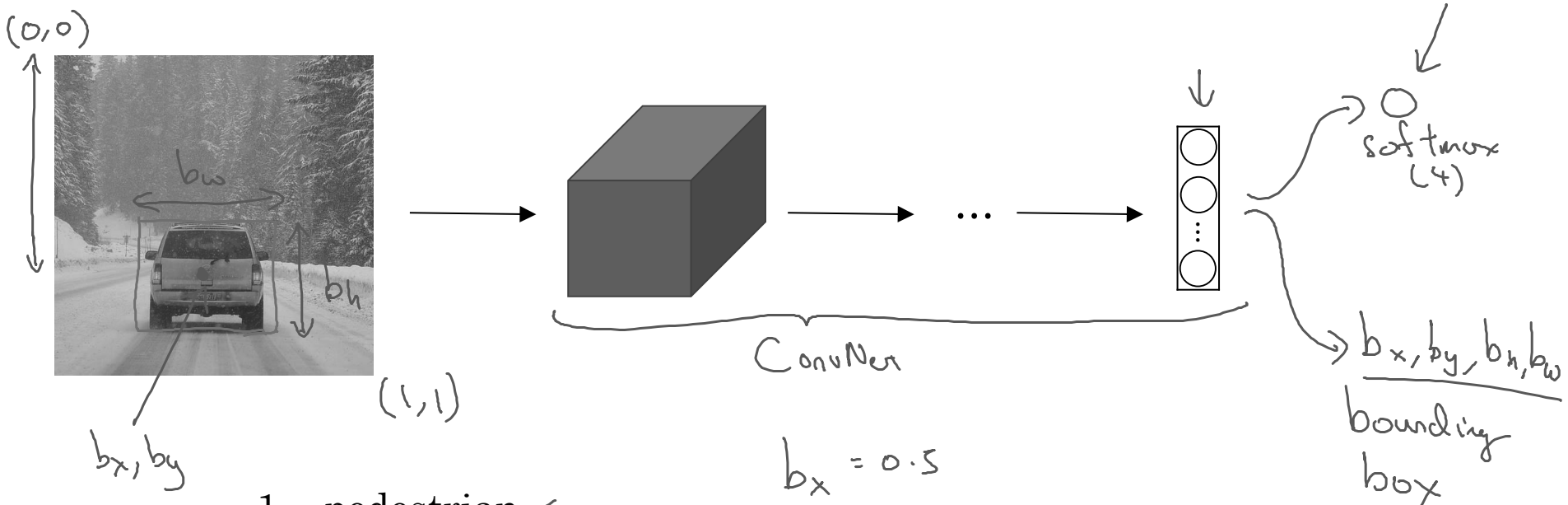
"Car"

1 object

Detection

multiple objects

# Classification with localization



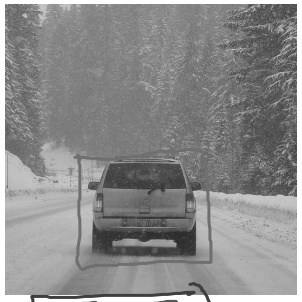

1 - pedestrian ⇐
2 - car ⇐
3 - motorcycle ⇐
4 - background

$b_x = 0.5$
$b_y = 0.7$
$b_h = 0.3$
$b_w = 0.4$

# Defining the target label y

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

Need to output $b_x, b_y, b_h, b_w$, class label (1-4)



$x =$

$y =$ $\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$ is there an object?

$(x, y)$ $\begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}$

$\begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix}$ $p_c$ ← "don't care"

$\mathcal{L}(\hat{y}, y) =$

$\begin{cases} (\hat{y}_1 - y_1)^2 + (\hat{y}_2 - y_2)^2 + \cdots + (\hat{y}_8 - y_8)^2 & \text{if } y_1 = 1 \\ (\hat{y}_1 - y_1)^2 & \text{if } y_1 = 0 \end{cases}$

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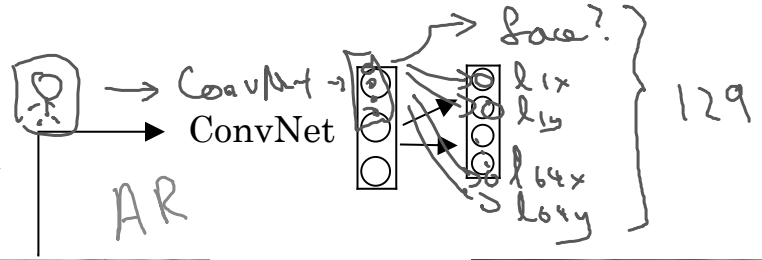
# Object Detection

## Landmark detection

# Landmark detection




$b_x, b_y, b_h, b_w$

$l_{1x}, l_{1y},$
$l_{2x}, l_{2y},$
$l_{3x}, l_{3y},$
$l_{4x}, l_{4y}$
$\vdots$
$l_{64}, l_{64y}$

$x, y$

$l_{1x}, l_{1y},$
$\vdots$
$l_{32x}$ $l_{32y}$

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# Object Detection

## Object detection

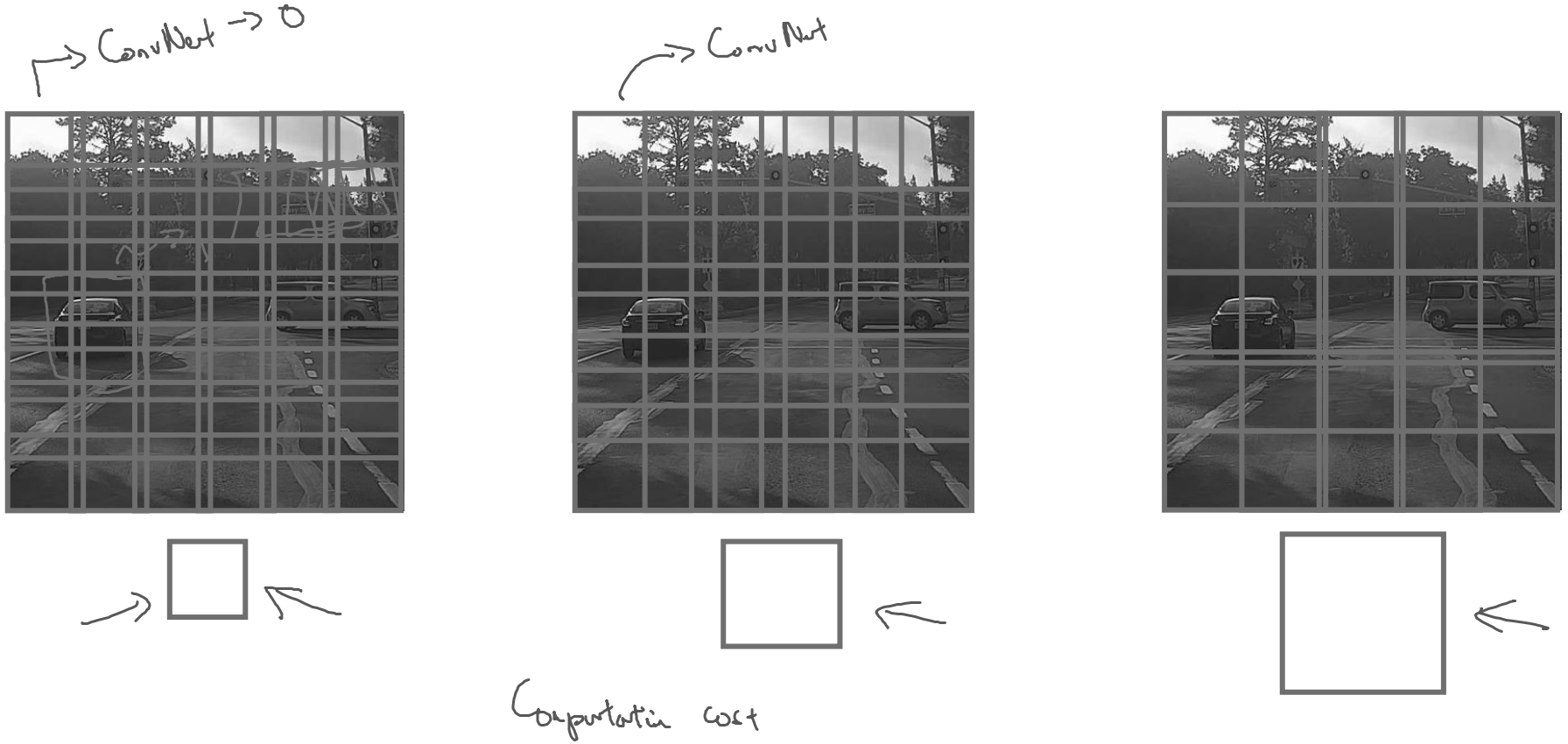
# Car detection example

Training set:

| x | y |
|---|---|
|  | 1 |
|  | 1 |
|  | 1 |
|  | 0 |
|  | 0 |

→ ConvNet → y

# Sliding windows detection



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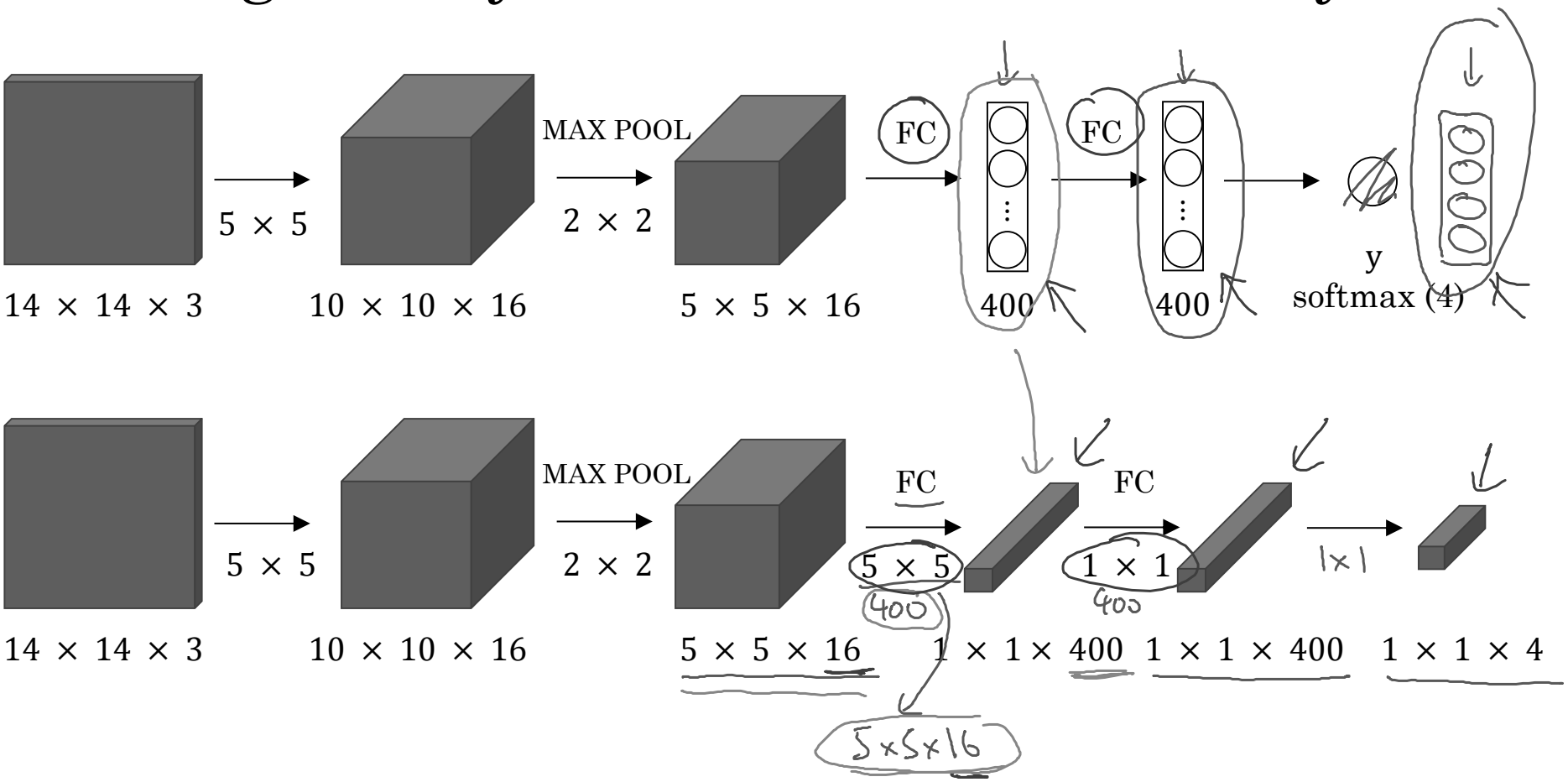
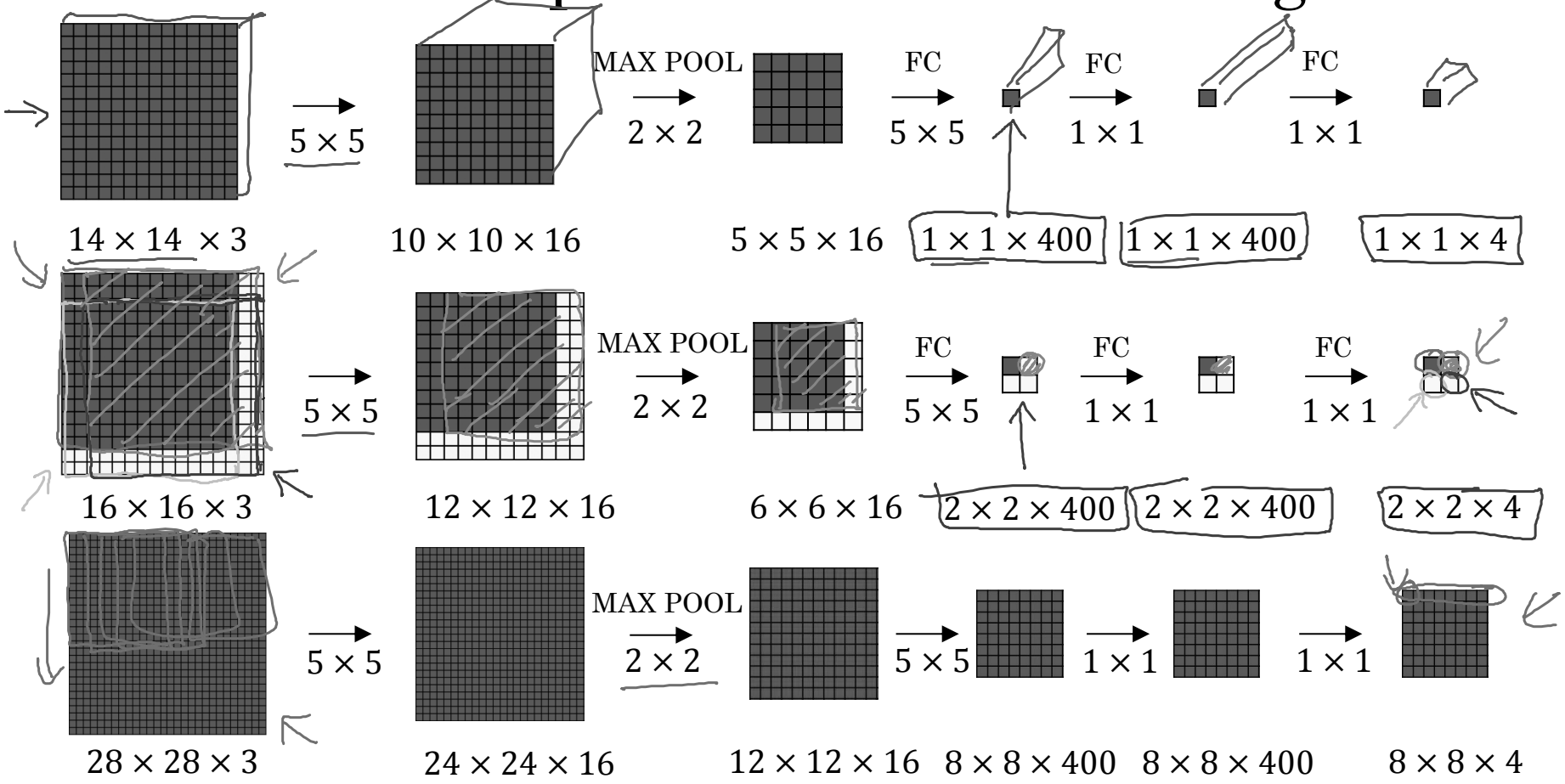
# Object Detection

# Convolutional implementation of sliding windows

# Turning FC layer into convolutional layers

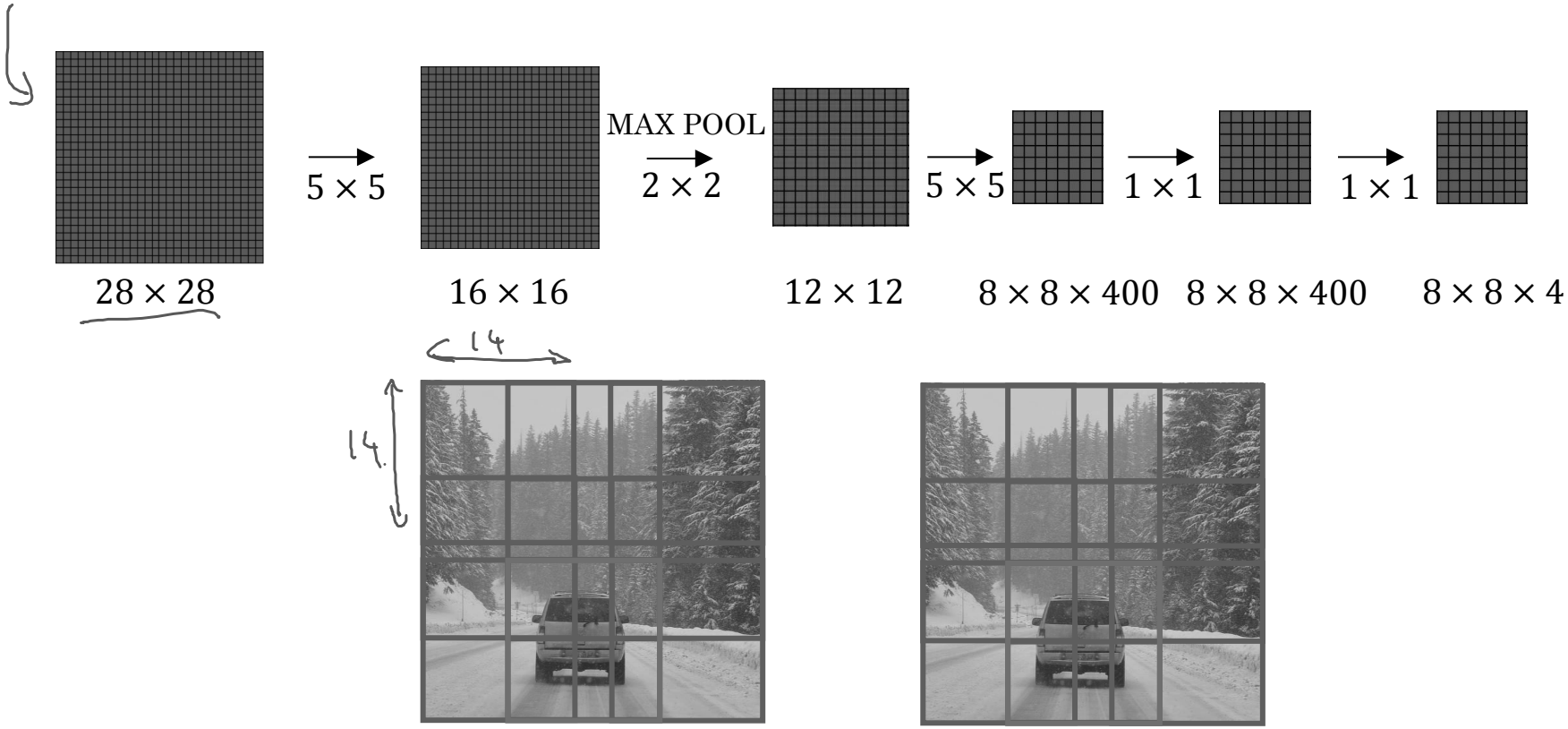


# Convolution implementation of sliding windows




[Sermanet et al., 2014, OverFeat: Integrated recognition, localization and detection using convolutional networks]

# Convolution implementation of sliding windows



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# Object Detection

## Intersection over union

# Evaluating object localization

Intersection over Union (IoU)

$$= \frac{\text{size of } \square}{\text{size of } \square}$$

"Correct" if IoU $\geq$ 0.5 ←

0.6 ←

More generally, IoU is a measure of the overlap between two bounding boxes.

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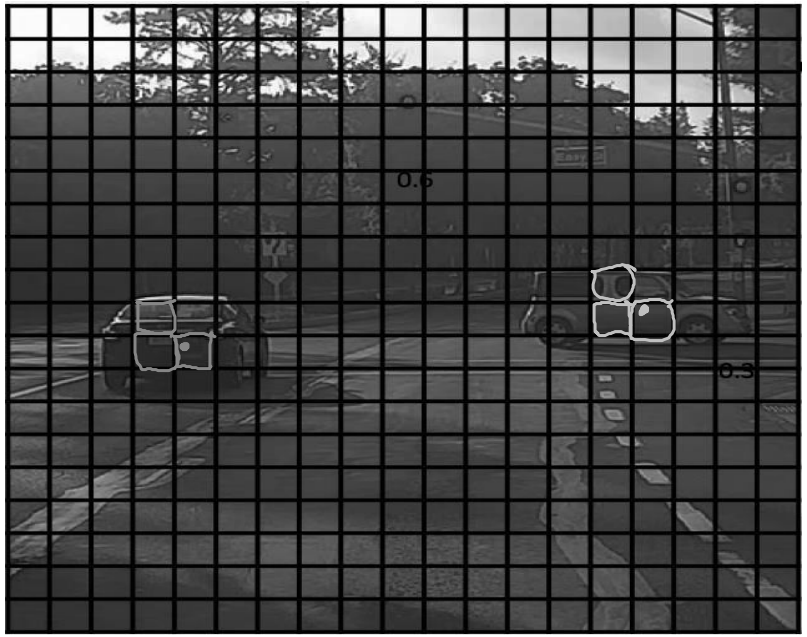
# Object Detection

## Non-max suppression

# Non-max suppression example

# Non-max suppression example

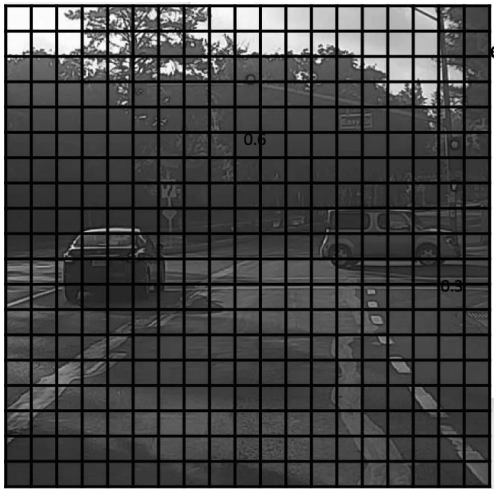



19×19

# Non-max suppression example


$p_c$

# Non-max suppression algorithm



19× 19

Each output prediction is:

$p_c$
$b_x$
$b_y$
$b_h$
$b_w$

Discard all boxes with $p_c \leq 0.6$

While there are any remaining boxes:

- Pick the box with the largest $p_c$
  Output that as a prediction.
- Discard any remaining box with IoU $\geq 0.5$ with the box output in the previous step

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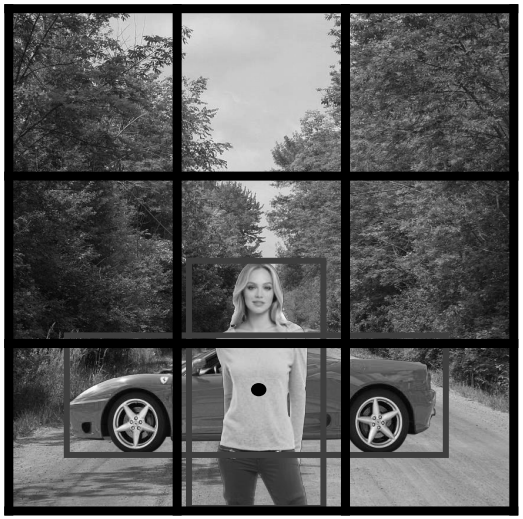
# Object Detection

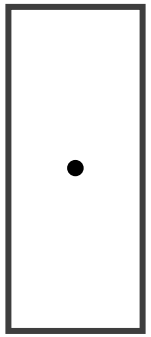
## Anchor boxes

# Overlapping objects:

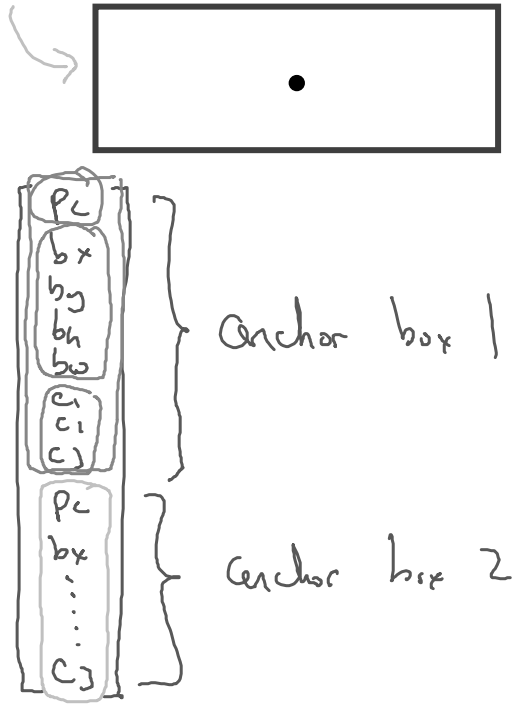


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:




[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

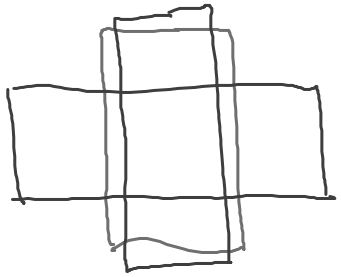
# Anchor box algorithm

Previously:

Each object in training image is assigned to grid cell that contains that object's midpoint.

Output $y$:

$3 \times 3 \times 8$



With two anchor boxes:

Each object in training image is assigned to grid cell that contains object's midpoint and anchor box for the grid cell with highest IoU.

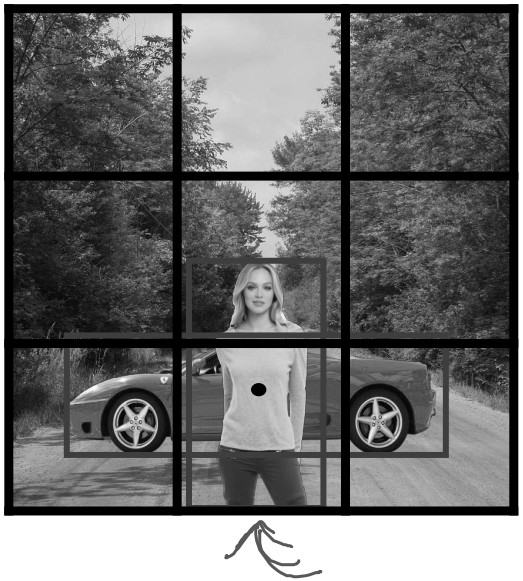
(grid cell, anchor box)

Output $y$:

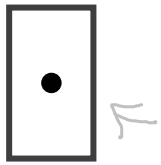
$3 \times 3 \times 16$

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

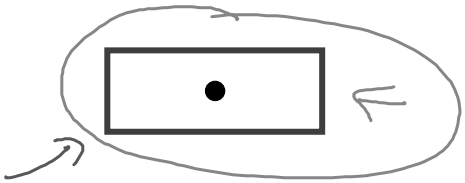
# Anchor box example



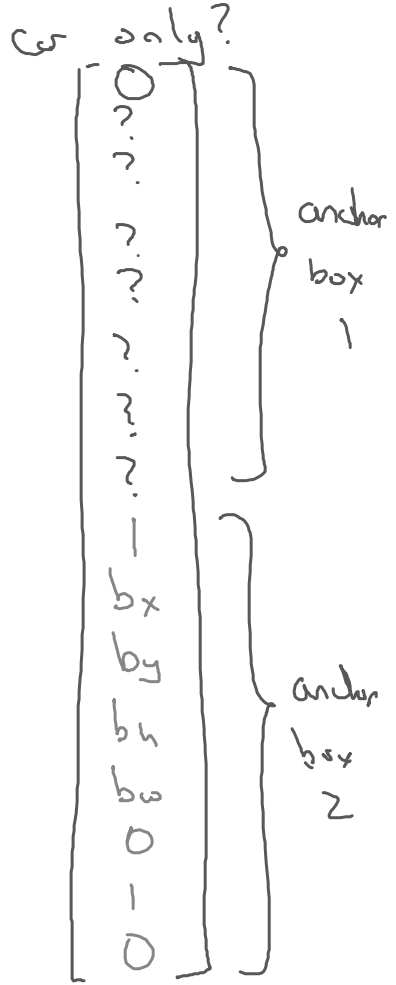
Anchor box 1:



Anchor box 2:



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



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# Object Detection

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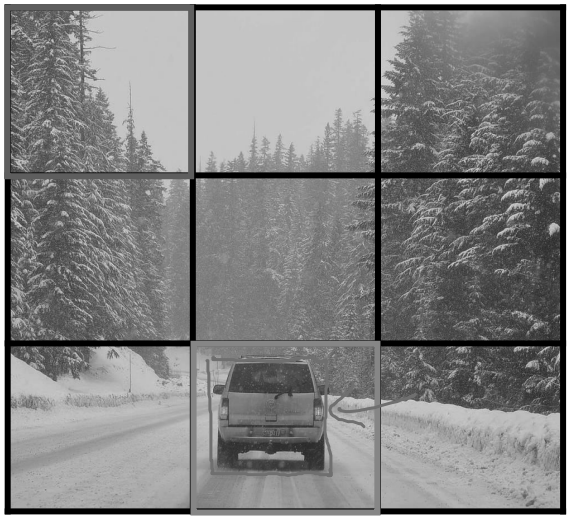
# Putting it together: YOLO algorithm

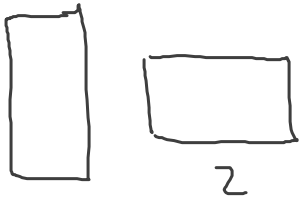
# Training



1 - pedestrian
2 - car
3 - motorcycle

$y =$

$$\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix} \rightarrow \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix} \rightarrow \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}$$



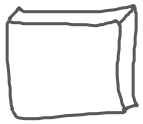

3 × 3 × 16

y is $3 \times 3 \times 2 \times 8$

19×19×16
19×19×40

#anchors

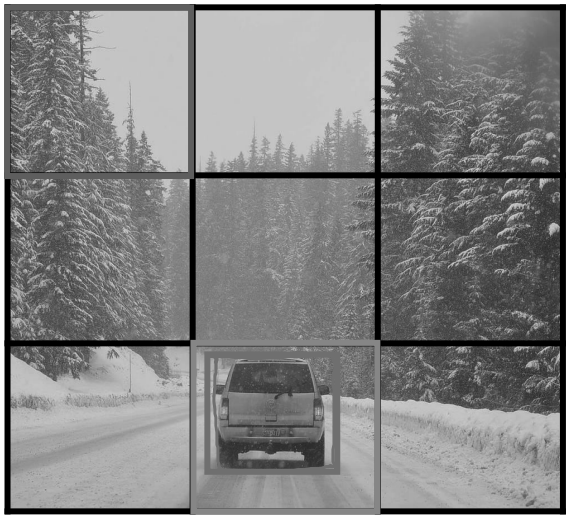
5 + #classes



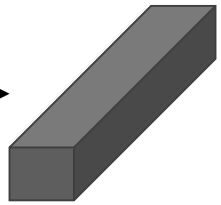

→ ConvNet →


[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

# Making predictions



$\rightarrow \cdots \rightarrow$



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

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

# Outputting the non-max supressed outputs

- For each grid call, get 2 predicted bounding boxes.
- Get rid of low probability predictions.
- For each class (pedestrian, car, motorcycle) use non-max suppression to generate final predictions.

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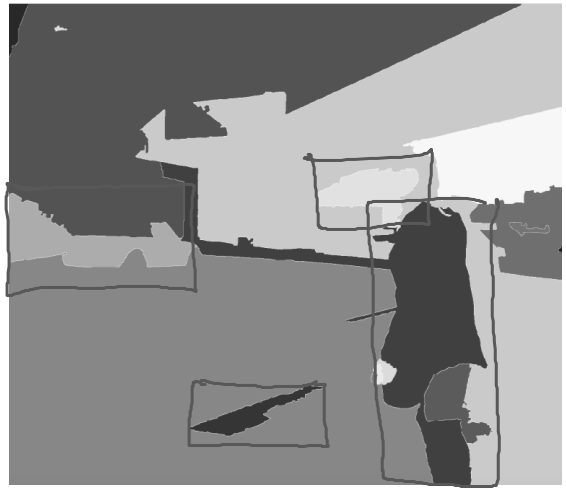
# Object Detection

## Region proposals (Optional)

# Region proposal: R-CNN



Segmentation algorithm

~2,000

[Girshik et. al, 2013, Rich feature hierarchies for accurate object detection and semantic segmentation]

# Faster algorithms

R-CNN: Propose regions. Classify proposed regions one at a time. Output label + bounding box.

Fast R-CNN: Propose regions. Use convolution implementation of sliding windows to classify all the proposed regions.

Faster R-CNN: Use convolutional network to propose regions.

[Girshik et. al, 2013. Rich feature hierarchies for accurate object detection and semantic segmentation]
[Girshik, 2015. Fast R-CNN]
[Ren et. al, 2016. Faster R-CNN: Towards real-time object detection with region proposal networks]