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Object Detection

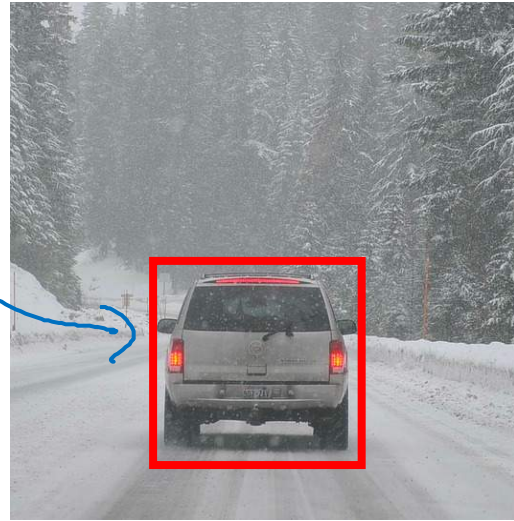
Object
localization

What are localization and detection?

Image classification



Classification with
localization



Detection



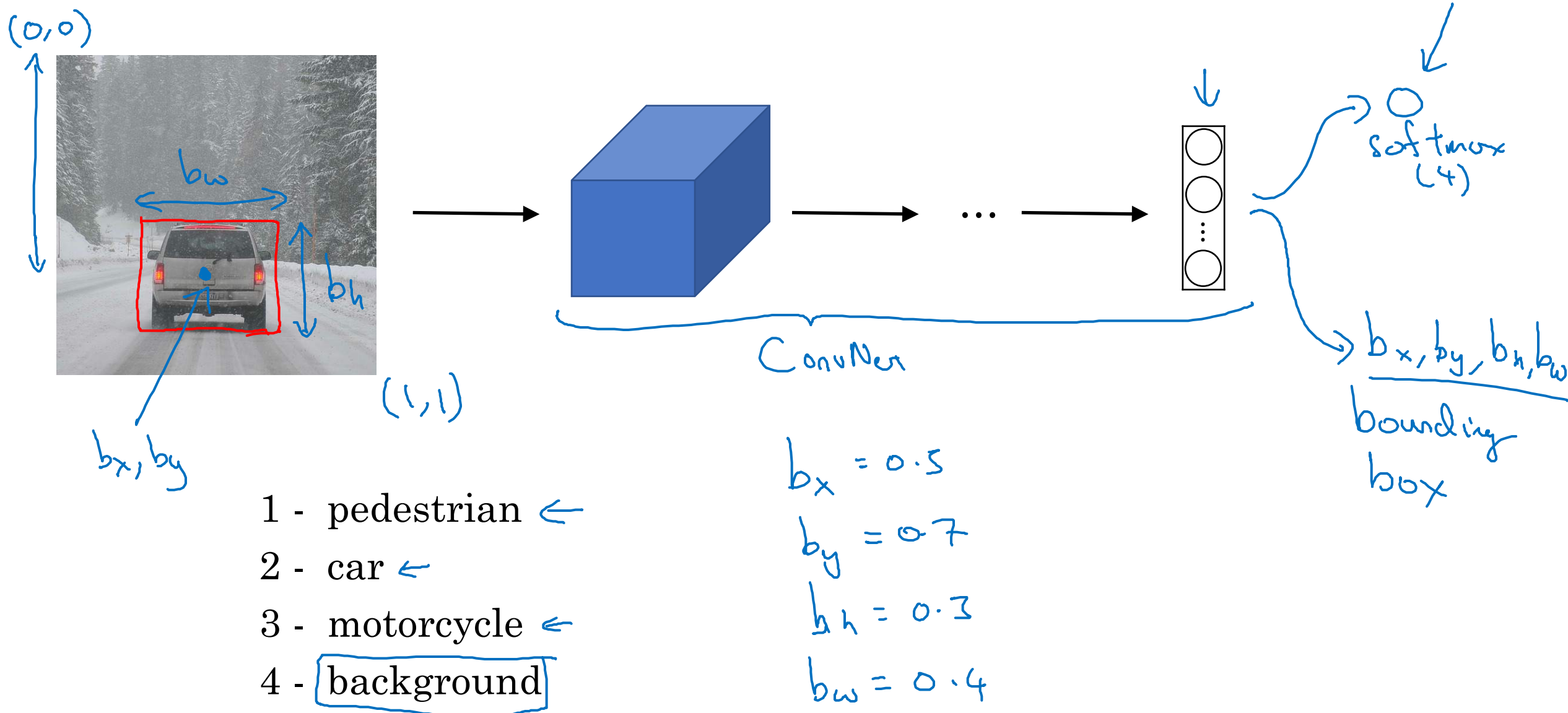
"Car"

"Car"

1 object

multiple
objects

Classification with localization

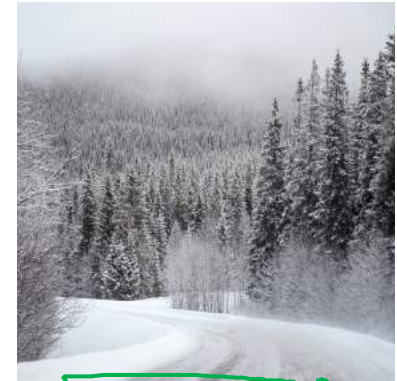
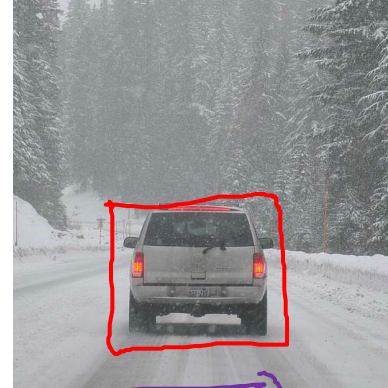


Defining the target label y

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

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

P - Is any of the class object present



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

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

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

is there any object?

(x, y)

$$\begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ \vdots \end{bmatrix}$$

question mark d

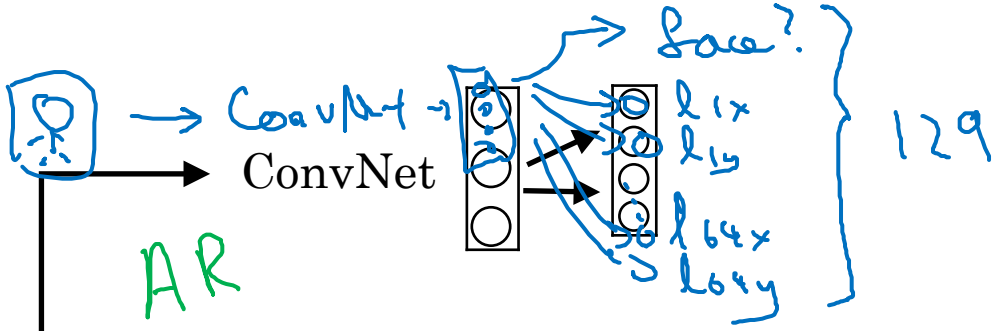


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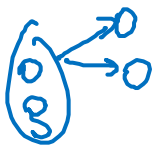
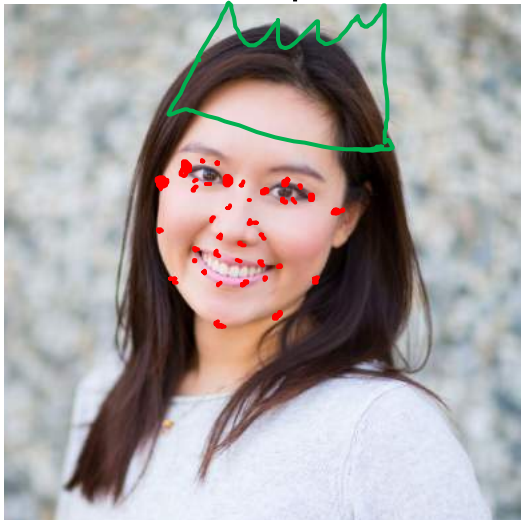
Object Detection

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_{64x}, 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

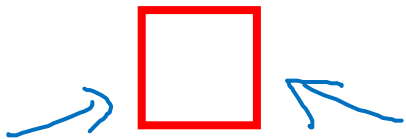
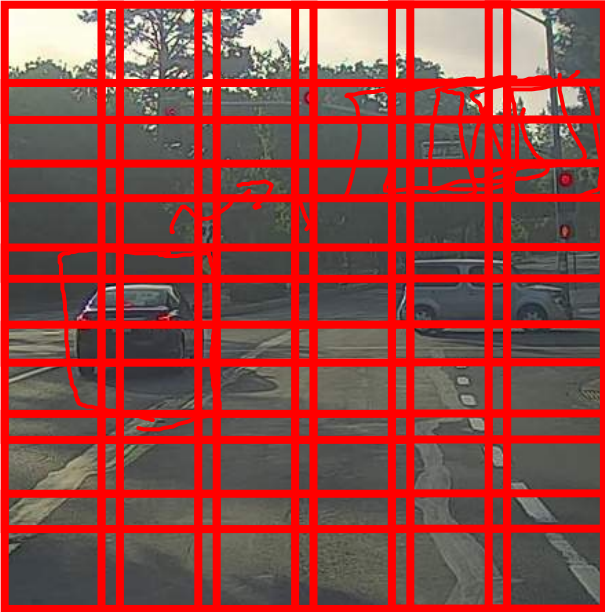
These are the closely cropped images of the dataset and



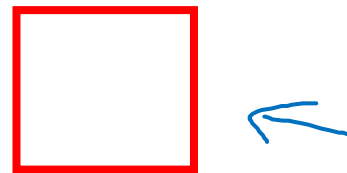
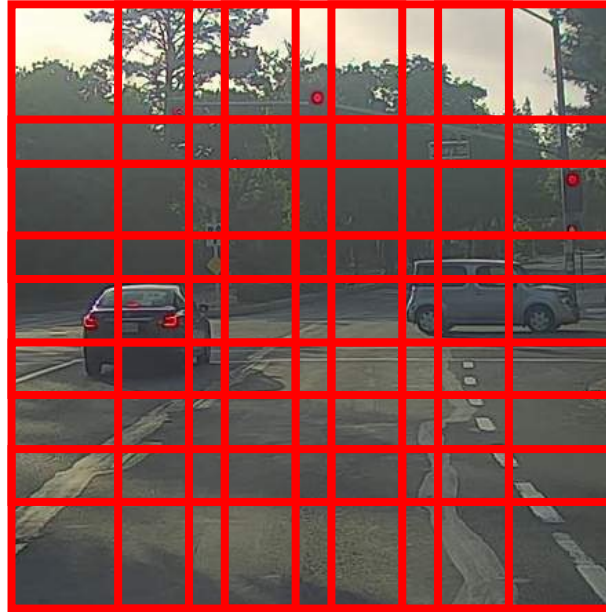
\rightarrow ConvNet $\rightarrow y$

Sliding windows detection

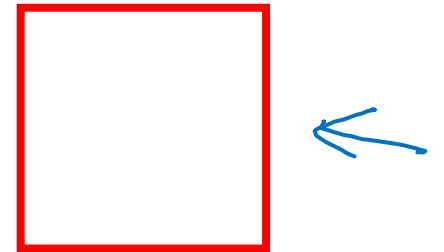
→ ConvNet → 0



→ ConvNet



Computation cost



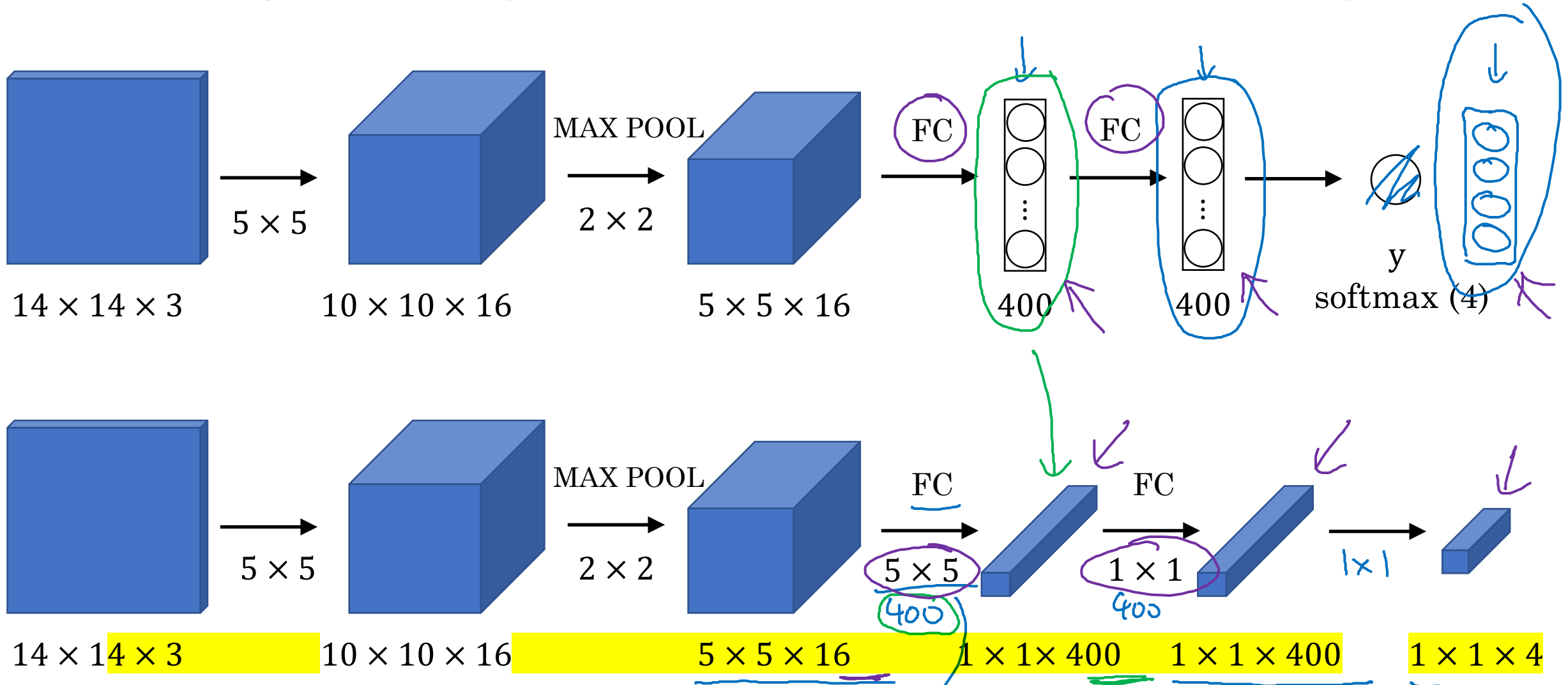


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Object Detection

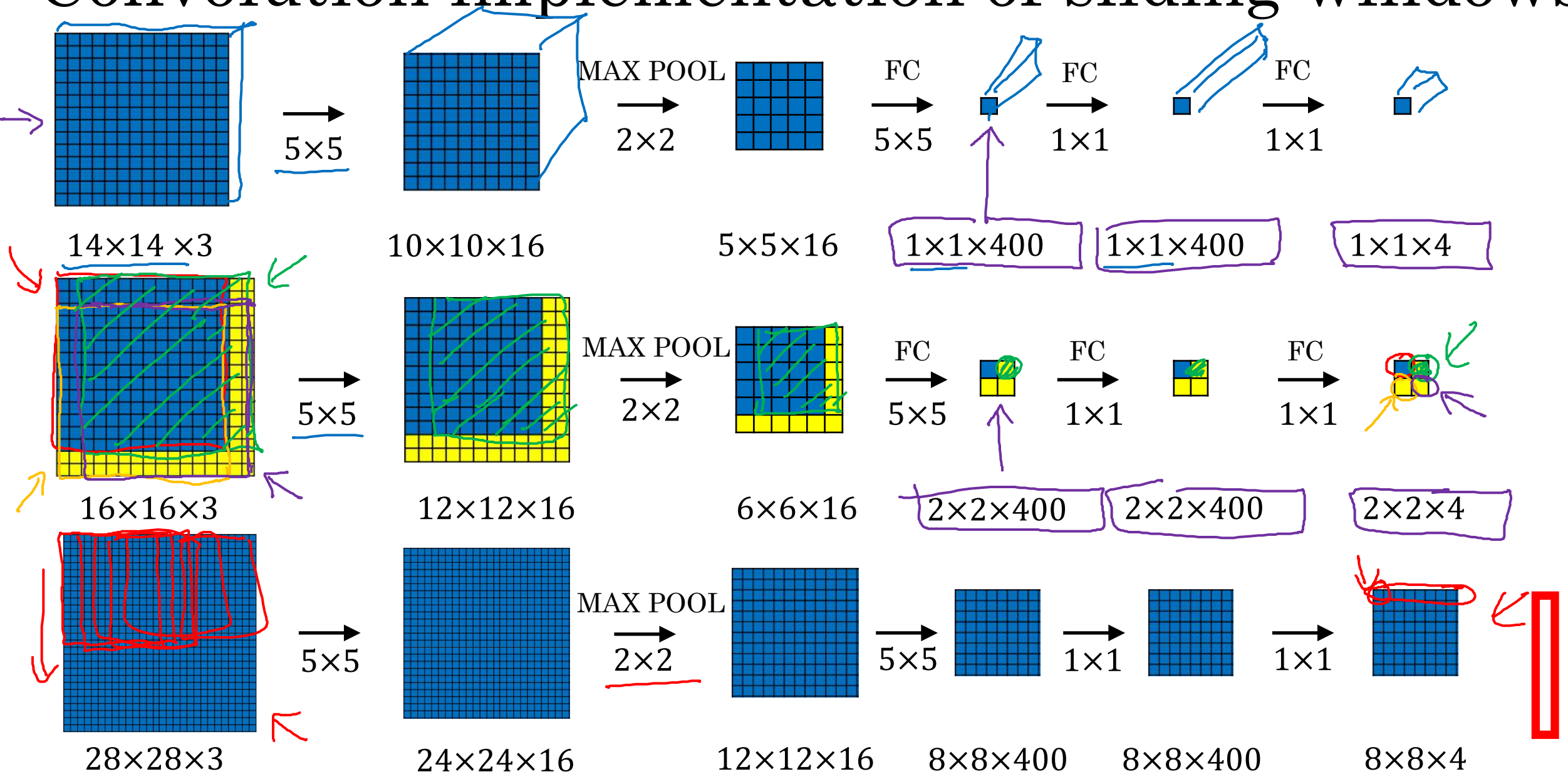
Convolutional
implementation of
sliding windows

Turning FC layer into convolutional layers

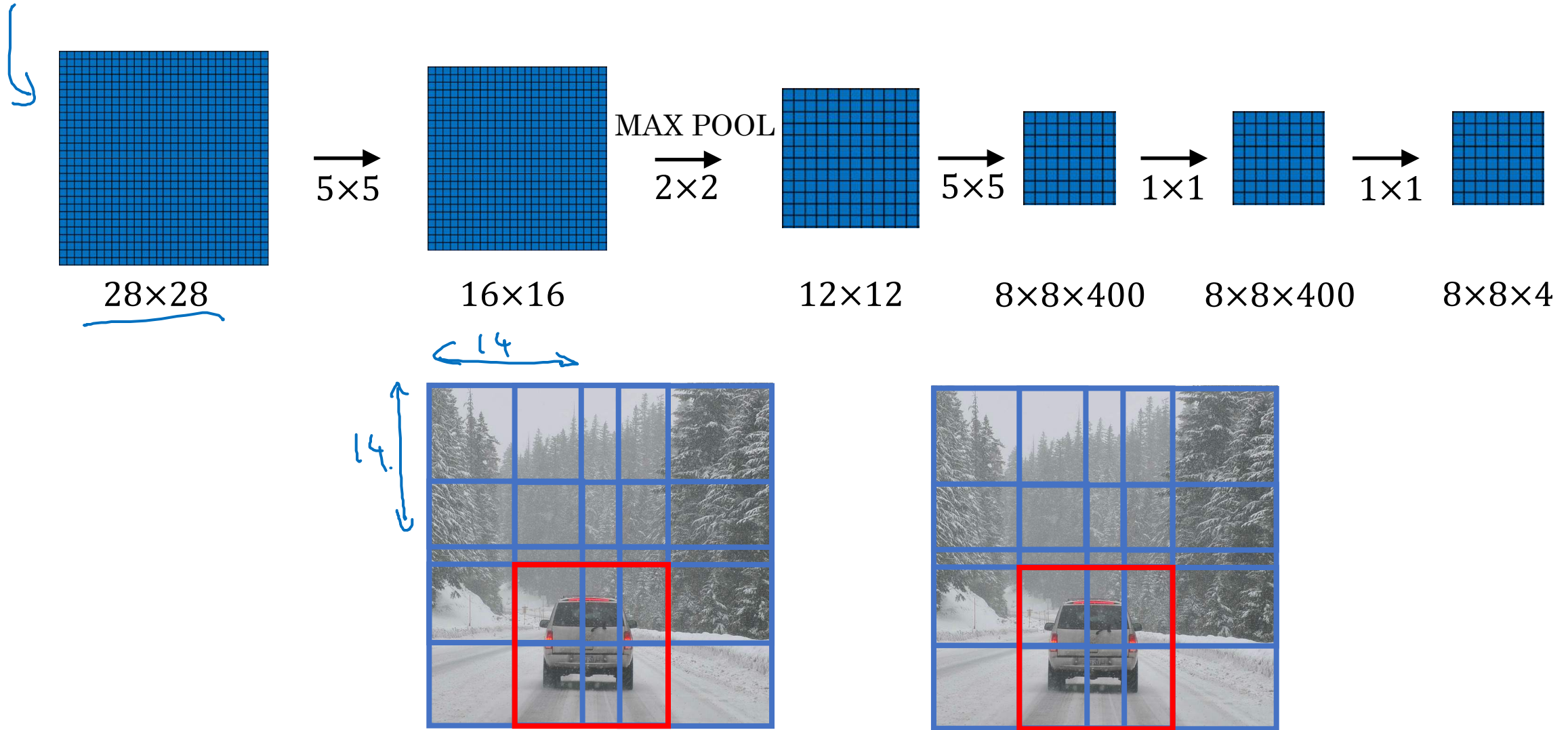


Below Slide : Let's say our input is $16 \times 16 \times 3$ and our window is $12 \times 12 \times 3$ then we will need to slide our window 4 times assuming stride of 2. As we see with different colored windows here, there involves a lot of duplication.

Convolution implementation of sliding windows



Convolution implementation of sliding windows



Sliding window approach may result in a rectangle such that none of the rectangle fits the object although it is there as shown below. So to overcome that

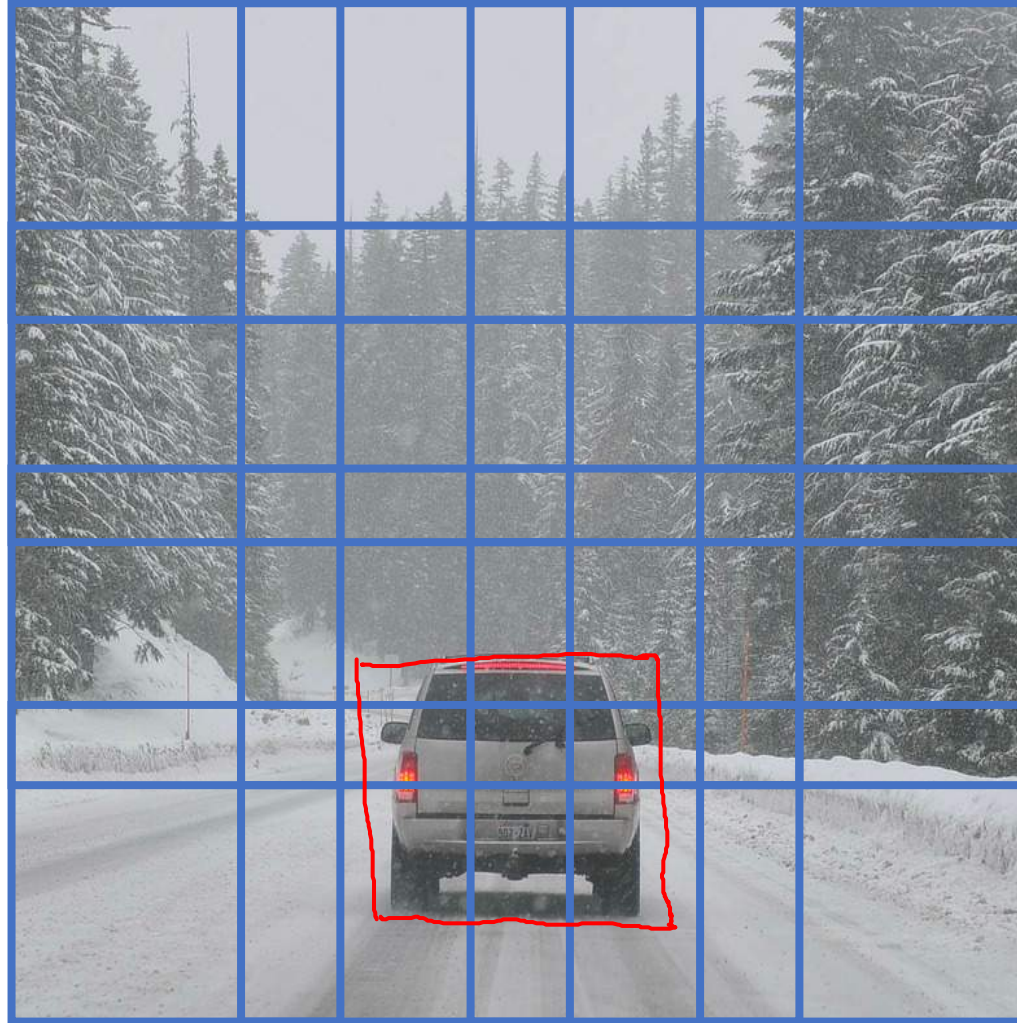


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Object Detection

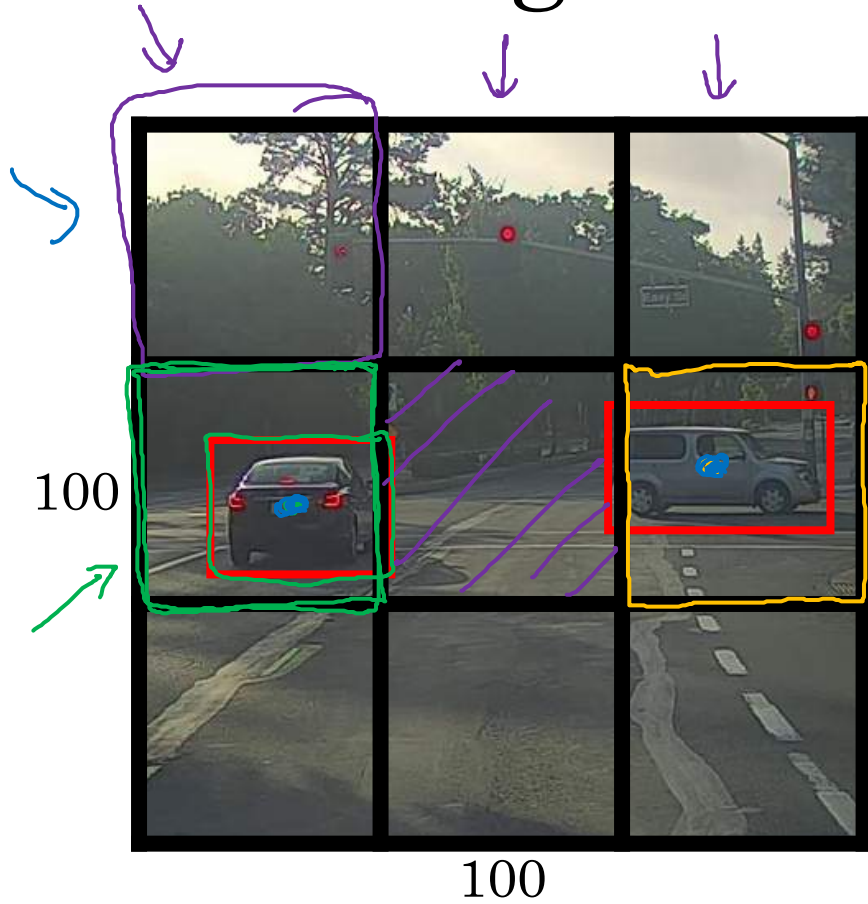
Bounding box predictions

Output accurate bounding boxes



YOLO algorithm

We will get a 8x1 output for every square box , so in total we will get 3x3x8 output. We will train

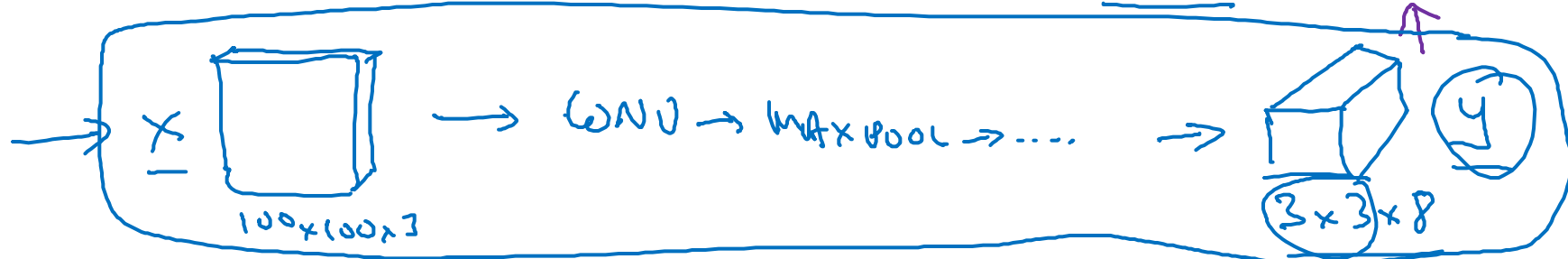
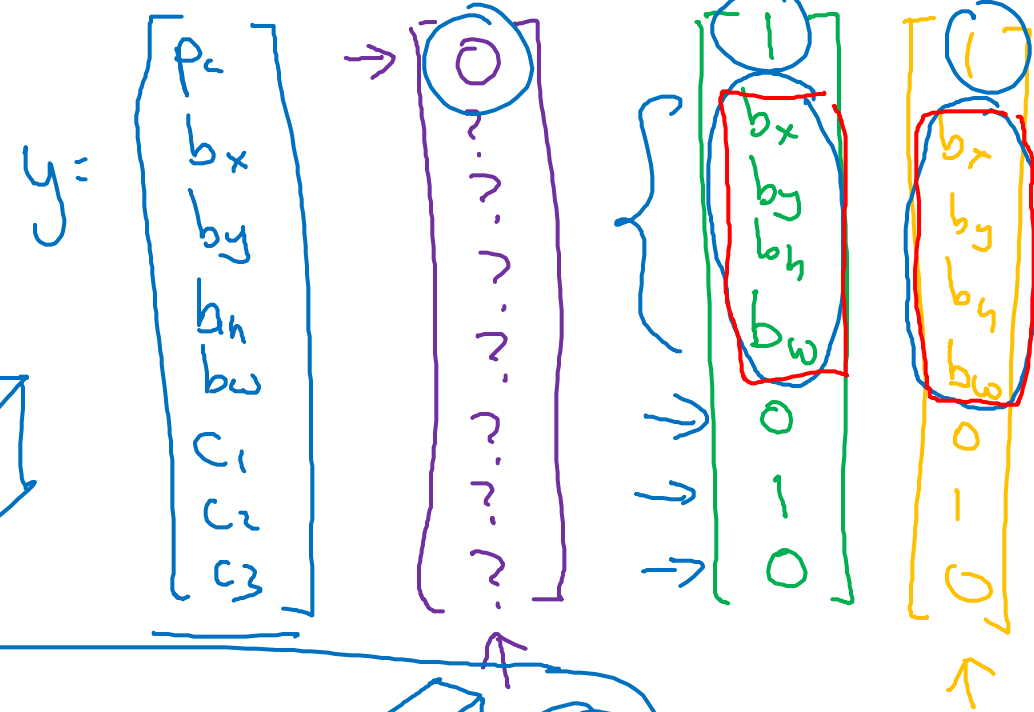
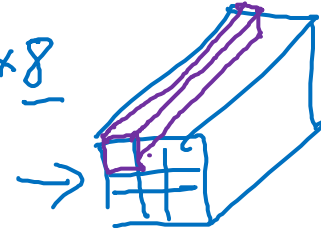


Labels for training

For each grid cell:

Target output:

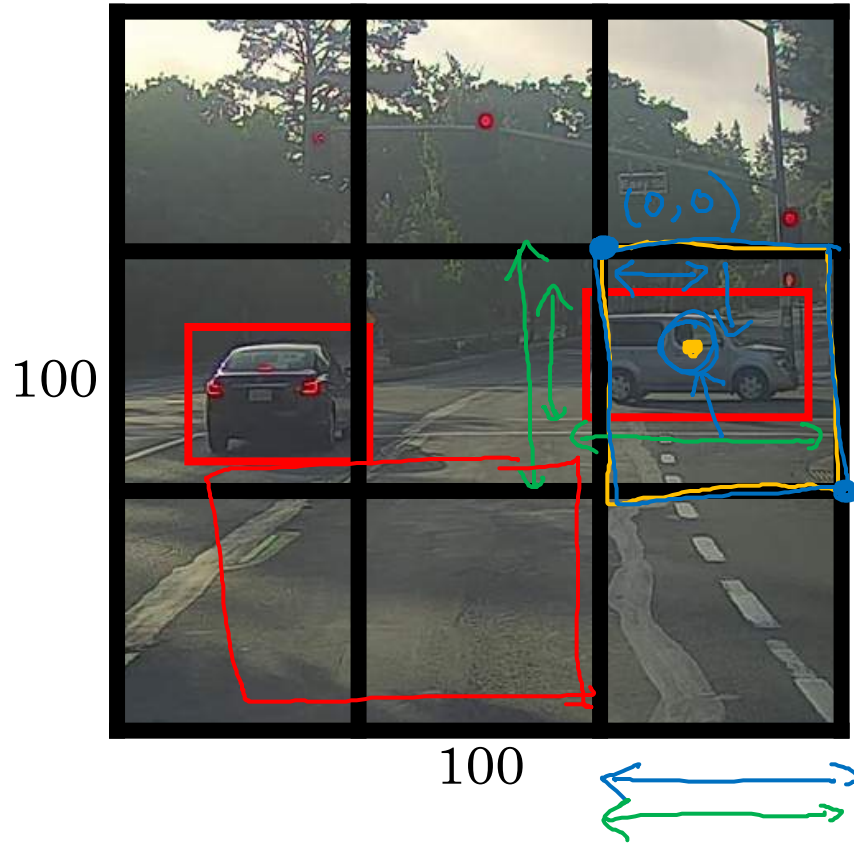
$3 \times 3 \times 8$



$\rightarrow 19 \times 19 \times 8$

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Specify the bounding boxes



$$y = \begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$\left. \begin{array}{l} 0.4 \\ 0.3 \\ 0.9 \\ 0.5 \end{array} \right\} \begin{array}{l} \text{between } 0 \text{ and } 1 \\ \text{could be } > 1 \end{array} \right\}$

how to specify the box? We take upper left corner as 0,0 and right b

Used to determine how well is our algorithm is doing in detecting the objects. If red is actual and our model predicts purple box, then we take ratio of inte

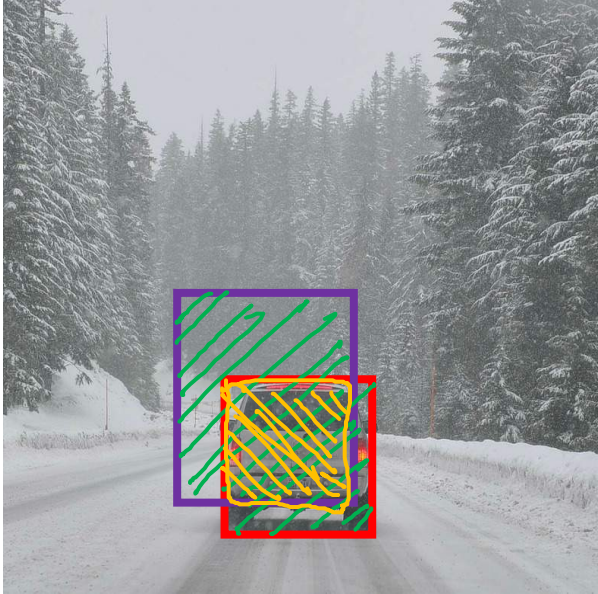


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Object Detection

Intersection over union

Evaluating object localization



Intersection over Union (IoU)

$$= \frac{\text{size of } \text{[yellow hatched box]}}{\text{size of } \text{[green hatched box]}}$$

“Correct” if IoU \geq 0.5 \leftarrow

0.6 \leftarrow

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



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Object Detection

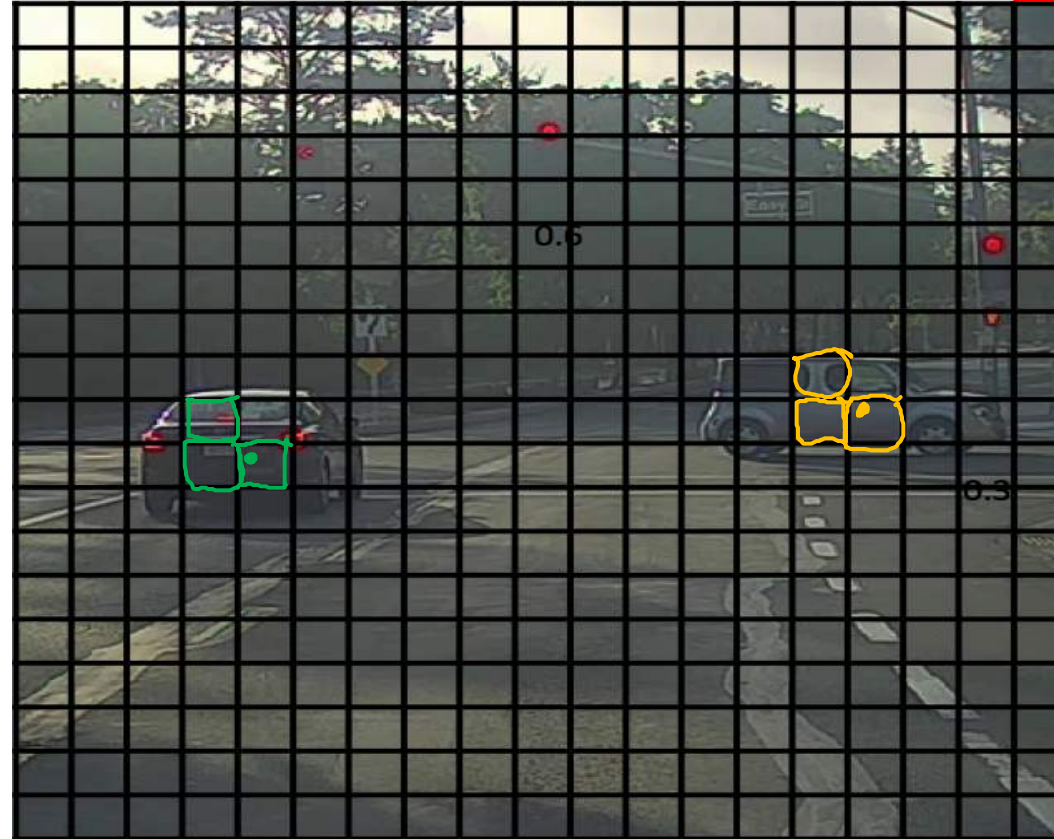
Non-max
suppression

Non-max suppression example



To avoid detecting same object twice we

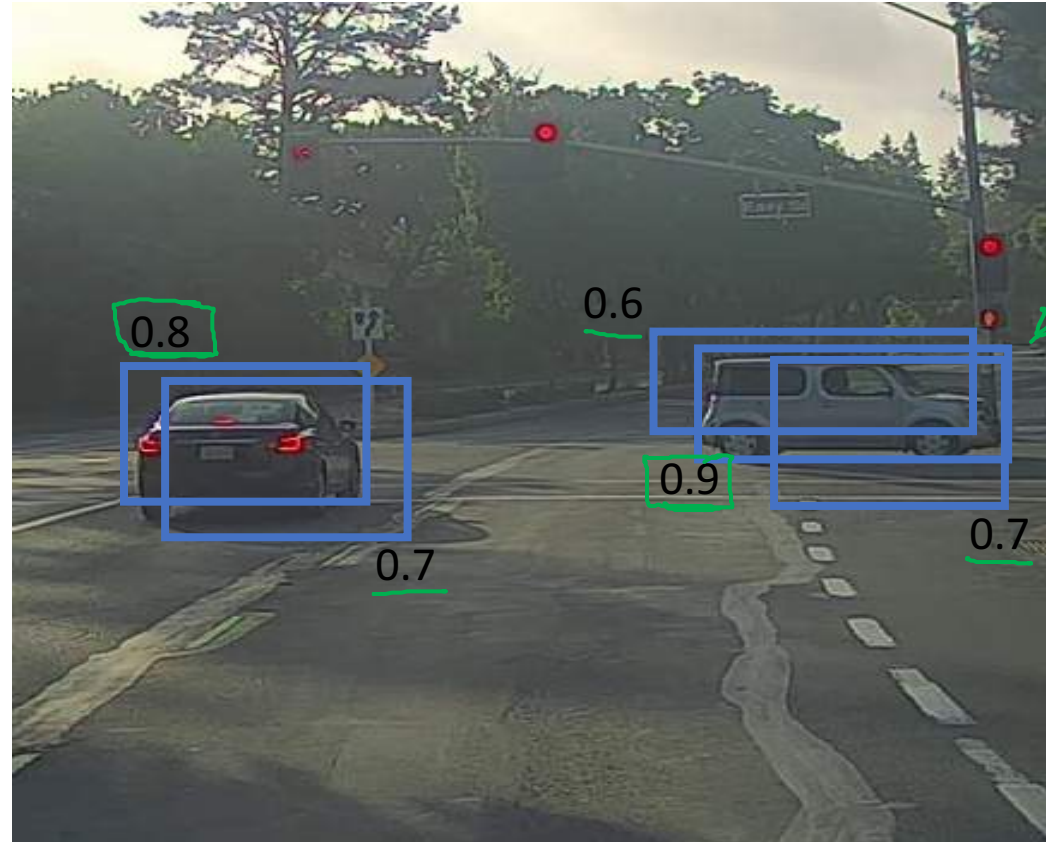
Non-max suppression example



19x19

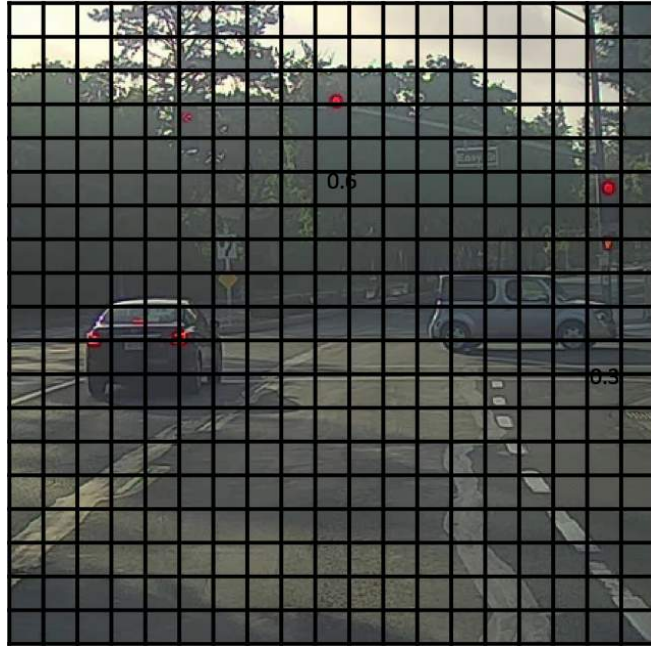
the real centre is at the marked position but

Non-max suppression example



P_c

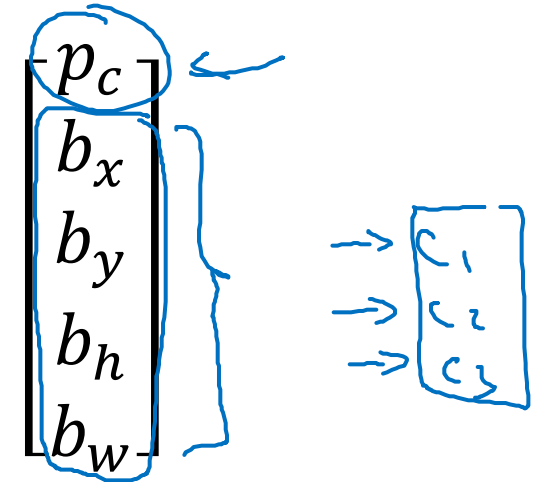
Non-max suppression algorithm



19x19

Jo pichle mein finally box chuna usse IOU nikalo au

Each output prediction is:



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 $\text{IoU} \geq 0.5$ with the box output in the previous step

What if our square box contains more than 1 object. In that case anchor boxes helps. We define 2 anchor boxes of different orientation and for each square

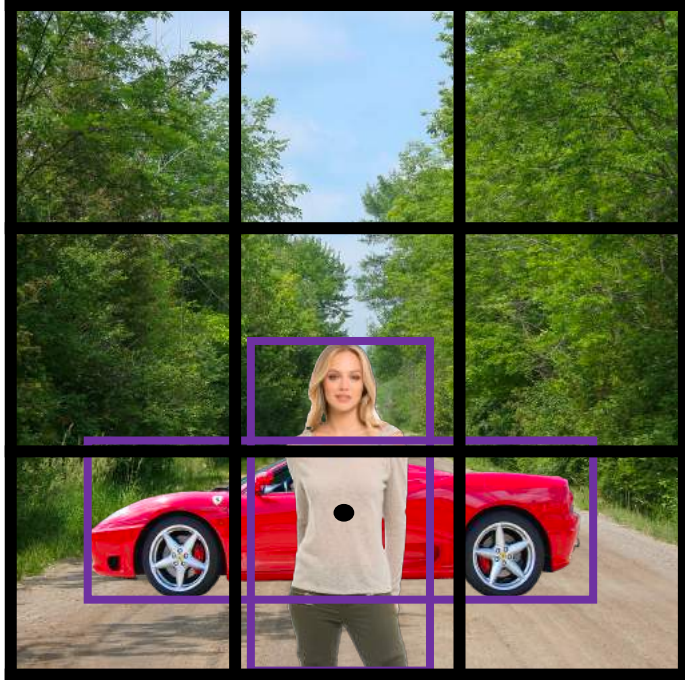


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Object Detection

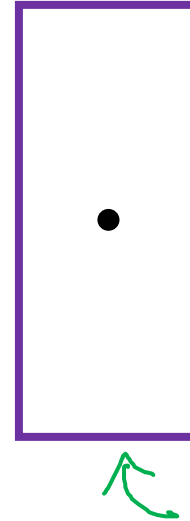
Anchor boxes

Overlapping objects:

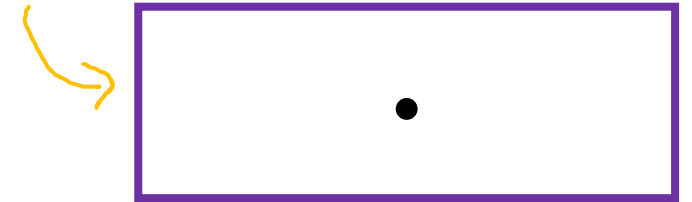


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

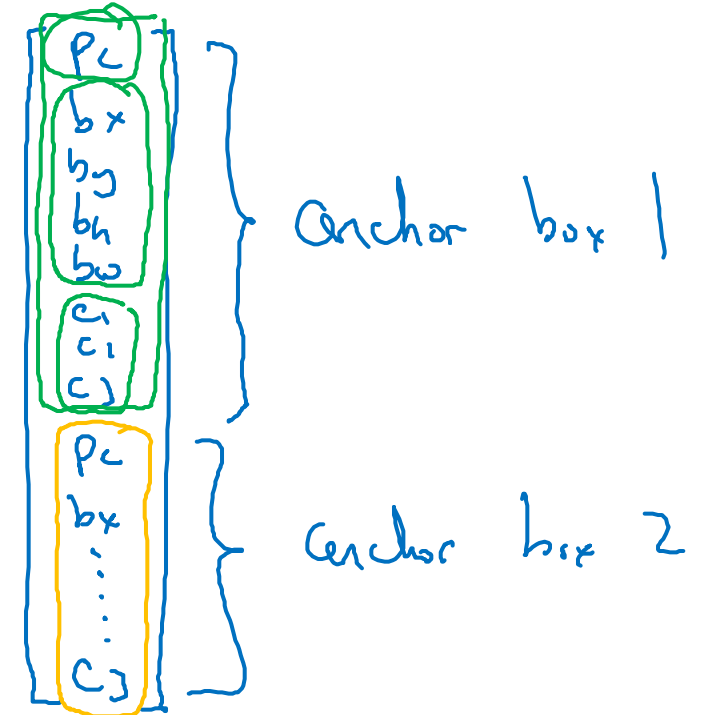
Anchor box 1:



Anchor box 2:



$y =$

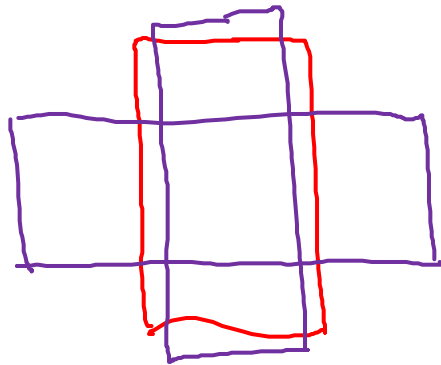


Anchor box algorithm

Previously:

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

Output y :
 $3 \times 3 \times 8$



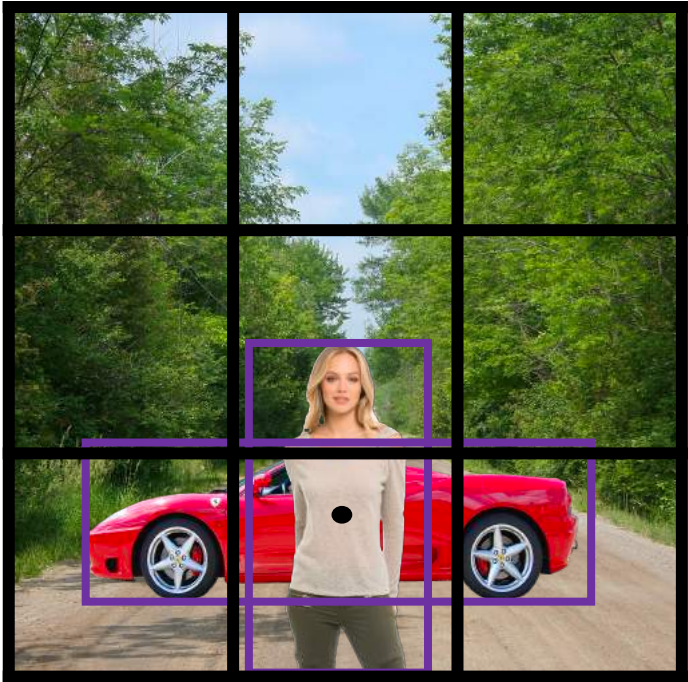
With two anchor boxes:

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.

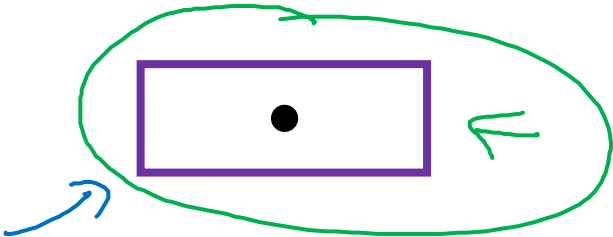
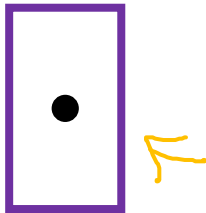
(grid cell, anchor box)

Output y :
 $3 \times 3 \times 16$
 $3 \times 3 \times 2 \times 8$

Anchor box example



Anchor box 1: Anchor box 2:



y =

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

$$\begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 1 \\ 0 \\ 0 \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

car only?

$$\begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 1 \\ 0 \\ 0 \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

anchor box 1

anchor box 2



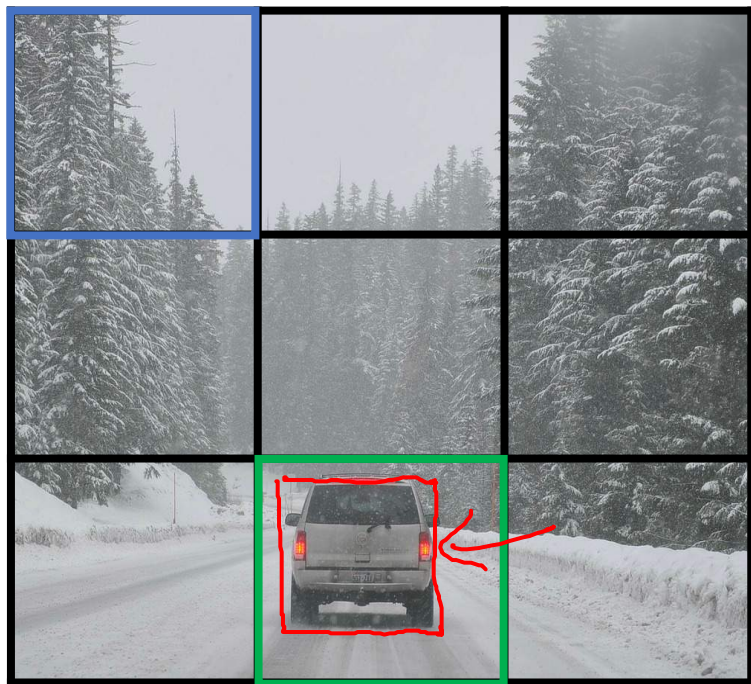
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Object Detection

Putting it together:
YOLO algorithm

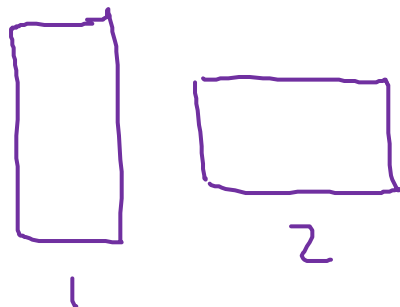
Training

- 1 - pedestrian
- 2 - car
- 3 - motorcycle



If we are using 2 anchor boxes then our output :

$$y =$$



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

0
 $?$
 $?$
 $?$
 $?$
 $?$
 $?$
 $?$
 0
 $?$
 $?$
 $?$
 $?$
 $?$
 $?$

0
 $?$
 $?$
 $?$
 $?$
 $?$
 $?$
 $?$
 1
 b_x
 b_y
 b_h
 b_w
 0
 1
 0

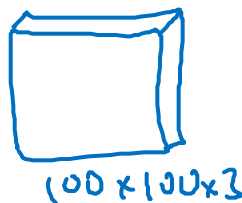
Ye to bas ek hai ese hi 3x3 honge har ek square k

$3 \times 3 \times 16$
y is $3 \times 3 \times 2 \times 8$

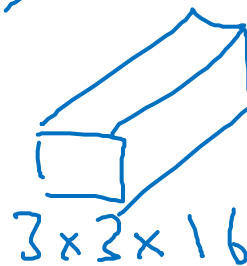
$19 \times 19 \times 16$
 $19 \times 19 \times 40$

#anchors

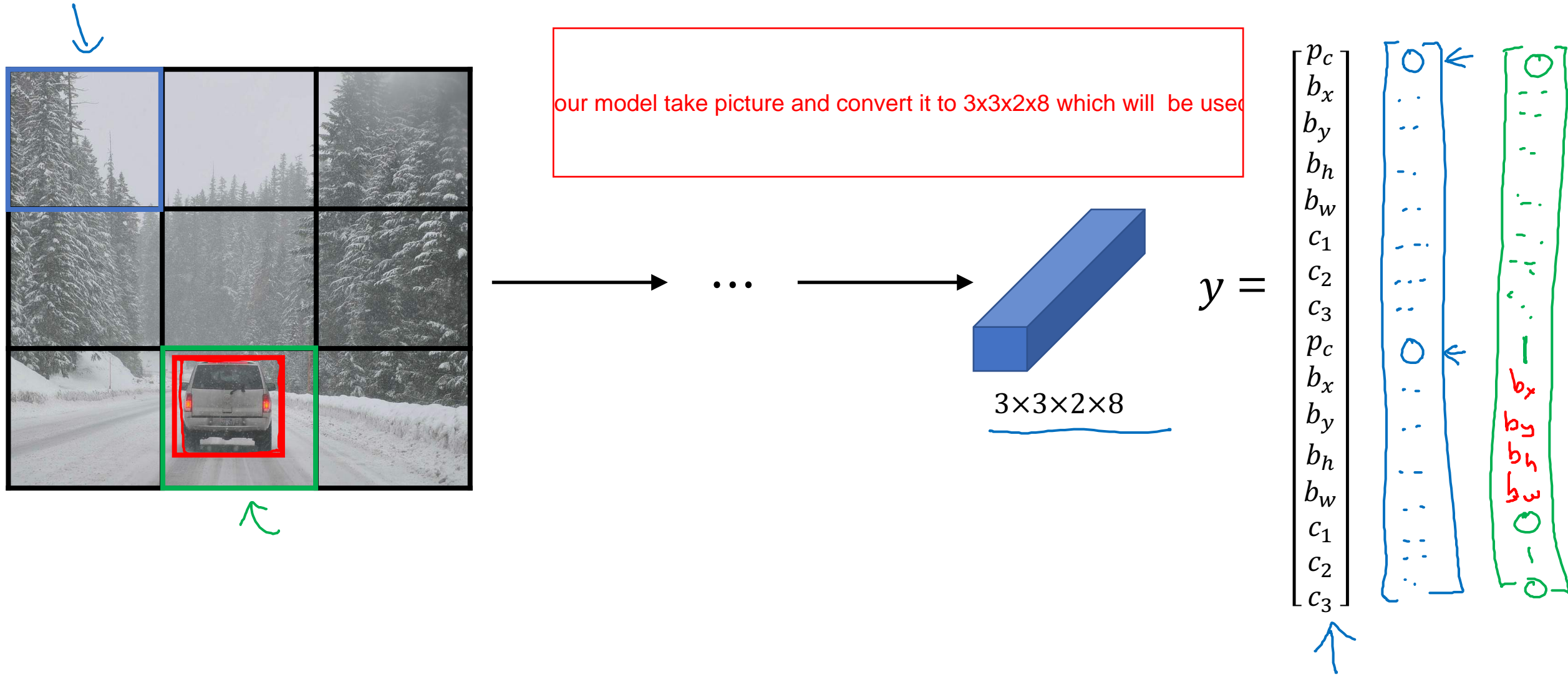
$5 + \#classes$



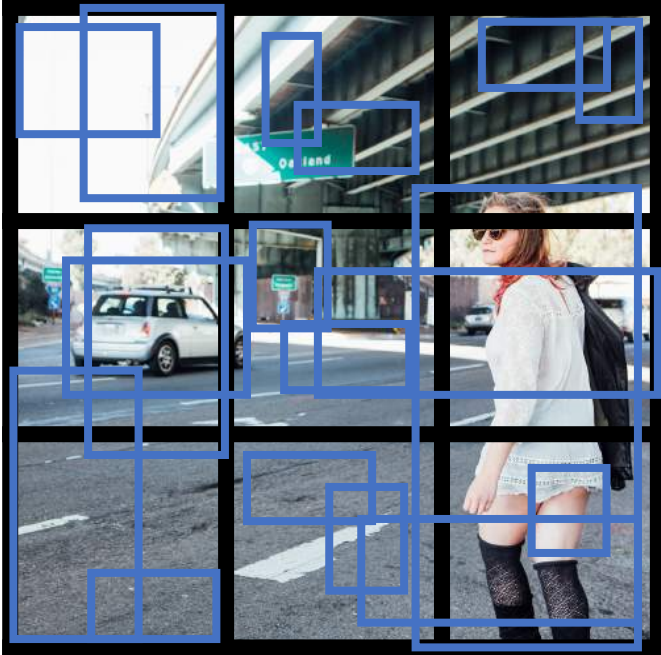
ConvNet



Making predictions



Outputting the non-max suppressed outputs



- For each grid cell, 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.

Instead of running sliding window everywhere where there are clearly no object we run our algo only on some regions of interest where objects can be

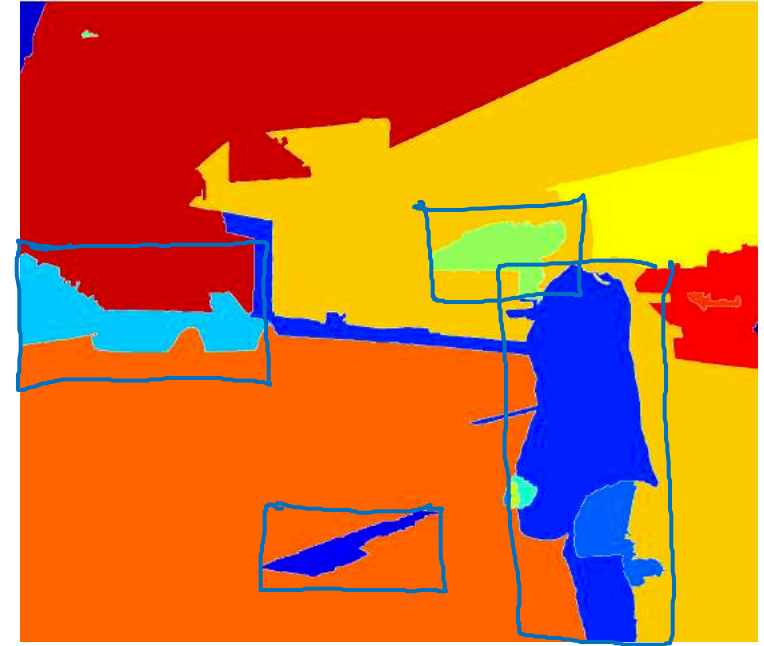
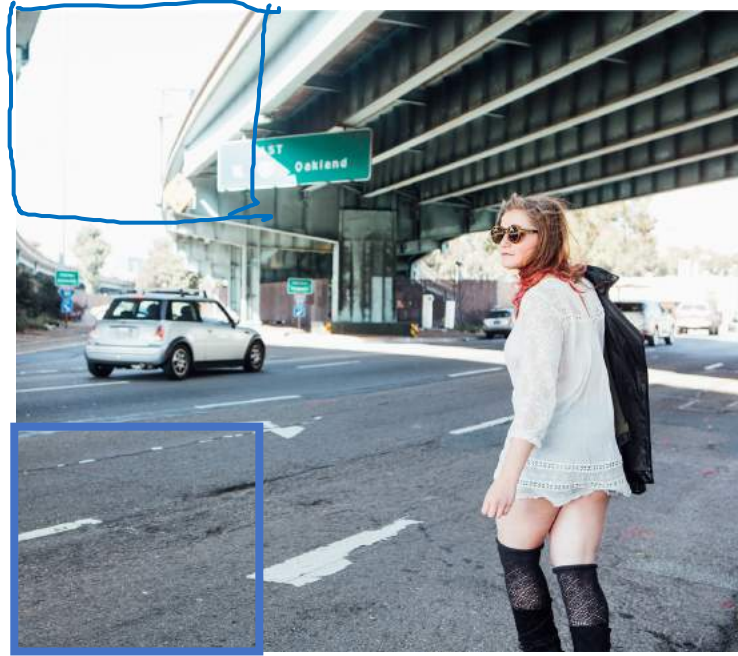
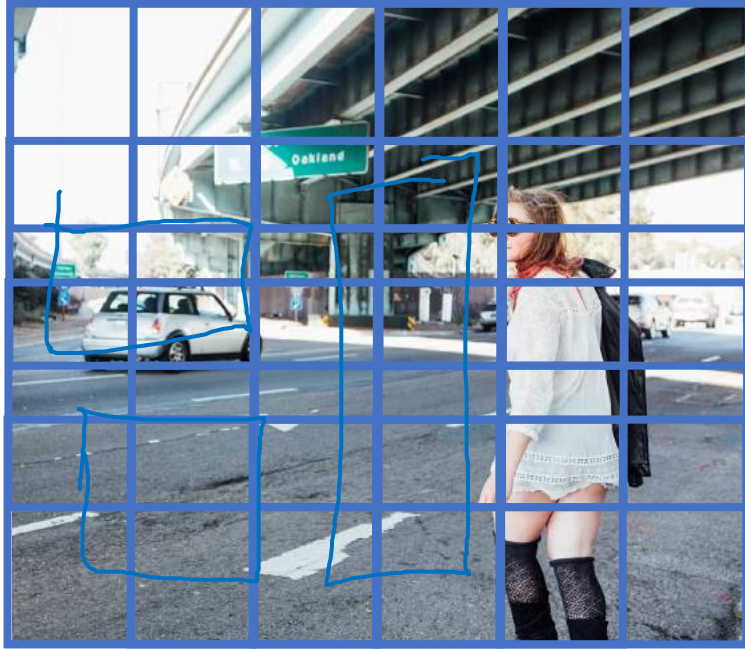


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Object Detection

Region proposals (Optional)

Region proposal: R-CNN



Segmentation algorithm

~2,000

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]

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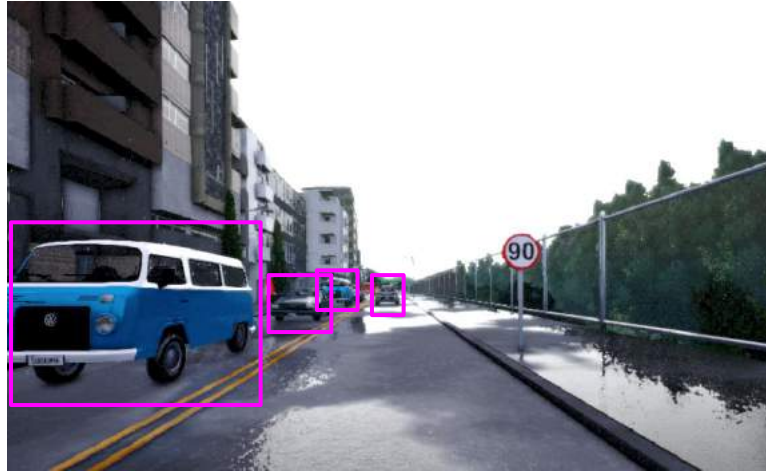
Convolutional Neural Networks

Semantic segmentation with U-Net

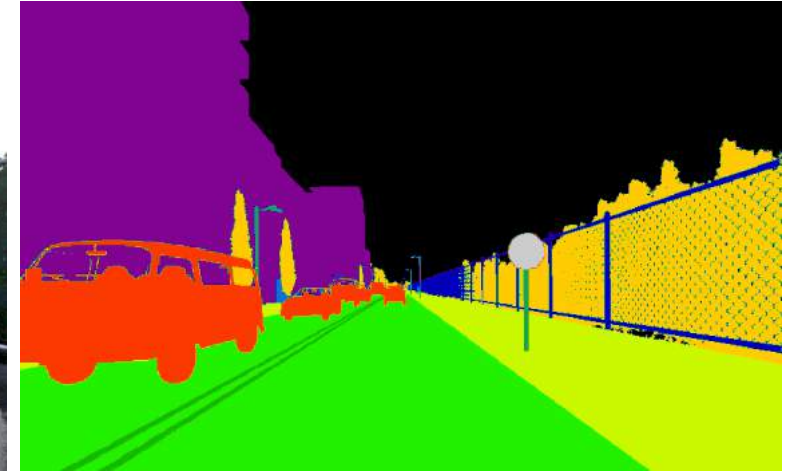
Object Detection vs. Semantic Segmentation



Input image



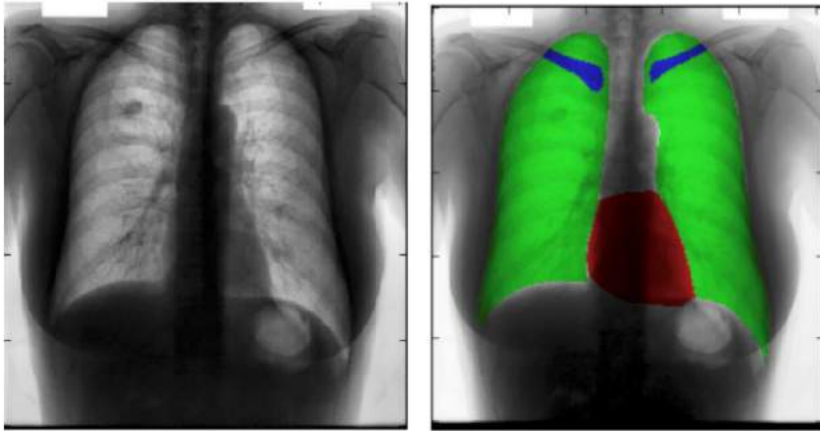
Object Detection



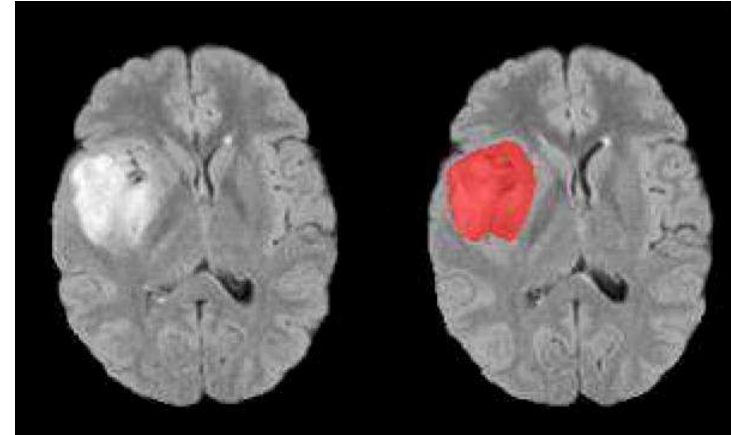
Semantic Segmentation

what segmentation does it tries to find out what each pixel is doing. Where, for example, rather than detecting the road and trying to draw a bound

Motivation for U-Net



Chest X-Ray

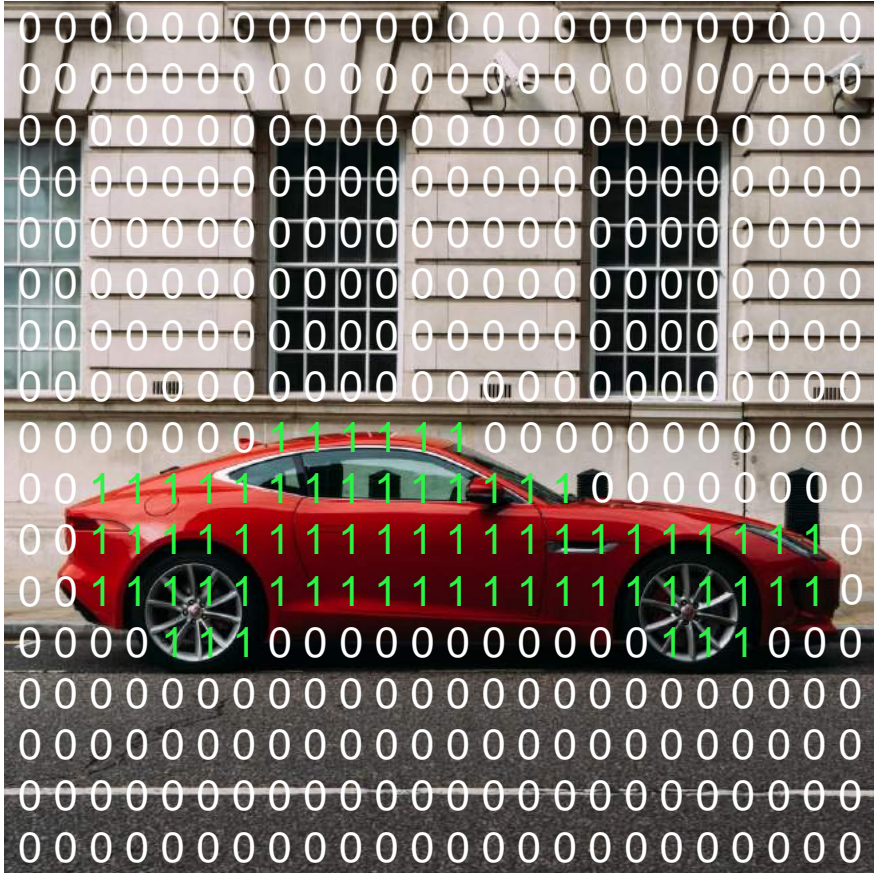


Brain MRI

[Novikov et al., 2017, Fully Convolutional Architectures for Multi-Class Segmentation in Chest Radiographs]

[Dong et al., 2017, Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks]

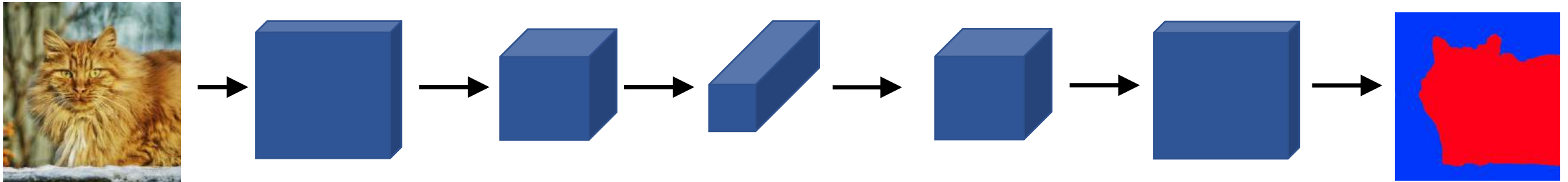
Per-pixel class labels



We want 0/1 for every pixel.

1. Car
0. Not Car

Deep Learning for Semantic Segmentation

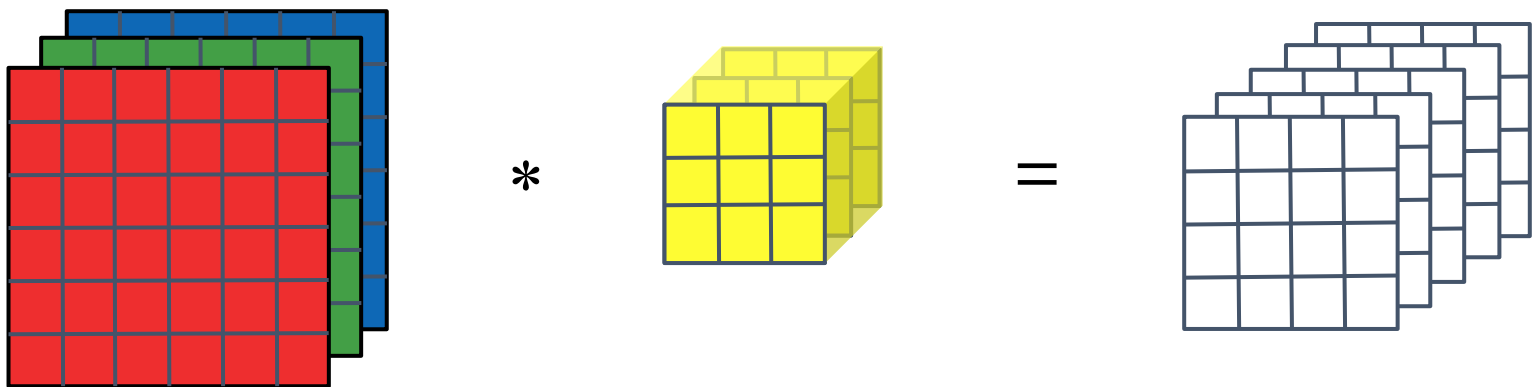


Input image, . one key point in semantic segmentation is that as we progress len and width goes decreasing and depth keeps on increasing. So

Transpose convolution helps us to make the input image blow up to higher shape and dimension. like blowing up 2x2 image to a 4x4 image.

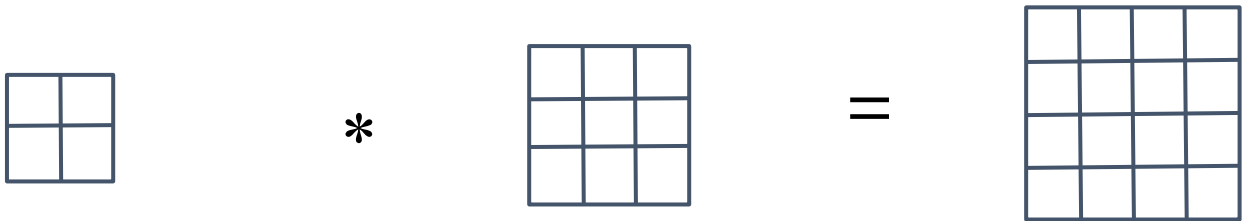
Transpose Convolution

Normal Convolution



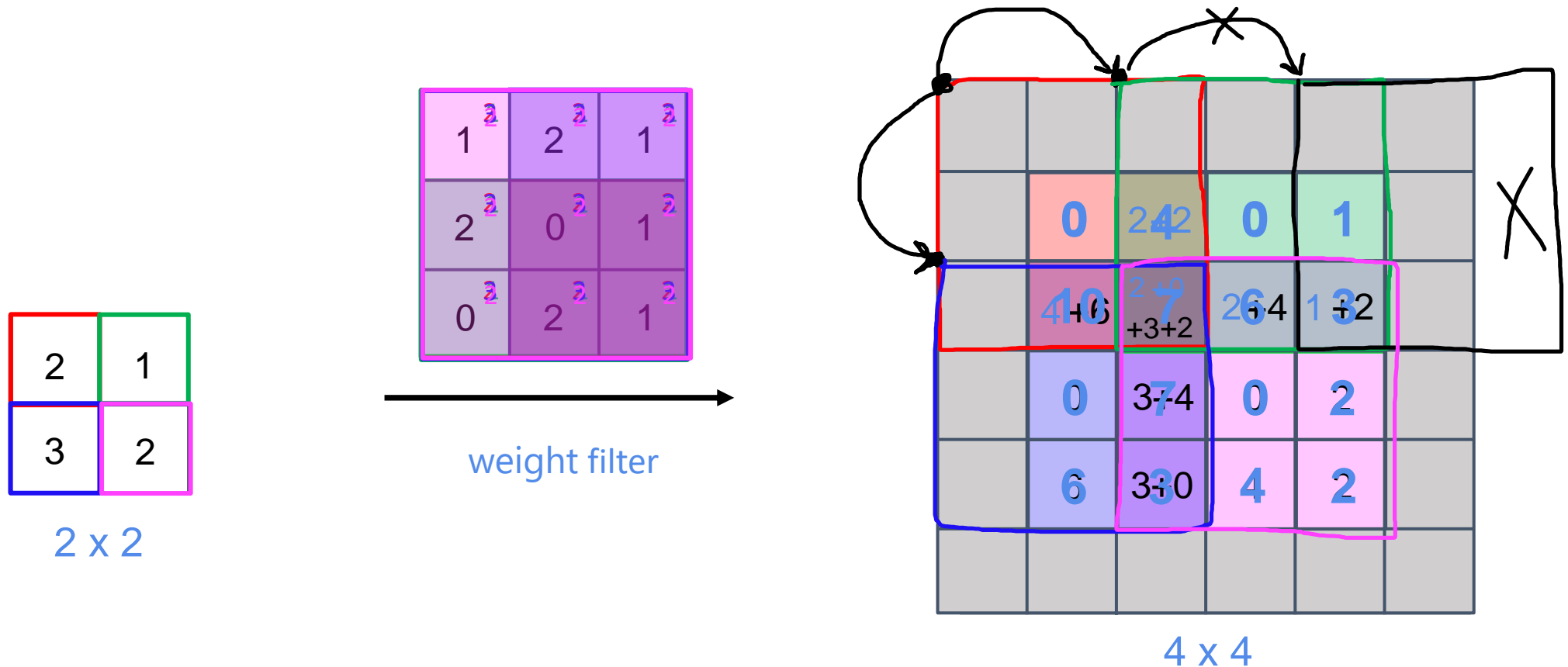
Transpose Convolution

Output bigger than the input.



In the regular convolution, you would take the filter and place it on top of the inputs and then multiply and sum up. In the transpose convolution, instead of

~~Transpose Convolution~~



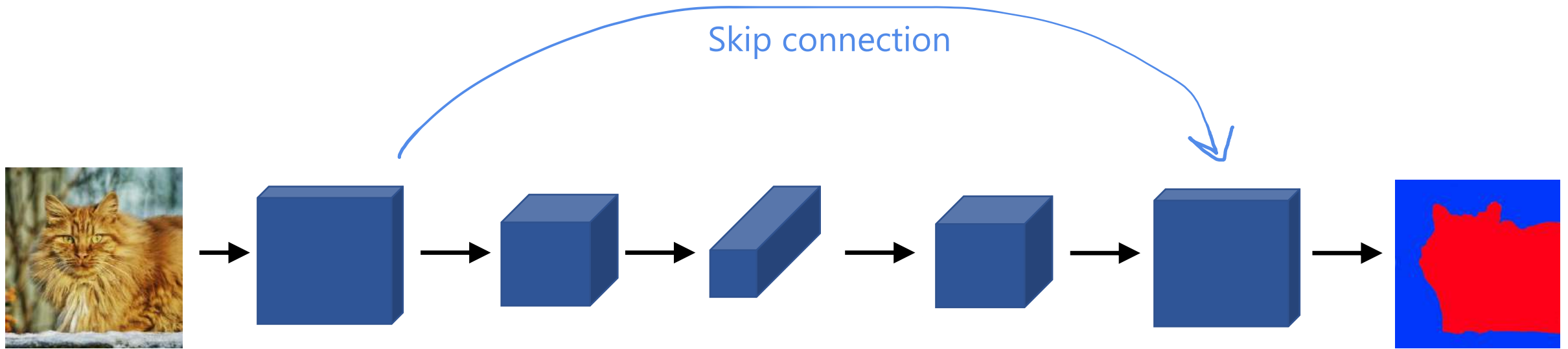
filter f x f = 3 x 3

padding $p = 1$

stride s = 2

Padding applied to the out

Deep Learning for Semantic Segmentation

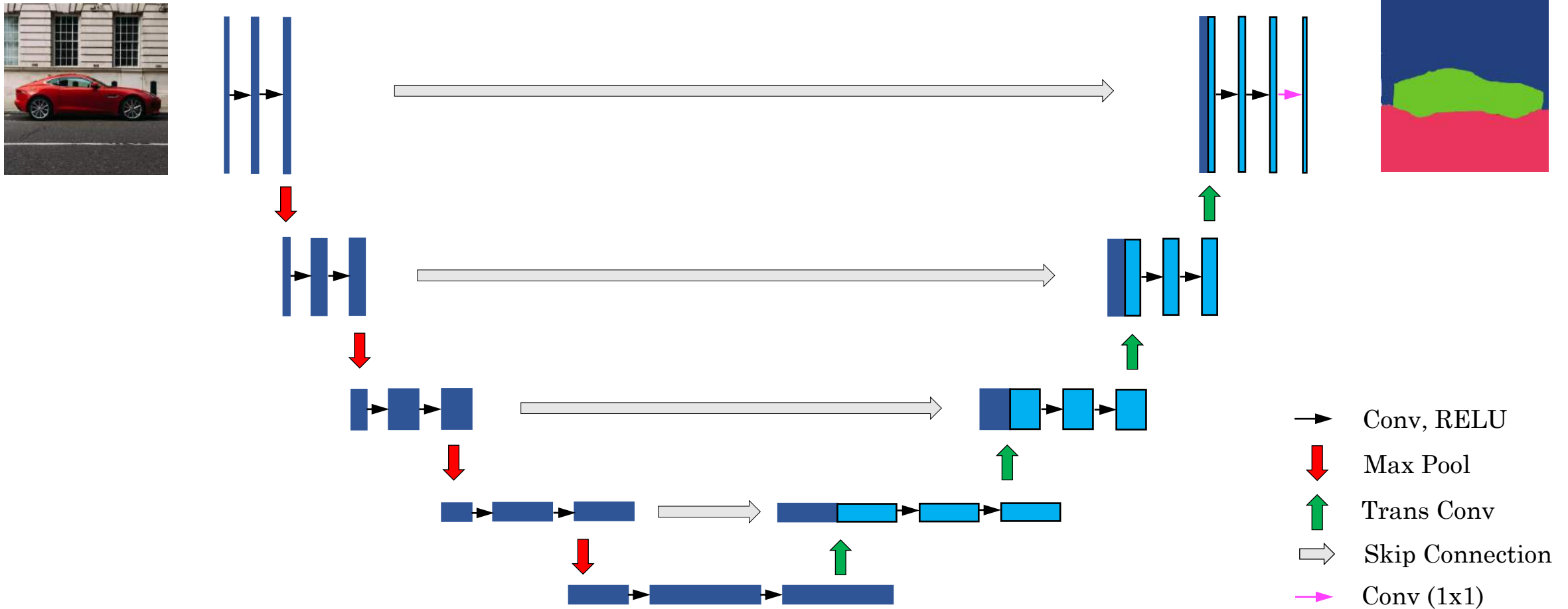


For the first part we will be using the normal

Second part uses transpose convolution to blow

U-Net

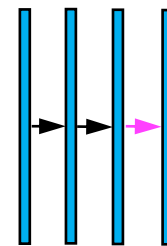
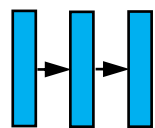
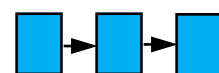
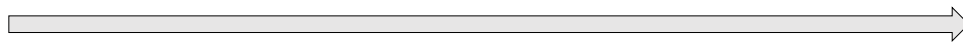
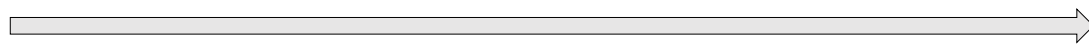
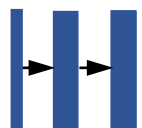
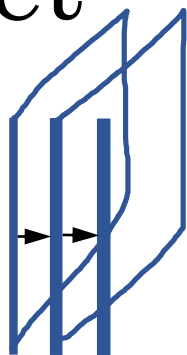
See it looks like a U and that's why called u-net.



U-Net



$h \times w \times 3$



$h \times w \times \# \text{ classes}$

- Conv, RELU
- ↓ Max Pool
- ↑ Trans Conv
- Skip Connection
- Conv (1x1)