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Object Detection

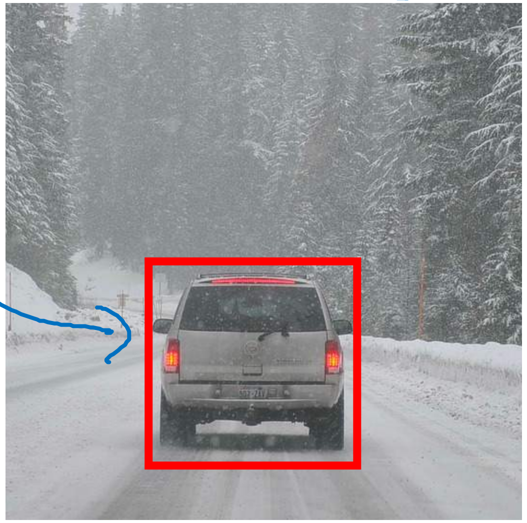
Object localization

What are localization and detection?

Image classification

"Car"

Classification with localization



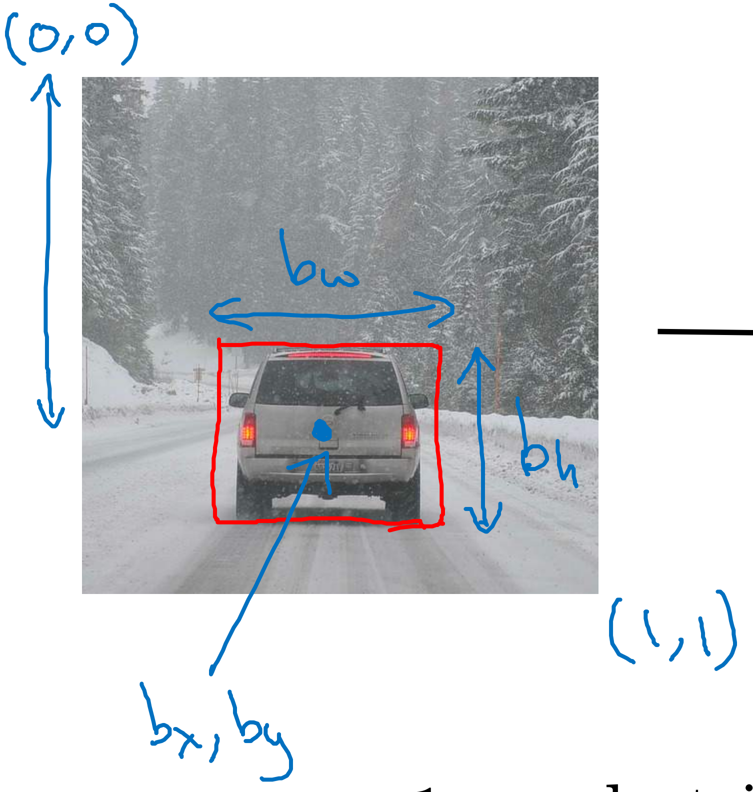
"Car"

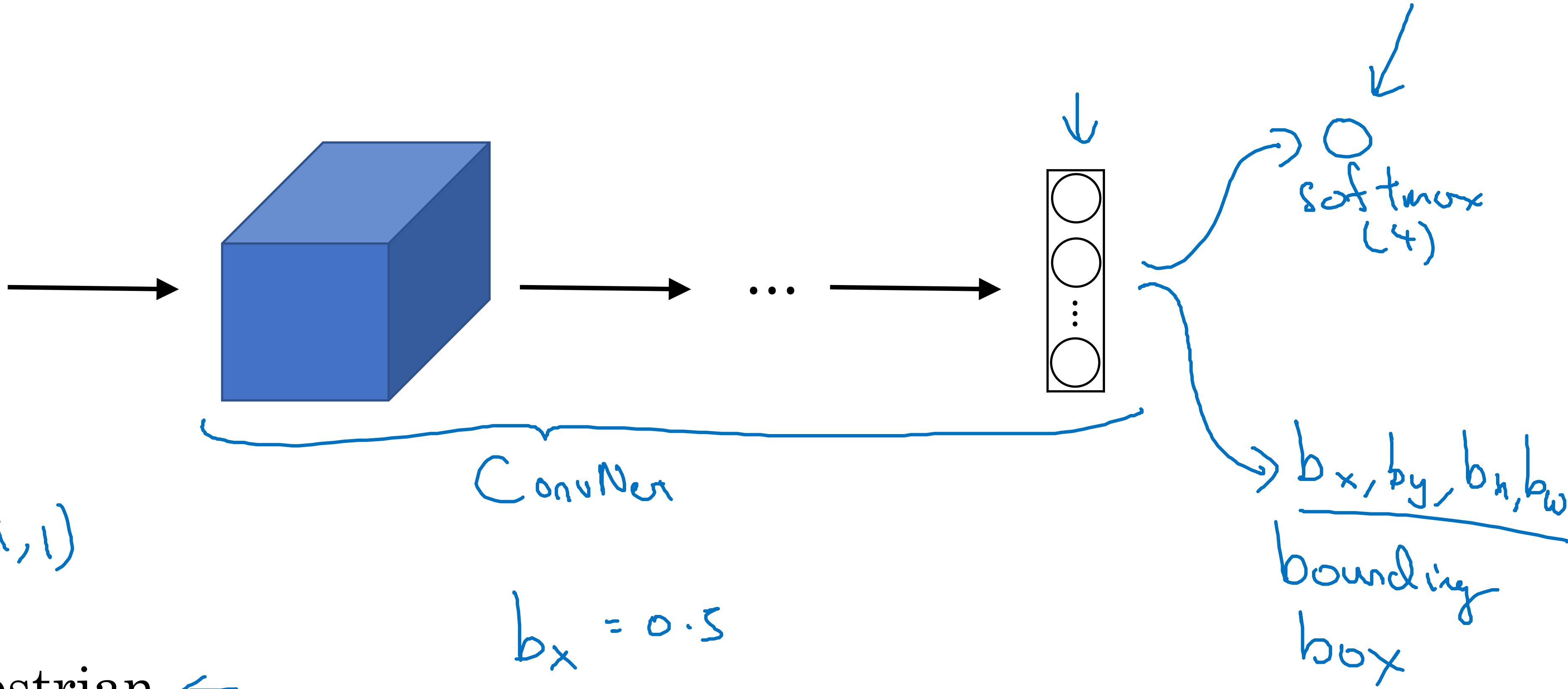
Detection

1 object

multiple objects

Classification with localization





1 - pedestrian ←

2 - car ←

3 - motorcycle ←

4 - $\boxed{\text{background}}$

$b_x = 0.5$

$b_y = 0.7$

$b_h = 0.3$

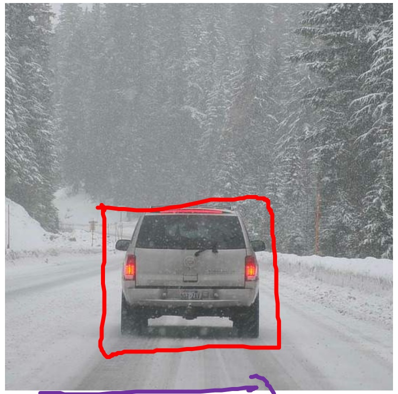
$b_w = 0.4$

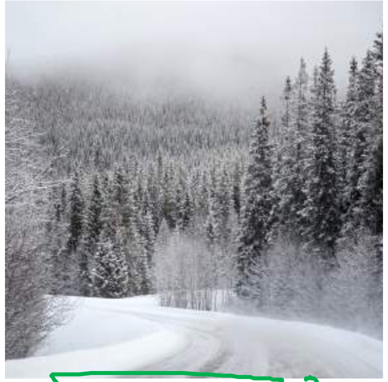
Defining the target label y

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

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

$x =$





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

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

is there any object?

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

p_c

"don't care"

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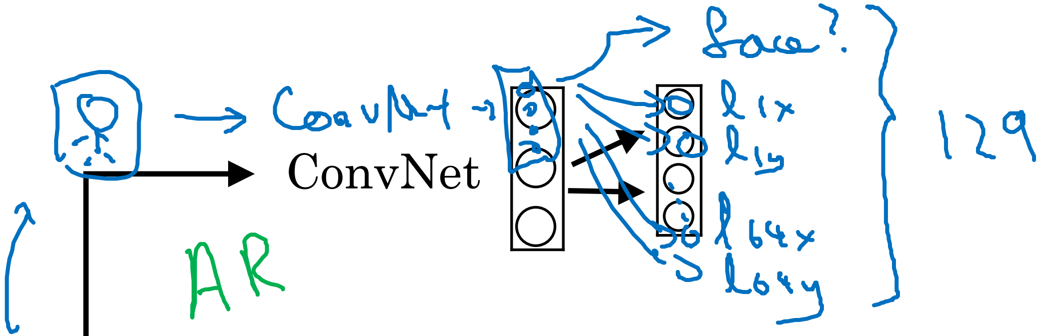
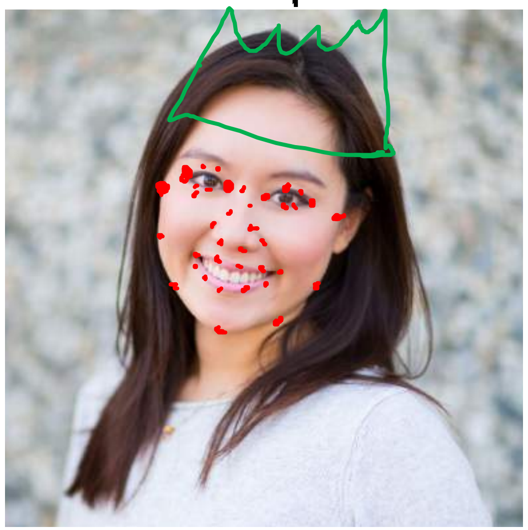
Object Detection

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

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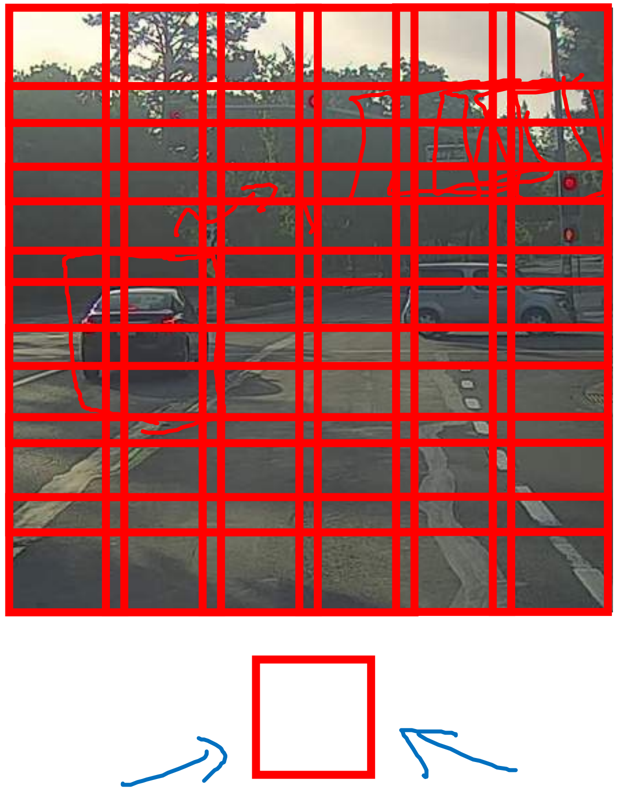
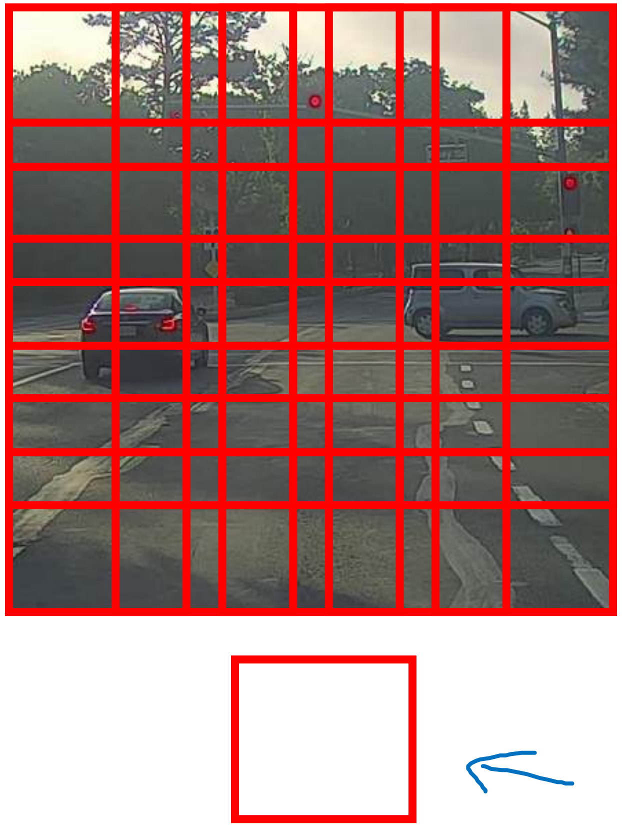
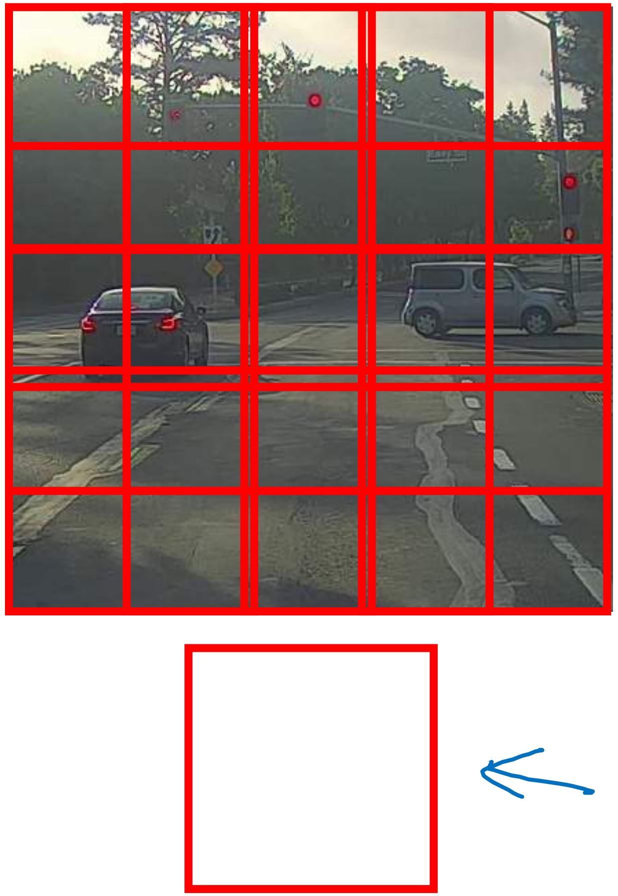
Sliding windows detection

ConvNet → 0

ConvNet







Computation cost

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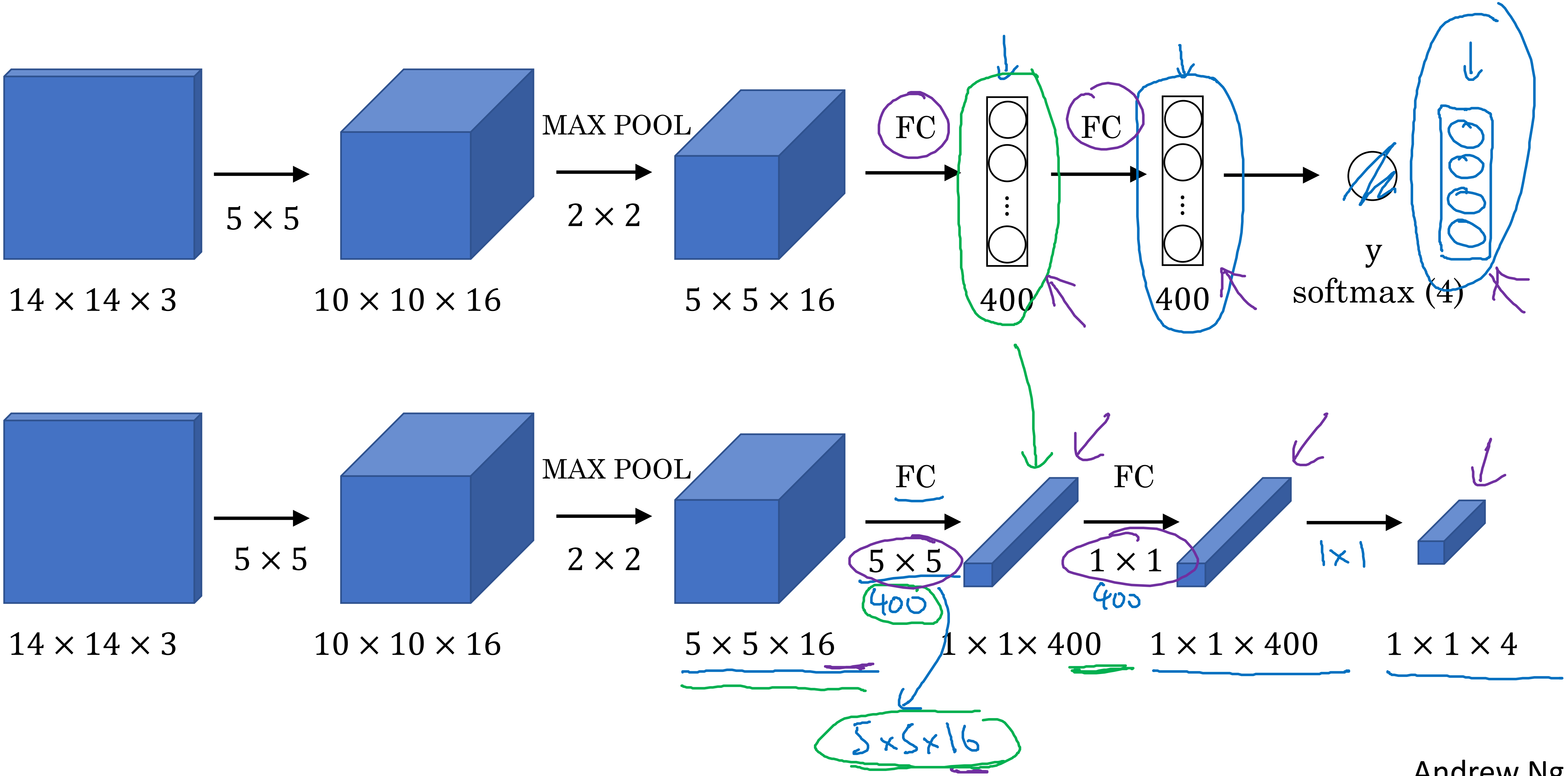
Object Detection

Convolutional implementation of sliding windows

Turning FC layer into convolutional layers



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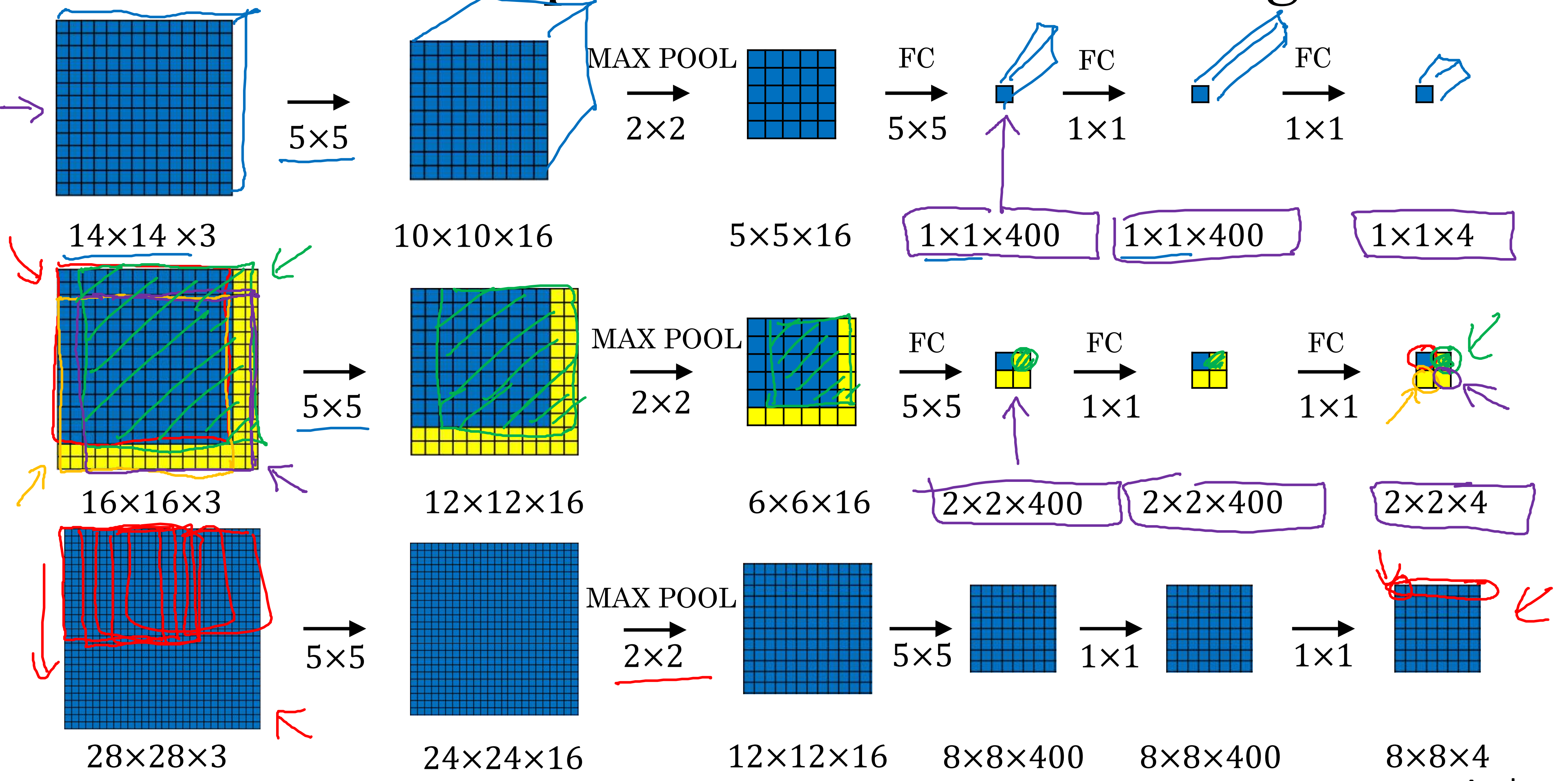
Convolution implementation of sliding windows



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

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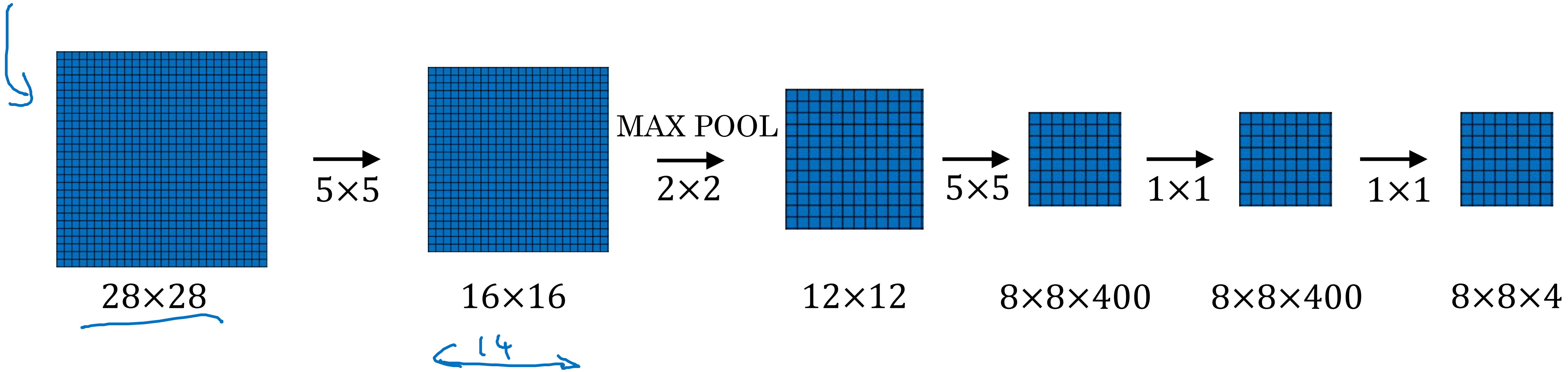
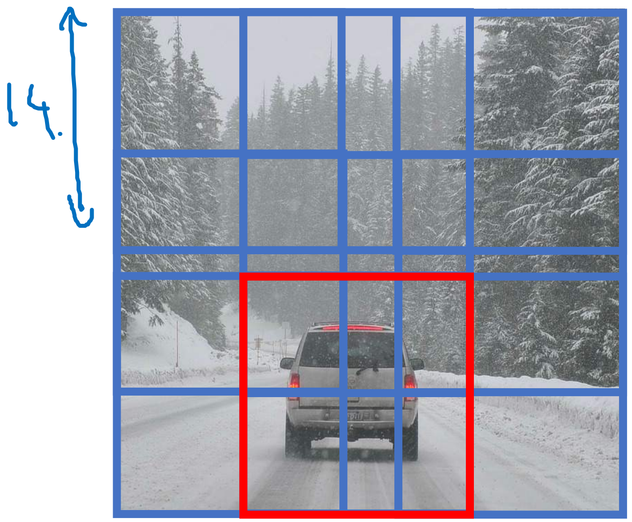
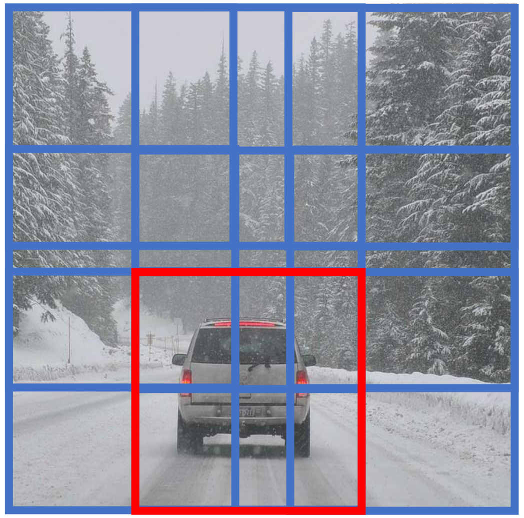
Convolution implementation of sliding windows







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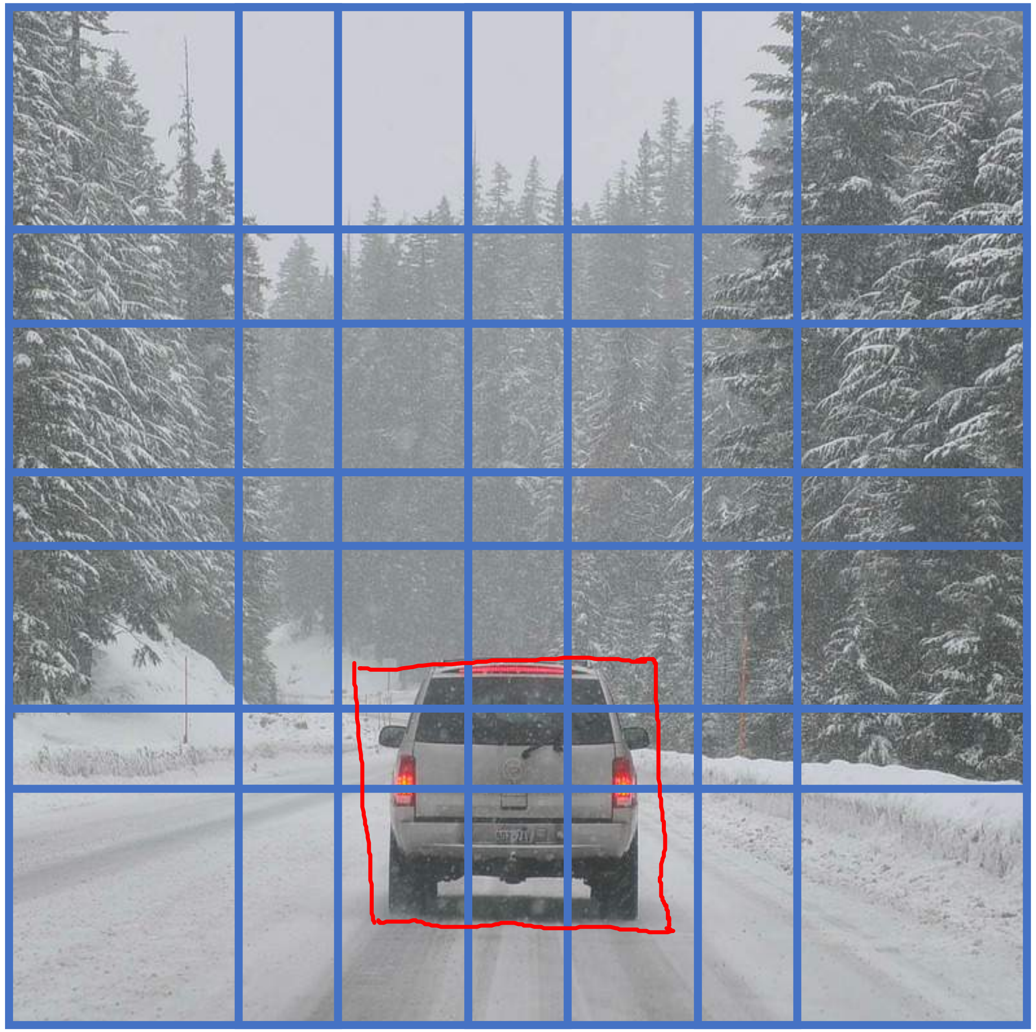
Object Detection

Bounding box predictions

Output accurate bounding boxes



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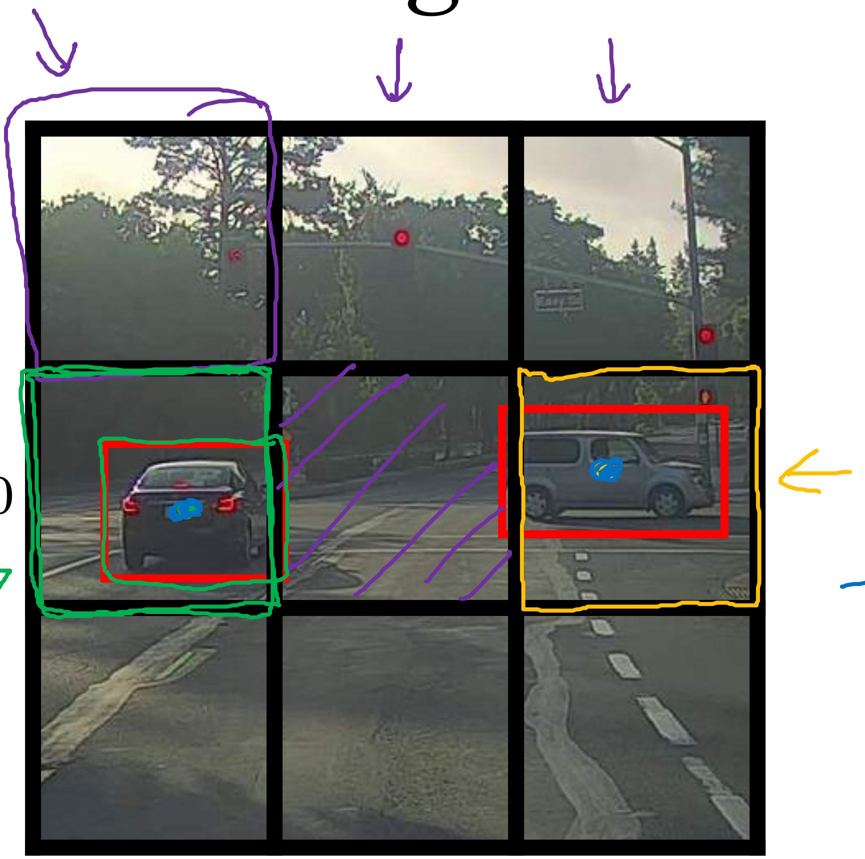
YOLO algorithm



100

100

Labels for training

For each grid cell:

Target output: 3×3×8

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

X → CONV → MAXPOOL → .... → y

100×100×3

3×3×8

→ 19×19×8

361

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

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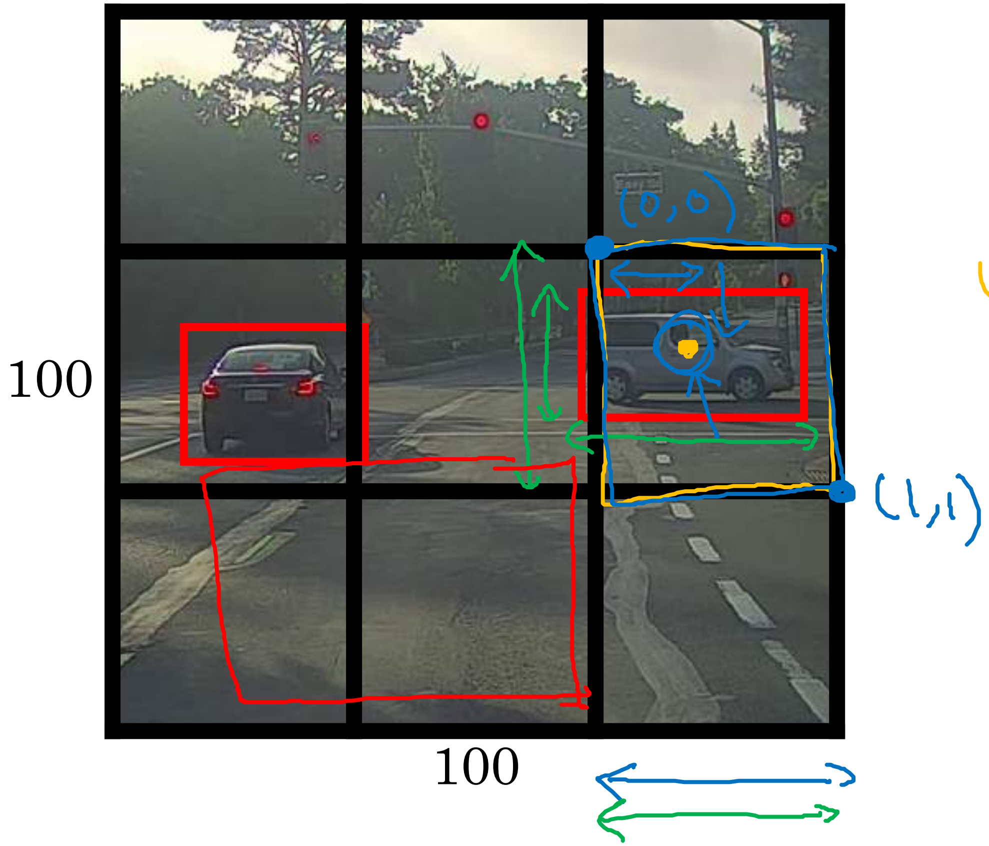
Specify the bounding boxes



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

0.4
0.3
between 0 and 1

0.5
0.9
could be > 1

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

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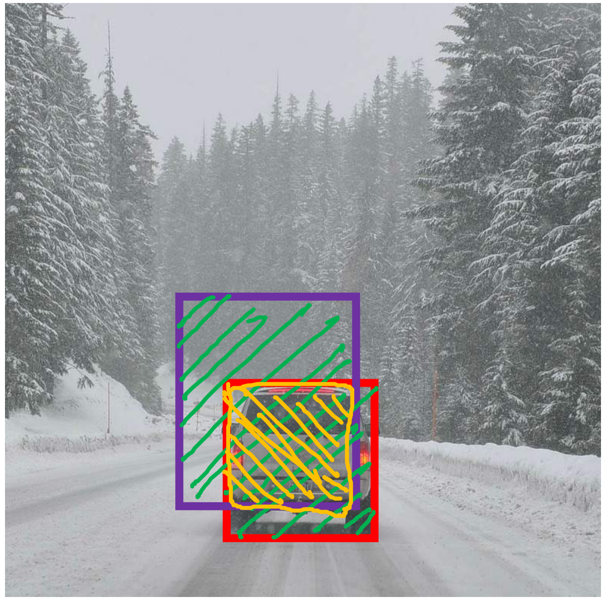
Object Detection

Intersection over union

Evaluating object localization



Intersection over Union (IoU)

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

"Correct" if IoU ≥ $\boxed{0.5}$

0.6

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

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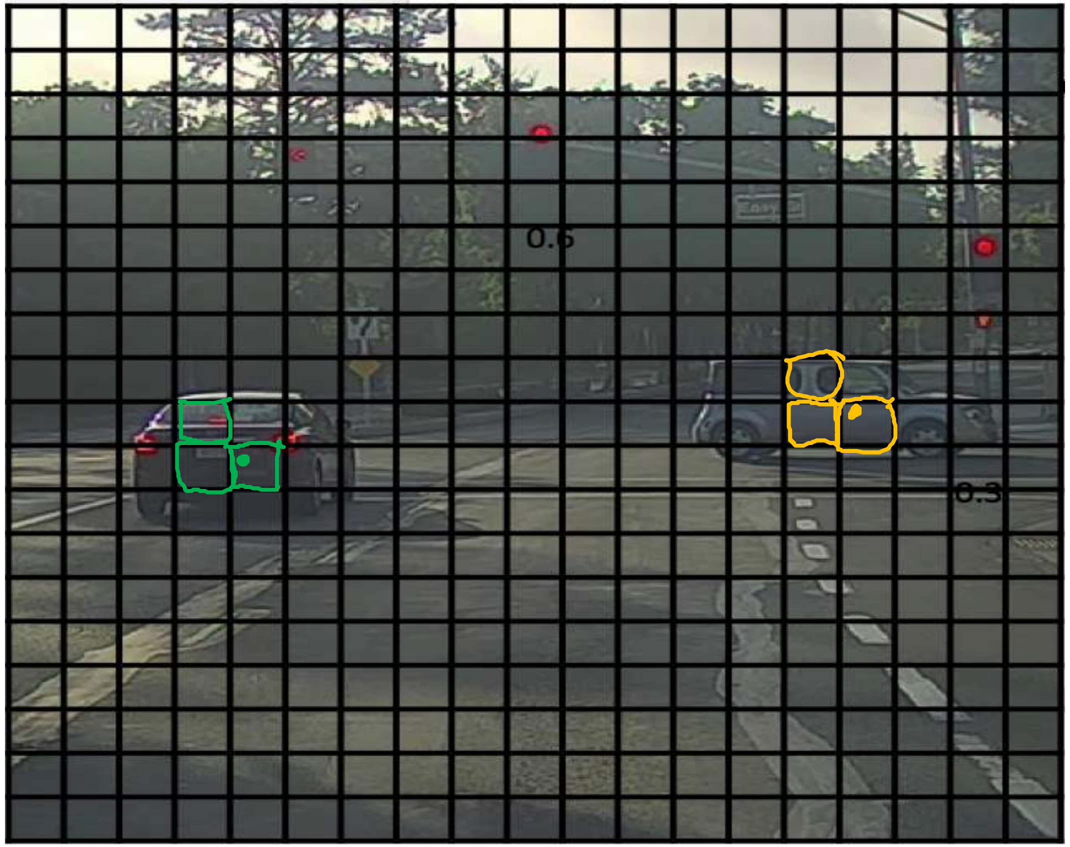
Object Detection

Non-max suppression

Non-max suppression example

Non-max suppression example



19x19

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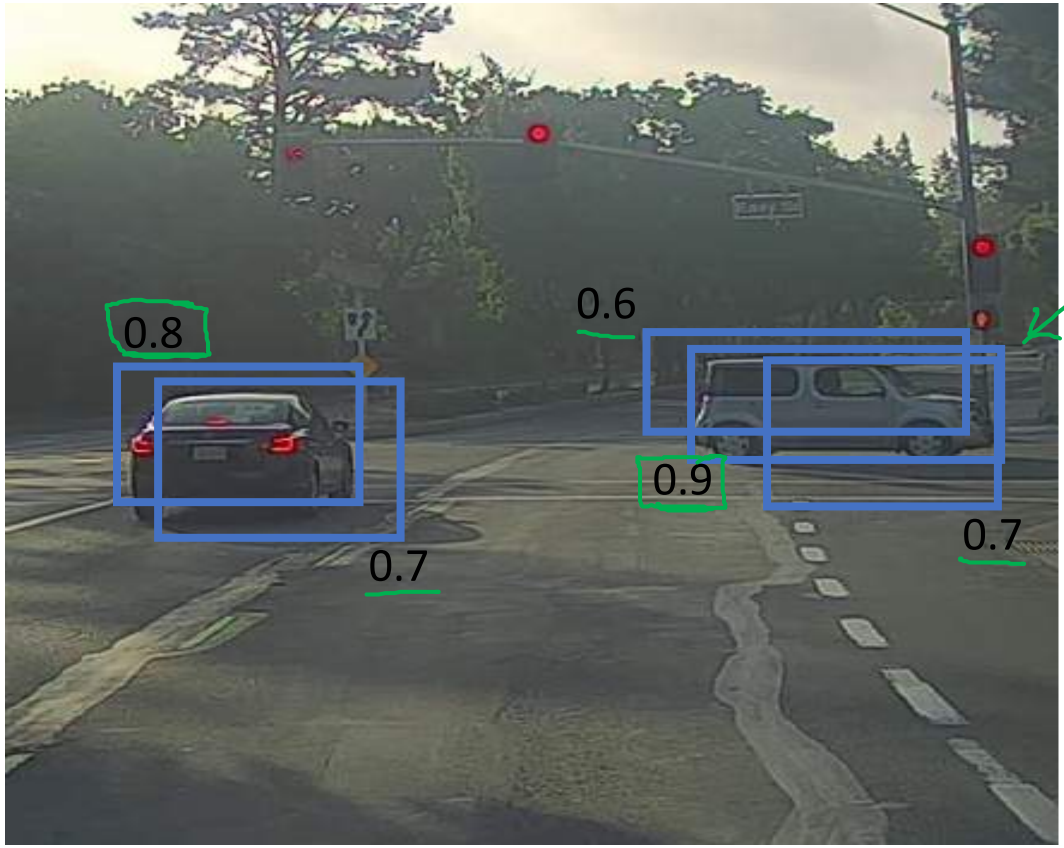
Non-max suppression example



p_c

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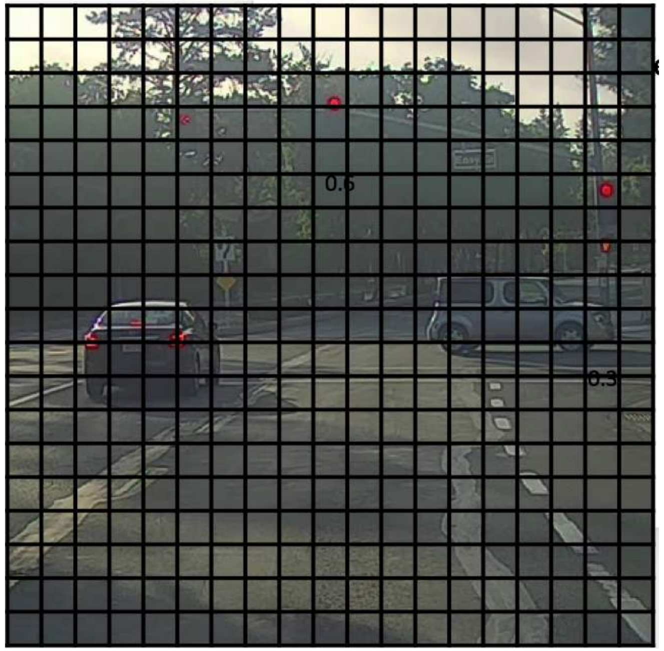
Non-max suppression algorithm



19×19

Each output prediction is: $\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \end{bmatrix}$ $\begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}$

STEP 1 Discard all boxes with $p_c \leq 0.6$

While there are any remaining boxes:

STEP 2 • Pick the box with the largest p_c. Output that as a prediction.

STEP 3 • Discard any remaining box with IoU ≥ 0.5 with the box output in the previous step

Here is a simple example, lets assume I have 5 boxes (5 P_c) here, and they are [0.2, 0.5, 0.6, 0.7, 0.9].
After step 1, the 0.2 and 0.5 will be gone. leftover are 0.6, 0.7, 0.9

step 2: box 0.9 is the highest in the leftover. So, 0.9 box here will be picked as the prediction.

step 3: the box of 0.6 will do IoU with 0.9, and box of 0.7 will do IoU with 0.9, whichever IoU >= 0.5 will be deleted.
(f IoU between box 0.6 and box 0.9 is >= 0.5, this means that there is a chance that both boxes are referring to the same object, so you want to keep only the box that has a higher probability (which is box 0.9), and drop the others (which is box 0.6).
If IoU between box 0.7 and box 0.9 is < 0.5, then there is a chance that these boxes are referring to two different objects, so we want to keep the box 0.7. After we have a list of boxes to keep, we pass it back to step 2 and then step 3 which will end up in a shorter list,and then step 2 and 3 again and again, until the list is empty

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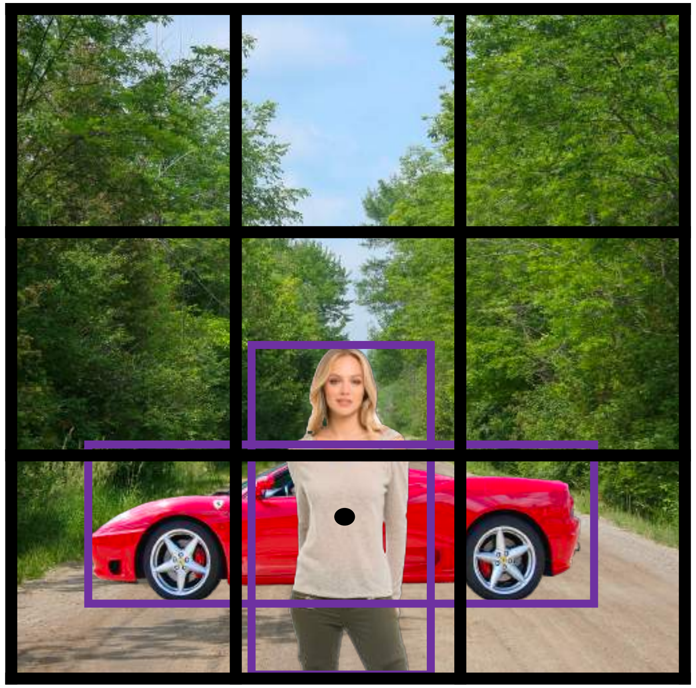
Object Detection

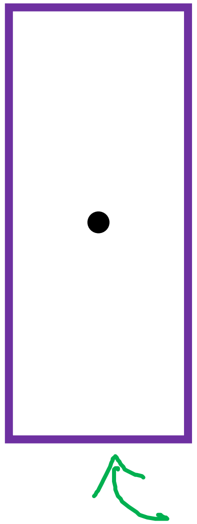
Anchor boxes

Overlapping objects:

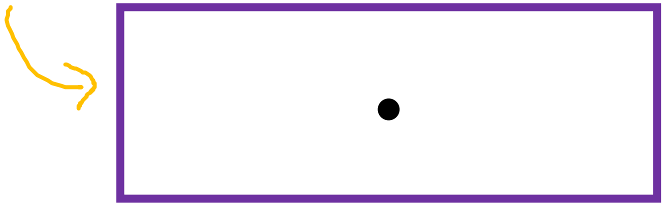


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ \vdots \\ c_3 \end{bmatrix} \begin{matrix} \left.\vphantom{\begin{matrix} 1\\1\\1\\1\\1\\1\\1\\1 \end{matrix}}\right\} \text{anchor box 1} \\ \left.\vphantom{\begin{matrix} 1\\1\\1\\1 \end{matrix}}\right\} \text{anchor box 2} \end{matrix}$$

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

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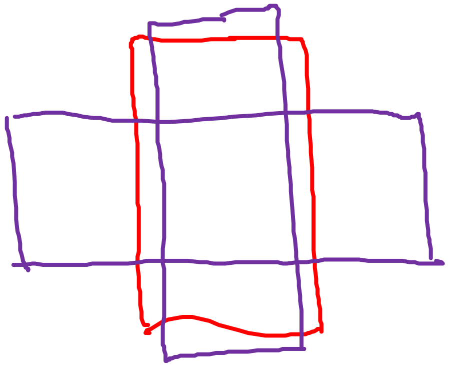
Anchor box algorithm

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:

$3 \times 3 \times 16$

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

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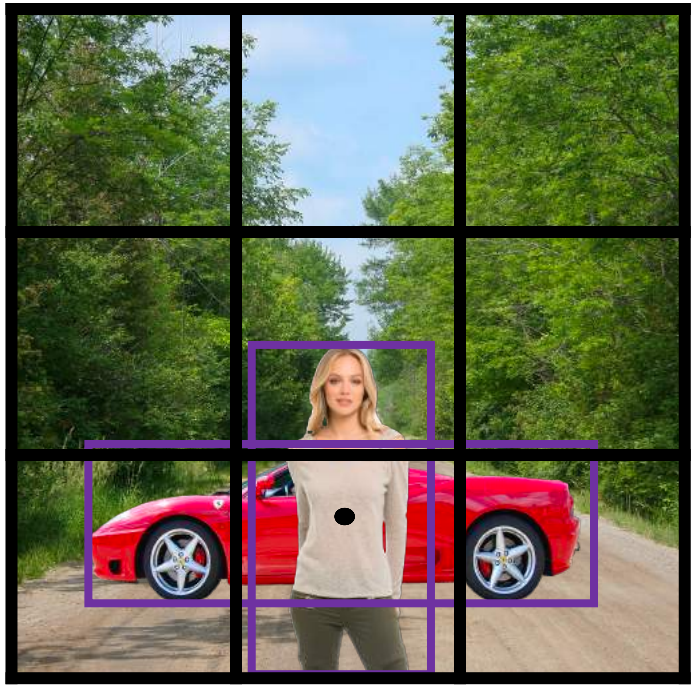
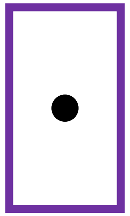
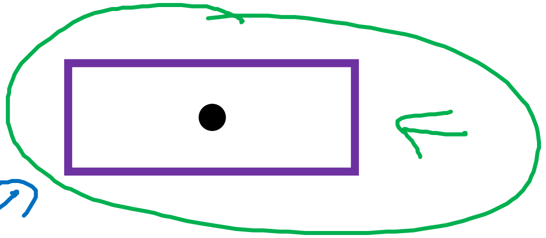
Anchor box example



Anchor box 1: Anchor box 2:

$$
y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}
\quad
\begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 1 \\ 0 \\ 0 \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}
\quad
\overset{\text{car only?}}{\begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}}
\begin{matrix} \left.\begin{matrix} \\ \\ \\ \\ \\ \\ \\ \\ \end{matrix}\right\} \text{anchor box 1} \\ \left.\begin{matrix} \\ \\ \\ \\ \\ \\ \\ \\ \end{matrix}\right\} \text{anchor box 2} \end{matrix}
$$

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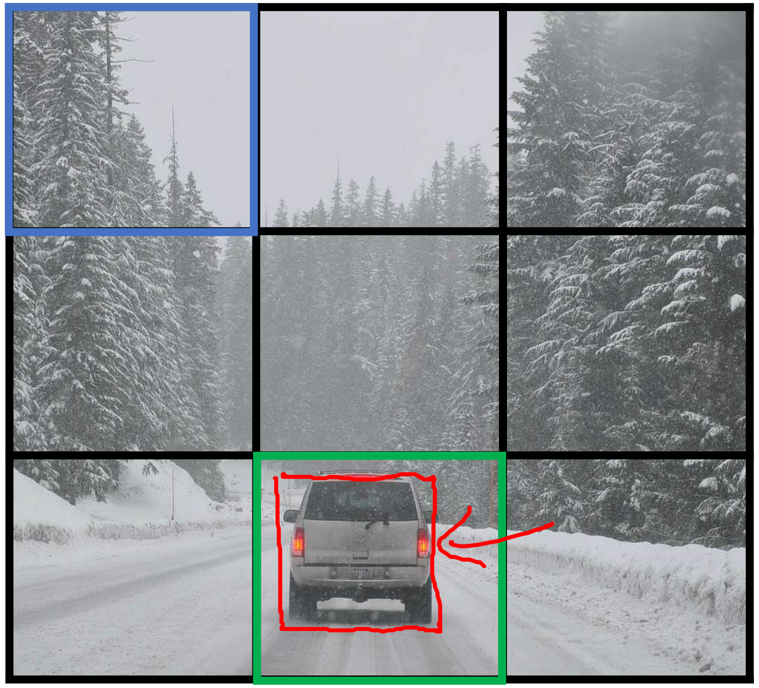
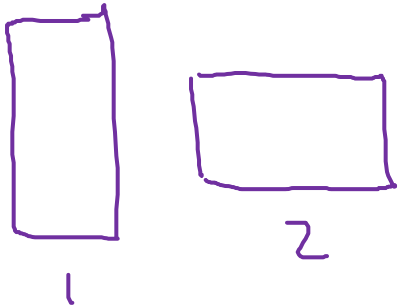
Object Detection

Putting it together: YOLO algorithm

Training

1 - pedestrian
2 - car
3 - motorcycle





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

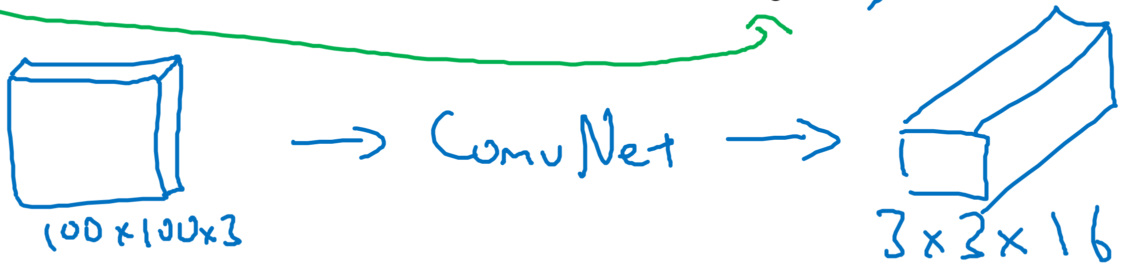
3 x 3 x 16

y is $\underbrace{3\times3}\times2\times8$

19x19x16
19x19x40

#anchors

5 + #classes



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

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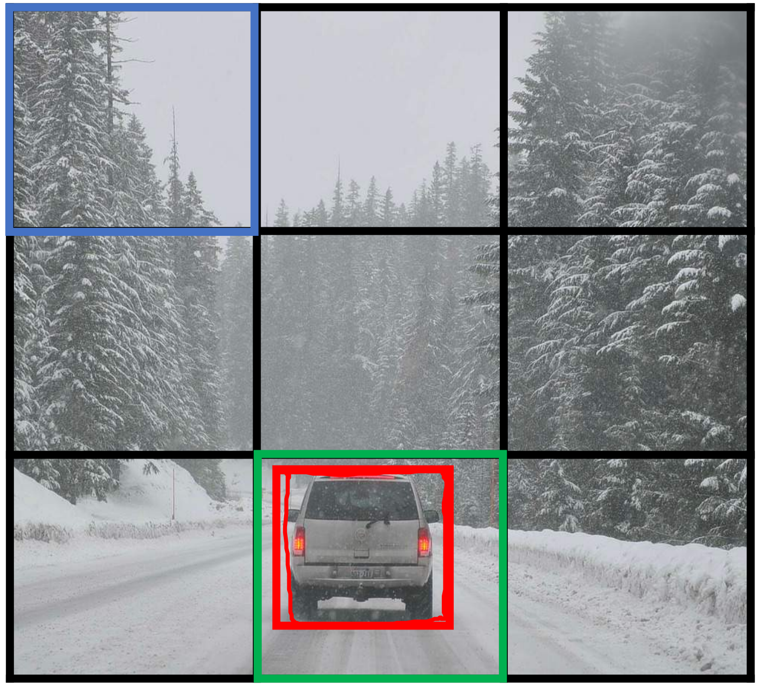
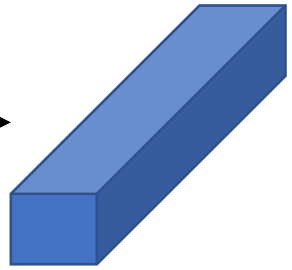
Making predictions



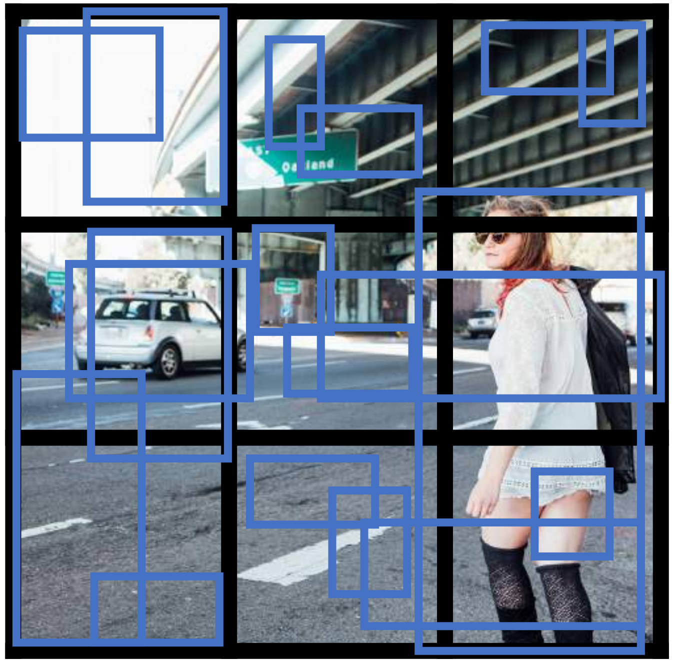
$\rightarrow \cdots \rightarrow$



$\underline{3 \times 3 \times 2 \times 8}$

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

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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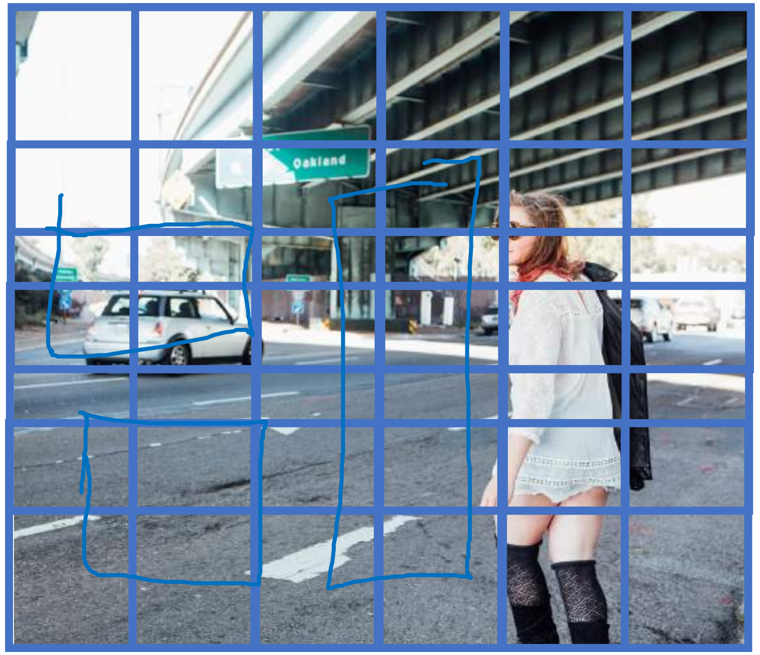
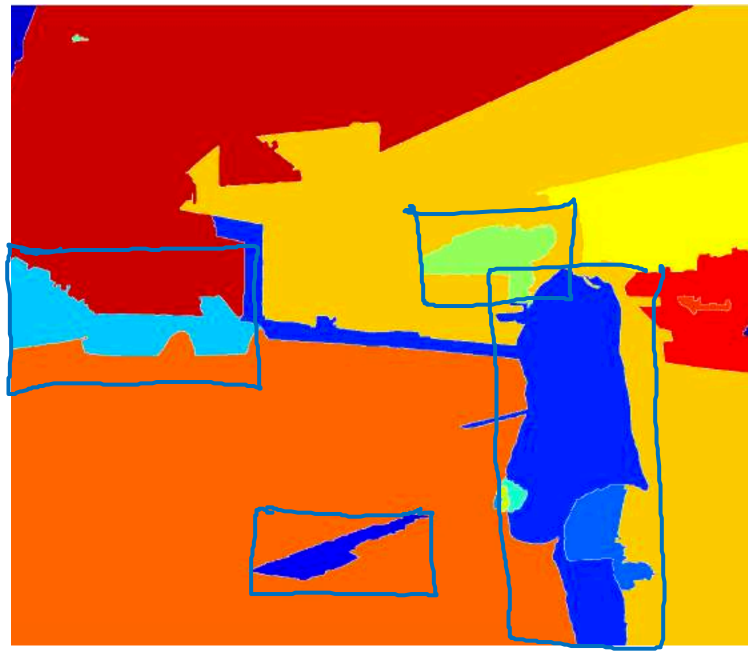
Object Detection

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] Andrew Ng

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]

Convolutional Neural Networks

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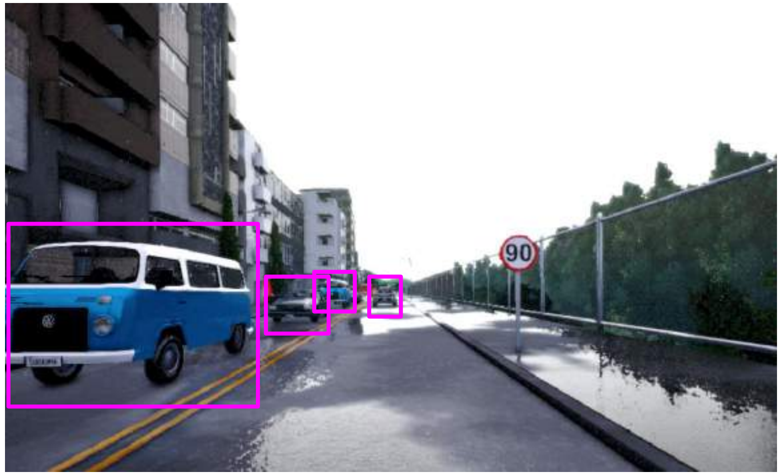
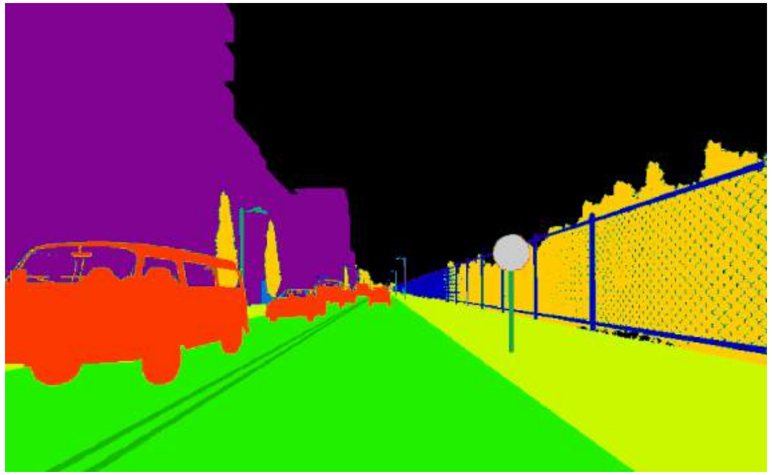
Semantic segmentation with U-Net

Object Detection vs. Semantic Segmentation

Input image

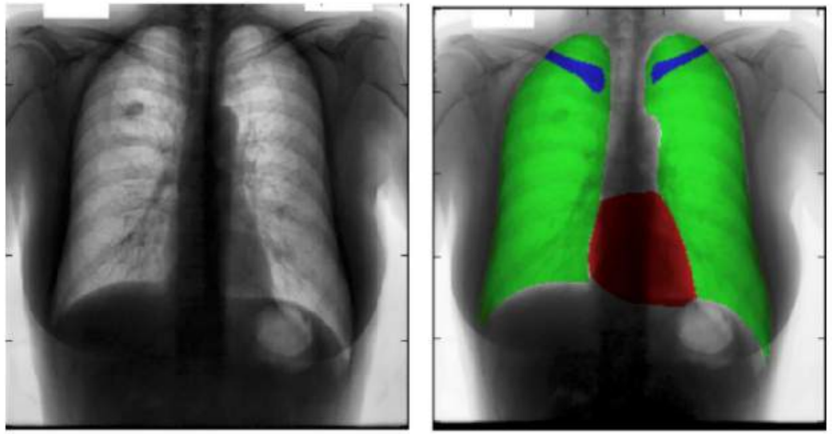


Object Detection

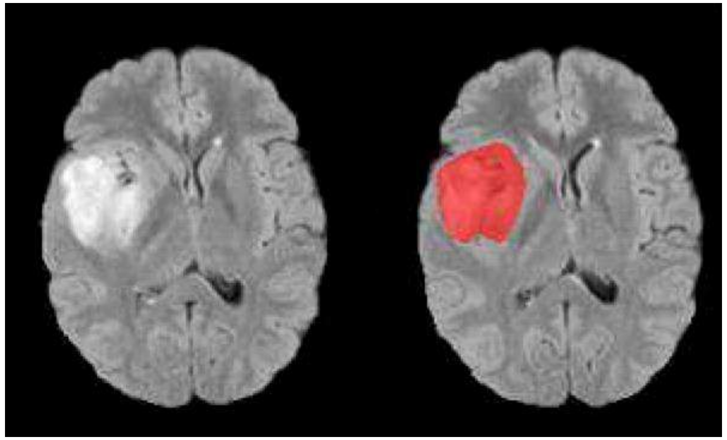


Semantic Segmentation

Motivation for U-Net



Chest X-Ray



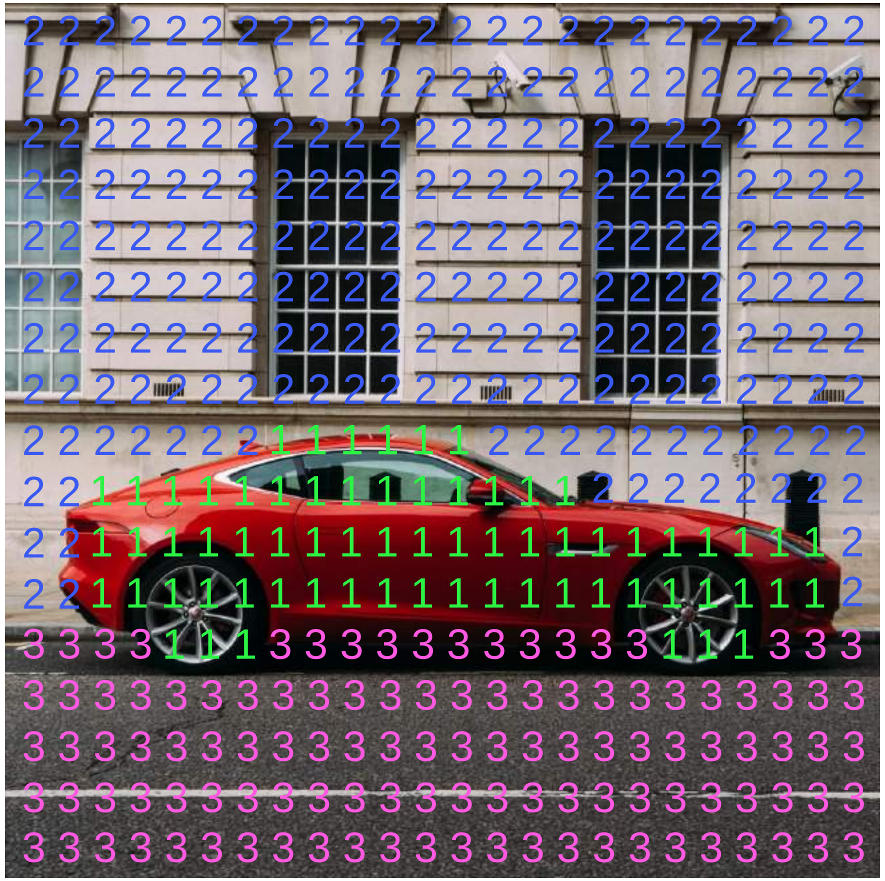
Brain MRI

[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

1. Car
0. Not Car

Per-pixel class labels



1. Car
2. Building
3. Road

2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
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2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
3	3	3	3	1	1	1	3	3	3	3	3	3	3	3	3	3	3	1	1	1	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

Segmentation Map

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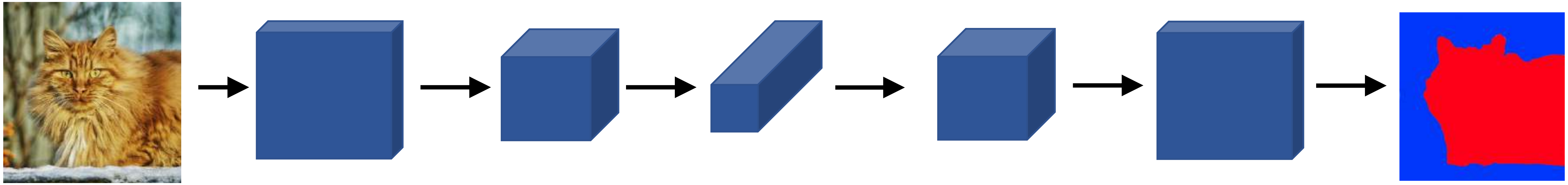
Deep Learning for Semantic Segmentation



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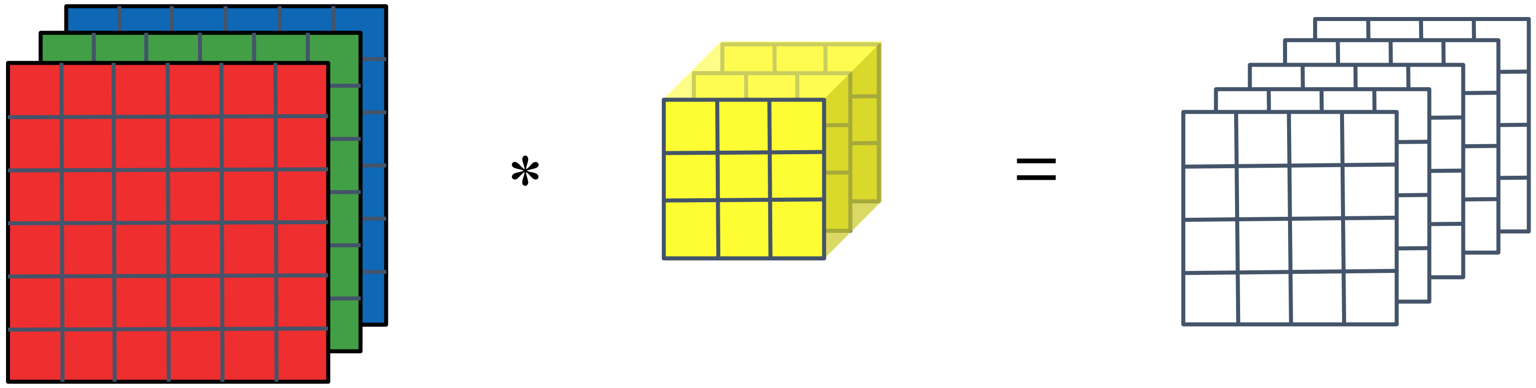
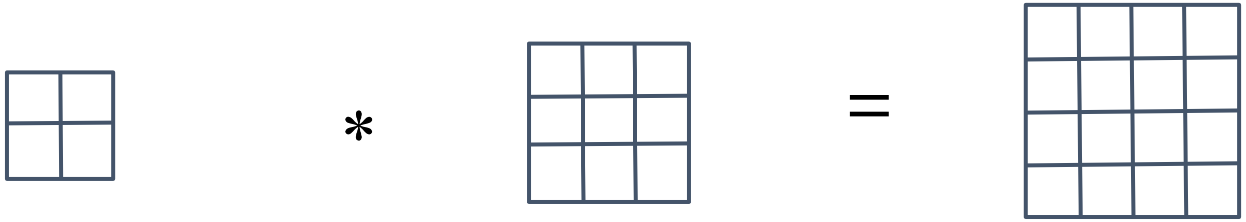
Transpose Convolution

Normal Convolution



Transpose Convolution



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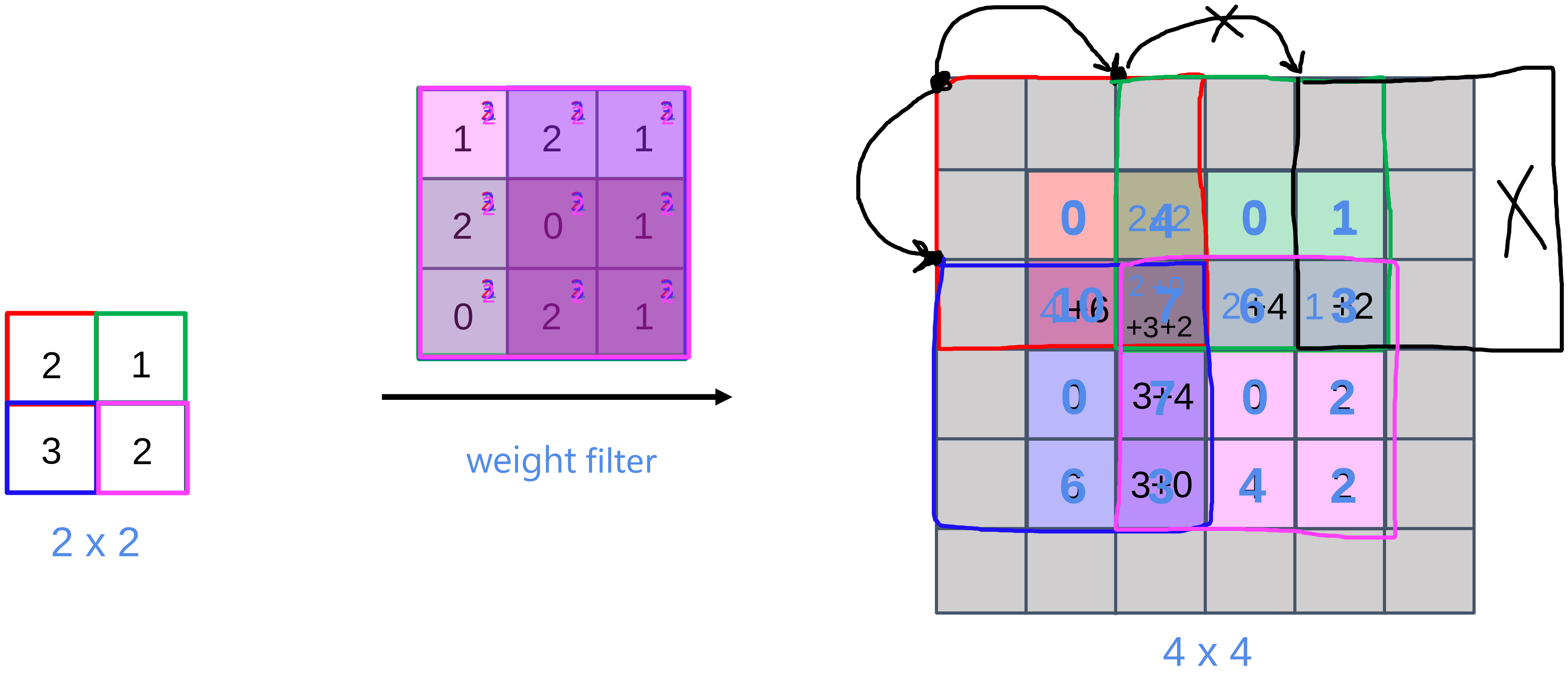
Transpose Convolution



filter f x f = 3 x 3   padding p = 1   stride s = 2

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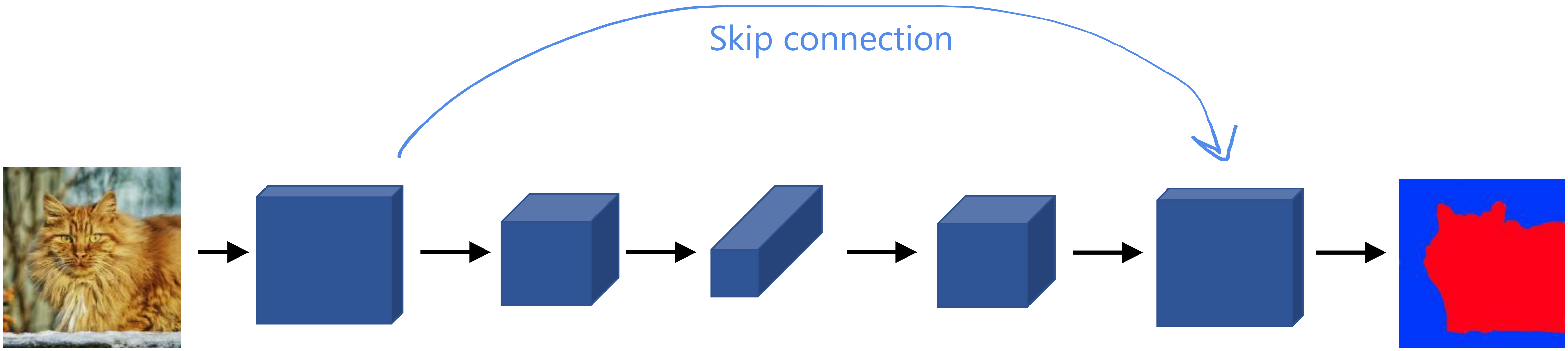
Deep Learning for Semantic Segmentation



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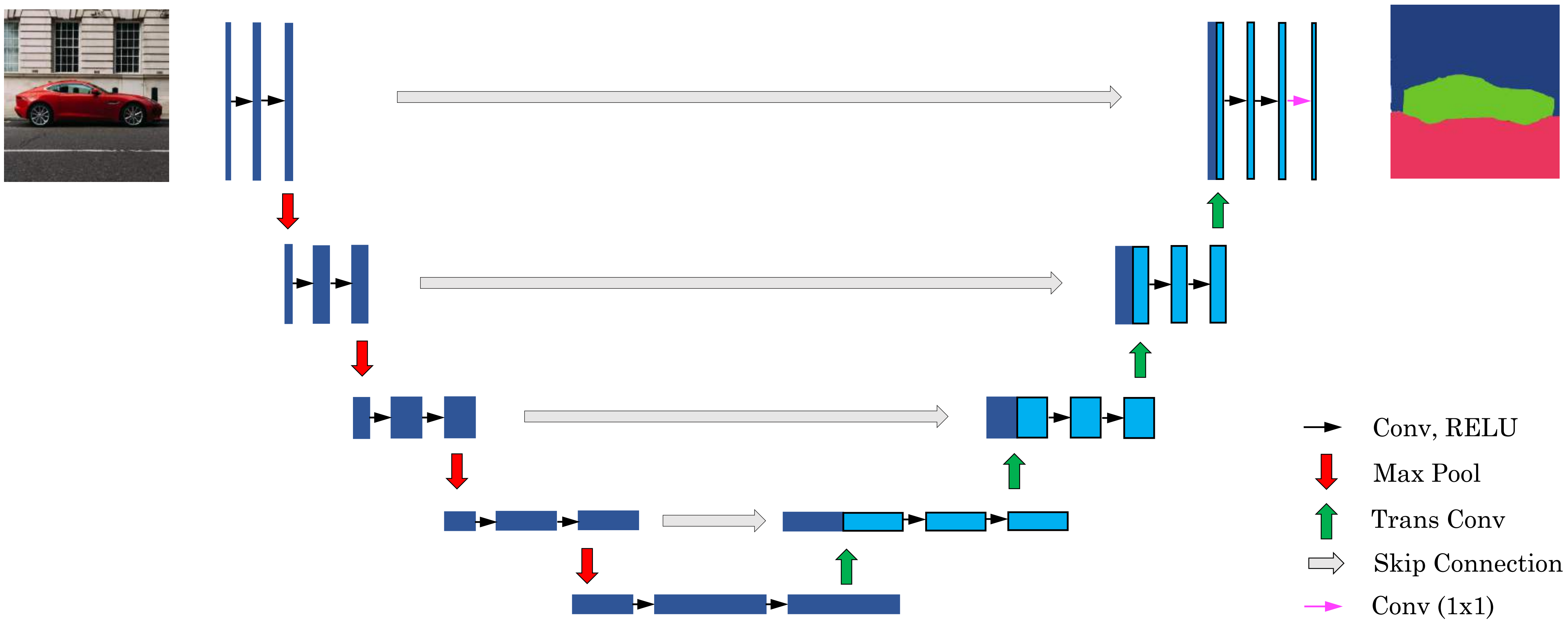
U-Net



[Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation]

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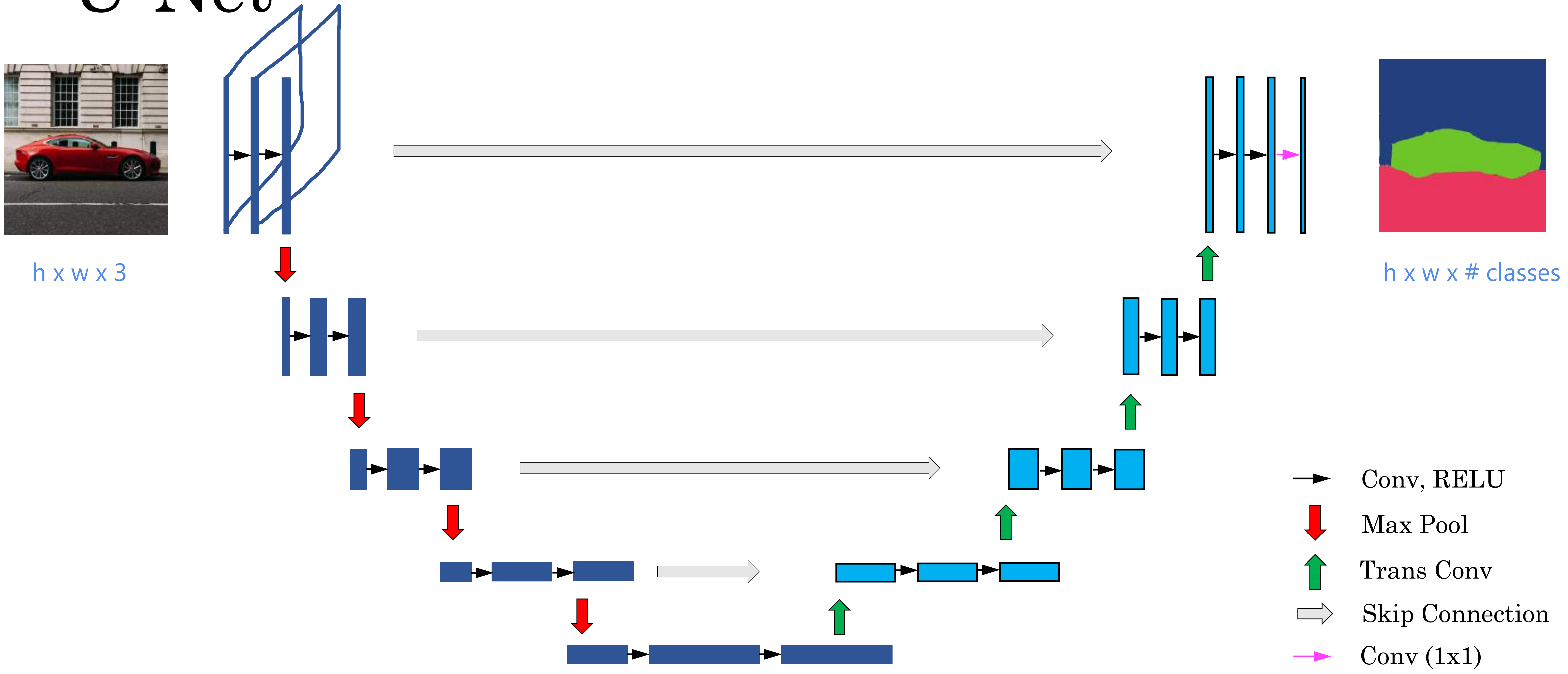
U-Net



[Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation]