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Object Detection

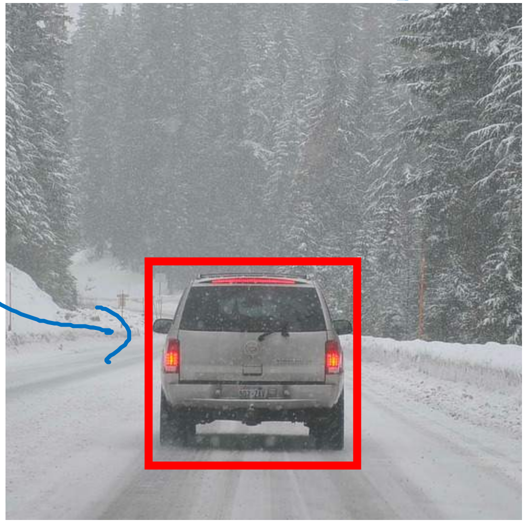
Object localization

What are localization and detection?

Image classification

"Car"

Classification with localization



"Car"

Detection

1 object

multiple objects

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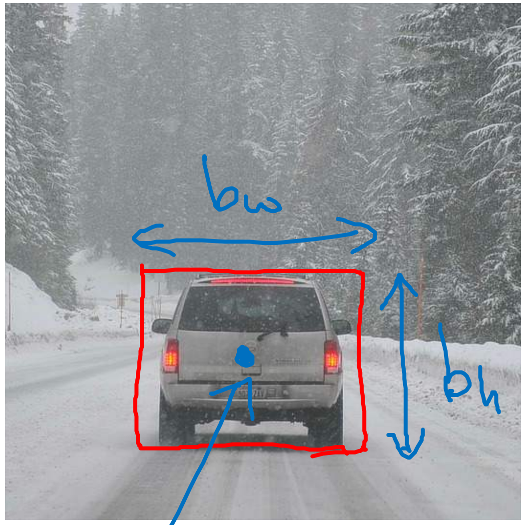
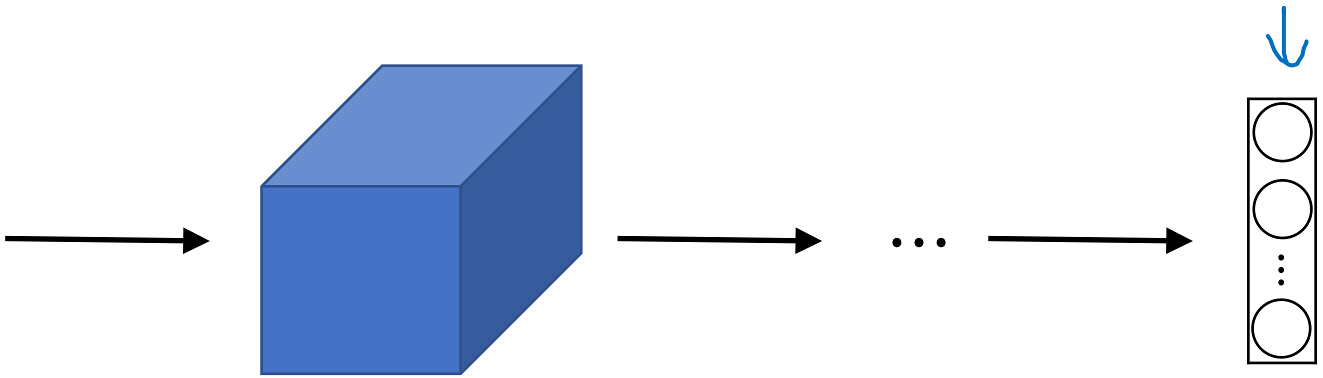
Classification with localization

(0,0)



(1,1)

b_x, b_y



ConvNet

softmax (4)

b_x, b_y, b_h, b_w

bounding box

1 - pedestrian

2 - car

3 - motorcycle

4 - background

$b_x = 0.5$

$b_y = 0.7$

$b_h = 0.3$

$b_w = 0.4$

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Defining the target label y

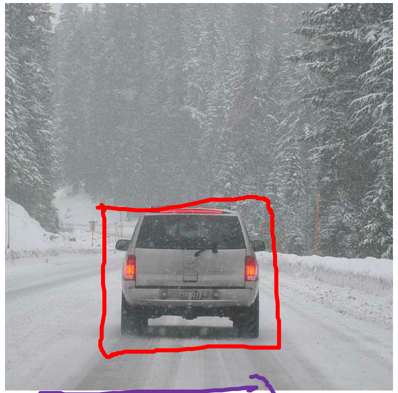
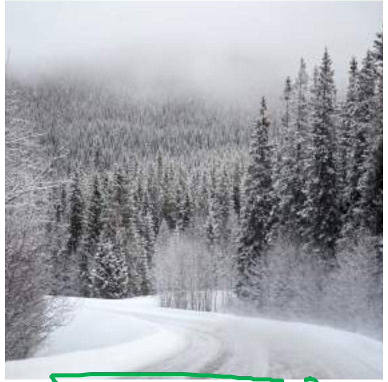
1 - pedestrian
2 - car
3 - motorcycle
4 - background

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

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

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

is there any object?

$x =$  

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

p_c

"don't care"

(x, y)

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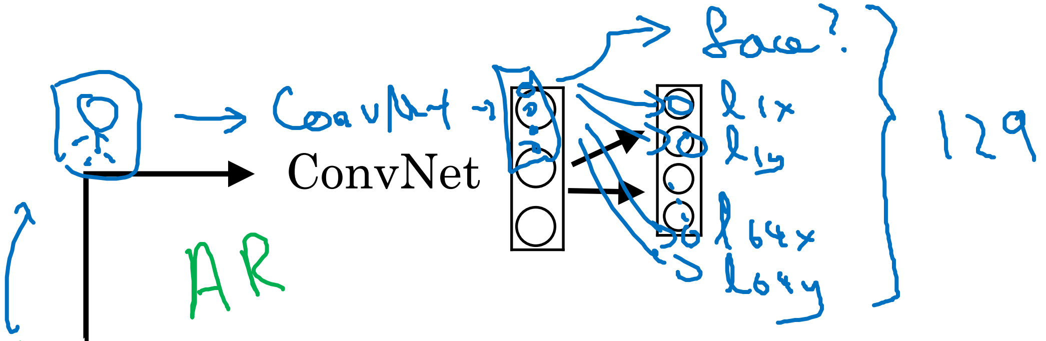
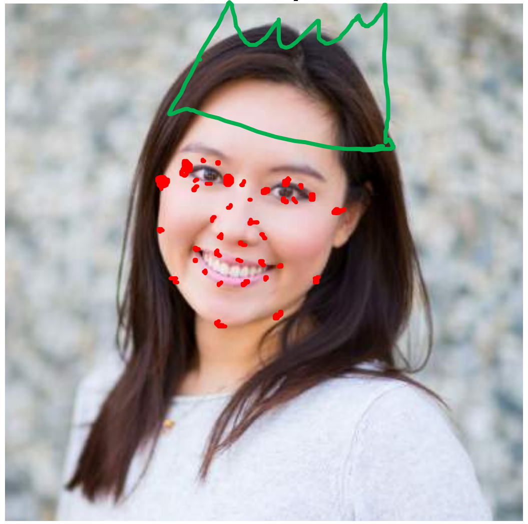
Object Detection

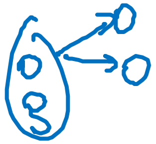
Landmark detection

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

 → ConvNet → y

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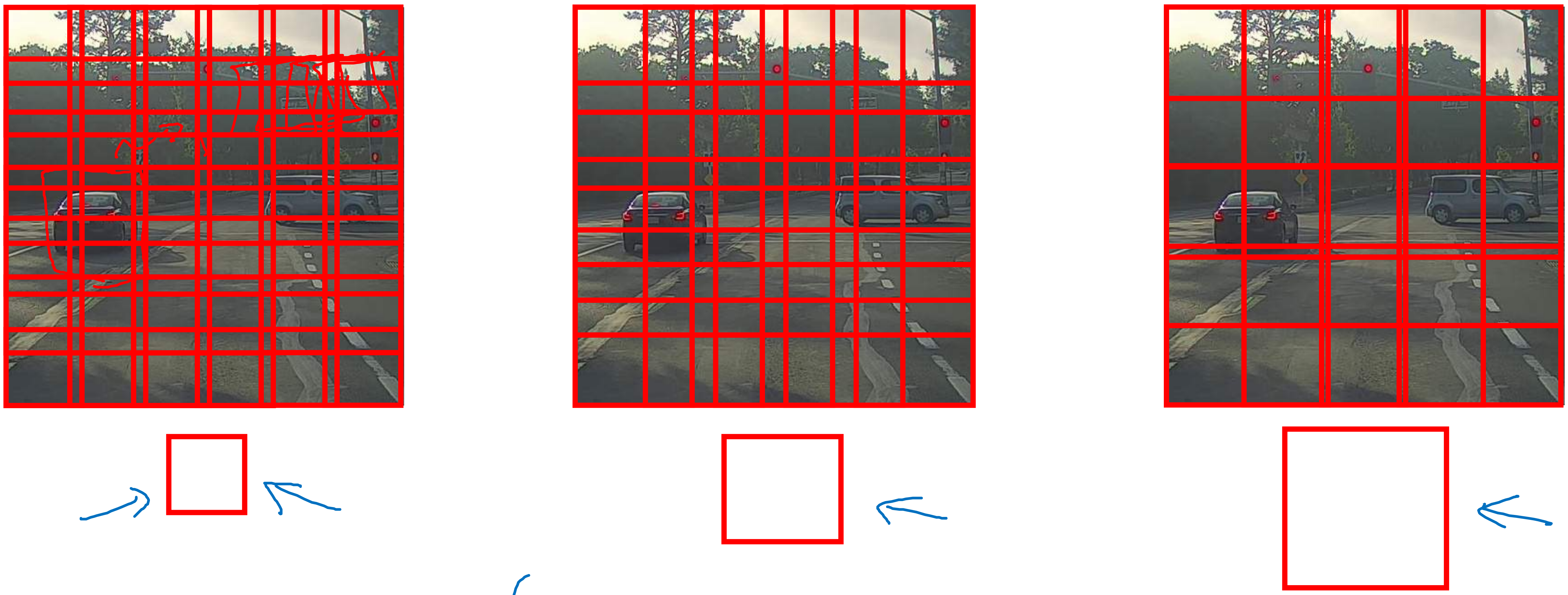
Sliding windows detection

ConvNet → 0

ConvNet



Computation cost

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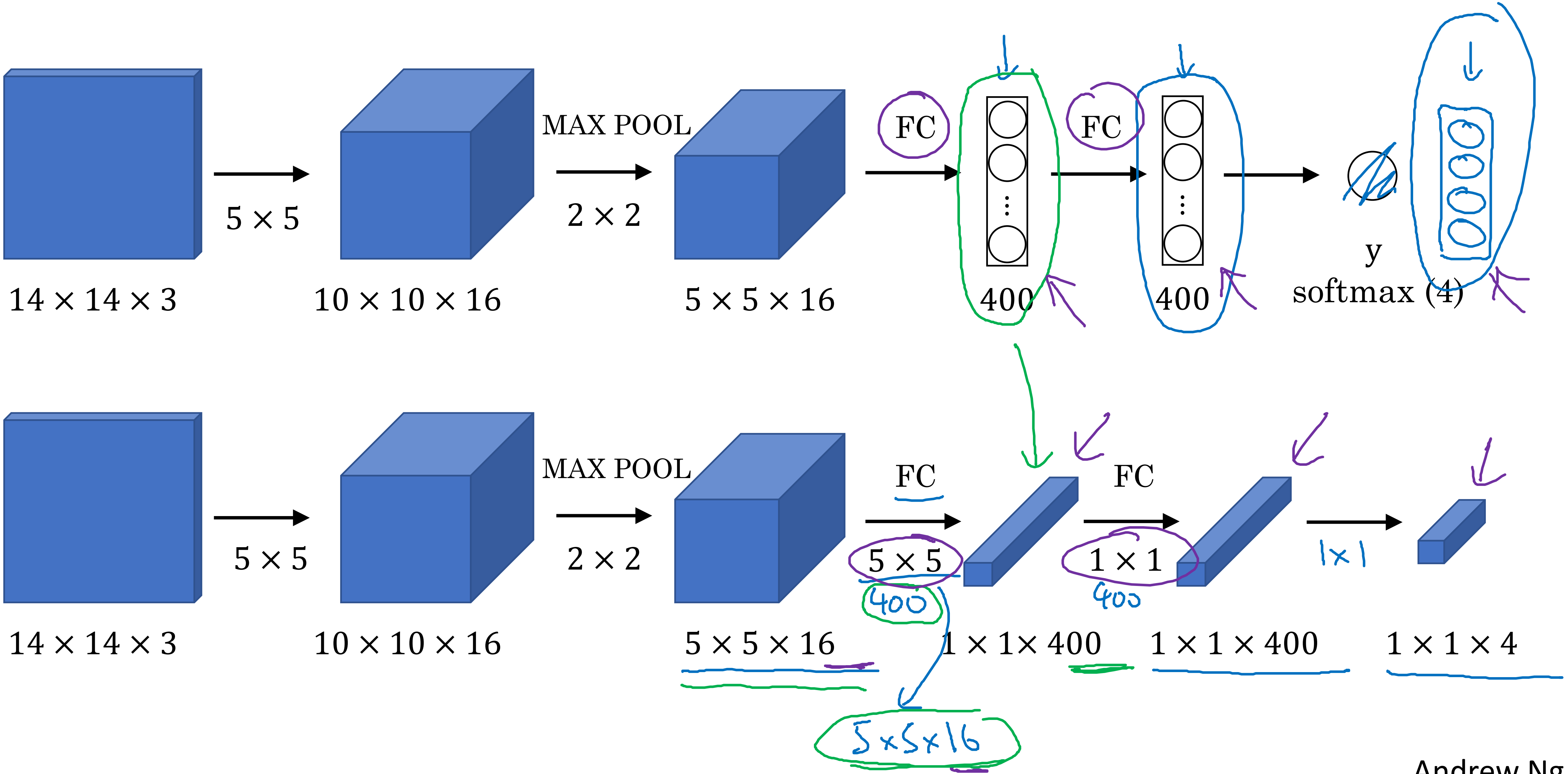
Object Detection

Convolutional implementation of sliding windows

Turning FC layer into convolutional layers



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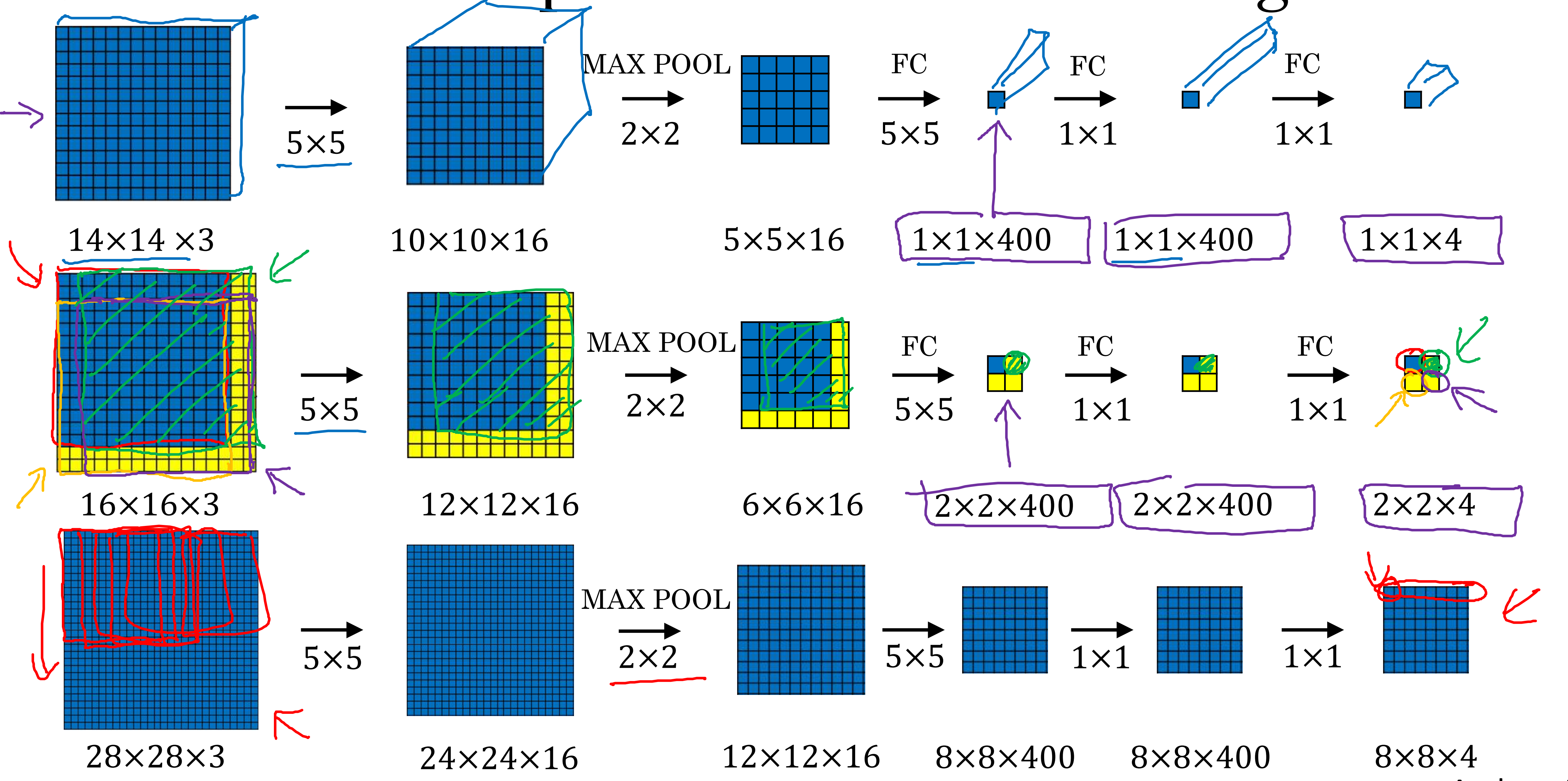
Convolution implementation of sliding windows



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

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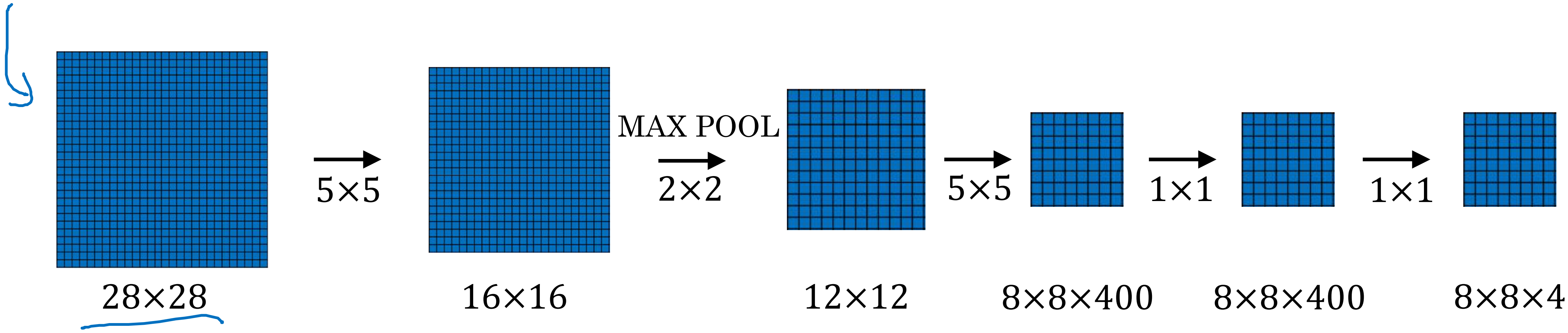
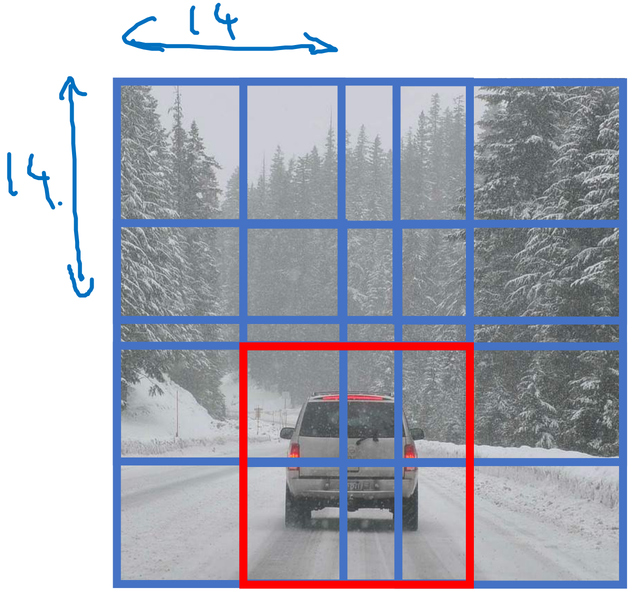
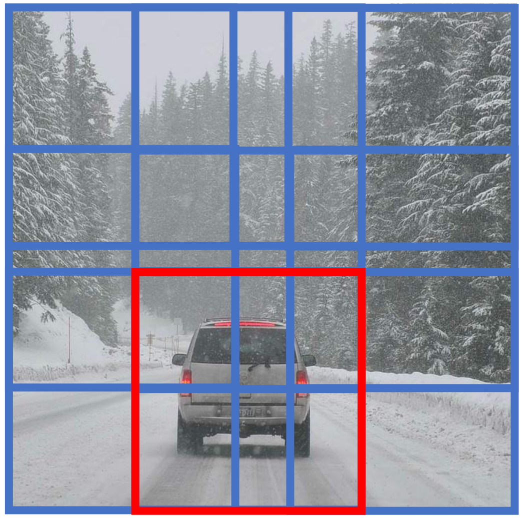
Convolution implementation of sliding windows







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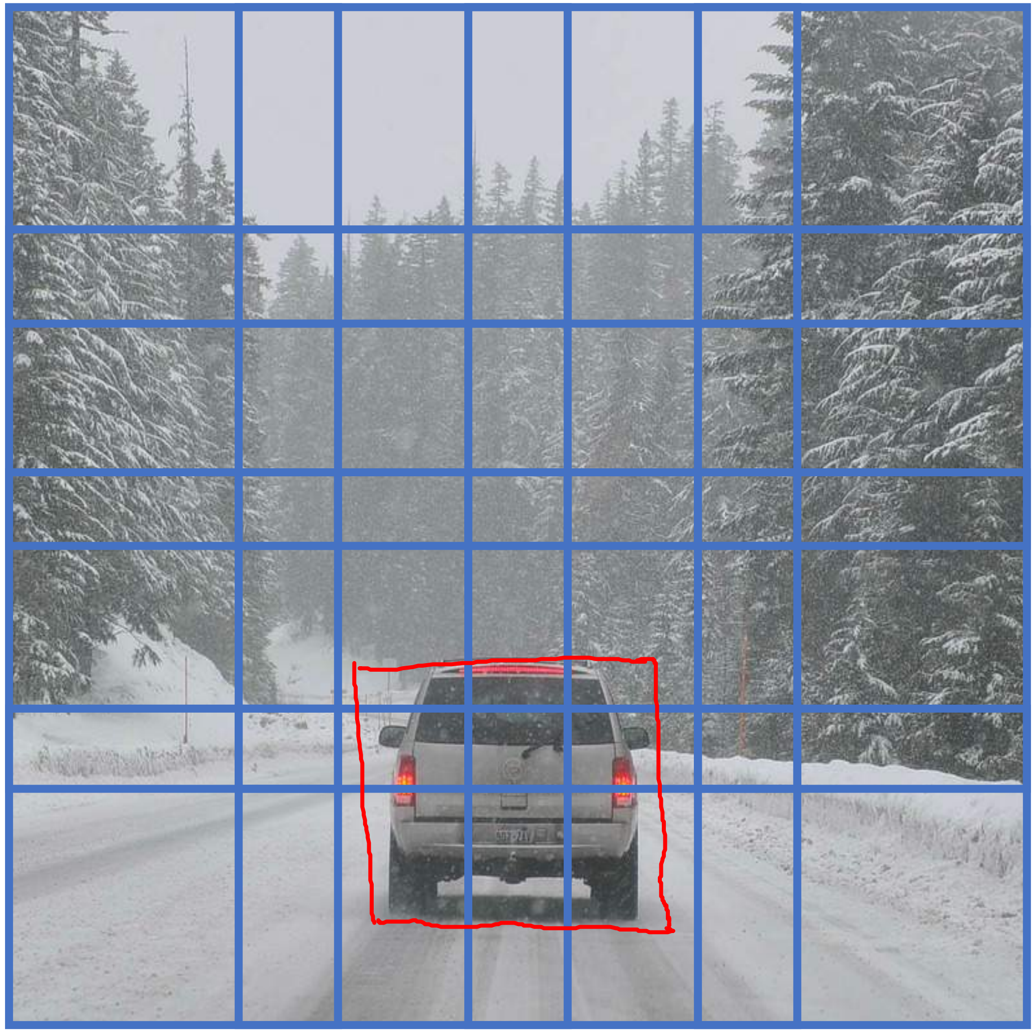
Object Detection

Bounding box predictions

Output accurate bounding boxes



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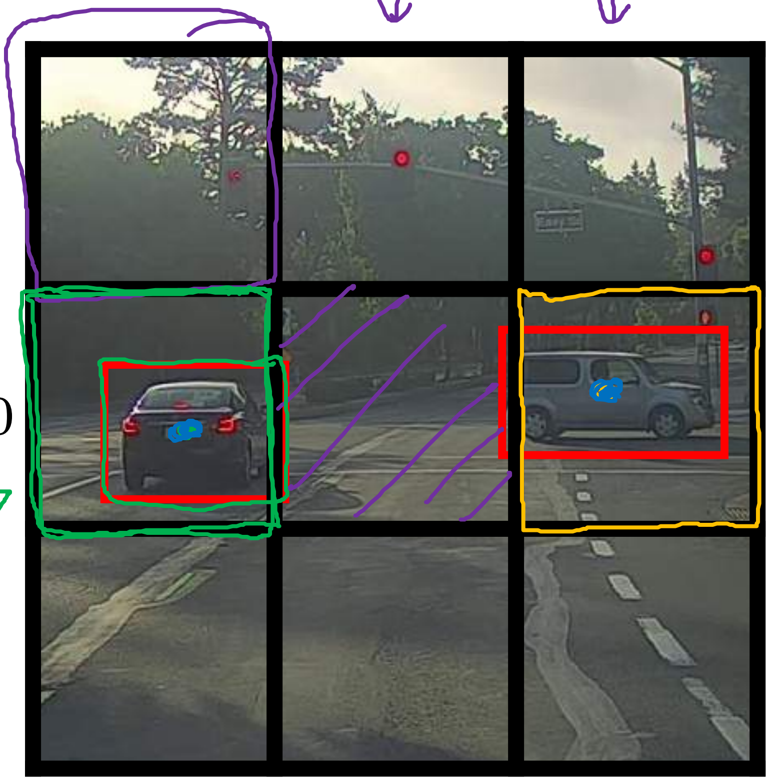
YOLO algorithm



100

100

Labels for training

For each grid cell:

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

Target output: $3 \times 3 \times 8$

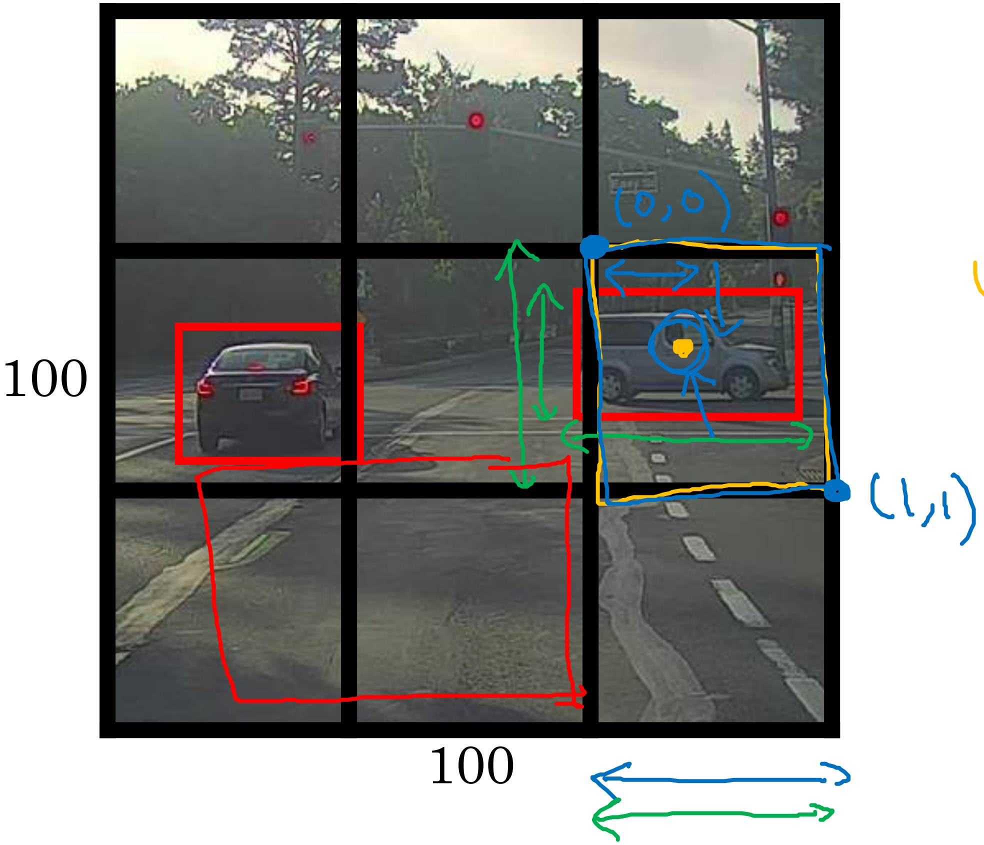
$\underline{x}$ → $100 \times 100 \times 3$ → CONV → MAXPOOL → .... → $3 \times 3 \times 8$ y

→ $19 \times 19 \times 8$

361

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

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]

Object Detection

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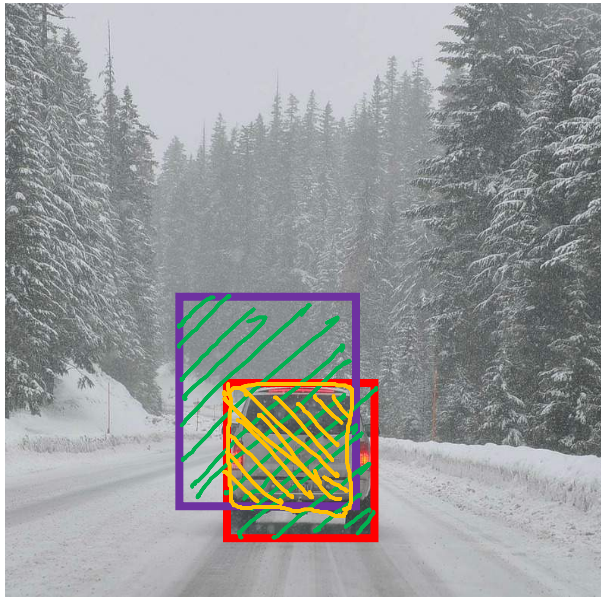
Intersection over union

Evaluating object localization



Intersection over Union (IoU)

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

"Correct" if IoU ≥ $\boxed{0.5}$

$\underline{0.6}$

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

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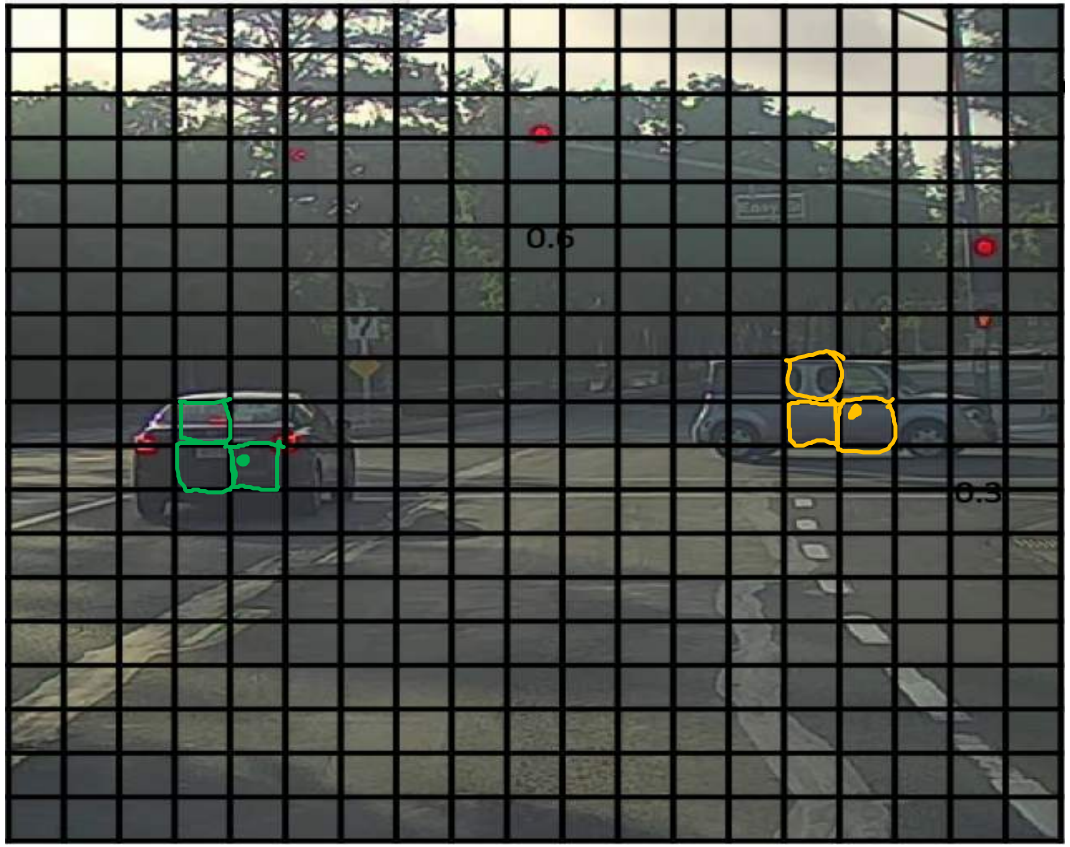
Object Detection

Non-max suppression

Non-max suppression example

Non-max suppression example



19x19

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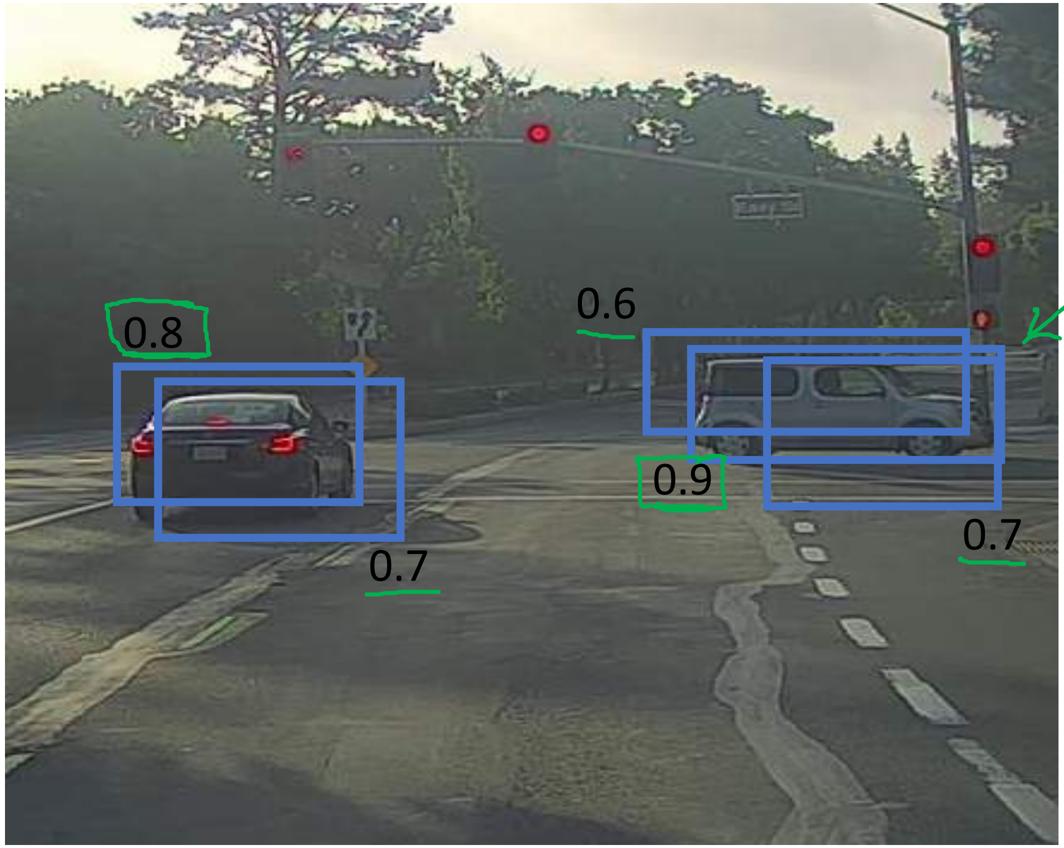
Non-max suppression example



P_c

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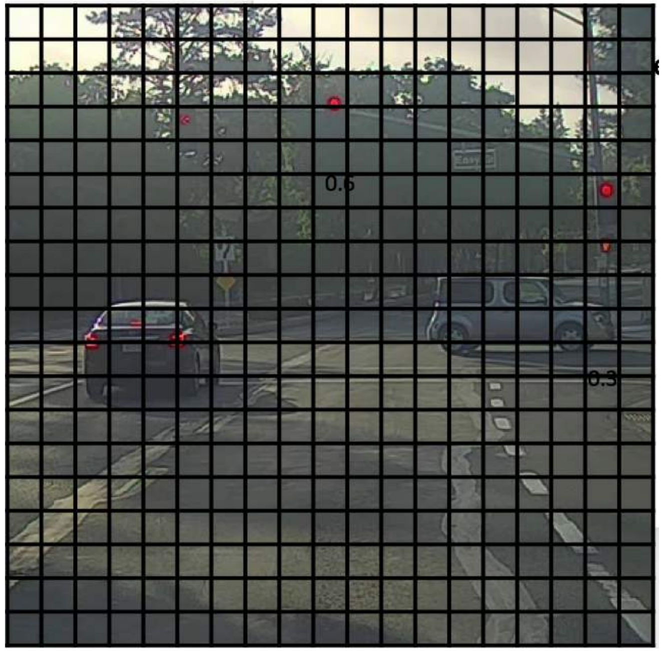
Non-max suppression algorithm



19×19

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

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

Object Detection

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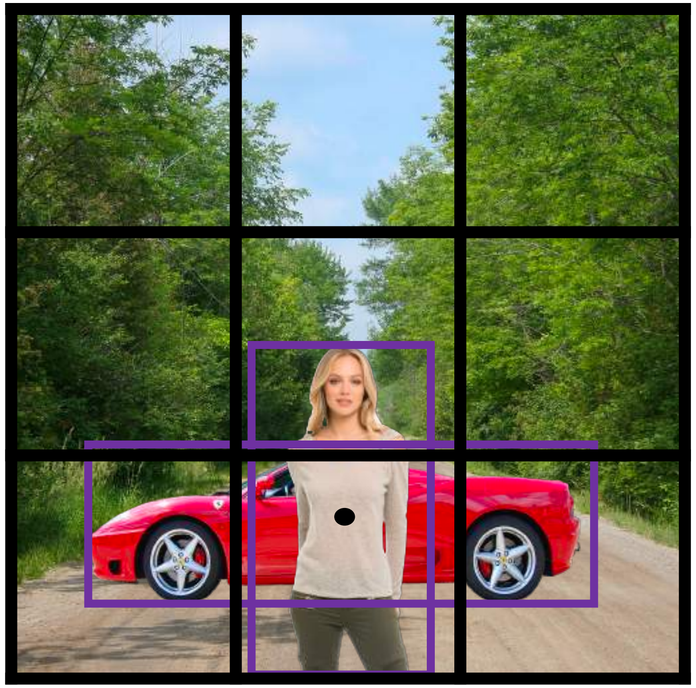
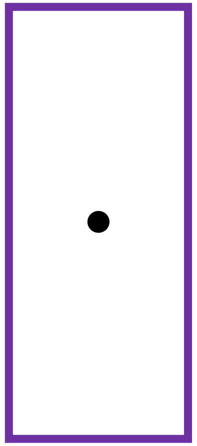
Anchor boxes

Overlapping objects:

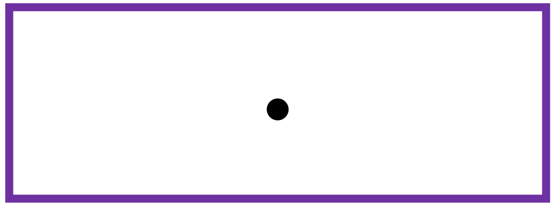


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:



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

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

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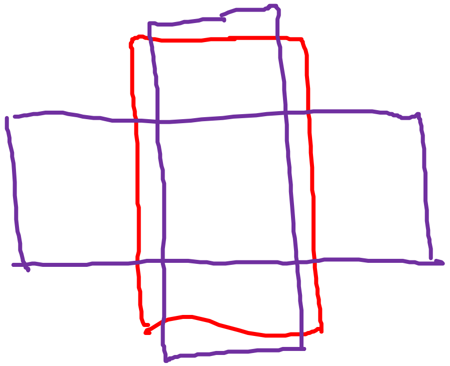
Anchor box algorithm

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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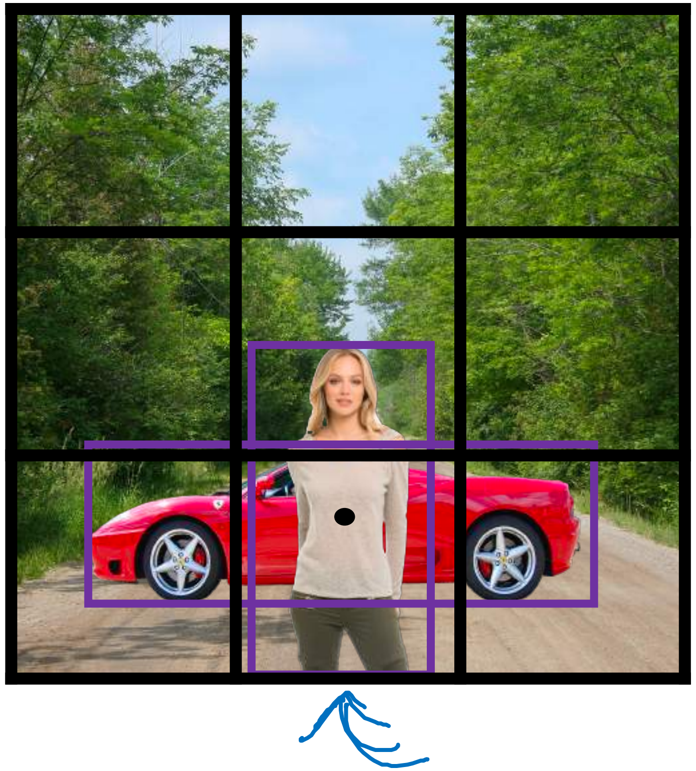
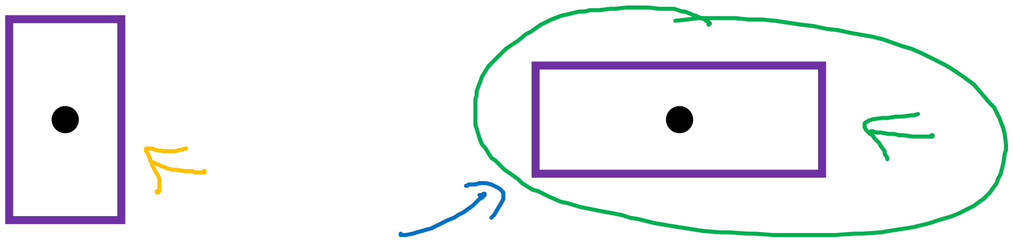
Anchor box example



Anchor box 1: Anchor box 2:



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

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Object Detection

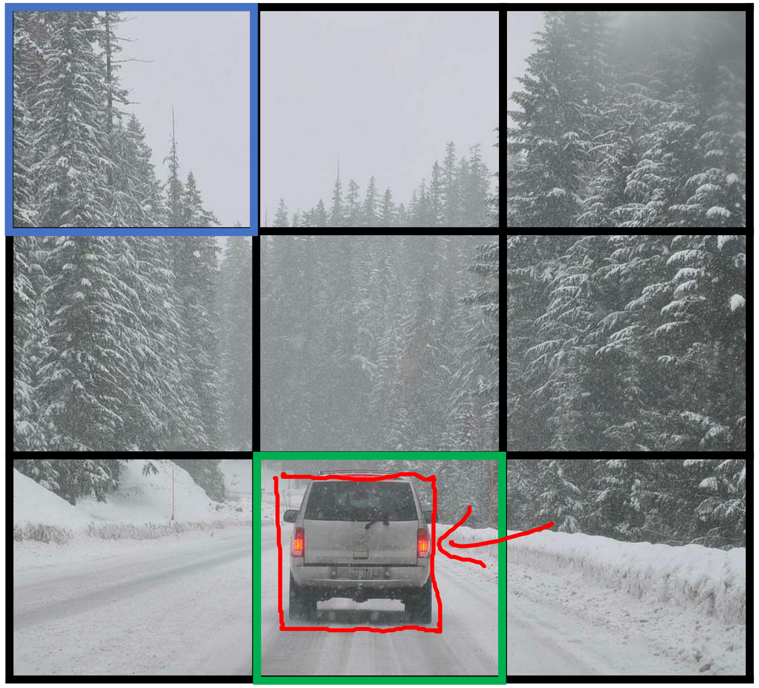
Putting it together: YOLO algorithm

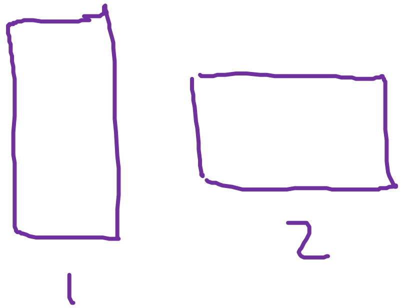
Training

1 - pedestrian

2 - car

3 - motorcycle





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

3×3×16

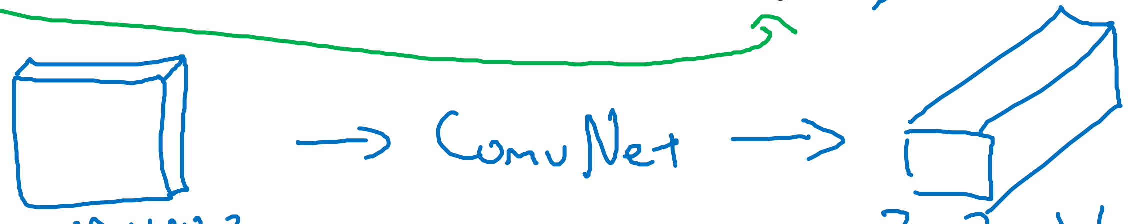
y is 3×3×2×8

19×19×16

19×19×40

#anchors

5 + #classes



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

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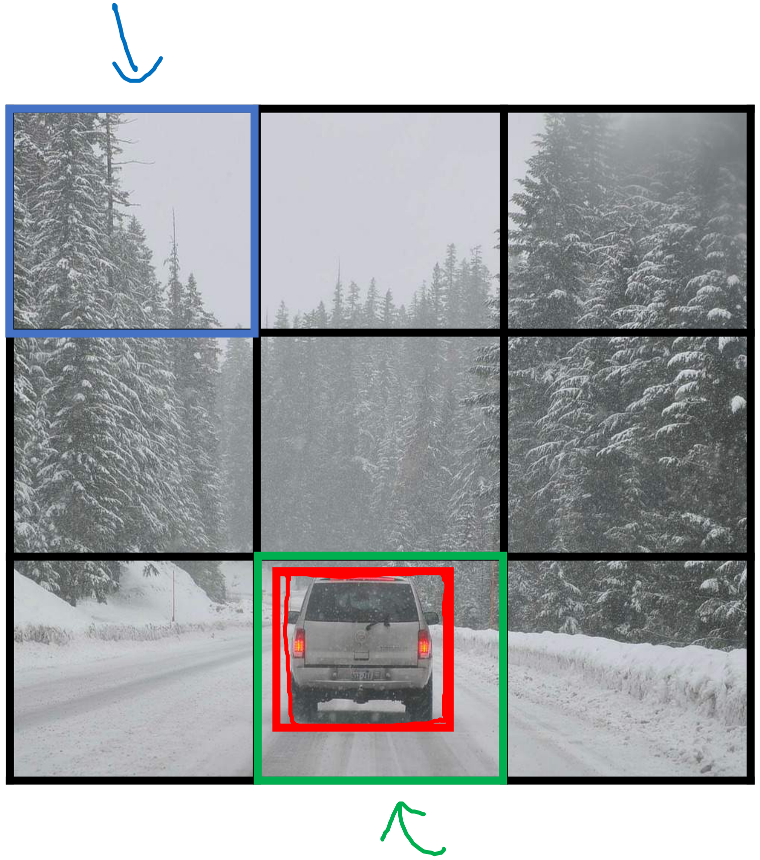
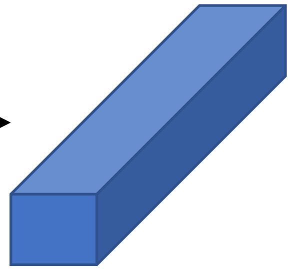
Making predictions



→ ⋯ →



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

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

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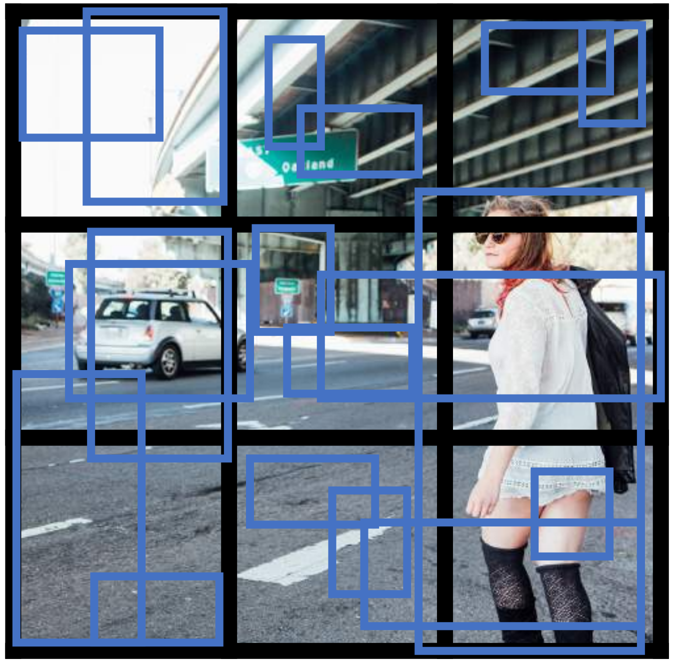
Outputting the non-max supressed outputs



- 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.

Object Detection

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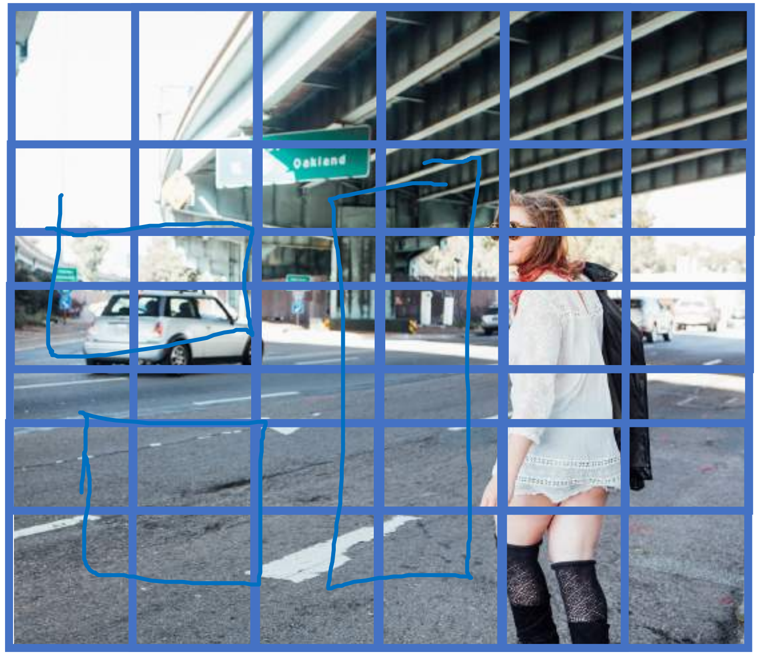
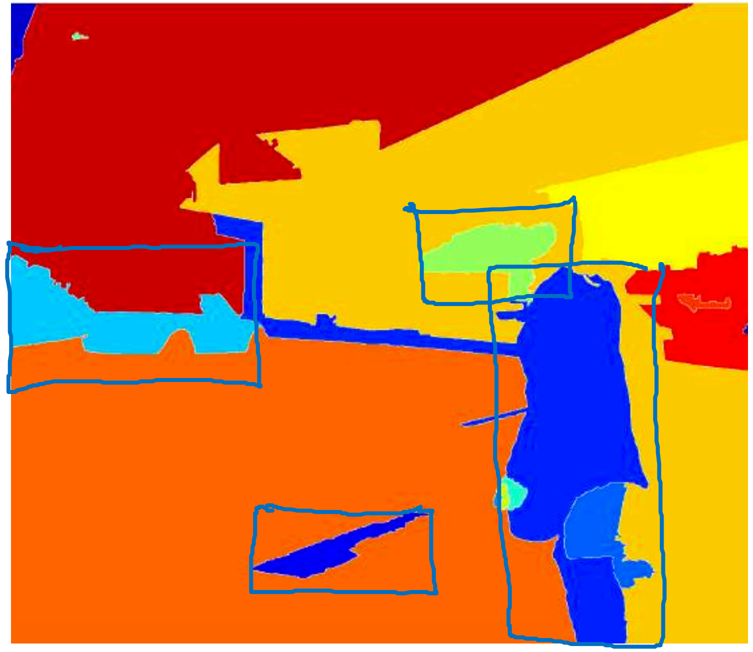
Region proposals (Optional)

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]

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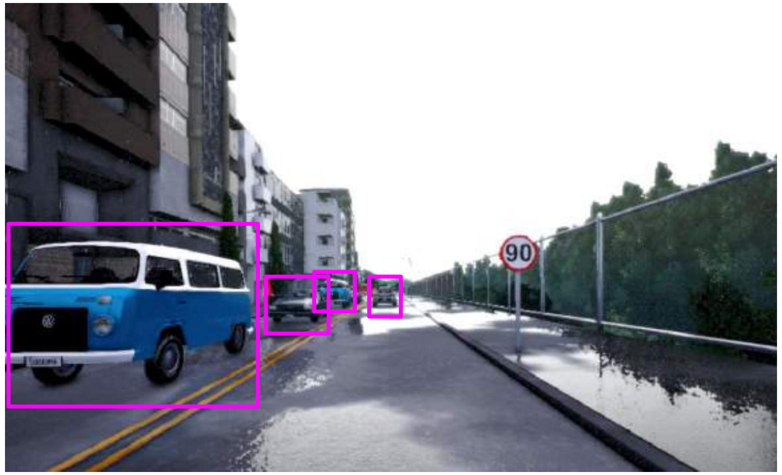
Convolutional Neural Networks

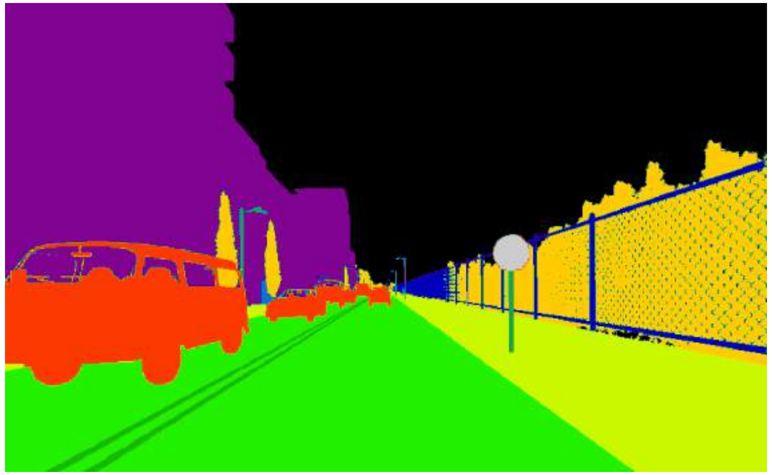
Semantic segmentation with U-Net

Object Detection vs. Semantic Segmentation

Input image



Object Detection



Semantic Segmentation

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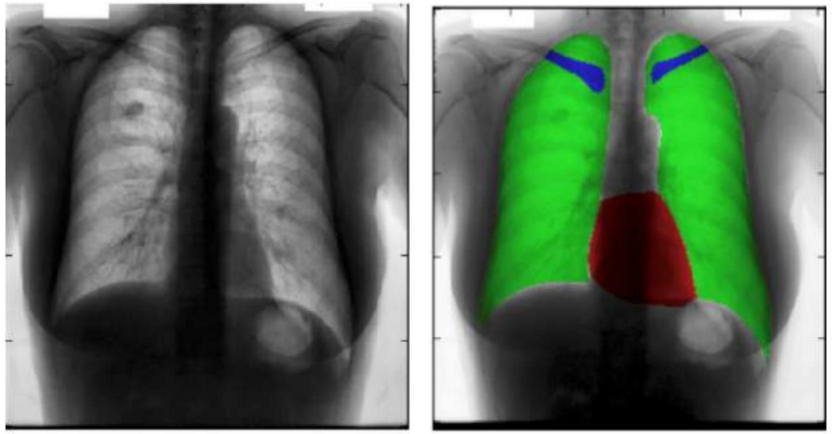
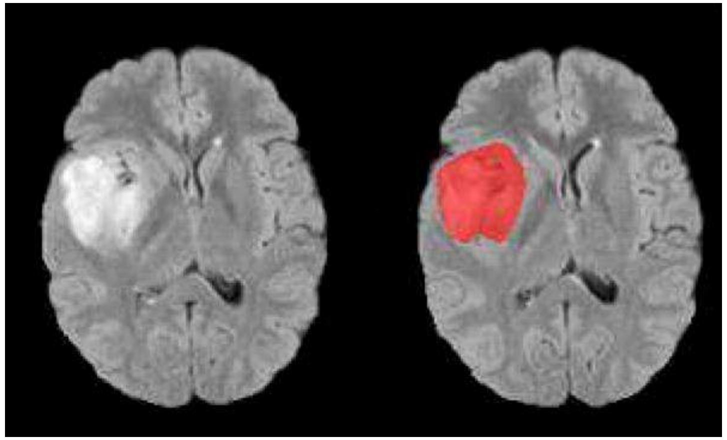
Motivation for U-Net



Chest X-Ray



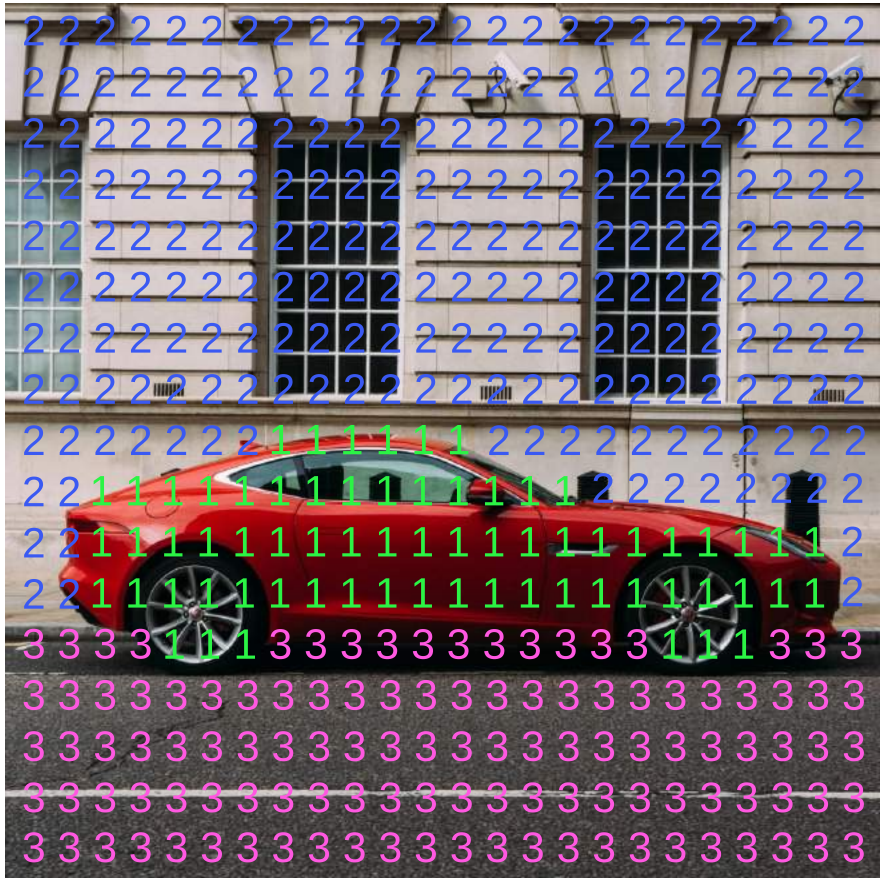
Brain MRI

[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
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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3	3	3	3	1	1	1	3	3	3	3	3	3	3	3	3	3	3	1	1	1	3	3	3
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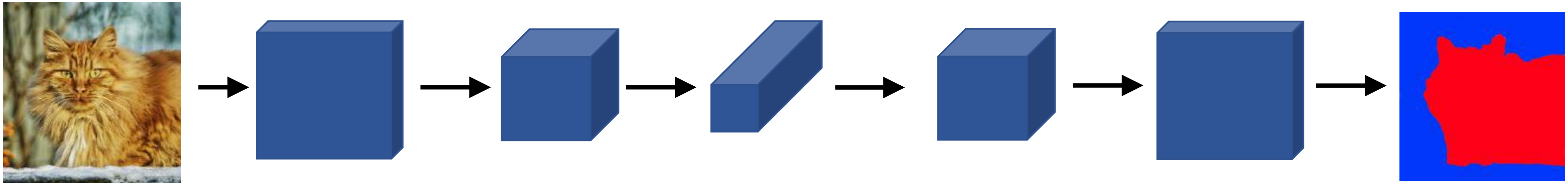
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

Segmentation Map

Deep Learning for Semantic Segmentation



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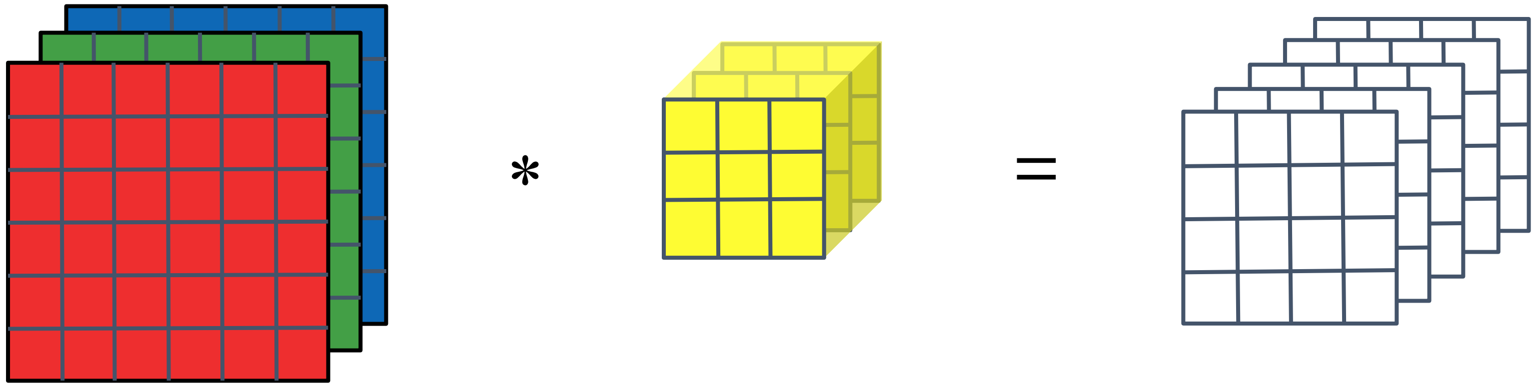
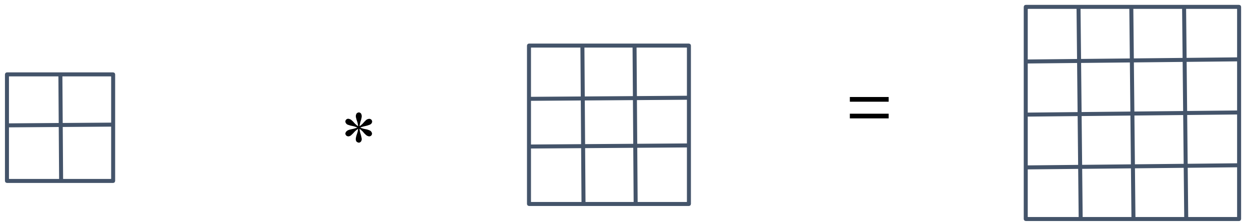
Transpose Convolution

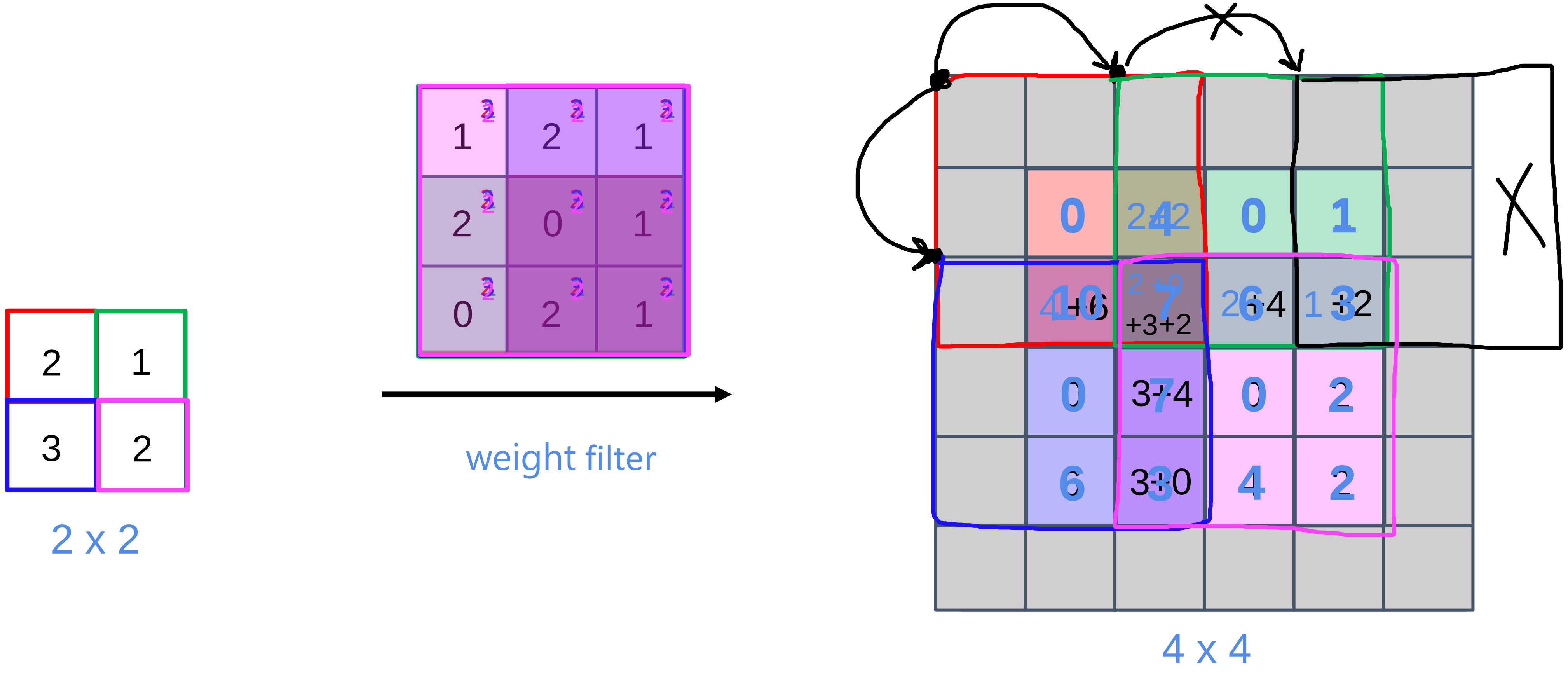
Normal Convolution



Transpose Convolution



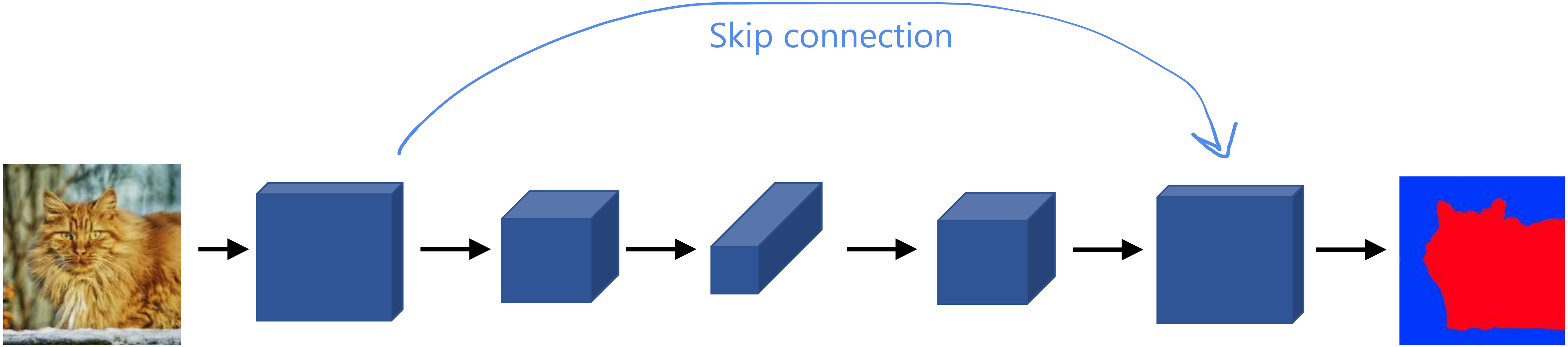
Transpose Convolution



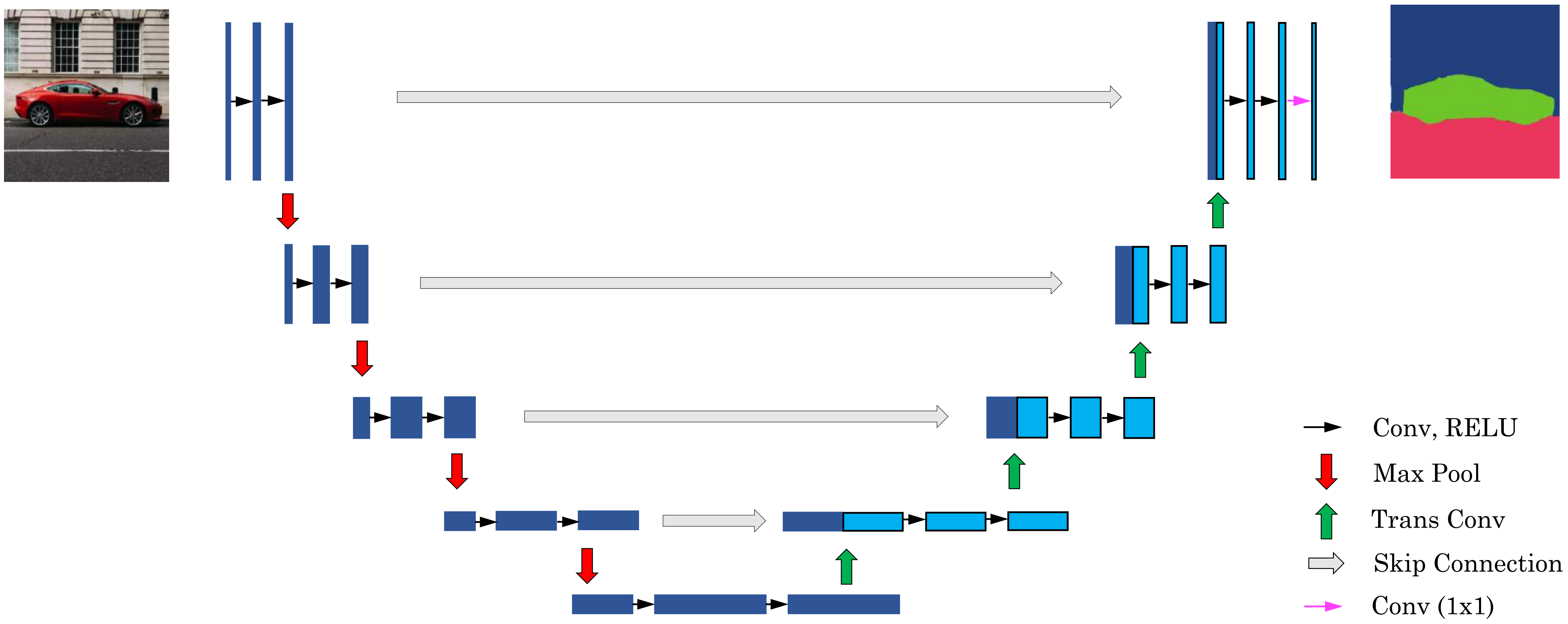
filter f x f = 3 x 3 padding p = 1 stride s = 2

Andrew Ng

Deep Learning for Semantic Segmentation

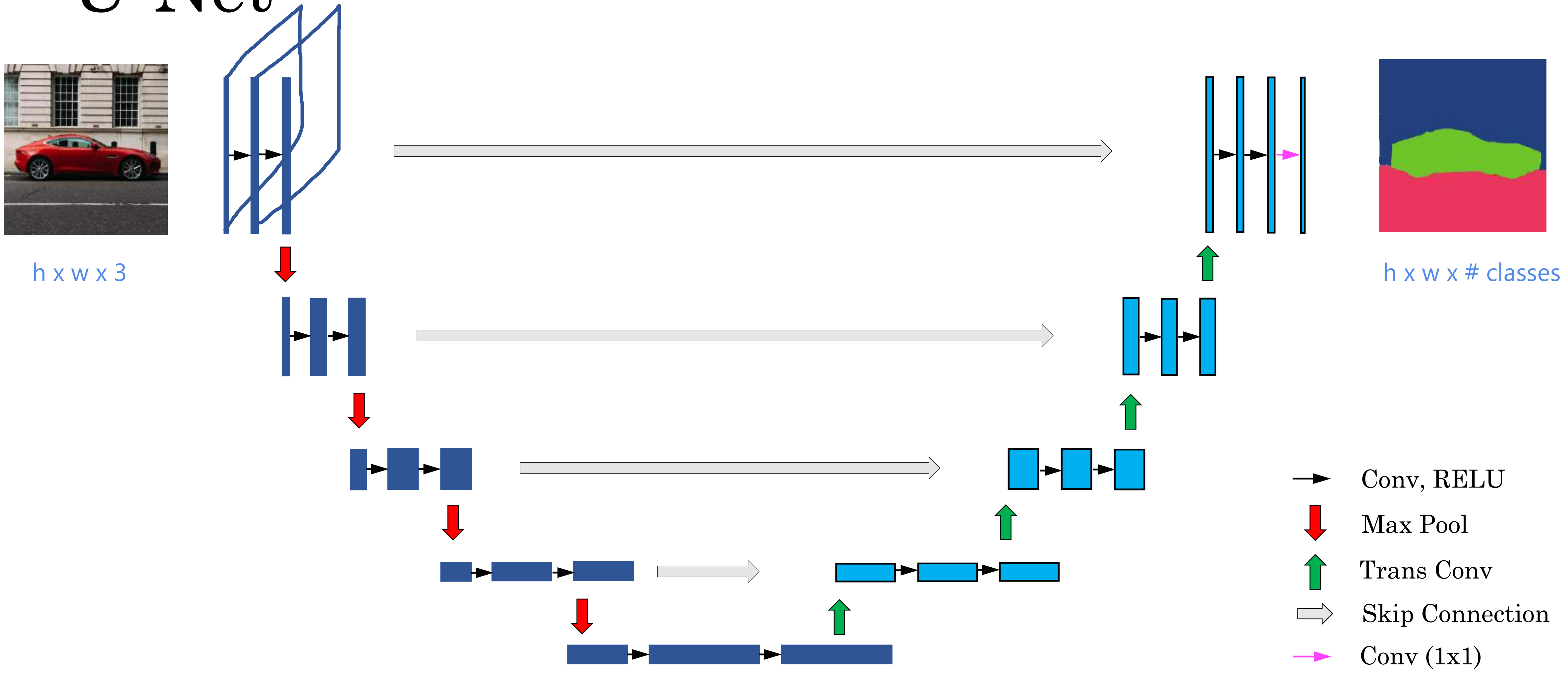


U-Net



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

U-Net



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