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Object Detection

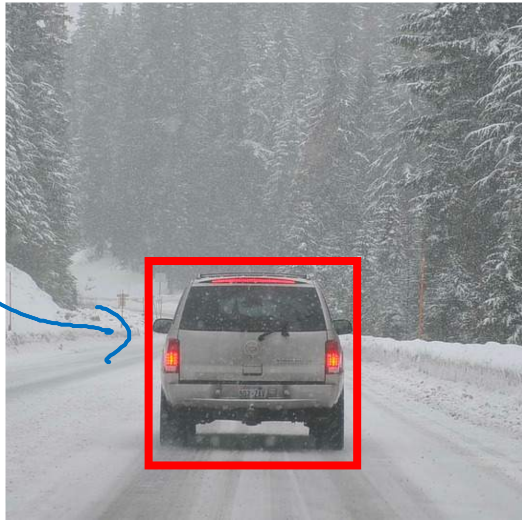
Object localization

What are localization and detection?

Image classification

"Car"

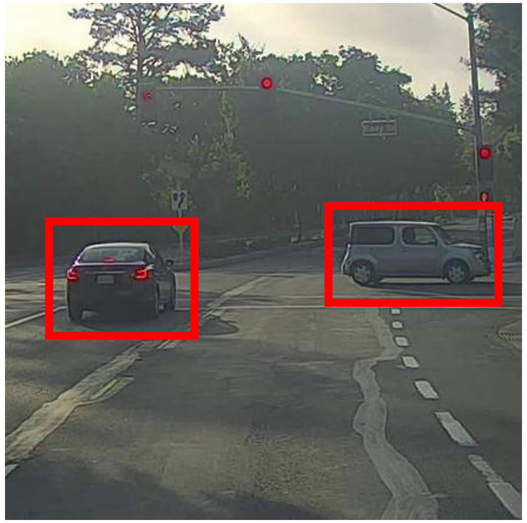
Classification with localization



"Car"

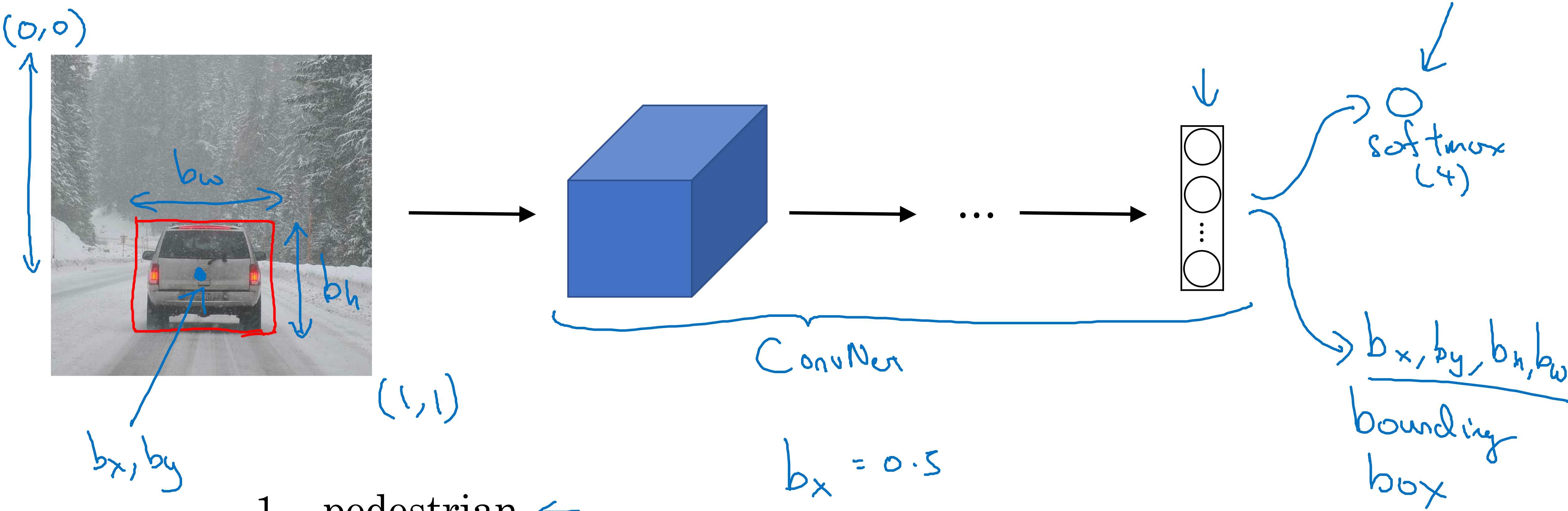
1 object

Detection



multiple objects

Classification with localization



1 - pedestrian ←

2 - car ←

3 - motorcycle ←

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

$b_x = 0.5$

$b_y = 0.7$

$b_h = 0.3$

$b_w = 0.4$

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Defining the target label y

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

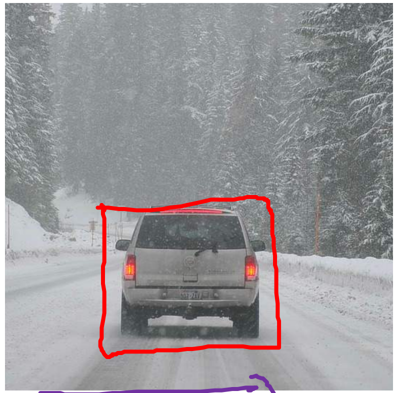
Need to output b_x, b_y, b_h, b_w, class label (1-4)

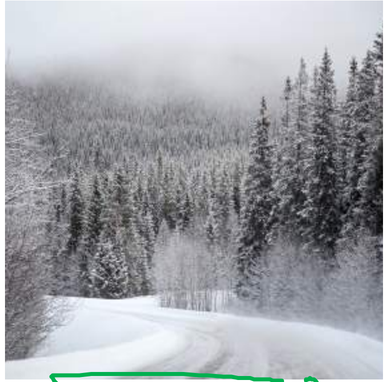
$$\mathcal{L}(\hat{y}, y) = \begin{cases} (\hat{y}_1 - y_1)^2 + (\hat{y}_2 - y_2)^2 + \dots + (\hat{y}_8 - y_8)^2 & \text{if } y_1 = 1 \\ (\hat{y}_1 - y_1)^2 & \text{if } y_1 = 0 \end{cases}$$

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

is there any object?

$x =$





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

(x, y)

p_c

← "don't care"

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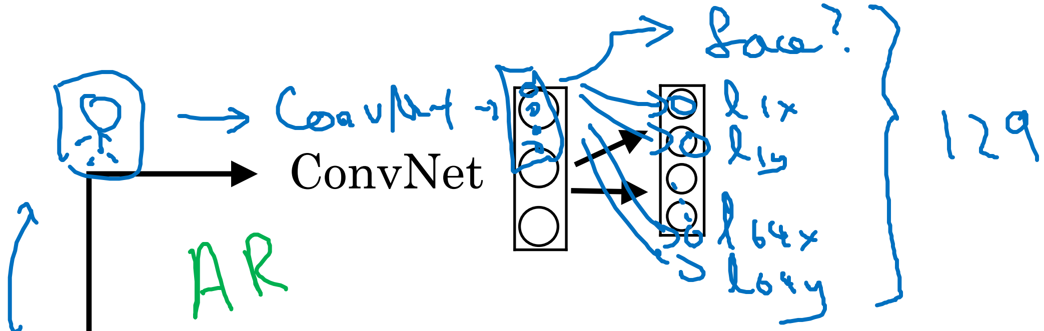
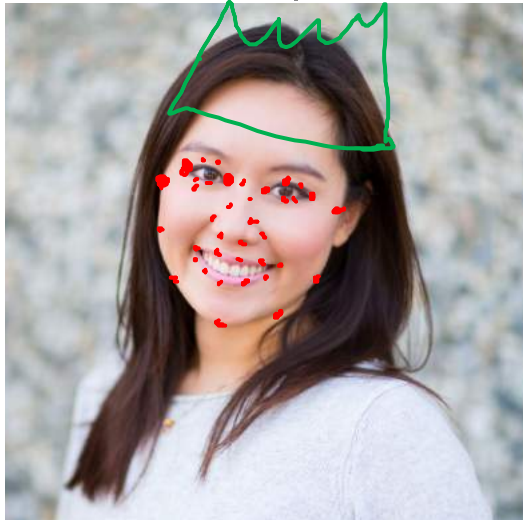
Object Detection

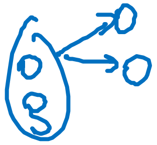
Landmark detection

Landmark detection

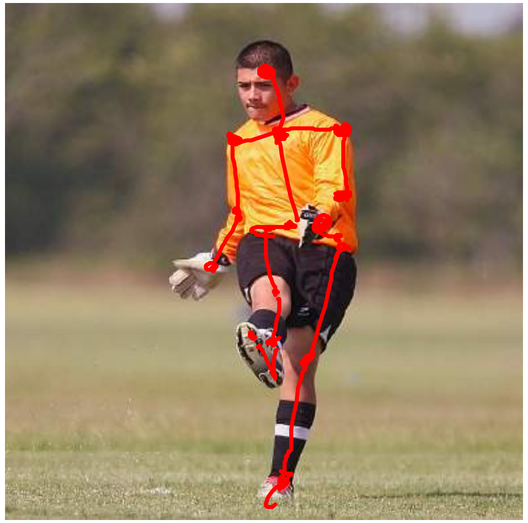


b_x, b_y, b_h, b_w





$$\left.\begin{array}{l} l_{1x}, l_{1y}, \\ l_{2x}, l_{2y}, \\ l_{3x}, l_{3y}, \\ l_{4x}, l_{4,y} \\ \vdots \\ l_{64}, l_{64y} \end{array}\right\} X, y$$



$l_{1x}, l_{1y},$

$\vdots$

l_{32x} l_{32y}

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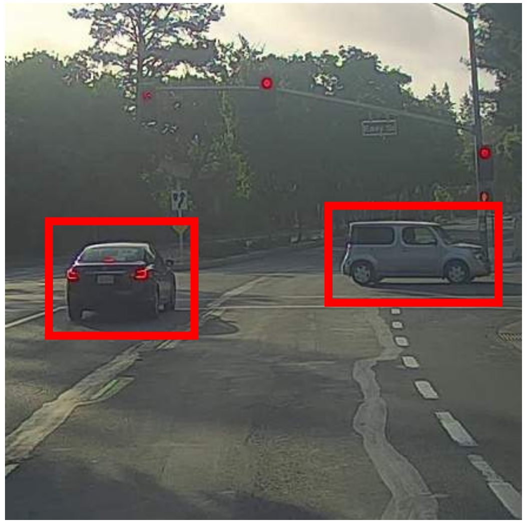
Object Detection

Object detection

Car detection example

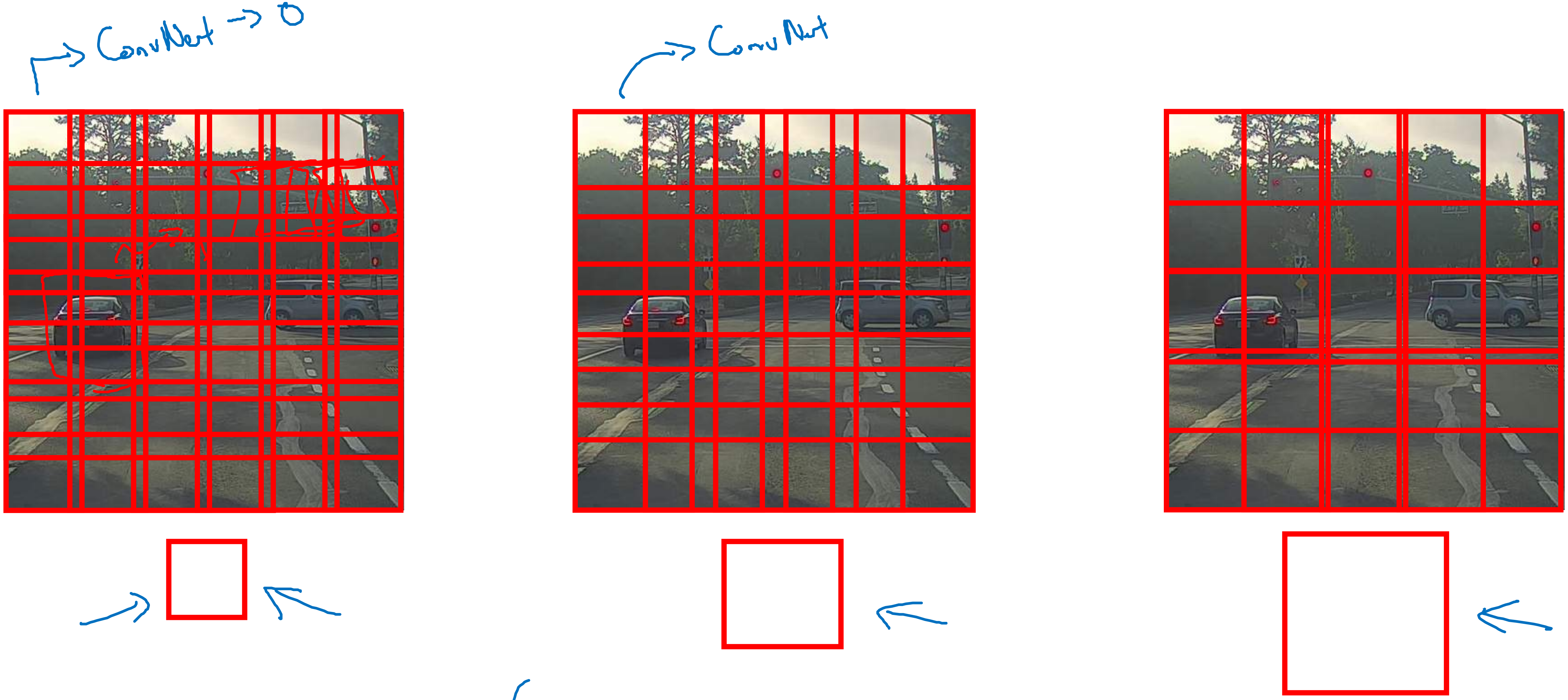


Training set:

x	y
	1
	1
	1
	0
	0

→ ConvNet → y

Sliding windows detection



Computation cost

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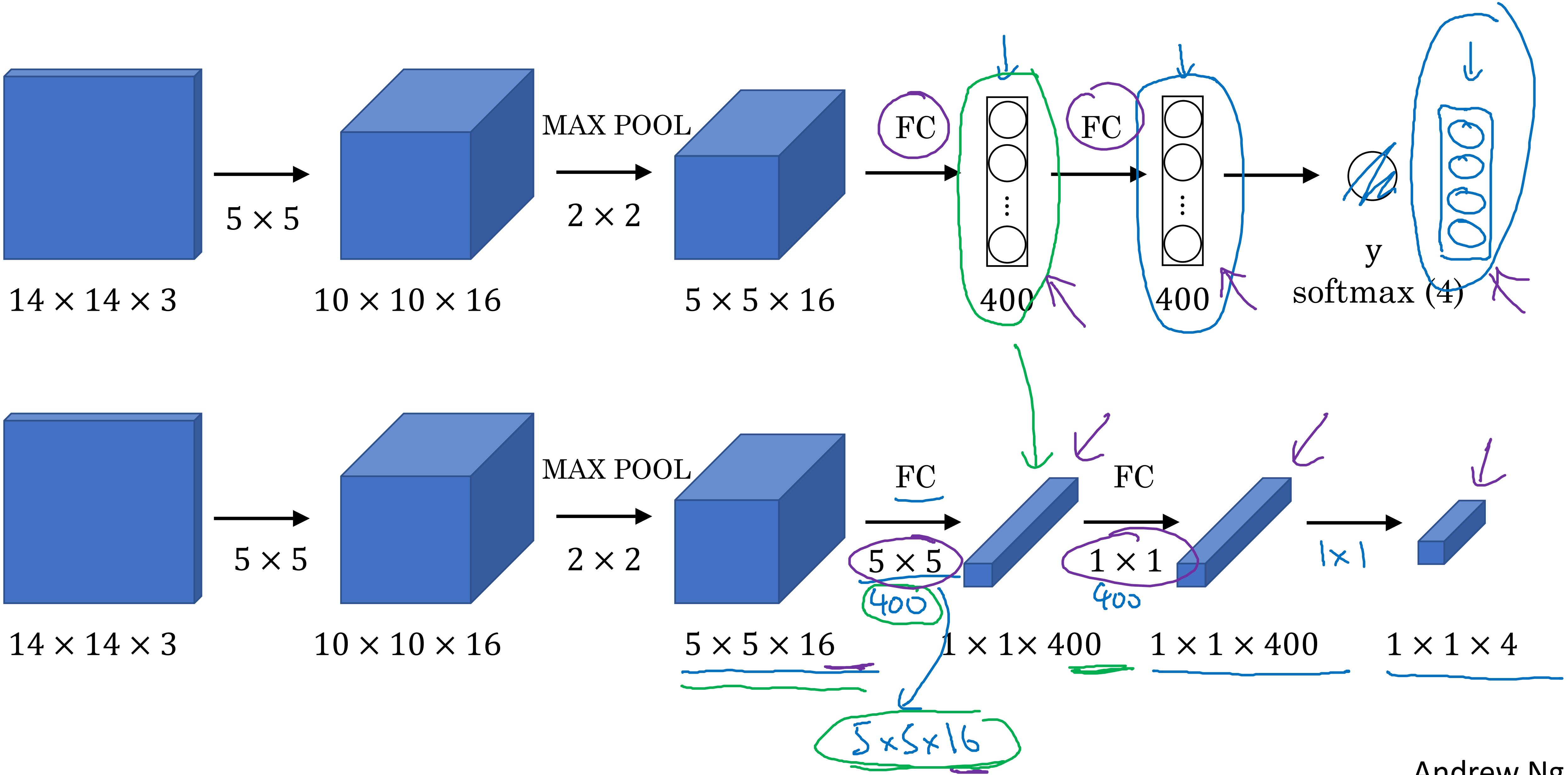
Object Detection

Convolutional implementation of sliding windows

Turning FC layer into convolutional layers



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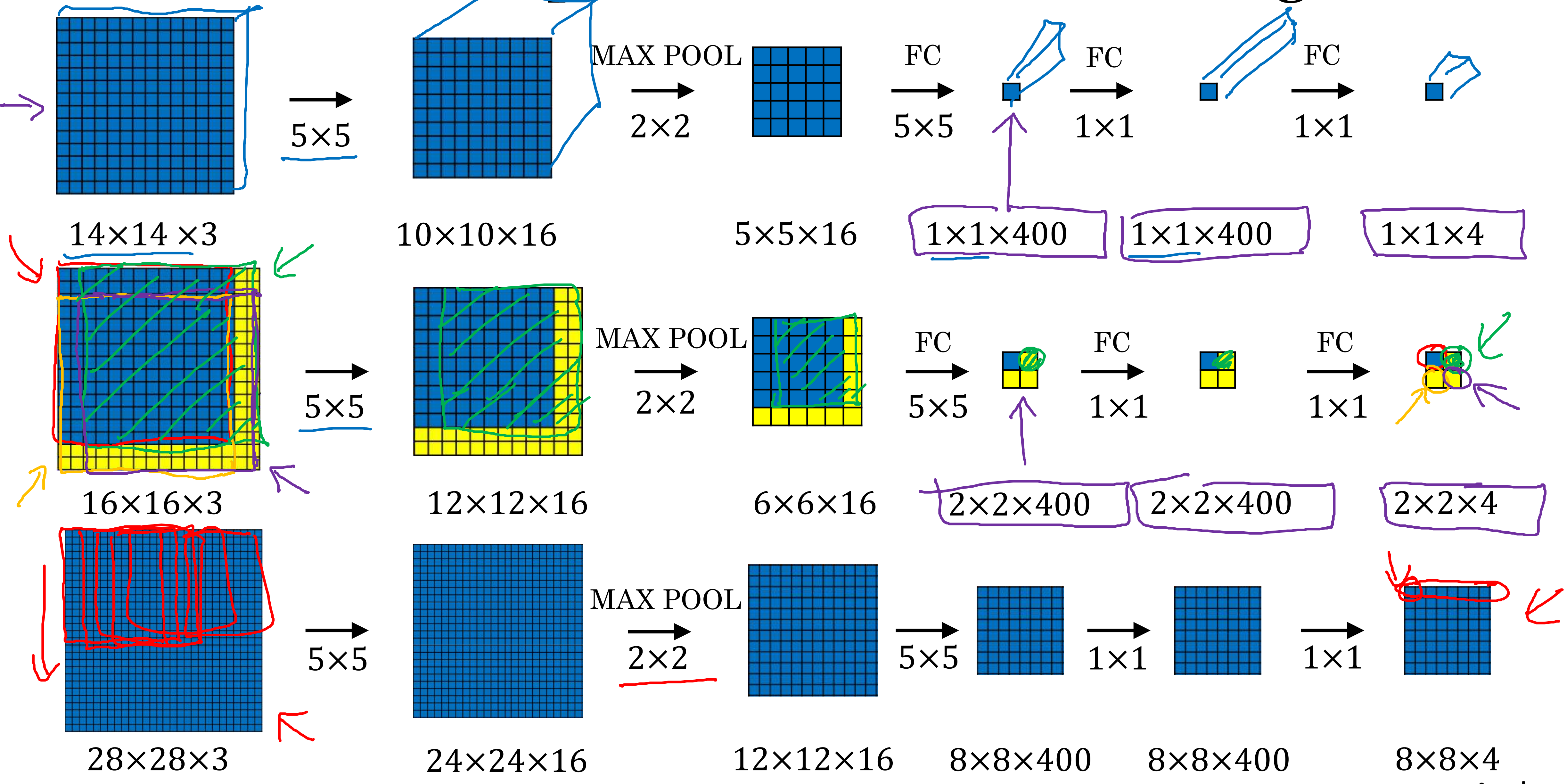
Convolution implementation of sliding windows



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

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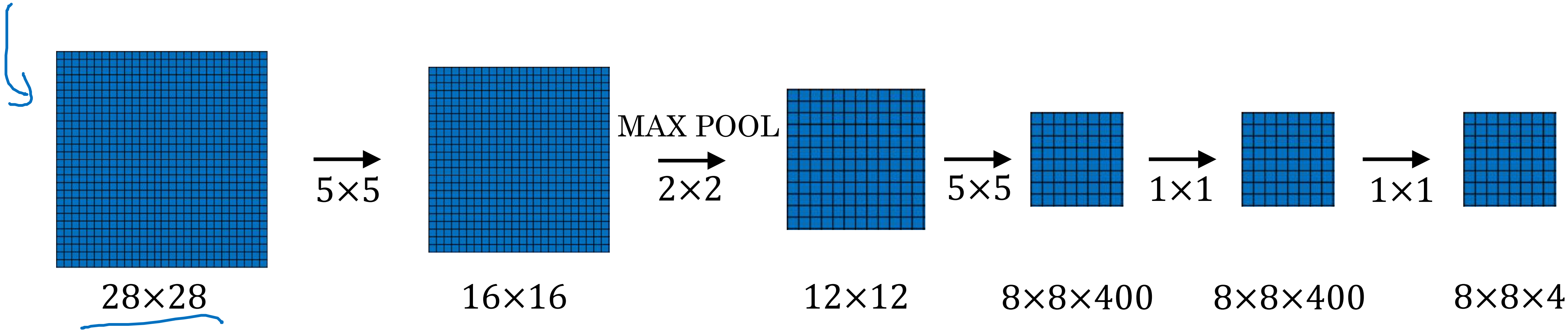
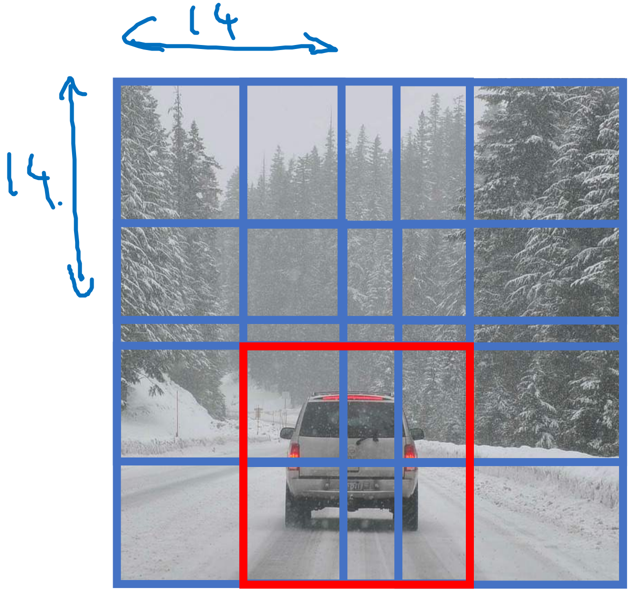
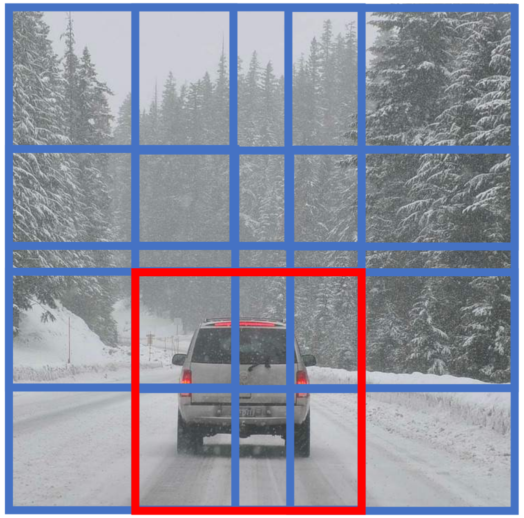
Convolution implementation of sliding windows







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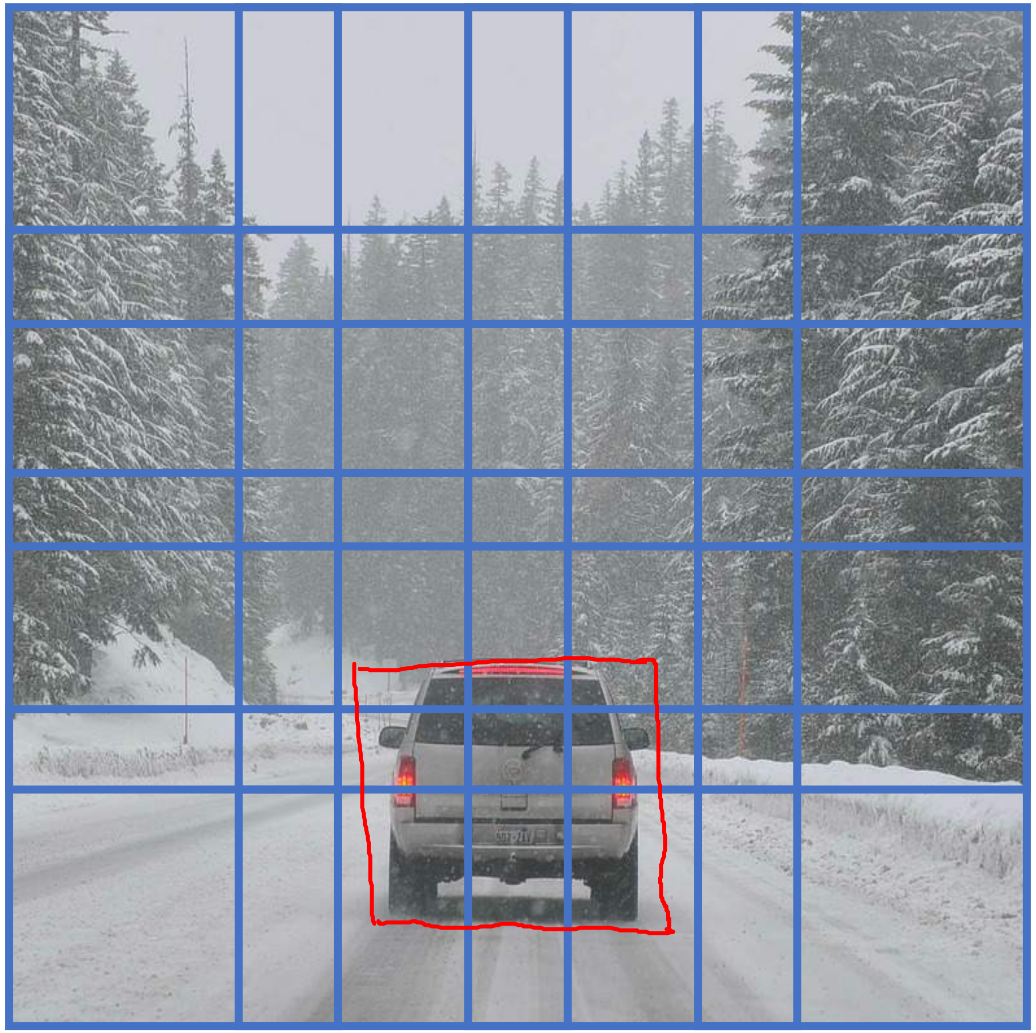
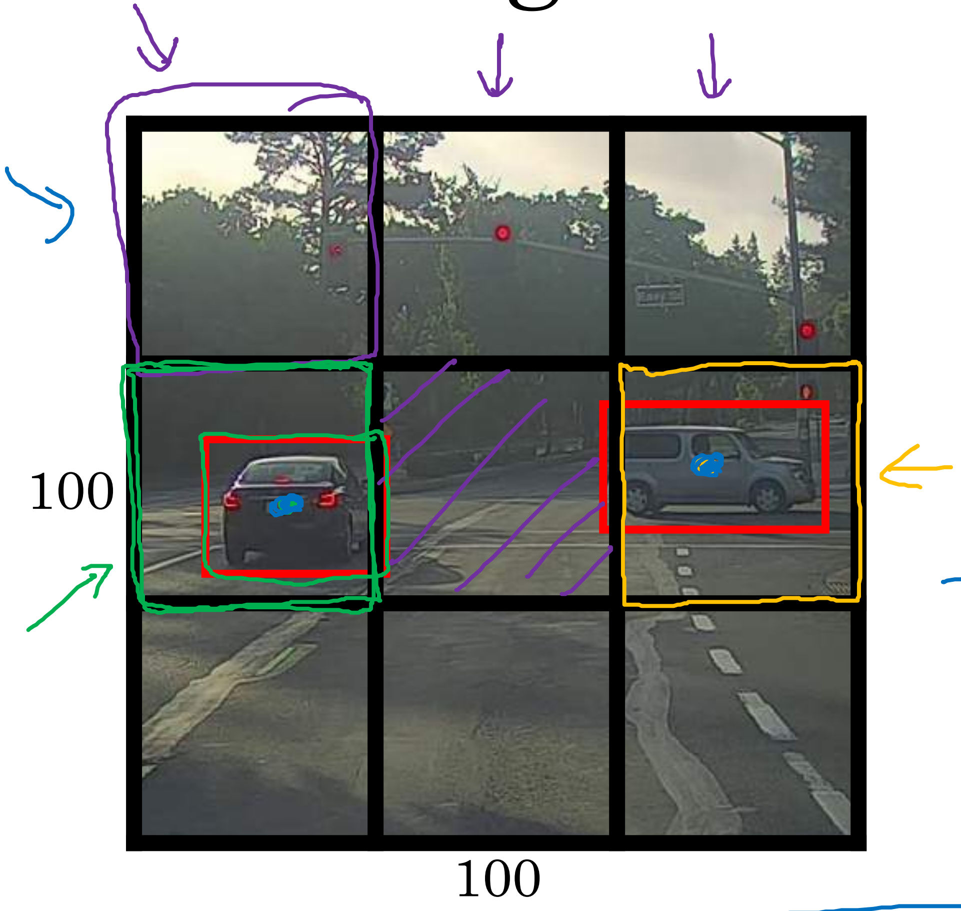
Object Detection

Bounding box predictions

Output accurate bounding boxes



YOLO algorithm

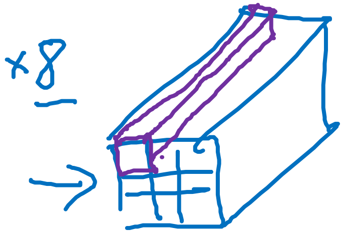


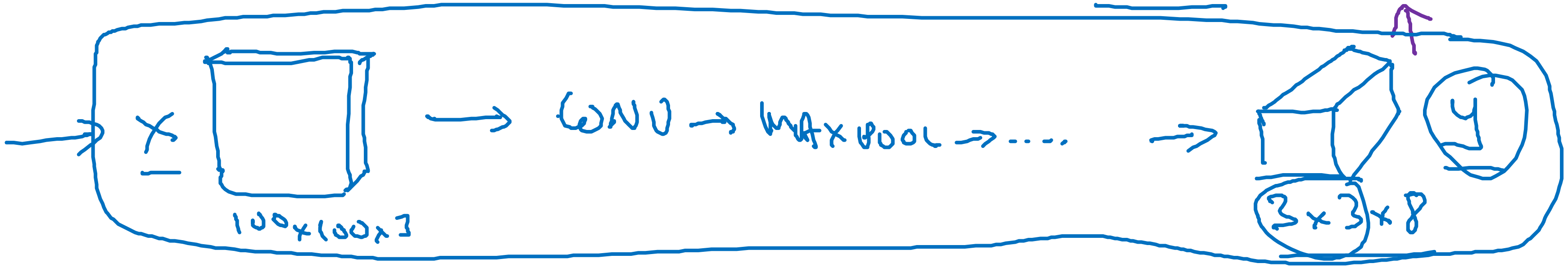
Labels for training

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: $3 \times 3 \times 8$





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

$100 \times 100 \times 3$

→ $19 \times 19 \times 8$

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

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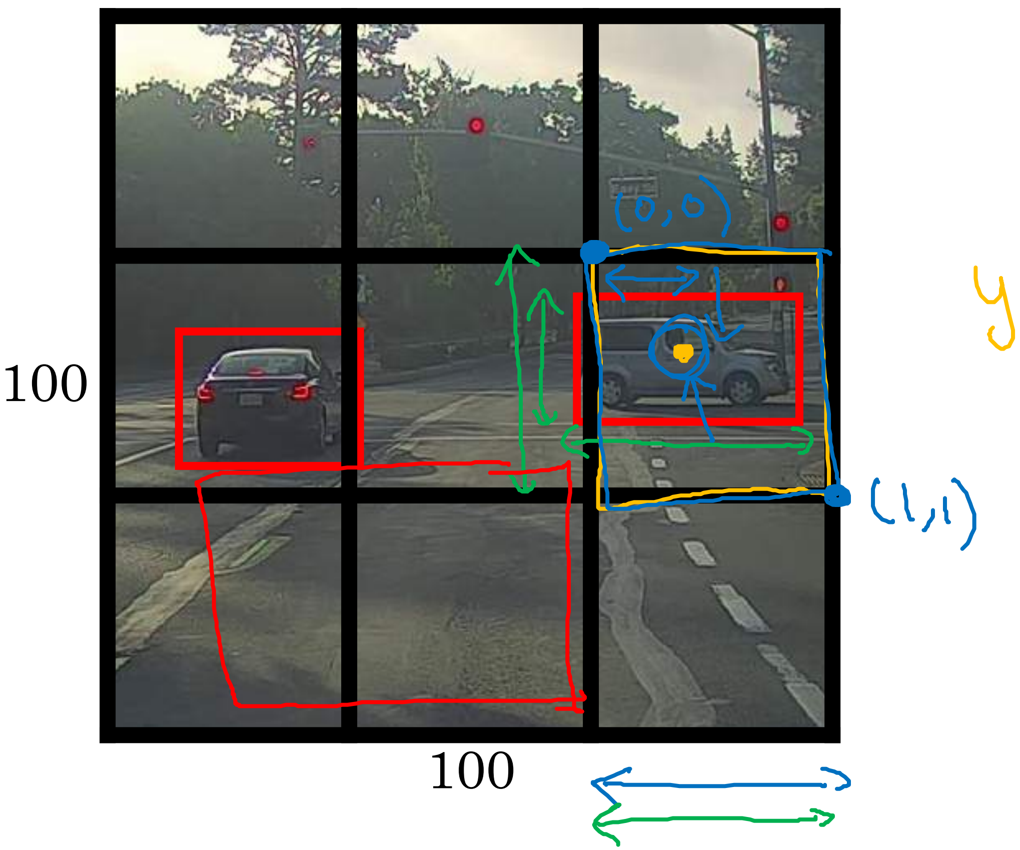
Specify the bounding boxes



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

0.4, 0.3 } between 0 and 1

0.9, 0.5 } could be > 1

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

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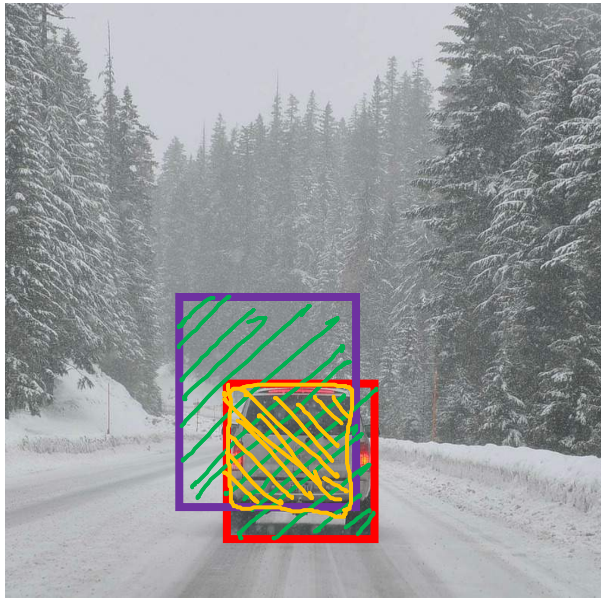
Object Detection

Intersection over union

Evaluating object localization



Intersection over Union (IoU)

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

“Correct” if IoU $\geq \boxed{0.5}$ ←

0.6 ←

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

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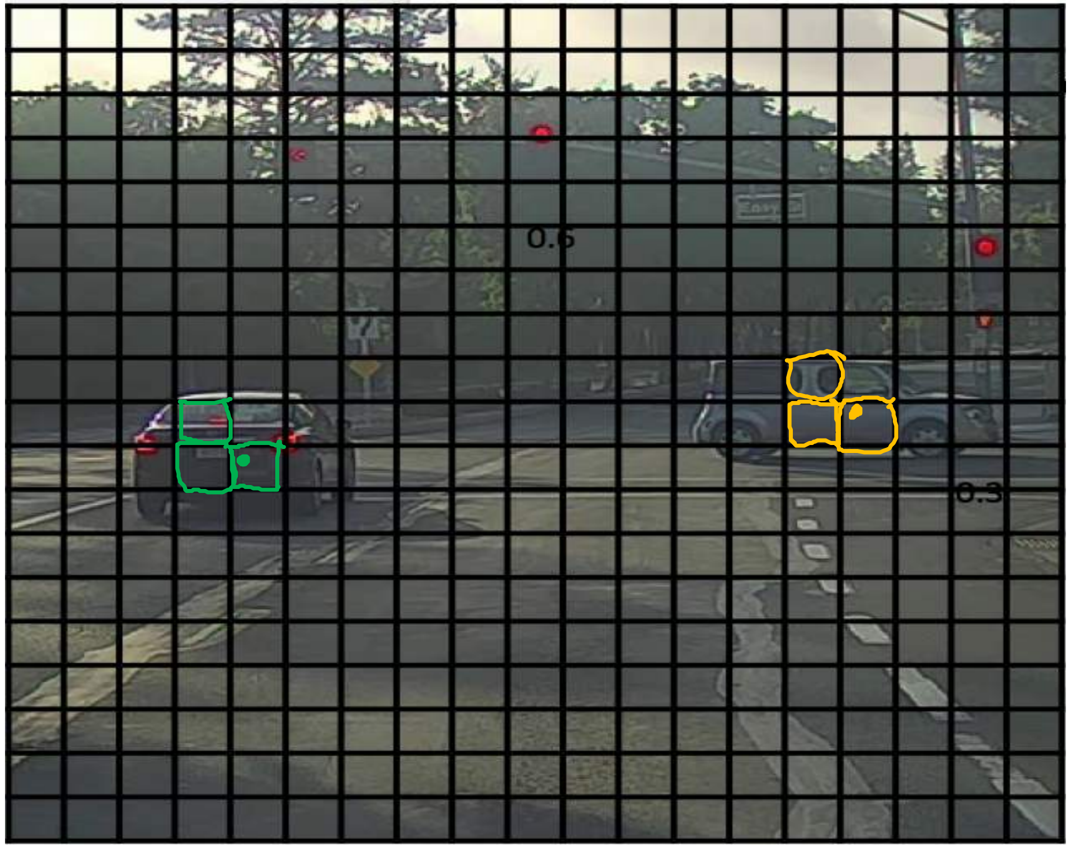
Object Detection

Non-max suppression

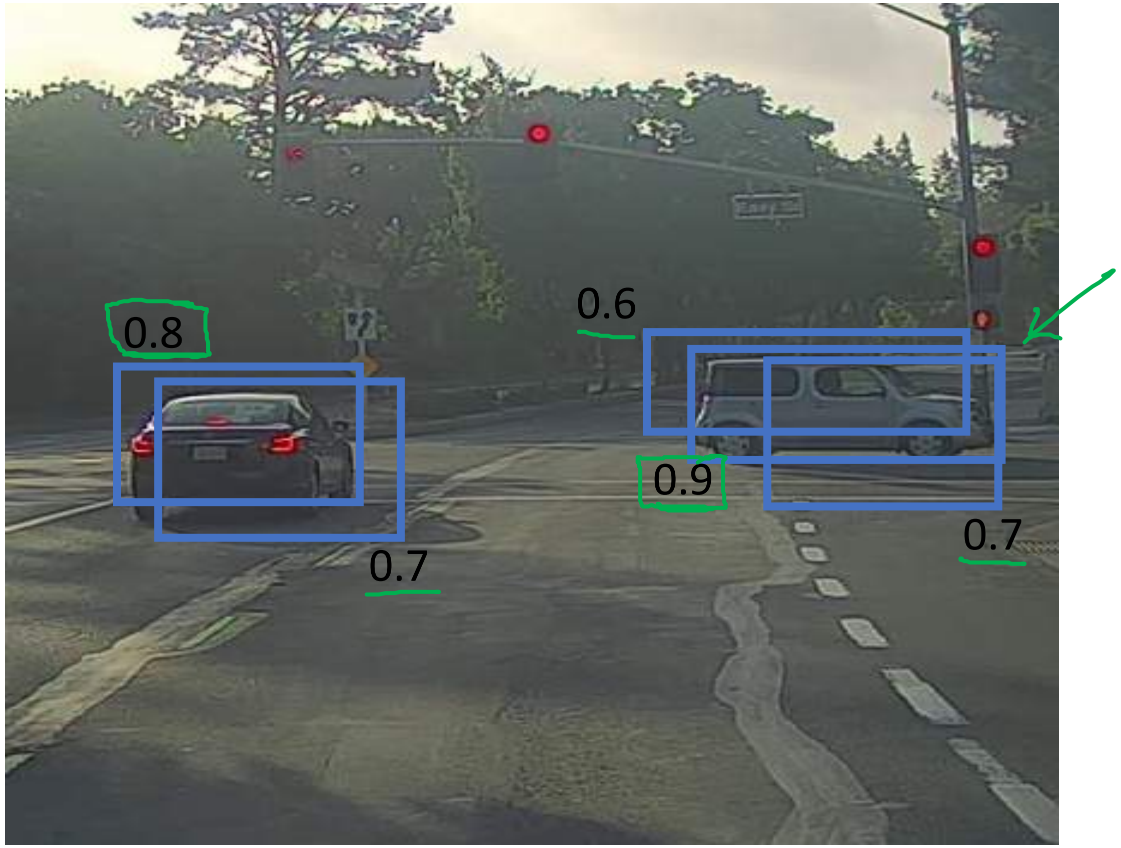
Non-max suppression example

Non-max suppression example



19x19

Non-max suppression example



P_c

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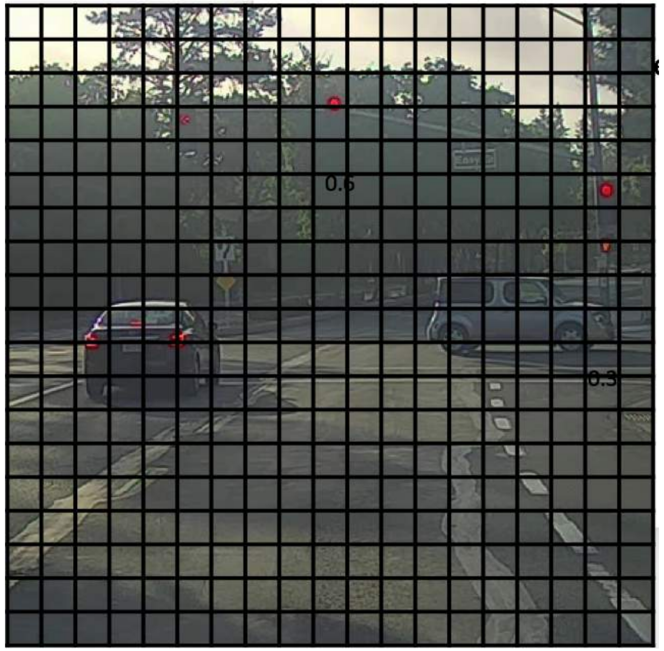
Non-max suppression algorithm



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 ≥ 0.5 with the box output in the previous step

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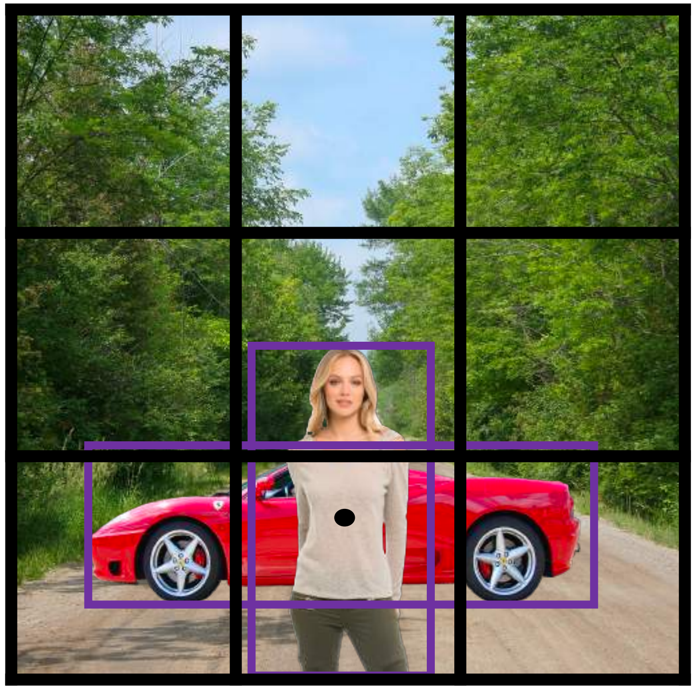
Object Detection

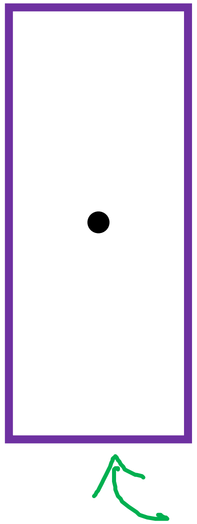
Anchor boxes

Overlapping objects:

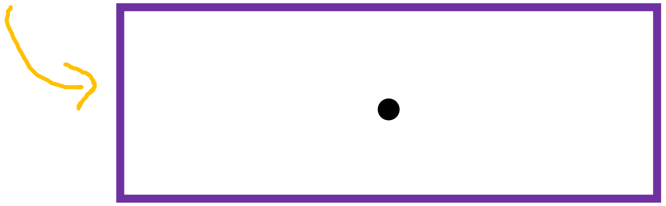


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:



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

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

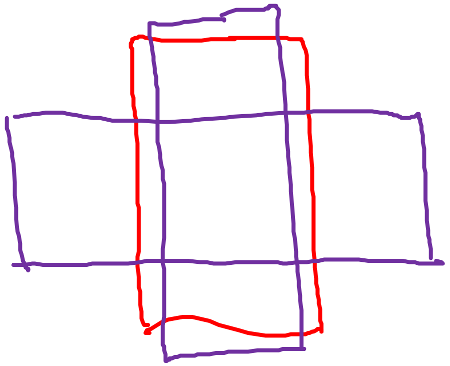
Anchor box algorithm

Previously:

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

Output y:

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



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.

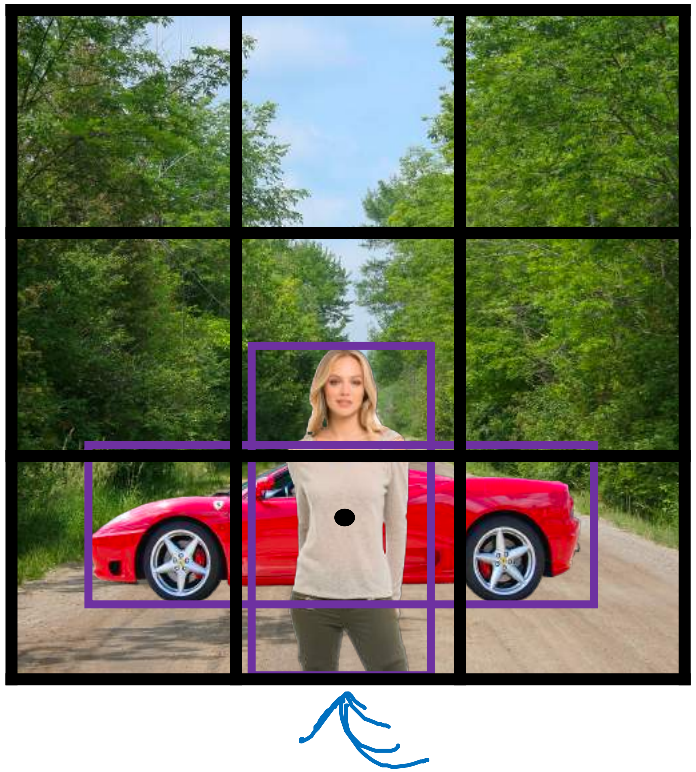
(grid cell, anchor box)

Output y:

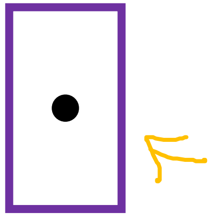
$3\times 3\times \underline{16}$

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

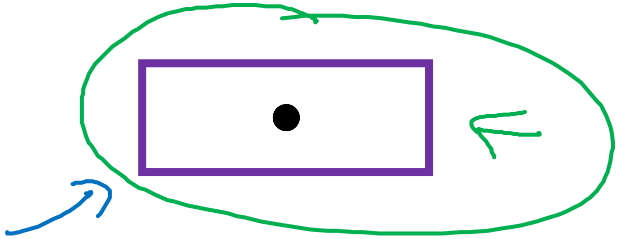
Anchor box example



Anchor box 1:



Anchor box 2:



car only?

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

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Object Detection

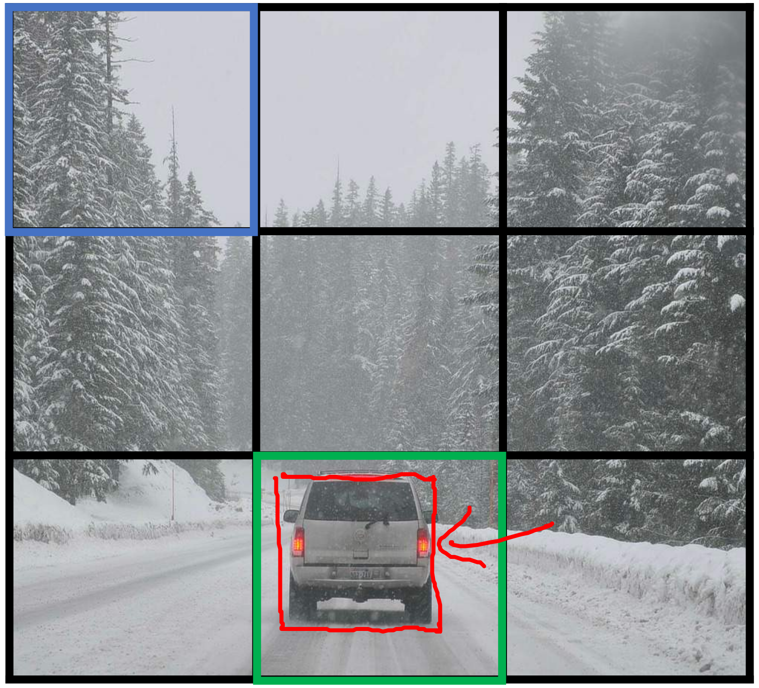
Putting it together: YOLO algorithm

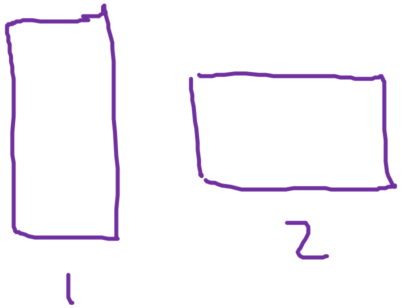
Training

1 - pedestrian

2 - car

3 - motorcycle





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

$3\times3\times16$

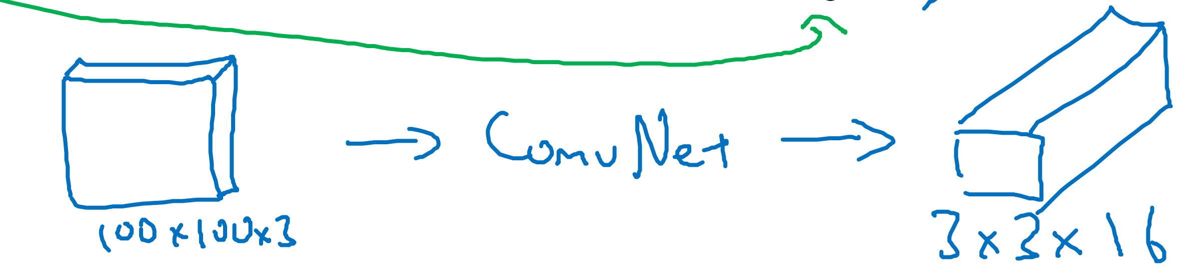
y is $\underbrace{3\times3}\times2\times8$

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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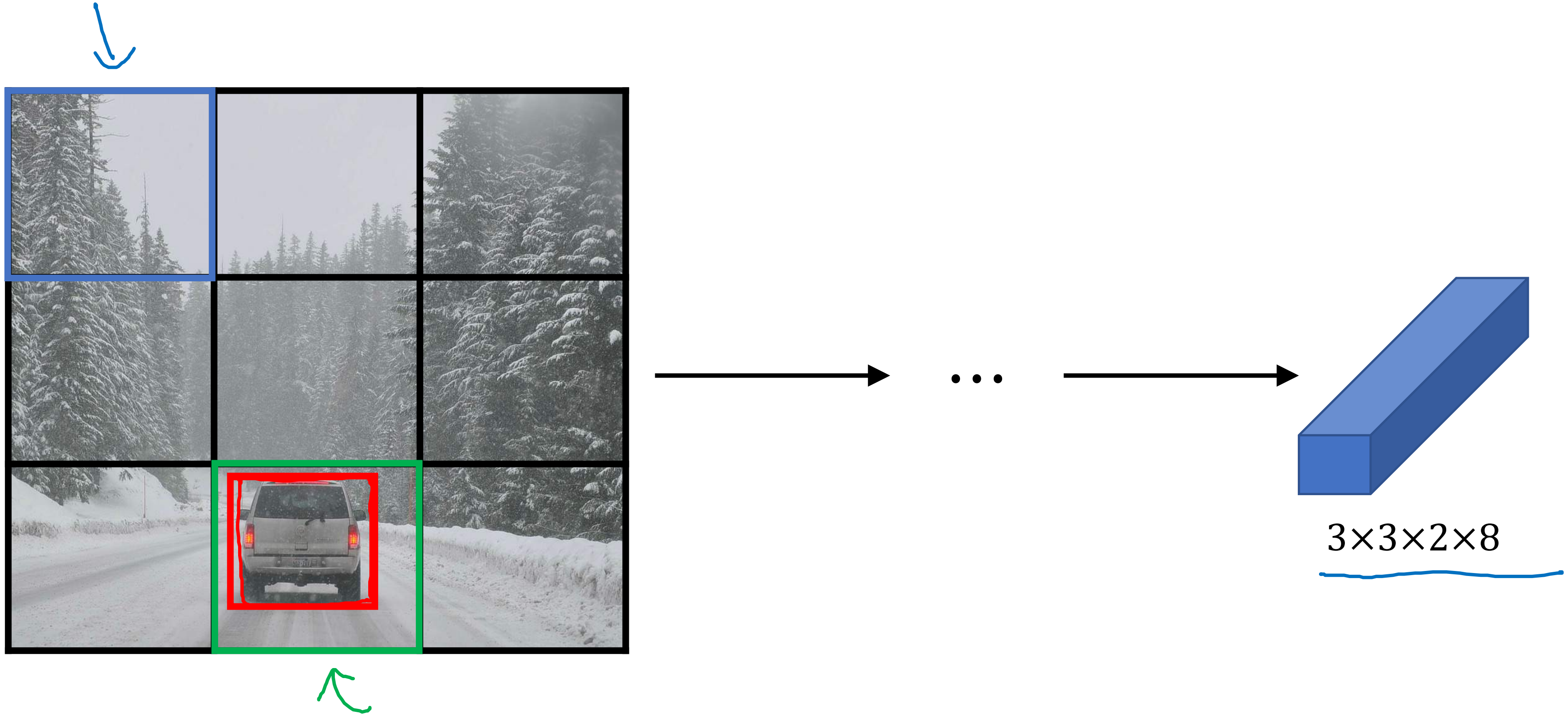
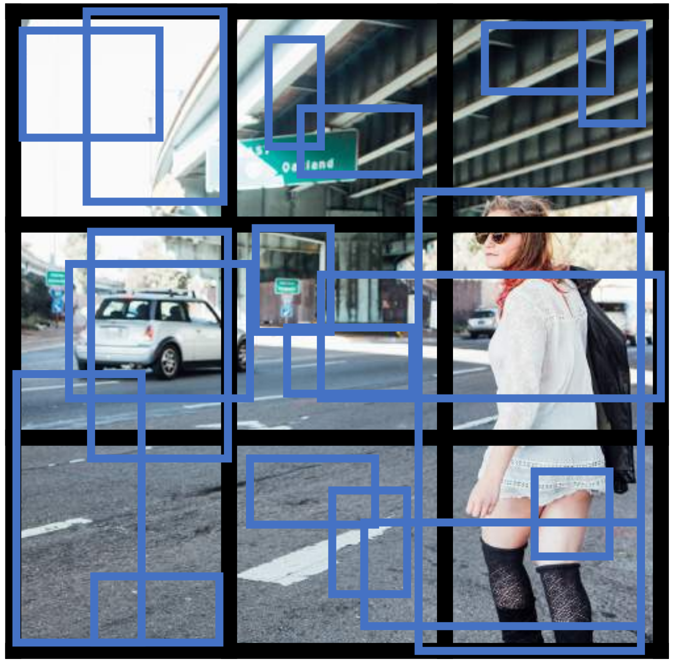
Making predictions



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

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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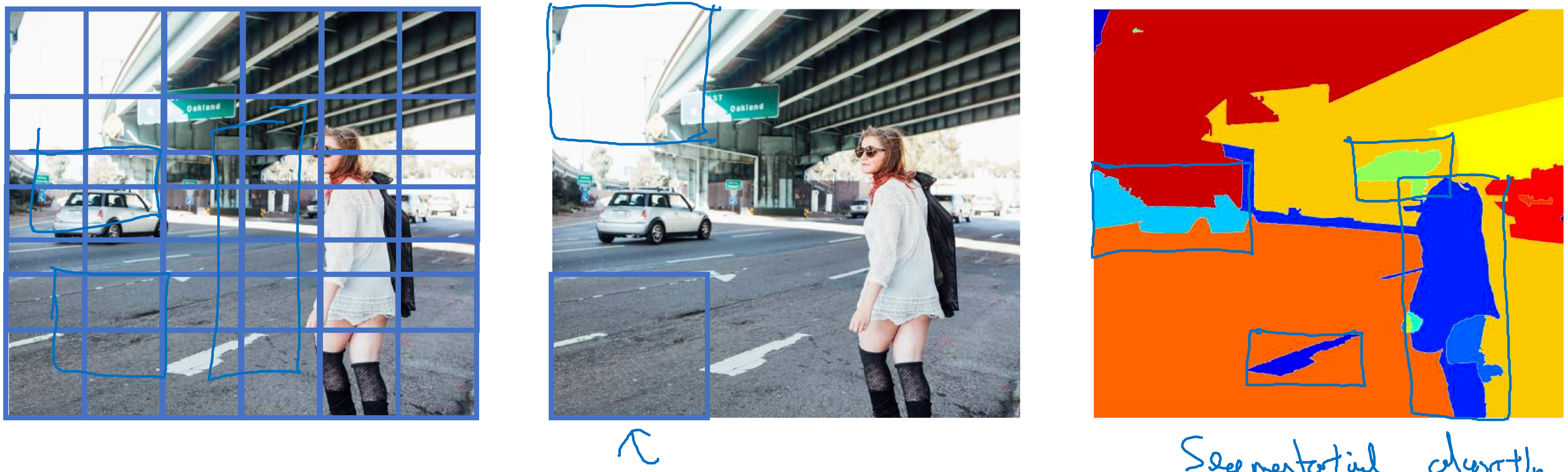
Object Detection

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]

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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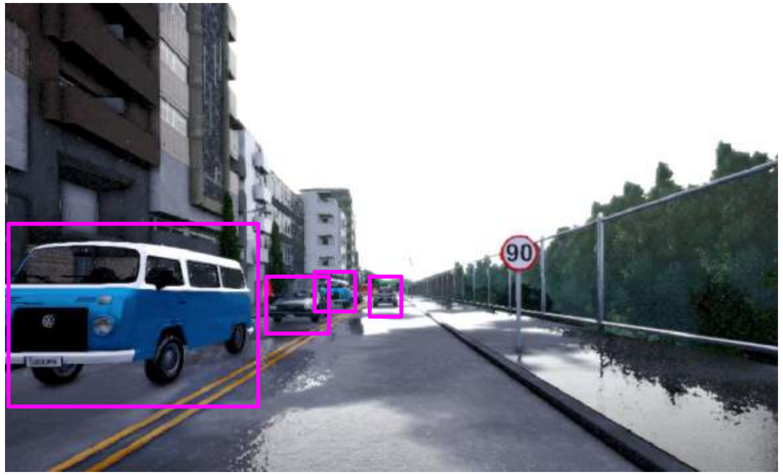
Convolutional Neural Networks

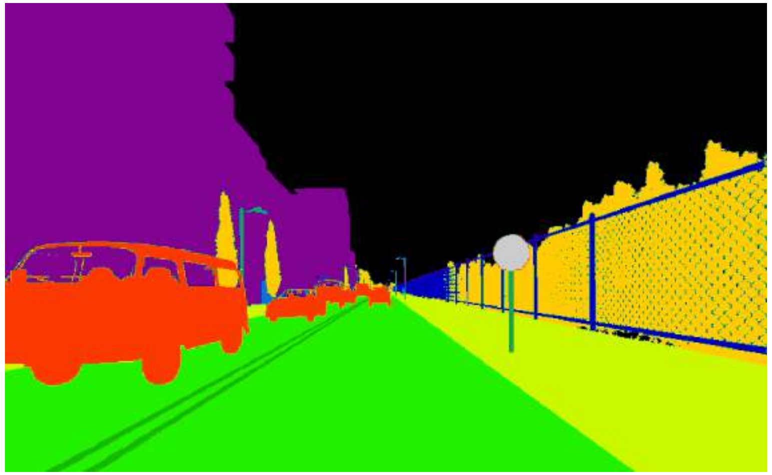
Semantic segmentation with U-Net

Object Detection vs. Semantic Segmentation

Input image

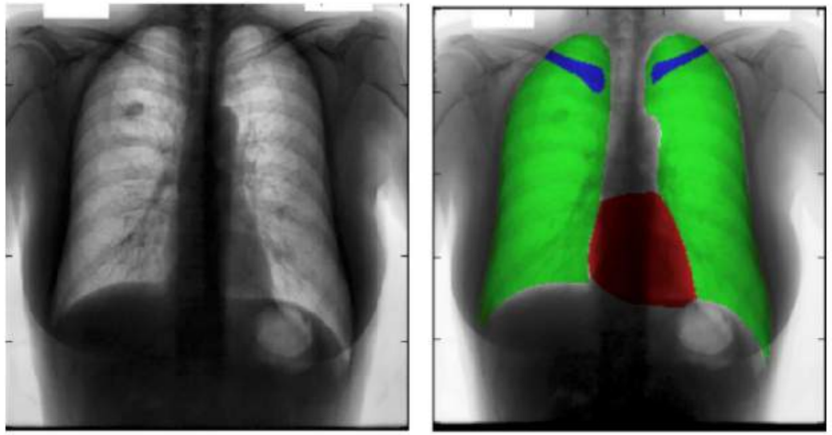


Object Detection

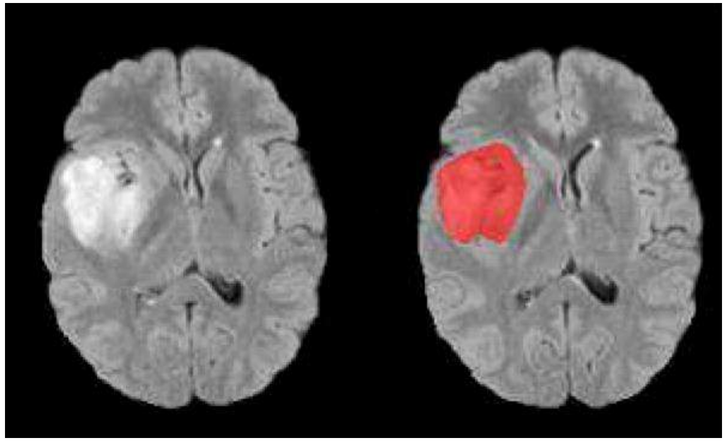


Semantic Segmentation

Motivation for U-Net



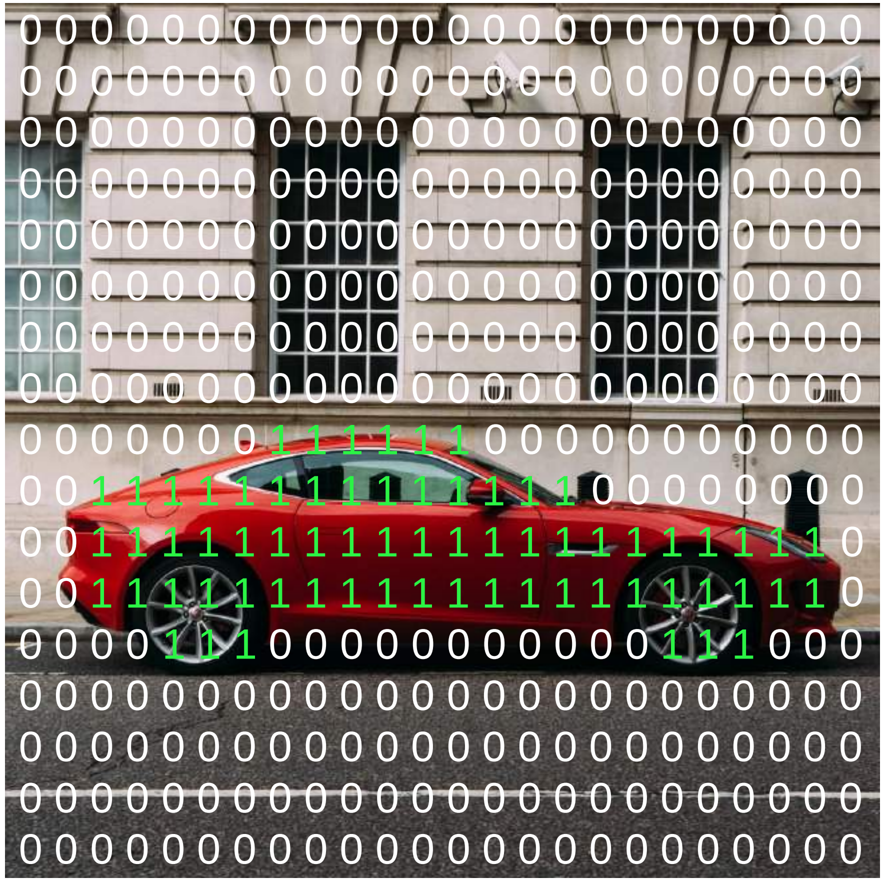
Chest X-Ray



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



```
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

1. Car
0. Not Car

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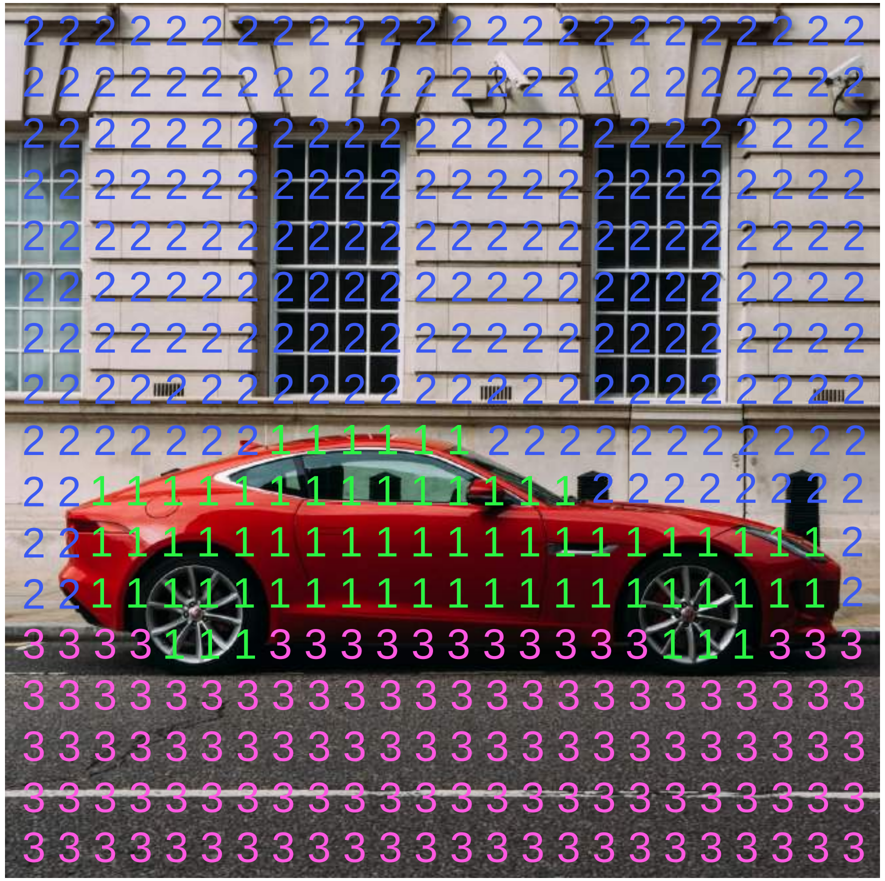
Per-pixel class labels



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
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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
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```
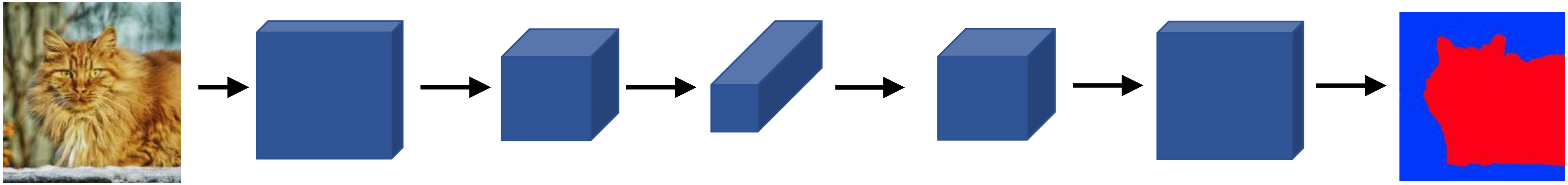
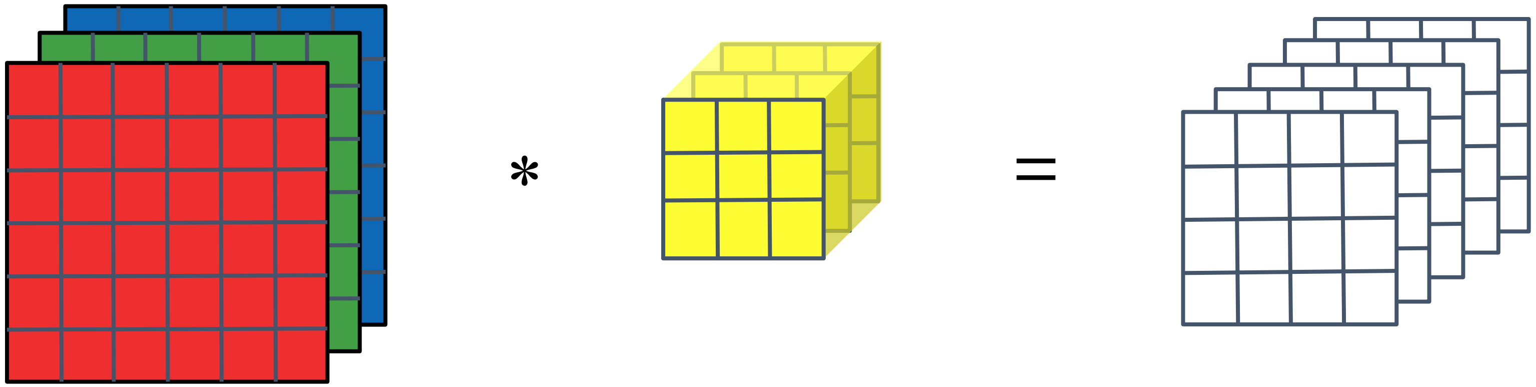

Segmentation Map

Deep Learning for Semantic Segmentation

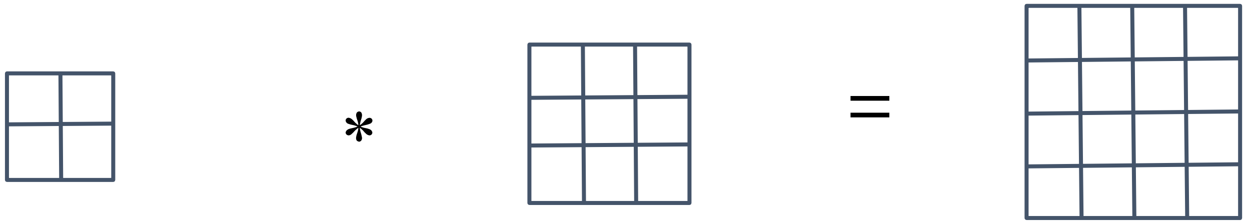


Transpose Convolution

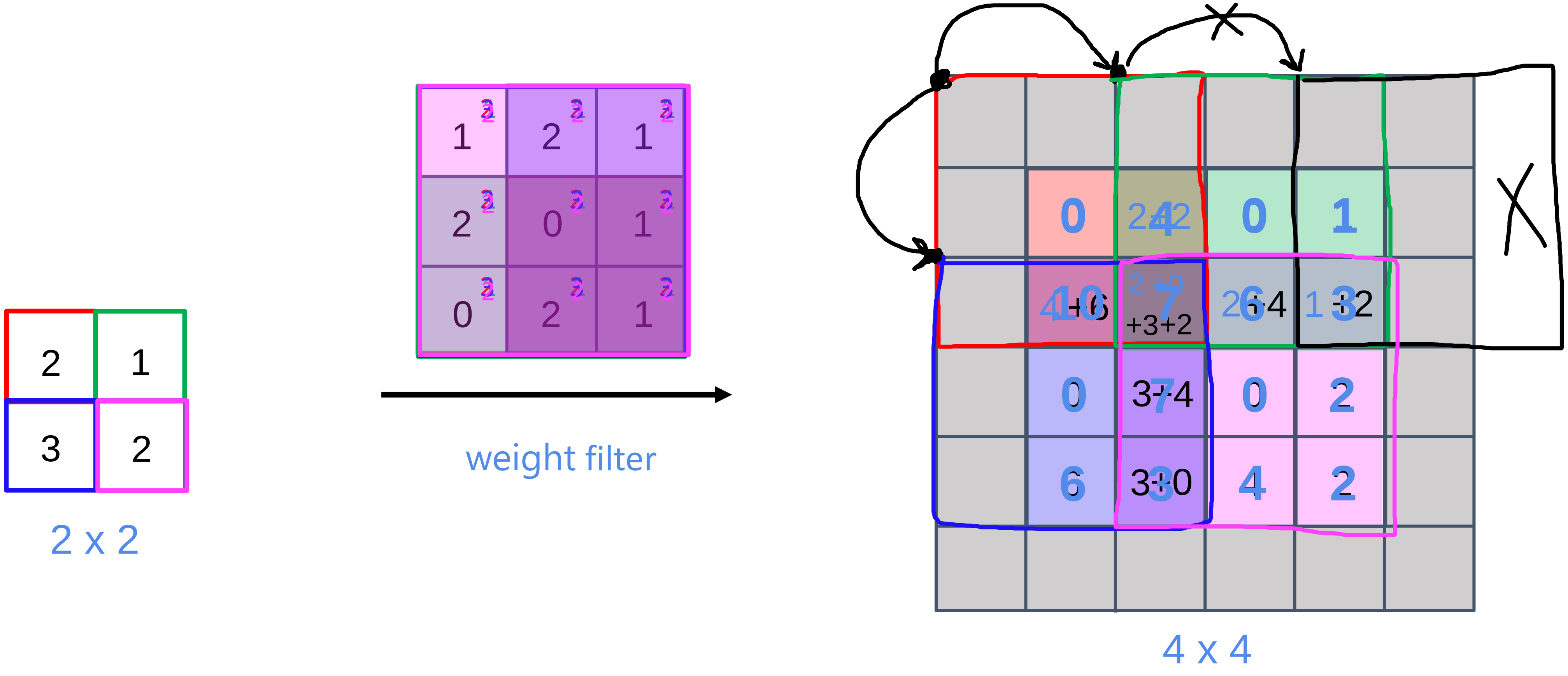
Normal Convolution



Transpose Convolution



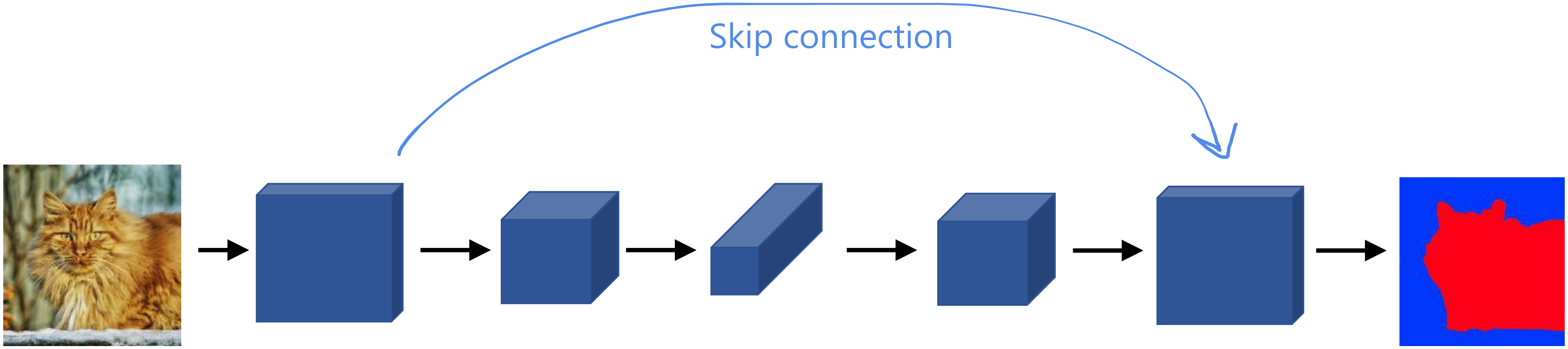
Transpose Convolution



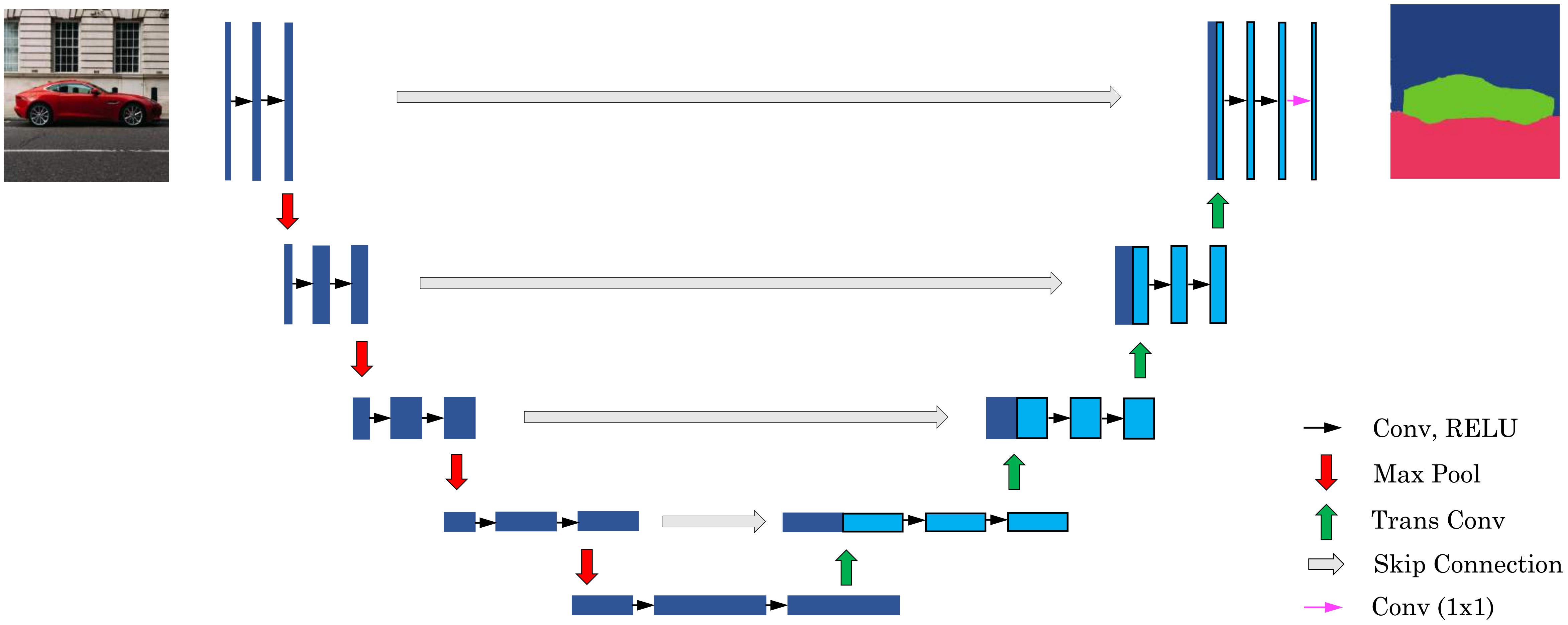
filter f x f = 3 x 3 padding p = 1 stride s = 2

Andrew Ng

Deep Learning for Semantic Segmentation



U-Net



→ Conv, RELU

Max Pool

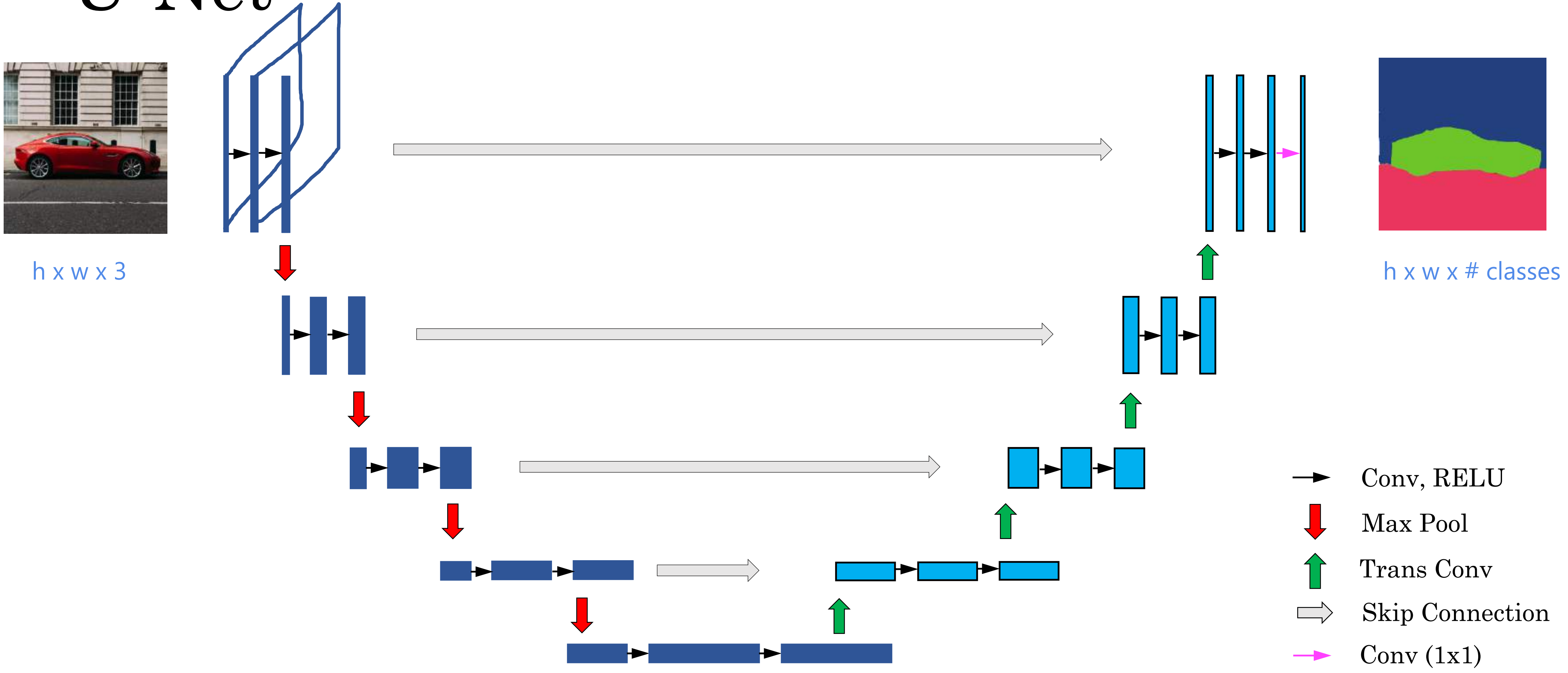
Trans Conv

Skip Connection

Conv (1x1)

[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]