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Object Detection

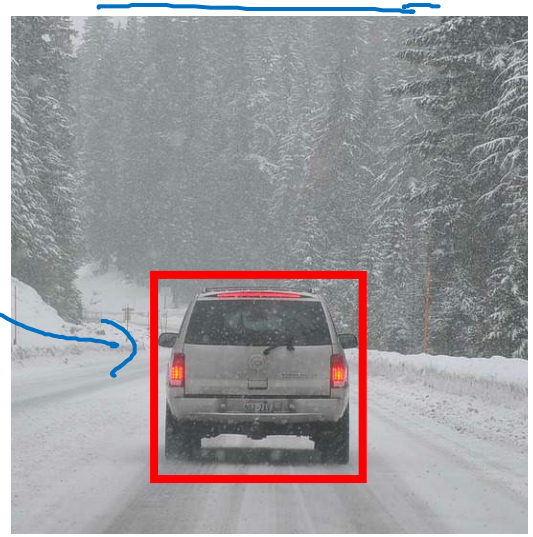
Object localization

What are localization and detection?

Image classification

"Car"

Classification with localization



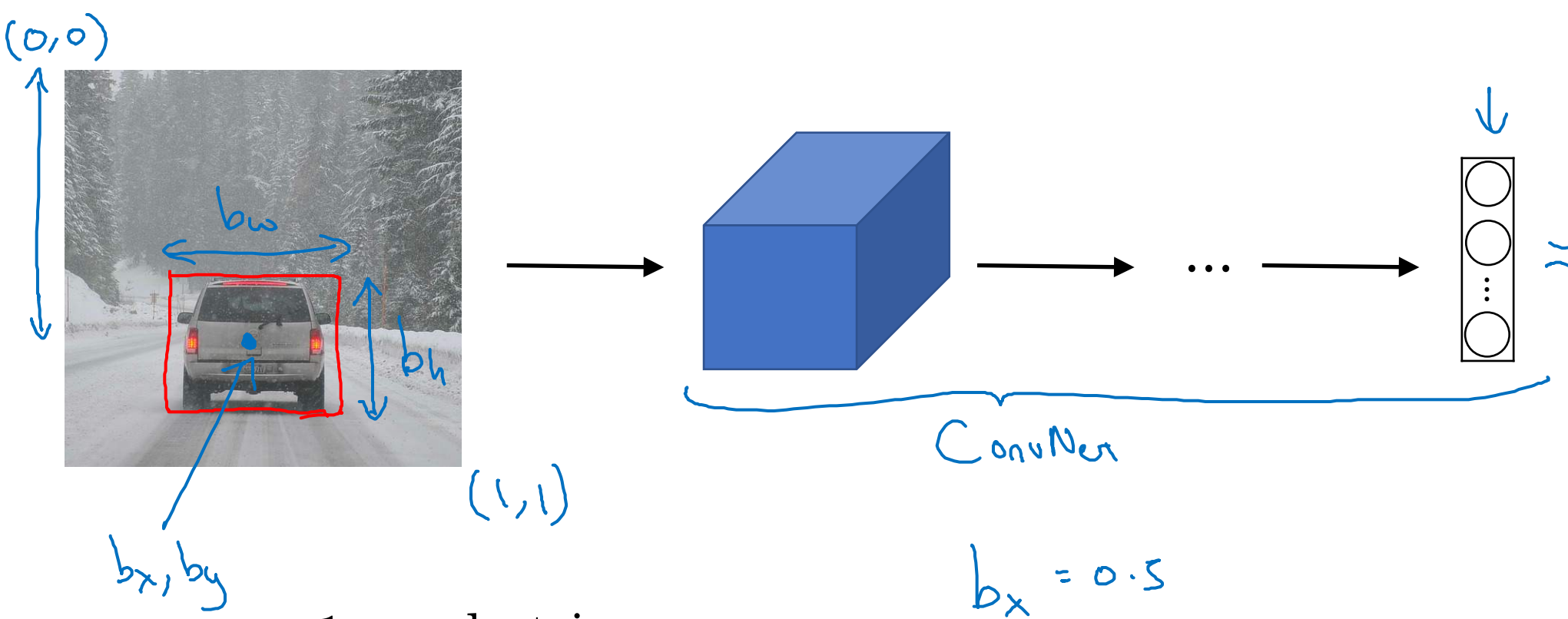
"Car"

1 object

Detection

multiple objects

Classification with localization



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

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

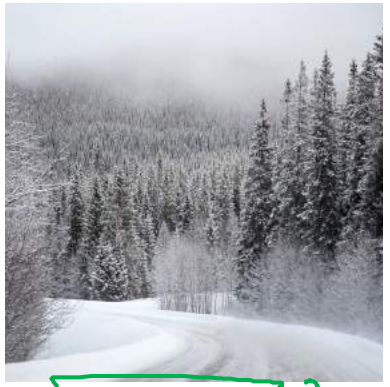
Defining the target label y

chạy bộ

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

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

$x =$



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

p_c: 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"

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

y1 -> y8 tương ứng với pc, bx, by, … c3

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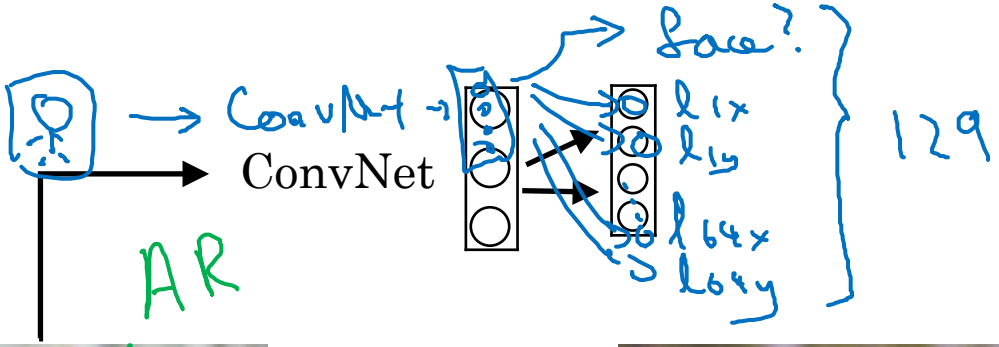
Object Detection

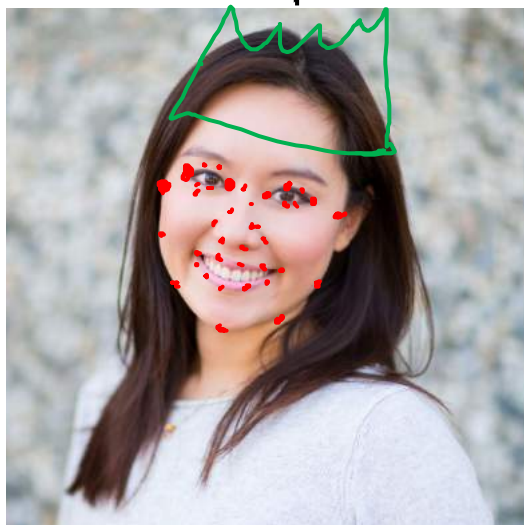
điểm mốc

Landmark detection

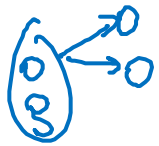
Landmark detection



b_x, b_y, b_h, b_w



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



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

x, y

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Object Detection

Object detection

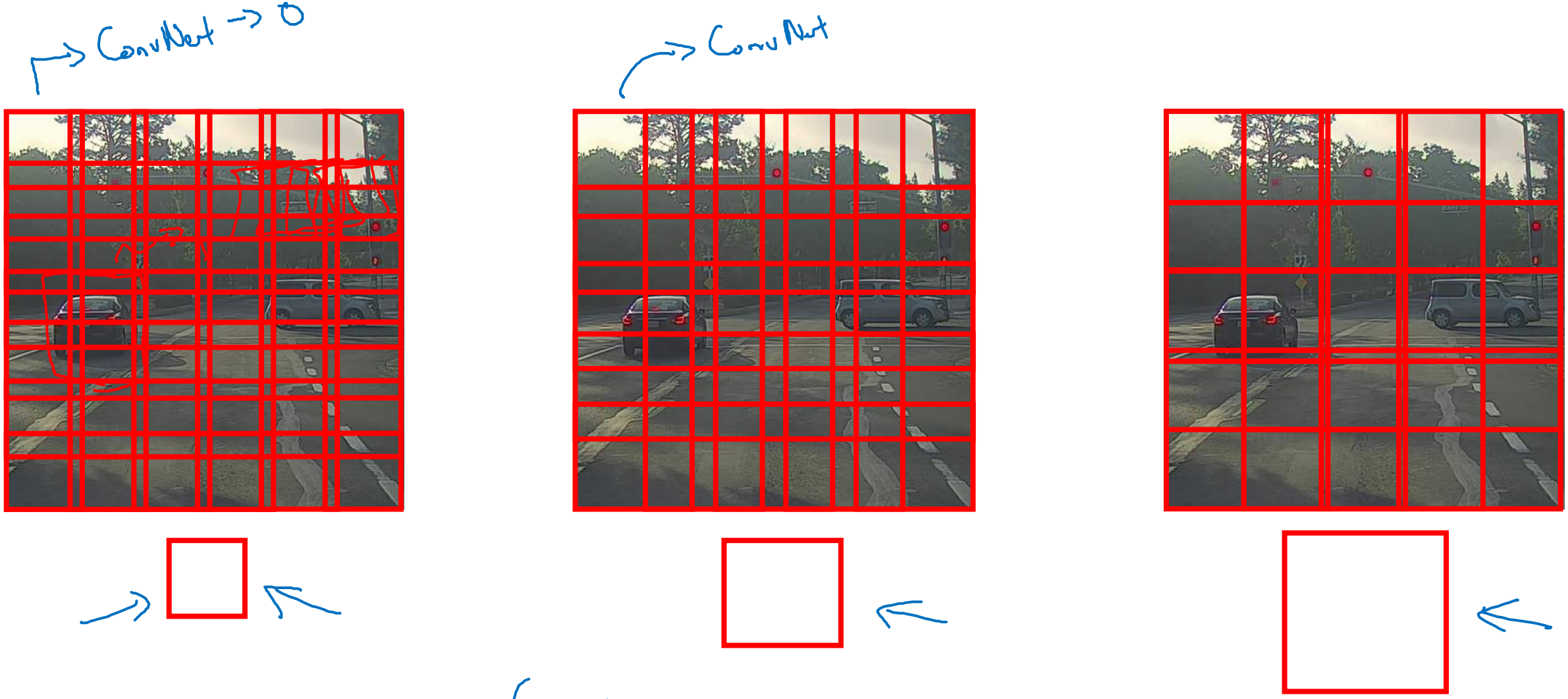
Car detection example

Training set:

x	y
	1
	1
	1
	0
	0

→ ConvNet → y

Sliding windows detection



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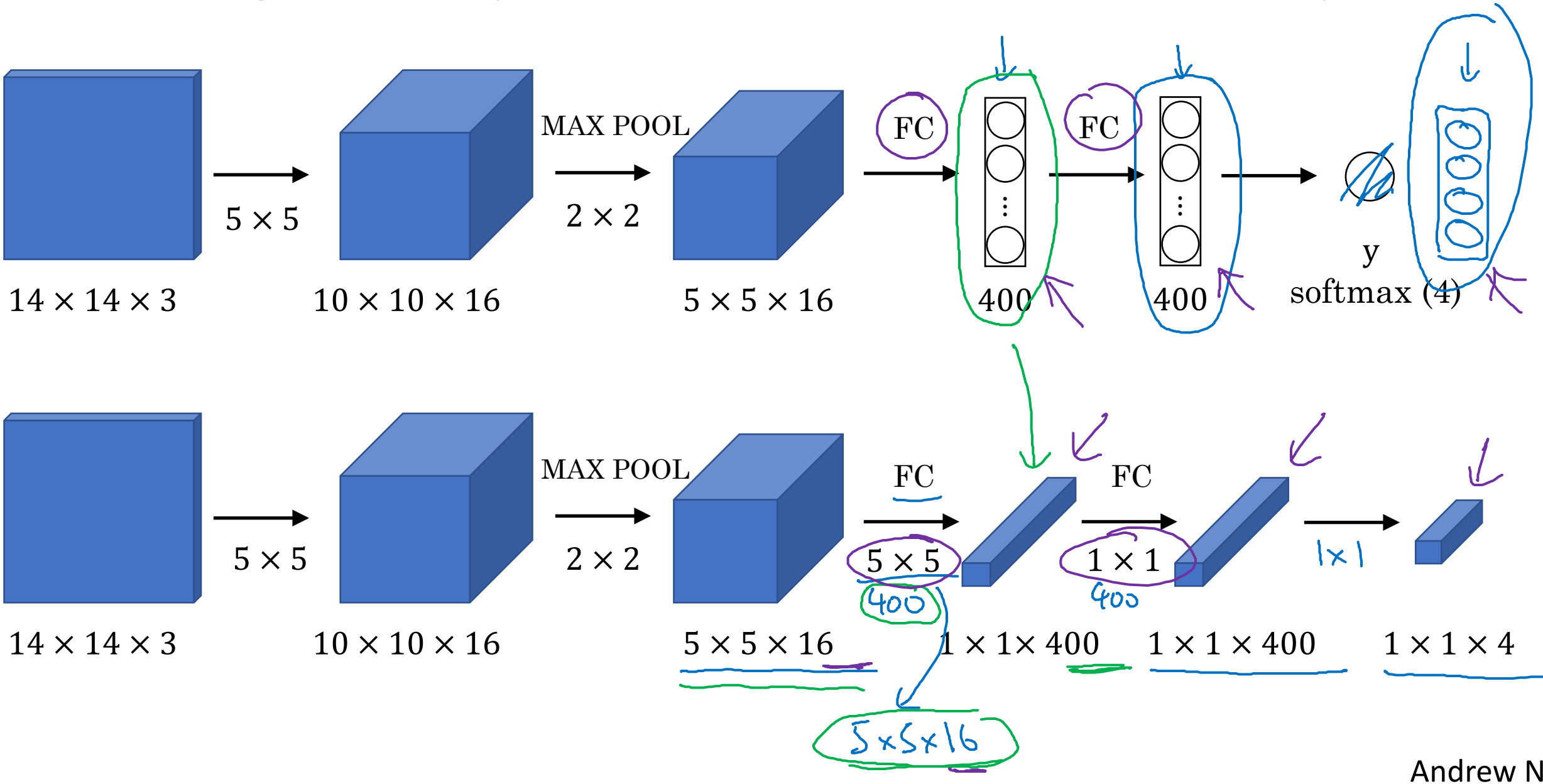
Object Detection

Convolutional implementation of sliding windows

Turning FC layer into convolutional layers



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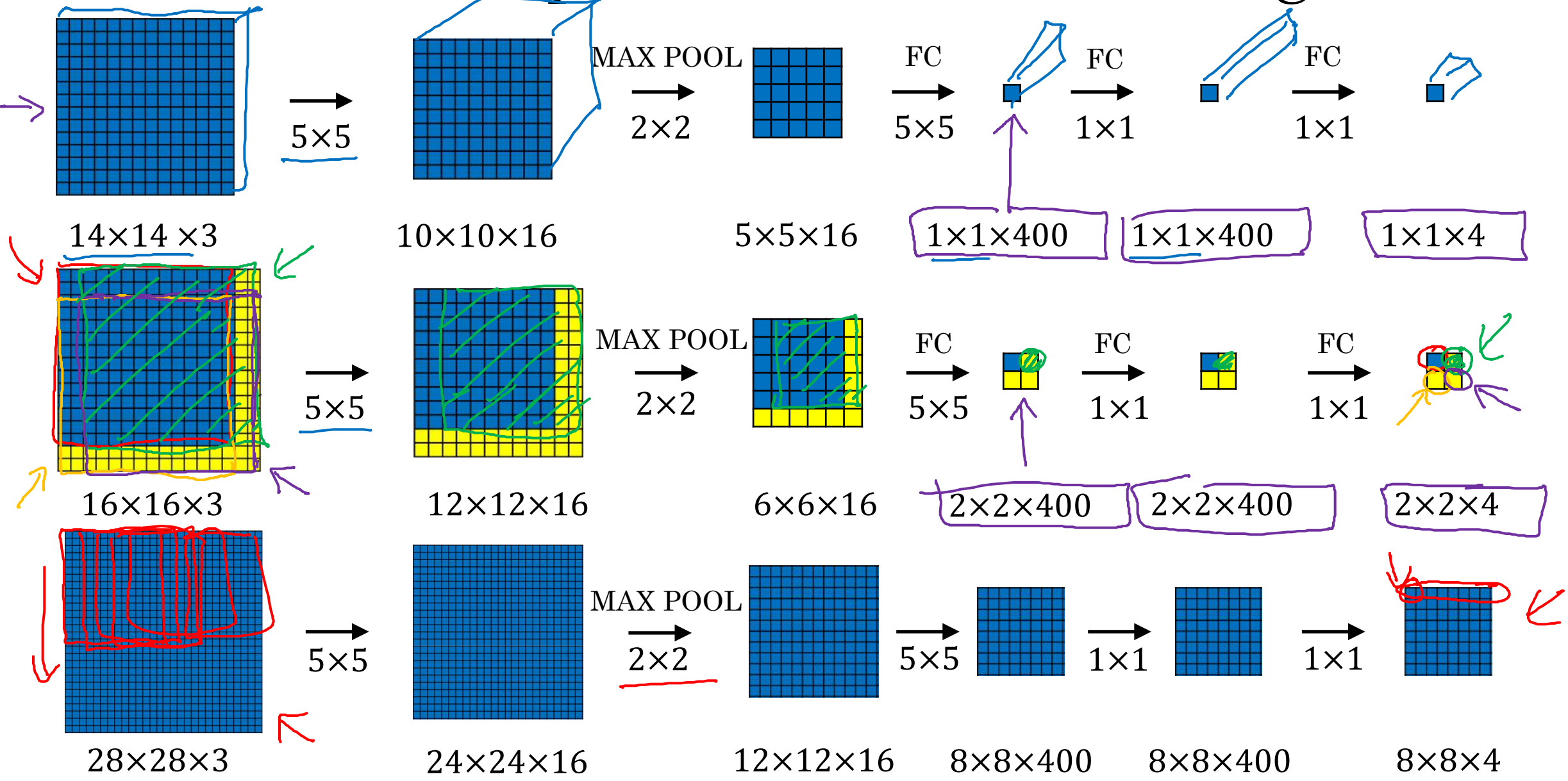
Convolution implementation of sliding windows



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

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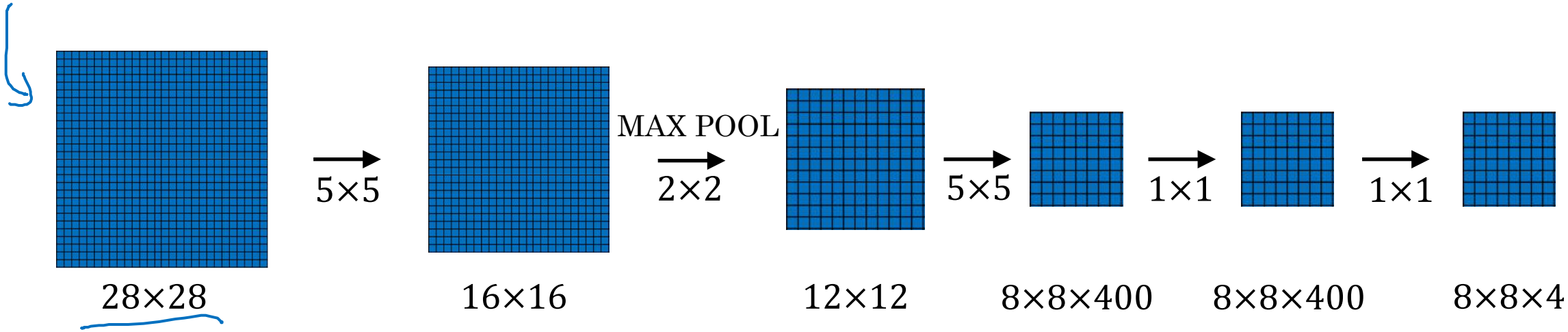
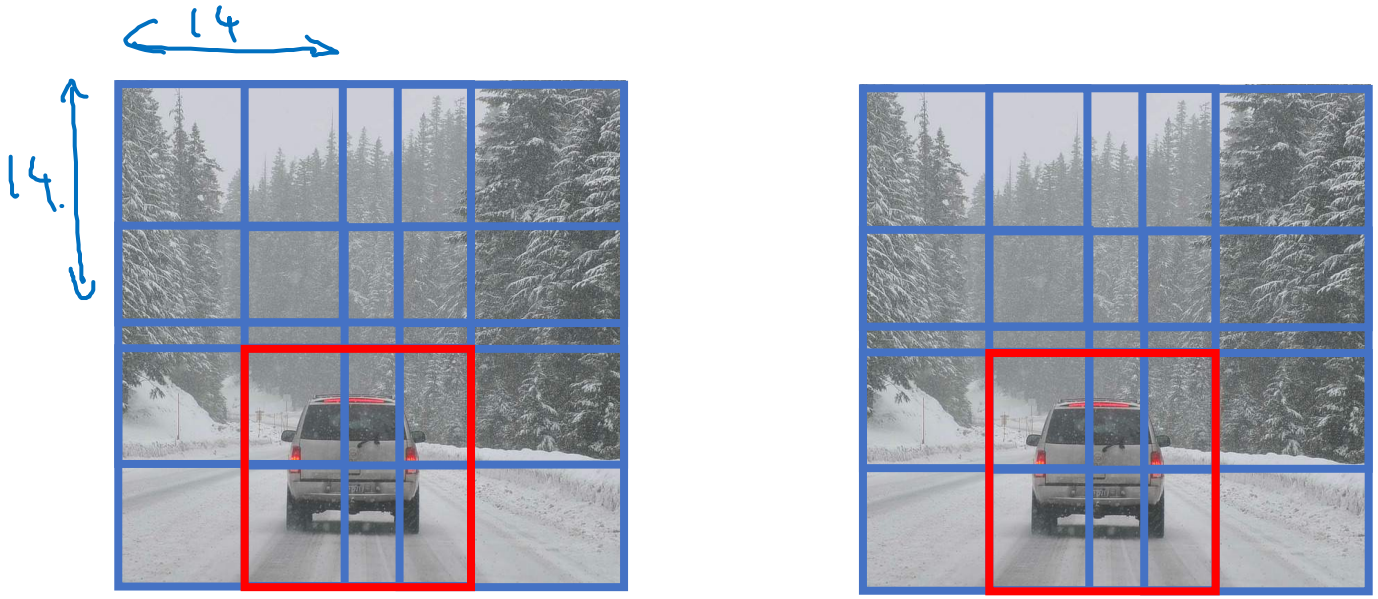
Convolution implementation of sliding windows





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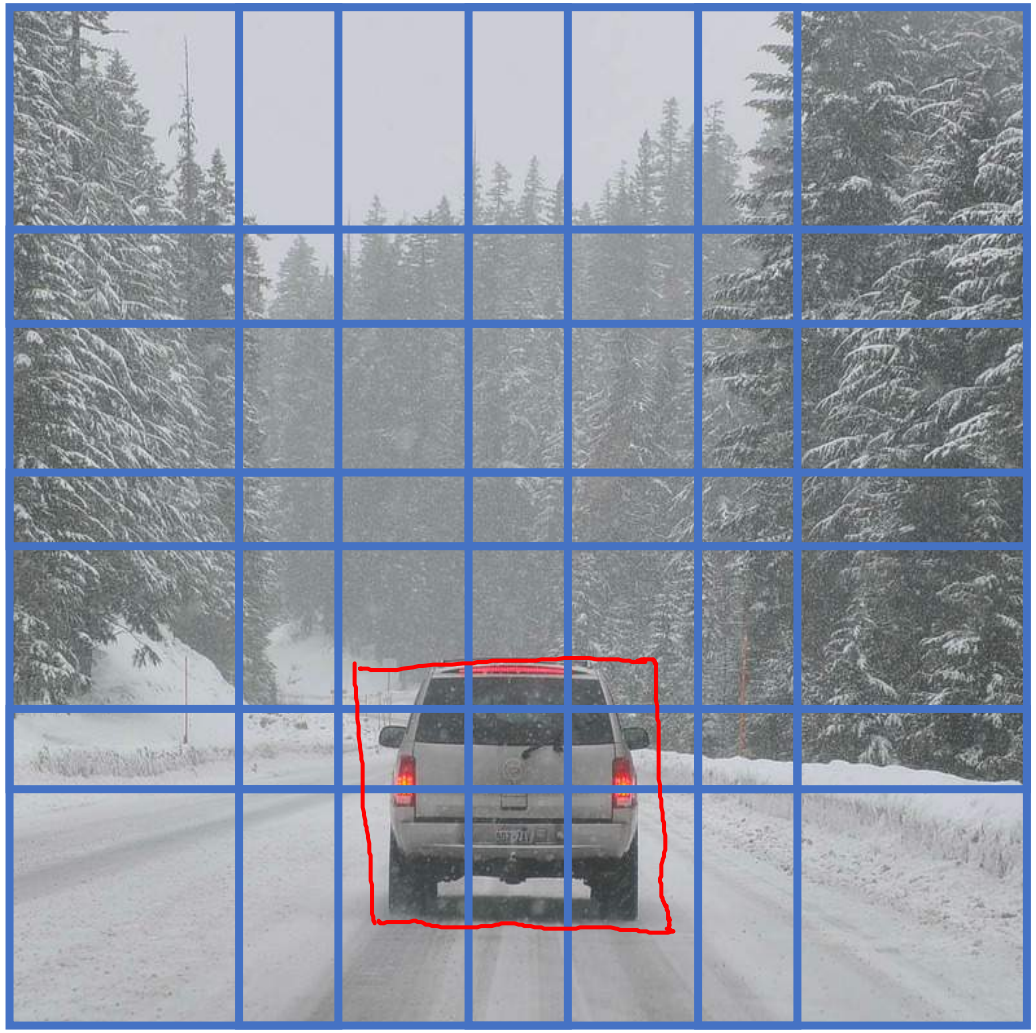
Object Detection

Bounding box predictions

Output accurate bounding boxes



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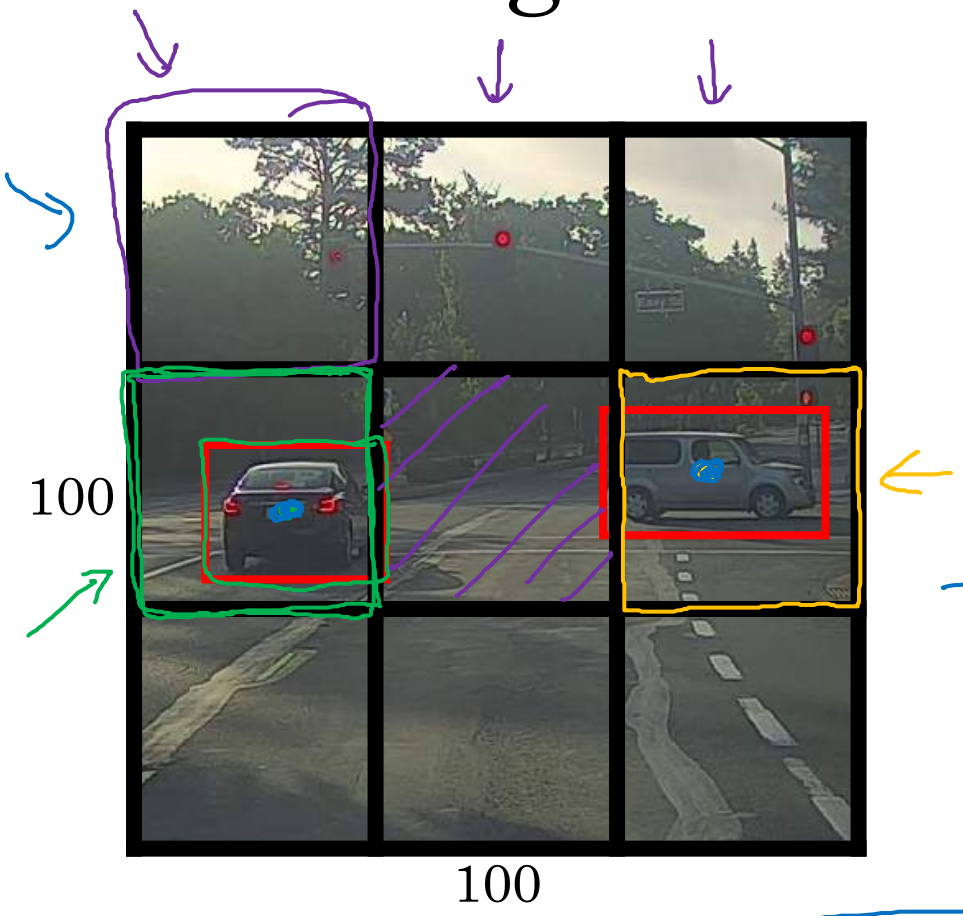
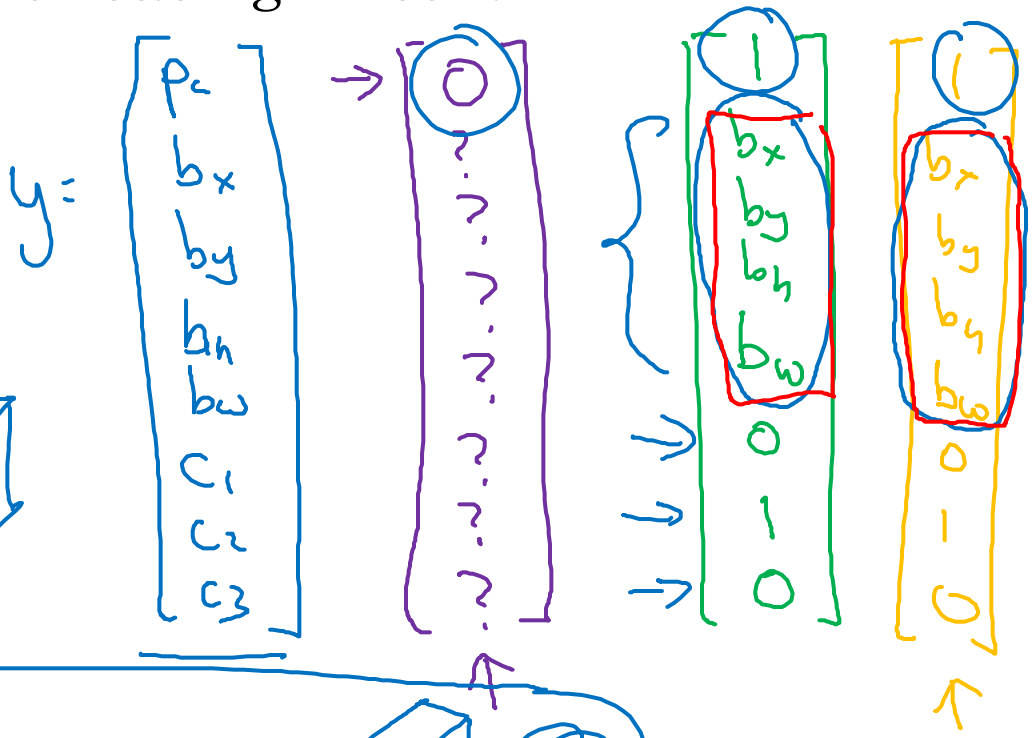
YOLO algorithm



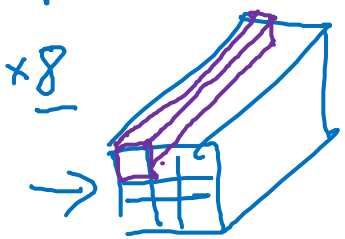
Labels for training

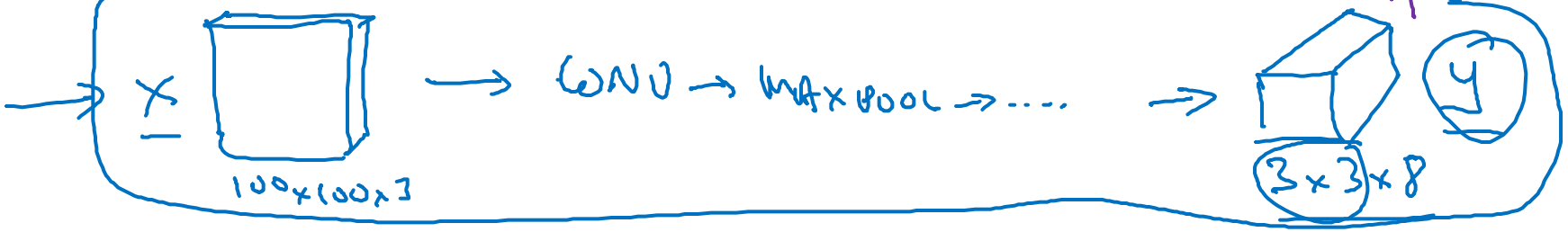
For each grid cell:



Target output:

3 × 3 × 8



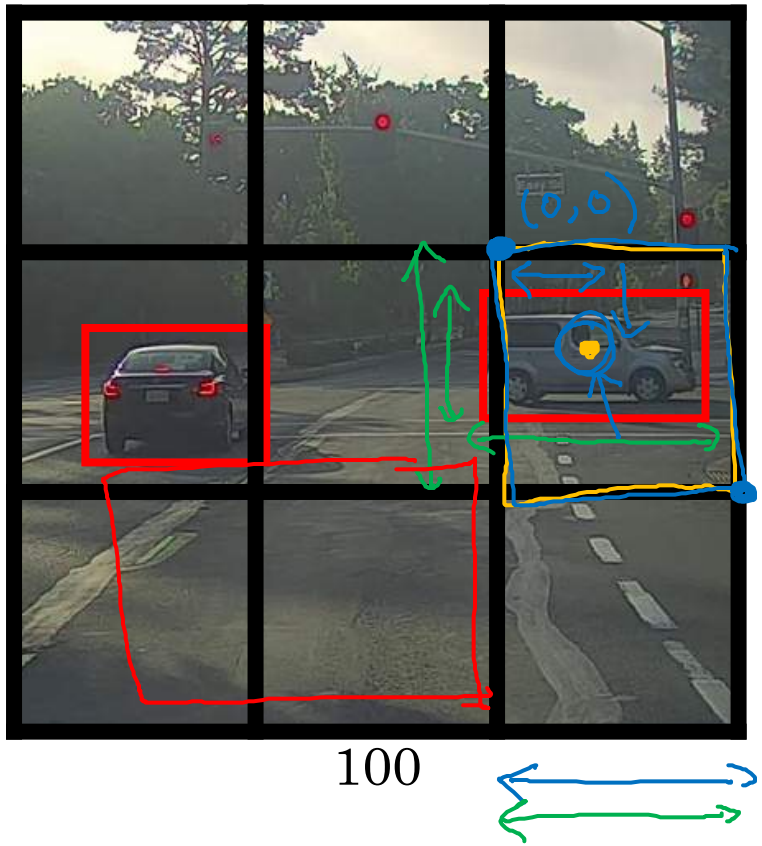


3 6 1

→ 19 × 19 × 8

[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, 0.9, 0.5 } between 0 and 1

could be > 1

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

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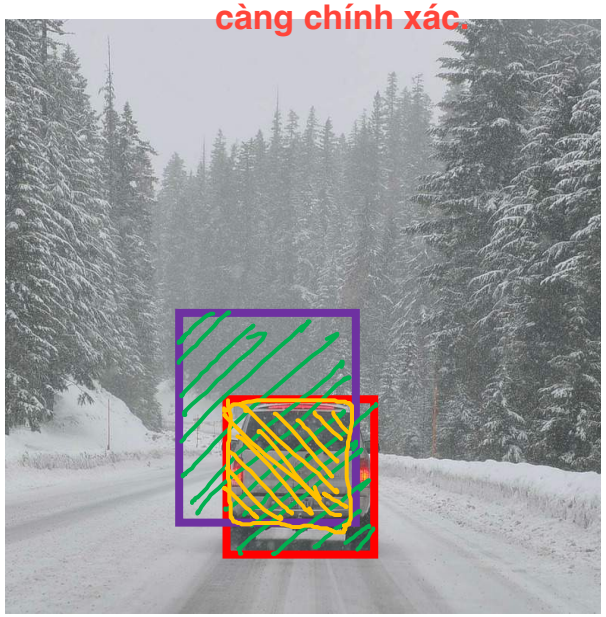
Object Detection

Intersection over union

Evaluating object localization

Để tính IoU, trước tiên, chúng ta tính diện tích phần hợp của hai hình chữ nhật, bằng "hình chữ nhật thứ nhất + hình chữ nhật thứ hai", sau đó tính diện tích giao nhau giữa hai hình chữ nhật này.

Cuối cùng, IOU = diện tích phần giao nhau/diện tích phần hợp. Nếu IOU >=0.5 thì tốt. Đáp án tốt nhất là 1. IOU càng cao thì càng chính xác.



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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Một trong những vấn đề mà chúng ta đã đề cập trong YOLO là nó có thể phát hiện một đối tượng nhiều lần. Non-max Suppression đảm bảo rằng YOLO sẽ chỉ phát hiện đối tượng một lần.

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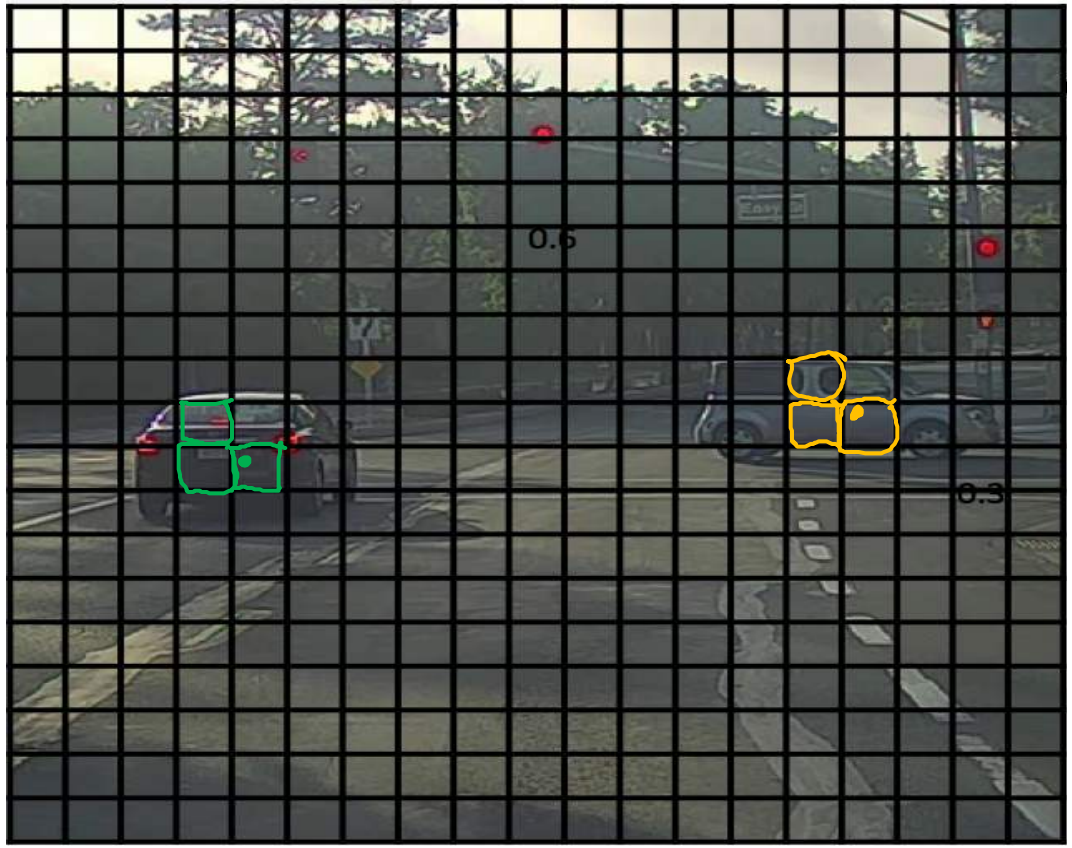
Object Detection

Non-max suppression

Non-max suppression example

Non-max suppression example



19×19

Non-max suppression example

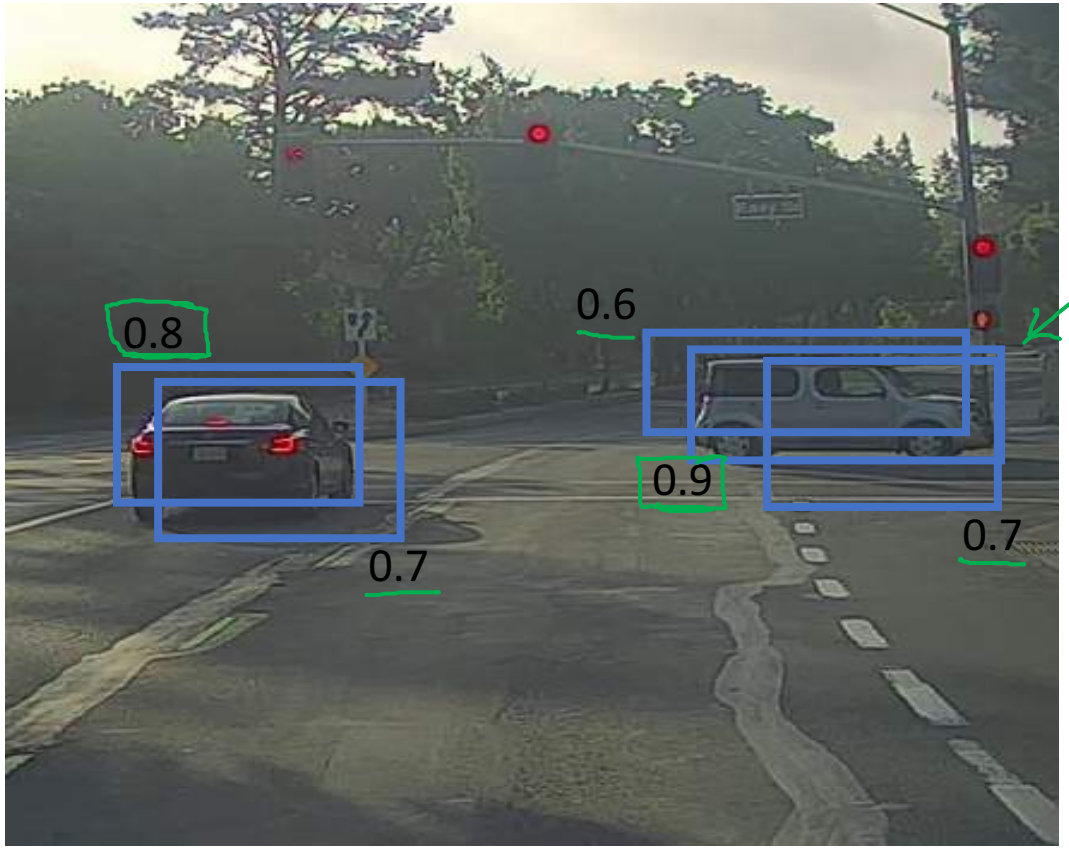
Giả sử chúng ta đang nhắm mục tiêu biến một lớp làm lớp đầu ra. Shape Y phải là [Pc, bx, by, bh, hw], trong đó Pc là xác suất xảy ra đối tượng đó. Loại bỏ tất cả các box có Pc <0.6

Trong các box còn lại:

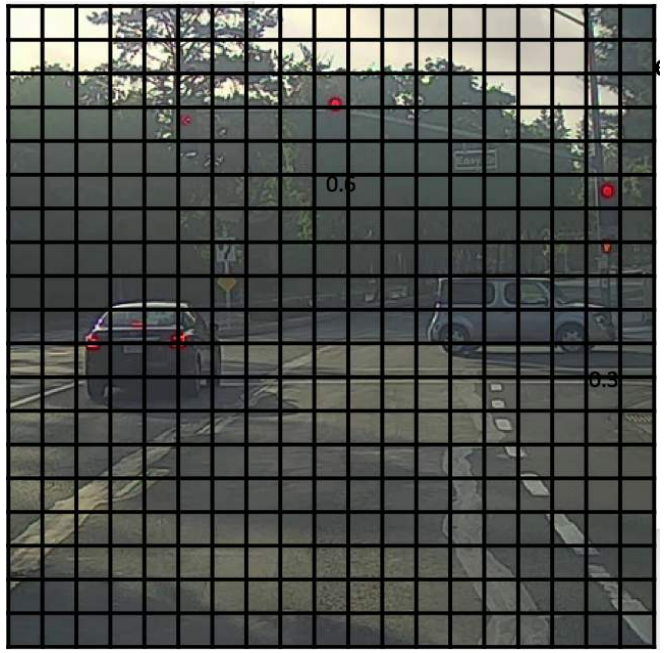
Chọn box có đầu ra Pc lớn nhất làm dự đoán.

Loại bỏ bất kỳ box còn lại nào có IoU > 0.5 với đầu ra của box đó ở bước trước, tức là bất kỳ box nào có độ chồng chéo cao (lớn hơn ngưỡng chồng chéo 0.5).

Nếu có nhiều lớp/kiểu đối tượng c cần phát hiện, nên chạy Non-max suppression c lần, mỗi lần cho một lớp đầu ra.



Non-max suppression algorithm



19×19

Each output prediction is:

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

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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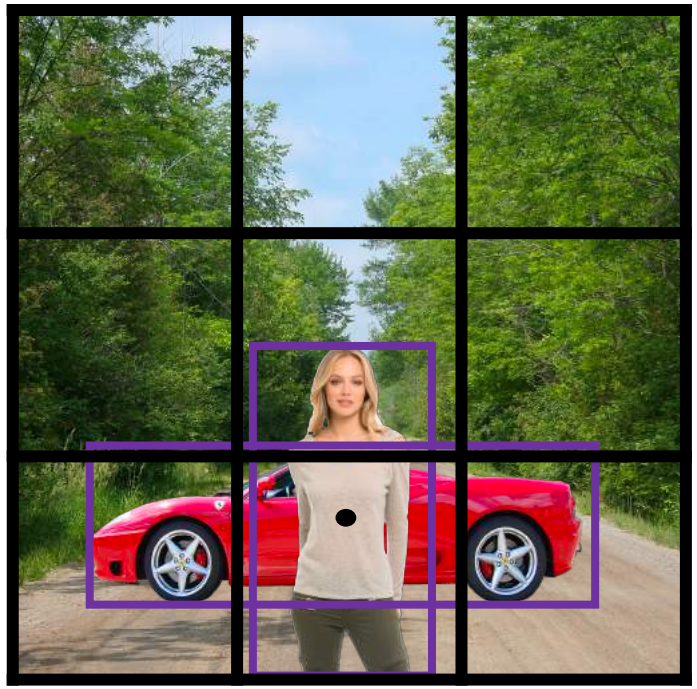
Object Detection

Anchor boxes

Trong YOLO, mỗi lưới chỉ phát hiện một đối tượng. Điều gì sẽ xảy ra nếu một ô lưới cần phát hiện nhiều đối tượng?

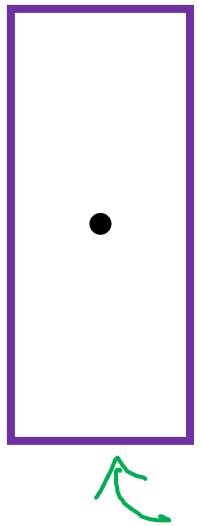
Làm thế nào để chọn các anchor box? Mọi người thường chọn thủ công, có thể chọn 5 hoặc 10 anchor box shape có hình dạng khác nhau liên quan tới các loại đối tượng thường được phát hiện. Bạn cũng có thể sử dụng thuật toán k-mean trên tập dữ liệu của mình để xác định điều đó. Anchor box cho phép thuật toán chuyên biệt hóa, nghĩa là trong trường hợp này có thể dễ dàng phát hiện hình ảnh rộng hơn hoặc cao hơn.

Overlapping objects:

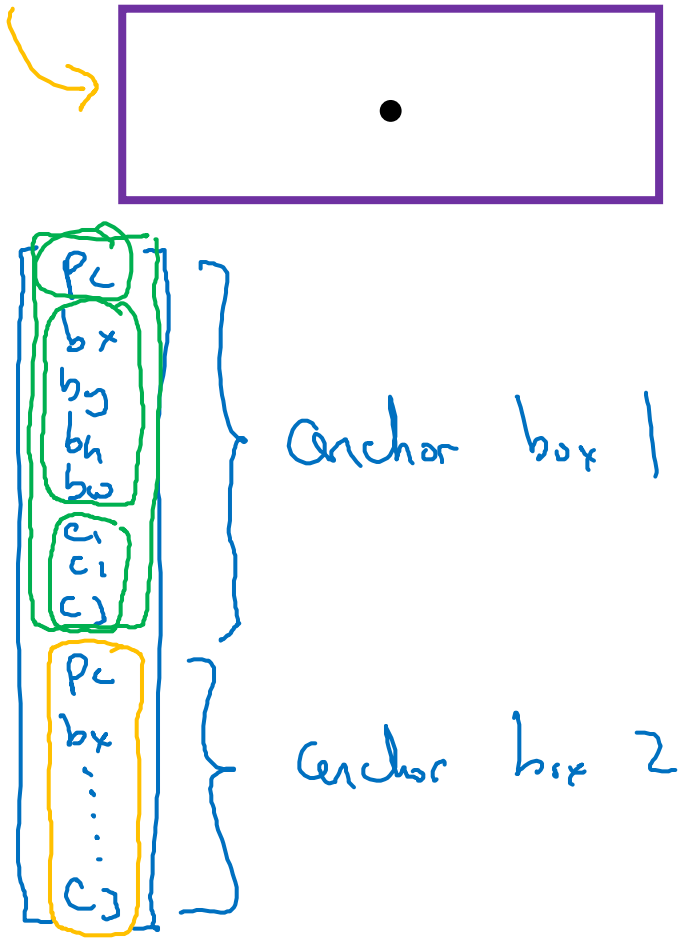


$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:



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

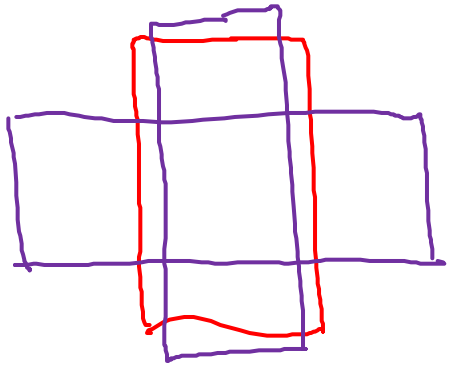
Anchor box algorithm

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.

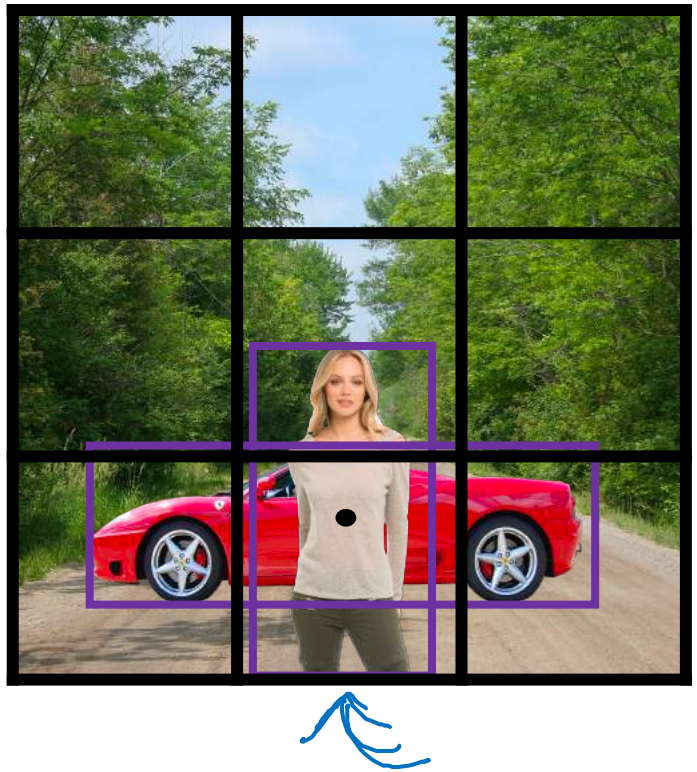
(grid cell, anchor box)

Output y:

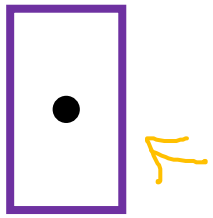
$3 \times 3 \times 16$

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

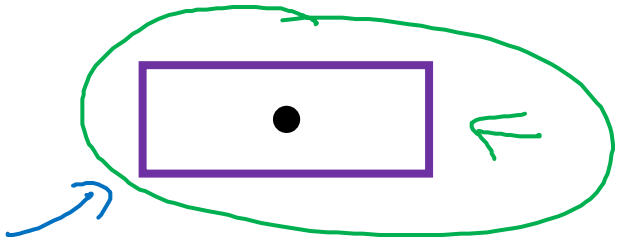
Anchor box example



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

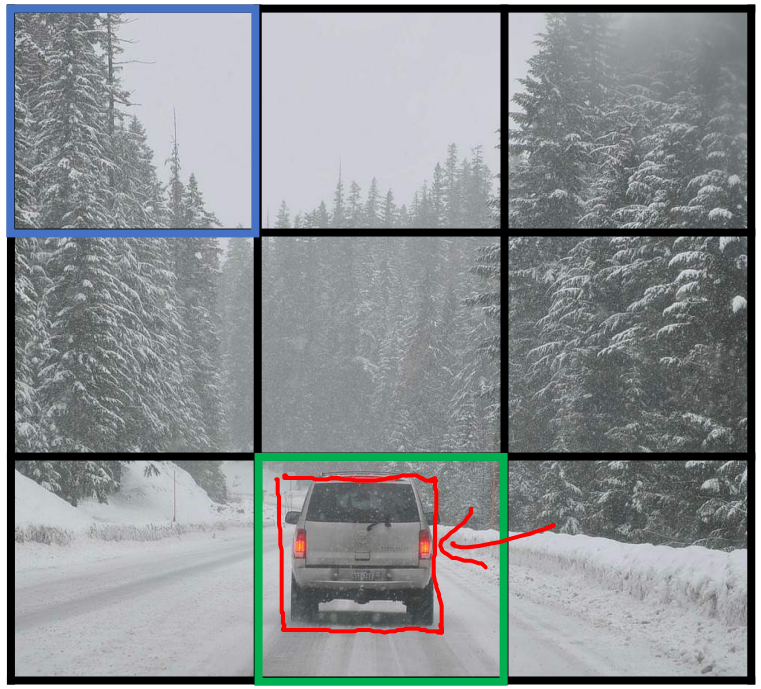
Putting it together: YOLO algorithm

Training

1 - pedestrian

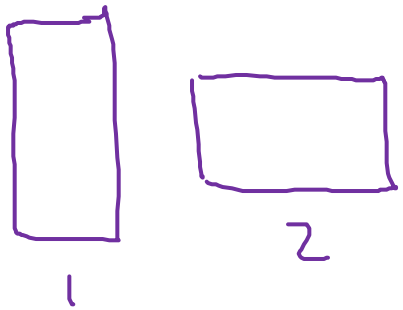
2 - car

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

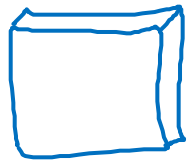
y is 3×3×2×8

19×19×16

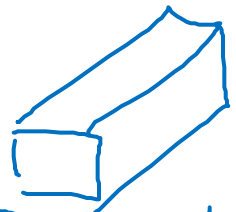
19×19×40

#anchors

5 + #classes

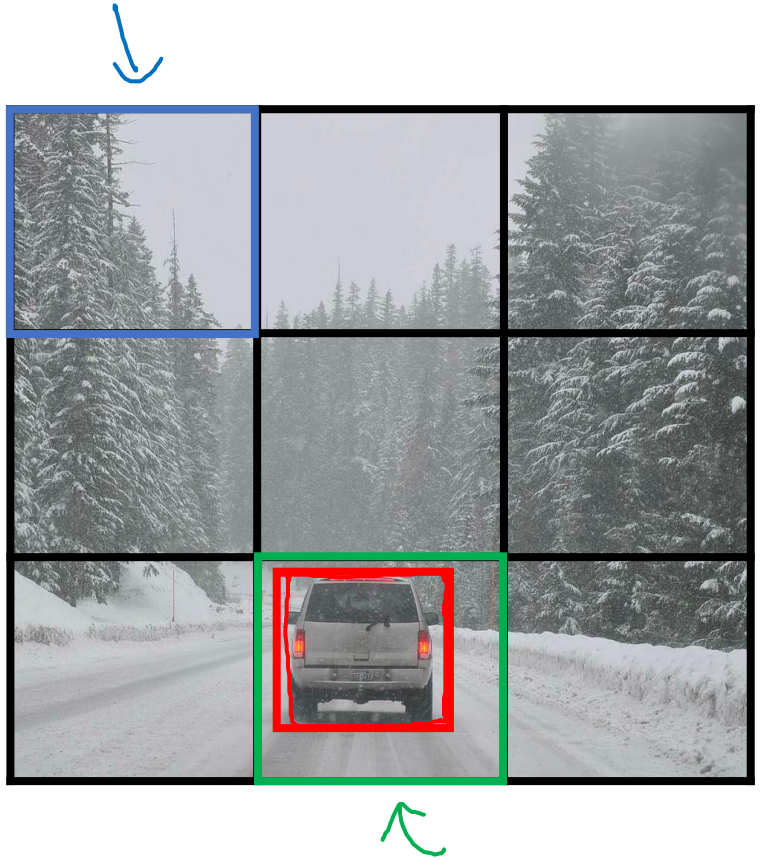


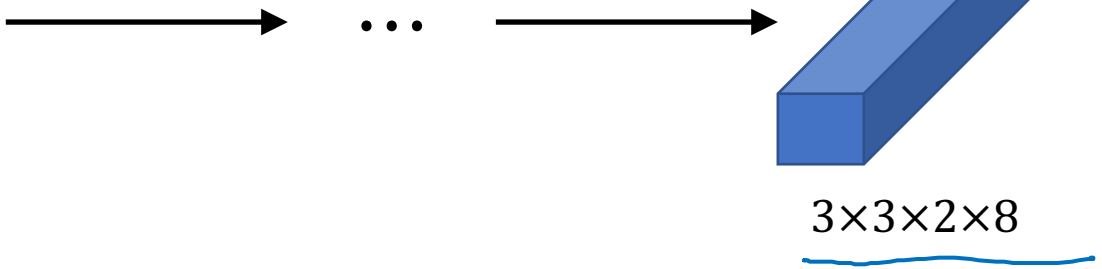
→ ConvNet →



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

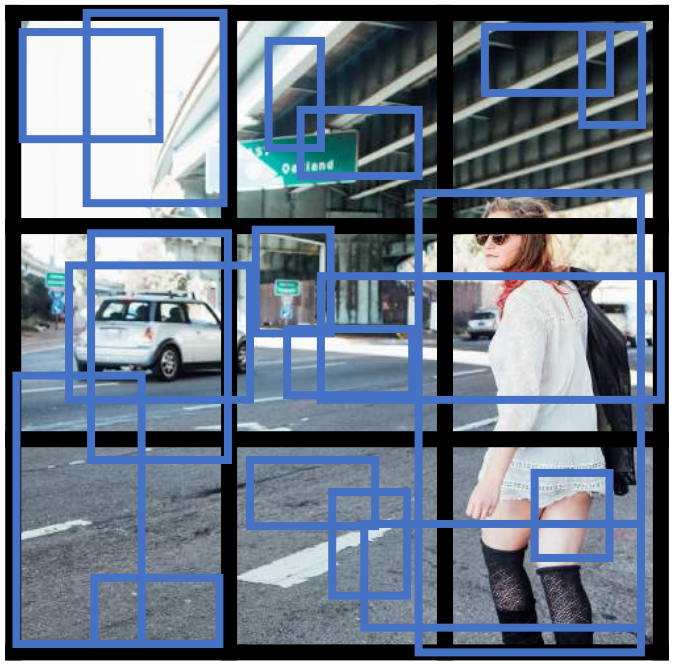
Making predictions





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

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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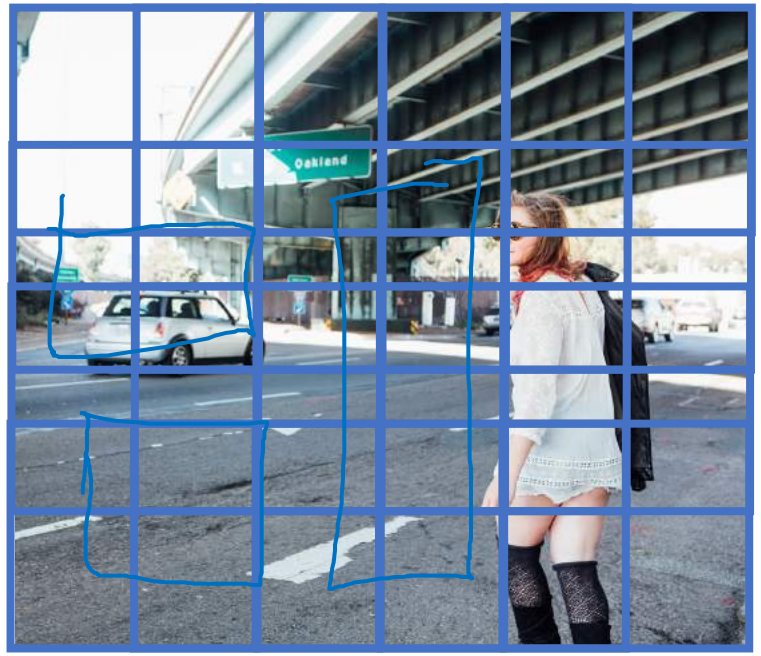
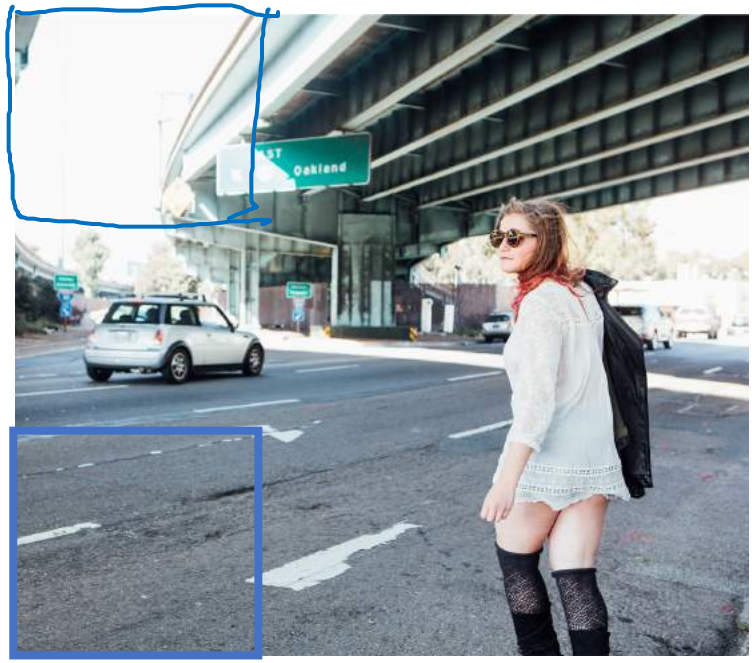
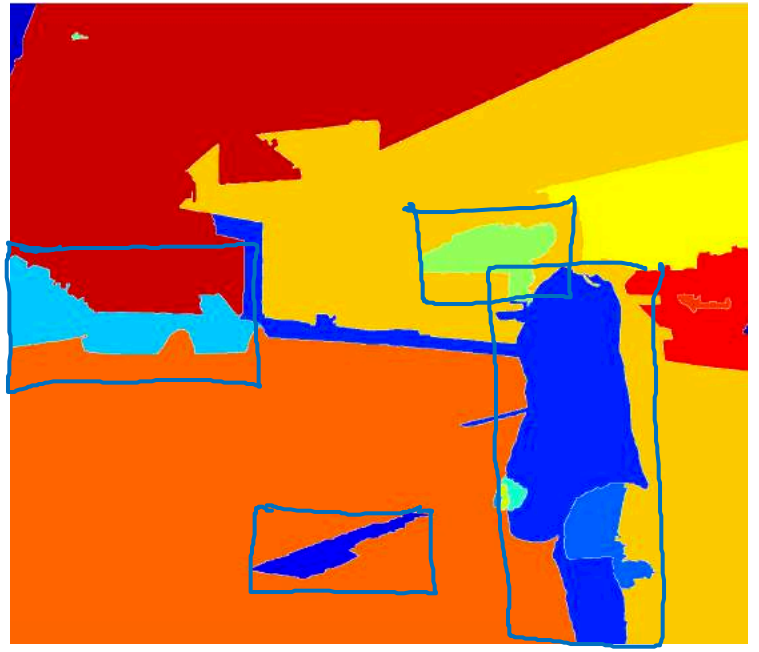
Object Detection

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.

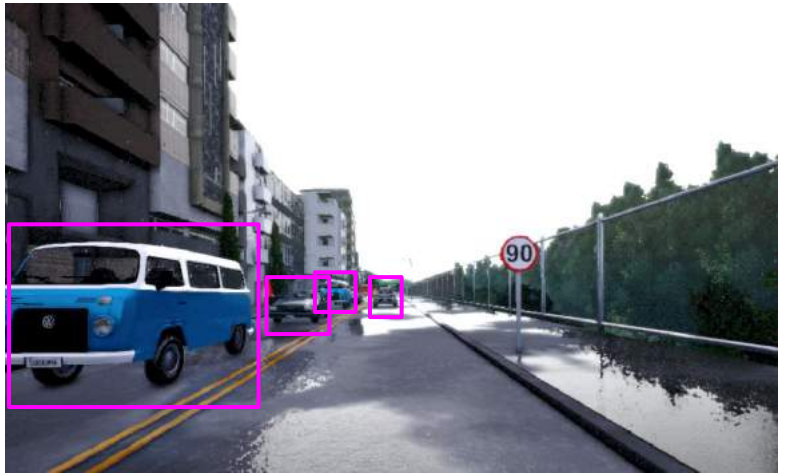
[Girshik et. al, 2013. Rich feature hierarchies for accurate object detection and semantic segmentation]
[Girshik, 2015. Fast R-CNN]
[Ren et. al, 2016. Faster R-CNN: Towards real-time object detection with region proposal networks]

Convolutional Neural Networks

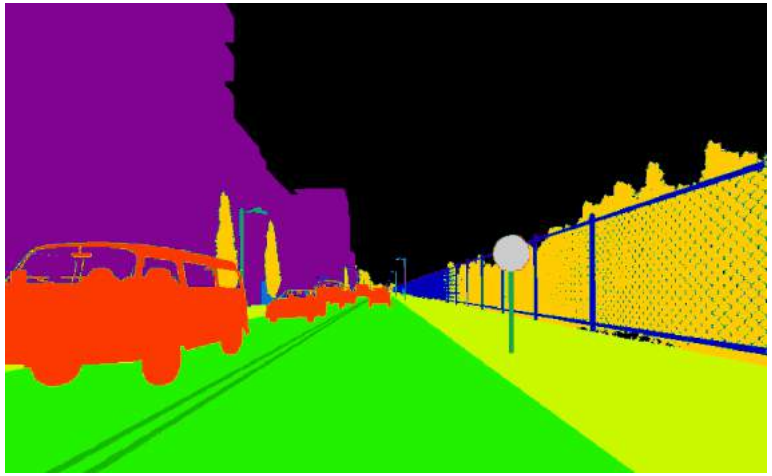
Semantic segmentation with U-Net

Object Detection vs. Semantic Segmentation

Input image

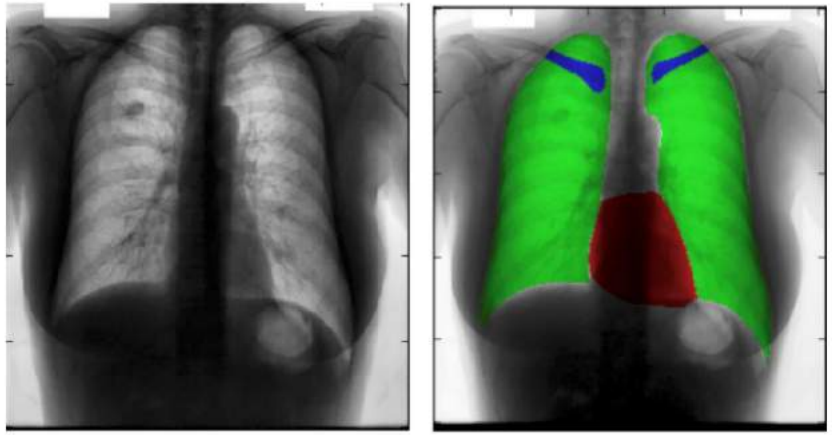


Object Detection

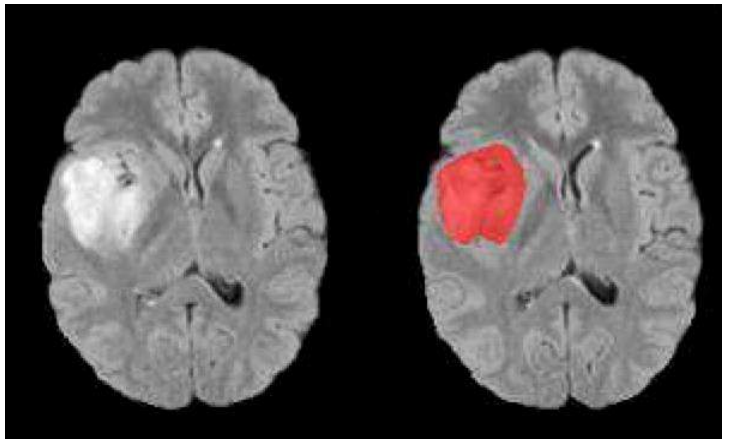


Semantic Segmentation

Motivation for U-Net



Chest X-Ray



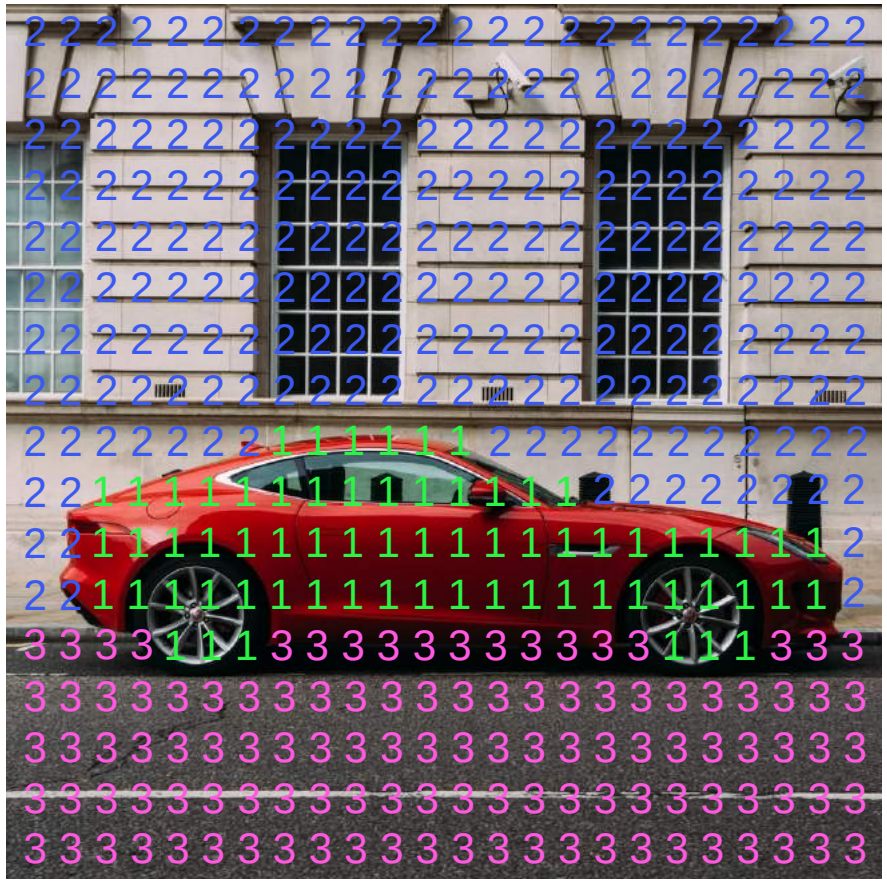
Brain MRI

[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

1. Car
0. Not Car

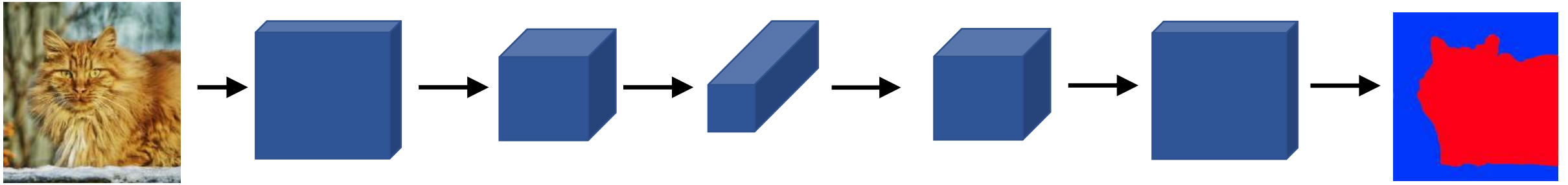
Per-pixel class labels



1. Car
2. Building
3. Road

Segmentation Map

Deep Learning for Semantic Segmentation



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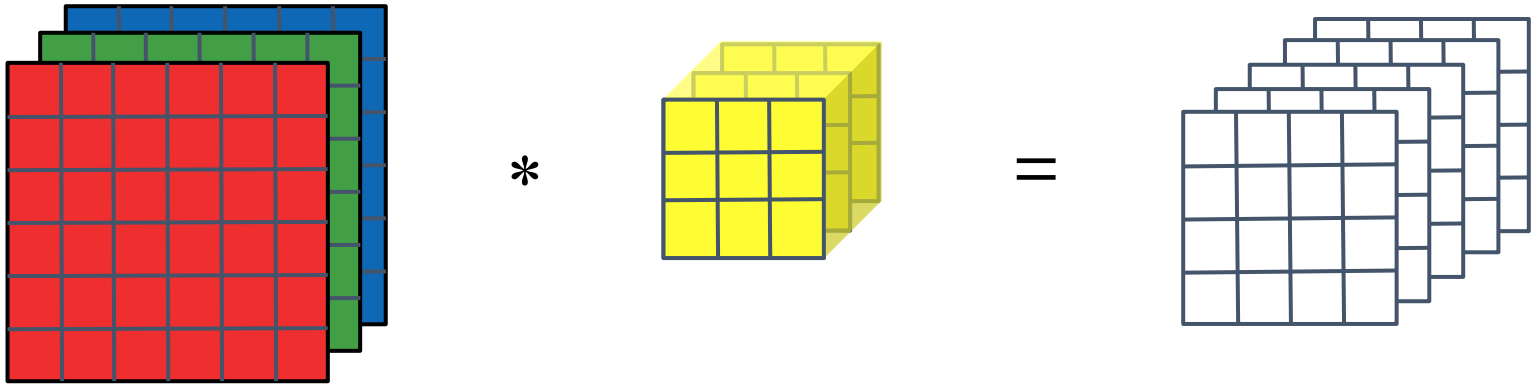
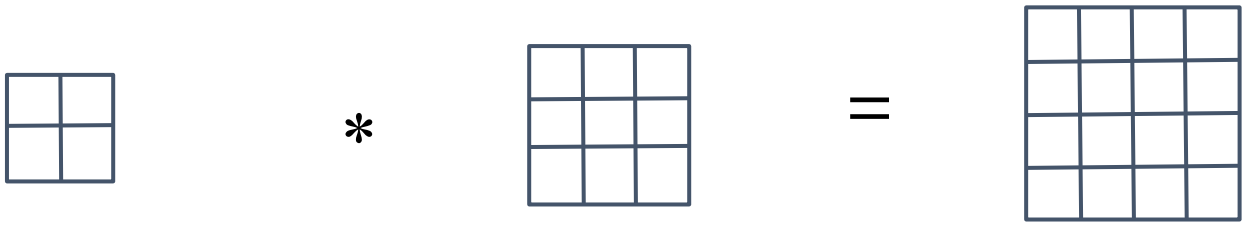
Transpose Convolution

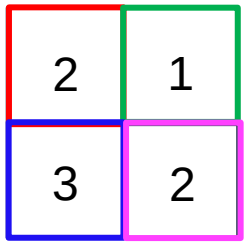
Normal Convolution



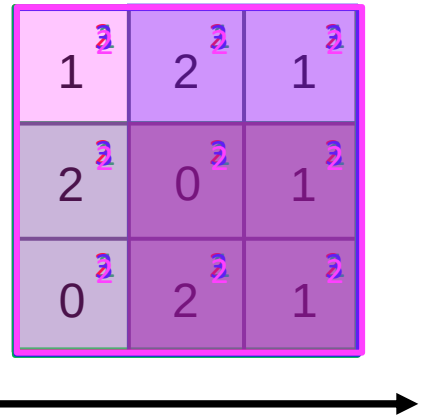
Transpose Convolution



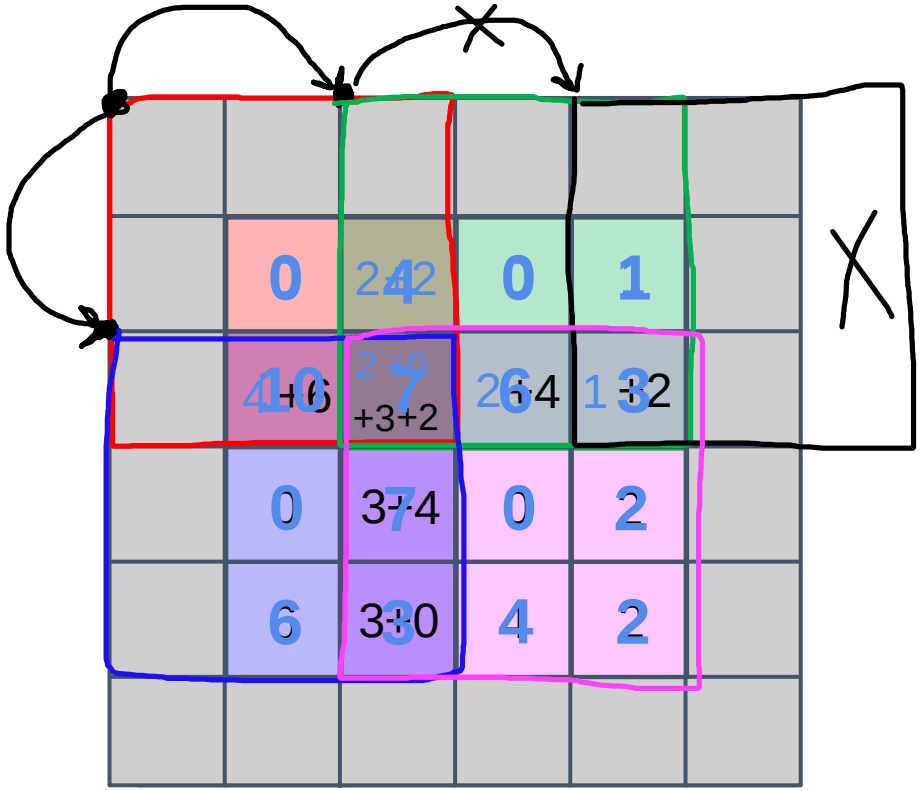
Transpose Convolution



2 x 2



weight filter



4 x 4

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

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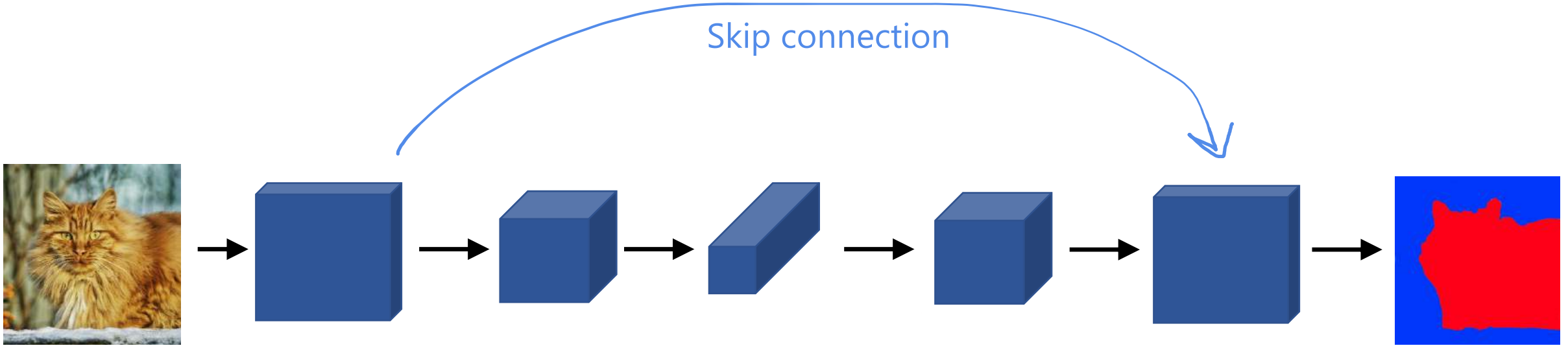
Deep Learning for Semantic Segmentation



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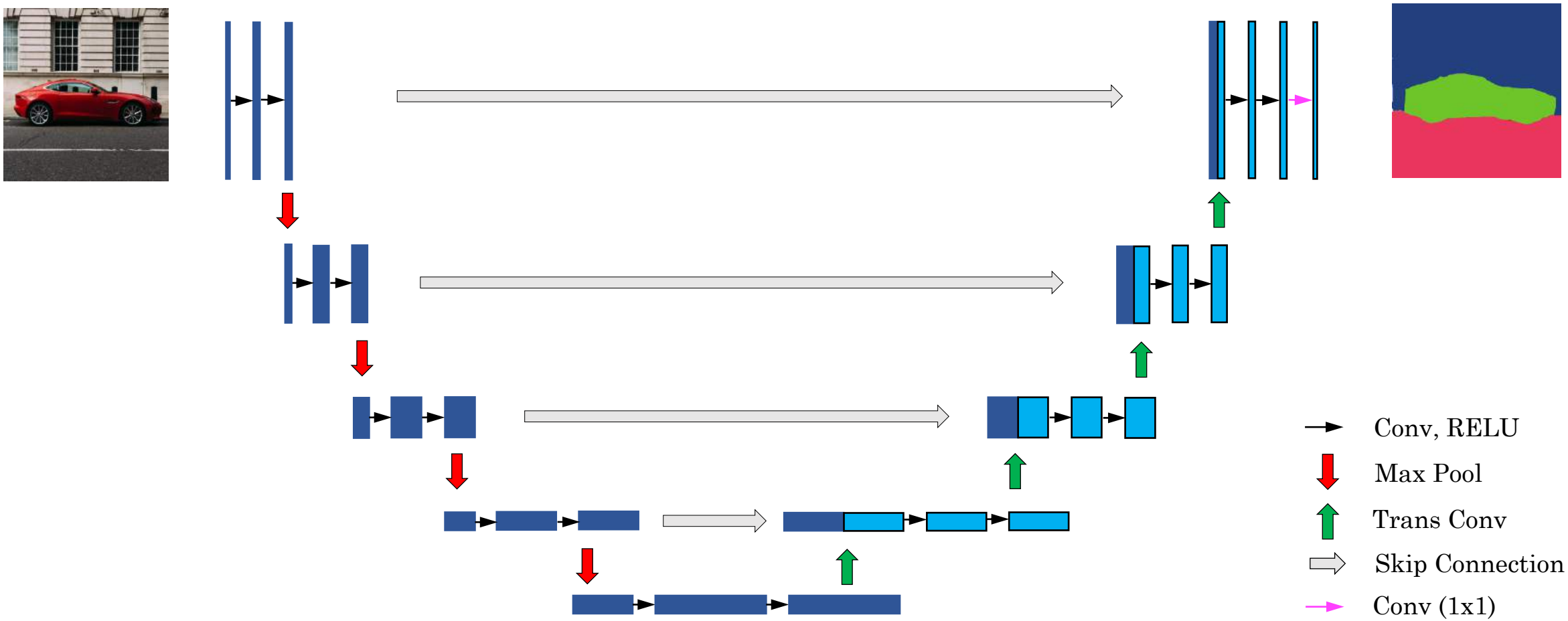
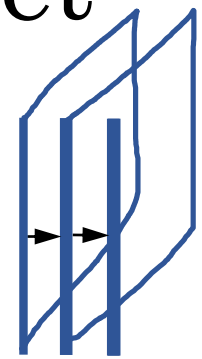
U-Net

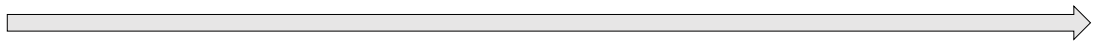


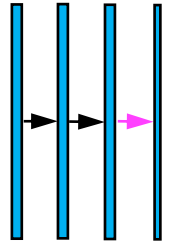
[Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation]

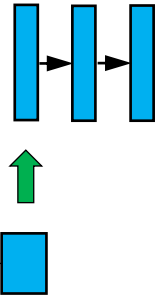
U-Net

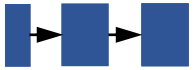
h x w x 3

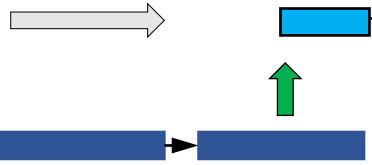


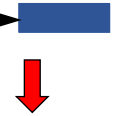


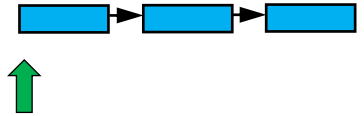




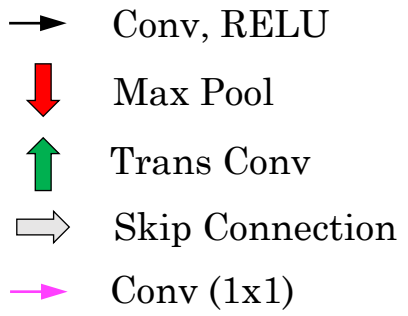








h x w x # classes



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

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