2D Object Detection With Convolutional Neural Networks

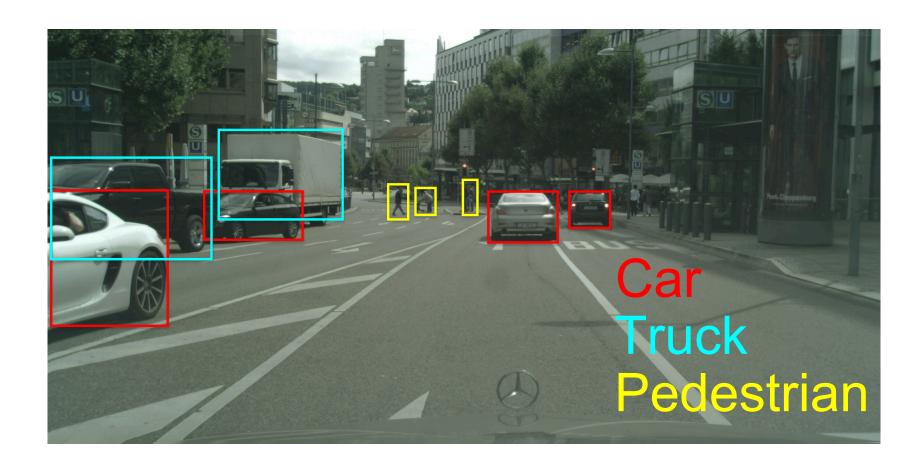
Course 3, Module 4, Lesson 2



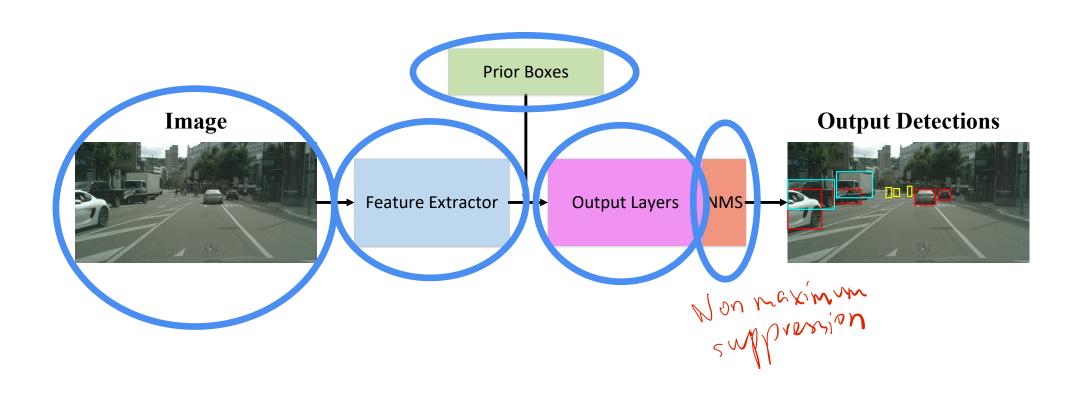
Learning Objectives

- Learn to build standard single stage architecture for 2D object detection
- Learn common neural network design choices for performing 2D object detection using the proposed architecture

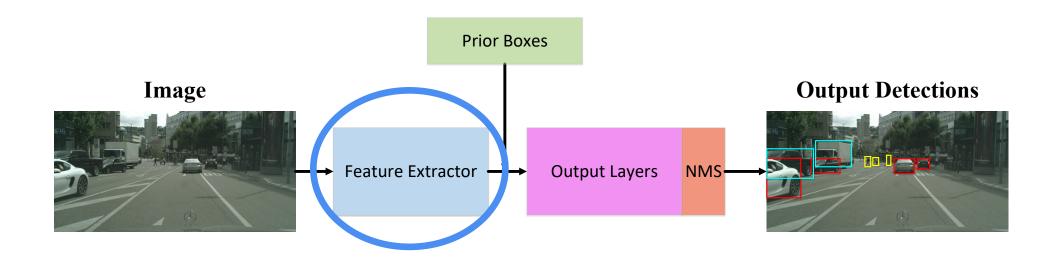
The Object Detection Problem



ConvNets For 2D Object Detection



The Feature Extractor



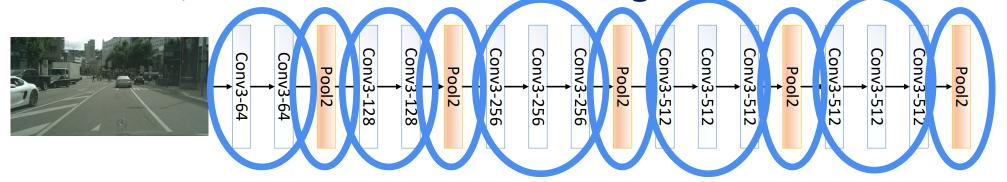
The Feature Extractor

 Feature extractors are the most computationally expensive component of the 2D object detector 90% conjutation

- The output of feature extractors usually has much lower width and height than those of the input image, but much greater depth
- Very active area of research, with new extractors proposed on regular basis
- Most common extractors are: VGG, ResNet, and Inception

VGG Feature Extractor

- Alternating convolutional and pooling layers
- All convolutional layers are of size 3x3xK, with stride 1 and 1 zero-padding
- All pooling layers use the max function, and are of size 2x2, with stride 2 and no padding



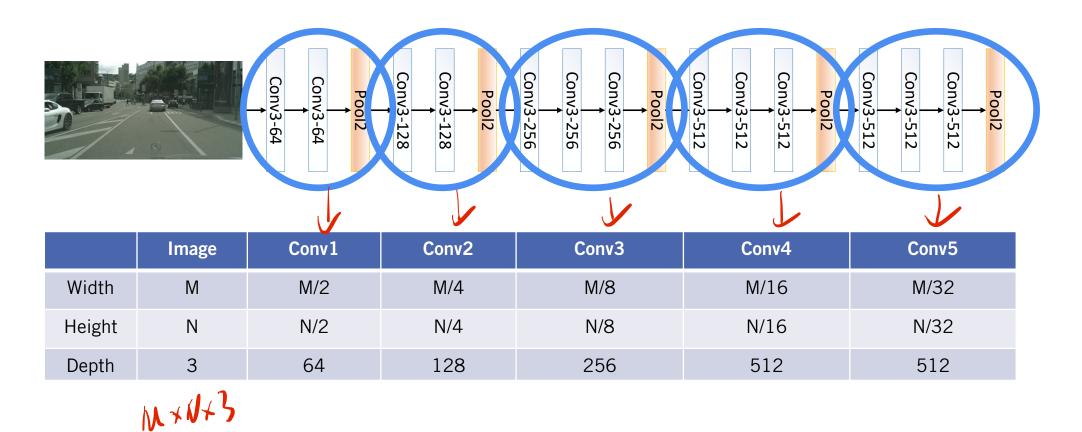
VGG Feature Extractor

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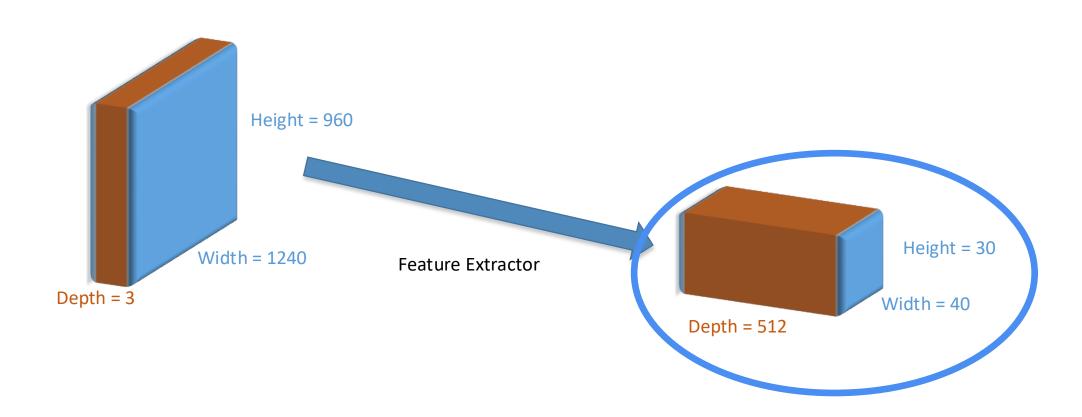
$$\begin{array}{l}
\mathbf{1}_{\circ} \mathbf{IP}_{out} = \mathbf{P}_{out}^{\mathbf{W}_{in}} \mathbf{P}_{out}^{\mathbf{Y}_{out}} + 1 \\
\mathbf{0}_{out} = \mathbf{P}_{out}^{\mathbf{W}_{in}} \mathbf{P}_{out}^{\mathbf{Y}_{out}} + 1 = \mathbf{P}_{in}^{\mathbf{W}_{in}} \mathbf{P}_{out}^{\mathbf{Y}_{out}} + 1 = \mathbf{W}_{in}^{\mathbf{H}_{in} - 3 + 2 \times 1} \\
\mathbf{0}_{out} = \mathbf{K}_{s}^{\mathbf{H}_{in} - m + 2 \times P} + 1 = \mathbf{H}_{in}^{\mathbf{H}_{in} - 3 + 2 \times 1} \\
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\mathbf{0}_{out} = \mathbf{H}_{in}^{\mathbf{H}_{in} - m + 2$$

- All pooling layers use the max function, and are of size 2x2, with stride 2 and no padding.
 - $OW_{out} = \frac{W_{in} m}{S} + 1 = \frac{W_{in} 2}{2} + 1 = \frac{W_{in}}{2}$ $OH_{out} = \frac{H_{in} m}{S} + 1 = \frac{H_{in} 2}{2} + 1 = \frac{H_{in}}{2}$ $OD_{out} = D_{in}$

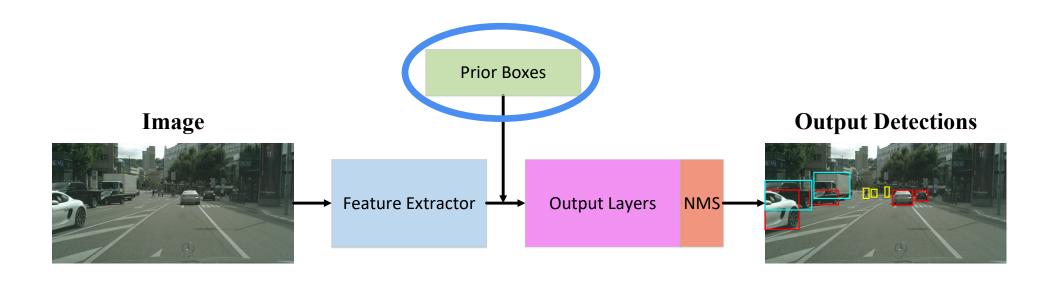
The Feature Extractor



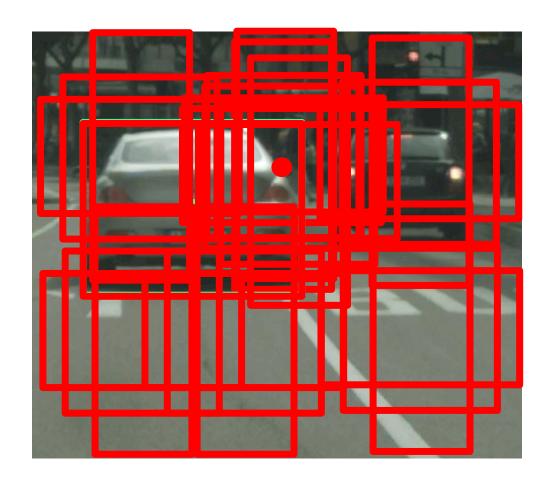
Output Volume Shape



Prior/Anchor Bounding Boxes

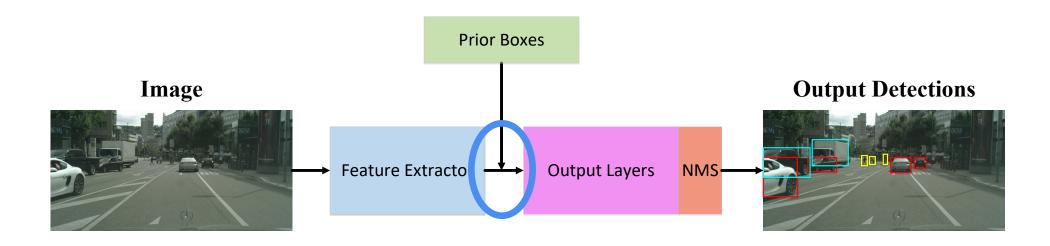


Prior/Anchor Bounding Boxes



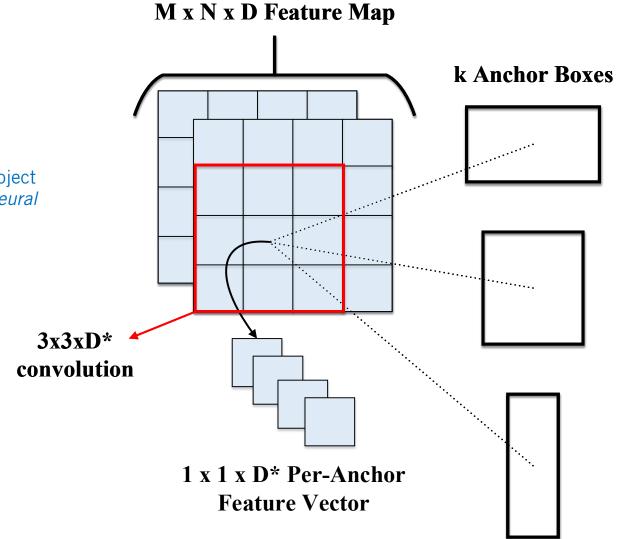
residual learning

Prior/Anchor Bounding Boxes

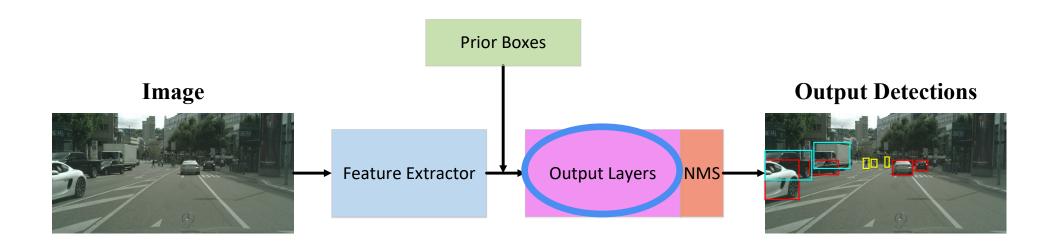


Using Anchor Boxes

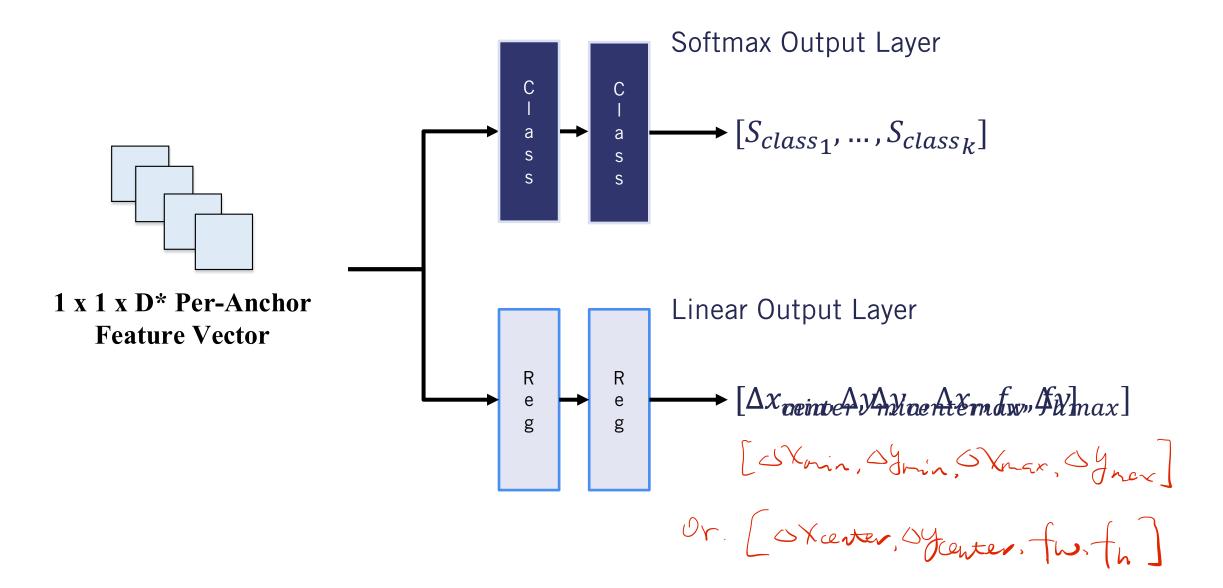
Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." *Advances in neural information processing systems*. 2015



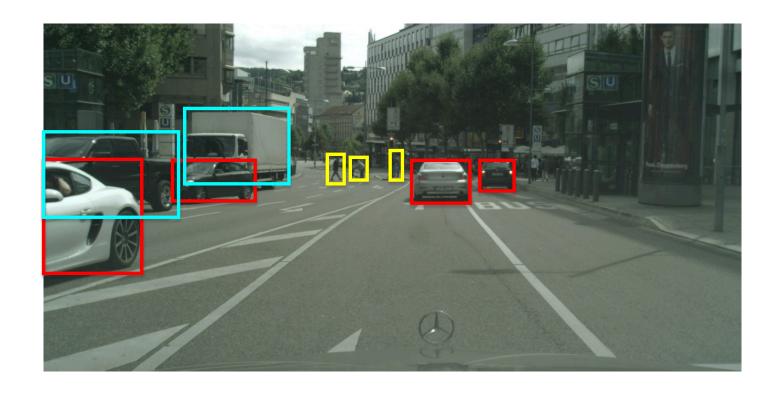
Output Layers



Classification VS Regression Heads



Output handling



Summary

- 2D object detectors can be performed using convolutional neural networks
- Usually, anchor boxes are used as priors for the neural network to shift around to achieve object classification and localization

Next: Training vs Inference