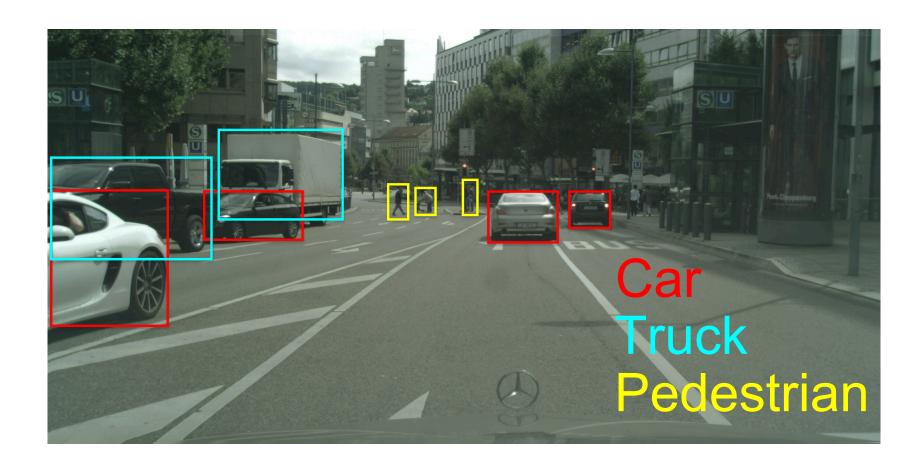
2D Object Detection With Convolutional Neural Networks

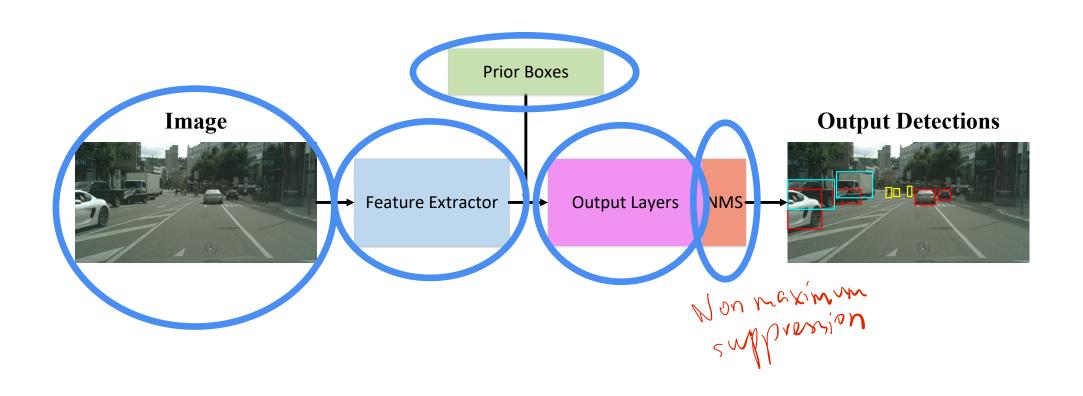
Course 3, Module 4, Lesson 2



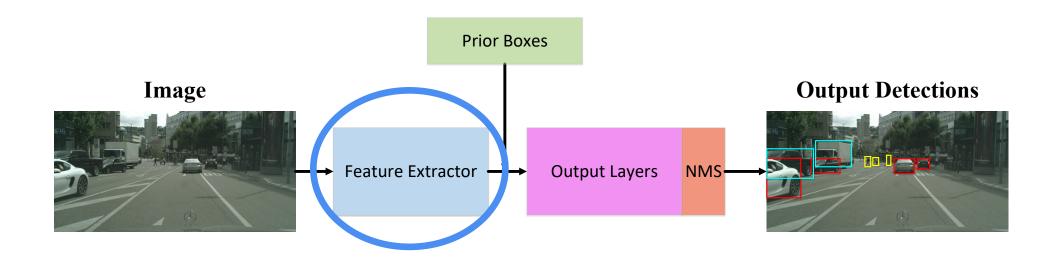
The Object Detection Problem



ConvNets For 2D Object Detection



The Feature Extractor



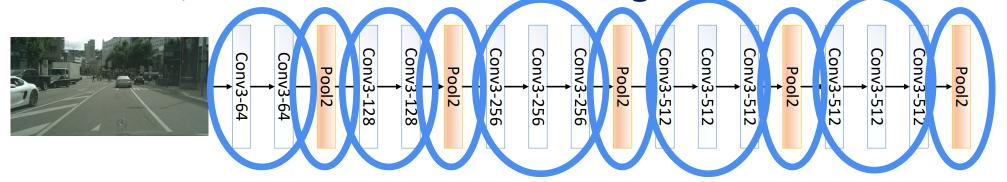
The Feature Extractor

 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



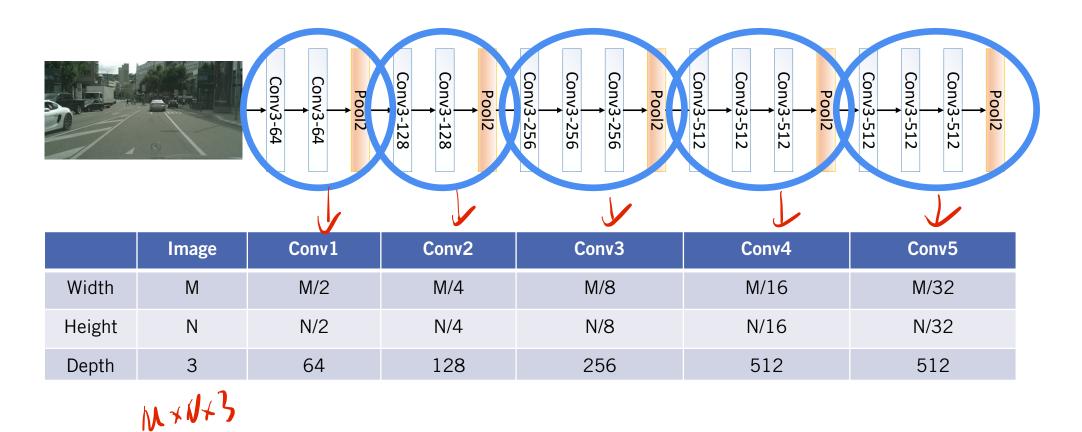
VGG Feature Extractor

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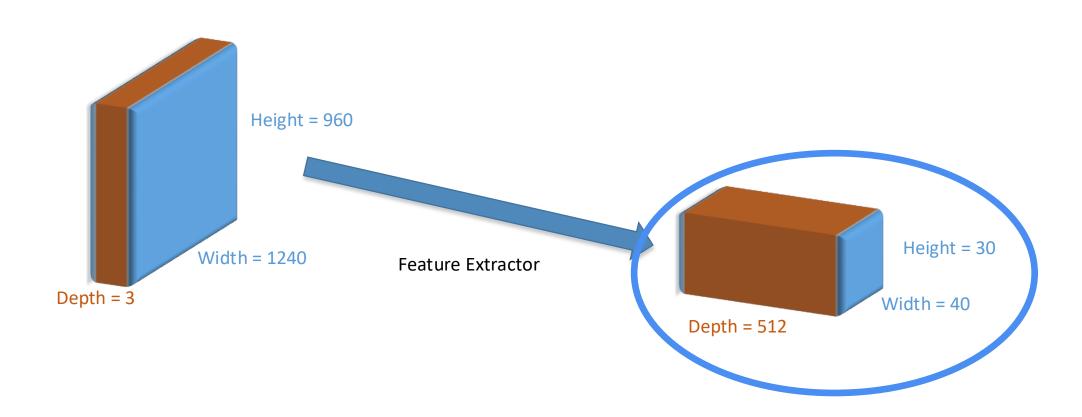
$$\begin{array}{l}
\mathbf{1}_{\circ} \mathbf{IP}_{out} = \mathbf{P}_{out}^{\mathbf{W}_{in}} \mathbf{P}_{out}^{\mathbf{Y}_{out}} + 1 \\
\mathbf{0}_{out} = \mathbf{P}_{out}^{\mathbf{W}_{in}} \mathbf{P}_{out}^{\mathbf{Y}_{out}} + 1 = \mathbf{P}_{in}^{\mathbf{W}_{in}} \mathbf{P}_{out}^{\mathbf{Y}_{out}}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

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

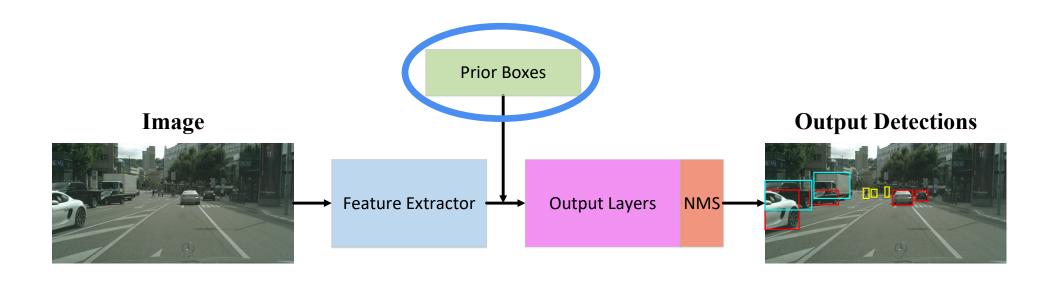
The Feature Extractor



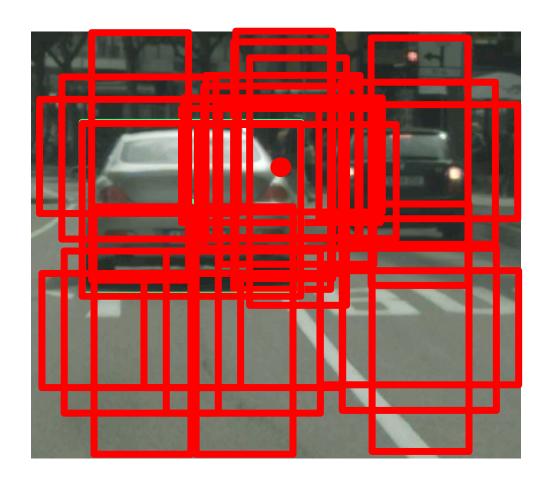
Output Volume Shape



Prior/Anchor Bounding Boxes

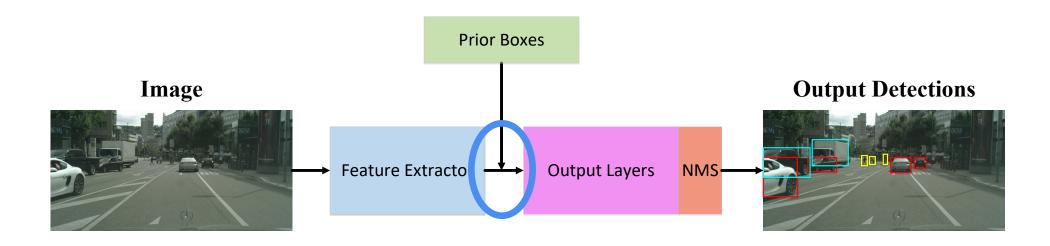


Prior/Anchor Bounding Boxes



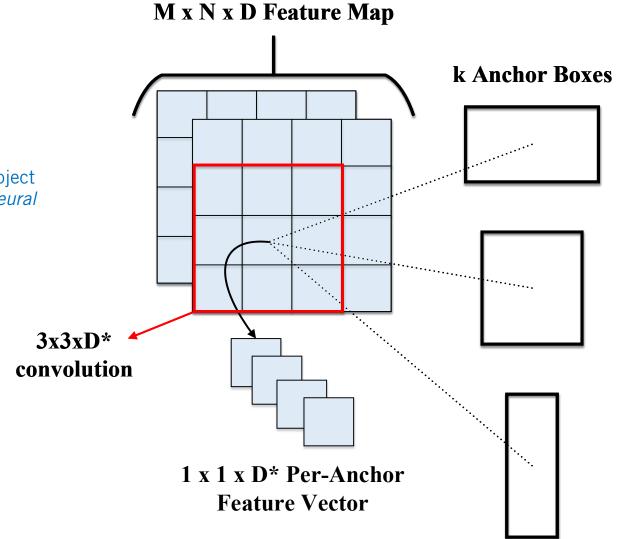
residual learning

Prior/Anchor Bounding Boxes

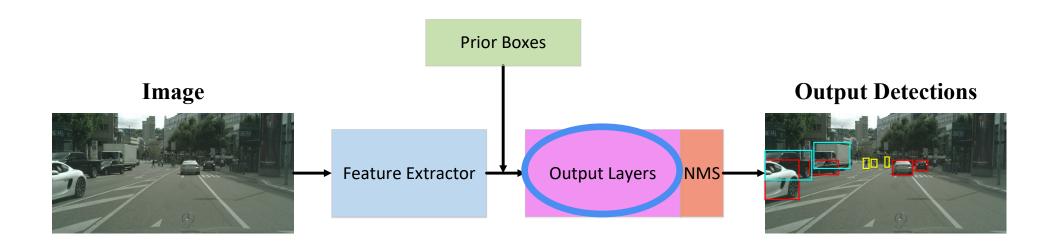


Using Anchor Boxes

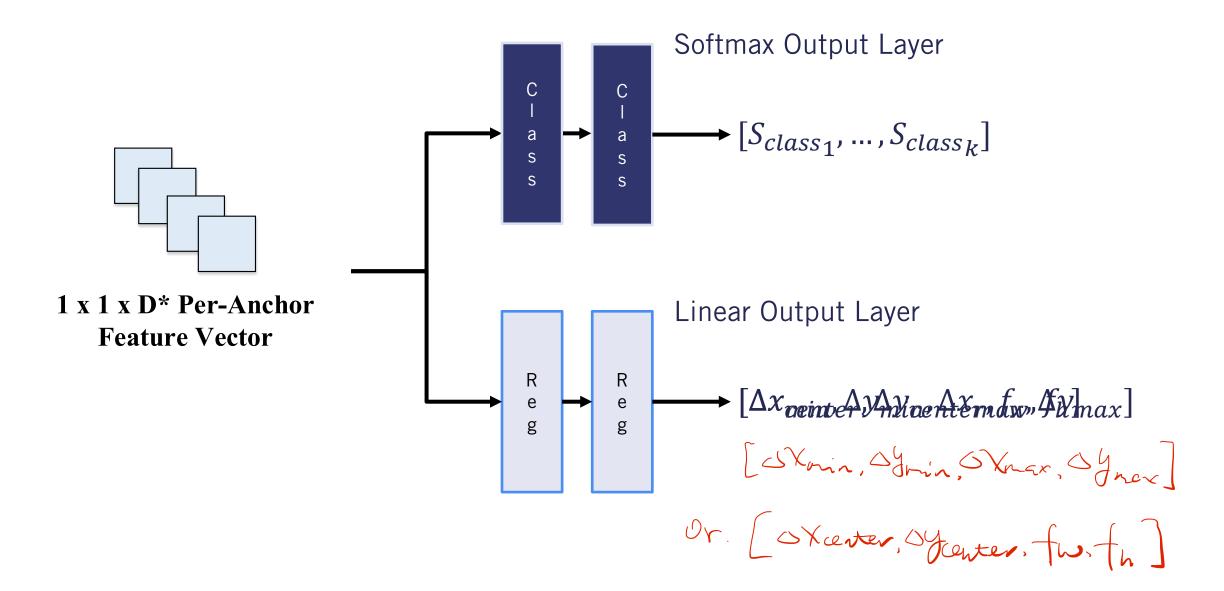
Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." *Advances in neural information processing systems*. 2015



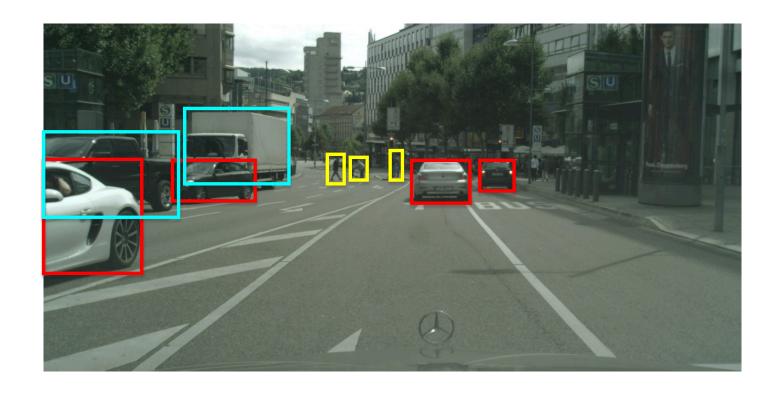
Output Layers



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