Neural Networks for Images

How to see like a human

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#DeepLearning

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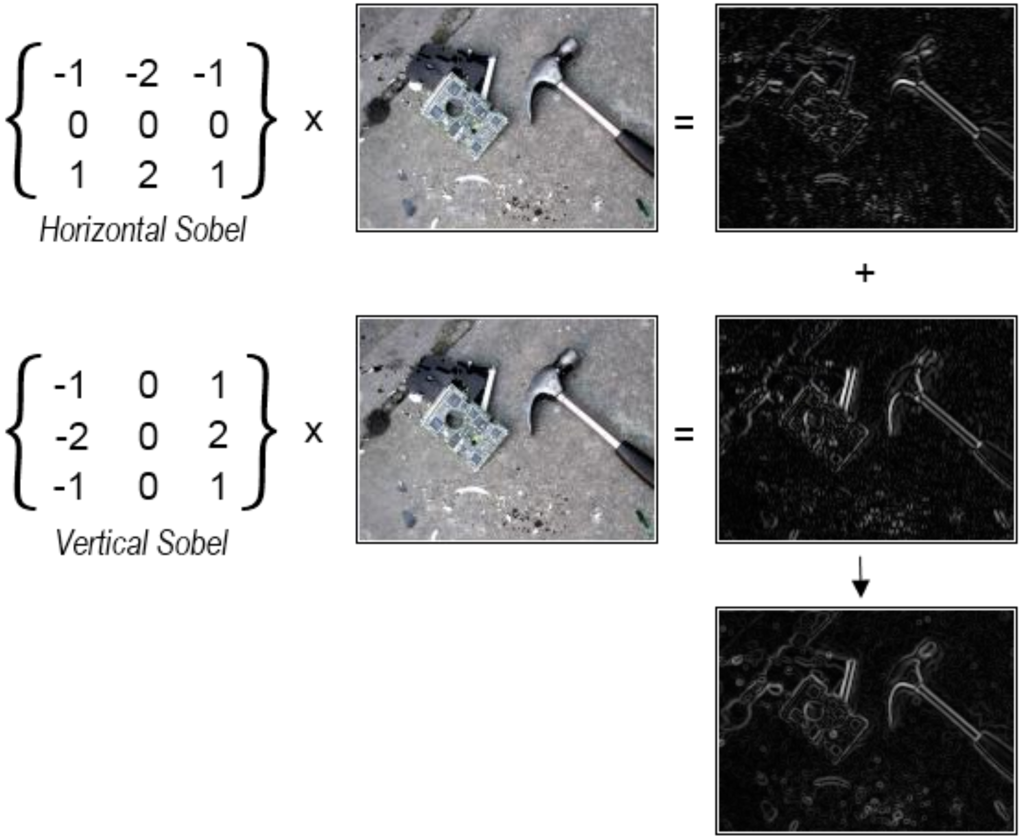
Convolutional Neural Networks

Learning from images

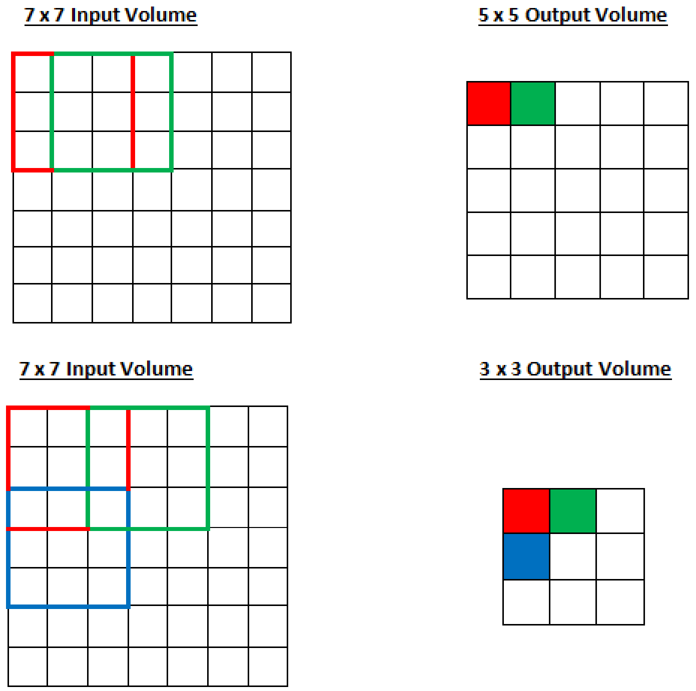
Convolution

- Given an image I and a filter F, $\mathrm{R} = I \circledast F$ is defined as
    - For each pixel (i,j), $R_{ij} = \sum\left(I_{ij} * F\right)$
- Depending on F, the result has different meanings
    - Example: Sobel edge detection
- F is usually square, with odd rank (so that it has a central pixel)
    - E.g., 3, 5, 7



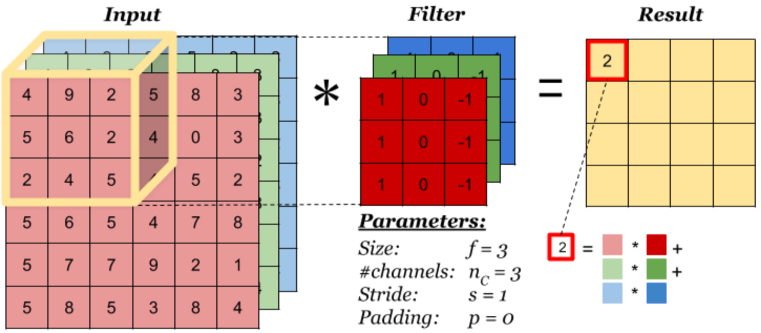
Convolution (2)

- Padding
  - "Valid convolution": no padding
  - "Same convolution": pad so that the output size remains unchanged: $p = \frac{f-1}{2}$, f – filter size
- Sliding window: stride s
  - How many pixels we should skip
- Summary
  - Input
    - $n \times n$ image
    - $f \times f$ filter
    - padding p
    - stride s
  - Output image dimensions: $\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$
  - If the image is non-square, adjust the dimensions in the formula



Convolution over Volume

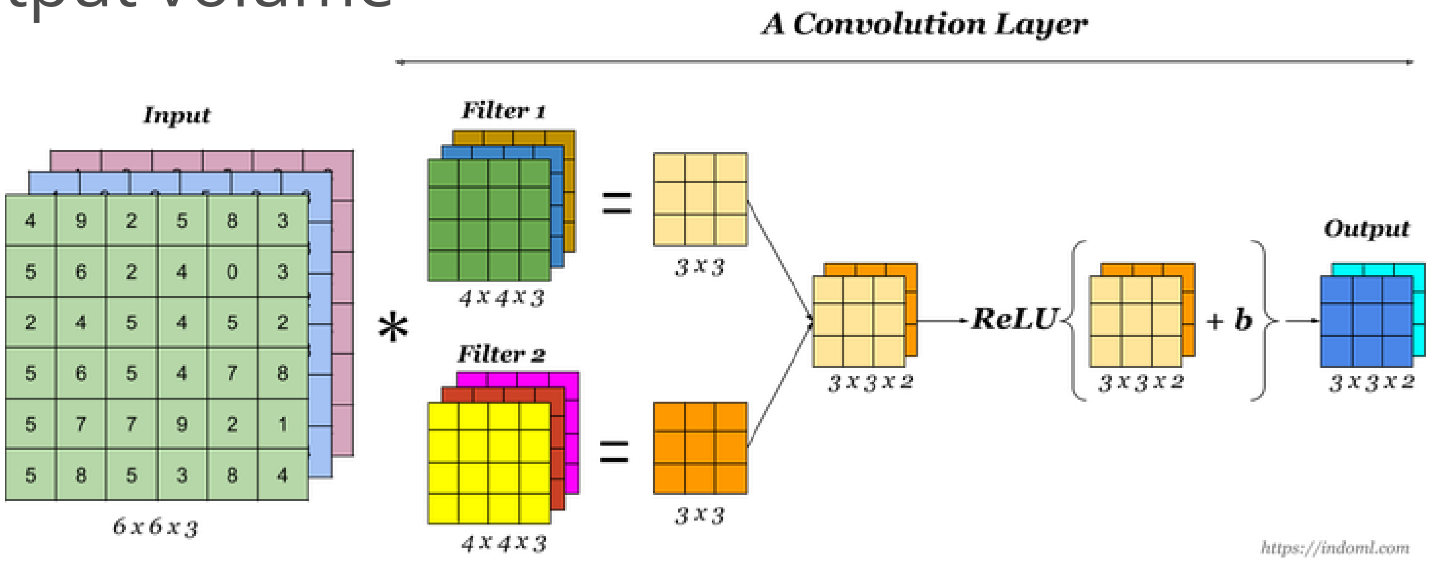
- If the image has many channels with dimensions $n \times n \times c$, just use an $f \times f \times c$ filter
  - I.e. apply the operation independently for each channel
  - Result: 2D image
- Many filters
  - Each one produces a 2D image
  - Stack them together (since they're independent) $\Rightarrow$ 3D volume



- The convolution operations we use operate over 3D volumes

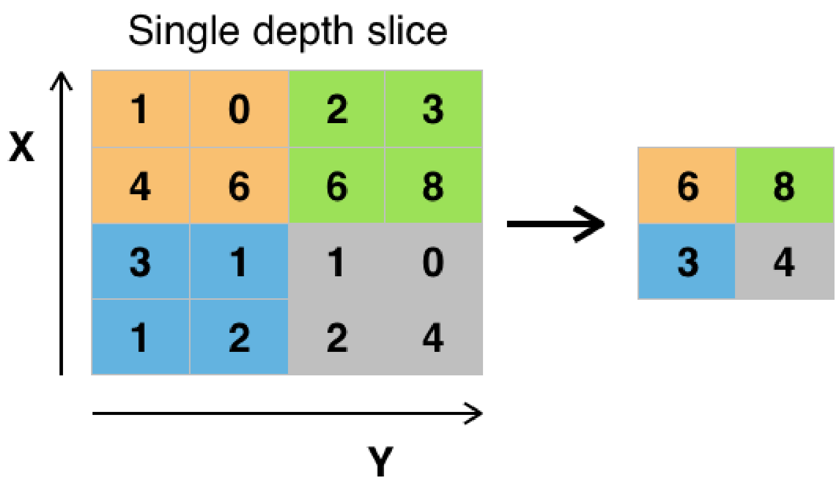
Convolutional Layers

- Just like a regular network
  - Input volume dimensions $n \times n \times c$
  - Choose f, n_f (number of filters), p, s
  - Learn each value of the filters, apply bias terms
  - Add non-linearity (e.g. ReLU)
    - Convolutions are linear operations
    - Sometimes, the convolution and activation layers are shown separately
  - Produce output volume



Pooling

- Used to reduce the number of parameters in the next layers
- Applied like convolution
- Parameters: window size f, stride s, operation
  - Most commonly used operation: max (max-pooling)
  - In the past: avg-pooling was also widely used
  - Other operations are possible but uncommon
- No trainable parameters



Why Do Convolutions Work?

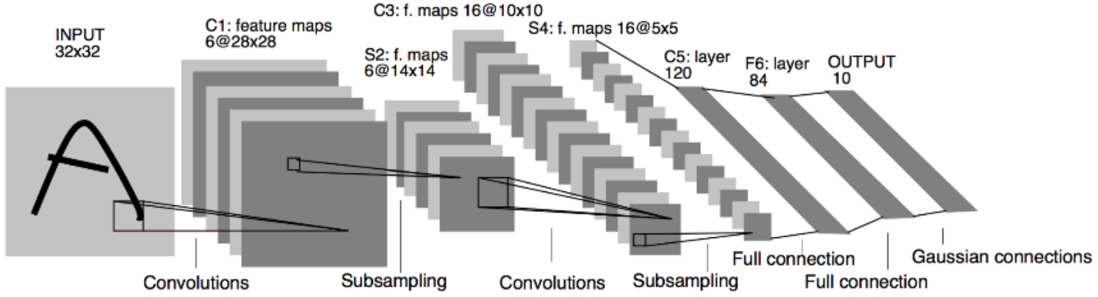
- Image assumptions
  - Individual features are relatively localized
  - The relative (not absolute) position of features is really important
- Convolutions help us to share computations
  - An edge detector is useful in many parts of the image
- Each filter has a low-dimensional input
  - Simplifies computations
- Visualizing and Understanding Convolutional Networks, Matthew Zeiler, 2014

Convolutional Layer Architecture

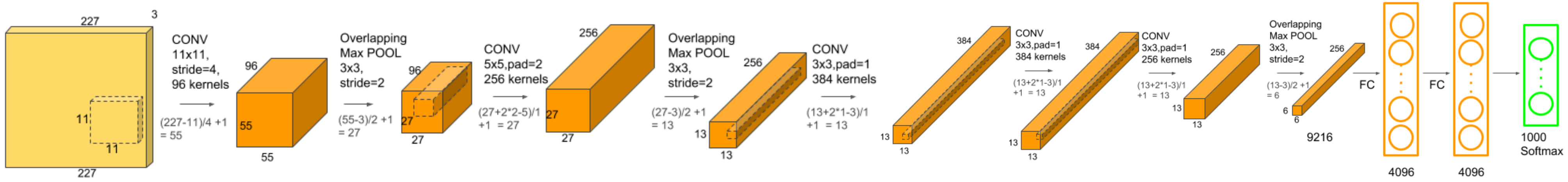
- Input volume: $h \times w \times c$
- Parameters: f, p, s, n_f
- $h' = \left\lfloor \frac{h+2p-f}{s} + 1 \right\rfloor, w' = \left\lfloor \frac{w+2p-f}{s} + 1 \right\rfloor$
- Filter dimensions: $f \times f \times c$, total of n_f filters
- Weights, biases: like fully-connected layers
  - $W = f \times f \times c \times n_f, b = 1 \times 1 \times 1 \times n_f$
- After computing, apply activation function
- Output volume: $h' \times w' \times n_f$

Convolutional Neural Networks

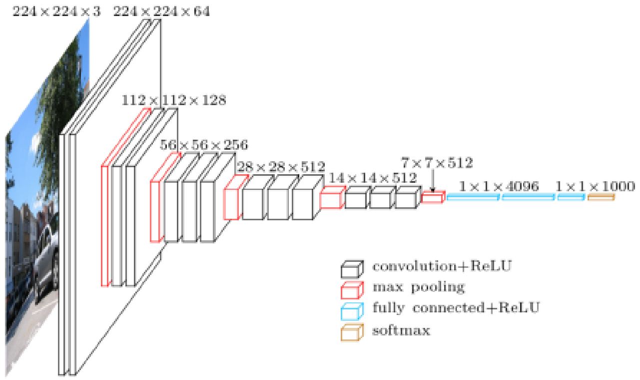
- LeNet-5 (Yann LeCun, 1998)



- AlexNet (Alex Krizhevsky, 2012)



- VGG-19 (Karen Simonyan, 2014)

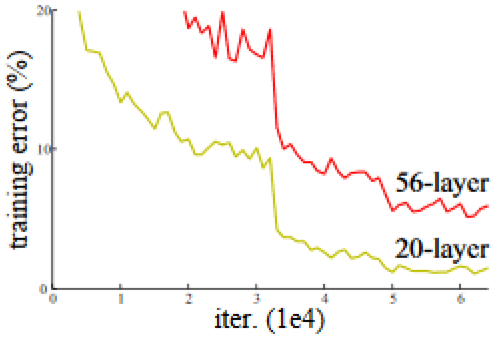


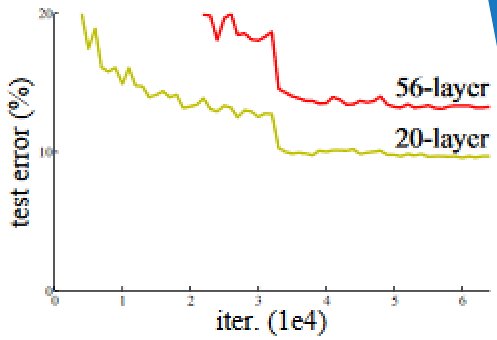
Generalizations and Expansions

Applying other tricks

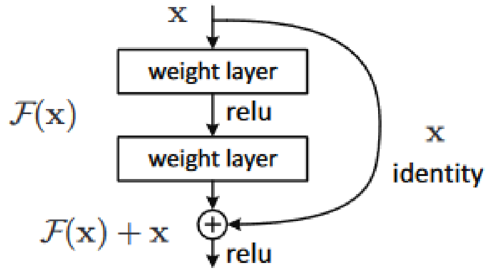
Residual Networks (ResNets)

- Deeper networks allow us to compute complex functions
  - But are difficult to train (e.g., vanishing gradients)
  - The validation error increases (not by overfitting)

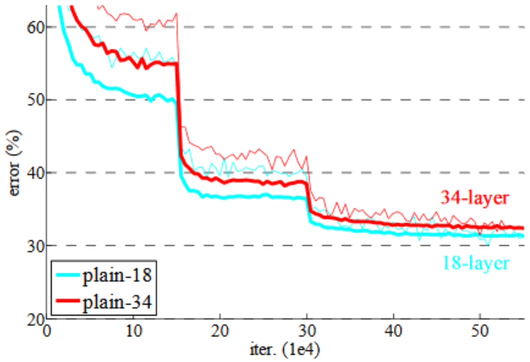


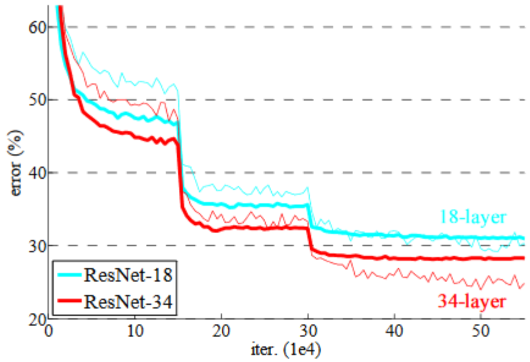


- Solution: shortcut connections
  - Pass the activation skipping 1 or more layers
  - Reason: the identity function $y = x$ is really easy to learn



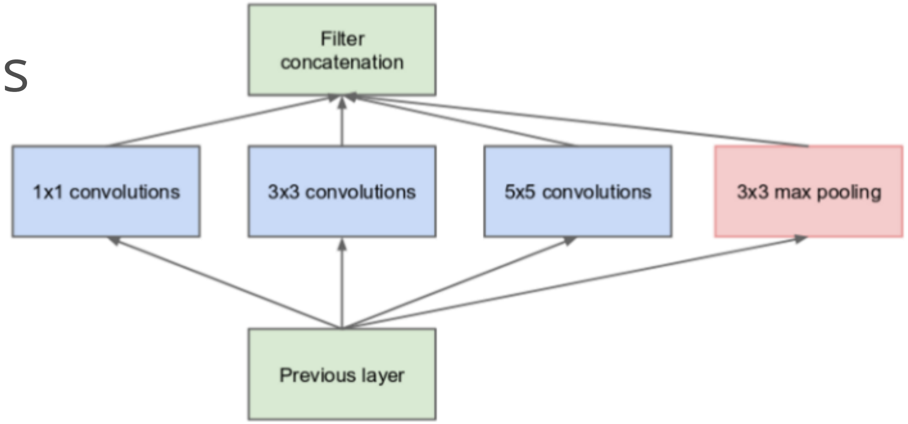
- Results
  - ImageNet
  - 18 / 34 layers
  - Runtime: faster than VGG





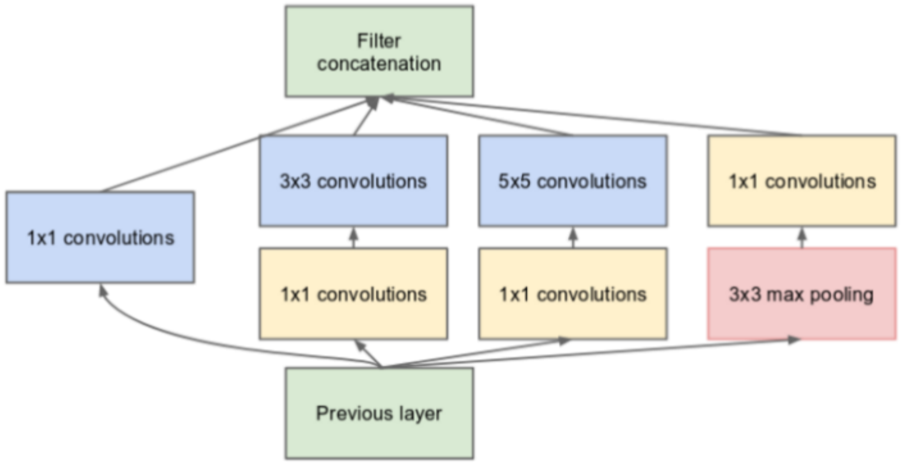
1x1 Convolutions

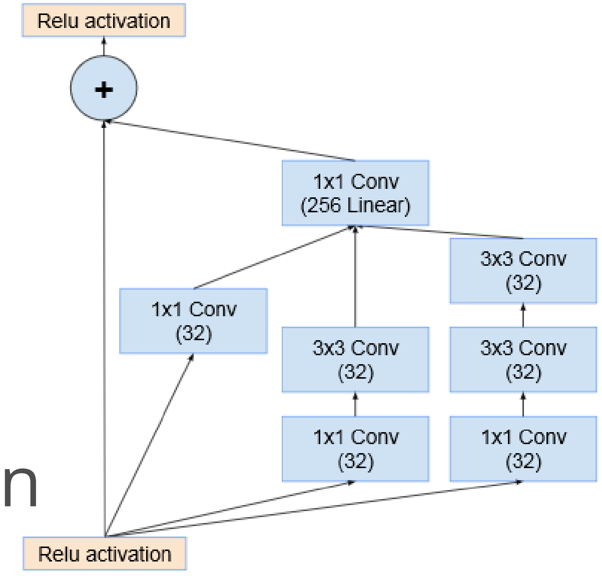
- Network in Network: Min Lin, 2013
- Single filter: does nothing (scales the input image)
- Many filters: $(w \times h \times c) \circledast (1 \times 1 \times c \times n_f) = (w \times h \times n_f)$
  - Keeps the image dimensions, changes the third dimension
    - Example: $(28 \times 28 \times 192)$, 32 filters $(1 \times 1 \times 192) \Rightarrow (28 \times 28 \times 32)$
  - Dimensionality reduction
- Inception (v1, v2 and v3, v4 and Inception-Res-Net)
  - Main idea
    - Kernel size corresponds to "size" of features
    - We can't know the kernel size f, so try many sizes and let the network decide what's most useful

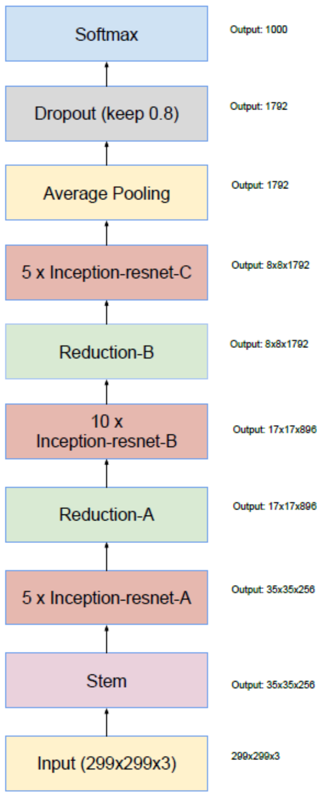


Inception

- Problem: lots of computations
  - Solution: dimensionality reduction before each convolution
  - "Inception block"
- GoogLeNet: 9 inception modules
- Inception-Res-Net
  - A simple combination of the two concepts
  - Idea: create a deeper inception block, simplifying learning through a ResNet connection

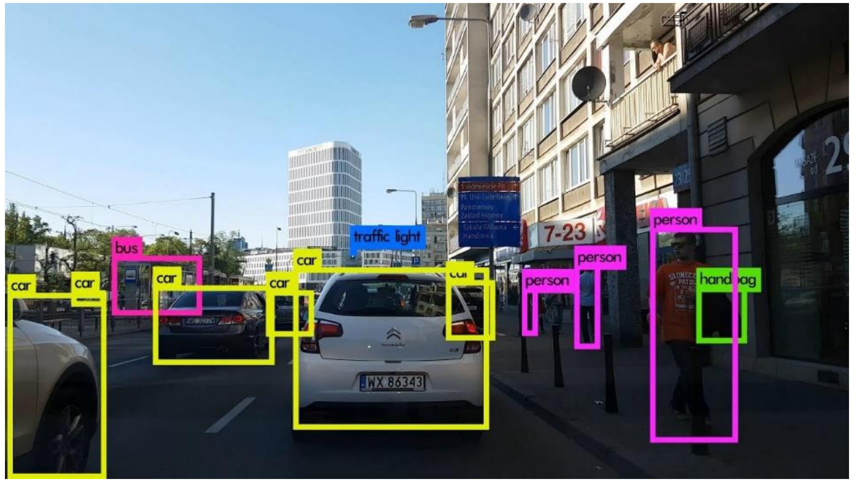






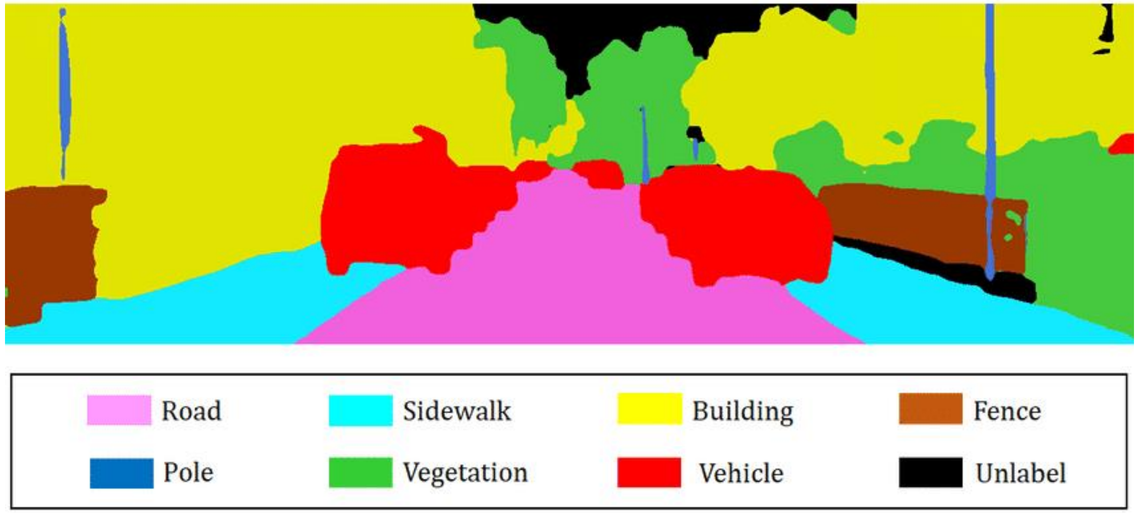
Object Detection

- Input: image; output: bounding box (x, y, w, h)
  - Regression
- Classification and localization
  - Simplest case: 1 object
  - Output a vector: $[p, x, y, w, h, c_1, c_2, \ldots, c_k]$
    - $p = 0 \Rightarrow$ no object detected; we don't care about the other numbers
    - $p = 1 \Rightarrow$ object detected; class: $c_1, \ldots, c_k$; bounding box x, y, w, h
  - Metrics: usually IoU or Dice (or Euclidean distance)
- Implementations: YOLO (You Only Look Once)
  - Also: R-CNN (Region-proposing network)



Semantic / Instance Segmentation

- Input: image; output: pixel classes
  - We may imagine it as classifying each pixel
- Results
  - Output an "image"
  - Metrics:
    usually cross-entropy
- Implementations:
  - R-CNN, SSD, YOLO
  - [tf-vision model garden]



Summary

- Convolutional neural networks
  - Operations
  - Architectures
- Generalizations
  - ResNet
  - 1x1 convolutions, "network-in-network"
- Object localization

Questions?