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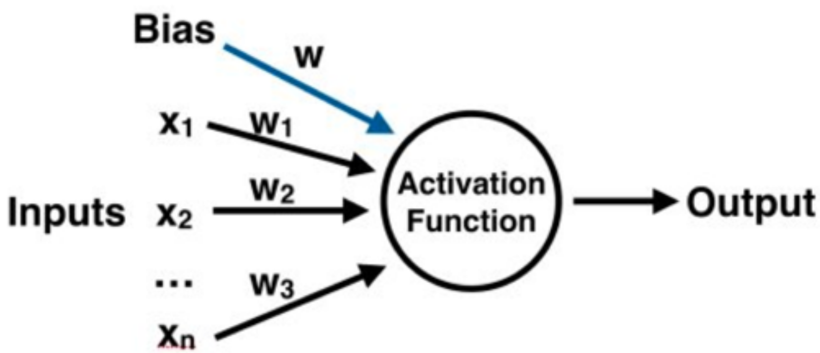
Neural Network and Deep Learning Workshop

Spring 2020

Neural Networks: Weights and Activation Functions



$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j + b \leq 0 \\ 1 & \text{if } \sum_j w_j x_j + b > 0 \end{cases}$$

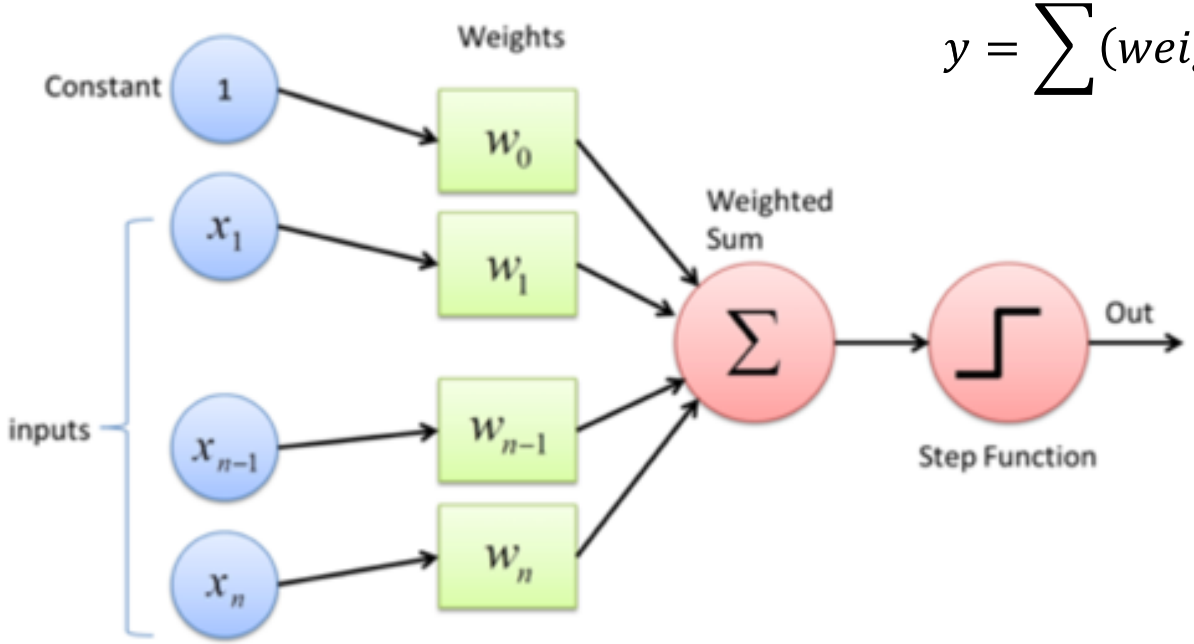
Simply y = $\sum_j w_j x_j + b$

$$y = \sum (weight * input) + bias$$

In this equation b denotes the intercept (also known as bias, and technically a weight itself) and w and x are vectors carrying the weights and values from all inputs

Activation Function

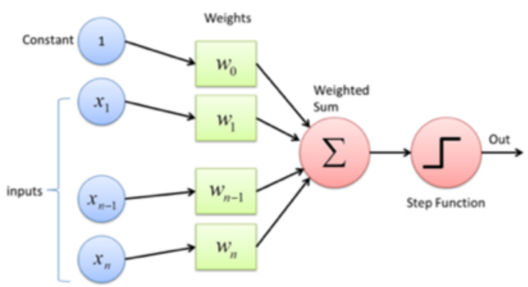
$$y = \sum(weight * input) + bias$$



A perceptron works on simple steps:

1. All the inputs x are multiplied with their weights w, lets call it k
2. Add all the multiplied values = weighted sum
3. Apply that weighted sum to the correct activation function

Activation Function: Step Function

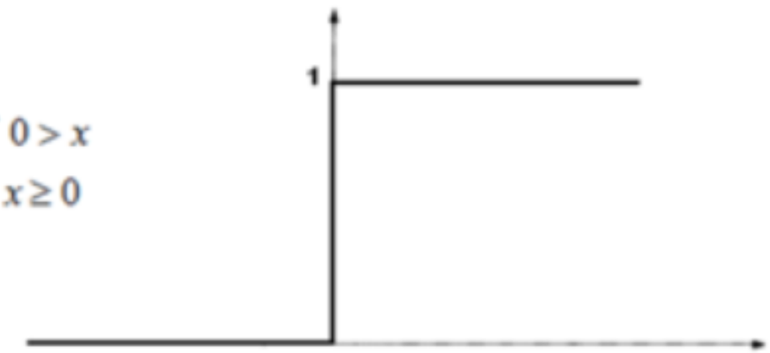


$$y = \sum(weight * input) + bias$$

If value of y is above a threshold > activated
A (function A) =1 if y> threshold, 0 otherwise

Unit step (threshold)

$$f(x) = \begin{cases} 0 \text{ if } 0 > x \\ 1 \text{ if } x \geq 0 \end{cases}$$



Disadvantage: Multiple classes in outcome (what if multiple neurons are activated)

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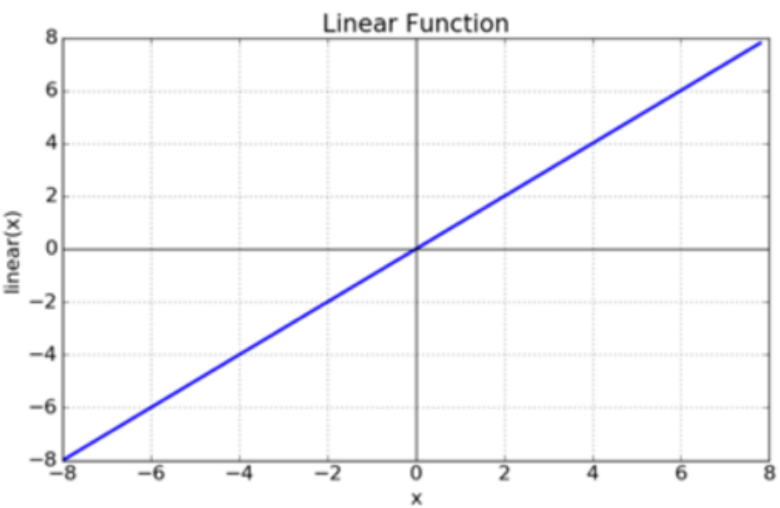
Activation Functions

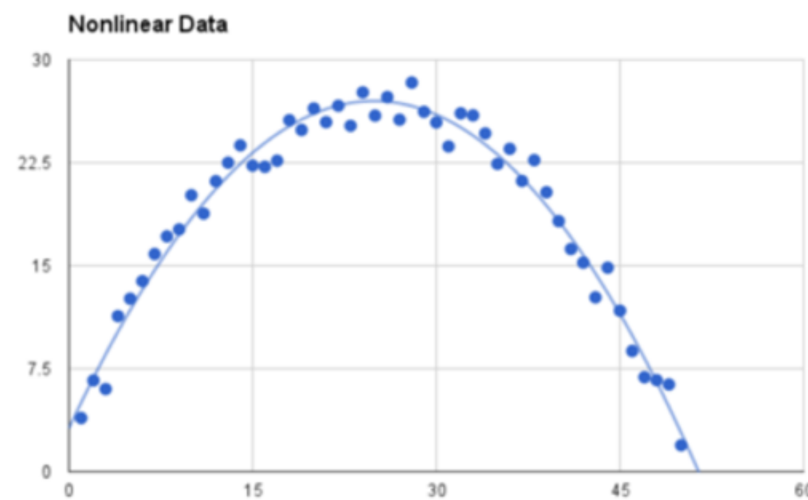
- Maps the resulting values in between output values

Linear activation



A=cx
Equation: f(x) = x
Range: (-infinity to infinity)

Non-linear activation



Makes the model to generalize with variety of data and differentiate between output

Non Linear Activation Functions

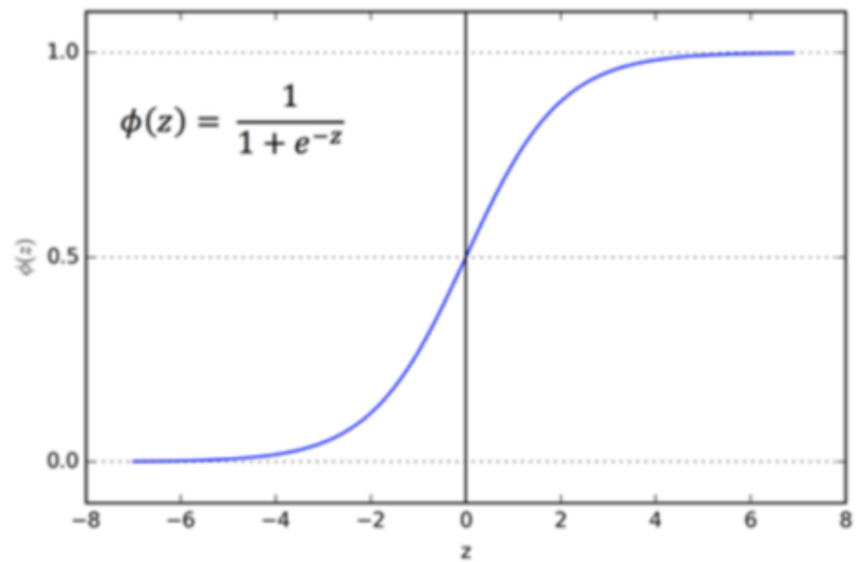
Logistic (A=$\frac{1}{1+e^{-x}}$)

- Smooth gradient
- Output between 0 and 1 (wouldn't blow up activations)
- Between values -2 and +2,

y is steep (any small change in x changes y significantly) but either ends, the y changes slow

= gradient will be small

= network refuses to learn further



Softmax function: more generalized function for multiclass classification

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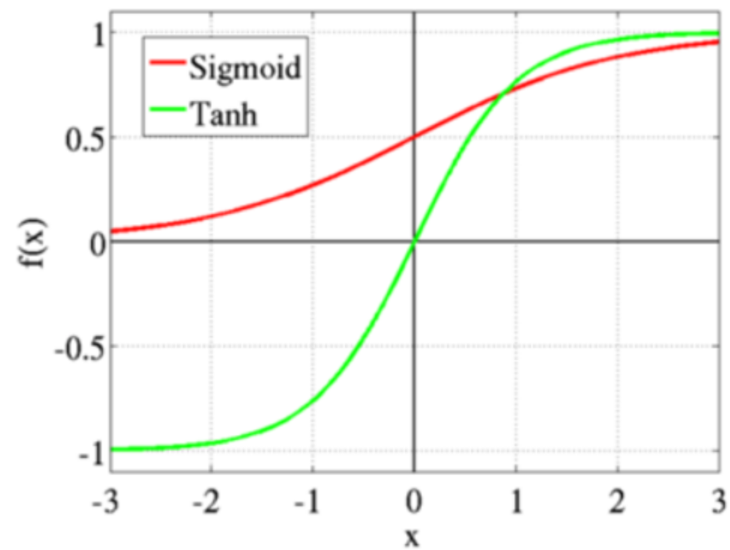
Non Linear Activation Functions

Tanh or hyperbolic tangent

$$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$$



- Output between -1, +1
- Derivatives are steeper

(gradient is stronger)

- Also has vanishing gradient problem

Negative inputs will be mapped strongly negative and the zero inputs will be mapped near 0

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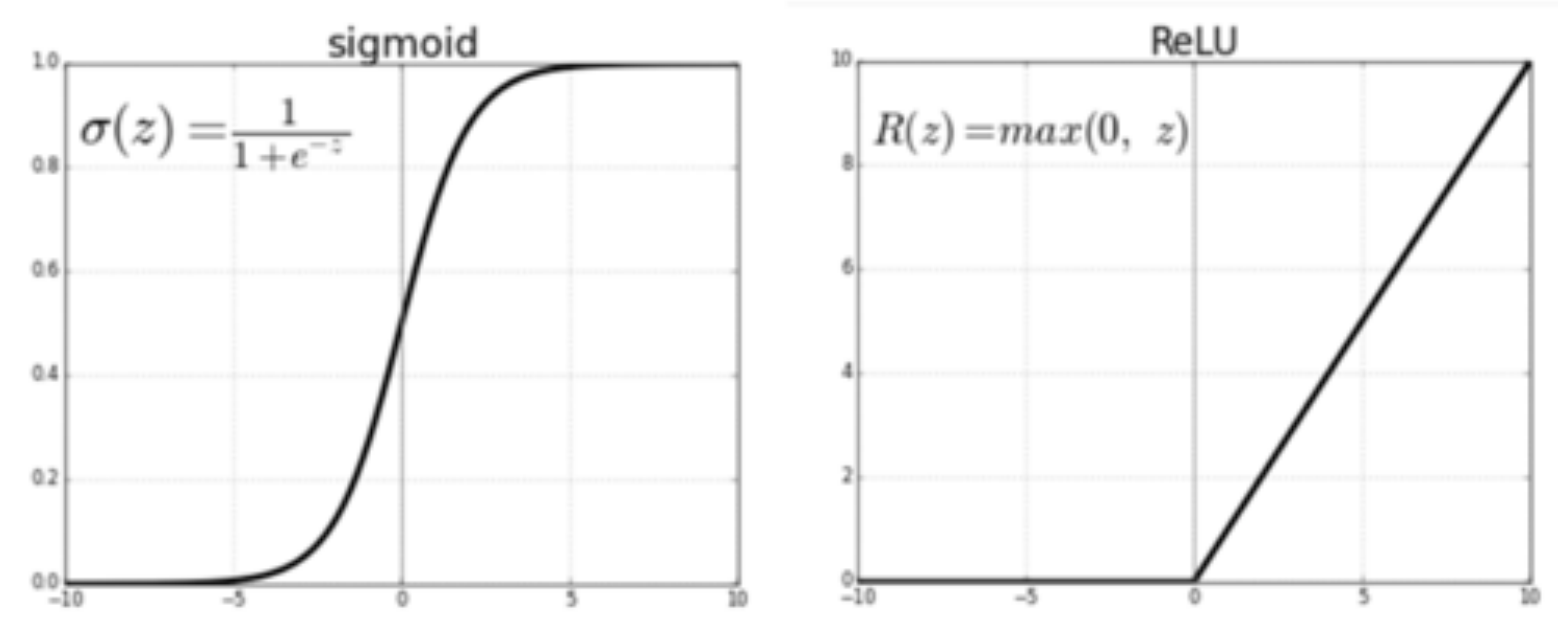
Non Linear Activation Functions

ReLU (Rectified Linear Unit)



- The ReLU is half rectified (from bottom). f(z) is zero when z is less than zero and f(z) is equal to z when z is above or equal to zero
- Range is 0-infinity
- Less computationally expensive compared to sigmoid or tanh = great for deep neural networks

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List of Activation Functions

Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2+1}$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1+e^{-x}}$

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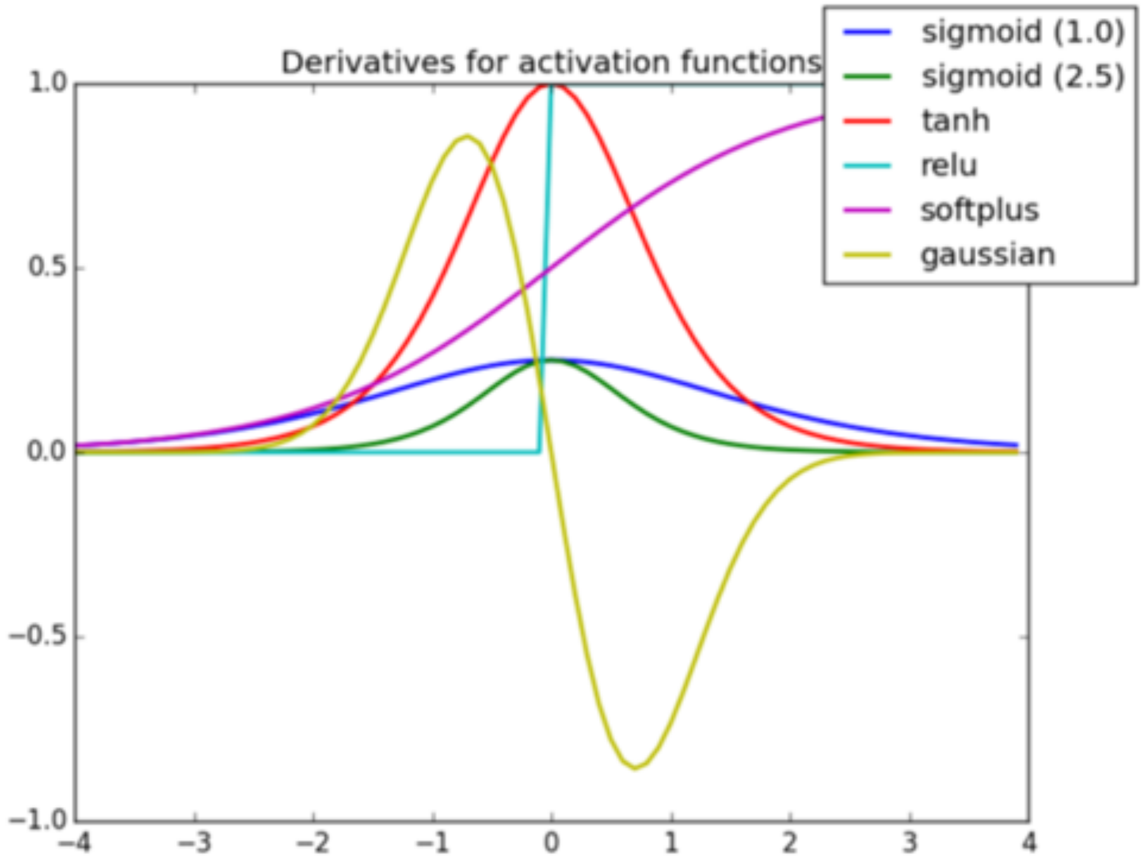
Derivatives of Activation Functions

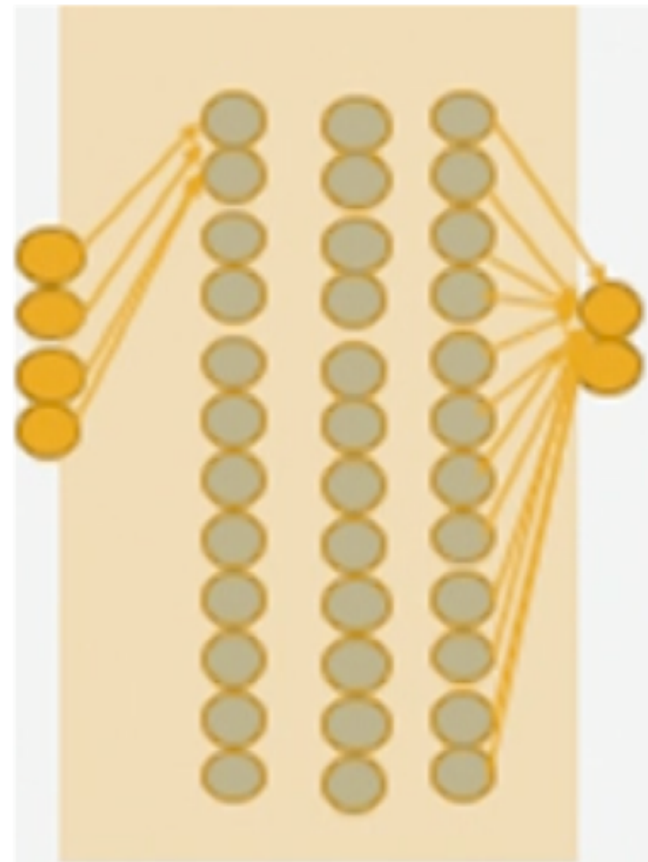


Back to it: What is a Deep Learning Neural Network?

Collection of inputs, wired to some central layers of perceptrons, and then to a desired number of inputs

There is some element of brute force high computing power to these approaches

Intense data requirements because there are vast numbers of parameters



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Tools and Deep Learning Progress

- Perceptron 1960
- Torch
- CUDA
- Theano
- TensorFlow 0.1 2015
- PyTorch 0.1 2017
- TensorFlow 1.0 2018
- PyTorch 1.0 2018
- TensorFlow 2.0 2019

- Perceptron 1957
- Backpropagation, RNN
- CNN, RNN
- Deep Learning 2006
- ImageNet 2009
- DeepFace 2014
- AlphaGo 2016
- BERT (Google) 2018

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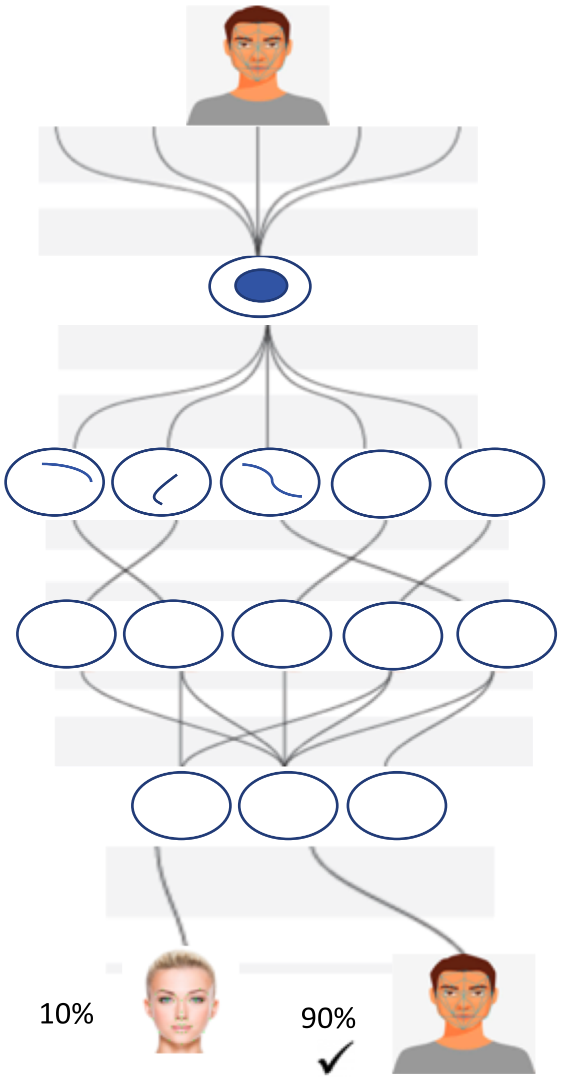
Deep Learning: How Neural Networks Recognize an Object



Training: During this phase, a neural network is fed thousands of labeled images of various faces, learning to classify them

Input: An unlabeled image is shown to a pretrained network

First Layer: the neurons respond to different simple shapes like edges

Higher Layer: Neurons respond to more complex structures such as nose, lips, forehead

Top Layer: Neurons respond to highly complex abstract concepts that we would identify as different faces

Output: The network predicts what the object most likely is, based on its training

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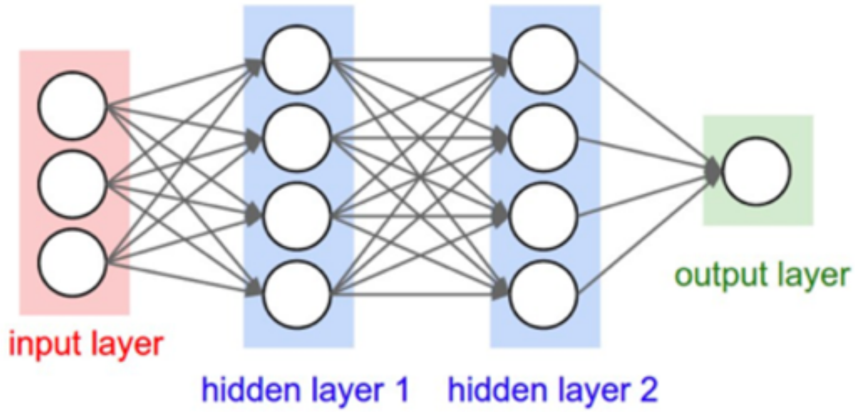
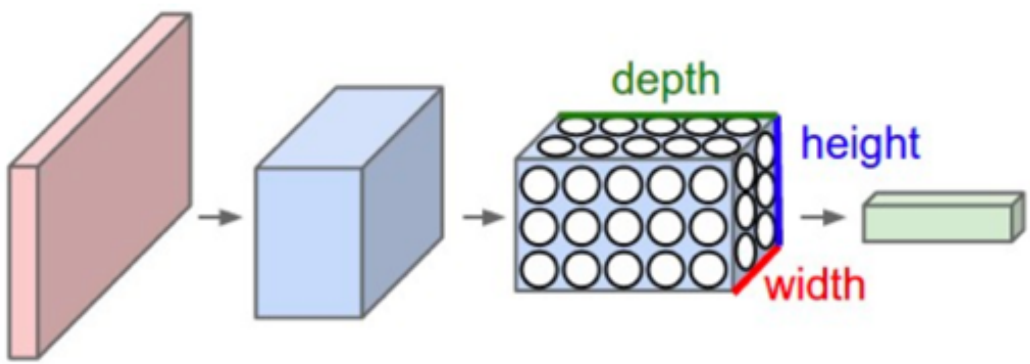
Convolutional Neural Network



Regular 3-layer NN

The convolutional neural networks are formed by neurons that have parameters in the form of weights and biases that can be learned



CNN

Source: http://cs231n.github.io/convolutional-networks/

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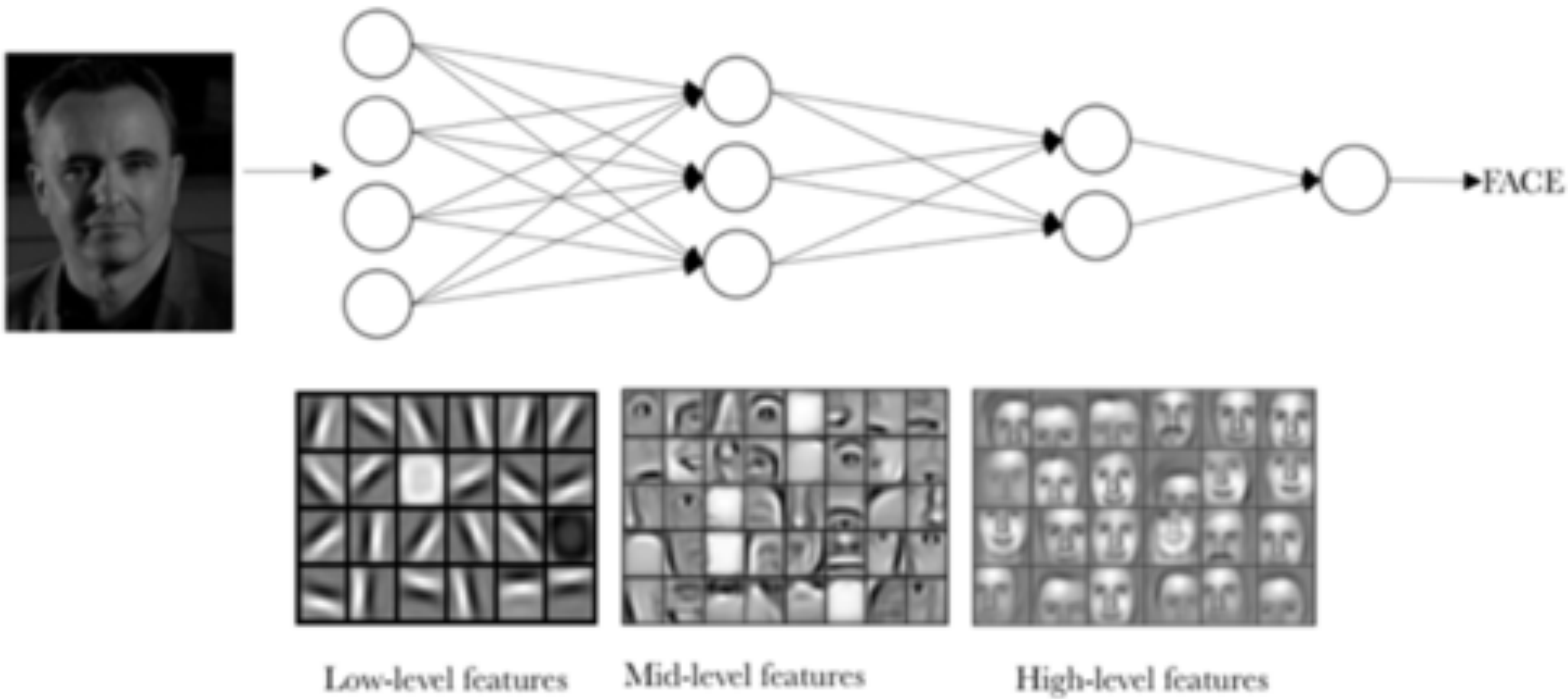
Convolutional Neural Network



Source: https://torres.ai/en/deeplearning/

CNN: Image Classification

What We See

What Computers See

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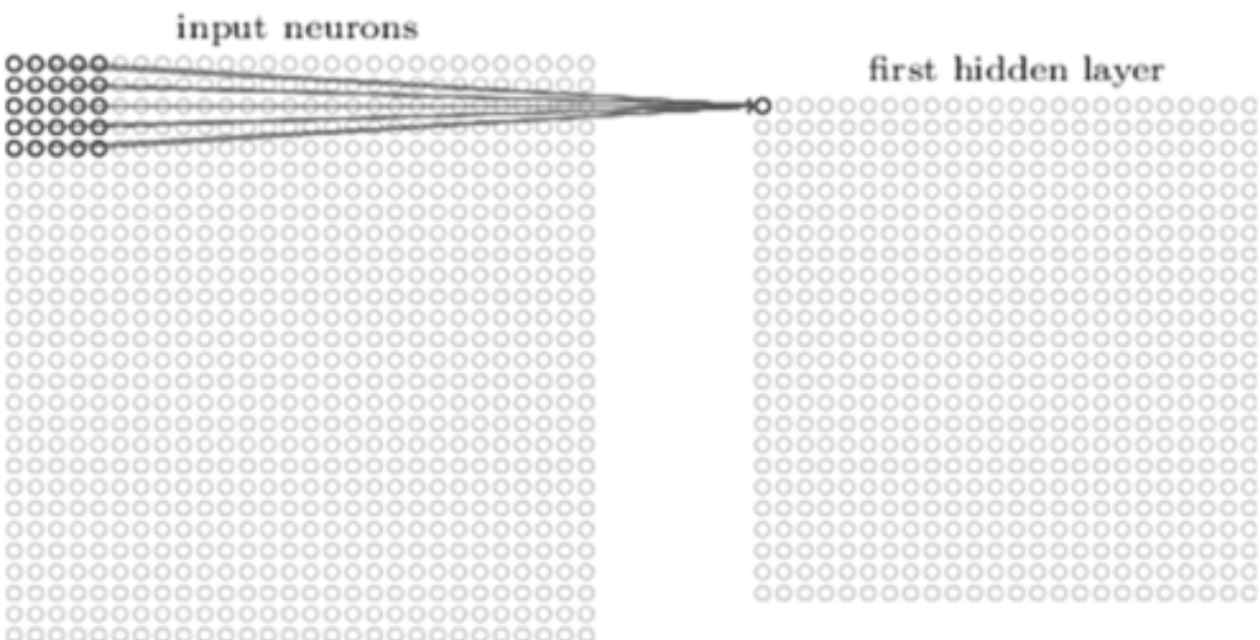
CNN: Pixel Representation

What do you Want the Computer to do?

Take the image, pass it through a series of convolutional, nonlinear, pooling (or what is defined as downsampling), and fully connected layers, and get an output layer



Visualization of 5 x 5 filter convolving around an input volume and producing an activation map

Image Processing: First Layer

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Visualization of a curve detector filter

Here you see a pixel representation of a filter which is a curve detection filter. Filters are feature identifiers.

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Visualization of the First Layer

Original image

Visualization of the filter on the image

Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

In the input image, if there is a shape that generally resembles the curve that this filter is representing, then all of the multiplications summed together will result in a large value

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Visualization of the First Layer

Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

There isn't anything in the image section that responded to the curve detector filter shown in earlier slide and thus the value in the activation map is zero

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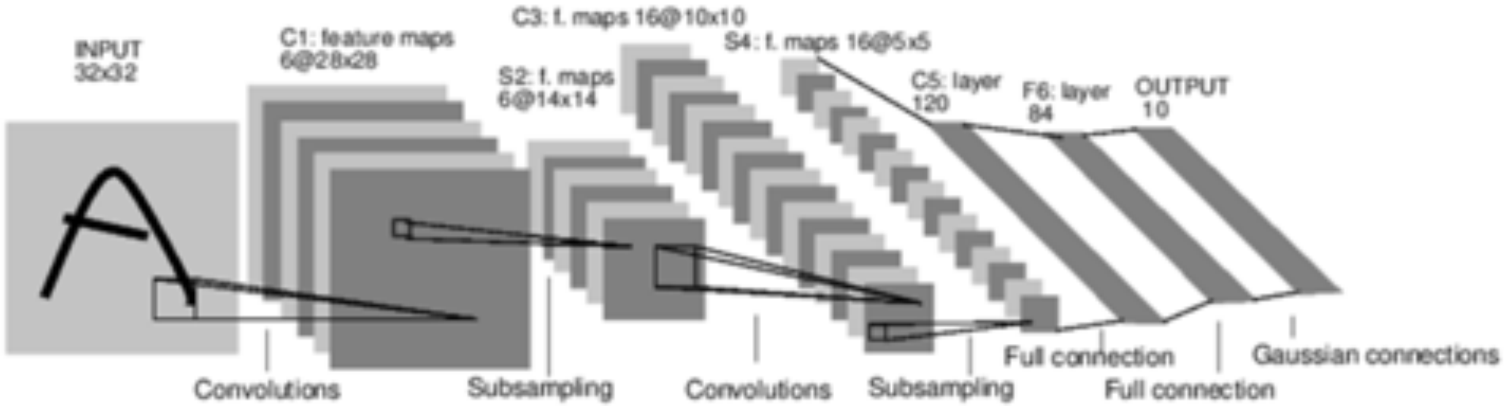
Going Deeper into the Layer

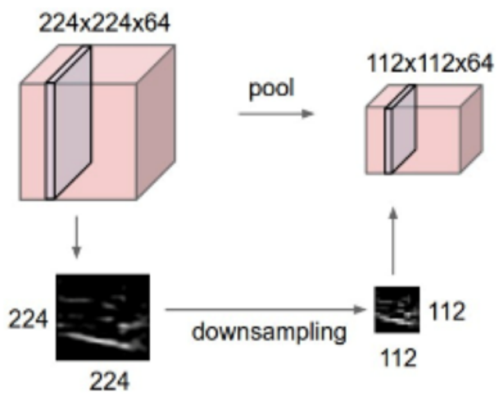
Input -> Conv -> ReLU -> Conv -> ReLU -> Pool -> ReLU -> Conv -> ReLU -> Pool ->Fully Connected



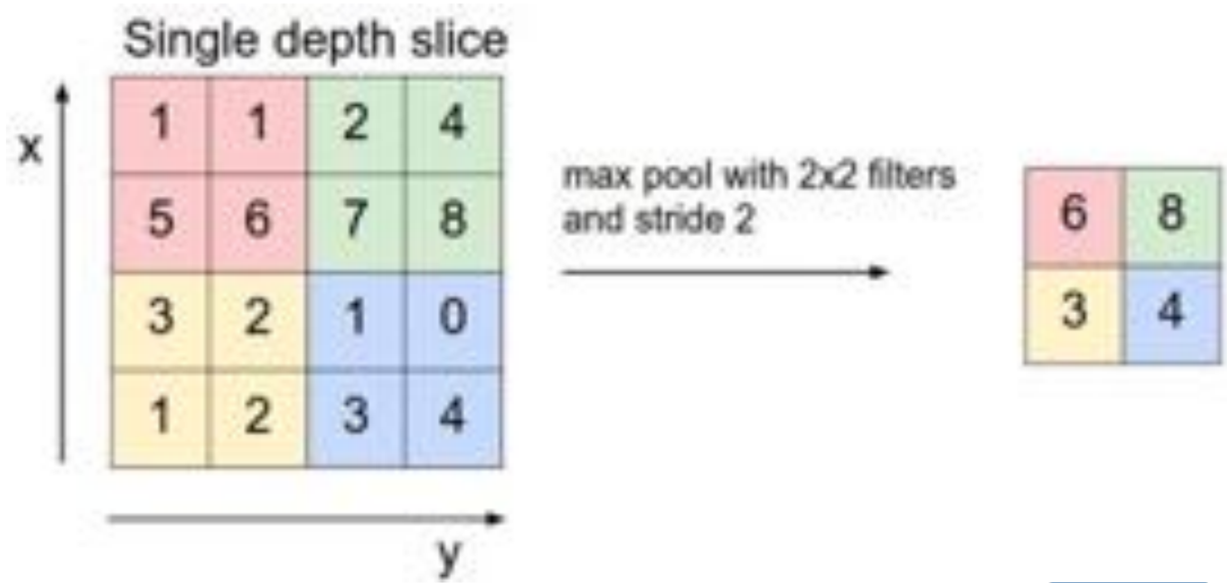
A Full Convolutional Neural Network (LeNet)

Source: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

CNN: Pooling Layer



Pooling layer creates a strategic down-sampling from a convolutional layer, rendering representations of predominant features in lower dimensions

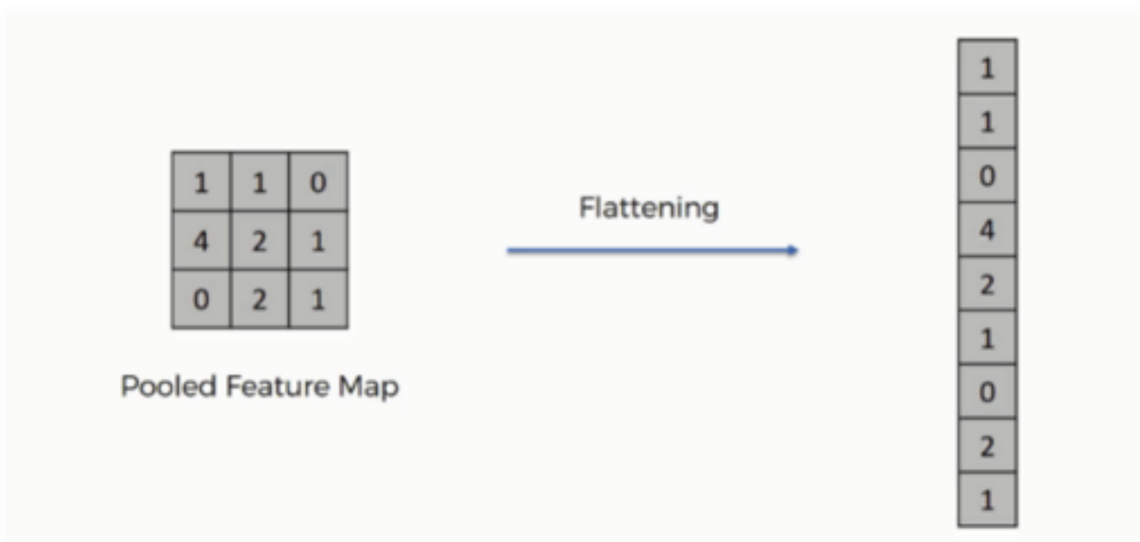


Source: https://cs231n.github.io/convolutional-networks/

CNN: Pooling and Flattening

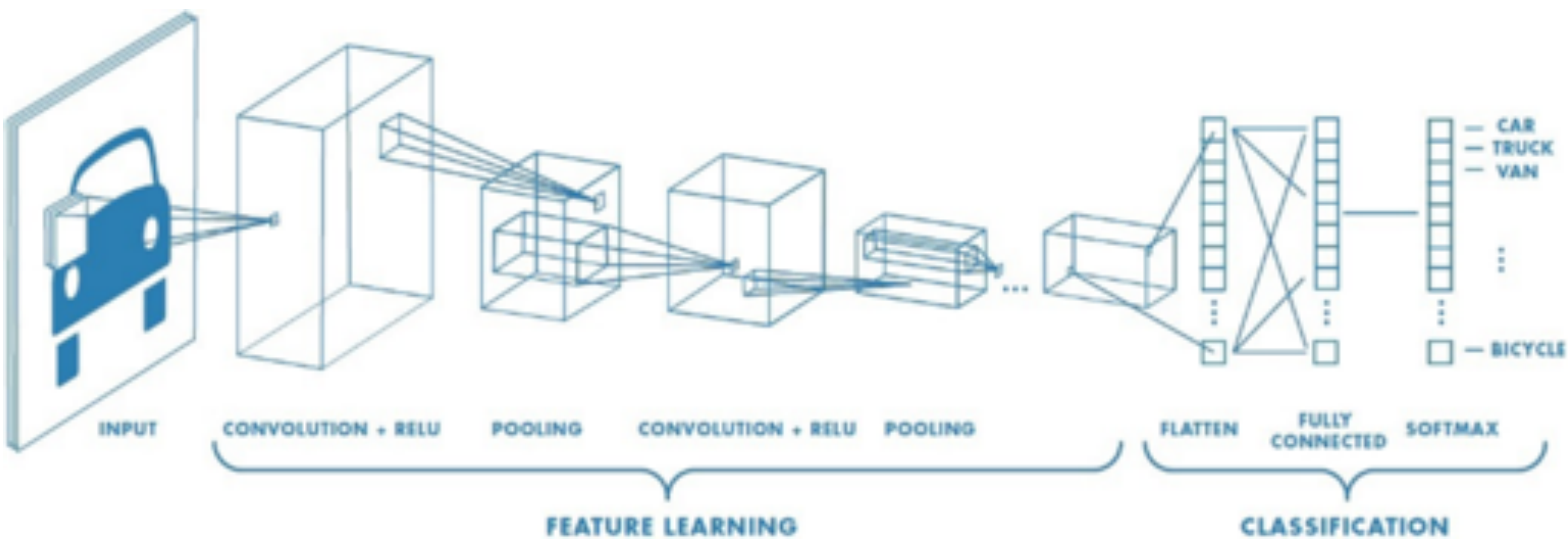
- Advantages of Pooling:
  - The first is that the amount of parameters or weights is reduced by 75%, thus lessening the computation cost
  - Prevents overfitting

- Flattening: Converts the last convolutional layer into a one dimensional neural network layer



CNN: Fully Connected Layer

This layer basically takes an input volume and outputs an N dimensional vector where N is the number of classes that the model has to choose from



If number of classes is four (car, truck, van and bicycle; the final output is a 4-dimensional vector (.55 .10 .30 .05):

A 55% probability that the image is a car

A 10% probability that image is a truck

A 30% probability that image is a van and 5% probability that it is a bicycle

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CNN Challenges and Opportunities

- Data, data, data (missing data; open source data)

The more training data that you can give to a network, the more training iterations you can make, the more weight updates you can make, and the better tuned to the network is when it goes to production

- Transfer Learning
- RNN: Sequential Data (e.g., time series, audio, video)
- Assist AI in HealthCare : Taking over standard interactions to relieve burden on healthcare (memorize and track flow charts)

Thanks
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