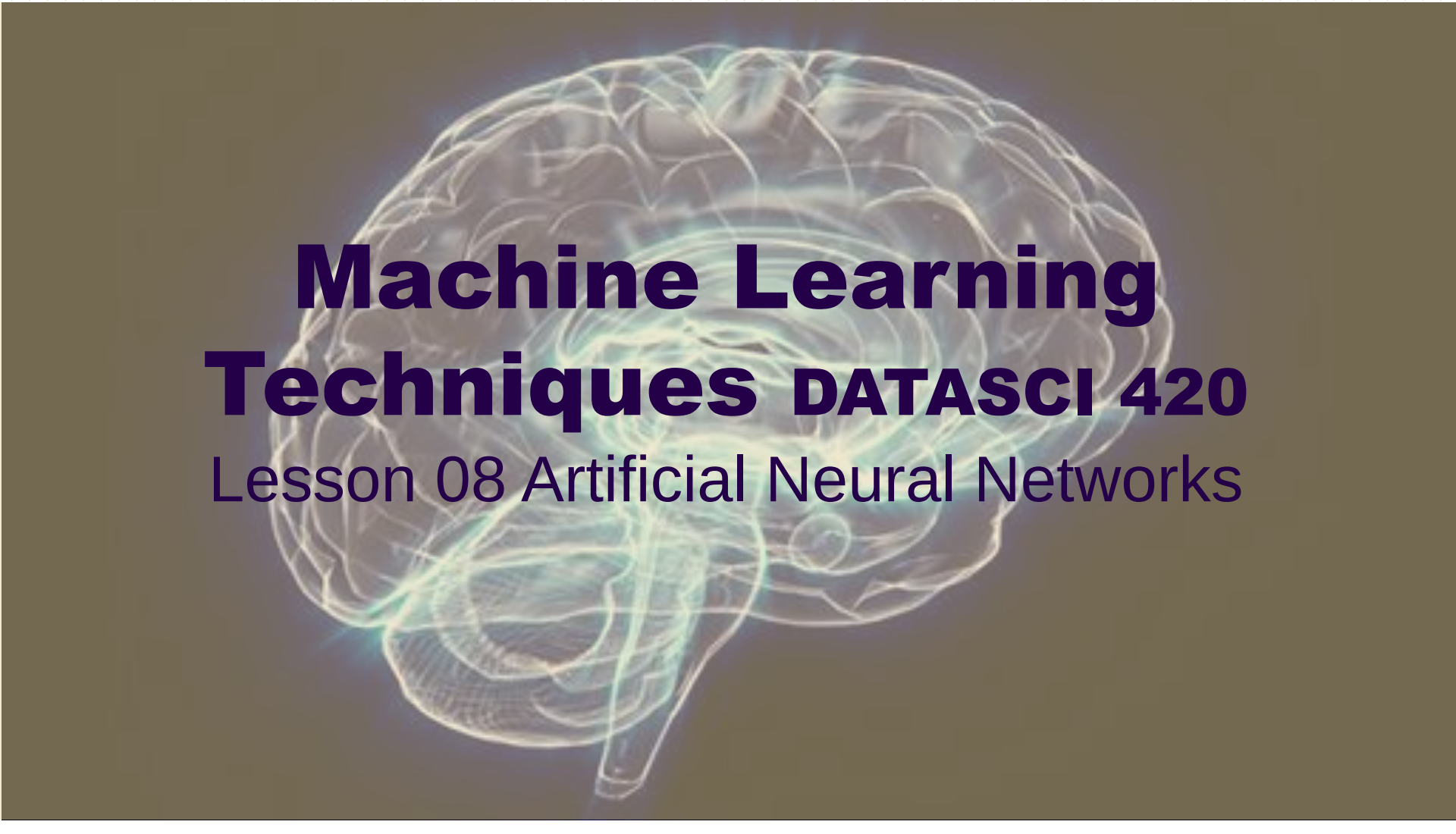
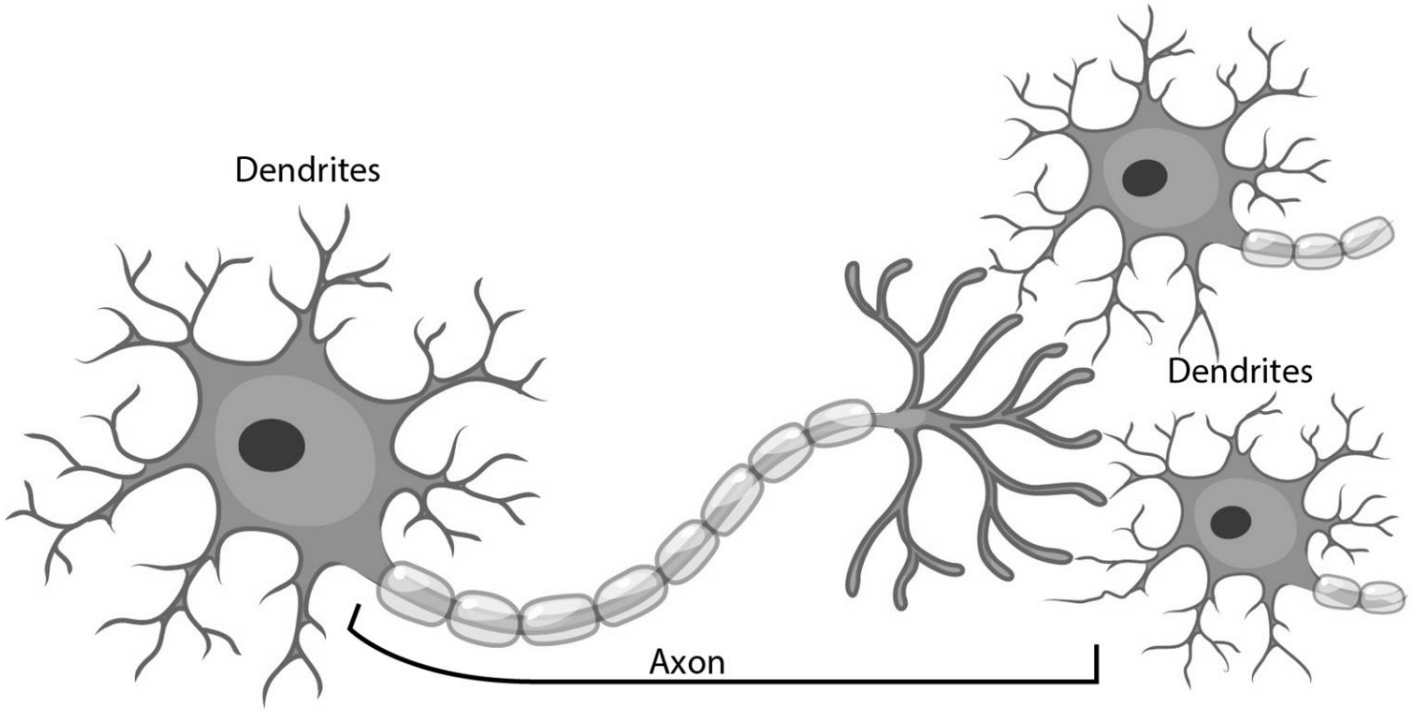


Machine Learning Techniques DATASCI 420

Lesson 08 Artificial Neural Networks

How an Actual Neuron Passes Information

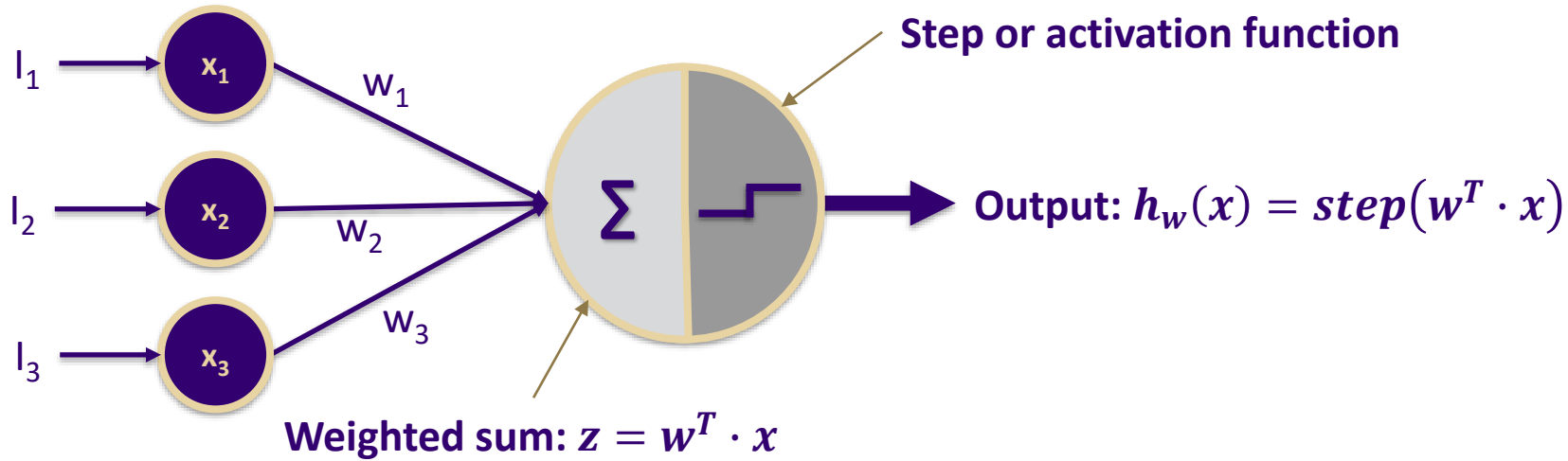


Artificial Neural Networks

- A simplification of a real neural network
- Early success, led to later disillusionment when ANNs had limited use
- Computational capability and access to more data have caused the resurgence in ANN development

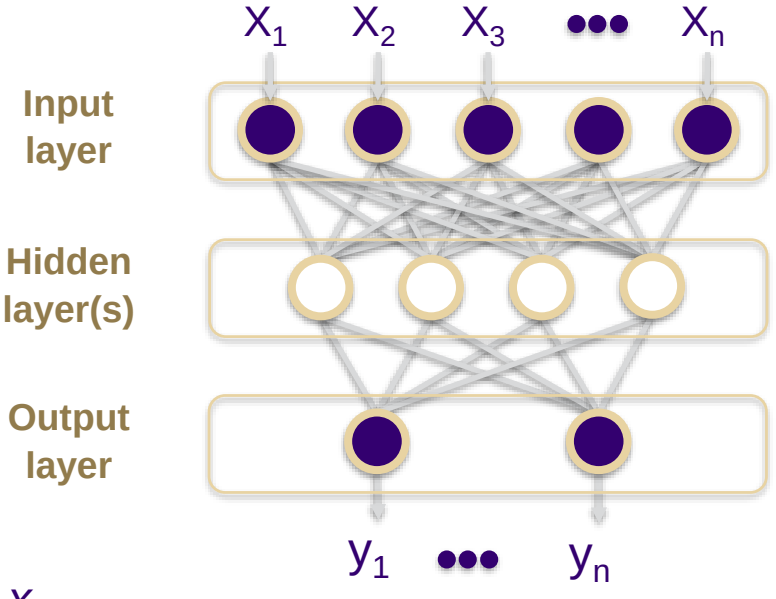
Perceptron

The simplest ANN architecture 2 layers: input and output



Structure of an Multi-layer ANN

- Multilayer ANNs consist of an input, hidden layer(s) and an output layer
- They can have multiple outputs
- Weights of an upstream layer is an input vector to the next
- Support data that is not linearly separable

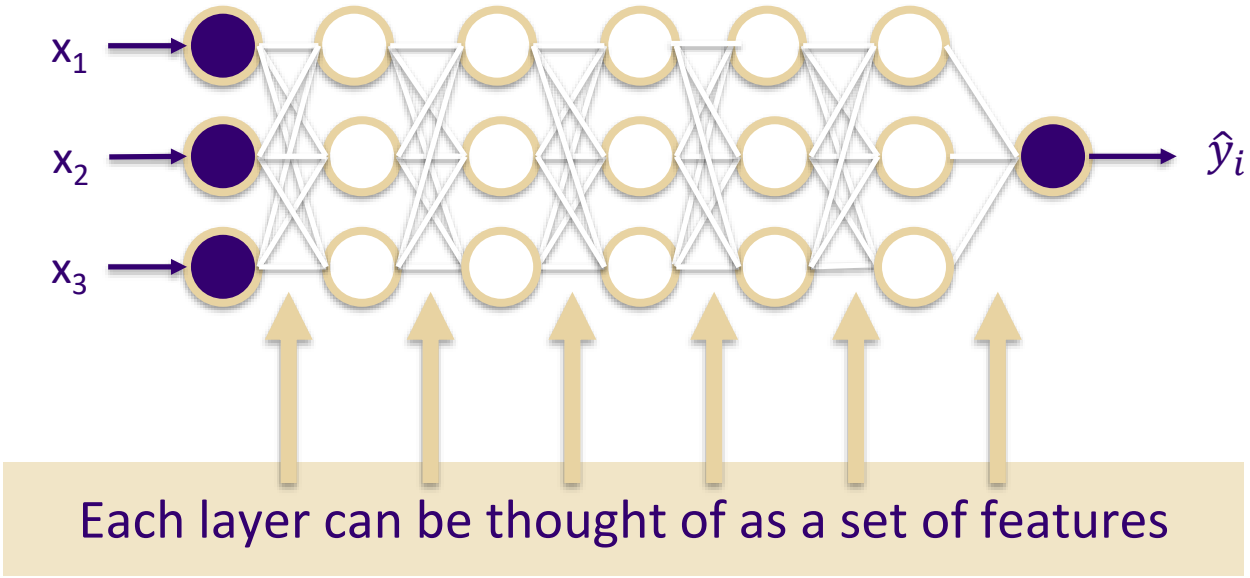


ANN Concepts

- Depth of Architecture
- Gradient Descent
- Forward-chaining
- Backpropagation
- Activation Functions
- Momentum
- Convergence
- Overfitting

Depth of Architecture

DoA refers to the number of levels of composition of non-linear operations in the function learned



Gradient Descent

- The purpose of gradient descent is to identify the minimum error or the maximum predictive capability on your training set
- You need to adjust your network in many dimensions, looking for the best “direction” to approach error=zero without over training and reducing generalizability to unseen data
- There are several types of gradient descent: Batch, Stochastic and Mini-batch

Steps for Gradient Descent

- Step 1: Initialize weights (0-1; -1-1; $-\frac{1}{\sqrt{i}}, \frac{1}{\sqrt{i}}$)
- Step 2: Calculate error (e.g. sum of squares: $\frac{1}{2}\sum(Y-\hat{y})^2$)
- Step 3: update the weights with the gradients to reach the optimal values where SSE is minimized based on a learning rate
- Step 4: Use the new weights for prediction and to calculate the new SSE
- Step 5: Repeat 2 and 3 until further updates to the weights do not significantly reduce the error

Learning Rate

- Learning rate is application dependent
- The lower the learning rate the longer it take to converge
- Used to prevent falling into local minimum
- Start small and increase, comparing across training runs
- Adaptive techniques, such as bold driver and annealing can also be used for creating an adjustable rate

Feeding forward

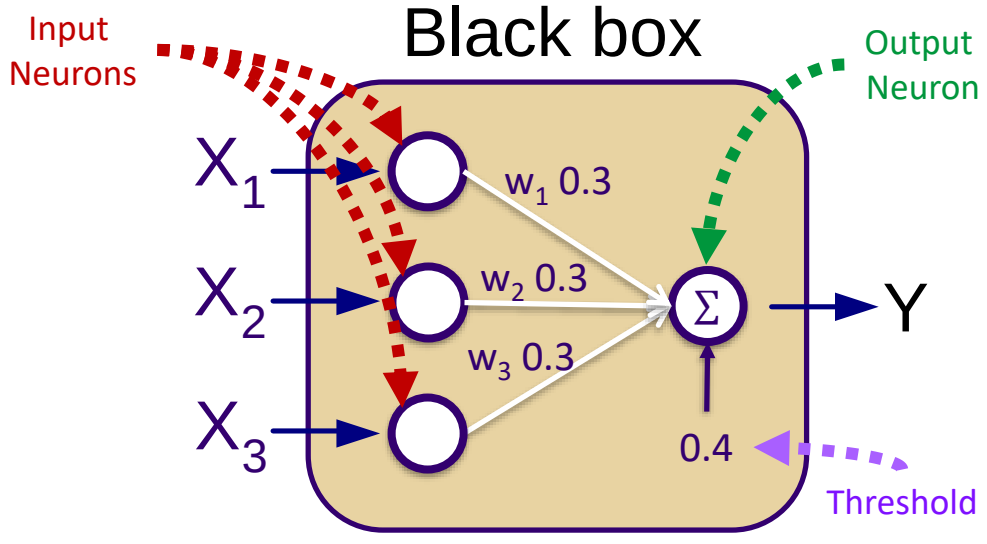
- Load a problem into the network by giving it some features (AKA inputs)
- These inputs might need to be normalized to range between -1 and 1 or 0 and 1. An example would be to do the following for each input:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} = \frac{10 - 2}{20 - 2} = \frac{8}{18} = .44\overline{4}$$

- Each connection gets a “signal” from its earlier node (either input or hidden layer)
- This signal is multiplied by its own weight
- Then the signal is passed on to later nodes
- A “predicted” classification ($\hat{y}$) is generated as the sum of these weights which is compared to the actual classification (Y)
- You could stop here using only reinforced learning

Simple Example

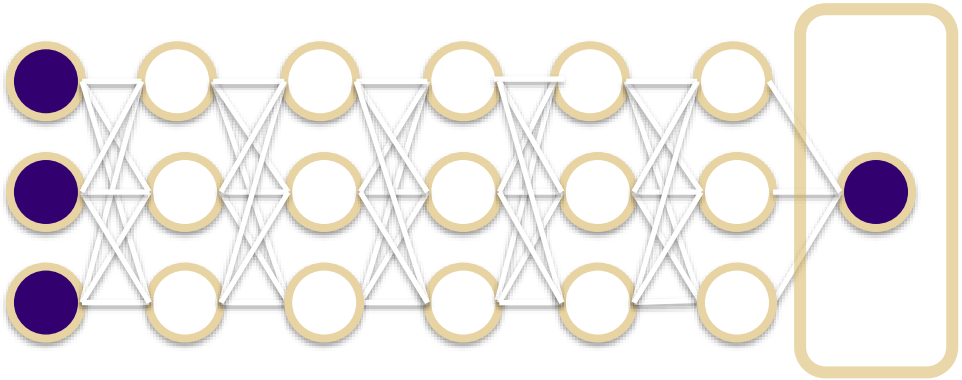
X_1	X_2	X_3	Y
1	0	0	**0**
1	0	1	**1**
1	1	0	**1**
1	1	1	**1**
0	0	1	**0**
0	1	0	**0**
0	1	1	**1**
0	0	0	**0**



$$y_1(t_0) = f(0.3X_1 + 0.3X_2 + 0.3X_3 - 0.4 > 0)$$

$$where\ f(z) = \begin{cases} 0\ if\ z < 0 \\ 1\ if\ z \geq 0 \end{cases}$$

Backpropagation Visual



Simple Example BP Weight Updates

X_1	X_2	X_3	Y
1	0	0	**0**

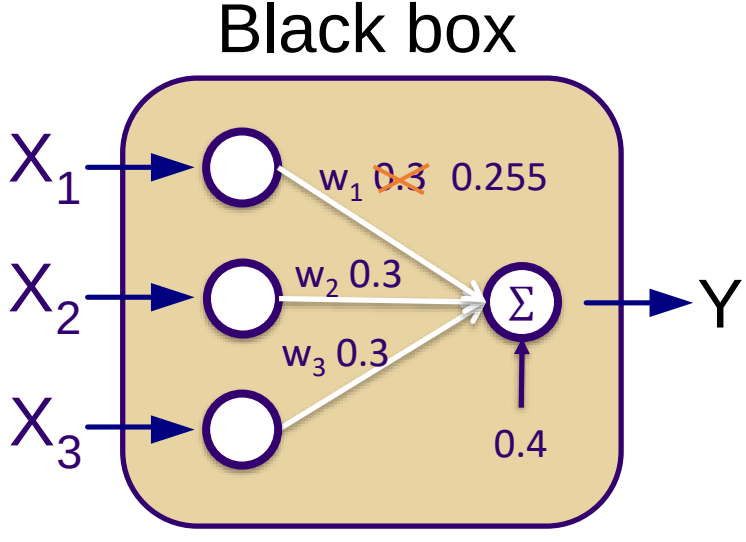
Assume Learning Rate = 0.01

$$w_1 = 0 - .01 \cdot \frac{1}{2}(0-1)^2 = -.045$$

$$w_2 = 0.1 \cdot \frac{1}{2}(0-0)^2 = 0$$

$$w_3 = 0.1 \cdot \frac{1}{2}(0-0)^2 = 0$$

Only w_1 is updated from 0.3 → 0.255 = $(0.3 - 0.045)$



Epoch v. Batch v. Iteration

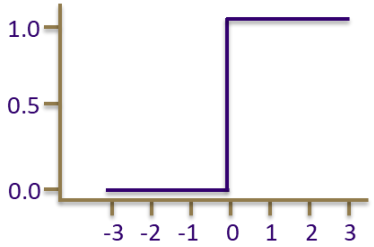
What's the difference?

Quick Terminology Pause

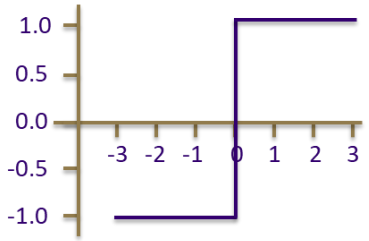
- Iterations are logical because we do this all the time in computer programming
- Batch is subsets of the input vector
- Epochs are important to understand because they are a settable hyperparameter

Common Binary Step (Activation) Functions

$$heaviside(z) = \begin{cases} 0 \; if \; z < 0 \\ 1 \; if \; z \geq 0 \end{cases}$$

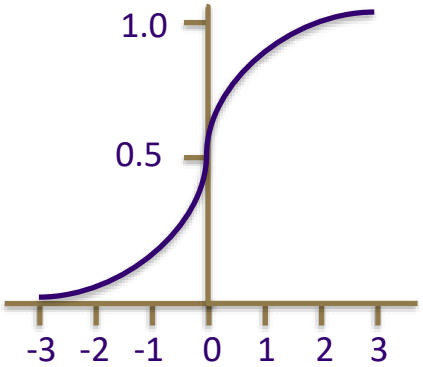


$$sign(z) = \begin{cases} -1 \; if \; z < 0 \\ 0 \; if \; z = 0 \\ 1 \; if \; z > 0 \end{cases}$$

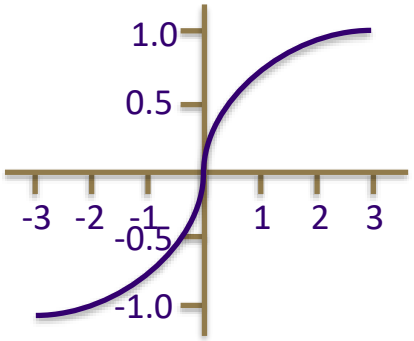


Common Non-linear (Activation) Functions

$$logistic\ (sigmoid)(z) = \frac{1}{1+e^{-z}}$$



$$Hyperbolic\ tangent(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$$



Let’s Take a Quick Look at a Simple Perceptron Feedforward-Backpropagation Neural Network

Momentum

- Momentum is a method for speeding up the ANN training process
- Can also reduce getting caught in local minima
- The tradeoff is speed vs. accuracy
- Easy to implement, difficult to find the right value

Convergence

- Some neural networks do not “converge”
- Often this is a result of incorrectly set hyperparameters
- Can also be badly “formatted” input data

Overfitting

Causes

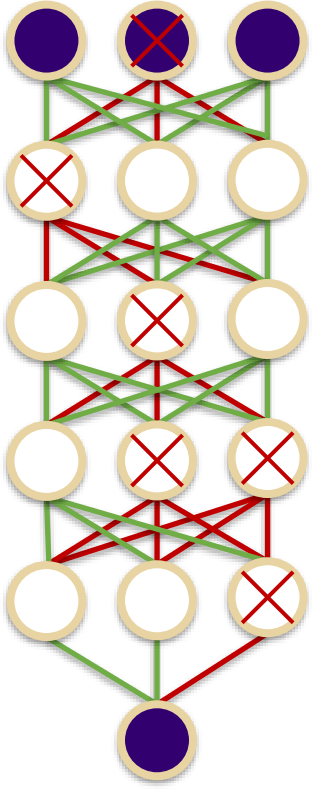
- More hidden layers can model more complex problems, but can also lead to overfitting
- Assuming the training data is fixed
- Too many iterations (overshooting generalizability)

Prevention

- Stopping early
- More data, randomly sampled
- Cross validation/ensemble neural nets
- Regularization
  - >L1 or L2 regularization
  - >Drop out

Dropout

- Randomly “thin” the network by dropping nodes (hidden and visible) and arcs
- Enables more complex networks with lower cost
- Used for regularization--multiple runs (averaged)



Pre-Trained Neural Networks

- Starting from scratch to build a neural network
- Reduces time to build a working model
- Accuracy can be either positively or negatively influenced

Comparison Between SVMs and ANNs

SVMs

- Deterministic algorithm
- Uses well-known, quadradic programming
- Generalizes well;
- Learns in batches only
- Uses kernels to learn complex functions

Neural Networks

- Deterministic or stochastic
- Uses learned weights
- Generalizes well
- Can be updated
- Learns complex functions natively