McGill **Artificial Intelligence** Society

Lecture 3:
Neural Networks

Slides based off of Machine Learning at Berkeley
https://github.com/mlberkeley/Machine-Learning-Decal-Fall-2018

Today's Lesson Plan

Linear and Logistic Regression Review

Motivation

The Perceptron

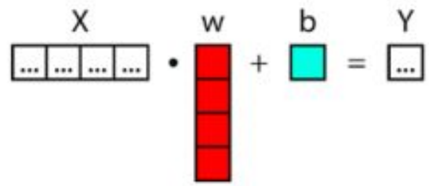
Feed-forward Neural Networks

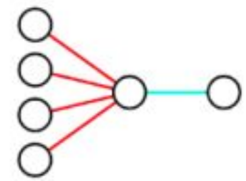
Learning In NNs

Coding Demo

Linear Regression Linear model

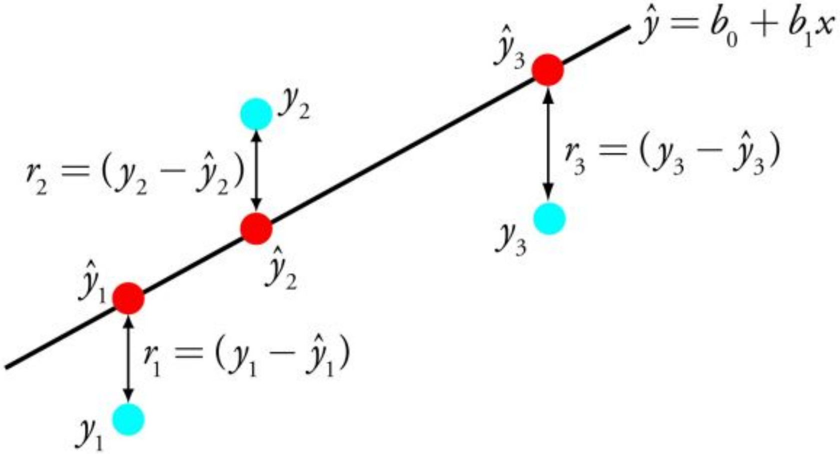
$$Y = f(X, w_1, b_1)$$
$$f(x, w, b) = x \cdot w + b$$





Let $\hat{y}_i = h(x) = b_0 + b_1 x$

min $J(b_0, b_1)$



Max likelihood = Negative likelihood

$$RSS(w) = \sum_{i=1}^{N} (y_i - w^T x_i)^2$$

derivate

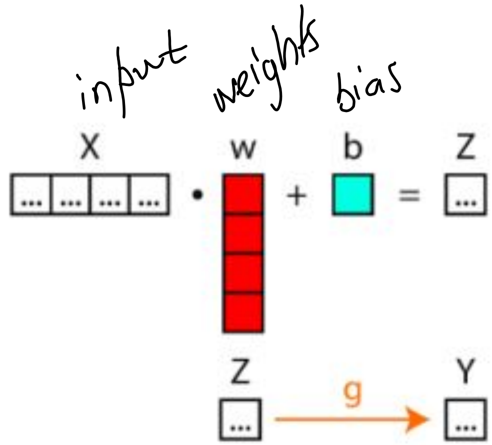
$$J(b_0, b_1) = \frac{1}{2m} \sum_{i=1}^{m} (h(x^{(i)}) - y^{(i)})^2$$

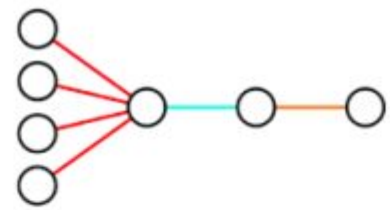
variance in our data described by goussian distribution

Logistic Regression

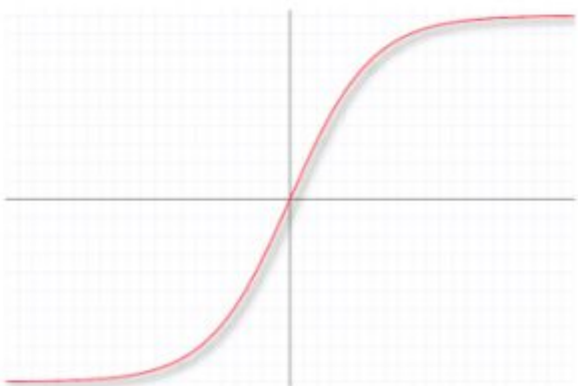
classification model

$$Z = f(X, w_1, b_1)$$
$$Y = g(Z)$$





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



$$J(b) = -\sum_{i=1}^{m}\left(y^{(i)} \cdot \ln z^{(i)} + (1 - y^{(i)}) \cdot \ln(1 - z^{(i)})\right)$$

Motivation

What I see

What a computer sees

2D array
pixel values

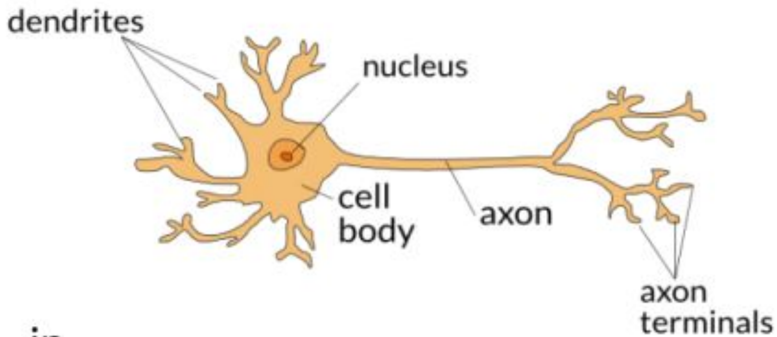
- Ability to learn complex, non-linear functions
- Does not impose fixed relationships in data

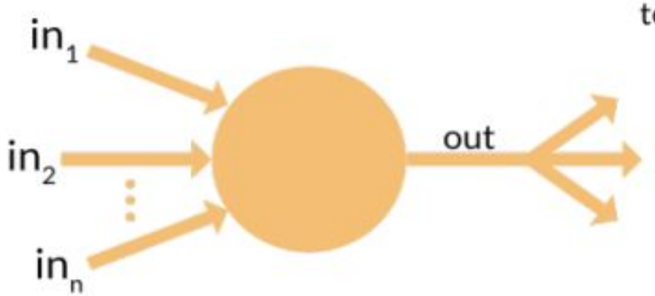
ex: lin seperable
or
linear relationship

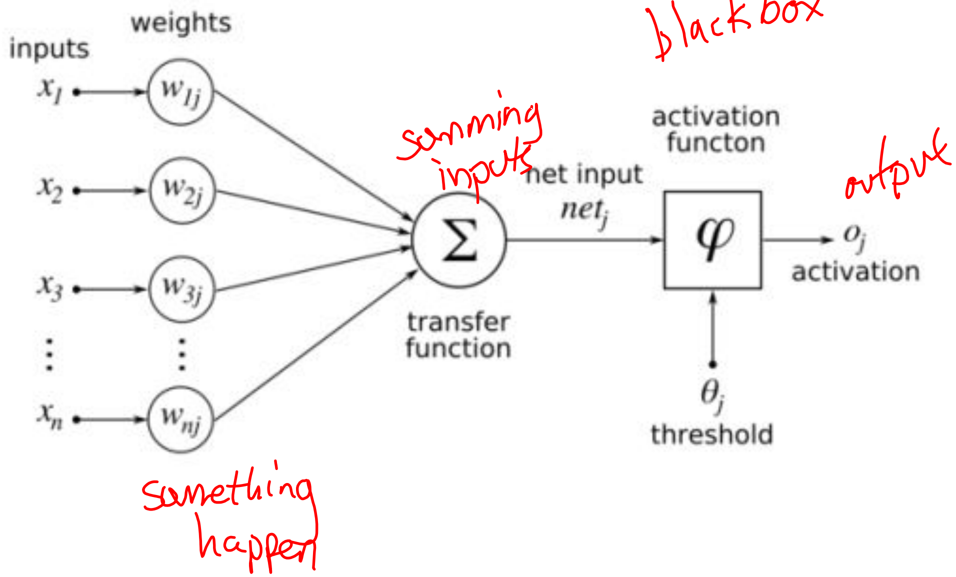
- Does not assume the inherent data distribution
  - Better at modeling non-constant variance

NN good for

Biological Inspiration



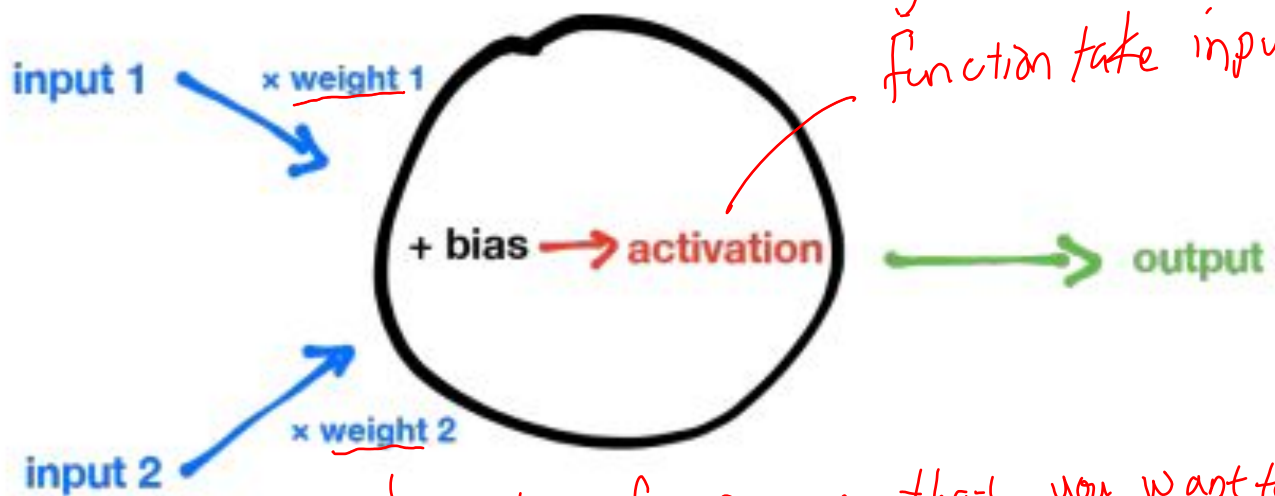




Biological Inspiration

ex: Sigmoid function $\frac{1}{1+e^{\underbrace{-B_1x+B_2}_{x}}}$

function take input and then outputs a number.

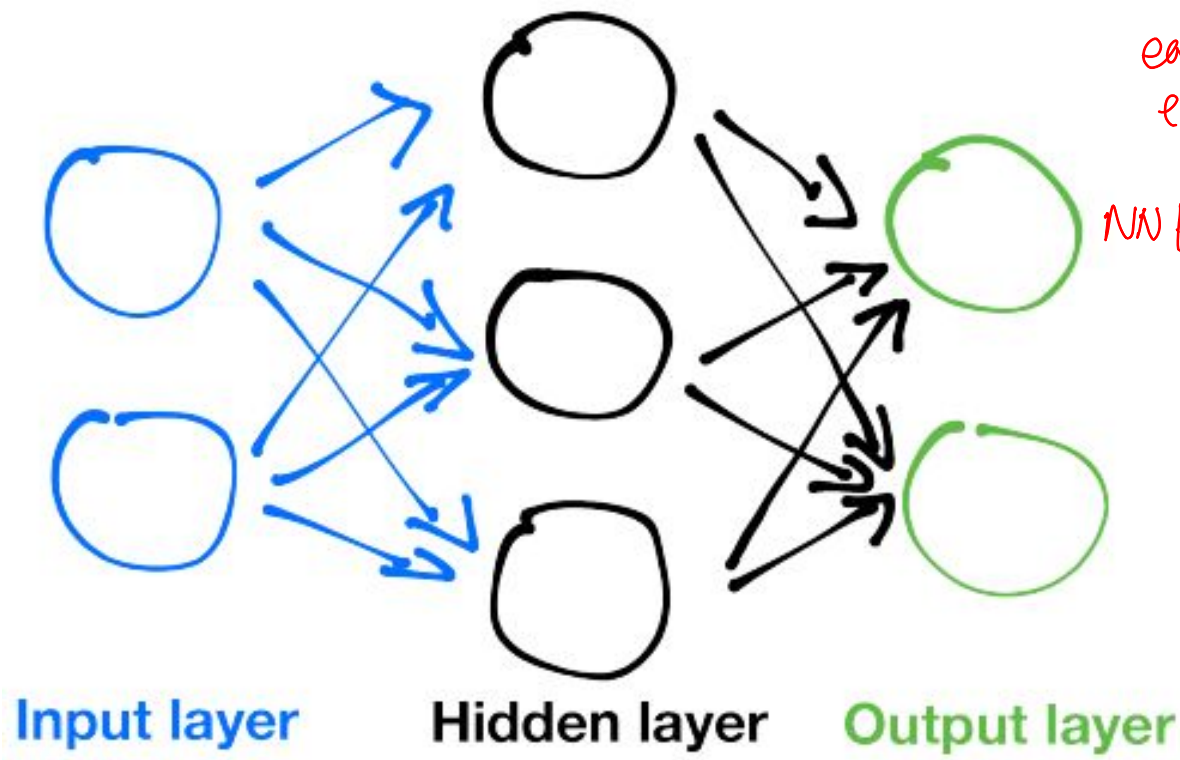


gen term for param that you want to learn from your model

- Inputs to the neuron are multiplied by weights
- Bias then summed with weighted inputs
- Non-linear activation function applied on wTx +b

gradient descent

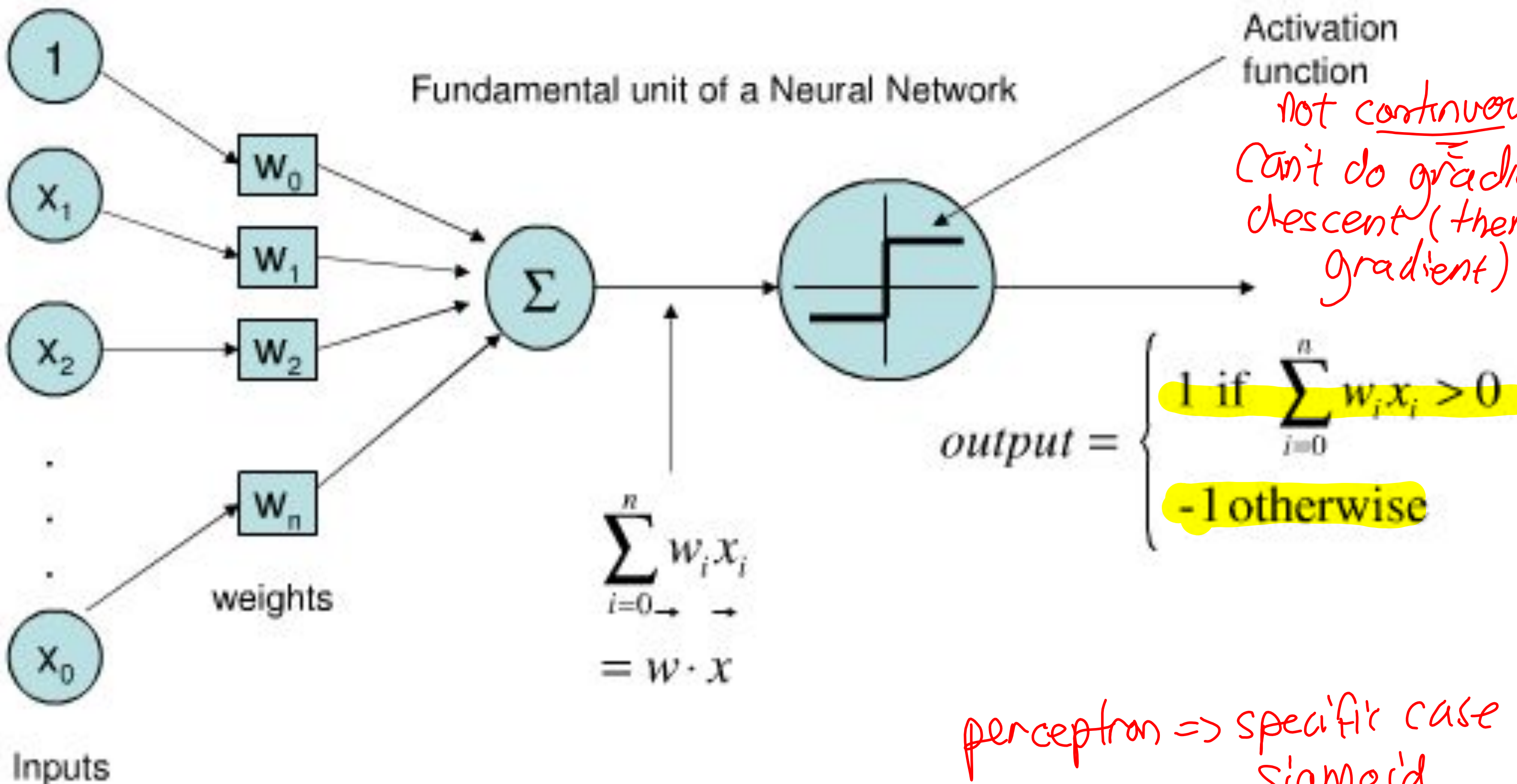
Biological Inspiration - A Layered Architecture



each neuron has an activation function
ex: Sigmoid (linear decision boundary)
NN Learn complex function

Input Layer: takes in input data (size corresponds to input space)
Hidden Layer: neurons hidden from view (this is where the magic happens)
Output Layer: neurons in this layer provide the output of the network

The Perceptron (model) line which will perfect split two class and decision boundaries



$$\sum_{i=0}^{n} w_i x_i = \vec{w} \cdot \vec{x}$$

$$output = \begin{cases} 1 \text{ if } \sum_{i=0}^{n} w_i x_i > 0 \\ -1 \text{ otherwise} \end{cases}$$

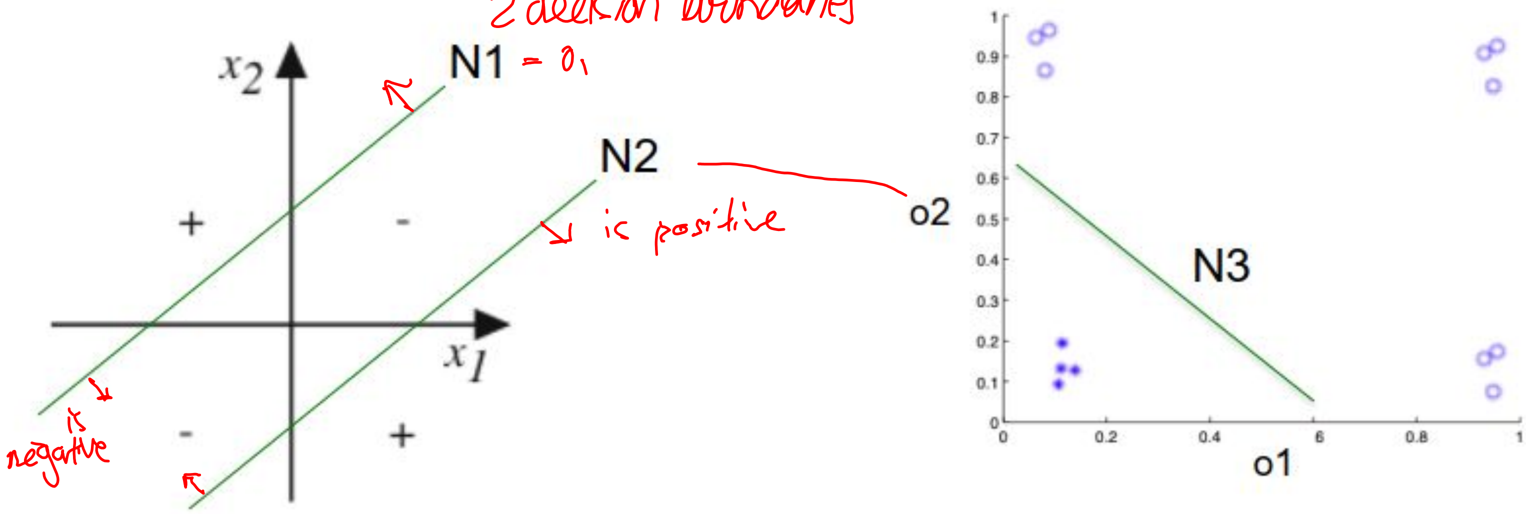
perceptron => specific case of sigmoid.
(more flexible

Image Credits From StackExchange

XOR functions

Perceptron Decision Boundary

2 decision boundaries



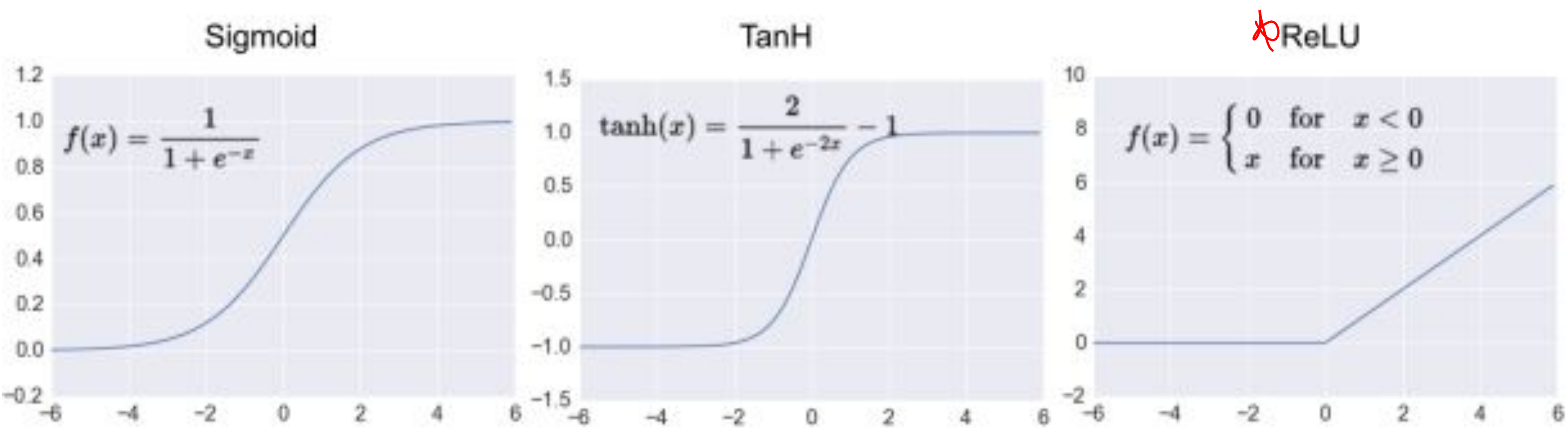
perceptron map your input space into something that can be linearly seperable

Image taken from Ryan Lowe's COMP551 Slides Lecture 14 Slide 5

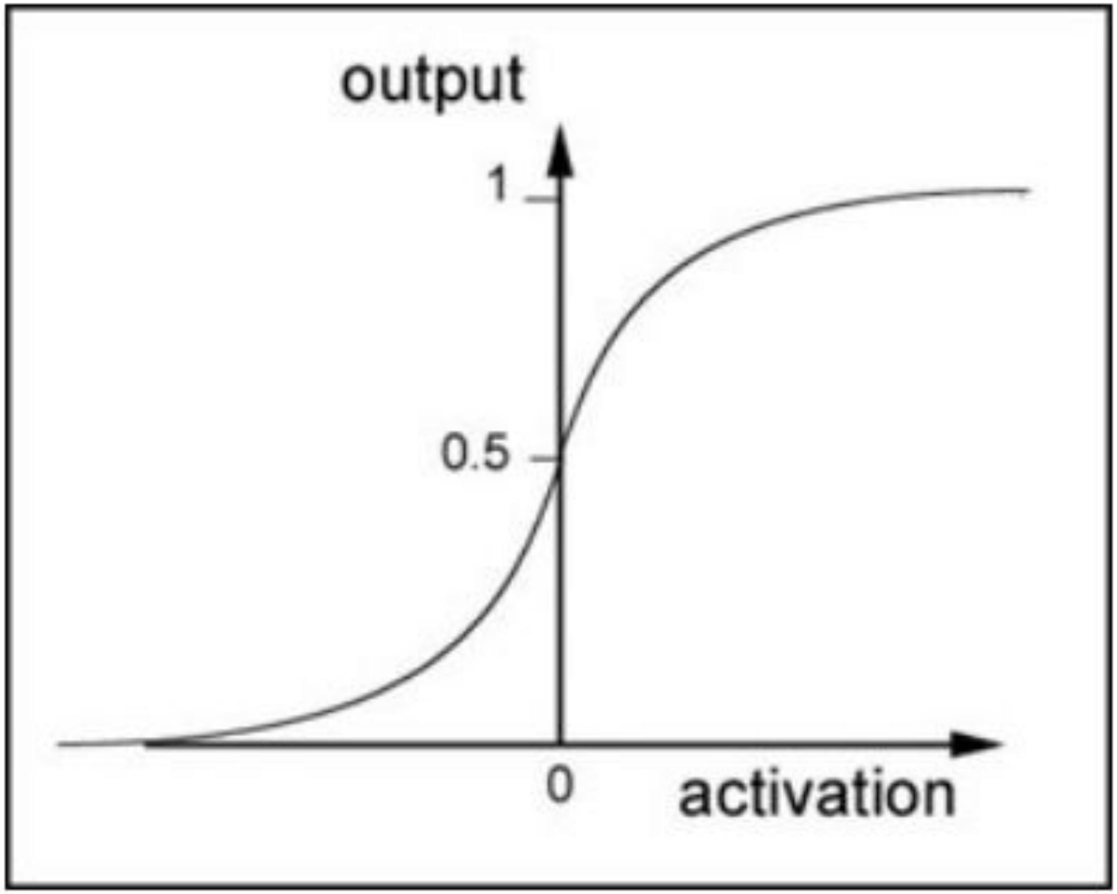
Activation Functions

For gradient descent to work, we need activation functions that are:

- Continuous
- Differentiable
- Monotonically Increasing

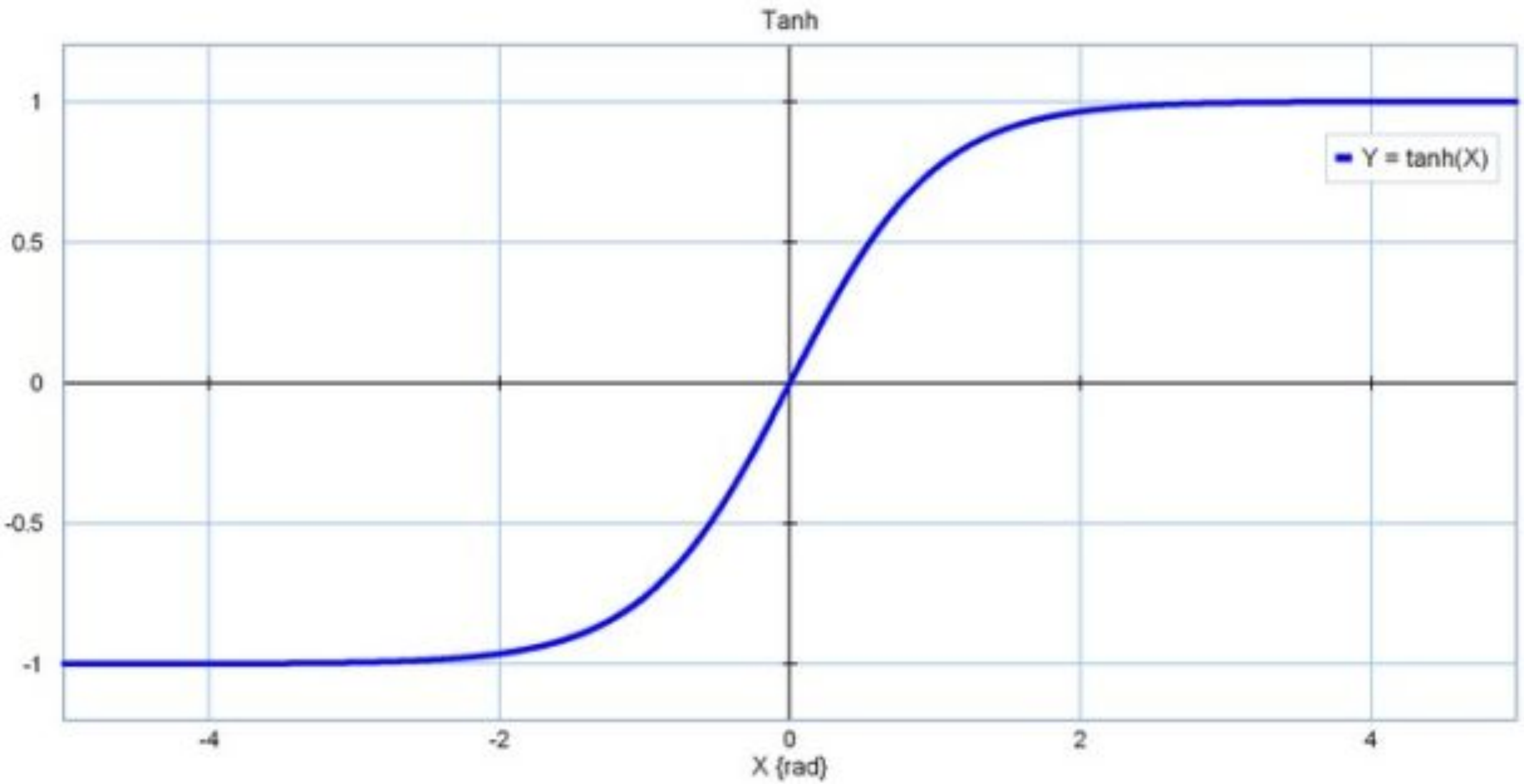


Sigmoid/Logistic



bounded 0-1

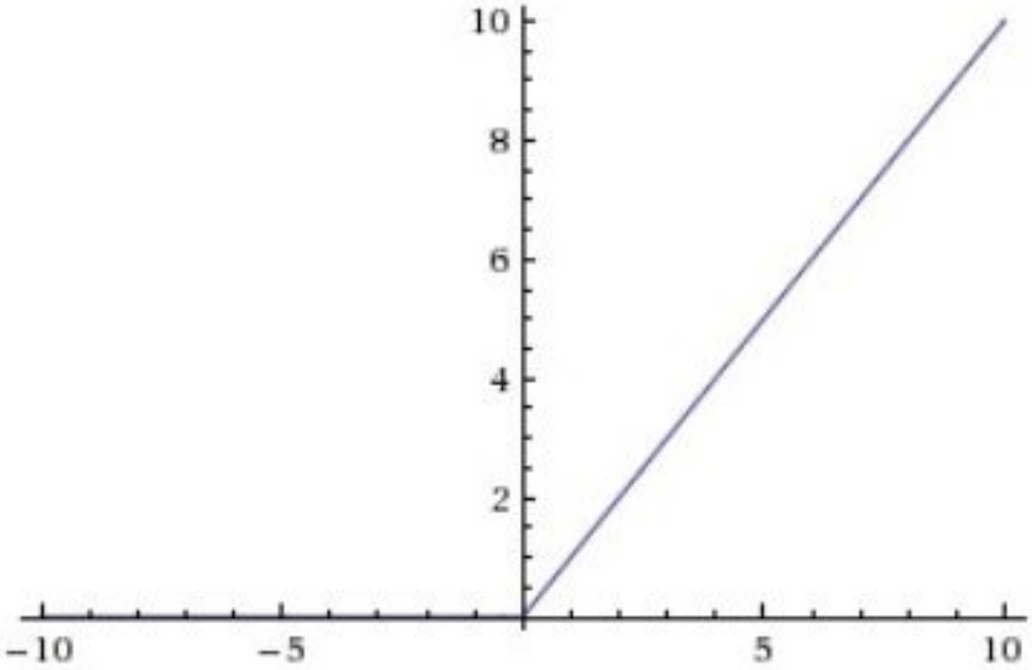
Hyperbolic tangent (tanh)



Bound [-1, 1]

Rectified Linear Unit (ReLU)

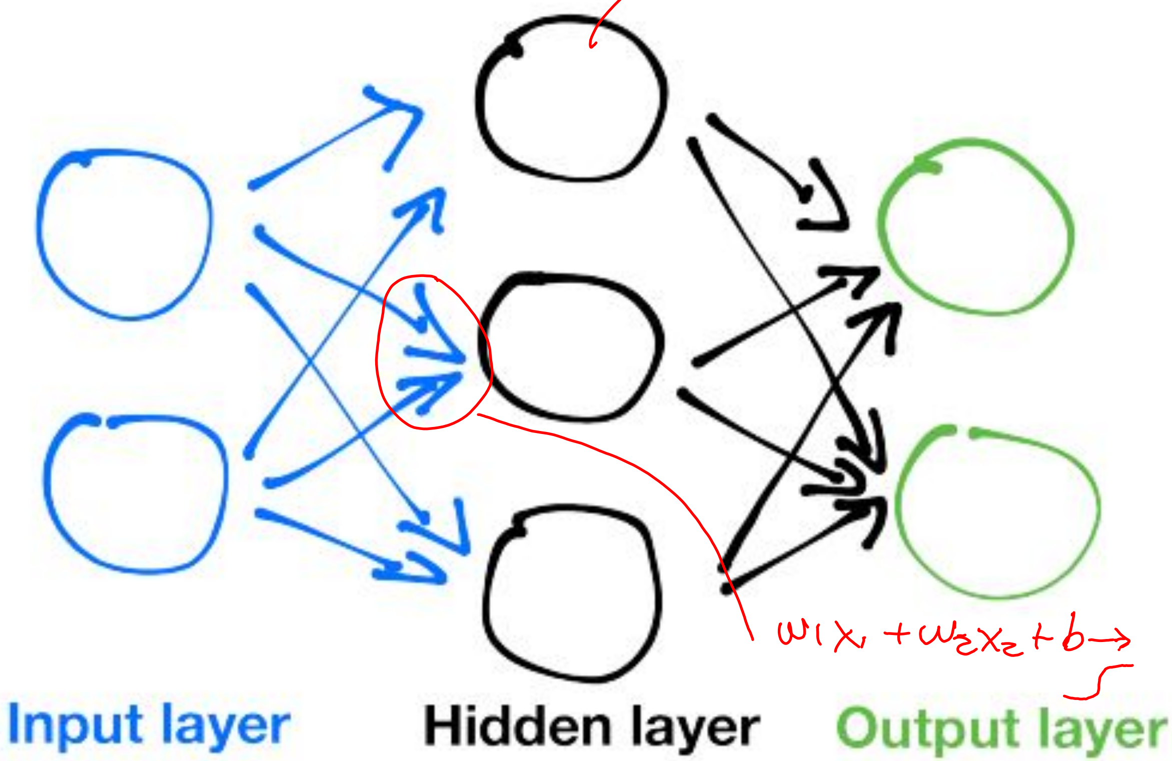
$$f(x) = \max(0, x)$$



don't face
gradient vanishing

Neural Networks

contains activation function



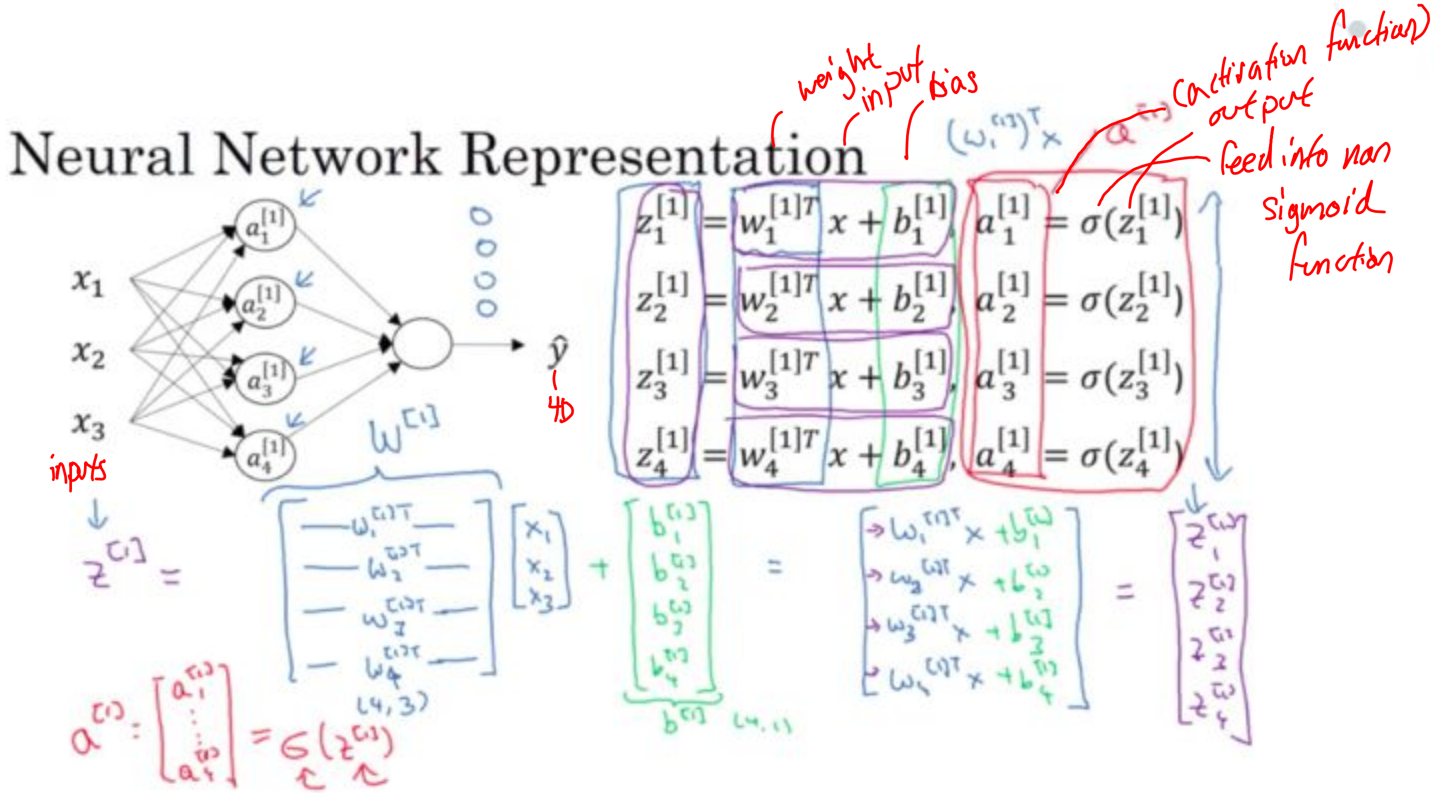
take output of previous layer

$w_1x_1 + w_2x_2 + b \rightarrow$

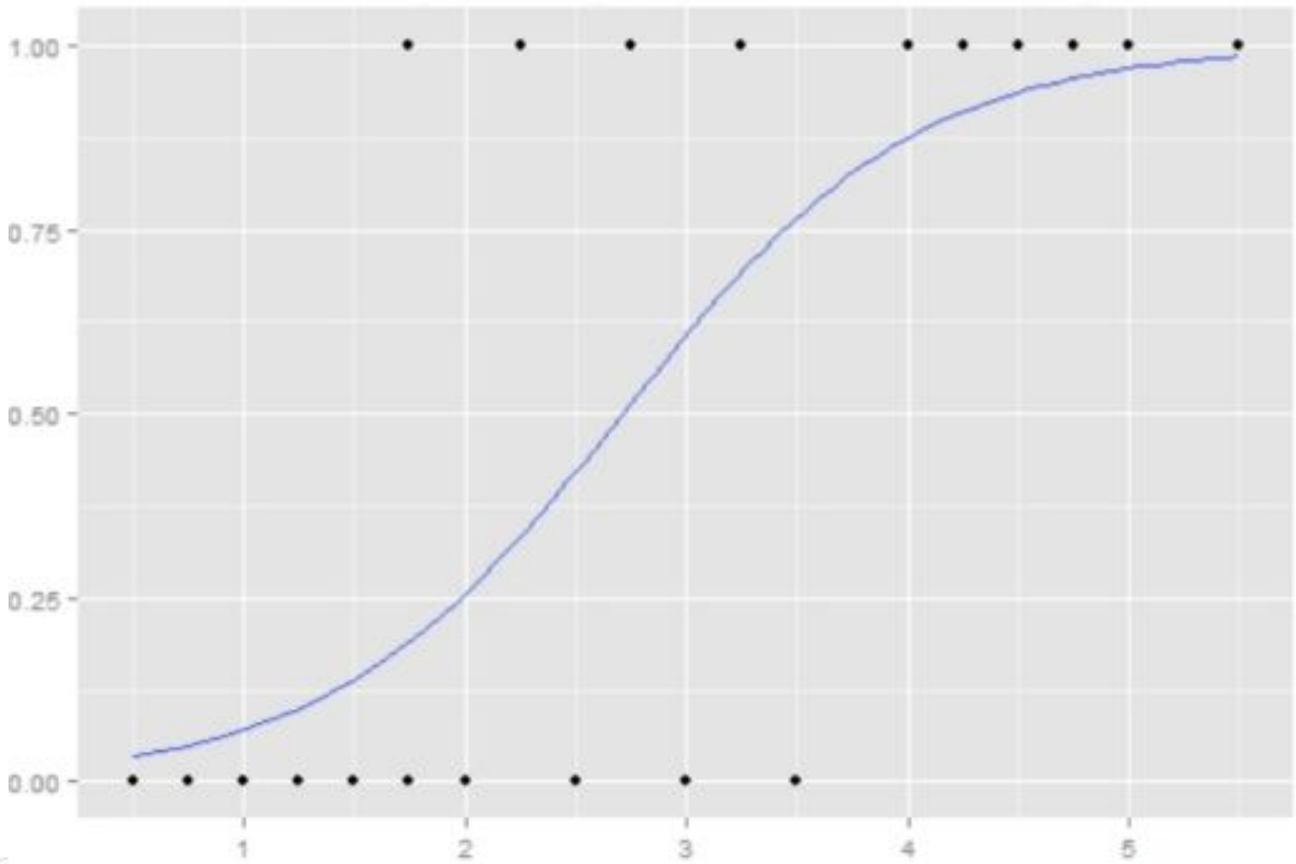
takes input
space = # input features

Input Layer: takes in input data (size corresponds to input space)
Hidden Layer: neurons hidden from view (this is where the magic happens)
Output Layer: neurons in this layer provide the output of the network

Neural Networks in Matrix Form



Neural Network Expressivity



Neural Network Expressivity

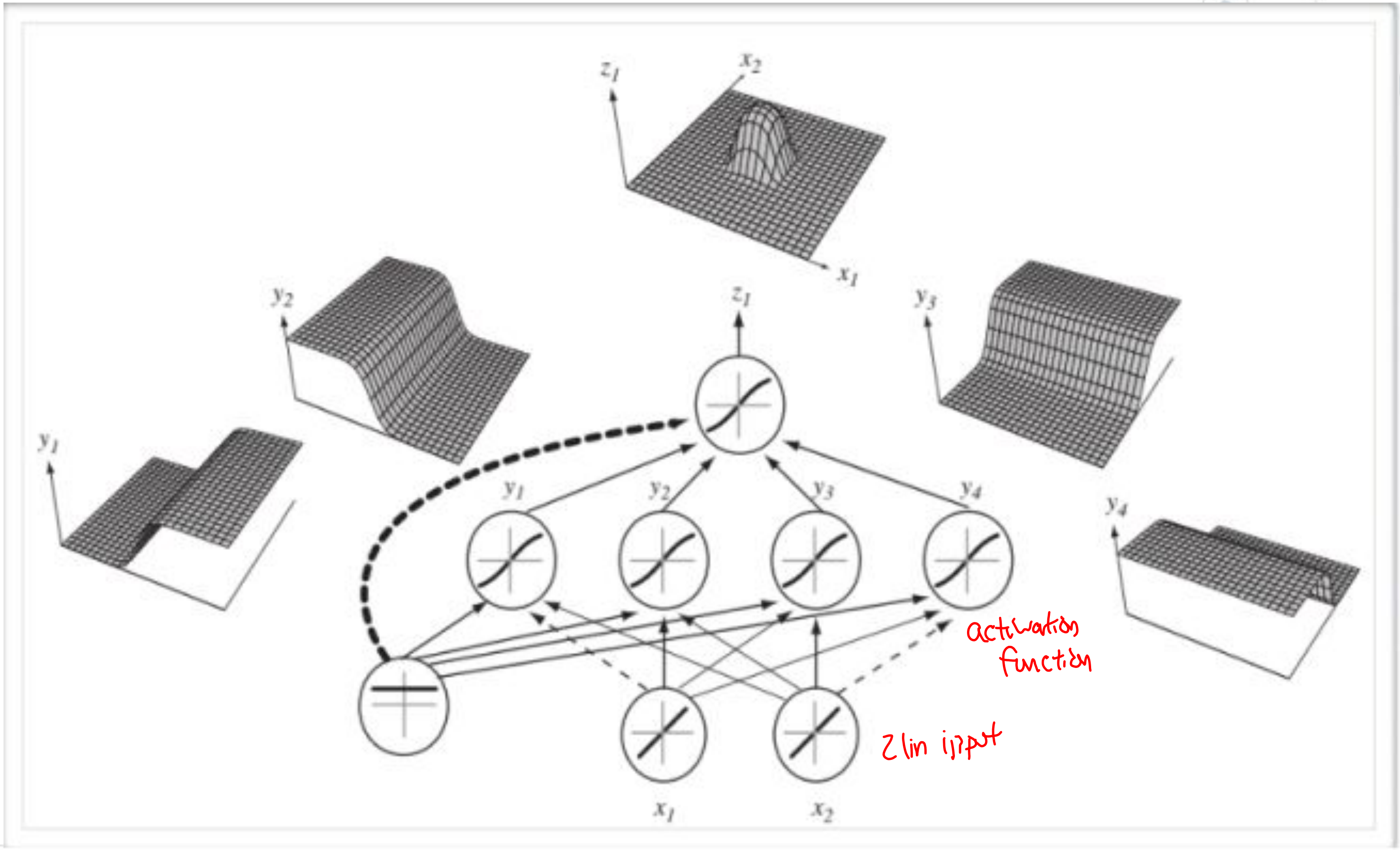


Image taken from Hugo Larochelle's Slides

Neural Network Expressiveness

- Neural networks approximate functions without assuming an initial data distribution approximate function
- NNs learn function approximations (anything that maps an input, to a single output)

$$f : X \rightarrow Y$$

Supervised learning if y given

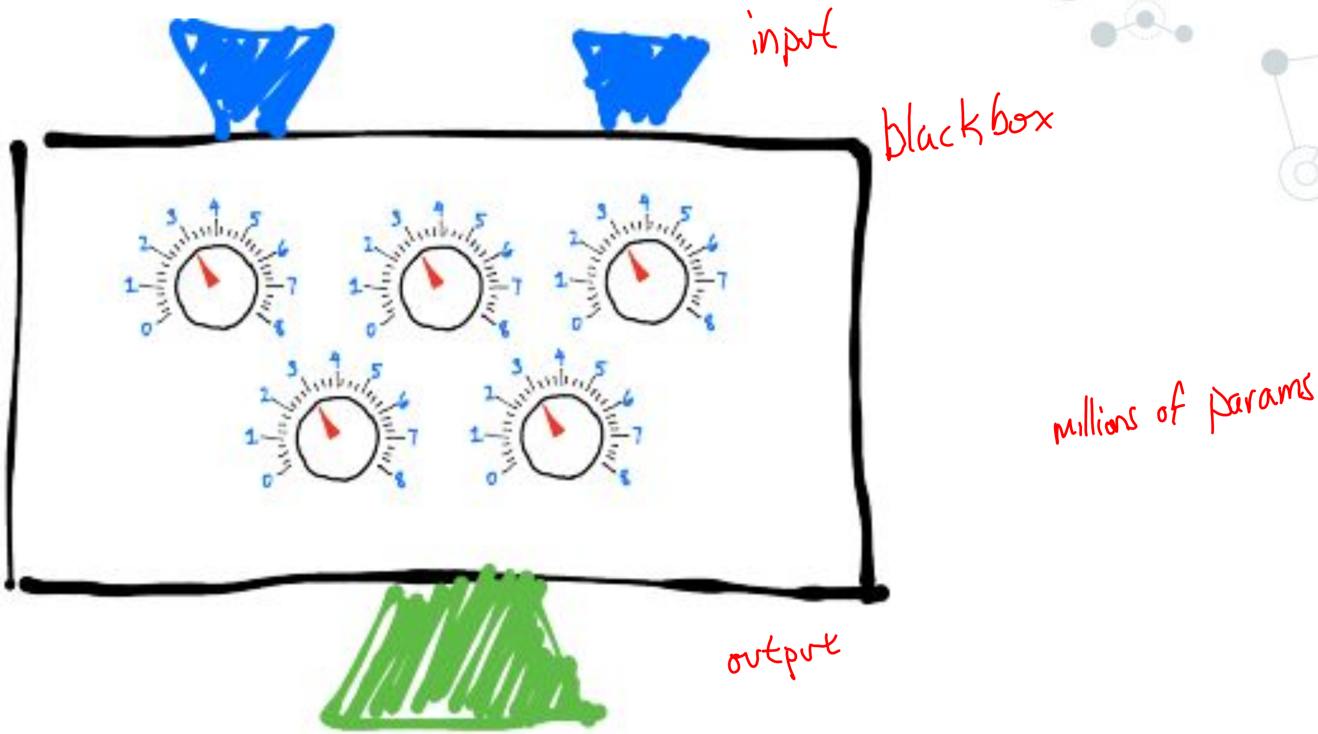
Universal Approximation Theorem

"Every bounded continuous function can be approximated with
arbitrary precision by a single-layer neural network"
(Hornik, 1991)

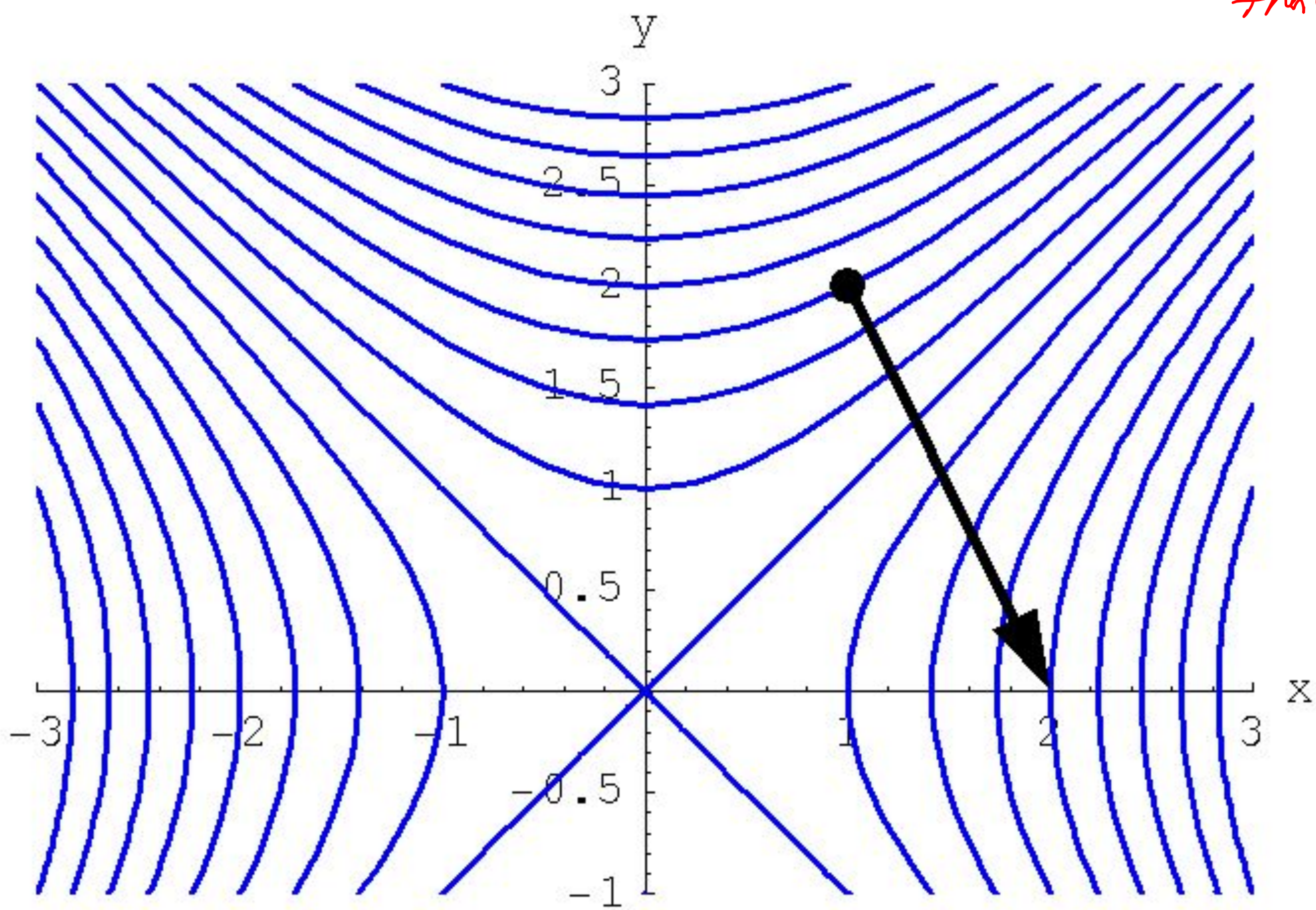
e^n

Image taken from Hugo Larochelle's Slides

Learning in Neural Networks



Optimization Via Gradient Descent → specify cost function that we want to minimize



Gradient Descent

Define a differentiable, convex objective to minimize:

$$C(x, \text{parameters}) = \frac{1}{2}(y - \hat{f}(x))^2$$

hypothesize function

Where:

- y is the actual output
- f_hat is our hypothesis function (output of the network) dependent on our learned parameters and inputs

:

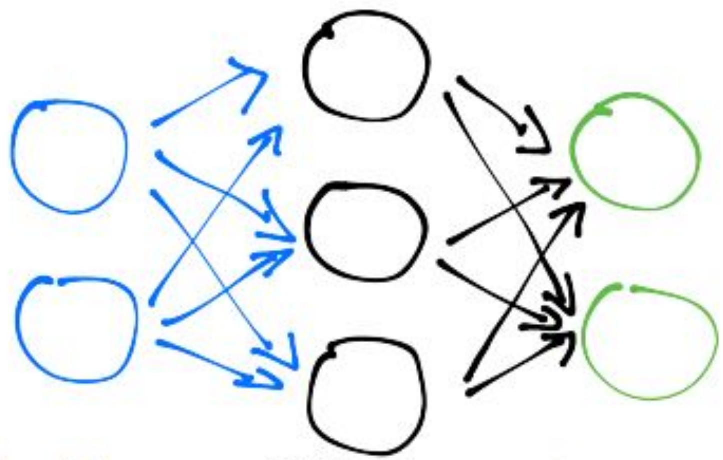
$$J(\mathbf{w}) = \frac{1}{2}(y - h_{\mathbf{w}}(\mathbf{x}))^2 = \frac{1}{2}(y - o_{N+H+1})^2$$

weights

hypothesis

We use gradient descent to allow us to find a local minima of C given the derivative of C with respect to its parameters

Backpropagation



partial derivative with respect to each weight

Neural network:

$$h_\Theta(x) \in \mathbb{R}^K \quad (h_\Theta(x))_i = i^{th} \text{ output}$$

$$J(\Theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{k=1}^{K} y_k^{(i)} \log(h_\Theta(x^{(i)}))_k + (1-y_k^{(i)})\log(1-(h_\Theta(x^{(i)}))_k)\right]$$
$$+\frac{\lambda}{2m}\sum_{l=1}^{L-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}(\Theta_{ji}^{(l)})^2$$

Stochastic Gradient Descent

- Initialize all weights to small random numbers. — Initialization
- Repeat until convergence:
  - Pick a training example. single input
  - Feed example through network to compute output $o = o_{N+H+1}$

  Forward pass

  - For the output unit, compute the correction:

$$\underbrace{\delta_{N+H+1}}_{\text{ex went through network}} \leftarrow o(1-o)(y-o)$$

  - For each hidden unit h, compute its share of the correction:

correction computed from output

$$\delta_h \leftarrow o_h(1-o_h)w_{N+H+1,h}\delta_{N+H+1}$$

  Backpropagation

  - Update each network weight: using gradient descent

$$w_{h,i} \leftarrow w_{h,i} + \alpha_{h,i}\delta_h x_{h,i}$$

which hidden unit

learning rate

Gradient descent

Image taken from Ryan Lowe's COMP551 Slides Lecture 14 Slide 17

Forms of Gradient Descent

Stochastic Gradient Descent: compute error using a single sample at a time, update weights, repeat

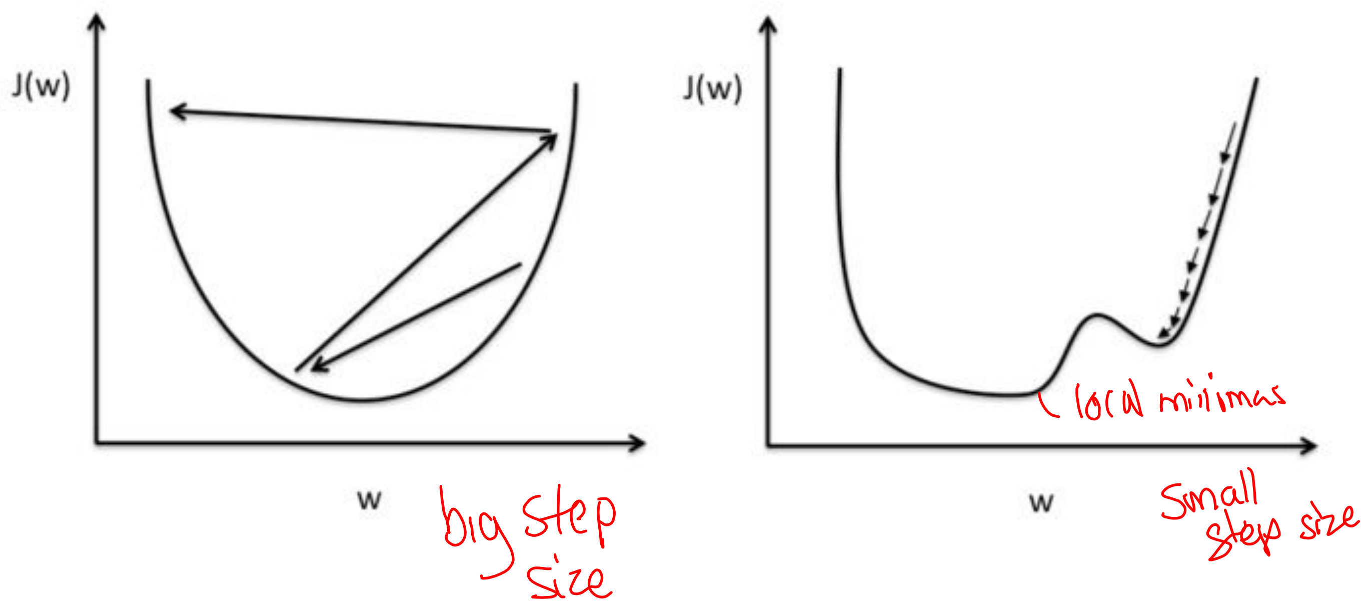
Batch Gradient Descent: compute error on all examples, update weights based on error, repeat

highest that you can

Mini-batch Gradient Descent: randomly select a subset from the training data, calculate error on subset, update weights, repeat

Larger sample size
better modelling
whole distribution
more accurate
gradient descent

Picking α - Adaptive Learning Rates



ADAM, RMSProp, Adagrad, etc.

[More Information on Stochastic Gradient Descent and Different Optimization Methods]

Coding Demo

Thanks!

Any questions?

Reminders:

Homework 2 due before next lecture.