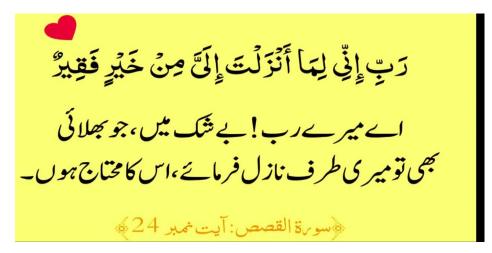


In the Name of Allah, the Most Gracious, the Most Merciful

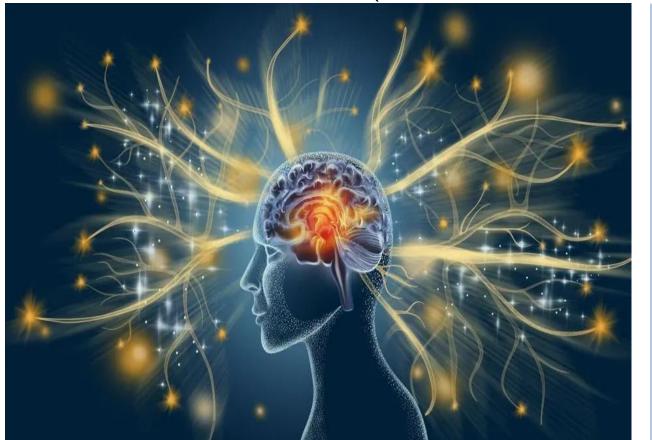
Surah Taha with Urdu Translation





# CS4152: Deep Learning and Neural Networks

Lecture 3 (Introduction to Neural Networks)



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# Lecture 3

Neural Networks
An Overview
Jameel Ahmad, PhD

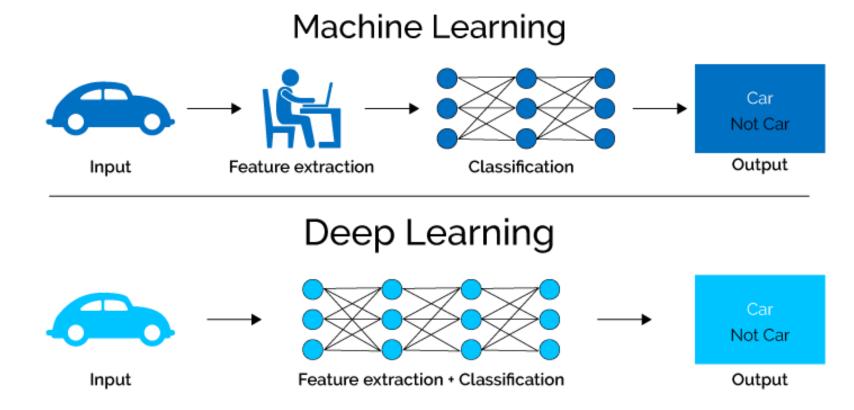
## Lecture Outline

- Elements of neural networks (NNs)
  - Activation functions
  - Single and Multilayer Perceptron

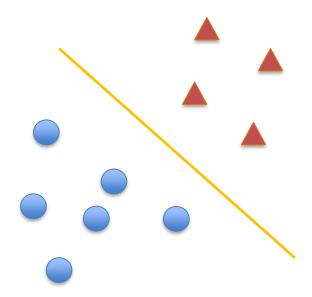
# ML vs. Deep Learning (DL)

Difference between Machine Learning and Deep Learning

- **Deep learning** (DL) is a machine learning subfield that uses multiple layers for learning data representations
  - DL is exceptionally effective at learning patterns



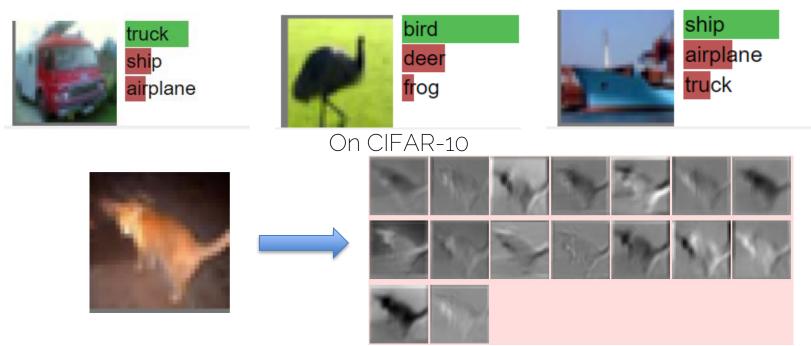
Logistic Regression



Neural Networks



• Non-linear score function  $f = ... (\max(0, W_1x))$ 

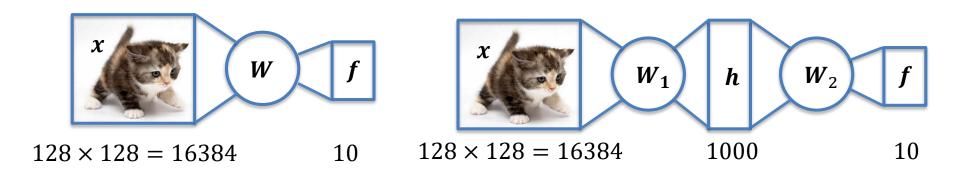


Visualizing activations of the first layer.

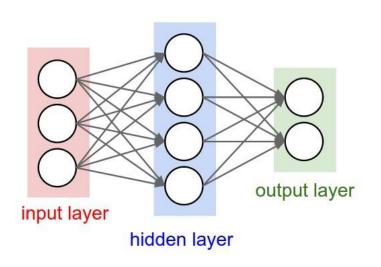
Source: ConvNetJS

1-layer network: f = Wx

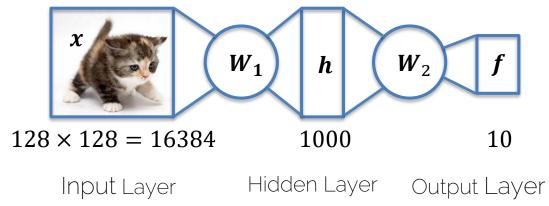
2-layer network:  $f = W_2 \max(0, W_1 x)$ 



Why is this structure useful?

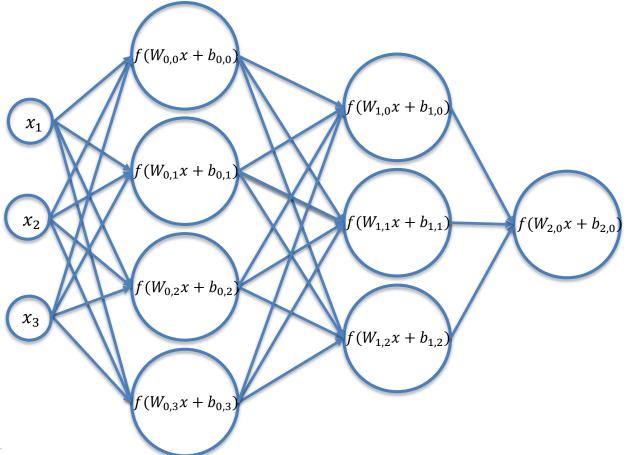


2-layer network:  $f = W_2 \max(0, W_1 x)$ 

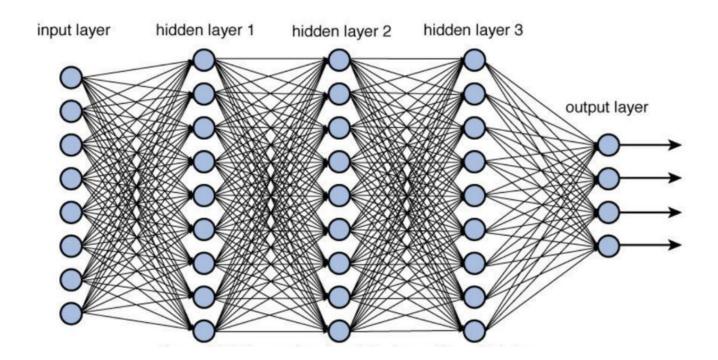


12DL: Prof. Niessner

## Net of Artificial Neurons



12DL: Prof. Niessner



Source: https://towardsdatascience.com/training-deep-neural-networks-9fdb1964b964

## **Activation Functions**

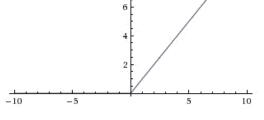
Sigmoid:  $\sigma(x) = \frac{1}{(1+e^{-x})}$ 

tanh: tanh(x)

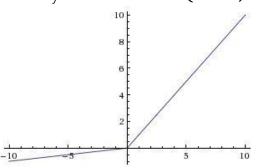
x) 10 10 8 6 4

0.5

ReLU: max(0, x)



Leaky ReLU: max(0.1x, x)



Parametric ReLU:  $max(\alpha x, x)$ 

Maxout 
$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

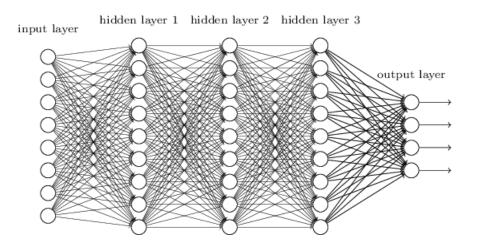
$$\text{ELU } f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(e^x - 1) & \text{if } x \le 0 \end{cases}$$

$$f = W_3 \cdot (W_2 \cdot (W_1 \cdot x)))$$

Why activation functions?

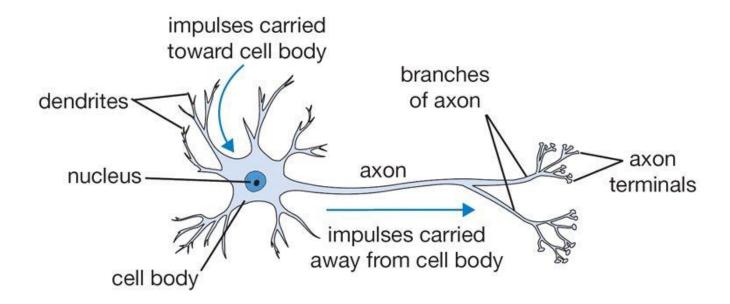
Simply concatenating linear layers would be so much cheaper...

Why organize a neural network into layers?



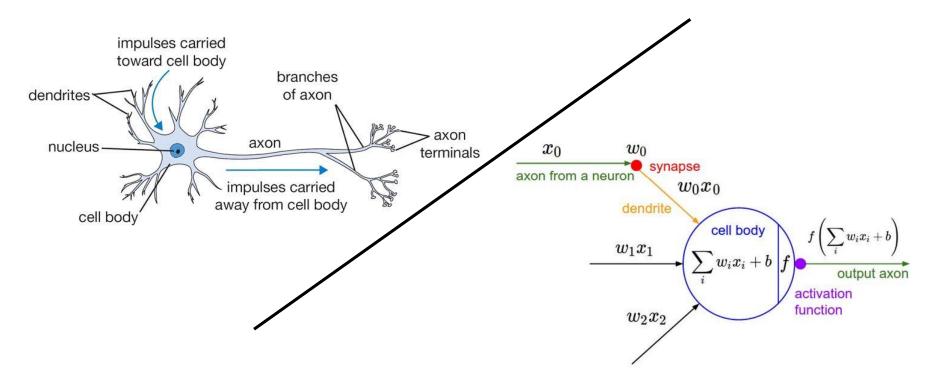
12DL: Prof. Niessner

# Biological Neurons



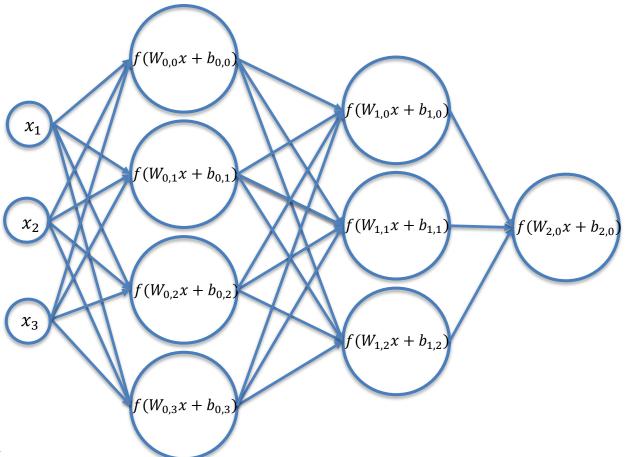
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# Biological Neurons



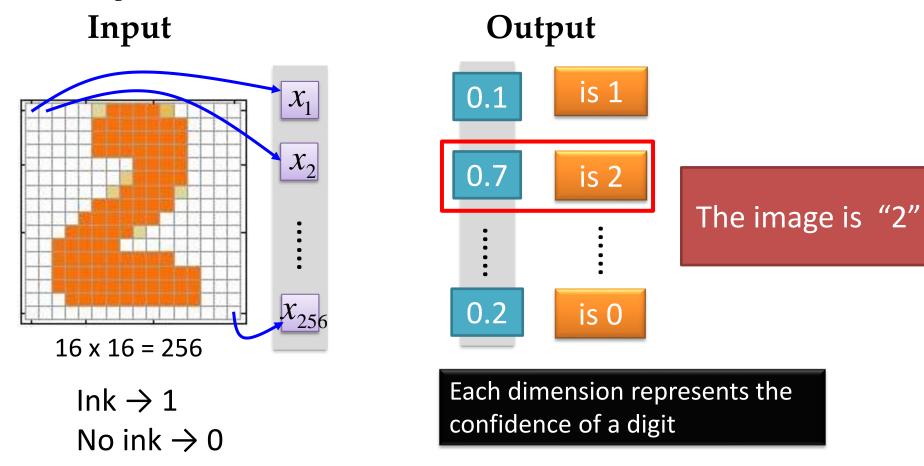
Credit: Stanford CS 231n

## Artificial Neural Network

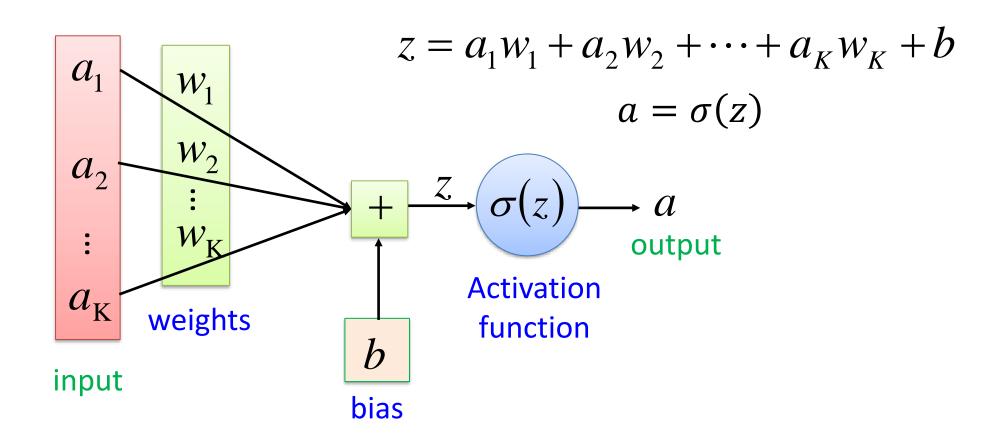


12DL: Prof. Niessner

- Handwritten digit recognition (MNIST dataset)
  - The intensity of each pixel is considered an input element
  - Output is the class of the digit

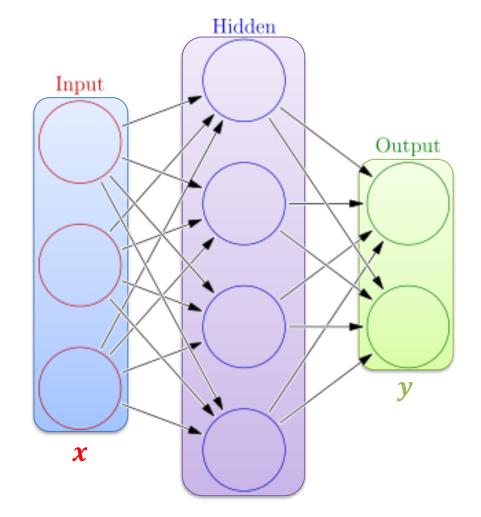


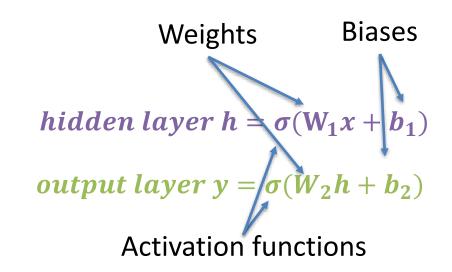
- NNs consist of hidden layers with neurons (i.e., computational units)
- A single neuron maps a set of inputs into an output number, or  $f: \mathbb{R}^K \to \mathbb{R}$



Introduction to Neural Networks

• A NN with one hidden layer and one output layer

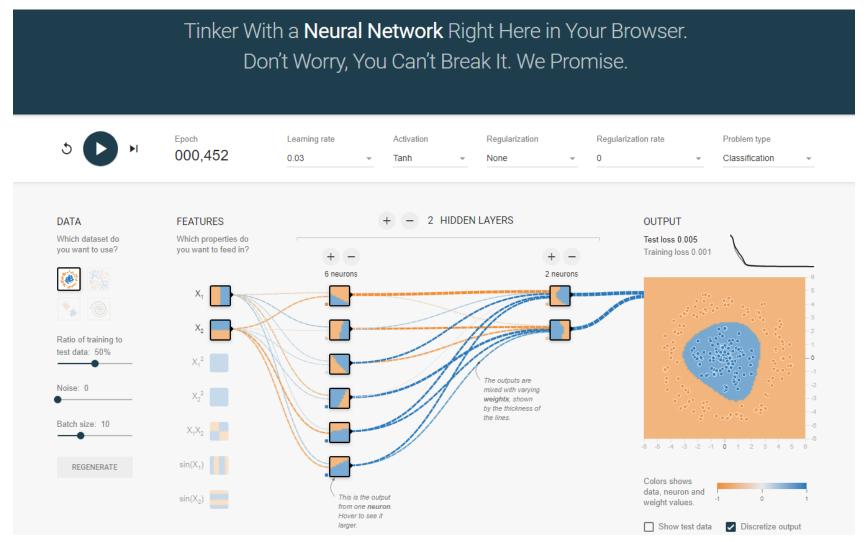




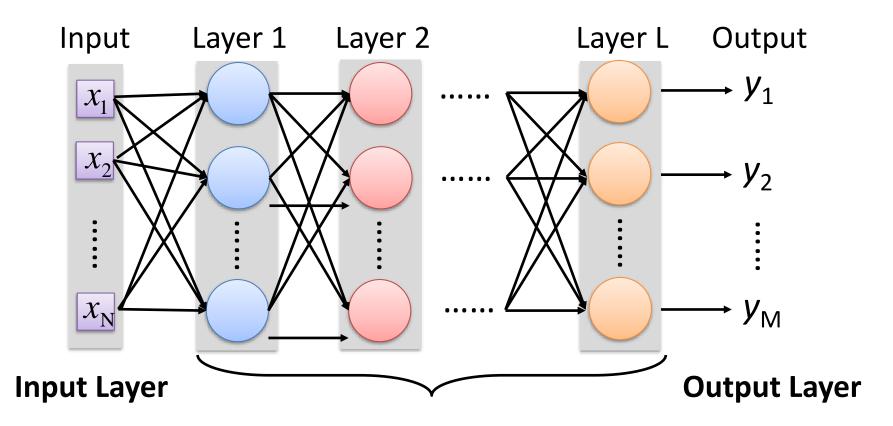
$$4 + 2 = 6$$
 neurons (not counting inputs)  
 $[3 \times 4] + [4 \times 2] = 20$  weights  
 $4 + 2 = 6$  biases  
26 learnable parameters

Introduction to Neural Networks

• A neural network playground <u>link</u>

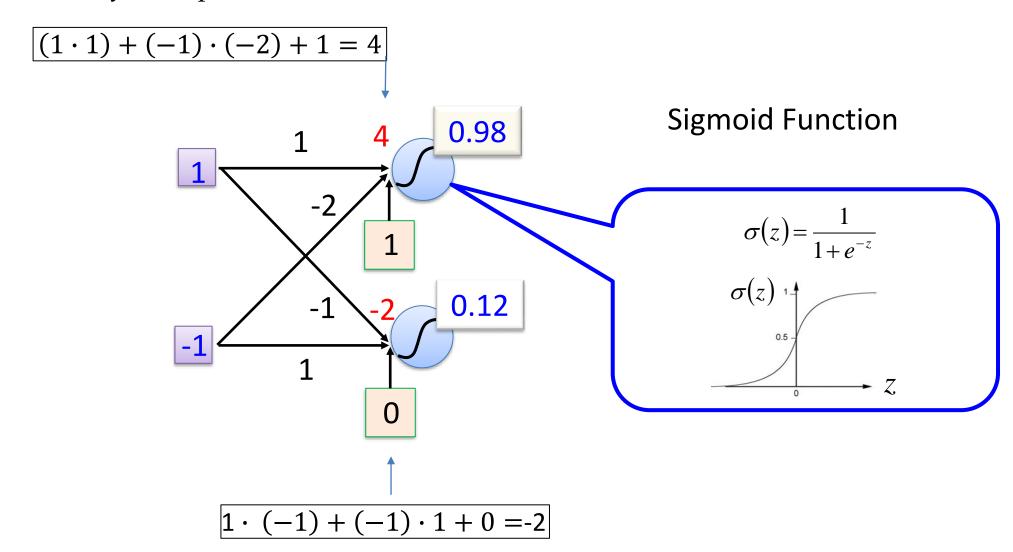


- Deep NNs have many hidden layers
  - Fully-connected (dense) layers (a.k.a. Multi-Layer Perceptron or MLP)
  - Each neuron is connected to all neurons in the succeeding layer

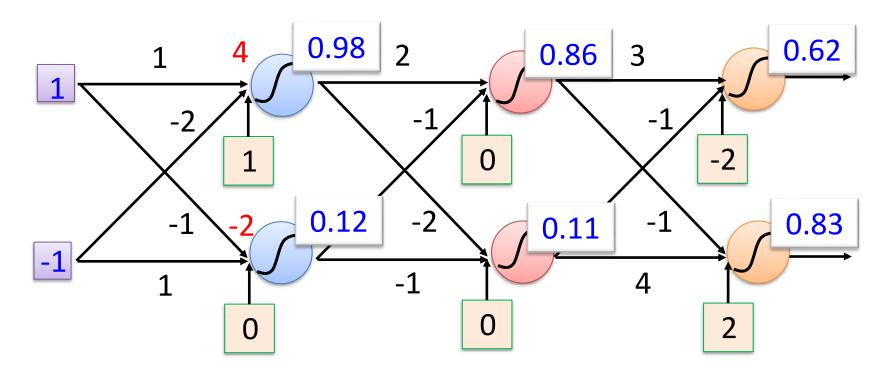


Introduction to Neural Networks

• A simple network, toy example



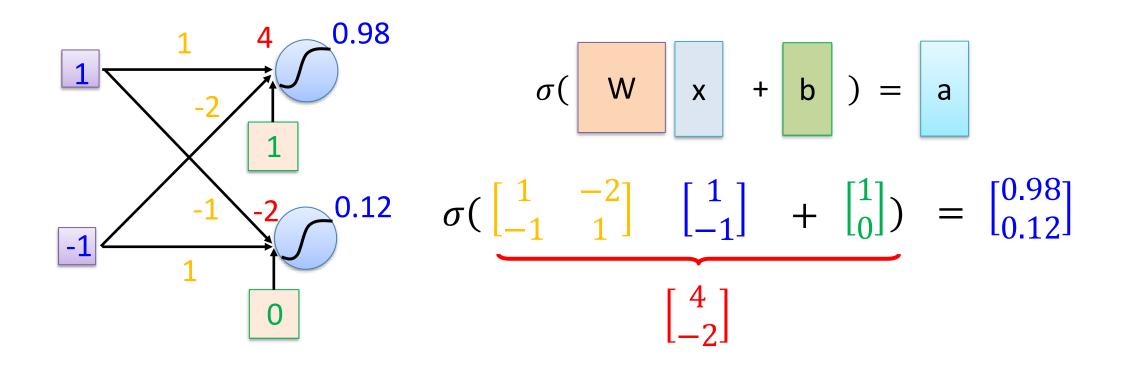
- A simple network, toy example (cont'd)
  - For an input vector  $\begin{bmatrix} 1 & -1 \end{bmatrix}^T$ , the output is  $\begin{bmatrix} 0.62 & 0.83 \end{bmatrix}^T$



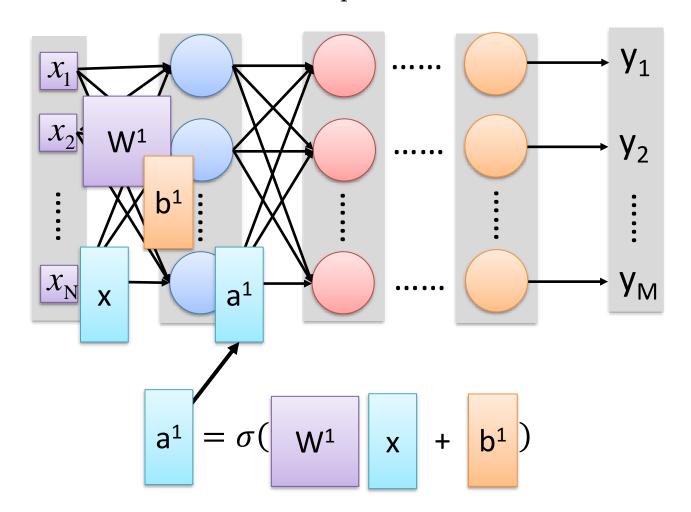
$$f: \mathbb{R}^2 \to \mathbb{R}^2$$
 
$$f\left(\begin{bmatrix} 1 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} 0.62 \\ 0.83 \end{bmatrix}$$

#### Introduction to Neural Networks

Matrix operations are helpful when working with multidimensional inputs and outputs

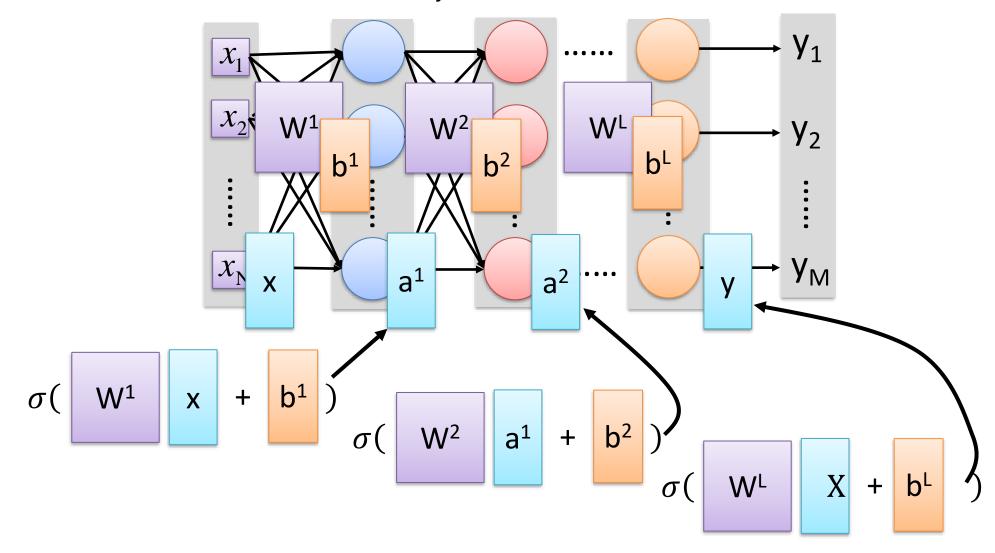


- Multilayer NN, matrix calculations for the first layer
  - Input vector x, weights matrix  $W^1$ , bias vector  $b^1$ , output vector  $a^1$



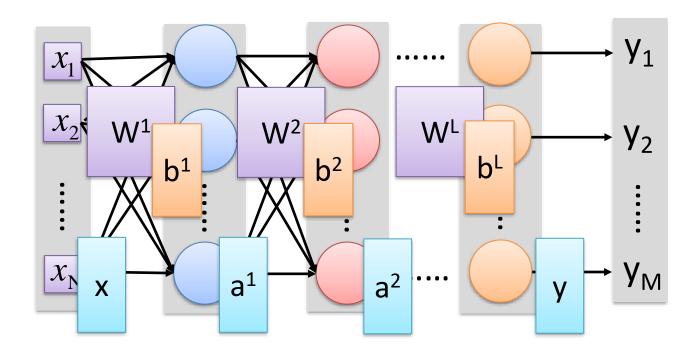
Introduction to Neural Networks

• Multilayer NN, matrix calculations for all layers



Introduction to Neural Networks

• Multilayer NN, function f maps inputs x to outputs y, i.e., y = f(x)



$$y = f(x) = \sigma(w^{L}) - \sigma(w^{L}) - \sigma(w^{L}) + b^{L}) + b^{L}) + b^{L}$$

# Softmax Layer

#### Introduction to Neural Networks

- In multi-class classification tasks, the output layer is typically a *softmax layer* 
  - I.e., it employs a *softmax activation function*
  - If a layer with a sigmoid activation function is used as the output layer instead, the predictions by the NN may not be easy to interpret
    - o Note that an output layer with sigmoid activations can still be used for binary classification

### A Layer with Sigmoid Activations

$$z_{1} \xrightarrow{3} \sigma \xrightarrow{0.95} y_{1} = \sigma(z_{1})$$

$$z_{2} \xrightarrow{1} \sigma \xrightarrow{0.73} y_{2} = \sigma(z_{2})$$

$$z_{3} \xrightarrow{-3} \sigma \xrightarrow{0.05} y_{3} = \sigma(z_{3})$$

# Softmax Layer

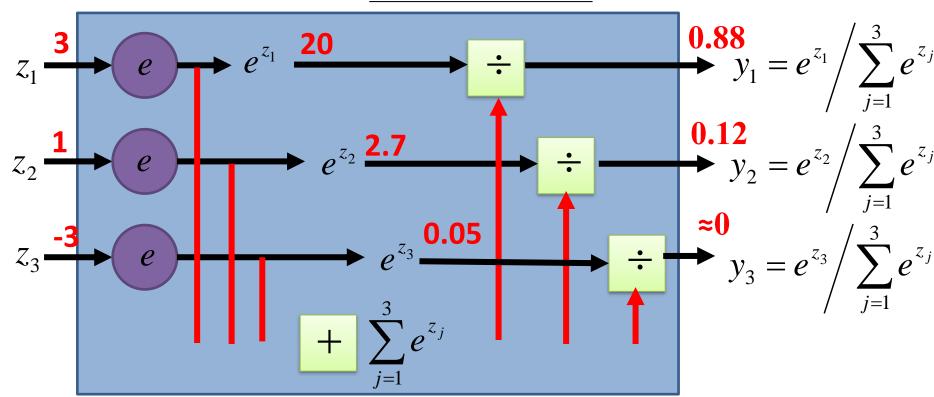
#### Introduction to Neural Networks

- The softmax layer applies softmax activations to output a probability value in the range [0, 1]
  - The values z inputted to the softmax layer are referred to as logits

### **Probability**:

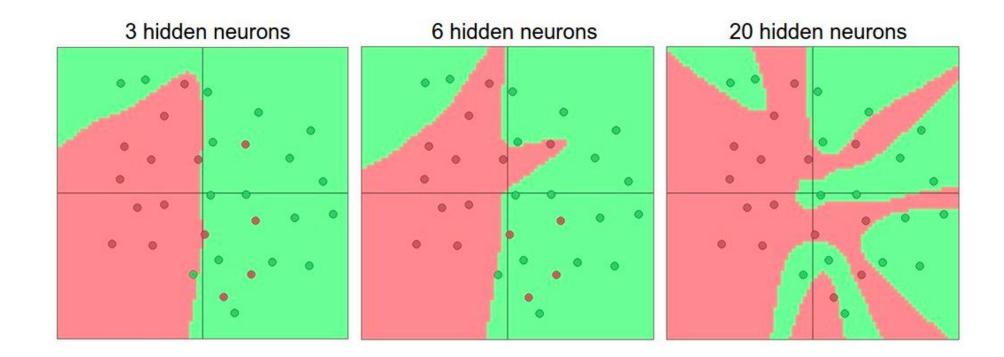
- $0 < y_i < 1$

### A Softmax Layer



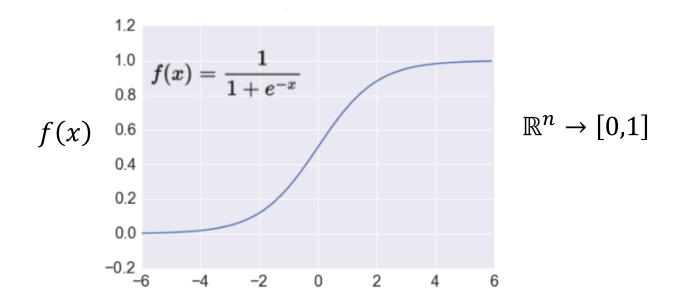
## **Activation Functions**

- Non-linear activations are needed to learn complex (non-linear) data representations
  - Otherwise, NNs would be just a linear function (such as  $W_1W_2x = Wx$ )
  - NNs with large number of layers (and neurons) can approximate more complex functions
    - o Figure: more neurons improve representation (but, may overfit)



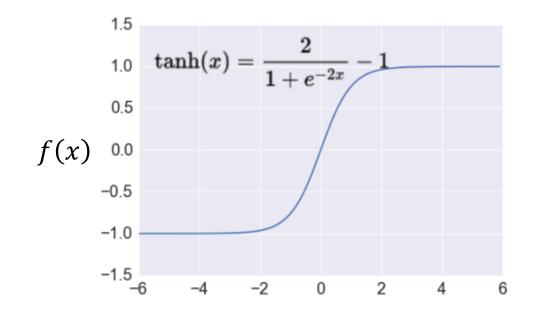
# Activation: Sigmoid

- Sigmoid function  $\sigma$ : takes a real-valued number and "squashes" it into the range between 0 and 1
  - The output can be interpreted as the firing rate of a biological neuron
    - Not firing = 0; Fully firing = 1
  - When the neuron's activation are 0 or 1, sigmoid neurons saturate
    - o Gradients at these regions are almost zero (almost no signal will flow)
  - Sigmoid activations are less common in modern NNs



## Activation: Tanh

- *Tanh function*: takes a real-valued number and "squashes" it into range between -1 and 1
  - Like sigmoid, tanh neurons saturate
  - Unlike sigmoid, the output is zero-centered
    - o It is therefore preferred than sigmoid
  - Tanh is a scaled sigmoid:  $tanh(x) = 2 \cdot \sigma(2x) 1$



$$\mathbb{R}^n \to [-1,1]$$

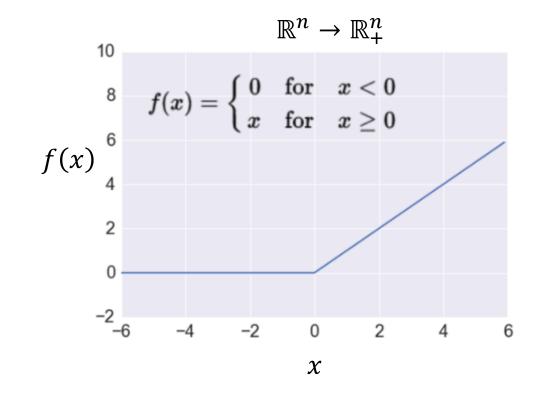
# Activation: ReLU

#### Introduction to Neural Networks

• ReLU (Rectified Linear Unit): takes a real-valued number and thresholds it at zero

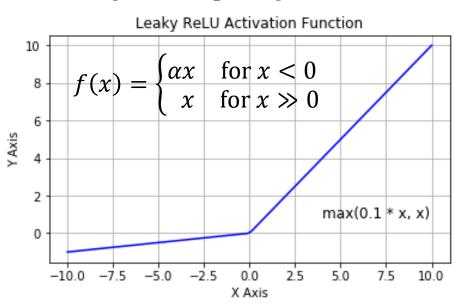
$$f(x) = \max(0, x)$$

- Most modern deep NNs use ReLU activations
- ReLU is fast to compute
  - o Compared to sigmoid, tanh
  - o Simply threshold a matrix at zero
- Accelerates the convergence of gradient descent
  - o Due to linear, non-saturating form
- Prevents the gradient vanishing problem



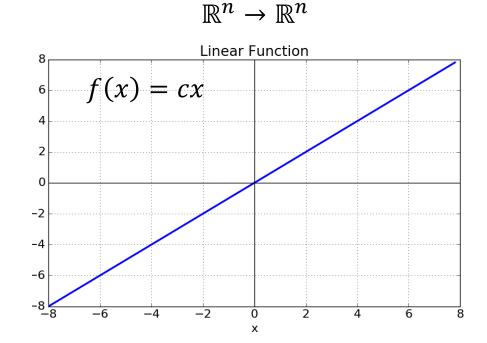
# Activation: Leaky ReLU

- The problem of ReLU activations: they can "die"
  - ReLU could cause weights to update in a way that the gradients can become zero and the neuron will not activate again on any data
  - E.g., when a large learning rate is used
- Leaky ReLU activation function is a variant of ReLU
  - Instead of the function being 0 when x < 0, a leaky ReLU has a small negative slope (e.g.,  $\alpha = 0.01$ , or similar)
    - This resolves the dying ReLU problem
    - Most current works still use ReLU
      - With a proper setting of the learning rate, the problem of dying ReLU can be avoided



## Activation: Linear Function

- *Linear function* means that the output signal is proportional to the input signal to the neuron
  - If the value of the constant *c* is 1, it is also called identity activation function
  - This activation type is used in regression problems
    - E.g., the last layer can have linear activation function, in order to output a real number (and not a class membership)



## References

- 1. Hung-yi Lee Deep Learning Tutorial
- 2. Ismini Lourentzou Introduction to Deep Learning
- 3. CS231n Convolutional Neural Networks for Visual Recognition (Stanford CS course) (<u>link</u>)
- 4. James Hays, Brown Machine Learning Overview
- 5. Param Vir Singh, Shunyuan Zhang, Nikhil Malik Deep Learning
- 6. Sebastian Ruder An Overview of Gradient Descent Optimization Algorithms (link)