This is CS5045!

GCR:ioc7cdl

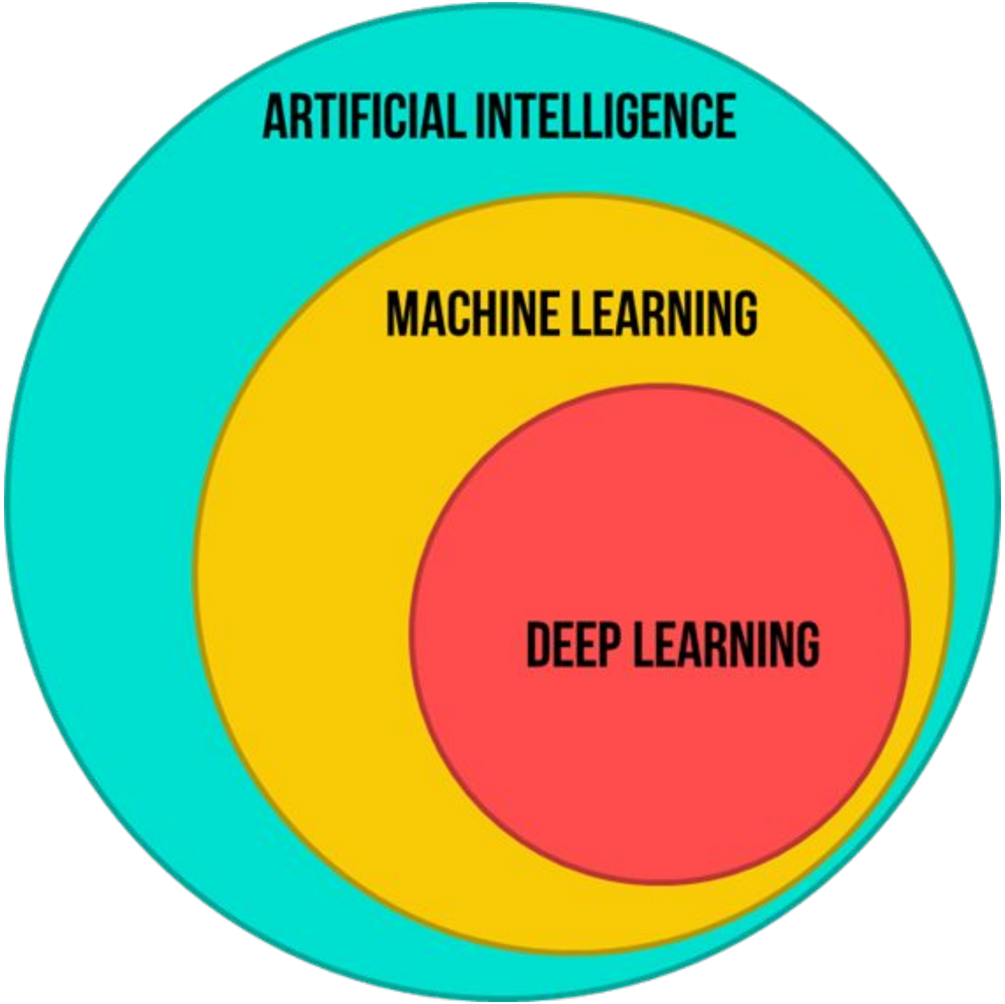
Hi,
I am Sumaiyah

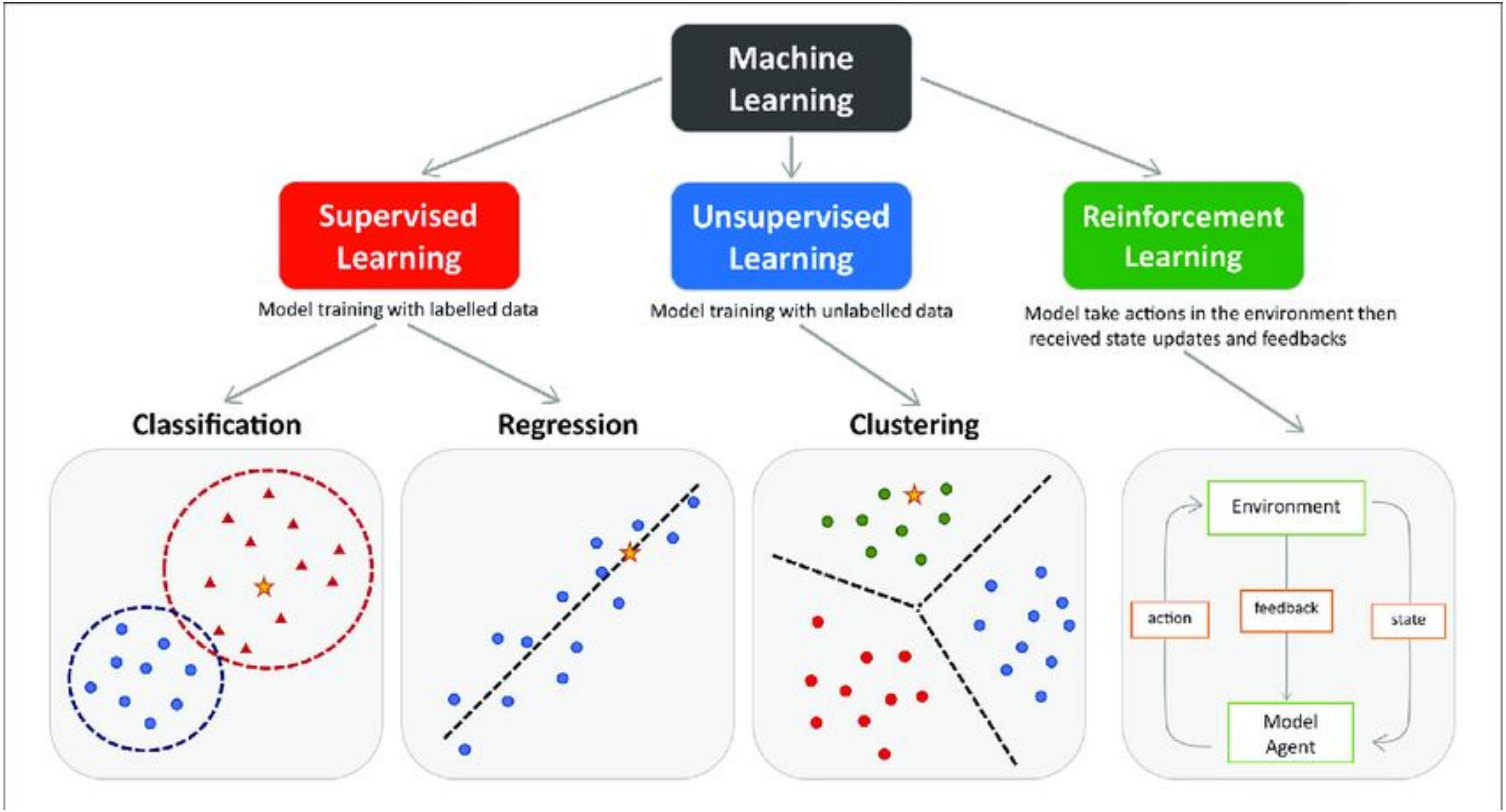
Email : Sumaiyah@nu.edu.pk

Office : In front of CS Secretariat

P.S. These slides are useless if you do not attend classes

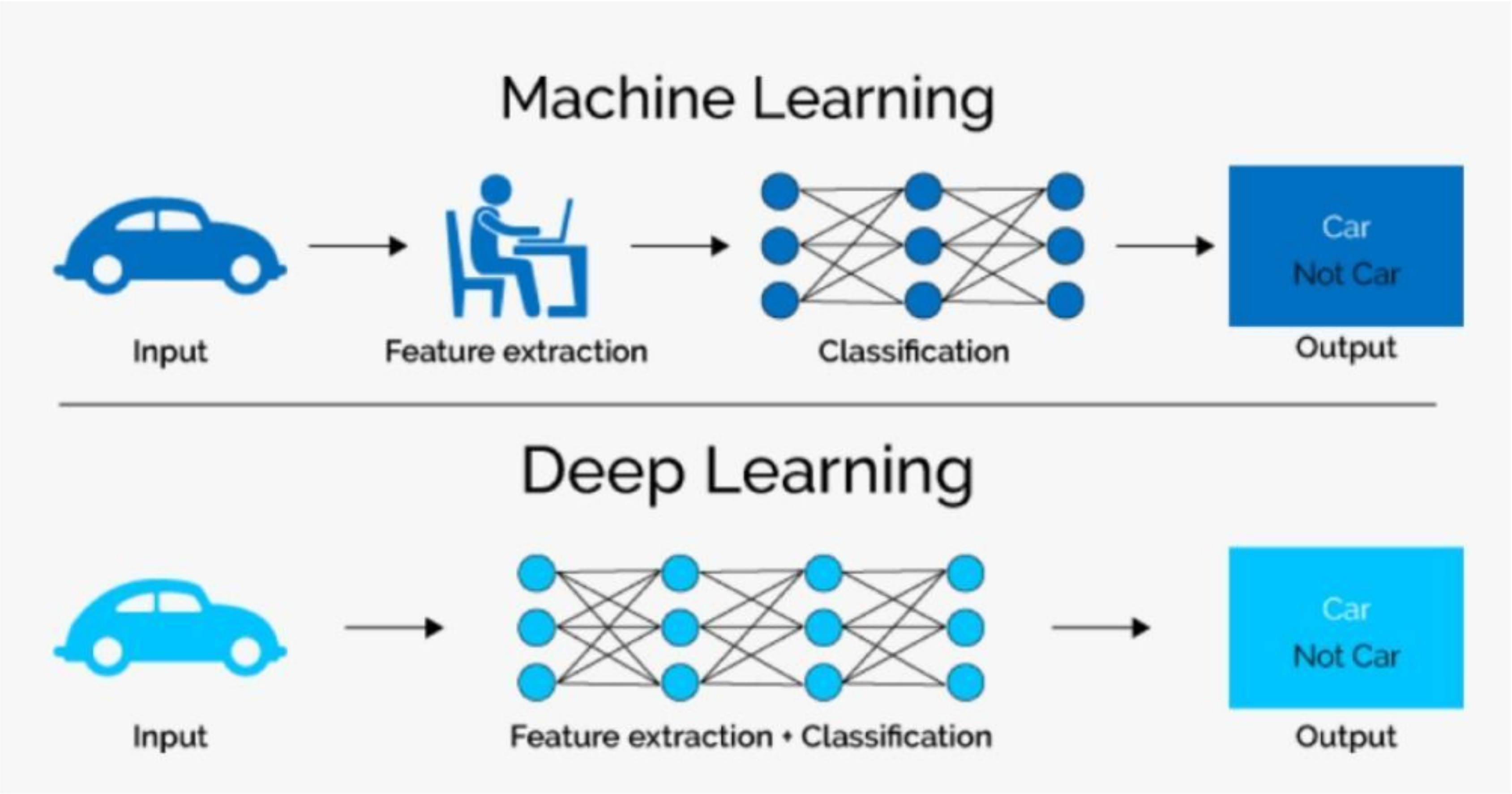
Machine Learning Recap


ARTIFICIAL INTELLIGENCE
MACHINE LEARNING
DEEP LEARNING


Machine Learning
Supervised Learning
Model training with labelled data
Unsupervised Learning
Model training with unlabelled data
Reinforcement Learning
Model take actions in the environment then received state updates and feedbacks
Classification
Regression
Clustering
Environment
action
feedback
state
Model Agent

Machine Learning Terms

- Overfitting
- Underfitting
- Training / Validation / Testing
- Cross Validation



Machine Learning

Input → Feature extraction → Classification → Output

Car

Not Car

Deep Learning

Input → Feature extraction + Classification → Output

Car

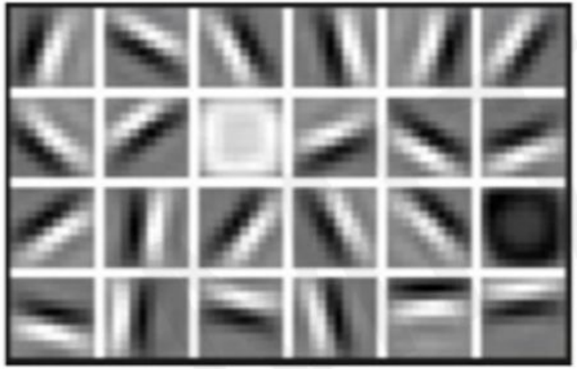
Not Car

Why Deep Learning?

Hand engineered features are time consuming, brittle, and not scalable in practice

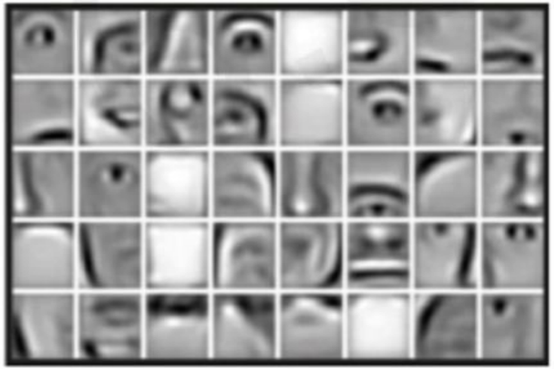
Can we learn the **underlying features** directly from data?

Low Level Features



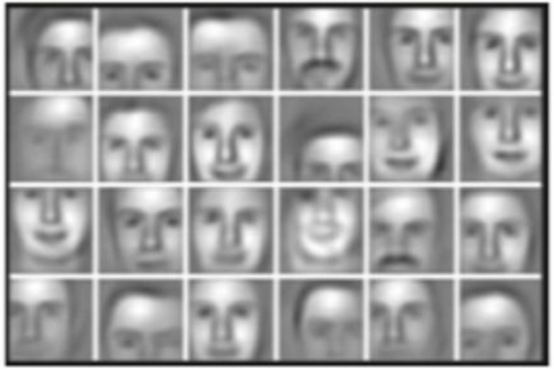
Lines & Edges

Mid Level Features



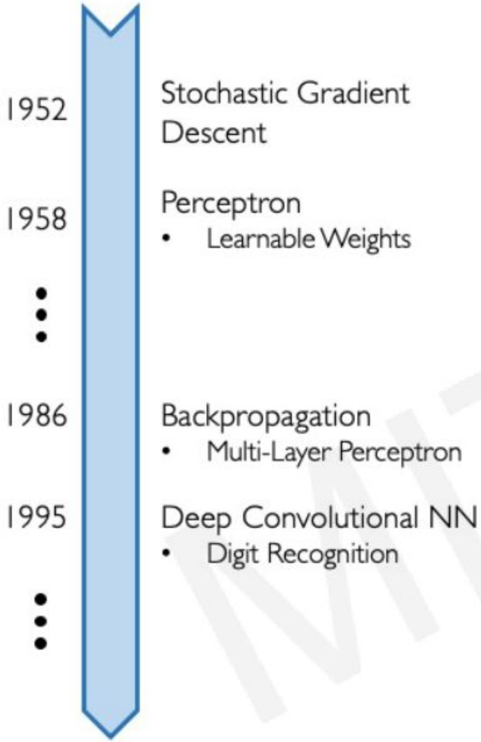
Eyes & Nose & Ears

High Level Features



Facial Structure

Why Now?



1952 Stochastic Gradient Descent

1958 Perceptron
- Learnable Weights

⋮

1986 Backpropagation
- Multi-Layer Perceptron

1995 Deep Convolutional NN
- Digit Recognition

⋮

Neural Networks date back decades, so why the resurgence?

1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET

WIKIPEDIA
The Free Encyclopedia

2. Hardware

- Graphics Processing Units (GPUs)
- Massively Parallelizable

3. Software

- Improved Techniques
- New Models
- Toolboxes

TensorFlow

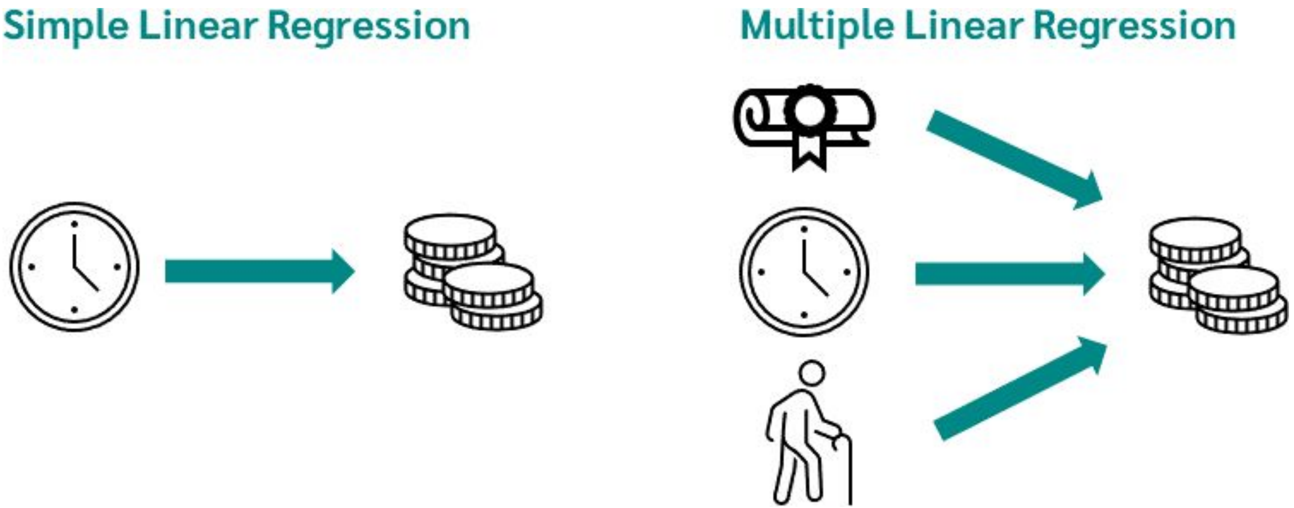
Deep Learning Applications

Discussed in class

Deep Learning Terms

- Input Layer
- Output Layer
- Hidden Layer
- Neurons/ Nodes
- Shallow Neural Network
- Deep Neural Network
- Epoch
- Hyperparameter vs Parameters
- Activation Function

Linear Regression



Simple Linear Regression

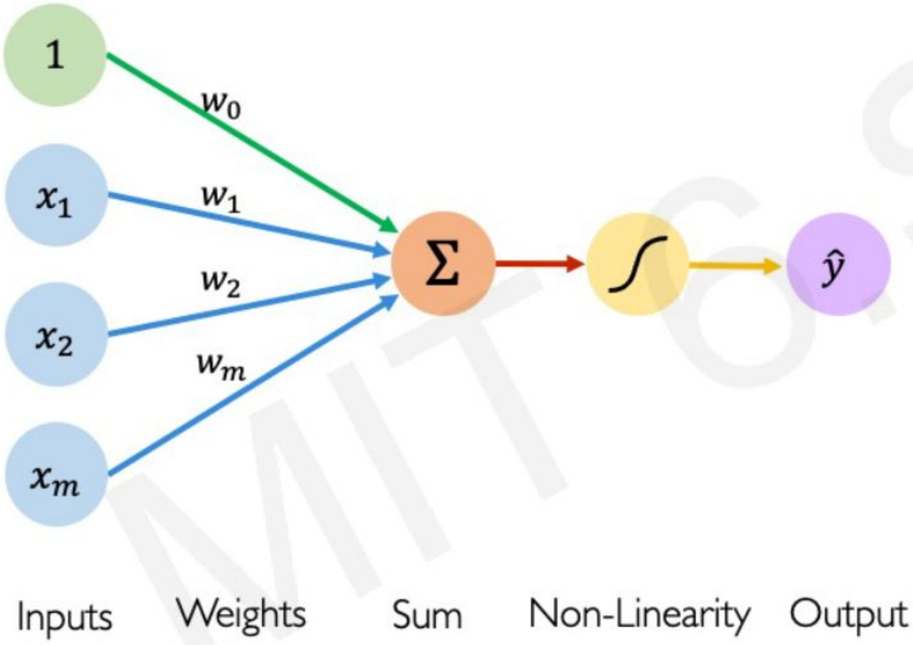
$$\hat{y} = b \cdot x + a$$

→

Multiple Linear Regression

$$\hat{y} = b_1 \cdot x_1 + b_2 \cdot x_2 + \ldots + b_k \cdot x_k + a$$

The Perceptron: Forward Propagation



Output

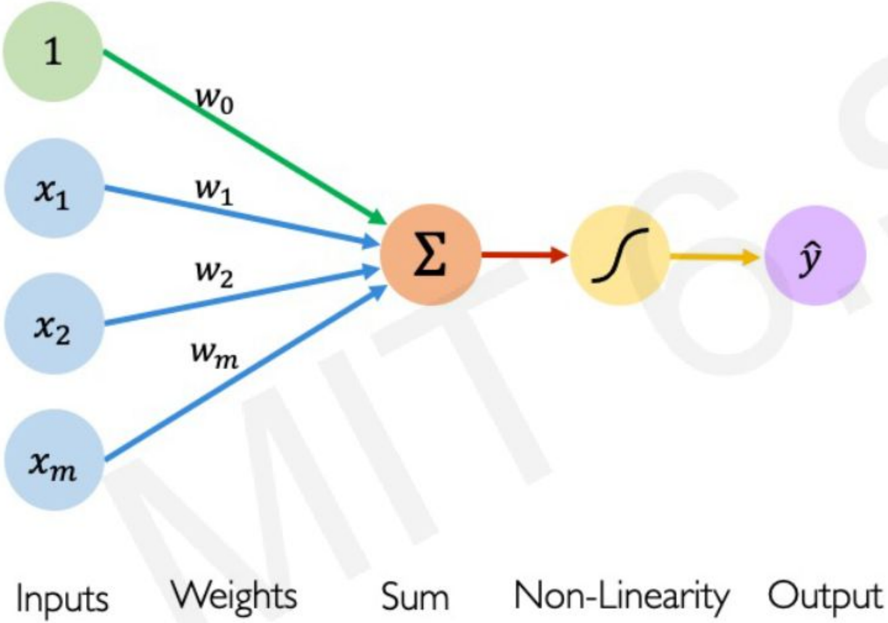
Linear combination of inputs

$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i \, w_i \right)$$

Non-linear activation function

Bias

The Perceptron: Forward Propagation

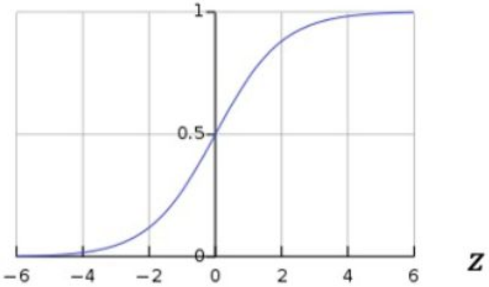


Activation Functions

$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W} \right)$$

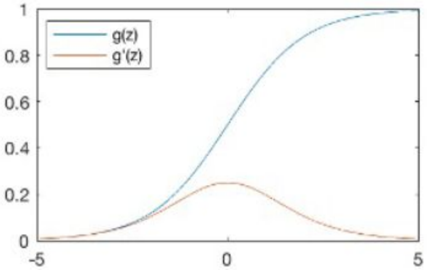
- Example: sigmoid function

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



Common Activation Functions

Sigmoid Function

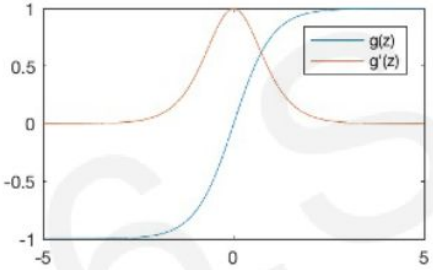


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

```
tf.math.sigmoid(z)
```

Hyperbolic Tangent

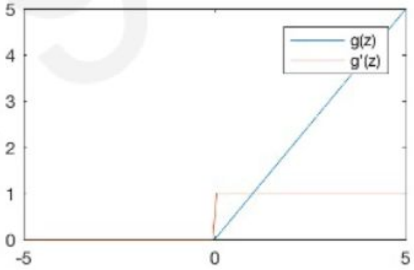


$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

```
tf.math.tanh(z)
```

Rectified Linear Unit (ReLU)



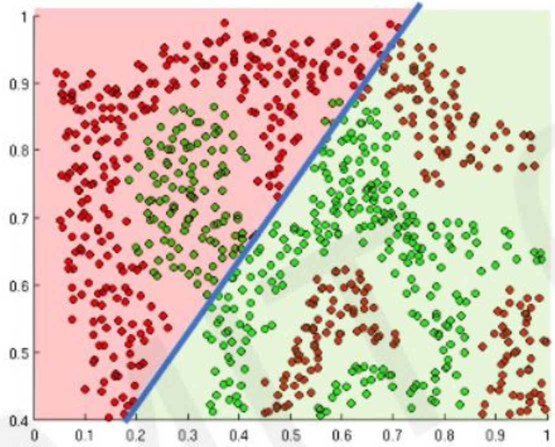
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

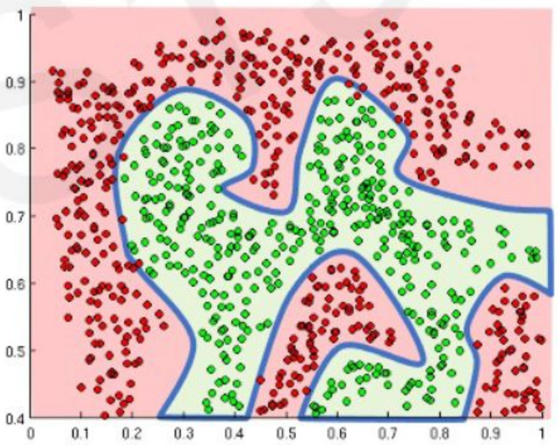
```
tf.nn.relu(z)
```

Importance of Activation Functions

The purpose of activation functions is to ***introduce non-linearities*** *into the network*



Linear activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions