

# NEURAL NETWORKS

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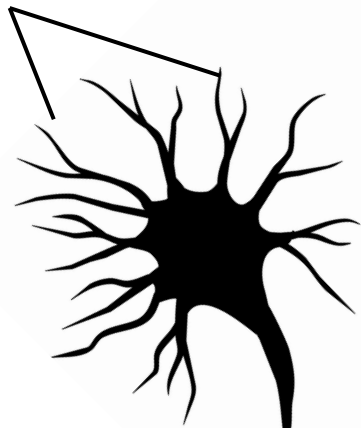
# ***Inspiration***

***In 1943, Warren McCulloch, a neurophysiologist, and a young mathematician, Walter Pitts, wrote a paper on how neurons might work.***

***The first artificial neural network was invented in 1958 by psychologist Frank Rosenblatt, it is called Perceptron.***

# ***Neuron***

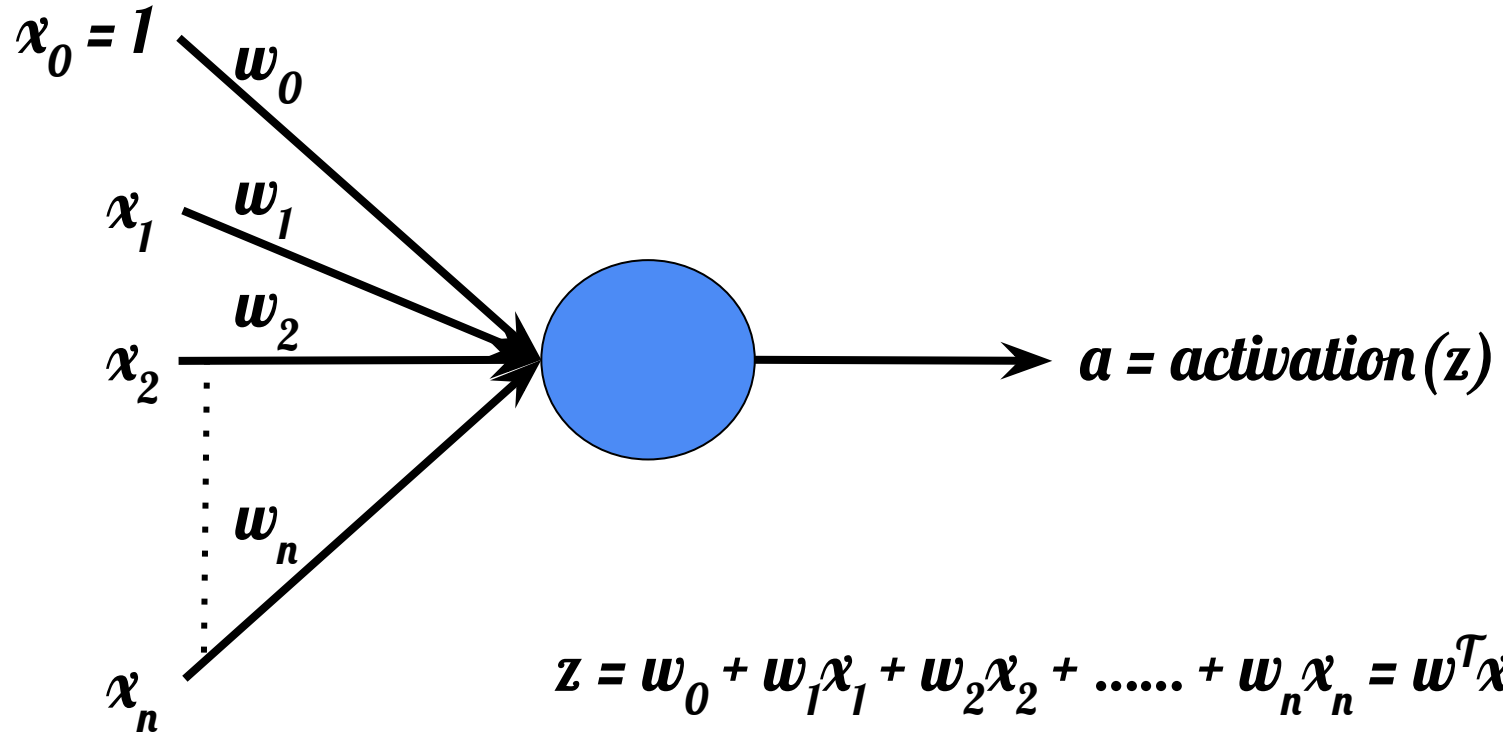
***Inputs***



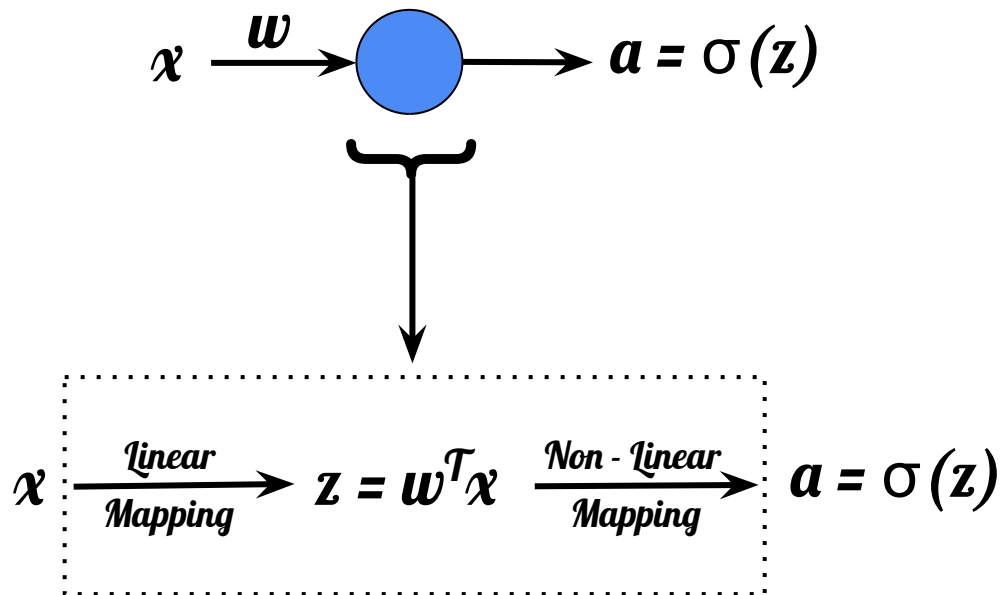
***Output***



# Neuron

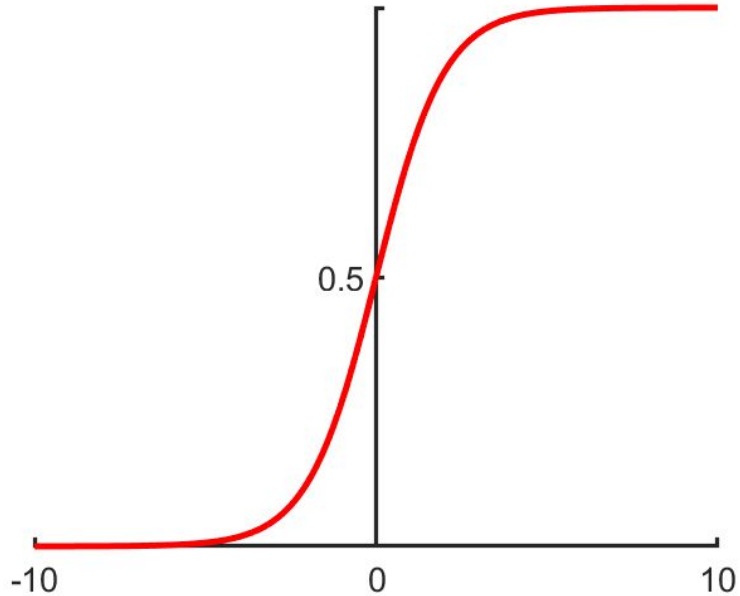


# Neuron

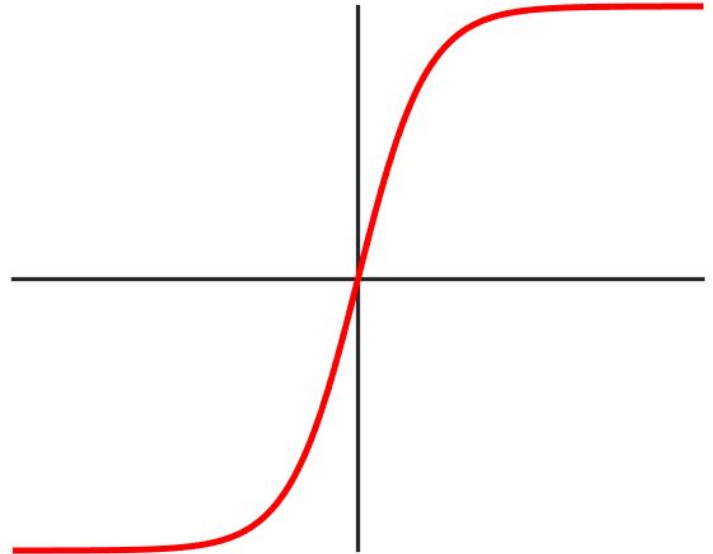


# *Activation Functions*

*Sigmoid*

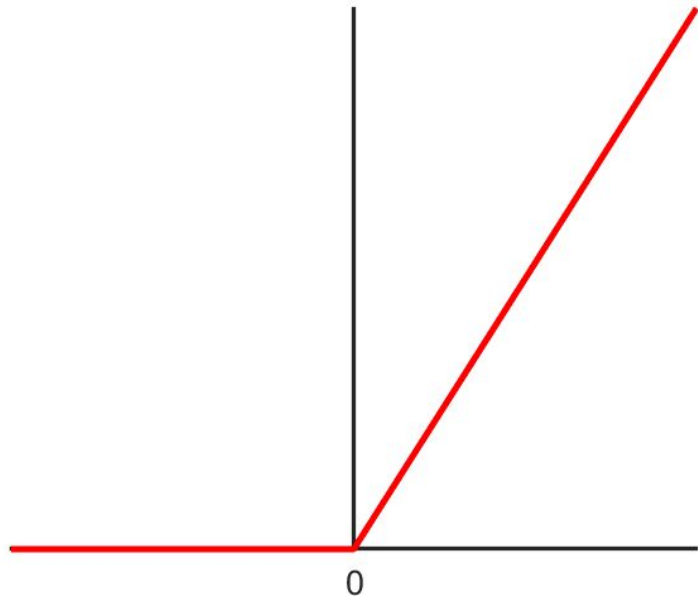


*Tanh*

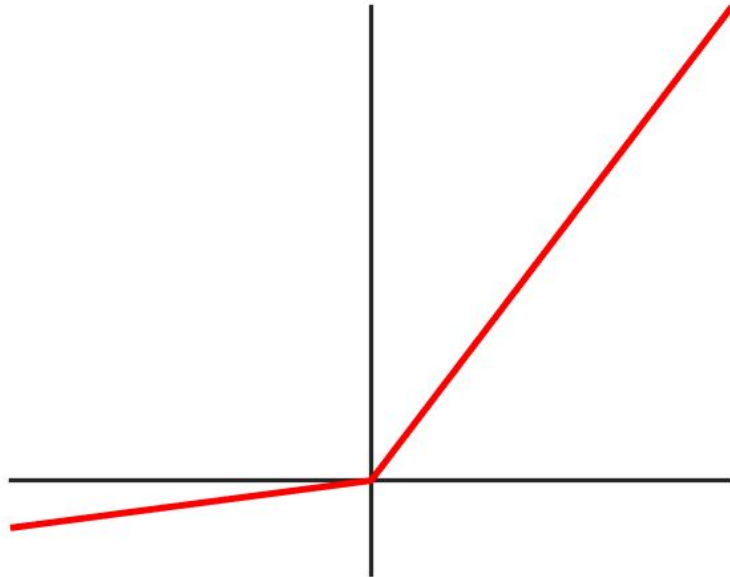


# *Activation Functions*

*ReLU - Rectified Linear Unit*

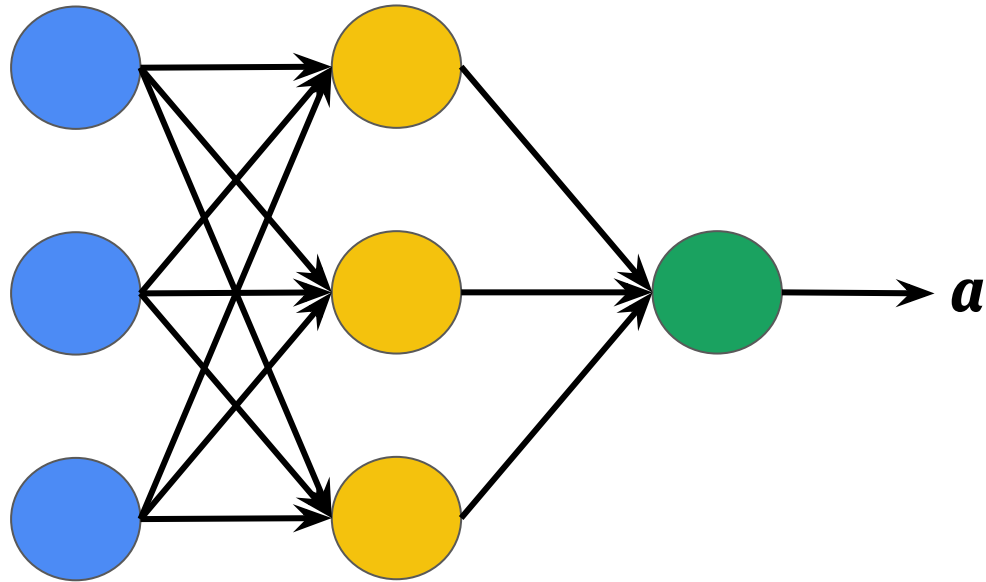


*Leaky ReLU*





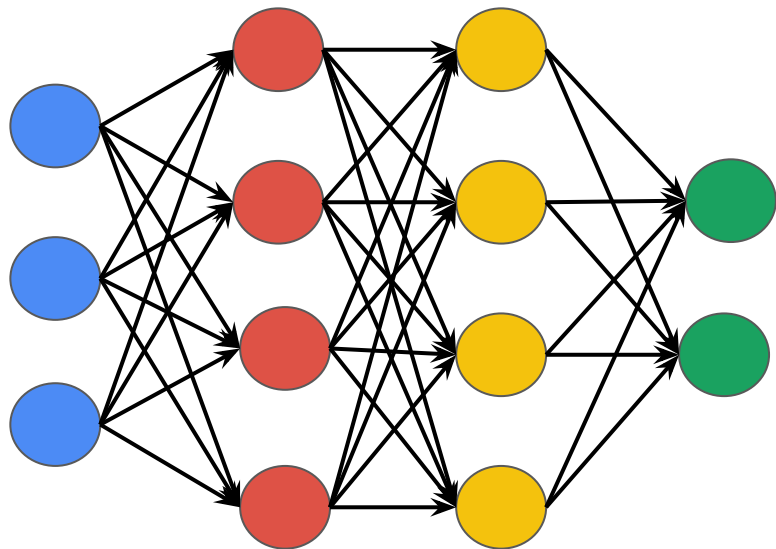
# ***Neural Network***



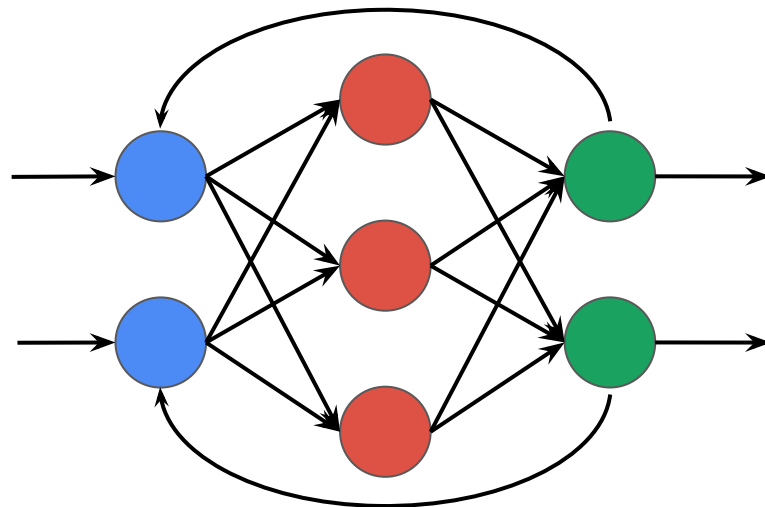
# ***Classification***

***Based on connection patterns***

***Feedforward NN***



***Feedback NN***



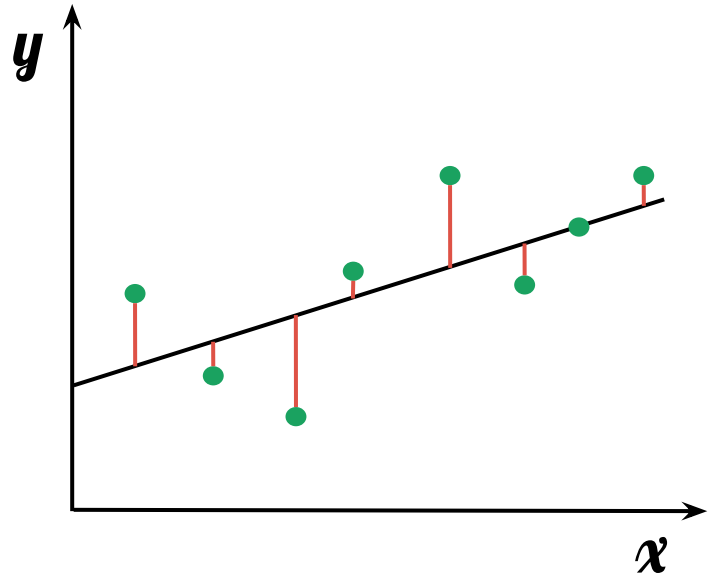
# Training

**Loss Function** - The output of loss function tells us how well our neural network model the given dataset.

## Loss Function in Regression

$$\mathcal{L} = \frac{\sum (\text{errors})^2}{m}$$

$m$  = No. of data points

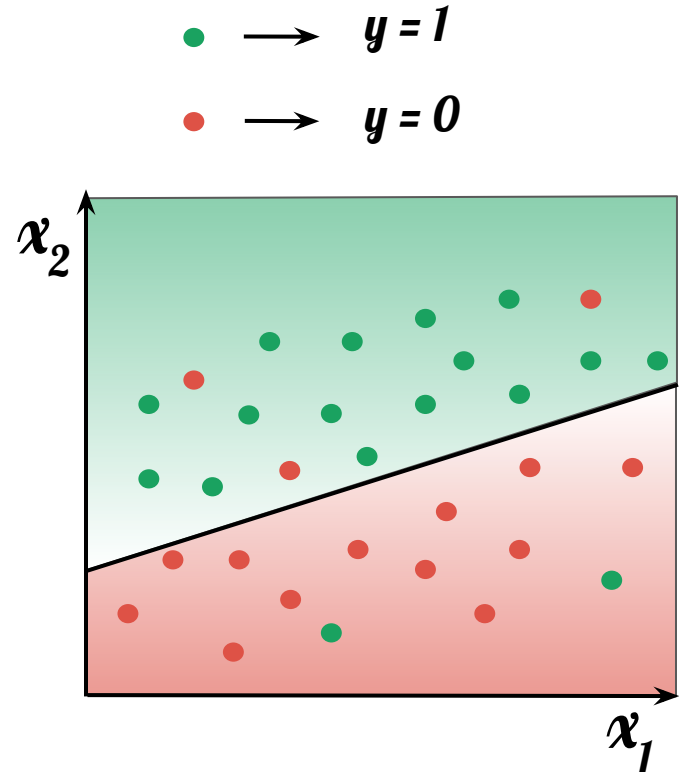


# Training

## Loss Function in Classification

$$\mathcal{L} = \frac{-\sum (y \log(p) + (1-y) \log(1-p))}{m}$$

$m$  = No. of data points

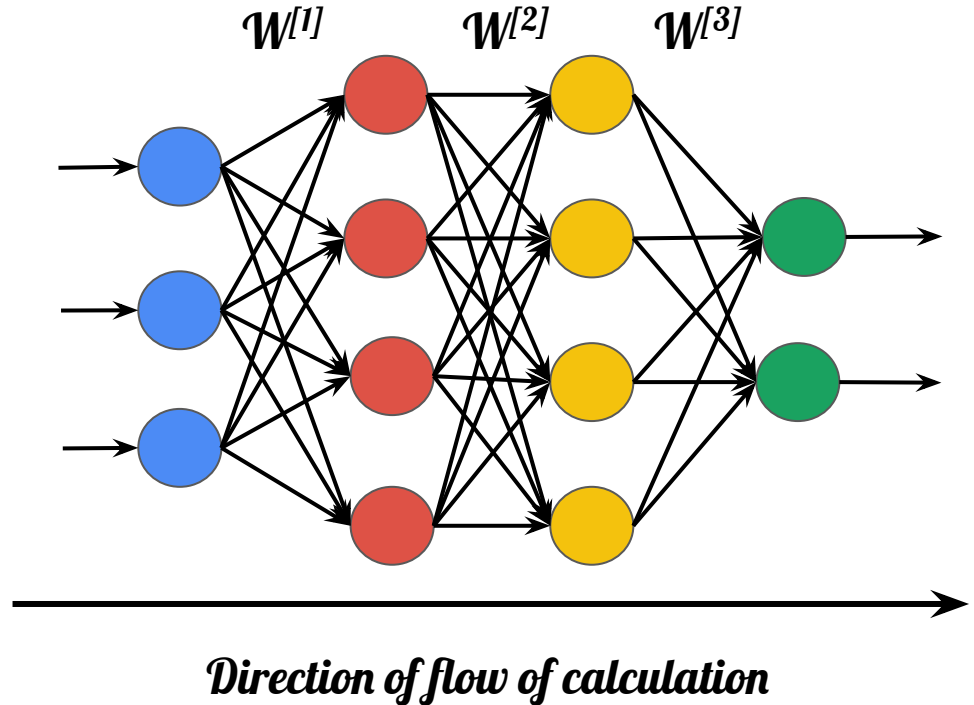


# Training

## Forward Propagation

$a^{[L]}$  = Activation  
of  $L$ - layer

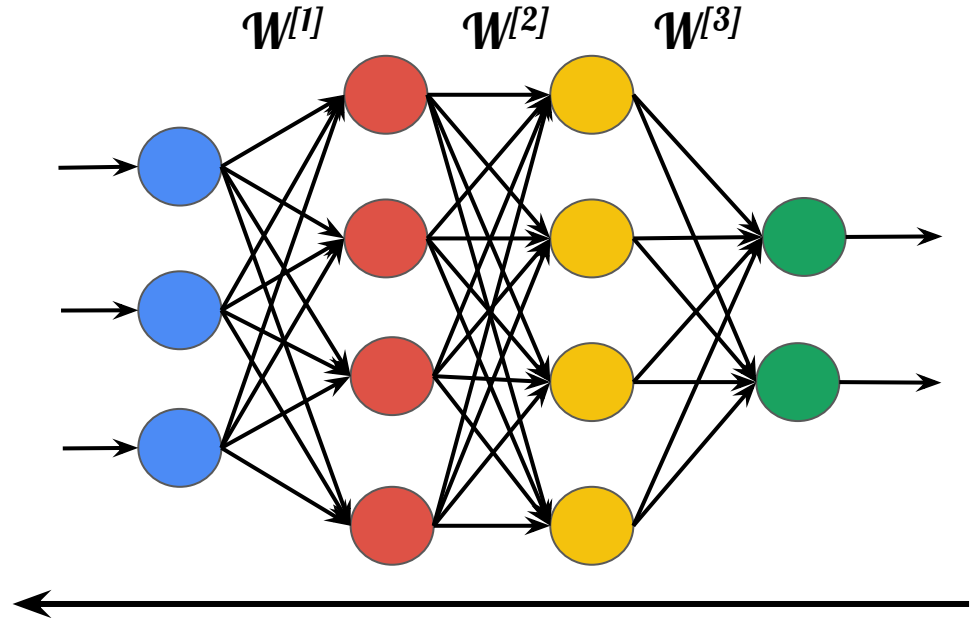
$a^{[0]} \longrightarrow a^{[1]} \longrightarrow a^{[2]} \longrightarrow a^{[3]}$



# Training

## Backward Propagation

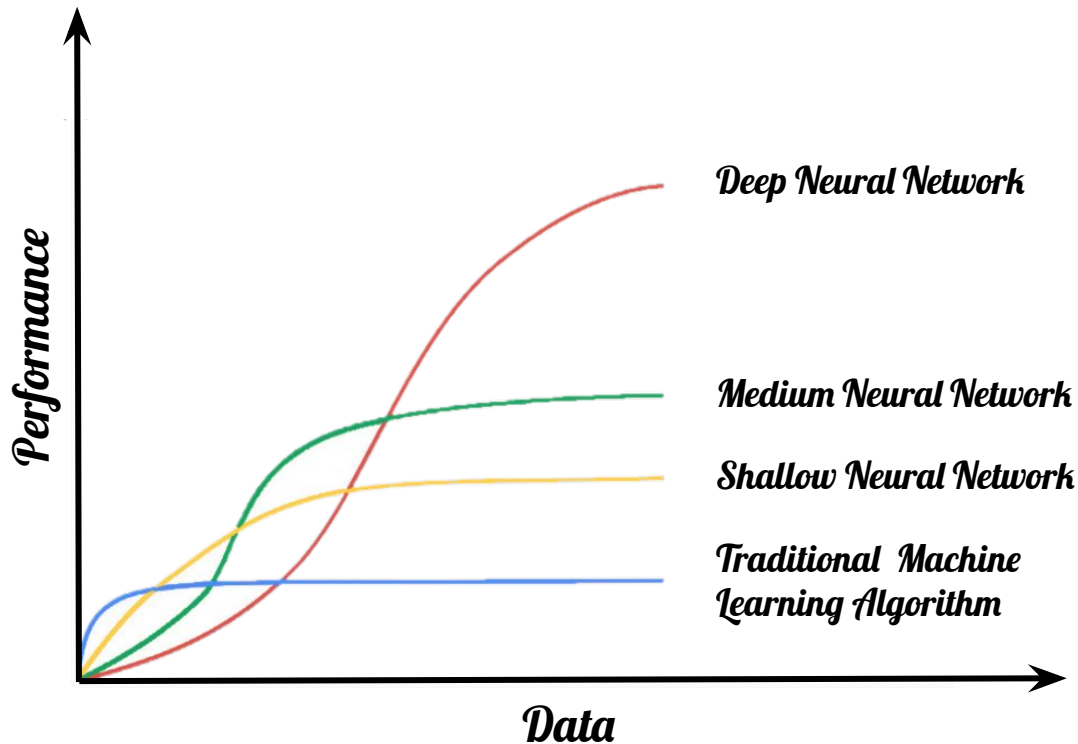
$$\begin{array}{ccccc} \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[3]}} & \longrightarrow & \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[3]}} & \longrightarrow & \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} \\ & & & & \downarrow \\ \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[1]}} & \longleftarrow & \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[1]}} & \longleftarrow & \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[2]}} \end{array}$$



*Direction of flow of calculation*

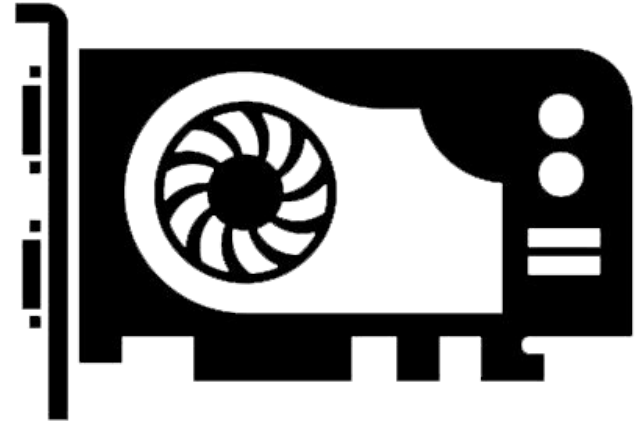
# *Advantages*

- *It can capture very complex patterns*
- *Universal Approximation Theorem*



# *Advantages*

- *Parallel processing capabilities*



*GPU*



# *Advantages*

- *High tolerance to noisy data*
- *Ability to work with incomplete knowledge*



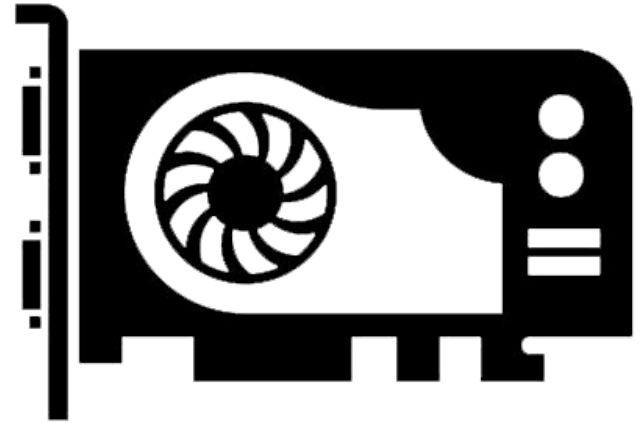
# *Disadvantages*

- *Requires a lot of data*



# *Disadvantages*

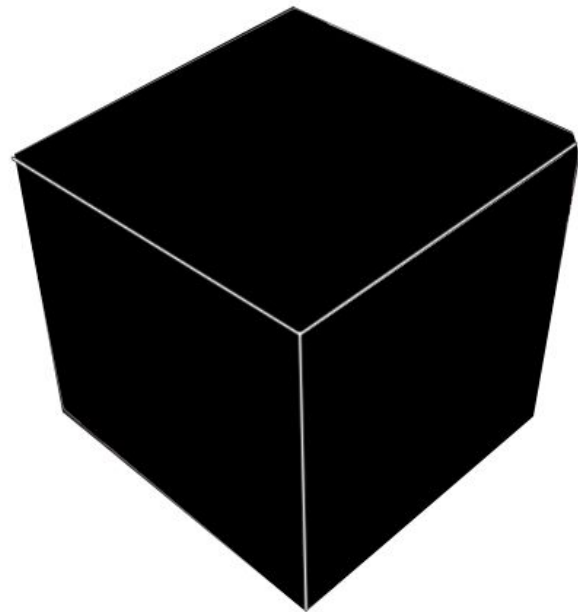
- *Require a huge computational power*
- *Takes a lot of time to train*



*GPU*

# ***Disadvantages***

- ***Unexplained behaviour of a neural network***



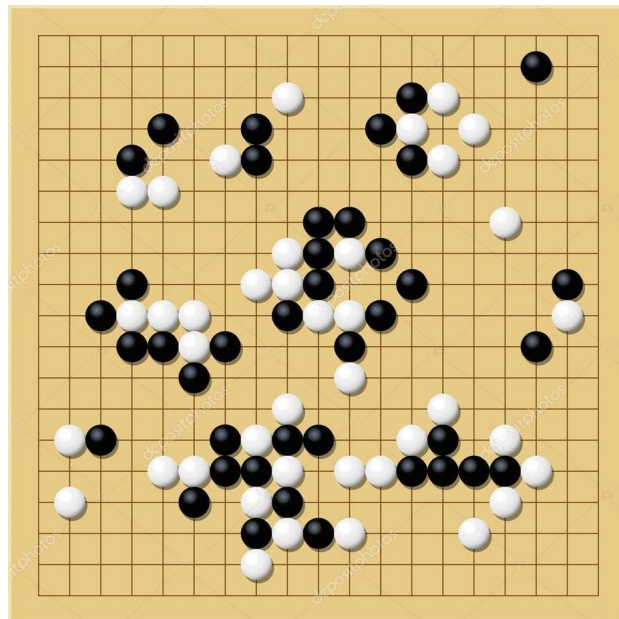
# *Applications*

- *Deepmind's AlphaGo Zero*

➤ *No. of atoms in the  
observable universe*  $= 10^{80}$

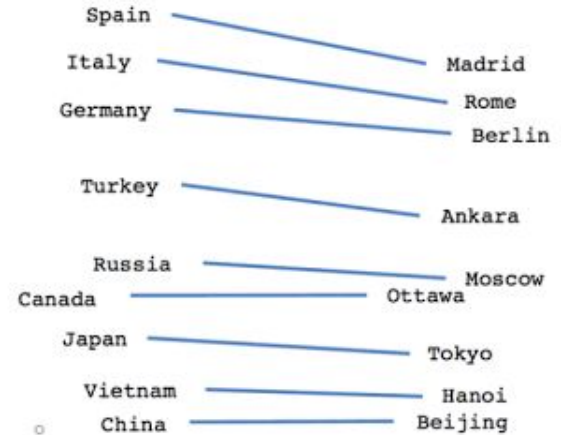
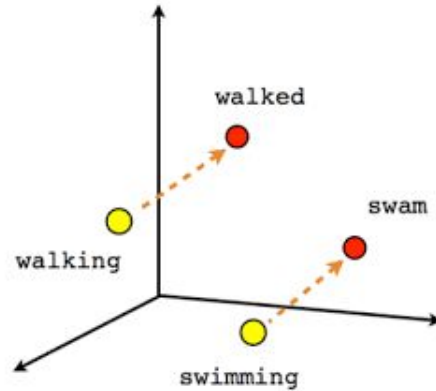
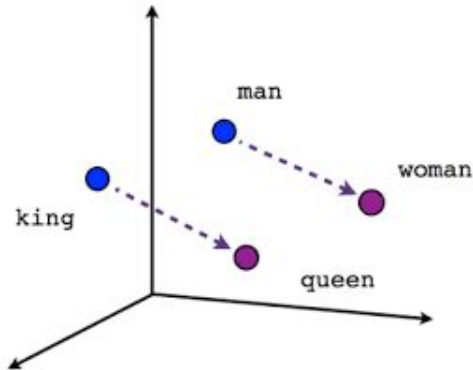
➤ *No. of board  
positions in the chess*  $= 10^{120}$

➤ *No. of board  
positions in the go*  $= 10^{170}$



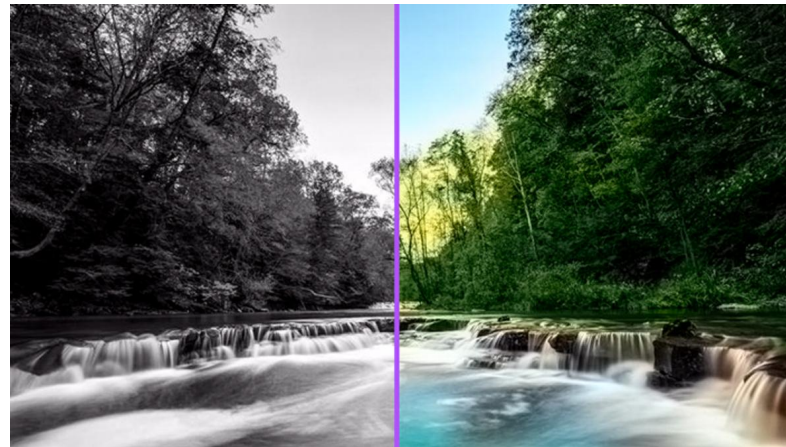
# Applications

- *Word Embedding*



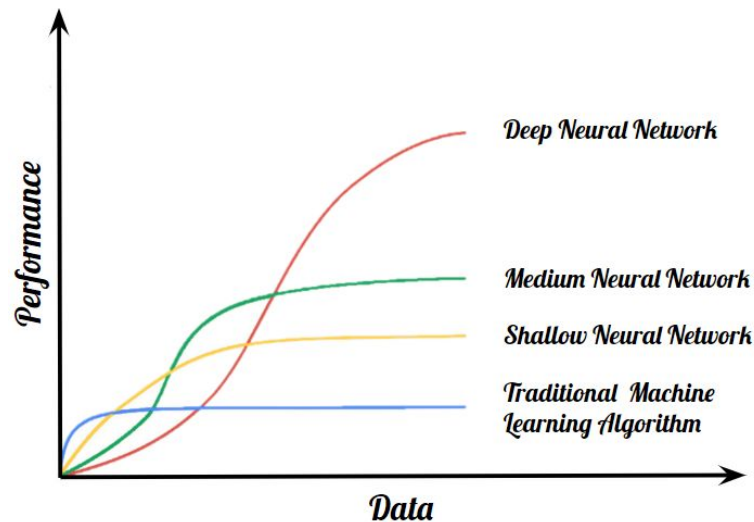
# *Applications*

- *Automatic Colorization*



# Conclusion

- *Neural Networks have ability to perform tasks at which humans are good and computers are bad.*
- *Other algorithms may perform better in easy tasks.*





# References

- *Graph illustrating the impact of data available on performance of traditional machine learning algorithms. - Research Gate. By : Benoit Gallix*
- *Image Colorization with Deep Convolutional Neural Networks  
By : Jeff Hwang and You Zhou*
- *Efficient Estimation of Word Representations in Vector Space.  
By : Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean*
- *Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm. By : David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dhharshan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, Demis Hassabis*



**THANK YOU**