Introduction to Neural Network and Deep Learning

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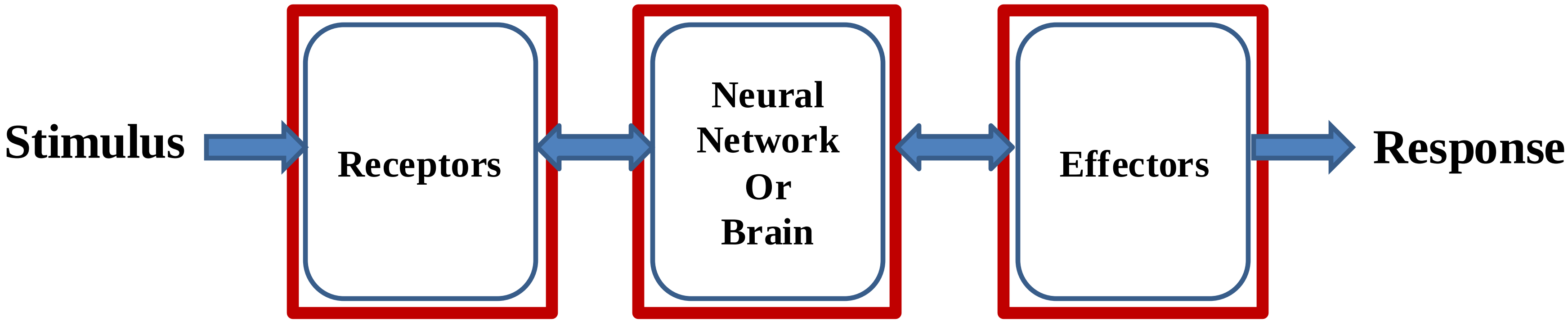
Outlines

- Introduction to Neural Network
- **Mathematical Model for Neural Network**
- Differentiation and its Application to Train Neural Network
- **Deep Neural Network**
- Recent Advances in Deep Learning
  - Activation Function, Weight Initialization (Xavier & Glorot, He)
  - Dropout and Regularization, Batch Normalization
  - Optimizers (SGD, NAG, AdaGrad, AdaDelta, RMSPROP, ADAM)
  - Building and Training Deep Neural Network using Python
- **Introduction to Hyper-Parameter Optimization**

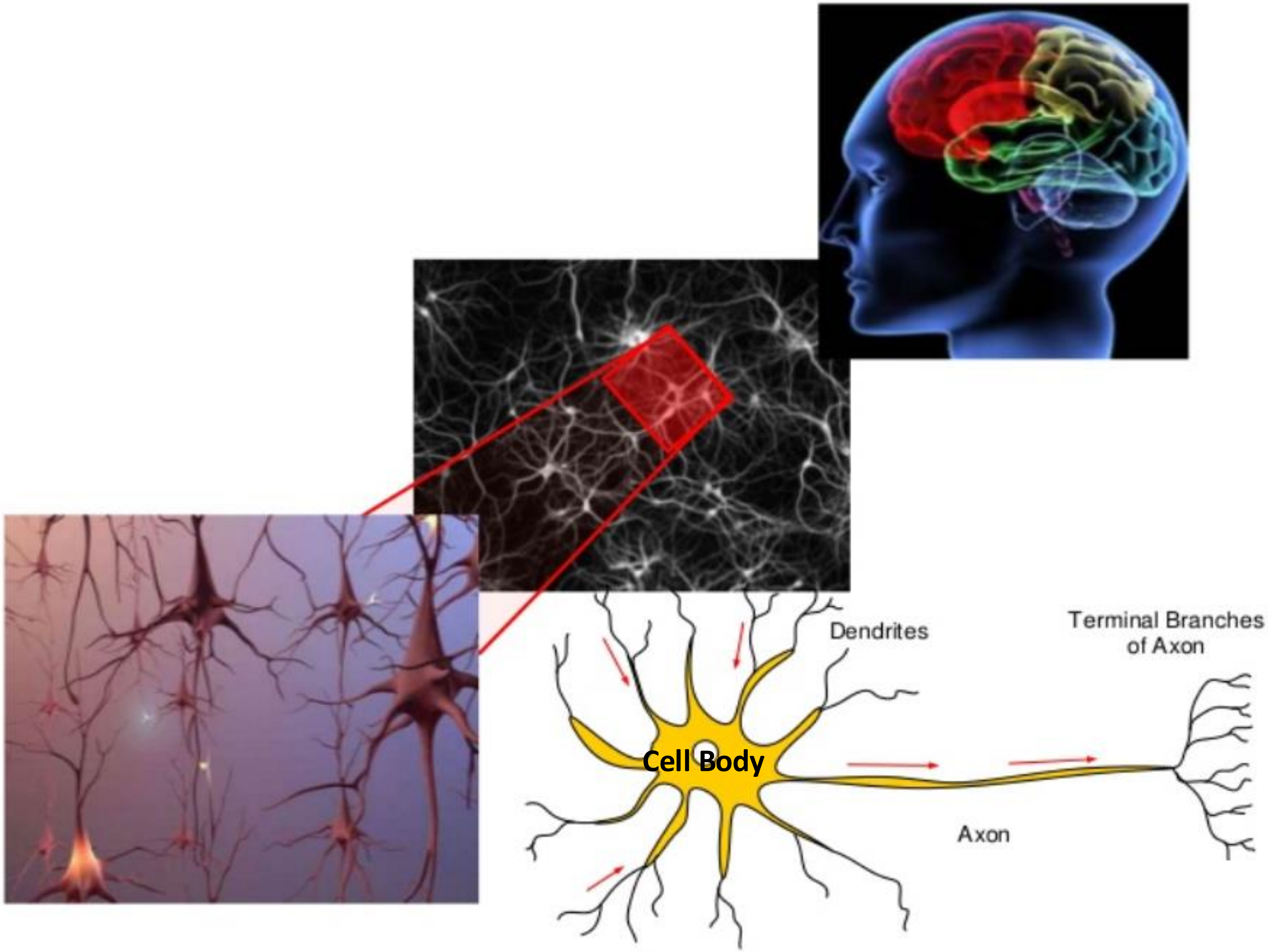
Artificial Neural Network

- An Artificial Neural Network (ANN) is a mathematical model that *loosely simulates* the structure and functionality of **Biological** nervous system to map the inputs to outputs.

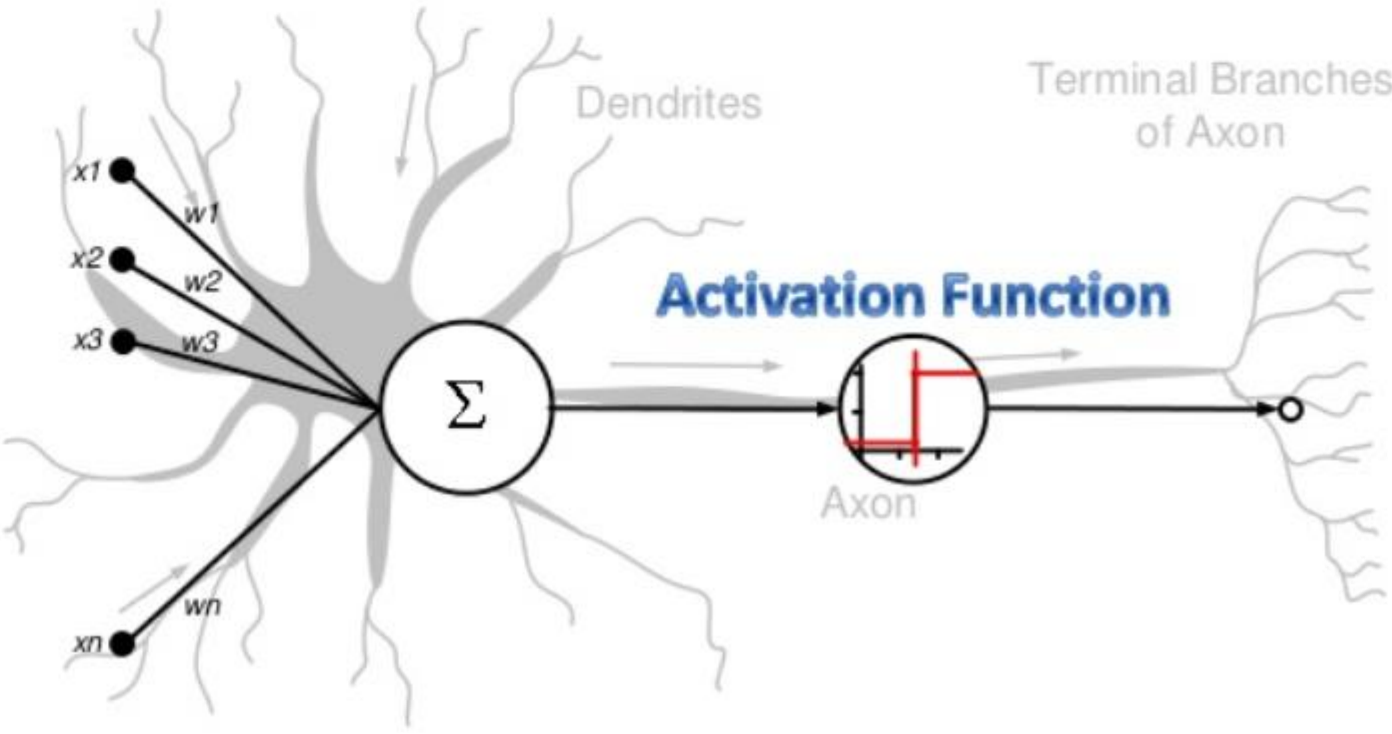
Block Diagram of Biological Nervous System



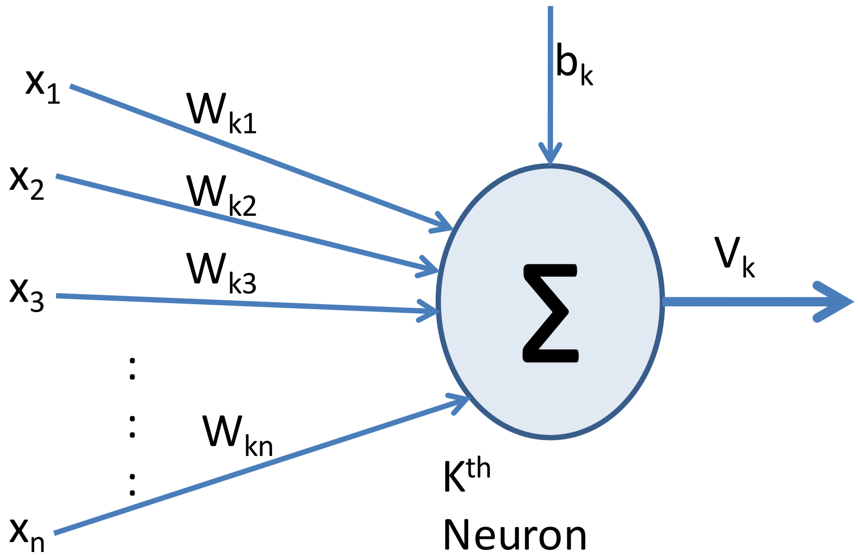
Typical Human Brain



Human Brain Neuron vs Artificial Neuron

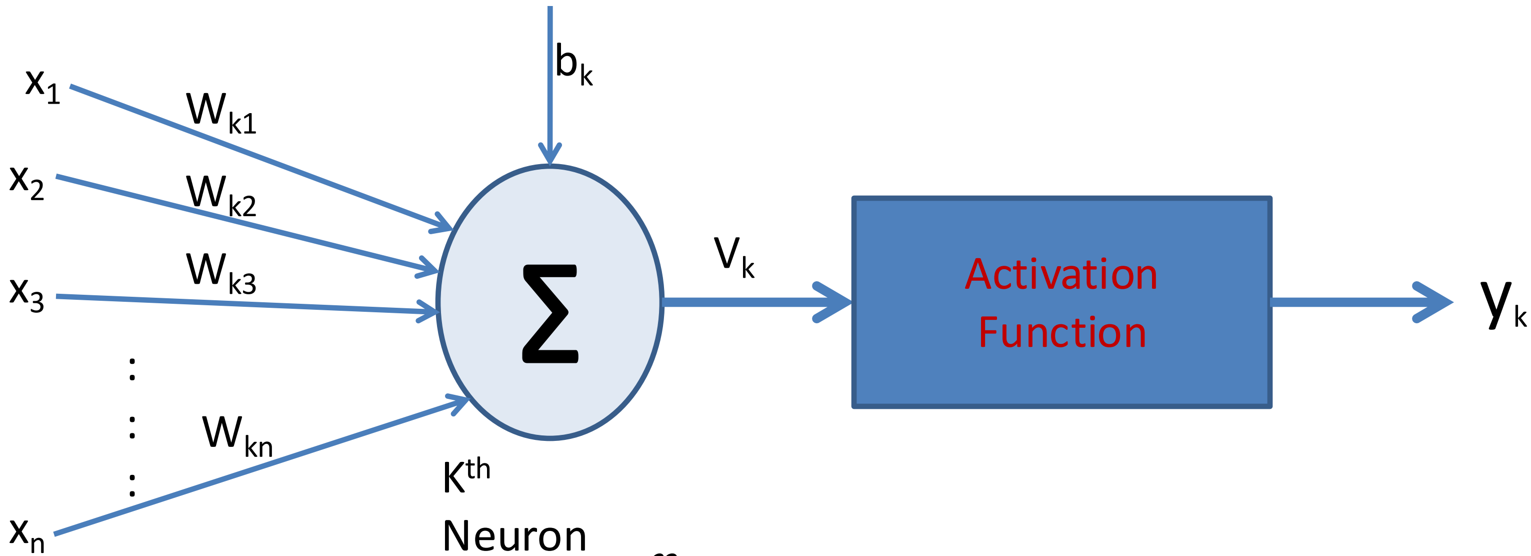


Artificial Neuron



$$V_k = W_{k1} * x_1 + Wk_2 * x_2 + Wk_3 * x_3 + \cdots + W_{kn} * x_n + b_k$$

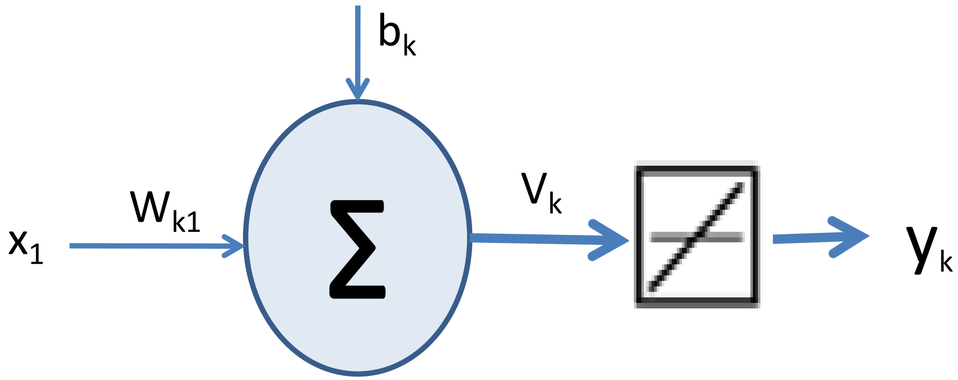
Artificial Neuron



$$V_k = \sum_{j=1}^{n} (W_{kj} * x_j) + b_k$$

$$y_k = f(V_k)$$

Single Neuron Model



Output is Linearly Dependent on Input Parameters

$$\boldsymbol{V_k} = \boldsymbol{W_{k1} * x_1} + \boldsymbol{b_k}$$

$$\boldsymbol{y_k} = \boldsymbol{f(V_k)} = \boldsymbol{W_{k1} * x_1} + \boldsymbol{b_k}$$

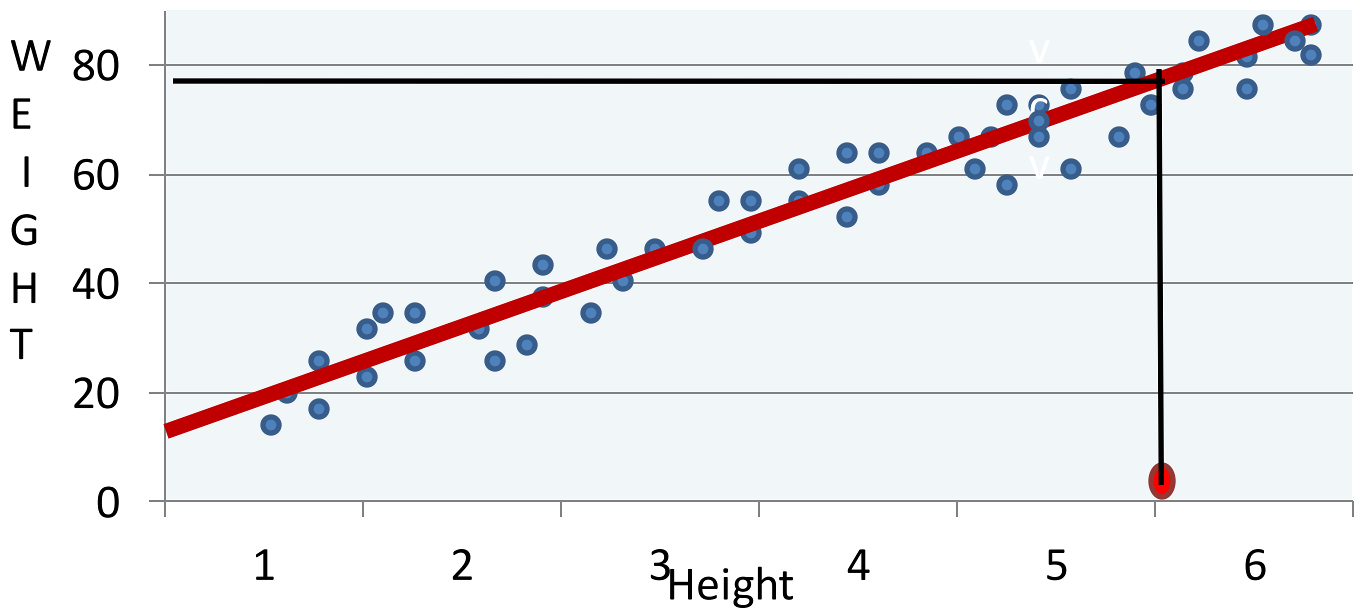
Single Neuron Model

- **<u>Application</u>**

y=mx+c

Where m=Slope Of Straight Line

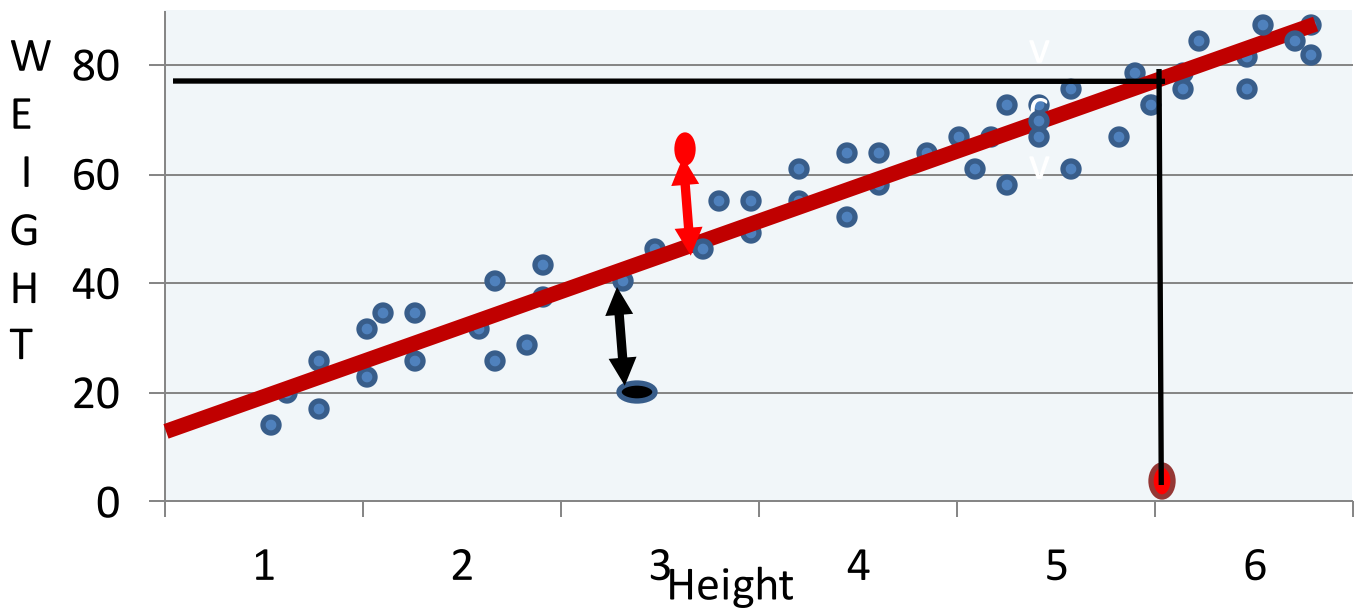
X=Height c=Intercept y=Weight



Single Neuron Model

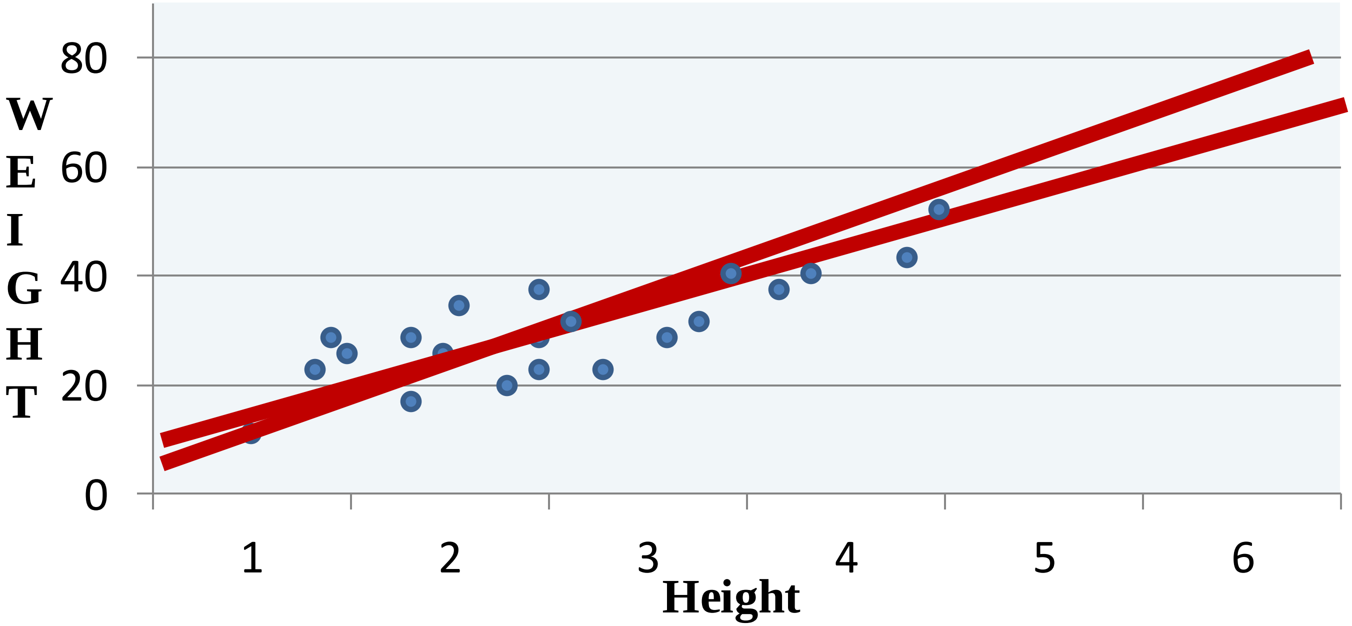
Error Calculation

- The error E_i=(Actual Value – Predicted value)=$(Ti - y_i)$
- For making +ve= $E_i = (T_i - y_i)^2$ [Error for i^{th} input instance]



Linear Neural Network

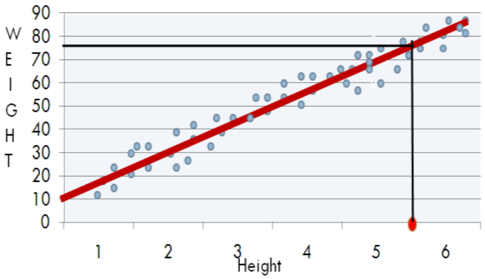
- **Error Calculation**
  - It is done to adjust the slope(m) and intercept for better fitting next time.

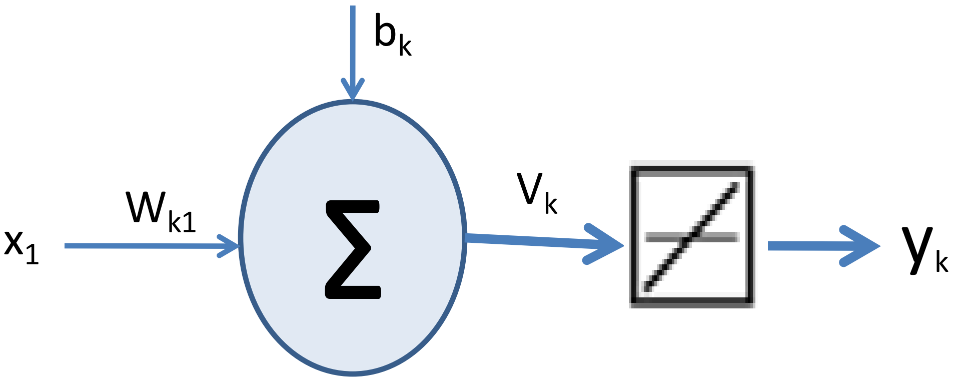


Linear Neural Network

$$y_k = W_{k1} * x_1 + b_k$$

$$y = m * x + c$$



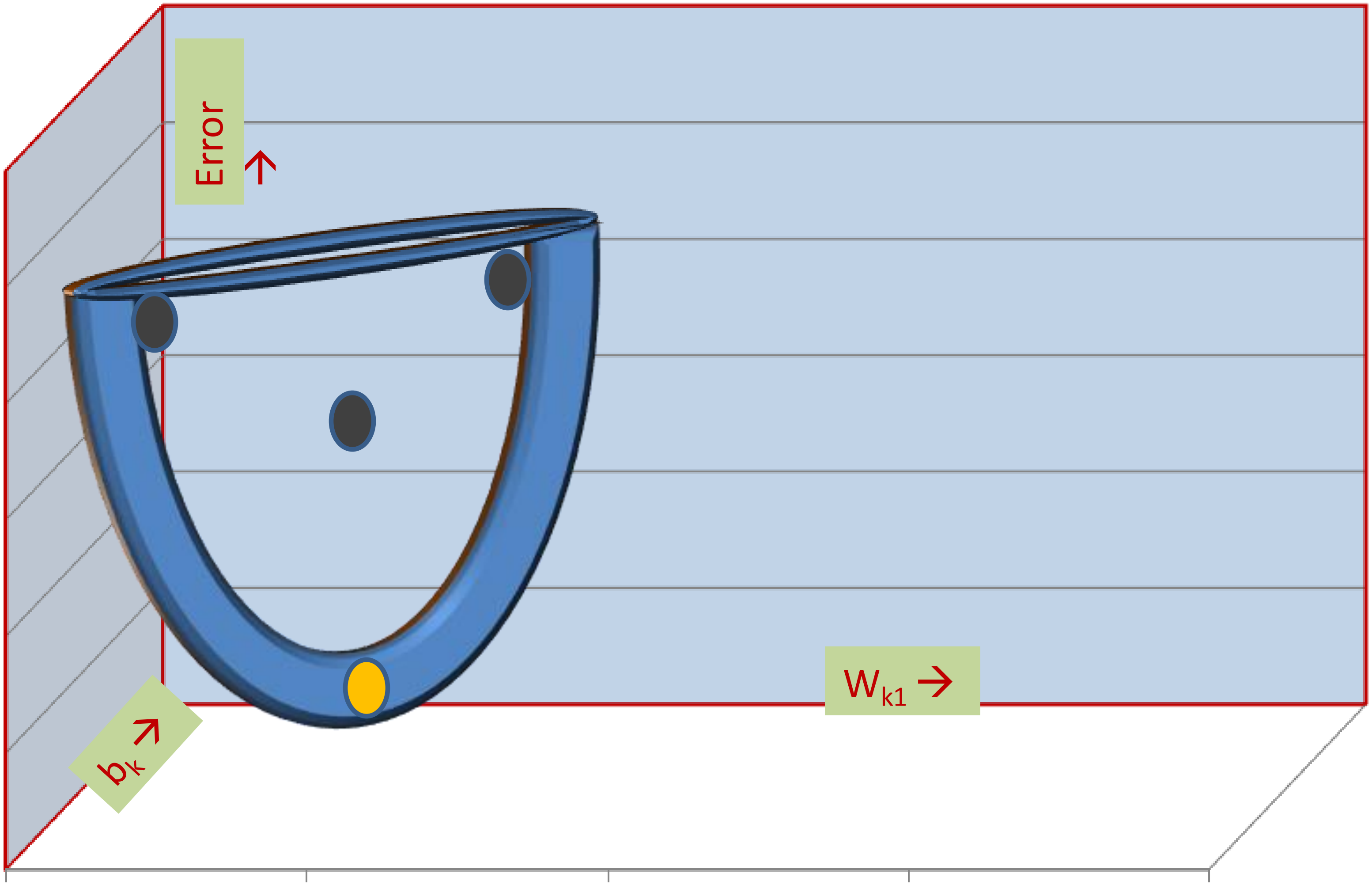


Output is Linearly Dependent on Input Parameters

$$V_k = W_{k1} * x_1 + b_k$$

$$y_k = f(V_k) = W_{k1} * x_1 + b_k$$

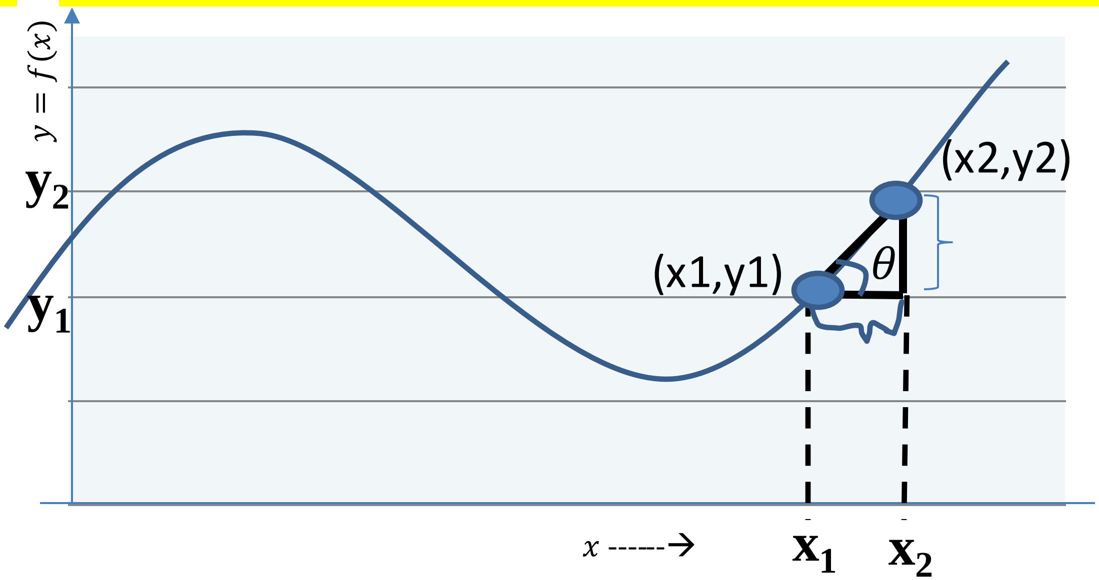
Plotting Error



Differentiation…

$$y = f(x)$$

$$\frac{dy}{dx} = \frac{df}{dx} = y' = f'$$



How much does y change as x changes= $\frac{\Delta y}{\Delta x} = \frac{y_2 - y_1}{x_2 - x_1} = \frac{p}{b} = \tan(\theta)$

$$\frac{dy}{dx} = \lim_{\Delta x \to 0} \frac{\Delta y}{\Delta x}$$

Differentiation…

$$\frac{dy}{dx} = \lim_{\Delta x \to 0} \frac{\Delta y}{\Delta x}$$

As $\Delta x \to 0$ we obtain a tangent at x.

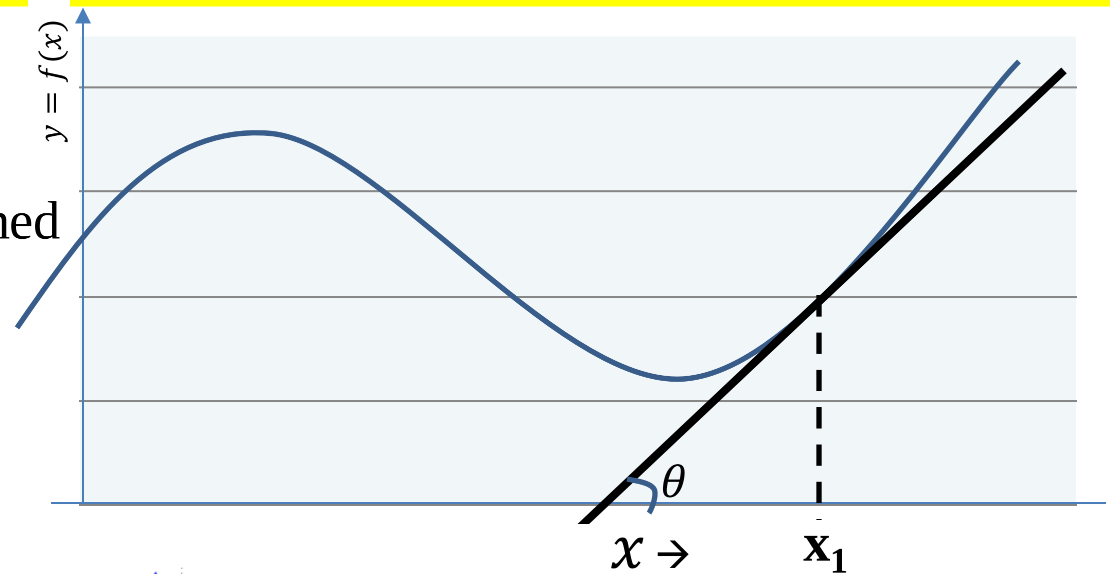
$\frac{dy}{dx} = \tan(\theta)$=slope of the tangent at x=x_1

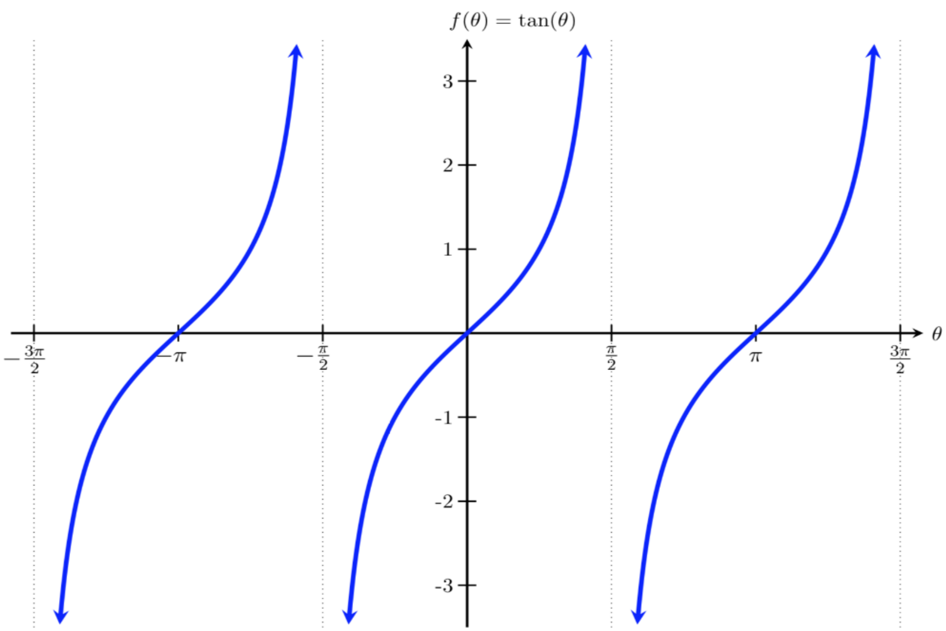
$\frac{dy}{dx} =$ Slope of the tangent to x-axis at x=x_1

Differentiation…

$0 < \theta < 90$ tan(θ)= +ve

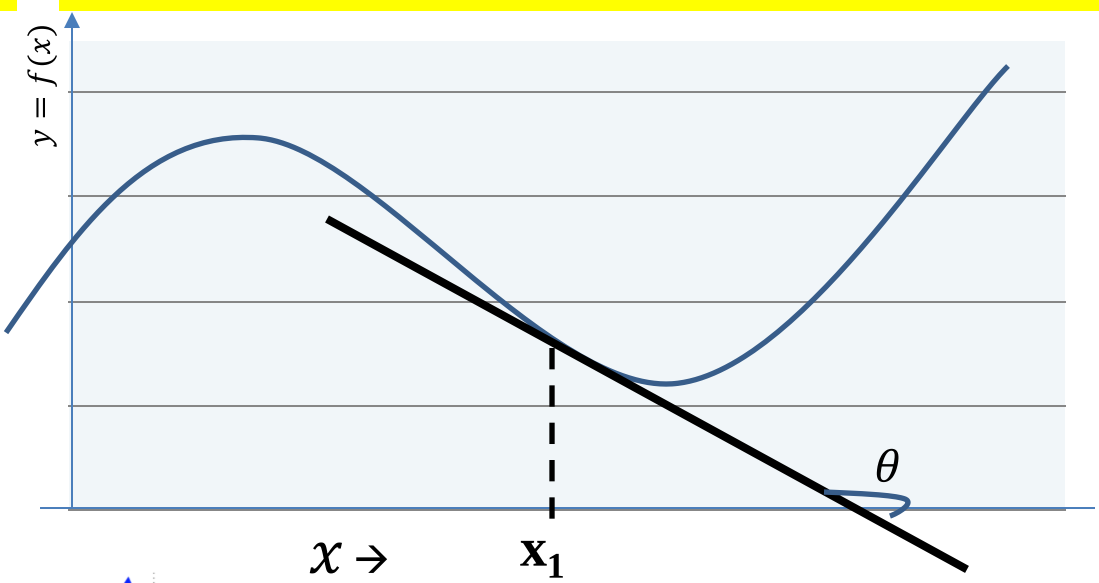
90 tan(90)=Undefined

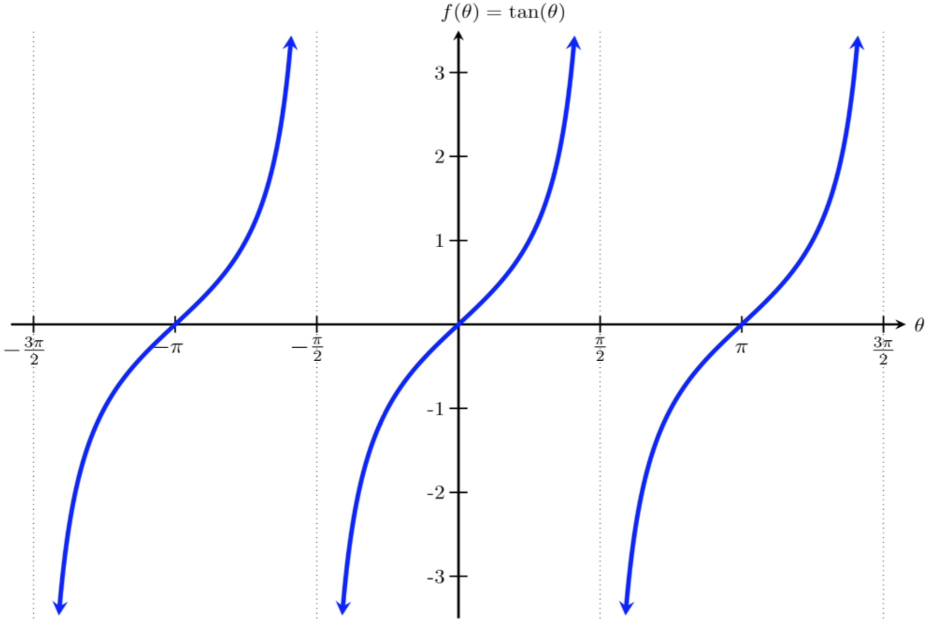




Differentiation…

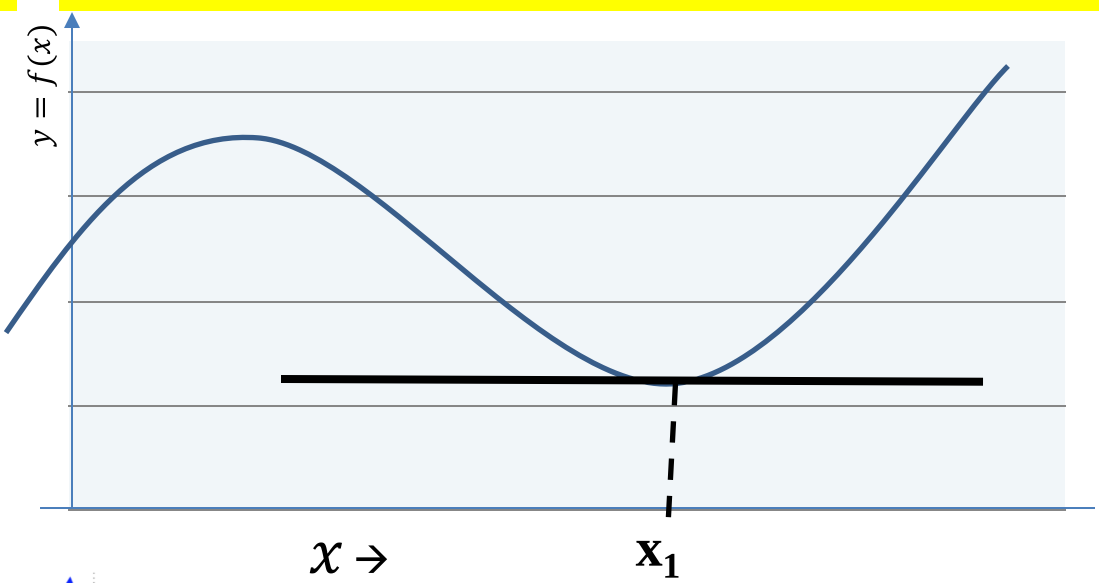
$\theta > 90$ tan(θ)= - ve

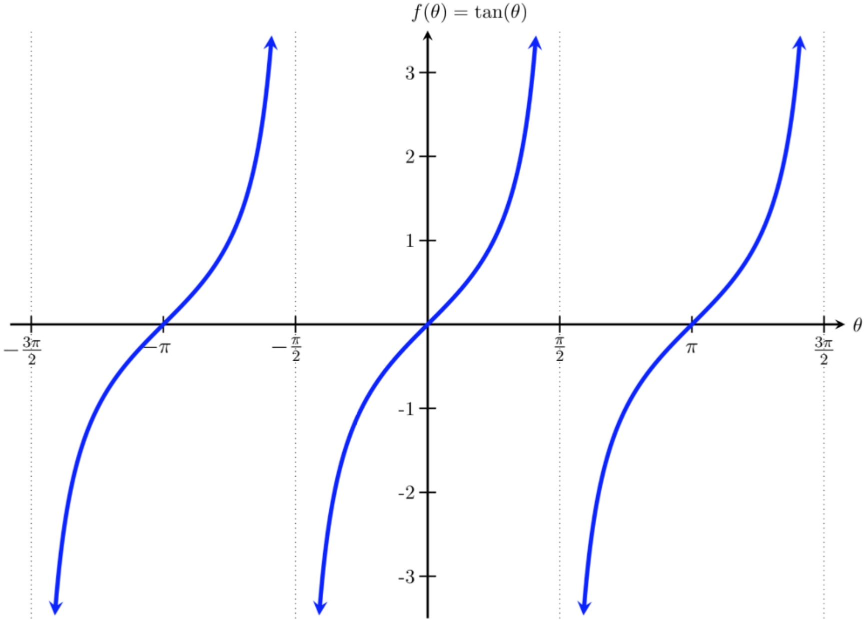




Differentiation…

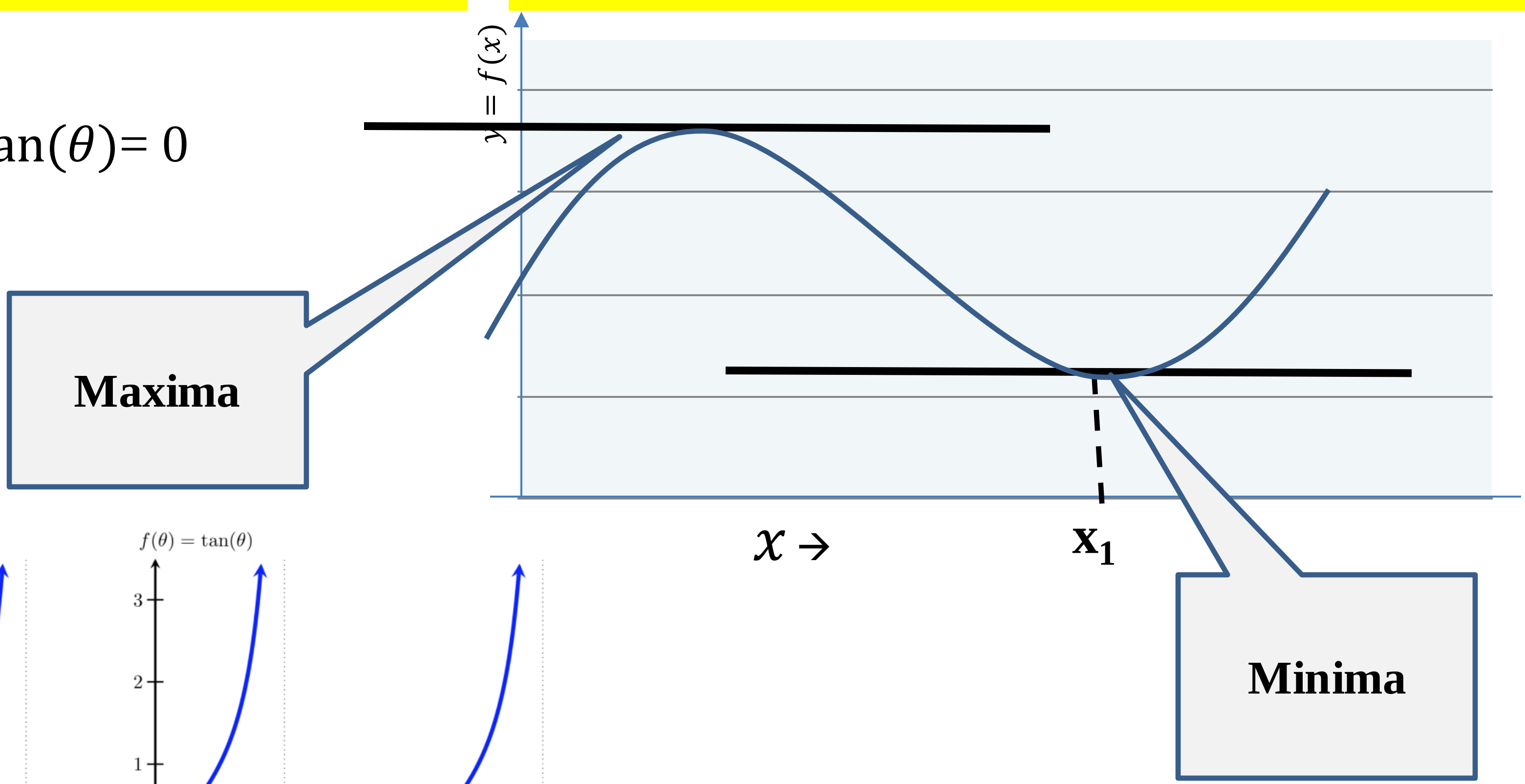
$\theta = 0$ $\tan(\theta) = 0$

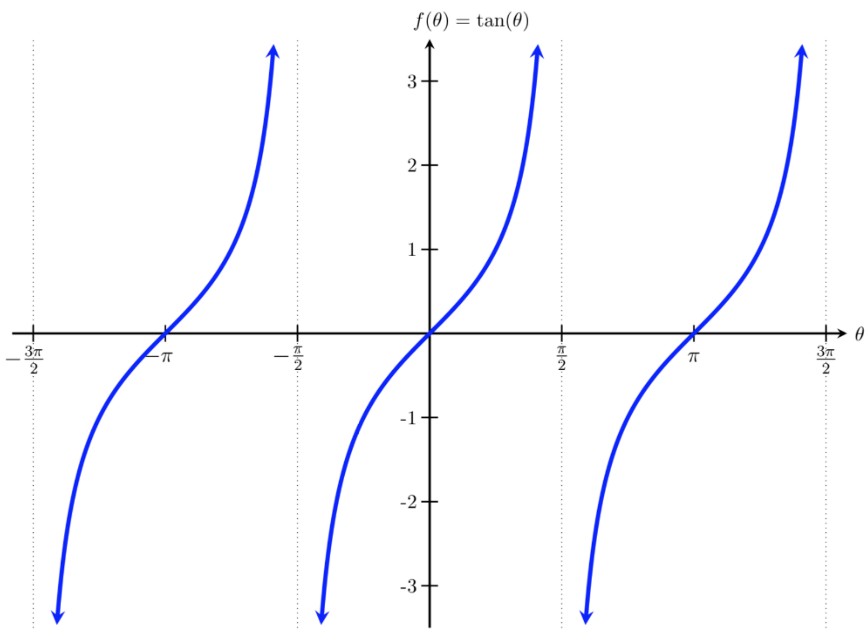




Differentiation…

$\theta = 0$ $\tan(\theta) = 0$





Note: At minima and Maxima the Slope is 0 ➔ tan(θ)=0 ➔ $\frac{dy}{dx} = 0$

Differentiation…

Distinguishing between a Minima & Maxima

Let $f(x) = X^2 - 3X + 2$

$\frac{df}{dx} = 0$

$2X - 3 = 0$

$X = 1.5$

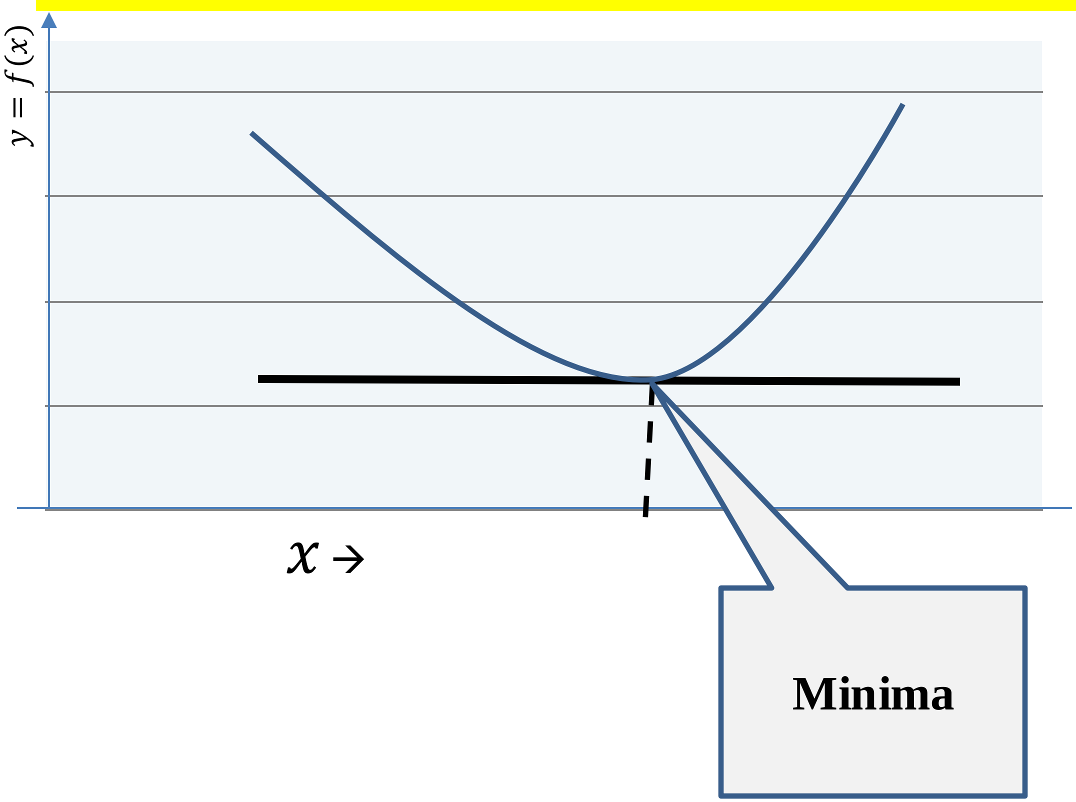
$f(1.5) = -0.25$

Take a point near 1.5, let $X=1$

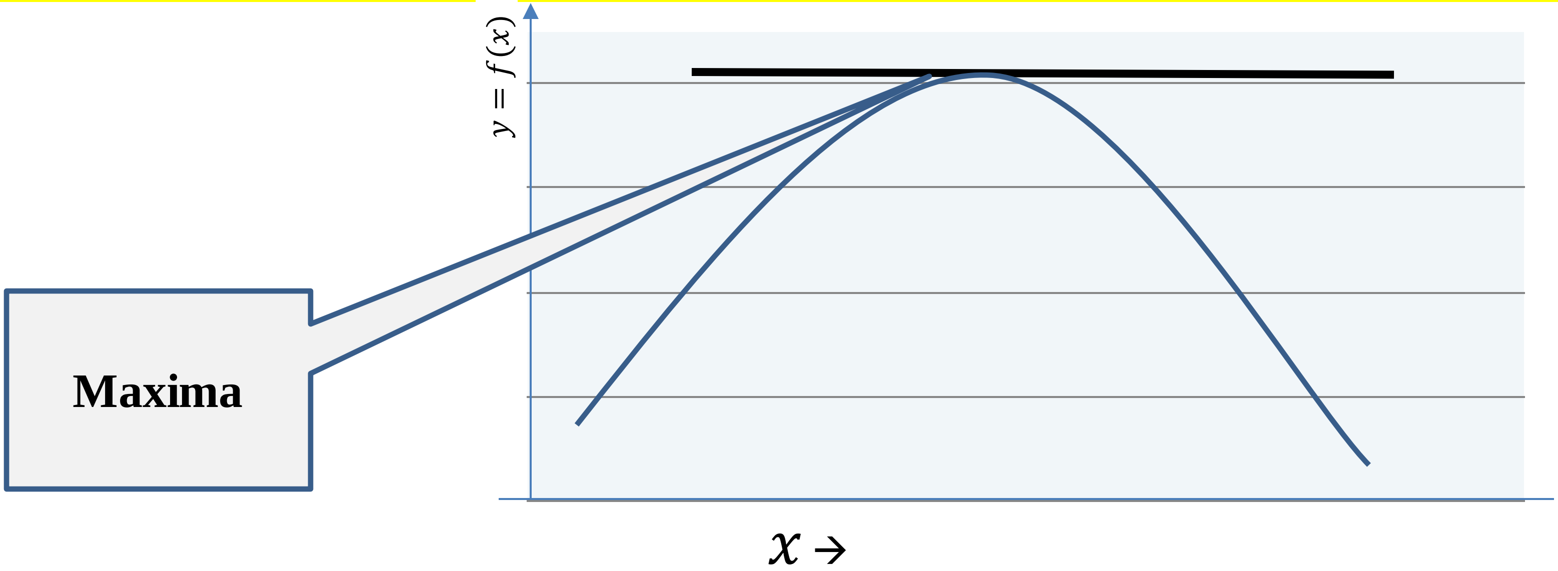
$f(1) = 1 - 3 + 2 = 0$

X=1.5 can't be maxima. It is a minima.

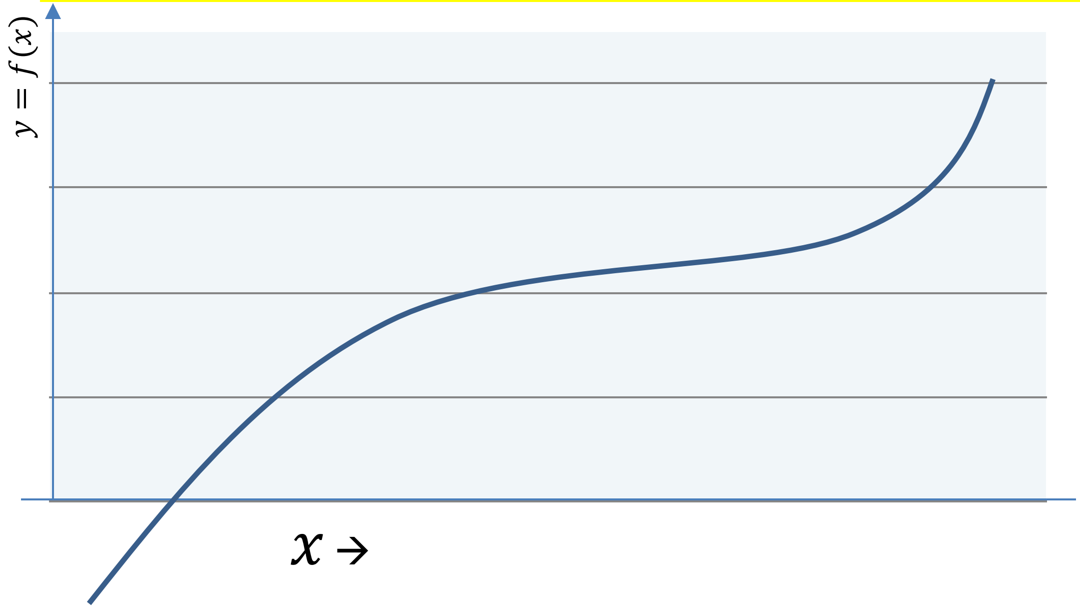
Error Function with Minima and No Maxima



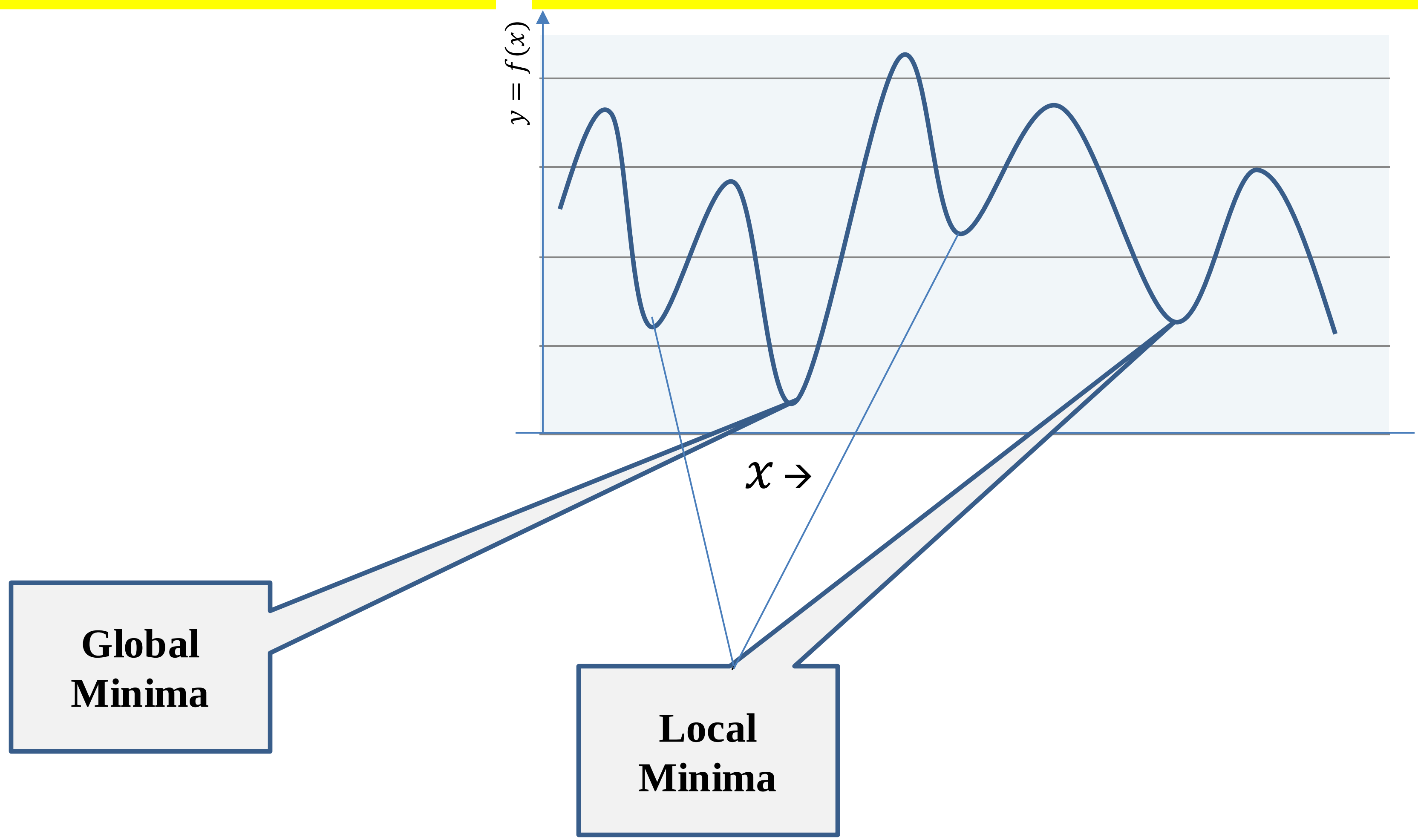
Error Function with a Maxima and No Minima



Error Function without a Maxima and Minima

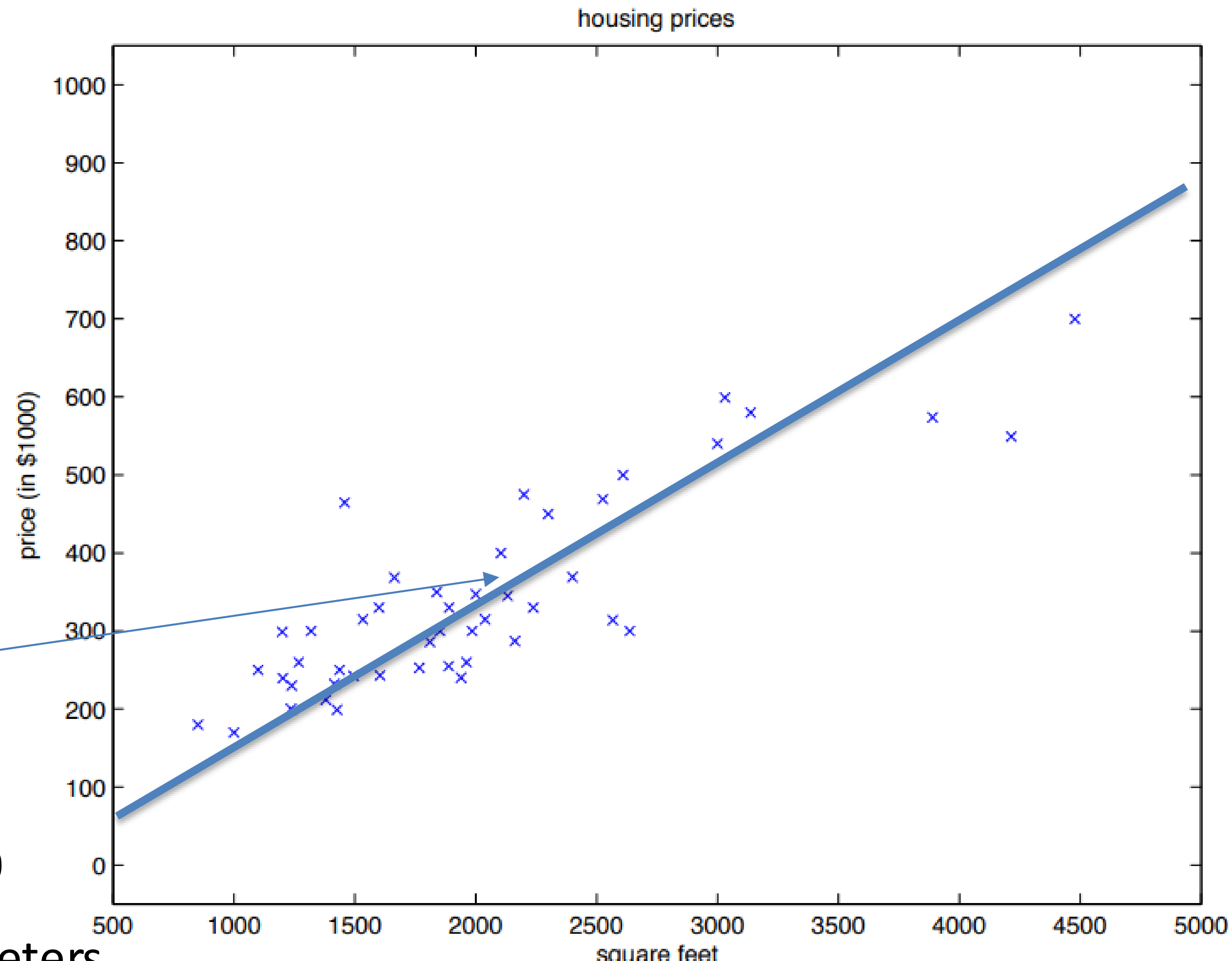


Error Function with multiple Maxima and Minima



Linear regression

Living area (feet^2)	Price (1000$s)
2104	40
1600	33
2400	36
1416	23
3000	54
⋮	⋮



$y = mx + c$

Rewrite as:

$h_\theta(x) = \theta_1 x + \theta_0$

Here, the θ_i's are the parameters (also called weights)

Intercept form of the hypothesis

- To perform supervised learning, we must decide how we're going to represent functions/hypotheses h in a computer:

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$$

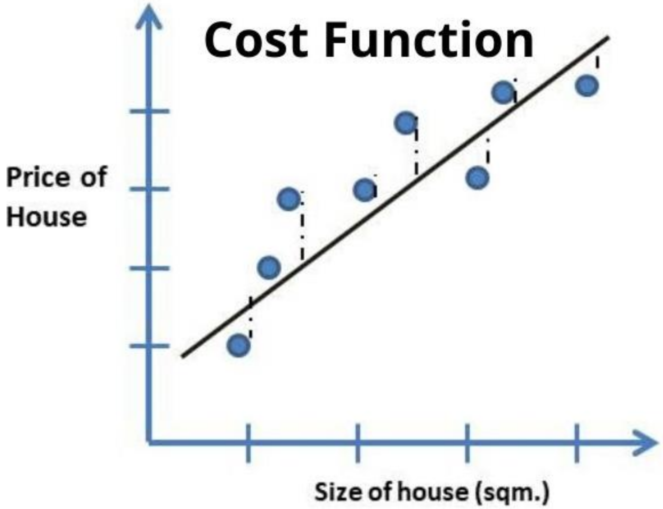
- To simplify our notation, we also introduce the convention of letting $x_0 = 1$
- Also, we will drop the θ subscript in $h_\theta(x)$,

$$h(x) = \sum_{i=0}^{n} \theta_i x_i = \theta^T x$$

Given a training set, how to pick the parameters θ

- Cost function:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$$



- Now the objective is to choose parameters θ to minimise the cost function j(θ)
- The update rule considering the gradient descent algorithm for this:

$$\theta_j := \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta)$$

Here, α is called the learning rate.

Gradient descent algorithm

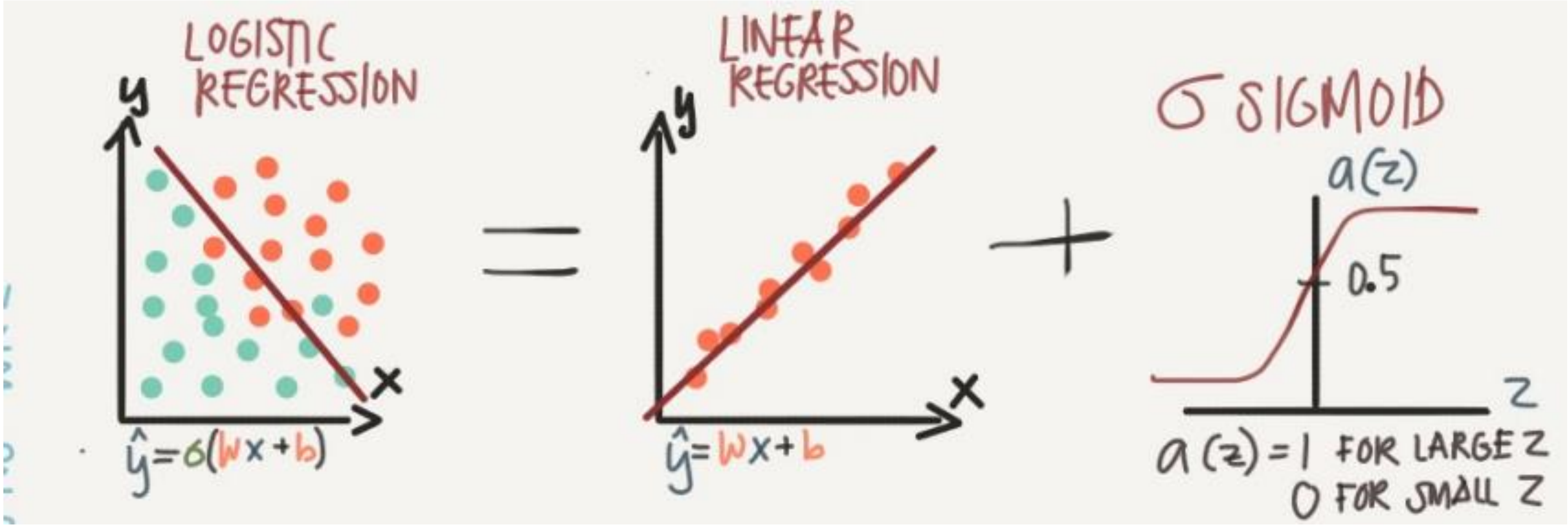
If we have only one training example (x, y),

$$
\begin{aligned}
\frac{\partial}{\partial \theta_j} J(\theta) &= \frac{\partial}{\partial \theta_j} \frac{1}{2} \left(h_\theta(x) - y\right)^2 \\
&= 2 \cdot \frac{1}{2} \left(h_\theta(x) - y\right) \cdot \frac{\partial}{\partial \theta_j} \left(h_\theta(x) - y\right) \\
&= \left(h_\theta(x) - y\right) \cdot \frac{\partial}{\partial \theta_j} \left(\sum_{i=0}^{n} \theta_i x_i - y \right) \\
&= \left(h_\theta(x) - y\right) x_j
\end{aligned}
$$

For a single training example, this gives the update rule:

$$
\theta_j := \theta_j + \alpha \left(y^{(i)} - h_\theta(x^{(i)}) \right) x_j^{(i)}
$$

Logistic regression



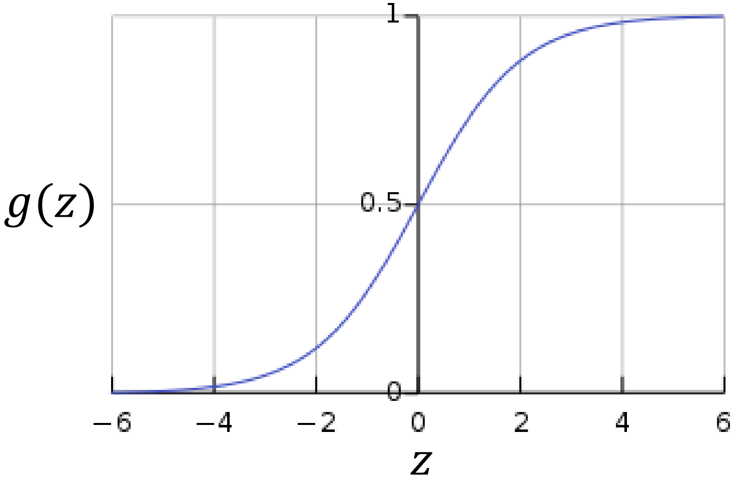
Hypothesis representation

- Want $0 \leq h_\theta(x) \leq 1$

- $h_\theta(x) = g(\theta^\top x)$,

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

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^\top x}}$$



Sigmoid function

Cost function for **Linear Regression**

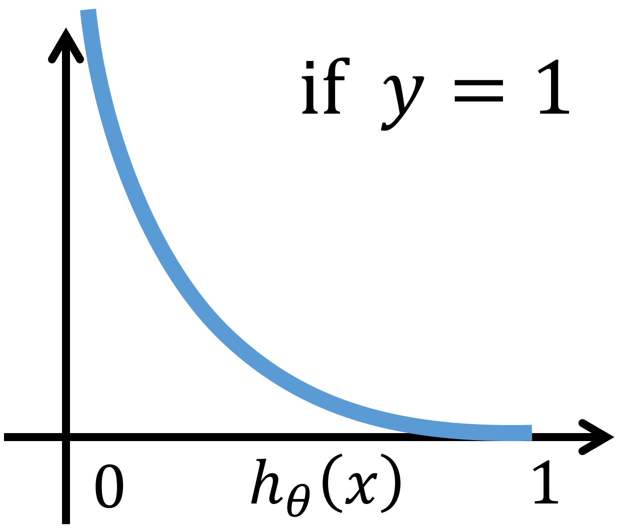
$$J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)^2 = \frac{1}{m}\sum_{i=1}^{m}\mathrm{Cost}(h_\theta(x^{(i)}), y))$$

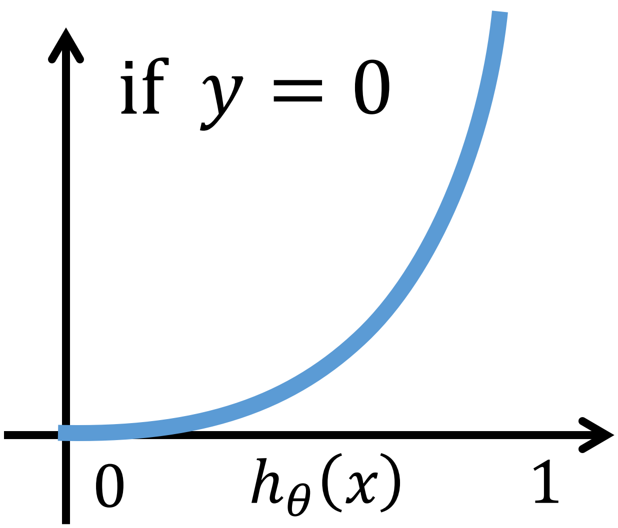
$$\boxed{\mathrm{Cost}(h_\theta(x), y) = \frac{1}{2}(h_\theta(x) - y)^2}$$

Cost function for **Logistic Regression**

$$\mathrm{Cost}(h_\theta(x), y) = \begin{cases} -\log\big(h_\theta(x)\big) & \text{if } y = 1 \\ -\log\big(1 - h_\theta(x)\big) & \text{if } y = 0 \end{cases}$$

$$\mathrm{Cost}(h_\theta(x), y) = -y\ \log\big(\mathrm{h}_\theta(\mathrm{x})\big) - (1 - \mathrm{y})\log\big(1 - h_\theta(x)\big)$$





Logistic regression

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} \mathrm{Cost}(h_\theta(x^{(i)}), y^{(i)}))$$

$$= -\frac{1}{m}\left[\sum_{i=1}^{m} y^{(i)}\ \log\left(h_\theta\left(x^{(i)}\right)\right) + (1-y^{(i)})\log\left(1-h_\theta\left(x^{(i)}\right)\right)\right]$$

Learning: fit parameter θ

$$\min_\theta J(\theta)$$

Prediction: given new x

Output $h_\theta(x) = \frac{1}{1+e^{-\theta^\top x}}$

Derivation of the cost function

$$\begin{aligned}
\frac{\partial}{\partial\theta_j}\ell(\theta) &= \left(y\frac{1}{g(\theta^T x)} - (1-y)\frac{1}{1-g(\theta^T x)}\right)\frac{\partial}{\partial\theta_j}g(\theta^T x)\\
&= \left(y\frac{1}{g(\theta^T x)} - (1-y)\frac{1}{1-g(\theta^T x)}\right)g(\theta^T x)(1-g(\theta^T x)\frac{\partial}{\partial\theta_j}\theta^T x\\
&= \left(y(1-g(\theta^T x)) - (1-y)g(\theta^T x)\right)x_j\\
&= \left(y - h_\theta(x)\right)x_j
\end{aligned}$$

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

$$\frac{d\big(\sigma(\mathrm{x})\big)}{dx} = \frac{0 * (1+e^{-\mathrm{x}}) - (1) * \big(e^{-\mathrm{x}} * (-1)\big)}{(1+e^{-\mathrm{x}})^2}$$

$$\frac{d\big(\sigma(\mathrm{x})\big)}{dx} = \frac{(e^{-\mathrm{x}})}{(1+e^{-\mathrm{x}})^2} = \frac{1\text{-}1+(e^{-\mathrm{x}})}{(1+e^{-\mathrm{x}})^2} = \frac{1+e^{-\mathrm{x}}}{(1+e^{-\mathrm{x}})^2} - \frac{1}{(1+e^{-\mathrm{x}})^2}$$

$$\frac{d\big(\sigma(\mathrm{x})\big)}{dx} = \frac{1}{1+e^{-\mathrm{x}}} * \left(1 - \frac{1}{1+e^{-\mathrm{x}}}\right) = \sigma(\mathrm{x})\big(1-\sigma(\mathrm{x})\big)$$

Gradient descent

Gradient descent for Linear Regression

Repeat {

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right) x_j^{(i)}$$

}

$$\boxed{h_\theta(x) = \theta^\top x}$$

Gradient descent for Logistic Regression

Repeat {

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right) x_j^{(i)}$$

}

$$\boxed{h_\theta(x) = \frac{1}{1 + e^{-\theta^\top x}}}$$

Feed-Forward network

- Lets begin with simple Feed-forward network

Output z can be expressed as weighted sum of inputs

$$z = b + \sum_i w_i x_i$$

express this weighted sum using vector notation

$$z = w \cdot x + b$$

instead of using z, a linear function of x, neural units apply a non-linear function f (activation function) to z.

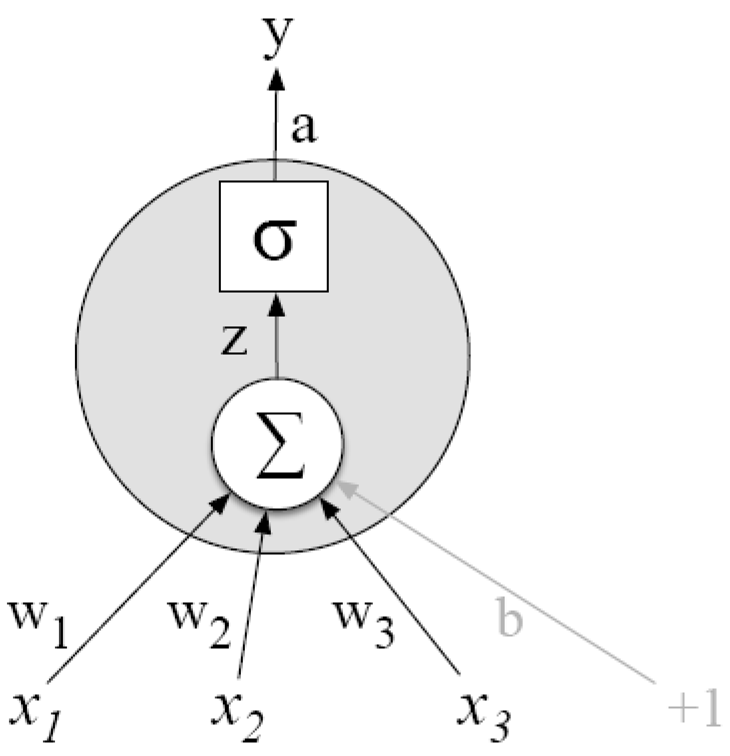
$$y = a = f(z)$$

sigmoid function as activation function

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

Substituting the sigmoid equation

$$y = \sigma(w \cdot x + b) = \frac{1}{1 + exp(-(w \cdot x + b))}$$



TYPES OF NEURAL NETWORK

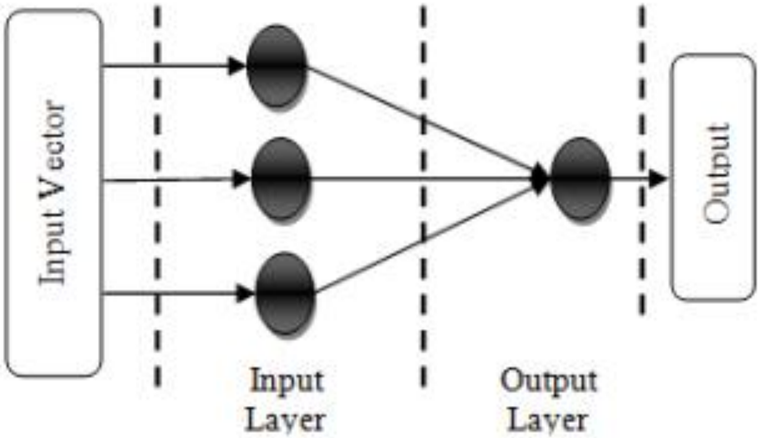


Figure 1.2: Single layer Neural Network

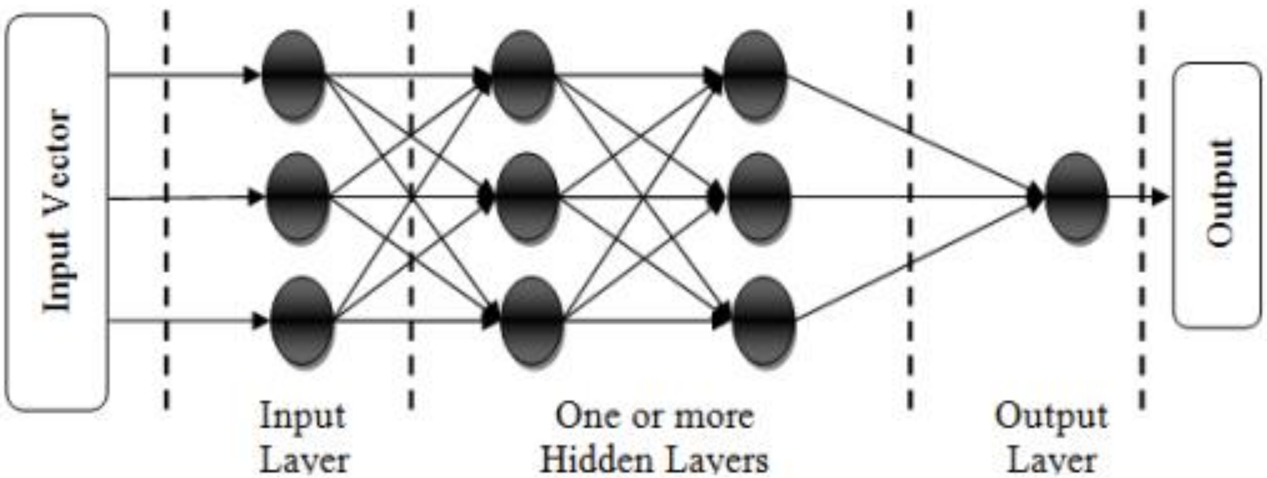
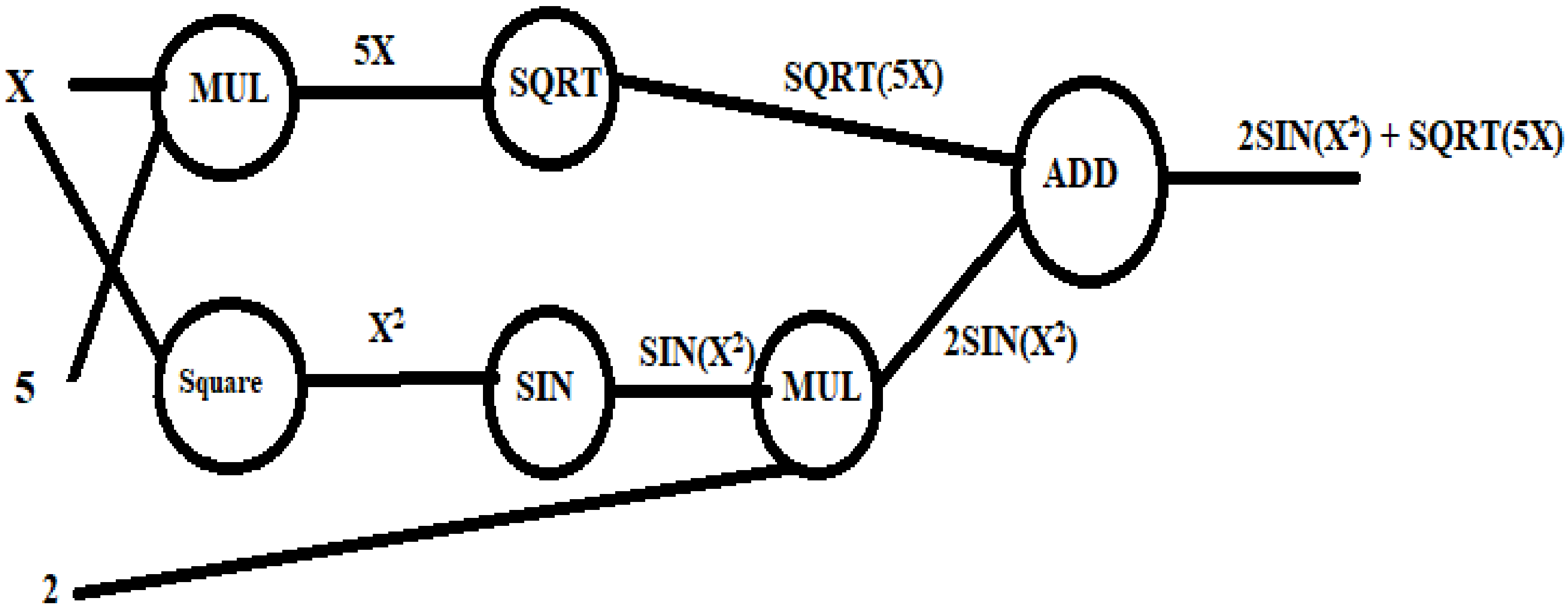


Figure 1.3: Multilayer Neural Network

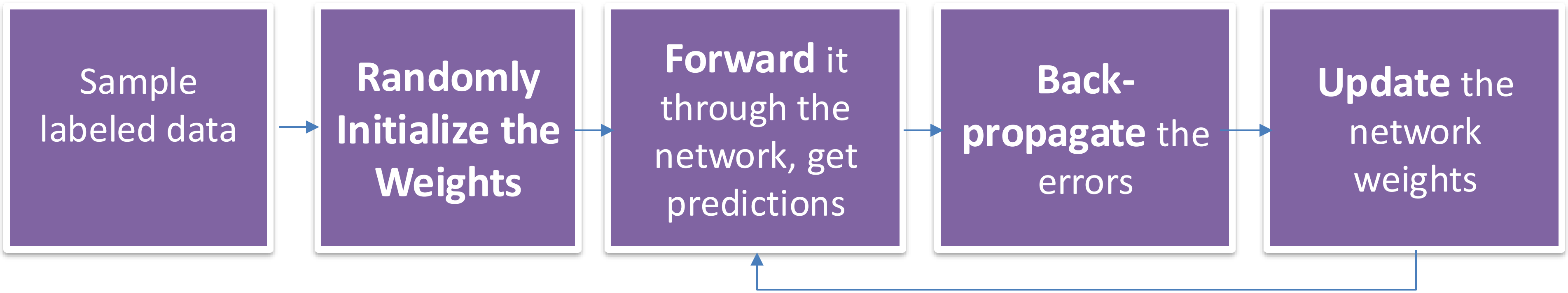
WHY MULTILAYER NEURAL NETWORK?

- **Biological Inspiration**
- **Universal Approximators:** Can approximate any nonlinear function to any desired level of accuracy.
- **Results in Powerful Models**

Graph for 2*sin(x^2)+sqrt(x*5)

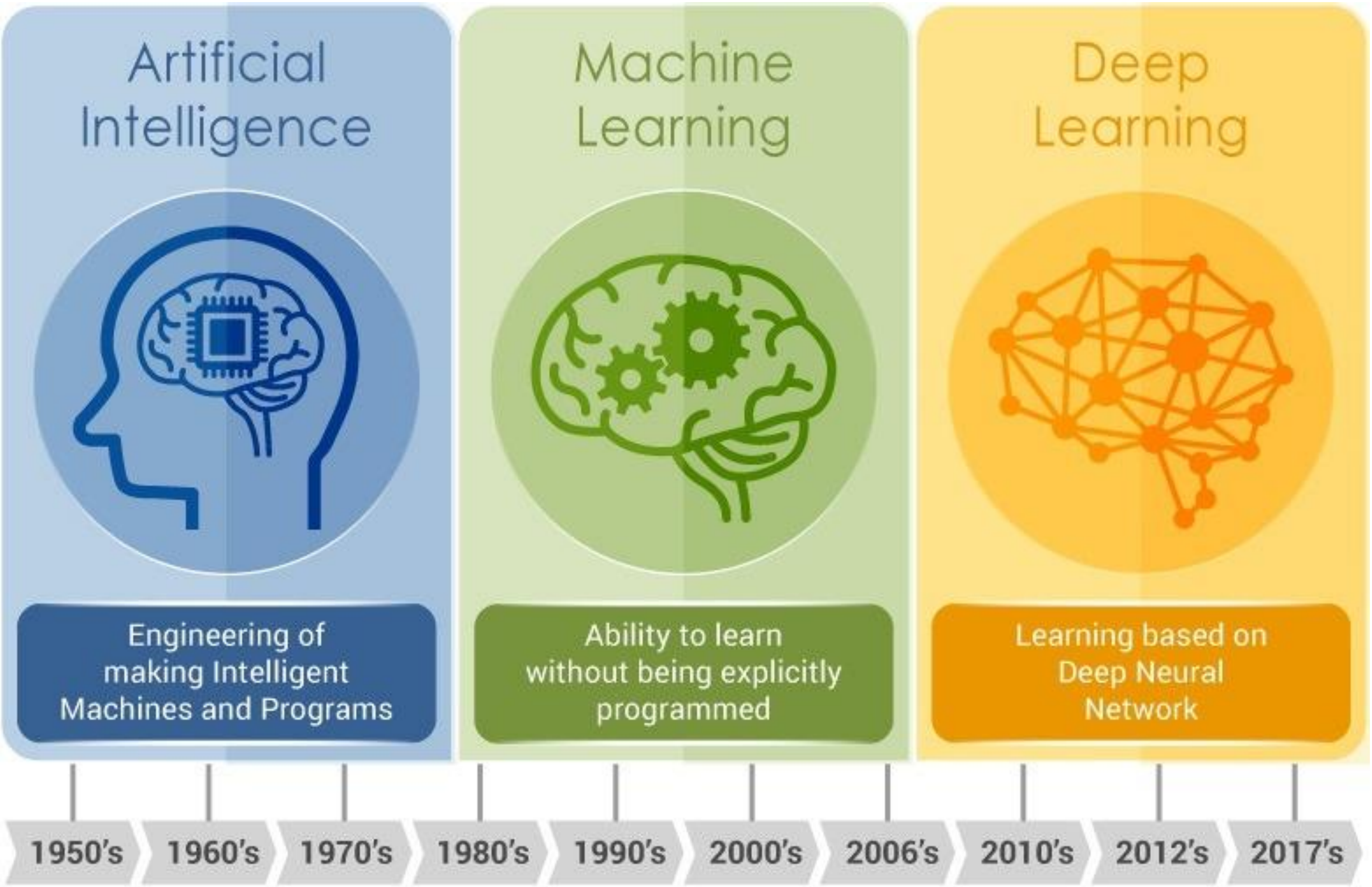


TRAINING MULTILAYER NEURAL NETWORK



- Back-Propagation: Chain Rule + Memoization
  - In Stochastic Gradient Descent (SGD) U take one point (Input Vector)
  - In Mini-Batch SGD, U take a set of points(input vectors)
  - In Gradient Descent, U take all the input vectors

AI vs Machine Learning vs Deep Learning



Deep Learning

- A type of ***machine learning*** based on ***artificial neural networks*** in which *multiple layers of processing* are used to *extract progressively higher level features* from data.

- "Deep Learning with Python" Francois Chollet

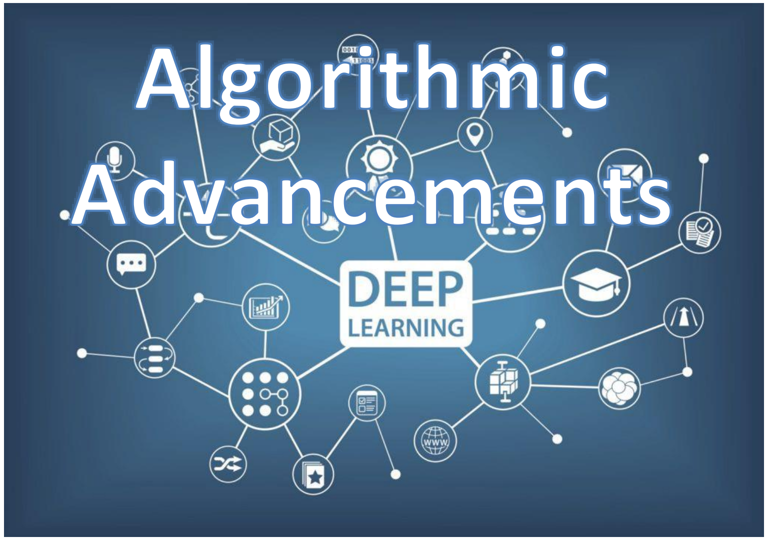
Why Deep Learning ? Why Now ?

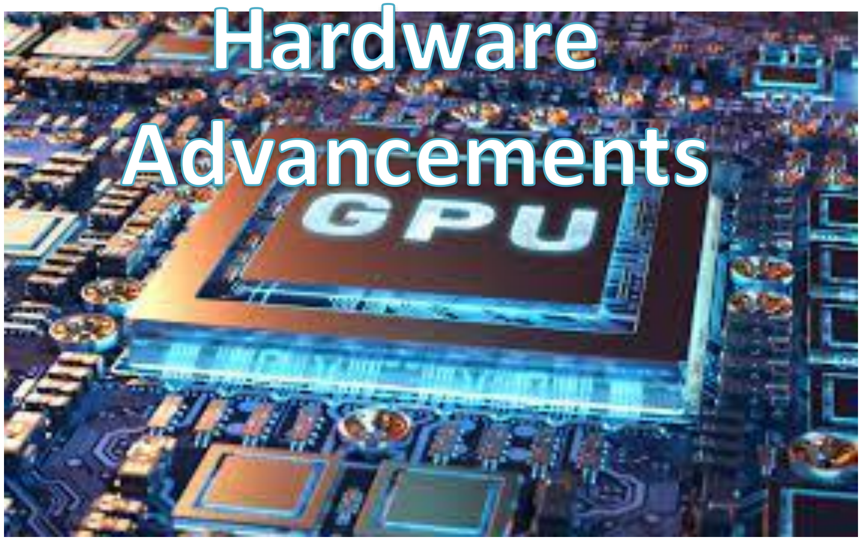
- **Computer Vision-** *Convolutional Neural Networks* and *Backpropagation* —well understood since 1989

- **Time Series Forecasting-** *Long Short-Term Memory* — well understood since 1997

- "Deep Learning with Python" Francois Chollet

Why Deep Learning ? Why Now ?



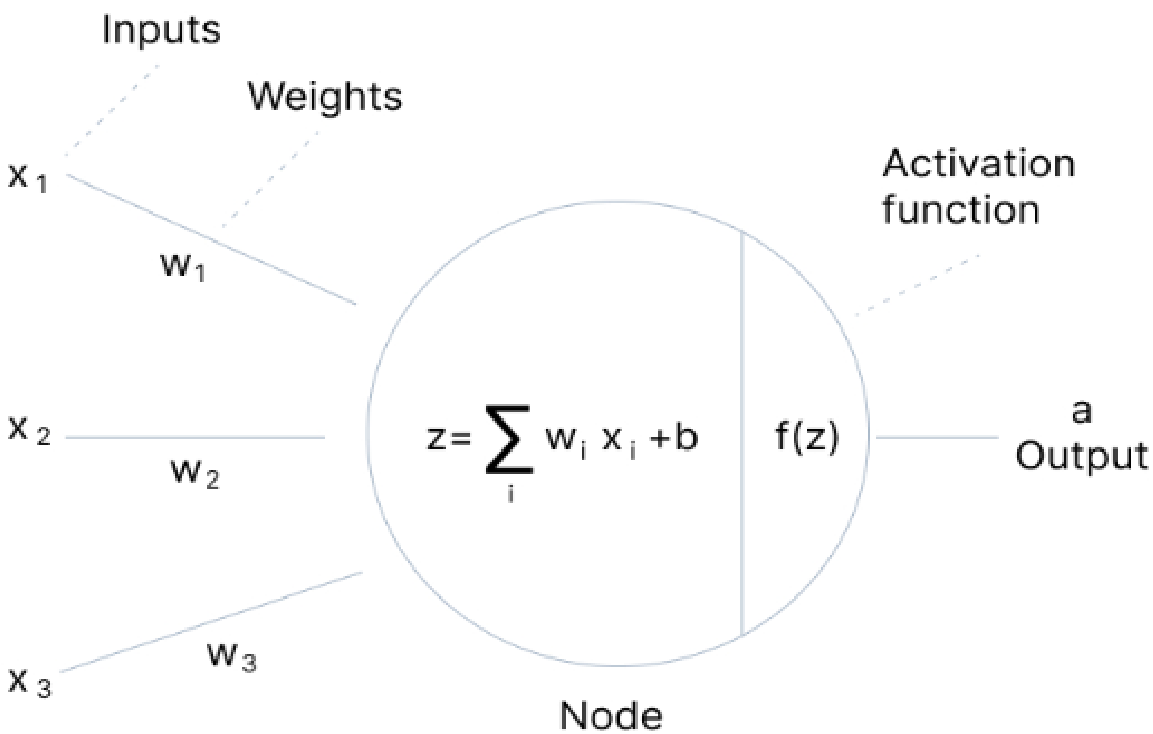


Algorithmic Advancements…

- Better ***Activation Functions*** for neural layers.
- Better ***Weight Initialization*** Schemes starting with layer-wise pretraining.
- To avoid Overfitting the Concepts like ***Dropout*** is Introduced.
- Better ***optimization schemes***, such as RMSProp and Adam.

Activation Functions…

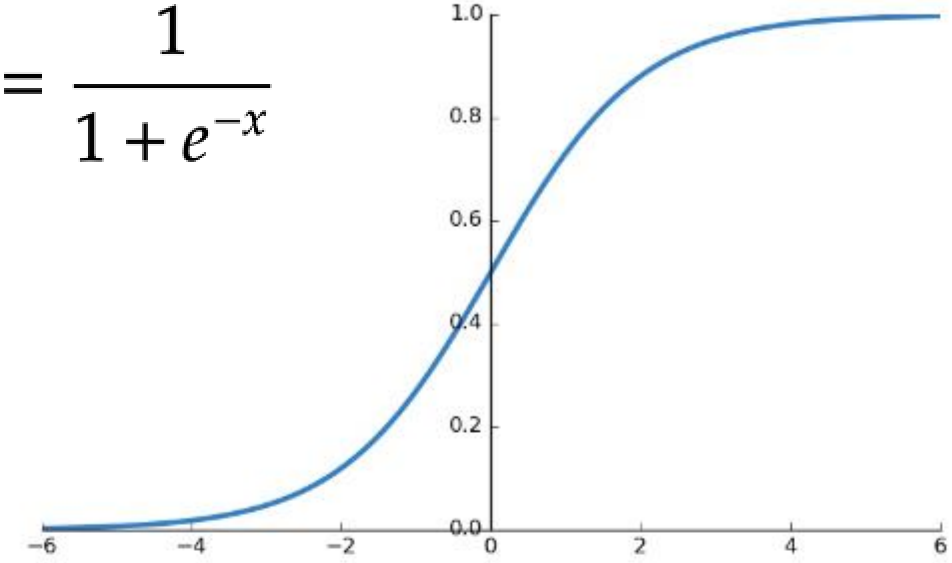
- An *Activation Function (Transfer Function)* maps the weighted summation of inputs to output.
- An Activation function is used to add ***Nonlinearity so that the network can learn complex patterns.***

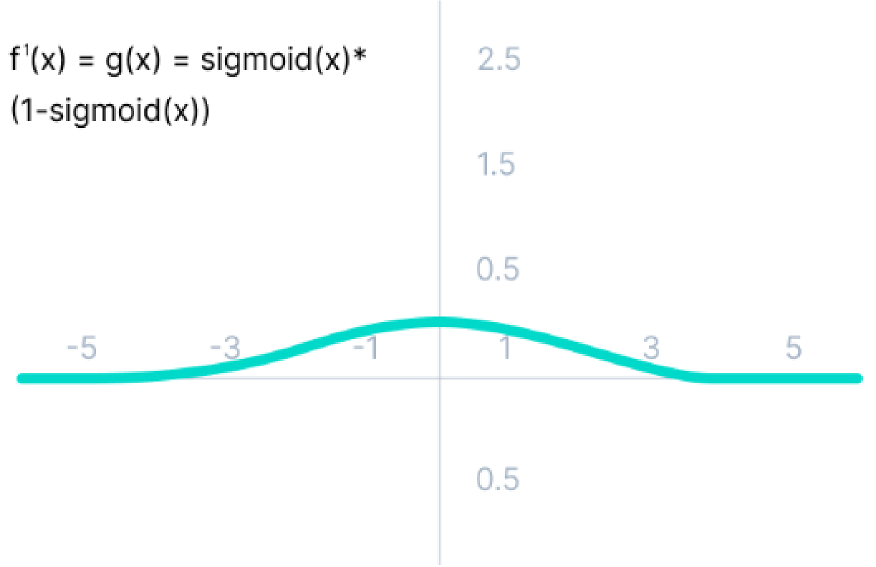


Sigmoid Activation Functions

- **Characteristics:**
  - Differentiable
  - Nonlinear
  - O/P lies in [0-1]
  - Fast
  - ***Vanishing Gradient Problem***

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





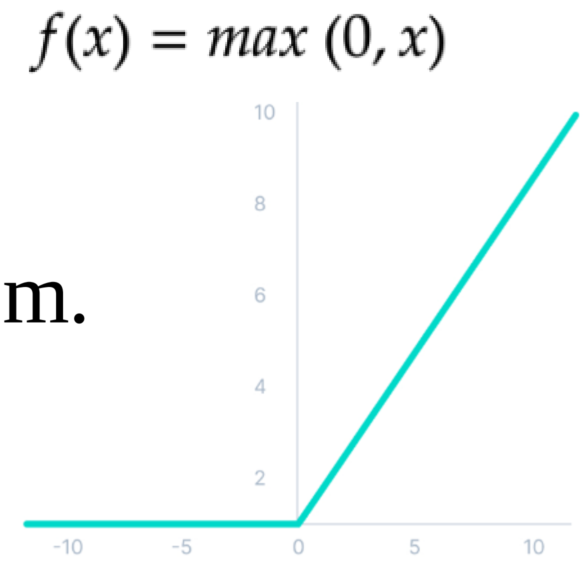
VANISHING GRADIENT PROBLEM

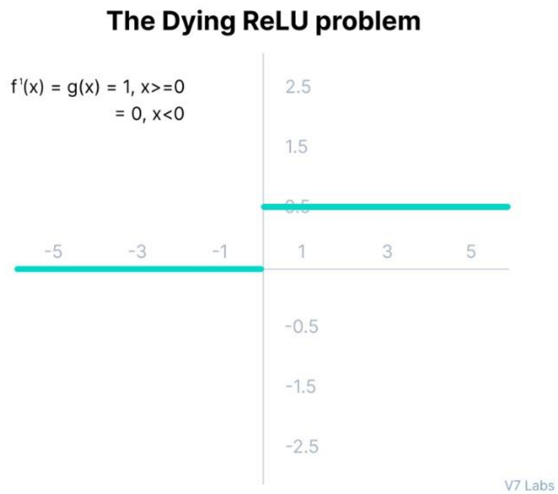
- Because of sigmoid activation function the derivative is ***less than 1*** and *when the derivatives are multiplied it gives a very small number* which ultimately changes the weight very less.
- *Usually occurs when the derivative is less than 1.*
- In case of ***sigmoid and tanh activation*** function it occurs frequently.

$$\frac{dL}{dw} = \frac{dL}{df_1} \times \frac{df_1}{df_2} \times \frac{df_2}{df_3} \times \cdots \ldots \ldots \ldots \ldots \ldots \times \frac{df_n}{dw}$$

ReLU Activation Function

- f(x)= x,   when x>0
  = 0,   when x<=0
- Avoids Vanishing Gradient Problem.
- Derivative is Simple
  - f'(x)= 1 for x>=0
    = 0 for x<0
- Problem:
  - Dead ReLU Units





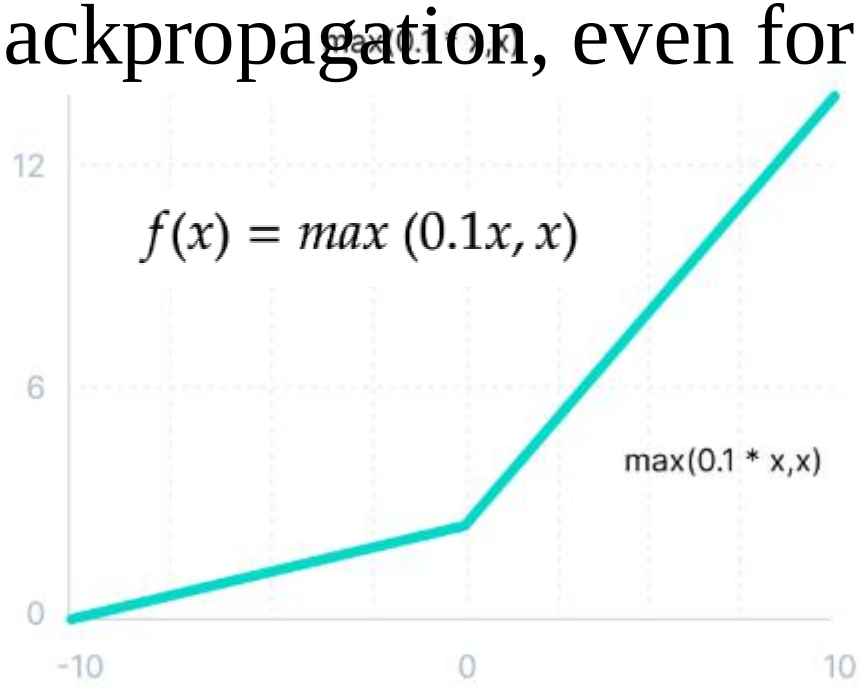
https://www.v7labs.com/blog/neural-networks-activation-functions

Leaky ReLU Activation Function

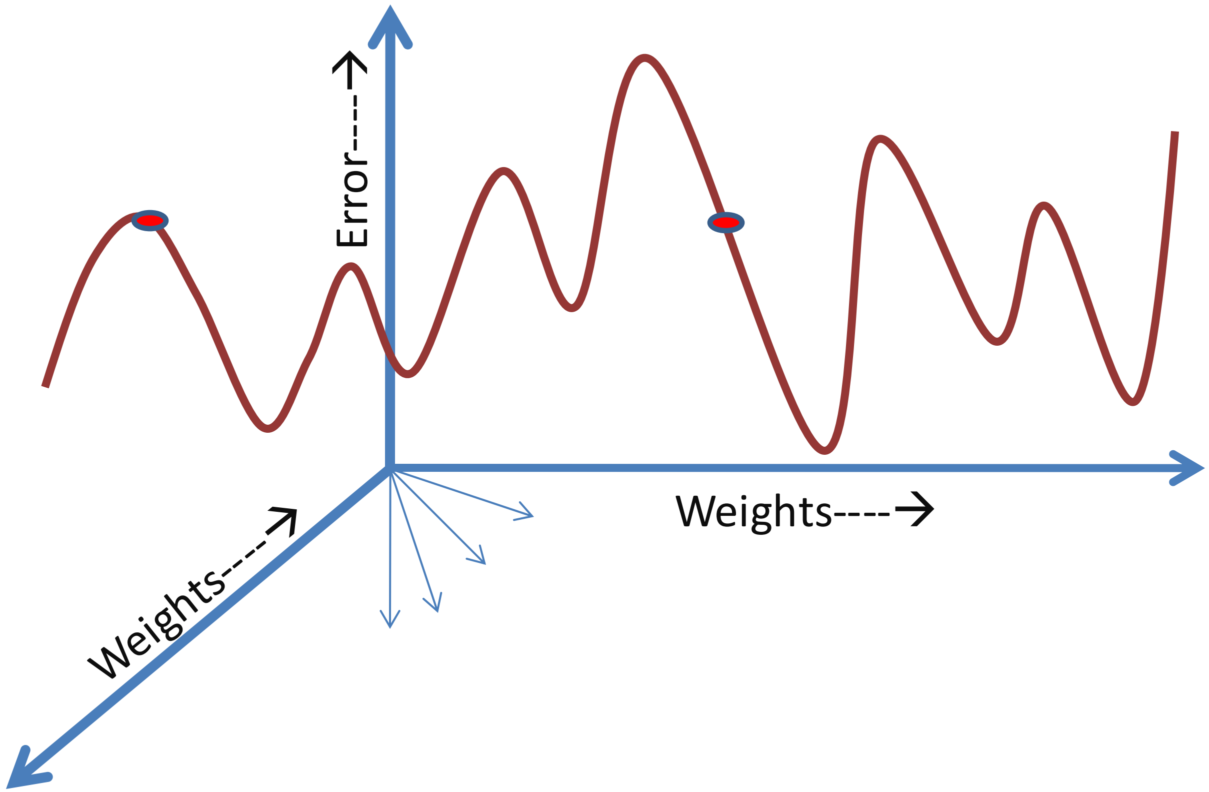
- f(x)= x, when x>0

  = 0.1x, when x<=0
- The advantages of Leaky ReLU are same as that of ReLU.
- In addition, it enables Backpropagation, even for negative input values.
- ***Avoids Dead ReLU***
- Simple Derivative
  - f'(x)= 1 for x>=0

    = 0.1 for x<0



WEIGHT INITIALIZATION

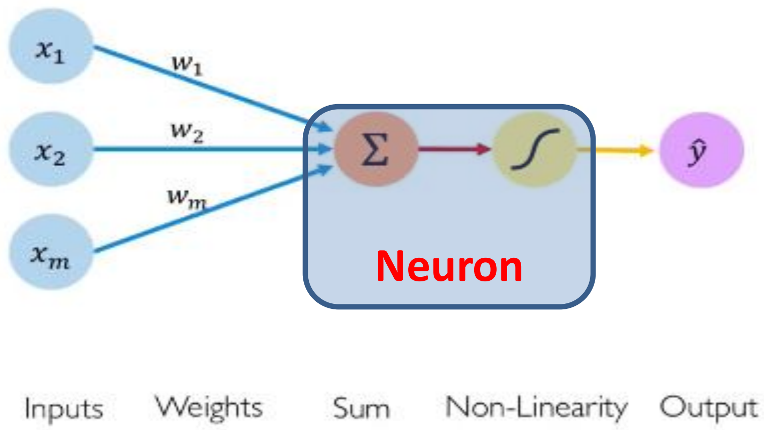


WEIGHT INITIALIZATION

- Mostly used
  - We should never initialize to same values.
    - Asymmetry is necessary
  - We should not initialize to large –ve values
    - Vanishing Gradient problems
  - Weights should be small (not too small)
  - Weights should have good variance
  - Weights should come from a Normal distribution with mean zero and small variance
  - Should have some +ve and Some –ve values

WEIGHT INITIALIZATION

- Better Strategies obtained from large experiments
  - Initialize weights based on Fan-in and Fan-out
  - Initialize your weights from a uniform distribution
    - $\left[-\frac{1}{\sqrt{fanin}}, \frac{1}{\sqrt{fanin}}\right]$
  - Works well for sigmoid activation function



WEIGHT INITIALIZATION

– Xavier/Glorot initialization in 2010- ***well for sigmoid activation function***

- First Variation – $W_{ij} = N(0, \sigma_{ij}), \quad \sigma_{ij} = \frac{2}{Fanin + Fanout}$
- Second Variation– $W_{ij} = U\left(-\frac{\sqrt{6}}{\sqrt{Fanin + Fanout}}, \frac{\sqrt{6}}{\sqrt{Fanin + Fanout}}\right)$

WEIGHT INITIALIZATION

– He Initializer, 2015 ***works well for ReLU***

- First Variation – $W_{ij} = N(0, \sigma_{ij}), \quad \sigma_{ij} = \sqrt{\frac{2}{Fanin}}$
- Second Variation– $W_{ij} = U\left(-\frac{\sqrt{6}}{\sqrt{Fanin}}, \frac{\sqrt{6}}{\sqrt{Fanin}}\right)$

BIAS-VARIANCE TRADE-OFF

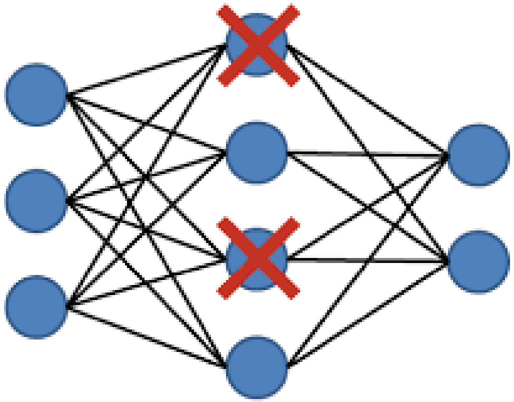
No. of Layers Increases → **More No. of Weights** → **Chances to Overfit is High** → **Problem of High Variance**

No. of Layers Decreases → **Less No. of Weights** → **Chances to Underfit is High** → **Problem of High Bias**

- Multilayer ANN has higher chance of overfitting.

DROPOUT AND REGULARIZATION

- Deep NN tend to overfit because of many layers and weights
- For this dropout and regularization is needed
- In Dropout, a certain percentage of inputs and hidden layer neurons are dropped out for an iteration
- Some call it as drop out network or layer.



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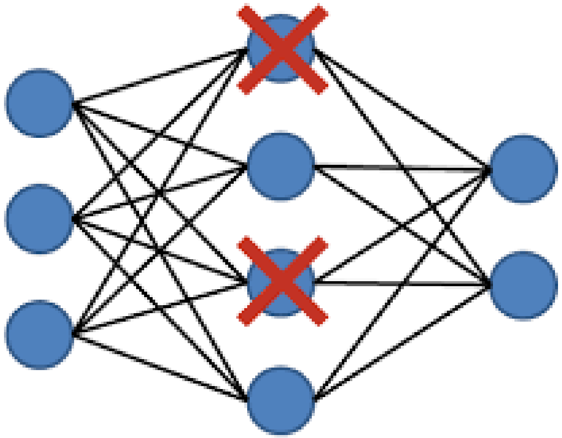
Dropout

- Procedure:
  - During training we decide with probability *p* to update a node's weights or not.
  - We set *p* to be typically 0.5
- Highly effective in deep learning:
  - Decreases overfitting
  - Reduces training time
- Can be loosely interpreted as ensemble of networks



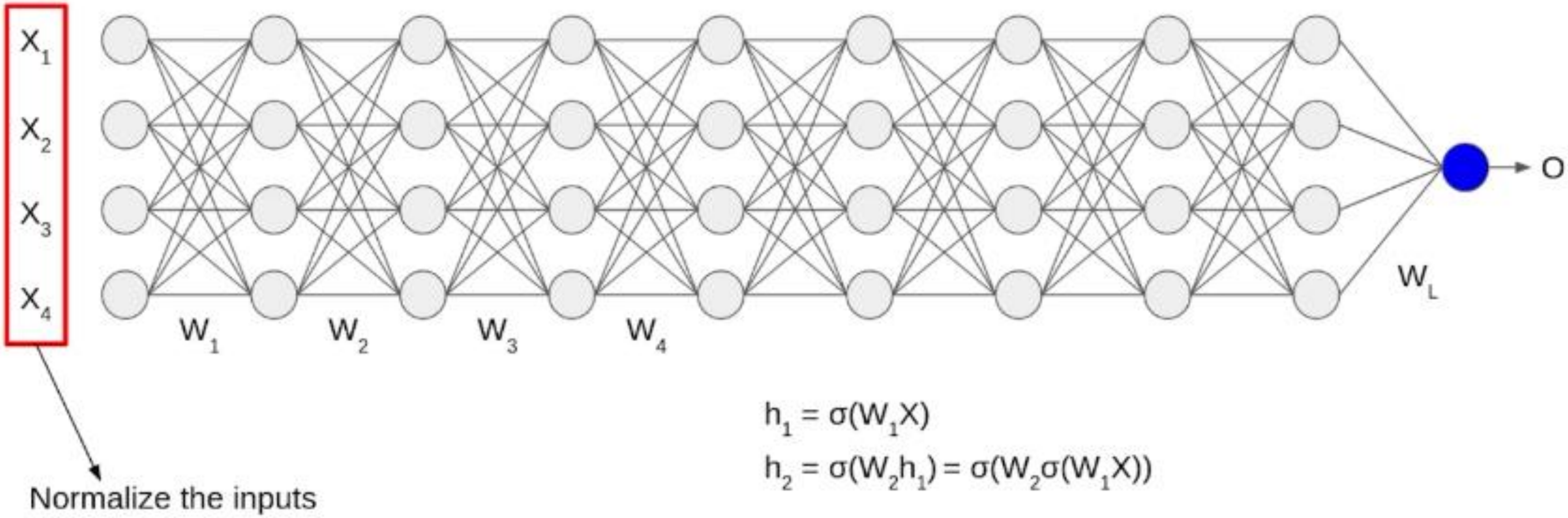
'

BATCH NORMALIZATION

- Normalization is a data pre-processing tool used to bring the numerical data to a common scale without distorting its shape.
  - Decimal Scaling: $N_i = \frac{T_i}{10^p}$
  - Median: $N_i = \frac{T_i}{\text{median}(T)}$
  - Min-Max: $N_i = \text{Min}_N + \frac{T_i - \text{Min}_T}{\text{Max}_T - \text{Min}_T} \times (\text{Max}_N - \text{Min}_N)$
  - Vector: $N_i = \frac{T_i}{\sqrt{\sum_{j=1}^{k} T_j^{\,2}}}$
  - Z-Score: $N_i = \frac{T_i - \mu_T}{\sigma_T}$

BATCH NORMALIZATION

- Motivation



$h_1 = \sigma(W_1 X)$

$h_2 = \sigma(W_2 h_1) = \sigma(W_2 \sigma(W_1 X))$

$O = \sigma(W_L h_{L-1})$

BATCH NORMALIZATION

$$\mu = \frac{1}{m}\sum h_i$$

$$\sigma = \sqrt{\frac{1}{m}\sum (h_i - \mu)^2}$$

$$h_{i(norm)} = \frac{h_i - \mu}{\sigma + \epsilon}$$

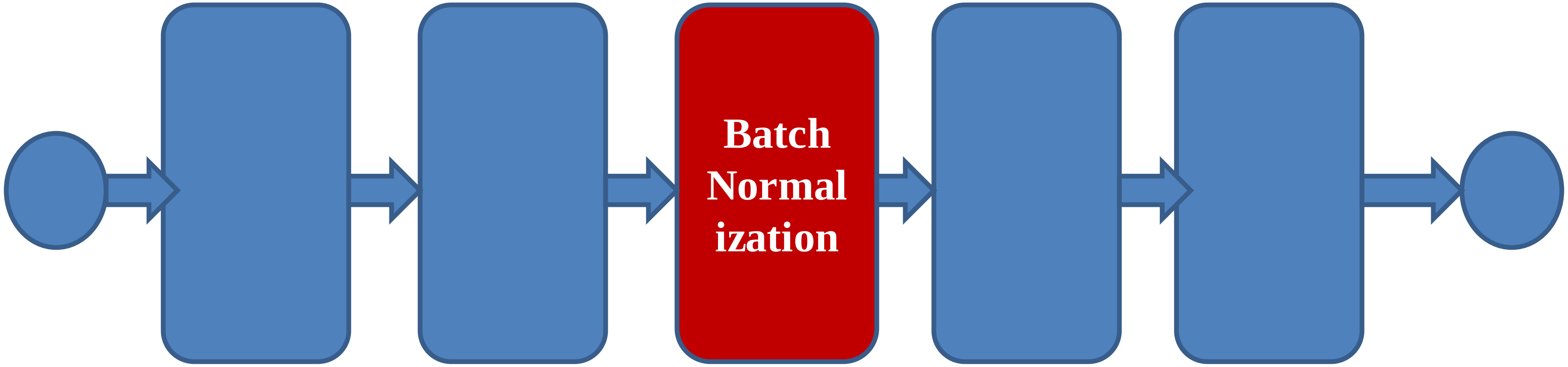
- Where m: Number of Neurons at h_i

$$h_i = \gamma . h_{i(norm)} + \beta$$

- Where γ and β are hyper parameters.

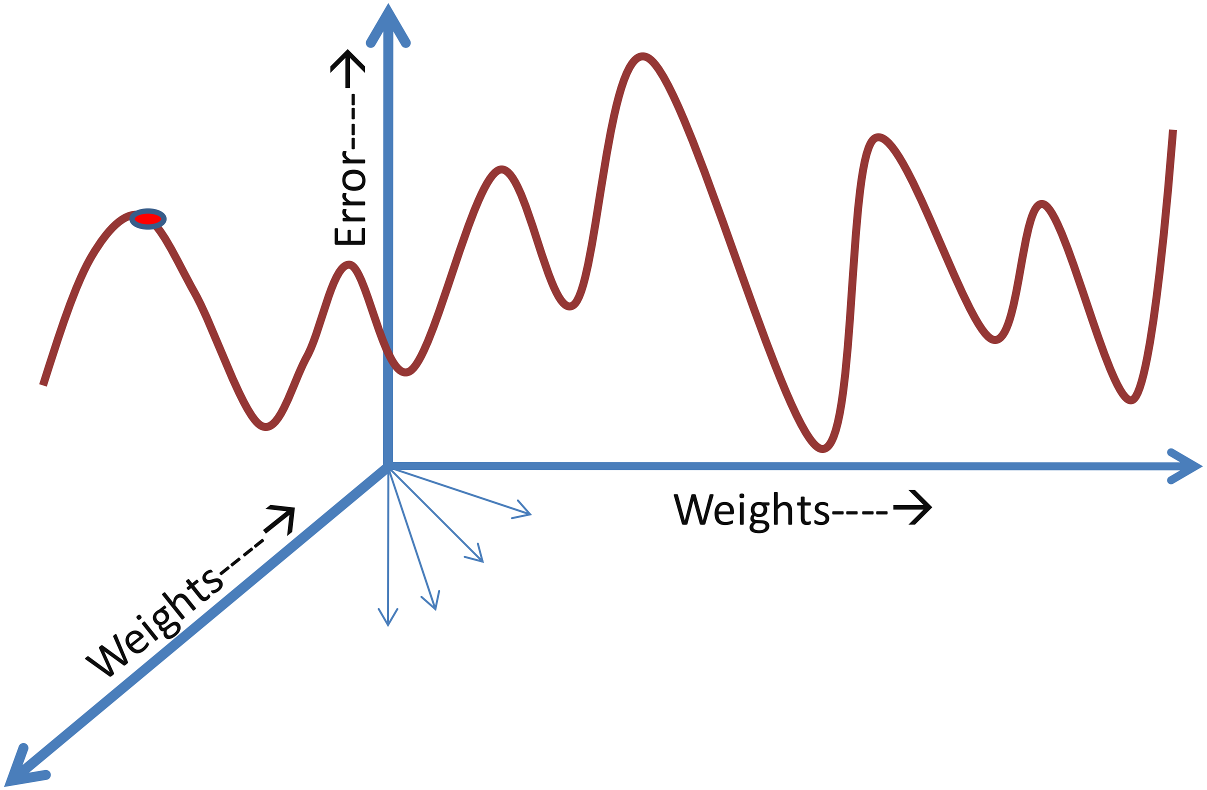
BATCH NORMALIZATION

- Advantages
  - Faster Convergence
  - Weak Regularizer (Batch Normalization + dropout)
  - Avoids internal covariate shift
- https://arxiv.org/pdf/1502.03167v3.pdf



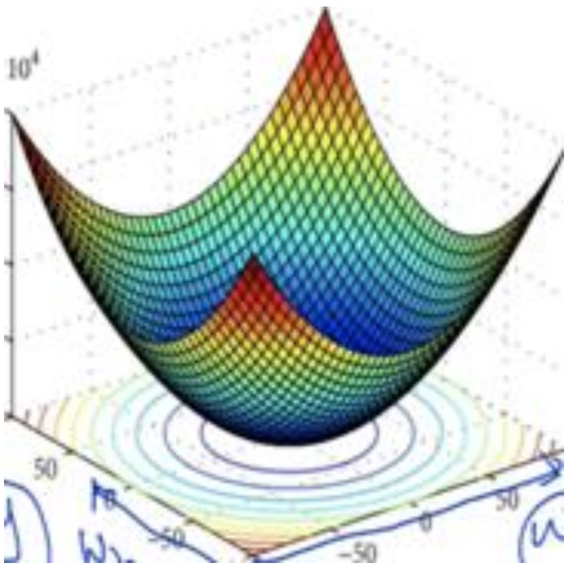
OPTIMIZERS

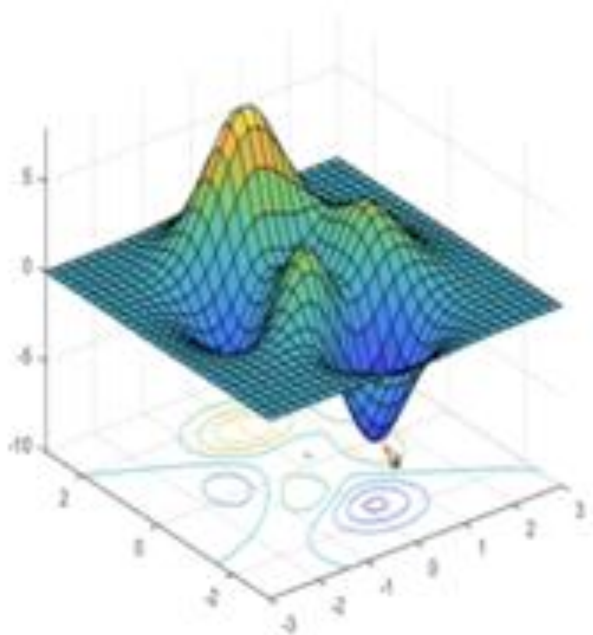
- At minima, maxima and saddle point, u have the gradient as Zero.

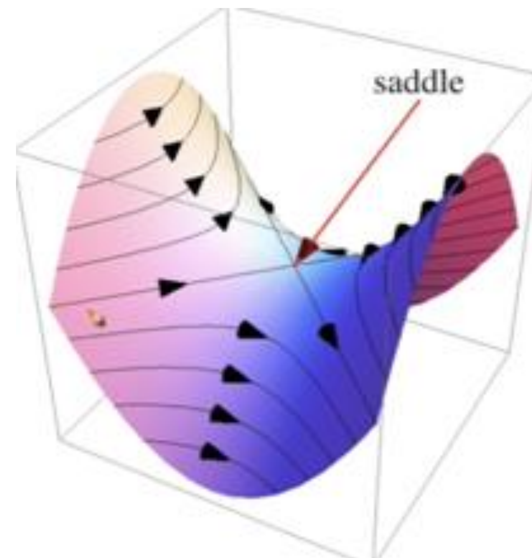


OPTIMIZERS

- Convex function and Non-Convex Function
- Convex functions have either 1 maxima or minima. (Local minima=global minima)
- Non-convex functions have more than one minima or maxima

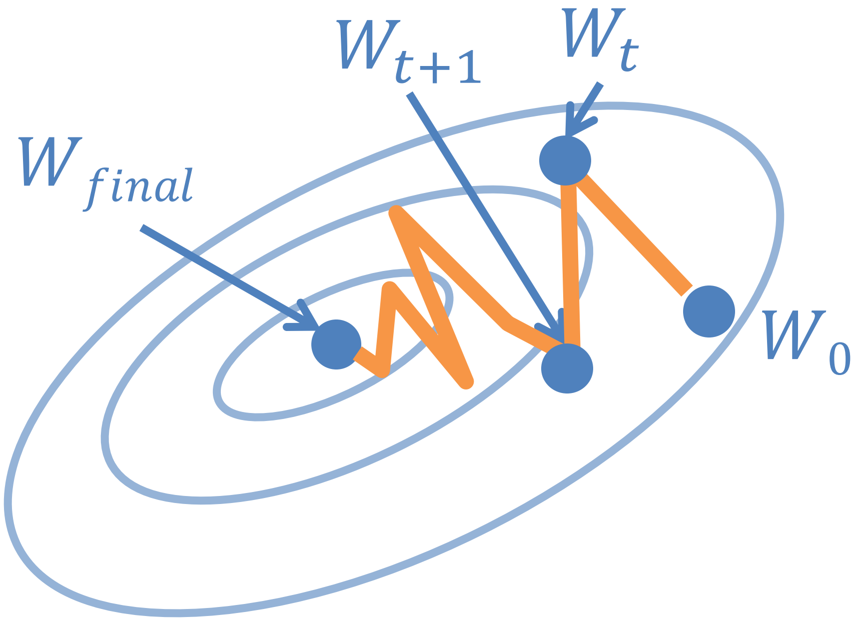






Stochastic gradient descent (SGD)

You take one point (Input Vector), Feed Forward it then update the weights by back-propagating the gradient of errors.



- Initialize W_0 randomly
- For t in $0,\ldots,T_{\text{maxiter}}$

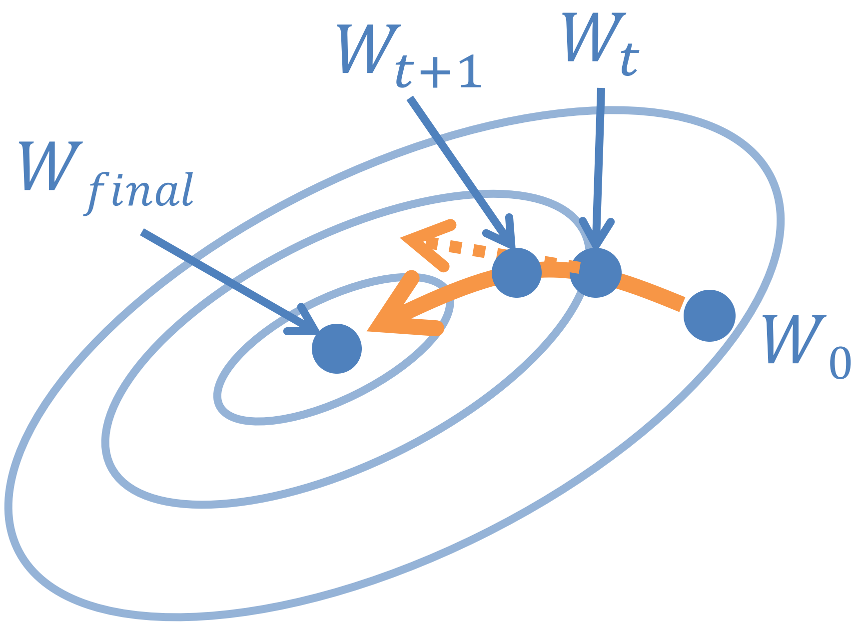
$$W^{t+1} = W^t - \eta_t \cdot \underbrace{\nabla Loss(f_w(x_i), y_i)}_{\text{Stochastic gradient}}$$

where index i is chosen randomly

- computation of $\nabla Loss(\ldots)$ requires only one training example
- Per-iteration comp. cost = O(1)

Gradient descent

You take all Input Vectors, Feed Forward it one by one, compute the error and get the mean error, then update the weights by back-propagating the gradient of errors.



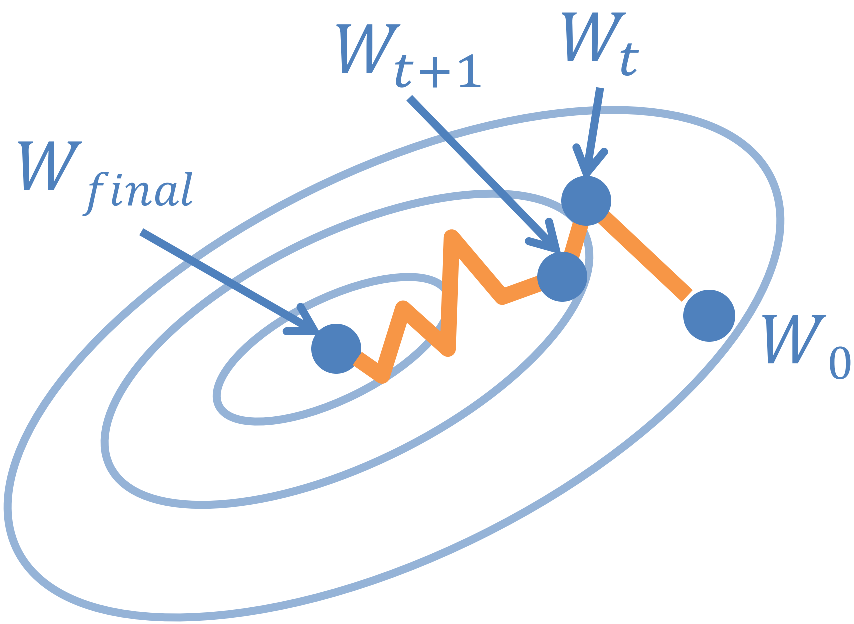
- Initialize W_0 randomly
- For t in 0,…, T_{maxiter}

$$W^{t+1} = W^t - \eta_t \cdot \nabla L(\underbrace{f_w(x_i)}_{\text{Gradient of the objective}}, y_i)$$

- computation of $\nabla L(W^t)$ requires a full sweep over the training data
- Per-iteration comp. cost = O(n)

Minibatch stochastic gradient descent

You take a subset of Input Vectors (more than one), Feed Forward it one by one, compute the error and get the mean error, then update the weights by back-propagating the gradient of errors.



- Initialize W_0 randomly
- For t in $0, \ldots, T_{\text{maxiter}}$

$$W^{t+1} = W^t - \underbrace{\eta_t \cdot \tilde{\nabla}_B L(W)}_{\text{minibatch gradient}}$$

where minibatch B is chosen randomly

- $\tilde{\nabla} L(\theta)$ is average gradient over random subset of data of size B
- Per-iteration comp. cost = O(B)

STOCHASTIC GRADIENT WITH MOMENTUM

- The **rate of convergence** of **Stochastic Gradient** can be improved by *adding a momentum* to the Gradient expression.
- This can be ***achieved by adding a fraction of previous weight change to the current weight change***.

$$(w_i)_{new} = (w_i)_{old} - \eta \left[\left[\frac{dL}{dw_i}\right]\right]$$

$$(\mathrm{w_i})_t = (\mathrm{w_i})_{t-1} + \alpha . \Delta w_{t-1} - \eta \frac{dL}{dw}$$

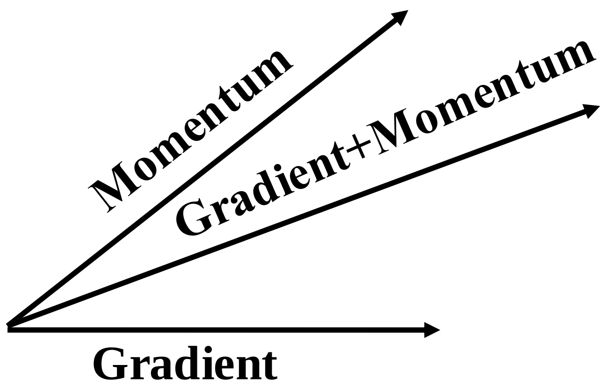
Momentum

Learning Rate

Nestrov Accelerated Gradient (NAG)

- SGD + Momentum

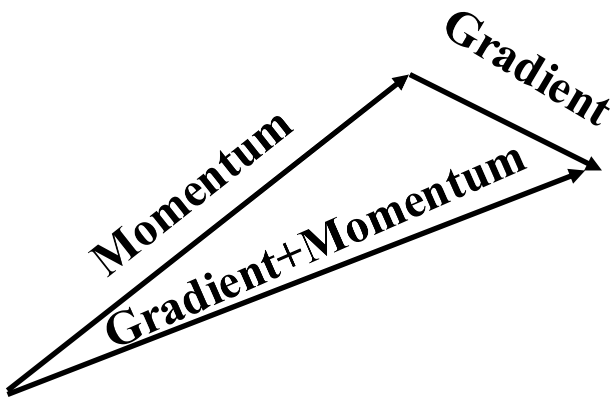
$$(\mathrm{w_i})_t = (\mathrm{w_i})_{t-1} + \alpha.\Delta w_{t-1} - \eta\frac{dL}{dw}$$



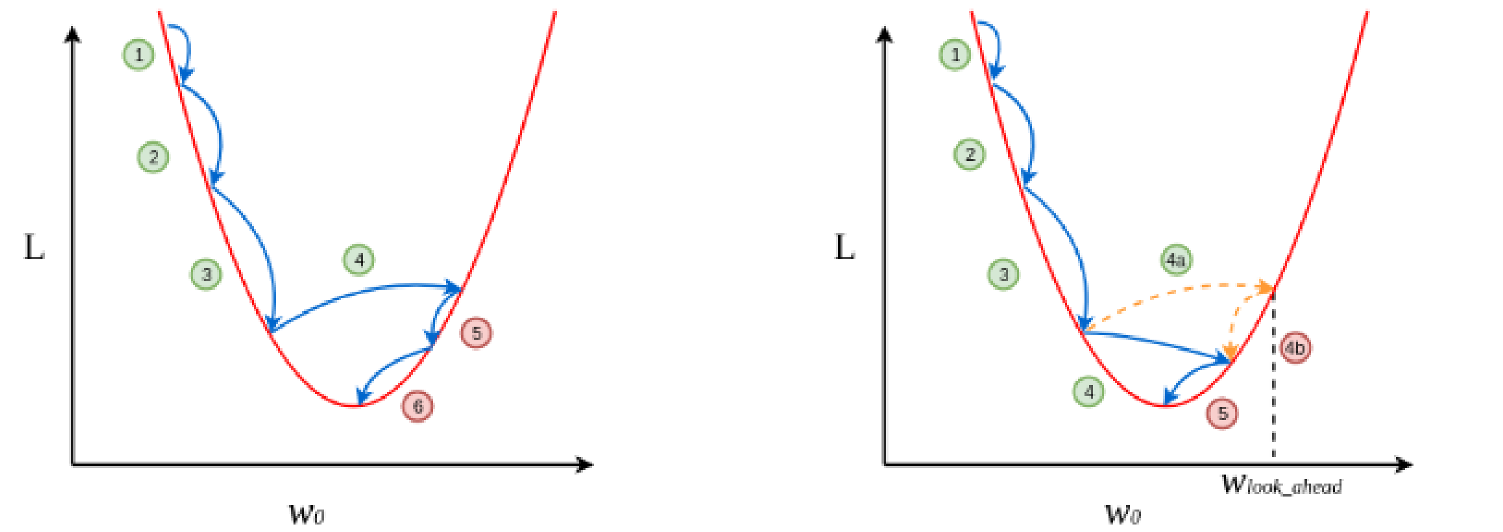
What we r doing in NAG?

Nestrov Accelerated Gradient (NAG)

- NAG



Nestrov Accelerated Gradient (NAG)



(a) Momentum-Based Gradient Descent

(b) Nesterov Accelerated Gradient Descent

ADAPTIVE GRADIENT(ADAGRAD)

- In SGD, SGD+Momentum and NAG, the learning rate is same for each weight.
- However, in Adagrad you have different learning rate for different weights.
- Why
  - Sparse Feature
  - Dense Feature

Mathematical formulation of AdaGrad

ADAPTIVE GRADIENT(ADAGRAD)

- SGD

$$(w_i)_{new} = (w_i)_{old} - \eta \left[\!\left[\frac{dL}{dw_i}\right]\!\right]$$

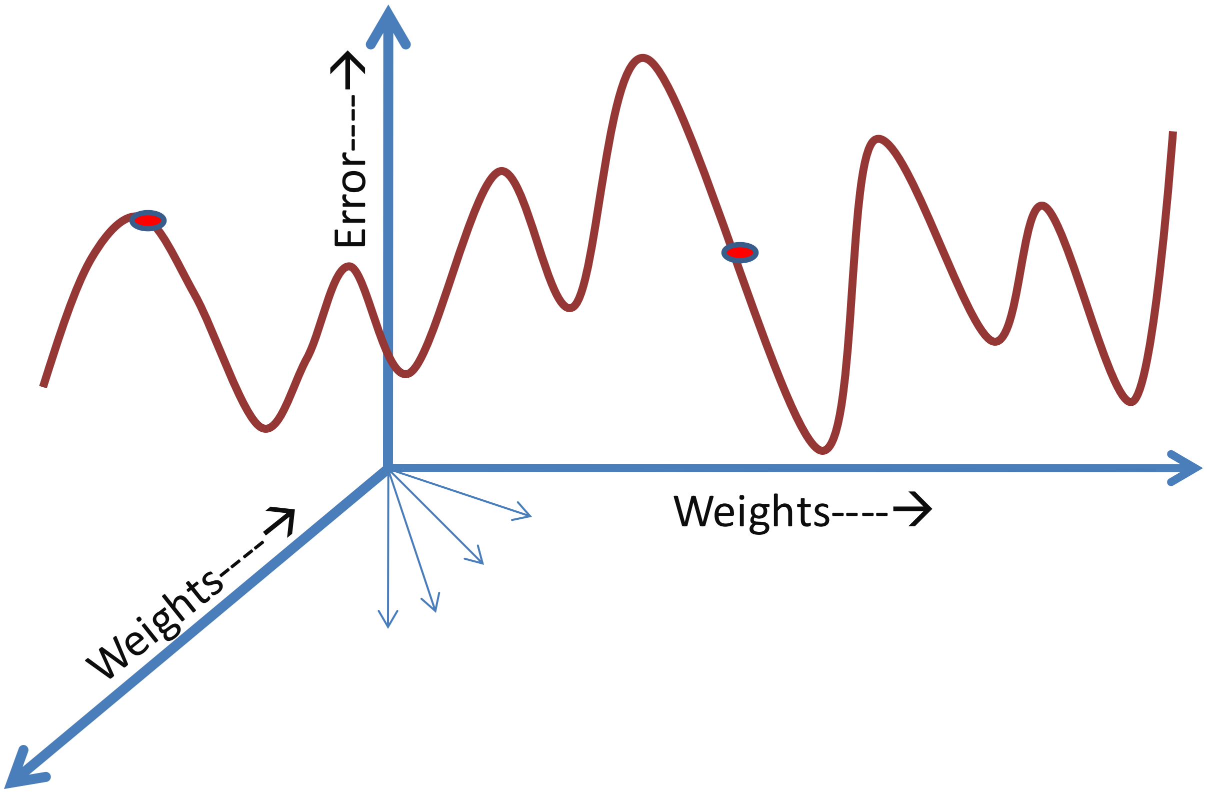
- Adagrad

$$\eta_t = \frac{\eta}{\sqrt{\alpha_{t-1} + \varepsilon}} \; with \; \alpha_t \geq \alpha_{t-1}$$

$$\alpha_{t-1} = \sum_{i=1}^{t-1} \left(\frac{dL}{dw}\right)_i^2$$

- As iteration increases the learning rate decreases.

ADAPTIVE GRADIENT(ADAGRAD)



ADAPTIVE GRADIENT(ADAGRAD)

- Advantages
  - No need of manual tuning
  - Works well for both Sparse and Dense Feature
- Disadvantages
  - As iteration increases, the learning rate will get low, which will result in Slow Convergence.
  - Computationally expensive.

AdaDelta

$$\eta'_t = \frac{\eta}{\sqrt{Exponentially\ Decaying(\alpha)_{t-1} + \epsilon}}$$

- $EDA_{t-1} = \gamma * EDA_{t-1} + (1-\gamma)\left(\frac{dL}{dw}\right)_{t-2}^{2}$
- Avoids the Problem of slow convergence of AdaGrad

Root Mean Square Propagation (RMSProp)

- It is same to AdaDelta however, it discards the history from extreme past while computing the exponentially decaying average.
- Converges faster once it finds a locally convex bowl as its error function.
- Faster convergence than AdaDelta.

ADAM(ADAPTIVE MOMENTUM ESTIMATION)

- https://arxiv.org/pdf/1412.6980.pdf
- Momentum is adaptive

$$w_{t+1} = w_t - \alpha m_t$$

where,

$$m_t = \beta m_{t-1} + (1-\beta)\left[\frac{\delta L}{\delta w_t}\right]$$

m_t = aggregate of gradients at time t [current] (initially, m_t = 0)

m_{t-1} = aggregate of gradients at time t-1 [previous]

W_t = weights at time t

W_{t+1} = weights at time t+1

α_t = learning rate at time t

∂L = derivative of Loss Function

∂W_t = derivative of weights at time t

β = Moving average parameter (const, 0.9)

WHICH OPTIMIZER TO USE

- MiniBatch-SGD:::::::: Small/Shallow ANN
- Momentum & NAG::: Works well in most cases but Slower
- AdaGrad:::::::::::::::::: Sparse Features
- AdaDelta & RMSProp: Preferred Over AdaGrad
- Adam:::::::::::::::::::::: Most Favorite

How to Train a Deep Neural Network?

1. **Pre-processing:** Data Narmalization
2. **Weight Initialization**
   - Xavier & Glorot (For Sigmoid)
   - He Initializer (For ReLU)
3. **Choose the Activation Function** (ReLU-Most Favourite)
4. **Batch Normalization** (Especially for later layers close to O/P Layer)
5. **Use Dropout**
6. **Choose the Optimizer** (Favourite- Adam)
7. **Hyper-parameters:** Architecture(# Layers, # Neurons), etc…
8. **Loss Function**
   - 2-Class Classification : Log Loss
   - Multi-Class Classification: Multi-Class Log Loss
   - Regression: Squared Loss

TENSORFLOW & KERAS

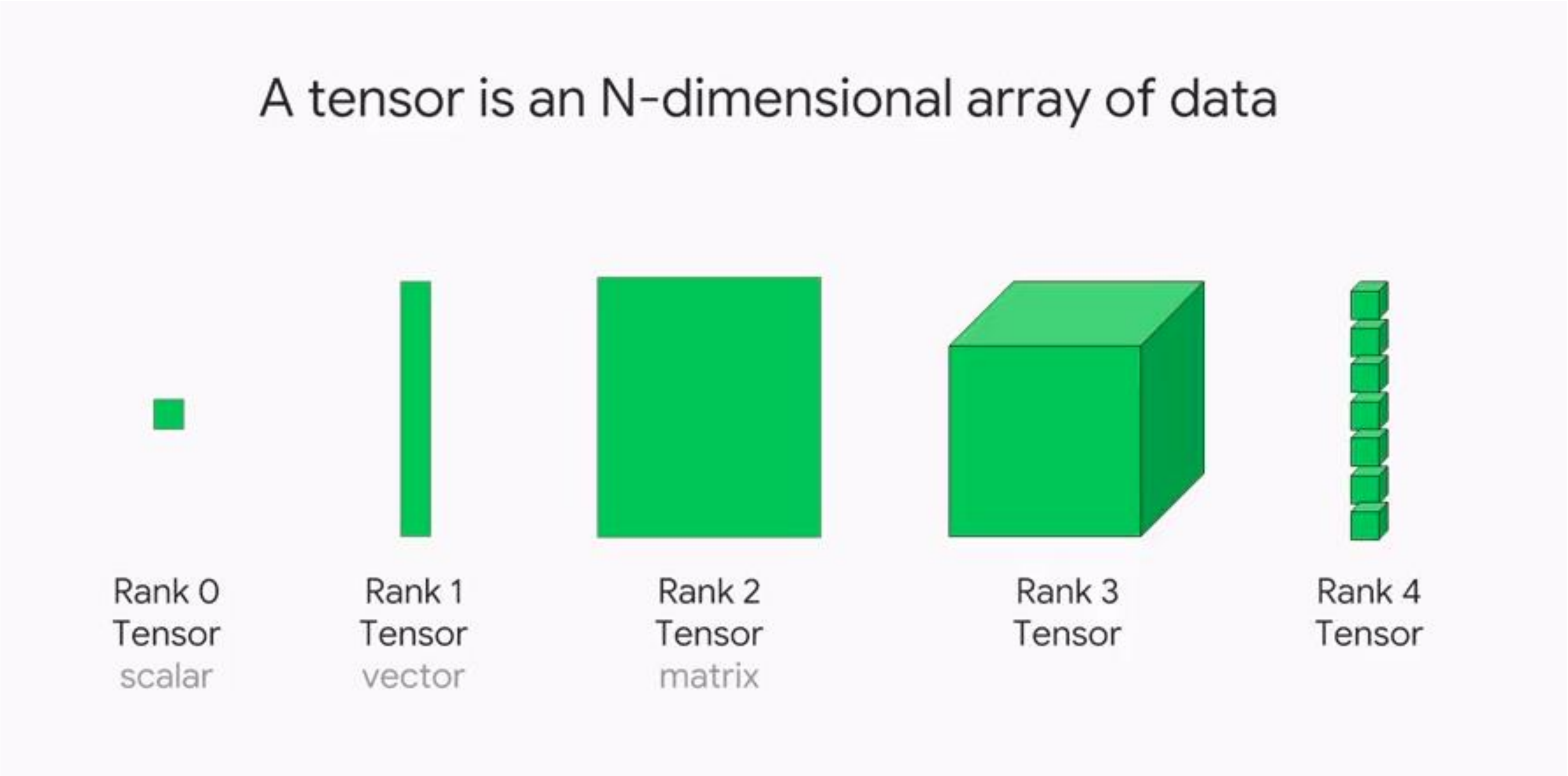
- One of the most popular Deep Learning Libraries.
- Developed by Google in November 2015.

Researcher | **Development** | **Deployment**

TENSORFLOW & KERAS

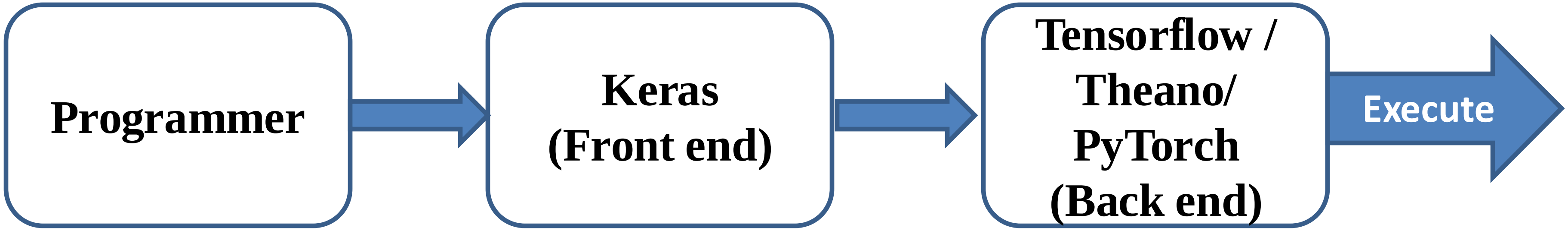
- Core is written in C & C++ making it faster.
- Supports:
  - Python
  - Java
  - Javascript
  - Android (Tensorflow Lite)

Tensorflow


A tensor is an N-dimensional array of data
Rank 0
Tensor
scalar
Rank 1
Tensor
vector
Rank 2
Tensor
matrix
Rank 3
Tensor
Rank 4
Tensor

Keras

- High-level Neural Network Library for developers and deployment.
- Easy to Learn
- Few Lines of Code



Google Colab

colab.research.google.com

DECISION SURFACES: PLAYGROUND

- http://playground.tensorflow.org/

BIG QUESTIONS?

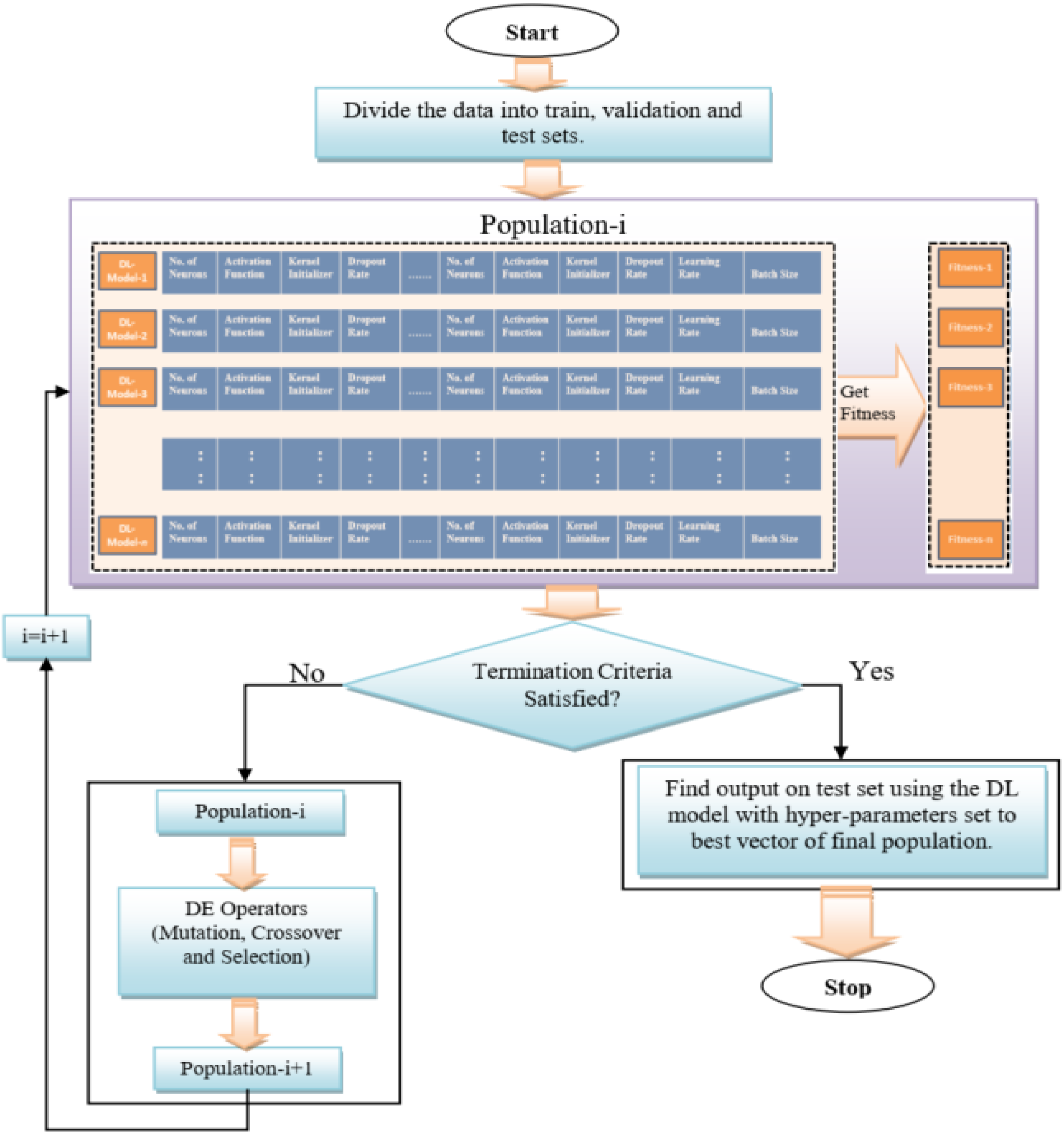
- **How many Inputs?**
- **How many Layers?**
- **How many neurons in each layer?**
- **Which Activation Function?**
- **Which Kernel Initializer?**
- **Which Optimizer?**
- **What is the Batch Size?**
- **What is the Learning Rate?**

End of the topic

SOLUTION

- Grid Search
- Bayesian Optimization
- Swarm and Evolutionary Algorithms

SWARM & EVOLUTIONARY ALGORITHM BASED DNN



SWARM & EVOLUTIONARY ALGORITHM BASED DNN

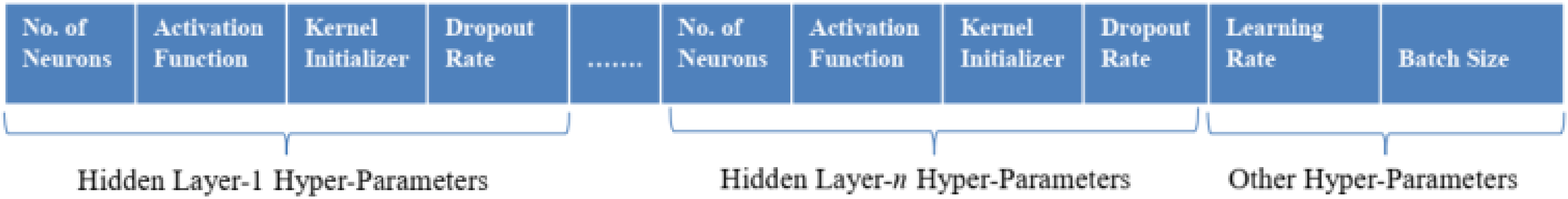


Figure 1 Encoding a DL model to a decision vector (chromosome).

Table 3 Example of real encoded DL model with hyper-parameters.

128.33	1.2	2.4	0.7	69.78	2.6	1.3	0.4	0.01	3.89

Table 4 Example of real encoded DL model with hyper-parameters and pruning of layer.

128.33	1.2	2.4	0.7	69.78	2.6	1.3	1	0.01	3.89

SWARM & EVOLUTIONARY ALGORITHM BASED DNN

Algorithm 1
Get the activation function: get_activation_function(v).

Input: Decision variable v
Output: Activation function

1: gene ← round (v)
2: **if** gene equals to 0 **then**
3: **return** "relu"
4: **else if** gene equals to 1 **then**
5: **return** "sigmoid"
6: **else if** gene equals to 2 **then**
7: **return** "tanh"
8: **else**
9: **return** "elu"
10: **endif**

Algorithm 2
Get the kernel initializer: get_kernel_initializer(v).

Input: Decision variable v
Output: Kernel Initializer

1: gene ← round (v)
2: **if** gene equals to 0 **then**
3: **return** " glorot_uniform"
4: **else if** gene equals to 1 **then**
5: **return** " glorot_normal"
6: **else if** gene equals to 2 **then**
7: **return** " he_uniform"
8: **else**
9: **return** " he_normal"
10: **endif**

SWARM & EVOLUTIONARY ALGORITHM BASED DNN

Algorithm 3

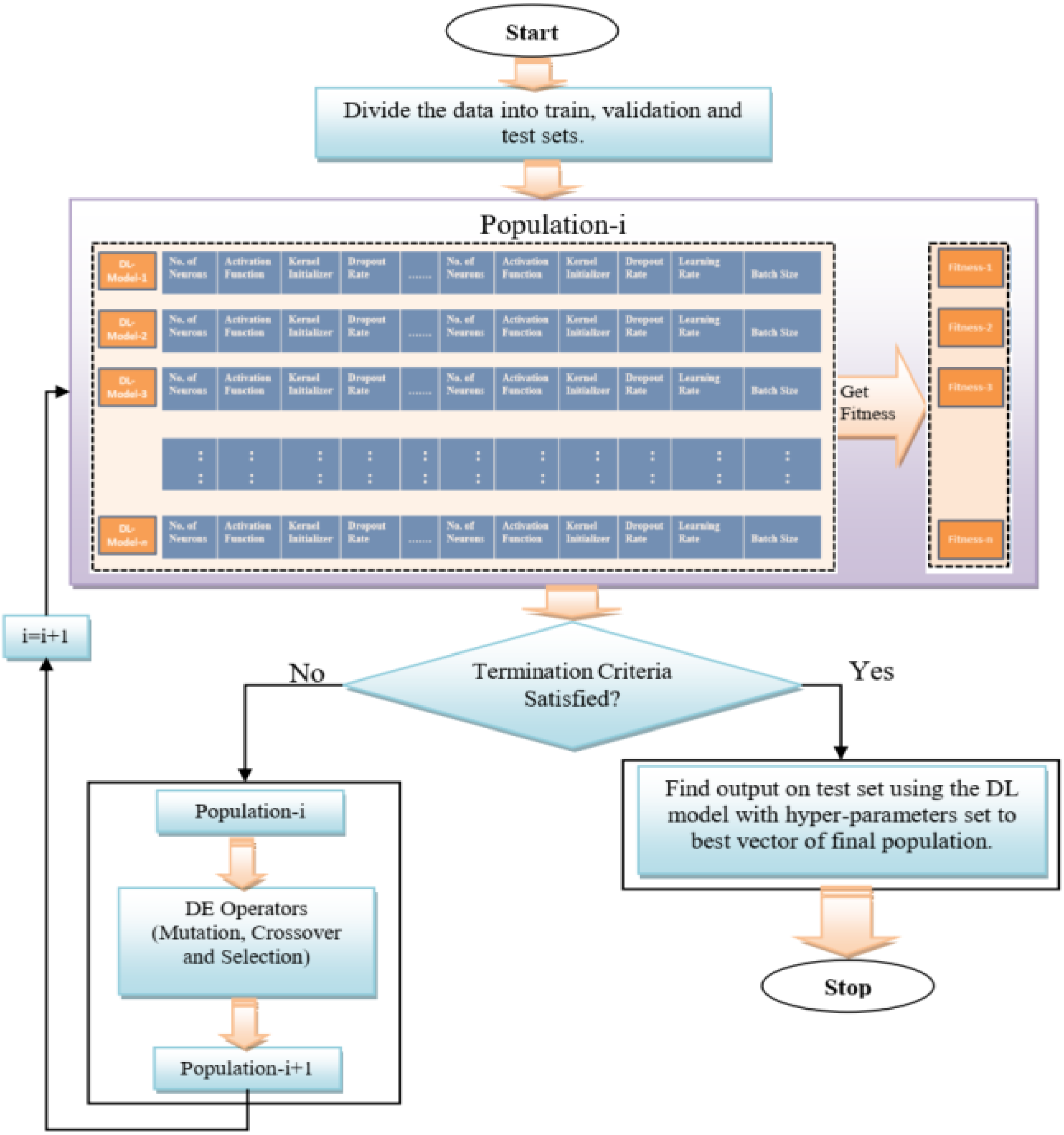
Decode a Decision Vector to a DL Model.

Input: Decision vector $V = [v_1, v_2, \ldots, v_d]$

Output: DL Model

model DL ← empty
add layer input to DL
for each hidden layer hyper-parameter in decision vector V
    if v_{i+4} not equal to 1 **then** // dropout !=1
        nn=round(v_i) // number of neuron
        af=get_activation_function(v_{i+1})
        ki=get_kernel_initializer(v_{i+2})
        add a layer to DL model with nn neurons, af as activation function, ki as kernel initializer and v_{i+4} as dropout rate.
    endif
endfor
add a layer with 1 neuron and linear activation function. // Output layer
batch_size=$2^{round(v_d)}$
learning_rate=v_{d-1}
Compile the DL model with mean square error as the loss, adam as the optimizer with Learning rate set to learning_rate.
return DL

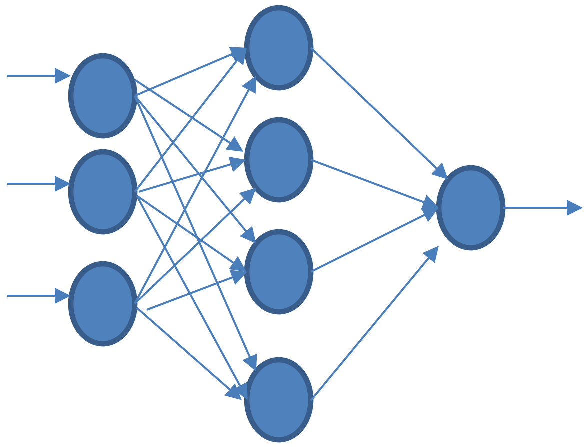
SWARM & EVOLUTIONARY ALGORITHM BASED DNN



HANDS ON

- Implement a neural network from scratch for mapping the following inputs to outputs.
- X=[0,0,1] y=[0]

X	y
[0,0,1]	[0]
[0,1,1]	[1]
[1,0,1]	[1]
[1,1,1]	[0]



Use Sigmoid activation function, neurons without biases and learning rate=1

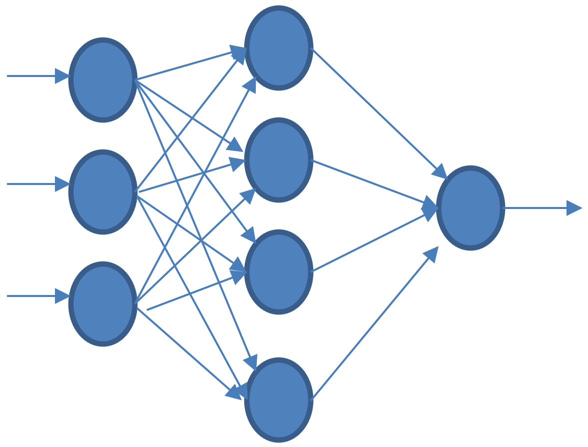
HANDS ON

- Implement a neural network from scratch for mapping the following inputs to outputs.
- X=[0,0,1] y=[0]

  [0,1,1] [1]

  [1,0,1] [1]

  [1,1,1] [0]

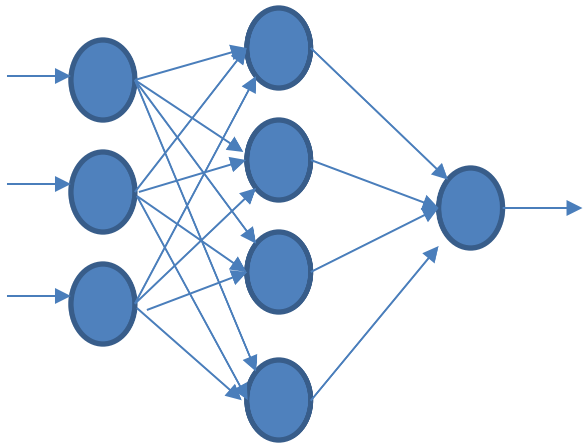


Use Sigmoid activation function, neurons without biases and **learning rate=0.5**

HANDS ON

- Implement a neural network from scratch for mapping the following inputs to outputs.
- X=[0,0,1] y=[0]

X	y
[0,0,1]	[0]
[0,1,1]	[1]
[1,0,1]	[1]
[1,1,1]	[0]

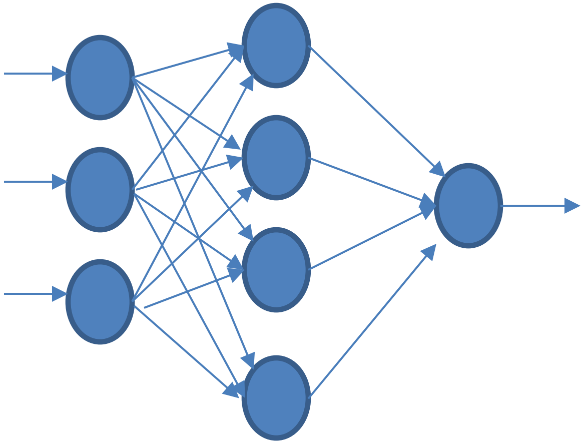


Use Sigmoid activation function, neurons without biases and **learning rate=0.1**

HANDS ON

- Implement a neural network from scratch for mapping the following inputs to outputs.
- X=[0,0,1] y=[0]

X	y
[0,0,1]	[0]
[0,1,1]	[1]
[1,0,1]	[1]
[1,1,1]	[0]

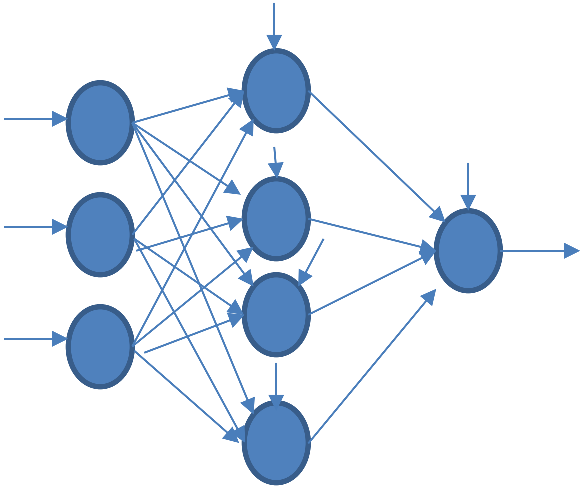


Use Sigmoid activation function, neurons without biases and **learning rate=0.1, Plot the Convergence Plot**

HANDS ON

- Implement a neural network from scratch for mapping the following inputs to outputs.
- X=[0,0,1] y=[0]

X	y
[0,0,1]	[0]
[0,1,1]	[1]
[1,0,1]	[1]
[1,1,1]	[0]

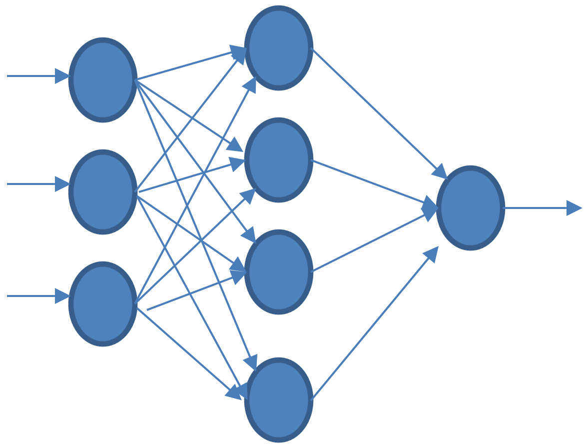


Use Sigmoid activation function, neurons with biases and **learning rate=0.1, Plot the Convergence Plot**

HANDS ON

- Implement a neural network from scratch for mapping the following inputs to outputs.
- X=[0,0,1] y=[0]

X	y
[0,0,1]	[0]
[0,1,1]	[1]
[1,0,1]	[1]
[1,1,1]	[0]



Use **ReLu activation function**, neurons without biases and **learning rate=0.1, Plot the Convergence Plot**

HANDS ON

- Using Keras library perform classification on MNIST data.

HANDS ON

- Using Keras library perform multivariate air quality index prediction of Delhi.