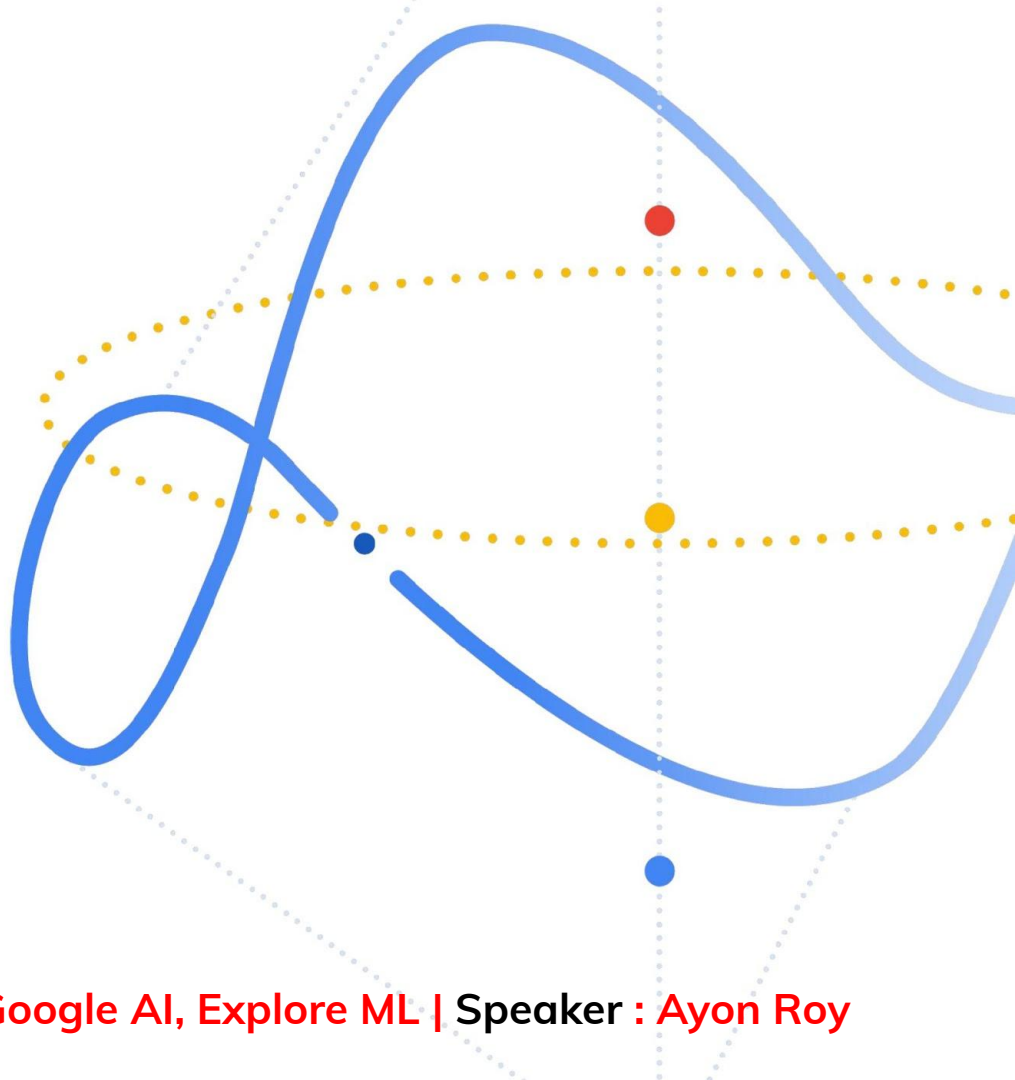


Neural Networks

Explore ML



Date : 4th September,2019 | Event : Google AI, Explore ML | Speaker : Ayon Roy



Hello BPITians!

I am **Ayon Roy**

B.Tech CSE (2017-2021)

Ex-Summer Intern at MateLabs, Bengaluru (**World's First Horizontal AI Startup**)

Email : ayon.roy2000@gmail.com

Telegram / Github / LinkedIn Username : ayonroy2000

Website : <https://AYONROY.ML/>

If you haven't heard about me yet, you might have been living under the rocks. Wake up !!

Agenda (4-09-2019)

- Introduction to Structure and operation of neural network
- Introduction to Tensorflow Playground
- Activity: TensorFlow Playground Neural Network Exercises
- Activity: Teachable Machine and the Limits of Neural Networks

Neural Networks



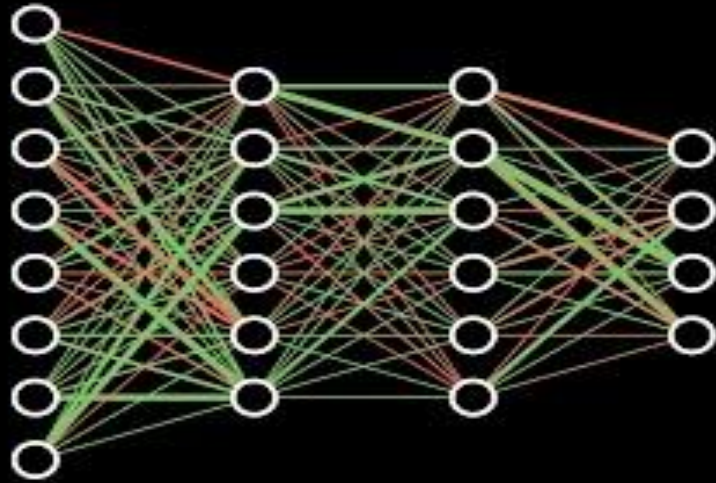
Let's Play

q.co/teachablemachine

If privacy is not an issue,
please use your laptop's webcam for this activity.

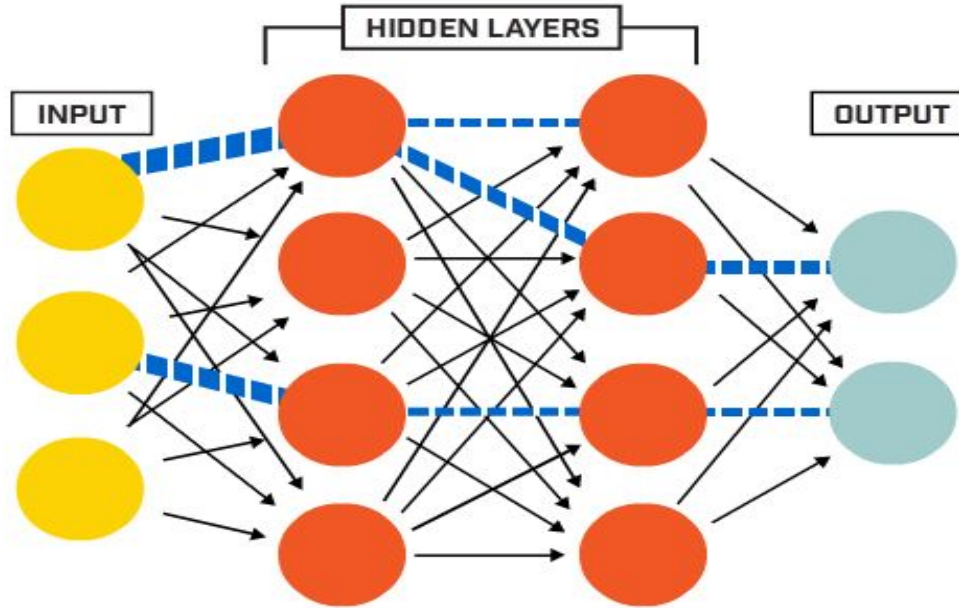
- See a Neural Network Demo at <http://bit.do/BPIT1>

Neural Networks

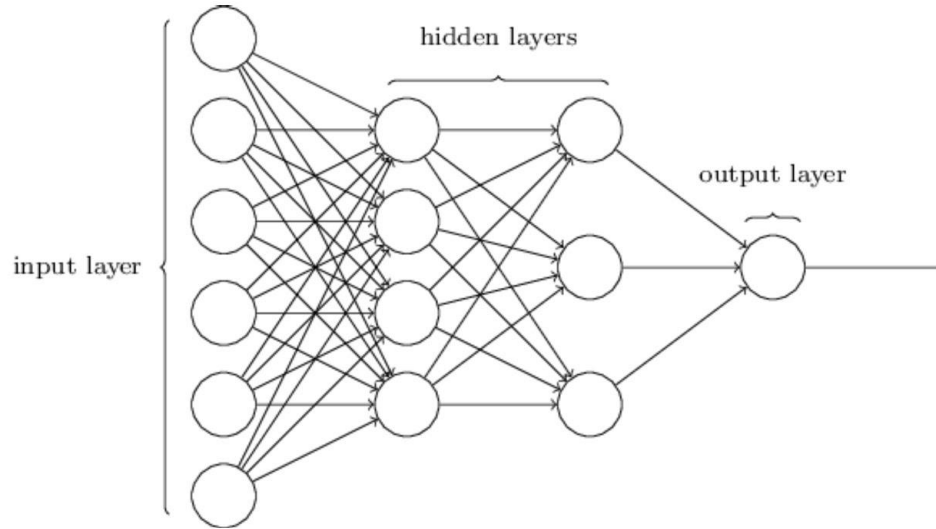


From the
ground up

What are Neural Networks ?

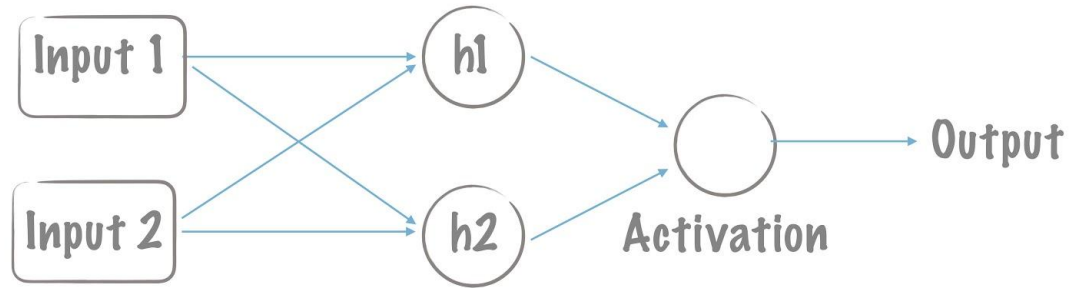


Neural Networks

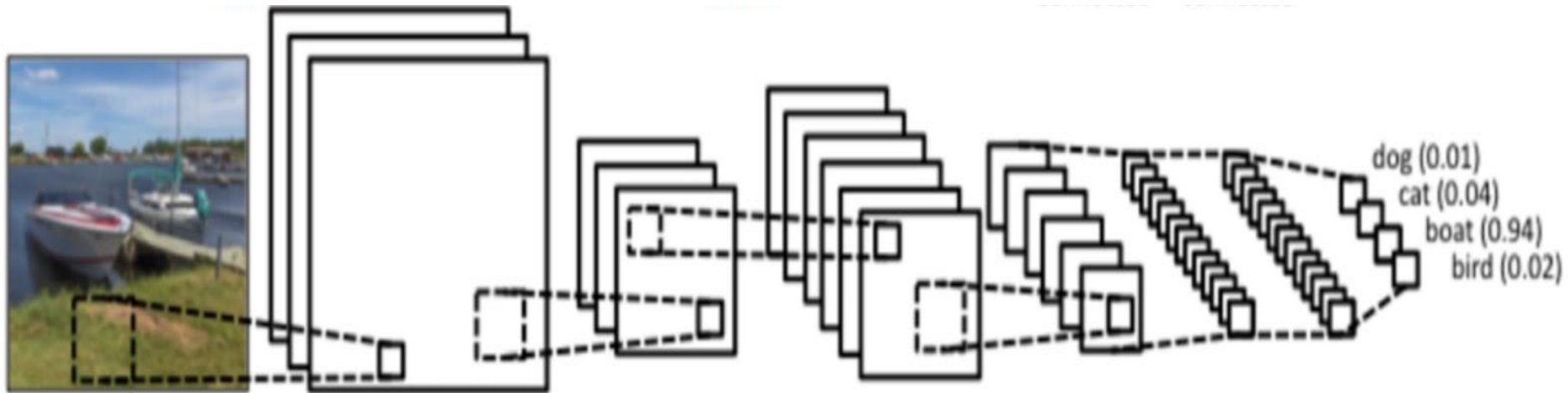


Its like Perceptrons are together in a defined fashion

Two Layered Neural Network

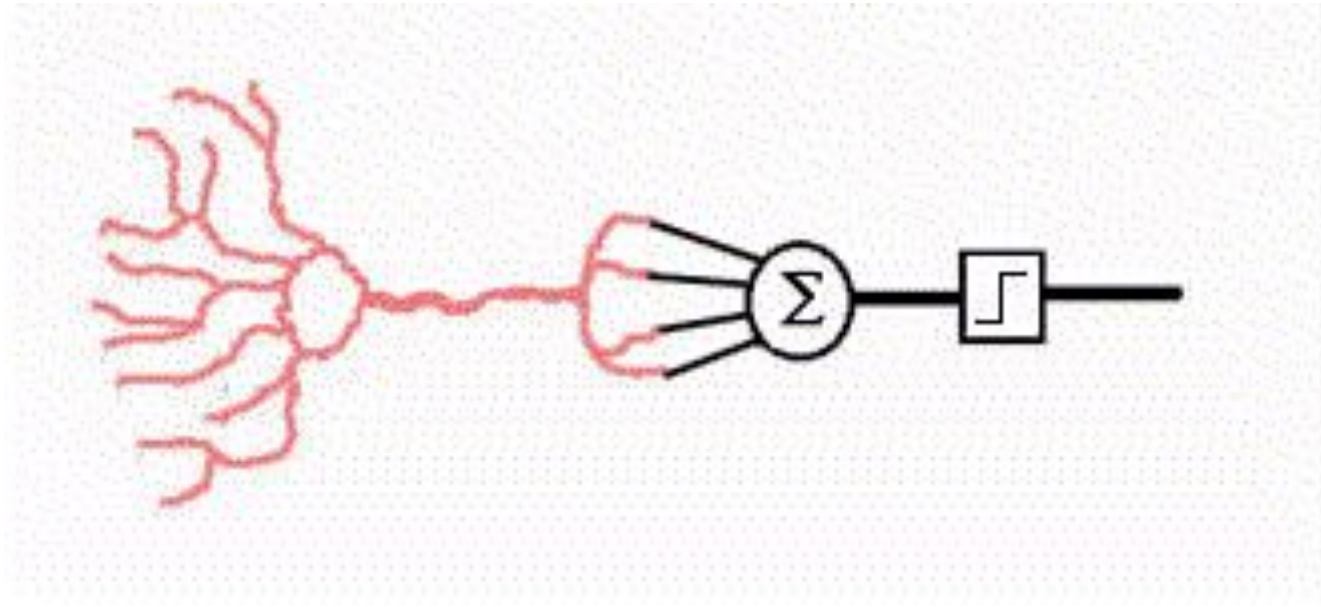


These array of perceptrons form the Neural Nets



Computer System inspired by biological networks of neurons that learn progressively i.e which improves performance to do tasks; by considering examples generally without task specific programming.

Why Neural Networks ?



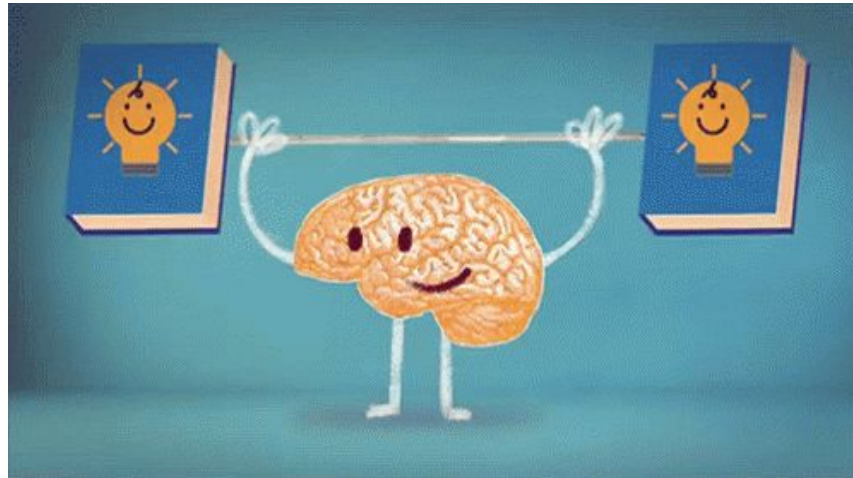
Problem before Neural Networks were introduced

Computers used to follow a set of instructions to solve a problem

But what now ?

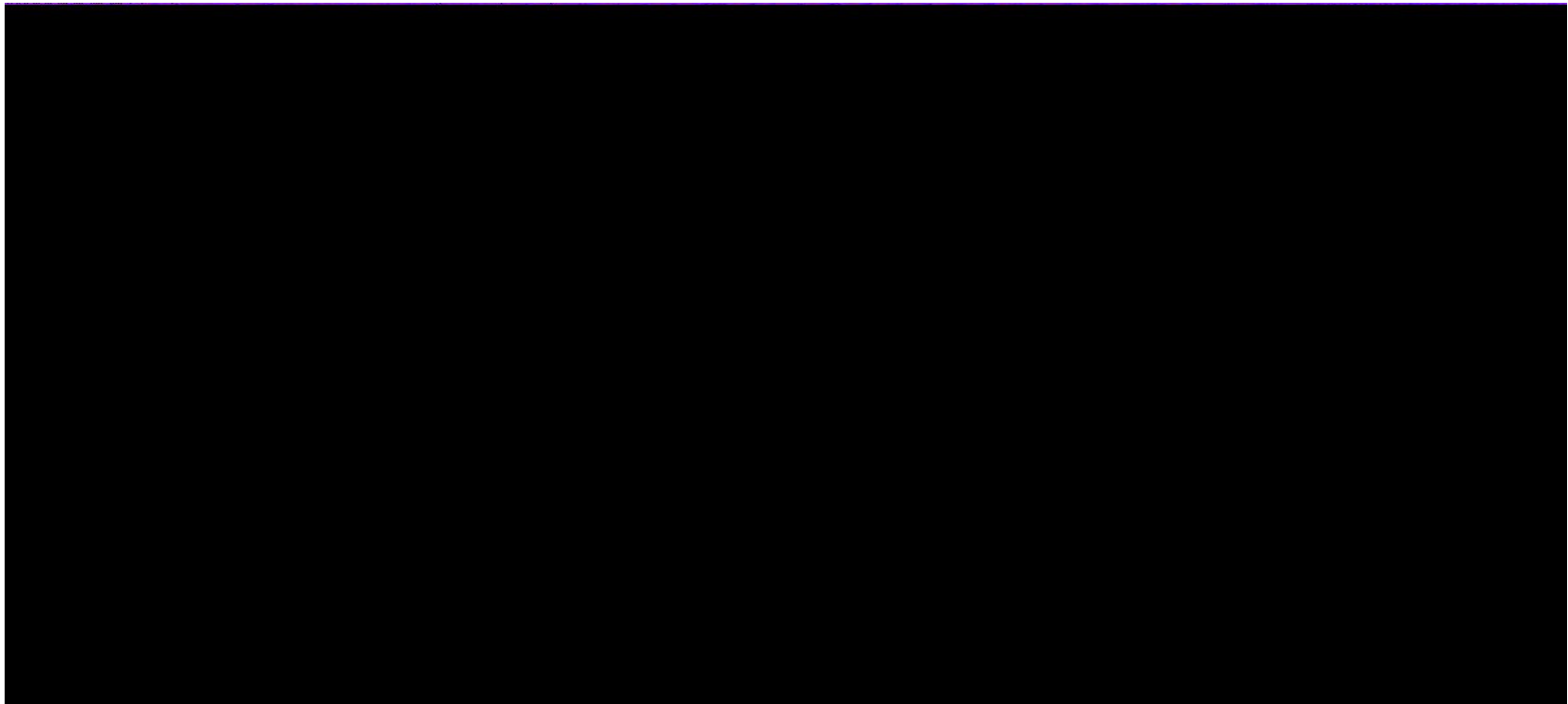
Neural Networks learn by example. So now computers can do things what we don't exactly know how to do.

Motivation behind Neural Networks ?



Application of Neural Networks

Is it only here ?



It's here too

Speech Recognition

- Multilayer networks with recurrent connections
- Kohonen self-organizing feature map

Character Recognition

- Backpropagation neural networks.
- Neocognitron

Signature Verification, Face Recognition etc.

But how it works ?



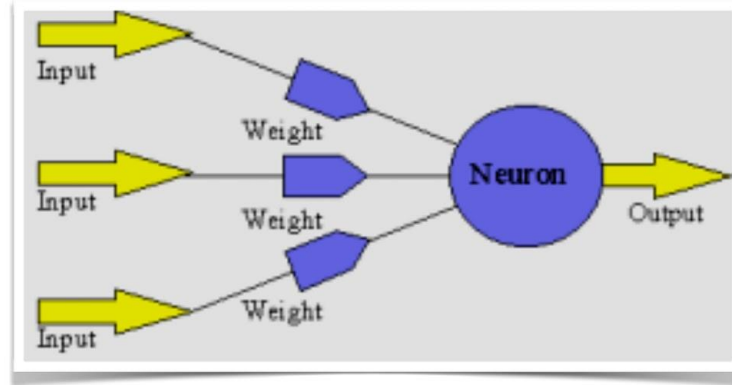
Single Layer & Multilayer Perceptron

Perceptron

The elementary entity of a neural network.

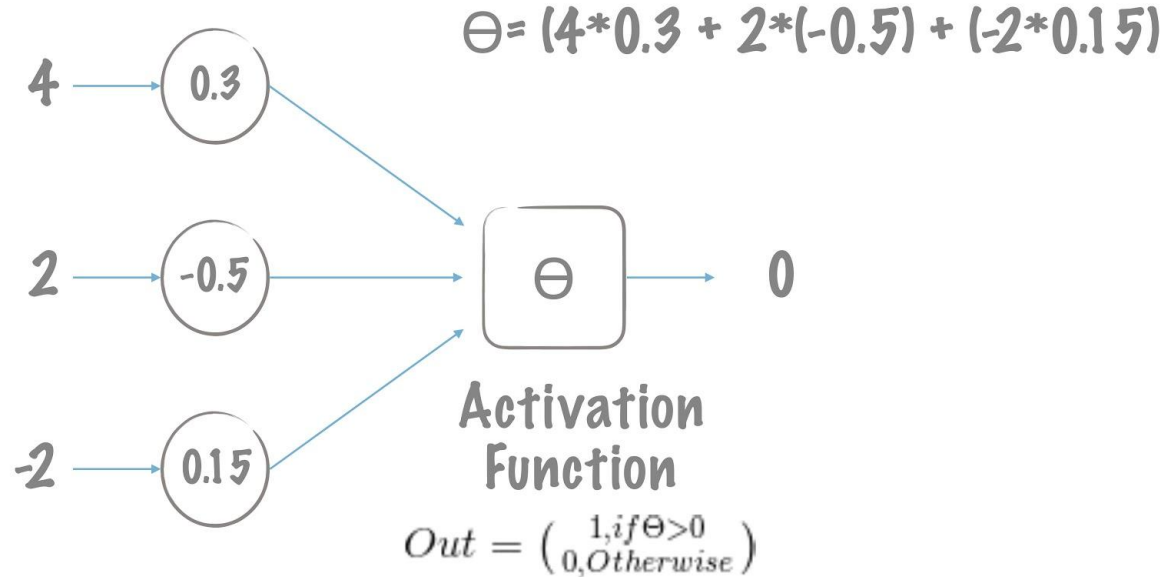
The most basic form of neural network which can also learn

Perceptron

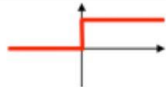
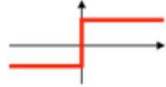

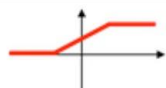




A Basic Linear discriminant Classifier

How Perceptron Work



Activation Functions

Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer NN	

Training a Perceptron

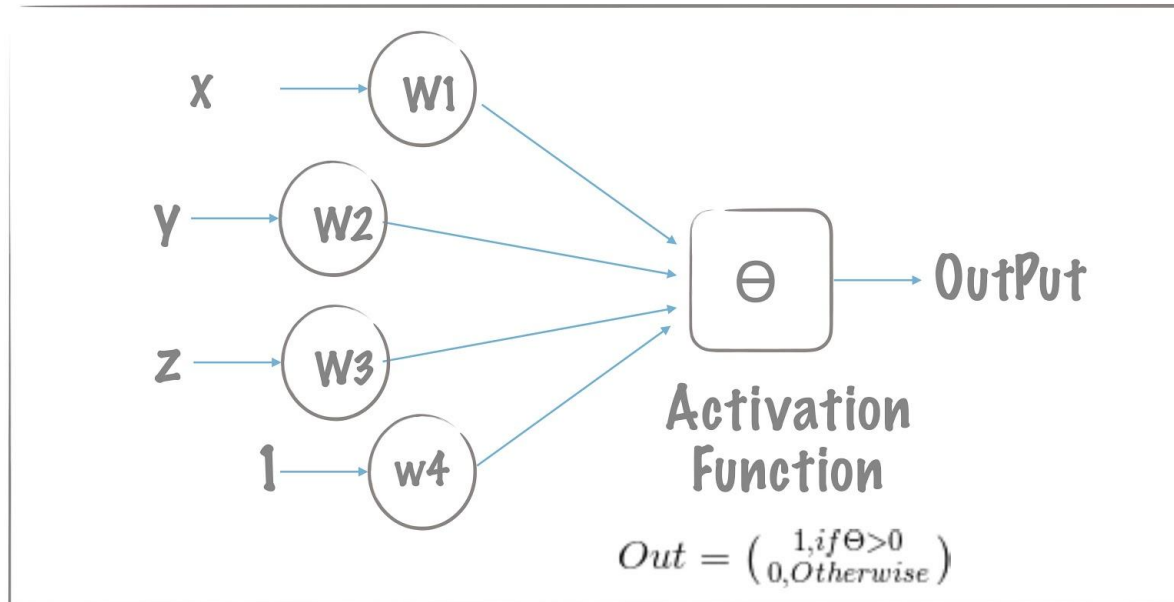
Let's train a Perceptron to mimic this pattern

Training Set T(out)

x	y	z	out
0	0	1	0
1	1	1	1
1	0	1	1
0	1	1	0

Training a Perceptron

Perceptron Model



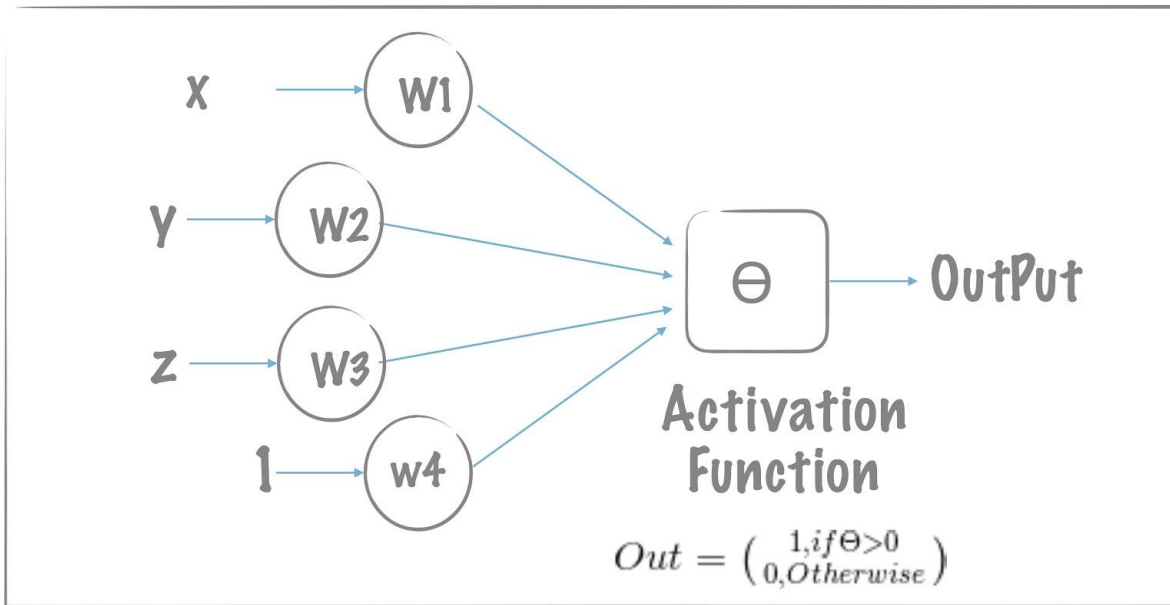
Training a Perceptron

Training Rules :

$$W_i = W_i + \Delta W_i$$

$$\Delta W = -\eta * (\text{target output} - \text{perceptron output}) * X$$

η is learning rate for perceptron



Training a Perceptron

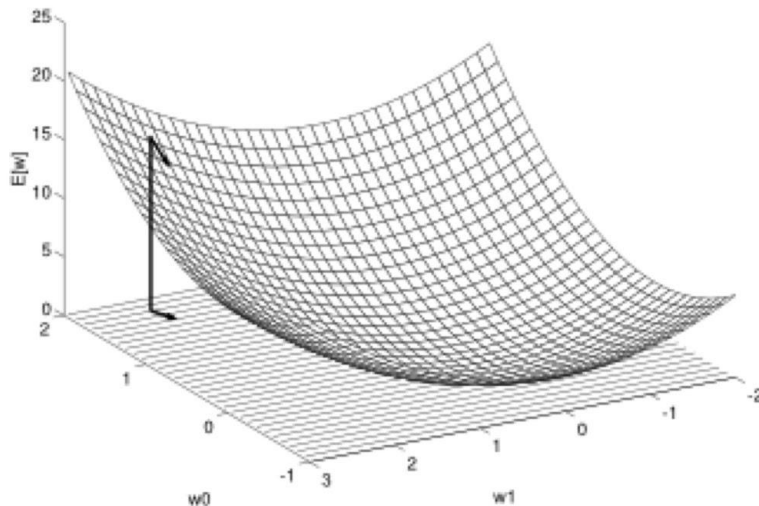
Let's learn w_i such that it minimizes the squared error

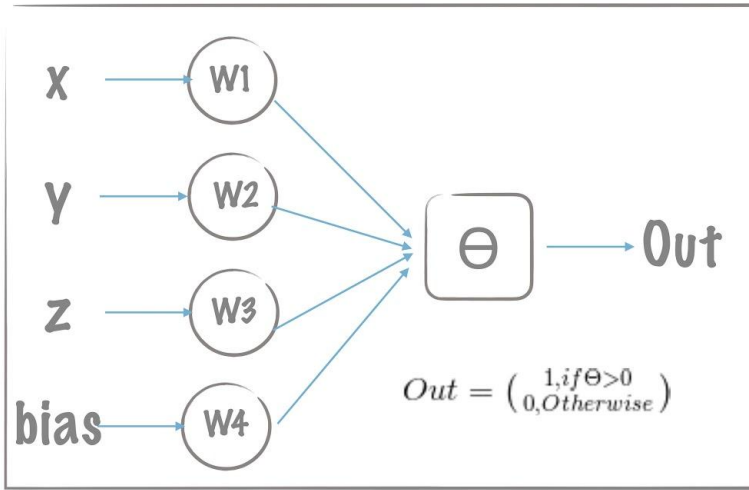
$$E[\vec{w}] \equiv \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2$$

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$$

On simplifying

$$\Delta w_i = \eta \sum_{d \in D} (t_d - o_d) x_{id}$$





$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

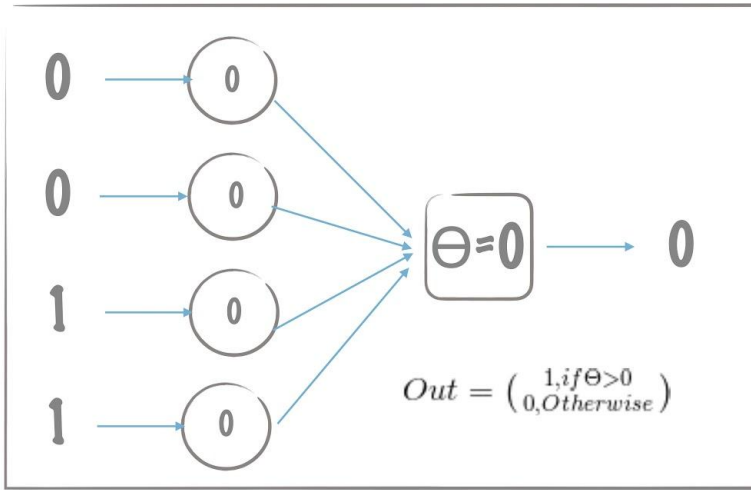
η is learning rate for perceptron

Training Set **T(out)**

x	y	z	bias	out
0	0	1	1	0
1	1	1	1	1
1	0	1	1	1
0	1	1	1	0
0	0	1	1	0
1	1	1	1	1
1	0	1	1	1
0	1	1	1	0

Assign random values to Weight Vector ([W1,W2,W3,W4])

epoch 1 {
 epoch 2 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
0	0	0	0

P(out)

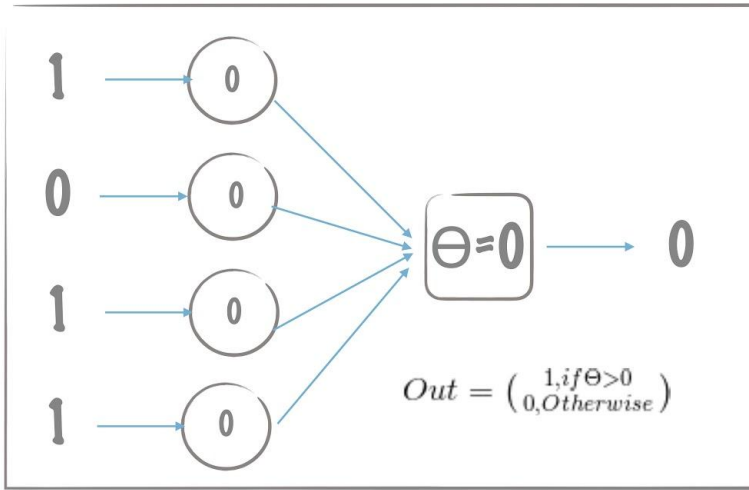
out
0

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0

epoch 1 {

epoch 2 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
0	0	0	0
0	0	0	0
1	1	1	1

P(out)

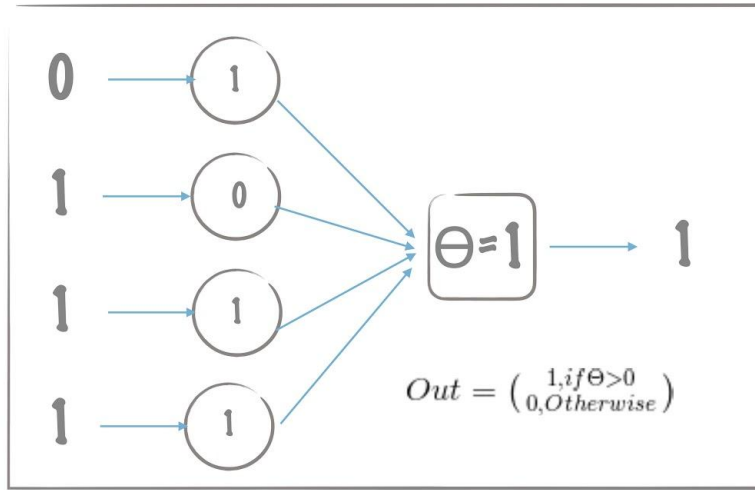
out
0
0
1

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
1	1	1	1
0	0	0	0

epoch 1 {

epoch 2 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

epoch 1 {
 epoch 2 {

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

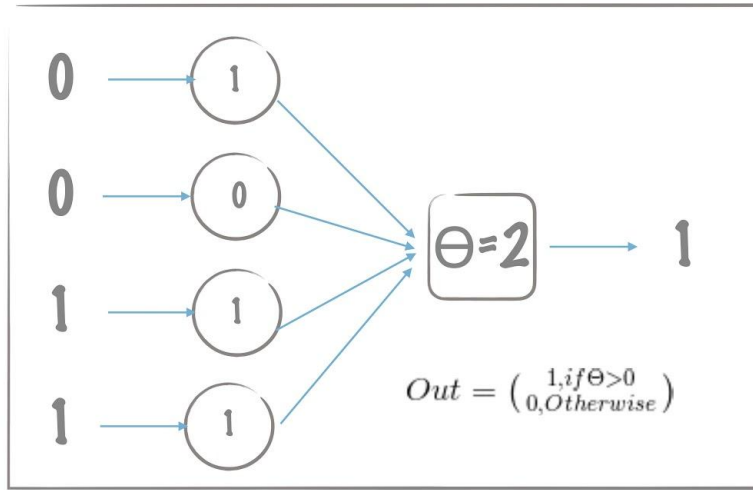
w1	w2	w3	w4
0	0	0	0
0	0	0	0
1	1	1	1
1	1	1	1

P(out)

out
0
0
1
1

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
1	1	1	1
0	0	0	0
0	-1	-1	-1



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

epoch 1 {
 epoch 2 {

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

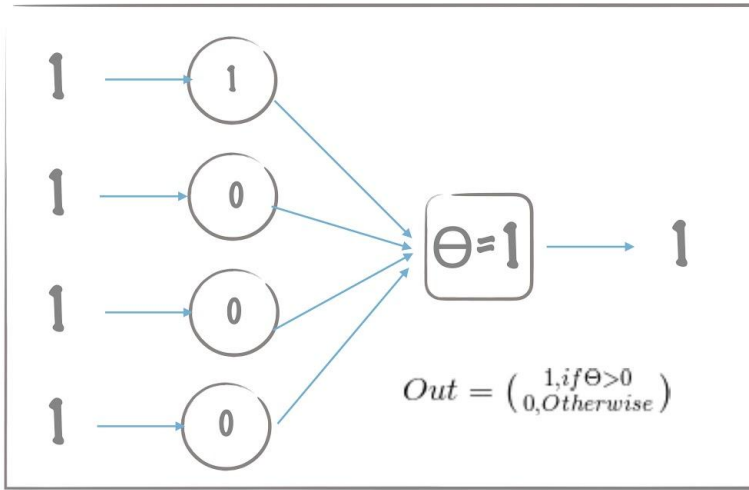
w1	w2	w3	w4
0	0	0	0
0	0	0	0
1	1	1	1
1	1	1	1
1	0	0	0

P(out)

out
0
0
1
1
0

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
1	1	1	1
0	0	0	0
0	-1	-1	-1
0	0	0	0



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
0	0	0	0
0	0	0	0
1	1	1	1
1	1	1	1
1	0	0	0
1	0	0	0
1	0	0	0

P(out)

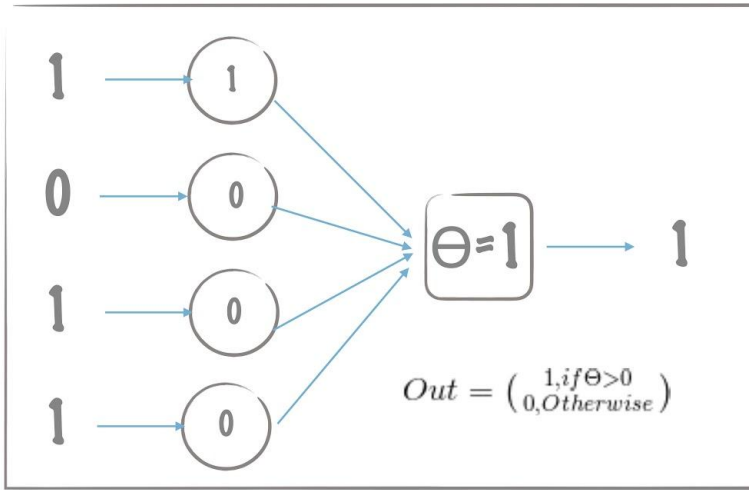
out
0
0
1
1
1
1

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
1	1	1	1
0	0	0	0
0	-1	-1	-1
0	0	0	0
0	0	0	0

epoch 1 {

epoch 2 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
0	0	0	0
0	0	0	0
1	1	1	1
1	1	1	1
1	0	0	0
1	0	0	0
1	0	0	0
1	0	0	0

P(out)

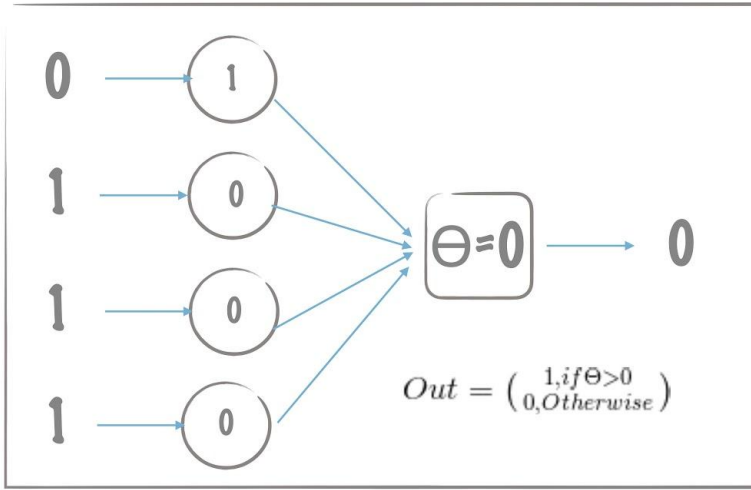
out
0
0
1
1
1
1
1
1

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
1	1	1	1
0	0	0	0
0	-1	-1	-1
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

epoch 1 {

epoch 2 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
0	0	0	0
0	0	0	0
1	1	1	1
1	1	1	1
1	0	0	0
1	0	0	0
1	0	0	0
1	0	0	0

P(out)

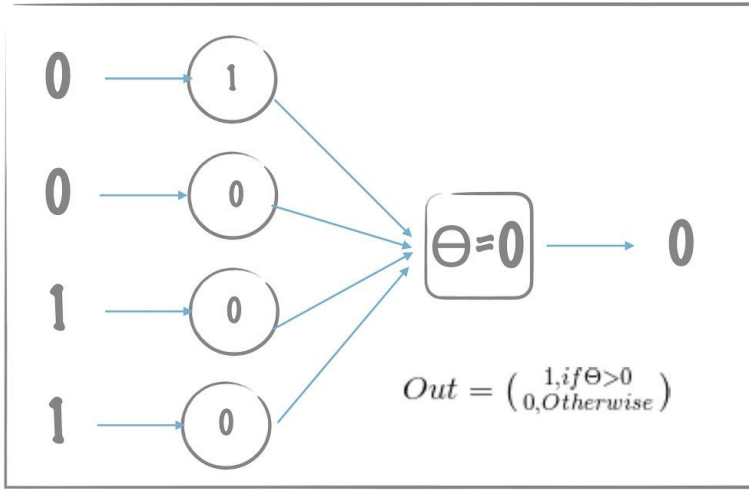
out
0
0
1
1
1
1
1
0

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
1	1	1	1
0	0	0	0
0	-1	-1	-1
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

epoch 1 {

epoch 2 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
1	0	0	0

P(out)

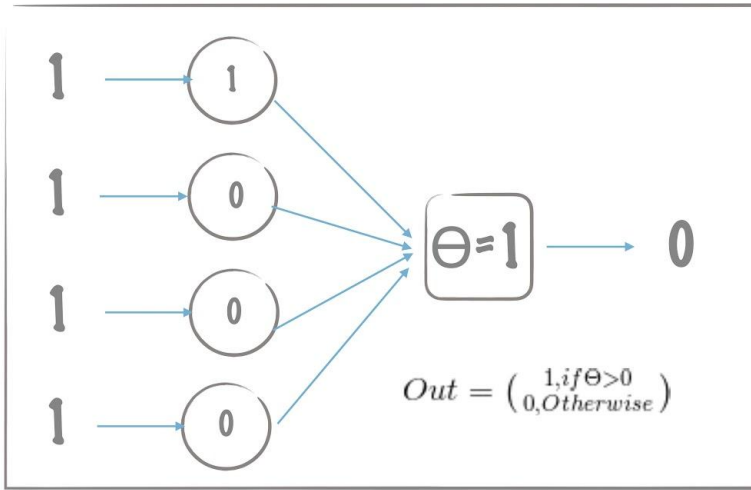
out
0

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0

epoch3 {

epoch4 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
1	0	0	0
1	0	0	0

P(out)

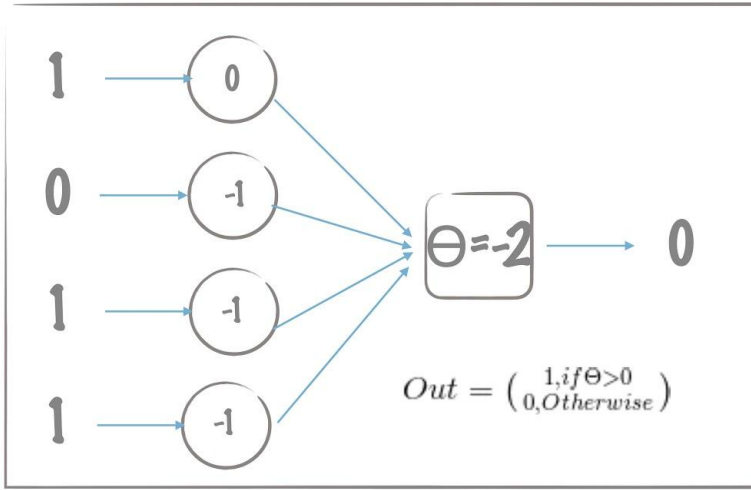
out
0
1

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
0	0	0	0

epoch3 {

epoch4 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
1	0	0	0
1	0	0	0
1	0	0	0

P(out)

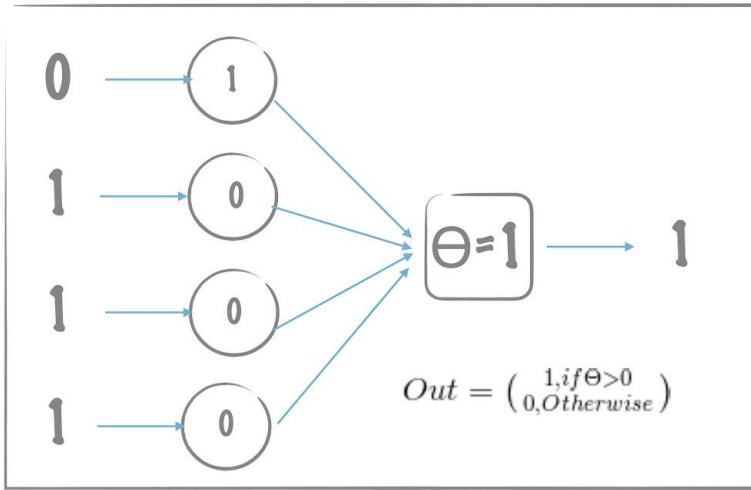
out
0
1
1

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
0	0	0	0
0	0	0	0

epoch3 {

epoch4 {



$$W_i = W_i + \Delta W_i$$

$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

Training Set

x	y	z	bias
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1
0	0	1	1
1	1	1	1
1	0	1	1
0	1	1	1

T(out)

out
0
1
1
0
0
1
1
0

Weights

w1	w2	w3	w4
1	0	0	0
1	0	0	0
1	0	0	0
1	0	0	0

P(out)

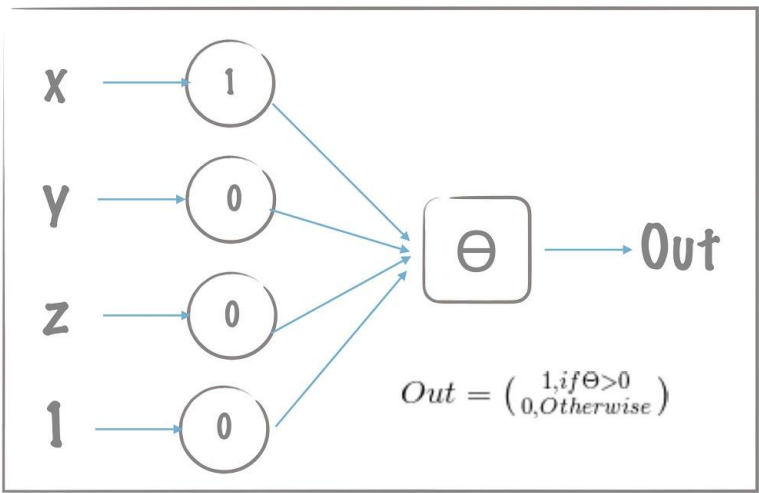
out
0
1
1
0

ΔWeights

Δw1	Δw2	Δw3	Δw4
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

epoch3 {

epoch4 {



$$W_i = W_i + \Delta W_i$$

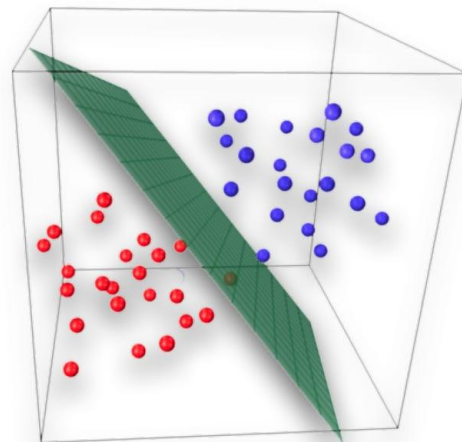
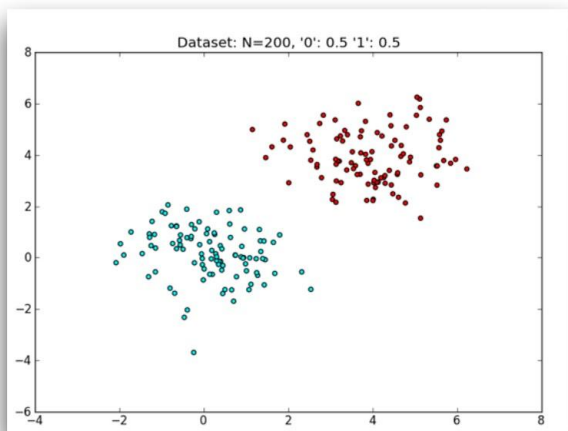
$$\Delta W_i = -\eta * [P(out) - T(Out)] * x_i$$

η is learning rate for perceptron

	Training Set				T(out)	Weights				P(out)	ΔWeights			
	x	y	z	bias	out	w1	w2	w3	w4	out	Δw1	Δw2	Δw3	Δw4
epoch3	0	0	1	1	0	1	0	0	0	0	0	0	0	0
	1	1	1	1	1	1	0	0	0	1	0	0	0	0
	1	0	1	1	1	1	0	0	0	1	0	0	0	0
	0	1	1	1	0	1	0	0	0	0	0	0	0	0
epoch4	0	0	1	1	0	1	0	0	0	0	0	0	0	0
	1	1	1	1	1	1	0	0	0	1	0	0	0	0
	1	0	1	1	1	1	0	0	0	1	0	0	0	0
	0	1	1	1	0	1	0	0	0	0	0	0	0	0

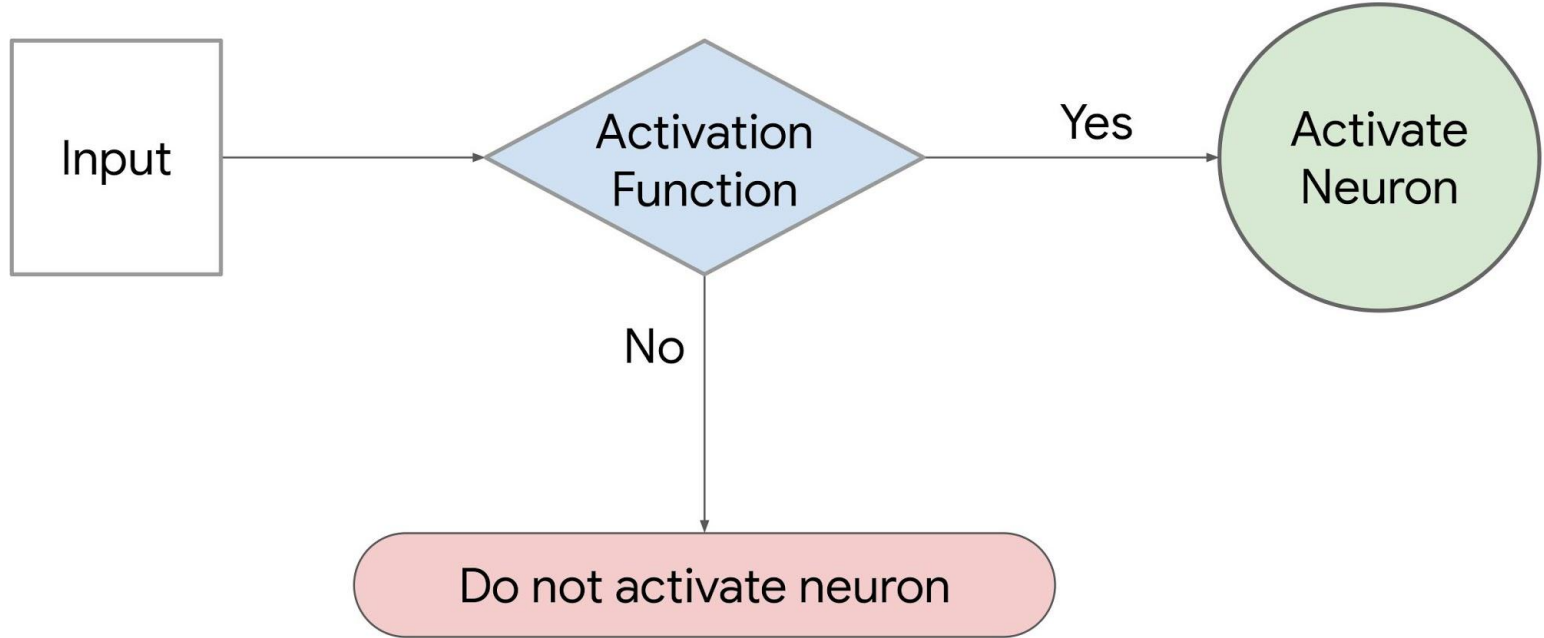
In epoch3, 'loss' is 0. So, we can assume that Perceptron has learnt the pattern

We trained our Perceptron Model

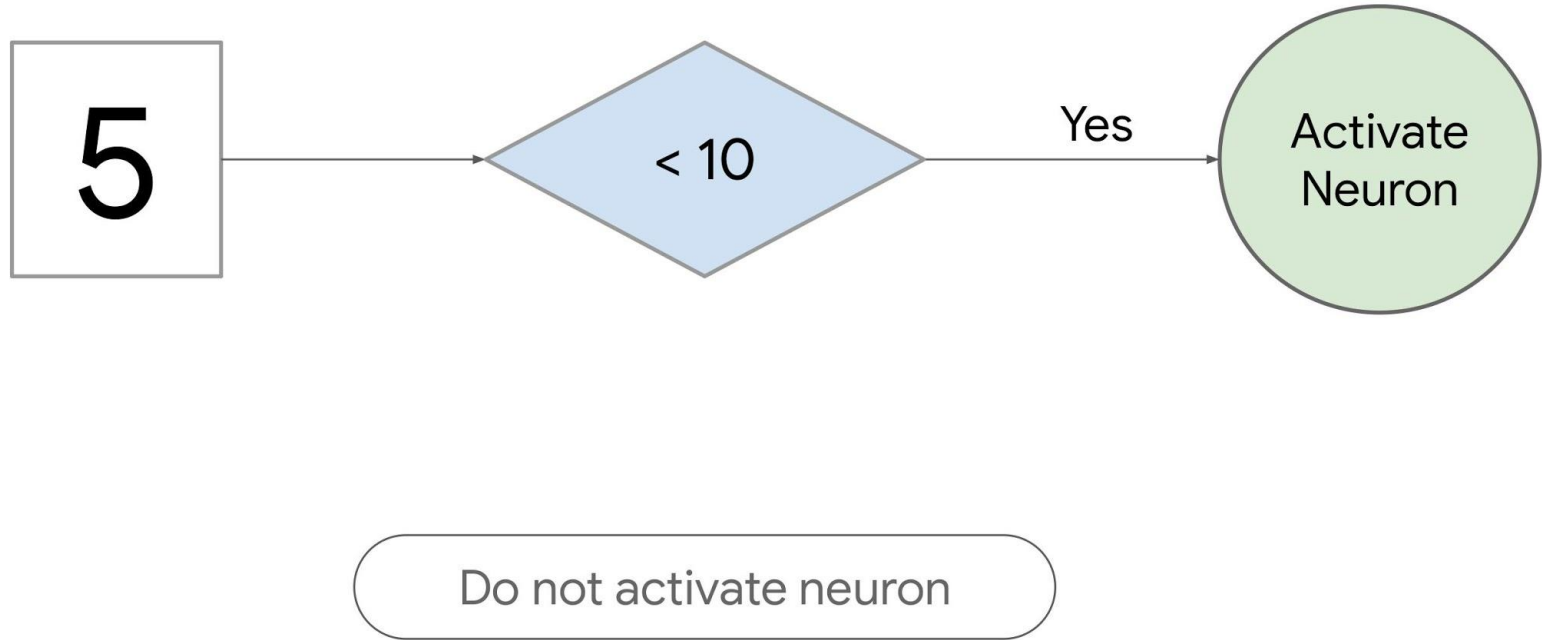


On a Linear Separable Distribution

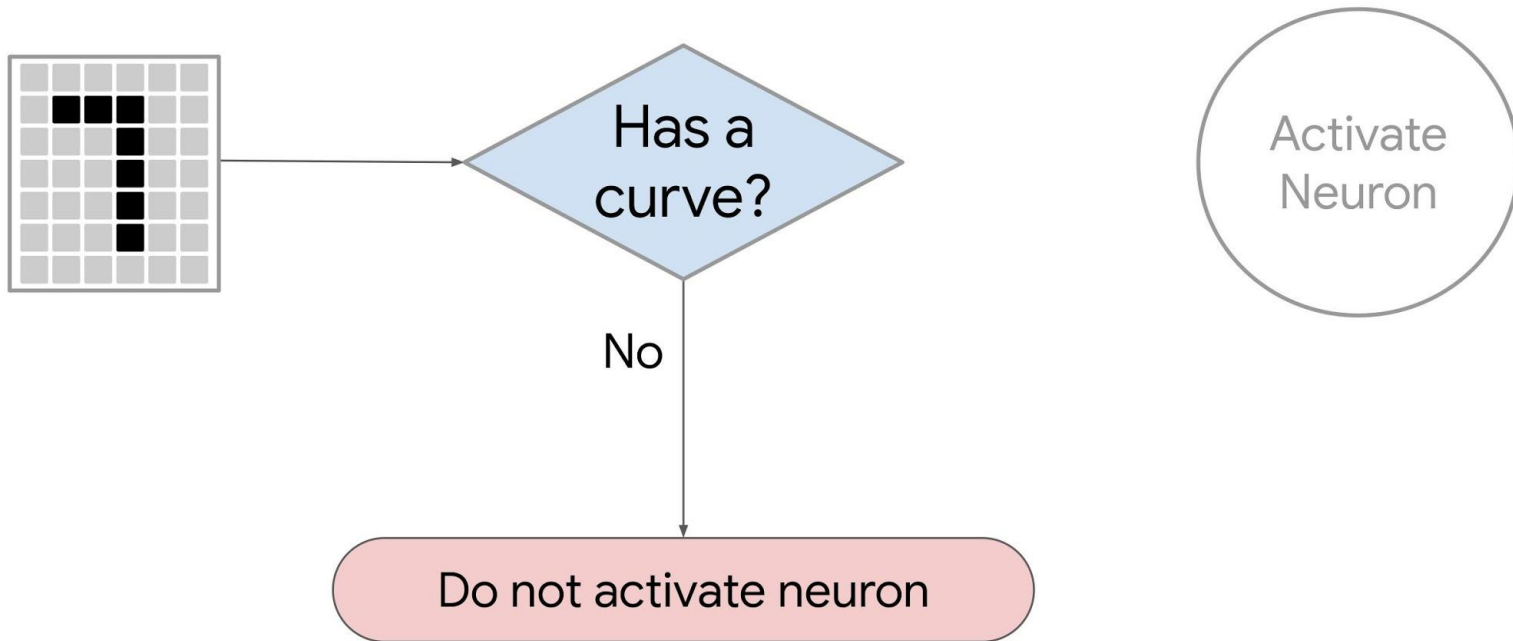
Perception of Artificial Neuron



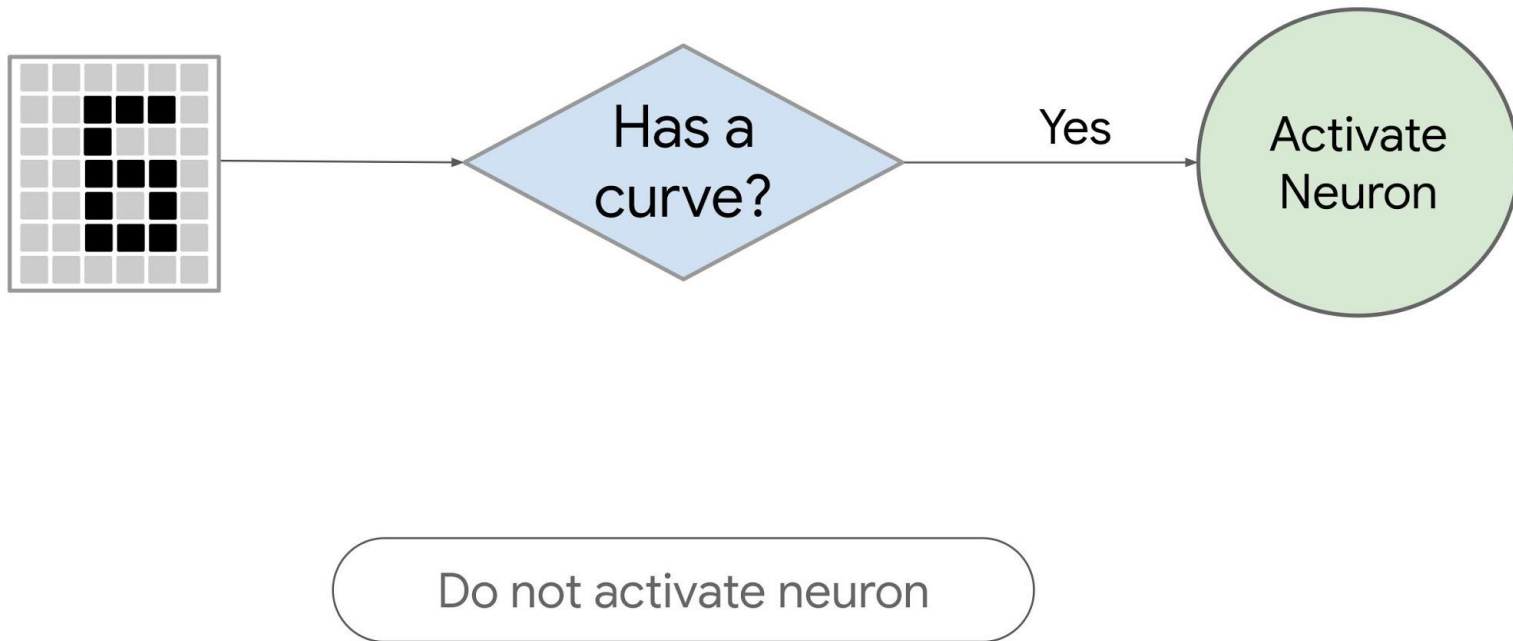
Perception of Artificial Neuron



Perception of Artificial Neuron



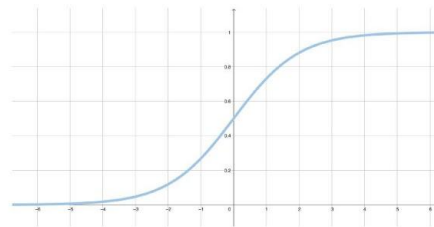
Perception of Artificial Neuron



Common Activation Functions

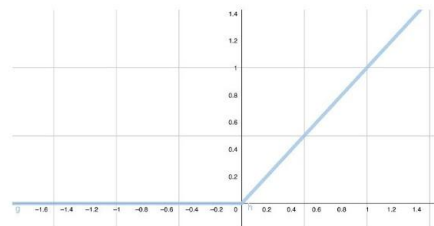
Sigmoid activation function converts the weighted sum to a value between **0** and **1**.

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



ReLU (Rectified Linear Unit) activation function often works a little better than a smooth function like the sigmoid, while also being significantly easier to compute.

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



Getting Bored ?

Let's Play with Neural Networks

But where to play in Edusat Lab ?

Let's play in the Tensorflow Playground

<http://bit.do/BPITPlay>



FEATURES

Which properties do you want to feed in?



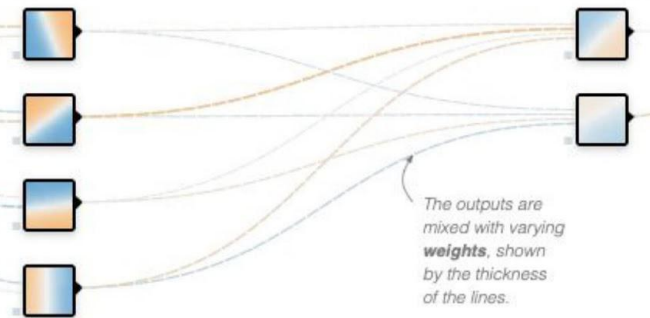
+ - 2 HIDDEN LAYERS

+ -

4 neurons

+ -

2 neurons



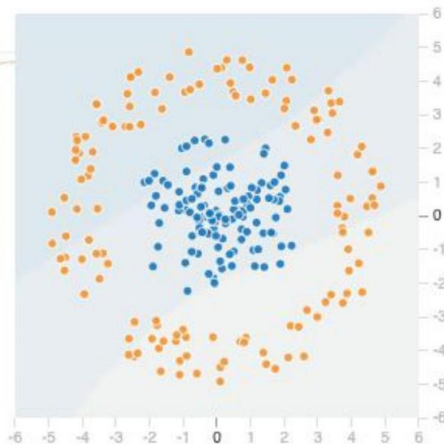
This is the output from one **neuron**. Hover to see it larger.

The outputs are mixed with varying **weights**, shown by the thickness of the lines.

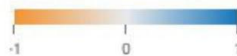
OUTPUT

Test loss 0.500

Training loss 0.508



Colors shows data, neuron and weight values.



Show test data

Discretize output

FEATURES

Which properties do you want to feed in?



+ - 2 HIDDEN LAYERS

+ -

4 neurons



This is the output from one **neuron**.
 Hover to see it larger.

+ -

2 neurons

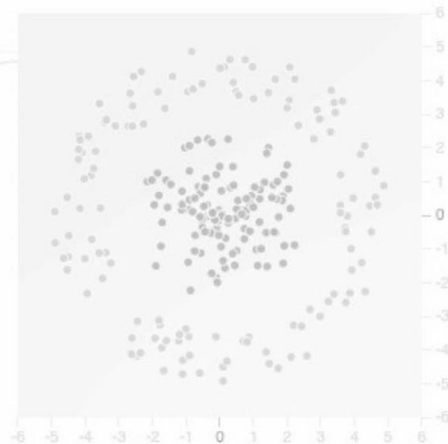


The outputs are mixed with varying **weights**, shown by the thickness of the lines.

OUTPUT

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Training loss 0.508



Colors shows

data, neuron and weight values.



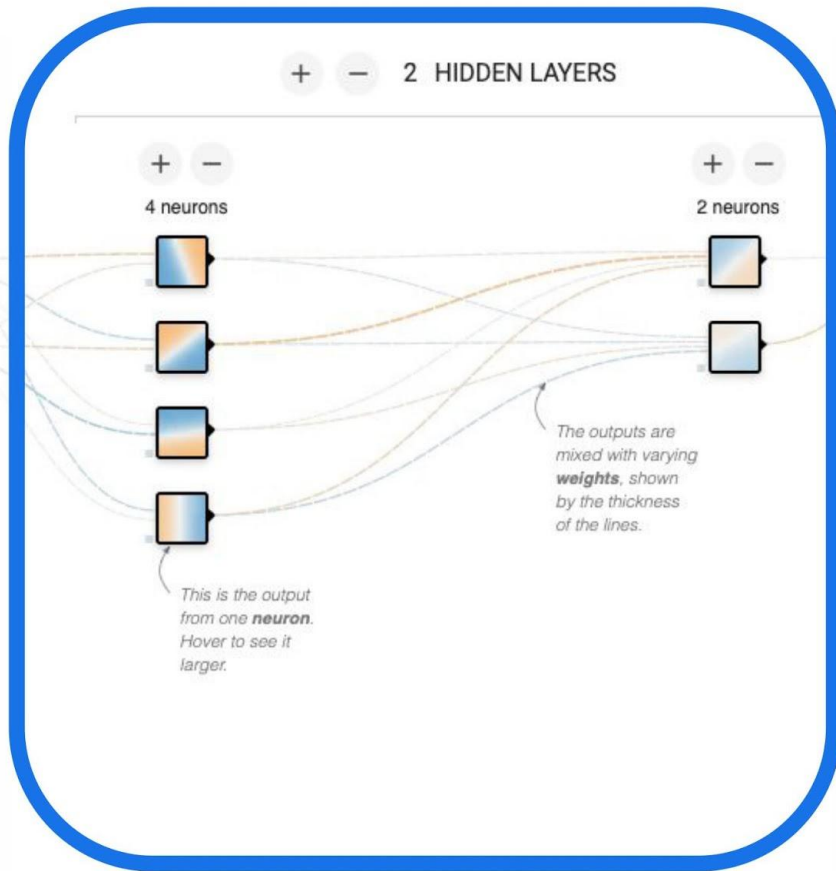
Show test data

Discretize output

FEATURES

Which properties do you want to feed in?

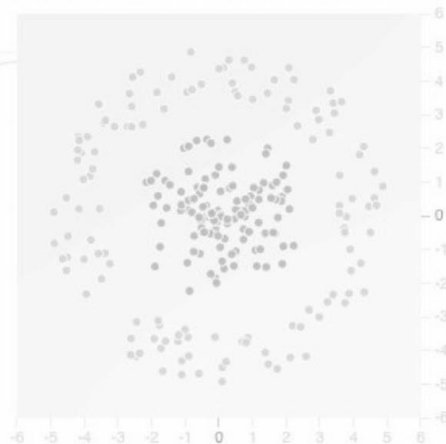
- X_1
- X_2
- X_1^2
- X_2^2
- $X_1 X_2$
- $\sin(X_1)$
- $\sin(X_2)$



OUTPUT

Test loss 0.500

Training loss 0.508

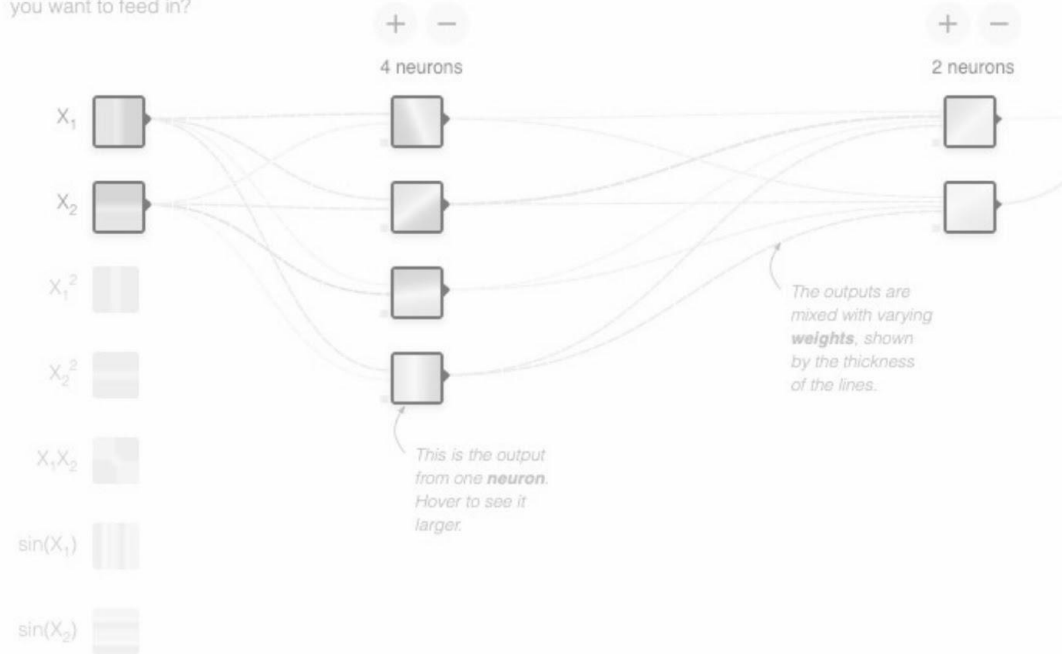


Colors shows data, neuron and weight values.

- Show test data
- Discretize output

FEATURES

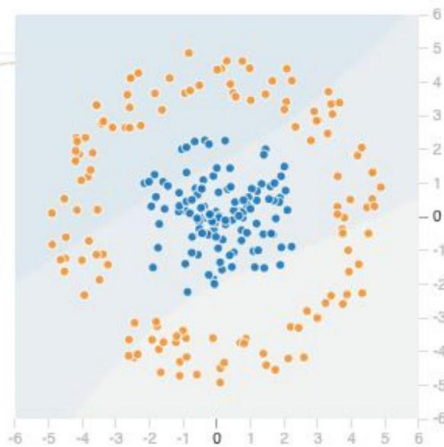
Which properties do you want to feed in?



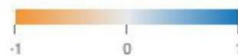
OUTPUT

Test loss 0.500

Training loss 0.508



Colors shows data, neuron and weight values.



Show test data

Discretize output

Still feeling Bored ?

Let's play an awesome game now.



<http://bit.do/BPITPlay1>

- Wanna play more ? Visit g.co/teachablemachine
- See a Neural Network Demo at <http://bit.do/BPIT1>

Let me answer your Questions now.

Finally, it's your time to speak.



Danke Scheon

Questions ? Any Feedbacks ? Did you like the talk?
Tell me about it.

If you think I can help you,
connect with me via

Email : ayonroy2000@gmail.com

LinkedIn / Github / Telegram Username : [ayonroy2000](#)

Website : <https://AYONROY.ML/>