Introduction to Neural Nets

By Sana Iqbal

What is a Neural Network?

Like other machine learning methods that we saw earlier in the class , it is a technique to:

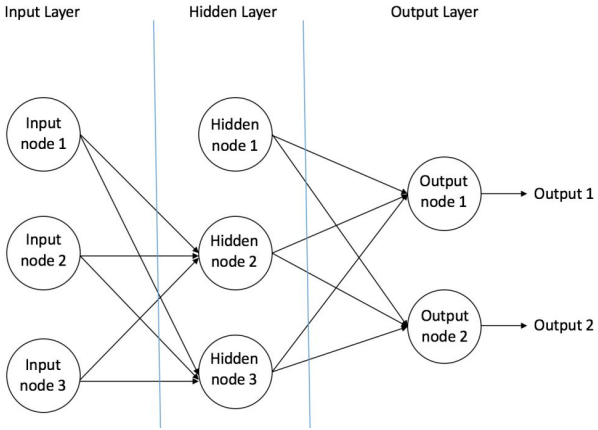
- ***map features*** *to labels or some dependant continuous value.*

or

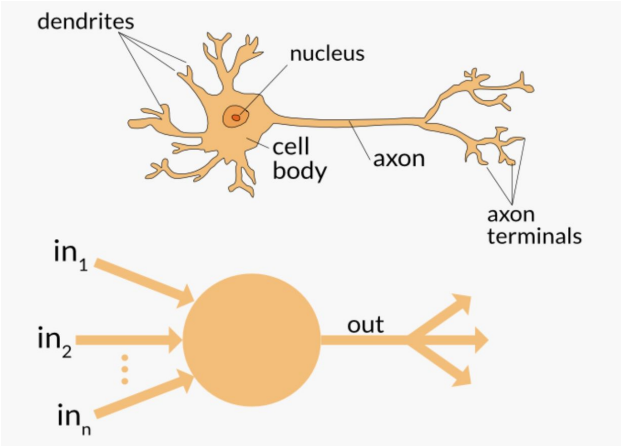
- ***compute the function*** *that relates features to labels or some dependant continuous value.*

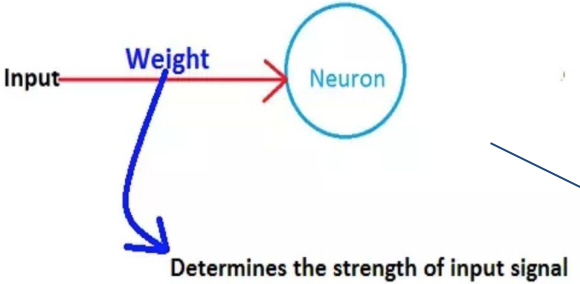
Neural Network

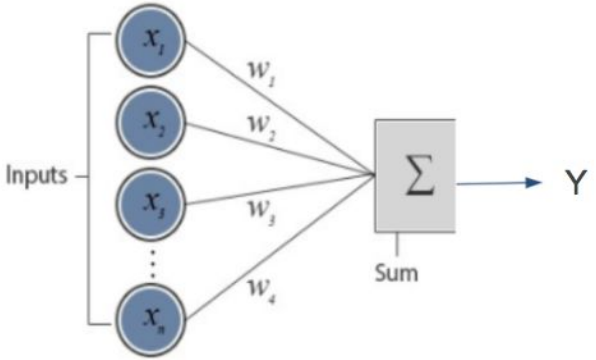
Network:
A network of neurons/nodes connected by a set of weights .



Neural:
Inspired by the way biological neural networks in the human brain process

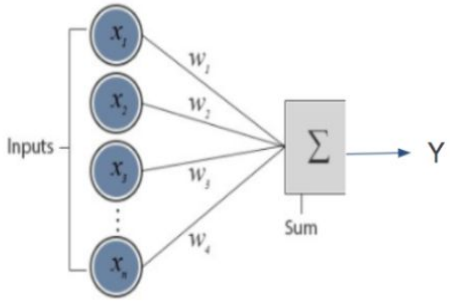






Y = x1∗w1 + x2∗w2 + x3∗w3 + · · · · · + xn∗wn **--linear regression**

Example:

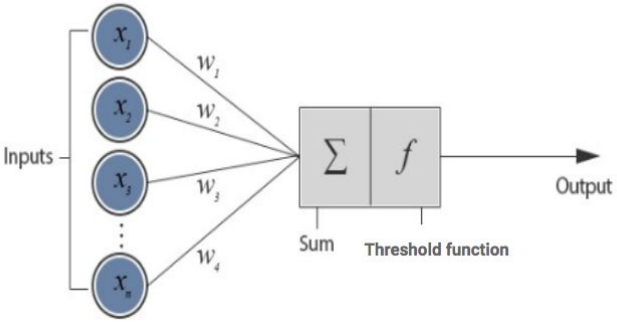


Y = x1∗w1 + x2∗w2 + x3∗w3 +·····+ xn∗wn **--linear regression**

For sample 1:				
x	6	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = sum(x * w) =**1.3**				

For sample 2:				
x	20	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = sum(x * w) = 5.5				

Lets us apply a **threshold function** on the output:

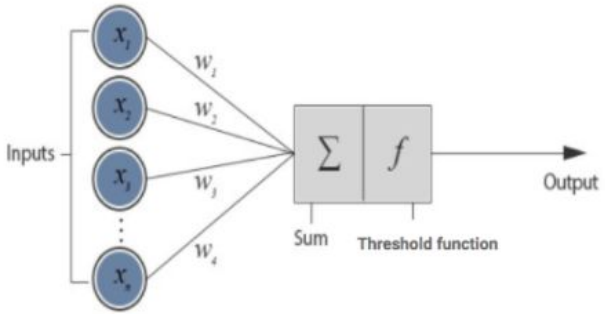


f(t) = { **t** *if* t <3
0 *otherwise* }

For sample 1:				
x	6	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = f(sum(x * w)) = f(1.3)= 1.3				

For sample 2:				
x	20	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = f(sum(x * w))= f(5.5)=0				

*Now, if we apply a **logistic/sigmoid function** on the output it will squeeze all the output between 0 and 1 :*



Y = Sigmoid(x1∗w1 + x2∗w2 + .. + xn∗wn) **--logistic regression**

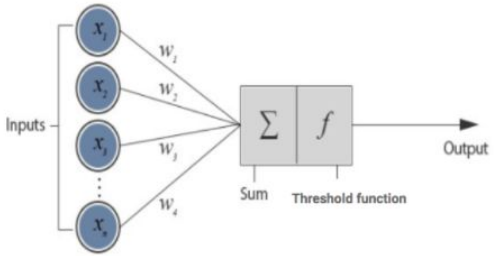
Logistic/sigmoid function

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

For sample 1:				
x	6	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = σ(sum(x * w)) = **σ(1.3) = 0.78**				

For sample 2:				
x	20	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = σ(sum(x * w)) = **σ(5.5) = 0.99**				

*Now, if we apply a **logistic/sigmoid function** on the output it will squeeze all the output between 0 and 1 :*



Y = Sigmoid(x1∗w1 + x2∗w2 + .. + xn∗wn) **--logistic regression**

Logistic/sigmoid function

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For sample 1:				
x	6	5	3	1
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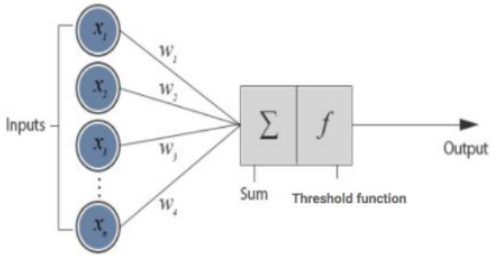
Y = σ(sum(x * w)) = **σ(1.3) =**	**0.78**			

For sample 2:				
x	20	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = σ(sum(x * w)) = **σ(5.5) =**	**0.99**			

Now, if we apply a threshold on the ***logistic/sigmoid*** *output it will set the final output as 0 or 1 :*



Logistic/sigmoid function

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

f(t) = { 1 if t > 0.6
0 *otherwise* }

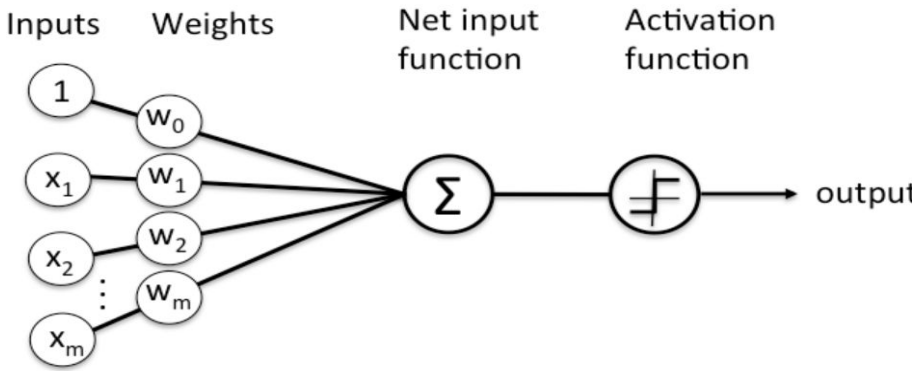
For sample 1:				
x	6	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = **f** (σ(sum(x * w)))= f(σ(1.3)) = f (0.78) =1				

For sample 2:				
x	20	5	3	1
w	**0.3**	**0.2**	**-0.5**	**0**
Y = **f**(σ(sum(x * w))) = f (σ(5.5)) = f (0.99)=1				

Review

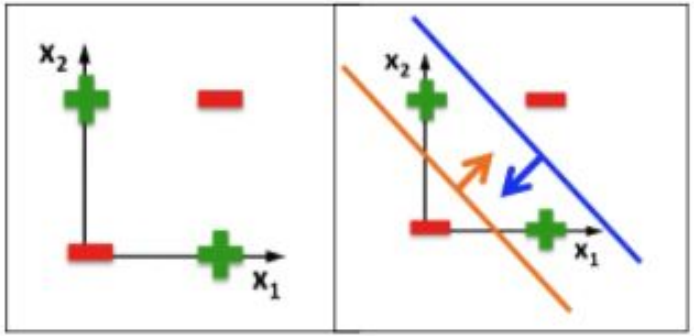
1. Neural nets want to find the function that maps features to outputs.
2. Neuron takes in weighted input(s)
3. Functions are used for transforming neuron output.

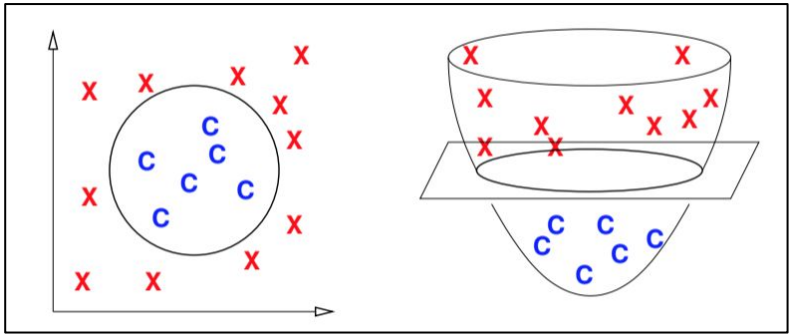
Basic Perceptron:



Schematic of Rosenblatt's perceptron.

All mapping functions are NOT linear

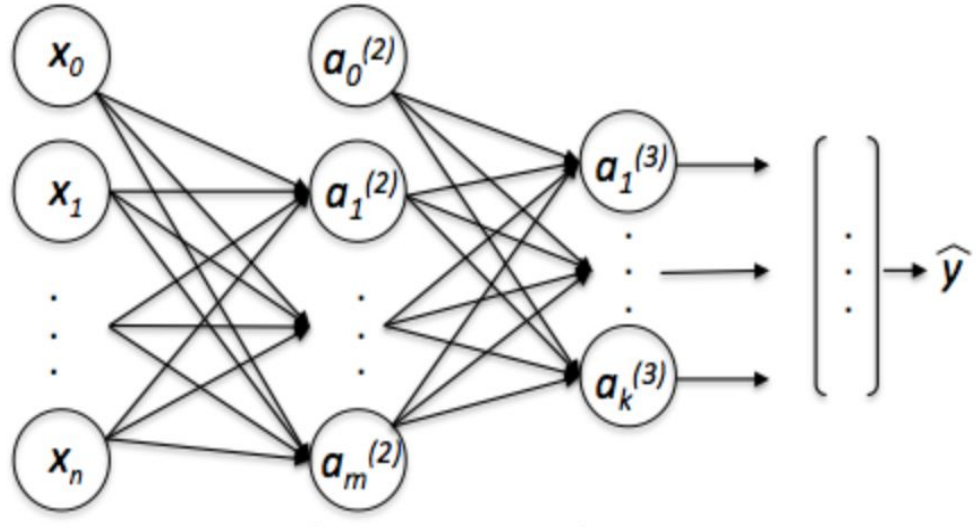




Activation functions

We use activation functions in neurons to induce nonlinearity in the neural nets so that it can learn complex functions also.

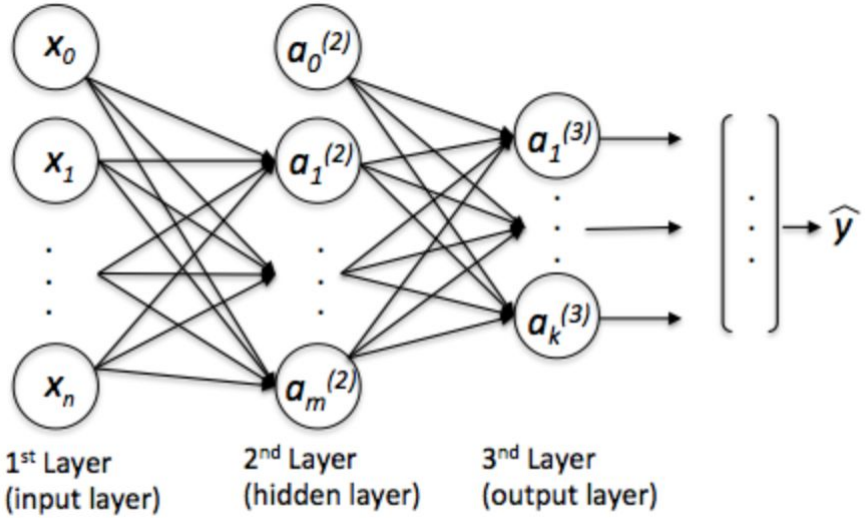
Neural Network Complexity



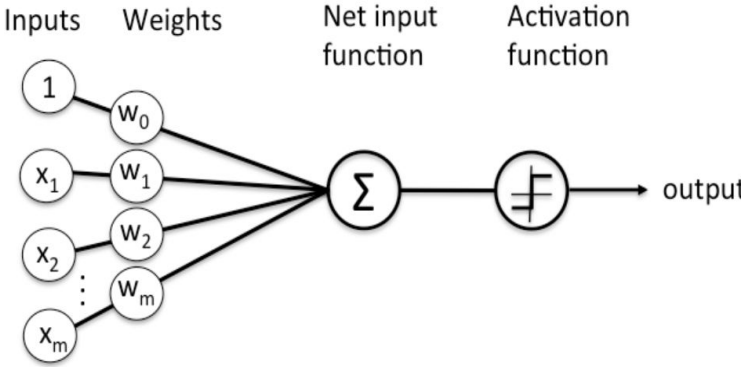
Schematic of a multi-layer perceptron.

- We use multiple combinations of inputs
- We use activation functions in neurons.

Compare the Complexity



Schematic of a multi-layer perceptron.



Schematic of Rosenblatt's perceptron.

How it works?

How does the network know the strength of connections between neurons?

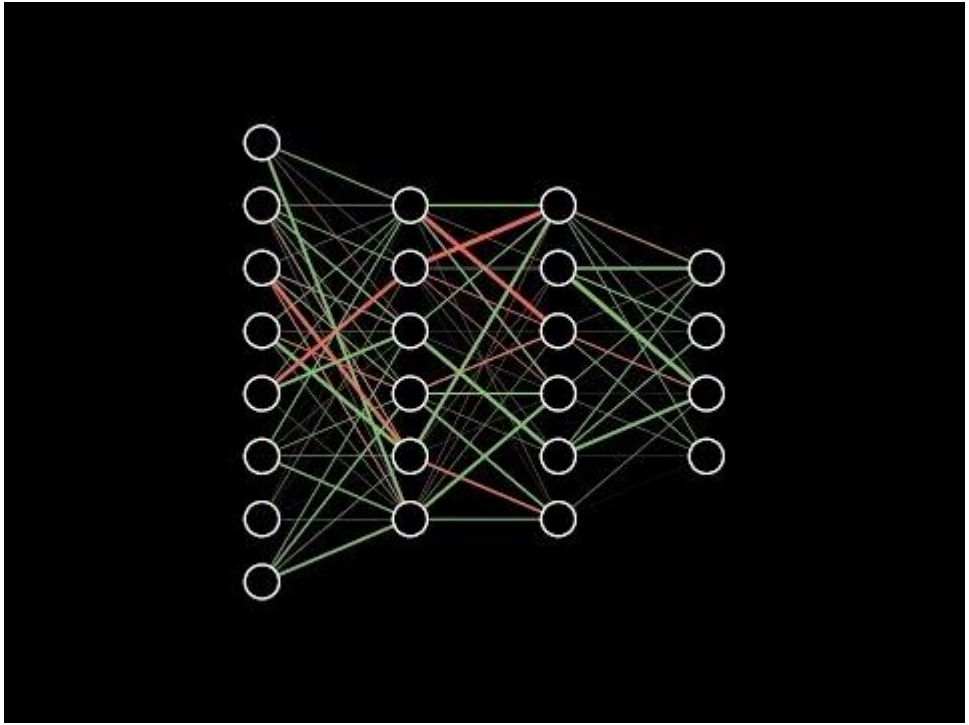
It learns them!

1. We start with random weights.
2. Input a set of features.
3. Calculate the output.
4. Calculate the Loss wrt to actual output value in the data.
5. Find the gradient of the Cost function.
6. The gradients are pushed back into the network and used for adjusting the weights - **Backpropagation**
7. The whole process is repeated again till we train a model of acceptable performance.

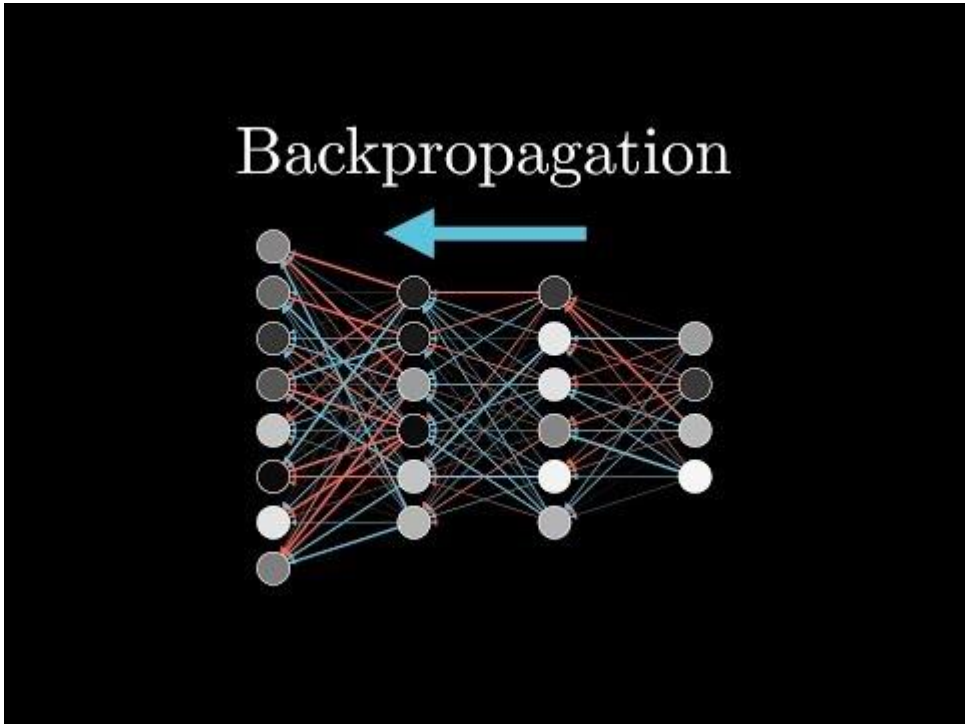
Basic Vocabulary Associated with Neural Networks

1. Input layer
2. Hidden layer
3. Output layer
4. Weights
5. Activation Functions
6. Back propagation
7. Gradient Descent
8. Stochastic Gradient Descent
9. Learning Rate
10. Batch Gradient Descent
11. Epochs

https://www.youtube.com/watch?v=aircAruvnKk



https://www.youtube.com/watch?v=Ilg3gGewQ5U



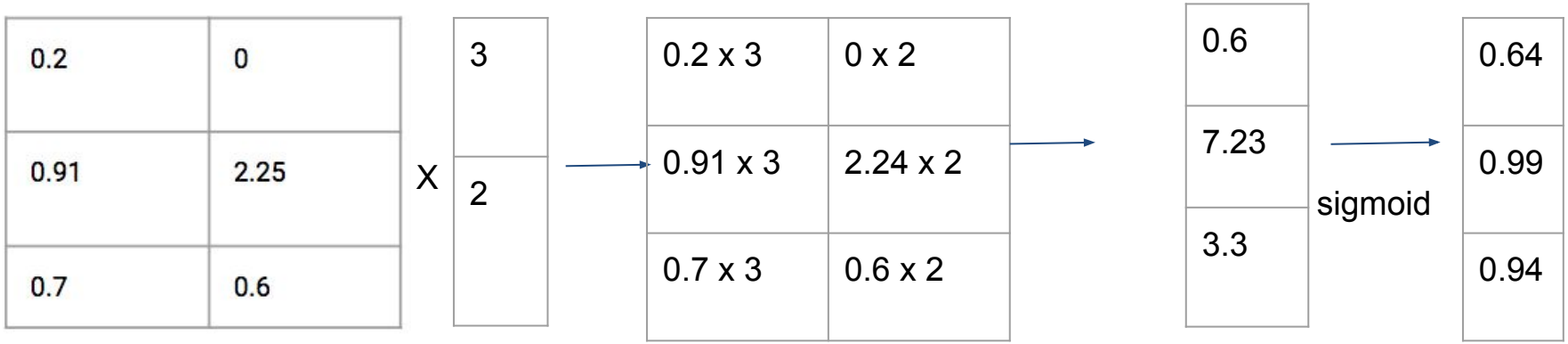
Review

1. Draw a 2 hidden layer neural net with input of size 2 units.
   Hidden layer-1 with 3 nodes
   Hidden layer -2 with 4 nodes.
   The output should be a number.
   How many weights are there?

2. Given an input= [3,2] and weight matrix W=
   Calculate the output, if the activation function is sigmoid.

w1	w2
0.2	0
0.91	2.25
0.7	0.6

Solution


0.2
0
0.91
2.25
0.7
0.6
X
3
2
0.2 x 3
0 x 2
0.91 x 3
2.24 x 2
0.7 x 3
0.6 x 2
0.6
7.23
3.3
sigmoid
0.64
0.99
0.94

Calculate Mean Square loss: sq(z-y), given

y=

0.64
0.99
0.94

Actual(z)=

0.40
0.89
0.64

Some activation Functions:

1. Sigmoid (0,1)

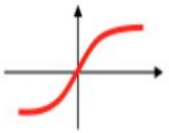
Logistic (sigmoid)

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

2. Tanh (-1,1)

Hyperbolic tangent

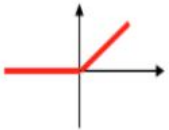
$$\phi(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$$



3. Relu (0, x)

Rectifier, ReLU (Rectified Linear Unit)

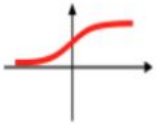
$$\phi(z) = max(0, z)$$



4. Softmax (0,1)

Softmax output

$$z_j(t) = \frac{e^{t_j}}{\sum_{i=1}^{k} e^{t_i}}.$$



Unit Saturation / vanishing gradients:

During back propagation we calculate gradients of activation functions, for sigmoid :

$$s' = s(1 - s)$$

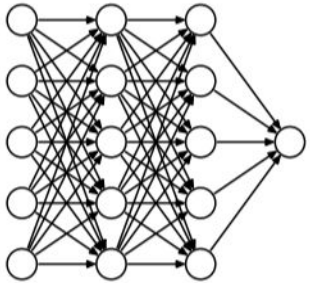
When: **s ≈ 0 or 1**

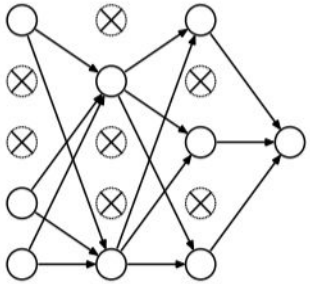
s`=s(1 − s) ≈ 0,

gradient descent changes very slowly, *making training slow.*

Regularization in neural nets

Dropout is an approach to regularization in neural networks which helps reducing interdependent learning amongst the neurons.





Advantages of Neural Nets :

It finds the best function approximation from a given set of inputs, we do not need to define features - Representational Learning.

Eg:

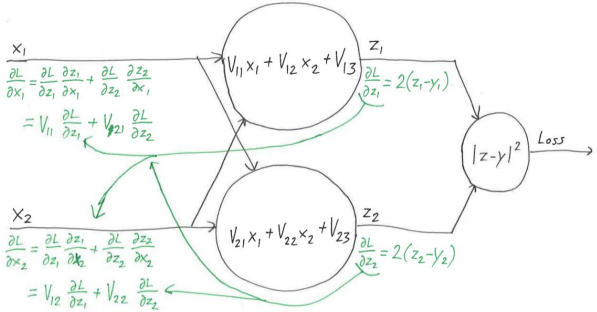
- Representational Learning is used to get Word Vectors.
- We do not need to handcraft image features

Cons of Neural Nets:

- Needs a lot of data, heavily parametrized by weights.

Notes:

1. **Why do we want activation functions?**
   https://towardsdatascience.com/activation-functions-and-its-types-which-is-better-a9a5310cc8f
2. Go through this diagram to understand backpropagation:



Ref:
http://neuralnetworksanddeeplearning.com/chap1.html

https://tinyurl.com/16thClassData-x