Student Detials

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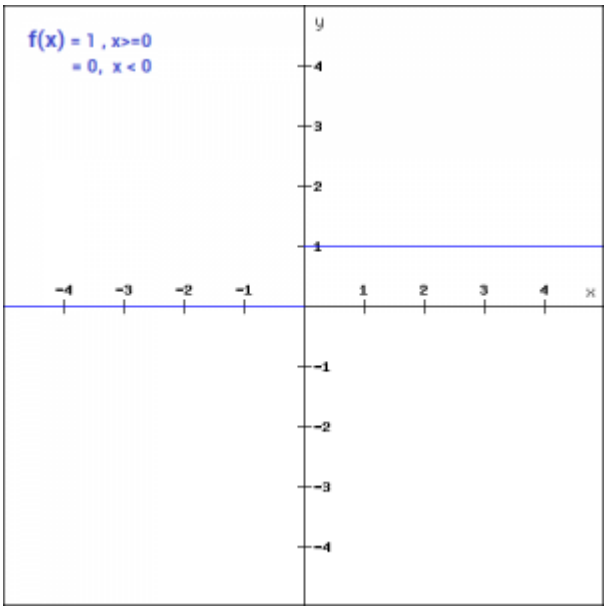
In this Notebook I am are going to Explore Actication Function used in Machine Learning

1. Binary Step Function

The first thing that comes to our mind when we have an activation function would be a threshold based classifier i.e. whether or not the neuron should be activated based on the value from the linear transformation.

In other words, if the input to the activation function is greater than a threshold, then the neuron is activated, else it is deactivated, i.e. its output is not considered for the next hidden layer. Let us look at it mathematically-

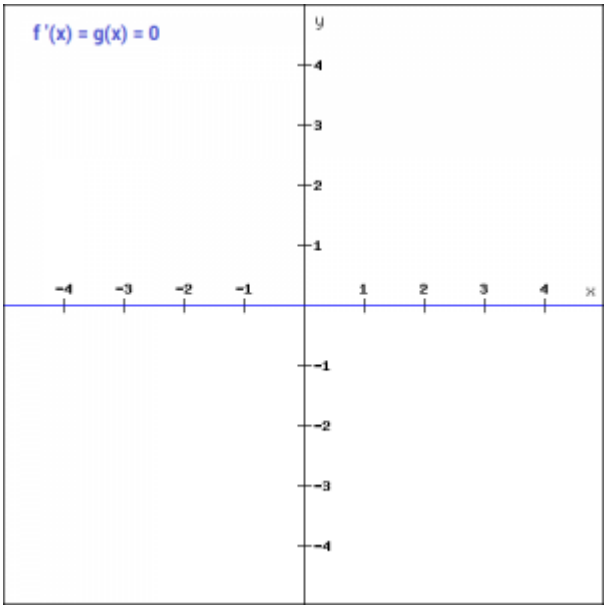
```
f(x) = 1, x>=0
     = 0, x<0
```



This is the simplest activation function, which can be implemented with a single if-else condition in python

```
def binary_step(x):
    if x<0:
        return 0
    else:
        return 1
```

`python binary_step(5), binary_step(-1)

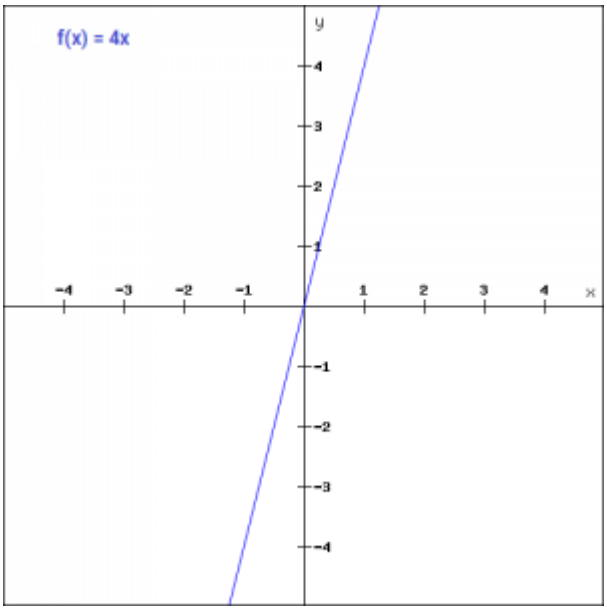


Gradients are calculated to update the weights and biases during the backprop process. Since the gradient of the function is zero, the weights and biases don't update.

2. Linear Function

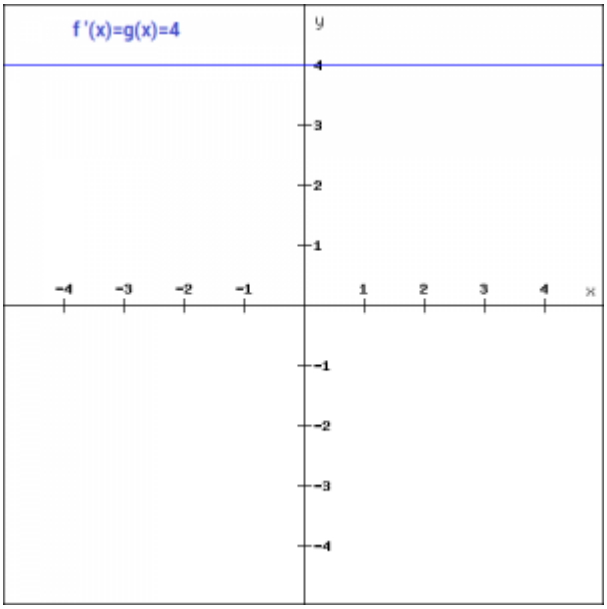
We saw the problem with the step function, the gradient of the function became zero. This is because there is no component of x in the binary step function. Instead of a binary function, we can use a linear function. We can define the function as-

$f(x)=ax$



Here the activation is proportional to the input.The variable 'a' in this case can be any constant value. Let's quickly define the function in python:

```
def linear_function(x):
    return 4*x
linear_function(4), linear_function(-2)
```



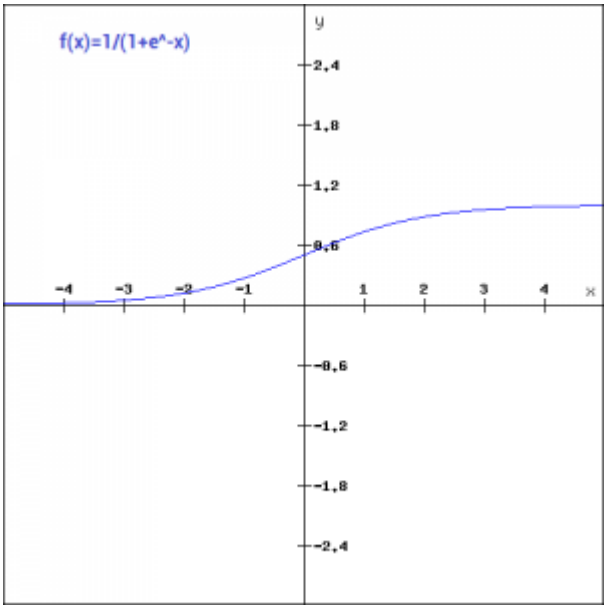
Although the gradient here does not become zero, but it is a constant which does not depend upon the input value x at all. This implies that the weights and biases will be updated during the backpropagation process but the updating factor would be the same.

In this scenario, the neural network will not really improve the error since the gradient is the same for every iteration. The network will not be able to train well and capture the complex patterns from the data. Hence, linear function might be ideal for simple tasks where interpretability is highly desired.

3. Sigmoid

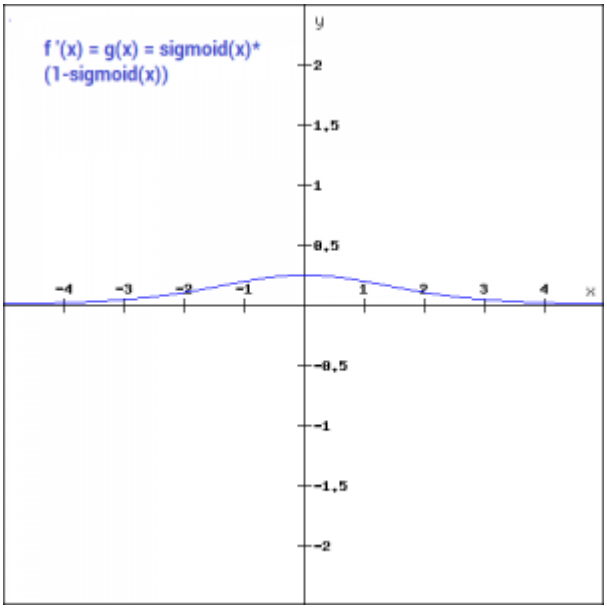
The next activation function that we are going to look at is the Sigmoid function. It is one of the most widely used non-linear activation function. Sigmoid transforms the values between the range 0 and 1. Here is the mathematical expression for sigmoid-

```
f(x) = 1/(1+e^-x)
```



A noteworthy point here is that unlike the binary step and linear functions, sigmoid is a non-linear function. This essentially means -when I have multiple neurons having sigmoid function as their activation function,the output is non linear as well. Here is the python code for defining the function in python-

```
import numpy as np
def sigmoid_function(x):
    z = (1/(1 + np.exp(-x)))
    return z
sigmoid_function(7),sigmoid_function(-22)
```



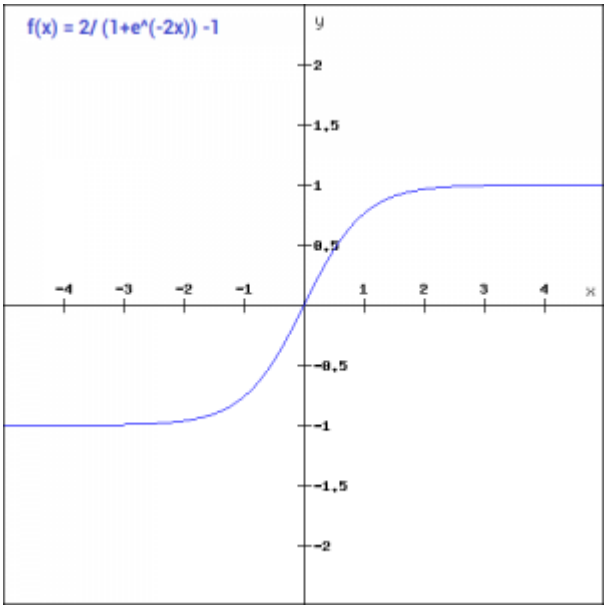
The gradient values are significant for range -3 and 3 but the graph gets much flatter in other regions. This implies that for values greater than 3 or less than -3, will have very small gradients. As the gradient value approaches zero, the network is not really learning.

Additionally, the sigmoid function is not symmetric around zero. So output of all the neurons will be of the same sign. This can be addressed by scaling the sigmoid function which is exactly what happens in the tanh function. Let's read on.

4. Tanh

The tanh function is very similar to the sigmoid function. The only difference is that it is symmetric around the origin. The range of values in this case is from -1 to 1. Thus the inputs to the next layers will not always be of the same sign. The tanh function is defined as-

```
tanh(x)=2sigmoid(2x)-1
```

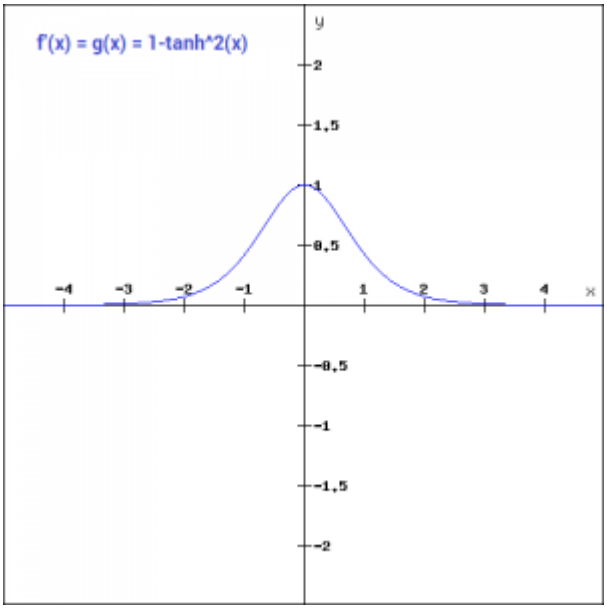


In order to code this is python, let us simplify the previous expression.

`tanh(x) = 2sigmoid(2x)-1 \ tanh(x) = 2/(1+e^(-2x)) -1` And here is the python code for the same:

```
def tanh_function(x):
    z = (2/(1 + np.exp(-2*x))) -1
    return z
tanh_function(0.5), tanh_function(-1)
```

the range of values is between -1 to 1. Apart from that, all other properties of tanh function are the same as that of the sigmoid function. Similar to sigmoid, the tanh function is continuous and differentiable at all points.



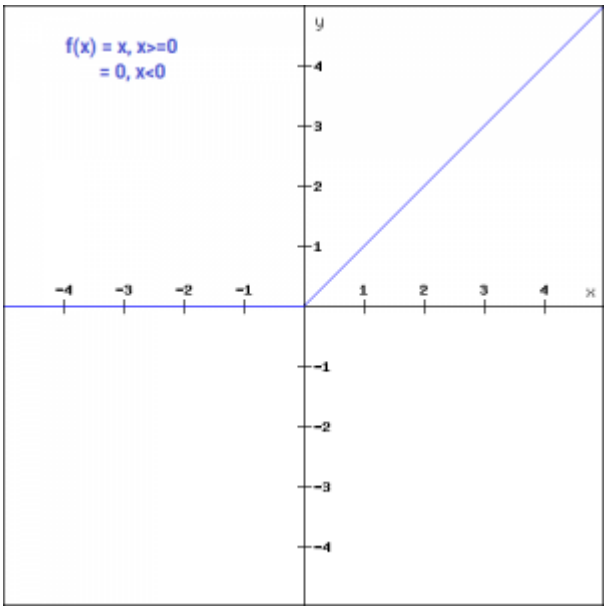
5. ReLU

The ReLU function is another non-linear activation function that has gained popularity in the deep learning domain. ReLU stands for Rectified Linear Unit. The main advantage of using the ReLU

function over other activation functions is that it does not activate all the neurons at the same time.

This means that the neurons will only be deactivated if the output of the linear transformation is less than 0. The plot below will help you understand this better-

```
f(x)=max(0,x)
```



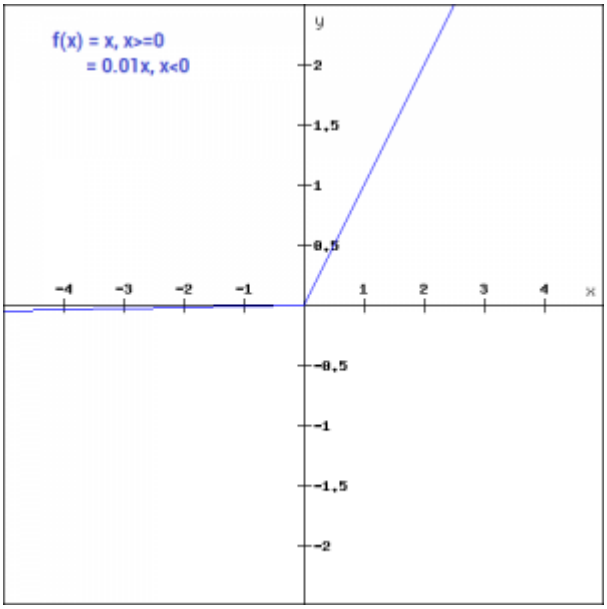
For the negative input values, the result is zero, that means the neuron does not get activated. Since only a certain number of neurons are activated, the ReLU function is far more computationally efficient when compared to the sigmoid and tanh function. Here is the python function for ReLU:

```
def relu_function(x):
    if x<0:
        return 0
    else:
        return x
relu_function(7), relu_function(-7)
```

6. Leaky ReLU

Leaky ReLU function is nothing but an improved version of the ReLU function. As we saw that for the ReLU function, the gradient is 0 for x<0, which would deactivate the neurons in that region.

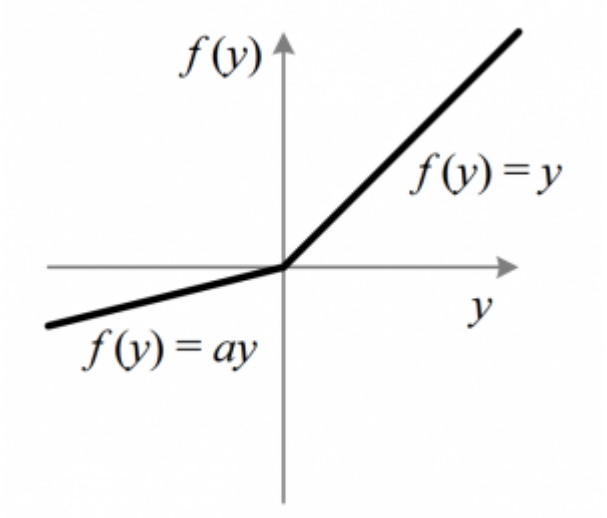
Leaky ReLU is defined to address this problem. Instead of defining the Relu function as 0 for negative values of x, we define it as an extremely small linear component of x. Here is the mathematical expression



By making this small modification, the gradient of the left side of the graph comes out to be a non zero value. Hence we would no longer encounter dead neurons in that region. Here is the derivative of the Leaky ReLU function

7. Parameterised ReLU

This is another variant of ReLU that aims to solve the problem of gradient's becoming zero for the left half of the axis. The parameterised ReLU, as the name suggests, introduces a new parameter as a slope of the negative part of the function. Here's how the ReLU function is modified to incorporate the slope parameter-



When the value of a is fixed to 0.01, the function acts as a Leaky ReLU function. However, in case of a parameterised ReLU function, 'a' is also a trainable parameter. The network also learns the value of 'a' for faster and more optimum convergence.

8. Softmax

Softmax function is often described as a combination of multiple sigmoids. We know that sigmoid returns values between 0 and 1, which can be treated as probabilities of a data point belonging to a particular class. Thus sigmoid is widely used for binary classification problems.

The softmax function can be used for multiclass classification problems. This function returns the probability for a datapoint belonging to each individual class. Here is the mathematical expression of the same-

While building a network for a multiclass problem, the output layer would have as many neurons as the number of classes in the target. For instance if you have three classes, there would be three neurons in the output layer. Suppose you got the output from the neurons as [1.2 , 0.9 , 0.75].

Applying the softmax function over these values, you will get the following result – [0.42 , 0.31, 0.27]. These represent the probability for the data point belonging to each class. Note that the sum of all the values is 1. Let us code this in python

```
def softmax_function(x):
    z = np.exp(x)
    z_ = z/z.sum()
    return z_
softmax_function([0.8, 1.2, 3.1])
```

Choosing the right Activation Function

Now that we have seen so many activation functions, we need some logic / heuristics to know which activation function should be used in which situation. Good or bad – there is no rule of thumb.

However depending upon the properties of the problem we might be able to make a better choice for easy and quicker convergence of the network.

- Sigmoid functions and their combinations generally work better in the case of classifiers
- Sigmoids and tanh functions are sometimes avoided due to the vanishing gradient problem
- ReLU function is a general activation function and is used in most cases these days
- If we encounter a case of dead neurons in our networks the leaky ReLU function is the best choice
- Always keep in mind that ReLU function should only be used in the hidden layers
- As a rule of thumb, you can begin with using ReLU function and then move over to other activation functions in case ReLU doesn't provide with optimum results