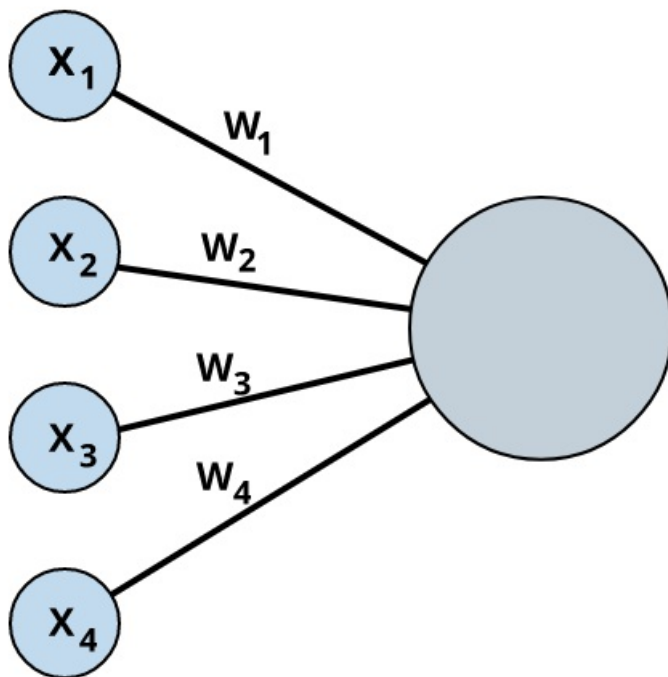


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HOW IT WORKS - THEORY

Neurons

Neural network consists, as the name indicates, of neurons. Each neuron takes an input from neurons connected to it. All inputs have their **weights**. Neuron sums inputs multiplied by their weights, and applies activation function to this sum.



All **inputs** typically have a range 0.00 to 1.00. Zero means that there is little to no chance of something and one means we are almost sure that there is something.

Weights have a range -1.00 to 1.00. -1 means that the inputs work against the thing we are trying to predict and 1 means it acts in favour of it.

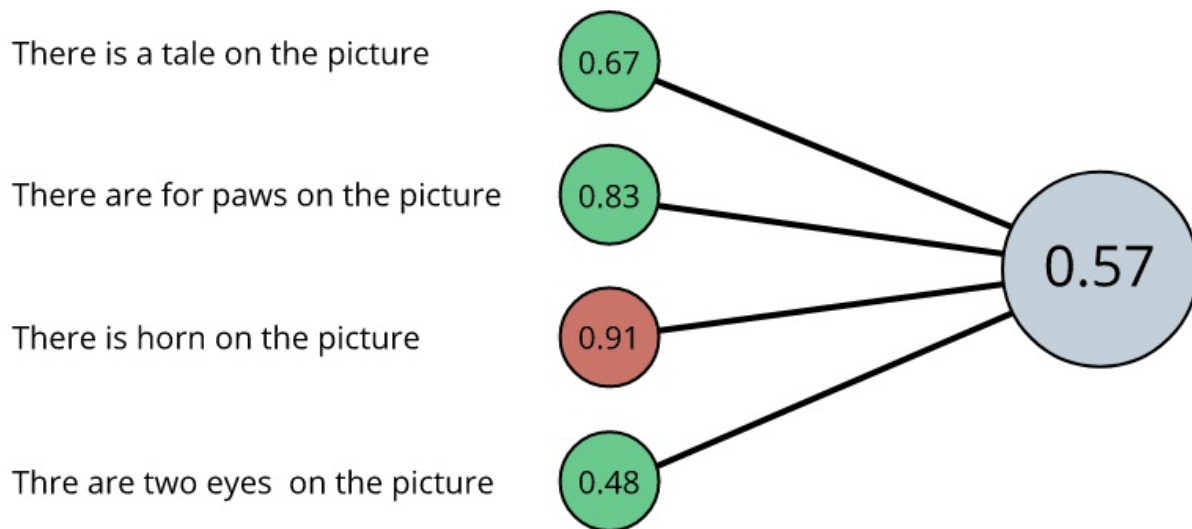
The goal of neural network is to adjust its weights so that it, with some certainty, can predict solution from the inputs. If some input is more important and it acts in favour of some action it should have positive weight close to 1. If it is not that important the weight should be around 0. and if the input works against an action it should have negative weight close to -1.

Example

Let's consider an example below. We are trying to predict if there is a cat on a given picture. Previous layer of neurons have stated there is 67% probability that

there is a tale on the image, 83% probability that there are four paw s on the picture, 91% probability that there is a horn and 48 % chance there are tw o eyes on the picture.

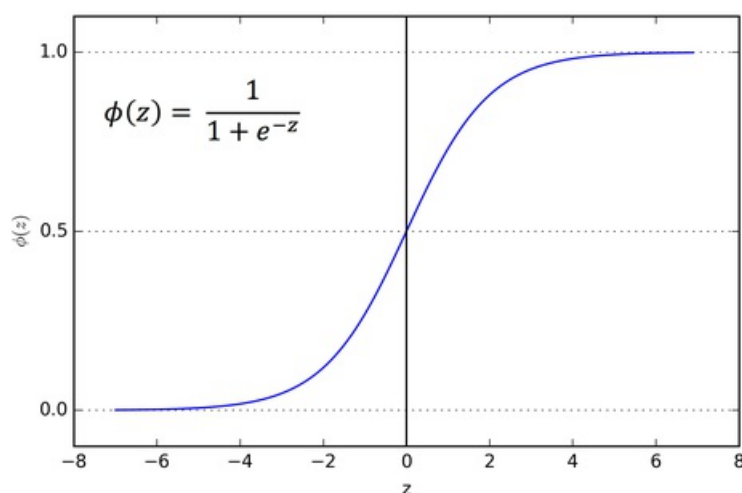
How probable is it that there is a cat on the picture?



Of course we know that cats have tails, four paw s and two eyes, but they don't have horns. That's why inputs **1, 2 and 4** should have **positive** weights. If we know there is a tail, this should increase the chance that there is a cat. On the other hand input 3 should have negative weight, because if we know there is a horn, we can be sceptical about image presenting a cat. If we have shown our neural network thousand of images of cats we can hope that it will learn that cats don't have horns and put negative weight in the input whose role was to deduce if there is a horn. However we can't know for sure what neural network picked as important and what it didn't, all inputs and outputs are just numbers that somehow lead to the solution

Activation Function

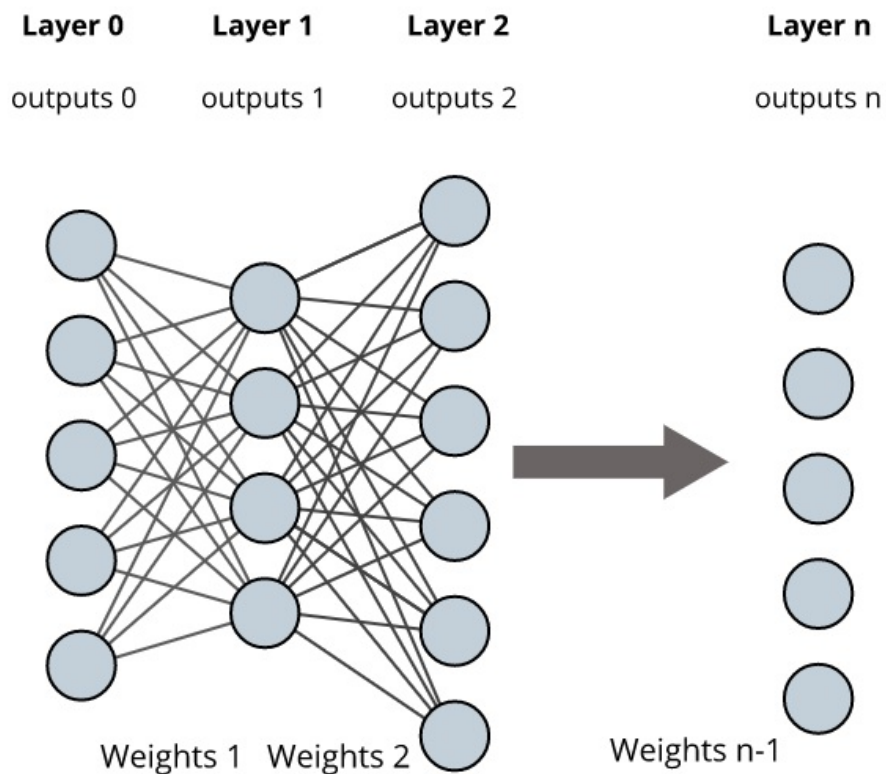
The sum of inputs multiplied by their weights can often be larger than 1 or less than 0, that's why we need something called **activation function**. Activation function applied to the output limits it to the range (0.00,1.00). An example of such funtion is **sigmoid**.



As the argumenst approach infinity the function aproches 1, as they approach minus nfinity it approaches 0 with the value of 0.5 at w hen the argument is equal to 0.

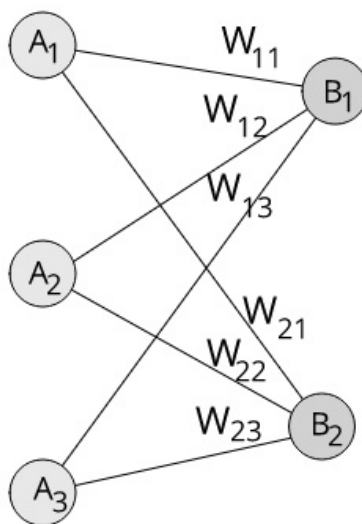
Layers

Full neural network consists of not one but many neurons arranged in **layers**, each layer takes the output of the previous one and treats it as input



Weights

Let's consider a neural network with 2 layers, the first one has 3 neurons and the second one has 2 neurons.



In this layer inputs to layer B should look like this:

$$InputB_1 = (A_1 \times W_{11}) + (A_2 \times W_{12}) + (A_3 \times W_{13})$$

$$InputB_2 = (A_1 \times W_{21}) + (A_2 \times W_{22}) + (A_3 \times W_{23})$$

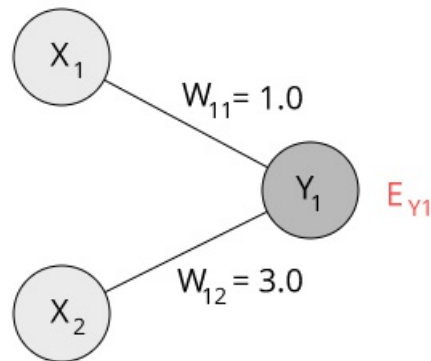
We can use **Matrix multiplication** to simplify this process

$$\begin{bmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & W_{23} \end{bmatrix} \odot \begin{bmatrix} A_1 \\ A_2 \\ A_3 \end{bmatrix} = \begin{bmatrix} (A_1 \times W_{11}) + (A_2 \times W_{12}) + (A_3 \times W_{13}) \\ (A_1 \times W_{21}) + (A_2 \times W_{22}) + (A_3 \times W_{23}) \end{bmatrix}$$

HOW DOES NEURAL NETWORK LEARN?

Errors

In order for neural network to learn it first has to know about the mistakes it's making. Let's consider following example:

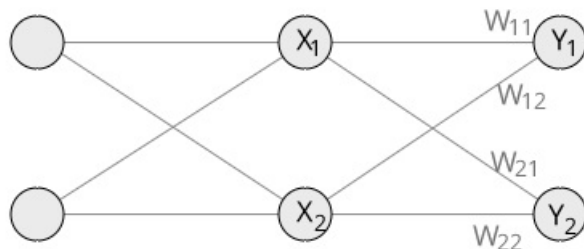


Let's say we guessed the value of Y1 but it's wrong and we know the error. Let's call this error EY1. What should be the error of X1 or X2? One might say we should split the error of Y1 evenly because there are two nodes connected to Y1, so error of X1 should be 1/2 of error of Y1 and error of X2 should be 1/2 of error of Y1. Well it's generally not a good way of doing this, because we can see that weight coming from X2 is 3 times larger than the of X1. Because of that X2 contributes to the mistake of Y1 3 times as much as X1. Therefore it would be better to describe the error of X1 as 1/4 the error of Y1 and error of X2 as 3/4 the error of Y1. This can lead to general principle:

$$ErrorX_1 = ErrorY_1 \times \frac{W_{11}}{W_{11} + W_{12}}$$

$$ErrorX_2 = ErrorY_1 \times \frac{W_{12}}{W_{11} + W_{12}}$$

Errors on layers



If we consider the following example then we see that X1 and X2 contribute to not only the error of Y1 but also Y2. Therefore their error should come for both Y1 and Y2. If we write it in equation it should look like this:

$$ErrorX_1 = ErrorY_1 \times \frac{W_{11}}{W_{11} + W_{21}} + ErrorY_2 \times \frac{W_{21}}{W_{11} + W_{21}}$$

$$ErrorX_2 = ErrorY_1 \times \frac{W_{12}}{W_{12} + W_{22}} + ErrorY_2 \times \frac{W_{22}}{W_{12} + W_{22}}$$

If we again write it in matrices we would get something like this:

$$ErrorX = \begin{bmatrix} \frac{W_{11}}{W_{11}+W_{21}} & \frac{W_{21}}{W_{11}+W_{21}} \\ \frac{W_{12}}{W_{12}+W_{22}} & \frac{W_{22}}{W_{12}+W_{22}} \end{bmatrix} \circ \begin{bmatrix} ErrorY1 \\ ErrorY2 \end{bmatrix}$$

We can then omit the values in the denominator. If we do this we only lose the information about the normalization of the errors not the information about how much each weight contributes to it.

$$ErrorX = \begin{bmatrix} W_{11} & W_{21} \\ W_{12} & W_{22} \end{bmatrix} \circ \begin{bmatrix} ErrorY1 \\ ErrorY2 \end{bmatrix}$$

We can now see then the weight matrix is the same one what we have been using for to feed forward values between the layers, except now it's transposed what means it is flipped along the diagonal line. And if you think about it, it makes perfect sense, we are now going backwards instead of forward what means we need to invert the matrix:

$$\begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix}^T = \begin{bmatrix} W_{11} & W_{21} \\ W_{12} & W_{22} \end{bmatrix}$$

We can now write the general principle:

$$Errors_{n-1} = (Weights_{n-1})^T \circ Errors_n$$

With this algorithm we can describe errors from the end to the beginning of the neural network

Learning

Ok we now know the errors but how can we adjust the weight to correct them?

HOW IT WORKS - PYTHON

works in progress

INSTALLATION

Requirements

Simple neuron requires libraries :

Numpy

Scipy

to install them you can simply do it with pip:

```
pip install numpy
```

```
pip install scipy
```

Installing SimpleNeuron

To install SimpleNeuron you all you have to do is copy the SimpleNeuron.py file to your directory

USAGE

First you need to import NeuralNetwork object

```
from SimpleNeuron import NeuralNetwork
```

then you need to initialize neural network object, it takes 2 parameters as input table consisting of numbers of neurons in each layer and learning rate, for example:

```
nn = NeuralNetwork([3,6,8],0.3)
```

will create a neural network with 3 layers consisting, as follows 3,6,8 neurons with learning rate of 0.3
Then you will have to train your network on some data for this you use:

```
nn.learn(input,output)
```

finally when your network is trained you can use predict function to predict output based on input:

```
nn.predict(input)
```