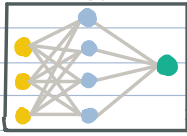


(evolving)

HOW A NEURAL NETWORK WORKS



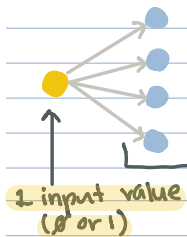
- Input layer: enter either a 0 or a 1 - training set
 - Hidden Layer: where the integration of the calculation occurs
 - Output layer: returns either a 0 or 1 (*best case scenario)
- this is what our neural network looks like. So cute!

X1	X2	X3	Y
0	0	1	0
0	1	1	1
1	0	1	1
1	1	1	0

Summary: In this example, we are taking 3 input values, passing each through 4 perceptrons (hidden layer), then summing the results into an output. To make things easier, the bias value will be 0.

each row is a set of #s we want our nn to learn

this column is the values we want our neural net to get close to for each corresponding dataset
ie. [0, 0, 1] should produce 0



each perceptron (●) has its own specific weight value that the input value is "fed through", or multiplied by.

1 input value (0 or 1)

Hidden Layer



① Let's say our first input is a 1. We'd multiply (1 * weight of the individual perceptron). We repeat this process with our other 2 input values (ie. 0, 0).

$$\begin{aligned} \rightarrow (1 * 0.3) &= 0.3 \\ (0 * 0.3) &= 0 \\ (0 * 0.3) &= 0 \end{aligned}$$

② We repeat this process for each individual perceptron (so, in this case 4 times).

③ Each perceptron should have 3 numbers "inside" - one from each input multiplied by its weight:

$$\begin{matrix} 0.3 \\ 0 \\ 0 \end{matrix}$$

$$\begin{matrix} 0.2 \\ 0 \\ 0 \end{matrix}$$

$$\begin{matrix} 0.1 \\ 0 \\ 0 \end{matrix}$$

$$\begin{matrix} 0.4 \\ 0 \\ 0 \end{matrix}$$

④ Next, we sum these values:

$$0.3$$

$$0.2$$

$$0.1$$

$$0.4$$

⑤ Here comes the fun part: we apply a non-linear activation function to each perceptron's sum - in this case, we're using a Sigmoid function: $\frac{1}{1+e^{-x}}$ (* these answers are truncated after the hundredths place and are not accurate). Plug in each sum to the x value of the sigmoid function!

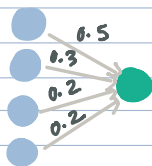
$$\frac{1}{1+e^{-0.3}} = 0.574...$$

$$\frac{1}{1+e^{-0.2}} = 0.549...$$

$$\frac{1}{1+e^{-0.1}} = 0.475...$$

$$\frac{1}{1+e^{-0.4}} = 0.401...$$

⑥ Almost there! Now we multiply each of these values by the 2nd set of weights (*note: weights are random at first, then are incrementally adjusted through back propagation)



$$\begin{aligned}
 0.574 \times 0.5 &= 0.287 \\
 0.549 \times 0.3 &= 0.165 \\
 0.479 \times 0.2 &= 0.096 \\
 0.401 \times 0.2 &= 0.080
 \end{aligned}$$

⑦ Now we sum all of these values to get ...

$$0.287 + 0.165 + 0.096 + 0.080 = 0.628$$

⑧ Last Step! (sort of) Remember that fun Sigmoid function from before? You guessed it, we're plugging in the sum of our weights into it to get our final answer...

$$\frac{1}{1 + e^{-x}} = 0.652!!!$$

⚠ But wait a minute, according to our table from before, the inputs $[1, 0, 0]$ should have given us a 0! We're way off! ; That's ok, that's where Back propagation comes in (I'll discuss that a separate time) which is what we'll use to adjust our weights until we get closer and closer to 0! This takes a TON of iterations (repetitions) — like 10,000! For reference, we only just walked through $1/2$ of an iteration!