

Discussion

13/July/2021

- (i) Understand how math behind neural networks works
- (ii) Do an example
- (iii) Try predicting for (x_1, \dots, x_{30}) together
- (iv) Explain how loss is taken into picture

Input

x_1	\dots	x_{30}	w_1	\dots	w_{30}	c	o_1	\dots	o_{30}
							0		0
							1		1
							0		0
							\vdots		\vdots

learning rate $\eta = 0.001$

$$\phi_1(v) = f(v) = \begin{cases} 0 & \text{for } v < 0 \\ v & \text{for } v \geq 0 \end{cases} = \phi_2(v) = \phi_3(v) = \phi_4(v)$$

$$\phi_5(v) = \frac{1}{1 + e^{-v}}$$

Model considerations

61 : 128 : 64 : 32 : 2 : 1

For mathematical purpose, we consider smaller model.

Let us consider only 2 D20 pairs

Note:

Not

true

data

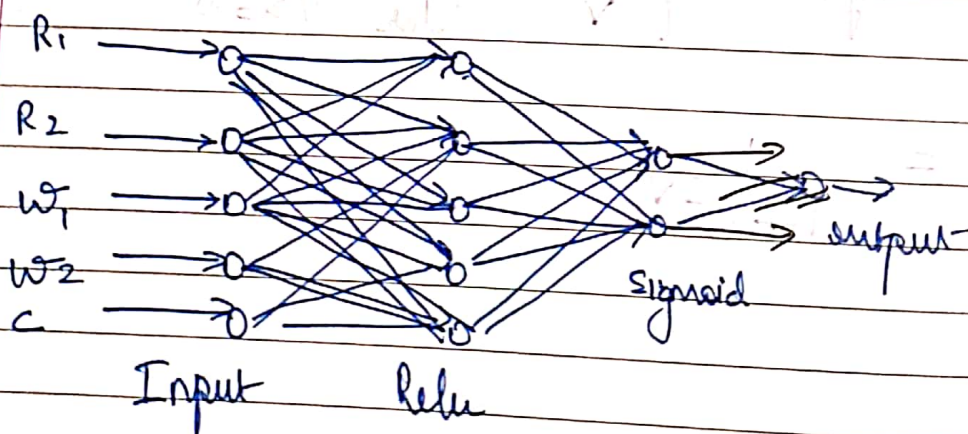
R_1	R_2	W_1	W_2	C	O_1	O_2
1	1.5	1	0.5	1	1	0
1.5	1	1	0.5	1	0	1
1	1.5	1.5	0.5	0	1	0
1.5	0.5	0.5	1.5	1	0	1

Let the model be

5 : 5 : 2 NN

input \rightarrow

\rightarrow output



$$\phi_1(v) \Rightarrow \begin{cases} v & \text{if } v \geq 0 \\ 0 & \text{else} \end{cases}$$

$$\phi_2(v) = \frac{1}{1 + e^{-v}}$$

Let weights be

$$W_1 = \begin{bmatrix} 0.2 & 1 & 0.2 & 1 & 0.2 & 1 \\ -0.2 & 1 & -0.2 & 1 & -0.2 & 1 \\ 0.2 & -1 & 0.2 & -1 & 0.2 & -1 \\ -0.2 & 1 & -0.2 & 1 & -0.2 & 1 \\ 0.2 & 1 & 0.2 & 1 & 0.2 & 1 \end{bmatrix}$$

Input $X_1 = \begin{bmatrix} 1 \\ 1 \\ 1.5 \\ 1 \\ 0.5 \\ 1 \end{bmatrix} \rightarrow \text{bias } b_0$

Forward Pass

$$V_1 = \begin{pmatrix} V_{11} \\ V_{12} \\ V_{13} \\ V_{14} \\ V_{15} \end{pmatrix} = W_1 X_1^T = \begin{bmatrix} 0.2 & 1 & 0.2 & 1 & 0.2 & 1 \\ -0.2 & 1 & -0.2 & 1 & -0.2 & 1 \\ 0.2 & -1 & 0.2 & -1 & 0.2 & -1 \\ -0.2 & 1 & -0.2 & 1 & -0.2 & 1 \\ 0.2 & 1 & 0.2 & 1 & 0.2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1.5 \\ 1 \\ 0.5 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 3.6 \\ 2.4 \\ -2.4 \\ 2.4 \\ 3.6 \end{bmatrix}$$

$$\bar{y}_1 = \begin{bmatrix} y_{11} \\ y_{12} \\ y_{13} \\ y_{14} \\ y_{15} \end{bmatrix} = \begin{bmatrix} \text{Relu}(3.6) \\ \text{Relu}(2.4) \\ \text{"}(-2.4)\text{"} \\ \text{"}(2.4)\text{"} \\ \text{"}(3.6)\text{"} \end{bmatrix} = \begin{bmatrix} 3.6 \\ 2.4 \\ 0 \\ 2.4 \\ 3.6 \end{bmatrix}$$

let weights 2 be as

$$W_2 = \begin{bmatrix} -1 & 1 & -1 & 1 & -1 & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix}$$

Now the function is sigmoid

$$V_2 = W_2 \cdot y_1^T$$

$$= \begin{bmatrix} -1 & 1 & -1 & 1 & -1 & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 3.6 \\ 2.4 \\ 0 \\ 2.4 \\ 3.6 \end{bmatrix}$$

$$= \begin{bmatrix} 1.4 \\ -1.4 \end{bmatrix}$$

$$\bar{y}_2 = \text{sigmoid}(V_2)$$

$$y_{21} = \frac{1}{1 + e^{-1.4}}$$

$$= 0.8022$$

for output 1

$$y_{22} = \frac{1}{1 + e^{1.4}}$$

$$= 0.1978$$

Calculating Error \Rightarrow squared error function

$$E = \frac{1}{2} (\text{target} - \text{output})^2$$

$$E_{01} = \frac{1}{2} (1 - 0.8022)^2 = 0.0195$$

$$E_{02} = \frac{1}{2} (0 - 0.1978)^2 = 0.0195$$

$$E_{\text{total}} = 0.0195 + 0.0195 \\ = 0.03912$$

Backward Pass

$\odot \rightarrow$ Hadamard Transform

$$\Delta W_2 = \eta_2 \cdot \delta_2 y_1^T$$

$$\text{let } \eta_2 = 0.01$$

$$\delta_2 = E_{01} \odot \phi'_2(v_2(k))$$

$$= E_{01} \odot (\text{partial derivative of sigmoid})$$

$$= E_{01} \odot \frac{\partial(\text{sigmoid})}{\partial v_2}$$

$$= E_{01} \odot (-1.4)(1-1.4)$$

$$= 0.0195 \times (-0.56)$$

$$= -0.01092$$

$$E_{02} \odot \frac{\partial(-1.4)}{\partial(1+1.4)}$$

$$= -0.0655$$

$$= -0.0655^2$$

$$\Delta W_{201} = 0.01 \times (-0.01092) \times \begin{bmatrix} 1 & 3.6 & 2.4 & 0 & 2.4 & 3.6 \end{bmatrix} \\ = \begin{bmatrix} -0.0001092 & -0.00039312 & -0.00026208 & 0 & -0.00026208 & -0.00039312 \end{bmatrix}$$

similarly

$$\Delta W_{202} = 0.01 \times (-0.06552) \times \begin{bmatrix} 1 & 3.6 & 2.4 & 0 & 2.4 & 3.6 \end{bmatrix}$$

$$W_2(k+1) = W_2(k) + \Delta W_2 = \begin{bmatrix} -0.0006552 & -0.245 & -0.16 & 0 & -0.011 & -0.245 \end{bmatrix} \\ W_2(2) = W_2(1) + \Delta W_2 \\ = \begin{bmatrix} 0.9998 & 3.5996 & 2.3997 & 0 & 2.3997 & 3.5996 \end{bmatrix}$$

$$= \begin{bmatrix} -1 & 1 & -1 & 1 & -1 & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix} + \begin{bmatrix} -0.0001902 & \dots & -0.44 \\ \dots & \dots & \dots \end{bmatrix}$$

$$W_2(2) = \begin{bmatrix} -1.0001902 & 0.9996 & -1.00026208 & -1.00026 & 0.9996 \\ 0.9993 & -1.245 & 0.84 & -1 & 0.84 & -1.245 \end{bmatrix}$$

$$s = w_2^T s_2 \odot \phi'(v_1)$$

$$\text{Note } \Rightarrow s_{ij} = w_{i+1}^T s_{j+1} \odot s_j'(v_j(k))$$

$$= \begin{bmatrix} -1.001902 & 0.9991 \\ 0.9996 & -1.245 \\ -1.000262 & 0.84 \\ 1 & -1 \\ -1.0002 & 0.84 \\ 0.9996 & -1.245 \end{bmatrix} \begin{bmatrix} -0.1092 \\ -0.6522 \end{bmatrix} \odot \begin{bmatrix} 3.6 \\ 2.4 \\ 2.4 \\ 2.4 \\ 3.6 \end{bmatrix}$$

$\begin{bmatrix} 3.6 & 2.4 \\ 2.4 & 2.4 \\ 2.4 & 3.6 \end{bmatrix}$
 1×5

$$= \begin{bmatrix} 0.5345 \\ 0.109 \\ -0.808 \\ -0.4386 \\ 0.53 \\ -0.4386 \\ -0.808 \end{bmatrix} \begin{bmatrix} 1 & 3.6 & 2.4 & 2.4 & 2.4 & 3.6 \end{bmatrix}$$

5×1
 1×5

$$\Delta W_1 = \begin{bmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix} 5 \times 5$$

$$\therefore \Delta W_1 = 0.01 \times s_1 \times \begin{bmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix} 1 \times 5$$

$$= \begin{bmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix} 5 \times 5$$

$$W_{k2} = W_{k1} + \Delta W_1 \Rightarrow \text{New weights for hidden layer}$$