

Homework 5 - Machine Learning.
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Q.1. For the given data ~~and~~ $\rightarrow x$ is attribute & y is class variable

a) Test sample $x = 4.2$

1-NN would be $x = 4$ & hence it would be classified as 'B'.

b) Test sample $x = 4.2$.

3-NN would make use of $x = 3, x = 4, x = 5$
having corresponding labels - $\{A, B, A\}$
Majority is 'A' & $x = 4.2$ would be labelled as 'A'.

c) Leave-one-out cross validation of 1-NN :-

For each datapoint in X , if the nearest neighbour has a different label, then x would be misclassified.

For the given dataset :-

$x = 3$ label - 'A' chooses $x = 4$ as 1-NN whose label is 'B'.

① So $x = 3$ would get classified as 'A'.

② $x = 4$ has $x = 3$ & $x = 5$ as 1NN. (choosing either would classify $x = 4$ as 'A' so error.

③ $x = 9$ chooses $x = 10$ as 1-NN & gets labelled as 'A'.

④ $x = 13$ chooses either of $x = 12$ or $x = 14$ as its 1NN.
& gets misclassified as $x = 'B'$.

so in the given dataset of 18 pts, at 4 instances datapts could be misclassified for 1NN.

⑤ $x = 5$ chooses $x = 4$ as its 1NN & gets misclassified.

~~Ans :- 4/18~~ ⑥ $x = 8$ chooses $x = 9$ as its 1NN & misclassified.

⑦ $x = 12$ chooses $x = 13$ & misclassified.

⑧ $x = 14$ chooses $x = 13$ as its 1NN & gets classified as 'A'.

of the given 18 datapts \rightarrow 8 cases where the misclassification happens.

$$\text{Ans} \rightarrow \underline{8/18}.$$

(2)	$X_1 = \text{Acid durability}$	$X_2 = \text{Strength}$	$Y = \text{classification}$
	7	7	Bad
	7	4	Bad
	3	4	Good
	1	4	Good
Test	3	7	

To find 3-nearest neighbours, we find euclidean distance betⁿ given pt & the data pts.

$$(x_1, x_2) \equiv (3, 7) \rightarrow \text{Test}.$$

$$d_{T1} = (7-3)^2 + (7-7)^2 = 4^2 \quad \checkmark \sqrt{d_{T1}} = 4$$

$$d_{T2} = (7-3)^2 + (7-4)^2 = 4^2 + 3^2 \quad \checkmark \sqrt{d_{T2}} = 5$$

$$d_{T3} = (3-3)^2 + (4-7)^2 = 3^2 \quad \checkmark \sqrt{d_{T3}} = 3$$

$$d_{T4} = (1-3)^2 + (4-7)^2 = 2^2 + 3^2 \quad \checkmark \sqrt{d_{T4}} = 3.605$$

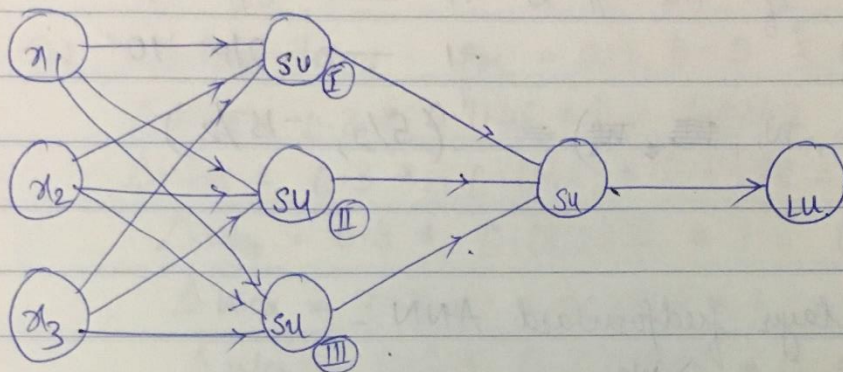
so the three nearest neighbours are 1, 3 & 4.

labelled as Bad, good & good respectively.

so the given new tissue would be classified as "good".

③. Represent $f(x_1, x_2, x_3)$ using ^{NN} ^{having} linear units and sign units

One solution is :- 2 hidden layers & 1 o/p node.



Function implemented at 'I' $\Rightarrow \bar{x}_1 \wedge \bar{x}_2 \wedge x_3$.

If True \rightarrow O/P = 1.
If False \rightarrow O/P = 0.

Weights (w_0, w_1, w_2, w_3) could be $(-0.5, -1, -1, 1)$

Function implemented at 'II' $\Rightarrow \bar{x}_1 \wedge x_2 \wedge \bar{x}_3$ If True \rightarrow O/P 1.
False \rightarrow O/P 0.

$(w_0, w_1, w_2, w_3) \equiv (-0.5, -1, 1, -1)$

Function implemented at 'III' $\rightarrow x_1 \wedge \bar{x}_2 \wedge \bar{x}_3$ If True \rightarrow O/P 1.
False \rightarrow O/P 0.

$(w_0, w_1, w_2, w_3) \equiv (-0.5, 1, -1, -1)$

The I/p to the ^{hidden} second layer is the O/P of all the hidden nodes in the first hidden layer. It should represent the following logic function :-

If at least one of the inputs is a +1, the unit O/p's at +1 otherwise it O/p's a -1. It thus represents an OR node

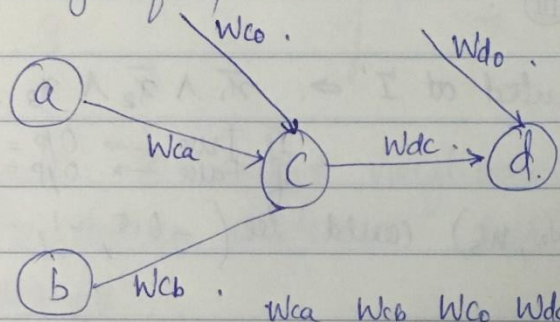
(w_0, w_1, w_2, w_3) here take the $(-0.5, 1, 1, 1)$ Values

The I/p to the O/p node is the O/p of the node in the second hidden layer. It represents the logic function :-

If the I/p is +1 \rightarrow O/p '-5'
 -1 \rightarrow O/p '10'

$$(w_0, w_1, \dots) = (5/2, -15/2)$$

Q.4. Two-layer feedforward ANN :-



Initial values (0.1, 0.1, 0.1, 0.1, 0.1)

$\eta = 0.3$ & $\alpha = 0.9$

Training set =

	a	b	d
	1	0	1
	0	1	0

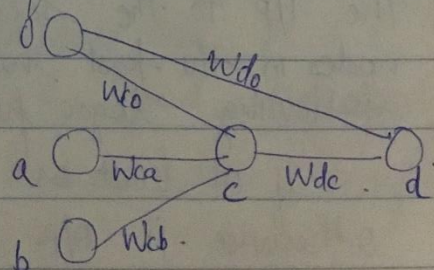
Solⁿ

The network and the sigmoid activation function are as follows :-

$$\sigma(y) = \frac{1}{1+e^{-y}}$$

Training example 1:-

a = 1 & b = 0



$$O_c = \sigma(0.1 \times 1 + 0.1 \times 0 + 0.1 \times 1) = \sigma(0.2) = 0.5498$$

$$O_d = \sigma(0.1 \times 0.5498 + 0.1 \times 1) = \sigma(0.15498) = 0.53867$$

The error terms δ for the two neurons, noting $d=1$ for training sample '1'.

$$\delta_d = 0.53867 * (1 - 0.53867) * (1 - 0.53867) = 0.1146$$

$$\delta_c = 0.5498 * (1 - 0.5498) * 0.1 * 0.1146 = 0.002836$$

The correction terms for $a=1, b=0$ & $\eta=0.3$ \therefore

$$\Delta W_{do} = 0.3 * 0.1146 * 1 = 0.0342$$

$$\Delta W_{dc} = 0.3 * 0.1146 * 0.5498 = 0.0189$$

$$\Delta W_{co} = 0.3 * 0.002836 * 1 = 0.000849$$

$$\Delta W_{ca} = 0.3 * 0.002836 * 1 = 0.000849$$

$$\Delta W_{cb} = 0.3 * 0.002836 * 0 = 0$$

and the new weights become:

$$W_{do} = 0.1 + 0.0342 = 0.1342$$

$$W_{dc} = 0.1 + 0.0189 = 0.1189$$

$$W_{co} = 0.1 + 0.000849 = 0.100849$$

$$W_{ca} = 0.1 + 0.000849 = 0.100849$$

$$W_{cb} = 0.1 + 0 = 0.1$$

Training example 2: \therefore

The OP for $a=0$ & $b=1$ is \therefore

$$\begin{aligned} O_c &= \sigma(0.100849 * 0 + 0.1 * 1 + 0.100849 * 1) \\ &= \sigma(0.200849) = 0.55 \end{aligned}$$

$$O_d = \sigma(0.1189 * 0.55 + 0.1342 * 1) = \sigma(0.1996)$$

$$d=0 \rightarrow \text{Error term} = 0.5497$$

$$\begin{aligned} \delta_d &= 0.5497 * (1 - 0.5497) * (0 - 0.5497) \\ &= -0.1361 \end{aligned}$$

$$\delta_c = 0.55 * (1 - 0.55) * 0.1189 * (-0.1361) = -0.004$$

Computing the correction terms as follows,

$$a=0 ; b=1 ; \eta=0.3 \text{ \& } \alpha=0.9$$

$$\Delta W_{do} = 0.3 \times (-0.1361) \times 1 + 0.9 \times 0.0342 = -0.01$$

$$\Delta W_{dc} = 0.3 \times (-0.1361) \times 0.55 + 0.9 \times 0.0189 \\ = -0.0055$$

$$\Delta W_{co} = 0.3 \times (-0.004) \times 1 + 0.9 \times 0.000849 \\ = -0.004$$

$$\Delta W_{ca} = 0.3 \times (-0.004) \times 0 + 0.9 \times 0.000849 \\ = 0.00086$$

$$\Delta W_{cb} = 0.3 \times (-0.004) \times 1 + 0.9 \times 0 = -0.0012$$

and the new weights become:

$$W_{do} = 0.1342 - 0.01 = 0.1242$$

$$W_{dc} = 0.1189 - 0.0055 = 0.1134$$

$$W_{co} = 0.100849 - 0.0004 = 0.100809$$

$$W_{ca} = 0.100849 + 0.00086 = 0.1016$$

$$W_{cb} = 0.1 - 0.0012 = 0.0988$$

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Original (as in Table 4.2)

$$\delta_h \leftarrow O_h (1 - O_h) \sum W_{kh} \delta_k$$

$$\delta_k \leftarrow O_k (1 - O_k) (t_k - O_k)$$

Assuming $\rightarrow O = \tanh(\bar{w} * \bar{x})$

$$\tanh'(x) = 1 - \tanh^2(x)$$

so the new updation rule becomes:

$$\delta_k \rightarrow (1 - O_k^2) (t_k - O_k)$$

$$\delta_h \rightarrow (1 - O_h^2) \sum W_{kh} \delta_k$$