
Assignment-1

CS771 Introduction to Machine Learning

Drashtant Singh Rathod(22111021)
Sudiksha Navik(22111059)
Taneya Soni(22111062)
Sonam(22111057)
Chetna Singh(22111018)

1 Solution-1

We have,

$$m : \{0, 1\} \rightarrow \{-1, +1\}$$
$$f : \{-1, +1\} \rightarrow \{0, 1\}$$

Let function, $m(x) = 1 - 2x$

if $x = 0$ then $m = 1$

if $x = 1$ then $m = -1$

and

function, $f = \frac{(1-x)}{2}$

if $x = -1$ then $f = 1$

if $x = 1$ then $f = 0$

To Prove,

$\text{XOR}(b_1, b_2, b_3, \dots, b_n) = f(\prod_{i=1}^n m(b_i))$ for any set of binary $b_1, b_2, b_3, \dots, b_n$ for any $n \in \mathbb{N}$

CASE :1

If n is even ,

Case a : If no of 1's are even, hence no of 0's are even

$$L.H.S = 0$$

$$\begin{aligned} R.H.S &= f(m(b_1).m(b_2).m(b_3) \dots m(b_n)) \\ &= f((1 - 2b_1).(1 - 2b_2).(1 - 2b_3) \dots (1 - 2b_n)) \\ &= f(-1 * -1 \dots +1 * +1) \\ &= f(1) \\ &= \frac{1 - (1)}{2} \\ &= 0 \end{aligned}$$

$$\rightarrow \text{hence } L.H.S = R.H.S$$

Case b: If no of 1's are odd, hence no of 0's are odd

$$L.H.S = 1$$

$$\begin{aligned} R.H.S &= f(m(b_1).m(b_2).m(b_3)..m(b_n)) \\ &= f((1 - 2b_1).(1 - 2b_2).(1 - 2b_3)...(1 - 2b_n)) \\ &= f(-1) \\ &= \frac{1 - (-1)}{2} \\ &= 1 \\ &\rightarrow \text{hence } L.H.S = R.H.S \end{aligned}$$

CASE :2

If n is odd ,

Case a: If no of 1's are even, hence no of 0's are odd

$$L.H.S = 0$$

$$\begin{aligned} R.H.S &= f(m(b_1).m(b_2).m(b_3)...m(b_n)) \\ &= f((1 - 2b_1).(1 - 2b_2).(1 - 2b_3)...(1 - 2b_n)) \\ &= f(1) \\ &= \frac{1 - (1)}{2} \\ &= 0 \\ &\rightarrow \text{hence } L.H.S = R.H.S \end{aligned}$$

Case b: If no of 1's are odd, hence no of 0's are even

$$L.H.S = 1$$

$$\begin{aligned} R.H.S &= f(m(b_1).m(b_2).m(b_3)...m(b_n)) \\ &= f((1 - 2b_1).(1 - 2b_2).(1 - 2b_3)...(1 - 2b_n)) \\ &= f(-1) \\ &= \frac{1 - (-1)}{2} \\ &= 1 \\ &\rightarrow \text{hence } L.H.S = R.H.S \end{aligned}$$

2 Solution-2

$$\prod_{i=1}^n \text{sign}(r_i) = \text{sign}(\prod_{i=1}^n r_i)$$

Taking LHS,

$$\begin{aligned} \therefore \text{sign}(r_i) &= \frac{r_i}{|r_i|} \text{ if } \forall r_i \notin 0 \text{ and } r_i \in R \\ \therefore \text{sign}(0) &= 0 \\ \therefore \text{sign}(r_i) &= 0 \end{aligned}$$

case-a) when there is atleast one r_i as zero

LHS : –

$$= \prod \text{sign}(r_i)$$

$$= \frac{r_1}{|r_1|} * \frac{r_2}{|r_2|} * \frac{r_3}{|r_3|} * \frac{r_4}{|r_4|} * \dots * \frac{r_n}{|r_n|}$$

if $\exists i$ such that $\text{sign}(r_i) = 0 \rightarrow r_i = 0$
then

$$\frac{r_1}{|r_1|} * \frac{r_2}{|r_2|} * \frac{r_3}{|r_3|} * \frac{r_4}{|r_4|} * \dots * \frac{r_9}{|r_n|} = 0$$

RHS:-

$$= \text{sign}(\prod r_i) \text{ if } \exists i \text{ such that } r_i = 0 \rightarrow \text{sign}(r_i) = 0$$

$$\therefore \text{sign}(r_1 * r_2 * r_3 * r_4 * \dots * r_{i-1} * r_i * r_{i+1} * \dots * r_n) = \text{sign}(0) = 0$$

$$LHS = RHS \quad \text{if } \exists i \text{ such that } r_i = 0$$

case-b) when $\forall i \ r_i \neq 0$

LHS : –

$$\text{sign}(r_i) = \frac{r_i}{|r_i|}$$

$$\therefore \forall i \ r_i \neq 0 \dots \dots \dots (1)$$

$$\prod \text{sign}(r_i) = \left(\frac{r_1}{|r_1|} * \frac{r_2}{|r_2|} * \frac{r_3}{|r_3|} * \frac{r_4}{|r_4|} * \dots * \frac{r_n}{|r_n|} \right)$$

RHS : –

$$= \text{sign}(\prod r_i)$$

$$= \text{sign}(r_1 * r_2 * r_3 * \dots * r_n) \forall i \ r_i \neq 0$$

using (1)

$$\text{sign}(r_1 * r_2 * r_3 * \dots * r_n) = \frac{r_1 * r_2 * r_3 * \dots * r_n}{|r_1 * r_2 * \dots * r_n|}$$

$$\therefore |a_1 * a_2 * a_3 * \dots * a_n| = |a_1| * |a_2| * |a_3| * \dots * |a_n|$$

$$\therefore \frac{r_1}{|r_1|} * \frac{r_2}{|r_2|} * \frac{r_3}{|r_3|} * \frac{r_4}{|r_4|} * \dots * \frac{r_n}{|r_n|}$$

$$\therefore LHS = RHS$$

3 Solution-3

We have given $(\tilde{u}^T \tilde{x}) \cdot (\tilde{v}^T \tilde{x}) \cdot (\tilde{w}^T \tilde{x})$. Number of features in each of 'x' feature vectors is 8. To make it simpler we hide the bias the term to get we get \tilde{x} which is 9 dimensional vector. We aim to model the prediction $(\tilde{u}^T \tilde{x}) \cdot (\tilde{v}^T \tilde{x}) \cdot (\tilde{w}^T \tilde{x})$ quantity into a single linear model with a different dimensionality D. Directly solving for three PUFs:

$$(\tilde{u}^T \tilde{x}) \cdot (\tilde{v}^T \tilde{x}) \cdot (\tilde{w}^T \tilde{x}) = \left(\sum_{i=1}^9 \tilde{u}_i \tilde{x}_i \right) \cdot \left(\sum_{j=1}^9 \tilde{v}_j \tilde{x}_j \right) \cdot \left(\sum_{k=1}^9 \tilde{w}_k \tilde{x}_k \right) \quad (1)$$

$$= \sum_{i=1}^9 \sum_{j=1}^9 \sum_{k=1}^9 \tilde{u}_i \tilde{v}_j \tilde{w}_k \tilde{x}_i \tilde{x}_j \tilde{x}_k \quad (2)$$

So,

$$(\tilde{u}^T \tilde{x}) \cdot (\tilde{v}^T \tilde{x}) \cdot (\tilde{w}^T \tilde{x}) = u_1 v_1 w_1 x_1 x_1 x_1 + u_1 v_1 w_2 x_1 x_1 x_2 + u_1 v_1 w_3 x_1 x_1 x_3 + \dots + u_9 v_9 w_9 x_9 x_9 x_9$$

There are $9 * 9 * 9 = 729$ terms in our linear equation where $i, j, k \in [1, 9]$.

Therefore $9^3 = 729$ dimensional function that maps $\tilde{x} = (\tilde{x}_1, \tilde{x}_2, \tilde{x}_3)$ to

$$\phi(\tilde{x}) = \begin{pmatrix} \tilde{x}_1 \tilde{x}_1 \tilde{x}_1 & \dots & \tilde{x}_1 \tilde{x}_1 \tilde{x}_9 & \dots & \tilde{x}_1 \tilde{x}_2 \tilde{x}_1 & \dots & \tilde{x}_1 \tilde{x}_2 \tilde{x}_9 \\ \tilde{x}_1 \tilde{x}_3 \tilde{x}_1 & \dots & \tilde{x}_1 \tilde{x}_3 \tilde{x}_9 & \dots & \tilde{x}_1 \tilde{x}_4 \tilde{x}_1 & \dots & \tilde{x}_1 \tilde{x}_4 \tilde{x}_9 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \tilde{x}_2 \tilde{x}_1 \tilde{x}_1 & \dots & \tilde{x}_2 \tilde{x}_1 \tilde{x}_9 & \dots & \tilde{x}_2 \tilde{x}_2 \tilde{x}_1 & \dots & \tilde{x}_2 \tilde{x}_2 \tilde{x}_9 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \tilde{x}_9 \tilde{x}_8 \tilde{x}_1 & \dots & \tilde{x}_9 \tilde{x}_8 \tilde{x}_9 & \dots & \tilde{x}_9 \tilde{x}_9 \tilde{x}_1 & \dots & \tilde{x}_9 \tilde{x}_9 \tilde{x}_9 \end{pmatrix}$$

$$(\tilde{u}^T \tilde{x}) \cdot (\tilde{v}^T \tilde{x}) \cdot (\tilde{w}^T \tilde{x}) = W^T \phi(\tilde{x})$$

$$W = \begin{pmatrix} \tilde{u}_1 \tilde{v}_1 \tilde{w}_1 & \tilde{u}_1 \tilde{v}_1 \tilde{w}_2 & \tilde{u}_1 \tilde{v}_1 \tilde{w}_3 & \dots & \tilde{u}_1 \tilde{v}_1 \tilde{w}_9 \\ \tilde{u}_1 \tilde{v}_2 \tilde{w}_1 & \tilde{u}_1 \tilde{v}_2 \tilde{w}_2 & \tilde{u}_1 \tilde{v}_2 \tilde{w}_3 & \dots & \tilde{u}_1 \tilde{v}_2 \tilde{w}_9 \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \tilde{u}_9 \tilde{v}_9 \tilde{w}_1 & \tilde{u}_9 \tilde{v}_9 \tilde{w}_2 & \tilde{u}_9 \tilde{v}_9 \tilde{w}_3 & \dots & \tilde{u}_9 \tilde{v}_9 \tilde{w}_9 \end{pmatrix}$$

Actually, $\phi(\tilde{x})$ and W is 1-Dimensional

Dimensionality (D) = $(8 + 1)^3 = 729$, which depends on number of PUFs i.e. 3 and dimensionality of $\tilde{x} = 8 + 1 = 9$

Hence proved.

4 Solution-4

Solved in submit.py file

5 Solution-5

In the method used, there are two hyperparameters

1 \rightarrow step length

2 \rightarrow C

The optimal values of the hyperparameters are obtained by random testing ,we tested a certain number of submission that we selected randomly.

The value of the hyperparameter C is highly affecting the missclassification error.

On decreasing the value of C , the average error increases. We found the optimal value that is $C=7$, by slowly increasing the value and found that there comes a point,at which on further increasing the value of C , the average error again starts increasing.

The value of step length η affects the value of hinge loss.We found the optimal value of step length is increased from the found optimal,the hinge loss value increases

The optimal values :- $\eta = 9.4e^{-6}$, $C = 7$

The optimal values provide a trade off between misclassification error and hinge loss.

6 Solution-6

