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# CS771: Introduction to Machine Learning

## Assignment 1

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### Problem 1 :

Given, set of binary digits  $b_1, b_2, b_3, \dots, b_n$  such that  $n \in \mathbb{N}$  where, each  $b_i \in \{0, 1\}$  for  $i = 1, 2, \dots, n$

Now, we know that for any set of binary digits  $b_1, b_2, \dots, b_n$

$$XOR(b_1, b_2, \dots, b_n) = \begin{cases} 1, & \text{if there are odd number of } b_i \text{ having value 1} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Now, if we choose a function  $m$  such that

$$m(0) = 1 \text{ and } m(1) = -1 \text{ or } m(x) = 1 - 2x \quad (2)$$

$$f(-1) = 1 \text{ and } f(1) = 0 \text{ or } f(x) = (1 - x)/2 \quad (3)$$

Then,

$$m(b_i) = \begin{cases} -1, & \text{if } b_i = 1 \\ 1, & \text{else if } b_i = 0 \end{cases} \quad (4)$$

This means that

$$\prod m(b_i) = \begin{cases} -1, & \text{if there are odd number of } b_i \text{ having value 1} \\ 1, & \text{if there are even number of } b_i \text{ having value 1} \end{cases} \quad (5)$$

Applying function  $f$  given in equation (3) on equation (5) we get,

$$f\left(\prod m(b_i)\right) = \begin{cases} 1 & \text{if there are odd number of } b_i \text{ having value 1} \\ 0 & \text{if there are even number of } b_i \text{ having value 1} \end{cases} \quad (6)$$

From equation (1) and (6) we can conclude that

$$XOR(b_1, b_2, \dots, b_n) = f\left(\prod m(b_i)\right) \quad (7)$$

for the function  $f$  and  $m$  as defined in equation 2 and equation 3

## Problem 2 :

Given, we are given set of  $n$  real numbers  $r_1, r_2, \dots, r_n$  such that  $\text{sign}(0) = 0$

To Prove:

$$\prod_{i=1}^n \text{sign}(r_i) = \text{sign} \left( \prod_{i=1}^n r_i \right) \text{ for any } n \in \mathbb{N} \quad (8)$$

**Case 1:** when value of atleast one of the  $r_i$  is zero. let us say  $r_k = 0$  where  $1 < k < n$  In this case, L.H.S is given by,

$$\left( \prod_{i=1}^{k-1} \text{sign}(r_i) \right) \cdot \text{sign}(r_k) \cdot \left( \prod_{i=k+1}^n \text{sign}(r_i) \right) \quad (9)$$

Now, since  $r_k = 0$  As product of real number with zero is 0. Therefore,  $\text{sign}(r_k) = 0$  (given)  
Therefore, L.H.S = 0

R.H.S. is given by

$$\text{sign} \left( \prod_{i=1}^n r_i \right) = \text{sign} \left( \left( \prod_{i=1}^{k-1} r_i \right) \cdot (r_k) \cdot \left( \prod_{i=k+1}^n r_i \right) \right) \quad (10)$$

Now, since  $r_k = 0$  Therefore,

$$\prod_{i=1}^n r_i = 0 \quad (11)$$

Since  $\text{sign}(0) = 0$  (Given). Therefore,

$$\text{sign} \left( \prod_{i=1}^n r_i \right) = 0 \quad (12)$$

From equation(9) and equation (12) we have L.H.S = R.H.S. Proved

**Case 2:**  $r_i \neq 0$  for  $i=1, 2, \dots, n$  for any  $n \in \mathbb{N}$

R.H.S is given by,

$$\text{sign} \left( \prod_{i=1}^n r_i \right) = \text{sign} \left( \prod_{i=1}^n |r_i| \cdot \prod_{i=1}^n \text{sign}(r_i) \right) \quad (13)$$

Now,  $|r_i|$  is always positive. Therefore,

$$\prod_{i=1}^n |r_i| \text{ is positive} \quad (14)$$

Therefore, equation (13) can be rewritten as

$$\text{sign} \left( \prod_{i=1}^n \text{sign}(r_i) \right) \quad (15)$$

And Thus R.H.S is same as

$$\text{sign} (L.H.S.) \quad (16)$$

Now, L.H.S is given by,

$$\prod_{i=1}^n \text{sign}(r_i) \quad (17)$$

We can see from above equation (17) that L.H.S can be either 1 or -1

Thus, if  $L.H.S = 1$  then,  $R.H.S = \text{sign}(L.H.S) = 1$

Else if  $L.H.S = -1$  then,  $R.H.S = \text{sign}(L.H.S) = -1$

Thus, in Case 2 also  $L.H.S = R.H.S$

From the above two cases we can conclude that  $L.H.S = R.H.S$  [proved]

### Problem 3 :

Given, expression

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) \cdot (\mathbf{w}^T \mathbf{x}) \quad (18)$$

We need to find a  $\mathbf{W}$  such that  $\mathbf{W} \in R^D$  and a function  $\phi: \mathcal{R}^9 \rightarrow \mathcal{R}^D$  such that for every vector  $\mathbf{x} \in R^9$ , we have,

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) \cdot (\mathbf{w}^T \mathbf{x}) = \mathbf{W}^T \phi(\mathbf{x}) \quad (19)$$

Let us first solve for case when we have two terms in the *L.H.S* i.e.

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) \quad (20)$$

Now, the above equation can be rewritten as

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) = \left( \sum_{i=1}^9 u_i x_i \right) \cdot \left( \sum_{j=1}^9 v_j x_j \right) \quad (21)$$

Now,

$$\left( \sum_{i=1}^9 u_i x_i \right) \cdot \left( \sum_{j=1}^9 v_j x_j \right) = \left( \sum_{i=1}^9 u_i x_i \right) \cdot (v_1 x_1 + v_2 x_2 + \dots + v_9 x_9) \quad (22)$$

$$= (u_1 x_1 + u_2 x_2 + \dots + u_9 x_9) v_1 x_1 + (u_1 x_1 + u_2 x_2 + \dots + u_9 x_9) v_2 x_2 + \dots \quad (23)$$

$$= u_1 x_1 v_1 x_1 + u_1 x_1 v_2 x_2 + \dots + u_2 x_2 v_1 x_1 + u_2 x_2 v_2 x_2 + \dots + u_9 x_9 v_1 x_1 + \dots + u_9 x_9 v_9 x_9 \quad (24)$$

Thus the above equation can be rewritten as,

$$= \sum_{i=1}^9 \sum_{j=1}^9 u_i v_j x_i x_j \quad (25)$$

$$= \sum_{i=1}^9 \sum_{j=1}^9 u_i v_j x_i x_j \quad (26)$$

From equation (22) and equation(26), we get

$$\left( \sum_{i=1}^9 u_i x_i \right) \cdot \left( \sum_{j=1}^9 v_j x_j \right) = \sum_{i=1}^9 \sum_{j=1}^9 u_i v_j x_i x_j \quad (27)$$

Thus, from above equation we see that we can create 81 dimensional function that maps  $\mathbf{x} = (x_1, \dots, x_9)$  to  $\phi(\mathbf{x}) = (x_1 x_1, x_1 x_2, \dots, x_1 x_9, x_2 x_1, \dots, x_9 x_9)$  Thus, from equation (21) and equation (26) we get

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) = \mathbf{W}^T \phi(\mathbf{x}) \quad (28)$$

Where,

$$\mathbf{W} = (u_1 v_1, u_1 v_2, \dots, u_1 v_9, u_2 v_1, \dots, u_9 v_9) \quad (29)$$

Now, Working on similar lines as above we can proceed and solve expression (18)

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) \cdot (\mathbf{w}^T \mathbf{x}) = \left( \sum_{i=1}^9 u_i x_i \right) \cdot \left( \sum_{j=1}^9 v_j x_j \right) \cdot \left( \sum_{k=1}^9 w_k x_k \right) \quad (30)$$

Now, using the result derived in equation(27), we can rewrite the equation as

$$= \left( \sum_{i=1}^9 u_i x_i \right) \cdot \left( \sum_{j=1}^9 \sum_{k=1}^9 v_j w_k x_j x_k \right) \quad (31)$$

Again, applying the result derived in equation(27), we can rewrite the above equation as

$$= \left( \sum_{i=1}^9 \sum_{j=1}^9 \sum_{k=1}^9 u_i v_j w_k x_i x_j x_k \right) \quad (32)$$

Thus, from above equation we see that we can create 729 dimensional function that maps  $\mathbf{x} = (x_1, \dots, x_9)$  to  $\phi(\mathbf{x}) = (x_1 x_1 x_1, x_1 x_1 x_2, \dots, x_1 x_1 x_9, x_1 x_2 x_1, \dots, x_9 x_9 x_9)$  Thus, from equation (30) and equation (32) we get

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) \cdot (\mathbf{w}^T \mathbf{x}) = \mathbf{W}^T \phi(\mathbf{x}) \quad (33)$$

Where,

$$\mathbf{W} = (u_1 v_1 w_1, u_1 v_1 w_2, \dots, u_1 v_1 w_9, u_1 v_2 w_1, \dots, u_9 v_9 w_9) \quad (34)$$

Thus, vector  $\mathbf{W} \in \mathcal{R}^{729}$  as given in equation(34) and a function  $\phi: \mathcal{R}^9 \rightarrow \mathcal{R}^{729}$  as given above exists such that

$$(\mathbf{u}^T \mathbf{x}) \cdot (\mathbf{v}^T \mathbf{x}) \cdot (\mathbf{w}^T \mathbf{x}) = \mathbf{W}^T \phi(\mathbf{x}) \quad (35)$$

## Problem : 5

Method Used For Optimization : **Stochastic Gradient Descent**

Policy used to choose the next data point from the Dataset : **Sequential**

Hyperparameters :

- Learning Rate or Step Length : **0.027**
  - We tried **constant** step length of 0.1, 0.01, 0.02, 0.027, turned out 0.027 was giving the best results among all. Moreover we tried making it linear with initial learning rate - 1, 2, 2.5, 3 as well but constant turned out to be the best.
- C : **3**
  - We tried C to be 1, 2, 4, 3, 2.5, 2.9, 3.1 of which 3 was giving the best results among all.
- Regularizer (r) :  **$10^{-5}$** 
  - We tried regularizer (r) to be  $10^{-1}$ ,  $10^{-3}$ ,  $10^{-4}$ ,  $10^{-5}$  of which  $10^{-5}$  was giving the best results among all.

## Problem : 6

