ASSIGNMENT 1

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1 Question 1

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Given, m: is a function that maps \{0,1\} \rightarrow \{-1,+1\}
f: is a function that maps \{-1, +1\} \rightarrow \{0, 1\}
Aim is to map \{0,1\} \rightarrow \{-1,+1\} and vice-versa
\Rightarrow XOR(b_1, b_2, \dots, b_n) = f(\prod_{i=n}^n m(b_i) \text{ for any } n \in N
\Rightarrow XOR(b_1, b_2, \cdots, b_n) = f(m(b_1).m(b_2)\cdots.m(b_n))
s_i \in \{-1, +1\} and b_i \in \{0, 1\}
\mathbf{m}(\mathbf{b}_i): s_i = 1 - 2b_i
found through line joining (0,+1) and (+1,-1)
m: { \{ \substack{+1; b_i = 0 \\ -1; b_i = 1 } \} }
f(s_i): b_i = (1 - s_i)/2
found through line joining (+1,0) and (-1,+1)
f: {0; s_i = +1 \atop 1; s_i = -1}
say B(b_1, b_2 \cdots, b_n) = (10101001)_2
lets see if XOR(B) = f(m(b_1).m(b_2).\cdots.m(b_n))
\Rightarrow XOR(1,0,1,0,1,0,0,1) = f(m(1).m(0).m(1).m(0).m(1).m(0).m(0).m(1))
\Rightarrow 0 = f((-1).(+1).(-1).(+1).(-1).(+1).(+1).(-1))
\Rightarrow 0 = f(+1)
\Rightarrow 0 = 0
LHS = RHS
Hence it is proved that there exists a way to map \{0,1\} \rightarrow \{-1,+1\} and viceversa
so that XOR(b_1, b_2, \dots, b_n) = f(m(b_1).m(b_2).\dots.m(b_n))i.e.
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Preprint. Under review.

we can represent XOR as product by functions m and f

2 Question 2

Given,
$$\prod_{i=1}^n (sign(r_i)) = sign(\prod_{i=1}^n (r_i)) \to EQ1$$

$$\operatorname{sign}(0) = 0$$
 +ve is short term for positive and -ve is short term for negative "We will Prove this by using Mathematical Induction" For $i=1$ $\Rightarrow sign(r_1) = sign(r_1)$ $\Rightarrow LHS = RHS$ For $i=2$ $\Rightarrow sign(r_1).sign(r_2) = sign(r_1.r_2)$ If $\operatorname{r}_1 is + ve$ then $\Rightarrow sign(r_2) = sign(r_2)$ $\Rightarrow LHS = RHS$ If $\operatorname{r}_1 is - ve$ then $\Rightarrow -sign(r_2) = sign(-(r_2))$ $\Rightarrow -sign(r_2) = -sign(r_2)$ $\Rightarrow LHS = RHS$ Lets assume EQ1 is valid for $i=k$ i.e.

Lets prove that EQ1 is also true for
$$i = k+1$$

i.e. $sign(r_1).sign(r_2).....sign(r_k).sign(r_{k+1}) = sign(r_1.r_2.....r_k.r_{k+1}) \rightarrow EQ2$

rewrite EQ2 as
$$\Rightarrow [sign(r_1).sign(r_2).\cdots.sign(r_k)].sign(r_{k+1}) = sign((r_1.r_2.\cdots.r_k).r_{k+1})$$

Our Hypothesis is $sign(r_1).sign(r_2).....sign(r_k) = sign(r_1.r_2.....r_k)$

Now lets prove by analysing possible cases of "sign (r_{k+1}) "

$$\begin{aligned} & \textit{CASE 1: If } \textit{sign}(r_{k+1}) = 0 \text{ then} \\ &\Rightarrow [\textit{sign}(r_1).\textit{sign}(r_2).\cdots.\textit{sign}(r_k)].0 = \textit{sign}((r_1.r_2.\cdots.r_k).0) \\ &\text{as from given } \textit{sign}(0) = 0 \\ &\Rightarrow 0 = \textit{sign}(0) \\ &\Rightarrow 0 = 0 \\ &\Rightarrow \textit{LHS} = \textit{RHS} \end{aligned}$$

$$& \textit{CASE 2: If } \textit{sign}(r_{k+1}) \text{ is } + \textit{ve then} \\ &\Rightarrow [\textit{sign}(r_1).\textit{sign}(r_2).\cdots.\textit{sign}(r_k)].(+\textit{ve}) = \textit{sign}((r_1.r_2.\cdots.r_k).(+\textit{ve})) \end{aligned}$$

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\Rightarrow Subcase 1: If(sign(r_1).sign(r_2).\cdots.sign(r_k)) is + ve then
sign((r_1.r_2.\cdots.r_k)) is also +ve, from hypothesis
So, \Rightarrow [+ve].(+ve) = sign((+ve).(+ve))
\Rightarrow +ve = sign(+ve)
\Rightarrow +ve = +ve
\Rightarrow LHS = RHS
\Rightarrow Subcase 2: If(sign(r_1).sign(r_2).\cdots.sign(r_k)) is -ve then
sign((r_1.r_2.\cdots.r_k)) is also -ve, from hypothesis
So, \Rightarrow [-ve].(+ve) = sign((-ve).(+ve))
\Rightarrow -ve = sign(-ve)
\Rightarrow -ve = -ve
\Rightarrow LHS = RHS
\Rightarrow Subcase 3: If(sign(r_1).sign(r_2).....sign(r_k)) is 0 ( due to any r_i(i:1 \text{ to } k)=0)
then sign((r_1.r_2.\cdots.r_k)) is also 0, from hypothesis
\Rightarrow [0].(+ve) = sign((0).(+ve))
\Rightarrow 0 = sign(0)
\Rightarrow 0 = 0
\Rightarrow LHS = RHS
CASE 3: If sign(r_{k+1}) is -ve then
\Rightarrow [sign(r_1).sign(r_2).\cdots.sign(r_k)].(-ve) = sign((r_1.r_2.\cdots.r_k).(-ve))
\Rightarrow 3 Subcases
\Rightarrow Subcase 1: If (sign(r1).sign(r2).....sign(rk)) is + ve then
sign((r1.r2.\cdots.rk)) is also +ve, from hypothesis
So, \Rightarrow [+ve].(-ve) = sign((+ve).(-ve))
\Rightarrow -ve = sign(-ve)
\Rightarrow -ve = -ve
\Rightarrow LHS = RHS
\Rightarrow Subcase 2: If (sign(r1).sign(r2).\cdots.sign(rk)) is -ve then
sign((r1.r2.\cdots.rk)) is also -ve, from hypothesis
So, \Rightarrow [-ve].(-ve) = sign((-ve).(-ve))
\Rightarrow +ve = sign(+ve)
\Rightarrow +ve = +ve
\Rightarrow LHS = RHS
\Rightarrow Subcase 3: If (sign(r1).sign(r2).....sign(rk)) is 0 (due to any r_i (1 to k) = 0)
then sign((r1.r2.\cdots.rk)) is also 0, from hypothesis
So, \Rightarrow [0].(-ve) = sign((0).(-ve))
\Rightarrow 0 = sign(0)
\Rightarrow 0 = 0
\Rightarrow LHS = RHS
From the above cases i.e. for r_{k+1} = \{-ve, 0, +ve\}
It is proven that,
sign(r_1).sign(r_2).\cdots.sign(r_k).sign(r_{k+1}) = sign(r_1.r_2.\cdots.r_k.r_{k+1}); k \in N
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 $\Rightarrow 3$ Subcases

3 **Question 3**

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Aim is to prove that there exists a way to map 9 dimensional vectors to D dimensional vectors as
\phi: R^9 - > R^D
such that for any triple (\tilde{u}, \tilde{v}, \tilde{w}), there always exists a vector W \in \mathbb{R}^D
such that for every \tilde{x} \in \mathbb{R}^9, we have
(\tilde{u}^T\tilde{x}).(\tilde{v}^T\tilde{x}).(\tilde{w}^T\tilde{x}) = W^T.\phi(\tilde{x}) \to EQ1
If we expand the terms on the LHS of EQ1 \Rightarrow (\tilde{u}^T\tilde{x}).(\tilde{v}^T\tilde{x}).(\tilde{w}^T\tilde{x}) = (\sum_{i=1}^9 \tilde{u}_i\tilde{x}_i)(\sum_{j=1}^9 \tilde{u}_j\tilde{x}_j)(\sum_{k=1}^9 \tilde{w}\tilde{x}_k)
we get \sum_{i=1}^{9} \sum_{j=1}^{9} \sum_{k=1}^{9} \tilde{u}_i \tilde{u}_j \tilde{u}_k \tilde{x}_i \tilde{x}_j \tilde{x}_k
Now, if we write a 9^3 = 729 dimensional function that maps
\Rightarrow \tilde{x} = (\tilde{x}_1, ..., \tilde{x}_9) \rightarrow \phi(\tilde{x}) = (\tilde{x}_1 \tilde{x}_1 \tilde{x}_1, \tilde{x}_1 \tilde{x}_1 \tilde{x}_2, \cdots, \tilde{x}_1 \tilde{x}_1 \tilde{x}_9, \tilde{x}_1 \tilde{x}_2 \tilde{x}_1, \cdots, \tilde{x}_9 \tilde{x}_9 \tilde{x}_9)
\Rightarrow \phi(\tilde{x}) = \tilde{x}.\tilde{x}.\tilde{x} \rightarrow cartesian \ product \ of \ vectors
\Rightarrow cardinality \ of \ vector(\phi(x)) = 729
so that we get (\tilde{u}^T \tilde{x}).(\tilde{v}^T \tilde{x}).(\tilde{w}^T \tilde{x}) = W^T.\phi(\tilde{x}) by taking
\Rightarrow W = \tilde{u}.\tilde{v}.\tilde{w} \rightarrow cartesian \ product \ of \ vectors
\Rightarrow W = (\tilde{u}_1 \tilde{v}_1 \tilde{w}_1, \tilde{u}_1 \tilde{v}_1 \tilde{w}_2, \cdots, \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}_9, \cdots, \tilde{u}_9 \tilde{v}_9 \tilde{w}_9)
\Rightarrow cardinality of vector(W) = 729
i.e.
\Rightarrow (\tilde{u}^T \tilde{x}).(\tilde{v}^T \tilde{x}).(\tilde{w}^T \tilde{x}) =
(\tilde{u}_1\tilde{v}_1\tilde{w}_1,\cdots,\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}_9,\cdots,\tilde{u}_9\tilde{v}_9\tilde{w}_9)^T.(\tilde{x}_1\tilde{x}_1\tilde{x}_1,\cdots,\tilde{x}_1\tilde{x}_1\tilde{x}_9,\tilde{x}_1\tilde{x}_2\tilde{x}_1,\cdots,\tilde{x}_9\tilde{x}_9\tilde{x}_9)
Hence it is proved that we can map 9 dimensional to D(729) dimensional vectors,
there always exists a vector W \in \tilde{R}^D for any triple (\tilde{u}, \tilde{v}, \tilde{w})
such that for every \tilde{x} \in \mathbb{R}^9,
we have (\tilde{u}^T \tilde{x}).(\tilde{v}^T \tilde{x}).(\tilde{w}^T \tilde{x}) = W^T.\phi(\tilde{x})
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4 Question 5

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The hyperparameters we used are C and \eta C in \nabla W = W + C(\tilde{x}.y) \eta in W = W - \eta(\nabla W)
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How we have set the final values of C and η is by following the technique of obtaining highest accuracy possible, with less punishment(C) for loss, a modable step-length(η) which doesn't lead to over-shooting around global minima.

From experimental history we have initialized η with 0.01 and C with 1 on tinkering with η with C = 1 we checked η for various values less than 0.01 like 0.008, 0.004, 0.002 and finally arrived @ $\eta=0.001$ for which we had an accuracy of 98.53% with less over-shooting around global minima. Now with $\eta=0.001$ we tuned C for which we can get near to 100% accuracy, the progression of accuracy with different C was like this.

C = 1	Accuracy = 98.53%
C = 3	Accuracy = 95.83%
C = 5	Accuracy = 99.36%
C = 5.5	Accuracy = 97.58%
C = 5.7	Accuracy = 100%
C = 6	Accuracy = 100%
C = 7	Accuracy = 100%
C = 30	Accuracy = 100%

Finally we concluded $\eta=0.001$ and C=5.7 as sweet-spot for our hyperparameters based on train data.

5 Question 6

