

Assignment3

Foundations of Machine Learning

IIT-Hyderabad

Aug-Dec 2021

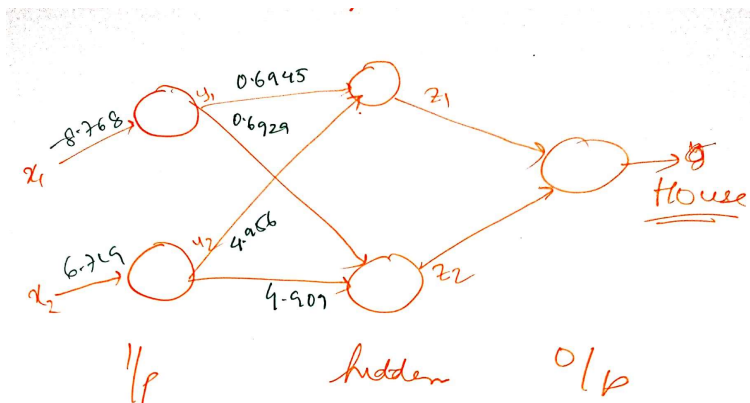
Submitted by:

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BM21MTECH14001

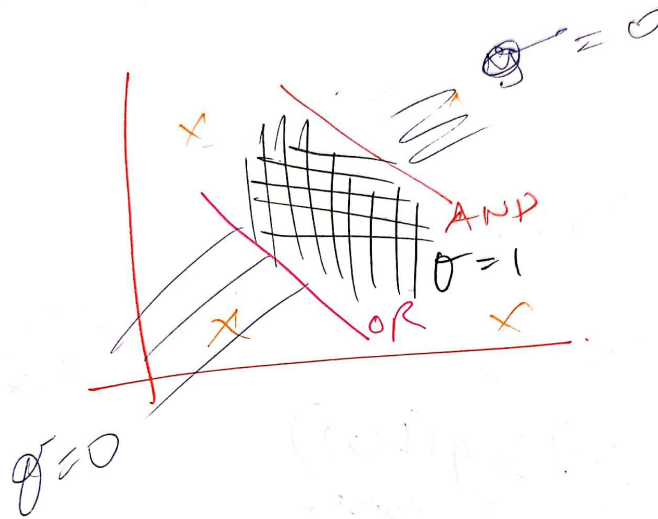
Questions: Theory

1a) Neural Networks (XOR)



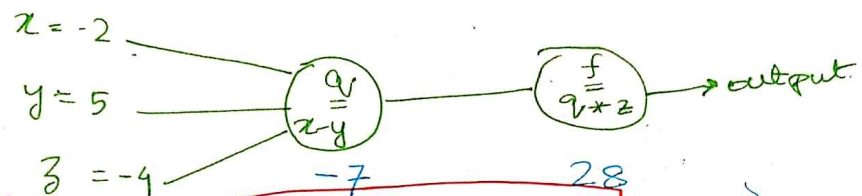
Working :

x_1	x_2	And	OR	XOR
		y_1	y_2	z_1
0	0	0	0	0
0	1	0	1	1
1	0	0	1	1
1	1	1	1	0



1b)

Graphical representation



Gradient of f w.r.t. x, y and z

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial x} = z * 1 = \boxed{z = \frac{\partial f}{\partial x}}$$

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial y} = z * (-1) = \boxed{-z = \frac{\partial f}{\partial y}}$$

$$\frac{\partial f}{\partial z} = \frac{\partial f}{\partial q} * \frac{\partial q}{\partial z} = q = \boxed{x - y = \frac{\partial f}{\partial z}}$$

3.

Given: $E_{AV} = \frac{1}{M} \sum_m E_x (y_m(x) - f(x))^2$

$E_{ENS} = E_x \left[\left(\frac{1}{M} \sum_m y_m(x) - f(x) \right)^2 \right]$

$f(x) = x^2$

To prove: $E_{ENS} \leq E_{AV}$

Proof

Jensen's Inequality

here: $x \rightarrow f(x) = x^2$

$E(g(x)) \geq g(E(x))$

using above $E \geq \sum$ can be

$E_{AV} = \frac{1}{M} \sum_m E_x (y_m(x) - f(x))^2$

$\therefore E \geq \sum = \frac{1}{M} \sum_m E_x (y_m(x))^2 - \frac{2}{M} \sum_m E_x y_m(x) f(x) + \frac{1}{M} \sum_m E_x (f(x))^2$

are under - changeable

No dependence on m

$= \frac{1}{M} \sum_m E_x (y_m(x))^2 - \frac{2}{M} \sum_m E_x y_m(x) f(x) + E_x (f(x))^2$

~~$E_{ENS} - E_{AV} \leq 0$~~

$E_{ENS} = E_x \left(\frac{1}{M} \sum_m y_m(x) \right)^2 - 2 E_x \left(\frac{1}{M} \sum_m y_m(x) f(x) \right) + E_x (f(x))^2$

$E_{ENS} - E_{AV} \leq 0$

$\frac{1}{M^2} - \frac{1}{M} \leq 0$ Hence proven.

Given $M \geq 0$

Let another kind of error be: RMSError

$E_{RMS} = \sqrt{\frac{1}{M} E \left[\sum_i (y_i(x) - f(x))^2 \right]}$

$= \sqrt{\frac{1}{M} \left(E \left[\sum_i y_i(x)^2 \right] + \frac{1}{M} E \left[f(x)^2 \right] \right)}$

$\leq \sqrt{\frac{1}{M} \left[\sum_i y_i(x)^2 \right]}$

On checking with E_{ENS}

$\frac{1}{M} - \frac{1}{M^2} > 0$

Hence $E_{RMS} < E_{ENS}$

Let another kind of error be: RMS error

$$E_{\text{RMS}} = E \left[\frac{1}{N} \left(\sum (y_i(n) - f(n))^2 \right) \right]^{1/2}$$

$$= \frac{1}{N} E \left(\sum y_i^2(n) - 2 \sum y_i(n) f(n) + \sum f^2(n) \right)$$

$$= E \left[\frac{1}{N} \left(\sum y_i^2(n) - 2 \sum y_i(n) f(n) + \sum f^2(n) \right) \right]$$

On checking with $E \in \text{NS}$

$$\frac{1}{N} - \frac{1}{N^2} > 0$$

Hence $E_{\text{RMS}} \in \mathcal{A}_R$

Given: Extension of the cross entropy error function for a multi-class classification problem:

$$E(w) = - \sum_{n=1}^N \sum_{k=1}^K t_{nk} \ln y_k(x_n, w) \quad \rightarrow (1)$$

where, $k = \text{no of classes}$; $N = \text{no. of data samples}$
 $t_n = \text{OHE for a data sample } x_n$

$$y_k = \eta/w \text{ o/p} = P(t_k = 1 | x)$$

$$0 \leq y_k(x, w) = \frac{\exp(a_k(x, w))}{\sum_j \exp(a_j(x, w))} \leq 1 \quad \rightarrow (2)$$

$a_k \rightarrow \text{pre softmax activation error function}$

To prove: $\frac{\partial E}{\partial a_k} = y_k - t_k$

Proof: wkt, $a_k = \frac{1}{1 + e^{-(x^T w + b)}}$

$$\frac{\partial E}{\partial a_k} = \frac{\partial E}{\partial y_k} \cdot \frac{\partial y_k}{\partial a_k}$$

Case(1) for $i=k$

$$\begin{aligned}\frac{\partial y_i}{\partial a_k} &= \frac{e^{a_i} \sum_j e^{a_j} - e^{a_i} e^{a_k}}{\left(\sum_j e^{a_j}\right)^2} \\ &= \frac{e^{a_i} \left(\sum_j e^{a_j} - e^{a_k}\right)}{\sum_j (e^{a_j})^2} \\ &= \left(\frac{e^{a_i}}{\sum_j e^{a_j}}\right) \cdot \left(1 - \frac{e^{a_i}}{\sum_j e^{a_j}}\right) \\ &= y_i (1 - y_i)\end{aligned}$$

Case(2) for $i \neq k$

$$\begin{aligned}\frac{\partial y_i}{\partial a_k} &= 0 - \frac{e^{a_i} e^{a_k}}{\sum_j e^{a_j} \sum_j e^{a_j}} \\ &= -y_i y_k\end{aligned}$$

Hence:

$$\frac{\partial y_i}{\partial a_k} = \begin{cases} y_i (1 - y_i) & \text{if } i=k \\ -y_i y_k & \text{if } i \neq k \end{cases} \quad \text{--- (1)}$$

Now $\frac{\partial E y}{\partial y_k} = \sum_k \sum_n \frac{t_{kn}}{y_k(x, w)} \quad \text{--- (2)}$

Now multiplying Eq (1) & (2)

$$\frac{\partial E}{\partial a_k} = - \sum_n \sum_{k \neq i} \frac{t_{kn}}{y_k(x_i, w)} \left[\frac{-y_i y_k}{i \neq k} - \frac{y_i (1 - y_i)}{i = k} \right]$$

$$= - \sum_{k, n} \frac{t_{kn}}{y_k} (-y_i y_k) - \sum_{k, n} \frac{t_{kn}}{y_k} (y_i - t_{ki})$$

$$= + y_i t_{kn} - \sum_{k, n} t_{kn} y_i + \sum_{k, n} \frac{t_{kn}}{y_k} y_i y_k$$

$$= y_i \left(\sum_{k \neq i} t_{kn} + t_{in} \right) - \sum_{k, n} t_{kn} + \sum_{k, n} \frac{t_{kn}}{y_k} y_i y_k$$

Summed over all values

$$\frac{\partial E}{\partial a_k} = y_i - t_i$$

How proven

1. Ensemble Methods

Question: Practical

4a) The results have been computed below for a from the scratch Random Forest Classification

Code from scratch

The accuracy was 94.4967414916727% on the test data with number of features = 42

Time taken = Time: 02:51:17

Built-in scikit-learn library

The accuracy was 93.9174511223751% on the test data with number of features =

Time taken = 0.34009859599973424 seconds

4b) b} Sensitivity of Random Forests to the parameter “no. of features”

The accuracy was 89.86241853729182% on the test data with number of features = 7

The accuracy was 92.32440260680667% on the test data with number of features = 12

The accuracy was 94.6415640839971% on the test data with number of features = 17

The accuracy was 94.93120926864592% on the test data with number of features = 22

The accuracy was 95.1484431571325% on the test data with number of features = 27

The accuracy was 95.2208544532947% on the test data with number of features = 32

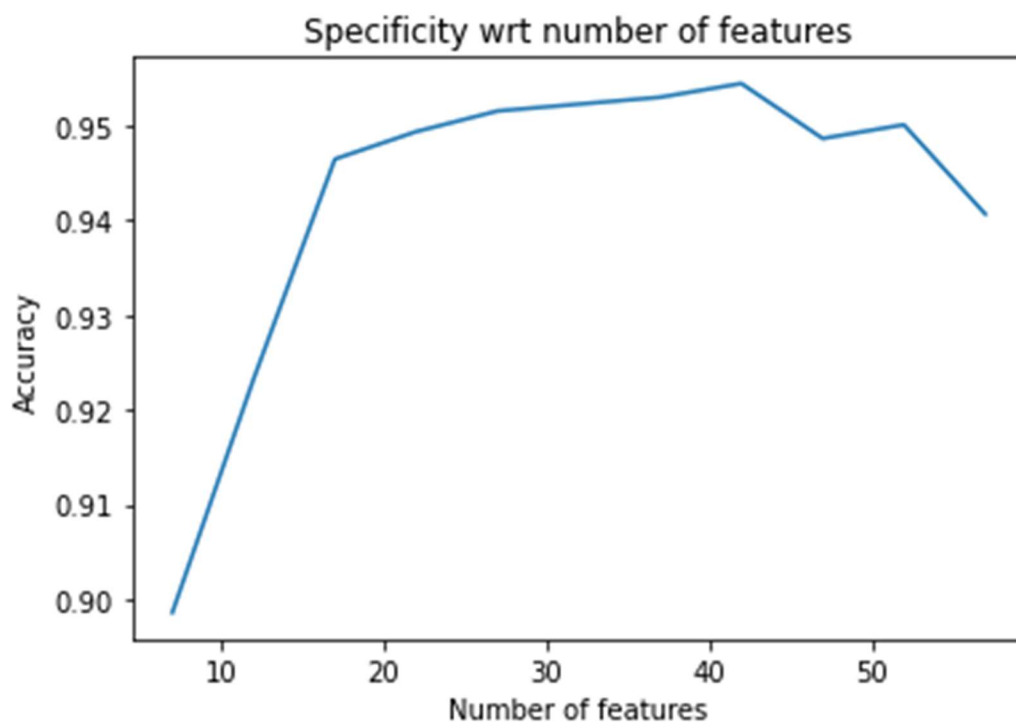
The accuracy was 95.2932657494569% on the test data with number of features = 37

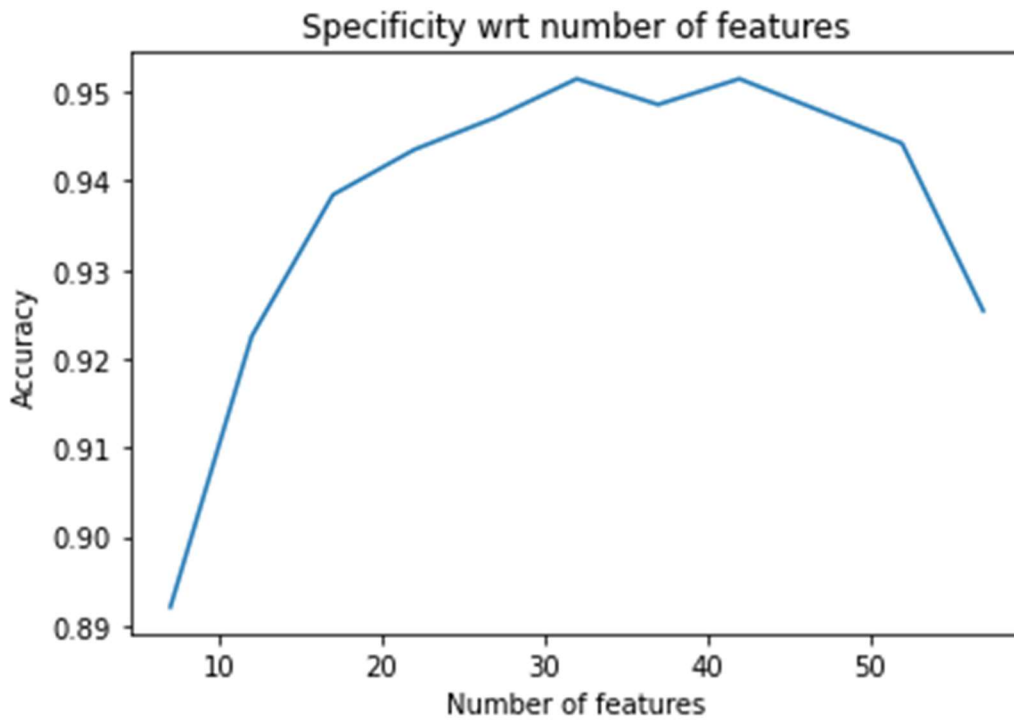
The accuracy was 95.43808834178131% on the test data with number of features = 42

The accuracy was 94.85879797248371% on the test data with number of features = 47

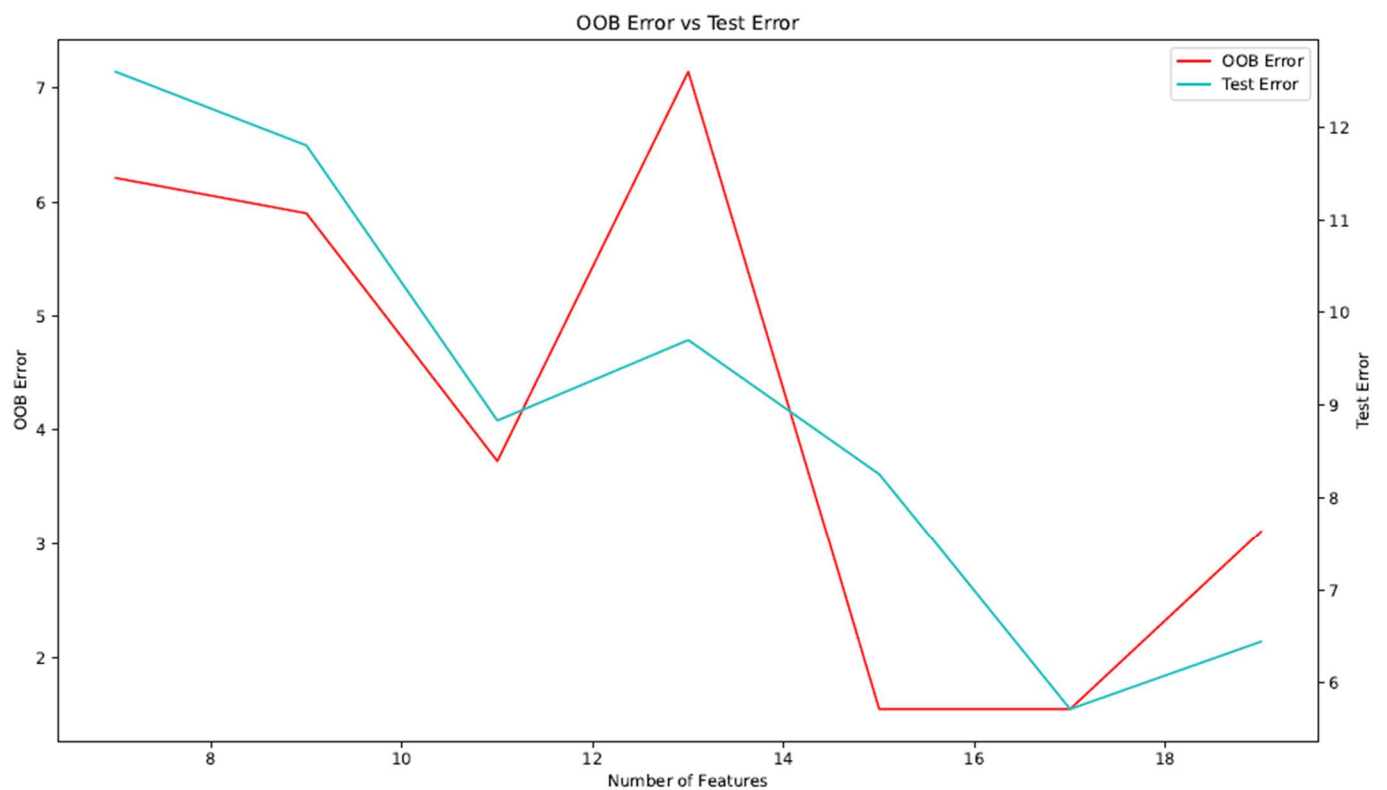
The accuracy was 95.00362056480812% on the test data with number of features = 52

The accuracy was 94.0622737146995% on the test data with number of features = 57





4c) The relation between oob accuracy and test accuracy



5. The preprocessing and machine learning classification of the given loan dataset has been performed and attached as a google colab IPython file:

<https://colab.research.google.com/github/JainAnki/SiameseNetworks/blob/main/5.ipynb>