Date .....

ML - Hax

(*) for minor DE, take each diagonal element, cross out that row & column & solve determinant for rest 4 elements

① Linear Regression :

(i) Find dependent (y) & independent (x) variable

(ii) Make table:

x_i	y_i	$x_i y_i$	x_i^2
⋮	⋮	⋮	⋮
$\bar{x_i}$	$\bar{y_i}$	$\overline{x_i y_i}$	$\overline{x_i^2}$

(iii) Linear Regression eq^n ⇒

$$\boxed{y = a_0 + a_1 x}$$

(iv) $$a_1 = \frac{\overline{xy} - (\bar{x}\bar{y})}{(\overline{x_i^2}) - (\bar{x})^2}$$

(v) $$\boxed{a_0 = \bar{y} - a_1 \bar{x}}$$

(vi) put values, find y, put x ⇒ get y ⇒ ans.

② SDV : Single Valued Decomposition $\boxed{= U \Sigma V^T}$ ⇒

for 3x3 matrix: Char eq^n for λ:
$\lambda^3 - \lambda^2$[sum of all DE] + λ[sum of minor DE (all)] − $|A| = 0$
(*)

(i) For $U \Rightarrow AA^T$, For $V = A^T A$

(ii) Find Eigen Values ⇒ $|AA^T - \lambda I| = 0$, $|A^T A - \lambda I| = 0$

(iii) " " Vectors ⇒ put value of each λ, get eq^n:

$$\begin{bmatrix} & & \\ & & \\ & & \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

take any two eq^n(s) ⇒ and apply cramers rule

(iv) $$\frac{x_1}{|\ |} = \frac{-x_2}{|\ |} = \frac{x_3}{|\ |}$$ ⇒ find determinant of variables other than the one under which you are (take x_2, x_3 if value x_1)

(v) Actual vector are when you take $\sqrt{(1)^2 + (2^2) + 3^2}$ ⇒ sum of sq(s) of EV & underroot & divide it by the value ← (the actual vector)

(vi) $$\Sigma = \begin{bmatrix} \sqrt{EV_1} & 0 & 0 \\ 0 & \sqrt{EV_2} & 0 \\ 0 & 0 & \sqrt{EV_3} \end{bmatrix}$$ ⇒ sq-root in decreasing order

(vii) Multiply and get ans. it should be close to actual given

(viii) For U & V, arrange E Vectors in decreasing order (max value = 1st column)

Spiral matrix

(1) PCA Steps:

(i) Find mean of given data $(\bar{x}_1, \bar{x}_2)$

(ii) Find Covariance Matrix $\Rightarrow S = \begin{bmatrix} cov(x_1, x_1) & cov(x_1, x_2) \\ cov(x_2, x_1) & cov(x_2, x_2) \end{bmatrix}$

(iii) $cov(x_1, x_1) = \frac{1}{N-1} \sum_{k=1}^{N} (x_{1k} - \bar{x}_1)(x_{1k} - \bar{x}_1)$ | $cov(x_1, x_2) = \frac{1}{N-1} \sum_{k=1}^{N} (x_{1k} - \bar{x}_1)(x_{2k} - \bar{x}_2)$

(iv) Find Eigen values & vectors of S

(v) Find kth Principal Component: $\boxed{e_i^T \begin{bmatrix} x_{1k} - \bar{x}_1 \\ x_{2k} - \bar{x}_2 \end{bmatrix}}$ for all x_{1k} & x_{2k}

① How to calculate Eigen Vector for PCA : let $U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$ ⇒ be Eigen Vector

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = [S - \lambda I] U \Rightarrow 0 = [S - \lambda I] \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

Imp. Always remember to use the bigger or greater Eigen Value

⇒ obtain eq^n after multiplying u_1 & u_2 :

$$--- u_1 + --- u_2 = 0$$

$$\Rightarrow \frac{u_1}{---} = \frac{u_2}{---} = t$$

$$u_1 = --- t \quad , \quad u_2 = --- t$$

put $t = 1$, you get u_1 & u_2

Spiral

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①

Features	E_1	E_2	E_3	E_4
x_1	2	3	4	5
x_2	4	6	8	10

(i) Calculate Mean:

$\bar{x}_1 = 3.5$, $\bar{x}_2 = 7$

(ii) Calculating S (covariance matrix):

$$S = \begin{bmatrix} cov(x_1, x_1) & cov(x_1, x_2) \\ cov(x_2, x_1) & cov(x_2, x_2) \end{bmatrix}$$

(iii) Calculating covariance:

$$cov(x_1, x_1) = \frac{1}{N-1} \sum_{k=1}^{N} (x_{1k} - \bar{x})(x_{1k} - \bar{x})$$

$$= \frac{1}{4-1} \sum_{k=1}^{4} (x_{1k} - 3.5)^2 = \frac{1}{3} \left[(2-3.5)^2 + (3-3.5)^2 + (4-3.5)^2 + (5-3.5)^2 \right]$$

$$= \frac{1}{3} \left[2.25 + 0.25 + 0.25 + 2.25 \right] = 1.66 \quad \text{--- (I)}$$

$$cov(x_1, x_2) = \frac{1}{N-1} \sum_{k=1}^{N} (x_{1k} - \bar{x}_1)(x_{2k} - \bar{x}_2) = \frac{1}{3} \sum_{k=1}^{4} (x_{1k} - 3.5)(x_{2k} - 7)$$

$$= \frac{1}{3} \left[(2-3.5)(4-7) + (3-3.5)(6-7) + (4-3.5)(8-7) + (5-3.5)(10-7) \right]$$

$$= \frac{1}{3} \left[4.5 + 0.5 + 0.5 + 4.5 \right] = 3.33 \quad \text{--- (II)}$$

$$cov(x_2, x_1) = cov(x_1, x_2) = 3.33 \quad \text{--- (II)}$$

$$cov(x_2, x_2) = \frac{1}{N-1} \sum_{k=1}^{N} (x_{2k} - \bar{x}_2)^2 = \frac{1}{3} \left[(4-7)^2 + (6-7)^2 + (8-7)^2 + (10-7)^2 \right]$$

$$= \frac{1}{3} \left[9 + 1 + 1 + 9 \right] = 6.66 \quad \text{--- (II)}$$

$$\therefore S = \begin{bmatrix} 1.66 & 3.33 \\ 3.33 & 6.66 \end{bmatrix}$$

PCA EX.

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(a) Finding Eigen Values of S:

$$S = \begin{bmatrix} 1.66 & 3.33 \\ 3.33 & 6.66 \end{bmatrix} \Rightarrow |S - \lambda I| = 0 \Rightarrow \begin{vmatrix} 1.66-\lambda & 3.33 \\ 3.33 & 6.66-\lambda \end{vmatrix} = 0$$

$$(11.05 - 1.66\lambda - 6.66\lambda + \lambda^2) - 11.08 = 0$$

$$\lambda^2 - 8.32\lambda - 0.75 = 0$$

$$\boxed{\lambda = 8.40, -0.089}$$

(b) Finding Eigen Vectors:

$$U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 \\ 0 \end{bmatrix} = (S - \lambda I)U$$

$$\begin{bmatrix} 1.66-\lambda & 3.33 \\ 3.33 & 6.66-\lambda \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = 0$$

$$\begin{bmatrix} (1.66-\lambda)u_1 & 3.33u_2 \\ 3.33u_1 & (6.66-\lambda)u_2 \end{bmatrix} = 0$$

$$\Rightarrow (1.66-\lambda)u_1 + 3.33u_2 = 0$$

$$\frac{u_1}{-3.33} = \frac{u_2}{1.66-\lambda} = t \quad \text{--- (1)}$$

$$\therefore u_1 = -3.33, \quad u_2 = 1.66-\lambda$$

$$\therefore U = \begin{bmatrix} -3.33 \\ 1.66-\lambda \end{bmatrix}$$

$$\text{vector} = e_1 = \begin{bmatrix} -3.33 / 7.51 \\ \frac{1.66 - 8.40}{7.51} \end{bmatrix}$$

$$\boxed{e_1 = \begin{bmatrix} -0.44 \\ -0.89 \end{bmatrix}}$$

(b). Considering larger Eigen Value:

$$\cancel{U = \begin{bmatrix} -3.33 \\ 1.66 - 8.40 \end{bmatrix}}$$

$$\text{length} = \sqrt{(-3.33)^2 + (1.66-\lambda)^2}$$

$$= \sqrt{11.08 + 45.42}$$

$$= 7.51 \quad \text{--- (1)}$$

Date .....

(v) Calculating Principal Component :

$$\boxed{e_1^T \begin{bmatrix} x_{1k} - \bar{x}_1 \\ x_{2k} - \bar{x}_2 \end{bmatrix}}$$

(a) $\begin{bmatrix} -0.44 & -0.89 \end{bmatrix} \begin{bmatrix} 2-3.5 \\ 4-7 \end{bmatrix}$

$\begin{bmatrix} -0.44 & -0.89 \end{bmatrix} \begin{bmatrix} -1.5 \\ -3 \end{bmatrix}$

$= 3.33$ — (i)

(b) $\begin{bmatrix} -0.44 & -0.89 \end{bmatrix} \begin{bmatrix} 3-3.5 \\ 6-7 \end{bmatrix}$

$\begin{bmatrix} -0.44 & -0.89 \end{bmatrix} \begin{bmatrix} -0.5 \\ -1 \end{bmatrix}$

$= 1.11$ — (ii)

(c) $\begin{bmatrix} -0.44 & -0.89 \end{bmatrix} \begin{bmatrix} 4-3.5 \\ 8-7 \end{bmatrix}$

$= -0.22 - 0.89$

$= -1.11$ — (iii)

(d) $\begin{bmatrix} -0.44 & -0.89 \end{bmatrix} \begin{bmatrix} 5-3.5 \\ 10-7 \end{bmatrix}$

$-0.66 - 2.67$

$= -3.33$ — (iv)

Ans:

Feature	E_1	E_2	E_3	E_4
X_1	2	3	4	5
X_2	4	3	8	10
1st Principal Component	3.33	1.11	-1.11	-3.33

SDV Ex.

Date .....

① SVD of $A = \begin{bmatrix} 3 & 1 & 1 \\ -1 & 3 & 1 \end{bmatrix}$

(i) $AA^T = \begin{bmatrix} 3 & 1 & 1 \\ -1 & 3 & 1 \end{bmatrix}_{2\times3} \begin{bmatrix} 3 & -1 \\ 1 & 3 \\ 1 & 1 \end{bmatrix}_{3\times2} = \begin{bmatrix} 11 & 1 \\ 1 & 11 \end{bmatrix}$

(ii) $|AA^T - \lambda I| = 0$

$\begin{vmatrix} 11-\lambda & 1 \\ 1 & 11-\lambda \end{vmatrix} = 0 \Rightarrow (11-\lambda)^2 - 1 = 0 \Rightarrow 121 + \lambda^2 - 22\lambda - 1 = 0$

$\lambda^2 - 22\lambda + 120 = 0$

$\boxed{\lambda = 12, 10} \Rightarrow$ Eigen Values

(iii) for $\lambda = 10$:

$\begin{bmatrix} 11-10 & 1 \\ 1 & 11-10 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 0 \Rightarrow x_1 + x_2 = 0 \Rightarrow \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

$x_1 = -x_2$

actual Eigen Vector $= \begin{bmatrix} -0.707 \\ 0.707 \end{bmatrix}$

for $\lambda = 12$:

$\begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 0 \Rightarrow -x_1 + x_2 = 0 \Rightarrow \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$x_1 = x_2$

actual Eigen Vector $= \begin{bmatrix} 0.707 \\ 0.707 \end{bmatrix}$

(iv) $U = \begin{bmatrix} 0.707 & -0.707 \\ 0.707 & 0.707 \end{bmatrix}$ ... ①

(v) $A^T A = \begin{bmatrix} 3 & -1 \\ 1 & 3 \\ 1 & 1 \end{bmatrix}_{3\times2} \begin{bmatrix} 3 & 1 & 1 \\ -1 & 3 & 1 \end{bmatrix}_{2\times3} = \begin{bmatrix} 10 & 0 & 2 \\ 0 & 10 & 4 \\ 2 & 4 & 2 \end{bmatrix}$

(vi) $|A^T A - \lambda I| = 0$

$\begin{vmatrix} 10-\lambda & 0 & 2 \\ 0 & 10-\lambda & 4 \\ 2 & 4 & 2-\lambda \end{vmatrix} = 0 \rightarrow$ General formula:

$\lambda^3 [\text{Sum of diagonal elements}] +$

Date .....

General Formula for finding Determinat:

$$\Rightarrow \lambda^3 - \lambda^2[\text{sum of diagonal elements}] + \lambda[\text{sum of minor diagonal elem}] - |A| = 0$$

$$\Rightarrow \lambda^3 - \lambda^2[10+10+2] + \lambda[10(2)-4(4) + 10(2)-2(2) + 10(10)-0(0)]$$
$$- [10(10(2)-4(4)) - 0 + 2(-10(2))] = 0$$
$$\Rightarrow \lambda^3 - \lambda^2[22] + \lambda[120] - [0] = 0$$
$$\lambda^3 - 22\lambda^2 + 120\lambda = 0 \quad \text{---} \quad (1)$$
$$\boxed{\lambda = 12, 0, 10} \Rightarrow \text{Eigen Values}$$

(vii) for $\lambda = 12$:

$$\begin{bmatrix} -2 & 0 & 2 \\ 0 & -2 & 4 \\ 2 & 4 & -10 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 0 \Rightarrow \cancel{\begin{matrix} -2x_1 + 2x_3 = 0 \Rightarrow -2x_1 + 0.x_2 + 2x_3 = 0 \\ 2x_1 + 4x_2 - 10x_3 = 0 \end{matrix}}$$

$$\cancel{\frac{x_1}{\begin{vmatrix} 0 & 2 \\ 4 & -10 \end{vmatrix}} = \frac{-x_2}{\begin{vmatrix} -2 & 2 \\ 2 & -10 \end{vmatrix}} = \frac{x_3}{\begin{vmatrix} -2 & 2 \\ 2 & 4 \end{vmatrix}} \Rightarrow \frac{x_1}{8} = \frac{-x_2}{16} = \frac{x_3}{-12}}$$

$$\cancel{\text{Vector} = \begin{bmatrix} 8 \\ -16 \\ -12 \end{bmatrix}}$$

$$\cancel{-2x_1 + 0.x_2 + 2x_3 = 0}$$
$$\cancel{0.x_1 - 2x_2 + 4x_3 = 0}$$

$$\frac{x_1}{\begin{vmatrix} 0 & 2 \\ -2 & 4 \end{vmatrix}} = \frac{-x_2}{\begin{vmatrix} -2 & 2 \\ 0 & 4 \end{vmatrix}} = \frac{x_3}{\begin{vmatrix} -2 & 0 \\ 0 & -2 \end{vmatrix}} \Rightarrow \frac{x_1}{4} = \frac{-x_2}{-8} = \frac{x_3}{4}$$

$$\text{vector} = \begin{bmatrix} 4 \\ 8 \\ 4 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{6}} \\ \frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} \end{bmatrix} = \begin{bmatrix} 0.408 \\ 0.816 \\ 0.408 \end{bmatrix}$$

for $\lambda = 0$:

$$\begin{bmatrix} 10 & 0 & 2 \\ 0 & 10 & 4 \\ 2 & 4 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 0 \Rightarrow \begin{matrix} 10x_1 + 0.x_2 + 2x_3 = 0 \\ 0.x_1 + 10x_2 + 4x_3 = 0 \end{matrix}$$

$$\frac{x_1}{-20} = \frac{-x_2}{40} = \frac{x_3}{100} = \begin{bmatrix} -20 \\ -40 \\ 100 \end{bmatrix} = \begin{bmatrix} -1 \\ -2 \\ 5 \end{bmatrix}$$

$$= \begin{bmatrix} 0.18 \\ 0.36 \\ 0.91 \end{bmatrix}$$

Spiral

for $\lambda = 10$:

$$\begin{bmatrix} 0 & 0 & 2 \\ 0 & 0 & 4 \\ 2 & 4 & -8 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 0$$

$0 \cdot x_1 + 0 \cdot x_2 + 2x_3 = 0$

$\cancel{0x_1 + 0x_2 + 4x_3 = 0}$

$2x_1 + 4x_2 - 8x_3 = 0$

$\cancel{\frac{x_1}{0} = \frac{-x_2}{0} = \frac{x_3}{0}}$

$$\frac{x_1}{-2} = \frac{-x_2}{}$$

$$\text{Vector} = \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.89 \\ -0.44 \\ 0 \end{bmatrix}$$

(iii) $V = \begin{array}{c} \begin{array}{ccc} \lambda=12 & \lambda=10 & \lambda=0 \end{array} \\ \begin{bmatrix} 0.408 & 0.89 & -0.18 \\ 0.816 & -0.44 & -0.36 \\ 0.408 & 0 & 0.91 \end{bmatrix} \end{array}$

$$V^T = \begin{bmatrix} 0.406 & 0.816 & 0.408 \\ 0.89 & -0.44 & 0 \\ -0.18 & -0.36 & 0.91 \end{bmatrix}$$

(iv) $\Sigma = \begin{bmatrix} \sqrt{12} & 0 & 0 \\ 0 & \sqrt{10} & 0 \\ 0 & 0 & \sqrt{0} \end{bmatrix}$

(v) $SDV = U \Sigma V^T =$

7:17 4G

1 Mansi Arora (JIIT)

Abhi steps jo h:

1. Find mean
2. Find covariance matrix
3. Find Eigen Values and Vectors of that matrix
4. Use that Eigen Vector to find the Principal Components from the formula: e1^T [X1k - X1 bar X2k - X2 bar]

7:16 PM

Last vala step mujhe aata ni tha 3 tk yhi krte h 7:16 PM

Pdh ke ni gyi thi tb 7:17 PM

Isse values nikal jati h, plane pe banane wala i don't know
Just put all points
Put mean
From mean, draw the Eigen Vectors equations roughly
And connect all points to those lines (e1 and e2: equations of Eigen Vectors on graph as line) 7:17 PM

① Linear Regression:

$$\boxed{y = a_0 + a_1 x}$$

$$\boxed{a_1 = \frac{\overline{xy} - (\bar{x}\,\bar{y})}{\overline{(x^2)} - (\bar{x})^2}}$$

$$\boxed{a_0 = \bar{y} - a_1 \bar{x}}$$

② SDV:

$$\boxed{SDV = U \Sigma V^T}$$

$\Downarrow$

$\lambda^3 - \lambda^2$ [sum of all DE]

$+ \lambda$ [sum of minor DE]

$- |A| = 0$

$U \Rightarrow AA^T \Rightarrow$ Eigen Values $\Rightarrow$ Eigen Vectors

$\Rightarrow$ length $\Rightarrow$ Actual Eigen Vector $\Rightarrow$ Decreasing order of λ

$V \Rightarrow A^T A \Rightarrow$ all same

$$\Sigma \Rightarrow \begin{bmatrix} \sqrt{EV_1} & 0 & 0 \\ 0 & \sqrt{EV_2} & 0 \\ 0 & 0 & \sqrt{EV_3} \end{bmatrix}$$

$EV_1 > EV_2 > EV_3$

(5) PCA :

$$\boxed{PCA = e_1^T \begin{bmatrix} x_{1k} - \bar{x}_1 \\ x_{2k} - \bar{x}_2 \end{bmatrix}} \Rightarrow \text{for all pairs}$$

Mean $\Rightarrow$ S (covariance matrix) $\Rightarrow$ Eigen Values $\Rightarrow$ Eigen Vectors

$$\boxed{S = \begin{bmatrix} cov(x_1, x_1) & cov(x_1, x_2) \\ cov(x_2, x_1) & cov(x_2, x_2) \end{bmatrix}}$$

$$\boxed{\underset{(x_1, x_1)}{cov} = \frac{1}{N-1} \sum_{k=1}^{N} (x_{1k} - \bar{x}_1)^2}$$

$$\boxed{cov(x_1, x_2) = \frac{1}{N-1} \sum_{k=1}^{N} (x_{1k} - \bar{x}_1)(x_{2k} - \bar{x}_2)}$$

for Eigen Vectors :

$$U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \Rightarrow [S - \lambda I] \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = 0$$

$\Rightarrow$ ---- u_1 + ---- u_2 = 0

$\Rightarrow$ u_1 + u_2 = t

$\Rightarrow$ u_1 = ..t , u_2 = ---t $\Rightarrow$ $\begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$

now put largest ~~value~~ of eigen value , find length and the find the actual vector

POSSESION OF MOBILE IN EXAM IS UFM PRACTICE

Name Anunay Dwivedi **Enrollment no** 9912102048

Jaypee Institute of Information Technology, Noida
Test-1, Examination- 2025
B. Tech, VI Semester

Course Name: Machine Learning for Signal Processing **Max Marks: 20**
Course Code: 18B13EC314 **Max Time:1 Hr.**

CO1	Illustrate various machine learning approaches.
CO2	Experiment with the different techniques for feature extraction and feature selection.
CO3	Apply and analyze various classifier models for typical machine learning applications.
CO4	Make use of deep learning techniques in real life problems.

NOTE: *1. Attempt **all** questions. Assume the required data.*

Q1 Calculate the spearman rank correlation for the following data

Mathematics	14	15	17	12	16	11	18	9	10
Accountancy	5	13	11	10	2	5	9	4	6

[(CO2), Applying, 5 Marks]

- Q2. The two-dimension feature samples are given using the principal component analysis (PCA) convert its in one-dimension feature. [(CO2) Applying, 5 Marks]

Feature	E1		E2	E3	E4
X1	3		4	5	6
X2	7		8	9	10

Q3 State that two variable, qualification and marital state have any relation or not using Chi square test. Data of qualification and marital status is given in table below. Perform the Chi square test using 5% Significant level and tabulate value of Chi square at 5% significant level is 21.03. [(CO2) Applying,5 Marks]

Qualification Marital status	Middle School	High School	Bachelor's	Master	PhD	Total
Never Married	18	36	21	9	6	90
Married	12	36	45	36	21	150
Divorced	6	9	9	3	3	30
Widowed	3	9	9	6	3	30
Total	39	90	84	54	33	300

Q.4 Find the glucose level for age of 55 using linear regression. Glucose level of patient for different age is given in table below [(CO3) Analyzing, 5 Marks]

Patient	1	2	3	4	5	6
Age	43	21	25	42	57	59
Glucose Level	99	65	79	75	89	81

Sol:

Step 1: C[illegible] Entropy for the tar[illegible] Job offer.

E[illegible]

Q) Decision Tree Learning

Assess a student performance during his course of study and predict whether a student will get a job offer or not in his final year of the course.

S.No	CGPA	Interactiveness	Practical knowledge	Communication skills	Job offer
1	≥9	Yes	VG	Good	Y
2	≥8	No	Good	moderate	Y
3	≥9	No	Average	poor	N
4	<8	No	A	G	N
5	≥8	Yes	G	M	Y
6	≥9	Yes	G	M	Y
7	<8	Yes	G	P	N
8	≥9	No	VG	G	Y
9	≥8	Yes	G	G	Y
10	≥8	Yes	A	G	Y

Naive Bayes Algorithm

1. Compute prior probability for the target Class. ✓
2. Compute frequency matrix and likelihood probability for each of the feature.
3. Use Bayes theorem to calculate the probability of all hypotheses
4. Use Maximum A posteriori (MAP) Hypotheses h_{MAP} to classify the test object to the hypotheses with the highest probability.

Likelihood probability of CGPA.

	P(Jo=yes)	P(Jo=no)
≥9	3/7	1/3
≥8	4/7	0
<8	0	$\frac{2}{3}$

Step 2

Compute frequency matrix and likelihood probability for each of the feature.

2. Frequency matrix.

CGPA	Joboffer = Yes	Job offer = no
≥9	3	1
≥8	4	0
<8	0	2
Total	7	3

ML- Hax

① Bayes' Theorem:

$$\boxed{P(E_1|A) = \frac{P(E_1)\,P(A|E_1)}{P(E_1)P(A|E_1) + P(E_2)P(A|E_2) + P(E_3)P(A|E_3)}}$$

judges wether the event A that has happened

↳ actually happend from which E_1, E_2, E_3

② Naive Bayes :

(i) You'll be given a dataset. Find "features" & "target variable"

(ii) Find P(target variable = yes, no) ⇒ both

(iii) Find conditional prob of all features for no. of yes's and no's (i.e. it will be divided by total no. of Yes's & No's)

(iv) Find "new instance" probability for both target variable = Yes & No

(v) If P(Yes) > P(No) ⇒ "Yes" o/w "No"

(vi) Normalize = $\frac{P(Yes)}{P(Yes)+P(No)}$ or $\frac{P(No)}{P(Yes)+P(No)}$

↳ (+) ↲

↳ "1"

③ KNN Algorith:

(i) From the data, (x_2, y_2) = new instance to be predicted. (x_1, y_1) = all other points

(ii) Find dis = $\sqrt{(x_2-x_1)^2 + (y_2-y_1)^2}$ or dis = $|x_2-x_1| + |y_2-y_1|$

or dis = $\max(|x_2-x_1|, |y_2-y_1|)$

(iii) Sort in ascending order of dis & call it Rank

(iv) Suppose k = 3, ∴ check for Rank 1 till 3, most occuring is the predicted label.

(v) If Hamming Dis = if same attribute = 0, "diff" " = 1 ⇒ dis.

Spiral

NAIVE BAYES CLASSIFIER - EXAMPLE - 2

$$P(M) = \frac{4}{8} = 0.5 \quad P(H) = \frac{4}{8} = 0.5$$

Color	M	H
White	2/4	3/4
Green	2/4	1/4

Legs	M	H
2	1/4	4/4
3	3/4	0/4

Height	M	H
Tall	3/4	2/4
Short	1/4	2/4

Smelly	M	H
Yes	3/4	1/4
No	1/4	3/4

$$p(M|New\ Instance) = p(M) * p(Color = Green|M) * p(Legs = 2|M) * p(Height = tall|M) * p(Smelly = no\ |M)$$

$$p(M|New\ Instance) = 0.5 * \frac{2}{4} * \frac{1}{4} * \frac{3}{4} * \frac{1}{4} = 0.0117$$

$$p(H|New\ Instance) = p(H) * p(Color = Green|H) * p(Legs = 2|H) * p(Height = tall|H) * p(Smelly = no\ |H)$$

Subscribe to Mahesh Huddar
Visit: vtupulse.com
5:37 / 6:51

Date .....

Normalized :

$P(H) = \frac{0.140}{0.140+0.0039} = 0.972$

$P(M) = \frac{0.0039}{0.0039+0.140} = 0.027$

The species is "H"

③

No.	Color	Type	Origin	Stolen
1	R	S	D	Y
2	R	S	D	N
3	R	S	D	Y
4	Y	S	D	N
5	Y	S	I	Y
6	Y	SUV	I	N
7	Y	SUV	I	Y
8	Y	SUV	D	N
9	R	SUV	I	N
10	R	S	I	Y

New instance = (Red, SUV, D)

$P(Stolen = Y) = \frac{5}{10} = \frac{1}{2}$

$P(Stolen = N) = \frac{5}{10} = \frac{1}{2}$

Conditional Prob :

Color	Y	N
R	3/5	2/5
Y	2/5	3/5

Type	Y	N
S	4/5	2/5
SUV	1/5	3/5

Origin	Y	N
D	2/5	3/5
I	3/5	2/5

$P(Y|New\ instance) = P(Yes)\ P(Color = red|Y,\ Type = SUV|Yes,\ Origin = D|Yes)$

$= \frac{1}{2} \cdot \frac{3}{5} \cdot \frac{1}{5} \cdot \frac{2}{5} = 0.024$

$P(N|New\ instance) = P(No)\ P(color = red|N,\ Type = SUV|No,\ Origin = D|No)$

$= \frac{1}{2} \cdot \frac{2}{5} \cdot \frac{3}{5} \cdot \frac{3}{5} = 0.072$

Normalized $\Rightarrow P(Y|New\ instance) = \frac{0.024}{0.024+0.072} = 0.25$

$P(N|new) = 0.75$

$\Downarrow$

Stolen = NO

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✅ Distance Formulas for Two Points

- **Euclidean Distance:**

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

- **Manhattan Distance:**

$$d = |x_2 - x_1| + |y_2 - y_1|$$

- **Chebyshev Distance:**

$$d = \max(|x_2 - x_1|, |y_2 - y_1|)$$

Ask anything
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(2)

Heigh	Weight	Class	Euclidian	Manhattan	Rank (Eu)
167	51	U	6.70	9	5
182	62	N	13	17	8
176	69	N	13.41	18	9
173	64	N	7.61	10	6
172	65	N	8.24	10	7
174	56	U	4.12	5	4
169	58	N	1.41	2	1
173	57	N	3	3	3
170	55	N	2	2	2
170	57				

Euclidian $\Rightarrow \sqrt{(170-x_1)^2+(57-y_2)^2}$

Manhattan $\Rightarrow |x_2-x_1|+|y_2-y_1| = |170-x_1| + |57-y_1|$

If

$k=1$	Normal
$k=2$	N
$k=3$	N
$k=4$	N
$k=5$	N
$k=6$	N

$\Rightarrow$ Normal for all values of k

ML - Max

(1) SVM : Support Vector Machine

(i) Find Support Vectors i.e. points closest to a line seperating the classes.

(ii) " Augmented ↓ i.e. just add "1" as a new dimension to SVs.

(iii) " α : $\alpha_1 s_1 s_1 + \alpha_2 s_2 s_1 + \alpha_3 s_3 s_1 = -1 \longrightarrow$ eq s_1 belog to -ve class (assumption)

Solve for "α"

$\alpha_1 s_1 s_2 + \alpha_2 s_2 s_2 + \alpha_3 s_3 s_2 = 1$

$\alpha_1 s_1 s_3 + \alpha_2 s_2 s_3 + \alpha_3 s_3 s_3 = 1 \hookrightarrow$ eq s_2 " "

(iv) " weight : $\tilde{w} = \sum_i \alpha_i s_i = \alpha_1 s_1 + \alpha_2 s_2 + \alpha_3 s_3$ +ve " (" "

(v) $\tilde{w} = \begin{pmatrix} - \\ - \\ - \end{pmatrix}$ → are weights, give x, y value, have orientation of the hyperplane

$\begin{pmatrix} 1 \\ 0 \end{pmatrix}$ = " y-axis

$\begin{pmatrix} 0 \\ 1 \end{pmatrix}$ = " x-axis

$\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ = 45° to x-axis

→ this is bias "b"

↳ where the line should be drawn in hyperplane

(vi) eq^n of hyperplane : $\boxed{y = wx + b}$

(3) (i) Support Vectors = $\left\{ \begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{pmatrix} 3 \\ 1 \end{pmatrix} \begin{pmatrix} 3 \\ -1 \end{pmatrix} \right\}$

(ii) Aug. = $\left\{ \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \begin{pmatrix} 3 \\ 1 \\ 1 \end{pmatrix} \begin{pmatrix} 3 \\ -1 \\ 1 \end{pmatrix} \right\}$

(iii) α:

$\alpha_1 s_1 s_1 + \alpha_2 s_2 s_1 + \alpha_3 s_3 s_1 = -1$

$\alpha_1 \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} + \alpha_2 \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix} + \alpha_3 \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix} = -1$

$2\alpha_1 + 4\alpha_2 + 4\alpha_3 = -1$

$4\alpha_1 + 11\alpha_2 + 9\alpha_3 = 1$

$4\alpha_1 + 9\alpha_2 + 11\alpha_3 = 1$

$\boxed{\alpha_1 = -3.5 \quad \alpha_2 = 0.75 \quad \alpha_3 = 0.75}$

$\alpha_1 s_1 s_2 + \alpha_2 s_2 s_2 + \alpha_3 s_3 s_2 = 1$

$\alpha_1 s_1 s_3 + \alpha_2 s_2 s_3 + \alpha_3 s_3 s_3 = 1$

$\alpha_1 \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix} + \alpha_2 \begin{pmatrix} 9 \\ 1 \\ 1 \end{pmatrix} + \alpha_3 \begin{pmatrix} 9 \\ -1 \\ 1 \end{pmatrix} = 1$

$\alpha_1 \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix} + \alpha_2 \begin{pmatrix} 9 \\ -1 \\ 1 \end{pmatrix} + \alpha_3 \begin{pmatrix} 9 \\ 1 \\ 1 \end{pmatrix} = 1$

(iv) $\tilde{w} = \sum_i s_i \alpha_i = \alpha_1 s_1 + \alpha_2 s_2 + \alpha_3 s_3$

$= -3.5 \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} + 0.75 \begin{pmatrix} 3 \\ 1 \\ 1 \end{pmatrix} + 0.75 \begin{pmatrix} 3 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} -3.5 \\ 0 \\ -3.5 \end{pmatrix} + \begin{pmatrix} 2.25 \\ 0.75 \\ 0.75 \end{pmatrix} + \begin{pmatrix} 2.25 \\ -0.75 \\ 0.75 \end{pmatrix}$

$\boxed{w = \begin{pmatrix} 1 \\ 0 \\ -2 \end{pmatrix}}$ $\boxed{w = \begin{pmatrix} 1 \\ 0 \end{pmatrix}}$ $\boxed{b = -2}$

Date .....

ML- Han

① Decision Tree learning:

Just sort the data from most attributes to lowest so that it can be classified in a Yes OR NO

$$\boxed{\text{Entropy}(S) = [a+\ b-] = \frac{-a}{a+b}\log_2\frac{a}{a+b} - \frac{b}{a+b}\lg_2\frac{b}{a+b}}$$

$$\text{Gain}(S \mid \text{Something}) = \text{Entropy}(S) - \frac{\text{Total no. of that thing}}{\text{total in dataset}}\ \text{Entropy}(\ ) - \ldots$$

↳ Same as before

(i) find entropy of entire dataset

(ii) " " of attributes & find Gain

(iii) Classify the decision tree

(iv) Select only the table w/o that attribute & repeat the same thing by taking Entropy(S) = Entropy( )

① (i) Finding Entropy of entire dataset:

$$E[9+\ 5-] = -\frac{9}{14}\log_2\frac{9}{14} - \frac{5}{14}\log_2\frac{5}{14} = 9.40 \quad \text{— (i)}$$

$$0.409 + 0.530 = 0.95$$

(ii) Finding Entropy of attributes:

(a) Outlook : Sunny, Overcast, Rain

$$\text{Entropy(Sunny)} \Rightarrow [2+\ 3-] = -\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5} = 0.97 \quad \text{— (ii)}$$

$$\text{Entropy(Overcast)} \Rightarrow [4+\ 0-] = -\frac{4}{4}\log_2\frac{4}{4} - 0 = 0 \quad \text{— (iii)}$$

$$\text{Entropy(Rain)} \Rightarrow [3+\ 2-] = -\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5} = 0.97 \quad \text{— (iii)}$$

$$\text{Gain} = \text{Entropy(S)} - \frac{5}{14}\text{Entropy(Sunny)} - \frac{4}{14}\text{entropy(Overcast)} - \frac{5}{14}\text{entropy(Rain)}$$

$$= 9.40 - \frac{5}{14}(0.97) - \frac{4}{14}(0) - \frac{5}{14}(0.97) = 8.70$$

$$= 9.40 - 0.346 - 0.346 = 0.94 - \left(\frac{13.52}{14}\right)(-2)$$

$$\boxed{\text{Gain} = 0.247} \quad \text{— (i)}$$

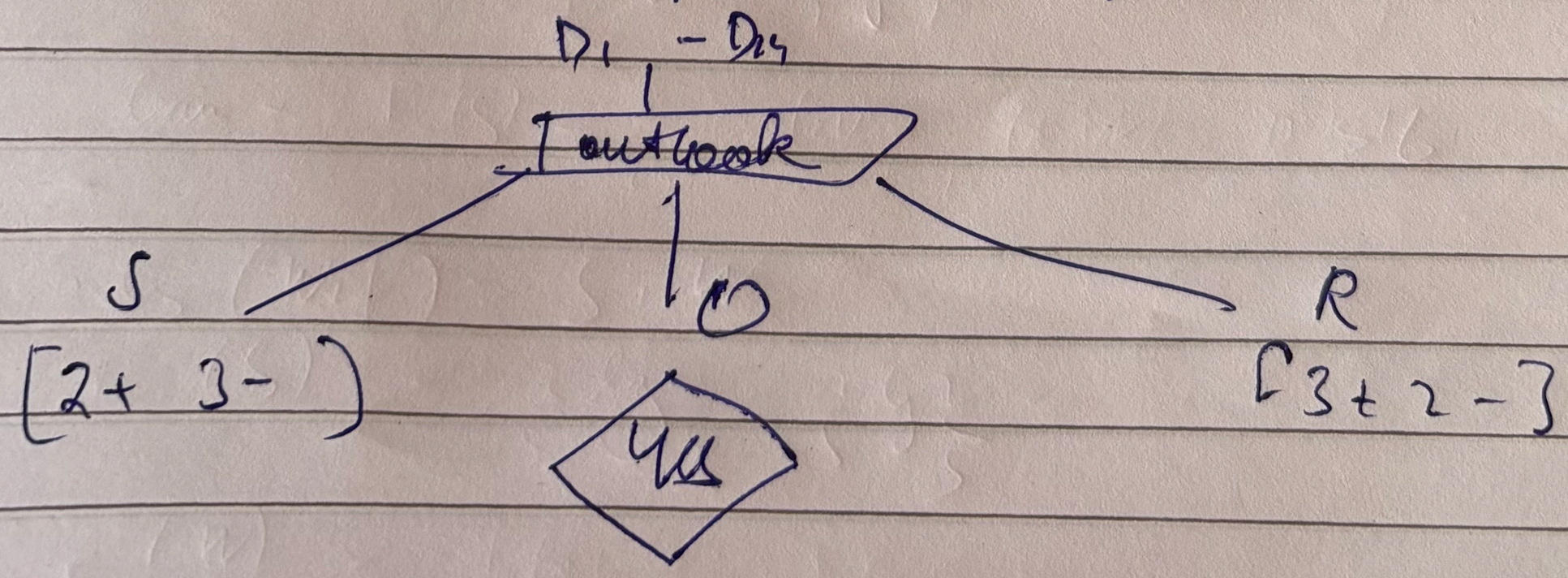
(b) temp = [Hot Mild Cool]

$$\text{Entropy(Hot)} = [2+\ 2-] = -\frac{2}{4}\log_2\frac{2}{4} - \frac{2}{4}\log_2\frac{2}{4} = 1$$

$$\text{Entry(Mild)} = [4+\ 2-] = -\frac{4}{6}\lg\frac{4}{6} - \frac{2}{6} = 0.91$$

$$= 0.811$$

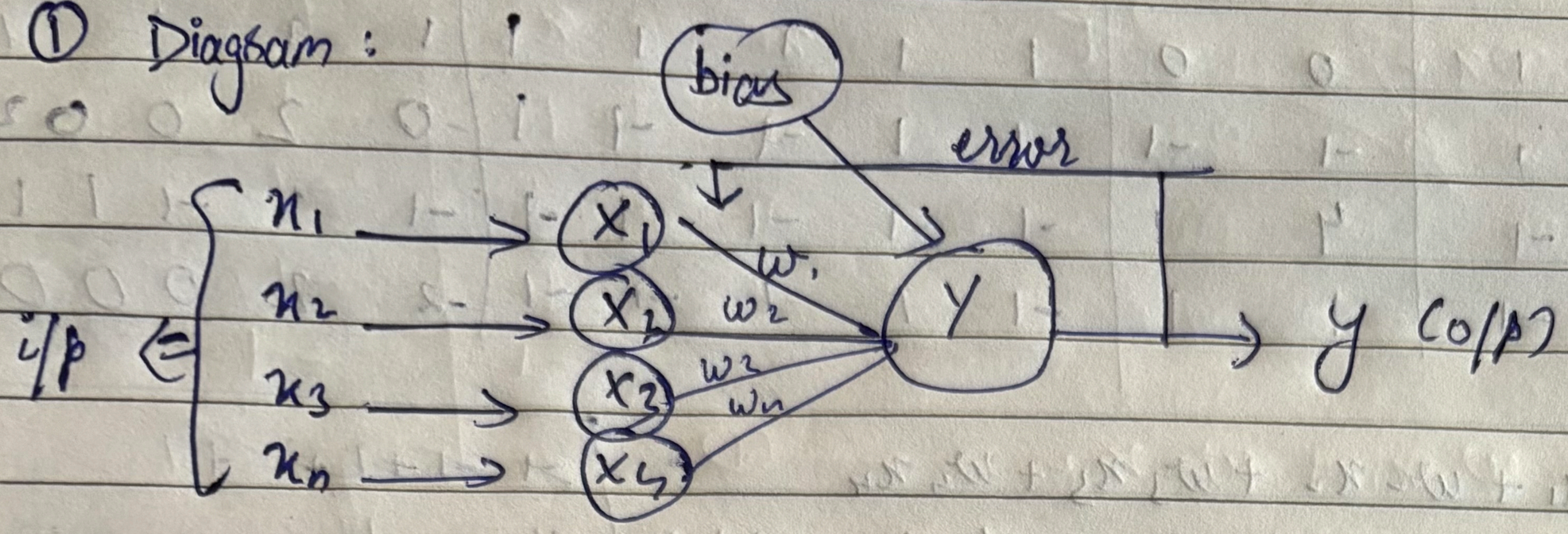
(iii) Write all gain in one place : Make diagram



(iv) Entry (Sny) = 0.97 ⇒ Make table w/o Sny

Single Perceptron Hebb

① Diagram :



② Table format :

i/p(PUS)	target	y_{in}	$y=f(y_{in})$	weight changes	weights
x_1 x_2 x_3 ... x_n				Δw_1 Δw_2 ... Δw_n Δb	w_1 w_2 ... w_n b

③ Equations :

$$\boxed{y_{in} = b + w_1 x_1 + w_2 x_2 + \cdots w_n x_n}$$

$$\boxed{\Delta w_1 = \alpha t x_1}$$

Learning Rate → always "1" if not given

target → t

x_1 → i/p

$$\boxed{\Delta b = \alpha t}$$

$$\boxed{y = f(y_{in}) = \begin{cases} 1, & y_{in} > \theta \\ 0, & y = \theta \\ -1, & y < \theta \end{cases}}$$

usually "0"

$$\boxed{\begin{aligned} w(new) &= w(old) + \Delta w \\ b(new) &= b(old) + \Delta b \end{aligned}}$$

④ (i) Initialize $\alpha = 1$, w & $b = 0$, find y_{in} & y.

(ii) If $y \neq t$, find weight changes & update weights

(iii) Keep repeating till it results in no weight changes ($\Delta w_{in} = 0$)

Multi-Layer Perceptron Max

① Find i/p & o/p at input layer (it's exactly same)
② " i/p & o/p at hidden layers by:

i/p = $\boxed{I_j = \underbrace{x_0 \theta_j}_{\text{bias}} + x_1 w_{1j} + x_2 w_{2j} + \cdots x_n w_{nj}}$

↳ just multiply i/p w/ weights and add all of them

o/p = $\boxed{O_j = \frac{1}{1+e^{-I_j}}}$

⇒ Calculate both for each neuron

③ Calculate Errors:

$$\boxed{\text{Error} = O_{desired} - O_{calculated}}$$

④ Backpropagation and updating the weights:

at o/p layer:

$$\boxed{\text{Error}_k = O_k (1-O_k)(O_{desired} - O_k)}$$

at hidden layers:

$$\boxed{\text{Error}_j = O_j (1-O_j) \sum_k \text{Error}_k \, w_{jk}}$$

⇒ Do for each neuron

⑤ Update the weights:

$$\boxed{w_{ij} = w_{ij} + (\alpha \, \text{Error}_j \, O_i)}$$

↳ update all weights

⑥ Update the bias:

$$\boxed{\theta_j = \theta_j + (\alpha \, \text{Error}_j)}$$

↳ do for all bias, for each connected neuron

⑦ Repeat till "③", find errors. if not satisfied, backpropagate
o/w, it's okay.

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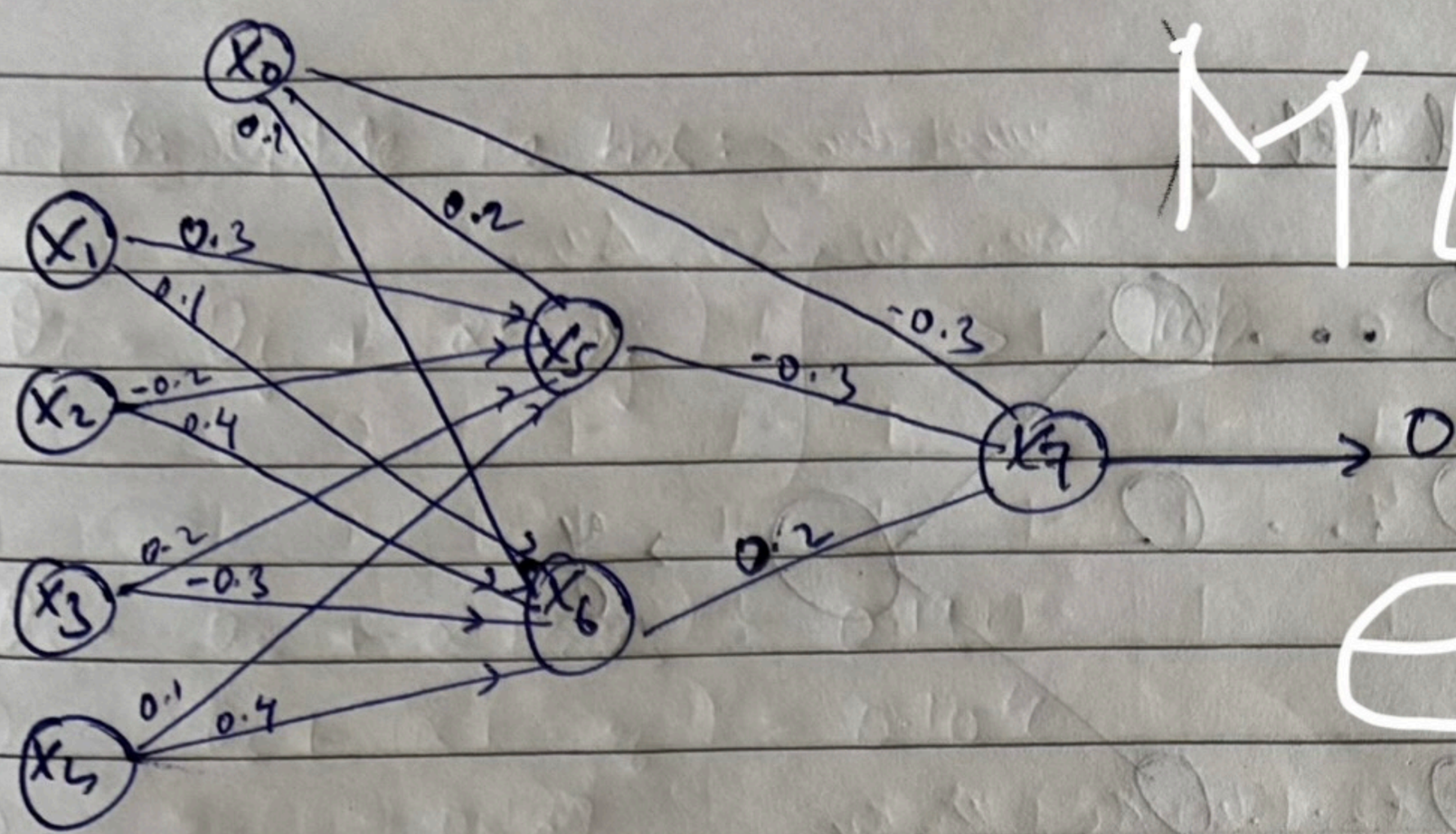
MLP ex



x_1	x_2	x_3	x_4	$O_{desired}$
1	1	0	1	1

Step 1: Calculate i/p & o/p at input layer:

x_1	x_2	x_3	x_4	W_{15}	W_{16}	W_{25}	W_{26}	W_{35}	W_{36}	W_{45}	W_{46}	θ_5	θ_6	θ_7
1	1	0	1	0.3	0.1	-0.2	0.4	0.2	-0.3	0.1	0.4	+0.2	+0.1	-0.3

i/p layer	I_j	O_j
x_1	1	1
x_2	1	1
x_3	0	0
x_4	1	1

$\Rightarrow$ i/p layer just transmits what it gets as it is

Step 2: Calculate net i/p & o/p at hidden layers:

i/p layer	net i/p I_j	o/p O_j
x_5	$I_5 = x_0\theta_5 + x_1 w_{15} + x_2 w_{25} + x_3 w_{35} + x_4 w_{45}$ $= 1(0.2) + 1(0.3) + 1(-0.2) + 0 + 1(0.1) = 0.4$	$O_5 = \frac{1}{1+e^{-I_5}} = \frac{1}{1+e^{-0.4}} = 0.599$
x_6	$I_6 = x_0\theta_6 + x_1 w_{16} + x_2 w_{26} + x_3 w_{36} + x_4 w_{46}$ $= 1(0.1) + 1(0.1) + 1(0.4) + 0 + 1(0.4) = 1$	$O_6 = \frac{1}{1+e^{-I_6}} = \frac{1}{1+e^{-1}} = 0.731$
x_7	$I_7 = x_0\theta_7 + x_5 w_{57} + x_6 w_{67}$ $= -0.3 + 0.599(-0.3) + 0.731(0.2)$ $= -0.335$	$O_7 = \frac{1}{1+e^{0.335}} = 0.582$

Spiral

Step 3 : Calculate error :

$$\boxed{\text{Error} = O_{desired} - O_7 = 1 - 0.582 = 0.418}$$

Step 4 : Backpropagate and update the weights :

at o/p layer for each node :

$$\boxed{\text{Error}_k = O_k (1 - O_k)(O_{desired} - O_k)}$$

at hidden layer " " " :

$$\boxed{\text{Error}_j = O_j (1 - O_j) \Sigma_k \text{Error}_k w_{jk}}$$

$\Rightarrow$ Imp

For o/p layer	Error_k
x_7	$\text{Error}_7 = O_7 (1 - O_7)(1 - O_7) = 0.582(1 - 0.582)(1 - 0.582)$ $= 0.101$
For hidden layer	Error_j
x_6	$\text{Error}_6 = O_6 (1 - O_6) \Sigma_k \text{Error}_k w_{jk}$ $= O_6 (1 - O_6)\ O_7 w_{67} = 0.731(1 - 0.731)(0.582)(0.2)$ $= 0.0022$
x_5	$\text{Error}_7 = O_5 (1 - O_5) \Sigma_k \text{Error}_k w_{jk} = O_5 (1 - O_5)\ O_7 w_{5j}$ $= 0.599(1 - 0.599)(0.582)(-0.3) = -0.041$

Step 5 : Update the weights :

$$\boxed{w_{ij} = w_{ij} + (\alpha\ \text{Error}_j\ O_i)}$$

$\Rightarrow$ Imp

$w_{15} = w_{15} + (0.8)\ \text{Error}_5\ O_1 = 0.3 + (0.8 \times -0.041 \times 1) = 0.267$

$w_{16} = w_{16} + (\alpha\ \text{Error}_6\ O_1) = 0.104$

$w_{25} = w_{25} + (\alpha\ \text{Error}_5\ O_2) = -0.208$

⋮

Similarly for all

Date .....

Step 6: Update the bias:

$$\boxed{\theta_j = \theta_j + (\alpha \text{Error}_j)} \Rightarrow \text{imp}$$

$\theta_5 = \theta_5 + (\alpha \text{ Error}_5) = 0.192$

$\theta_6 = \theta_6 + (\alpha \text{ Error}_6) = 0.104$

$\theta_7 = -0.187$

Step 7: Repeat all steps till step 3:

↳ w/ updated weights

the error should've been reduced & that was the point.

CART Max

① Find Gini_Index of whole dataset for target attribute:

$$\boxed{Gini = 1 - \sum_{i=1}^{m} P_i^2}$$

where P_i : Prob of attribute

② Find Gini-Index for each attribute & its subsets by taking combinations. Once found, compare it:

$$\boxed{Gini = \frac{|S_1|}{|T|} Gini(S_1) + \frac{|S_2|}{|T|} Gini(S_2)}$$

where: S = total in that subset
T = total in dataset

Keep in mind we're finding prob a/c to our target variable
Should be divided by the total in that subset & not the whole dataset

③ Compare all subsets:

subsets	Gini

→ find the min. one

④ Find Δ Gini for that attribute: $\boxed{Gini(T) - G(\ )}$

⑤ Do this step for all attributes

⑥ Make table w/ all values:

Attribute	Gini	Δ Gini

⑦ find max Δ Gini. use that as top level for decision tree

⑧ now repeat the same after excluding that attribute
↳ from step ①.

⑨ Make the final tree

Classification and Regression Trees Decision Tree | CART Algorithm Solved Example by Mahesh Huddar

Classification and Regression Trees – Solved Example

Step 1: Calculate the Gini_Index for the dataset. The target attribute 'Job Offer' has 7 instances as Yes and 3 instances as No.

CGPA	Inter active	Practical Knowledge	Comm Skills	Job Offer
>=9	Yes	Very good	Good	Yes
>=8	No	Good	Moderate	Yes
>=9	No	Average	Poor	No
<8	No	Average	Good	No
>=8	Yes	Good	Moderate	Yes
>=9	Yes	Good	Moderate	Yes
<8	Yes	Good	Poor	No
>=9	No	Very good	Good	Yes
>=8	Yes	Good	Good	Yes
>=8	Yes	Average	Good	Yes

$$\text{Gini_Index}(T) = 1 - \sum_{i=1}^{m} P_i^2$$

$$\text{Gini_Index}(T) = 1 - \left(\frac{7}{10}\right)^2 - \left(\frac{3}{10}\right)^2$$

$$= 1 - 0.49 - 0.09$$

$$= 1 - 0.58$$

$$\text{Gini_Index}(T) = 0.42$$

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① CART : Classification & Regression Tree Algorithm

② Numerical :

GINI EX

Target = "Job offer"

(i) Calculate Gini Index :

$$\boxed{\text{Gini_Index}(T) = 1 - \sum_{i=1}^{m} P_i^2}$$

where: P_i = Probability of target attribute

$$= 1 - \left(\frac{7}{10}\right)^2 - \left(\frac{3}{10}\right)^2 = \boxed{0.42} \quad \text{—— ①}$$

(ii) Calculate Gini-Index for all attributes & each subset in the attribute :

CGPA :

CG	Job = Yes	Job = No
≥ 9	3	1
≥ 8	4	0
< 8	0	2

Imp. Now for calculating GI for the subset, we take combinations and figure which one is the best suitable. Keep in mind, the value that we don't consider, won't be counted.

Taking ≥ 9 & ≥ 8 :

$$\text{Gini_Index}(T, CG \in \{\geq 9, \geq 8\}) = 1 - \left(\frac{7}{8}\right)^2 - \left(\frac{1}{8}\right)^2 = 0.2194 \quad \text{—— ①}$$

$$\text{Gini_Index}(T, CG \in \{< 8\}) = 1 - 1 = 0 \quad \text{—— ①}$$

Then we compare the Gini_Index :

Gini_Index (T, CG ∈ {(≥9, ≥8), <8})

$= \frac{8}{10}(0.2195) + \frac{2}{10}(0)$

$= 0.17552$ — (i)

$$\text{Gini_Index}(T, A) = \frac{|S_1|}{|T|}\text{Gini}(S_1) + \frac{|S_2|}{|T|}\text{Gini}(S_2)$$

⇒ where : T = total in dataset
S = total in that subset

Considering (C ≥ 9 & <8) :

Gini_Index $= 1 - \left(\frac{3}{6}\right)^2 - \left(\frac{3}{6}\right)^2 = 0.5$

Gini_Index $= 1 - 1 = 0$

Comparing : $\frac{6}{10}(0.5) = 0.3$ — (ii)

Considering (≥8, <8)

Gini_Index $= 1 - \left(\frac{4}{6}\right)^2 - \left(\frac{2}{8}\right)^2 = 0.445$

$= 1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2 = 0.375$

Comparing : $\frac{6}{10}(0.445) + \frac{4}{10}(0.375) = 0.417$ — (iii)

writing all together:

Subsets		Gini_Index
≥9, ≥8	<8	0.17552
≥9, <8	≥8	0.3
≥8, <8	≥9	0.417

⇒ Best cuz its min.

Δ Gini of that attribute = Gini (T) − G(T, CG, PA)

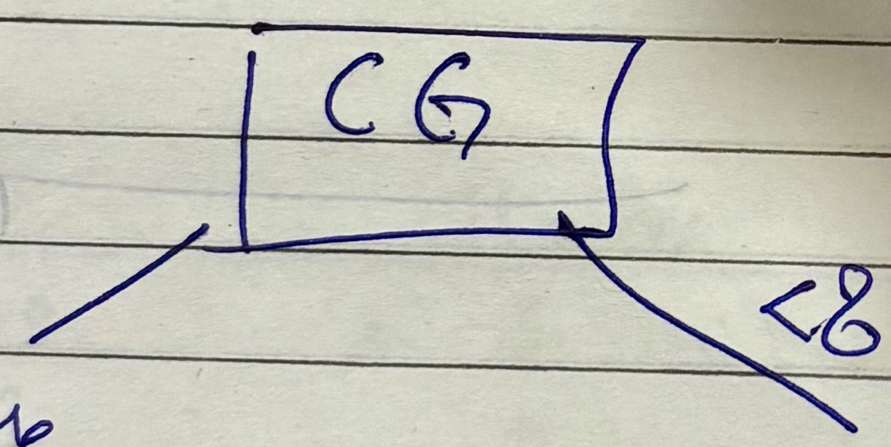
= 0.42 − 0.1755

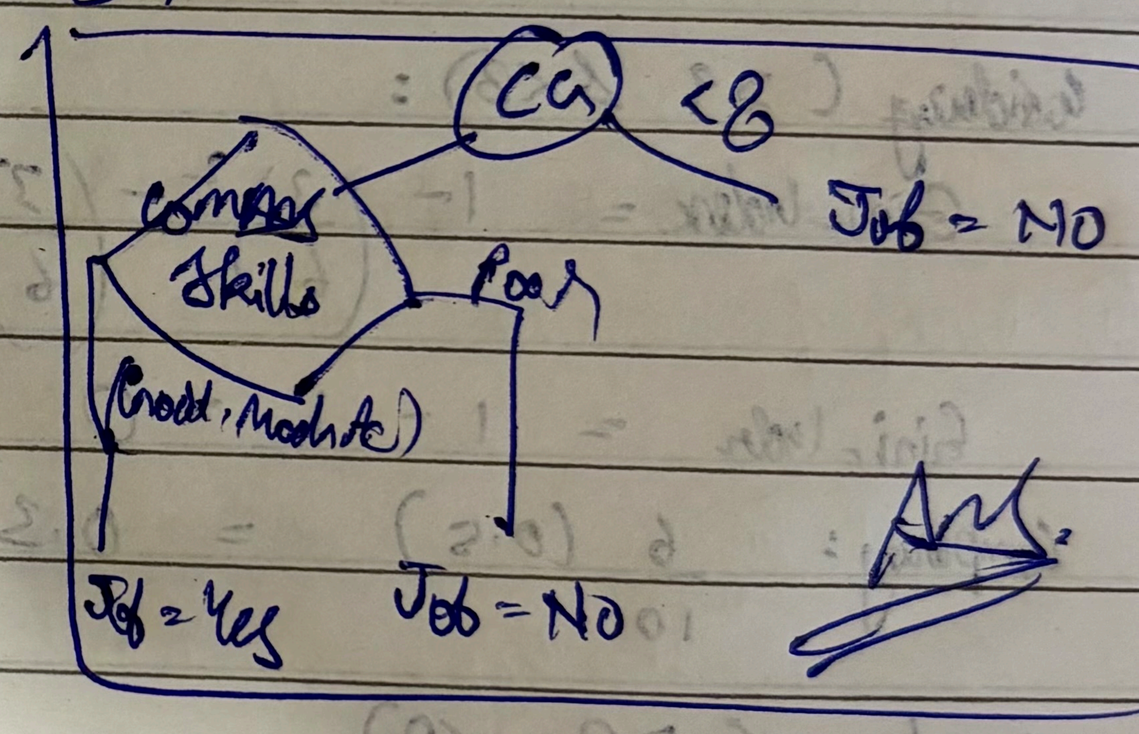
$\boxed{= 0.2445}$

Make table after computing GINI for all:

Attribute	Gini_Index	ΔGini
CG	0.1755	0.2445
Inter	0.368	0.052
Prac know	0.3057	0.1146
Comms	0.1755	0.2445

Considering max Δ Gini





Ans.

Rest of the dataset

Job offer = NO

↓

Repeat the same Gini-Index thing again put more one under it, and the classify on your own basis.

K-Means Clustering

1. Write given data points and centroids and compute dis b/w them
2. Randomly assign clusters to each centroid
3. Assign cluster to the smallest value
4. Find new centroids by adding points & averaging them from the same cluster.
5. Keep doing this until "clus" & "new clus" are same.

6. Euc $= \sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$

   Man $= |x_2-x_1| + |y_2-y_1|$

   cheb $= \max\left(|x_2-x_1|, |y_2-y_1|\right)$

Date .....

① K-Means Clustering:

② Numerical: Centroids = A1 (2,10), B1 (5,8), C1 (1,2)

Data Points			Distance to 2,10	Distance to 5,8	Distance to 1,2	Cluster	New Cluster
A_1	2	10	0	3.61	8.06	1	
A_2	2	5	5	4.24	3.16	3	
A_3	8	4	8.49	5	7.28	2	
B_1	5	8	3.61	0	7.21	2	
B_2	7	5	7.07	3.61	6.71	2	
B_3	6	4	7.21	4.12	5.39	2	
C_1	1	2	8.06	7.21	0	3	
C_2	4	9	2.24	1.41	7.62	2	
			Clus-1	Clus-2	Clus-3		

Euc Dis = $\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$

New Centroids:

for clus-1 ⇒ same (2,10)

for clus-2 ⇒ $\frac{8+5+7+6+4}{5}, \frac{4+8+5+4+9}{5} = (6,6)$

for clus-3 ⇒ $\frac{3}{2}, \frac{7}{2} \Rightarrow (1.5, 3.5)$

Calculating dis again from from these centroids:

Data Points			Distance to			Cluster	New Cluster
			2 10	6 6	1.5 3.5		
A_1	2	10	0	5.66	6.52	1	1
A_2	2	5	5	4.12	1.58	3	3
A_3	8	4	8.49	2.83	6.52	2	2
B_1	5	8	3.61	2.24	5.70	2	2
B_2	7	5	7.07	1.41	5.70	2	2
B_3	6	4	7.21	2	4.53	2	2
C_1	1	2	8.06	6.40	1.58	3	3
C_2	4	9	2.24	3.61	6.02	2 →	1

Calculating Centroids again:

for clus-1 ⇒ (3, 9.5)

for clus-2 ⇒ (6.5, 5.25)

for clus-3 ⇒ (1.5, 3.5)

Do it again, calculate it for these centroids, keep doing this process until "cluster" and "new cluster" are same