

Decol

Statistical Foundations

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Quiz 3

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Q2.

let's

R be the real autocorrelation Matrix.

7 eigen values.

for \underline{x} Eigen vector,

Then:

$R\underline{x} - \lambda \underline{x} = 0$... (1) We know that R is a Hermitian matrix, then $R = R^H$

$$\Rightarrow R\underline{x} = \lambda \underline{x} \quad \text{and } R^H \underline{x} = \lambda \underline{x}$$

$$\Rightarrow (R\underline{x})^H = (\lambda \underline{x})^H$$

$$\Rightarrow \underline{x}^H R^H = \lambda^* \underline{x}^H \quad \text{as } \lambda \text{ is a scalar}$$

$$\Rightarrow \underline{x}^H R^H = \lambda^* \underline{x}^H \quad (R = R^H)$$

Multiplying both sides by \underline{x}

$$\Rightarrow \underline{x}^H R \underline{x} = \lambda^* \underline{x}^H \underline{x}$$

$$\Rightarrow \underline{x}^H \lambda \underline{x} = \lambda^* \underline{x}^H \underline{x}$$

$$\Rightarrow \lambda \cdot \underline{x}^H \underline{x} = \lambda^* \underline{x}^H \underline{x}$$

$$\Rightarrow (\lambda - \lambda^*) \cdot \underline{x}^H \underline{x} = 0$$

As $\underline{x} \neq 0$, Hence $\underline{x}^H \underline{x} \neq 0$

From above

$$\lambda - \lambda^* = 0$$

$\therefore \boxed{\lambda = \lambda^*}$ \rightarrow It implies that all eigenvalues of a real auto correlation matrix are also real.

Prove Eigen vectors corresponding to distinct

Eigen values of R are mutually orthogonal.

Let's assume λ_1 and λ_2 are two distinct

Eigen values of R and \underline{x}_1 and \underline{x}_2 are the

corresponding Eigen vectors.

Then. $R \underline{x}_1 - \lambda_1 \underline{x}_1 = 0$

$$R \underline{x}_1 - \lambda_1 \underline{x}_1 = 0$$

$$\Rightarrow R \underline{x}_1 = \lambda_1 \underline{x}_1 \quad \dots (1)$$

$$R \underline{x}_2 - \lambda_2 \underline{x}_2 = 0$$

$$\Rightarrow R \underline{x}_2 = \lambda_2 \underline{x}_2$$

Taking Hermitian of both sides of eqn. 2

$$(R \underline{x}_2)^H = (\lambda_2 \underline{x}_2)^H$$

$$\Rightarrow \underline{x}_2^H R^H = \lambda_2^* \underline{x}_2^H$$

we know that for R real autocorrelation

matrix $\gamma = \gamma^*$ (all the eigenvalues are real)

$$\text{so, } \underline{\gamma}_1 = \underline{\gamma}_1^* \quad \underline{\gamma}_2 = \underline{\gamma}_2^*$$

$$\underline{x}_2^H R \underline{x}_2 = \underline{\gamma}_2^* \underline{x}_2^H$$

$$\Rightarrow \underline{x}_2^H R \underline{x}_2 = \underline{\gamma}_2 \underline{x}_2^H \quad [\text{As, } R = R^H \text{ and } \underline{\gamma}_2 = \underline{\gamma}_2^*]$$

Multiplying both sides by \underline{x}_1

$$\underline{x}_2^H R \underline{x}_1 = \underline{\gamma}_2 \underline{x}_2^H \underline{x}_1$$

$$\Rightarrow \underline{x}_2^H \underline{\gamma}_1 \underline{x}_1 = \underline{\gamma}_2 \underline{x}_2^H \underline{x}_1 \quad [\text{Replacing } R \underline{x}_1 = \underline{x}_1 \underline{x}_1^H]$$

$$\Rightarrow \underline{\gamma}_1 \underline{x}_2^H \underline{x}_1 = \underline{\gamma}_2 \underline{x}_2^H \underline{x}_1$$

$$\Rightarrow (\underline{\gamma}_1 - \underline{\gamma}_2) \underline{x}_2^H \underline{x}_1 = 0$$

As $(\underline{\gamma}_1 - \underline{\gamma}_2) \neq 0$

$$\underline{x}_2^H \underline{x}_1 = 0$$

This implies that \underline{x}_1 and \underline{x}_2 are mutually

orthogonal to each other.

Q3. If X and Y are independent Random Variable
a) then Prove $H(XY) = H(X) + H(Y)$

Ans we know that

$$H(X) = - \sum_x P(x) \log P(x)$$

$$H(Y) = - \sum_y P(y) \log P(y)$$

$$H(X, Y) = - \sum_{x,y} P(x, y) \log P(x, y)$$

$$\left. \begin{aligned} & A, B, X, Y \text{ are independent,} \\ & P(X, Y) = P(X) \cdot P(Y) \\ & \sum_x P(x, y) = P(y) \\ & \sum_y P(x, y) = P(x) \end{aligned} \right\}$$

$$\left[H(X, Y) = - \sum_{x,y} P(x, y) [\log [P(x) \cdot P(y)]] \right]$$

$$= - \sum_{x,y} P(x, y) [\log P(x) + \log P(y)]$$

$$= - \sum_{x,y} P(x, y) \log P(x) - \sum_y \sum_x P(x, y) \log P(y)$$

$$= - \sum_x P(x) \log P(x) - \sum_y P(y) \log P(y)$$

$$H(X, Y) = H(X) + H(Y)$$

Hence Proved

b) In the given distribution.

~~P(X)~~ for x distribution.

$$P(1) = \frac{5}{9} \text{ and } P(0) = \frac{4}{9}$$

$$H(x) = - \sum_x P(x) \log P(x)$$

$$H(x)$$

$$= - \left[5 \times P(1) \times \log P(1) + 4 \times P(0) \times \log P(0) \right]$$

$$= - \left[5 \times \frac{5}{9} \times \log_2 \frac{5}{9} + 4 \times \frac{4}{9} \times \log_2 \frac{4}{9} \right]$$

$$= - \left[\frac{25}{9} \times (-0.848) + \frac{16}{9} \times (-1.17) \right]$$

$$= \frac{25 \times 0.848}{9} + \frac{16 \times 1.17}{9}$$

$$= \frac{21.2 + 18.72}{9} = \frac{39.92}{9} = 4.43$$

$$H(x) = 4.43$$

For y distribution.

22.12 + 34.8

$$P(1) = \frac{1}{9}$$

$$P(a) = \frac{2}{9}, P(b) = \frac{2}{9}$$

$$P(c) = \frac{2}{9}, P(d) = \frac{2}{9} \Rightarrow (B) .18$$

H(y)

(B) .18

$$= - \sum_y P(y) \log P(y)$$

(B) .18

$$= - [P(1) \times \log P(1) + 2 \times P(a) \times \log P(a) +$$

$$2 \times P(b) \times \log P(b) + 2 \times P(c) \times \log P(c) +$$

$$2 \times P(d) \times \log P(d)]$$

$$= - \left[\frac{1}{9} \times \log \frac{1}{9} + 2 \times \frac{2}{9} \times \log \frac{2}{9} + 2 \times \frac{2}{9} \times \log \frac{2}{9} \right]$$

$$+ 2 \times \frac{2}{9} \times \log \frac{2}{9} + 2 \times \frac{2}{9} \times \log \frac{2}{9}$$

$$= - \left[\frac{1}{9} \log (0.11) + 4 \times 2 \times \frac{2}{9} \log (0.22) \right]$$

(B) .18

$$= + \left[\frac{3.18}{9} + \frac{16}{9} \times 2.18 \right] = \frac{33.18}{9}$$

$$= \frac{3.18 + 34.88}{9}$$

$$= \frac{38.06}{9} = 4.22 \quad , \quad \frac{2}{9} = 0.22$$

$$H(Y) = 4.22 = 0.22 \quad , \quad \frac{2}{9} = 0.22$$

$$H(XY)$$

$$= - \sum_{x,y} P(x,y) \log P(x,y)$$

$$= - \left[\frac{1}{2} \times \log \frac{1}{2} + 8 \times \frac{1}{16} \times \log \frac{1}{16} \right]$$

$$= \left[(0.5) \log 2 + (0.5) \log 16 \right]$$

$$= \left[\frac{1}{2} \times 1 + 8 \times \frac{1}{16} \times 4 \right] = \frac{1}{2} + 2$$

$$= \frac{1}{2} + \frac{4 \times 8}{16} = \frac{1}{2} + 2$$

$$H(XY) = 2.5$$

$$= 2.5$$

Q4. $w(n+1) = w(n) + \mu [P - R w(n)]$

Cross correlation vector $P = \begin{bmatrix} 0.8 \\ 0.3 \end{bmatrix}$

Auto correlation matrix

$$R = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

$$\mu = 1.0$$

Optimal weight $w = R^{-1} P$

$$R^{-1} = \frac{1}{|\det R|} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix}$$

$$|\det R| = 1 - 0.25 = 0.75$$

$$R^{-1} = \frac{1}{0.75} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} = \begin{bmatrix} 1.33 & -0.66 \\ -0.66 & 1.33 \end{bmatrix}$$

$$w = R^{-1} P$$

$$= \begin{bmatrix} 1.33 & -0.66 \\ -0.66 & 1.33 \end{bmatrix}_{2 \times 2} \begin{bmatrix} 0.8 \\ 0.3 \end{bmatrix}_{2 \times 1}$$

$$= \begin{bmatrix} 1.064 - 0.198 \\ -0.528 + 0.399 \end{bmatrix} = \begin{bmatrix} 0.866 \\ -0.129 \end{bmatrix}$$

Hence,

$$W_{\text{opt}} = \frac{(n)(0.9 - 0.75) + (n)(0)}{(n)(0.866 - 0.129)} = \frac{(1+n)(0.14)}{(n)(0.7367)}$$

$$\left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = \cancel{\left[\begin{array}{c} 0.14 \\ n \\ 0.7367 \end{array} \right]}$$

$$0.14 = 0.7367$$

$$\Rightarrow \frac{1}{n} = \frac{0.14}{0.7367} = 0.188$$

$$\left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = \frac{1}{0.188} = 5.3$$

$$EF = 1 - 0.188 = 0.812 = 81.2\%$$

$$\left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = \left[\begin{array}{c} 0.9 - 1 \\ n \\ 0.866 - 0.129 \end{array} \right] = \frac{1}{0.188} = 5.3$$

$$\left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = \left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = 5.3$$

$$\left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = \left[\begin{array}{c} 0.9 - 0.75 \\ n \\ 0.866 - 0.129 \end{array} \right] = 5.3$$