

الف) مطلب می باشد اد دین

$$\Rightarrow \iiint_{-\infty}^{\infty} xy(c-x-y) dx dy = \iiint_{-\infty}^{\infty} (cxy - x^2y - xy^2) dx dy$$

$$= \int_0^1 \left(\frac{cyx^2}{2} - \frac{yx^3}{3} - \frac{y^2x^2}{2} \Big|_0^1 \right) dy$$

$$= \int_0^1 (cy_2 - y_3 - y_2^2) dy = \frac{cy^2}{4} - \frac{y^3}{6} - \frac{y^4}{6} \Big|_0^2$$

$$\therefore c - \frac{2}{3} - \frac{4}{3} = 1 \Rightarrow c = 3$$

$$f_x(x) = \int_0^2 f_{XY}(x,y) dy = \int_0^2 xy(3-x-y) dy \quad (\text{ب})$$

$$= \int_0^2 (3xy - x^2y - xy^2) dy = \frac{3xy^2}{2} - \frac{x^2y^2}{2} - \frac{xy^3}{3} \Big|_0^2$$

$$\Rightarrow f_x(x) = 6x - 2x^2 - \frac{8}{3}x = 2x^2 - \frac{10}{3}x$$

$$f_x(x) = \begin{cases} -2x^2 - \frac{10}{3}x & 0 < x < 1 \\ 0 & \text{o.w.} \end{cases}$$

E[E[X|Y]] مسئلہ ۲ (iii) میں

LOTUS $\int_{-\infty}^{\infty} E[X|Y=y] f_Y(y) dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{X|Y}(x|y) f_Y(y) dx dy$

conditional $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{XY}(x,y) dx dy = \int_{-\infty}^{\infty} x \int_{-\infty}^{\infty} f_{XY}(x,y) dy dx$

marginal $\int_{-\infty}^{\infty} x f_X(x) dx = E[X]$

$$E[E[X|Y]]$$

حالات ممكنة (possible outcomes) : x_1, x_2, \dots, x_n

$$= \sum_y E[X|Y=y] P(Y=y) = \sum_y \sum_x x P(X=x|Y=y) P(Y=y)$$

conditional $\sum_y \sum_x x P(X=x, Y=y) = \sum_x x \sum_y P(X=x, Y=y)$

marginal $\sum_x x P(X=x) = E[X]$

$$1) E[Var(X|Y)] = E[E[X^2|Y]] - E[(E[X|Y])^2] \quad (\rightarrow)$$

طريق اول $* E[Var(X|Y)] = E[X^2] - E[(E[X|Y])^2]$

$$2) Var(E[X|Y]) = E[(E[X|Y])^2] - E[E[X|Y]]^2$$

طريق اول $** Var(E[X|Y]) = E[(E[X|Y])^2] - E[X]^2$

+ $\underbrace{E[X^2] - E[X]^2}_{Var(X)} = E[Var(X|Y)] + Var(E[X|Y])$

$$\text{پیش Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)] \quad (\rightarrow)$$

$$\rightarrow Cov(ax+b, cy+d) = E[(ax+b - \mu_{ax+b})(cy+d - \mu_{cy+d})]$$

$$= E[(ax+b - a\mu_X - b)(cy+d - c\mu_Y - d)]$$

$$= E[a(X - \mu_X)c(Y - \mu_Y)] = ac E[(X - \mu_X)(Y - \mu_Y)] \\ = ac Cov(X, Y)$$

Subject :

$$\underbrace{L(\theta | x_1, x_2, \dots, x_N)}_{\text{Likelihood}} = P(x_1 | \theta) \cdots P(x_N | \theta) \quad (\leftarrow \text{Joint PDF})$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_1-\theta)^2}{2\sigma^2}} \times \cdots \times \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_N-\theta)^2}{2\sigma^2}}$$

$$\log \underbrace{\text{likelihood}}_{\rightarrow} \ln L(\theta | X) = \frac{-1}{\sigma\sqrt{2\pi}} \left(\frac{(x_1-\theta)^2}{2} + \cdots + \frac{(x_N-\theta)^2}{2} \right)$$

$$\rightarrow \frac{d \ln L(\theta | X)}{d\theta} = 0 \rightarrow \frac{\theta - x_1}{\sigma^2} + \cdots + \frac{\theta - x_N}{\sigma^2} = 0$$

$$\rightarrow \frac{N\theta}{\sigma^2} = \frac{x_1 + x_2 + \cdots + x_N}{\sigma^2} \Rightarrow \hat{\theta}_{\text{MLE}} = \frac{x_1 + x_2 + \cdots + x_N}{N}$$

$$\hat{\theta}_{\text{MAP}}(x) = \underset{\theta}{\operatorname{argmax}} f(\theta | X) = \underset{\theta}{\operatorname{argmax}} \underbrace{f(x | \theta)}_{\text{likelihood}} \underbrace{f(\theta)}_{\text{prior}} \quad (\leftarrow)$$

$$\rightarrow \frac{-1}{\sigma\sqrt{2\pi}} \left(\frac{(x_1-\theta)^2}{2} + \cdots + \frac{(x_N-\theta)^2}{2} + \frac{(\theta-\nu)^2}{\beta^2}/2 \right)$$

$$\rightarrow \frac{d}{d\theta} \text{MAP} = 0 \rightarrow \frac{\theta - x_1}{\sigma^2} + \cdots + \frac{\theta - x_N}{\sigma^2} + \frac{\theta - \nu}{\beta^2} = 0$$

$$\rightarrow \frac{N\theta}{\sigma^2} + \frac{\theta}{\beta^2} = \frac{x_1 + \cdots + x_N}{\sigma^2} + \frac{\nu}{\beta^2}$$

$$\rightarrow \theta \left(\frac{N\beta^2 + \sigma^2}{\sigma^2\beta^2} \right) = \frac{x_1 + \cdots + x_N}{N\sigma^2} + \frac{\nu}{\beta^2}$$

$$\rightarrow \hat{\theta}_{\text{MAP}} = \frac{\beta^2}{N\beta^2 + \sigma^2} (x_1 + \cdots + x_N) + \frac{\sigma^2}{N\beta^2 + \sigma^2} \nu$$

$$\Rightarrow \hat{\theta}_{\text{MAP}} = \frac{\beta^2 N}{N\beta^2 + \sigma^2} \left(\frac{x_1 + \cdots + x_N}{N} \right) + \frac{\sigma^2}{N\beta^2 + \sigma^2} \nu$$

Subject :

$$\lim_{N \rightarrow \infty} \hat{\theta}_{MAP} = \frac{N\beta^2}{N\beta^2} \left(\frac{x_1 + \dots + x_N}{N} \right) + \frac{1}{N} \xrightarrow{0}$$

$$= \frac{x_1 + \dots + x_N}{N}$$

$$\Rightarrow n \rightarrow \infty : \hat{\theta}_{MAP} = \hat{\theta}_{MLE}$$

مسئلہ ۲۔ (الف) متغیر تصادی بذریغتہ شد

$x \sim \text{Bern}(p)$, p : احتمال بذریغتہ شد: $P(x=1)$

$$P = \frac{v}{n} \quad \text{حال با ترجیح } v \text{ دریم. data}$$

$$\rightarrow \text{انتدیبی: } H(x) = - \sum_x P(x=x) \log_p P(x=x)$$

$$= - \left(P(x=0) \log_p P(x=0) + P(x=1) \log_p P(x=1) \right)$$

$$= - \left(\frac{5}{12} \log_2 \frac{5}{12} + \frac{7}{12} \log_2 \frac{7}{12} \right)$$

$$= 0,9798$$

ب) متغیر تصادی فکار، R ، $P = 0.5$ ، متغیر تصادی توسیعی، x ، $P(x=r)$

$$\Rightarrow IG(x, R) = H(x) - H(x|R)$$

$$H(x|R) = - \sum_r P(r) \log \frac{P(r)}{P(R)}$$

$$\Rightarrow H(x|R) = - \left[\frac{1}{6} \log \frac{\frac{1}{6}}{\frac{1}{3}} \times 2 + \frac{1}{6} \log \frac{\frac{1}{6}}{\frac{1}{3}} \times 2 + \frac{1}{12} \log \frac{\frac{1}{12}}{\frac{1}{3}} \right. \\ \left. + \frac{1}{4} \log \frac{\frac{1}{4}}{\frac{1}{3}} \right] = 0.9371$$

$$\rightarrow IG(x, R) = H(x) - H(x|R) = 0,9798 - 0,9371 = 0,0427$$

$$IG(x, P) = H(x) - H(x|P)$$

$$\rightarrow H(x|P) = - \left[\frac{5}{12} \log \frac{5/12}{5/12} + \frac{2}{12} \log \frac{2/12}{7/12} \right] = 0$$

$$+ \frac{5}{12} \log \frac{5/12}{2/12}] = 0,503$$

$$\Rightarrow IG(x, Z) = 0,9798 - 0,503 = 0,4768$$

$a_{n \times 1} > x_{n \times 1} > Ax_{n \times n}$

Date _____

Subject :

$$\hookrightarrow \frac{d}{dx} \underbrace{\bar{ax}}_{\text{scalar}} = \left[\frac{d}{dx_1} \bar{ax} \quad \frac{d}{dx_2} \bar{ax} \dots \quad \frac{d}{dx_n} \bar{ax} \right] \quad (1.0)$$

$$\bar{ax} = \bar{ax} = a_1x_1 + a_2x_2 + \dots + a_nx_n \Rightarrow \frac{d\bar{ax}}{dx_j} = a_j, \quad \frac{d\bar{x}^T a}{dx_j} = a_j$$

$$\Rightarrow \frac{d\bar{x}}{dx} = \frac{d}{dx} \bar{ax} = [a_1 \quad a_2 \dots \quad a_n] = \bar{a}^T$$

$$\hookrightarrow \frac{d}{dx} \underbrace{\bar{x}^T x}_{\text{scalar}} = \left[\frac{d}{dx_1} \bar{x}^T x \quad \dots \quad \frac{d}{dx_n} \bar{x}^T x \right]$$

$$\bar{x}^T x = x_1^2 + \dots + x_n^2 \Rightarrow \frac{d}{dx_j} \bar{x}^T x = 2x_j$$

$$\Rightarrow \frac{d}{dx} \bar{x}^T x = [2x_1 \quad 2x_2 \dots \quad 2x_n] = 2\bar{x}^T$$

$$\hookrightarrow \frac{d}{dx} \underbrace{(\bar{x}^T a)^2}_{\text{scalar}} = \left[\frac{d}{dx_1} (\bar{x}^T a)^2 \quad \dots \quad \frac{d}{dx_n} (\bar{x}^T a)^2 \right]$$

$$(\bar{x}^T a)^2 = (a_1x_1 + \dots + a_nx_n)^2 \Rightarrow \frac{d(\bar{x}^T a)^2}{dx_j} = 2a_j(a_1x_1 + \dots + a_nx_n)$$

$$\Rightarrow \frac{d}{dx} \underbrace{(\bar{x}^T a)^2}_{\text{scalar}} = [2(a_1x_1 + \dots + a_nx_n)a_1 \quad 2(a_1x_1 + \dots + a_nx_n)a_2 \dots \quad 2(a_1x_1 + \dots + a_nx_n)a_n]$$

$$= 2(a_1x_1 + \dots + a_nx_n) \underbrace{[a_1 \quad a_2 \dots \quad a_n]}_{\bar{a}^T}$$

$$= 2\bar{x}^T \underbrace{\bar{a} \bar{a}^T}_{\bar{a}^T}$$

$$\hookrightarrow \frac{d}{dx} \underbrace{Ax}_{\text{vector}} = \begin{bmatrix} \frac{d}{dx_1} (Ax)_1 & \dots & \frac{d}{dx_n} (Ax)_1 \\ \vdots & & \vdots \\ \frac{d}{dx_1} (Ax)_n & \dots & \frac{d}{dx_n} (Ax)_n \end{bmatrix}$$

$$(Ax)_i = a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n \Rightarrow \frac{d(Ax)_i}{dx_j} = a_{ij}$$

@ MICRO

Subject :

$$\Rightarrow \frac{d}{dx_j} (Ax)_i = a_{ij} \Rightarrow \frac{d}{dx} Ax = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ | & | & \ddots & | \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} = A$$

$$\therefore \frac{d}{dx} \underbrace{x^T A}_{\text{vector}} \rightarrow x^T A = [(x^T A)_1, (x^T A)_2, \dots, (x^T A)_n]$$

$$\Rightarrow \frac{d}{dx} \vec{x}^T A = \begin{bmatrix} \frac{d}{dx_1} (\vec{x}^T A)_1 & \frac{d}{dx_2} (\vec{x}^T A)_1 & \cdots & \frac{d}{dx_n} (\vec{x}^T A)_1 \\ \vdots & & & \vdots \\ \frac{d}{dx_1} (\vec{x}^T A)_n & \frac{d}{dx_2} (\vec{x}^T A)_n & \cdots & \frac{d}{dx_n} (\vec{x}^T A)_n \end{bmatrix}$$

$$(\bar{x}^T A)_i = x_1 a_{1i} + x_2 a_{2i} + \dots + x_n a_{ni}$$

$$\Rightarrow \frac{d}{x_j} (x^T A)_i = a_{ji} \Rightarrow \frac{d}{dx} x^T A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & \dots & \dots & a_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ a_{n1} & \dots & \dots & a_{nn} \end{bmatrix} = A^T$$

$$2.) \frac{d}{dx} x^T A x : f(x) = x^T A x - \sum_{j=1}^n a_j y_j$$

$$\rightarrow f(x+h) = (x+h)^T A (x+h) = x^T A x + x^T A h + h^T A x + h^T A h$$

$$\Rightarrow \frac{f(x+h) - f(x)}{h} = \frac{x^T A h + h^T A x + h^T A h}{h}$$

$$h^T A x : \text{scalar} \rightarrow h^T A x = (h^T A x)^T = x^T A^T h$$

$$\Rightarrow \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} = \lim_{h \rightarrow 0} \frac{(x^T A + x^T A^T) h + h^T A h}{h} \underset{h \rightarrow 0}{=} x^T A + x^T A^T$$

$$= x^T (A + A^T)$$

Subject :

$$\alpha = \sum_{j=1}^n x_j y_j, \quad z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}$$

(r. 2015)

$$\frac{\partial \alpha}{\partial z_k} = \sum_{j=1}^n \left(x_j \frac{\partial y_j}{\partial z_k} + y_j \frac{\partial x_j}{\partial z_k} \right)$$

$$\Rightarrow k=1, 2, \dots, n \Rightarrow \frac{\partial \alpha}{\partial z} = \frac{\partial \alpha}{\partial y} \frac{\partial y}{\partial z} + \frac{\partial \alpha}{\partial x} \frac{\partial x}{\partial z}$$

$$\Rightarrow x^T \frac{\partial y}{\partial z} + y^T \frac{\partial x}{\partial z}$$

$$HH^T = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 2 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 5 & 2 \\ 2 & 2 \end{bmatrix} = 4 \quad (\text{r. 2015})$$

$$Ax = \lambda x \rightarrow (A - \lambda I)x = 0 \rightarrow \det(A - \lambda I) = 0$$

$$\rightarrow \begin{vmatrix} 5-\lambda & 2 \\ 2 & 2-\lambda \end{vmatrix} = 10 - 7\lambda + \lambda^2 - 4 = \lambda^2 - 7\lambda + 6$$

$$= (\lambda - 6)(\lambda - 1) = 0 \rightarrow \lambda_1 = 6, \quad \lambda_2 = 1$$

$$\Rightarrow \lambda_1 = 6 \rightarrow \underbrace{N(A - 6I)}_{\text{Null}} = N \begin{pmatrix} -1 & 2 \\ 2 & -4 \end{pmatrix} \Rightarrow \underbrace{x_1}_{\text{بذر داشت}} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad \text{و هر ضریبی} \rightarrow$$

$$\Rightarrow \lambda_2 = 1 \rightarrow N(A - I) = N \begin{pmatrix} 4 & 2 \\ 2 & 1 \end{pmatrix} \Rightarrow \underbrace{x_2}_{\text{بذر داشت}} = \begin{bmatrix} -1 \\ 2 \end{bmatrix} \quad \text{و هر ضریبی از آن}$$

Subject :

$$\text{برهان دلخواهی ۵.۴: } \det(A) = \det(A^T)$$

حال برای بررسی آمدن مقدار دزه بیک ماتریس علی باعث معادله $\det(A - \lambda I) = 0$

معلم نیم، با توجه به (*) که تراویم داریم

$$\det((A - \lambda I)^T) = \det(A^T - \lambda I^T) \quad \text{حال دریم:}$$

از این مکاره نتیجه می شود λ عکس از A^T نیز معرف می شود.

$$\frac{\partial Y}{\partial X} = \frac{\partial}{\partial X} AX + \frac{\partial z}{\partial x}$$

$$\frac{\partial A X}{\partial X} = A \rightarrow \text{خط مسندی از}$$

$$Z = \begin{bmatrix} (x_1 x_2 + 1)^2 \\ (x_2 x_3 + 1)^2 \\ (x_3 x_1 + 1)^2 \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix}$$

$$\Rightarrow \frac{\partial Z}{\partial x} = \begin{bmatrix} \frac{\partial z_1}{\partial x_1} & \frac{\partial z_1}{\partial x_2} & \frac{\partial z_1}{\partial x_3} \\ \vdots & \ddots & \vdots \\ \frac{\partial z_3}{\partial x_1} & \cdots & \frac{\partial z_3}{\partial x_3} \end{bmatrix} \begin{bmatrix} 2(x_1x_3 + 1)x_2 & 2(x_2x_3 + 1)x_1 \\ 0 & 2(x_1x_3 + 1)x_2 \end{bmatrix}$$

$$= \begin{bmatrix} 2(x_1x_2+1)x_2 & 2(x_1x_2+1)x_1 & 0 \\ 0 & 2(x_2x_3+1)x_3 & 2(x_2x_3+1)x_2 \\ 2(x_3x_1+1)x_3 & 0 & 2(x_3x_1+1)x_1 \end{bmatrix}$$

$$\Rightarrow \frac{\partial Y}{\partial X} = \begin{bmatrix} 1 & 2 & -1 \\ 0 & 3 & 2 \\ 1 & 4 & -2 \end{bmatrix} + \begin{bmatrix} 24 & 8 & 0 \\ 0 & 4 & -12 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 25 & 10 & -1 \\ 0 & 7 & -10 \\ 1 & 4 & -2 \end{bmatrix}$$