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## Assignment-2

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Q2) a) Prior  $P(\theta) = \prod_{i=1}^d \theta_i e^{-\sum_{i=1}^d \theta_i}$

for  $d$ -dimensional multivariate Bernoulli space

$$P(D|\theta) = \prod_{i=1}^n \prod_{j=1}^{n_i} \theta_j^{n_{ij}} (1-\theta_j)^{1-n_{ij}}$$

$$\arg \max_{\theta} P(\theta) \cdot P(D|\theta) = \arg \max_{\theta} \prod_{i=1}^d \theta_i e^{-\sum_{i=1}^d \theta_i} \prod_{i=1}^n \prod_{j=1}^{n_i} \theta_j^{n_{ij}} (1-\theta_j)^{1-n_{ij}}$$

$$\Rightarrow \sum_{i=1}^d \ln \theta_i - \sum_{i=1}^d \theta_i + \sum_{i=1}^n \sum_{j=1}^{n_i} n_{ij} \ln \theta_j + (1-n_{ij}) \ln (1-\theta_j)$$

Now, differentiating w.r.t  $\theta_j$ , we get

$$\Rightarrow \theta_j^{-1} - 1 + \sum_{j=1}^n n_j / \theta_j - (1-n_j) / (1-\theta_j) = 0$$

$$\Rightarrow 1 - \theta_j + \sum_{j=1}^n n_j (1-\theta_j) - \theta_j (1-n_j) = 0$$

$$\Rightarrow \frac{1 - \theta_j}{\theta_j} + \sum_{j=1}^n \frac{n_j - n_j \theta_j}{\theta_j (1 - \theta_j)} - \theta_j + \theta_j n_j = 0$$

$$\Rightarrow \frac{1 - \theta_j}{\theta_j} + \sum_{j=1}^n \frac{n_j - \theta_j}{\theta_j (1 - \theta_j)} = 0$$

$$\Rightarrow \frac{\theta_j / (1 - \theta_j)}{\theta_j} - \theta_j (1 - \theta_j) + \sum_{j=1}^n (n_j - \theta_j) = 0$$

~~cancel out terms~~ ~~cancel out terms~~ = 0

$$\Rightarrow 1 - \theta_j - \theta_j + \theta_j^2 + \sum_{j=1}^n n_j - n \theta_j = 0$$

$$\Rightarrow 1 - 2\theta_j + \theta_j^2 + \sum_{j=1}^n n_j - n \theta_j = 0$$

$$\Rightarrow \theta_j^2 - \theta_j(n+2) + 1 + \sum_{j=1}^n n_j = 0$$

Therefore,

$$\sigma_{MAP} = 2 + n \pm \sqrt{(2+n)^2 - 4 \left( \sum_{j=1}^n u_j + 1 \right)} \quad (1)$$

b) Given,  $\mathbf{u} = \begin{bmatrix} 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \end{bmatrix}$

no. of samples ( $n$ ) = 4  
 from eq (i)

$$\sigma_{MAP} = 2 + 4 \pm \sqrt{(2+4)^2 - 4 \left( \sum_{j=1}^4 u_j + 1 \right)}$$

$$= 6 \pm \sqrt{6^2 - 4(3+1)}$$

$$= \frac{6 \pm \sqrt{36-16}}{2} = \frac{6 \pm \sqrt{20}}{2} = \cancel{\alpha} \frac{(3 \pm \sqrt{5})}{2}$$

$$\sigma_{MAP} = 8 \pm \sqrt{5}$$

$$\sigma_{MAP}^2 = 6 \pm \sqrt{6^2 - 4(3-1)}$$

$$= 6 \pm \sqrt{36-8}$$

$$= \frac{6 \pm \sqrt{28}}{2} = \cancel{\alpha} \frac{(8 \pm \sqrt{7})}{2}$$

$$\sigma_{MAP} = 8 \pm \sqrt{7}$$

Q 1) b) we know that for a multivariate Bernoulli variable with d dimensions and N samples.

$$x_i = [x_{i1} \ x_{i2} \ \dots \ x_{id}]^T$$

$$x = [x_1 \ x_2 \ \dots \ \dots \ x_N]$$

$$\theta = \{\theta_1 \ \theta_2 \ \dots \ \dots \ \theta_d\}$$

$$P(x_i|\theta) = \prod_{j=1}^d \theta_j^{x_{ij}} (1-\theta_j)^{1-x_{ij}}$$

$$P(x|\theta) = \prod_{i=1}^N \prod_{j=1}^d \theta_j^{x_{ij}} (1-\theta_j)^{1-x_{ij}}$$

Taking ln on both sides we have -

$$\ln P(x|\theta) = \ln \left\{ \prod_{i=1}^N \prod_{j=1}^d \theta_j^{x_{ij}} (1-\theta_j)^{1-x_{ij}} \right\}$$

$$= \sum_{i=1}^N \sum_{j=1}^d \ln \left\{ \theta_j^{x_{ij}} (1-\theta_j)^{1-x_{ij}} \right\}$$

$$= \sum_{i=1}^N \sum_{j=1}^d \{ x_{ij} \ln \theta_j + (1-x_{ij}) \ln (1-\theta_j) \}$$

log likelihood function  $L(\theta)$  is

$$L(\theta) = \sum_{i=1}^N \sum_{j=1}^d \{ x_{ij} \ln \theta_j + (1-x_{ij}) \ln (1-\theta_j) \}$$

$$\frac{\partial L(\theta)}{\partial \theta_j} = \sum_{i=1}^N \left\{ \frac{x_{ij}}{\theta_j} - \frac{(1-x_{ij})}{1-\theta_j} \right\}$$

Equating above to 0

$$\sum_{i=1}^N \left\{ \frac{x_{ij}}{\theta_j} - \frac{(1-x_{ij})}{1-\theta_j} \right\} = 0$$

$$\sum_{i=1}^N \{x_{ij} - \alpha_j/\alpha_j - \alpha_j + \alpha_j/\alpha_j\} = 0$$

$$\sum_{i=1}^N x_{ij} - N\alpha_j = 0$$

$$N\alpha_j = \sum_{i=1}^N x_{ij}$$

$$\boxed{\alpha_j = \frac{1}{N} \sum_{i=1}^N x_{ij}} \quad \text{eMLE}$$

Using the above formula all  $\alpha_j$   $j=1, 2, \dots, d$   
can be calculated to come up with  $\alpha$ .

Observation in Graphs for MLE v/s  $n$  where  
 $m=1, 2, 3, \dots, 50$  is

for low values of  $n$ , MLE gives incorrect estimates. However as the size of the sample grows i.e.  $n$  increases, the estimates of  $\alpha$  comes closer and closer to the real value of the mean.

- e) Let  $x$  be a sample of multivariate Bernoulli with  $d$  dimensions

$$x = [x_1, x_2, \dots, x_d]^T$$

Let  $w_i$  be the classes where  $i=1, 2, \dots, c$

$$P(x|w_i) = \prod_{j=1}^d p_{ij}^{x_j} (1-p_{ij})^{(1-x_j)} \quad \text{--- (1)}$$

We know that

$$g_i(x) = P(w_i|x) - 1$$

$$g_i(x) = \ln(w_j/x)$$

$$g_i(x) = P(x/w_i) \cdot \ln(w_i)$$

taking ln on both sides

$$\ln g_i(x) = \ln(P(x/w_i)) + \ln P(w_i)$$

from eq ①

$$g_i(x) = \ln P(x/w_i) + \ln P(w_i)$$

$$g_i(x) = \ln \left[ \prod_{j=1}^d P_{ij}^{x_j} (1-P_{ij})^{1-x_j} \right] + \ln P(w_i)$$

$$g_i(x) = \sum_{j=1}^d [x_j \ln P_{ij} + (1-x_j) \ln (1-P_{ij}) + \ln P(w_i)]$$

formulae for discriminant of class  $w_i$

Given, For class 1

$$\text{Prior} = P(w_1) = P(w_2) = 0.5$$

$$P_1 = \begin{bmatrix} 0.5 \\ 0.8 \end{bmatrix}$$

$$P_{11} = 0.5$$

$$P_{12} = 0.8$$

$$X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

therefore

$$g_1(x) = \sum_{j=1}^2 [x_j \ln P_{1j} + (1-x_j) \ln (1-P_{1j})] + \ln 0.5$$

$$g_1(x) = x_1 \ln P_{11} + (1-x_1) \ln (1-P_{11}) + x_2 \ln P_{12} + (1-x_2) \ln (1-P_{12}) + \ln 0.5$$

$$= x_1 \ln 0.5 + (1-x_1) \ln 0.5 + x_2 \ln 0.8 + (1-x_2) \ln 0.2$$

$$\begin{aligned}
 & (x_1 + 1 - x_1) \ln 0.5 + x_1 \ln 0.6 + (1-x_2) \ln 0.2 + \ln 0.5 \\
 = & x_2 [\ln 0.8 - \ln 0.2] + \ln 0.2 + \ln 0.5 + \ln 0.5 \\
 = & 1.886 x_2 - 2.995
 \end{aligned}$$

$$\Rightarrow g_1(x) = 1.886 x_2 - 2.995$$

for class 2

$$P_2 = \begin{bmatrix} 0.9 \\ 0.2 \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$p_{21} = 0.9 \quad \text{and} \quad p_{22} = 0.2$$

$$g_2(x) = \sum_{j=1}^2 [x_j \ln p_{2j} + (1-x_j) \ln (1-p_{2j})] + \ln 0.5$$

$$\begin{aligned}
 = & x_1 \ln p_{21} + (1-x_1) \ln (1-p_{21}) + x_2 \ln p_{22} + (1-x_2) \\
 & \ln (1-p_{22}) + \ln 0.5
 \end{aligned}$$

$$\begin{aligned}
 = & x_1 \ln (0.9) + (1-x_1) \ln (0.1) + x_2 \ln (0.2) + (1-x_2) \\
 & \ln (0.8) + \ln 0.5
 \end{aligned}$$

$$\begin{aligned}
 = & x_1 [\ln 0.9 - \ln 0.1] + x_2 [\ln 0.2 - \ln 0.8] + \\
 & \ln 0.1 + \ln 0.8 + \ln 0.5
 \end{aligned}$$

$$= 2.194 x_1 - 1.886 x_2 - 3.218$$

$$g_2(x) = 2.194 x_1 - 1.886 x_2 - 3.218$$

3) a) Let us assume an arbitrary matrix

$$X = \begin{bmatrix} 6 & 6 \\ 0 & 6 \end{bmatrix}$$

$$U = \begin{bmatrix} (6+6)/2 \\ (0+6)/2 \end{bmatrix}, \begin{bmatrix} 6 \\ 3 \end{bmatrix}$$

computing centralized  $(x) = x - c$

$$x - c = x - U = \begin{bmatrix} 6-6 & 6-6 \\ 0-3 & 6-3 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ -3 & 3 \end{bmatrix}$$

covariance matrix

$$S = \frac{1}{N} (x - c)(x - c)^T$$

$$= \frac{1}{2} \begin{bmatrix} 0 & 0 \\ -3 & 3 \end{bmatrix} \begin{bmatrix} 0 & -3 \\ 0 & 3 \end{bmatrix}$$

$$\frac{1}{2} \left\{ \begin{bmatrix} 0 & 0 \\ 0 & 18 \end{bmatrix} \right\} = \begin{bmatrix} 0 & 0 \\ 0 & 9 \end{bmatrix}$$

$$S = \begin{bmatrix} 0 & 0 \\ 0 & 9 \end{bmatrix}$$

computing eigenvalues & eigenvectors for  
above matrix

Let  $\lambda_1$  &  $\lambda_2$  be the eigen values for  
eigen vectors.

$$|s - \lambda I| = 0$$

$$\begin{vmatrix} s-\lambda & 0 \\ 0 & s-\lambda \end{vmatrix} = 0$$

$$-(s-\lambda)(s-\lambda) = 0$$

$$\lambda_1 = 0 \quad \lambda_2 = s$$

Eigen vectors  $\vec{v}$

$$(A - \lambda_1 I) \cdot \vec{v} = 0$$

$$\text{for } \lambda_1 = 0$$

$$(s - \lambda_1 I) \vec{v} = 0$$

$$\vec{v} = \begin{bmatrix} a \\ b \end{bmatrix}$$

thus

$$\begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = 0$$

$$sa = 0$$

$$a = 0$$

$$b = b$$

$$\vec{v} = \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 0 \\ b \end{bmatrix} = b \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\vec{v}_1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\text{for } \lambda_2 = s$$

$$(s - \lambda_2 I) \vec{v} = 0$$

$$\vec{v} = \begin{bmatrix} c \\ d \end{bmatrix}$$

$$\begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = 0$$

$$\begin{bmatrix} sc & 0 \\ 0 & sd \end{bmatrix} = 0$$

$$9d \geq 0$$

$$d \geq 0$$

$$c = C$$

$$\vec{v} = \begin{bmatrix} c \\ d \end{bmatrix} = c \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\text{Eigenvalues} = 9, 0$$

$$\text{Eigenvectors} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$\text{for } \lambda_1 = 9 \quad \lambda_2 \geq 0$$

$$U = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \{\vec{v}_1, \vec{v}_2\} \quad \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Eigenvectors arranged are in descending order of eigenvalues.

$$U = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

$$Y = U^T \cdot X - C$$

$$U^T = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad X - C = \begin{bmatrix} 0 & 0 \\ -3 & 3 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$Y = U^T \cdot X - C$$

$$= \begin{bmatrix} -3 & 3 \\ 0 & 0 \end{bmatrix}$$

$$Y = \begin{bmatrix} -3 & 3 \\ 0 & 0 \end{bmatrix}$$

b) Let  $A = UY + \text{mean}(x)$

$B = x$

$A = UY + \text{mean}(x)$

$$U = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

$$Y = \begin{bmatrix} -8 & 3 \\ 0 & 0 \end{bmatrix} \quad \text{mean}(x) = \begin{bmatrix} 6 \\ 3 \end{bmatrix}$$

$$A = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \begin{bmatrix} -8 & 3 \\ 0 & 0 \end{bmatrix} + \text{mean}(x)$$

$$= \begin{bmatrix} 0 & 0 \\ -8 & 3 \end{bmatrix} + \begin{bmatrix} 6 \\ 3 \end{bmatrix}$$

$$A = \begin{bmatrix} 6 & 6 \\ 0 & 6 \end{bmatrix}$$

$$B = \begin{bmatrix} 6 & 6 \\ 0 & 6 \end{bmatrix}$$

finding MSG b/w A & B

$$MSG = \frac{1}{q} \sum_{i=1}^q \sum_{j=1}^q (a_{ij} - b_{ij})^2$$

$$= \frac{1}{4} \sum_{i=1}^2 \sum_{j=1}^2 \left( \begin{bmatrix} 6 & 6 \\ 0 & 6 \end{bmatrix} - \begin{bmatrix} 6 & 6 \\ 0 & 6 \end{bmatrix} \right)$$

$$= \frac{1}{4} \sum_{i=1}^2 \sum_{j=1}^2 \left( \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \right)$$

$$= \frac{1}{4} \times 0$$

$$\boxed{MSG = 0}$$