

1.

山东财经大学实验报告

学院:

班级:

姓名:

学号:

年 月

课程名称:

实验名称:

实验内容:

$$\begin{aligned}
 1. (a) \quad p(x|\theta) &= \frac{1}{\sqrt{2\pi}\theta} \exp\left(-\frac{(x-2)^2}{2\theta^2}\right) \\
 L(\theta|x) &= \prod_{t=1}^n p(x^t|\theta) = \left(\frac{1}{\sqrt{2\pi}\theta}\right)^n \exp\left(-\frac{(x_1-2)^2}{2\theta^2} - \frac{(x_2-2)^2}{2\theta^2} - \dots - \frac{(x_n-2)^2}{2\theta^2}\right) \\
 \log L(\theta|x) &= \log\left(\frac{1}{\sqrt{2\pi}\theta}\right)^n + \left(-\frac{(x_1-2)^2 + (x_2-2)^2 + \dots + (x_n-2)^2}{2\theta^2}\right) \\
 \frac{\partial \log L(\theta|x)}{\partial \theta^2} &= 0 \Rightarrow \hat{\theta}^2 = \frac{1}{n} \sum_{t=1}^n (x_t - 2)^2
 \end{aligned}$$

$$\begin{aligned}
 (b) \quad p(x|\theta) &= \frac{1}{\theta} \exp\left(-\frac{x}{\theta}\right) \\
 L(\theta|x) &= \prod_{t=1}^n p(x^t|\theta) = \frac{1}{\theta^n} \exp\left(-\sum_{t=1}^n \frac{x_t}{\theta}\right) \\
 \log L(\theta|x) &= -\log \theta^n - \frac{\sum_{t=1}^n x_t}{\theta} \\
 \frac{\partial \log L(\theta|x)}{\partial \theta} &= 0 \Rightarrow \hat{\theta} = \frac{1}{n} \sum_{t=1}^n x_t = \bar{x}
 \end{aligned}$$

$$\begin{aligned}
 (c) \quad p(x|\theta) &= \frac{1}{2\theta^3} x^2 \exp\left(-\frac{x}{\theta}\right) \\
 L(\theta|x) &= \prod_{t=1}^n p(x^t|\theta) = \left(\frac{1}{2\theta^3}\right)^n \prod_{t=1}^n x_t^2 \exp\left(-\sum_{t=1}^n \frac{x_t}{\theta}\right) \\
 \log L(\theta|x) &= n \log\left(\frac{1}{2\theta^3}\right) + \log\left(\prod_{t=1}^n x_t^2\right) + \left(-\sum_{t=1}^n \frac{x_t}{\theta}\right) \\
 \frac{\partial \log L(\theta|x)}{\partial \theta} &= 0 \Rightarrow \hat{\theta} = \frac{1}{3n} \sum_{t=1}^n x_t = \frac{1}{3} \bar{x}
 \end{aligned}$$

$$\begin{aligned}
 (d) \quad p(x|\theta) &= \theta x^{\theta-1} \\
 L(\theta|x) &= \theta^n \prod_{t=1}^n x_t^{\theta-1} \\
 \log L(\theta|x) &= n \log \theta + (\theta-1) \sum_{t=1}^n \log x_t \\
 \frac{\partial \log L(\theta|x)}{\partial \theta} &= 0 \Rightarrow \hat{\theta} = \frac{n}{\sum_{t=1}^n \log x_t}
 \end{aligned}$$

$$\frac{\partial \log l(\theta|x)}{\partial \theta} = \frac{n}{\theta} \Rightarrow \hat{\theta} = 0$$

$$e) P(x|\theta) = \begin{cases} \frac{1}{\theta} & 0 < x \leq \theta \\ 0 & \text{o.w.} \end{cases}$$

$$L(\theta|x) = \prod_{i=1}^n \frac{1}{\theta} I(0 < X_i \leq \theta) = \frac{1}{\theta^n} \prod_{i=1}^n I(0 < X_i \leq \theta)$$

Since $\frac{1}{\theta^n}$ decreasing when θ increasing

We should get the smallest value of θ

$$\text{Therefore, } \hat{\theta} = \max \{X_1, \dots, X_n\}$$

2.

$$2. (a) p(x|\mu, \Sigma) = \frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma|^{\frac{1}{2}}} \exp \left[-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right]$$

$$L(\mu, \Sigma) = (2\pi)^{-\frac{dN}{2}} |\Sigma|^{-\frac{N}{2}} \exp \left[-\frac{1}{2} \sum_{t=1}^N (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]$$

$$\log L(\mu, \Sigma) = -\frac{dN}{2} \ln(2\pi) - \frac{N}{2} \log |\Sigma| - \frac{1}{2} \sum_{t=1}^N (x^t - \mu)^T \Sigma^{-1} (x^t - \mu)$$

$$\frac{\partial \log L(\mu, \Sigma)}{\partial \mu} = 0 \Rightarrow \frac{\partial \left[-\frac{1}{2} \sum_{t=1}^N (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]}{\partial \mu} + \frac{\partial (N \mu^T \Sigma^{-1} \mu)}{\partial \mu} = 0$$

$$-2 \sum_{t=1}^N \Sigma^{-1} x^t + 2N \Sigma^{-1} \mu = 0$$

$$\hat{\mu} = \frac{1}{N} \sum_{t=1}^N x^t = \bar{x}$$

$$\frac{\partial \log L(\mu, \Sigma)}{\partial \Sigma} = 0 \Rightarrow \frac{\partial \left[\log |\Sigma| + \frac{1}{N} \sum_{t=1}^N (x^t - \mu)^T \Sigma^{-1} (x^t - \mu) \right]}{\partial \Sigma} = 0$$

$$d \log L(\mu, \Sigma) = \text{tr}(\Sigma^{-1} d\Sigma) + \text{tr} \left(-\Sigma^{-1} \frac{1}{N} \sum_{t=1}^N (x^t - \mu) (x^t - \mu)^T \Sigma^{-1} d\Sigma \right)$$

$$d \log L(\mu, \Sigma) = \text{tr} \left(\left(\Sigma^{-1} - \Sigma^{-1} \frac{1}{N} \sum_{t=1}^N (x^t - \mu) (x^t - \mu)^T \Sigma^{-1} \right) d\Sigma \right)$$

$$\frac{\partial \log L(\mu, \Sigma)}{\partial \Sigma} = \left(\Sigma^{-1} - \Sigma^{-1} \frac{1}{N} \sum_{t=1}^N (x^t - \mu) (x^t - \mu)^T \Sigma^{-1} \right)^T = 0$$

$$\hat{\Sigma} = \frac{1}{N} \sum_{t=1}^N (x^t - \mu) (x^t - \mu)^T$$

$$\text{since } \hat{\mu} = \bar{x}$$

$$\hat{\Sigma} = \frac{1}{N} \sum_{t=1}^N (x^t - \bar{x}) (x^t - \bar{x})^T$$

$$(b) E[\hat{\mu}_n] = E\left[\frac{1}{N} \sum_{t=1}^N x^t\right] = \frac{1}{N} \sum_{t=1}^N E[x^t] = \frac{N\mu}{N} = \mu$$

Therefore, $\hat{\mu}_n$ is unbiased.

$$\begin{aligned} (c) E(\hat{\Sigma}_n) &= E\left[\frac{1}{N} \sum_{t=1}^N (x^t - \bar{x})(x^t - \bar{x})^T\right] \\ &= \frac{1}{N} E\left[\sum_{t=1}^N (x^t - \bar{x})(x^t - \bar{x})^T\right] \\ &= \frac{1}{N} \sum_{t=1}^N E[x_t x_t^T] - N E[\mu \mu^T] \\ &= \frac{N-1}{N} \Sigma \neq \Sigma \end{aligned}$$

Therefore, $\hat{\Sigma}_n$ is ~~un~~biased estimate.

3.

Error rates for MultiGaussClassify with full covariance matrix on Boston50						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.4554455 44554455 4	0.5049504 95049505	0.1089108 910891089	0.4059405 940594059 7	0.1782178 217821782 7	0.3306930 693069307	0.1574973 372288964 4

Error rates for MultiGaussClassify with full covariance matrix on Boston25						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.1683168 31683168 36	0.8217821 782178218	0.0	0.3366336 633663366	0.4356435 643564357	0.3524752 475247525	0.2776940 914577515

Error rates for MultiGaussClassify with full covariance matrix on Digits						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.8941504 17827298 1	0.9025069 637883009	0.9080779 944289694	0.8969359 331476323	0.9025069 637883009	0.9008356 545961002	0.0048567 119148085 576

Error rates for MultiGaussdiagClassify with diagonal covariance matrix on Boston50						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.4257425 74257425 8	0.5049504 95049505	0.8910891 089108911	0.4059405 940594059 7	0.1782178 217821782 7	0.4811881 188118813	0.2319960 652611108

Error rates for MultiGaussdiagClassify with diagonal covariance matrix on Boston25						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.8514851 48514851 5	0.1782178 217821782 7	0.0	0.3366336 633663366	0.5643564 356435644	0.3861386 138613861 5	0.2976890 371955031 6

Error rates for MultiGaussClassify with diagonal covariance matrix on Digits						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.8997214 48467966 5	0.8997214 484679665	0.9025069 637883009	0.8969359 331476323	0.8969359 331476323	0.8991643 454038997	0.0020844 887948601 384

Error rates for LogisticRegression with Boston50						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.1386138 61386138 63	0.1386138 613861386 3	0.0990099 009900989 9	0.2772277 227722772 5	0.0990099 009900989 9	0.1504950 495049505	0.0657950 40498361

Error rates for LogisticRegression with Boston25						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.1584158 41584158 45	0.2178217 821782178	0.0396039 603960396 4	0.1287128 712871287 2	0.1386138 613861386 3	0.1366336 633663366 4	0.0575280 754310255 26

Error rates for LogisticRegression with Digits						
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	SD
0.0696378 83008356 5	0.1197771 587743732 3	0.0584958 217270195 04	0.0612813 370473537 2	0.0	0.0618384 401114205 9	0.0380872 749529519 9