

1.5.2 h.w.2

$$\prod_{i=1}^n X_i = X_1 \cdot X_2 \cdots X_n$$

$$X = \{x_1, \dots, x_n\}$$

$$(1) L(\theta) = \prod_{i=1}^n P(X=x_i) = \left(\frac{1}{\sqrt{2\pi}\theta}\right)^n \exp\left(-\frac{1}{2\theta^2} \sum_{i=1}^n X_i^2\right)$$

$$(2) \log L(\theta) = n \log\left(\frac{1}{\sqrt{2\pi}\theta}\right) - \frac{1}{2\theta^2} \sum_{i=1}^n X_i^2 = -n \log(\sqrt{2\pi}\theta) - \frac{1}{2\theta^2} \sum_{i=1}^n X_i^2$$

$$\frac{\partial \log L(\theta)}{\partial \theta} = -\frac{n}{\theta} + \frac{1}{\theta^3} \sum_{i=1}^n X_i^2$$

$$\frac{\partial \log L(\theta)}{\partial \theta} = 0 \Leftrightarrow \frac{1}{\theta^3} \sum_{i=1}^n X_i^2 = \frac{n}{\theta} \Rightarrow \theta^2 = \frac{\sum_{i=1}^n X_i^2}{n} \Rightarrow \theta = \sqrt{\frac{\sum_{i=1}^n X_i^2}{n}}$$

$$(b) L(\theta) = \prod_{i=1}^n P(X_i=x_i) = \left(\frac{1}{\theta}\right)^n \exp\left(-\frac{\sum_{i=1}^n X_i}{\theta}\right)$$

$$\log L(\theta) = -n \log \theta - \frac{1}{\theta} \sum_{i=1}^n X_i$$

$$\frac{\partial \log L(\theta)}{\partial \theta} = 0 \Leftrightarrow -\frac{n}{\theta} + \frac{1}{\theta^2} \sum_{i=1}^n X_i = 0 \Rightarrow \theta = \frac{\sum_{i=1}^n X_i}{n}$$

$$(c) L(\theta) = \prod_{i=1}^n P(X_i=x_i) = \theta^n \left[\prod_{i=1}^n x_i \right]^{\theta-1}$$

$$\log L(\theta) = n \log \theta + (\theta-1) \log \left[\prod_{i=1}^n x_i \right]$$

$$\frac{\partial \log L(\theta)}{\partial \theta} = 0 \Leftrightarrow \frac{n}{\theta} + \log \left[\prod_{i=1}^n x_i \right] = 0 \Rightarrow \theta = -\frac{n}{\log \left[\prod_{i=1}^n x_i \right]}$$

$$(d) L(\theta) = \prod_{i=1}^n P(X_i=x_i) = \left(\frac{1}{\theta}\right)^n \prod_{i=1}^n \mathbb{1}_{[0,\theta]}(x_i) = \begin{cases} \frac{1}{\theta^n}, & 0 \leq x_i \leq \theta \\ 0, & \text{otherwise} \end{cases}$$

$$i) L = \frac{1}{\theta^n} \text{ if } \theta \geq x_n$$

$$ii) L = 0 \text{ if } \theta < x_n$$

L is maximized at $\theta = x_n$ since $\frac{1}{\theta^n}$ is decreasing as θ increases
it should be the smallest value of θ such that $\theta \geq x_i$,

$$\text{so } \hat{\theta} = \max(x_1, \dots, x_n)$$

$$\begin{aligned}
 2. \quad L(\mu, \Sigma) &= \prod_{i=1}^n P(X_i = x_i) = (\lambda)^{-\frac{n\alpha}{2}} \cdot (\Sigma)^{-\frac{n}{2}} \cdot \exp\left[-\frac{1}{2} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu)\right] \\
 (a) \quad \log L(\mu, \Sigma) &= -\frac{n\alpha}{2} \log(\lambda) - \frac{n}{2} \log \Sigma - \frac{1}{2} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) \quad (*) \\
 \frac{\partial \log L(\mu, \Sigma)}{\partial \mu} &= 0 \Leftrightarrow -\frac{n}{2} \Sigma^{-1} \mu + \frac{n}{2} \Sigma^{-1} \sum_{i=1}^n x_i = 0 \Leftrightarrow \mu = \frac{1}{n} \sum_{i=1}^n x_i \\
 \frac{\partial \log L(\mu, \Sigma)}{\partial \Sigma} &= 0 \Leftrightarrow -\frac{n}{2} \Sigma^{-1} + \frac{1}{2} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) = 0 \Leftrightarrow \Sigma = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T
 \end{aligned}$$

(b) $\hat{\mu}_n = \frac{1}{n} \sum_{i=1}^n x_i$, $E[\hat{\mu}_n] = E\left[\frac{1}{n} \sum_{i=1}^n x_i\right] = \frac{1}{n} E\left[\sum_{i=1}^n x_i\right] = \frac{1}{n} \sum_{i=1}^n E(x_i) = \frac{1}{n} \cdot n \cdot \mu = \mu$
 where $\mu = E(x_i)$ for $i=1, 2, \dots, n$, the mean of the estimate of the mean and the true mean converge, so $\hat{\mu}_n$ is a unbiased estimate of the true mean μ .

$$\begin{aligned}
 (c) \quad \hat{\Sigma}_n &= \frac{1}{n} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T \quad E[\hat{\Sigma}_n] = \frac{1}{n} E\left[\sum_{i=1}^n x_i x_i^T - 2 \sum_{i=1}^n x_i \mu^T + \sum_{i=1}^n \mu \mu^T\right] \\
 &= \frac{1}{n} E\left[\sum_{i=1}^n x_i x_i^T - n \mu \mu^T\right] = \frac{1}{n} E\left[\sum_{i=1}^n x_i x_i^T\right] - E(\mu \mu^T) = E(x x^T) - E(\mu \mu^T) \quad (+) \\
 \Sigma_x &= E(x x^T) - (E(x))^2 \quad \Sigma_\mu = E(\mu \mu^T) - (E(\mu))^2 \\
 (=) \quad &= \Sigma_x + (E(x))^2 - (\Sigma_\mu + (E(\mu))^2) \\
 &= \Sigma_x - \Sigma_\mu \\
 &= \Sigma_x - \frac{1}{n^2} \cdot n \cdot \bar{\Sigma}_x \\
 &= \frac{n-1}{n} \Sigma_x \neq \Sigma_x
 \end{aligned}$$

the covariance of the estimate and the true covariance don't converge, so $\hat{\Sigma}_n$ is a biased estimate of the true covariance Σ_x

Q3

Summary

MultiGaussClassify with Boston50

K=0	K=1	K=2	K=3	K=4	Mean	Std
0.326732673 267	0.29702970 297	0.0990099009 901	0.346534653 465	0.117647058 824	0.237390797 903	0.106713622 914

MultiGaussClassify with Boston75

K=0	K=1	K=2	K=3	K=4	Mean	Std
0.386138613 861	0.138613861 386	0.39603960 396	0.445544554 455	0.0392156862 745	0.281110463 988	0.161305024 613

MultiGaussClassify with Digits

K=0	K=1	K=2	K=3	K=4	Mean	Std
0.161559888 579	0.194986072 423	0.177777777 778	0.105849582 173	0.147222222 222	0.157479108 635	0.0303521755 008

LogisticRegression with Boston50

K=0	K=1	K=2	K=3	K=4	Mean	Std
0.128712871 287	0.108910891 089	0.0891089108 911	0.277227722 772	0.107843137 255	0.142360706 659	0.0685878735 016

LogisticRegression with Boston75

K=0	K=1	K=2	K=3	K=4	Mean	Std
0.0891089108 911	0.128712871 287	0.138613861 386	0.108910891 089	0.0490196078 431	0.102873228 499	0.0318471419 286

LogisticRegression with Digits

K=0	K=1	K=2	K=3	K=4	Mean	Std
0.0696378830 084	0.111420612 813	0.0444444444 444	0.041782729 805	0.0111111111 111	0.0556793562 365	0.033489091 051