

1. 《Machine Learning A Probabilistic Perspective》这本书的练习题: Exercise 2.16(15分)
2. Exercise 3.6(10分)
3. Exercise 3.7(20分)
4. Exercise 3.15(20分)
5. Exercise 4.3(10分)
6. Exercise 4.4(10分)
7. Exercise 4.5(10分)
8. 求解问题(5分):

$$\begin{aligned} \max_x \quad & \sum p_k \log(x_k) \\ \text{s.t.} \quad & \sum x_k = 1 \end{aligned}$$

1 Ex2.16 解:

$$\begin{aligned} E(\theta) &= \int_{-\infty}^{\infty} \theta \cdot \beta(\theta|a, b) d\theta = \int_0^1 \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \cdot \theta^{a-1} \cdot (1-\theta)^{b-1} d\theta \\ &= \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \cdot \int_0^1 \theta^{(a+1)-1} \cdot (1-\theta)^{b-1} d\theta = \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \cdot \frac{\Gamma(a+1) \cdot \Gamma(b)}{\Gamma(a+1+b)} \\ &= \frac{(a+b-1)! \cdot a!}{(a-1)! \cdot (a+b)!} = \frac{a}{a+b} \end{aligned}$$

$$\begin{aligned} E(\theta^2) &= \int_{-\infty}^{\infty} \theta^2 \cdot \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \cdot \theta^{a-1} \cdot (1-\theta)^{b-1} d\theta \\ &= \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \cdot \int_0^1 \theta^{(a+2)-1} \cdot (1-\theta)^{b-1} d\theta = \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \cdot \frac{\Gamma(a+2) \cdot \Gamma(b)}{\Gamma(a+2+b)} \\ &= \frac{(a+b-1)! \cdot (a+1)!}{(a-1)! \cdot (a+b+1)!} = \frac{a(a+1)}{(a+b)(a+b+1)} \end{aligned}$$

$$\begin{aligned} D(\theta) &= E[\theta - E(\theta)]^2 = E[\theta^2 + E^2(\theta) - 2\theta \cdot E(\theta)] = E(\theta^2) - E^2(\theta) \\ &= \frac{a(a+1)}{(a+b)(a+b+1)} - \frac{a^2}{(a+b)^2} = \frac{ab}{(a+b)^2 \cdot (a+b+1)} \end{aligned}$$

$\beta(\theta|a, b) = \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} \theta^{a-1} \cdot (1-\theta)^{b-1}$, 对 θ 求导, 得到 $\beta'(\theta|a, b) = \frac{\Gamma(a+b)}{\Gamma(a) \cdot \Gamma(b)} (a-1)\theta^{a-2} \cdot (1-b)(1-\theta)^{b-2}$,
令 $\beta'(\theta|a, b) = 0$, 则有 $mode(\beta) = \frac{a-1}{a+b-2}$

2 Ex3.6 解:

$$\begin{aligned} L(\lambda) &= \log \prod_{i=1}^n f(x_i|\lambda) = \sum_{i=1}^n \log\left(\frac{e^{-\lambda} \lambda^{x_i}}{x_i!}\right) \\ &= -n\lambda + \left(\sum_{i=1}^n x_i\right) \log(\lambda) - \log\left(\sum_{i=1}^n x_i!\right) \end{aligned}$$

对 λ 求导并令其等于 0:

$$\frac{d}{d\lambda} L(\lambda) = 0 \Leftrightarrow -n + \left(\sum_{i=1}^n x_i\right) \frac{1}{\lambda} = 0$$

解得

$$\lambda_{MLE} = \frac{1}{n} \sum_{i=1}^n x_i$$

3 Ex3.7 解:

1) 由贝叶斯公式,

$$p(\theta|x) = \frac{p(x|\theta)f(\theta|a, b)}{p(x)}$$

其中 $p(x) = \int g(\theta)p(x|\theta)d\theta$ 与 θ 无关. 那么

$$p(x|\lambda)g(\lambda|a, b) = \frac{\lambda^x e^{-\lambda}}{x!} \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} \propto \lambda^{a+x-1} e^{-(\lambda(b+1))} \propto g(\lambda|a+x, b+1)$$

则有

$$p(\lambda|D) = g(\lambda|a+D, b+1) = \Gamma(\lambda|a+D, b+1)$$

2) 当 $a \rightarrow 0, b \rightarrow 0$ 时, $p(\lambda|D) = \Gamma(\lambda|D, 1)$, 由于 Gamma 分布 $\Gamma(a, b)$ 的均值为 $\frac{a}{b}$, 那么其均值为 D.

4 Ex3.15 解:

$$E(\theta) = m = \frac{\alpha_1}{\alpha_1 + \alpha_2}, \quad \text{var}(\theta) = v = \frac{\alpha_1 \alpha_2}{(\alpha_1 + \alpha_2)^2 (\alpha_1 + \alpha_2 + 1)}$$

$$\Rightarrow \alpha_1 = \frac{m^2(1-m)}{v} - m, \quad \alpha_2 = \frac{m(1-m)^2}{v} + m - 1$$

当 $m = 0.7$, $v = 0.2^2$ 时, $\alpha_1 = 2.975$, $\alpha_2 = 1.275$.

5 Ex4.3 解:

$$\text{Cov}(X, Y)^2 = E[(X - \mu_x)(Y - \mu_y)]^2 \leq E[(X - \mu_x)^2]E[(Y - \mu_y)^2] = \text{Var}(X)\text{Var}(Y)$$

$$\text{Cov}(X, Y)^2 \leq \text{Var}(X)\text{Var}(Y) \Rightarrow -1 \leq \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = \rho(X, Y) \leq 1$$

6 Ex4.4 解:

$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - E[X]E[Y] = E[aX^2 + bX] - E[X](aE[X] + b) \\ &= aE[X^2] + bE[X] - aE[X]^2 - bE[X] = a(E[X^2] - E[X]^2) \\ &= a\text{Var}(X) \end{aligned}$$

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = \frac{a\text{Var}(X)}{\sqrt{a^2\text{Var}(X)^2}} = \frac{a\text{Var}(X)}{|a|\text{Var}(X)}$$

故容易知道, 当 $a > 0$ 时, $\rho = 1$; 当 $a < 0$ 时, $\rho = -1$.

7 Ex4.5 解:

$$\int \exp(-\frac{1}{2}(x - \mu)^t \Sigma^{-1}(x - \mu)) dx = \int \exp(-\frac{1}{2}(x - \mu)^t U \Lambda^{-1} U^t (x - \mu)) dx$$

令 $y = U^t(x - \mu)$,

$$\begin{aligned} \int \exp(-\frac{1}{2}(x - \mu)^t U \Lambda^{-1} U^t (x - \mu)) dx &= \int \exp(-\frac{1}{2}y^t \Lambda^{-1} y) dy = \\ \int \exp(-\frac{1}{2} \sum_i \frac{y_i^2}{\lambda_i}) dy &= \int \exp(-\frac{1}{2} \sum_i \frac{y_i^2}{\lambda_i}) \frac{\partial(x_1, x_2, \dots, x_n)}{\partial(y_1, y_2, \dots, y_n)} dy \end{aligned}$$

计算雅各比:

$$y = U^t(x - \mu) \Rightarrow x = Uy + \mu$$

$$J_{ij} = \frac{\partial x_i}{\partial y_j} = u_{ij}$$

因此有 $J = U$, $\frac{\partial(x_1, x_2, \dots, x_n)}{\partial(y_1, y_2, \dots, y_n)} = \det(U) = 1$

$$\begin{aligned} \int \exp(-\frac{1}{2} \sum_i \frac{y_i^2}{\lambda_i}) dy &= \prod_i \int \exp(-\frac{1}{2} \frac{y_i^2}{\lambda_i}) dy_i \\ &= \prod_{i=1}^D \sqrt{(2\pi\lambda_i)} = \sqrt{(2\pi)^D} \prod_{i=1}^D \sqrt{\lambda_i} \\ &= (2\pi)^{D/2} |\Sigma|^{1/2} \end{aligned}$$

8 解: 令 $F(x_1, \dots, x_k, \lambda) = \sum_{i=1}^k p_i \log(x_i) + \lambda(\sum_{i=1}^k x_i - 1)$, 对 x_1, \dots, x_k, λ 求导, 得 $\frac{p_1}{x_1} + \lambda = 0, \dots, \frac{p_k}{x_k} + \lambda = 0$, $\sum_{i=1}^k x_i = 1$. 解得 $\lambda = -(x_1 + \dots + x_k)$, 则

$$x_i = \frac{p_i}{p_1 + \dots + p_k}, i = 1, \dots, k$$