2016 Spring Notes

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各种相关背景知识 1

1.1 概率论

1.1.1 条件概率期望:

$$E(X) = E(E(X|Y)) \tag{1}$$

1.1.2 Correlation coefficient(相关系数)

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \qquad (2)$$

$$= \frac{E(X - E(X))(Y - E(Y))}{\sigma_X \sigma_Y} \qquad (3)$$

$$= \frac{E(XY) - E(X)E(Y)}{\sigma_X \sigma_Y} \qquad (4)$$

$$= \frac{E(X - E(X))(Y - E(Y))}{\sigma_{xx}\sigma_{xx}} \tag{3}$$

$$= \frac{E(XY) - E(X)E(Y)}{\sigma_X \sigma_Y} \tag{4}$$

1.1.3 协方差矩阵

$$X = [X_1, \dots, X_n]^T \tag{5}$$

$$\Sigma = \mathbf{E} \Big[(\mathbf{X} - \mathbf{E}(\mathbf{X}))(\mathbf{X} - \mathbf{E}(\mathbf{X}))^T \Big]$$
 (6)

$$\Sigma_{i,j} = Cov(X_i, X_j) \tag{7}$$

$$= \mathbb{E}\left[(X_i - \mu_i)(X_j - \mu_j) \right] \tag{8}$$

1.1.4 Multivariate normal distribution

• 多维高斯联合分布:

$$f_X(x_1,...,x_n) = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} \exp(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu))$$

当为二维高斯分布时(ρ为相关系数):

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho)^2} \left[\frac{(x-\mu_x)}{\sigma_x^2} + \frac{(y-\mu_y)}{\sigma_y^2} - \frac{2\rho(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y} \right] \right)$$

条件概率服从:

$$P(X_1|X_2 = x_2) \sim N(\mu_1 + \frac{\sigma_1}{\sigma_2}\rho(x_2 - \mu_2), (1 - \rho^2)\sigma_1^2)$$

1.1.5 Laplace Distribution:

• 概率密度函数

$$f(x|\mu, b) = \frac{1}{2b} \exp\left(-\frac{|x-\mu|}{b}\right)$$

期望

 μ

方差

 $2b^2$

1.2 矩阵求导法则:

$$\frac{\partial \mathbf{u}^{\mathbf{T}} \mathbf{A} \mathbf{v}}{\partial \mathbf{x}} = \frac{\partial \mathbf{u}}{\partial \mathbf{x}} \mathbf{A} \mathbf{v} + \frac{\partial \mathbf{v}}{\partial \mathbf{x}} \mathbf{A}^{\mathbf{T}} \mathbf{u}$$
(9)

$$\frac{\partial \mathbf{u}^{\mathbf{T}} \mathbf{A} \mathbf{v}}{\partial \mathbf{x}} = \frac{\partial \mathbf{u}}{\partial \mathbf{x}} \mathbf{A} \mathbf{v} + \frac{\partial \mathbf{v}}{\partial \mathbf{x}} \mathbf{A}^{\mathbf{T}} \mathbf{u} \tag{9}$$

$$\frac{\partial (\mathbf{u}(\mathbf{x}) + \mathbf{v}(\mathbf{x}))}{\partial \mathbf{x}} = \frac{\partial \mathbf{u}(\mathbf{x})}{\partial \mathbf{x}} + \frac{\partial \mathbf{v}(\mathbf{x})}{\partial \mathbf{x}} \tag{10}$$

$$\frac{\partial \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = \mathbf{A}^{\mathbf{T}} \tag{11}$$

$$\frac{\partial \mathbf{a}}{\partial \mathbf{x}} = \mathbf{0} \tag{12}$$

$$\frac{\partial \mathbf{x}^{\mathbf{T}} \mathbf{A} \mathbf{b}}{\partial \mathbf{x}} = \mathbf{A} \mathbf{b} \tag{13}$$

$$\frac{\partial \mathbf{x}^{\mathbf{T}} \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = (\mathbf{A} + \mathbf{A}^{\mathbf{T}}) \mathbf{x} \tag{14}$$

$$= \mathbf{2} \mathbf{A} \mathbf{x} \qquad \text{如果 A} \quad \text{为对称阵}$$

$$\frac{\partial |\mathbf{X}|}{\partial \mathbf{X}} = |\mathbf{X}| (\mathbf{X}^{-1})^{\mathbf{T}} \tag{16}$$

$$\frac{\partial \ln |\mathbf{X}|}{\partial \mathbf{X}} = (\mathbf{X}^{-1})^{\mathbf{T}} \tag{17}$$

$$\frac{\partial \mathbf{A} \mathbf{x}}{\partial x} = \mathbf{A}^{\mathbf{T}} \tag{11}$$

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$$\frac{\partial \mathbf{x}^{\mathbf{T}} \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = (\mathbf{A} + \mathbf{A}^{\mathbf{T}}) \mathbf{x} \tag{14}$$

$$= 2Ax 如果 A 为对称阵 (15)$$

$$\frac{\partial |\mathbf{X}|}{\partial \mathbf{Y}} = |\mathbf{X}|(\mathbf{X}^{-1})^{\mathbf{T}} \tag{16}$$

$$\frac{\partial \ln |\mathbf{X}|}{\partial \mathbf{Y}} = (\mathbf{X}^{-1})^{\mathbf{T}} \tag{17}$$

2 Information Theory

2.1 Differential Entropy

2.1.1 常见 Differential Entropy

 \bullet Uniform distribution(from 0 to a)

$$h(X) = \log(a)$$

• Normal Distribution

$$X \sim N(0, \sigma^2)$$

$$h(X) = \frac{1}{2} \log 2\pi e \sigma^2$$

• Multivariate Normal Distribution

$$N_n \sim (\mu, K)$$

 μ is mean and K is covariance matrix

$$h(X_1, \dots, X_n) = \frac{1}{2} \log(2\pi e)^n |K|$$

2.1.2 Properties

- h(X+c) = h(X)
- $h(aX) = h(X) + \log|a|$
- $h(AX) = h(X) + \log |\det(A)|$