

## 理论题 1

- 令  $\mathbf{X}_s$  表示经标准化后的特征, 即  $\mathbf{X}_s = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_p)$  中  $n^{-1} \sum_{i=1}^n x_{ij} = 0$  而  $\sum_{i=1}^n x_{ij}^2 = 1$ 。  $\mathbf{X}_s$  的相关系数矩阵为  $(\mathbf{X}_s' \mathbf{X}_s)$ , 其逆矩阵为  $(\mathbf{X}_s' \mathbf{X}_s)^{-1} = \mathbf{C} = \{c_{ij}\}$ 。我们将  $x_j$  作为因变量, 而将剩余的特征作为自变量, 建立多元线性回归模型, 即

$$x_j = \beta_1^j x_1 + \dots + \beta_{j-1}^j x_{j-1} + \beta_{j+1}^j x_{j+1} + \dots + \beta_p^j x_p + \varepsilon^j.$$

令  $R_j^2$  为该回归模型的复决定系数。证明:

$$c_{jj} = \frac{1}{1 - R_j^2}.$$

证明: 对任意  $j \in \{1, 2, \dots, p\}$ , 设

$$\mathbf{T}_j = \begin{bmatrix} 1 & & & \\ & \ddots & & \\ & & 1 & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix}$$

则

$$\mathbf{T}_j^{-1} = \begin{bmatrix} 1 & & & \\ & \ddots & & \\ & & 1 & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix} = \mathbf{T}_j^T.$$

若令  $X_t = (x_j, x_0)$ , 其中  $x_0 = (x_1, \dots, x_{j-1}, x_{j+1}, \dots, x_p)$

则  $X_t = X_s T_j$ .  $\therefore X_s = X_t T_j^T$ .

$$\begin{aligned} \therefore C &= (X_s^T X_s)^{-1} \\ &= ((X_t T_j^T)^T (X_t T_j^T))^{-1} \\ &= (T_j X_t^T X_t T_j^T)^{-1} \\ &= T_j (X_t^T X_t)^{-1} T_j^T. \end{aligned}$$

$$\therefore X_t^T X_t = \begin{pmatrix} x_j^T & x_0^T \end{pmatrix} \begin{pmatrix} x_j & x_0 \end{pmatrix} = \begin{pmatrix} x_j^T x_j & x_j^T x_0 \\ x_0^T x_j & x_0^T x_0 \end{pmatrix}$$

$$\therefore (X_t^T X_t)^{-1} = \begin{pmatrix} X_{11}^* & X_{12}^* \\ X_{21}^* & X_{22}^* \end{pmatrix}.$$

其中,  $X_{11}^* = (x_j^T x_j - x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j)^{-1}$ .

$$X_{12}^* = -(x_j^T x_j - x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j)^{-1} x_j^T x_0 (x_0^T x_0)^{-1}$$

$$X_{21}^* = -(x_0^T x_0)^{-1} x_0^T x_j (x_j^T x_j - x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j)^{-1}$$

$$X_{22}^* = (x_0^T x_0)^{-1} + (x_0^T x_0)^{-1} x_0^T x_j (x_j^T x_j - x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j)^{-1} x_j^T x_0 (x_0^T x_0)^{-1}.$$

$$x_j^T x_j = 1.$$

$$\begin{aligned} \therefore C_{jj} &= X_{11}^* = (x_j^T x_j - x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j)^{-1} \\ &= (1 - x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j)^{-1}. \end{aligned}$$

$$\therefore \bar{x}_j = \frac{1}{n} \sum_{k=1}^n x_{jk} = 0.$$

$$\begin{aligned} \therefore SS_R^j &= \sum_{k=1}^n (\hat{x}_{jk} - \bar{x}_j)^2 = \sum_{k=1}^n \hat{x}_{jk}^2 = \hat{x}_j^T \hat{x}_j \\ &= (x_0 \hat{\beta})^T x_0 \hat{\beta} \\ &= x_j^T x_0 (x_0^T x_0)^{-1} x_0^T x_j; \end{aligned}$$

$$\therefore SS_T^j = \sum_{k=1}^n (x_{jk} - \bar{x}_j)^2 = \sum_{k=1}^n x_{jk}^2 = 1.$$

$$\therefore R^2 = \frac{SSR^j}{SS_T^j} = x_j^T X_0 (X_0^T X_0)^{-1} X_0^T x_j$$

$$\therefore C_{jj} = (1 - x_j^T X_0 (X_0^T X_0)^{-1} X_0^T x_j)^{-1} \\ = \frac{1}{1 - R^2}.$$

## 理论题 2

- 经中心化后因变量  $y$  以及经标准化后的自变量  $X$ 。我们建立多元线性回归模型，其最小二乘估计为

$$\hat{\beta} = (X'X)^{-1} X'y.$$

请计算

$$MSE(\hat{\beta}) = E(\hat{\beta} - \beta)'(\hat{\beta} - \beta),$$

需要写出推导过程。

解:  $\because E(\hat{\beta}) = \beta.$

$$\text{Cov}(\hat{\beta}) = \sigma^2 (X^T X)^{-1}.$$

$$\therefore MSE(\hat{\beta}) = E[(\hat{\beta} - \beta)^T (\hat{\beta} - \beta)]$$

$$= E[(\hat{\beta} - E(\hat{\beta}) + E(\hat{\beta}) - \beta)^T (\hat{\beta} - E(\hat{\beta}) + E(\hat{\beta}) - \beta)]$$

$$= E[(\hat{\beta} - E(\hat{\beta}))^T (\hat{\beta} - E(\hat{\beta}))]$$

$$= \text{tr}(\text{Cov}(\hat{\beta}))$$

$$= \sigma^2 \text{tr}((X^T X)^{-1}).$$

令  $X^T X$  的特征值为  $\lambda_1, \lambda_2, \dots, \lambda_{p+1}$ , 则

$(X^T X)^{-1}$  的特征值为  $\frac{1}{\lambda_1}, \frac{1}{\lambda_2}, \dots, \frac{1}{\lambda_{p+1}}$ .

$$\therefore MSE(\hat{\beta}) = \sigma^2 \text{tr}[(X^T X)^{-1}]$$

$$= \sigma^2 \sum_{i=1}^N \frac{1}{\lambda_i}.$$