

Preliminaries.

Sep 18

1. Expectation, variance & covariance.

Given r.v.'s X, Y , constants a, b

- Expectation $\mathbb{E}X$. $\mathbb{E}(aX+b) = a\mathbb{E}X + b$.

- Variance $\text{Var}X = \mathbb{E}(X - \mathbb{E}X)^2 = \mathbb{E}X^2 - (\mathbb{E}X)^2$

$$\text{Var}(aX+b) = a^2 \text{Var}X.$$

- Covariance. $\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)] = \mathbb{E}(XY) - \mathbb{E}X \cdot \mathbb{E}Y$.

Theorem 3.1: Let Y_1, \dots, Y_n be uncorrelated random variables with $\text{Var}(Y_i) = \sigma^2$ for all $i = 1, \dots, n$. Let c_1, \dots, c_n and d_1, \dots, d_n be two sets of constants. Then

$$\text{Cov}(Y_i, Y_j) = 0, i \neq j$$

$$\text{Cov}\left(\sum_{i=1}^n c_i Y_i, \sum_{i=1}^n d_i Y_i\right) = \left(\sum_{i=1}^n c_i d_i\right) \sigma^2$$

Pf: LHS $\stackrel{\text{def}}{=} \mathbb{E}\left[\underbrace{\left(\sum_{i=1}^n c_i (Y_i - \mathbb{E}Y_i)\right)}_{\sum c_i Y_i - \mathbb{E} \sum c_i Y_i} \left(\sum_{j=1}^n d_j (Y_j - \mathbb{E}Y_j)\right)\right]$

$$= \mathbb{E}\left[\left(\sum_{i=1}^n c_i \tilde{Y}_i\right) \left(\sum_{j=1}^n d_j \tilde{Y}_j\right)\right], \quad \tilde{Y}_i := Y_i - \mathbb{E}Y_i.$$

$$= \mathbb{E}\left[\sum_{i,j=1}^n c_i d_j \tilde{Y}_i \tilde{Y}_j\right]$$

$$= \mathbb{E}\sum_{i=1}^n c_i d_i \tilde{Y}_i^2 + \mathbb{E}\sum_{i \neq j} c_i d_j \tilde{Y}_i \tilde{Y}_j$$

$$= \sum_{i=1}^n c_i d_i \underbrace{\mathbb{E}\tilde{Y}_i^2}_{\mathbb{E}(Y_i - \mathbb{E}Y_i)^2 = \text{Var}Y_i = \sigma^2} + \sum_{i \neq j} c_i d_j \underbrace{\mathbb{E}\tilde{Y}_i \tilde{Y}_j}_{= \text{Cov}(Y_i, Y_j) = 0, i \neq j}$$

$$= \sum_{i=1}^n c_i d_i \sigma^2 = \left(\sum_{i=1}^n c_i d_i\right) \sigma^2$$

Given r.vec's $X, Y \in \mathbb{R}^d$, where $X = (X_1, \dots, X_d)^T$, const vec. $a, b \in \mathbb{R}^{d \times 1}$

- Expectation $\mathbb{E}X = (\mathbb{E}X_1, \dots, \mathbb{E}X_d)^T$.

- Covariance matrix.

Def. $\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)^T]$ $d \times d$

$$\text{Cov}(X) = \text{Cov}(X, X) = \mathbb{E}[(X - \mathbb{E}X)(X - \mathbb{E}X)^T]$$

Property $\text{Cov}(a^T X, b^T Y) = a^T \text{Cov}(X, Y) b$. 1×1

2. Normal, χ^2 , t , F distributions

► Constructions / Relations

① $X_1, X_2, \dots, X_r \stackrel{\text{iid}}{\sim} N(0, 1)$. Then $Z = \sum_{i=1}^r X_i^2 \sim \chi^2(r)$

② $X \sim N(0, 1) \perp\!\!\!\perp Z \stackrel{=X^2}{\sim} \chi^2(r)$. Then $T = \frac{X}{\sqrt{Z/r}} \sim t(r)$

③ $X_1 \sim \chi^2(r_1) \perp\!\!\!\perp X_2 \sim \chi^2(r_2)$. Then $F = \frac{X_1/r_1}{X_2/r_2} \sim F(r_1, r_2)$

► Additivity of indep χ^2 .

Assume $Z_1 \sim \chi^2(r_1) \perp\!\!\!\perp Z_2 \sim \chi^2(r_2)$. Then $Z_1 + Z_2 \sim \chi^2(r_1 + r_2)$

Pf: Let $X_1, \dots, X_{r_1+r_2} \stackrel{\text{iid}}{\sim} N(0, 1)$.

$$Z_1 \stackrel{d}{=} X_1 + \dots + X_{r_1}, \quad Z_2 \stackrel{d}{=} X_{r_1+1} + \dots + X_{r_1+r_2}.$$

$$\text{Then } Z_1 + Z_2 \stackrel{d}{=} X_1 + \dots + X_{r_1+r_2} \sim \chi^2(r_1 + r_2).$$

► Thm. 3.4 Let $X \sim N(0, I_n)$. A is a symmetric idempotent matrix of rank k . Then $X^T A X \sim \chi^2(k)$.

Review

1. Regression model

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip} + e_i, \quad i=1, \dots, n$$

(matrix form) $Y = X\beta + e$.

randomness: $e \xrightarrow{\Delta} Y$. X is deterministic.

With some assumptions e_i 's $\stackrel{iid}{\sim} N(0, \sigma^2)$

2. Estimation.

2.1 β .

Method: LS (= MLE in Gaussian cases)

Optimization: (objective)

$$\begin{aligned}\hat{\beta} &= \underset{\beta'}{\operatorname{argmin}} \sum (y_i - (\beta_0' + \beta_1' x_{i1} + \dots + \beta_p' x_{ip}))^2 = \sum \hat{e}_i^2 = \text{RSS} \\ &= \underset{\beta'}{\operatorname{argmin}} (Y - X\beta)^T (Y - X\beta).\end{aligned}$$

Solution by first order conditions: $\hat{\beta} = (X^T X)^{-1} X^T Y$

- Case of $p=1$:

$$\begin{cases} \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}_1 \\ \hat{\beta}_1 = \frac{\sum_{i=1}^n (x_{i1} - \bar{x}_1)(y_i - \bar{y})}{\sum_{i=1}^n (x_{i1} - \bar{x}_1)^2} = \frac{S_{x_1 y}}{S_{x_1 x_1}} \end{cases}$$

- Centered model.

2.2. σ^2

$$\hat{\sigma}_{MLE}^2 = \frac{\text{RSS}}{n}$$

$$\hat{\sigma}_{UE}^2 = \frac{\text{RSS}}{n-p} \quad (\text{by the properties of RSS in Sec. 2.3})$$

- Specific forms for different cases of $p=1$, $p \geq 1$.