Section for Applied Statistics and Data Analysis

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Office Hour: Wednesday 10:00AM - 12:00PM

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Overview

- Some Statistics
 - Linear Combinations of Two Normals
 - Least Squares Estimation
 - Goodness of Fit

- Some Programming
 - Exercises in Faraway

Review

Recall

For random variables X_1, X_2, \dots, X_n

$$\mathbb{E}\left[\sum_{i=1}^{n}X_{i}\right]=\sum_{i=1}^{n}\mathbb{E}\left[X_{i}\right].$$

$$\operatorname{Var}\left[\sum_{i=1}^{n} X_{i}\right] = \sum_{i=1}^{n} \operatorname{Var}\left[X_{i}\right] + \sum_{i \neq j} \operatorname{Cov}\left[X_{i}, X_{j}\right].$$

Review

Recall

Given $f_{X_1,X_2}(x_1,x_2)$ with $Y_1 = g_1(X_1,X_2)$ and $Y_2 = g_2(X_1,X_2)$

$$f_{Y_1,Y_2}(y_1,y_2) = f_{X_1,X_2}(x_1,x_2) |J(x_1,x_2)|^{-1}.$$

where

$$J(x_1, x_2) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix} = \frac{\partial g_1}{\partial x_1} \frac{\partial g_2}{\partial x_2} - \frac{\partial g_1}{\partial x_2} \frac{\partial g_2}{\partial x_1}$$

and

$$x_1 = h_1(y_1, y_2), x_2 = h_2(y_1, y_2)$$

Linear Combinations of Two Normals

Claim

Let $U = \alpha X_1$, $V = b X_2$ where $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$ and $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$. Then $U \sim \mathcal{N}(\alpha \mu_1, \alpha^2 \sigma_1^2)$ and $V \sim \mathcal{N}(b \mu_2, b^2 \sigma_2^2)$.

Question

Assume X_1 and X_2 are independent. What can you say about Y = U + V?

Question

How to show a random variable follows some distribution?

Least Squares Formulation

Recall

$$y = X\beta + \varepsilon$$
 where $\varepsilon = \begin{bmatrix} \varepsilon_1 & \varepsilon_2 & \cdots & \varepsilon_n \end{bmatrix}^\top$.

To minimize the sum of the squared errors

$$\begin{split} L &= \sum_{i=1}^n \varepsilon_i^2 = \varepsilon^\top \varepsilon = (y - X\beta)^\top \left(y - X\beta \right). \\ &\frac{\partial L}{\partial \beta} = 0 \qquad \Longrightarrow \qquad \left(X^\top X \right) \beta = X^\top y. \\ &\widehat{\beta} = \left(X^\top X \right)^{-1} X^\top y, \qquad \widehat{y} = X \widehat{\beta} = X \left(X^\top X \right)^{-1} X^\top y. \end{split}$$

Goodness of Fit

$$SSTO = SSR + SSE, \qquad R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

where

$$\begin{aligned} & \text{SSTO} = \sum_{i=1}^{n} \left(y_i - \bar{y} \right)^2 \\ & \text{SSR} = \sum_{i=1}^{n} \left(\widehat{y}_i - \bar{y} \right)^2 \\ & \text{SSE} = \sum_{i=1}^{n} \left(y_i - \widehat{y}_i \right)^2 \end{aligned}$$

Exercises in Faraway Chapter 2

- Exercise 2: uswages dataset
- Exercise 3: artificial data
- Exercise 4: prostate dataset

Thanks for listening!

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