

Multivariate Data Analysis

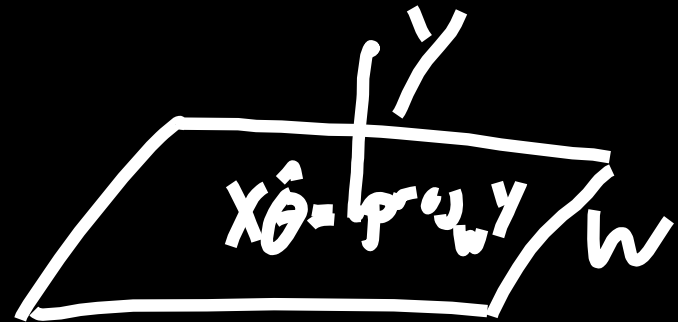
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$$y \in \mathbb{R}^n \quad X \in \mathbb{R}^{n \times p} \quad \theta \in \mathbb{R}^p \quad \varepsilon \in \mathbb{R}^n$$

$$y = X\theta + \varepsilon$$

↑ ↑
known unknown

$$W = \text{Col } X$$



$$y - X\hat{\theta} \perp \text{Col } X$$

$$\Rightarrow (X_j)^T (y - X\hat{\theta}) = 0 \quad \text{for all columns } X_j \text{ of } X$$

$$\Rightarrow X^T (y - X\hat{\theta}) = 0$$

$$X \in \mathbb{R}^{n \times p}$$

$$\Rightarrow X^T y = X^T X \hat{\theta}$$

$$\text{If } X \text{ has full rank} \quad \hat{\theta} = (X^T X)^{-1} X^T y$$

X full rank requires $p \leq n$

$$\begin{aligned}
\text{Cov}(\mathbf{y}) &= E[(\mathbf{y} - E(\mathbf{y}))(\mathbf{y} - E(\mathbf{y}))^T] \\
&= E[\mathbf{y}\mathbf{y}^T - E(\mathbf{y})\mathbf{y}^T - \mathbf{y}E(\mathbf{y})^T + E(\mathbf{y})E(\mathbf{y})^T] \\
&= E[\mathbf{y}\mathbf{y}^T] - E(\mathbf{y})E(\mathbf{y})^T
\end{aligned}$$

$$X_2 = V \sim \mathcal{N}(0, 1)$$

$$U, V \sim \mathcal{N}(0, 1)$$

$$E[X_1] = \sqrt{1-\rho^2} \underbrace{E[U]}_{=0} + \rho \underbrace{E[V]}_{=0} = 0$$

$$\text{Var}(X_1) = \text{Var}(\sqrt{1-\rho^2} U) + 2 \text{Cov}(\sqrt{1-\rho^2} U, \rho V)$$

$$\begin{aligned} &+ \text{Var}(\rho V) \\ &= (1-\rho^2) \underbrace{\text{Var}(U)}_{=1} + 2\sqrt{1-\rho^2} \rho \underbrace{\text{Cov}(U, V)}_{=0} + \rho^2 \underbrace{\text{Var}(V)}_{=1} \\ &= 1-\rho^2 + \rho^2 = 1 \end{aligned}$$

$$X_2 \sim N(0, 1)$$

$E[X_1] = 0$, $\text{Var}(X_1) = 1$, X_1 is normal as
Linear combination of normal random variables
(RVs) U and V

$$\Rightarrow X_1 \sim N(0, 1)$$

$$\text{Corr}(X_1, X_2) = 0$$

X, Y normal RVs

X, Y independent $\Leftrightarrow X, Y$ uncorrelated
($\text{Cov}(X, Y) = 0$)

For general RVs

X, Y independent $\Rightarrow X, Y$ uncorrelated

Converse is not true in general

Example $Z \sim N(0, 1)$, $X = Z$, $Y = Z^2$
not independent, but uncorrelated

$$Y = X\theta + \varepsilon \quad \varepsilon \sim \mathcal{N}(0, \sigma^2 I)$$

$$\hat{\theta} = (X^T X)^{-1} X^T Y = (X^T X)^{-1} X^T X \theta + (X^T X)^{-1} X^T \varepsilon = \theta + \underbrace{(X^T X)^{-1} X^T}_{\text{matrix}} \varepsilon$$

$$E[\hat{\theta}] = (X^T X)^{-1} X^T \underbrace{E[Y]}_{= X\theta} = (X^T X)^{-1} (X^T X) \theta = \theta$$

$$\begin{aligned} \text{Cov}(\hat{\theta}) &= E[(\hat{\theta} - \theta)(\hat{\theta} - \theta)^T] \\ &= E[(X^T X)^{-1} X^T \varepsilon \varepsilon^T X (X^T X)^{-1}] \\ &= (X^T X)^{-1} X^T \underbrace{E[\varepsilon \varepsilon^T]}_{= \sigma^2 I} X (X^T X)^{-1} = \sigma^2 (X^T X)^{-1} \end{aligned}$$

$$\hat{\theta} \sim \mathcal{N}(\theta, \sigma^2 (X^T X)^{-1})$$