

# STAT 151A Lecture 8

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## Remark 0.1 (Recap)

$$\mathbf{Y} = \mathbf{X}\hat{\beta} + \vec{e} = \mathbf{Y}_{\parallel \text{span}(\mathbf{X})} + \mathbf{Y}_{\perp \text{span}(\mathbf{X})}$$
$$\hat{\beta} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{Y}$$

## Remark 0.2 (Enter Probability)

$$\vec{Y} = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}, \vec{Y} \text{ a random vector}$$

$$\mathbb{E}(\vec{Y}) = \begin{pmatrix} \mathbb{E}(Y_1) \\ \vdots \\ \mathbb{E}(Y_n) \end{pmatrix}$$

$$\text{Var}(\vec{Y}) = \Sigma_{\vec{Y}\vec{Y}} = \begin{pmatrix} \text{Var}(Y_1) & \text{Cov}(Y_1, Y_2) & \text{Cov}(Y_1, Y_3) & \cdots & \text{Cov}(Y_1, Y_n) \\ \text{Cov}(Y_2, Y_1) & \text{Var}(Y_2) & \text{Cov}(Y_2, Y_3) & \cdots & \text{Cov}(Y_2, Y_n) \\ \text{Cov}(Y_3, Y_1) & \text{Cov}(Y_3, Y_2) & \text{Var}(Y_3) & \cdots & \text{Cov}(Y_3, Y_n) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(Y_n, Y_1) & \text{Cov}(Y_n, Y_2) & \text{Cov}(Y_n, Y_3) & \cdots & \text{Var}(Y_n) \end{pmatrix}$$

$$\Sigma_{\vec{Y}\vec{Y}} \in \mathbb{R}^{n \times n}$$

## Remark 0.3 (Linear Transformations)

Random Vectors:  $\vec{V} \in \mathbb{R}^m, \vec{U} \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n}, c \in \mathbb{R}^m$

$$\vec{V} = \vec{c} + A\vec{U}$$

$$\mathbb{E}(\vec{V}) = \vec{c} + A\mathbb{E}(\vec{U})$$

$$\Sigma_{\vec{V}\vec{V}} = A\Sigma_{\vec{U}\vec{U}}A^\top \rightarrow \Sigma_{\vec{V}\vec{V}}(i,j) = \sum_{k=1}^n \sum_{l=1}^n a_{ik}a_{jl} \text{Cov}(U_k, U_l)$$

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**Remark 0.4 (Quadratic Form)**

Random Vector  $\vec{V} \in \mathbb{R}^n$ , Constant Matrix  $A \in \mathbb{R}^{n \times n}$

Quadratic Form:  $\vec{v}^\top A \vec{v}$

$$\mathbb{E}(\vec{v}^\top A \vec{v}) = \mathbb{E}(\vec{v})^\top A \mathbb{E}(\vec{V}) + \text{Tr}(A \Sigma_{\vec{V}})$$

Random Vectors  $\vec{V} \in \mathbb{R}^p, \vec{W} \in \mathbb{R}^m, \vec{U} \in \mathbb{R}^n$

$\vec{V} = A\vec{U}, \vec{W} = B\vec{U}$

$$\Sigma_{\vec{V}\vec{W}} = A \Sigma_{\vec{U}} B^\top$$

**Remark 0.5 (Classical Linear Probabilty Model, Gauss-Markov Model)**

Reminder: Simple Regression

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

$$\mathbb{E}(\varepsilon_i | x_i) = 0, \text{Var}(\varepsilon_i | x_i) = \sigma^2, \Sigma_{\vec{e}ps \vec{e}ps | X} = \sigma^2 \mathbb{I}_n$$

$$Y = X\hat{\beta} + \vec{e}, \hat{\beta} = (X^\top X)^{-1} X^\top Y, \vec{e} = Y - X(X^\top X)^{-1} X^\top Y$$

$$\begin{aligned} \mathbb{E}(\hat{\beta} | X) &= \mathbb{E}[(X^\top X)^{-1} X^\top Y | X] \\ &= (X^\top X)^{-1} X^\top \mathbb{E}[Y | X] \\ &= (X^\top X)^{-1} X^\top \mathbb{E}[X\hat{\beta} + \vec{e} | X] \\ &= (X^\top X)^{-1} X^\top X \mathbb{E}[\hat{\beta} | X] + (X^\top X)^{-1} X^\top \mathbb{E}[\vec{e} | X] \\ &= \hat{\beta} \end{aligned}$$

$$\begin{aligned} \text{Var}(\hat{\beta} | X) &= \Sigma_{\hat{\beta}\hat{\beta} | X} = (X^\top X)^{-1} X^\top \Sigma_{\vec{Y}\vec{Y} | X} [(X^\top X)^{-1} X^\top]^\top \\ &= [(X^\top X)^{-1} X^\top] \sigma^2 \mathbb{I} [X(X^\top X)^{-1}] \\ &= \sigma^2 (X^\top X)^{-1} X^\top X (X^\top X)^{-1} \\ &= \sigma^2 (X^\top X)^{-1} \end{aligned}$$