

degrees of freedom for the error term). Explain your reasoning briefly.

AVP

1. $Y \sim X + G$
2. $Y \sim X$
3. $Y_r \sim X_n$ where Y_r is the residual of Y regressed on G and similarly for X_r

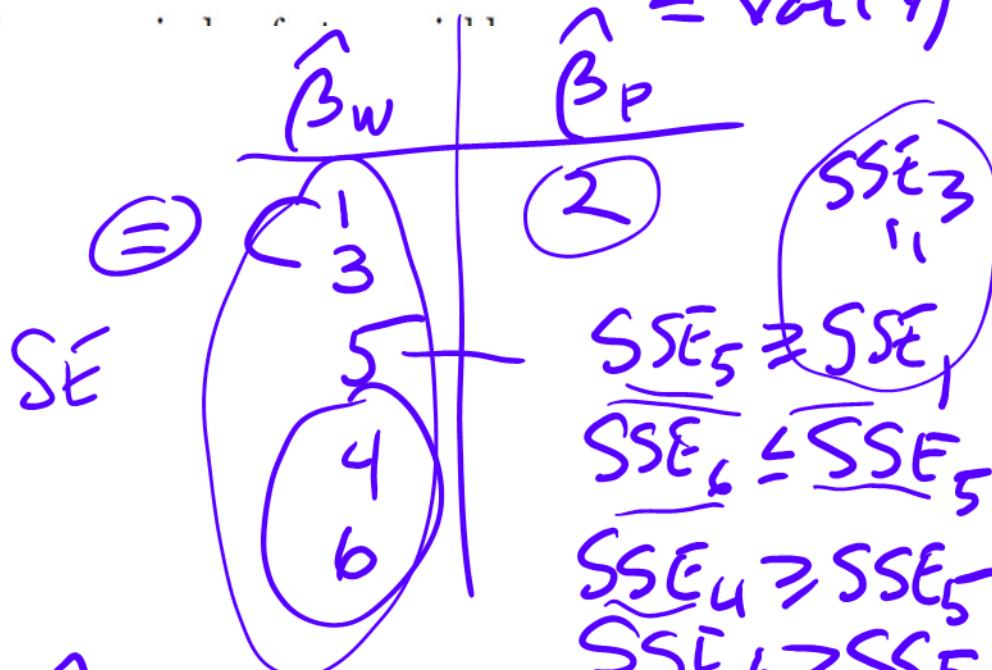
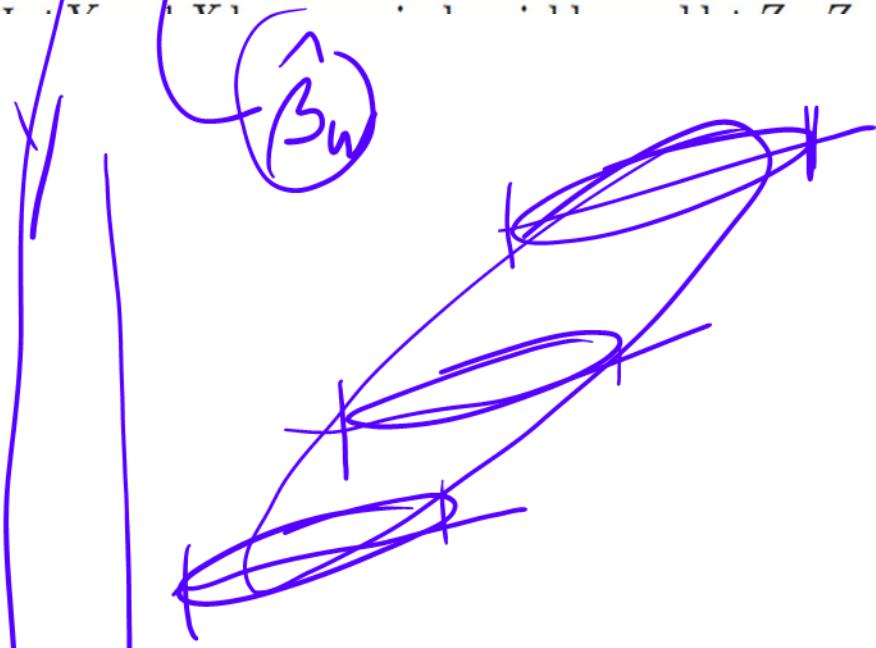
$$4. Y \sim X_r$$

$$5. Y \sim X + X_h \text{ where } X_h \text{ is the least-squares predictor of } X \text{ based on } G$$

$$6. Y \sim X + X_h + Z_g \text{ where } Z_g \text{ is a } G\text{-level numerical variable, i.e. it has the same value for all observations with a common value of } G.$$

$$X_h \in \mathcal{L}(G)$$

$$\begin{aligned} & -\hat{\beta}_w \quad \cancel{X_n} \\ & \text{Var}(Y|X_h) \leq \text{Var}(Y) \end{aligned}$$



Resid $Y|X_n$ - Resid of X on X_n \hat{X}_G

$$\text{var}(Y|X_h) \geq \text{var}(Y|G) \quad \overline{SSE_5} \geq \overline{SSE_3}$$

$$X - \hat{X}_G = X_r$$

$$A = \Gamma \Lambda \underline{\Gamma'}$$

$$A = \Gamma^* \Lambda \underline{\Gamma'^*}$$

$$\Lambda = \begin{bmatrix} \lambda_1 & \cdots & \lambda_p \\ 0 & \cdots & 0 \end{bmatrix} \quad \begin{array}{l} \lambda_i \neq \lambda_j \\ i \neq j \end{array}$$

$$\gamma_i^* = \pm \gamma_i$$

$$(A\gamma_i = \lambda_i \gamma_i) \quad \left[\begin{array}{l} \Gamma \Lambda \underline{\Gamma'} \gamma_i = \Gamma (\Lambda \underline{\Gamma'} \gamma_i) \\ = \Gamma \begin{pmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{pmatrix} = \gamma_i \end{array} \right]$$

$$A\gamma_i^* = \lambda_i \gamma_i^*$$

$$(A - \lambda_i I) \gamma_i = 0$$

$$(A - \lambda_i I) \gamma_i^* = 0$$

$$\gamma_i \text{ and } \gamma_i^* \in \ker(A - \lambda_i I)$$

$$A - \lambda_i I = \Gamma \Lambda \Gamma^* - \lambda_i \Gamma \Gamma^*$$

$$= \underbrace{(\Gamma(A - \lambda_i) \Gamma)}_{\text{one } 0}$$

oh $\ker(A) = \mathbb{I}$

$\gamma_i + f_i^*$ in same space of dim 1

$$\therefore \gamma_i = \pm f_i^*$$

EX 5

Equiv.

- a) A is a var $\underline{n \times n}$
 - b) A has SpD with $\underline{\min(\lambda_i) \geq 0}$
 - c) A is NND
 - d) $\exists a, B \ni A = BB^T$
-

Pf : a) \exists r.v. $\underline{x} \ni A = \text{Var}(\underline{x})$

(a) \Rightarrow (c) Let $\underline{c} \in \mathbb{R}^n$

then $\underline{0} \in \text{Var}(\underline{c}' \underline{x}) = \underline{c}' A \underline{c}$

$\therefore A$ is NND

(c) \Rightarrow (b) $A = \sum \lambda_i F_i^T F_i$

$\sum \lambda_i F_i^T \lambda F_i = (0 \ 0 \dots 1) \lambda \begin{pmatrix} 0 \\ 0 \end{pmatrix} = \lambda_1$

Since A is NND $\therefore \lambda_1 \geq 0$

(b) \Rightarrow (d) $A = \Gamma X \Gamma'$ where $\lambda_i \geq 0$

$$\therefore \Lambda = \Lambda^{1/2} \Lambda^{1/2}$$

Let $B = \Gamma \Lambda^{1/2}$ and $BB^T = \Gamma \Lambda^{1/2} \Lambda^{1/2} \Gamma^T$
 $= \Gamma \Lambda \Gamma^T = A.$

(d) \Rightarrow (a) Let $Z_n \sim N(0, I)$

$$\text{Let } X = BZ$$

$$\text{Var}(X) = B \underbrace{\text{Var}(Z)}_{=I} B^T = BB^T = A$$

Ex 7 $(x'y)^2 \leq (x^T A x)(y^T A^{-1} y)$ is AmpD.

Let $A = BB^T$ B^{-1} exists.

$$(x'y)^2 = (x^T B B^{-1} y)^2 = ((\underline{B^T x})^T (\underline{B^{-1} y}))^2$$

$$= (\underline{x}^T B B^T \underline{x}) (\underline{y}^T B^{-1 T} B^{-1} \underline{y})$$

$$= (\underline{x}^T A \underline{x}) (\underline{y}^T B^{-1} \underline{y})$$

EX 5 $\mathcal{E} = \{ \underline{x} : \underline{x}^T A^{-1} \underline{x} = 1 \}$



Let $x \in \Sigma$



$$\begin{aligned} (u'x)^2 &\leq (u' A u)(x' A^{-1} x) \\ &\leq u' A u \quad 1 \end{aligned}$$

with equality if $\underline{x} = k A \underline{u}$

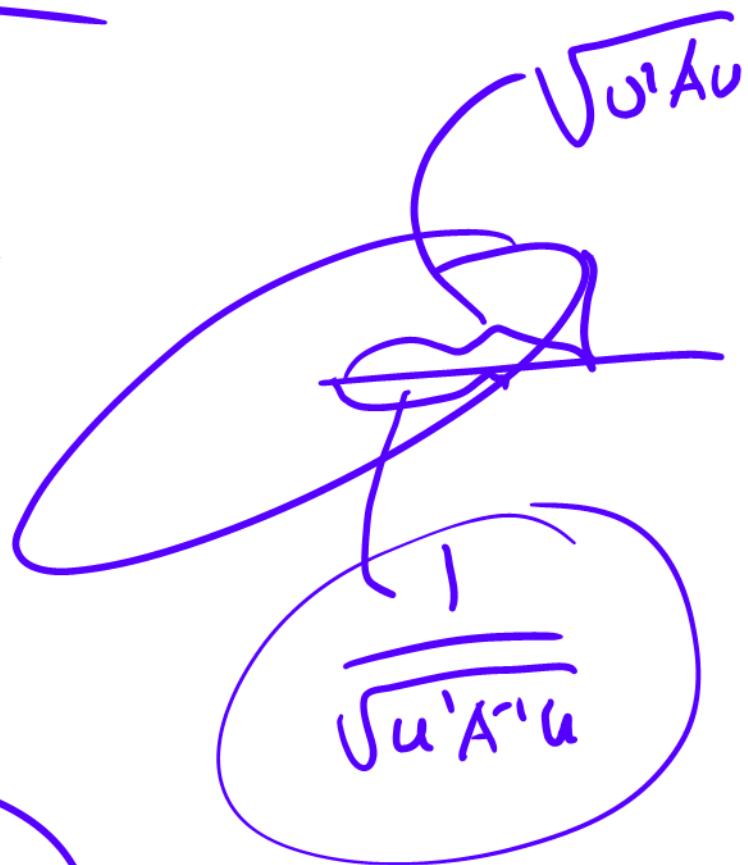
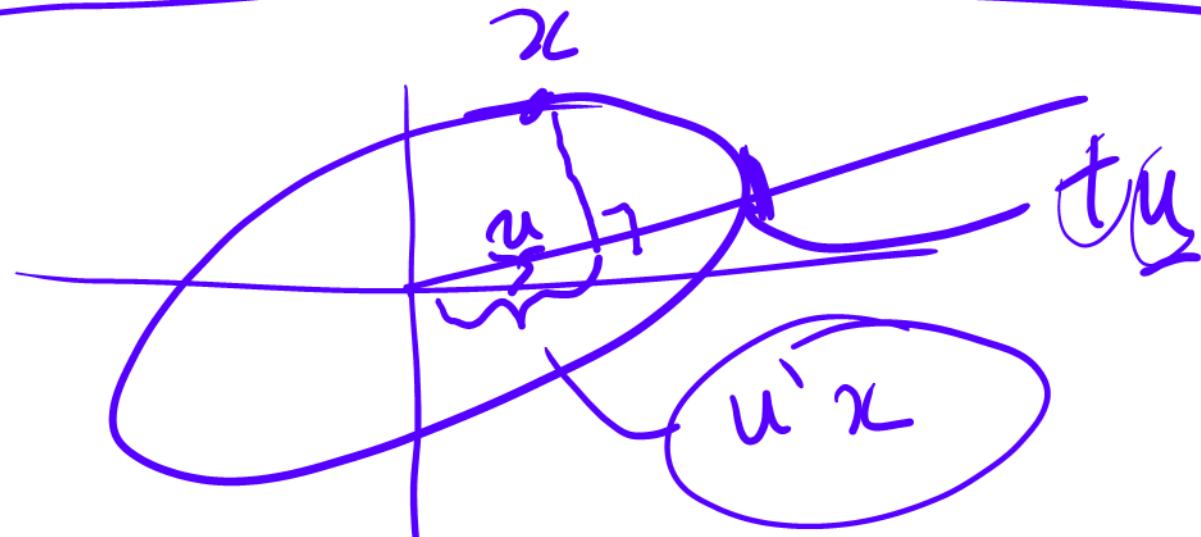
$$k: \underline{x} = x' A^{-1} x = k u' A A' A k u$$

$$= k^2 u' A u$$

$$k^2 = \frac{1}{u' A u}$$

(not max)

$$\max |u^T x| = \sqrt{u^T A u} \quad \text{max length}$$



Find: $\underline{x} = t \underline{u} \Rightarrow \underline{x} \in E$

$$t u^T A^{-1} t u = 1$$

$$t^2 = \frac{1}{u^T A^{-1} u}$$

$$t = \frac{1}{\sqrt{u^T A^{-1} u}}$$

Let $v = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$

$$u = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$\left\{ x : x^T \Sigma^{-1} x = 1 \right\}$$

$$u = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$U = \left(\begin{matrix} 0 & 1 \\ 1 & 0 \end{matrix} \right)$$

A WTS that $B = A^{-1}$

A
sq.

A WTS that $B = A^{-1}$

$$B^A = \dots - \cup - \cup - \cup \dots$$

$$\therefore B = A^{-1}$$

$$(A+B)^{-1} = A^{-1} - A^{-1}(B^{-1} + A^{-1})^{-1} A^{-1}$$

$$(A+UDV)^{-1} = A^{-1} - A^{-1}U(D^{-1} + VD^{-1}U)^{-1}VA^{-1}$$

$$D = B \quad U = V = I$$

$$(A + xx')^{-1} = A^{-1} - \underline{A^{-1}x} \underline{(1 + x'A^{-1}x)^{-1}} \underline{x'A^{-1}}$$

$$A = X'X$$

$$\underset{m \times n}{A} = \underset{m \times r}{U} \underset{r \times r}{D} \underset{r \times n}{V^T}$$

$$r = \text{rank}(A)$$

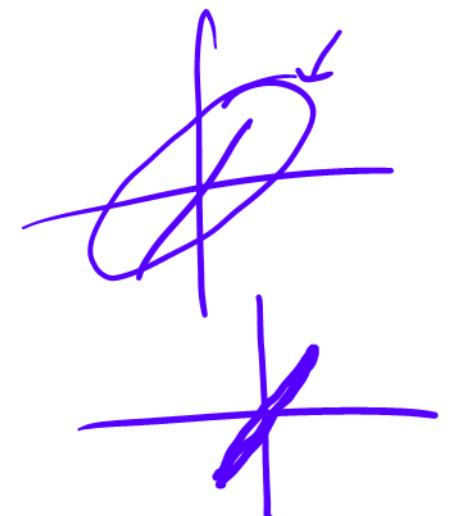
$$\mathcal{L}(A) = \mathcal{L}(U)$$

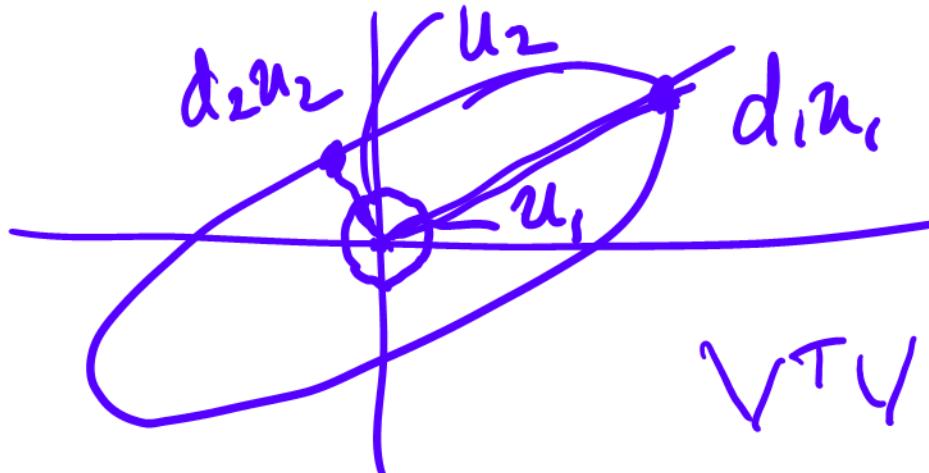
$$\ker(A) = \mathcal{L}^\perp(V)$$

Let \mathcal{U} = unit sphere in \mathbb{R}^n

$$\mathcal{U} = \{u : u^T u = 1\}.$$

$$\mathcal{E} = AU$$





VTU

$$d_i u_i = \underline{A} \mathcal{V}_i$$

\mathcal{V}_i is preimage of $d_i u_i$ under A

$$= \underline{UDV} \underline{\text{for } \mathcal{V}_i}$$

$$= UD \left(\begin{smallmatrix} 0 & \\ & I - i \theta_{\text{pos}} \end{smallmatrix} \right)$$

$$= U \left(\begin{smallmatrix} 0 & \\ & \frac{0}{d_i} & 0 \end{smallmatrix} \right) = d_i u_i$$

