

2010 Theory II #2

unfinished!

$$2a) \quad Y = X\beta + UJ + \varepsilon$$

$$U \sim N(\alpha J, k\sigma^2 JJ')$$

$$\varepsilon \sim N(0, \sigma^2 I)$$

Since $U \perp \varepsilon$ we have

$$\text{Var}[Y] = \text{Var}[U] + \text{Var}[\varepsilon] = k\sigma^2 JJ' + \sigma^2 I = \sigma^2 (I + kJJ')$$

so that

$$Y \sim N(0, \sigma^2 \Sigma) \quad \text{where } \Sigma = I + kJJ'$$

Let $0 \neq v \in \mathbb{R}^n$. Then

$$v' \Sigma v = \underbrace{\sigma^2}_{>0} \left[\underbrace{v'v}_{>0} + \underbrace{k(\sum v_i)^2}_{\geq 0} \right] > 0$$

2c) We can express the model as

$$Y = W\theta + \gamma = (1, X) \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \underbrace{\gamma}_{\sim N(0, \sigma^2 \Sigma)}$$

Then

$$\begin{aligned} L_n(\theta, \Sigma) &= (2\pi)^{-n/2} |\sigma^2 \Sigma|^{-1/2} \exp \left\{ -\frac{1}{2\sigma^2} (Y - W\theta)' \Sigma^{-1} (Y - W\theta) \right\} \\ &= (2\pi)^{-n/2} |\sigma^2 \Sigma|^{-1/2} \exp \left\{ -\frac{1}{2\sigma^2} [Y' \Sigma^{-1} Y - 2Y' \Sigma^{-1} W\theta + \theta' W' \Sigma^{-1} W\theta] \right\} \end{aligned}$$

so that

$$\begin{aligned} \frac{\partial}{\partial \theta} L_n(\theta, \Sigma) &= \sigma^2 W' \Sigma^{-1} Y - \sigma^2 W' \Sigma^{-1} W\theta \stackrel{\text{set}}{=} 0 \quad \left[\begin{array}{l} W \text{ is } p \times d \\ W' \Sigma^{-1} W \text{ is } p \times p \end{array} \right] \\ \Rightarrow \hat{\theta} &= (W' \Sigma^{-1} W)^{-1} W' \Sigma^{-1} Y \quad \text{since } \text{rank}(W' \Sigma^{-1} W) \stackrel{\text{rank}(W' \Sigma^{-1/2} \Sigma^{-1/2} W)}{=} \text{rank}(W' \Sigma^{-1/2} \Sigma^{-1/2} W) \end{aligned}$$

Next,

$$\begin{aligned} \stackrel{\text{rank}(A'A) = \text{rank}(A)}{=} \text{rank}(W' \Sigma^{-1/2}) &\stackrel{\text{rank}(AB) = \text{rank}(A) \text{ if } B \text{ is nonsingular}}{=} \text{rank}(W) = p+1 \end{aligned}$$

$$L_n(\theta, \Sigma) = -\frac{n}{2} \log(2\pi) + \frac{1}{2} \log(|\Sigma^{-1}|) - \frac{1}{2} \text{tr} \left\{ \Sigma^{-1} (Y - W\theta)(Y - W\theta)' \right\}$$

so that

$$\frac{\partial}{\partial \Sigma^{-1}} L_n(\theta, \Sigma) = \frac{1}{2} \frac{1}{|\Sigma^{-1}|} |\Sigma^{-1}| \Sigma - \frac{1}{2} (Y - W\theta)(Y - W\theta)'$$

$$= \frac{1}{2} \Sigma - \frac{1}{2} (Y - W\hat{\theta})(Y - W\hat{\theta})' \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \hat{\Sigma} = (Y - W\hat{\theta})(Y - W\hat{\theta})'$$

don't need

Then $\hat{\theta}$ is normally distributed with

$$E\hat{\theta} = (W' \Sigma^{-1} W)^{-1} W' \Sigma^{-1} EY = (W' \Sigma^{-1} W)^{-1} W' \Sigma^{-1} W\theta = \theta$$

$$\begin{aligned} \text{Var}[\hat{\theta}] &= (W' \Sigma^{-1} W)^{-1} W' \Sigma^{-1} \text{Var}[Y] \Sigma^{-1} W (W' \Sigma^{-1} W)^{-1} \\ &= (W' \Sigma^{-1} W)^{-1} W' \Sigma^{-1} \sigma^2 \Sigma \Sigma^{-1} W (W' \Sigma^{-1} W)^{-1} = (W' \Sigma^{-1} W)^{-1} \end{aligned}$$

$$20) \frac{\partial}{\partial \theta} \sum_{i=1}^n [y_i - (\alpha + x_{i1}\beta_1 + \dots + x_{ip}\beta_p)]^2 = \frac{\partial}{\partial \theta} (Y - W\theta)'(Y - W\theta)$$

$$= \frac{\partial}{\partial \theta} \{Y'Y - 2\theta'W'Y + \theta'W'W\theta\} = -2W'Y + 2W'W\theta \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \tilde{\theta} = (W'W)^{-1}W'Y$$

Wish to determine if $v'(\text{Var}[\hat{\theta}] - \text{Var}[\tilde{\theta}])v < 0 \quad \forall v \neq 0$.

Recall Gauss-Markov thm: let $\hat{\beta}$ be the least-squares estimate of β . then $v'\hat{\beta}$ is an unbiased estimate of $v'\beta$. Let $d'Y$ be any other unbiased estimate of $v'\beta$. Then

$\text{Var}[d'Y] \geq \text{Var}[v'\hat{\beta}]$ with equality only if

$$(I - P)d = 0 \iff d = Pd \quad \leftarrow \text{part of the thm}$$

Now we write this theorem in terms of the transformed model. We

$$\text{have } \underbrace{\Sigma^{-1/2}Y}_{Z} = \underbrace{\Sigma^{-1/2}W}_{B}\theta + \varepsilon$$

Then for $d'Y$ an unbiased estimate of $v'\theta$

$\text{Var}[d'Y] \geq \text{Var}[v'\hat{\theta}]$ with equality only if

$$d'Y = (v'(W'\Sigma^{-1}W)^{-1}W'\Sigma^{-1}Y = v'\hat{\theta}$$

Notice that $E\tilde{\theta} = \theta$ so Gauss-Markov applies

(5)

Thus letting $d = v'(W'W)^{-1}W'$

$$v'(\text{Var}[\hat{\theta}] - \text{Var}[\tilde{\theta}])v = \text{Var}[v'\hat{\theta}] - \text{Var}[v'\tilde{\theta}] = \text{Var}[v'\hat{\theta}] - \text{Var}[d'Y] \leq 0$$

with equality only if

$$v'(W'\Sigma^{-1}W)^{-1}W'\Sigma^{-1} = v'(W'W)^{-1}W'$$

Updating (Sherman-Morrison) formula: suppose A is invertible and u, v are vectors s.t. $1 + v'A^{-1}u \neq 0$. Then

$$(A + uv')^{-1} = A^{-1} - \frac{A^{-1}uv'A^{-1}}{1 + v'A^{-1}u}$$

$$\text{LHS} = v' \left\{ (W'W)^{-1} - \frac{p(W'W)^{-1}W'JJ'W(W'W)^{-1}}{1 + pJ'W(W'W)^{-1}W'J} \right\} W' [I + pJJ']$$

$$= v'(W'W)^{-1}W + p \frac{v'(W'W)^{-1}W'JJ'W(W'W)^{-1}W'[I + pJJ']}{1 + pJ'W(W'W)^{-1}W'J}$$

$$+ v'(W'W)^{-1}W'[I + pJJ']$$

$$= v'(W'W)^{-1}W - \frac{p}{1 + p\lambda} v'(W'W)^{-1}WJJ'[I + pJJ'] + v'(W'W)^{-1}W'[I + pJJ']$$