

**Problem Set 4**  
 (due: Monday week 5, 11:00am)

**Submission Instructions:** Same as last week.

## Exercises

Provide transparent derivations. Justify steps that are not obvious. Use self sufficient proofs. Make reasonable assumptions where necessary.

- Let  $X$  be a binary random variable with  $\Pr(X = 0) = \Pr(X = 1) = \frac{1}{2}$ . Let  $Y$  satisfy  $Y | X = 0 \sim \mathcal{N}(0, 1)$ , and  $Y | X = 1 \sim \mathcal{N}(2, 4)$ .
  - Compute  $E(Y | X)$ .
  - Compute  $\text{Var}(Y | X)$ . Is this a homoskedastic setting?
  - Compute  $E(\text{Var}(Y | X))$ .
  - Compute  $\text{Var}(E(Y | X))$ .
  - Using parts (c) and (d), compute  $\text{Var}(Y)$  from the law of total variance:

$$\text{Var}(Y) = E(\text{Var}(Y | X)) + \text{Var}(E(Y | X)).$$

- In the linear regression model in which  $X_{i1}$  is the constant term, show that we can safely presume that  $E(e_i) = 0$ . (This exercise justifies why we always want to include a constant term when running regressions.)
- Prove that the OLS estimator  $\hat{\beta}^{\text{OLS}}$  for  $\beta$  in the linear regression model is consistent. In your derivation, employ the  $o_p(1)$  and  $O_p(1)$  notation!
- The linear regression model in matrix format is  $Y = X\beta + e$ , with the usual definitions. Let  $E(e|X) = 0$  and

$$E(ee'|X) = \sigma^2\Gamma = \sigma^2 \begin{bmatrix} \gamma_1 & 0 & 0 & \cdots & 0 \\ 0 & \gamma_2 & 0 & \cdots & 0 \\ \vdots & & & \ddots & 0 \\ 0 & 0 & 0 & \cdots & \gamma_N \end{bmatrix} = \begin{bmatrix} \sigma_1^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & 0 & \cdots & 0 \\ \vdots & & & \ddots & 0 \\ 0 & 0 & 0 & \cdots & \sigma_N^2 \end{bmatrix} = \Sigma.$$

Notice that as a covariance matrix,  $\Sigma$  is symmetric and nonnegative definite.

- (a) Derive  $\text{Var}(\hat{\beta}^{\text{OLS}}|X)$ .
- (b) Let  $\tilde{\beta} := C'Y$  be any other linear unbiased estimator where  $C$  is an  $N \times K$ -dimensional matrix that is based on  $X$ . Following the lecture notes, prove that  $\text{Var}(\tilde{\beta}|X) \geq (X'\Sigma^{-1}X)^{-1}$ .
- (c) An oracle tells you  $\Gamma$ . Let  $\tilde{Y} := \Gamma^{-1/2}Y$  and  $\tilde{X} := \Gamma^{-1/2}X$ . Define the *generalized least squares (GLS)* estimator  $\hat{\beta}_{\text{GLS}} := (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y}$ . This defines the GLS estimator as the OLS estimator of  $\tilde{Y}$  on  $\tilde{X}$ .  
Derive  $\text{Var}(\hat{\beta}_{\text{GLS}}|X)$ . How does it compare to  $\text{Var}(\tilde{\beta}|X)$  from part (b)?