

1) Suppose  $\mathbf{x}_1, \dots, \mathbf{x}_n$  are iid  $p \times 1$  random vectors where

$$\mathbf{x}_i \sim (1 - \gamma)N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) + \gamma N_p(\boldsymbol{\mu}, c\boldsymbol{\Sigma})$$

with  $0 < \gamma < 1$  and  $c > 0$ . Then  $E(\mathbf{x}_i) = \boldsymbol{\mu}$  and  $\text{Cov}(\mathbf{x}_i) = [1 + \gamma(c - 1)]\boldsymbol{\Sigma}$ . Find the limiting distribution of  $\sqrt{n}(\bar{\mathbf{x}} - \boldsymbol{\mu})$  for appropriate vector  $\boldsymbol{d}$ .

$$\sqrt{n}(\bar{\mathbf{x}} - \boldsymbol{\mu}) \xrightarrow{D} N_p(\mathbf{0}, [1 + \gamma(c-1)]\boldsymbol{\Sigma})$$

by the MCLT

2) Suppose  $\mathbf{Y} \sim N_n(\mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I})$ . Find the distribution of  $\mathbf{H}\mathbf{Y}$  if  $\mathbf{H}$  is an  $n \times n$  constant matrix such that  $\mathbf{H}\mathbf{X} = \mathbf{X}$  and  $\mathbf{H} = \mathbf{H}^T = \mathbf{H}\mathbf{H} = \mathbf{H}^2$ . Simplify.

$$\mathbf{H}\mathbf{Y} \sim N_n(\mathbf{H}\mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{H}\mathbf{H}^T)$$

$$\sim N_n(\mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{H})$$

3) Suppose that  $Y_i = \alpha + \mathbf{x}_i^T \boldsymbol{\beta} + e_i$  where the  $e_i = \sigma_i \epsilon_i$  where the  $\epsilon_i$  iid with  $E(\epsilon_i) = 0$  and  $V(\epsilon_i) = 1$ . Then the  $e_i$  are independent with  $E(e_i) = 0$  and  $V(e_i) = \sigma_i^2$ . This MLR model can be written as  $\mathbf{Y} = \alpha \mathbf{1} + \mathbf{X} \boldsymbol{\beta} + \mathbf{e}$ . We will assume that the cases  $(\mathbf{x}_i^T, Y_i)^T$  are iid. Fit the model with OLS to get  $(\hat{\alpha}, \hat{\boldsymbol{\beta}})$  and the residuals  $r_i$ . The nonparametric bootstrap samples the  $(\mathbf{x}_i, Y_i, r_i)$  with replacement to form the MLR model  $\mathbf{Y}^* = \hat{\alpha} \mathbf{1} + \mathbf{X}^* \hat{\boldsymbol{\beta}} + \mathbf{r}^*$  where with respect to the bootstrap distribution, the  $r_i^*$  are iid with  $E(r_i^*) = 0$ . This bootstrap model has the  $(\mathbf{x}_i^{*T}, Y_i^*)^T$  iid with respect to the bootstrap distribution.

The MLR model  $\mathbf{Y}^* = \hat{\alpha} \mathbf{1} + \mathbf{X}^* \hat{\boldsymbol{\beta}} + \mathbf{r}^*$  is the bootstrap data set, and OLS is fit to the model to obtain the bootstrapped statistic  $(\hat{\alpha}^* = \bar{Y}^* - \hat{\boldsymbol{\beta}}^{*T} \bar{\mathbf{x}}^*, \hat{\boldsymbol{\beta}}^* = \tilde{\boldsymbol{\Sigma}}_{\mathbf{x}^*}^{-1} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x}^* \mathbf{Y}^*})$ .

a) By the second method to compute OLS,  $\hat{\boldsymbol{\beta}} = \tilde{\boldsymbol{\Sigma}}_{\mathbf{x}}^{-1} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x} \mathbf{Y}}$ . Since the bootstrap distribution for the nonparametric bootstrap is the empirical distribution, it can be shown that  $[\tilde{\boldsymbol{\Sigma}}_{\mathbf{x}}^*]^{-1} \xrightarrow{P} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x}}^{-1}$  and  $\tilde{\boldsymbol{\Sigma}}_{\mathbf{x} \mathbf{Y}}^* \xrightarrow{P} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x} \mathbf{Y}}$ . Prove that  $\hat{\boldsymbol{\beta}}^* = [\tilde{\boldsymbol{\Sigma}}_{\mathbf{x}}^*]^{-1} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x} \mathbf{Y}}^* \xrightarrow{P} \hat{\boldsymbol{\beta}}$ .

$$[\tilde{\boldsymbol{\Sigma}}_{\mathbf{x}}^*]^{-1} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x} \mathbf{Y}}^* \xrightarrow{P} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x}}^{-1} \tilde{\boldsymbol{\Sigma}}_{\mathbf{x} \mathbf{Y}} = \hat{\boldsymbol{\beta}}$$

b) By the second method to compute OLS,  $\hat{\alpha} = \bar{Y} - \hat{\boldsymbol{\beta}}^T \bar{\mathbf{x}}$ . It can be shown that  $\bar{Y}^* \xrightarrow{P} \bar{Y}$  and  $\bar{\mathbf{x}}^* \xrightarrow{P} \bar{\mathbf{x}}$ . Prove that  $\hat{\alpha}^* = \bar{Y}^* - \hat{\boldsymbol{\beta}}^{*T} \bar{\mathbf{x}}^* \xrightarrow{P} \hat{\alpha}$ .

$$\bar{Y}^* - \hat{\boldsymbol{\beta}}^{*T} \bar{\mathbf{x}}^* \xrightarrow{P} \bar{Y} - \hat{\boldsymbol{\beta}}^T \bar{\mathbf{x}} = \hat{\alpha}$$