

2010 Theory II #3

$$3a) P(\beta'X \geq \beta'Y) = P(\beta'(X-Y) \geq 0)$$

$$= P\left(\frac{\beta'(X-Y) - \beta'(\mu_1 - \mu_2)}{\sqrt{2\beta'\Sigma\beta}} \geq \frac{\beta'(\mu_1 - \mu_2)}{\sqrt{2\beta'\Sigma\beta}}\right)$$

$$= P\left(N(0,1) \geq \frac{\beta'(\mu_1 - \mu_2)}{\sqrt{2\beta'\Sigma\beta}}\right) = P\left(N(0,1) \leq \frac{\beta'(\mu_1 - \mu_2)}{\sqrt{2\beta'\Sigma\beta}}\right)$$



3b) Recall the Cauchy-Schwartz inequality: for a, b vectors of an inner product space
 $\|a'b\| \leq \|a\| \|b\| \Rightarrow (a'b)^2 \leq (a'a)(b'b)$

Then

$$\frac{\beta'(\mu_1 - \mu_2)}{\sqrt{2\beta'\Sigma\beta}} = \left\{ \frac{[\beta'(\mu_1 - \mu_2)]^2}{2\beta'\Sigma\beta} \right\}^{1/2}$$

$$\Sigma \text{ is pd} \Rightarrow \left\{ \frac{[(\Sigma^{1/2}\beta)'(\Sigma^{-1/2}(\mu_1 - \mu_2))]^2}{2\beta'\Sigma\beta} \right\}^{1/2}$$

$$\stackrel{\text{C-S}}{\leq} \left\{ \frac{[(\Sigma^{1/2}\beta)' \Sigma^{1/2}\beta] [(\Sigma^{-1/2}(\mu_1 - \mu_2))' \Sigma^{-1/2}(\mu_1 - \mu_2)]}{2\beta'\Sigma\beta} \right\}^{1/2}$$

$$= \sqrt{\frac{1}{2}(\mu_1 - \mu_2)' \Sigma^{-1}(\mu_1 - \mu_2)}$$

But choosing $\beta = \Sigma^{-1}(\mu_1 - \mu_2)$ yields $\frac{\beta'(\mu_1 - \mu_2)}{2\sqrt{\beta'\Sigma^{-1}\beta}} = \sqrt{\frac{(\mu_1 - \mu_2)' \Sigma^{-1}(\mu_1 - \mu_2)}{2}}$

and since Φ is monotone this choice of β maximizes $AUC(\beta)$

$$p(\underline{x}, \underline{y}; \mu_1, \mu_2, \Sigma) = \left(\prod_{i=1}^n (2\pi)^{-1} |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (\underline{x}_i - \mu_1)' \Sigma^{-1} (\underline{x}_i - \mu_1) \right\} \right) \\ \times \left(\prod_{j=1}^m (2\pi)^{-1} |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (\underline{y}_j - \mu_2)' \Sigma^{-1} (\underline{y}_j - \mu_2) \right\} \right)$$

$$\ell_n(\mu_1, \mu_2, \Sigma) = -(n+m) \log(2\pi) - \frac{n+m}{2} \log(|\Sigma|) \\ - \frac{1}{2} \sum_{i=1}^n (\underline{x}_i - \mu_1)' \Sigma^{-1} (\underline{x}_i - \mu_1) - \frac{1}{2} \sum_{j=1}^m (\underline{y}_j - \mu_2)' \Sigma^{-1} (\underline{y}_j - \mu_2)$$

$$\frac{\partial}{\partial \mu_1} \ell_n(\mu_1, \mu_2, \Sigma) = \frac{\partial}{\partial \mu_1} \left\{ -n \mu_1' \Sigma^{-1} \bar{\underline{x}}_n - \frac{n}{2} \mu_1' \Sigma^{-1} \mu_1 \right\} \\ = n \Sigma^{-1} \bar{\underline{x}}_n - n \Sigma^{-1} \mu_1 \stackrel{\text{set}}{=} 0 \Rightarrow \hat{\mu}_1 = \bar{\underline{x}}_n$$

Similarly we obtain

$$\hat{\mu}_2 = \bar{\underline{y}}_m$$

Next,

$$\frac{\partial}{\partial \Sigma^{-1}} \ell_n(\mu_1, \mu_2, \Sigma) = \frac{n+m}{2} \log(|\Sigma^{-1}|) - \frac{1}{2} \sum_{i=1}^n \text{tr} \left[\Sigma^{-1} (\underline{x}_i - \mu_1) (\underline{x}_i - \mu_1)' \right] \\ - \frac{1}{2} \sum_{j=1}^m \text{tr} \left[\Sigma^{-1} (\underline{y}_j - \mu_2) (\underline{y}_j - \mu_2)' \right] \\ = \frac{n+m}{2} \Sigma - \frac{1}{2} \sum_{i=1}^n (\underline{x}_i - \mu_1) (\underline{x}_i - \mu_1)' - \frac{1}{2} \sum_{j=1}^m (\underline{y}_j - \mu_2) (\underline{y}_j - \mu_2)' \stackrel{\text{set}}{=} 0 \\ \Rightarrow \hat{\Sigma} = \frac{1}{n+m} \sum_{i=1}^n (\underline{x}_i - \hat{\mu}_1) (\underline{x}_i - \hat{\mu}_1)' + \frac{1}{n+m} \sum_{j=1}^m (\underline{y}_j - \hat{\mu}_2) (\underline{y}_j - \hat{\mu}_2)'$$

then by the invariance property of MLEs,

$$\hat{A} = \Phi\left(\sqrt{\frac{1}{2}} (\hat{\mu}_1 - \hat{\mu}_2)' \hat{\Sigma}^{-1} (\hat{\mu}_1 - \hat{\mu}_2)\right)$$

3d) By CLT and since $X_n \xrightarrow{L} X$, $Y_n \xrightarrow{L} Y$ all independent
 $\Rightarrow \begin{pmatrix} X_n \\ Y_n \end{pmatrix} \xrightarrow{L} N\left(0, \begin{bmatrix} \Sigma_X & 0 \\ 0 & \Sigma_Y \end{bmatrix}\right)$

$$\sqrt{n} \begin{pmatrix} \bar{X}_{n1} \\ \bar{X}_{n2} \\ \bar{X}_{n1}^2 \\ \bar{X}_{n2}^2 \\ \bar{X}_{n1}X_{n2} \\ \bar{Y}_{n1} \\ \bar{Y}_{n2} \\ \bar{Y}_{n1}^2 \\ \bar{Y}_{n2}^2 \\ \bar{Y}_{n1}Y_{n2} \end{pmatrix} \rightarrow N\left(0, \begin{bmatrix} \tau_X & 0 \\ 0 & \tau_Y \end{bmatrix}\right)$$

$$= \begin{pmatrix} \mu_{11} \\ \mu_{21} \\ \sigma_{11} + \mu_{11}^2 \\ \sigma_{22} + \mu_{21}^2 \\ \sigma_{12} + \mu_{11}\mu_{12} \\ \mu_{12} \\ \mu_{22} \\ \sigma_{11} + \mu_{12}^2 \\ \sigma_{22} + \mu_{22}^2 \\ \sigma_{12} + \mu_{12}\mu_{22} \end{pmatrix}$$

where τ_X and τ_Y can be calculated using mgfs

$$\text{Now } \Sigma^{-1} = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix}^{-1} = \frac{1}{\sigma_{11}\sigma_{22} - \sigma_{12}^2} \begin{bmatrix} \sigma_{22} - \sigma_{12} \\ -\sigma_{12} & \sigma_{11} \end{bmatrix}$$

so that

$$(\mu_1 - \mu_2)' \Sigma^{-1} (\mu_1 - \mu_2) = \frac{1}{\sigma_{11}\sigma_{22} - \sigma_{12}^2} \left\{ (\mu_{11} - \mu_{12})^2 \sigma_{22} - 2(\mu_{11} - \mu_{12})(\mu_{21} - \mu_{22}) \sigma_{12} + (\mu_{21} - \mu_{22})^2 \sigma_{11} \right\}$$

Now we can construct a function $g: \mathbb{R}^{10} \mapsto \mathbb{R}$ s.t.

$$g(\bar{x}_{n1}, \bar{x}_{n2}, \bar{x}_{n1}^2, \bar{x}_{n2}^2, \bar{x}_{n1}\bar{x}_{n2}, \bar{y}_{n1}, \bar{y}_{n2}, \bar{y}_{n1}^2, \bar{y}_{n2}^2, \bar{y}_{n1}\bar{y}_{n2}) = \hat{A}$$

and it can be easily verified that

$$g(\mu_{11}, \mu_{21}, \sigma_{11} + \mu_{11}^2, \sigma_{22} + \mu_{21}^2, \sigma_{12} + \mu_{11}\mu_{12}, \mu_{12}, \mu_{22}, \sigma_{11} + \mu_{12}, \sigma_{22} + \mu_{22}^2, \sigma_{12} + \mu_{12}\mu_{22}) = A^{\text{optimal}}$$

Then ~~the~~ by the delta method, the asymptotic variance is given by $\dot{g}(\xi) \begin{bmatrix} \tilde{\gamma}_x & 0 \\ 0 & \tilde{\gamma}_y \end{bmatrix} [\dot{g}(\xi)]'$

* Alternatively, we could verify the regularity conditions for MLE estimates. Then

$$\sqrt{n} \left(\begin{bmatrix} \hat{\mu}_1 \\ \hat{\mu}_2 \\ \hat{\varepsilon} \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \\ \varepsilon \end{bmatrix} \right) \xrightarrow{L} N \left(0, \left[\lim_{n \rightarrow \infty} \frac{1}{n} I_n(\mu_2, \mu_2, \varepsilon) \right]^{-1} \right)$$

and we could again use the delta method to obtain the desired quantity

Need to do 3e!!