

# 2010 Theory I #1

$$\begin{aligned}
 1a) p((x_1, y_1), \dots, (x_n, y_n)) &= \prod_{i=1}^n (2\pi)^{-1} |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} \left( \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right)' \Sigma^{-1} \right. \\
 &\quad \left. \left( \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right) \right\} \\
 &= \prod_{i=1}^n (2\pi)^{-1} (\sigma_1^2 \sigma_2^2)^{-1/2} \exp \left\{ -\frac{1}{2\sigma_1^2} (x_i - \mu_1)^2 - \frac{1}{2\sigma_2^2} (y_i - \mu_2)^2 \right\} \\
 &= (2\pi)^{-n} (\sigma_1^2 \sigma_2^2)^{-n/2} \exp \left\{ -\frac{1}{2\sigma_1^2} \sum_{i=1}^n (x_i - \mu_1)^2 - \frac{1}{2\sigma_2^2} \sum_{i=1}^n (y_i - \mu_2)^2 \right\} \\
 &= (2\pi)^{-n} (\sigma_1^2 \sigma_2^2)^{-n/2} \exp \left\{ -\frac{1}{2\sigma_1^2} \sum_{i=1}^n (x_i^2 - 2x_i\mu_1 + \mu_1^2) - \frac{1}{2\sigma_2^2} \sum_{i=1}^n (y_i^2 - 2y_i\mu_2 + \mu_2^2) \right\} \\
 &= (2\pi)^{-n} (\sigma_1^2 \sigma_2^2)^{-n/2} \exp \left\{ -\frac{1}{2\sigma_1^2} \sum x_i^2 + \frac{n\mu_1^2}{\sigma_1^2} \bar{x}_n - \frac{n\mu_1^2}{2\sigma_1^2} \right. \\
 &\quad \left. - \frac{1}{2\sigma_2^2} \sum y_i^2 + \frac{n\mu_2^2}{\sigma_2^2} \bar{y}_n - \frac{n\mu_2^2}{2\sigma_2^2} \right\} \\
 &= (2\pi)^{-n} (\sigma_1^2 \sigma_2^2)^{-n/2} \exp \left\{ \left( \frac{1}{2\sigma_2^2} - \frac{1}{2\sigma_1^2} \right) \bar{x}_n^2 + \frac{n\mu_1^2}{\sigma_1^2} \bar{x}_n - \frac{n\mu_1^2}{2\sigma_1^2} \right. \\
 &\quad \left. - \frac{1}{2\sigma_2^2} (\bar{x}_n^2 + \bar{y}_n^2) + \frac{n\mu_2^2}{\sigma_2^2} \bar{y}_n - \frac{n\mu_2^2}{2\sigma_2^2} \right\}
 \end{aligned}$$

which is exponential family with

$$T_1 = \bar{x}_n^2 \qquad \theta_1 = \frac{1}{2\sigma_2^2} - \frac{1}{2\sigma_1^2}$$

$$T_2 = \bar{x}_n^2 + \bar{y}_n^2 \qquad \theta_2 = -\frac{1}{2\sigma_2^2}$$

$$T_3 = \bar{x}_n \qquad \theta_3 = \frac{n\mu_1}{\sigma_1^2}$$

$$T_4 = \bar{y}_n \qquad \theta_4 = \frac{n\mu_2}{\sigma_2^2}$$

It is clear that we can find an open set ~~about~~ in the neighborhood of, say,  $(0, -1, 0, 0)$  so that the density is full-rank. ~~and~~ Thus  $\underline{T}$  is sufficient for  $\Theta$ .

~~Also~~ The hypothesis is equivalent to  $H_0: \theta_2 = 0$  vs.  $H_1: \theta_2 \neq 0$ . By Thm 2.7 ~~as~~ a UMPU test is of the form

$$\phi(t_2) = \begin{cases} 1, & t_2 < c_1(t_2, t_3, t_4) \text{ or } t_2 > c_2(t_2, t_3, t_4) \\ 0, & \text{else} \end{cases} \quad * \text{Note assume wlog } \Delta_0 = 1$$

where  $c_1(\cdot), c_2(\cdot)$  satisfy

$$\begin{cases} E_{\theta_0}[\phi(T_2) | T_2, T_3, T_4] = \alpha \\ E_{\theta_0}[T_2 \phi(T_2) | T_2, T_3, T_4] = \alpha E_{\theta_0}[T_2 | T_2, T_3, T_4] \end{cases}$$

Consider

want to find an increasing fun of  $T$  which satisfies Basu's theorem and that we can work toward an F-test

$$V = \frac{T_2 - T_3^2}{T_2 - T_3 - T_4} = \frac{\sum X_i^2 - n\bar{X}_n^2}{\sum X_i^2 + \sum Y_i^2 - n\bar{X}_n^2 - n\bar{Y}_n^2} = \frac{\sum (X_i - \bar{X}_n)^2}{\sum (X_i - \bar{X}_n)^2 + \sum (Y_i - \bar{Y}_n)^2}$$

$\downarrow [a(t)V + b(t) \text{ for } a(t) > 0]$

Now since  $V$  is increasing in  $T_2$  for fixed  $(T_2, T_3, T_4)$ , the hypothesis is unchanged if we replace  $t_2$  with  $V$ .

Now  $V$  is a linear function of  $T_2$ . ~~Need~~ to verify Basu's conditions, ~~because~~ Firstly  $T_2$  as ~~a~~ exponential family implies that it is complete sufficient. Notice that complete ~~mean~~ is stronger than bounded complete as is needed for Basu's.

Next, under  $H_0$ , (write  $\sigma^2 = \sigma_x^2 = \sigma_y^2$ )

$$V = \frac{(n-1) \sum (X_i - \bar{X}_n)^2 / \sigma^2}{(n-1) \sum (X_i - \bar{X}_n)^2 / \sigma^2 + (n-1) \sum (Y_i - \bar{Y}_n)^2 / \sigma^2} = \frac{\chi_{n-1}^2}{\chi_{n-1}^2 + \chi_{n-1}^2}$$

so that  $V$  is ancillary of  $(T_2, T_3, T_4)$  and Basu's thm conditions are satisfied. Thus we may rewrite our UMPU test as

$$\phi(v) = \begin{cases} 1, & v < c_1 \text{ or } v > c_2 \\ 0, & \text{else} \end{cases}$$

where  $c_1, c_2$  satisfy

$$\begin{cases} E_{\theta_0}[\phi(v)] = \alpha \\ E_{\theta_0}[v \phi(v)] = \alpha E_{\theta_0}[v] \end{cases}$$

Now

$$c_1 > v = \frac{\sum (X_i - \bar{X}_n)^2}{\sum (X_i - \bar{X}_n)^2 + \sum (Y_i - \bar{Y}_n)^2}$$

$$\Leftrightarrow c_1^* < 1 + \frac{\sum (Y_i - \bar{Y}_n)^2}{\sum (X_i - \bar{X}_n)^2}$$

$$\Leftrightarrow c_1^{**} < \frac{\sum (Y_i - \bar{Y}_n)^2 / (n-1)}{\sum (X_i - \bar{X}_n)^2 / (n-1)}$$

$$\Leftrightarrow c_1^{***} > F = \frac{\sum (X_i - \bar{X}_n)^2 / (n-1)}{\sum (Y_i - \bar{Y}_n)^2 / (n-1)} \stackrel{H_0}{\sim} F_{n-1, n-1}$$

Similarly,

$c_2 < V \Leftrightarrow c_2 < F$ . Thus we have our UMPU

test of the form

~~The decision rule is~~

$$\phi(F) = \begin{cases} 1, & F < c_1 \text{ or } F > c_2 \\ 0, & \text{else} \end{cases}$$

Note that  $F \stackrel{d}{=} Y_F$  so that

$$\begin{aligned} P(F < c_1 \text{ or } F > c_2) &= P(Y_F < c_1 \text{ or } Y_F > c_2) \\ &= P\left(F > \frac{1}{c_2} \text{ or } F < \frac{1}{c_1}\right) \end{aligned}$$

But since the test is UMPU it must be that  $c_1 = \frac{1}{c_2}$ . Thus  
we can solve

$$\alpha = E_{\theta_0}[\phi(F)] = P_{\theta_0}[F < c_1] + P_{\theta_0}[F > \frac{1}{c_1}]$$

$$= 2P_{\theta_0}[F < c_1] \Rightarrow c_1 = F_{n-1, n-1}(\alpha/2)$$

and similarly

$$\alpha = 2P_{\theta_0}[F > c_2] \Rightarrow c_2 = F_{n-1, n-1}(1 - \alpha/2)$$

Thus the test is

~~(B, S)~~

1b) Again assume wlog  $\Delta_0 = 1$ . It is easy to show that under  $H_0: \sigma^2 = \sigma_1^2 = \sigma_2^2$  we have

$$\tilde{\mu}_1 = \bar{x}_n, \quad \tilde{\mu}_2 = \bar{y}_n, \quad \text{and} \quad \tilde{\sigma}^2 = \frac{1}{2n} \left[ \sum (x_i - \bar{x}_n)^2 + \sum (y_i - \bar{y}_n)^2 \right]$$

and that ~~is the case~~ in the unrestricted case

$$\hat{\mu}_1 = \bar{x}_n, \quad \hat{\mu}_2 = \bar{y}_n, \quad \hat{\sigma}_1^2 = \frac{1}{n} \sum (x_i - \bar{x}_n)^2, \quad \hat{\sigma}_2^2 = \frac{1}{n} \sum (y_i - \bar{y}_n)^2$$

$$\begin{aligned} LRT_n &= \frac{(2\pi)^{-n} (\tilde{\sigma}^2)^{-n} \exp \left\{ -\frac{1}{2\tilde{\sigma}^2} \left[ \sum (x_i - \tilde{\mu}_1)^2 + \sum (y_i - \tilde{\mu}_2)^2 \right] \right\}}{(2\pi)^{-n} (\hat{\sigma}_1^2 \hat{\sigma}_2^2)^{-n/2} \exp \left\{ -\frac{1}{2\hat{\sigma}_1^2} \sum (x_i - \hat{\mu}_1)^2 - \frac{1}{2\hat{\sigma}_2^2} \sum (y_i - \hat{\mu}_2)^2 \right\}} \\ &= \left\{ \frac{\hat{\sigma}_1^2 \hat{\sigma}_2^2}{(\tilde{\sigma}^2)^2} \right\}^n \frac{\exp \{-n\}}{\exp \{-n\}} = \left\{ \frac{\frac{1}{n^2} [\sum (x_i - \bar{x}_n)^2] [\sum (y_i - \bar{y}_n)^2]}{\frac{1}{4n^2} [\sum (x_i - \bar{x}_n)^2 + \sum (y_i - \bar{y}_n)^2]^2} \right\}^n \end{aligned}$$

Thus we reject if

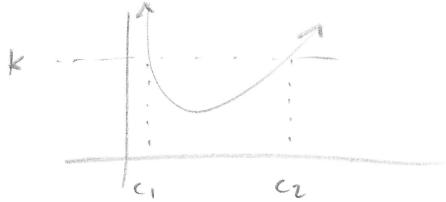
$$k < \left\{ \cdot \right\} \Leftrightarrow k^* < \frac{[\sum (x_i - \bar{x}_n)^2] [\sum (y_i - \bar{y}_n)^2]}{[\sum (x_i - \bar{x}_n)^2 + \sum (y_i - \bar{y}_n)^2]^2}$$

$$= \frac{[\sum (x_i - \bar{x}_n)^2] [\sum (y_i - \bar{y}_n)^2]}{[\sum (x_i - \bar{x}_n)^2 + \sum (y_i - \bar{y}_n)^2]^2} \cdot \frac{1 / [\sum (y_i - \bar{y}_n)^2]^2}{1 / [\sum (x_i - \bar{x}_n)^2]^2}$$

$$= \frac{\sum (x_i - \bar{x}_n)^2}{\sum (y_i - \bar{y}_n)^2} = \frac{\mathbb{F}}{(1 + \mathbb{F})^2} \quad \text{for } \mathbb{F} \text{ as before}$$

$$\Leftrightarrow k^{**} > \frac{(1+F)^2}{F} \quad \text{[crossed out]}$$

Now  $\frac{d^2}{dt^2} \frac{(1+t)^2}{t} = \frac{2}{t^3} > 0$  for  $t > 0$  so we see that the graph of  $f(t) = \frac{(1+t)^2}{t}$  is given by



so we reject if  $F < c_2$  or  $F > c_2$ . But ~~then~~ we then do ~~the same argument as in (1a)~~ follows so that we obtain the same test.

$$\hat{\sigma}_{12}^2 = \frac{1}{n} \sum (x_i - \bar{x})(y_i - \bar{y})$$

1c) In the unrestricted model

$$\hat{\mu}_1 = \bar{x}_n, \quad \hat{\mu}_2 = \bar{y}_n, \quad \hat{\sigma}_1^2 = \frac{1}{n} \sum (x_i - \bar{x}_n)^2, \quad \hat{\sigma}_2^2 = \frac{1}{n} \sum (y_i - \bar{y}_n)^2$$

$$\hat{\sigma}_{12} = \frac{1}{n} \sum (x_i - \bar{x}_n)(y_i - \bar{y}_n)$$

$$\text{Since } \rho = \frac{\hat{\sigma}_{12}}{\sqrt{\hat{\sigma}_1^2 \hat{\sigma}_2^2}} \text{ we have } R = \frac{\hat{\sigma}_{12}}{\sqrt{\hat{\sigma}_1^2 \hat{\sigma}_2^2}}$$

then

$$L(\mu, \Sigma) = (2\pi)^{-n} |\Sigma|^{-n/2} \exp \left\{ -\frac{1}{2} \sum_{i=1}^n \left( \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right)' \Sigma^{-1} \left( \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right) \right\}$$

$$\boxed{\begin{aligned} |\Sigma| &= \sigma_1^2 \sigma_2^2 - \rho^2 \sigma_1^2 = \sigma_1^2 \sigma_2^2 - \sigma_1^2 \sigma_2^2 \rho^2 = \sigma_1^2 \sigma_2^2 (1 - \rho^2) \\ \Sigma^{-1} &= \frac{1}{\sigma_1^2 \sigma_2^2 (1 - \rho^2)} \begin{bmatrix} \sigma_2^2 & -\rho \sigma_1 \sigma_2 \\ -\rho \sigma_1 \sigma_2 & \sigma_1^2 \end{bmatrix} \\ (a \ b) \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \end{bmatrix} \begin{pmatrix} a \\ b \end{pmatrix} &= (a \ b) \begin{bmatrix} ax_{11} + bx_{12} \\ ax_{21} + bx_{22} \end{bmatrix} = a^2 x_{11} + 2abx_{12} + b^2 x_{22} \end{aligned}}$$

$$= (2\pi)^{-n} [\sigma_1^2 \sigma_2^2 (1 - \rho^2)]^{-n/2} \exp \left\{ -\frac{1}{2\sigma_1^2 \sigma_2^2 (1 - \rho^2)} \sum_{i=1}^n \left[ (x_i - \mu_1)^2 \sigma_2^2 \right. \right. \\ \left. \left. - 2(x_i - \mu_1)(y_i - \mu_2)\sigma_{12} + (y_i - \mu_2)^2 \right] \right\}$$

$$= (2\pi)^{-n} [\sigma_1^2 \sigma_2^2 (1 - \rho^2)]^{-n/2} \exp \left\{ -\frac{1}{2(1 - \rho^2)} \sum_{i=1}^n \left[ \frac{(x_i - \mu_1)^2}{\sigma_1^2} - \frac{2(x_i - \mu_1)(y_i - \mu_2)\sigma_{12}}{\sigma_1^2 \sigma_2^2} + \frac{(y_i - \mu_2)^2}{\sigma_2^2} \right] \right\}$$

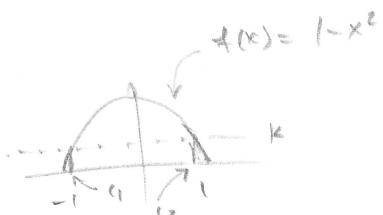
so that

$$-\frac{2n(1 - \rho^2)}{2(1 - \rho^2)} = -n$$

$$L(\hat{\mu}, \hat{\Sigma}) = (2\pi)^{-n} [\hat{\sigma}_1^2 \hat{\sigma}_2^2 (1 - R^2)]^{-n/2} \exp \left\{ -\frac{1}{2(1 - R^2)} [n - 2nR^2 + n] \right\}$$

then

$$\lambda = \frac{L(\tilde{\mu}, \tilde{\Sigma})}{L(\hat{\mu}, \hat{\Sigma})} = (1 - R^2)^{-n/2}$$



so we reject when

$$k < 1 - R^2 \Leftrightarrow R^2 < k^* \Leftrightarrow |R| < k^{**}$$

~~Under H<sub>0</sub> f is symmetric about 0 so the test rejects when~~ Under H<sub>0</sub> f is symmetric about 0 so choosing k that satisfies

$E_{\theta_0}[\phi(R)] = \alpha$  yields rejection region symmetric about 0

$$1c.iii) \text{ We have } R = \frac{\sum (x_i - \bar{x}_n)^2 (y_i - \bar{y}_n)^2}{\sum (x_i - \bar{x}_n)^2 \sum (y_i - \bar{y}_n)^2} = \frac{s_{xy}^2}{s_x^2 s_y^2}$$

Want to find the distribution of

$$\frac{\sqrt{n-2} R}{\sqrt{1-R^2}} \stackrel{?}{=} \frac{s_{xy}}{\sqrt{s_x^2 s_y^2}} / \sqrt{1 - \frac{s_{xy}^2}{s_x^2 s_y^2}} = \frac{s_{xy}}{\sqrt{s_x^2 s_y^2}} / \sqrt{\frac{s_x^2 s_y^2 - s_{xy}^2}{s_x^2 s_y^2}}$$

can't get the coefficients to work out

~~$$\frac{s_{xy}}{\sqrt{s_x^2 s_y^2}} / \sqrt{1 - \frac{s_{xy}^2}{s_x^2 s_y^2}} = \frac{s_{xy}}{\sqrt{s_x^2 s_y^2 - s_{xy}^2}} = \frac{s_{xy}}{\sigma_{xy}} \sqrt{\frac{\sigma_x \sigma_y}{s_x^2 s_y^2 - s_{xy}^2}}$$~~

We observe that

$$s_{xy} = \frac{1}{n} \sum (x_i - \bar{x})(y_i - \bar{y}) = \frac{1}{n} \sum (x_i y_i - \bar{x} \bar{y} - \bar{x} y_i + \bar{x} \bar{y}) \\ = \frac{1}{n} [\sum x_i y_i - n \bar{x} \bar{y}]$$

$$\sum_{i=1}^n x_i y_i \mid Y_i \sim N(\mu_x \bar{Y}, \sigma_x^2 \sum Y_i^2)$$

$$E[\sum x_i y_i \mid Y_i] = \sum Y_i E X_i = \mu_x \sum Y_i = \mu_x \bar{Y}$$

$$\text{Var}[\sum x_i y_i \mid Y_i] = \sum Y_i^2 \text{Var}[X_i] = \sigma_x^2 \sum Y_i^2$$

(a)

$$n\bar{X}\bar{Y}|Y \stackrel{d}{=} n\bar{Y}N(\mu_x, \frac{\sigma_x^2}{n}) | Y \sim N(n\mu_x\bar{Y}, n\sigma_x^2\bar{Y}^2)$$

~~( $\Sigma X_i Y_i - n\bar{X}\bar{Y}$ )~~ ~~BC~~  ~~$n\sigma_x^2(\bar{X}^2 + \bar{Y}^2)$~~

~~BC~~  ~~$n\sigma_x^2(\bar{X}^2 + \bar{Y}^2)$~~

$$\text{Cov}[\Sigma X_i Y_i, n\bar{X}\bar{Y}|Y] = n\bar{Y} \text{Cov}[\Sigma X_i Y_i, \Sigma X_i|Y]$$

$$= \bar{Y} \sum \text{Cov}[X_i Y_i, X_i|Y] = n\bar{Y} \sum Y_i \sigma_x^2 = n\sigma_x^2 \bar{Y}^2$$

Then

$$\text{Var}[S_{xy}|Y] = \frac{1}{n^2} \text{Var}[\Sigma X_i Y_i - n\bar{X}\bar{Y}|Y]$$

$$= \frac{1}{n^2} \left\{ \text{Var}[\Sigma X_i Y_i] - 2 \text{Cov}[\Sigma X_i Y_i, n\bar{X}\bar{Y}|Y] + \text{Var}[n\bar{X}\bar{Y}|Y] \right\}$$

$$= \frac{1}{n^2} \left\{ \sigma_x^2 \sum Y_i^2 - 2n\sigma_x^2 \bar{Y}^2 + n\sigma_x^2 \bar{Y}^2 \right\} = \frac{1}{n} \left\{ \sigma_x^2 (\sum Y_i^2 - n\bar{Y}^2) \right\} = \frac{\sigma_x^2 s_y^2}{n}$$

So that

$$S_{xy}|Y \sim N(0, \frac{\sigma_x^2 s_y^2}{n})$$