

Biostat 250A HW5

Elvis Cui

Han Cui

Dept. of Biostat
UCLA /

- 1 Suppose Y is a p -dimensional multivariate normal distribution with mean m and covariance matrix V . Let Y be partitioned into Y_1 and Y_2 so that $Y' = (Y_1', Y_2')$ and the dimension of Y_1 and Y_2 are, respectively, p_1 and p_2 with $p_1+p_2=p$. Find the distribution of Y_1 given Y_2 if V is singular and express the conditional distribution in terms of only m , p_1 and the 4 submatrices in the partitioned matrix V and an appropriate g-inverse.

- 2 Do Miscellaneous Exercise 2, problem 15 on p.32 of text.

- 3 If m is a $p \times 1$ vector of constants, $y \sim N_p(m, I)$ and A is idempotent of rank k . Write down the distribution of $(y-a)^T A (y-a)$? Justify your answer.

- 3a (Define a non-central chi-square distribution by its density). Let p_m be the density of a central chi-square distribution with m degrees of freedom, and for each nonnegative s , let $q_j = \exp(-s/2) (s/2)^j / j!$. For $s=0$, $q_0 = 1$ and $q_j = 0$ for $j > 0$. A random variable with density

$$h(z) = \sum_{j=0}^{\infty} q_j p_{m+2j}(z), \quad z > 0$$

is said to have a non-central chi-square distribution with m degrees of freedom and non-centrality parameter s . Use the power series expansion of $\exp(x)$ to find the moment generating function of such a random variable.

- 3b Use (4a) to show that if X_i is chi-squared random variable with n_i degrees of freedom and non-centrality parameter c_i , $i = 1, 2$, and X_1, X_2 are independent, then X_1+X_2 is a chi-square random variable with n_1+n_2 degrees of freedom and non-centrality parameter c_1+c_2 . Find the mean and variance of X_1+X_2 .

- 4 Let X_1, \dots, X_{n_1} and Y_1, \dots, Y_{n_2} be independent random samples from $N(\mu_1, \sigma_1^2)$ and $N(\mu_2, \sigma_2^2)$ respectively. Let \bar{X}, \bar{Y}, S_1^2 and S_2^2 denote the respective sample means and variances, and let c be a fixed constant. For (a)-(d), identify the distribution of each of the following statistics by finding a suitable value of k :

$$(a) \sqrt{n_2} (\bar{Y}-c) / k\sigma_2; (b) k\sqrt{n_1} (\bar{X}-c) / S_1; (c) k (X_1+\dots+X_n) / |Y_1-\dots-Y_n| \text{ and (d)} k\{(X_1-c)^2 + (X_2-c)^2\} / S_2^2.$$

- 5 Let (X_j, Y_j) , $j = 1, 2, \dots, n$ be a random sample from the bivariate normal distribution with parameters $m_1, m_2, \sigma_1^2, \sigma_2^2$ and correlation r . If d is a fixed constant, find a constant k so that

$$T = \frac{k(\bar{X} - \bar{Y} - d)}{\left\{ \sum_{i=1}^n (X_i - Y_i - \bar{X} + \bar{Y})^2 \right\}^{1/2}}$$

has a non-central t distribution with m degrees of freedom and non-centrality parameter s . Express m and s as a function of the parameters and the constant d . What is the expectation of T ?

- 6 Find the expectation of a non-central F-distribution with numerator and denominator degrees of freedom n and m , respectively, and non-centrality parameter Φ .

P1:

- 1 Suppose Y is a p -dimensional multivariate normal distribution with mean m and covariance matrix V . Let Y be partitioned into Y_1 and Y_2 so that $Y = (Y_1, Y_2)$ and the dimension of Y_1 and Y_2 are, respectively, p_1 and p_2 with $p_1+p_2=p$. Find the distribution of Y_1 given Y_2 if V is singular and express the conditional distribution in terms of only m , p_i and the 4 submatrices in the partitioned matrix V and an appropriate g-inverse.

Sol. $Y \sim \mathcal{N}_p(m, V)$, $m = \begin{pmatrix} m_1 \\ m_2 \end{pmatrix}$, $V = \begin{pmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{pmatrix}$

$$\text{Let } Z = \begin{pmatrix} Z_1 \\ Z_2 \end{pmatrix} = \begin{pmatrix} I & -V_{12}V_{22}^+ \\ 0 & I \end{pmatrix} \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix}$$

where V_{22}^+ is the Moore-Penrose inverse.

Then we have

$$\begin{aligned} \text{Var } Z &= \begin{pmatrix} I & -V_{12}V_{22}^+ \\ 0 & I \end{pmatrix} \begin{pmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{pmatrix} \begin{pmatrix} I & -V_{12}V_{22}^+ \\ 0 & I \end{pmatrix} \\ &= \begin{pmatrix} V_{11} - V_{12}V_{22}^+V_{21} & V_{12} - V_{12}V_{22}^+V_{22} \\ V_{21} - V_{21}V_{22}^+V_{22} & V_{22} \end{pmatrix} \end{aligned}$$

Lemma: $V_{12} - V_{12}V_{22}^+V_{21} = 0$ & (V_{22}^- is any g-inv)
 $V_{21} - V_{21}V_{22}^+V_{22} = 0$.

PF: $V \geq 0$ (maybe singular)

$\Rightarrow B^T V B \geq 0 \quad \forall B \in \mathbb{R}^{p \times k}$

Let $B^T = (\mathbf{0}, I - V_{22}^+V_{22})$, then

$$B^T V B = \mathbf{0} \quad \& \quad VB = \begin{pmatrix} V_{12} - V_{12}V_{22}^+V_{21} \\ \mathbf{0} \end{pmatrix}$$

$$\Rightarrow (B^T V^{\frac{1}{2}}) (V^{\frac{1}{2}} B) = \mathbf{0} \quad \stackrel{V \geq 0 \Rightarrow}{\stackrel{V^{\frac{1}{2}} \exists}{}}$$

$$\Rightarrow V^{\frac{1}{2}} B = \mathbf{0} \Rightarrow VB = \mathbf{0}$$

$$\Rightarrow V_{12} - V_{12}V_{22}^+V_{21} = 0$$

$$\text{Similarly, } B^T V = \mathbf{0} \Rightarrow V_{21} - V_{21}V_{22}^+V_{22} = 0$$

$$\Rightarrow \text{Var } Z = \begin{pmatrix} V_{11} - V_{12}V_{22}^+V_{21} & \mathbf{0} \\ \mathbf{0} & V_{22} \end{pmatrix}$$

Thus, $Z_1 \perp\!\!\!\perp Z_2$

$$\Rightarrow Z_1 | Z_2 = z_2 \sim \mathcal{N}_{p_1}(m_1 - V_{12}V_{22}^+m_2, V_{11} - V_{12}V_{22}^+V_{21})$$

$$\Rightarrow Y_1 | Y_2 = y_2 \sim$$

$$\mathcal{N}_{p_1}(m_1 + V_{12}V_{22}^+(y_2 - m_2), V_{11} - V_{12}V_{22}^+V_{21})$$

Note: in fact, V_{22}^+ does not have to be Moore-Penrose inv., it can be the g-inv. s.t.

$$V_{22}V_{22}^-V_{22} = V_{22}$$

&

$$V_{22}^-V_{22}V_{22}^- = V_{22}^-$$

P₂:

15. Suppose that $\mathbf{Y} = (Y_1, Y_2, Y_3, Y_4)' \sim N_4(\mathbf{0}, \mathbf{I}_4)$, and let $Q = Y_1 Y_2 - Y_3 Y_4$.

- (a) Prove that Q does not have a chi-square distribution.
- (b) Find the m.g.f. of Q .

Sol. $Q = \mathbf{Y}' \mathbf{A} \mathbf{Y}$ where $\mathbf{A} = \begin{pmatrix} 0 & \frac{1}{2} & 0 & 0 \\ \frac{1}{2} & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{2} \\ 0 & 0 & \frac{1}{2} & 0 \end{pmatrix}$

Since $\left| \frac{1}{2} \right| < 0$ so

A is not p.s.d. $\Rightarrow Q \not\sim \chi^2$ by the fundamental theorem.

MGF of Q :

$$\begin{aligned} \mathbb{E} e^{tQ} &= \mathbb{E} e^{t\mathbf{Y}' \mathbf{A} \mathbf{Y}} \quad (\text{law of SILLY statisticians}) \\ &= \int_{\mathbb{R}^4} e^{t\mathbf{y}' \mathbf{A} \mathbf{y}} (k e^{-\frac{1}{2}\mathbf{y}' \mathbf{y}}) \lambda(d\mathbf{y}) \\ &= \int_{\mathbb{R}^4} k e^{-\frac{1}{2}\mathbf{y}' (\mathbf{I} - 2t\mathbf{A}) \mathbf{y}} \lambda(d\mathbf{y}) \\ &\quad (\text{plug-in } k = \frac{1}{(2\pi)^4}) \\ &= \det |\mathbf{I} - 2t\mathbf{A}|^{-\frac{1}{2}} \\ &= \frac{1}{\sqrt{\left| \begin{matrix} 1-t & 0 & 0 & 0 \\ 0 & 1-t & 0 & 0 \\ 0 & 0 & 1+t & 0 \\ 0 & 0 & 0 & 1+t \end{matrix} \right|}} = \frac{1}{\sqrt{|1-t||1+t|}} \\ &= \frac{1}{1-t^2}, \quad -1 < t < 1. \end{aligned}$$

P₃:

3a (Define a non-central chi-square distribution by its density). Let p_m be the density of a central chi-square distribution with m degrees of freedom, and for each nonnegative s ,

let $q_j = \frac{\exp(-s/2)}{(s/2)^j j!}$. For $s=0$, $q_0 = 1$ and $q_j = 0$ for $j > 0$. A random variable with density

$$h(z) = \sum_{j=0}^{\infty} q_j p_{m+2j}(z), \quad z > 0$$

is said to have a non-central chi-square distribution with m degrees of freedom and non-centrality parameter s . Use the power series expansion of $\exp(x)$ to find the moment generating function of such a random variable.

3b Use 3a to show that if X_i is chi-squared random variable with n_i degrees of freedom and non-centrality parameter c_i , $i = 1, 2$, and X_1, X_2 are independent, then $X_1 + X_2$ is a chi-square random variable with $n_1 + n_2$ degrees of freedom and non-centrality parameter $c_1 + c_2$. Find the mean and variance of $X_1 + X_2$.

Sol. (a): $Z \sim \chi_m^2(s)$

$$\mathbb{E} e^{tz} = \int_{\mathbb{R}^+} e^{tz} \sum_{j=0}^{\infty} q_j p_{m+2j}(z) dz$$

(monotone convergence thm) $= \sum_{j=0}^{\infty} q_j \int_{\mathbb{R}^+} e^{tz} p_{m+2j}(z) dz$

$$= \sum_{j=0}^{\infty} q_j \frac{1}{(1-\beta t)^{\alpha_j}}, \quad \beta = 2, \alpha_j = \frac{m}{2} + j$$

$$= \sum_{j=0}^{\infty} \frac{e^{-\frac{s}{2}}}{(s/2)^j j!} \frac{1}{(1-2t)^j} (1-2t)^{-\frac{m}{2}}$$

$$= e^{\frac{st}{1-2t}} (1-2t)^{-\frac{m}{2}}, \quad t < \frac{1}{2}$$

(b): $X_i \sim \chi_{n_i}^2(c_i)$, $i=1, 2 \Rightarrow$

$$\mathbb{E} e^{tX_i} = e^{\frac{c_i t}{1-2t} (1-2t)^{-\frac{n_i}{2}}}, \quad i=1, 2 \Rightarrow$$

$$\begin{aligned} \mathbb{E} e^{t(X_1 + X_2)} &\stackrel{\text{(indep)}}{=} \mathbb{E} e^{tX_1} \mathbb{E} e^{tX_2} \\ &= e^{\frac{(c_1+c_2)t}{1-2t} (1-2t)^{-\frac{n_1+n_2}{2}}} \Rightarrow \end{aligned}$$

$$X_1 + X_2 \sim \chi_{n_1+n_2}^2(c_1 + c_2)$$

P4:

- 4 Let X_1, \dots, X_{n_1} and Y_1, \dots, Y_{n_2} be independent random samples from $N(\mu_1, \sigma_1^2)$ and $N(\mu_2, \sigma_2^2)$ respectively. Let \bar{X}, \bar{Y}, S_1^2 and S_2^2 denote the respective sample means and variances, and let c be a fixed constant. For (a)-(d), identify the distribution of each of the following statistics by finding a suitable value of k :
- (a) $\sqrt{n_2}(\bar{Y}-c)/\sigma_2$; (b) $k\sqrt{n_1}(\bar{X}-c)/S_1$; (c) $k(X_1+X_2)/|Y_1-Y_2|$ and (d) $k((X_1-c)^2 + (X_2-c)^2)/S_2^2$.

$$\text{Sol. (a): } \bar{Y} \sim N(\mu_2, \frac{\sigma_2^2}{n_2}) \Rightarrow$$

$$\sqrt{n_2}(\bar{Y}-c) \sim N(\sqrt{n_2}(\mu_2-c), \sigma_2^2) \Rightarrow$$

$$\frac{\sqrt{n_2}(\bar{Y}-c)}{\sigma_2} \sim N\left(\frac{\sqrt{n_2}(\mu_2-c)}{\sigma_2}, \frac{1}{n_2}\right).$$

with $k = \sqrt{n_2}$ we know RHS $\stackrel{d}{=} N\left(\frac{\mu_2-c}{\sigma_2}, \frac{1}{n_2}\right)$

(b): From 2021 we know that

$$\frac{\bar{X}-\mu_1}{\sqrt{\frac{S_1^2}{n_1}}} \sim t_{n_1-1}(0)$$

Thus, let $k=1$ & we know

$$\frac{\sqrt{n_1}(\bar{X}-c)}{S_1} = \frac{\sqrt{n_1}(\bar{X}-c)/\sigma_1}{\sqrt{(n_1-1)S_1^2/\sigma_1^2}} \quad \& \quad \bar{X} \perp\!\!\!\perp S_1$$

$$\text{Denominator} \sim \sqrt{\chi_{n_1-1}^2(0)}/\sqrt{n_1-1}$$

$$\text{Numerator} \sim N\left(\frac{\sqrt{n_1}(\mu_1-c)}{\sigma_1}, 1\right)$$

$$\Rightarrow \frac{\sqrt{n_1}(\bar{X}-c)}{S_1} \sim t_{n_1-1}\left(\frac{\sqrt{n_1}(\mu_1-c)}{\sigma_1}\right)$$

$$(c): \bar{X}_1 + \bar{X}_2 \sim N(\mu_1 + \mu_2, 2\sigma_1^2)$$

$$Y_1 - Y_2 \sim N(0, 2\sigma_2^2)$$

$$\Rightarrow \frac{\bar{X}_1 + \bar{X}_2}{|Y_1 - Y_2|} = \frac{(\bar{X}_1 + \bar{X}_2)/\sqrt{2\sigma_1^2}}{\sqrt{(|Y_1 - Y_2|)^2/2\sigma_2^2}} \frac{\sigma_1}{\sigma_2} \Rightarrow$$

$$\text{Numerator} \sim N\left(\frac{(\mu_1 + \mu_2)\sqrt{2\sigma_1^2}}{\sigma_2}, 1\right) \Rightarrow$$

$$\text{Denominator}^2 \sim \chi_1^2 \quad \& \perp\!\!\!\perp$$

$$\frac{\bar{X}_1 + \bar{X}_2}{|Y_1 - Y_2|} \sim \frac{\sigma_1}{\sigma_2} t_1\left(\frac{\mu_1 + \mu_2}{\sqrt{2\sigma_1^2}}\right), \text{ let } k = \frac{\sigma_2}{\sigma_1}$$

$$\Rightarrow \frac{\sigma_2}{\sigma_1} \frac{\bar{X}_1 + \bar{X}_2}{|Y_1 - Y_2|} \sim t_1\left(\frac{\mu_1 + \mu_2}{\sqrt{2\sigma_1^2}}\right)$$

$$(d): \frac{(\bar{X}_1 - c)^2}{\sigma_1^2} \sim \chi_1^2 (\mu_1 - c)^2$$

$$\frac{(\bar{X}_2 - c)^2}{\sigma_2^2} \sim \chi_1^2 (\mu_2 - c)^2$$

$$\frac{(n_2-1)S_2^2}{\sigma_2^2} \sim \chi_{(n_2-1)}^2(0)$$

Let $k = \left(\frac{\sigma_2^2}{\sigma_1^2}\right)$, then

$$\frac{\sigma_2^2}{\sigma_1^2} \frac{(\bar{X}_1 - c)^2 + (\bar{X}_2 - c)^2}{S_2^2} \sim$$

$$F_{2, n_2-1}(2(\mu_1 - c)^2)$$

P5:

- 5 Let (X_j, Y_j) , $j = 1, 2, \dots, n$ be a random sample from the bivariate normal distribution with parameters m_1, m_2, v_1^2, v_2^2 and correlation r . If d is a fixed constant, find a constant k so that

$$T = \frac{k(\bar{X} - \bar{Y} - d)}{\sum_{j=1}^n (X_j - Y_j - \bar{X} + \bar{Y})^2}^{1/2}$$

has a non-central t distribution with m degrees of freedom and non-centrality parameter s . Express m and s as a function of the parameters and the constant d . What is the expectation of T ?

$$\text{Sol. } (X_j, Y_j) \sim \mathcal{N}((m_1, m_2), (v_1^2, r v_1 v_2, v_2^2))$$

$$\bar{X} - \bar{Y} - d \sim \mathcal{N}(m_1 - m_2 - d, \frac{v_1^2 + v_2^2 - 2rv_1v_2}{n})$$

$$\text{Note that } X_i - Y_i \sim \mathcal{N}(m_1 - m_2, v_1^2 + v_2^2 - 2rv_1v_2)$$

$$\text{Let } Z_i = X_i - Y_i \quad \& \quad Z_i \perp\!\!\! \perp Z_j \quad \forall i \neq j \leq n.$$

$$\text{Then } \sum_{i=1}^n (X_i - Y_i - \bar{X} + \bar{Y})^2$$

$$\begin{aligned} &= \sum_{i=1}^n Z_i^2 - n(\bar{Z})^2, \quad \bar{Z} = \frac{1}{n} \sum_i Z_i \\ &= Z^T (I - \frac{11^T}{n}) Z \end{aligned}$$

$$\text{But } Z^T Z = Z^T (I - \frac{11^T}{n}) Z + Z^T \frac{11^T}{n} Z$$

\Rightarrow By Fisher-Cochran, (General Version)
The proof is the same.

$$C Z^T (I - \frac{11^T}{n}) Z \sim \chi_{n-1}^2 (\delta^2) \text{ where}$$

$$\delta^2 = (m_1 - m_2) 1^T (I - \frac{11^T}{n}) 1 (m_1 - m_2)$$

$$= 0, \text{ and } C = (v_1^2 + v_2^2 - 2rv_1v_2)^{-1}$$

More importantly,

$$\bar{X} - \bar{Y} = \bar{Z} = \frac{1}{n} 1^T Z, \quad \&$$

$$\text{Cov}(1^T Z, (I - \frac{11^T}{n}) Z) = 0 \Rightarrow$$

$$\bar{Z} \perp\!\!\! \perp Z^T (I - \frac{11^T}{n}) Z$$

$$\text{Thus, } T = \frac{k(\bar{Z} - d)}{(Z^T (I - \frac{11^T}{n}) Z)^{1/2}}$$

$$\text{Let } K = \sqrt{n(n-1)}$$

$$\text{we have } T \sim t_{n-1}(m)$$

$$m = \sqrt{n} (m_1 - m_2 - d) / \sqrt{v_1^2 + v_2^2 - 2rv_1v_2}$$

$$\text{Let } \tilde{T} = \frac{N(m, 1)}{\sqrt{\chi_{n-1}^2(0)/(n-1)}} \quad \& \quad N(m, 1) \perp\!\!\! \perp \chi_{n-1}^2(0)$$

Then

$$\tilde{T} = d T.$$

$$\mathbb{E} \tilde{T} = \sqrt{n-1} m \mathbb{E} ((\chi_{n-1}^2(0))^{\frac{1}{2}})$$

$$\begin{aligned} &= \sqrt{n-1} m \int \frac{1}{\Gamma(\frac{n-1}{2})^{\frac{n-1}{2}}} x^{\frac{n-1}{2}-1} e^{-\frac{x}{2}} \cdot x^{\frac{1}{2}} dx \\ &= \sqrt{\frac{n-1}{2}} m \frac{\Gamma(\frac{n-1}{2})}{\Gamma(\frac{n-1}{2})} \end{aligned}$$

P6:

- 6 Find the expectation of a non-central F-distribution with numerator and denominator degrees of freedom n and m , respectively, and non-centrality parameter ϕ .

Sol. $X \sim F_{n,m}(\phi) \stackrel{d}{=} \frac{X_1}{X_2} \frac{m}{n}$ where

$X_1 \sim \chi^2_n(\phi)$, $X_2 \sim \chi^2_m(0)$, $X_1 \perp\!\!\!\perp X_2$

$$\begin{aligned}\Rightarrow \mathbb{E}X &= \mathbb{E}X_1 \mathbb{E}\left(\frac{1}{X_2}\right) \frac{m}{n} \\ &= \frac{m}{2n} \frac{\Gamma(\frac{m}{2}-1)}{\Gamma(\frac{m}{2})} \mathbb{E}X_1\end{aligned}$$

By 3a, we have the pdf for X_1 :

$$f_{X_1}(x) = \sum_{j=0}^{\infty} q_j P_{n+2j}(x),$$

by Monotone Convergence thm,

$$\mathbb{E}X_1 = \sum_{j=0}^{\infty} q_j (n+2j) = n + 2 \sum_{j=0}^{\infty} j q_j = n + \phi$$

(Or $\mathbb{E}X_1 = \mathbb{E}\text{Tr}(Y^T Y) = \text{Tr}(\mu\mu^T + I) = n + \phi$)

$$\text{Also, } \frac{\Gamma(\frac{m}{2}-1)}{\Gamma(\frac{m}{2})} = \frac{2}{m-2} \Rightarrow$$

$$\mathbb{E}X = \frac{m}{n} \frac{n+\phi}{m-2} \quad \square,$$