

Solutions to Exercises - Lecture 12 up to Ex. 6.

Ex. 8.1 From an earlier exercise we have that $T = x_1 + \dots + x_n \sim \text{binomial}(n, p_1 + \dots + p_r)$. Therefore

$$P_{(x_1, \dots, x_n) | Y} = \frac{\binom{n}{x_1, x_2, \dots, x_n} p_1^{x_1} \dots p_r^{x_r}}{\binom{n}{y} \left(\sum_{i=1}^r p_i\right)^y \left(1 - \sum_{i=1}^r p_i\right)^{n-y}}$$

$$= \frac{y!}{x_1! \dots x_r!} \left(\frac{p_1}{\sum_{i=1}^r p_i}\right)^{x_1} \dots \left(\frac{p_r}{\sum_{i=1}^r p_i}\right)^{x_r} \times$$

$$\frac{(n-y)!}{(x_{r+1})! \dots x_n!} \left(\frac{p_{r+1}}{\sum_{i=r+1}^n p_i}\right)^{x_{r+1}} \dots \left(\frac{p_r}{\sum_{i=r+1}^n p_i}\right)^{x_n} \times$$

$$= \text{multinomial} \left(y, \frac{p_1}{\sum_{i=1}^r p_i}, \dots, \frac{p_r}{\sum_{i=1}^r p_i} \right) \times$$

$$\text{multinomial} \left(n-y, \frac{p_{r+1}}{\sum_{i=r+1}^n p_i}, \dots, \frac{p_r}{\sum_{i=r+1}^n p_i} \right)$$

Ex. 8.2 Since $T(x_1, \dots, x_n) = x_1, \int_T(x_1, \dots, x_n)$

$$= \left| \det \begin{pmatrix} \frac{\partial T}{\partial x_1} & \frac{\partial T}{\partial x_2} & \dots & \frac{\partial T}{\partial x_n} \\ \frac{\partial T}{\partial x_1} & \frac{\partial T}{\partial x_2} & \dots & \frac{\partial T}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial T}{\partial x_1} & \frac{\partial T}{\partial x_2} & \dots & \frac{\partial T}{\partial x_n} \end{pmatrix} \right|^{-1/2}$$

$$\left| \det \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{pmatrix} \right|^{-1/2} = \left| \det(I_n) \right|^{-1/2} = 1 \text{ and}$$

$$f_{x_1, (x_2)} = \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} f_{(x_1, x_2, \dots, x_n)} dx_2 \dots dx_n$$

Therefore $f(x_2, \dots, x_n | x_1) = \frac{f(x_1, \dots, x_n) J_T(x_1, \dots, x_n)}{f_{x_1}(x_1)}$

$= f_{(x_1, \dots, x_n)} / f_{x_1}(x_1)$.

11.8.3

We know

$$0 \leq x_1' \Sigma x_1 = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}' \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12}' & \Sigma_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$= (x_1' \Sigma_{11} + x_2' \Sigma_{12} \quad x_1' \Sigma_{12}' + x_2' \Sigma_{22}) \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$= x_1' \Sigma_{11} x_1 + x_2' \Sigma_{12} x_1 + x_1' \Sigma_{12}' x_2 + x_2' \Sigma_{22} x_2$$

$$= x_1' \Sigma_{11} x_1 + 2 x_1' \Sigma_{12} x_2 + x_2' \Sigma_{22} x_2 > 0$$

whenever $x_1 \neq 0$. So putting $x_2 = 0$ we have

$x_1' \Sigma_{11} x_1 = x_1' \Sigma x_1 > 0$ whenever $x_1 \neq 0$ which implies Σ_{11} is p.d. Similarly Σ_{22} is p.d.

11.8.4

Suppose $A = QR_1 = \tilde{Q}R_2$ where

R_1, R_2 are upper Δ with positive diagonal.

Then $Q'A = R_1 = R_2$.

11.8.5

(i) $\begin{pmatrix} a_1 & b_1 \\ 0 & c_1 \end{pmatrix} \begin{pmatrix} a_2 & b_2 \\ 0 & c_2 \end{pmatrix}$

$= \begin{pmatrix} a_1 a_2 & a_1 b_2 + b_1 c_2 \\ 0 & c_1 c_2 \end{pmatrix}$ is upper Δ and if

$a_1 > 0, c_1 > 0, a_2 > 0, c_2 > 0$ then $a_1 a_2 > 0, c_1 c_2 > 0$

(ii) $\det \begin{pmatrix} a & b \\ 0 & c \end{pmatrix} = ac - 0 \cdot b = ac > 0$ and

so $\begin{pmatrix} a & b \\ 0 & c \end{pmatrix}$ is nonsingular when $a > 0, c > 0$.

Also $\begin{pmatrix} a & b \\ 0 & c \end{pmatrix}^{-1} = \frac{1}{ac} \begin{pmatrix} c & -b \\ 0 & a \end{pmatrix} = \begin{pmatrix} \frac{1}{a} & -\frac{b}{ac} \\ 0 & \frac{1}{c} \end{pmatrix}$

since $\begin{pmatrix} \frac{1}{a} & -\frac{b}{ac} \\ 0 & \frac{1}{c} \end{pmatrix} \begin{pmatrix} a & b \\ 0 & c \end{pmatrix} = \begin{pmatrix} 1 & \frac{b}{c} - \frac{b}{c} \\ 0 & 1 \end{pmatrix} = I$.

(iii) Suppose $\Sigma = R_1' R_1 = R_2' R_2$ where R_1, R_2 are upper Δ with positive diagonal.

Then $[(R_1')^{-1} R_2'] R_2 R_1^{-1} = A' A = I, \Rightarrow$

$A = (R_2 R_1^{-1})^{-1} = R_1 R_2^{-1} = (R_1')^{-1} R_2' = A'$.

But $R_1 R_2^{-1}$ is upper Δ while $(R_1')^{-1} R_2'$ is

lower Δ so they are both diagonal as is

$(R_1 R_2^{-1})^{-1} = R_2 R_1^{-1} = A$. But this implies

that A is a diagonal orthogonal matrix with positive diagonal which implies $A=I$ which implies $R_2 R_1^{-1} = I$ or $R_1 = R_2$.

$$\begin{aligned}
 (iv) & \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1k} \\ 0 & a_{22} & \dots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & a_{nn} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1k} \\ 0 & b_{22} & \dots & b_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & b_{nn} \end{pmatrix} \\
 &= \begin{pmatrix} a_{11}b_{11} & a_{11}b_{12} + a_{22}b_{22} & \dots & a_{11}b_{1k} + \dots + a_{12}b_{2k} \\ 0 & a_{22}b_{22} & \dots & a_{22}b_{2k} + \dots + a_{2n}b_{nk} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & a_{kk}b_{kk} \end{pmatrix}
 \end{aligned}$$

so the product of two upper A matrices with positive diagonals is upper A with positive diagonal.

Also $\det A = \sum_{\sigma \in S_n} \text{sgn } \sigma \prod_{i=1}^n a_{i\sigma_i}$

where S_n is the set of all permutations of $(1, \dots, n)$ and $\sigma = (\sigma_1, \dots, \sigma_n) \in S_n$ and $\text{sgn } \sigma = 1$ when $(\sigma_1, \dots, \sigma_n)$ is obtained from $(1, \dots, n)$ by an even number of pairwise switches (transpositions) and otherwise $\text{sgn } \sigma = -1$. Note that $\prod_{i=1}^n a_{i\sigma_i}$ contains one element from each

column and one element from each row of A in the product. When A is upper A the only product term that is nonzero is $a_{11} a_{22} \dots a_{nn}$ and this is $\neq 0$ when $a_{ii} \neq 0 \forall i$. Since $\sigma = \text{identity}$ in this case $\text{sgn } \sigma = 1$ and so $\det A = a_{11} a_{22} \dots a_{nn}$. Therefore A is upper A .

For $B = \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1k} \\ 0 & b_{22} & & \\ & & \ddots & \\ 0 & & & 0 \end{pmatrix}$ to be the inverse of A we must have

$$\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1k} \\ 0 & a_{22} & & \\ \vdots & & \ddots & \\ 0 & & & a_{nn} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1k} \\ 0 & b_{22} & & b_{2k} \\ \vdots & & \ddots & \vdots \\ 0 & & & b_{kk} \end{pmatrix} = I \text{ so}$$

$a_{ii} b_{ii} = 1$ implying $b_{ii} = 1/a_{ii} \quad i=1, \dots, k$

then backsolving

$$0 = a_{k+1, k-1} b_{k-1, k} + a_{k+1, k} b_{k, k} = a_{k+1, k-1} b_{k-1, k} + \frac{a_{k+1, k}}{a_{k, k}}$$

$$\text{so } b_{k-1, k} = - \frac{a_{k+1, k}}{a_{k+1, k-1}} b_{k, k}$$

$$0 = a_{k+2, k-2} b_{k-2, k} + a_{k+2, k-1} b_{k-1, k} + a_{k+2, k} b_{k, k}$$

$$\text{or } b_{k-2, k} = - \frac{a_{k+2, k-1} b_{k-1, k}}{a_{k+2, k-2}} - \frac{a_{k+2, k}}{a_{k+2, k-2}} b_{k, k}$$

and so we can determine all the entries of B in this way which proves A^{-1} is upper A with positive diagonal whenever A is.

The proof that the Cholesky Factor is unique is as in (iii).

A.8.6 Suppose $(x_{i_1}, \dots, x_{i_n})$ is a sub vector of $x \in \mathbb{N}_n(\mathbb{M}, \mathbb{R})$. Let $A \in \mathbb{R}^{k \times n}$ be a matrix with 1st row equal to the standard basis vector e_{i_1} (1 in i_1 's place and 0's elsewhere), with 2nd row equal to the standard basis vector e_{i_2} , etc. and with the last $k-1$ rows equal to the remaining basis vectors in any order. Now let

$$z = Ax = \begin{pmatrix} A_1 \\ \vdots \\ A_k \end{pmatrix} x = \begin{pmatrix} A_1 x \\ \vdots \\ A_k x \end{pmatrix}$$

where $A_i x = \begin{pmatrix} x_{i_1} \\ \vdots \\ x_{i_n} \end{pmatrix}$

$\in \mathbb{N}_k(\mathbb{R}^n, \mathbb{R} \cong \mathbb{R}^1)$ and,

$$A_M = \begin{pmatrix} A_{1M} \\ \vdots \\ A_{kM} \end{pmatrix}, \quad A \cong A' = \begin{pmatrix} A_1 \cong A'_1 & A_2 \cong A'_2 \\ \vdots & \vdots \\ A_k \cong A'_k & A_k \cong A'_k \end{pmatrix}$$

Therefore $\mathbf{y} = \begin{pmatrix} x_{i1} \\ x_{i2} \end{pmatrix} \sim N(\mathbf{A}_i \boldsymbol{\mu}_i, \mathbf{A}_i \boldsymbol{\Sigma}_i \mathbf{A}_i')$

and $\mathbf{A}_i \boldsymbol{\mu}_i = \begin{pmatrix} \mu_{i1} \\ \mu_{i2} \end{pmatrix}$, $\mathbf{A}_i \boldsymbol{\Sigma}_i \mathbf{A}_i' = \begin{pmatrix} \sigma_{i11} & \sigma_{i12} - \sigma_{i21} \\ \sigma_{i12} - \sigma_{i21} & \sigma_{i22} \end{pmatrix}$