

Solutions 9

1. (a) $Z_k = \sum_{i=1}^k X_i^2$ for $k < n$. Due to theorem 4.7, $Z_k \sim \chi^2(k)$.
- (b) $Y_1 = \delta Z_k$ for $\delta \in (0, \infty)$. Since $Z_k \sim \chi^2(k)$, it holds that $Z_k \sim \text{Gamma}(k/2, 2)$. Then according to theorem 4.3

$$Y_1 \sim \text{Gamma}\left(\frac{k}{2}, 2\delta\right)$$

(c) $Y_2 = \frac{1}{n} \sum_{i=1}^n \frac{X_i + a}{\sqrt{b}}$ for $a, b \in \mathbb{R}_+$.

$$\begin{aligned} X_i + a &\sim \mathcal{N}(a, 1) \\ \frac{X_i + a}{\sqrt{b}} &\sim \mathcal{N}\left(\frac{a}{\sqrt{b}}, \frac{1}{b}\right) \\ \sum_{i=1}^n \frac{X_i + a}{\sqrt{b}} &\sim \mathcal{N}\left(\frac{an}{\sqrt{b}}, \frac{n}{b}\right) \\ Y_2 &\sim \mathcal{N}\left(\frac{a}{\sqrt{b}}, \frac{1}{nb}\right) \end{aligned}$$

2. Given $X_1 \sim \mathcal{N}(1, 1)$ and $X_2 \sim \mathcal{N}(1, 1)$ with $\rho = 0.6$. Rewrite

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{21} & 1 \end{bmatrix}$$

Since

$$\rho = \frac{\text{Cov}[X_1, X_2]}{\sqrt{\text{Var}[X_1]\text{Var}[X_2]}} = \frac{\sigma_{21}}{\sigma_1 \sigma_2} = \sigma_{21},$$

it follows that $\sigma_{21} = \sigma_{12} = 0.6$. Using theorem 4.12 we get

$$X_1|X_2 = 2 \sim \mathcal{N}(1 + 0.6 \cdot 1(2 - 1), 1 - 0.6^2/1) = \mathcal{N}(1.6, 0.64)$$

3. (a) It belongs to the multivariate (bivariate) normal family.
- (b)

$$\begin{aligned} \Sigma^{-1} &= \begin{pmatrix} 2 & -3 \\ -3 & 5 \end{pmatrix} \\ \Sigma &= \frac{1}{2 \cdot 5 - (-3)^2} \begin{pmatrix} 5 & 3 \\ 3 & 2 \end{pmatrix} \\ |\Sigma| &= \det(\Sigma) = 2 \cdot 5 - (-3)^2 = 1 \\ k &= \frac{1}{\sqrt{(2\pi)^2 |\Sigma|}} = \frac{1}{2\pi} \end{aligned}$$

- (c) Apply theorem 4.11 for the marginal pdf's to obtain $X_1 \sim \mathcal{N}(1, 5)$ and $X_2 \sim \mathcal{N}(-5, 2)$. For the conditional pdf's use theorem 4.12

$$X_1|X_2 = x_2 \sim \mathcal{N}(1 + 3 \cdot 2^{-1}(x_2 - (-5)), 5 - 3 \cdot 2^{-1} \cdot 3) = \mathcal{N}\left(\frac{3}{2}x_2 + \frac{17}{2}, \frac{1}{2}\right)$$

$$X_2|X_1 = x_1 \sim \mathcal{N}(-5 + 3 \cdot 5^{-1}(x_1 - 1), 2 - 3 \cdot 5^{-1} \cdot 3) = \mathcal{N}\left(\frac{3}{5}x_1 - \frac{28}{5}, \frac{1}{5}\right)$$

(d) $E(x_1|x_2) = \frac{3}{2}x_2 + \frac{17}{2}$

4. (a) Theorem 4.10:

$$\begin{aligned} Y = (Y_1, Y_2, Y_3)' &\sim \mathcal{N}(A \cdot 0 + b, AIA') = \mathcal{N}\left(\begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix}\right) \\ &= \mathcal{N}\left(\begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 1 & 1 \end{pmatrix}\right) \end{aligned}$$

Special case: $A = (w_1, \dots, w_m) \Rightarrow Y = \sum_{i=1}^m w_i x_i + b$
 \rightarrow Linear transformations of normal is again normal!

(b) Reorder Y :

$$\begin{aligned} \tilde{Y} = \begin{pmatrix} Y_1 \\ Y_3 \\ Y_2 \end{pmatrix} &\sim \mathcal{N}\left(\begin{pmatrix} 1 \\ 3 \\ 2 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 2 \end{pmatrix}\right) \\ &= \begin{pmatrix} Y_{(1)} \\ Y_{(2)} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_{(1)} \\ \mu_{(2)} \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}\right) \end{aligned}$$

$$\mu_{(1)} = \begin{pmatrix} 1 \\ 3 \end{pmatrix}, \quad \mu_{(2)} = 2$$

$$\Sigma_{11} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad \Sigma_{12} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \quad \Sigma_{21} = (0 \quad 1), \quad \Sigma_{22} = 2$$

By theorem 4.11:

$$Y_{(1)} \sim \mathcal{N}(\mu_{(1)}, \Sigma_{11}) = \mathcal{N}\left(\begin{pmatrix} 1 \\ 3 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right)$$

$$Y_{(2)} \sim \mathcal{N}(\mu_{(2)}, \Sigma_{22}) = \mathcal{N}(2, 2)$$

(c) Theorem 4.12

$$\begin{aligned}
Y_{(1)}|Y_{(2)} = \alpha &\sim \mathcal{N}\left(\boldsymbol{\mu}_{(1)} + \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}[\alpha - \boldsymbol{\mu}_{(2)}], \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}\right) \\
&= \mathcal{N}\left(\begin{pmatrix} 1 \\ 3 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \cdot 2^{-1} \cdot [\alpha - 2], \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} 0 \\ 1 \end{pmatrix} \cdot 2^{-1} \cdot \begin{pmatrix} 0 & 1 \end{pmatrix}\right) \\
&= \mathcal{N}\left(\begin{pmatrix} 1 \\ 2 + 0.5\alpha \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 0.5 \end{pmatrix}\right)
\end{aligned}$$

$$\begin{aligned}
Y_{(2)}|Y_{(1)} = \beta &\sim \mathcal{N}\left(\boldsymbol{\mu}_{(2)} + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}[\beta - \boldsymbol{\mu}_{(1)}], \boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}\right) \\
&= \mathcal{N}\left(2 + \begin{pmatrix} 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \beta_1 - 1 \\ \beta_2 - 3 \end{pmatrix}, 2 - \begin{pmatrix} 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix}\right) \\
&= \mathcal{N}(\beta_2 - 1, 1)
\end{aligned}$$

5. $X \sim \mathcal{N}(0, 1)$, thus

$$\begin{aligned}
f(x) &= \frac{1}{\sqrt{2\pi}}e^{-x^2/2}\mathcal{I}_{(-\infty, \infty)}(x) = \frac{1}{\sqrt{2\pi}}e^{-x^2/2}\mathcal{I}_{(-\infty, 0)}(x) + \frac{1}{\sqrt{2\pi}}e^{-x^2/2}\mathcal{I}_{(0, \infty)}(x) \\
&\equiv f_-(x) + f_+(x)
\end{aligned}$$

Use the transformation theorem for $f_{\pm}(x)$ and check the requirements:

- i) $Y = X^2 = g(x) \Rightarrow \frac{\partial g(x)}{\partial x} \neq 0 \forall x \checkmark$
- ii) $X = \pm\sqrt{Y} = g_{\pm}^{-1}(Y)$ exists $\forall y \checkmark$

Note that $Y \in (0, \infty)$ for both parts of the pdf.

$$\begin{aligned}
\frac{\partial g_{\pm}^{-1}(y)}{\partial y} &= \pm \frac{1}{2\sqrt{y}} \Rightarrow \left| \frac{\partial g_{\pm}^{-1}(y)}{\partial y} \right| = \frac{1}{2\sqrt{y}} \\
h(y) &= h_-(y) + h_+(y) = f_-(g_-^{-1}(y)) \left| \frac{\partial g_-^{-1}(y)}{\partial y} \right| + f_+(g_+^{-1}(y)) \left| \frac{\partial g_+^{-1}(y)}{\partial y} \right| \\
&= \frac{1}{\sqrt{2\pi}}e^{-y/2} \frac{1}{2\sqrt{y}} + \frac{1}{\sqrt{2\pi}}e^{-y/2} \frac{1}{2\sqrt{y}} = \frac{1}{\sqrt{2\pi}}y^{-1/2}e^{-y/2}\mathcal{I}_{(0, \infty)}(y),
\end{aligned}$$

which is the same pdf as of a chi-squared with one degree since $\Gamma(0.5) = \sqrt{\pi}$.