

## Homework 3:

### Problem 1:

$$\text{Univariate Gaussian PDF: } f(x) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}$$

a) prove  $f(x)$  is normalized  $\sim$  prove  $\int f(x) dx = 1$

$$\begin{aligned} \int f(x) dx &= \frac{1}{\sqrt{2\pi}\sigma^2} \int \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx & \text{let } z = \frac{x-\mu}{\sigma} \rightarrow dz = \frac{1}{\sigma} dx \\ &= \frac{1}{\sqrt{2\pi}\sigma^2} \int \exp\left\{-\frac{z^2}{2}\right\} \sigma \cdot dz & \text{let } u = \frac{z}{\sqrt{2}} \rightarrow du = \frac{1}{\sqrt{2}} dz \\ &= \frac{1}{\sqrt{2\pi}} \int \exp(-u^2) \cdot \sqrt{2} \cdot du & \text{Gaussian Integral} \\ &= \frac{1}{\sqrt{\pi}} \cdot \sqrt{\pi} \\ &= 1. \end{aligned}$$

$$\begin{aligned} \text{let } I &= \int \exp(-x^2) dx \\ \rightarrow I^2 &= \iint \exp(-x^2) dx dy \\ dx \cdot dy &= r \cdot dr \cdot d\theta \\ \rightarrow I^2 &= \int_0^{2\pi} \int_0^\infty \exp(-r^2) r \cdot dr \cdot d\theta \\ &= 2\pi \int_0^\infty \exp(-r^2) r \cdot dr \\ &= 2\pi \int_0^\infty \exp(-x) \frac{1}{2} dx \quad \left. \vphantom{\int_0^\infty} \right\} x=r^2 \\ &= \pi \left[ -\exp(-x) \right]_0^\infty \\ &= \pi \\ \rightarrow I^2 &= \pi \rightarrow I = \sqrt{\pi} \end{aligned}$$

b) prove  $E(X) = \mu$ .

$$\begin{aligned} E(X) &= \int x f(x) \cdot dx & \text{let } u = \frac{x-\mu}{\sqrt{2\sigma^2}} \rightarrow du = \frac{1}{\sqrt{2\sigma^2}} \cdot dx \\ &= \int x \cdot \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) dx & \rightarrow x = \sqrt{2\sigma^2} \cdot u + \mu \\ &= \frac{1}{\sqrt{2\pi}\sigma^2} \int (\sqrt{2\sigma^2} \cdot u + \mu) \exp(-u^2) \cdot \sqrt{2\sigma^2} \cdot du \\ &= \frac{\sqrt{2\sigma^2}}{\sqrt{\pi}} \int_{-\infty}^{\infty} u \cdot \exp(-u^2) du + \frac{\mu}{\sqrt{\pi}} \int \exp(-u^2) du \\ &= \frac{\sqrt{2\sigma^2}}{\sqrt{\pi}} \cdot \frac{1}{2} \int \exp(t) \cdot dt + \frac{\mu}{\sqrt{\pi}} \cdot \sqrt{\pi} & \text{let } t = -u^2 \rightarrow dt = -2u \cdot du \\ &= \frac{\sqrt{2\sigma^2}}{\sqrt{\pi}} \cdot \frac{1}{2} \exp(-u^2) \Big|_{-\infty}^{\infty} + \mu = 0 + \mu = \mu \end{aligned}$$

c) prove  $\text{sd}(X) = \sigma^2 \sim \text{prove } V(X) = \sigma^2$

$$V(X) = \int (x-\mu)^2 f(x) dx$$

$$= \int (x-\mu)^2 \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \cdot dx$$

$$\text{let } u = \frac{x-\mu}{\sqrt{2\sigma^2}} \rightarrow du = \frac{1}{\sqrt{2\sigma^2}} \cdot dx$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int 2\sigma^2 \cdot u^2 \cdot \exp(-u^2) \sqrt{2\sigma^2} \cdot du$$

$$\rightarrow x-\mu = \sqrt{2\sigma^2} \cdot u$$

$$\rightarrow (x-\mu)^2 = 2\sigma^2 \cdot u^2$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \int u^2 \cdot \exp(-u^2) du$$

$$\left. \begin{array}{l} u = u \\ dv = u \cdot \exp(-u^2) \cdot du \end{array} \right\} \begin{array}{l} du = du \\ v = -\frac{1}{2} \exp(-u^2) \end{array} \quad (\text{proven above})$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \left[ -\frac{1}{2} \cdot u \cdot \exp(-u^2) \right]_{-\infty}^{\infty} + \frac{1}{2} \int \exp(-u^2) \cdot du$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \left( 0 + \frac{\sqrt{\pi}}{2} \right) = \sigma^2$$

Problem 2:

Multi-variate Gaussian PDF:  $f(x) = \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \exp\left(-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu)\right)$

a) prove  $f(x)$  is normalized  $\sim \text{prove } \int_{\mathbb{R}^n} f(x) \cdot dx = 1$

$$\int f(x) \cdot dx = \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \int \exp\left(-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu)\right) \cdot dx$$

$$\text{let } y = x-\mu \rightarrow dy = dx$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \cdot \frac{1}{2} \int \exp\left(-y^T \Sigma^{-1} y\right) dy \quad (1)$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \cdot \int \exp\left[\frac{-z_1^2}{2\lambda_1} + \dots + \frac{-z_n^2}{2\lambda_n}\right] dz$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \cdot \int \prod \exp\left(\frac{-z_i^2}{2\lambda_i}\right) dz$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \cdot \prod_{i=1}^n \sqrt{2\pi\lambda_i}$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \cdot \prod \sqrt{2\pi} \cdot \prod \sqrt{\lambda_i} \quad (2)$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \cdot \sqrt{(2\pi)^n} \cdot \sqrt{|\Sigma|}$$

$$= 1$$

$$(1) y^T \Sigma^{-1} y = y^T U \Lambda^{-1} U^T y \quad (3)$$

$$= (U^T y)^T \Lambda^{-1} (U^T y) = Z^T \Lambda^{-1} Z$$

$$= \begin{bmatrix} z_1 & \dots & z_n \end{bmatrix} \begin{bmatrix} \frac{1}{\lambda_1} & & 0 \\ & \ddots & \\ 0 & & \frac{1}{\lambda_n} \end{bmatrix} \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}$$

$$= \frac{z_1^2}{\lambda_1} + \frac{z_2^2}{\lambda_2} + \dots + \frac{z_n^2}{\lambda_n}$$

$$E = -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu)$$

$$= -\frac{1}{2} [x^T A x - 2 x^T A \mu + \text{const}]$$

$$= -\frac{1}{2} x^T A x + x^T A \mu + \text{const}$$

$$(2) |\Sigma| = |U \Lambda U^T| = |U| |\Lambda| |U^T| = |U^T U| |\Lambda| = |I| |\Lambda| = \prod_{i=1}^n \lambda_i$$

$$(3) \begin{array}{l} \Sigma \text{ is sym \& positive definite} \rightarrow \Sigma = U \Lambda U^T \text{ where } \left\{ \begin{array}{l} U \text{ is orthogonal} \rightarrow U^T U = I \rightarrow |U^T U| = 1 \\ \Lambda \text{ is diagonal matrix of eigenvalues } \lambda_i \rightarrow |\Sigma| = \prod_{i=1}^n \lambda_i \end{array} \right. \\ \downarrow \\ \Sigma^{-1} \rightarrow \Sigma^{-1} = U \Lambda^{-1} U^T \text{ where } \left\{ \begin{array}{l} U \dots \\ \Lambda^{-1} \dots \frac{1}{\lambda_i} \end{array} \right. \end{array}$$

b) Find marginal distribution.

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \quad \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \rightarrow \Sigma^{-1} = A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$g(x_1, x_2) = -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu)$$

$$= -\frac{1}{2} (x_1 - \mu_1)^T A_{11} (x_1 - \mu_1) - \frac{1}{2} (x_1 - \mu_1)^T A_{12} (x_2 - \mu_2)$$

$$- \frac{1}{2} (x_2 - \mu_2)^T A_{21} (x_1 - \mu_1) - \frac{1}{2} (x_2 - \mu_2)^T A_{22} (x_2 - \mu_2)$$

$$= -\frac{1}{2} \left[ \begin{array}{l} x_1^T A_{11} x_1 - x_1^T A_{11} \mu_1 - \mu_1^T A_{11} x_1 + \mu_1^T A_{11} \mu_1 \\ + x_1^T A_{12} x_2 - x_1^T A_{12} \mu_2 - \mu_1^T A_{12} x_2 + \mu_1^T A_{12} \mu_2 \\ + x_2^T A_{12} \mu_1 - x_2^T A_{12} \mu_1 - \mu_2^T A_{12} x_1 + \mu_2^T A_{12} \mu_1 \\ + x_2^T A_{22} x_2 - x_2^T A_{22} \mu_2 - \mu_2^T A_{22} x_2 + \mu_2^T A_{22} \mu_2 \end{array} \right]$$

$$= -\frac{1}{2} \left[ \begin{array}{l} x_1^T A_{11} x_1 + 2 x_1^T A_{12} x_2 + x_2^T A_{22} x_2 \\ - x_1^T A_{11} \mu_1 - x_1^T A_{12} \mu_2 - x_2^T A_{12} \mu_1 - x_2^T A_{22} \mu_2 \\ - \mu_1^T A_{11} x_1 - \mu_1^T A_{12} x_2 - \mu_2^T A_{12} x_1 - \mu_2^T A_{22} x_2 \end{array} \right] + \text{const}$$

$$= -\frac{1}{2} (x_1^T A_{11} x_1) - x_1^T A_{12} x_2 - \frac{1}{2} x_2^T A_{22} x_2 + x_1^T A_{11} \mu_1 + x_1^T A_{12} \mu_2 + x_2^T A_{12} \mu_1 + x_2^T A_{22} \mu_2 + \text{const}$$

$$= -\frac{1}{2} x_1^T A_{11} x_1 - x_1^T A_{12} x_2 + x_1^T A_{11} \mu_1 + x_1^T A_{12} \mu_2 + x_2^T A_{12} \mu_1 + \frac{1}{2} x_2^T A_{22} x_2 + \text{const}$$

$$= -\frac{1}{2} x_1^T A_{11} x_1 + x_1^T [-A_{12} x_2 + A_{11} \mu_1 + A_{12} \mu_2] + \text{const}$$

$$= -\frac{1}{2} x_1^T A_{11} x_1 + x_1^T [A_{11} \mu_1 - A_{12} (x_2 - \mu_2)] + \text{const} \sim -\frac{1}{2} x^T A x + x^T A \mu + \text{const}$$

$\rightarrow x_1 \sim \text{Gaussian}$

Schur complement (proof: (4))

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} M & -MBD^{-1} \\ -D^{-1}CMD^{-1} & D^{-1} + D^{-1}CMBD^{-1} \end{bmatrix}, \quad M = (A - BD^{-1}C)^{-1}$$

$$\rightarrow \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}^{-1} = \begin{bmatrix} (\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})^{-1} & \leftarrow -(\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})^{-1}\Sigma_{12}\Sigma_{22}^{-1} \\ \sim & \Sigma_{22}^{-1}\Sigma_{21}(\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})^{-1}\Sigma_{12}\Sigma_{22}^{-1} \end{bmatrix}$$

$$p(x_2) = \int f(x_1, x_2) dx_1 = \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \int \exp(g(x_1, x_2)) dx_1$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \int \exp \left[ -\frac{1}{2} x_1^T A_{11} x_1 + x_1^T [A_{11}\mu_1 - A_{12}(x_2 - \mu_2)] + \text{const} \right] dx_1$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \int \exp \left[ \frac{1}{2} (x_1 - A_{11}^{-1} m)^T A_{11} (x_1 - A_{11}^{-1} m) \right] dx_1 \quad (5)$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \int \exp \left[ \frac{1}{2} [A_{11}\mu_1 - A_{12}(x_2 - \mu_2)]^T A_{11}^{-1} [A_{11}\mu_1 - A_{12}(x_2 - \mu_2)] - \frac{1}{2} x_2^T A_{22} x_2 + x_2^T (A_{22}\mu_2 + A_{12}\mu_1) + \text{const} \right] dx_2 \quad (6)$$

$$= \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} \int \exp \left[ -\frac{1}{2} x_2^T (A_{22} - A_{12} A_{11}^{-1} A_{12}) x_2 + x_2^T (A_{22}\mu_2 + A_{12}\mu_1 - A_{12} A_{11}^{-1} A_{12} \mu_1) + \text{const} \right] dx_2$$

$$\rightarrow \text{cov}(x_2) = \Sigma_2 = (A_{22} - A_{12} A_{11}^{-1} A_{12})^{-1} = \Sigma_{22}$$

$$E(x_2) = \mu_2 = \Sigma_2 (A_{22}\mu_2 + A_{12}\mu_1 - A_{12} A_{11}^{-1} A_{12} \mu_1) = \mu_2$$

$$(4) \quad \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{pmatrix} A & B \\ C & D \end{pmatrix}^{-1} = I = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{pmatrix} M & -MBD^{-1} \\ -D^{-1}CM & D^{-1} + D^{-1}CMBD^{-1} \end{pmatrix}$$

$$\text{top left: } \underline{AM + B(-D^{-1}CM)} = (A - BD^{-1}C)M = M^{-1}M = I$$

$$\begin{aligned} \text{top right: } & A(-MBD^{-1}) + B(D^{-1} + D^{-1}CMBD^{-1}) \\ &= -AMB D^{-1} + BD^{-1} + BD^{-1}(CMBD^{-1}) \\ &= \underline{(-AM + BD^{-1}CM)} BD^{-1} + BD^{-1} \\ &= -IBD^{-1} + BD^{-1} \\ &= 0 \end{aligned}$$

$$\begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix}$$

$$\text{bottom left: } CM + D(-D^{-1}CM) = CM - CM = 0$$

$$\begin{aligned} \text{bottom right: } & C(-MBD^{-1}) + D(D^{-1} + D^{-1}CMBD^{-1}) \\ &= -CMBD^{-1} + I + CMBD^{-1} \\ &= I \end{aligned}$$

$$(5) \quad m = A_{11} \mu_1 - A_{12} (x_2 - \mu_2) \rightarrow A_{11}^{-1} m = A_{11}^{-1} (A_{11} \mu_1 - A_{12} (x_2 - \mu_2)) = \mu_1 - A_{11}^{-1} A_{12} (x_2 - \mu_2)$$

$$\begin{aligned} -\frac{1}{2} x_1^T A_{11} x_1 + x_1^T [A_{11} \mu_1 - A_{12} (x_2 - \mu_2)] + \text{const} &= -\frac{1}{2} x_1^T A_{11} x_1 + x_1^T m \\ &= -\frac{1}{2} (x_1 - A_{11}^{-1} m)^T A_{11} (x_1 - A_{11}^{-1} m) + \frac{1}{2} m^T A_{11}^{-1} m \end{aligned}$$

$$\begin{aligned} (6) \quad -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) &= \\ -\frac{1}{2} (x_a - \mu_a)^T \Lambda_{aa} (x_a - \mu_a) - \frac{1}{2} (x_a - \mu_a)^T \Lambda_{ab} (x_b - \mu_b) \\ -\frac{1}{2} (x_b - \mu_b)^T \Lambda_{ba} (x_a - \mu_a) - \frac{1}{2} (x_b - \mu_b)^T \Lambda_{bb} (x_b - \mu_b). \end{aligned}$$

c) Find conditional distribution.

$$\begin{aligned} p(x_1 | x_2) &= \frac{p(x_1, x_2)}{p(x_2)} = \frac{\mathcal{N}(x; \mu, \Sigma)}{\mathcal{N}(x_2; \mu_2, \Sigma_{22})} \\ &= \frac{1/\sqrt{(2\pi)^n |\Sigma|} \cdot \exp \left[ -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right]}{1/\sqrt{(2\pi)^{n_2} |\Sigma_{22}|} \exp \left[ -\frac{1}{2} (x_2 - \mu_2)^T \Sigma_{22}^{-1} (x_2 - \mu_2) \right]} \\ &= \frac{1}{\sqrt{(2\pi)^{n-n_2}}} \sqrt{\frac{|\Sigma_{22}|}{|\Sigma|}} \exp \left[ -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) + \frac{1}{2} (x_2 - \mu_2)^T \Sigma_{22}^{-1} (x_2 - \mu_2) \right] \\ &= \frac{1}{\sqrt{(2\pi)^{n-n_2}}} \sqrt{\frac{|\Sigma_{22}|}{|\Sigma|}} \exp \left\{ -\frac{1}{2} \left[ (x_1 - \mu_1)^T A_{11} (x_1 - \mu_1) + 2(x_1 - \mu_1)^T A_{12} (x_2 - \mu_2) \right. \right. \\ &\quad \left. \left. + (x_2 - \mu_2)^T A_{22} (x_2 - \mu_2) \right] \right\} \\ &= \frac{1}{\sqrt{(2\pi)^{n-n_2}}} \sqrt{\frac{|\Sigma_{22}|}{|\Sigma|}} \exp \left\{ -\frac{1}{2} \left[ (x_1 - \mu_1)^T (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} (x_1 - \mu_1) \right. \right. \\ &\quad + 2(x_1 - \mu_1)^T (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \\ &\quad \left. \left. + (x_2 - \mu_2)^T \Sigma_{22}^{-1} \Sigma_{21} (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \right] \right\} \\ (7) \quad &= \frac{1}{\sqrt{(2\pi)^{n-n_2} |\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}|}} \\ &\exp \left\{ -\frac{1}{2} \left[ \left[ (x_1 - \mu_1) - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \right]^T (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} \left[ \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \right] \right] \right\} \end{aligned}$$

$$\begin{aligned} \rightarrow E(x_1 | x_2) &= \mu_{x_1 | x_2} = \mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \\ \Sigma_{x_1 | x_2} &= \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \end{aligned}$$

$$(7) \quad \begin{vmatrix} A & B \\ C & D \end{vmatrix} = |D| \cdot |A - B D^{-1} C| \rightarrow \begin{vmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{vmatrix} = |\Sigma_{22}| \cdot |\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}|$$