

## Exercise 1

$$E[(\hat{X} - X)^2] = E[(aY + b - X)^2] =$$

$$E[(ahX + a\varepsilon + b - X)^2] = E[(X(ah-1) + a\varepsilon + b)^2]$$

$$= E[X^2](ah-1)^2 + a^2 E[\varepsilon^2] + b^2$$

$$\begin{aligned} &= \text{Var}[X] + E[X]^2 \\ &= \sigma^2 + \bar{x}^2 \end{aligned}$$

$$\begin{aligned} &= r^2 \end{aligned}$$

$$+ 2(ah-1)a E[X\varepsilon] + 2(ah-1)b E[X] + 2ab E[\varepsilon]$$

$$\begin{aligned} &= E[X]E[\varepsilon] = 0 \\ &\quad \uparrow \text{since indep.} \end{aligned}$$

$$= \bar{x}$$

$$= 0 \text{ since mean is 0}$$

$$= (ah-1)^2 (\sigma^2 + \bar{x}^2) + a^2 r^2 + b^2 + 2(ah-1)b\bar{x} = Q(a, b)$$

To minimize we set the gradient to 0

$$\frac{\partial Q}{\partial b} = 2b + 2(ah-1)\bar{x} \stackrel{!}{=} 0$$

$$\Rightarrow b = (1-ah)\bar{x}$$

Plug this in  $Q \Rightarrow$

$$Q(a) = (ah-1)^2 \sigma^2 + a^2 r^2$$

$$= a^2 (h^2 \sigma^2 + r^2) - 2ah \sigma^2 + \sigma^2$$

Setting derivative to 0 gives us

$$a^* = \frac{h \sigma^2}{h^2 \sigma^2 + r^2}$$

$$\Rightarrow b^* = \frac{r^2}{h^2 \sigma^2 + r^2} \bar{x}$$

Since  $Q$  is a quadratic polynomial in  $a, b$  with positive coefficients before  $a^2$  and  $b^2$  we know it has only one critical point which is its global minimum  
 $\Rightarrow a^*, b^*$  minimize  $Q$

## Exercise 2

$$C = \pi(x_1)$$

$$\pi(x_1, x_2) = \exp(-x_1^2 - x_2^2 - x_1 x_2^2)$$

$$\pi(x_2 | x_1) = \frac{\pi(x_1, x_2)}{C}$$

$$C := \int_{-\infty}^{\infty} \pi(x_1, x_2) dx_2$$

$$C = \int_{-\infty}^{\infty} \frac{1}{\sqrt{1+x_1^2}} e^{-x_2^2(1+x_1^2)} dx_2$$

pdf of  $N(0, \frac{1}{2(1+x_1^2)})$   
integrates to 1

$$= \frac{\sqrt{\pi}}{\sqrt{1+x_1^2}}$$

$$\Rightarrow C = \frac{1}{\sqrt{1+x_1^2}}$$

$$\begin{aligned} e^{-x_2^2/2\sigma^2} &= \\ e^{-x_2^2/(2 \cdot \frac{1}{2(1+x_1^2)})} &= * \end{aligned}$$

Shorter way: One can also use that

$\pi(x_2 | x_1)$  is a pdf which is proportional to  $e^{-x_2^2(1+x_1^2)}$ . Since it has to integrate to 1, the constant in front is clear.

Variance of  $N(0, \frac{1}{2(1+x_1^2)})$

$$\begin{aligned} E[x_1 x_2^2 | x_1 = x_1] &= x_1 E[x_2^2 | x_1 = x_1] \\ &= x_1 \frac{1}{2(1+x_1^2)} \end{aligned}$$

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From the script, Ex. 2.18 we have

$$P^{-1} = \frac{1}{\sigma_c^2} \begin{pmatrix} 1 - \left(\frac{\sigma_{12}}{\sigma_{22}}\right)^2 & -\left(\frac{\sigma_{12}}{\sigma_{22}}\right) \left(\frac{\sigma_{11}}{\sigma_{22}}\right) \\ -\left(\frac{\sigma_{12}}{\sigma_{22}}\right) \left(\frac{\sigma_{11}}{\sigma_{22}}\right) & \left(\frac{\sigma_{11}}{\sigma_{22}}\right)^2 \end{pmatrix} \quad \text{with} \quad \sigma_c^2 = \sigma_{11}^2 - \sigma_{12}^2 \sigma_{22}^{-2} \sigma_{21}^2$$

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$

Let  $\bar{x}_c = \bar{x}_1 + \sigma_{12}^2 \sigma_{22}^{-2} (x_2 - \bar{x}_2)$

$$= x_1 a y_1 + x_1 b y_2 + x_2 c y_1 + x_2 d y_2$$

We treat the exponent separately and multiply it with  $\sigma_c^2$ :

$$\sigma_c^2 (z - \bar{z})^t P^{-1} (z - \bar{z}) = (x_1 - \bar{x}_1)^2 + \left(\frac{\sigma_{11}}{\sigma_{22}}\right)^2 (x_2 - \bar{x}_2)^2 + 2 \left(\frac{\sigma_{12}}{\sigma_{22}}\right)^2 (x_1 - \bar{x}_1) (x_2 - \bar{x}_2) =: \textcircled{b}$$

We want to show that  $\textcircled{a} = \textcircled{b}$  where

$$\begin{aligned} (x_1 - \bar{x}_c)^2 &= (x_1 - \bar{x}_1 - \sigma_{12} \sigma_{22}^{-2} (x_2 - \bar{x}_2))^2 \\ &= (x_1 - \bar{x}_1)^2 - 2 \sigma_{12} \sigma_{22}^{-2} (x_1 - \bar{x}_1) (x_2 - \bar{x}_2) + \sigma_{12}^2 \sigma_{22}^{-4} (x_2 - \bar{x}_2)^2 \end{aligned}$$

$$\textcircled{a} = (x_1 - \bar{x}_c)^2 + \frac{\sigma_c^2}{\sigma_{22}^2} (x_2 - \bar{x}_2)^2$$

$$\frac{\sigma_c^2}{\sigma_{22}^2} = \frac{\sigma_{11}^2}{\sigma_{22}^2} - \frac{\sigma_{12}^4}{\sigma_{22}^4}$$

$$\begin{aligned} \textcircled{a} &= (x_1 - \bar{x}_1)^2 + 2 \frac{\sigma_{12}^2}{\sigma_{22}^2} (x_1 - \bar{x}_1) (x_2 - \bar{x}_2) + \\ &+ \left( \frac{\sigma_{12}^4}{\sigma_{22}^4} + \frac{\sigma_{11}^2}{\sigma_{22}^2} - \frac{\sigma_{12}^4}{\sigma_{22}^4} \right) (x_2 - \bar{x}_2)^2 \end{aligned}$$

We see that  $\textcircled{a} = \textcircled{b}$

Now for the factor before the  $e^{-}$

$$\begin{aligned} \frac{1}{2\pi |P|^{1/2}} &= \frac{1}{2\pi} \frac{1}{\sigma_{11}^2 \sigma_{22}^2 - \sigma_{12}^2 \sigma_{21}^2} \\ &= \frac{1}{2\pi} \frac{1}{\sigma_c^2 \sigma_{22}^2} = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_c^2} \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_{22}^2} \end{aligned}$$

Density of  $\pi(x_1) = \int \pi(x_1, x_2) dx_2$

$\frac{1}{\sqrt{2\pi}\sigma_c} \exp\left(-\frac{1}{2\sigma_c^2}(x_1 - \bar{x}_1)^2\right)$  since the density

$$\frac{1}{\sqrt{2\pi}\sigma_{22}} \exp\left(-\frac{1}{2\sigma_{22}^2}(x_2 - \bar{x}_2)^2\right) = N(x_2, \sigma_{22}^2)$$

integrates to 1

$$\pi(x_2|x_1) = \frac{\pi(x_1, x_2)}{\pi(x_1)} = \frac{1}{\sqrt{2\pi}\sigma_{22}^2}$$

We now factored  $\pi(x_1, x_2) = \pi(x_1|x_2)\pi(x_2)$

For the formulas for  $\pi(x_1)$ ,  $\pi(x_2|x_1)$  we would have to switch things around:

$$\pi(x_1) = \frac{1}{\sqrt{2\pi}\sigma_{11}^2} \exp\left(-\frac{1}{2\sigma_{11}^2}(x_1 - \bar{x}_1)^2\right)$$

$$\pi(x_2|x_1) = \frac{1}{\sqrt{2\pi}\sigma_d^2} \exp\left(-\frac{1}{2\sigma_d^2}(x_2 - \bar{x}_d)^2\right)$$

with

$$\sigma_d^2 = \sigma_{22}^2 - \sigma_{12}^2 \sigma_{11}^{-2}$$
$$\bar{x}_d = \bar{x}_2 + \frac{\sigma_{12}^2}{\sigma_{11}^2}(x_1 - \bar{x}_1)$$

#### Exercise 4

$$\begin{aligned} d_{\text{Hell}}^2(p, q) &= 1 - \int \sqrt{pq} \, dx \\ &= \underbrace{\int p \, dx}_{\text{density integrates to 1}} - \int \sqrt{\frac{q}{p}} p \, dx \end{aligned}$$

$$= \int p \left(1 - \sqrt{\frac{q}{p}}\right) dx$$

$$\stackrel{\textcircled{*}}{\leq} - \int p \log\left(\sqrt{\frac{q}{p}}\right) dx$$

$$= -\frac{1}{2} \int p \log\left(\frac{q}{p}\right) dx$$

$$= KL(p \parallel q)$$

① Claim:  $1 - x \leq -\log x \Leftrightarrow x - 1 - \log x \geq 0$

Pf:  $x - 1$  convex,  $-\log x$  strictly convex

$\Rightarrow x - 1 + (-\log x)$  strictly convex

$\Rightarrow x - 1 - \log x$  has unique minimum

Take derivative w.r.t.  $x$

$$\nabla_x x - 1 - \log x = 1 - \frac{1}{x} \stackrel{!}{=} 0$$

$$\Rightarrow x^* = 1$$

$$\Rightarrow x - 1 - \log x \geq x^* - 1 - \log x^* = 1 - 1 - 0 = 0$$

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