

Homework # 1

1. Consider the following block matrix

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}$$

where $|A| \neq 0$, $|D| \neq 0$ ($|\cdot|$ denotes the determinant).

a) Derive the block UDL factorization of

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}$$

i.e. find X , Y and Δ_1 , Δ_2 such that

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} = \begin{bmatrix} I & X \\ 0 & I \end{bmatrix} \begin{bmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{bmatrix} \begin{bmatrix} I & 0 \\ Y & I \end{bmatrix} .$$

b) Derive the inverse of

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} .$$

c) Show that

$$\left| \begin{bmatrix} A & B \\ C & D \end{bmatrix} \right| = |A - BD^{-1}C| |D| .$$

2. Let

$$\begin{bmatrix} x \\ y \end{bmatrix} \sim N \left(\begin{bmatrix} \bar{x} \\ \bar{y} \end{bmatrix}, \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{bmatrix} \right) .$$

Show that the conditional pdf, $f_{X|Y}(x|y)$, is Gaussian with mean

$$\bar{x} + \Sigma_{xy} \Sigma_{yy}^{-1} (y - \bar{y})$$

and covariance

$$\Sigma_{xx} - \Sigma_{xy} \Sigma_{yy}^{-1} \Sigma_{yx} .$$

The results from 1. are useful.

3. Suppose X and Y are jointly distributed random variables. When Y is unknown, an intelligent estimate of the value of X is

$$\bar{x} = E\{X\} .$$

This estimate has the property that

$$E\{\|X - \bar{x}\|^2\} \leq E\{\|X - z\|^2\}$$

for all z , and has average error $E\{\|X - \bar{x}\|^2\}$. Now suppose that one is told that $Y = y$. Let $\hat{x} = E\{X|Y = y\}$. Show that

$$E\{\|X - \hat{x}\|^2|Y = y\} = E\{\|X - \bar{x}\|^2|Y = y\} - \|\hat{x} - \bar{x}\|^2 .$$

Conclude the intuitively reasonable result that the mean estimation error $E\{\|X - \hat{x}\|^2\}$ averaged over all values of X and Y will be bounded above by $E\{\|X - \bar{x}\|^2\}$. When will the bound be attained, i.e., when will there not be a strict improvement in the knowledge of X ?

4. Given a zero-mean process $y(\cdot)$ and its covariance function, find the linear least-squares estimate of

$$\int_0^T y(t) dt$$

in terms of its values at the end points $y(0)$ and $y(T)$. When the covariance function is

$$e^{-\alpha|t|}$$

show that the estimate is

$$\frac{1}{\alpha} \tanh \frac{\alpha T}{2} (y(0) + y(T)) .$$

What is the estimate for small T ?

5. Assume X and N are independent Gaussian random variables with means \bar{x} and \bar{n} and with covariance matrices Σ_x and Σ_n . Then $Y = X + N$ is Gaussian and $f_{X|Y}(x|y)$ is a Gaussian density function. Show that the associated conditional mean and covariance are

$$\Sigma_n(\Sigma_x + \Sigma_n)^{-1}\bar{x} + \Sigma_x(\Sigma_x + \Sigma_n)^{-1}(y - \bar{n})$$

and

$$\Sigma_x - \Sigma_x(\Sigma_x + \Sigma_n)^{-1}\Sigma_x = \Sigma_x(\Sigma_x + \Sigma_n)^{-1}\Sigma_n = (\Sigma_x^{-1} + \Sigma_n^{-1})^{-1} .$$

Find the joint density $f_{X,Y}(x, y)$ first and assume that the inverses exist.