Soham Chatterjee
Email: soham.chatterjee@tifr.res.in
Course: Probability Theory

Assignment - 3
Dept: STCS
Date: October 5, 2024

Problem 1

We know that independent random variables are uncorrelated. Argue that uncorrelated jointly Gaussian random variables are independent.
Hint: do this for two random variables first. For n random variables, you might find it easier to use the characteristic function.

Solution: Let $\overline{U} = (U_1, \dots, U_n)^T$ be the n uncorrelated jointly Gaussian random variables. Let K be the covarince matrix of $\overline{U}$ where for each $i \in [n]$ we have $Z_i \sim N(\mu_i, \sigma_i^2)$. So $\overline{U} = \overline{\mu} + \overline{Z}$ where $\overline{Z} = (Z_1, \dots, Z_n)^T$ and $\overline{Z}$ is zero mean Gaussian random variables. Since the Gaussian random variables are uncorrelated the matrix K is diagonal. Hence the K^{-1} is also diagonal. Then we know the density function of $\overline{U}$ is

$$f_{\overline{U}}(\overline{u}) = \frac{\exp\left[-\frac{1}{2}(\overline{u}-\overline{\mu})^T K^{-1}(\overline{u}-\overline{\mu})\right]}{(2\pi)^{\frac{n}{2}}\sqrt{\det K}}$$

Since K is diagonal

$$K = \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_n^2 \end{bmatrix} \implies K^{-1} = \begin{bmatrix} \frac{1}{\sigma_1^2} & & & \\ & \frac{1}{\sigma_2^2} & & \\ & & \ddots & \\ & & & \frac{1}{\sigma_n^2} \end{bmatrix}$$

Therefore we have

$$(\overline{u}-\overline{\mu})^T K^{-1}(\overline{u}-\overline{\mu}) = \sum_{i=1}^n (u_i - \mu_i)\frac{1}{\sigma_i^2}(u_i-\mu_i) = \sum_{i=1}^n \frac{(u_i-\mu_i)^2}{\sigma_i^2}$$

Hence we have

$$f_{\overline{U}}(\overline{u}) = \frac{\exp\left[-\frac{1}{2}\sum\limits_{i=1}^n \frac{(u_i-\mu_i)^2}{\sigma_i^2}\right]}{(2\pi)^{\frac{n}{2}}\sqrt{\det K}} = \frac{\prod\limits_{i=1}^n \exp\left[-\frac{1}{2}\frac{(u_i-\mu_i)^2}{\sigma_i^2}\right]}{(2\pi)^{\frac{n}{2}}\sqrt{\prod\limits_{i=1}^n \sigma_i^2}} = \prod_{i=1}^n \frac{\exp\left[-\frac{(u_i-\mu_i)^2}{2\sigma_i^2}\right]}{\sqrt{2\pi\sigma_i^2}} = \prod_{i=1}^n f_{U_i}(u_i)$$

Therefore U_i's are independent. ■
[I discussed with Aakash]

Problem 2

(i) * Let X and Y be independent random variables. $X_1 \sim N(0,1)$; and $Y = +1$ with probability p and $Y = -1$ with probability $1-p$. We define $X_2 = YX_1$. Is X_2 Gaussian? Are X_1, X_2 jointly Gaussian? Justify your answers.

[See Example 3.3.4 from [G] for a solution]

(ii) Repeat (i) if $X_1 \sim N(m, 1)$ and $m > 0$

Solution: We know for any random variable $Z \sim N(\mu, \sigma^2)$ the characteristic function of Z is $\mathbb{E}[\exp(itZ)] = \exp\left(it\mu - \frac{1}{2}\sigma^2 t^2\right)$.

Now we know $X_1 \sim N(m,1)$ where $m > 0$. Therefore $\mathbb{E}[X_1] = m$ and $\mathrm{Var}[X_1] = 1$. Therefore $\mathbb{E}[X_1^2] = \mathrm{Var}[X_1] + \mathbb{E}[X_1]^2 = 1 + m^2$. Also for Y we have $\mathbb{E}[Y] = p - (1-p) = 2p - 1$ and $\mathbb{E}[Y^2] = p + (1-p) = 1$. Now we will calculate the mean and the variance and the characteristic function of $X_2 = X_1 Y$.

$$\mathbb{E}[X_2] = \mathbb{E}[X_1 Y] = \mathbb{E}[X_1]\mathbb{E}[Y] = (2p-1)m$$

Now

$$\mathbb{E}[X_2^2] = \mathbb{E}[X_1^2Y^2] = \mathbb{E}[X_1^2]\mathbb{E}[Y^2] = m^2 + 1$$

Hence we have

$$\text{Var}[X_2] = \mathbb{E}[X_2^2] - \mathbb{E}[X_2]^2 = m^2 + 1 - (2p-1)^2m^2 = m^2 + 1 - (4p^2 - 4p + 1)m^2 = 1 - 4m^2(p^2 - p)$$

Hence if X_2 is Gaussian then we have $X_2 \sim N((2p-1)m, 1 - 4m^2(p^2 - p))$. Then the characteristic function of X_2 would have become $\exp\left(it(2p-1)m - \frac{t^2}{2}(1 - 4m^2(p^2 - p))\right)$. Now let's calculate the characteristic function of X_2.

$$\mathbb{E}[\exp(itX_2)] = \mathbb{E}[\exp(itX_1)]\mathbb{E}[\exp(itY)] = \exp\left(itm - \frac{t^2}{2}\right)\left[pe^{it} + (1-p)e^{-it}\right]$$

So comparing the two equations we have

$$\begin{aligned}
&\exp\left(it(2p-1)m - \frac{t^2}{2}(1 - 4m^2(p^2 - p))\right) = \exp\left(itm - \frac{t^2}{2}\right)\left[pe^{it} + (1-p)e^{-it}\right] \\
\implies &\exp\left(it(2p-1)m - \frac{t^2}{2}(1 - 4m^2(p^2 - p)) - \left[itm - \frac{t^2}{2}\right]\right) = pe^{it} + (1-p)e^{-it} \\
\implies &\exp\left(2it(p-1)m + \frac{t^2}{2}(4m^2(p^2 - p))\right) = pe^{it} + (1-p)e^{-it} \\
\implies &\exp\left(2it(p-1)m + 2t^2m^2(p^2 - p)\right) = pe^{it} + (1-p)e^{-it}
\end{aligned}$$

Now notice that $p \leq 1$. Hence $p - 1 \leq 0$ and $p^2 - p \leq 0$. Therefore we have

$$2it(p-1)m + 2t^2m^2(p^2 - p) \leq 0 \implies \exp\left(2it(p-1)m + 2t^2m^2(p^2 - p)\right) \leq 1$$

But in the *RHS* we have

$$pe^{it} + (1-p)e^{-it} = p(\cos t + i\sin t) + (1-p)(\cos t - i\sin t) = \cos t + i(2p-1)\sin t$$

Therefore $|pe^{it} + (1-p)e^{-it}| = \sqrt{1 + (2p-1)^2} > 1$. But this is not possible. Hence contradiction. X_2 is not Gaussian.

If X_1, X_2 is jointly Gaussian then the marginal distribution on X_2 is also Gaussian. Since we know the marginal distribution on X_2 is not Gaussian we have X_1, X_2 are not jointly Gaussian. ■

Problem 4 [G] Exercise 3.8

(a) Let $[K] = \begin{bmatrix} 0.75 & 0.25 \\ 0.25 & 0.75 \end{bmatrix}$. Show that 1 and $\frac{1}{2}$ are eigenvalues of $[K]$ and find the normalized eigenvectors. Express $[K]$ ad $[Q\Lambda Q^{-1}]$, where $[\Lambda]$ is diagonal and $[Q]$ is orthonormal.

(b) Let $[K'] = \alpha[K]$ for real $\alpha \neq 0$. Find the eigenvalues and eigenvectors of $[K']$. Don't not use brute force - think!

(c) Find the eigenvalues and eigenvectors of $[K^m]$, where $[K^m]$ is the mth power of $[K]$.

Solution:

(a) Let the vector $\begin{bmatrix} 1 & 1 \end{bmatrix}^T$ and $\begin{bmatrix} 1 & -1 \end{bmatrix}^T$. We claim they are the eigenvectors corresponding to eigenvalues 1 and -1 respectively.

$$\begin{bmatrix} 0.75 & 0.25 \\ 0.25 & 0.75 \end{bmatrix}\begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.75 + 0.25 \\ 0.25 + 0.75 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ and } \begin{bmatrix} 0.75 & 0.25 \\ 0.25 & 0.75 \end{bmatrix}\begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0.75 - 0.25 \\ 0.25 - 0.75 \end{bmatrix} = \begin{bmatrix} 0.5 \\ -0.5 \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Hence $\begin{bmatrix} 1 & 1 \end{bmatrix}^T$ and $\begin{bmatrix} 1 & -1 \end{bmatrix}^T$ are indeed eigenvector corresponding to eigenvalues 1 and -1 respectively.

Now the vectors $\begin{bmatrix}1 & 1\end{bmatrix}^T$ and $\begin{bmatrix}1 & -1\end{bmatrix}^T$ are orthogonal but they are not normalized vectors. Hence consider the vectors $\frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\end{bmatrix}^T$ and $\frac{1}{\sqrt{2}}\begin{bmatrix}1 & -1\end{bmatrix}^T$. They are orthogonal and also they are normalized. Hence they are orthonormal. Hence we claim $[Q] = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}$. Since we already knew the eigenvalues we also have $[\Lambda] = \begin{bmatrix}1 & 0\\ 0 & \frac{1}{2}\end{bmatrix}$. First we will show that $[Q^T] = [Q^{-1}]$. Now $\det[Q] = \left(\frac{1}{\sqrt{2}}\right)^2 (1\times(-1) - 1\times 1) = \frac{1}{2}\times(-2) = -1$. Now

$$[Q^{-1}] = \frac{1}{\det[Q]}\begin{bmatrix}-\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}\\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix} = [Q^T]$$

So now

$$[Q\Lambda Q^{-1}] = \frac{1}{2}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}\begin{bmatrix}1 & 0\\ 0 & 0.5\end{bmatrix}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix} = \frac{1}{2}\begin{bmatrix}1 & 0.5\\ 1 & -0.5\end{bmatrix}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix} = \frac{1}{2}\begin{bmatrix}1.5 & 0.5\\ 0.5 & 1.5\end{bmatrix} = \begin{bmatrix}0.75 & 0.25\\ 0.25 & 0.75\end{bmatrix} = [K]$$

(b) If v is an eigenvector with corresponding eigenvalue λ of $[K]$ then we have

$$[K']v = \alpha[K]v = \alpha\lambda v = (\alpha\lambda)v$$

So v is also an eigenvector of $[K']$ but the corresponding eigenvalue is $\alpha\lambda$. Since by the previous part we know the eigenvector of $[K]$ are $\begin{bmatrix}1 & 1\end{bmatrix}^T$ and $\begin{bmatrix}1 & -1\end{bmatrix}^T$ with corresponding eigenvalues 1 and $\frac{1}{2}$ respectively the eigenvectors of $[K']$ are the same $\begin{bmatrix}1 & 1\end{bmatrix}^T$ and $\begin{bmatrix}1 & -1\end{bmatrix}^T$ with corresponding eigenvalues α and $\frac{\alpha}{2}$ respectively.

(c) If v is an eigenvector with corresponding eigenvalue λ of $[K]$ then we have

$$[K^m]v = [K^{m-1}][K]v = [K^{m-1}]\alpha v = \alpha[K^{m-1}]v = \alpha^2[K^{m-2}]v = \cdots = \alpha^{m-1}[K]v = \alpha^m v$$

Therefore v is also an eigenvector of $[K^m]$ but the corresponding eigenvalue is λ^v. Since by the part (a) we know the eigenvector of $[K]$ are $\begin{bmatrix}1 & 1\end{bmatrix}^T$ and $\begin{bmatrix}1 & -1\end{bmatrix}^T$ with corresponding eigenvalues 1 and -1 respectively the eigenvectors of $[K^m]$ are the same $\begin{bmatrix}1 & 1\end{bmatrix}^T$ and $\begin{bmatrix}1 & -1\end{bmatrix}^T$ with corresponding eigenvalues 1 and $\frac{1}{2^m}$ respectively.

■

Problem 6 [G] Problem 3.9

Let X and Y be jointly Gaussian with means m_X, m_Y, variances σ_X^2, σ_Y^2, and normalized covariance ρ. Find the conditional density $f_{X|Y}(x \mid y)$.

Solution: We have $\mathbb{E}[X] = m_X$ and $\mathbb{E}[Y] = m_Y$. Hence $\rho = \frac{\mathbb{E}[(X-\mathbb{E}[X])(Y-\mathbb{E}[Y])]}{\sigma_X\sigma_Y} = \frac{\mathbb{E}[(X-m_X)(Y-m_Y)]}{\sigma_X\sigma_Y}$. So $\mathrm{Cov}(X,Y) = \rho\sigma_X\sigma_Y$. Hence the covariance matrix is

$$K = \begin{bmatrix}\sigma_X^2 & \rho\sigma_X\sigma_Y\\ \rho\sigma_X\sigma_Y & \sigma_Y^2\end{bmatrix}$$

Now $\det K = \sigma_X^2\sigma_Y^2 - \rho^2\sigma_X^2\sigma_Y^2 = \sigma_X^2\sigma_Y^2(1-\rho^2)$. Then

$$K^{-1} = \frac{1}{\sigma_X^2\sigma_Y^2(1-\rho^2)}\begin{bmatrix}\sigma_Y^2 & -\rho\sigma_X\sigma_Y\\ -\rho\sigma_X\sigma_Y & \sigma_X^2\end{bmatrix} = \frac{1}{1-\rho^2}\begin{bmatrix}\frac{1}{\sigma_X^2} & -\frac{\rho}{\sigma_X\sigma_Y}\\ -\frac{\rho}{\sigma_X\sigma_Y} & \frac{1}{\sigma_Y^2}\end{bmatrix}$$

Now we know the joint density function of X, Y is

$$
\begin{aligned}
f_{X,Y}(x,y) &= \frac{1}{2\pi\sqrt{\det K}} \exp\left(-\frac{1}{2(1-\rho^2)} \begin{bmatrix} x-m_X & y-m_Y \end{bmatrix} \begin{bmatrix} \frac{1}{\sigma_x^2} & -\frac{\rho}{\sigma_x\sigma_Y} \\ -\frac{\rho}{\sigma_x\sigma_Y} & \frac{1}{\sigma_Y^2} \end{bmatrix} \begin{bmatrix} x-m_X \\ y-m_Y \end{bmatrix}\right) \\
&= \frac{1}{2\pi\sigma_x\sigma_Y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)} \begin{bmatrix} x-m_X & y-m_Y \end{bmatrix} \begin{bmatrix} \frac{x-m_X}{\sigma_x^2} - \rho\frac{y-m_Y}{\sigma_x\sigma_Y} \\ -\rho\frac{x-m_X}{\sigma_x\sigma_Y} + \frac{y-m_Y}{\sigma_Y^2} \end{bmatrix}\right) \\
&= \frac{1}{2\pi\sigma_x\sigma_Y\sqrt{1-\rho^2}} \exp\left(-\frac{(x-m_X)\left[\frac{x-m_X}{\sigma_x^2} - \rho\frac{y-m_Y}{\sigma_x\sigma_Y}\right] + (y-m_Y)\left[-\rho\frac{x-m_X}{\sigma_x\sigma_Y} + \frac{y-m_Y}{\sigma_Y^2}\right]}{2(1-\rho^2)}\right) \\
&= \frac{1}{2\pi\sigma_x\sigma_Y\sqrt{1-\rho^2}} \exp\left(-\frac{\frac{(x-m_X)^2}{\sigma_x^2} - \rho\frac{(x-m_X)(y-m_Y)}{\sigma_x\sigma_Y} - \rho\frac{(x-m_X)(y-m_Y)}{\sigma_x\sigma_Y} + \frac{(y-m_Y)^2}{\sigma_Y^2}}{2(1-\rho^2)}\right) \\
&= \frac{1}{2\pi\sigma_x\sigma_Y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\left[\frac{(x-m_X)^2}{\sigma_x^2} - 2\rho\frac{(x-m_X)(y-m_Y)}{\sigma_x\sigma_Y} + \frac{(y-m_Y)^2}{\sigma_Y^2}\right]\right)
\end{aligned}
$$

Now we have $f_Y(y) = \frac{1}{\sigma_Y\sqrt{2\pi}}\exp\left(-\frac{(y-m_Y)^2}{2\sigma_Y^2}\right)$. We know for conditional density function $f_{X|Y}(x \mid y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$. Hence we have

$$
\begin{aligned}
f_{X|Y}(x \mid y) &= \frac{\frac{1}{2\pi\sigma_x\sigma_Y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\left[\frac{(x-m_X)^2}{\sigma_x^2} - 2\rho\frac{(x-m_X)(y-m_Y)}{\sigma_x\sigma_Y} + \frac{(y-m_Y)^2}{\sigma_Y^2}\right]\right)}{\frac{1}{\sigma_Y\sqrt{2\pi}}\exp\left(-\frac{(y-m_Y)^2}{2\sigma_Y^2}\right)} \\
&= \frac{1}{\sigma_x\sqrt{2\pi(1-\rho^2)}} \exp\left(-\frac{\left[\frac{(x-m_X)^2}{\sigma_x^2} - 2\rho\frac{(x-m_X)(y-m_Y)}{\sigma_x\sigma_Y} + \frac{(y-m_Y)^2}{\sigma_Y^2} - (1-\rho^2)\frac{(y-m_Y)^2}{2\sigma_Y^2}\right]}{2(1-\rho^2)}\right) \\
&= \frac{1}{\sigma_x\sqrt{2\pi(1-\rho^2)}} \exp\left(-\frac{\left[\frac{(x-m_X)^2}{\sigma_x^2} - 2\rho\frac{(x-m_X)(y-m_Y)}{\sigma_x\sigma_Y} + \rho^2\frac{(y-m_Y)^2}{\sigma_Y^2}\right]}{2(1-\rho^2)}\right) \\
&= \frac{1}{\sigma_x\sqrt{2\pi(1-\rho^2)}} \exp\left(-\frac{1}{2(1-\rho^2)}\left[\frac{x-m_X}{\sigma_x} - \rho\frac{y-m_Y}{\sigma_Y}\right]^2\right) \\
&= \frac{1}{\sigma_x\sqrt{2\pi(1-\rho^2)}} \exp\left(-\frac{1}{2\sigma_X^2(1-\rho^2)}\left[x - \left(\rho\frac{\sigma_X}{\sigma_Y}(y-m_Y) + m_X\right)\right]^2\right)
\end{aligned}
$$

Hence we have $X \mid Y = y \sim N\left(\rho\frac{\sigma_X}{\sigma_Y}(y-m_Y) + m_X, \sigma_X^2(1-\rho^2)\right)$. ■

In the next two problems we will use a common model for communication systems. The transmitted signal $\vec{X}$ is a Gaussian random vector of size m (vector since there are several, say m, transmit antennas and each component of the vector stands for the input to a separate antenna). The signal goes over a linear and additive Gaussian noise channel and is picked up by a receiver which also has n antennas. The received vector of length n has the form.

$$\vec{Y} = H\vec{X} + \vec{Z}, \tag{1}$$

where H is a constant $n \times m$ vector and $\vec{Z}$ is a Gaussian random vector of size n and independent of $\vec{X}$.

Problem 7

Let us first consider the simpler case of $m = 1$ and $n = 2$. So X is a scalar random variable. Let X have the standard normal distribution $N(0, 1)$. The received signals are

$$Y_i = h_i X + Z_i, \qquad i = 1, 2,$$

where $Z_i \sim N(0, \sigma^2)$ are i.i.d and independent of X. And h_i's are constants which represent the channel "gains" from the transmit antenna to the receive antennas.

(a) Find the conditional joint distribution of Y_1, Y_2 conditioned on $X = x$.

(b) Find the conditional joint distribution of X conditioned on $Y_1 = y_1$, $Y_2 = y_2$.

(c) Using (b), what is your estimate of the transmitted signal X if you are told that the receive antennas observed $Y_1 = y_1$, $Y_2 = y_2$. **Interpret your results**. Does your answer make intuitive sense? What happens to the estimate when the noise variance σ^2 becomes small? or large?

Solution: Now $\tilde{Z} = \begin{bmatrix} X & Z_1 & Z_2 \end{bmatrix}^T$ forms independent zero mean Gaussian 3-random vectors since $X \sim N(0, 1)$, $Z_1 \sim N(0, \sigma^2)$, $Z_2 \sim N(0, \sigma^2)$. Hence the covariance matrix of $\tilde{Z}$ is

$$\mathbb{E}[\tilde{Z}\tilde{Z}^T] = \begin{bmatrix} 1 & & \\ & \sigma^2 & \\ & & \sigma^2 \end{bmatrix}$$

Consider the matrix

$$A = \begin{bmatrix} 1 & 0 & 0 \\ h_1 & 1 & 0 \\ h_2 & 0 & 1 \end{bmatrix}$$

Then we have

$$\begin{bmatrix} X \\ Y_1 \\ Y_2 \end{bmatrix} = A \begin{bmatrix} X \\ Z_1 \\ Z_2 \end{bmatrix}$$

Hence the 3-random vector $\tilde{Y} = \begin{bmatrix} X & Y_1 & Y_2 \end{bmatrix}^T$ is a zero mean Gaussian 3–random vectors. Now let K denote the covariance matrix of $\tilde{Y}$. Then

$$K = \mathbb{E}[\tilde{Y}\tilde{Y}^T] = \mathbb{E}[A\tilde{Z}\tilde{Z}^T A^T] = A\mathbb{E}[\tilde{Z}\tilde{Z}^T]A^T = \begin{bmatrix} 1 & 0 & 0 \\ h_1 & 1 & 0 \\ h_2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \sigma^2 & 0 \\ 0 & 0 & \sigma^2 \end{bmatrix} \begin{bmatrix} 1 & h_1 & h_1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & h_1 & h_2 \\ h_1 & h_1 + \sigma^2 & h_1 h_2 \\ h_2 & h_1 h_2 & h_2^2 + \sigma^2 \end{bmatrix}$$

Now

$$K = \begin{bmatrix} K_X & K_{X \cdot Y} \\ K_{X \cdot Y}^T & K_Y \end{bmatrix} = \left[\begin{array}{c|cc} 1 & h_1 & h_2 \\ \hline h_1 & h_1 + \sigma^2 & h_1 h_2 \\ h_2 & h_1 h_2 & h_2^2 + \sigma^2 \end{array}\right]$$

Therefore $K_X = \begin{bmatrix} 1 \end{bmatrix}$, $K_Y = \begin{bmatrix} h_1 + \sigma^2 & h_1 h_2 \\ h_1 h_2 & h_2^2 + \sigma^2 \end{bmatrix}$ and $K_{X \cdot Y} = K_{Y \cdot X}^T = \begin{bmatrix} h_1 & h_2 \end{bmatrix}$.

(a) Let $\overline{Y} = \begin{bmatrix} Y_1 & Y_2 \end{bmatrix}^T$. Then we are asked to find $\overline{Y} \mid X = x$. We know $\overline{Y} \mid X = x$ is Gaussian bivariate random vector. The mean of $\overline{Y} \mid X = x$ is

$$K_{Y \cdot X} K_X^{-1} x = K_{X \cdot Y}^T K_X^{-1} x = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} x = \begin{bmatrix} h_1 x \\ h_2 x \end{bmatrix}$$

The variance of $\overline{Y} \mid X = x$ is

$$K_Y - K_{Y\cdot X}K_X^{-1}K_{Y\cdot X}^T = \begin{bmatrix} h_1+\sigma^2 & h_1h_2 \\ h_1h_2 & h_2^2+\sigma^2 \end{bmatrix} - \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}\begin{bmatrix} h_1 & h_2 \end{bmatrix} = \begin{bmatrix} h_1+\sigma^2 & h_1h_2 \\ h_1h_2 & h_2^2+\sigma^2 \end{bmatrix} - \begin{bmatrix} h_1^2 & h_1h_2 \\ h_1h_2 & h_2^2 \end{bmatrix} = \begin{bmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{bmatrix}$$

Therefore we have $Y_1 \mid X = x \sim N(h_1x, \sigma^2)$ and $Y_2 \mid X = x \sim N(h_2x, \sigma^2)$.

(b) Let $\overline{y} = \begin{bmatrix} y_1 & y_2 \end{bmatrix}^T$. We are asked to find $X \mid \overline{Y} = \overline{Y}$. We know $X \mid \overline{Y} = \overline{y}$ is a Gaussian distribution. But we will find the mean and the variance of the distribution now. First we will find K_Y^{-1}.

$$K_Y^{-1} = \begin{bmatrix} h_1+\sigma^2 & h_1h_2 \\ h_1h_2 & h_2^2+\sigma^2 \end{bmatrix}^{-1} = \frac{1}{\sigma^4+\sigma^2(h_1^2+h_2^2)}\begin{bmatrix} h_2^2+\sigma^2 & -h_1h_2 \\ -h_1h_2 & h_1^2+\sigma^2 \end{bmatrix}$$

The mean of $X \mid \overline{Y} = \overline{y}$ is

$$K_{X\cdot Y}K_Y^{-1}\,\overline{y} = \frac{1}{\sigma^4+\sigma^2(h_1^2+h_2^2)}\begin{bmatrix} h_1 & h_2 \end{bmatrix}\begin{bmatrix} h_2^2+\sigma^2 & -h_1h_2 \\ -h_1h_2 & h_1^2+\sigma^2 \end{bmatrix}\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \frac{\sigma^2(h_1y_1+h_2y_2)}{\sigma^4+\sigma^2(h_1^2+h_2^2)} = \frac{h_1y_1+h_2y_2}{\sigma^2+h_1^2+h_2^2}$$

The variance of $X \mid \overline{Y} = \overline{y}$ is

$$K_X - K_{X\cdot Y}K_Y^{-1}K_{X\cdot Y}^T = 1 - \frac{1}{\sigma^4+\sigma^2(h_1^2+h_2^2)}\begin{bmatrix} h_1 & h_2 \end{bmatrix}\begin{bmatrix} h_2^2+\sigma^2 & -h_1h_2 \\ -h_1h_2 & h_1^2+\sigma^2 \end{bmatrix}\begin{bmatrix} h_1 \\ h_2 \end{bmatrix} = 1 - \frac{\sigma^2(h_1+h_2)}{\sigma^4+\sigma^2(h_1^2+h_2^2)} = \frac{\sigma^2}{\sigma^2+h_1^2+h_2^2}$$

Therefore we have $X \mid \overline{Y} = \overline{y} \sim N\left(\frac{h_1y_1+h_2y_2}{\sigma^2+h_1^2+h_2^2}, \frac{\sigma^2}{\sigma^2+h_1^2+h_2^2}\right)$

(c) Hence the estimated transmitted signal X if observed $Y_1 = y_1$ and $Y_2 = y_2$ is $\frac{h_1y_1+h_2y_2}{\sigma^2+h_1^2+h_2^2}$.

Now

$$\lim_{\sigma^2\to 0}\frac{h_1y_1+h_2y_2}{\sigma^2+h_1^2+h_2^2} = \frac{h_1y_1+h_2y_2}{h_1^2+h_2^2}$$

Hence if σ^2 becomes very small then the estimated transmitted signal is $\frac{h_1y_1+h_2y_2}{h_1^2+h_2^2}$.

If σ^2 becomes large

$$\lim_{\sigma^2\to\infty}\frac{h_1y_1+h_2y_2}{\sigma^2+h_1^2+h_2^2} = 0$$

then the estimated transmitted signal is 0.

■

Problem 8

Now consider the general model in (1) for general n, m. Let $\vec{X} \sim N(\vec{0}, K_X)$, $\vec{Z} \sim N(\vec{0}, K_Z)$ and $\vec{Z}$ is independent of $\vec{X}$.

(a) Show that $\vec{U} = (\vec{X}, \vec{Y})$ is jointly Gaussian. You may use any of the equivalent definitions we saw in class

(b) Find a simple condition on H, K_X, K_Z so that K_U is invertible.

(c) What is the conditional distribution of the input $\vec{X}$ given the output $\vec{Y} = \vec{y}$.

Solution:

(a) Now $\hat{Z} = \left[\vec{X}^T, \vec{Z}^T\right]^T$ forms independent zero mean Gaussian $(n+m)$-random variable since $\vec{X} \sim N(\vec{0}, K_X)$ and $\vec{Z} \sim N(\vec{0}, K_Z)$. Also denote $\hat{Y} = \left[\vec{X}^T, \vec{Y}^T\right]^T$. Now we know

$$\vec{Y} = H\vec{X} + \vec{Z} \implies \vec{Y} = [H \mid I_n]\begin{bmatrix} \vec{X} \\ \vec{Z} \end{bmatrix} \implies \begin{bmatrix} \vec{X} \\ \vec{Y} \end{bmatrix} = \underbrace{\left[\begin{array}{c|c} I_m & \\ \hline H & I_n \end{array}\right]}_{A}\begin{bmatrix} \vec{X} \\ \vec{Z} \end{bmatrix} \implies \hat{Y} = A\hat{Z}$$

Since $\hat{Z}$ is zero mean Gaussian $(n+m)$-random vector $hatY$ is also a zero mean Gaussian $(n+m)$-random vector. Hence $\vec{U} = (\vec{X}, \vec{Y})$ is jointly Gaussian.

(b) Now covariance matrix of $\vec{U}$ or $\hat{Y}$ is K_U. The covariance matrix of $\hat{Z}$ is

$$\mathbb{E}[\hat{Z}\hat{Z}^T] = \begin{bmatrix} K_X & \\ & K_Z \end{bmatrix}$$

Then we have

$$K_U = \mathbb{E}[\hat{Y}\hat{Y}^T] = \mathbb{E}[A\hat{Z}\hat{Z}^T A^T] = A\mathbb{E}[\hat{Z}\hat{Z}^T]A^T = \begin{bmatrix} I_m & \\ H & I_n \end{bmatrix} \begin{bmatrix} K_X & \\ & K_Z \end{bmatrix} \begin{bmatrix} I_m & H^T \\ & I_n \end{bmatrix} = \begin{bmatrix} K_X & K_X H^T \\ HK_X & HK_X H^T + K_Z \end{bmatrix}$$

Let the inverse of K_U is

$$K_U^{-1} = \begin{bmatrix} P & Q \\ R & S \end{bmatrix} \implies K_U K_U^{-1} = \begin{bmatrix} K_X P + K_X H^T R & K_X Q + K_X H^T S \\ HK_X P + (HK_X H^T + K_Z)R & HK_X Q + (HK_X H^T + K_Z)S \end{bmatrix} = \begin{bmatrix} I_m & \\ & I_n \end{bmatrix}$$

Then we have

$$K_X P + K_X H^T R = I_m \implies K_X(P + H^T R) = I_n \implies K_X \text{ is invertible}$$

Now we have

$$HK_X P + (HK_X H^T + K_Z)R = 0 \implies HK_X(P + H^T R) + K_Z R = 0 \implies H + K_Z R = 0$$

We also have

$$HK_X Q + (HK_X H^T + K_Z)S = I_n \implies H(K_X Q + K_X H^T S) + K_Z S = I_n \implies K_Z S = I_n \implies K_Z \text{ is invertible}$$

If K_X, K_Z are invertible then we have $S = K_Z^{-1}$. $H + KZR = 0 \implies R = -K_Z^{-1}H$.

$$K_X Q + K_X H^T K_Z^{-1} = 0 \implies Q = -H^T K_Z^{-1}$$

And finally

$$P + H^T R = K_X^{-1} \implies P = K_X^{-1} + H^T K_Z^{-1} H$$

Therefore if K_X, K_Y and $HK_X H^T + K_Z$ are invertible then K_U becomes invertible.

(c) We have $K_U = \begin{bmatrix} K_X & K_X H^T \\ HK_X & HK_X H^T + K_Z \end{bmatrix}$. Also from this we get

$$K_U^{-1} = \begin{bmatrix} K_X^{-1} + H^T K_Z^{-1} H & -H^T K_Z^{-1} \\ -K_Z^{-1} H & K_Z^{-1} \end{bmatrix}$$

Now we know $\vec{X} \mid \vec{Y} = \vec{y}$ is a Gaussian m-random variable. The mean of $\vec{X} \mid \vec{Y} = \vec{y}$ is $P^{-1}Q = -(K_X^{-1} + H^T K_Z^{-1} H)^{-1} H^T K_Z^{-1}$. And the variance is $(K_X^{-1} + H^T K_Z^{-1} H)^{-1}$. Therefore we have the distribution function of $\vec{X} \mid \vec{Y} = \vec{y}$ is $N\left(-(K_X^{-1} + H^T K_Z^{-1} H)^{-1} H^T K_Z^{-1}, (K_X^{-1} + H^T K_Z^{-1} H)^{-1}\right)$.

■