## Lecture Activities Bayesian approach to Data Assimilation

## 1. Statistics review.

Given that

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

$$Cov(X,Y) = E[(X - \mu_x)(Y - \mu_y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_x)(y - \mu_y) f_{XY}(x,y) dxdy$$

(a) Find E[c] where c is a constant.

Solution: E[c] = c

(b) Show that Cov(X, Y) = Cov(Y, X)

Solution: Use the definition above and see that  $(x - \mu_x)(y - \mu_y) = (y - \mu_y)(x - \mu_x)$ .

(c) If  $\mathbf{Y} = (Y_2, Y_3)^T$ , find the general matrix  $Cov(\mathbf{Y})$ .

Solution:

$$Cov(\mathbf{Y}) = \begin{bmatrix} Var(Y_2) & Cov(Y_2, Y_3) \\ Cov(Y_3, Y_2) & Var(Y_3) \end{bmatrix}$$

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(d) Suppose  $X_1 \sim \mathcal{N}(\mu, \sigma^2)$  and that  $X_2 = \alpha X_1$ . Then  $X_2$  is also normally distributed. Find the mean and variance of  $X_2$ .

Solution:

$$E[X_2] = E[\alpha X_1] = \alpha E[X_1] = \alpha \mu,$$
  

$$Var[X_2] = Var[\alpha X_1] = \alpha^2 Var[X_1] = \alpha^2 \sigma^2.$$
  

$$X_2 \sim \mathcal{N}(\alpha \mu, \alpha^2 \sigma^2)$$

2. Consider the process model

$$X_{i+1} = \alpha X_i, \ i = 1, 2, 3,$$

and data model

$$Y_i = X_i + \epsilon_i, \ i = 2, 3.$$

along with

$$X_1 \sim \mathcal{N}(\mu_0, \sigma^2), \quad \epsilon_i \sim \mathcal{N}(0, \tau^2).$$

- (a) Find the means of  $X_2$ ,  $X_3$  and  $X_4$ . Solution:  $E[X_2] = \alpha \mu_0$ ,  $E[X_3] = \alpha^2 \mu_0$ ,  $E[X_4] = \alpha^3 \mu_0$ . Thus  $\mathbf{X} = (X_1, X_2, X_3, X_4)$  has mean vector  $\boldsymbol{\mu} = (\mu_0, \alpha \mu_0, \alpha^2 \mu_0, \alpha^3 \mu_0)^T$
- (b) Find the variances of  $X_2$ ,  $X_3$  and  $X_4$ . Solution:  $Var(X_2) = \alpha^2 \sigma^2$ ,  $Var(X_3) = \alpha^4 \sigma^2$ ,  $Var(X_4) = \alpha^6 \sigma^2$ .
- (c) Find  $Cov(X_1, X_2)$ ,  $Cov(X_1, X_3)$ ,  $Cov(X_1, X_4)$ ,  $Cov(X_2, X_3)$ ,  $Cov(X_2, X_4)$ ,  $Cov(X_3, X_4)$ . Solution:  $Cov(X_1, X_2) = \alpha \sigma^2$ ,  $Cov(X_1, X_3) = \alpha^2 \sigma^2$ ,  $Cov(X_1, X_4) = \alpha^3 \sigma^2$ ,  $Cov(X_2, X_4) = \alpha^4 \sigma^2$ ,  $Cov(X_3, X_4) = \alpha^5 \sigma^2$ .

(d) Use your answers to  $(\ref{eq:initial})$  and  $(\ref{eq:initial})$  to form the covariance matrix  $\Sigma_X$ . Solution:

$$\Sigma_X = \sigma^2 \begin{bmatrix} 1 & \alpha & \alpha^2 & \alpha^3 \\ \alpha & \alpha^2 & \alpha^3 & \alpha^4 \\ \alpha^2 & \alpha^3 & \alpha^4 & \alpha^5 \\ \alpha^3 & \alpha^4 & \alpha^5 & \alpha^6 \end{bmatrix}$$

- 3. Assume we have process and data models for which
  - the prior distribution is  $\mathbf{X} \sim \mathcal{N}(\mathbf{0}, \sigma_x^2 \mathbf{I}), \mathbf{X} \in \mathbb{R}^2$
  - the conditional distribution is  $\mathbf{Y}|\mathbf{X} \sim \mathcal{N}(\mathbf{X}, \sigma_{y}^{2}\mathbf{I}), \mathbf{Y} \in \mathbb{R}^{2}$

and we use the Bayesian method to assimilate data.

(a) Find the gain matrix  $\mathbf{K}$ .

Solution:  $\frac{\sigma_x^2}{\sigma_x^2 + \sigma_y^2} \mathbf{I}$ 

(b) Find the mean  $\mu^*$  of the posterior distribution  $\mathbf{X}|\mathbf{Y}$ , and discuss how the data informed the state estimates.

Solution:

$$oldsymbol{\mu}^* = rac{\sigma_x^2}{\sigma_x^2 + \sigma_y^2} \left(egin{array}{c} y_1 \ y_2 \end{array}
ight)$$

State estimates are the data scaled by  $\frac{\sigma_x^2}{\sigma_x^2 + \sigma_y^2}$ .

(c) Find covariance matrix  $\Sigma^*$  of the posterior distribution X|Y and discuss the meaning its elements.

Solution:

$$\mathbf{\Sigma}^* = rac{\sigma_x^2 \sigma_y^2}{\sigma_x^2 + \sigma_y^2} \mathbf{I}$$

The first diagonal element of  $\Sigma^*$  is  $\operatorname{Var}(X_1|\mathbf{Y})$  and the second diagonal element is  $\operatorname{Var}(X_2|\mathbf{Y})$ . The variance of both state estimates are the same. Since the off diagonal elements are zero, the estimates  $x_1^* = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_y^2} y_1$  and  $x_2^* = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_y^2} y_2$  have zero covariance.