

Notes ¹

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¹This document contains my notes on miscellaneous topics.

Part I

Mathematics

Chapter 1

Linear Algebra

1.1 Matrix Inverse Formulas

This chapter contains formulas for the inverses of various sums of matrices.

1.1.1 Inverse of $A + B$

Let $C + D$ be the inverse of $A + B$, then

$$\begin{aligned}(C + D)(A + B) &= I \\ \Rightarrow CA + CB + DA + DB &= I.\end{aligned}\tag{1.1}$$

Now let $C = A^{-1}$, then

$$\begin{aligned}A^{-1}A + A^{-1}B + DA + DB &= I \\ \Rightarrow A^{-1}B + DA + DB &= 0.\end{aligned}\tag{1.2}$$

Now let $D = A^{-1}MA^{-1}$, then

$$\begin{aligned}A^{-1}B + A^{-1}M + A^{-1}MA^{-1}B &= 0 \\ \Rightarrow A^{-1}(B + M + MA^{-1}B) &= 0 \\ \Rightarrow B + M + MA^{-1}B &= 0.\end{aligned}\tag{1.3}$$

Now let $M = BFB$, then

$$\begin{aligned}B + BFB + BFBA^{-1}B &= 0 \\ \Rightarrow B(I + FB + FBA^{-1}B) &= 0 \\ \Rightarrow I + FB + FBA^{-1}B &= 0 \\ \Rightarrow F(B + BA^{-1}B) &= -I \\ \Rightarrow F &= (B + BA^{-1}B)^{-1}.\end{aligned}\tag{1.4}$$

Therefore $D = A^{-1}B(B + BA^{-1}B)^{-1}BA^{-1}$. Substituting for C and D , the inverse of $A + B$ is then

$$(A + B)^{-1} = A^{-1} - A^{-1}B(B + BA^{-1}B)^{-1}BA^{-1} \quad (1.5)$$

Note that (1.5) only requires A to be invertible. If B is invertible (1.5) can be simplified to

$$(A + B)^{-1} = A^{-1} - A^{-1}B(I + A^{-1}B)^{-1}A^{-1} \quad (1.6)$$

or

$$(A + B)^{-1} = A^{-1} - A^{-1}(I + BA^{-1})BA^{-1} \quad (1.7)$$

1.1.2 Inverse of $A + BCD$

Using (1.5)

$$\begin{aligned} (A + BCD)^{-1} &= A^{-1} - A^{-1}BCD(BCD + BCDA^{-1}BCD)^{-1}BCDA^{-1} \\ &= A^{-1} + A^{-1}BCD(BC(D + DA^{-1}BCD))^{-1}BCDA^{-1} \\ &= A^{-1} + A^{-1}BCD(D + DA^{-1}BCD)DA^{-1} \\ &= A^{-1} + A^{-1}BCD((D(CD)^{-1} + DA^{-1}B)CD)^{-1}DA^{-1} \\ &= A^{-1} + A^{-1}B(C^{-1} + DA^{-1}B)^{-1}DA^{-1} \end{aligned} \quad (1.8)$$

1.1.3 Inverse of $AB + CD$

Using (1.5)

$$\begin{aligned} (AB + CD)^{-1} &= B^{-1}A^{-1} - (AB)^{-1}CD(CD + CD(AB)^{-1}CD)^{-1}CD(AB)^{-1} \\ &= B^{-1}A^{-1} - B^{-1}A^{-1}CD(CD(I + (AB)^{-1}CD))^{-1}CDB^{-1}A^{-1} \\ &= B^{-1}A^{-1} - B^{-1}A^{-1}CD(I + B^{-1}A^{-1}CD)^{-1}B^{-1}A^{-1} \end{aligned} \quad (1.9)$$

Chapter 2

Probability

2.1 Gaussian Distributions

2.1.1 Conditional Multivariate Gaussian Distribution

The PDF of a multivariate Gaussian vector is given by

$$P(\mathbf{x}) = \frac{1}{\sqrt{2\pi|\Sigma|}} e^{(\mathbf{x}-\boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x}-\boldsymbol{\mu})}. \quad (2.1)$$

Let

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}, \quad (2.2)$$

and let \mathbf{x}_2 be given. We then wish to find $P(\mathbf{x}_1|\mathbf{x}_2)$, the conditional distribution of \mathbf{x}_1 given \mathbf{x}_2 . To do this we need to find the block form of Σ^{-1} .

Let

$$\Sigma = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix}, \quad \Sigma^{-1} = \begin{bmatrix} \tilde{A} & \tilde{B} \\ \tilde{B}^T & \tilde{C} \end{bmatrix} \quad (2.3)$$

. Using $\Sigma \Sigma^{-1} = I$ we then end up with the following four equations:

$$A\tilde{A} + B\tilde{B}^T = I, \quad (2.4)$$

$$A\tilde{B} + B\tilde{C} = 0, \quad (2.5)$$

$$B^T \tilde{A} + C\tilde{B}^T = 0, \quad (2.6)$$

$$B^T \tilde{B} + C\tilde{C} = I. \quad (2.7)$$

From (2.5) and (2.6) we obtain

$$\tilde{B} = -A^{-1}B\tilde{C}, \quad \tilde{B}^T = -C^{-1}B^T \tilde{A} \quad (2.8)$$

Then inserting into (2.4) and (2.7) we get

$$(A - BC^{-1}B^T)\tilde{A} = I \Rightarrow \tilde{A} = (A - BC^{-1}B^T)^{-1} \quad (2.9)$$

$$(C - B^T A^{-1} B) \tilde{C} = I \Rightarrow \tilde{C} = (C - B^T A^{-1} B)^{-1} \quad (2.10)$$

Using (1.5) we then have

$$\begin{aligned} \tilde{A} &= A^{-1} - A^{-1} B (C + (-B^T) A^{-1} B)^{-1} (-B^T) A^{-1} \\ &= A^{-1} + A^{-1} B (C - B^T A^{-1} B)^{-1} B^T A^{-1} \end{aligned} \quad (2.11)$$

$$\begin{aligned} \tilde{C} &= C^{-1} - C^{-1} (-B^T) (A + B C^{-1} (-B^T))^{-1} B C^{-1} \\ &= C^{-1} + C^{-1} B^T (A - B C^{-1} B^T)^{-1} B C^{-1} \end{aligned} \quad (2.12)$$

Using the block form Σ^{-1} ,

$$\begin{aligned} (\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) &= (\mathbf{x}_1 - \boldsymbol{\mu}_1)^T (A - B C^{-1} B^T)^{-1} (\mathbf{x}_1 - \boldsymbol{\mu}_1) \\ &\quad - 2(\mathbf{x}_1 - \boldsymbol{\mu}_1)^T (A - B C^{-1} B^T)^{-1} B C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2) \\ &\quad + (\mathbf{x}_2 - \boldsymbol{\mu}_2)^T (C^{-1} + C^{-1} B^T (A - B C^{-1} B^T)^{-1} B C^{-1}) (\mathbf{x}_2 - \boldsymbol{\mu}_2). \end{aligned} \quad (2.13)$$

Letting $(A - B C^{-1} B^T) = H$ and $B C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2) = \mathbf{b}$ we then have

$$\begin{aligned} (\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) &= (\mathbf{x}_2 - \boldsymbol{\mu}_2)^T C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2) \\ &\quad + (\mathbf{x}_1 - \boldsymbol{\mu}_1 - \mathbf{b})^T H^{-1} (\mathbf{x}_1 - \boldsymbol{\mu}_1 - \mathbf{b}). \end{aligned} \quad (2.14)$$

Using (2.14) we can write the joint density of \mathbf{x}_1 and \mathbf{x}_2 as

$$P(\mathbf{x}_1, \mathbf{x}_2) = \frac{1}{D} e^{(\mathbf{x}_2 - \boldsymbol{\mu}_2)^T C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2) + (\mathbf{x}_1 - \boldsymbol{\mu}_1 - \mathbf{b})^T H^{-1} (\mathbf{x}_1 - \boldsymbol{\mu}_1 - \mathbf{b})}. \quad (2.15)$$

From which it follows that

$$P(\mathbf{x}_2) = \int P(\mathbf{x}_1, \mathbf{x}_2) d\mathbf{x}_1 = \frac{M}{D} e^{(\mathbf{x}_2 - \boldsymbol{\mu}_2)^T C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2)} \quad (2.16)$$

Using Bayes' theorem, the conditional density of \mathbf{x}_1 , given \mathbf{x}_2 , is then

$$P(\mathbf{x}_1 | \mathbf{x}_2) = \frac{P(\mathbf{x}_1, \mathbf{x}_2)}{P(\mathbf{x}_2)} = \frac{1}{M} e^{(\mathbf{x}_1 - \boldsymbol{\mu}_1 - \mathbf{b})^T H^{-1} (\mathbf{x}_1 - \boldsymbol{\mu}_1 - \mathbf{b})}. \quad (2.17)$$

So we see that the distribution of $\mathbf{x}_1 | \mathbf{x}_2$ is

$$(\mathbf{x}_1 | \mathbf{x}_2) \sim N(\boldsymbol{\mu}_1 + B C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2), (A - B C^{-1} B^T)) \quad (2.18)$$

Note that since Σ is positive definite, then C and C^{-1} are positive definite. Therefore $A - B C^{-1} B$ is smaller than A in some sense and $\mathbf{x}_1 | \mathbf{x}_2$ will have smaller variance depending on the correlation matrix B . Additionally the maximum likelihood estimate for $\mathbf{x}_1 | \mathbf{x}_2$ is simply $\boldsymbol{\mu}_1 + B C^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2)$, the conditional mean.

Bibliography