



Inversion Homework #1

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October 4, 2020

Appendix A

Exercise 4

Let

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 2 & 1 & 3 \\ 4 & 6 & 7 & 11 \end{bmatrix} \quad (1)$$

Find bases for $\mathcal{N}(\mathbf{A})$, $\mathcal{R}(\mathbf{A})$, $\mathcal{N}(\mathbf{A}^T)$, and $\mathcal{R}(\mathbf{A}^T)$. What are the dimensions of the four subspaces?

Solution:

To find $\mathcal{N}(\mathbf{A})$, we solve the system of equations $\mathbf{A}\mathbf{x} = \mathbf{0}$,

$$\mathbf{A}\mathbf{x} = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 2 & 1 & 3 \\ 4 & 6 & 7 & 11 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad (2)$$

Put the system of equations into an augmented matrix,

$$\left[\begin{array}{cccc|c} 1 & 2 & 3 & 4 & 0 \\ 2 & 2 & 1 & 3 & 0 \\ 4 & 6 & 7 & 11 & 0 \end{array} \right] \quad (3)$$

and then find the reduced row echelon form (**RREF**),

$$\left[\begin{array}{cccc|c} 1 & 0 & -2 & -1 & 0 \\ 0 & 1 & \frac{5}{2} & \frac{5}{2} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{array} \right] \quad (4)$$

We can find that

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 2x_3 + x_4 \\ -\frac{5}{2}x_3 - \frac{5}{2}x_4 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 2 \\ -\frac{5}{2} \\ 1 \\ 0 \end{bmatrix} x_3 + \begin{bmatrix} 1 \\ -\frac{5}{2} \\ 0 \\ 1 \end{bmatrix} x_4 \quad (5)$$

So,

$$\mathcal{N}(\mathbf{A}) = \text{space} \left(\left(\begin{bmatrix} 2 \\ -\frac{5}{2} \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ -\frac{5}{2} \\ 0 \\ 1 \end{bmatrix} \right) \right), \quad (6)$$

and the dimension of $\mathcal{N}(\mathbf{A})$ is **2**.

To find $\mathcal{R}(\mathbf{A})$, the equations becomes $\mathbf{A}\mathbf{x} = \mathbf{b}$,

$$\mathbf{A}\mathbf{x} = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 2 & 1 & 3 \\ 4 & 6 & 7 & 11 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = \mathbf{b} \quad (7)$$

Because the **RREF** of \mathbf{A} is

$$\left[\begin{array}{cccc} 1 & 0 & -2 & -1 \\ 0 & 1 & \frac{5}{2} & \frac{5}{2} \\ 0 & 0 & 0 & 0 \end{array} \right] \quad (8)$$

We can write \mathbf{b} as a linear combination of the first two columns of \mathbf{A} :

$$\mathbf{b} = x_1 \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} + x_2 \begin{bmatrix} 2 \\ 2 \\ 6 \end{bmatrix}, \quad (9)$$

i.e.

$$\mathcal{R}(\mathbf{A}) = \text{space} \left(\begin{pmatrix} \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ 6 \end{bmatrix} \end{pmatrix} \right), \quad (10)$$

and the dimension of $\mathcal{R}(\mathbf{A})$ is $\mathbf{2}$.

To find $\mathcal{N}(\mathbf{A}^T)$ and $\mathcal{R}(\mathbf{A}^T)$, we first calculate the **RREF** of \mathbf{A}^T .

$$\mathbf{A}^T = \begin{bmatrix} 1 & 2 & 4 \\ 2 & 2 & 6 \\ 3 & 1 & 7 \\ 4 & 3 & 11 \end{bmatrix}, \quad (11)$$

$$\text{RREF of } \mathbf{A} \text{ is } \begin{bmatrix} 1 & 0 & 2 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}. \quad (12)$$

So,

$$\mathbf{x} = \begin{bmatrix} -2 \\ -1 \\ 0 \end{bmatrix} x_3, \quad (13)$$

i.e.

$$\begin{aligned} \mathcal{N}(\mathbf{A}^T) &= \text{space} \left(\begin{pmatrix} \begin{bmatrix} -2 \\ -1 \\ 0 \end{bmatrix} \end{pmatrix} \right), \\ \mathcal{R}(\mathbf{A}^T) &= \text{space} \left(\begin{pmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ 1 \\ 3 \end{bmatrix} \end{pmatrix} \right). \end{aligned} \quad (14)$$

And the dimension of $\mathcal{N}(\mathbf{A}^T)$ is $\mathbf{1}$, the dimension of $\mathcal{R}(\mathbf{A}^T)$ is $\mathbf{2}$.

Exercise 10

Show that if $\mathbf{x} \perp \mathbf{y}$, then

$$\|\mathbf{x} + \mathbf{y}\|_2^2 = \|\mathbf{x}\|_2^2 + \|\mathbf{y}\|_2^2. \quad (15)$$

Solution:

$$\|\mathbf{x} + \mathbf{y}\|_2^2 = \|\mathbf{x}\|_2^2 + \|\mathbf{y}\|_2^2 + 2\|\mathbf{x}\|_2\|\mathbf{y}\|_2 \cos \theta \quad (16)$$

Because $\mathbf{x} \perp \mathbf{y}$, so $\cos \theta = 0$, i.e.

$$\|\mathbf{x} + \mathbf{y}\|_2^2 = \|\mathbf{x}\|_2^2 + \|\mathbf{y}\|_2^2 \quad (17)$$

We can consider another solution,

$$\|\mathbf{x} + \mathbf{y}\|_2^2 = \sum_{i=1}^n (x_i + y_i)^2 = \sum_{i=1}^n x_i^2 + \sum_{i=1}^n y_i^2 + 2 \sum_{i=1}^n x_i^2 y_i^2 = \|\mathbf{x}\|_2^2 + \|\mathbf{y}\|_2^2 \quad (18)$$

because $\mathbf{x}^T \mathbf{y} = \sum_{i=1}^n x_i^2 y_i^2 = 0$ when $\mathbf{x} \perp \mathbf{y}$.

Exercise 11

In this exercise, we will derive the formula (A.88) for the 1-norm of a matrix. Begin with the optimization problem

$$\|\mathbf{A}\|_1 = \max_{\|\mathbf{x}\|_1=1} \|\mathbf{Ax}\|_1. \quad (19)$$

(a) Show that if $\|\mathbf{x}\|_1 = 1$, then

$$\|\mathbf{Ax}\|_1 \leq \max_j \sum_{i=1}^m |A_{i,j}|. \quad (20)$$

Solution:

We define that \mathbf{A} is a $m \times n$ matrix and \mathbf{x} is a $m \times 1$ vector. Then we can write that:

$$\begin{aligned} \|\mathbf{Ax}\|_1 &= \sum_{i=1}^m |\mathbf{Ax}|_i = \sum_{i=1}^m \left| \sum_{j=1}^n A_{i,j} x_j \right| \\ &\leq \sum_{i=1}^m \sum_{j=1}^n |A_{i,j}| |x_j| = \sum_{j=1}^n \left(\sum_{i=1}^m |A_{i,j}| \right) |x_j| \\ &\leq \left(\max_j \sum_{i=1}^m |A_{i,j}| \right) \sum_{j=1}^n |x_j| = \max_j \sum_{i=1}^m |A_{i,j}|, \end{aligned} \quad (21)$$

i.e.

$$\|\mathbf{Ax}\|_1 \leq \max_j \sum_{i=1}^m |A_{i,j}|. \quad (22)$$

Note that $\|\mathbf{x}\|_1 = \sum_{j=1}^n |x_j| = 1$.

(b) Find a vector \mathbf{x} such that $\|\mathbf{x}\|_1 = 1$, and

$$\|\mathbf{Ax}\|_1 = \max_j \sum_{i=1}^m |A_{i,j}|. \quad (23)$$

Solution:

To find such \mathbf{x} , we assume that the maximum is arrived in the k^{th} column, i.e.

$$\max_j \sum_{i=1}^m |A_{i,j}| = \sum_{i=1}^m |A_{i,k}|. \quad (24)$$

So, we can write that:

$$\begin{aligned} \|\mathbf{Ax}\|_1 &= \sum_{i=1}^m \left| \sum_{j=1}^n A_{i,j} x_j \right| = \sum_{i=1}^m |A_{i,k}|, \\ \Rightarrow \left| \sum_{j=1}^n A_{i,j} x_j \right| &= |A_{i,k}|, \\ \Rightarrow x_j &= \begin{cases} 0 & j \neq k \\ 1 & j = k \end{cases}. \end{aligned} \quad (25)$$

Thus, the vector $\mathbf{x} = (0, 0, \dots, 1, 0, \dots, 0)^T$, i.e. the k^{th} component of the vector is $\mathbf{1}$, otherwise is $\mathbf{0}$.

(c) Conclude that

$$\|\mathbf{A}\|_1 = \max_{\|\mathbf{x}\|_1=1} \|\mathbf{Ax}\|_1 = \max_j \sum_{i=1}^m |A_{i,j}|. \quad (26)$$

Solution:

$$\begin{aligned} \|\mathbf{A}\|_1 &= \|\mathbf{A}\|_1 \|\mathbf{x}\|_1 \geq \|\mathbf{Ax}\|_1, \\ \Rightarrow \|\mathbf{A}\|_1 &= \max_{\|\mathbf{x}\|_1=1} \|\mathbf{Ax}\|_1 = \max_j \sum_{i=1}^m |A_{i,j}|. \end{aligned} \quad (27)$$

Appendix B

Exercise 6

Suppose that $\mathbf{x} = (X_1, X_2)^T$ is a vector composed of two random variables with a multivariate normal distribution with expected value μ and covariance matrix \mathbf{C} , and that \mathbf{A} is a 2 by 2 matrix. Use properties of expected value and covariance to show that $\mathbf{y} = \mathbf{A}\mathbf{x}$ has expected value $\mathbf{A}\mu$ and covariance \mathbf{ACA}^T

Solution:

Accroding to the question, we know that the JDF of this multivariate normal distribution (the dimension is 2) is:

$$f(\mathbf{x}) = |2\pi\mathbf{C}|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mu)^T \mathbf{C}^{-1}(\mathbf{x} - \mu)\right), \quad (28)$$

and we can simply define $D = |2\pi\mathbf{C}|^{-\frac{1}{2}}$ as D is a constant. Thus,

$$f(\mathbf{x}) = D \exp\left(-\frac{1}{2}(\mathbf{x} - \mu)^T \mathbf{C}^{-1}(\mathbf{x} - \mu)\right). \quad (29)$$

So,

$$E[\mathbf{y}] = E[\mathbf{A}\mathbf{x}] = \int_{-\infty}^{\infty} \mathbf{A}\mathbf{x}f(\mathbf{x}) d\mathbf{x} = \mathbf{A} \int_{-\infty}^{\infty} \mathbf{x}f(\mathbf{x}) d\mathbf{x} = \mathbf{A}E[\mathbf{x}] = \mathbf{A}\mu. \quad (30)$$

To covariance matrix of \mathbf{y} , we consider that:

$$\mathbf{y} = \mathbf{A}\mathbf{x}, \implies \mathbf{x} = \mathbf{A}^{-1}\mathbf{y}, \quad (31)$$

and then, we replace \mathbf{x} with $\mathbf{A}^{-1}\mathbf{y}$ in $f(\mathbf{x})$:

$$\begin{aligned} f &= D \exp\left(-\frac{1}{2}(\mathbf{x} - \mu)^T \mathbf{C}^{-1}(\mathbf{x} - \mu)\right) \\ &= D \exp\left(-\frac{1}{2}(\mathbf{A}^{-1}\mathbf{y} - \mu)^T \mathbf{C}^{-1}(\mathbf{A}^{-1}\mathbf{y} - \mu)\right) \\ &= D \exp\left(-\frac{1}{2}(\mathbf{A}^{-1}\mathbf{y} - \mathbf{A}^{-1}\mathbf{A}\mu)^T \mathbf{C}^{-1}(\mathbf{A}^{-1}\mathbf{y} - \mathbf{A}^{-1}\mathbf{A}\mu)\right). \\ &= D \exp\left(-\frac{1}{2}(\mathbf{y} - \mathbf{A}\mu)^T (\mathbf{A}^T)^{-1} \mathbf{C}^{-1} \mathbf{A}^{-1}(\mathbf{y} - \mathbf{A}\mu)\right) \\ &= D \exp\left(-\frac{1}{2}(\mathbf{y} - \mathbf{A}\mu)^T (\mathbf{ACA}^T)^{-1}(\mathbf{y} - \mathbf{A}\mu)\right) \end{aligned} \quad (32)$$

It's obvious that the covariance matrix of \mathbf{y} is \mathbf{ACA}^T

Exercise 9

Using MATLAB, repeat the following experiment 1000 times. Generate five exponentially distributed random numbers from the exponential probability density function (B.10) with means $\mu = 1/\lambda = 10$. You may find the library function **exp rand** to be useful here. Use (B.74) to calculate a 95% confidence interval for the 1000 mean determinations. How many times out of the 1000 experiments did the 95% confidence interval cover the expected value of 10? What happens if you instead generate 50 exponentially distributed random numbers at time? Discuss your results.

Solution:

Appendix C**Exercise 1**

Let

$$f(\mathbf{x}) = x_1^2 x_2^2 - 2x_1 x_2^2 + x_2^2 - 3x_1^2 x_2 + 12x_1 x_2 - 12x_2 + 6. \quad (33)$$

Find the gradient, $\nabla f(\mathbf{x})$, and Hessian, $\mathbf{H}(f(\mathbf{x}))$. What are the critical points of f ? Which of these are minima and maxima of f ?

Solution:

$$\begin{aligned} \nabla f(\mathbf{x}) &= \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{bmatrix} \\ &= \begin{bmatrix} 2x_1 x_2^2 - 2x_2^2 - 6x_1 x_2 + 12x_2 \\ 2x_1^2 x_2 - 4x_1 x_2 + 2x_2 - 3x_1^2 + 12x_1 - 12 \end{bmatrix}. \end{aligned} \quad (34)$$

And

$$\begin{aligned} \mathbf{H}(f(\mathbf{x})) &= \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix} \\ &= \begin{bmatrix} 2x_2^2 - 6x_2 & 4x_1 x_2 - 4x_2 - 6x_1 + 12 \\ 4x_1 x_2 - 4x_2 - 6x_1 + 12 & 2x_1^2 - 4x_1 + 2 \end{bmatrix}. \end{aligned} \quad (35)$$

A point \mathbf{x}^* is a critical point when $\nabla f(\mathbf{x}^*) = \mathbf{0}$,

$$\nabla f(\mathbf{x}) = \begin{bmatrix} 2x_1 x_2^2 - 2x_2^2 - 6x_1 x_2 + 12x_2 \\ 2x_1^2 x_2 - 4x_1 x_2 + 2x_2 - 3x_1^2 + 12x_1 - 12 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \quad (36)$$

Solving the function, we can get **2** critical points:

$$\mathbf{x}^* = (x_1, x_2) : (0, 6), (2, 0). \quad (37)$$

$(0, 6)$ is minima of f , and f doesn't exist maxima or its maxima is a infinite value.

Exercise 2

Find a Taylor's series approximation for $f(\mathbf{x} + \Delta\mathbf{x})$, where

$$f(\mathbf{x}) = e^{-(x_1 + x_2)^2} \quad (38)$$

is near the point

$$\mathbf{x} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}. \quad (39)$$

Solution:

$$\begin{aligned} \nabla f(\mathbf{x}) &= \begin{bmatrix} -2(x_1 + x_2)e^{-(x_1+x_2)^2} \\ -2(x_1 + x_2)e^{-(x_1+x_2)^2} \end{bmatrix}, \\ \mathbf{H}(f(\mathbf{x})) &= \begin{bmatrix} -2(1 - 2(x_1 + x_2)^2)e^{-(x_1+x_2)^2} & -2(1 - 2(x_1 + x_2)^2)e^{-(x_1+x_2)^2} \\ -2(1 - 2(x_1 + x_2)^2)e^{-(x_1+x_2)^2} & -2(1 - 2(x_1 + x_2)^2)e^{-(x_1+x_2)^2} \end{bmatrix}, \\ f(\mathbf{x} + \Delta\mathbf{x}) &= f(\mathbf{x}) + \nabla f(\mathbf{x})^T \Delta\mathbf{x} + \frac{1}{2} \Delta\mathbf{x}^T \mathbf{H}(f(\mathbf{x})) \Delta\mathbf{x} + o^n. \end{aligned} \quad (40)$$

Because $\mathbf{x} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$, so:

$$f(\mathbf{x} + \Delta\mathbf{x}) = e^{-25} + [-10e^{-25}, -10e^{-25}] \Delta\mathbf{x} + \frac{1}{2} \Delta\mathbf{x}^T \begin{bmatrix} 98e^{-25} & 98e^{-25} \\ 98e^{-25} & 98e^{-25} \end{bmatrix} \Delta\mathbf{x} + o^n \quad (41)$$