

Assignment 3

MATH 7502 - Semester 2, 2018

Mathematics for Data Science 2

Created by Zhihao Qiao, Maria Kleshnina and Yoni Nazarathy

Question 1

Consider the following recursion,

$$x_{t+1} = A_1 x_t + A_2 x_{t-1}, \quad t = 2, 3, \dots$$

where x_t is n -vector and A_1 and A_2 are $n \times n$ matrices. Define $z_t = (x_t, x_{t-1})$.

Show that z_t satisfies the linear dynamical system equation $z_{t+1} = Bz_t$, for $t = 2, 3, \dots$, where B is a $(2n) \times (2n)$ matrix.

Solution

z_t is a stack vector with size $(2n)$, which is

$$z_t = \begin{bmatrix} x_t \\ x_{t-1} \end{bmatrix}$$

Now Let

$$B = \begin{bmatrix} A_1 & 0_n \\ 0_n & A_2 \end{bmatrix}$$

0_n denotes that an $n \times n$ matrix with all zeros.

Therefore, we have

$$Bz_t = \begin{bmatrix} A_1 & 0_n \\ 0_n & A_2 \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \end{bmatrix} = A_1 x_t + A_2 x_{t-1}$$

Question 2

Consider the Fibonacci sequence y_0, y_1, y_2, \dots with $y_0 = 0, y_1 = 1, y_2 = 1, y_3 = 2, \dots$, and for $t = 2, 3, \dots, y_t$ is the sum of the previous two terms y_{t-1} and y_{t-2} .

(a) Express the Fibonacci sequence as a time-invariant dynamical system with state $x_t = (y_t, y_{t-1})$ and output y_t for $t = 1, 2, 3, \dots$ as

$$x_{t+1} = Ax_t$$

(b) For the matrix, A , compute the eigenvalues and describe the Fibonacci sequence in terms of eigenvalues and eigenvectors. How does the golden ratio play a role?

Solution

(a) we know that $y_{t+1} = y_t + y_{t-1}$

therefore

$$\begin{bmatrix} y_t \\ y_{t-1} \end{bmatrix} = \begin{bmatrix} y_{t-1} + y_{t-2} \\ y_{t-1} \end{bmatrix} = A \begin{bmatrix} y_{t-1} \\ y_{t-2} \end{bmatrix}$$

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

(b) The eigenvalues of A are $(A - \lambda I) = 0$ we have the quadratic

$$\lambda^2 - \lambda - 1 = 0$$

Therefore, the eigenvalues are $\lambda_1 = \frac{1+\sqrt{5}}{2}$ and $\lambda_2 = \frac{1-\sqrt{5}}{2}$, λ_1 is the golden ratio.

The eigenvectors of λ_1 is

$$v_1 = \begin{bmatrix} \frac{1+\sqrt{5}}{2} \\ 1 \end{bmatrix}$$

and the eigenvectors of λ_2 is

$$v_1 = \begin{bmatrix} \frac{1-\sqrt{5}}{2} \\ 1 \end{bmatrix}$$

Question 3

In the special case $n = 1$, the general least square problem reduces to finding a scalar x that minimizes $\|ax - b\|^2$, where a and b are m -vectors. Assuming a and b are nonzero, show that $\|a\hat{x} - b\|^2 = \|b\|^2 \sin^2(\theta)$, where $\theta = \angle(a, b)$.

Solution

correspond least square problem of this one is

$$f(x) = (a_1x - b_1)^2 + (a_2x - b_2)^2 + \dots + (a_mx - b_m)^2$$

set the derivative of $f(x)$ to be zero, which is

$$f'(x) = 2a_1(a_1x - b_1) + 2a_2(a_2x - b_2) + \dots + 2a_m(a_mx - b_m) = 0$$

$$2[(a_1)^2 + (a_2)^2 + \dots + (a_m)^2]x - 2(a_1b_1 + a_2b_2 + \dots + a_mb_m) = 0$$

$$2x(a^T a) - 2a^T b = 0$$

$$\hat{x} = \frac{a^T b}{a^T a}$$

$$\begin{aligned} \left\| a \left(\frac{a^T b}{a^T a} \right) - b \right\|^2 &= \left\| \frac{a^T b}{a^T a} \right\|^2 \|a\|^2 + \|b\|^2 - 2 \left\| \frac{a^T b}{a^T a} \right\| \|a^T b\| \\ &= \frac{\|a^T b\|^2}{\|a\|^2} + \|b\|^2 - 2 \frac{\|a^T b\|^2}{\|a\|^2} \\ &= \|b\|^2 \left(1 - \frac{\|a^T b\|^2}{\|a\|^2 \|b\|^2} \right) \\ &= \|b\|^2 (1 - \cos^2(\theta)) \\ &= \|b\|^2 \sin^2(\theta). \end{aligned}$$

Question 4

Consider a time-invariant linear dynamical system with offset

$$x_{t+1} = Ax_t + c$$

where x_t is the state n -vector. We say that a vector z is an equilibrium point of the linear dynamical system if $x_1 = z$ implies $x_2 = z, x_3 = z, \dots$

(a) Find a matrix F and a vector g for which the set of linear equations $Fz = g$ characterizes equilibrium points. (This means: If z is an equilibrium point, then $Fz = g$; conversely if $Fz = g$, then z is an equilibrium point.)

Express F and g in terms of A, c any standard matrices or vectors and matrix and vector operations.

Solution

if z is an equilibrium point, we have

$$\begin{aligned} z &= Az + c \\ A(z) &= A(Az) + A(c) \\ A(z) - A(Az) &= A(c) \\ A(I - A)z &= A(c) \end{aligned}$$

Therefore $F = A(I - A)$ and $g = A(c)$.

Now if

$$\begin{aligned} Fz &= g \\ A(I - A)z &= A(c) \\ (I - A)z &= c \\ z - Az &= c \\ z &= Az + c \end{aligned}$$

Question 5

Suppose that $m \times n$ matrix Q has orthonormal columns and b is an m -vector. Show that $\hat{x} = Q^T b$ is the vector that minimizes $\|Qx - b\|^2$.

Comment on the complexity of finding \hat{x} given Q and b in this case. Compare the complexity with it is a general least squares problem and Q is a coefficient matrix.

Solution

if $\hat{x} = Q^T b$, and if Q has orthonormal columns, then

$$\begin{aligned} QQ^T &= I \\ \|Q\hat{x} - b\|^2 &= \|QQ^T b - b\|^2 \\ &= \|b - b\|^2 \\ &= 0 \end{aligned}$$

Question 6

Suppose $m \times n$ matrix A has linearly independent columns, and b is a m -vector. Let $\hat{x} = A^\dagger b$ denote the least squares approximate solution of $Ax = b$.

(a) Show that for any n -vector x , $(Ax)^T b = (Ax)^T (A\hat{x})$. Hint: Use $(Ax)^T b = x^T (A^T b)$, and $(A^T A)\hat{x} = A^T b$.

(b) Show that when $A\hat{x}$ and b are both nonzero, we have

$$\frac{(A\hat{x})^T b}{\|A\hat{x}\| \|b\|} = \frac{\|A\hat{x}\|}{\|b\|}$$

(c) The choice of $x = \hat{x}$ minimizes the distance between Ax and b . Show that $x = \hat{x}$ also minimizes the angle between Ax and b .

Solution

(a) we have

$$\begin{aligned}(Ax)^T b &= x^T (A^T b) \\ &= x^T (A^T A) \hat{x} \\ &= (Ax)^T (A\hat{x})\end{aligned}$$

(b) using (a) , we have

$$(A\hat{x})^T b = (A\hat{x})^T (A\hat{x})$$

Therefore

$$\begin{aligned}\frac{(A\hat{x})^T b}{\|A\hat{x}\| \|b\|} &= \frac{(A\hat{x})^T (A\hat{x})}{\|A\hat{x}\| \|b\|} \\ &= \frac{\|A\hat{x}\|^2}{\|A\hat{x}\| \|b\|} \\ &= \frac{\|A\hat{x}\|}{\|b\|}\end{aligned}$$

(c) By definition, the angle between Ax and b is defined as

$$\theta = \cos^{-1} \left(\frac{(Ax)^T b}{\|Ax\| \|b\|} \right) = \cos^{-1} \left(\frac{\|Ax\|}{\|b\|} \right)$$

from (b), since $x = \hat{x}$ is the least square approximation, therefore $\|A\hat{x}\|$ is minimized for all x , therefore, θ is also minimized in this expression.

Question 7

Suppose A is an $m \times n$ matrix with linearly independent columns and QR factorization $A = QR$, and b is the m -vector. The vector $A\hat{x}$ is the linear combination of the columns of A that is closet to the vector b , i.e., it is the projection of b onto the set of linear combinations of the columns of A .

(a) Show that $A\hat{x} = QQ^T b$.

(b) Show that $\|A\hat{x} - b\|^2 = \|b\|^2 - \|Q^T b\|^2$.

Solution

(a) If \hat{x} is a solution of the least square problem, then

$$\begin{aligned}\hat{x} &= (A^T A)^{-1} A^T b \\ \hat{x} &= A^{-1} (A^T)^{-1} A^T b \\ A\hat{x} &= ((QR)^T)^{-1} (QR)^T b \\ &= (R^T Q^T)^{-1} (R^T Q^T) b \\ &= (Q^T)^{-1} (R^T)^{-1} R^T Q^T b \\ &= (Q^{-1})^{-1} Q^T b \\ &= QQ^T b\end{aligned}$$

(b)

First consider the norm

$$\|QQ^T b\|^2 = (QQ^T b, QQ^T b) = (Q^T QQ^T b, Q^T b) = (Q^T b, Q^T b) = \|Q^T b\|^2$$

and the norm

$$\begin{aligned}(QQ^T b, b) &= (Q^T QQ^T b, Q^T b) = (Q^T b, Q^T b) = \|Q^T b\|^2 \\ \|A\hat{x} - b\|^2 &= (QQ^T b, QQ^T b) - 2(Q^T QQ^T b, Q^T b) + \|b\|^2 \\ &= \|Q^T b\|^2 - 2\|Q^T b\|^2 + \|b\|^2 \\ &= \|b\|^2 - \|Q^T b\|^2\end{aligned}$$

Question 8

A generalization of the least squares problem adds an affine function to the least squares objective

$$\text{minimize} \quad \|Ax - b\|^2 + c^T x + d$$

where x is an n -vector as a variable to be chosen, and the data are the $m \times n$ matrix A , the m -vector b , the n -vector c , and the number d . The columns of A are linearly independent.

Show that that objective of the problem above can be expressed in the form

$$\|Ax - b\|^2 + c^T x + d = \|Ax - b + f\|^2 + g$$

for some m -vector f and some constant g . It follows that we can solve the generalized least squares problem by minimizing $\|Ax - (b - f)\|$, an ordinary least squares problem with solution $\hat{x} = A^\dagger(b - f)$.

Hint: Express the norm squared term on the right-hand side as $\|(Ax - b) + f\|^2$ and expand it.

Solution

If we expand the term

$$\begin{aligned}\|(Ax - b) + f\|^2 &= \|Ax - b\|^2 + 2f^T(Ax - b) + \|f\|^2 \\ &= \|Ax - b\|^2 + 2f^T Ax - 2f^T b + \|f\|^2 \\ &= \|Ax - b\|^2 + 2(A^T f)^T x + (\|f\|^2 - 2f^T b)\end{aligned}$$

Therefore, $c = A^T f$, and $d = \|f\|^2 - 2f^T b$

