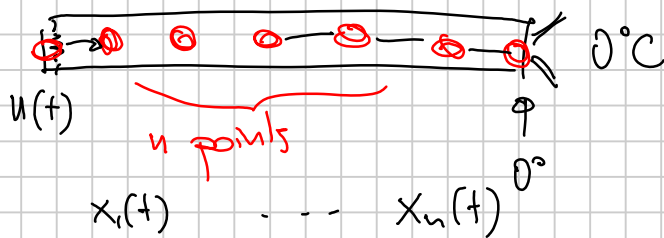


Matrix equations in control theory

Note Title

2025-05-26

Heating a corridor:



$$\dot{x}_k(t) = \alpha (x_{k+1}(t) - x_k(t)) + \alpha (x_{k-1}(t) - x_k(t))$$

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \alpha \begin{bmatrix} -2 & 1 & & 0 \\ & 1 & \ddots & \\ & & \ddots & 1 \\ 0 & & & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} u(t)$$

$$\frac{d}{dt} x(t) = A x(t) + b u(t)$$

linear control system

Goal: reach a comfortable $x(t)$ by setting $u(t)$ appropriately

$$A \in \mathbb{C}^{n \times n}, \quad x: [0, \infty) \rightarrow \mathbb{C}^n, \quad u(t): [0, \infty) \rightarrow \mathbb{C}$$

$$b \in \mathbb{C}^n$$

Stein equation (discrete-time Lyapunov equation)

$$(S) \quad X - A^* X A = Q$$

$$A \in \mathbb{C}^{n \times n},$$

$$Q \in \mathbb{C}^{n \times n}$$

$$X \in \mathbb{C}^{n \times n}$$

$$Q \succcurlyeq 0$$

(pos. semidefinite)

Discrete-time dynamical system

$$\begin{cases} x_{k+1} = A x_k \\ x_0 \text{ given} \end{cases}$$

$$x_k = A^k x_0 \quad \text{if } \rho(A) < 1,$$

then $\lim_{k \rightarrow \infty} x_k = 0$ for all x_0

Lemma: Let $Q > 0$, ^{be given} and ^{suppose} the equation (5) has solution $X > 0$, then $\rho(A) < 1$

Proof: $Av = v\lambda$ $v^* Q v = v^* X v - v^* A^* X A v$
 $= v^* X v - \bar{\lambda} v^* X v \lambda$
 $= (1 - \bar{\lambda} \lambda) v^* X v$

$$1 - \bar{\lambda} \lambda = \frac{v^* Q v}{v^* X v} > 0 \Rightarrow |\lambda| < 1 \text{ for all } \lambda. \quad \square$$

- ① Check $Q > 0$
- ② Solve equation
- ③ If $X > 0$, then $\rho(A) < 1$

Lemma: Suppose $\rho(A) < 1$, then the solution of (5) is

$$X = \sum_{k=0}^{\infty} (A^*)^k Q A^k = Q + A^* Q A + (A^*)^2 Q A^2 + \dots$$

Proof:

$$\underline{X} = Q + A^* \left(\sum_{k=0}^{\infty} (A^*)^k Q A^k \right) A = \underline{Q + A^* X A}$$

$$\|A^k\| \sim \rho(A)^k$$

From the formula for X , we see $X > 0$ if $Q > 0$.

Lyapunov's argument: consider the "energy function"

$$V(x) = x^* X x.$$

$$\begin{cases} x_{k+1} = A x_k \\ x_0 \text{ given} \end{cases}$$

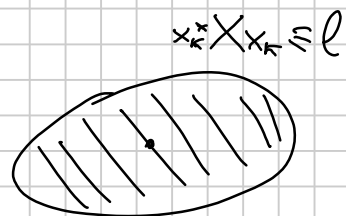
$$\begin{aligned} V(x_k) - V(x_{k+1}) &= x_k^* X x_k - x_{k+1}^* X x_{k+1} \\ &= x_k^* X x_k - x_k^* A^* X A x_k \end{aligned}$$

$$= x_k^* Q x_k \geq 0$$

$V(x_k)$ decreasing $\Rightarrow x_k$ bounded

A slightly stronger argument:

$$x_k^* Q x_k \geq \lambda_{\min}(Q) \|x_k\|^2$$



If $\|x_k\| \geq \epsilon$ for all k , contradiction

Numerical methods for $X - A^* X A = Q$

#1: vectorization.

$$\begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix} \rightarrow \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{bmatrix}$$

Given X , $\text{vec } X$ is the vector obtained by stacking its columns.

$$\mathbb{C}^{n \times n} \rightarrow \mathbb{C}^{n^2}$$

The map $X \rightarrow B X A$

$$A, B, X \in \mathbb{C}^{n \times n}$$

is linear.

There must be a matrix such that

$$\boxed{\text{vec}(B X A) = M \text{vec}(X)}$$

←

$$M = A^T \otimes B = \begin{bmatrix} a_{11}B & a_{12}B & \dots & a_{1n}B \\ a_{21}B & & & \\ \vdots & & & \\ a_{n1}B & \dots & \dots & a_{nn}B \end{bmatrix}$$

block matrix

⚠ Truly a T , not a $*$ (or an H , $\dagger$).

$$(A^T \otimes B)(C^T \otimes D) = A^T C^T \otimes BD$$

With these tools, we can turn (S) into a vector problem:

$$X - A^* X A = Q \Leftrightarrow \text{vec}(X) - \text{vec}(A^* X A) = \text{vec}(Q)$$

$$\Leftrightarrow \text{vec}(X) - (A^T \otimes A^*) \text{vec}(X) = \text{vec}(Q)$$

$$= (\mathbb{I}_{n^2} - \overbrace{A^T \otimes A^*}^M) \text{vec } X = \text{vec } Q$$

$n^2 \times n^2$ linear system.

$$\boxed{} \mathbb{I} = \mathbb{I}$$

$$O(n^6)$$

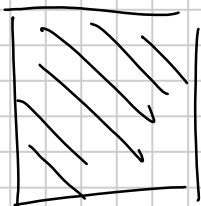
Let $M = A^T \otimes A^*$, let $A = U T U^*$ Schur factorization

U unitary, T upper triangular

$$T = \begin{bmatrix} \lambda_1 & * & * \\ & \ddots & * \\ 0 & & \lambda_n \end{bmatrix} \quad \text{diag}(T) = \Lambda(A)$$

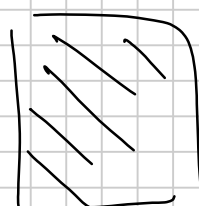
$$M = (U T U^*)^T \otimes (U T U^*)^* = \bar{U} T^T U^T \otimes U T^* U^*$$

$$= (\bar{U} \otimes U) \cdot (T^T \otimes T^*) \cdot (U^T \otimes U^*)$$



orthogonal





orthogonal*

This is a Schur-like factorization!

$$\Lambda(M) = \Lambda(\text{lower tr. matrix}) = \begin{pmatrix} \lambda_i & \bar{\lambda}_j & \\ & \ddots & \\ & & \lambda_n \end{pmatrix} \quad i, j = 1, \dots, n$$

where $(\lambda_1, \dots, \lambda_n) = \text{eig}(A)$

$$\text{Stem equation} \Leftrightarrow (I-M) \text{vec}(X) = \text{vec}(Q)$$

$\Lambda(M)$ given by expression above

If $\rho(A) < 1$, then $\rho(M) < 1$

$$(I-M)^{-1} = I + M + M^2 + \dots$$

$$\text{vec}(X) = (I + M + M^2 + \dots) \text{vec}(Q) = \text{vec}(Q) + M \text{vec}(Q) + M^2 \text{vec}(Q) + \dots$$

$$X = Q + A^* X A + (A^*)^2 X A^2 + \dots$$

$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \otimes \begin{bmatrix} \mu & 1 \\ 0 & \mu \end{bmatrix} = \begin{bmatrix} \lambda\mu & \lambda & \mu & 1 \\ & \lambda\mu & 0 & \mu \\ 0 & & \lambda\mu & \lambda \\ & & & \lambda\mu \end{bmatrix} - \lambda\mu I = \text{rank } 2$$

Controllability of dynamical systems

$$x_{k+1} = A x_k + b u_k$$

$$\Leftrightarrow \dot{x}(t) = A x(t) + b u(t)$$

We can alter the behavior of this system by adding a multiple of $b \in \mathbb{C}^n$ at each step

$$x_1 = A x_0 + b u_0$$

$$x_2 = A^2 x_0 + A b u_0 + b u_1$$

$$x_3 = A^3 x_0 + A^2 b u_0 + A b u_1 + b u_2$$

$$x_k = A^k x_0 + A^{k-1} b u_0 + A^{k-2} b u_1 + \dots + b u_{k-1}$$

If I choose u appropriately, I can reach every

possible x_k in the space

$$A^k x_0 + \underbrace{\text{span}(b, Ab, A^2b, \dots, A^{k-1}b)}_{= K_k(A, b) \quad \text{Krylov space}}$$

$$= \{p(A)b : p(z) \text{ polynomial of degree } < k\}$$

The vectors x_F then I can reach as final states starting from $x_0 = 0$ are those in

$$K(A, B) = \text{span}([b, Ab, A^2b, \dots, A^{n-1}b])$$

remark: if $A \in \mathbb{C}^{n \times n}$ matrix, then A^n is a linear combination of $I, A, A^2, \dots, A^{n-1}$ (Cayley-Hamilton theorem)

Def: a pair (A, b) (or a dynamical system $x_{k+1} = Ax_k + bu_k$) is called controllable if $K(A, B) = \mathbb{C}^n$

$\Rightarrow$ we can choose (u_k) to reach every possible vector x_F .

Note that there are indeed examples where the $A^i b$ are very linearly dependent, e.g.

$$\boxed{A = \begin{bmatrix} * & * \\ 0 & 1 \end{bmatrix} \quad b = \begin{bmatrix} 1 \\ 0 \end{bmatrix}}$$

$$x_{k+1} = Ax_k + bu_k$$

second entry constant!

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

$$A^k b = \begin{bmatrix} * \\ 0 \end{bmatrix}$$

$$K(A, b) = \text{span}([b, A^1b, A^2b, \dots])$$

$$= \text{span}(\begin{bmatrix} 1 \\ 0 \end{bmatrix})$$

Stein equations and controllability:

Consider the equation

$$X_{k+1} = AX_k \quad \begin{cases} X - AXA^* = G \\ X - A^*XA = Q \end{cases} \quad G = bb^* \quad (CS)$$

(CS) has solution

$$\begin{aligned} X &= G + AGA^* + A^2G(A^*)^2 + \dots \\ &= bb^* + (Ab)(Ab)^* + (A^2b)(A^2b)^* + \dots \\ &= [b \quad Ab \quad A^2b \quad \dots] \cdot [b \quad Ab \quad A^2b \quad \dots]^* \end{aligned}$$

$$X \succ 0 \Leftrightarrow [b \quad Ab \quad A^2b \quad \dots] \text{ has full row rank}$$

$$\Leftrightarrow \text{span}(b, Ab, A^2b, \dots) = \mathbb{C}^n$$

$$\Leftrightarrow (A, b) \text{ controllable.}$$

To check if I can reach every possible state x_F by setting (u_k) , it is sufficient to

① solve $X - AXA^* = bb^*$

② check if $X \succ 0$ or not.

$$\text{Im}[b \quad Ab \quad A^2b \quad \dots] = \text{Im}[b \quad Ab \quad A^2b \quad \dots \quad A^{n-1}b]$$

Suppose you want to reach x_F (given) starting from $x_0 = 0$. Among all possible sequences that get to x_F at time k , i.e. $x_k = x_F$, we want to find the one with smallest

$$|u_0|^2 + |u_1|^2 + |u_2|^2 + \dots + |u_{k-1}|^2$$

$$X_k = \cancel{A^k} X_0 + A^{k-1} b u_0 + \dots + A b u_{k-2} + b u_{k-1}$$

$$\begin{bmatrix} A^{k-1} b & A^{k-2} b & \dots & A b & b \end{bmatrix} \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{k-1} \end{bmatrix} = X_k$$

Smallest - norm solution : $\begin{bmatrix} u_0 \\ \vdots \\ u_{k-1} \end{bmatrix} = \begin{bmatrix} A^{k-1} b & \dots & A b & b \end{bmatrix}^+ X_F$

$$\|u\|^2 = X_F^* \left(\begin{bmatrix} A^{k-1} b & \dots & A b & b \end{bmatrix}^+ \right)^* \begin{bmatrix} A^{k-1} b & \dots & A b & b \end{bmatrix}^+ X_F$$

$$X_F^* \left(b b^* + A b b^* A^* + A^2 b b^* (A^*)^2 + \dots + A^{k-1} b b^* (A^*)^{k-1} \right)^{-1} X_F$$

If $k \rightarrow \infty$, we get

$X_F^* X^{-1} X_F = \text{minimum amount of energy needed to reach } X_F \text{ from } X_0 = 0$

$$F = \begin{bmatrix} b & A b & \dots & A^{k-1} b \end{bmatrix}$$

$$F^* = Q R$$

$$\begin{bmatrix} Q \\ R \end{bmatrix}$$

$$\begin{aligned} (F^+) (F^+)^* &= R^{-1} \cancel{Q^*} \cancel{Q} R^{-*} \\ &= R^{-1} R^{-*} \end{aligned}$$

$$R^{-1} Q^* = A^* \cdot Q$$