Project

Chenyang Zhao

problem 1

More generally, with suitable assumptions on the smoothness of f, the solution to the inhomogeneous system

$$\frac{dy}{dt} = Ay + f(t, y), \quad y(0) = c, \quad y \in \mathbb{C}^n, A \in \mathbb{C}^{n \times n}$$
 (1)

satisfies

$$y(t) = e^{At}c + \int_0^t e^{A(t-s)}f(s,y)ds$$
 (2)

By the deriviation formula, we get this:

$$\frac{d}{dt}(e^{-At}y) = -Ae^{-At}y + e^{-At}y'(t) = e^{-At}(y'(t) - Ay)$$
(3)

*And we let *

$$(y'(t) - Ay) = f(t, y)$$

$$e^{0}y(0) = c$$

$$(4)$$

integrate it from 0 to t, thus we have:

$$e^{-At}y - e^{0}y(0) = \int_{0}^{t} e^{-As}f(s,y)ds$$

$$e^{-At}y - c = \int_{0}^{t} e^{-As}f(s,y)ds$$

$$y = e^{At}c + \int_{0}^{t} e^{A(t-s)}f(s,y)ds$$
(5)

Problem 2

Trigonometric matrix functions, as well as matrix roots, arise in the solution of second order differential equations. For example, the problem

$$\frac{d^2y}{dt^2} + Ay = 0, y(0) = y_0, y'(0) = y'_0 (2.7)$$

has solution

$$y(t) = \cos(\sqrt{A}t)y_0 + (\sqrt{A})^{-1}\sin(\sqrt{A}t)y_0',$$
 (2.8)

where \sqrt{A} denotes any square root of A (see Problems 2.2 and 4.1). The solution exists for all A. When A is singular (and \sqrt{A} possibly does not exist) this formula is interpreted by expanding $\cos(\sqrt{A}t)$ and $(\sqrt{A})^{-1}\sin(\sqrt{A}t)$ as power series in A.

First, any even function f(x) only have even power of x as it's expansion.

(If some power of x are odd, then f(x) could not be a even function)

And we know odd function time odd function would be an even function, even function plus an even function would still get an even function, hence $f(x) = cosx + x^{-1}sinx$ is a even function for x. So the expansion of $y(t) = cos(\sqrt{A}t)y_0 + (\sqrt{A})^{-1}sin(\sqrt{A}t)y_0'$ is even power of \sqrt{A} . Since $(\sqrt{A})^{2n} = A^n$, then the expansion of y(t) is just the power series of x. Since the solution actually never depends on which \sqrt{A} we choose, so $y(t) = cos(\sqrt{A}t)y_0 + (\sqrt{A})^{-1}sin(\sqrt{A}t)y_0'$ is a solution for any square root \sqrt{A} of A.

Problem 3

Theorem 2.1 (spectrum splitting via sign function). Let $A \in \mathbb{R}^{n \times n}$ have no pure imaginary eigenvalues and define $W = (\operatorname{sign}(A) + I)/2$. Let

$$Q^T W \Pi = \begin{bmatrix} q & n-q \\ R_{11} & R_{12} \\ 0 & 0 \end{bmatrix}$$

be a rank-revealing QR factorization, where Π is a permutation matrix and $q = \operatorname{rank}(W)$. Then

$$Q^{T}AQ = {}^{q}_{n-q} \, \begin{bmatrix} {}^{q}_{} & {}^{n-q}_{} \\ {}^{A}_{11} & {}^{A}_{12} \\ {}^{0}_{} & {}^{A}_{22} \end{bmatrix} ,$$

where the eigenvalues of A_{11} lie in the open right half-plane and those of A_{22} lie in the open left half-plane.

For the Jordan Canonical Form of A, we have $A=ZJZ^{-1}, Z=[Z_1,Z_2], J=\begin{bmatrix}J_1&\\&J_2\end{bmatrix}$, where p+q=n, and J_1 is $p\times p$ with all eigenvalues lying in the left complex plane, and J_2 is $q\times q$ with all eigenvalues lying in the right complex plane. Hence:

$$egin{aligned} \operatorname{sign}(A) = & Z \left[egin{aligned} \operatorname{sign}(J_1) & & & \\ & & \operatorname{sign}(J_2) \end{aligned}
ight] Z^{-1} \ & = & Z \left[egin{aligned} -I_p & & \\ & & I_q \end{aligned}
ight] Z^{-1} \end{aligned}$$

By definition, Since $W=(\mathrm{sign}(A)+I)/2=Z\begin{bmatrix}O\\I_q\end{bmatrix}Z^{-1}$, rank(W)=q, and we know Range(W) is the invariant subspace for these eigenvalues of A which are in the open right half-plane.

Let $Q=[Q_1,Q_2]$, where Q_1 is n imes q and Q_2 is n imes p. Hence:

$$W\Pi = [Q_1 Q_2] \begin{bmatrix} R_{11} & R_{12} \\ O & O \end{bmatrix} = Q_1 [R_{11} R_{12}]$$
(6)

And since $\frac{\pi}{1}$ is a permutation matrix. we have: $\frac{\pi^{-1}}{1} = \frac{\pi}{1}$, so:

$$W = Q_1 \left[R_{11} R_{12} \right] \Pi^T \tag{7}$$

Because $\operatorname{rank}(W) = q$, and Q_1 has full column rank, then the column of Q_1 is a set of orthogonal basis of $\operatorname{range}(W)$. Then $AQ_1 = Q_1X$, where X is a $q \times q$ matrix whose eigenvalues are those of A which are in the open right half-plane.

Note that columns of Q span the who vector space, so $\mathrm{range}(Q_2)$ is the invariant subspace for these eigenvalues of A which are in the open left half-plane. So similarly,we have $AQ_2 = Q_2Y$ where Y is a $p \times p$ matrix matrix whose eigenvalues are those of A which are in the open left half-plane.

Since Q is a matrix in QR factorization, then Q is orthogonal, hence $Q_1^TQ_1=I,\,Q_2^TQ_2=I$, then $Q_1^TAQ_1=X,\,Q_2^TAQ_1=Q_2^TQ_1X=0,\,Q_2^TAQ_2=Y$

All in all, we have:

$$\begin{aligned} Q^TAQ &= \begin{bmatrix} Q_1^T & Q_2^T \end{bmatrix} A \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} = \begin{bmatrix} Q_1^TAQ_1 & Q_1^TAQ_2 \\ Q_2^TAQ_1 & Q_2^TAQ_2 \end{bmatrix} \\ &= \begin{bmatrix} X & Q_1^TAQ_2 \\ Q_2^TQ_1X & Y \end{bmatrix} \\ &= \begin{bmatrix} X & Q_1^TAQ_2 \\ Q_2^TQ_1X & Y \end{bmatrix} := \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} \end{aligned}$$

Problem 4

The geometric mean of positive scalars can be generalized to Hermitian positive definite matrices in various ways, which to a greater or lesser extent possess the properties one would like of a mean. Let $A, B \in \mathbb{C}^{n \times n}$ be Hermitian positive definite. The geometric mean A # B is defined as the unique Hermitian positive definite solution to $XA^{-1}X = B$, or (cf. (2.19)–(2.21))

$$X = B^{1/2} (B^{-1/2} A B^{-1/2})^{1/2} B^{1/2} = B(B^{-1} A)^{1/2} = (A B^{-1})^{1/2} B,$$
 (2.26)

where the last equality can be seen using Corollary 1.34. The geometric mean has the properties (see Problem 2.5)

$$A \# A = A, \tag{2.27a}$$

$$(A \# B)^{-1} = A^{-1} \# B^{-1}, \tag{2.27b}$$

$$A \# B = B \# A,$$
 (2.27c)

$$A \# B \le \frac{1}{2}(A+B),$$
 (2.27d)

If A and B commute, then **whatever** completely depend on A would commute with **whatever** completely depend on B. Thus we have $A^{1/2}$ commute with $B^{1/2}$, $\log(A)$ commute with $\log(B)$ and finally $\log(A^{1/2})$ commute with $\log(B^{1/2})$

By the definition above, A#B is the unique Hermitian positive definite solution to $XA^{-1}X=B$. Suppose the solution is $X=A^{1/2}B^{1/2}$ Then

$$X^* = (B^*)^{1/2} (A^*)^{1/2} = B^{1/2} A^{1/2} = A^{1/2} B^{1/2} = X.$$
(8)

Wow X is Hermitian.

From our lecture note, at least, a Hermitian positive definite matrix is always diagonalizable. On the other hand A and B commute, then they are simultaneously diagonalizable.

Hence $\exists P$, s.t., $A=P\Lambda_aP^{-1}$. $B=P\Lambda_bP^{-1}$, Λ_a , Λ_b are both diagonal matrix with positive entry on the diagonal. So $X=P\sqrt{\Lambda_a}P^{-1}P\sqrt{\Lambda_b}P^{-1}=P\sqrt{\Lambda_a\Lambda_b}P^{-1}$, which is still positive definite.

All in all, we get:

$$XA^{-1}X = A^{1/2}B^{1/2}A^{-1}A^{1/2}B^{1/2} = A^{1/2}B^{1/2}A^{-1/2}B^{1/2}$$

$$= A^{1/2}A^{-1/2}B^{1/2}B^{1/2} = B$$
(9)

Surely $X=A^{1/2}B^{1/2}$ is the geometric mean A#B we are searching for.

We have seen that $\log(A^{1/2})$ commute with $\log(B^{1/2})$, and From our lecture note , we know that if AB=BA , then $e^{A+B}=e^Ae^B=e^Be^A$.

So in the end:

$$E(A,B) = e^{\frac{1}{2}\log(A) + \frac{1}{2}\log(B)} = e^{\frac{1}{2}\log(A)}e^{\frac{1}{2}\log(B)}$$

$$= e^{\log(\sqrt{A})}e^{\log(\sqrt{B})}$$

$$= A^{\frac{1}{2}}B^{\frac{1}{2}}$$
(10)

Problem 5

$$A \# A = A, \tag{2.27a}$$

$$(A \# B)^{-1} = A^{-1} \# B^{-1}, \tag{2.27b}$$

$$A \# B = B \# A,$$
 (2.27c)

$$A \# B \le \frac{1}{2}(A+B),$$
 (2.27d)

2.27 a:

By the definition above, A#B is the unique Hermitian positive definite solution to $XA^{-1}X=B$. Since the solution is unique, and we know $AA^{-1}A=A$, and A itself is a Hermitian positive definite matrix. So A is the solution, i.e. A#A=A

2.27 b:

By definition, we have: $A\#B=\left(AB^{-1}\right)^{1/2}B$. On the other hand, the inverse of a Hermitian positive definite matrix is still a Hermitian positive definite matrix. So

$$A^{-1}\#B^{-1}=\left(A^{-1}B\right)^{1/2}B^{-1}.$$
 All in all
$$(A\#B)^{-1}=\left(AB^{-1}\right)^{-1/2}B^{-1}=B^{1/2}A^{-1/2}B^{-1}=\left(A^{-1}B\right)^{1/2}B^{-1}=A^{-1}\#B^{-1}.$$

2.27 c:

Let $X_1=A\#B$, which is the unique Hermitian positive definite matrix that satisfies $X_1A^{-1}X_1=B$. And Let $X_2=B\#A$, which is the unique Hermitian positive definite matrix that satisfies $X_2B^{-1}X_2=A$. Apply X_1^{-1} on both side of $X_1A^{-1}X_1=B$, then we have $A^{-1}=X_1^{-1}BX_1^{-1}$. Take inverse of both side, $X_1B^{-1}X_1=A$. This is the same as $X_2=B\#A$ which satisfies $X_2B^{-1}X_2=A$. Since the solution is unique, so we have $X_1=A\#B=X_2=B\#A$

2.27 d:

From page 46, we know Here, $X \ge 0$ denotes that the Hermitian matrix X is positive semidefinite. And by the original definition, we have: $A\#B = \left(B^{-1/2}AB^{-1/2}\right)^{1/2}$

We want to prove that $X:=rac{A+B}{2}-A\#B$ is positive semidefinite. Here we go.

Since we know that if B is semipositive then $B^{1/2}$ is also semipositive, and the result of two semipositive matrix's product is still semipositive.

We denote T as $B^{-1/2}AB^{-1/2}$, and $T^*=\left(B^*\right)^{-1/2}A^*\left(B^*\right)^{-1/2}=B^{-1/2}AB^{-1/2}=T$. From problems above, it's positive-definite, so it can be diagonalized into $T=B\Lambda B^{-1}$ *for some positive diagonal matrix * Λ . *Thus we have * $T^{1/2}=B\Lambda^{1/2}B^{-1}$, let $\Lambda'=I-\Lambda^{1/2}$, okay:

$$\frac{1}{2} \left(B^{-1/2} A B^{-1/2} + I \right) - \left(B^{-1/2} A B^{-1/2} \right)^{1/2}$$

$$= \frac{1}{2} (T + I) - T^{1/2}$$

$$= \frac{1}{2} \left(I - T^{1/2} \right)^{2}$$

$$= \frac{1}{2} \left(B \Lambda' B^{-1} \right)^{2}$$

$$= \frac{1}{2} B (\Lambda')^{2} B^{-1}$$
(11)

*And we see $(\Lambda')^2$ is semipositive. So $\frac{1}{2} \left(B^{-1/2}AB^{-1/2}+I\right)-\left(B^{-1/2}AB^{-1/2}\right)^{1/2}$ is semipositive. Apply $B^{1/2}$ on both side.\$

$$X := \frac{A+B}{2} - A \# B$$

$$= \frac{1}{2} (A+B) - B^{1/2} \left(B^{-1/2} A B^{-1/2} \right)^{1/2}$$

$$= B^{1/2} \left(\frac{1}{2} \left(B^{-1/2} A B^{-1/2} + I \right) - \left(B^{-1/2} A B^{-1/2} \right)^{1/2} \right) B^{1/2}$$
(12)

So X is positive semidefinite in the end.

Problem 6

2.6. (Bhatia [65, 2007, p. 111]) Show that for Hermitian positive definite $A, B \in \mathbb{C}^{2 \times 2}$,

$$A \# B = \frac{\sqrt{\alpha \beta}}{\sqrt{\det(\alpha^{-1}A + \beta^{-1}B)}} (\alpha^{-1}A + \beta^{-1}B),$$

with $\alpha^2 = \det(A)$, $\beta^2 = \det(B)$.

Because A, B are both hermitian positive definite, they have real positive determinant. **WLOG**, assume $\alpha, \beta > 0$. Let $T = \left(A^{-1}B\right)^{1/2}$ with two eigenvalue $\lambda_1, \lambda_2 \in \mathbb{C}$.

Thus we have $\operatorname{trace}(T) = \lambda_1 + \lambda_2$, $\det(T) = \lambda_1 \lambda_2 = \det \left(A^{-1/2}\right) \det \left(B^{1/2}\right) = \frac{\beta}{\alpha}$.

*Furthermore, we see that the eigenvalue of $(\alpha^{-1}I+\beta^{-1}T^2)$ are $(\beta^{-1}\lambda_1^2+\alpha^{-1})$ and $(\beta^{-1}\lambda_2^2+\alpha^{-1})$. Hence:

$$\det(\alpha^{-1}I + \beta^{-1}X^{2}) = (\beta^{-1}\lambda_{1}^{2} + \alpha^{-1})(\beta^{-1}\lambda_{2}^{2} + \alpha^{-1})$$

$$= 1 + \frac{\alpha}{\beta}\lambda_{1}^{2} + \frac{\alpha}{\beta}\lambda_{2}^{2} + \frac{\alpha^{2}}{\beta^{2}}\lambda_{1}^{2}\lambda_{2}^{2} = \frac{\alpha}{\beta} \times \frac{\beta}{\alpha} + \frac{\alpha}{\beta}\lambda_{1}^{2} + \frac{\alpha}{\beta}\lambda_{2}^{2} + \frac{\alpha}{\beta}\lambda_{1}\lambda_{2}$$

$$= \frac{\alpha}{\beta}\lambda_{1}^{2} + \frac{\alpha}{\beta}\lambda_{2}^{2} + 2\frac{\alpha}{\beta}\lambda_{1}\lambda_{2} = \frac{\alpha}{\beta}(\lambda_{1} + \lambda_{2})^{2}$$
(13)

All in all:

$$\det(\alpha^{-1}A + \beta^{-1}B) = \det(A)\det(\alpha^{-1}I + \beta^{-1}X^{2})$$

$$= \alpha^{2}(\beta^{-1}\lambda_{1}^{2} + \alpha^{-1})(\beta^{-1}\lambda_{2}^{2} + \alpha^{-1})$$

$$= \frac{\alpha}{\beta}(\lambda_{1} + \lambda_{2})^{2}$$

$$= \frac{\alpha}{2}\operatorname{trace}(T)^{2}$$
(14)

The product of two hermitian positive definite matrix is still hermitian positive definite, so T is still hermitian positive definite, $\mathrm{trace}(T)>0$; So $\mathrm{trace}(T)=\sqrt{\frac{\beta}{\alpha}\mathrm{det}(\alpha^{-1}A+\beta^{-1}B)}$

From Cayley-Hamiltion theorem, we have:

When A has characteristic polynomial $p(x) = \det(A - \lambda I) = x^n + c_1 x^{n-1} + \ldots + c_n$

then p(A) = 0

And the characteristic polynomial for A is $(x-\lambda_1)(x-\lambda_2)=x^2-(\lambda_1+\lambda_2)+\lambda_1\lambda_2$

Hence We know that $\,T^2-{
m trace}(T)T+{
m det}(T)I=0$

Then $\operatorname{trace}(T) \left(A^{-1}B\right)^{1/2} = T^2 + \det(T)I$ Multiply A from the left,we have

$$trace(T)A(A^{-1}B)^{1/2} = B + det(T)A.$$

$$trace(T)(B\#A) = B + det(T)A.$$

$$trace(T)(A\#B) = B + det(T)A.$$

$$A\#B = \frac{B + det(T)A}{trace(T)}$$

$$= \frac{B + \frac{\beta}{\alpha}A}{\sqrt{\frac{\beta}{\alpha}det(\alpha^{-1}A + \beta^{-1}B)}}$$

$$= \frac{\sqrt{\alpha\beta}}{\sqrt{det(\alpha^{-1}A + \beta^{-1}B)}}(a^{-1}A + \beta^{-1}B).$$
(15)

Problem 7

2.7. Consider the Riccati equation XAX = B, where A and B are Hermitian positive definite. Show that the Hermitian positive definite solution X can be computed as $R^{-1}(RBR^*)^{1/2}R^{-*}$, where $A = R^*R$ is a Cholesky factorization.

P161 the Cholesky factor of A: $A = R^*R$ (Cholesky factorization: R upper triangular)

From **problem 5**, we define A > 0 if A is hermitian positive definite.

Since B>0, thus for $\forall x\in\mathbb{C}^n, x^*RBR^*x=(R^*x)^*B(R^*x)>0$. thus $RBR^*>0$, $\sqrt{RBR^*}>0$.

Similarly,for $\forall x\in\mathbb{C}^{\mathrm{n}}, x^*R^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}x=(R^{-*}x)^*(RBR^*)^{\frac{1}{2}}(R^{-*}x)>0.$ So $R^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}>0$ as well.

From the definition of A#B, we know that the solution to X>0, XAX=B is unique. Thus we only need to prove: $R^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}AR^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}=B$.

$$R^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}AR^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}$$

$$= R^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}R^*RR^{-1}(RBR^*)^{\frac{1}{2}}R^{-*}$$

$$= R^{-1}(RBR^*)R^{-*}$$

$$= (R^{-1}R)B(R^*R^{-*}) = B.$$
(16)

So $X=R^{-1}(RBR^*)^{rac{1}{2}}R^{-*}$ is the solution to XAX=B that we are searching for.