第五章

矩阵分析

1 矩阵序列与矩阵级数

设 $m \times n$ 型矩阵序列为 $\{A^{(k)}\}$, 其中

$$A^{(k)} = \begin{bmatrix} a_{11}^{(k)} & a_{12}^{(k)} & \cdots & a_{1n}^{(k)} \\ a_{21}^{(k)} & a_{22}^{(k)} & \cdots & a_{2n}^{(k)} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1}^{(k)} & a_{m2}^{(k)} & \cdots & a_{mn}^{(k)} \end{bmatrix}, \quad k = 1, 2, \cdots,$$

定义 1:
$$\lim_{k\to\infty} a_{ij}^{(k)} = a_{ij} \iff \lim_{k\to\infty} A^{(k)} = A$$

定理 1: 设 $\lim_{k \to +\infty} A^{(k)} = A$, $\lim_{k \to +\infty} B^{(k)} = B$. $\alpha, \beta \in C$,则

$$(1) \lim_{k \to +\infty} (\alpha A^{(k)} + \beta B^{(k)}) = \alpha A + \beta B;$$

$$(2) \lim_{k \to +\infty} A^{(k)} B^{(k)} = AB;$$

$$(3)$$
当 $A^{(k)}$ 与 A 都可逆时, $\lim_{k \to +\infty} (A^{(k)})^{-1} = A^{-1}$.

定理 2: 设 $\|\bullet\|$ 是 $C^{m\times n}$ 上任一矩阵范数, $C^{m\times n}$ 中矩阵序列 $\{A^{(k)}\}$ 收敛于 A 的充要条件是

$$\lim_{k \to +\infty} ||A^{(k)} - A|| = 0$$

定义2:设 $A \in C^{n \times n}$,若 $\lim_{k \to \infty} A^k = 0$ (k为正整数),则称A为收敛矩阵.

定理 3 设 $A \in C^{n \times n}$,则A为收敛矩阵的充要 条件是r(A) < 1.

$$\begin{array}{ll} \operatorname{Pr} oof: & (1) 充分性: & A \in C^{n \times n} \Longrightarrow \\ & P^{-1}AP = J = \operatorname{diag}(J_{r_1}(\lambda_1), J_{r_2}(\lambda_2), \cdots, J_{r_s}(\lambda_s)) \\ & \Longrightarrow A^k = PJ^kP^{-1} \Longrightarrow A^k \to 0 \iff J^k \to 0 \\ & \Longrightarrow J^k_{r_i}(\lambda_i) \to 0 \end{array}$$

$$\boldsymbol{J}_{r_i}^{k}(\boldsymbol{\lambda}_{\boldsymbol{i}}) = \begin{bmatrix} \boldsymbol{\lambda}_{\boldsymbol{i}}^{k} & \boldsymbol{C}_{k}^{1}\boldsymbol{\lambda}_{\boldsymbol{i}}^{k-1}) & \cdots & \boldsymbol{C}_{k}^{r_{i}-1}\boldsymbol{\lambda}_{\boldsymbol{i}}^{k-r_{i}+1} \\ & \boldsymbol{\lambda}_{\boldsymbol{i}}^{k} & \cdots & \boldsymbol{C}_{k}^{r_{i}-2}\boldsymbol{\lambda}_{\boldsymbol{i}}^{k-r_{i}+2} \\ & & \ddots & \vdots \\ & & & \boldsymbol{\lambda}_{\boldsymbol{i}}^{k} \end{bmatrix}, \ k > r_{i}$$

$$\begin{array}{ll} \underline{|\lambda_i| < 1} & C_k^l \lambda_i^{k-l+1} \to 0 \ (l = 1, \cdots, r_i - 1) \\ \\ \Longrightarrow J_{r_i}^k (\lambda_i) \to 0 & \Longrightarrow J^k \to 0 \\ \\ \Longrightarrow A^k \to 0 \end{array}$$

推论: $\partial A \in C^{n \times n}, \forall \varepsilon > 0$,则存在与 A, ε 有关的常数c,使得

$$|\left(A^{k}\right)_{ij}| \leq c[r(A)+\varepsilon]^{k}, k=1,2,\cdots;i,j=1,\cdots,n.$$

定义 3: 设
$$\{A^{(k)}\}$$
是 $C^{m imes n}$ 的矩阵序列,称
$$\sum_{k=1}^{\infty} A^{(k)} = A^{(1)} + A^{(2)} + \dots + A^{(k)} + \dots$$
 为矩阵级数 . 称 $S^{(N)} = \sum_{k=1}^{N} A^{(k)}$ 为矩阵级数的部分和. 如果 $\lim_{N \to \infty} S^{(N)} = S$,则称 $\sum_{k=1}^{\infty} A^{(k)}$ 收敛 .

定义
$$4$$
: 如果 mn 个数项级数
$$\sum_{k=1}^{\infty} a_{ij}^{(k)}, i=1,2,\cdots,m; j=1,2,\cdots,n$$
 都绝对收敛,则称矩阵级数 $\sum_{k=1}^{\infty} A^{(k)}$ 绝对收敛. 定理 4 在 $C^{n\times n}$ 中, $\sum_{k=1}^{\infty} A^{(k)}$ 绝对收敛的充要条件 是正项级数 $\sum_{k=1}^{\infty} \|A^{(k)}\|$ 收敛.
$$\sum_{k=1}^{N} |a_{ij}^{(k)}| \le M \Longrightarrow$$
 $Proof: \sum_{k=1}^{\infty} A^{(k)}$ 绝对收敛 $\Longrightarrow \sum_{k=1}^{N} |a_{ij}^{(k)}| \le M \Longrightarrow$

$$\begin{split} &\sum_{k=1}^{N} \|A^{(k)}\|_{m_{1}} = \sum_{k=1}^{N} \left(\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{ij}^{(k)}|\right) \leq mnM \\ & \Longrightarrow \sum_{k=1}^{\infty} \|A^{(k)}\|_{m_{1}} \mathbf{收敛} \implies \sum_{k=1}^{\infty} \|A^{(k)}\|\mathbf{收敛} \\ & \& \mathbf{要性} \colon \sum_{k=1}^{\infty} \|A^{(k)}\|\mathbf{收敛} \implies \sum_{k=1}^{\infty} \|A^{(k)}\|_{m_{1}} \mathbf{收敛} \\ & \frac{|a_{ij}^{(k)}| \leq \|A^{(k)}\|_{m_{1}}}{\sum_{k=1}^{\infty} a_{ij}^{(k)}} & \& \mathbf{对收敛} \end{split}$$

定理
$$5$$
(Neumann定理) 方阵 A 的Neumann级数
$$\sum_{k=0}^{\infty}A^{k}=I+A+A^{2}+\cdots+A^{k}+\cdots$$
 收敛的充要条件是 $r(A)<1$,且收敛时,其和为 $(I-A)^{-1}$. Pr $oof:$ 充分性: $r(A)<1$ \Longrightarrow $I-A$ 可逆 \Longrightarrow
$$(I+A+A^{2}+\cdots+A^{k})(I-A)=I-A^{k+1} \Longrightarrow$$

$$I+A+\cdots+A^{k}=(I-A)^{-1}-A^{k+1}(I-A)^{-1}$$

$$\xrightarrow{r(A)<1} I+A+A^{2}+\cdots+A^{k} \to (I-A)^{-1}$$

必要性:
$$\sum_{k=0}^{\infty} A^k$$
 收敛 \Longrightarrow $\delta_{ij} + (A)_{ij} + (A^2)_{ij} + \dots + (A^k)_{ij} + \dots$ 收敛 \Longrightarrow $(A^k)_{ij} \to 0 \implies A^k = ((A^k)_{ij}) \to 0 \implies$ $r(A) < 1$

$$f(z) = \sum_{k=0}^{\infty} c_k z^k$$
 收敛半径为 r ,如果方阵 A 满足 $r(A) < r$,则矩阵幂级数 $\sum_{k=0}^{\infty} c_k A^k$ 绝对收敛;如果 $r(A) < r$,则矩阵幂级数 $\sum_{k=0}^{\infty} c_k A^k$ 发散.

设幂级数

定理6

2 矩阵函数

一、矩阵函数的定义

定义 设幂级数 $\sum_{k=0}^{\infty} c_k z^k$ 收敛半径为r,且当

|z| < r时,幂级数收敛于f(z),即

$$f(z) = \sum_{k=0}^{\infty} c_k z^k, \quad |z| < r$$

如果 $A \in C^{n \times n}$ 满足r(A) < r,则称收敛的矩阵幂级

数 $\sum_{k=0}^{\infty} a_k A^k$ 的和为矩阵函数,记为f(A),即

$$f(A) = \sum_{k=0}^{\infty} c_k A^k,$$

把 f(A)的方阵A换为At,t为参数,则得到

$$f(At) = \sum_{k=0}^{\infty} c_k (At)^k.$$

常用的矩阵函数:

(1)
$$e^A = \sum_{k=0}^{\infty} \frac{1}{k!} A^k$$
, $A \in C^{n \times n}$

(2)
$$\sin A = \sum_{k=0}^{\infty} \frac{(-1)^k}{(2k+1)!} A^{2k+1}, \quad A \in C^{n \times n}$$

(3)
$$\cos A = \sum_{k=0}^{\infty} \frac{(-1)^k}{(2k)!} A^{2k}, \quad A \in \mathbb{C}^{n \times n}$$

(4)
$$(E-A)^{-1} = \sum_{k=0}^{\infty} A^k$$
, $r(A) < 1$

(5)
$$\ln(E+A) = \sum_{k=0}^{\infty} \frac{(-1)^k}{k+1} A^{k+1}, \quad r(A) < 1$$

二、矩阵函数值的计算

1、利用相似对角化:

$$\mathfrak{g}P^{-1}AP = diag(\lambda_1, \lambda_2, \dots, \lambda_n) = D$$
 \Longrightarrow

$$f(A) = \sum_{k=0}^{\infty} c_k A^k = \sum_{k=0}^{\infty} c_k (PDP^{-1})^k = P \left(\sum_{k=0}^{\infty} c_k D^k \right) P^{-1}$$

$$= P \begin{pmatrix} \sum_{k=0}^{\infty} c_k \lambda_1^k \\ \vdots \\ \sum_{k=0}^{\infty} c_k \lambda_n^k \end{pmatrix} P^{-1}$$

$$= P \begin{pmatrix} f(\lambda_1) \\ \vdots \\ f(\lambda_n) \end{pmatrix} P^{-1}$$

$$f(At) = Pdiag(f(\lambda_1 t), f(\lambda_2 t), \dots, f(\lambda_n t)).$$

例

设
$$A = \begin{pmatrix} 4 & 6 & 0 \\ -3 & -5 & 0 \\ -3 & -6 & 1 \end{pmatrix}$$
, 求 e^{At} .

$$\mathcal{M}$$
: 1) det $(\lambda E - A) = (\lambda + 2)(\lambda - 1)^2$ \Longrightarrow $\lambda_1 = -2, \lambda_2 = \lambda_3 = 1$

2) 对应的特征向量:

$$\lambda_1 = -2 : \xi_1 = (-1,1,1)^T$$

$$\lambda_2 = \lambda_3 = 1: \ \xi_2 = (-2,1,0)^T, \xi_3 = (0,0,1)^T \iff$$

$$P = \begin{pmatrix} -1 & -2 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} \Longrightarrow$$

$$e^{At} = P \begin{pmatrix} e^{-2t} & & \\ & e^t & \\ & & e^t \end{pmatrix} P^{-1}$$

$$= \begin{pmatrix} 2e^t - e^{-2t} & 2e^t - 2e^{-2t} & 0 \\ e^{2t} - e^{-t} & 2e^{-2t} - e^t & 0 \\ e^{-2t} - e^t & 2e^{-2t} - 2e^t & e^t \end{pmatrix}$$

2、Jordan 标准形法:

设
$$P^{-1}AP = J = diag(J_1, J_2, \dots, J_s)$$
 \Longrightarrow

$$f(J_i) = \sum_{k=1}^{\infty} a_k J_i^k$$

$$=\sum_{k=1}^{\infty}a_{k}\begin{pmatrix}\lambda_{i}^{k}&C_{k}^{1}\lambda_{i}^{k-1}&\cdots&C_{k}^{m_{i}-1}\lambda_{i}^{k-(m_{i}-1)}\\\lambda_{i}^{k}&\vdots&\\&\ddots&C_{k}^{1}\lambda_{i}^{k-1}\\\lambda_{i}^{k}&\end{pmatrix}$$

$$= \begin{bmatrix} f(\lambda_i) & \frac{1}{1!}f'(\lambda_i) & \cdots & \frac{1}{(m_i-1)!}f^{(m_i-1)}(\lambda_i) \\ & f(\lambda_i) & \cdots & \frac{1}{(m_i-2)!}f^{(m_i-2)}(\lambda_i) \\ & \ddots & \vdots \\ & f(\lambda_i) \end{bmatrix}$$

$$\implies f(A) = \sum_{k=0}^{\infty} a_k P J^k P^{-1} = P \left(\sum_{k=0}^{\infty} a_k J^k \right) P^{-1}$$

$$=P\begin{pmatrix} \sum_{k=0}^{\infty} a_k J_1^k & & & \\ \sum_{k=0}^{\infty} a_k J_s^k & & & \\ & & \sum_{k=0}^{\infty} a_k J_s^k \end{pmatrix} P^{-1}$$

$$=P\begin{pmatrix} f(J_1) & & & \\ & \ddots & & \\ & & f(J_s) \end{pmatrix} P^{-1}$$

解: 1) 化为 Jordan 标准形

$$A \iff J_1 = 1, J_2 = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$$
2) it it is in J :

$$(2)$$
 计算 $\sin J_i$

$$\sin J_1 = \sin 1, \sin J_2 = \begin{pmatrix} \sin 1 & \frac{1}{1!} \cos 0 \\ 0 & \sin 1 \end{pmatrix}$$

3、数项级数求和法:

哈密尔顿-凯莱定理: 设A 是数域 P 上的一个 $n \times n$ 矩阵, $f(\lambda) = |\lambda E - A|$ 是A 的特征多项式,则

$$f(A) = A^{n} - b_{n-1}A^{n-1} - \dots - b_{1}A - b_{0}E = 0$$

$$\Longrightarrow A^{n} = b_{n-1}A^{n-1} + \dots + b_{1}A + b_{0}E$$

$$\Longrightarrow \begin{cases} A^{n+1} = b_{n-1}^{(1)}A^{n-1} + \dots + b_{1}^{(1)}A + b_{0}^{(1)}E \\ \dots & \dots & \dots \\ A^{n+l} = b_{n-1}^{(l)}A^{n-1} + \dots + b_{1}^{(l)}A + b_{0}^{(l)} \\ \dots & \dots & \dots & \dots \end{cases}$$

$$\Longrightarrow f(A) = \sum_{k=0}^{\infty} c_{k}A^{k} = (c_{0}E + c_{1}A + \dots + c_{n}A^{n}) + \dots$$

$$\begin{split} &= (c_0 + \sum_{l=1}^{\infty} c_{n+l} b_0^{(l)}) E + (c_1 + \sum_{l=1}^{\infty} c_{n+l} b_1^{(l)}) A + \cdots \\ &\quad + (c_{n-1} + \sum_{l=1}^{\infty} c_{n+l} b_{n-1}^{(l)}) A^{n-1} \end{split}$$

三、矩阵函数的一些性质

性质 如果AB = BA,则 $e^A e^B = e^B e^A = e^{A+B}$.

1: 性质 如果*AB* = *BA*,则

- 2: (1) $\cos(A+B) = \cos A \cos B \sin A \sin B$
 - (2) $\sin(A+B) = \sin A \cos B + \cos A \sin B$

5.3 矩阵的微分和积分

§ 1. 函数矩阵的微分积分

定义1. 矩阵 $A = (a_{ij}(t))_{m \times n}$ 称为函数矩阵, 如果 $a_{ij}(t)$ 是以变量t的函数.

定义2. 如果 $a_{ij}(t)$ 在 $t \in [a,b]$ 上连续,可微,可积,则称 矩阵 $A = (a_{ij}(t))_{m \times n}$ 在[a,b]上连续,可微,可积.

$$A'(t) = (a_{ij}'(t))_{m \times n}$$

$$\int_a^b A(t)dt = (\int_a^b a_{ij}(t)dt)$$

$$\Leftrightarrow \Leftrightarrow \Leftrightarrow$$

例:求函数矩阵

$$A(t) = \begin{pmatrix} t & \sin t & 4 & t^2 \\ \cos t & e^t & \ln t & a^t \end{pmatrix}$$
的导数.

$$\mathbf{\widetilde{R}}: \frac{d}{dt}A(t) = \begin{pmatrix} 1 & \cos t & 0 & 2t \\ -\sin t & e^t & \frac{1}{t} & a^t \ln a \end{pmatrix}$$

性质: $\partial A(t), B(t) \in C^{m \times n}$ 是两个可微函数,则

$$(1) \frac{d}{dt}(A(t) + B(t)) = \frac{d}{dt}A(t) + \frac{d}{dt}B(t)$$

(2)
$$\frac{d}{dt}(A(t)B(t)) = \frac{d}{dt}A(t) \cdot B(t) + A(t)\frac{d}{dt}B(t)$$

(3)
$$\frac{d}{dt}(a(t)A(t)) = \frac{d}{dt}a(t) \cdot A(t) + a(t)\frac{d}{dt}A(t)$$

性质2:设 $A \in C^{n \times n}$ 是常数矩阵,则

(1)
$$\frac{d}{dt}e^{tA} = A e^{tA} = e^{tA}A;$$

(2)
$$\frac{d}{dt}\cos(tA) = -A\sin(tA) = -\sin(tA)A;$$

(3)
$$\frac{d}{dt}\sin(tA) = A\cos(tA) = \cos(tA)A;$$

性质3:设A(t), $B(t) \in C^{m \times n}$ 在[a,b]上可积,则

(1)
$$\int_{a}^{b} (A(t) \pm B(t))dt = \int_{a}^{b} A(t)dt \pm \int_{a}^{b} B(t)dt$$

(2)
$$\int_{a}^{b} \lambda A(t)dt = \lambda \int_{a}^{b} A(t)dt;$$

(3)
$$\int_{a}^{b} (A(t)B)dt = \int_{a}^{b} A(t)dt \cdot B;$$
$$\int_{a}^{b} (AB(t))dt = A \int_{a}^{b} B(t)dt.$$

二.数量函数对矩阵变量的导数

定义:设 $X = (x_{ii}) \in C^{m \times n}, f(X)$ 是以X为

自变量的mn元函数,且 $\frac{\partial f}{\partial x_{ii}}$ 都存在,则

f 对 X 的 导 数 为

$$\frac{df}{dX} = \begin{pmatrix} \frac{\partial f}{\partial x_{11}} & \dots & \frac{\partial f}{\partial x_{1n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial f}{\partial x_{m1}} & \dots & \frac{\partial f}{\partial x_{mn}} \end{pmatrix}.$$

例2.设
$$x = (x_1, \dots, x_n)^T$$
, $f(x) = x^T x$, 求 $\frac{df}{dx}$, $\frac{df}{dx^T}$.

$$\mathbf{f}(x) = x^{T} x = \sum_{i=1}^{n} x_{i}^{2},$$

$$\frac{\partial f}{\partial x_i} = 2x_i, i = 1, 2, \cdots, n.$$

$$\frac{df}{dx} = 2x = 2(x_1, x_2, \dots, x_n)^T,$$

$$\frac{df}{dx^{T}} = 2x^{T} = 2(x_{1}, x_{2}, \dots, x_{n}).$$

例3.设
$$A = (a_{ij})_{n \times n}$$
 为常数矩阵, $f(X) = tr(AX)$, 求 $\frac{df}{dX}$.

$$\mathbf{K}$$
: $f(X) = tr(AX) = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_{ji}$

$$\frac{\partial f}{\partial x_{ii}} = a_{ji}, \quad \frac{\partial f}{\partial x_{ij}} = a_{ij},$$

$$\frac{df}{dX} = \left(\frac{\partial f}{\partial x_{ij}}\right) = \left(a_{ji}\right)_{n \times n} = A^{T}.$$

$$A = I \quad \frac{df}{dX} = (\frac{\partial f}{\partial x_{ii}}) = I.$$

三.矩阵值函数对矩阵变量的导数

def: 设 $X = (x_{st}) \in C^{m \times n}$, $f_{ij}(X)$ 是mn元函数 $i = 1, \dots, r; j = 1, \dots, s; F(X) = (f_{ij}(X)) \in C^{r \times s}$

则 F (X) 对 钜 阵 X 的 异 数 为

$$\frac{dF}{dX} = \begin{pmatrix} \frac{\partial F}{\partial x_{11}} & \cdots & \frac{\partial F}{\partial x_{1n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial F}{\partial x_{m1}} & \cdots & \frac{\partial F}{\partial x_{mn}} \end{pmatrix}, \qquad \underset{0}{\underbrace{\sharp \Phi}} \frac{dF}{dx_{ij}} = \begin{pmatrix} \frac{\partial f_{11}}{\partial x_{ij}} & \cdots & \frac{\partial f_{1s}}{\partial x_{ij}} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_{r1}}{\partial x_{ij}} & \cdots & \frac{\partial f_{rs}}{\partial x_{ij}} \end{pmatrix},$$

例:设
$$x = (x_1, \dots, x_n)^T$$
是向量变量,求
$$\frac{dx^T}{dx}, \frac{dx}{dx^T}?$$

$$\mathbf{W}: \frac{dx^T}{dx} = \begin{pmatrix} \frac{\partial x^T}{\partial x_1} \\ \vdots \\ \frac{\partial x^T}{\partial x_n} \end{pmatrix} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

$$\frac{dx}{dx^T} = \begin{pmatrix} \frac{\partial x}{\partial x_1} & \cdots & \frac{\partial x}{\partial x_n} \end{pmatrix} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

例:设
$$x = (x_1, \dots, x_n)^T$$
是向量变量,求
$$\frac{dx^T}{dx}, \frac{dx}{dx^T}?$$

$$\pi: \frac{dx^T}{dx} = \begin{pmatrix} \frac{\partial x^T}{\partial x_1} \\ \vdots \\ \frac{\partial x^T}{\partial x_n} \end{pmatrix} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

$$\frac{dx}{dx^T} = \begin{pmatrix} \frac{\partial x}{\partial x_1} & \cdots & \frac{\partial x}{\partial x_n} \end{pmatrix} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

$$\Rightarrow \begin{cases} \frac{\mathrm{d}x(t)}{\mathrm{d}t} = Ax(t) + f(t) \\ x(t_0) = c \end{cases}$$

$$\not\exists t \mapsto A = (a_{ij})_{n \times n}, \ x(t) = (x_1(t), x_2(t), \dots, x_n(t))^T,$$

$$c = (c_1, c_2, \dots, c_n)^T, \ f(t) = (f_1(t), f_2(t), \dots, f_n(t))^T,$$

$$\Rightarrow \frac{\mathrm{d}}{\mathrm{d}t} (e^{-At}x(t)) = e^{-At}(-A)x(t) + e^{-At} \frac{\mathrm{d}x(t)}{\mathrm{d}t}$$

$$= e^{-At} (\frac{\mathrm{d}x(t)}{\mathrm{d}t} - Ax(t)) = e^{-At} f(t) \quad \angle E[t_0, t] \bot \angle B / D.$$

$$c = (c_1, c_2, \dots, c_n)^T, \quad f(t) = (f_1(t), f_2(t), \dots, f_n(t))^T,$$

$$\Rightarrow \frac{d}{dt}(e^{-At}x(t)) = e^{-At}(-A)x(t) + e^{-At}\frac{dx(t)}{dt}$$

$$= e^{-At}(\frac{dx(t)}{dt} - Ax(t)) = e^{-At}f(t) \quad \underline{\triangle[t_0, t] \bot \triangle \triangle}.$$

解:
$$A = \begin{pmatrix} -1 & -2 & 6 \\ -1 & 0 & 3 \\ -1 & -1 & 4 \end{pmatrix}, c = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, f(t) = \begin{pmatrix} -e^t \\ 0 \\ e^t \end{pmatrix} \Rightarrow$$

$$e^{At} = e^t \begin{pmatrix} 1 - 2t & -2t & 6t \\ -t & 1 - t & 3t \\ -t & -t & 1 + 3t \end{pmatrix},$$

$$e^{At} c = e^t \begin{pmatrix} 1 - 2t \\ -t \\ -t \end{pmatrix} \Rightarrow \int_0^t e^{-A\tau} f(\tau) d\tau = \int_0^t \begin{pmatrix} -1 - 8\tau \\ -4\tau \\ 1 - 4\tau \end{pmatrix} d\tau \Rightarrow$$

$$\begin{cases} \frac{\mathrm{d}x_1(t)}{\mathrm{d}t} = a_{11}x_1(t) + a_{12}x_2(t) + \dots + a_{1n}x_n(t) + f_1(t) \\ \frac{\mathrm{d}x_2(t)}{\mathrm{d}t} = a_{21}x_1(t) + a_{22}x_2(t) + \dots + a_{2n}x_n(t) + f_2(t) \\ \dots & \dots & \dots \\ \frac{\mathrm{d}x_n(t)}{\mathrm{d}t} = a_{n1}x_1(t) + a_{n2}x_2(t) + \dots + a_{nn}x_n(t) + f_n(t) \end{cases}$$
 满足初始条件 $x_i(t_0) = c_i, i = 1, 2, \dots, n$

4 一阶线性常系数微分方程组

⇒
$$e^{-At}x(t) - e^{-At_0}x(t_0) = \int_{t_0}^t e^{-A\tau}f(\tau)d\tau$$

⇒ $x(t) = e^{A(t-t_0)}c + e^{At}\int_{t_0}^t e^{-A\tau}f(\tau)d\tau$
例 1: 求解初値问題

$$\begin{cases} \frac{dx_1(t)}{dt} = -x_1(t) - 2x_2(t) + 6x_3(t) - e^t \\ \frac{dx_2(t)}{dt} = -x_1(t) + 3x_3(t) \\ \frac{dx_3(t)}{dt} = -x_1(t) - x_2(t) + 4x_3(t) + e^t \\ x_1(0) = 1, x_2(0) = 0, x_3(0) = 0 \end{cases}$$

$$\int_{0}^{t} e^{-A\tau} f(\tau) d\tau = \begin{pmatrix} -t - 4t^{2} \\ -2t^{2} \\ t - 2t^{2} \end{pmatrix} \Rightarrow e^{At} \int_{0}^{t} e^{-A\tau} f(\tau) d\tau = e^{t} \begin{pmatrix} 4t^{2} - 1 \\ 2t^{2} \\ 2t^{2} + 2 \end{pmatrix} \Rightarrow$$

$$x(t) = e^{A(t - t_{0})} c + e^{At} \int_{t_{0}}^{t} e^{-A\tau} f(\tau) d\tau$$

$$x(t) = e^{At} c + e^{At} \int_{0}^{t} e^{-A\tau} f(\tau) d\tau = e^{t} \begin{pmatrix} 1 - 3t + 4t^{2} \\ -t + 2t^{2} \\ 2t^{2} \end{pmatrix}$$

定义 设A是n阶常系数矩阵,如果对任意的 t_0 和 x_0 ,初值问题

$$\begin{cases} \frac{\mathrm{d}x(t)}{\mathrm{d}t} = Ax(t) \\ x(t_0) = x_0 \end{cases}$$

的解x(t)满足 $\lim_{t\to +\infty} x(t) = 0$,则称 $\frac{\mathrm{d}x(t)}{\mathrm{d}t} = Ax(t)$ 的

解是渐进稳定的.

定理 对任意的 t_0 和 x_0 ,初值问题

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = Ax(t), x(t_0) = x_0$$

的解x(t)是渐进稳定的充要条件是A的特征值都 有负字部。

证:必要性:
$$A\xi_1 = \lambda_1 \xi_1$$
 $(\lambda_1 = \alpha_1 + i\beta_1, \alpha_1 \ge 0) \Rightarrow$
$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = Ax(t), x(0) = \xi_1 \mathbf{n} \mathbf{m} \mathbf{n} x(t) = e^{At} \xi_1$$
$$= e^{\lambda_1 t} \xi_1 = e^{\alpha_1 t} (\cos \beta_1 t + i \sin \beta_1 t) \xi_1 \xrightarrow{t \to \infty} x(t) \mathbf{n} \mathbf{n} \mathbf{n} (\mathbf{n} \mathbf{n} \mathbf{n})$$

充分性: 对任意的 t_0 和 x_0 , 初值问题 $\frac{\mathrm{d}x(t)}{\mathrm{d}t} = Ax(t)$, $x(t_0) = x_0$ 的解为 $x(t) = e^{A(t-t_0)}x_0$ $\underline{\lambda(A)}$ 都有负实部

$$\lim_{t\to +\infty} x(t) = \lim_{t\to +\infty} e^{A(t-t_0)} x_0 = 0$$