

Exponential Matrix and Stability of Systems.

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1 Exponential Matrix.

Definition 1.1. For $n \times n$ -matrix A , the **exponential matrix function**

$$e^{tA} = I + \frac{t}{1!}A + \frac{t^2}{2!}A^2 + \dots = \sum_{k=0}^{\infty} \frac{t^k}{k!}A^k. \quad (1.1)$$

Lemma 1.2. $X = X(t) = e^{tA}$ is the unique solution of the Cauchy problem

$$X' = \frac{dX}{dt} = AX, \quad X(0) = I. \quad (1.2)$$

Proof. It is easy to see that

$$\frac{d}{dt}e^{tA} = A + \frac{t}{1!}A^2 + \dots = Ae^{tA},$$

so that $X = e^{tA}$ is a solution of (1.2). Moreover, we can treat $n \times n$ -matrix function X as a vector functions with values in \mathbb{R}^{n^2} (or \mathbb{C}^{n^2}). we only need to rewrite the matrix equation $X' = AX$ in the vector form $X' = BX$ with a $n^2 \times n^2$ -matrix B . Then the uniqueness for the Cauchy problem in the vector form implies the uniqueness for the problem (1.2). \square

Definition 1.3. If $AV = \lambda V$, for some vector $V \neq 0$, then λ is an **eigenvalue** of A , and V is an **eigenvector** corresponding to λ .

We have $AV = \lambda V \iff (A - \lambda I)V = 0$. The last system has nontrivial solutions $V \neq 0 \iff |A - \lambda I| = 0$. We introduce the **characteristic** polynomial of A by the formula $p(\lambda) = |\lambda I - A|$. Now we can conclude:

(i) The eigenvalues of A are roots of the **characteristic** equation

$$p(\lambda) = |\lambda I - A| = 0. \quad (1.3)$$

(ii) For each eigenvalue λ , the corresponding eigenvectors V are nontrivial solutions of the system

$$(A - \lambda I)V = 0. \quad (1.4)$$

Lemma 1.4. Let A be a constant $n \times n$ matrix, and let $AV = \lambda V$ for some vector V . Then the matrix function $U = U(t) = e^{\lambda t}V$ satisfies $U' = AU$.

Proof. $U'(t) = (e^{\lambda t})' V = e^{\lambda t} \lambda V = e^{\lambda t} A V = A U(t)$. □

Lemma 1.5. For distinct eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_m$ of the matrix A , the corresponding eigenvectors V_1, V_2, \dots, V_m are linearly independent.

Proof. For $m = 1$, this is trivial:

$$V_1 \neq 0, \quad c_1 V_1 = 0 \quad \Rightarrow \quad c_1 = 0.$$

Now suppose this statement is true for some $m = k$, i.e. V_1, V_2, \dots, V_k are linearly independent. We will prove that it remains true for $m = k + 1$, i.e. the equality

$$c_1 V_1 + \dots + c_k V_k + c_{k+1} V_{k+1} = 0 \tag{1.5}$$

holds only in case $c_1 = \dots = c_k = c_{k+1} = 0$. Multiplying (1.5) by the matrix A and using the equalities $AV_j = \lambda_j V_j$, we get

$$c_1 \lambda_1 V_1 + \dots + c_k \lambda_k V_k + c_{k+1} \lambda_{k+1} V_{k+1} = 0.$$

Now subtract (1.5) multiplied by λ_{k+1} . This gives us

$$c_1 (\lambda_1 - \lambda_{k+1}) V_1 + \dots + c_k (\lambda_k - \lambda_{k+1}) V_k = 0.$$

By our assumption, V_1, V_2, \dots, V_k are linearly independent. Therefore,

$$c_1 (\lambda_1 - \lambda_{k+1}) = \dots = c_k (\lambda_k - \lambda_{k+1}) = 0.$$

Since all the eigenvalues are distinct, this implies $c_1 = \dots = c_k = 0$. Now from (1.5) it follows $c_{k+1} = 0$. This proves our statement for $m = k + 1$, and by induction, it is true for arbitrary m . □

Another way of computation e^{tA} is based on the following famous result.

Theorem 1.6 (Cayley-Hamilton). Let $A = (a_{ij})$ be a $n \times n$ matrix, and let $p(\lambda) = |\lambda I - A|$. Then $p(A) = 0$.

Proof. Denote

$$p(\lambda) = |\lambda I - A| = \sum_{j=0}^n p_j \lambda^j, \quad (p_n = 1).$$

Similarly to the geometric series for large $\lambda > 0$, we have a convergent series

$$(\lambda I - A)^{-1} = \frac{1}{\lambda} \cdot \left(I - \frac{1}{\lambda} \cdot A \right)^{-1} = \frac{1}{\lambda} \cdot \sum_{k=0}^{\infty} \lambda^{-k} A^k.$$

On the other hand, the elements of this function are co-factors of $\lambda I - A$ divided by $p(\lambda) = |\lambda I - A|$. Therefore, the product

$$p(\lambda) \cdot (\lambda I - A)^{-1} = \frac{1}{\lambda} \cdot \sum_{j,k} p_j \lambda^{j-k} A^k$$

is a polynomial of λ with matrix coefficient, so that the coefficients of all negative powers of λ must be 0. In particular, the coefficient of λ^{-1} , which corresponds to a part of the above sum for $j = k$, is

$$0 = \sum_j p_j A^j = p(A).$$

□

Let $\lambda_1, \lambda_2, \dots, \lambda_s$ denote all the distinct eigenvalues of a matrix A (real and complex). Then we can write the characteristic polynomial of A in the form

$$p(\lambda) = |\lambda I - A| = \prod_{k=1}^s (\lambda - \lambda_k)^{m_k}, \quad (1.6)$$

where m_k is the multiplicity of λ_k . We have

$$\frac{1}{p(\lambda)} = \sum_{k=1}^s \frac{a_k(\lambda)}{(\lambda - \lambda_k)^{m_k}}, \quad (1.7)$$

where $a_k(\lambda)$ is a polynomial of degree $\leq m_k - 1$ for each k . Therefore,

$$1 = \sum_{k=1}^s a_k(\lambda) p_k(\lambda), \quad I = \sum_{k=1}^s a_k(A) p_k(A), \quad (1.8)$$

where

$$p_k(\lambda) = \frac{p(\lambda)}{(\lambda - \lambda_k)^{m_k}} = \prod_{j \neq k} (\lambda - \lambda_j)^{m_j}. \quad (1.9)$$

Theorem 1.6. Let $\lambda_1, \lambda_2, \dots, \lambda_s$ be all the distinct eigenvalues of a matrix A with the characteristic polynomial $p(\lambda)$ in (1.6). Then

$$e^{tA} = \sum_{k=1}^s e^{\lambda_k t} a_k(A) p_k(A) \sum_{j=0}^{m_k-1} \frac{t^j}{j!} (A - \lambda_k I)^j, \quad (1.10)$$

where a_k are polynomials of degree $\leq m_k - 1$, which are defined from the decomposition (1.7), and p_k are polynomials in (1.9).

First we prove a lemma, which allows us to use the equalities

$$e^{tA} = e^{t\lambda I} e^{t(A-\lambda A)} = e^{\lambda t} e^{t(A-\lambda A)}. \quad (1.11)$$

Lemma 1.7. Let A and B be $n \times n$ matrices satisfying $AB = BA$. Then

$$e^{tA} e^{tB} \equiv e^{t(A+B)}.$$

Proof of Lemma. We have

$$AB = BA \implies A^k B = B A^k \implies e^{tA} B = B e^{tA}.$$

Therefore, the matrix function $X(t) = e^{tA} e^{tB}$ satisfies

$$X' = (e^{tA})' e^{tB} + e^{tA} (e^{tB})' = A e^{tA} e^{tB} + B e^{tA} e^{tB} = (A + B)X, \quad X(0) = I.$$

By Lemma 1.2, we have $X(t) \equiv e^{t(A+B)}$. □

Proof of Theorem 1.6. Using the equalities (1.8) and (1.11) we get

$$e^{tA} = \sum_{k=1}^s a_k(A) p_k(A) e^{tA} = \sum_{k=1}^s e^{\lambda_k t} a_k(A) p_k(A) e^{t(A - \lambda_k I)}. \quad (1.12)$$

Since $p_k(A)(A - \lambda_k I)^{m_k} = p(A) = 0$,

$$p_k(A) e^{t(A - \lambda_k I)} = p_k(A) \sum_{j=0}^{\infty} \frac{t^j}{j!} (A - \lambda_k I)^j = p_k(A) \sum_{j=0}^{m_k-1} \frac{t^j}{j!} (A - \lambda_k I)^j.$$

Together with (1.12), this gives us the equality (1.10). □

Example 1.8. Consider the matrix $A = \begin{pmatrix} -1 & 1 & -2 \\ 0 & -1 & 4 \\ 0 & 0 & 1 \end{pmatrix}$. We have

$$p(\lambda) = |\lambda I - A| = (\lambda + 1)^2(\lambda - 1) \implies$$

$$\lambda_1 = -1, \quad m_1 = 2, \quad \lambda_2 = 1, \quad m_2 = 1, \quad p_1(\lambda) = \lambda - 1, \quad p_2(\lambda) = (\lambda + 1)^2;$$

$$\frac{1}{p(\lambda)} = \frac{1}{(\lambda + 1)^2(\lambda - 1)} = \frac{1}{4} \left(\frac{1}{\lambda - 1} - \frac{\lambda + 3}{(\lambda + 1)^2} \right) \implies a_1(\lambda) = -\frac{1}{4}(\lambda + 3), \quad a_2(\lambda) = \frac{1}{4}.$$

By (1.10), we have

$$e^{tA} = -\frac{1}{4} e^{-t} (A + 3I)(A - I)[I + t(A + I)] + \frac{1}{4} e^t (A + I)^2.$$

Finally,

$$\begin{aligned} -\frac{1}{4} (A + 3I)(A - I) &= \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \end{pmatrix}, \quad \frac{1}{4} (A + I)^2 = \frac{1}{4} \begin{pmatrix} 0 & 1 & -2 \\ 0 & 0 & 4 \\ 0 & 0 & 2 \end{pmatrix}^2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 1 \end{pmatrix} \\ \implies e^{tA} &= e^{-t} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \end{pmatrix} + t e^{-t} \begin{pmatrix} 0 & 1 & -2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} + e^t \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 1 \end{pmatrix}. \end{aligned}$$

Example 1.9. Consider the matrix $A = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}$. We have

$$p(\lambda) = \lambda^2 + 1, \quad \lambda_1 = i, \quad p_1(\lambda) = \lambda + i; \quad \lambda_2 = -i, \quad p_2(\lambda) = \lambda - i, \quad m_1 = m_2 = 1;$$

$$\frac{1}{\lambda^2 + 1} = \frac{a_1}{\lambda - i} + \frac{a_2}{\lambda + i}, \quad \text{where } a_1 = \lim_{\lambda \rightarrow i} \frac{\lambda - i}{\lambda^2 + 1} = \frac{1}{2i}, \quad a_2 = -\frac{1}{2i};$$

$$\begin{aligned} e^{tA} &= \sum e^{\lambda_k t} a_k p_k(A) = e^{it} \cdot \frac{1}{2i} \cdot (A + iI) + e^{-it} \cdot \frac{-1}{2i} \cdot (A - iI) = \frac{e^{it} - e^{-it}}{2i} \cdot A + \frac{e^{it} + e^{-it}}{2} \cdot I \\ &= \cos t \cdot I + \sin t \cdot A = \begin{pmatrix} \cos t & -\sin t \\ \sin t & \cos t \end{pmatrix}. \end{aligned}$$