

Lecture 22: Exponentiating Matrices

Recall the basic problem introduced in Lecture 21: solving a system of n first-order DEs

$$\begin{cases} x_1'(t) = a_{11}x_1(t) + \dots + a_{1n}x_n(t) \\ \vdots \\ x_n'(t) = a_{n1}x_1(t) + \dots + a_{nn}x_n(t) \end{cases} \quad (*)$$

or
Equivalently

$\vec{x}'(t) = A \vec{x}(t)$

(where $A = [a_{ij}]$).

We devised a method in the case that $A = P D P^{-1}$

(i.e. A is diagonalizable), by substituting $\vec{x}(t) = P \vec{y}(t)$

$$\Rightarrow P \vec{y}'(t) = \vec{x}'(t) = A P \vec{y}(t) = P D P^{-1} P \vec{y}(t) = P D \vec{y}(t)$$

$$\Rightarrow \vec{y}'(t) = D \vec{y}(t) \Rightarrow y_j'(t) = \lambda_j y_j(t) \Rightarrow y_j(t) = c_j e^{\lambda_j t}$$

(where $\vec{c} = P^{-1} \vec{x}(0)$). But what about the "general A " case?

What if we could simply solve $(*)$ by writing

$$\vec{x}(t) := e^{tA} \vec{x}(0) \Rightarrow \vec{x}'(t) = A e^{tA} \vec{x}(0) = A \vec{x}(t) ?$$

To do this, we need to introduce calculus for matrix-valued functions $M = M(t) = [m_{ij}(t)]$ (that is, n^2 functions if M

is $n \times n$). We define $M' = M'(t) = [m'_{ij}(t)]$ and notice that

$$(M+N)' = M' + N' \text{ and } (MN)' = M'N + MN' \text{ (why?)}$$

We'll also need series of matrices: given a sequence

$\{C_k\}_{k \geq 0}$ with $C_k = [c_{ij}^{(k)}]$, define $\sum_{k=0}^{\infty} C_k := \left[\sum_k c_{ij}^{(k)} \right]$
 (that is, "convergence" means that every matrix entry converges).

Lemma: If $\sum \|C_k\|$ converges (the norm of a matrix $\|A\| := \sum_i \sum_j |a_{ij}|$), then $\sum C_k$ converges.

Proof: $|c_{ij}^{(k)}| \leq \|C_k\| \Rightarrow \sum |c_{ij}^{(k)}| \leq \sum \|C_k\|$. So
 if $\sum \|C_k\|$ converges, $\sum c_{ij}^{(k)}$ converges absolutely (\Rightarrow converges). \square

Ex / First note that $\|AB\| = \sum_i \sum_k \left| \sum_j a_{ij} b_{jk} \right| \leq \sum_i \sum_j |a_{ij}| \sum_k |b_{jk}|$
 $\leq \sum_i \sum_j |a_{ij}| \|B\| \leq \|A\| \|B\|$, so $\|A^k\| \leq \|A\|^k$.

Taking $C_k = \frac{1}{k!} A^k$, $\|C_k\| = \frac{1}{k!} \|A^k\| \leq \frac{1}{k!} \|A\|^k \Rightarrow$
 $\sum \|C_k\| \leq \sum \frac{\|A\|^k}{k!} = e^{\|A\|} \Rightarrow \sum C_k = \sum \frac{1}{k!} A^k$ converges.

Define $e^A := \sum_{k=0}^{\infty} \frac{1}{k!} A^k$. (The 0th term is by defn. I .)

e.g. $e^0 = I$

$$e^{tA} = \sum_k \frac{(tA)^k}{k!} = \sum_k \frac{t^k}{k!} A^k$$

$$\text{if } A = D = \text{diag}(\lambda_1, \dots, \lambda_n), \quad e^{tD} = \sum_k \frac{t^k}{k!} \begin{pmatrix} \lambda_1^k & & \\ & \dots & \\ & & \lambda_n^k \end{pmatrix} = \begin{pmatrix} e^{t\lambda_1} & & \\ & \dots & \\ & & e^{t\lambda_n} \end{pmatrix} //$$

Theorem 1: The matrix differential equation

$$M'(t) = A M(t) \quad \text{with initial cond. } M(0) = B$$

has the unique solution $M(t) = e^{tA} B$.

Proof: Write $A^k = [c_{ij}^{(k)}]$. Then

$$e^{tA} = \sum_{k=0}^{\infty} \frac{t^k}{k!} A^k = \left[\sum_{k=0}^{\infty} \frac{t^k}{k!} c_{ij}^{(k)} \right] \quad \text{while}$$

$$(e^{tA})' = \left[\sum_{k=1}^{\infty} \frac{k t^{k-1}}{k!} c_{ij}^{(k)} \right] = \left[\sum_{k=0}^{\infty} \frac{t^k}{k!} c_{ij}^{(k+1)} \right] = \sum_{k=0}^{\infty} \frac{t^k}{k!} \underbrace{[c_{ij}^{(k+1)}]}_{A^{k+1}}$$

replace k by k+1

$$= \sum_{k=0}^{\infty} \frac{t^k}{k!} A A^k = A \sum_{k=0}^{\infty} \frac{t^k}{k!} A^k = A e^{tA}.$$

Note that $A^{k+1} = A A^k = A^k A \Rightarrow A e^{tA} = e^{tA} A.$

So $(e^{tA} B)' = (e^{tA})' B = A (e^{tA} B) \Rightarrow M(t) = e^{tA} B$
 gives a solution.

Next write $F(t) := e^{tA} e^{-tA}$, so that

$$F'(t) = (e^{tA})' e^{-tA} + e^{tA} (e^{-tA})' = A e^{tA} e^{-tA} + e^{tA} (-A e^{-tA})$$

$$= A e^{tA} e^{-tA} - A e^{tA} e^{-tA} = 0 \Rightarrow F(t) \text{ is constant}$$

$$\Rightarrow F(t) = F(0) = e^0 e^0 = I \Rightarrow e^{-tA} = \text{inverse of } e^{tA}.$$

Therefore given any solution $M(t)$, putting

$$G(t) := e^{-tA} M(t) \text{ gives } G'(t) = -A e^{-tA} M(t) + e^{-tA} \underbrace{M'(t)}_{A M(t)} = 0$$

$$\Rightarrow G(t) \text{ constant} \Rightarrow G(t) = G(0) = M(0) = B$$

$$\Rightarrow B = e^{-tA} M(t) \Rightarrow e^{tA} B = e^{tA} e^{-tA} M(t) = M(t). \quad \square$$

Corollary: If $AB = BA$, then $e^{A+B} = e^A e^B$. (The statement is false if $AB \neq BA$.)

Proof: By induction on k , $A^k B = B A^k$; hence $e^{tA} B = B e^{tA}$.

Both $e^{t(A+B)}$ and $e^{tA} e^{tB}$ therefore solve $M'(t) = (A+B)M(t)$, with initial condition $M(0) = I$. Hence they are equal. \square

Theorem 2: Given A $n \times n$ matrix, $\vec{b} \in \mathbb{R}^n$ and $a \in \mathbb{R}$, there exists a unique solution to $\vec{x}'(t) = A\vec{x}(t)$ with $\vec{x}(a) = \vec{b}$.

Proof: Suppose $\vec{x}(t)$ is a solution. Then set $\vec{w}(t) := e^{-tA}\vec{x}(t)$,

$$\text{compute } \vec{w}'(t) = -Ae^{-tA}\vec{x}(t) + e^{-tA} \underbrace{\vec{x}'(t)}_{A\vec{x}(t)} = -A\vec{w}(t) + A\vec{w}(t) = \vec{0}$$

$\Rightarrow \vec{w}(t)$ is constant

$$\Rightarrow \vec{w}(t) = \vec{w}(a) = e^{-aA}\vec{x}(a) = e^{-aA}\vec{b}$$

$$\Rightarrow \vec{x}(t) = e^{tA}\vec{w}(t) = e^{(t-a)A}\vec{b}. \quad \text{Check that this works:}$$

$$\vec{x}'(t) = Ae^{(t-a)A}\vec{b} = A\vec{x}(t). \quad \square$$

Corollary: Given b_1, \dots, b_n and $a, a_1, \dots, a_n \in \mathbb{R}$, there exists a unique solution $f(t)$ to

$$\begin{cases} f^{(n)}(t) + a_1 f^{(n-1)}(t) + \dots + a_n f(t) = 0 \\ f(a) = b_1, f'(a) = b_2, \dots, f^{(n-1)}(a) = b_n. \end{cases}$$

Proof: Let $A = \begin{pmatrix} 0 & 1 & & 0 \\ & & \ddots & \\ & & & 1 \\ -a_n & -a_{n-1} & \dots & -a_1 \end{pmatrix}$, $\vec{b} = \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix}$

Then $\begin{cases} \vec{x}'(t) = A\vec{x}(t) \\ + \vec{x}(a) = \vec{b} \end{cases} \iff \begin{cases} x_1'(t) = x_2(t) \\ x_2'(t) = x_3(t) \\ \vdots \\ x_{n-1}'(t) = x_n(t) \\ x_n'(t) = -a_1 x_n(t) - \dots - a_n x_1(t) \end{cases} + \vec{x}(a) = \vec{b}$

$$\begin{array}{l}
 \leftarrow \\
 \uparrow \\
 \text{writing} \\
 x_1(t) = f(t)
 \end{array}
 \left\{ \begin{array}{l}
 x_2(t) = f'(t) \\
 x_3(t) = f''(t) \\
 \vdots \\
 x_n(t) = f^{(n-1)}(t) \\
 f^{(n)}(t) = -a_1 f^{(n-1)}(t) - \dots - a_n f(t)
 \end{array} \right.
 + \left\{ \begin{array}{l}
 f(a) = b_1 \\
 \vdots \\
 f^{(n-1)}(a) = b_n
 \end{array} \right.$$

Since the first system has a unique solution, so does the last. \square

Great! So how do we compute this thing e^{tA} that solves everything? In general, that's the topic of next lecture, but here are a couple of examples.

• If $A = PDP^{-1}$ (is diagonalizable), then

$$A^k = PD^kP^{-1} \Rightarrow e^{tA} = \sum \frac{t^k}{k!} A^k = P \sum \frac{t^k}{k!} P^{-1} = P e^{tD} P^{-1}$$

where $e^{tD} = \begin{pmatrix} e^{\lambda_1 t} & & 0 \\ & \ddots & \\ 0 & & e^{\lambda_n t} \end{pmatrix}$.

$$\text{Ex/ } A = \begin{pmatrix} 1 & 2 \\ -1 & 4 \end{pmatrix} = \underbrace{\begin{pmatrix} 2 & 1 \\ 1 & 1 \end{pmatrix}}_P \underbrace{\begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}}_D \underbrace{\begin{pmatrix} 1 & -1 \\ -1 & 2 \end{pmatrix}}_{P^{-1}}$$

$$\Rightarrow e^{tA} = \begin{pmatrix} 2 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} e^{2t} & 0 \\ 0 & e^{3t} \end{pmatrix} \begin{pmatrix} 1 & -1 \\ -1 & 2 \end{pmatrix} = \left(\begin{array}{c|c} 2e^{2t} - e^{3t} & -2e^{2t} + 2e^{3t} \\ \hline e^{2t} - e^{3t} & -e^{2t} + 2e^{3t} \end{array} \right)$$

\Rightarrow Sol'n to $\dot{\vec{x}}(t) = A\vec{x}(t)$ w/ init. conditions $\vec{x}(0) = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ is

$$\vec{x}(t) = e^{tA} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 2e^{2t} - e^{3t} \\ e^{2t} - e^{3t} \end{pmatrix} //$$

• What if (say) $A = \begin{pmatrix} 1 & \alpha \\ 0 & 1 \end{pmatrix}$? By induction on k ,

$$A^k = \begin{pmatrix} 1 & k\alpha \\ 0 & 1 \end{pmatrix}. \quad \text{So (using } \sum \frac{t^k}{k!} k\alpha = \alpha \sum \frac{t^k}{(k-1)!} = \alpha \sum \frac{t^{k+1}}{k!} = \alpha t e^t \text{)}$$

$$e^{\tau A} = \sum_{k=0}^{\infty} \frac{\tau^k}{k!} \begin{pmatrix} 1 & k\alpha \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} e^{\tau} & \alpha t e^{\tau} \\ 0 & e^{\tau} \end{pmatrix}$$

\Rightarrow Solution with initial condition $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$ is $e^{\tau A} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} e^{\tau} \\ 0 \end{pmatrix}$
" " " " " $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$ is $e^{\tau A} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} \alpha t e^{\tau} \\ e^{\tau} \end{pmatrix}.$