

(7)

The step $2) \rightarrow 3)$ is trivial.

To prove $3) \rightarrow 1)$ suppose that $\sum \lambda_i y_i = 0$ in $C^1(\mathbb{J}, \mathbb{R}^n)$ we want to prove $\lambda_1, \dots, \lambda_k = 0$

$$\sum \lambda_i y_i = 0 \text{ in } C^1(\mathbb{J}, \mathbb{R}^n) \Leftrightarrow$$

$\sum \lambda_i y_i(x) = 0$ for all $x \in \mathbb{J}$, in particular for any $x_0 \in \mathbb{J}$. Then

$$\sum \lambda_i y_i(x_0) = 0 \Rightarrow \lambda_i = 0, i=1, \dots, k \quad (\text{because})$$

$\{y_i(x)\}$ are independent in \mathbb{R}^n . \blacksquare

To prove $1) \rightarrow 2)$ Assume $\sum_{i=1}^k \lambda_i y_i(x_0) = 0$

for some $x_0 \in \mathbb{J}$. Want to prove $\lambda_1, \dots, \lambda_k = 0$

$$\text{Let } y(x) = \sum \lambda_i y_i(x). \text{ Then}$$

$$y'(x) \text{ satisfies } \begin{cases} y' = A(x)y \\ y(x_0) = 0 \end{cases} \Rightarrow y(x) \equiv 0$$

$$\Rightarrow y(x) \equiv 0 \Rightarrow \sum \lambda_i y_i = 0 \text{ in } C^1(\mathbb{J}, \mathbb{R})$$

$\Rightarrow \lambda_i = 0, i=1, \dots, k$ because the y_i were assumed to be independent in $C^1(\mathbb{J}, \mathbb{R})$.

Theorem Let $V = \{y \in C^1(\mathbb{J}, \mathbb{R}^n), y \text{ solves } y' = A(x)y\}$

Then V is an n -dimensional vector space, a subspace of $C^1(\mathbb{J}, \mathbb{R}^n)$

Proof Pick any $x_0 \in \mathbb{J}$. The set of possible initial values is n -dimensional, so one can have exactly n independent $y(x_0)$, call them $y_1(x_0), \dots, y_n(x_0)$.

$$\text{The solutions to } \begin{cases} y'_j = A(x)y_j \\ y_j(x_0) = y_{j0} \end{cases}$$

are then a (maximal) number of independent solutions to $y' = A(x)y$.

Def Let $y_1, \dots, y_n \in V$ be n independent solutions to $y' = A(x)y$.

Let

$$Y = [y_1 \dots y_n], \text{ i.e. an } n \times n\text{-matrix}$$

whose columns are the n independent solutions (not that this choice is not unique!)

Then $Y(x)$ solves the equation

$Y'(x) = A(x)Y(x)$, and it is called a fundamental solution.

Some remarks Sometimes it is convenient to write $y = y(x, x_0, y_0)$ for the solution to

$$\begin{cases} y' = A(x)y \\ y(x_0) = y_0 \end{cases}$$

Then the map $y_0 \mapsto y(x, x_0, y_0)$ is a bijective (1-1) map.

A special fundamental matrix is obtained by solving

$$\begin{cases} X' = A(x)X & (\text{all } n \times n\text{-matrices}) \\ X(x_0) = I \end{cases}$$

Then ANY fundamental matrix $Y(x)$ can be obtained as

$$Y(x) = X(x) Y(x_0)$$

(exercise: prove this)

The Wronskian

Let $\mathbf{Y}(x)$ be a solution of $\mathbf{Y}' = A(x)\mathbf{Y}$.

Let $\phi(x) = \det \mathbf{Y}(x)$. $\phi(x)$ is called the Wronskian of \mathbf{Y} .

Theorem If $A(x)$ is continuous in \mathbb{J} , then $\phi(x)$ satisfies

$$\phi'(x) = \text{tr } A(x) \phi(x) \quad \text{in } \mathbb{J}.$$

(Recall that $\text{tr } M = \sum_{j=1}^n m_{jj}$, for an $n \times n$ -matrix $M = (m_{ij})$; this is called the trace of M)

Proof Let \mathbf{X} solve $\begin{cases} \mathbf{X}' = A(x)\mathbf{X} \\ \mathbf{X}(x_0) = I \end{cases}$

$$\text{Then } (\det \mathbf{X}(x))' = \sum_{i=1}^n \det [\mathbf{x}_1 \ \mathbf{x}_2 \ \mathbf{x}_i' \ \mathbf{x}_n]$$

$$\text{But } \mathbf{x}_i'(x_0) = A(x_0) \mathbf{e}_i \quad (\text{because } x_i(x_0) = \mathbf{e}_i)$$

and therefore

$$\begin{aligned} (\det \mathbf{X}(x))' &= \sum_{i=1}^n \det (\mathbf{e}_1, \dots, \mathbf{e}_{i-1}, A(x_0) \mathbf{e}_i, \mathbf{e}_{i+1}, \dots, \mathbf{e}_n) \\ &= \sum_{i=1}^n a_{ii}(x_0) = \text{tr } A(x_0). \end{aligned}$$

$$\text{But } \mathbf{Y}(x) = \mathbf{X}(x) \mathbf{Y}(x_0)$$

$$\Rightarrow \det \mathbf{Y}(x) = \det \mathbf{X}(x) \det \mathbf{Y}(x_0)$$

$$\Rightarrow \phi'(x) = \phi(x_0) (\det \mathbf{X}(x))'$$

$$\Rightarrow \phi'(x) = \underbrace{\phi(x_0)}_{\neq 0} \text{tr } A(x_0)$$

Note hence the Wronskian is always $\neq 0$, if that holds at one single point.

Proof of continuous dependence

We want to prove 1) and 2) on page 38.

$$1). \quad y' = Ay + b. \quad \text{Note that} \quad |y(x_0)| < \eta$$

$$\frac{d}{dt} |y|^2 = 2y \cdot y' = 2y^T y'$$

$$\text{and} \quad |y^T A y| \leq \|A\| |y|^2 \quad (\text{now we consider the operator norm of } A)$$

$$|y^T b| \leq |y| \|b\|$$

$$\text{Then if } b \neq 0 \quad \frac{d}{dt} |y|^2 \leq 2\|A\| |y|^2 + 2|b| |y|$$

$$\Rightarrow 2|y| \frac{d|y|}{dt} \leq 2\|A\| |y|^2 + 2|b| |y|$$

$$\Rightarrow \frac{d|y|}{dt} \leq \|A\| |y| + |b|$$

$$\Rightarrow |y| \leq \eta e^{L(x-x_0)} + \frac{\delta}{L} (e^{L(x-x_0)} - 1)$$

$$\left. \begin{array}{l} \|A\| < L \\ |b| < \delta \\ |y_0| < \eta \end{array} \right\}$$

according to the lemma page 34.



2) We give a proof of this statement which is based on 1). Note that the norm used for matrices is the operator norm, but any compatible norm could have been used.

Consider y and z , solutions to

$$\begin{cases} y' = Ay + b \\ y(x_0) = y_0 \end{cases} \quad \begin{cases} z' = Bz + c \\ z(x_0) = x_0 \end{cases}$$

Let $\mathcal{J}' \subset \mathcal{J}$ be a compact (i.e. closed and (505)

bounded) interval. Let $L_1 = \max_{x \in \mathcal{J}'} \|Ax\|$, $L_2 = \max_{x \in \mathcal{J}'} \|Bx\|$,

$$\eta_1 = |y(x_0)| \quad \eta_2 = |z(x_0)|$$

$$\delta_1 = \max_{x \in \mathcal{J}'} |b| \quad \delta_2 = \max_{x \in \mathcal{J}'} |c|$$

Let $w = y - z$. Then

$$w' = Ay - Bz + b - c = A(y - z) + (A - B)z + (b - c)$$

$$\text{If } \gamma = |w_0| = |y(x_0) - z(x_0)| \quad \text{and} \quad \delta = \max_{x \in \mathcal{J}'} |(A - B)z + (b - c)|,$$

then 1) implies that

$$|w(x)| \leq \gamma e^{L_1|x-x_0|} + \frac{\delta}{L_1}(e^{L_1|x-x_0|} - 1) \quad \text{in } \mathcal{J}'.$$

Let $p = |\mathcal{J}'|$, the length of the interval \mathcal{J}' .

If we can achieve $\gamma + \frac{\delta}{L_1} < \varepsilon / e^{L_1 p}$, then we are done.

But $\gamma \leq \beta$. We can use 1) to estimate δ , in the following way:

$$|(A - B)z + (b - c)| \leq |(A - B)z| + |b - c| \leq \|A - B\| |z| + |b - c| \leq \beta |z| + \beta$$

according to the hypothesis for 2). But according

to 1), $|z| \leq \eta_2 e^{L_2 p} + \frac{\delta_2}{L_2}(e^{L_2 p} - 1)$. Note that

because $\|B - A\|$ should be small, and $|b - c|$ and $|y(x_0) - z(x_0)|$ too, it is reasonable to estimate η_2 by $2\eta_1$ etc,

and hence $|z| \leq 2\eta_1 e^{2L_1 p} + \frac{\delta_2}{L_2}(e^{2L_1 p} - 1)$ for all B close to A

$$\text{Hence } \gamma + \frac{\delta}{L_1} < \beta + \beta \left(2\eta_1 e^{2L_1 p} + \frac{\delta_1}{L_1}(e^{2L_1 p} - 1) \right) + \beta$$

which is smaller than $\varepsilon / e^{L_1 p}$ if β is small enough.

Inhomogeneous differential equations

We wish to solve

$$\begin{cases} y' = A(x)y + b(x) & y \in \mathbb{R}^n \\ y(x_0) = y_0 & x_0 \in \mathbb{J} \end{cases}$$

Note If \tilde{y} is any solution $y' = A(x)y + b(x)$, then all other solutions can be obtained by adding a solution to the homogeneous equation.

In this case \tilde{y} is called a particular solution.

The variation of constants formula

Let $\Sigma(x)$ be a fundamental solution, and set $\Xi(x) = \Sigma(x)v(x)$, where $v(x)$ is an unknown vector. Then

$$\begin{aligned} \Xi'(x) &= \Sigma'(x)v(x) + \Sigma(x)v'(x) \\ &= A(x)\Sigma(x)v(x) + \Sigma(x)v'(x). \end{aligned}$$

$$\begin{aligned} \text{We hope to find } \Xi'(x) &= A(x)\Xi(x) + b(x) \\ &= A(x)\Sigma(x)v(x) + b(x). \end{aligned}$$

But this requires $\Sigma(x)v'(x) = b(x)$, or
(because $\Sigma(x)$ is invertible)

$$v'(x) = \Sigma^{-1}(x)b(x).$$

$$\begin{aligned} \text{and hence } v(x) &= v(x_0) + \int_{x_0}^x \Sigma^{-1}(z)b(z)dz \\ \Rightarrow \quad \Xi(x) &= \Sigma(x)v(x_0) + \int_{x_0}^x \Sigma(x)\Sigma^{-1}(z)b(z)dz. \end{aligned}$$

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One can take e.g. the fundamental matrix
 \mathbf{X} that satisfies $\mathbf{X}(x_0) = \mathbf{I}$.

Then we find

$$y(x) = \mathbf{X}(x) y_0 + \int_{x_0}^x \mathbf{X}(x) \mathbf{X}^{-1}(\bar{x}) b(\bar{x}) d\bar{x}$$

to be the solution to $\begin{cases} y' = A(x)y + b(x) \\ y(x_0) = y_0 \end{cases}$

Note because any fundamental solution
 can be written $\mathbf{Y}(x) = \mathbf{X}(x) \mathbf{Y}(x_0)$
 $\Leftrightarrow \mathbf{X}(x) = \mathbf{Y}(x) \mathbf{Y}^{-1}(x_0)$

it also is true that

$$\begin{aligned} y(x) &= \mathbf{Y}(x) \mathbf{Y}^{-1}(x_0) y_0 \\ &+ \int_{x_0}^x \mathbf{Y}(x) \mathbf{Y}^{-1}(\bar{x}) b(\bar{x}) d\bar{x}. \end{aligned}$$

Positive solutions

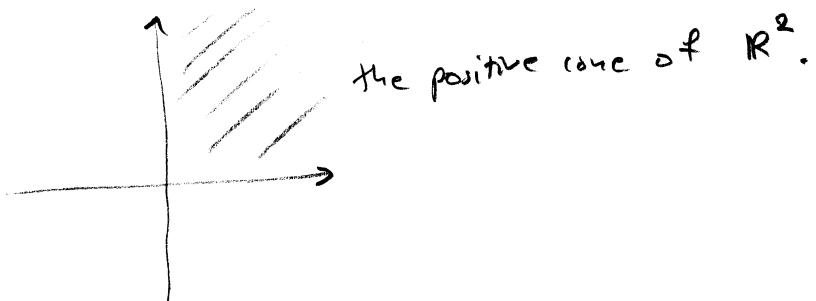
Many models using ordinary differential equations require positive solutions. This can be population models, models for chemical reactions etc. Populations and chemical concentrations are non-negative.

Def A matrix $A(t) = (a_{ij}(t))$ is said to be essentially positive if $a_{ij}(t) \geq 0$ when $i \neq j$.

Theorem If $A(t)$ is essentially positive and

$$\begin{cases} \frac{du}{dt} \geq A(t)u \\ u(t_0) \geq 0 \end{cases} \quad (\text{meaning that all coordinates are non-negative}),$$

then $u(t) \geq 0$ for all t . We say that $u(t)$ belongs to the positive cone



Proof Let $B(t) = A(t) + h(t)I$, where

$$h(t) = \max_{i \in \mathbb{N}} (-a_{ii}(t)). \text{ Then } B(t) = (b_{ij}(t)), \text{ where}$$

all elements $b_{ij}(t)$ are non-negative.

Then $\frac{du}{dt} + h(t)u(t) \geq B(t)u(t)$

That means that each component $u^i(t)$ of $u(t)$ satisfies

* $\frac{du^i}{dt} + h(t)u(t) \geq 0 \text{ at } t=t_0 \text{ and hence that}$

$$\frac{d}{dt} \left(e^{\int_{t_0}^t h(s) ds} u(t) \right) \geq 0 \text{ at } t=t_0, \text{ thus it is non-decreasing,}$$

and * remains true for all t , and so $u(t) \geq 0$ for all $t \geq t_0$

Systems with constant coefficients

Functions of exponentials.

Recall that $x' = ax$ has the solution $x(t) = e^{at} x_0$ (in \mathbb{R})

What about $x' = Ax$ in \mathbb{R}^n ? Can we write

$x(t) = e^{At} x_0$ in \mathbb{R}^n , where A is an $n \times n$ -matrix?

Yes. Consider the matrix equation

$$\begin{cases} \dot{X}(t) = AX(t) \\ X(t_0) = I \end{cases}$$

The Picard method gives

$$\begin{aligned} X_0 &= I \\ X_1(t) &= I + \int_{t_0}^t AX_0(\tau) d\tau = I + \int_{t_0}^t A I d\tau = I + At \\ X_2(t) &= I + \int_{t_0}^t A(I + At) d\tau = I + At + A^2 \frac{t^2}{2} \\ X_n(t) &= I + At + \frac{A^2 t^2}{2} + \dots + \frac{A^n t^n}{n!} \\ \Rightarrow X(t) &= I + At + \dots + \frac{A^n t^n}{n!} + \dots \\ &= \sum_{k=0}^{\infty} \frac{(At)^k}{k!} \end{aligned}$$

So at least formally $X(t)$ is a power series in At with the same coefficients as e^t , and so it is natural to write

$$X(t) = e^{At}.$$

Note also that this series is convergent, because

$$\begin{aligned}\|X_n(t)\| &\leq 1 + \sum_{k=1}^n \frac{\|(At)^k\|}{k!} \leq \\ &\leq 1 + \sum_{k=1}^n \frac{\|A\|^k t^k}{k!} \leq e^{\|At\|} \quad (\text{the usual exponential})\end{aligned}$$

(recall that $\|AB\| \leq \|A\|\|B\|$, and so
 $\|A^k\| \leq \|A\|^k$).

General power series of matrices

Let $p(s)$ be a (complex) polynomial of one variable s , so $p(s) = c_0 + c_1 s + \dots + c_k s^k$.

Then we define

$$p(A) = c_0 I + c_1 A + c_2 A^2 + \dots + c_k A^k,$$

$$\text{and } p(tA) = c_0 I + c_1 At + c_2 A^2 t^2 + \dots + c_k A^k t^k.$$

and similarly for (formal) power series.

Lemma a) if $BC = CB$ (the matrices A and B commute)

$$e^{B+C} = e^B e^C$$

b) If $\det C \neq 0$, then

$$e^{C^{-1}BC} = C^{-1} e^B C$$

c) Let $\text{diag}(\mu_1, \dots, \mu_n) = \begin{pmatrix} \mu_1 & 0 \\ 0 & \mu_2 \\ & \ddots & \ddots & \mu_n \end{pmatrix}$. We have

$$e^{\text{diag}(\lambda_1, \dots, \lambda_n)} = \text{diag}(e^{\lambda_1}, e^{\lambda_2}, \dots, e^{\lambda_n}).$$

Proof

$$\begin{aligned}
 a) \quad e^{B+C} &= \sum_{k=0}^{\infty} \frac{1}{k!} (B+C)^k = \\
 &= \sum_{k=0}^{\infty} \frac{1}{k!} \sum_{j=0}^k \binom{k}{j} B^j C^{k-j} \\
 &= \sum_{j=0}^{\infty} \sum_{k=j}^{\infty} \frac{1}{(k-j)!} \frac{1}{j!} B^j C^{k-j} \\
 &= \sum_{j=0}^{\infty} \sum_{k=j}^{\infty} \frac{1}{k!} \frac{1}{j!} B^j C^k = \left(\sum_{j=0}^{\infty} \frac{1}{j!} B^j \right) \left(\sum_{k=0}^{\infty} \frac{1}{k!} C^k \right)
 \end{aligned}$$

(this is where we use $BC = CB$.
 For example
 $(B+C)^2 = (B+C)(B+C) = B^2 + BC + CB + C^2$
 $= B^2 + 2BC + C^2$)

Note that this is allowed because each series is absolutely convergent.

$$\begin{aligned}
 b) \quad \text{Note that } (\bar{C}^{-1} B C)^k &= \bar{C}^{-1} B C \underbrace{\bar{C}^{-1} B C \bar{C}^{-1} B C \dots \bar{C}^{-1} B C}_{k \text{ times}} \\
 &= \underbrace{\bar{C}^{-1} B}_{\text{k times}} \underbrace{B}_{\text{k times}} \dots \underbrace{B}_{\text{k times}} C = \bar{C}^{-1} B^k C. \\
 \Rightarrow \sum_{k=0}^{\infty} \frac{1}{k!} (\bar{C}^{-1} B C)^k &= \bar{C}^{-1} \left(\sum_{k=0}^{\infty} \frac{1}{k!} B^k \right) C = \bar{C}^{-1} e^B C.
 \end{aligned}$$

$$c) (\text{diag}(\lambda_1, \dots, \lambda_n))^k = \text{diag}(\lambda_1^k, \dots, \lambda_n^k).$$

Corollaries

$$(e^A)^{-1} = e^{-A}$$

$$e^{A(s+t)} = e^{As} e^{At}$$

$$e^{A+\lambda I} = e^A e^\lambda$$

We have seen that $X(t) = e^{At}$ is a fundamental matrix to the equation

$$\dot{y} = A y.$$

But it seems hard to evaluate the powerseries since it involves many matrix multiplications.