

Linear systems with constant coefficients

Consider

$$\textcircled{B} \quad \dot{\mathbf{y}} = A\mathbf{y}.$$

since the scalar equation $\dot{y} = ay$ has solution $y = e^{at}$, try a solution of the same form for the system:

$$\text{Ansatz } \mathbf{y}(t) = e^{\lambda t} \mathbf{c} \quad \text{for some } \lambda \text{ and vector } \mathbf{c}.$$

$$\text{Then } \dot{\mathbf{y}}(t) = \lambda e^{\lambda t} \mathbf{c} \quad \text{and then}$$

$$\lambda e^{\lambda t} \mathbf{c} = A e^{\lambda t} \mathbf{c} \Leftrightarrow A\mathbf{c} = \lambda \mathbf{c}.$$

That means that λ is an eigenvalue to A , and \mathbf{c} an eigenvector to λ .

Def $p_n(\lambda) = \det(A - \lambda I)$ is called the characteristic polynomial to A , and the n zeros (counted with multiplicity) are the eigenvalues.

Theorem $\mathbf{y} = e^{\lambda t} \mathbf{c}$ is a solution to \textcircled{B} if and only if λ is an eigenvalue and \mathbf{c} an eigenvector.

If the eigenvalues $\lambda_1, \dots, \lambda_k$ are different, then

$e^{\lambda_1 t} \mathbf{c}_1, \dots, e^{\lambda_k t} \mathbf{c}_k$ are independent solutions, and

$\therefore \Sigma(t) = [e^{\lambda_1 t} \mathbf{c}_1 \quad e^{\lambda_2 t} \mathbf{c}_2 \quad \dots \quad e^{\lambda_k t} \mathbf{c}_k]$ is a fundamental matrix.

Proof We only need to recall that eigenvectors corresponding to different eigenvalues are independent.

If $A\mathbf{c}_j = \lambda_j \mathbf{c}_j \quad j=1 \dots k, \quad \lambda_j \neq \lambda_i \text{ if } i \neq j$, then if

$$\sum_{j=1}^k \alpha_j \mathbf{c}_j = 0 \Rightarrow \sum_{j=1}^k \alpha_j A\mathbf{c}_j = 0 \Rightarrow \sum_{j=1}^k \alpha_j \lambda_j \mathbf{c}_j = 0$$

We want to show that $\sum \alpha_j \mathbf{c}_j = 0$ and $\sum \alpha_j \lambda_j \mathbf{c}_j = 0 \Rightarrow \alpha_1 = \dots = \alpha_k = 0$.

This is obviously true for $k=1$. Suppose it holds for $k=t_0$. Then with $k=t_0+1$, assume

that $\sum_{j=1}^{k+1} \alpha_j c_j = 0$ and $\sum_{j=1}^{k+1} \alpha_j \lambda_j c_j = 0$.

and that all $\alpha_j \neq 0$. Then also $\sum_{j=1}^{k+1} \alpha_j \lambda_{k+1} c_j = 0$

and therefore $\sum_{j=1}^{k+1} \alpha_j (\lambda_j - \lambda_{k+1}) c_j = 0$

$$\Rightarrow \sum_{j=1}^k \alpha_j (\lambda_j - \lambda_{k+1}) c_j = 0. \quad \text{But } \lambda_j - \lambda_{k+1} \neq 0,$$

and therefore $\sum_{j=1}^k \beta_j c_j = 0$, and multiplying by A ,

$$\sum_{j=1}^k \beta_j \lambda_j c_j = 0. \quad \text{By the induction hypothesis}$$

this implies $\beta_j = 0 \quad j=1 \dots k$, and because $\alpha_j = \frac{\beta_j}{\lambda_j - \lambda_{k+1}}$

also $\alpha_j = 0 \quad (j=0 \dots k)$. Then obviously also $\alpha_{k+1} = 0$

and the result follows by the induction principle.

Note that here the λ_i and also the eigenvectors may be complex, but we really look for real solutions to $y' = Ay$.

Theorem (real version) Let $\lambda = p + iq$ be a complex eigenvalue, and $c = a + ib$ a complex eigenvector. Then $y = e^{\lambda t} c$ provides two real solutions $u = \operatorname{Re} y$ and $v = \operatorname{Im} y$. These are independent solutions.

Proof If $Ac = \lambda c$, then $A\bar{c} = \bar{\lambda} \bar{c}$, and so $\bar{\lambda}$ is an eigen vector with eigenvector c and \bar{c} are independent because $\lambda \neq \bar{\lambda}$ and so also u and v must be independent.

Another example that can be treated rather easily is when A is a symmetric matrix. Then there is an orthogonal matrix C such that $C^T A C = \text{diag}(\lambda_1, \dots, \lambda_n)$, where the λ_i are eigenvalues of A .

The λ_i 's are in this case real.

The fundamental matrix

$X = e^{At}$ can then be computed easily:

$$C^T X C = e^{C^T A C t} = e^{\text{diag}(\lambda_1, \dots, \lambda_n) t} = \text{diag}(e^{\lambda_1 t}, \dots, e^{\lambda_n t}),$$

because $C^{-1} = C^T$. So

$$X(t) = C \text{diag}(e^{\lambda_1 t}, \dots, e^{\lambda_n t}) C^T$$

Note that in the two cases, if

in

$$y' = Ay,$$

we write $y = Cz$, we find

$$\frac{d}{dt}(Cz) = ACz \quad \text{and then}$$

$$\frac{d}{dt}(C'z) = C'ACz$$

$$\begin{aligned} z' &= C'ACz = \cancel{C'} \cancel{AC} z \\ &= C' \begin{pmatrix} \lambda_1 c_1 & \lambda_2 c_2 & \lambda_n c_n \end{pmatrix} z \end{aligned}$$

$$= \text{diag}(\lambda_1, \dots, \lambda_n) z$$

This essentially solves our problem in case of n different eigenvalues, or for symmetric matrices.

The Jordan form

Let A be a (complex) non-singular matrix.

There exists a nonsingular matrix C so that

$$B = C^{-1}AC$$

has the form

$$\begin{pmatrix} J_1 & & & \\ & J_2 & & \\ & & \ddots & \\ & & & J_k \end{pmatrix}$$

where $J_i = \begin{pmatrix} \lambda_i^{n_i}, 0 \\ 0 \lambda_i^{n_i} \end{pmatrix}$, a matrix of type $n_i \times n_i$.

Each block J_i corresponds to one eigenvalue λ_i , and $\sum n_i = n$. The form of B corresponds to the characteristic polynomial of A ,

$$p(\lambda) = \det(A - \lambda I) = (-1)^n (\lambda - \lambda_1)^{n_1} (\lambda - \lambda_2)^{n_2} \cdots (\lambda - \lambda_k)^{n_k}.$$

Note that a differential equation

$y' = Ay$ is transformed to a simpler form

$$\text{by writing } z = y \Rightarrow z' = C^{-1}AC(z) = Bz.$$

If we let $z = \begin{pmatrix} z_1 \\ \vdots \\ z_k \end{pmatrix}$, where z_i is a vector in \mathbb{R}^{n_i} ,

we obtain k different systems:

$$\dot{z}_i = \begin{pmatrix} \lambda_i^{n_i}, 0 \\ 0 \lambda_i^{n_i} \end{pmatrix} z_i, \quad \text{which we will analyse next.}$$

Note 2

The Jordan form corresponds to "invariant subspaces" of a matrix A.

An invariant subspace is by definition a linear subspace $\Lambda \subset \mathbb{R}^n$, so that for any $v \in \Lambda$, $Av \in \Lambda$. For a diagonalizable matrix, every eigenvector is the basis of a one-dimensional invariant subspace.

Prop: If λ is an eigenvalue to A,

$$\text{then } \{v \in \mathbb{R}^n : Av = \lambda v\}$$

is an invariant subspace.

Def A generalized eigenvector (to the eigenvalue λ) is a vector $\neq 0$ that satisfies

$$(A - \lambda I)^k v = 0 \quad (k \geq 1)$$

note that for a Jordan block,

$$(J - \lambda I)^k = \left(\begin{pmatrix} \lambda & 1 & 0 \\ 0 & \ddots & \vdots \\ 0 & 0 & \lambda \end{pmatrix} - \lambda I \right)^k = \begin{pmatrix} 0 & 1 & 0 \\ 0 & \ddots & \vdots \\ 0 & 0 & 0 \end{pmatrix}^k$$

$$= 0 \text{ if } k > n-1,$$

Note 1 If the characteristic polynomial is

$$p(\lambda) = (-1)^n (\lambda - \lambda_1)^{n_1} \cdots (\lambda - \lambda_k)^{n_k},$$

we call n_i the algebraic multiplicity of the eigenvalue λ_i . The number of eigenvectors corresponding to λ_i must be a number r_i , $1 \leq r_i \leq n_i$. The number r_i is called the geometric multiplicity.

If $r_i = n_i$, then the Jordan blocks corresponding to λ_i is

$$\begin{pmatrix} \lambda_i & 0 \\ 0 & \lambda_i \end{pmatrix}$$
, so in fact it consists of n_i trivial blocks. The other extreme,

$$J_i = \begin{pmatrix} \lambda_i & 0 \\ 0 & \lambda_i \end{pmatrix}$$
, an $n \times n$ -matrix corresponds to the case with only one eigenvector.

The fundamental matrix to $\dot{z}_i = J_i z_i$ is $X_i = \begin{pmatrix} e^{\lambda_i t} & t e^{\lambda_i t} & t^2 e^{\lambda_i t} \\ 0 & e^{\lambda_i t} & t e^{\lambda_i t} \\ 0 & 0 & e^{\lambda_i t} \end{pmatrix}$

(so X_i solves

$$\begin{cases} \dot{X}_i(t) = J_i X_i(t) \\ X_i(0) = I \end{cases}$$

The Cayley-Hamilton Theorem

Theorem

Let A be an $n \times n$ -matrix, and let

$p_A(\lambda) = \det(A - \lambda I)$ be the characteristic polynomial. Then $p_A(\lambda) = 0$

Proof see special notes.

$$\text{Ex} \quad A = \begin{pmatrix} 1 & 0 \\ 3 & 2 \end{pmatrix} \Rightarrow p_A(\lambda) = (1-\lambda)(2-\lambda) = 2 - 3\lambda + \lambda^2$$

$$A^2 = \begin{pmatrix} 1 & 0 \\ 3 & 2 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 3 & 2 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 9 & 4 \end{pmatrix}$$

$$2I - 3A + A^2 = \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} - \begin{pmatrix} 3 & 0 \\ 9 & 6 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 9 & 4 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}.$$

A consequence is that any power of a matrix A ($n \times n$) is a linear combination of $I, A, A^2, \dots, A^{n-1}$.

If $p_A(\lambda) = (-1)^n (\lambda^n + a_{n-1}\lambda^{n-1} + \dots + a_0)$, then

$$\begin{aligned} p_A(A) = 0 &\Rightarrow A^n = -(a_{n-1}A^{n-1} + a_{n-2}A^{n-2} + \dots + a_1A + a_0I) \\ A^{n+1} &= -(a_{n-1}A^n + a_{n-2}A^{n-1} + \dots + a_1A^2 + a_0A) \\ &= (a_{n-1}^2 + a_{n-2})A^{n-1} + (a_{n-1}a_{n-2} - a_{n-3})A^{n-2} + \dots \\ &\quad + (a_{n-1}a_1 - a_0)A + a_{n-1}a_0I \end{aligned}$$

etc.

This means that to compute powerseries it is enough compute small powers. But it is not trivial to compute the coefficients.

There is a better way.

Lemma

Let f be an analytic function, and p a polynomial of degree n . There is an analytic function g and a polynomial q of degree at most $n-1$ so that

$$f(z) = g(z)p(z) + q(z)$$

Remark so $g(z)$ is the "remainder" when $f(z)$ is divided by $p(z)$.

Proof by induction. Assume that $p(z) = z - c$.

If $c=0$, then

$$f(z) = \sum_{k=0}^{\infty} a_k z^k = z \left(\sum_{k=1}^{\infty} a_k z^{k-1} \right) + a_0$$

so the result holds with $g(z) = a_0$ and $q(z) = \sum_{k=0}^{\infty} a_k z^k$.

For a general c , let $w = z - c$, and let

$$\begin{aligned} F(w) &= f(w+c). \quad \text{Then } F(w) = f(w)w + \tilde{a}_0 \\ &\Leftrightarrow f(z) = g(z-c)(z-c) + \tilde{a}_0. \end{aligned}$$

so the result is ok for $n=1$.

Suppose the lemma holds for $n=k-1$.

Let $p(z)$ be a polynomial of degree k .

Then $p(z) = p_1(z)(z-c)$, where $p(c)=0$.

By the induction hypothesis

$$f(z) = g_1(z)p_1(z) + q_1(z), \quad \text{where } \deg(g_1) \leq k-2.$$

Also, $g_1(z)$ is analytic, and it can be written

$$g_1(z) = g(z)(z-c) + g_0 \quad (g_0 \text{ a constant}).$$

Hence

$$\begin{aligned}
 f(z) &= g_1(z) p_1(z) + g_1(z) \\
 &= (g(z)(z-c) + g_0) p_1(z) + g_1(z) = \\
 &= \underbrace{g(z)(z-c) p_1(z)}_{p(z)} + \underbrace{g_0 p_1(z) + g_1(z)}_{g(z)}
 \end{aligned}$$

We have proven that the result also holds for $n=1$, and by induction for all $n \geq 1$.

How do we use that?

If we wish to compute $f(\lambda)$, where $f(z)$ is an analytical function, then we write

$$f(z) = g(z) p_\lambda(z) + g(z), \text{ and find that}$$

$$f(\lambda) = g(\lambda) p_\lambda(\lambda) + g(\lambda) = g(\lambda).$$

$$\text{Ex} \quad A = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix} \Rightarrow p_\lambda(\lambda) = (\lambda-1)(\lambda-2)$$

$$\sin(z) = g(z)(z-1)(z-2) + g(z) \quad g(z) = g_0 + g_1 z$$

$$\Rightarrow \begin{aligned} \sin(1) &= g(1) \\ \sin(2) &= g(2) \end{aligned} \Rightarrow \begin{cases} g_0 + g_1 = \sin(1) \\ g_0 + 2g_1 = \sin(2) \end{cases}$$

$$\Rightarrow \begin{cases} g_1 = \sin(2) - \sin(1) \\ g_0 = \sin(1) - g_1 = 2\sin(1) - \sin(2) \end{cases}$$

$$\Rightarrow g(z) = 2\sin(1) - \sin(2) + (\sin(2) - \sin(1))z$$

$$\Rightarrow \sin(A) = (2\sin(1) - \sin(2)) I + (\sin(2) - \sin(1)) A$$

$$= \begin{pmatrix} 2\sin 1 - \sin 2 & 0 \\ 0 & 2\sin 1 - \sin 2 \end{pmatrix} + \begin{pmatrix} \sin 2 - \sin 1 & 0 \\ 3\sin 2 - 3\sin 1 & 2\sin 2 - 2\sin 1 \end{pmatrix} = \begin{pmatrix} \sin 1 & 0 \\ 3\sin 2 - 3\sin 1 & \sin 2 \end{pmatrix}$$

Linear systems of order n

(note that here
the coefficients may depend on t)

A scalar equation of order n can be written

$$L(t, \frac{d}{dt}) y = g, \quad \text{where}$$

$L(t, \lambda) = \lambda^n + a_{n-1}\lambda^{n-1} + \dots + a_1\lambda + a_0$ is a (real)
polynomial of degree n, and where

$$L(t, \frac{d}{dt}) \text{ mean. } \frac{d^n}{dt^n} + a_{n-1} \frac{d^{n-1}}{dt^{n-1}} + \dots + a_1 \frac{d}{dt} + a_0$$

$$\text{Ex} \quad y'' + ay' + b = L(t, \frac{d}{dt}) y,$$

$$\text{where } L(t, \frac{d}{dt}) = \lambda^2 + a\lambda + b.$$

The equation

$$L(t, D) y = g$$

can be written

$$\text{where } x = \begin{pmatrix} y \\ y' \\ y'' \\ \vdots \\ y^{(n-1)} \end{pmatrix}, \quad x' = A x + b, \quad A = \begin{pmatrix} 0 & 1 & & & 0 \\ 0 & 0 & \ddots & & \\ 0 & & 0 & \ddots & 1 \\ \vdots & & & \ddots & 0 \\ -a_0 & -a_1 & \dots & \dots & -a_{n-1} \end{pmatrix}$$

$$\text{and } b = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ g \end{pmatrix}. \quad \text{Note that all coefficients may depend on } t.$$

Let $F(t)$ be a fundamental matrix to $x' = Ax + b$,

$$F(t) = \begin{pmatrix} y_1(t) & y_2(t) & \dots & y_n(t) \\ y'_1(t) & y'_2(t) & \dots & y'_n(t) \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{(n-1)}(t) & y_2^{(n-1)}(t) & \dots & y_n^{(n-1)}(t) \end{pmatrix} = \begin{pmatrix} R_1(t) \\ R_2(t) \\ \vdots \\ R_n(t) \end{pmatrix}$$

Note that the rows satisfy

$$R_{knn} = R_k \quad (k=1, \dots, n-1)$$

We know that

$$\begin{aligned} \mathbf{x}(t) &= F(t) F^{-1}(0) \mathbf{x}(0) + F(t) \int_0^t F^{-1}(s) b(s) ds \\ &= F(t) F^{-1}(0) \mathbf{x}(0) + \\ &\quad + F(t) \int_0^t K_n(s) g(s) ds \\ &\quad \uparrow \text{last column of } F^{-1}(s) \end{aligned}$$

If we are interested in $y(t)$ only, then we look for the first element of \mathbf{x} , i.e.

$$y(t) = R_1(t) F^{-1}(0) \mathbf{x}(0) + \int_0^t R_1(s) K_n(s) g(s) ds.$$

Note that the initial value problem requires information on $y^{(0)}, y^{(1)}(0), \dots, y^{(n-1)}(0)$, and therefore the full vector $\mathbf{x}(0)$.

Def $E(t, s) = R_1(t) K_n(s)$ is called the fundamental solution to $L(t, \frac{d}{dt}) y = g$.

Theorem ⑥ $E(t, s)$ is the unique solution to

$$\left\{ \begin{array}{l} L(t, \frac{d}{dt}) u = 0 \\ u(s) = u'(s) = \dots = u^{(n-2)}(s) = 0 \\ u^{(n-1)}(s) = 1 \end{array} \right.$$

$$\textcircled{6} \quad \left\{ \begin{array}{l} L(t, \frac{d}{dt}) y = g \\ y(t_0) = \dots = y^{(n-1)}(t_0) = 0 \end{array} \right.$$

has the unique solution

$$y(t) = \int_{t_0}^t E(t, s) g(s) ds.$$

Higher order equations with constant coefficients

$$Lu = \sum_{i=0}^n a_i u^{(i)}(x) = 0 \quad a_n \neq 1, \quad a_i \text{ const.}$$

In the form of a system: $y_1 = u$

$$y_n = u^{(n-1)}$$

$$\frac{dy}{dx} = \begin{pmatrix} 0 & 1 & & & 0 \\ & \ddots & \ddots & & \\ & 0 & \ddots & & 0 & 1 \\ & & -a_0 & -a_1 & \cdots & -a_{n-1} \end{pmatrix} \vec{y}$$

The characteristic polynomial is

$$P(\lambda) = \det \begin{pmatrix} -\lambda & 1 & & & 0 \\ 0 & \ddots & \ddots & & \\ & -\lambda & 1 & & \\ -a_0 & -a_1 & \cdots & -\lambda - a_{n-1} & \end{pmatrix}$$

$$= -\lambda \det \begin{pmatrix} -\lambda & 1 & & & 0 \\ 0 & \ddots & \ddots & & \\ & -\lambda & 1 & & \\ -a_1 & -a_2 & \cdots & -\lambda - a_{n-1} & \end{pmatrix} \leftarrow \textcircled{R}$$

$$+ (-1)^{n-1} (-a_0) \det \begin{pmatrix} 1 & & & 0 \\ -\lambda & \ddots & & \\ 0 & \ddots & -\lambda & 1 \\ & & 0 & \end{pmatrix} =$$

$$= (-1)^n a_0 - \lambda \det \begin{pmatrix} \textcircled{R} \end{pmatrix} = \dots =$$

$$= (-1)^n (a_0 + a_1 \lambda + \dots + a_n \lambda^n)$$

Theorem If λ_0 is a solution to $P(x)=0$, multiplicity k
 then $e^{\lambda_0 t}, te^{\lambda_0 t}, \dots, t^{k-1}e^{\lambda_0 t}$ are
 independent solutions to $Lx=0$.

Proof $0 = L(e^{\lambda_0 t}) = \sum a_i (\lambda_0^i e^{\lambda_0 t}) = (-1)^n e^{\lambda_0 t} p(t)$

$\Rightarrow \lambda_0$ is a solution to $p(\lambda)=0$.

Note that $t^q e^{\lambda_0 t} = \frac{d^q}{dx^q} e^{\lambda_0 t}$

$$\begin{aligned} \Rightarrow L(t^q e^{\lambda_0 t}) &= L\left(\frac{d^q}{dx^q} e^{\lambda_0 t}\right) = \frac{d^q}{dx^q} L(e^{\lambda_0 t}) \\ &= (-1)^n \frac{d^q}{dx^q} (e^{\lambda_0 t} p(\lambda)) \end{aligned}$$

Here $P(\lambda) = Q(\lambda) (\lambda - \lambda_0)^k \Rightarrow L(t^q e^{\lambda_0 t}) = 0$ if $\lambda = \lambda_0$, $q < k$.

We have to prove that they are independent, i.e.

if λ_i are solutions to $p(\lambda)=0$ mult t_i , and

$$\sum_{i=1}^m r_i(t) e^{\lambda_i t} = 0$$

then $r_i(t) = 0$.

Proof: clearly true if $m=1$.

Suppose it is true for $m=k$. Then

$$\begin{aligned} 0 &= \sum_{i=1}^k r_i(t) e^{\lambda_i t} = \sum_{i=1}^{k-1} r_i(t) e^{\lambda_i t} + r_k(t) e^{\lambda_k t} \\ \Rightarrow \sum_{i=1}^{k-1} r_i(t) e^{(\lambda_i - \lambda_k)t} + r_k(t) e^{\lambda_k t} &= 0 \end{aligned}$$

If we differentiate $s = (\deg r_k(t) + 1)$ times

we find that

$$\begin{aligned} \sum_{i=1}^{k-1} \left(\frac{d^s}{dt^s} (r_i(t) e^{(\lambda_i - \lambda_k)t}) \right) &= 0 & i=1, \dots, k-1 \\ = e^{-\lambda_k t} \sum_{i=1}^{k-1} q_i(t) e^{\lambda_i t} &\Rightarrow q_i(t) = 0 \Rightarrow r_i(t) = 0 \end{aligned}$$

Stability

Consider again

$$\dot{y} = Ay \quad A \text{ a constant } nxn\text{-matrix.}$$

Choose C so that $C^TAC = J$, a Jordan matrix.

$$J = \begin{pmatrix} & & & \\ & & & \\ & B_k & & \\ & & & \\ & & & \end{pmatrix} \quad B_k = \underbrace{\begin{pmatrix} \lambda_k & 1 & 0 \\ 0 & \ddots & 1 \\ 0 & 0 & \lambda_k \end{pmatrix}}_{n_k}$$

$$\text{with } z = Cy \quad (y = Cz) \Rightarrow$$

$$\dot{z} = Jz, \quad \text{and if } z = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \end{pmatrix}^{n_x}$$

$$\dot{z}_k = \begin{pmatrix} \lambda_k & 1 & 0 \\ 0 & \ddots & 1 \\ 0 & 0 & \lambda_k \end{pmatrix} z_k$$

Recall that $e^{tB_k} = \begin{pmatrix} e^{\lambda_k t} & t e^{\lambda_k t} & \frac{1}{2!} t^2 e^{\lambda_k t} \\ 0 & e^{\lambda_k t} & t e^{\lambda_k t} \\ 0 & 0 & e^{\lambda_k t} \end{pmatrix}$

(this is what we may recall: the solutions are of the form $p(t)e^{\lambda_k t}$, where $p^{(k)}$ has degree at most $k-1$)

Conclusion: if $\operatorname{Re} \lambda_k > 0$, then the solution is exponentially increasing

if $\operatorname{Re} \lambda_k < 0$ exponentially decreasing

if $\operatorname{Re} \lambda_k = 0$ polynomial

Consider a 2×2 -system

$$\frac{d}{dt} \begin{pmatrix} x \\ y \end{pmatrix} = \underbrace{\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}}_{A} \begin{pmatrix} x \\ y \end{pmatrix}$$

The characteristic polynomial $p_A(\lambda) = \lambda^2 - s\lambda + D$

where $s = \text{Tr } A = a_{11} + a_{22}$ $D = \det A$

The zeros: $\lambda = \frac{1}{2}(s - \sqrt{s^2 - 4D})$

$$\mu = \frac{1}{2}(s + \sqrt{s^2 - 4D})$$

Three cases:

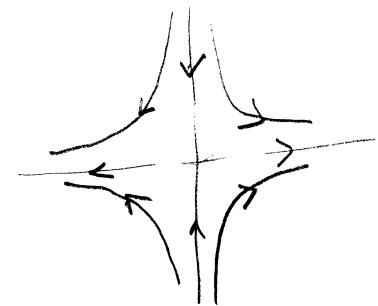
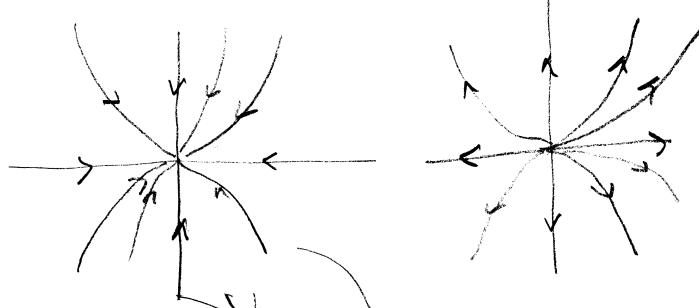
1) $A \rightarrow \begin{pmatrix} \lambda & 0 \\ 0 & \mu \end{pmatrix}$

2) $A \rightarrow \begin{pmatrix} \lambda & 1 \\ 0 & \lambda \end{pmatrix}$

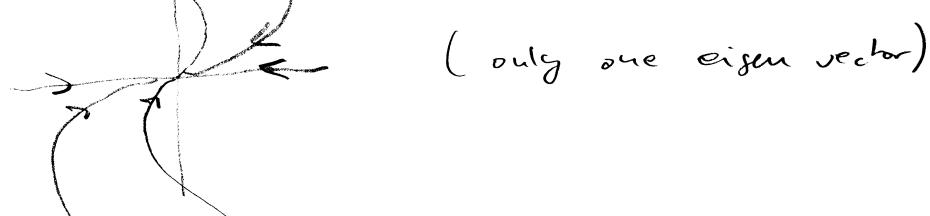
3) $A \rightarrow \begin{pmatrix} \alpha & \omega \\ -\omega & \alpha \end{pmatrix} \quad (\lambda = \alpha + i\omega)$

Three phase portraits

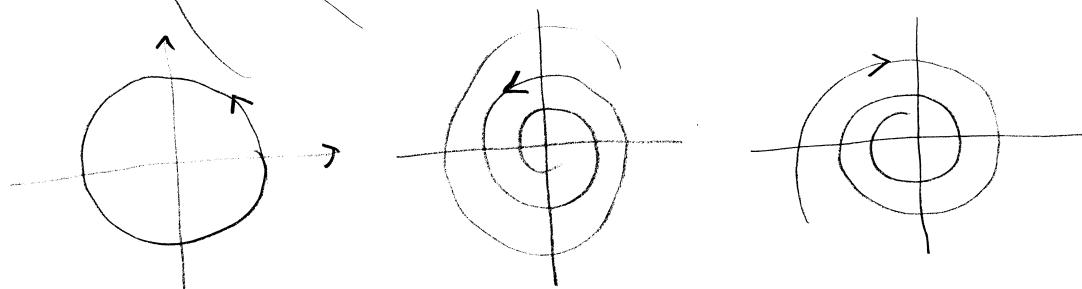
A



B



C



Definition Consider $y' = f(t, y)$ $\textcircled{2}$

A solution $x(t)$ to $\textcircled{2}$ is said to be
stable (in the sense of Lyapunov) if

$\forall \varepsilon > 0, \exists \delta > 0$ so that

$$|y(0) - x(0)| < \delta \Rightarrow |y(t) - x(t)| < \varepsilon \text{ for all } t > 0.$$

("if $y(t)$ starts near $x(t)$ at $t=0$, then
 $y(t)$ and $x(t)$ remain close to each other for all t ")

The solution $x(t)$ is said to be asymptotically stable
if there is $\beta > 0$ so that if

$$|y(0) - x(0)| < \beta$$

then

$$|y(t) - x(t)| \rightarrow 0$$

when $t \rightarrow \infty$.

Otherwise the solution is unstable otherwise.

Note Usually $x(t)$ is a stationary solution, i.e., $x(t) = \tilde{x}$
such that $f(t, \tilde{x}) = 0$.

Stability for linear systems

Theorem Consider $y' = A(t)y + b$ where $A(t)$ and $b(t)$ are continuous.

Suppose that $y(t) \geq 0$ is a stable solution to the homogeneous equation, then every solution to $\textcircled{2}$ is stable.

Proof if $y' = A(t)y + b$
 $x' = A(t)x + b$,
then $(y-x)' = A(t)(y-x)$, or if $z = y-x$
 $z' = A(t)z$.

Because $z=0$ is a stable solution to the homogeneous equation, then for all $\varepsilon > 0$ there is $\delta > 0$ so that

$$|z(0)| < \delta \Rightarrow |z(t)| < \varepsilon \text{ for all } t \geq 0.$$

Theorem If $\{\lambda_i\}$ are the eigenvalues of a constant matrix A , and if $\operatorname{Re} \lambda_i < \alpha$ for all i , then there is a constant C so that

$$|e^{At}| < Ce^{\alpha t} \quad (\text{if a compatible matrix norm})$$

Proof $y' = Ay$ has n independent solutions of the form $y = e^{\lambda t} p(t)$, where $p(t)$ is a polynomial of degree $\leq n$. If $\alpha - \operatorname{Re} \lambda_i = \varepsilon > 0$, then

$$|p_i(t)| < c_i e^{\varepsilon t} \Rightarrow$$

$$|e^{\lambda t} p_i(t)| \leq c_i e^{(\varepsilon + \operatorname{Re} \lambda_i)t} = c_i e^{\varepsilon t}.$$

A stability theorem for perturbations of
linear systems with constant coefficients.

Theorem Consider the equation

$y' = Ay + g(y, t)$ where $g(y, t)$ is continuous
 for $t \geq 0$, $|y| < \alpha$ (some $\alpha > 0$).

Assume also that $\lim_{|y| \rightarrow 0} \frac{|g(y, t)|}{|y|} = 0$

uniformly in $t \geq 0$. Assume also that
 $\operatorname{Re} \lambda_i < 0$ for all eigenvalues to λ .

Then $x(t) = 0$ is an asymptotically stable
 solution to $y' = Ay + g(y, t)$.

Proof There are $C, \beta > 0$ so that

$$|e^{At}| \leq C e^{\beta t} \quad (\operatorname{Re} \lambda_i < -\beta).$$

Next, $\frac{|g(y, t)|}{|y|} \rightarrow 0$ when $|y| \rightarrow 0$ implies

that there is a $\delta > 0$ so that $0 < \delta < \alpha$ and

$$|g(z, t)| \leq \frac{\beta}{2C} |z| \quad \text{for all } t \geq 0, |z| \leq \delta.$$

We have

$$y(t) = e^{At} y_0 + \int_0^t e^{A(t-s)} g(y(s), s) ds$$

(this holds if $g(y(s), s)$ is replaced by a given
 function $b(s)$)

Then

$$|y(t)| \leq |e^{\lambda t} y_0| + \int_0^t |e^{\lambda(t-s)} g(y(s), s)| ds$$

$$\leq \zeta |y_0| e^{\beta t} + \int_0^t e^{-\beta(t-s)} \frac{\beta}{2C} |y(s)| ds$$

(if $|y(s)| < \delta$ for $\alpha \leq s \leq t$, we have
to verify that afterwards!)

Let $|y_0| < \varepsilon$ and let $\phi(t) = |y(t)| e^{\beta t}$

$$\begin{aligned} \text{Then } \phi(t) &\leq C\varepsilon + \frac{\beta}{2} \int_0^t e^{-\beta s} \phi(s) ds \\ &\leq C\varepsilon + \frac{\beta}{2} \int_0^t \phi(s) ds. \end{aligned}$$

But then the Gronwall inequality implies

$$\phi(t) \leq C\varepsilon e^{\beta t/2} \Rightarrow |y(t)| \leq C\varepsilon e^{-\frac{\beta t}{2}}$$

if $|y(t)| < \delta$! That can be achieved

$$\text{letting } \varepsilon < \min(\varepsilon, \frac{\delta}{2C})$$

Theorem Consider again $y' = Ay + g(t, y)$,

where g satisfies the same conditions as
in the previous theorem.

If at least one of the eigenvalues has
a positive real part, then

$y \equiv 0$ is an unstable solution.

Proof First we note that we may assume that A is in the Jordan form, so that

$$A = \begin{pmatrix} \lambda_1 & k_1 & & \\ & \ddots & \ddots & 0 \\ & & \ddots & k_{n-1} \\ 0 & & & \lambda_n \end{pmatrix}, \text{ where } k_i = 0 \text{ or } k_i = 1.$$

A first problem to solve is that if $|t|$ are very small, it may seem that the t 's may dominate.

But let $H = \begin{pmatrix} 2^{-\frac{1}{2}} & 0 \\ 0 & \gamma^n \end{pmatrix}$ (and so $H^{-1} = \begin{pmatrix} 2^{\frac{1}{2}} & 0 \\ 0 & \gamma^{-n} \end{pmatrix}$)

Then

$$H^{-1}AH = \begin{pmatrix} \lambda_1 & 0 & & \\ & \ddots & \ddots & 0 \\ & & \ddots & \gamma^{n-1} \\ 0 & & & \lambda_n \end{pmatrix} \quad \text{where } \gamma, \dots, \gamma^{n-1} = 0 \text{ or } y.$$

This is easily proven by writing $A = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} + \begin{pmatrix} 0 & k_1 \\ 0 & 0 \end{pmatrix}$

$$\begin{aligned} \therefore H^{-1}AH &= H^{-1} \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} H + \begin{pmatrix} 2^{-\frac{1}{2}} & 0 \\ 0 & \gamma^n \end{pmatrix} \begin{pmatrix} 0 & k_1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 2^{\frac{1}{2}} & 0 \\ 0 & \gamma^{-n} \end{pmatrix} \\ &= \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} + \begin{pmatrix} 2^{-\frac{1}{2}} & 0 \\ 0 & \gamma^n \end{pmatrix} \begin{pmatrix} 0 & k_1 \gamma^{-\frac{1}{2}} \\ 0 & 0 \end{pmatrix} = \\ &= \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} + \begin{pmatrix} 0 & k_1 \gamma^{-\frac{1}{2}} \\ 0 & 0 \end{pmatrix}. \end{aligned}$$

Hence with $y = Hz$,

$$z' = \underbrace{H^{-1}AH}_A z \xrightarrow{H^{-1}g(t, Hz)} \underbrace{f(t, z)}_{f(t, z)}$$

We note that now \tilde{A} has the same eigenvalues as A , and that $\frac{|f(t, z)|}{|z|} = \frac{|H^{-1}g(t, Hz)|}{|Hz|} \frac{|Hz|}{|z|}$

But $|Hz| < |H| |z| \rightarrow 0$ when $|z| \rightarrow 0$ (but depending on η)

and $\frac{|H'| g(t, Hz)|}{|Hz|} \leq |H'| \frac{|g(t, Hz)|}{|Hz|} \rightarrow 0$ when $Hz \rightarrow 0$,

so $\frac{|f(t, z)|}{|z|} \rightarrow 0$ when $|z| \rightarrow 0$.

In fact, if $\eta < 1$, then $|H| = \eta$ and $|H'| = \eta^n$.

$$\text{so } \frac{|f(t, z)|}{|z|} \leq \frac{|H'|}{|Hz|} \frac{|g(t, Hz)|}{|Hz|} \frac{|Hz|}{|z|} \leq \eta^{1-n} \frac{|g(t, Hz)|}{|Hz|}.$$

Given $\eta > 0$, choose δ_0 so that $\frac{|g(t, z)|}{|z|} < \eta^n$ when $|z| < \delta_0$.

Then $\frac{|g(t, Hz)|}{|Hz|} < \eta^n$ when $|Hz| < \delta_0$,

but that is true if $|z| < \delta_0/\eta \equiv \delta$.

So for each $\eta > 0$, there is $\delta > 0$ so that

$$|z| < \delta \Rightarrow |f(t, z)| \leq \eta |z|.$$

componentwise we have

$$\dot{z}_j = \lambda_j z_j + \tau_j z_{j+1} + f_j(t, z) \quad , \text{ where } \tau_j = 0 \text{ or } \eta.$$

$$\text{Let } \phi(t) = \sum_{\operatorname{Re} \lambda_j > 0} |z_j|^2 \quad , \quad \psi(t) = \sum_{\operatorname{Re} \lambda_j \leq 0} |z_j|^2$$

$$\text{so } |z|^2 = \phi(t) + \psi(t).$$

We shall prove that $\frac{d}{dt}(\phi - \psi) \geq \eta(\phi - \psi)$.

which implies instability, because then

$$\phi(t) - \psi(t) \geq e^{\eta t} (\phi(0) - \psi(0))$$

(we can choose initial data so that
 $\phi(0) - \psi(0) > 0$)

First,

$$\begin{aligned}\phi' &= \sum_{I_1} \frac{d}{dt} |z_i|^2 = \sum_{I_1} 2 \operatorname{Re} z_i \bar{z}_i & I_1 = \{i : \operatorname{Re} \lambda_i > 0\} \\ &= \sum_{I_1} 2 \operatorname{Re} (\lambda_i z_i \bar{z}_i + \gamma_j z_{j+1} \bar{z}_i + f_i \bar{z}_i) \\ &= \sum_{I_1} 2 \operatorname{Re} \lambda_i |z_i|^2 + \sum_{I_1} 2 \gamma_j \operatorname{Re}(z_{j+1} \bar{z}_i) + \sum_{I_1} 2 \operatorname{Re}(f_i \bar{z}_i) \\ &= A + B + C.\end{aligned}$$

(note: we use the complex Jordan form, so solutions may be complex).

$$\text{Let } \eta = \frac{1}{6} \min_{I_1} \operatorname{Re} \lambda_i \Rightarrow A \geq 2 \cdot 6 \eta \phi$$

$$\text{and } |B| \leq 2 \eta \left| \sum_{I_1} \operatorname{Re}(z_{j+1} \bar{z}_i) \right| \leq 2 \eta \phi$$

$$\begin{aligned}|C| &\leq 2 \left| \sum_{I_1} \operatorname{Re}(f_i \bar{z}_i) \right| \leq 2 \sqrt{\phi} \sqrt{|f(t, z)|^2} \\ &\leq \eta \phi + \frac{|f|^2}{\eta}.\end{aligned}$$

Hence we used the Cauchy inequality:

$$\left| \sum a_i b_i \right| \leq \sqrt{\left(\sum a_i^2 \right) \left(\sum b_i^2 \right)}$$

and the fact that

$$|ab| \leq \frac{1}{2} (a^2 + b^2) \Leftrightarrow |ab| = \left| ab \frac{b}{|b|} \right| \leq \frac{1}{2} \left(\eta a^2 + \frac{b^2}{\eta} \right).$$

We thus obtain

$$\begin{aligned}\phi' &= A + B + C \geq 12\gamma\phi - 8\gamma\phi - \gamma\phi - \frac{\|x\|^2}{\gamma} \\ &= 9\gamma\phi - \frac{\|x\|^2}{\gamma}.\end{aligned}$$

If $|z_i| = \sqrt{\phi + t} \leq \delta$, then $\|x\|^2 \leq \gamma^2(\phi + t)$

$$\Rightarrow \frac{\|x\|^2}{\gamma} \leq \gamma\phi + \gamma t \quad \text{, and so, finally}$$

$$\phi'(t) \geq 8\gamma\phi - \gamma t.$$

Next we need an estimate for t .

As before,

$$\begin{aligned}\phi' &= \underbrace{\sum_{I_2} 2\operatorname{Re}(\lambda_j |z_{j1}|^2)}_{\leq 0} + \underbrace{\sum_{I_2} 2\operatorname{Re} \tau_j z_{j1} \bar{z}_{j1}}_{\leq 2\gamma\phi} + \underbrace{\sum_{I_2} 2\operatorname{Re}(t^{\frac{j-1}{2}})}_{\leq \gamma^2 + \gamma^{(\phi+t)}} \\ &\leq 4\gamma\phi + \gamma t\end{aligned}$$

But then

$$\begin{aligned}\frac{d}{dt}(\phi + t) &\geq 8\gamma\phi - \gamma t - 4\gamma\phi - \gamma t \\ &= 7\gamma\phi - 5\gamma t \geq 5\gamma(t - \phi) \geq \gamma(t - \phi)\end{aligned}$$

B

Note why is $|\sum_{I_1} 2\operatorname{Re} \tau_j z_{j1} \bar{z}_{j1}| \leq 2\gamma\phi$, (and similarly $|\sum_{I_2} 2\operatorname{Re} \tau_j z_{j1} \bar{z}_{j1}| \leq 2\gamma t$)?

It is because of the structure of the Jordan matrices.

If $\tau_j \neq 0$, then z_j and z_{j1} correspond to the same Jordan block, and hence the same eigenvalue.