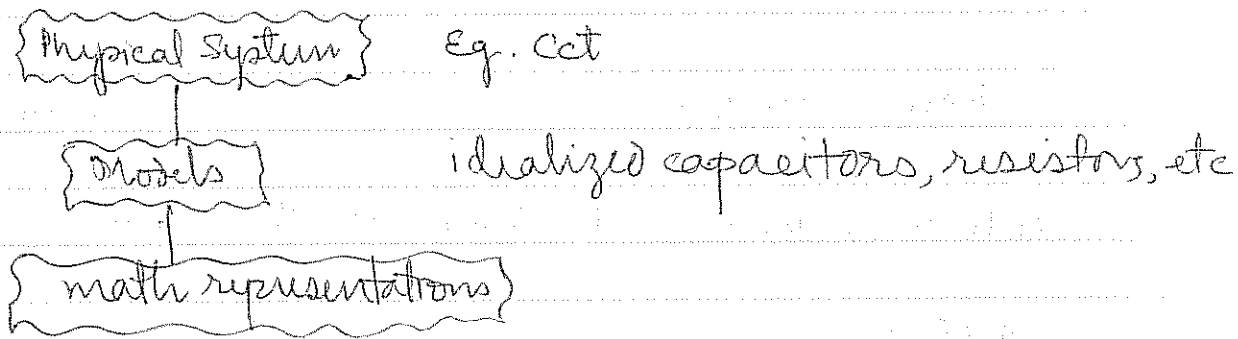


Monday 29 Aug '18

EE221a & LINEAR SYSTEM THEORY - Dr Felix Wu

What is System Theory:



Sup. Thry. deals w Math Representation

→ develop analysis & design tools based on math tools

This course

- 1 Mostly linear systems (to be defined later)
- 2 Attempt to assist you to be able to develop analysis & design tools. (provide nice training)
- 3 Emphasis on rigorous & precision

Same spirit in exams, HW.

Control System

- 1 ^{- simulation} measurement of I/P or O/P study properties of the solution (output) _{- numerical soln} che stability
- 2 O/p not satisfactory
 - how can we change it
 - how " " " "

$$Ae_1 = a_{11}b + a_{12}Ab + a_{13}A^2b + \dots + a_{1n}A^{n-1}b$$

$$Ae_2 = a_{21}b + a_{22}Ab + a_{23}A^2b + \dots + a_{2n}A^{n-1}b$$

$$Ae_n = a_{n1}b + \dots + a_{nn}A^{n-1}b$$

We wish to represent this in the form of a single Eqn.

$$A \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{pmatrix} = \begin{matrix} \text{complex elements} \\ \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \begin{pmatrix} b \\ Ab \\ A^2b \\ \vdots \\ A^{n-1}b \end{pmatrix} \end{matrix}$$

$$\tilde{A} \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{pmatrix} = \tilde{A} \begin{pmatrix} b \\ Ab \\ \vdots \\ A^{n-1}b \end{pmatrix}$$

$$\tilde{A}e_1 = \tilde{A}b \quad \tilde{A}e_1 = Ab$$

$$\tilde{A}e_2 = \tilde{A}Ab \quad \boxed{\tilde{A}e_m = \tilde{A}^m b}$$

$$\tilde{A}e_3 = \tilde{A}A^2b$$

$$\tilde{A} (e_1 \ e_2 \ \dots \ e_n) = \tilde{A} (b \ Ab \ A^2b \ \dots \ A^{n-1}b)$$

$$\tilde{A} I = \tilde{A} (b \ Ab \ \dots \ A^{n-1}b)$$

$b = \begin{bmatrix} b \\ 0 \\ \vdots \\ 0 \end{bmatrix}$
 = News & Sacramento
 1/2 City

~~11:00 am~~
 10:30 am
 1509 Hearst
 #23
 Apt 201

1-2: Lin Alg & Diff Eqns

3-4: General Lin. Sys. Fundamentals

5-8: Time Inv.

9: Stability

10-13: Controllability, Observability

14-15: Discrete Event Systems

COPYMAT: 2560 Bancroft → Dr Desoer's Notes

HW: Every Thursday give on Friday next

↳ Seems to be very important (visa vis your grade)

Discussion: TA will work out examples. Stress discrete time systems.

✓ Kailath: explains more but a little confusing

✓ Chen: more mathematical, all details worked out

Callier & Desoer: for last part

Ogata: //¹ development in discrete time control

Chapter 1: Math Background

Linear System - define linearity

Two main topics in this chapter

① Linear function

- representation

② Diff eqns

- solution (existence & uniqueness questions)

Where do we start -

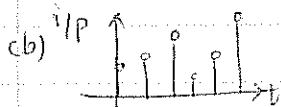
General Setting



1) Classification ^(a) _t

^(b) _t

(a): cont. time systems



(b): discrete time

(c) 01001 ^(a) _t

00110 ^(b) _t

(c): digital

leads us to math. concept of function

$u(t)$: value of u at t

$u(\cdot)$: waveform

Roughly speaking the "system" assigns an o/p $y(\cdot)$ for a given i/p $u(\cdot)$. This is a "function"!

Defn of function

$$f: X \rightarrow Y$$

$\forall x \in X$ f assigns a unique $f(x)$ in Y

We are familiar \approx functions ~~xxxxx~~ which move a pt to another pt.

eg. $y = Ax$ \rightarrow $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \dots \\ \dots \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

$$Y = \begin{bmatrix} 1/\sqrt{2} & -1/\sqrt{2} \\ 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix} X$$

1. $\int \frac{1}{x^2} dx$

$\int \frac{1}{x^2} dx = -\frac{1}{x} + C$

2. $\int \frac{1}{x^3} dx$

$\int \frac{1}{x^3} dx = -\frac{1}{2x^2} + C$

3. $\int \frac{1}{x^4} dx$

$\int \frac{1}{x^4} dx = -\frac{1}{3x^3} + C$

4. $\int \frac{1}{x^5} dx$

$\int \frac{1}{x^5} dx = -\frac{1}{4x^4} + C$

5. $\int \frac{1}{x^6} dx$

$\int \frac{1}{x^6} dx = -\frac{1}{5x^5} + C$

6. $\int \frac{1}{x^7} dx$

$\int \frac{1}{x^7} dx = -\frac{1}{6x^6} + C$

7. $\int \frac{1}{x^8} dx$

$\int \frac{1}{x^8} dx = -\frac{1}{7x^7} + C$

8. $\int \frac{1}{x^9} dx$

$\int \frac{1}{x^9} dx = -\frac{1}{8x^8} + C$

9. $\int \frac{1}{x^{10}} dx$

$\int \frac{1}{x^{10}} dx = -\frac{1}{9x^9} + C$

10. $\int \frac{1}{x^{11}} dx$

$\int \frac{1}{x^{11}} dx = -\frac{1}{10x^{10}} + C$

11. $\int \frac{1}{x^{12}} dx$

$\int \frac{1}{x^{12}} dx = -\frac{1}{11x^{11}} + C$

12. $\int \frac{1}{x^{13}} dx$

$\int \frac{1}{x^{13}} dx = -\frac{1}{12x^{12}} + C$

Our system doesn't geometrically move pts in this way. It shifts ^(wave forms) functions to other ^(wave forms) functions

Q. What do $u(x)$, $y(x)$ have in common?
 - They are "vectors" in a "vector space".

- A vector space is defined over a "field".

1) Vector Space

- 1) F is a field iff
- (A) $\forall \alpha, \beta \in F \quad \alpha + \beta \in F$ uniquely defined
 - (A1) $\alpha + \beta = \beta + \alpha$; commutative
 - (A2) $(\alpha + \beta) + \gamma = \alpha + (\beta + \gamma)$; associativity $\forall \alpha, \beta, \gamma \in F$
 - (A3) $\exists 0 \in F$ s.t. $\alpha + 0 = \alpha \quad \forall \alpha \in F$; (additive identity)
 - (A4) $\forall \alpha \in F \exists (-\alpha) \in F$ s.t. $\alpha + (-\alpha) = 0$; (additive inverse)
 - (M) $\forall \alpha, \beta \in F \quad \alpha \beta \in F$, uniquely defined
 - (M1) $\alpha \beta = \beta \alpha$; commutativity
 - (M2) $(\alpha \beta) \gamma = \alpha (\beta \gamma)$; associativity
 - (M3) $\exists 1 \in F$ s.t. $\alpha \cdot 1 = \alpha$; (multiplicative identity)
 - (M4) $\forall \alpha \neq 0 \exists \alpha^{-1}$ s.t. $\alpha \cdot \alpha^{-1} = 1$; (multiplicative inverse)
 - (D) $\alpha(\beta + \gamma) = \alpha\beta + \alpha\gamma$; distributive

eg. $[\mathbb{R}, +, \times]$ $[\mathbb{C}, +, \times]$ $[\mathbb{Z}, +, \times]$ $[[0, 1], \oplus, \cdot]$
 [set of rational functions]

2) Vector Space (Linear Space)

(V, F) V is a vector space over the field F iff

- (A) $\forall x, y \in V \quad x + y \in V$ uniquely defined
 - (A1) $x + y = y + x$
 - (A2) $x + (y + z) = (x + y) + z$
 - (A3) $\exists \theta \in V$ s.t. $x + \theta = x$
 - (A4) $\forall x \in V \exists (-x) \in V$ s.t. $x + (-x) = \theta$
- (SM) $\forall \alpha \in F \forall x \in V \quad \alpha x \in V$ uniquely defined
 - (SM1) $(\alpha \beta)x = \alpha(\beta x)$
 - (SM2) $\alpha(x + y) = \alpha x + \alpha y$
 - (SM3) $(\alpha + \beta)x = \alpha x + \beta x$

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Third block of handwritten text, showing further development of the content.

Fourth block of handwritten text, possibly containing a diagram or a specific example.

Fifth and final block of handwritten text at the bottom of the page.

$$\begin{aligned} x + (-x) &= 0 \\ x + (-x)' &= 0 \\ x + (-x) &= x + (-x)' \\ (-x) &= (-x)' \end{aligned}$$

eg Show θ is unique ^{on any vector space}

Suppose both θ & θ' are zeroes
We want to show $\theta = \theta'$.

by defn $\left\{ \begin{array}{l} \forall x \in V, x + \theta = x \\ \forall x \in V, \exists (-x) \text{ s.t. } x + (-x) = \theta \end{array} \right\}$ also $\left\{ \begin{array}{l} \forall x \in V, x + \theta' = x \\ \forall x \in V, \exists (-x)' \text{ s.t. } x + (-x)' = \theta' \end{array} \right\}$
 \uparrow is it nec. the same? \uparrow

$$\Rightarrow (x + \theta) + (-x)' = \theta'$$

$$\stackrel{\text{comm}}{=} (\theta + x) + (-x)'$$

$$\stackrel{\text{assoc}}{=} \theta + (x + (-x)')$$

$$= \theta + \theta'$$

$$\text{sim } (x + \theta') + (-x) = \theta$$

\vdots

$$= \theta + \theta'$$

$$\text{com} = \theta' + \theta$$

$$\Rightarrow \theta' = \theta + \theta' = \theta$$

Canonical Examples: \mathbb{R}^n & Functions

Thursday
31 Aug '89

LST-2

Vector Space [Linear Space]

(V, F)

(A) $\forall x, y \in V \quad x + y \in V$ uniquely defined

(A1) $x + y = y + x$

(A2) $x + (y + z) = (x + y) + z$

(A3) $\exists \theta \in V$ s.t. $x + \theta = x$

(A4) $\forall x \in V \exists (-x) \in V$ s.t. $x + (-x) = \theta$

(SM) $\forall \alpha \in F \forall x \in V \quad \alpha x \in V$ uniquely defined

(SM1) $(\alpha\beta)x = \alpha(\beta x)$

(SM2) $\alpha(x+y) = \alpha x + \alpha y$

(SM3) $(\alpha + \beta)x = \alpha x + \beta x$

(SM4) $1 =$ mult identity in $F \quad 1x = x$

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3) Canonical Examples

(a) (F^n, F) $F^n = n$ tuples of F
 eg. $(\mathbb{R}^n, \mathbb{R})$ $x \in \mathbb{R}^n$ if $x = [x_1, x_2, \dots, x_n]^T$; $x_n \in \mathbb{R}$
 $(\mathbb{C}^n, \mathbb{C})$

Exc: Show this is a v.s.

(b) (\mathcal{D}, V)
 F : set of all functions $f: \mathcal{D} \rightarrow V$
Any set \mathcal{D} \uparrow \uparrow vector space over \mathbb{R} or \mathbb{C} (or any field)

Can make F into a vector space by defining $+$,
 define (A): $f, g \in F(\mathcal{D}, V)$

we want to define $f+g \in F(\mathcal{D}, V)$

$$\forall d \in \mathcal{D} \quad (f+g)(d) \in V$$

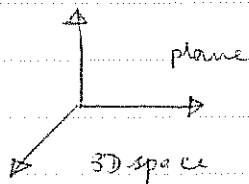
$$\therefore \text{define } (f+g)(d) := \underbrace{f(d)}_{\in V} + \underbrace{g(d)}_{\in V} \leftarrow \text{addition is defined in this vector space.}$$

an element in V !

define (SM): Take $\alpha \in \mathbb{R}$

$$\text{want to define } \underbrace{(\alpha f)}_{\in F(\mathcal{D}, V)}(d) = \underbrace{\alpha}_{\text{S.M. in } V} \underbrace{f(d)}_{\in V}$$

Having defined (A) & (SM) we must ~~define~~ ^{confirm} the props.



- plane a subspace of 3D space
 motiv. for defining subspaces.

W is a subspace of (V, F)

iff (1) $W \subset V$ (that's $W \subset V$)

(2) (W, F) itself qualifies as a vector space

$$\left. \begin{cases} w_1, w_2 \in W \Rightarrow w_1 + w_2 \in W \\ \alpha \in F, w \in W \Rightarrow \alpha w \in W \end{cases} \right\} \text{ don't need to check any further!}$$

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Let's examine the set of functions $F(C, V)$
 (a) Set of continuous functions $f: [t_0, t_1] \rightarrow \mathbb{R}$ [\mathbb{C}]
in \mathbb{R}

Notation $C[t_0, t_1]$ denotes " " " [";"]

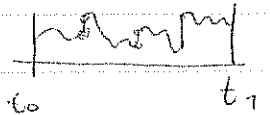
(b) Set of continuous functions $f: [t_0, t_1] \rightarrow \mathbb{R}^n$ [\mathbb{C}^n]
 $C^n[t_0, t_1]$

if of infinite intervals, could we get countably infinite pts?

(c) Piecewise continuous functions

(i) discontinuous points ^{strictly} finite

(ii) at a discontinuous pt, limits of a fn. from either side exist and are finite.



2. LINEAR TRANSFORMATION

(1) Linear Independence

(V, F) vector space

X set of vectors in V

X is a set of linearly independent vectors

iff for any ~~set~~ ^{finite} collection of distinct elements in X say $\{x_1, \dots, x_n\}$

for any scalars $\alpha_1, \dots, \alpha_n$

if $\alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_n x_n = 0 \Rightarrow$ all $\alpha_i = 0$.

If not say set X is lin dep.

then at least one can be written as a lin comb. of others

$$\alpha_1' x_1 + \alpha_2' x_2 + \dots + \alpha_m' x_m = 0$$

say $\alpha_2' = 0$

$$\alpha_2' = -\alpha_1' / \alpha_2' x_1' - \dots - \dots$$

(2) Span of a set of vectors

(V, F)

$X \subset V$

Span of $X =$ set of all l.c. of vectors in X ,

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$$\text{Sp}\{X\} = \left\{ \sum_{i=1}^n \alpha_i x_i, \alpha_i \in F, x_i \in V \right\}$$

finite sum

(3) BASIS

The set of vectors X is said to be a basis of V iff

(i) X linearly & independent

(ii) $\text{Sp}(X) = V$

elements in X are called basis vectors

$\dim(V) = \text{cardinality of } X$ could be ∞ eq. Perceps (F.S.)

(4) COORDINATE SYSTEM

$(V, F) \{b_1, b_2, \dots, b_n\}$ (finite dim. implicit)
an ordered set of basis vectors.

Then there ⁽¹⁾exists a ⁽²⁾unique set of scalars

$(\xi_1, \xi_2, \xi_3, \dots, \xi_n)$ for any vector $x \in V$ s.t.

$$x = \sum_{i=1}^n \xi_i b_i; \quad \xi_i \text{ called components of } x \text{ wrt basis } \{b_1, \dots, b_n\}$$

Pf(1) (Existence): The fact that b_1, \dots, b_n spans $V \Rightarrow$
 $\forall x \in V, x = \sum_{i=1}^n \xi_i b_i$

Pf(2) (Uniqueness): Suppose not. \Rightarrow

$$x = \sum_{i=1}^n \xi_i b_i \quad \Rightarrow \quad 0 = x - x = \sum_{i=1}^n (\xi_i - \tilde{\xi}_i) b_i; \quad \text{LI} \Rightarrow \xi_i = \tilde{\xi}_i$$

Geometrically $V \leftarrow F^n \{b_i\}_{i=1}^n$ once you pick a basis can view V as $\left\{ \left\{ \xi_i \right\}_{i=1}^n \right\} \subset F^n$

(5) LINEAR TRANSFORMATION

vector spaces $(U, F) \quad (V, F)$

same (over the same field)

$\mathcal{A}: U \rightarrow V$ is a linear function (or transformation or map or operator)

$$\text{iff } \mathcal{A}(\alpha_1 u_1 + \alpha_2 u_2) = \alpha_1 \mathcal{A}(u_1) + \alpha_2 \mathcal{A}(u_2)$$

\uparrow in U in V in V

with

V

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Examples

(i) $A: \mathbb{R}^2 \rightarrow \mathbb{R}^2$ over \mathbb{R}

$$[x_1 \ x_2]^T \mapsto [\alpha x_1 - \beta x_2 \ \beta x_1 + \alpha x_2]^T; \alpha, \beta \text{ are fixed}$$

(ii) $A: P[0, T] \mapsto P[0, T]$

$u(\cdot)$

$v(\cdot)$

$$v(t) = (Au)(t) = \int_0^t e^{-(t-s)} u(s) ds$$

$t \in [0, T]$

show (i) & (ii) are linear operators.



HW: show $0_u \rightarrow 0_v$

It is possible more than one $u \in U \rightarrow 0_v$

Nullspace of A : $N(A) = \{u \in U \text{ s.t. } Au = 0_v\}$

Claim: $N(A) \subset U$ and is a subspace in U .

$$\hookrightarrow u_1 \in N(A) \quad u_2 \in N(A)$$

$$u_1 + u_2 \in N(A) \quad (\text{trivial})$$

range
of A .

$R(A) = \{v \in V \text{ s.t. } v = Au \text{ for some } u \in U\}$

can show $R(A)$ is a subspace of V .

(6) MATRIX REPRESENTATION

$$A: U \rightarrow V$$

$\left\{ \begin{array}{l} \{v_j\}_{j=1}^m \\ \{u_i\}_{i=1}^n \text{ basis} \end{array} \right\}$

$$x = \sum_{i=1}^n \xi_i u_i \quad \xrightarrow{?} \quad y = \sum_{j=1}^m \eta_j v_j$$

$\left[\begin{array}{c} \eta_j \end{array} \right]$ coordinates of y pulled through A

Let $y = Ax$ (y is image of x)

How can we directly express A in terms of the coordinate system? Ans: matrix.

$$y = Ax; \quad Ax = A\left(\sum_{i=1}^n \xi_i u_i\right) = \sum_{i=1}^n \xi_i (Au_i); \text{ from lin. of } A$$

If we know what A does to u_i , then we know how it acts on any vector x .

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Consider $A(u_i)$

$$\downarrow \Delta u_1 = a_{11} v_1 + a_{12} v_2 + \dots + a_{1n} v_n$$

$$\Delta u_2 = a_{21} v_1 + a_{22} v_2 + \dots + a_{2n} v_n$$

$$\Delta u_m = a_{m1} v_1 + a_{m2} v_2 + \dots + a_{mn} v_n$$

$$\begin{aligned} \Delta x &= a_{11} \xi_1 v_1 + a_{12} \xi_1 v_2 + \dots + a_{1n} \xi_1 v_n \\ &+ a_{12} \xi_2 v_1 + a_{22} \xi_2 v_2 + \dots + a_{m2} \xi_2 v_m \\ &\dots \\ &+ a_{1n} \xi_n v_1 + a_{2n} \xi_n v_2 + \dots + a_{mn} \xi_n v_m \\ &= \eta_1 v_1 + \eta_2 v_2 + \dots + \eta_m v_m \end{aligned}$$

$$\Rightarrow \eta_1 = a_{11} \xi_1 + a_{12} \xi_2 + \dots + a_{1n} \xi_n$$

$$\eta_2 = \dots$$

$$\eta_m = a_{m1} \xi_1 + a_{m2} \xi_2 + \dots + a_{mn} \xi_n$$

$$\begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_m \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_n \end{bmatrix}$$

← matrix →

i^{th} column of matrix = the coordinate of Δu_i expressed
wrt $\{v_j\}_{j=1}^m$

This is imp. of generality there!

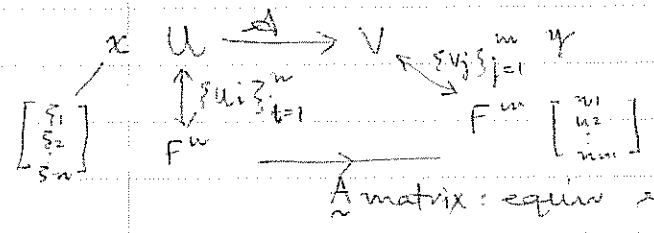
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Monday
Sept 189

LST

Friday 3:00-3:50 TA
3:30-5:00 Lecture

Last time - matrix representation of a linear map.

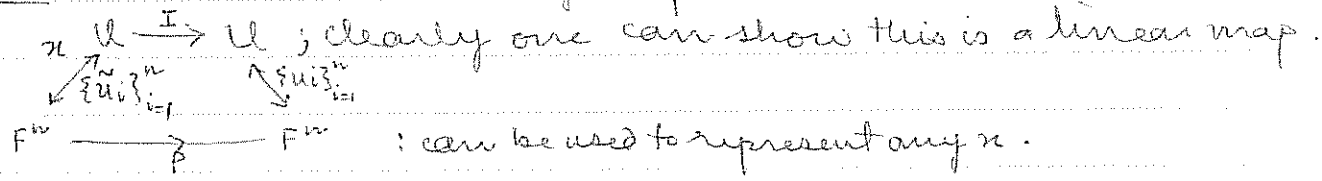


$$\begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_m \end{bmatrix} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \vdots \\ \xi_n \end{bmatrix}$$

matrix
i-th column

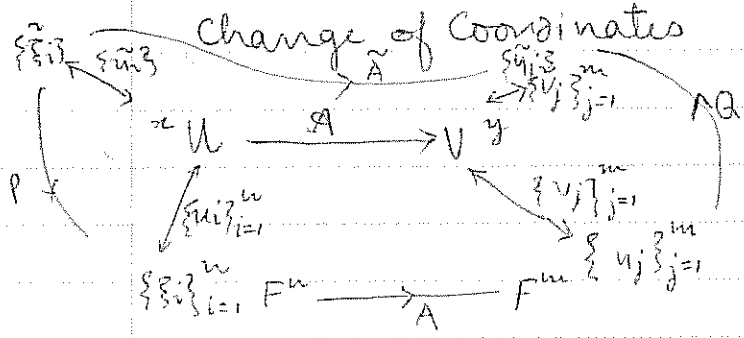
$\begin{bmatrix} a_{1i} \\ a_{2i} \\ \vdots \\ a_{mi} \end{bmatrix}$ = Au_i expressed wrt $\{v_j\}$
 may be obtained by taking the i-th basis vectors
 $Au_i = \sum_{j=1}^m a_{ji} v_j$

Ex. Consider an Identity Map



i-th column
 $\tilde{u}_i = \sum_{j=1}^n p_{ji} u_j$

Change of Coordinates



Q: how is A related to \tilde{A} ?

A, \tilde{A} maps as follows:
 $[\tilde{\eta}_j]_{F^{\tilde{V}}} = \tilde{A} [\tilde{\xi}_i]$
 $[\eta_j]_{F^V} = A [\xi_i]$

$P [\tilde{\xi}_i] = [\xi_i]$
 $Q [\tilde{\eta}_j] = [\eta_j]$

$\Rightarrow \tilde{A} = QAP$ This is not a proof. (See reader & real pf.)

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3. DIFFERENTIAL EQUATIONS

4) Normed linear Space

motivation: notion of length in $(\mathbb{R}^3, \mathbb{R})$

non negative

Δ inequality

independent of the basis ?

$x \cdot y$ symmetric

Properties $\|x\|$, length of vector x , ≥ 0 ($= 0 \iff x = 0$)

$$\|x+y\| \leq \|x\| + \|y\|$$

$$\|x\| = \|-x\|$$

$$\|\alpha x\| = |\alpha| \|x\| \quad ; \text{ (in } \mathbb{R}^3 \text{)}$$

By
consider
 $(\mathbb{R}^3, \mathbb{R})$

$(\mathbb{R} \text{ or } \mathbb{C})$

A linear space (V, F) is said to be a normed linear space iff \exists a fn, denoted by $\|\cdot\|$ mapping from

$V \rightarrow \mathbb{R}_+ = \{x \mid x \in \mathbb{R}, x \geq 0\}$ satisfying (1) $\|x\| = 0 \iff x = 0$

$$(2) \|\alpha x\| = |\alpha| \|x\|$$

$$(3) \|x+y\| \leq \|x\| + \|y\|$$

Ex (a) $(\mathbb{R}^n, \mathbb{R})$ $x = (x_1, x_2, \dots, x_n)$

$(\mathbb{C}^n, \mathbb{C})$ define $\|x\|_\infty := \max |x_i|$; show it satisfies (i) - (iii)
follows

$$\|x\|_1 := \sum_{i=1}^n |x_i| ; \quad \text{" " " " " "}$$

$$\|x\|_2 := \left(\sum_{i=1}^n |x_i|^2 \right)^{1/2} ; \quad \text{" " " " " "}$$

$$\text{in general } \|x\|_p := \left(\sum_{i=1}^n |x_i|^p \right)^{1/p} ; \quad \text{" " " " " "}$$

Ex (b) $(F \subset \mathbb{C}, V)$

(i) $C([t_0, t_1], \mathbb{R})$; ^{real} cont. fns. on $[t_0, t_1]$; could do by ^{fund} \int

$$\|f\|_\infty := \max_{t \in [t_0, t_1]} |f(t)| \quad \text{cont. fn on a bdd interval} \Rightarrow \text{max. exists}$$

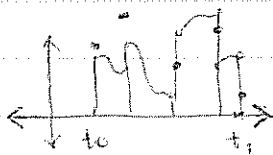
$$\|f\|_1 := \int_{t_0}^{t_1} |f(t)| dt$$

In this course $\|\cdot\|_\infty$ taken for norm in \mathbb{C}^n

(ii) $C([t_0, t_1], \mathbb{C}^n)$ \leftarrow in \mathbb{C}^n

$$\|f\|_\infty = \max_{t \in [t_0, t_1]} \|f(t)\| \quad \leftarrow \text{norm in } \mathbb{C}^n$$

(ii) $P([t_0, t_1], \mathbb{R})$: Piece wise continuous



@ disc. fu may have any value
Req. L & R limits exist (in non ∞)

The right norm is not going to consider pts. of disc.
but will consider lim. pts.

$\|f\|_\infty := \text{ess sup } |f(t)|$ (a value attained @ a pt, which has other pts in any nbhd of it.)

(2) Linear Maps : Induced Norm

$$x \in U \xrightarrow{A} V \ni y$$

$\| \cdot \|_U$ $\| \cdot \|_V$

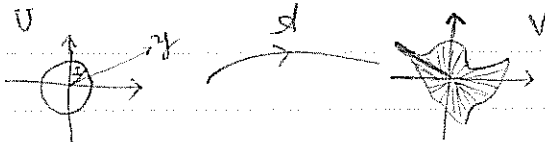
$$y = Ax$$

$\|y\|_V$ $\|x\|_U$

Q: any relation between the two?

Ans: Yes if one introduces norm induced ^{or} by Lin. Map, A

geometrically $\{x \in U : \|x\|_U = 1\}$



$$\sup_{\|x\|_U=1} \|Ax\|_V$$

$$\|A\| := \sup_{\|x\|_U=1} \|Ax\|_V$$

or $\|x\|_U=1$, then immediately $\|Ax\|_V \leq \|A\|$; This is only true on the unit ball.

Excessively Restrictive

↳ However \because of linearity can scale up & down!
 \therefore will hold in general! (can remove the restriction)

Pick $y \in U$ to be any vector $x := y/\|y\|_U$ then $\|x\|_U=1$.

$$\|Ax\|_V = \|Ay/\|y\|_U\|_V = \|Ay\|_V/\|y\|_U$$

$$\|A\| = \sup_{\|x\|_U=1} \|Ax\|_V = \sup_{y \neq 0} \frac{\|Ay\|_V}{\|y\|_U} \Rightarrow \|Ay\|_V \leq \|A\| \cdot \|y\|_U$$

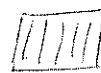
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Ex. $A: \mathbb{C}^n \rightarrow \mathbb{C}^n$

$$\|A\|_0 = \max_i \sum_{j=1}^n |a_{ij}| \quad (\text{row sum})$$

$$\|A\|_1 = \max_j \sum_{i=1}^n |a_{ij}| \quad (\text{column sum})$$

$$\|A\|_2 = \max_i (\lambda_i (A^* A))^{1/2} \quad (\text{eigen values})$$



How is this connected to DE?

\therefore of convergence!

(3) Convergence

A seq. of vectors $v_1, v_2, v_3, \dots, v_k, \dots$ in (V, F) , $F = \mathbb{R} \text{ or } \mathbb{C}$
 conv. to a vector v if

$$\|v_k - v\| \rightarrow 0 \text{ as } k \rightarrow \infty$$

(in terms of convergence of seq. of real #s)

(4) Differential Equations

$$\dot{x}(t) = p(x(t), t) ; x(0) = x_0 \quad x(t) \in \mathbb{C}^n$$

Q: [c/o solving eqn, we want to know if there is a sol, and if a soln exists whether its unique] ^{exh1} [if not unique how many, if yes to unique Q. can a basis be picked.] ^{exh2}

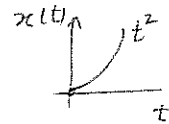
Don't Physical Systems always have ^{existing} unique solns
 * - often modelling is incorrect.

- Chaotic systems: very innocent eqns

Ex 1.) $\dot{x} = -1/x ; x(0) = 0$ no soln exists

Ex 2.) $\dot{x} = 2\sqrt{|x|} ; x(0) = 0$

$$dx / (2\sqrt{|x|}) = dt \Rightarrow \sqrt{|x|} = t ; x(t) = t^2 \quad \forall t \geq 0$$



$$\text{claim } \begin{cases} (t-c)^2 = x(t) & \forall t \geq c \\ 0 = x(t) & \forall t \in [0, c) \end{cases}$$

is also a soln \forall all $c!$ \Rightarrow ∞ # of solns, sep. can take off @ anytime.

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Monday
15 September '18

LST: EE221a - Discussion

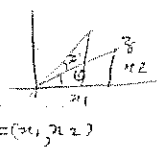
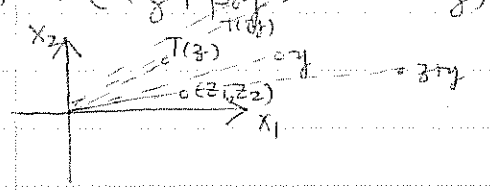
Ben's office hours

M 11-12 145 Cory

* Th 10-11 642-6954 bbanham@stan

- (1) Ex of Linear Transformation: Rotation in 2D
- (2) " " " " : Convolution
- (3) Matrix rep.
- (4) change of coord
- (5) induced norms: l_1, l_2, l_∞

(1) $T(\alpha z + \beta y) = \alpha T(z) + \beta T(y)$



$$\begin{aligned} z_1' + jy_1' &= \cos(\theta) z_1 - \sin(\theta) z_2 \\ z_2' + jy_2' &= \sin(\theta) z_1 + \cos(\theta) z_2 \end{aligned}$$

$$T(z) = (z_1 \sqrt{3}/2 - z_2 1/2, z_1 1/2 + z_2 \sqrt{3}/2)$$

$$\alpha z + \beta y = (\alpha z_1 + \beta y_1, \alpha z_2 + \beta y_2)$$

$$\begin{aligned} T(\alpha z + \beta y) &= [(\alpha z_1 + \beta y_1) \sqrt{3}/2 - (\alpha z_2 + \beta y_2) 1/2, (\alpha z_1 + \beta y_1) 1/2 + (\alpha z_2 + \beta y_2) \sqrt{3}/2] \\ &= \alpha (z_1 \sqrt{3}/2 - z_2 1/2) + \beta (y_1 \sqrt{3}/2 - y_2 1/2), \alpha (z_1 1/2 + z_2 \sqrt{3}/2) + \beta (y_1 1/2 + y_2 \sqrt{3}/2) \\ &= \alpha T(z) + \beta T(y) \end{aligned}$$

(2) $A: f \rightarrow g$

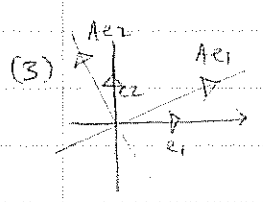
$$g(t) = \int_0^t f(t-c) u(c) dc$$

↑
kernel

$$x(t) = \int_0^t g(t-c) u(c) dc$$

$$x(t) = \int_0^t g(c) u(t-c) dc$$

$$\begin{aligned} A \cdot \alpha f_1 + \beta f_2 &\rightarrow \int_0^t (\alpha f_1 + \beta f_2)(t-c) u(c) dc = \int_0^t (\alpha f_1(t-c) + \beta f_2(t-c)) u(c) dc \\ &= \alpha A f_1 + \beta A f_2 \end{aligned}$$

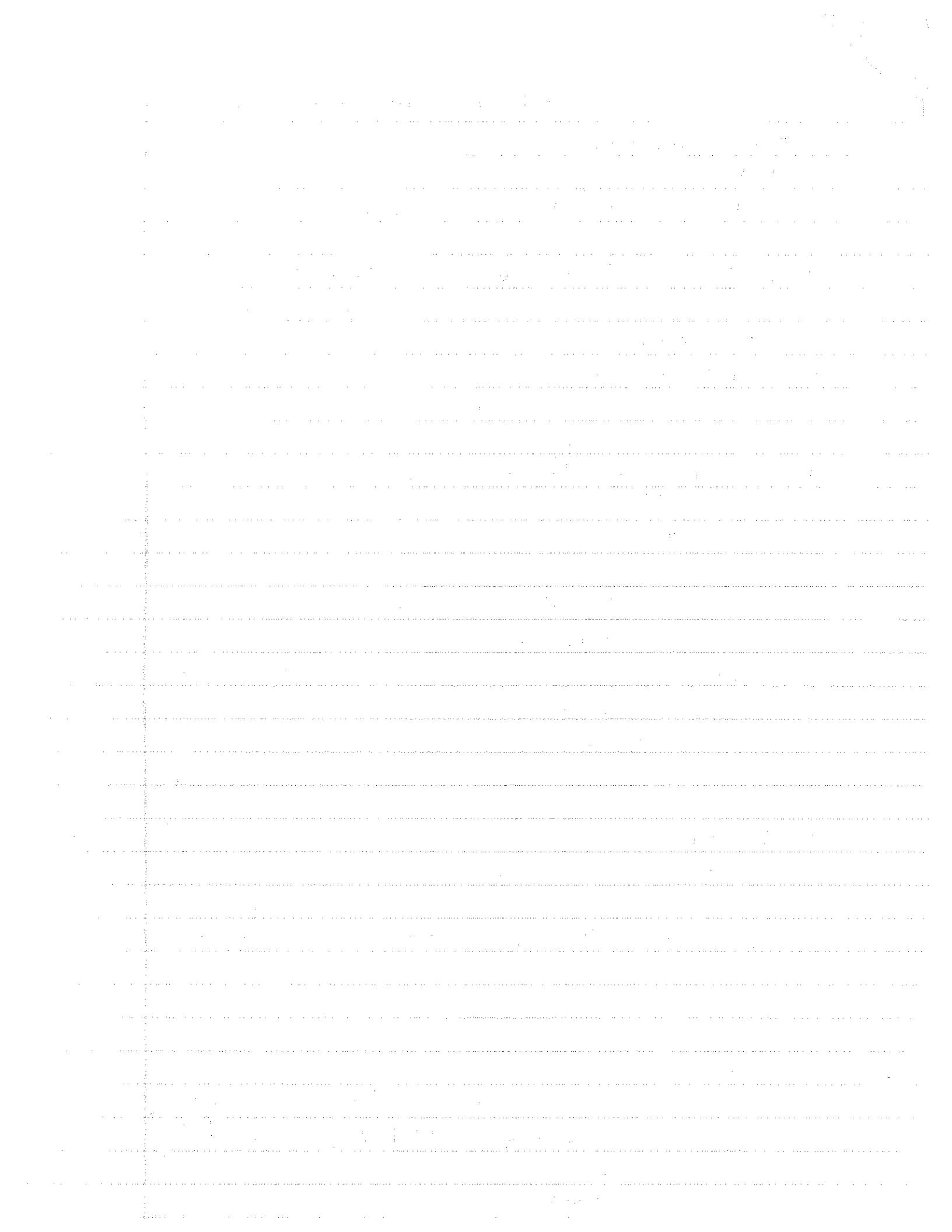


$$A = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$$

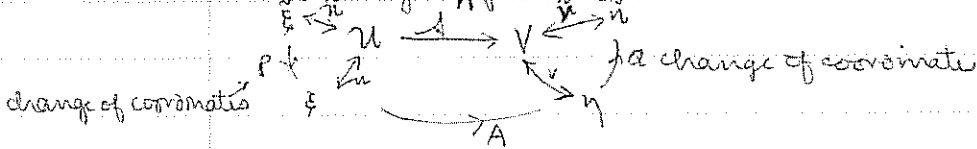
\mathbb{R}^2 transformed i^{th} basis vector in terms of original basis vectors

$$\alpha e_1 = (\cos \theta, \sin \theta) = A e_1 = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix} = A \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad Ae_2 = \begin{bmatrix} -\sin \theta \\ \cos \theta \end{bmatrix}$$

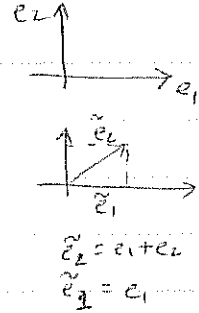
$$A = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$



(4) change of coordinates



$$A = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \quad \tilde{A} = ?$$



consider conditions under which P is inverse of Q?

change of coordinates

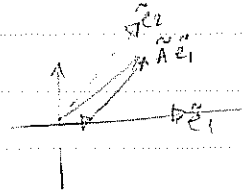
original i^{th} basis vectors in terms of new basis vectors. eg. from \tilde{e} to e basis

$$P = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \quad Q = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$$

$$\eta = A\xi = AP\tilde{\xi}$$

$$\tilde{\eta} = Q\eta = \underbrace{QAP}_{\tilde{A}}\tilde{\xi}$$

$$\tilde{A} = \begin{bmatrix} (\cos \theta - \sin \theta) & -2\sin \theta \\ \sin \theta & (\sin \theta + \cos \theta) \end{bmatrix}$$



$$\tilde{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\tilde{A} \tilde{e}_1 = \begin{bmatrix} 1/2(\sqrt{3}-1) \\ 1/2 \end{bmatrix} \begin{matrix} \tilde{e}_1 \text{ dir} \\ \tilde{e}_2 \text{ dir} \end{matrix}$$

\Rightarrow does work

$$A: \mathbb{R}^2 \rightarrow C^2 [0,1]$$

$$(U \rightarrow V)$$

$\left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$ basis for \mathbb{R}^2

$$A: (x_1, x_2) \mapsto t(x_1) + (1-t)x_2 \quad t \in [0,1] \quad \left\{ (t, 0), (0, (1-t)) \right\}$$

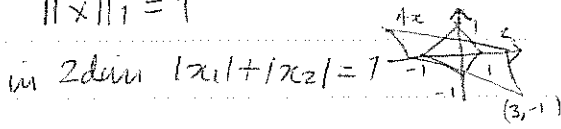
(5) induced Norm vector space, \mathbb{R} , norm $\|\cdot\|_1$

$$\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p} ; \|x\|_1 = \sum_{i=1}^n |x_i|$$

$$\|A\|_1 = \sup_{\|x\|_1=1} \|Ax\|$$

$$A = \begin{bmatrix} 3 & 2 \\ -1 & 0 \end{bmatrix}$$

$$\|x\|_1 = 1$$

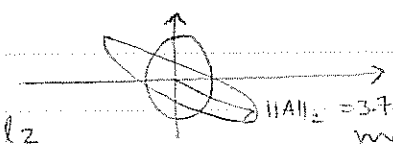
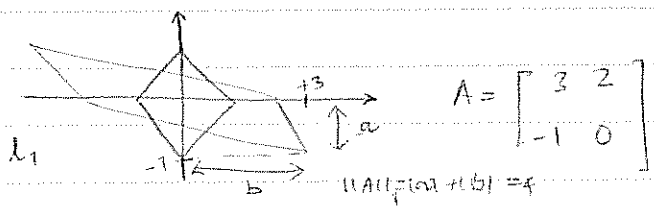


in 2dim $|x_1| + |x_2| = 1$; suppose the matrix A multiplies this unit sphere; get Δ pm type shape. Then obtain Norm from this is $(|3| + |1|) = 4$.

Handwritten text on lined paper, mostly illegible due to extreme fading and bleed-through from the reverse side of the page. The text appears to be organized into several paragraphs, with some lines being more distinct than others. The handwriting is cursive and somewhat slanted. There are some faint markings that could be numbers or symbols, but they are not clearly identifiable. The overall appearance is that of a very old or poorly preserved document.

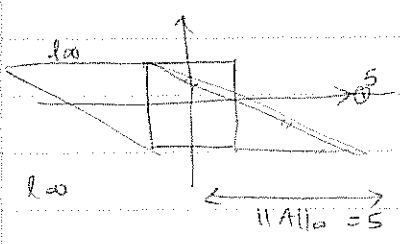
Friday
8 September 1989

LST - Disc + Lect



A as above \Rightarrow ellipse

major & minor axis determined by e.v.
 $\|x\|_2 = (\sum x_i^2)^{1/2}$ $\|A\|_2$ is by max. val. of ~~eigen~~ eigenvalues of A^*A



l_1 norm: column sum

Proof: $\|A\|_1 = \sup_{\|x\|_1=1} \|Ax\|_1 = \sup_{\|x\|_1=1} (\sum_i |\sum_j (a_{ij}x_j)|)$ by defn of l_1 norm

$$(Ax)_i = (\sum_j a_{ij} x_j)$$

$$\sup_{\|y\|_1=1} \sum_i |y_i|$$

$$\sum_i |\sum_j a_{ij} x_j| \leq \sum_i \sum_j |a_{ij} x_j| = \sum_j \sum_i |a_{ij} x_j|$$

by ameq.

$$\leq \sum_j \sum_i |a_{ij}| |x_j|$$

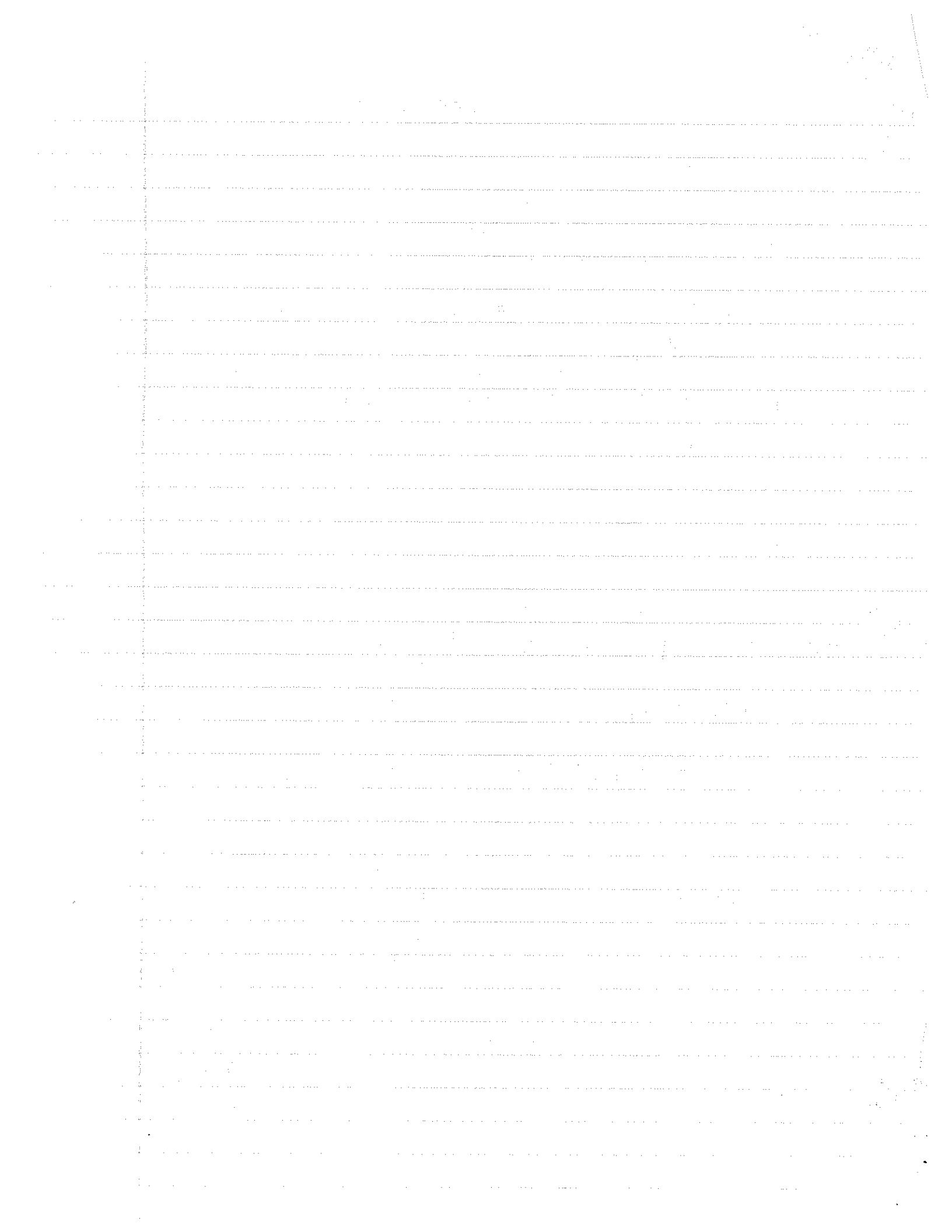
$$= \sum_j (|x_j| \sum_i |a_{ij}|)$$

$$\sum_j (|x_j| \sum_i |a_{ij}|) \leq \sum_j (|x_j| \max_i \sum_i |a_{ij}|)$$

$$= \max_j \sum_i |a_{ij}| \cdot \sum_j |x_j|$$

$$= \max_j \sum_i |a_{ij}| \quad \leftarrow = 1 \text{ (by constraint)}$$

ie $\|A\|_1 \leq \max_j \sum_i |a_{ij}|$; to show equality \rightarrow correct x to choose $\begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$ \leftarrow position of max column sum



$$\|A\|_\infty = \sup_{\|y\|_\infty=1} \left(\max_k \left| \sum_j a_{kj} y_j \right| \right)$$

$$\max_j |y_j| = 1 \quad (\text{from defn of } \|y\|_\infty = \max_j |y_j|)$$

$$\therefore \max_k \left| \sum_j a_{kj} y_j \right| \leq \max_k \sum_j |a_{kj}| \quad (*)$$

$$\text{let } m = \text{index of } \max_k \sum_j |a_{kj}| = \sum_j |a_{mj}|$$

$$\text{define } y_i = \text{sgn}(a_{mi}) \quad y_0^T = (y_1^0 \ y_2^0 \ \dots \ y_n^0)$$

$$\begin{aligned} \text{So } \|Ay_0\|_\infty &= \max_k \left| \sum_j a_{kj} \text{sgn}(a_{mj}) \right| \\ &\geq \left| \sum_j a_{mj} \text{sgn}(a_{mj}) \right| = \sum_j |a_{mj}| \quad (**)$$

compare (***) & (*)

$$\|Ay_0\|_\infty \leq \max_k \sum_j |a_{kj}| \leq \|A\|_\infty$$

$$\forall \|y\|_\infty = 1 \quad \|Ay\|_\infty = \max_k \sum_j |a_{kj}|$$

LST-lecture

(A) DIFFERENTIAL EQUATIONS

$$\dot{x} = p(x, t) \quad x(t_0) = x_0$$

Q: Is there a soln $(\exists!)$ solving it)

Is the soln. unique

dep. on initial condition

Ex. (i) $\dot{x} = -1/x \quad x(0) = 0$ no soln

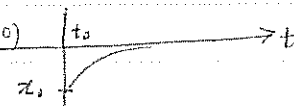
(ii) $\dot{x} = 2\sqrt{|x|} \quad x(0) = 0$ inf soln

(iii) $\dot{x} = x^2 \quad x(t_0) = x_0$

$$dx/x^2 = -dt \Rightarrow -1/x + 1/x_0 = t - t_0$$

$$x = \frac{1}{(1 - (t - t_0)x_0)} \cdot x_0$$

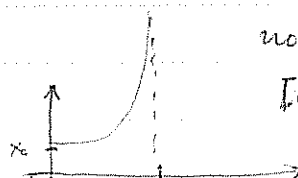
case (1) x_0 is negative (actually ≤ 0)



case (2) x_0 is positive

$$1 - (t - t_0)x_0 < 0 \text{ for } t > t_0$$

$$\text{when } (t - t_0)x_0 = 1 \Rightarrow t = t_0 + 1/x_0$$



no solution outside

$$[t_0, t_0 + 1/x_0)$$

No soln on (t_0, ∞)

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(5) Fundamental Theorem of Diff Eqn

- Existence, Uniqueness of soln $\dot{x} = p(x,t) \quad x(t_0) = x_0$

Suppose $p: \mathbb{R}^n \times \mathbb{R}_+ \rightarrow \mathbb{R}^n$ satisfying

(a) $\forall x \in \mathbb{R}^n \quad t \mapsto p(x,t)$ piecewise continuous; finitely LHR & limits
 set of DIS continuous points Δ (maybe empty)

(b) $\forall t \in \mathbb{R}_+ \quad \exists K(t)$ piecewise continuous st $\forall \xi, \xi' \in \mathbb{R}^n$
 $\|p(\xi, t) - p(\xi', t)\| \leq K(t) \|\xi - \xi'\| \Rightarrow p(\xi, t)$ is cont at each t .
 (Lipschitz condition)

Then

(i) existence

$$\forall x_0 \in \mathbb{R}^n, \forall t \in \mathbb{R}_+$$

\exists continuous function $\phi: \mathbb{R}_+ \rightarrow \mathbb{R}^n$ s.t.

$$\phi'(t) = p(\phi(t), t) \quad \phi(t_0) = x_0$$

ϕ is called to soln. of $\dot{x} = p(x,t) \quad x(t_0) = x_0$

(ii) uniqueness

soln is unique

(iii) soln. dep. on x_0 continuously

Note: all ex. don't satisfy Lipschitz cond.

Nice proof in Desoer.

Idea of proof

$$(1) \quad \dot{x}(t) = p(x(t), t), \quad x(t_0) = x_0$$

$$\text{integrate} \Rightarrow x(t) = x_0 + \int_{t_0}^t p(x(t'), t') dt' \quad (2)$$

\downarrow by Fund. thm of calc.

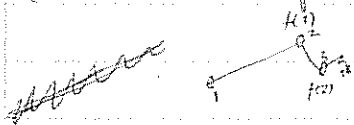
RHS is a mapping $F: C^n[0, \infty) \rightarrow C^n[0, \infty)$

$$x(\cdot) \mapsto (Fx)(\cdot)$$

$$(Fx)(t) = x_0 + \int_{t_0}^t p(x(t'), t') dt'$$

Eqn(2) $\Rightarrow x(\cdot)$ is a solution to (2) $\Leftrightarrow Fx = x$

(iv) consider $f: \mathbb{R}^2 \rightarrow \mathbb{R}^2$



contraction mapping fixed point thm
 let $(V, \|\cdot\|)$ complete normed linear space

$$\text{let } F: V \rightarrow V$$

then (i) \exists exactly one x^* in V

s.t. $Fx^* = x^*$

(ii) for any $x_0 \in V$ then the sequence $\{x_n\} = \{x_0, Fx_0, F(Fx_0), \dots\}$
 $x_n \rightarrow x^*$

(v) Lipschitz condition $\Rightarrow F$ is a contraction $\Rightarrow F$ has a fixed pt
 $\Rightarrow \text{DE has a solution.}$

The application of contraction mapping provides a solution technique:

(Picard Method) (IC problems use waveform relaxation techniques which are in essence Picard's method)

Consider $\dot{x} = F(x); x(0) = x_0$

$F: x(\cdot) \mapsto (Fx)(\cdot)$

$(Fx)(t) = x_0 + \int_0^t p(x(t'), t') dt'$

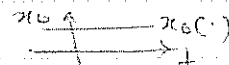
$x_0(\cdot) = x_0 + \int_0^t x_0(t') dt'$

$F x_0(\cdot) = x_1(\cdot)$

$F x_1(\cdot) = x_2(\cdot)$

\vdots

gives soln to DE eventually: Can start from any fn. eg

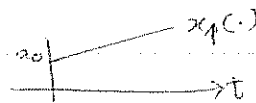
const. $x_0(t) = x_0$ 

$x_1(t) = (Fx_0)(t)$

$= x_0 + \int_0^t x_0 dt'$

$= x_0 + x_0 t$

$= x_0(1+t)$



$x_2(t) = (Fx_1)(t)$

$= x_0 + \int_0^t x_0(1+t') dt'$

$= x_0(1+t+\frac{t^2}{2})$

$x_n(t) = x_0(1+t+\dots+\frac{t^n}{n!})$

$n \rightarrow \infty \quad x_{\infty}(t) = x_0 e^t$

Computationally very slow.

(6) Cont. dependance on x_0

→ Bellman - Gronwall inequality

$$\dot{x} = p(x(t), t); \quad x(t_0) = x_0$$

$$\dot{y} = p(y(t), t); \quad y(t_0) = y_0 \quad \forall t \in [t_0, \infty)$$

$$\text{if } \|x_0 - y_0\| \rightarrow 0 \text{ then } \|x(\cdot) - y(\cdot)\|_{\infty} \rightarrow 0$$

↑ norm in \mathbb{R}^n

↑ norm in function space

defined on $C^1([t_0, T])$

Derivation of Bellman - Gronwall inequality

Pre analysis

$$x(t) = x_0 + \int_{t_0}^t p(x(t'), t') dt'$$

$$y(t) = y_0 + \int_{t_0}^t p(y(t'), t') dt'$$

$$[x(t) - y(t)] = (x_0 - y_0) + \int_{t_0}^t [p(x(t'), t') - p(y(t'), t')] dt'$$

$$\|x(t) - y(t)\| \leq \|x_0 - y_0\| + \int_{t_0}^t \| \cdot \| dt'$$

$$\leq \|x_0 - y_0\| + \int_{t_0}^t \| \cdot \| dt'$$

use L. Cond.

$$\Rightarrow \leq \|x_0 - y_0\| + \int_{t_0}^t k(t') \|x(t') - y(t')\| dt'$$

want $\underbrace{\|x(t) - y(t)\|}_{u(t)} \leq \Theta \|x_0 - y_0\|$

$$u(t) \leq c_1 + \int_{t_0}^t k(t') u(t') dt'$$

want $u(t) \leq \Theta c_1$

If we had equality

$$u(t) = c_1 + \int_{t_0}^t k(t') u(t') dt'$$

Take derivative $\dot{u}(t) = k(t) u(t)$ $u(t_0) = c_1$ Back to DE

we know soln of DE.

$$\Rightarrow u(t) = c_1 e^{\int_{t_0}^t k(t') dt'}$$

But we have inequality

$$\Theta : (1) \Rightarrow u(t) \leq c_1 e^{\int_{t_0}^t k(t') dt'}$$

Result is Bellman - Gronwall inequality

Suppose $k(t) \geq 0 \quad \forall t \in \mathbb{R}_+$

$$\text{If } u(t) \leq c_1 + \int_{t_0}^t k(t') u(t') dt' \quad \forall t \in \mathbb{R}_+$$

$$\text{then } u(t) \leq c_1 e^{\int_{t_0}^t k(t') dt'} \quad \forall t \in \mathbb{R}_+$$

This would imply incr.

2 September 2011
Tuesday

LST lecture

cont dep on x_0

$$\dot{x} = p(x,t) \quad x(t_0) = x_0$$

$$\dot{y} = p(y,t) \quad y(t_0) = y_0$$

want $\|x_0 - y_0\| \rightarrow 0 \Rightarrow \|x_0 - y_0\| \rightarrow 0$

$$x(t) = x_0 + \int_{t_0}^t p(x(t'), t') dt'$$

$$y(t) = y_0 + \int_{t_0}^t p(y(t'), t') dt'$$

$$\Rightarrow \|x(t) - y(t)\| \leq \|x_0 - y_0\| + \int_{t_0}^t k(t') \|x(t') - y(t')\| dt'$$

want $\|x(t) - y(t)\| \leq \boxed{?} \|x_0 - y_0\|$

Use: Bellman-Gronwall Ineq.

Suppose $k(t) \geq 0 \quad \forall t$

$$\text{if } u(t) \leq c_1 + \int_{t_0}^t k(t') u(t') dt' \quad \forall t$$

$$\text{then } u(t) \leq c_1 e^{\int_{t_0}^t k(t') dt'} \quad \forall t$$

Proof: Desoer's notes very concise; understand each line.

How to prove this?

$$(2) \Leftrightarrow u(t) e^{\int_{t_0}^t -k(t') dt'} \leq c_1 \quad (3) \text{ more tractable}$$

does it hold for $t=t_0$? yes! (from (1))

To prove LHS of (3) is a decreasing fn of t , look at the derivative.

$$\frac{d}{dt} [u(t) e^{\int_{t_0}^t -k(t') dt'}] \leq 0 \quad \forall t \geq t_0$$

show (3) would be true if $u(t) \leq c_1$ but we don't have it

\Rightarrow No good

look for bounding value/function

$$\text{consider (1)} \quad u(t) \leq V(t) \quad (4)$$

$$\text{if we can show } V(t) \exp \int_{t_0}^t -k(t') dt' \leq c_1 \quad (5)$$

(4) & (5) combined \Rightarrow (3)

consider (5) at $t=t_0$

$$\text{at } t=t_0 \quad V(t_0) \leq c_1 \quad \text{true!}$$

$$\frac{d}{dt} [V(t) e^{-\int_{t_0}^t k(t') dt'}] \leq 0$$

$$\text{LHS} = V'(t) e^{-\int_{t_0}^t k(t') dt'} - k(t) V(t) e^{-\int_{t_0}^t k(t') dt'} \quad (\text{diff in parts})$$

$$= k(t) u(t) e^{-\int_{t_0}^t k(t') dt'} - k(t) V(t) e^{-\int_{t_0}^t k(t') dt'}$$

$$= k(t) e^{-\int_{t_0}^t k(t') dt'} [u(t) - V(t)]$$

$$\leq 0 \quad \text{QED}$$

From BG ineq:

$$\|x(t) - y(t)\| \leq \|x_0 - y_0\| + \int_{t_0}^t k(t') \|x(t') - y(t')\| dt'$$

$$\Rightarrow \|x(t) - y(t)\| \leq \|x_0 - y_0\| \exp\left(\int_{t_0}^t k(t') dt'\right)$$

So as $\|x_0 - y_0\| \rightarrow 0 \Rightarrow \|x(t) - y(t)\| \rightarrow 0 \quad \forall t$
 i.e. $\|x - y\|_{\infty} \rightarrow 0$ (norm used here)

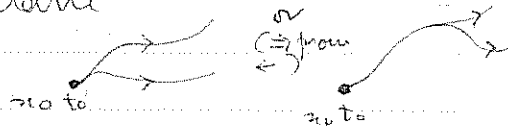
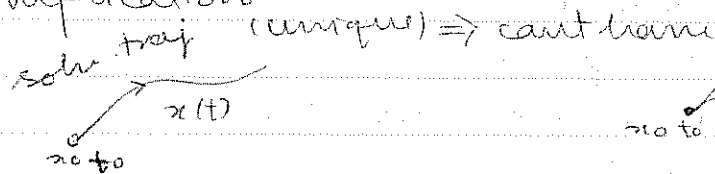
In particular $x_0 = y_0 \Rightarrow x(t) = y(t) \quad \forall t$
 Soln is UNIQUE

(8) Reverse time

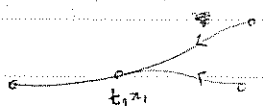
$$\dot{x} = p(x, t), \quad x(t_0) = x_0 \quad (1)$$

p satisfies the conditions in the Fund. Thm then (1) has a unique soln.

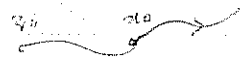
Implication



How about



Time reversed i.e. then what happens



Thm RT $\dot{x} = p(x, t) \quad x(t_0) = x_0 \quad t_0 \in [0, \infty)$ ①

if p satisfies the cond's of the Fund. Thm then \exists unique $z_0 \in \mathbb{R}^n$ s.t. the unique soln of $\dot{x} = p(x, t) \quad x(0) = z_0$ ②

satisfies $x(t_0) = x_0$ ③

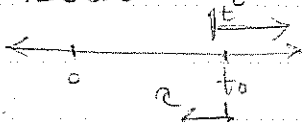
Need to show (i) Find z_0

(ii) Soln to the d.e. (1) sat. (3)

(iii) unique

How to find z_0 ?

Start from x_0 , 'reverse' time of the d.e. ① the soln. at $t=0$ is z_0 . How to reverse the time?



$$\dot{x} = x^2 \Rightarrow x = \frac{x^3}{3}$$

$$\propto \frac{x^3}{3} + A$$

Relation between reverse time & forward time

$$\tau = t_0 - t$$

Let the soln of the reversed d.e. be $z(\tau)$

$$\frac{d}{d\tau} z(\tau) = \bar{p}[z(\tau), \tau] ; z(0) = x_0$$

what $\bar{p}(z, \tau)$ should be?

$$\text{For } \tau = t_0 - t$$

$$x(t) = z(\tau)$$

$$\text{consider } \frac{d}{d\tau} z(\tau) = -\frac{d}{dt} x(t) ; \text{ from } \frac{d}{d\tau} z(\tau) = \frac{dx(t)}{dt} \frac{dt}{d\tau} = -\frac{dx(t)}{dt}$$

$$\begin{aligned} &= \bar{p}(z, \tau) \quad \downarrow \quad \downarrow \\ &= -\frac{d}{dt} [p(x(t), t)] \\ &= -p(z(\tau), t_0 - \tau) \end{aligned}$$

$$\text{So } \bar{p}(z, \tau) = -p(z, t_0 - \tau)$$

Proof (not in descr!) \Rightarrow

$$\text{Let } \bar{p}(z, \tau) := -p(z, t_0 - \tau) \quad \forall \tau \in [0, t_0]$$

p satisfies Lip condition.

$\Rightarrow \bar{p}$ " " " " "

$$\frac{d}{d\tau} z(\tau) = \bar{p}(z, \tau) \quad z(0) = x_0 \quad (6)$$

has a unique soln. $\tau \in [0, t_0]$

Let us define $z_0 = z(t_0)$ (well defined from fund. thm.)

$$\text{show now let } x(t) := z(t_0 - t) \quad t \in [0, t_0] \quad (7)$$

$$\begin{aligned} \frac{d}{dt} x(t) &= -\frac{d}{d\tau} z(t_0 - \tau) = \frac{d}{d\tau} z(t_0 - \tau) \cdot \frac{d(t_0 - \tau)}{dt} = -\frac{d}{d\tau} z(t_0 - \tau) \\ &\stackrel{(6)}{=} -\bar{p}(z(t_0 - \tau), t_0 - \tau) \\ &\stackrel{(5)}{=} p(z(t_0 - \tau), \tau) \\ &\stackrel{(7)}{=} p(x(t), t) \end{aligned}$$

$$x(0) \stackrel{(7)}{=} z(t_0) = z_0 \quad (6 \text{ } 1/2)$$

$$x(t_0) = z(0) \stackrel{(6)}{=} x_0$$

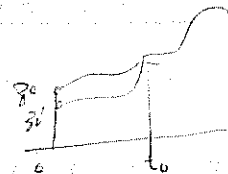
Uniqueness

Suppose $\exists z'_0 \neq z_0$ s.t.

$$\begin{cases} \frac{d}{dt} y(t) = p(y(t), t) & y(0) = z'_0 \\ y(t_0) = x_0 \end{cases}$$

We had already shown for sat. Lip cond & soln exist

$$z'(\tau) := y(t_0 - \tau) \quad \frac{d}{d\tau} [z'(\tau)] = \bar{p}(z', \tau) \quad z'(0) = x_0$$



Compare ** $z(t)$ $z'(t)$ sat. the same i.c.
 \in initial cond - \bar{p} p.c. & Lipschitz.

Soln is unique

$$z'(t) = z(t) \quad \forall t$$

$$z'(t_0) = z(t_0)$$

$$z_0' = z_0$$

4. Systems Fundamentals

$$\dot{x} = A(t)x(t) + B(t)u(t) ; x(t_0) = x_0 \quad (1)$$

$x(t) \in \mathbb{R}^n$
 $u(t) \in \mathbb{R}^r$

$A(t) \in \mathbb{R}^{n \times n}$
 $B(t) \in \mathbb{R}^{n \times r}$

}

components of are
p.c. for of t

For any $x(t)$ $u(t)$ the d.e. (1) satisfies the conditions in the fundamental theorem

\Rightarrow soln exists and is unique.

Proof:

$$p(x, t) := A(t)x + B(t)u(t)$$

(i) For fixed x

$$p(x, \cdot) \quad t \mapsto A(t)x + B(t)u(t) ; \text{ is p.c.}$$

(ii) For fixed t

$$p(\xi, t) - p(\xi', t) = [A(t)\xi + B(t)u(t)] - [A(t)\xi' + B(t)u(t)] \\ = A(t)(\xi - \xi')$$

$$\therefore \|p(\xi, t) - p(\xi', t)\| = \|A(t)(\xi - \xi')\|$$

$$\leq \|A(t)\| \|\xi - \xi'\|$$

Norm the bit about row sums & col sums being Norm. (strictly)
induced norm of $A(t)$ is cont. fun. of elements \Rightarrow its p.c. for of t $\Rightarrow k(t)$ p.c.

$$\Rightarrow \exists \text{ a unique soln to } (1) \Rightarrow \frac{d}{dt} S(t, t_0, x_0, u) = A(t)S(t, t_0, x_0, u) + B(t)u(t)$$

The soln depends onto x_0, u

lets write explicitly the dependance

$$(S(t_0, t_0, x_0, u) = x_0)$$

soln = $S(t, t_0, x_0, u)$ at any time t soln is $S(t, t_0, x_0, u)$

time $\xrightarrow{\text{need these because will examine dep. on these.}}$

Soln is defined for $t \geq t_0$ (by fund thm). By thm RT, soln also

21/10/2017
AS 981
is done

LST-L

Chapter 2 & 3

1. Linear Dynamical Systems

consider $\dot{x} = A(t)x + B(t)u(t); x(t_0) = x_0$ (1)

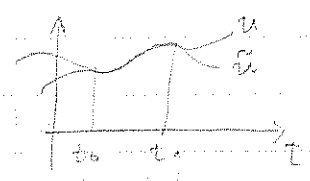
(1) Solutions

For any $u(\cdot)$, d.e. (1) has a unique solution.

(By the fundamental Theorem)

lets denote $S(t, t_0, x_0, u)$

$$\begin{cases} \frac{d}{dt} S(t, t_0, x_0, u) = A(t)S(t, t_0, x_0, u) + B(t)u(t) \\ S(t_0, t_0, x_0, u) = x_0 \end{cases}$$



(2) State Transition Property

If $u(t) = \tilde{u}(t) \quad t \in [t_0, t_1]$ *

then $S(t_1, t_0, x_0, u) = S(t_1, t_0, x_0, \tilde{u})$

Proof: $S(t, t_0, x_0, u)$
 $S(t, t_0, x_0, \tilde{u})$

By defn $\frac{d}{dt} S(t, t_0, x_0, u) = A(t)S(t, t_0, x_0, u) + B(t)u(t)$ (3)
 $S(t_0, t_0, x_0, u) = x_0$

$\frac{d}{dt} S(t, t_0, x_0, \tilde{u}) = A(t)S(t, t_0, x_0, \tilde{u}) + B(t)\tilde{u}(t)$ (4)
 $S(t_0, t_0, x_0, \tilde{u}) = x_0$

$\forall t \in [t_0, t_1]$

d. eqn. (3) = d. eqn. (4)

Fund Thm Sol is unique

$S(t, t_0, x_0, u) = S(t, t_0, x_0, \tilde{u}) \quad t \in [t_0, t_1]$

in particular $S(t_1, t_0, x_0, u) = S(t_1, t_0, x_0, \tilde{u})$

We write $S(t, t_0, x_0, u_{[t_0, t_1]})$

Implication

(1) Given (t_0, x_0)

$x(t) \quad t \in [t_0, t_1]$

independent of u prior to t_0 .

in other words, x_0 summarizes the past history,

ie everything having happened prior to t_0 .

(ii) $x(t) \quad t \in [t_0, t_1]$

is independent of u after t_1 , i.e. system is non-anticipative.

(iii) Semigroup property

$$S(t_2, t_1, S(t_1, t_0, x_0, u_{[t_0, t_1]}), u_{[t_1, t_2]})$$

$$= S(t_2, t_0, x_0, u_{[t_0, t_2]})$$

$$u_{[t_0, t_2]} = u_{[t_0, t_1]} \cup u_{[t_1, t_2]}$$

Proof: Fund Thm

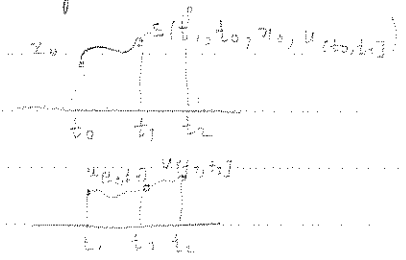
(A) Readout function

$$\dot{x} = A(t)x + B(t)u$$

$$y = C(t)x + D(t)u$$

$y(t) \in \mathbb{R}^m$ output

$$y(t) = r(t, x(t), u(t)) \text{ readout}$$



not used here!

Dynamical System

In general we say the model of a physical system is a dynamical system if we can associate with the following entities -

U : a set of fns called input

Σ : a set of fns called state

\mathcal{Y} : a set of fns called output

S : State Transition Fn

$$x(t) = S(t, t_0, x_0, u)$$

r : readout function $\rightarrow t, t_0, x_0, u \Rightarrow y(t) = r(t, t_0, x_0, u)$: atleast form.

$$y(t) = r(t, x(t), u(t))$$

The state transition fn. satisfies the following axioms:

(1) State Transition Axiom

(2) Semigroup Axiom

(3) Linearity

$$\text{Case } \dot{x} = A(t)x + B(t)u ; x(t_0) = x_0$$

$$S(t, t_0, x_0, u)$$

For any fixed t_0 ,
 $S: \Sigma \times U \rightarrow \mathcal{Y}$

Claim: S is linear map from $\Sigma \times \mathcal{U} \rightarrow \mathcal{Y}$.

Proof: $\alpha(x_0, u)$

$(\alpha x_0 + \alpha' x_0', \alpha u + \alpha' u')$

$$S(t, t_0, \alpha x_0 + \alpha' x_0', \alpha u + \alpha' u') = \alpha S(t, t_0, x_0, u) + \alpha' S(t, t_0, x_0', u')$$

show $\lambda(t) = r(t)$; By fundamental thm.

$$\lambda(t_0) = \alpha x_0 + \alpha' x_0'$$

$$\dot{\lambda}(t) = A(t)\lambda(t) + B(t)[\alpha u + \alpha' u']$$

$$r(t_0) = \alpha x_0 + \alpha' x_0'$$

$$\begin{aligned} \dot{r}(t) &= \alpha [A(t)S(t, t_0, x_0, u) + B(t)u] + \alpha' [A(t)S(t, t_0, x_0', u')] \\ &= A(t)r(t) + B(t)(\alpha u + \alpha' u') \end{aligned}$$

\Rightarrow By fund thm $\lambda(t) = r(t) \quad \forall t \geq t_0$

Linear dynamical system

In general we say a dynamical system is linear if the output map $\rho(t, t_0, x_0, u) = y(t)$ is a linear map from $\Sigma \times \mathcal{U} \rightarrow \mathcal{Y}$ i.e.

$$\rho(t, t_0, \alpha x_0 + \alpha' x_0', \alpha u + \alpha' u') = \alpha \rho(t, t_0, x_0, u) + \alpha' \rho(t, t_0, x_0', u') \quad \textcircled{5}$$

(6) Decomposition

In $\textcircled{5}$ we have $x_0 = \theta_\Sigma$ $u = u$ $\alpha = 1$ $x_0' = x_0$ $u' = \theta_{\mathcal{U}}$ $\alpha' = 1$

Then

$$\rho(t, t_0, x_0, u) = \rho(t, t_0, \theta_\Sigma, u) + \rho(t, t_0, x_0, \theta_{\mathcal{U}})$$

$\xleftarrow{\text{Total Response}} \quad \xleftarrow{\text{zero state resp}} \quad \xleftarrow{\text{zero i/p response}}$

(i) linearity of zero state response

$$\rho(t, t_0, \theta_\Sigma, \alpha u + \alpha' u') = \alpha \rho(t, t_0, \theta_\Sigma, u) + \alpha' \rho(t, t_0, \theta_\Sigma, u')$$

(ii) linearity of zero i/p response

$$\rho(t, t_0, \alpha x_0 + \alpha' x_0', \theta_{\mathcal{U}}) = \alpha \rho(t, t_0, x_0, \theta_{\mathcal{U}}) + \alpha' \rho(t, t_0, x_0', \theta_{\mathcal{U}})$$

Corollary: $S(\cdot, t_0, x_0, u) : \Sigma \times \mathcal{U} \rightarrow \mathcal{Y}$ (Not linear in general for $\Sigma \neq \theta$ each unless other is zero vector)

ZS.R. linear map of i/p

ZIP linear map of initial states

2. Zero Input Response of $\dot{X} = A(t)X + B(t)u$; $X(t_0) = x_0$
 $u(t) \equiv 0$ $\dot{X} = A(t)X$; $X(t_0) = x_0$

Soln is $S(t, t_0, x_0, u)$

∴ soln is fn of $\phi(t, t_0, x_0)$ ($\because u=0$)

ie $\begin{cases} \uparrow \phi(t, t_0, x_0) \\ \downarrow \phi(t_0, t_0, x_0) = x_0 \end{cases}$
 $\phi(t, t_0, x_0) = x_0$

zero i/p response $\phi(t, t_0, x_0)$ is a linear map of x_0
 For a fixed t $\phi(t, t_0, \cdot) : \mathbb{R}^n \rightarrow \mathbb{R}^n$

arb. basis $\{v_i\} \xrightarrow{x_0} x_0 \mapsto x(t) = \phi(t, t_0, x_0) \leftarrow \text{standard basis } \{e_i\}$

Linear Map from $\mathbb{R}^n \rightarrow \mathbb{R}^n$ has a matrix representation

$x_0 = \sum_{i=1}^n \alpha_i v_i$ coord. in this basis $[\alpha_1 \ \alpha_2 \ \dots \ \alpha_n]^T$
 $X(t) \quad \phi(t, t_0, x_0) = [\phi_1(t, t_0, x_0); \phi_2(t, t_0, x_0); \dots]^T$

$X(t)$ is matrix representation of this linear map
 w.r.t. $\{v_i\}$ & $\{e_i\}$

ie $\boxed{\phi(t, t_0, x_0) = X(t)x_0}$

What is $X(t)$?

① $\phi(t, t_0, x_0) = \phi(t, t_0, \sum_{i=1}^n \alpha_i v_i)$ ← MATRIX →
 $= \sum_{i=1}^n \alpha_i \phi(t, t_0, v_i) = [\phi(t, t_0, v_1) \mid \phi(t, t_0, v_2) \mid \dots \mid \phi(t, t_0, v_n)]$
 This must be $X(t)$

② i th col of $X(t)$ is $= (v_i)^T \rightarrow (\cdot)$ expressed in terms of $\{e_i\}$

$= \phi(t, t_0, v_i)$ expressed in terms of $\{e_i\}$

To summarize,

$x_0 \xrightarrow{X(t)}$ linear map, has matrix representation
 if you know what sys. does to basis, know what it does for all states

algebraic approach

conceptual approach

Friday
15 Sept 1989

LST-discussion

1. Uniqueness of soln to $\dot{x} = P(x)$
2. l_2 norm for diagonal matrix
3. existence of soln for cont + discrete time example
4. time reversal for discrete time systems
5. Norms in finite dimension

of γ - what if tangents same?

$$\dot{x} = P(x)$$

$$x(t) = \int_0^t P(x) dt + x(0)$$

$$\|x - y\| = \left\| \int_0^t [P(x) - P(y)] dt' + (x(0) - y(0)) \right\|$$

$$= \left\| \int_0^t (P(x) - P(y)) dt' \right\|$$

$$\leq \int_0^t \|P(x) - P(y)\| dt'$$

$$\|x - y\| \leq \int_0^t K(t) \|x - y\| dt \quad \text{if } \|x - y\| \leq 0 + \int_0^t K(t) \|x - y\| dt \Rightarrow \|x - y\| \leq 0 \cdot e^{\int_0^t K(t) dt} \leq 0$$

Suppose $K(t) \geq 0 \forall t$

$$\|x - y\| \leq 0 \text{ by B.G. if } u(t) \geq c + \int_0^t K(t) u(t) dt \quad \forall t$$

then $u(t) \leq c \cdot e^{\int_0^t K(t) dt} \quad \forall t$

l_2 norm for diagonal matrix $D = \begin{bmatrix} d_1 & 0 \\ 0 & d_n \end{bmatrix}$

$$\|A\| = \sup_{\|x\|_2=1} \left(\sum_i \left(\sum_j a_{ij} x_j \right)^2 \right)^{1/2}$$

$$= \sup_{\|x\|_2=1} \left(\sum_i (d_i x_i)^2 \right)^{1/2}$$

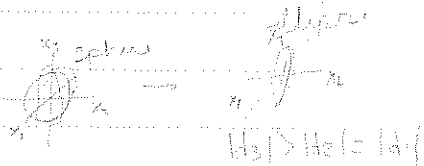
max $\left(\sum_i (d_i x_i)^2 \right)^{1/2}$ s.t. the constraint $\|x\|_2 = 1$

$$g(x) \equiv \left(\sum_i x_i^2 \right) - 1 = 0$$

use Lagrange multipliers

$\exists \lambda$ s.t. $\nabla f = \lambda \nabla g$ @ each extremum

$$\nabla f = \begin{bmatrix} 2d_1^2 x_1 \\ \vdots \\ 2d_n^2 x_n \end{bmatrix} = \lambda \nabla g = \begin{bmatrix} 2\lambda x_1 \\ \vdots \\ 2\lambda x_n \end{bmatrix}$$



$$d_i^2 x_i = \lambda x_i \quad i=1..n$$

either $x_i = 0$ or $x_i \neq 0 \Rightarrow d_i^2 = \lambda$ = same extremum

$$|f|^{1/2} = \left(\sum_i \lambda (x_i)^2 \right)^{1/2} = \lambda^{1/2} \left(\sum_i x_i^2 \right)^{1/2} = \lambda^{1/2} |x|$$

Matrix not diagonal: eigenvalues

$$\|A\|_2 = \left[\max \sigma(A^*A) \right]^{1/2}$$

(spectrum eigenvalues)

- (A) $\dot{x} = -\sqrt{x}$; does it satisfy Lipschitz cond? NO (maybe locally)
 (B) $\dot{x} = x^2$;

$$\exists? K \text{ s.t. } \|\sqrt{x_1} - \sqrt{x_2}\| \leq K \|x_1 - x_2\|$$

$$\|\frac{x_1 - x_2}{\sqrt{x_1 x_2}}\| \leq ?$$

$$\|x_1 - x_2\| \sqrt{\|x_1 x_2\|} \leq ? K \|x_1 - x_2\|$$

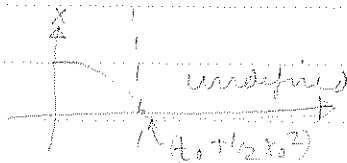
is there a K s.t. $\sqrt{\|x_1 x_2\|} \leq K$? NO

$$x dx = -dt$$

$$\frac{1}{2} x^2 = -t + \text{const.}$$

$$\frac{1}{2} x^2 = -t + \frac{1}{2} x_0^2 + t_0$$

$$x = \sqrt{x_0^2 - 2(t - t_0)}$$



Discrete Time : soln always defined

Approximate

$\dot{x}_{k/k} = \dot{x} = (x_{k+1} - x_k) / \Delta T$; standard approximation

$$x_{k+1} = x_k + \Delta T / x_k$$

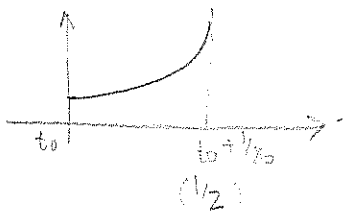
$$\Delta T = .25 ; x_0 = 2$$

k	0	1	2	3	4	5	6	7	8	9	10	11	12
x_k	2	1.77	1.74	1.59	1.49	1.26	1.07	0.83	0.54	0.37	-3.21	-3.14	

← no good →

$$x_{k+1} = x_k - \Delta T / x_k$$

③ $\dot{x} = x^2$



k	0	1	2	3	4
$x(k)$	2	3	5.2	12.1	480

→ blows up slower.

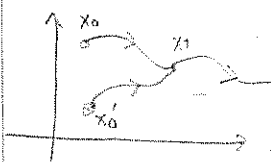
➤ Non unique from

$$\dot{x} = 3|x|^{2/3} \quad x(0) = 0$$

(i) $x(t) = 0$

(ii) $x(t) = t^3$

④ Time reversal for discrete time systems



$$x_{k+1} = f(x_k)$$

$$x_{k+2} = f(f(x_k))$$

$$x_{k+m} = f(f(f \dots f(x_k)))$$

← n time →

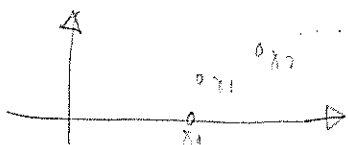
Given x_{k+m} can you find x_k ?

ex in \mathbb{R}^2
$$x_{k+1} = \begin{bmatrix} 1 & 3 \\ 1/6 & 1/2 \end{bmatrix} x_k \quad ; \quad x_{k+1} = A x_k$$

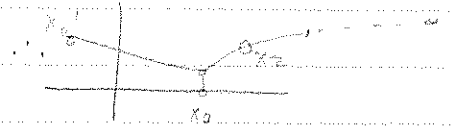
$$x_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$x_1 = A x_0 = \begin{bmatrix} 1 \\ 1/6 \end{bmatrix}$$

$$x_2 = A x_1 = \begin{bmatrix} 3/2 \\ 1/4 \end{bmatrix}$$



$$x_0' = \begin{bmatrix} -2 \\ 1 \end{bmatrix} \quad x' = Ax_0' = \begin{bmatrix} 1 \\ 1/6 \end{bmatrix}$$



when the matrix is invertible, you can work backwards.

A: If an inverse exists

$$f^{-1}(x_{k+1}) = f^{-1}(f(x_k))$$

in general inverse of f exists \Rightarrow unique trajectory

③ Norms finite dimensions

$$\|x\|_p > \|y\|_p \Rightarrow \|x\|_q > \|y\|_q$$

$$\exists c_1, c_2 < \infty \cdot c_1 \|x\|_p \leq \|x\|_q \leq c_2 \|x\|_p \quad \text{Schwarz inequality}$$

$$\text{ex: } \|x\|_1 = \sum_{i=1}^n |x_i| = \sum_{i=1}^n 1 \cdot |x_i| \leq \sqrt{\sum_{i=1}^n 1^2} \cdot \sqrt{\sum_{i=1}^n |x_i|^2} = n \|x\|_2$$

$$\|x\|_2 = \sqrt{\sum_{i=1}^n |x_i|^2} \leq \sqrt{\sum_{i=1}^n \|x\|_1^2} = \sqrt{n} \|x\|_1$$

$$\|x\|_1 \leq n \|x\|_2$$

$$\|x\|_2 \leq \sqrt{n} \|x\|_1$$

$$\sqrt{n} \|x\|_1 \leq \|x\|_2 \leq \sqrt{n} \|x\|_1$$

$$\sqrt{n} \|x\|_2 \leq \|x\|_1 \leq n \|x\|_2$$

try out for 1-norm.

my presentation

EE 321a: Lecture

Last time

Defined Lin Sys. decomposed to ZIR, ZSR; \mathbb{R}^n v_i & v_j etc

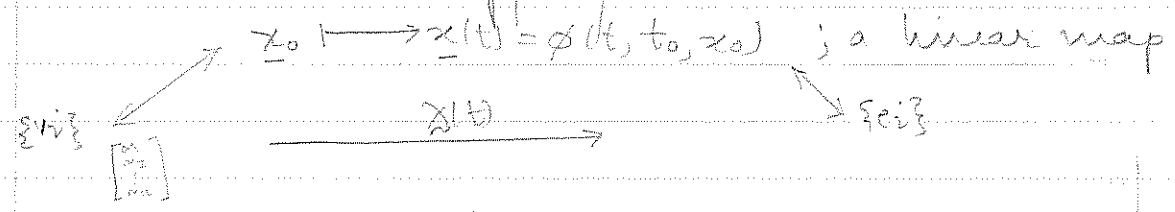
2. Zeroinput response

$\dot{x} = \underline{A}(t)x$; $x(t_0) = x_0$
vector vector

$x(t) = \phi(t, t_0, x_0)$

$x(t) = \phi(t, t_0, x_0)$
 t_0

Can view as a mapping $\mathbb{C}^n \rightarrow \mathbb{C}^n$



$X(t)$ = matrix representation of linear map.

i^{th} col $X(t) = v_i$ after map = $\phi(t, t_0, v_i)$
 expressed in terms of $\{e_i\}$

$\therefore X(t) = [\phi(t, t_0, v_1) \mid \phi(t, t_0, v_2) \mid \dots \mid \phi(t, t_0, v_n)]$

Properties of $X(t)$

(1) $X(t_0) = [\phi(t_0, t_0, v_1) \mid \dots \mid \phi(t_0, t_0, v_n)]$; (By notation used)
 $= [v_1 \mid v_2 \mid \dots \mid v_n] =: x_0$

Since $\{v_i\}$ basis $\Rightarrow \det x_0 \neq 0$ (else $x_0 \Delta = 0$ would have a non-trivial soln for Δ)

(2) By defn. $\phi(t, t_0, v_i) = A(t) \phi(t, t_0, v_i)$ $i=1..n$
 $\phi(t_0, t_0, v_i) = v_i$

$\begin{bmatrix} \phi(t, t_0, v_1) & \dots & \phi(t, t_0, v_n) \end{bmatrix} = \begin{bmatrix} A(t) \phi(t, t_0, v_1) & \dots & A(t) \phi(t, t_0, v_n) \end{bmatrix}$
 $\xrightarrow{\text{matrix}} \xrightarrow{\text{matrix}} \xrightarrow{\text{matrix}} \xrightarrow{\text{matrix}}$
 $\text{matrix } X(t) = A(t) \begin{bmatrix} \phi(t, t_0, v_1) & \dots & \phi(t, t_0, v_n) \end{bmatrix}$

$\dot{X}(t) = A(t) X(t)$ $X(t_0) = x_0$

view x_0 & $X(t_0)$ as x_0 (matrix!)
 well there is a relationship between them

$X(t)$ is called fund. matrix of the de

2nd col v_i

STATE TRANSITION MATRIX

We pick $\{v_i\}$ to be standard basis $\{e_i\}$

$$[\phi(t, t_0, e_1) \quad \phi(t, t_0, e_2) \quad \dots \quad \phi(t, t_0, e_n)] =: \Phi(t, t_0) \text{ (S.T.M.)}$$

Note: $\Phi(t_0, t_0) = [e_1 \quad e_2 \quad \dots \quad e_n] = I$ NOTE $\frac{d}{dt} \Phi(t, t_0) = A(t) \Phi(t, t_0)$

Properties of $\Phi(t, t_0)$

(1) By defn

$$x(t) = \phi(t, t_0, x_0) = \Phi(t, t_0) x_0$$

(2) $\Phi(t, t_0)$ is non-singular $\forall t$. (if from t_0 state to x_0 \Rightarrow x_0 to t_0 ?)

Pf: Suppose $\Phi(t, t_0)$ is singular @ t_1

ic \exists const. $C \neq \theta$ s.t. $\Phi(t, t_0) C = \theta$

Consider $\Phi(t, t_0) C =: \psi(t)$ remember - $(\psi(t_0, t_0) = I)$

$\psi(t_0) = 0$ (By construction)

$\psi(t) = A(t) \psi(t)$ // satisfies LIP cond $\Rightarrow \exists$ unique soln

$\psi(t_0) = \theta$

we know $\psi(t) = 0 \forall t$ is a soln.

By LIP soln is unique.

\Rightarrow unique soln is $\psi(t) = 0 \forall t$ < goes both ways >

$\Rightarrow \psi(t_0) = C = \theta = \text{contradiction!}$

(3) Semigroup property

$$\phi(t, t_0, x_0) = \phi(t, t_1, \phi(t_1, t_0, x_0))$$

$$\Phi(t, t_0) x_0 = \Phi(t, t_1) \Phi(t_1, t_0) x_0$$

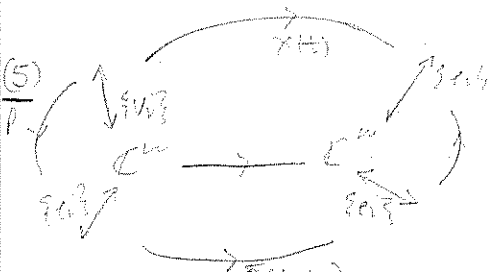
$$\Phi(t, t_0) x_0 = \Phi(t, t_1) \Phi(t_1, t_0) x_0 \text{ (Repeat above step)}$$

x_0 arb.

Does this mean $\Phi(t, t_0) = \Phi(t, t_1) \Phi(t_1, t_0)$

Yes (take $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$)

(4) $\Phi(t_1, t_0) = [\Phi(t_0, t_1)]^{-1}$ (from above)



$P \rightarrow$ i th col. of $P = v_i$ expressed in $\{e_i\}$ basis

matrix matrix matrix matrix
 $P = [v_1 \quad v_2 \quad \dots \quad v_n] = X(t_0) = X_0$

$x(t) = I \Phi(t, t_0) P$

$\Phi(t, t_0) = X(t) [X_0(t_0)]^{-1}$

\rightarrow rep. of $\{v_i\}$ as $\{e_i\}$ in column form

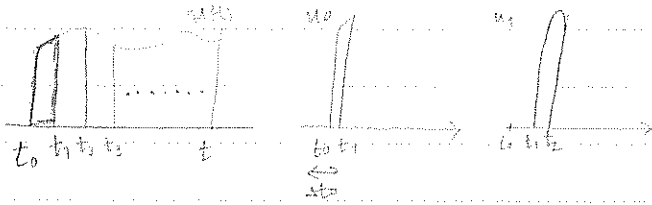
look at this ISK

ZERO STATE RESPONSE

$$\dot{x}(t) = A(t)x(t) + B(t)u(t); \quad x(t_0) = 0$$

known: Z.S. response is a lin. fn. of $u(t)$
 derive an expression for this linear map.

DERIVATION: Consider $u(t)$: break up $u(t)$ to $u_0(t) + u_1(t) + \dots$



$x_0(t)$ due to u_0
 $x_0(t) = A(t)x(t) + B(t)u(t)$; examine at t_0
 $x_1(t)$ due to u_1 $\Rightarrow x_1(t_1) = B(t_1)u(t_1)$
 when Δt_0 very small
 $x_0(t) \approx B(t_0)u(t_0)\Delta t_0$

$$x(t) = x_0(t) + x_1(t) + x_2(t) + \dots$$

From t_1 on u_0 is equal to zero!
 looking @ zero u_0 response, & we know what that is!

$$x_0(t) \approx \Phi(t, t_0) B(t_0) u(t_0) \Delta t_0 = x_0(t_0)$$

so the same for $x_1(t)$ due to u_1

$$\dot{x}_1(t) = B(t_1)u_1 \quad \text{integrate } x_1(t_2) \approx B(t_1)u(t_1)\Delta t_1$$

$$\text{from } t_2 \text{ on } \mathbb{R}, \quad x(t) \approx \Phi(t, t_1) B(t_1) u(t_1) \Delta t_1$$

observe pattern in eqns.

$$x(t) = x_0(t) + x_1(t) + x_2(t) + \dots$$

$$\approx \sum_{i=0}^n \Phi(t, t_i) B(t_i) u(t_i) \Delta t_i \quad ; \quad \infty \Delta t_i \rightarrow 0 \quad \Sigma \rightarrow \int$$

$$x(t) \stackrel{?}{=} \int_{t_0}^t \Phi(t, t') B(t') u(t') dt' \quad ; \text{ this is indeed the soln.}$$

Proof of $x(t) = \int_{t_0}^t \Phi(t, t') B(t') u(t') dt'$: Plug into DE! y works, OK (FTW)
 $\longleftarrow x(t_1) \longrightarrow$

$$x(t_0) = 0$$

$$\begin{aligned} \dot{x}(t) &= \Phi(t, t) B(t) u(t) + \int_{t_0}^t \frac{\partial}{\partial t} \Phi(t, t') B(t') u(t') dt' \quad ; \text{ see Calc} \\ &= \int_{t_0}^t \underbrace{A(t) \Phi(t, t')}_{A(t) \Phi(t, t')} B(t') u(t') dt' \\ &= \int_{t_0}^t B(t') u(t') dt' + A(t) \int_{t_0}^t \Phi(t, t') B(t') u(t') dt' \end{aligned}$$

$$\dot{x}(t) = A(t)x(t) + B(t)u(t) \quad ; \quad x(t) \text{ is indeed the soln. of 1. eqn.}$$

$$\frac{\partial}{\partial t} \int_{t_0}^t f(t, \tau) d\tau = \frac{\partial}{\partial t}$$

(4) Complete response ZIR + ZSR

$$\dot{x}(t) = A(t)x(t) + B(t)u(t); x(t_0) = x_0$$

$$x(t) = \Phi(t, t_0)x_0 + \int_{t_0}^t \Phi(t, \tau)B(\tau)u(\tau)d\tau$$

Z.S. Response $\begin{matrix} \text{for space} \\ u(\cdot) \end{matrix} \rightarrow x(t) = \int_{t_0}^t \Phi(t, \tau)B(\tau)u(\tau)d\tau$
 $\mathcal{F}^*[t_0, t] \rightarrow \mathbb{C}^n$

Z.I. Resp. $\mathbb{C}^n \rightarrow \mathbb{C}^n$

$x_0 \mapsto x(t)$ pt to pt

$x_0 \mapsto x(t)$ pt. to pw.

(5) Impulse Response Matrix (Zero state response)

$$\dot{x}(t) = A(t)x(t) + B(t)u(t); x(t_0) = 0$$

or $y(t) = C(t)x(t)$

$$y(t) = \int_{t_0}^t [C(t) \cdot \Phi(t, \tau) \cdot B(\tau)] u(\tau) d\tau$$

Let $u(t) = [0 \dots 0 \delta(t-\tau) 0 \dots 0]^T \leftarrow \tau^{\text{th}} \text{ comp. is } \delta @ t = \tau$

output = $[C(t) \Phi(t, \tau) B(\tau)]^T$ col.

Impulse response matrix

$$H(t, \tau) = C(t) \Phi(t, \tau) B(\tau)$$

548-4750

Thursday
21 SEP 1989

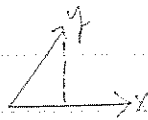
LST-lecture

Mathem Oct 12 Thursday

(VIII) Adjoint of Linear Map

1 Scalar Product

motivation: inner product in \mathbb{R}^3



$$\langle x, y \rangle = \sum_{i=1}^n x_i y_i$$

Properties: (in \mathbb{R}^n)

① linear fn of y

② $\langle ax, y \rangle = \langle x, ay \rangle$

$$\textcircled{3} \langle x, x \rangle = 0 \Leftrightarrow x = \theta$$

in \mathbb{C}^3 we can't define exactly the same (complex)
 $x = [1, 0]^T \Rightarrow \sum_{i=1}^3 x_i^2 = 0$ but $x \neq \theta$

For $\textcircled{3}$ to hold

$$\langle x, y \rangle = \sum_{i=1}^n \bar{x}_i y_i \quad ; \langle x, x \rangle \in \mathbb{R} = 0 \Leftrightarrow x = \theta$$

$$\hookrightarrow \langle x, y \rangle = \overline{\langle y, x \rangle}$$

in a general vector space, (V, \mathbb{F}) $\mathbb{F} = \mathbb{R}$ or \mathbb{C}

The fn. $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{F}$ is called an inner product or scalar product iff

$$\textcircled{1} \langle x, y+z \rangle = \langle x, y \rangle + \langle x, z \rangle$$

$$\textcircled{2} \langle x, \alpha y \rangle = \alpha \langle x, y \rangle$$

$$\textcircled{3} \langle x, y \rangle = \overline{\langle y, x \rangle}$$

$$\textcircled{4} (\langle x, x \rangle \geq 0) \wedge (\langle x, x \rangle = 0 \Leftrightarrow x = \theta)$$

(Not really linear in first var $(\cdot : x)$)

Ex1: $(V, \mathbb{F}) = (\mathbb{C}^n, \mathbb{C})$

$$\langle x, y \rangle := \sum_{i=1}^n \bar{x}_i y_i$$

Ex2: $(V, \mathbb{F}) = (P[t_0, t_1], \mathbb{C})$; $P[t_0, t_1] = \{ \text{p.c. fns on } [t_0, t_1] \}$

$$\langle x(\cdot), y(\cdot) \rangle := \int_{t_0}^{t_1} \bar{x}(t) y(t) dt$$

Ex3: $(V, \mathbb{F}) = (P^m[t_0, t_1], \mathbb{C})$

$$\langle x(\cdot), y(\cdot) \rangle_{P^m} := \int_{t_0}^{t_1} \langle x(t), y(t) \rangle_{P^m} dt = \int_{t_0}^{t_1} \sum_{i=1}^m \bar{x}_i(t) y_i(t) dt$$

Define $\langle x, y \rangle = 0$ we say x & y are orthogonal.

Thm^m: $\langle \cdot, \cdot \rangle$ inner product $\Rightarrow \|x\| := \sqrt{\langle x, x \rangle}$ is a norm

Proof: Norm $\textcircled{1} \|x\| \geq 0$ $x = \theta \Leftrightarrow \|x\| = 0$

$$\textcircled{2} \|\alpha x\| = |\alpha| \|x\|$$

$$\textcircled{3} \|x+y\| \leq \|x\| + \|y\|$$

$\textcircled{1}$ follows from $\textcircled{4}$

$\textcircled{2}$ follows from $\textcircled{2}$

$$\textcircled{3} \|x+y\|^2 = \langle x+y, x+y \rangle = \|x\|^2 + \langle x, y \rangle + \langle y, x \rangle + \|y\|^2$$

$$\text{so show } \leq (\|x\| + \|y\|)^2$$

If we can show $\langle x, y \rangle + \langle y, x \rangle \leq 2\|x\|\|y\|$

we know $\langle x-ty, x-ty \rangle \geq 0$ from \oplus

$$= t^2 \langle y, y \rangle - t(\langle x, y \rangle + \langle y, x \rangle) + \langle x, x \rangle \geq 0 \quad \forall t$$

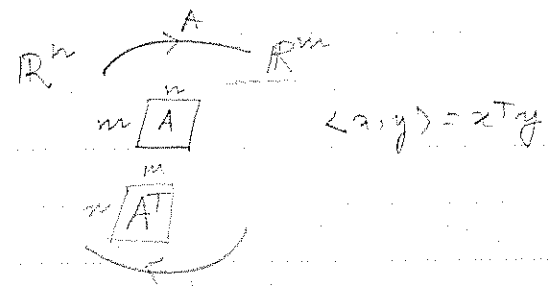
$$\Rightarrow (\langle x, y \rangle + \langle y, x \rangle)^2 - 4 \langle x, x \rangle \langle y, y \rangle \leq 0$$

$$\Rightarrow |\langle x, y \rangle + \langle y, x \rangle| \leq 2 \|x\| \|y\| \quad \text{Q.E.D.}$$

$a^2 + b^2 + c \geq 0$
 \uparrow true $\Rightarrow b^2 - 4ac \leq 0$
 (no touching x-axis!)

2. ADJOINT

motivation

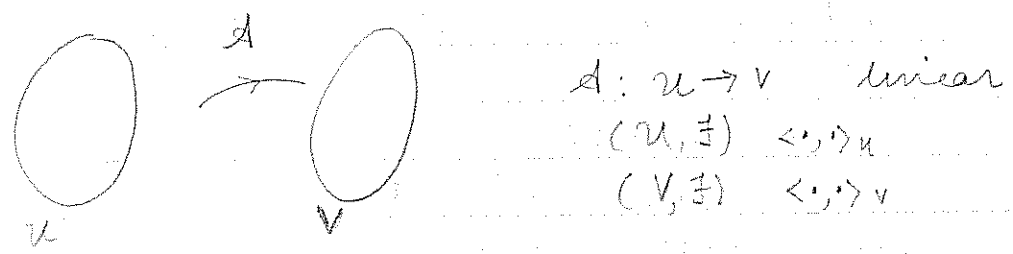


Note: $\langle y, Ax \rangle = y^T Ax$; by defn

$$= x^T A^T y \quad (\because \text{it's a scalar})$$

$$= \langle x, A^T y \rangle \quad \text{this is well defined!}$$

$$= \langle A^T y, x \rangle ; \text{ true } \forall x \in \mathbb{R}^n, y \in \mathbb{R}^m$$



The adjoint of the linear map $A: U \rightarrow V$ is defined by $A^*: V \rightarrow U$ is defined by

$$\forall x \in U, \forall y \in V \quad \langle y, Ax \rangle = \langle A^* y, x \rangle$$

Ex 1

$$A: \mathbb{C}^n \rightarrow \mathbb{C}^m$$

$$\langle y, Ax \rangle_m = \sum_{i=1}^m \bar{y}_i \sum_{j=1}^n a_{ij} x_j$$

$$\langle A^* y, x \rangle_n = \sum_{j=1}^n \left(\sum_{i=1}^m y_i \bar{a}_{ij} \right) x_j$$

$A^* :=$ conjugate transpose of A

(EZ2.) ZERO INPUT RESPONSE

$$\begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u(t) \\ y(t) = C(t)x(t) \end{cases}$$

ZIR = $\begin{cases} \Phi(t, t_0)x_0 \\ y(t) = C(t)\Phi(t, t_0)x_0 \end{cases}$ (t, t_0, x_0, 0u) \rightarrow using 2 instead of 1

Two views of ZIR

(i) for any given t ,

$$x_0 \mapsto C(t)\Phi(t, t_0)x_0$$

$$\mathbb{C}^n \rightarrow \mathbb{C}^m$$

adjoint $\Phi^*(t, t_0)C^*(t)$ (* \Rightarrow $\bar{}$ complex conj & transpose)

(ii) view $y(\cdot)$ as a fn of time

$$x_0 \mapsto C(\cdot)\Phi(\cdot, t_0)x_0$$

$$\mathbb{C}^n \rightarrow \mathcal{Y} = \mathcal{P}[t_0, t_1]$$

Define $L_0: x_0 \mapsto C(\cdot)\Phi(\cdot, t_0)x_0$

Find the adjoint $\forall x \in \mathbb{C}^n, \forall y(\cdot) \in \mathcal{P}^m$

$$\langle y(\cdot), L_0 x_0 \rangle_{\mathcal{P}^m} = \langle y(\cdot), C(\cdot)\Phi(\cdot, t_0)x_0 \rangle_{\mathcal{P}^m}$$

$$= \int_{t_0}^{t_1} y^*(t) C(t) \Phi(t, t_0) x_0 dt$$

$$\langle L_0^* y, x_0 \rangle_{\mathbb{C}^n} = \left[\int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) y(t) dt \right]^* x_0$$

$$\Rightarrow L_0^*: y(\cdot) \mapsto \int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) y(t) dt ; \text{ compare with ZSR}$$

$$\text{ZSR} = \int_{t_0}^{t_1} \Phi(t, t_0) B(t) u(t) dt ; \text{ integ. is ext 2nd argument here!}$$

$$\begin{array}{ccc} \downarrow & \downarrow & \downarrow \\ \Phi^*(t, t_0) & C^*(t) & y(t) \end{array}$$

Q. Can we make this $\Phi^*(t, t_0)$ a state transition matrix of something?

Say $\Psi(t_0, t)$ is a s.t.m. from a d.e.

$$\Phi^*(t, t_0) = \Psi(t_0, t) ; \text{ use } \tau \text{ in place of } t_0$$

$$\Phi^*(t, \tau) = \Psi(\tau, t)$$

In order to find $\Psi(\tau, t)$ is the state transition matrix of what, lets what d.e. it satisfies.

$$\partial_{\tau} \Psi(\tau, t) = ?$$

$$\partial_{\tau} \Psi(\tau, t) = \partial_{\tau} [\Phi^*(\tau, t)]^{-1}$$

How do you find this deriv? By defn

$$\Phi^*(\tau, t) [\Phi^*(\tau, t)]^{-1} = I$$

$$\left[\frac{\partial}{\partial t} \Phi^*(\tau, t) \right] [\]^{-1} + \Phi^*(\tau, t) \frac{\partial}{\partial \tau} [\]^{-1} = 0$$

↳ $\frac{\partial}{\partial \tau} \Phi^*$ & $[\]^{-1}$ commute!

$$\therefore \left[\frac{\partial}{\partial t} \Phi^*(\tau, t) \right]^* [\]^{-1} + \Phi^*(\tau, t) \frac{\partial}{\partial \tau} [\]^{-1} = 0$$

$$[A(\tau) \Phi(\tau, t)]^*$$

$$\Phi^*(\tau, t) A^*(\tau) [\]^{-1} + \Phi^*(\tau, t) \frac{\partial}{\partial \tau} [\]^{-1} = 0$$

$$[\Phi^*(\tau, t)]^{-1} = I \frac{\partial}{\partial \tau} [\Phi^*(\tau, t)]^{-1} = -A^*(\tau) [\Phi^*(\tau, t)]^{-1}$$

indeed $\Psi(\tau, t)$ is indeed the state transition matrix of $\dot{p}(\tau) = -A^*(\tau) p(\tau)$

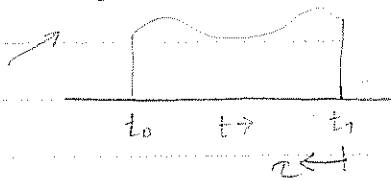
$$p(t) = p_0 \text{ i. c.}$$

$$\text{Back to } L_0^* y = \int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) y(t) dt$$

$$= \int_{t_0}^{t_1} \Psi(t_0, t) C^*(t) y(t) dt \quad ; \text{ no problem (just change up)}$$

$$= \int_{t_1}^{t_0} \Psi(t_0, t) [-C^*(t)] y(t) dt$$

looking @



↑ it is the ZSR of a d.e.

$$\begin{cases} \frac{d}{dt} p(t) = -A^*(t) p(t) - C^*(t) \\ p(t_1) = 0 \end{cases}$$

↳ the adjoint of the ZIR

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

$$y(t) = C(t) X(t)$$

(Ex 3) ZSR

$$p(t, t_0, \theta_\Sigma, u) = \int_{t_0}^{t_1} C(t) \Phi(t, \tau) B(\tau) u(\tau) d\tau$$

Two views: (i) for a given t

$$u(\cdot) \mapsto \int_{t_0}^{t_1} C(t) \Phi(t, \tau) B(\tau) u(\tau) d\tau$$

$$P^x[t_0, t_1] \mapsto \mathbb{C}^n$$

adjoint of this will be from $\mathbb{C}^n \rightarrow P^r[t_0, t_1]$

(ii) view $y(\cdot)$ as a fn. $u(\cdot) \mapsto y(\cdot)$
 $\mathcal{P}^2[t_0, t_1] \rightarrow \mathcal{P}^m[t_0, t_1]$

find its adjoint
 (will do next time)

Friday
 22 Sept 1989

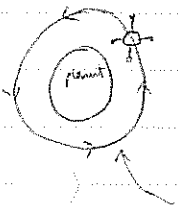
LST-Discussion

$\{x \in \mathbb{R}^n\}$ locally Lipschitz.

Lipschitz in an open set,
 what about for $t < t_0$

$\forall x, y \in U$
 $\exists K(t)$ p.c.

$\Phi(t, 0)$ $\Phi(t, t_0) = \Phi(t, 0) \Phi^{*y}(0, t_0)$
 $\hookrightarrow \Phi'(t_0, 0)$



$\dot{x} = f(x, u, t)$: non linear

control this \exists non linear control
 solu is an \ni point.

(x_0, t_0) with specific control
 $\tilde{u}(t)$

what happens to x if we change control from $\tilde{u} \rightarrow \tilde{u} + \delta u$

$\tilde{x} = \text{soln } \tau \tilde{u}$

$\tilde{x} + \delta x = \dots \tilde{u} + \delta u$

$(\tilde{x} + \delta x) = f(\tilde{x} + \delta x, \tilde{u} + \delta u, t)$

$f(\tilde{x} + \delta x, \tilde{u} + \delta u, t) \approx f(\tilde{x}, \tilde{u}, t) + \frac{\partial f}{\partial x} \Big|_{\tilde{x}, \tilde{u}} \delta x + \frac{\partial f}{\partial u} \Big|_{\tilde{x}, \tilde{u}} \delta u$

$\tilde{x} + \delta x = f(\tilde{x}, \tilde{u}, t) + \frac{\partial f}{\partial x} \Big|_{\tilde{x}, \tilde{u}} \delta x + \frac{\partial f}{\partial u} \Big|_{\tilde{x}, \tilde{u}} \delta u$

$\delta \dot{x} = \frac{\partial f}{\partial x} \Big|_{\tilde{x}, \tilde{u}, t} \delta x + \frac{\partial f}{\partial u} \Big|_{\tilde{x}, \tilde{u}, t} \delta u$
 Jacobian

$\delta \dot{x} = A(t) \delta x + B(t) \delta u$

$f(x, u, t) = \cos x + 3u$

$\dot{x} = \cos x + 3u$

linearize @ $x=1 \Rightarrow \frac{\partial f}{\partial x} = -\sin x \Big|_{x=1} = -\sin 1$

$\frac{\partial f}{\partial u} = 3$

$\delta \dot{x} = -\sin 1 \delta x + 3 \delta u$

$$f(x, u) = \begin{bmatrix} \cos(x_1 + x_2) + 3u \\ e^{x_2} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \end{bmatrix}$$

$$\frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} \\ \frac{\partial f_1}{\partial x_2} \end{bmatrix} = \begin{bmatrix} -\sin(x_1 + x_2) & -\sin(x_1 + x_2) \\ 0 & 1 \end{bmatrix}$$

DISCRETE TIME SYSTEMS

$$R = \begin{cases} x_{k+1} = A(k)x_k + B(k)u_k \\ y_k = C(k)x_k + D(k)u_k \end{cases} \quad x_k \in \mathbb{R}^n$$

$\forall x_{k_0}, \{x_k\}_0^\infty$ & $\{y_k\}_0^\infty$ exist for any $\{u_k\}_0^\infty$

Then The ZIR of the system represented by R is given by

$$x_k = \Phi(k, k_0)x_{k_0} \quad \forall k \geq k_0$$

where $\Phi(k, k_0) = I$

$$\Phi(k, k_0) = A(k-1)A(k-2) \dots A(k_0)$$

Pf: By induction

assume true for k'

$$\begin{aligned} \text{Then } x_{k'} &= \Phi(k', k_0)x_{k_0} \\ &= A(k'-1) \dots A(k_0) \end{aligned}$$

From (*)

$$\begin{aligned} x_{k'+1} &= A(k')x_{k'} \\ &= A(k')\Phi(k', k_0)x_{k_0} \\ &= A(k')A(k'-1) \dots A(k_0)x_{k_0} \\ &= \Phi(k'+1, k_0)x_{k_0} \end{aligned}$$

$$\begin{aligned} \text{Now for } x_{k+1} &= A(k)x_k \\ &= \Phi(k+1, k_0)x_{k_0} \quad \square \end{aligned}$$

$$\begin{aligned} \Phi(k+1, k_0) &= A(k) \dots A(k_0) \\ &= A(k) \Phi(k, k_0) \end{aligned}$$

Complete State Response:

$$x_{k_0+1} = A(k_0)x_{k_0} + B(k_0)u_{k_0}$$

$$\begin{aligned} x_{k_0+2} &= A(k_1) [A(k_0)x_{k_0} + B(k_0)u_{k_0}] + B(k_1)u_{k_1} \\ &= \underbrace{A(k_1)A(k_0)}_{\Phi(k_0+2, k_0)} x_{k_0} + \underbrace{A(k_1)B(k_0)}_{\substack{\text{ } \\ \triangleright k_1 = k_0+1}} u_{k_0} + B(k_1)u_{k_1} \end{aligned}$$

$$x_{k_0+3} = \text{(big expression)}$$

$$\Phi(k_0+3, k_0)x_{k_0} + \sum_{k'=k_0}^{k_0+2} \Phi(k_0+3, k'+1) B(k')u_{k'} \quad ; \text{ can know by induction}$$

$$x_k = \Phi(k, k_0)x_{k_0} + \sum_{k'=k_0}^{k-1} \Phi(k, k'+1) B(k')u_{k'}$$

↑ state transition function.

$[k, k_0]$ discrete time sys. backwards

$$y_k = C(k)\Phi(k, k_0)x_{k_0} + \sum_{k'=k_0}^{k-1} C(k)\Phi(k, k'+1)B(k')u_{k'} + D(k)u_k$$

← ZSR →

↑ response function

$$x(t) = \left[C(t)\phi(t, t_0)x_0 + \int_{t_0}^t C(t)\phi(t, \tau)B(\tau)u(\tau)d\tau \right] + D(t)u(t) \quad \boxed{vt}$$

Adjoint for discrete time systems

$$x_{k+1} = A(k)x_k$$

$$x_k = \phi(k, k_0)x_{k_0} \quad \forall k \geq k_0$$

$$p_k = A(k)^* p_{k+1}$$

$A(k)^*$ = conj. transpose of $A(k)$

$$A = \begin{bmatrix} 1 & 1-j \\ 2+j & 0 \end{bmatrix} \quad A^* = \begin{bmatrix} 1 & 2-j \\ 1+j & 0 \end{bmatrix}$$

Start at p_{k_0} next step $\rightarrow p_{k_0-1}$ (A could be singular)

$$J : u[t_0, t_1] \rightarrow x_1$$

↑ in time.

$$J^* : x_1 \rightarrow u[t_0, t_1]$$

$$p_{k_0} = [A(k_0)^*]^{-1} p_{k_0-1}$$

$$x_{k_0} = A(k_0)x_{k_0-1}$$

← p_k is not in the null space of A^*
 $\{p_k \notin R(A^*)\}$

examples: (1) $A^* = \begin{bmatrix} 0 & 1 \\ 0 & 2 \end{bmatrix}$ $\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$

$2y=0; y=1$ no soln.

(2) $A^* = \begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix}$ an ∞ of solns.

$\{p_k \in R(A^*)\}$

$\Psi(\lambda, k) = A(\lambda)^* A(\lambda+1)^* \dots A(k)^*$
 $\Psi(\lambda, k)^* = \Phi(k, \lambda)$

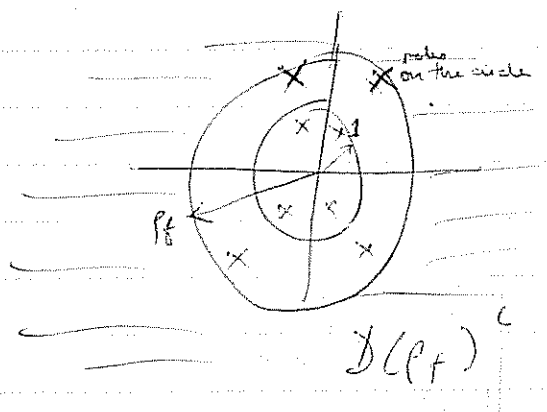
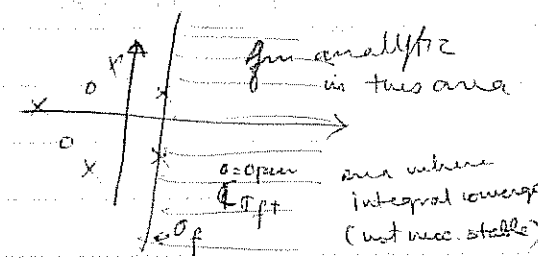
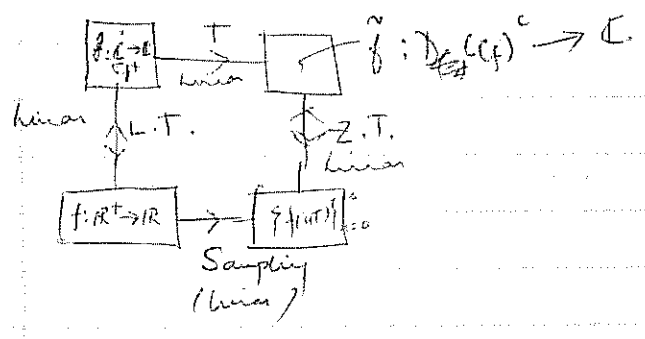
SAMPLED DATA SYSTEMS

$\hat{f} = L.T.$ $f: \mathbb{R}^+ \rightarrow \mathbb{R}$ then $\hat{f} = \int_0^{\infty} f(\omega) e^{-s\omega} d\omega$ $\forall s$ s.t. ^{inter} conv

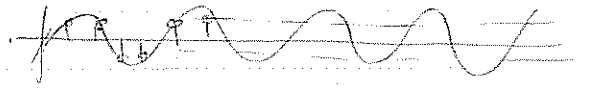
Z.T. = \tilde{f} $\{f_n\}_{n=0}^{\infty}$ $\tilde{f}(z) = \sum_{n=0}^{\infty} z^{-n} f_n$

function $f(t)$: $\tilde{f}(t) = \sum_{n=0}^{\infty} z^{-n} f(nT)$ defined for all z s.t. Σ conv

Reln between Z.T. & L.T.



S is not injective (1-1)



If f is Bandlimited you end up bijective
 a (1-1) & onto

$$f(t) = \sum_{\omega=0}^{\infty} f(nT) \frac{\sin(\omega_T(t-nT))}{\omega_T(t-nT)}$$

TUESDAY
 26 Sept 1999

L.S.T. lecture

Ex3 Zero State Response

$\mathcal{R}: u(\cdot) \rightarrow y(\cdot)$

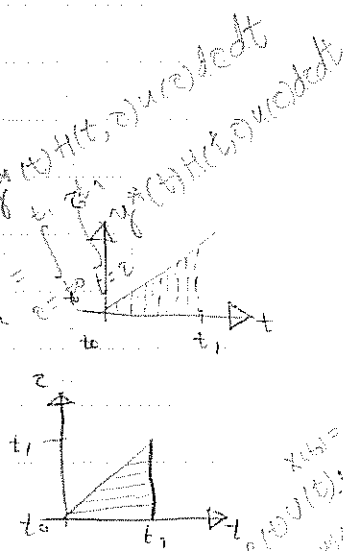
$\mathcal{R}: P^n[t_0, t_1] \rightarrow P^m[t_0, t_1]$

$$(Ru)(t) = \int_{t_0}^{t_1} \underbrace{\Phi(t, \tau)}_{\leftarrow H(t, \tau)} B(\tau) u(\tau) d\tau$$

Find adjoint of \mathcal{R}

$$\begin{aligned} \langle y, Ru \rangle_{P^m} &= \int_{t_0}^{t_1} y^*(t) [Ru(t)] dt = \int_{t_0}^{t_1} y^*(t) \int_{t_0}^{t_1} \Phi(t, \tau) B(\tau) u(\tau) d\tau dt \\ &= \int_{t_0}^{t_1} [R^*y(\tau)]^* u(\tau) d\tau \end{aligned}$$

change order of integration is required.



$$\begin{aligned} &\Rightarrow \int_{t_0}^{t_1} \int_{\tau}^{t_1} y^*(t) \Phi(t, \tau) B(\tau) u(\tau) dt d\tau \\ &\Rightarrow \int_{t_0}^{t_1} \left[\int_{\tau}^{t_1} \Phi^*(t, \tau) y(t) dt \right]^* u(\tau) d\tau \end{aligned}$$

$R^*: P^m[t_0, t_1] \rightarrow P^n[t_0, t_1]$

$$[R^*y](\tau) = \int_{\tau}^{t_1} \Phi^*(t, \tau) y(t) dt$$

$$= \int_{\tau}^{t_1} B^*(\tau) \Phi^*(t, \tau) C^*(t) y(t) dt$$

$z(t) = B^*(t) p(t)$

$p(t) = \int_{t_0}^{t_1} \Phi^*(t, \tau) C^*(\tau) y(\tau) d\tau$

$p(t)$ = zsr of the "adjoint system"

$\dot{p}(t) = -A^*(t)p(t) - C^*(t)y(t); p(t_1) = 0$

the zsr of the adjoint system

output of system
 $z(t) = B^*(t)p(t)$

Duality

$$R: u(\cdot) \rightarrow y(\cdot)$$

$$A(t)$$

$$B(t)$$

$$C(t)$$

$$R^{\#}: y(\cdot) \rightarrow x(\cdot)$$

$$-A^{\#}(t)$$

$$-B^{\#}(t)$$

$$C^{\#}(t)$$

Chapter IV

$[A, B, C]$

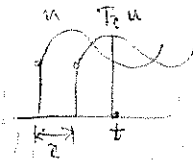
$$\dot{x}(t) = A x(t) + B u(t)$$

$$y(t) = C x(t)$$

1. Time Invariant

translation operator T_c

$$(T_c u)(t) = u(t-c)$$



A dynamical system is time invariant \Leftrightarrow

(a) $u \in \mathcal{U} \quad T_c u \in \mathcal{U} \quad \forall c$

(\mathcal{U} is closed under the translation operation)

(b) $f(t, t_0, x_0, u) = f(t+c, t_0+c, x_0, T_c u) \quad \forall t_0, t, c \neq x_0, u$

- a response depends only on $(t_1 - t_0)$

- ~~time invariant~~ systems may always take $t_0 = 0$.

Ex. Show Φ is time invariant.

2. State Transition Matrix

$$\dot{x}(t) = A x(t) ; x(0) = x_0 \quad (\text{take } t_0 = 0)$$

$$\Phi(t) := \Phi(t, 0)$$

$$\frac{d}{dt} \Phi(t) = A \Phi(t) ; \Phi(0) = I \Leftrightarrow \Phi(t) - I = \int_0^t A \Phi(t') dt'$$

Picard iteration: $\Phi_0(t) = I$

$$\Phi_1(t) = I + \int_0^t A \Phi_0(t') dt' = I + At$$

$$\Phi_2(t) = I + \int_0^t A (I + A t') dt'$$

$$= I + At + A^2 t^2 / 2!$$

$$\Phi(t) = I + At + A^2 t^2 / 2! + A^3 t^3 / 3! + \dots$$

$$\Phi(t) = \sum_{k=0}^{\infty} \frac{A^k t^k}{k!}, \text{ ; in the scalar case this would be } \exp(\cdot)$$

then lets define $\mathbb{R} = \exp(At)$ for matrices.

$$x(t) = [\exp(At)] x_0 \text{ ; different modes of the system response}$$

Properties

(1) If $A = PBP^{-1}$; correspond to change of coord on both domain & range

$$\text{then } \exp A = P(\exp B)P^{-1}$$

$$P \left(\sum_{k=0}^N \frac{B^k}{k!} \right) P^{-1} = \sum_{k=0}^N \frac{PB^kP^{-1}}{k!} \text{ ; examine } (PB^kP^{-1})^k \xrightarrow{\leftarrow k \text{ times}} = PBP^{-1}PBP^{-1} \dots P = P B^k P^{-1}$$

$$= \sum_{k=0}^N \frac{(PBP^{-1})^k}{k!}$$

$$N \rightarrow \infty \Rightarrow \text{proved}$$

(2) Scalars $\exp(a+b) = \exp a \cdot \exp b$

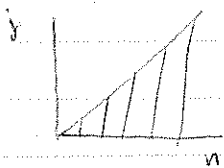
matrix if $a \cdot b = b \cdot a$ then $\exp(A+B) = \exp A \exp B$

$$\exp(A+B) = \sum_{n=0}^{\infty} \frac{(A+B)^n}{n!}$$

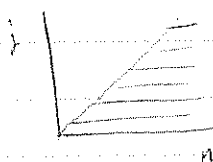
$$(A+B)^2 = (A+B)(A+B) = A^2 + AB + BA + B^2$$

$$\text{if commute } (A+B)^n = \sum_{j=0}^n \binom{n}{j} A^j B^{n-j} \quad \text{E/E}$$

$$\exp(A+B) = \sum_{n=0}^{\infty} \sum_{j=0}^n \frac{A^j B^{n-j}}{j!(n-j)!}$$



$$= \sum_{j=0}^{\infty} \sum_{n=j}^{\infty} \frac{A^j B^{n-j}}{j!(n-j)!}$$



$$= \sum_{j=0}^{\infty} \frac{A^j}{j!} \cdot \sum_{k=0}^{\infty} \frac{B^k}{k!}$$

$$= \exp(A) \cdot \exp(B)$$

$$(3) \exp A(t_1+t_2) = \exp At_1 \exp At_2$$

$$(4) (\exp(A))^{-1} = \exp(-A)$$

T.3. Cayley-Hamilton Theorem

$$d/dt \Phi(t) = A \Phi(t)$$

$$\Phi(0) = I$$

Take Laplace Transform (can do : T.I.)

$$\Phi(t) \rightarrow \hat{\Phi}(s)$$

$$s \hat{\Phi}(s) - I = A \hat{\Phi}(s)$$

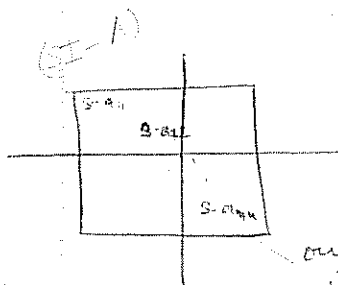
L.T. of state transition matrix

$$\hat{\Phi}(s) = (sI - A)^{-1}$$

$$\hat{\Phi}(s) = (sI - A)^{-1} \text{ ; obtain by cramer's rule}$$

$$= \frac{1}{\det(sI - A)} \cdot [\quad] \leftarrow \text{adjugate of } A$$

\rightarrow ifth term = $(-1)^{i+j}$, ifth cofactor of A^T



= poly. in s
order = $(n-1)$

only diagonal has s
in it.

actually this is the
adjugate matrix

POST MULTIPLY
by $(sI - A)$

$$(sI - A)^{-1} = \frac{[s^{n-1} B_0 + s^{n-2} B_1 + \dots + B_{n-1}]}{s^n + d_1 s^{n-1} + \dots + d_n}$$

$$\Rightarrow (s^n + d_1 s^{n-1} + \dots + d_n) I = [s^{n-1} B_0 + s^{n-2} B_1 + \dots + B_{n-1}] (sI - A)$$

$$= s^n B_0 + s^{n-1} (B_1 - B_0 A) + s^{n-2} (B_2 - B_1 A) + \dots + (-B_{n-1} A)$$

$$\therefore B_0 = I$$

$$B_1 - B_0 A = d_1 I \Rightarrow B_1 = B_0 A + d_1 I$$

$$\Delta B_2 = B_1 A + d_2 I$$

$$B_k = B_{k-1} A + d_k I$$

$$0 = B_{n-1} A + d_n I$$

remember
formula
for B_k 's
in terms
of A & I

$d(s) = \det(sI - A)$; can do in principal but computationally messy.

what do we get when subs backwards?

$$\begin{aligned} 0 &= B_{n-1}A + d_n I \\ &= (B_{n-2}A + d_{n-1}I)A + d_n I = B_{n-2}A^2 + d_{n-1}A + d_n I \\ &= B_{n-3}A^3 + d_{n-2}A^2 + d_{n-1}A + d_n I \\ &\dots \end{aligned}$$

$$0 = A^n + d_1 A^{n-1} + \dots + d_n I$$

$d(s) = \det(sI - A) = s^n + d_1 s^{n-1} + \dots + d_n$

then $d(A) = 0$ matrix

alternatively $\det(sI - A)$ called charac. poly

$= (-1)^n \det(A - sI)$

$\Delta(A) = 0$

The above result is refined to as the Cayley Hamilton Thm.

implications

(1) $A^n = -d_1 A^{n-1} - \dots - d_n I \Rightarrow A^n$ is l.c. of (I, A, \dots, A^{n-1})

(2) A^{n+1} is an l.c. of (1)

(3) $\exp(A)$ is an l.c. of (1)

when A is 2×2 $\exp(A) = \alpha_1 I + \alpha_2 A$

Thurs 20
28 Sept 1989

LST - Lecture

$$\dot{x}(t) = Ax(t)$$

$$x(t) = (\exp At) x_0$$

4. Spectral Decomposition (distinct values)

(1) Eigenvalues & Eigenvectors

If $\exists e \neq 0$ s.t. $Ae = \lambda e$ for some λ

λ eigenvalue of A

e corresponding eigenvector

$$\text{Note: } (A - \lambda I)e = 0$$

$\Rightarrow e$ lies in null space of $(A - \lambda I)$ & $e \in \mathcal{N}(A - \lambda I)$
[eigenvector corresp. to λ lies in null space of $A - \lambda I$]

$$(ii) \exists e \neq 0 \text{ s.t. } (A - \lambda I)e = 0$$

\Rightarrow (matrix) is singular

$$\Leftrightarrow \det(\lambda I - A) = 0$$

$$\Leftrightarrow \Delta(\lambda) = 0$$

eigen values ^{are} roots of ch. poly

$$(iii) \text{ when } A \in \mathbb{R}^{n \times n}$$

$\lambda \text{ real} \Rightarrow e \text{ real}$

$\text{complex} \Rightarrow \text{complex}$

(2) Basis of e-values

assume: A has distinct e-values $(\lambda_1, \lambda_2, \dots, \lambda_n)$

one corresponding e-vectors $\{e_1, \dots, e_n\}$ form a basis for \mathbb{R}^n

proof: Need to show l.i.

$$\text{i.e. } \sum_{i=1}^n \alpha_i e_i = 0 \Rightarrow \alpha_i = 0 \quad \forall i$$

Motivation: Looking for something to "isolate" a component or to find a "projection" of $\sum \alpha_i e_i$ onto e_k .

$$\Delta(A) = (A - \lambda_1 I)(A - \lambda_2 I) \cdots (A - \lambda_n I) = 0$$

$$\text{Note: } (A - \lambda_n I) e_{n-1} = e_{n-1} (\lambda_{n-1} - \lambda_n)$$

$$P_k := (A - \lambda_1 I) \cdots (A - \lambda_k I) \cdots (A - \lambda_n I)$$

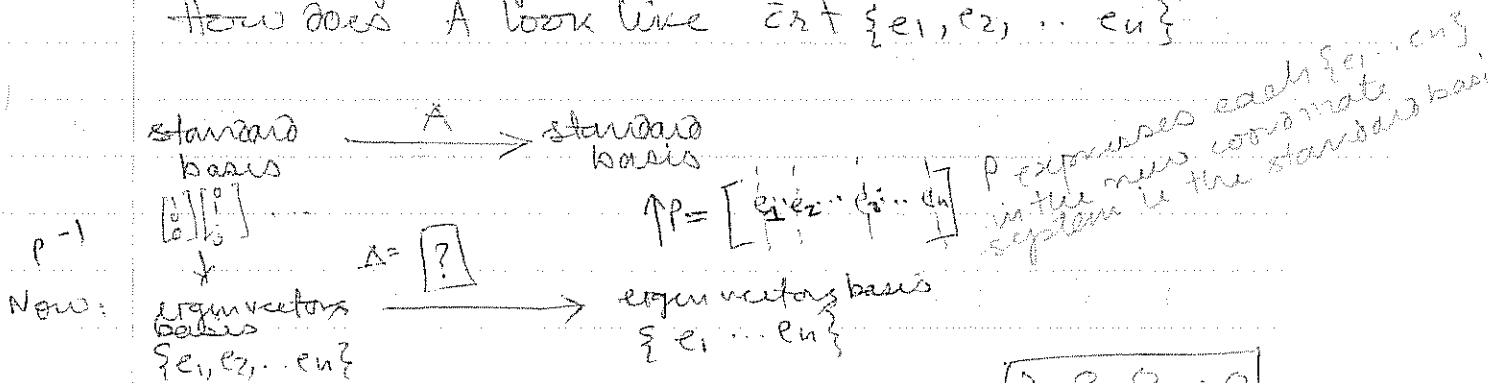
$$P_k [\sum \alpha_i e_i] = \alpha_k (A_k - \lambda_1) \cdots (A_k - \lambda_n) e_k = P_k [e] = 0$$

$e_k \neq 0$ (\because e.v.)

none of the others can be zero either. $\Rightarrow \alpha_k = 0$

(3) Change of basis

How does A look like \bar{e} w.r.t. $\{e_1, e_2, \dots, e_n\}$



$$A e_i = 0 \cdot e_1 + 0 \cdot e_2 + \lambda_i e_i + 0 \cdot e_n = \lambda_i e_i$$

$$A = P \Lambda P^{-1} \quad \Lambda = \begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \lambda_n \end{bmatrix}$$

$$\begin{bmatrix} \lambda_1 & 0 & 0 & \dots & 0 \\ 0 & \lambda_2 & & & 0 \\ 0 & & \lambda_3 & & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & & & & \lambda_n \end{bmatrix}$$

Algebraic Derivation

$$A \begin{bmatrix} | & | & | \\ e_1 & e_2 & \dots & e_n \\ | & | & | \end{bmatrix} = \begin{bmatrix} | & | & | \\ \lambda_1 e_1 & \lambda_2 e_2 & \dots & \lambda_n e_n \\ | & | & | \end{bmatrix} = \begin{bmatrix} | & | & | \\ e_1 & e_2 & \dots & e_n \\ | & | & | \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & & \\ \vdots & & \ddots & \\ 0 & & & \lambda_n \end{bmatrix}$$

$AP = P \Lambda$; first is a P for something (i.e. $\{e_1, \dots, e_n\}$) \rightarrow standard basis
 then do an A on it
 $AP = P \Lambda$; do a A on something (i.e. $\{e_1, \dots, e_n\}$) \rightarrow equal then $\cdot P^{-1}$

$A = P \Lambda P^{-1}$
 let $Q := P^{-1}$
 $\Rightarrow A = P \Lambda Q$

(LEFT EIGENVECTOR)

4) Let $Q = \begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix}$ $\{f_i^T\}$ rows of Q

$QA = \Delta Q$

$\begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix} \begin{bmatrix} A \end{bmatrix} = \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \ddots \\ & & & \lambda_n \end{bmatrix} \begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix} = \begin{bmatrix} -\lambda_1 f_1^T & \dots \\ -\lambda_2 f_2^T & \dots \\ \vdots & \vdots \\ -\lambda_n f_n^T & \dots \end{bmatrix}$

$f_i^T A = \lambda_i f_i^T$; defining 'left eigenvectors',
 → eigenvectors of A^T .

5) Reln between f_i^T & e_j

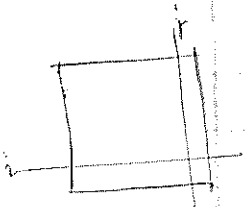
$QP = I$

$\begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix} \begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} f_i^T e_j = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases}$: orthogonal

A & A^T have same eigenvalues

6) $PQ = I$; does this give us anything?

SPECTRAL DECOMPOSITION



$\begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} \begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix} = \begin{bmatrix} 1 & & 0 \\ & 1 & \\ 0 & & 1 \end{bmatrix}$

product of the form

$\begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} \begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix} = \begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} + \begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} + \dots$

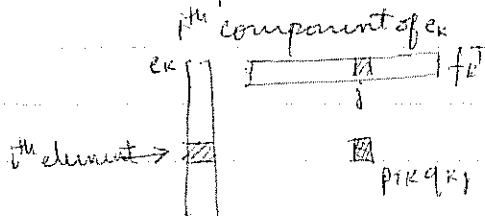
i, j th element of PQ

$\sum_{k=1}^n p_{ik} q_{kj}$

p_{ik} is the i th component of e_k

the cross terms not out!

$\begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} \begin{bmatrix} -f_1^T & \dots \\ -f_2^T & \dots \\ \vdots & \vdots \\ -f_n^T & \dots \end{bmatrix} = \begin{bmatrix} | & | & | \\ e_1 & e_2 & e_3 \\ | & | & | \end{bmatrix} + \dots$



matrix $PQ = \sum_{k=1}^n e_k f_k^T$ matrix

$$\text{let } R_k := c_k f_k^T$$

$$I = \sum_{k=1}^n R_k$$

$$A = P \Delta Q$$

$$= \begin{bmatrix} | & | & & | \\ \lambda_1 e_1 & \lambda_2 e_2 & & \lambda_n e_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \hline \hline \hline \hline \hline \\ f_1^T \\ \vdots \\ f_n^T \\ \hline \hline \hline \hline \hline \end{bmatrix} = \sum_{k=1}^n \lambda_k e_k f_k^T$$

$$A = \sum_{k=1}^n \lambda_k R_k$$

$$\exp(At) = P(\exp \Delta t) Q = \begin{bmatrix} | & | & & | \\ e_1 & e_2 & & e_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \exp \lambda_1 t & & & 0 \\ & \exp \lambda_2 t & & 0 \\ & & \ddots & \\ 0 & & & \exp \lambda_n t \end{bmatrix} \begin{bmatrix} \hline \hline \hline \hline \\ f_1^T \\ \vdots \\ f_n^T \\ \hline \hline \hline \hline \end{bmatrix}$$

$$\boxed{\exp(At) = \sum_{k=1}^n e^{\lambda_k t} \cdot R_k^e}$$

↑
constants
↑
constants

7) Complex eigenvalues

$$\text{let } A \in \mathbb{R}^{n \times n}$$

If λ_i complex $\Rightarrow e_i$ complex $\Rightarrow P, Q$ complex.

Q: Can we pick diff basis s.t. its of all real vectors.

Suppose $\lambda = \alpha + j\beta$ ($\beta \neq 0$) complex e-value of A
let e be the corresponding egn vector

$$Ae = \lambda e$$

$$\Rightarrow \overline{Ae} = \overline{\lambda e}$$

$$\Rightarrow \overline{A} \overline{e} = \overline{\lambda} \overline{e} ; A \in \mathbb{R}^{n \times n}$$

$$\Rightarrow A \overline{e} = \overline{\lambda} \overline{e} \text{, if } \lambda \in \mathbb{C} \Rightarrow \overline{\lambda} \text{ also eigenvalue.}$$

corresponding egn vector is \overline{e} .

(λ e.v. an from charac. poly, which has all

complex \rightarrow real coefficients.

$$\Rightarrow \{e_1, \overline{e_1}, e_2, \dots\} \quad e_1 = e_1' + j e_1'' \quad (e_1', e_1'' \text{ are real})$$

$$\lambda_1 = \alpha + j\beta$$

claim $\{e_1', e_1''\}$ are l.i.
 then $\{e_1', e_1'', e_3, \dots\}$
 is real

Proof of the claim:

Suppose not then $c_1 e_1' + c_2 e_1'' = 0 \quad \forall c_1, c_2 \neq 0$

will show

$\Rightarrow c_1 e_1' + c_2 \bar{e}_1' = 0$
 (non zero)

let $a_1 = \frac{1}{2}(c_1 - j c_2)$ $a_2 = \frac{1}{2}(c_1 + j c_2)$; $a_1, a_2 \neq 0$

\hookrightarrow then $a_1 e_1' + a_2 \bar{e}_1' = c_1 e_1' + c_2 e_1'' = 0$

$O = (P')^{-1}$

standard basis \xrightarrow{A} standard basis $\nwarrow P' = [e_1' \ e_1'' \ e_3 \ \dots \ e_n]$

$\{e_1', e_1'', e_3, \dots\} \xrightarrow{\Delta'} \{e_1', e_1'', e_3, \dots\}$

To find Δ' need $A e_1'$ and $A e_1''$

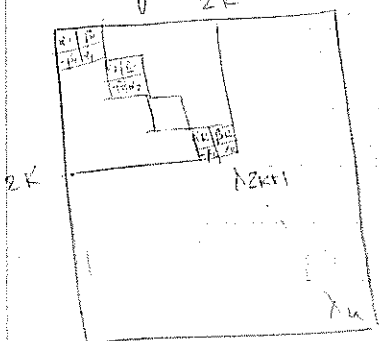
$A \underbrace{(c_1 e_1' + j c_2 e_1'')}_{e_1} = (\alpha + j \beta) \underbrace{(c_1 e_1' + j c_2 e_1'')}_{e_1}$

$\Rightarrow A e_1' = \alpha e_1' - \beta e_1''$

$A e_1'' = \beta e_1' + \alpha e_1''$

$\Delta' = \begin{bmatrix} \alpha & \beta \\ -\beta & \alpha \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix}$
 $\lambda_3 \quad \lambda_4$

in general A has k complex eigen values & their conj, and $(n-2k)$ real



$A = P' \Delta' Q'$
 all real matrices

5. Modal Decomposition

$$\dot{x}(t) = Ax(t) \quad x(0) = x_0$$

ZIR response

$$x(t) = (\exp At) x_0$$

(1) Algebraic Derivation

$$(1) x_0 = \sum_{i=1}^n \alpha_i e_i$$

$$\Rightarrow x(t) = \sum_{k=1}^n e^{\lambda_k t} R_k \left(\sum_{i=1}^n \alpha_i e_i \right)$$

$$R_k e_i = (e_k f_k^T) e_i \quad ; \quad R_k = (e_k f_k^T)$$

$$= e_k \quad \text{if } i=k$$

$$= 0 \quad \text{if } i \neq k$$

$$x(t) = \sum_{k=1}^n \alpha_k e^{\lambda_k t} e_k$$

(2) If $x(0) = C e_k$ in the space spanned by e_k

$x(t) = C e^{\lambda_k t} e_k$ stays in the same space



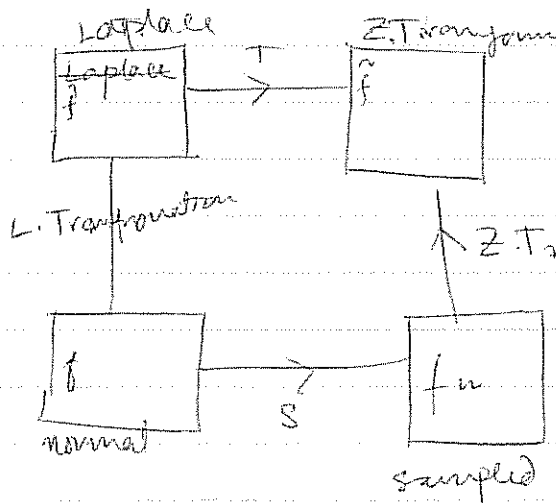
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Friday
29 Sept 1989

EE221a LST Discussion

- Sampled Data (cont)
- Zeros of a transfer fn

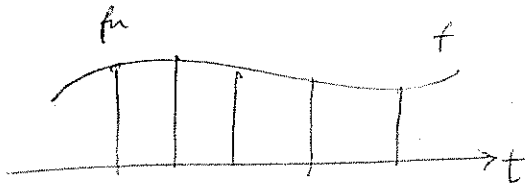
- Cayley Hamilton
- Numerical aspects of $\exp(At)$



if $f \in B_1$ and spectrum is supported in $[-\pi/T, \pi/T]$ then

S is injective and

$$f(t) = \sum f_n \left\{ \frac{\sin \pi T (t - nT)}{\pi T (t - nT)} \right\}$$



$$f_c = f(t) \sum_{n=0}^{\infty} \delta(t-nT)$$

$$= \sum_{n=0}^{\infty} f(nT) \delta(t-nT)$$

$\{f_n\}$ = sequence of samples

$$\mathcal{L}(f_c(t)) = \sum_{n=0}^{\infty} \int_{-\infty}^{\infty} f(nT) \delta(t-nT) e^{-st} dt$$

$$\tilde{f}(s) = \sum_{n=0}^{\infty} f(nT) e^{-snT}$$

$$= \sum_{n=0}^{\infty} f_n e^{-nTs}$$

$$\tilde{f}(z) = \sum_{n=0}^{\infty} f(nT) z^{-n}$$

$$\tilde{f}_c(s) = \tilde{f}(z) \Big|_{z=e^{sT}}$$

for f_c , z transform = L.T. evaluated at $z=e^{sT}$

$$f(nT) = \frac{1}{2\pi j} \int_{c-j\infty}^{c+j\infty} \tilde{f}(p) e^{pnT} dp$$

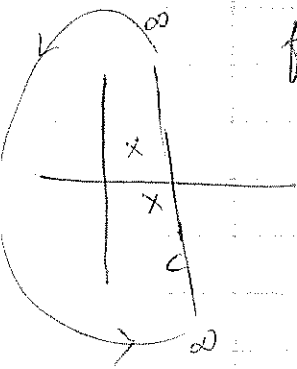
$$= f(nT)$$

assume $f(t)$ is continuous

$$\therefore f(nT+) = f(nT-) = f(nT)$$

$$\tilde{f}(z) = \sum f_n z^{-n}$$

$$= \sum \left[\left(\frac{1}{2\pi j} \right) \int \tilde{f}(p) e^{pnT} dp \right] z^{-n}$$



ntd 221a
29 Sept 1989

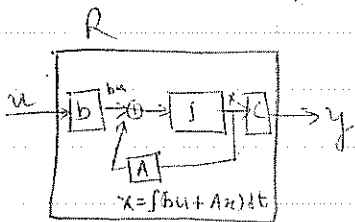
EECS 221a: LINEAR SYS.

$$\begin{aligned}
 f(e^{sT}) &= \sum_{n=0}^{\infty} \frac{1}{2\pi j} \int_{\Gamma} f(p) e^{p n T} dp e^{-s n T} \\
 &= \frac{1}{2\pi j} \int_{\Gamma} f(p) \left(\sum_{n=0}^{\infty} e^{(p-s)nT} \right) dp \\
 &= \frac{1}{2\pi j} \int_{\Gamma} \frac{f(p)}{1 - e^{p-sT}} dp
 \end{aligned}$$

$$\sum_{n=0}^{\infty} x^n = 1 + x + x^2 + \dots = \frac{1}{1-x} \quad ; \text{see App. in Reader}$$

----- X -----

$$h(s) = \frac{\prod_i (s - z_i)}{\prod_j (s - p_j)} = C (sI - A)^{-1} b$$



$$\begin{aligned}
 \dot{x} &= Ax + bu \\
 y &= Cx
 \end{aligned}$$

→ z is a zero

$$h(z) = 0 \Rightarrow C(zI - A)^{-1} b = 0 \quad (\text{take } t_0 = 0)$$

$$y(t) = C e^{At} x_0 + \int_0^t C e^{A(t-\tau)} b u(\tau) d\tau$$

Taking Laplace Transform,

$$\hat{y}(s) = C (sI - A)^{-1} x_0 + C (sI - A)^{-1} b \hat{u}(s)$$

$$(zI - A) = (zI - A) + (s - z)I \quad (\text{alg. identity})$$

$$(zI - A)^{-1} (sI - A) = I + (s - z)(zI - A)^{-1}$$

$$(zI - A)^{-1} = (sI - A)^{-1} + (s - z)(zI - A)^{-1} (sI - A)^{-1}$$

$$\hat{y}(s) = C (sI - A)^{-1} x_0 + C \left[(zI - A)^{-1} - (s - z)(zI - A)^{-1} (sI - A)^{-1} \right] b \hat{u}(s)$$

$$\hat{y}(s) = C (sI - A)^{-1} x_0 - C (s - z)(zI - A)^{-1} (sI - A)^{-1} b \hat{u}(s)$$

choose $\hat{u}(s) = \frac{1}{s - z}$ & $x_0 = (zI - A)^{-1} b$

$$\Rightarrow \hat{y}(s) = 0 \quad \Downarrow \quad \text{any initial state went wrong}$$

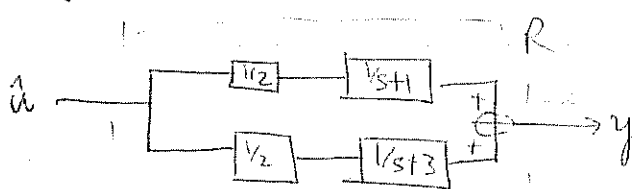
$$v(t) = \frac{1}{(t-1)!} e^{zt} \quad (\text{this or a multiple})$$

Response for

$$\dot{y}(s) = 0 \Rightarrow f(t, 0, (sI - A)^{-1} b, 1(t)) e^{zt} = 0 \text{ for } t > 0$$

example $h(s) = \frac{c(s+2)}{(s+1)(s+3)} = \frac{1/2}{(s+1)} + \frac{1/2}{(s+3)}$

$$h(t) = 1/2 e^{-t} + 1/2 e^{-3t}$$



$$\dot{x} = Ax + B$$

as in $y = cx + d$

$$d = [0] \quad A = \begin{bmatrix} -1 & 0 \\ 0 & -3 \end{bmatrix} \quad b = \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} \quad c = [1 \quad 1]$$

$$(sI - A) = \begin{bmatrix} s+1 & 0 \\ 0 & s+3 \end{bmatrix} \Rightarrow (sI - A)^{-1} = \begin{bmatrix} 1/(s+1) & 0 \\ 0 & 1/(s+3) \end{bmatrix}$$

find up 2 v.c. s.t. $\sigma_p = 0$

$$x_0 = (zI - A)^{-1} b$$

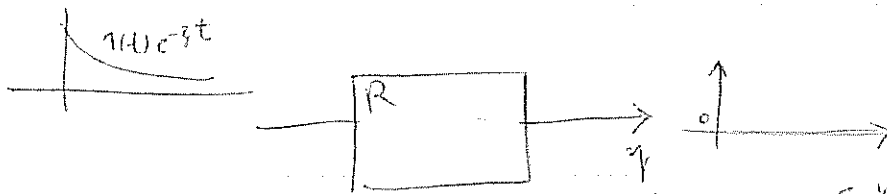
$$= \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} -1/2 \\ 1/2 \end{bmatrix}$$

(mitte b!) \uparrow

$$u(t) = 1(t) e^{zt}$$

$$u(t) = 1(t) e^{-2t}$$

\uparrow $z = -2$ (zero) of t.f.



for $\alpha_0 = \begin{bmatrix} -1/2 \\ 1/2 \end{bmatrix}$

$$c(sI - A)^{-1} x_0 + (sI - A)^{-1} b u(s) = 0 \quad \alpha(s) = (zI - A)^{-1} b$$

$$f(t) = c e^{At} x_0 + \int_0^t c e^{A(t-\tau)} b u(\tau) d\tau$$

$$e^{At} = \begin{bmatrix} e^{-t} & 0 \\ 0 & e^{-3t} \end{bmatrix} \quad u(t) = e^{-2t} 1(t)$$

$$y(t) = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} e^{-t} & 0 \\ 0 & e^{-2t} \end{bmatrix} \begin{bmatrix} -1/2 \\ 1/2 \end{bmatrix} + \int_0^t \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} e^{-(t-\tau)} & 0 \\ 0 & e^{-3(t-\tau)} \end{bmatrix} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} e^{-2\tau} d\tau$$

$$= 1/2 e^{-t} + 1/2 e^{-3t} + 1/2 \left\{ -e^{-2t} + e^{-t} + e^{-2t} - e^{-3t} \right\}$$

$$= 0 \quad \checkmark$$

Look in Reader
ch.

Main thing to remember: ~~if~~ ~~is~~ ~~a~~ ~~specification~~ &
 "If z is any zero of the t.f. there is at least one initial state x_0 s.t. the response of the system to the exponential $?(t)e^{zt}$ starting at $t=0$ from x_0 is identically 0."

$$\hat{\phi}(s) = (sI - A)^{-1} = \frac{s^{n-1} B_0 + s^{n-2} B_1 + \dots + B_{n-1}}{s^n + s^{n-1} d_1 + \dots + d_n} \quad \} = d(s)$$

$$d(s) = (sI - A)(s^{n-1} B_0 + \dots + B_{n-1})$$

$$B_0 = I$$

$$B_1 = B_0 A + d_1 I$$

$$B_2 = \dots$$

$$\dots$$

$$B_{n-1} = B_{n-2} A + d_{n-1} I$$

$$0 = B_{n-1} A + d_n I$$

$$B_1 = A + d_1 I$$

$$B_2 = (A + d_1 I) A + d_2 I = A^2 + d_1 A + d_2 I$$

$$0 = d(A)$$

$$A \in \mathbb{R}^{n \times n}$$

$$A^m \quad m \geq n = f(I, A, A^2, \dots, A^{n-1}) \leftarrow \text{linear comb.}$$

$$\exp(A) = \alpha_0 I + \alpha_1 A + \dots + \alpha_{n-1} A^{n-1} \quad ; \text{ finding the } \alpha\text{'s may not be easy.}$$

$$x \in \mathbb{R}^1$$

$$\exp(x) = e^x$$

$$= e^x \cdot 1$$

example matrix $A = \begin{bmatrix} \frac{59}{5} & \frac{12}{5} \\ \frac{12}{5} & \frac{66}{5} \end{bmatrix}$

$$(sI - A)^{-1} = \frac{1}{(s - \frac{59}{5})(s - \frac{66}{5}) - \frac{144}{5}}$$

$$= \frac{1}{(s-10)(s-15)}$$

Residual matrix

$$R_i = \lim_{s \rightarrow \lambda_i} (s - \lambda_i) \frac{B(s)}{\phi(s)}$$

$$\exp(A) = \sum_{i=1}^n R_i e^{\lambda_i}$$

$$R_1 = \lim_{s \rightarrow 15} \frac{1}{(s-15)(s-10)} \begin{bmatrix} \leftarrow \\ \leftarrow \end{bmatrix}$$

$$= \frac{1}{5} \begin{bmatrix} 9/5 & 12/5 \\ 12/5 & 16/5 \end{bmatrix}$$

$$R_2 = \lim_{s \rightarrow 10} \frac{1}{(s-15)} \begin{bmatrix} \leftarrow \\ \leftarrow \end{bmatrix} = \frac{-1}{5} \begin{bmatrix} -16/5 & 12/5 \\ 12/5 & -9/5 \end{bmatrix}$$

Prop.: $R_1 + R_2 = I$ (in general $\sum_{i=1}^n R_i = I$) & $(\sum_{i=1}^n \lambda_i R_i = A)$

$$\sum_{i=1}^n R_i e^{\lambda_i t} = e^{At} \quad \sum_{i=1}^n f(\lambda_i) R_i = f(A)$$

$$\phi(t, 0) = ? = \exp(At)$$

$$e^{A \cdot t} = \sum_{i=1}^2 R_i e^{\lambda_i t} = \frac{1}{25} \begin{bmatrix} 9 & 12 \\ 12 & 16 \end{bmatrix} e^{15t} + \frac{1}{25} \begin{bmatrix} 16 & -12 \\ -12 & 9 \end{bmatrix} e^{10t}$$

$\underbrace{\qquad\qquad\qquad}_{R_1} \underbrace{\qquad\qquad\qquad}_{e^{\lambda_1 t}}$

$$\therefore \frac{1}{25} \begin{bmatrix} 9e^{15t} + 16e^{10t} & 12e^{15t} - 12e^{10t} \\ 12e^{15t} - 12e^{10t} & 16e^{15t} + 9e^{10t} \end{bmatrix}$$

$$t=0 \Rightarrow = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$t=1 \Rightarrow = \frac{1}{25} \begin{bmatrix} 9e^{15} + 16e^{10} & 12(e^{15} - e^{10}) \\ 12(e^{15} - e^{10}) & 16e^{15} + 9e^{10} \end{bmatrix}$$

$$= \left(\frac{e^{15} - e^{10}}{5} \right) A + (-2e^{15} + 3e^{10}) I$$

$\exp(A) = \alpha_1 A + \alpha_0 I$; It's obvious that it's rather tough to get dis.

numerical aspects of $\exp(At)$

$$\exp(At) = I + \dots$$

$$\exp(-6) = 1 - 6 + \frac{36}{2!} - \frac{216}{3!} + \frac{1296}{4!} - \frac{7776}{5!} + \dots$$

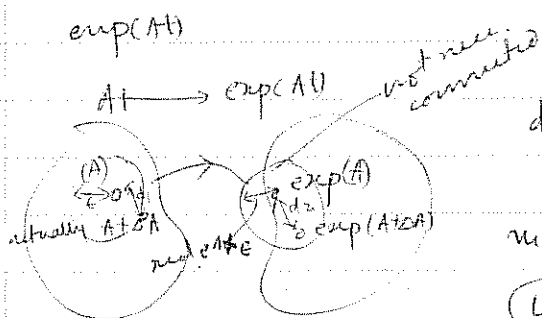
your algo. terminates at s_k^{th} (= partial sum upto k)
when $[s_{k+1}] = [s_k]$

Say quits @ 8th term $e^{-6} = 17.1143$ (!)

could do by $e^{-6} = (e^6)^{-1}$
 $= \left(1 + 6 + \frac{36}{2!} + \dots \right)^{-1} = (341.8)^{-1} = 2.926 \times 10^{-3}$
 (8 terms) real answer = 2.479

$$A = \begin{bmatrix} -49 & 29 \\ -64 & 31 \end{bmatrix}$$

direct method $\Rightarrow \begin{bmatrix} -22.2 & -1.4 \\ -61.5 & -3.5 \end{bmatrix}$ real answer = $\begin{bmatrix} -0.73 & 0.55 \\ -1.47 & 1.10 \end{bmatrix}$



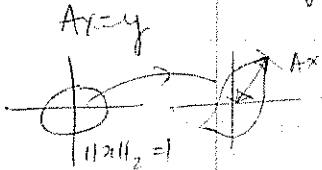
$d_1, d_2 =$ measure of sensitivity

with epsilon:

(L.V.B.) $\epsilon: (1+\epsilon) > ?$ (least upper bound)

Algorithm for $\exp(A)$ stable: ball to ball ^(w/c argument)
reliable: tells you if its working error
general: works for broad class of matrices
efficient: fast

Taylor Series $\exp(0.5)$ converges fast (any close to zero)



~~Problems~~
 Comments

- (1) $\|A\|_2$ isn't always small
- (2) good insight
- (3) $\exp(A)$ known doesn't guarantee that $\exp(Ant) = (\exp At)^n$ will be a good answer.

Padé method

$$1+x+x^2+\dots = \frac{1}{1-x} \quad |x| < 1 \quad ; \text{rational fn. expression}$$

valid when $\|A\|_2$ "small"

$$P_{pq}(A) \equiv [D_{pq}(A)]^{-1} N_{pq}(A) \approx \exp(A)$$

$$D_{pq} \equiv \sum_{j=0}^q \frac{(p+q-j)! q! (-A)^j}{(p+q)! j! (q-j)!}$$

$$N_{pq} \equiv \sum_{j=0}^p \frac{(p+q-j)! p! (A)^j}{(p+q)! j! (p-j)!}$$

$p=q \gg$ large $N_{pq} \rightarrow \exp \cdot SA$
 $\rightarrow \exp^{-SA}$ } severe trouble as Taylors

$l=p$ optimal Padé expansion

when A isn't small \Rightarrow scaling & squaring

$$\exp A = [\exp(A/m)]^{2^k} \quad \text{pick } m=2^k \quad \text{make } \|A/m\|_2 \text{ small then use Taylor expansion}$$

May
#1989

KST Lecture

5. Modal Decomposition

$$\dot{x}(t) = Ax(t) \quad x(0) = x_0$$

$$x(t) = [e^{PCAt}] x_0$$

(2) Geometric Derivation

(1) $x(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix}$ expressed in terms of standard basis $\{e_1, e_2, \dots, e_n\}$ (if complex $\{e_1, e_1', e_2, \dots\}$)

change of coordinates into basis of eigenvectors $\{e_k\}$

Standard basis $x(t) \leftarrow P = \begin{bmatrix} | & | & & | \\ e_1 & e_2 & & e_n \\ | & | & & | \end{bmatrix}$

eigenvectors $\{e_1, \dots, e_n\}$ coordinates $\xi(t)$

$$\begin{aligned} x(t) &= \xi_1(t)e_1 + \xi_2(t)e_2 + \dots + \xi_n(t)e_n \\ &= \begin{bmatrix} | & | & & | \\ e_1 & e_2 & & e_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \xi_1(t) \\ \xi_2(t) \\ \vdots \\ \xi_n(t) \end{bmatrix} \\ &= P\xi(t) \end{aligned}$$

$$\dot{x}(t) = Ax(t)$$

$$P\dot{\xi}(t) = AP\xi(t)$$

$$\dot{\xi}(t) = P^{-1}AP\xi(t) = \Delta\xi(t)$$

(ii) If $x(0) = ce_k \Rightarrow \xi(0) = \begin{bmatrix} 0 \\ \vdots \\ c \\ \vdots \\ 0 \end{bmatrix} \leftarrow x^k$

$$\xi_k(t) = \lambda_k \xi_k(t) \quad \xi_k(0) = c$$

$$\xi_k(t) = ce^{\lambda_k t}$$

$$x(t) = ce^{\lambda_k t} \cdot e_k$$

start in e. vec. dir \Rightarrow stay in it.

(iii) complex e-value conjug. basis e_k, e_k'

$$\begin{bmatrix} \xi_k(t) \\ \xi_{k+1}(t) \end{bmatrix} = \begin{bmatrix} \alpha & \beta \\ -\beta & \alpha \end{bmatrix} \begin{bmatrix} \xi_k(t) \\ \xi_{k+1}(t) \end{bmatrix} \quad \begin{aligned} \xi_k(0) &= c \\ \xi_{k+1}(0) &= 0 \end{aligned} \quad \xi_j(0) = 0$$

$$\begin{aligned} \xi_k(t) &= ce^{\alpha t} \cos \beta t \\ \xi_{k+1}(t) &= ce^{\alpha t} \sin \beta t \end{aligned}$$

If initially $x(0)$ is in the subspace spanned by $\{e_k, e_k'\}$ $x(t)$ will stay

6. BLOCK DIAGRAM

$$\dot{x}(t) = Ax(t) + Bu(t) ; x(0) = x_0$$

$$y(t) = Cx(t)$$

$$x(t) = P\xi(t)$$

$$\dot{\xi}(t) = \Delta \xi(t) + \Pi u(t) ; \Pi = P^{-1}B$$

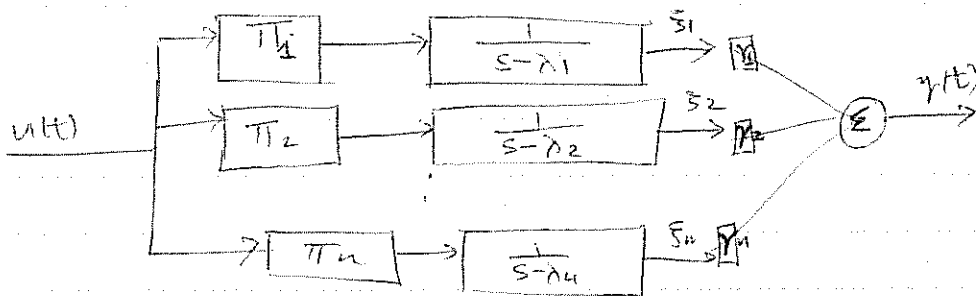
$$y(t) = T\xi(t) ; T = CP$$

let's consider SISO (for case of drawing)

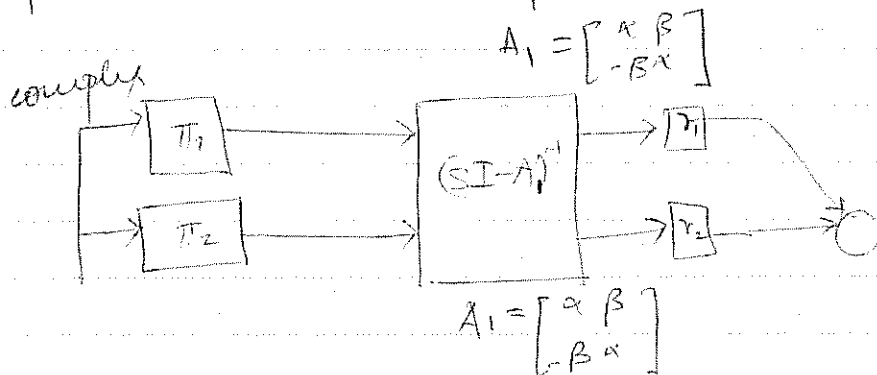
$$\dot{\xi}_1(t) = \lambda_1 \xi_1(t) + \pi_1 u(t)$$

$$\dot{\xi}_2(t) = \lambda_2 \xi_2(t) + \pi_2 u(t)$$

$$y(t) = \gamma_1 \xi_1(t) + \gamma_2 \xi_2(t) + \dots$$



depends on whether input excites that particular mode



$\pi_k \neq 0 \Rightarrow k^{th}$ mode is excited

When A doesn't have distinct eigen values, R can still do some sort of decomposition.

anv

$$R = \{A, B, C, D\}$$

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad x(0) = x_0$$

A has distinct eigen values $\Rightarrow A \sim \Lambda$ ($P^{-1}AP = \Lambda$)
 \Rightarrow Modal decomposition

A has multiple e. values $\Rightarrow A \sim ?$
 $\Rightarrow ?$

Recall A has distinct e-values

$\Rightarrow \{e_1, e_2, \dots, e_n\}$ form a basis

$\Rightarrow x = \sum_{i=1}^n \xi_i e_i$ (decomposition)

where $e_i \in \mathcal{N}(A - \lambda_i I)$ (eigenspace = ^{sub.}space spanned by the ⁱⁿe-vector)

For A multiple e-values need to generalize this decomposition, & eigenspace.

choice of subspace

$$e \in \mathcal{N}(A - \lambda_i I) \quad Ae = \lambda_i e \in \mathcal{N}(A - \lambda_i I)$$

(i) Invariant subspace

(V, F) vector space

M subspace of V .

M is said to be an invariant subspace of A iff

$$x \in M \Rightarrow Ax \in M$$

Ex (i) $\mathcal{N}(A)$ ($\because x \in \mathcal{N}(A) \Rightarrow Ax = 0$)

claim $Ax \in \mathcal{N}(A)$

($\because A(Ax) = 0$)

(ii) $\mathcal{R}(A)$

(iii) (Motivating example) $\mathcal{N}(A - \lambda_i I)$

f - polynomial of A (any degree)
 (iv) $\mathcal{N}(f(A))$

(2) Direct sum

M_1, M_2 subspaces of (V, F)

V is direct sum of M_1 & $M_2 \iff \forall x \in V \exists$ unique rep. $x = x_1 + x_2$
 where $x_1 \in M_1$ & $x_2 \in M_2$

(Expressed as $V = M_1 \oplus M_2$)

M_1, M_2, \dots, M_k subspaces of V

$V = M_1 \oplus M_2 \oplus \dots \oplus M_k$

$\iff \forall x \in V \exists$ unique representation $x = x_1 + x_2 + \dots + x_k$ $x_i \in M_i$

A has distinct e-values

ex. $x = \sum_{i=1}^n \xi_i e_i \implies \mathbb{C}^n = \mathcal{N}(A - \lambda_1 I) \oplus \mathcal{N}(A - \lambda_2 I) \oplus \dots \oplus \mathcal{N}(A)$

We say x_i is the "projection" of x onto M_i .

(3) Representation Theorem

$F = \mathbb{C} \text{ or } \mathbb{R}; F^n = M_1 \oplus M_2$

$A: F^n \rightarrow F^n$ linear

M_1 invariant under A

$\implies \exists$ a basis for F^n s.t.

A has the matrix representation

	k	$n-k$
k	A_{11}	A_{12}
$n-k$	0	A_{22}

$\dim M_1 = k$

pick k lin. ind. vectors in M_1

$\{u_1, u_2, \dots, u_k, u_{k+1}, \dots, u_n\}$

$M_1 \leftarrow$ argument basis

1st column = Au_1 , expressed in terms of $\{u_1, \dots, u_n\}$

but $Au_1 \in M_1$ is a l.c. of u_1, \dots, u_k .

Corollary M_1, M_2 invariant under A

$$A \sim \begin{bmatrix} \cdot & 0 \\ 0 & \cdot \end{bmatrix}$$

Ex. A distinct eigen values

$\mathcal{N}(A - \lambda_i I)$ invariant under A

$$\mathbb{C}^n = \mathcal{N}(A - \lambda_1 I) \oplus \mathcal{N}(A - \lambda_2 I) \cdots \oplus \mathcal{N}(A - \lambda_n I)$$

$$A \sim \begin{bmatrix} \lambda_1 & & & 0 \\ & \lambda_2 & & \\ & & \ddots & \\ 0 & & & \lambda_n \end{bmatrix} \quad (\text{applying thm } n \text{ times})$$

2. Decomposition

Recall A distinct e. values

Cayley-Hamilton Theorem ~~ch. poly~~ ch. poly $\Delta(s)$

$$\Delta(s) = (s - \lambda_1)(s - \lambda_2) \cdots (s - \lambda_n)$$

$$\rightarrow \text{substitut } A \Rightarrow (A - \lambda_1 I)(A - \lambda_2 I) \cdots (A - \lambda_n I) = 0$$

we use CH thm to show eigen vectors are lin ind.

$$\text{We can write } \mathbb{C}^n = \mathcal{N}(A - \lambda_1 I) \oplus \mathcal{N}(A - \lambda_2 I) \cdots \oplus \mathcal{N}(A - \lambda_n I)$$

In general A might have multiple eigen values

$$\text{ch. poly } \Delta(s) = (s - \lambda_1)^{d_1} (s - \lambda_2)^{d_2} \cdots (s - \lambda_\sigma)^{d_\sigma}; \sigma \leq n$$

$$[d_1 + d_2 + \cdots + d_\sigma = n]$$

$$\text{Cayley Hamilton } (A - \lambda_1 I)^{d_1} \cdots (A - \lambda_\sigma I)^{d_\sigma} = 0$$

$$\text{So we } \mathbb{C}^n \stackrel{?}{=} \mathcal{N}(A - \lambda_1 I)^{d_1} \oplus \mathcal{N}(A - \lambda_2 I)^{d_2} \cdots \oplus \mathcal{N}(A - \lambda_\sigma I)^{d_\sigma}$$

$$\text{Ex } A = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\text{ch. poly} = (A - 1)^2 (A - 2)$$

$$\text{CH: } (A - I)^2 (A - 2I) = 0$$

$$\mathbb{C}^n \stackrel{?}{=} \mathcal{N}(A - I)^2 \oplus \mathcal{N}(A - 2I) \quad \underline{\text{yes}}$$

However, for this example we also have
 $(A-I)(A-2I) = 0$ matrix.

$$C^u = N(A-I) \oplus N(A-2I) \quad \neq \emptyset$$

Thursday
 5 Oct 1989

DST - Lecture

Midterm - 1hr duration (Friday)

Ch I: except Schwartz inequality p.22 see 9, 10

Ch II: except sec 2

Ch III: except sec 1

Ch IV: except sec 6[†]

Ch V: sec 1-5

VIII A, B, E [Supplementary Notes]

allowed to bring one sheet of paper (one side)

ex. $A = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \quad \lambda = 1, 1, 2$

Cayley Hamilton $(A-I)^2(A-2I) = 0$

But we also have $(A-I)(A-2I) = 0$ (by direct calc. for th

Def: $\Psi(\cdot)$ is the min^m polynomial of A

$$\Leftrightarrow \text{(i)} \Psi(A) = 0$$

(ii) Lowest degree polynomial s.t. $\Psi(A) = 0$

(iii) The coefficient of the highest order term = 1. (same)

Fact: Roots of the min^m poly = 0 \Leftrightarrow roots of $\Delta(\lambda) = \det(\lambda I - A) =$
 $=$ e. values of A .

Pf (\Leftarrow) λ_i e. value $\Rightarrow \exists e_i \neq 0$ s.t.

$$\text{by defn } A e_i = \lambda_i e_i$$

want to show $\Psi(\lambda_i) = 0$

$$A^k e_i = \lambda_i^k e_i$$

$$\Psi(A) e_i = \Psi(\lambda_i) e_i$$

$$\Rightarrow 0 = \Psi(\lambda_i) e_i \Rightarrow \Psi(\lambda_i) = 0$$

(note: $Ae_i = \lambda_i e_i \Rightarrow A^2 e_i = \lambda_i A e_i = \lambda_i^2 e_i$ & $A^n e_i = \lambda_i^n e_i$)

Proof (\Rightarrow) \square λ_i is a root of $\psi(s) = 0$

$$\psi(s) = (s - \lambda_i) q(s)$$

now $\deg[q(s)] < \deg[\psi(s)]$

$$\psi(A) = \underbrace{0}_{\parallel 0} = \cancel{(A - \lambda_i I)} q(A) \neq 0 \Rightarrow \exists v \text{ s.t. } v \notin \mathcal{N}[q(A)]$$

$$0 = (A - \lambda_i I) q(A) v \neq 0 \parallel v'$$

$\therefore Av' = \lambda_i v'$ i.e. v' is an eigen vector
 $\Rightarrow \lambda_i$ is an eigen value.

charac polynomial $\Delta(s) = (s - \lambda_1)^{d_1} \dots (s - \lambda_r)^{d_r}$

Fact $\Rightarrow \psi(s) = (s - \lambda_1)^{m_1} (s - \lambda_2)^{m_2} \dots (s - \lambda_r)^{m_r}$

where $m_k \leq d_k$ for all k . $\psi(s)$ divides $\Delta(s)$ (if not \Rightarrow could construct larger degree)

$$\psi(A) = (A - \lambda_1 I)^{m_1} (A - \lambda_2 I)^{m_2} \dots (A - \lambda_r I)^{m_r} = 0$$

Recall in distinct case $\Delta(A) = (A - \lambda_1 I)(A - \lambda_2 I) \dots (A - \lambda_r I) = 0$

$$x = \alpha_1 e_1 + \dots + \alpha_n e_n$$

$$\mathbb{C}^n = \mathcal{N}(A - \lambda_1 I) \oplus \mathcal{N}(A - \lambda_2 I) \dots$$

Now $\mathbb{C}^n \stackrel{?}{=} \mathcal{N}(A - \lambda_1 I)^{m_1} \oplus \mathcal{N}(A - \lambda_2 I)^{m_2} \oplus \dots \oplus \mathcal{N}(A - \lambda_r I)^{m_r}$

Assume C-H: $\Delta(A) = (A - \lambda_1 I)^{d_1} \dots (A - \lambda_r I)^{d_r} = 0$

$$\mathbb{C}^n \stackrel{?}{=} \mathcal{N}(A - \lambda_1 I)^{d_1} \oplus \mathcal{N}(A - \lambda_2 I)^{d_2} \dots \oplus \mathcal{N}(A - \lambda_r I)^{d_r}$$

If $\mathcal{N}(A - \lambda_k I)^{m_k} = \mathcal{N}(A - \lambda_k I)^{d_k}$ Fact (in discussion)

Conjecture: $\mathbb{C}^n = \mathcal{N}(A - \lambda_1 I)^{m_1} \oplus \mathcal{N}(A - \lambda_2 I)^{m_2} \oplus \dots \oplus \mathcal{N}(A - \lambda_r I)^{m_r}$ Fact

\hookrightarrow proof needed Need to show $\forall x \in \mathbb{C}^n$

$$\exists x_1, x_2, \dots, x_r \text{ s.t. } x_k \in \mathcal{N}(A - \lambda_k I)^{m_k}$$

and $\chi = \chi_1 + \chi_2 + \dots + \chi_\sigma$
 representation is unique.

How to find χ_k ?

= Find the "projection" ~~is~~ R_k st.

$$\chi_k = R_k \cdot \chi \in \mathcal{N}(A - \lambda_k I)^{m_k}$$

and $\chi = \chi_1 + \chi_2 + \dots + \chi_\sigma$

$$= \sum_{k=1}^{\sigma} R_k \chi$$

$$\Leftrightarrow \sum_{k=1}^{\sigma} R_k = I$$

(i) $R_k \chi \in \mathcal{N}(A - \lambda_k I)^{m_k}$

$\Rightarrow (A - \lambda_k I)^{m_k} \cdot R_k \chi = 0$ is required

but we know $\psi(A) = (A - \lambda_1 I)^{m_1} \dots (A - \lambda_\sigma I)^{m_\sigma} = 0$

\Rightarrow so pick R_k having factors $(A - \lambda_1 I)^{m_1} \dots (A - \lambda_k I)^{m_k} \dots (A - \lambda_\sigma I)^{m_\sigma}$

$$R_k = (A - \lambda_1 I)^{m_1} \dots (A - \lambda_k I)^{m_k} \dots (A - \lambda_\sigma I)^{m_\sigma}$$

in general have to multiply by $v_k(A)$ i.e.

$$R_k = v_k(A) (A - \lambda_1 I)^{m_1} \dots (A - \lambda_k I)^{m_k} \dots (A - \lambda_\sigma I)^{m_\sigma}$$

(ii) Want $\sum_{k=1}^{\sigma} R_k = I$

$$\text{i.e. } v_1(A) (A - \lambda_2 I)^{m_2} \dots (A - \lambda_\sigma I)^{m_\sigma}$$

$$+ v_2(A) (A - \lambda_1 I)^{m_1} \dots (A - \lambda_\sigma I)^{m_\sigma}$$

+

$$+ v_\sigma(A) (A - \lambda_1 I)^{m_1} \dots (A - \lambda_{\sigma-1} I)^{m_{\sigma-1}}$$

$$= I$$

work at in a fashion analogous to polynomials

$$v_1(s) (s - \lambda_2)^{m_2} \dots (s - \lambda_\sigma)^{m_\sigma}$$

$$+ v_2(s) (s - \lambda_1)^{m_1} \dots (s - \lambda_\sigma)^{m_\sigma}$$

...

$$+ v_\sigma(s) (s - \lambda_1)^{m_1} \dots (s - \lambda_{\sigma-1})^{m_{\sigma-1}} = I$$

4 points
 1. 1 point
 2. 1 point
 3. 1 point
 4. 1 point

at an appropriate
 place in the
 answer

divided through by minimal polynomial

$$h_1(s)/(s-\lambda_1)^{m_1} + h_2(s)/(s-\lambda_2)^{m_2} + \dots + h_r(s)/(s-\lambda_r)^{m_r} = 1/\psi(s)$$

Partial Fraction Expansion of $1/\psi(s)$

$$1/\psi(s) = \frac{h_1(s)}{(s-\lambda_1)^{m_1}} + \dots + \frac{h_r(s)}{(s-\lambda_r)^{m_r}} ; \text{ use } h_1(s), h_2(s) \text{ polynomials in partial fraction expansion}$$

obtain $R_k = h_k(CA) (A - \lambda_1 I)^{m_1} \dots (A - \lambda_k I)^{m_k} \dots (A - \lambda_r I)^{m_r}$
 where $h_k(s)$ is obtained from *

Then $x_k := R_k x \in \mathcal{N}(A - \lambda_k I)^{m_k}$ well defined
 and $x = x_1 + x_2 + \dots + x_r$

to show uniqueness of decomposition:

Suppose $x = x_1 + x_2 + \dots + x_r ; x_k = R_k x \in \mathcal{N}(A - \lambda_k I)^{m_k}$
 and also $x = x'_1 + x'_2 + \dots + x'_r ; x'_k \in \mathcal{N}(A - \lambda_k I)^{m_k}$

want $x'_k = x_k \forall k$

$$\theta = (x_1 - x'_1) + (x_2 - x'_2) + \dots + (x_r - x'_r)$$

if say $x_1 - x'_1 \neq \theta$

$$(x_1 - x'_1) = (x'_2 - x_2) + (x'_3 - x_3) + \dots + (x'_r - x_r)$$

could construct diff. will span

Multiply by $[(A - \lambda_2 I)^{m_2} \dots (A - \lambda_r I)^{m_r}]$

vectors of diff. will span don't have to be lin.

$$\therefore [\quad] (x_1 - x'_1) = \theta$$

$$\Rightarrow R_1(A) [\quad] (x_1 - x'_1) = \theta$$

** i.e. $R_1(x_1 - x'_1) = \theta$; but don't know if R_1 is non-singular!

consider $(A - \lambda_1 I)^{m_1} ; (s - \lambda_1)^{m_1}$

$$R_1(A) ; R_1(s)$$

Since $R_1(s)$ and $(s - \lambda_1)^{m_1}$ have no common factors (else could lead to a contradiction)

$$\frac{1}{(s - \lambda_1)^{m_1}} = \frac{h_1(s)}{(s - \lambda_1)^{m_1}} + \frac{h_2(s)}{R_1(s)}$$

Existence of $h_1(s)$ is guaranteed by Partial Fraction Expansion Theorem!

$x_k \in \mathcal{N}(A - \lambda_k I)^{m_k}$
 $(A - \lambda_1 I)^{m_1} \dots (A - \lambda_r I)^{m_r} x_k = 0$
 $(s - \lambda_1)^{m_1} \dots (s - \lambda_r)^{m_r} h_1(s) = 1$
 $h_1(s) = \frac{1}{(s - \lambda_1)^{m_1} \dots (s - \lambda_r)^{m_r}}$
 substitute work

$$\text{or } 1 = h_1(s) R_1(s) + h_2(s) (s - \lambda_1)^{m_1}$$

substitute s by A

$$I = h_1(A) R_1(A) + h_2(A) (A - \lambda_1 I)^{m_1}; \text{ mult. both sides by } (X_1 - X_1')$$

$$\Rightarrow (X_1 - X_1') = \underbrace{h_1(A) R_1(A)}_{=0} (X_1 - X_1') + \underbrace{h_2(A) (A - \lambda_1 I)^{m_1}}_{=0} (X_1 - X_1')$$

$$\Rightarrow X_1 = X_1'$$

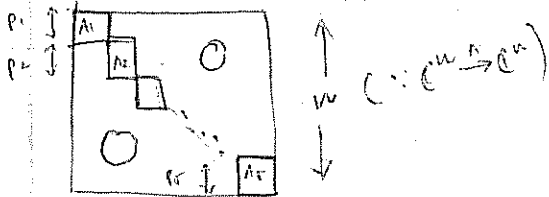
wrong \rightarrow (Eigen value - eigen vector) \Rightarrow $(A - \lambda_1 I)^{m_1}$

(3) MATRIX REPRESENTATION

$$\mathbb{C}^n = \mathcal{N}(A - \lambda_1 I)^{m_1} \oplus \mathcal{N}(A - \lambda_2 I)^{m_2} \dots \oplus \mathcal{N}(A - \lambda_\sigma I)^{m_\sigma}$$

$\Rightarrow \exists$ basis for \mathbb{C}^n such that \rightarrow (union of lin ind. vectors in $\mathcal{N}(A - \lambda_k I)$)
wrt basis A has matrix representation

$V = \mathcal{N}_1 \oplus \mathcal{N}_2$
 \Rightarrow union of vectors in $\mathcal{N}_1, \mathcal{N}_2$ are linearly independent



where $p_k := \dim \mathcal{N}(A - \lambda_k I)^{m_k}$
we know $p_1 + p_2 + \dots + p_\sigma = n$

But we also have

$$\Delta(s) = (s - \lambda_1)^{d_1} \dots (s - \lambda_\sigma)^{d_\sigma}$$

such that $d_1 + \dots + d_\sigma = n$

Fact

decomposition $\mathcal{N}(A - \lambda_k I)^{m_k} = d_k$
 Pf: $\det(A - sI) = (-1)^n \prod_{k=1}^{\sigma} (s - \lambda_k)^{d_k}$

$$= \prod_{k=1}^{\sigma} \det(A_k - sI_k)$$

$$\det PAP^{-1} = \det P \det A \det P^{-1} = \det A$$

want to show $\det(A_k - sI_k) = (-1)^{p_k} (s - \lambda_k)^{p_k}$

$\det(A_k - sI_k)$ has only λ_k as its root zero.

$$\det(A_k - sI_k) = (-1)^{p_k} (s - \lambda_k)^{p_k}$$

Friday
1 Oct 1989

EECS 221(A) Discussion

- continue $\exp(A)$
- examples sit. e-value sensitivity
- real/complex basis vectors
- complex basis vectors
- proof of $N(A - \lambda_k I)^{m_k} = N(A + \lambda_k I)^{d_k}$
- sampled data systems
- Matlab

$$N_{pq}(A) \triangleq \sum_{j=0}^p \frac{(p+q-j)! p!}{(p+q)! j! (p-j)!} A^j \quad ; \text{ Padé Formula}$$

if $A = PMP^{-1}$ (M diagonal)

$$\begin{aligned} \exp(A) &= I + A + \frac{1}{2!} A^2 + \dots \\ &= I + PMP^{-1} + \frac{1}{2!} (PMP^{-1})(PMP^{-1}) + \dots \\ &= PP^{-1} + PMP^{-1} + \frac{1}{2!} P M^2 P^{-1} \\ &= P \exp(M) P^{-1} \end{aligned}$$

Diagonal matrix $\begin{bmatrix} m_1 & 0 & 0 & \dots \\ 0 & m_2 & 0 & \dots \\ 0 & 0 & m_3 & \dots \\ \dots & \dots & \dots & m_n \end{bmatrix}$

$$\exp(M) = \begin{bmatrix} e^{m_1} & & 0 \\ & e^{m_2} & \\ 0 & & e^{m_n} \end{bmatrix}$$

Problem: P is ill conditioned to inversion (near singular)

Schur decomposition $A = Q M Q^T$ where M is upper triangular
 $\exp(M)$ is also upper triangular $Q^T = Q^{-1}$

Set up so that Q is well conditioned

Eigenvalue / Eigenvector Method

If A is non defective (E values are distinct)
 $\exists T$ s.t. $A = TDT^{-1}$
 \uparrow Diagonal

also works for block diagonal.

$$A = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} \Rightarrow \exp(A) = \begin{bmatrix} e^{\lambda_1 t} & & 0 \\ & \ddots & \\ 0 & & e^{\lambda_n t} \end{bmatrix}$$

$$A = \begin{bmatrix} 20 & 20 & 0 & \dots & 0 \\ 0 & 19 & 20 & 0 & \dots & 0 \\ 0 & 0 & 18 & 20 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 20 & \dots & 0 \\ 0 & 0 & \dots & 0 & \dots & 0 \end{bmatrix}$$

\Rightarrow eigenvalues are 1, 2, 3, ..., 20 (column no δ)

let $\lambda_i(\delta) = \lambda_i + \xi_i \delta$

turns out $\xi_{20} = -\xi_1 = 4 \times 10^7$

$\xi_{10} = -\xi_{11} = 4 \times 10^{12}$

non diagonalization

JORDAN FORM

$\exists T$ s.t. $A = TDT^{-1}$; D diagonal

$\exists T$ s.t. $A = TJT^{-1}$ $J =$ Jordan Form Matrix

(e-values don't have to be distinct)

Jordan Form:
$$\begin{bmatrix} \lambda_1 & & & & 0 \\ & \lambda_2 & & & \\ & & \lambda_3 & & \\ 0 & & & \lambda_n & \\ & & & & \lambda_n \end{bmatrix}$$

Jordan blocks
$$\begin{bmatrix} \lambda_1 & & & & 0 \\ & \lambda_1 & & & \\ 0 & \lambda_1 & & & \\ & & \lambda_2 & & \\ & & & \lambda_3 & \\ 0 & & & & \lambda_n \end{bmatrix}$$

Size of largest Jordan block is ($m_1 =$ degree in minimal poly)

$$e^{Jt} = \begin{bmatrix} e^{\lambda_1 t} & t e^{\lambda_1 t} & \frac{t^2}{2} e^{\lambda_1 t} \\ 0 & e^{\lambda_2 t} & t e^{\lambda_2 t} \\ 0 & 0 & e^{\lambda_3 t} \end{bmatrix}$$

The T values are generalized eigenvectors.

$$J = \begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_1 & \\ 0 & & \lambda_1 \end{bmatrix} \rightarrow J^4 = \begin{bmatrix} \lambda_1^4 & 4\lambda_1^3 & 6\lambda_1^2 & 4\lambda_1 \\ & \lambda_1^4 & 4\lambda_1^3 & 6\lambda_1^2 \\ & & \lambda_1^4 & 4\lambda_1^3 \\ 0 & & & \lambda_1^4 \end{bmatrix}$$

λ^{k-1}

Singular Value decomposition

$$A = U \Sigma V$$

$$U U^T = I$$

$$V V^T = I$$

$$\Sigma = \begin{bmatrix} \sigma_1 & & 0 \\ & \sigma_2 & \\ 0 & & \sigma_{k-1} \end{bmatrix}$$

σ_i s are singular values
 $\#$ of σ_i s $\neq 0$ tell you the rank of A .

- eigenvalue/eigenvector sensitivity

$$E+ A = \begin{bmatrix} 1 & 100 \\ -10^{-5} & 2 \end{bmatrix}$$

$$\lambda_1 = 1 \quad \lambda_2 = 2$$

$$\lambda_2' = 1.999 \quad \lambda_1' = 1.001$$

$$E+ A = \begin{bmatrix} 1 & 0 \\ 0 & .99999 \end{bmatrix}$$

$$\lambda_1 = 1$$

$$\lambda_2 = .99999$$

$$e_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad e_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\lambda_1' = \lambda_2'$$

$$e_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad e_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (1)$$

- Residues & Projection Matrices

Residue Matrix: $R_i \equiv c_i f_i^T$
distinct eigenvalues

c_i are right e.vectors

f_i^T are left e.vectors

(normalised eigenvectors)

$$A = \sum_{i=1}^n \lambda_i R_i$$

$$R_i X = \sum_{j=1}^n \alpha_j e_j$$

$$R_i X = \sum_{j=1}^n R_i \alpha_j$$

$$\sum \alpha_j e_i f_i^T e_j$$

$\underbrace{f_i^T e_j}_{\delta_{ij}}$

(set up your system so that this holds)

$$\boxed{R_i X = \alpha_i e_i}$$

component of X in the i^{th} eigenspace

$$AX = \sum \lambda_i R_i X$$

$$= \sum \lambda_i \alpha_i e_i$$

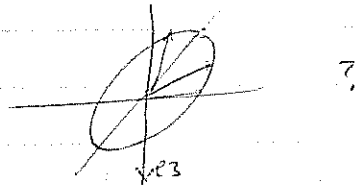
component in the i^{th} dir.

$$f_i^T e_j = \delta_{ij} \alpha_i$$

$$f_i^T e_1 = \alpha_1$$

$$f_i^T e_2 = 0$$

$$f_i^T e_3 = 0$$



- proof of $N(A - \lambda_k I)^{m_k} = N(A - \lambda_k I)^{d_k}$
by \equiv

where m_k is minimal poly. coeff

d_k charac. poly coeff

$$m_k \leq d_k$$

\subseteq

$$(A - \lambda_k I)^{m_k} x = 0$$

$$\Rightarrow (A - \lambda_k I)^{m_k + n} x = 0 \quad \text{EB}$$

(2): Suppose $\exists v$ s.t. $(A - \lambda_k I)^{m_k} v \neq 0$; $(A - \lambda_k I)^{m_k+1} v = 0$

Since $(s - \lambda_k)$ and $P_k(s) = (s - \lambda_1)^{m_1} \dots (s - \lambda_r)^{m_r}$ have no common terms \Rightarrow can do partial fraction expansion

$$1/P_k(s)(s - \lambda_k) = h_1(s)/(s - \lambda_k) + h_2(s)/P_k(s)$$

$$1 = h_1(s)P_k(s) + h_2(s)(s - \lambda_k)$$

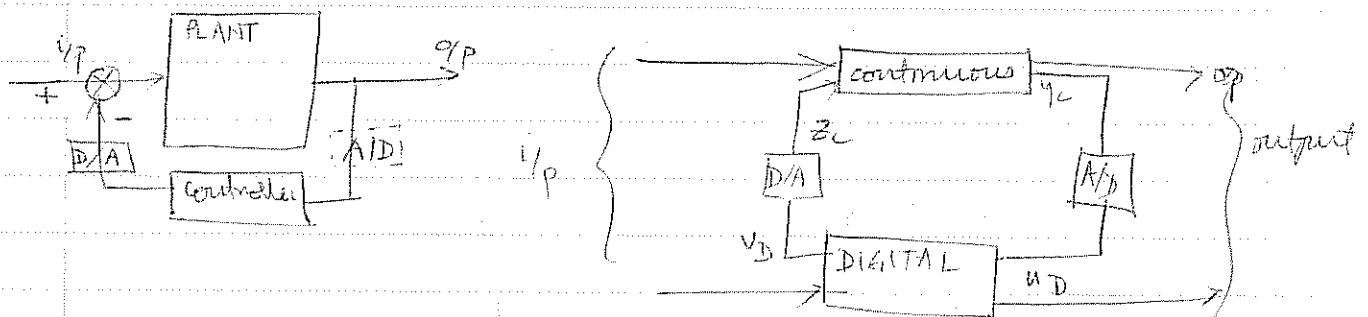
$\Rightarrow I = h_1(A)P_k(A) + h_2(A)(A - \lambda_k I)$; an identity

$$[(A - \lambda_k I)^{m_k} v] I = [h_1(A)P_k(A) + h_2(A)(A - \lambda_k I)](A - \lambda_k I)^{m_k} v$$

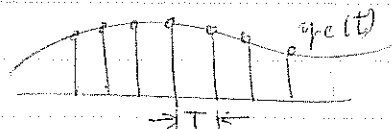
$$\neq 0 = \underbrace{h_1(A)P_k(A)(A - \lambda_k I)^{m_k} v}_{\substack{\text{minimal poly} \\ P(A) = 0}} + \underbrace{h_2(A)(A - \lambda_k I)^{m_k+1} v}_{0 \text{ (by sup.)}}$$

contradiction.

-sampled data systems



A/D converter



$$u_D(nT) = y_c(nT)$$

$$\tilde{u}_D(z) = \tilde{y}_c(z) = T \left[\tilde{y}_c(s) \right]$$

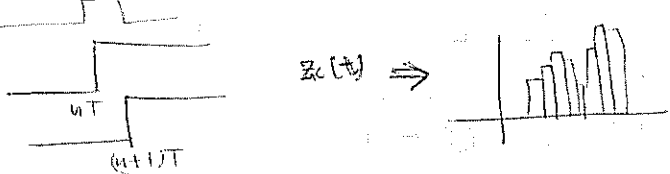
\uparrow
d[$y_c(t)$]

$$\tilde{u}_D(e^{sT}) = \frac{1}{2} y_c(0^+) + \frac{1}{T} \sum_{k=-\infty}^{\infty} \hat{y}_c \left(\frac{s+T}{T} \right)$$

D/A converter:

$$v_D = \{ v_D(nT) \}_{n=0}^{\infty}$$

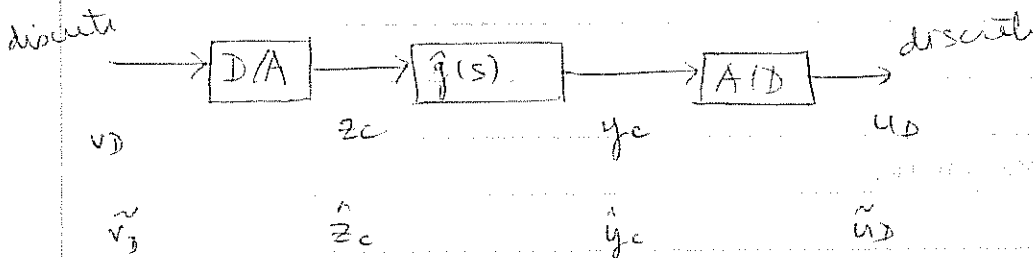
$$z_c(t) = \sum_0^{\infty} v_D(nT) [1(t-nT) - 1(t-nT+T)]$$



$$\hat{z}_c(s) = \sum v_D(nT) e^{-nTs} \left(\frac{1-e^{-sT}}{s} \right)$$

$$= \tilde{v}_D(e^{sT}) (1-e^{-sT})/s = \hat{g}(s) \left(\frac{1-e^{-sT}}{s} \right)$$

Q: what is the total transfer function



Assuming ① A/D & D/A are synchronised to time \$T\$

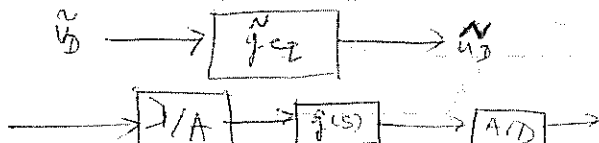
② \$\hat{g}(s)\$ is strictly proper / rational, with \$\hat{g}(s) \rightarrow 0\$ as \$|s| \rightarrow \infty\$

③ \$\hat{g}(s)\$ zero state at \$t=0\$

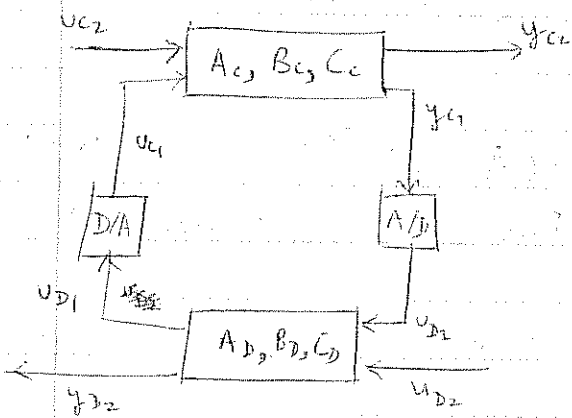
$$\hat{u}_D(z) = T [\hat{y}_c(s)](z) = T [\hat{g}_{eq}(s) \tilde{v}_D(e^{sT})](z)$$

$$\hat{u}_D(z) = T [\hat{g}_{eq}(s) \tilde{v}_D(e^{sT})](z) = \tilde{g}_{eq}(z) \tilde{v}_D(z)$$

$$\hat{u}_D(z) = \tilde{g}_{eq}(z) \cdot \tilde{v}_D(z)$$



look in back of reader

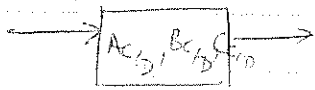


$$\dot{X}_c = A_c X_c + \begin{bmatrix} B_{c1} \\ B_{c2} \end{bmatrix} \begin{bmatrix} u_{c1} \\ u_{c2} \end{bmatrix}$$

$$y_c = C_c X_c$$

$$X_D(k+T) = A_D X_D(k) + \begin{bmatrix} B_{D1} \\ B_{D2} \end{bmatrix} \begin{bmatrix} u_{D1} \\ u_{D2} \end{bmatrix}$$

$$y_D(k) = C_D X_D(k)$$



$$X_c(k+1)T = \phi(k+1)T, kT) X_c(kT) + \int_{kT}^{(k+1)T} \phi(k+1)T, \tau) B_c u_c(\tau) d\tau$$

$$= e^{A_c(k+1)T - kT} X_c(kT) + \int_{kT}^{(k+1)T} e^{A_c(k+1)T - \tau} [B_{c1} u_{c1}(\tau) + B_{c2} u_{c2}(\tau)] d\tau$$

$$u'_{c2}(kT) \triangleq \int_{kT}^{(k+1)T} e^{A_c(k+1)T - \tau} B_{c2} u_{c2}(\tau) d\tau$$

$$X_c[(k+1)T] = \underbrace{e^{A_c T}}_{A_{c/D}} X_c(kT) + \underbrace{\int_0^T e^{A_c \tau} d\tau}_{B_{c/D}} \{ B_{c1} u_{c1}(kT) + u'_{c2}(kT) \}$$

$$X_D[(k+1)T] = A_{c/D} X_c(kT) + B_{c/D} \{ u_{c1}(kT) + u'_{c2}(kT) \}$$

Tuesday
10 Oct 1989

EECS 221a - Lecture

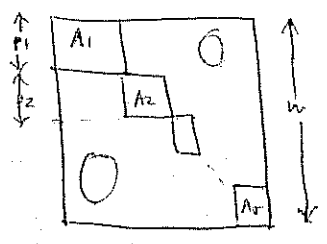
3) Matrix Representation

$$\mathbb{C}^n = \mathcal{N}(A - \lambda_1 I)^{m_1} \oplus \mathcal{N}(A - \lambda_2 I)^{m_2} \dots \oplus \mathcal{N}(A - \lambda_r I)^{m_r}$$

$\mathcal{N}(A - \lambda_k I)^{m_k}$ is invariant under A

\exists basis (union of lin ind. vectors in $\mathcal{N}(A - \lambda_k I)^{m_k}$)

A has the matrix representation



$$\dim \mathcal{N}(A - \lambda_k I)^{m_k} = p_k$$

Fact: $\dim \mathcal{N}(A - \lambda_k I)^{m_k} = d_k$ (from Ch. 12)
where $\det(A - sI) = (-1)^n (s - \lambda_1)^{d_1} \dots (s - \lambda_r)^{d_r}$

Proof: $\det(A - sI) = \det \begin{bmatrix} A_1 - sI_{p_1} & & 0 \\ & A_2 - sI_{p_2} & \\ 0 & & A_r - sI_{p_r} \end{bmatrix}$

$$= \prod_{k=1}^r \det(A_k - sI_{p_k})$$

(from det of block diagonal = product of det of blocks)

consider $\det(A_k - sI_{p_k})$

claim: poly in s , $\det(A_k - sI_{p_k})$ has only λ_k as zero
i.e. $\det(A_k - sI_{p_k}) = (s - \lambda_k)^{q \rightarrow p_k} (-1)^{p_k}$

$$\Rightarrow \det(A - sI) = (-1)^n \prod_{k=1}^r (s - \lambda_k)^{p_k}$$

λ_k can be a zero of $\det(A_k - sI_{p_k})$

i.e., $\det(A_k - \lambda_k I_{p_k}) = 0$; singular matrix

$$\exists z_k \neq 0 \text{ s.t. } (A_k - \lambda_k I_{p_k}) z_k = 0 \quad (1)$$

but $z = \begin{bmatrix} 0 \\ \vdots \\ z_k \\ \vdots \\ 0 \end{bmatrix} \in \mathbb{C}^{p_1} \oplus \dots \oplus \mathbb{C}^{p_r}$

$$\in \mathcal{N}(A - \lambda_k I)^{m_k}$$

$$\in \mathcal{N} \left(\begin{bmatrix} A_1 - \lambda_k I & & 0 \\ & \ddots & \\ 0 & & A_r - \lambda_k I \end{bmatrix} \right)^{m_k}$$

$$z_k \in \mathcal{N}(A_k - \lambda_k I)^{m_k}$$

$$\text{i.e., } (A_k - \lambda_k I)^{m_k} z_k = \theta \quad (2)$$

$$\Rightarrow A_k z_k = \mu I_k z_k \Rightarrow \begin{bmatrix} A_k^{m_k} - \mu I_k^{m_k} (\lambda_k I) & \dots & (-1)^{m_k} (\lambda_k I)^{m_k} \end{bmatrix} z_k$$

$$(1) \text{ subs. into } (2) \quad \underbrace{(\mu - \lambda_k)}_{\text{scalar}} \underbrace{z_k}_{\text{nonzero}} = \theta$$

$$\Rightarrow (\mu - \lambda_k) = 0$$

$$\Rightarrow \boxed{\mu = \lambda_k}$$

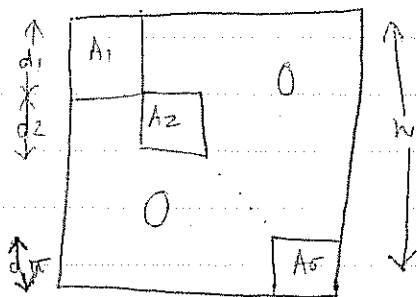
$$\Rightarrow \det(A_k - sI_k) = (-1)^{p_k} (s - \lambda_k)^{p_k}$$

$$\Rightarrow \det(A - sI) = (-1)^n \prod_{k=1}^r (s - \lambda_k)^{p_k}$$

$$\text{But } = (-1)^n \prod_{k=1}^r (s - \lambda_k)^{d_k}$$

$$\Rightarrow p_{ik} = d_k$$

A has matrix representation:



In order to find out the form of A_k we need to specify a set of lin ind vectors in $\mathcal{N}(A - \lambda_k I)^{m_k}$

(3) Generalized Eigenvectors

$$\text{Ex. } A = \begin{bmatrix} 2 & -1 & & & \\ & 1 & 0 & -1 & \\ & & 1 & 0 & \\ & & & 1 & -1 \\ & & & & 1 \end{bmatrix} \quad \text{SAS matrix}$$

$$-\Delta(s) = \det(A - sI) = (s - \lambda)^5 \quad ; \quad \lambda = 1$$

$$\mathbb{C}^5 = \mathcal{N}(A - \lambda I)^5$$

$$(\mathcal{N}(A - \lambda I)^3)$$

$$(A - \lambda I) = \begin{bmatrix} 1 & -1 & & & \\ & 1 & -1 & & \\ & & 0 & 0 & \\ & & & 0 & -1 \\ & & & & 0 \end{bmatrix}$$

$$\text{Rank} = 3$$

$$\dim(\mathcal{N}(A - \lambda I)) = 2$$

Similarly $(A - \lambda I)^2$ has rank = 1

$(A - \lambda I)^3$ has rank 0.

$$\psi(s) = (s - \lambda)^3$$

$$\dim \mathcal{N}(A - \lambda I)^2 = 4$$

$$\dim \mathcal{N}(A - \lambda I)^3 = 5$$

$\mathcal{N}(A - \lambda I)^3$	dim	u^3	v^2
$\mathcal{N}(A - \lambda I)^2$	4	u^2	v^1
$\mathcal{N}(A - \lambda I)$	2	u^1	v^1

One way of selecting 5 lin ind vectors in $\mathcal{N}(A - \lambda I)$

(i) select one vector u^3 in $\mathcal{N}(A - \lambda I)^3$ but not in $\mathcal{N}(A - \lambda I)^2$

(ii) select two lin ind vectors u^2, v^2 in $\mathcal{N}(A - \lambda I)^2$ but not in $\mathcal{N}(A - \lambda I)$

(iii) select two lin ind vectors u^1, v^1 in $\mathcal{N}(A - \lambda I)$ but not in $\mathcal{N}(A - \lambda I)^2$ or not equal to zero

$$(i) (A - \lambda I)^3 u^3 = 0 \text{ but } (A - \lambda I)^2 u^3 \neq 0 \quad (1)$$

$$(ii) (A - \lambda I)^2 u^2 = 0 \text{ but } (A - \lambda I) u^2 \neq 0 \quad (2)$$

(1) & (2) can be combined if we pick $u^2 = (A - \lambda I) u^3$

Similarly $u^1 = (A - \lambda I)^2 u^3$

amp

In general a vector v is called a generalized eigenvector (of rank k) of A assoc. λ -value λ

$$\Leftrightarrow (A - \lambda I)^k v = 0 \quad \text{but} \quad (A - \lambda I)^{k-1} v \neq 0$$

$$\text{Let } v_k^k = v_k$$

$$v_{k-1}^k = (A - \lambda I) v_k^k$$

$$v_1^k = (A - \lambda I) v_2^k$$

The set of vectors $\{v_1^k, v_2^k, \dots, v_k^k\}$ is called a chain of g.e. vectors of length k .

(Had two chains in example - v^3, v^2, v^1 ; v^2, v^1)

Properties of generalized eigenvectors:

1) $v_i^k \in N(A - \lambda I)^i$ but $v_i^k \notin N(A - \lambda I)^{i-1}$
 i is the rank

2) $v_i^k \in N(A - \lambda I)^k$

3) $v^1 \in N(A - \lambda I)$

v^1 is an eigenvector of A .

$$\begin{aligned} v^1 &= (A - \lambda I) v^2 \\ &= (A - \lambda I)^{k-1} v \\ \Rightarrow (A - \lambda I) v^1 &= (A - \lambda I)^k v = 0 \end{aligned}$$

4) $\{v^1, v^2, \dots, v^k\}$: these k vectors are lin. ind.

Proof $\alpha_1 v^1 + \alpha_2 v^2 + \dots + \alpha_k v^k = 0$ Given.
 show $\Rightarrow \alpha_1, \dots, \alpha_k = 0$

Let $\alpha_1 (A - \lambda I)^{k-1} v + \alpha_2 (A - \lambda I)^{k-2} v + \dots + \alpha_{k-1} (A - \lambda I) v + \alpha_k v = 0$

mult by $(A - \lambda I)^{k-1}$

$$\Rightarrow \alpha_k \underbrace{(A - \lambda I)^{k-1}}_{\neq 0} v = 0$$

$$\Rightarrow \alpha_k = 0$$

Similarly can prove all the coeff must be zero.

initial
 as done
 to be (1, 1)

(5) $\{u^1, \dots, u^k\}$ and $\{v^1, \dots, v^k\}$ are two chains of generalized vectors, then they are linearly independent.
 (Pf similar to (4))

(6) The generalized vectors of A assoc. λ differ evaluate are lin independent.

4. JORDAN BLOCK

$\{u^1, u^2, u^3, v^1, v^2\}$ lin ind
 form a basis for \mathbb{C}^5 .

What is the matrix representation of A with this

$$\begin{matrix} Au^1 \\ Au^2 \\ Au^3 \\ Av^1 \\ Av^2 \end{matrix} \rightsquigarrow \begin{Bmatrix} \lambda & 1 & 0 & 0 & 0 \\ 0 & \lambda & 1 & 0 & 0 \\ 0 & 0 & \lambda & 0 & 0 \\ 0 & 0 & 0 & \lambda & 1 \\ 0 & 0 & 0 & 0 & \lambda \end{Bmatrix}$$

$Au^1 = \lambda u^1$ (u^1 eigenvector)

$u^1 = (A - \lambda I)u^2$

$Au^2 = u^1 + \lambda u^2$

$Au^3 = u^2 + \lambda u^3$

$Av^1 = \lambda v^1$

$Av^2 = \lambda v^2$

λv^1
 λv^2

$u^1 = (A - \lambda I)u^2$

$u^2 = (A - \lambda I)u^3$

v^1 e. vector

$v^1 = (A - \lambda I)v^2$

Standard Basis \xrightarrow{A} Standard basis

$P^{-1} \downarrow$

gen. vectors

$\uparrow P = [u^1, u^2, u^3, v^1, v^2]$

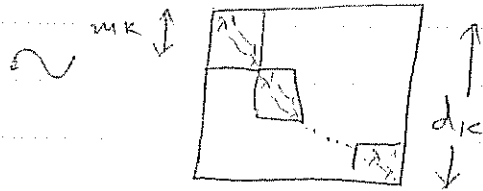
\xrightarrow{J} Gen vectors

$A = PJP^{-1}$

$J = P^{-1}AP$

Also

in general A_k



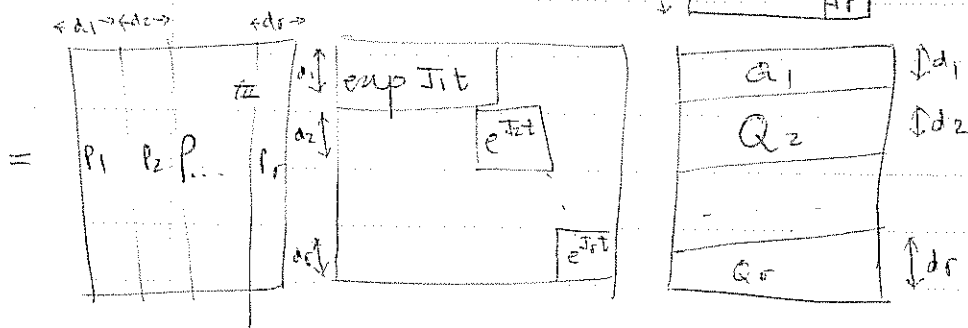
dim of the largest block = m^k
 $\#$ of blocks = $\#$ of lin ind eigin vectors
 $= \dim \mathcal{N}(A - \lambda^k I)$

Why do we do all this?

$[\exp(At)]x_0$; A diagonal \Rightarrow modal decomposition

5. STATE TRANSITION MATRIX

$$P^{-1}AP = J = \begin{matrix} \begin{matrix} \downarrow d_1 \\ \downarrow d_2 \\ \downarrow d_r \end{matrix} \begin{bmatrix} J_1 & & \\ & J_2 & 0 \\ & & \ddots \\ 0 & & & J_r \end{bmatrix} \end{matrix} \quad \exp At = P(\exp Jt)P^{-1}$$



$$= P_1 (\exp(J_1 t)) Q_1 + P_2 (\exp(J_2 t)) Q_2 + \dots + P_r (\exp(J_r t)) Q_r$$

cols of $P \Rightarrow$ con. sp. to generalized e-vectors assoc. λ_i

$\exp(J_k t) = ?$ Given $J_k = \begin{matrix} \begin{matrix} \downarrow m_k \\ \downarrow d_k \end{matrix} \begin{bmatrix} \lambda^k & & \\ & \lambda^k & \\ & & \ddots \\ & & & \lambda^k \end{bmatrix} \end{matrix}$

Monday
12 Oct 1989

KST: DISC

Field Axioms -

- (A) $(\alpha + \beta) + \gamma = (\beta + \alpha) + \gamma$ $\alpha + (\beta + \gamma) = (\alpha + \beta) + \gamma$ $\exists \theta \text{ s.t. } \forall \alpha \quad \alpha + \theta = \alpha$
- $\forall \alpha, \exists (-\alpha) \text{ s.t. } \alpha + (-\alpha) = \theta$
- (M) $\alpha\beta = \beta\alpha$ $\alpha(\beta\gamma) = (\alpha\beta)\gamma$ $\exists \rho \text{ s.t. } \alpha \cdot \rho = \alpha$
- (D) $\alpha(\beta + \gamma) = \alpha\beta + \alpha\gamma$ $\forall \alpha \neq \theta, \exists \alpha^{-1} \text{ s.t. } \alpha\alpha^{-1} = \rho$

Vector Space Axioms -

- (A) basically the same
- (SM) $\alpha, \beta \in \mathbb{F}, x, y \in V$
- $\alpha(\beta x) = (\alpha\beta)x$ $\alpha(\beta x + \gamma) = \alpha\beta x + \alpha\gamma$ $(\alpha + \beta)x = \alpha x + \beta x$
- $\exists f. x = x$

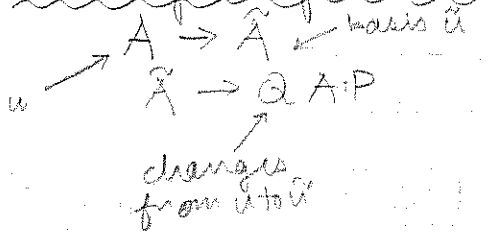
Linearity

$A(\alpha x + \beta y) = \alpha A(x) + \beta A(y)$

↑
transformation

$\alpha, \beta \in \mathbb{F}$
 $x, y \in V$

Change of Basis



the i th column of $Q =$
 i th basis vector in
 \hat{u} coordinates

P : opposition

Norm

1. $\|x + y\| \leq \|x\| + \|y\|$
2. $\|x\| \geq 0$; $\|x\| = 0 \iff x = \theta$
3. $\|c x\| = |c| \|x\|$

lp norm? $\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}$; $x \in \mathbb{C}^n$

7th
8-2-55
-1=0
5677
basis u
z
z-1
z

Induced norm:

$$\sup_{\|x\|=1} \|Ax\|$$

$\|A\|_1 = \max_j \sum_{i=1}^n |a_{ij}|$ = max of col. sums

$$\|A\|_\infty = \max_i \left[\sum_{j=1}^n |a_{ij}| \right]$$

$$\|\phi(\cdot)\|_\infty = \sup_{t \in [t_0, t_1]} \|\phi(t)\|$$

all norms in any finite dim space are equivalent.

Fundamental Thm

$$\dot{x} = p(x, t)$$

(i) $t \mapsto p(x, t)$ piecewise continuous ε a finite # of disc.

(ii) Lipschitz

Fund thm. given $p(x, t)$ which satisfies (i) & (ii)

(a) $\forall x_0, t_0 \exists \phi$ cont. s.t. $\phi(t_0) = x_0$ & $\dot{\phi}(t) = p(\phi(t), t)$

(b) ϕ is unique

Picard Iteration

$$x_{n+1}(t) = x(t_0) + \int_{t_0}^t p(x_n(s), s) ds$$

Bellman's Gronwall

Prove something equal to zero. p. 39 & 40

Dynamical System

Definition

Need

(i) $(\mathcal{U}, \mathcal{Y}, \Sigma, \alpha, \beta)$

(ii) S satisfies state transition axiom

(iii) S satisfies Semigroup axiom

$$\text{(i)} \quad x(t_1) = S(t_1, t_0, x_0, u|_{[t_0, t_1]})$$

given x_0 , $x(t)$ depends only on $u|_{[t_0, t]}$

not on u outside interval

$$S(t_1, t_0, x_0, u) = S(t_1, t_2, \underbrace{S(t_2, t_0, x_0, u|_{[t_0, t_2]})}_{x(t_2)}, \underbrace{u|_{[t_2, t_1]}}_u)$$

Linear Dynamical Systems

(i) $\rho(t, t_0, x_0, u) = \rho(t, t_0, x_0, \theta_u) + \rho(t, t_0, \theta_x, u)$

$\rho(t, t_0, x_0, u) = \rho(t, t_0, x(t), u(t))$

$x(t) = s(t, t_0, x_0, u)$

(ii) Superposition property

$\rho(t, t_0, \theta_x, \alpha u + \beta v) = \alpha \rho(t, t_0, \theta_x, u) + \beta \rho(t, t_0, \theta_x, v)$

(iii) $\rho(t, t_0, \alpha x_0 + \beta x_1, \theta_u) =$ same idea

$y(t) = (1/x) \phi(A) C(t) \phi(t, t_0) x_0 + \int_{t_0}^t C(t) \phi(t, \tau) B(\tau) u(\tau) d\tau$

$\leftarrow \rho(t, t_0, x_0, \theta_u) \rightleftarrows \leftarrow \rho(t, t_0, \theta_x, u) \rightarrow$

ZIR

ZSR

$\theta_u = \begin{bmatrix} u(t) = 0 \\ 0 \end{bmatrix}$

$\theta_x = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

ZSR = $\begin{bmatrix} 1 \\ 0 \end{bmatrix} e^{-3t} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} e^{-2t}$

ZIR = $\begin{bmatrix} 1 \\ -1 \end{bmatrix} e^{-2t}$ starting from x_0

what is the output starting @ $-x_0$ to z/p $2u(t)$

$o/p = 2(ZSR) - (ZIR)$

State Transition Matrix

(a) Unique comb. of ρ of time

(b) If $\dot{x} = AX$, $x(t_0) = x_0$ then trajectory $\phi(t, t_0, x_0) = \Phi(t, t_0)x_0$

(c) $\Phi(t_1, t_1) = \Phi(t_1, t_2)\Phi(t_2, t_0)$ for all t_0, t_1, t_2 (we BT $\Phi(t_1, t_2) = \Phi(t_1, t_0)\Phi(t_0, t_2)$)

(d) $\Phi(t_0, t_0) = I$

where $t_0 \leq t_1 \leq t_2$

$\Phi^{-1} = \Phi(t_0, t)$

(e) $\frac{\partial}{\partial t} \Phi(t, t_0) = A(t)\Phi(t, t_0)$

non-invariant

(f) For cont time systems $\Phi(t, t_0)$ is always non-invariant

when Φ not singular at t_0

(9) for any fundamental matrix X

$$\Phi(t, t_0) = X(t) X^{-1}(t_0)$$

$$\text{Is } \Phi(t, 0) = \begin{bmatrix} 4(3e^{3t} + 4) & 2 - 2e^{-t} \\ 0 & 1/5(3e^t + 2e^{2t}) \end{bmatrix}$$

an STM?

non-singular for t

$$\text{(ii) } \Phi(0, 0) = I$$

Yes it is an STM

What system is it an STM of?

$$\partial \Phi / \partial t = \begin{bmatrix} 1/5(3e^{3t} + 4) & 3e^{-t} \\ 0 & 1/5(3e^t + 2e^{2t}) \end{bmatrix}$$

must it $\partial \Phi / \partial t \Phi^{-1} = A \Phi \Phi^{-1}$; solves $\dot{X} = A(t)X$

State Transition Function $\in (S/R)Y + (K/S/R)$ for linear sys

$$x(t) = \Phi(t, t_0)x_0 + \int_{t_0}^t \Phi(t, \tau) B(\tau) U(\tau) d\tau$$

$$\text{response fn} = C(t) x(t) + D(t) U(t)$$

Scalar Product (inner product)

$$\text{(i) } \langle x | y+z \rangle = \langle x | y \rangle + \langle x | z \rangle$$

$$\text{(ii) } \langle \alpha x | z \rangle = \alpha \langle x | z \rangle$$

$$\text{(iii) } \langle x | x \rangle = 0 \iff x=0$$

$$\text{(iv) } \langle x | y \rangle = \overline{\langle y | x \rangle}$$

Schwartz Inequality $|\langle x | y \rangle| \leq \|x\| \|y\|$

$\| \cdot \|$ is norm induced by inner product

Adjoint

$$\langle y | Ax \rangle = \langle A^* y | x \rangle$$

where A^* = adjoint of A

blockwise residue matrices (RK's) (Gives you 1st part of full)

Cayley Hamilton

conclusion $A^n = 1.c. \sum_{i=0}^{n-1} \alpha_i A^i$

$$P_i = e_i / i! \in \text{u.h.v.}$$

$$\sum P_i = I$$

$$\sum \lambda P_i = A$$

$$P_i P_j = \delta_{ij} P_i$$

Eigen of t.f. (transfer)

13 Friday Oct 189

AST - Lecture

5. State Transition Matrix

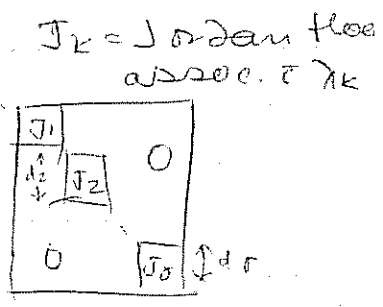
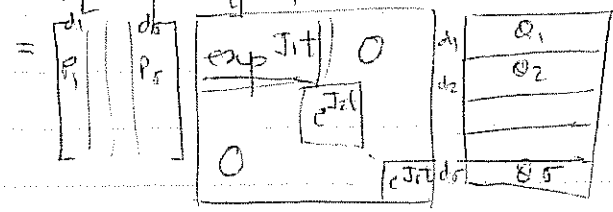
A (may have multiple eigen values)
 can always get $P \Lambda P^{-1}$ ← generalized eigen vectors
 but gen. e. vectors A has representation in
 form of Jordan blocks.

want e^{At} (struc)

$A = P J P^{-1} = P J Q$

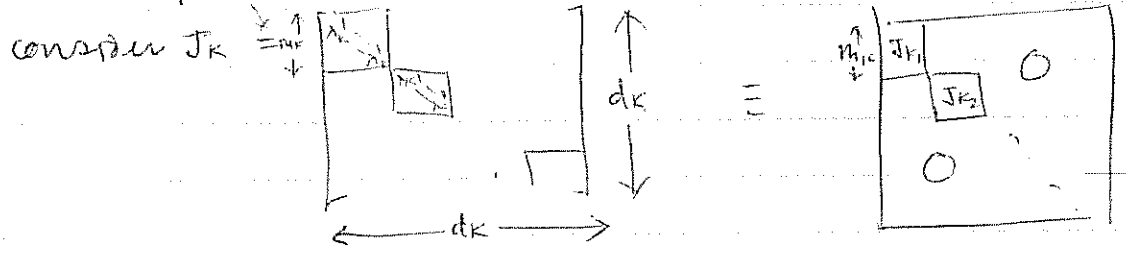
$J = P^{-1} A P =$

$\exp(At) = P [\exp Jt] Q$

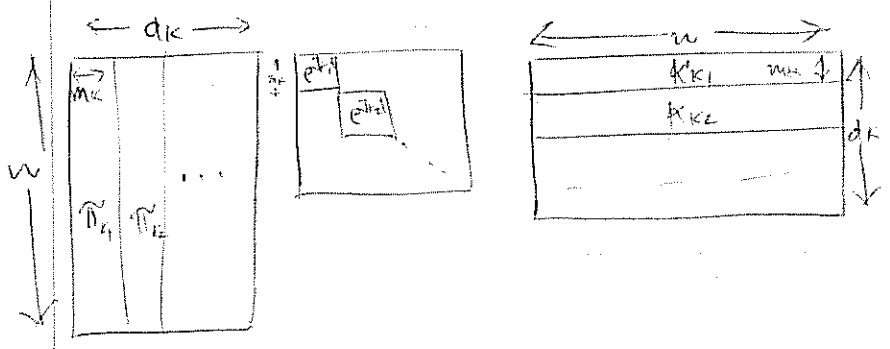


$= P_1 (\exp J_1 t) Q_1 + P_2 \exp J_2 t Q_2 + \dots + P_s \exp(J_s t) Q_s$

largest dimension $n \times d_1 \times d_2 \times \dots \times d_s \times n$

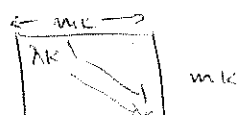


$P_k \exp J_k t Q_k$; can be further decomposed

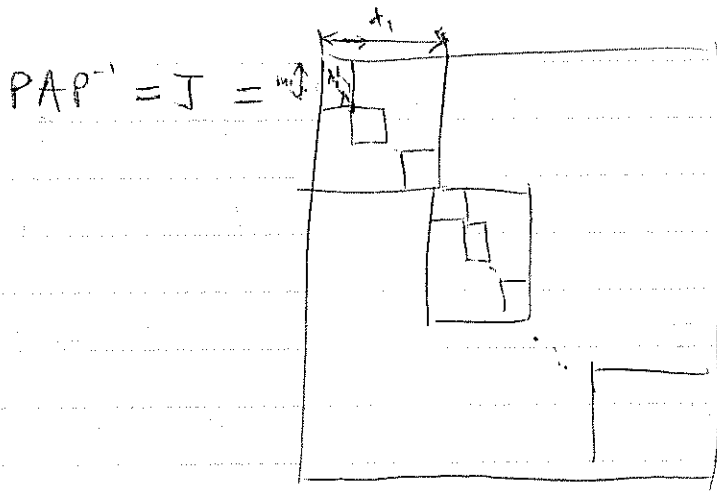


$= \pi_{k1} \exp J_{k1} t K_{k1} + \pi_{k2} (\exp J_{k2} t) K_{k2} + \dots$

Consider the 1st term $J_{k1} =$



$\exp(J_{k1} t) =$

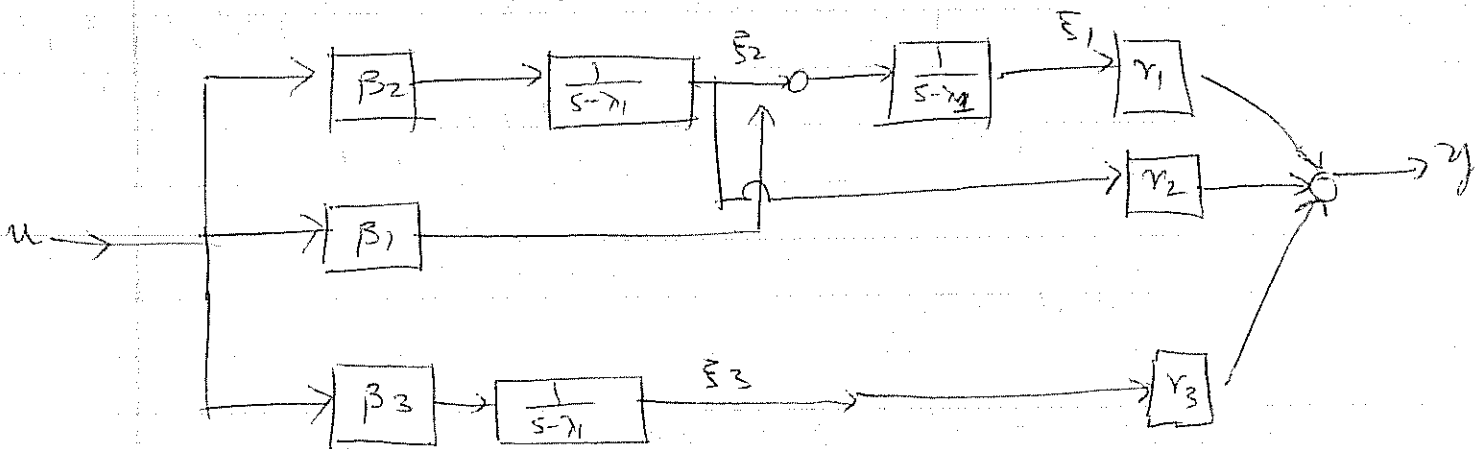


$$\begin{cases} \dot{\xi} = J\xi + \beta u \\ y = \gamma \xi \end{cases}$$

$$\begin{bmatrix} \dot{\xi}_1 \\ \dot{\xi}_2 \\ \dot{\xi}_3 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 1 & 0 \\ 0 & \lambda_1 & 0 \\ 0 & 0 & \lambda_1 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix} + \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} u$$

Ex. $J =$

$$\begin{aligned} \dot{\xi}_1 &= \lambda_1 \xi_1 + \beta_2 + \beta_1 u & \xi_1 &= \frac{1}{s-\lambda_1} (\beta_2 + \beta_1 u) \\ \dot{\xi}_2 &= \lambda_1 \xi_2 + \beta_2 u & \xi_2 &= \frac{\beta_2 u}{s-\lambda_1} \\ \dot{\xi}_3 &= \lambda_1 \xi_3 + \beta_3 u & \xi_3 &= \frac{\beta_3 u}{s-\lambda_1} \end{aligned}$$



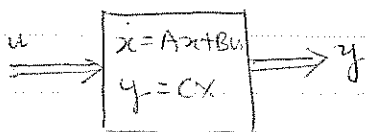
Note which are coupled, which aren't.

say \leq probably
Oct 1989

XST-lecture

Ch VI stability

1. Motivation

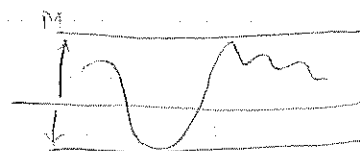


u, x, y are vectors in some normed vector space.

system response to be bdd.

Defn: $f: \mathbb{F} \rightarrow V$, $\mathbb{F} = \mathbb{R}$ or \mathbb{C}

f is bdd iff $\exists M$ s.t. $\forall t \in \mathbb{F} \|f(t)\| \leq M$



u is bdd, will y be bdd?

will x be bdd?

BIBO stable

$\Rightarrow \forall$ bdd u , y is bdd

CTI system $\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases}$

$x(0) = x_0$

$$x(t) = e^{At} x_0 + \int_0^t e^{A(t-\tau)} B u(\tau) d\tau$$

$$\exp(At) = \sum_{k=1}^m \sum_{l=0}^{m_k-1} t^l e^{\lambda_k t} P_{kl}(A)$$

time behaviour of the resp. $y(t)$ completely charac. by λ_k (location) and m_k \rightarrow independent of t .

1) Conditions under which system is BIBO stable (this Chap)
 \uparrow
 exp. in terms of location of λ_k .

2) how to control location of eigen values? (sec XII)

3) when is it possible to do that? (controllability/ob-^{av II} _{sup 1-5, 11})
 condition expressed in terms of rank of a matrix.

4) Numerical Aspects of rank of matrix
 other geometriz concepts (useful math background)
 (Singular Value Decomposition, see VIII)

* Generalize to time varying system

$$\dot{x} = A(t)x + B(t)u$$

$$Y = C(t)x$$

Review

(i) $\|u(t)\|$ for fixed t . $u(t) \in \mathbb{R}^r$

$$\|u(t)\| := \max_i |u_i(t)|$$

for $u: [0, T] \rightarrow \mathbb{R}^r$

$$\|u(\cdot)\| = \max_{t \in [0, T]} \|u(t)\| = \max_{t \in [0, T]} \max_i |u_i(t)|$$

(ii) $H(t, \tau)$

for fixed t, τ $H(t, \tau)$ matrix

induced norm

$$\|H(t, \tau)\| := \max_i \sum_{j=1}^n |h_{ij}(t, \tau)| \quad (\text{row sum norm})$$

(iii) $\|H(t, \tau)u(\tau)\| \leq \|H(t, \tau)\| \cdot \|u(\tau)\|$

2. Zero Input Response

$$\dot{x}(t) = A(t)x(t) \quad x(t_0) = x_0$$

$$x(t) = \Phi(t, t_0)x_0$$

Fact $\Phi(t, t_0)$ bdd $\Leftrightarrow x(t)$ bdd.

Proof: $x(t) = \Phi(t, t_0)\Phi(t_0, 0)\Phi(0, t_0)x_0$

$$\Phi(t, t_0) \text{ bdd} \Rightarrow x(t) \text{ bdd} \quad \|x(t)\| \leq \|\Phi(t, t_0)\| \cdot \|\Phi(t_0, 0)\| \cdot \|\Phi(0, t_0)\| \cdot \|x_0\|$$

$$\Phi(t, t_0) \text{ is bdd} \Rightarrow \exists N \text{ s.t. } \|\Phi(t, t_0)\| < N \quad \forall t \Rightarrow x(t) \text{ is bdd}$$

converse:

$$\Phi(t, t_0) \text{ not bdd} \Rightarrow x(t) \text{ not bdd} \quad [\text{equivalent}]$$

$$\exists M \text{ s.t. } \forall t \quad \max_i \sum_{j=1}^n |\phi_{ij}(t, t_0)| \leq M$$

$$\text{negate: } \forall M \exists t_1 \text{ s.t. } \max_i \sum_{j=1}^n |\phi_{ij}(t_1, t_0)| > M$$

$$\forall M \exists t_1 \quad \max_i \sum_{j=1}^n |\phi_{ij}(t_1, t_0)| > M \quad \Rightarrow \text{say max occurs at } i < \sum_{j=1}^n |\phi_{ij}(t_1, t_0)| > M$$

want to show
 $\forall K, \exists t_L, \exists \bar{x}_0$ s.t. $\forall x(0) \|\bar{x}(t_L)\| > K$
 i.e. show $\max_i |x_i(t)| > K$

~~$x(t) = \Phi(t, 0) \Phi(0, t_0) x_0$~~
 $x(t) = \Phi(t, 0) \Phi(0, t_0) x_0$
 $\leftarrow x_0 \rightarrow$

$x(t) = \Phi(t, 0) x_0'$
 i.e. $\max_i |\sum_j \phi_{ij}(t_L, 0) (\bar{x}_0')_j| > K$

no just change in notation actually we just putting $t_0 = t_L$

pick $t_L = t_1$

~~$\sum_j \phi_{ij}(t_L, 0) (\bar{x}_0')_j$~~
 $\geq \left| \sum_{k=1}^n \phi_{kj}(t_1, 0) (\bar{x}_0')_j \right|$

can do $\sum_{k=1}^n \phi_{kj}(t_1, 0) (\bar{x}_0')_j$ from $\Phi(t_1, 0) x_0$

pick $(\bar{x}_0')_j$ s.t. it is [sgn $\phi_{kj}(t_1, 0)$]

then $\sum |\phi_{kj}(t_1, 0) (\bar{x}_0')_j| = \sum |\phi_{kj}(t_1, 0)| > K$

But by conjecture can find such a K ($\forall K \exists t_L$ s.t. ...)

<TI

$\Phi(t, 0) = \exp(At) = \sum_{k=1}^{\sigma} \sum_{l=0}^{m_k-1} t^l e^{\lambda_k t} P_{kl}$

conclusion $x(t) \rightarrow 0 \iff$ (i) $\text{Re}(\lambda_k) < 0$ close to LHP.

(ii) $\text{Re}(\lambda_k) = 0$ then $m_k = 1$; \rightarrow e. value on jw axis
 can esp. order in min poly

3. Zero State Response

$\begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u(t) & x(t_0) = 0 \\ y(t) = C(t)x(t) \end{cases}$

$y(t) = \int_{t_0}^t C(t) \Phi(t, \tau) B(\tau) u(\tau) d\tau$
 $\leftarrow H(t, \tau) \rightarrow$

$y(t) = \int_{t_0}^t H(t, \tau) u(\tau) d\tau$

* is BIBO stable $\iff \forall u$ s.t. $\|u(\cdot)\| \leq u_m \implies \|y(\cdot)\| \leq K u_m$

Ques * is BIBO stable

$$\begin{aligned} \|y(t)\| &\leq \int_{t_0}^t \|H(t, \tau)\| \|u(\tau)\| d\tau \\ &\leq \left[\int_{t_0}^t \|H(t, \tau)\| d\tau \right] \|u(\cdot)\| \end{aligned}$$

\longleftarrow must be ∞ \downarrow ∞

$$\Leftarrow \int_{t_0}^t \|H(t, \tau)\| d\tau \infty$$

Proof (\Leftarrow): $\|y(t)\| = \left\| \int_{t_0}^t H(t, \tau) u(\tau) d\tau \right\|$

$$\begin{aligned} &\leq \int_{t_0}^t \|H(t, \tau)\| \|u(\tau)\| d\tau \\ &\leq \left(\int_{t_0}^t \|H(t, \tau)\| d\tau \right) u_M \end{aligned}$$

Conversely works in both directions.

(\Rightarrow) Difficult

Do analysis

$$(P \Rightarrow Q) \Leftrightarrow (Q' \Rightarrow P') \Leftrightarrow \int_{t_0}^{t_L} \max_i \sum_{j=1}^r |h_{ij}(t_L, \tau)| d\tau > M$$

$$\forall M \exists t_L \text{ s.t. } \int_{t_0}^{t_L} \|H(t_L, \tau)\| d\tau > M$$

$$\Rightarrow \forall K \exists u(\cdot) \|u(\cdot)\| \leq u_M$$

$$\exists t_1 \|y(t_1)\| > K u_M$$

$$\Leftrightarrow \{ \exists K \|y_K(t_1)\| > K u_M \}$$

Set $t_1 = t_L$

consider $y_K(t_L) = \int_{t_0}^{t_L} \sum_{j=1}^r h_{kj}(t_L, \tau) u_j(\tau) d\tau$

$$= \int_{t_0}^{t_L} \sum_{j=1}^r |h_{kj}(t_L, \tau)| d\tau$$

$$\uparrow u_j(\tau) = \text{sgn } h_{kj}(t_L, \tau)$$

well defined

pick $k =$ the one which $\max \sum_{j=1}^r |h_{kj}(t_L, \tau)|$

but the max is a fun of z .
 \therefore Can't do this!

Thursday
19 Oct 1989

KST-lecture

3. Zero State Response

$$y(t) = \int_{t_0}^t H(t, z) u(z) dz$$

Thm (1) is BIBO stable

$$\Leftrightarrow \int_{t_0}^t \|H(t, z)\| dz < \infty$$

(\Rightarrow) Analysis

(1) If $\forall M \exists t_L \int_{t_0}^{t_L} \max_i \sum_{j=1}^m |h_{ij}(t_L, z)| dz > M$

want $\forall K \exists u(\cdot) \|u(\cdot)\| \leq u_m \exists t_1, \exists K |y_K(t_1)| > K u_m$

consider $y_K(t_1) = \int_{t_0}^{t_1} \sum_{j=1}^m h_{kj}(t_1, z) u_j(z) dz$



set $t_1 = t_L, u_j(z) = \text{sgn } h_{kj}(t_L, z)$

$$y_K(t_L) = \int_{t_0}^{t_L} \sum_{j=1}^m |h_{kj}(t_L, z)| dz \quad \text{, want work directly}$$

may be really small

we know $\int_{t_0}^{t_L} \max_i \sum_j |h_{ij}(t_L, z)| dz > M$

$$y_K(t_L) > \alpha M > K$$

pick $M > K/\alpha$

What do we know?

$$\int_{t_0}^{t_L} \max_i \sum_j |h_{ij}(t_L, z)| dz$$



$$\textcircled{1} \int_{t_0}^{t_L} \sum_i \sum_j |h_{ij}(t_L, c)| dc \geq \int_{t_0}^{t_L} \max_i \sum_j |h_{ij}(t_L, c)| dc$$

$$\textcircled{2} \exists K \int_{t_0}^{t_L} \sum_j |h_{kj}(t_L, c)| dc \geq \frac{1}{M} \int_{t_0}^{t_L} \sum_i \sum_j |h_{ij}(t_L, c)| dc$$

pick k s.t. $\textcircled{2}$

want $M/m > K$

$$y_k(t_L) > \frac{1}{m} M$$

pick $M > mK$

\Rightarrow Formal Proof -

let $M > mK$

then $\exists t_L$ s.t. $\int_{t_0}^{t_L} \max_i \sum_j |h_{ij}(t_L, c)| dc > mK$

pick k s.t. $\int_{t_0}^{t_L} \sum_j |h_{kj}(t_L, c)| dc \geq \frac{1}{m} \int_{t_0}^{t_L} \sum_i \sum_j |h_{ij}(t_L, c)| dc$

let $u_j(c) = \text{sgn } h_{kj}(t_L, c)$ so $\|u(c)\| \leq 1$

consider $|y_k(t_L)| = \int_{t_0}^{t_L} \sum_j |h_{kj}(t_L, c)| dc \quad \cancel{> \frac{1}{m} M}$

$$> \frac{1}{m} \int_{t_0}^{t_L} \sum_j \dots dc > \frac{1}{m} \int_{t_0}^{t_L} \max_i \dots > \frac{1}{m} mK$$

Q.E.D.

$$y(t) = \int_{t_0}^t H(t, c) u(c) dc \quad ; y(t_0) = 0$$

BIBO stable

$$\Leftrightarrow \int_{t_0}^t \|H(t, c)\| dc < \infty$$

Note: t_0 could be anything even $-\infty$ (this is Bessov's approx)

Corollary: ΔT

$$y(t) = \int_{t_0}^t H(t-c) u(c) dc \quad \text{BIBO stable}$$

$$\Leftrightarrow \int_{t_0}^t \|H(c)\| dc < \infty$$

$H(c) = C(\exp \bar{A}c)B$ impulse response matrix
can do change of coordinates

wrong
correct

- (i) $\forall \delta \|x_0\| < \delta \Rightarrow \exists \epsilon > 0 \exists t_0 \forall t \geq t_0 \| \phi(t, t_0, x_0) \| < \epsilon$
- (ii) $\forall \epsilon > 0 \exists \delta > 0 \text{ s.t. } \|x_0\| < \delta \Rightarrow \| \phi(t, t_0, x_0) \| < \epsilon \forall t \geq t_0$

Defn: Θ of $\dot{X} = A(t)X$ is stable i.s.L.

$\Leftrightarrow \forall t_0, \forall \epsilon > 0 \exists \delta(\epsilon, t_0)$ s.t.
 $\forall \|x_0\| \leq \delta(t_0) \forall t \geq t_0 \| \phi(t, t_0, x_0) \| < \epsilon$

fact Θ is stable i.s.L. $\Leftrightarrow \Phi(t, 0)$ is bdd $\Leftrightarrow \exists M \forall t \| \Phi(t, 0) \| < M$
 \Rightarrow proof $(\Leftarrow) \| \phi(t, t_0, x_0) \| \leq \| \Phi(t, 0) \| \cdot \| \Phi(0, t_0) \| \cdot \| x_0 \|$
 $\Phi(t, 0)$ is bdd $\Leftrightarrow \exists M \forall t \| \Phi(t, 0) \| < M$
 let $\| \Phi(0, t_0) \| =: \alpha$

So, if we choose $\delta = \epsilon / (M \alpha)$
 then $\|x_0\| < \delta \Rightarrow \| \phi(t, t_0, x_0) \| < \epsilon$

Proof $(\Rightarrow) \Rightarrow \exists M \exists t_0 \exists K \sum_j | \phi_{kj}(t_0, 0) | > M$

want $\exists \epsilon > 0 \forall \delta > 0 \exists t_0 \forall t \geq t_0 \forall \|x_0\| < \delta \| \phi(t, t_0, x_0) \| > \epsilon$

$x_0 = \epsilon/2 \text{ sgn } \phi_{kj}(t_0, 0)$ evidently $\|x_0\| < \delta$
 $M = 2(\epsilon/\delta)$

See Besov's Notes
 if Θ is asymptotically stable
 then component $\phi_{kj}(t, 0)$
 goes to 0 as $t \rightarrow \infty$
 which is wrong

2) asymptotic stability
Defn Θ of $\dot{X} = A(t)X$ is as

- (i) it is stable in sense Liapunov (i.s.L.)
- (ii) $\phi(t, t_0, x_0) \rightarrow \Theta$ as $t \rightarrow \infty$

fact Θ a.s. \Leftrightarrow (i) $\Phi(t, 0)$ is bdd
 (ii) $\| \Phi(t, 0) \| \rightarrow 0$ as $t \rightarrow \infty$

Corollary Θ of $\dot{X} = AX$ a.s. $\Leftrightarrow \rho_c(\lambda_k) < 0$

5) Exponential Stability

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases}$$

$$y(t) = C \exp(At) x_0 + \int_0^t C \exp(A(t-\tau)) B u(\tau) d\tau$$

$$\exp(At) = \sum_{k=0}^{\infty} \sum_{l=0}^{m_k-1} \frac{t^l}{l!} e^{\lambda_k t} p_{kl}$$

if $\operatorname{Re}(\lambda_k) < 0$

⇒ (i) ZIR is $\text{bdd} \rightarrow 0$

(ii) ZSR is $\text{bdd} + \text{bdd } u$ ~~XXXX~~

moreover the rate @ which $y(t) \rightarrow 0$ is exponential
we say (1) is exp stable
(all e-values of A lie in open LHP)

20 Oct 1989

KST - discussion

mean 11.1/20

high 20

0-5 : 7

6-10 : 8

11-15 : 14

16-20 : 9

(5.) Also need property

$$e(t, t_0, x_0, u) = \underbrace{e(t, t_0, x_0, 0)}_{\text{ZIR}} + \underbrace{e(t, t_0, 0, u)}_{\text{ZSR}}$$

$$6.L: x_0 \mapsto (y(0), y(1), \dots, y(k))$$

$$x_0 \in X$$

$$y_k \in Y^{k+1}$$

$$L_0: X \rightarrow Y^{k+1}$$

$$L_0^*: Y^{k+1} \rightarrow X$$

but L_0^* gives maps

$$L_0^*: Y' \rightarrow X$$

counter (example): $\langle z, L_0 x \rangle = \sum_{i=0}^K z_i^* y(i) x$

$$\langle L_0^* z, x \rangle = \left[\sum_{i=0}^K (A^*)^i C^* z_i \right]^* x_0$$

we want the form $[L_0^* z]^* x$

$$L_0^* = \left\{ C^*, (A^*) C^*, (A^*)^2 C^*, \dots, (A^*)^K C^* \right\}$$

HW prob.

For cont. time system is exp stable if $\lambda \in \mathbb{C}_-$ (open LHP plane)

$$\dot{x} = A_c x; \text{ cont sys.}$$

with discretized version be stable

$$x(k+1T) = A_{D/C} x(kT)$$

$$A_{D/C} = \exp(A_c T)$$

where T is the sampling period

for $A_c \in \mathbb{C}$ distinct eigenvalues

$$\exp(A_c T) = \sum_{i=1}^N \exp(\lambda_i T) R_i \quad \text{when } \lambda_i \in \mathbb{C}_-, \text{ then}$$

$$|\exp(\lambda_i T)| < 1, \text{ so}$$

$$\text{let } \lambda_{Di} = \exp(\lambda_i T) = \sum_{i=1}^N \lambda_{Di} R_i$$

$$\text{with } |\lambda_{Di}| < 1$$

will be stable!

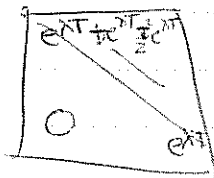
(λ_{Di} in unit disk)

Non distinct: look @ Jordan form term by term

Jordan Form

$e^{At} (JT)$ will have its diagonal element

$$|i|. T^i e^{At} (JT)$$



upper triangular

↑ c. values are diag. elem
c.v. are e^{At}

⇒ again will be stable
if $\text{Re}(\lambda) < 0$

1. The first part of the document discusses the importance of maintaining accurate records of all transactions.

2. It is essential to ensure that all data is entered correctly and that the system is regularly updated.

3. The second part of the document outlines the various methods used to collect and analyze data.

4. These methods include surveys, interviews, and focus groups, each with its own strengths and weaknesses.

5. The third part of the document describes the process of data analysis and the tools used to facilitate this process.

6. It is important to choose the right tools and techniques for the specific data being analyzed.

7. The fourth part of the document discusses the challenges of data analysis and how to overcome them.

8. These challenges include data quality, data quantity, and data complexity, and they can be addressed through careful planning and execution.

9. The fifth part of the document provides a summary of the key points discussed in the document.

10. It is hoped that this document will provide a useful overview of the field of data analysis and its applications.

11. The document concludes with a list of references and a bibliography of the sources used in the research.

12. This document is intended for use as a reference and is not to be distributed outside of the organization.

13. The document is the property of the organization and is to be kept confidential.

Sday
24, 1989

AST-lecture

Singular Value Decomposition

1. Review of adjoint

$A: V \rightarrow U$ linear

The adjoint of A

$A^*: U \rightarrow V$,

$\forall y \in V, \forall x \in U \quad \langle x, Ax \rangle_V = \langle A^*y, x \rangle_U$

Q: - Existence of adjoint
- uniqueness

Properties of A^*

(1) A^* is unique

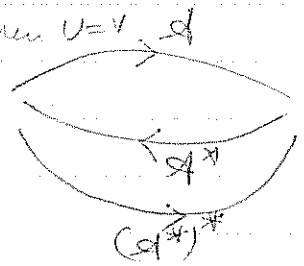
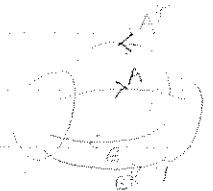
(2) A^* is a linear map also

$A^* + B^* = (A+B)^*$

$(\alpha A)^* = \bar{\alpha} A^*$

(3) $(AB)^* = B^*A^*$; makes sense only when $U=V$

(4) $(A^*)^* = A$



A, B both $V \rightarrow V$

2. Structure of a linear map

If $U = M_1 \oplus M_2$

$\forall x \in M_1, \langle x, y \rangle = 0 \quad \forall y \in M_2$

M_1 and M_2 are orthogonal

$M_1 \perp M_2 \quad U = M_1 \oplus M_2$

$U = M_1 \oplus M_1^\perp$

$M_2 = M_1^\perp$

$M_1 = M_2^\perp$

Note that for a finite dimensional space we can always write $U = M_1 \oplus M_1^\perp$ where M_1 is a subspace of U .
for let x_1, \dots, x_m span M_1 . Then $(x_1, \dots, x_m, x_{m+1}, \dots, x_n)$ span U [we always choose x_{m+1}, \dots, x_n].
do Gram-Schmidt orthogonalization on $x_1, \dots, x_m, x_{m+1}, \dots, x_n$ to get $(e_1, \dots, e_m, e_{m+1}, \dots, e_n)$. Clearly e_1, \dots, e_m span M_1 .
 M_1^\perp is all l.c. of $e_{m+1}, \dots, e_n \Rightarrow U = M_1 \oplus M_1^\perp$

Note: M^\perp = set of vectors that are orthogonal to every vector in M .

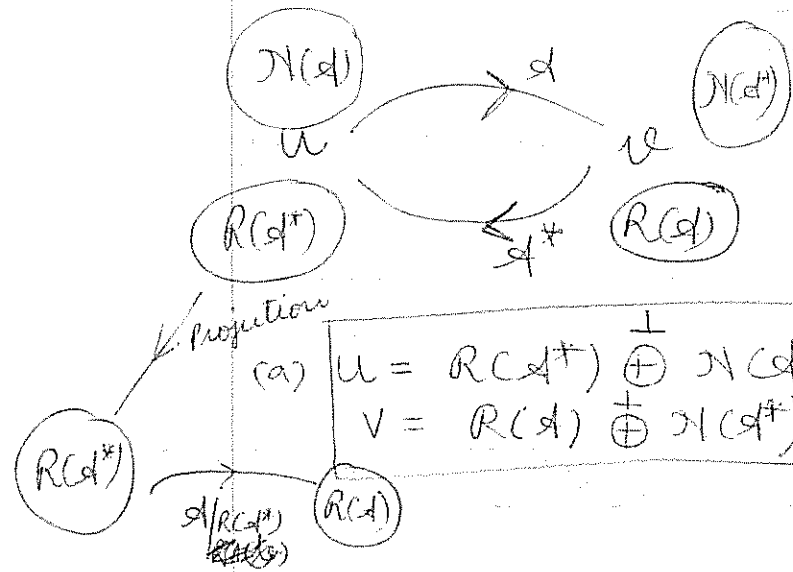
$(M^\perp)^\perp = M$ (for finite dimensional spaces)

1) Let $A: U \rightarrow V$ linear

so $A^*: V \rightarrow U$



linear are finite

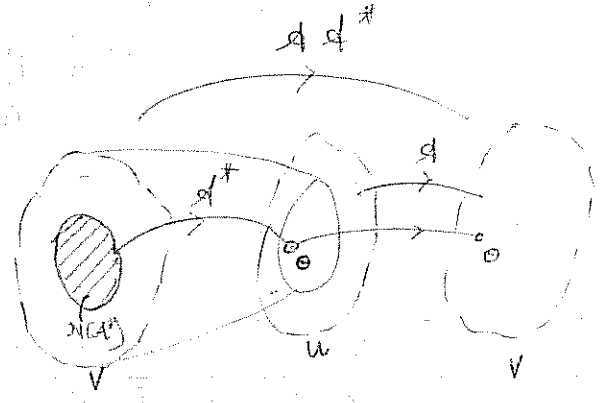


(a) $u = R(A^*) \oplus N(A)$
 $v = R(A) \oplus N(A^*)$

|| fundamental decomposition!
 [can obtain matrix repns]

(b) $A|_{R(A^*)} : R(A^*) \rightarrow R(A)$
 one to one, onto

(c) $N(A^*) = N(AA^*)$



$N(AA^*) \supseteq N(A^*)$ (clear)
 also $N(AA^*) = N(A^*)$

(d) $R(A) = R(AA^*)$

Proof (a) $V^* = R(A) \oplus R(A)^{\perp}$
 $R(A)^{\perp} =$

$y \in R(A)^{\perp} \Leftrightarrow \langle y, Ax \rangle = 0 \forall x$
 $\Leftrightarrow \langle A^*y, x \rangle = 0 \forall x$; $x = A^*y$
 $\Leftrightarrow A^*y = 0$
 $\Leftrightarrow y \in N(A^*)$

$\Rightarrow R(A)^{\perp} = N(A^*)$

proof (b) onto $\forall y \in R(d)$ want to show $\exists x_1 \in R(d^*)$
 s.t. $dx_1 = y$

$\forall y \in R(d)$ by defn $\exists x \in U$ s.t. $dx = y$
 but a) $\Rightarrow x = x_1 + x_2, x_1 \in R(d^*) \quad x_2 \in N(d)$
 $dx = dx_1 + dx_2 = dx_1$
 $\Rightarrow \exists x_1 \in R(d^*)$ s.t. $dx_1 = y$ (onto)

(1-1) : suppose $dx_1 = d\bar{x}_1 = y$
 want to show $x_1 = \bar{x}_1$

$x_1, \bar{x}_1 \in R(d^*)$
 on the other hand

$d(x_1 - \bar{x}_1) = 0$
 $\therefore (x_1 - \bar{x}_1) \in N(d)$
 but $(x_1 - \bar{x}_1) \in R(d^*)$ (i.e. elements of $R(d^*)$)
 but only element in common is zero.
 $\therefore x_1 = \bar{x}_1$

(c) $N(d^*) \subseteq N(d d^*)$

(i) $y \in N(d^*)$

$$\Leftrightarrow d^* y = 0$$

$$\Rightarrow d d^* y = d 0 = 0 \Rightarrow y \in N(d d^*)$$

(ii) $N(d d^*) \subseteq N(d^*)$

$$y \in N(d d^*) \Leftrightarrow d d^* y = 0 \Rightarrow \langle y, d d^* y \rangle = 0$$

only one way!

$$\Rightarrow \langle d^* y, d^* y \rangle = 0$$

$$\Rightarrow \|d^* y\|_2^2 = 0$$

$$\Rightarrow d^* y = 0$$

$$\Rightarrow y \in N(d^*)$$

$$(d) \quad R(d) = (N(d^*))^\perp = (N(d d^*))^\perp$$

$$= (R(d d^*))^\perp$$

$$= R(d^*)$$

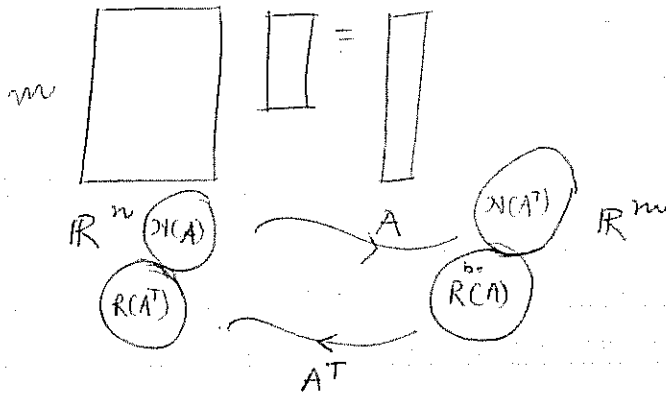
$$\text{recall } R(d^*)^\perp = N(d^*)$$

$$R(d d^*)^\perp = N(d d^*) \quad (NR)^\perp = R^*$$

$$= N(d^*)$$

3 Least Squares

$$Ax = b \quad ; \quad A \in \mathbb{R}^{m \times n} \quad (m > n)$$



SCENARIO I

$$b \in R(A)$$

\exists unique $x_1 \in R(A^T)$ s.t. $Ax_1 = b$

case 1) $N(A) = \{0\}$ i.e. columns are lin ind
i.e. matrix has full (col) rank

$\therefore R^n = R(A^T) \Rightarrow \exists$ unique $x \in \mathbb{R}^n$ s.t. $Ax = b$

if A doesn't have full rank then AT doesn't have full rank
if AT doesn't have full rank, then there are fewer than n lin ind columns (i.e. fewer than n lin ind rows) so can't span \mathbb{R}^m

algebraically,

$$Ax = b$$

solve this by:

$$A^T A z = A^T b$$

$(A^T A)^{-1} \neq A^{-1} (A^T)^{-1}$ in general, \therefore may not be conformable!

$$z = (A^T A)^{-1} A^T b \quad ; \quad \text{assume } (\)^{-1} \text{ exists}$$

$$= (\)^{-1} \begin{bmatrix} A^T \\ \parallel \end{bmatrix} ; \quad \text{Hilbert/Kar, } x \in R(A^T)$$

case (2) $N(A)$ contains non zero elements

$$x = x_1 + x_2 \quad x_2 \in N(A)$$

$Ax = b$; an ∞ of solns, ; but in all of them x_1 is same!

but $\|x\|_2^2 = \|x_1\|_2^2 + \|x_2\|_2^2$

x_1 is the solution which has minimal norm

Euclidean norm

$\because A: R(A^T) \rightarrow R(A)$ is 1-1 onto
 $x \in R(A)$

scenario

II $\Rightarrow b \in \mathbb{R}(A)$

$b = b_1 + b_2 \quad b_1 \in \mathbb{R}(A) \quad b_2 \in \mathcal{N}(A^T)$

\exists unique $x_1 \in \mathbb{R}(A^T)$

s.t. $Ax_1 = b_1$

consider $(Ax - b)$
 $= (Ax - b_1 - b_2)$ $\therefore \|Ax - b_1 - b_2\|_2^2 = \|Ax - b_1\|_2^2 + \|b_2\|_2^2$
 $b_2 \in \mathcal{N}(A^T) = \{\mathbb{R}(A)\}^\perp$

i.e. x_1 is ~~the~~ vector which minimizes $\|Ax - b\|_2^2$ (equiv to minimizing $\|Ax - b_1\|_2^2$)

case 1) $\mathcal{N}(A) = \{0\}$; A has full rank

\exists a unique x_1 s.t. $\|Ax - b\|$ is minimized (least sq. soln)

$Ax - b - b_2 \in \mathcal{N}(A^T) \Rightarrow A^T(Ax - b) = 0$
 $A^T(Ax) = A^T b = A^T(b_1 + b_2) = A^T b_1 + A^T b_2 = 0$

$(A^T A)x_1 = A^T b$

A full rank \Rightarrow can solve for x_1 (any b)

The soln of this eqn gives us the least squares soln

case 2) $\mathcal{N}(A) \neq \{0\} \Rightarrow$ A has not full rank (col. rank $<$ row rank)

$\Rightarrow \exists$ a unique x_1 s.t. $Ax - b_1 = 0$

just solve for $Ax = b_1$ (an ∞ of solns)

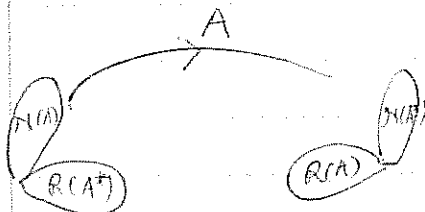
& choose that x_1 which has min norm \rightarrow it will lie in $\mathbb{R}(A)$
 \hookrightarrow Hilbert theory indicates that its unique!

usually we will have x_1 in $\mathbb{R}(A)$ which has min norm
 \Rightarrow basically \exists unique x_1 in \mathbb{R}^n s.t. $Ax = b$

we will find x_1 in $\mathbb{R}(A)$ which has min norm
 \Rightarrow x_1 will lie in $\mathbb{R}(A)$ (col. rank $<$ row rank)

Thursday
25 Oct 1989

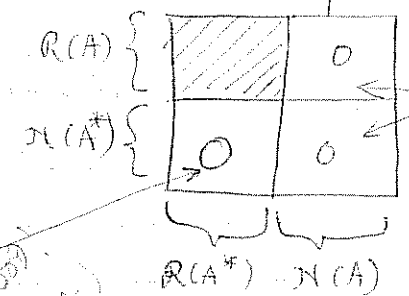
LST-Lecture



wrt bases
A has matrix rep.

choose basis
 $R(A^*), N(A)$

$R(A^*) \quad N(A^*)$



$u_i \in R(A^*)$
 $Au_i \in R(AA^*)$
 $Au_i \in R(A)$

\Rightarrow

(mutually linear)

$u_i \in N(A)$
 $Au_i = 0$

So choose basis to simplify

We know $R(A^*) = R(A^*A)$
 $N(A) = N(A^*A)$

A^*A is better: it has property that
 $(A^*A)^* = A^*A$

one can
write a matrix
with A^*A

4. Hermitian matrices
defn A Hermitian $\Leftrightarrow (A^* = A)$
(special case: A Real \Rightarrow A symmetric)

Properties

- (1) all eigen values are real
- (2) $\lambda_i \neq \lambda_j \Rightarrow \langle e_i, e_j \rangle = 0$ (more than just li.)
- (3) $\mathbb{C}^n = N(A - \lambda_1 I) \oplus N(A - \lambda_2 I) \dots \oplus N(A - \lambda_k I)$ (previously $N(A - \lambda_i I)$)
- (4) $\lambda_{\min} \leq \frac{\langle x, Ax \rangle}{\langle x, x \rangle} \leq \lambda_{\max}$

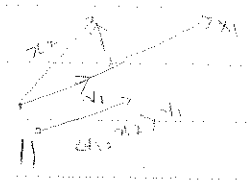
(3) $\Rightarrow m_k = 1$

\Rightarrow every chain of generalized eigenvector has length 1.
 $\Rightarrow \exists$ basis consisting of just eigen vectors.

linearly independent

Can prove by ind vector
 you find norm orthonormal basis
 you give you an orthonormal set
 $v_1 = x_1 / \|x_1\|$
 $v_2 = (x_2 - \langle v_1, x_2 \rangle v_1) / \|x_2 - \langle v_1, x_2 \rangle v_1\|$
 $v_3 = (x_3 - \langle v_1, x_3 \rangle v_1 - \langle v_2, x_3 \rangle v_2) / \|x_3 - \langle v_1, x_3 \rangle v_1 - \langle v_2, x_3 \rangle v_2\|$
 but v_1, v_2, v_3 is orthonormal
 \Rightarrow process

Claim Given a set of lin ind. eigen vectors $\{x_1, x_2, \dots, x_m\}$



$$v_1 = x_1 / \|x_1\|$$

$$v_2 = (x_2 - \langle v_1, x_2 \rangle v_1) / \|x_2 - \langle v_1, x_2 \rangle v_1\|$$

$$v_3 = (x_3 - \langle v_1, x_3 \rangle v_1 - \langle v_2, x_3 \rangle v_2) / \|x_3 - \langle v_1, x_3 \rangle v_1 - \langle v_2, x_3 \rangle v_2\|$$

$\{v_1, \dots, v_m\}$ set of orthonormal vectors.

$$U = \begin{bmatrix} | & | & & | \\ e_1 & e_2 & \dots & e_n \\ | & | & & | \end{bmatrix}$$

from (3) $u_i \cdot u_k = \delta_{ik}$

every chain of gen e-vectors has length 1. \exists basis consisting of e-vectors which is also orthonormal.

U^{-1} exists (lin ind)

also $U^* U = I$ (\because orthonormal)

$\Rightarrow U^{-1} = U^*$ (unitary matrix)

\downarrow when $\lambda_i \neq \lambda_j$ orthonormal vectors are orthogonal. \Rightarrow if $\lambda_i = \lambda_j$ then any set of them is also orthogonal. \Rightarrow if $\lambda_i = \lambda_j$ then any set of them is also orthogonal.

$$AU = U\Delta \quad \Delta = \text{diag}(\text{e-values}) \quad (\because A[e_1, e_2, \dots, e_n] = [Ae_1, Ae_2, \dots, Ae_n] = [\lambda_1 e_1, \lambda_2 e_2, \dots, \lambda_n e_n])$$

$$\therefore A = U\Delta U^* \quad \text{not nec. distinct}$$

\therefore Hermitian matrix can always be diagonalized.

Pf 1) λ_i e-value $\Rightarrow \lambda_i = \bar{\lambda}_i$ (want)

e_i corresp e-vector $\leftarrow \langle e_i, Ae_i \rangle = \langle e_i, \lambda_i e_i \rangle = \lambda_i \|e_i\|^2$

$$= \langle A^* e_i, e_i \rangle$$

$$= \langle Ae_i, e_i \rangle \quad (\text{defn of Hermitian})$$

$$= \langle \bar{\lambda}_i e_i, e_i \rangle$$

$$= \bar{\lambda}_i \langle e_i, e_i \rangle$$

$$= \bar{\lambda}_i \|e_i\|^2$$

$$\Rightarrow (\lambda_i - \bar{\lambda}_i) \|e_i\|^2 = 0 \Rightarrow \lambda_i = \bar{\lambda}_i$$

how do you show $AA^* = I$ $\Rightarrow A^{-1} = A^*$



$$A\underline{b} = \underline{0} \Rightarrow A = 0 \text{ or } \underline{b} = \underline{0} \text{ (if matrix not singular)}$$

$$2) \langle e_i, e_j \rangle = \lambda_j \langle e_i, e_j \rangle \\ = \langle A e_i, e_j \rangle = \lambda_i \langle e_i, e_j \rangle$$

$$\therefore (\lambda_j - \lambda_i) \langle e_i, e_j \rangle = 0 \quad ; \text{ but } \lambda_i \neq \lambda_j \quad \forall i \neq j$$

$$\therefore \langle e_i, e_j \rangle = 0 \quad \forall i \neq j \quad e_i^* e_j = 0 \text{ in vector formal}$$

3) want to show $m_k = 1$

suppose $m_k \geq 2$

$$\Rightarrow \exists \underline{z} \neq \underline{0} \text{ (gen. eigen vector)} \text{ s.t. } (A - \lambda_k I)^{m_k} \underline{z} = \underline{0}$$

$$= \langle (A - \lambda_k I)^{m_k/2} \underline{z}, (A - \lambda_k I)^{m_k/2} \underline{z} \rangle \quad (A - \lambda_k I)^{m_k-1} \underline{z} \neq \underline{0}$$

(\therefore Hermitian) get a contradiction

$$0 = \langle \underline{z}, (A - \lambda_k I)^{m_k} \underline{z} \rangle = \|(A - \lambda_k I)^{m_k/2} \underline{z}\|^2 = 0 \quad ; \text{ no problem when you have } m_k \text{ even.}$$

$$\left([(A - \lambda_k I)^{m_k}]^* = [(A^* - \lambda_k I)^{m_k}] = (A - \lambda_k I)^{m_k} \therefore \text{Hermitian} \right)$$

if m_k ~~odd~~ even set $m_k = 2\mu_k$
if m_k odd set $m_k + 1 = 2\mu_k$

$$\text{So } (A - \lambda_k I)^{2\mu_k} \underline{z} = \underline{0}$$

consider

$$0 = \langle \underline{z}, (A - \lambda_k I)^{2\mu_k} \underline{z} \rangle = \langle (A - \lambda_k I)^{\mu_k} \underline{z}, (A - \lambda_k I)^{\mu_k} \underline{z} \rangle$$

$$\Rightarrow (A - \lambda_k I)^{\mu_k} \underline{z} = \underline{0} \quad ; \text{ where } \mu_k < m_k$$

$$\Rightarrow \text{contradiction (} \therefore (A - \lambda_k I)^{m_k-1} \underline{z} \neq \underline{0} \text{)}$$

TPT.

$$4) \lambda_{\min} \leq \langle \frac{x}{\|x\|}, A \frac{x}{\|x\|} \rangle \leq \lambda_{\max}$$

$\leftarrow y \rightarrow \quad \leftarrow y \rightarrow$

$$\text{put } y = \frac{x}{\|x\|} \Rightarrow \|y\| = 1$$

$$\text{TPT } \lambda_{\min} \leq \langle y, Ay \rangle \leq \lambda_{\max}$$

$$\text{where } \langle y, y \rangle = 1$$

$$i \quad \max \langle y, Ay \rangle \leq \lambda_{\max} \quad \text{when } \|y\| = 1$$

$$\min \langle y, Ay \rangle \geq \lambda_{\min} \quad \text{when } \|y\| = 1$$

max/min $y^* A y$ s.t. $y^* y = 1$; max of multimp
 under one constraint

Solution $L(y, \lambda) = \frac{1}{2} y^* A y - \lambda (y^* y - 1)$; sort of quadratic
 (diff by expanding)

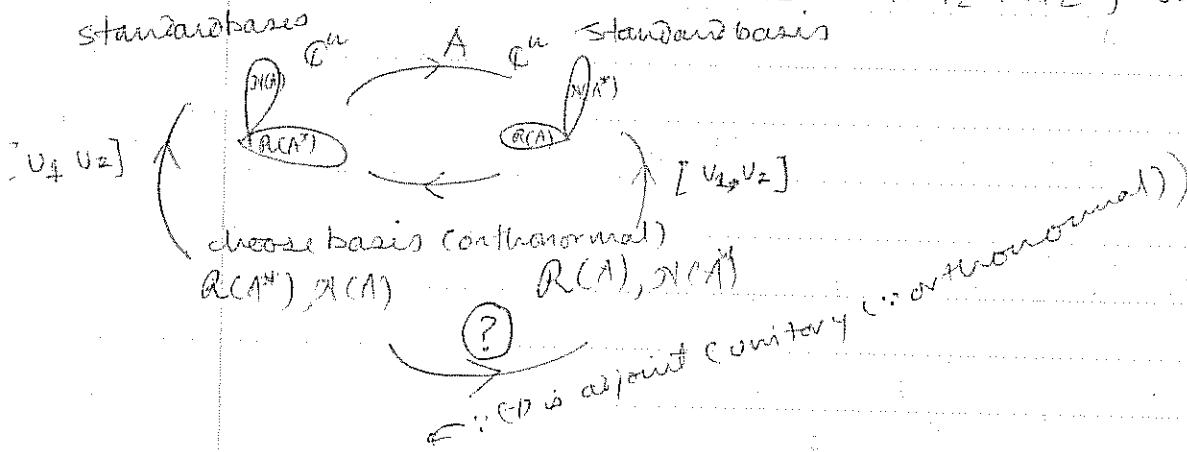
$$\begin{aligned} \partial L / \partial y = 0 &\Rightarrow y^* A - \lambda y^* = 0 \\ &\Rightarrow A y = \lambda y \end{aligned} \quad \left(\text{Hermitian!} \right)$$

ie max or min^m occurs when y is an eigen vec
 $\langle y, A y \rangle = \lambda \langle y, y \rangle = \lambda$
 so the maxima is λ_{\max}
 minima is λ_{\min}

A real, implication $\Rightarrow \langle x, A^T A x \rangle = \|A x\|_2^2$
 $\langle x, A^T A x \rangle \leq [\lambda_{\max}(A^T A)] \langle x, x \rangle$ ($T = \neq$ when A is complex)
 $= [\lambda_{\max}(A^T A)] \|x\|_2^2$

Define $\|A\|_2 = \sqrt{\lambda_{\max}(A^T A)}$

then we have $\|A x\|_2 \leq \|A\|_2 \|x\|_2$; induced norm.



$$? = \begin{bmatrix} v_1^* & v_2^* \\ v_1^* & v_2^* \end{bmatrix} [A] \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$= \begin{bmatrix} v_1^* A u_1 & 0 \\ 0 & 0 \end{bmatrix}$$

How can we simplify $v_1^* A u_1$?

$$\begin{bmatrix} v_1 & v_2 \end{bmatrix}^T R(A^*) = R(A^* A)$$

$$\Rightarrow N(A) = N(A^* A)$$

$$\begin{aligned} v_1^* A u_1 &= v_1^* \begin{bmatrix} v_1 & v_2 \end{bmatrix}^T R(A^*) \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ &= v_1^* \begin{bmatrix} v_1 & v_2 \end{bmatrix}^T \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ &= v_1^* \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ &= v_1^* \begin{bmatrix} u_1 \\ 0 \end{bmatrix} \\ &= v_1^* u_1 \end{aligned}$$

look at

$A^* A$: hermitian \therefore can diagonalize!
 \Rightarrow representation $\text{sm}(\text{eigenvalues})$

A^*A Hermitian

- ⇒ (i) e-values are real
- (ii) e-vectors orthonormal basis
- (iii) e-values are non negative

*repeated vector for same e-value ⇒ all vectors for it are orthogonal to each other
property of vector
Hermitian matrix
work of span all basis
will still work all
equivalent*

let (λ, e) be eigenvalue / eigenvector of A^*A

$$\langle e, A^*Ae \rangle = \|Ae\|_2^2 \geq 0$$

$$= \lambda \langle e, e \rangle = \lambda \|e\|^2 \geq 0 \Rightarrow \lambda \geq 0. \quad \text{QED}$$

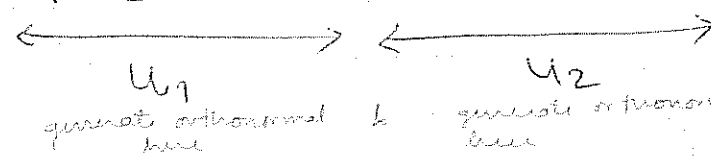
Let eigenvalues of A^*A be $\sigma_1^2, \sigma_2^2, \dots, \sigma_r^2, \sigma_{r+1}^2, \dots, \sigma_n^2$
(: non negative)

(multiple eigenvalues appear with their multiplicity)

order them $\rightarrow \sigma_1 > \sigma_2 > \dots > \sigma_r > 0 \quad \sigma_{r+1} = \dots = \sigma_n = 0$

e-vectors of A^*A

$u_1, u_2, \dots, u_r, u_{r+1}, \dots, u_n$: basis for \mathbb{R}^n



*they are already orthogonal (: $u_1, \dots, u_r, u_{r+1}, \dots, u_n$)
if u_{r+1}, \dots, u_n span 0*

pick u_1, u_2 to be orthogonal i.e. $\begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = I$

~~and $[A^*A]$~~ and $\begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix} [A^*A] \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} \Sigma^2 & 0 \\ 0 & 0 \end{bmatrix}$

where $\Sigma^2 = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_r^2 \end{bmatrix}$

columns of U_2 span null space $N(A^*A) = N(A)$ ∴ right vectors to use (look at B^A diagram)

columns of U_1 span $R(A^*A) = R(A^*)$; same

compare to the property of Hermitian matrices:

$$C^n = N(A - \lambda I) \oplus N(A - \lambda^* I) \quad \dots \quad \oplus N(A - \lambda I)$$

choose u_1 ?

Au_1 spans Range Space of $A = \mathcal{R}(A)$ my p.m. figure
in general $v_1 = [Au_1] \begin{bmatrix} \sigma_1 \\ 0 \end{bmatrix}$

each col. results in l.c. of $[Au_1]$

can form a basis like this

want $v_1^* v_1 = I$ (orthonormal)

$$\therefore \begin{bmatrix} \sigma_1 \\ 0 \end{bmatrix}^* u_1^* A^* A u_1 \begin{bmatrix} \sigma_1 \\ 0 \end{bmatrix} = I \quad ; \text{ looks familiar (recall } \begin{bmatrix} \sigma^2 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\xrightarrow{\Sigma^2}$$

$$\begin{bmatrix} \sigma \\ 0 \end{bmatrix}^* = \begin{bmatrix} \sigma^{-1} & 0 \end{bmatrix}$$

$$\therefore \begin{bmatrix} \sigma_1 \\ 0 \end{bmatrix} = \Sigma^{-1} \quad ; \quad \Sigma^2 = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

$$Au_1 = \Sigma v_1$$
$$Au_1 = \begin{bmatrix} \sigma_1 v_1 \\ \sigma_2 v_2 \end{bmatrix}$$

So $v_1 = Au_1 \Sigma^{-1}$ will do the job

\hookrightarrow this even if A isn't square you can move it home!

choose $v_2 =$ orthonormal complement (we aren't interested in it)

w/ this choice of $[u_1, u_2]$ & $[v_1, v_2]$

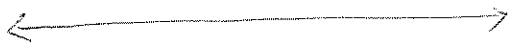
$$v_1^* A u_1 = (\Sigma^{-1} u_1^* A^*) (A u_1) = \Sigma \quad ; \text{ a diagonal matrix}$$

$$\therefore \textcircled{?} = \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \quad ; \quad \Sigma = \begin{bmatrix} \sigma_1 & & 0 \\ & \sigma_2 & \\ 0 & & \sigma_2 \end{bmatrix}$$

Final result: choose basis $[u_1, u_2]$ $[v_1, v_2]$

then matrix up is diagonal matrix

$$A = [v_1, v_2] \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix} \quad ; \quad \sigma_i \text{ are called singular values of } A.$$



this expression is called a singular value decomposition, **(SVD)**

$$A = \sum_{i=1}^r \sigma_i v_i v_i^*$$

|| —————

here v_i is an e.v. of $A^* A$
 σ_i are $\sqrt{\text{e.v. of } A^* A}$

Friday
25 Oct 1989

Discussion KST-KRAMER

- ① Adjoints
- ② Stability (motivation)
- ③ SVD
- ④ more stability (discrete time system)

Properties of Adjoints

Let E & F be Hilbert spaces

Let $A, B : E \rightarrow F$

$$(i) (A+B)^* = A^* + B^*$$

$$(ii) (\alpha A)^* = \alpha^* A^* ; \alpha \in \mathbb{F}$$

$$(iii) (AB)^* = B^* A^* ; E = F$$

$$(iv) A^{**} = A$$

pf (iii) $\forall z \in E, y \in F$

$$\begin{aligned} \langle z | (AB)^* y \rangle &= \langle ABz | y \rangle = \langle A(Bz) | y \rangle \\ &= \langle Bz | A^* y \rangle = \langle z | B^* A^* y \rangle \end{aligned}$$

$$\text{now } \langle z | (B^* A^*) y - (AB)^* y \rangle = 0 \quad (\forall \text{ all } z, y)$$

$$\text{choose } z = (B^* A^*) y - (AB)^* y$$

$$\text{let } x = B^* A^* y - (AB)^* y \Rightarrow \langle B^* A^* y - (AB)^* y | B^* A^* y - (AB)^* y \rangle$$

$$\therefore \| (B^* A^* - (AB)^*) y \|^2 = 0$$

$$\Rightarrow B^* A^* - (AB)^* = 0$$

$$A : E \rightarrow F \quad A^* : F \rightarrow E$$

$$B : F \rightarrow E \quad B^* : E \rightarrow F$$

$$AB : F \rightarrow F \quad B^* A^* : F \rightarrow F$$

$$\dot{x}_1 = x_1(x_1^2 - 3x_1 + 3) - x_2$$

$$\dot{x}_2 = x_1 - x_2$$

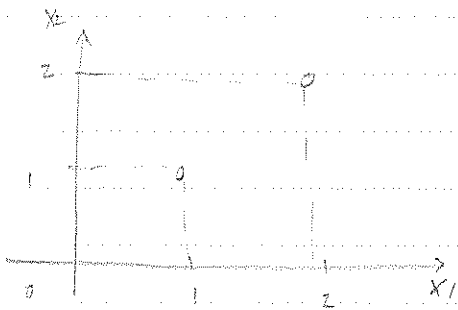
// Eq pts : places where
derivatives are zero

equilibrium pts: $\dot{x} = 0$

$$x_1 = x_2$$

$$x_1(x_1^2 - 3x_1 + 3) - x_2 = 0$$

Eq. pts: $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $\begin{bmatrix} 2 \\ 2 \end{bmatrix}$



linearize around each eq. pt (via Jacobian)

$$f_1(x_1, x_2) = x_1^3 - 3x_1^2 + 3x_1 - x_2$$

$$\partial f_1 / \partial x_1 = 3x_1^2 - 6x_1 + 3$$

$$\partial f_1 / \partial x_2 = -1$$

$$\partial f_2 / \partial x_1 = 1 \quad \partial f_2 / \partial x_2 = -1$$

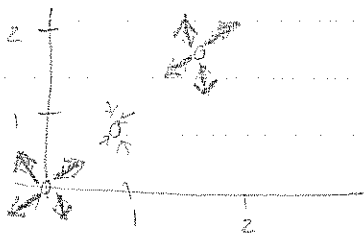
$$\dot{x} = Ax \quad A(x) = \begin{bmatrix} 3x_1^2 - 6x_1 + 3 & -1 \\ 1 & -1 \end{bmatrix}$$

$$A\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 3 & -1 \\ 1 & -1 \end{bmatrix} = A\left(\begin{bmatrix} 2 \\ 2 \end{bmatrix}\right)$$

$$A\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 0 & -1 \\ 1 & -1 \end{bmatrix}$$

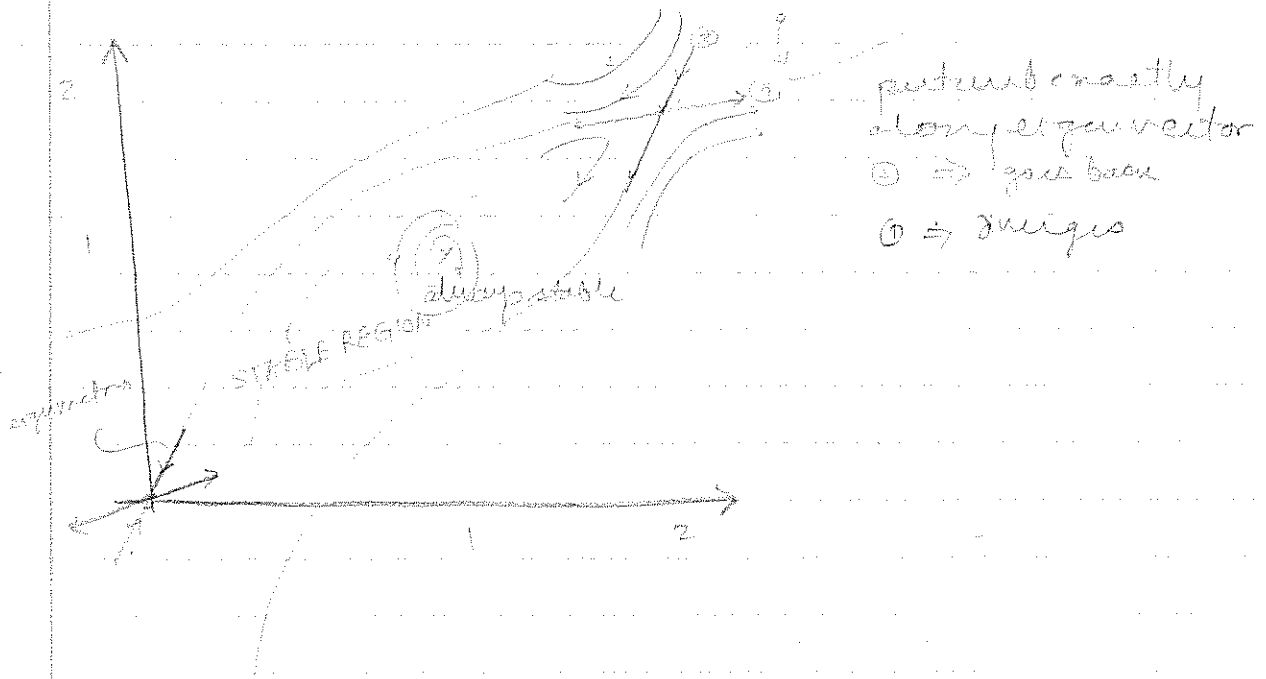
eigenvalues at $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ $\lambda_{1,2} = \frac{1}{2}(2 \pm \sqrt{12})$

one positive $\text{Re}(\lambda) \Rightarrow$ unstable



one value +ve, one -ve
 \Rightarrow saddle pt (not quite top/bottom of hill)

$$e_1 = \begin{bmatrix} 1 \\ 2 - \sqrt{3} \end{bmatrix} \quad e_2 = \begin{bmatrix} 1 \\ 2 + \sqrt{3} \end{bmatrix}$$



SVD - why bother?

- Controllability & observability issues

OBSERVABILITY - given input $u[t_0, t_1]$ and given the observation of output $y[t_0, t_1]$, the system is called completely observable if the initial state $x(t_0)$ can be uniquely determined.

CONTROLLABILITY - Given $x_0, x_1 \in \mathbb{R}^n$ $\exists u[t_0, t_1]$ s.t. $x(t_0) = x_0; x(t_1) = x_1$
 \uparrow initial state \uparrow final state

example)
$$\begin{bmatrix} -1 & 1 & 1 & 1 & -1 \\ & -1 & 1 & 1 & 1 \\ & & -1 & 1 & 1 \\ 0 & & & -1 & \\ & & & & -1 \end{bmatrix}$$

eigenvalues are all -1.
 non singular ($\det[E] = (-1)^n$)

(A-E) perturbation =
$$\begin{bmatrix} -1 + \frac{1}{2^{2^i}} & 1 & 1 & 1 & 1 \\ \frac{1}{2^{2^i}} & -1 & 1 & 1 & 1 \\ \frac{1}{2^{2^i}} & & -1 & 1 & 1 \\ \frac{1}{2^{2^i}} & & & -1 & 1 \\ \frac{1}{2^{2^i}} & & & & -1 \end{bmatrix}$$
 matrix is sing.

$$(A+B) \begin{bmatrix} 1 \\ 1/2 \\ \vdots \\ 1/2^{n-1} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

smallest singular value of $(A+B) \sim 1/2^{n-1}$

Example ($n=3$)

$$A = \begin{bmatrix} -1 & 1 & 1 \\ 0 & -1 & 1 \\ 0 & 0 & -1 \end{bmatrix} \quad A^*A = \begin{bmatrix} 1 & -1 & -1 \\ -1 & 2 & 0 \\ -1 & 0 & 2 \end{bmatrix}$$

$\Delta(\lambda) = \lambda^3 - 6\lambda^2 + 9\lambda - 1 = 0$ for eigenvalues
(all e.v. > 0 (characteristic))

for λ really small $\Delta(\lambda) \sim -1$

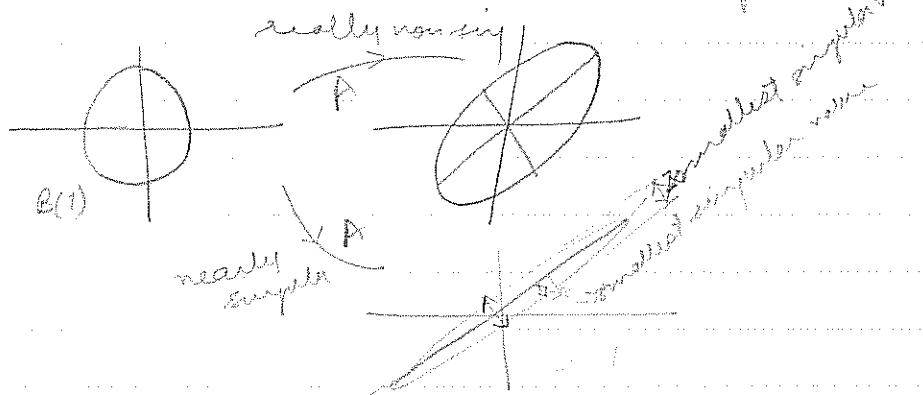
$$\lambda \sim 1/6 \Rightarrow (1/6)^3 - 6(1/6)^2 + 9(1/6) - 1 > 0$$

$\Rightarrow \exists$ eigenvalue between 0 & $1/6$

say near $1/6 = \lambda_3$

$$\lambda_2 \sim 1/\sqrt{6} \sim 1/2.5 \quad ; \text{ close to 0.}$$

tells you something about the "condition" of the matrix is (even though e.v. are all 1 & far away)



wrong example
wrong solution!

example:

let $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 8 & 24 \\ 0 & 24 & 32 \end{bmatrix}$ singular

$\lambda_1 = 50$
 $\lambda_2 = 1$
 $\lambda_3 = 0$

$\begin{bmatrix} 0 \\ 3 \\ 4 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ -4 \\ 3 \end{bmatrix}$

normalized \Rightarrow \div by 5 $\begin{bmatrix} 0 \\ 3/5 \\ 4/5 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ -4/5 \\ 3/5 \end{bmatrix}$

$N(A)$ spanned by e_3

$U_2 = [e_3]$ (complete the basis) $U_1 = [e_1 | e_2]$

$\Sigma^2 = U^* A^* A U$

$= \begin{bmatrix} 2500 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

$\sigma_1 = 50$
 $\sigma_2 = 1$
 $\sigma_3 = 0$ | same as e_i

want to get the decomposition of $A = V \Sigma U$

let $V_1 = A U_1 \Sigma^{-1} = \begin{bmatrix} 0 & 1 \\ 3/5 & 0 \\ 4/5 & 0 \end{bmatrix}$

complete the V basis $\rightarrow v_3 = \begin{bmatrix} 0 \\ 4/5 \\ -3/5 \end{bmatrix}$

$A = V \Sigma U$ $V = [v_1 | v_2 | v_3]$
 $U = [e_1 | e_2 | e_3] = [u_1 | u_2]$

$Ax = b$ given A, b find x

let $A = V \Sigma U$

$V \Sigma U x = b$; $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r$; order the singular values

now suppose $b = u_1 = (1^{st} \text{ column of } V \text{ basis})$

$$\underbrace{V^* V}_{I} \Sigma U^* x = V^* b \quad | \text{ Recall } U^* = U^{-1}; V^* = V^{-1}$$

$$\Sigma U^* x = \begin{bmatrix} v_1^* \\ v_2^* \\ \vdots \\ v_n^* \end{bmatrix} \begin{bmatrix} v_1 \\ \vdots \\ \vdots \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\Sigma U^* x = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}; \Sigma = \begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_n & & \\ & & & & & 0 & \\ & & & & & & \ddots & \\ & & & & & & & 0 \end{bmatrix}; \Sigma^{-1} = \begin{bmatrix} 1/\sigma_1 & & & \\ & 1/\sigma_2 & & \\ & & \ddots & \\ & & & 1/\sigma_n & & \\ & & & & & & & \\ & & & & & & & & & 0 & \\ & & & & & & & & & & \ddots & \\ & & & & & & & & & & & & & 0 \end{bmatrix}$$

$$\Sigma^{-1} \Sigma = \begin{bmatrix} 1 & & \\ & 1 & \\ & & \ddots \\ & & & 1 \end{bmatrix}$$

$$\therefore \Sigma^{-1} \Sigma U^* x = \Sigma^{-1} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} u_1^* \\ v_2^* \\ \vdots \\ v_n^* \end{bmatrix} x = \begin{bmatrix} 1/\sigma_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} | & | & | & | \\ | & U & | & | \\ | & | & | & | \end{bmatrix} \begin{bmatrix} u_1^* \\ \vdots \\ v_n^* \end{bmatrix} x = \begin{bmatrix} | & | & | & | \\ | & U & | & | \\ | & | & | & | \end{bmatrix} \begin{bmatrix} 1/\sigma_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix} x = 1/\sigma_1 \begin{bmatrix} u_1 \\ \vdots \\ \vdots \end{bmatrix}$$

Now say all σ_i are non zero

$$\Rightarrow x = 1/\sigma_1 [u_1]$$

Supposing real problem was $A(x + \delta x) = (b + \delta b)$
 $A \delta x = \delta b$ left over

suppose $\delta b = \epsilon \frac{v_n}{\|v_n\|}$; replace $1/\sigma_1$ by $1/\sigma_n$

By some
reasoning

$$\Rightarrow \delta x = \epsilon \frac{u_n}{\|u_n\|}$$

$$\frac{\|\delta x\|}{\|x\|} = \frac{\|\epsilon \frac{1}{\sigma_n} \frac{u_n}{\|u_n\|}\|}{\|1/\sigma_1 u_1\|} = \frac{\epsilon / \sigma_n}{1/\sigma_1} = \epsilon / \sigma_n$$

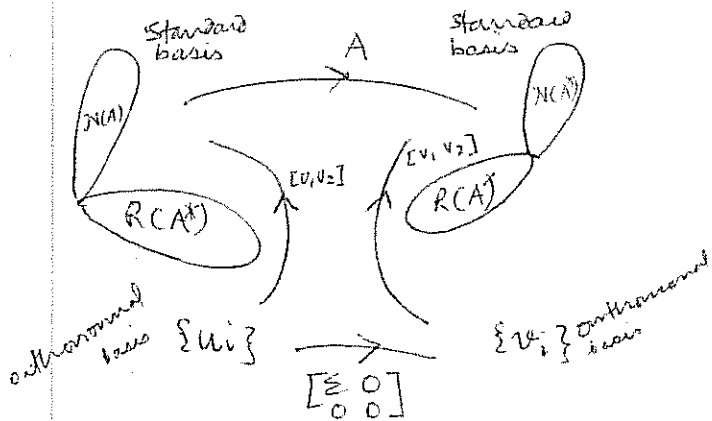
$$\| \delta x \| / \| x \| = [\| \epsilon \| / \sigma_n] / (\| \sigma \|) = \| \epsilon \| \sigma_1 / \sigma_n = \underbrace{\left[\frac{\sigma_1}{\sigma_n} \right]}_{\text{maximum magnification of error in soln}} \frac{\| \epsilon \|}{\| \sigma \|}$$

initial vector b in σ_1 dirn
 max δb in σ_n dirn

Tuesday
 31 October '89

AST-lecture

SVD Summary



$[u_1, u_2]$ columns are eigenvectors of A^*A

Σ = diagonal matrix (non zero σ -values of A^*A)^{1/2}

$$v_1 = A u_1 \Sigma^{-1}$$

v_2 = orthogonal complement

$$A = [v_1 \ v_2] \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix} = [v_1 \ v_2] \begin{bmatrix} \sigma_1 & & & 0 \\ & \sigma_2 & & 0 \\ & & \dots & 0 \\ & & & \sigma_n \\ & & & & 0 \\ & & & & & \dots \\ & & & & & & 0 \end{bmatrix} \begin{bmatrix} u_{11} & u_{12} & u_{13} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & & u_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ u_{n1} & u_{n2} & \dots & \dots & u_{nn} \end{bmatrix}$$

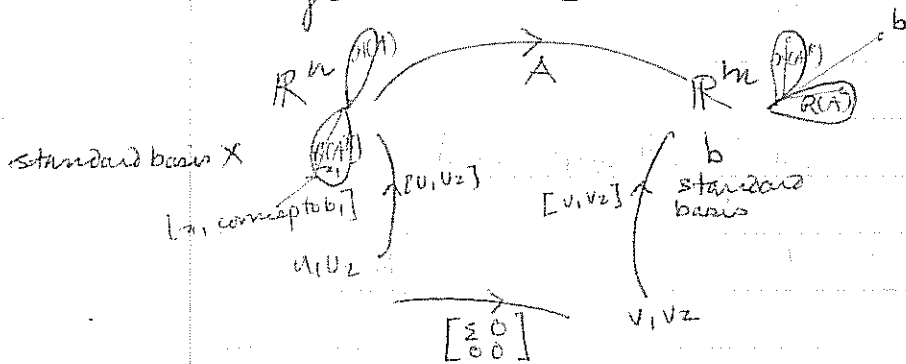
$$A = \sum_{k=1}^n \sigma_k v_k u_k^*$$

$$\begin{bmatrix} v_1^* \\ v_2^* \end{bmatrix} [A] \begin{bmatrix} u_1 & u_2 \end{bmatrix} = \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix}$$

$$= \sum_{k=1}^n v_k v_k^* A$$

Least Squares Problem

general case



$$\min \|Ax - b\|^2$$

$$b = b_1 + b_2$$

$$b_1 \in R(A)$$

x_1 is the one which minimizes $\|Ax - b\|^2$ & has minimum norm.

$$\min \|Ax - b\|^2$$

$$b \text{ in SVD coordinates} = \begin{bmatrix} v_1^* \\ v_2^* \end{bmatrix} b$$

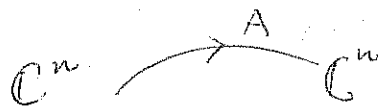
$$b_1 \text{ in SVD coordinates} = \begin{bmatrix} v_1^* b \\ 0 \end{bmatrix}$$

$$x_1 \text{ in SVD coordinates} = \begin{bmatrix} \Sigma^{-1} v_1^* b \\ 0 \end{bmatrix} = A^+ b$$

$$x_1 \text{ in standard basis} = [u_1 \ u_2] \begin{bmatrix} \Sigma^{-1} v_1^* b \\ 0 \end{bmatrix}$$

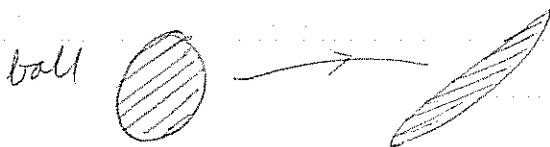
$$= u_1 \Sigma^{-1} v_1^* b$$

6. Geometric interpretation of SVD -
let A be $n \times n$ matrix, non singular



Span of A : should be \mathbb{C}^n

intuitively: not uniform mapping

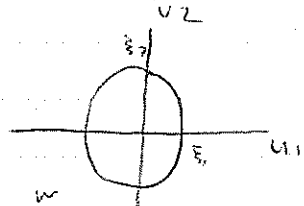


Examining a full unit will give us some idea of sp
 $B = \{x \in \mathbb{C}^n, \|x\|=1\}$

$$u \quad \mathbb{C}^n \xrightarrow{A} \mathbb{C}^n \quad v$$

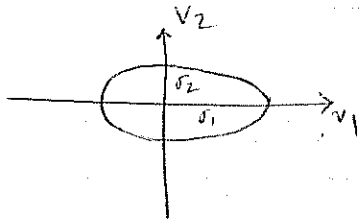
let $x = \sum_{i=1}^n \xi_i u_i$ $\{u_i\}$ orthonormal

$$\|x\|=1 \Leftrightarrow \sum_{i=1}^n \xi_i^2 = 1$$

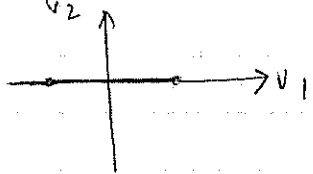


$$y = Ax = \sum_{i=1}^n \xi_i A u_i = \sum_{i=1}^n \xi_i \sigma_i v_i = \sum_{i=1}^n \eta_i v_i$$

$$\sum_{i=1}^n \xi_i^2 = 1 \Leftrightarrow \sum_{i=1}^n (\eta_i / \sigma_i)^2 = 1 \quad \therefore \text{Ellipsoid}$$



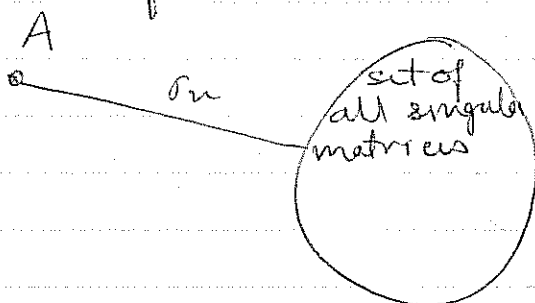
when $\sigma_2 = 0$: Matrix is singular



σ_2 small \Rightarrow gives idea of how close we are to singularity.

roughly speaking smallest singular value indication how the matrix is away from being singular.

Set of all $n \times n$ matrices



σ_n is (in some way) the distance between A & the set of all singular matrices

Thm: $A \in \mathbb{C}^{m \times n}$
 $A = \sum_{i=1}^r \sigma_i v_i u_i^*$ $\text{rank } A = r$

Let $A' = \sum_{i=1}^{r-1} \sigma_i v_i u_i^*$ $\therefore \text{rank } A' = r-1$

then (i) $\|A - A'\|_2 = \sigma_r$

(ii) $\|A - B\|_2$ ($B = \text{rank } B = r-1$)

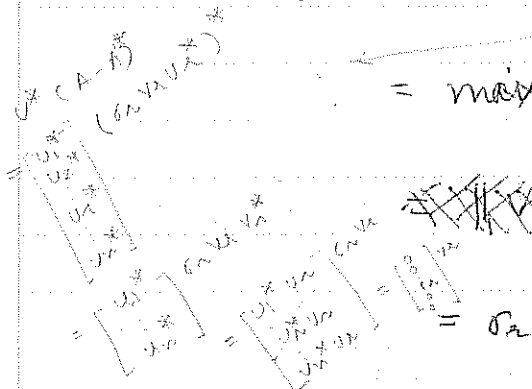
(ii) $\min_{\text{rank } B = r-1} \|A - B\|_2 = \sigma_r$

Pf (i) $\|A - A'\|_2 = \max \sqrt{\lambda (A - A')^* (A - A')}$

$= \max \sqrt{\lambda (U^* (A - A')^* (A - A') U)}$

$= \max \sqrt{\lambda (U^* (A - A')^* V V^* (A - A') U)}$

$= \max \sqrt{\lambda \begin{pmatrix} \sigma_r^2 & & \\ & \dots & \\ & & 0 \end{pmatrix}}$

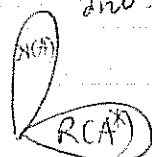


$(A - A')^*$ has rank 1
 $(A - A')^* (A - A')$ has rank 1
 Its eigenvalues is σ_r^2

(ii) Let $B \in \mathbb{C}^{m \times n}$ $\text{rank } B = r-1$

$\dim \mathcal{N}(B) = n - r + 1$

$\dim \mathcal{N}(A) = n - r$



$\dim \mathcal{N}(B) > \dim \mathcal{N}(A)$

$\therefore \mathcal{N}(B) \not\subseteq \mathcal{N}(A)$

$\exists z \neq 0$ in the intersection of $\mathcal{N}(B) \cap \text{span of } U$

$\|A - B\|_2 = \max_{\|z\|=1} \|(A - B)z\|_2$

$\geq \|(A - B)z\|_2$ (we choose $\|z\|=1$)

$\geq \|(A - B)z\|_2 = \left[\sum \sigma_i^2 (u_i^* z)^2 \right]^{1/2}$

$= \sum \sigma_i^2 (u_i^* z)^2 = \sum \sigma_i^2 \|u_i^* z\|^2$

Examine $\|A - B\|_2 = \max_{\|z\|=1} \|(A - B)z\|_2 \geq \|(A - B)z\|_2$

$\|z\|=1$

$\geq \|A z\|_2$

$= \|A z\|_2^2$

$= \sum_{i=1}^r \sigma_i^2 (u_i^* z)^2$

$\geq \sigma_r^2$

$\sum \sigma_i^2 (u_i^* z)^2$

$z = \alpha u_r$ (B)

Let z in span of u_i

$\leq \sigma_r^2 \alpha^2$

$\geq \sigma_r^2 \alpha^2$

exhibited a lower bound but we know the bound (at A) from

distance between $\|A-B\|_2 \geq \sigma_2$
 but we have already defined one
 s.t. it has $\|A-A'\|_2 = \sigma_1$ & $\text{rank}(A') = r-1$

we used only $\dim \mathcal{N}(A) > \dim \mathcal{N}(A')$

↑ if $\text{rank } B = k, k \leq r-1$
 still true!

In numerical analysis SVD imp

(i) error prop.

(ii) numerical stability

Ch VII
 PK →

CONTROLLABILITY & OBSERVABILITY (Supp see I-V)

1. Controllability

① Dynamical system $D = \{u, \dot{x}, y, s, r\}$



$t_0, t_1 \in T \quad t_1 > t_0$

$[t_0, t_1]$

def D is said to be completely
 controllable (c.c.) on $[t_0, t_1]$

$\Leftrightarrow \forall x_0, x_1 \in \Sigma \quad \exists u_{[t_0, t_1]}$ s.t. $(x_0, t_0) \rightarrow (x_1, t_1)$
 i.e. $x_1 = s(t_1, t_0, x_0, u_{[t_0, t_1]})$

Special Cases

a) $x_1 = \theta$

D is completely controllable to the origin
 on $[t_0, t_1]$

$\forall x_0 \in \Sigma \quad \exists u_{[t_0, t_1]}$ s.t. $\theta = s(t_1, t_0, x_0, u_{[t_0, t_1]})$

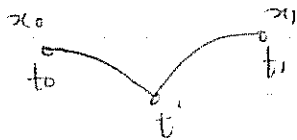
b.) $x_0 = \theta$ D is completely reachable \mathcal{R}

the origin on $[t_0, t_1]$

$$\forall x_1 \in \Sigma \exists u_{[t_0, t_1]} \text{ s.t. } x_1 = S(t_1, t_0, \theta, u_{[t_0, t_1]})$$

- (i) c.c. on $[t_0, t_1] \Rightarrow$ c.c. to θ on $[t_0, t_1]$; conv. not
 (ii) " " " \Rightarrow c.r. from θ on $[t_0, t_1]$; true in gen.

- (iii) c.c. to θ on $[t_0, t_1]$ } \Rightarrow c.c. on $[t_0, t_1]$
 + c.r. from θ on $[t', t_1]$ } $t_0 < t' < t_1$



For linear dynamical systems: \Leftrightarrow

(2) Linear System $R = [A(\cdot), B(\cdot), C(\cdot)]$

$$\dot{x}(t) = A(t)x(t) + B(t)u(t)$$

$$y(t) = C(t)x(t) + D(t)u(t)$$

\leftarrow directly added from i/p to o/p.
 doesn't change anything

c.c. on $[t_0, t_1] \Leftrightarrow$ (a) c.c. to θ on $[t_0, t_1]$
 (b) c.r. from θ on $[t_0, t_1]$

Proof: (\Leftarrow) (a) c.c. to θ on $[t_0, t_1]$
 $\Leftrightarrow \forall \xi_0 \exists \tilde{u} \text{ s.t. } \theta = \underbrace{\Phi(t_1, t_0)}_{ZIR} \xi_0 + \int_{t_0}^{t_1} \underbrace{\Phi(t_1, \tau)}_{ESR} B(\tau) \tilde{u}(\tau) d\tau$

want $\forall x_0, x_1 \exists \bar{u} \text{ s.t. } t_1$
 $x_1 = \Phi(t_1, t_0)x_0 + \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) \bar{u}(\tau) d\tau$

Need to make $\Phi(t_1, t_0)x_0 - x_1 = \Phi(t_1, t_0)\xi_0$

$$\Phi(t_1, t_0) \overbrace{(x_0 - \Phi^{-1}(t_1, t_0)x_1)}^{\xi_0} = \Phi(t_1, t_0)\xi_0$$

total response = ZIR + ZSR

$\Phi(t_1, t_0)$ nonsingular (not so in discrete time sys)

Thursday
November 2, 1989

XST-lecture

c.c. on $[t_0, t_1]$

$\forall x_0, x_1 \exists u_{[t_0, t_1]}$

$x_1 = \Phi(t_1, t_0)x_0 + \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) u(\tau) d\tau$



linear system represented by $[A(\cdot), B(\cdot), C(\cdot)]$

$$\dot{x}(t) = A(t)x(t) + B(t)u(t)$$

$$y(t) = C(t)x(t)$$

c.c. on $[t_0, t_1] \Leftrightarrow$ (a) c.c. to 0 on $[t_0, t_1]$

(total response = ZIR + ZSR)
& STM is nonsingular $\Phi(t_1, t_0)$

c.c. on $[t_0, t_1] \Leftrightarrow$ (b) c.r. from 0 on $[t_0, t_1]$

(\Rightarrow special case)

(\Leftarrow) c.r. from the origin on $[t_0, t_1]$

$$\Leftrightarrow \forall \xi_1 \exists \bar{u}_{[t_0, t_1]} \text{ s.t. } \xi_1 = \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) \bar{u}(\tau) d\tau$$

want $\forall x_0, x_1 \exists u_{[t_0, t_1]}$

$$\text{s.t. } x_1 = \Phi(t_1, t_0)x_0 + \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) u(\tau) d\tau$$

pick $\xi_1 = x_1 - \Phi(t_1, t_0)x_0$

$$\therefore \exists \bar{u}_{[t_0, t_1]} \text{ s.t. } x_1 - \Phi(t_1, t_0)x_0 = \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) \bar{u}(\tau) d\tau$$

$$\Rightarrow x_1 = \Phi(t_1, t_0)x_0 + \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) \bar{u}(\tau) d\tau$$

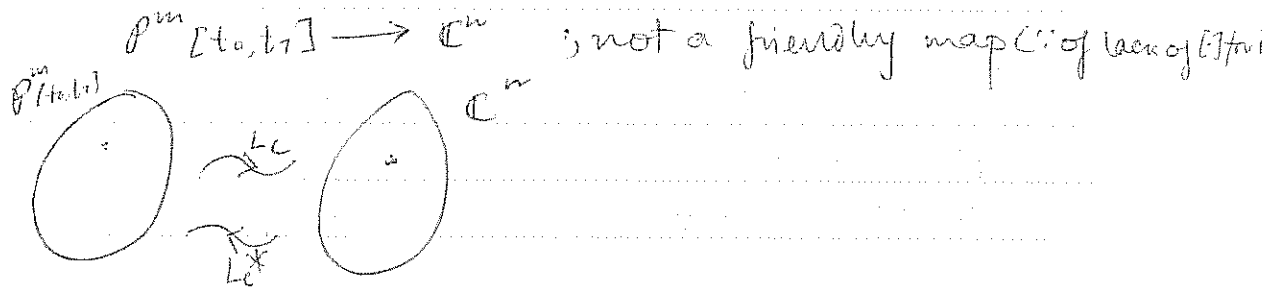
all we need for this to go through is
separability of ZIR & ZSR. (don't use nonsingular $\Phi(t_1, t_0)$)
consequently this is true for Discrete Time Systems

Since linear systems

c.c. on $[t_0, t_1] \Leftrightarrow$ c.r. from 0 on $[t_0, t_1]$

need only consider ZSR

$$L_c: U[t_0, t_1] \rightarrow \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) u(\tau) d\tau$$



\Rightarrow (i) x is reachable from the origin

$$\Leftrightarrow x \in R(L_c)$$

(ii) $R(L_c) :=$ set of reachable states (from 0) on $[t_0, t_1]$

(iii) c.c. on $[t_0, t_1] \Leftrightarrow R(L_c) = \mathbb{C}^n$

But $R(L_c) = R(L_c L_c^*)$

$L_c L_c^*: \mathbb{C}^n \rightarrow \mathbb{C}^n$; a nice map. (matrix)

$L_c^*: \mathbb{C}^n \rightarrow P^m [t_0, t_1]$; this is $z \mapsto B^*(\tau) \Phi^*(t_1, \tau) z$ (ZVR of the adjoint system)

$$L_c L_c^*: \mathbb{C}^n \rightarrow \mathbb{C}^n$$

$$z \mapsto \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) [L_c^*(z)](\tau) d\tau$$

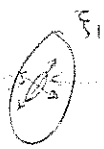
$$= \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) B^*(\tau) \Phi^*(t_1, \tau) d\tau \cdot z$$

\longleftarrow $n \times n$ matrix $= M(t_0, t_1)$
(constant matrix)

(i) $R(L_c) = R(M(t_0, t_1))$

(ii) $R(L_c) = \mathbb{C}^n \Leftrightarrow M(t_0, t_1)$ non singular (!) it's a bijective mapping!

\therefore can numerically test con cont.
(eg, det / Sing values)



\hookrightarrow practically zero \Rightarrow practically singular
very small \Rightarrow need very large u to achieve it
there. (practically not possible)

which input u would bring it to the desired state?

To find the input $u[t_0, t_1]$ driving (x_0, t_0) to (x_1, t_1)
 [Given $M(t_0, t_1)$ non-singular]
 want $x_1 = \Phi(t_1, t_0)x_0 + \int_{t_0}^{t_1} \Phi(t_1, \tau) B(\tau) u(\tau) d\tau$

$$B^*(\tau) \Phi^*(t_1, \tau) [M(t_0, t_1)]^{-1} (x_1 - \Phi(t_1, t_0)x_0) \quad \xrightarrow{\text{known}} \quad \int_{t_0}^{t_1} \Phi^*(t_1, \tau) B^*(\tau) d\tau$$

think about uniqueness of soln!
 its unique
 \Rightarrow into
 not unique

3) Linear Time Invariant $[A, B, C]$

x reachable from the origin on $[t_0, t_1]$
 i.e. $x \in R(L_c)$

$$x \in R(L_c) \Rightarrow \exists u[t_0, t_1] \text{ s.t. } x = L_c u = \int_{t_0}^{t_1} \exp(A(t_1 - \tau)) B u(\tau) d\tau$$

C-H: $e^{A(t_1 - \tau)} = \sum_{i=0}^{n-1} \alpha_i A^i = \sum_{i=0}^{n-1} \alpha_i (t_1 - \tau)^i A^i$ (jus of time)

$$x = \int_{t_0}^{t_1} \sum_{i=0}^{n-1} \alpha_i (t_1 - \tau)^i A^i B u(\tau) d\tau$$

$$= \sum_{i=0}^{n-1} A^i B \int_{t_0}^{t_1} \alpha_i (t_1 - \tau)^i u(\tau) d\tau = [B \alpha_0 (t_1 - \tau)^0 u(\tau) + AB \alpha_1 (t_1 - \tau)^1 u(\tau) + \dots + A^{n-1} B \alpha_{n-1} (t_1 - \tau)^{n-1} u(\tau)]$$

$\therefore x =$ l.c. of columns of $[B | AB | \dots | A^{n-1}B]$

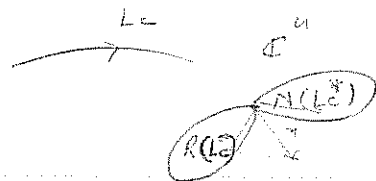
Let $Q = [B | AB | \dots | A^{n-1}B] \quad x \in R(Q)$

$x \in R(L_c)$

$\Rightarrow x \in R(Q)$ where $Q = [B | AB | \dots | A^{n-1}B]$

now about (\Leftarrow) ?

so by $x \in R(L_c) \stackrel{(*)}{\Rightarrow} x \in R(Q)$



$$x = x_1 + x_2 \quad x_1 \in R(L_c) \quad x_2 \in N(L_c^*)$$

$x_2 \neq \emptyset$
Handwritten note: $x_2 \neq \emptyset$ is not in $R(L_c)$

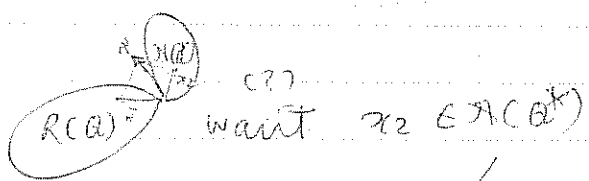
$$L_c^* : x_2 \mapsto B^* e^{A^*(t_1 - \tau)} x_2$$

known

$$B^* e^{A^*(t_1 - \tau)} x_2 = \emptyset \quad \forall \tau \in [t_0, t_1]$$

Handwritten note: should be for all $\tau \in [t_0, t_1]$ means x_2 is not in $R(L_c^)$ but is in $N(L_c^*)$*

want



$$\begin{aligned} B^* x_2 &= \emptyset \\ B^* A^* x_2 &= \emptyset \\ \vdots \\ B^* (A^*)^{n-1} x_2 &= \emptyset \end{aligned}$$



Handwritten note: this would imply $x_2 \in R(Q)$ (or $x_2 = \emptyset$)

$$B^* \left(I + A^*(t_1 - \tau) + \frac{(A^*)^2 (t_1 - \tau)^2}{2!} + \dots \right) x_2 = \emptyset \quad \forall \tau \in [t_0, t_1]$$

$$\tau = t_1 \Rightarrow B^* x_2 = \emptyset$$

differentiate w.r.t τ , $\Rightarrow B^* A^* x_2 = \emptyset$
 set $\tau = t_1$

$$B^* (A^*)^{n-1} x_2 = \emptyset$$

Note that the same could be for any $[t_0, t_1]$,
 $\therefore x$ reachable from the origin on any interval of finite length. $\Leftrightarrow x \in R(Q)$; $Q = [B^T, A^T B^T, \dots, A^{n-1} B^T]$
 $n \times nm$

$R(Q) :=$ set of reachable states
 $[A, B, C] c.c. \quad \text{rank}(Q) = n$ (full row rank)

$$[A, B, C] \text{ c.c.} \Leftrightarrow R(A) = C^n$$

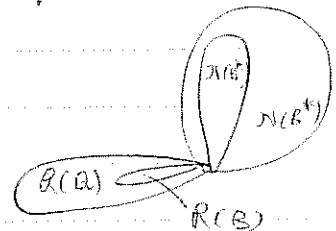
$$\Leftrightarrow N(A^*) = \{0\}$$

Properties of $R(A)$ & $N(A^*)$

$$(a) x \in R(A) \Leftrightarrow x \text{ is lin comb of } [B^*AB \quad \dots \quad A^{n-1}B]$$

if I have a vector which is l.c. of vectors of B $x \in R(B)$
 $\Rightarrow x \in R(A)$

$$R(B) \subseteq R(A)$$



$$(b) x \in R(A) \quad x = \sum_{i=0}^{n-1} B A^i \alpha_i \quad ; \alpha_i \text{ are vectors!}$$

$$Ax = \sum_{i=0}^{n-1} B A^{i+1} \alpha_i$$

$$= \cancel{B A^0} A \alpha_0 + A^2 B \alpha_1 + \dots + A^{n-1} B \alpha_{n-2} + \underbrace{A^n B \alpha_{n-1}}_{\text{C.H.}}$$

$$= \cancel{B A^0} B \alpha_0 + A B \alpha_1 + \dots + A^{n-1} B \alpha_{n-1}$$

$$\Rightarrow Ax \in R(A)$$

\therefore Range space of A is invariant under A .

$$(c) x \in N(A^*) \Leftrightarrow \begin{bmatrix} B^* \\ B^* A^* \\ \vdots \\ B^* (A^*)^{n-1} \end{bmatrix} x = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\Rightarrow B^* x = 0$$

$$x \in N(A^*) \Rightarrow x \in N(B^*)$$

$$(d) x \in N(A^*) \stackrel{\text{(L.H.)}}{\Rightarrow} A^* x \in N(A^*)$$

$N(A^*)$ is invariant under A^* .

November 189

ST-lecture

HW#9 11.14.89

Next exam Friday 11 Nov

Starting from Jordan form to end of this week.

$$[A, B, C] \text{ c.c.} \Leftrightarrow \mathcal{R}(Q) = \mathbb{C}^n$$

$$\Leftrightarrow \mathcal{N}(Q^*) = \{0\}$$

- (a) $\mathcal{R}(B) \subseteq \mathcal{R}(Q)$
- (b) $\mathcal{R}(Q)$ invariant under A
- (c) $\mathcal{N}(Q^*) \subseteq \mathcal{N}(B^*)$
- (d) $\mathcal{N}(Q^*)$ invariant under A^*
- (e) $A^*: \mathcal{N}(Q^*) \rightarrow \mathcal{N}(Q^*)$ linear

if dimension $\mathcal{N}(Q^*) > 1$

then \exists an eigenvector of A^* in $\mathcal{N}(Q^*)$

fundamental fact

Further characterization on c.c.

(analysis)

$$[A, B, C] \text{ c.c.}$$

$$\Leftrightarrow \mathcal{N}(Q^*) = \{0\} \Leftrightarrow \# \text{ eigenvector of } A^* \text{ in } \mathcal{N}(Q^*)$$

$$\therefore \text{c.c.} \Rightarrow \# \text{ eigenvector of } A^* \text{ in } \mathcal{N}(Q^*)$$

$\# \text{ vector of } A^* \text{ in } \mathcal{N}(Q^*) \Rightarrow \mathcal{N}(Q^*) = \{0\} \Rightarrow \mathcal{R}(Q) = \mathbb{C}^n$

$$\text{c.c.} \Leftrightarrow \# \text{ eigenvector of } A^* \text{ in } \mathcal{N}(B^*)$$

how? $A^*: \mathcal{N}(B^*) \rightarrow \mathcal{N}(B^*)$ (invariant) the two subspaces \Rightarrow separate the eigenvectors. \Rightarrow c.c.

PROOF!
if not true \exists eigenvector of A^* in $\mathcal{N}(B^*)$
 $\hookrightarrow f_k$

could not use this? argument? wrong argument?

$$\therefore \text{we have } A^* f_k = \lambda_k f_k \text{ and } B^* f_k = 0$$

$$\Rightarrow f_k^* [\lambda_k I - A^* | B] = 0^T$$

$$\Rightarrow \text{rank of } [\lambda_k I - A | B] < n \text{ (dim of } A)$$

$$\text{If } \text{rank}[\lambda I - A | B] = n \Rightarrow \# \text{ eigenvector of } A^* \text{ in } \mathcal{N}(B^*) \Rightarrow [A, B, C] \text{ c.c.}$$

what about (\Leftarrow) ?

trying to show is done to $\text{rank}[A, B] = n$

Fact: $[A, B, C]$ c.c. $\Leftrightarrow \text{rank}[\lambda I - A | B] = n \quad \forall \lambda \in \mathbb{C}$

Proof: (\Rightarrow) Suppose $\text{rank}[\lambda I - A | B] < n$
 $\Rightarrow \exists \alpha^* \neq \theta^T$ s.t. $\alpha^* [\lambda I - A | B] = \theta^T$

$$\lambda \alpha^* = \alpha^* A \quad ; \quad \alpha^* B = \theta^T$$

consider: $\alpha^* [B \quad AB \quad \dots \quad A^{n-1}B] = [\alpha^* B \quad \underbrace{\alpha^* AB}_{\lambda \alpha^* B} \quad \dots \quad \alpha^* A^{n-1}B]$
 $= [\alpha^* B \quad \lambda \alpha^* B \quad \dots \quad \lambda^{n-1} \alpha^* B]$
 $= \theta^T$

$\Rightarrow [A, B, C]$ is not c.c.

Q.E.D.

2. Observability

(1) Dynamical System $\mathcal{D} = \{u, \varepsilon, y, s, \tau\}$
 t_0, t_1 ; $t_1 > t_0$

\mathcal{D} is said to be completely observable (c.o.) on $[t_0, t_1]$
 $\Leftrightarrow \forall u[t_0, t_1]$ & corresp. $y[t_0, t_1]$ together \bar{c}
determine uniquely the state of x_0 of \mathcal{D} at t_0 .

Note: once x_0 is determined

$s(t, t_0, x_0, u[t_0, t_1])$
the state at t

$x(t)$ is uniquely determined



(2) Linear System $[A(\cdot), B(\cdot), C(\cdot)]$

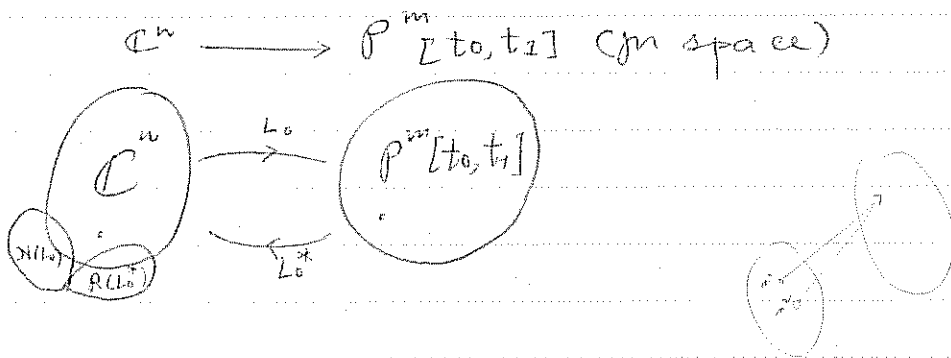
$$y(t) = \underbrace{C(t)}_{\in \mathbb{R}} \underbrace{\Phi(t, t_0)}_{\in \mathbb{R}} x_0 + \int_{t_0}^t \underbrace{C(\tau)}_{\in \mathbb{R}} \underbrace{\Phi(t, \tau)}_{\in \mathbb{R}} u(\tau) d\tau$$

Φ can be "calculated" from $v_{[t_0, t_1]}$ $[A(\cdot), B(\cdot), C]$
can be subtracted from y

For a linear system:

c.o. on $[t_0, t_1] \Leftrightarrow$ c.o. of the ZIR on $[t_0, t_1]$

$$L_0: x_0 \mapsto (C(\cdot) \Phi(\cdot, t_0)) x_0$$



$R(A^*) = R(C^* \Phi^*)$
 $N(A) = N(C^* \Phi^*)$

$(L_0 x)_i = \int_{t_0}^{t_1} C^*(t) \Phi^*(t, t_0) x dt$
 $\Rightarrow N(L_0) = \{x \mid \int_{t_0}^{t_1} C^*(t) \Phi^*(t, t_0) x dt = 0\}$
 \Rightarrow needs to understand $\Phi^*(t, t_0) = \Phi(t_0, t)^T$

(i) System $[A(\cdot), B(\cdot), C(\cdot)]$ is c.o. on $[t_0, t_1] \Leftrightarrow N(L_0) = \{0\}$
 $\Leftrightarrow R(L_0^*) = \mathbb{C}^n$

(compare c.c. case where it was reqd that $R(L_0) = \mathbb{C}^n$;
 here ZSR of adjoint needs to be mapped onto \mathbb{C}^n)

$[A(\cdot), B(\cdot), C(\cdot)]$ not c.o.
 $N(L_0)$ contains nonzerovectors.

$x \in N(L_0) \quad L_0 x = 0$ zero function
 $L_0^* 0 = 0$ zero function

we say x is not observable state.

The set $N(L_0) \hat{=}$ set of unobservable states

not at all about
 transfer function that maps to
 just a defn of observability

$[A(\cdot), B(\cdot), C(\cdot)]$ c.o. $\Leftrightarrow R(L_0^*) = \mathbb{C}^n$

$R(L_0^*) = R(L_0^* L_0)$

$L_0^* L_0: \mathbb{C}^n \rightarrow \mathbb{C}^n$

for onto \Rightarrow matrix representation should be nonsingular

$$L_0^* L_0 : \mathbb{C}^n \rightarrow \mathbb{C}^n$$

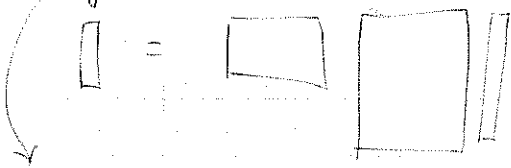
$$x_0 \mapsto \int_{t_0}^{t_1} \Phi^*(z, t_0) C^*(z) (z) \Phi(z, t_0) dz x_0$$

$$\longleftarrow N(t_0, t_1) \longrightarrow$$

$$[A(\cdot), B(\cdot), C(\cdot)] \text{ c.o.} \Leftrightarrow \mathcal{R}(L_0^*) = \mathbb{C}^n \Leftrightarrow N(t_0, t_1) \text{ non singular}$$

Suppose $[A(\cdot), B(\cdot), C(\cdot)]$ is c.o. $\Leftrightarrow N(t_0, t_1)$ non singular
 ie from $\mathbb{Z} \cap \mathbb{R}$ should be det x_0 uniquely
 how to find x_0 .

$$y(t) = C(t) \Phi(t, t_0) x_0$$

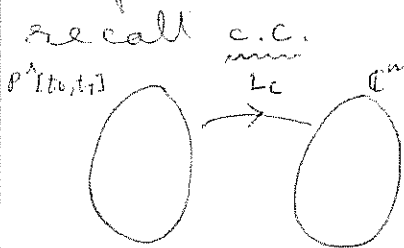


$$\int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) y(t) dt = \int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) (t) \Phi(t, t_0) dt x_0$$

multiply by inverse $\Rightarrow [N(t_0, t_1)]^{-1} \int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) y(t) dt = x_0$

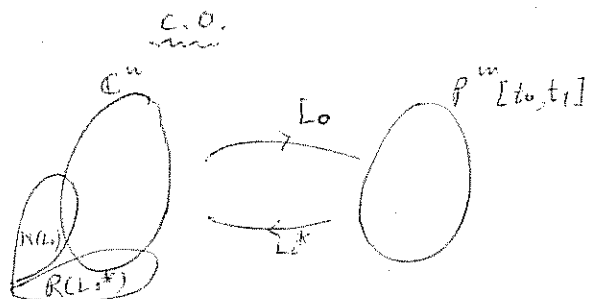
Duality between observability & controllability obvious

Compare c.o. w/ c.c.



c.c. $\Leftrightarrow \mathcal{R}(L) = \mathbb{C}^n$

$$L_c : u \mapsto \int_{t_0}^{t_1} \Phi(t_1, \sigma) B(\sigma) u(\sigma) d\sigma$$



c.o. $\Leftrightarrow \mathcal{R}(L_0^*) = \mathbb{C}^n$

$$L_0^* : y \mapsto \int_{t_0}^{t_1} \Phi^*(t, t_0) C^*(t) y(t) dt$$

duality

<u>c.c.</u>	<u>c.o.</u>
L_c	L_c^*
u	y
$B(\cdot)$	$C^*(\cdot)$
$\Phi(t_0, \tau)$	$\Phi^*(\tau, t_0)$
$A(\cdot)$	$-A^*(\cdot)$ (1)

no further derivations reqd!

(3) linear time invariant case $[A, B, C]$

$[A, B, C]$ c.o. on any interval of positive length
 $\Leftrightarrow \text{rank } R = n$

$\therefore Q = [B | AB | A^2B | \dots | A^{n-1}B] \xleftrightarrow{\text{determinant}} [C^* | A^*C^* | \dots | (A^*)^{n-1}C^*]$
n columns

$R = \text{conj transpose of } \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix} \begin{matrix} m \\ n \\ \vdots \\ n \end{matrix}$; m rows

$\Leftrightarrow \text{rank } \begin{bmatrix} \lambda I - A \\ C \end{bmatrix} = n$; look @ this intuitively.

$R(Q) \neq \mathbb{C}^n$; some states are reachable some aren't.

check about (1) if it's not the same as the previous one! ; (1) is not the same!

1. The first part of the document discusses the importance of maintaining accurate records of all transactions. This is essential for ensuring the integrity of the financial data and for providing a clear audit trail. The records should be kept up-to-date and should be accessible to all relevant parties.

2. The second part of the document outlines the procedures for handling incoming payments. It is important to ensure that all payments are recorded promptly and accurately. The procedures should include verifying the amount and source of the payment, and ensuring that the funds are deposited into the correct account.

3. The third part of the document describes the process for issuing invoices. Invoices should be generated and sent to customers in a timely manner. The invoices should clearly state the amount due and the terms of payment. It is also important to keep a copy of each invoice for your records.

4. The fourth part of the document discusses the process for reconciling the bank statements. This involves comparing the bank's records of transactions with the company's records. Any discrepancies should be investigated and resolved promptly. Regular reconciliation helps to ensure that the company's financial records are accurate.

5. The fifth part of the document outlines the process for preparing the financial statements. These statements provide a summary of the company's financial performance over a specific period. They are essential for management decision-making and for providing information to stakeholders. The statements should be prepared accurately and on a regular basis.

6. The sixth part of the document discusses the process for budgeting. A budget is a financial plan that outlines the expected income and expenses for a specific period. It is a key tool for managing the company's finances and for ensuring that the company stays on track with its financial goals. The budget should be reviewed and updated regularly.

7. The seventh part of the document outlines the process for managing cash flow. Cash flow is the amount of money that is coming in and out of the company. It is essential for ensuring that the company has enough cash to cover its obligations. Cash flow should be monitored closely and managed proactively.

8. The eighth part of the document discusses the process for managing debt. Debt is a liability that the company owes to others. It is important to manage debt carefully to avoid financial distress. The company should ensure that it is making timely payments on its debt and that it is not taking on too much debt.

9. The ninth part of the document outlines the process for managing risk. Risk is the possibility of loss or damage. It is important to identify and manage risk to protect the company's assets and ensure its long-term success. Risk management should be an ongoing process.

9 Nov 1989

↳ ST-lecture

ch V sect-5, 8-9

ch VI sect-4

ch VII sect-4

Suppl 1-V, VIII, sec B, C, D

colles & Reson ch I sec 2 (S V)

MT: mainly derivations (< 5 Questions) 1 hour

3. Decomposition

(1) Separation of controllable part

Given $[A, B, C]$ not c.c.

not c.c. $\Leftrightarrow \text{rank } Q = \dim R(Q) = f < n$

(i) Range Space of $Q = R(Q) =$ set of reachable states

(ii) Range Space of $Q = R(Q)$ invariant under A

(iii) $R(B) \subseteq R(Q)$ \Rightarrow why \subseteq and not $R(0)$?

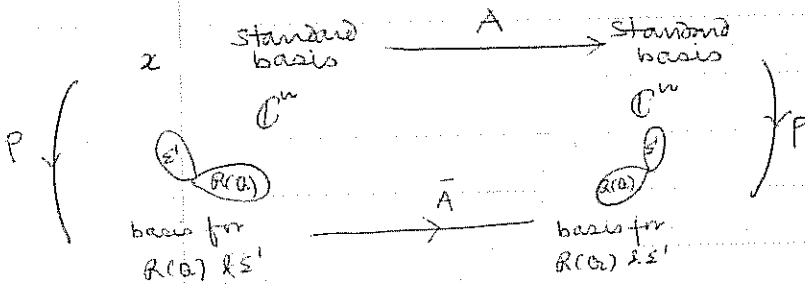
even if B has just one l.i. col, AB may have a diff. lin ind column (col from output)

$A \in \mathbb{R}^{n \times n}$ $\mathbb{C}^n = R(Q) \oplus \Sigma'$

$A = \begin{bmatrix} 1 & 2 \\ 0 & 2 \end{bmatrix}$ $B = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$ $AB = \begin{bmatrix} 7 & 14 \\ 4 & 8 \end{bmatrix}$

l.i. col is $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ \uparrow 1. col is $\begin{bmatrix} 7 \\ 4 \end{bmatrix}$

l.i.v. calculation so \subseteq could be \subset in some cases



$\exists P$ s.t. $\bar{x} = Px$

\bar{x} basis for $R(Q) \& \Sigma'$

$[A, B, C] \leftarrow [\bar{A}, \bar{B}, \bar{C}]$

$\bar{A} = PAP^{-1}$

$\bar{B} = PB$

$\bar{C} = CP^{-1}$

$P\dot{x} = PAx + PBu$

$y = Cx$

$\dot{\bar{x}} = P\dot{x}$

$\dot{\bar{x}} = PAP^{-1}\bar{x} + PBu$

$y = CP^{-1}\bar{x}$

Range space of A invariant under $A \Rightarrow$

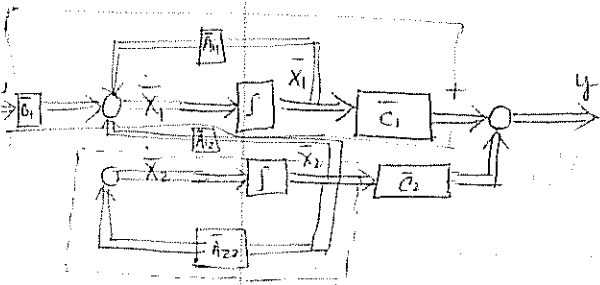
$\begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ 0 & \bar{A}_{22} \end{bmatrix} = \bar{A}$

use the range of B is contained in range space of Q in representation of Q about Σ' part pass examine $\bar{B} = PB \Rightarrow$ property (iii)

$\begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix}$

$\bar{C} = CP^{-1} = \begin{bmatrix} \bar{C}_1 & \bar{C}_2 \end{bmatrix}$ (no info on it)

$$\begin{bmatrix} \dot{\bar{x}}_1 \\ \dot{\bar{x}}_2 \end{bmatrix} = \begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ 0 & \bar{A}_{22} \end{bmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} + \begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix} u$$



$$[\bar{A}_{11}, \bar{B}_1, \bar{C}_1] \quad \dot{\bar{x}}_1 = \bar{A}_{11} \bar{x}_1 + \bar{B}_1 u$$

$$y = \bar{C}_1 \bar{x}_1$$

$\bar{x}_2(0) = 0 \Rightarrow$ system reduces to above block only.

ZSR response of the top system = ZSR of the total system.
 \rightarrow Examining a picture is not a proof.

$$\text{ZSR of } [A, B, C] = \text{ZSR of } [\bar{A}_{11}, \bar{B}_1, \bar{C}_1]$$

Need to show $\int_0^t H(t-\tau) u(\tau) d\tau = \int_0^t \bar{C}_1 e^{\bar{A}_{11}(t-\tau)} \bar{B}_1 u(\tau) d\tau$

$\int_0^t (t-\tau) e^{A(t-\tau)} B u(\tau) d\tau$
 \uparrow constant matrices

equiv to examine Laplace transform

$$y \quad C (sI - A)^{-1} B = \bar{C}_1 (sI - \bar{A}_{11})^{-1} \bar{B}_1$$

$$\begin{aligned} \text{RHS} \quad C (sI - A)^{-1} B &= \bar{C} P (sI - A)^{-1} P^{-1} \bar{B} \\ &= \bar{C} (P sI P^{-1} - P A P^{-1})^{-1} \bar{B} \\ &= \bar{C} (sI - \bar{A})^{-1} \bar{B} \quad \text{t.f. unchanged when you} \\ &= [\bar{C}_1 \quad \bar{C}_2] \begin{bmatrix} sI - \bar{A}_{11} & \bar{A}_{12} \\ 0 & sI - \bar{A}_{22} \end{bmatrix}^{-1} \begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix} \quad \text{change coordinate systems} \end{aligned}$$

inverse of singular matrix must be singular in same sense

$$\therefore [\bar{C}_1, \bar{C}_2] \begin{bmatrix} (sI - \bar{A}_{11})^{-1} & x \\ 0 & -x \end{bmatrix} \begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix}$$

$$= \bar{C}_1 (sI - \bar{A}_{11})^{-1} \bar{B}_1 \quad \rightarrow \text{t.f. of reduced system} \quad \text{Q.E.D.}$$

$$\begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ 0 & \bar{A}_{22} \end{bmatrix}^{-1} = \begin{bmatrix} \bar{A}_{11}^{-1} & \bar{A}_{12} \bar{A}_{11}^{-1} \\ 0 & \bar{A}_{22}^{-1} \end{bmatrix}$$

ie t.f. doesn't change if you cut out that portion.

$$Q: \underset{\sim}{C} (\underset{\sim}{sI} - \underset{\sim}{A})^{-1} \underset{\sim}{B} = \frac{1}{\det(\underset{\sim}{sI} - \underset{\sim}{A})} \underset{\sim}{C} (\underset{\sim}{\sqrt{\quad}}) \underset{\sim}{B} \leftarrow \text{adjugate [as before]}$$

What is the order of this polynomial $\det(sI - A)$? n

$$\bar{C}_1 (sI - \bar{A}_{11})^{-1} \bar{B}_1 = \frac{1}{\det(sI - \bar{A}_{11})} \bar{C}_1 [x] \bar{B}_1$$

order of this polynomial is q .

what happened to the missing order?
Cancellation.

two systems one \bar{C} lower order have same t.f. after pole zero cancellation.

$$\begin{bmatrix} \bar{x}_1 \\ 0 \end{bmatrix} \leftarrow \text{reachable states}$$

$$[\bar{A}_{11}, \bar{B}_1, \bar{C}_1] \text{ c.c. ?}$$

$$\dot{\bar{x}}_1 = \bar{A}_{11} \bar{x}_1 + \bar{B}_1 u$$

$$y = \bar{C}_1 \bar{x}_1$$

$$\text{rank } \bar{Q}_1 = \text{rank} \begin{bmatrix} \bar{B}_1 & | & \bar{A}_{11} \bar{B}_1 & | & \dots & | & \bar{A}_{11}^{n-1} \bar{B}_1 \end{bmatrix} \stackrel{?}{=} n$$

$$\text{Given } Q = [B | AB | \dots | A^{n-1} B]$$

$$\bar{A} = PAP^{-1} \quad \bar{B} = PB \quad \begin{matrix} A & n \times n & & B & n \times m \end{matrix}$$

$$PQ = [PB | PAB | \dots | PA^{n-1} B] = [\bar{B} | \bar{A}\bar{B} | \dots | \bar{A}^{n-1} \bar{B}]$$

$$= \left[\begin{array}{c|c|c} \bar{B}_1 & \bar{A}_{11}\bar{B}_1 & \bar{A}_{11}^{n-1}\bar{B}_1 \\ \hline 0 & 0 & 0 \end{array} \right] \} q$$

$$\text{rank } Q = q < n \text{ (initial)}$$

$$2. \text{rank } PA = q \text{ too (} \because P \text{ invertible, its rows l.i.)}$$

$$\therefore \text{rank } \bar{Q} = q$$

\therefore The top system is completely controllable.
The other part \rightarrow don't know.

$$\begin{array}{l} [\bar{A}_{11}, \bar{B}_1, \bar{C}_1] \text{ ZSR} \\ \parallel \\ [A, B, C] \text{ ZSR} \end{array} \Rightarrow \text{"Zero State Equivalent"}$$

ZS Equiv: $H(s)$ same (if they have the same t.f.m. matrix)

$[A, B, C]$ state space representation
if $C(sI - A)^{-1}B = H(s)$
then this rep. is a realization of $H(s)$.

(2) Separation of observable part:

Given $[A, B, C]$ not c.o.

$$\text{we require } R = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix}$$

$$\text{not c.o.} \Rightarrow \text{rank } R = r < n$$

$$\dim N(R) = n - r > 0$$

Recall (i) $N(R)$ set of unobservable states

(ii) invariant under A

(iii) $N(R) \subset N(C)$

$$C^w = \Sigma'' \oplus N(R)$$

in terms of basis for Σ'' & $N(R)$

$$\hat{A} = \begin{bmatrix} \hat{A}_{11} & 0 \\ \hat{A}_{21} & \hat{A}_{22} \end{bmatrix} \in N(R)$$

$$\hat{B} = \begin{bmatrix} \hat{B}_1 \\ \hat{B}_2 \end{bmatrix}$$

$$\hat{C} = \begin{bmatrix} \hat{C}_1 & \hat{C}_2 \end{bmatrix}$$

$$\hat{x} \in N(R) \Rightarrow \hat{x} \in N(C)$$

$$\begin{bmatrix} 0 \\ x_2 \end{bmatrix}$$

$$[\hat{C}_1 \ \hat{C}_2] \begin{bmatrix} 0 \\ x_2 \end{bmatrix} = 0$$

$$\Rightarrow \hat{C}_2 x_2 = 0$$

$$\Rightarrow \hat{C}_2 = 0$$

$$\text{li } \hat{C} = \begin{bmatrix} \hat{C}_1 & 0 \end{bmatrix}$$

Verify (i) $[\hat{A}_{11}, \hat{B}_1, \hat{C}_1]$ z.s. eq. to $[A, B, C]$
(straight forward)

(ii) $[\hat{A}_{11}, \hat{B}_1, \hat{C}_1]$ c.o.

combine the above to get c.o. + c.c. subsystem which has same t.f. as original system.

(3) Kalman Canonical Structure Theorem

Given $[A, B, C]$ not c.c., not c.o.

$$C^w = R(Q) \oplus \Sigma'$$

$$C^w = \Sigma'' \oplus N(R)$$

$\Sigma_2 := R(Q) \cap N(R)$: is a subspace! (in C^w)

$$\Sigma_1 \oplus \Sigma_2 \oplus \Sigma_3 \oplus \Sigma_4 = C^w$$

$\Sigma_1 := \text{span}(\text{lin ind vectors in } R(Q) \text{ but not in } \Sigma_2) =: \Sigma_1$

$\Sigma_4 := \text{span}(\text{lin ind vectors in } N(R) \text{ but not in } \Sigma_2)$

$\cup \Sigma_2 \cap N(R)$

Handwritten notes on the right side of the page, including "Kalman Canonical Structure Theorem" and "N(R) = set of vectors" with arrows pointing to the equations above.

$\mathcal{E}_3 := \text{span}(\text{lin ind vectors not in } \mathcal{R}(A) \text{ nor in } \mathcal{N}(A))$

$$[A, B, C] \leftarrow [\tilde{A}, \tilde{B}, \tilde{C}]$$

$$\tilde{A} = \begin{bmatrix} \tilde{A}_{11} & 0 & \tilde{A}_{13} & 0 \\ \tilde{A}_{21} & \tilde{A}_{22} & \tilde{A}_{23} & \tilde{A}_{24} \\ 0 & 0 & \tilde{A}_{33} & 0 \\ 0 & 0 & \tilde{A}_{43} & \tilde{A}_{44} \end{bmatrix}$$

$$\tilde{B} = \begin{bmatrix} \tilde{B}_1 \\ \tilde{B}_2 \\ 0 \\ 0 \end{bmatrix}$$

$\therefore \mathcal{R}(A) \leftarrow$
invariant under A

$$\tilde{C} = \begin{bmatrix} \tilde{C}_1 & 0 & \tilde{C}_3 & 0 \end{bmatrix}$$

(i) $[\tilde{A}_{11}, \tilde{B}_1, \tilde{C}_1]$ c.c. & c.o. (easy)

(ii) $[\tilde{A}_{11}, \tilde{B}_1, \tilde{C}_1]$ ZSR to $[A, B, C]$

$\hat{=}$ $[\tilde{A}_{11}, \tilde{B}_1, \tilde{C}_1]$ is a realization of $H(s) = C(sI - A)^{-1}B$

(iii) there are many realizations

but this has the lowest dimension

Friday
Nov 10, 1989

ST-VK discussion

- 1 Pole Zero cancellation.
- 2 PBH test for c.c./c.o.
- 3 realization of LTI SISO systems.
- 4 SVS - alternate proof from Wub's notes.

$$\dot{X} = AX + Bu$$

$\det(sI - A)$ = denominator of transfer fn

$$A = \begin{bmatrix} 1 & 3 \\ 7 & 5 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad C = \begin{bmatrix} 1/2 & 1/2 \end{bmatrix}$$

$$g(s) = C(sI - A)^{-1}B = \begin{bmatrix} 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} (s-5) & 3 \\ 7 & (s-1) \end{bmatrix} \underbrace{\frac{1}{(s+2)(s-8)}}_{\text{scalar}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$g(s) = \frac{(s+2)}{(s+2)(s-8)} = \frac{1}{s-8} \quad \therefore \text{sys not c.c./c.o.} \leftarrow \text{let see which.}$$

Cont. Matrix

$$Q = [B \mid AB] = \begin{bmatrix} 1 & 4 \\ 1 & 4 \end{bmatrix} \Rightarrow \text{c.c.}$$

$$R = \begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 \\ 4 & 4 \end{bmatrix} \Rightarrow \text{not c.o.}$$

rank $Q = n$ for controllability

$$\text{where } Q = [B \mid AB \mid \dots \mid A^{n-1}B]$$

PBH test: examine $[\lambda I - A \mid B]$ (Popov-Belevitch-Hautus)

for rank

$$\text{Thm. } \{A, B\} \text{ is c.c.} \Leftrightarrow \text{rank } [\lambda I - A \mid B] = n \quad \forall \lambda \in \mathbb{C}$$

if λ not e.v. of $A \Rightarrow \lambda I - A$ nonsingular.
 \Rightarrow you only need to check $\lambda \in \sigma(A)$

Proof: (\Rightarrow) supposing $\text{rank} [\lambda I - A \mid B] \neq n$

then $\exists \alpha^T$ s.t. $\alpha^T [\lambda I - A \mid B] = 0$ α^T must be e.v
else $\lambda I - A$ is
non singular

$$\alpha^T B = 0$$

$$\alpha^T \lambda I = \alpha^T A$$

$$\lambda \alpha^T A = \alpha^T A^2$$

$$\Rightarrow \alpha^T A^j = \lambda^j \alpha^T$$

but we know $\{A, B\}$ c.c. $\Leftrightarrow \text{rank } Q = n$; $Q = [B \mid AB \mid \dots \mid A^{n-1}B]$

$$\alpha^T Q = [\alpha^T B \mid \alpha^T AB \mid \dots \mid \alpha^T A^{n-1}B]$$

$$\Rightarrow 0 \quad \Rightarrow \lambda \alpha^T B = \lambda \alpha^T B \quad \dots \quad \lambda^{n-1} \alpha^T B = 0$$

\Rightarrow contradiction

Proved (\Rightarrow)

(\Leftarrow) suppose $\{A, B\}$ not c.c.

$$\Rightarrow \text{P s.t. } A \sim \bar{A} = \begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ 0 & \bar{A}_{22} \end{bmatrix} = PAP^{-1}$$

from HW

$$\rightarrow B \sim \bar{B} = \begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix} = PB$$

let λ be an eigenvalue of \bar{A}_{22} (so eigenvalue of \bar{A})
(use all Karlt's formulas)

β^T be a corresponding left eigenvector of \bar{A}_{22}

$$\text{let } \alpha^T = [0 \mid \beta^T]$$

from HW
↓

$$\alpha^T [\lambda I - \bar{A} \mid \bar{B}] = [0 \mid \beta^T] \left[\begin{array}{cc|c} \lambda I - \bar{A}_{11} - \bar{A}_{12} & & \bar{B}_1 \\ 0 & \lambda I - \bar{A}_{22} & 0 \end{array} \right]$$

$$= \left[0 \mid \underbrace{\beta^T (\lambda I - \bar{A}_{22})}_{0} \mid 0 \right] \Rightarrow \text{not full rank}$$

$$= \alpha^T [P(\lambda I - A)P^{-1} ; PB]$$

$$= \alpha^T P [(\lambda I - A)P^{-1} ; B]$$

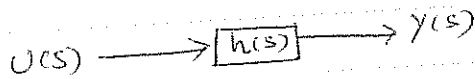
$$\underbrace{\alpha^T}_{\bar{\alpha}^T}$$

P, P^{-1} non singular $\Rightarrow \bar{\alpha}^T \neq 0$

$$\bar{\alpha}^T (\lambda I - A) = 0$$

$$\bar{\alpha}^T [\lambda I -$$

ATI system (SISO)



$$h(s) = (\beta_1 s^2 + \beta_2 s + \beta_3) / (s^3 + \alpha_1 s^2 + \alpha_2 s + \alpha_3)$$

Let $z(s)$ be the input u of the new system

$$\hookrightarrow h_d(s) = \frac{1}{s^3 + \alpha_1 s^2 + \alpha_2 s + \alpha_3}$$

$$y(s)(s^3 + \alpha_1 s^2 + \alpha_2 s + \alpha_3) = (\beta_1 s^2 + \beta_2 s + \beta_3) u$$

$$z(s) = h_d(s) u(s)$$

$$z(s)(s^3 + \alpha_1 s^2 + \alpha_2 s + \alpha_3) = u(s)$$

$$\ddot{z} + \alpha_1 \dot{z} + \alpha_2 z + \alpha_3 z = u$$

By superposition

$$u(s) = \beta_1 s^2 h_d(s) + \beta_2 s h_d(s) + \beta_3 h_d(s)$$

$$y(s) = \beta_1 s^2 h_d(s) u(s) + \beta_2 s h_d(s) u(s) + \beta_3 h_d(s) u(s)$$

$$y(s) = \beta_1 s^2 z(s) + \beta_2 s z(s) + \beta_3 z(s)$$

$$X(s) \leftrightarrow X(t)$$

$$\text{if } X'(t) = 0 \quad X(t) = 0$$

$$y(t) = \beta_1 \ddot{x} + \beta_2 \dot{x} + \beta_3 x$$

↑
z.c.

Now let $x_1 = \dot{x}$
 $x_2 = \ddot{x} = \dot{x}_1$
 $x_3 = \ddot{x}_2 = \dot{x}_1$

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = x_3$$

$$\dot{x}_3 = -\alpha_1 x_3 - \alpha_2 x_2 - \alpha_3 x_1 + U$$

$$\ddot{x} + \alpha_1 \dot{x} + \alpha_2 x + \alpha_3 x = U$$

$$\dot{x}_3 + \alpha_1 x_3 + \alpha_2 x_2 + \alpha_3 x_1 = U$$

$$y = \beta_1 x_3 + \beta_2 x_2 + \beta_3 x_1$$

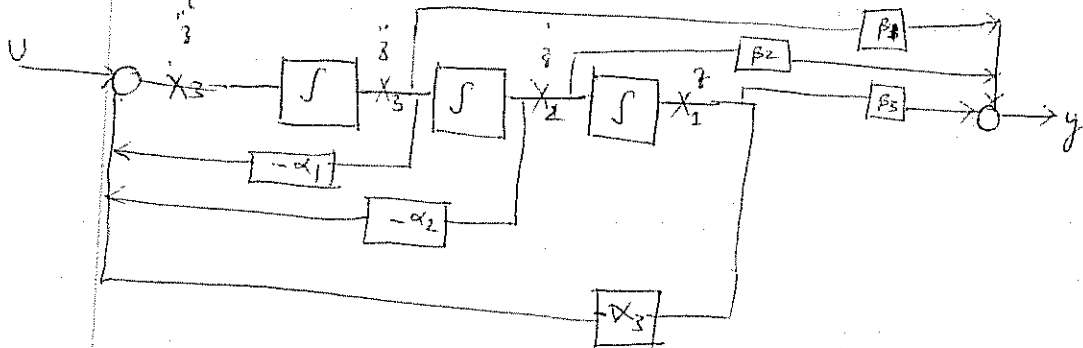
$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -\alpha_3 & -\alpha_2 & -\alpha_1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} U$$

$$y = [\beta_3 \ \beta_2 \ \beta_1] x$$

e.c. form

controllable
 reachable
 m

Implementation



How do we know system is c.c.?

$$Q = [B \ | \ AB \ | \ A^2B] = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & -\alpha_1 \\ 1 & -\alpha_1 & -\alpha_2 + \alpha_1^2 \end{bmatrix}$$

↔ non-singular

observable canonical form:

$$\ddot{y} + \alpha_1 \dot{y} + \alpha_2 y = \beta_1 \ddot{u} + \beta_2 \dot{u} + \beta_3 u$$

$$\ddot{y} + (\alpha_1 \dot{y} - \beta_1 \ddot{u}) + (\alpha_2 y - \beta_2 \dot{u}) + (\alpha_3 y - \beta_3 u) = 0$$

\dot{x}_2

x_2

x_1

$$\dot{x}_3 = y \rightarrow x_3 = \int y$$

$$\dot{x}_2 = \ddot{y} + (\alpha_1 \dot{y} - \beta_1 \ddot{u})$$

$$x_2 = \dot{y} + (\alpha_1 y + \beta_1 u)$$

$$\dot{x}_2 = \dot{x}_3 + (\alpha_1 x_3 + \beta_1 u)$$

$$\dot{x}_3 = x_2 - \alpha_1 x_3 - \beta_1 u$$

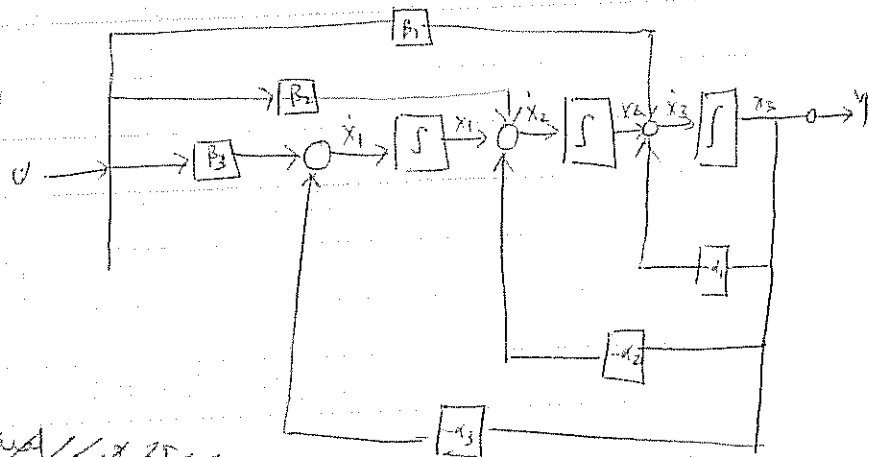
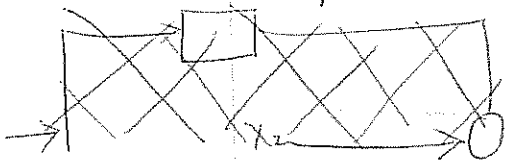
$$x_1 = x_2 + \alpha_2 x_3 - \beta_2 u$$

$$0 = \dot{x}_1 + \alpha_3 x_3 - \beta_3 u$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 0 & 0 & -\alpha_3 \\ 1 & 0 & -\alpha_2 \\ 0 & 1 & -\alpha_1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} \beta_3 \\ \beta_2 \\ \beta_1 \end{bmatrix} u$$

obs. can. form

$$y = [0 \ 0 \ 1] x$$



duob

$$(A, B, C) \leftrightarrow (A^T, B^T, C)$$

$$(A, b, c) \leftrightarrow (A^T, c^T, b^T)$$

use dms on block diagrams

Jordan Form Realization

$$h(s) = \frac{(\beta_1 s^2 + \dots)}{(s^3 + \alpha_1 s^2 + \dots)} = \frac{r_1}{(s-\lambda_1)} + \frac{r_2}{(s-\lambda_2)} + \frac{r_3}{(s-\lambda_2)^2}; \text{ Pf exp}$$

change coordinates to generalized eigenvectors
 $x = Tz$ $\dot{x} = Ax + Bu$
 $y = Cx$

$$\dot{z} = T^{-1}AT z + T^{-1}Bu$$

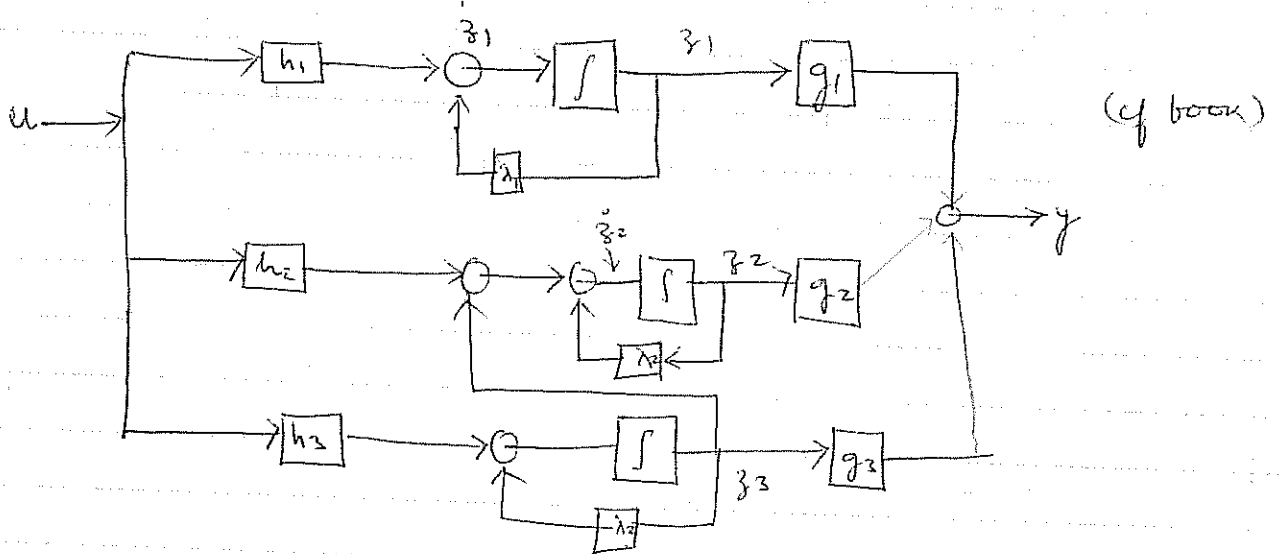
$$y = \underbrace{CT}_{g} z$$

$$T^{-1}B \triangleq h$$

$$CT \triangleq g$$

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 1 \\ 0 & 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} + \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} u$$

$$y = [g_1 \ g_2 \ g_3] z$$



c.c. $\Leftrightarrow h_1, h_2, h_3 \neq 0$
 also c.o. $\Leftrightarrow g_1, g_2, g_3 \neq 0$

Proof from Dr Wu's notes of SVD (p. 16 of Class Notes)

$$A \in \mathbb{C}^{m \times n} \text{ rank } r$$

$$B \in \mathbb{C}^{m \times n} \text{ rank } r-1$$

$$z \in N(B) \cap R(A^*)$$

(to show min $\|A-B\|_2 = \sigma_r$)

$$\text{rank } B = r-1$$

We know $\mathbb{C}^n = N(A) \oplus R(A^*)$ \Rightarrow at least one dim can pick z 's out of.

$$Bz = \theta$$

$$A = \sum_{i=1}^r \sigma_i v_i v_i^*$$

$$Az = \sum_{i=1}^r \sigma_i v_i v_i^* z$$

σ_i = scalar, v_i = vector, $v_i^* z$ = scalar

$$\|Az\|^2 = \sum_{i=1}^r \overline{\sigma_i v_i^* z} v_i^* \cdot \sum_{j=1}^r \sigma_j (v_j^* z) v_j$$

$$v_i \text{'s are orthonormal} \Rightarrow \sum_i \sum_j \sigma_i \sigma_j (v_i^* z) (v_j^* z) v_i^* v_j$$

$$= \sum_{i=1}^r \sigma_i^2 (v_i^* z)^2$$

$$\|v_i^* z\|^2 \leq \|v_i^*\|_2 \cdot \|z\|_2 \quad \text{Schwartz inequality}$$

= 1 = 1

$$\therefore \|v_i^* z\| \leq 1$$

$$\sum_{i=1}^r \sigma_i^2 (v_i^* z)^2 \geq \sum_{i=1}^r \sigma_i^2 (v_i^* z)^2 = \sigma_r^2 \sum_{i=1}^r (v_i^* z)^2 \geq \sigma_r^2 = 1 \text{ (Norm)}$$

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Minimality not in course for MT2.
Exam at 3:00pm

(3) Kalman Decomposition

Given $[A, B, C]$ not c.c. not e.o.
~~not~~ $R(Q)$ charac. controllability
 $N(R)$ not obs states

$\Sigma_2 := R(Q) \cap N(R)$ c.c.

$C^n = \Sigma_1 \oplus \Sigma_2 \oplus \Sigma_3 \oplus \Sigma_4$

Annotations:
 Σ_1 : c.c., c.o.
 Σ_2 : c.c.
 Σ_3 : c.c., e.o.
 Σ_4 : c.c., e.o.

summary

$[A, B, C] \leftarrow [\tilde{A}, \tilde{B}, \tilde{C}]$

$\tilde{A} =$

\tilde{A}_{11}	0		0
0	0		0
0	0		

$\tilde{B} =$

\tilde{b}_1
\tilde{b}_2
0
0

$\tilde{C} =$

\tilde{c}_1	0	\tilde{c}_3	0
---------------	---	---------------	---

① $[\tilde{A}_{11}, \tilde{B}_1, \tilde{C}_1]$ c.c. & e.o.

② can show $[\tilde{A}_{11}, \tilde{B}_1, \tilde{C}_1]$ is equivalent to $[A, B, C]$

③ $[\tilde{A}_{11}, \tilde{B}_1, \tilde{C}_1]$ realization $H(s) = C(sI - A)^{-1}B$

↳ this realization has minimal dimension.

Fact: $[A, B, C]$ c.c. & e.o.
 $\Leftrightarrow [A, B, C]$ is a minimal realization

Proof (\Leftarrow) Suppose not c.c. or not e.o. want to find a minimal realization.

MINIMAL REALIZATION MEANS LOWEST DIMENSION

27/11/18
proof

not c.c. \Rightarrow separate controllable part
 \Rightarrow not minimal realization

not c.o. \Rightarrow separate observable part
 \Rightarrow not minimal realization

Pf (\Rightarrow) suppose not min realization to show \Rightarrow not c.c.
 not min realization

$$\Rightarrow \exists [\bar{A}, \bar{B}, \bar{C}] \text{ z.s. eq to } [A, B, C] \quad \bar{A} \in \mathbb{R}^{n \times n}$$

dim $\bar{n} <$ dim n

z.s. equivalent $\Rightarrow ce^{At}B = \bar{c}e^{\bar{A}t}\bar{B}$

$$(I + At + A^2t^2/2! + \dots)B = \bar{c}(I + \bar{A}t + \dots)\bar{B}$$

$$CB = \bar{c}\bar{B}; \text{ take deriv } \Rightarrow CAB = \bar{c}A\bar{B} \text{ in gen. } CA^k B = \bar{c}A^k \bar{B}$$

c.c. c.o.

$$Q = [B \ AB \ \dots \ A^{n-1}B] \quad R = \begin{bmatrix} c \\ cA \\ cA^2 \\ \vdots \\ cA^{n-1} \end{bmatrix}$$

$$RQ = \begin{bmatrix} c \\ cA \\ \vdots \\ cA^{n-1} \end{bmatrix} [B \ AB \ \dots \ A^{n-1}B] = \begin{bmatrix} CB & CAB & \dots \\ CAB & CA^2B & \dots \\ \vdots & \vdots & \ddots \\ CA^{n-1}B & \dots & CA^{2n-2}B \end{bmatrix}$$

$$= \bar{R}\bar{Q}$$

$$\text{rank } RQ = \text{rank } \bar{R}\bar{Q}$$

Suppose $[A, B, C]$ is c.c. \wedge c.o.

want to reach a contradiction

$$\text{rank } B = n \quad \text{rank } Q = n$$

$$\text{rank } \bar{R} \leq \bar{n} / \text{rank } \bar{Q} \leq \bar{n}$$

ion

sh

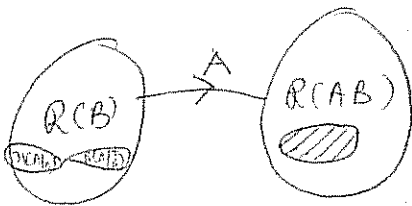
General: $\text{rank}(AB) \leq \min(\text{rank } A, \text{rank } B)$

columns of $(AB) = A \begin{bmatrix} | & & | \end{bmatrix} = \text{l.c. of columns of } A$

rows of $(AB) = \begin{bmatrix} \text{---} \\ \text{---} \\ \text{---} \end{bmatrix} B = \text{l.c. of rows of } B$

$$\begin{aligned} \text{rank}(AB) &= \text{# of l.i. rows/cols} \\ &\leq \text{rank } B \\ &\leq \text{rank } A \\ &\leq \min(\text{rank } A, \text{rank } B) \end{aligned}$$

$$\begin{aligned} \text{rank } R &= n \\ \text{rank } Q &= n \end{aligned} \Rightarrow \text{rank } RQ = n$$



$$R(A) \cap A = R(B) \rightarrow R(AB)$$

$$A |_{R(B)}$$

$$R(A |_{R(B)}) = R(AB) \text{ (rank)}$$

$$\begin{aligned} \dim R(B) &= \underbrace{\dim R(A |_{R(B)})}_{= \dim R(AB)} + \dim N(A |_{R(B)}) \\ &\leq \dim N(A) \end{aligned}$$

$$\text{rank}(B) \leq \text{rank}(AB) + \dim N(A)$$

Sylvester's inequality: $\text{rank } B - \dim N(A) \leq \text{rank}(AB) \leq \min(\text{rank } A, \text{rank } B)$

RETURN

$$\text{rank } \bar{R} \bar{Q} \leq \min(\text{rank } \bar{R}, \text{rank } \bar{Q}) \leq \bar{n} \leq n$$

$$\text{rank } RQ \geq \text{rank } Q - \dim N(R) = n$$

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$n \leq \text{rank } BQ = \text{rank } \bar{R}\bar{D} \leq \bar{n} < n$ * contradiction!

$[A, B, C]$ c.c. & c.o.

$\Leftrightarrow [A, B, C]$ is minimal realization of $H(s) = (C(sI-A)^{-1}B)$

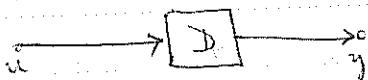
SISO case: $h(s) = c(sI-A)^{-1}b$

$[A, b, c]$ c.c. c.o. $\Rightarrow n^{\text{th}}$ order (no pole-zero cancel)

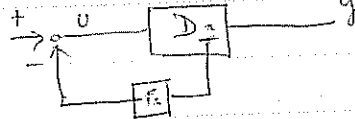
4. Effect of Feedback on c. & o.

(1) on controllability

$\mathcal{D} = \{U, \dot{x}, y, s, r\}$



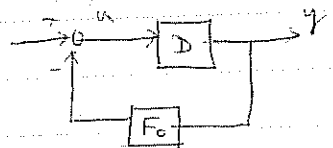
w/o FB



w/ state FB

↑ must be instantaneous

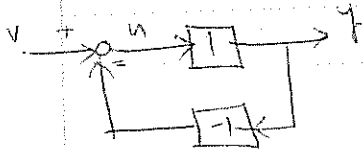
$u(t) = v(t) - F_s(x(t))$



w/ output FB.

↑ should this also be instantaneous?

It could be very general



$\left. \begin{aligned} y(t) &= u(t) \\ u(t) &= v(t) + y(t) \end{aligned} \right\} \text{ make sense?}$

Drive only if $v(t) \neq 0$ $\Rightarrow D_{F_o}$ is not well defined

Assume D_{F_s}, D_{F_o} well defined dynamical system

iff $\forall (x_0, t_0) \neq \forall (t_0, t_1)$

\exists unique $u[t_0, t_1]$ satisfying the system rules

Fact: If $D_{F_s} \neq D_{F_o}$ well defined

D is c.c. on $[t_0, t_1]$

\Leftrightarrow (a) D_{F_s} is c.c. on $[t_0, t_1]$

\Rightarrow (b) D_{F_o} is c.c. on $[t_0, t_1]$

if there was pole-zero cancellation, it would be a minimal realization, but it wouldn't be. This is why we need to check for minimality.

Pf (a) $(\Rightarrow) \forall x_0, x_1 \exists \tilde{u} \in \tilde{U}[t_0, t_1]$ drives (x_0, t_0) to (x_1, t_1)
 For D_{F_s} want to show $\forall x_0, x_1 \exists \tilde{v} \in \tilde{V}[t_0, t_1]$ drives
 (x_0, t_0) to (x_1, t_1)

try $\tilde{v}(t) = \tilde{u}(t) + F_s [s(t, t_0, x_0, \tilde{u}_{[t_0, t_1]})]$

By assumption \exists a unique u satisfying the
 eqn. \tilde{u} (stable pt.)

so $\tilde{v} \in \tilde{V}[t_0, t_1]$ drives (x_0, t_0) to (x_1, t_1)

$(\Leftarrow) \forall x_0, x_1 \exists \tilde{v} \in \tilde{V}[t_0, t_1]$ drives (x_0, t_0) to (x_1, t_1)

Ass. $\Rightarrow \exists$ a unique u s.t. $u(t) = u(t) - F_s [s(t, t_0, x_0, u)]$

$u \in \tilde{U}[t_0, t_1]$ drives (x_0, t_0) to (x_1, t_1)

for (b) identical proof

(2) on observability

Fact: if D_{F_0} is well-defined then D is c.o. on $[t_0, t_1]$
 $\Leftrightarrow D_{F_0}$ c.o. $[t_0, t_1]$

But no need ^{using D_{F_s}} c.o. ! See plus Assign

16 Nov 1989

AST-lecture Discussion

1. Prior to MT1
2. calculate SVD

$$A = \begin{bmatrix} -2.896 & -2.292 \\ 1.369 & .738 \end{bmatrix}$$

$$A^*A = \begin{bmatrix} 10.26 & 7.65 \\ 7.65 & 5.8 \end{bmatrix} \quad ; \text{ obtain eigenvalues}$$

eigenvalues of A^*A are σ^2 ; (0.0625, 16)

$$\Sigma = \begin{bmatrix} 1/4 & 0 \\ 0 & 4 \end{bmatrix} \quad \text{Rank} = 2 ; \text{ but nearly singular}$$

$$N(A^*A) = \{\emptyset\} \quad u = [u_1, u_2]$$

↳ empty

$$u = \begin{bmatrix} .6 & +.8 \\ -.8 & .6 \end{bmatrix} \quad \text{eigenvector of } A^*A$$

$$V = A u \Sigma^{-1} = \begin{bmatrix} .385 & .923 \\ .923 & .385 \end{bmatrix}$$

$A = V \Sigma U^*$ works fine : good to do this to understand.

Gram Schmidt orthonormalization

→ def

Hermitians: if M is Hermitian

(1) all real eigenvalues

(2) Jordan form is diagonal matrix

(3) eigenvectors are orthogonal \neq diff eigenvalues

(4) $\exists P$ s.t. $P^*P = I$ & $PM P^*$ is a diagonal matrix.

Zeros of a transfer fn: Require an initial state and an input.

given $h(s) = \frac{s-2}{(s+1)(s+3)}$
and some realization $\{A, \overset{b}{B}, C\}$

find an i/p and an initial state s.t.
the output $\equiv 0$.

$$\text{input} = \mathcal{L}^{-1}\left(\frac{1}{s-2}\right) = 1(t) e^{2t} \quad (\text{inv. of realization})$$

initial state depends on realization.

$$A = \begin{bmatrix} 0 & 1 \\ -3 & -4 \end{bmatrix} \quad b = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad c = \begin{bmatrix} -2 & 1 \end{bmatrix}$$

$$h(s) = c(sI - A)^{-1} b$$

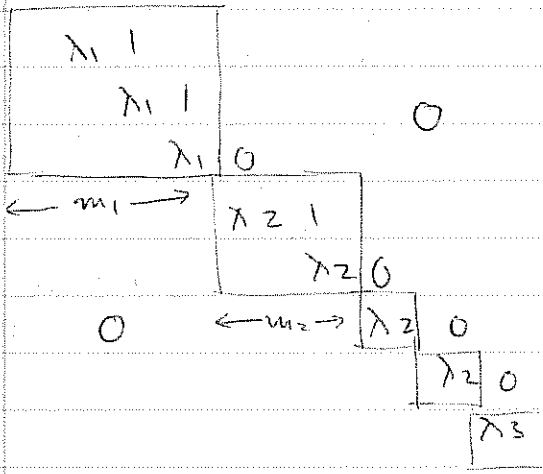
$$\text{total response} = z_{IR} + z_{SR} \neq$$

$$z_{SR} = h(s) u(s) = \frac{(s-2)}{(s+1)(s+3)} \cdot \frac{1}{s-2} = \frac{1}{(s+1)(s+3)}$$

$$\text{total response} = 0 \Rightarrow z_{IR} = -z_{SR}$$

$$z_{IR} = -\frac{1}{(s+1)(s+3)} \quad ; \text{controllable canonical form}$$

Know what the controllable, Observable, Jordan canonical forms look like. (cf discussion)



chr. poly: $(s-\lambda_1)^3 (s-\lambda_2)^4 (s-\lambda_3)$
 $= \Delta^5$

min poly: $(s-\lambda_1)^3 (s-\lambda_2)^2 (s-\lambda_3)$
 $= \Psi(s)$

look at power series exp of e^{At} for Jordan Block

least squares

Solve $Ax=b$

(i) A^{-1} exists $x=A^{-1}b$

$b \notin R(A)$ then decompose $b = b_1 + b_2$ $b_1 \in R(A)$ $b_2 \in N(A^*)$

non unique soln: decompose x into $x = x_1 + x_2$ $x_1 \in R(A)$ $x_2 \in N(A^*)$

$$Ax = A(x_1 + x_2)$$

$$= Ax_r = b$$

$$A^* Ax_r = A^* b$$

$$x_r = (A^* A)^{-1} A^* b$$

$$Ax = b_r \quad A^* b_u = 0$$

~~$$A^* A b_r = 0$$~~

$$A^* b_r = x_r$$

BIBO: depends not on state only I/P \neq O/P

~~BIBO~~ - BIBO $\Leftrightarrow \exists M$ s.t. $\int_{-\infty}^t \|H(t, \tau)\| d\tau < M \quad \forall t \in \mathbb{R}_+$

LTI $H(t, \tau) = H(t-\tau)$

Discrete-time systems $W(k_0, k_1) \triangleq [B_{k_1} \dots | \Phi(k_1, k_1-1)B_{k_1-2} | \dots | \Phi(\dots)B_{k_0}]$

controllable from the origin iff $\text{rank}(W) = n$

c.c. to the origin $\Leftrightarrow R(\Phi) \subseteq R(W)$

for LTI replace W by Φ

is L $\forall t \geq 0 \quad \epsilon > 0$

$A_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $B_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $B_k = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ ($k \neq 0$)

$\exists \delta(t_0, \epsilon)$ s.t. $\|x_0\| < \delta(t_0, \epsilon)$
 $\|x(t)\| < \epsilon \quad \forall t \geq t_0$

so this c.c. to 0 in 1 step?

no!
 $W(0,1) = B_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ rank 1
 $W(0,2) = [B_1 | AB_0] = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ rank = 2

Say $X(s) = \frac{1}{(s+1)^2} X_0$, given ϵ find appropriate δ .

$x(t) = te^{-t} X_0$

max at $t=1$, max = 1

$\|x(t)\| \leq \|x_0\| \quad \delta = \frac{1}{\epsilon} \|x_0\|$

LTI: is L \Leftrightarrow poles in LHP

or ~~for~~ simple zeros of minimal poly on $j\omega$ axis

as stab. : LTI \Rightarrow strictly all poles in LHP

BIBS stable: Require all poles in LHP, simple ones on $j\omega$ axis, the $j\omega$ poles not controllable from the input.

know tests for c.c.

$\langle T \rangle - \Phi$ full rank

M full rank

~~rank~~ $[\lambda I - A | B]$ full rank,

rows of $X^{-1}(z) B(z)$ indep
 \uparrow full matrix.

How do you find c.c. part?

Change of basis to $\begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix}$ $\begin{bmatrix} B_1 \\ 0 \end{bmatrix}$

this part not controllable

$R \xrightarrow{T} \tilde{R}$

new ops

$\begin{bmatrix} 0 & I \end{bmatrix}$ perform elementary row ops on this to get $\begin{bmatrix} 0s & I \end{bmatrix}$ Then $\tilde{A} = TAT^{-1}$ $\tilde{B} = TB$ etc.

Day
12~~th~~, 1989

AST-lecture

New Chapter: XII Eigenvalue Assignment

1. Motivation: \dot{x} TI system

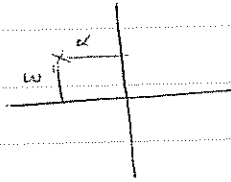
$$\dot{x} = Ax + Bu$$

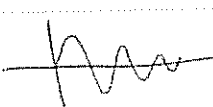
$$y = Cx$$

w/o solving we know soln charac by STM i.e.

$$\Phi(t, 0) = e^{At} = \sum_{k=1}^m \sum_{l=0}^{m_k-1} t^l e^{\lambda_k t} P_{kl}$$

location of the eigenvalues (eigenvalues of A that is)

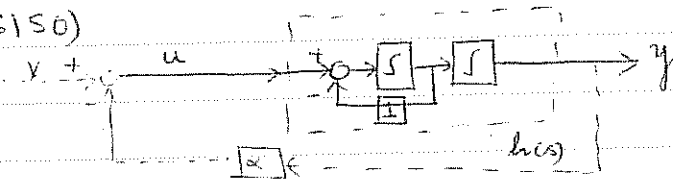


since response will have one component  exp(t) envelope
time = ω

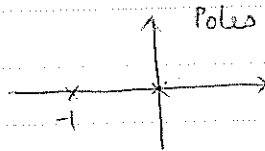
If time response not good, change location of eigenvalues.

- Can this be done
- How do we do it.

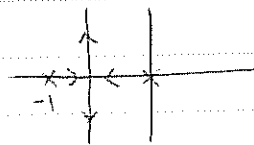
Ex (SISO)



$$\begin{aligned} \dot{y} &= u - y \\ \Rightarrow \dot{y} + y &= u \\ h(s) &= 1/s(s+1) \end{aligned}$$



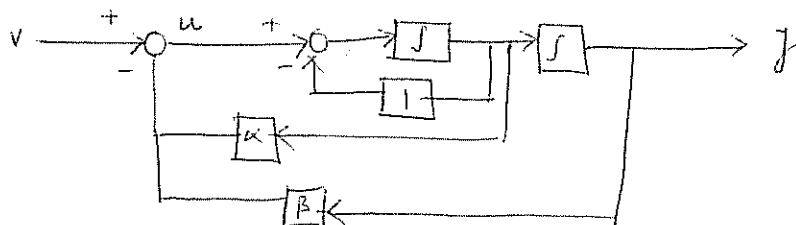
$$\begin{aligned} u &= v - \alpha y \\ \dot{y} + y &= v - \alpha y \\ h'(s) &= 1/(s^2 + s + \alpha) \end{aligned}$$



poles of $h'(s)$ changes as α changes
moves along "root locus"

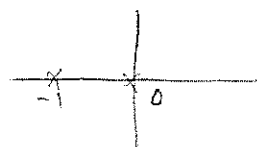
one parameter - one degree of freedom for poles to move.

what happens if we introduce 2 parameters?



$$\ddot{y} + \dot{y} = u = v - \alpha \dot{y} - \beta y$$

$$\therefore h(s) = \frac{1}{s^2 + (1+\alpha)s + \beta}$$



poles can move anywhere we want.

Q: Can state feedback move the eigenvalues anywhere we want?
(equiv. control the modes)

Will show

- ① If the system representation for single i/p single o/p, is in special form (controllable canonical form) then can be done
- ② Given arbitrary $[A, b, c]$ transform to cont. canon form k then see.

Q: Can this be transformed into controllable canonical form $\left[\begin{matrix} \text{Trans} \\ \text{out} \end{matrix} \right] [A, b, c] \text{ c.c. }$

- ③ combine ① & ② state f.b. control
- ④ Generalize to MIMO

Next Chap: if internal states unavailable, the observer design

2. SISO

(1) State F.B. in controllable form.

$$\dot{\xi} = \begin{bmatrix} 0 & 1 & & \\ & \ddots & \ddots & \\ & & -\alpha_{n-1} & -\alpha_n \end{bmatrix} \xi + \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} u \quad \text{Controllable Canonical Form}$$

A_c b_c

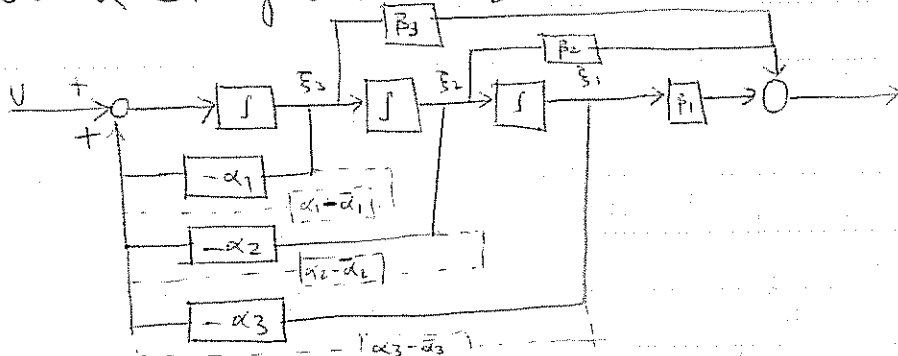
eigen values: $\lambda_1 \dots \lambda_n$ (multiple e.v. are allowed)
 \rightarrow req. complex conj. (for real α_i 's)

charac. polynomial $d(s) = (s - \lambda_1)(s - \lambda_2) \dots (s - \lambda_n)$
 $= s^n + \alpha_1 s^{n-1} + \dots + \alpha_n$ (minus in char. poly)

Desired eigen values are $\tilde{\lambda}_1 \dots \tilde{\lambda}_n$ [any place but conj.]

$$\tilde{d}(s) = s^n + \tilde{\alpha}_1 s^{n-1} + \dots + \tilde{\alpha}_{n-1} s + \tilde{\alpha}_n$$

Block Diagram: [Ex dim=3]



changing is trivial [to $\tilde{\alpha}_1, \tilde{\alpha}_2, \dots$]

Algebraically:

want $\tilde{A}_c = \begin{bmatrix} 0 & 1 & & \\ & \ddots & \ddots & \\ & & -\tilde{\alpha}_{n-1} & -\tilde{\alpha}_n \end{bmatrix}$

$$\tilde{A}_c - A_c = \begin{bmatrix} 0 & 0 & 0 \\ & 0 & 0 \\ \alpha_n - \tilde{\alpha}_n & \alpha_{n-1} - \tilde{\alpha}_{n-1} & \dots & \alpha_1 - \tilde{\alpha}_1 \end{bmatrix}$$

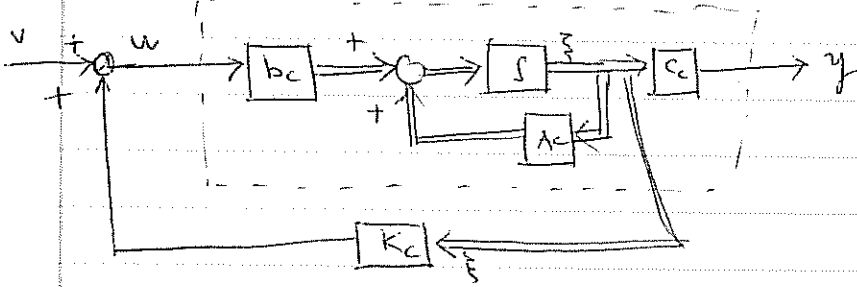
$$\tilde{A}_c - A_c = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} [\alpha_n - \tilde{\alpha}_n \quad \dots \quad \alpha_1 - \tilde{\alpha}_1] = b_c k_c$$

$$\tilde{A}_c = A_c + b_c k_c$$

$$\dot{\xi} = A_c \xi + b_c u$$

want $\dot{\xi} = (A_c + b_c k_c) \xi + b_c v$
 (state feedback) \rightarrow

let $u = v + k_c \xi$; this works!



(2) Controllable Form

Given $[A, b, c]$

$$\begin{cases} \dot{x} = Ax + bu \\ y = cx \end{cases}$$

$$d(s) = s^n + \alpha_1 s^{n-1} + \dots + \alpha_n$$

- Don't know how to change e-values.

But if in cont canon form: trivial, $\dot{\xi} = A_c \xi + b_c u$

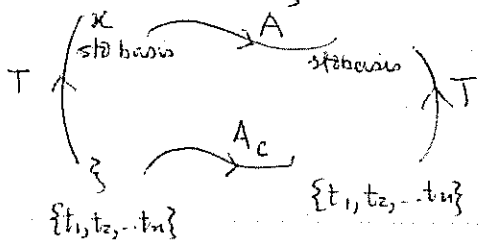
where $A_c = \begin{bmatrix} 0 & 1 & & \\ & & \ddots & \\ & & & 1 \\ -\alpha_n & \dots & -\alpha_2 & -\alpha_1 \end{bmatrix}$

$$b_c = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

$$y = c_c \xi$$

Is there a coordinate transformation expressing this?

$$x = T \xi$$



$$\begin{aligned} A &= T A_c T^{-1} \\ b &= T b_c \end{aligned}$$

let try and find T.

$$T = [t_1 \ t_2 \ \dots \ t_n]$$

$$b = T b_c$$

$$A T = T A_c$$

Note:
 bases $b, Ab, \dots, A^{n-1}b$
 $\Rightarrow \begin{bmatrix} 0 & 1 & & \\ & & \ddots & \\ & & & 1 \\ \alpha_n & \dots & \alpha_2 & \alpha_1 \end{bmatrix} = A_c$
 $A[T] = T A_c$
 $T A = A_c T$
 So A_c is transfer matrix
 $A \xrightarrow{T} A_c$
 $A_c \xleftarrow{T^{-1}} A$

$$\therefore b = T^{-1}bc$$

$$\Rightarrow t_n = bc$$

$$AT = TA_c$$

$$[t_1 | t_2 \dots | t_n] \begin{bmatrix} 0 & 1 & & \\ & & \ddots & \\ & & & -\alpha_n & \dots & -\alpha_1 \end{bmatrix} = \boxed{A} \boxed{t_1 | t_2 \dots | t_n}$$

$$t_{n-1} - \alpha_1 t_n = A t_n$$
 ; from last column.

$$\Rightarrow t_{n-1} = \alpha_1 t_n + A t_n$$

$$t_{n-2} - \alpha_2 t_n = A t_{n-1}$$
 ; from 2nd last column

$$\Rightarrow t_{n-2} = \alpha_2 t_n + A t_{n-1}$$

Recursion allows us to obtain all upto $t_1 = \alpha_{n-1} t_n + A t_2$; from 2nd column

Provides Recursive Formula for computing columns of T.

First col : $0 = \alpha_n t_n + A t_1$; an identity (ie redundant)

To qualify as a basis $\{t_1, \dots, t_n\}$ must be l.i.
 : check T for singularity!

$$t_{n-1} = \alpha_1 b + A b$$

$$t_{n-2} = \alpha_2 b + A(\alpha_1 b + A b) = \alpha_2 b + \alpha_1 A b + A^2 b$$

\vdots
 \vdots
 \vdots

non-singular
 iff α non-singular
 iff T non-singular

$$[t_1 | t_2 \dots | t_n] = \left[\begin{array}{c|c|c|c} b & Ab & \dots & A^{n-1} b \end{array} \right] \begin{bmatrix} \alpha_{n-1} & \dots & -\alpha_2 & \alpha_1 & 1 \\ \vdots & & \alpha_1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

T nonsingular $\Leftrightarrow Q$ nonsingular

If $[A, b, c]$ c.c.

$\Rightarrow \exists T$ nonsingular s.t. $x = T\xi$
transforms $[A, b, c] \leftrightarrow [A_c, b_c, c_c]$

[ex: show \Leftarrow true]

(3) state feedback \bar{c} / arbitrary $[A, b, c]$

Given $[A, b, c]$
use state feedback to move eigenvalues
anywhere we want.
 $\Leftrightarrow [A, b, c]$ c.c.

Proof: (\Leftarrow) $[A, b, c]$ c.c. $\Rightarrow \exists T$ nonsingular

$$x = T\xi$$

$$[A, b, c] \leftarrow [A_c, b_c, c_c]$$

$A_c = T^{-1}AT$ same eigenvalues

\Rightarrow S.F. moves eigenvalues of A_c . (hence A)

Proof (\Rightarrow) suppose not c.c.

separation of controllable part

$$\begin{bmatrix} \dot{\bar{x}}_1 \\ \dot{\bar{x}}_2 \end{bmatrix} = \begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ 0 & \bar{A}_{22} \end{bmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} + \begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix} u$$

e-values of $A =$ (eigenvalues of \bar{A}_{11}) \cup (e.v. of \bar{A}_{22})

state feedback $u = v + K\bar{x}$

$$= v + [K_1 \ K_2] \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}$$

$$\begin{bmatrix} \dot{\bar{x}}_1 \\ \dot{\bar{x}}_2 \end{bmatrix} = \begin{bmatrix} \bar{A}_{11} + \bar{B}_1 K_1 & \bar{A}_{12} + \bar{B}_1 K_2 \\ 0 & \bar{A}_{22} \end{bmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} + \begin{bmatrix} \bar{B}_1 \\ 0 \end{bmatrix} v$$

unchanged!

eigenvalues = (eigenvalues of $\bar{A} + \bar{B}K$) \cup (e-values of A)

there are portions of the eigenvalues of A which will not change!

Procedure [Explicit]

$$\dot{x} = Ax + bu$$

$$y = Cx \quad \text{c.c.}$$

$$d(s) = s^n + \alpha_1 s^{n-1} + \dots + \alpha_n$$

$$\text{want } \bar{d}(s) = s^n + \bar{\alpha}_1 s^{n-1} + \dots + \bar{\alpha}_n$$

State Feedback $u = v + Kx$

$$\dot{x} = Ax + bu$$

$$= Ax + b(v + Kx)$$

$$= (A + bK)x + bv$$

$$x = Tz$$

$$\dot{z} = T^{-1}(A + bK)Tz + (T^{-1}b)v$$

$$= \bar{A}z$$

$$= \bar{A}z + bcv$$

$$= (\bar{A} + bcK)z + bcv$$

$$\Rightarrow Kc = KT$$

$$Kc = [\alpha_n - \bar{\alpha}_n, \alpha_{n-1} - \bar{\alpha}_{n-1}, \dots, \alpha_1 - \bar{\alpha}_1]$$

Obtained from recursive formula.

$$[T^{-1}] [K^T] = [Kc^T]$$

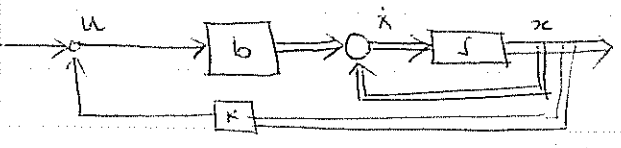
$$\begin{bmatrix} \square & \square & \square \end{bmatrix} = \begin{bmatrix} \square \end{bmatrix} ; \text{ can solve}$$

no obtain K !
from which we get K !
no K !

Monday
28 Nov 1989

KST-lecture

Single input



$$\dot{x} = Ax + bu \quad ; \text{original}$$

$$[A, b] \text{ c.c.}$$

$$\dot{x} = (A + bk)x + bv$$

3. Multiple input

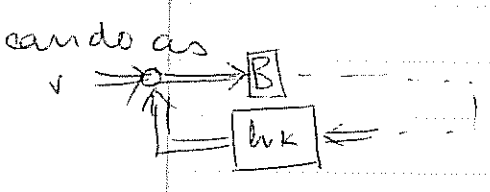
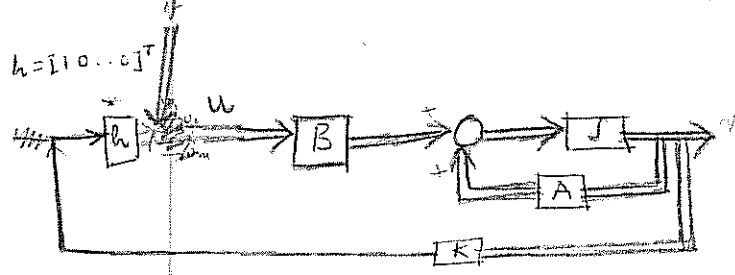
$$[A, B, C] \quad \dot{x} = Ax + Bu$$

$$y = Cx$$

assume $[A, B]$ c.c. $\Leftrightarrow \text{rank } Q = [B \ AB \ \dots \ A^{n-1}B] = n$

$$\text{let } B = [b_1 \ b_2 \ \dots \ b_m]$$

$\Leftrightarrow [b_1 \ b_2 \ \dots \ b_m \ Ab_1 \ Ab_2 \ \dots \ Ab_m \ A^2b_1 \ \dots]$
 $\exists n$ l.i. vectors among the columns of



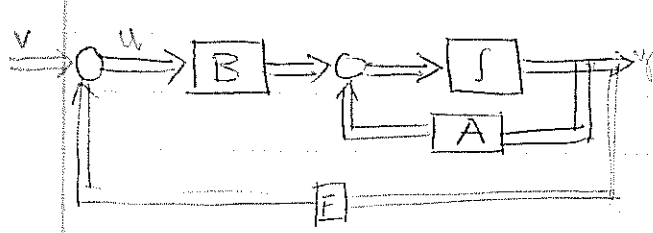
* (v) Sp. case $[b_1 \ Ab_1 \ \dots \ A^{n-1}b_1]$ non sing
 Then c.c. from just first input!
 so use single input statif. b.
 design \tilde{w}_1
 K overall state feedback.

2) General Case

$$[A, B] \text{ c.c.}$$

However $[b_1 \ Ab_1 \ \dots \ A^{n-1}b_1]$ not nonsingular
 (of course $[b_k \ Ab_k \ \dots \ A^{n-1}b_k]$ all not nonsingular else stuff?)

that feedback through c.c.



basically $[A, B]$ c.c. $\Leftrightarrow [G, B]$ c.c. $G = A + BF$
 $[A, B]$ c.c. $\Leftrightarrow \exists p \tilde{F}$ also c.c.

$$\dot{x} = Ax + Bu \quad \text{originally}$$

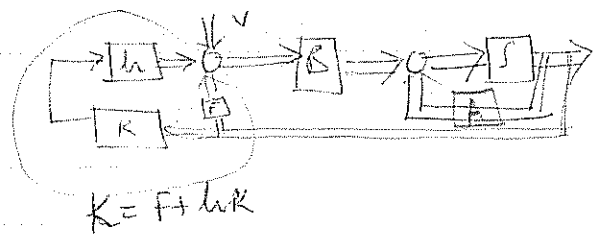
$$\dot{x} = Ax + Bv + BFx$$

$$= (A + BF)x + Bv$$

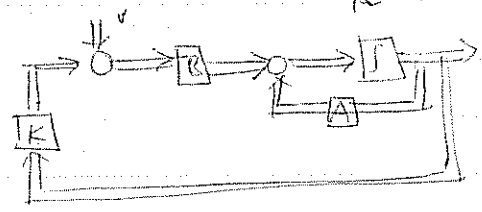
27 5610M
(10.10-15.14)

maybe $[b_1 \ Gb_1 \ \dots \ G^{n-1}b_1]$ can be made nonsingular

if we can do that,



becomes



Two step design

1. Find $G = A + BF$
so that $[b_1 \ Gb_1 \ \dots \ G^{n-1}b_1]$ non singular
2. Design K to move eigenvalue of G using single input case.
 $K = F + hK$

no process is one
 to go as to
 should be
 should be

How do we find G .

① Select n lin ind columns from B
 $M = [b_1 \ -Ab_1 \ \dots \ A^{n-1}b_1 \ b_2 \ \dots \ A^{n-1}b_2 \ \dots \ b_k \ \dots \ A^{k-1}b_k]$
 ↑
 select k E/pers. ind

M nonsingular

② want to generate $[b_1 \ Gb_1 \ \dots \ G^{n-1}b_1]$ from M nonsingular

let $[b_1 \ Gb_1 \ \dots \ G^{n-1}b_1] = [u_1 \ \dots \ u_n] \Leftarrow$ has nothing to do w/ on the one hand

$u_1 = b_1$
 $u_{k+1} = (A + BF)u_k$

on the other hand

u_1, u_2, \dots, u_n derived from columns of M

Should process of choice of b_1, b_2, \dots

$$u_1 = b_1$$

$$u_2 = \alpha A b_1 + \beta b_1 ; \text{ obviously } \alpha=1, \beta=1 \text{ (from } u_{k+1} = (A+B)u_k \text{)}$$

$$u_3 = A u_2 + \text{lin comb of } b_1, b_2, \dots, b_m$$

$\rightarrow b_1$ should be chosen

$$u_{n+1} = A u_n + b_2 ; \text{ without } A u_{n+1} \neq B u_n \text{ } u_{n+1} = A u_n + b_1$$

would want to put $u_{n+1} = A u_n + b_2 + b_1$

now we have a pattern

$$u_1 = b_1$$

$$u_2 = A b_1 + b_1$$

$$u_3 = A u_2 + b_1$$

$$\dots$$

$$u_n = A u_{n-1} + b_1$$

In general

$$u_1 = b_1$$

$$u_{k+1} = A u_k + \tilde{b}_k$$

$$\tilde{b}_k \in \mathcal{R}(B)$$

$$\tilde{b}_k = B \tilde{h}_k$$

$$u_{n+1} = A u_n + b_2$$

$$\tilde{h}_k = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \tilde{h}_k = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$k=1, \dots, n$ $k=n+1, \dots, n+2$ if b_2 indep. w/ previous ones

w/ this defn $u_{k+1} = A u_k + B \tilde{h}_k$

Compare w/ $u_{k+1} = A u_k + B F u_k$

$$F u_k = \tilde{h}_k$$

$$F [u_1, u_2, \dots, u_n] = [\tilde{h}_1, \tilde{h}_2, \dots, \tilde{h}_n]$$

$$F U = H$$

$$F = H U^{-1}$$

; \exists this choice of F , $[b_1 | G b_1 | \dots | G^{n-1} b_1]$ is non-si
 (if we had taken b_1, b_2 there, diff F would result, which would still do the job)

$$K = \underset{w}{F} + h_k : \text{ not unique}$$

$m \times n$ $K \leftarrow m \times n$ parameters n eigenvalues \Rightarrow lots of degrees of freedom.

This process is...
 we should use...
 linear indep. of b_1, b_2, \dots, b_m
 can also solve with...
 time...
 Are b_1, b_2, \dots, b_m linear independent?

b_1, b_2, \dots, b_m
 $A^{-1} b_1, \dots, A^{-1} b_m$
 $A^{-1} b_1$ not b_1 then choice independent?

PROCEDURE

- 1) Find $b_1 \dots b_k$ from B $n_1 \dots n_k$
 s.t. $M = [b_1, Ab_1, \dots, A^{n_1-1}b_1, \dots, b_k, \dots, A^{n_k-1}b_k]$ is nonsingular
- 2) $\tilde{h}_i = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad i=1 \dots n_1-1$
 $\tilde{h}_i = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad i=n_1+1 \dots n_1+n_2-1$
- 3) $u_1 = b_1$
 $u_{k+1} = Au_k + B\tilde{h}_k \quad U = [u_1, u_2, \dots, u_n]$
- 4) $F = HU^{-1}$
- 5) Apply single ~~state~~ ^{input} Eigen value Assignment
 TO $\dot{x} = (A+BF)x + b_1 v_1$
 find K
- 6) The reqd. state feedback is
 $K = F + h_k \quad \text{where } h = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$

The states are not necessarily available

$[A, B, C]$ e.c.

"Can use state fbk to move eigenvalues"
 (i control modes) XI OBSERVERS

What if the states are inaccessible?

Try to "observe" the states "estimate"
 device which estimates states is called the ^{ESTIMATOR} or OBSERVER

① design (design) an observer

SISO; MIMO Asymptotically (error $\rightarrow 0$ time)

design how fast the ~~error~~ ^{error} dies out. DUAL to state fb design

- ② State fdbk = observer (use of observer doesn't change spet performance of state FB)
- ③ improvement: reduced order observer

30 Nov 189

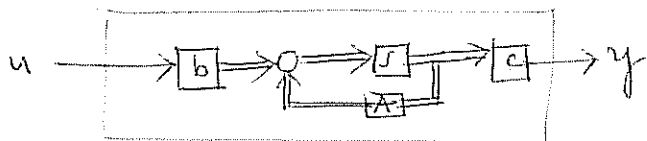
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correction: $\hat{h}_i = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad i=1,2,\dots,n-1$

(1) OPEN LOOP OBSERVER

XI OBSERVERS

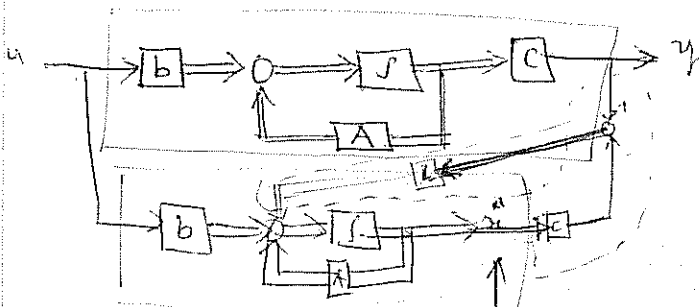
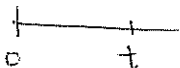
SISO $\dot{x} = Ax + bu$
 $y = cx$



states not accessible.

- 2. full order observer - SISO
- (1) open loop observer
- [A, b, c] c.o.

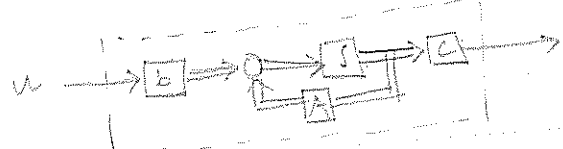
$u[0,t]$ & $y[0,t]$ det uniquely $x(0)$
 thus have all the states, i.e. $x(t)$



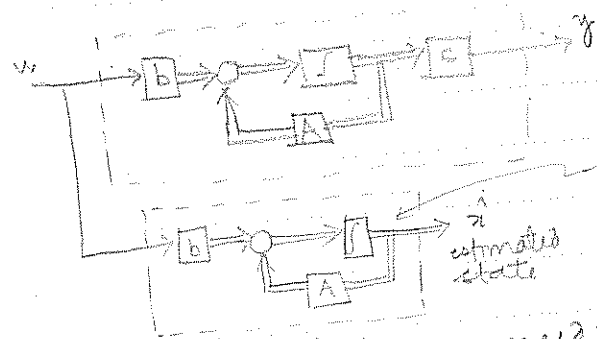
allways believe!

2. FULL ORDER OBSERVER - SISO

$$\begin{cases} \dot{x} = Ax + bu \\ y = cx \end{cases}$$



(1) open loop observer: $y(A, b, c)$ c.o. $y[0, t]$ & $u[0, t]$ determine $x(t)$ (hence $\hat{x}(t)$)



initial state $\hat{x}(0)$ computed from $y[0, t]$ and $u[0, t]$ hence $\hat{x}(t)$

$$\dot{\hat{x}} = A\hat{x} + bu$$

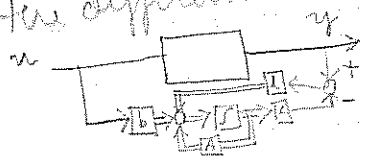
need to adjust $\hat{x}(t)$ based on observed $y[0, t]$ & $u[0, t]$ \hat{x} and x are identical afterwards

computation requires zero time

(2) Asymptotic Observer

idea of using feedback (error)

the output $y = cx$ is compared w/ $\hat{y} = c\hat{x}$ the difference is used to sum as a "correction" term



$$\dot{\hat{x}} = A\hat{x} + bu + l(y - \hat{y}) \text{ Feedback correction term.}$$

what about error in estimation $e = \hat{x} - x$?

$$\text{observer } \begin{cases} \dot{\hat{x}} = A\hat{x} + bu \\ y = c\hat{x} \\ \dot{\hat{x}} = A\hat{x} + bu + l(c\hat{x} - cy) \end{cases}$$

subtracting, we obtain (i) the dynamics of the error $\dot{e} = (A - lc)e$ \Rightarrow $\dot{e}(t)$ are decoupled from $\hat{x}(t)$

$$(ii) e(t) = [\exp(A - lc)t]$$

Can we control the eigenvalues of $CA = lc$?

(3) (A, b, c) in observable Canonical form

$$A_0 = \begin{bmatrix} 0 & -a_{n-1} & & \\ 1 & -a_{n-2} & & \\ & & \ddots & \\ & & & 1 & -a_1 \end{bmatrix}$$

$$c_0 = [0 \ 0 \ \dots \ 0 \ 1]$$

desired eigenvalues of $(A - lc) \Rightarrow \bar{\alpha}_1, \bar{\alpha}_2, \dots, \bar{\alpha}_n$

$$\bar{A}_0 = \begin{bmatrix} 0 & -\bar{\alpha}_{n-1} & & \\ 1 & -\bar{\alpha}_{n-2} & & \\ & & \ddots & \\ & & & 1 & -\bar{\alpha}_1 \end{bmatrix} = A_0 - lc_0 = \begin{bmatrix} 0 & -a_{n-1} & & \\ 1 & -a_{n-2} & & \\ & & \ddots & \\ & & & 1 & -a_1 \end{bmatrix} - \begin{bmatrix} 0 & & & \\ & & & \\ & & & \\ & & & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & \dots & 0 & 1 \end{bmatrix}$$

$$\begin{aligned} \bar{\alpha}_1 &= \alpha_n - \alpha_n \\ \bar{\alpha}_n &= \alpha_1 - \alpha_1 \end{aligned}$$

we can select l to move e -values of $(A - lc)$ can make $e(t) \rightarrow 0$ according to $\hat{x}(t) \rightarrow x(t)$ exponential transformation

controllability - rank FB

$$\begin{matrix} K \\ A - BK \\ A_c \\ b_c \end{matrix}$$

OBSERVER

$$\begin{matrix} l \\ A - lC \\ A_o \\ c_o \end{matrix}$$

$$\begin{matrix} A_o = A_c^T \\ c_o = b_c^T \\ l = K^T \end{matrix}$$

Problem: Given (A, b, c) find s.t. the e-values of $(A - bk)$ are desired local
 1. Find the state F.B. k which moves the e-values of $(A - c^T k)$ to the given location
 2. $l = k^T$

3. FULL ORDER OBSERVER-MIMO

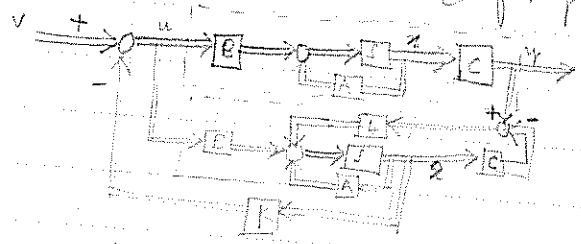
multiple output (A, c) c.o.

Find L s.t. $(A - LC)$ given eigenvalues
 1) Find the state feedback k (MIMO case) which moves e-values of $(A^T - (TK)^T)$ to desired location
 2. $L = k^T$

4. Observer & State Feedback

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases} \text{ c.c. \& c.o.}$$

use estimated state $\hat{x}(t)$ for feedback to place eigenvalues



Q1) Is $\hat{x}(t) \rightarrow x(t)$ stable?
 Q2) Overall system response according to e-values of $A + BK$?

$$\dot{\hat{x}} = A\hat{x} - BK\hat{x} + BV$$

$$\dot{\hat{x}} = LC\hat{x} + (A - LC - BK)\hat{x} + BV$$

error in estimation $e = \hat{x} - x$
 $\Rightarrow \dot{e} = (A - LC)e$ (**)

(i) Dynamics of the error $e \rightarrow e(t)$ decoupled from $x(t) \rightarrow x(t)$

(ii) $e(t) = [exp(A - LC)t] e(0)$ determined by eigenvalues of $(A - LC)$ which can be assigned arbitrarily if (A, C) c.o. by selecting of L

(iii) $e(t) = e(t)$ state F.B. doesn't affect the estimation

$$\dot{\hat{x}} = (A - BK)\hat{x} - BK e + BV$$

(*) the state $x(t)$ is affected by the estimation error $e(t)$ initially, but as $t \rightarrow \infty$, (*) $\dot{x} = (A + BK)x + BV$

(*) & (***) taken together characterize the total system

$$\dot{x} = (A - BK)x + BK e + BV$$

$$\dot{e} = (A - LC)e$$

$$y = [C \ 0] \begin{bmatrix} x \\ e \end{bmatrix}$$

transfer function $v \rightarrow y$

$$H(s) = [C \ 0] \begin{bmatrix} sI - (A - BK) & BK \\ 0 & sI - (A - LC) \end{bmatrix}^{-1} \begin{bmatrix} B \\ 0 \end{bmatrix}$$

$$= C [sI - (A - BK)]^{-1} B$$

same as \hat{x} state feedback only
 Note that TRANSFER FN is associated \hat{x} zero state

character polynomial: $d(s) = \det(sI - (A - BK)) \det[sI - (A - LC)]$
 No result. one can design the observer and the state feedback separately. (Actually sort of zero-state feedback, as we feedback the estimated state)

Due to dynamics of observer not controllable.
 $\dot{e} = (A - LC)e$ not controllable

(2) Asymptotic observer

idea of using feedback compare of y & estimate $\hat{y} = c\hat{x}$
 \hat{y} used as a correction term.

$$\dot{\hat{x}} = A\hat{x} + bu + (fback correction term) l(y - \hat{y})$$

Q: (i) what does it mean? it does $\hat{x}(t) \rightarrow x(t)$
 (ii) How to use proper selection of l

consider estimation error

$$e \equiv \hat{x} - x$$

system has to satisfy $\dot{x} = Ax + bu$ — (1)

observer has to satisfy $\dot{\hat{x}} = A\hat{x} + bu + l(cx - c\hat{x})$ — (2)

$$(2) - (1) \Rightarrow \dot{e} = (A - lc)e$$

$$e(t) = [\exp(A - lc)t] e(0)$$

independent of $u(t)$

" " " $x(t)$

$e(t) \rightarrow 0$ determined by eigenvalue of $(A - lc)$
 \therefore if we can move the e.v. of this matrix we can make the error go to zero!
 Can we select l to move eigenvalues of $(A - lc)$?

(a) special case: (A, b, c) in observable canonical form.

$$A_0 = \begin{bmatrix} 0 & \dots & -a_n \\ \vdots & \dots & -a_{n-1} \\ \vdots & \dots & \vdots \\ \vdots & \dots & -a_1 \end{bmatrix}$$

$$C_0 = [0 \dots 0 \ 1]$$

$$d(s) = s^n + a_1 s^{n-1} + \dots + a_n$$

desired eigenvalues give rise to $\bar{d}(s), \bar{\alpha}_1, \bar{\alpha}_2, \dots, \bar{\alpha}_n$

i.e. $\bar{A}_c = \begin{bmatrix} 0 & \dots & -\bar{\alpha}_n \\ 1 & & \vdots \\ & \ddots & \vdots \\ & & 1 & -\bar{\alpha}_1 \end{bmatrix} = \begin{bmatrix} 0 & & & -\alpha_n \\ & \ddots & & \vdots \\ & & 1 & -\alpha_1 \end{bmatrix} - \begin{bmatrix} & & & -\alpha_n + \bar{\alpha}_n \\ 0 & & & \vdots \\ & & & -\alpha_1 + \bar{\alpha}_1 \end{bmatrix} = \bar{A}_c + \bar{L}c_0$ $\bar{L} = \begin{bmatrix} \bar{\alpha}_n - \alpha_n \\ \vdots \\ \bar{\alpha}_1 - \alpha_1 \end{bmatrix}$

Answer: yes if $[A, b, c]$ in observable canonical form
 can move eigenvalues of $[A - lc]$ where u man

(d) $[A, b, c]$ general
 coord transformation
 into observable canonical form
 can show if (A, b, c) c.o.
 can do

Duality

state FB
 k $\boxed{\quad}$

$A + bk$
 A_c
 b_c

Observer

l $\boxed{\quad}$
 $A - lc$
 A_o
 c_o

$A_o = A_c^T$
 $c_o = b_c^T$

Given $[A, B, c]$ c.o.

find l s.t. $[A - lc]$ has desired eigenvalues

(1) find state feedback k s.t. $(A - b_k)$ has desired eigenvalues.

$[A, c]$ c.o. $\Rightarrow (A^T, c^T)$ c.c.

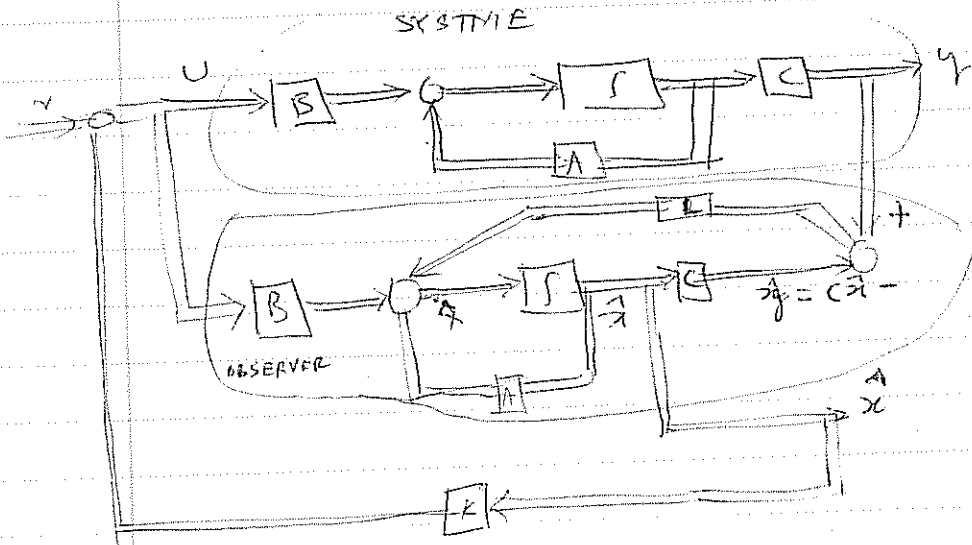
(2) $l = k^T$

3. Full Order Observer - MIMO
Find L

1) Find K (MIMO)

s.t. $(A - BK)$ desired eigenvalues

2) $L = K^T$; careful of signs!



use estimate states $\hat{x}(t)$ for state FB to meet eigenvalues (overall sys response)

Q1: $\hat{x}(t) \rightarrow x(t)$

Q2: overall sys. response, does it go as ev. of $A - BK$?

look at us: $\dot{\hat{x}} = A\hat{x} - BK\hat{x} + Bu$
 $\dot{\hat{x}} = A\hat{x} + L(C\hat{x} - y) + B(-K\hat{x} + u)$

$$\dot{\hat{x}} = LC\hat{x} + (A - LC - BK)\hat{x} + Bu$$

Estimation error $\hat{x} - x$ $\dot{e} = (A - LC)e$

Eigen of error again is negative

~~FB~~ s. FB block s. FB doesn't affect obs. design

[Get X-posed Notes]

~~3) $\dot{x} = (A - BK)x + BV$~~

$$3) \dot{x} = (A - BK)x - BK e + BV$$

~~$e(t) \rightarrow 0$~~ $e(t) \rightarrow 0$

~~$BKx = BK(A - BK)x + BK e$~~ $\approx \dot{x} = (A - BK)x + BV$

Transfer fn of overall system
 $v \rightarrow y$

$$\dot{x} = (A - BK)x - BK e + BV$$

$$\dot{e} = (A - LC)e$$

$$y = Cx$$

$$y = [C \ 0] \begin{bmatrix} x \\ e \end{bmatrix}$$

~~$A = \begin{bmatrix} A - BK & -BK \\ 0 & A - LC \end{bmatrix}$~~

~~$H(s) = [C \ 0]$~~

$$A = \begin{bmatrix} A - BK & -BK \\ 0 & A - LC \end{bmatrix}$$

$$\therefore H(s) = [C \ 0] \begin{bmatrix} sI - (A - BK) & BK \\ 0 & sI - (A - LC) \end{bmatrix}^{-1} \begin{bmatrix} B \\ 0 \end{bmatrix} = C [sI - (A - BK)]^{-1} B$$

$$= [C \ 0] \begin{bmatrix} [sI - (A - BK)]^{-1} & x \\ 0 & x \end{bmatrix} \begin{bmatrix} B \\ 0 \end{bmatrix}$$

~~same as earlier~~
 \Rightarrow same as w/ STFB only!

$$\text{chc. poly. det}(s) = \underbrace{\det[sI - (A - BK)]}_{\text{controller}} \underbrace{\det[sI - (A - LC)]}_{\text{observer}}$$

Uncontrollable from the up.

(cf. eqn $\dot{e} = (A - LC)e$)

can do observer & FB designs indep. (for linear system) same thing in stochastic case

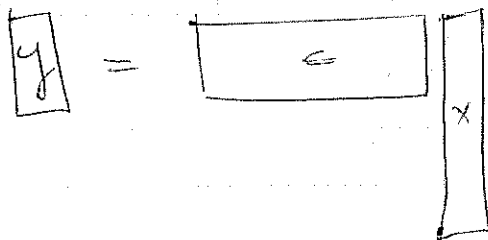
only requirement on c so far was $[A, C]$ c.o.

sp. case: $C = I$ $y = x$; observer couples variables

n^{th} order \rightarrow o^{th} order

sp. case C sq. nonsingular
this too is n^{th} order

in general $m \times \begin{matrix} u \\ C \end{matrix}$ $m < n$



: Do have some
maneuverability

∴ Scope for designing a reduced order observer

17.2 any /30

max 29 shots me!!

min 8

SD = 4.9

Friday
01 Dec '89

AST-discussion

In Wu will ask questions from discussions sections (will examine notes of Ben)

$$\begin{aligned}x_{k+1} &= Ax_k & \rightarrow & \quad x_k = A^k x_0 \\y_k &= Cx_k & & \quad y_k = CA^k x_0\end{aligned}$$

$$y = \begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} CA^0 x_0 \\ CA^1 x_0 \\ \vdots \\ CA^{m-1} x_0 \end{bmatrix} = \underbrace{\begin{bmatrix} C \\ CA \\ \vdots \\ CA^{m-1} \end{bmatrix}}_R x_0$$

$$R = V \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} V^*$$

$$x_0 = V_1 \Sigma^{-1} V_1^* y$$

show $R \bar{x}_0 = y$

$$\text{Multiplication: } R \bar{x}_0 = [V_1 | V_2] \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^* \\ V_2^* \end{bmatrix} V_1 \Sigma^{-1} V_1^* y$$

$$= [V_1 | V_2] \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} I \\ 0 \end{bmatrix} \Sigma^{-1} V_1^* y$$

$$= [V_1 | V_2] \begin{bmatrix} \Sigma \\ 0 \end{bmatrix} \Sigma^{-1} V_1^* y$$

$$= [V_1 | V_2] \begin{bmatrix} I \\ 0 \end{bmatrix} V_1^* y$$

$$R \bar{x}_0 = \boxed{V_1 V_1^*} y \neq I$$

$$\text{we know } V_1 V_1^* + V_2 V_2^* = I$$

$$I y = [V_1 | V_2] \begin{bmatrix} V_1^* \\ V_2^* \end{bmatrix} y$$

$$= V_1 V_1^* y + V_2 V_2^* y$$

$$y \in \mathcal{R}(R) \Rightarrow y \perp V_2$$

$$\boxed{y = V_1 V_1^* y}$$

← comp an sv)

$$Q_3 \quad \Phi(t,0) = \int_0^t \Phi(t,\tau) B \cdot B^* \Phi^*(t,\tau) d\tau = [v_1 | v_2] \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix}$$

$$\text{let } u(t) = B^* \Phi^*(t,0) u_1 \text{ and } v_1^* z$$

$$x(t) = z$$

Assign $x_{k+1} = Ax_k + bu_k$

$$Q = [b | Ab | \dots | A^{n-1}b] \text{ has full rank}$$

$$b \in \mathbb{R}^n, A \in \mathbb{R}^{n \times n}$$

$\Rightarrow Q^{-1}$ exists

$$x_n = A^n x_0 + \sum_{j=0}^{n-1} A^j b u_{n-j-1} = A^n x_0 + Q U \quad U = \begin{bmatrix} u_{n-1} \\ \vdots \\ u_0 \end{bmatrix}$$

$$x_n = 0$$

$$0 = A^n x_0 + Q U$$

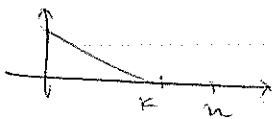
$$-A^n x_0 = Q U$$

$$-Q^{-1} A^n x_0 = U$$

U is the unique i/p which steers $x \rightarrow 0$ at time n_0 .

$$Q^{-1} = \begin{bmatrix} v_1^T \\ \vdots \\ v_n^T \end{bmatrix} \rightarrow u_i = -v_{n-i}^T A^n x_0$$

(i) Assume $\{u_0, \dots, u_{k-1}\}$ ($k < n-1$) which steers $x_0 \rightarrow 0$ at time $k+1$.



then the sequence $\{u_0, \dots, u_k, 0, \dots, 0\}$ steers $x_0 \rightarrow 0$ at time n_0

$$x_{k+1} = A x_k + b u_k$$

↳ But we know from above it's unique. \blacksquare

$$(PAP^{-1})(PAP^{-1})^T = PAP^{-1}(P^{-1})^T A^T P^T$$

singular values of similar matrices are different.

$[A, b, c]$ c.o. & c.c.

Many realizations which give same t.f.

① is this the "optimal" realization for the given h(s) (transfer fn)?

- What does optimal mean?

(i) don't want very large & very small numbers

(ii) balanced realization spec. we don't want

_____ nearly singular

$Q \rightarrow$ nearly singular \Rightarrow need large gains to control

$R \rightarrow$ " " \Rightarrow Hard to observe states

eigenvalues are defined by t.f. so realization makes no difference
 could have a singular but still same c.c.

A
 x small perturbations may drastically change the system!

$$A = \begin{bmatrix} -1 & 20 \\ 0 & -1 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad C = [\sqrt{20} \quad \sqrt{20}] = [0.22 \quad 4.47]$$

$$Q = \begin{bmatrix} 1 & 19 \\ 1 & -1 \end{bmatrix}$$

$\sigma_1 \approx 19$
 $\sigma_2 \approx 1$

$$R = \begin{bmatrix} 0.22 & 4.47 \\ -0.22 & 0 \end{bmatrix}$$

$\sigma_1 = 4.47$
 $\sigma_2 = 0.22$

condition # $= \sigma_1/\sigma_2 = 18$

$\sigma_1/\sigma_2 = 20$

big cond # \Rightarrow close to being singular

transform to Jordan form Realization:

$$A_J = \begin{bmatrix} -1 & 1 \\ 0 & -1 \end{bmatrix} \quad B_J = \begin{bmatrix} .22 \\ 4.47 \end{bmatrix} \quad C_J = [1 \quad 1]$$

$Q_J = \sigma_1/\sigma_2 \approx 2.5$ $R_J \sigma_1/\sigma_2 \approx 2.6$

some lots better

$$Q_J = \begin{bmatrix} .22 & 4.47 \\ 4.47 & -1.1 \end{bmatrix}$$

$$R_J = \begin{bmatrix} 1 & 1 \\ -1 & 0 \end{bmatrix} \quad (3)$$

Thursday
Dec 5/1997

KST-lecture

5. Reduced order Observer

1) derivation

$$y = Cx$$
$$\begin{bmatrix} y \\ \vdots \end{bmatrix} = \begin{bmatrix} \\ \\ \end{bmatrix} \begin{bmatrix} x \\ \vdots \end{bmatrix} \quad C^{m \times n} \quad (m < n)$$

Assume C has full rank!

Coordinate Transformation

$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} = \begin{bmatrix} C \\ c_1 \end{bmatrix} x \quad \begin{bmatrix} C \\ c_1 \end{bmatrix} \text{ nonsingular}$$

$$\bar{x}_1 = y$$

system: $\dot{x} = Ax + Bu$
 $y = Cx$

new coordinates $\begin{bmatrix} \dot{\bar{x}}_1 \\ \dot{\bar{x}}_2 \end{bmatrix} = \begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} \\ \bar{A}_{21} & \bar{A}_{22} \end{bmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} + \begin{bmatrix} \bar{B}_1 \\ \bar{B}_2 \end{bmatrix} u$

$$y = [I \quad 0] \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}$$

observer: $\bar{x}_1 = y$ available (no observer needed)
 $\bar{x}_2 = $

open loop observer

$$\dot{\hat{x}}_2 = \bar{A}_{22} \hat{x}_2 + \bar{A}_{21} y + \bar{B}_2 u$$

asymptotically observer

$$\dot{\hat{x}}_2 = \bar{A}_{22} \hat{x}_2 + \bar{A}_{21} y + \bar{B}_2 u + (\text{feedback correction term})$$

$(\bar{x}_2 - \hat{x}_2)$ \bar{x}_2 not accessible to us

compromise

look for l.c. form of \bar{x}_2

$$\dot{\bar{x}}_1 = \underbrace{A_{11} \bar{x}_1 + \bar{A}_{12} \bar{x}_2}_{\text{computable}} + \bar{B}_1 u$$

$$= A_{11} y + \bar{B}_1 u + \bar{A}_{12} \bar{x}_2$$

$$y_2 = \dot{y} - \bar{A}_{11} y - \bar{B}_1 u = \bar{A}_{12} \bar{x}_2$$

← computable →

(\bar{A}_{12} typically would be rectangular)

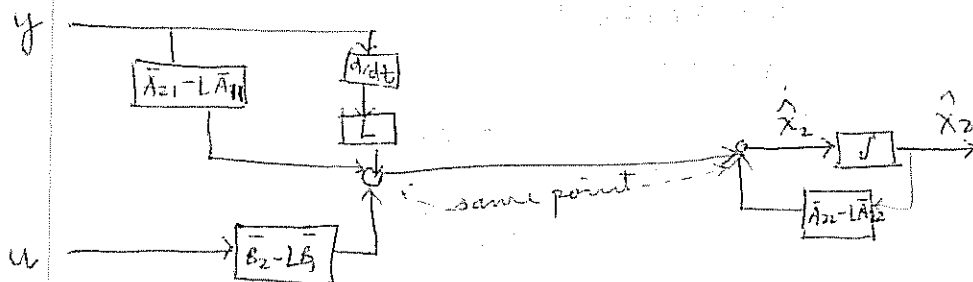
$$L \bar{A}_{12} (\bar{x}_2 - \hat{x}_2)$$

↑ to keep correct order

∴ use $L(y_2 - \bar{A}_{12} \hat{x}_2)$ as feedback

$$\dot{\hat{x}}_2 = \bar{A}_{22} \hat{x}_2 + \bar{A}_{21} y + \bar{B}_2 u + L(y_2 - \bar{A}_{12} \hat{x}_2)$$

$$= (\bar{A}_{22} - L \bar{A}_{12}) \hat{x}_2 + (\bar{A}_{21} - L \bar{A}_{11}) y + L \dot{y} + (\bar{B}_2 - L \bar{B}_1) u$$



Q. Does it work?

look @ the error and show that the error goes to zero.

estimation error $e = \bar{x}_2 - \hat{x}_2$

system $\dot{\bar{x}}_2 = \bar{A}_{22}\bar{x}_2 + \bar{A}_{21}y + \bar{B}_2u$

observer $\dot{\hat{x}}_2 = \bar{A}_{22}\hat{x}_2 + \bar{A}_{21}y + \bar{B}_2u + L\bar{A}_{12}e$

$$\dot{e} = \bar{A}_{22}e - L\bar{A}_{12}e = (\bar{A}_{22} - L\bar{A}_{12})e$$

encouraging

- error ind of state.
- error ind of input.

$e(t) \rightarrow 0$ if e -values of $(\bar{A}_{22} - L\bar{A}_{12})$ can be placed in the open LHP.

question becomes can we move eigen values of $(\bar{A}_{22} - L\bar{A}_{12})$?

looks familiar! Observability type!

System \bar{c} eqn $(\bar{A}_{22}, \bar{A}_{12})$ c.o.?

original c.o. $\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases}$

\therefore new coord $\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} = \bar{A} \Rightarrow$ c.o.
 $y = \begin{bmatrix} I & 0 \\ \bar{c} \end{bmatrix} \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}$

by defn $v \in [0, T], y \in [0, T]$ det uniquely $\begin{cases} \bar{x}_1(0) \\ \bar{x}_2(0) \end{cases} \Rightarrow \begin{cases} \bar{x}_1(0) \\ \bar{x}_2(0) \end{cases}$
 can be determined as $\begin{bmatrix} \bar{x}_1(0) \\ \bar{x}_2(0) \end{bmatrix} = \begin{pmatrix} C \\ C_1 \end{pmatrix} \begin{pmatrix} x_1(0) \\ x_2(0) \end{pmatrix}$
 rewrite

Starting from here, can show
 system $\begin{cases} \dot{\bar{x}} = \bar{A}\bar{x} + \bar{B}u \\ \dot{e} = (C\bar{A}_{22} - L\bar{A}_{12})e \end{cases}$

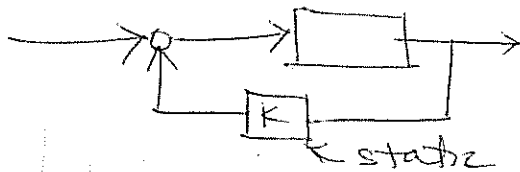
whole system

$$d(s) = \left[\det(sI - A) \det(sI - (C\bar{A}_{22} - L\bar{A}_{12})) \right]$$

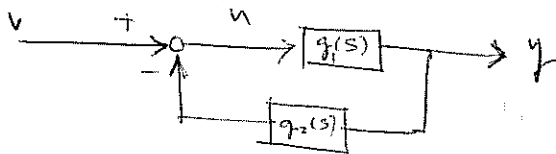
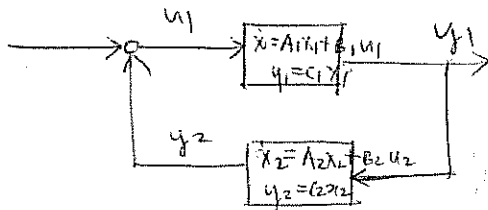
\uparrow eigenvalues of system \uparrow e. values of observer

VII MULTIVARIABLE NYQUIST

1 Motivation: one input application of state F.B. is to stabilize the system.



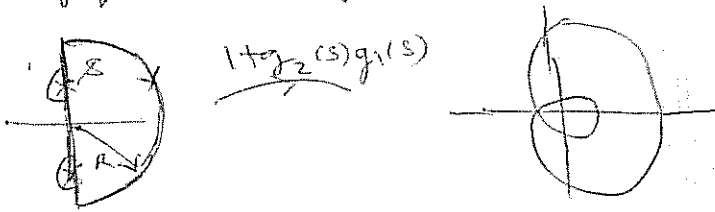
more generally use 2 dynamics in K



Nyquist: graphical method gives insight

$$\begin{aligned}
 y(s) &= g_1(s) u(s) \\
 u(s) &= v(s) - g_2(s) y(s) \\
 &= v(s) - g_2(s) g_1(s) u(s) \\
 y(s) &= \frac{g_1(s)}{1 + g_2(s) g_1(s)} v(s)
 \end{aligned}$$

Nyquist diagram



$P_{of} := \# \text{ of } P(g_2(s)g_1(s)) \text{ in } \bar{C}_+$ [closed RHP, C includes $j\omega$ axis]

the closed loop system = $g_1(s) / (1 + g_2(s)g_1(s))$ is exp stable

\Leftrightarrow (i) Nyquist diagram of $1 + g_2(s)g_1(s)$ doesn't go through the origin

(ii) Does encircle origin P_{of} times in CCW dirⁿ

The proof is based on the principle of the argument.

C : closed curve on s-plane (simple curve)
 $F(s)$: rational fn

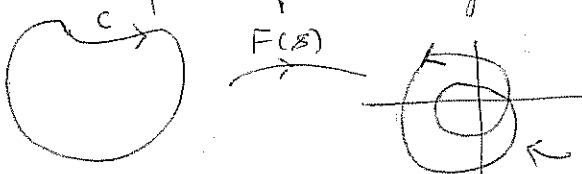
as s traverses C in the CW dirⁿ, the trajectory of $F(s)$ encircles the origin $(p-s)$ times in the CCW dirⁿ.

\uparrow # of poles of $F(s)$ enclosed in C
 \uparrow # of zeros of $F(s)$ enclosed in C

Monday
 Dec 7, 1989

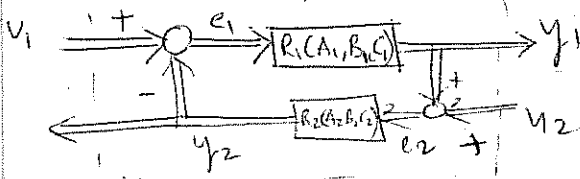
AST-lecture

Principle of the argument



\leftarrow * ccw encirclement of origin
 $= \#P - \#Z$
 \downarrow poles of $F(s)$ enclosed in C
 \uparrow zeros of $F(s)$

3. System Representation



$$R_1: \dot{x}_1 = A_1 x_1 + B_1 e_1$$

$$y_1 = C_1 x_1$$

$$R_2: \dot{x}_2 = A_2 x_2 + B_2 e_2$$

$$y_2 = C_2 x_2$$

connexions

$$e_1 = u_1 - y_2$$

$$e_2 = u_2 + y_1$$

combined system: i/p u_1, u_2 o/p y_1, y_2
to formulate eqns eliminate e_1, e_2

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} A_1 & -B_1 C_2 \\ B_2 C_1 & A_2 \end{bmatrix}}_A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{\begin{bmatrix} B_1 & 0 \\ 0 & B_2 \end{bmatrix}}_B \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \underbrace{\begin{bmatrix} C_1 & 0 \\ 0 & C_2 \end{bmatrix}}_C \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$R_c(A, B, C)$: Representation of closed loop system

stability: e-values of A
zeros at $(sI - A)$

$$(sI - A) = \begin{bmatrix} sI - A_1 & B_1 C_2 \\ -B_2 C_1 & sI - A_2 \end{bmatrix}$$

want to relate these eigenvalues
with those of original systems

$$sI - A = \begin{bmatrix} sI - A_1 & 0 \\ 0 & sI - A_2 \end{bmatrix} \begin{bmatrix} B_1 C_1 \\ B_2 C_2 \end{bmatrix} \begin{bmatrix} I & (sI - A_1)^{-1} B_1 C_1 \\ -(sI - A_2)^{-1} B_2 C_2 & I \end{bmatrix}$$

Perform Gaussian Elimination (LU decomposition)

$$= \begin{bmatrix} sI - A_1 & B_1 C_1 \\ sI - A_2 & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ -(sI - A_2)^{-1} B_2 C_2 & I \end{bmatrix} \begin{bmatrix} I & (sI - A_1)^{-1} B_1 C_2 \\ 0 & I + (sI - A_2)^{-1} B_2 C_2 + (sI - A_1)^{-1} B_1 C_2 \end{bmatrix}$$

$$\det(sI - A) = \det(sI - A_1) \det(sI - A_2) \det \{ I + (sI - A_2)^{-1} B_2 C_2 + (sI - A_1)^{-1} B_1 C_2 \}$$

* $C_1 (sI - A_1)^{-1} B_1$: T.F. matrix $G_1(s)$

in general, $\det(I + MN) \rightarrow$ could it be $\det\{I + NM\}$?

$$\begin{bmatrix} I - N & \\ M & I \end{bmatrix} = \begin{bmatrix} I & 0 \\ M & I \end{bmatrix} \begin{bmatrix} I & -N \\ 0 & I + MN \end{bmatrix}$$

$$\det \begin{bmatrix} I - N & \\ M & I \end{bmatrix} = \det\{I + MN\}$$

Went to ...
 $\Delta = \det \begin{bmatrix} I - N & \\ 0 & I \end{bmatrix} \det \begin{bmatrix} I + MN & 0 \\ M & I \end{bmatrix} = \det(I + MN)$

$$\Delta = \det(I + MN) \begin{bmatrix} I - N & \\ M & I \end{bmatrix} \equiv \begin{bmatrix} I - N & \\ 0 & I \end{bmatrix} \begin{bmatrix} I + NM & 0 \\ M & I \end{bmatrix}$$

Gauss Elim is essentially matrix factorization

$$\det [\quad] = \det\{I + NM\}$$

elements are rational fns

$$\det(sI - A) = \det(sI - A_1) \det(sI - A_2) \det(I + G_2(s)G_1(s))$$

poly. poly poly rational fn.

in other words, some of the eigenvalues will get cancelled out (\therefore poles of rational fn have to cancel out)

Under what conditions is the closed loop system stable?

Turns out that the closed loop system $R_c(A, B, C)$ is exp stable

\Leftrightarrow The Nyquist diagram of $\det\{I + G_2(s)G_1(s)\}$
 (i) doesn't go thru the origin
 (ii) does encircle the origin

p_{0+} times in ccw dir.
 $p_{0+} := \# \text{ of } \frac{1}{z} \{ \det(sI - A_1) \det(sI - A_2) \}$
 in closed RHP.

Proof

$$\det(sI - A) = \det(sI - A_1) \cdot \det(sI - A_2) \cdot \det\{I + G_2(s)G_1(s)\}$$

$\leftarrow d_A(s) \qquad \underbrace{\hspace{15em}}_{P_R(s)}$

$R_c(A, B, C)$ exp stable

$\Leftrightarrow d_A(s)$ no zeros in \bar{C}_+

$\Leftrightarrow P_R(s)$ no zeros in \bar{C}_+

shabby!
 algebraic requirement on both sides only poles
 if it's not then control poles is not cancelled!

(i) All poles of $\det(I + G_2 G_1)$ cancelled by $\det(sI - A_1) \det(sI - A_2)$
 (ii) Maximum $\#$ of poles of $\det[I + G_2 G_1]$ in \bar{C}_+
 $= p_{0+}$ ($\#$ of zeros of $\det(sI - A_1) \det(sI - A_2)$ in \bar{C}_+)
 because $\det(I + G_2 G_1(s)) = \frac{\det(sI - A)}{\det(sI - A_1) \det(sI - A_2)} \Rightarrow \# \text{ poles of } \det(I + G_2 G_1) = \# \text{ zeros of } \det(sI - A_1) \det(sI - A_2)$

$R_c(A, B, C)$ exp stable

\Leftrightarrow * $\left\{ \begin{array}{l} \text{(i) all } \bar{C}_+ \text{-zeros of } \det(sI - A_1) \det(sI - A_2) \text{ must be cancelled by the } \bar{C}_+ \text{ poles of } \det[I + G_2 G_1] \\ \text{(ii) } \det[I + G_2 G_1] \text{ has no zeros in } \bar{C}_+ \text{ (else these would not be cancelled)} \end{array} \right.$

want to show (*) \Rightarrow Nyquist

- * (i) \Rightarrow # of \bar{c} poles of $\det [I + G_2 G_1] = p_+$
- * (ii) \Rightarrow # of \bar{z} zeros of $\det [I + G_2 G_1] = 0$

proof of Nyquist (2)

principle of the argument

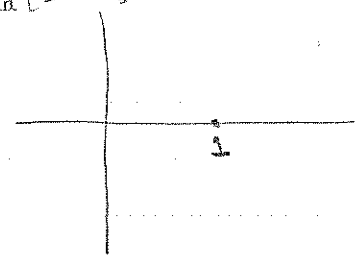
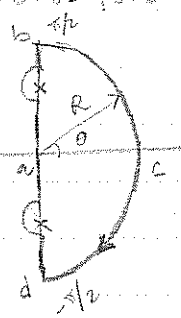
\Rightarrow # c.c.w. encirclement = p_+

Nyquist (ii)

[Nyquist (i) \checkmark]

Consider Nyquist (i)

$$\det [I + G_2(s) G_1(s)] = \det [I + \frac{c_2 B_2 c_1 B_1}{s} + \dots] \approx 1$$



$s: b \rightarrow c \rightarrow d$

$$z = R e^{i\theta} \quad \theta \sim \pi \rightarrow -\frac{\pi}{2}$$

$R \rightarrow \infty \quad |s| \rightarrow \infty \quad \frac{1}{s}$ small

$$G_1(s) = C_1 [sI - A_1]^{-1} B_1$$

if $s > \max |e(A)|$

$$= C_1 B_1 / s + C_1 A_1 B_1 / s^2 + \dots$$

$$G_2(s) = C_2 B_2 / s + C_2 A_2 B_2 / s^2 + \dots$$

$$\det [I + G_2(s) G_1(s)] = \det [I + \frac{C_2 B_2 C_1 B_1}{s^2} + \dots]$$

≈ 1

\therefore the portion $b \rightarrow c \rightarrow d$ is close to 1. (won't pass thru origin)

$s: d \rightarrow a \rightarrow b$ on $j\omega$ axis

" $s = j\omega$ $\omega: -R$ to $+R$ (let $R \rightarrow \infty$)

contour \Rightarrow Nyquist

$$* (ii) \Rightarrow \det[I + G_2(j\omega)G_1(j\omega)] \neq 0$$

\therefore NYQUIST (i) is satisfied!

\therefore NYQUIST conditions are SUFFICIENT,

↓ he got these mixed up

\Rightarrow show Nyquist conditions are necessary

Nyquist diagram $\det[I + G_2(s)G_1(s)]$
encircles the origin p_{0+} times in CCW dir.

principle of the argument,

$$p_{0+} = \left(\begin{array}{l} \# \text{ of poles} \\ \text{of } \det[I + G_2(s)G_1(s)] \\ \text{inside } \bar{C}_+ \end{array} \right) - \left(\begin{array}{l} \# \text{ of zeros} \\ \text{of } \det[I + G_2(s)G_1(s)] \\ \text{inside } \bar{C}_+ \end{array} \right)$$

$$0 \leq \checkmark \leq p_{0+}$$

$$0 \leq \checkmark \leq ?$$

but only comb which allows this integer eqn to be satisfied is

$$\# \text{ of poles} = p_{0+}$$

$$\# \text{ of zeros} = 0$$

concl: # of RH side poles of this det must be p_{0+}

of RH side zeros " " "

" " 0

\therefore Nyquist is necessary

from (ii)
Cancellation
by s.t.

① not c.c./c.o. ← still looking at all modes (not need c.c./c.o.) Very STRONG.

② not c.c./c.o. of component systems (but have to know # of RH poles/zeros of c.c./c.o.)

if origin is passed thru, then how do you know it circles.

Friday
11/2/89

LST - discussion

$$f_1(x_1, x_2, x_3) = \dot{x}_1 = x_1(x_3 - x_2) + 3(x_2^2 - x_2x_3 + x_2) + 4x_3 - 5$$

$$f_2(x_1, x_2, x_3) = \dot{x}_2 = 6x_1 - 5x_2 - 4x_3 + 51$$

$$f_3(x_1, x_2, x_3) = \dot{x}_3 = -2x_1^2 + x_1x_2 + x_2^2 - x_2x_3 - 5x_2 + 3x_3 + 13 + u$$

$$y = \frac{1}{2}(x_1 - x_2 - x_3)$$

$$x_s = \begin{bmatrix} 1 \\ 5 \\ 8 \end{bmatrix} \leftarrow \text{an eq pt of the system.}$$

Q: Is it a stable equilibrium point?

Q: If not how do you design observer to approx sp?

Q: How do you design controller

linearize: take Jacobian

$$\begin{bmatrix} \delta x_1 \\ \delta x_2 \\ \delta x_3 \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \dots & \dots \\ \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} \delta x_1 \\ \delta x_2 \\ \delta x_3 \end{bmatrix} + \begin{bmatrix} \frac{\partial f_1}{\partial u} \\ \frac{\partial f_2}{\partial u} \\ \frac{\partial f_3}{\partial u} \end{bmatrix} u$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 1 \\ 5 \\ 8 \end{bmatrix}$$

$$A = \begin{bmatrix} 5 & -4 & -4 \\ 6 & -5 & -4 \\ 1 & -2 & -2 \end{bmatrix}$$

$$b = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\delta y = \begin{bmatrix} 1/2 & -1/2 & -1/2 \end{bmatrix} \begin{bmatrix} \delta x_1 \\ \delta x_2 \\ \delta x_3 \end{bmatrix}$$

$$\begin{aligned} \lambda_1 &= 1 + \delta x_1 \\ \lambda_2 &= 5 + \delta x_2 \\ \lambda_3 &= 8 + \delta x_3 \end{aligned}$$

$$y = -6 + \delta y$$

$$\begin{aligned} \det(sI - A) &= s^3 - 2s^2 - 5s - 6 \\ &= (s-2)(s+1)(s+3) \end{aligned}$$

↑ Eigenvalue in RHP
∴ system unstable.

Form R & Q matrices: Full Rank
⇒ c.c. & c.o.

Observer:

chang coord so in obs. can. form

$$\begin{aligned} z &= T^{-1} \delta x ; (\delta x = Tz) \\ \dot{z} &= TAT^{-1}z + Tb u = A_0 z + b_0 u \\ \delta y &= cTz = c_0 z \end{aligned}$$

$$T = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 2 & 0 \\ 1 & -1 & -1 \end{bmatrix}$$

$$A_0 = \begin{bmatrix} 0 & 0 & 6 \\ 1 & 0 & 5 \\ 0 & 1 & -2 \end{bmatrix}$$

could write by looking at ch. poly right off

$$b_0 = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} \quad c_0 = [0 \quad 0 \quad 1]$$

$$T^{-1}A_0 = AT^{-1} \quad ; \quad b_c = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = Tb$$

$$T^{-1}b_c = b$$

$$T^{-1} \begin{bmatrix} t_1 & t_2 & t_3 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = b \Rightarrow t_3 = b$$

that if eigenvalue for δQ then that mode could still control (eg. cost Q in MTF)

and
$$\begin{bmatrix} | & | & | \\ t_1 & t_2 & b \\ | & | & | \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -\alpha_3 & -\alpha_2 & -\alpha_1 \end{bmatrix} = \begin{bmatrix} A \end{bmatrix} \begin{bmatrix} t_1 & t_2 & b \end{bmatrix}$$

look into this

$$t_2 - \alpha_1 b = Ab$$

$$t_2 = (A + \alpha_1 I)b$$

canonical observable form (take transpose to get c.o)

$$\dot{\bar{z}} = A_0 \bar{z} + b_0 u$$

$$\dot{\bar{z}} = A_0 \bar{z} + b_0 u + \underbrace{L_0 c (z - \bar{z})}_{L_0 (sY - \delta Y)}$$

$$\dot{\bar{z}} = (A_0 - L_0 c) \bar{z} + \underbrace{c b u + L_0 c z}_{\uparrow \text{"input"}}$$

go "rapidly" to states of system

eg $\lambda = -3$ then want -6 (so faster dumping)

$$\begin{matrix} A_0 & L_0 & c \\ \begin{bmatrix} 0 & 0 & 6 \\ 1 & 0 & 5 \\ 0 & 1 & -2 \end{bmatrix} & - \begin{bmatrix} l_1 \\ l_2 \\ l_3 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} & = \begin{bmatrix} 0 & 0 & 6-l_1 \\ 1 & 0 & 5-l_2 \\ 0 & 1 & -2-l_3 \end{bmatrix} \begin{matrix} -\alpha_3 \\ -\alpha_2 \\ -\alpha_1 \end{matrix} \end{matrix}$$

$$\alpha_1' = 18$$

$$\alpha_2' = 108$$

$$\alpha_3' = 216$$

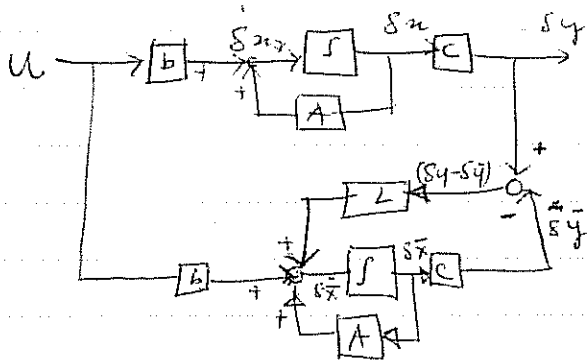
$$\therefore L_0 = \begin{bmatrix} 222 \\ 113 \\ 16 \end{bmatrix}$$

$$\begin{aligned} \dot{\bar{z}} &= (A_0 - L_0 c) \bar{z} + b_0 u + L_0 c y \\ &= A_0 \bar{z} + b_0 u + L_0 c (z - \bar{z}) \\ \dot{\bar{z}} &= A_0 \bar{z} + b_0 u + L_0 (sY - \delta Y) \end{aligned}$$

$$T^{-1} \dot{\bar{z}}_n = A_0 T^{-1} \bar{x} + b_0 u + L_0 (sY - \delta Y)$$

$$\dot{\bar{z}}_n = \underline{T A_0 T^{-1}} \bar{x} + \underline{T b_0} u + \underline{T L_0} (sY - \delta Y)$$

$$\dot{\delta x} = A \delta x + b u + L(\delta y - \bar{\delta y})$$



controller transform to c.c. form, by "observation"
 choose f.b. matrix k_c and transform back to
 original coords.

$$k_c = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 6 & 5 & -2 \end{bmatrix} \quad b_c = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad c = \begin{bmatrix} \cdot & \cdot & \cdot \end{bmatrix} \quad \text{not imp}$$

more unstable pole on stable side of jw axis.
 \uparrow $s=2$ \uparrow $s=-1$

char. polynomial we want $(s+1)^2(s+3)$

$$s^3 + 5s^2 + 7s + 3$$

$$\alpha_1 \quad \alpha_2 \quad \alpha_3$$

$$A_c - b_c k_c = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -3 & -7 & -5 \end{bmatrix}$$

$$k_c = [9 \quad 12 \quad 3]$$

$$\dot{\delta x}_1 = A \delta x_1 - b k \delta \bar{x}$$

$$\dot{\delta x}_2 = A \delta x_2 - b k \delta \bar{x} + L(\delta y - \bar{\delta y})$$

$$\delta y = c \delta x$$

$$\bar{\delta y} = c \bar{\delta x}$$

behaviour at \Rightarrow pt of linearized system
 should be same as on original system at eq pt.

A_2 ← can we find any trajectory

$$\dot{x} = \begin{bmatrix} 5 & -4 & -4 \\ 6 & -5 & -4 \\ 1 & -2 & -2 \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u$$

suppose we want trajectory to be const.
 then $Su = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}$ $\dot{x} = \begin{bmatrix} -0.3 \\ -0.3 \\ -0.3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ u \end{bmatrix}$

previous end sem -

1. $\dot{x} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} u$ $x(0) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$

- (a) For $u(t) \equiv 0$, what is the space in \mathbb{R}^3 in which $x(t)$ lies?
 (b) What conditions on b_1, b_2, b_3 will guarantee that $\exists u(t) \ t \in [0, 1]$ s.t. $x(0) \neq x(1) = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$

2. $\ddot{x} + d\dot{x} + kx = 0$

- (a) find the eq. pts
 (b) for what values of $k \neq d$ is the eq. pt. asymptotically stable?
 (c) (b) but stable is 2.
 (d) $\ddot{x} + d\dot{x} + kx = u$ $k \neq d$ bibs stable

suppose for some $\lambda_k \in \sigma(A) \exists \eta$ st

$$\begin{bmatrix} \lambda_k I - A \\ -C \end{bmatrix} \eta = 0$$

Show set of all observable states is orthogonal to η .

$$\dot{x} = Ax + Bu$$

consider sampled data system
 with 0-order hold ($u(t)$ const. over $t \in [k, k+h]$)

$$A^T P A - P = -Q$$

$$A A^T P A - A P = -A Q$$

$$x_d(k+1) = A_d x_d(k) + B_d u(k) \quad \left| \quad P A - (A^T)^{-1} A^T A P = \cancel{A^T P} \right.$$

$$= -(A^T)^{-1} Q$$

$$A_d = \exp(A h)$$

$$B_d = \int_0^h e^{A t} dt B$$

$$P A = (A^T)^{-1} P - (A^T)^{-1} Q$$

$$= (A^T)^{-1} (P - Q)$$

$$A (A^T)^{-1} = P^{-1} (P - Q)$$

show that if $\{A, B\}$ not c.c., then $\{A_d, B_d\}$ not c.c.

Suppose char poly = $d(s) = (s+1)^4$
 min poly = $\psi(s) = (s+1)^2$

Does ZSR of $\dot{x} = Ax + bu, y = Cx$
 have a term $t^4 e^{-t}$
 $u(t) = \text{unit step fn.}$

Let $C: \mathbb{R}^n \rightarrow \mathbb{R}^m$

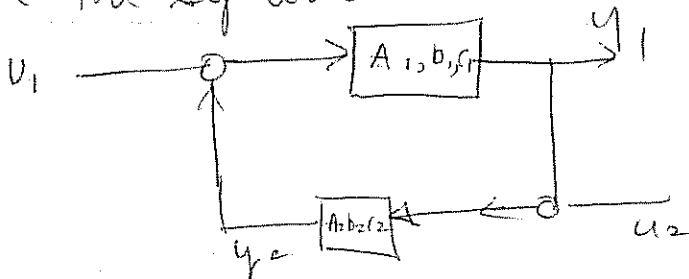
given $y \in \mathbb{R}^m$, consider
 $Cx = y$

(i) suppose C is onto / C column满秩
 find min norm soln

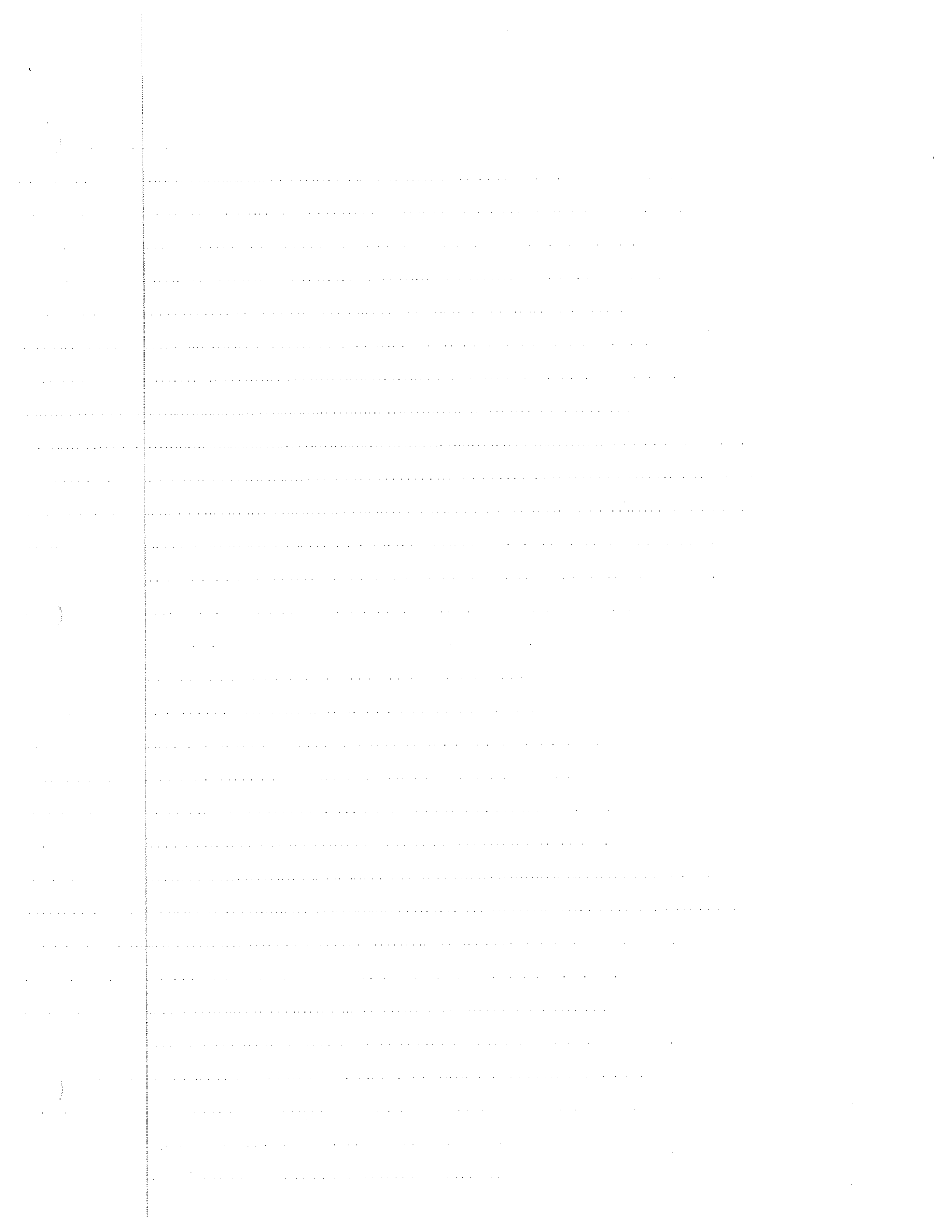
(ii) suppose C is not
 find best "approx" soln

Suppose $[A, B, C, D]$ is a minimal system
 right & characterize zeros of the representation.

Given the system



derive A, B, C matrices for total system



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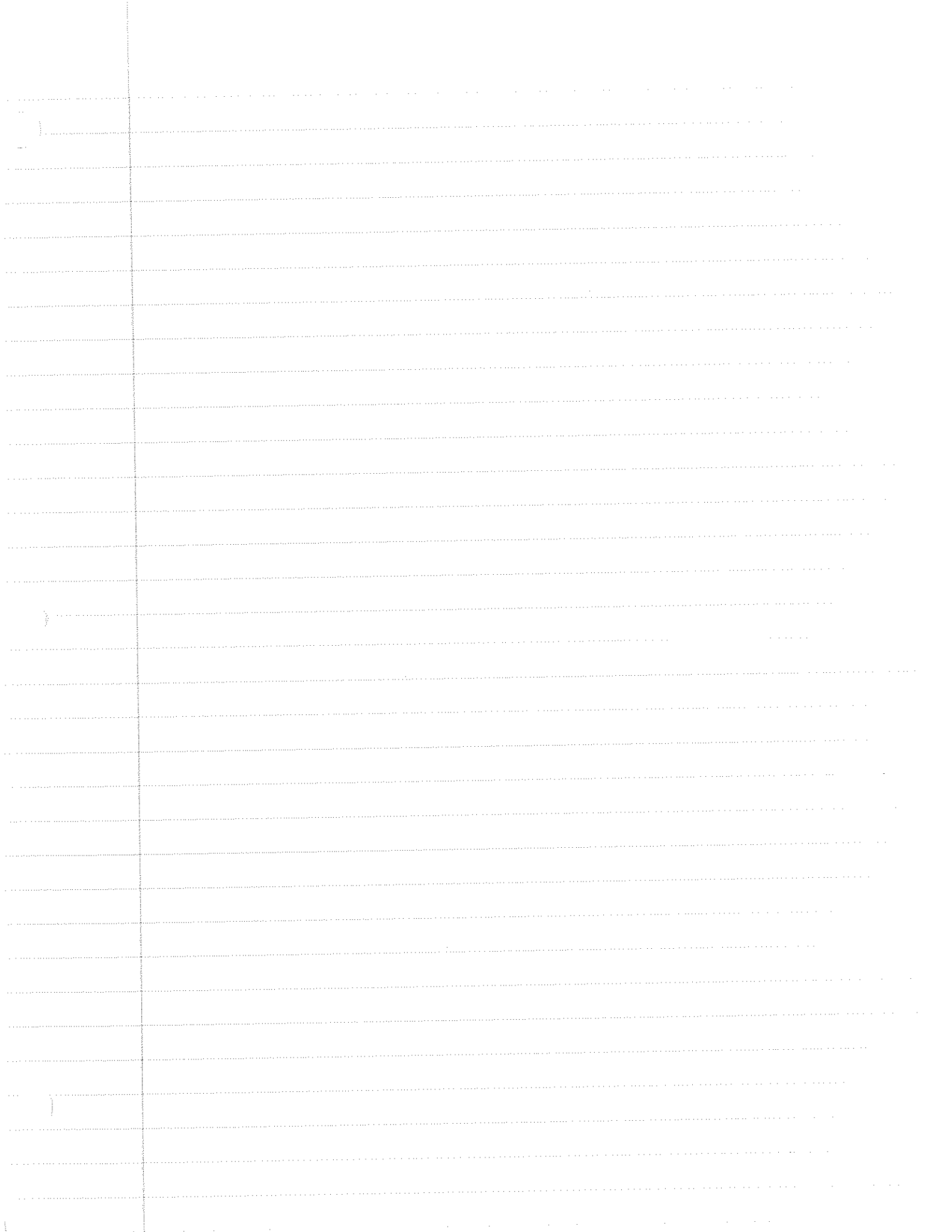
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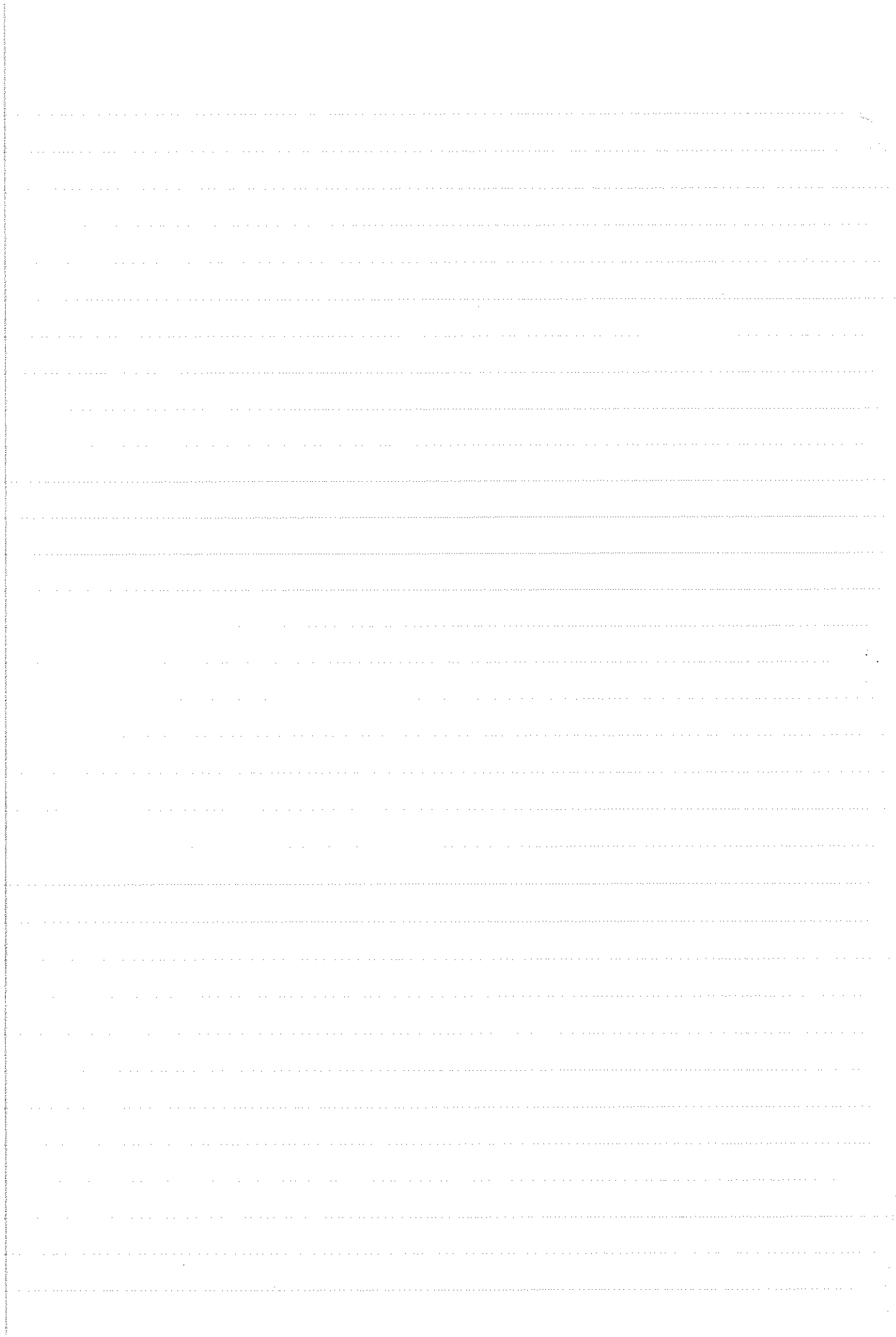
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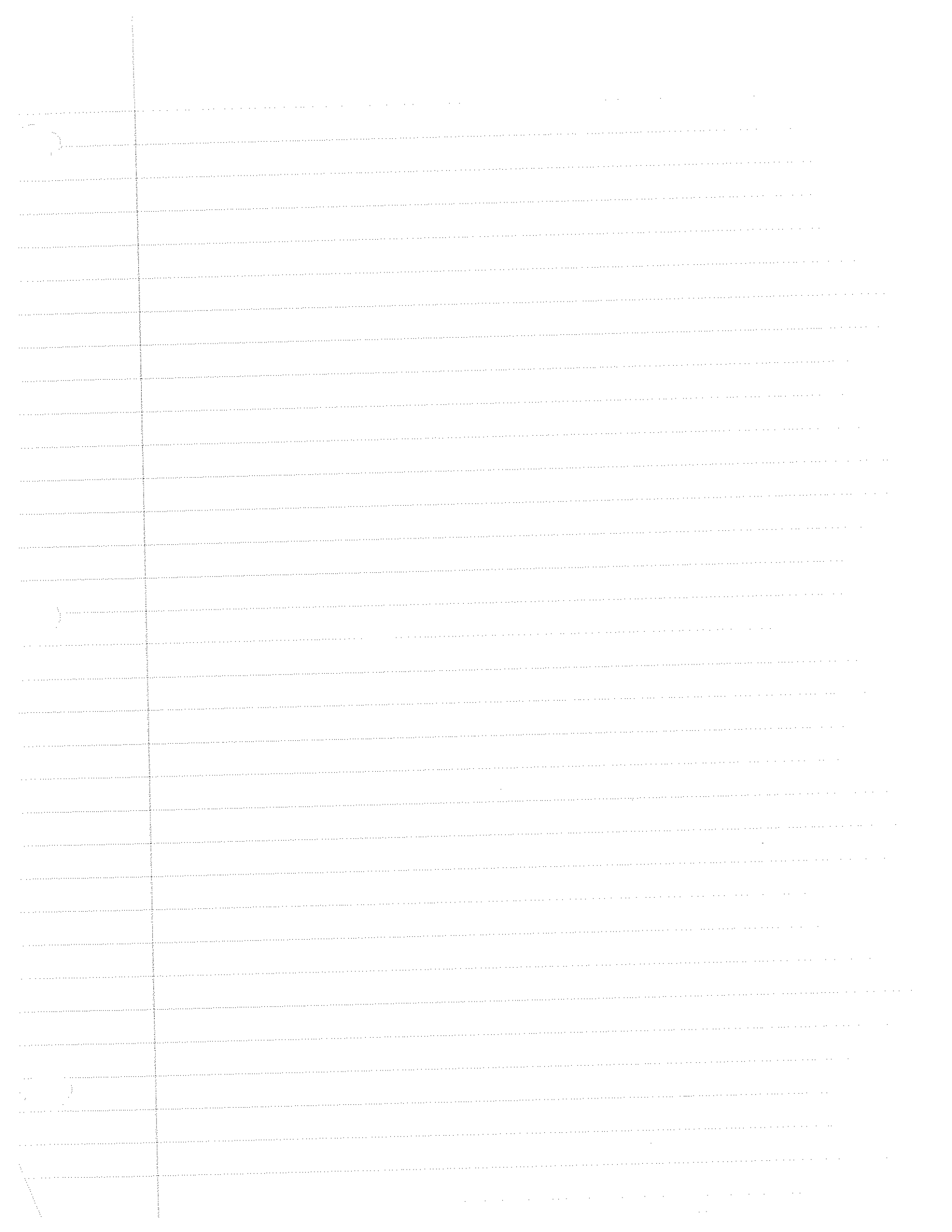
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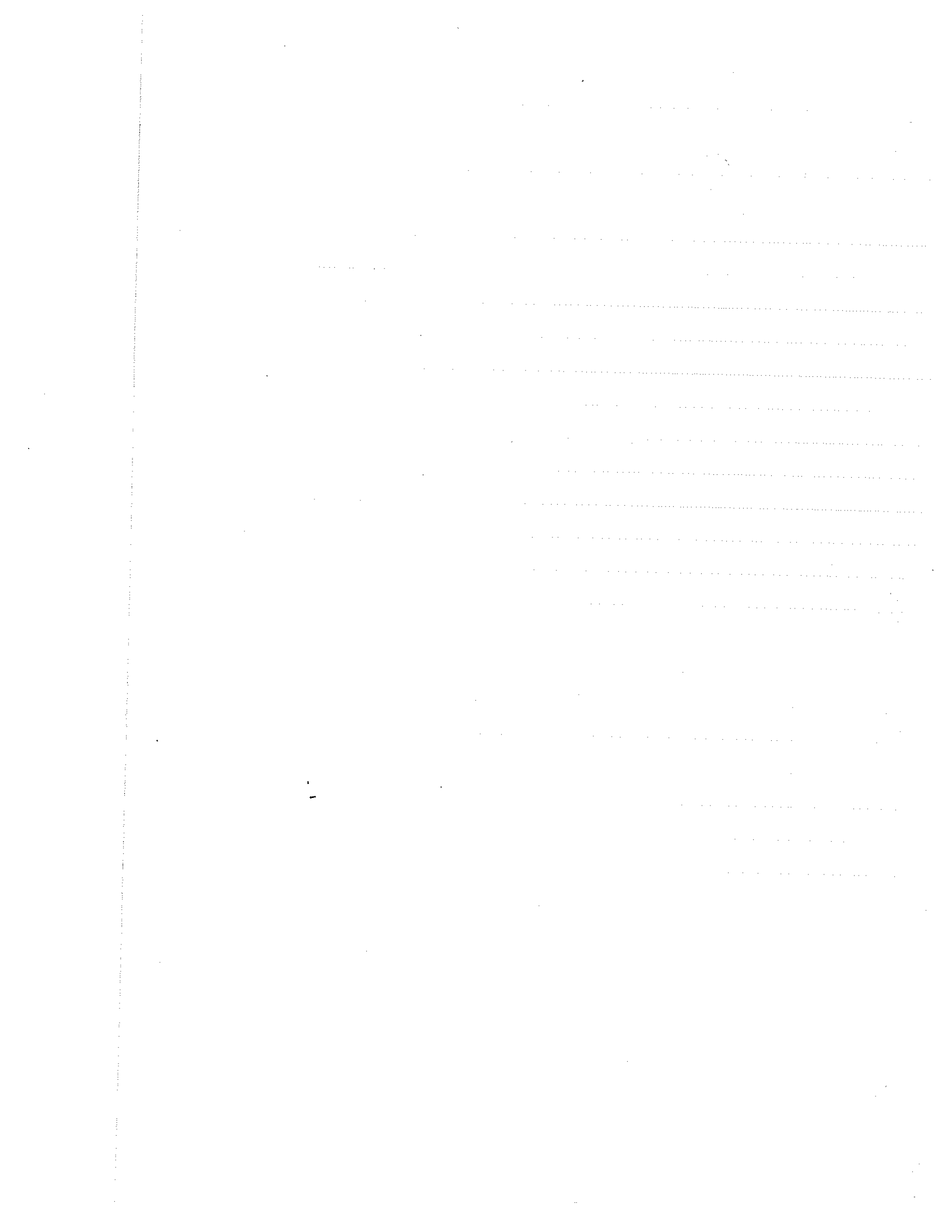
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9/88

Sample 221A prelims

Richard and I tried to make the following tests resemble actual full prelims as given by each of the usual 221 examiners. Most of the questions come straight from old prelims. The solutions are at best sketchy, and in some cases may be wrong, but should at least point you in the right direction.

Kris Pister
Richard Murray

Sample problem 1 [Sectry]

① Consider the linear operator $L: \mathbb{R}^{n \times n} \rightarrow \mathbb{R}^{n \times n}$ given by

$$L(X) = BXA - X$$

- What are the eigenvalues of L in terms of the eigenvalues of A & B ?
- When is the map L bijective?
- What are the eigenvalues of the linear map $M: \mathbb{R}^{n \times n} \rightarrow \mathbb{R}^{n \times n}$ defined by

$$M(Y) = AY + YB$$

② You are given a T -periodic linear system $\dot{x} = A(t)x + B(t)u$ with a periodic input $u(t)$ of period T .

- Find a T -periodic trajectory of the system
- When do solns of the differential equation converge towards the periodic solution.

③ You are given a transfer function $G(s) \in \mathbb{R}^{n \times n}(s)$. Describe how you would build a minimal realization of $G(s)$.

[Hint: Start w/ a partial fraction expansion of $G(s)$]

$$G(s) = \sum_{i=1}^p \frac{R_i}{(s-\lambda_i)}$$

Sample prelim 2 L Varaiya

① True or false

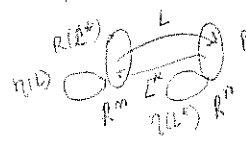
a. $AE = BA$, $f(\cdot)$ analytic $\Rightarrow f(A)e^B = e^B f(A)$ ✓

b. $\mathcal{R}(L) = \mathcal{R}(L^*L)$ ✓

c. $\mathcal{R}(A) \perp \mathcal{N}(A^*)$. Prove or disprove ✓

d. $L: \mathbb{R}^m \rightarrow \mathbb{R}^n$ is a surjective map. The least norm sol'n of $Lx = y$ is given by

$$x = L^T (LL^T)^{-1} y$$



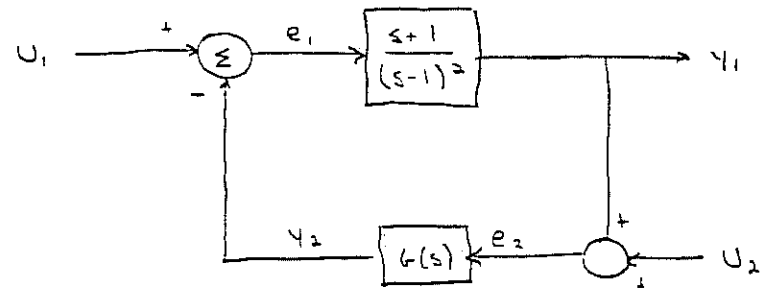
① onto \Rightarrow given $y \exists x \Rightarrow \dim(\mathcal{R}(L)) = n$
 ② $x = L^* \xi$
 $LL^* \xi = y$
 $\xi = (LL^*)^{-1} y$ (invertible)
 ③ $x = L^* (LL^*)^{-1} y$

② Consider the system

$$\frac{\partial^3 y}{\partial t^3} + y = \dot{u} + u$$

- a. Write down the controllable canonical form of the system
- b. Is it observable? Why?

③ Consider the block diagram



- a) Is the system open loop stable?
- b) what is $G(s)$ so that the characteristic polynomial is $(s+2)^2$

④ Explain the design of a reduced-order observer.

Give bounds on the dimension of an observer given all information about a plant (i.e. $\#$ inputs, $\#$ outputs, $\#$ states (controllable, observable, etc))

- ① a. Define complete controllability (be precise)
b. Describe all the tests you know of for determining if a system is completely controllable. Describe the conditions under which each test may be used.

② a. $\dot{x} = Ax + Bu$
 $y = Cx$

Define a minimal representation of this system

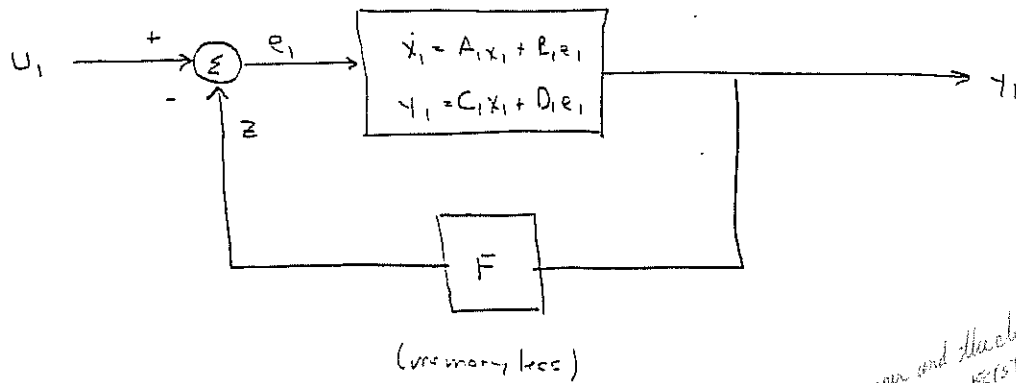
- b. How would you extract a minimal representation? *make co/oi by a transformation?*
c. Effect of state feedback on controllability and observability (proof or counterexample)
d. Effect of output feedback on controllability & observability (proof or counterexample)

③ $\dot{x} = Ax + Bu$

$$A = \begin{bmatrix} \alpha_1 & & & 0 \\ & \ddots & & \\ & & \ddots & \\ 0 & & & \alpha_n \end{bmatrix} \quad B = \begin{bmatrix} 1 & & & 0 \\ & \ddots & & \\ & & \ddots & \\ 0 & & & 1 \end{bmatrix}$$

Find a feedback of the form $u = v + Kx$ (K diagonal) so that the eigenvalues of the closed loop system have low sensitivity to perturbations in the eigenvalues of A .

Sample prelim 4 [WU]



① When is the overall system well-posed?
Suppose it is well-posed:

if any subsystem is proper and the closed loop system is proper and well-posed (assuming \$D_1=0\$)
 $H_{cl}(s) = C(sI-A)^{-1}B \cdot (I + K(sI-A)^{-1}B)$

- a. A_1 has an eigenvalue in \mathbb{C}_+ . Will it appear in the overall system?
- b. Can we use F to eliminate such an eigenvalue?
- c. A_1 has eigenvalue 1 of multiplicity 2. Characterize the behavior of this mode.

② Replace F with $\begin{cases} \dot{x}_2 = A_2 x_2 + B_2 y_1 \\ z = C_2 x_2 + D_2 y_1 \end{cases}$

- a. The overall system has an eigenvalue at λ_1 . Presuming no other knowledge of the transfer function, how would you determine whether or not this mode is observed in the transfer function?
- b. What conditions imply the overall system transfer function exists and is proper? Are these conditions necessary?
- c. Give the conditions for exponential stability of the overall system transfer function (in terms of $G_1(s)$ & $G_2(s)$)

use an input at that frequency and see if $y(t) \rightarrow 0$.

$$\begin{cases} G_1(s) = C_1(sI - A_1)^{-1}B_1 + D_1 \\ G_2(s) = C_2(sI - A_2)^{-1}B_2 + D_2 \end{cases}$$

exponential stability of closed loop system in \mathbb{C}_-

d. How would you check for exponential stability?

[Desoer] Sample Prelim 5

① $\dot{x} = A(t)x + B(t)u(t)$

$A(t) = A(t+T) \quad \forall t$

a) show $\Phi(t, \tau)$ satisfies $\Phi(t+T, \tau+T) = \Phi(t, \tau)$

b) what conditions are necessary for a T -periodic solution if:

i) $B(t) = 0$

ii) $B(t+T)u(t+T) = B(t)u(t) \quad \forall t$

c) assume $B(t) = 0$, and the eigenvalues of $\Phi(T, 0)$

lie inside the unit disk, except 1 at -1 .

$x(t)$ periodic?

② P, Q pos. def.

$A^T P A - P = -Q$

what can you say about the eigenvalues of A ?
(consider discrete time)

assume eigenvalue = $(|\lambda_i| - 1) < 0$

$\Rightarrow |\lambda_i| < 1$

special case when

$|\lambda_i| < 1$

$\Rightarrow -1 < \lambda_i < 1$

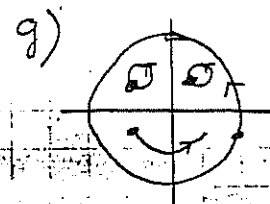
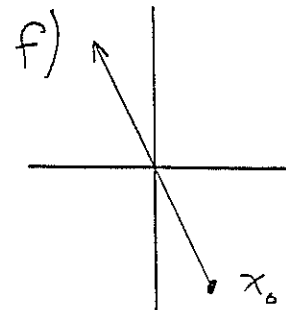
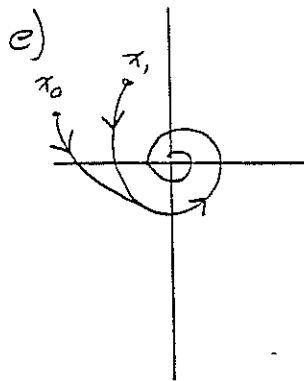
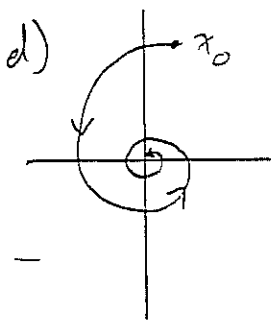
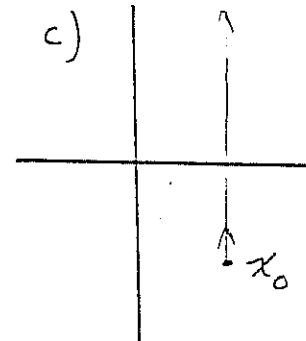
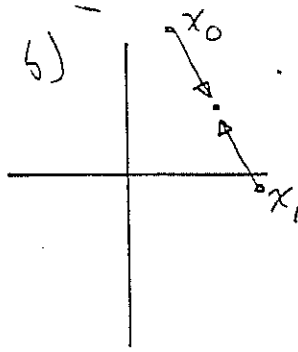
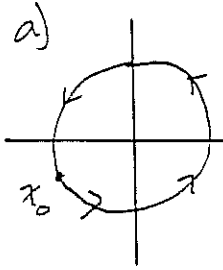
Sample Prelim 6

① [wu]

$$\dot{x}(t) = Ax(t) \quad A \in \mathbb{R}^{2 \times 2}$$

Which of the following state space plots is possible?

Why, why not, who cares?



② [varaiya]

a) give a controllable canonical realization of

$$\frac{d^3}{dt^3} y(t) + y(t) = \frac{d}{dt} u(t) + u(t)$$

is it observable?

b) ocf of same. controllable?

c) How do controllability and observability pertain to transfer functions?

2011

STUDY GUIDE FOR THE DOCTORAL PRELIMINARY EXAMINATION

*Published by the Electrical Engineering Graduate Students Association
University of California at Berkeley*

GENERAL INFORMATION

This document is a collection of practice questions for most of the courses in which students can take the doctoral preliminary examination. It is by no means complete but we hope it will help students in preparing for the exam.

Be aware that the prelim system at Berkeley has the unfortunate feature that professors test based on the material they covered (or would like to have covered) when they taught the course, and this content can vary widely from professor to professor. To prepare properly for the prelims, you really must cover not just the topics listed in the course description but whatever has been taught in the course plus whatever might have been taught had there been more time. In other words, it is the ill-defined closure of the subject for which you are responsible.

The questions in this study guide are not meant to be comprehensive. They should however give you an idea of what type of questions to expect from the examiners. Notice that there is a wide disparity between the easiest questions and the most difficult ones. This is another feature of prelims at Berkeley. Different professors have different styles. Most of these questions are questions from previous prelim exams, most of them from the quarter version of the courses; however, every effort has been made to include questions from last spring's exam, the first one on the semester version of the courses.

A given examination may involve a number questions, so speed of response is important. Hints are often given freely. Take advantage of them! If you get stuck, it is often better to ask for a hint than to flounder, wasting precious time. If you don't understand a question or a hint, don't pretend! You won't fool anyone, and a simple question might clear things up very quickly.

Finally, remember that this document in no way reflects official departmental policy. It is prepared by graduate students in an attempt to make practice questions *uniformly available* to all students taking prelims.

The EEGSA would like to thank all the students who helped in the preparation of this document.

Spring 1986

1

EECS 221A - LINEAR SYSTEM THEORY

Problem 1

$R = (A, B, C, D)$ is a binary system, i.e. every value appearing in this system is either 0 or 1. Is the following system observable? Is it completely reachable from the origin? Is it completely controllable to the origin?

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \end{bmatrix}$$

$$y(k) = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \end{bmatrix}$$

Problem 2

a) Is the system $\dot{x} = Ax + Bxu$ linear?

b) If u is the unit step function i.e. $\dot{x} = Ax + Bx, t > 0$ can we write $x(t) = e^{At} e^{Bt} x_0$?

Problem 3

Consider the response of the system in question 1.

$$x(k+1) = A(k)x \quad x(0) = x_0$$

$$y(k) = C(k)x$$

Define the map $\alpha : x_0 \mapsto y(\cdot)$ (the function $y(\cdot)$). Find the adjoint of α .

Problem 4

Show that $\dot{x} = A(t)x + B(t)u$ has a unique solution.

Problem 5

Show that: (A, b) is c.c. \iff There exists k such that $\sigma(A - bk)$ can be assigned to an arbitrary spectrum ("constellation") Σ .

1. Let an operator Λ be defined by:

$$\Lambda u = y(t) = \int_0^t \lambda(\tau) u(t-\tau) d\tau$$

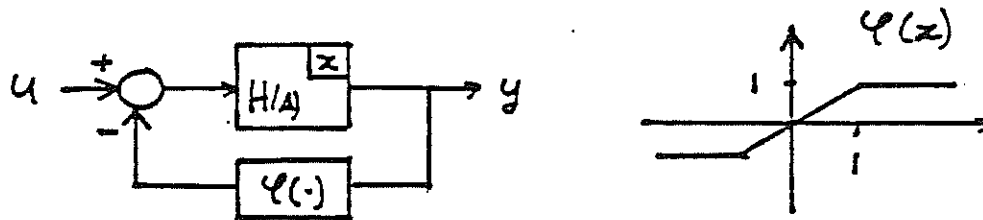
When is Λ BIBO stable? What if λ is a matrix?

2. We are given (A, b) . For what polynomials $p(s)$ can we find a row vector such that $p(s) = \det(sI - A - bf)$? If (A, b) is controllable, how would you find such an f ?

3. $\dot{x} = A(t)x$, $A(t+T) = A(t)$ and $A(t)$ is continuous.

- (a) What can we say about $\Phi(t, \tau)$?
- (b) When is this system stable? (in terms of Φ)
- (c) When does it have a periodic solution?

4. The realization $H(s)$ is minimal. We apply non-linear feedback:



Is the closed-loop system controllable? Observable?

5. Consider the following implicit algorithm to integrate $\dot{x} = f(x)$:

$$\frac{1}{h}(x_{n+1} - x_n) = \frac{1}{2}(f(x_n) + f(x_{n+1}))$$

$$x_n = \hat{x}(nh)$$

Professor B uses this algorithm to simulate $\dot{x} = Ax$; one simulation run is exponentially unstable, so he says $\dot{x} = Ax$ is unstable. Professor A, however, says "A could be stable - you just used a stepsize h which is too big." Who's right? Discuss.

B is right
 $\frac{1-h\lambda}{1+h\lambda} < 1$
 $1-h\lambda < 1+h\lambda$
 $-h\lambda < h\lambda$
 $-1 < \lambda < 1$
 True for any $h > 0$
 False for any $h > 0$

6. $C(s)$ is 1-input, 3-output, P is 3-input, 1 output and both are stable. An old timer control engineer who is not familiar with the subtleties of MIMO control systems sketches the Nyquist plot of PC : Is the system actually stable? Discuss.

Question 1 : True or false

- a. If $A \in \mathcal{R}^{n \times n}$. then $\det(A) = 0$.
- b. If $\mathcal{R}(A) = \mathcal{R}(A^T A)$?
- c. If $AB = BA$, then $e^{A+B} = e^A \cdot e^B$.
- d. $\mathcal{R}(A) \perp \mathcal{N}(A^*)$. prove it.

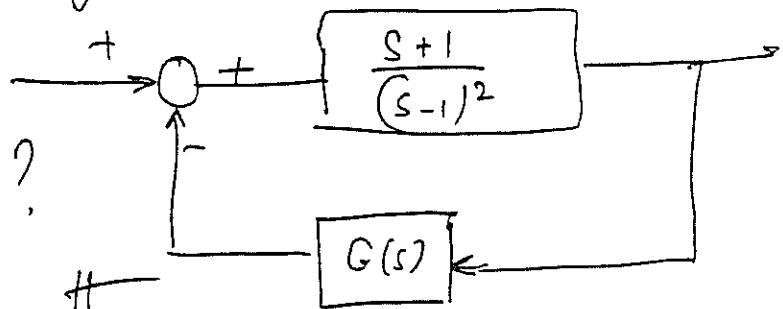
Question 2:

System.

$$\frac{\partial^3 y}{\partial t^3} + y = \ddot{u} + u.$$

(a) Give the controllable canonical form of the system.

(b) Is it observable? why?

Question 3: Given.(a) Is it open-loop stable?(b) What is $G(s)$ so that the characteristic polynomial is $(s+2)^2$ Question 4.

Explain design of reduced-order (minimal) compensator.

Given $\dot{x} = Ax$, $A \in \mathbb{R}^n$, $x \in \mathbb{R}^n$, $\sigma(A) \in \mathbb{C}^-$, $x(0) = x_0$,
discretize the system using the following formulae

$$BE) \quad x_{k+1} = x_k + h \dot{x}_{k+1}$$

$$FE) \quad x_{k+1} = x_k + h \dot{x}_k$$

$$TR) \quad x_{k+1} = x_k + \frac{1}{2}h (\dot{x}_{k+1} + \dot{x}_k)$$

$$h = \Delta t \quad h \triangleq (t_{k+1} - t_k)$$

discuss the stability of the discretized system as a function of h and $\sigma(A)$.

A.S.U.

1) Compute

$$\frac{d}{dh} (I - hD)^{-1}$$

where $I \in \mathbb{R}^{n \times n}$ is the identity matrix, $D \in \mathbb{R}^{n \times n}$,
 $h \in \mathbb{R}^1$.

Compute the sum of the series

$$I + A + A^2 + \dots$$

A.S.V.

(iii) Apply ...
 the matrix F satisfies $Fx_0 = u_0$ (where $x_0 \in \mathbb{R}^n$ is an initial condition ~~and~~ such that when an input $u(t) = u_0 e^{\lambda t}$, $t \geq 0$ ~~is applied~~ is applied results in a zero output ~~is~~ (this can be done if λ is a zero ...))
 Is the feedback system still C.O.?

221 A / Desoer

① Consider the linear system $\dot{x} = A(t)x$ such that
 $A(t) = A(t+T) \quad \forall t \in \mathbb{R}$ (for some $T > 0$)

- Under what conditions does the above system accept at least one periodic solution?
- When is the system stable?

② Consider now $\dot{x} = A(t)x + u(t)$ with
 $A(t) = A(t+T)$, $u(t) = u(t+T) \quad \forall t \in \mathbb{R}$ (for some $T > 0$)

- The same questions.

221 A / Polak

① • Given a feedback system as in the next figure.

Write down the A, B, C matrices of the total system. 13

Problem 1

11-01
SASTRY

You are told the linear system

$$\dot{x} = A(t)x + B(t)u$$

$$y = C(t)x$$

is completely observable on $[t_0, t_1]$. Given $y(t)$ on the interval $[t_0, t_1]$ find $x(t_0)$.

Reduced Order Observers

221
Sastry

You are given the linear system

$$\dot{x} = Ax + Bu$$

$$x \in \mathbb{R}^n, u \in \mathbb{R}^{n_i}$$

$$y = Cx$$

$$y \in \mathbb{R}^{n_o}$$

Further you are told that C has the form

$$n_o \downarrow \begin{matrix} \xleftarrow{n} \\ \left[\begin{array}{c|c} I_{n_o} & 0 \end{array} \right] \end{matrix}$$

Write down a reduced order ($n - n_o$) observer for

this system.

II

Consider

$$\dot{x} = Ax + Bu$$

You are told $\text{rank} [sI - A \mid B] = n$ for all $s \in \mathbb{C}_+$

the closed right half plane \iff The linear system is stabilisable

Is this true or false? If true prove, if false give

Counterexample

Q.

$$A = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\therefore [sI - A \mid B] = \begin{bmatrix} s-1 & 0 & 1 \\ 0 & s+1 & 0 \end{bmatrix}$$

$$\begin{aligned} A + B B^T &= \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 2 & 0 \\ 0 & -1 \end{bmatrix} \end{aligned}$$

but does it mean we can't get to the pole at -1?

but $\lambda = 1$ is full rank $\forall s \in \mathbb{C}_+$
 \Rightarrow unstable, 17
 $[B^T A B] = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$
 \Rightarrow not c.c. 19

11.11.11
You are given a T -periodic linear system

$$\dot{x} = A(t)x + B(t)u \quad (1)$$

with periodic input $u(t)$ of period T . Find a T -period trajectory of the system. Discuss when all solutions of (1) converge towards the periodic solution.

2. Define the matrix $P(t) \in \mathbb{R}^{n \times n}$ for given

$A \in \mathbb{R}^{n \times n}$, $C \in \mathbb{R}^{n_0 \times n}$ by

$$P(t) = \int_0^t e^{A^T(t-\tau)} C^T C e^{A(t-\tau)} d\tau.$$

$$\dot{P}(t) = e^{A^T(t-t)} C^T C e^{A(t-t)} - 0 + A^T P(t) + P(t) A = C^T C + A^T P(t) + P(t) A$$

(a) Find the differential equation that P satisfies?

(b) Find the limit as $t \rightarrow \infty$ of $P(t)$ given that

$$\sigma(A) \subset \mathbb{C}_- \quad \rightarrow \quad \lim_{t \rightarrow \infty} P(t) = \int_0^{\infty} e^{A^T(t-\tau)} C^T C e^{A(t-\tau)} d\tau$$

(c) Give conditions so that $P(\infty)$ is positive definite.

[10 marks]

3. You are given a transfer function

$G(s) \in \mathbb{R}^{n_o \times n_i}(s)$. How would you proceed to

build a minimal realisation of it.

HINT: - You may wish to start

with a partial fraction expansion

of $G(s) = \left(\sum_{i=1}^p \frac{R_i}{(s - \lambda_i)} \right)$, for starters for e.g.).

[10 points]

PROBLEM 2

Consider the system:

$$S: \begin{cases} \dot{x} = Ax + Bu \\ y_1 = Cx + Du \end{cases}$$

where A is an $n \times n$ matrix.

(a) Denote the characteristic polynomial of this system by $\chi(s)$. Show that S is asymptotically stable if and only if there exists a polynomial $d(s)$, with real coefficients, of the same degree as $\chi(s)$, such that all of its zeros are in the *open left half complex plane*, $\overset{o}{C}_-$, and

$$\operatorname{Re}[\chi(j\omega)/d(j\omega)] > 0, \quad \forall \omega \in (-\infty, \infty)$$

(b) Suppose that there exist constants $T, \beta \in (0, \infty)$, and $\alpha \in (0, 1)$ such that for all $x_0 \in \mathbb{R}^n$,

$$\|e^{TA}x_0\| \leq \alpha\|x_0\|$$

and

$$\|e^{tA}x_0\| \leq \beta\|x_0\|, \quad \forall t \in [0, T]$$

Show that the system S is asymptotically stable.

221A

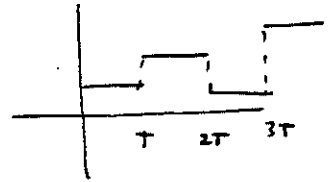
I. Consider the LTI system described by

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t)$$

Suppose one uses piecewise constant control inputs:

$$u(t) = u_k, \quad kT \leq t < (k+1)T$$



Then there is a representation of the discrete time system in the form:

$$x_{k+1} = A_d x_k + B_d u_k$$

$$y_k = C_d x_k$$

where $x_k := x(kT)$, $y_k = y(kT)$.

Find A_d, B_d, C_d in terms of A, B, C, T .

II

Consider

$$\dot{x}(t) = Ax(t) + Bu(t)$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^1$. Suppose

$$u(t) = u_0 \cos \omega_0 t \quad ; \quad u_0, \omega_0 \text{ are constant.}$$

Suppose

$$\sigma(A) \subset \mathbb{C}_-$$

Show that the state trajectory $t \mapsto x(t)$ tends to an ellipse, centered at 0, and lying in a two-dimensional subspace of \mathbb{R}^n .

III

A rotating wheel is governed by

$$\ddot{\theta} + 0.01 \dot{\theta} + \theta = 0$$

An instrument measures θ accurately. Design an observer to measure $\dot{\theta}$ with a time constant of 1.

PROBLEM 1

(a) Consider the polynomial ratio

$$r(s) = \frac{n(s)}{d(s)},$$

where $d(s) = \prod_{i=1}^N (s - \lambda_i)$, with the λ_i known. Establish a frequency domain test for determining if all the zeros of $n(s)$ are in $\overset{o}{\mathbb{C}}_-$. What would be an advantageous selection of the polynomial $d(s)$?

(b) Consider the system

$$S: \begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u(t) \\ y(t) = C(t)x(t) \end{cases},$$

where $x(t) \in \mathbb{R}^n$, $y(t) \in \mathbb{R}^m$ and the matrices $A(t)$, $B(t)$, $C(t)$ are continuous.

Define what is meant by this system being (i) b.i.b.o. stable, and (ii) asymptotically stable.

(c) Consider the interconnected system:

$$S_1: \begin{cases} \dot{x}_1 = A_1x_1 + B_1u_1 \\ y_1 = C_1x_1 \end{cases}$$

$$S_2: \begin{cases} \dot{x}_2 = A_2x_2 + B_2u_2 \\ y_2 = C_2x_2 \end{cases}$$

$$\begin{cases} u_1 = v_1 - y_2 \\ u_2 = v_2 + y_1 \end{cases}$$

(i) Obtain two formulae for the characteristic polynomial of the above interconnected system.

(ii) State and prove the multivariable Nyquist stability criterion, as it applies to the above interconnected system, and discuss its value in determining the asymptotic stability of interconnected systems.

PROBLEM 2

(a) Consider the system:

$$S: \begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases}$$

where A is an $n \times n$ matrix.

Denote the characteristic polynomial of this system by $\chi(s)$. Show that S is asymptotically stable if and only if there exists a polynomial $d(s)$, with real coefficients, of the same degree as $\chi(s)$, such that all of its zeros are in the *open left half complex plane*, $\overset{\circ}{C}_-$, and

$$\operatorname{Re}[\chi(j\omega)/d(j\omega)] > 0, \quad \forall \omega \in (-\infty, \infty)$$

(b) How would you modify the above test so as to be able to determine if the zeros of $\chi(s)$ are in the sector $C \triangleq \{s = \alpha + j\omega \in \mathbb{C} \mid \alpha = -2|\omega|, \omega \in (-\infty, \infty)\}$.

3. Given A, B a completely controllable pair and $\phi: \mathbb{R}^n \rightarrow \mathbb{R}^m$ ~~of~~ a Lipschitz function; can you say something about the controllability of

$$\dot{x} = Ax + B\phi(x) + Bu$$

(5 points)

① What is Jordan form for matrix $A \in \mathbb{R}^{n \times n}$?

a) How does one obtain Jordan Form?

(distinct λ_i)

b) Non-distinct eigenvalues?

c) Given system

$$\dot{x} = Jx + bu$$

How does one test controllability?

- example

d) True or False: Any two LTI systems with identical char. polynomial have similar A-matrices

e) T or F: Any two controllable, single-input systems with same char. poly have similar A-matrices

Problem 1

Consider a controllable system

$$\dot{x} = Ax + bu.$$

Your friend from CMU says that he can use state feedback $u = f^T x + v$ to place all the closed loop eigenvalues at $s=0$ and thereby get

$$\dot{x} = 16v$$

TRUE or FALSE ?

PROBLEM 2.

2

Consider a minimal, SISO linear system

$$\dot{x} = Ax + bu \quad u \in \mathbb{R}$$

$$y = cx + du \quad y \in \mathbb{R}$$

The transfer function $\hat{h}(s) = c(sI - A)^{-1}b + d$.

Consider the following feedback laws:

$$\textcircled{1} \quad \dot{x} = Ax + b(f^T x + v) \quad \text{STATE FEEDBACK}$$

$$y = cx + d(f^T x + v)$$

$$\textcircled{2} \quad \dot{x} = Ax + bu + \underline{l}(cx + du) \quad \text{OUTPUT INJECTION}$$

$$y = cx + du$$

Discuss what happens to controllability, observability and ~~time~~ in each case

What are the 'zeros' of the linear systems (1), (2) (before cancellation).

PROBLEM 3.

3. What you are told that

$$z_1 = C_1 x$$

$$z_2 = C_2 x$$

\vdots

$$z_n = C_n x$$

$$x \in \mathbb{R}^n, z_i \in \mathbb{R}$$

and that C_i 's are linearly independent, ~~and surjective~~ ^{rows and they are surjective}

What is the linear least squares estimate of x given z_1 ?

(Call it \hat{x}_1)

Now about the linear least squares estimate of x given

z_1, z_2 ? (Call it \hat{x}_2). \therefore Can you relate \hat{x}_2 to \hat{x}_1 .

Do you see the recursion?

1

2

3

4

5

6

7

8

9

1. Define addition and multiplication on $\{0, 1\}$ to form a field.
2. Show that the set of all polynomials in S of degree k or less with real coefficients is a vector space over \mathbb{R} . Find a basis. What is the dimension of the vector space.
3. Consider the derivative operator on the set of polynomials of degree 3 or less. Is it a linear transformation? If so find its matrix representation with respect to the bases of your choice.
4. Consider the set of sequences $\{f_k\}_{k=0}^{\infty} := \{f_0, f_1, f_2, \dots\}$ satisfying $f_k = f_{k-1} + f_{k-2}$ where f_0 and f_1 are arbitrary real numbers. Is this a subspace in the vector space of all sequences of real numbers?
5. The unit sphere is defined by $\|x\| = 1$. Draw the unit spheres of the normed vector space $(\mathbb{R}^2, \mathbb{R}, \|\cdot\|)$ with the norm defined by i) $\|(x_1, x_2)\|_{\infty} = \max(|x_1|, |x_2|)$, ii) $\|(x_1, x_2)\|_1 = |x_1| + |x_2|$, and iii) $\|(x_1, x_2)\|_2 = \sqrt{x_1^2 + x_2^2}$.

