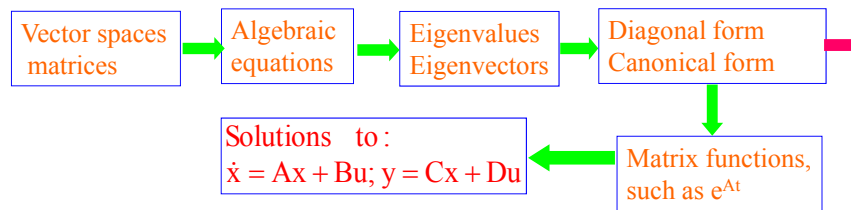


16.513 Control Systems (Lecture note #7)

- Last Time:
 - Generalized eigenvectors, Jordan form
 - Polynomial functions of a square matrix, e^{At}

A big picture: one branch of the course



The linear algebra tools will also be useful for other objectives.

1

Review: diagonal form and Jordan form

- All eigenvalues of A are distinct \Rightarrow diagonalizable
- There are repeated eigenvalues, e.g., λ_i with multiplicity k .
 - If $v(A-\lambda_i I) = n - \rho(A-\lambda_i I) = k$, there exist k LI solutions to $(A-\lambda_i I)v=0$ and they are all eigenvectors.
If this is the case for all repeated eigenvalues \Rightarrow diagonalizable
 - If $v(A-\lambda_i I) = n - \rho(A-\lambda_i I) < k$, there exist generalized eigenvectors, \Rightarrow not diagonalizable, there exist **Jordan blocks**

2

Definition. A vector v is a **generalized eigenvector of grade k** associated with λ if

$$(A - \lambda I)^k v = 0, \quad \text{but } (A - \lambda I)^{k-1} v \neq 0$$

Denote $v_k \equiv v$,

$$v_{k-1} \equiv (A - \lambda I)v = (A - \lambda I)v_k,$$

$$v_{k-2} \equiv (A - \lambda I)^2 v = (A - \lambda I)v_{k-1},$$

$$v_1 \equiv (A - \lambda I)^{k-1} v = (A - \lambda I)v_2,$$

$$(A - \lambda I)v_1 = (A - \lambda I)^k v = 0,$$

$$Av_k = v_{k-1} + \lambda v_k$$

$$Av_{k-1} = v_{k-2} + \lambda v_{k-1}$$

$$Av_2 = v_1 + \lambda v_2$$

$$Av_1 = \lambda v_1$$

– What is the new representation w.r.t. $\{v_1, v_2, \dots, v_k\}$? i.e.,

$$A[v_1 \ v_2 \ \dots \ v_k] = [v_1 \ v_2 \ \dots \ v_k]\bar{A}$$

$$\bar{A} = \begin{bmatrix} \lambda & 1 & \dots & 0 \\ 0 & \lambda & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda \end{bmatrix}$$

A Jordan block

3

Polynomial functions of a square matrix

- Let $f(A) = \sum_{i=1}^k \alpha_i A^i$ be a polynomial function of A . If $A = Q\bar{A}Q^{-1}$, then $f(A) = Qf(\bar{A})Q^{-1}$.
- Let $\Delta(\lambda)$ be the characteristic polynomial of A .

Cayley-Hamilton Theorem: $\Delta(A) = 0$



- Any polynomial can be expressed as a polynomial of degree $n-1$

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Theorem. Given $A \in \mathbb{C}^{n \times n}$ and a polynomial $f(\lambda)$. Let the distinct eigenvalues of A be $\lambda_i, i=1,2,\dots,m$, each with multiplicity n_i , ($n_1+n_2+\dots+n_m = n$). Let

$$g(\lambda) = \beta_0 + \beta_1\lambda + \dots + \beta_{n-1}\lambda^{n-1}$$

Then $f(A)=g(A)$ iff

$$f^{(l)}(\lambda_i) = g^{(l)}(\lambda_i), l = 0, 1, \dots, n_i - 1, i = 1, \dots, m$$

$$\text{where } f^{(l)}(\lambda_i) = \left. \frac{d^{(l)}f(\lambda)}{d\lambda^l} \right|_{\lambda=\lambda_i}, \quad f^{(0)}(\lambda_i) = f(\lambda_i)$$

Under the above condition, the coefficients β_i 's can be determined

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General functions of a square matrix:

Definition: Given $A \in \mathbb{C}^{n \times n}$. Let the distinct eigenvalues of A be $\lambda_i, i=1,2,\dots,m$, each with multiplicity n_i , ($n_1+n_2+\dots+n_m = n$). Let $f(\lambda)$ be a general function with $\{f^{(l)}(\lambda_i)\}$ well defined. Suppose that $g(\lambda)$ is a polynomial satisfying

$$f^{(l)}(\lambda_i) = g^{(l)}(\lambda_i), l = 0, 1, \dots, n_i - 1, i = 1, \dots, m$$

Then $f(A) \equiv g(A)$.

Generally, g is a polynomial of degree $n-1$.

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Today:

- Some properties of e^{At} ;
- Solution to a continuous-time system

$$\dot{x} = Ax + Bu; \quad y = Cx + Du$$

- Solution to the discrete-time system

$$x[k+1] = A[k]x[k] + Bu[k]; \quad y[k] = Cx[k] + Du[k]$$

- Equivalent state equations

7

Some properties for e^{At}

From the definition,

$$e^{At} = \sum_{k=0}^{\infty} \frac{A^k t^k}{k!} = I + At + \frac{A^2 t^2}{2} + \frac{A^3 t^3}{3!} + \dots$$

The following can be verified

$$e^0 = I;$$

$$e^{A(t_1+t_2)} = e^{At_1} e^{At_2};$$

$$e^{-At} = \left(e^{At}\right)^{-1};$$

Caution: e^{A+B} usually does not equal to $e^A e^B$.
We only have $e^{A+B} = e^A e^B$ when $AB=BA$

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More properties:

$$\frac{d(e^{At})}{dt} = ?$$

$$e^{At} = \sum_{k=0}^{\infty} \frac{A^k t^k}{k!} = I + At + \frac{A^2 t^2}{2} + \frac{A^3 t^3}{3!} + \dots$$

$$\frac{d(e^{At})}{dt} = \sum_{k=1}^{\infty} \frac{A^k t^{k-1}}{(k-1)!} = A \left(\sum_{k=1}^{\infty} \frac{A^{k-1} t^{k-1}}{(k-1)!} \right) \overset{\text{Let } \bar{k} = k-1}{=} A \left(\sum_{\bar{k}=0}^{\infty} \frac{A^{\bar{k}} t^{\bar{k}}}{\bar{k}!} \right) = Ae^{At} = e^{At}A$$

$$\frac{d(e^{\lambda t})}{dt} = \lambda e^{\lambda t} \Leftrightarrow \frac{d(e^{At})}{dt} = Ae^{At} = e^{At}A$$

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More properties:

$$\int_0^t e^{A\tau} d\tau = ? \quad e^{At} = \sum_{k=0}^{\infty} \frac{A^k t^k}{k!} \quad \sim \text{Assuming that } A^{-1} \text{ exists}$$

$$\int_0^t e^{A\tau} d\tau = \sum_{k=0}^{\infty} \frac{A^k t^{k+1}}{(k+1)!} = A^{-1} \left(\sum_{k=0}^{\infty} \frac{A^{k+1} t^{k+1}}{(k+1)!} \right) \overset{\bar{k}+1 \rightarrow k}{=} A^{-1} \left(\sum_{k=1}^{\infty} \frac{A^k t^k}{k!} \right)$$

$$= A^{-1} \left(\sum_{k=1}^{\infty} \frac{A^k t^k}{k!} + I - I \right) = A^{-1} (e^{At} - I) = (e^{At} - I)A^{-1}$$

$$\int_0^t e^{A\tau} B d\tau = \left(\int_0^t e^{A\tau} d\tau \right) B = (e^{At} - I)A^{-1}B$$

- This will be used to compute the output response under constant inputs.

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Example. Laplace Transform of e^{At}

$$L\{e^{At}\} = \sum_{k=0}^{\infty} L\left\{\frac{t^k}{k!}\right\} A^k = \sum_{k=0}^{\infty} \left(\frac{A^k}{s^{k+1}}\right) = \frac{1}{s} \sum_{k=0}^{\infty} \left(\frac{A}{s}\right)^k$$

$$\sum_{k=0}^{\infty} \lambda^k = \frac{1}{1-\lambda} \quad \Rightarrow \quad \sum_{k=0}^{\infty} \left(\frac{A}{s}\right)^k = \left(I - \frac{A}{s}\right)^{-1} = s(sI - A)^{-1}$$

~ Assuming $|\lambda| < 1$ ~ Assuming s is sufficiently large

$$L\{e^{At}\} = (sI - A)^{-1}, \quad \text{or } e^{At} = L^{-1}\{(sI - A)^{-1}\}$$

$$L\{e^{\lambda t}\} = \frac{1}{s-\lambda} \quad \Leftrightarrow \quad L\{e^{At}\} = (sI - A)^{-1}$$

- How to compute $(sI - A)^{-1}$?

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Example. $f(\lambda) = (s - \lambda)^{-1}$. Compute $f(A) = (sI - A)^{-1}$,

$$A = \begin{bmatrix} \lambda_1 & 1 & 0 \\ 0 & \lambda_1 & 1 \\ 0 & 0 & \lambda_1 \end{bmatrix}$$

- $\Delta(\lambda) = (\lambda - \lambda_1)^3$, with λ_1 of multiplicity 3
- $f^{(0)}(\lambda_1) = (s - \lambda_1)^{-1}$, $f^{(1)}(\lambda_1) = (s - \lambda_1)^{-2}$, $f^{(2)}(\lambda_1) = 2(s - \lambda_1)^{-3}$
- $g(\lambda) = \beta_0 + \beta_1(\lambda - \lambda_1) + \beta_2(\lambda - \lambda_1)^2$
- $g^{(0)}(\lambda_1) = \beta_0 = (s - \lambda_1)^{-1}$, $g^{(1)}(\lambda_1) = \beta_1 = (s - \lambda_1)^{-2}$
- $g^{(2)}(\lambda_1) = 2\beta_2 = 2(s - \lambda_1)^{-3}$
- $g(\lambda) = (s - \lambda_1)^{-1} + (s - \lambda_1)^{-2}(\lambda - \lambda_1) + (s - \lambda_1)^{-3}(\lambda - \lambda_1)^2$
- $g(A) = (s - \lambda_1)^{-1}I + (s - \lambda_1)^{-2}(A - \lambda_1) + (s - \lambda_1)^{-3}(A - \lambda_1)^2$

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$$A - \lambda_1 I = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \quad (A - \lambda_1 I)^2 = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$g(A) = (s - \lambda_1)^{-1} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} + (s - \lambda_1)^{-2} \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} + (s - \lambda_1)^{-3} \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$(sI - A)^{-1} = g(A) = \begin{bmatrix} \frac{1}{s - \lambda_1} & \frac{1}{(s - \lambda_1)^2} & \frac{1}{(s - \lambda_1)^3} \\ 0 & \frac{1}{s - \lambda_1} & \frac{1}{(s - \lambda_1)^2} \\ 0 & 0 & \frac{1}{s - \lambda_1} \end{bmatrix} = L(e^{At}) = L \left(\begin{bmatrix} e^{\lambda_1 t} & te^{\lambda_1 t} & t^2 e^{\lambda_1 t} / 2 \\ 0 & e^{\lambda_1 t} & te^{\lambda_1 t} \\ 0 & 0 & e^{\lambda_1 t} \end{bmatrix} \right)$$

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Today:

- We will compute e^{At} ;
- Some of its properties;
- **Solution to a continuous-time system**

$$\dot{x} = Ax + Bu; \quad y = Cx + Du$$

- Solution to the discrete-time system

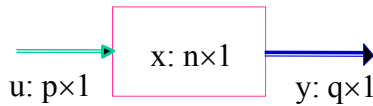
$$x[k + 1] = A[k]x[k] + Bu[k]; \quad y[k] = Cx[k] + Du[k]$$

- Equivalent state equations

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State-Space Solutions and Realizations

Solutions of Dynamic Equations



- Consider a linear system:

$$\dot{x} = Ax + Bu; \quad y = Cx + Du$$

- A: $n \times n$ real matrix; B: $n \times p$ real matrix
- C: $q \times n$ real matrix; D: $q \times p$ real matrix
- Given $x(t_0) = x_0$ and $u(\cdot) \Rightarrow$ A unique solution $x(\cdot), y(\cdot)$
- What is the solution?

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- Recall that earlier we derived the solution for the input/output description based on superposition:

$$y(t) = \int_{t_0}^t G(t-\tau)u(\tau)d\tau, \quad G(t-\tau) = \begin{bmatrix} g_{11}(t-\tau) & g_{12}(t-\tau) & g_{1p}(t-\tau) \\ g_{21}(t-\tau) & g_{22}(t-\tau) & g_{2p}(t-\tau) \\ g_{q1}(t-\tau) & g_{q2}(t-\tau) & g_{qp}(t-\tau) \end{bmatrix}$$

Questions:

- Given system matrices, A,B,C,D, what is G(t)?
- What is the response due to initial state?
- Another approach is by using Laplace transform:

$$\hat{y}(s) = C(sI - A)^{-1}x(0) + [C(sI - A)^{-1}B + D]\hat{u}(s)$$
 - A downside: the Laplace transform of $u(t)$ may be not available, you may need to approximate it. ¹⁶

State-Space Solutions

The system: $\dot{x} = Ax + Bu$; $y = Cx + Du$

Given $x(0)$ and $u(t)$ for $t \geq 0$. The solution for x and y is

$$\begin{aligned} x(t) &= e^{At} x(0) + \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau; \\ y(t) &= Ce^{At} x(0) + \int_0^t Ce^{A(t-\tau)} Bu(\tau) d\tau + Du(t) \end{aligned}$$

$$G(t-\tau) = Ce^{A(t-\tau)} B$$

- Clearly two parts: zero-input resp. + zero-state resp.
- Linearity also obvious.
- We know how to compute e^{At} . The integration can be done numerically through discretization.

$$\int_0^{k\Delta} e^{A(t-\tau)} Bu(\tau) d\tau \approx \sum_{i=0}^{k-1} e^{A(k-i)\Delta} Bu(i\Delta) \Delta \quad 17$$

We first consider the state x :

$$\dot{x}(t) = Ax(t) + Bu(t); \quad (*)$$

Recall that $\frac{d}{dt} e^{At} = Ae^{At} = e^{At} A$ ← The key part

$$\frac{d}{dt} e^{-At} x = e^{-At} \dot{x} + \frac{d}{dt} (e^{-At}) x = e^{-At} \dot{x} - e^{-At} Ax \quad (**)$$

Plug (*) into (**): $\frac{d}{dt} e^{-At} x = e^{-At} Ax + e^{-At} Bu - e^{-At} Ax = e^{-At} Bu$

$$\Rightarrow de^{-At} x(t) = e^{-At} Bu(t) dt$$

Integrate from 0 to t ; $[e^{-A\tau} x(\tau)]_0^t = \int_0^t e^{-A\tau} Bu(\tau) d\tau$

$$e^{-At} x(t) - x(0) = \int_0^t e^{-A\tau} Bu(\tau) d\tau$$

Premultiplying e^{At} to both sides, noting $e^{At} e^{-At} = I$

$$x(t) = e^{At} x(0) + \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau \quad 18$$

We verify that the solution

$$\mathbf{x}(t) = e^{At} \mathbf{x}(0) + \int_0^t e^{A(t-\tau)} \mathbf{B} \mathbf{u}(\tau) d\tau$$

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

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \frac{d}{dt} \left[e^{At} \mathbf{x}(0) + \int_0^t e^{A(t-\tau)} \mathbf{B} \mathbf{u}(\tau) d\tau \right] \\ &= \mathbf{A} e^{At} \mathbf{x}(0) + \int_0^t \mathbf{A} e^{A(t-\tau)} \mathbf{B} \mathbf{u}(\tau) d\tau + e^{A(t-t)} \mathbf{B} \mathbf{u}(t) \Big|_{\tau=t} \\ &= \mathbf{A} \left(e^{At} \mathbf{x}(0) + \int_0^t e^{A(t-\tau)} \mathbf{B} \mathbf{u}(\tau) d\tau \right) + \mathbf{B} \mathbf{u}(t) \\ &= \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) \quad \checkmark \end{aligned}$$

Also, it is clear that the initial condition is satisfied.

Finally,
$$\begin{aligned} \mathbf{y}(t) &= \mathbf{C} \mathbf{x}(t) + \mathbf{D} \mathbf{u}(t) \\ &= \mathbf{C} e^{At} \mathbf{x}(0) + \int_0^t \mathbf{C} e^{A(t-\tau)} \mathbf{B} \mathbf{u}(\tau) d\tau + \mathbf{D} \mathbf{u}(t) \end{aligned}$$

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Different ways to compute e^{At} :

- From Definition 1:
 - Form $\Delta(\lambda)$, and find $\{\lambda_i\}$ and $(e^{\lambda t})^{(l)}|_{\lambda=\lambda_i}$
 - Construct an $(n - 1)$ th order polynomial such that $g^{(l)}(\lambda_i) = (e^{\lambda t})^{(l)}|_{\lambda=\lambda_i}$ for all i and l
 - $e^{At} = g(A)$
- From Definition 2: $e^{At} = \sum_{k=0}^{\infty} \frac{A^k t^k}{k!}$, suitable for computer
- Use Jordan form $A = \mathbf{Q} \bar{\mathbf{A}} \mathbf{Q}^{-1}$, $e^{At} = \mathbf{Q} e^{\bar{\mathbf{A}} t} \mathbf{Q}^{-1}$
- Use the inverse Laplace transform of $(s\mathbf{I} - \mathbf{A})^{-1}$.

$$e^{At} = \mathcal{L}^{-1} (s\mathbf{I} - \mathbf{A})^{-1}$$

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Example: An LTI system:

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t); \quad y = [1 \ 0]x$$

Given $x(0)=0$; $u(t)=1$, for $t \geq 0$. Compute $y(t)$, $t \geq 0$.

Step 1: Compute e^{At} . Eigenvalues of A are $\lambda_1=-1$; $\lambda_2=-2$.

$$\text{Let } g(\lambda) = a\lambda + b; \quad f(\lambda) = e^{\lambda t}.$$

$$\text{From } g(-1) = -a + b = e^{-t}; \quad g(-2) = -2a + b = e^{-2t}. \Rightarrow a = e^{-t} - e^{-2t}; \quad b = 2e^{-t} - e^{-2t};$$

$$\begin{aligned} e^{At} &= aA + bI = (e^{-t} - e^{-2t}) \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix} + (2e^{-t} - e^{-2t}) \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} 2e^{-t} - e^{-2t} & e^{-t} - e^{-2t} \\ -2e^{-t} + 2e^{-2t} & -e^{-t} + 2e^{-2t} \end{bmatrix} \end{aligned}$$

Step 2: From $y(t) = Ce^{At}x(0) + \int_0^t Ce^{A(t-\tau)}Bu(\tau)d\tau$

$$\begin{aligned} y(t) &= \int_0^t [1 \ 0] e^{A(t-\tau)} \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(\tau) d\tau = \int_0^t (e^{-(t-\tau)} - e^{-2(t-\tau)}) d\tau \\ &= e^{-t} [e^\tau]_0^t - \frac{1}{2} e^{-2t} [e^{2\tau}]_0^t = \frac{1}{2} - e^{-t} + \frac{1}{2} e^{-2t} \end{aligned}$$

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Some properties about the zero-input response

$$x(t) = e^{At} x_0$$

Consider a Jordan block $e^{At} = \begin{bmatrix} e^{\lambda t} & te^{\lambda t} & t^2 e^{\lambda t}/2! & t^3 e^{\lambda t}/3! \\ 0 & e^{\lambda t} & te^{\lambda t} & t^2 e^{\lambda t}/2! \\ 0 & 0 & e^{\lambda t} & te^{\lambda t} \\ 0 & 0 & 0 & e^{\lambda t} \end{bmatrix}$

For a general A, the terms of e^{At} are linear combinations of

$$e^{\lambda_i t}, te^{\lambda_i t}, t^2 e^{\lambda_i t}, \dots, t^{n_i-1} e^{\lambda_i t}, \quad i = 1, 2, \dots, m$$

- **Re(λ_i) < 0, for all .i**, then as $t \rightarrow \infty$, all terms converges to 0, $e^{At} \rightarrow 0$, $x(t)$ always converges to 0. \rightarrow **Stable system**.
- **Re(λ_i) > 0, for some .i**, then as $t \rightarrow \infty$, some terms diverge. There exist x_0 such that $x(t)$ grows unbounded. **Unstable**
- **Re(λ_i) \leq 0 for all .i**, all eigenvalues with 0 real parts are simple, e^{At} is bounded for all t but not converge to 0. **critical case**
- **Re(λ_i) \leq 0 for all .i**, some eigenvalues with 0 real parts are repeated, e^{At} unbounded; $x(t)$ unbounded for some x_0 . **unstable**

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Today:

- We will compute e^{At} ;
- Some of its properties;
- Solution to a continuous-time system

$$\dot{x} = Ax + Bu; \quad y = Cx + Du$$

➤ Solution to the discrete-time system

$$x[k+1] = A[k]x[k] + Bu[k]; \quad y[k] = Cx[k] + Du[k]$$

- Equivalent state equations

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Discretization

$$x(t) \rightarrow x(T), x(2T), \dots, x(kT), \dots$$

A continuous-time system $\dot{x} = Ax + Bu; \quad y = Cx + Du$

We use discretization for

- Digital simulation with computer;
- Implementation through a digital controller

Approach 1: Suppose we know $x(kT)$. If T is small enough,

$$x(kT + T) - x(kT) \approx \dot{x}(kT)T = (Ax(kT) + Bu(kT))T$$

$$x((k+1)T) \approx x(kT) + ATx(kT) + BTu(kT) = (I + AT)x(kT) + BTu(kT)$$

$$y(kT) \approx Cx(kT) + Dy(kT)$$

$$x[k] := x(kT); \quad \rightarrow \quad x[k+1] = (I + AT)x[k] + BTu(k)$$

$$u[k] := u(kT) \quad \rightarrow \quad y[k] = Cx[k] + Du[k]$$

Simple but not accurate.

Approach 2:

Real situation: control u implemented by computer and a digital-analog converter. During a holding period,

$$u(t) = u(kT) \text{ for all } t \in [kT, (k+1)T), k=0,1,2,\dots$$

Solution at kT and $(k+1)T$,

$$\begin{aligned} x[k] &:= x(kT) = e^{AkT}x(0) + \int_0^{kT} e^{A(kT-\tau)}Bu(\tau)d\tau \\ x[k+1] &= e^{A(k+1)T}x(0) + \int_0^{(k+1)T} e^{A((k+1)T-\tau)}Bu(\tau)d\tau \\ &= e^{AT} \left[e^{AkT}x(0) + \int_0^{(k+1)T} e^{A(kT-\tau)}Bu(\tau)d\tau \right] \\ &= e^{AT} \left[e^{AkT}x(0) + \int_0^{kT} e^{A(kT-\tau)}Bu(\tau)d\tau \right] + \int_{kT}^{kT+T} e^{A((k+1)T-\tau)}Bu(\tau)d\tau \\ &= e^{AT}x[k] + \int_0^T e^{A(T-\tau)}Bu[k]d\tau \\ &= e^{AT}x[k] + \left(\int_0^T e^{A(T-\tau)}d\tau \right)Bu[k] =: A_d x[k] + B_d u[k] \end{aligned} \quad 25$$

The discretized system:

$$x[k+1] = A_d x[k] + B_d u[k]$$

$$y[k] = C_d x[k] + D_d u[k]$$

where $A_d = e^{AT}$, $B_d = \left(\int_0^T e^{A(T-\tau)}d\tau \right)B$, $C_d = C$, $D_d = D$

- This exactly describes the input-state, input-output relationship at instants $T, 2T, \dots, kT, \dots$

For B_d , notice that

$$\begin{aligned} \int_0^T e^{A(T-\tau)}d\tau &= e^{AT} \int_0^T e^{-A\tau}d\tau = -e^{AT}A^{-1} \int_0^T (-Ae^{-A\tau})d\tau \\ &= -e^{AT}A^{-1} \int_0^T de^{-A\tau} = -e^{AT}A^{-1} \left[e^{-A\tau} \right]_0^T \\ &= -e^{AT}A^{-1} \left[e^{-AT} - I \right] = A^{-1} \left[A_d - I \right] \Rightarrow \boxed{B_d = A^{-1} \left[A_d - I \right] B} \end{aligned} \quad 26$$

From CT sys. to DT sys.

$$\begin{aligned} \dot{x} &= Ax + Bu & \rightarrow & \quad x[k+1] = A_d x[k] + B_d u[k] \\ y &= Cx + Du & \rightarrow & \quad y[k] = C_d x[k] + D_d u[k] \end{aligned}$$

Let the sampling period be T. Then

$$A_d = e^{AT}, \quad B_d = A^{-1}[A_d - I]B, \quad C_d = C, \quad D_d = D$$

Example: $A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -1 & -2 & -3 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \quad T = 0.1$

Use matlab: `Ad=expm(A*T); Bd=inv(A)*(Ad-eye(3))*B;`

Ad	Bd
0.9998 0.0997 0.0045	0.0002
-0.0045 0.9908 0.0861	0.0045
-0.0861 -0.1767 0.7325	0.0861

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Solution of Discrete-time Equations

The DT system:

$$\begin{aligned} x[k+1] &= Ax[k] + Bu[k] \\ y[k] &= Cx[k] + Du[k] \end{aligned}$$

The solution is derived in a straightforward way:

$$\begin{aligned} x[1] &= Ax[0] + Bu[0] \\ x[2] &= Ax[1] + Bu[1] = A(Ax[0] + Bu[0]) + Bu[1] \\ &= A^2x[0] + ABu[0] + Bu[1] \\ x[3] &= Ax[2] + Bu[2] = A^3x[0] + A^2Bu[0] + ABu[1] + Bu[2] \end{aligned}$$

$$\begin{aligned} x[k] &= A^k x[0] + \sum_{m=0}^{k-1} A^{k-m-1} Bu[m] \\ y[k] &= CA^k x[0] + \sum_{m=0}^{k-1} CA^{k-m-1} Bu[m] + Du[k] \end{aligned}$$

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Some properties about the zero-input response

$$x[k] = A^k x_0$$

Consider a Jordan block

$$A^k = \begin{bmatrix} \lambda^k & k\lambda^k & k(k-1)\lambda^k/2! & k(k-1)(k-2)\lambda^k/3! \\ 0 & \lambda^k & k\lambda^k & k(k-1)\lambda^k/2! \\ 0 & 0 & \lambda^k & k\lambda^k \\ 0 & 0 & 0 & \lambda^k \end{bmatrix}$$

For a general A, the terms of A^k are linear combinations of

$$\lambda_i^k, k\lambda_i^k, k(k-1)\lambda_i^k, \dots, \quad i = 1, 2, \dots, m$$

- $|\lambda_i| < 1$, for all i , then as $k \rightarrow \infty$, all terms converges to 0, $A^k \rightarrow 0$, $x[k]$ always converges to 0. \rightarrow **Stable system**.
- $|\lambda_i| > 1$, for some i , then as $k \rightarrow \infty$, some terms diverge. There exist x_0 such that $x[k]$ grows unbounded. **Unstable**
- $|\lambda_i| \leq 1$ for all i , all eigenvalues with unit magnitude are simple, A^k is bounded for all k but not converge to 0. **Critical case**
- $|\lambda_i| \leq 1$ for all i , some eigenvalues with unit magnitude are repeated, A^k unbounded; $x[k]$ unbounded for some x_0 **Unstable**₂₉

An Earlier Example: Interest and Amortization

- How to describe paying back a car loan over four years with initial debt D , interest r , and monthly payment p ?
 - Let $x[k]$ be the amount you owe at the beginning of the k th month. Then

$$x[k+1] = (1 + r)x[k] - p$$
 - Initial and terminal conditions: $x[0] = D$ and final condition $x[48] = 0$
 - How to find p ?
- By solving the system, $x[48] = a_1 D + a_2 p \rightarrow p$

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The system:

$$x[k+1] = \underbrace{(1+r)}_A x[k] + \underbrace{(-1)}_B \underbrace{p}_u$$

Solution:

$$\begin{aligned} x[k] &= A^k x[0] + \sum_{m=0}^{k-1} A^{k-m-1} B u[m] \\ &= (1+r)^k x[0] + \sum_{m=0}^{k-1} (1+r)^{k-m-1} (-1)p \\ &= (1+r)^k D - \left(\sum_{m=0}^{k-1} (1+r)^{k-m-1} \right) p = (1+r)^k D - \frac{(1+r)^k - 1}{r} p \end{aligned}$$

Given $D=20000$; $r=0.004$; $x[48]=0$;

Your monthly payment

$$0 = (1+0.004)^{48} 20000 - \frac{(1+0.004)^{48} - 1}{0.004} p \quad p=458.7761$$

Today:

- We will compute e^{At} ;
- Some of its properties;
- Solution to a continuous-time system

$$\dot{x} = Ax + Bu; \quad y = Cx + Du$$

- Solution to the discrete-time system

$$x[k+1] = A[k]x[k] + Bu[k]; \quad y[k] = Cx[k] + Du[k]$$

➤ Equivalent state equations

Equivalent state equations

Given state-space description:

$$\dot{x} = Ax + Bu; \quad y = Cx + Du \quad (*)$$

Let P be a nonsingular matrix.

Define $\bar{x} = Px$, then $x = P^{-1}\bar{x}$

$$\dot{\bar{x}} = P\dot{x} = PAx + PBu = PAP^{-1}\bar{x} + PBu$$

$$y = Cx + Du = CP^{-1}\bar{x} + Du$$

Denote $\bar{A} = PAP^{-1}$, $\bar{B} = PB$, $\bar{C} = CP^{-1}$, $\bar{D} = D$

$$\dot{\bar{x}} = \bar{A}\bar{x} + \bar{B}u; \quad y = \bar{C}\bar{x} + \bar{D}u \quad (**)$$

- (*) and (**) are said to be equivalent to each other and the procedure from (*) to (**) is called an equivalent transformation

Note: For DT systems, the equivalent transformation is the same.

Recall: $\bar{A} = PAP^{-1}$ and A are similar to each other

- They have same eigenvalues. Same stability perf.

What do we expect from the two transfer functions:

$$G(s) = C(sI - A)^{-1}B + D \quad \text{and} \quad \bar{G}(s) = \bar{C}(sI - \bar{A})^{-1}\bar{B} + \bar{D}$$

➔ $G(s) = \bar{G}(s)$

To verify,

$$\bar{G}(s) = \bar{C}(sI - \bar{A})^{-1}\bar{B} + \bar{D}$$

$$= CP^{-1}(sPP^{-1} - PAP^{-1})^{-1}PB + D$$

$$= CP^{-1}(P(sI - A)P^{-1})^{-1}PB + D \quad \text{span style="border: 1px solid green; padding: 2px;"> $(XYZ)^{-1} = Z^{-1}Y^{-1}X^{-1}$$$

$$= CP^{-1}P(sI - A)^{-1}P^{-1}PB + D = C(sI - A)^{-1}B + D$$

Example: Given a state equation

$$\dot{x} = Ax + Bu, \quad A = \begin{bmatrix} 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 \\ 4 & 3 & 2 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ -1 \\ 1 \\ -1 \end{bmatrix}$$

Let $Q = [B \quad A^2B \quad AB \quad A^3B]$ (the inverse exist). Define $z = Q^{-1}x$

Compute \bar{A} and \bar{B} such that $\dot{z} = \bar{A}z + \bar{B}u$

Solution: $Q^{-1}AQ = \bar{A} \Leftrightarrow AQ = Q\bar{A}$ Let $\bar{A} = [a_1 \quad a_2 \quad a_3 \quad a_4]$
 $Q^{-1}B = \bar{B} \Leftrightarrow B = Q\bar{B}$

$$AQ = A[B \quad A^2B \quad AB \quad A^3B] = [AB \quad A^3B \quad A^2B \quad A^4B]$$

$$Q\bar{A} = [Qa_1 \quad Qa_2 \quad Qa_3 \quad Qa_4]$$

$$AB = Qa_1 = [B \quad A^2B \quad AB \quad A^3B]a_1; \quad A^3B = Qa_2 = [B \quad A^2B \quad AB \quad A^3B]a_2;$$

$$A^2B = Qa_3 = [B \quad A^2B \quad AB \quad A^3B]a_3; \quad A^4B = Qa_4 = [B \quad A^2B \quad AB \quad A^3B]a_4$$

Immediately, $a_1 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, a_2 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}, a_3 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$. How to get a_4 ? 35

a_4 has to satisfy $A^4B = [B \quad A^2B \quad AB \quad A^3B]a_4$ (*)

$$A = \begin{bmatrix} 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 \\ 4 & 3 & 2 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ -1 \\ 1 \\ -1 \end{bmatrix}$$

Let $a_4 = [k_1 \quad k_2 \quad k_3 \quad k_4]^T$, (*) can be written as

$$A^4B = k_1B + k_2A^2B + k_3AB + k_4A^3B \quad (**)$$

From Cayley-Hamilton's theorem: $\Delta(A) = 0$.

$$\Delta(s) = |sI - A| = (s^2 + 1)(s^2 - s - 2) = s^4 - s^3 - s^2 - s - 2$$

$$\Delta(A) = A^4 - A^3 - A^2 - A - 2I = 0 \quad \rightarrow \quad A^4B - A^3B - A^2B - AB - 2B = 0$$

$$\rightarrow A^4B = 2B + A^2B + AB + A^3B \quad \rightarrow \quad k_1 = 2, k_2 = k_3 = k_4 = 1$$

$$a_4 = [2 \quad 1 \quad 1 \quad 1]^T,$$

$$\downarrow \quad A = \begin{bmatrix} 0 & 0 & 0 & 2 \\ 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \end{bmatrix}$$

For \bar{B} , it satisfies $B = [B \quad A^2B \quad AB \quad A^3B]\bar{B} \rightarrow \bar{B} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$

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Next Time:

- How to deal with complex eigenvalues
- Realization of a transfer function
- Simulation of systems by using Simulink
– [Course project](#)

And more from linear algebra

- Quadratic functions and positive-definiteness

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Problem Set #7

1. The system:

$$\dot{x} = \begin{bmatrix} -2 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & -2 \end{bmatrix} x, \quad x(0) = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

Compute $x(t)$ for $t \geq 0$.

2. For the LTI system

$$\dot{x}(t) = \begin{bmatrix} -2 & -1 \\ -1 & -2 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ -1 \end{bmatrix} u(t); \quad y = [-1 \quad 1]x$$

- Given $x(0)=[1 \ 1]^T$, compute the zero-input response $y(t)$;
- Given $u(t)=1$ for $t \geq 0$, compute the zero-state response $y(t)$;
- Let the sampling period be $T=0.1$. Use matlab to compute the discretized system matrices A_d, B_d .

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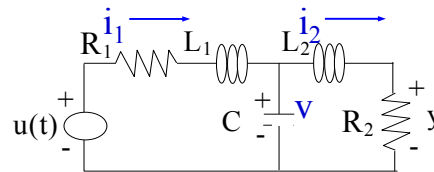
Midterm Review (Lecture #1-Lecture #6)

- Modeling of LTI systems
- Linear algebra
 - Vector spaces: LI, LD, basis, inner product, orthogonal
 - Linear algebraic equation: range space, null space, conditions for the existence of solution, all solutions
 - Eigenvalues, eigenvectors, diagonal form
 - Generalized eigenvectors, Jordan form
 - Polynomial functions of a matrix
 - e^{At}

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Model of a circuit:

- State variables?
 - i_1 , i_2 , and v ,
- State and output equations?



$$\begin{aligned}
 L_1 \frac{di_1}{dt} &= v_{L_1} = u - R_1 i_1 - v \\
 L_2 \frac{di_2}{dt} &= v_{L_2} = v - R_2 i_2 \\
 C \frac{dv}{dt} &= i_C = i_1 - i_2
 \end{aligned}
 \quad \Rightarrow \quad
 \begin{aligned}
 \frac{di_1}{dt} &= -\frac{R_1}{L_1} i_1 - \frac{1}{L_1} v + \frac{1}{L_1} u \\
 \frac{di_2}{dt} &= -\frac{R_2}{L_2} i_2 + \frac{1}{L_2} v \\
 \frac{dv}{dt} &= \frac{1}{C} i_1 - \frac{v}{C} i_2
 \end{aligned}$$

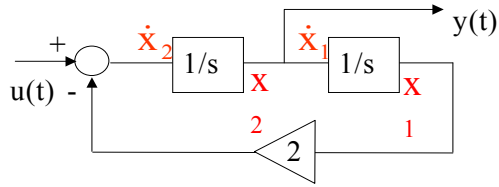
$$\underbrace{\begin{bmatrix} \frac{di_1}{dt} \\ \frac{di_2}{dt} \\ \frac{dv}{dt} \end{bmatrix}}_{\dot{\mathbf{x}}} = \begin{bmatrix} -\frac{R_1}{L_1} & 0 & -\frac{1}{L_1} \\ 0 & -\frac{R_2}{L_2} & \frac{1}{L_2} \\ \frac{1}{C} & -\frac{1}{C} & 0 \end{bmatrix} \underbrace{\begin{bmatrix} i_1 \\ i_2 \\ v \end{bmatrix}}_{\mathbf{x}} + \begin{bmatrix} \frac{1}{L_1} \\ 0 \\ 0 \end{bmatrix} u$$

$$y = R_2 i_2 = \begin{bmatrix} 0 & R_2 & 0 \end{bmatrix} \begin{bmatrix} i_1 \\ i_2 \\ v \end{bmatrix}$$

$$\begin{aligned}
 \dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}u \\
 y &= \mathbf{C}\mathbf{x} + \mathbf{D}u
 \end{aligned}$$

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Integrators + amplifiers



- What are the state variables?
- **Select output of integrators as SVs**
- What are the state and output equations?

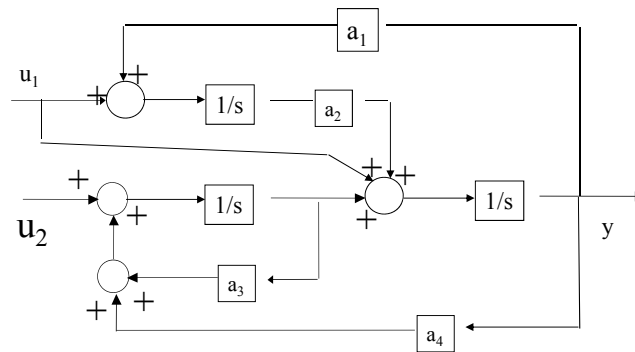
$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = u - 2x_1 \quad y = x_2$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ -2 & 0 \end{bmatrix}}_A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_B u \quad y = \underbrace{\begin{bmatrix} 0 & 1 \end{bmatrix}}_C \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{0}_D u$$

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Example



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Linear Algebra Basics

- Elementary operations that preserve determinant
- Elementary operations that preserve rank
- Use elementary operation to transform a matrix into upper or lower triangular form

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Linear Independence

- A set of vectors $\{x_1, x_2, \dots, x_m\}$ in \mathbb{R}^n is **LI** if
 $\exists \{\alpha_1, \alpha_2, \dots, \alpha_m\}$ in \mathbb{R} , not all zero, s.t.
$$\alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_m x_m = 0 \quad (*)$$
- If the only set of $\{\alpha_i\}_{i=1 \text{ to } m}$ s.t. the above holds is
$$\alpha_1 = \alpha_2 = \dots = \alpha_m = 0$$

then $\{x_i\}_{i=1 \text{ to } m}$ is said to be **LI**
- Given $\{x_1, x_2, \dots, x_m\}$, form $A = [x_1 \ x_2 \ \dots \ x_m]$
If $A\alpha=0$ has a unique solution, **LI**;
If $A\alpha=0$ has nonunique solution, **LD**.

If $\text{rank}(A)=m$, the solution is unique \Rightarrow **LI**
If $\text{rank}(A)<m$, the solution is not unique \Rightarrow **LD**.

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Examples: are the following sets of vectors LI, or LD?

$$\{[1],[2]\}, \quad \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}, \quad \left\{ \begin{bmatrix} 1 \\ a \end{bmatrix}, \begin{bmatrix} a \\ -1 \end{bmatrix} \right\}, \quad \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} \right\},$$

$$\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} a \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} b \\ c \\ 3 \end{bmatrix} \right\}, \quad \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} a \\ 2 \\ f \end{bmatrix}, \begin{bmatrix} b \\ d \\ 3 \end{bmatrix}, \begin{bmatrix} c \\ e \\ 4 \end{bmatrix} \right\}$$

$$\left\{ \begin{bmatrix} 1 \\ a \\ 0 \end{bmatrix}, \begin{bmatrix} a \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} b \\ c \\ 3 \end{bmatrix} \right\}, \quad \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix} \right\}$$

- LI if the rank of the matrix equals the number of columns

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Basis and Representations

- A set of **LI** vectors $\{e_1, e_2, \dots, e_n\}$ of \mathbb{R}^n is said to be a **basis** of \mathbb{R}^n if **every vector in \mathbb{R}^n** can be expressed as a **unique linear combination** of them

– For any $x \in \mathbb{R}^n$, there exist unique $\{\beta_1, \beta_2, \dots, \beta_n\}$ s.t.

$$x = \beta_1 e_1 + \beta_2 e_2 + \dots + \beta_n e_n = \sum_{i=1}^n \beta_i e_i$$

$$x = [e_1 \quad e_2 \quad \dots \quad e_n] \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}$$

– β : **Representation** of x with respect to the basis

Theorem: In an n -dimensional vector space (or subspace), **any** set of **n LI vectors** qualifies as a basis

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Change of basis:

- Given a basis $(e_1 \ e_2 \ \dots \ e_n)$;
- Let the new basis be:

$$(\bar{e}_1 \ \bar{e}_2 \ \dots \ \bar{e}_n) = (e_1 \ e_2 \ \dots \ e_n)Q$$

Then,

$$(e_1 \ e_2 \ \dots \ e_n) = (\bar{e}_1 \ \bar{e}_2 \ \dots \ \bar{e}_n)Q^{-1}$$

- For x such that

$$x = (e_1 \ e_2 \ \dots \ e_n)\beta$$

$$\text{We have } x = (\bar{e}_1 \ \bar{e}_2 \ \dots \ \bar{e}_n)Q^{-1}\beta$$

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Linear algebraic equation $Ax = y$

- If $\rho(A) \neq \rho([A : y])$ (i.e., $y \notin \mathcal{R}(A)$), then the equations are inconsistent, and there is **no solution**
- If $\rho(A) = \rho([A : y])$, then \exists at least one solution
 - If $\rho(A) = \rho([A : y]) < n$ (i.e., $v(A) > 0$), then there are **infinite number of solutions**
 - If $\rho(A) = \rho([A : y]) = n$ (i.e., $v(A) = 0$), then there is a **unique solution**
- For an $n \times n$ matrix, $Ax = y$ has a unique solution $\forall y \in \mathbb{R}^n$ iff A^{-1} exists, or $|A| \neq 0$

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Key concepts: Assume $A \in \mathbb{R}^{m \times n}$.

Range space $R(A)$: $\{y \in \mathbb{R}^m: \text{exists } x \in \mathbb{R}^n \text{ s.t. } y = Ax\}$

- subspace of \mathbb{R}^m ,
- dimension = $\rho(A)$, rank of A
- basis: formed by the maximal number of LI columns of A

Null space $N(A)$: $\{x \in \mathbb{R}^n: Ax = 0\}$

- subspace of \mathbb{R}^n ,
- dimension $\nu(A) = n - \rho(A)$
- basis: formed by $\nu(A)$ LI solutions to $Ax = 0$.

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Example:

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & -1 & -2 & 2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$a_1 \quad a_2 \quad a_3 \quad a_4$

The range space $R(A)$ is spanned by $\{a_1, a_2, a_3, a_4\}$

What is the relationship among the vectors?

What are $\rho(A)$, $\nu(A)$? The dimension of $R(A)$?

The basis of $R(A)$? The null spaces?

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Parameterization of all solutions

Theorem: Given $m \times n$ matrix A and a $m \times 1$ vector y .

- Let x_p be a solution to $Ax = y$.
- Let $v(A)=k$.
- Suppose $k > 0$ and the null space is spanned by $\{n_1, n_2, \dots, n_k\}$

➤ The set of all solutions is given by $\{x = x_p + \alpha_1 n_1 + \alpha_2 n_2 + \dots + \alpha_k n_k : \alpha_i \in \mathbb{R}\}$

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Eigenvalues, eigenvectors and diagonal form

A scalar λ is called an **eigenvalue** of $A \in \mathbb{C}^{n \times n}$ if \exists a **nonzero** $x \in \mathbb{C}^n$, such that $Ax = \lambda x$ and x is the **eigenvector** associated with λ .

Case 1: All eigenvalues are distinct

Theorem: the sets of eigenvectors $\{v_1, v_2, \dots, v_n\}$ is LI.
Let $Q = [v_1 \ v_2 \ \dots \ v_n]$, then

$$Q^{-1}AQ = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix}$$

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Definition. A vector v is a **generalized eigenvector of grade k** associated with λ if

$$(A - \lambda I)^k v = 0, \quad \text{but } (A - \lambda I)^{k-1} v \neq 0$$

Denote $v_k \equiv v$,

$$v_{k-1} \equiv (A - \lambda I)v = (A - \lambda I)v_k,$$

$$v_{k-2} \equiv (A - \lambda I)^2 v = (A - \lambda I)v_{k-1},$$

$$v_1 \equiv (A - \lambda I)^{k-1} v = (A - \lambda I)v_2,$$

$$(A - \lambda I)v_1 = (A - \lambda I)^k v = 0,$$

$$Av_k = v_{k-1} + \lambda v_k$$

$$Av_{k-1} = v_{k-2} + \lambda v_{k-1}$$

$$Av_2 = v_1 + \lambda v_2$$

$$Av_1 = \lambda v_1$$

– What is the new representation w.r.t. $\{v_1, v_2, \dots, v_k\}$? i.e.,

$$A[v_1 \ v_2 \ \dots \ v_k] = [v_1 \ v_2 \ \dots \ v_k]\bar{A}$$

$$\lambda \ 0 \ \dots \ 0$$

$$1 \ \lambda \ \dots \ 0$$

$$\bar{A} = \begin{bmatrix} \lambda & 1 & \dots & 0 \\ 0 & \lambda & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda \end{bmatrix}$$

A Jordan block

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- Polynomial functions of a square matrix.
- Computation of e^{At} .

Today's material will not be included in the midterm.

Questions?

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Midterm exam: 6.30-9:30 pm, Oct 20 (Thursday)

Open book, open notes

No calculator, No Laptop

Good luck!