

vv214: Eigenvalue problems. Diagonalization.

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This week

1. Discrete dynamical systems
2. Eigenvectors/eigenfunctions and eigenvalues
3. Algebraic and geometric multiplicities
4. Eigenbasis
5. Diagonalization

Discrete Dynamical Systems

Consider a mathematical model

$$\begin{cases} \text{predator} & c(t+1) = a_1c(t) + b_1r(t), \\ \text{prey} & r(t+1) = a_2c(t) + b_2r(t) \end{cases}$$

that describes the dynamic of two populations as time changes
(say, a predator-prey model).

$$t = t_0, t_1, t_2$$

$$\bar{x}(1) = A\bar{x}(0)$$

$$\bar{x}(2) = A\bar{x}(1) = A^2\bar{x}(0)$$

$$\bar{x}(3) = A^3\bar{x}(0)$$

$$\begin{aligned} \bar{x}(t) &= A^t \bar{x}(0) \Rightarrow 0 < a_1, b_1 < 1, b_2 > 1, a_2 < 0 \\ &= A^t \begin{pmatrix} c_0 \\ r_0 \end{pmatrix} \end{aligned}$$

$$a_1 = 0.86, b_1 = 0.08, a_2 = -0.12, b_2 = 1.14$$
$$\bar{x}(t) = \begin{pmatrix} c(t) \\ r(t) \end{pmatrix} \Rightarrow \bar{x}(t+1) = A\bar{x}(t), A = \begin{pmatrix} 0.86 & 0.08 \\ -0.12 & 1.14 \end{pmatrix}$$

$$\bar{x}_0(t) = \begin{pmatrix} c_0 \\ r_0 \end{pmatrix} \xrightarrow{A} \bar{x}_1 = \bar{x}(1) = \begin{pmatrix} c(1) \\ r(1) \end{pmatrix} \xrightarrow{A} \dots \xrightarrow{A} \bar{x}(t) \xrightarrow{A} \dots$$

$$\bar{x}_1 = A\bar{x}_0, \bar{x}_2 = A\bar{x}_1 = A^2\bar{x}_0, \dots, \boxed{\bar{x}(t) = A^t\bar{x}_0}$$

Discrete Dynamical Systems

Case 1: Let $c_0 = 100$, $r_0 = 300$.

$$\bar{x}(1) = \begin{pmatrix} 0.86 & 0.08 \\ -0.12 & 1.14 \end{pmatrix} \begin{pmatrix} 100 \\ 100 \end{pmatrix} = \begin{pmatrix} 110 \\ 330 \end{pmatrix} = 1.1\bar{x}_0 \Rightarrow$$

$$\bar{x}(t) = (1.1)^t \bar{x}_0 \Rightarrow \begin{aligned} c(t) &= (1.1)^t 100 \\ r(t) &= (1.1)^t 300 \end{aligned} \Rightarrow 10\% growth$$

Case 2: Let $c_0 = 200$, $r_0 = 100$.

$$\bar{x}(1) = \begin{pmatrix} 0.86 & 0.08 \\ -0.12 & 1.14 \end{pmatrix} \begin{pmatrix} 200 \\ 100 \end{pmatrix} = \begin{pmatrix} 180 \\ 90 \end{pmatrix} = 0.9\bar{x}_0 \Rightarrow$$

$$\bar{x}(t) = (0.9)^t \bar{x}_0 \Rightarrow \begin{aligned} c(t) &= (0.9)^t 200 \\ r(t) &= (0.9)^t 100 \end{aligned} \Rightarrow 10\% declination$$

Discrete Dynamical Systems

Case 3: Let $c_0 = 1000$, $r_0 = 1000$.

$$\bar{x}(1) = \begin{pmatrix} 0.86 & 0.08 \\ -0.12 & 1.14 \end{pmatrix} \begin{pmatrix} 1000 \\ 1000 \end{pmatrix} = \begin{pmatrix} 940 \\ 1020 \end{pmatrix} = ?C\bar{x}_0$$

* find C .

$$C_1\bar{x}_0 + C_2\bar{x}_{02}$$

Since it worked in Cases 1,2, so let

$$\bar{x}_0 = \begin{pmatrix} 1000 \\ 1000 \end{pmatrix} = C_1 \underbrace{\begin{pmatrix} 100 \\ 300 \end{pmatrix}}_{\bar{v}_1} + C_2 \underbrace{\begin{pmatrix} 200 \\ 100 \end{pmatrix}}_{\bar{v}_2} = 2\bar{v}_1 + 4\bar{v}_2$$

$$\bar{x}(1) = A\bar{x}_0 = A(2\bar{v}_1 + 4\bar{v}_2) = 2(1.1)\bar{v}_1 + 4(0.9)\bar{v}_2 \Rightarrow (A\bar{v}_1 = (1.1)\bar{v}_1)$$

$$\bar{x}(t) = 2(1.1)^t \bar{v}_1 + 4(0.9)^t \bar{v}_2$$

$$c(t) = 200(1.1)^t + 800(0.9)^t$$

$$r(t) = 600(1.1)^t + 400(0.9)^t$$

Eigenvectors and Eigenvalues

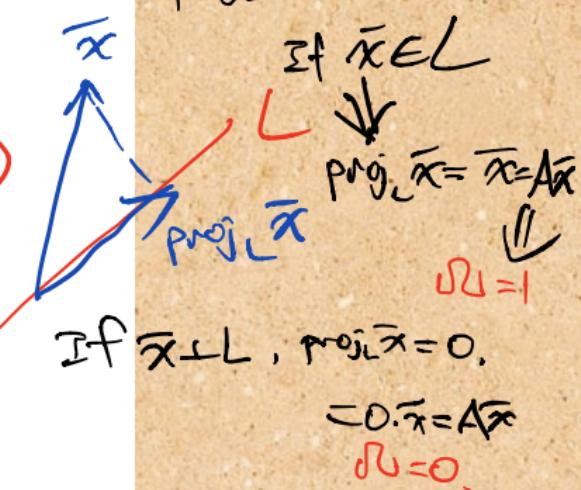
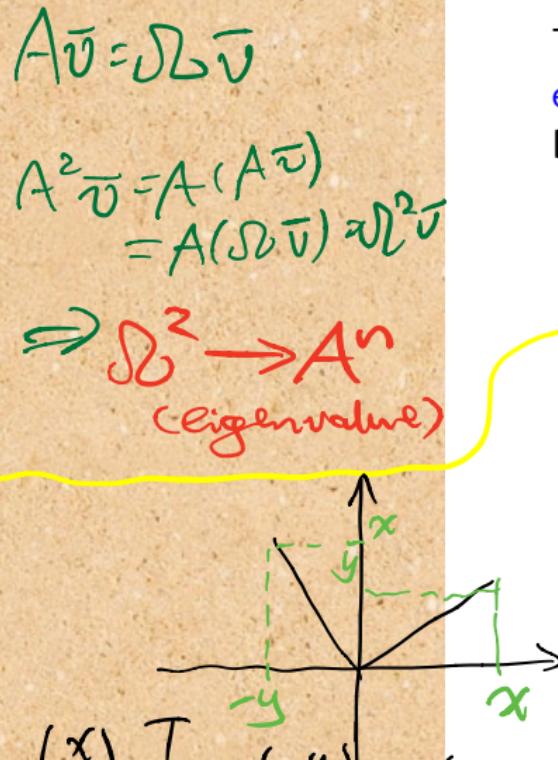
Definition: A non-zero vector $\bar{v} \in \mathbb{R}^n$ is called an **eigenvector** of the matrix $A_{n \times n}$ if

$$\exists \lambda \in \mathbb{K}: A\bar{v} = \lambda \bar{v}$$

The scalar λ is called the **eigenvalue associated with the eigenvector \bar{v}** .

Remarks:

1. $A\bar{v} \parallel \bar{v} \Rightarrow \bar{v}$ is the eigenvector.
2. \bar{v} is the eigenvector of $A \Rightarrow \bar{v}$ is the eigenvector of A^2, A^3, \dots
3. $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is the orthogonal projection onto a line L
 $\Rightarrow \bar{w} \perp L, \bar{v} \subset L$ are eigenvectors ($\lambda = 0, \lambda = 1$)
4. $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is the counterclockwise rotation through $\frac{\pi}{2}$
 \Rightarrow there are no real eigenvalues and eigenvectors
5. $A_{n \times n}$ is orthogonal \Rightarrow the eigenvalues are ± 1



$$\begin{aligned}
 (y) &\rightarrow \begin{pmatrix} -y \\ x \end{pmatrix} \\
 &= \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \\
 \exists \Sigma (?) & A\bar{v} = \bar{b} \Rightarrow \begin{cases} -y = \bar{b}_1 x \\ x = \bar{b}_2 y \end{cases} \\
 A\bar{v} = \bar{b} \Rightarrow & \begin{cases} -y = \bar{b}_1 x \\ x = \bar{b}_2 y \end{cases} \\
 \Rightarrow -y = \bar{b}_1^2 y & \\
 \bar{b}_1^2 = -1 & \\
 \bar{b}_1 = \pm i &
 \end{aligned}$$

Discrete Dynamical Systems

Definition: If a state $\bar{x}(t)$ of a physical system at any given time t is described by n values $x_1(t), \dots, x_n(t)$, then the *law of change* of the state of the system from time t to time $t + 1$ in the linear form

$$\bar{x}(t+1) = A_{n \times n} \bar{x}(t)$$

is called a **discrete dynamical system**.

Remarks:

1. $\bar{x}(t) = A^t \bar{x}_0$ if the initial state \bar{x}_0 is known.
2. If a basis $\{\bar{v}_1, \dots, \bar{v}_n\} \subset \mathbb{R}^n$ consists of eigenvalues of A :

$$A\bar{v}_i = \lambda_i \bar{v}_i, \quad i = 1..n,$$

then

$$\bar{x}(t) = \underbrace{(\bar{v}_1 \ \bar{v}_2 \ \dots \ \bar{v}_n)}_S \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \lambda_n \end{pmatrix}^t S^{-1} \bar{x}_0$$

If $\bar{x}(0) = \bar{x}_0$

$$= \alpha_1 \bar{v}_1 + \alpha_2 \bar{v}_2 + \dots + \alpha_n \bar{v}_n$$

$$\bar{x}(t) = A^t \bar{x}_0 = A^t (\alpha_1 \bar{v}_1 + \dots + \alpha_n \bar{v}_n)$$

$$= \alpha_1 A^t \bar{v}_1 + \dots + \alpha_n A^t \bar{v}_n$$

$$\Re^t \bar{v}_1$$

$$\Re^t \bar{v}_n$$

$$= \alpha_1 \Re^t \bar{v}_1 + \dots + \alpha_n \Re^t \bar{v}_n$$

$$= (\bar{v}_1 \ \dots \ \bar{v}_n) \begin{pmatrix} \bar{x}_1^t & & & \\ & \bar{x}_2^t & & \\ & & \ddots & \\ & & & \bar{x}_n^t \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{pmatrix}$$

↓

↓

↓

↓

Lilac Bush Growth Model

Year 1

$$n(1)=1$$

$$a(1)=1$$

Year 2

$$n_2=0$$

$$a(2)=1$$

Year 3

$$n_3=2$$

$$a(3)=1$$

Year 4

$$n(4)=2$$

$$a(4)=3$$

Year 5

$$n(5)=6$$

$$a(5)=5$$

Year 6

$$\bar{x}_0 = \alpha_1 \bar{v}_1 + \dots + \alpha_n \bar{v}_n$$

$$(\bar{x}_0)_{\underbrace{\bar{v}_1, \dots, \bar{v}_n}_{S}} = \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{pmatrix}$$

$$(\bar{x}_0)_{\bar{v}_1, \dots, \bar{v}_n} = (\bar{v}_1, \bar{v}_2, \dots, \bar{v}_n) \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{pmatrix}$$

$n(t)$ is the number of new branches and
 $a(t)$ is the number of old branches

$$a(t+1) = n(t) + a(t), \quad n(t+1) = 2a(t)$$

$$\begin{pmatrix} n(t+1) \\ a(t+1) \end{pmatrix} = \underbrace{\begin{pmatrix} 0 & 2 \\ 1 & 1 \end{pmatrix}}_A \begin{pmatrix} n(t) \\ a(t) \end{pmatrix}$$

Lilac Bush Growth Model

$$A \begin{pmatrix} 1 \\ 1 \end{pmatrix} = 2 \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \quad A \begin{pmatrix} 2 \\ -1 \end{pmatrix} = -1 \begin{pmatrix} 2 \\ -1 \end{pmatrix}$$

Since $n(0) = 1$ and $a(0) = 0$, so

$$\begin{pmatrix} 1 \\ 0 \end{pmatrix} = c_1 \begin{pmatrix} 1 \\ 1 \end{pmatrix} + c_2 \begin{pmatrix} 2 \\ -1 \end{pmatrix} \Rightarrow c_1 = c_2 = \frac{1}{3}$$

$$\begin{pmatrix} n(t+1) \\ a(t+1) \end{pmatrix} = \frac{2^t}{3} \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \frac{(-1)^t}{3} \begin{pmatrix} 2 \\ -1 \end{pmatrix}$$

Invariant Subspaces

Definition: Let $A_{n \times n}$. A linear subspace $V \subset \mathbb{R}^n$ is A -invariant if

$$A\bar{v} \in V \quad \forall v \in V$$

Let $\dim V = 1$.

1. If $\bar{v} \in V, \bar{v} \neq 0$, then

$$A\bar{v} \in V \Rightarrow A\bar{v} \in \underbrace{\text{span } \bar{v}}_{\text{green underline}} \Rightarrow A\bar{v} = \lambda\bar{v}$$

$\Rightarrow \bar{v}$ is an eigenvector of A .

2. If $A\bar{v} = \lambda\bar{v}$ then

$$A\bar{v} = \lambda\bar{v} \in \text{span } \bar{v} = V$$

\Rightarrow as $\dim V = 1$, so V is A -invariant.

Therefore, one-dimensional A -invariant subspaces V of \mathbb{R}^n are

$$V = \{\text{span } \bar{v}: A\bar{v} = \lambda\bar{v}\}$$

Eigenvalues and eigenfunctions

Definition: A scalar λ is called an eigenvalue of a linear operator $T: V \rightarrow V$ if

$$\exists f \in V, f \neq 0: Tf = \lambda f.$$

The element $f \in V$ is called an eigenfunction.

1. $T(x_1, x_2, x_3, \dots) = (x_1, x_3, x_5, x_7, \dots)$

$$T(\bar{x}) = (x_1, x_3, x_5, x_7, \dots) = \lambda(x_1, x_2, x_3, x_4, x_5, \dots)$$

$$\bar{x} = (x_1 = \lambda x_1, x_2, x_3 = \lambda x_2, x_4, x_5 = \lambda x_3, \dots)$$

$$x_{2n} \text{ is arbitrary, } x_{2n+1} = \lambda x_{n+1}$$

$$\lambda = 5 \Rightarrow \bar{x} = (0, x_2, 5x_2, x_4, 25x_2, x_5, \dots)$$

All real λ are eigenvalues with infinite number of eigensequences .

Eigenvalues and eigenfunctions

Shift operator



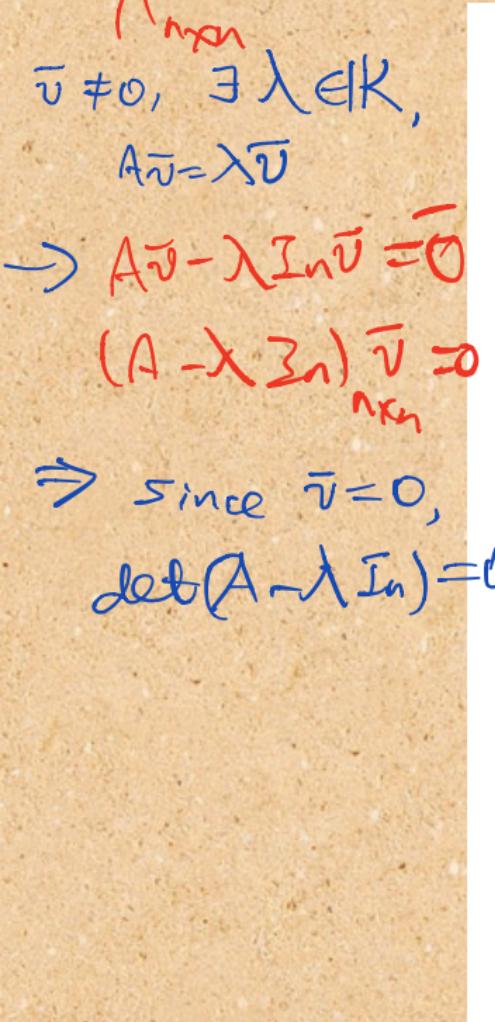
2. $T(x_1, x_2, x_3, \dots) = (x_2, x_3, x_4, \dots)$

$$T(\bar{x}) = (x_2, x_3, x_4, x_5, \dots) = (\lambda x_1, \lambda x_2, \lambda x_3, \lambda x_4, \lambda x_5, \dots)$$

$$x_2 = \lambda x_1, \quad x_3 = \lambda x_2 = \lambda^2 x_1, \quad x_4 = \lambda x_3 = \lambda^3 x_1, \dots$$

$$\bar{x} = (x_1, x_2, x_3, \dots) = (x_1, \lambda x_1, \lambda^2 x_1, \dots) = x_1(1, \lambda, \lambda^2, \dots)$$

All real λ are eigenvalues and $(1, \lambda, \lambda^2, \dots)$ is the eigensequence.



Eigenvalues of a Matrix

Theorem: A scalar $\lambda \in \mathbb{R}$ is an eigenvalue of the matrix $A_{n \times n}$ iff

$$\det(A - \lambda I_n) = 0.$$

The equation $f_A(\lambda) = \det(A - \lambda I_n) = 0$ is called the characteristic equation of the matrix A .

Remarks:

1. The eigenvalues of a diagonal matrix $A = \text{diag}(d_1, \dots, d_n)$ are d_1, \dots, d_n .
2. $\det(A - \lambda I_n) = (-\lambda)^n + (\text{tr } A)(-\lambda)^{n-1} + \dots + \det A$
3. There are n eigenvalues of a $n \times n$ matrix A .
4. For $A_{n \times n}$, with eigenvalues $\lambda_1, \dots, \lambda_n$ listed with their algebraic multiplicities

$$\det A = \lambda_1 \cdot \lambda_2 \cdots \lambda_n, \quad \text{tr } A = \lambda_1 + \lambda_2 + \dots + \lambda_n$$

Algebraic Multiplicity

Definition: An eigenvalue λ_0 of a square matrix A has **algebraic multiplicity** k if λ_0 is the root of multiplicity k of the characteristic polynomial $f_A(\lambda) \Rightarrow f_A(\lambda) = (\lambda - \lambda_0)^k g(\lambda)$, $g(\lambda_0) \neq 0$

Examples:

$$1. \quad A = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \Rightarrow \det(A - \lambda I_3) = 0 \Rightarrow \lambda_{1,2} = 0, \lambda_3 = 3$$

$$2. \quad A = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix} \Rightarrow \det(A - \lambda I_2) = 0$$
$$\Rightarrow \lambda^2 - \underbrace{(1+3)}_{\text{tr } A} \lambda + \underbrace{1 \cdot 3 - 2 \cdot 4}_{\det A} = 0$$

Eigenspace

Definition: The kernel of the matrix $A - \lambda I_n$ is called the eigenspace E_λ associated with λ :

$$E_\lambda = \text{Ker}(A - \lambda I_n) = \{\bar{v} \in \mathbb{R}^n : A\bar{v} = \lambda\bar{v}, \bar{v} \neq 0\}$$

Examples:

1. $T: \mathbb{R}^3 \rightarrow \mathbb{R}^3$ is an orthogonal projection onto a plane V in \mathbb{R}^3

$$\lambda = 1 \Rightarrow E_1 = V \quad \text{OR} \quad \lambda = 0 \Rightarrow E_0 = V^\perp$$

2. $A = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix} \Rightarrow \lambda_1 = 5, \lambda_2 = -1$

$$E_5 = \{\bar{v} \in \mathbb{R}^2 : A\bar{v} = 5\bar{v}\} = \text{Ker} \begin{pmatrix} -4 & 2 \\ 4 & -2 \end{pmatrix} = \text{span} \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

$$E_{-1} = \{\bar{v} \in \mathbb{R}^2 : A\bar{v} = -\bar{v}\} = \text{Ker} \begin{pmatrix} 2 & 2 \\ 4 & 4 \end{pmatrix} = \text{span} \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

Eigenspace

$$3. A = \begin{pmatrix} -2 & -1 \\ 5 & 2 \end{pmatrix} \Rightarrow \lambda^2 = -1 \Rightarrow \lambda_{1,2} = \pm i$$

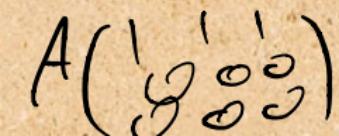
$$E_i = \{\bar{v} \in \mathbb{R}^2 : A\bar{v} = i\bar{v}\} = \text{Ker} \begin{pmatrix} -2-i & -1 \\ 5 & 2-i \end{pmatrix}$$

$$\begin{pmatrix} -2-i & -1 \\ 5 & 2-i \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$-(2+i)v_1 - v_2 = 0 \Rightarrow \bar{v} = \begin{pmatrix} -1 \\ 2+i \end{pmatrix}$$

$$E_i = \text{span} \begin{pmatrix} -1 \\ 2+i \end{pmatrix}$$

Remark: If λ is an eigenvalue of a real matrix $A_{n \times n}$ with the associated eigenvector \bar{v} , then $\bar{\lambda}$ is also an eigenvalue of A whose associated eigenvector \bar{v}^* is the complex conjugate of \bar{v} .



$$|A - \lambda I| = \begin{pmatrix} 1-\lambda & 1 & 1 \\ 0 & -\lambda & 0 \\ 0 & 0 & -\lambda \end{pmatrix}$$

$$\Rightarrow (-\lambda^2)(1-\lambda) = 0$$

$$\lambda_{1,2} = 0, \lambda_3 = 1.$$

$\boxed{\lambda_{1,2}=0} \quad (A - \lambda I)\bar{v} = 0$
 $\Rightarrow A\bar{v} = 0$

$$\Rightarrow \begin{pmatrix} -v_2 - v_3 \\ v_2 \\ v_3 \end{pmatrix} = v_2 \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} + v_3 \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix}$$

$$\Rightarrow E_0 = \{ \bar{v} : A\bar{v} = 0\bar{v} \}$$

$$= \{ \bar{v} : \bar{v} = c_1 \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} + c_2 \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix} \}$$

$$\dim E_0 = 2, \quad G.M_0 = 2$$

$$\boxed{\lambda_3 = 1} \quad \boxed{(A - 1I)\bar{v} = 0}$$

Geometric Multiplicity

$$4. A = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix} \Rightarrow \lambda_{1,2} = 1, \lambda_3 = 0$$

$$E_1 = \text{Ker} \begin{pmatrix} 0 & 1 & 1 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{pmatrix} = \text{span} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

$$E_0 = \text{Ker} \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix} = \text{span} \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix}$$

Definition: The dimension of eigenspace E_λ is called the **geometric multiplicity** of the eigenvalue λ .

$$G.M. = n - \text{rank}(A - \lambda I_n)$$

$$1 + \bar{v}_1 = \alpha \bar{v}_1 + \dots + \alpha_{m-1} \bar{v}_{m-1}$$

$$\begin{pmatrix} 0 & 1 \\ 0 & -1 \end{pmatrix} \bar{v} = 0$$

$\Rightarrow E_1 = \{\bar{v} : \bar{v} = C \begin{pmatrix} 1 \\ 0 \end{pmatrix}\}$

$\dim E_1 = \text{dim } M_1 = 1.$

$\dim E_0 + \dim E_1 = 3$
 $= \dim \mathbb{R}^3$

Eigenbasis

Theorem:

1. The system $\bar{v}_1, \dots, \bar{v}_s$ consisting of all basis vectors of each eigenspace of $A_{n \times n}$ is linearly independent; s is the sum of all geometric multiplicities of eigenvalues of A .
2. There exists an eigenbasis for $A_{n \times n}$ iff the geometric multiplicities add up to $n \Rightarrow s = n$.

Remark: If $A_{n \times n}$ has n distinct eigenvalues then there exists an eigenbasis for A .

Example: Let

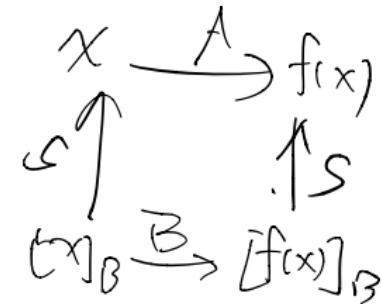
$$T: \mathbb{R}^2 \rightarrow \mathbb{R}^2, T\bar{x} = T \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} x_1 + x_2 \\ x_2 \end{pmatrix}$$

$$A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \Rightarrow \lambda_{1,2} = 1 \quad \text{BUT} \quad \text{Ker}(A - \lambda I_2) = \text{span} \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$\dim E_1 = 1 \Rightarrow G.M. = 1 < 2 = n$$

be the
1st reduced ...
 If $\bar{v}_k, \bar{v}_m \in E_{\lambda^*}, 1 \leq k < m-1 \Rightarrow \bar{v}_m \neq \alpha \bar{v}_k$
 $\Rightarrow \bar{v}_1, \dots, \bar{v}_{m-1} \Rightarrow \exists \bar{v}_r: \lambda_r \neq \lambda^*$
 $A\bar{v}_r = \lambda_r \bar{v}_r, A\bar{v}_t = \lambda^* \bar{v}_t$
 $(A - \lambda^* I)\bar{v}_m = (A - \lambda^* I)(\alpha_1 \bar{v}_1 + \dots + \alpha_{m-1} \bar{v}_{m-1}) \neq 0$
 $A\bar{v}_m - \lambda^* \bar{v}_m = \alpha_1(\lambda_r - \lambda^*)\bar{v}_1 + \dots$
 $\underbrace{= 0}_{\Rightarrow} + \alpha_r(\lambda_r - \lambda^*)\bar{v}_r + \dots + \alpha_{m-1}(\lambda_{m-1} - \lambda^*)\bar{v}_{m-1}$

Similar Matrices



Theorem: Let $B = S^{-1}AS$, i.e. A, B be similar matrices. Then

1. $f_A(\lambda) = f_B(\lambda)$
2. $\text{rank}(A) = \text{rank}(B)$, $\text{nullity}(A) = \text{nullity}(B)$
3. A, B have the same eigenvalues with the same AM, GM
4. $\det A = \det B$, $\text{tr}(A) = \text{tr}(B)$

$$\begin{aligned} 1. f_B(\lambda) &= \det(B - \lambda I) = \det(S^{-1}AS - \lambda S^{-1}S) \\ &= \det(S^{-1}(A - \lambda I)S) \\ &= \det(S^{-1}) \det(A - \lambda I) \det S \\ &= f_A(\lambda) \end{aligned}$$

Also, if $A_{n \times n}, B_{n \times n}$,
then $n = \dim \ker A + \dim \text{im } A$
 $= \dim \ker B + \dim \text{im } B$

$$2. \text{Let } \bar{x} \in \ker B \Rightarrow B\bar{x} = \bar{0} \Rightarrow S^{-1}AS\bar{x} = \bar{0}$$

$S\bar{x} \in \ker A$
 $T: \ker B \rightarrow \ker A$, $T\bar{x} = S\bar{x}$
 T is linear, one-to-one &
 onto

$\Rightarrow T$ is an isomorphism

$$\begin{aligned} S^+AS\bar{x} &= S\bar{0} \\ A\bar{x} &= \bar{0} \\ \bar{x} &= \bar{0} \end{aligned}$$

$\ker T = \{\bar{0}\}$

\downarrow
 $\ker A$

$$T\bar{x} = S\bar{x}$$

$$T(\alpha\bar{x}_1 + \beta\bar{x}_2) = S(\alpha\bar{x}_1 + \beta\bar{x}_2)$$

Motivation

$\dim(\ker B) = \dim(\ker A)$

$$S\bar{x}_1 = S\bar{x}_2 \Rightarrow S(\bar{x}_1 - \bar{x}_2) = \bar{0}$$

$$\Rightarrow \underbrace{S^{-1}S}_{=I}(\bar{x}_1 - \bar{x}_2) = S\bar{0} = \bar{0}$$

Let $y = \underbrace{\begin{pmatrix} I \\ \ker A \end{pmatrix}}_{\text{onto one-to-one}} \bar{x}$ (onto one-to-one)

$$A = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix} \Rightarrow \lambda_1 = -1, \lambda_2 = 5 \Rightarrow \bar{v}_1 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}, \bar{v}_2 = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

$$\exists \bar{x} = S^{-1}\bar{y} \in \ker B$$

$\Rightarrow \mathcal{B} = \{\bar{v}_1, \bar{v}_2\}$ is the eigenbasis for A .

$$\bar{x} = \alpha_1 \bar{v}_1 + \alpha_2 \bar{v}_2 \xrightarrow{A} T\bar{x} = -\alpha_1 \bar{v}_1 + 5\alpha_2 \bar{v}_2$$

$$\bar{x}_{\mathcal{B}} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \xrightarrow{B} (T\bar{x})_{\mathcal{B}} = \begin{pmatrix} -\alpha_1 \\ 5\alpha_2 \end{pmatrix}$$

$$B = \begin{pmatrix} -1 & 0 \\ 0 & 5 \end{pmatrix}$$

B is diagonal \Rightarrow we denote $B = D$, $\mathcal{D} = \{\bar{v}_1, \bar{v}_2\}$

Diagonalizable Matrices

Theorem: Consider a linear transformation $T\bar{x} = A\bar{x}$, $A_{n \times n}$. Let $\mathfrak{D} = \{\bar{v}_1, \bar{v}_2, \dots, \bar{v}_n\}$ be an eigenbasis for T : $A\bar{v}_i = \lambda_i\bar{v}_i$. Then the \mathfrak{D} -matrix D of T is

$$D = S^{-1}AS = \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \lambda_n \end{pmatrix}$$

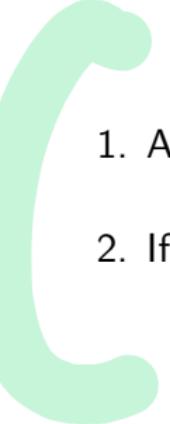
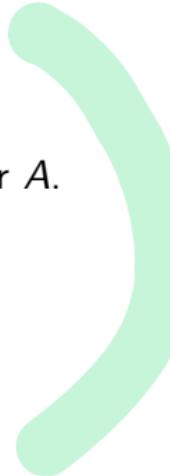
Definition: An $n \times n$ matrix A is called **diagonalizable** if A is similar to a diagonal matrix D :

$$\exists \text{ invertible } S_{n \times n}: D = S^{-1}AS$$

Remark: The matrix $S^{-1}AS$ is diagonal iff the columns of S form an eigenbasis of A .



Theorem

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1. A matrix A is diagonalizable iff there exists an eigenbasis for A .
 2. If $A_{n \times n}$ has n distinct eigenvalues then A is diagonalizable.

Example 1

$$A = \begin{pmatrix} 1 & a & b \\ 0 & 0 & c \\ 0 & 0 & 1 \end{pmatrix} \Rightarrow \lambda_1 = 0, \lambda_{2,3} = 1$$

$$E_0 = \ker A \Rightarrow \dim E_0 = \dim \ker A = 1$$

$$E_1 = \ker \begin{pmatrix} 0 & a & b \\ 0 & -1 & c \\ 0 & 0 & 0 \end{pmatrix} \Rightarrow \dim E_1 = 2 \text{ iff } b = -ac$$

$$\dim E_0 + \dim E_1 = 3 = n$$

$$\bar{v}_1 = \begin{pmatrix} -a \\ 1 \\ 0 \end{pmatrix}, \bar{v}_2 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \bar{v}_3 = \begin{pmatrix} 0 \\ c \\ 1 \end{pmatrix} \Rightarrow S = \begin{pmatrix} -a & 1 & 0 \\ 1 & 0 & c \\ 0 & 0 & 1 \end{pmatrix}$$

$$D = S^{-1}AS = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

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Example 2

$$A = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \Rightarrow \lambda_1 = 1, \lambda_{2,3} = 0$$

$$E_0 = A \Rightarrow \dim E_0 = \dim \text{Ker } A = 2$$

$$E_1 = \begin{pmatrix} 0 & 1 & 1 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{pmatrix} \Rightarrow \text{Ker } E_1 = \text{span} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \dim E_1 = 1$$

$$\Rightarrow \dim E_0 + \dim E_1 = 3 = n \Rightarrow A \text{ is diagonalizable}$$

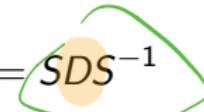
Example 2

$$\bar{v}_1 = \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix}, \bar{v}_2 = \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix}, \bar{v}_3 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \Rightarrow S = \begin{pmatrix} -1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

$$D = S^{-1}AS = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Remark

$A_{n \times n}$ is diagonalizable $\Rightarrow \exists$ invertible $S_{n \times n}$: $D = S^{-1}AS$

$$A = SDS^{-1}$$

$$\Downarrow$$

$$A^t = (SDS^{-1})^t = SDS^{-1}SDS^{-1}\dots SDS^{-1} = SD^T S^{-1}$$



$$A^t = SD^t S^{-1}$$


Example

Let

$$A = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix} \Rightarrow \lambda_1 = 5, \lambda_2 = -1 \Rightarrow A \text{ is diagonalizable}$$

$$E_5 = \text{Ker} \begin{pmatrix} -4 & 2 \\ 4 & -2 \end{pmatrix} \Rightarrow \bar{v}_1 = \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \dim E_5 = 1$$

$$E_{-1} = \text{Ker} \begin{pmatrix} 2 & 2 \\ 4 & 4 \end{pmatrix} \Rightarrow \bar{v}_1 = \begin{pmatrix} -1 \\ 1 \end{pmatrix}, \dim E_{-1} = 1$$

$$A = \underbrace{\begin{pmatrix} 1 & -1 \\ 2 & 1 \end{pmatrix}}_S \underbrace{\begin{pmatrix} 5 & 0 \\ 0 & -1 \end{pmatrix}}_D \underbrace{\frac{1}{3} \begin{pmatrix} 1 & 1 \\ -2 & 1 \end{pmatrix}}_{S^{-1}}$$

$$A^t = \begin{pmatrix} 1 & -1 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} 5^t & 0 \\ 0 & (-1)^t \end{pmatrix} \frac{1}{3} \begin{pmatrix} 1 & 1 \\ -2 & 1 \end{pmatrix}$$

$$= \frac{1}{3} \begin{pmatrix} 5^t + 2(-1)^t & 5^t + (-1)^{t+1} \\ 2 \cdot 5^t - 2(-1)^t & 2 \cdot 5^t + (-1)^t \end{pmatrix}$$

Diagonalizable Linear Operators

Definition: A scalar λ is called an eigenvalue of a linear operator $T : V \rightarrow V$ if

$$\exists f \in V, f \neq 0: Tf = \underline{\lambda f}.$$

The element $f \in V$ is called an **eigenfunction**.

If $\dim V < +\infty$, then a basis \mathfrak{D} consisting of eigenfunctions of V is called an **eigenbasis** for T .

A linear operator T is diagonalizable if the matrix of T w.r.t. some basis is diagonal \Leftrightarrow there exists an eigenbasis for T .

Example 1

$$T: P_2 \rightarrow P_2, \quad Tf(x) = f(2x - 1), \quad \mathfrak{B} = \{1, x, x^2\}$$

$$a + bx + cx^2 \xrightarrow{T} a - b + c + (2b - 4c)x + 4cx^2$$

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} \xrightarrow{L_{\mathfrak{B}}} \begin{pmatrix} a - b + c \\ 2b - 4c \\ 4c \end{pmatrix}$$

$$A = \begin{pmatrix} 1 & -1 & 1 \\ 0 & 2 & -4 \\ 0 & 0 & 4 \end{pmatrix} \Rightarrow \lambda_1 = 1, \lambda_2 = 2, \lambda_3 = 4$$

$\Rightarrow A$ is diagonalizable

$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} -1 \\ 2 \\ 1 \end{pmatrix}$ is the eigebasis for T

Example 1

$$S_{\mathfrak{D} \rightarrow \mathfrak{B}} = \begin{pmatrix} 1 & -1 & 1 \\ 0 & 1 & -2 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\Rightarrow f_1 = 1, f_2 = -1 + x, f_3 = 1 - 2x + x^2$$

$$T(1) = \underbrace{1}_{\lambda_1}, T(x-1) = \underbrace{2}_{\lambda_2}(x-1), T(x-1)^2 = \underbrace{4}_{\lambda_3}(x-1)^2$$

$$D = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 4 \end{pmatrix}$$

Example 2

$$L: \mathbb{M}_{2 \times 2} \rightarrow \mathbb{M}_{2 \times 2}, \quad L(A) = A - A^T$$

$$L(A) = \lambda A$$

1. A is symmetric $\Rightarrow A^T = A \Rightarrow L(A) = 0 = 0 \cdot A \Rightarrow \lambda = 0$

$$A = \begin{pmatrix} a & b \\ b & c \end{pmatrix} = a \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} + b \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} + c \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

$$\dim E_0 = 3$$

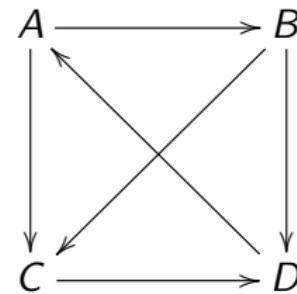
2. A is skew-symmetric $\Rightarrow A^T = -A \Rightarrow L(A) = 2A \Rightarrow \lambda = 2$

$$A = \begin{pmatrix} 0 & a \\ -a & 0 \end{pmatrix} = a \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$$

$$\dim E_2 = 1$$

Ranking Problem

- * Consider the results of a tournament



where " $A \rightarrow B$ " means A defeated B .

How to rank the players fairly?

- * The Page-Brin idea: it should *be worth more* to defeat a *better player* ⇐ based on Perron (1907)-Frobenius (1912) Theorem

How do we know who is better before ranking them?

- * Define recursion!

Ranking Problem

- * Give everyone the initial score of 1

$$\bar{x}_0 = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \quad \begin{matrix} DU \\ SHAOXIONG \\ C \\ OLGA \end{matrix}$$

- * Define for all $n \geq 0$

$$\bar{x}_{n+1} = A\bar{x}_n,$$

where

$$A = \begin{array}{cccccc} & & DU & SHAOXIONG & C & O \\ & DU & \left(\begin{array}{cccc} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{array} \right) \\ SHAOXIONG & & & & & \\ C & & & & & \\ O & & & & & \end{array}$$

Ranking Problem

$$\bar{x}_1 = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 2 \\ 2 \\ 1 \\ 1 \end{pmatrix} \begin{matrix} A \\ B \\ C \\ D \end{matrix}$$

$$\bar{x}_2 = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 2 \\ 2 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 3 \\ 2 \\ 1 \\ 2 \end{pmatrix} \begin{matrix} A \\ B \\ C \\ D \end{matrix}$$

$$\bar{x}_3 = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 3 \\ 2 \\ 1 \\ 2 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \\ 2 \\ 3 \end{pmatrix} \begin{matrix} A \\ B \\ C \\ D \end{matrix}$$

The $(n+1)$ th score of a player A is the sum of the n th scores of the players that the player A defeated.

Ranking Problem

$$\bar{x}_5 = \begin{pmatrix} 8 \\ 6 \\ 3 \\ 5 \end{pmatrix}, \bar{x}_{10} = \begin{pmatrix} 35 \\ 34 \\ 21 \\ 26 \end{pmatrix}, \bar{x}_{100} = \begin{pmatrix} 1037 \\ 933 \\ 547 \\ 731 \end{pmatrix}$$

Is $A > B > D > C?$ \Rightarrow analyze $\bar{x}_n = A^n \bar{x}_0$ as $n \rightarrow \infty$

Theorem (Perron-Frobenius): There exists a *largest positive* eigenvalue λ_{PF} for a nonnegative matrix A such that the rescaled system

$$\bar{x}_n = \left(\frac{1}{\lambda_{PF}} A \right)^n \bar{x}_0$$

converges to an equilibrium state \bar{x}_∞ .

$$\bar{x}_\infty = \bar{x}_{\infty+1} = \frac{1}{\lambda_{PF}} A \bar{x}_\infty \Rightarrow A \bar{x}_\infty = \lambda_{PF} \bar{x}_\infty$$

The equilibrium state is the eigenvector associated with $\lambda_{PF}!!!$

Ranking Problem

The largest positive eigenvalue is

$$\lambda_{PF} = 1.3953369\dots$$

and

$$\bar{x}_\infty = \begin{pmatrix} 0.321\dots \\ 0.288\dots \\ 0.165\dots \\ 0.230\dots \end{pmatrix} \begin{matrix} A \\ B \\ C \\ D \end{matrix}$$

$$A > B > D > C$$