

Linear Algebra

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* Please take a look at the
typed lecture notes

Last Lecture:

Def 6.1.10. Given $A \in \mathbb{R}^{n \times n}$ the trace of A is defined as $\text{Tr}(A) := \sum_{i=1}^n A_{ii}$

Prop 6.1.11. Let $A \in \mathbb{R}^{n \times n}$ and $\lambda_1, \dots, \lambda_n$ its n eigenvalues, repeated as in (31).

multiplicity, then:

$$\text{Tr}(A) = \sum_{i=1}^n \lambda_i$$

$$\det(A) = \prod_{i=1}^n \lambda_i$$

of

$$(-1)^n \det(A - zI) = \det(zI - A) = (31)$$
$$(z - \lambda_1)(z - \lambda_2) \dots (z - \lambda_n)$$

Characteristic Polynomial of a Matrix.

Proof (of Prop 6.1.11)

(Goal 1)

$$\det(A) = \prod_{i=1}^n \lambda_i$$

Let's set $z=0$ in (31)

$$(-1)^n \det(A - 0I) = \prod_{i=1}^n (-\lambda_i)$$
$$(-1)^n \det(A) = (-1)^n \prod_{i=1}^n \lambda_i \quad \checkmark$$

(Goal 2)

$$\text{tr}(A) = \sum_{i=1}^n \lambda_i$$

$$\det(zI - A) = (z - \lambda_1)(z - \lambda_2) \dots (z - \lambda_n)$$

$$\det(zI - A) = z^n + \underbrace{\quad}_{-\sum_{i=1}^n A_{ii} = -\text{Tr}(A)} z^{n-1} + \dots$$

$$\begin{bmatrix} z - A_{11} & -A_{12} & \dots \\ -A_{21} & z - A_{22} & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

$$(z - \lambda_1)(z - \lambda_2) \dots (z - \lambda_n) = z^n + \underbrace{\quad}_{-\sum_{i=1}^n \lambda_i} z^{n-1} + \dots + \underbrace{\quad}_{(-1)^n \det(A)} z + \dots$$

$$\rightarrow -\text{Tr}(A) = -\sum_{i=1}^n \lambda_i \quad \square$$

HW: try your favorite 3x3-matrix.

Cautions!

- (i) Even though the eigenvalues of A and A^T are the same, the eigenvectors are not!
- (ii) eigenvalues of $A+B$ are not easy to write for eigenvalues of A and B .
- (iii) same for AB .
- (iv) Gaussian elimination does not preserve eigenvalues. The eigenvalues of A are NOT the diagonal elements of U in $PA = LU$!

Example 6.1.21.

Let $D \in \mathbb{R}^{n \times n}$ be a diagonal matrix: $D_{ij} = 0$ if $i \neq j$.

What are the e-values of D ?
(and e-vectors)

$\lambda_i = D_{ii}$ is an e-value

and $v_i = e_i$

$$D e_i = D_{ii} e_i$$

$$\left(e_i = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \right)$$

What about for a triangular matrix?

$$M = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$$

$$\lambda_1 = \frac{1 + \sqrt{5}}{2}$$

$$\lambda_2 = \frac{1 - \sqrt{5}}{2}$$

HW

Example 6.1.14.

The eigenvalues of $A = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$?

$$\begin{vmatrix} -\lambda & -1 \\ 1 & -\lambda \end{vmatrix} = \lambda^2 + 1$$

There is no real eigenvalue.

$$\lambda_1 = i, \quad \lambda_2 = -i$$

$$A - \lambda_1 I = \begin{bmatrix} -i & -1 \\ 1 & -i \end{bmatrix}$$

$$\rightarrow \begin{bmatrix} -i & -1 \\ 1 & -i \end{bmatrix} \begin{bmatrix} (v_1)_1 \\ (v_1)_2 \end{bmatrix} = 0$$

$$v_1 = \begin{bmatrix} i \\ 1 \end{bmatrix}$$

$$v_2 = \begin{bmatrix} -i \\ 1 \end{bmatrix}.$$

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} i \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ i \end{bmatrix} = i \begin{bmatrix} i \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} -i \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ -i \end{bmatrix} = (-i) \begin{bmatrix} -i \\ 1 \end{bmatrix}$$

$$v = \alpha_1 v_1 + \alpha_2 v_2 \dots$$

Prop 6.1.15: Let $Q \in \mathbb{R}^{n \times n}$ be an orthogonal matrix.

If $\lambda \in \mathbb{C}$ is an eigenvalue for Q then $|\lambda| = 1$.

Proof: Let $v \in \mathbb{C}^n$ be an eigenvector ($v \neq 0$) associated with λ .

$$Qv = \lambda v$$

Since Q is orthogonal, $\|Qv\|^2 = \|v\|^2$

$$\|v\|^2 = \|Qv\|^2 = \|\lambda v\|^2 = |\lambda|^2 \|v\|^2.$$

$$\Rightarrow |\lambda| = 1.$$

————— || ————— , || —————
Repeated eigenvalues.

Example 6.1.16.

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

$$\lambda_1 = 0$$

$$\lambda_2 = 0$$

$$\begin{vmatrix} -\lambda & 1 \\ 0 & -\lambda \end{vmatrix} = \lambda^2.$$

$\lambda = 0$ has algebraic multiplicity 2.

$N(A - 0I) = N(A)$ ← has dimension 1.

$$N(A) = \left\{ \begin{bmatrix} \alpha \\ 0 \end{bmatrix}, \text{ for some } \alpha \in \mathbb{R} \right\}$$

$v_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ is an eigenvector of A

There is no basis of \mathbb{R}^2 made with eigenvectors of $\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$.

$$\rightarrow A^2 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \text{ Nilpotent.}$$

"block Jordan form"

Exempl 6.1.17

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}. \quad \begin{array}{l} \lambda_1 = 0 \\ \lambda_2 = 0 \end{array}$$

$$N(A) = \mathbb{R}^2.$$

$$v_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad v_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

There is a basis of \mathbb{R}^2 with eigenvectors of $A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$.

Def. Given a matrix A and an eigenvalue λ , we call $\dim N(A - \lambda I)$ the geometric multiplicity of λ .

Unfortunately the geometric multiplicity may be smaller than the algebraic multiplicity.

Def: Given $A \in \mathbb{R}^{n \times n}$, if we can build a basis of \mathbb{R}^n with evecs of A we say A has a complete set of eigenvectors.

Example 6.1.19.

Let U be a subspace of \mathbb{R}^n and P the projection matrix for U .

$N(P) = U^\perp$ any $w \in U^\perp$ satisfies $Pw = 0w$.

let $k = \dim U$. $n-k = \dim U^\perp$

w_1, \dots, w_{n-k} lin ind

s.t. $Pw_j = 0w_j$
 $j=1, \dots, n-k$.

If $u \in U$ then $Pu = u$.

u_1, \dots, u_k lin ind such that $Pu_i = 1 \cdot u_i$
 $i=1, \dots, k$.

u_1, \dots, u_k k ind e-vectors with evalue 1

w_1, \dots, w_{n-k} $n-k$ ind with evalue 0.

P has a complete set of eigenvectors.

There is an orthonormal basis of \mathbb{R}^n made up of e-vectors of P .

$$A \in \mathbb{R}^{m \times n}$$

$$(e_i)_j = \delta_{ij}.$$

Change of basis.

$L: \mathbb{R}^n \rightarrow \mathbb{R}^m$ linear transformation

$$x \in \mathbb{R}^n \rightarrow Ax \in \mathbb{R}^m$$

$$x = \sum_{j=1}^n x_j e_j \longrightarrow L(x) = \sum_{i=1}^m (Ax)_i e_i$$

u_1, \dots, u_n be a basis for \mathbb{R}^n

v_1, \dots, v_m be a basis for \mathbb{R}^m

$$x = \sum_{j=1}^n \alpha_j u_j \longrightarrow L(x) = \sum_{i=1}^m \beta_i v_i$$

$\alpha \longrightarrow \beta$

what is the matrix $B \in \mathbb{R}^{m \times n}$

s.t. $B\alpha = \beta.$

$$L(x) = Ax$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix}$$

$$x = \sum \alpha_j u_j = U\alpha, \quad U = \begin{bmatrix} | & | & & | \\ u_1 & u_2 & \dots & u_n \\ | & | & & | \end{bmatrix} n \times n$$

$$\alpha = U^{-1}x$$

$$L(x) = \sum \beta_i v_i = V\beta, \quad V = \begin{bmatrix} | & & | \\ v_1 & \dots & v_m \\ | & & | \end{bmatrix} m \times m$$
$$\beta = V^{-1}L(x)$$

$$L(x) = Ax = A(U\alpha)$$

$$V\beta = L(x)$$

$$V\beta = AU\alpha$$

$$\beta = V^{-1}AU\alpha$$

$$B = V^{-1}AU.$$

L , written in the basis u_1, \dots, u_n and v_1, \dots, v_m is described by the matrix $V^{-1}AU$.

where A is the matrix representing L in the canonical basis.

$L: \mathbb{R}^n \longrightarrow \mathbb{R}^m$ linear transf.

$$L\left(\sum_{j=1}^n x_j e_j\right) = \sum_{i=1}^m (Ax)_i e_i \quad x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$$L\left(\sum_{j=1}^n \alpha_j u_j\right) = \sum_{i=1}^m (B\alpha)_i v_i \quad \alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}$$

$$B = V^{-1} A U$$