

Lecture 13

Last week we introduced the concept of eigenvectors and eigenvalues. That is if there exists a nonzero vector \vec{v} and scalar τ s.t.

$$A\vec{v} = \tau\vec{v}$$

then τ is an eigenvalue with associated eigenvector \vec{v} .

\vec{v} is an invariant direction under the linear transformation

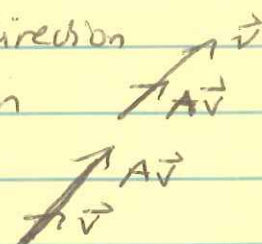
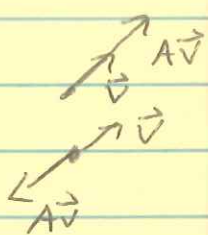
If τ

$\tau > 0$ \vec{v} and $A\vec{v}$ have the same direction

$\tau < 0$ " " " " " " opposite direction

$|\tau| < 1$ eigenvalue is a factor of contraction

$|\tau| > 1$ " " " " extension



If an $n \times n$ square matrix A has n linearly independent eigenvectors then there exists a transition matrix P (lecture 11) s.t.

$$P^{-1}AP = \begin{bmatrix} \tau_1 & 0 & \dots & 0 \\ 0 & \tau_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & \tau_n \end{bmatrix}$$

that is there exists a basis representation for which the transformation matrix A is a diagonal matrix.

P is the transition matrix from a basis composed of eigenvectors to the standard basis

Let-

$$B = \{ \vec{e}_1, \vec{e}_2, \dots, \vec{e}_n \} \text{ and } B' = \{ \vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \}$$

standard basis
n linearly independent eigenvectors

From Lecture 11

$$[\vec{v}]_B = P [\vec{v}]_{B'}$$

Then P is composed of the eigenvectors

$$P = [\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n]$$

$$\begin{aligned}
 AP &= A [\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n] = [A\vec{v}_1, A\vec{v}_2, \dots, A\vec{v}_n] \\
 &= [\tau_1 \vec{v}_1, \tau_2 \vec{v}_2, \dots, \tau_n \vec{v}_n] \\
 &= \underbrace{[\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n]}_P \begin{bmatrix} \tau_1 & & & \\ & \tau_2 & & \\ & & \dots & \\ & & & \tau_n \end{bmatrix} \\
 &= PD
 \end{aligned}$$

$$\boxed{D = P^{-1}AP}$$

In the diagonalized matrix the coordinate axis' line up with the eigenvectors. A ~~trans~~ transformation along one of the axis results in a vector along the same axis.

(3)

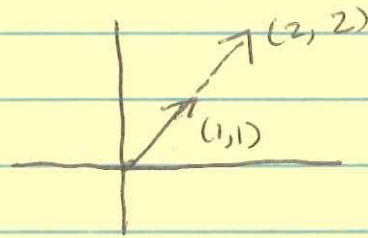
$$\begin{aligned}
 \det(D) &= \det(P^{-1}AP) \\
 &= \det(P^{-1}) \det(A) \det(P) \\
 &= \det(P^{-1}) \cdot \det(P) \det(A) \\
 &= \frac{1}{\det(P)} \cdot \det(P) \det(A) \\
 &= \det(A)
 \end{aligned}$$

$$\det(D) = \tau_1 \tau_2 \tau_3 \dots \tau_n$$

$\det(A)$ is equal to the product of the eigenvalues

In Thursday's lecture we explored the example where we had a matrix with eigenvalue 2 and associated eigenvector $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$

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



$$A \begin{bmatrix} 1 \\ 1 \end{bmatrix} = 2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

Propose a second eigenvector $\begin{bmatrix} -1 \\ 1 \end{bmatrix}$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow A\vec{v} = \tau\vec{v} \text{ where } \tau = 0$$

So A has two linearly independent eigenvectors

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ and } \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Note that A does not necessarily have linearly indep. column/row vectors!

Our theorem says we can construct a matrix P from the eigenvectors

$P = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$ and that $P^{-1}AP$ will give us a matrix with the eigenvalues along the diagonal.

$$D = P^{-1}AP = \begin{bmatrix} 1/2 & 1/2 \\ -1/2 & 1/2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} \tau_1 & 0 \\ 0 & \tau_2 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 \\ 0 & 2 \end{bmatrix} \quad \begin{matrix} \tau_1 = 0 & \checkmark \\ \tau_2 = 2 & \checkmark \end{matrix}$$

A is called diagonalizable.

$$P(D = P^{-1}AP)P^{-1}$$

$$PDP^{-1} = \underbrace{PP^{-1}}_I A \underbrace{PP^{-1}}_I$$

$$\Rightarrow \boxed{A = PDP^{-1}}$$

$$A^m = (PDP^{-1})^m = P \begin{bmatrix} T_1^m & & \\ & T_2^m & \\ & & \dots \\ & & & T_n^m \end{bmatrix} P^{-1}$$

$$\begin{aligned} A^2 &= (PDP^{-1})^2 \\ &= (PDP^{-1})(PDP^{-1}) \\ &= PD^2P^{-1} \end{aligned}$$

$$\begin{aligned} A^3 &= A^2A = (PD^2P^{-1})(PDP^{-1}) \\ &= PD^3P^{-1} \end{aligned}$$

⋮

$$A^m = PD^mP^{-1}$$

For a diagonal matrix, we have

$$P = \begin{bmatrix} d_1 & & \\ & d_2 & \\ & & \dots \\ & & & d_n \end{bmatrix} \Rightarrow D^m = \begin{bmatrix} d_1^m & & \\ & d_2^m & \\ & & \dots \\ & & & d_n^m \end{bmatrix}$$

which one can verify through induction as well.

Properties of eigenvalues and eigenvectors

Theorem: Let A be a square matrix, then the following are equivalent

- (i) A scalar λ is an eigenvalue of A
- (ii) The matrix $M = A - \lambda I$ is singular (singular meaning $\det(M) = 0$ or equiv. column vectors are linearly dependent)
- (iii) The scalar λ is a root of the characteristic polynomial $p(s)$ of A
 $p(s) = \det(sI - A)$

A closer look at (ii)

Singular and nonsingular linear mappings

Linear matrix mapping

$F_A : \mathbb{R}^n \rightarrow \mathbb{R}^n$, where $F_A(\vec{v}) = A\vec{v}$

The mapping F_A is said to be singular if the image of some nonzero vector

\vec{v} is $\vec{0}$, that is, if \exists ("there exists")

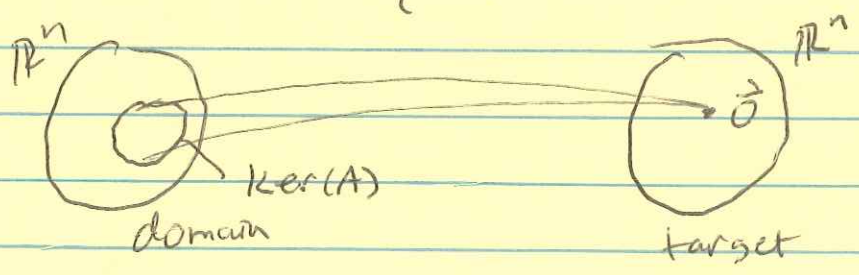
$v \neq 0$ s.t. $F_A(\vec{v}) = \vec{0}$ ($A\vec{v} = \vec{0}$).

Thus $F_A : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is nonsingular if the zero vector $\vec{0}$ is the only

vector whose image under F_A is $\vec{0}$

($A\vec{v} = 0$ iff $\vec{v} = 0$), in other words,

if $\text{Ker } A = \{ \vec{0} \}$



⑦

Note that if $\ker A = \{0\}$ then

$\text{rank}(A) = n$ the matrix is full rank

$$\dim(\mathbb{R}^n) = \text{rank}(A)$$

$$\left(\dim(\ker(A))\right) = 0$$

(ii) "is saying" that the matrix

$M = A - \tau I$ is guaranteed to have

a set of vectors (nonzero) that

map to the zero vector,

The set of vectors include the

eigenvectors associated with eigenvalue τ

$$A\vec{v} = \tau\vec{v}$$

$$A\vec{v} - \tau\vec{v} = 0$$

$$(A - \tau I)\vec{v} = 0$$

$$\underbrace{\quad}_{M}\vec{v}$$

$$\therefore \vec{v} \in \ker(A - \tau I) \quad I \in \mathbb{R}^{n \times n}$$

$n \times n$ identity

matrix

(iii) characteristic polynomial $p(s)$ is as defined

$$p(s) = \det(sI - A)$$

Consider 2×2 matrix $A = \begin{bmatrix} 1 & -2 \\ 0 & 4 \end{bmatrix}$

$$\text{then } sI - A = s \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} 1 & -2 \\ 0 & 4 \end{bmatrix}$$

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

$$\det(sI - A) = (s-1)(s-4) - 0 \cdot 2$$

$$= s^2 - 5s + 4$$

$$\Rightarrow p(s) = s^2 - 5s + 4$$

(iii) "is saying"

$$p(\lambda) = 0 \quad \lambda \text{ is a root of } p(s)$$

$$\Rightarrow \lambda^2 - 5\lambda + 4 = 0$$

(side note: It is also true that $p(A) = 0$)

$$\begin{bmatrix} 1 & -2 \\ 0 & 4 \end{bmatrix}^2 - 5 \begin{bmatrix} 1 & -2 \\ 0 & 4 \end{bmatrix} + 4 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Cayley-Hamilton theorem: Every matrix A is a root of its characteristic polynomial

(i), (ii), (iii) are properties that help us to find eigenvalues and eigenvectors and, hence, factorized representation of $A \in \mathbb{R}^{n \times n}$