

LINEAR ALGEBRA

Chapters 5 & 6. (6 with 5 squeezed in)

* Square Matrices! (mostly)

↓ we'll return to
matrix at the
end of ch 6.

* Think now of A as a gadget
matrix that "transforms" \vec{x} into a
new vector

$$A\vec{x}_1 = \vec{x}_2 \leftarrow \text{new } \vec{x}$$

A might rotate, flip, stretch, project
↑
chop out
pieces of
 \vec{x} .

* Especially interested in what
happens when we make repeated
transformations:

what is $A^n \vec{x}$?? (n large)

3 reasons why we care about A^n :

Ch 6
L1

before
lectures
on chapter
5

better

$$\vec{a}_2 = \vec{c}_2 + \hat{q}_1 \hat{q}_1^T \vec{a}_2$$
$$\hat{q}_1^T \times \left\{ \begin{array}{l} \hat{q}_2^T \vec{a}_2 = \hat{q}_2^T \vec{c}_2 \\ = \hat{q}_2^T \hat{q}_2 \cdot \|\vec{c}_2\| \end{array} \right.$$

$$\|\vec{c}_2\| \hat{q}_2 \quad \checkmark$$
$$(\hat{q}_2^T \vec{a}_2) \hat{q}_2 \quad \checkmark$$

Linear Algebra (Square matrices only) !!

A^n : why we care.

Reasons to love arbitrary powers of square matrices.

(1) $\vec{x}_{t+1} = A \vec{x}_t$
 ↑
 system evolution may be expressed as matrix multiplication.

eg. probabilistic
 $\vec{x}_t = \begin{bmatrix} x_{1,t} \\ \vdots \\ x_{n,t} \end{bmatrix}$ contains probability of being in state i at time t

A is a "transition" matrix containing conditional probabilities

$(A)_{ij} = P_{ij} = \text{prob of moving to state } i \text{ given in state } j$

must have $\sum_{i=1}^n P_{ij} = 1$ so columns add to 1

(Markov chain)

$\vec{x}_t = A^t \vec{x}_0$
 ↑
 how this behaves governs system

(2) Solving linear diff eq's

$\frac{dy}{dt} = at \Rightarrow y = y_0 e^{at}$

$\frac{dx_1}{dt} = a x_1 + b x_2$
 $\frac{dx_2}{dt} = c x_1 + d x_2$

$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$
 ↑
 constants

$\frac{d}{dt} \vec{x} = A \vec{x}$

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L2

Solution is

$\begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = e^{At} \begin{bmatrix} x_1(0) \\ x_2(0) \end{bmatrix}$

$I + A + \frac{A^2}{2!} + \frac{1}{3!} A^3 + \dots + \frac{1}{n!} A^n + \dots$

need to be able to handle these powers

(3) Solving diff. eqs
 c.g.

$F_{n+2} = F_{n+1} + F_n$

$\vec{x}_n = \begin{bmatrix} F_{n+1} \\ F_n \end{bmatrix}$

$\vec{x}_{n+1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \vec{x}_n = \dots = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}^n \vec{x}_0$
 $\vec{x}_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

If we can compute $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ then we have a way of solving for the n th Fibonacci #.

(4) other reasons: for fun
 self-flagellation
 etc.

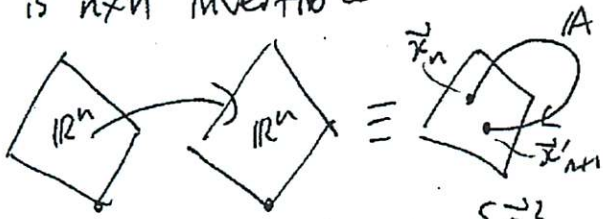
To get to A^n , we must first go through eigenvalues. e-values also deepen our appreciation for $A \vec{x} = \vec{b}$

~~Eigen = self or same.~~
 ↓
 down

Note change of focus:
 Interested in how A transforms \vec{x}
 Before $A \vec{x} = \vec{b}$ task = find \vec{x}
 Now $A \vec{x}_n = \vec{x}_{n+1}$ or $A \vec{x} = \vec{x}'$
 ↑ known ↑
 ← understand how

Linear Algebra

A is $n \times n$ invertible



nullspace = $\{ \vec{0} \}$
 left nullsp = $\{ \vec{0} \}$.

An example:

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

observe

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

$$A^2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} = (3/2)^2 \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\vdots$$

$$A^n \begin{bmatrix} 1 \\ 1 \end{bmatrix} = (3/2)^n \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\lambda^n = e^{n \ln \lambda}$$

at most n vectors

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

$$A^n \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \left(\frac{1}{2}\right)^n \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

what about

$$A \begin{bmatrix} 2 \\ 0 \end{bmatrix} \text{ say for example}$$

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

$$A^2 \begin{bmatrix} 2 \\ 0 \end{bmatrix} = \begin{bmatrix} 5/2 \\ 2 \end{bmatrix} \leftarrow \text{not as clean}$$

but

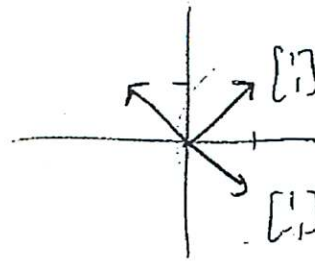
$$A \left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right) = A \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$

$$\Rightarrow A \begin{bmatrix} 2 \\ 0 \end{bmatrix} = \frac{3}{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$A^2 \begin{bmatrix} 2 \\ 0 \end{bmatrix} = \left(\frac{3}{2}\right)^2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \left(\frac{1}{2}\right)^2 \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

disappears

Ch 6
L 3



$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ natural basis for "A"

A stretches a vector in the $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ direction
 contracts a " " " $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ direction

These directions are A's "own" directions

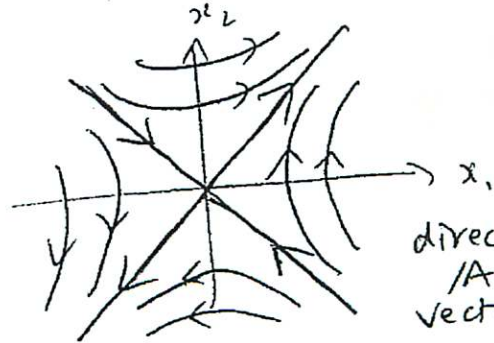
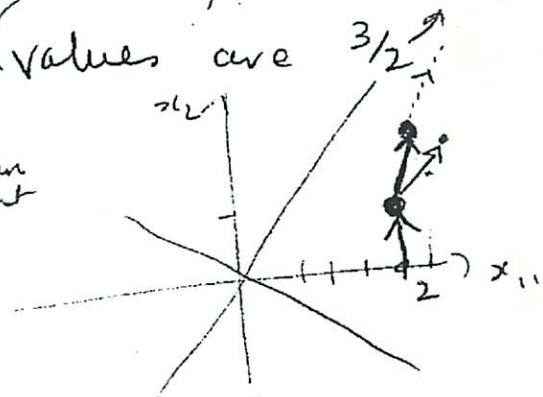
German for own: Eigen

Plum: Pigen

Eigenvectors for A are $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$

Eigenvalues are $3/2$ $1/2$

makes an excellent basis



directions A moves vectors in.

$\lambda > 1 \rightarrow$ vectors grows exponentially in direction of evector

$\lambda = 1 \rightarrow$ stay the same

$\lambda = 0 \rightarrow$ vanish straight away

$0 < \lambda < 1 \rightarrow$ shrink

$\lambda < 0 \rightarrow$ jump back for the origin

Linear Algebra

How do we find eigen vectors?

Solve

$$A \vec{x} = \lambda \vec{x}$$

Scalar, $\lambda \in \mathbb{R}$

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

key manoeuvres

$$(A - \lambda I) \vec{x} = \vec{0}$$

For \vec{x} to be non-zero, λ must be such that $(A - \lambda I)$ has

① rank $< n$

② have no inverse

③ be singular

④ have a non-trivial nullspace $n - r > 0$

⑤ have zero determinant = 0.

* $\det(A - \lambda I)$ note notation

$$= |A - \lambda I|$$

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

$$= (1-\lambda)^2 - 1/4$$

$$= \lambda^2 - 2\lambda - 3/4$$

$$= (\lambda - 3/2)(\lambda - 1/2)$$

$$\lambda_1 = 3/2, \quad \lambda_2 = 1/2$$

The Characteristic Equation

remember these?

Now find solutions to $(A - 3/2 I) \vec{x} = \vec{0}$

Ch 6 L 4

In other words, find basis vectors for nullspaces of $A - 3/2 I$ & $A - 1/2 I$

$$(A - 3/2 I) \vec{x} = \begin{bmatrix} -1/2 & 1/2 \\ 1/2 & -1/2 \end{bmatrix}$$

$$\begin{bmatrix} -1/2 & 1/2 & 0 \\ 1/2 & -1/2 & 0 \end{bmatrix} \rightarrow \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Similarly, $\vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$.

These eigenvectors are the "natural basis" for A .

Special Matrices have special values & vectors

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \lambda_1 = 1, \lambda_2 = 1$$

$$IP_{[0]} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \quad \lambda_1 = 1, \lambda_2 = 0$$

$$\vec{v}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$IP_{[1]} = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \quad \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$IP_{90^\circ} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad \lambda_1 = +i, \lambda_2 = -i$$

$$IP_{\mathbb{F}} = \begin{bmatrix} 0 & 1 \\ \phi & 0 \end{bmatrix} \quad \lambda_{1/2} = \pm 1, \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



if A is symmetric \rightarrow e vectors are orthogonal
 A is singular $\rightarrow \lambda = 0$ is an e vector

Pieces that follow:

$$\left[\begin{array}{l} \det A = \pm \det U \\ \uparrow \\ \text{depends on \# row swaps} \\ \leftarrow \text{as in } A = LU \\ \det \Delta \text{ or } \nabla = \text{product of diagonal elements} \\ \det A = \pm \text{product of } A\text{'s pivots.} \end{array} \right.$$

Reasons

(a) if A has two rows the same the $\det(A) = 0$

parallel is missing a side!

sign change $\begin{vmatrix} 3 & 4 \\ 3 & 4 \end{vmatrix} = 3 \cdot 4 - 3 \cdot 4 = 0$

$$\begin{vmatrix} 3 & 6 & 6 \\ 3 & 6 & 6 \\ 2 & -2 & 1 \end{vmatrix} = \begin{vmatrix} 3 & 6 & 6 \\ 3 & 6 & 6 \\ 2 & -2 & 1 \end{vmatrix} = 0$$

(b) row reduction doesn't change val of det.

$$\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} - \begin{vmatrix} a_{21} & a_{12} \\ a_{11} & a_{22} \end{vmatrix} = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} - a_{11} & a_{22} - a_{12} \end{vmatrix}$$

$\Rightarrow \det A = \pm \det U$

(c) if rows are in dep, we can make a row of 0's with row reduction $\Rightarrow \det(A) = 0$

(h) $|A| = |A^T|$

$(P/A) = LU \Rightarrow$ row \rightarrow columns \leftarrow multilinearity

now finding a volume of a parallelepiped with one side of zero length!

Ch 5
2a

(d) keep going past U to fully reduced form. Caution - do not divide by pivots!
call this RE_A (row echelon form)

$$\begin{bmatrix} 2 & 3 \\ 1 & 4 \end{bmatrix} \sim \begin{bmatrix} 2 & 0 \\ 0 & 5/2 \end{bmatrix} = \begin{bmatrix} 2 \cdot 5/2 & | & 1 & 0 \\ 0 & | & 0 & 1 \end{bmatrix} = 5$$



$\Rightarrow \det A = \pm \det U_A = \pm \prod_{i=1}^n p_i$

\rightarrow turns out another way we need for evaluate problem. big deal.

(e) $|AB| = |A||B|$ * see Ch 5 product of volumes. 2b
n.b $|A+B| \neq |A|+|B|$ multilinear only!!!

Sneaky reason

Show $\det \begin{pmatrix} A & B \\ B & A \end{pmatrix}$ satisfies DP 1, 2, 3

(1) if $A = I$, both I & $|B|$ $\Rightarrow \det 1$ ✓

(2) if swap two rows of A , we swap the same two rows of $A|B|$. \Rightarrow both dets change sign

(3) if we multiply a row of A by t , we multiply the same row of $A|B|$ by t .

(ii) if we split a row of A , we split the same row of $A|B|$ in same way \Rightarrow dets add.

(f) (e) $\Rightarrow |A^{-1}| = \frac{1}{|A|}$
n.b. if $|A|=0$, $|A^{-1}| = \infty$ ouch!

What can we say about

(e) $|AB|$?

know
 $IP|E A = R_A^e$
 ↑ perms ↖ eliminat

$|A| = \pm |R_A^e|$
 ↑ row swaps

$|IP|E (A|B)| = |R_A^e B|$
 $= \left(\prod_{i=1}^n P_i \right) |B|$
 $= |A| |B|$

* back to (f)

Example: ← used again later.

Use row ops to find
 determinant of

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

$|A| = 2$

I^u

(g) $\det D, \nabla = \prod$ entries on diagonal

$\begin{bmatrix} 4 & -1 & 4 & 7 \\ 0 & -3 & 6 & 8 \\ 0 & 0 & 2 & 1 \\ 0 & 0 & 7 & \end{bmatrix} = 4 \times (-3) \times (2) \times (7)$

(i) One or more pivots = 0
 $\Rightarrow |A| = 0$

$|IP|A| = |LU|$

$|IP| = |IP^T| = \pm 1$

bc $IP^{-1} = IP^T$

$\therefore |IP^T IP| = 1 = |IP^T| |IP|$
 ± 1

Linear Algebra

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3

The eigenvalue problem:
For given A , find all λ, \vec{v}
 $n \times n$ such that $A\vec{v} = \lambda\vec{v}$

We turned this into a problem of algebra: ~~solve~~ ~~find~~ n^{th} order polynomial in λ .

- find λ s.t. $|A - \lambda I| = 0$
- find \vec{v}

$$\begin{vmatrix} a_{11} - \lambda & 0 & 0 \\ 0 & a_{22} - \lambda & 0 \\ 0 & 0 & a_{33} - \lambda \end{vmatrix} = 0$$

part ② is "bigger bit"

with \vec{v} (find solution)

Really: finding basis for nullspace of $(A - \lambda I)$

① is the tricky bit:

We have to compute determinants of $n \times n$ matrices

So: Determinantama

(Reason: if $|A - \lambda I| = 0$ $(A - \lambda I)$ has no inverse \leftarrow we still have to prove that we will!

\Rightarrow nullspace of $A - \lambda I$ non-trivial

\Rightarrow vectors exist!

2x2's $\begin{vmatrix} a_{11} & b_{12} \\ a_{21} & d_{22} \end{vmatrix} = ad - bc$

3x3's? 4x4's?

recall $\frac{1}{A^{-1}}$ with $\begin{pmatrix} a & b \\ c & d \end{pmatrix}$ if $d \neq 0$ $\begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$

Warning:

Determinants have many properties & uses you must concentrate

See 3a

usual way for evaluate probs

In general, determinants are computed recursively.

(First - recipe later - understanding) *save for later* *grasshopper*



3x3's $\begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix}$ use multilinearity



column way $= a_{11} \begin{vmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{vmatrix} - a_{12} \begin{vmatrix} a_{21} & a_{23} \\ a_{31} & a_{33} \end{vmatrix} + a_{13} \begin{vmatrix} a_{21} & a_{22} \\ a_{31} & a_{32} \end{vmatrix}$

and show piece of work

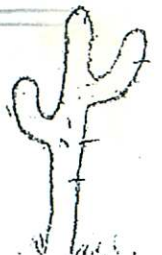
$= a_{31} \begin{vmatrix} a_{12} & a_{13} \\ a_{22} & a_{23} \end{vmatrix} - a_{32} \begin{vmatrix} a_{11} & a_{13} \\ a_{21} & a_{23} \end{vmatrix} + a_{33} \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}$

and $= a_{13} \begin{vmatrix} a_{21} & a_{22} \\ a_{31} & a_{32} \end{vmatrix} - a_{12} \begin{vmatrix} a_{21} & a_{23} \\ a_{31} & a_{33} \end{vmatrix} + a_{11} \begin{vmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{vmatrix}$

crazy!!

example

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



So 3x3 det's are built out of 2x2's (3 of them)

In general $n \times n$'s involve $(n-1) \times (n-1)$ matrices (n of them)

each of these involve $(n-2) \times (n-2)$'s ... etc.

Linear Algebra

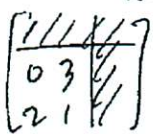
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Ch 5


Submatrices are called minors (defn) ~~matrices~~
~~or~~ minor matrices

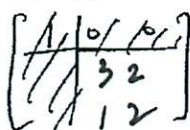
e.g. $A = \begin{bmatrix} 1 & \phi & \phi \\ 0 & 3 & 2 \\ 2 & 1 & 2 \end{bmatrix}$ has

a total of nine ^{minor} matrices $(3 \times 3)^{\uparrow}$ n^2 for an $n \times n$.

$M_{13} = \begin{bmatrix} 0 & 3 \\ 2 & 1 \end{bmatrix}$ 

Strike out row 1 & column 3

$M_{22} = \begin{bmatrix} 1 & \phi \\ 2 & 2 \end{bmatrix}$ 

$M_{11} = \begin{bmatrix} 3 & 2 \\ 1 & 2 \end{bmatrix}$ 

(defn) $\det(M_{ij})$ is ~~the~~ ^{called a} minor (A has $n \times n$ minors)

(defn) $C_{ij} = (-1)^{i+j} \det(M_{ij})$

These are Cofactors of A 

Theorem Determinant of A is given by the sum of A's cofactors ^{dot product with A's entries} along any one row or column.

e.g. summing along row 1
 $\det(A) = \sum_{j=1}^n (-1)^{1+j} \det(M_{1j}) a_{1j}$
~~down~~ ^{column} C_{1j} C_{12}

$\det(A) = \sum_{i=1}^n (-1)^{i+2} \det(M_{i2}) a_{i2}$

* explain why...

* ~~Show 2x2 works~~ ^{improve section on determinants}

Example: $A = \begin{bmatrix} 1 & \phi & \phi \\ 0 & 3 & 2 \\ 2 & 1 & 2 \end{bmatrix}$

$M_{11} = \begin{bmatrix} 3 & 2 \\ 1 & 2 \end{bmatrix} \Rightarrow C_{11} = (-1)^{1+1} \det(M_{11}) = (-1)^2 (3 \cdot 2 - 1 \cdot 2) = 4$
 $C_{12} = \dots$

Cofactor Matrix

$A_{\text{cofactor}} = \begin{bmatrix} 4 & 4 & -6 \\ -1 & 0 & 1 \\ -1 & -2 & 3 \end{bmatrix}$
 (C_{ij})

even better
 $A^{-1} = \frac{1}{\det A} C^T$
 adjoint of A
 water

$(a_{ij} C_{ij}) = \begin{bmatrix} 4 & 4 & -6 \\ 0 & 0 & 2 \\ -2 & -2 & 6 \end{bmatrix}$

$\det(A) = 2$

check sum of each row & column

* ^{general} show 2x2 works

explain why... (3)

Sneaky methods:

B/c of Theorem choose row or col with most 0's.

e.g.  $\det \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & -1 \\ 2 & 1 & 3 \end{bmatrix} = 7$

$\det \begin{bmatrix} 2 & 0 & 0 \\ 0 & 3 & 0 \\ -1 & 2 & 3 \end{bmatrix} = 2 \cdot 3 \cdot 3 = 18$
 or $3 \cdot 6 = 18$

show slow way

~~upper & lower triangular~~

for upper & lower triangular matrices, det is product of entries on leading diagonal

Cramer's Rule

determinants & $A\vec{x} = \vec{b}$
 \uparrow
 $n \times n$ only.

$$A \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} A\vec{x} & A \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \\ \vec{b} \end{bmatrix} \quad A \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

(do for 2nd & 3rd columns)

LHS

$$|A| \begin{vmatrix} x_1 & 0 & 0 \\ x_2 & 1 & 0 \\ x_3 & 0 & 1 \end{vmatrix} = |A| x_1$$

RHS

$$|B_1| = \begin{vmatrix} \vec{b} & \vec{a}_2 & \vec{a}_3 \end{vmatrix} \quad \leftarrow \text{Use col ops}$$

$$x_1 = \frac{|B_1|}{|A|}$$

Similarly $x_2 = \frac{|B_2|}{|A|}$, $x_3 = \frac{|B_3|}{|A|}$

A solution to $A\vec{x} = \vec{b}$ with a formula ~ no need to solve numerically!!

But finding determinants is horribly slow!!
 Utility \rightarrow theoretical.

$n \times n$

$$x_i = \frac{|B_i|}{|A|} \quad \leftarrow A \text{ with } i\text{th column replaced by } \vec{b}$$

\Rightarrow A formula for A^{-1} :

When $\vec{b}_i = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$ we find \vec{x}_i

Solve all these problems

$$\left. \begin{aligned} A\vec{x}_1 &= \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \\ A\vec{x}_2 &= \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \\ A\vec{x}_3 &= \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \end{aligned} \right\} A \begin{bmatrix} \vec{x}_1 & \vec{x}_2 & \vec{x}_3 \end{bmatrix} = I$$

$A^{-1} !!!$

Ch 5
5

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

\uparrow
prev. example

What are B_1, B_2, B_3 when $\vec{b} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$?

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 3 & 2 \\ 2 & 1 & 2 \end{bmatrix}, \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 2 \\ 2 & 0 & 2 \end{bmatrix}, \begin{bmatrix} 1 & 1 & 1 \\ 0 & 3 & 0 \\ 2 & 1 & 0 \end{bmatrix}$$

\uparrow c_{11} \uparrow c_{12} \uparrow c_{13}

$$\vec{x}_1 = \frac{1}{|A|} \begin{bmatrix} c_{11} \\ c_{12} \\ c_{13} \end{bmatrix}$$

$$\Rightarrow A^{-1} = \frac{1}{|A|} \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{bmatrix}$$

$$= \frac{1}{|A|} C^T \quad \text{incredible!}$$

exercise \rightarrow Show we get $n \times n$

$$A^{-1} = \frac{1}{2} \begin{bmatrix} 4 & -1 & -1 \\ 4 & 0 & -2 \\ -6 & 1 & 3 \end{bmatrix}$$

exercise \rightarrow check this works

LINEAR ALGEBRA

Back to eigenvalues & eigenvectors

$$|A\vec{v} = \lambda\vec{v}|$$

Again:

① solve $|A - \lambda I| = 0$ for λ 's values

② plug λ 's back into $(A - \lambda I)\vec{v} = \vec{0}$ to find eigenvectors

characteristic polynomial of A
 $n \times n$

find basis for nullspace of $(A - \lambda I)$

Today: Some sneaky tricks (another) and a glorious factorization of A .

we are good at doing this!

A small example

$$A = \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix} \rightarrow \lambda_1 = 3/2, \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\lambda_2 = 1/2, \vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

ST1: $\prod_{i=1}^n \lambda_i = |A|$

The determinant of A is equal to the product of its eigenvalues

\Rightarrow if $|A| = 0$, at least one eigenvalue is 0.

check $\lambda_1 \times \lambda_2 = 3/4$

$$|A| = 1 - \frac{1}{2} \cdot \frac{1}{2} = 3/4 \quad \checkmark$$

Why? ex: $|A - \lambda I| = (1 - \lambda)(1 - \lambda) - \frac{1}{4}$

$$= \left(\frac{3}{2} - \lambda\right) \left(\frac{1}{2} - \lambda\right)$$

equality true for all λ . so we can happily set $\lambda = 0$

$$|A - 0 \cdot I| = \frac{3}{2} \cdot \frac{1}{2}$$

$$= |A| = \lambda_1 \lambda_2$$

Make a table

In general

$$|A - \lambda I| = (\lambda_1 - \lambda)(\lambda_2 - \lambda)(\lambda_3 - \lambda) \dots (\lambda_n - \lambda)$$

Set $\lambda = 0$: $|A| = \prod_{i=1}^n \lambda_i$

Ch6
1

ST2: $\text{Tr}(A) = \sum_{i=1}^n \lambda_i$

Tr = "trace" = sum of the main diagonal elements

our example:

$$\text{Tr}(A) = 1 + 1 = 2$$

$$\lambda_1 + \lambda_2 = 3/2 + 1/2 = 2 \quad \text{oh boy!}$$

General 2×2 :

$$|A - \lambda I| = (\lambda_1 - \lambda)(\lambda_2 - \lambda)$$

$$\begin{vmatrix} a - \lambda & b \\ c & d - \lambda \end{vmatrix} = \lambda^2 - (\lambda_1 + \lambda_2)\lambda + \lambda_1 \lambda_2$$

$$\lambda^2 - (a + d)\lambda - bc =$$

use example know straight away

General $n \times n$ $|A - \lambda I| =$

$$(-\lambda)^n + (\text{Tr} A)(-\lambda)^{n-1} + \dots = (-\lambda)^n + (\sum \lambda_i)(-\lambda)^{n-1} + \dots$$

* So when finding eigenvalues always check $\text{Tr}(A) = \sum \lambda_i$ & $|A| = \prod \lambda_i$

(easy)

harder to calc but okay for 2×2 's, 3×3 's.

$$(-\lambda)^n + (\sum \lambda_i)(-\lambda)^{n-1} + \dots = |A - \lambda I|$$

$$(-\lambda)^2 + (\text{Tr} A)(-\lambda)^{n-1} + \dots$$

LINEAR ALGEBRA

ex. $A = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}$ $\lambda = 2$ has algebr. mult 1
 $\lambda = 3$ " " 2.

Another term:

Geometric Multiplicity λ is the dimension of the nullspace of $A - \lambda I$. OR, the # independent vectors corresponding to λ .

In above example

$\lambda_1 = 2 \Rightarrow \vec{v}_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$, $\lambda_2 = 3, \vec{v}_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
 $\vec{v}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$

$A = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix}$ $|A - \lambda I| = (1 - \lambda)^3 = 0$
 $\lambda = 1, 1, 1$

$(A - (1)I)\vec{v} \Rightarrow \vec{v} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ only.

$\lambda = 1$ has A.M. of 3 but G.M. of only 1

in sum, A is a very naughty matrix

add $(A - 1I)$ not big enough

just
 Let's pretend this didn't happen & focus on good matrices (ones with n e vectors)

Observation:

Diagonal matrices are highly appealing. They make us happy.

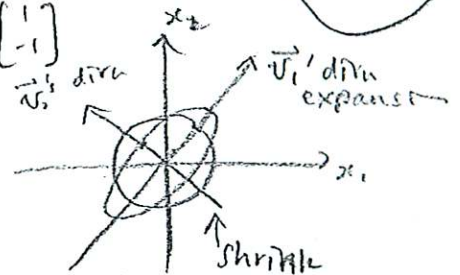
ex $A = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 4 \end{bmatrix}$ $A^n = \begin{bmatrix} 3^n & 0 & 0 \\ 0 & 2^n & 0 \\ 0 & 0 & 4^n \end{bmatrix}$ easy

$A\vec{x} = \begin{bmatrix} 3x_1 \\ 2x_2 \\ 4x_3 \end{bmatrix}$ $\lambda_1 = 3, \lambda_2 = 2, \lambda_3 = 4$
 $\vec{v}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \vec{v}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
 how A changes \vec{x} is simple.

Recall $A = \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix}$

$\lambda_1 = 3/2, \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$\lambda_2 = 1/2, \vec{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$



if we could rotate the axes, our A 's "action" would be simple. More generally - if we could change to our e vector basis, we would be pretty happy

Well, we can if A has n independent e vectors.

Let's Diagonalize A:

know $A\vec{v}_i = \lambda_i \vec{v}_i$ $i=1, \dots, n$.

create a new matrix with e vectors as columns

$S = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_n \\ | & | & & | \end{bmatrix}$

Consider

$AS = \begin{bmatrix} A\vec{v}_1 & A\vec{v}_2 & \dots & A\vec{v}_n \\ | & | & & | \end{bmatrix}$

$= \begin{bmatrix} \lambda_1 \vec{v}_1 & \lambda_2 \vec{v}_2 & \dots & \lambda_n \vec{v}_n \\ | & | & & | \end{bmatrix}$

$\left[S \begin{bmatrix} \lambda_1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad S \begin{bmatrix} 0 \\ \lambda_2 \\ 0 \\ 0 \end{bmatrix} \quad \dots \quad S \begin{bmatrix} 0 \\ 0 \\ 0 \\ \lambda_n \end{bmatrix} \right]$

sneaky observation

$= \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & & 0 \\ 0 & \lambda_2 & & 0 \\ & & \ddots & \\ 0 & & & \lambda_n \end{bmatrix}$

$= S \Lambda$

capital lambda lambda

Ch 6, 3

LINEAR ALGEBRA

We are assuming the vectors are independent so S^{-1} exists!

$$\Rightarrow \boxed{S^{-1}AS = \Lambda}$$

← similarity transform

↑
Special example of two matrices being similar

OR
$$\boxed{A = S\Lambda S^{-1}}$$

← fabulous factorization

How A works:

$$A\vec{x} = S\Lambda S^{-1}\vec{x}$$

changes back to natural basis
 ↑ simple modification b/c Λ is diagonal
 ← changes \vec{x} to A 's vector basis
 ↑ come back to this later

For $A = \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix}$

$$S = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

$$\Lambda = \begin{bmatrix} 3/2 & 0 \\ 0 & 1/2 \end{bmatrix}$$

$$S^{-1} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

So $A = S\Lambda S^{-1}$

$$\begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 3/2 & 0 \\ 0 & 1/2 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

more later
 notice $S^{-1} = S^T$
 $S = Q$

Example: $\vec{x} = \frac{2}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \frac{5}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} -3 \\ 7 \end{bmatrix}$

$$S^{-1} \frac{1}{\sqrt{2}} \begin{bmatrix} -3 \\ 7 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} -4 \\ 10 \end{bmatrix} = \begin{bmatrix} 2 \\ 5 \end{bmatrix} \leftarrow \vec{x} \text{ in vector basis!}$$

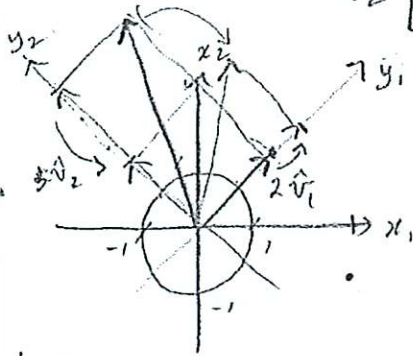
$\frac{1}{\sqrt{2}}$ too messy $\vec{x} = 2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + 5 \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 7 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$

$$\Lambda S^{-1} \frac{1}{\sqrt{2}} \begin{bmatrix} 7 \\ -3 \end{bmatrix} = \begin{bmatrix} 3 \\ 5/2 \end{bmatrix}$$

Ch 6, 4

Change basis back

$$S\Lambda S^{-1}\vec{x} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 3 \\ 5/2 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 11/2 \\ -1/2 \end{bmatrix}$$



← big clear picture on board.

For many calculations, diagonalization brings happiness.

$$A^2 = (S\Lambda S^{-1})(S\Lambda S^{-1})$$

$$= S\Lambda^2 S^{-1}$$

$$A^k = S\Lambda^k S^{-1}$$

1st

easy to calculate!

$$\Lambda^k = \begin{bmatrix} \lambda_1^k & & 0 \\ & \lambda_2^k & \\ 0 & & \ddots \\ & & & \lambda_n^k \end{bmatrix}$$

So $\begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix}^{523}$

$$= \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} (3/2)^{523} & 0 \\ 0 & (1/2)^{523} \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

→ large

$$= \left(\frac{3}{2}\right)^{523} \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

Bonus
 $A^0 = I$
 A^{-1} works too

Next up: use all this to find Fibonacci numbers

only if vectors are independent
 $\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$

gen f_n

LINEAR ALGEBRA

Rabbits:

Fibonacci: 1, 1, 2, 3, 5

see Wikipedia

known first writing: over 2000 years ago in India

patterns of speech and song

Fibonacci: 1200

(Crazy) model of rabbit breeding

$F_n = \#$ pairs of rabbits at time n (month n)

Rabbits can only breed after they reach 2 months of age (replacement)

So $F_n = F_{n-1} + F_{n-2}$
↑ not yet breeding ← replacement

1 pair begets 1 pair.

Population explosion:

Exponential...



spirals

= set (as before)

$\vec{f}_n = \begin{bmatrix} F_n \\ F_{n-1} \end{bmatrix}$

define

$f_1 = \begin{bmatrix} F_1 \\ F_0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

then $\vec{f}_n = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \vec{f}_{n-1}$ redo!

What is the n^{th} Fibonacci Number?

$= \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}^{n-1} f_1$ just set up

So we need to diagonalize $A = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$

values:

$0 = |A - \lambda I| = \begin{vmatrix} 1-\lambda & 1 \\ 1 & -\lambda \end{vmatrix} = -\lambda(1-\lambda) - 1 = \lambda^2 - \lambda - 1$

$\lambda = \frac{1 \pm \sqrt{5}}{2}$ set $\lambda_1 = \frac{1 + \sqrt{5}}{2} = \phi$ (golden ratio)

Note

$\lambda_1 + \lambda_2 = 1 = \text{Tr}(A)$

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

$\lambda_1 \lambda_2 = -1 = |A|$

LINEAR ALGEBRA

(We are nearing greatness...)

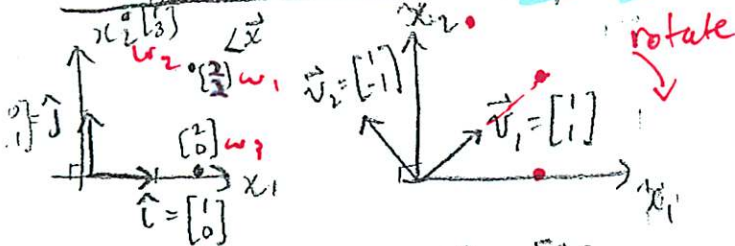
Some key points:

- A is diagonalizable only if A has n independent vectors
- if one or more λ 's = 0, A^{-1} does not exist (evaluates)
- A matrix with no inverse may or may not be diagonalizable (evaluates)
- And if A can be diagonalized it may have no inverse
- \mathcal{S} is always made up of eigenvectors.

Lecture 21

Today Move deeply
 Next steps: see diagonalization as a change of basis and see what happens for symmetric matrices.

Change of Basis (super important!)



$$\vec{w}_1 = \begin{bmatrix} 2 \\ 2 \end{bmatrix}, \vec{w}_2 = \begin{bmatrix} 1 \\ 3 \end{bmatrix}, \vec{w}_3 = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$$

↑ all in terms of our natural basis

$$\vec{w}_1 = 2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 2\hat{i} + 2\hat{j}$$

← we hardly ever think about this

How do we systematically find $\vec{w}_1, \vec{w}_2, \vec{w}_3$ in terms of \vec{v}_1, \vec{v}_2 new basis?

By solving on $A\vec{x} = \vec{b}$!! (Ch 6) problem... (sound of drooling)

$$\vec{w}_1 = \begin{bmatrix} 2 \\ 2 \end{bmatrix} = g_1 \vec{v}_1 + g_2 \vec{v}_2 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} g_1 \\ g_2 \end{bmatrix}$$

↑ column picture

$$= M \vec{w}'$$

↑ \vec{w}_1 in new basis

$$\Rightarrow \vec{w}'_1 = M^{-1} \vec{w}_1 \leftarrow \text{natural basis}$$

$$\vec{w}'_1 = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

↑ new basis

draw pictures

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

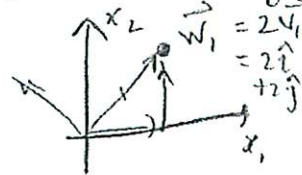
similarly

$$\vec{w}'_2 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \vec{w}'_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \checkmark \checkmark$$

To change back: $\vec{w} = M \vec{w}'$
 (Draw examples) ↑ natural basis (\hat{i}, \hat{j}) ↑ new basis

We say, In basis $\left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$
 \vec{w}_1 is represented as $\begin{bmatrix} 2 \\ 2 \end{bmatrix}$
 In basis $\left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\}$,
 \vec{w}_1 " " " $\begin{bmatrix} 2 \\ 0 \end{bmatrix}$

The point \vec{w}_1 never changes, just our representation changes



The big deal: We change basis to make action of A as simple as possible, then change back (e.g. diagonal)

$$A = S \Lambda S^{-1}$$

↑ change basis only M ↑ M^{-1} point

LINEAR ALGEBRA

already covered

vector basis
B super groovy

leave out

e.g. $A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$

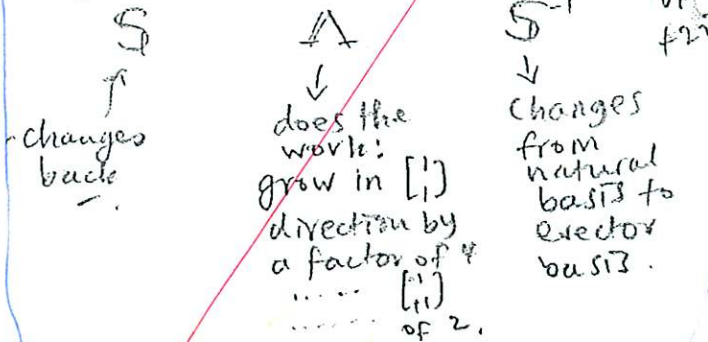
$\lambda_1 = 4, \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}; \lambda_2 = 2, \vec{v}_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

$A =$

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

draw picture

eg. $\vec{x} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$
 \vec{v}_1
 $\frac{1}{2}\vec{v}_2$



(We write M as $S^{-1}AS$ b/c vectors are so special)

So diagonalizing is joyous but we must have n indep. fun vectors (and our matrix must be square!).

Crazy significant result: Real Symmetric matrices ($A = A^T$) always have n independent eigenvectors (even if they have repeated values)

- Not only that but
- all values are real
 - the vectors form an orthogonal basis for \mathbb{R}^n
(we can then make it orthonormal)
Mindblowing...

(These astounding results will matter hugely for our friend $A\vec{x} = \vec{b}$...)



EX For $\begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$ we had real values $\in \mathbb{R}$ and \perp vectors $\begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

Proof of ①

Assume $A = A^T$ & A is real (all entries are real)

Take $A\vec{v} = \lambda\vec{v}$

we wonder if λ is real or complex

skip

top of board

Denote complex conjugate by over bar
 $a + bi = a - bi$ $i = \sqrt{-1}$

$A\vec{v} = \lambda\vec{v}$	$\overline{A\vec{v}} = \overline{\lambda\vec{v}}$
\downarrow transpose	\downarrow real
$\vec{v}^T A^T = \lambda \vec{v}^T$	$A \overline{\vec{v}} = \overline{\lambda} \overline{\vec{v}}$
\downarrow sym	\downarrow transpose
$\vec{v}^T A = \lambda \vec{v}^T$	$\overline{\vec{v}}^T A^T = \overline{\lambda} \overline{\vec{v}}^T$
	\downarrow symmetric
	$\overline{\vec{v}}^T A = \overline{\lambda} \overline{\vec{v}}^T$

now pre & post multiply by $\overline{\vec{v}}$ & \vec{v} respectively

$\overline{\vec{v}}^T A \vec{v} = \overline{\lambda} \overline{\vec{v}}^T \vec{v} \quad | \quad \vec{v}^T A \vec{v} = \lambda \vec{v}^T \vec{v}$

everything else matches so $\lambda = \overline{\lambda} \Rightarrow \lambda$ is real.

Proof of ②

Assume A is real and $A = A^T$
If A 's values are all different (algebraic multiplicity = 1)

if $A\vec{v}_1 = \lambda_1\vec{v}_1$ & $A\vec{v}_2 = \lambda_2\vec{v}_2$
we want to show $\vec{v}_1^T \vec{v}_2 = 0$

LINEAR ALGEBRA

More sneakiness

$$\vec{v}_1^T A \vec{v}_2$$

$$\vec{v}_1^T A \vec{v}_2 \Rightarrow \vec{v}_1^T (A \vec{v}_2) = \lambda_2 \vec{v}_1^T \vec{v}_2$$

$$(\vec{v}_1^T A) \vec{v}_2$$

$$(A^T \vec{v}_1)^T \vec{v}_2 = (\lambda_1 \vec{v}_1)^T \vec{v}_2 = \lambda_1 \vec{v}_1^T \vec{v}_2$$

symmetric

only equal if $\vec{v}_1^T \vec{v}_2 = 0$
since $\lambda_1 \neq \lambda_2$

phew...

Since vectors are orthogonal we now write Q , instead of S
And even more, $Q^{-1} = Q^T$ as we have seen before

So for real, symmetric matrices:

$$A = Q \Lambda Q^T \text{ always}$$

Spectral Theorem or principle axis theorem. $A = \sum_{i=1}^n \lambda_i \vec{v}_i \vec{v}_i^T$

Strang: The best matrices have orthogonal eigenvectors

For $A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$ choose $\vec{v}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$
& $\vec{v}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 1 \end{bmatrix}$

then

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

$Q \quad \Lambda \quad Q$

$$+ A = 4 \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \end{bmatrix} + 2 \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 1 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \end{bmatrix} \quad !!!$$

+

Recall

Diagonalization fails when there are not enough eigenvectors

This can only happen when an eigenvalue is repeated. e.g. $(A - \lambda I) = (\lambda - 3)(\lambda - 3) \lambda$

e.g. $\lambda = 3$ has algebraic multiplicity 1

defn

geometric multiplicity of $\lambda = \#$ indep eigenvectors associated w. $\lambda = \dim N(A - \lambda I)$

[Must have a.m. = g.m. for all eigenvalues for diag to be possible]

Final observation:

(All symmetric matrices have) n orthogonal eigenvectors even if eigenvalues are repeated. very happy matrices

Reason: We know that if all eigenvalues are different, & if $A = A^T$, eigenvectors are orthogonal.

So take problem matrices and tweak them so their eigenvalues separate.

e.g.

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

$$\lambda_1 = \lambda_2 = 1$$

one eigenvector $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$

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

$$\lambda_1 = \lambda_2 = 1$$

$\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

general truth.

LINEAR ALGEBRA

"Tweaks"

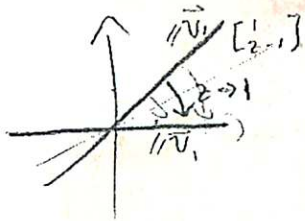
$$A = \begin{bmatrix} 1 & 1 \\ 0 & z \end{bmatrix}$$

$$\lambda_1 = 1, \lambda_2 = z$$

$$\vec{v}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 1 \\ z-1 \end{bmatrix}$$

as $z \rightarrow 1$,
eigenvalues become
the same and
eigenvectors collapse

Really: eigenspace
collapses

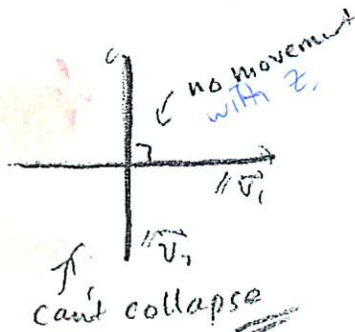


$$A = \begin{bmatrix} 1 & 0 \\ 0 & z \end{bmatrix}$$

$$\lambda_1 = 1, \lambda_2 = z$$

$$\vec{v}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

eigenvectors
remain
independent
as they are
orthogonal
 $\forall z \neq 1$



Exam 3

① $A = \mathbb{R} \text{ or } \mathbb{C}$ (4-4)
Gram-Schmidt
Process
orthogonal base

② Eigenthings
6-1, 6-2, 6-4, 7-3

③ Determinants
5-1, 5-2, 5-3

Spectral theorem
for symmetric
matrices

rotational
matrices?
 λ complex.

Trace stuff...

$$A = Q \Lambda Q^T$$

$$= \begin{bmatrix} \hat{v}_1 & \hat{v}_2 & \dots & \hat{v}_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & & 0 \\ & \ddots & & \\ & & \lambda_n & \\ 0 & & & 0 \end{bmatrix} \begin{bmatrix} -\hat{v}_1^T \\ -\hat{v}_2^T \\ \dots \\ -\hat{v}_n^T \end{bmatrix}$$

$$= \begin{bmatrix} \hat{v}_1 & \hat{v}_2 & \dots & \hat{v}_n \end{bmatrix} \begin{bmatrix} \lambda_1 \hat{v}_1^T \\ \lambda_2 \hat{v}_2^T \\ \dots \\ \lambda_n \hat{v}_n^T \end{bmatrix} \sim \text{big dot product}$$

$$= \lambda_1 \hat{v}_1 \hat{v}_1^T + \lambda_2 \hat{v}_2 \hat{v}_2^T + \dots + \lambda_n \hat{v}_n \hat{v}_n^T$$

projection operators

$A \vec{x}$
 \rightarrow if $A = A^T$, $A \vec{x}$ is very special!