

# Eigenvalue background (ch 6.4 and ch 9.1-9.2)

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## Determinants (see ch 6.4)

The determinant of a <sup>square</sup> linear transformation  $\vec{x} \mapsto A \cdot \vec{x}$ , denoted  $\det(A)$  or  $|A|$ , measures how the transformation changes area/volume, so is used in change-of-variables for integration.



$|A|$  can be negative, don't let the notation confuse you.

It's not absolute value.

A is invertible iff  $\det(A) \neq 0$

Misc. Facts: let  $A \in \mathbb{R}^n$  w/ eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$

duplicates OK

$$\det(c \cdot A) = c^n \det(A)$$

$$\det(A \cdot B) = \det(A) \cdot \det(B)$$

$$\det(A+B) \neq \det(A) + \det(B)$$

in general

$$\det(A^{-1}) = 1/\det(A)$$

$$\det(A^T) = \det(A)$$

if A is upper or lower triangular (or diagonal)

$$\text{then } \det(A) = a_{11} \cdot a_{22} \cdot a_3 \cdots a_{nn} = \prod_{i=1}^n a_{ii}$$

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

$$\dots \text{and } \text{trace}(A) := \sum_{i=1}^n a_{ii} \text{ is equal to } \sum_{i=1}^n \lambda_i$$

## Computing the determinant

Method 1: cofactor expansion

define  $M_{i,j} = \det(\text{A with row } i, \text{ col. } j \text{ removed})$   
"minor"

$$\text{then } \det(A) = \sum_{j=1}^n a_{i,j} \cdot (-1)^{i+j} M_{i,j} \quad \text{Recursive!}$$

for any row  $i$  you want

and if  $A \in \mathbb{R}^{1 \times 1}$ ,  $\det(A) = a_{1,1}$  [or, use  $\det(A) = \det(A^T) \dots$ ]

Cost: let  $T = \text{time to compute } \det(A) \text{ for a } n \times n \text{ matrix}$

$$T(n) = n \cdot T(n-1)$$

$$= n \cdot (n-1) \cdot T(n-2)$$

So  $O(n!)$  time.

= ...

= constant  $\cdot n!$

i.e. NOT RECOMMENDED!

Method 2

Gaussian-elimination / LU Let  $A = P^T \cdot L \cdot U$

$$\text{so } \det(A) = \det(P^T L U)$$

$$= \underbrace{\det(P)}_{\substack{\det \text{ is } \pm 1 \\ \text{depending on} \\ \text{exact permutations}}} \cdot \underbrace{\det(L)}_{\text{triangular}} \cdot \underbrace{\det(U)}_{\text{the product of the diagonals}}$$

(every row or column swap flips sign of determinant)

Overall cost is dominated by cost of the LU factorization:  $O(n^3)$   
MUCH BETTER

Eigenvalues

... of a square matrix  $A$ ,  $n \times n$  (allow  $A \in \mathbb{C}^{n \times n}$ )

Def  $\lambda \in \mathbb{C}$  is an eigenvalue of  $A$  if  $\exists \vec{x} \in \mathbb{C}^n$ ,  $\vec{x} \neq \vec{0}$ , s.t.

$$A \cdot \vec{x} = \lambda \cdot \vec{x} \quad \vec{x} \text{ is the eigenvector.}$$



We exclude  $\vec{x} = \vec{0}$  since  $A \cdot \vec{0} = \lambda \cdot \vec{0}$  is always true.  
we do allow  $\lambda = 0$ .

There's never a single unique eigenvector since if  $\vec{x}$  is an eigenvector,  
so is  $c \cdot \vec{x}$  for any  $c \neq 0$ . So instead we speak of  
an eigenspace of  $\lambda$ : the subspace of  $\mathbb{C}^n$  of all  
eigenvectors for  $\lambda$  (and also include  $\vec{0}$ ).

How to find eigenvalues/vectors?

$$A \vec{x} = \lambda \vec{x} \iff (A - \lambda I) \cdot \vec{x} = 0 \iff A - \lambda I \text{ is singular} \quad (\text{else } \vec{x} = \vec{0} \text{ is only sol'n})$$

$$\iff \underbrace{\det(A - \lambda I)}_{P_A(\lambda)} = 0 \quad \text{"characteristic polynomial"}$$

... so, find a root of  $P_A$

$\iff \lambda$  is a root of  $P_A(\lambda)$

(which is a  $n$ -dimensional polynomial,  
so has exactly  $n$  (possibly complex) roots if  
you count w/ multiplicity)

OK, so we compute  $P_A(\lambda) = \det(A - \lambda I)$

... how?

In linear algebra 101, you do this by hand w,

(1a) cofactor expansion ... so  $O(n!)$ . BAD

Also, what to do about  $\lambda$  indeterminate

### (1b) Faddeev-Leverrier Expansion

Formula to compute coefficients of  $P_A$ ,

but involves  $\text{tr}(A^k)$  for  $k=1, 2, \dots, n$

i.e.  $n$  matrix-matrix multiplies, each costs  $O(n^3)$

so  $O(n^4)$  time ... and also not stable either!

(2) or, rather than find the polynomial in closed form, evaluate  $\det(A - \lambda I)$ , for a given estimate of  $\lambda$ , using LU, and do a generic root-finding method to estimate  $\lambda$ .

This costs  $O(n^3)$  every step

and it's not numerically stable.

It would also only give you a single eigenvalue, not all of them.

So hopefully you're convinced that finding eigenvalues isn't trivial.

See related demo

Ch 9 - Eigenvalues The Bad Way.ipynb

## More background

Def: multiplicities. Let  $A \in \mathbb{C}^{n \times n}$  (or  $\mathbb{R}^{n \times n}$ ) and  $\lambda_k \in \mathbb{C}$  an eigenvalue

The algebraic multiplicity of  $\lambda_k$  is the degree of the root  $\lambda_k$  in  $P_A$ ,

i.e. alg. mult. is 3 means  $P_A(\lambda) = (\lambda - \lambda_k)^3 \cdot g(\lambda)$  and  $g(\lambda_k) \neq 0$

$$\text{ex: } P_A(\lambda) = (\lambda - 4)^2(\lambda + 5)$$

$\lambda = 4$  has alg. mult. 2,  $\lambda = -5$  has alg. mult. 1

The eigenspace  $E_k = \text{Null}(A - \lambda_k I)$

The geometric multiplicity of  $\lambda_k$  is  $\dim(E_k)$ .

FACTS:  $1 \leq \text{geometric mult.} \leq \text{algebraic mult.} \leq n$

The matrix is diagonalizable iff all geometric mult. = algebraic mult.

Sufficient conditions:  $A = A^T$ , or, all eigenvalues simple (i.e. alg. mult. = 1)

Def Similarity If  $A, B \in \mathbb{C}^{n \times n}$ , they're similar, written  $A \sim B$ , if

$\exists$  nonsingular  $P \in \mathbb{C}^{n \times n}$  s.t.  $B = P^{-1}AP$

Proposition If  $A \sim B$  then 1)  $P_A(\lambda) = P_B(\lambda)$

2)  $\text{tr}(A) = \text{tr}(B)$ ,  $\det(A) = \det(B)$

3)  $A$  and  $B$  have the same eigenvalues

## Thm Schur Normal Form

If  $A \in \mathbb{C}^{n \times n}$ ,  $\exists$  a unitary matrix  $U \in \mathbb{C}^{n \times n}$  and upper triangular matrix  $T$

$$\begin{array}{l} i) U^{-1} = U^* \\ ii) U^* := \overline{U}^T \end{array} \quad \text{s.t. } T = U^* A U$$

hence  $A = U T U^*$  and  $A \sim T$

## Thm Spectral Theorem, ver 1

If  $A \in \mathbb{C}^{n \times n}$  is Hermitian (i.e.  $A = A^*$ , or,  $A \in \mathbb{R}^{n \times n}$  and  $A = A^T$ )

then  $\exists$  diagonal  $D$ , unitary  $U$ , and  $d_{kk} \in \mathbb{R}$  for  $k=1, \dots, n$

s.t.  $D = U^* A U$  i.e.  $A = U D U^*$  i.e.  $A \cdot U = D \cdot U$  i.e.  $A \vec{u}_k = d_{kk} \vec{u}_k$

i.e. columns of  $U$  are eigenvectors, eigenvalues are  $d_{kk}$  and eigenvalues are real

## Version 2

$A$  need not be Hermitian but it's "normal",  $A A^* = A^* A$ .

Same as version 1 but  $d_{kk} \in \mathbb{C}$  is possible

of ver. 1  
Proof Use Schur form:  
 $A = U T U^*$   $\Rightarrow T = T^*$  triangular  
 $A^* = U T^* U^*$  So  $T$  is diagonal

## Gershgorin Circle (or Disc) Theorem 1931

Optional

Let  $A \in \mathbb{C}^{n \times n}$ ,  $A = [a_{ij}]$

define radii  $r_i = \sum_{j \neq i} |a_{ij}|$

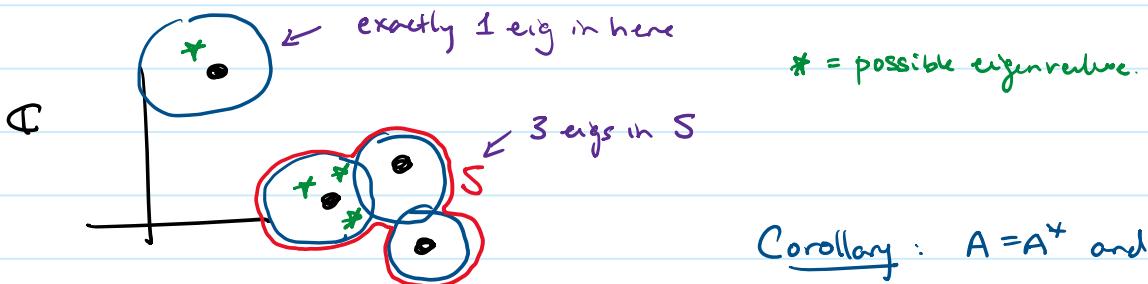
and discs  $D_i = \{z \in \mathbb{C} : |z - a_{ii}| \leq r_i\}$

Thm

(1) All eigenvalues  $\lambda$  of  $A$  lie inside  $D = \bigcup_{i=1}^n D_i$

(2) [refined estimate] If  $m$  discs form a connected set  $S$ , disjoint from other discs,  $S$  contains  $m$  eigenvalues (counted with multiplicity)

(3)  $\lambda(A) = \lambda(A^T)$  so you can apply to rows or columns



Corollary:  $A = A^T$  and  
Strictly diagonally dominant  
(i.e.,  $a_{ii} - r_i > 0$ )  
then it's positive definite.