

# Math 381 - Fall 2021

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Week 11

# Last Time

- 1 Low rank approximations
- 2 Gaussian elimination with complete pivoting

# Today

## ① Eigenvalue problems

# Eigenvalue problems

$$Ar = \lambda r$$
$$\ell^t A = \lambda \ell^t$$

complex conjugate and transpose

## Eigenvalues and eigenvectors

For square matrices  $A$ , an eigenvalue  $\lambda$  and eigenvector  $v$  satisfy

$$Av = \lambda v.$$

## Characteristic equation

Eigenvalues of  $A$  are the roots of the characteristic polynomial; that is, they satisfy

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

$$\begin{array}{l|l} z = x + iy & \bar{z} = x - iy \\ z = re^{i\theta} & \bar{z} = re^{-i\theta} \end{array}$$

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$$z = r(\cos(\theta) + i\sin(\theta))$$

# Conditioning of the eigenvalue problem (simple eigenvalues)

$$(A + \delta A)r = \lambda r. \quad A_0 = A, \quad \epsilon \lambda_1 = \delta A$$

Rewrite as  $(A_0 + \epsilon A_1)r = \lambda r$  for  $0 < \epsilon \ll 1$ .

Will show that  $\lambda \sim \lambda_0 + \epsilon \frac{l_0^* A_1 r_0}{l_0^* r_0}$ .

Let  $\lambda \sim \lambda_0 + \epsilon \lambda_1$  and  $r \sim r_0 + \epsilon r_1$ . want to know

$$(\underbrace{A_0}_{\text{known}} + \epsilon \underbrace{A_1}_{\text{known}})(\underbrace{r_0}_{\text{known}} + \epsilon \underbrace{r_1}_{\text{known}}) = (\underbrace{\lambda_0}_{\text{known}} + \epsilon \underbrace{\lambda_1}_{\text{known}})(\underbrace{r_0}_{\text{known}} + \epsilon \underbrace{r_1}_{\text{known}})$$

unperturbed

$$O(1): A_0 r_0 = \lambda_0 r_0$$

$$O(\epsilon): \cancel{A_0 r_0} + \epsilon A_0 r_1 + \epsilon A_1 r_0 = \cancel{\lambda_0 r_0} + \epsilon \lambda_0 r_1 + \epsilon \lambda_1 r_0 \quad l^* A_0 = \lambda_0 l^*$$

$$\Rightarrow A_0 r_1 + A_1 r_0 = \lambda_0 r_1 + \lambda_1 r_0$$

$$\Rightarrow [A_0 - \lambda_0 I] r_1 = -[A_1 - \lambda_1 I] r_0$$

Need "solvability condition" for  $\lambda_1$

Fredholm Alternative

$$l_0^* [A_0 - \lambda_0 I] = 0$$

$$\Rightarrow l_0^* [A_1 - \lambda_1 I] r_0 = 0$$

## Conditioning of the eigenvalue problem (continued)

$$\ell_0^* [A_1 - \lambda_1 I] r_0 = 0 \Rightarrow \ell_0^* A_1 r_0 - \lambda_1 \ell_0^* r_0 = 0$$

$$\Rightarrow \lambda_1 = \frac{\ell_0^* A_1 r_0}{\ell_0^* r_0}$$

Assume  
 $\|\ell_0\| = \|r_0\| = 1$

↑  
Condition number of eigenvalue  
 $\kappa(\lambda)$

# Conditioning of the eigenvalue problem (simple eigenvalues)

Let  $\lambda_0$  be a simple eigenvalue of the matrix  $A_0$ . Consider

$$(A_0 + \epsilon A_1)r = \lambda, \quad 0 < \epsilon \ll 1.$$

Assuming that  $\|r_0\| = \|l_0\| = 1$  we have

$$|\lambda - \lambda_0| \leq \frac{\epsilon \|A_1\|}{|l_0^* r_0|}.$$

## Condition number of an eigenvalue

Let  $r$  and  $l$  be a right and left eigenvector of  $A$  (respectively) corresponding to the simple eigenvalue  $\lambda$ . The condition number of  $\lambda$  is

$$\kappa(\lambda) = \frac{\|r\| \|l\|}{|l^* r|}.$$

# Why don't we simply solve for the roots of the characteristic polynomial?

## Example

$$\lambda^2 - 2\lambda + 1 - \epsilon = 0$$

## Example

$$\lambda^2 - 2\lambda + 1 + \epsilon = 0$$

unperturbed

$$\lambda^2 - 2\lambda + 1 = (\lambda - 1)^2$$

$$\lambda = 1$$

$$\lambda \approx 1 \pm \sqrt{\epsilon}$$

$$\lambda \approx 1 \pm i\sqrt{\epsilon}$$

Previous examples we have seen  
(big number)  $\epsilon$  of ill-conditional problems





### III conditioned eigenvalue problems: eigenvalues with degenerate eigenspaces are ill conditioned

Example:  $A = \begin{bmatrix} 1 & 1 \\ \epsilon & 1 \end{bmatrix}$

Unperturbed problem

$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \quad \lambda = 1$$

$$r = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Finish Friday

# General eigenvalue solvers must be iterative

## Theorem: Abel 1824

For any  $n \geq 5$ , there is a polynomial  $p(z)$  of degree  $n$  with rational coefficients that has a real root  $p(r) = 0$  with the property that  $r$  cannot be written using any expression involving rational numbers, addition, subtraction, multiplication, division, and  $k$ th roots.

# Daily Linear Algebra

## Definition: similar matrix

A matrix  $A \in \mathbb{C}^{n \times n}$  is *similar* to a matrix  $B \in \mathbb{C}^{n \times n}$  if there exists a nonsingular  $S \in \mathbb{C}^{n \times n}$  such that

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

# Daily Linear Algebra

## Claim:

If  $A \in \mathbb{C}^{n \times n}$  and  $B \in \mathbb{C}^{n \times n}$  are similar, then they have the same eigenvalues.

Proof:

# Eigenvalue revealing decompositions

- ➊ Diagonalization  $A = X\Lambda X^{-1}$  (only if the matrix is diagonalizable)
- ➋ Unitary diagonalization  $A = Q\Lambda Q^*$  (only normal matrices  $A^T A = A A^T$ )
- ➌ Schur factorization  $A = QTQ^*$  (all square matrices)

## Theorem: Schur factorization

Every Square matrix  $A$  has a Schur factorization such that

$$A = QRQ^*$$

where  $Q$  is unitary and  $R$  is upper triangular.

Proof: (time permitting)