

# Math 381 - Fall 2022

Jay Newby

University of Alberta

Week 11

# Last Week

- ① Backward error analysis
- ② Conditioning of least squares problem
- ③ Backward stability of least squares algorithms
- ④ Low rank approximations
- ⑤ Gaussian elimination with complete pivoting

# This Week

## ① Eigenvalue solvers

# Eigenvalue problems

## 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

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

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

$$A^* = \bar{A}^T \quad \text{Transpose and complex conjugate of each element}$$

# Conditioning of the eigenvalue problem (simple eigenvalues)

$$(A + \delta A)r = \lambda r.$$

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

Will show that  $\lambda \approx \lambda_0 + \epsilon \frac{l_0^* A_1 r_0}{l_0^* r_0} \Rightarrow |\lambda - \lambda_0| \leq \left| \frac{l_0^* A_1 r_0}{l_0^* r_0} \right| \epsilon$

$$r \approx r_0 + \epsilon r_1, \quad \lambda \approx \lambda_0 + \epsilon \lambda_1 \quad \text{unknowns}$$

$$(A_0 + \epsilon A_1)(r_0 + \epsilon r_1) = (\lambda_0 + \epsilon \lambda_1)(r_0 + \epsilon r_1)$$

$$O(1): (\epsilon=0) \quad A_0 r_0 = \lambda_0 r_0 \quad \text{Assume we know } r_0, \lambda_0$$

$$\begin{aligned} O(\epsilon): & \begin{aligned} & \text{i) expand} \\ & \text{ii) keep terms like } \epsilon \\ & \text{iii) ignore terms like } \epsilon^2 \end{aligned} & \begin{aligned} & \cancel{A_0} r_0 + \epsilon A_1 r_0 + \epsilon A_0 r_1 + \cancel{\epsilon^2 A_1 r_1} = \lambda_0 \cancel{r_0} + \epsilon \lambda_1 r_0 + \epsilon \lambda_0 r_1 + \cancel{\epsilon^2 \lambda_1 r_1} \\ & \Rightarrow A_1 r_0 + A_0 r_1 = \lambda_1 r_0 + \lambda_0 r_1 \\ & \Rightarrow A_0 r_1 - \lambda_0 r_1 = -A_1 r_0 + \lambda_1 r_0 \\ & \Rightarrow [A_0 - \lambda_0 I] r_1 = -A_1 r_0 + \lambda_1 r_0 \end{aligned} \end{aligned}$$

## Conditioning of the eigenvalue problem (continued)

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

solution  $r_0$  exists?

Fredholm Alternative Theorem

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

require

$$l_0^* (-A_1 r_0 + \lambda_1 r_0) = 0$$

$$\Rightarrow -l_0^* A_1 r_0 + \lambda_1 l_0^* r_0 = 0$$

$$\lambda_1 = \frac{l_0^* A_1 r_0}{l_0^* r_0}$$

$$\lambda \sim \lambda_0 + \frac{l_0^* A_1 r_0}{l_0^* r_0} \epsilon$$

Assume

$$\|l_0\| = \|r_0\| = 1$$

# 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

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

$$\lambda \sim 1 + \lambda \epsilon^\alpha$$

$$(1 + \lambda \epsilon^\alpha)^2 - 2(1 + \lambda \epsilon^\alpha) + 1 - \epsilon = 0$$

$$1 + 2\lambda \epsilon^\alpha + \lambda^2 \epsilon^{2\alpha} - 2 - 2\lambda \epsilon^\alpha + 1 - \epsilon = 0$$

$$\alpha = 1$$

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

$$-\epsilon = 0$$

can't solve  
:-)

$$\alpha = 1/2$$

$$2\lambda \epsilon^{1/2} + \lambda^2 \epsilon - 2\lambda \epsilon^{1/2} - \epsilon = 0$$

$$\lambda^2 - 1 = 0 \Rightarrow \lambda = \pm 1$$

unperturbed problem

$$(\lambda - 1)^2 = 0$$

$$\lambda = 1$$

repeated root

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

Bad :-)

$$(\sqrt{\epsilon})' = \frac{1}{2\sqrt{\epsilon}}$$



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

$$\epsilon \lambda^2 + b\lambda + c = 0$$

singular perturbation

$$\left. \frac{d\lambda}{d\epsilon} \right|_{\epsilon \rightarrow 0} = \infty$$



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

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

$$[A - \lambda I]^2 z = r$$

# 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

- 1 Diagonalization  $A = X\Lambda X^{-1}$  (only if the matrix is diagonalizable)
- 2 Unitary diagonalization  $A = Q\Lambda Q^*$  (only normal matrices  
 $A^T A = A A^T$ )
- 3 Schur factorization  $A = \overbrace{Q\Lambda Q^*}^{Q\Lambda Q^*}$  (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)