

# AMS526: Numerical Analysis I (Numerical Linear Algebra)

## Lecture 16: Linear Algebra Software; Overview of Eigenvalue Problems

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# Outline

1 Software for Linear Algebra

2 Eigenvalue Problems

# Software for Linear Algebra

- LAPACK: Linear Algebra PACKage ([www.netlib.org/lapack/lug](http://www.netlib.org/lapack/lug))
  - ▶ Standard library for solving linear systems and eigenvalue problems
  - ▶ Successor of LINPACK ([www.netlib.org/linpack](http://www.netlib.org/linpack)) and EISPACK ([www.netlib.org/eispack](http://www.netlib.org/eispack))
  - ▶ Depends on BLAS (Basic Linear Algebra Subprograms)
  - ▶ Parallel extensions include ScaLAPACK and PLAPACK
  - ▶ Note: Uses Fortran conventions for matrix arrangements
- MATLAB
  - ▶ Factorization  $\mathbf{A}$ :  $\text{lu}(\mathbf{A})$  and  $\text{chol}(\mathbf{A})$
  - ▶ Solve  $\mathbf{Ax} = \mathbf{b}$ :  $x = \mathbf{A} \setminus \mathbf{b}$ 
    - ★ Uses back/forward substitution for triangular matrices
    - ★ Uses Cholesky factorization for positive-definite matrices
    - ★ Uses LU factorization with column pivoting for nonsymmetric matrices
    - ★ Uses Householder QR for least squares problems
    - ★ Uses some special routines for matrices with special sparsity patterns
  - ▶ Uses LAPACK and other packages internally
- Serial and parallel solvers for sparse matrices (e.g., SuperLU, TAUCS)

## Some Commonly Used Functions

Example BLAS routines: Matrix-vector multip.: dgemv; Matrix-matrix multip: dgemm

	LU Factorization		Solve linear system		Est. cond
	General	Symmetric	General	Symmetric	
LAPACK	dgetrf	dpotrf/dsytrf	<b>dgesv</b>	<b>dposv/dposvx</b>	dgecon
LINPACK	dgefa	dpofa/dsifa	dgesl	dposl/dsisl	dgeco
MATLAB	lu	chol	\	\	rcond

	Linear least squares			Eigenvalue/vector		SVD
	QR	Solve	Rank-deficient	General	Sym.	
LAPACK	dgeqrf	<b>dgels</b>	<b>dgelsy/s/d</b>	<b>dgeev</b>	<b>dsyev</b>	<b>dgesvd</b>
LINPACK	dqrdc	dqrsl	dqrst	-	-	dsvdc
MATLAB	qr	\	\	eig	eig	svd

For BLAS, LINPACK, and LAPACK, first letter s stands for single-precision real, d for double-precision real, c for single-precision complex, and z for double-precision complex. Boldface LAPACK routines are **driver** routines; others are **computational** routines.

# Using LAPACK Routines in C Programs

- LAPACK was written in Fortran 77. Special attention is required when calling from C.
- Key differences between C and Fortran
  - ① Storage of matrices: column major (Fortran) versus row major (C/C++)
  - ② Argument passing for subroutines in C and Fortran: pass by reference (Fortran) and pass by value (C/C++)
- Simple example C code, `example.c`, for solving linear system using `sgesv`.
  - ▶ See class website for sample code.
  - ▶ To compile, issue command `cc -o example example.c -llapack -lblas`
- Hint: To find a function name, refer to LAPACK Users' Guide.
- To find out arguments for a given function, search on [netlib.org](http://netlib.org)

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# Eigenvalue Decomposition

- *Eigenvalue problem* of  $m \times m$  matrix  $\mathbf{A}$  is

$$\mathbf{Ax} = \lambda \mathbf{x}$$

with eigenvalues  $\lambda$  and eigenvectors  $\mathbf{x}$  (nonzero)

- *Eigenvalue decomposition* of  $\mathbf{A}$  is

$$\mathbf{A} = \mathbf{X}\mathbf{\Lambda}\mathbf{X}^{-1} \text{ or } \mathbf{AX} = \mathbf{X}\mathbf{\Lambda}$$

with eigenvectors as columns of  $\mathbf{X}$  and eigenvalues along diagonal of  $\mathbf{\Lambda}$

- Eigenvalue decomposition is change of basis to “eigenvector coordinates”

$$\mathbf{Ax} = \mathbf{b} \rightarrow (\mathbf{X}^{-1}\mathbf{b}) = \mathbf{\Lambda}(\mathbf{X}^{-1}\mathbf{x})$$

- Question: How does eigenvalue decomposition differ from SVD?

# Multiplicity

- Eigenvectors corresponding to a single eigenvalue  $\lambda$  form an *eigenspace*  $E_\lambda \subseteq \mathbb{C}^{m \times m}$
- *Geometric multiplicity* of  $\lambda$  is dimension of  $E_\lambda$ , i.e.,  $\dim(\text{null}(\mathbf{A} - \lambda\mathbf{I}))$
- The *characteristic polynomial* of  $\mathbf{A}$  is

$$p_{\mathbf{A}}(z) = \det(z\mathbf{I} - \mathbf{A}) = (z - \lambda_1)(z - \lambda_2) \cdots (z - \lambda_m)$$

- $\lambda$  is eigenvalue of  $\mathbf{A}$  iff  $p_{\mathbf{A}}(\lambda) = 0$ 
  - ▶ If  $\lambda$  is eigenvalue, then by definition,  $\lambda\mathbf{x} - \mathbf{A}\mathbf{x} = (\lambda\mathbf{I} - \mathbf{A})\mathbf{x} = 0$ , so  $(\lambda\mathbf{I} - \mathbf{A})$  is singular and its determinant is 0
  - ▶ If  $(\lambda\mathbf{I} - \mathbf{A})$  is singular, then for  $\mathbf{x} \in \text{null}(\lambda\mathbf{I} - \mathbf{A})$  we have  $\lambda\mathbf{x} - \mathbf{A}\mathbf{x} = 0$
- *Algebraic multiplicity* of  $\lambda$  is its multiplicity as a root of  $p_{\mathbf{A}}$
- Any matrix  $\mathbf{A}$  has  $m$  eigenvalues, counted with algebraic multiplicity
- Question: What are the eigenvalues of a triangular matrix?

# Similarity Transformations

- The map  $\mathbf{A} \rightarrow \mathbf{Y}^{-1}\mathbf{A}\mathbf{Y}$  is a *similarity transformation* of  $\mathbf{A}$  for any nonsingular  $\mathbf{Y} \in \mathbb{C}^{m \times m}$
- $\mathbf{A}$  and  $\mathbf{B}$  are *similar* if there is a similarity transformation  $\mathbf{B} = \mathbf{Y}^{-1}\mathbf{A}\mathbf{Y}$

## Theorem

If  $\mathbf{Y}$  is nonsingular, then  $\mathbf{A}$  and  $\mathbf{Y}^{-1}\mathbf{A}\mathbf{Y}$  have the same characteristic polynomials, eigenvalues, and algebraic and geometric multiplicities.

- 1 For characteristic polynomial:

$$\det(z\mathbf{I} - \mathbf{Y}^{-1}\mathbf{A}\mathbf{Y}) = \det(\mathbf{Y}^{-1}(z\mathbf{I} - \mathbf{A})\mathbf{Y}) = \det(z\mathbf{I} - \mathbf{A})$$

so algebraic multiplicities remain the same

- 2 If  $\mathbf{x} \in E_\lambda$  for  $\mathbf{A}$ , then  $\mathbf{Y}^{-1}\mathbf{x}$  is in eigenspace of  $\mathbf{Y}^{-1}\mathbf{A}\mathbf{Y}$  corresponding to  $\lambda$ , and vice versa, so geometric multiplicities remain the same

## Algebraic Multiplicity $\geq$ Geometric Multiplicity

- Let  $n$  be the geometric multiplicity of  $\lambda$  for  $\mathbf{A}$ . Let  $\hat{\mathbf{V}} \in \mathbb{C}^{m \times n}$  constitute an orthonormal basis of the  $E_\lambda$
- Extend  $\hat{\mathbf{V}}$  to a unitary  $\mathbf{V} \equiv [\hat{\mathbf{V}}, \tilde{\mathbf{V}}] \in \mathbb{C}^{m \times m}$  and form

$$\mathbf{B} = \mathbf{V}^* \mathbf{A} \mathbf{V} = \begin{bmatrix} \hat{\mathbf{V}}^* \mathbf{A} \hat{\mathbf{V}} & \hat{\mathbf{V}}^* \mathbf{A} \tilde{\mathbf{V}} \\ \tilde{\mathbf{V}}^* \mathbf{A} \hat{\mathbf{V}} & \tilde{\mathbf{V}}^* \mathbf{A} \tilde{\mathbf{V}} \end{bmatrix} = \begin{bmatrix} \lambda \mathbf{I} & \mathbf{C} \\ \mathbf{0} & \mathbf{D} \end{bmatrix}$$

- $\det(z\mathbf{I} - \mathbf{B}) = \det(z\mathbf{I} - \lambda\mathbf{I})\det(z\mathbf{I} - \lambda\mathbf{D}) = (z - \lambda)^n \det(z\mathbf{I} - \lambda\mathbf{D})$ , so the algebraic multiplicity of  $\lambda$  as an eigenvalue of  $\mathbf{B}$  is  $\geq n$
- $\mathbf{A}$  and  $\mathbf{B}$  are similar, so the algebraic multiplicity of  $\lambda$  as an eigenvalue of  $\mathbf{A}$  is at least  $\geq n$
- Examples:

$$\mathbf{A} = \begin{bmatrix} 2 & & \\ & 2 & \\ & & 2 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 2 & 1 & \\ & 2 & 1 \\ & & 2 \end{bmatrix}$$

Their characteristic polynomial is  $(z - 2)^3$ , so the algebraic multiplicity of  $\lambda = 2$  is 3. But the geometric multiplicity of  $\mathbf{A}$  is 3 and that of  $\mathbf{B}$  is 1.

# Defective and Diagonalizable Matrices

- An eigenvalue of a matrix is *defective* if its algebraic multiplicity  $>$  its geometric multiplicity
- A matrix is *defective* if it has a defective eigenvalue. Otherwise, it is called *nondefective*.

## Theorem

An  $m \times m$  matrix  $\mathbf{A}$  is nondefective iff it has an eigenvalue decomposition  $\mathbf{A} = \mathbf{X}\mathbf{\Lambda}\mathbf{X}^{-1}$ .

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- ( $\Leftarrow$ )  $\mathbf{\Lambda}$  is nondefective, and  $\mathbf{A}$  is similar to  $\mathbf{\Lambda}$ , so  $\mathbf{A}$  is nondefective.
- ( $\Rightarrow$ ) A nondefective matrix has  $m$  linearly independent eigenvectors. Take them as columns of  $\mathbf{X}$  to obtain  $\mathbf{A} = \mathbf{X}\mathbf{\Lambda}\mathbf{X}^{-1}$ .
- Nondefective matrices are therefore also said to be *diagonalizable*.