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Lecture Notes 9, Math/Comp 128, Math 250

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# More on Eigenvalues

Recall the eigenvector/eigenvalue equation:

$$Ax = \lambda x$$

- $\lambda$  is a scalar (can be complex, even if  $A$  is not)
- $x$  is the eigenvector corresponding to  $\lambda$ 
  - is **never** the zero vector!)
  - can have complex entries (even if  $A$  is real)

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# Definitions

- $p(z) = \det(A - zI)$  is the **characteristic polynomial**
- $\det(A - zI) = 0$  is the **characteristic equation**, and its roots  $\lambda_1, \dots, \lambda_m$  are the eigenvalues.
- Algebraic multiplicity of  $\lambda_i$ : the multiplicity of this root in the characteristic polynomial. For example, if

$$p(z) = (z - \lambda_1)(z - \lambda_2) \cdots (z - \lambda_m) = (z - 2)^3(z + 1)^2(z + 4)$$

then 2 is an eigenvalue of algebraic multiplicity 3; -1 has algebraic multiplicity 2; the two eigenvalues  $\pm 2i$  have multiplicity 1.

- Geometric multiplicity of  $\lambda_i$ : the dimension of the eigenspace corresponding to  $\lambda_i$ . Must be at least 1, at most the algebraic multiplicity.
  - A **defective eigenvalue** is one for which the algebraic multiplicity is strictly greater than the geometric multiplicity.
  - A matrix that has one or more defective eigenvalues is a **defective matrix**.
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# Important Facts

- (24.5) An  $m \times m$  matrix  $A$  is nondefective iff it has an eigenvalue decomposition  $A = X\Lambda X^{-1}$ .
- (24.6) The determinant  $\det(A)$  and trace  $\operatorname{tr}(A)$  are equal to the product and sum of the eigenvalues of  $A$ , respectively, counted with algebraic multiplicity.

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# Unitary Diagonalization

A matrix is **unitarily diagonalizable** if there exists a unitary  $Q$  such that

$$A = Q\Lambda Q^*.$$

Theorem 24.7 A hermitian matrix is unitarily diagonalizable, and its eigenvalues are real.

Proof that the eigenvalues are real on board.

A matrix  $A$  is **normal** if  $A^*A = AA^*$ .

Theorem 24.8 A matrix is unitarily diagonalizable iff it is normal.

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# Similarity Transforms

Two matrices  $A$  and  $B$  are similar if there exists an invertible  $X$  such that  $A = XBX^{-1}$ .

Note that these two matrices have the same eigenvalues (with same algebraic multiplicities), but not the same eigenvectors (unless  $X = I$ ).

We will make use of similarity transformations in the algorithms for computing eigenvalues. In particular, note that if  $B$  is upper triangular, then you know the eigenvalues of  $A$ ...

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# Schur Factorization

A **Schur Factorization** of  $A$  is a factorization

$$A = QTQ^*$$

where  $T$  is upper-triangular and  $Q$  is unitary.

So  $A$  is similar to  $T$ .

Theorem 24.9 Every square matrix  $A$  has a Schur factorization! (Proof is by induction, Math 250 students should understand this)

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# Summary

- A diagonalization  $A = X\Lambda X^{-1}$  exists iff  $A$  is nondefective.
- A unitary diagonalization  $A = Q\Lambda Q^*$  exists iff  $A$  is normal.
- The Schur factorization  $A = QTQ^*$  always exists.

Bottom line for designing algorithms: the last two are more ideal, as they give rise to numerically stable algorithms (because of the orthogonal  $Q$ 's). IF  $A$  IS normal, then the Schur factorization comes out diagonal anyway. IF  $A$  IS hermitian, can take advantage and reduce amt. of work to 1/2.

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# One exercise

True or False: If  $\lambda$  is an eigenvalue of  $A$ , and  $c$  is a real number, then  $\lambda - c$  is an eigenvalue of  $A - cI$ .

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True: (pf. on board.)

Note that the eigenvectors are unchanged!

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# Hermitian Positive Definite Matrices

Let  $A$  be real and symmetric positive definite. Then all the eigenvalues are real AND positive!

Likewise, if  $A$  is complex, hermitian and positive definite.

(Proof positive, on board.)

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# Reminder: Singular Matrices

Recall that an  $m \times m$  matrix  $A$  is singular (non-invertible) iff 0 is an eigenvalue of  $A$ .

WHY?

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# Beginning Computations

The “obvious” algorithm: Find the roots of the characteristic polynomial.

Cursed by degree, and by ill-posedness of the rootfinding problem.

Theorem 25.1 For any  $m \geq 5$ , there is a polynomial of degree  $m$  with rational coefficients that has a real root with the property that it cannot be written using any expression involving rational numbers, addition, subtraction, division, and  $k$ th roots.

## Consequences

- Even in **exact** arithmetic, we couldn't produce the exact roots of an arbitrary polynomial in a finite number of steps.
- Any eigenvalue solver must be **iterative** (and avoid the root finding problem, when necessary)

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# Next Obvious Algorithm

The Power Iteration.

Let's assume that  $|\lambda_1| > |\lambda_2| > |\lambda_3| > \cdots > |\lambda_m| > 0$ , so that there is a single, largest magnitude eigenvalue, and all the eigenvalues are distinct. Then there is a complete set of eigenvectors,  $x_1, \dots, x_m$ , and this set spans all of  $\mathbb{C}^m$ . We can assume the eigenvectors have unit length.

So let  $v$  be any vector (assume it has unit length) in  $\mathbb{C}^m$ . Expand  $v = \sum_{i=1}^m c_i x_i$ . (We don't know the  $c_i$ 's, but it doesn't matter as long as we know  $c_1 \neq 0$ .)

Set

$$v^{(1)} = Av = \sum_{i=1}^m c_i Ax_i = \sum_{i=1}^m c_i \lambda_i x_i,$$

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$$v^{(2)} = Av^{(1)} = A^2v = \sum_{i=1}^m c_i \lambda_i A x_i = \sum_{i=1}^m c_i \lambda_i^2 x_i$$

$$v^{(m)} = A^m v = \sum_{i=1}^m c_i \lambda_i^m x_i$$

Clearly, the dominant term is the first in the sum, for large enough  $m$ .

If we normalize at each step  $w^{(m)} \leftarrow \frac{v^{(m)}}{\|v^{(m)}\|}$  (see symmetric  $A$ , for example), the sequence converges to the eigenvector corresponding to the largest eigenvalue of  $A$ .

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# General, Two-Step Process

Preliminaries: A matrix is called **upper Hessenberg** if the everything below the first subdiagonal is zero.

Example: A  $5 \times 5$  upper Hessenberg matrix

$$\begin{bmatrix} 4 & 1.5 & 2 & 0 & 3.7 \\ 1 & 3.2 & 5 & 7 & 1.4 \\ 0 & 9 & 11 & 3 & 6 \\ 0 & 0 & 3 & 2.3 & 8 \\ 0 & 0 & 0 & 6.2 & 1 \end{bmatrix}$$

Note that a symmetric (Hermitian)  $n \times n$  upper Hessenberg must be **tridiagonal**.

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# Two-Step Process

For a \*non-symmetric\* (non-Hermitian) matrix

- **Phase-1** Reduce the matrix to upper Hessenberg form with orthogonal similarity transforms
  - Householder reflectors
  - Givens rotations
  - Requires  $O(m^3)$  flops, is a “direct” process
- **Phase-2** Reduce the upper Hessenberg to upper triangular form with similarity transforms
  - this is iterative, never runs to completion, but converges to the machine precision in  $O(m)$  iterations. Each iteration costs  $O(m^2)$  flops, therefore,  $O(m^3)$  for this phase applied to the upper Hessenberg matrix.

If Phase-2 were applied directly to a non-reduced form, it would cost  $O(m^4)$  flops!!

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# Two-Step Process

For a symmetric (Hermitian  $A$ ),

- **Phase-I** Reduce the matrix to tridiagonal form with orthogonal similarity transforms
  - Householder reflectors
  - Givens rotations
  - Requires  $O(m^3)$  flops, is a “direct” process
- **Phase-2** Reduce the upper Hessenberg to diagonal form with similarity transforms
  - this is iterative, never runs to completion, but converges to the machine precision in  $O(m)$  flops.

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# Phase I

Why can't we reduce to upper triangular form directly with similarity transforms??

See board.

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# Phase I

Why upper Hessenberg (tridiagonal) form??

See board.