

October 10, 2024

Announcements

- Exam 1
- HW 5

Goals

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- Eigenvalues
- CA review
- Sensitivity
- Methods

Review

Comparing the Methods

Methods to solve least squares with A an $m \times n$ matrix:

- ▶ Form: $A^T A$: $n^2 m / 2$ (symmetric—only need to fill half)
Solve with $A^T A$: $n^3 / 6$ (Cholesky)
- ▶ Solve with Householder: $mn^2 - n^3 / 3$
- ▶ If $m \approx n$, about the same
- ▶ If $m \gg n$: Householder QR requires about twice as much work as normal equations
- ▶ SVD: $mn^2 + n^3$ (with a large constant)

Demo: Relative cost of matrix factorizations [cleared]

Outline

Introduction to Scientific Computing

Systems of Linear Equations

Linear Least Squares

Eigenvalue Problems

Properties and Transformations

Sensitivity

Computing Eigenvalues

Krylov Space Methods

Nonlinear Equations

Optimization

Interpolation

Numerical Integration and Differentiation

Initial Value Problems for ODEs

Boundary Value Problems for ODEs

Partial Differential Equations and Sparse Linear Algebra

Fast Fourier Transform

Additional Topics

Eigenvalue Problems: Setup/Math Recap

A is an $n \times n$ matrix.

- ▶ $\mathbf{x} \neq 0$ is called an *eigenvector* of A if there exists a λ so that

$$A\mathbf{x} = \lambda\mathbf{x}.$$

- ▶ In that case, λ is called an *eigenvalue*.
- ▶ The set of all eigenvalues $\lambda(A)$ is called the *spectrum*.
- ▶ The *spectral radius* is the magnitude of the biggest eigenvalue:

$$\rho(A) = \max \{ |\lambda| : \lambda \in \lambda(A) \}$$

(Note: A blue arrow points from the text "magnitude of the biggest eigenvalue" to the expression $\max \{ |\lambda| : \lambda \in \lambda(A) \}$. Another blue arrow points from the expression $\lambda(A)$ to the symbol $\sigma(A)$ in the original image, which is a common notation for the spectrum.)

Eigenvalue Problems: Motivation from Mechanics

Consider mass-spring systems, e.g. as modeled in (e.g.) myphysicslab.com

What is needed to model?

$$\vec{F} = m \vec{a} \quad \vec{a} = \frac{\partial^2}{\partial t^2} \vec{x} \quad \vec{F} = \alpha (\vec{x} - \vec{x}_0)$$

$$\vec{F} = A \vec{x} \quad \Leftrightarrow \quad A \vec{x} = m \vec{a} = m \frac{\partial^2 \vec{x}}{\partial t^2}$$

$$\vec{x}(t) = \sin(\omega t) \cdot \vec{x}$$

$$\cancel{\sin(\omega t)} A \vec{x}_0 = (-\omega^2 \cancel{\sin(\omega t)}) \vec{x}$$

Finding Eigenvalues

How do you find eigenvalues?

$$\vec{x} \neq \vec{0}$$

$$\begin{aligned} A\mathbf{x} = \lambda\mathbf{x} &\Leftrightarrow (A - \lambda I)\mathbf{x} = 0 \\ &\Leftrightarrow A - \lambda I \text{ singular} \Leftrightarrow \det(A - \lambda I) = 0 \end{aligned}$$

$\det(A - \lambda I)$ is called the *characteristic polynomial*, which has degree n , and therefore n (potentially complex) roots.

Does that help algorithmically? Abel-Ruffini theorem: for $n \geq 5$ is no general formula for roots of polynomial. IOW: no.

- ▶ For LU and QR, we obtain *exact* answers (except rounding).
- ▶ For eigenvalue problems: not possible—must *iterate*.

Demo: Rounding in characteristic polynomial using SymPy [cleared]

Multiplicity

What is the *multiplicity* of an eigenvalue?

Actually, there are two notions called multiplicity:

- ▶ *Algebraic Multiplicity*: multiplicity of the root of the characteristic polynomial
- ▶ *Geometric Multiplicity*: #of lin. indep. eigenvectors

In general: $AM \geq GM$.

If $AM > GM$, the matrix is called *defective*.

An Example

Give characteristic polynomial, eigenvalues, eigenvectors of

$$\begin{bmatrix} 1 & 1 \\ & 1 \end{bmatrix}.$$

$$CP: (t-\lambda)^2$$

AM: 2 for both eigenvalues of 1

$$A \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} \Leftrightarrow x+y = x \Leftrightarrow y=0$$

eigenspace spanned by $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$

Diagonalizability

When is a matrix called *diagonalizable*?

If it's not defective
 \Rightarrow n eigen vectors \Rightarrow a basis of eigen vectors x_i

$$X = \left(x_1 \mid \dots \mid x_n \right)$$

$$A x_i = \lambda_i x_i$$

$$AX =$$

$$X \begin{matrix} D \\ \downarrow \\ \left(\begin{matrix} \lambda_1 & & \\ & \dots & \\ & & \lambda_n \end{matrix} \right) \end{matrix}$$

$$X^{-1} A X = D$$

$\hat{=}$ similarity transform

Similar Matrices

$$X^{-1}A = BX^{-1}$$

$$X^{-1}AX = B$$

Related **definition**: Two matrices A and B are called similar if there exists an invertible matrix X so that $A = XBX^{-1}$.

In that sense: "Diagonalizable" = "Similar to a diagonal matrix".

Observe: Similar A and B have same eigenvalues. (Why?)

$$\text{Suppose } A\vec{v} = \lambda\vec{v} \quad (\vec{v} \neq \vec{0}).$$

$$\vec{w} = X^{-1}\vec{v}$$

$$B\vec{w} = X^{-1}A \underbrace{X X^{-1}}_{Id} \vec{v} = X^{-1}A\vec{v} = \lambda X^{-1}\vec{v} = \lambda\vec{w}$$

Eigenvalue Transformations (I)

What do the following transformations of the eigenvalue problem $Ax = \lambda x$ do?

$$\text{Suppose } A\vec{v} = \lambda\vec{v} \quad (\vec{v} \neq 0).$$

Shift. $A \rightarrow A - \sigma I$

$$(A - \sigma I)\vec{v} = A\vec{v} - \sigma\vec{v} = \lambda\vec{v} - \sigma\vec{v} = (\lambda - \sigma)\vec{v}$$

Inversion. $A \rightarrow A^{-1}$

$$A\vec{x} = \lambda\vec{x} \quad | A^{-1}. \quad (\Leftrightarrow) \quad \vec{x} = \lambda A^{-1}\vec{x} \quad (\Leftrightarrow) \quad \frac{1}{\lambda}\vec{x} = A^{-1}\vec{x}$$

Power. $A \rightarrow A^k$

$$A^3 = A \cdot A \cdot A$$

$$A^k \vec{x} = A^{k-1} A \vec{x} = A^{k-1} \lambda \vec{x} = \dots = \lambda^k \vec{x}$$

Eigenvalue Transformations (II)

Polynomial $A \rightarrow aA^2 + bA + cI$

$$(aA^2 + bA + cI) \vec{x} = (a\lambda^2 + b\lambda + c) \vec{x}$$

Similarity $T^{-1}AT$ with T invertible

$$\vec{y} = T^{-1}\vec{x}$$

$$T^{-1}AT \vec{y} = T^{-1}A \underbrace{TT^{-1}}_{Id} \vec{x} = \lambda \vec{y}.$$

eigral: same
eigenvectors; basis
transformation

Sensitivity (I)

Assume A not defective. Suppose $X^{-1}AX = D$. Perturb $A \rightarrow A + E$.
What happens to the eigenvalues?

$$X^{-1} (A + E) X = D + F \quad (F \text{ not necessarily diagonal})$$

Suppose $\vec{v} \neq \vec{0}$ is eigenvector of $D + F$. Same eigenvectors because similar.

$$(D + F) \vec{v} = \mu \vec{v}$$

$$F \vec{v} = (\mu I - D) \vec{v} \quad | \quad (\mu I - D)^{-1}$$

assume μ is not an eigenvalue of A .

$$\vec{v} = (\mu I - D)^{-1} F \vec{v}$$

$$\|\vec{v}\| \leq \|(\mu I - D)^{-1}\| \|F\| \|\vec{v}\|$$

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Sensitivity (II)

$X^{-1}(A + E)X = D + F$. Have $\|(\mu I - D)^{-1}\|^{-1} \leq \|F\|$.

Demo: Bauer-Fike Eigenvalue Sensitivity Bound [cleared]

$\|(\mu I - D)^{-1}\|^{-1}$ is the distance between μ and the closest eigenvalue of A for μ

$|\mu - \lambda_n| \leq \|F\| = \|X^{-1}EX\| \leq \kappa(X) \|E\|$

$F = X^{-1}EX$