

Numerical Linear Algebra Applications of Tropical Mathematics

Françoise Tisseur School of Mathematics The University of Manchester

ftisseur@ma.man.ac.uk http://www.ma.man.ac.uk/~ftisseur/

> Prospects in Mathematics December 18–19, 2012 Manchester

A Definition of Numerical Linear Algebra

Numerical linear algebra is the study of algorithms for performing linear algebra computations.

For example,

- Solve a system of linear equations, Ax = b, $A \in \mathbb{R}^{n \times n}$.
- Find eigenvalues and eigenvectors, $Ax = \lambda x$, $A \in \mathbb{R}^{n \times n}$.
- Compute (when it exists) e^A , $A^{1/2}$, $\log(A)$, $A \in \mathbb{R}^{n \times n}$.
- Find $x \in \mathbb{R}^n$ minimizing ||Ax b||, $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ $(m \ge n)$.



How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.



How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.

Better: solve by Gaussian elimination (LU factorization).



How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.

Better: solve by Gaussian elimination (LU factorization). **Better**: solve by Gaussian elimination with partial pivoting.



How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.

Better: solve by Gaussian elimination (LU factorization).

Better: solve by Gaussian elimination with partial pivoting.

Also ask: is A large and sparse?

If so, try to preserve sparsity.

How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.

Better: solve by Gaussian elimination (LU factorization).

Better: solve by Gaussian elimination with partial pivoting.

Also ask: is A large and sparse? If so, try to preserve sparsity.

But first ask: what algebraic properties does A have? If A is orthogonal then $x = A^T b$.

How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.

Better: solve by Gaussian elimination (LU factorization).

Better: solve by Gaussian elimination with partial pivoting.

Also ask: is A large and sparse? If so, try to preserve sparsity.

But first ask: what algebraic properties does A have? If A is orthogonal then $x = A^T b$.

Don't forget to ask: what accuracy is required? If low accuracy, consider an iterative method.



How to solve Ax = b, where $A \in \mathbb{R}^{n \times n}$ is nonsingular?

Answer: $x = A^{-1}b$.

Better: solve by Gaussian elimination (LU factorization).

Better: solve by Gaussian elimination with partial pivoting.

Also ask: is A large and sparse? If so, try to preserve sparsity.

But first ask: what algebraic properties does A have? If A is orthogonal then $x = A^T b$.

Don't forget to ask: what accuracy is required? If low accuracy, consider an iterative method.

Also: what if we don't know whether A is nonsingular?



Beam Problem



Transverse displacement u(x, t) governed by

$$\rho A \frac{\partial^2 u}{\partial t^2} + c(\mathbf{x}) \frac{\partial u}{\partial t} + E I \frac{\partial^4 u}{\partial \mathbf{x}^4} = 0.$$
$$u(0, t) = u''(0, t) = u(L, t) = u''(L, t) = 0.$$

Separation of variables u(x, t) = e^{λt}v(x, λ) yields the eigenvalue problem for the free vibrations:

$$\lambda^2 \rho A v(\mathbf{x}, \lambda) + \lambda c(\mathbf{x}) v(\mathbf{x}, \lambda) + E I \frac{\partial^4}{\partial \mathbf{x}^4} v(\mathbf{x}, \lambda) = \mathbf{0}.$$



Discretized Beam Problem

Finite element method leads to

$$Q(\lambda)v = (\lambda^2 M + \lambda D + K)v = 0 \qquad (*)$$

with symmetric $M, D, K \in \mathbb{R}^{n \times n}$.

• (*) is a quadratic eigenvalue problem (generalizes $Av = \lambda v$).

• λ is an eigenvalue with corresponding eigenvector v.

■ $Q(\lambda)$ has 2*n* eigenvalues, solutions of det($Q(\lambda)$) = 0.



Solution Process

Find all λ and v satisfying $Q(\lambda)v = (\lambda^2 M + \lambda D + K)v = 0$.

Commonly solved by linearization:

• Convert $Q(\lambda)v = 0$ into $(\mathcal{A} - \lambda \mathcal{B})\xi = 0$, e.g.,

$$\mathcal{A} - \lambda \mathcal{B} = \begin{bmatrix} \mathcal{K} & \mathbf{0} \\ \mathbf{0} & \mathcal{I} \end{bmatrix} - \lambda \begin{bmatrix} -D & -M \\ \mathcal{I} & \mathbf{0} \end{bmatrix}, \quad \xi = \begin{bmatrix} \mathbf{v} \\ \lambda \mathbf{v} \end{bmatrix}.$$

- Solve (A λB)ξ = 0 with a numerical method (e.g., QZ algorithm).
- Recover eigenvectors of $Q(\lambda)$ from those of $\mathcal{A} \lambda \mathcal{B}$.

Eigenvalues of
$$Q(\lambda) = \lambda^2 M + \lambda D + K$$

When M, K are nonsingular then theoretically

$$\begin{aligned} \boldsymbol{C}_{1}(\lambda) &= \lambda \begin{bmatrix} \boldsymbol{M} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} + \begin{bmatrix} \boldsymbol{D} & \boldsymbol{K} \\ -\boldsymbol{I} & \boldsymbol{0} \end{bmatrix}, \\ \boldsymbol{L}_{1}(\lambda) &= \lambda \begin{bmatrix} \boldsymbol{M} & \boldsymbol{0} \\ \boldsymbol{0} & -\boldsymbol{K} \end{bmatrix} + \begin{bmatrix} \boldsymbol{D} & \boldsymbol{K} \\ \boldsymbol{K} & \boldsymbol{0} \end{bmatrix}, \\ \boldsymbol{L}_{2}(\lambda) &= \lambda \begin{bmatrix} \boldsymbol{0} & \boldsymbol{M} \\ \boldsymbol{M} & \boldsymbol{D} \end{bmatrix} + \begin{bmatrix} -\boldsymbol{M} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{K} \end{bmatrix} \end{aligned}$$

have the same eigenvalues as $Q(\lambda) = \lambda^2 M + \lambda D + K$.



Eigenvalues of
$$Q(\lambda) = \lambda^2 M + \lambda D + K$$

When M, K are nonsingular then theoretically

$$\begin{aligned} \boldsymbol{C}_{1}(\lambda) &= \lambda \begin{bmatrix} \boldsymbol{M} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} + \begin{bmatrix} \boldsymbol{D} & \boldsymbol{K} \\ -\boldsymbol{I} & \boldsymbol{0} \end{bmatrix}, \\ \boldsymbol{L}_{1}(\lambda) &= \lambda \begin{bmatrix} \boldsymbol{M} & \boldsymbol{0} \\ \boldsymbol{0} & -\boldsymbol{K} \end{bmatrix} + \begin{bmatrix} \boldsymbol{D} & \boldsymbol{K} \\ \boldsymbol{K} & \boldsymbol{0} \end{bmatrix}, \\ \boldsymbol{L}_{2}(\lambda) &= \lambda \begin{bmatrix} \boldsymbol{0} & \boldsymbol{M} \\ \boldsymbol{M} & \boldsymbol{D} \end{bmatrix} + \begin{bmatrix} -\boldsymbol{M} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{K} \end{bmatrix} \end{aligned}$$

have the same eigenvalues as $Q(\lambda) = \lambda^2 M + \lambda D + K$.

What about numerically? Let's try for the beam problem.

Computed Spectra of C_1 , L_1 and L_2



MIMS

Françoise Tisseur

Conditioning and Backward Error

- Condition number measures sensitivity of the solution of a problem to perturbations in the data.
- Backward error measures how well the problem has been solved.

error in solution \leq condition number \times backward error.



Conditioning and Backward Error

- Condition number measures sensitivity of the solution of a problem to perturbations in the data.
- Backward error measures how well the problem has been solved.

error in solution \leq condition number \times backward error.

- Can we modify the problem into an equivalent one whose solution is less sensitive to perturbations?
- Can we develop a numerically stable procedure to solve the problem?

Eigenvalue Parameter Scaling

Let $\lambda = \mu \gamma$, $\gamma \neq 0$ and convert $Q(\lambda) = \lambda^2 M + \lambda D + K$ to

$$Q(\mu\gamma) = \mu^2(\gamma^2 M) + \mu(\gamma D) + K = \frac{\mu^2 \widetilde{M} + \mu \widetilde{D} + \widetilde{K} =: \widetilde{Q}(\mu)}{\mu^2 \widetilde{M} + \mu \widetilde{D} + \widetilde{K} =: \widetilde{Q}(\mu)}.$$

Can we choose γ such that

- the standard solution process in numerically stable,
- the eigenvalues of the linearizations are less sensitive to perturbations?

Eigenvalue Parameter Scaling

Let $\lambda = \mu \gamma$, $\gamma \neq 0$ and convert $Q(\lambda) = \lambda^2 M + \lambda D + K$ to

$$Q(\mu\gamma) = \mu^2(\gamma^2 M) + \mu(\gamma D) + K = \frac{\mu^2 \widetilde{M} + \mu \widetilde{D} + \widetilde{K} =: \widetilde{Q}(\mu)}{\mu^2 \widetilde{M} + \mu \widetilde{D} + \widetilde{K} =: \widetilde{Q}(\mu)}.$$

Can we choose γ such that

- the standard solution process in numerically stable,
- the eigenvalues of the linearizations are less sensitive to perturbations?

Try $\gamma = \exp(r)$, where *r* is a **tropical root** of a **tropical scalar quadratic** (Gaubert & Sharify 2009).



Tropical Scalar Polynomials

• Let $(\mathbb{R} \cup \{-\infty\}, \oplus, \otimes)$ be the tropical semiring with

 $a \oplus b = \max(a, b), \quad a \otimes b = a + b \text{ for all } a, b \in \mathbb{R} \cup \{-\infty\}.$

The piecewise affine function

$$p(x) = \bigoplus_{k=0}^{d} p_k \otimes x^{\otimes k} = \max_{0 \le k \le d} (p_k + kx), \quad p_k \in \mathbb{R} \cup \{-\infty\}$$

is a **tropical polynomial** of degree *d*.

The tropical roots of p(x) are the points of nondifferentiability of p(x).



Tropical Roots

■ max(1, -1 + x, 2x, -2 + 3x) has roots 1/2, 1/2 and 2.

- Tropical roots can be computed in **linear time**.
- Classical roots of p(x) = a₀ + a₁x + ··· + a_nxⁿ can be bounded in terms of tropical roots of p_{trop}(x) = max(log|a₀|, log|a₁| + x, ..., log|a_n| + nx).
- Let r_1, r_2 be the **tropical roots** of $p_{\text{trop}}(r) = \max(\log(||K||), \log(||D||) + r, \log(||M||) + 2r)$. Under some assumptions, e^{r_1} and e^{r_2} are good approximations of largest and smallest eigenvalues in modulus of $Q(\lambda) = \lambda^2 M + \lambda D + K$.



Spectrum of C_1, L_2 before/after Scaling



Françoise Tisseur

Where to Study Tropical Mathematics?

Vibrant area of research in both pure and applied mathematics.

- Birmingham: Peter Butkovič.
- Manchester: Marianne Johnson, Mark Kambites, Mark Muldoon.
- Warwick: Diane Maclagan.

Where to Study Numerical Linear Algebra?

- Bath: Melina Freitag and Alastair Spence.
- Manchester: Jack Dongarra, Stefan Güttel, Nick Higham, Françoise Tisseur.
- Oxford: Nick Trefethen, Andy Wathen.
- Strathclyde Des Higham, Philip Knight, Alison Ramage.

