

Lecture #4: When Algorithms Run Into Problems: Numerical Error; Ill-conditioning, and Tolerances

Homework

- find balance between concise and detailed → manager is audience
- include solutions in word document
- include any issues you had

Factorization

All NxN real matrices can be written: $\underline{A} \rightarrow \underline{P}^T \underline{L} \underline{U}$
 (\underline{L} : lower triangular, \underline{U} : upper, \underline{P} : permutation)

MATLAB is an offshoot of LAPACK (linear algebra package) } Linear algebra is a WELL-DEVELOPED area of study
 • Can download LAPACK from netlib

$\underline{Ax} = \underline{b}$ in MATLAB: $\underline{x} = \underline{A} \setminus \underline{b}$ '\ ' is an "amazing function" – very powerful
 * WARNING: do not always know what it's doing

Uniqueness and Existence of Solution

if $\text{rank}(\underline{A}) = N$ NxN -- solution exists

if $\text{rank}(\underline{A}) < N$, $\det(\underline{A}) = 0$ -- singular, rank deficient $\underline{Az} = \underline{0}$, where $\underline{z} \neq \underline{0}$
 find additional equation at least one eigenvalue = 0
 no inverse: $\underline{z} \neq \underline{A}^{-1} * \underline{0}$

$\underline{Ax} = \underline{b}$ does $\text{rank}(\underline{A}) = \text{rank}([\underline{A} \ \underline{b}])$?
 if yes, there is a solution
 if yes and $\text{rank}(\underline{A}) < N$, there are an infinite number of solutions

Symmetry

$\underline{A}^T = \underline{A}$ Also called Hermitian Matrix if all coefficients are real
 General Hermitian matrix: transpose and complex-conjugate.
 positive definite: $\underline{x}^T \underline{Ax} > \underline{0}$ for all $\underline{x} \neq \underline{0}$ (all eigenvalues are positive)

If symmetric and positive definite: $\underline{A} = \underline{U}^T \underline{U}$; $O(N^2)$ operation (takes less memory)

$$\underline{L} = \underline{U}^T \quad \text{Cholesky factorization: } \underline{U} = \text{chol}(\underline{A})$$

if not symmetric/positive definite: 'chol' gives incomplete factorization

Vector Norms

Recall definition of vector norms: $\|\underline{v}\|_p = \left(\sum |v_i|^p\right)^{1/p}$ - vector norm

Matrix Norms

$$\|\underline{A}\| = \max_{\underline{x} \neq 0} \frac{\|\underline{A} * \underline{x}\|_p}{\|\underline{x}\|_p} \quad \text{finds } \underline{x} \text{ that stretches matrix } \underline{A} \text{ the most}$$

$$\|\underline{\underline{A}}\|_1 = \max_j \sum_{i=1}^N |a_{ij}| \quad \text{add up elements of columns and find biggest value}$$

($\|\underline{\underline{A}}\|_1 = \max$ column sum)

$$\|\underline{\underline{A}}\|_\infty = \max_i \sum_{j=1}^N |a_{ij}| \quad (\|\underline{\underline{A}}\|_\infty = \max \text{ row sum})$$

When $p = 1$ or ∞ , easy to compute matrix norm;
when p is anything else, very complex solution

$$\|\underline{\underline{A}}\|_2 = \sqrt{\text{largest eigenvalue of } \underline{\underline{A}}^T \underline{\underline{A}}} = \text{largest singular value of } \underline{\underline{A}}$$

$$\|\underline{\underline{A}}\| > 0 \text{ if } \underline{\underline{A}} \neq 0$$

$$\|c\underline{\underline{A}}\| = |c| \|\underline{\underline{A}}\|$$

$$\|\underline{\underline{A}} + \underline{\underline{B}}\| \leq \|\underline{\underline{A}}\| + \|\underline{\underline{B}}\| \quad (\text{triangle inequality})$$

$$\|\underline{\underline{A}} \cdot \underline{\underline{B}}\| \leq \|\underline{\underline{A}}\| \cdot \|\underline{\underline{B}}\|$$

$$\|\underline{\underline{A}} \cdot \underline{\underline{x}}\| \leq \|\underline{\underline{A}}\| \cdot \|\underline{\underline{x}}\|$$

Ill-conditioning

$$y = m_1x + b_1$$

$$y = m_2x + b_2$$

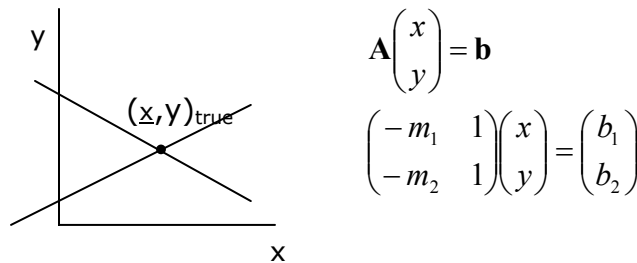


Figure 1. As long as the matrix is not singular, there is a solution (intersection).

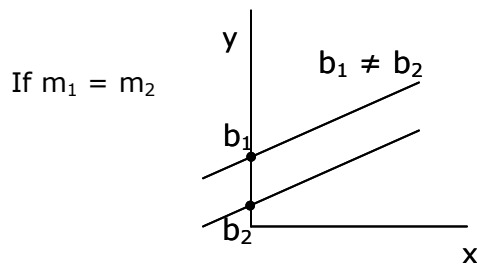


Figure 2. 2 vectors that have no solutions.

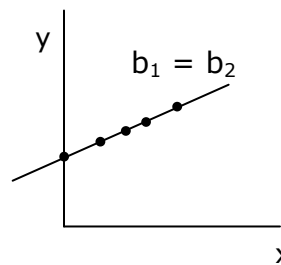


Figure 3. 2 vectors that have an infinite number of solutions.

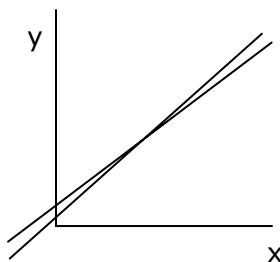


Figure 4. Poor conditioning.

Slopes are very similar: big range of (x, y) where:
*may be unable to discern difference numerically

$$y \approx m_1x + b_1$$

$$y \approx m_2x + b_2$$

$$\underline{A}^{\text{true}} \underline{x}^{\text{true}} = \underline{b}^{\text{true}}$$

$$\text{Residual: } r = \underline{b} - \underline{A}\underline{x}$$

$$\|r\| < \text{tolerance} \quad \text{-- "good enough"}$$

Absolute tolerance: # with units defined for specific problem

Relative tolerance: ~# of significant figures, scales with size of characteristic quantity

tolerance: "a" - number (atol)

$$\epsilon \|\underline{b}\| \text{ - \% (rtol)}$$

$$\|\Delta x\| < \text{rtol} * \|\underline{x}^{\text{true}} + \Delta x\|$$

- best you can do to being exact
- but you don't know $\underline{x}^{\text{true}}$

guaranteed

$$\|r\| < 2^{N-1} N \epsilon_{\text{mach}} \|\underline{A}\| \|\underline{x}\|$$

$$\epsilon_{\text{machine}} = \text{usually } 10^{-14}$$

in reality, typically

$$\|r\| < N \epsilon_{\text{mach}} \|\underline{A}\| \|\underline{x}\|$$

Even if matrix is $N = 10^9$, can still achieve an rtol of 10^{-5}

$\underline{A}\underline{x}^{\text{sol}} \approx \underline{b}$: just because you satisfy the equation, doesn't mean it is the exact solution (ill conditioning)

$$\underline{x}^{\text{soln}} = \underline{x}^{\text{true}} + \Delta x$$

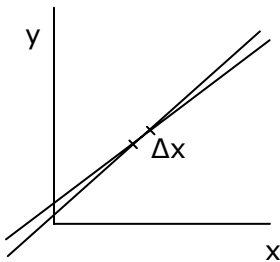


Figure 5. 2 vectors with similar slopes.

$$(\underline{A} + \delta \underline{A})(\underline{x} + \delta \underline{x}) = (\underline{b} + \delta \underline{b})$$

$$\frac{\|\delta \underline{x}\|}{\|\underline{x}\|} < \boxed{\|\underline{A}\| \cdot \|\underline{A}^{-1}\|} \left(\frac{\|\delta \underline{A}\|}{\|\underline{A}\|} + \frac{\|\delta \underline{b}\|}{\|\underline{b}\|} \right)$$

Condition number of $\underline{A} \rightarrow \text{cond}(\underline{A})$

If the condition number is large, a small change in A or b leads to a large change in $\delta \underline{x}$.

If \underline{A} is singular, there is no \underline{A}^{-1} and $\text{cond}(\underline{A}) = \infty$

Start next time: how scaling affects the condition number