Chapter 11

Matrix Inverse and Condition

Chapter Objectives

- Understanding the meaning of matrix and vector norms and how they are computed.
- Knowing how to use norms to compute the matrix condition number.
- Understanding how the magnitude of the condition number can be used to estimate the precision of solutions of linear algebraic equations.

Matrix Inverse

Recall that if a matrix [A] is square, there is another matrix [A]⁻¹, called the inverse of [A], for which [A][A]⁻¹=[A]⁻¹[A]=[I]

Vector and Matrix Norms

- A norm is a real-valued function that provides a measure of the size or "length" of multi-component mathematical entities such as vectors and matrices.
- Vector norms and matrix norms may be computed in different ways.

Vector Norms

For a vector {X} of size n, the p-norm is:

$$||X||_p = \left(\sum_{i=1}^n |x_i|^p\right)^{1/p}$$

Important examples of vector p-norms include:

$$p=1$$
: sum of the absolute values $||X||_1 = \sum_{i=1}^n |x_i|$

$$p=2$$
: Euclidian norm (length) $||X||_2 = ||X||_e = \sqrt{\sum_{i=1}^n x_i^2}$

$$p=\infty$$
: maximum—magnitude $||X||_\infty = \max_{1 \le i \le n} |x_i|$

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Consider the vector B=[1 -2 0]

||B||_1 = np.linalg.norm (B,1)= 3

||B||_2 = np.linalg.norm(B,2) = np.linalg.norm(B)=2.236

||B||_{\infty} = np.linalg.norm (B,np.inf)= 2
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Matrix Norms

Common matrix norms for a matrix [A] include:

column-sum norm
$$||A||_1 = \max_{1 \le j \le n} \sum_{i=1}^n |a_{ij}|$$
Frobenius norm
$$||A||_f = \sqrt{\sum_{i=1}^n \sum_{j=1}^n a_{ij}^2}$$
row-sum norm
$$||A||_{\infty} = \max_{1 \le i \le n} \sum_{j=1}^n |a_{ij}|$$
spectral norm (2 norm) $||A||_2 = (\mu_{\text{max}})^{1/2}$

• Note that μ_{max} is the largest eigenvalue of A^T or A.

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Consider A=[1
                          4].
||A||_1 = np.linalg.norm(A,1) = 6,
||A||_{\infty}=np.linalg.norm (A,np.inf)= 7
||A||_f = \text{np.linalg.norm (A,'fro')} = \sqrt{25} = 5
||A||_2 = np.linalg.norm (A,2) = np.linalg.norm
(A)= 4.89 (largest eigenvalue)
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Matrix Condition Number

- The matrix condition number Cond[A] is obtained by calculating Cond[A]=||A||·||A-1||
 Using A above find cond(A). Also calculate norm(A)*norm(inv(A))
- It can be shown that for *AX*=*b*:

$$\frac{\|\Delta X\|}{\|X\|} \le \operatorname{Cond}[A] \frac{\|\Delta A\|}{\|A\|}$$

 The relative error of the norm of the computed solution can be as large as the relative error of the norm of the coefficients of [A] multiplied by the condition number.

Summary: Python Commands

- Python has built-in functions to compute both norms and condition numbers:
 - norm(X,p)

Compute the p norm of vector X, where p can be any number, inf, or 'fro' (for the Euclidean norm)

norm (A, p)

Compute a norm of matrix A, where p can be 1, 2, inf, or 'fro' (for the Frobenius norm)

• cond(X,p) or cond(A,p)

Calculate the condition number of vector *X* or matrix *A* using the norm specified by *p*.

n = np.linalg.norm(A,p) returns a different kind of norm, depending on the value of p.

If p	Then norm returns
1	The 1-norm, or largest column sum of A, max(sum(abs(A))).
2	The largest singular value (same as norm(A)).
inf	The infinity norm, or largest row sum of A, max(sum(abs(A'))).
'fro'	The Frobenius-norm of matrix A, sqrt(sum(diag(A'*A)))

Example

Solve by hand the equations

$$x + 2y = 1$$
$$3x - y = 2$$

And the slightly perturbed equation

$$x + 2y = 1$$
$$3.001x - y = 2$$

The determinant of A is -7

$$cond(A) = 1.46$$