Lec 16: Square Linear Systems – Further Analysis

Vector and Matrix Norms

Vector Norms

The "length" of a vector $\mathbf{v}$ can be measured by its **norm**.

Definition 1 (p-Norm of a Vector)

Let $p \in [1, \infty)$. The p-norm of $\mathbf{v} \in \mathbb{R}^m$ is denoted by $\|\mathbf{v}\|_p$ and is defined by

$$\|\mathbf{v}\|_p = \left(\sum_{i=1}^{m} |v_i|^p \right)^{1/p} .$$

When $p = \infty$,

$$\|\mathbf{v}\|_\infty = \max_{1 \leqslant i \leqslant m} |v_i| .$$

The most commonly used p values are 1, 2, and ∞:

$$\|\mathbf{v}\|_1 = \sum_{i=1}^{m} |v_i| , \quad \|\mathbf{v}\|_2 = \sqrt{\sum_{i=1}^{m} |v_i|^2}.$$

Vector Norms

In general, any function $\|\cdot\| : \mathbb{R}^m \to \mathbb{R}^+ \cup \{0\}$ is called a **vector norm** if it satisfies the following three properties:

1. $\|\mathbf{x}\| = 0$ if and only if $\mathbf{x} = 0$.
2. $\|\alpha\mathbf{x}\| = |\alpha| \, \|\mathbf{x}\|$ for any constant α and any $\mathbf{x} \in \mathbb{R}^m$.
3. $\|\mathbf{x} + \mathbf{y}\| \leqslant \|\mathbf{x}\| + \|\mathbf{y}\|$ for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^m$. This is called the *triangle inequality*.

Unit Vectors

- A vector $\mathbf{u}$ is called a **unit vector** if $\|\mathbf{u}\| = 1$.
- Depending on the norm used, unit vectors will be different.
- For instance:

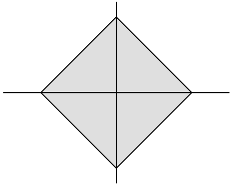

Figure 1: 1-norm

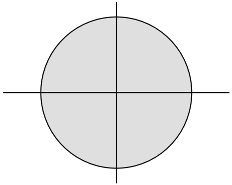

Figure 2: 2-norm

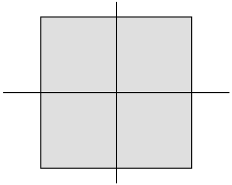

Figure 3: ∞-norm

Matrix Norms

The "size" of a matrix $A \in \mathbb{R}^{m \times n}$ can be measured by its **norm** as well. As above, we say that a function $\|\cdot\| : \mathbb{R}^{m \times n} \to \mathbb{R}^+ \cup \{0\}$ is a **matrix norm** if it satisfies the following three properties:

1. $\|A\| = 0$ if and only if $A = 0$.
2. $\|\alpha A\| = |\alpha| \, \|A\|$ for any constant α and any $A \in \mathbb{R}^{m \times n}$.
3. $\|A + B\| \leqslant \|A\| + \|B\|$ for any $A, B \in \mathbb{R}^{m \times n}$. This is called the *triangle inequality*.

Matrix Norms (Cont')

- If, in addition to satisfying the three conditions, it satisfies

$$\|AB\| \leqslant \|A\| \, \|B\| \quad \text{for all } A \in \mathbb{R}^{m\times n} \text{ and all } B \in \mathbb{R}^{n\times p},$$

  it is said to be **consistent**.
- If, in addition to satisfying the three conditions, it satisfies

$$\|A\mathbf{x}\| \leqslant \|A\| \, \|\mathbf{x}\| \quad \text{for all } A \in \mathbb{R}^{m\times n} \text{ and all } \mathbf{x} \in \mathbb{R}^{n},$$

  then we say that it is **compatible** with a vector norm.

Induced Matrix Norms

Definition 2 (p-Norm of a Matrix)

Let $p \in [1, \infty]$. The p-norm of $A \in \mathbb{R}^{m \times n}$ is given by

$$\|A\|_p = \max_{\mathbf{x} \neq 0} \frac{\|A\mathbf{x}\|_p}{\|\mathbf{x}\|_p} = \max_{\|\mathbf{x}\|_p = 1} \|A\mathbf{x}\|_p \ .$$

- The definition of this particular matrix norm is **induced** from the vector p-norm.
- By construction, matrix p-norm is a compatible norm.
- Induced norms describe how the matrix stretches unit vectors with respect to the vector norm.

Induced Matrix Norms

The commonly used p-norms (for $p = 1, 2, \infty$) can also be calculated by

$$
\begin{aligned}
\|A\|_1 &= \max_{1 \leqslant j \leqslant n} \sum_{i=1}^{m} \left|a_{ij}\right|, \\
\|A\|_2 &= \sqrt{\lambda_{\max}(A^{\mathrm{T}} A)} = \sigma_{\max}(A), \\
\|A\|_\infty &= \max_{1 \leqslant i \leqslant m} \sum_{j=1}^{n} \left|a_{ij}\right|.
\end{aligned}
$$

In words,

- The 1-norm of A is the maximum of the 1-norms of all column vectors.
- The 2-norm of A is the square root of the largest eigenvalue of $A^{\mathrm{T}} A$.
- The ∞-norm of A is the maximum of the 1-norms of all row vectors.

Non-Induced Matrix Norm – Frobenius Norm

Definition 3 (Frobenius Norm of a Matrix)

The Frobenius norm of $A \in \mathbb{R}^{m\times n}$ is given by

$$\|A\|_F = \left(\sum_{i=1}^{m}\sum_{j=1}^{n}\left|a_{ij}\right|^2\right)^{1/2}.$$

- This is not induced from a vector p-norm.
- However, both p-norm and the Frobenius norm are consistent and compatible.
- For compatibility of the Frobenius norm, the vector norm must be the 2-norm, that is, $\|A\mathbf{x}\|_2 \leqslant \|A\|_F \|\mathbf{x}\|_2$.

Norms in MATLAB

- Vector p-norms can be easily computed:

```
norm(v, 1)       % = sum(abs(v))
norm(v, 2)       % = sqrt(v'*v)  if v is a column
norm(v, 'inf')   % = max(abs(v))
```

- The same function `norm` is used to calculate matrix p-norms:

```
norm(A, 1)        % = max(sum(abs(A), 1))
norm(A, 2)        % = max(sqrt(eig(A'*A)))
norm(A, Inf)      % = max(sum(abs(A), 2))
```

- To calculate the Frobenius norm:

```
norm(A, 'fro')    % = sqrt(A(:)'*A(:))
                  % = norm(A(:), 2)
```

Conditioning

Conditioning of Solving Linear Systems: Overview

- Analyze how robust (or sensitive) the solutions of $A\mathbf{x} = \mathbf{b}$ are to perturbations of A and $\mathbf{b}$.
- For simplicity, consider separately the cases where

  1. $\mathbf{b}$ changes to $\mathbf{b} + \delta\mathbf{b}$, while A remains unchanged, that is

  $$A\mathbf{x} = \mathbf{b} \quad \longrightarrow \quad A(\mathbf{x} + \delta\mathbf{x}) = \mathbf{b} + \delta\mathbf{b}.$$

  2. A changes to $A + \delta A$, while $\mathbf{b}$ remains unchanged, that is

  $$A\mathbf{x} = \mathbf{b} \quad \longrightarrow \quad (A + \delta A)(\mathbf{x} + \delta\mathbf{x}) = \mathbf{b}.$$

Sensitivity to Perturbation of RHS

Case 1. $A\mathbf{x} = \mathbf{b} \;\to\; A(\mathbf{x} + \delta\mathbf{x}) = \mathbf{b} + \delta\mathbf{b}$

- Bound $\|\delta\mathbf{x}\|$ in terms of $\|\delta\mathbf{b}\|$:

$$\begin{aligned} A\mathbf{x} + A\delta\mathbf{x} &= \mathbf{b} + \delta\mathbf{b} \\ A\delta\mathbf{x} &= \delta\mathbf{b} \\ \delta\mathbf{x} &= A^{-1}\delta\mathbf{b} \end{aligned} \qquad \Longrightarrow \qquad \|\delta\mathbf{x}\| \leqslant \|A^{-1}\|\|\delta\mathbf{b}\|.$$

- Sensitivity in terms of relative errors:

$$\frac{\dfrac{\|\delta\mathbf{x}\|}{\|\mathbf{x}\|}}{\dfrac{\|\delta\mathbf{b}\|}{\|\mathbf{b}\|}} = \frac{\|\delta\mathbf{x}\|\,\|\mathbf{b}\|}{\|\delta\mathbf{b}\|\,\|\mathbf{x}\|} \leqslant \frac{\|A^{-1}\|\,\|\delta\mathbf{b}\| \cdot \|A\|\,\|\mathbf{x}\|}{\|\delta\mathbf{b}\|\,\|\mathbf{x}\|} = \|A^{-1}\|\|A\|.$$

Sensitivity to Perturbation of Matrix

Case 2. $A\mathbf{x} = \mathbf{b} \;\to\; (A + \delta A)(\mathbf{x} + \delta\mathbf{x}) = \mathbf{b}$

- Bound $\|\delta\mathbf{x}\|$ now in terms of $\|\delta A\|$:

$$\begin{aligned} A\mathbf{x} + A\delta\mathbf{x} + (\delta A)\mathbf{x} + (\delta A)\delta\mathbf{x} &= \mathbf{b} \\ A\delta\mathbf{x} &= -(\delta A)\mathbf{x} - (\delta A)\delta\mathbf{x} \\ \delta\mathbf{x} &= -A^{-1}(\delta A)\mathbf{x} - A^{-1}(\delta A)\delta\mathbf{x} \end{aligned} \quad \Longrightarrow \quad \|\delta\mathbf{x}\| \lesssim \|A^{-1}\| \|\delta A\| \|\mathbf{x}\| .$$

(first-order truncation)

- Sensitivity in terms of relative errors:

$$\frac{\frac{\|\delta\mathbf{x}\|}{\|\mathbf{x}\|}}{\frac{\|\delta A\|}{\|A\|}} = \frac{\|\delta\mathbf{x}\| \|A\|}{\|\delta A\| \|\mathbf{x}\|} \lesssim \frac{\|A^{-1}\| \|\delta A\| \|\mathbf{x}\| \cdot \|A\|}{\|\delta A\| \|\mathbf{x}\|} = \|A^{-1}\| \|A\|.$$

Matrix Condition Number

- Motivated by the previous estimations, we define the **matrix condition number** by
$$\kappa(A) = \|A^{-1}\|\|A\|,$$
where the norms can be any p-norm or the Frobenius norm.
- A subscript on κ such as 1, 2, ∞, or F(robenius) is used if clarification is needed.

Matrix Condition Number (Cont')

- We can write

$$\frac{\|\delta \mathbf{x}\|}{\|\mathbf{x}\|} \leqslant \kappa(A) \frac{\|\delta \mathbf{b}\|}{\|\mathbf{b}\|}, \qquad \frac{\|\delta \mathbf{x}\|}{\|\mathbf{x}\|} \leqslant \kappa(A) \frac{\|\delta A\|}{\|A\|},$$

  where the second inequality is true only in the limit of infinitesimal perturbations δA.

- The matrix condition number $\kappa(A)$ is equal to the condition number of solving a linear system of equation $A\mathbf{x} = \mathbf{b}$.

- The exponent of $\kappa(A)$ in scientific notation determines the approximate number of digits of accuracy that will be lost in calculation of $\mathbf{x}$.

- Since $1 = \|I\| = \|A^{-1}A\| \leqslant \|A^{-1}\|\|A\| = \kappa(A)$, a condition number of 1 is the best we can hope for.

- If $\kappa(A) > \boxed{\text{eps}}^{-1}$, then for computational purposes the matrix is singular.

Condition Numbers in MATLAB

- Use `cond` to calculate various condition numbers:

```
cond(A)              % the 2-norm; or  cond(A, 2)
cond(A, 1)           % the 1-norm
cond(A, Inf)         % the infinity-norm
cond(A, 'fro')       % the Frobenius norm
```

- A condition number estimator (in 1-norm)

```
condest(A)           % faster than cond
```

- The fastest method to estimate the condition number is to use `linsolve` function as below:

```
[x, inv_condest] = linsolve(A, b);
fast_condest = 1/inv_condest;
```