

Matrices - Linear Algebra

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We will focus mostly on square matrices

$$A = \begin{bmatrix} A_{00} & A_{01} & A_{02} \\ A_{10} & A_{11} & A_{12} \\ A_{20} & A_{21} & A_{22} \end{bmatrix} \quad A_{ij} = \begin{matrix} i^{\text{th}} \text{ row} \\ j^{\text{th}} \text{ column} \end{matrix}$$

$$\vec{x} = \begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix} \text{ vector}$$

Matrix-vector multiplication $\vec{y} = A \vec{x}$

$$y_i = \sum_{j=0}^{n-1} A_{ij} x_j$$

$$\text{Ex } y_1 = \sum_{j=0}^2 A_{1j} x_j = A_{10} x_0 + A_{11} x_1 + A_{12} x_2$$

Matrix multiplication

$$C = AB \quad C_{ij} = \sum_{k=0}^{n-1} A_{ik} B_{kj}$$

transpose $B = A^T \quad B_{ij} = A_{ji}$

$$\text{Ex } A = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix} \quad AB = ?$$

$$AB = \begin{bmatrix} 1 & -2 \\ 3 & 4 \end{bmatrix}$$

Determinant is a number: $\det(A)$

$$2 \times 2 \quad |A| = \begin{vmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{vmatrix} = A_{00}A_{11} - A_{01}A_{10}$$

$$3 \times 3 \quad |A| = \begin{vmatrix} A_{00} & A_{01} & A_{02} \\ A_{10} & A_{11} & A_{12} \\ A_{20} & A_{21} & A_{22} \end{vmatrix} = A_{00}A_{11}A_{22} - A_{01}A_{12}A_{20} - A_{02}A_{10}A_{21} + A_{02}A_{11}A_{20} + A_{01}A_{10}A_{22}$$

$$= A_{00} \begin{vmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{vmatrix} - A_{01} \begin{vmatrix} A_{10} & A_{12} \\ A_{20} & A_{22} \end{vmatrix} + A_{02} \begin{vmatrix} A_{10} & A_{11} \\ A_{20} & A_{21} \end{vmatrix}$$

Triangular matrix (upper and lower)

$$\begin{bmatrix} A_{00} & A_{01} & A_{02} \\ 0 & A_{11} & A_{12} \\ 0 & 0 & A_{22} \end{bmatrix} \quad \begin{bmatrix} A_{00} & 0 & 0 \\ A_{10} & A_{11} & 0 \\ A_{20} & A_{21} & A_{22} \end{bmatrix}$$

Note $\det(\text{triangular matrix}) = \text{product main diagonal}$

$$|A_{\text{triangular}}| = \prod_{i=0}^{n-1} A_{ii}$$

Inverse $A^{-1} \Rightarrow A^{-1}A = AA^{-1} = \mathbb{I} \sim \text{identity matrix}$

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

If $\det(A) = 0$ A is singular and
 A^{-1} does not exist

(rows, columns of A are not linearly independent)

Solving n linear equations w/ n unknowns

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$$A\vec{x} = \vec{b} \quad n \text{ unknowns} \quad \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{pmatrix}$$

$n \times n$ coefficients in A , and n constants in $\vec{b} = \begin{pmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{pmatrix}$

We need $\det(A) \neq 0$ for solution.

We create augmented coeff matrix of A and b

$$(A|b) = \left[\begin{array}{cccc|c} A_{0,0} & A_{0,1} & \dots & A_{0,n-1} & b_0 \\ \vdots & \vdots & & \vdots & \vdots \\ A_{n-1,0} & A_{n-1,1} & \dots & A_{n-1,n-1} & b_{n-1} \end{array} \right]$$

In solving linear eqns we can

scale row by a constant

pivot: two rows can be interchanged

eliminate: a row can be replaced by the sum of that row w/ a multiple of any other row

We will also solve eigenvalue problem

$$A\vec{v} = \lambda\vec{v}$$

$\lambda \in$ a scalar (number)

$$A\vec{v} - \lambda\vec{v} = \vec{0}$$

$$(A - \lambda I)\vec{v} = \vec{0}$$

We have n linear equations and

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n unknowns in \vec{v} plus 1 unknown in λ

→ We won't find unique solutions

For a non trivial solution ($\vec{v} \neq \vec{0}$) we need

$A - \lambda \underline{I}$ not to have an inverse so

$$|A - \lambda \underline{I}| = 0$$

Error Analysis (Worst case scenario)

Consider special 2×2 example

$$(A|b) = \left(\begin{array}{cc|c} 0.2161 & 0.1441 & 0.1440 \\ 1.2969 & 0.8648 & 0.8642 \end{array} \right)$$

You are given approx solution $\tilde{x} = \begin{pmatrix} .9911 \\ -.4870 \end{pmatrix}$

Create residual vector \vec{r}

$$\vec{r} = \vec{b} - A\tilde{x} \Rightarrow \vec{r} = \begin{pmatrix} -1e-8 \\ 1e-8 \end{pmatrix} \quad \begin{matrix} \text{not} \\ \text{bad} \end{matrix}$$

exact solution $\vec{x} = \begin{pmatrix} 2 \\ -2 \end{pmatrix}$!?!

Weird. Very small changes to A will yield
very big changes to our solution.

Maybe A is 'close to' having $\det(A) = 0$ 4-5
(close to being singular)

(in our case $\det(A) = -9.9992 \times 10^{-9}$)

Define

Frobenius norm $\|A\|_F = \left[\sum_i \sum_j |A_{ij}|^2 \right]^{1/2}$

Infinity norm $\|A\|_\infty = \max_{0 \leq i \leq n-1} \sum_{j=0}^{n-1} |A_{ij}|$

(Maximum absolute row-sum norm)

We can show that condition number $K(A)$

$K(A) = \|A\| \|A^{-1}\|$ determines sensitivity to (Egn)
small perturbation (4.31)

Solving $A\vec{x} = \vec{b}$

First solve $L\vec{x} = \vec{b}$

$L \equiv$ lower triangular matrix

For $n=3$

$$\begin{pmatrix} L_{00} & 0 & 0 \\ L_{10} & L_{11} & 0 \\ L_{20} & L_{21} & L_{22} \end{pmatrix} \begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} b_0 \\ b_1 \\ b_2 \end{pmatrix}$$

$$L_{00} x_0 = b_0$$

$$x_0 = b_0 / L_{00}$$

$$L_{10} x_0 + L_{11} x_1 = b_1$$

$$x_1 = \frac{b_1 - L_{10} x_0}{L_{11}}$$

$$L_{20} x_0 + L_{21} x_1 + L_{22} x_2 = b_2$$

$$x_2 = \frac{b_2 - L_{20} x_0 - L_{21} x_1}{L_{22}}$$