

Introduction to Linear Algebra

Midterm 1 Review Class

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Outline

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- 6 Lecture 7 and 8
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- 8 Simple Exercises

- ① A system of linear equations is **consistent** if it has at least one solution;
- ② Every system of linear equations has either **zero, one, or infinitely** many solutions;
- ③ Every **homogeneous** system of linear equations is consistent;
- ④ **Back substitution**;
- ⑤ **Elementary row operations**:
 - Type I: Interchange two rows ($E_{i,j}$)
 - Type II: Multiply a row by a nonzero constant ($E_{(\alpha)i}$)
 - Type III: Add a constant times one row to another ($E_{(\alpha)i,j} \neq E_{i,(\alpha)j}$)
- ⑥ Gaussian Elimination: reduce the matrix to **ref** and apply back substitution.

Question1

Construct a system of equations with the general solution

$$\mathbf{x} = c_1 \begin{bmatrix} 2 \\ -3 \\ 1 \\ 0 \end{bmatrix} + c_2 \begin{bmatrix} -2 \\ 4 \\ 0 \\ 1 \end{bmatrix}$$

Question2

For the following equation

$$B = \begin{bmatrix} 1 & 1 & 1 + \lambda & \lambda \\ 1 & 1 + \lambda & 1 & 3 \\ 1 + \lambda & 1 & 1 & 0 \end{bmatrix}$$

for what λ will the equation have

- (a) unique solution?
- (b) no solution?
- (c) infinite many solutions?

① Reduced row echelon form (rref):

- If a row does not consist entirely of zeros, then the first nonzero entry of this row is **1**, which is known as a **leading 1**;
- If the matrix has any rows that consist entirely of zeros, they occur at the **bottom** of the matrix;
- In any two successive rows that do not consist entirely of zeros, the leading 1 in the **lower** row occurs further to the **right** than the leading 1 above;
- Each column that contains a leading 1 has zeros everywhere else.

② Row echelon form (ref): satisfy the first three properties.

③ A linear system is consistent **if and only if** there **exists** a ref of the corresponding augmented matrix that has no row of $[0 \ \cdots \ 0 \ a]$ where $a \neq 0$.

④ Gauss-Jordan Elimination: result in **rref**;

⑤ The rref of a matrix is **unique**;

⑥ The number of pivots is the **rank** of the matrix;

⑦ A **homogeneous** system of linear equations with more unknowns than equations has infinitely many solutions (not hold for nonhomogeneous system).

pivot column: a pivot column is a column of matrix that contains a pivot position, *i.e.*, the leftmost nonzero column.

$$\begin{aligned}
 & \left[\begin{array}{ccc|c} 1 & 1 & 1 & 5 \\ 2 & 3 & 5 & 8 \\ 4 & 0 & 5 & 2 \end{array} \right] \xrightarrow{R_2 - 2R_1} \left[\begin{array}{ccc|c} 1 & 1 & 1 & 5 \\ 0 & 1 & 3 & -2 \\ 4 & 0 & 5 & 2 \end{array} \right] \\
 & \xrightarrow{R_3 - 4R_1} \left[\begin{array}{ccc|c} 1 & 1 & 1 & 5 \\ 0 & 1 & 3 & -2 \\ 0 & -4 & 1 & -18 \end{array} \right] \\
 & \xrightarrow{R_3 + 4R_2} \left[\begin{array}{ccc|c} 1 & 1 & 1 & 5 \\ 0 & 1 & 3 & -2 \\ 0 & 0 & 13 & -26 \end{array} \right] \\
 & \xrightarrow{\frac{1}{13}R_3} \left[\begin{array}{ccc|c} 1 & 1 & 1 & 5 \\ 0 & 1 & 3 & -2 \\ 0 & 0 & 1 & -2 \end{array} \right] \\
 & \xrightarrow{R_2 - 3R_3} \left[\begin{array}{ccc|c} 1 & 1 & 1 & 5 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & -2 \end{array} \right] \\
 & \xrightarrow{R_1 - R_3} \left[\begin{array}{ccc|c} 1 & 1 & 0 & 7 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & -2 \end{array} \right] \\
 & \xrightarrow{R_1 - R_2} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 3 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & -2 \end{array} \right]
 \end{aligned}$$

Figure: Working Example of Gaussian-Jordan Elimination

- 1 $A(BC) = (AB)C$;
- 2 A matrix can be understood from three perspectives: **row (intersection)**, **column (combination)** and **matrix (inverse image)**;
- 3 Matrix multiplication by row and by column (left matrix always involved with rows and right matrix always involved with columns);
- 4 Elementary matrix differs from the identity matrix by **one single** elementary row operation.

Validity with **square matrix**:

- ① Mutual relationship of the inverse: $AB = BA = I$ (**unique**);
- ② $(AB \cdots Z)^{-1} = Z^{-1} \cdots B^{-1}A^{-1}$;
- ③ $(A^n)^{-1} = A^{-n} = (A^{-1})^n$;
- ④ Equivalence theorem;
- ⑤ Inversion algorithm (augment the matrix with identity matrix and eliminate the original matrix into identity matrix);
- ⑥ Either $\text{rref}(A)$ has a row of zeros or $\text{rref}(A)=I$;
- ⑦ If AB is invertible, then A and B must also be invertible;

Equivalent statements of a square matrix A being invertible:

- $A\mathbf{x} = \mathbf{0}$ has only the trivial solution;
- The rref of A is identity matrix;
- A is expressible as a product of elementary matrices;
- $A\mathbf{x} = \mathbf{b}$ is consistent for every $\mathbf{b} \in \mathbb{R}^n$;
- $A\mathbf{x} = \mathbf{b}$ has exactly one solution for every $\mathbf{b} \in \mathbb{R}^n$;
- $\det(A) \neq 0$.

Inverse of triangular matrix:

$$\begin{bmatrix} a & b & c \\ 0 & d & e \\ 0 & 0 & f \end{bmatrix}^{-1} = \begin{bmatrix} \frac{1}{a} & -\frac{b}{ad} & \frac{be-cd}{afd} \\ 0 & \frac{1}{d} & -\frac{e}{fd} \\ 0 & 0 & \frac{1}{f} \end{bmatrix}$$

Question1: Suppose A , B and C are matrices where the following matrix multiplications are defined, and A is invertible. Show

$$C(A - B) = A^{-1}B$$

given

$$(A - B)C = BA^{-1}$$

Solution:

$$I + (A - B)C = I + BA^{-1}$$

$$AA^{-1} + (A - B)C - BA^{-1} = I$$

$$(A - B)(C + A^{-1}) = I, (C + A^{-1})(A - B) = I$$

$$C(A - B) = A^{-1}B$$

- ① Upper triangular matrix, lower triangular matrix, diagonal matrix, symmetric matrix, skew-symmetric matrix, sparse matrix;
- ② A diagonal matrix (triangular matrix) is invertible **if and only if** all of its diagonal entries are nonzero;
- ③ The product and inverse of triangular matrix do not change its property;
- ④ Symmetric ($A = A^T$) and skew-symmetric ($A = -A^T$);
- ⑤ Every square matrix A can be uniquely decomposed into a sum of symmetric and skew-symmetric matrices:
$$A = \frac{1}{2}(A + A^T) + \frac{1}{2}(A - A^T);$$
- ⑥ If A is an invertible matrix, then AA^T and $A^T A$ are also invertible;
- ⑦ Block-form matrix.

Permutation:

Any arrangement of a set $\mathcal{S} = \{1, 2, \dots, n\}$ in a specific order, for example,

$$\sigma_{\text{no}} = (1, 2, \dots, n) \quad \text{or} \quad \sigma = (k_1, k_2, \dots, k_i, \dots, k_j, \dots, k_n)$$

is called a permutation of \mathcal{S} , where σ_{no} above is defined to be in the **nature order**.

Out of the nature order:

A pair of elements (k_i, k_j) in σ satisfies $k_i > k_j$ where $i < j$.

- Even permutation: even number of pairs out of the nature order;
- Odd permutation: odd number of pairs out of the nature order.

Levi-Civita symbol:

$$\epsilon_{\sigma} = \epsilon_{k_1 \dots k_n} = \begin{cases} +1 & \text{if } \sigma \text{ is an even permutation} \\ -1 & \text{if } \sigma \text{ is an odd permutation} \\ 0 & \text{otherwise} \end{cases}$$

- ① $\det(A) = \sum_{k_1=1}^n \sum_{k_2=1}^n \cdots \sum_{k_n=1}^n \epsilon_{k_1 \cdots k_n} a_{1k_1} a_{2k_2} a_{3k_3} \cdots a_{nk_n}$ (this explains why determinant is not defined for non-square matrix);
- ② $\det(E_{i,j}A) = -\det(A)$;
- ③ $\det(E_{(\alpha)}A) = \alpha \det(A)$;
- ④ $\det(E_{(\alpha)}A) = \det(A)$;
- ⑤ $\det(A^T) = \det(A)$;
- ⑥ $\det(AB) = \det(A)\det(B)$;
- ⑦ $\text{adj}(A) = C^T$;
- ⑧ If $\det(A) \neq 0$, then $A^{-1} = \frac{1}{\det(A)} \text{adj}(A)$;
- ⑨ The determinant of diagonal and triangular matrices is the product of diagonal entries.

Question1:

Find the determinant of the matrix

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 & 1 \\ 0 & -1 & 2 & 4 & 2 \\ 0 & 0 & 4 & 0 & 0 \\ -3 & -6 & -9 & -12 & 4 \\ 0 & 0 & 1 & 1 & 1 \end{bmatrix}$$

(using some properties to quickly find the answer)

Reasons to introduce LU decomposition

- ① *Previous ways of calculating determinant can sometimes be very tedious when the size becomes large;*
- ② *The calculation of a triangular matrix's determinant is simple.(product of diagonal entries);*
- ③ *Transforming a matrix into triangular form is simple (Gauss Elimination);*
- ④ *Estimating the influence of transformation on the determinant is simple(there are only elementary row operations).*

Solving $A\mathbf{x} = \mathbf{b}$ with LU decomposition: first solve $L\mathbf{c} = \mathbf{b}$, then solve $U\mathbf{x} = \mathbf{c}$.

Interesting facts

- ① When a row of A **starts with** zeros, so does that row of L ; When a column of A **starts with** zeros, so does that column of U ;
- ② U has the pivots on its diagonal; L has all the 1's on its diagonal;
- ③ The multipliers $l_{i,j}$ are below the diagonal of L ;
- ④ If A is symmetric, it can be shown that $A = LDL^T$.

Consider $A = \begin{bmatrix} 2 & 1 & 3 \\ 4 & 2 & 1 \\ 6 & -3 & 4 \end{bmatrix}$, we can perform the LU decomposition to

obtain $A = E_{(2)1,2}E_{(3)1,3}E_{3,2}U = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 1 \\ 3 & 1 & 0 \end{bmatrix} \begin{bmatrix} 2 & 1 & 3 \\ 0 & -6 & -5 \\ 0 & 0 & -5 \end{bmatrix}$, which

seems to contradict with our observation. What goes wrong?

Note: If only **Type III** operations are used when applying Gaussian elimination to reduce A to U , then $A = LU$.

Better balance for this decomposition ...

$A = LU$ is "unsymmetric" because U has the pivots on its diagonals where L has 1's. Therefore, we may prefer more the decomposition $A = LD\hat{U}$, where D is the diagonal matrix with pivots. Each row of \hat{U} is that of the original U divided by its pivot.

If A is **invertible** and $A = \hat{L}D\hat{U}$ **exists** where \hat{L} and \hat{U} are upper and lower triangular with unit diagonal and D is a diagonal matrix, then this decomposition is unique.

Suppose A is an invertible $n \times n$ matrix. The leading principle submatrices A_k of A are invertible for $k = 1, \dots, n - 1$ **if and only if** A has the decomposition $A = \hat{L}U$.

Back to our question on the last slide, how to adapt LU decomposition to matrix for which row interchanges are necessary during Gaussian elimination.

- ① A permutation matrix, often denoted by P , is a product of elementary matrices corresponding to row interchanges;
- ② If P is a permutation matrix, then $P^{-1} = P^T$;
- ③ Every invertible matrix A has a decomposition of the form $A = P^T \hat{L} U$;

In common practice, row exchanges are done in advance, which results in $PA = \hat{L} U$. Here row exchanges mean bringing the pivot into its usual place.

Jacobi iteration (slow convergence for large linear systems):

$$\mathbf{x}^{(k+1)} = D^{-1}(\mathbf{b} + (D - A)\mathbf{x}^{(k)})$$

$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij}x_j^{(k)} - \sum_{j=i+1}^n a_{ij}x_j^{(k)} \right), \text{ for } i = 1, 2, \dots, n$$

Gauss-Seidel iteration:

$$\mathbf{x}^{(k+1)} = (D + L)^{-1}(\mathbf{b} - U\mathbf{x}^{(k)})$$

$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij}x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij}x_j^{(k)} \right), \text{ for } i = 1, 2, \dots, n$$

Suppose we are given the following linear system:

$$\begin{aligned} 10x_1 - x_2 + 2x_3 &= 6, \\ -x_1 + 11x_2 - x_3 + 3x_4 &= 25, \\ 2x_1 - x_2 + 10x_3 - x_4 &= -11, \\ 3x_2 - x_3 + 8x_4 &= 15. \end{aligned}$$

If we choose $(0, 0, 0, 0)$ as the initial approximation, then the first approximate solution is given by

$$\begin{aligned} x_1 &= (6 + 0 - (2 * 0))/10 = 0.6, \\ x_2 &= (25 + 0 + 0 - (3 * 0))/11 = 25/11 = 2.2727, \\ x_3 &= (-11 - (2 * 0) + 0 + 0)/10 = -1.1, \\ x_4 &= (15 - (3 * 0) + 0)/8 = 1.875. \end{aligned}$$

Using the approximations obtained, the iterative procedure is repeated until the desired accuracy has been reached. The following are the approximated solutions after five iterations.

x_1	x_2	x_3	x_4
0.6	2.27272	-1.1	1.875
1.04727	1.7159	-0.80522	0.88522
0.93263	2.05330	-1.0493	1.13088
1.01519	1.95369	-0.9681	0.97384
0.98899	2.0114	-1.0102	1.02135

The exact solution of the system is $(1, 2, -1, 1)$.

Figure: Working Example of Jacobi iteration

Convergence of the iteration:

- 1 A **square** matrix is **strictly diagonally dominant** if

$$|a_{ii}| > \sum_{j=1}^{i-1} |a_{ij}| + \sum_{j=i+1}^n |a_{ij}| \text{ for all } i = 1, 2, \dots, n.$$

- 2 If A is strictly diagonally dominant, then $A\mathbf{x} = \mathbf{b}$ has a unique solution (**invertible**) and for any choice of the initial guess $\mathbf{x}^{(0)}$, the sequence $\{\mathbf{x}^{(k)}\}$ produced by Jacobi or Gauss-Seidel iteration **converge** to the exact solution.

Question: Why is this lecture called “sparse”?

Save storage requirements to large extent.

Ex.1: Suppose $Q^T = Q^{-1}$ (Q is then called **orthogonal matrix**).

- (a) Show that the columns q_1, \dots, q_n are unit vectors;
- (b) Show that every two columns of Q are perpendicular;
- (c) Find a 2 by 2 example with first entry $q_{11} = \cos \theta$.

Ex.2: Show that $I + BA$ and $I + AB$ are both invertible or both singular.
(*hint: consider the identity $A(I + BA) = (I + AB)A$*)

Ex.3: Find the inverse of $\begin{bmatrix} 1 & -a & 0 & 0 \\ 0 & 1 & -b & 0 \\ 0 & 0 & 1 & -c \\ 0 & 0 & 0 & 1 \end{bmatrix}$ with **proper** method.

Thank you!
Good luck for Midterm 1!