## SC223 - Linear Algebra

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Lecture 7



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### LU Decomposition

$$A = \left[ \begin{array}{rrrr} 1 & -2 & -1 & -1 \\ 2 & 0 & 3 & 2 \\ -2 & 3 & -2 & 1 \\ 3 & -4 & 2 & 1 \end{array} \right]$$

- $\bullet \ E_3E_2E_1A=EA=U \ \Rightarrow A=E^{-1}U.$
- ullet By Theorem 2,  $E^{-1}$  is a lower triangular matrix. Define  $L:=E^{-1}$ .

Thus A = LU, known as the **LU decomposition**.

For this example:

$$\underbrace{\begin{bmatrix} 1 & -2 & -1 & -1 \\ 2 & 0 & 3 & 2 \\ -2 & 3 & -2 & 1 \\ 3 & -4 & 2 & 1 \end{bmatrix}}_{A} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 2 & 1 & 0 & 0 \\ -2 & -1/4 & 1 & 0 \\ 3 & 1/2 & -10/11 & 1 \end{bmatrix}}_{L} \underbrace{\begin{bmatrix} 1 & -2 & -1 & -1 \\ 0 & 4 & 5 & 4 \\ 0 & 0 & -11/4 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix}}_{U}$$

$$\left[\begin{array}{cccc|cccc}
1 & 2 & 1 & -2 & 3 \\
2 & 4 & 0 & 1 & 4 \\
-2 & -3 & 0 & 5 & -4 \\
0 & 1 & 2 & 1 & 2
\end{array}\right]$$

$$\bullet \ E_1 = \left| \begin{array}{cccc} 1 & 0 & 0 & 0 \\ -2 & 1 & 0 & 0 \\ 2 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right|,$$

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$$\bullet \ \ P_{23} = \left[ \begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right],$$

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$$P_{23}A = \begin{bmatrix} 1 & 2 & 1 & -2 \\ -2 & -3 & 0 & 5 \\ 2 & 4 & 0 & 1 \\ 0 & 1 & 2 & 1 \end{bmatrix} \quad E_1 = \begin{bmatrix} 7 & 0 & 0 & 0 \\ 21 & 0 & 0 & 0 \\ -2 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 1 & -2 \\ 0 & 1 & 2 & 1 \\ 0 & 0 & -2 & 5 \\ 0 & 1 & 2 & 1 \end{bmatrix}$$

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$$\overline{E_2E_1P_2}A = \overline{U}$$

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$$\frac{\overline{E}_{3} P_{14} \overline{E}_{2} P_{23} \overline{E}_{1} A = 0}{E_{3}' E_{2}' E_{1}' (P_{14} \cdot P_{23}) A = 0}$$

$$\frac{\overline{E}_{3}' E_{2}' E_{1}' (P_{14} \cdot P_{23}) A = 0}{(P_{14} \cdot P_{23}) A = (E_{3}') (E_{2}') (E_{3}') U}$$

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- ▶ **Column Space:** The set of all possible linear combinations of columns of A is called the Column space of matrix A, and is denoted by C(A).

$$C(A) = \{Ax \mid \forall x \in \mathbb{R}^n\}, C(A) \subseteq \mathbb{R}^m$$

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**Beware of the notation:**  $a_{i*}$  denotes the  $i^{th}$  row of A written as a column matrix.

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- The Column Space, Row Space, Null Space and Left Nullspace are called the Four Fundamental Subspaces associated with a matrix.