

Linear Control and Estimation

Matrices

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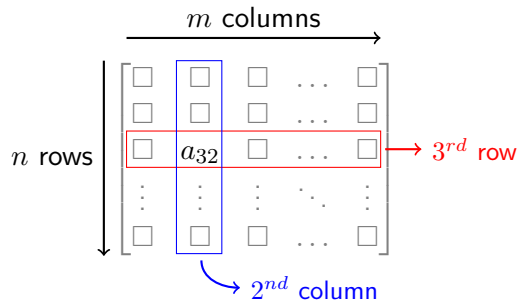
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References

- ▶ S Boyd, Applied Linear Algebra: Chapters 6, 7, 8, 10 and 11.
- ▶ G Strang, Linear Algebra: Chapters 1 and 2.

Matrices

- **Matrices** are rectangular array of numbers. $\begin{bmatrix} 1.1 & -24 & \sqrt{2} \\ 0 & 1.12 & -5.24 \end{bmatrix}$



- Consider a matrix A with n rows and m columns. $\begin{cases} \text{Tall/Skinny} & n > m \\ \text{Square} & n = m \\ \text{Wide/Fat} & n < m \end{cases}$

Matrices

- ▶ n -vectors can be interpreted as $n \times 1$ matrices. These are called *column vectors*.
- ▶ A matrix with only one row is called a *row vector*, which can be referred to as n -row-vector. $x = [1.45 \quad -3.1 \quad 12.4]$
- ▶ **Block matrices & Submatrices:** $A = \begin{bmatrix} B & C \\ D & E \end{bmatrix}$. What are the dimensions of the different matrices?
- ▶ Matrices are also compact way to give a set of indexed column n -vectors, $x_1, x_2, x_3 \dots x_m$.

$$X = [x_1 \quad x_2 \quad x_3 \quad \dots \quad x_m]$$

▶ **Zero matrix** $= 0_{n \times m} =$
$$\begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix}$$

Matrices

- **Identity matrix** is a square $n \times n$ matrix with all zero elements, except the diagonals where all elements are 1.

$$I_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \quad I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = [e_1 \quad e_2 \quad e_3]$$

- **Diagonal matrices** is a square matrix with non-zero elements on its diagonal.

$$\begin{bmatrix} 0.4 & 0 & 0 & 0 \\ 0 & -11 & 0 & 0 \\ 0 & 0 & 21 & 0 \\ 0 & 0 & 0 & 9.3 \end{bmatrix} = \mathbf{diag}(0.4, -11, 21, 9.3)$$

- **Triangular matrices:** Are square matrices. *Upper triangular* $A_{ij} = 0, \forall i > j$; *Lower triangular* $A_{ij} = 0, \forall i < j$.

Matrix operations

- **Transpose** switches the rows and columns of a matrix. A is a $n \times m$ matrix, then its transpose is represented by A^T , which is a $m \times n$ matrix.

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix} \implies A^T = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \\ a_{13} & a_{23} \end{bmatrix}$$

Transpose converts between column and row vectors.

What is the transpose of a block matrix? $A = \begin{bmatrix} B & C \\ D & E \end{bmatrix}$

- **Matrix addition** can only be carried out with matrices of same size. Like vectors we perform element wise addition.

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} = \begin{bmatrix} a_{11} + b_{11} & a_{12} + b_{12} \\ a_{21} + b_{21} & a_{22} + b_{22} \end{bmatrix}$$

Matrix operations

► Properties of matrix addition:

- *Commutative*: $A + B = B + A$
- *Associative*: $(A + B) + C = A + (B + C)$
- *Addition with zero matrix*: $A + 0 = 0 + A$
- *Transpose of sum*: $(A + B)^T = A^T + B^T$

► **Scalar multiplication** Each element of the matrix gets multiplied by the scalar.

$$\alpha \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} \alpha a_{11} & \alpha a_{12} \\ \alpha a_{21} & \alpha a_{22} \end{bmatrix}$$

- We will mostly only deal with matrices with real entries. Such matrices are elements of the set $\mathbb{R}^{n \times m}$.
- Given the aforementioned matrix operations and their properties, is $\mathbb{R}^{n \times m}$ a vector space?

Matrix multiplication

- ▶ It is possible to *multiply* two matrices $A \in \mathbb{R}^{n \times p}$ and $B \in \mathbb{R}^{p \times m}$ through *matrix multiplication* procedure.
- ▶ There is a product matrix $C := AB \in \mathbb{R}^{n \times m}$, if the number of columns of A is equal to the number of rows of B .

$$C_{ij} := \sum_{k=1}^p A_{ik} B_{kj} \quad \forall i \in \{1, \dots, n\} \quad \& \quad j \in \{1 \dots m\}$$

- ▶ *Inner product* is a special case of matrix multiplication between a *row vector* and a *column vector*.

$$x^T y = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}^T \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \sum_{i=1}^n x_i y_i$$

Matrix multiplication

- Consider a matrix $A \in \mathbb{R}^{n \times m}$ and a m -vector $x \in \mathbb{R}^m$. We can multiply A and x to obtain $y = Ax \in \mathbb{R}^n$.

$$y = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} \tilde{a}_1^T \\ \tilde{a}_2^T \\ \vdots \\ \tilde{a}_n^T \end{bmatrix} x = \begin{bmatrix} \tilde{a}_1^T x \\ \tilde{a}_2^T x \\ \vdots \\ \tilde{a}_n^T x \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^m a_{1i}x_i \\ \sum_{i=1}^m a_{2i}x_i \\ \vdots \\ \sum_{i=1}^m a_{ni}x_i \end{bmatrix}$$

$$y = \sum_{i=1}^m x_i \begin{bmatrix} a_{1i} \\ a_{2i} \\ \vdots \\ a_{ni} \end{bmatrix} = x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{n1} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{n2} \end{bmatrix} + \dots + x_m \begin{bmatrix} a_{1m} \\ a_{2m} \\ \vdots \\ a_{nm} \end{bmatrix}$$

- Multiplying a matrix A by a column vector x produces a linear combination of the columns of matrix A . The column mixture is provided by x .

Matrix multiplication

- ▶ We see a similar process in play when we multiply a row vector $x^T \in \mathbb{R}^n$ by a matrix $A \in \mathbb{R}^{n \times m}$.

$$y = x^T A = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}^T \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} = x^T \begin{bmatrix} a_1 & a_2 & \dots & a_m \end{bmatrix}$$

$$y = \begin{bmatrix} x^T a_1 & x^T a_2 & \dots & x^T a_m \end{bmatrix} = \sum_{i=1}^n x_i \begin{bmatrix} a_{i1} & a_{i2} & \dots & a_{im} \end{bmatrix}$$

- ▶ Multiplying a row vector x by a matrix A produces a linear combination of the row of matrix A . The row mixture is provided by x .

Matrix multiplication

- ▶ Multiplying two matrices $A \in \mathbb{R}^{n \times p}$ and $B \in \mathbb{R}^{p \times m}$, we have $C \in \mathbb{R}^{n \times m}$,

$$C = AB = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1p} \\ a_{21} & a_{22} & \dots & a_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{np} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{p1} & b_{p2} & \dots & b_{pm} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1m} \\ c_{21} & c_{22} & \dots & c_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{p1} & c_{n2} & \dots & c_{nm} \end{bmatrix}$$

- ▶ **Inner product interpretation:** $c_{ij} = \tilde{a}_i^T b_j$, $i \in \{1 \dots n\}$, $j \in \{1 \dots m\}$
- ▶ **Column interpretation:** $C = A \begin{bmatrix} b_1 & b_2 & \dots & b_m \end{bmatrix} = \begin{bmatrix} Ab_1 & Ab_2 & \dots & Ab_m \end{bmatrix}$

- ▶ **Row interpretation :** $C = \begin{bmatrix} \tilde{a}_1^T \\ \tilde{a}_2^T \\ \vdots \\ \tilde{a}_n^T \end{bmatrix} B = \begin{bmatrix} \tilde{a}_1^T B \\ \tilde{a}_2^T B \\ \vdots \\ \tilde{a}_n^T B \end{bmatrix}$

Matrix multiplication

- **Outer product interpretation** Consider two n -vectors $x, y \in \mathbb{R}^n$. The *outer product* is defined as,

$$xy^T = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} \begin{bmatrix} y_1 & y_2 & y_3 & \dots & y_n \end{bmatrix} = \begin{bmatrix} x_1 y_1 & x_1 y_2 & x_1 y_3 & \dots & x_1 y_n \\ x_2 y_1 & x_2 y_2 & x_2 y_3 & \dots & x_2 y_n \\ x_3 y_1 & x_3 y_2 & x_3 y_3 & \dots & x_3 y_n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_n y_1 & x_n y_2 & x_n y_3 & \dots & x_n y_n \end{bmatrix}$$

- We can represent the product between two matrices as the sum of outer products between the columns and A and rows of B .

$$AB = \begin{bmatrix} a_1 & a_2 & a_3 & \dots & a_p \end{bmatrix} \begin{bmatrix} \tilde{b}_1^T \\ \tilde{b}_2^T \\ \tilde{b}_3^T \\ \vdots \\ \tilde{b}_p^T \end{bmatrix} = \sum_{i=1}^p a_i \tilde{b}_i^T$$

Properties of matrix multiplication

- ▶ **Not commutative:** $AB \neq BA$

The product of two matrices might not always be defined. When it is defined, AB and BA need not match.

- ▶ **Distributive:** $A(B + C) = AB + AC$ and $(A + B)C = AC + BC$
- ▶ **Associative:** $A(BC) = (AB)C$
- ▶ **Transpose:** $(AB)^T = B^T A^T$
- ▶ **Scalar product:** $\alpha(AB) = (\alpha A)B = A(\alpha B)$

Linear equations

- ▶ Matrices present a compact way to represent a set of linear equations. Consider the following,

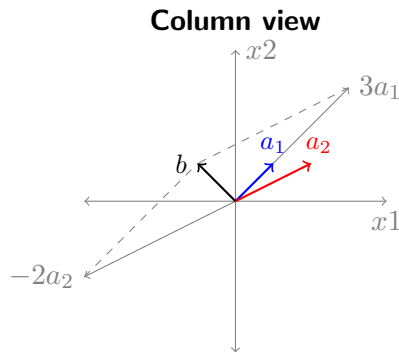
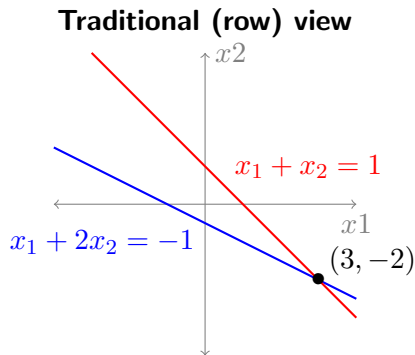
$$\left. \begin{array}{l} a_{11}x_1 + a_{12}x_2 \dots + a_{1n}x_n = b_1 \\ a_{21}x_1 + a_{22}x_2 \dots + a_{2n}x_n = b_2 \\ a_{31}x_1 + a_{32}x_2 \dots + a_{3n}x_n = b_3 \\ \vdots \\ a_{m1}x_1 + a_{m2}x_2 \dots + a_{mn}x_n = b_m \end{array} \right\} \longrightarrow Ax = b, \quad A \in \mathbb{R}^{m \times n}, \quad x \in \mathbb{R}^n, \quad b \in \mathbb{R}^m$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

Geometry of linear equations

$$\left. \begin{array}{l} x_1 + 2x_2 = -1 \\ x_1 + x_2 = 1 \end{array} \right\} \longrightarrow \begin{bmatrix} 1 & 2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Two ways to view this: **row view** and the **column view**.

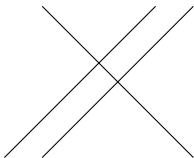


Solving linear equations

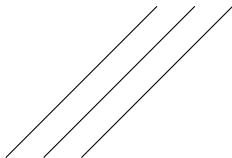
$$Ax = b, \quad A \in \mathbb{R}^{m \times n}, \quad x \in \mathbb{R}^n, \quad b \in \mathbb{R}^m$$

- ▶ **Three possible situations:** NO SOLUTION, INFINITELY MANY SOLUTIONS, or UNIQUE SOLUTION.
- ▶ When do we have infinitely many or no solutions? In \mathbb{R}^3 , we can visualize the different situations.

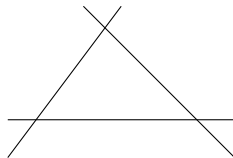
Two parallel planes



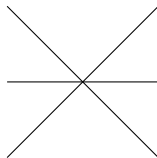
Three parallel planes



No intersection



Line intersection



Solving linear equations: Gaussian Elimination

$$a_{11}x_1 + a_{12}x_2 \dots + a_{1n}x_n = b_1 : E_1$$

$$a_{21}x_1 + a_{22}x_2 \dots + a_{2n}x_n = b_2 : E_2$$

$$a_{31}x_1 + a_{32}x_2 \dots + a_{3n}x_n = b_3 : E_3$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 \dots + a_{mn}x_n = b_m : E_m$$

- ▶ Gaussian elimination is a systematic way of simplifying the above equations to an equivalent system that can be easily solved.
- ▶ Three simple operations are repeatedly performed:
 - ▶ Interchanging of equations E_i and E_j .
 - ▶ Replacing equation E_i by αE_i , $\alpha \neq 0$.
 - ▶ Replacing equation E_j by $E_j + \alpha E_i$, $\alpha \neq 0$.
- ▶ These three operations do not change the solution of the given linear system.

Solving linear equations: Gaussian Elimination

Augmented matrix:

$$\left[\begin{array}{cccc|c} a_{11} & a_{12} & \cdots & a_{1n} & b_1 \\ a_{21} & a_{22} & \cdots & a_{2n} & b_2 \\ a_{31} & a_{32} & \cdots & a_{3n} & b_3 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} & b_m \end{array} \right]$$

- ▶ We can work with the augmented matrix instead of the equations.
- ▶ Gaussian elimination is carried out on the entire matrix.
- ▶ The matrix is simplified to a point, from where one can easily:
 - ▶ find out the nature of the solutions for the system of equations; and
 - ▶ find the solution (with a bit of extra work), if they exist.

Solving linear equations: Gaussian Elimination

$$\left. \begin{array}{rrcr} x_1 & + & 2x_2 & - & x_3 & = & 1 \\ 2x_1 & + & 3x_2 & + & 4x_3 & = & 4 \\ -2x_1 & - & 4x_2 & + & x_3 & = & -3 \end{array} \right\} \longrightarrow \left[\begin{array}{ccc|c} 1 & 2 & -1 & 1 \\ 2 & 3 & 4 & 4 \\ -2 & -4 & 1 & -3 \end{array} \right]$$

Gaussian Elimination

$$\left[\begin{array}{ccc|c} \underline{1} & 2 & -1 & 1 \\ 2 & 3 & 4 & 4 \\ -2 & -4 & 1 & -3 \end{array} \right] \longrightarrow \left[\begin{array}{ccc|c} \underline{1} & 2 & -1 & 1 \\ 0 & -1 & 6 & 2 \\ -2 & -4 & 1 & -3 \end{array} \right] \longrightarrow \left[\begin{array}{ccc|c} \underline{1} & 2 & -1 & 1 \\ 0 & \underline{-1} & 6 & 2 \\ 0 & 0 & \underline{-1} & -1 \end{array} \right]$$

Now, we can perform **back substitution** on this triangularized system of linear equations,

$$x_3 = 1; \quad x_2 = 4; \quad x_1 = -6$$

We can continue the simplification process through the **Gauss-Jordan** method.

Solving linear equations: Gaussian-Jordan Method

Continue the elimination upwards until all elements, except the ones in the main diagonal, are zero.

$$\left[\begin{array}{ccc|c} 1 & 2 & -1 & 1 \\ 0 & -1 & 6 & 2 \\ 0 & 0 & -1 & -1 \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 2 & -1 & 1 \\ 0 & -1 & 0 & -4 \\ 0 & 0 & 1 & 1 \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 2 & -1 & 1 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & 1 \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 2 & 0 & 2 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & 1 \end{array} \right]$$

$$\left[\begin{array}{ccc|c} 1 & 2 & 0 & 2 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & 1 \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 0 & 0 & -6 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & 1 \end{array} \right] \Rightarrow x_1 = -6; \quad x_2 = 4; \quad x_3 = 1;$$

Everything worked out well without any problems. What can go wrong here?

Try solving the these systems, $\left[\begin{array}{ccc|c} 1 & 2 & -1 & 1 \\ 2 & 3 & 4 & 4 \\ -2 & -4 & 2 & -3 \end{array} \right], \left[\begin{array}{ccc|c} 1 & 2 & -1 & 1 \\ 2 & 3 & 4 & 4 \\ -2 & -4 & 2 & -2 \end{array} \right]$

What is the difference between these two systems?

Solving linear equations: Rectangular systems and Row Echelon Form

$$\begin{aligned}
 a_{11}x_1 + a_{12}x_2 \dots + a_{1n}x_n &= b_1 : E_1 \\
 a_{21}x_1 + a_{22}x_2 \dots + a_{2n}x_n &= b_2 : E_2 \\
 a_{31}x_1 + a_{32}x_2 \dots + a_{3n}x_n &= b_3 : E_3 \\
 &\vdots \\
 a_{m1}x_1 + a_{m2}x_2 \dots + a_{mn}x_n &= b_m : E_m
 \end{aligned}
 \longrightarrow
 \left[\begin{array}{cccc|c}
 a_{11} & a_{12} & \cdots & a_{1n} & b_1 \\
 a_{21} & a_{22} & \cdots & a_{2n} & b_2 \\
 a_{31} & a_{32} & \cdots & a_{3n} & b_3 \\
 \vdots & \vdots & \ddots & \vdots & \vdots \\
 a_{m1} & a_{m2} & \cdots & a_{mn} & b_m
 \end{array} \right]$$

Consider the following example,

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

Solving linear equations: Rectangular systems and Row Echelon Form

$$\left[\begin{array}{cccc|c} a_{11} & a_{12} & \cdots & a_{1n} & b_1 \\ a_{21} & a_{22} & \cdots & a_{2n} & b_2 \\ a_{31} & a_{32} & \cdots & a_{3n} & b_3 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} & b_m \end{array} \right] \longrightarrow \left[\begin{array}{ccccccc} \underline{*} & * & * & * & * & * & * \\ 0 & 0 & \underline{*} & * & * & * & * \\ 0 & 0 & 0 & \underline{*} & * & * & * \\ 0 & 0 & 0 & 0 & \underline{*} & * & * \\ 0 & 0 & 0 & 0 & 0 & 0 & \underline{*} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right]$$

Things to notice about the echelon form:

- ▶ If a particular row consists entirely of zeros, then all rows below that row also contain entirely of zeros.
- ▶ If the first non-zero entry in the i^{th} row occurs in the j^{th} position, then all elements below the i^{th} row are zero from columns 1 to j .

Columns containing pivot are called the **basic columns**.

Rank of a matrix A is defined as the number of basic columns in the row echelon form of the matrix A .

Solving linear equations: Reduced Row Echelon Form

$$\begin{bmatrix}
 \underline{*} & * & * & * & * & * & * \\
 0 & 0 & \underline{*} & * & * & * & * \\
 0 & 0 & 0 & \underline{*} & * & * & * \\
 0 & 0 & 0 & 0 & \underline{*} & * & * \\
 0 & 0 & 0 & 0 & 0 & 0 & \underline{*} \\
 0 & 0 & 0 & 0 & 0 & 0 & 0
 \end{bmatrix}
 \xrightarrow{\text{Gaussian-Jordan}}
 \begin{bmatrix}
 \underline{1} & * & 0 & 0 & 0 & * & 0 \\
 0 & 0 & \underline{1} & 0 & 0 & * & 0 \\
 0 & 0 & 0 & \underline{1} & 0 & * & 0 \\
 0 & 0 & 0 & 0 & \underline{1} & * & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & \underline{1} \\
 0 & 0 & 0 & 0 & 0 & 0 & 0
 \end{bmatrix}$$

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

- ▶ All non-basic columns can be represented as a linear combination of the basic columns.
- ▶ A non-basic columns is a linear combination of only the columns before it.
- ▶ Scaling factors for each basic columns is determined by the corresponding elements of the non-basic columns.

The reduced row echelon form reveals structure in the original matrix A .

Solving linear equations: Homogenous Systems

$$\begin{aligned}
 a_{11}x_1 + a_{12}x_2 \dots + a_{1n}x_n &= 0 \\
 a_{21}x_1 + a_{22}x_2 \dots + a_{2n}x_n &= 0 \\
 a_{31}x_1 + a_{32}x_2 \dots + a_{3n}x_n &= 0 \\
 &\vdots \\
 a_{m1}x_1 + a_{m2}x_2 \dots + a_{mn}x_n &= 0
 \end{aligned}
 \longrightarrow
 \left[\begin{array}{cccc|c}
 a_{11} & a_{12} & \cdots & a_{1n} & 0 \\
 a_{21} & a_{22} & \cdots & a_{2n} & 0 \\
 a_{31} & a_{32} & \cdots & a_{3n} & 0 \\
 \vdots & \vdots & \ddots & \vdots & \vdots \\
 a_{m1} & a_{m2} & \cdots & a_{mn} & 0
 \end{array} \right]$$

Consider the following case,

$$\left[\begin{array}{ccccc|c}
 1 & -2 & 1 & 0 & 1 & 0 \\
 2 & -4 & 1 & -1 & -2 & 0 \\
 -1 & 2 & 1 & 1 & 2 & 0
 \end{array} \right] \longrightarrow \left[\begin{array}{ccccc|c}
 1 & -2 & 0 & 0 & 2 & 0 \\
 0 & 0 & 1 & 0 & -1 & 0 \\
 0 & 0 & 0 & 1 & 5 & 0
 \end{array} \right]$$

$$\begin{aligned}
 x_1 - 2x_2 + 2x_5 &= 0 & x_1 &= 2x_2 - 2x_5 \\
 x_3 - x_5 &= 0 & \longrightarrow & x_3 = x_5 \\
 x_4 + 5x_5 &= 0 & x_4 &= -5x_5
 \end{aligned}
 \longrightarrow
 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}
 = \begin{bmatrix} 2x_2 - 2x_5 \\ x_2 \\ x_5 \\ 5x_5 \\ x_5 \end{bmatrix}
 = x_2 \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}
 + x_5 \begin{bmatrix} -2 \\ 0 \\ 1 \\ -5 \\ 1 \end{bmatrix}$$

Solving linear equations: Homogenous Systems

► $\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = x_2 \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} -2 \\ 0 \\ 1 \\ -5 \\ 1 \end{bmatrix}$ represents the general solution of the system of equations.

- In general, any system $[A \mid 0]$ with $\text{rank}(A) = r$ has the general solution of the form,

$$x = x_{f_1} \mathbf{h}_1 + x_{f_2} \mathbf{h}_2 + \dots + x_{f_r} \mathbf{h}_r$$

where, the variables $x_{f_1}, x_{f_2}, \dots, x_{f_r}$ are called the **free variables**.

- Free variables are the one corresponding to the non-basic columns; the variable variables corresponding to the basic columns are the **basic variables**.
- When does a homogenous system have a unique solution solution? $\longrightarrow \text{rank}(A) = m$.

Solving linear equations: Non-homogenous Systems

$$a_{11}x_1 + a_{12}x_2 \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 \dots + a_{2n}x_n = b_2$$

$$a_{31}x_1 + a_{32}x_2 \dots + a_{3n}x_n = b_3 \longrightarrow [A \mid b]$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 \dots + a_{mn}x_n = b_m$$

Consider the following case,

$$\left[\begin{array}{ccccc|c} 1 & -2 & 1 & 0 & 1 & 1 \\ 2 & -4 & 1 & -1 & -2 & 2 \\ -1 & 2 & 1 & 1 & 2 & -1 \end{array} \right] \longrightarrow \left[\begin{array}{ccccc|c} 1 & -2 & 0 & 0 & 2 & 1 \\ 0 & 0 & 1 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 & 5 & 0 \end{array} \right]$$

$$\begin{array}{ll} x_1 - 2x_2 + 2x_5 = 1 & x_1 = 1 + 2x_2 - 2x_5 \\ x_3 - x_5 = 0 \longrightarrow x_3 = x_5 & \\ x_4 + 5x_5 = 0 & x_4 = -5x_5 \end{array} \longrightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 1 + 2x_2 - 2x_5 \\ x_2 \\ x_5 \\ -5x_5 \\ x_5 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} -2 \\ 0 \\ 1 \\ -5 \\ 1 \end{bmatrix}$$

The general solution of a non-homogenous system is sum of the particular solution and the general solution of the associated homogenous system.

Solving linear equations: Non-homogenous Systems

- ▶ The general solution for $[A \mid 0]$ with $\text{rank}(A) = r$,

$$x = \mathbf{p} + x_{f_1} \mathbf{h}_1 + x_{f_2} \mathbf{h}_2 + \dots + x_{f_r} \mathbf{h}_r$$

where, \mathbf{p} is the particular solution and $x_{f_1}, x_{f_2}, \dots, x_{f_r}$ are the free variables.

- ▶ When do we have a unique solution to this system? $\rightarrow \text{rank}(A) = m$.
- ▶ What about the case when there are no solutions? When does that happen? \rightarrow *When the system is not consistent.*

$$\left[\begin{array}{cccc|c} a_{11} & a_{12} & \cdots & a_{1n} & b_1 \\ a_{21} & a_{22} & \cdots & a_{2n} & b_2 \\ a_{31} & a_{32} & \cdots & a_{3n} & b_3 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} & b_m \end{array} \right] \longrightarrow \left[\begin{array}{cccccc|c} 1 & * & 0 & 0 & 0 & * & c_1 \\ 0 & 0 & 1 & 0 & 0 & * & c_2 \\ 0 & 0 & 0 & 1 & 0 & * & c_3 \\ 0 & 0 & 0 & 0 & 1 & * & c_4 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & c_m \end{array} \right]$$

There is a problem when $c_m \neq 0$

- ▶ The augmented matrix $[A \mid b]$ has the same number of basic columns as A .
- ▶ $[A \mid b] \rightarrow [E \mid c]$: c is a non-basic column.
- ▶ $\text{rank}(A) = \text{rank}([A \mid b])$

LU Factorization of a Matrix

- ▶ A major theme of matrix algebra is to decompose matrices into simpler components that provide insights into the nature of the matrix.
- ▶ A full rank square matrix $A \in \mathbb{R}^{n \times n}$ can be decomposed into the product of a lower triangular and an upper triangular matrix.
- ▶ Matrices associated with the three elementary operations:

**Inter-changing
rows 2 and 4**

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

**Scaling
row 2**

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \alpha & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

**Adding a multiple of
row 2 to row 3**

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \alpha & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

LU Factorization of a Matrix

- ▶ Consider the case: $A = \begin{bmatrix} 1 & -1 & 2 \\ 2 & 0 & 2 \\ 4 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 4 & 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 & 2 \\ 0 & 2 & -2 \\ 0 & 0 & -1 \end{bmatrix} = LU$
- ▶ LU factorization can be done only when no zero pivot is encountered during the Gaussian elimination process.
- ▶ $Ax = b$ becomes $LUx = b$: This is decomposed into two triangular systems, $Ux = y$, $Ly = b$. First solve $Ly = b$ and then solve $Ux = y$
- ▶ Properties:
 - ▶ Diagonal elements of L are 1, and U are not equal to zero.
 - ▶ U is the final result of Gaussian elimination, and L is the matrix that reverses this process.
 - ▶ Element l_{ij} of L is the multiple of row j used to eliminate the a_{ij} element of A .
- ▶ Uses of the LU factorization:
 - ▶ Solving $Ax = b_i$ for several b_i s. LU need to be calculated only once.
 - ▶ Factorization requires not extra space.

$PA = LU$ Factorization of a Matrix

- ▶ Consider the case: $A = \begin{bmatrix} 1 & 1 & 0 \\ 2 & 2 & 1 \\ 3 & 4 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \neq LU$
- ▶ It turns out the second pivot become zero after the first elimination step, so LU factorization cannot be done on A .
- ▶ The following however fixes this issue,

$$PA = LU$$

where, P is the permutation matrix, which is the elementary matrix for row exchanges.

- ▶ In the current example, the following allows matrix factorization.

$$PA = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 2 & 2 & 1 \\ 3 & 4 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = LU$$

Linear functions

- ▶ We had earlier seen linear functions of the form $f : \mathbb{R}^n \mapsto \mathbb{R}$, which had the form,

$$y = f(x) = w^T x; \quad w, x \in \mathbb{R}^n, \quad y \in \mathbb{R}$$

- ▶ A generalization of this is when the range of the function is not in \mathbb{R} but in \mathbb{R}^m :

$$y = f(x); \quad x \in \mathbb{R}^n, \quad y \in \mathbb{R}^m$$

- ▶ Such a function has a natural representation of the form $y = Ax$, $A \in \mathbb{R}^{m \times n}$. Can you prove that $y = Ax$ is linear?
- ▶ Any linear function can be represented in the form $y = Ax$. So, matrices can be viewed as representing a linear transformation.

Another look at matrix multiplication

Why does matrix multiplication have this strange definition?

Consider the following two functions,

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = f \left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) = \begin{bmatrix} ax_1 + bx_2 \\ cx_1 + dx_2 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = g \left(\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \right) = \begin{bmatrix} \alpha u_1 + \beta u_2 \\ \gamma u_1 + \delta u_2 \end{bmatrix} = \begin{bmatrix} \alpha & \beta \\ \gamma & \delta \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\begin{aligned} h(u) &= f(g(u)) = f \left(\begin{bmatrix} \alpha u_1 + \beta u_2 \\ \gamma u_1 + \delta u_2 \end{bmatrix} \right) = \begin{bmatrix} a\alpha u_1 + a\beta u_2 + b\gamma u_1 + b\delta u_2 \\ c\alpha u_1 + c\beta u_2 + d\gamma u_1 + d\delta u_2 \end{bmatrix} \\ &= \begin{bmatrix} (a\alpha + b\gamma) u_1 + (a\beta + b\delta) u_2 \\ (c\alpha + d\gamma) u_1 + (c\beta + d\delta) u_2 \end{bmatrix} = \begin{bmatrix} a\alpha + b\gamma & a\beta + b\delta \\ c\alpha + d\gamma & c\beta + d\delta \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ &\implies \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} \alpha & \beta \\ \gamma & \delta \end{bmatrix} = \begin{bmatrix} a\alpha + b\gamma & a\beta + b\delta \\ c\alpha + d\gamma & c\beta + d\delta \end{bmatrix} \end{aligned}$$

This definition of matrix multiplication is the most natural for dealing with composition of linear functions. It also turns out to be the most useful.

Four Fundamental Subspaces

- ▶ $C(A)$: **Column Space of A** – the span of the columns of A .

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

- ▶ $N(A)$: **Nullspace of A** – the set of all $x \in \mathbb{R}^n$ that are mapped to zero.

$$N(A) = \{x \mid Ax = 0\} \subseteq \mathbb{R}^n$$

- ▶ $C(A^T)$: **Row Space of A** – the span of the rows of A .

$$C(A^T) = \{A^T y \mid y \in \mathbb{R}^m\} \subseteq \mathbb{R}^n$$

- ▶ $N(A^T)$: **Nullspace of A^T** – the set of all $y \in \mathbb{R}^m$ that are mapped to zero by A^T .

$$N(A^T) = \{y \mid A^T y = 0\} \subseteq \mathbb{R}^m$$

This is also called the **left nullspace** of A .

Linear Independence

- ▶ Given a set of vectors $\{v_1, v_2, \dots, v_n\}$, $v_i \in \mathbb{R}^m$, how can we determine if this set is linear independent? Remember the Gram-Schmit algorithm?
- ▶ We need to verify, $\alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n = 0$

$$\left[v_1 \quad v_2 \quad \dots \quad v_n \right] \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = V\alpha = 0 \left\} N(A) = \{0\}, \text{rank}(V) = n \right.$$

- ▶ This is also equivalent to saying that when the $\text{rank}(A) = n \implies$ the columns of A form an independent set of vectors.
- ▶ When do the rows of A form an independent set?
- ▶ What about both rows and columns? When does that happen?

Dimension and basis of the four fundamental subspaces

$$A = \begin{bmatrix} 1 & -2 & 1 & 0 & 1 \\ 2 & -4 & 1 & -1 & -2 \\ -1 & 2 & 1 & 1 & 2 \\ 2 & -4 & -2 & -2 & -4 \end{bmatrix}; \quad EA = R$$

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ -2 & 1 & 0 & 0 \\ -1 & 2 & 1 & 1 \\ 2 & -4 & -2 & -2 \end{bmatrix}}_E A = \underbrace{\begin{bmatrix} 1 & -2 & 1 & 0 & 1 \\ 0 & 0 & -1 & -1 & -4 \\ 0 & 0 & 0 & -1 & -5 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}}_R$$

Pivot columns of A : $\left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \\ -2 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 1 \\ -2 \end{bmatrix} \right\}$

Nullspace of A : $x_2 h_1 + x_5 h_2$; $h_1 = \begin{bmatrix} -2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $h_2 = \begin{bmatrix} 2 \\ 0 \\ -1 \\ -5 \\ 1 \end{bmatrix}$

We can restructure $EA = R \rightarrow \begin{bmatrix} E_1 \\ E_2 \end{bmatrix} A = \begin{bmatrix} R_1 \\ 0 \end{bmatrix}$

Consider the matrix $A \in \mathbb{R}^{m \times n}$

► Column space $N(A)$

- $\dim C(A) = \text{rank}(A) = r$
- Basis of $C(A)$ = Pivot columns of A .

► Nullspace $N(A)$

- $\dim N(A) = n - r$
- Basis of $N(A) = \{h_1, h_2 \dots h_{n-r}\}$.

► Row space $C(A^T)$

- $\dim C(A) = \text{rank}(A^T) = \text{rank}(A) = r$
- Basis of $C(A^T)$ = Columns of R_1^T .

► Nullspace $N(A)$

- $\dim N(A) = n - r$
- Basis of $N(A)$ = Columns of E_2^T

Matrix Inverse

- ▶ Consider the square matrix $A \in \mathbb{R}^{n \times n}$. $B \in \mathbb{R}^{n \times n}$ is the inverse of A , if $AB = BA = I_n$, and B is represented as A^{-1} .
- ▶ Not all matrices have inverses. A matrix with an inverse is called **non-singular**, and a matrix that does not have an inverse is called **singular**.
- ▶ For a non-singular matrix A , A^{-1} is unique. A^{-1} is both the left and right inverse.
- ▶ A matrix A has an inverse, if and only if A is full rank, i.e. $\text{rank}(A) = n$
- ▶ The inverse of a non-singular matrix can be determined through Gauss-Jordan method. $[A|I] \xrightarrow{\text{Gaussian-Jordan}} [I|A^{-1}]$
- ▶ $Ax = b$ can be solved as follows, $x = A^{-1}b$. *It is never solved like this in practice.*
- ▶ Inverse of product of matrices, $(AB)^{-1} = B^{-1}A^{-1}$
- ▶ $(A^{-1})^{-1} = A$ and $(A^{-1})^T = (A^T)^{-1}$