## Lecture 21 - Linear systems, Column Space, and Null Space

November 16, 2022

Goals: Define column/null space for any matrix, compute an orthogonal basis of the column space, and use it to determine if  $A\mathbf{x} = \mathbf{b}$  has a solution.

We have discussed systems of equations  $A\mathbf{x} = \mathbf{b}$  where A is square to some extent; namely, we know such a system has only one solution precisely when A is invertible, in which case  $\mathbf{x} = A^{-1}\mathbf{b}$ . Otherwise, how do we determine if is no solution or infinitely many? Moreover, how do we answer these if our A is an  $m \times n$  matrix,  $\mathbf{x} \in \mathbb{R}^n$ ,  $\mathbf{b} \in \mathbb{R}^m$ ?

<u>Definition</u>: The column space of an  $m \times n$  matrix A is the span in  $\mathbb{R}^m$  of the columns of A (remember: columns of A are m-vectors). It is denoted C(A).

**Important:** This means that the system has a solution precisely when  $\mathbf{b}$  is in C(A) (it doesn't tell us how many solutions though. More on that later).

**Example 1:** Does the following system have a solution?

$$\begin{bmatrix}
-1 \\
-1 \\
-1
\end{bmatrix}$$

$$A^{2} \begin{bmatrix}
-1 \\
-1 \\
0
\end{bmatrix}$$

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

$$\begin{bmatrix}
-1 \\
0 \\
-2
\end{bmatrix}$$

$$\begin{bmatrix}
-1 \\
0 \\
-2
\end{bmatrix}$$

$$\begin{bmatrix}
-1 \\
0 \\
-2
\end{bmatrix}$$

$$\begin{bmatrix}
-1 \\
-2
\end{bmatrix}$$

$$2x - 3y + 2z = -1$$

$$x + y - 4z = 2$$

$$y - 2z = 1$$

The first  $\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ -2 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$ 

The first  $\begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$ 

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The first  $\begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$ 

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The first  $\begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$ 

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The first  $\begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -3 \\ 1 \\ 0$ 

**Example 2:** Determine the column space of the following matrix:

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

$$Check \text{ In depositive}$$

$$O \text{ note on such milb}$$

$$Check \text{ line comb}$$

$$\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} = -1 \begin{pmatrix} -3 \\ 1 \\ 0 \end{pmatrix} - \frac{1}{2} \begin{pmatrix} -3 \\ -4 \\ 0 \end{pmatrix}$$

$$\therefore \text{ such on to linearly deposite,}$$

$$Check \text{ line comb}$$

$$\begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} = x \begin{pmatrix} -3 \\ 1 \\ 0 \end{pmatrix} + y \begin{pmatrix} -3 \\ -4 \\ 0 \end{pmatrix}$$

$$\therefore \text{ such on to linearly deposite,}$$

$$2x - 3x + 2y - 3z - 3x - 1 - 3y -$$

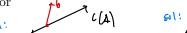
In general, we can just apply Gram-Schmidt to the columns of A to compute a basis for its span.

<u>Definition</u>: For any two sets V and W, the notation " $V \subset W$ " read as "V contained in W" or "V is a subset of W" means every object in V also belongs to W (e.g. a line V contained in a plane W).

The following two propositions give a more geometric description about the solutions to a 2×3 or a 3×3 system.

Proposition 21.2.5: Let A be a  $2 \times 3$  matrix who columns are all nonzero. The subspace  $C(A) \subset \mathbb{R}^2$  is a line when all columns are multiples of one another, or equivalently, "have the same slope"; if this is not the case, then  $C(A) = \mathbb{R}^2$ . For any such matrix A and any  $\mathbf{b} \in \mathbb{R}^2$ , the linear system  $A\mathbf{x} = \mathbf{b}$  of 2 equations in 3 unknowns has a solution precisely in the following circumstances:

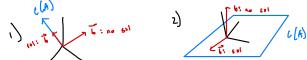
- if C(A) is a line then there is a solution exactly when b lies on that line (so either b = 0 or the slope  $b_2/b_1$  is the same as that of all nonzero vectors in the line C(A), or
- •• if  $C(A) = \mathbb{R}^2$ , then there is a solution for any **b**.

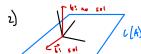


**Proposition 21.2.6:** Let A be a  $3 \times 3$  matrix whose columns are all nonzero. The subspace  $C(A) \subset \mathbb{R}^3$ is a line when all columns are scalar multiples of each other, it is equal to  $\mathbb{R}^3$  when the three columns are linearly independent, and in all other cases, it is a plane.

For such A and any  $\mathbf{b} \in \mathbb{R}^3$ , the linear system  $A\mathbf{x} = \mathbf{b}$  of 3 equations and 3 unknowns has a solution precisely in the following circumstances:

- if C(A) is a line, then there is a solution exactly when **b** lies in that line.
- $\mathsf{L} \bullet$  if C(A) is a plane, then there is a solution exactly when **b** lies in that plane.
- if  $C(A) = \mathbb{R}^3$ , then there is a solution for any **b**.





More generally, how can we tell if  $\mathbf{b} \in C(A)$  for any  $m \times n$  matrix A? One way is as follows:

• if  $\mathbf{b} \in C(A)$ , then  $\mathbf{Proj}_{C(A)}(\mathbf{b}) = \mathbf{b}$ .

So calculating the projection will tell us exactly if there is a solution.

**Example 3:** Do the following systems have solutions?

$$x + z = 2$$

$$x + y + z = -2$$

$$y + z = 2$$

$$z - 6$$

z=6 z=6

Step =) chulc projectives
$$\begin{bmatrix}
1 \\
2 \\
3
\end{bmatrix}$$
where the line is the constant of the constant of

Recall that the **image** of a linear transformation  $f: \mathbb{R}^n \to \mathbb{R}^m$  is the collection of vectors  $\mathbf{b} \in \mathbb{R}^m$  obtained as output of f, i.e. the vectors **b** such that  $\mathbf{b} = f(\mathbf{x})$  for some **x**.

$$= f(x) \text{ for some } x.$$

$$= A \overrightarrow{x} \qquad \text{inage } (f) = C(A')$$

We have now discussed the question "When does  $A\mathbf{x} = \mathbf{b}$  have a solution?" We will now address the questions "If there is a solution, is there more than one? How do we describe the set of all solutions?"

Let 
$$\vec{x}_1, \vec{x}_2$$
 be shifting to  $A\vec{x} = \vec{b}$ , this means  $A\vec{x}_1 = \vec{b}$ ,  $A\vec{x}_2 = \vec{b}$ 

$$A\vec{x}_1 - A\vec{x}_2 = \vec{b} - \vec{b} = 0 \implies A(\vec{x}_1 - \vec{x}_2) = \vec{0} \implies \vec{x}_1 - \vec{x}_2 \implies A\vec{x}_2 = \vec{0}$$

$$A\vec{x}_1 = \vec{0} \implies \text{ore solution } (\vec{x}_2 = \vec{0}) \implies \vec{x}_1 - \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2$$

$$A\vec{x}_1 = \vec{0} \implies \text{ore solution } (\vec{x}_2 = \vec{0}) \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_3 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{0} \implies \vec{x}_1 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{x}_1 + \vec{x}_2 \implies \vec{x}_2 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{x}_1 + \vec{x}_2 \implies \vec{x}_2 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{x}_2 + \vec{x}_2 \implies \vec{x}_2 = \vec{x}_1 + \vec{x}_2 \implies \vec$$

We see that the number of solutions to  $A\mathbf{x} = \mathbf{b}$  is closely related to whether or not there is a nonzero solution to Ax = 0; we call this the **homogeneous system** associated with A.

**Definition:** The null space of A, denoted N(A), is the set of all solutions in  $\mathbb{R}^n$  to the homogeneous system  $A\mathbf{x} = \mathbf{0}$ .

In the context of linear transformations, N(A) is everything that  $T_A$  sends to  $\mathbf{0}$ . So if  $T_A$  is invertible,  $N(A) = \{ \vec{D} \}$ 

**Example 4:** Let V be a linear subspace of  $\mathbb{R}^n$ , and  $T:\mathbb{R}^n\to\mathbb{R}^n$  be the projection of a vector onto

V. What is 
$$N(A)$$
, where  $A$  is the matrix associated with  $T$ ? not space is  $T(\bar{x}) = \bar{0}$ 

$$T(\bar{x}) = \lim_{N \to \infty} |\nabla x| = \sum_{i=1}^{N} |\nabla x_i|^2 + \sum$$

Therefore, if 
$$T(\vec{x}) \ge \vec{0}$$
, the  $\vec{x} \in V^{\perp}$ . Considerly, it  $\vec{x} \in V^{\perp}$ , the  $T(\vec{x}) = \vec{0}$  [orthogonal complement)

**Proposition 21.3.5:** For any  $m \times n$  matrix A,  $N(A) \subset \mathbb{R}^n$  contains 0. Also, if  $\mathbf{x}_1, \dots, \mathbf{x}_k \in N(A)$ , then any linear combination  $c_1 \mathbf{x}_1 + \dots + c_k \mathbf{x}_k \in N(A)$ .

contains 
$$\vec{0}$$
 . A $\vec{0}$ :  $\vec{0}$  =>  $\vec{0}$   $\in$  N(A)

respects anti-tion . A  $(c_1\vec{x}_1+...+c_k\vec{y}_k)=c_1A\vec{x}_1+...+c_kA\vec{x}_k=c_1L\vec{0})+...+c_kL\vec{0}=\vec{0}$ 

and senter

multiprentian

**Proposition 21.3.6:** The null space N(A) is a linear subspace of  $\mathbb{R}^n$ .

So in general, to find N(A), one needs to solve Ax = 0 and express x as a linear combination of vectors.

**Theorem 21.3.7:** If  $V \subset \mathbb{R}^n$  satisfies (i)  $\mathbf{0} \in V$  and (ii) for any  $\mathbf{x}_1, \dots, \mathbf{x}_k \in V$  and all scalars  $c_1, \dots, c_k$ ,  $c_1 \mathbf{x}_1 + \dots + c_k \mathbf{x}_k \in V$ , then V is a linear subspace of  $\mathbb{R}^n$ .

For any  $m \times n$  matrix A and  $\mathbf{b} \in \mathbb{R}^m$  for which the vector equation  $A\mathbf{x} = \mathbf{b}$ has some solution  $\mathbf{x}_0 \in \mathbb{R}^n$ , the solutions to  $A\mathbf{x} = \mathbf{b}$  are precisely the vectors of the form  $\mathbf{x}_0 + \mathbf{d}$ , where  $\mathbf{d} \in N(A)$ . There are infinitely many solutions whenever N(A) contains a nonzero vector.

$$\chi(\bar{\chi}_0 + \bar{J}) = A\bar{\chi}_0 + A\bar{J} = \bar{J} + \bar{O} = \bar{J}$$

**Example 5:** How many solutions does the following system of linear equations?

$$x + y = 2$$

$$x - y + z = 2$$

$$2y - z = 0$$

$$X = \begin{cases} 1 & 1 & 0 \\ 1 & -1 & 0 \\ 1 & 2 & -1 \end{cases}$$

More generally, how can we tell if  $\mathbf{b} \in C(A)$  for any  $m \times n$  matrix A? One way is as follows:

• if  $\mathbf{b} \in C(A)$ , then  $\mathbf{Proj}_{C(A)}(\mathbf{b}) = \mathbf{b}$ .

So calculating the projection will tell us exactly if there is a solution.

Project 
$$\vec{b} = 2\vec{\omega}_1 + 0\vec{\omega}_2 = \begin{pmatrix} 2 \\ 2 \end{pmatrix} = \vec{b}$$
 . Here's at least 1 solution

How may chitae?

(Audust N(t) 
$$\rightarrow A\vec{x} = \vec{0}$$
  $\rightarrow x = -\gamma$   $\rightarrow y = -\vec{x}$ 

(Audust N(t)  $\rightarrow A\vec{x} = \vec{0}$   $\rightarrow x + \gamma \cdot 2x = 0$ 
 $x + y = 0$   $\rightarrow x + \gamma \cdot 2x = 0$ 
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 $x + y = 0$   $\rightarrow x + \gamma \cdot 2x = 0$ 
 $x + y = 0$   $\rightarrow x + \gamma \cdot 2x = 0$ 
 $x + y =$ 

$$A\bar{x} = 0$$
 of  $\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} x \\ -x \\ -2x \end{pmatrix} = x \begin{pmatrix} -1 \\ -2 \end{pmatrix} : D(A) = span \left\{ \begin{pmatrix} -1 \\ -2 \end{pmatrix} \right\}, dim D(A) = 1$ 

solutions: (2) + t (-1), t & A

To summarize:

**Theorem 21.3.14:** Let A be an  $m \times n$  matrix. The equation  $A\mathbf{x} = \mathbf{b}$  has

- no solution if  $\mathbf{b} \notin C(A)$ .
- exactly one solution if  $\mathbf{b} \in C(A)$  and N(A) consists of only  $\mathbf{0}$ .
- infinitely many solutions if  $\mathbf{b} \in C(A)$  and N(A) contains a **nonzero** vector.

**Theorem 21.3.16 (Rank-Nullity Theorem):** For every  $m \times n$  matrix A.

$$\dim(C(A)) + \dim(N(A)) = n \qquad \longrightarrow \left(\overrightarrow{Y}_1, \dots, \overrightarrow{Y}_k\right), \qquad \overrightarrow{Y}_{k+1}, \dots, \qquad \overrightarrow{Y}_k$$

These results give a sort of "guideline" to determining the number of solutions to over/under determined systems:

Suppose  $A\mathbf{x} = \mathbf{b}$  is a system with m equations in n unknowns (so A is  $m \times n$ ).

- If the system is overdetermined (m > n), then it often fails to have any solution since there are "too many equations" happening simultaneously.
- If the system is underdetermined (m < n), then if there is a solution, there is automatically infinitely many since there are 'too few equations' so there is not enough information to pin down exactly one solution.

Again, these are not always the case; they are simply a guideline.

to the open of the hometre tooter to receive, the a basic of C(r) (as is only hometre scalar multiple of v). The null space N(A) consists of vectors  $\mathbf{x} \in \mathbf{R}^3$  that are orthogonal to each row of A (by the meaning of Ax and of N(A)), but those rows are multiples of  $\mathbf{w}^{\top}$ , so this is the same as authoroughlite to us. In other monds, M(A) is the linear subances of D3 appointing