

Last time: We discussed basis & dimension of two subspaces:

- $\text{Col}(A)$: basis = pivot cols; dim = rank = # pivot
- $\text{Nul}(A)$: basis = vectors in PVF; dim = # free vars

Today we'll discuss the other two subspaces (just replace A by A^T).

Why? This is the setup for orthogonality theory
↳ least squares / approximate solutions of $Ax=b$.

The Row Space

Def: The **row space** of A is $\text{Row}(A) = \text{Col}(A^T)$.

The columns of A^T are the rows of A , so

$$\text{Row}(A) = \text{Span}\{\text{rows of } A\}.$$

This is a subspace of \mathbb{R}^n $n = \#\text{columns of } A$

\rightsquigarrow **row picture.** $= \#\text{entries of each row}$

(That's why we call it the "row picture.")

The row space is a span \rightsquigarrow **parametric** description.

Eg: $\text{Row} \begin{pmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{pmatrix} = \text{Col} \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} = \text{Span} \left\{ \begin{pmatrix} 1 \\ 4 \\ 7 \end{pmatrix}, \begin{pmatrix} 2 \\ 5 \\ 8 \end{pmatrix}, \begin{pmatrix} 3 \\ 6 \\ 9 \end{pmatrix} \right\}$

Fact: Row operations **do not** change the row space.

Proof: Say the rows are v_1, v_2, v_3 .

- $R_2 \leftarrow 2R_1$: the new rows are $v_1, v_2 + 2v_1, v_3$.

$$\text{Span}\{v_1, v_2, v_3\} = \text{Span}\{v_1, v_2 + 2v_1, v_3\}$$

because $v_1 + 2v_2 \in \text{Span}\{v_1, v_2, v_3\}$ and

$$v_2 = (v_2 + 2v_1) - 2v_1 \in \text{Span}\{v_1, v_2 + 2v_1, v_3\}$$

- $R_1 \leftrightarrow R_2$: the new rows are v_2, v_1, v_3 , and

$$\text{Span}\{v_1, v_2, v_3\} = \text{Span}\{v_2, v_1, v_3\}$$



• $R_2 \times 2$: the new rows are $v_1, 2v_2, v_3$, and

$$\text{Span}\{v_1, v_2, v_3\} = \text{Span}\{v_1, 2v_2, v_3\} \quad \checkmark \quad //$$

This is a column space (of A^T), so we know how to find a basis (pivot cols of A^T). Here's a way to find a basis for $\text{Row}(A)$ by doing elimination on A , not A^T .

Thm: The nonzero rows in any REF of A form a basis for $\text{Row}(A)$.

Each nonzero row in an REF of A has exactly one pivot in it, so:

Consequence: $\boxed{\dim \text{Row}(A) = \#\text{pivots} = \text{rank}(A)}$

NB: This implies

$$\text{rank}(A^T) = \dim \text{Col}(A^T) = \dim \text{Row}(A) = \text{rank}(A)$$

which is not obvious! It says A & A^T have the same #pivots, but they may be in different positions! We don't get this without the **Thm**.

$$\boxed{\text{Row Rank} = \text{Column Rank}}$$

$$\text{rank}(A) = \text{rank}(A^T)$$

Eg: Find a basis for $\text{Row} \begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix}$

$$\begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix} \xrightarrow{\text{ref}} \begin{pmatrix} 1 & 2 & 2 & 1 \\ 0 & 0 & -3 & -3 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

\rightsquigarrow basis: $\left\{ \begin{pmatrix} 1 \\ 2 \\ 2 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ -3 \\ -3 \end{pmatrix} \right\}$

You can use any ref, eg. the ref:

$$\begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix} \xrightarrow{\text{ref}} \begin{pmatrix} 1 & 2 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

\rightsquigarrow another basis: $\left\{ \begin{pmatrix} 1 \\ 2 \\ 0 \\ -1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \\ 1 \end{pmatrix} \right\}$

Proof of the Thm:

(1) **Spans**: row ops don't change the row space, and the zero rows don't make the span any bigger.

(2) **LI**: A matrix in RREF looks like this:

$$\left(\begin{array}{ccc|c} \textcolor{red}{\bullet} & \textcolor{green}{\bullet} & \textcolor{green}{\bullet} & \textcolor{green}{\bullet} \\ \textcolor{red}{\bullet} & \textcolor{red}{\bullet} & \textcolor{green}{\bullet} & \textcolor{green}{\bullet} \\ \textcolor{red}{\bullet} & \textcolor{red}{\bullet} & \textcolor{red}{\bullet} & \textcolor{green}{\bullet} \\ \hline 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right) \quad \begin{array}{l} \textcolor{red}{\bullet} = \text{pivot} \\ \textcolor{green}{\bullet} = \text{anything} \end{array}$$

Let's solve the vector equation

$$x_1(\text{row 1}) + x_2(\text{row 2}) + x_3(\text{row 3}) = \mathbf{0}:$$

$$x_1 \left(\begin{array}{c} \textcolor{red}{\bullet} \\ \textcolor{green}{\bullet} \\ \textcolor{green}{\bullet} \\ \textcolor{green}{\bullet} \end{array} \right) + x_2 \left(\begin{array}{c} 0 \\ 0 \\ \textcolor{red}{\bullet} \\ \textcolor{green}{\bullet} \end{array} \right) + x_3 \left(\begin{array}{c} 0 \\ 0 \\ 0 \\ \textcolor{red}{\bullet} \end{array} \right) = \left(\begin{array}{c} 0 \\ 0 \\ 0 \\ 0 \end{array} \right)$$

The first coordinate is $\textcolor{red}{\bullet} x_1 = 0 \Rightarrow x_1 = 0$
because $\textcolor{red}{\bullet} \neq 0$. So this simplifies to

$$x_2 \left(\begin{array}{c} 0 \\ 0 \\ \textcolor{red}{\bullet} \\ \textcolor{green}{\bullet} \end{array} \right) + x_3 \left(\begin{array}{c} 0 \\ 0 \\ 0 \\ \textcolor{red}{\bullet} \end{array} \right) = \left(\begin{array}{c} 0 \\ 0 \\ 0 \\ 0 \end{array} \right)$$

Now the 3rd coordinate is $\textcolor{red}{\bullet} x_2 = 0 \Rightarrow x_2 = 0$.
Then $\textcolor{red}{\bullet} x_3 = 0 \Rightarrow x_3 = 0$. So the only solution
is $x_1 = x_2 = x_3 = 0$

//

The Left Null Space

Def: The **left null space** of A is $\text{Nul}(A^T)$. (no new notation)

This is the **solution set** of $A^T x = 0$.

This is a subspace of \mathbb{R}^n $m = \# \text{rows of } A$
 $\hookrightarrow \text{column picture.} \quad = \# \text{cols of } A^T$

The left null space is a solution set \hookrightarrow **implicit** description.

Why is it called the "left null space"?

$$A^T x = 0 \iff 0 = (A^T x)^T = x^T A, \text{ so}$$

$$\text{Nul}(A^T) = \{ \text{row vectors } x \in \mathbb{R}^m : x^T A = 0 \}$$

$\text{Nul}(A^T)$ is a null space, so you know how to compute a basis (PVF of $A^T x = 0$). You can also find a basis by doing **elimination** on A , not A^T .

Thm / Procedure: To find a basis of $\text{Nul}(A^T)$:

(1) Form the augmented matrix $(A | I_m)$.

(2) Eliminate to REF (U | E).

The **rows of E** to the right of the **zero rows of U** form a basis for $\text{Nul}(A^T)$.

In fact, you can stop elimination once U is in REF; you don't need all of $(U | E)$ to be in REF.

There's a slick proof in the supplement.

Eg: Find a basis for $\text{Nul} \begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix}^T$.

Form the augmented matrix & eliminate:

$$\left(\begin{array}{cccc|ccc} 1 & 2 & 2 & 1 & 1 & 0 & 0 \\ 2 & 4 & 1 & -1 & 0 & 1 & 0 \\ 1 & 2 & -1 & -2 & 0 & 0 & 1 \end{array} \right) \xrightarrow{\text{ref}} \left(\begin{array}{cccc|ccc} 1 & 2 & 2 & 1 & 1 & 0 & 0 \\ 0 & 0 & -3 & -3 & -2 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 1 \end{array} \right)$$

zero ↑

\rightsquigarrow basis $\left\{ \begin{pmatrix} 1 \\ -1 \\ 1 \end{pmatrix} \right\}$

Check: $(1 \ -1 \ 1) \begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix} = (0 \ 0 \ 0)$ ✓

NB: if you just want a basis for $\text{Nul}(A^T)$ and don't have any other reason to do elimination on A , it's easier to just find the PVF of $A^T x = 0$.

Since U is an REF of A , the #nonzero rows is the # pivots of A = the rank of A .

Consequence: $\dim \text{Nul}(A^T) = \# \text{rows} - \text{rank}(A)$

NB: row operations **change** $\text{Nul}(A^T)$.

eg: According to the Thm, to find a basis for

$\text{Nul}\begin{pmatrix} 1 & 2 & 2 & 1 \\ 0 & 0 & -3 & -3 \\ 0 & 0 & 0 & 0 \end{pmatrix}^T$, we put this matrix in REF:

$$\left(\begin{array}{cccc|ccc} 1 & 2 & 2 & 1 & 1 & 0 & 0 \\ 0 & 0 & -3 & -3 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array} \right)$$

It's already in REF, so a basis is $\left\{ \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \right\}$.

But we computed in a previous example that

$$\left(\begin{array}{cccc} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{array} \right) \xrightarrow{\text{ref}} \left(\begin{array}{cccc} 1 & 2 & 2 & 1 \\ 0 & 0 & -3 & -3 \\ 0 & 0 & 0 & 0 \end{array} \right)$$

and $\text{Nul}\begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix}^T$ has basis $\left\{ \begin{pmatrix} 1 \\ -1 \\ 1 \end{pmatrix} \right\}$

so $\text{Nul}\begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 1 & -1 \\ 1 & 2 & -1 & -2 \end{pmatrix}^T \neq \text{Nul}\begin{pmatrix} 1 & 2 & 2 & 1 \\ 0 & 0 & -3 & -3 \\ 0 & 0 & 0 & 0 \end{pmatrix}^T$.

Summary: The Four Subspaces

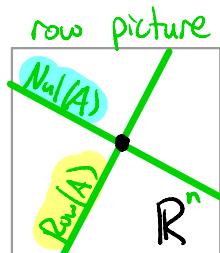
$A: m \times n$ matrix of rank r

Subspace	of	row/ col	dim	basis	implicit/ parametric
$\text{Col}(A)$	\mathbb{R}^m	col	r	pivot cols of A	parametric
$\text{Nul}(A)$	\mathbb{R}^n	row	$n-r$	vectors in PVF	implicit
$\text{Row}(A)$	\mathbb{R}^n	row	r	nonzero rows in $\text{REF}(A)$	parametric
$\text{Nul}(A^T)$	\mathbb{R}^m	col	$m-r$	last $m-r$ rows of E	implicit

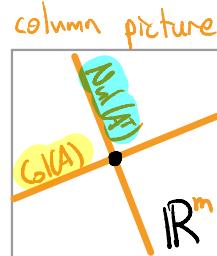
The row picture subspaces $\text{Nul}(A)$, $\text{Row}(A)$ are unchanged by row operations

The column picture subspaces $\text{Col}(A)$, $\text{Nul}(A^T)$ are changed by row operations

The row & column pictures each have one parametric & one implicit form subspace.



$$\begin{aligned} \dim \text{Nul}(A) \\ + \dim \text{Row}(A) \\ = n \end{aligned}$$



$$\begin{aligned} \dim \text{Col}(A) \\ + \dim \text{Nul}(A^T) \\ = m \end{aligned}$$

♪ The row space lives in the... row picture!
The null space lives in the... row picture!
the other two live in the... column picture!
That's how you keep them straight! ♪

Here's an important numerical consequence. It relates the dimension ("size") of the column space to the dimension of the null space.

Rank-Nullity Theorem

$$\dim \text{Col}(A) + \dim \text{Nul}(A) = n = \#\text{columns of } A$$

[DEMO 1]

[DEMO 2]

[DEMO 3]

[DEMO 4]

NB: You can compute bases for all four subspaces by doing elimination once on $(A | I_m) \rightsquigarrow (U | E)$

(1) An REF of $A \rightsquigarrow$ pivots \rightsquigarrow basis of $\text{Col}(A)$

(2) The RREF of $A \rightsquigarrow$ PIV \rightsquigarrow basis of $\text{Nul}(A)$

(3) An REF of $A \rightsquigarrow$ nonzero rows \rightsquigarrow basis of $\text{Row}(A)$

(4) Last $m-r$ rows of $E \rightsquigarrow$ basis of $\text{Nul}(A^T)$.

(However, if you only need a basis for $\text{Nul}(A^T)$, just find the RREF of A^T instead.)

Full-Rank Matrices

Since each row and each col has at most one pivot,

$$\#\text{pivots} = \text{rank}(A) \leq \min\{\#\text{rows}, \#\text{cols}\}$$

A "random" matrix will have the largest rank possible: ie, this will be an equality. This is a very important special case.

Def: An $m \times n$ matrix of rank r has:

- full column rank (FCR) if $r=n$

(every **column** has a pivot)

$$\begin{pmatrix} \bullet & \bullet & \bullet \\ 0 & \bullet & \bullet \\ 0 & 0 & \bullet \\ 0 & 0 & 0 \end{pmatrix} \quad 3=3$$

- full row rank (FRR) if $r=m$

(every **row** has a pivot)

$$\begin{pmatrix} \bullet & \bullet & \bullet & \bullet \\ 0 & \bullet & \bullet & \bullet \\ 0 & 0 & 0 & \bullet \end{pmatrix} \quad 3=3$$

NB:

- If A has FCR then $n=r \leq m$

$\Rightarrow A$ is **tall** or **square** ($\#\text{rows} \geq \#\text{cols}$)

- If A has FRR then $m=r \leq n$

$\Rightarrow A$ is **wide** or **square** ($\#\text{cols} \geq \#\text{rows}$)

- If A has FCR and FRR then $n=r=m$

$\Rightarrow A$ is **square**.

Here is a list of properties of matrices that translate into "pivot in every column":

Thm: Let A be an $m \times n$ matrix.

The Following Are Equivalent:

(1) A has full column rank

(1') A has a pivot in every column

(1'') A has no free columns

(2) $\text{Nul}(A) = \{0\}$ ← simple description of $\text{Nul}(A)$

(2') $Ax=0$ only has the trivial solution

(3) $Ax=b$ has 0 or 1 solution for every $b \in \mathbb{R}^m$.

(4) A has linearly independent columns.

(4') $\dim \text{Col}(A) = n$

(4'') $\dim \text{Row}(A) = n$

(5) $\text{Row}(A) = \mathbb{R}^n$ ← simple description of $\text{Row}(A)$

(6) A^T has full row rank.

Notes: • (1) \Leftrightarrow (6) because $\text{rank}(A) = \text{rank}(A^T)$.

• (2), (3), (4) all mean "no free variables" = (1'')

• (4'), (4'') are because $\dim \text{Col}(A) = \dim \text{Row}(A) = \text{rank} = n$.

• (4'') \Leftrightarrow (5) because the only n -dimensional subspace of \mathbb{R}^n is all of \mathbb{R}^n (L7).

(for a given matrix, either they're all true or they're all false.)

Here is a list of properties of matrices that translate into "pivot in every row":

Thm: Let A be an $m \times n$ matrix.

The Following Are Equivalent:

(1) A has full row rank

(1') A has a pivot in every row

(2) $\text{Col}(A) = \mathbb{R}^m$ ← simple description of $\text{Col}(A)$

(3) $Ax = b$ is consistent for every $b \in \mathbb{R}^m$

(4) A has linearly independent rows

(4') $\dim \text{Col}(A) = m$

(4'') $\dim \text{Row}(A) = m$

(5) $\text{Nul}(A^T) = \{0\}$ ← simple description of $\text{Nul}(A^T)$

(6) A^T has full column rank.

Notes:

- (2) \Leftrightarrow (3) is the column picture criterion for consistency.
- (5) \Leftrightarrow (1) because $\dim \text{Nul}(A^T) = m - \text{rank} = m - m = 0$
- (5) \Leftrightarrow (4) because the rows of A are the cols of A^T .
- (4') \Leftrightarrow (2) because the only m -dimensional subspace of \mathbb{R}^m is all of \mathbb{R}^m (L7).

If A has full column rank and full row rank then
 $r=m=n \Rightarrow$ square and invertible (n pivots)

Thm: Let A be an $n \times n$ (square) matrix.

The Following Are Equivalent:

(1) A is invertible.

(1') A has n pivots.

(1'') A has full column rank.

↳ all of the equivalent conditions for FCR

(1''') A has full row rank.

↳ all of the equivalent conditions for FRR

(2) There is a matrix A^{-1} such that $A^{-1}A=I_n$

(2') There is a matrix A^{-1} such that $AA^{-1}=I_n$

(3) $Ax=b$ has exactly 1 solution for every $b \in \mathbb{R}^n$

↳ namely $x=A^{-1}b$

(4) A^T is invertible.

Notes:

- We discussed $(1) \Leftrightarrow (1') \Leftrightarrow (2) \Leftrightarrow (2') \Leftrightarrow (3)$ in L3.
- $(1) \Leftrightarrow (4)$ because $\text{rank}(A) = \text{rank}(A^T)$.

Consequence: Let v_1, v_2, \dots, v_n be vectors in \mathbb{R}^n

\rightarrow $n \times n$ matrix $A = \begin{pmatrix} v_1 & \dots & v_n \end{pmatrix}$

(1) $\text{Span}\{v_1, v_2, \dots, v_n\} = \mathbb{R}^n \iff \text{Col}(A) = \mathbb{R}^n$

$\iff A$ has FRR $\iff A$ is invertible

(2) $\{v_1, v_2, \dots, v_n\}$ is LI $\iff \text{Nul}(A) = \{0\}$

$\iff A$ has FCR $\iff A$ is invertible

Recall: $\text{Span}\{v_1, v_2, \dots, v_n\} = \mathbb{R}^n$ and $\{v_1, v_2, \dots, v_n\}$ is LI
mean $\{v_1, v_2, \dots, v_n\}$ is a basis for \mathbb{R}^n .

Upshot:

