

1.3 Matrices Multiplying Vectors : A times x

An m by n matrix A has m rows and n columns

Those columns a_1, a_2, \dots, a_n are in m -dimensional space

$$A = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix}$$

Their combinations are $x_1 a_1 + \cdots + x_n a_n = Ax = \mathbf{matrix } A \text{ times vector } x$

There is a **row way** to multiply Ax and also a **column way** to compute the vector Ax

Row way = Dot product of vector x with each row of A

$$Ax = \begin{bmatrix} 2 & 5 \\ 3 & 7 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 2v_1 + 5v_2 \\ 3v_1 + 7v_2 \end{bmatrix} \quad \begin{bmatrix} 2 & 5 \\ 3 & 7 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 7 \\ 10 \end{bmatrix} \quad \begin{array}{l} \text{Find 7} \\ \text{Then 10} \end{array}$$

Column way = Ax is a combination of the columns of A

$$Ax = \begin{bmatrix} 2 & 5 \\ 3 & 7 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = v_1 \begin{bmatrix} \text{column} \\ 1 \end{bmatrix} + v_2 \begin{bmatrix} \text{column} \\ 2 \end{bmatrix} \quad \begin{bmatrix} 2 & 5 \\ 3 & 7 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix} + \begin{bmatrix} 5 \\ 7 \end{bmatrix} = \begin{bmatrix} 7 \\ 10 \end{bmatrix} \quad \begin{array}{l} 7 \text{ and } 10 \\ \text{together} \end{array}$$

Which way to choose ? Dot products with **rows** or combination of **columns** ?

For computing with numbers, I use the row way : dot products

For understanding with vectors, I use the column way : combine columns

Same result Ax from the same multiply-adds. Just in a different order

$C(A) = \text{Column space of } A = \text{all combinations of the columns} = \text{all outputs } Ax$

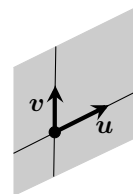
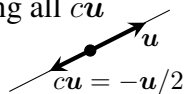
The **identity matrix** has $Ix = x$ for every x

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

The column space of the 3 by 3 identity matrix I is the whole space \mathbf{R}^3 .

If all columns are multiples of column 1 (not zero), the column space $C(A)$ is a line.

Line containing all cu



Plane from
all $cu + dv$

3.3 Independent Columns and Rows : Bases by Elimination

Remember $A = CR$ with r independent columns in C (but how to find them?)

The good way is **elimination on the m rows of A** (not the columns)

In Chapter 2, elimination reduced A to the n by n identity matrix : A was invertible

Now elimination will produce an **r by r identity matrix inside R**

That identity matrix locates the **r independent columns of A**

Here is an example of elimination

$$A = \begin{bmatrix} 1 & 2 & 4 \\ 3 & 8 & 14 \\ 0 & 4 & 4 \end{bmatrix} \xrightarrow[\text{steps}]{\text{two}} \begin{bmatrix} 1 & 2 & 4 \\ 0 & 2 & 2 \\ 0 & 0 & 0 \end{bmatrix} \xrightarrow[\text{steps}]{\text{two}} \begin{bmatrix} 1 & 0 & 2 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} = \begin{matrix} \text{“reduced row} \\ \text{echelon form”} \\ R_0 \end{matrix}$$

This last matrix R_0 reveals the row space and column space and nullspace of A

Basis for the row space of $A =$ **Rows of $R =$ Rows 1 and 2 of R_0**

Basis for the column space of $A =$ **Columns 1 and 2 of A . Then $A = CR$**

Basis for the nullspace of A : Solve $R_0x = 0$ to find $x = \begin{bmatrix} -2 \\ -1 \\ 1 \end{bmatrix}$ in Section 3.4

We will show how elimination works to reach this special form $R_0 : m - r$ zero rows

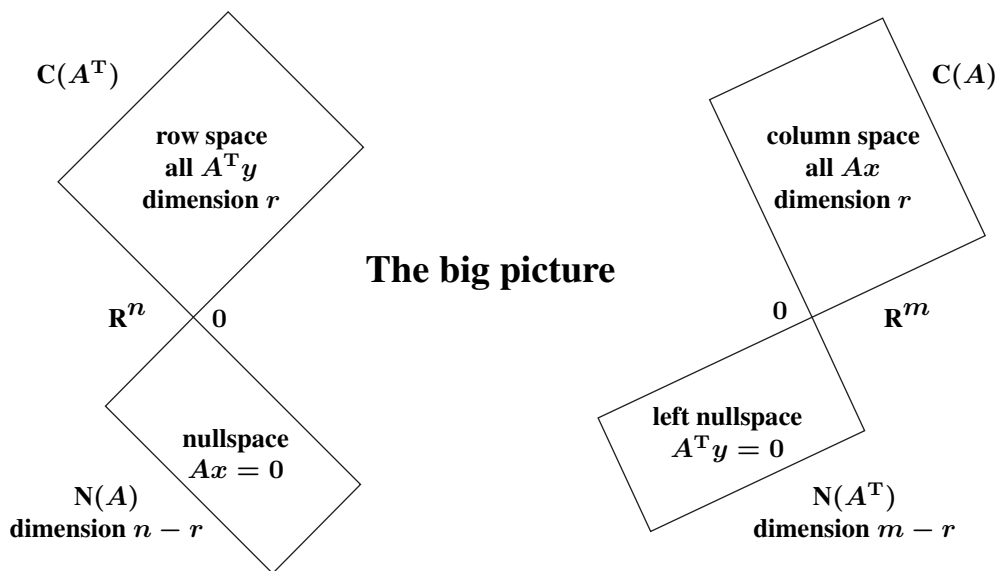
Three types of elimination steps All of them can be reversed !

- 1 Subtract a multiple of one row from another row (below or above)
- 2 Multiply a row by a nonzero number (to produce pivot = first nonzero = 1)
- 3 Exchange rows (to move pivot rows in R above any zero rows in R_0)

Key point Those steps do not change the row space of a matrix

The result $R_0 = \begin{bmatrix} R \\ 0 \end{bmatrix}$ has the same row space as A : simpler rows and $m - r$ zero rows

3.5 Four Fundamental Subspaces $C(A)$, $C(A^T)$, $N(A)$, $N(A^T)$



Fundamental Theorem of Linear Algebra, Part 1

*The column space and row space both have dimension r .
The nullspaces have dimensions $n - r$ and $m - r$.*

This tells us the **Counting Theorem**: How many solutions to $Ax = 0$? $n - r$ m equations, n unknowns, rank $r \Rightarrow Ax = 0$ has $n - r$ independent solutions
At least $n - m$ solutions. More solutions for dependent equations (then $r < m$)

There is always a nonzero solution x to $Ax = 0$ if $n > m$ Good to know

Fundamental Theorem, Part 2: **Subspaces are orthogonal**: Chapter 4

Fundamental Theorem, Part 3: **Perfect bases = singular vectors v, u** : Chapter 7

Row space: Basis v_1 to v_r

Column space: Basis u_1 to u_r

Nullspace: Basis v_{r+1} to v_n

Nullspace of A^T : Basis u_{r+1} to u_m

Part 7 : Singular Values and Vectors : $Av = \sigma u$ and $A = U\Sigma V^T$

7.1 Singular Vectors in U and V —Singular Values in Σ

An example shows **orthogonal inputs** v going into **orthogonal outputs** Av

$$Av_1 = \begin{bmatrix} 3 & 0 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 9 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 3 \end{bmatrix} \quad \text{and} \quad Av_2 = \begin{bmatrix} 3 & 0 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} -3 \\ 1 \end{bmatrix}$$

$$v_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \text{ is orthogonal to } v_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad u_1 = \begin{bmatrix} 1 \\ 3 \end{bmatrix} \text{ is orthogonal to } u_2 = \begin{bmatrix} -3 \\ 1 \end{bmatrix}$$

Divide inputs v_1 and v_2 by $\sqrt{2}$

Divide outputs u_1 and u_2 by $\sqrt{10}$

Four unit vectors with $Av_1 = 3\sqrt{5}u_1$ and $Av_2 = \sqrt{5}u_2$

Notice $\sqrt{10}/\sqrt{2} = \sqrt{5}$

$v_1, v_2 =$ orthogonal basis for the **row space** of $A =$ right singular vectors in V

$u_1, u_2 =$ orthogonal basis for the **column space** of $A =$ left singular vectors in U

$\sigma_1 = 3\sqrt{5}$ and $\sigma_2 = \sqrt{5}$ are the **singular values** of A in the diagonal matrix Σ

Express $Av_1 = 3\sqrt{5}u_1$ and $Av_2 = \sqrt{5}u_2$ in matrix form $AV = U\Sigma$

$$V = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} / \sqrt{2} \quad \text{and} \quad U = \begin{bmatrix} 1 & -3 \\ 3 & 1 \end{bmatrix} / \sqrt{10} \text{ are orthogonal matrices} \quad \begin{array}{l} V^T V = I \\ U^T U = I \end{array}$$

$$\text{Matrix form} \quad AV = U\Sigma \quad \begin{bmatrix} 3 & 0 \\ 4 & 5 \end{bmatrix} \begin{bmatrix} v_1 & v_2 \end{bmatrix} = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} 3\sqrt{5} & 0 \\ 0 & \sqrt{5} \end{bmatrix} \quad \begin{array}{l} \text{Multiply by} \\ V^{-1} = V^T \end{array}$$

$A = U\Sigma V^T$ is the perfect decomposition of A : **orthogonal–diagonal–orthogonal**