

BLOCK MATRIX MULTI.

$$AB = A[B_1 \dots B_p] = [AB_1 \dots AB_p]$$

2 MORE EXAMPLES:

$$\textcircled{1} \quad ABC = \begin{bmatrix} -\bar{a}_1^T & & \\ -\bar{a}_m^T & & \end{bmatrix} \left[\begin{array}{c|c} B & \\ \hline C_1 & \dots & C_q \end{array} \right]$$

$A \in \mathbb{R}^{m \times n}$
 $B \in \mathbb{R}^{n \times p}$
 $C \in \mathbb{R}^{p \times q}$

$$\begin{bmatrix} -\bar{a}_1^T & & \\ -\bar{a}_m^T & & \end{bmatrix} \left[\begin{array}{c|c} BC_1 & \dots & BC_q \\ \hline \bar{a}_1^T \bar{B} C_1 & \dots & \bar{a}_m^T \bar{B} C_q \end{array} \right]$$

Recall ...

$$\begin{bmatrix} -\bar{a}_1^T & & \\ -\bar{a}_m^T & & \end{bmatrix} \left[\begin{array}{c|c} C_1 & \dots & C_q \\ \hline C_1 & \dots & C_q \end{array} \right] = \begin{bmatrix} \bar{a}_1^T C_1 & \bar{a}_1^T C_q \\ \bar{a}_m^T C_1 & \bar{a}_m^T C_q \end{bmatrix}$$

$$\textcircled{2} \quad ABC = \begin{bmatrix} A_1 & & & & & \\ & \ddots & & & & \\ & & A_n & B_{11} & \dots & B_{1p} \\ & & & B_{n1} & \dots & B_{np} \\ & & & & \ddots & \\ & & & & & A_p \end{bmatrix} \begin{bmatrix} -\bar{C}_1^T & & \\ -\bar{C}_m^T & & \\ -\bar{C}_p^T & & \end{bmatrix}$$

$$= \begin{bmatrix} A_1 B_{11} + \dots + A_n B_{n1} & & & & \\ & \vdots & & & \\ & & A_1 B_{1p} + \dots + A_n B_{np} & & \end{bmatrix} \begin{bmatrix} -\bar{C}_1^T & & \\ -\bar{C}_m^T & & \\ -\bar{C}_p^T & & \end{bmatrix}$$

$$= [A_1 B_{11} \bar{C}_1^T + \dots + A_n B_{n1} \bar{C}_1^T] + \dots + (A_1 B_{1p} \bar{C}_p^T + \dots + A_n B_{np} \bar{C}_p^T)$$

$$= \sum_{i=1}^n \sum_{j=1}^p (A_i B_{ij} \bar{C}_j^T) = \sum_{ij} A_i B_{ij} \bar{C}_j^T$$

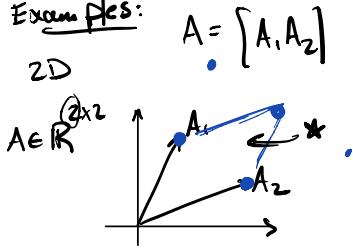
$$3 \begin{bmatrix} \bar{a}_1^T \\ \hline A & | & b \\ \hline 2 \times 2 & & 2 \times 1 \end{bmatrix} \leftarrow \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$\begin{bmatrix} B_{ij} & -\bar{C}_j^T \\ \hline A_i & \end{bmatrix}$$

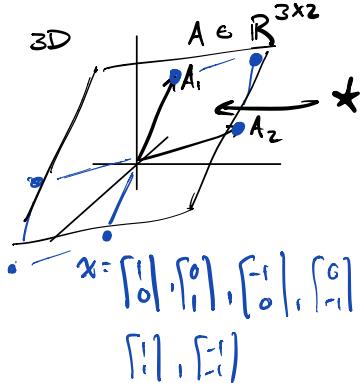
$$Ax = \begin{bmatrix} -\bar{a}_1^T \\ -\bar{a}_m^T \end{bmatrix} x = \begin{bmatrix} A_1 & \cdots & A_n \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$$= \begin{bmatrix} \bar{a}_1^T x \\ \bar{a}_m^T x \end{bmatrix} = A_1 x_1 + \cdots + A_n x_n \quad \text{linear comb of the cols of } A$$

Example:



$$Ax: x = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$



Linear Comb's. $A \in \mathbb{R}^{m \times n}$

$\{y \mid y = Ax, x \in \mathbb{R}^n\} \rightarrow$ set of lin combs or subspace } \rightarrow span of cols of A .
 such that for a particular $y \dots$ "every possible lin comb"

if $\exists x$ s.t. $y = Ax$ say " $y \in$ span of the cols of A "

Tech Defn: of Subspace vector space W , $V \subseteq W$

subspace is a set of vectors V (infinite / continuum)

s.t. if $A_1, A_2 \in V$ then $A_1 x_1 + A_2 x_2 \in V \leftarrow A_1, A_2$ vectors
 subspaces are sets of vectors that are x_1, x_2 scalars
 "closed under linear combinations"

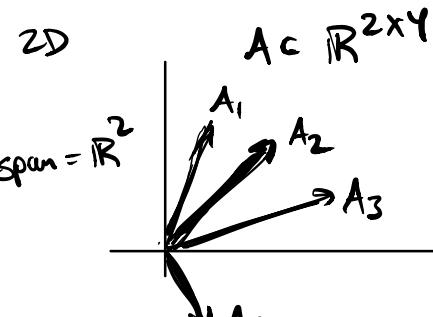
- all of W is a subspace

- 0 is in every subspace

$$A_1 0 + A_2 0 = 0$$

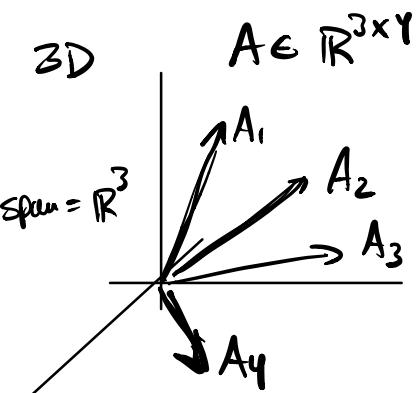
↑ zero scalars ↑ zero vector

$$A = [A_1 \ A_2 \ A_3 \ A_4]$$



What is the span?
⇒ redundant vectors...

More lin independent cols than dims



Tech Defn : Linearly Dep.

A_1 is lin dep on $\{A_2 \dots A_n\}$

if $A_1 = A_2y_2 + \dots + A_ny_n$

$$A_1 = A_2 \left(\frac{y_2}{x_1} \right) + \dots + A_n \left(\frac{y_n}{x_1} \right)$$

$$A = [A_1 \ A_2 \ A_3 \ A_4]$$

cols are lin dep

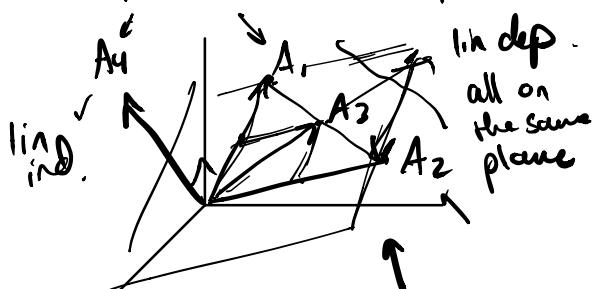
set of vectors $[A_1 \dots A_n]$ is lin dep

If $\exists \underline{x} \neq 0 \in$

$$\underline{A_1x_1 + \dots + A_nx_n = 0}$$

$$A_4 \frac{x_1}{x_4} = -A_1 \frac{x_1}{x_4} - A_2 \frac{x_2}{x_4} - A_3 \frac{x_3}{x_4}$$

if $x_i = 0$ for all i
 $\Rightarrow A_i$ lin ind. s.t. $A\underline{x} = 0$
of A_j $j \neq i$



$$A_3 = A_1 \frac{1}{2} + A_2 \frac{1}{2}$$

$$A_1 = 2A_3 - A_2$$

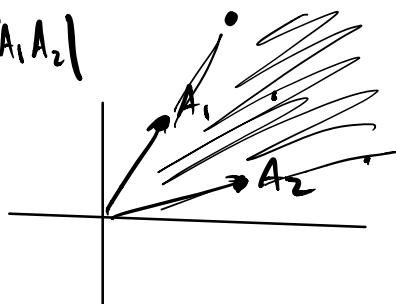
$$A_2 = 2A_3 - A_1$$

$\{A_1, A_2, A_3\}$ lin dep

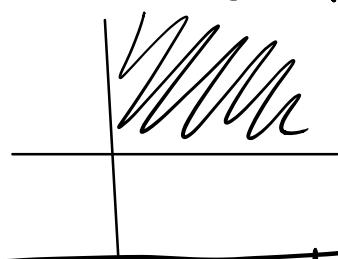
"Positive comb" (cone)

$$\{y \mid y = Ax, x \geq 0, x \in \mathbb{R}^n\}$$

$$A = [A_1 \ A_2]$$



$$\text{if } A = I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$



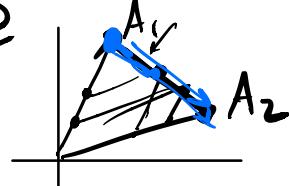
$$\rightarrow \{y \mid y = Ix, x \geq 0\}$$

"positive orthant."

Convex comb

$$\{y \mid y = Ax, x \geq 0, \underline{x}^T x = 1\}$$

2D



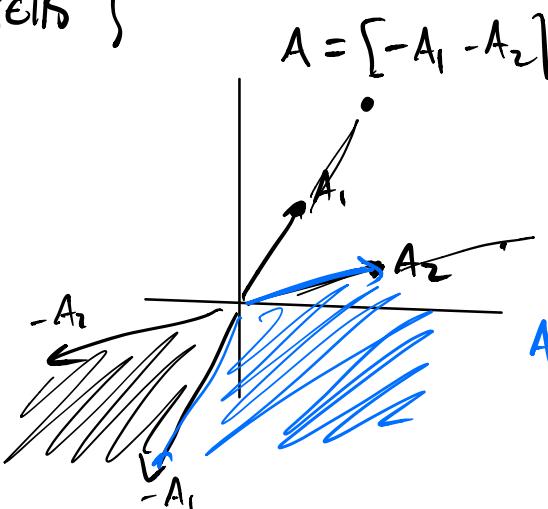
$$A = [A_1 \ A_2]$$

$$x = \left[\begin{smallmatrix} 1 \\ 0 \end{smallmatrix} \right], \left[\begin{smallmatrix} 0 \\ 1 \end{smallmatrix} \right], \left[\begin{smallmatrix} 1/2 \\ 1/2 \end{smallmatrix} \right], \left[\begin{smallmatrix} 1/4 \\ 3/4 \end{smallmatrix} \right]$$

$$A_1 x_1 + A_2 x_2 \quad \boxed{x_1 + x_2 = 1}$$

$$A_1 x_1 + A_1 x_2 - A_1 x_2 + A_2 x_2$$

linear comb $\{y \mid y = Ax, x \in \mathbb{R}^n\}$



$$A = [-A_1 \ A_2]$$

SIDE NOTES:

$$\underline{1} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\underline{1}^T x = 1$$

$$\sum_i x_i = 1$$

$$\Delta_n = \{x \mid x \geq 0, \underline{1}^T x = 1, x \in \mathbb{R}^n\}$$

"simplex in \mathbb{R}^n "

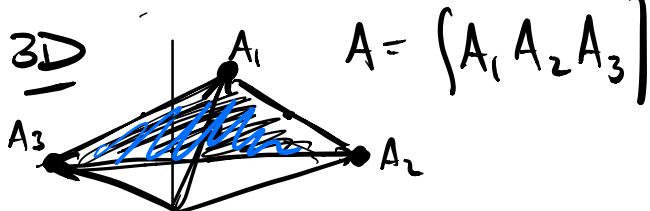
probability dist of
dim n

$$A_1(x_1 + x_2) + (A_2 - A_1)x_2$$

$A_1 + (A_2 - A_1)x_2 \quad x_2 \in [0, 1]$

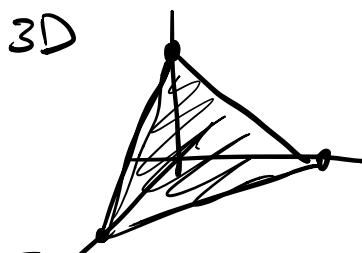
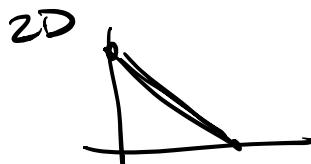
similarly

$$A_2 + (A_1 - A_2)x_1$$



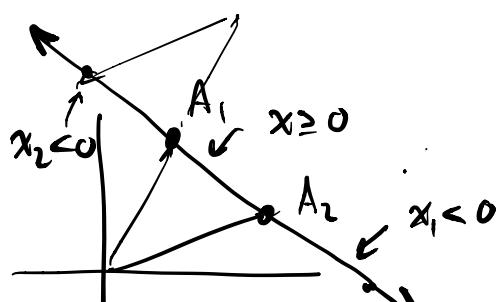
$$x = \left[\begin{matrix} 1 \\ 0 \\ 0 \end{matrix}, \begin{matrix} 0 \\ 1 \\ 0 \end{matrix}, \begin{matrix} 0 \\ 0 \\ 1 \end{matrix}, \begin{matrix} 1 \\ 1 \\ 1 \end{matrix}, \begin{matrix} 1 \\ 1 \\ 0 \end{matrix}, \begin{matrix} 1 \\ 0 \\ 1 \end{matrix} \right]$$

simplex: $A = I$

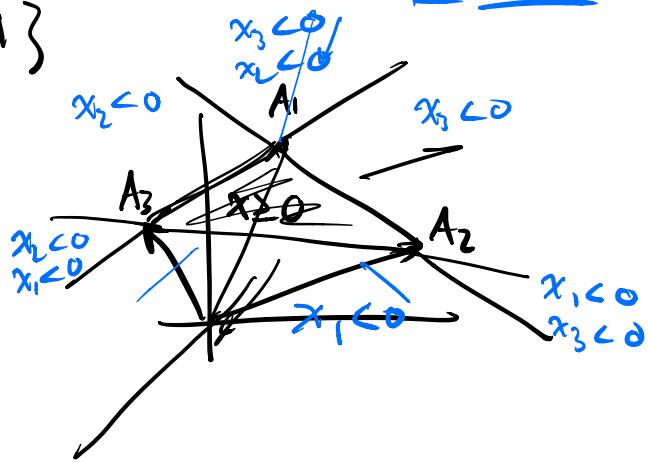


$$\{y | y = Ax, x \geq 0, \mathbf{1}^T x = 1\}$$

NOT SURE:



$$x = \left[\begin{matrix} 1 \\ 0 \\ 0 \end{matrix}, \begin{matrix} 0 \\ 1 \\ 0 \end{matrix}, \begin{matrix} 2 \\ -1 \\ 1 \end{matrix}, \begin{matrix} -1 \\ 2 \\ 1 \end{matrix} \right]$$



INNER PRODUCTS

Adjoint Map: Adjoint map \Rightarrow transpose for real vectors
 $\langle y, x \rangle$ ↓ of A
 $\langle y, Ax \rangle = \langle A^*y, x \rangle$ conjugate transpose for complex vectors

Ex. $x, y \in \mathbb{R}^n$

$$y^T A x = (A^* y)^T x \Rightarrow A^* = A^T$$

$$\int g(t) A(f(t)) dt \quad A^*(g(\cdot))$$

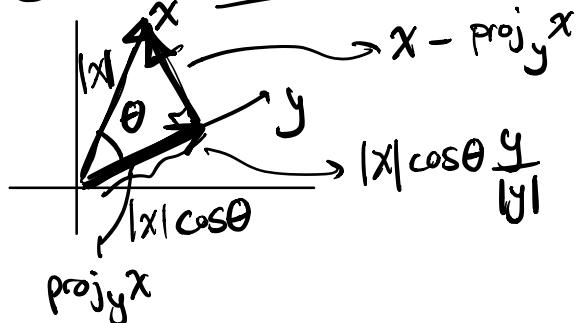
Transpose: $A_{ij} = (A^T)_{ji}$

- $(A^T)^T = A$
- $(ABC)^T = C^T B^T A^T$

\Rightarrow np. eisum $\omega \int_0^\infty |w f(t)|$

PROJECTIONS:

$$y^T x = \|x\| \|y\| \cos \theta$$



$$\text{proj}_y x = \frac{y}{\|y\|} \|x\| \cos \theta \quad \| \cdot \| - \text{2 norm}$$

$$= \frac{y}{\|y\|^2} \|y\| \|x\| \cos \theta$$

$$\text{proj}_y x = \left(\frac{1}{\|y\|^2} y y^T \right) x$$

$$x - \text{proj}_y x = x - \frac{1}{\|y\|^2} \left[\begin{matrix} 1 & |y| & |y| \\ |y| & y^T & -y^T \\ |y| & -y^T & 1 \end{matrix} \right] x$$

$$= \left(I - \frac{1}{\|y\|^2} y y^T \right) x$$

$\underbrace{\frac{1}{\|y\|^2} \left[\begin{matrix} 1 & |y| & |y| \\ |y| & y^T & -y^T \\ |y| & -y^T & 1 \end{matrix} \right]}$ outer product of y w itself

$A = \begin{bmatrix} A_1 & A_2 \end{bmatrix}$
 x
 $\rightarrow x - \text{proj}_A x$
 $\text{proj}_A x = \left[A_1 \ A_2 \right] \left[\frac{A_1^T}{A_2^T} \right] x$
 $= A (A^T A)^{-1} A^T x$
 $x - \text{proj}_A x = \left[I - A (A^T A)^{-1} A^T \right] x$
 likely $\frac{1}{(y^T y)^{1/2}} = \frac{1}{((y^T y)^{1/2})^2}$

Tech Defn:

projection

$\text{proj}_A(x)$

$$\boxed{\text{proj}_A(\text{proj}_A x) = \text{proj}_A x}$$

$$A \underline{(A^T A)^{-1} A^T} (A (A^T A)^{-1} A^T x) = \underline{A (A^T A)^{-1} A^T} x$$

$$(I - A (A^T A)^{-1} A^T) (I - A (A^T A)^{-1} A^T) x =$$

$$I - 2 \underline{A (A^T A)^{-1} A^T} + A \underline{(A^T A)^{-1} A^T} \underline{A (A^T A)^{-1} A^T}$$

$$I - \underline{A (A^T A)^{-1} A^T} \quad \underline{A (A^T A)^{-1} A^T}$$

SIDE NOTE : $\underline{A (A^T A)^{-1} A^T} \quad \cancel{A^T (A A^T)^{-1} A}$

transposes usually appear as

$$A^T (A A^T)^{-1} A$$