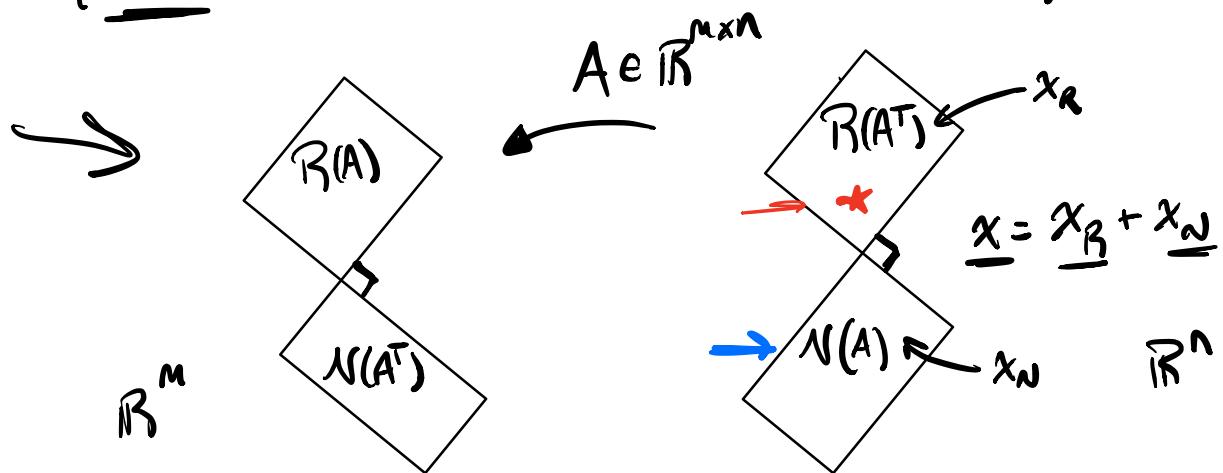


HW2 PROBLEM 7 $A \in \mathbb{R}^{m \times n}$

$\text{rank } [A^T N] \in \mathbb{R}^{n \times n}$ N : cols basis for $N(A)$
 A : lin ind rows

$N \in \mathbb{R}^{n \times (n-m)}$ \rightarrow # of lin ind vectors in $N(A)$

$$[\underline{A^T N}]^{-1} = ?$$

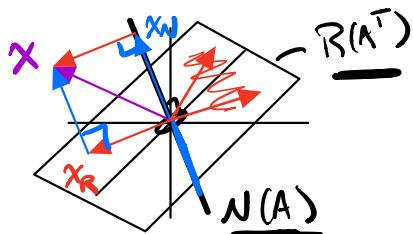


$$\text{codomain} = R(A) \oplus N(A^T) \quad \underline{\text{domain}} = \underline{R(A^T)} \oplus \underline{N(A)}$$

$$\begin{aligned} & x \in \mathbb{R}^n \xrightarrow{\text{coord transform}} \\ & \text{Coord transform} \Rightarrow x = [A^T N] \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \xrightarrow{z_1 \in \mathbb{R}^m} z_1 \in \mathbb{R}^{n-m} \\ & x = [A^T N] \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \\ & = \underline{A^T z_1} + \underline{N z_2} \end{aligned}$$

$$x = [A^T N] \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = [\underline{A^T N}]^{-1} x$$



$$\left[A^T N \right]^{-1} \doteq \left[\begin{array}{c} A \\ N^T \end{array} \right] = \left[A^T N \right]^T$$

$$\left[\begin{array}{c} A \\ N^T \end{array} \right] \left[A^T N \right] = \left[\begin{array}{cc} AA^T & AN \\ NA^T & N^T N \end{array} \right] = \left[\begin{array}{cc} AA^T & O \\ O & N^T N \end{array} \right]$$

$O \in \mathbb{R}^{m \times n-m}$

$$A^T N = A \left[\begin{array}{c} N_1 \\ \vdots \\ N_{n-m} \end{array} \right]$$

$$\left[\begin{array}{cc} AA^T & O \\ O & N^T N \end{array} \right]^{-1} = \left[\begin{array}{cc} (AA^T)^{-1} & O \\ O & (N^T N)^{-1} \end{array} \right] = \left[\begin{array}{cc} AN_1 & \cdots AN_{n-m} \\ \hline O & O \end{array} \right]$$

$$\xrightarrow{\left[\begin{array}{cc} (AA^T)^{-1} & O \\ O & (N^T N)^{-1} \end{array} \right] \left[\begin{array}{c} A \\ N^T \end{array} \right]} \left[\begin{array}{c} A^T N \end{array} \right] = \left[\begin{array}{cc} (AA^T)^{-1} & O \\ O & (N^T N)^{-1} \end{array} \right] \left[\begin{array}{cc} AA^T & O \\ O & N^T N \end{array} \right] = \left[\begin{array}{cc} I & O \\ O & I \end{array} \right]$$

$$\left[A^T N \right]^{-1} = \left[\begin{array}{c} (AA^T)^{-1} A \\ (N^T N)^{-1} N^T \end{array} \right] \quad x = \left[A^T N \right] \left[\begin{array}{c} z_1 \\ z_2 \end{array} \right]$$

$$\left[\begin{array}{c} z_1 \\ z_2 \end{array} \right] = \left[\begin{array}{c} (AA^T)^{-1} Ax \\ (N^T N)^{-1} N^T x \end{array} \right] \Leftarrow \begin{array}{c} \text{proj}_{A^T} x \\ \text{proj}_N x \end{array}$$

$$x = A^T z_1 + N z_2 = \underbrace{A^T (AA^T)^{-1} Ax}_{x_R} + \underbrace{N(N^T N)^{-1} N^T x}_{x_N}$$

$$\boxed{\text{Row rank} = \text{col rank}} \iff$$

↓ # of lin ind rows ↓ # of lin ind cols
 $A \in \mathbb{R}^{m \times n}$ eqns } m

sys eqns: n equations
 n unknowns

$$\text{WTS: } r \leq k \quad k \leq r \quad \Rightarrow r = k$$

row rank: r
 \rightarrow col rank: k

\Leftrightarrow $r \leq k$

$A = CV$

lin ind \vec{c}_i form basis for $R(A)$

$$C = [C_1 \dots C_k] = \begin{bmatrix} \vec{c}_1^T \\ \vdots \\ \vec{c}_m^T \end{bmatrix} \in \mathbb{R}^{m \times k}$$

$$V = [v_1 \dots v_n] = \begin{bmatrix} \vec{v}_1^T \\ \vdots \\ \vec{v}_k^T \end{bmatrix} \in \mathbb{R}^{k \times n}$$

$$= \underbrace{n \begin{bmatrix} C_1 & \dots & C_k \end{bmatrix}}_{\substack{\text{cols are} \\ \text{basis for}}} \underbrace{\begin{bmatrix} v_1 & \dots & v_n \end{bmatrix}}_{\substack{\text{coeffs of ea.} \\ \text{col of } A}} = \begin{bmatrix} CV_1 & CV_2 & \dots & CV_n \end{bmatrix}$$

$R(A)$ w.r.t. the C basis

$$= \begin{bmatrix} -\vec{c}_1^T \\ \vdots \\ -\vec{c}_m^T \end{bmatrix} \begin{bmatrix} -\vec{v}_1^T \\ \vdots \\ -\vec{v}_k^T \end{bmatrix} \quad \xrightarrow{\text{spanning } R(A^T)}$$

coeffs of rows of A

$$\begin{bmatrix} A_1 & \dots & A_k \end{bmatrix} \left| \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \right| V_{k+1} \dots V_n$$

$$A_{k+1} = [A_1 \dots A_k | V_{k+1}]$$

$$= \begin{bmatrix} \bar{c}_1^T V \\ \vdots \\ \bar{c}_m^T V \end{bmatrix} \leftarrow \text{lin comb of rows of } V$$

\Rightarrow ea row of A is a lin comb of rows of V

V has k rows

$$\Rightarrow \dim R(A^T) \leq k \Rightarrow \boxed{r \leq k}$$

2) $\boxed{k \leq r}$

$$A = \underbrace{W}_{\substack{\text{ea row} \\ \text{is coeffs} \\ \text{of that} \\ \text{row of} \\ \text{A w.r.t.} \\ \text{basis of} \\ \text{rows of } R}} \underbrace{R}_{\substack{\text{rows} \\ \text{are basis} \\ \text{for} \\ R(A^T)}}$$

$$R \in \mathbb{R}^{r \times n}$$

$$W \in \mathbb{R}^{m \times r}$$

$$R = \begin{bmatrix} \bar{R}_1^T \\ \vdots \\ \bar{R}_r^T \end{bmatrix} = [R_1 \dots R_r]$$

$$W = \begin{bmatrix} \bar{W}_1^T \\ \vdots \\ \bar{W}_m^T \end{bmatrix} = [W_1 \dots W_r]$$

span. pol.
wikipedia
(rank)

$$= \begin{bmatrix} \bar{W}_1^T \\ \vdots \\ \bar{W}_m^T \end{bmatrix} \begin{bmatrix} \bar{R}_1^T \\ \vdots \\ \bar{R}_r^T \end{bmatrix} \leftarrow \text{rows are basis}$$

$$= [W_1 \dots W_r] [R_1 \dots R_r]$$

$$\text{span of cols of } A \leq r \Rightarrow \boxed{k \leq r}$$

Inverses

systems of eqns: $y = Ax$

$A \in \mathbb{R}^{n \times n}$ invertible \rightarrow row reduce $A \sim I$

Gaussian Elimination / Row reduction

Solve for x $y = Ax \Leftrightarrow A^{-1}y = x$

Augmented system: $[A|y] \xrightarrow{\text{row operations}} [I|x]$

Elementary Matrices
 E_i

$$E_i [A|y] = [E_i A | E_i y]$$

performs a row operation

$$E_k \cdots E_1 [A|y] = [E_k \cdots E_1 A | E_k \cdots E_1 y]$$

$$\tilde{A}' = E_k \cdots E_1 A \quad \leftarrow \frac{A^{-1}A}{I} \quad \tilde{A}'y = x$$

Elementary Matrices perform row operations:

Ex.

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -\bar{A}_1^T \\ -\bar{A}_2^T \\ -\bar{A}_3^T \end{bmatrix} = \begin{bmatrix} -\bar{A}_2^T \\ -\bar{A}_1^T \\ -\bar{A}_3^T \end{bmatrix}$$

switching rows

Ex.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & \alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -\bar{A}_1^T \\ -\bar{A}_2^T \\ -\bar{A}_3^T \end{bmatrix} = \begin{bmatrix} -\bar{A}_1^T \\ \alpha \bar{A}_2^T \\ -\bar{A}_3^T \end{bmatrix}$$

scaling a row

$$R_j \xrightarrow{i} \begin{bmatrix} I & & 0 & & 0 \\ 0 & \alpha & 1 & & 0 \\ 0 & 0 & I & & 0 \\ 0 & 0 & 0 & I & \end{bmatrix}$$

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

$$\begin{bmatrix} \alpha_1 & \alpha_2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -\bar{A}_1^T \\ -\bar{A}_2^T \\ -\bar{A}_3^T \end{bmatrix} = \begin{bmatrix} \alpha_1 \bar{A}_1^T + \alpha_2 \bar{A}_2^T \\ -\bar{A}_2^T \\ -\bar{A}_3^T \end{bmatrix}$$

lin combs. of rows

$$\begin{bmatrix} I_{\alpha_1 \dots \alpha_j} \\ I \\ I \end{bmatrix}$$

Equiv: row reduce $\begin{bmatrix} A | I' \end{bmatrix} \sim \begin{bmatrix} I | A' \end{bmatrix}$

A not square: $A \in \mathbb{R}^{m \times n}$

fat: $A = [A' \ A^2] \quad A' \in \mathbb{R}^{m \times m}$
 $m < n$
 $A^2 \in \mathbb{R}^{m \times n-m}$

$$\begin{bmatrix} A' \ A^2 | y \end{bmatrix} \sim \boxed{\begin{bmatrix} I & (A')^{-1} A^2 \\ (A')^{-1} y & \end{bmatrix}} | (A')^{-1} y]$$

$$y = [A' \ A^2 | \boxed{(A')^{-1} y} \underbrace{\quad}_{X}] = (A')(A')^{-1} y + 0$$

$$x = \begin{bmatrix} (A')^{-1} y \\ 0 \end{bmatrix} + \boxed{- (A')^{-1} A^2} \underbrace{z}_{\text{specific soln}}$$

$$A \sim \boxed{\begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix}} \sim I$$

$$\begin{aligned} I [A' \ A^2] &= \underline{A'} \underline{(A')^{-1}} [A' \ A^2] \\ &= \underline{A'} \underline{[I \ (A')^{-1} A^2]} \end{aligned}$$

if matrix
doesn't have
m lin ind rows

↓ basis cols ↓ ↓ coeffs
 A^2 wrt.
 A^1

$\left. \begin{array}{c} \\ \\ \end{array} \right\} \begin{array}{c} (A^1)^{-1} A^2 \\ \vdash \end{array}$

$$A \sim \left[\begin{array}{c|cc} I & \bar{A} \\ \hline 0 & 0 & 0 \end{array} \right]$$

A tall full col rank

$$\bar{A}^T \bar{A} = I \quad \bar{A}^T y = x$$

$$A = \left[\begin{array}{c|c} \bar{A}^1 & y_1 \\ \hline \bar{A}^2 & y_2 \end{array} \right] \sim \left[\begin{array}{c|c} \underline{I} & * \\ \hline \underline{0} & \boxed{1} \end{array} \right]$$

$$\tilde{A} = \left[\begin{array}{c|c} \bar{A}^1 & y_1 \\ \hline \bar{A}^2 & y_2 \end{array} \right] \sim \left[\begin{array}{c|c} \underline{I} & \boxed{1} \\ \hline \underline{0} & \boxed{1} \end{array} \right] \xrightarrow{\quad \quad \quad}$$

$y = Ax$

$$I = \left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right] \quad \underline{\left[\begin{array}{ccc} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{array} \right]} \quad \left[\begin{array}{ccc} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{array} \right]$$

(More next week...)

Inverse Properties $A \in \mathbb{R}^{n \times n}$

- A invertible/nonsingular/nondegenerate
 - A can be row reduced to I
 - A can be col reduced to I \times
 - A : n pivot positions \times
-
- $\det(A) \neq 0$ —
 - A has full rank (n) \leftarrow
 - $Ax=0 \Rightarrow x=0$ (cols lin ind) \leftarrow
 - $Ax=y \Rightarrow$ unique solution $x = A^{-1}y$ for every y
 - cols of A lin ind
 - cols of A span \mathbb{R}^n } \rightarrow cols of A form basis for \mathbb{R}^n
 - rows of A lin ind
 - rows of A span \mathbb{R}^n } \rightarrow rows of A basis for \mathbb{R}^n
 - A^T is invertible
 - A is a bijection —
-
- 0 is not an eigenvalue of A —
 - A = finite product of elementary matrices

ea of these
Prop. gives
you all the
others

trying to
invert a
noninvertible
matrix is
like dividing
by 0

Algebraic Properties

- $(A^{-1})^{-1} = A$
- $(kA)^{-1} = \frac{1}{k}A^{-1}$ for non-zero scalar k
- $(A^{-1})^T = (A^T)^{-1} = A^{-T}$
- $(ABC)^{-1} = C^{-1}B^{-1}A^{-1}$ $A, B, C \in \mathbb{R}^{n \times n}$, invertible
- $\det(A^{-1}) = \frac{1}{\det(A)}$

Note $(AB)^T = B^T A^T$

$$\begin{aligned} |A^{-1}| &= |A|^{-1} \\ (A^T B)^T &= B^T A \\ \frac{x^T y}{x \cdot y} &= \frac{y^T x}{y \cdot x} \end{aligned}$$

Inverses Formula

$$x^T A y = y^T A^T x$$

$$\bar{A}^{-1} = \frac{1}{\det(A)} \underline{\text{Adj}(A)} \rightarrow \underline{\text{Adjugate of } A}$$

2x2 matrix

$$\rightarrow \bar{A}^{-1} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \frac{1}{ad - cb} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} \leftarrow \underline{\text{memorize}}$$

Block Matrix Inversion LEMMA

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \bar{A}^{-1} + \bar{A}^{-1} B (\bar{D} - \bar{C} \bar{A}^{-1} \bar{B})^{-1} \bar{C} \bar{A}^{-1} \\ -(\bar{D} - \bar{C} \bar{A}^{-1} \bar{B}) \bar{C} \bar{A}^{-1} \end{bmatrix} \quad \begin{bmatrix} \bar{A}^{-1} B (\bar{D} - \bar{C} \bar{A}^{-1} \bar{B})^{-1} \\ (\bar{D} - \bar{C} \bar{A}^{-1} \bar{B})^{-1} \end{bmatrix}$$

$$= \begin{bmatrix} (A - B \bar{D}^{-1} C)^{-1} & (A - B \bar{D}^{-1} C) \bar{B} \bar{D}^{-1} \\ -\bar{D}^{-1} C (A - B \bar{D}^{-1} C)^{-1} & \bar{D}^{-1} - \bar{D}^{-1} C (A - B \bar{D}^{-1} C)^{-1} \bar{B} \bar{D}^{-1} \end{bmatrix}$$

$$\bar{D} - \bar{C} \bar{A}^{-1} \bar{B} \quad A - B \bar{D}^{-1} C$$

Schur complements of $\begin{bmatrix} A & B \\ C & D \end{bmatrix}$

A, D square

$A, \bar{D} - \bar{C} \bar{A}^{-1} \bar{B}$ invertible

or

$$\begin{bmatrix} B \\ D \end{bmatrix}$$

$D, A - B \bar{D}^{-1} C$ invertible

$$PDI = \frac{1}{\Gamma} \left[\begin{matrix} \bar{A} \\ \bar{B} \end{matrix} \right] \quad \Gamma = \left[\begin{matrix} \bar{A}^{-1} & \bar{B} \\ \bar{B}^T & \Gamma \end{matrix} \right]$$

Woodbury Matrix Identity \leftarrow useful for practical implementations of (Sherman Morrison formula)

$$(A+B)^{-1} \neq A^{-1} + B^{-1} \quad \frac{1}{a+b} \neq \frac{1}{a} + \frac{1}{b} \quad \text{KF}$$

$$\boxed{(A+UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + V A^{-1} U)^{-1} V A^{-1}}$$

- $A \in \mathbb{R}^{n \times n}$ invertible

- $U \in \mathbb{R}^{n \times k}$

- $C \in \mathbb{R}^{k \times k}$

- $V \in \mathbb{R}^{k \times m}$

$$A = \underbrace{A}_{\substack{\text{spars} \\ \text{cols}}} + \underbrace{U}_{\substack{\text{C small}}} \underbrace{C}_{\substack{\text{low rank}}} \underbrace{V}_{\substack{\text{high rank}}}$$

A know \bar{A}^{-1}

$A+UCV$: add low rank component to A

want to update \bar{A}^{-1}

$$\bar{A}^{-1} - \bar{A}^{-1} \left[\underbrace{U}_{\substack{\text{only} \\ \text{have to invert}}} \underbrace{[C^{-1} + V \bar{A}^{-1} U]^{-1} V}_{\substack{\text{invert}}} \right] \bar{A}^{-1}$$

if $k=1 \rightarrow$ scalar inverse

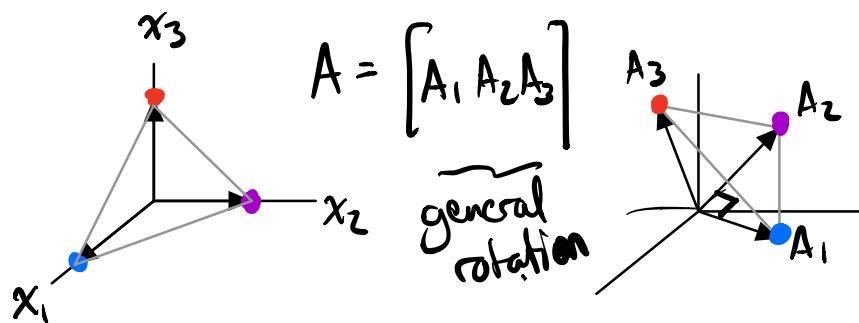
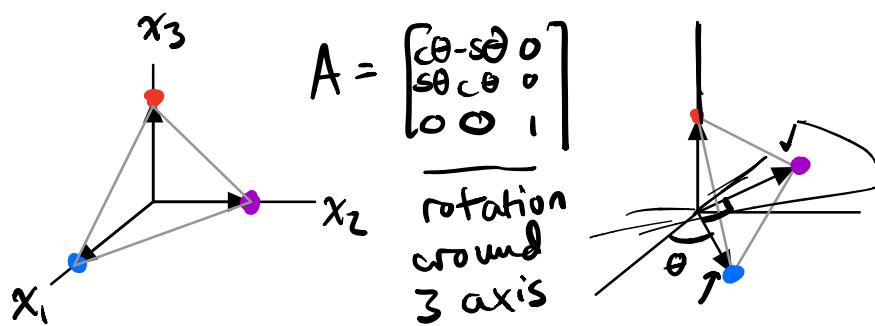
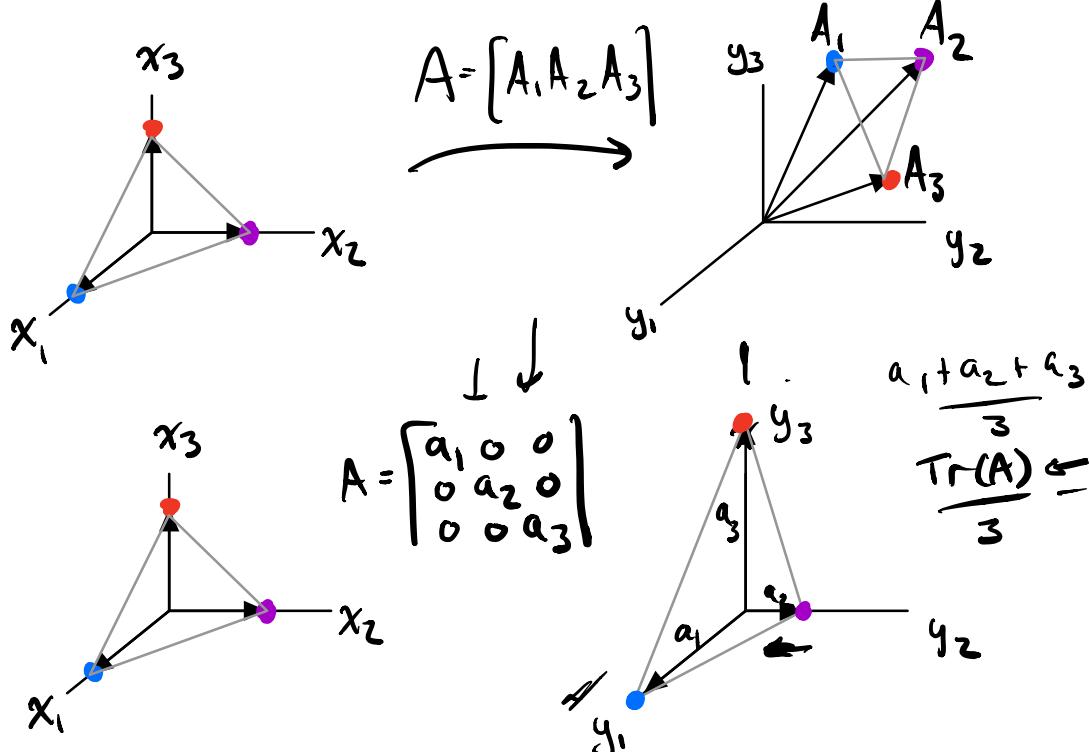
if $k=1$: Sherman Morrison formula

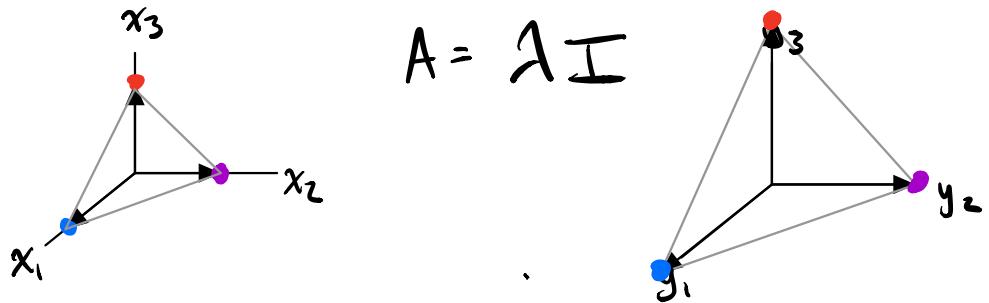
$$A + \frac{f}{\|u\|^2} u v^T$$

rank 1:

$$\begin{array}{lcl} UCV & = & \left[\begin{matrix} f \\ u \end{matrix} \right] [v_1 \dots v_n] = \left[\begin{matrix} f \\ uv_1 \dots uv_n \end{matrix} \right] \\ \downarrow \quad \downarrow \quad \downarrow \\ \text{col} \quad \text{scalar row} \quad \text{vec} \\ \text{vec} & = & \left[\begin{matrix} f \\ u \\ \vdots \\ u_n \end{matrix} \right] [v_1 \dots v_n] = \left[\begin{matrix} u, v_1 & uv_1 \\ u, v_2 & uv_2 \\ \vdots & \vdots \\ u, v_n & uv_n \end{matrix} \right] \end{array}$$

Eigenvalues & Eigenvectors: $A \in \mathbb{R}^{n \times n}$





multiply by a number:

⇒ stretch / flip position on # line

multiply by a matrix

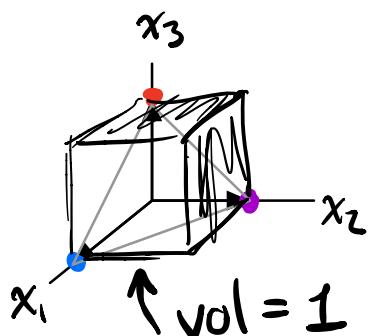
⇒ stretching / skewing / flipping / rotating your location in a vector space

Scalar valued functions used to measure how a matrix is transforming a space

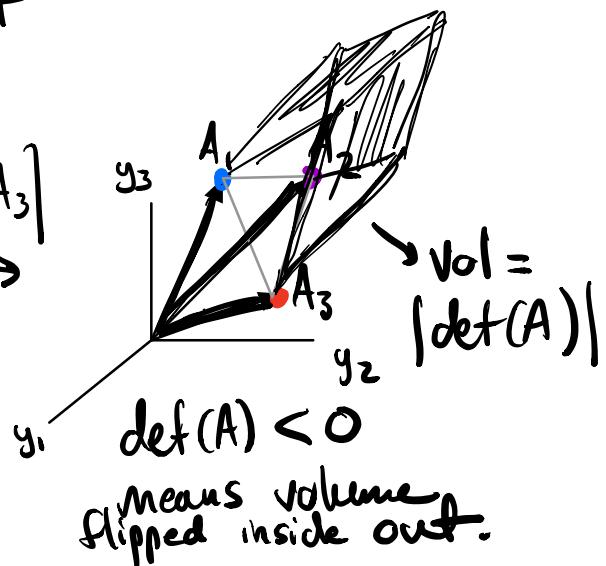
specifically --

- $\det(A)$: determinant

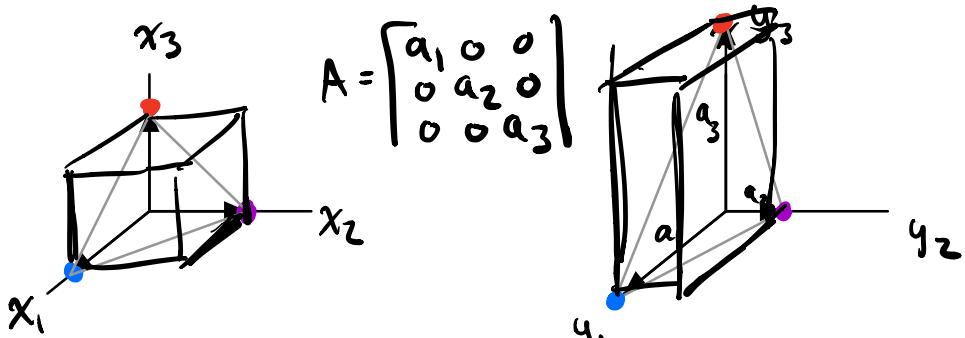
"volume transformation"



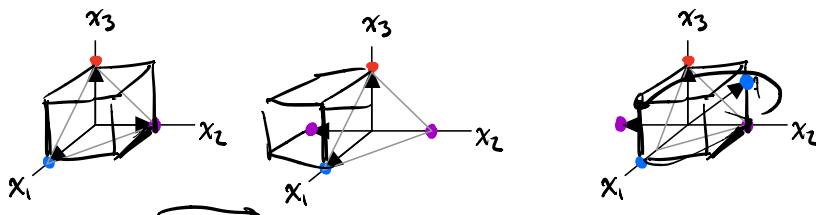
$$A = [A_1 \ A_2 \ A_3]$$



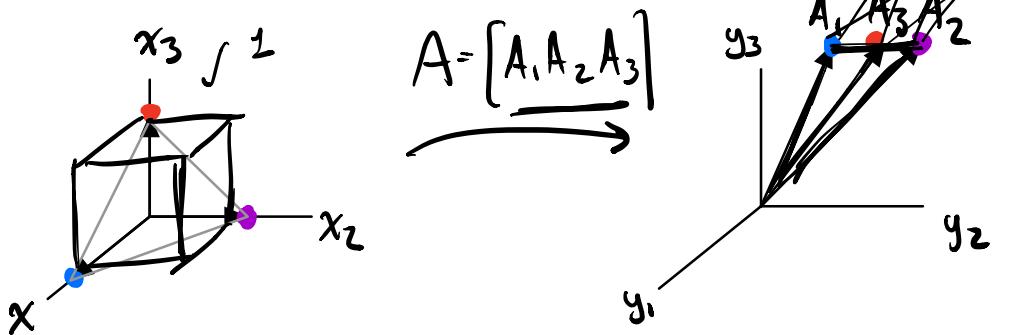
$\det(A) \Rightarrow$ degree n polynomial in the elements of A



$$\det(A) = \underline{a_1 a_2 a_3}$$



$$\det \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = -1 \quad \det \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = 1$$

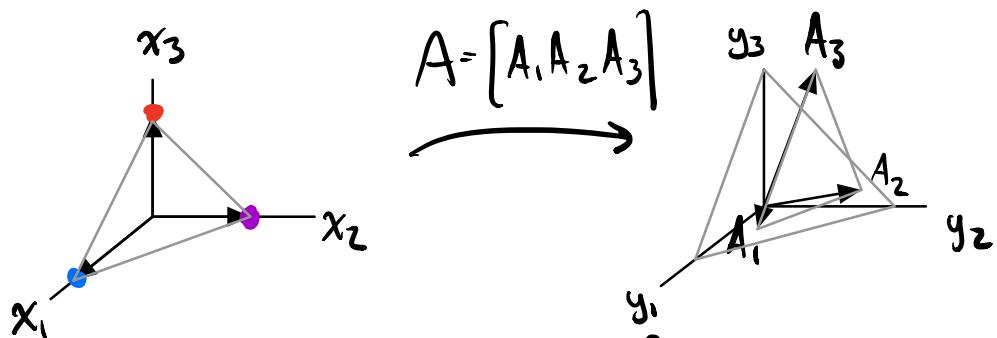


- $\text{Tr}(A)$: trace

$$\text{Tr}(A) = \sum_i A_{ii} \rightarrow \text{sum of diagonal elements}$$

$\frac{\text{Tr}(A)}{n}$: "average" amount the space gets stretched

Eigenvalues / Eigenvectors



Eigenvector of A ; $V \in \mathbb{R}^n$

vector such that $AV = \lambda V$

Eigenvalue Eqn: $\lambda \in \mathbb{C}$ scalar

$$\underbrace{AV = \lambda V}_{\text{nonlinear eqn}} \quad V \in \mathbb{C}^n$$

because we have λV

if fix $\lambda \Rightarrow$ system of equations to solve for V .

$$\lambda V - AV = 0$$

$$\lambda IV - AV = 0$$

$$\underline{(\lambda I - A)V = 0} \Rightarrow V \in N(\underline{\underline{\lambda I - A}})$$

$\det(sI - A) = 0 \Rightarrow$ roots of
 Polynomial in s $\det(sI - A)$
 gives us λ .

Characteristic Polynomial of A : $A \in \mathbb{R}^{n \times n}$

$$\chi_A(s) = \det(sI - A) = s^n + \alpha_{n-1}s^{n-1} + \dots + \alpha_1s + \alpha_0$$

solutions to $\chi_A(s) = 0 \Rightarrow$ eigenvalues

i.e. λ is an eigenvalue then $\chi_A(\lambda) = 0$

$\Rightarrow \lambda I - A$ has a nontrivial nullspace

$\Rightarrow v$ is an eigenvector w eigenvalue

$$\lambda \text{ if } (\lambda I - A)v = 0 \quad Av = \lambda v$$

How many solns to $\chi_A(s) = 0$

Answer : n solutions

n "roots of $\chi_A(s)$ "

Fundamental
Thm of
Algebra

$\Rightarrow n$ eigenvalues

if a matrix has some kind of rotation action

$\Rightarrow \chi_A(s)$ may have complex roots

Complex eigenvalues for $A \in \mathbb{R}^{n \times n}$
come in conjugate pairs \nwarrow real matrix

$$\left\{ \begin{array}{l} \lambda = a + bi \quad (\text{for } b \neq 0) \quad \leftarrow \text{if eigenvalue} \\ \bar{\lambda} = \lambda^* = a - bi \quad \leftarrow \text{then eigenvalue} \end{array} \right.$$

\searrow used to represent rotations.

\hookrightarrow corresponding pairs of eigenvectors give plane of rotation.

Note: length of eigenvector doesn't matter

$$A\underline{v} = \lambda \underline{v} \Rightarrow A \underline{x} v = \lambda \underline{x} v$$

eigenvector is imprecise ...

eigen subspace \Leftarrow better description

Diagonalizing a Matrix:

$A \in \mathbb{R}^{n \times n}$ roots of $X_A(s) \Rightarrow$ eigenvalues
 find eigenvectors: $\lambda_1 \neq \lambda_2 \neq \dots \neq \lambda_n$

$$Av_i = \lambda_i v_i \quad i = 1, \dots, n$$

$$\begin{bmatrix} Av_1 & \dots & Av_n \end{bmatrix} = \begin{bmatrix} \lambda_1 v_1 & \dots & \lambda_n v_n \end{bmatrix}$$

$$A \begin{bmatrix} v_1 & \dots & v_n \end{bmatrix} = \begin{bmatrix} v_1 & \dots & v_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & 0 \\ 0 & \ddots & 0 \\ & & \lambda_n \end{bmatrix}$$

$$AP = PD$$

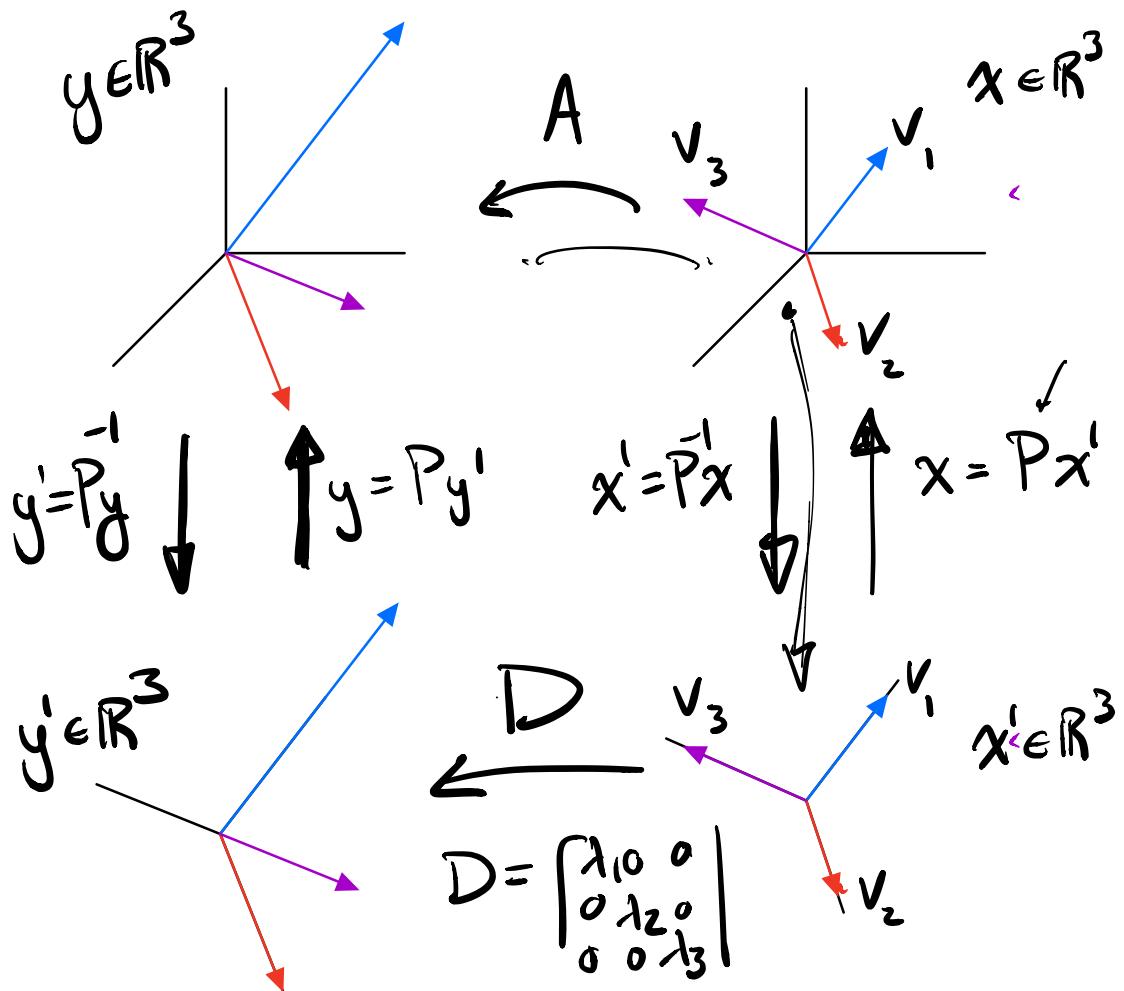
Assume P invertible

$$\overbrace{P^{-1}AP}^{\text{similarity transform}} = D \leftarrow \text{called } \underline{\text{diagonalizing }} A$$

$$\boxed{A = PDP^{-1}}$$

cols of P are eigenvectors

diagonalization of A
 eigen decomposition
 diagonal of D are eigenvalues



$$D = P^{-1} A P \rightarrow \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$$A = P \underbrace{\begin{bmatrix} D \end{bmatrix}}_{\substack{\text{Put back in original coords}}} P^{-1} \underbrace{x}_{\substack{\text{write } x \\ \text{Scale in eigenvector basis} \\ \text{Coord by eigenvalues}}}$$

$$\begin{aligned}
 A^k &= A \times \cdots \times A \\
 \underline{\underline{=}} \quad &= P \underline{D} \underline{P^{-1}} \times \underline{P} \underline{D} \underline{P^{-1}} \times \cdots \times \underline{P} \underline{D} \underline{P^{-1}} \\
 &= \underline{\underline{PD^k P^{-1}}} = P \begin{bmatrix} \lambda_1^k & & \\ & \ddots & 0 \\ 0 & & \lambda_n^k \end{bmatrix} \underline{\underline{P^{-1}}}
 \end{aligned}$$

$$\begin{aligned}
 \underline{\underline{C^{At}}} &= I + At + \frac{1}{2} \underline{\underline{At^2}} + \frac{1}{3!} A^3 t^3 \\
 \downarrow \quad &\dot{x} = Ax \rightarrow x(t) = e^{At} x(0)
 \end{aligned}$$

(more next week...)