

# Linear Alg Study Guide (row #, col #)

## Transpose

$$(A_{ij})^T = A_{ji}$$

$$\rightarrow (A+B)^T = A^T + B^T$$

$$\rightarrow (AC)^T = C^T A^T$$

Vectors  $\rightarrow n \times 1$  matrix

## Linear combo

$\rightarrow$  row  $\rightarrow \Sigma \text{col}_1, \Sigma \text{col}_2, \Sigma \text{col}_3$   
 $\rightarrow$  col  $\rightarrow \Sigma \text{row}_1, \Sigma \text{row}_2, \Sigma \text{row}_3$   
 $\rightarrow$  becomes  $1 \times 1$  col.

## Rotation Matrix

$$A_\theta = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

multiply by  $A_\theta$   $\forall \theta = \angle$   
 clockwise

## Row Echelon

- 0 rows @ bottom
- leading entries to right of prev
- entries under leading  $\rightarrow 0$

## Reduced RE

- in RE form
- leading entries = 1
- entries above & below leading are 0

## Free Variables

- Found in nonpivot cols
- $\infty$  solutions
- Linear Dependant  $\rightarrow n > m$
- $A\vec{x} = \vec{b}$  non  $\emptyset$  solution  $\rightarrow \infty$  solutions

## Linear Independence

- $A\vec{x} = \vec{0}$   $\emptyset$  solution  $\rightarrow 1$  solution for each  $\vec{b} \in \mathbb{R}^n$
- rank =  $n$
- 1 vector is a multiple of another

## Span

- all possible vectors which can be achieved as linear combos of a set of vectors
- is  $\vec{v}$  in the span of  $S$ ?  $\Rightarrow$  can  $\vec{v}$  be made by the vectors in  $S$ ?
- $\vec{v}$  belongs to  $S$  if  $A\vec{x} = \vec{v}$  is consistent
- augment  $[A|\vec{v}]$
- find RE of  $[A|\vec{v}]$

- $\rightarrow$  cols of  $A$  span  $\mathbb{R}^m$
- $\rightarrow$  every  $\vec{b} \in \mathbb{R}^m, A\vec{x} = \vec{b}$  has solution
- $\rightarrow$  RREF( $A$ ) has pivot in every row

## Consistency

- $A\vec{x} = \vec{b}$  is consistent
- $\vec{b}$  linear combo of col vectors in  $A$
- RREF of  $[A|\vec{b}]$  has no  $[0 \dots 0 | d]$

## Multiplication

- $(A_{m \times n})(B_{n \times m}) = AB_{m \times m}$
- entry  $ij = \sum (A_{row i} \cdot B_{col j})$

## Inverse

- $AB = BA = I_n$  if RREF( $A$ ) =  $I_n$
- $[A | B] \xrightarrow{\text{row ops}} [I_n | A^{-1}B]$
- $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \rightarrow A^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$
- $(AB)^{-1} = B^{-1}A^{-1}$
- elementary row ops are invertible & reversible
- $P = (E_1)(E_2) \dots (E_k)$
- $\rightarrow PA = R$  &  $P^{-1} = A$
- Set up  $[A | I_n]$
- Find RREF( $A$ ) so  $[R | B]$
- if  $R = I_n, A^{-1} = B$

## Column Correspondance

- if RREF( $A$ ) =  $R$ , if  $j$ th col  $R$  is lin combo of other col in  $R$ , then  $j$ th col  $A$  is also lin combo of same col in  $A$  as  $R$  & same coeff
- used often in lin dep spans / sets of vectors

## LU Decomposition

- $U = \text{RREF}(A)$  no exch
- $L = I_n$  w/  $r_i + cr_j \rightarrow r_i$  on  $U$  means  $L_{ji} = -C$
- $[A] = U \& [L] = L$
- $A\vec{x} = \vec{b} \rightarrow LU\vec{x} = \vec{b}$  where  $U\vec{x} = \vec{y} \rightarrow L\vec{y} = \vec{b}$
- Find  $L$  &  $U$
- Solve for  $\vec{y}$   $\forall [L|\vec{b}]$
- Solve for  $\vec{x}$   $\forall [U|\vec{y}]$

## Exam 2 (3.1-5.3)-

## Determinant $n \times n$

### Cofactor Expansion

$$A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

$\rightarrow$  along row 1  
 $a(1 \times 1 \times 1) - b(1 \times 1 \times 1) + c(1 \times 1 \times 1)$   
 $\rightarrow$  along col 1  
 $a(1 \times 1 \times 1) - d(1 \times 1 \times 1) + g(1 \times 1 \times 1)$

- det  $\Delta$  or diag = product of diagonal
- if det = 0, lin indep & invertible
- det( $AB$ ) = (det  $A$ )(det  $B$ )
- det( $A^{-1}$ ) =  $\frac{1}{\det A}$

- row swap  $\rightarrow \det B = -\det A$
- row mult  $\rightarrow \det B = k \det A$
- for each row multiplied
- det using row ops
- Find RE form
- det = product diag
- apply

## Cramer's Rule ( $A\vec{x} = \vec{b}$ )

- $\vec{x}_i = \frac{\det M_i}{\det A}$
- $M_i = [\vec{b} \ \vec{A}_1 \ \vec{A}_2] \ M_2 = [\vec{A}_1 \ \vec{b} \ \vec{A}_3]$
- Find det  $A$
- Find det of  $M_i$ 's
- $\vec{x} = [\frac{\det M_1}{\det A} \ \frac{\det M_2}{\det A} \ \dots]^T$

## Subspace of $\mathbb{R}^n$

- includes  $\{\vec{0}\}$
- closed under addition  
 $\vec{u} \& \vec{w}$  in, so is  $\vec{u} + \vec{w}$
- closed under scalar mult  
 $\vec{u}$  in, so is  $c\vec{u}$
- subspace = span of vector set
- generating set = vectors in the set of the span

## Basis (exclude $\{\vec{0}\}$ )

- lin indep generating set
- null space - all vectors who are solutions to  $A\vec{x} = \vec{0}$  (set other free vars to 0)
- Find RE or RREF of  $A$
- null  $A$  = span of coefficients of free variables
- column space - subspace generated by col vectors

- Col  $A = \text{span} \{ \vec{A}_1, \vec{A}_2, \dots \}$
- in  $\mathbb{R}^m$
- $\vec{w}$  in Col  $A$ ?
- $[A|\vec{w}]$
- rref  $\uparrow$  consistent?
- basis of Col  $A$
- rref  $A$
- basis = pivot cols of  $A$  (not pivot of rref  $A$ )

- row space - subspace generated by rows of  $A$
- $m \geq 1$ : rows  $A$  = cols  $A^T$
- $m \geq 2$ : non  $\emptyset$  rows of rref( $A$ )
- Dimension
- # vectors in basis of  $V$
- prove set  $S$  basis of  $V$

## Eigenvalues & Eigenvectors

- show  $B$  contained inv (solution)
- $B$  lin indep
- dim  $V = \#$  vectors in  $B$  (nullity)
- dim(Null) = # free vars
- dim(Row) = rank = rank  $A^T$
- dim(Col) = dim(Row  $A$ )
- any basis of  $V$  has dim( $V$ ) # of vectors (gen sets  $\geq$  dim # vectors)

- $A\vec{v} = \lambda\vec{v}$  (multiplying  $A$  by vector only stretches vector)
- eigenvector has 1 value
- value can have  $\geq 1$  eigenvector
- det( $A - \lambda I$ ) for char poly
- $\lambda$  = roots of char poly
- null( $A - \lambda I$ ) or rref( $A - \lambda I$ ) gives eigenvectors for  $\lambda$  & eigen span
- if det  $A = 0$ , 0 is an eigenvalue (dim space)
- geo multiplicity  $\leq$  alg mult
- diag values in  $\Delta$  matrix are eigenvalues

## Diagonalization

- $A = PDP^{-1}$
- $A$  is similar to  $D \rightarrow$  same character poly, same eigenvalues & # independant eigenvectors
- $P = [\text{eigenvectors}]$
- $D = \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \ddots \end{bmatrix}$
- $A$  diagonalizable if eigenvectors of  $A$  form a basis for  $\mathbb{R}^n$
- $\Sigma$  multiplicities =  $n$  & dim(space) = multiplicity of corresponding  $\lambda$
- $A^n = PD^nP^{-1}$

## Norm & Dot Product

- norm =  $\|\vec{v}\| = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$
- unit vector  $\vec{v} \div \|\vec{v}\|$
- dist  $\vec{u} \leftrightarrow \vec{v}$  is  $\|\vec{u} - \vec{v}\|$
- dot product  $\vec{u} \cdot \vec{v} = u_1v_1 + u_2v_2 + \dots$
- $\vec{u} \perp \vec{v}$  if  $\vec{u} \cdot \vec{v} = 0$
- $\vec{u} - \vec{v} = \vec{u} + (-\vec{v})$
- $\vec{u} \cdot \vec{u} = \|\vec{u}\|^2$
- proj  $\vec{u}$  on  $\vec{v} = \frac{\vec{u} \cdot \vec{v}}{\|\vec{v}\|^2} \vec{v}$
- $\vec{z} = \|\vec{u} - \vec{w}\|$  dist pt  $\vec{u}$  to line  $\vec{w}$
- if  $\vec{u} \& \vec{v}$  in  $\mathbb{R}^n$  to line  $\vec{w}$
- $\|\vec{u} - \vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\|$
- $\|\vec{u} + \vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\|$

## Orthogonal

- set of vectors ortho if each pair is ortho
- will be lin indep
- if dim =  $n$ , will be a basis for  $\mathbb{R}^n$
- Gramm Schmidt
- $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_k$
- $\vec{v}_1 = \vec{u}_1$
- $\vec{v}_2 = \vec{u}_2 - \text{proj}_{\vec{v}_1} \vec{u}_2$
- $\vec{v}_k = \vec{u}_k - \text{proj}_{\vec{v}_1} \vec{u}_k - \dots - \text{proj}_{\vec{v}_{k-1}} \vec{u}_k$
- $\vec{v}_1, \dots, \vec{v}_k$  is an orthogonal basis of  $\mathbb{R}^n$
- orthogonal complement  $S^\perp$   $\rightarrow$   $\vec{v}$  in  $\mathbb{R}^n$
- $\perp$  subspace
- $(\text{Row } A)^\perp = \text{Null } A$
- $(\text{Col } A)^\perp = (\text{Row } A^T)^\perp = \text{Null } A^T$
- dim  $S + \dim S^\perp = n$
- basis of  $S^\perp =$  basis Null  $A$

- Ortho decomp  $\vec{w} = (\vec{u}_1 \cdot \vec{v}_1)\vec{v}_1 + \dots + (\vec{u}_1 \cdot \vec{v}_k)\vec{v}_k$
- $\vec{z} = \vec{u} - \vec{w}$
- $\vec{w}$  is vector in subspace closest to  $\vec{u}$
- Projection Matrix  $P_w = C(C^TC)^{-1}C^T$
- cols of  $C$  for basis of  $W$
- $\vec{w} = P_w \vec{u}$
- $\vec{z} = \vec{u} - \vec{w}$
- $\|\vec{z}\| = \text{dist } \vec{u} \text{ to } W$

## Least Square Approx

- line of best fit w/ min  $\sum \text{dist}^2$

$$\begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = (C^T C)^{-1} C^T \vec{y}$$

$$C = [\vec{v}_1, \vec{v}_2] \quad \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad \vec{v}_2 = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$\text{line} \rightarrow y = a_0 + a_1 x$$

## Orthogonal Matrices

-  $n \times n$  matrix is orthogonal if cols are an orthonormal basis of  $\mathbb{R}^n$

- equivalents

-  $Q$  orthogonal

-  $Q^T Q = I_n$   $\rightarrow$  can use to test orthogonality

-  $Q^{-1} = Q^T$

-  $\vec{u} \cdot \vec{v} = Q\vec{u} \cdot Q\vec{v}$

-  $\|Q\vec{u}\| = \|\vec{u}\|$

- properties

-  $\det Q = \pm 1$

- product of 2 ortho matrices is ortho

-  $Q^T$  &  $Q^{-1}$  ortho

## Symmetric Matrices ( $A^T = A$ )

-  $A_{\text{symm}}$  w/ evectors  $\vec{u}$  &  $\vec{v}$  who have distinct evals  $\lambda_u$  &  $\lambda_v$ ,  $\rightarrow \vec{u} \perp \vec{v}$   
(but if  $\vec{u} \perp \vec{v}$  & distinct  $\rightarrow A$  not always symm)

-  $A$  symm iff evectors of  $A$  are orthonorm basis of  $\mathbb{R}^n$

- if  $A$  symm,  $A$  is diagonalizable &  $P_{\text{ortho}} \rightarrow P^T A P = D$

- Find ortho diag

① Find evals & evector

② Make evectors into orthonorm w/ GramSchmidt

$$\textcircled{3} P = [\vec{z}_1, \vec{z}_2, \dots, \vec{z}_n] \quad D = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \end{bmatrix}$$

- Spectral decomposition (if  $A_{\text{symm}}$ )  $\rightarrow$  same

$$A = P D P^T, \quad P = [\vec{u}_1, \dots, \vec{u}_n] \quad D = [\lambda_1 \dots]$$

$$= \lambda_1 \vec{u}_1 \vec{u}_1^T + \dots + \lambda_n \vec{u}_n \vec{u}_n^T$$

$$= \lambda_1 [P_1] + \dots + \lambda_n [P_n]$$