

Review I Linear Algebra from orthogonality

Final Exam: Thurs, Dec 14, 3-6pm, RSF

Covers all material with emphasis

on material covered since Midterm 2

Tomorrow Wed, Dec 6, 12-2pm, 891 Evans

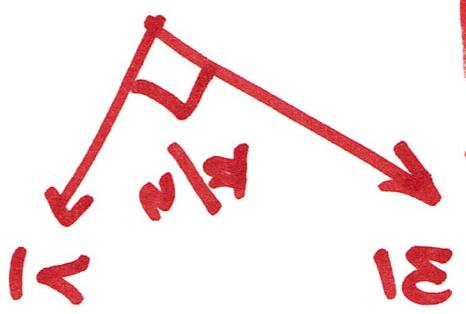
Office Hours

When

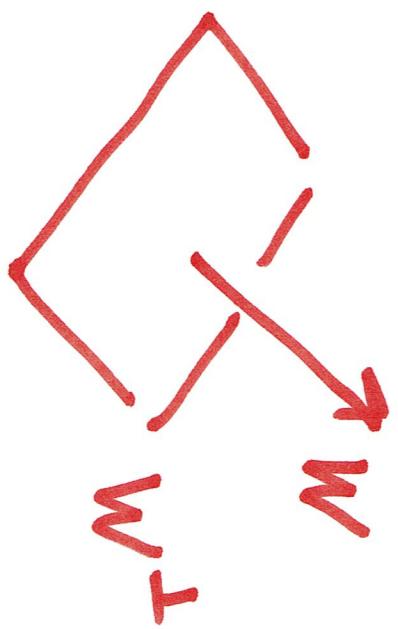
Orthogonality

$\bar{w} \cdot \bar{v} = 0$ we say $\bar{v} \perp \bar{w}$

" v orthogonal to w "



Orthogonal subspaces
 $w \in \mathbb{R}^n \quad w^\perp \subset \mathbb{R}^n$
 $w^\perp = \{v \in \mathbb{R}^n \mid v \perp w \text{ all } w \in w\}$



Orthogonal sets

$$\{ \underline{v}_1, \underline{v}_2, \dots, \underline{v}_k \}$$

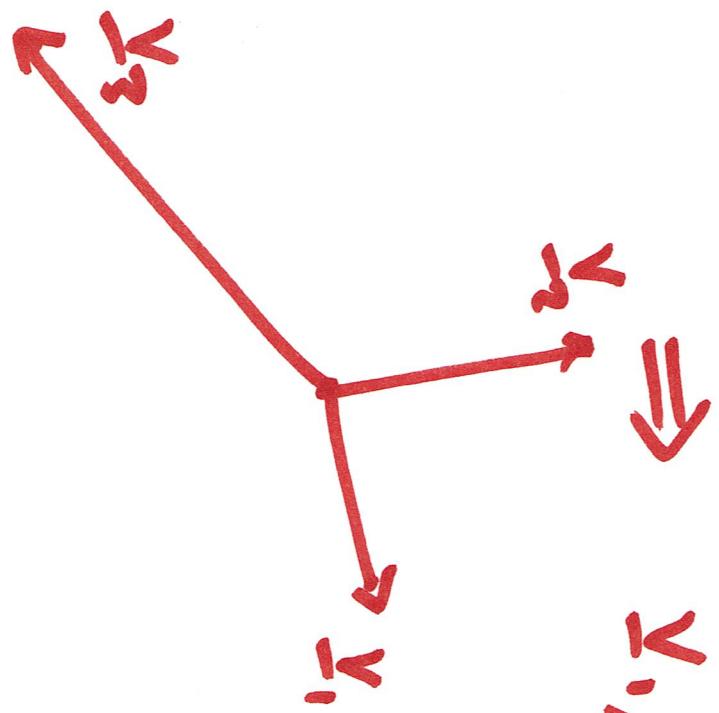
$$\underline{v}_i \perp \underline{v}_j \quad \text{all } i \neq j$$

$$(\text{allows for } v_i = 0 \dots)$$

Fact

$\underline{v}_1, \dots, \underline{v}_k$ orthog. and all nonzero

$\underline{v}_1, \dots, \underline{v}_k$ lin. indep



Orthog basis v_1, \dots, v_n orthog & basis
(or equivalently orthog, non-zero, span)

We have orthog bases : coord of \bar{v}
w.r.t. orthog basis $\bar{v}_1, \dots, \bar{v}_n$ in

$$\bar{v} = \frac{\bar{v} \cdot \bar{v}_1}{\bar{v}_1 \cdot \bar{v}_1} \bar{v}_1 + \dots + \frac{\bar{v} \cdot \bar{v}_n}{\bar{v}_n \cdot \bar{v}_n} \bar{v}_n$$

Orthog proj

$W \subset \mathbb{R}^n$ subspace

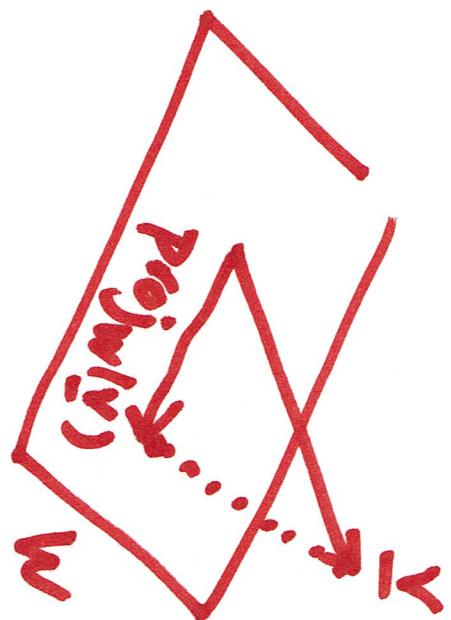
$\bar{v} \in \mathbb{R}^n$ vector

Choose orthog basis

$$w_1, \dots, w_k$$

w

Seek: $\text{proj}_W(\bar{v})$



$$\text{proj}_W(\bar{v}) = \frac{\bar{v} \cdot w_1}{w_1 \cdot w_1} w_1 + \dots + \frac{\bar{v} \cdot w_k}{w_k \cdot w_k} w_k$$

Orthogonal matrix U $n \times n$ matrix
such that any of the following equiv.
conditions holds:

$$1) \quad U\bar{v} \cdot U\bar{w} = \bar{v} \cdot \bar{w}$$

(preserve dot prod)

$$2) \quad U^{-1} = U^T$$

3) cols of U are orthon. basis.

(= orthog basis + unit length)

More generally A $m \times n$ matrix
the following are equiv:

$$1) A^T A = I_n$$

2) cols of A are orthon.

(but do not nec span)

S_e in part $m \geq n$.

G.S.

Construct

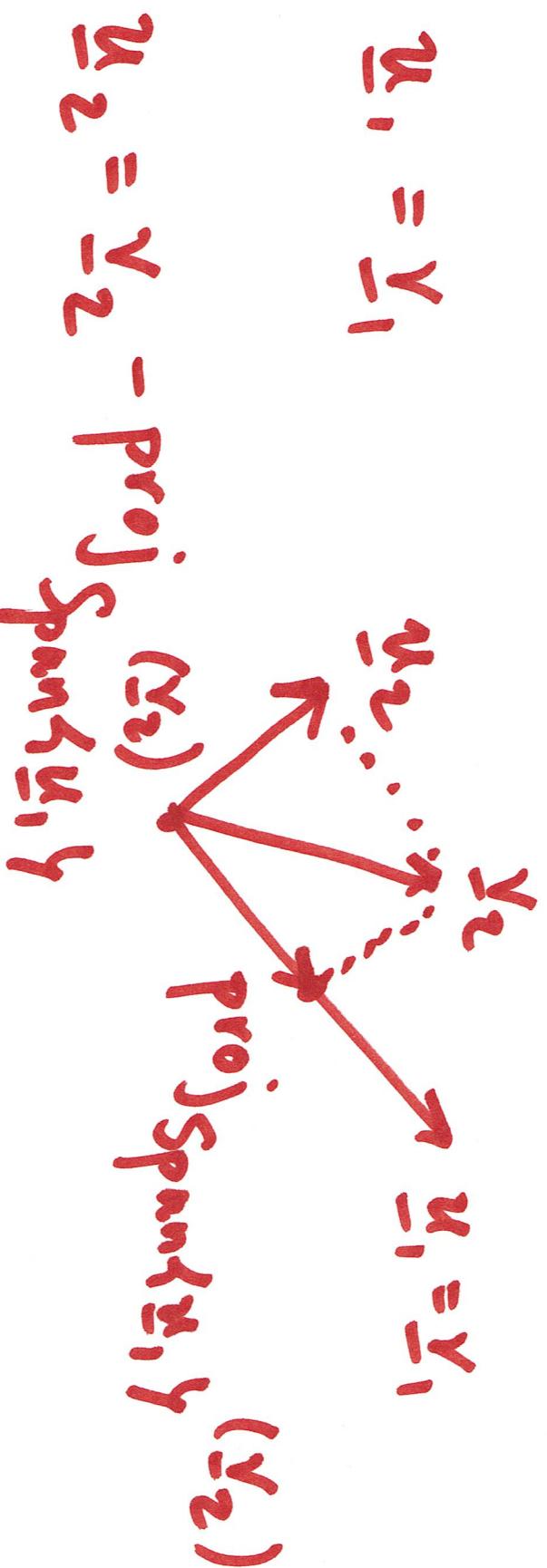
lin indep



orthog

$\underline{v}_1, \dots, \underline{v}_k$

$\underline{u}_1, \dots, \underline{u}_k$



$$\begin{aligned} \underline{u}_3 &= \underline{v}_3 - \text{proj}_{\text{Span}(\underline{u}_1, \underline{u}_2)}(\underline{v}_3) \\ &\vdots \end{aligned}$$

$$\begin{aligned} \underline{u}_2 &= \underline{v}_2 - \text{proj}_{\text{Span}(\underline{u}_1)}(\underline{v}_2) \\ \underline{u}_1 &= \underline{v}_1 \end{aligned}$$

QR factorization

encodes G.S.

$$A = \left[\begin{array}{c} v_1 \\ \vdots \\ v_k \end{array} \right] \quad \text{G.S. + normalize}$$

$$Q = \left[\begin{array}{c} \hat{u}_1 \\ \vdots \\ \hat{u}_k \end{array} \right] \quad Q = \left[\begin{array}{c} u_1 \\ \vdots \\ u_k \end{array} \right]$$

$$A = QR$$

$k \times k$

orthon. cols.

encodes col ops

Formula for $R:$

to go back $Q \rightsquigarrow A$

$$R = Q^T A \quad \text{since}$$

$$Q^T Q = I_k$$

$$Q^T A = R$$

Sky again ?? why is \bar{u}_3

upper Δ-var?

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

$$Q = \begin{bmatrix} 1 & \bar{u}_1 & \bar{u}_2 \\ \bar{u}_1 & 1 & \bar{u}_3 \\ \bar{u}_2 & \bar{u}_3 & 1 \end{bmatrix}$$

$$R = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix}$$

$$\bar{y}_3 = a_{13}\bar{u}_1 + a_{23}\bar{u}_2 + a_{33}\bar{u}_3$$

$$\bar{y}_1 = a_{11}\bar{u}_1 + a_{21}\bar{u}_2$$

$$\bar{y}_2 = a_{12}\bar{u}_1 + a_{22}\bar{u}_2$$

Least Squares Solutions

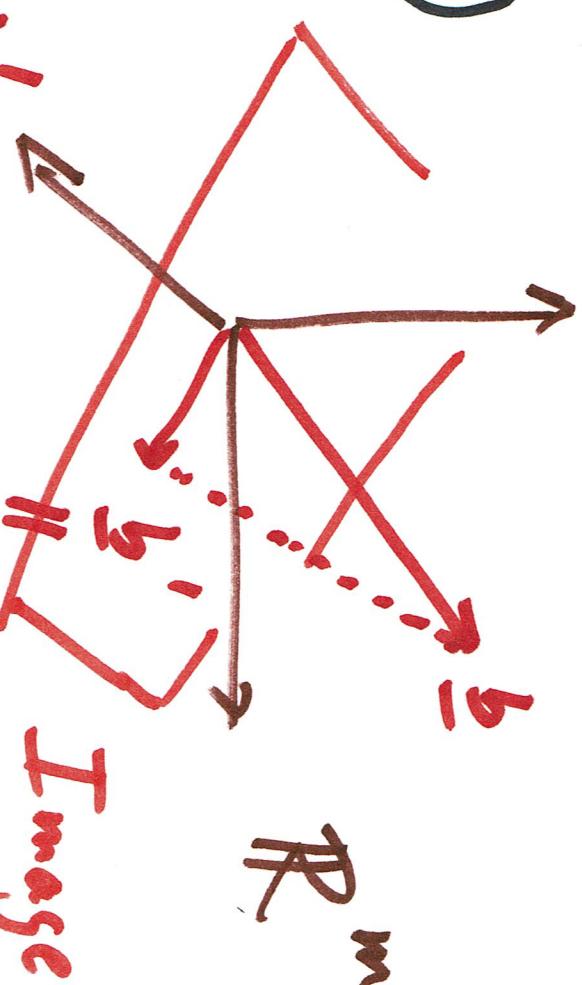
$$A \underline{x} = \underline{b}$$

Inconsistent

\rightarrow $\underline{b} \notin \text{Im}(A)$

\rightarrow \underline{b} $\in \mathbb{R}^m$ n -vector

\nwarrow \underline{b}' $\in \text{Im}(A)$ m -vector



$$\underline{x}' = \underline{b}' / \| \underline{b}' \|$$

" x' is taken by

A to vector nearest \underline{b}' in image of A"

Nice formula

$$A\underline{x} = \bar{b} \Rightarrow A^T A \underline{x} = A^T \bar{b}$$

This system is consistent
and can be solved by row red..

$$\underline{C} \underline{x}' = \bar{\epsilon}$$

Soln to $C \underline{x}' = \bar{\epsilon}$ will satisfy
 $A \underline{x}' = \bar{b}'$

Spectral Thm

The following are equiv
for an $n \times n$ matrix A
(of real numbers)

1) $A = A^T$ symmetric

2) \mathbb{R}^n has orthog basis of e-vectors
of A

3) $D = P^{-1} A P$

Diagonal
orthog matrix
cols are normalized
orthog e-vectors

Question Why can't we find orthonormal basis
of e-vectors for any diagonalizable
matrix A ?

Why not apply GS to basis
of e-vectors?

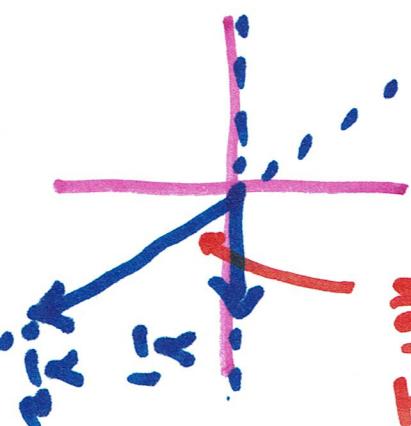
Ex $A = \begin{bmatrix} 1 & 1 \\ 0 & -1 \end{bmatrix}$

$$\lambda_1 = 1, \text{ and } \lambda_2 = -1$$

but $A \neq A^T$

not!

e-vectors $v_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, v_2 = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$



Singular Value Decomp.:

A $m \times n$ matrix

i) We can choose bases $\beta = \{y_1, \dots, y_n\}$ of \mathbb{R}^n

$$\delta = \{w_1, \dots, w_m\} \text{ if } \mathbb{R}^m$$

so that $[A]_{\beta}^{\delta} =$

$$\begin{bmatrix} I_r & 0 \\ \vdots & \ddots \\ 0 & 0 \end{bmatrix}$$

$$r = \text{rk}(A)$$

In other words, we can find

invertible $n \times n$ matrix P_R

$m \times m$ matrix Q_R

So that

$$Q_R^{-1} A P_R = \begin{pmatrix} I_r & \\ & 0 \end{pmatrix}$$

cols of P_R

y_1, \dots, y_n

cols of Q_R

w_1, \dots, w_m

2) If we insist $\beta = \lambda_1, \dots, \lambda_n$ by orthog.

$$\delta = (\underline{w}_1, \dots, \underline{w}_m)$$
 orthon.

then S.V.D. says we can arrange

$$[A]_{\beta} = \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_r \\ \hline & 0 & \\ & 0 & \\ & 0 & \end{bmatrix}$$

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$$

(singular values)

Equivalently

$$Q_\beta^{-1} A P_\beta = Q_\beta^T A P_\beta =$$

$$\left[\begin{array}{cccc} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_r & \\ \hline & & & 0 \\ & & & 0 \\ & & & 0 \end{array} \right]$$

where P_β, Q_β

are orthogonal matrices

Finding Sing values :

$A^T A$ Sym - matrix $n \times n$

Spectral Thm
 \Rightarrow

$\lambda_1, \dots, \lambda_n$ real e-values.

In fact: $\lambda_1, \dots, \lambda_n \geq 0$

(Key identity $\nabla \cdot A^T A \nabla$
 $= A \nabla \cdot A \nabla$)

Sing values order $\lambda_1 \geq \lambda_2 \geq \dots$
take $\sigma_1 = \sqrt{\lambda_1}, r_2 = \sqrt{\lambda_2}, \dots$