

Exam 1

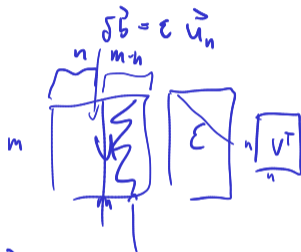
Jupyter like breachage ⊕ 1 pt.

look at exam in office hours

hw hints → hw 6 p1

$$A = U \Sigma V^T$$

$m \times n$   $m > n$



$$A \vec{x} \approx \vec{b}$$

For any ONB:  $\vec{w}_1, \dots, \vec{w}_n$

$$\vec{z} = \sum_i \underbrace{(\vec{z}^T \vec{u}_i)}_{\uparrow ?} \vec{u}_i$$

$$\vec{r} = \sum_{i=n+1}^m (r^T \vec{u}_i) \vec{u}_i$$

$$\|Ax - b\|_2$$

$$\begin{aligned} &= \|Q^T(QAx - b)\|_2 = \|R^T x - Q^T b\|_2 \\ &\quad \begin{matrix} \boxed{x} \\ \times \\ \boxed{Q^T b} \end{matrix} \end{aligned}$$

# Computing QR

- ▶ Gram-Schmidt ✓
- ▶ Householder Reflectors
- ▶ Givens Rotations

Demo: Gram-Schmidt–The Movie [cleared] (shows *modified G-S*)

Demo: Gram-Schmidt and Modified Gram-Schmidt [cleared]

Demo: Keeping track of coefficients in Gram-Schmidt [cleared]

Seen: Even modified Gram-Schmidt still unsatisfactory in finite precision arithmetic because of roundoff.

**NOTE:** Textbook makes further modification to ‘modified’ Gram-Schmidt:

- ▶ Orthogonalize *subsequent* rather than *preceding* vectors.
- ▶ Numerically: no difference, but sometimes algorithmically helpful.

## Economical/Reduced QR



Is QR with square  $Q$  for  $A \in \mathbb{R}^{m \times n}$  with  $m > n$  efficient?

"economy QR":



$$x^U = R_{\text{top}}^{-1} (Q^T b)_{\text{top}}$$

↑ still works, even with economy

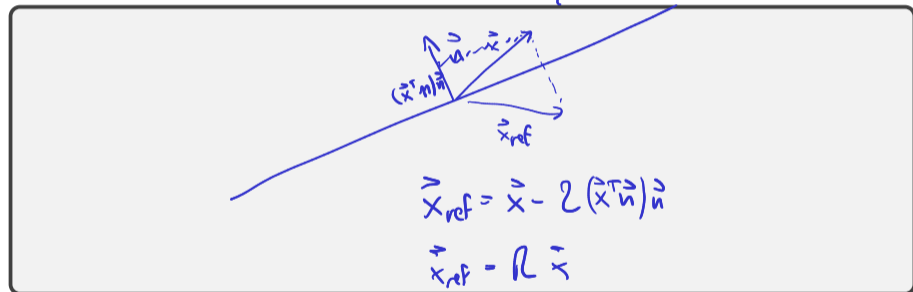
## Economical/Reduced QR

Is QR with square  $Q$  for  $A \in \mathbb{R}^{m \times n}$  with  $m > n$  efficient?

No. Can obtain **economical** or **reduced QR** with  $Q \in \mathbb{R}^{m \times n}$  and  $R \in \mathbb{R}^{n \times n}$ . Least squares solution process works unmodified with the economical form, though the equivalence proof relies on the 'full' form.

# Constructing Reflections

Given a plane represented by its (unit) normal vector  $\mathbf{n}$ , construct a reflection about that plane.



$$\mathbf{R} = \mathbf{I} - 2\hat{\mathbf{n}}\hat{\mathbf{n}}^T \quad \leftarrow \text{reflection}$$

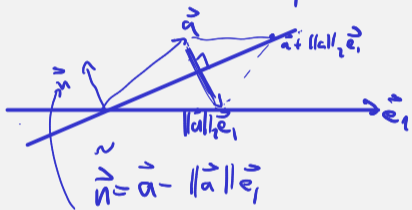
$$\mathbf{R}\vec{x} = \vec{x} - 2\hat{\mathbf{n}}(\hat{\mathbf{n}}^T \vec{x})$$

# Householder Transformations

Find an *orthogonal* matrix  $Q$  to zero out the lower part of a vector  $\mathbf{a}$ .

Let  $\vec{a}$  = first col of  $A$

Want: reflector  $H$ , s.t.  $H \vec{a} = \alpha \vec{e}_1 = \begin{pmatrix} \alpha \\ 0 \\ \vdots \\ 0 \end{pmatrix}$  (first col of  $R$ )



$$\vec{n} = \frac{2\|\mathbf{a}\|}{\|\mathbf{a}\|^2} \vec{a}$$

$$H = I - 2\vec{n}\vec{n}^T = I - 2 \frac{2\|\mathbf{a}\|}{\|\mathbf{a}\|^2} \vec{a}\vec{a}^T$$

cost of  $H\vec{x}$ ?

$$I\vec{x} : O(n)$$

$$2\vec{n}\vec{n}^T\vec{x} : O(n)$$

# Householder Reflectors: Properties

Seen from picture (and easy to see with algebra):

$$H\mathbf{a} = \pm \|\mathbf{a}\|_2 \mathbf{e}_1.$$

Remarks:

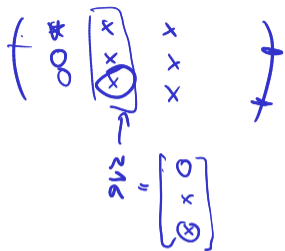
- ▶ **Q:** What if we want to zero out only the  $i + 1$ th through  $n$ th entry?  
**A:** Use  $\mathbf{e}_i$  above.
- ▶ A product  $H_n \cdots H_1 A = R$  of Householders makes it easy (and quite efficient!) to build a QR factorization.
- ▶ It turns out  $\mathbf{q} = \mathbf{a} + \|\mathbf{a}\|_2 \mathbf{e}_1$  works out, too—just pick whichever one causes less cancellation.  
 $\mathbf{q} = \mathbf{a} + \|\mathbf{a}\|_2 \mathbf{e}_1$
- ▶  $H$  is symmetric
- ▶  $H$  is orthogonal

Demo: 3x3 Householder demo [cleared]

$$\begin{pmatrix} | & t & | \\ \hline & \pm & \hline & 0 & | \\ | & \vdots & | \\ \hline & 0 & \hline & 0 & | \end{pmatrix} \begin{matrix} \|\mathbf{a}\|_2 \\ 0 \\ \vdots \\ 0 \end{matrix}$$

choose so no subtraction  
appears





$$\vec{v} = \vec{a} - \|a_2\| e_2 = \begin{pmatrix} 0 \\ x \\ 0 \end{pmatrix}$$

$$P = I - \frac{v v^T}{v^T v}$$

## Givens Rotations

If reflections work, can we make rotations work, too?

$$\begin{bmatrix} c & s \\ -s & c \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \pm \sqrt{a_1^2 + a_2^2} \\ 0 \end{bmatrix}$$

$\hat{=} \hat{a}$

$$c = a_1 / \|\hat{a}\|_2$$

$$s = a_2 / \|\hat{a}\|_2$$

Demo: 3x3 Givens demo [cleared]

$$\underbrace{G_3 G_2 G_1}_{Q^T} \begin{pmatrix} x & x & x \\ x & x & x \\ x & x & x \end{pmatrix} = \begin{pmatrix} r & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$G_1 = \begin{pmatrix} 1 & & \\ & c_1 & s_1 \\ & -s_1 & c_1 \end{pmatrix}$$

$$G_2 = \begin{pmatrix} c_2 & s_2 & \\ -s_2 & c_2 & \\ & & 1 \end{pmatrix}$$

$$G_3 = \begin{pmatrix} 1 & & \\ & c_3 & s_3 \\ & -s_3 & c_3 \end{pmatrix}$$

$$Q^T A = R$$

## Rank-Deficient Matrices and QR

What happens with QR for rank-deficient matrices?

