

QR-decomposition

- ✦ A $m \times k$ matrix with columns w_1, w_2, \dots, w_k . m -vectors.
- ✦ We find an orthonormal basis $q_1, q_2, \dots, q_k, q_{k+1}, \dots, q_m$ of \mathbb{R}^m .
- ✦ Then since q_i is orthogonal to w_1, \dots, w_{k-1} .
 - ✦ $w_1 = (w_1 \cdot q_1)q_1$
 - ✦ $w_2 = (w_2 \cdot q_1)q_1 + (w_2 \cdot q_2)q_2$.
 - ✦
 - ✦ $w_k = (w_k \cdot q_1)q_1 + (w_k \cdot q_2)q_2 + \dots + (w_k \cdot q_k)q_k$.

✦ Use Theorem 3.1.8, $A=QR$

$$\begin{bmatrix} w_1 & w_2 & \cdots & w_k \end{bmatrix} = \begin{bmatrix} q_1 & q_2 & \cdots & q_k \end{bmatrix} \begin{bmatrix} (w_1 \cdot q_1) & (w_2 \cdot q_1) & \cdots & (w_1 \cdot q_k) \\ 0 & (w_2 \cdot q_2) & \cdots & (w_2 \cdot q_k) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & (w_k \cdot q_k) \end{bmatrix}$$

Theorem 7.10.1 (QR-Decomposition) *If A is an $m \times k$ matrix with full column rank, then A can be factored as*

$$A = QR \tag{4}$$

where Q is an $m \times k$ matrix whose column vectors form an orthonormal basis for the column space of A and R is a $k \times k$ invertible upper triangular matrix.

✦ $A=QR$.

✦ Since the inverse of Q is Q^T , we have $R=Q^T A$.

✦ See Example 1.

QR-decompositions and the least square problem

- ✦ $Ax=b$. best approximate solution $x'=(A^T A)^{-1}A^T b$.
- ✦ We write $A=QR$. $A^T=R^T Q^T$.
- ✦ $A^T A x'=A^T b$.
- ✦ $R^T Q^T Q R x=R^T Q^T b$.
- ✦ $R^T R x=R^T Q^T b$ and $x'=R^{-1} Q^T b$.

Theorem 7.10.2 *If A is an $m \times k$ matrix with full column rank, and if $A = QR$ is a QR-decomposition of A , then the normal system for $Ax = b$ can be expressed as*

$$R\mathbf{x} = Q^T \mathbf{b} \tag{9}$$

and the least squares solution can be expressed as

$$\hat{\mathbf{x}} = R^{-1} Q^T \mathbf{b} \tag{10}$$

- ✦ Example 2.
- ✦ We will use Householder reflections to find Q instead since it has advantages in computer calculations.
- ✦ We obtain a formula for reflections:
 - ✦ Let a^\perp be the orthogonal hyperplane to $\text{span}\{a\}$
 - ✦ $x - \text{refl}_{a^\perp}(x) = 2\text{proj}_a(x)$.
 - ✦ Thus $\text{refl}_{a^\perp}(x) = x - 2\text{proj}_a(x) = x - 2a(x \cdot a) / \|a\|^2$.

Definition 7.10.3 If \mathbf{a} is a nonzero vector in R^n , and if \mathbf{x} is any vector in R^n , then the *reflection of \mathbf{x} about the hyperplane \mathbf{a}^\perp* is denoted by $\text{refl}_{\mathbf{a}^\perp} \mathbf{x}$ and defined as

$$\text{refl}_{\mathbf{a}^\perp} \mathbf{x} = \mathbf{x} - 2\text{proj}_{\mathbf{a}} \mathbf{x} \quad (11)$$

The operator $T : R^n \rightarrow R^n$ defined by $T(\mathbf{x}) = \text{refl}_{\mathbf{a}^\perp} \mathbf{x}$ is called the *reflection of R^n about the hyperplane \mathbf{a}^\perp* .

- ✦ Thus the matrix $H_{\mathbf{a}^c}$ for $\text{refl}_{\mathbf{a}^c}$ is $H_{\mathbf{a}^c} = I - 2\mathbf{a}\mathbf{a}^T / \mathbf{a}^T\mathbf{a}$.
- ✦ If \mathbf{a} is a unit vector \mathbf{u} , then $\mathbf{u}^T\mathbf{u} = \|\mathbf{u}\|^2 = 1$.
- ✦ $\text{refl}_{\mathbf{a}^c} = \mathbf{x} - 2(\mathbf{x} \cdot \mathbf{u})\mathbf{u}$ and $H_{\mathbf{u}^c} = I - \mathbf{u}\mathbf{u}^T$.
- ✦ See Example 3 and 4.

Definition 7.10.4 An $n \times n$ matrix of the form

$$H = I - \frac{2}{\mathbf{a}^T\mathbf{a}}\mathbf{a}\mathbf{a}^T \quad (16)$$

in which \mathbf{a} is a nonzero vector in R^n is called a **Householder matrix**. Geometrically, H is the standard matrix for the Householder reflection about the hyperplane \mathbf{a}^\perp .

Theorem 7.10.5 *Householder matrices are symmetric and orthogonal.*

✦ Proof: $H^T = I - (2/a^T a)(aa^T)^T = H.$

$$\begin{aligned} HH &= (I - 2aa^T/a^T a) (I - 2aa^T/a^T a) = I - 4aa^T/a^T a \\ &+ (2aa^T/(a^T a))(2aa^T/(a^T a)) = I \text{ (since } 4(1/(a^T a)^2)(aa^T aa^T) = \\ &4(1/(a^T a)^2)((a^T a)aa^T) = 4(1/(a^T a))(aa^T).) \end{aligned}$$

Theorem 7.10.6 *If \mathbf{v} and \mathbf{w} are distinct vectors in R^n with the same length, then the Householder reflection about the hyperplane $(\mathbf{v} - \mathbf{w})^\perp$ maps \mathbf{v} into \mathbf{w} , and conversely.*

QR-decomposition using householder reflections

- ✦ The steps given A nxn matrix
- ✦ We apply a Householder matrix Q_1 so that Q_1A has $(1,0,\dots,0)$ as the first column by choosing Q_1 so that $Q_1a_1=[1,0,\dots,0]^T$.
- ✦ Now choose Q_2 which is 1 at $(1,1)$ -entry and zero on elsewhere in the 1-st row and the 1-st column.
- ✦ Now concentrate on $(n-1)\times(n-1)$ -matrix in Q_1A removing 1st column and the 1st-row
- ✦ Q_2 sends the 2nd column a'_2 of Q_1A to $[*,1,0,\dots,0]^T$.
- ✦ We keep doing this... $Q_{n-1}\dots Q_2Q_1A$ is upper triangular. We let it be R and $Q=Q_n\dots Q_2Q_1$.

✦ Example 7:

