6. QR factorization

- triangular matrices
- QR factorization
- Gram-Schmidt algorithm
- Householder algorithm
Triangular matrix

A square matrix $A$ is **lower triangular** if $A_{ij} = 0$ for $j > i$

\[
A = \begin{bmatrix}
A_{11} & 0 & \cdots & 0 & 0 \\
A_{21} & A_{22} & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & 0 & 0 \\
A_{n-1,1} & A_{n-1,2} & \cdots & A_{n-1,n-1} & 0 \\
A_{n1} & A_{n2} & \cdots & A_{n,n-1} & A_{nn}
\end{bmatrix}
\]

$A$ is **upper triangular** if $A_{ij} = 0$ for $j < i$ (the transpose $A^T$ is lower triangular)

A triangular matrix is **unit** upper/lower triangular if $A_{ii} = 1$ for all $i$
Forward substitution

solve $Ax = b$ when $A$ is lower triangular with nonzero diagonal elements

Algorithm

$$x_1 = b_1/A_{11}$$
$$x_2 = (b_2 - A_{21}x_1)/A_{22}$$
$$x_3 = (b_3 - A_{31}x_1 - A_{32}x_2)/A_{33}$$
$$\vdots$$
$$x_n = (b_n - A_{n1}x_1 - A_{n2}x_2 - \cdots - A_{n,n-1}x_{n-1})/A_{nn}$$

Complexity: $1 + 3 + 5 + \cdots + (2n - 1) = n^2$ flops
Back substitution

solve \( Ax = b \) when \( A \) is upper triangular with nonzero diagonal elements

Algorithm

\[
\begin{align*}
x_n &= b_n / A_{nn} \\
x_{n-1} &= (b_{n-1} - A_{n-1,n}x_n) / A_{n-1,n-1} \\
x_{n-2} &= (b_{n-2} - A_{n-2,n-1}x_{n-1} - A_{n-2,n}x_n) / A_{n-2,n-2} \\ & \quad \vdots \\
x_1 &= (b_1 - A_{12}x_2 - A_{13}x_3 - \cdots - A_{1n}x_n) / A_{11}
\end{align*}
\]

Complexity: \( n^2 \) flops
Inverse of a triangular matrix

A triangular matrix $A$ with nonzero diagonal elements is nonsingular:

$$Ax = 0 \implies x = 0$$

this follows from forward or back substitution applied to the equation $Ax = 0$

- inverse of $A$ can be computed by solving $AX = I$ column by column

$$A \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} = \begin{bmatrix} e_1 & e_2 & \cdots & e_n \end{bmatrix} \quad (x_i \text{ is column } i \text{ of } X)$$

- inverse of lower triangular matrix is lower triangular

- inverse of upper triangular matrix is upper triangular

- complexity of computing inverse of $n \times n$ triangular matrix is

$$n^2 + (n - 1)^2 + \cdots + 1 \approx \frac{1}{3}n^3 \text{ flops}$$
Outline

• triangular matrices

• QR factorization

• Gram-Schmidt algorithm

• Householder algorithm
**QR factorization**

If \( A \in \mathbb{R}^{m \times n} \) has linearly independent columns then it can be factored as

\[
A = \begin{bmatrix}
q_1 & q_2 & \cdots & q_n
\end{bmatrix}
\begin{bmatrix}
R_{11} & R_{12} & \cdots & R_{1n} \\
0 & R_{22} & \cdots & R_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & R_{nn}
\end{bmatrix}
\]

- vectors \( q_1, \ldots, q_n \) are orthonormal \( m \)-vectors:

\[
\|q_i\| = 1, \quad q_i^T q_j = 0 \quad \text{if } i \neq j
\]

- diagonal elements \( R_{ii} \) are nonzero

- if \( R_{ii} < 0 \), we can switch the signs of \( R_{ii}, \ldots, R_{in} \), and the vector \( q_i \)

- most definitions require \( R_{ii} > 0 \); this makes \( Q \) and \( R \) unique
QR factorization in matrix notation

if \( A \in \mathbb{R}^{m \times n} \) has linearly independent columns then it can be factored as

\[
A = QR
\]

Q-factor

- \( Q \) is \( m \times n \) with orthonormal columns (\( Q^T Q = I \))
- if \( A \) is square (\( m = n \)), then \( Q \) is orthogonal (\( Q^T Q = QQ^T = I \))

R-factor

- \( R \) is \( n \times n \), upper triangular, with nonzero diagonal elements
- \( R \) is nonsingular (diagonal elements are nonzero)
### Example

\[
\begin{bmatrix}
-1 & -1 & 1 \\
1 & 3 & 3 \\
-1 & -1 & 5 \\
1 & 3 & 7
\end{bmatrix}
= \begin{bmatrix}
-1/2 & 1/2 & -1/2 \\
1/2 & 1/2 & -1/2 \\
-1/2 & 1/2 & 1/2 \\
1/2 & 1/2 & 1/2
\end{bmatrix}
\begin{bmatrix}
2 & 4 & 2 \\
0 & 2 & 8 \\
0 & 0 & 4
\end{bmatrix}
\]

\[
= \begin{bmatrix}
q_1 & q_2 & q_3
\end{bmatrix}
\begin{bmatrix}
R_{11} & R_{12} & R_{13} \\
0 & R_{22} & R_{23} \\
0 & 0 & R_{33}
\end{bmatrix}
\]

\[
= QR
\]
Applications

in the following lectures, we will use the QR factorization to solve

- linear equations
- least squares problems
- constrained least squares problems

here, we show that it gives useful simple formulas for

- the pseudo-inverse of a matrix with linearly independent columns
- the inverse of a nonsingular matrix
- projection on the range of a matrix with linearly independent columns
QR factorization and (pseudo-)inverse

pseudo-inverse of matrix $A$ with linearly independent columns (page 4-23)

$$A^\dagger = (A^T A)^{-1} A^T$$

**pseudo-inverse in terms of QR factors of $A$:**

$$A^\dagger = ((QR)^T (QR))^{-1} (QR)^T$$

$$= (R^T Q^T Q R)^{-1} R^T Q^T$$

$$= (R^T R)^{-1} R^T Q^T \quad (Q^T Q = I)$$

$$= R^{-1} R^{-T} R^T Q^T \quad (R \text{ is nonsingular})$$

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

**for square nonsingular $A$ this is the inverse:**

$$A^{-1} = (QR)^{-1} = R^{-1} Q^T$$
Range

recall definition of range of a matrix $A \in \mathbb{R}^{m \times n}$ (page 5-14):

$$\text{range}(A) = \{Ax \mid x \in \mathbb{R}^n\}$$

suppose $A$ has linearly independent columns with QR factors $Q, R$

- $Q$ has the same range as $A$:

  $$y \in \text{range}(A) \iff y = Ax \text{ for some } x$$
  $$\iff y = QRx \text{ for some } x$$
  $$\iff y = Qz \text{ for some } z$$
  $$\iff y \in \text{range}(Q)$$

- columns of $Q$ are orthonormal and have the same span as columns of $A$
Projection on range

- combining $A = QR$ and $A^\dagger = R^{-1}Q^T$ (from page 6-10) gives

\[ AA^\dagger = QRR^{-1}Q^T = QQ^T \]

note the order of the product in $AA^\dagger$ and the difference with $A^\dagger A = I$

- recall (from page 5-15) that $QQ^T x$ is the projection of $x$ on the range of $Q$

\[ range(A) = range(Q) \]

\[ QQ^T x = AA^\dagger x \]
QR factorization of complex matrices

if $A \in \mathbb{C}^{m \times n}$ has linearly independent columns then it can be factored as

$$A = QR$$

- $Q \in \mathbb{C}^{m \times n}$ has orthonormal columns ($Q^H Q = I$)
- $R \in \mathbb{C}^{n \times n}$ is upper triangular with real nonzero diagonal elements
- most definitions choose diagonal elements $R_{ii}$ to be positive
- in the rest of the lecture we assume $A$ is real
Algorithms for QR factorization

**Gram-Schmidt algorithm** (page 6-15)
- complexity is $2mn^2$ flops
- not recommended in practice (sensitive to rounding errors)

**Modified Gram-Schmidt algorithm**
- complexity is $2mn^2$ flops
- better numerical properties

**Householder algorithm** (page 6-25)
- complexity is $2mn^2 - (2/3)n^3$ flops
- represents $Q$ as a product of elementary orthogonal matrices
- the most widely used algorithm (MATLAB’s `qr` function)

in the rest of the course we will take $2mn^2$ for the complexity of QR factorization
Outline

- triangular matrices
- QR factorization
- **Gram-Schmidt algorithm**
- Householder algorithm
Gram-Schmidt algorithm

Gram-Schmidt QR algorithm computes $Q$ and $R$ column by column

- after $k$ steps we have a partial QR factorization

$$
\begin{bmatrix}
    a_1 & a_2 & \cdots & a_k
\end{bmatrix} =
\begin{bmatrix}
    q_1 & q_2 & \cdots & q_k
\end{bmatrix}
$$

$$
\begin{bmatrix}
    R_{11} & R_{12} & \cdots & R_{1k} \\
    0 & R_{22} & \cdots & R_{2k} \\
    \vdots & \vdots & \ddots & \vdots \\
    0 & 0 & \cdots & R_{kk}
\end{bmatrix}
$$

- columns $q_1, \ldots, q_k$ are orthonormal
- diagonal elements $R_{11}, R_{22}, \ldots, R_{kk}$ are positive
- columns $q_1, \ldots, q_k$ have the same span as $a_1, \ldots, a_k$ (see page 6-11)
Computing column $k$

suppose we have completed the factorization for the first $k-1$ columns

• column $k$ of the equation $A = QR$ reads

$$a_k = R_{1k}q_1 + R_{2k}q_2 + \cdots + R_{k-1,k}q_{k-1} + R_{kk}q_k$$

• regardless of how we choose $R_{1k}, \ldots, R_{k-1,k}$, the vector

$$\tilde{q}_k = a_k - R_{1k}q_1 - R_{2k}q_2 - \cdots - R_{k-1,k}q_{k-1}$$

will be nonzero: $a_1, a_2, \ldots, a_k$ are linearly independent and therefore

$$a_k \not\in \text{span}\{a_1, \ldots, a_{k-1}\} = \text{span}\{q_1, \ldots, q_{k-1}\}$$

• $q_k$ is $\tilde{q}_k$ normalized: choose $R_{kk} = \|\tilde{q}_k\|$ and $q_k = (1/R_{kk})\tilde{q}_k$

• $\tilde{q}_k$ and $q_k$ are orthogonal to $q_1, \ldots, q_{k-1}$ if we choose

$$R_{1k} = q_1^Ta_k, \quad R_{2k} = q_2^Ta_k, \quad \ldots, \quad R_{k-1,k} = q_{k-1}^Ta_k$$
Gram-Schmidt algorithm

**Given:** $m \times n$ matrix $A$ with linearly independent columns $a_1, \ldots, a_n$

**Algorithm**

for $k = 1$ to $n$

$$R_{1k} = q_1^T a_k$$
$$R_{2k} = q_2^T a_k$$
$$\vdots$$
$$R_{k-1,k} = q_{k-1}^T a_k$$

$$\tilde{q}_k = a_k - (R_{1k} q_1 + R_{2k} q_2 + \cdots + R_{k-1,k} q_{k-1})$$

$$R_{kk} = \|\tilde{q}_k\|$$

$$q_k = \frac{1}{R_{kk}} \tilde{q}_k$$
Example

example on page 6-8:

\[
\begin{bmatrix}
a_1 & a_2 & a_3 \\
\end{bmatrix}
= \begin{bmatrix}
-1 & -1 & 1 \\
1 & 3 & 3 \\
-1 & -1 & 5 \\
1 & 3 & 7 \\
\end{bmatrix}
= \begin{bmatrix}
q_1 & q_2 & q_3 \\
\end{bmatrix}
\begin{bmatrix}
R_{11} & R_{12} & R_{13} \\
0 & R_{22} & R_{23} \\
0 & 0 & R_{33} \\
\end{bmatrix}
\]

First column of \(Q\) and \(R\)

\[
\tilde{q}_1 = a_1 = \begin{bmatrix}
-1 \\
1 \\
-1 \\
1 \\
\end{bmatrix}, \quad R_{11} = \|\tilde{q}_1\| = 2, \quad q_1 = \frac{1}{R_{11}}\tilde{q}_1 = \begin{bmatrix}
-1/2 \\
1/2 \\
-1/2 \\
1/2 \\
\end{bmatrix}
\]
Example

Second column of $Q$ and $R$

- compute $R_{12} = q_1^T a_2 = 4$

- compute

$$\tilde{q}_2 = a_2 - R_{12} q_1 = \begin{bmatrix} -1 \\ 3 \\ -1 \\ 3 \end{bmatrix} - 4 \begin{bmatrix} -1/2 \\ 1/2 \\ -1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

- normalize to get

$$R_{22} = \|\tilde{q}_2\| = 2, \quad q_2 = \frac{1}{R_{22}} \tilde{q}_2 = \begin{bmatrix} 1/2 \\ 1/2 \\ 1/2 \\ 1/2 \end{bmatrix}$$
Example

Third column of $Q$ and $R$

- compute $R_{13} = q_1^T a_3 = 2$ and $R_{23} = q_2^T a_3 = 8$

- compute

$$\tilde{q}_3 = a_3 - R_{13}q_1 - R_{23}q_2 = \begin{bmatrix} 1 \\ 3 \\ 5 \\ 7 \end{bmatrix} - 2 \begin{bmatrix} -1/2 \\ 1/2 \\ -1/2 \\ 1/2 \end{bmatrix} - 8 \begin{bmatrix} 1/2 \\ 1/2 \\ 1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} -2 \\ -2 \\ 2 \\ 2 \end{bmatrix}$$

- normalize to get

$$R_{33} = \|\tilde{q}_3\| = 4, \quad q_3 = \frac{1}{R_{33}} \tilde{q}_3 = \begin{bmatrix} -1/2 \\ -1/2 \\ 1/2 \\ 1/2 \end{bmatrix}$$
Example

Final result

\[
\begin{bmatrix}
-1 & -1 & 1 \\
1 & 3 & 3 \\
-1 & -1 & 5 \\
1 & 3 & 7
\end{bmatrix} = \begin{bmatrix}
q_1 & q_2 & q_3
\end{bmatrix}
\begin{bmatrix}
R_{11} & R_{12} & R_{13} \\
0 & R_{22} & R_{23} \\
0 & 0 & R_{33}
\end{bmatrix}
\]

\[
= \begin{bmatrix}
-1/2 & 1/2 & -1/2 \\
1/2 & 1/2 & -1/2 \\
-1/2 & 1/2 & 1/2 \\
1/2 & 1/2 & 1/2
\end{bmatrix}
\begin{bmatrix}
2 & 4 & 2 \\
0 & 2 & 8 \\
0 & 0 & 4
\end{bmatrix}
\]
Complexity

**Complexity of cycle** $k$ (of algorithm on page 6-17)

- $k - 1$ inner products with $a_k$: $(k - 1)(2m - 1)$ flops
- computation of $\tilde{q}_k$: $2(k - 1)m$ flops
- computing $R_{kk}$ and $q_k$: $3m$ flops

Total for cycle $k$: $(4m - 1)(k - 1) + 3m$ flops

**Complexity** for $m \times n$ factorization:

$$\sum_{k=1}^{n} ((4m - 1)(k - 1) + 3m) = (4m - 1)\frac{n(n - 1)}{2} + 3mn$$

$$\approx 2mn^2 \text{ flops}$$
Numerical experiment

• we use the following MATLAB code

\[
[m, n] = \text{size}(A);
Q = \text{zeros}(m,n);
R = \text{zeros}(n,n);
\text{for } k = 1:n
   R(1:k-1,k) = Q(:,1:k-1)' * A(:,k);
   v = A(:,k) - Q(:,1:k-1) * R(1:k-1,k);
   R(k,k) = \text{norm}(v);
   Q(:,k) = v / R(k,k);
\text{end};
\]

• we apply this to a square matrix \( A \) of size \( m = n = 50 \)

• \( A \) is constructed as \( A = USV \) with \( U, V \) orthogonal, \( S \) diagonal with

\[
S_{ii} = 10^{-10(i-1)/(n-1)}, \quad i = 1, \ldots, n
\]
Numerical experiment

plot shows deviation from orthogonality between $q_k$ and previous columns

$$e_k = \max_{1 \leq i < k} |q_i^T q_k|, \quad k = 2, \ldots, n$$

loss of orthogonality is due to rounding error
Outline

- triangular matrices
- QR factorization
- Gram-Schmidt algorithm
- Householder algorithm
Householder algorithm

• the most widely used algorithm for QR factorization (qr in MATLAB)

• less sensitive to rounding error than Gram-Schmidt algorithm

• computes a ‘full’ QR factorization

\[
A = \begin{bmatrix} \tilde{Q} & \tilde{Q} \end{bmatrix} \begin{bmatrix} R \\ 0 \end{bmatrix}, \quad \begin{bmatrix} \tilde{Q} & \tilde{Q} \end{bmatrix} \text{ orthogonal}
\]

• the full Q-factor is constructed as a product of orthogonal matrices

\[
\begin{bmatrix} \tilde{Q} & \tilde{Q} \end{bmatrix} = H_1 H_2 \cdots H_n
\]

each \( H_i \) is an \( m \times m \) symmetric, orthogonal ‘reflector’ (page 5-10)
Reflector

\[ H = I - 2vv^T \quad \text{with } ||v|| = 1 \]

- \( Hx \) is reflection of \( x \) through hyperplane \( \{ z \mid v^T z = 0 \} \) (see page 5-10)

- \( H \) is symmetric

- \( H \) is orthogonal

- matrix-vector product \( Hx \) can be computed efficiently as

\[ Hx = x - 2(v^T x)x \]

complexity is \( 4p \) flops if \( v \) and \( x \) have length \( p \)
Reflection to multiple of unit vector

given nonzero $p$-vector $y = (y_1, y_2, \ldots, y_p)$, define

$$w = \begin{bmatrix}
y_1 + \text{sign}(y_1)\|y\| \\
y_2 \\
\vdots \\
y_p
\end{bmatrix}, \quad v = \frac{1}{\|w\|}w$$

- we define $\text{sign}(0) = 1$

- vector $w$ satisfies

$$\|w\|^2 = 2 (w^T y) = 2\|y\| (\|y\| + |y_1|)$$

- reflector $H = I - 2vv^T$ maps $y$ to multiple of $e_1 = (1, 0, \ldots, 0)$:

$$Hy = y - \frac{2(w^T y)}{\|w\|^2}w = y - w = -\text{sign}(y_1)\|y\|e_1$$
Geometry

First coordinate axis

$\begin{align*}
-\text{sign}(y_1) \|y\| e_1
\end{align*}$

Hyperplane $\{x \mid w^T x = 0\}$

Reflection through the hyperplane $\{x \mid w^T x = 0\}$ with normal vector

$w = y + \text{sign}(y_1) \|y\| e_1$

Maps $y$ to the vector $-\text{sign}(y_1) \|y\| e_1$
Householder triangularization

• computes reflectors $H_1, \ldots, H_n$ that reduce $A$ to triangular form:

$$H_n H_{n-1} \cdots H_1 A = \begin{bmatrix} R \\ 0 \end{bmatrix}$$

• after step $k$, the matrix $H_k H_{k-1} \cdots H_1 A$ has the following structure:

(elements in positions $i, j$ for $i > j$ and $j \leq k$ are zero)
Householder algorithm

the following algorithm overwrites $A$ with $\begin{bmatrix} R \\ 0 \end{bmatrix}$

**Algorithm:** for $k = 1$ to $n$,

1. define $y = A_{k:m,k}^m$ and compute $(m - k + 1)$-vector $v_k$:

   $$w = y + \text{sign}(y_1)\|y\|e_1, \quad v_k = \frac{1}{\|w\|}w$$

2. multiply $A_{k:m,k:n}^m$ with reflector $I - 2v_kv_k^T$:

   $$A_{k:m,k:n}^m := A_{k:m,k:n}^m - 2v_k(v_k^TA_{k:m,k:n}^m)$$

(see page 107 in textbook for ‘slice’ notation for submatrices)
• in step 2 we multiply $A_{k:m,k:n}$ with the reflector $I - 2v_kv_k^T$:

$$(I - 2v_kv_k^T)A_{k:m,k:n} = A_{k:m,k:n} - 2v_k(v_k^TA_{k:m,k:n})$$

• this is equivalent to multiplying $A$ with $m \times m$ reflector

$$H_k = \begin{bmatrix} I & 0 \\ 0 & I - 2v_kv_k^T \end{bmatrix} = I - 2\begin{bmatrix} 0 \\ v_k \end{bmatrix}\begin{bmatrix} 0 \\ v_k \end{bmatrix}^T$$

• algorithm overwrites $A$ with

$$\begin{bmatrix} R \\ 0 \end{bmatrix}$$

and returns the vectors $v_1, \ldots, v_n$, with $v_k$ of length $m - k + 1$
Example

example on page 6-8:

\[ A = \begin{bmatrix} -1 & -1 & 1 \\ 1 & 3 & 3 \\ -1 & -1 & 5 \\ 1 & 3 & 7 \end{bmatrix} = H_1 H_2 H_3 \begin{bmatrix} R \\ 0 \end{bmatrix} \]

we compute reflectors \( H_1, H_2, H_3 \) that triangularize \( A \):

\[ H_3 H_2 H_1 A = \begin{bmatrix} R_{11} & R_{12} & R_{13} \\ 0 & R_{22} & R_{23} \\ 0 & 0 & R_{33} \\ 0 & 0 & 0 \end{bmatrix} \]
Example

First column of $R$

- compute reflector that maps first column of $A$ to multiple of $e_1$:

\[
y = \begin{bmatrix} -1 \\ 1 \\ -1 \\ 1 \end{bmatrix}, \quad w = y - \|y\|e_1 = \begin{bmatrix} -3 \\ 1 \\ -1 \\ 1 \end{bmatrix}, \quad v_1 = \frac{1}{\|w\|} w = \frac{1}{2\sqrt{3}} \begin{bmatrix} -3 \\ 1 \\ -1 \\ 1 \end{bmatrix}
\]

- overwrite $A$ with product of $I - 2v_1v_1^T$ and $A$

\[
A := (I - 2v_1v_1^T)A = \begin{bmatrix} 2 & 4 & 2 \\ 0 & 4/3 & 8/3 \\ 0 & 2/3 & 16/3 \\ 0 & 4/3 & 20/3 \end{bmatrix}
\]
Example

Second column of $R$

- compute reflector that maps $A_{2:4,2}$ to multiple of $e_1$:

$$y = \begin{bmatrix} 4/3 \\ 2/3 \\ 4/3 \end{bmatrix}, \quad w = y + \|y\|e_1 = \begin{bmatrix} 10/3 \\ 2/3 \\ 4/3 \end{bmatrix}, \quad v_2 = \frac{1}{\|w\|}w = \frac{1}{\sqrt{30}} \begin{bmatrix} 5 \\ 1 \\ 2 \end{bmatrix}$$

- overwrite $A_{2:4,2:3}$ with product of $I - 2v_2v_2^T$ and $A_{2:4,2:3}$:

$$A := \begin{bmatrix} 1 & 0 \\ 0 & I - 2v_2v_2^T \end{bmatrix} A = \begin{bmatrix} 2 & 4 & 2 \\ 0 & -2 & -8 \\ 0 & 0 & 16/5 \\ 0 & 0 & 12/5 \end{bmatrix}$$
Example

Third column of $R$

- compute reflector that maps $A_{3:4,3}$ to multiple of $e_1$:

$$y = \begin{bmatrix} 16/5 \\ 12/5 \end{bmatrix}, \quad w = y + \|y\|e_1 = \begin{bmatrix} 36/5 \\ 12/5 \end{bmatrix}, \quad v_3 = \frac{1}{\|w\|}w = \frac{1}{\sqrt{10}} \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

- overwrite $A_{3:4,3}$ with product of $I - 2v_3v_3^T$ and $A_{3:4,3}$:

$$A := \begin{bmatrix} I & 0 \\ 0 & I - 2v_3v_3^T \end{bmatrix} A = \begin{bmatrix} 2 & 4 & 2 \\ 0 & -2 & -8 \\ 0 & 0 & -4 \\ 0 & 0 & 0 \end{bmatrix}$$
Example

Final result

\[
H_3H_2H_1A = \begin{bmatrix} I & 0 \\ 0 & I - 2v_3v_3^T \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & I - 2v_2v_2^T \end{bmatrix} (I - 2v_1v_1^T)A
\]

\[
= \begin{bmatrix} I & 0 \\ 0 & I - 2v_3v_3^T \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & I - 2v_2v_2^T \end{bmatrix} \begin{bmatrix} 2 & 4 & 2 \\ 0 & 4/3 & 8/3 \\ 0 & 2/3 & 16/3 \\ 0 & 4/3 & 20/3 \end{bmatrix}
\]

\[
= \begin{bmatrix} I & 0 \\ 0 & I - 2v_3v_3^T \end{bmatrix} \begin{bmatrix} 2 & 4 & 2 \\ 0 & -2 & -8 \\ 0 & 0 & 16/5 \\ 0 & 0 & 12/5 \end{bmatrix}
\]

\[
= \begin{bmatrix} 2 & 4 & 2 \\ 0 & -2 & -8 \\ 0 & 0 & -4 \\ 0 & 0 & 0 \end{bmatrix}
\]
Complexity

**Complexity in cycle** $k$ (of algorithm on page 6-30): the dominant terms are

- $(2(m - k + 1) - 1)(n - k + 1)$ flops for product $v_k^T(A_{k:m,k:n})$
- $(m - k + 1)(n - k + 1)$ flops for outer product with $v_k$
- $(m - k + 1)(n - k + 1)$ flops for subtraction from $A_{k:m,k:n}$

sum is roughly $4(m - k + 1)(n - k + 1)$ flops

**Total** for computing $R$ and vectors $v_1, \ldots, v_n$:

$$\sum_{k=1}^{n} 4(m - k + 1)(n - k + 1) \approx \int_{0}^{n} 4(m - t)(n - t)dt$$

$$= 2mn^2 - \frac{2}{3}n^3$$ flops
the Householder algorithm returns the vectors $v_1, \ldots, v_n$ that define

$$\begin{bmatrix} Q & \tilde{Q} \end{bmatrix} = H_1 H_2 \cdots H_n$$

- usually there is no need to compute the matrix $\begin{bmatrix} Q & \tilde{Q} \end{bmatrix}$ explicitly
- the vectors $v_1, \ldots, v_n$ are an economical representation of $\begin{bmatrix} Q & \tilde{Q} \end{bmatrix}$
- products with $\begin{bmatrix} Q & \tilde{Q} \end{bmatrix}$ or its transpose can be computed as

$$\begin{bmatrix} Q & \tilde{Q} \end{bmatrix} x = H_1 H_2 \cdots H_n x$$

$$\begin{bmatrix} Q & \tilde{Q} \end{bmatrix}^T y = H_n H_{n-1} \cdots H_1 y$$
Multiplication with Q-factor

• the matrix-vector product $H_k x$ is defined as

\[ H_k x = \begin{bmatrix} I & 0 \\ 0 & I - 2 v_k v_k^T \end{bmatrix} \begin{bmatrix} x_{1:k-1} \\ x_{k:m} \end{bmatrix} = \begin{bmatrix} x_{1:k-1} \\ x_{k:m} - 2(v_k^T x_{k:m}) v_k \end{bmatrix} \]

• complexity of multiplication $H_k x$ is $4(m - k + 1)$ flops:

• complexity of multiplication with $H_1 H_2 \cdots H_n$ or its transpose is

\[
\sum_{k=1}^{n} 4(m - k + 1) \approx 4mn - 2n^2 \text{ flops}
\]

• roughly equal to matrix-vector product with $m \times n$ matrix ($2mn$ flops)