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 $j > i$

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

$A$ 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

\begin{align*}
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}
\end{align*}

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**

\[ x_n = \frac{b_n}{A_{nn}} \]
\[ x_{n-1} = \frac{(b_{n-1} - A_{n-1,n}x_n)}{A_{n-1,n-1}} \]
\[ x_{n-2} = \frac{(b_{n-2} - A_{n-2,n-1}x_{n-1} - A_{n-2,n}x_n)}{A_{n-2,n-2}} \]
\[ \vdots \]
\[ x_1 = \frac{(b_1 - A_{12}x_2 - A_{13}x_3 - \cdots - A_{1n}x_n)}{A_{11}} \]

**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 a 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 $A$:

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

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

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

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

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

- 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 5.16):

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

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 5.17) that $QQ^T x$ is the projection of $x$ on the range of $Q$

$$AA^\dagger x = QQ^T x$$

range($A$) = range($Q$)
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 (used by the function qr in MATLAB and Julia)

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

$$a_k \notin \text{span}\{a_1, \ldots, a_{k-1}\} = \text{span}\{q_1, \ldots, q_{k-1}\}$$

• $q_k$ 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 $R_{1k}, \ldots, R_{k-1,k}$ as

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

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

**Algorithm**

for $k = 1$ to $n$

\[
R_{1k} = q_1^T a_k
\]
\[
R_{2k} = q_2^T a_k
\]
\[\vdots\]
\[
R_{k-1,k} = q_{k-1}^T a_k
\]
\[
\tilde{q}_k = a_k - (R_{1k} q_1 + R_{2k} q_2 + \cdots + R_{k-1,k} q_{k-1})
\]
\[
R_{kk} = \left\| \tilde{q}_k \right\|
\]
\[
q_k = \frac{1}{R_{kk}} \tilde{q}_k
\]

QR factorization: 6.17
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 $R$

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

QR factorization 6.18
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

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

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

QR factorization

6.21
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] = size(A);
Q = zeros(m,n);
R = zeros(n,n);
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) = norm(v);
    Q(:,k) = v / R(k,k);
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 and Julia)
- less sensitive to rounding error than Gram–Schmidt algorithm
- computes a ‘full’ QR factorization

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

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

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

each \(H_i\) is an \(m \times m\) symmetric, orthogonal ‘reflector’ (page 5.10)
Reflector

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

- \( Hx \) is reflection of \( x \) through hyperplane \( \{ z \mid v^Tz = 0 \} \) (see page 5.10)
- \( H \) is symmetric
- \( H \) is orthogonal
- matrix-vector product \( Hx \) can be computed efficiently as
  \[ Hx = x - 2(v^Tx)v \]
  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

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

- 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

The 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 $y = A_{k:m,k}$ 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 $A_{k:m,k:n}$ with reflector $I - 2v_kv^T_k$:

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

(see page 109 in textbook for ‘slice’ notation for submatrices)
Comments

• 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

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

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

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

\[ = \begin{bmatrix} 2 & 4 & 2 \\ 0 & -2 & -8 \\ 0 & 0 & -4 \\ 0 & 0 & 0 \end{bmatrix} \]
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 $v_1, \ldots, v_n$:

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

$$= 2mn^2 - \frac{2}{3}n^3 \text{ flops}$$

QR factorization

6.37
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

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

- 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

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

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