

Algorithm endpoint

For algorithm illustration, we use an $n \times n$ matrix ($n = 5$)

$$A = \left[\begin{array}{c|c|c|c|c} \vec{a}_1 & \vec{a}_2 & \vec{a}_3 & \vec{a}_4 & \vec{a}_5 \\ \hline \hline \hline \hline \hline \end{array} \right] = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ \hline a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ \hline a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ \hline a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \\ \hline a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix}$$

The algorithm uses orthogonal reflection matrices $H_1 \dots H_{n-1}$

Each H_i works as follows:

- $H_i \vec{a}_j = \vec{a}_j$ for all $j < i$

\leftrightarrow

H_i acts as identity on the first $i-1$ coordinates

\downarrow

$$H_i \text{ has the form } \left[\begin{array}{c|c} I_{(i-1) \times (i-1)} & 0_{(i-1) \times (n-i+1)} \\ \hline 0_{(n-i+1) \times (i-1)} & K_{(n-i+1) \times (n-i+1)} \end{array} \right]$$

- $H_i \vec{a}_i = \vec{a}_i'$
- $(\vec{a}_i')_k = 0$ for all $k > i$

\leftrightarrow

\vec{a}_i' lies in the span $\{ \vec{e}_1 \dots \vec{e}_i \}$



$$H_{n-1} \dots H_1 A = \left[\begin{array}{c|c|c|c|c} \vec{a}_1' & \vec{a}_2' & \vec{a}_3' & \vec{a}_4' & \vec{a}_5' \end{array} \right] = R$$

R is upper-triangular



Target vector \vec{a}_i' is chosen so that

- entries 1 ... i-1 stay unchanged
 - $(\vec{a}_i')_k = 0$ for all $k > i$
- for H_i to function as a reflector,

$(\vec{a}_i')_i$ is adjusted so that $|\vec{a}_i'| = |\vec{a}_i|$



$$\vec{a}_i' = \begin{bmatrix} (a_i)_1 \\ \vdots \\ (a_i)_{i-1} \\ \pm \sqrt{((\vec{a}_i)_i)^2 + \dots + ((\vec{a}_i)_n)^2} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

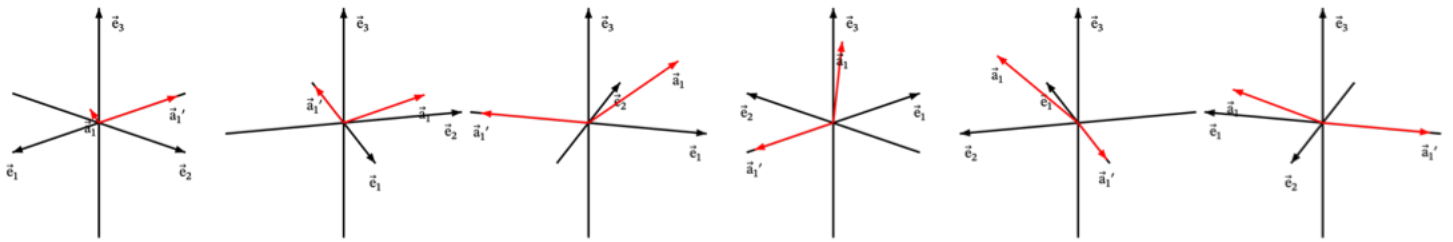
The sign of $(\vec{a}_i')_i$ is usually chosen opposite to $(\vec{a}_i)_i$

to use the longer reflector vector $\vec{v} = \vec{a}_i' - \vec{a}_i$ and minimize numerical error

Numerical example: $A = \begin{bmatrix} 1.2 & 0.4 & 1.1 \\ 1 & 1.6 & -0.3 \\ 0.8 & -0.7 & 1.4 \end{bmatrix}$

$$\vec{a}_1' = \begin{bmatrix} \approx -1.755 \\ 0 \\ 0 \end{bmatrix}$$

- is in the span $\{\vec{e}_1\}$
- sign of $(\vec{a}_1')_1$ is opposite to $(\vec{a}_1)_1$
- $|\vec{a}_1'| = |\vec{a}_1|$



While further steps to obtain H_1 will be shown later,

next set of images shows how \vec{a}_2' is obtained from $H_1 A$

$$H_1 A = \begin{bmatrix} \approx -1.755 & \approx -0.866 & \approx -1.219 \\ 0 & \approx 1.172 & \approx -1.085 \\ 0 & \approx -1.043 & \approx 0.772 \end{bmatrix}$$

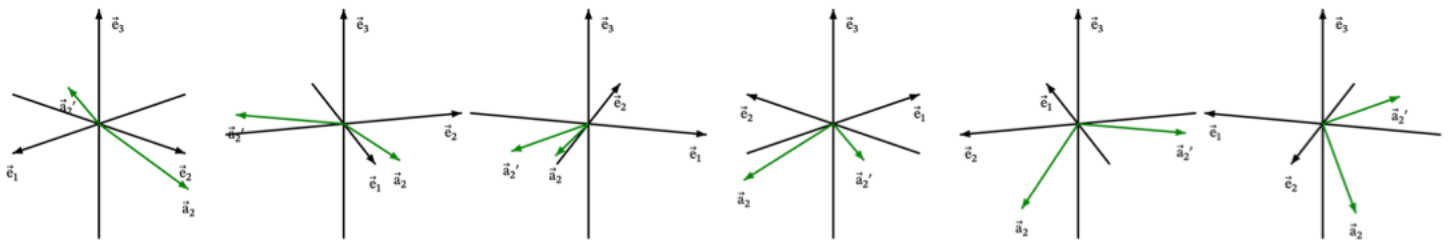
$$\vec{a}_2' = \begin{bmatrix} \approx -0.866 \\ \approx -1.568 \\ 0 \end{bmatrix}$$

- is in the span $\{\vec{e}_1, \vec{e}_2\}$

- $(\vec{a}_2')_1 = (\vec{a}_2)_1$

- sign of $(\vec{a}_2')_2$ is opposite to $(\vec{a}_2)_2$

- $|\vec{a}_2'| = |\vec{a}_2|$



Reflector matrix H_i ;
derivation from the target \vec{a}'

Reflection across fixed subspace S in \mathbb{R}^n

- $\mathbb{R}^n = S \oplus S^\perp$
- for any $\vec{x} \in \mathbb{R}^n$:
 - $\vec{x}_{||} \in S$ is fixed
 - $\vec{x}_\perp \in S^\perp$ is negated

↓

Reflection matrix $H = I - 2P$

where P is projection onto the negated subspace S^\perp

- If $\vec{y} = H \vec{x}$, then $H \vec{y} = \vec{x}$

$$|\vec{a}| = |\vec{a}'|$$

↓

there should be a matrix H that acts as a reflection:

- $H \vec{a} = \vec{a}'$

- $H \vec{a}' = \vec{a}$

↓

- $(I - 2P) \vec{a} = \vec{a}'$

- $(I - 2P) \vec{a}' = \vec{a}$

↓

- $2P \vec{a} = \vec{a} - \vec{a}'$

- $2P \vec{a}' = \vec{a}' - \vec{a}$

① Adding the equations gives

$$2P \vec{a} + 2P \vec{a}' = \vec{0}$$

↓

$$P (\vec{a} + \vec{a}') = \vec{0}$$

↓

$\vec{a} + \vec{a}'$ is in $\text{null}(P)$ or in the fixed subspace

② Subtracting the first equation from the second gives

$$2P \vec{a}' - 2P \vec{a} = 2\vec{a}' - 2\vec{a}$$

↓

$$2P (\vec{a}' - \vec{a}) = 2 (\vec{a}' - \vec{a})$$

↓

$$P (\vec{a}' - \vec{a}) = \vec{a}' - \vec{a}$$

↓

P acts as identity on $\vec{a}' - \vec{a}$

For projection P onto S^\perp ,

$$P \vec{x} = \vec{x} \text{ means } \vec{x} \in S^\perp$$

$$\vec{a}' - \vec{a} \in S^\perp$$

↓

P projects onto $\text{span}(\vec{a}' - \vec{a})$

$$\text{if } \vec{v} = \vec{a}' - \vec{a},$$

$$P = \frac{\vec{v} \vec{v}^T}{\vec{v}^T \vec{v}}$$

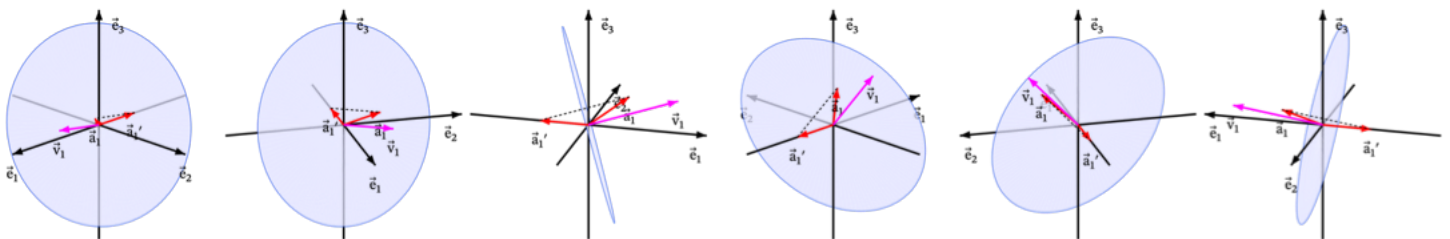
↓

$$\text{reflector } H = I - \frac{2 \vec{v} \vec{v}^T}{\vec{v}^T \vec{v}}$$

For col 1 of the same A =

$$\begin{bmatrix} 1.2 & 0.4 & 1.1 \\ 1 & 1.6 & -0.3 \\ 0.8 & -0.7 & 1.4 \end{bmatrix}$$

$$\vec{a}_i' = \begin{bmatrix} \approx -1.755 \\ 0 \\ 0 \end{bmatrix} \quad \vec{v} = \vec{a}' - \vec{a} = \begin{bmatrix} \approx 2.955 \\ 1 \\ 0.8 \end{bmatrix}$$



- the negated subspace S_{\perp} is always one-dimensional: $\text{span}(\vec{v})$
- the fixed subspace S is the $n-1$ dimensional orthogonal complement (plane in \mathbb{R}^3)
- for computation, only \vec{v} is used

$$H = I - \frac{2 \vec{v} \vec{v}^T}{\vec{v}^T \vec{v}} = \begin{bmatrix} \approx -0.684 & \approx -0.57 & \approx -0.456 \\ \approx -0.57 & \approx 0.807 & \approx -0.154 \\ \approx -0.456 & \approx -0.154 & \approx 0.877 \end{bmatrix}$$



Summary

Householder QR step summary

At step i :

- choose \vec{a}_i' so that entries below i are zero
- keep $|\vec{a}_i'| = |\vec{a}_i|$ so reflection is possible
 - form $\vec{v}_i = \vec{a}_i' - \vec{a}_i$
- build $H_i = I - \frac{2\vec{v}_i \vec{v}_i^T}{\vec{v}_i^T \vec{v}_i}$

Then

$$H_i \vec{a}_i = \vec{a}_i'$$

and H_i leaves the previous columns unchanged

After all steps,

$$H_{n-1} \dots H_1 A = R$$

where R is upper-triangular

↓

$$A = QR$$

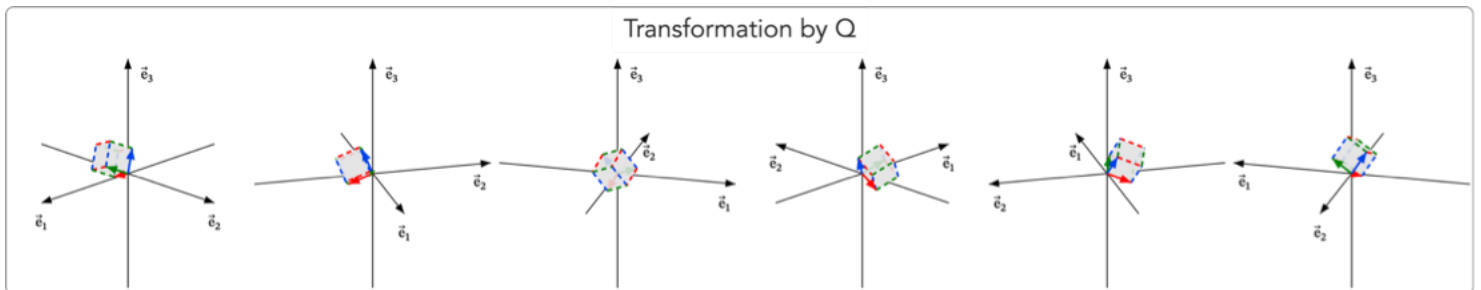
$$\text{with } Q = (H_{n-1} \dots H_1)^T$$



Three geometric routes to QR decomposition:

- Gram-Schmidt orthogonalization
 - Givens rotation
 - Householder reflection

$$A = \begin{bmatrix} -0.34 & 1.21 & -2.41 \\ -2 & 0.38 & -1.62 \\ -0.89 & 0.88 & 0.03 \end{bmatrix} = QR = \begin{bmatrix} \approx -0.153 & \approx 0.848 & \approx -0.507 \\ \approx -0.903 & \approx -0.329 & \approx -0.277 \\ \approx -0.402 & \approx 0.415 & \approx 0.816 \end{bmatrix} \begin{bmatrix} \approx 2.215 & \approx -0.882 & \approx 1.82 \\ 0 & \approx 1.267 & \approx -1.499 \\ 0 & 0 & \approx 1.695 \end{bmatrix}$$

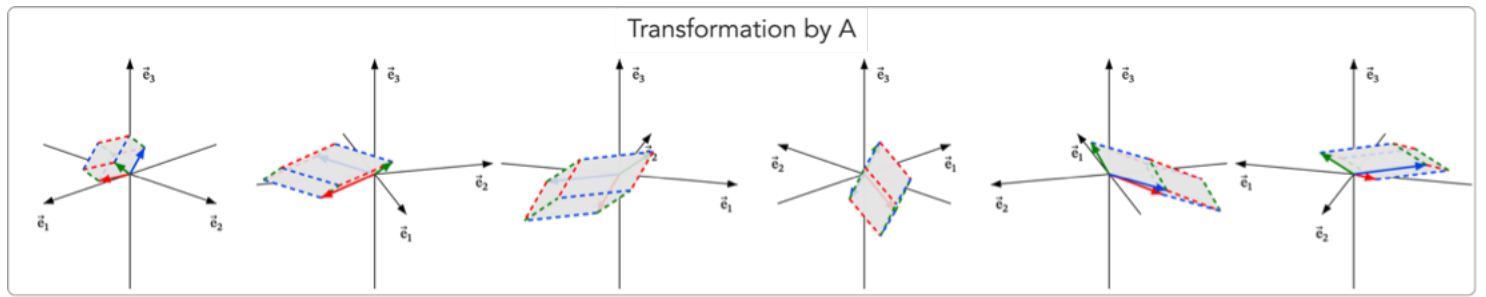


GS orthogonalization:
Serial column shear and scaling
reshape the figure so that

- columns become orthogonal
- each column has unit length



- A is transformed into Q
- R is computed as $Q^T A$



Givens rotation:
 Serial coordinate-plane rotations
 reorient the figure so that

- \vec{a}_1 aligns with \vec{e}_1
- \vec{a}_2 lies in $\text{span}(\vec{e}_1, \vec{e}_2)$

↓

- A is transformed into R
- $Q = (G_j \dots G_1)^{-1}$

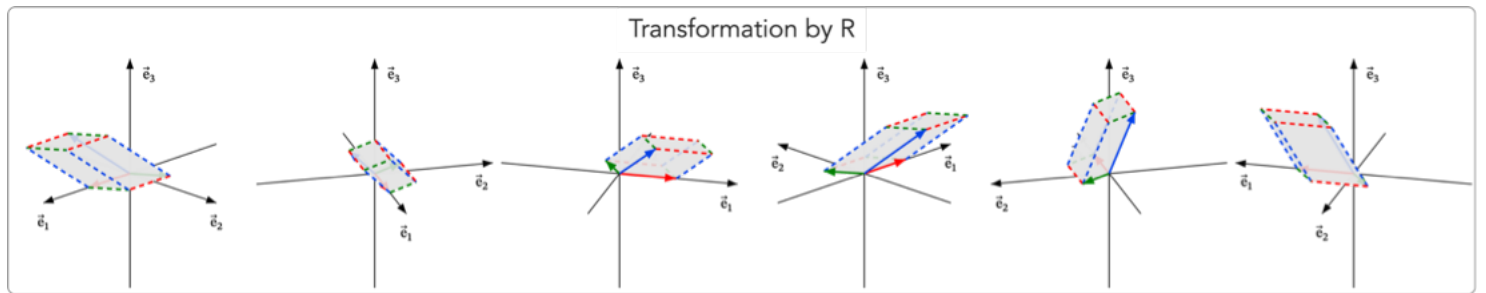
Both produce upper triangular R
 with possibly different diagonal signs

Householder reflection:
 Serial hyperplane reflections
 reorient the figure so that

- \vec{a}_1 aligns with \vec{e}_1
- \vec{a}_2 lies in $\text{span}(\vec{e}_1, \vec{e}_2)$

↓

- A is transformed into R
- $Q = (H_j \dots H_1)^{-1}$



Comparison of QR factorization algorithms

	Gram-Schmidt orthogonalization	Givens rotation	Householder reflection
Transforms A into	Q	R	R
Second factor computed as	$R = Q^T A$	$Q = (G_k \dots G_1)^{-1}$	$Q = (H_k \dots H_1)^{-1}$
Algebraic step operation	right-multiplication by scaling and shear matrices	left-multiplication by rotation matrices	left-multiplication by reflection matrices
Geometric step operation	<ul style="list-style-type: none"> • subtracts projections onto previous directions • normalizes the remaining component 	rotates in a coordinate plane	reflects across a hyperplane
Singular A: geometric behavior	dependent column ↓ 0 residual	flat shape rotated into place	flat shape reflected into place
Sign of diagonal entries R_{ii}	non-negative	any	any
Default dimensions of Q & R for $A(m \times n, \text{rank-}r)$	<ul style="list-style-type: none"> • Q is $m \times r$ • R is $r \times n$ 	<ul style="list-style-type: none"> • Q is $m \times m$ • R is $m \times n$ 	<ul style="list-style-type: none"> • Q is $m \times m$ • R is $m \times n$
Numerical stability	small residual directions amplify error	stable	stable
Efficiency	less efficient	efficient for sparse A	preferred for dense A

