

QR factorization example using Householder reflections.

$$H_v = I - 2vv^T \text{ where}$$

~~this~~

$$v = \frac{a_1 - ce_1}{\|a_1 - ce_1\|}$$

$$c = \pm \|a_1\|$$

choose + or - minus to maximize $\|a_1 - ce_1\|$

Example:

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 8 & 9 & 4 \\ 7 & 6 & 5 \end{bmatrix}$$

$$A = [a_1 | a_2 | a_3]$$

```
julia> A=[1 2 3; 8 9 4; 7 6 5]
3×3 Matrix{Int64}:
 1  2  3
 8  9  4
 7  6  5
```

```
julia> A[:,1]
3-element Vector{Int64}:
 1
 8
 7
```

```
julia> e1=[1,0,0]
3-element Vector{Int64}:
 1
 0
 0
```

```
julia> using LinearAlgebra
```

```
julia> c=norm(A[:,1])
10.677078252031311
```

```
julia> v=A[:,1]-c*e1
3-element Vector{Float64}:
-9.677078252031311
 8.0
 7.0
```

```
julia> norm(v)
14.375181511756205
```

```
julia> v=A[:,1]+c*e1
3-element Vector{Float64}:
11.677078252031311
 8.0
 7.0
```

```
julia> norm(v)
15.790951728887737
```

which is bigger?

bigger

make it into a unit vector...

```
julia> v=v/norm(v)
3-element Vector{Float64}:
 0.7394790670323838
 0.5066192422946184
 0.4432918370077911

julia> H1=I-2*v*v'
3x3 Matrix{Float64}:
-0.0936586 -0.749269 -0.65561
-0.749269  0.486674 -0.44916
-0.65561  -0.44916  0.606985
```

supposed to have that

$$H_1 A = \begin{bmatrix} c & & \\ 0 & H_{1,2} & \\ 0 & & H_{1,3} \end{bmatrix}$$

```
julia> H1*A
3x3 Matrix{Float64}:
-10.6771 -10.8644 -6.5561
-4.44089e-16 0.186566 -2.54691
-8.88178e-16 -1.71176 -0.728548
```

Now do the same thing to transform this submatrix so it looks like $\begin{bmatrix} c & ? \\ 0 & ? \end{bmatrix}$

these are equal 0 up to rounding...

```

julia> H1*A
3x3 Matrix{Float64}:
-10.6771      -10.8644      -6.5561
-4.44089e-16  0.186566     -2.54691
-8.88178e-16 -1.71176     -0.728548

julia> A2=(H1*A)[2:3,2:3]
2x2 Matrix{Float64}:
0.186566  -2.54691
-1.71176  -0.728548

```

$v = \frac{a_1 - ce_1}{\|a_1 - ce_1\|}$
 $c = \pm \|a_1\|$

```

julia> e1=[1,0]
2-element Vector{Int64}:
 1
 0 ← e1 in 2D

julia> c=norm(A2[:,1])
1.7218920641845576

julia> norm(A2[:,1]-c*e1)
2.2994201346160796

julia> norm(A2[:,1]+c*e1)
2.5636528952510704 ← bigger

```

```

julia> v2=A2[:,1]+c*e1
2-element Vector{Float64}:
 1.9084576507534088
-1.7117551117522556

julia> v2=v2/norm(v2)
2-element Vector{Float64}:
 0.7444290349480033
-0.667701588979976

```

Now need to find H_2 , but I want it to act on the 3×3 matrix...

```

julia> v2pad=[0; v2]
3-element Vector{Float64}:
 0.0
 0.7444290349480033
-0.667701588979976

julia> H2=I-2*v2pad*v2pad'
3x3 Matrix{Float64}:
 1.0  -0.0  0.0
-0.0 -0.108349  0.994113
 0.0  0.994113  0.108349

```

Supposed to be that

$H_2 H_1 A = R$

↑ upper triangular...

```

julia> H2*H1*A = R
3x3 Matrix{Float64}:
-10.6771 -10.8644 -6.5561
-8.88178e-16 -1.72189 -0.448303
-8.88178e-16 4.44089e-16 -2.61086

```

↑ this part is 0 up to rounding errors.

```

julia> R=H2*H1*A
3x3 Matrix{Float64}:
-10.6771 -10.8644 -6.5561
-8.88178e-16 -1.72189 -0.448303
-8.88178e-16 4.44089e-16 -2.61086

```

So what's the QR factorization?

$$H_2 H_1 A = R$$

$$A = H_1^{-1} H_2^{-1} R$$

← Since H's are orthogonal.

$$A = H_1^T H_2^T R$$

← Since the H's are symmetric.

$$A = H_1 H_2 R$$

↪

$$Q = H_1 H_2$$

```

julia> Q=H1*H2
3x3 Matrix{Float64}:
-0.0936586 -0.570568 -0.815892
-0.749269 -0.499247 0.435143
-0.65561 0.652077 -0.38075

```

```

julia> Q*R
3x3 Matrix{Float64}:
1.0 2.0 3.0
8.0 9.0 4.0
7.0 6.0 5.0

```

This is the QR factorization of A

```
julia> A
3x3 Matrix{Int64}:
 1  2  3
 8  9  4
 7  6  5
```

Julia has QR built in...

```
julia> qr(A)
LinearAlgebra.QRCompactWY{Float64, Matrix{Float64}}
Q factor:
3x3 LinearAlgebra.QRCompactWYQ{Float64, Matrix{Float64}}:
-0.0936586 -0.570568 -0.815892
-0.749269 -0.499247  0.435143
-0.65561   0.652077 -0.38075
R factor:
3x3 Matrix{Float64}:
-10.6771 -10.8644 -6.5561
  0.0    -1.72189 -0.448303
  0.0     0.0    -2.61086
```

```
julia> R=H2*H1*A
3x3 Matrix{Float64}:
-10.6771 -10.8644 -6.5561
-8.88178e-16 -1.72189 -0.448303
-8.88178e-16  4.44089e-16 -2.61086
```

Linear Algebra:

Gaussian elimination:

$$A = P L U$$

upper triangular matrix

lower triangular with 1's on the diagonal

permutation matrix that encodes the row swaps during the elimination

Gram Schmidt:

$$A = \tilde{Q} \tilde{R}$$

$m \times n$ $m \times n$ $n \times n$ ← upper triangular.

matrix with orthonormal columns... $\tilde{Q}^T \tilde{Q} = I$

Hausholder reflectors:

$$A = QR$$

$m \times n$ $m \times m$ $m \times n$ ← upper triangular with a block of 0's at the bottom

orthogonal matrix; square and $Q^T Q = I$

Eigenvalue-Eigenvectors:

$$A = SDS^{-1}$$

← matrix of eigenvectors.

← diagonal matrix of eigenvalues

Spectral theorem:

$$A = A^T$$

orthonormal basis of eigenvectors

$$A = QDQ^{-1}$$

← matrix of eigenvectors

← diagonal matrix of eigenvalues...

But eigenvalues are real and Q is an orthogonal matrix. $Q^T Q = I$.

Singular value decomposition

$$B = A^T A$$

and note that $B^T = B$

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

← orthogonal matrix

← orthogonal matrix.

← diagonal matrix of singular values ($\sqrt{\text{eigenvalues of } B}$)

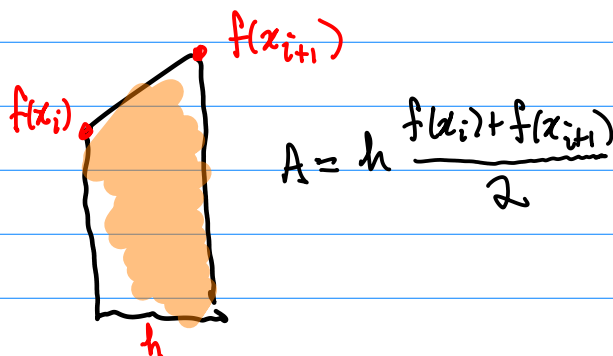
Numerical Quadrature. Approximating $\int_a^b f(x) dx$.

STEP 30

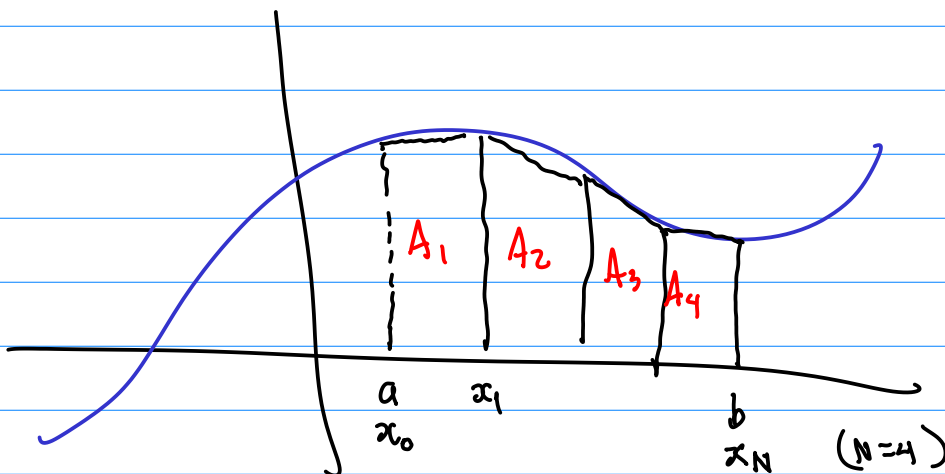
NUMERICAL INTEGRATION I

The trapezoidal rule

Use trapezoids to approximate areas...



To approximate area under a curve use lots of trapezoids...



$$x_i = x_0 + hi \quad \text{where} \quad h = \frac{b-a}{N}$$

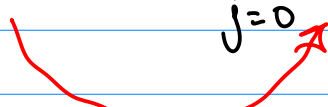
$$\int_a^b f(x) dx \approx h \frac{f(x_0) + f(x_1)}{2} + h \frac{f(x_1) + f(x_2)}{2} + \dots + h \frac{f(x_{N-1}) + f(x_N)}{2}$$

$$\int_a^b f(x) dx = \sum_{j=0}^{N-1} h \frac{f(x_j) + f(x_{j+1})}{2}$$

we know that $\lim_{N \rightarrow \infty} \sum_{j=0}^{N-1} h \frac{f(x_j) + f(x_{j+1})}{2} = \int_a^b f(x) dx \dots$

What is the error for finite N ?

Total error

$$E = \int_a^b f(x) dx - \sum_{j=0}^{N-1} h \frac{f(x_j) + f(x_{j+1})}{2}$$


$$= \sum_{j=0}^{N-1} \left[\int_{x_j}^{x_{j+1}} f(x) dx - h \frac{f(x_j) + f(x_{j+1})}{2} \right] = \sum_{j=0}^{N-1} E_j$$

The truncation error

$$E_j = \int_{x_j}^{x_{j+1}} f(x) dx - h \frac{f(x_j) + f(x_{j+1})}{2}$$