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Lecture 7: QR factorization (continued)

Agenda

- ▶ Solving the least squares problem using QR
- ▶ QR algorithm using Householder reflections
- ▶ Complexity of the QR algorithm
- ▶ Review some old exam questions

Solving the least squares problem using QR factorization

Coming back to the least squares problem:

find $\mathbf{x} \in \mathbb{R}^n$ such that $\|\mathbf{Ax} - \mathbf{b}\|_2$ is minimized

- Remember that orthogonal matrices preserve norm 2:

$$\begin{aligned}\|\mathbf{Ax} - \mathbf{b}\|_2^2 &= \|\mathbf{QRx} - \mathbf{b}\|_2^2 = \|\mathbf{Q}^T(\mathbf{QRx} - \mathbf{b})\|_2^2 = \|\mathbf{Rx} - \mathbf{Q}^T\mathbf{b}\|_2^2 \\ &= \left\| \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \mathbf{x} - \begin{bmatrix} Q_1^T \mathbf{b} \\ Q_2^T \mathbf{b} \end{bmatrix} \right\|_2^2 = \|\mathbf{R}_1 \mathbf{x} - \mathbf{Q}_1^T \mathbf{b}\|_2^2 + \|\mathbf{Q}_2^T \mathbf{b}\|_2^2\end{aligned}$$

- The minimum is obtained if

$$\mathbf{R}_1 \mathbf{x} = \mathbf{Q}_1^T \mathbf{b}$$

- So, a backward substitution gives a least square solution \mathbf{x}
- The residual then is

$$residual = \|\mathbf{Ax} - \mathbf{b}\|_2 = \|\mathbf{Q}_2^T \mathbf{b}\|_2$$

- If the residual is not important a reduced QR factorization is enough for obtaining the least squares solution

Steps of the algorithm

Steps for obtaining least squares solution of $Ax = b$ using QR factorization:

- ▶ Compute the reduced QR factorization of A such that $A = Q_1 R_1$
- ▶ Solve the triangular system $R_1 x = Q_1^T b$ for x with backward substitution
- ▶ If you need to compute the residual then Q_2 is also needed, so a complete QR must be obtained to compute $residual = \|Q_2^T b\|_2$.

Example from polynomial curve fitting

Least squares fitting, quadratic polynomial:

x	1	2	3	4	5
y	1	2	1	2	3

$$\begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \\ 1 & x_4 & x_4^2 \\ 1 & x_5 & x_5^2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} \approx \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 4 \\ 1 & 3 & 9 \\ 1 & 4 & 16 \\ 1 & 5 & 25 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} \approx \begin{bmatrix} 1 \\ 2 \\ 1 \\ 2 \\ 3 \end{bmatrix}$$

```
import numpy as np
from scipy.linalg import solve_triangular

A = np.array([[1,1,1],[1,2,4],[1,3,9],[1,4,16],[1,5,25]])
b = np.array([1,2,1,2,3])

Q,R = np.linalg.qr(A, mode = 'reduced')
a = solve_triangular(R, Q.T@b, lower = False)
print("a = ", a)
```

numpy/scipy and least squares

- ▶ `numpy.Polynomial.fit` one option
- ▶ Another option is `numpy.linalg.lstsq`: uses Lapack-drivers (written in C and Fortran)
- ▶ Another option is `scipy.linalg.lstsq`: the same as numpy

```
import scipy as sp
sp.linalg.lstsq(A,b, lapack_driver = 'gelsy')
```

LAPACK driver:

- ▶ `'gelsy'`, faster, uses QR as discussed above
- ▶ `'gelss'`, uses SVD (later in course)
- ▶ `'gelsd'`, (default), uses SVD (uses a divide and conquer technique. For large matrices it is often much faster than `'gelss'` but uses more workspace)

1TD352_Algorithm_04

For a quadratic least squares problem (with ansatz $y = a_0 + a_1x + a_2x^2$) on four points with function values $y = [-2, 1, 3, 2]$, the QR factorization of the matrix results in factors (rounded to 2 decimal places)

$$Q = \begin{bmatrix} -0.5 & -0.59 & 0.56 & -0.29 \\ -0.5 & -0.25 & -0.32 & 0.76 \\ -0.5 & 0.08 & -0.64 & -0.57 \\ -0.5 & 0.76 & 0.40 & 0.10 \end{bmatrix} \quad R = \begin{bmatrix} -2. & 0.25 & -1.12 \\ 0. & 1.48 & 0.11 \\ 0. & 0. & 0.89 \\ 0. & 0. & 0. \end{bmatrix}$$

What is the computed coefficient a_2 and what is the residual of the solution (round to 2 decimal places)?
(You can use python as a calculator)

Select one alternative:

- ☐ $a_2 = 3.12$, *residual* = 0.17
- ☐ $a_2 = 3.12$, *residual* = 0.23
- ☐ $a_2 = -0.50$, *residual* = 0.00
- ☐ $a_2 = -2.88$, *residual* = 0.17
- ☐ $a_2 = -2.88$, *residual* = 0.23

Computing QR factorization via Householder reflections

The idea is to construct some appropriate orthogonal matrices H_1, H_2, \dots, H_n and multiplying them from the left by the original matrix A to construct the upper triangular matrix R .

Step 1: Find an orthogonal matrix H_1 such that

$$H_1 A = H_1 \begin{pmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{pmatrix} = \begin{pmatrix} + & + & + \\ 0 & + & + \\ 0 & + & + \\ 0 & + & + \\ 0 & + & + \end{pmatrix} =: A^{(1)}$$

Step 2: Find an orthogonal matrix H_2 such that

$$H_2 A^{(1)} = H_2 \begin{pmatrix} + & + & + \\ 0 & + & + \\ 0 & + & + \\ 0 & + & + \\ 0 & + & + \end{pmatrix} = \begin{pmatrix} + & + & + \\ 0 & * & * \\ 0 & 0 & * \\ 0 & 0 & * \\ 0 & 0 & * \end{pmatrix} =: A^{(2)}$$

Computing QR factorization via Householder reflections

Step 3: Find an orthogonal matrix H_3 such that

$$H_3 A^{(2)} = H_3 \begin{pmatrix} + & + & + \\ 0 & * & * \\ 0 & 0 & * \\ 0 & 0 & * \\ 0 & 0 & * \end{pmatrix} = \begin{pmatrix} + & + & + \\ 0 & * & * \\ 0 & 0 & * \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} =: A^{(3)} =: R$$

Then we have

$$R = A^{(3)} = H_3 A^{(2)} = H_3 H_2 A^{(1)} = H_3 H_2 H_1 A$$

If we define $Q^T = H_3 H_2 H_1$ then $R = Q^T A$ or

$$A = QR$$

Matrices H_k are called **Householder matrices** or Householder reflections.

How to construct Householder matrices? (next slides)

Householder reflections

A matrix of the form

$$H = I - \frac{2}{\mathbf{u}^T \mathbf{u}} \mathbf{u} \mathbf{u}^T$$

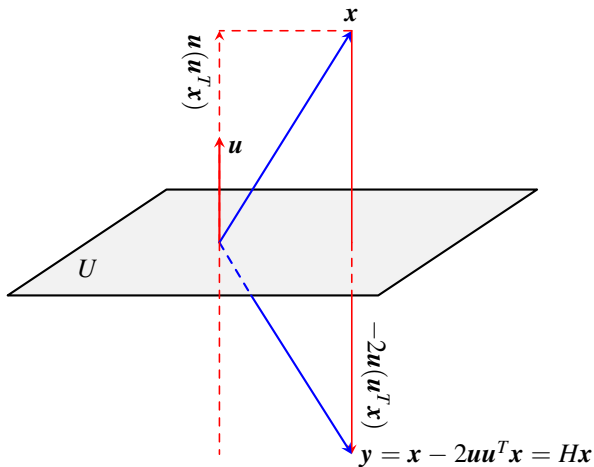
where \mathbf{u} is a non-zero vector in \mathbb{R}^n is called a Householder matrix or a **Householder reflection**.

Example:

$$\begin{aligned} \mathbf{u} = \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix} &\Rightarrow H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \frac{2}{\begin{bmatrix} 2 & 1 & 3 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}} \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix} \begin{bmatrix} 2 & 1 & 3 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \frac{2}{14} \begin{bmatrix} 4 & 2 & 6 \\ 2 & 1 & 3 \\ 6 & 3 & 9 \end{bmatrix} = \frac{1}{7} \begin{bmatrix} 3 & -2 & -6 \\ -2 & 6 & -3 \\ -6 & -3 & -2 \end{bmatrix} \end{aligned}$$

Householder reflections

If u is the normal vector of a plane U then $y = Hx$ is the **reflection** of x with respect to plane U . (U acts as a **mirror**).



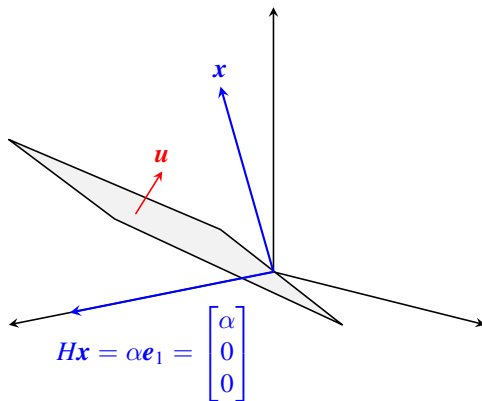
Some properties of Householder matrices

Let $H = I - 2\mathbf{u}\mathbf{u}^T / \mathbf{u}^T \mathbf{u}$ be a Householder matrix with vector $\mathbf{u} \in \mathbb{R}^n$.
Then

1. H is symmetric (why?)
2. $H^2 = I$ (why?)
3. H is orthogonal (why?)
4. $H\mathbf{u} = -\mathbf{u}$ (why?)
5. $H\mathbf{v} = \mathbf{v}$ if $\mathbf{u}^T \mathbf{v} = 0$ i.e. (if \mathbf{v} is in plane U) (why?)
6. If $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ are such that $\mathbf{x} \neq \mathbf{y}$ and $\|\mathbf{x}\|_2 = \|\mathbf{y}\|_2$, and \mathbf{u} is chosen parallel to $\mathbf{x} - \mathbf{y}$ then $H\mathbf{x} = \mathbf{y}$ (why?)

How to make zeros?

Given a vector x , we want to find a reflection matrix H (or the **mirror**) such that $Hx = \alpha e_1$ (reflect x on x -axis)



- ▶ u must be parallel to $x - \alpha e_1$
- ▶ α is indeed $\mp \|x\|_2$ because H preserves the length

How to make zeros?

An important property for our purpose: Given a nonzero vector $\mathbf{x} \neq \mathbf{e}_1$, the Householder matrix H define by

$$\mathbf{u} = \mathbf{x} \pm \|\mathbf{x}\|_2 \mathbf{e}_1 \text{ gives } H\mathbf{x} = \mp \|\mathbf{x}\|_2 \mathbf{e}_1$$

This is a simple consequence of item 5 above by letting $\mathbf{y} = \mp \|\mathbf{x}\|_2 \mathbf{e}_1$.

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \implies \mathbf{u} = \begin{bmatrix} x_1 \pm \|\mathbf{x}\|_2 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$
$$\implies H = I - \frac{2}{\mathbf{u}^T \mathbf{u}} \mathbf{u} \mathbf{u}^T \implies H\mathbf{x} = \begin{bmatrix} \times \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Both signs \pm work but to avoid cancellations error in computing u_1 , we always use $\text{sign}(x_1)$ instead of \pm (to always have addition)

Example: making zeros using Householder matrices

Example 1: Transferring a vector to another vector with zeros under its first element:

$$\begin{aligned} \mathbf{x} = \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} &\Rightarrow \mathbf{u} = \begin{bmatrix} x_1 + \text{sign}(x_1) \|\mathbf{x}\|_2 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 2 + 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 5 \\ 2 \\ 1 \end{bmatrix} \\ \Rightarrow H &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \frac{2}{30} \begin{bmatrix} 25 & 10 & 5 \\ 10 & 4 & 2 \\ 5 & 2 & 1 \end{bmatrix} = \frac{1}{15} \begin{bmatrix} -10 & -10 & -5 \\ -10 & 11 & -2 \\ -5 & -2 & 14 \end{bmatrix} \end{aligned}$$

Now check:

$$H\mathbf{x} = \frac{1}{15} \begin{bmatrix} -10 & -10 & -5 \\ -10 & 11 & -2 \\ -5 & -2 & 14 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} -3 \\ 0 \\ 0 \end{bmatrix}$$

QR factorization using Householder matrices

Step 1: Use a Householder transformation to transfer matrix A into a new matrix that all the components of its first column except the first are annihilated:

$$A = \begin{bmatrix} 2 & 3 & 5 \\ 1 & 2 & -1 \\ 2 & 5 & 3 \\ 1 & -1 & 0 \end{bmatrix}, \text{ set } x := a_1 = \begin{bmatrix} 2 \\ 1 \\ 2 \\ 1 \end{bmatrix} \Rightarrow u = \begin{bmatrix} 2 + \sqrt{10} \\ 1 \\ 2 \\ 1 \end{bmatrix}$$

$$H_1 = I - \frac{2}{u^T u} u u^T \doteq \begin{bmatrix} -0.636 & -0.316 & -0.633 & -0.316 \\ -0.316 & +0.939 & -0.123 & -0.061 \\ -0.633 & -0.123 & +0.755 & -0.123 \\ -0.316 & -0.061 & -0.123 & +0.939 \end{bmatrix}$$

$$H_1 A \doteq \begin{bmatrix} -3.162 & -5.376 & -4.743 \\ 0.000 & +0.378 & -2.888 \\ 0.000 & +1.755 & -0.775 \\ 0.000 & -2.623 & -1.887 \end{bmatrix}$$

Note: All numbers are edited into 3 decimals to keep some spaces.

QR factorization using Householder matrices

Step 2: From step 1 assume $A^{(1)} = H_1 A$. Use another Householder matrix to annihilate the entries under the diagonal of the second column of $A^{(1)}$:

$$A^{(1)} \doteq \begin{bmatrix} -3.162 & -5.376 & -4.743 \\ 0.000 & +0.378 & -2.888 \\ 0.000 & +1.755 & -0.775 \\ 0.000 & -2.623 & -1.887 \end{bmatrix}, \text{ set } \mathbf{x} := \begin{bmatrix} +0.378 \\ +1.755 \\ -2.623 \end{bmatrix}$$

$$\mathbf{u} = \mathbf{x} + \text{sign}(x_1) \|\mathbf{x}\|_2 \doteq \begin{bmatrix} +3.556 \\ +1.755 \\ -2.623 \end{bmatrix} \Rightarrow \tilde{H} \doteq \begin{bmatrix} -0.119 & -0.552 & 0.825 \\ -0.552 & 0.727 & 0.407 \\ 0.825 & 0.407 & 0.391 \end{bmatrix}$$

$$H_2 \doteq \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -0.119 & -0.552 & 0.825 \\ 0 & -0.552 & 0.727 & 0.407 \\ 0 & 0.825 & 0.407 & 0.391 \end{bmatrix} \Rightarrow H_2 A^{(1)} \doteq \begin{bmatrix} -3.162 & -5.376 & -4.743 \\ 0.000 & -3.178 & -0.787 \\ 0.000 & 0.000 & 0.262 \\ 0.000 & 0.000 & -3.437 \end{bmatrix}$$

Note: The first row and the first column of $A^{(1)}$ remain unchanged!
So, previous zeros are not destroyed.

QR factorization using Householder matrices

Step 3: From step 2 assume $A^{(2)} = H_2 A^{(1)}$. Use another Householder matrix to annihilate the entries under the diagonal of the third column of $A^{(2)}$:

$$A^{(2)} \doteq \begin{bmatrix} -3.162 & -5.376 & -4.743 \\ 0.000 & -3.178 & -0.787 \\ 0.000 & 0.000 & +0.262 \\ 0.000 & 0.000 & -3.437 \end{bmatrix} \Rightarrow \mathbf{x} := \begin{bmatrix} +0.262 \\ -3.437 \end{bmatrix}$$

$$\mathbf{u} = \mathbf{x} + \text{sign}(x_1) \|\mathbf{x}\|_2 \doteq \begin{bmatrix} +3.709 \\ -3.437 \end{bmatrix} \Rightarrow \tilde{H} \doteq \begin{bmatrix} -0.076 & 0.997 \\ +0.997 & 0.076 \end{bmatrix}$$

$$H_3 \doteq \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -0.076 & 0.997 \\ 0 & 0 & +0.997 & 0.076 \end{bmatrix} \Rightarrow H_3 A^{(2)} \doteq \begin{bmatrix} -3.162 & -5.376 & -4.743 \\ 0.000 & -3.178 & -0.787 \\ 0.000 & 0.000 & -3.447 \\ 0.000 & 0.000 & 0.000 \end{bmatrix} =: R$$

Note: Previous zeros are not destroyed.

QR factorization using Householder matrices

Substituting back we have:

$$R = H_3 A^{(2)} = H_3 H_2 A^{(1)} = H_3 H_2 H_1 A =: Q^T A$$

Since H_1, H_2, H_3 are symmetric and orthogonal we have

$$A = QR, \quad Q = H_1 H_2 H_3$$

In the example above:

$$Q = H_1 H_2 H_3 \doteq \begin{bmatrix} -0.633 & +0.126 & -0.609 & -0.462 \\ -0.316 & -0.094 & +0.747 & -0.577 \\ -0.633 & -0.504 & +0.115 & +0.577 \\ -0.316 & +0.850 & +0.241 & +0.346 \end{bmatrix}$$
$$R \doteq \begin{bmatrix} -3.162 & -5.376 & -4.743 \\ 0.000 & -3.178 & -0.787 \\ 0.000 & 0.000 & -3.447 \\ 0.000 & 0.000 & 0.000 \end{bmatrix}$$

The procedure for a $m \times n$ matrix A is similar. It requires n steps and n Householder matrices

About time complexity

Complexity (computational cost) is total number of operations (+, −, ×, /) in the algorithm. For example the cost of inner product $\mathbf{x}^T \mathbf{y}$ is about $2n$

- ▶ If A is $m \times n$ then H_k matrices are $m \times m$ and $A^{(k)}$ matrices are $m \times n$.
- ▶ The majority of QR cost comes from products $H_k A^{(k-1)}$ in each step to produce R and n products $H_1 H_2 \cdots H_n$ to produce Q .
- ▶ Direct computation of HA needs $2m^2 n$ flops (**f**loating-point **o**perators). (because of mn inner products)
- ▶ Direct computation of products of two Householder matrices costs $2m^3$ flops. Why?
- ▶ The total cost then is $2m^2 n^2 + 2m^3 n$ because n products of each type are needed. If $m = n$ (square case) the cost is $4n^4$ which is not efficient!
- ▶ However, this is not the right way the QR factorization is implemented. See the next page!

Efficient implementation:

- ▶ The idea is to avoid forming H explicitly, but working with u directly.
- ▶ **Exercise:** If $H = I - (2/u^T u)uu^T$ show that the cost of Hx is about $6m$
- ▶ **Exercise:** If $H = I - (2/u^T u)uu^T$ show that the cost of HA is about $4mn$
- ▶ Another point: Since the first k rows and columns of $A^{(k)}$ and $A^{(k+1)}$ are the same, at step k we can only multiply \tilde{H}_k and the corresponding submatrix of size $(m-k) \times (n-k)$.
- ▶ These all result in final cost $2mn^2 - \frac{2}{3}n^3$ for computing R and $\frac{4}{3}m^3$ for Q . If $m = n$ the complexity is $\frac{4}{3}n^3$ for both R and Q .
- ▶ **Exercise:** How can we optimize the *space complexity* in QR algorithm?

QR factorization: conclusion and some points

- ▶ QR-factorization $A = QR$ (where Q is orthogonal and R is triangular) is one example of matrix decomposition
- ▶ The reduced QR-factorization $A = Q_1 R_1$ can be used to solve the least square problem $\min \|Ax - b\|_2$ by reducing it to triangular system

$$R_1 x = Q_1^T b$$

- ▶ If the residual is requested, use a full QR and $residual = \|Q_2^T b\|_2$
- ▶ The computational cost using Householder matrices for the case of $m = n$ (when A is square) is approximately $\frac{4}{3}n^3$. This cost is twice of that of Gaussian elimination (LU decomposition).
- ▶ Using QR factorization for solving square systems offers **better stability**, but at a **higher computational cost**, when compared to Gaussian elimination.
- ▶ QR-factorization has applications in many other areas, for example in **computations of eigenvalues** (later in the course)

1TD352_concept_01

Select all correct statements regarding the QR factorization:

- ☐ *The Householder method is the only algorithm to compute it*
- ☒ *Its time complexity using Householder method is $O(n^3)$ when the matrix is $(n \times n)$*
- ☒ *If A is a square matrix then both its Q and R factors are square*
- ☐ *Both matrices Q and R are orthogonal*
- ☒ *It can be used for solving the least squares problem*
- ☒ *It can be used for solving the square linear system $Ax = b$ for nonsingular matrix A*
- ☐ *Its time complexity using Householder method is $O(n^4)$ when the matrix is $(n \times n)$*

3 (Algorithm)

A matrix A has the QR-factorization

$$Q = \begin{pmatrix} -\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{pmatrix}, \quad R = \begin{pmatrix} -2 & -3 & -2 \\ 0 & -5 & 2 \\ 0 & 0 & -4 \end{pmatrix}.$$

Given a right-hand-side

$$y = \begin{pmatrix} 2 \\ -2 \\ 8 \\ -4 \end{pmatrix}$$

solve the least squares problem $Ax = y$ using the QR-factorization and without forming the matrix A explicitly.