QR Factorization

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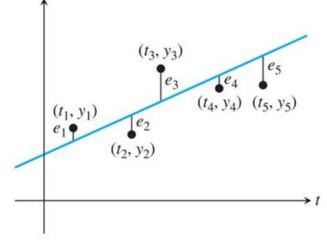
Review: Normal equations for least squares

Given an inconsistent system

$$A\underline{x}=\underline{b},$$

solve

$$A^T A \underline{\tilde{x}} = A^T \underline{b}$$



for the least squares solution $\underline{\tilde{x}}$ that minimizes the Euclidean length of the residual $\underline{r} = \underline{b} - A\underline{\tilde{x}}$.

Review: Fitting data

$$A^T A \underline{\tilde{x}} = A^T \underline{b}$$

Given a set of m data points $(t_1, y_1),...,(t_m, y_m)$

- 1. Choose a model. Example: $y = c_1 + c_2 t$
- 2. Force the model to fit the data
 - Let the unknown *x* represents the model parameters
 - #unknowns: #model parameters
 - #equations: *m*
- 3. Solve the normal equations

$$\square \quad A^T A \underline{\tilde{x}} = A^T \underline{b}$$

$$A^T A \underline{\tilde{x}} = A^T \underline{b}$$

• How accurately can be the least squares solution $\underline{\tilde{x}}$ be determined?

Example

- $x_1 = 2.0$, $x_2 = 2.2$, $x_3 = 2.4$, ..., $x_{11} = 4.0$
- $y_i = 1 + x_i + x_i^2 + ... + x_i^7$

Find the least squared polynomial $P(x) = c_1 + c_2 x + ... + c_8 x^7$ fitting (x_i, y_i)

• What are the coefficients c_i ?

$$x_1 = 2.0, x_2 = 2.2, x_3 = 2.4, ..., x_{11} = 4.0$$

 $y_i = 1 + x_i + x_i^2 + ... + x_i^7$
 $P(x) = c_1 + c_2 x + ... + c_8 x^7$

Least squares solution: #unknown? #equations?

$$\begin{bmatrix} 1 & \cdots & x_1^7 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & x_{11}^7 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_8 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{11} \end{bmatrix}$$

Get <u>c</u> = 1.5134

-0.2644

2.3211

0.2408

0.9474

1.0059

0.9997

Solve the normal equation with MATLAB (double precision)

Solving the normal equations in double precision **cannot** deliver an accurate value for the least squares solution!

Conditioning of least squares

• Recall that we compute cond(A) for error estimation on solving $A^Tx = b$

error magnification factor =
$$\frac{\text{relative forward error}}{\text{relative backward error}} = \text{cond(A)}$$

= $||A|| \times ||A^{-1}||$

Back to the example

$$A^{\mathrm{T}}A\underline{\tilde{x}} = A^{\mathrm{T}}\underline{b}$$

- $cond(A^TA) = 1.4359e+019$
 - Too large to deal with in double precision arithmetic
 - The normal equations are ill-conditioned!
- Remedy: avoid forming A^TA

Today

- QR factorization
- Gram-Schmidt orthogonalization

Analogy to LU factorization

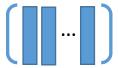
- Solving matrix equations: LU factorization
- What are the benefits using LU?
- Solving least squares: QR factorization

Preliminaries

- Orthogonal set
 - A set of vectors in which $v_i^T v_i = 0$ whenever $i \neq j$.
 - Example: $\{[1, 1, 1]^T, [2, 1, -3]^T, [4, -5, 1]^T\}$
- Orthonormal set

a vector of length 1

- An orthogonal set of unit vectors.
- $||v||_2 = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2} = 1$
- Example: $\{[0, 0, 1]^T, [0, 1, 0]^T, [1, 0, 0]^T\}$
- Normalizing a vector? $u/||u||_2$
- Orthogonal matrix
 - The column vectors form an orthonormal set.
 - $Q^{-1} = Q^T$



QR Factorization: Output

- Given a matrix A (m x n)
- Reduced QR factorization

q_i: mutually perpendicular unit vectors (orthonormal set)

$$(A_{1}|\cdots|A_{n}) = \underbrace{(q_{1}|\cdots|q_{n})}_{m \times n} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{nn} & & & & \\ n \times n & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & \\ & & & \\ & & \\ & & & \\ &$$

Full QR factorization

$$(A_{1}|\cdots|A_{n}) = \underbrace{(q_{1}|\cdots|q_{m})}_{m \times n} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & 0 \end{bmatrix}. \qquad (4.27)$$

QR for solving least squares

- A = QR
 - Q is orthogonal $\implies Q^{-1} = Q^T$
 - R is upper-triangular

QR vs. Normal equations? Avoid computing $A^{T}A$

- Given an $m \times n$ inconsistent system Ax = b
 - Ax = b
 - QRx = b
 - $\bullet \ Q^{-1}QRx = Q^{-1}b = Q^Tb$
 - $Rx = Q^Tb$ directly using back substitution to solve $\underline{x} \odot$

$$(A_1|\cdots|A_n) = \underbrace{(q_1|\cdots|q_n)}_{m \times n} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{22} & \cdots & r_{2n} \\ & \ddots & \vdots \\ & & &$$

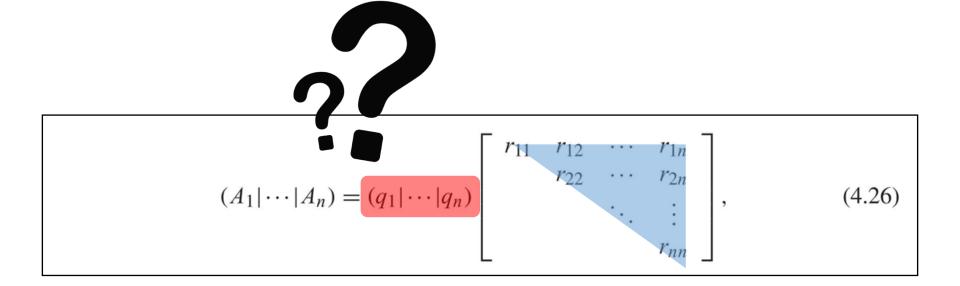
Gram-Schmidt method

Orthogonalizes a set of vectors

Input: n linearly independent input vectors (A_i)

Output: n mutually perpendicular unit vectors

spanning the same space (q_i)

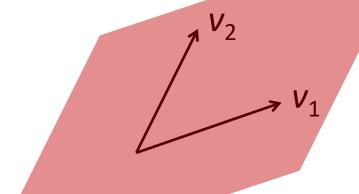


Preliminaries

- Span: The set of all linear combinations of v_1 , ..., v_n is the *span* of v_1 , ..., v_n .
- Examples

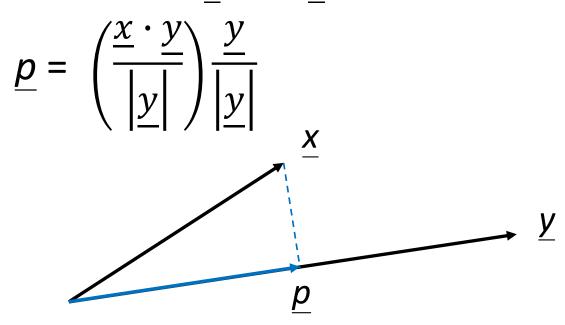
One vector (n = 1)

Two vectors (n = 2)



Preliminaries

• Vector project of <u>x</u> onto <u>y</u>:



Gram-Schmidt method

 https://www.khanacademy.org/math/linearalgebra/alternate_bases/orthonormal_basis/v/line ar-algebra-the-gram-schmidt-process

Gram-Schmidt method

Input: n linearly independent input vectors $\{A_i\}$

Output: n mutually perpendicular unit vectors spanning the same space $\{q_i\}$

- 1st unit vector: $y_1 = A_1$ and $q_1 = \frac{y_1}{||y_1||_2}$.
- 2nd unit vector:

$$y_2 = A_2 - q_1(q_1^T A_2)$$
, and $q_2 = \frac{y_2}{||y_2||_2}$.

• *j*-th unit vector:

$$y_j = A_j - q_1(q_1^T A_j) - q_2(q_2^T A_j) - \dots - q_{j-1}(q_{j-1}^T A_j)$$
 and $q_j = \frac{y_j}{||y_j||_2}$.

Example

Orthogonal?

- Find the **reduced** QR factorization of $A = \begin{bmatrix} 1 & 1 \\ 2 & 3 \\ 2 & 2 \end{bmatrix}$
- 3-dimension, 2 column vectors
- Solution:

$$y_{1} = A_{1} = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \qquad r_{11} = ||y_{1}||_{2} = \sqrt{1^{2} + 2^{2} + 2^{2}} = 3,$$

$$q_{1} = \frac{y_{1}}{||y_{1}||_{2}} = \begin{bmatrix} \frac{1}{3} \\ \frac{2}{3} \\ \frac{2}{3} \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & -4 \\ 2 & 3 \\ 2 & 2 \end{bmatrix}$$

Then, find the 2nd unit vector

$$y_2 = A_2 - q_1 \underline{q_1}^T A_2 = \begin{bmatrix} -4 \\ 3 \\ 2 \end{bmatrix} - \begin{bmatrix} \frac{1}{3} \\ \frac{2}{3} \\ \frac{2}{3} \end{bmatrix} 2 = \begin{bmatrix} -\frac{14}{3} \\ \frac{5}{3} \\ \frac{2}{3} \end{bmatrix}$$

$$q_{2} = \frac{y_{2}}{\frac{||y_{2}||_{2}}{r_{22}}} = \frac{1}{5} \begin{bmatrix} -\frac{14}{3} \\ \frac{5}{3} \\ \frac{2}{3} \end{bmatrix} = \begin{bmatrix} -\frac{14}{15} \\ \frac{1}{3} \\ \frac{2}{15} \end{bmatrix}$$

Orthogonal?

$$A = \begin{bmatrix} 1 & -4 \\ 2 & 3 \\ 2 & 2 \end{bmatrix} = \begin{bmatrix} 1/3 & -14/15 \\ 2/3 & 1/3 \\ 2/3 & 2/15 \end{bmatrix} \begin{bmatrix} 3 & 2 \\ 0 & 5 \end{bmatrix} = QR$$

$$Q_1 \qquad Q_2$$

$$r_{11} = ||y_1||_2 = \sqrt{1^2 + 2^2 + 2^2} = 3$$

$$r_{22} = ||y_2||_2 = 5$$

$$r_{12} = q_1^T A_2 = 2$$

$$r_{jj} = ||y||_2$$
$$r_{ij} = q_i^T A_j$$

$$y_j = A_j - q_1(q_1^T A_j) - q_2(q_2^T A_j) - \dots - q_{j-1}(q_{j-1}^T A_j)$$
 and $q_j = \frac{y_j}{||y_j||_2}$.

from reduced to full QR

• Find the **full** QR factorization of
$$A = \begin{bmatrix} 1 & 1 \\ 2 & 3 \\ 2 & 2 \end{bmatrix}$$

• Add a 3rd vector
$$A_3 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$
 (arbitrary)

$$y_3 = A_3 - q_1 q_1^T A_3 - q_2 q_2^T A_3$$

$$= \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} \frac{1}{3} \\ \frac{2}{3} \\ \frac{2}{3} \end{bmatrix} \frac{1}{3} - \begin{bmatrix} -\frac{14}{15} \\ \frac{1}{3} \\ -\frac{2}{15} \end{bmatrix} \left(-\frac{14}{15} \right) = \frac{2}{225} \begin{bmatrix} 2 \\ 10 \\ -11 \end{bmatrix}$$

$$y_3 = A_3 - q_1 q_1^T A_3 - q_2 q_2^T A_3$$

$$= \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} \frac{1}{3} \\ \frac{2}{3} \\ \frac{2}{3} \end{bmatrix} \frac{1}{3} - \begin{bmatrix} -\frac{14}{15} \\ \frac{1}{3} \\ -\frac{2}{15} \end{bmatrix} \left(-\frac{14}{15} \right) = \frac{2}{225} \begin{bmatrix} 2 \\ 10 \\ -11 \end{bmatrix}$$

$$q_3 = y_3/||y_3|| = \begin{bmatrix} \frac{2}{15} \\ \frac{10}{15} \\ -\frac{11}{15} \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & -4 \\ 2 & 3 \\ 2 & 2 \end{bmatrix} = \begin{bmatrix} 1/3 & -14/15 & 2/15 \\ 2/3 & 1/3 & 2/3 \\ 2/3 & 2/15 & -11/15 \end{bmatrix} \begin{bmatrix} 3 & 2 \\ 0 & 5 \\ 0 & 0 \end{bmatrix} = QR.$$

Analogy

- LU factorization → recording the information of Gaussian elimination
- QR factorization →?

recording the orthogonalization of a matrix!

The ill-conditioned A^TA example

- $x_1 = 2.0$, $x_2 = 2.2$, $x_3 = 2.4$, ..., $x_{11} = 4.0$
- $y_i = 1 + x_i + x_i^2 + ... + x_i^7$
- Find the least squared polynomial $P(x) = c_1 + c_2 x + ... + c_8 x^7$ fitting (x_i, y_i)
- What are the coefficients c_i ?

$$x_1 = 2.0, x_2 = 2.2, x_3 = 2.4, ..., x_{11} = 4.0$$

 $y_i = 1 + x_i + x_i^2 + ... + x_i^7$
 $P(x) = c_1 + c_2 x + ... + c_8 x^7$

$$\begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^7 \\ 1 & x_2 & x_2^2 & \cdots & x_2^7 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{11}x_{11}^2 & \cdots & x_{11}^7 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_8 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{11} \end{bmatrix}$$

$$>> x = (2+(0:10)/5)';$$

$$>> y = 1+x+x.^2+x.^3+x.^4+x.^5+x.^6+x.^7;$$

$$>> A = [x.^0 x x.^2 x.^3 x.^4 x.^5 x.^6 x.^7];$$

$$>> [Q, R] = qr(A);$$

$$>> c = R(1:8, 1:8) b(1:8);$$

Get *c* =

1.000

1.000

1.000

1.000

1.000

1.000

1.000

程式練習

And, please upload your program on moodle.

Apply Gram-Schmidt orthogonalization to find the reduced QR factorization of the matrix:

$$\begin{bmatrix} 4 & 2 & 3 & 0 \\ -2 & 3 & -1 & 1 \\ 1 & 3 & -4 & 2 \\ 1 & 0 & 1 & -1 \\ 3 & 1 & 3 & -2 \end{bmatrix}$$

Report Q and R.