

Announcements

1) HW2 due Thursday!

2) MATLAB training
sessions, 2/20

Kochhoff C

10-12 (basic)

1-3:30 (advanced)

The QR Decomposition

Remember Gram Schmidt!

Given $\{x_1, x_2, \dots, x_n\}$

linearly independent and

nonzero. Gram-Schmidt

produces $\{y_1, \dots, y_n\}$

Orthogonal with

$$\text{span}(\{x_1, \dots, x_n\}) = \text{span}(\{y_1, \dots, y_n\})$$

$$y_1 = \frac{x_1}{\|x_1\|_2}$$

$$y_2 = \frac{x_2 - (y_1^* x_2) y_1}{\|x_2 - (y_1^* x_2) y_1\|_2}$$

$$y_3 = \frac{x_3 - (y_2^* x_3) y_2 - (y_1^* x_3) y_1}{\|x_3 - (y_2^* x_3) y_2 - (y_1^* x_3) y_1\|_2}$$

$$\vdots$$

$$y_n = \frac{x_n - \sum_{i=1}^{n-1} (y_i^* x_n) y_i}{\|x_n - \sum_{i=1}^{n-1} (y_i^* x_n) y_i\|_2}$$

$$\|x_n - \sum_{i=1}^{n-1} (y_i^* x_n) y_i\|_2$$

This procedure produces an orthonormal set and is the basis for the existence of orthogonal projections in finite dimensions:

Let V be finite dimensional over \mathbb{R} or \mathbb{C} , let W be a subspace of V .

Let $\{x_1, \dots, x_n\}$ be a basis for W . Let

$\{y_1, \dots, y_n\}$ be the vectors from Gram-Schmidt.

Define the orthogonal projection $P: V \rightarrow W$ by

$$P(x) = \sum_{i=1}^n (y_i^* x) y_i$$

$$\forall x \in V.$$

The QR decomposition
is the Gram-Schmidt
algorithm in matrix
form.

Example 1: $A = \begin{bmatrix} 1 & i \\ 2 & 6 \end{bmatrix}$

The vectors $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and

$\begin{bmatrix} i \\ 6 \end{bmatrix}$ are linearly

independent. Use

Gram-Schmidt, but
as matrices!

Write $x_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$, $x_2 = \begin{bmatrix} i \\ 6 \end{bmatrix}$

Step 1: Normalize x_1

$$\begin{bmatrix} 1 & i \\ 2 & 6 \end{bmatrix} \begin{bmatrix} 1/\sqrt{5} & 0 \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1/\sqrt{5} & i \\ 2/\sqrt{5} & 6 \end{bmatrix}$$

$$\text{Let } q_1 = \begin{bmatrix} 1/\sqrt{5} \\ 2/\sqrt{5} \end{bmatrix}$$

Step 2: Orthogonalize
the columns (without
changing q_1).

$$\begin{bmatrix} 1/\sqrt{5} & i \\ 2/\sqrt{5} & 6 \end{bmatrix} \begin{bmatrix} 1 & -q_1^* x_2 \\ 0 & 1 \end{bmatrix}$$

$$\begin{aligned} q_1^* x_2 &= \begin{bmatrix} 1/\sqrt{5} & 2/\sqrt{5} \end{bmatrix} \begin{bmatrix} i \\ 6 \end{bmatrix} \\ &= \frac{1}{\sqrt{5}} (i+12) \end{aligned}$$

$$\begin{bmatrix} 1/\sqrt{5} & i \\ 2/\sqrt{5} & 6 \end{bmatrix} \begin{bmatrix} 1 & -\frac{1}{\sqrt{5}}(i+12) \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1/\sqrt{5} & -\frac{1}{5}(i+12)+i \\ 2/\sqrt{5} & -\frac{2}{5}(i+12)+6 \end{bmatrix}$$

$$= \begin{bmatrix} 1/\sqrt{5} & -\frac{12}{5} + \frac{4i}{5} \\ 2/\sqrt{5} & \frac{6}{5} - \frac{2i}{5} \end{bmatrix} \quad \checkmark$$

Step 3: Normalize the second column.

$$\left\| \begin{bmatrix} -\frac{12}{5} + \frac{4i}{5} \\ \frac{6}{5} - \frac{2i}{5} \end{bmatrix} \right\|_2$$

$$\frac{2}{5} \left\| \begin{bmatrix} -6 + 2i \\ 3 - i \end{bmatrix} \right\|_2$$

$$= \frac{2}{5} \sqrt{40 + 10}$$

$$= \frac{2\sqrt{50}}{5}$$

$$= 2\sqrt{2}$$

$$\begin{bmatrix} \frac{1}{\sqrt{5}} & -\frac{12}{5} + \frac{4i}{5} \\ \frac{2}{\sqrt{5}} & \frac{6}{5} - \frac{2i}{5} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{2\sqrt{2}} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{1}{5\sqrt{2}}(-6+2i) \\ \frac{2}{\sqrt{5}} & \frac{1}{5\sqrt{2}}(3-i) \end{bmatrix}$$

$$= Q$$

Then Q is a unitary matrix!

Moreover, Q was obtained from A

by multiplying A

on the right by

$$T = \begin{bmatrix} \frac{1}{\sqrt{5}} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & \frac{1}{\sqrt{5}}(i+12) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{2\sqrt{2}} \end{bmatrix}$$

= some upper triangular matrix
(invertible!)

Definition: (reduced QR)

Let $A \in \mathbb{C}^{m \times n}$. The reduced QR factorization

of A is the decomposition

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

with $\hat{Q} \in \mathbb{C}^{m \times n}$ with orthonormal columns and $\hat{R} \in \mathbb{C}^{n \times n}$ upper triangular.

Just like SVD, \exists

full QR:

$$A = QR$$

with $Q \in \mathbb{C}^{m \times m}$ unitary

and $R \in \mathbb{C}^{m \times n}$ "upper
triangular".

Theorem: (Existence of QR decomposition)

Let $A \in \mathbb{C}^{m \times n}$. Then

A has both a full and reduced QR decomposition.

The decomposition $A = \hat{Q} \hat{R}$

is unique up to signs.

proof: Gram-Schmidt!



Matlab Calling Command

$$[Q,R] = \text{qr}(A,0) \text{ (reduced)}$$

$$[Q,R] = \text{qr}(A) \text{ (full)}$$

Example 2: $A = \begin{bmatrix} 1 & -1 \\ 3+i & 2 \\ 0 & 6 \end{bmatrix}$

Using Matlab,

$$\hat{Q} = \begin{bmatrix} -0.3015 & 0.2348 - 0.0294i \\ -0.9045 - 0.3015i & -0.0734 - 0.0147i \\ 0 & -0.9687 \end{bmatrix}$$

$$\hat{R} = \begin{bmatrix} -3.3166 & -1.5676 + 0.6030i \\ 0 & -6.1938 \end{bmatrix}$$

$$\hat{Q} = \begin{bmatrix} -0.3015 & 0.2348 - 0.0294i & 0.8964 - 0.2227i \\ -0.9045 - 0.3015i & -0.0734 - 0.0147i & -0.2912 - 0.0228i \\ 0 & -0.9687 & 0.2465 - 0.0295i \end{bmatrix}$$

$$\hat{R} = \begin{bmatrix} -3.3166 & -1.5076 + 0.6030i \\ 0 & -6.1938 \\ 0 & 0 \end{bmatrix}$$

Notice how Q and R
are obtained from \hat{Q} and \hat{R} !

Algorithm for QR Decomposition

Matlab

A a matrix, in

Matlab,

$A(:, j)$ returns the

j^{th} column of A .

$A(i, :)$ returns
the i^{th} row.