

Lecture Notes 4: QR Factorization

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1 QR Factorization

1.1 Orthonormal Basis and QR Factorization

Consider $A \in \mathbb{R}^{m \times n}$, where $m \geq n$ and $\text{rank}(A) = n$. We write A as $A = (\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n)$. Then

$$\text{span}(\mathbf{a}_1) \subseteq \text{span}(\mathbf{a}_1, \mathbf{a}_2) \subseteq \dots \subseteq \text{span}(\mathbf{a}_1, \dots, \mathbf{a}_n)$$

And related *orthonormal* basis such

$$\text{span}(\mathbf{q}_1) \subseteq \text{span}(\mathbf{q}_1, \mathbf{q}_2) \subseteq \dots \subseteq \text{span}(\mathbf{q}_1, \dots, \mathbf{q}_n)$$

With

$$\begin{aligned} \mathbf{a}_1 &= r_{11} \mathbf{q}_1 \\ \mathbf{a}_2 &= r_{12} \mathbf{q}_1 + r_{22} \mathbf{q}_2 \\ &\vdots \\ \mathbf{a}_n &= r_{1n} \mathbf{q}_1 + \dots + r_{nn} \mathbf{q}_n \end{aligned} \tag{1}$$

we can define $\mathbf{Q}_{m \times n} = (\mathbf{q}_1, \dots, \mathbf{q}_n)$, $\mathbf{R}_{n \times n} = \begin{pmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ 0 & r_{22} & \ddots & \vdots \\ & \ddots & \ddots & \ddots \\ \vdots & & \ddots & \ddots & r_{(n-1)n} \\ 0 & \dots & 0 & r_{nn} \end{pmatrix}$, such that

$$\mathbf{A}_{m \times n} = (\mathbf{a}_1, \dots, \mathbf{a}_n) = \mathbf{Q}_{m \times n} \mathbf{R}_{n \times n}$$

where \mathbf{Q} is *column orthogonal*, i.e., $\mathbf{Q}^T \mathbf{Q} = \mathbf{I}_n$.

1.2 Full QR Factorization

With standard result from introductory linear algebra, there exists $\tilde{\mathbf{Q}} \in \mathbb{R}^{m \times (m-n)}$ such that $\mathbf{Q}_{\text{full}} = \begin{pmatrix} \mathbf{Q} & \tilde{\mathbf{Q}} \end{pmatrix} \in \mathbb{R}^{m \times m}$ is orthogonal.

Write $\mathbf{R}_{\text{full}} = \begin{pmatrix} \mathbf{R} \\ \mathbf{O} \end{pmatrix}$, we have *full QR factorization*

$$\mathbf{A} = \mathbf{Q}_{\text{full}} \mathbf{R}_{\text{full}}$$

1.3 Classical Gram-Schmidt (CGS)

With (1), we have $\mathbf{a}_1 = r_{11}\mathbf{q}_1 \Rightarrow \|\mathbf{a}_1\|_2 = |r_{11}|$. Let

$$r_{11} = \|\mathbf{a}_1\|_2 \quad \mathbf{q}_1 = \frac{\mathbf{a}_1}{r_{11}}$$

Similarly, $\mathbf{a}_2 = r_{12}\mathbf{q}_1 + r_{22}\mathbf{q}_2 \Rightarrow \mathbf{q}_1^T \mathbf{a}_2 = |r_{12}|$. Let

$$r_{12} = \mathbf{q}_1^T \mathbf{a}_2 \quad r_{22} = \|\mathbf{a}_2 - r_{12}\mathbf{q}_1\|_2 \quad \mathbf{q}_2 = \frac{\mathbf{a}_2 - r_{12}\mathbf{q}_1}{r_{22}}$$

Notice that

$$\mathbf{a}_j = r_{1j}\mathbf{q}_1 + r_{2j}\mathbf{q}_2 + \cdots + r_{jj}\mathbf{q}_j \quad \mathbf{q}_i^T \mathbf{a}_j = r_{ij} \quad (i \neq j)$$

This leads to the *classical Gram-Schmidt* (CGS) algorithm for computing QR Factorization.

Input: $A_{(m \times n)}$ with $\text{rank}(A) = n$
Output: $Q_{(m \times n)}, R_{(n \times n)}$

- 1 $R(1, 1) = \|A(:, 1)\|_2$;
- 2 $Q(:, 1) = A(:, 1)/R(1, 1)$;
- 3 **for** $k = 2 : n$ **do**
- 4 $R(1 : k - 1, k) = Q(1 : m, 1 : k - 1)^T A(1 : m, k)$;
- 5 $z = A(1 : m, k) - Q(1 : m, 1 : k - 1)R(1 : k - 1, k)$;
- 6 $R(k, k) = \|z\|_2$;
- 7 $Q(1 : m, k) = z/R(k, k)$;
- 8 **end**
- 9 return Q, R ;

Algorithm 1: Classical Gram-Schmidt

1.4 Existence of QR Factorization

Theorem 1.1 Every $A \in \mathbb{R}^{m \times n}$ ($m \geq n$) has a QR Factorization.

Proof: If $\text{rank}(A) = n$, then use CGS algorithm we get the conclusion directly.

Otherwise, if $q = \text{rank}(A) < n$, we partition A as

$$A_{m \times n} = \begin{pmatrix} A_1 & A_2 \\ m \times q & m \times (n - q) \end{pmatrix}$$

Since $q = \text{rank}(A)$, the columns of A_1 are the bases of $\text{ran}(A)$. Namely, A_2 can be represented by A_1 . Write

$$A_2 = A_1 X = Q_1 R_1 X \stackrel{R_2 = R_1 X}{=} Q_1 R_2$$

Then,

$$\begin{aligned} A &= (Q_1 R_1, \quad Q_1 R_2) \\ &= (Q_1, \quad Q_1) \begin{pmatrix} R_1 & R_2 \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \\ &= QR \quad \square \end{aligned}$$

Theorem 1.2 Every $A \in \mathbb{R}^{m \times n}$ ($m \geq n$) of full rank has a unique reduced QR factorization $A = QR$ with $r_{jj} > 0$.

1.5 Modified Gram-Schmidt (MGS)

Input: $A_{(m \times n)}$ with $\text{rank}(A) = n$
Output: $Q_{(m \times n)}$, $R_{(n \times n)}$

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1 for  $k = 1 : n$  do
2    $R(k, k) = \|A(1 : m, k)\|_2$ ;
3    $Q(1 : m, k) = A(1 : m, k) / R(k, k)$ ;
4   for  $j = k + 1 : n$  do
5      $R(k, j) = Q(1 : m, k)^T A(1 : m, j)$ ;
6      $A(1 : m, j) = A(1 : m, j) - Q(1 : m, k)R(k, j)$ ;
7   end
8 end
9 return  $Q, R$ ;

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Algorithm 2: Modified Gram-Schmidt

Remarks: In the k th step of MGS, the k th column of Q and the k th row of R are determined. Comparing with CGS, MGS is more robust.

Derivation of MGS:

$$\begin{aligned}
 A &= \sum_{i=1}^n q_i r_i^T \\
 \Rightarrow A - \sum_{i=1}^{k-1} q_i r_i^T &= \sum_{i=1}^n q_i r_i^T - \sum_{i=1}^{k-1} q_i r_i^T = \begin{pmatrix} \mathbf{0} & A^{(k)} \\ k-1 & n-k+1 \end{pmatrix}
 \end{aligned}$$

Write $A^{(k)}$ as $A^{(k)} = \begin{pmatrix} z & B \\ 1 & n-k \end{pmatrix}$, we have $q_k^T A^{(k)} = (q_k^T z, q_k^T B)$. Thus,

$$q_k^T \left(A - \sum_{i=1}^{k-1} q_i r_i^T \right) = \begin{pmatrix} \mathbf{0} & q_k^T A^{(k)} \end{pmatrix} = \begin{pmatrix} \mathbf{0} & q_k^T z & q_k^T B \\ k-1 & 1 & n-k \end{pmatrix}$$

On the other hand,

$$q_k^T \left(A - \sum_{i=1}^{k-1} q_i r_i^T \right) = q_k^T A = q_k^T \sum_{i=1}^n q_i r_i^T = r_k^T$$

Thus,

$$r_k^T = \begin{pmatrix} \mathbf{0} & q_k^T z & q_k^T B \\ k-1 & 1 & n-k \end{pmatrix} \Rightarrow q_k = \frac{z}{r_{kk}}$$

To derive the inner loop, notice that

$$\begin{aligned}
\begin{pmatrix} \mathbf{0} & \mathbf{A}^{(k+1)} \end{pmatrix} &= \mathbf{A} - \sum_{i=1}^k \mathbf{q}_i \mathbf{r}_i^T = \mathbf{A} - \sum_{i=1}^{k-1} \mathbf{q}_i \mathbf{r}_i^T - \mathbf{q}_k \mathbf{r}_k^T \\
&= \begin{pmatrix} \mathbf{0} & \mathbf{A}^{(k)} \\ \mathbf{z} & \mathbf{B} \end{pmatrix} - \mathbf{q}_k \mathbf{r}_k^T \\
&= \begin{pmatrix} \mathbf{0} & \mathbf{z} & \mathbf{B} \end{pmatrix} - \mathbf{q}_k \begin{pmatrix} \mathbf{0} & r_{kk}, r_{k,k+1}, \dots, r_{kn} \end{pmatrix} \\
&= \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{B} - \mathbf{q}_k (r_{k,k+1}, \dots, r_{kn}) \end{pmatrix} \quad \square
\end{aligned}$$