

# QR and least square

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March 3, 2023

## 1 QR factorization

We study  $A \in \mathbb{R}^{m \times n}$  matrix with linearly independent columns. QR algorithm is a key algorithm in numerical linear algebra. We want to study the column space of  $A$ .

Recall the Gram–Schmidt process for producing an orthogonal or an orthonormal basis for any nonzero subspace of  $\mathbb{R}^n$ . Given a basis  $\{x_1, \dots, x_p\}$  for a nonzero subspace  $W$ , define

$$\begin{aligned}q_1 &= a_1/r_{11} \\q_2 &= a_2/r_{22} - \frac{r_{12}}{r_{22}}q_1 \\q_3 &= a_3/r_{33} - \frac{r_{13}}{r_{33}}q_1 - \frac{r_{23}}{r_{33}}q_2 \\&\dots \\q_p &= a_p/r_{pp} - \frac{r_{1p}}{r_{pp}}a_1 - \frac{r_{2p}}{r_{pp}}q_2 - \frac{r_{(p-1)p}}{r_{pp}}q_{p-1},\end{aligned}$$

where  $r_{ij} = q_i^T a_j$  and  $r_{jj} = \|a_j - \sum_{i=1}^j r_{ij}q_i\|$ . Then  $\{q_1, \dots, q_p\}$  is an orthonormal basis for  $W$ , i.e.,  $\text{span}\{a_1, a_2, \dots, a_p\} = \text{span}\{q_1, q_2, \dots, q_p\}$ .

**Theorem 1.1.** If  $A$  is an  $m \times n$  matrix with linearly independent columns, then  $A$  can be factored as  $A = QR$ , where  $Q$  is an  $m \times n$  matrix whose columns form an orthonormal basis for  $\text{Col } A$  and  $R$  is an  $n \times n$  upper triangular invertible matrix with positive entries on its diagonal.

*Proof.* Let  $a_1, \dots, a_n$  be columns of  $A$ . Perform Gram-Schmidt, we obtain  $Q = [q_1, \dots, q_n]$ , which is an orthonormal set of vectors whose span is  $\text{col}(A)$ . For  $a_k$ ,  $a_k$  is in  $\text{span}\{a_1, \dots, a_k\} = \text{span}\{q_1, \dots, q_k\}$ . That is there exists  $r_{1k}, \dots, r_{kk}$  such that  $a_k = r_{1k}q_1 + \dots + r_{kk}q_k + 0q_{k+1} \dots 0q_n$ . Without loss of generality, we assume  $r_{kk} > 0$ , otherwise multiply  $r_{kk}$  and  $q_k$  by  $-1$  simultaneously. Denote  $Q = [q_1, q_2, \dots, q_n]$ ,  $R = [r_1, \dots, r_n]$  where  $r_k = [r_{1k}, \dots, r_{kk}, 0, \dots, 0]^t \in \mathbb{R}^n$ , recall the matrix multiplication we have  $A = QR$ . We now claim that  $R$  is upper triangular with a positive diagonal (easy to verify) and invertible. Recall  $\text{rank}(QR) \leq \min(\text{rank}(Q), \text{rank}(R))$ . Since  $\text{rank}(A) = n = \text{rank}(Q)$ , this implies that  $\text{rank}(R) = n$ .  $\square$

When  $m > n$ , we can append  $m - n$  columns to  $Q$  to make it a  $m \times m$  unitary matrix  $\tilde{Q}$ . In this process, we will append  $m - n$  0 rows to  $R$  to obtain  $\tilde{R}$ . We call  $A = \tilde{Q}\tilde{R}$  full QR of  $A$ .

## 2 Modified QR

The GS-QR algorithm is not numerically stable. For the moment, a stable algorithm is one that is not too sensitive to the effects of rounding off errors. The modified GS is the way to improve

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**Algorithm 1:** Gram Schmidt

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**Data:**  $n \geq 0$ 

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1 for  $j = 1$  to  $n$  do
2    $v_j = a_j$ 
3   for  $i = 1$  to  $j - 1$  do
4      $r_{ij} = q_i^t a_j$ 
5      $v_j = v_j - r_{ij} q_i$ 
6    $r_{jj} = \|v_j\|_2$ 
7    $q_j = v_j / r_{jj}$ 
```

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the stability of the QR algorithm. GS can be expressed as an orthogonal projection:

$$q_1 = \frac{P_1 a_1}{\|P_1 a_1\|}, q_2 = \frac{P_2 a_2}{\|P_2 a_2\|}, \dots, q_n = \frac{P_n a_n}{\|P_n a_n\|}, \quad (1)$$

where  $P_j \in \mathbb{R}^{m \times m}$  denotes the orthogonal projector onto space spanned by  $\{q_1, \dots, q_{j-1}\}$ .

For each  $j$ , the GS algorithm computes a single orthogonal projection of rank  $m - (j - 1)$ ,  $v_j = P_j a_j$ . Recall that:  $P_{\perp q}$  denotes the rank  $m - 1$  orthogonal projection onto the space orthogonal to  $q$ . By the definition of  $P_j$ , we can verify (without proof here):

$$P_j = P_{\perp q_{j-1}} \dots P_{\perp q_2} P_{\perp q_1}, \quad (2)$$

and  $P_1 = I$ . As a result,

$$v_j = P_j a_j = P_{\perp q_{j-1}} \dots P_{\perp q_2} P_{\perp q_1} a_j. \quad (3)$$

Specifically,

$$\begin{aligned} v_j^1 &= a_j, \\ v_j^2 &= P_{\perp q_1} v_j^1 = v_j^1 - q_1 q_1^t v_j^1, \\ v_j^3 &= P_{\perp q_2} v_j^2 = v_j^2 - q_2 q_2^t v_j^2, \\ &\dots \dots \\ v_j &= P_{\perp q_{j-1}} v_j^{j-1} = v_j^{j-1} - q_{j-1} q_{j-1}^t v_j^{j-1}. \end{aligned}$$

We summarize the algorithm in 2.

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**Algorithm 2:** Modified Gram Schmidt

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1 for  $i = 1$  to  $n$  do
2    $v_i = a_i$ 
3   for  $j = i + 1$  to  $n$  do
4      $r_{ij} = \|v_i\|$ 
5      $q_i = v_i / r_{ii}$ 
6     for  $j = i + 1$  to  $n$  do
7        $r_{ij} = q_i^t v_j$ 
8        $v_j = v_j - r_{ij} q_i$ 
```

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