



## 1. Least Squares and Gram-Schmidt

Consider the least squares problem

$$\vec{x}^* = \operatorname{argmin}_{\vec{x} \in \mathbb{R}^n} \|A\vec{x} - \vec{b}\|_2^2 \quad (1)$$

where  $A \in \mathbb{R}^{m \times n}$ ,  $\vec{b} \in \mathbb{R}^m$  and assume  $A$  is full column rank. One way to solve this least-squares problem is to use Gram-Schmidt Orthonormalization (GSO). Using GSO, the matrix  $A$  can be written as,

$$A = QR = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \quad (2)$$

where  $Q$  is an orthonormal matrix and  $R$  is an upper-triangular matrix. The columns of  $Q_1$  form an orthonormal basis for the range space  $\mathcal{R}(A)$  and columns of  $Q_2$  form an orthonormal basis for the range space  $\mathcal{R}(A)^\perp$ . Moreover,  $R_1$  is upper triangular and invertible.

(a) Show that the squared norm of the residual is given by

$$\|\vec{r}\|_2^2 := \|\vec{b} - A\vec{x}\|_2^2 = \|Q_1^\top \vec{b} - R_1 \vec{x}\|_2^2 + \|Q_2^\top \vec{b}\|_2^2. \quad (3)$$

**Solution:** We have,

$$\|\vec{r}\|_2^2 := \|\vec{b} - A\vec{x}\|_2^2 \quad (4)$$

$$= \left\| \vec{b} - Q \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \vec{x} \right\|_2^2. \quad (5)$$

Since multiplying by an orthonormal matrix does not change the  $\ell_2$ -norm of a vector we can multiply by  $Q^\top$  to get,

$$\|\vec{r}\|_2^2 = \left\| Q^\top \left( \vec{b} - Q \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \vec{x} \right) \right\|_2^2 \quad (6)$$

$$= \left\| \begin{bmatrix} Q_1^\top \vec{b} \\ Q_2^\top \vec{b} \end{bmatrix} - \begin{bmatrix} R_1 \vec{x} \\ 0 \end{bmatrix} \right\|_2^2 \quad (7)$$

$$= \left\| \begin{bmatrix} Q_1^\top \vec{b} - R_1 \vec{x} \\ Q_2^\top \vec{b} \end{bmatrix} \right\|_2^2 \quad (8)$$

$$= \|Q_1^\top \vec{b} - R_1 \vec{x}\|_2^2 + \|Q_2^\top \vec{b}\|_2^2. \quad (9)$$

(b) Find  $\vec{x}^*$  such that the squared norm of the residual in Equation (3) is minimized. Your expression for  $\vec{x}^*$  should only use some or all of the following terms:  $Q_1, Q_2, R_1, \vec{b}$ .

**Solution:** We have,

$$\|\vec{r}\|_2^2 = \|Q_1^\top \vec{b} - R_1 \vec{x}\|_2^2 + \|Q_2^\top \vec{b}\|_2^2. \quad (10)$$

Since we have no control over the term  $\|Q_2^\top \vec{b}\|_2^2$  (i.e., no matter how we change  $\vec{x}$ , that term stays constant because it doesn't involve  $\vec{x}$  at all), it is irrelevant from the perspective of the optimization, and so the optimal  $\vec{x}^*$  is one which minimizes  $\|Q_1^\top \vec{b} - R_1 \vec{x}\|_2^2$ . This expression is minimized when  $Q_1^\top \vec{b} = R_1 \vec{x}$ , and using the fact that  $R_1$  is invertible we have  $\vec{x}^* = R_1^{-1} Q_1^\top \vec{b}$ .

- (c) Check if the expression for  $\vec{x}^*$  obtained in the previous part is equivalent to the one obtained by the formula,  $\vec{x}^* = (A^T A)^{-1} A^T \vec{b}$ .

**Solution:** We have  $A = QR = Q_1 R_1$  (block multiplication for matrices). Substituting,

$$\vec{x}^* = (R_1^T R_1)^{-1} R_1^T Q_1^T \vec{b} \quad (11)$$

$$= R_1^{-1} (R_1^T)^{-1} R_1^T Q_1^T \vec{b} \quad (12)$$

$$= R_1^{-1} Q_1^T \vec{b}. \quad (13)$$

This is the same as we got in the previous part.