

① Recall:

1. Least Squares Approximation.

Given a $n \times n$ matrix A , $b \in \mathbb{R}^n$, find $\hat{x} \in \mathbb{R}^n$ such that $\|b - A\hat{x}\|^2$ is minimal

2. By geometry, $A^T(b - A\hat{x}) = 0$

$$A^T A \hat{x} = A^T b$$

3. By calculus,

$E = \|Ax - b\|^2$ is minimal

$$\Rightarrow \frac{\partial E}{\partial x_i} = 0, i=1, \dots, n$$

$$\Leftrightarrow A^T A \hat{x} = A^T b$$

4. Application: Line Fitting.

§ 4.4 Orthogonal Bases and Gram-Schmidt

Motivation: Consider

$$A^T A \hat{x} = A^T b$$

if $A^T A = I$, $\Rightarrow \hat{x} = A^T b$

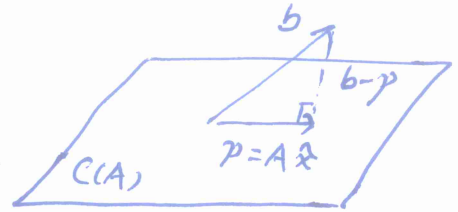
$A \xrightarrow{\text{Gram-Schmidt}} A = QR$, where $Q^T Q = I$, R is upper triangular

Def Vectors q_1, \dots, q_n are orthonormal if

$$q_i^T q_j = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$$

Set $Q = [q_1, \dots, q_n]$ (to be a matrix with orthonormal columns).

Then $Q^T Q = I$



$$Q^T Q = \begin{bmatrix} q_1^T \\ q_2^T \\ \vdots \\ q_n^T \end{bmatrix} [q_1, q_2, \dots, q_n] = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} = I$$

If Q is square, $Q^T Q = I \Rightarrow Q^T = Q^{-1}$

In this case, we

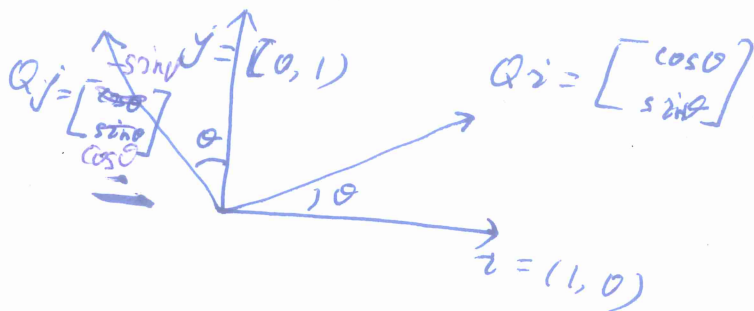
In square case, we call Q an orthogonal matrix.

(Let us look at three important ~~ex~~ examples of orthogonal matrices)

Ex 1 (Rotation)

$$Q = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}, \quad Q^T = Q^{-1} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$$

$$Q Q^T = I$$



Ex 2 (Permutation)

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} y \\ z \\ x \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} y \\ x \end{bmatrix}$$

inverse
" transpose

$$\begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} y \\ z \\ x \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} y \\ x \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}$$

every permutation matrix is an orthogonal matrix.

Ex 3 (Reflection)

If u is a unit vector, set $Q = I - 2uu^T$.

Then $Q^T = I - 2uu^T = Q$ and $Q^T Q = I - 4uu^T + 4u(u^T u)u^T = I$.

Q is called a reflection matrix.

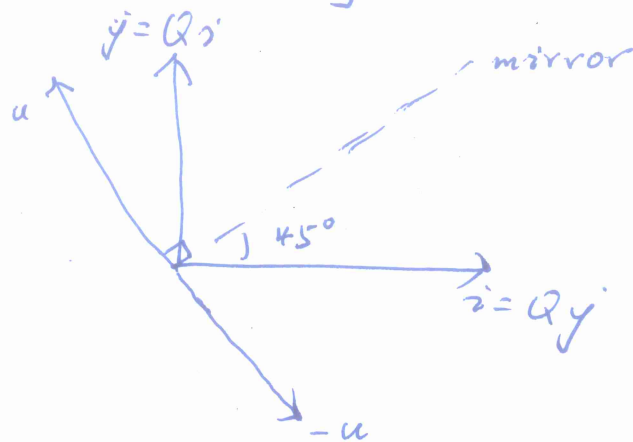
③

$$Q^2 = Q^T Q = I$$

(Reflecting twice through a mirror will get the original one)

$$\text{Let } u = \left(-\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right)$$

$$\text{Then } Q = I - 2uu^T = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad Q \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} y \\ x \end{bmatrix}$$



Note: Orthogonal matrices preserve lengths and angles

If Q ~~is~~ ^{has} ~~orthogonal~~ orthonormal columns ($Q^T Q = I$), then

$$\|Qx\| = \|x\| \text{ for each } x$$

Q preserves dot ^(\cdot) product. $(Qx)^T (Qy) = x^T Q^T Q y = x^T y$.

Projections Using Orthonormal Bases, Q Replaces A .

Assume $A = Q$, where Q has orthonormal columns

Then the least squares solution of $Qx = b$ ($Q^T Q \hat{x} = Q^T b$)

$$\text{is } \hat{x} = Q^T b \quad (Q^T Q = I)$$

The projection matrix is

$$P = Q(Q^T Q)^{-1} Q^T$$

$$= QQ^T$$

The projection

$$p = Q \hat{x} = QQ^T b$$

④

$$P = [q_1 \dots q_n] \begin{bmatrix} q_1^T b \\ \vdots \\ q_n^T b \end{bmatrix}$$

$$= q_1(q_1^T b) + \dots + q_n(q_n^T b)$$

P is a sum of ~~pro~~ projections of b onto ~~the~~ lines in direction of ~~the~~ q 's.

Note: If Q is square, then

$$P = QQ^T = I$$

$$P = b \Leftrightarrow b = QQ^T b$$

$$= q_1(q_1^T b) + q_2(q_2^T b) + \dots + q_n(q_n^T b)$$

Ex 4. Consider Q with orthonormal columns

$$Q = \frac{1}{3} \begin{bmatrix} q_1 & q_2 & q_3 \\ -1 & 2 & 2 \\ 2 & -1 & 2 \\ 2 & 2 & -1 \end{bmatrix}$$

Let $b = (0, 0, 1)$. projections into q 's.

$$q_1(q_1^T b) = \frac{2}{3} q_1, \quad q_2(q_2^T b) = \frac{2}{3} q_2, \quad q_3(q_3^T b) = -\frac{1}{3} q_3$$

$$b = p_1 + p_2 + p_3$$

$$= \frac{2}{3} q_1 + \frac{2}{3} q_2 - \frac{1}{3} q_3$$

The Gram-Schmidt Process.

Let a, b, c be independent vectors.

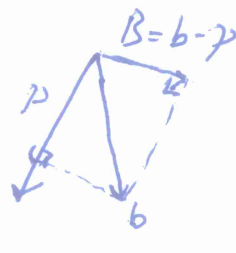
Goal: construct orthogonal vectors A, B, C in the ~~vec~~ vector space spanned by a, b, c .

Set $q_1 = A/\|A\|$, $q_2 = B/\|B\|$, $q_3 = C/\|C\|$.

Gram-Schmidt: Set $A = a$.

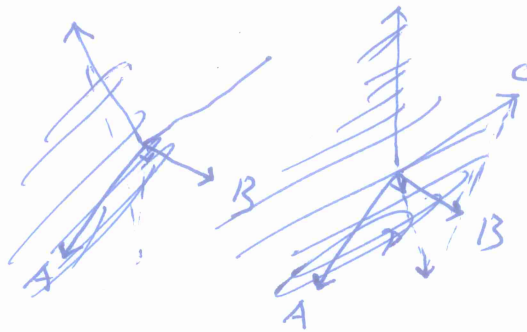
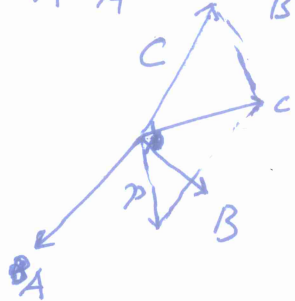
⑤ Step 1. Set $B = b - \frac{A^T b}{A^T A} A$

Note: $B \neq 0$ because a and b are independent



Step 2:

$$C = c - \frac{A^T c}{A^T A} A - \frac{B^T c}{B^T B} B$$



Step 3. Set $q_1 = \frac{A}{\|A\|}$, $q_2 = \frac{B}{\|B\|}$, $q_3 = \frac{C}{\|C\|}$.

Ex Let

$$a = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}, \quad b = \begin{bmatrix} 2 \\ 0 \\ -2 \end{bmatrix}, \quad c = \begin{bmatrix} 2 \\ -3 \\ 3 \end{bmatrix}$$

$$A = a, \quad A^T A = 2, \quad A^T b = 2$$

$$B = b - \frac{A^T b}{A^T A} A = \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix}$$

$$C = c - \frac{A^T c}{A^T A} A - \frac{B^T c}{B^T B} B = c - \frac{6}{2} A + \frac{6}{6} B = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\Rightarrow q_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}, \quad q_2 = \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix}, \quad q_3 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

The Factorization $A = QR$. (put Gram-Schmidt process in a nutshell)

$$\text{Let } A = [a \ b \ c]$$

$$a, b, c \xrightarrow{\text{Gram-Schmidt}} q_1, q_2, q_3$$

⑥

$$a = q_1(q_1^T a)$$

$$b = q_1(q_1^T b) + q_2(q_2^T b)$$

$$c = q_1(q_1^T c) + q_2(q_2^T c) + q_3(q_3^T c)$$

$$A = [a \ b \ c] = [q_1 \ q_2 \ q_3] \begin{bmatrix} q_1^T a & q_1^T b & q_1^T c \\ & q_2^T b & q_2^T c \\ & & q_3^T c \end{bmatrix}$$

$$= QR$$

Note: it can be generalized to n -dimensional case

~~Ex~~ Least squares:

$$A^T A x = A^T b \Leftrightarrow R^T R \hat{x} = R^T Q^T b$$

$$A^T A = (QR)^T QR$$

$$= R^T (Q^T Q) R$$

$$= R^T R$$

$$\Rightarrow R \hat{x} = Q^T b$$

(R^T is invertible by independence of columns of A)

$$\Rightarrow \hat{x} = R^{-1} Q^T b \text{ (back substituting)}$$