

# **Linear Algebra**

## **Orthogonal Bases and Gram-Schmidt**

Source: Introduction to Linear Algebra by Gilbert Strang

- How orthogonality and orthonormality helps
- How to construct orthonormal vectors from original vectors

The vectors  $\mathbf{q}_1, \dots, \mathbf{q}_n$  are *orthogonal* when their dot products  $\mathbf{q}_i \cdot \mathbf{q}_j$  are zero. More exactly  $\mathbf{q}_i^T \mathbf{q}_j = 0$  whenever  $i \neq j$ . With one more step—just divide each vector by its length—the vectors become *orthogonal unit vectors*. Their lengths are all 1. Then the basis is called *orthonormal*.

**DEFINITION** The vectors  $\mathbf{q}_1, \dots, \mathbf{q}_n$  are *orthonormal* if

$$\mathbf{q}_i^T \mathbf{q}_j = \begin{cases} 0 & \text{when } i \neq j \quad (\text{orthogonal vectors}) \\ 1 & \text{when } i = j \quad (\text{unit vectors: } \|\mathbf{q}_i\| = 1) \end{cases}$$

A matrix with orthonormal columns is assigned the special letter  $Q$ .

**The matrix  $Q$  is easy to work with because  $Q^T Q = I$ .** This repeats in matrix language that the columns  $\mathbf{q}_1, \dots, \mathbf{q}_n$  are orthonormal. It is equation (1) below, and  $Q$  is not required to be square.

When  $Q$  is square,  $Q^T Q = I$  means that  $Q^T = Q^{-1}$ : *transpose = inverse*.

41 A matrix  $Q$  with orthonormal columns satisfies  $Q^T Q = I$ :

$$Q^T Q = \begin{bmatrix} -\mathbf{q}_1^T & - \\ -\mathbf{q}_2^T & - \\ -\mathbf{q}_n^T & - \end{bmatrix} \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} = I. \quad (1)$$

If the columns are only orthogonal (not unit vectors), then  $Q^T Q$  is a diagonal matrix (not the identity matrix). We wouldn't use the letter  $Q$ . But this matrix is almost as good. The important thing is orthogonality—then it is easy to produce unit vectors.

*To repeat:*  $Q^T Q = I$  even when  $Q$  is rectangular. In that case  $Q^T$  is only an inverse from the left. For square matrices we also have  $Q Q^T = I$ , so  $Q^T$  is the two-sided inverse of  $Q$ . The rows of a square  $Q$  are orthonormal like the columns. ***The inverse is the transpose.*** In this square case we call  $Q$  an *orthogonal matrix*.<sup>2</sup>

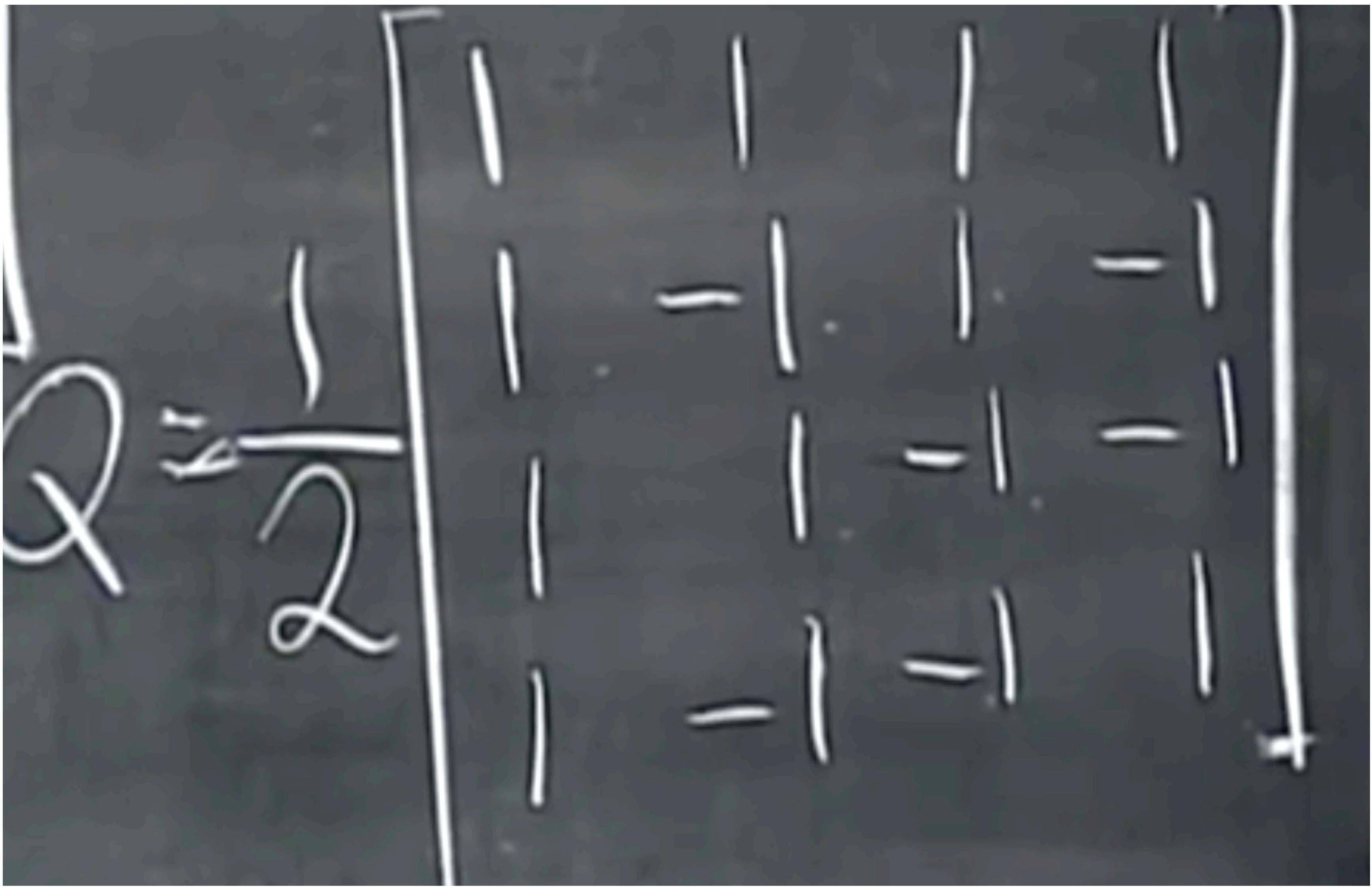
We have  $Q^T Q = I$  and  $Q Q^T = I$ .

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

*Every permutation matrix is an orthogonal matrix.*

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

The columns of  $Q$  are orthogonal (take their dot product). They are unit vectors because  $\sin^2 \theta + \cos^2 \theta = 1$ . Those columns give an *orthonormal basis* for the plane  $\mathbf{R}^2$ .



4] If  $Q$  has orthonormal columns ( $Q^T Q = I$ ), it leaves lengths unchanged:

$$\|Qx\| = \|x\| \text{ for every vector } x. \quad (3)$$

$Q$  also preserves dot products:  $(Qx)^T(Qy) = x^T Q^T Q y = x^T y$ . Just use  $Q^T Q = I$ !

This chapter is about projections onto subspaces. We developed the equations for  $\hat{x}$  and  $p$  and  $P$ . When the columns of  $A$  were a basis for the subspace, all formulas involved  $A^T A$ . The entries of  $A^T A$  are the dot products  $a_i^T a_j$ .

Suppose the basis vectors are actually orthonormal. The  $a$ 's become  $q$ 's. Then  $A^T A$  simplifies to  $Q^T Q = I$ . Look at the improvements in  $\hat{x}$  and  $p$  and  $P$ . Instead of  $Q^T Q$  we print a blank for the identity matrix:

$$\hat{x} = Q^T b \quad \text{and} \quad p = Q \hat{x} \quad \text{and} \quad P = Q \quad Q^T. \quad (4)$$

The point of this section is that “orthogonal is good.” Projections and least squares always involve  $A^T A$ . When this matrix becomes  $Q^T Q = I$ , the inverse is no problem.

For this to be true, we had to say “*If* the vectors are orthonormal.”  
*Now we find a way to create orthonormal vectors.*

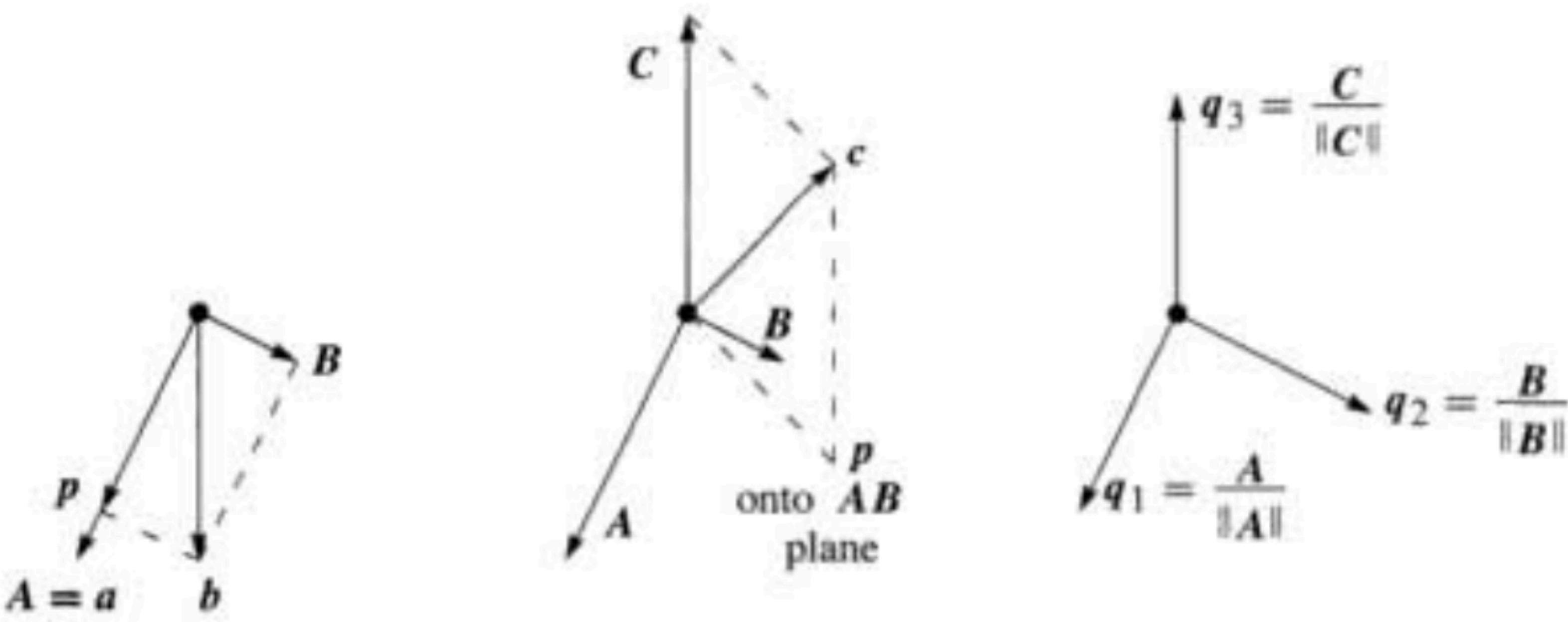
Start with three independent vectors  $\mathbf{a}, \mathbf{b}, \mathbf{c}$ . We intend to construct three orthogonal vectors  $\mathbf{A}, \mathbf{B}, \mathbf{C}$ . Then (at the end is easiest) we divide  $\mathbf{A}, \mathbf{B}, \mathbf{C}$  by their lengths. That produces three orthonormal vectors  $\mathbf{q}_1 = \mathbf{A}/\|\mathbf{A}\|$ ,  $\mathbf{q}_2 = \mathbf{B}/\|\mathbf{B}\|$ ,  $\mathbf{q}_3 = \mathbf{C}/\|\mathbf{C}\|$ .

**Gram-Schmidt** Begin by choosing  $\mathbf{A} = \mathbf{a}$ . This first direction is accepted. The next direction  $\mathbf{B}$  must be perpendicular to  $\mathbf{A}$ . *Start with b and subtract its projection along*

- This leaves the perpendicular part, which is the orthogonal vector  $\mathbf{B}$ :

**Gram-Schmidt idea**

$$\mathbf{B} = \mathbf{b} - \frac{\mathbf{A}^T \mathbf{b}}{\mathbf{A}^T \mathbf{A}} \mathbf{A}. \quad (7)$$



**Figure 4.11** First project  $\mathbf{b}$  onto the line through  $\mathbf{a}$  and find  $\mathbf{B}$  as  $\mathbf{b} - \mathbf{p}$ . Then project  $\mathbf{c}$  onto the  $\mathbf{AB}$  plane and find  $\mathbf{C}$  as  $\mathbf{c} - \mathbf{p}$ . Then divide by  $\|\mathbf{A}\|$ ,  $\|\mathbf{B}\|$ , and  $\|\mathbf{C}\|$ .

$\mathbf{A}$  and  $\mathbf{B}$  are orthogonal in Figure 4.11. Take the dot product with  $\mathbf{A}$  to verify that  $\mathbf{A}^T \mathbf{B} = \mathbf{A}^T \mathbf{b} - \mathbf{A}^T \mathbf{p} = 0$ . This vector  $\mathbf{B}$  is what we have called the error vector  $\mathbf{e}$ , perpendicular to  $\mathbf{A}$ . Notice that  $\mathbf{B}$  in equation (7) is not zero (otherwise  $\mathbf{a}$  and  $\mathbf{b}$  would be dependent). The directions  $\mathbf{A}$  and  $\mathbf{B}$  are now set.

The third direction starts with  $\mathbf{c}$ . This is not a combination of  $\mathbf{A}$  and  $\mathbf{B}$  (because  $\mathbf{c}$  is not a combination of  $\mathbf{a}$  and  $\mathbf{b}$ ). But most likely  $\mathbf{c}$  is not perpendicular to  $\mathbf{A}$  and  $\mathbf{B}$ . So subtract off its components in those two directions to get  $\mathbf{C}$ :

$$\mathbf{C} = \mathbf{c} - \frac{\mathbf{A}^T \mathbf{c}}{\mathbf{A}^T \mathbf{A}} \mathbf{A} - \frac{\mathbf{B}^T \mathbf{c}}{\mathbf{B}^T \mathbf{B}} \mathbf{B}. \quad (8)$$

This is the one and only idea of the Gram-Schmidt process. ***Subtract from every new vector its projections in the directions already set.*** That idea is repeated at every step.<sup>2</sup> If we also had a fourth vector  $\mathbf{d}$ , we would subtract its projections onto  $\mathbf{A}, \mathbf{B}, \mathbf{C}$  to get  $\mathbf{D}$ . At the end, divide the orthogonal vectors  $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}$  by their lengths. The resulting vectors  $\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3, \mathbf{q}_4$  are orthonormal.

**Example 5** Suppose the independent non-orthogonal vectors  $\mathbf{a}, \mathbf{b}, \mathbf{c}$  are

$$\mathbf{a} = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} 2 \\ 0 \\ -2 \end{bmatrix} \quad \text{and} \quad \mathbf{c} = \begin{bmatrix} 3 \\ -3 \\ 3 \end{bmatrix}.$$

Then  $\mathbf{A} = \mathbf{a}$  has  $\mathbf{A}^T \mathbf{A} = 2$ . Subtract from  $\mathbf{b}$  its projection along  $\mathbf{A} = (1, -1, 0)$ :

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

Check:  $\mathbf{A}^T \mathbf{B} = 0$  as required. Now subtract two projections from  $\mathbf{c}$  to get  $\mathbf{C}$ :

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

Check:  $\mathbf{C} = (1, 1, 1)$  is perpendicular to  $\mathbf{A}$  and  $\mathbf{B}$ . Finally convert  $\mathbf{A}, \mathbf{B}, \mathbf{C}$  to unit vectors (length 1, orthonormal). The lengths of  $\mathbf{A}, \mathbf{B}, \mathbf{C}$  are  $\sqrt{2}$  and  $\sqrt{6}$  and  $\sqrt{3}$ . Divide by those lengths, for an orthonormal basis:

$$\mathbf{q}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} \quad \text{and} \quad \mathbf{q}_2 = \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix} \quad \text{and} \quad \mathbf{q}_3 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}.$$

$$\begin{bmatrix} a & b & c \end{bmatrix} = \begin{bmatrix} q_1 & q_2 & q_3 \end{bmatrix} \begin{bmatrix} q_1^\top a & q_1^\top b & q_1^\top c \\ q_2^\top b & q_2^\top c \\ q_3^\top c \end{bmatrix} \quad \text{or} \quad A = QR. \quad (9)$$

$A = QR$  is Gram-Schmidt in a nutshell. Multiply by  $Q^T$  to see why  $R = Q^T A$ .

**4K (Gram-Schmidt)** From independent vectors  $a_1, \dots, a_n$ , Gram-Schmidt constructs orthonormal vectors  $q_1, \dots, q_n$ . The matrices with these columns satisfy  $A = QR$ . Then  $R = Q^T A$  is *triangular* because later  $q$ 's are orthogonal to earlier  $a$ 's.

Here are the  $\mathbf{a}$ 's and  $\mathbf{q}$ 's from the example. The  $i, j$  entry of  $R = Q^T A$  is row  $i$  of  $Q^T$  times column  $j$  of  $A$ . This is the dot product of  $\mathbf{q}_i$  with  $\mathbf{a}_j$ :

$$A = \begin{bmatrix} 1 & 2 & 3 \\ -1 & 0 & -3 \\ 0 & -2 & 3 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{6} & 1/\sqrt{3} \\ -1/\sqrt{2} & 1/\sqrt{6} & 1/\sqrt{3} \\ 0 & -2/\sqrt{6} & 1/\sqrt{3} \end{bmatrix} \begin{bmatrix} \sqrt{2} & \sqrt{2} & \sqrt{18} \\ 0 & \sqrt{6} & -\sqrt{6} \\ 0 & 0 & \sqrt{3} \end{bmatrix} = QR.$$

The lengths of  $\mathbf{A}, \mathbf{B}, \mathbf{C}$  are the numbers  $\sqrt{2}, \sqrt{6}, \sqrt{3}$  on the diagonal of  $R$ . Because of the square roots,  $QR$  looks less beautiful than  $LU$ . Both factorizations are absolutely central to calculations in linear algebra.

Any  $m$  by  $n$  matrix  $A$  with independent columns can be factored into  $QR$ . The  $m$  by  $n$  matrix  $Q$  has orthonormal columns, and the square matrix  $R$  is upper triangular with positive diagonal.