instability that affects both the modified and classical Gram-Schmidt algorithms. In floating point arithmetic, these algorithms may produce vectors q_j that are far from orthogonal. The loss of orthogonality occurs when A is close to rank-deficient, and, like most instabilities, it can appear even in low dimensions.

Starting on paper rather than in MATLAB, consider the case of a matrix

$$A = \begin{bmatrix} 0.70000 & 0.70711 \\ 0.70001 & 0.70711 \end{bmatrix}$$
 (9.1)

on a computer that rounds all computed results to five digits of relative accuracy (Lecture 13). The classical and modified algorithms are identical in the 2×2 case. At step j = 1, the first column is normalized, yielding

$$r_{11} = 0.98996, \quad q_1 = a_1/r_{11} = \begin{bmatrix} 0.70000/0.98996 \\ 0.70001/0.98996 \end{bmatrix} = \begin{bmatrix} 0.70710 \\ 0.70711 \end{bmatrix}$$

in five-digit arithmetic. At step j=2, the component of a_2 in the direction of q_1 is computed and subtracted out:

$$\begin{split} r_{12} &= q_1^* a_2 = 0.70710 \times 0.70711 + 0.70711 \times 0.70711 = 1.0000, \\ v_2 &= a_2 - r_{12} q_1 = \begin{bmatrix} 0.70711 \\ 0.70711 \end{bmatrix} - \begin{bmatrix} 0.70710 \\ 0.70711 \end{bmatrix} = \begin{bmatrix} 0.00001 \\ 0.00000 \end{bmatrix}, \end{split}$$

again with rounding to five digits. This computed v_2 is dominated by errors. The final computed Q is

$$Q = \left[\begin{array}{cc} 0.70710 & 1.0000 \\ 0.70711 & 0.0000 \end{array} \right],$$

which is not close to any orthogonal matrix.

On a computer with sixteen-digit precision, we still lose about five digits of orthogonality if we apply modified Gram-Schmidt to the matrix (9.1). Here is the MATLAB evidence. The "eye" function generates the identity of the indicated dimension.

The lines without semicolons produce the following printed output:

ans =
$$2.3515e-16$$
, ans = $2.3014e-11$.