## ENGR 695 Advanced Topics in Engineering Mathematics Fall 2024

## Lecture Outline for Friday, Aug. 30

- 1. Basic problems and computations in linear algebra:  $A\mathbf{x} = \mathbf{b}$  [review]
  - a. A, x given: geometric transformations (images, outputs from inputs)
  - b. *A*, **b** given: system solution (inputs from outputs)
  - c. Size & shape matter in defining the solution
- 2. A first look at solvability. When does  $A\mathbf{x} = \mathbf{b}$  have a solution? When is the solution "iffy?" Start with an example: Express the 2-D vectors  $\mathbf{a}$  and  $\mathbf{b}$  defined below in terms of the nonorthogonal unit vectors  $\hat{\mathbf{u}}_1$  and  $\hat{\mathbf{u}}_2$ .



Expressing vectors like **a** and **b** in terms of orthonormal unit vectors like  $\hat{\mathbf{x}}$  and  $\hat{\mathbf{y}}$  is simple because the *x* and *y*-components can be determined by inspection. Finding the components in terms of a nonorthogonal set like  $\hat{\mathbf{u}}_1$  and  $\hat{\mathbf{u}}_2$  is more challenging, but it will help illustrate the concept of solvability (and the concepts of rank and eigenvectors later).

To express **a** in terms of  $\hat{\mathbf{u}}_1$  and  $\hat{\mathbf{u}}_2$ , we need to find its  $u_1$ -component  $a_1$  and its  $u_2$ -component  $a_2$ . One approach is to find the dot product of **a** with  $\hat{\mathbf{u}}_1$  and then with  $\hat{\mathbf{u}}_2$ :

$$\mathbf{a} \cdot \hat{\mathbf{u}}_{1} = (\hat{\mathbf{u}}_{1}a_{1} + \hat{\mathbf{u}}_{2}a_{2}) \cdot \hat{\mathbf{u}}_{1} = a_{1}(\hat{\mathbf{u}}_{1} \cdot \hat{\mathbf{u}}_{1}) + a_{2}(\hat{\mathbf{u}}_{1} \cdot \hat{\mathbf{u}}_{2}) = a_{1} + a_{2}(\hat{\mathbf{u}}_{1} \cdot \hat{\mathbf{u}}_{2})$$
  
and  
$$\mathbf{a} \cdot \hat{\mathbf{u}}_{2} = (\hat{\mathbf{u}}_{1}a_{1} + \hat{\mathbf{u}}_{2}a_{2}) \cdot \hat{\mathbf{u}}_{2} = a_{1}(\hat{\mathbf{u}}_{1} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) = a_{1}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) = a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) = a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}_{2} \cdot \hat{\mathbf{u}}_{2}) + a_{2}(\hat{\mathbf{u}}$$

These two equations in the unknowns  $a_1$  and  $a_2$  can be expressed in matrix form as

$$\begin{bmatrix} 1 & \hat{\mathbf{u}}_1 \cdot \hat{\mathbf{u}}_2 \\ \hat{\mathbf{u}}_1 \cdot \hat{\mathbf{u}}_2 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \mathbf{a} \cdot \hat{\mathbf{u}}_1 \\ \mathbf{a} \cdot \hat{\mathbf{u}}_2 \end{bmatrix}$$

The result is  $\mathbf{a} = \hat{\mathbf{u}}_1 a_1 + \hat{\mathbf{u}}_2 a_2 = \hat{\mathbf{u}}_1 1.9598 + \hat{\mathbf{u}}_2 2.0142$ , a vector with "nice," small components that are of the same order as the *x* and *y*-components of **a**. (**a** is roughly in the same direction as  $\hat{\mathbf{u}}_1$  and  $\hat{\mathbf{u}}_2$ .)

Applying the same approach to express **b** in terms of  $\hat{\mathbf{u}}_1$  and  $\hat{\mathbf{u}}_2$  yields

$$\begin{bmatrix} 1 & \hat{\mathbf{u}}_1 \cdot \hat{\mathbf{u}}_2 \\ \hat{\mathbf{u}}_1 \cdot \hat{\mathbf{u}}_2 & 1 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} \mathbf{b} \cdot \hat{\mathbf{u}}_1 \\ \mathbf{b} \cdot \hat{\mathbf{u}}_2 \end{bmatrix},$$

which gives the result  $\mathbf{b} = -\hat{\mathbf{u}}_1 161.1314 + \hat{\mathbf{u}}_2 161.1353$ .

The components are two orders of magnitude larger than the x and y-components, and they are almost exact negatives of each other. The differences do not appear until the sixth significant digit. (**b** is perpendicular to  $\hat{\mathbf{u}}_1$  and almost perpendicular to  $\hat{\mathbf{u}}_2$ .)

Examine the parts of the matrix equations above:

$$\begin{bmatrix} 1 & \hat{\mathbf{u}}_{1} \cdot \hat{\mathbf{u}}_{2} \\ \hat{\mathbf{u}}_{1} \cdot \hat{\mathbf{u}}_{2} & 1 \end{bmatrix} = \begin{bmatrix} 1.00000000 & 0.99997535 \\ 0.99997535 & 1.00000000 \end{bmatrix}$$
$$\begin{bmatrix} \mathbf{a} \cdot \hat{\mathbf{u}}_{1} \\ \mathbf{a} \cdot \hat{\mathbf{u}}_{2} \end{bmatrix} = \begin{bmatrix} 3.97394011 \\ 3.97394145 \end{bmatrix} \qquad \begin{bmatrix} \mathbf{b} \cdot \hat{\mathbf{u}}_{1} \\ \mathbf{b} \cdot \hat{\mathbf{u}}_{2} \end{bmatrix} = \begin{bmatrix} 0.000000 \\ 0.007944 \end{bmatrix}$$

What if the basis vectors were collinear (and in this case not unit vectors)? For example, suppose that

$$\mathbf{u}_1 = \hat{\mathbf{x}}2 + \hat{\mathbf{y}}2$$
 and  $\mathbf{u}_2 = \hat{\mathbf{x}}10 + \hat{\mathbf{y}}10$  (note that  $\mathbf{u}_2 = 5\mathbf{u}_1$ )

Then:

$$\mathbf{a} \cdot \mathbf{u}_1 = (\mathbf{u}_1 a_1 + \mathbf{u}_2 a_2) \cdot \mathbf{u}_1 = a_1 (\mathbf{u}_1 \cdot \mathbf{u}_1) + a_2 (\mathbf{u}_1 \cdot \mathbf{u}_2) = 8a_1 + 40a_2$$
  
and  
$$\mathbf{a} \cdot \mathbf{u}_2 = (\mathbf{u}_1 a_1 + \mathbf{u}_2 a_2) \cdot \mathbf{u}_2 = a_1 (\mathbf{u}_1 \cdot \mathbf{u}_2) + a_2 (\mathbf{u}_2 \cdot \mathbf{u}_2) = 40a_1 + 200a_2$$

which becomes, in matrix form,

$$\begin{bmatrix} 8 & 40 \\ 40 & 200 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \mathbf{a} \cdot \hat{\mathbf{u}}_1 \\ \mathbf{a} \cdot \hat{\mathbf{u}}_2 \end{bmatrix} = \begin{bmatrix} 11.24 \\ 56.20 \end{bmatrix} \quad \text{(note that } 5 \times 11.24 = 56.20)$$

Does this system of equations have a solution? If so, how many?

Is the matrix singular or nonsingular? Does the matrix have an inverse? What is the determinant of the matrix?

- 3. Solution of  $A\mathbf{x} = \mathbf{b}$  using the inverse. For an  $N \times N$  (square) system, the following statements are equivalent for the purpose of determining the solvability of the problem.
  - a.  $A\mathbf{x} = \mathbf{b}$  has a unique solution
  - b. A has a unique inverse  $(A^{-1})$
  - c. *A* is nonsingular
  - d.  $det(A) = |\mathbf{A}| \neq 0$
  - e. A has full rank (i.e., rank(A) = N) more on this later
- 4. Route to finding solutions of  $A\mathbf{x} = \mathbf{b}$  (implicit inverse computation)
  - a. Form augmented matrix  $[A \mid \mathbf{b}]$
  - b. Process: for augmented matrix, reduce (transform) a system to an easier-to-solve form
  - c.  $A\mathbf{x} = \mathbf{b}$  becomes  $U\mathbf{x} = \mathbf{d}$  and solution ensues (U is upper triangular)
  - d. Method: row reduction using elementary row operations (EROs); Gaussian elimination or Gauss-Jordan elimination
    - i. Multiply a row (*j*) by a value (*c*)
    - ii. Add a multiple (c) of one row (j) to another (k)
    - iii. Interchange rows j and k

## Example Problems in Solving Systems of Linear Equations

Prob. 1:

$$3x_{1} - x_{2} + x_{3} = -1$$
  

$$9x_{1} - 2x_{2} + x_{3} = -9$$
  

$$3x_{1} + x_{2} - 2x_{3} = -9$$
  
Augmented matrix:  

$$\begin{bmatrix} 3 & -1 & 1 & | & -1 \\ 9 & -2 & 1 & | & -9 \\ 3 & 1 & -2 & | & -9 \\ 3 & 1 & -2 & | & -9 \end{bmatrix}$$

Prob. 2:

$$3x - y - 2z = 0$$
  

$$-6x + 2y + 6z = 4$$
  

$$2x + y + 6z = 13$$
  
Augmented matrix:  

$$\begin{bmatrix} 3 & -1 & -2 & 0 \\ -6 & 2 & 6 & 4 \\ 2 & 1 & 6 & 13 \end{bmatrix}$$

Prob. 3:

| x + 2y - 5z = 2  |                   | [1 | 2  | -52  |
|------------------|-------------------|----|----|------|
| 2x - 3y + 4z = 4 | Augmented matrix: | 2  | -3 | 4 4  |
| 4x + y - 6z = 8  |                   | 4  | 1  | -6 8 |