

Lecture Outline for Monday, Sept. 4

1. Generality #1: Overdetermined systems are usually (but not always) inconsistent.

$$\text{Examples: } A = \begin{bmatrix} 1 & 2 \\ 4 & 3 \\ 1 & 1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} 3 \\ 7 \\ 2 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} 1 \\ 3 \\ 4 \end{bmatrix}$$

Although an overdetermined system might not have an exact solution, it could still have a “best” approximate solution.

2. Generality #2: Underdetermined systems are usually (but not always) consistent:

$$\text{Examples: } A = \begin{bmatrix} 1 & 2 & 4 \\ 1 & 3 & 5 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} 7 \\ 9 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 2 & 4 \\ 2 & 4 & 8 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} 7 \\ 3 \end{bmatrix}$$

Underdetermined systems can have infinitely many solutions or no solution but never a unique solution because $\text{rank}(A) \leq M < N$ always.

3. Application of overdetermined systems: Curve-fitting and the method of least squares

- a. Start with an example. Consider the following small data set. How can we estimate the value of $y(3)$, that is, the value of y at $x = 3$?

i	x_i	y_i
1	1.0	1.1
2	2.0	3.2
3	4.0	5.2

- b. One possible approach: Set up a matrix expression that computes the coefficients of the quadratic expression for a curve that passes through the data points.

$$y = c_0 + c_1x + c_2x^2$$

Is the matrix equation solvable? If so, is the solution acceptable?

- c. Another possible approach: Set up a matrix expression that computes the coefficients of the linear expression for a line that passes through the data points.

$$y = c_0 + c_1x$$

Is the matrix equation solvable? If so, is the solution acceptable?

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4. Curve-fitting: the basic idea

- a. Given a data set: (x_i, y_i) , $i = 1$ to $M \rightarrow$ data vectors \mathbf{x} and \mathbf{y}
- b. Define model: a set of functions $\{f_j(x_i)\}_{j=1 \text{ to } N}$ and coefficients $\{c_j\}_{j=1 \text{ to } N}$ that yield the best approximations to $\{y_i\}_{i=1 \text{ to } M}$:

$$y(x) \approx \hat{y}(x) = \sum_{j=1}^N c_j f_j(x) \rightarrow \hat{\mathbf{y}} = F\mathbf{c}, \text{ where } F_{ij} = f_j(x_i) \text{ and } \hat{\mathbf{y}} \text{ contains best fit}$$

- c. Functions $\{f_j(x)\}$ (often called basis functions) can be almost anything; popular choices are 1 and x (linear fit), polynomials (including quadratic and cubic), sin/cos, exponentials, and logarithms
- d. Least squares approach:
 - i. Residual vector: $\mathbf{r} = \mathbf{y} - \hat{\mathbf{y}}$ ($r_i =$ distance from actual y_i to approximation \hat{y}_i for each data point i ; \mathbf{r} has M rows)
 - ii. Minimize $|\mathbf{r}|^2 = \mathbf{r}^T \mathbf{r}$ or make residual orthogonal to approximation ($\mathbf{r}^T \hat{\mathbf{y}} = 0$)
 - iii. Either way, the *normal equation* results (LS solution)

5. Derivation of normal equation from $\mathbf{r}^T \hat{\mathbf{y}} = 0$. Solution:

$$F^T F \mathbf{c} = F^T \mathbf{y} \rightarrow \mathbf{c} = (F^T F)^{-1} F^T \mathbf{y}$$

6. Practical considerations:

- a. In *Matlab*, can write $\mathbf{c} = F \backslash \mathbf{y}$; automatically forms solution using normal equations (or its equivalent)
- b. $F^T F$ is symmetric and nonsingular if there are no repeated data points
- c. F is $M \times N$, so $F^T F$ is $N \times N$