

# Linear equations: Case of singular square matrix

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Version 1.1, March 2, 2005

For a set of linear equations  $\mathbf{Ax} = \mathbf{b}$  when  $\mathbf{A}$  is square but singular, there are two cases:

- Case I: There are no solutions (so we look for the best approximation).
- Case II: There is a solution (in which case there are many solutions).

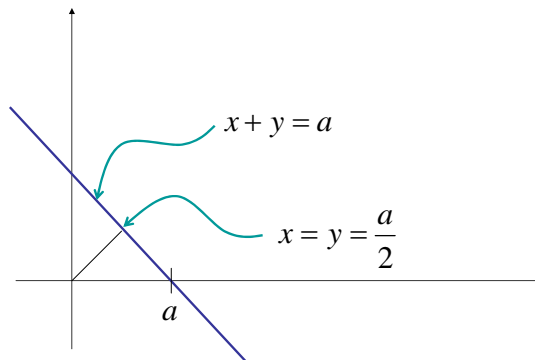
**Example:** Consider the equations:

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix} = x \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} + y \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} = (x+y) \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

**Case I:** When  $a = b$ , there are many solutions, since  $\begin{bmatrix} a \\ a \end{bmatrix} = (x+y) \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix}$  or  $x+y = a$ . One possible solution—the one that falls in the column space spanned by  $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ -- is  $x = y = \frac{a}{2}$ .

A vector that lies in the null space of  $\mathbf{A}$  is  $\begin{bmatrix} 1 \\ -1 \end{bmatrix}$ . Thus, the set of possible solutions can be characterized as  $\begin{bmatrix} a/2 \\ a/2 \end{bmatrix} + \alpha \cdot \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} a/2 + \alpha \\ a/2 - \alpha \end{bmatrix}$ . We might choose the solution that has minimum norm, which is easily shown to be  $\alpha = 0$  or  $x = y = \frac{a}{2}$ . That is, the minimum norm solution is the one that falls in the column subspace spanned by  $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ . This is illustrated geometrically below.

## Case I

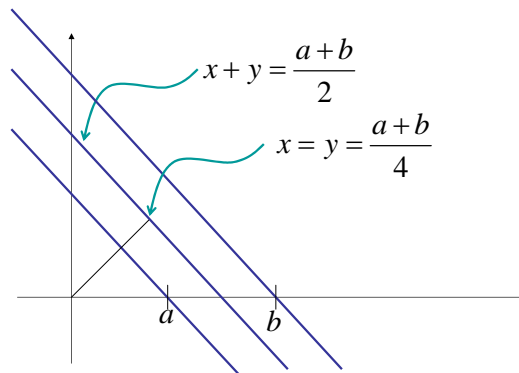


**Case II:** When  $a \neq b$ , there is no solution. The best approximate solution (in the mean-square sense) would minimize

$$\|\mathbf{b} - \mathbf{Ax}\|^2 = \left\| \begin{bmatrix} a - x - y \\ b - x - y \end{bmatrix} \right\|^2 = (a - x - y)^2 + (b - x - y)^2.$$

This can be solved the conventional way (differentiation) to establish that the stationary point satisfies  $x + y = \frac{a+b}{2}$ . Thus, the LS approximation is not unique (it lies anywhere on a line falling midway between  $x + y = a$  and  $x + y = b$ ). So, we might again choose to pick the minimum-norm solution—examining the geometry, this is clearly at  $x = y$ , or  $x = y = \frac{a+b}{4}$ . This approaches the same solution as in Case I as  $a \rightarrow b$ . This case is illustrated below.

### Case II



An alternative approach is to use the projection theorem. The minimization is restated as minimizing

$$\left\| \begin{bmatrix} a \\ b \end{bmatrix} - (x + y) \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\|^2.$$

While the projection on the subspace spanned by  $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$  must be unique, this still does not uniquely specify  $\mathbf{x}$ . The orthogonality principle states that

$$\begin{bmatrix} 1 & 1 \end{bmatrix} \left\{ \begin{bmatrix} a \\ b \end{bmatrix} - (x + y) \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} = 0 \quad \text{or} \quad x + y = \frac{a+b}{2}.$$

Thus, this gives us the same answer as before—the projection theorem actually gives us many solutions—and we still have to minimize the norm to arrive at a unique answer.