

## Overdetermined System of Equations

$$A \underline{x} = \underline{y}$$

$$A = n \times m \quad \text{with} \quad n > m$$

$$\underline{x} = m \times 1 \quad \text{and} \quad \text{unknown}$$

$$\underline{y} = n \times 1 \quad \text{and} \quad \text{known}$$

Overdetermined means more equations than unknowns.

There are four possibilities for the solution,  $\underline{x}$ :

unique and exact

unique and approximate

non-unique and exact

non-unique and approximate

To figure out which of these applies we have to define

$$A_{\text{aug}} = [A \mid y]$$

$$\text{Matlab: } \underline{A_{\text{aug}} = [A \ y];}$$

The rank of a matrix is the number of linearly independent rows and/or columns in the matrix.

By looking at the rank(A) and rank(A<sub>aug</sub>) we can tell which of the four cases we have.

rank(A) is the Matlab command

Matrix  $A$  is full rank if

$\text{rank}(A) = \min(n, m) = m$  in our case.

If  $A$  is not full rank, there is not a unique solution, rather it is non-unique (an infinite number of equivalent solutions).

If  $\text{rank}(A) = \text{rank}(A_{\text{aug}})$  the solution is exact, i.e.  $Ax = y$ .

If  $\text{rank}(A) < \text{rank}(A_{\text{aug}})$  the solution is approximate, i.e.,  $Ax \approx y$ .

# Least Squares (LS) Solution

Define the errors

$$\underline{e} = A\underline{x} - \underline{y}$$

The sum of the squared errors is

$$E = \underline{e}^T \underline{e} = \underline{x}^T A^T A \underline{x} - \underline{x}^T A^T \underline{y} - \underline{y}^T A \underline{x} + \underline{y}^T \underline{y}$$

We want to find  $\underline{x}$  to minimize

$E$ .

$$\nabla E = \begin{bmatrix} \frac{\partial E}{\partial x_1} \\ \vdots \\ \frac{\partial E}{\partial x_m} \end{bmatrix} = 2(A^T A)\underline{x} - 2A^T \underline{y} = \underline{0}$$

$$\boxed{\hat{\underline{x}}_{LS} = (A^T A)^{-1} A^T \underline{y}} \quad \star \star \star$$

If  $\text{rank}(A) < m$  the  $A^T A$  is singular,  
i.e., not invertible.

In this case we need to use the pseudoinverse, also called the Moore-Penrose inverse.

$$\hat{x}_{LS} = \text{pinv}(A)y$$

Alternate notation:  $A^{\dagger}$

Matlab

$$x_{hatLS} = \text{pinv}(A) * y;$$

The result is the unique  
minimum norm solution for  $\underline{x}$ .