

# LEAST SQUARES

Example:

$A$ :  $2 \times 2$  matrix (given matrix)

$\bar{b} \in \mathbb{R}^2$  vector (given vector)

find the vector  $\bar{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$  that fulfills  $A\bar{x} = \bar{b}$

$$A = \begin{pmatrix} 2 & 3 \\ 3 & 4 \end{pmatrix} \quad \bar{b} = \begin{pmatrix} -1 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 3 \\ 3 & 4 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} -1 \\ 0 \end{pmatrix}$$

i.e. find the solution to the following system of equations

$$\begin{cases} 2x_1 + 3x_2 = -1 \\ 3x_1 + 4x_2 = 0 \end{cases} \Rightarrow \text{The solution is } \boxed{\begin{matrix} x_1 = 4 \\ x_2 = -3 \end{matrix}}$$

but what happens if we add another constraint

$$x_1 + 2x_2 = 2$$

We have an over-determined system of equations

$$\begin{pmatrix} 2 & 3 \\ 3 & 4 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} -1 \\ 0 \\ 2 \end{pmatrix} \Rightarrow \text{There is no } \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \text{ that fulfills the three equations!!}$$

but we can find some solution that minimizes some kind of an error.

Let write the "error"

$$\|A\bar{x} - \bar{b}\|_2^2$$

then the problem is

$$\min_{\bar{x} \in \mathbb{R}^2} \|A\bar{x} - \bar{b}\|_2^2$$



$$\min_{\bar{x} \in \mathbb{R}^2} \langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle$$

in our example  $A\bar{x} - \bar{b}$  is

$$A\bar{x} - \bar{b} = \begin{pmatrix} 2 & 3 \\ 3 & 4 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} -1 \\ 0 \\ 2 \end{pmatrix} = \begin{pmatrix} 2x_1 + 3x_2 + 1 \\ 3x_1 + 4x_2 - 0 \\ x_1 - 2x_2 - 2 \end{pmatrix}$$

$$\langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle = (2x_1 + 3x_2 + 1)^2 + (3x_1 + 4x_2 - 0)^2 + (x_1 - 2x_2 - 2)^2$$

⇓  
name this as  $f(\bar{x})$

then we have to find the  $\min_{\bar{x} \in \mathbb{R}^2} f(\bar{x})$

For doing that we have several options:

- 1- Compute gradient of  $f(\bar{x})$  and set to 0
  - 2- Normal equations
  - 3- Gradient descent
- Actually use the same

1. Compute  $\nabla f(x)$  and set to zero  
in our example:

$$f(\bar{x}) = (2x_1 + 3x_2 + 1)^2 + (3x_1 + 4x_2 - 0)^2 + (x_1 - 2x_2 - 2)^2$$

$$\frac{\partial f(x)}{\partial x_1} = 2(2x_1 + 3x_2 + 1) \cdot 2 + 2(3x_1 + 4x_2 - 0) \cdot 3 + 2(x_1 - 2x_2 - 2)$$

$$\frac{\partial f(x)}{\partial x_2} = 2(2x_1 + 3x_2 + 1) \cdot 3 + 2(3x_1 + 4x_2 - 0) \cdot 4 + 2(x_1 - 2x_2 - 2) \cdot (-2)$$

⋮

# NORMAL EQUATIONS

Remember  $D_{\bar{v}} f(\bar{x}) = \lim_{\epsilon \rightarrow 0} \frac{f(\bar{x} + \epsilon \bar{v}) - f(\bar{x})}{\epsilon}$

Take the  $D_{\bar{v}} \langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle$

$$\lim_{\epsilon \rightarrow 0} \frac{\langle A(\bar{x} + \epsilon \bar{v}) - \bar{b}, A(\bar{x} + \epsilon \bar{v}) - \bar{b} \rangle - \langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle}{\epsilon}$$

$$\lim_{\epsilon \rightarrow 0} \frac{\langle A\bar{x} + \epsilon A\bar{v} - \bar{b}, A\bar{x} + \epsilon A\bar{v} - \bar{b} \rangle - \langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle}{\epsilon}$$

$$\lim_{\epsilon \rightarrow 0} \frac{\langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle + \langle A\bar{x} - \bar{b}, \epsilon A\bar{v} \rangle + \langle \epsilon A\bar{v}, A\bar{x} - \bar{b} \rangle + \langle \epsilon A\bar{v}, \epsilon A\bar{v} \rangle - \langle A\bar{x} - \bar{b}, A\bar{x} - \bar{b} \rangle}{\epsilon}$$

$$\lim_{\epsilon \rightarrow 0} \frac{2 \langle A\bar{x} - \bar{b}, \epsilon A\bar{v} \rangle + \langle \epsilon A\bar{v}, \epsilon A\bar{v} \rangle}{\epsilon}$$

$$\lim_{\epsilon \rightarrow 0} \frac{2 \cancel{\langle A\bar{x} - \bar{b}, A\bar{v} \rangle} + \epsilon^2 \langle A\bar{v}, A\bar{v} \rangle}{\cancel{\epsilon}}$$

$$\lim_{\epsilon \rightarrow 0} 2 \langle A\bar{x} - \bar{b}, A\bar{v} \rangle + \epsilon \langle A\bar{v}, A\bar{v} \rangle = 2 \langle A\bar{x} - \bar{b}, A\bar{v} \rangle = \langle 2A^T A\bar{x} - \bar{b}, \bar{v} \rangle$$

Remember:

$$D_{\bar{v}} f(\bar{x}) = \langle \nabla f(\bar{x}), \bar{v} \rangle$$

$$\nabla f(\bar{x}) = 2A^T A\bar{x} - A^T \bar{b}$$

Remember the necessary condition for minimum:  $\nabla f(\bar{x}) = 0$ , then

$$\langle A^T A\bar{x} - \bar{b}, \bar{v} \rangle = 0 \Rightarrow A^T A\bar{x} - \bar{b} = 0 \Rightarrow$$

$$\bar{x} = (A^T A)^{-1} A^T \bar{b}$$

( $\hookrightarrow$ ) Normal equations

In our example:

$$A^T = \begin{pmatrix} 2 & 3 & 1 \\ 3 & 4 & 2 \end{pmatrix} ; A^T A = \begin{pmatrix} 14 & 20 \\ 20 & 29 \end{pmatrix}$$

$$(A^T A)^{-1} = \begin{pmatrix} 4.83 & -3.3 \\ -3.3 & 2.3 \end{pmatrix} ; (A^T A)^{-1} A^T = \begin{pmatrix} -0.33 & 1.16 & -1.83 \\ 0.33 & -0.66 & 1.33 \end{pmatrix}$$

$$(A^T A)^{-1} A^T \bar{b} = \begin{pmatrix} -3.33 \\ 2.33 \end{pmatrix} = \bar{x}$$



We can also solve the problem using the SVD Decomposition for computing the pseudo-inverse

$$\bar{x} = V \Sigma^+ U^T \bar{b}$$

$$\left. \begin{aligned} A &= U \Sigma V^T \\ A^T &= V \Sigma^+ U^T \Rightarrow \text{PSEUDO INVERSE} \end{aligned} \right\}$$

Notice that this is equivalent to solve the normal equations

Proof:

Let's start with the normal equations

$$\bar{x} = (A^T A)^{-1} A^T \bar{b}$$

$$A^T A \bar{x} = A^T \bar{b}$$

Decompose A using SVD  $\Rightarrow A = U \Sigma V^T$

$$A^T A = (U \Sigma V^T)^T (U \Sigma V^T) = \overbrace{(V \Sigma^T U^T)}^{A^T} (U \Sigma V^T) =$$

Remember  $U^T = U^{-1}$

$$A^T A = V \Sigma^2 V^T$$

$$A^T A \bar{x} = A^T \bar{b} \Rightarrow \cancel{V} \Sigma^2 \cancel{V^T} \bar{x} = \cancel{V} \cancel{\Sigma} U^T \bar{b} \Rightarrow$$

$$\Rightarrow \Sigma V^T \bar{x} = U^T \bar{b} \Rightarrow V^T \bar{x} = \underbrace{\Sigma^{-1}}_{\Sigma^+} U^T \bar{b} \Rightarrow$$

$$\Rightarrow \bar{x} = \underbrace{V \Sigma^+ U^T}_{A^+ \text{ (pseudo-inverse)}} \bar{b}$$