

$$A_{n \times n}$$

$$P = A(A^T A)^{-1} A^T \text{ exists if}$$

$$P_{n \times n}$$

$$= A A^+$$

$$A^+ = (A^T A)^{-1} A^T$$

A is skinny
full rank

$$\underline{Ax=b} \text{ Not } \underline{\text{lucky}}$$

$$b \notin R(A)$$

$$\begin{bmatrix} A \end{bmatrix}_{m \times n} \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} b \end{bmatrix}$$

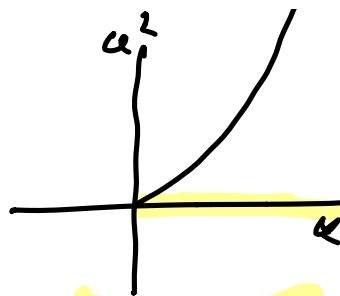
m eq's

n unknown

$$n < m$$

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|^2$$

equiv



$$\min_{x \in \mathbb{R}^n} \|Ax - b\|$$

$$f(x) = \|Ax - b\|^2 = (Ax - b)^T (Ax - b)$$

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\nabla f(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} f(x) \\ \frac{\partial}{\partial x_2} f(x) \\ \vdots \\ \frac{\partial}{\partial x_n} f(x) \end{bmatrix}$$

Loss function

$$= 2A^T(Ax - b)$$

$$\nabla f(x) = 0$$

$$2A^T(Ax - b) = 0$$

$$A^T Ax = A^T b$$

$$A^T A$$

$$A^T b$$

$$AX=b$$

Normal
Equations

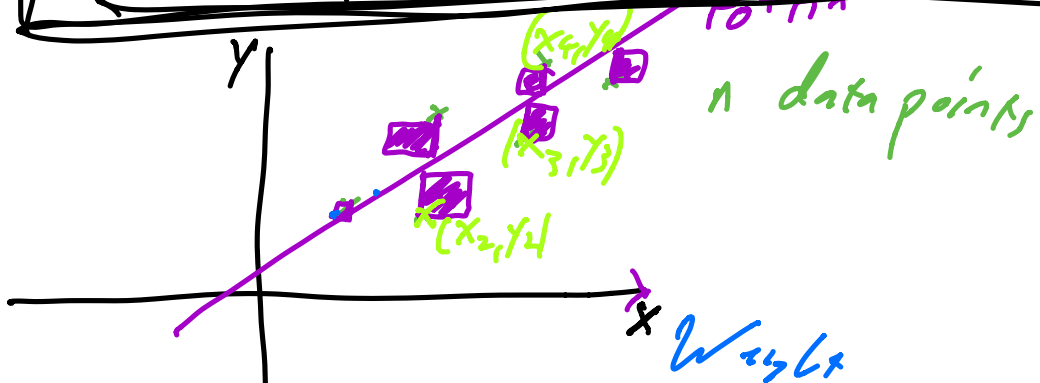
$$\hat{X} = (A^T A)^{-1} A^T b$$

A^+ Moore Penrose
pseudo-inverse

$$A^+ A \hat{X} = A^+ b$$

$$X = A^+ b$$

Least Squares Data Fitting



$$A = \begin{bmatrix} 1 & x_2 & \dots & x_n \\ 1 & x_3 & \dots & x_n \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_5 & \dots & x_n \end{bmatrix} \quad \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}_{2 \times 1} = \begin{bmatrix} y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix}$$

design matrix

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$$

$$\begin{aligned} \beta_0 1 + \beta_1 x_1 &\approx y_1 \\ &\vdots \\ \beta_0 1 + \beta_5 x_5 &\approx y_5 \end{aligned}$$

$n \times p = 2$

$$A\beta = y$$

$$Ax = b$$

$$\hat{\beta} = A^+ y$$

$$P = \frac{1}{n} (A^T A) A^T Y$$

$$A^T = \begin{bmatrix} | & & | \\ x_1 & & x_n \\ | & & | \end{bmatrix}_{n \times 2}$$

$$\begin{bmatrix} A & A \end{bmatrix} \begin{bmatrix} -I \\ I \end{bmatrix}^T A$$

$$= \begin{bmatrix} \sum x_i^2 \end{bmatrix}$$

$$A^T A$$