

March 3, 2021

$$\vec{A} \vec{x} = \vec{b}$$

$$\vec{A} \vec{x} \approx \vec{b}$$

$$m > n$$

$$b_i \approx a_i^T x + c$$

$$[A \ 1] \begin{pmatrix} x \\ c \end{pmatrix} \approx b$$

$$\sum (b_i - a_i^T x)^2$$

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_2^2$$

linear least squares

Examples:

(1) Data fitting

$$(z_1, f(z_1)), \dots, (z_m, f(z_m))$$

$$f(z) \approx x_3 z^3 + x_2 z^2 + x_1 z + x_0$$

$$a_i^T = [1 \ z_i \ z_i^2 \ z_i^3] \quad b_i = f(z_i)$$

$$b_i \approx a_i^T x \quad \sum_{i=1}^m (b_i - a_i^T x)^2$$

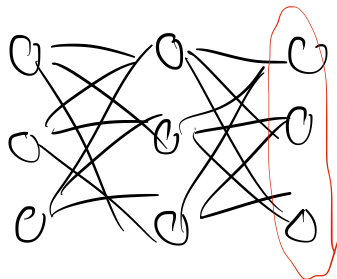
$$\|Ax - b\|_2^2 \quad n=4$$

(2) Stats / ML

a_i = data about page i

b_i = #clicks

$$\|Ax - b\|_2^2 \approx a_i^T x \quad (\text{linear regression})$$



final layer
= a_i

$$\min_x \|Ax - b\|_2^2 \quad \text{Why squared error?}$$

One reason: "right" norm for reasonable stat models

$$\bullet b_i = a_i^T x + \varepsilon_i \quad \varepsilon_i \sim N(0, \sigma^2) \quad \text{i.i.d.} \quad p(\varepsilon) = \frac{\exp(-\frac{1}{2} \varepsilon^2 / \sigma^2)}{\sqrt{2\pi} \sigma}$$

$$\underline{b_i - a_i^T x} = \varepsilon_i$$

Given x , likelihood (A, b) is

$$\begin{aligned} & \prod_{i=1}^3 p(b_i - a_i^T x) \\ &= \prod_{i=1}^3 \exp(-\frac{1}{2} (b_i - a_i^T x)^2 / \sigma^2) / \sqrt{2\pi} \sigma \\ & \quad \frac{1}{2} \sum_{i=1}^3 (b_i - a_i^T x)^2 / \sigma^2 \end{aligned}$$

minimize \Rightarrow maximize likelihood

$$H_{ij} = \frac{\partial^2}{\partial x_i \partial x_j}$$

