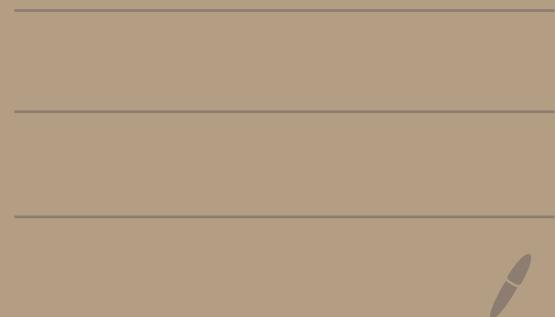
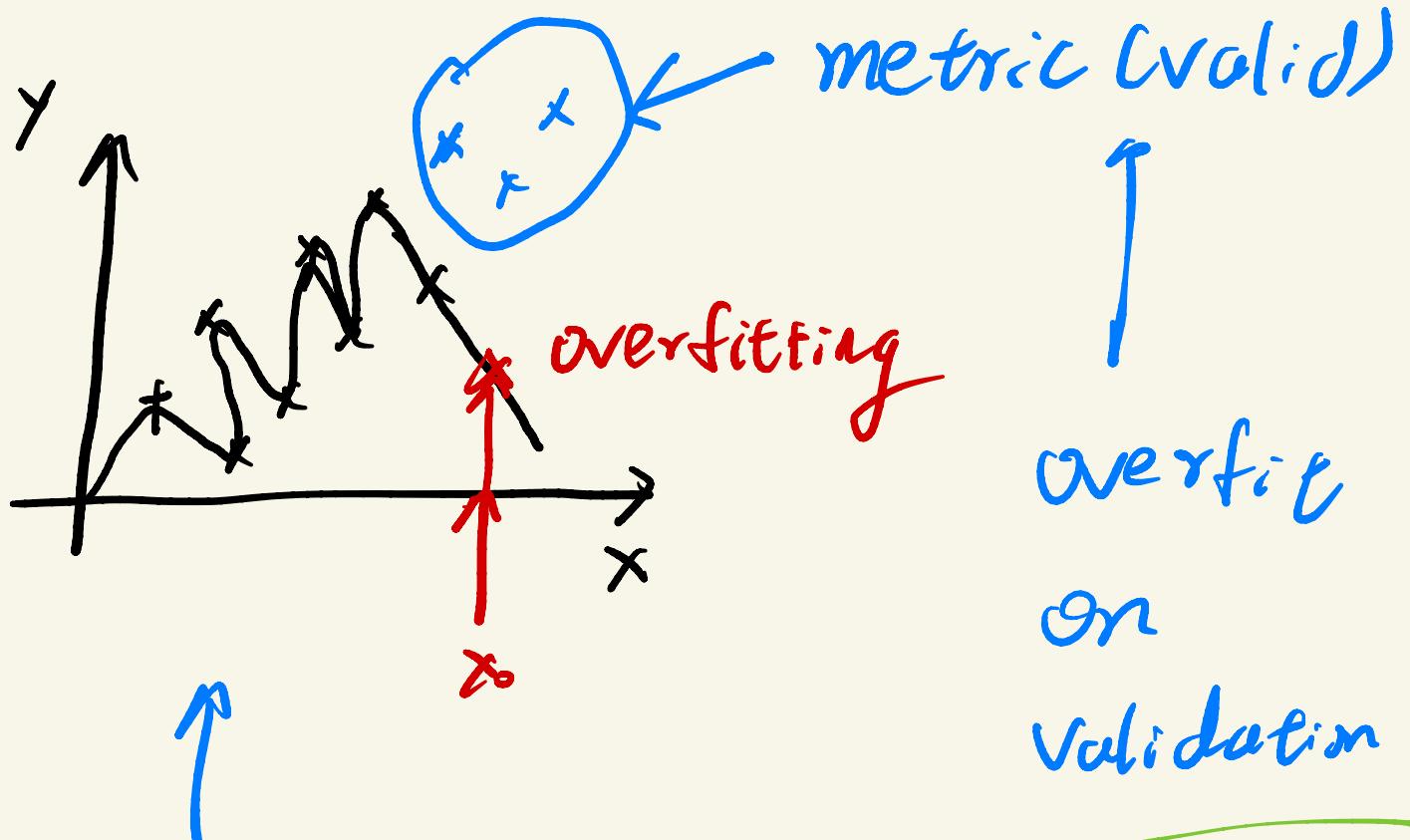


Lecture 2 Linear Regression





$$h_{\theta}(x) = \vec{\theta}^T \vec{x} \quad \text{dot product}$$

$$\begin{aligned} x &= \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_3 \end{bmatrix} & \theta &= \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_3 \end{bmatrix} \\ \Rightarrow & (x^{(i)}, y^{(i)}) & n \end{aligned}$$

linear

$$\left| h_{\theta_1}(x^{(i)}) - y^{(i)} \right| > \left| h_{\theta_2}(x^{(i)}) - y^{(i)} \right|$$

$$\left| h_{\theta_1}(x^{(i)}) - y^{(i)} \right|^2 > \left| h_{\theta_2}(x^{(i)}) - y^{(i)} \right|^2$$

?

$$x\theta \rightarrow R^{n \times 1}$$

$$J(\theta) = \frac{1}{2} \underbrace{(h_\theta(x) - y)}_{\text{vector } R^n}^\top \underbrace{(h_\theta(x) - y)}_{\text{vector } R^n}$$

$X \rightarrow R^{n \times (d+1)}$ vector R^n $n \rightarrow \# \text{ samples}$

$$\nabla_\theta J(\theta) = 0$$

$$\nabla_\theta J(\theta) = \frac{1}{2} \nabla_\theta \left[\underbrace{\theta^\top (X^\top X) \theta}_{+ y^\top y} - \underbrace{2(X^\top y)^\top \theta} \right]$$

$$= \frac{1}{2} [2X^\top X \theta - 2X^\top y]$$

$$= X^\top X \theta - X^\top y = 0 \quad \text{not invertible}$$

$$\theta = (X^\top X)^{-1} X^\top y$$

$$x^T x \rightarrow R^{(d+1) \times (d+1)}$$

$$x \rightarrow R^{n \times (d+1)}$$

$$\min] = 0$$

1.

$$\overbrace{x^T x}^{\text{II}} \rightarrow R^{(d+1) \times (d+1)}$$

$$\text{rank}(x^T x) = d+1$$

$$n < d+1$$

$$\text{rank}(AB) \leq \min(\text{rank}(A), \text{rank}(B))$$

$$\text{rank}(x) \leq \min(n, d+1) < d+1$$

$$x^T x \leq \text{rank}(x) < d+1$$

$$d+1$$

$$X = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\Leftrightarrow \text{rank}(x) < d+1$$

x y

$x^{(i)}$ $y^{(i)}$

$\varepsilon^{(i)} \sim N(0, \sigma^2)$

$\theta^\top x^{(i)} + \varepsilon^{(i)} = y^{(i)}$

$y^{(i)}$ given $x^{(i)}$

maximize $L(\theta)$,

$\arg\max L(\theta)$

$\hat{\theta} = \arg\max \log L(\theta)$

$\log L(\theta) \rightarrow \text{log likelihood}$

$$\hat{\theta} = n \left(\log \frac{1}{\sqrt{n} \sigma} - \frac{1}{n} \cdot \frac{1}{2} \sum_{i=1}^n (y^{(i)} - \theta^T x^{(i)})^2 \right)$$

$\hat{\theta}$

maximum Likelihood
Estimator (MLE)

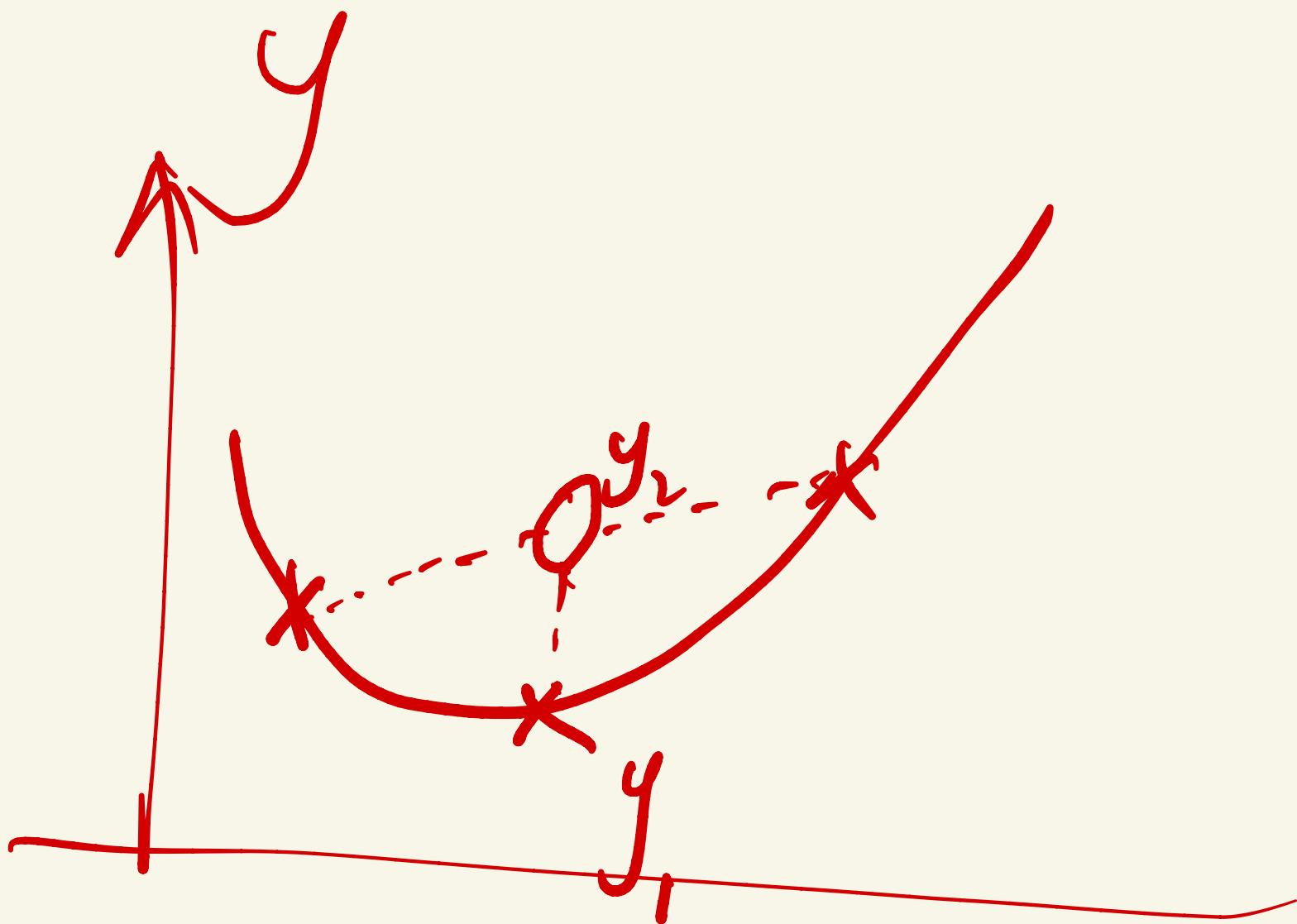
θ^* $\hat{\theta}$

relation

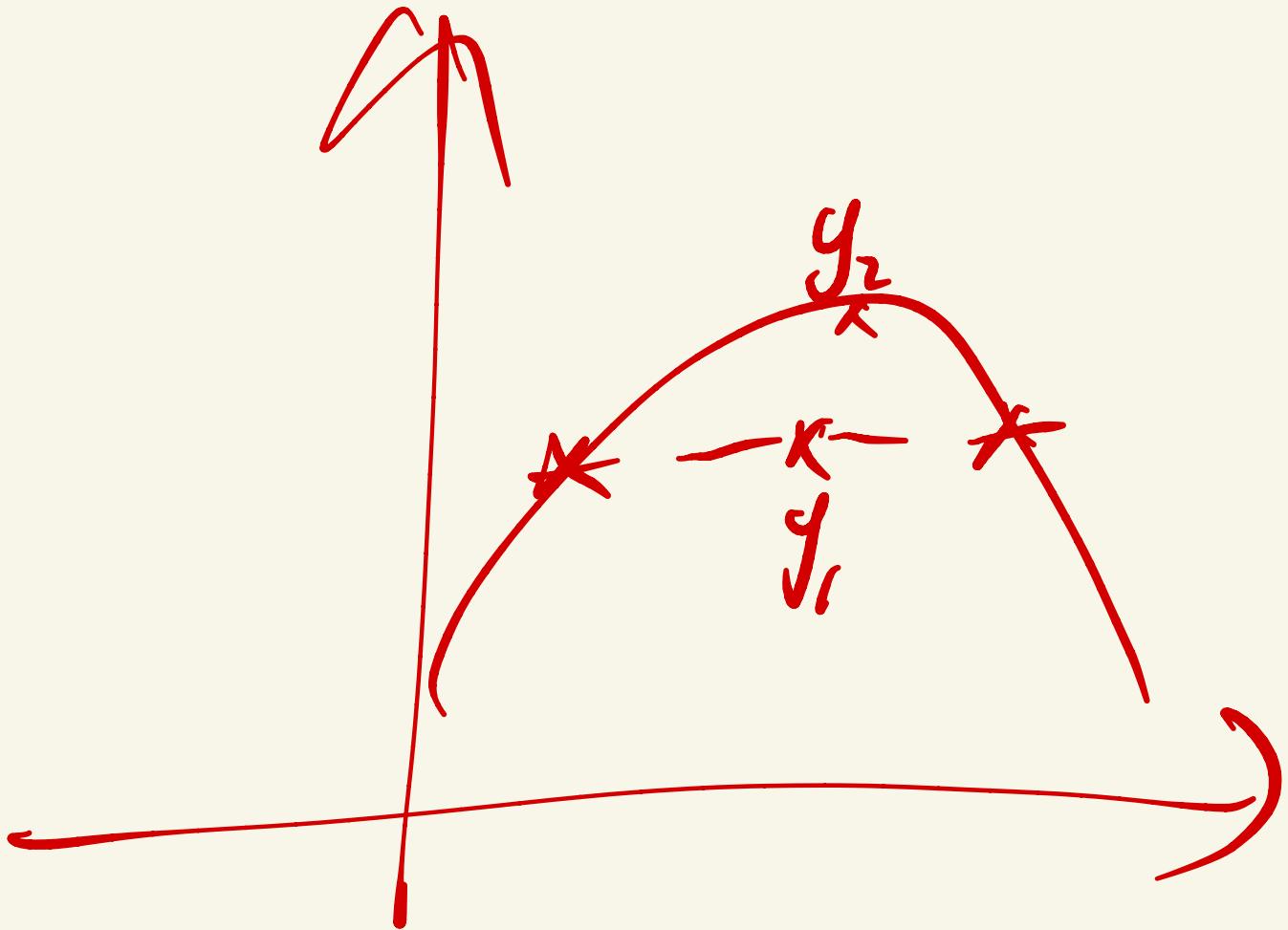


$$\theta_j := \theta_j + \alpha (Ch_\theta(x) - y)^T x_j$$

$$x = \begin{bmatrix} x \\ \vdots \\ x_{d+1} \end{bmatrix}$$



$y_2 > y_1$, convex



$y_2 \geq y_1$, concave