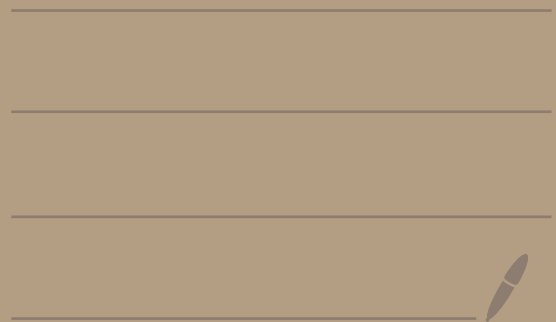
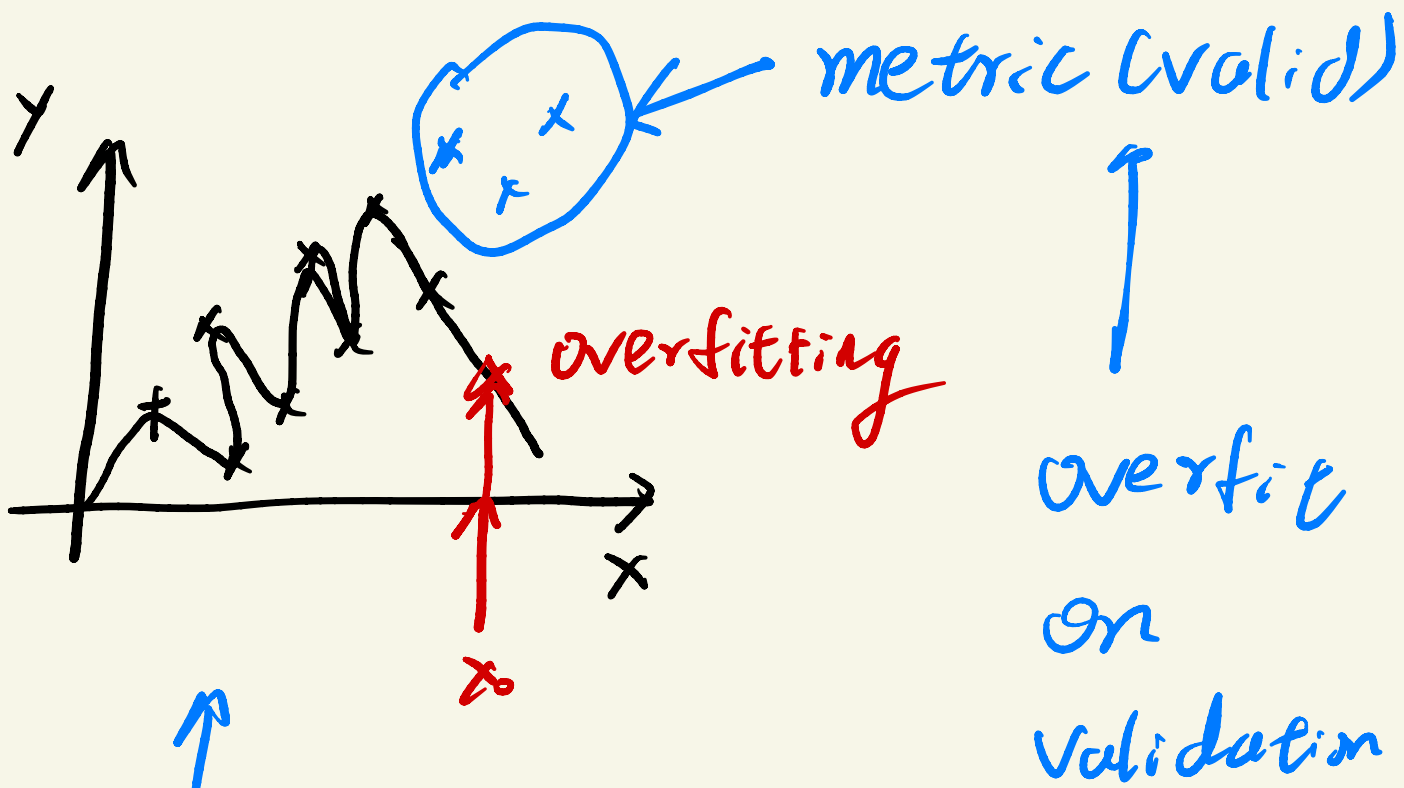


# Lecture 2 Linear Regression

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loss (train)

test data

x x

x x x

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

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_3 \end{bmatrix}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_3 \end{bmatrix}$$



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

$n$

linear

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

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↓

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

?

$$J(\theta) = \frac{1}{2} (\underbrace{h_{\theta}(x) - y}_{\text{vector } \mathbb{R}^n \text{ } n \rightarrow \# \text{ samples}})^T (\underbrace{h_{\theta}(x) - y}_{\text{vector } \mathbb{R}^n \text{ } n \rightarrow \# \text{ samples}})$$

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

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

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

$$\nabla_{\theta} J(\theta) = \frac{1}{2} \nabla_{\theta} [\underbrace{\theta^T (X^T X) \theta}_{\text{scalar}} - \underbrace{2(X^T y)^T \theta}_{\text{scalar}}]$$

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

$$= X^T X \theta - X^T y = 0 \quad \text{not including } \theta$$

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

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

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

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

$$\min J = 0$$

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

1.

$$n < d+1$$

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

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

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



2.

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

$x$        $y$

$x^{(i)}$        $y^{(i)}$

$$\Sigma^{(i)} \sim \mathcal{N}(0, \sigma^2)$$
$$\theta^T x^{(i)} + \Sigma^{(i)} = y^{(i)}$$

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

maximize  $L(\theta)$

$\arg \max L(\theta)$

$\equiv \arg \max \log L(\theta)$

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

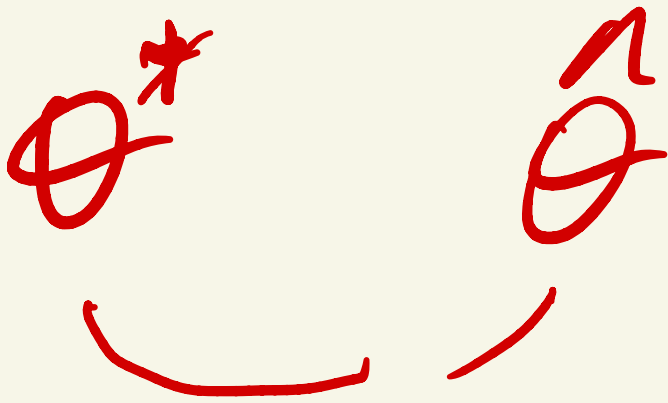
$$\approx n \log \frac{1}{\sqrt{\pi \sigma^2}} - \frac{1}{\sigma^2} \cdot \frac{1}{2} \sum_{i=1}^n (y^{(i)} - \theta x^{(i)})^2$$



$\hat{\theta}$

Maximum Likelihood  
Estimator (MLE)

$\theta^*$   $\hat{\theta}$

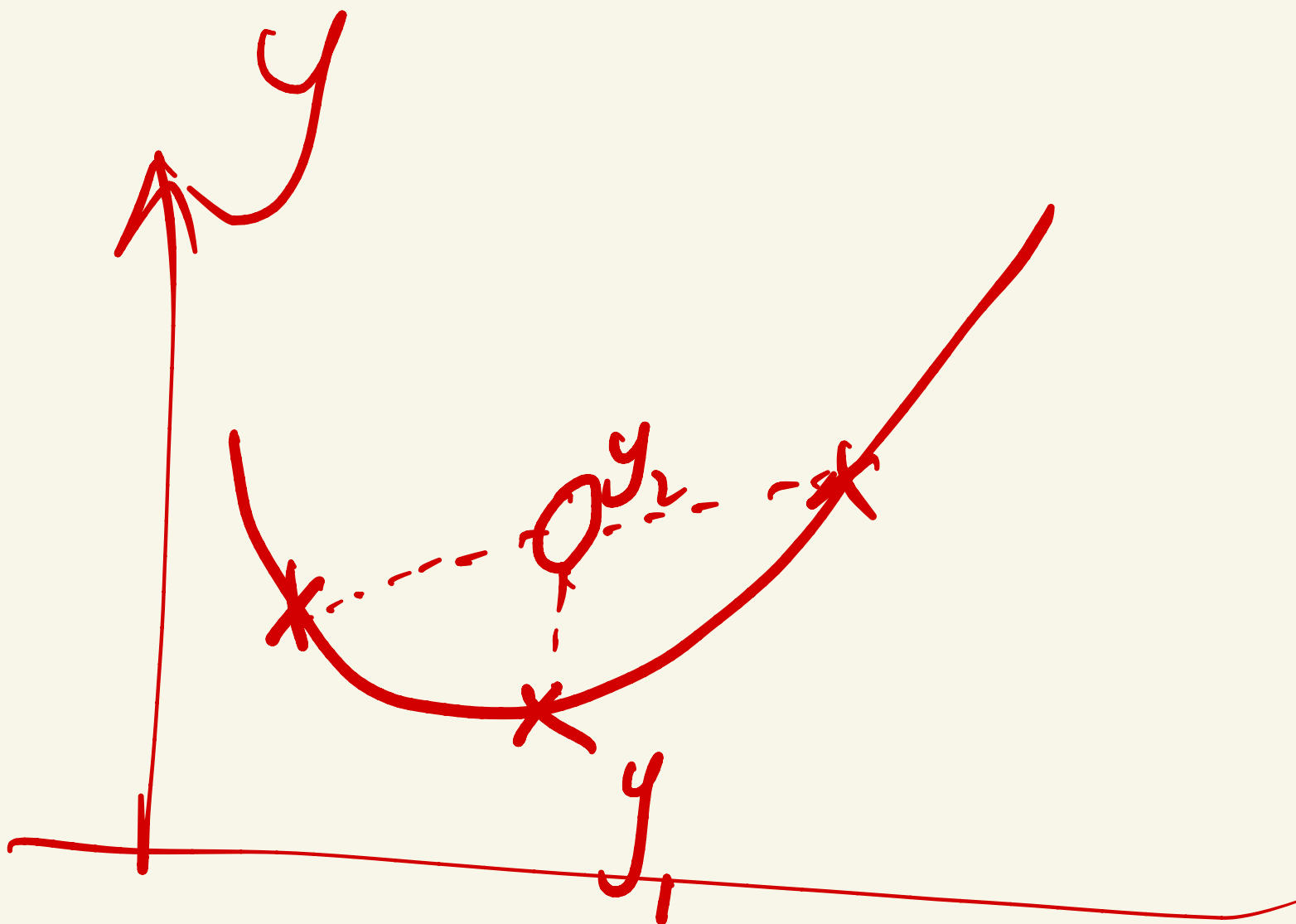


relation

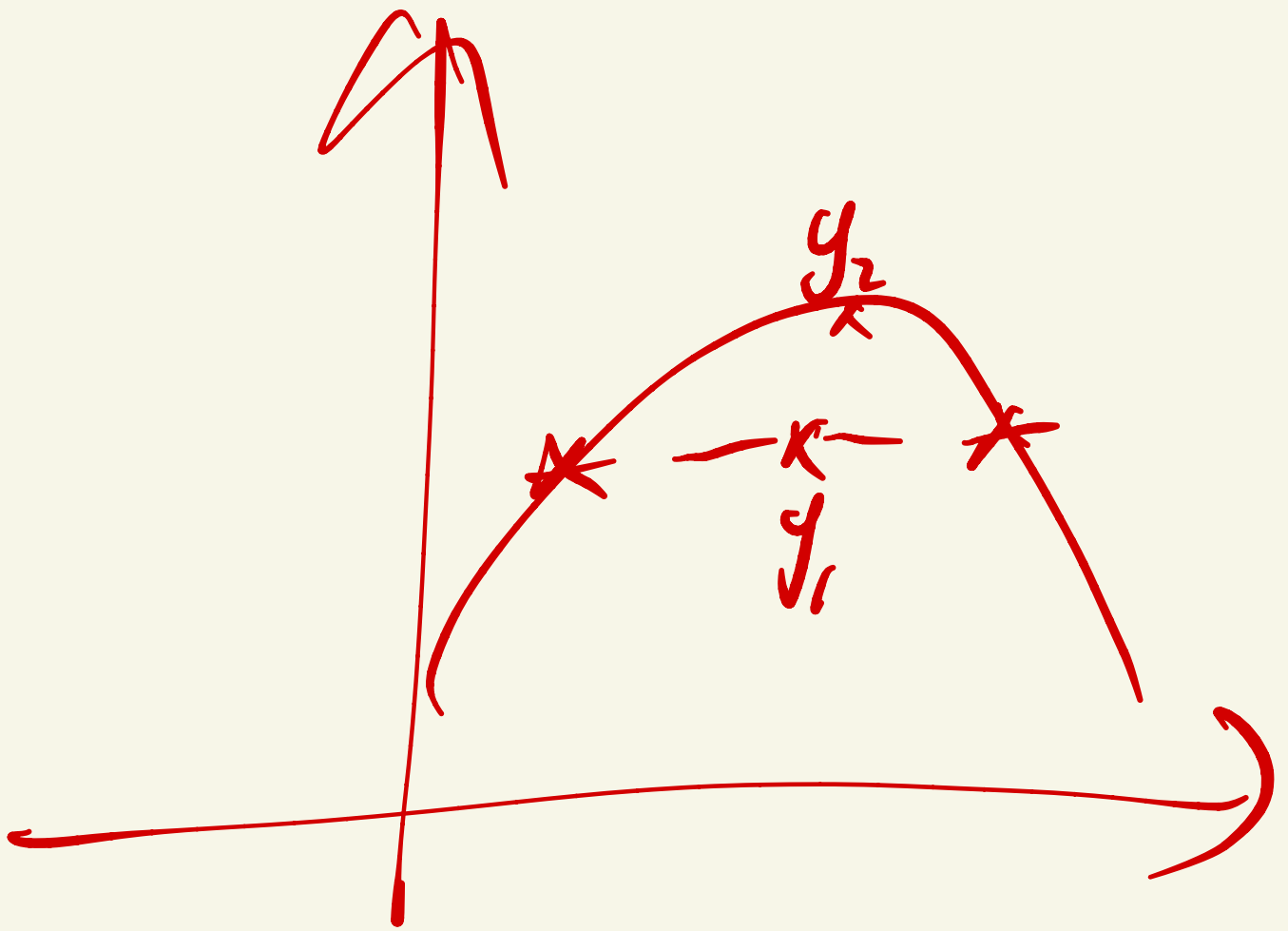


$$\theta_j := \theta_j + \alpha \text{Chosen}(\alpha) \cdot (y - \hat{y})^T \vec{x}_j$$

$$X = \begin{bmatrix} x & \text{data} & x \\ & \vdots & \\ & & x \end{bmatrix}$$



$y_2 > y_1$  convex



$y_2 \geq y_1$ , concave