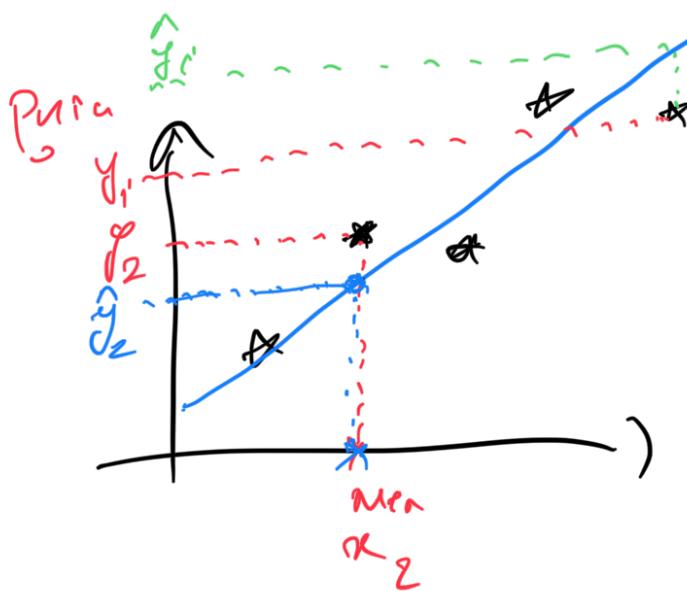
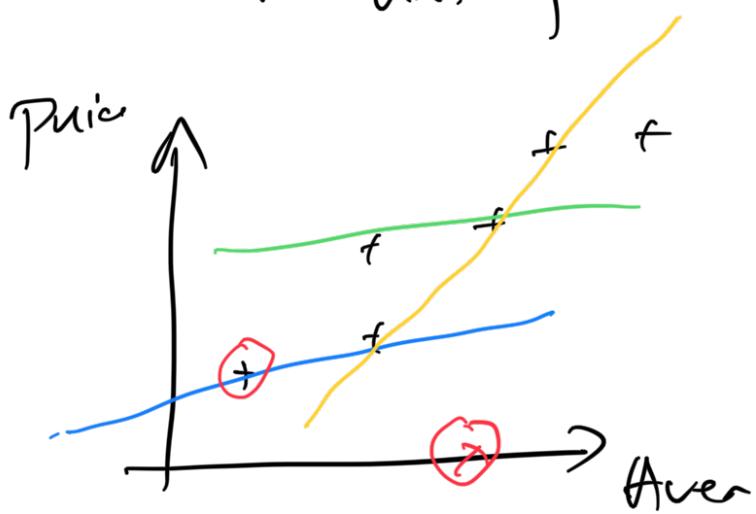


Linear Regression

Avec
 x_i |
Price
 y_i
n data points



$$Q_i = (y_i - \hat{y}_i)^2$$



$$\mathcal{L} = \sum_{i=1} (y_i - (\underline{\hat{y}}_i))$$

$\hat{y} = mx + b$

param

 $\theta = \begin{bmatrix} b \\ m \end{bmatrix}$

$$\mathcal{L}(\theta) = \frac{1}{n} \sum_{i=1}^n \left[(y_i - (\underline{mx_i + b})) \right]$$

m, b

$$f(u)$$

$$f'(u) = 0$$

$$\frac{\partial \mathcal{L}}{\partial m} = 0$$

m^*

$$\frac{\partial \mathcal{L}}{\partial b} = 0$$

b^*

$$h(u) = f(g(u))$$

$$f: u \mapsto u^2$$

$$g: u \mapsto \exp(u)$$

$$\begin{aligned} h(u) &= (\exp(u))^2 \\ &= \exp(2u) \\ &= 2 \exp(u^2) \end{aligned}$$

$$h(u) = g(u) \cdot f(g(u))$$

$$g(u) = y_i - m u_i - b$$

$$g'(u) = -u_i$$

$$\hat{y}_i = m u_i + b \cdot 1$$

$$1, \dots, m u_i^2 + b \cdot 1$$

$$\star \hat{y}_i = m_1 u_i + \dots + b$$

$$\hat{y} = \begin{bmatrix} \hat{y}_1 \\ \vdots \\ \hat{y}_i \\ \vdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} m u_1 + b \cdot 1 \\ \vdots \\ m u_i + b \cdot 1 \\ \vdots \\ m u_n + b \cdot 1 \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} 1 & u_1 \\ \vdots & \vdots \\ 1 & u_n \end{bmatrix}}_{X} \cdot \begin{bmatrix} b \\ m \end{bmatrix} \stackrel{\Theta}{=} \hat{y}$$

$$X \Theta = \hat{y}$$

$$M \cdot M^{-1} = I$$

$$X\theta = \hat{y}$$

X square and invertible

$$\underline{X^{-1}X\theta = X^{-1}\hat{y}}$$

$$I\cdot\theta = X^{-1}\hat{y}$$

$\theta = X^{-1}\hat{y}$

$$X\theta = \hat{y}$$

$X^T X\theta = X^T \hat{y}$

Normal Equations

X size $[n \times m]$ $X^T X$ size $[m \times m]$

X^T size $[m \times n]$

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

$$\theta^* = \begin{bmatrix} s^* \\ m^* \end{bmatrix}$$

$v - \Gamma \begin{pmatrix} 1 \\ n_1 \end{pmatrix}$ House 2

$$\lambda = \sum_i \text{inc}_{\text{House } i}$$

$$\hat{y} = X\theta^*$$

$$X' = \begin{bmatrix} 1 & x_1^1 & \dots & x_n^1 \\ \vdots & \vdots & & \vdots \\ 1 & x_1^k & \dots & x_n^k \end{bmatrix} \quad (n, k+1)$$

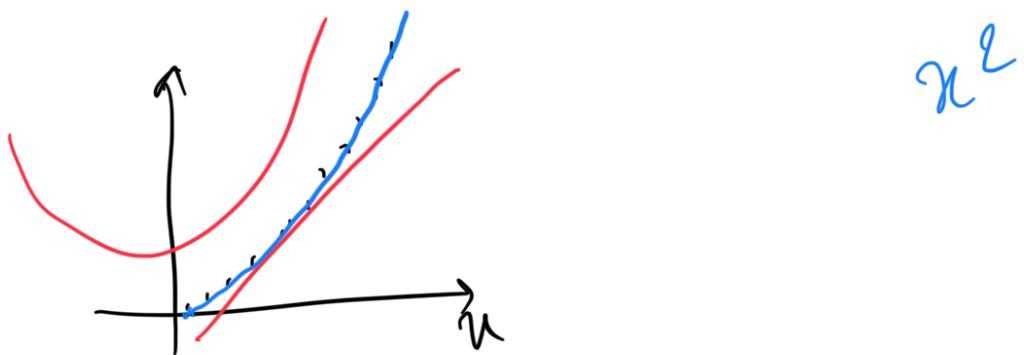
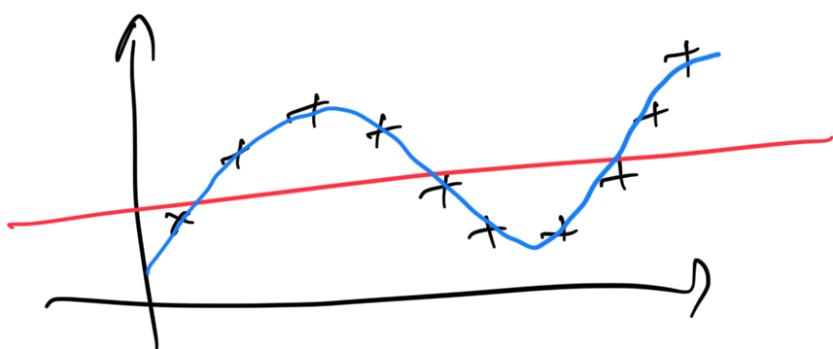
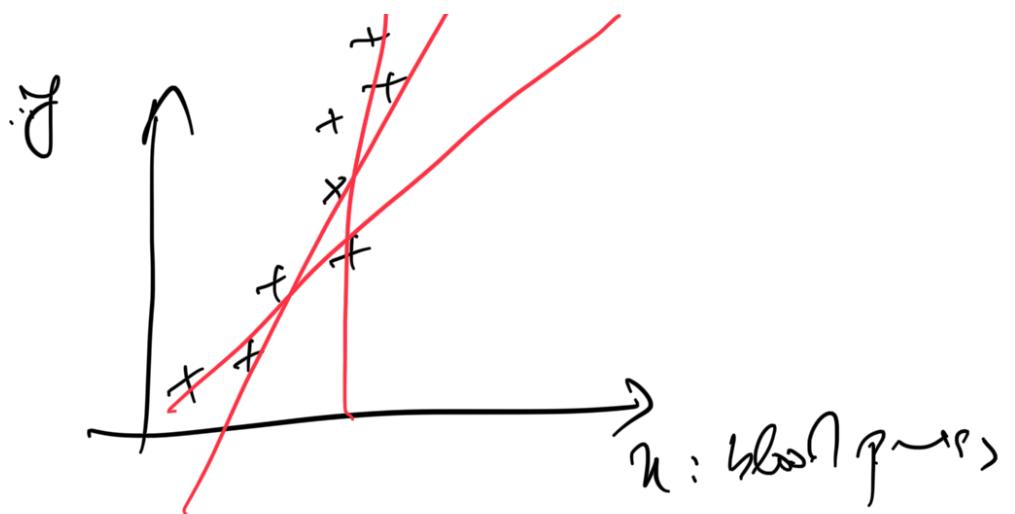
$$\theta = \begin{bmatrix} b \\ w_1 \\ \vdots \\ w_k \end{bmatrix} \rightsquigarrow \theta' = \begin{bmatrix} w_0 \\ \vdots \\ w_k \end{bmatrix} \quad k+1$$

$$X'\theta' = \hat{y}$$

$$X'^T X' \theta' = X'^T \hat{y}$$

$$\theta'^* = (X'^T X')^{-1} X'^T \hat{y}$$

Non Linear Problem



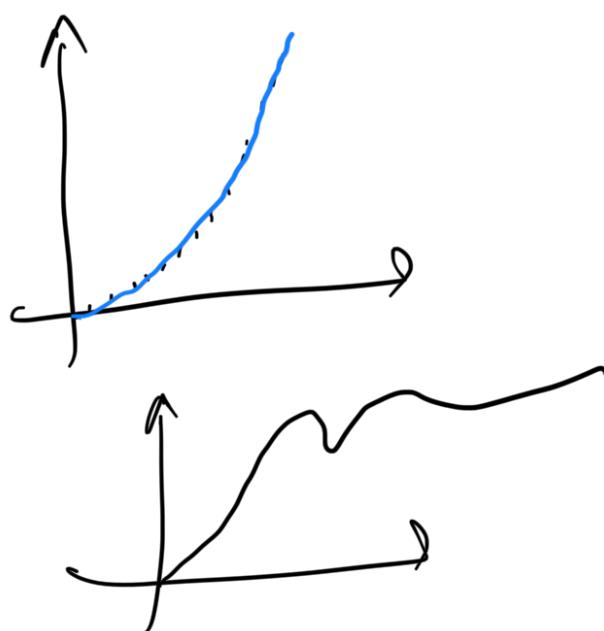
$$\hat{y} = m u + b$$

$$\hat{y} = \underline{m} u^2 + \underline{b}$$

$$1, u, u^2, \dots, u^n$$

n^0 n^+ 

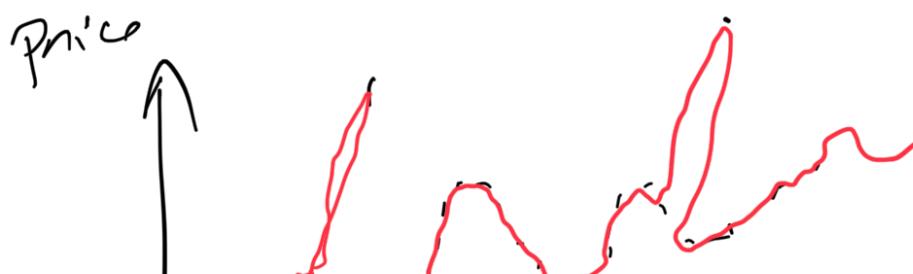
$$y = \omega_2 n^2$$

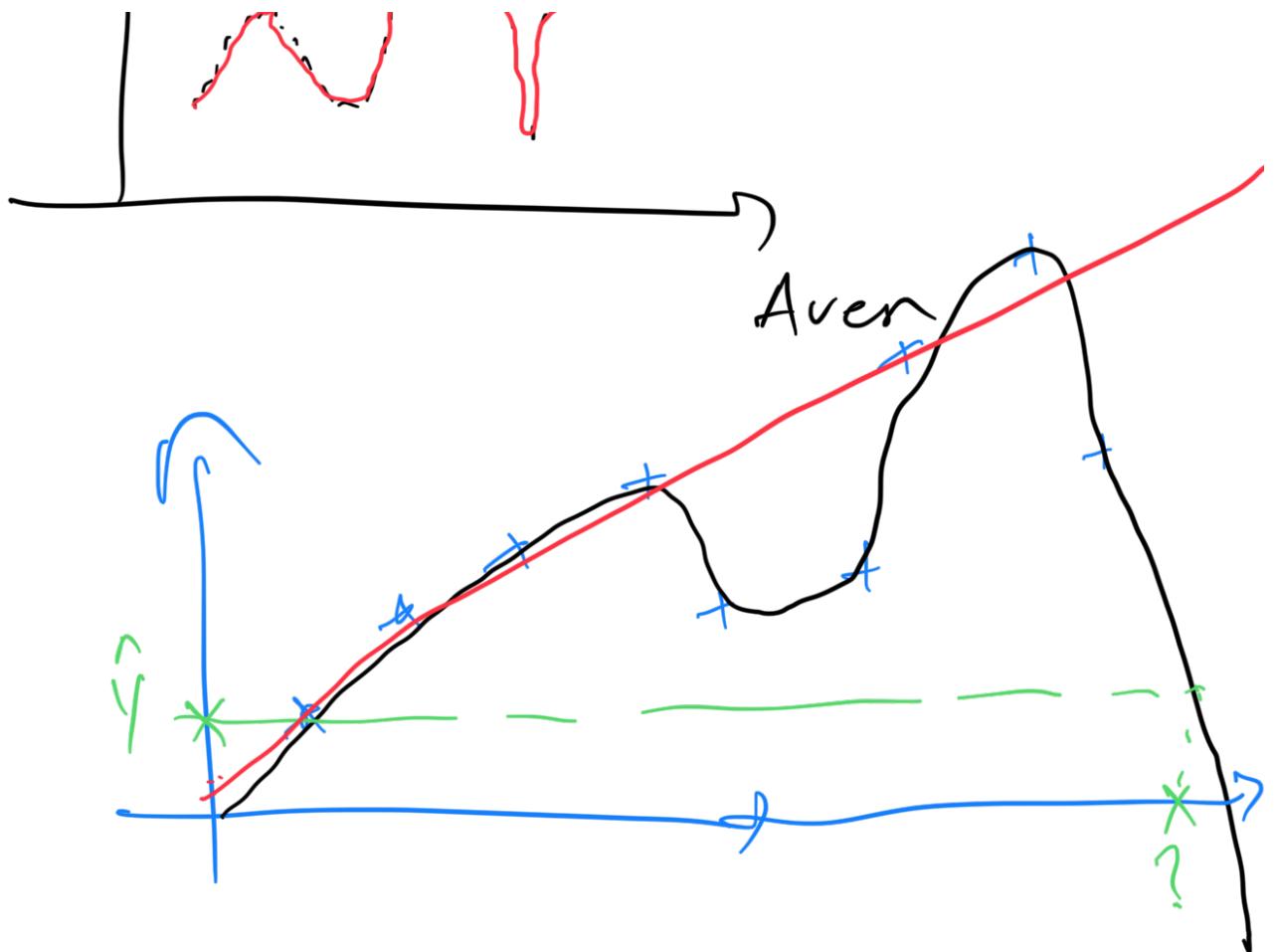


$$X = \begin{bmatrix} 1 & n_1^1 & \dots & n_1^k \\ \vdots & \vdots & & \vdots \\ 2 & n_n^1 & \dots & n_n^k \end{bmatrix}$$

↑
Aven
↑
place

$$X^* = \begin{bmatrix} 1 & n_1^1 & (n_1^1)^2 & (n_1^1)^3 & \dots \\ \vdots & \vdots & & \vdots & \dots \\ n & \vdots & & \vdots & \dots \end{bmatrix}$$





Overfitting :

Very good on training data
Very bad on validation data
unseen

Underfitting.

Bad even on the training.