

FoDA

L12

Multiple **Linear**  
**Regression**  
& Polynomial Regression

Input data  $(X, y) = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$   
 $x_i \in \mathbb{R}^d$   $y_i \in \mathbb{R}$

Ex  $x_2 = (3, 2, 5, 6) \in \mathbb{R}^4$   $y_2 = -3$

linear model

$x_i \in \mathbb{R}^d$

$x_i = (x_{i1}, x_{i2}, \dots, x_{id})$   
 dependent var

$$\hat{y}_i = M_{\alpha}(x_i) = \alpha_0 + x_{i1} \alpha_1 + x_{i2} \alpha_2 + \dots + x_{id} \alpha_d$$

$$\alpha = (\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_d) \in \mathbb{R}^{d+1}$$

$$= \alpha_0 \mathbf{1} + \sum_{j=1}^d x_{ij} \alpha_j \quad \in \mathbb{R}^{d+1}$$

$$= \langle \alpha, (1, x_{i1}, x_{i2}, \dots, x_{id}) \rangle = \langle \alpha, (1, x_i) \rangle$$

Data  $(X, y)$  Model  $M_\alpha$   $\alpha \in \mathbb{R}^{d+1}$   
 $X \in \mathbb{R}^d$   $y \in \mathbb{R}$

residual

Error  $SSE(X, y, M_\alpha) = \sum_{i=1}^n r_i^2 = \sum_{i=1}^n (y_i - M_\alpha(x_i))^2$

$X \in \mathbb{R}^{n \times d}$

$X = \begin{bmatrix} 2 & 4 & 3 \\ 1 & 7 & 6 \end{bmatrix} \in \mathbb{R}^{2 \times 3}$

$d=1$   
 $\alpha = \frac{\langle \vec{x}, \vec{v} \rangle}{\|\vec{x}\|}$

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

$\vec{X} = \begin{bmatrix} 1 & 2 & 4 & 3 \\ 1 & 1 & 7 & 6 \end{bmatrix} \in \mathbb{R}^{2 \times 4}$

all 1s column

$\vec{X} = [\mathbf{1}; X_1, X_2, \dots, X_d]$

$X_j = \begin{bmatrix} x_{1j} \\ x_{2j} \\ \vdots \\ x_{nj} \end{bmatrix}$

jth column

optimal SSE soln  $\alpha^* = (\vec{X}^T \vec{X})^{-1} \vec{X}^T y$

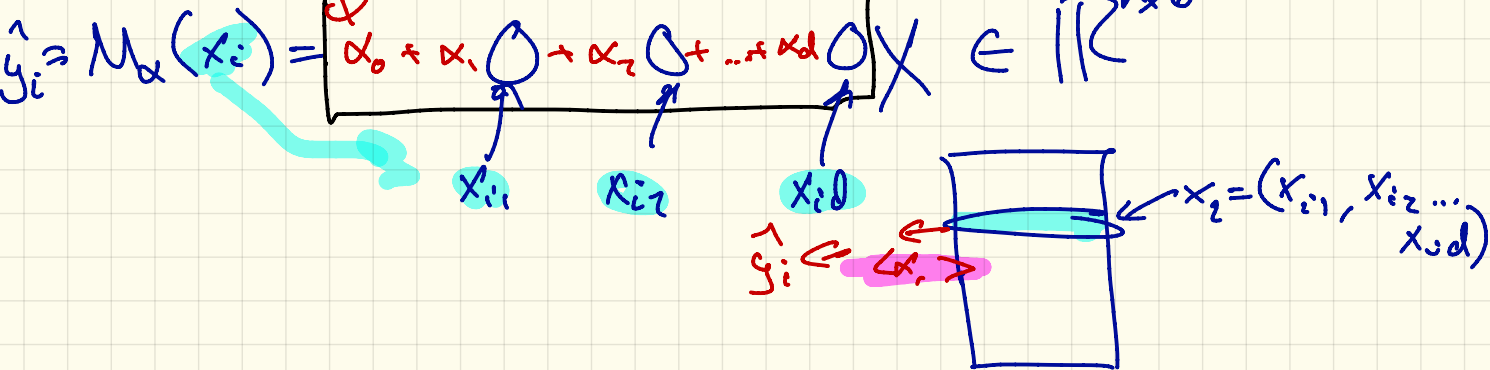
$\hat{X}$  is  $M_x$  (linear model)  
?

---

input to linear model

to make a prediction

Model  $f$  is one row  $x_i \in \mathbb{R}^d$



# website tracking customers

$n = 11$  customers

track  $\Rightarrow$  explanatory variables  
 $X \in \mathbb{R}^{n \times d} = \mathbb{R}^{11 \times 3}$   
 1. time on site (sec)  
 2. jiggle (cm)  
 3. scroll (cm)

track  $\downarrow$   
 dependent var  
 sales in cents

time:  $X_1$  jiggle:  $X_2$  scroll:  $X_3$  sales:  $y$

232	33	402	2201
10	22	160	0
6437	343	231	7650
512	101	17	5599
441	212	55	8900
453	53	99	1742
2	2	10	0
332	79	154	1215
182	20	89	699
123	223	12	2101
424	32	15	8789

customer  $\leftarrow$   
 $= y \in \mathbb{R}^n$

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

$\alpha_0 = 2626$   $\leftarrow$  come on site

$\alpha_1 = 0.42$  (time on site)

$\alpha_2 = 17.72$  (jiggle cm)

$\alpha_3 = -6.50$  (scroll cm)

# Polynomial Regression

Input  $(X, y)$   $X \in \mathbb{R}^{n \times d}$   $y \in \mathbb{R}^n$  *(assome d=1)*

---

poly-degree-2 (quadratic) model

$$\hat{y} = M_x^{(2)}(x) = \alpha_0 + \alpha_1 x + \alpha_2 x^2$$

$$M_x^{(2)}: \mathbb{R} \rightarrow \mathbb{R}$$

---

$$\hat{y} = M_x^{(p)}(x) = \alpha_0 + \alpha_1 x + \dots + \alpha_p x^p$$

$$= \alpha_0 + \sum_{j=1}^p \alpha_j x^j = \sum_{j=0}^p \alpha_j x^j$$

$$= \left\langle \alpha, (1, x, x^2, \dots, x^p) \right\rangle \quad \alpha \in \mathbb{R}^{p+1} \quad (1, x, x^2, \dots, x^p) \in \mathbb{R}^{p+1}$$

Residual for  $(x_i, y_i)$  as

$$r_i = \hat{y}_i - y_i = M_{\alpha}^{(p)}(x_i) - y_i$$

$$SSE((x, y), M_{\alpha}^{(p)}) = \sum_{i=1}^n r_i^2 = \sum_{i=1}^n (M_{\alpha}^{(p)}(x_i) - y_i)^2$$

input

$$= \sum_{i=1}^n \left( \langle \alpha, (1, x, x^2, \dots, x^p) \rangle - y_i \right)^2$$

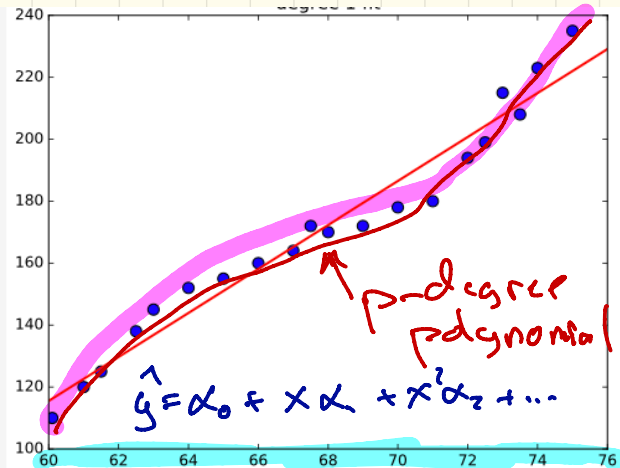
$$x \in \mathbb{R}^1$$

$$X_P = \begin{bmatrix} \vdots & x_1 & x_1^2 & \dots & x_1^p \\ \vdots & x_2 & x_2^2 & \dots & x_2^p \\ \vdots & \vdots & \vdots & \dots & \vdots \\ \vdots & x_n & x_n^2 & \dots & x_n^p \end{bmatrix}$$

$$X^2 = (1, x, x^2, \dots, x^p) \in \mathbb{R}^{p+1}$$

$$\alpha_{(p)}^* = (X_P^T X_P)^{-1} X_P^T y$$

$x$ height (in)	$y$ weight (lbs)	$x$ height (in)	$y$ weight (lbs)
66	160	61.5	125
68	170	73.5	208
60	110	62.5	138
70	178	63	145
65	155	64	152
61	120	71	180
74	223	69	172
73	215	72.5	199
75	235	72	194
67	164	67.5	172





$$X = \begin{bmatrix} 2 \\ 3 \\ 4 \end{bmatrix} \in \mathbb{R}^{n=3}$$

$$y = \begin{bmatrix} 1 \\ 6 \\ 5 \end{bmatrix}$$

$$p=5$$

$$X_p = \begin{bmatrix} 1 & 2 & 4 & 8 & 16 & 32 \\ 1 & 4 & 16 & 64 & 256 & 1024 \\ 1 & 3 & 9 & 27 & 81 & 243 \end{bmatrix}$$

$\alpha_0 \quad \alpha_1 \quad \alpha_2 \quad \alpha_3 \quad \alpha_4 \quad \alpha_5$

$\Rightarrow 151$