

Chapter 3:

Linear Regression

Linear regression in classical statistics

Linear regression in machine learning

- Given a dataset:

$$\{(\mathbf{x}^{(i)}, y^{(i)}) \mid i=1^n\}$$

Of n data points.

- Vector \mathbf{x} represents the input features.
- Dimension of \mathbf{x} denotes number of input features. We call this d .
- Scalar y represents the output.

- We propose a hypothesis h parameterized by θ in the form:

$$h_{\theta}(x) = \sum_{i=0}^d \theta_i x_i = \theta^T \mathbf{x}$$

- Where we define $x_0 = 1$ for all data points.
- Thus $\theta \in \mathbb{R}^{n+1}$

Linear regression in machine learning

- To assess how “good” the prediction is, we define the **cost function** as:

$$L(\theta) = (\hat{\mathbf{y}} - \mathbf{y})^2 = \frac{1}{2} \sum_{i=1}^n (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

- We need to choose θ so as to minimize $L(\theta)$
- For this we use an optimization algorithm called **Gradient Descent**. Which is defined as:

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} L(\theta)$$

- Where α is the **learning rate**. And θ gets updated in each step.

Linear regression in machine learning

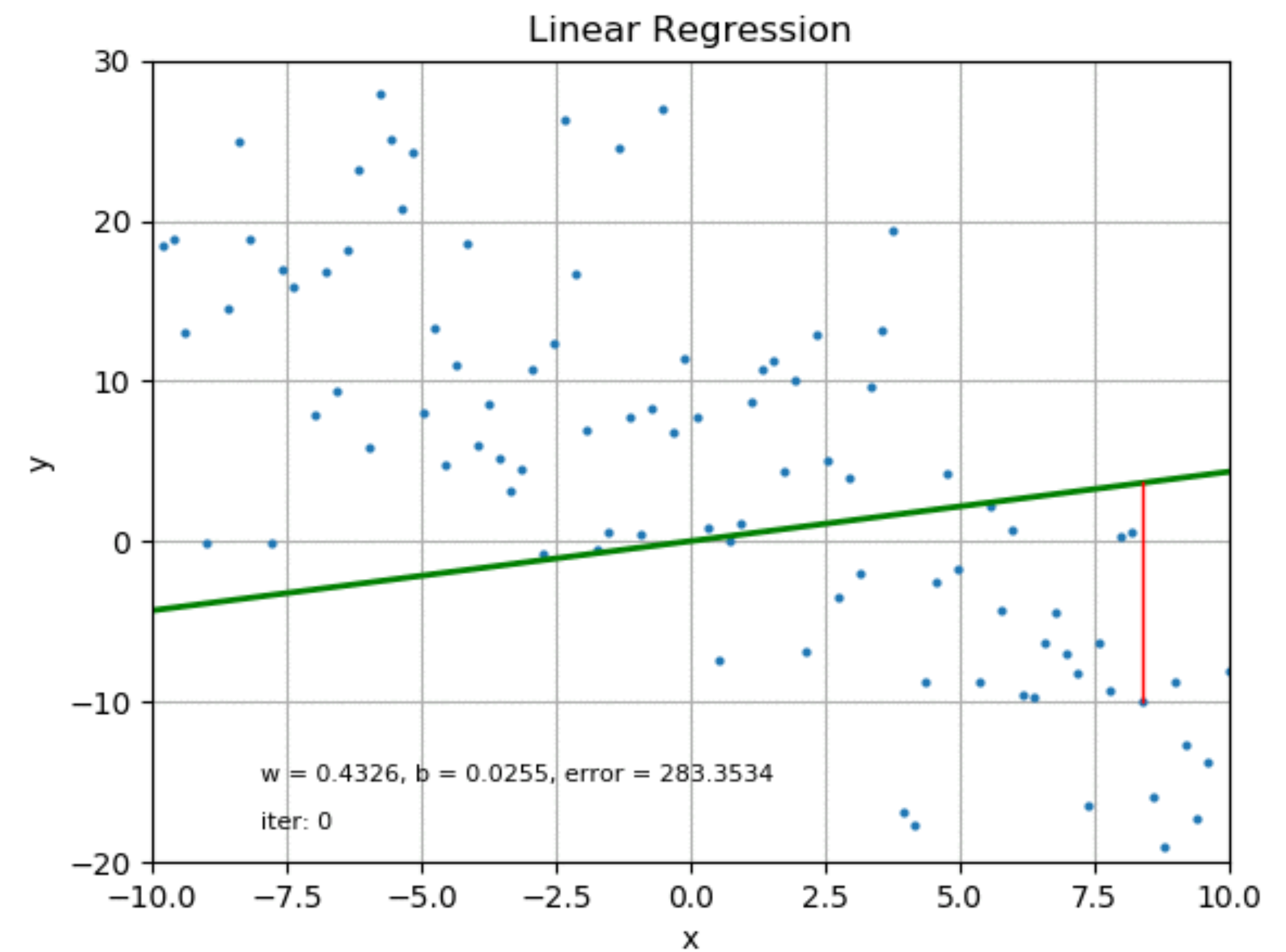
$$\begin{aligned}\frac{\partial}{\partial \theta_j} L(\theta) &= \frac{\partial}{\partial \theta_j} \frac{1}{2} (h_{\theta}(x) - y)^2 \\ &= \frac{1}{2} \cdot 2(h_{\theta}(x) - y) \cdot \frac{\partial}{\partial \theta_j} (h_{\theta}(x) - y) \\ &= (h_{\theta}(x) - y) \cdot \frac{\partial}{\partial \theta_j} \left(\sum_{j=1}^n \theta_j x_j - y \right) \\ &= (h_{\theta}(x) - y) x_j\end{aligned}$$

- Thus:

$$\theta_j := \theta_j + \alpha \sum_{i=1}^n (y^{(i)} - h_{\theta}(x^{(i)})) x_j^{(i)}$$

Linear regression in machine learning

$$\theta_j := \theta_j + \alpha \sum_{i=1}^n (y^{(i)} - h_{\theta}(x^{(i)}))x_j^{(i)}$$



learning supervised IR

هوش مصنوعی
رگرسیون خطی

	x_0	x_1	x_2	y
1	1	75	2	4.5
1	1	123	3	11.5
1	1	40	1	2.5
1	1	230	4	17

feature target

$$\{ (x, y), i \in [1, n] \}$$

$[x_1, x_2]$ $[y]$

$$\begin{bmatrix} 1 & 415 & 8 \end{bmatrix} \rightarrow \boxed{}$$

learning

① فرض فناکار

② معیار ای فقد بدون
عملکرد بیش بیشی

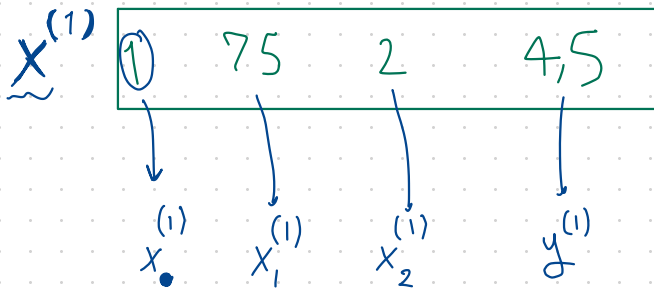
③ عملکرد بیش بیشی

Loss کمینه کرن
gradient descent

$$\begin{aligned} h_{\theta} &= \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 \\ &= [\theta_0, \theta_1, \theta_2] \cdot [x_0, x_1, x_2] \\ &= \theta^T x \end{aligned}$$

بگذار θ دو مربع بر = مربع اول

$$\begin{aligned} \theta &= [\theta_0, \theta_1, \theta_2] \\ &= [7, 1.5, 3] \end{aligned}$$



$$\theta = [7 \quad 1,5 \quad 3]$$

so:

$$\theta^T x = \begin{bmatrix} 7 \\ 1,5 \\ 3 \end{bmatrix} \begin{bmatrix} 1 & 75 & 2 \end{bmatrix} =$$

$$7 \times 1 + 1,5 \times 75 + 3 \times 2$$

$$y^{(1)} = 4,5$$

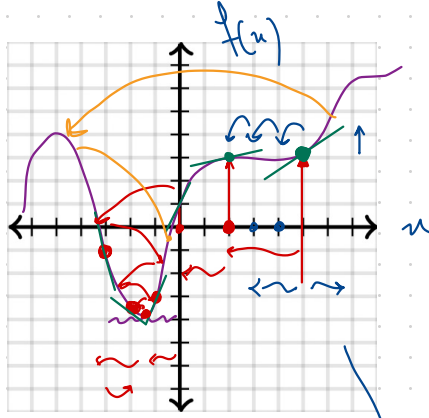
$$\hat{y}^{(1)} = \boxed{1462,5}$$

$$\downarrow \mathcal{L}(\theta) = \sum_{i=1}^n \frac{1}{2} (\hat{y}^{(i)} - y^{(i)})^2$$

loss function

Optimization

↳ gradient descent



$$h_{\theta} = \theta^T x = \hat{y}$$

$$L(\theta) = \sum_{i=1}^n \frac{1}{2} (\hat{y}^{(i)} - y^{(i)})^2$$

pair θ do

$$\theta_{t+1} = \theta_t - \alpha \frac{\partial L}{\partial \theta} \quad \text{learning rate}$$

$$\theta_{t+1} = \theta_t - \alpha \nabla L$$

$$(\theta^T x - y) x$$

$$\begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_j \end{bmatrix} = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_j \end{bmatrix} - \alpha \frac{\partial L}{\partial \theta_j}$$

$$\frac{\partial L}{\partial \theta_j} = \frac{\partial}{\partial \theta_j} \sum_{i=1}^n \frac{1}{2} (\hat{y}^{(i)} - y^{(i)})^2$$

$$= \frac{\partial}{\partial \theta_j} \sum_{i=1}^n \frac{1}{2} (\theta^T x^{(i)} - y^{(i)})^2$$

ملاحظة: $\frac{\partial}{\partial \theta_j} \left(\frac{1}{2} (\theta^T x - y)^2 \right)$ chain rule

$$= \cancel{\frac{1}{2}} \cdot 2 (\theta^T x - y) \cdot \frac{\partial}{\partial \theta} (\theta^T x - y)$$

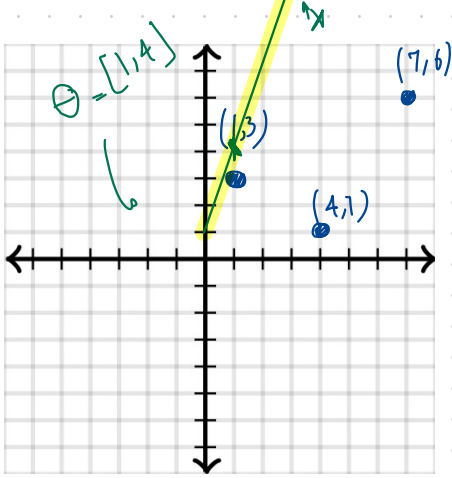
اختصار $= (\theta^T x - y) \cdot \frac{\partial}{\partial \theta} (\theta^T x - y)$

$$\rightarrow (\theta^T x - y) \cdot x$$

$$\frac{\partial}{\partial \theta_0} (\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 - y) = x_0$$

$$\frac{\partial}{\partial \theta_1} (\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 - y) = x_1$$

$$\frac{\partial}{\partial \theta_2} (\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 - y) = x_2$$



x_0	x_1	y	$\theta x_0 + \theta_1 x_1$	
1	1	3	$1 \times 1 + 4 \times 1$	5
1	4	1	$1 \times 1 + 4 \times 4$	17
1	7	6	$1 \times 1 + 4 \times 7$	29

$$h_{\theta} = \hat{y} = \theta^T x$$

θ for

$$\theta = [e., \theta_1]$$

$$\theta = [1, 4]$$

$$L_{\theta} = \sum \frac{1}{2} (\hat{y} - y)^2$$

$$L \quad (37.5) =$$

=

=

$$\begin{aligned} & \frac{1}{2} (5-3)^2 \\ & + \frac{1}{2} (17-1)^2 \\ & + \frac{1}{2} (29-6)^2 \end{aligned}$$

x_0	x_1	y	$\theta x_0 + \theta_1 x_1$	
1	1	3	$1 \times 1 + 4 \times 1$	5
1	4	1	$1 \times 1 + 4 \times 4$	17
1	7	6	$1 \times 1 + 4 \times 7$	29

x_0	x_1	y	\hat{y}	$(\hat{y} - y)$	$(\hat{y} - y)x_0$	$(\hat{y} - y)x_1$
1	1	3	5	2	2	2
1	4	1	17	16	16	64
1	7	6	29	23	23	203
					41	269

$$\theta = [1 \ 4]$$

$$\theta_0 = \theta_0 - \alpha \frac{\partial \mathcal{L}}{\partial \theta_0}$$

$$\theta_1 = \theta_1 - \alpha \frac{\partial \mathcal{L}}{\partial \theta_1}$$

$$\theta_0 = 1 - \alpha 41 =$$

$$\theta_1 = 4 - \alpha 269$$

$$\sum (\hat{y} - y)x_0$$

$$\sum (\hat{y} - y)x_1$$

$$1 - 41 = -59$$

$$4 - 269 = -131$$

$$\alpha = 0.01$$

$$\theta = [59 \quad 1,31]$$

