

8/24/2023

Linear Regression

linear function of input

Predicting a real number

Features x (d total)

target (y)

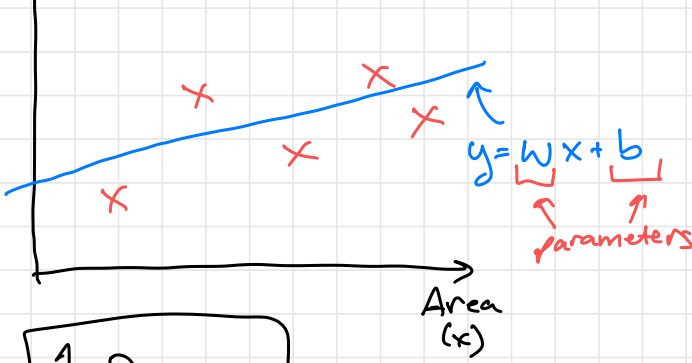
target (y)	Area	#Bedrooms	has garage?	(constant)
\$500K $y^{(1)}$	1200	2	0	1
\$800K	1500	3	1	1
	\vdots			\vdots

$x^{(i)} \in \mathbb{R}^d$

Training dataset $D = \{(x^{(1)}, y^{(1)}), \dots, (x^{(n)}, y^{(n)})\}$

$|D| = n$

Sale price (y)



1-D case

In d dimensions

predicted $y = \sum_{i=1}^d w_i x_i + b$

$= w^T x + b$

$1 \times d \quad d \times 1 = d$

parameters $w \in \mathbb{R}^d, b \in \mathbb{R}$

Q: how do we choose good w & b ?

A: Define a loss function

$L(w, b) = \text{[how bad does } w \& b \text{ fit our observed data]}$

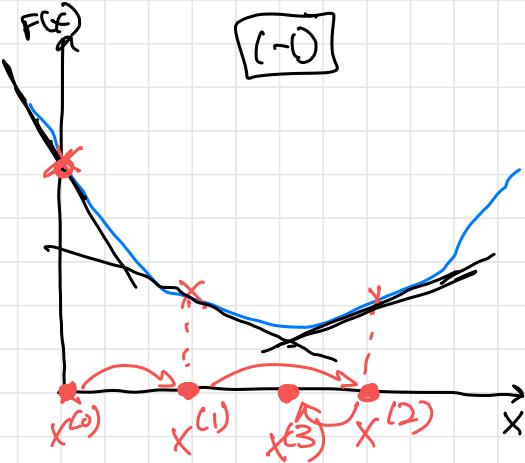
$= \frac{1}{n} \sum_{i=1}^n (\underbrace{w^T x^{(i)} + b}_{\text{model prediction}} - \underbrace{y^{(i)}}_{\text{true output}})^2$

Goal: minimize $L(w, b)$ with respect to w & b

Optimization Problem

Gradient Descent

Function F from $\mathbb{R}^d \rightarrow \mathbb{R}$, differentiable
Goal: minimize F



d-dimensional

How should $x_i^{(t)}$ change?

Same except we use $\frac{\partial F}{\partial x_i}$ "partial derivative"

New rule:
If $\frac{\partial F}{\partial x_i} |_{x^{(t)}} < 0$, increase $x_i^{(t)}$
If $\frac{\partial F}{\partial x_i} |_{x^{(t)}} > 0$, decrease $x_i^{(t)}$

Have a current guess $x^{(t)}$

If $F'(x^{(t)}) < 0$, increase $x^{(t)}$ to get $x^{(t+1)}$

If $F'(x^{(t)}) > 0$, decrease $x^{(t)}$ to get $x^{(t+1)}$

"=0", Stop

$$\text{Gradient } \nabla_x F(x) = \left[\frac{\partial F}{\partial x_1}, \frac{\partial F}{\partial x_2}, \dots, \frac{\partial F}{\partial x_d} \right]$$

Starting at $x^{(t)}$, we should step in direction of the negative gradient

Bonus justification (see notes):

Negative gradient is direction of steepest descent

Gradient descent algorithm:

$$x^{(0)} \leftarrow [0, \dots, 0] \in \mathbb{R}^d$$

for $t=1, \dots, T$

$$x^{(t)} \leftarrow x^{(t-1)} - \eta \nabla_x F(x^{(t-1)})$$

return $x^{(T)}$

learning rate (e.g. 0.01)

total steps

Back to linear regression

$$\frac{d}{dx} 8x = 8$$

$$L(w) = \frac{1}{n} \sum_{i=1}^n (w^T x^{(i)} - y^{(i)})^2$$

$$\begin{aligned} \nabla_w L(w) &= \frac{1}{n} \sum_{i=1}^n 2 (w^T x^{(i)} - y^{(i)}) \cdot \nabla_w [w^T x^{(i)} - y^{(i)}] \\ &= \frac{1}{n} \sum_{i=1}^n \underbrace{2 (w^T x^{(i)} - y^{(i)})}_{\text{Scalar}} \cdot \underbrace{x^{(i)}}_{\text{Vector}} \end{aligned}$$

G.D. for linear regression

$$w^{(0)} \leftarrow [0, \dots, 0] \in \mathbb{R}^d$$

for $t=1, \dots, T$:

$$w^{(t)} \leftarrow w^{(t-1)} - \eta \cdot \frac{1}{n} \sum_{i=1}^n 2 (w^{(t-1)T} x^{(i)} - y^{(i)}) \cdot x^{(i)}$$

return $w^{(T)}$