

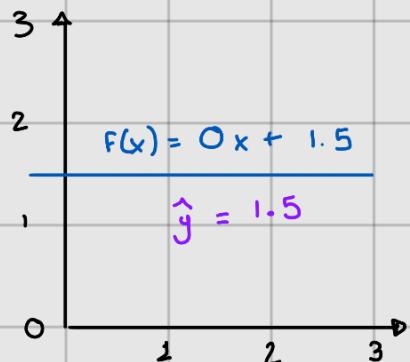
Training set

Features	target + \$
size in feet ² (x)	price \$1000's (y)
2000	400
1000	200
...	...

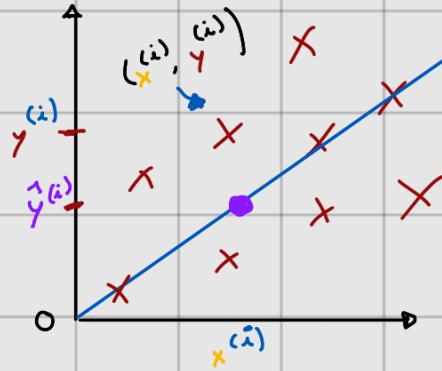
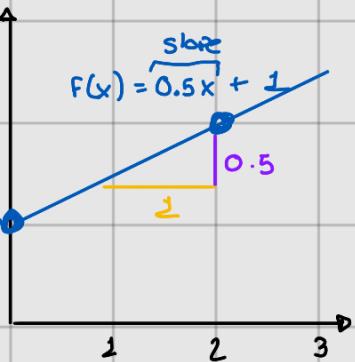
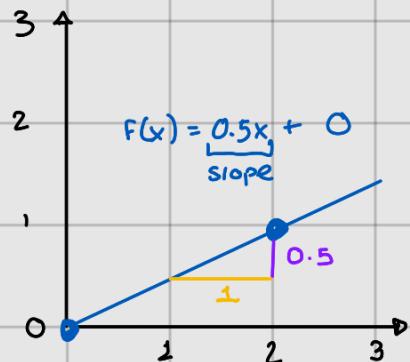
$$\text{model: } f_{w,b}(x) = w x + b$$

w, b : parameters
 • coefficients
 • weights

What do w, b do?



$w = 0$
 $b = 1.5$
 ↪ y -intercept



$$\hat{y}^{(i)} = f_{w,b}(x^{(i)})$$

$$f_{w,b}(x^{(i)}) = w x^{(i)} + b$$

Find w, b

$\hat{y}^{(i)}$ is close to $y^{(i)}$ for all $(x^{(i)}, y^{(i)})$

Cost Function : Squared error cost function

$$J(w, b) = \frac{1}{2m} \sum_{i=1}^m (\hat{y}^{(i)} - y^{(i)})^2$$

Error

m = number of training examples

$$J(w, b) = \frac{1}{2m} \sum_{i=1}^m (f_{w,b}(x^{(i)}) - y^{(i)})^2$$

Cost Function Intuition

model: $f_{w,b}(x) = w x + b$

parameters: w, b

cost function: $J(w, b) = \frac{1}{2m} \sum_{i=1}^m (f_{w,b}(x^{(i)}) - y^{(i)})^2$

goal: We want to minimize $J(w, b)$

Simplified

If we get a $f_w(x) = w x$ $b = 0$

$$J(w) = \frac{1}{2m} \sum_{i=1}^m (w x^{(i)} - y^{(i)})^2$$

minimize w $J(w)$

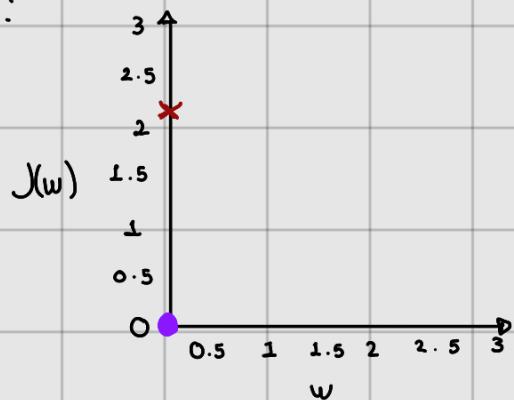
Activity

What is the cost function when w is 0?

$$J(0) = \frac{1}{2(3)} \left[(0(1) - 1)^2 + (0(2) - 2)^2 + (0(3) - 3)^2 \right] =$$

$$\frac{(-1)^2 + (-2)^2 + (-3)^2}{2 + 4 + 9} = \frac{9}{9} = 1$$

$$\frac{1}{2(3)} [14] = \frac{7}{3} = 2.3$$



goal of linear regression: minimize $J(w)$
general case: minimize $J(w, b)$

when the cost is relatively small, it means the model fits the data better compared to other choices for w and b