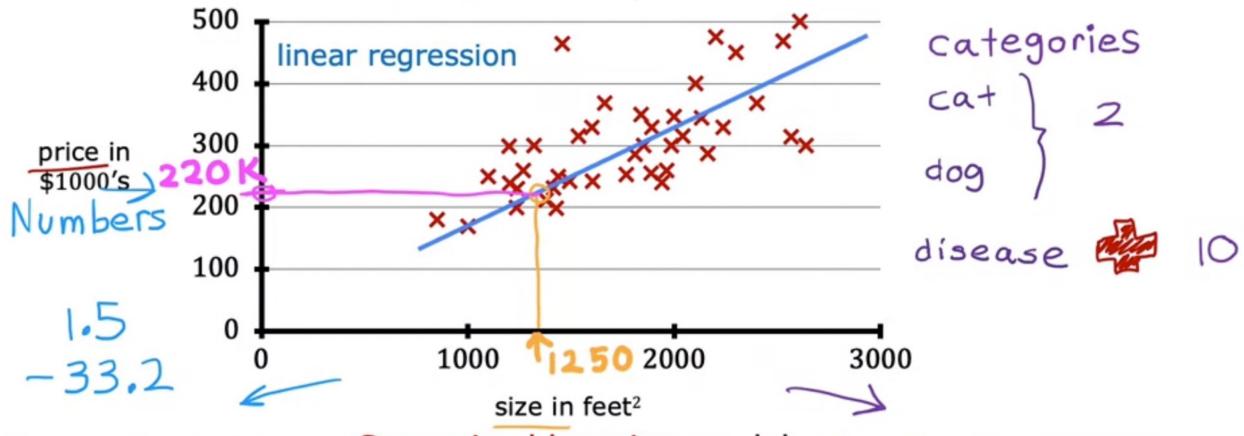
# ML – Regression and Cost Function

draft

#### House sizes and prices

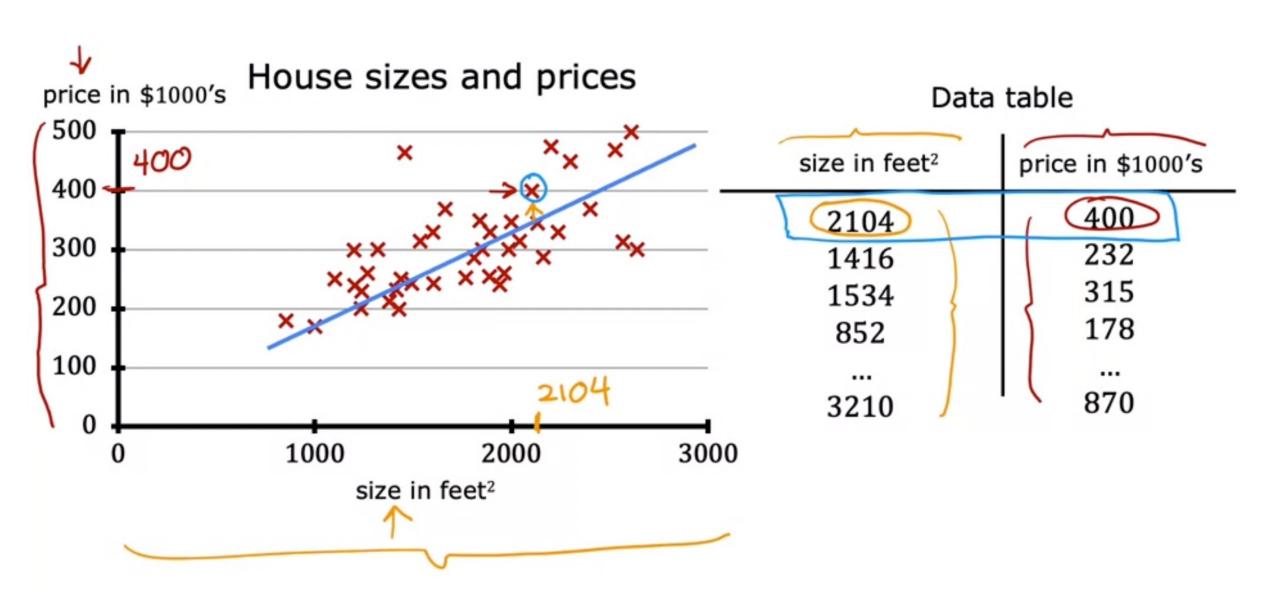


Regression model Predicts numbers Supervised learning model Data has "right answers"

nodel Classification model

ers" Predicts categories

Small number of possible outputs



#### Terminology

Training Data used to train the model set:

315

178

size in feet<sup>2</sup> price in \$1000's

(1) 2104 
$$400$$
(2) 1416  $232$ 

$$(\chi^{(1)}, \gamma^{(1)}) = (2104, 400)$$

$$\chi^{(2)} = 1416$$

$$\chi^{(2)} = 1416$$
  $\chi^{(2)} + \chi^2$  not exponent

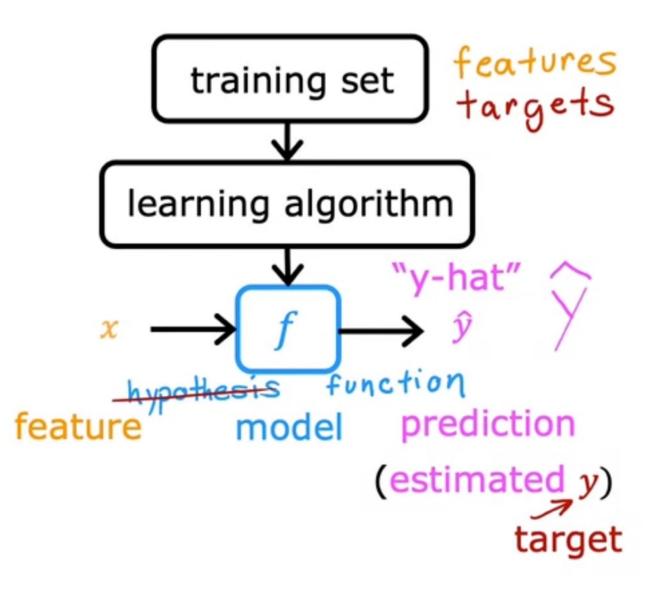
m = 47

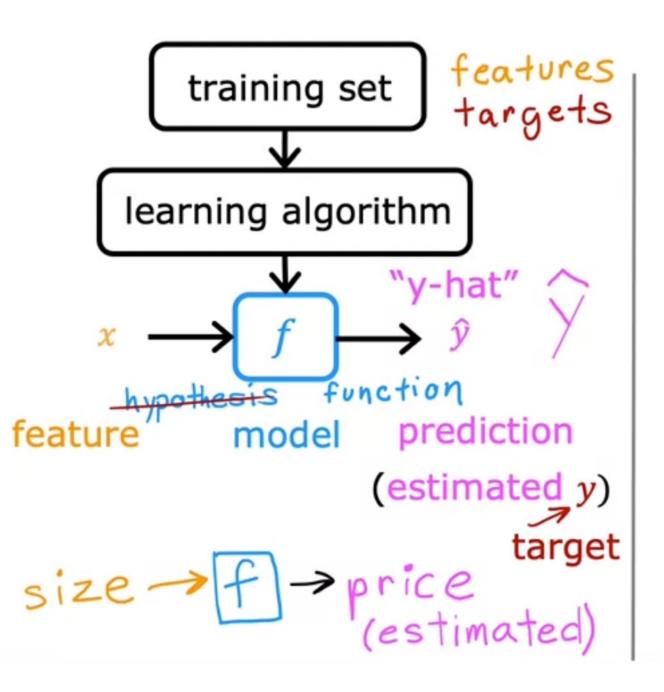
#### Notation:

$$m = number of training examples$$

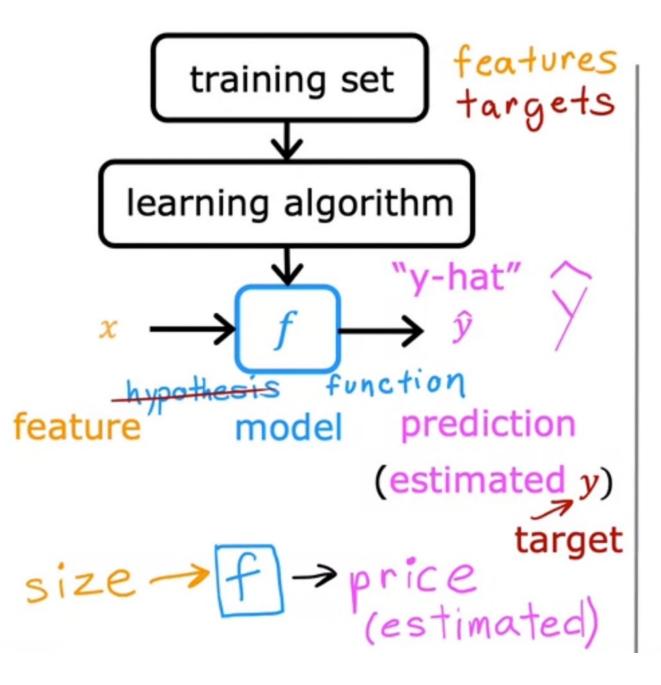
$$(x, y) = \text{single training example}$$

$$(x^{(i)}, y^{(i)})$$
  
 $(x^{(i)}, y^{(i)}) = i^{th}$  training example index  $(1^{st}, 2^{nd}, 3^{rd} ...)$ 





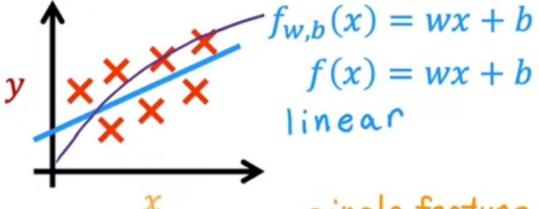
How to represent *f*?



# How to represent f?

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

$$f(x)$$



Linear regression with one variable.

size

Univariate linear regression.

one variable

#### Cost Function

How well the model is doing

#### Training set

| features size in feet $^2(x)$ | targets<br>price \$1000's (y) |
|-------------------------------|-------------------------------|
| 2104                          | 460                           |
| 1416                          | 232                           |
| 1534                          | 315                           |
| 852                           | 178                           |
|                               |                               |

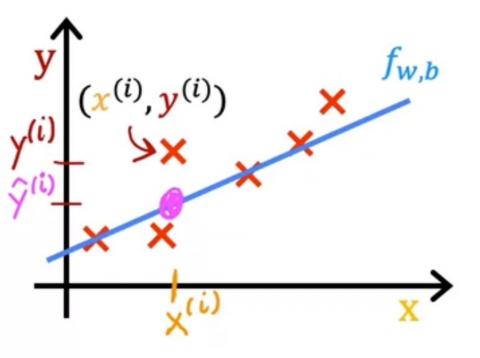
Model:  $f_{w,b}(x) = wx + b$ 

w,b: parameters

coefficients

weights

What do w, b do?



ANS: We use a cost function to measure how close is Type equation here.y-hat to y.

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

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

Find 
$$w, b$$
:  
 $\hat{y}^{(i)}$  is close to  $y^{(i)}$  for all  $(x^{(i)}, y^{(i)})$ .

# $y = \begin{pmatrix} x^{(i)}, y^{(i)} \\ y^{(i)} \\ x \end{pmatrix} \times x$ $x = \begin{pmatrix} x^{(i)}, y^{(i)} \\ x \end{pmatrix} \times x$ $x = \begin{pmatrix} x^{(i)}, y^{(i)} \\ x \end{pmatrix} \times x$

$$\left(\begin{array}{cc} \hat{y}^{(i)} - y^{(i)} \end{array}\right)^2$$

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

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

Find w, b:  $\hat{y}^{(i)}$  is close to  $y^{(i)}$  for all  $(x^{(i)}, y^{(i)})$ .

$$\sum_{i=1}^{m} \left( \hat{y}^{(i)} - y^{(i)} \right)^2$$
error

m = number of training examples

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

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

Find w, b:

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

# $y = \begin{pmatrix} x^{(i)}, y^{(i)} \\ y^{(i)} \\ y^{(i)} \\ x \end{pmatrix}$

#### Cost function

$$\frac{1}{m} \sum_{i=1}^{m} \left( \hat{y}^{(i)} - y^{(i)} \right)^2$$
error

m = number of training examples

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

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

Find w, b:

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

# $y = \begin{cases} x^{(i)}, y^{(i)} \\ y^{(i)} \\ y^{(i)} \\ x \\ x \end{cases}$

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

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

### Cost function: Squared error cost function

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

m = number of training examples

There could be other cost function in different ML Algo, however, this one is the most common one.

Find w, b:  $\hat{y}^{(i)}$  is close to  $y^{(i)}$  for all  $(x^{(i)}, y^{(i)})$ .

# $y = \begin{cases} x^{(i)}, y^{(i)} \\ y^{(i)} \\ x \\ x \end{cases}$

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

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

### Cost function: Squared error cost function

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

m = number of training examples

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

#### Find w, b:

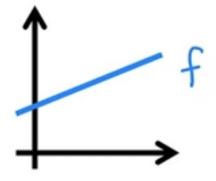
 $\hat{y}^{(i)}$  is close to  $y^{(i)}$  for all  $(x^{(i)}, y^{(i)})$ .

#### model:

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

### parameters:

w, b



#### cost function:

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

## goal:

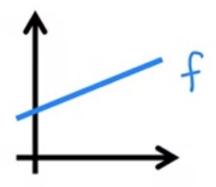
 $\underset{w,b}{\text{minimize}} J(w,b)$ 

#### model:

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

### parameters:

w, b



#### cost function:

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

### goal:

 $\underset{w,b}{\operatorname{minimize}} J(w,b)$ 

# simplified

$$f_w(x) = \underline{wx}$$
  $b = \emptyset$ 

w

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

$$\min_{w} \underline{J(w)}$$

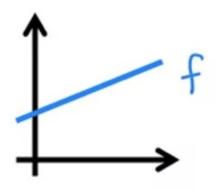
$$w \times^{(i)}$$

#### model:

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

### parameters:

w, b



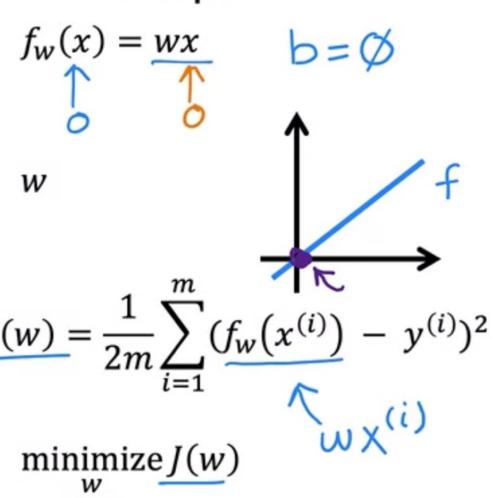
#### cost function:

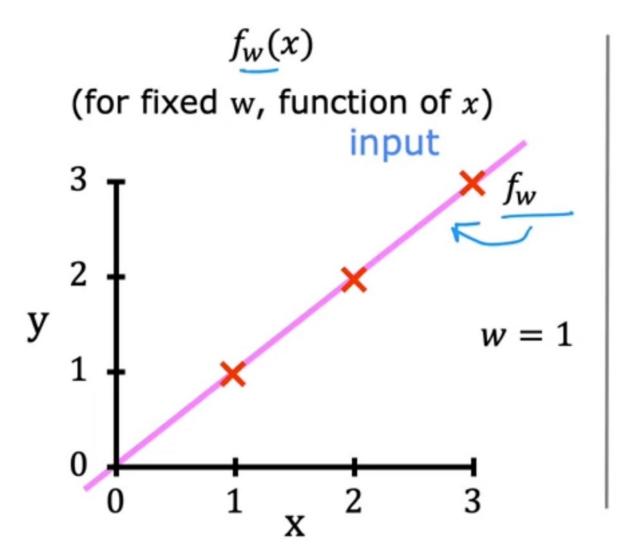
$$J(w,b) = \frac{1}{2m} \sum_{i=1}^{m} (f_{w,b}(x^{(i)}) - y^{(i)})^2$$

# goal:

 $\underset{w,b}{\operatorname{minimize}} J(w,b)$ 

# simplified





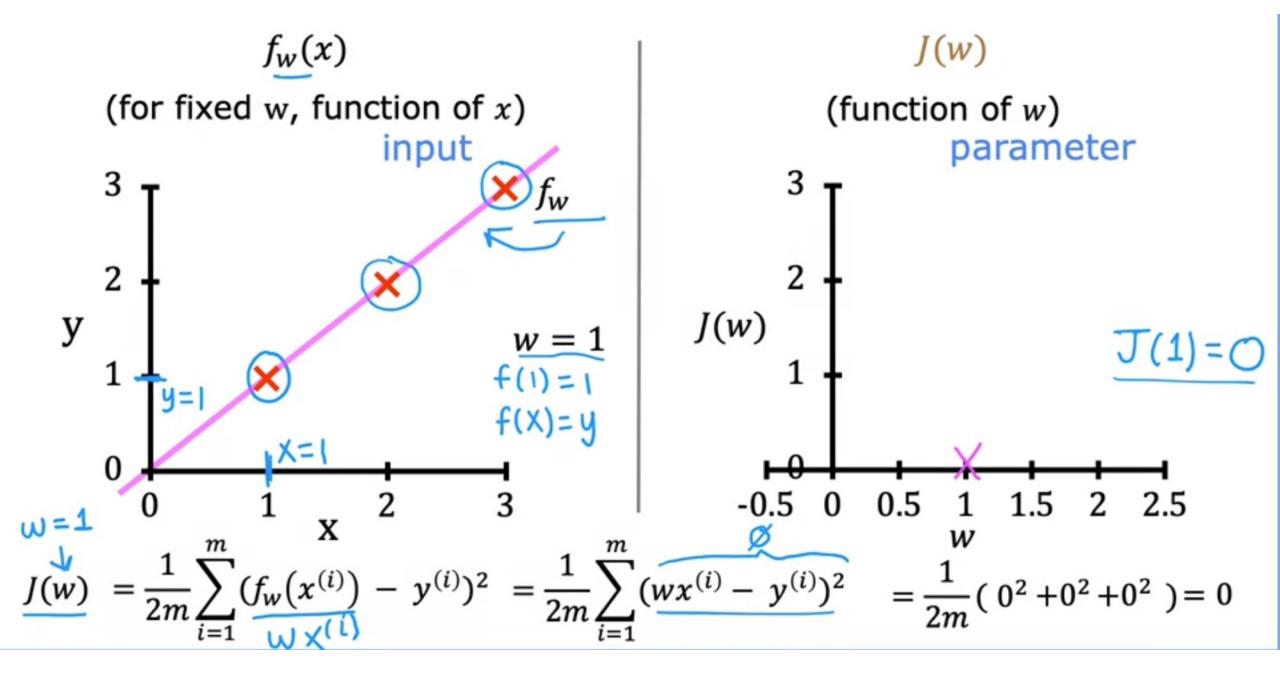
J(w)
(function of w)
parameter

# $f_w(x)$ (for fixed w, function of x) input y= f(X) = y

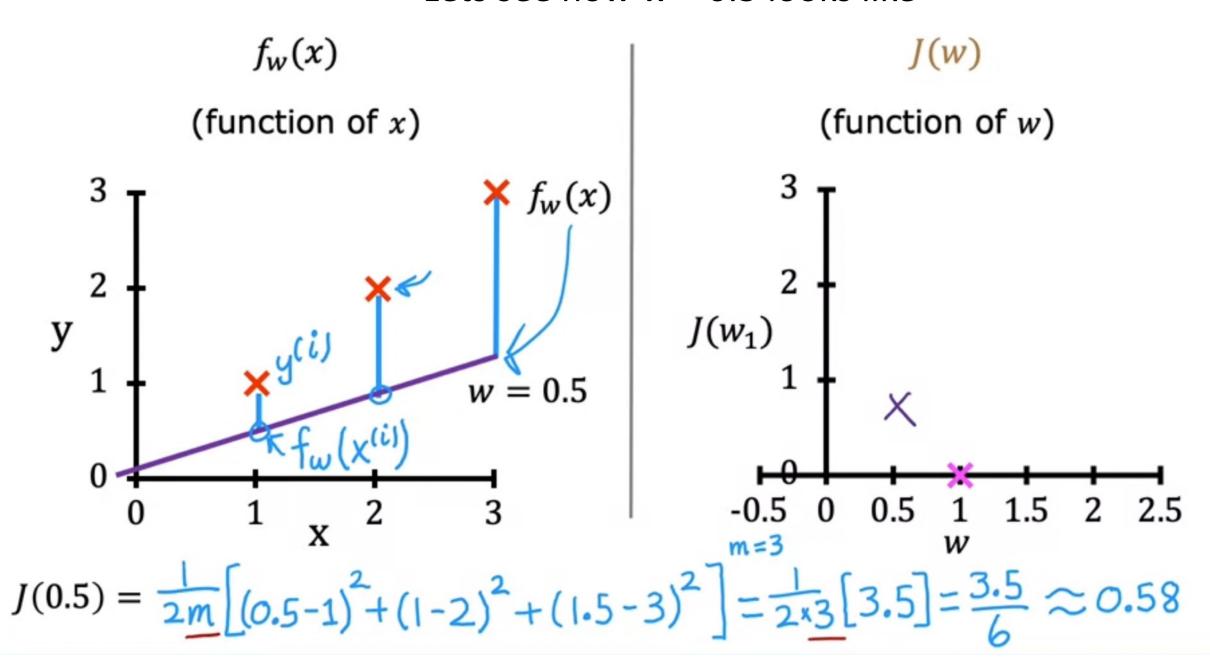
J(w)

(function of w) parameter

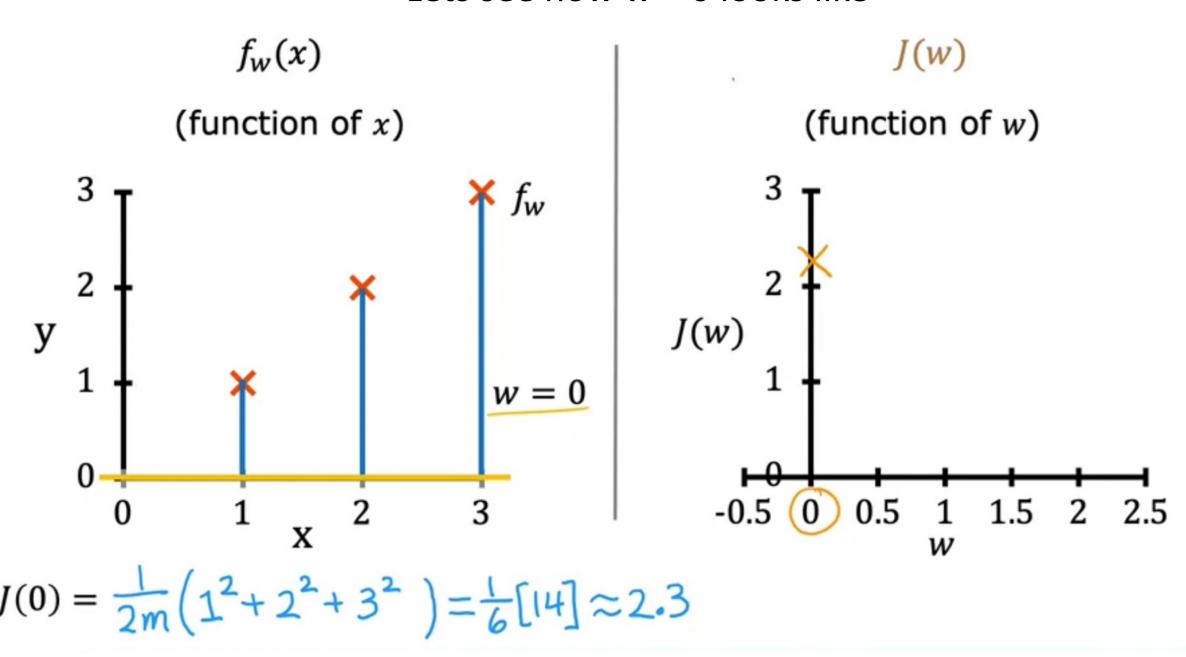
$$(wx^{(i)} - y^{(i)})^2 = \frac{1}{2m}(0^2 + 0^2 + 0^2)$$



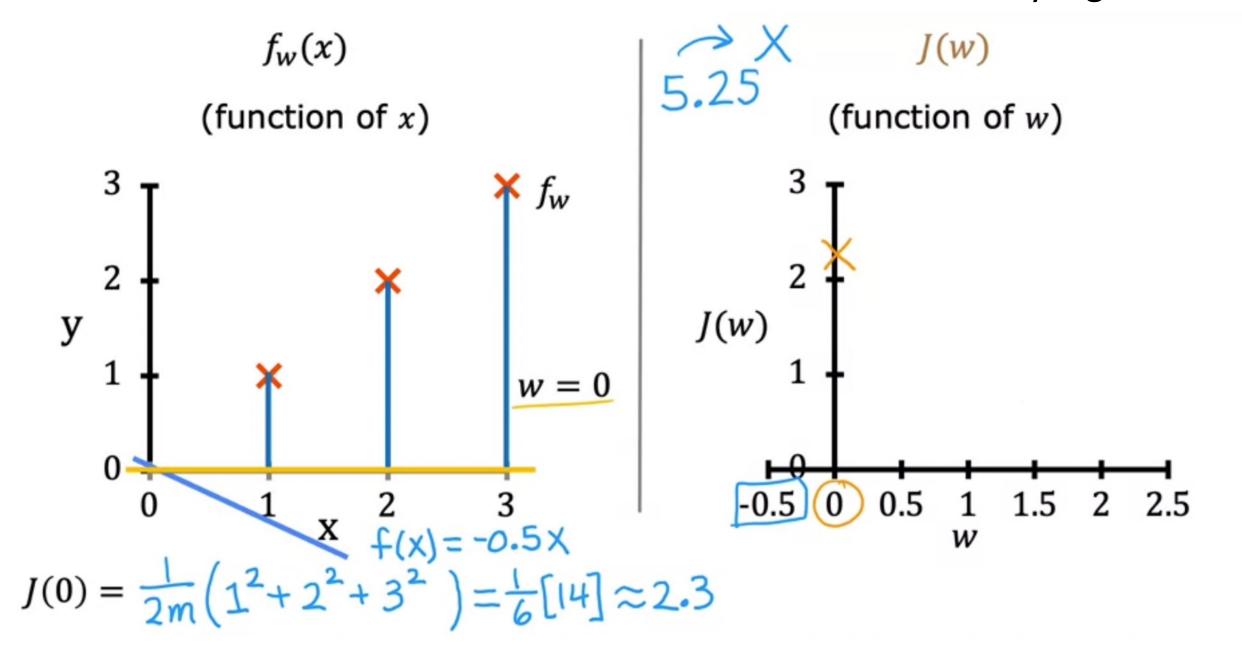
#### Lets see how w = 0.5 looks like



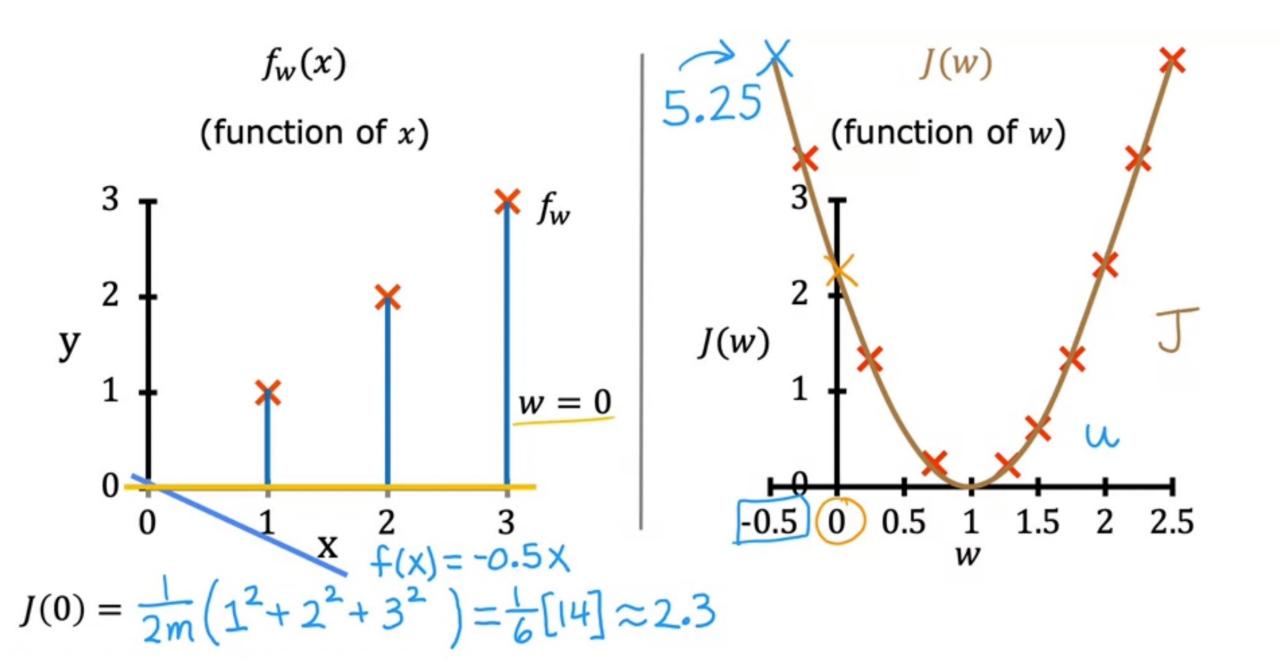
#### Lets see how w = 0 looks like



Lets see how w = -0.5 looks like = very high cost!



We can put different value of w and find the cost function



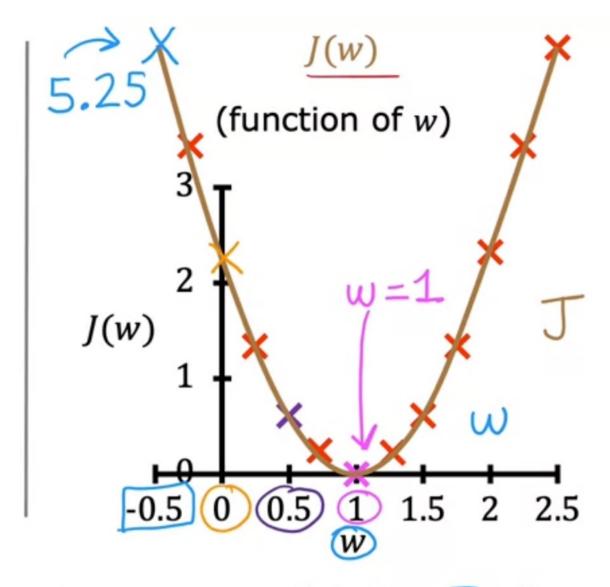
How to choose a w such that it minimizes the cost???

# goal of linear regression:

 $\min_{w} \operatorname{imize} J(w)$ 

### general case:

 $\underset{w,b}{\operatorname{minimize}} J(w,b)$ 



choose w to minimize J(w)