

# Machine Learning Study Notes

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April 24, 2019

This is my personal machine learning study notes for academic purposes only.

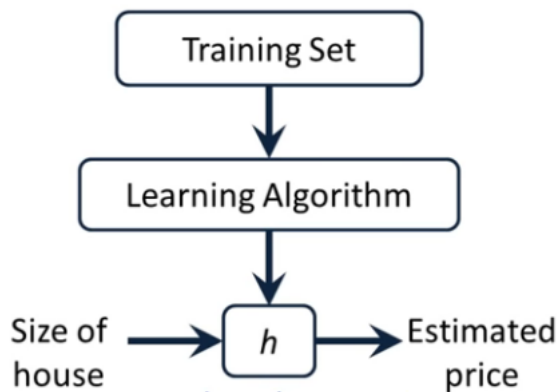
# Linear Regression

- **Supervised Learning:** Given the "right answer" for each example in the data.
- **Two types of Supervised Learning:** Regression problem, Classification problem.
- **Regression Problem:** Predict real-valued output.
- **Classification Problem:** Predict discrete-valued output.

## Traning Set

- **Notation:**
- **m**– Number of training examples
- **x**– "input" variable(data)
- **y**– "output" variable(predict)
- **(x,y)**– one training example
- **( $x^i, y^i$ )**–  $i^{th}$  training example

## Supervised Learning



The learning algorithm output a function based on the training set.  
The function  $h$  is a hypothesis that maps from  $x$  to  $y$ .

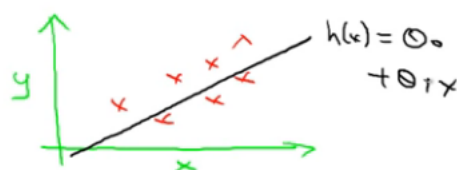
- $h_{\theta}(x) = \theta_0 + \theta_1 x$  (shorthand:  $h(x)$ )

- $h$  : predicting  $y$  is a linear function of  $x$ ,  $\theta_i$ s are parameters.

**How do we represent  $h$  ?**

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

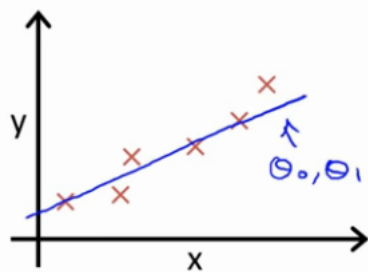
Short-hand:  $h(x)$



## Univariate Linear Regression

Linear regression with one variable (like above).

## Cost Function



Idea: Choose  $\theta_0, \theta_1$  so that  $h_{\theta}(x)$  is close to  $y$  for our training examples  $(x, y)$

- Cost Function (Squared error function):

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^i) - y^i)^2$$

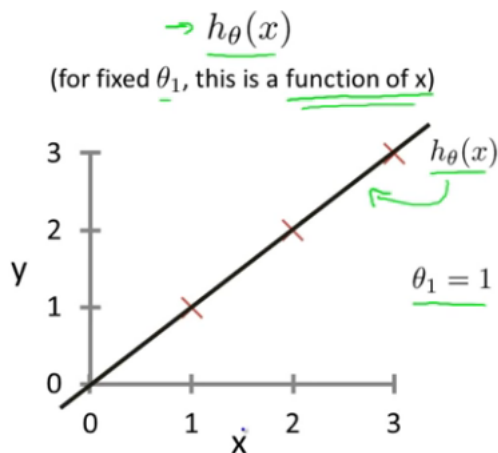
$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

Minimize  $\theta_0$  and  $\theta_1$  will minimize cost function

Goal : Minimize J

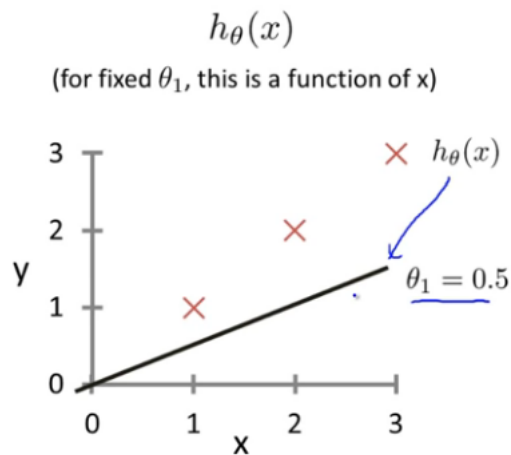
most commonly used for linear regression problems

- Example with  $\theta_0 = 0$



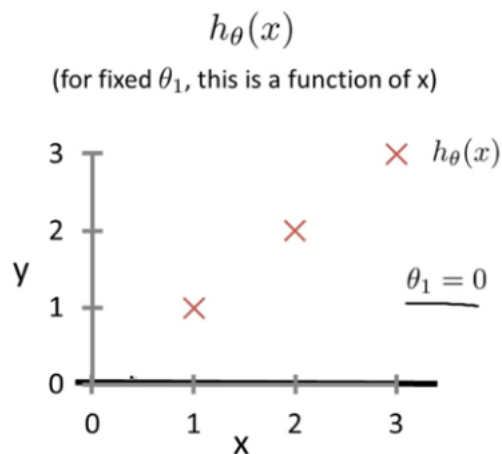
$$\theta_1 = 1$$

$$\begin{aligned} J(\theta_1) &= \frac{1}{2m} \sum_{i=1}^m (\theta_1(x^i) - y^i)^2 \\ &= \frac{1}{2m} \sum_{i=1}^m (0^2 + 0^2 + 0^2) \\ &= 0^2 \end{aligned}$$



$$\theta_1 = 0.5$$

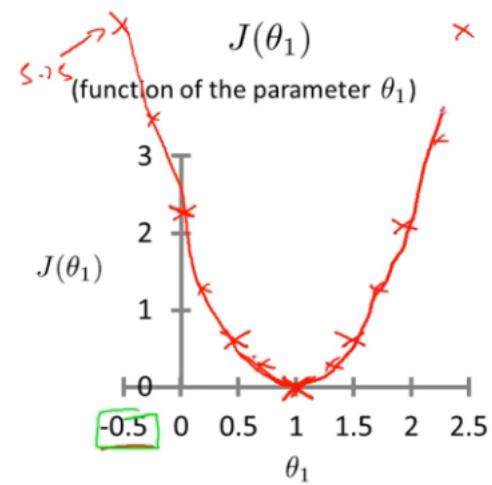
$$\begin{aligned} J(\theta_1) &= \frac{1}{2m} \sum_{i=1}^m (\theta_1(x^i) - y^i)^2 \\ &= \frac{1}{2m} \sum_{i=1}^m ((0.5 - 1)^2 + (1 - 2)^2 + (1.5 - 3)^2) \\ &= \frac{1}{2 \times 3} (3.5) \\ &= 0.68 \end{aligned}$$



$$\theta_1 = 0$$

$$\begin{aligned} J(\theta_1) &= \frac{1}{2m} \sum_{i=1}^m (\theta_1(x^i) - y^i)^2 \\ &= \frac{1}{2m} \sum_{i=1}^m ((0 - 1)^2 + (0 - 2)^2 + (0 - 3)^2) \\ &= \frac{1}{2 \times 3} (14) \\ &= 2.3 \end{aligned}$$

Using result plot cost function:



The value of  $\theta_1$  that minimize cost function is 1

- Cost function with two parameters

