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This Course: Machine Learning

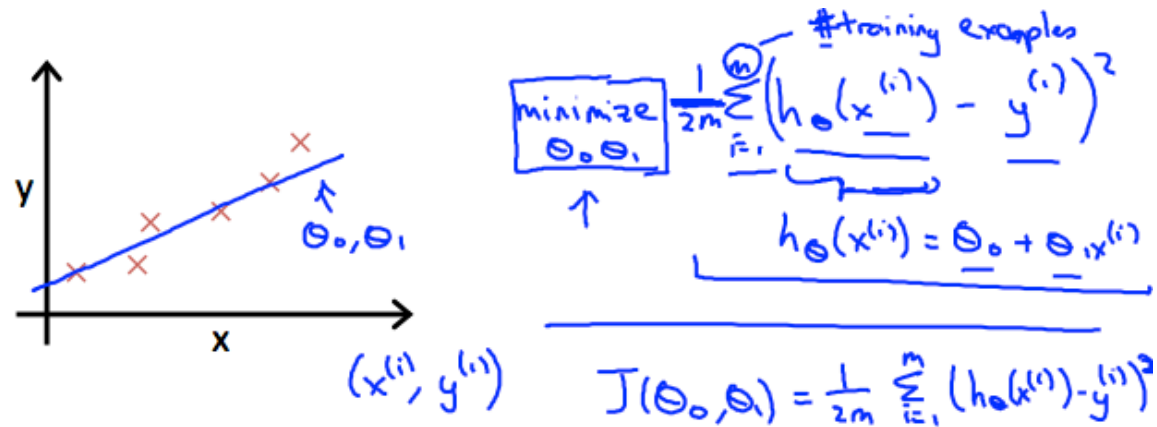
Cost Function

We can measure the accuracy of our hypothesis function by using a **cost function**. This takes an average difference (actually a fancier version of an average) of all the results of the hypothesis with inputs from x 's and the actual output y 's.

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

To break it apart, it is $\frac{1}{2} \bar{x}$ where \bar{x} is the mean of the squares of $h_{\theta}(x_i) - y_i$, or the difference between the predicted value and the actual value.

This function is otherwise called the "Squared error function", or "Mean squared error". The mean is halved ($\frac{1}{2}$) as a convenience for the computation of the gradient descent, as the derivative term of the square function will cancel out the $\frac{1}{2}$ term. The following image summarizes what the cost function does:



Idea: Choose θ_0, θ_1 so that
 $h_{\theta}(x)$ is close to y for our
 training examples (x, y)

x, y

minimize $J(\theta_0, \theta_1)$
 θ_0, θ_1

Cost function

Squared error function

Andrew Ng

Mark as completed

