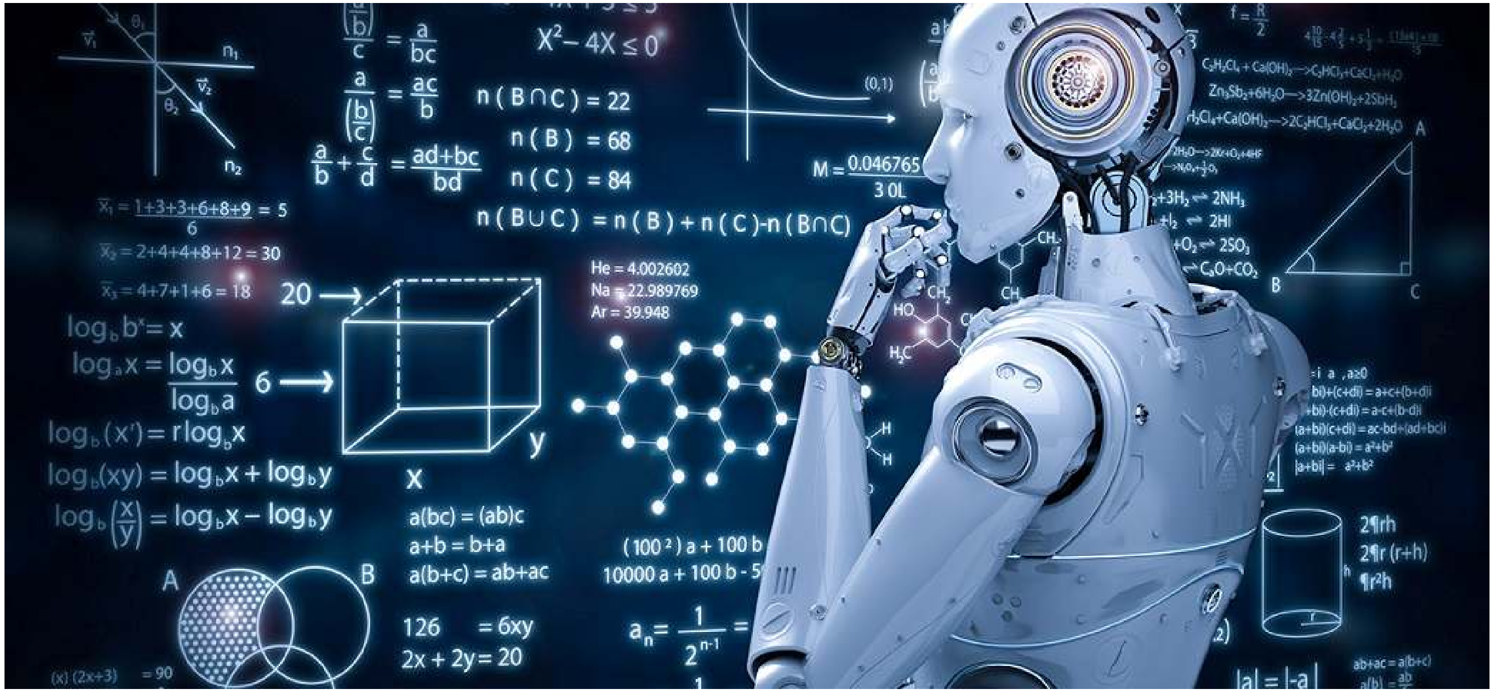


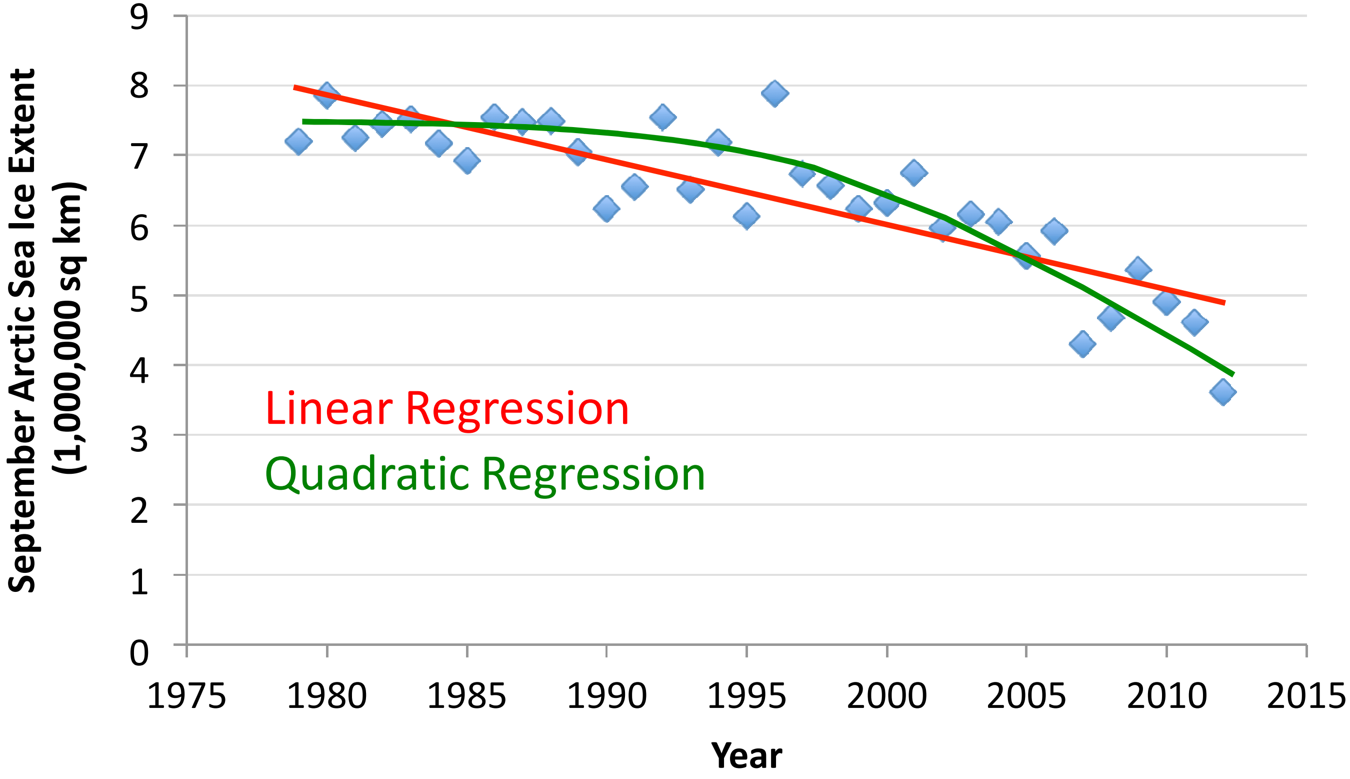
# BBM406: Fundamentals of Machine Learning

## Linear Regression, Cost Function, Gradient Descent

# Regression

Given:

- Data $X = \{x^{(1)}, x^{(2)}, \cdots, x^{(n)}\}$ , where $x^{(i)} \in R$
- Corresponding labels $y = \{y^{(1)}, y^{(2)}, \cdots, y^{(n)}\}$, where $x^{(i)} \in R$



Data from G. Witt. Journal of Statistics Education, Volume 21, Number 1 (2013)

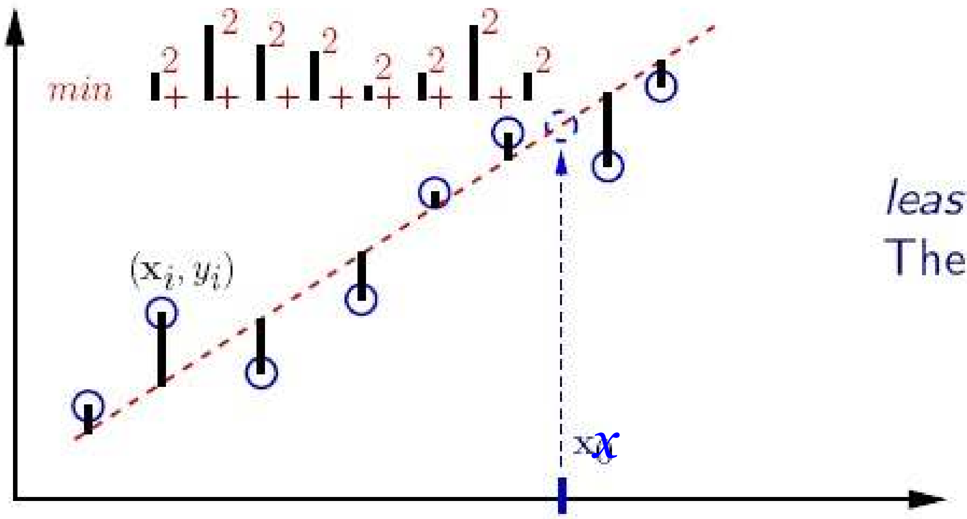
# Linear Regression

- Hypothesis:

Assume $x_0$ = 1

$$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_d x_d = \sum_{j=0}^{d} \theta_j x_j = h_\theta(X)$$

- Fit model by minimizing sum of squared errors



*least squares* (LSQ)
The fitted line is used as a predictor

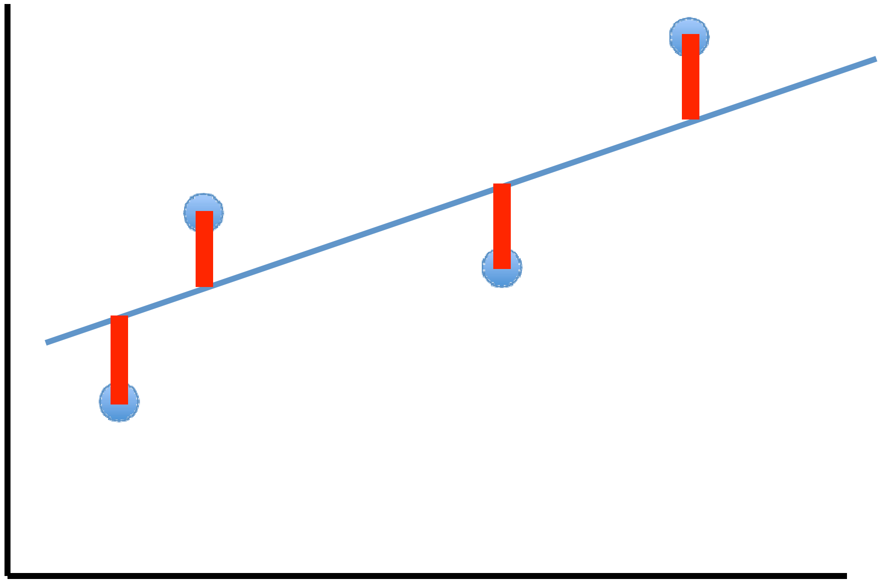
Figures are courtesy of Greg Shakhnarovich

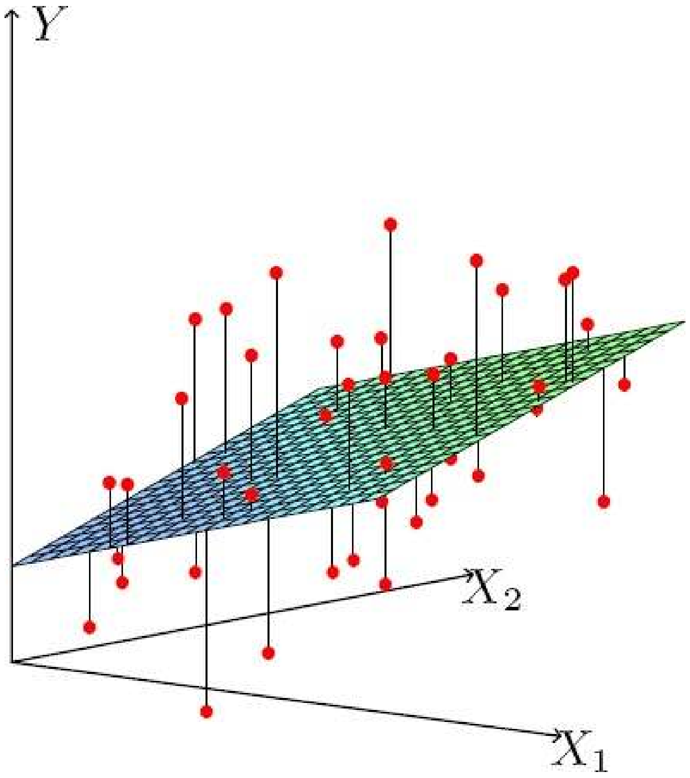
# Least Squares Linear Regression

- Cost Function

$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

- Fit by solving





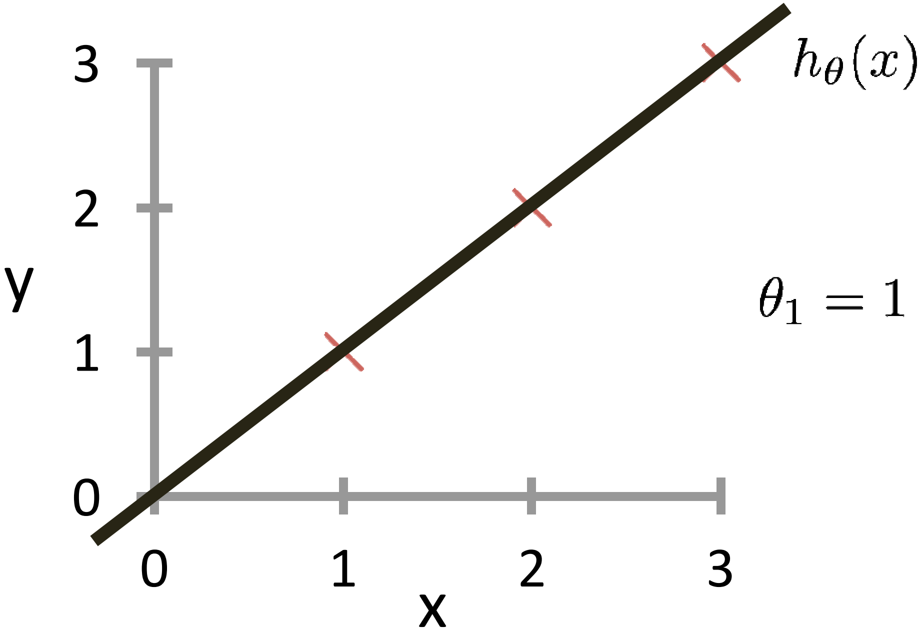
# Intuition Behind Cost Function

$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

For insight on $J()$, let's assume $x^{(i)} \in R$ and $\theta = [\theta_0, \theta_1]$

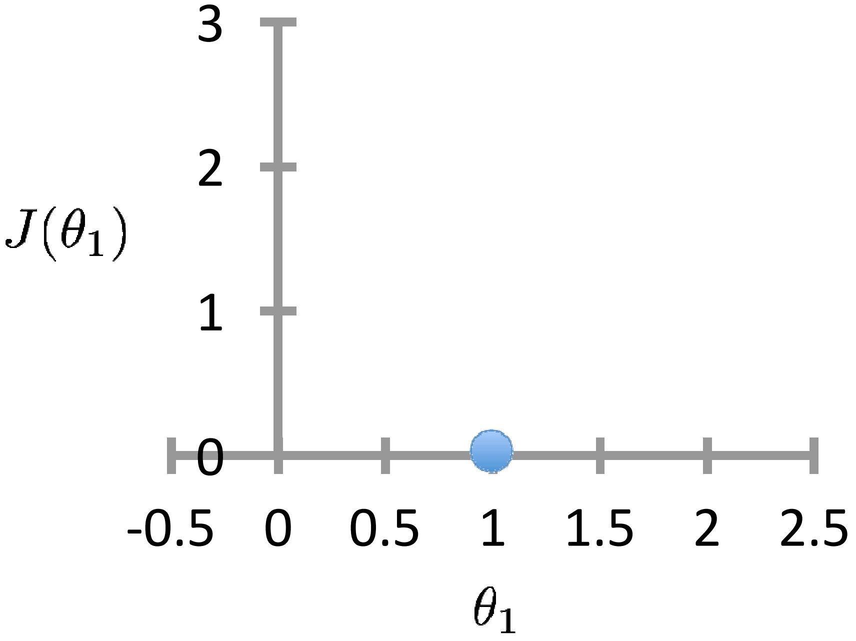
$h_\theta(x)$

(for fixed $\theta_1$, this is a function of x)



$J(\theta_1)$

(function of the parameter $\theta_1$)



$$J([0,1]) = \frac{1}{2\times3}[(1-1)^2+(2-2)^2+(3-3)^2] = 0$$

Based on example by Andrew Ng

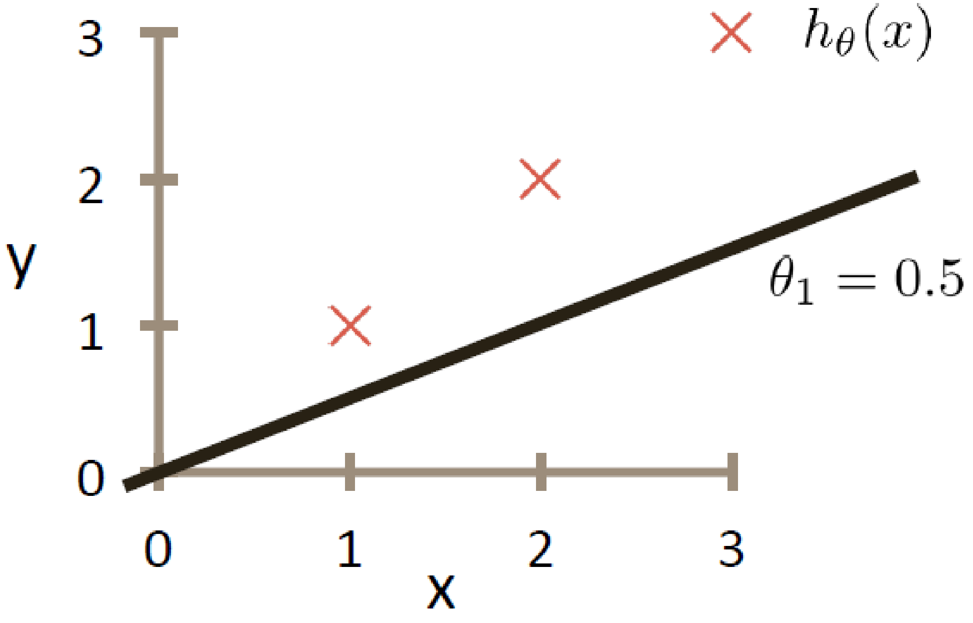
# Intuition Behind Cost Function

$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

For insight on $J()$, let's assume $x^{(i)} \in R$ and $\theta = [\theta_0, \theta_1]$

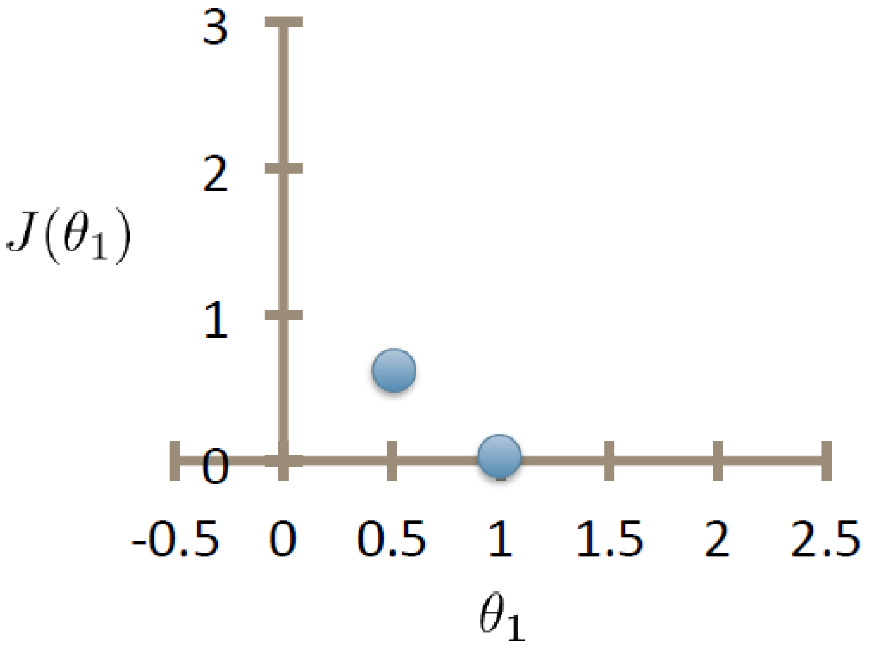
$h_\theta(x)$

(for fixed $\theta_1$, this is a function of x)



$J(\theta_1)$

(function of the parameter $\theta_1$)



$J([0,0.5]) = \frac{1}{2\times3}[(0.5-1)^2+(1-2)^2+(1.5-3)^2] \approx 0.58$

Based on example by Andrew Ng

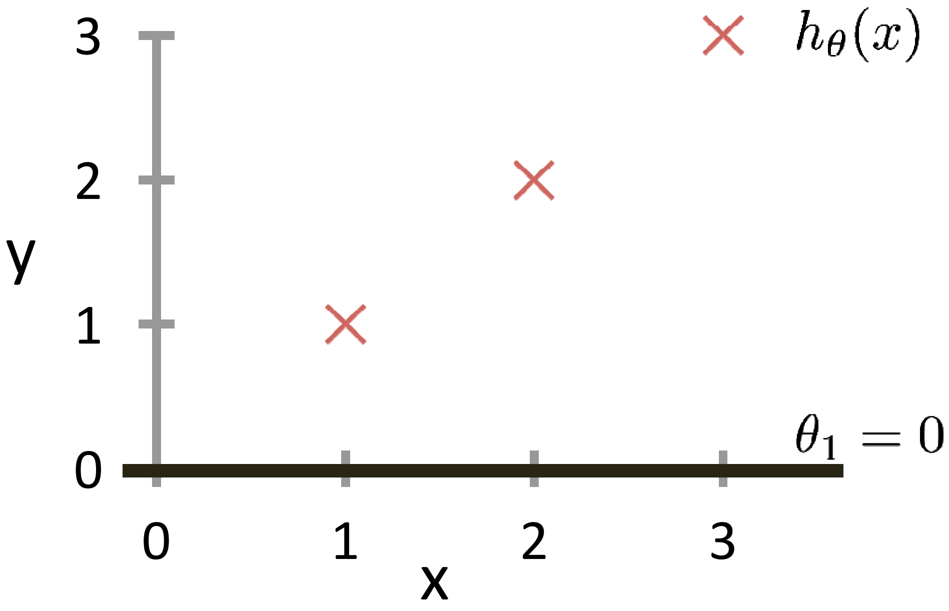
# Intuition Behind Cost Function

$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

For insight on $J()$, let's assume $x^{(i)} \in R$ and $\theta = [\theta_0, \theta_1]$

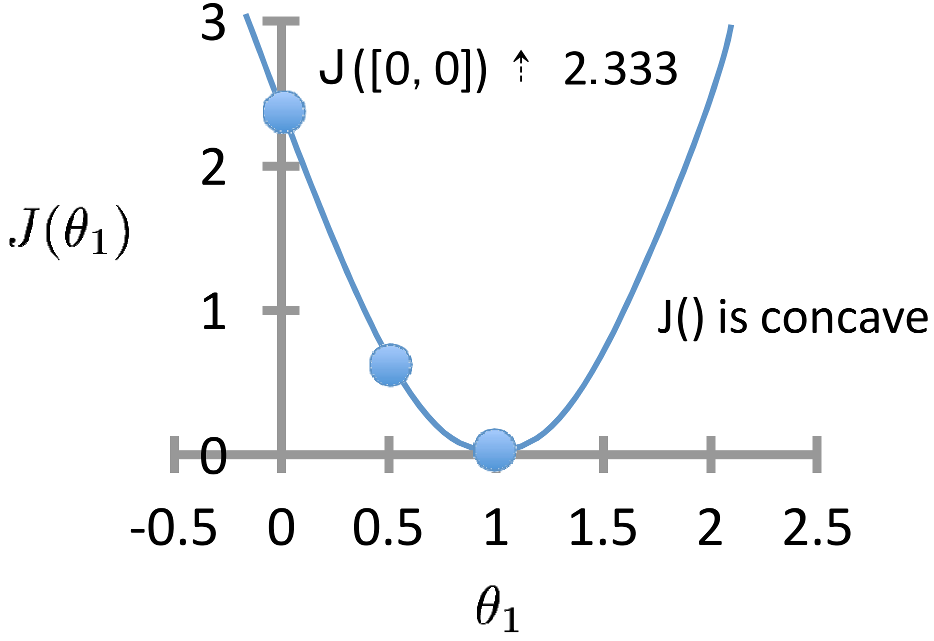
$h_\theta(x)$

(for fixed $\theta_1$, this is a function of x)



$J(\theta_1)$

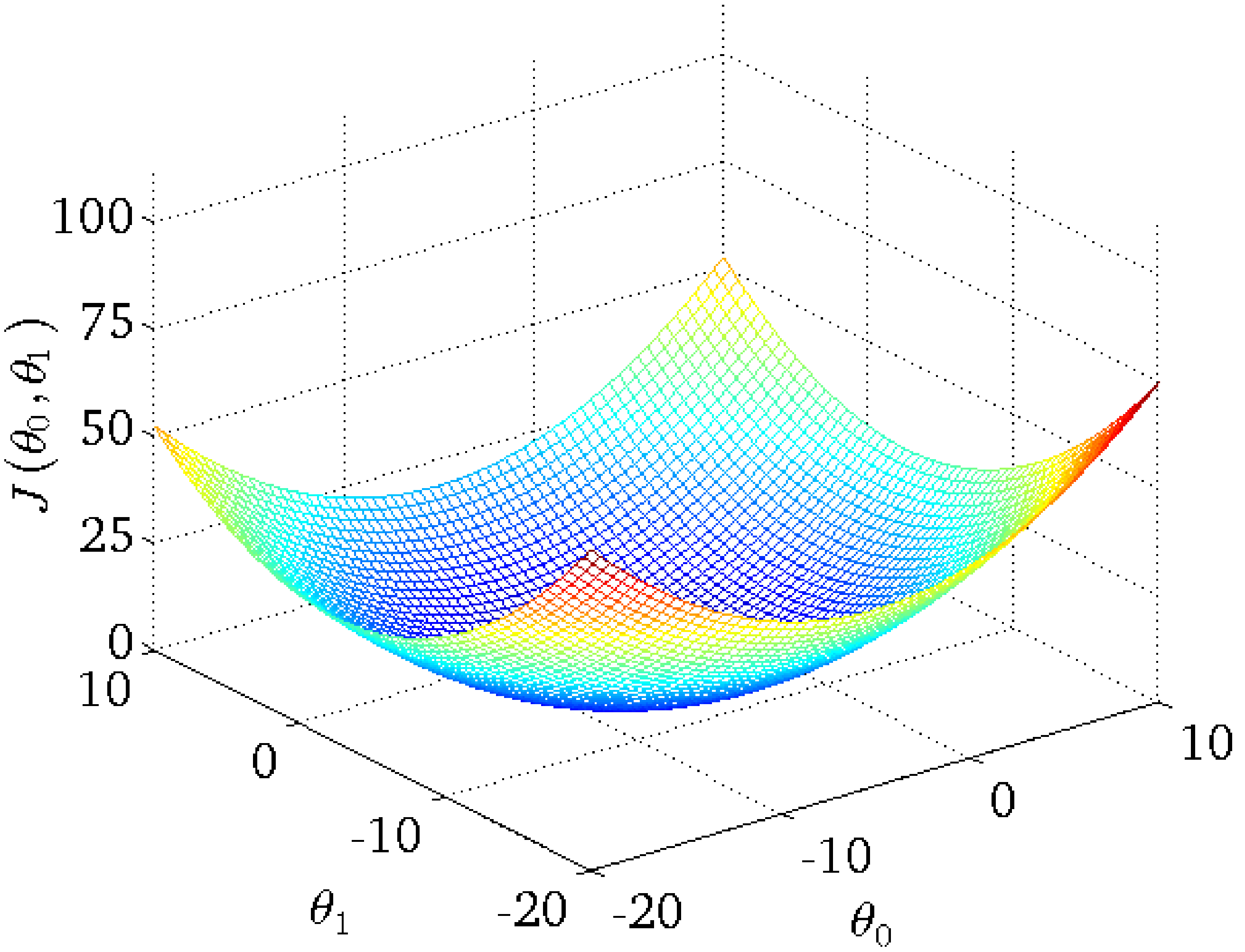
(function of the parameter $\theta_1$)



$$J([0,0]) = \frac{1}{2\times3}[(0-1)^2+(0-2)^2+(0-3)^2] \approx 2.33$$

Based on example
by Andrew Ng

# Intuition Behind Cost Function



Slide by Andrew Ng

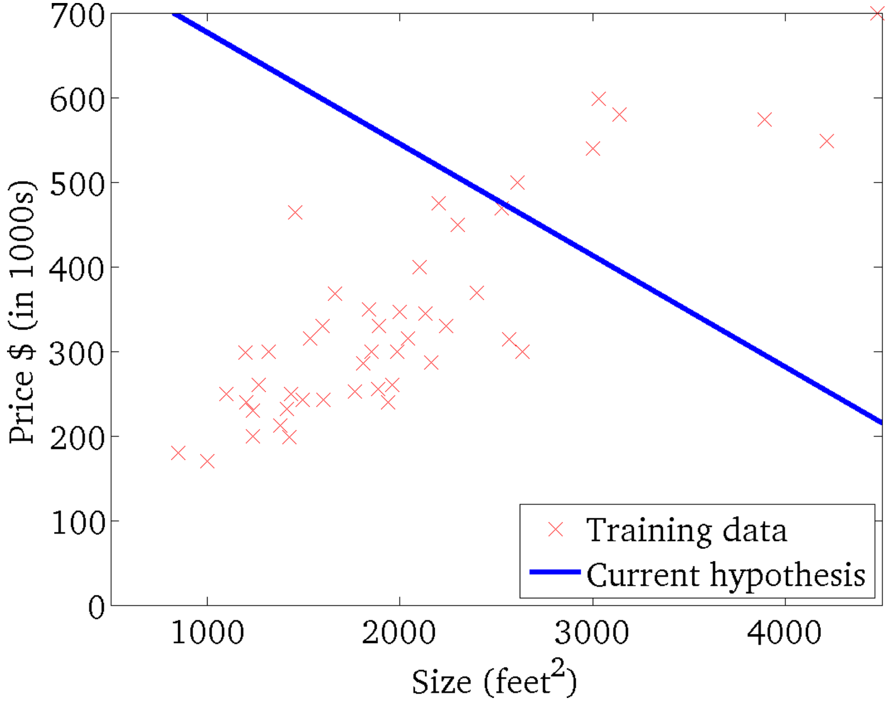
# Intuition Behind Cost Function

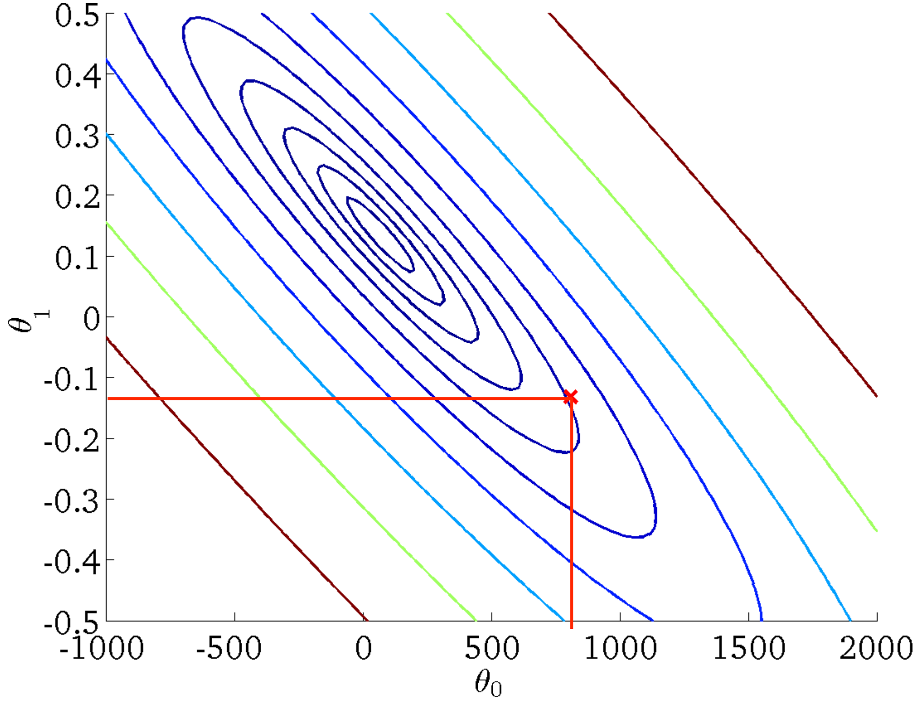
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)

$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)





Slide by Andrew Ng

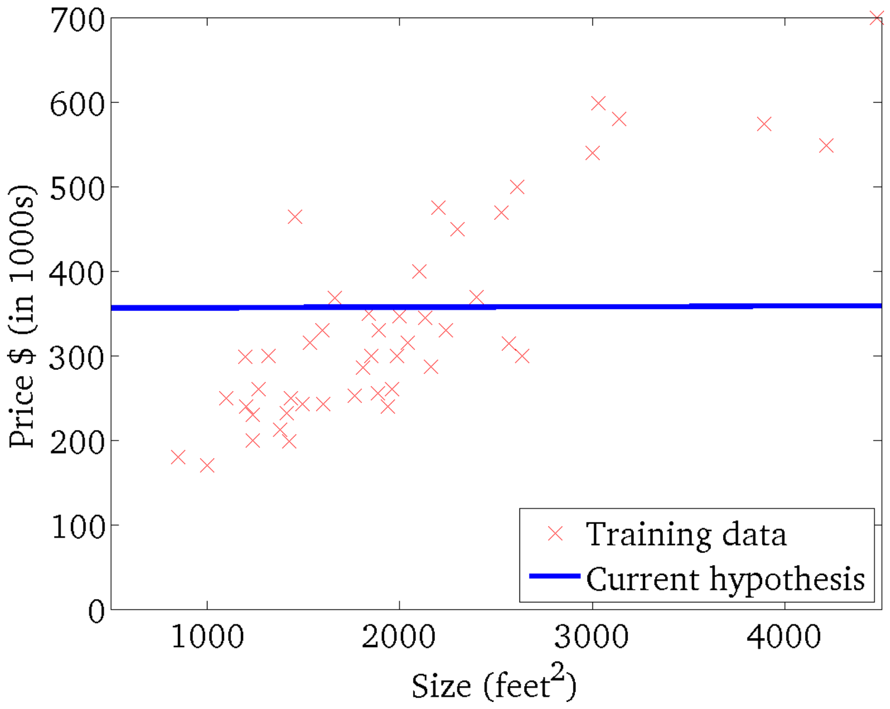
# Intuition Behind Cost Function

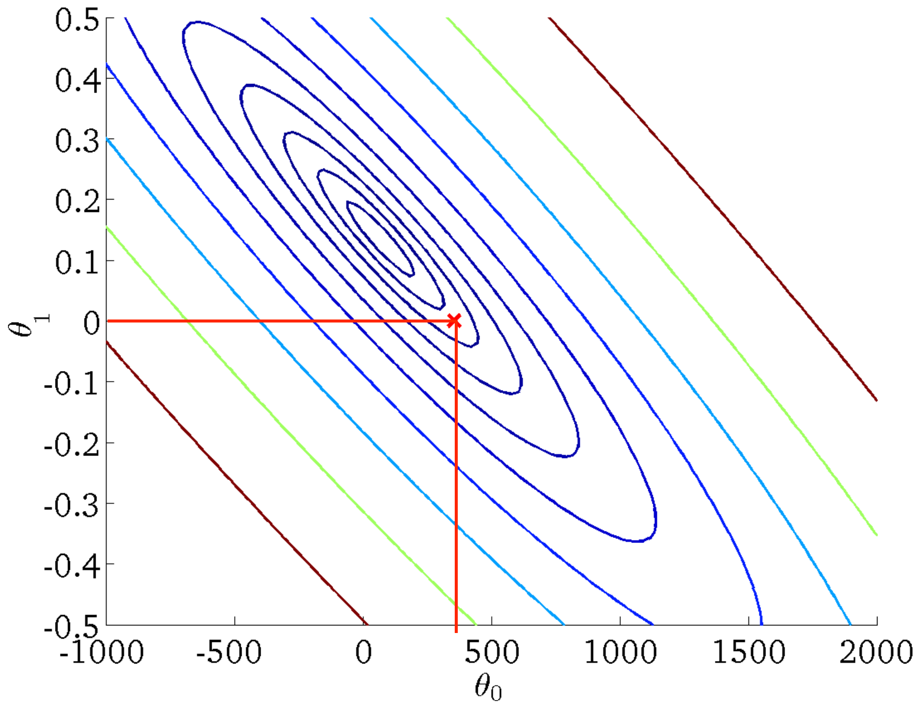
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)

$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)



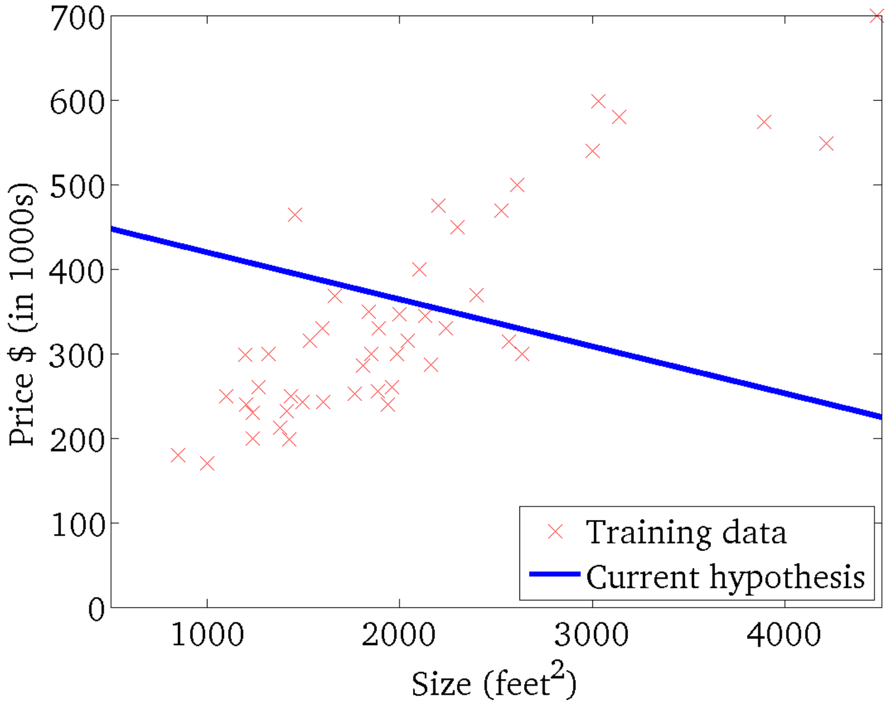


Slide by Andrew Ng

# Intuition Behind Cost Function

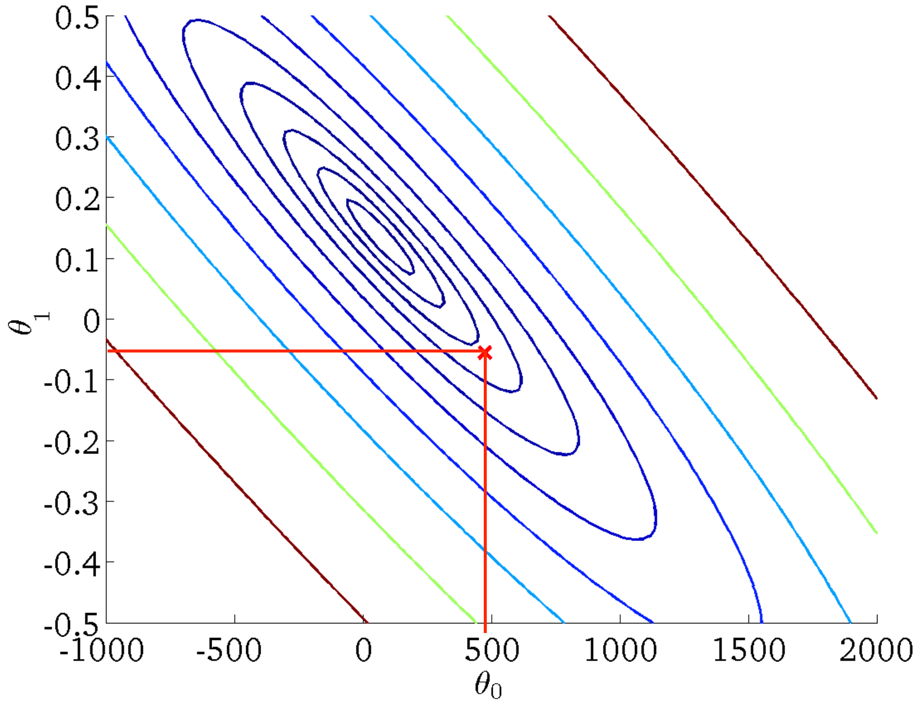
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)

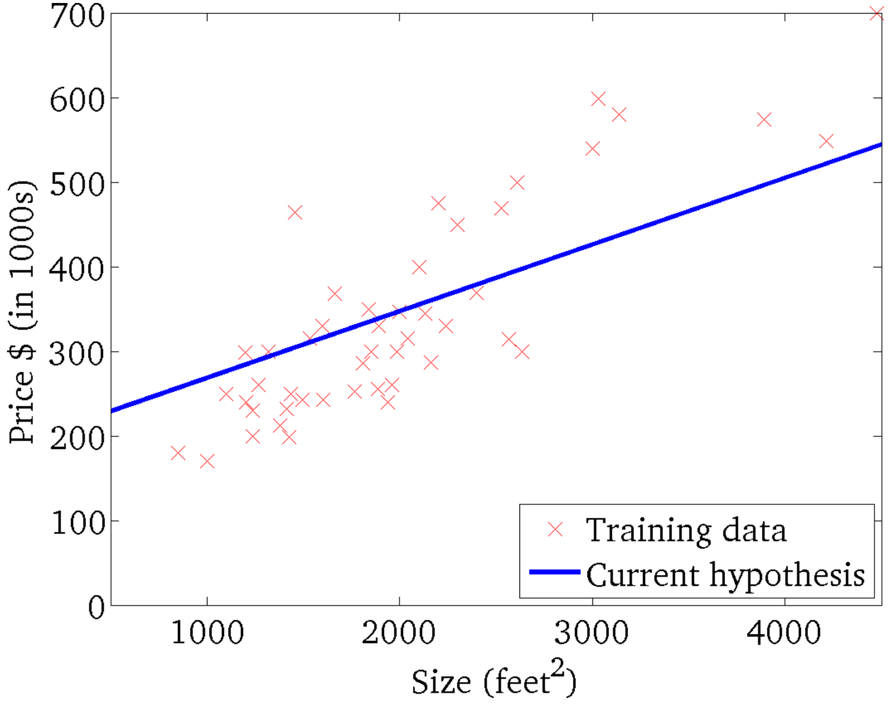


Slide by Andrew Ng

# Intuition Behind Cost Function

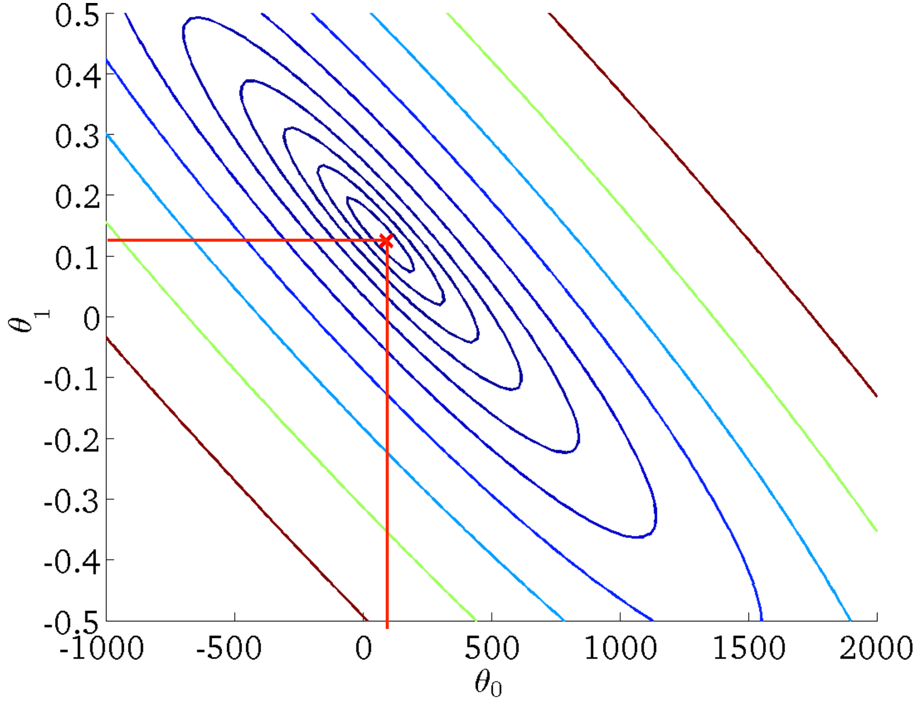
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)



Slide by Andrew Ng

# Basic Search Procedure

- Choose initial value for θ
- Until we reach a minimum:
  - Choose a new value for θ to reduce J (θ)

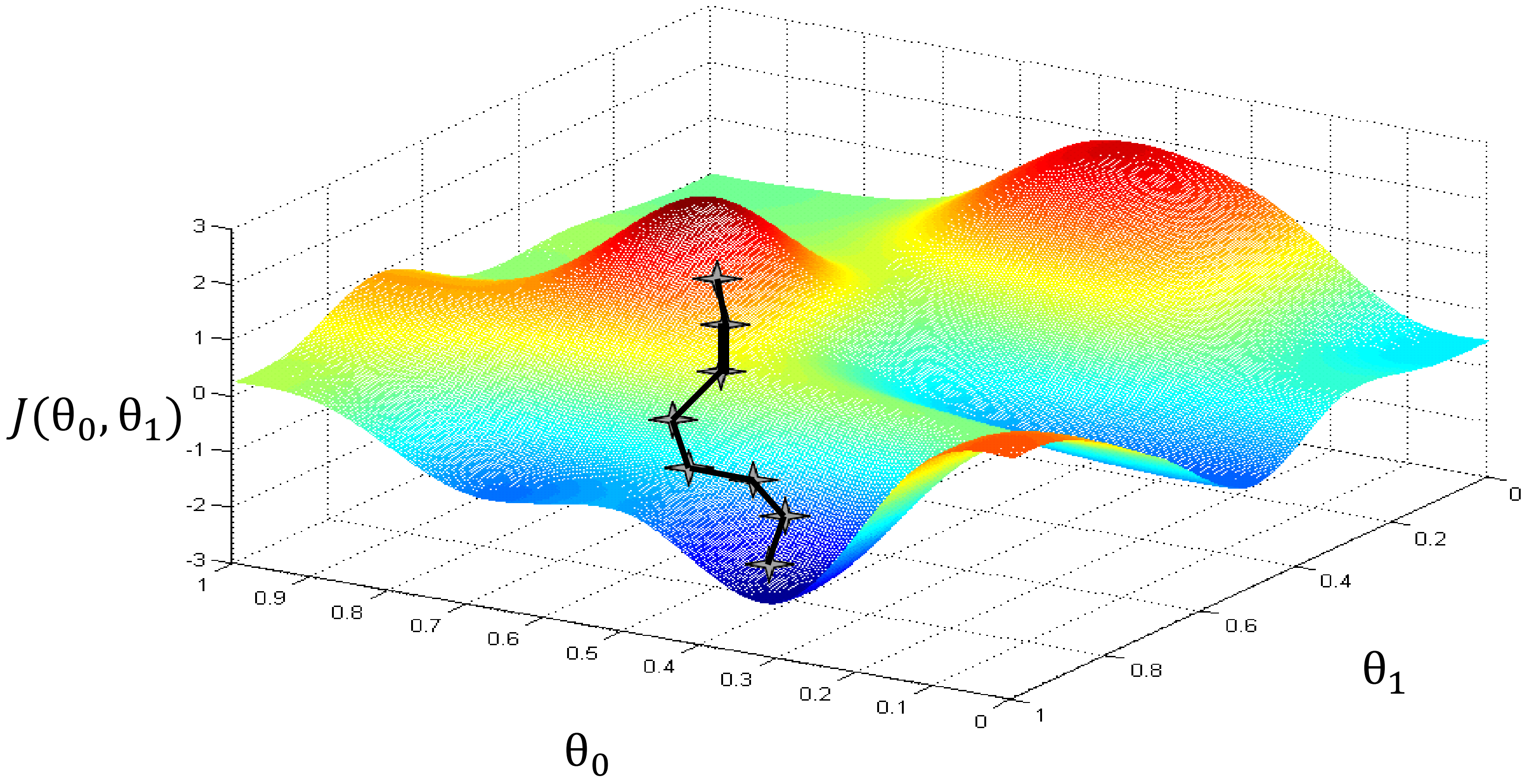


Figure by Andrew Ng

# Basic Search Procedure

- Choose initial value for θ
- Until we reach a minimum:
  - Choose a new value for θ to reduce J(θ)

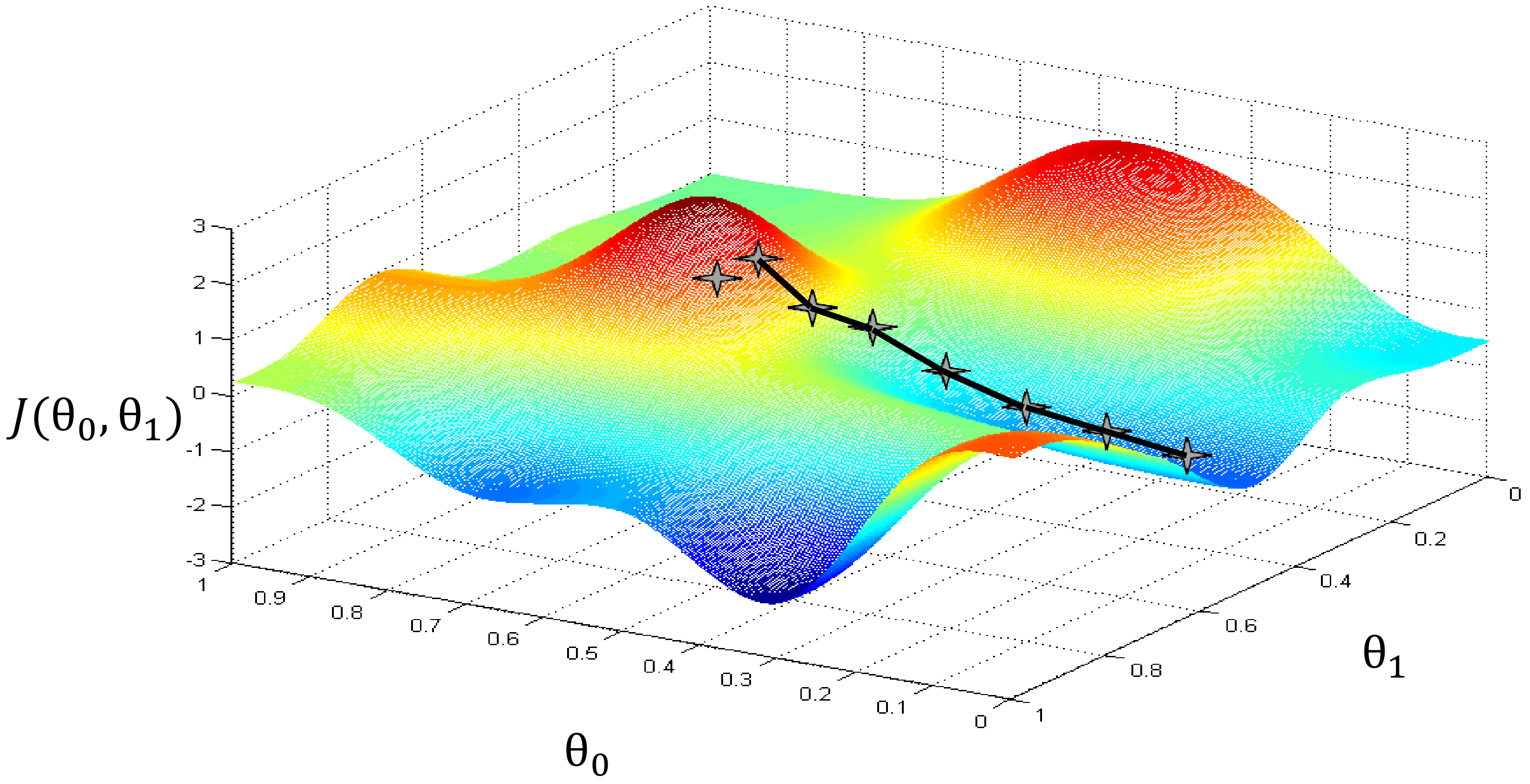
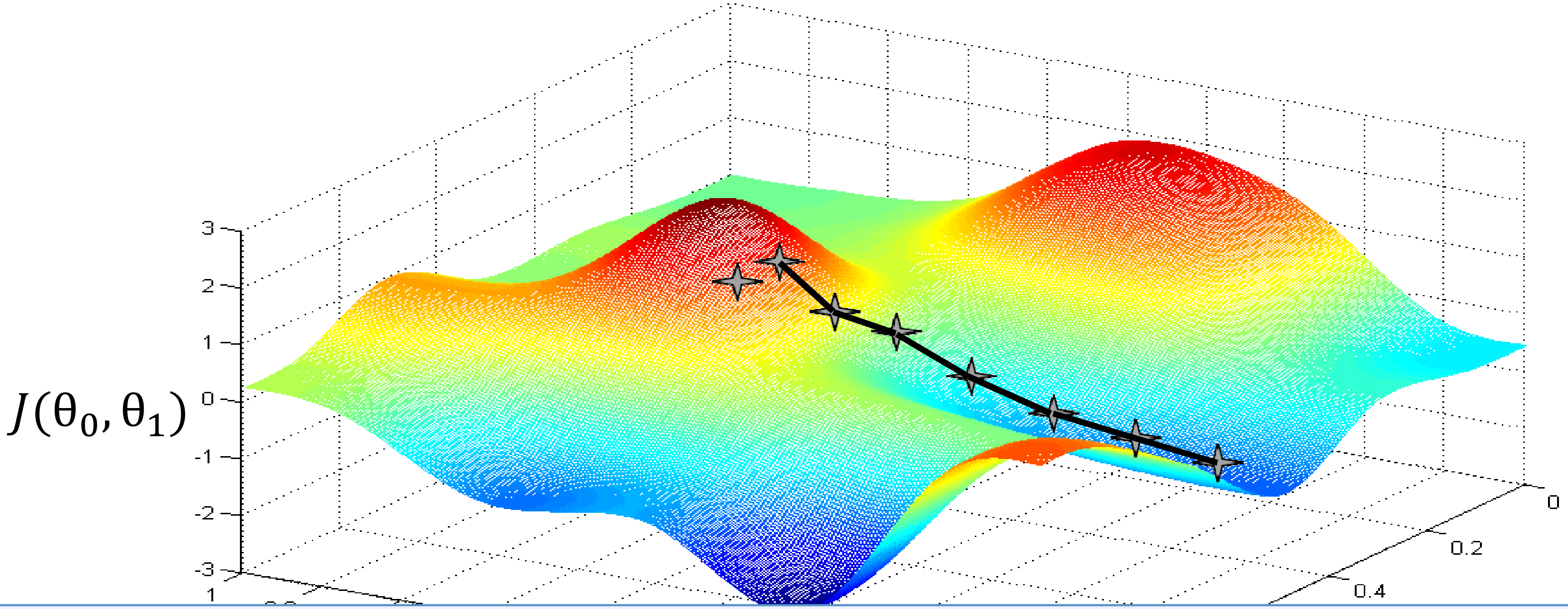


Figure by Andrew Ng

# Basic Search Procedure

- Choose initial value for θ
- Until we reach a minimum:
  - Choose a new value for θ to reduce J(θ)



Since the least squares objective function is convex (concave), we don't need to worry about local minima

Figure by Andrew Ng

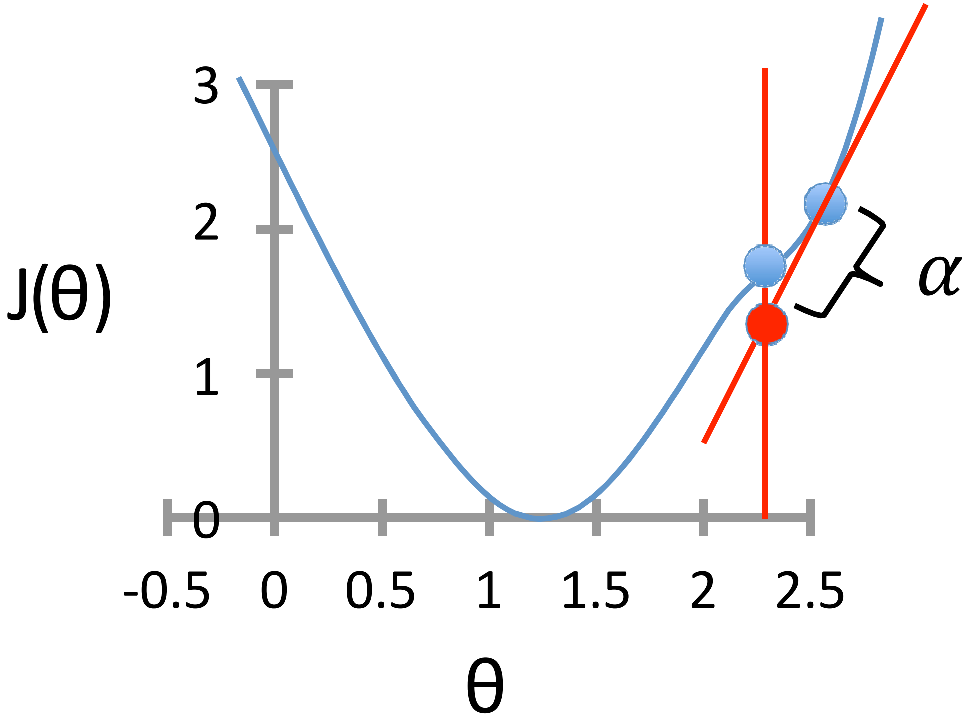
# Gradient Descent

- Initialize θ
- Repeat until convergence

$$\theta \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

simultaneous update
for $j$ = 0 ... d

learning rate (small)
e.g., α = 0.05



# Gradient Descent

- Initialize θ
- Repeat until convergence

$$\theta \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

simultaneous update
for $j$ = 0 ... d

# Gradient Descent

- Initialize θ
- Repeat until convergence

$$\theta \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

simultaneous update
for $j$ = 0 ... d

$$J(\theta) = \frac{1}{2n} \sum_{i=1}^{n} \left( h_{\theta}(x^{(i)}) - y^{(i)} \right)^2$$

For linear regression: $\frac{\partial}{\partial \theta_{\mathrm{j}}} \mathrm{J}(\theta) = \frac{\partial}{\partial \theta_{\mathrm{j}}} \frac{1}{2n} \sum_{i=1}^{n} (h_{\theta}(x^{(i)}) - y^{(i)})^2$

# Gradient Descent

- Initialize θ
- Repeat until convergence

$$\theta \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

simultaneous update
for $j$ = 0 ... d

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_d x_d = \sum_{j=0}^{d} \theta_j x_j$$

For linear regression:

$$\frac{\partial}{\partial \theta_j} J(\theta) = \frac{\partial}{\partial \theta_j} \frac{1}{2n} \sum_{i=1}^{n} \left( h_\theta(x^{(i)}) - y^{(i)} \right)^2$$

$$= \frac{\partial}{\partial \theta_j} \frac{1}{2n} \sum_{i=1}^{n} \left( \sum_{j=0}^{d} \theta_j x_j^{(i)} - y^{(i)} \right)^2$$

# Gradient Descent

- Initialize θ
- Repeat until convergence

$$\theta \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

simultaneous update
for $j$ = 0 ... d

For linear regression:
$$\frac{\partial}{\partial \theta_{\mathrm{j}}} \mathrm{J}(\theta) = \frac{\partial}{\partial \theta_{\mathrm{j}}} \frac{1}{2n} \sum_{i=1}^{n} \left( \sum_{j=0}^{d} \theta_j x_j^{(i)} - y^{(i)} \right)^2$$

$$= \frac{1}{n} \sum_{i=1}^{n} \left( \sum_{j=0}^{d} \theta_j x_j^{(i)} - y^{(i)} \right) \frac{\partial}{\partial \theta_{\mathrm{j}}} \left( \sum_{j=0}^{d} \theta_j x_j^{(i)} - y^{(i)} \right)$$

$$= \frac{1}{n} \sum_{i=1}^{n} \left( \sum_{j=0}^{d} \theta_j x_j^{(i)} - y^{(i)} \right) x_j^{(i)}$$

# Gradient Descent

- Initialize θ
- Repeat until convergence

$$\theta_j \leftarrow \theta_j - \propto \frac{1}{n}\sum_{i=1}^{n}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right) x_j^{(i)}$$

simultaneous update

for $j$ = 0 ... d

- To achieve simultaneous update
  - At the start of each GD iteration, compute $h_\theta\left(x^{(i)}\right)$
  - Use this stored value in the update step loop

- Assume convergence when $\|\theta_{new} - \theta_{old}\|_2 < \epsilon$

L$_2$ norm : $\|v\|_2 = \sqrt{\sum_i v_i^2} = \sqrt{v_1^2 + v_2^2 + \cdots + v_{|v|}^2}$

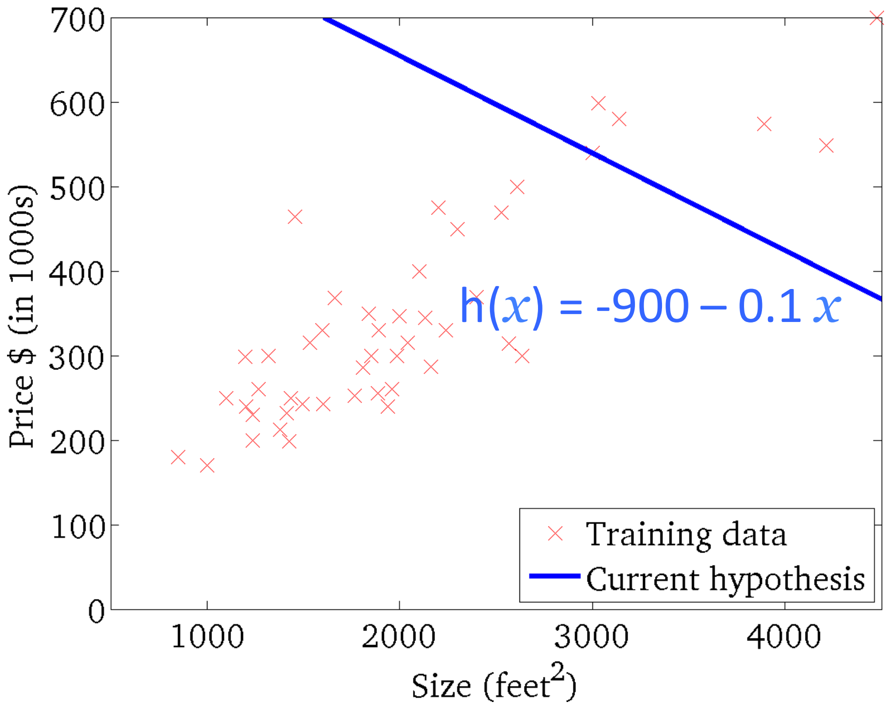
# Gradient Descent

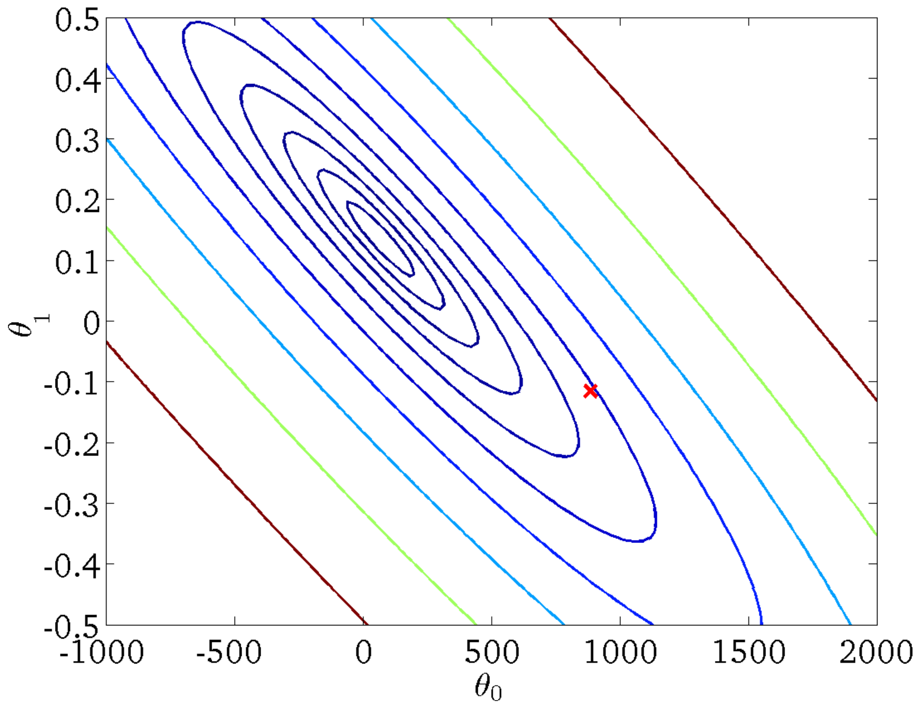
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)

$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)



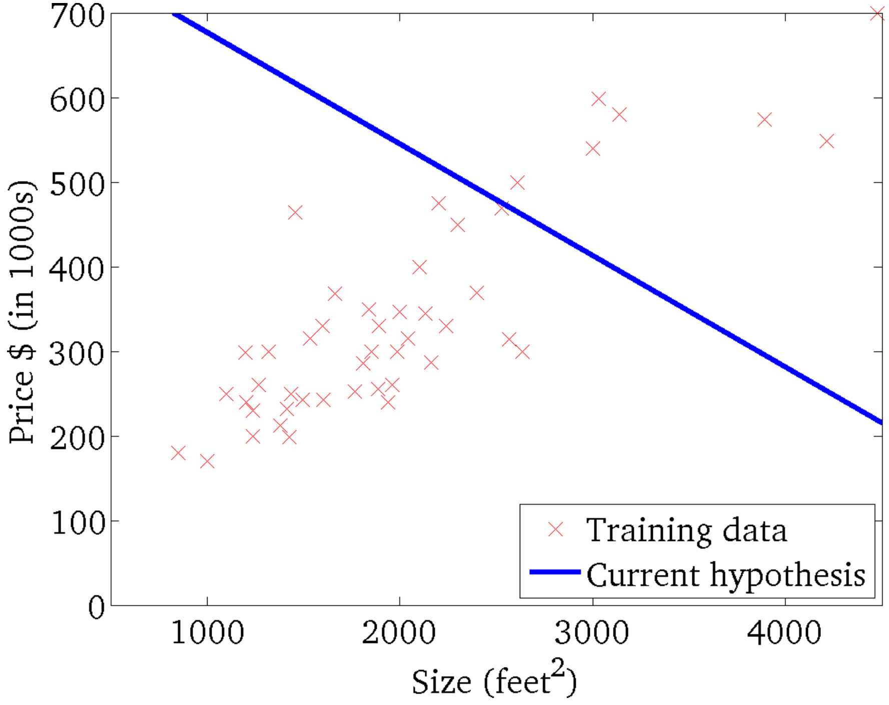


Slide by Andrew Ng

# Gradient Descent

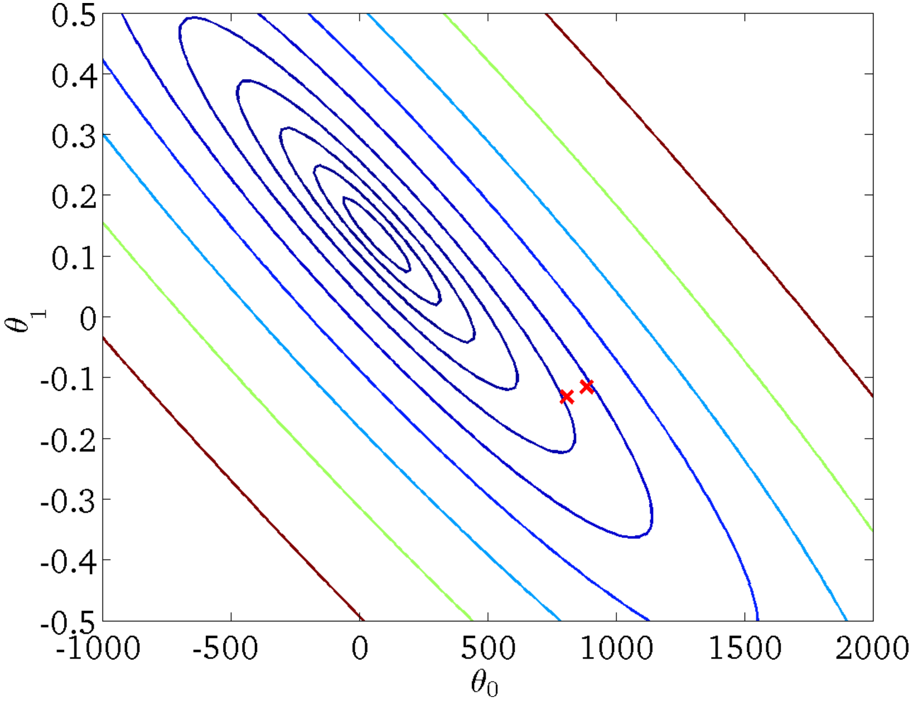
$$h_\theta(x)$$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$$J(\theta_0, \theta_1)$$

(function of the parameters $\theta_0, \theta_1$)



Slide by Andrew Ng

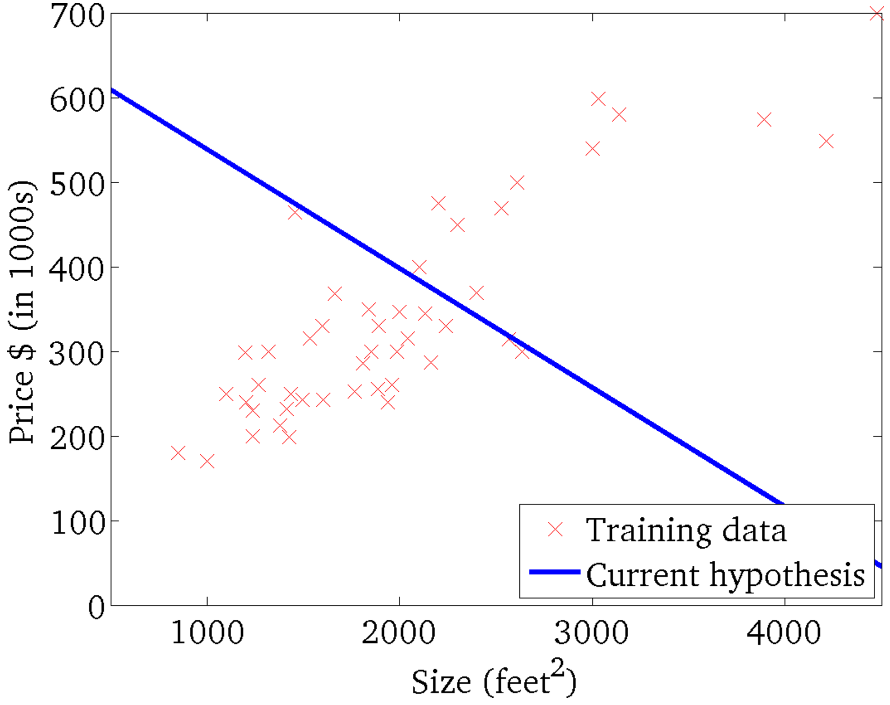
# Gradient Descent

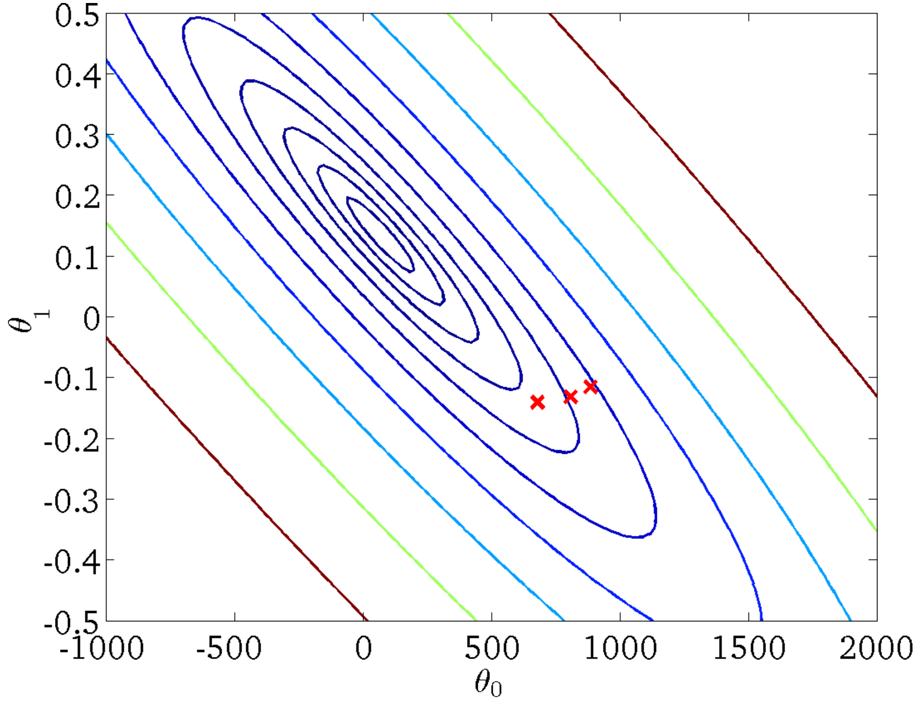
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)

$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)



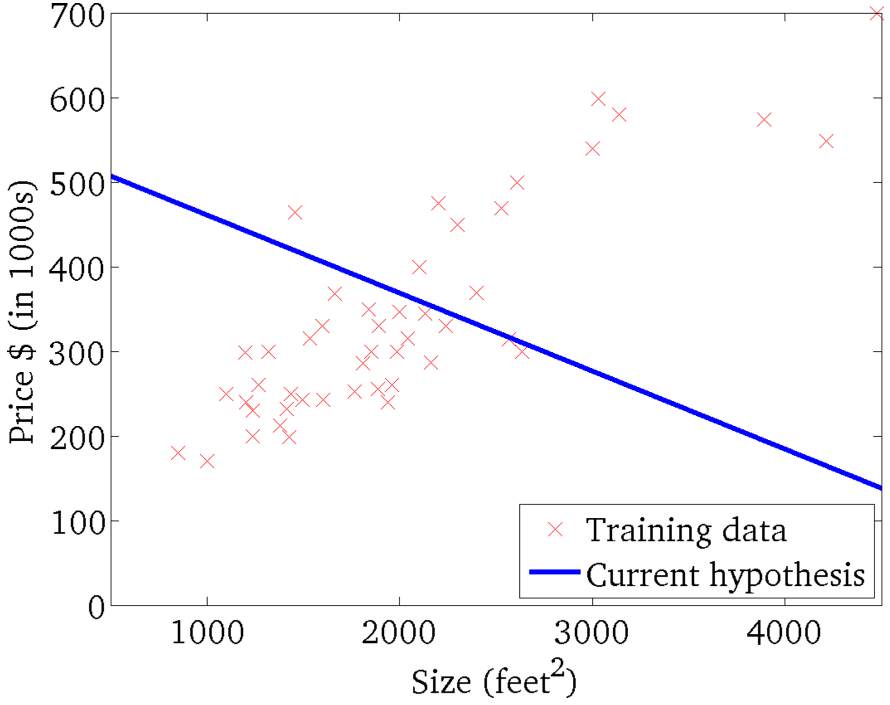


Slide by Andrew Ng

# Gradient Descent

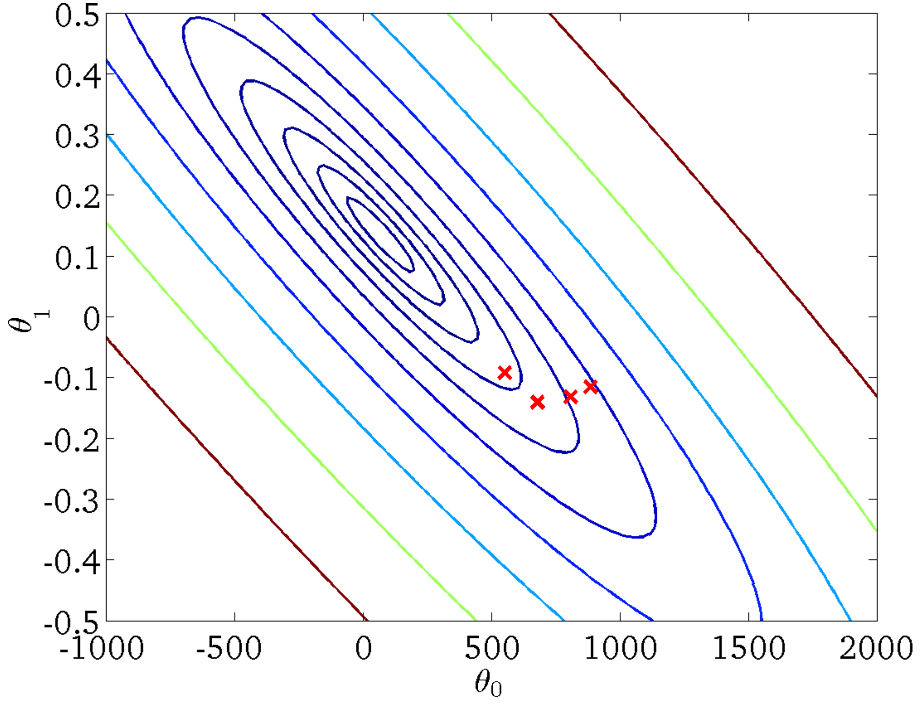
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)

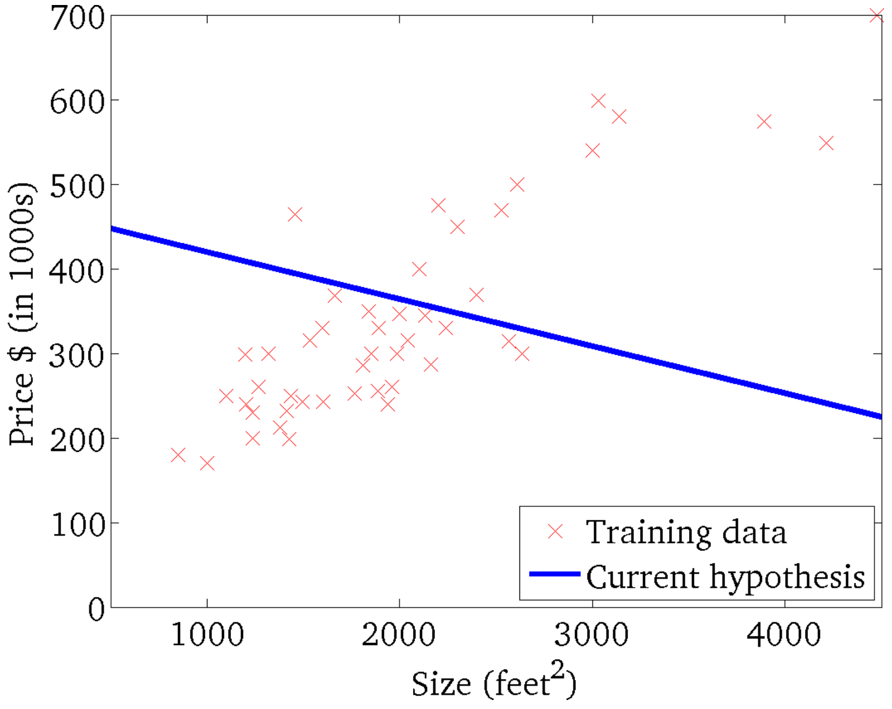


Slide by Andrew Ng

# Gradient Descent

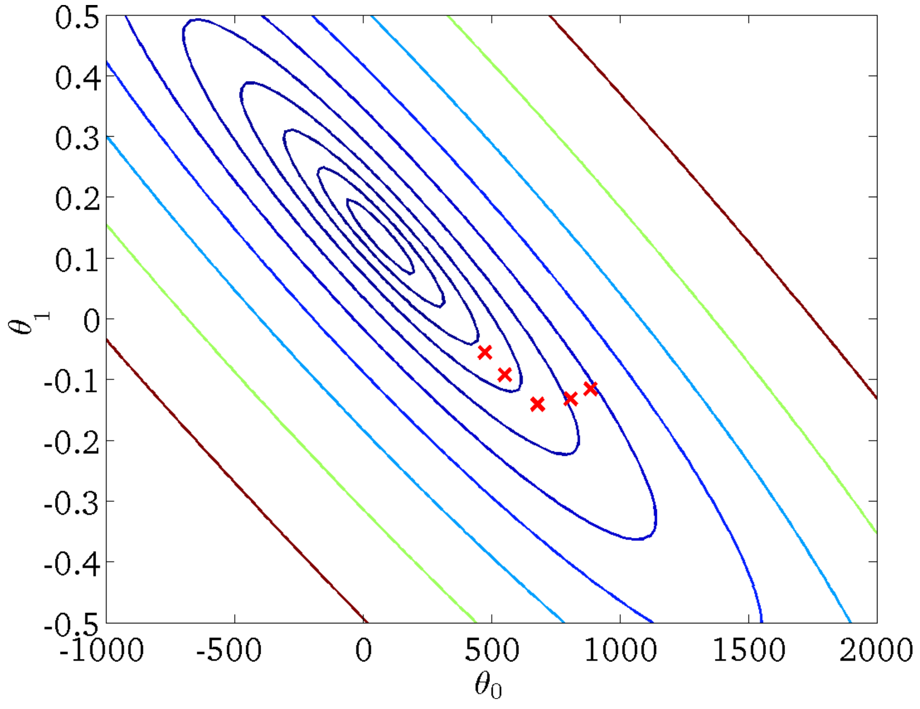
$$h_\theta(x)$$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$$J(\theta_0, \theta_1)$$

(function of the parameters $\theta_0, \theta_1$)

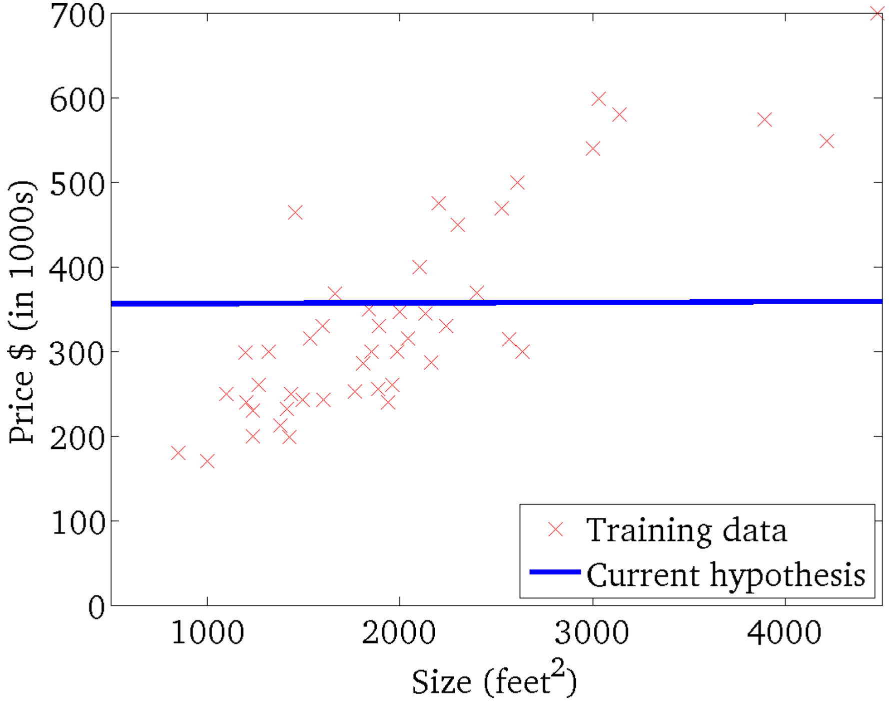


Slide by Andrew Ng

# Gradient Descent

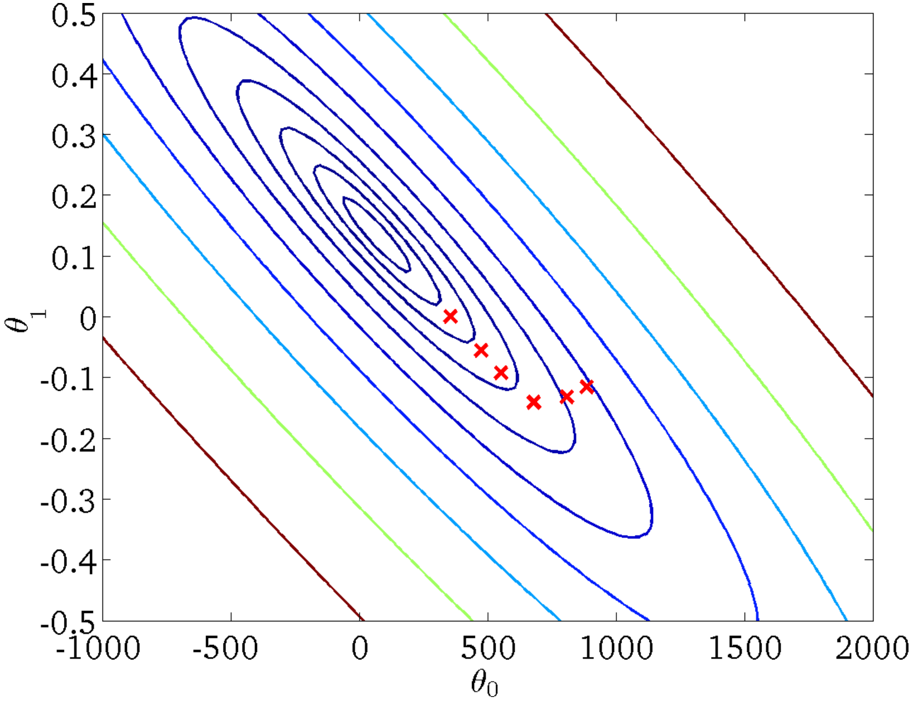
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)

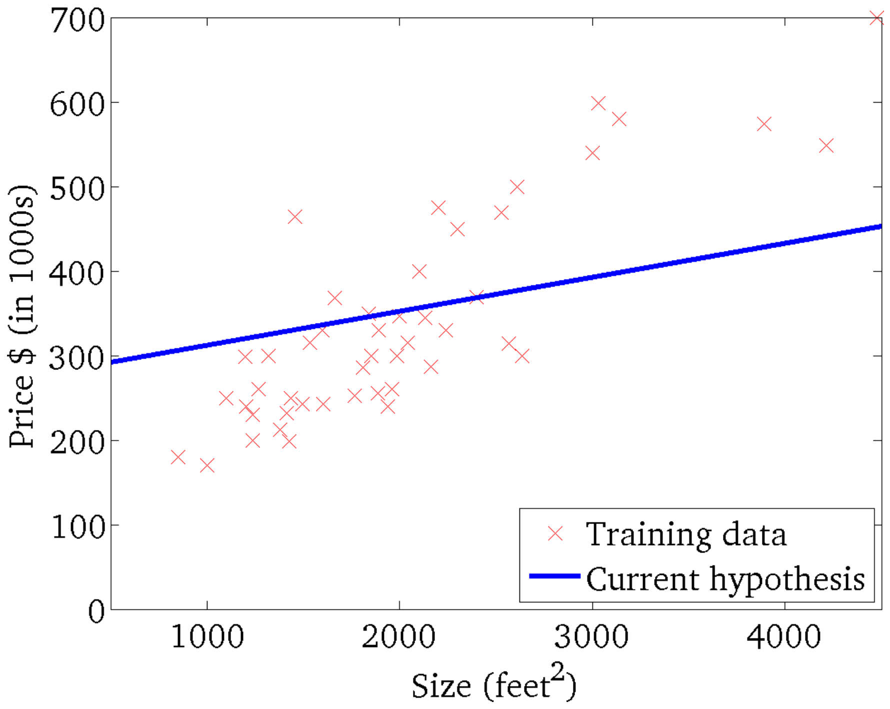


Slide by Andrew Ng

# Gradient Descent

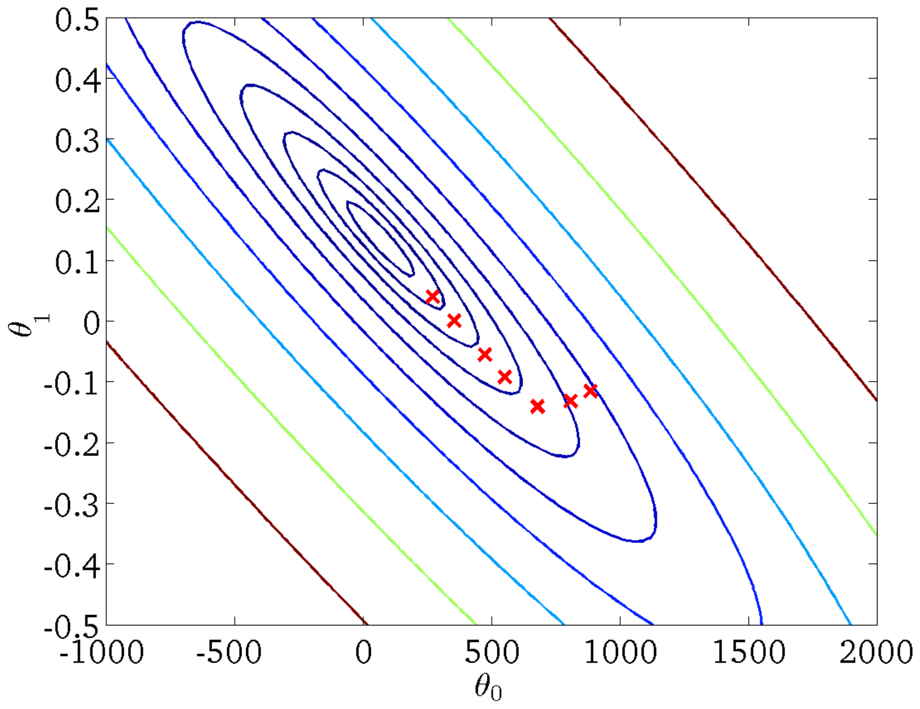
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)



Slide by Andrew Ng

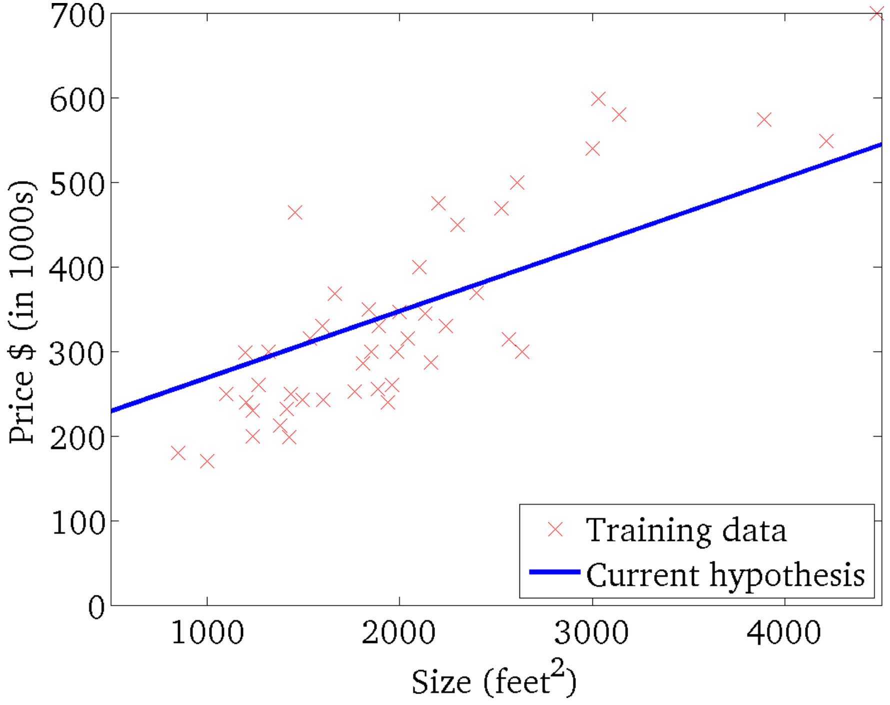
# Gradient Descent

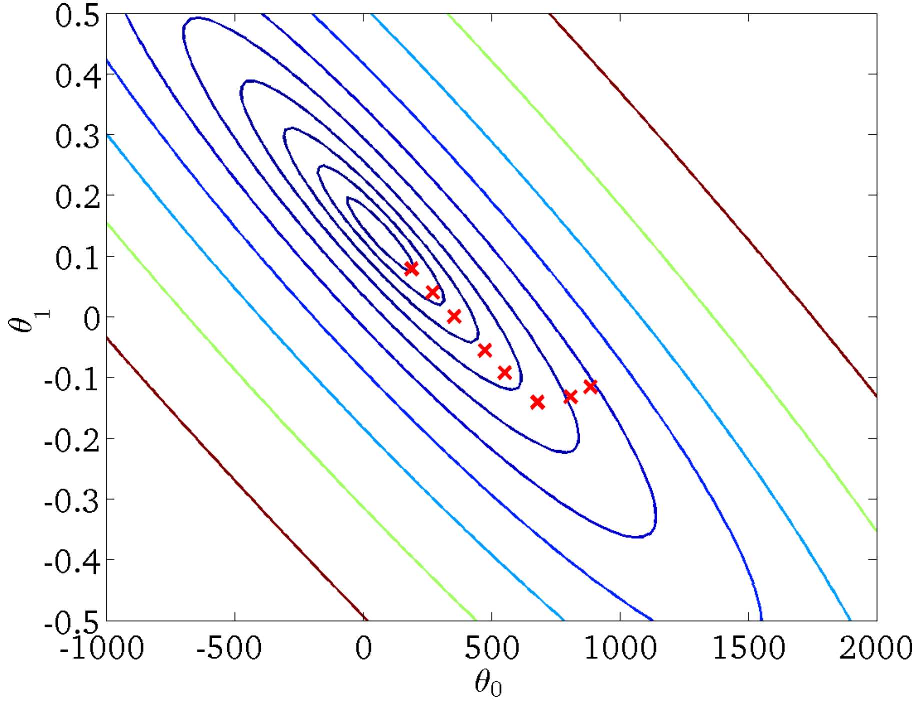
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)

$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)





Slide by Andrew Ng

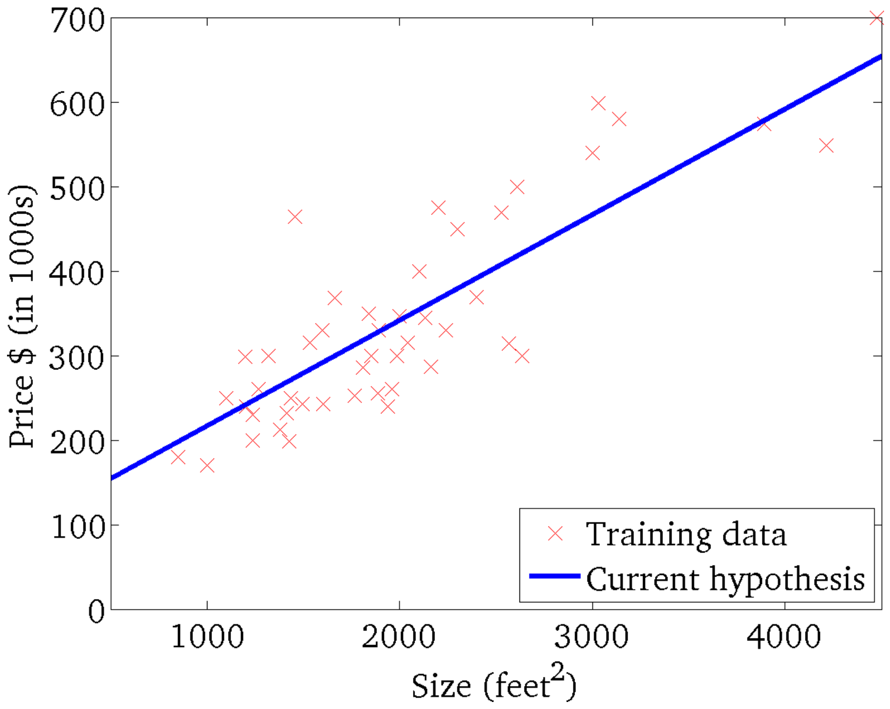
# Gradient Descent

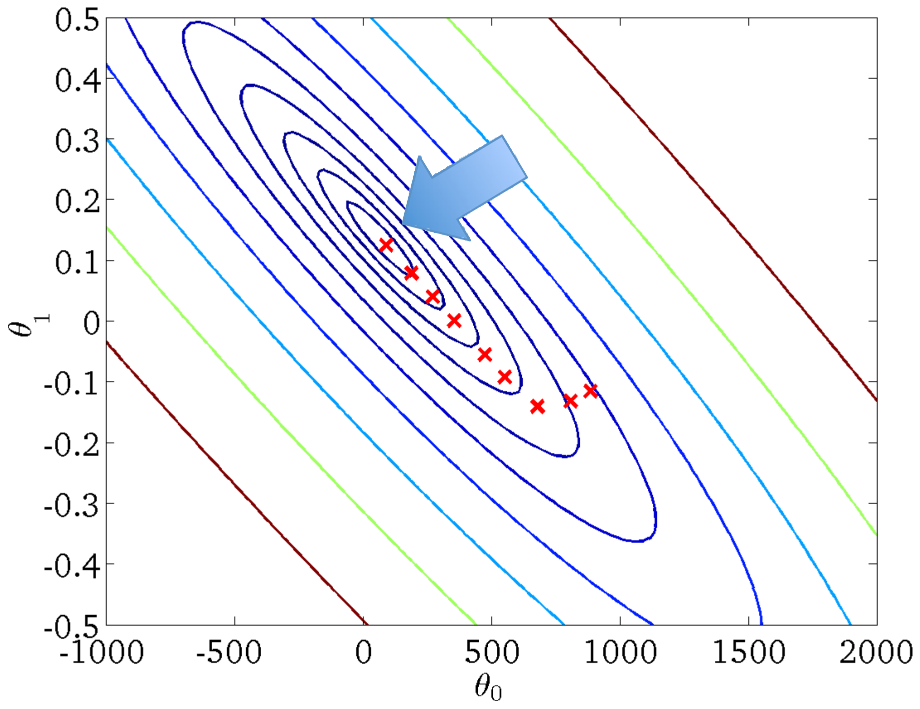
$h_\theta(x)$

(for fixed $\theta_0, \theta_1$, this is a function of x)

$J(\theta_0, \theta_1)$

(function of the parameters $\theta_0, \theta_1$)

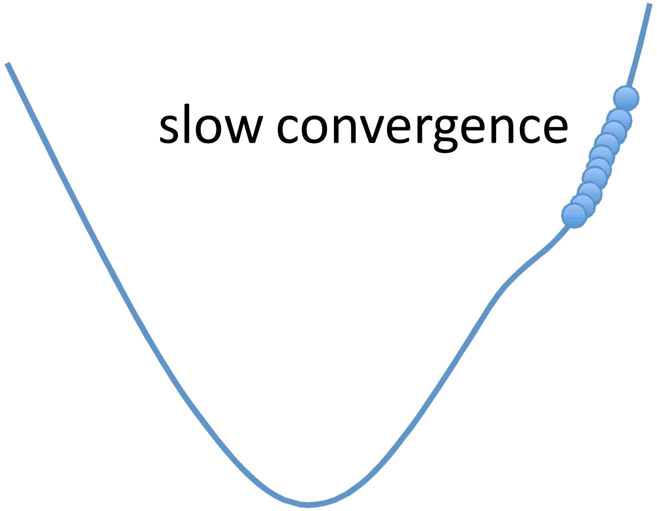




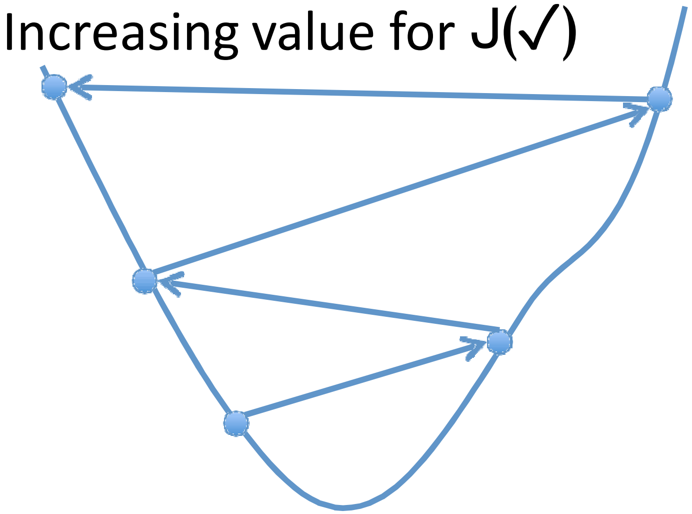
Slide by Andrew Ng

# Choosing α

## α too small


slow convergence

## α too large


Increasing value for J(✓)

- May overshoot the minimum
- May fail to converge
- May even diverge

To see if gradient descent is working, print out J(✓) each iteration

- The value should decrease at each iteration
- If it doesn’t, adjust α