

Machine Learning

Linear Regression with multiple variables

Multiple features

Multiple features (variables).

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

Multiple features (variables).

Size (feet ²)	Number of bedrooms	Number of floors	Age of home (years)	Price (\$1000)
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178
	•••			

Multiple features (variables).

Size (feet²)	Number of bedrooms	Number of floors	Age of home (years)	Price (\$1000)
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178
			•••	•••

Notation:

n = number of features

 $x^{(i)}$ = input (features) of i^{th} training example.

 $x_j^{(i)}$ = value of feature j in i^{th} training example.

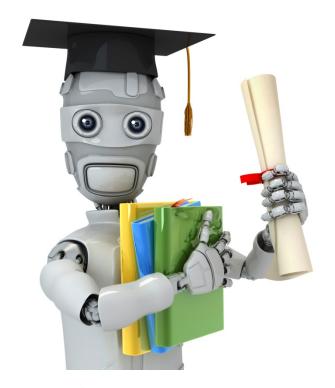
Hypothesis:

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

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

For convenience of notation, define $x_0 = 1$.

Multivariate linear regression.



Machine Learning

Linear Regression with multiple variables

Gradient descent for multiple variables

Hypothesis: $h_{\theta}(x) = \theta^T x = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$

Parameters: $\theta_0, \theta_1, \dots, \theta_n$

Cost function:

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

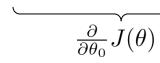
Gradient descent:

Repeat $\{$ $\theta_j:=\theta_j-\alpha\frac{\partial}{\partial\theta_j}J(\theta_0,\dots,\theta_n)$ $\}$ (simultaneously update for every $j=0,\dots,n$)

Gradient Descent

Previously (n=1):

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})$$



$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x^{(i)}$$

(simultaneously update
$$\, heta_0, heta_1)$$

New algorithm $(n \ge 1)$:

Repeat {

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

 $\frac{\sigma_j := \sigma_j - \alpha}{m} \underbrace{\sum_{i=1}^{m} (n_\theta(x^i) - g^{-i}) x_j}_{i=1}$ (simultaneously update θ_j for $j=0,\dots,n$)

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_0^{(i)}$$

$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)}) x_1^{(i)}$$

$$\theta_2 := \theta_2 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)}) x_2^{(i)}$$



Machine Learning

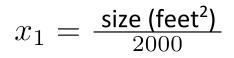
Linear Regression with multiple variables

Gradient descent in practice I: Feature Scaling

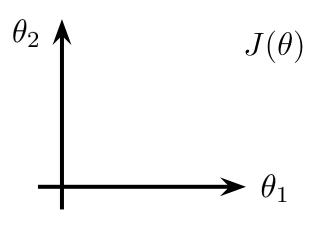
Feature Scaling

Idea: Make sure features are on a similar scale.

E.g.
$$x_1$$
 = size (0-2000 feet²)
 x_2 = number of bedrooms (1-5)
 θ_2



$$x_2 = \frac{\text{number of bedrooms}}{5}$$



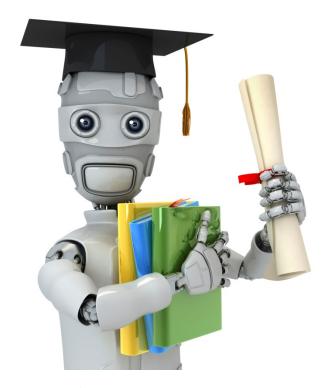
Feature Scaling

Get every feature into approximately a $-1 \le x_i \le 1$ range.

Mean normalization

Replace x_i with $x_i - \mu_i$ to make features have approximately zero mean (Do not apply to $x_0 = 1$).

E.g.
$$x_1 = \frac{size - 1000}{2000}$$
 $x_2 = \frac{\#bedrooms - 2}{5}$ $-0.5 < x_1 < 0.5, -0.5 < x_2 < 0.5$



Machine Learning

Linear Regression with multiple variables

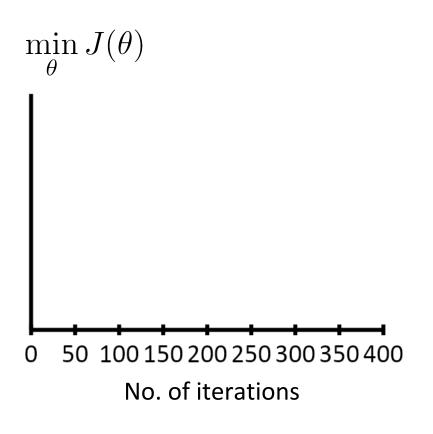
Gradient descent in practice II: Learning rate

Gradient descent

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

- "Debugging": How to make sure gradient descent is working correctly.
- How to choose learning rate α .

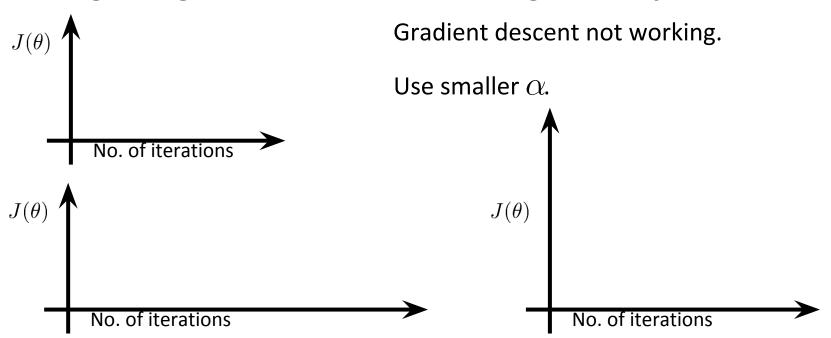
Making sure gradient descent is working correctly.



Example automatic convergence test:

Declare convergence if $J(\theta)$ decreases by less than 10^{-3} in one iteration.

Making sure gradient descent is working correctly.



- For sufficiently small lpha, J(heta) should decrease on every iteration.
- But if lpha is too small, gradient descent can be slow to converge.

Summary:

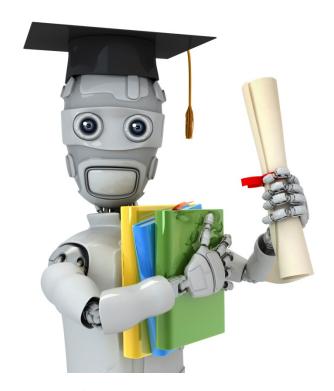
- If α is too small: slow convergence.
- If α is too large: $J(\theta)$ may not decrease on every iteration; may not converge.

To choose α , try

$$\dots, 0.001,$$

$$, 0.01, , 0.1, , 1, \dots$$

$$,1,\dots$$



Machine Learning

Linear Regression with multiple variables

Features and polynomial regression

Housing prices prediction

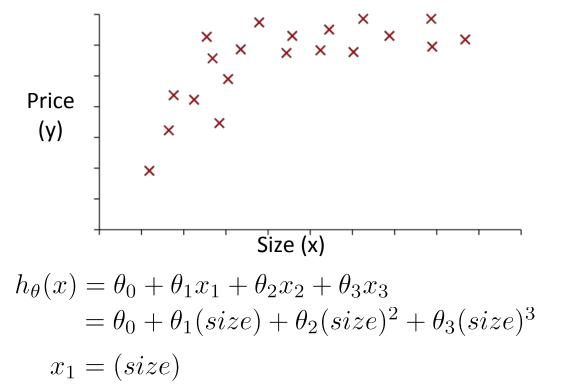
$$h_{\theta}(x) = \theta_0 + \theta_1 \times frontage + \theta_2 \times depth$$



Polynomial regression

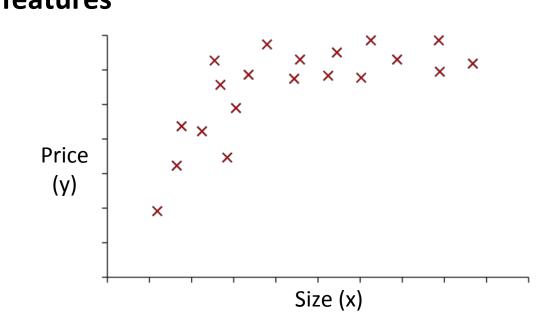
 $x_2 = (size)^2$

 $x_3 = (size)^3$



$$\theta_0 + \theta_1 x + \theta_2 x^2$$
$$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3$$

Choice of features



$$h_{\theta}(x) = \theta_0 + \theta_1(size) + \theta_2(size)^2$$
$$h_{\theta}(x) = \theta_0 + \theta_1(size) + \theta_2\sqrt{(size)}$$