

# Machine Learning — Week 2 Assignment

compute cost. m

## 2.2.1 Update Equations

The objective of linear regression is to minimize the cost function

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

where the hypothesis  $h_{\theta}(x)$  is given by the linear model

$$h_{\theta}(x) = \theta^T x = \theta_0 + \theta_1 x_1$$

```
function J = computeCost(X, y, theta)
%COMPUTECOST Compute cost for linear regression
% J = COMPUTECOST(X, y, theta) computes the cost of using theta as the
% parameter for linear regression to fit the data points in X and y
```

```
% Initialize some useful values
m = length(y); % number of training examples
```

```
% You need to return the following variables correctly
J = 0;
```

```
% ===== YOUR CODE HERE
```

```
% =====
```

```
% Instructions: Compute the cost of a particular choice of theta
% You should set J to the cost.
```

```
J = 1/(2*m)*((X*theta-y)'*(X*theta-y));
```

```
%
```

```
% =====
```

```
end
```

$$X = \begin{bmatrix} 1 & 6.1101 \\ 1 & 5.3277 \\ \vdots & \vdots \\ 1 & 5.4369 \end{bmatrix} \quad \theta = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} \quad \rightarrow \quad X * \theta = \begin{bmatrix} \theta_1 + 6.1101\theta_2 \\ \theta_1 + 5.3277\theta_2 \\ \vdots \\ \theta_1 + 5.4369\theta_2 \end{bmatrix}$$

$$Z = X * \theta - y = \begin{bmatrix} \theta_1 + 6.1101\theta_2 - 17.592 \\ \vdots \\ \theta_1 + 5.4369\theta_2 - 0.61705 \end{bmatrix} \rightarrow h_{\theta}(x^{(i)}) - y^{(i)}$$

$$Z' \rightarrow 1 \times 97$$

$$\Rightarrow Z' * Z = (X * \theta - y)' * (X * \theta - y) = \sum_{i=0}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

1x1

## 2. gradient Descent. m

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} \quad (\text{simultaneously update } \theta_j \text{ for all } j).$$

```
function [theta, J_history] = gradientDescent(X, y, theta, alpha, num_iters)
%GRADIENDESCENT Performs gradient descent to learn theta
% theta = GRADIENDESCENT(X, y, theta, alpha, num_iters) updates theta by
% taking num_iters gradient steps with learning rate alpha
```

```
% Initialize some useful values
m = length(y); % number of training examples
J_history = zeros(num_iters, 1);
```

```
for iter = 1:num_iters
```

```
% ===== YOUR CODE HERE
```

```
=====
```

```
% Instructions: Perform a single gradient step on the parameter vector
% theta.
```

```
%
```

```
% Hint: While debugging, it can be useful to print out the values
% of the cost function (computeCost) and gradient here.
```

```
%
```

```
theta = theta - alpha/m * X' * (X * theta - y);
```

```
%
```

```
=====
```

```
=====
```

```
% Save the cost J in every iteration
```

```
J_history(iter) = computeCost(X, y, theta);
```

```
end
```

```
end
```

2x1

2x97

97x1

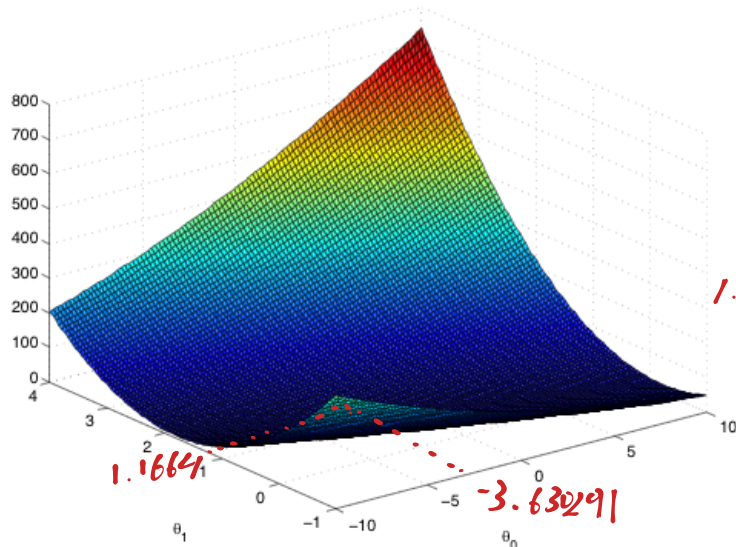
$$\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} = \frac{\alpha}{m} \begin{bmatrix} 1 & 1 & \dots & 1 \\ 6.1101 & 5.5277 & \dots & 5.4369 \end{bmatrix} \cdot \begin{bmatrix} \theta_1 + 6.1101\theta_2 - 17.592 \\ \vdots \\ \theta_1 + 5.4369\theta_2 - 0.61705 \end{bmatrix}$$

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

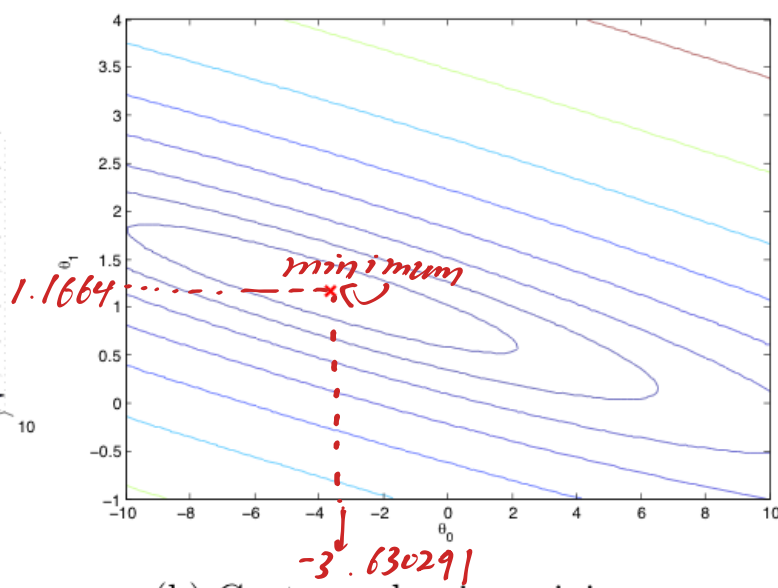
2x/

$$\theta_2 = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_1^{(i)}$$

### 3. Visualizing $J(\theta)$



(a) Surface



(b) Contour, showing minimum

In 3D surface,  $\theta_0$  and  $\theta_1$  can be changed from different value, which reduce the value of  $J(\theta)$ , and finally  $J(\theta) = 0$

### 4. Optional exercises

not different, pay attention that gradient descent needs feature scaling while normal equation doesn't need it

(1) gradient descent:

$$J(\theta) = \frac{1}{2m} (X\theta - \vec{y})^T (X\theta - \vec{y})$$

$$J = 1/(2*m) * ((X*theta - y)' * (X*theta - y));$$

(2) normal equation:

$$\theta = (X^T X)^{-1} X^T \vec{y}.$$

$$\theta = \text{pinv}(X' * X) * X' * y;$$

$$x_i := \frac{x_i - \mu_i}{\sigma_i} \rightarrow \text{average}$$

standard deviation