# Logistic Regression

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## 1 Problem of Linear Regression in Binary Classfication

In linear regression, y=0 or 1, yet  $h_{\theta}(x)$  can be greater than one or less than zero. In logistic regression,  $0 \le h_{\theta}(x) \le 1$ .

### 2 Hypothesis

To make  $0 \le h_{\theta}(x) \le 1$ , define it as:

$$g(x) = \frac{1}{1 + e^{-x}}$$
 (the Sigmoid function) (1)

$$h_{\theta}(x) = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$
 (2)

Interpret  $h_{\theta}(x)$  as the probability that y = 1. The **decision boundary**: predict y = 1 if  $h_{\theta}(x) \ge 0.5$  which is equivalent to  $\theta^T x \ge 0$ .

#### 3 Cost Function

In linear regression, cost function is defined as

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

It can be shown that the above Cost function is not a convex one in the case of logistic regression. Therefore, define the Cost function for logistic regression

$$Cost(h_{\theta}(x), y) = -y \log h_{\theta}(x) - (1 - y) \log (1 - h_{\theta}(x)),$$

therefore the cost function for logistic regression is

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} Cost(h_{\theta}(x^{(i)}), y^{(i)})$$
(3)

$$= -\frac{1}{m} \left[ \sum_{i=1}^{m} y^{(i)} \log h_{\theta}(x^{(i)}) + (1 - y^{(i)}) \log (1 - h_{\theta}(x^{(i)})) \right]. \tag{4}$$

It can be shown via the principle of maximum likelihood estimation that the cost function  $J(\theta)$  is convex. In addition, notice that  $J(\theta) \geq 0$  at all times.

Taking the partial derivative:

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

so the gradient descent algorithm for logistic regression is

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \tag{5}$$

$$= \alpha \frac{1}{m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}.$$
 (6)

### 4 Optimization Algorithms

gradient descent, and more advanced ones (faster, no need to manually pick  $\alpha$ , more complex): conjugate gradient, BFGS, L-BFGS.