

Logistic Resression

Logistic regression is used to deal with binary classification problem in mechine learning. for dataset $(x^{(i)}, y^{(i)})$, all output $y^{(i)} \in \{0, 1\}$, the model's prediction is

$$h_{\theta}(x) = g(\theta^T x)$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

that makes prediction in the interval (0,1), that means, if $h_{\theta}(x) = 0.7$, gives us a probability of 70% that our output is 1, so the predicted output is "1", that is to say,

$$y = \begin{cases} 0 & h_{\theta}(x) < 0.5 \\ 1 & h_{\theta}(x) \geq 0.5 \end{cases}$$

that is,

$$h_{\theta}(x) = P(y = 1|x; \theta) = 1 - P(y = 0|x; \theta)$$

Cost function

Our cost function of logistic regression is

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

and

$$Cost(h_{\theta}(x^{(i)}), y^{(i)}) = \begin{cases} -\log(h_{\theta}(x)) & y = 1 \\ -\log(1 - h_{\theta}(x)) & y = 0 \end{cases}$$

when $y = 1$ and $h_{\theta}(x)$ close to 1, $J(\theta)$ will be smaller, so do $y = 0$. In summary,

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

Gradient Descent

$$\begin{aligned} & \text{Repeat}\{ \\ & \theta_j = \theta_j - \alpha \cdot \frac{\partial}{\partial \theta_j} J(\theta) \\ & = \theta_j - \frac{\alpha}{m} \cdot \sum_{i=1}^m ((h_{\theta}(x^{(i)}) - y^{(i)})x_j^{(i)}) \\ & \} \end{aligned}$$

Reference

[machine learning](#)