

Computer Vision

Assignment 3



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1 Problem 1(Math)

In our lecture, we mentioned that for logistic regression, the cost function is,

$$J(\theta) = - \sum_{i=1}^m y_i \log(h_{\theta}(\mathbf{x}_i)) + (1 - y_i) \log(1 - h_{\theta}(\mathbf{x}_i)) \quad (1)$$

Please verify that the gradient of this cost function is

$$\nabla_{\theta} J(\theta) = \sum_{i=1}^m \mathbf{x}_i (h_{\theta}(\mathbf{x}_i) - y_i) \quad (2)$$

Solution: According to the definition of gradient,

$$\nabla_{\theta} J(\theta) = \begin{bmatrix} \frac{\partial J(\theta)}{\partial \theta_1} \\ \frac{\partial J(\theta)}{\partial \theta_2} \\ \vdots \\ \frac{\partial J(\theta)}{\partial \theta_m} \end{bmatrix} \quad (3)$$

where x is the input vector, y is the ground-truth, θ is the parameter vector

For one item $\frac{\partial J(\theta)}{\partial \theta_j}$, the calculation process is showing below:

$$\begin{aligned} \frac{\partial J(\theta)}{\partial \theta_j} &= - \sum_{i=1}^m \left[y_i \frac{1}{h_{\theta}(x_i)} \frac{\partial h_{\theta}(x_i)}{\partial \theta_j} + (1 - y_i) \frac{-\frac{\partial h_{\theta}(x_i)}{\partial \theta_j}}{1 - h_{\theta}(x_i)} \right] \\ &= - \sum_{i=1}^m \left[\frac{\partial h_{\theta}(x_i)}{\partial \theta_j} \left(\frac{y_i}{h_{\theta}(x_i)} + \frac{y_i - 1}{1 - h_{\theta}(x_i)} \right) \right] \\ &= \frac{h_{\theta}(x_i)}{1 - h_{\theta}(x_i)} e^{-\theta^T x} x_{ij} (y_i - h_{\theta}(x_i)) \\ &= x_{ij} (y_i - h_{\theta}(x_i)) \end{aligned} \quad (4)$$

During the calculation, I omitted part of the calculation, add them below:

$$\begin{aligned} h_{\theta}(x_i) &= \frac{1}{1 + \exp(-\theta^T x_i)} \\ \frac{\partial h_{\theta}(x_i)}{\partial \theta_j} &= - \frac{e^{-\theta^T x} (-x_j)}{[1 + \exp(-\theta^T x)]^2} \\ &= (h_{\theta}(x_i))^2 e^{-\theta^T x} x_{ij} \\ \frac{h_{\theta}(x_i)}{1 - h_{\theta}(x_i)} e^{-\theta^T x} &= \frac{\frac{1}{1 + \exp(-\theta^T x_i)}}{1 - \frac{1}{1 + \exp(-\theta^T x_i)}} \exp(-\theta^T x_i) \\ &= \frac{\frac{1}{1 + \exp(-\theta^T x_i)}}{\frac{\exp(-\theta^T x_i)}{1 + \exp(-\theta^T x_i)}} \exp(-\theta^T x_i) \\ &= 1 \end{aligned}$$

From what have been mentioned above, $\frac{\partial J(\theta)}{\partial \theta_j} = \sum_{i=1}^m (h_{\theta}(x_i) - y_i)x_{ij}$. Hence, the gradient of this cost function is $\nabla_{\theta} J(\boldsymbol{\theta}) = \sum_{i=1}^m \mathbf{x}_i (h_{\theta}(\mathbf{x}_i) - y_i)$.