≮Back to Week 3

XLessons

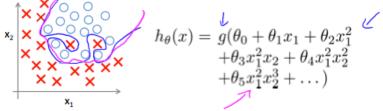
Prev

Next

Regularized Logistic Regression

We can regularize logistic regression in a similar way that we regularize linear regression. As a result, we can avoid overfitting. The following image shows how the regularized function, displayed by the pink line, is less likely to overfit than the non-regularized function represented by the blue line:

Regularized logistic regression.



Cost function:

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

$$+ \frac{\lambda}{2m} \sum_{j=1}^{n} \bigotimes_{j}^{n} \left[\bigcirc_{i}, \bigcirc_{i}, \dots, \bigcirc_{n} \right]$$

Cost Function

Recall that our cost function for logistic regression was:

$$J(heta) = -rac{1}{m}\sum_{i=1}^m ig[y^{(i)} \; \log(h_ heta(x^{(i)})) + (1-y^{(i)}) \; \log(1-h_ heta(x^{(i)}))ig]$$

We can regularize this equation by adding a term to the end:

$$J(heta) = -rac{1}{m} \sum_{i=1}^m [y^{(i)} \; \log(h_ heta(x^{(i)})) + (1-y^{(i)}) \; \log(1-h_ heta(x^{(i)}))] + rac{\lambda}{2m} \sum_{j=1}^n heta_j^2$$

The second sum, $\sum_{j=1}^{n} \theta_{j}^{2}$ means to explicitly exclude the bias term, θ_{0} . I.e. the θ vector is indexed from 0 to n (holding n+1 values, θ_{0} through θ_{n}), and this sum explicitly skips θ_{0} , by running from 1 to n, skipping 0. Thus, when computing the equation, we should continuously update the two following equations:

Gradient descent

Repeat {
$$\Theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_0^{(i)}$$

$$\Theta_j := \theta_j - \alpha \underbrace{\left[\frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)} + \frac{\lambda}{m} \Theta_j\right]}_{\{j = \mathbf{X}, 1, 2, 3, \dots, n\}}$$
 }
$$\underbrace{\frac{\lambda}{\lambda \Theta_j} \underbrace{\mathsf{I}(\Theta)}_{\{j = \mathbf{X}, 1, 2, 3, \dots, n\}}}_{\{j = \mathbf{X}, 1, 2, 3, \dots, n\}}$$

Mark as completed





