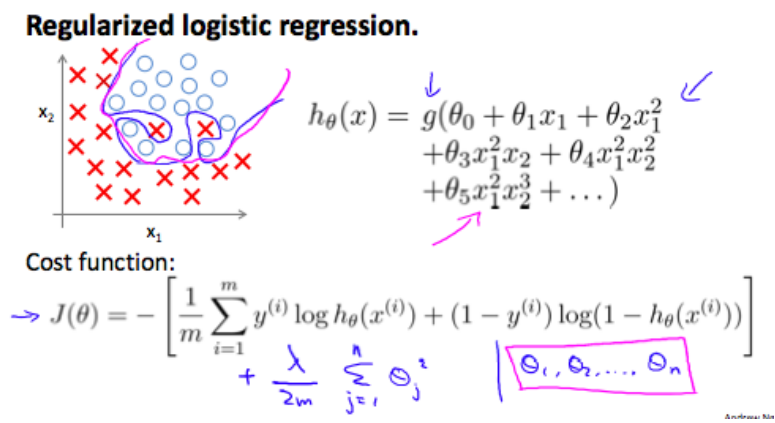


Regularized Logistic Regression

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:



Cost Function

Recall that our cost function for logistic regression was:

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

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

$$J(\theta) = - \frac{1}{m} \sum_{i=1}^m [y^{(i)} \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)}))] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$

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 {

$$\rightarrow \theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_0^{(i)}$$
$$\rightarrow \theta_j := \theta_j - \alpha \left[\frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} + \frac{\lambda}{m} \theta_j \right]$$

}

$\frac{\partial}{\partial \theta_j} J(\theta)$

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

✓ Complete