

Classification and Representation

- ✓ **Video:** Classification
8 min
- ✓ **Reading:** Classification
2 min
- ✓ **Video:** Hypothesis Representation
7 min
- ✓ **Reading:** Hypothesis Representation
3 min
- ✓ **Video:** Decision Boundary
14 min
- ✓ **Reading:** Decision Boundary
3 min

Logistic Regression Model

- ✓ **Video:** Cost Function
10 min
- ✓ **Reading:** Cost Function
3 min
- ✓ **Video:** Simplified Cost Function and Gradient Descent
10 min
- ✓ **Reading:** Simplified Cost Function and Gradient Descent
3 min
- ✓ **Video:** Advanced Optimization
14 min
- ✓ **Reading:** Advanced Optimization
3 min

Multiclass Classification

- ✓ **Video:** Multiclass Classification: One-vs-all
6 min
- ✓ **Reading:** Multiclass Classification: One-vs-all
3 min

Review

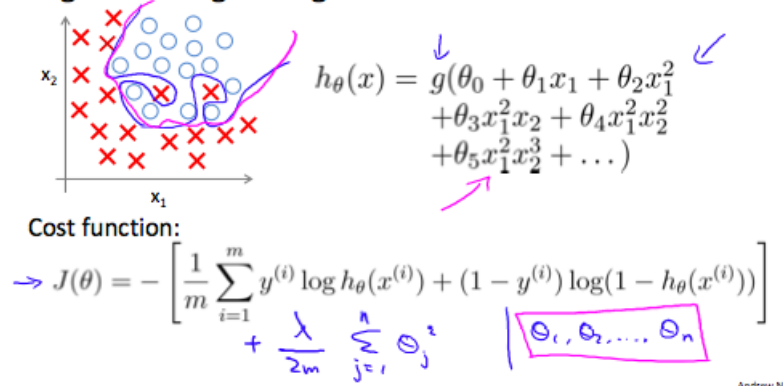
Solving the Problem of Overfitting

- ✓ **Video:** The Problem of Overfitting
9 min
- ✓ **Reading:** The Problem of

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

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 {

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

(j = 1, 2, 3, ..., n)
 $\theta_1, \dots, \theta_n$

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

✓ Complete

Go to next item