



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

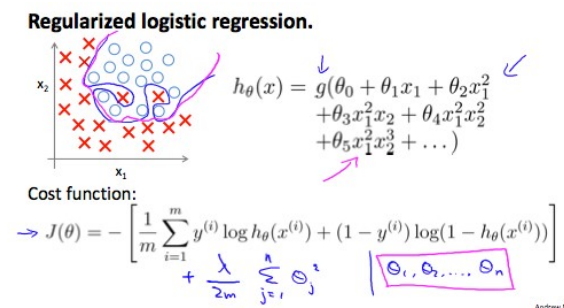
Logistic Regression Model

- ✓ **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



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:

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