Evaluating a Hypothesis

Once we have done some trouble shooting for errors in our predictions by:

- Getting more training examples
- Trying smaller sets of features
- Trying additional features
- Trying polynomial features
- Increasing or decreasing λ

We can move on to evaluate our new hypothesis.

A hypothesis may have a low error for the training examples but still be inaccurate (because of overfitting). Thus, to evaluate a hypothesis, given a dataset of training examples, we can split up the data into two sets: a training set and a test set. Typically, the **training set** consists of 70 % of your data and the **test set** is the remaining 30 %.

The new procedure using these two sets is then:

1. Learn Θ and minimize $J_{test}(\Theta)$ using the training set

2. Compute the test set error $J_{test}(\Theta)$

The test set error

1. For linear regression: $J_{test}(\Theta) = \frac{1}{2m_{test}}\sum_{i=1}^{m_{test}}(h_\Theta(x_{test}^{(i)}) - y_{test}^{(i)})^2$
2. For classification ~ Misclassification error (aka 0/1 misclassification error):

$err(h_\Theta(x), y) = \begin{cases} 1 & \text{if } h_\Theta(x) \geq 0.5 \text{ and } y=0 \text{ or } h_\Theta(x) < 0.5 \text{ and } y=1 \\ 0 & \text{otherwise} \end{cases}$

This gives us a binary 0 or 1 error result based on a misclassification. The average test error for the test set is:

Test Error $= \frac{1}{m_{test}}\sum_{i=1}^{m_{test}} err(h_\Theta(x_{test}^{(i)}), y_{test}^{(i)})$

This gives us the proportion of the test data that was misclassified.