

# 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  $\lambda$

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  $\Theta$  and minimize  $J_{\text{test}}(\Theta)$  using the training set
2. Compute the test set error  $J_{\text{test}}(\Theta)$

## The test set error

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

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

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

$$\text{Test Error} = \frac{1}{m_{\text{test}}} \sum_{i=1}^{m_{\text{test}}} \text{err}(\mathbf{h}_{\Theta}(\mathbf{x}_{\text{test}}^{(i)}), y_{\text{test}}^{(i)})$$

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