



## Evaluating a Learning Algorithm



**Video:** Deciding What to Try Next  
5 min



**Video:** Evaluating a Hypothesis  
7 min



**Reading:** Evaluating a Hypothesis  
4 min



**Video:** Model Selection and Train/Validation/Test Sets  
12 min



**Reading:** Model Selection and Train/Validation/Test Sets  
3 min

## Bias vs. Variance

## Review

## Building a Spam Classifier

## Handling Skewed Data

## Using Large Data Sets

## Review



# Evaluating a Hypothesis

Once we have done some trouble shooting for errors in our 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 inaccurate (because of overfitting). Thus, to evaluate a hypothesis on a dataset of training examples, we can split up the data into **training set** and a **test set**. Typically, the training set consists 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  $J_{train}(\Theta)$  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):

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

This gives us a binary 0 or 1 error result based on a misclassification