

# **Evaluating a Learning Algorithm**

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  Next
  5 min
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- Video: Model Selection and Train/Validation/Test Sets
  12 min
- Reading: Model Selection and Train/Validation/Test Sets
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#### Bias vs. Variance

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  Variance
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- Reading: Diagnosing Bias vs. Variance
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- Video: Regularization and Bias/Variance
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- Video: Learning Curves
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#### Review

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  10 min
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- Programming Assignment:
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#### **Building a Spam Classifier**

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- Reading: Prioritizing What to Work On 3 min

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

$$err(h_{\Theta}(x),y) = egin{array}{ll} & ext{if } h_{\Theta}(x) \geq 0.5 \ and \ y = 0 \ or \ h_{\Theta}(x) < 0.5 \ and \ y = 1 \ & ext{otherwise} \end{array}$$

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

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

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

✓ Complete

Go to next item

