

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

- ✔ **Video:** Diagnosing Bias vs. Variance  
7 min
- ✔ **Reading:** Diagnosing Bias vs. Variance  
3 min
- ✔ **Video:** Regularization and Bias/Variance  
11 min
- ✔ **Reading:** Regularization and Bias/Variance  
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- ✔ **Video:** Learning Curves  
11 min
- ✔ **Reading:** Learning Curves  
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- ✔ **Video:** Deciding What to Do Next Revisited  
6 min
- ✔ **Reading:** Deciding What to do Next Revisited  
3 min

Review

- ✔ **Reading:** Lecture Slides  
10 min
- 📋 **Quiz:** Advice for Applying Machine Learning  
5 questions
- 📄 **Programming Assignment:** Regularized Linear Regression and Bias/Variance  
3h

Building a Spam Classifier

- ▶ **Video:** Prioritizing What to Work On  
9 min
- 📖 **Reading:** Prioritizing What to Work On  
3 min



# Deciding What to Do Next Revisited

Our decision process can be broken down as follows:

- **Getting more training examples:** Fixes high variance
- **Trying smaller sets of features:** Fixes high variance
- **Adding features:** Fixes high bias
- **Adding polynomial features:** Fixes high bias
- **Decreasing  $\lambda$ :** Fixes high bias
- **Increasing  $\lambda$ :** Fixes high variance.

## Diagnosing Neural Networks

- A neural network with fewer parameters is **prone to underfitting**. It is also **computationally cheaper**.
- A large neural network with more parameters is **prone to overfitting**. It is also **computationally expensive**. In this case you can use regularization (increase  $\lambda$ ) to address the overfitting.

Using a single hidden layer is a good starting default. You can train your neural network on a number of hidden layers using your cross validation set. You can then select the one that performs best.

## Model Complexity Effects:

- Lower-order polynomials (low model complexity) have high bias and low variance. In this case, the model fits poorly consistently.
- Higher-order polynomials (high model complexity) fit the training data extremely well and the test data extremely poorly. These have low bias on the training data, but very high variance.
- In reality, we would want to choose a model somewhere in between, that can generalize well but also fits the data reasonably well.

✔ Complete

Go to next item