



Experimentation and Evaluation

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The instructor gratefully acknowledges Eric Eaton (UPenn), David Kauchak (Pomona), and the many others who made their course materials freely available online.

Robot Image Credit: Viktoriya Sukhanova © 123RF.com

Evaluation Basics

Learning Goals

- Describe problems with using training set to evaluate performance
- Define metrics for evaluating performance
 - accuracy, error
 - confusion matrix
 - sensitivity, specificity
 - receiver operating curve (ROC)

Comparing Classifiers

Given: two classifiers, C_1 and C_2

Goal: choose the best one to use for future predictions

C_1 and C_2 may be

- same learning model with **different complexities** or **hyperparameters**
 - decision trees : different depths
 - k -NN : different choices of k
- different learning models

Can we use training accuracy to choose between them?

- No!
e.g., C_1 = pruned decision tree, C_2 = 1-NN
training_accuracy(1-NN) = 100% but may not be best
- Instead, choose based on test accuracy...

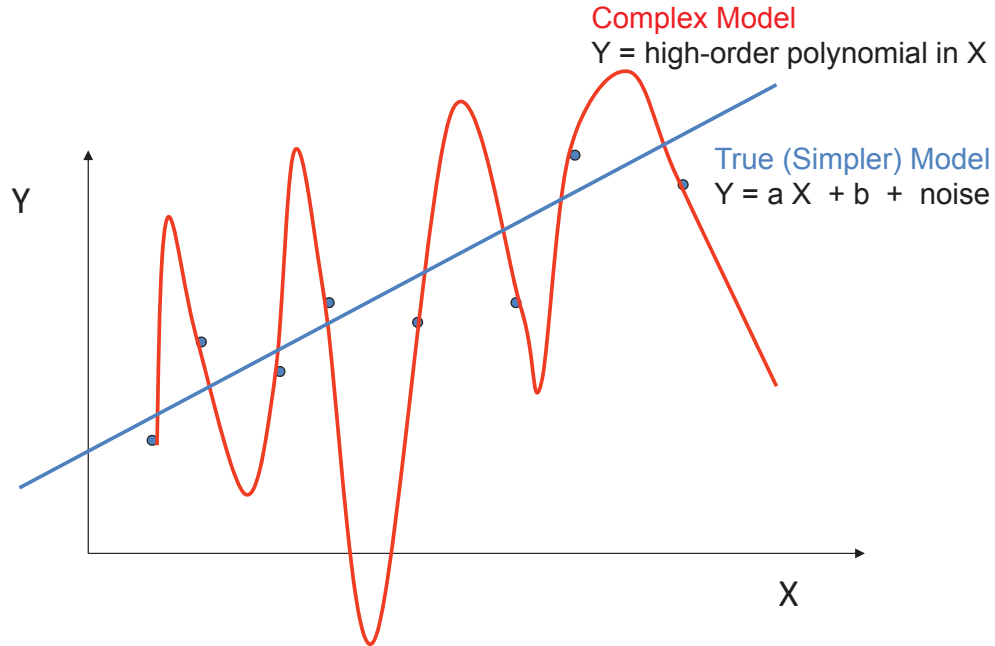
Based on slides by Piyush Rai and Eric Eaton (originally by Padhraic Smyth)

Training Data and Test Data

- Training data: data used to build model
- Test data: new data, not used in training process
- Training performance is often poor indicator of generalization performance
 - generalization is what we really care about in ML
 - easy to overfit to training data
 - performance on test data is good indicator of generalization performance
- Test accuracy more important than training accuracy

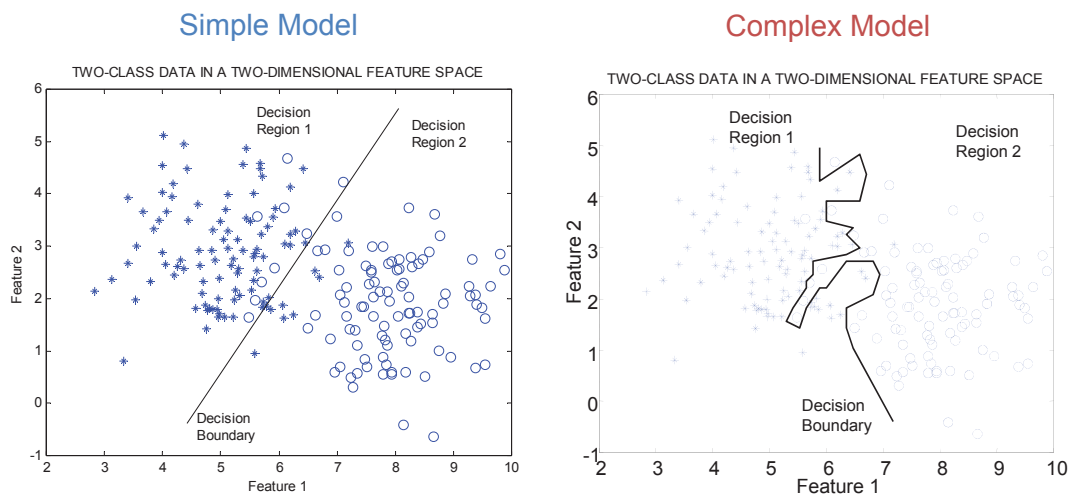
Based on slide by Eric Eaton

Example: The Overfitting Phenomenon



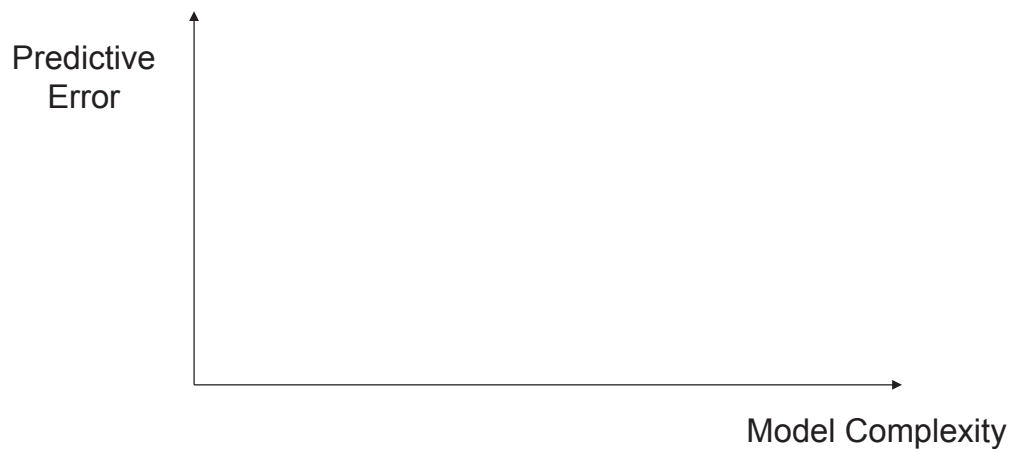
Based on slide by Padhraic Smyth, UCLrvine

Example: The Overfitting Phenomenon



Based on slide by Padhraic Smyth, UCLrvine

How Overfitting Affects Prediction



Based on slide by Padhraic Smyth, UCIrvine



Real-world classification

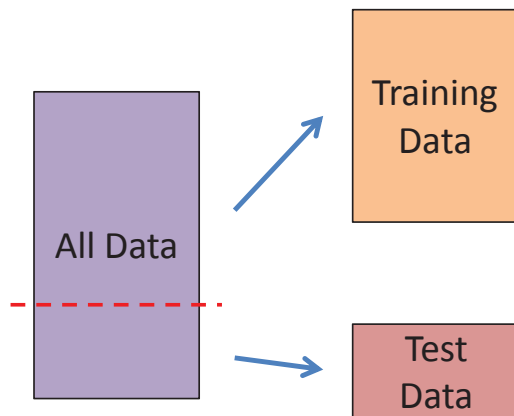
But how do we get test data?

Google has labeled training data, for example from people clicking “spam” button, but when new messages come in, they are not labeled

[illegible]

Based on slide by David Kauchak

Classification Evaluation



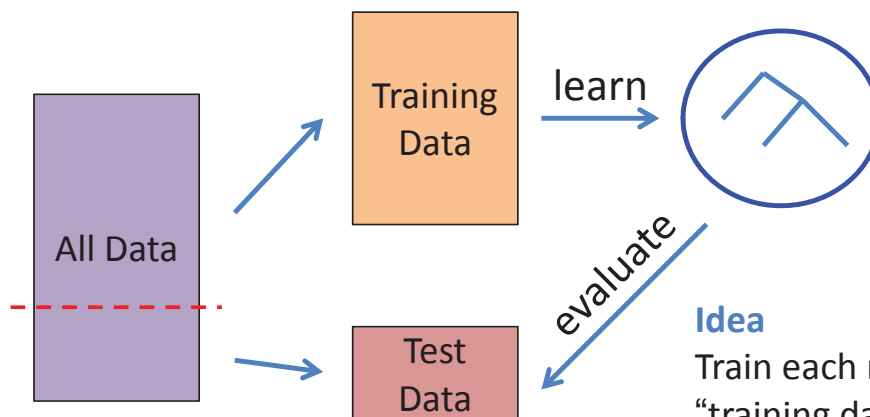
Use labeled data we have already to create test set with known labels!

Why can we do this?

Remember, we assume there's an underlying distribution that generates both training and test examples

Based on slides by Eric Eaton and David Kauchak

Classification Evaluation



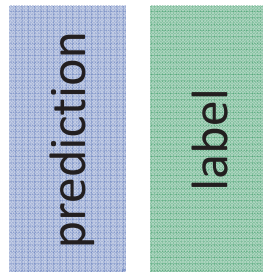
Idea

Train each model on "training data"...
...and then test each model on test data

Based on slide by Eric Eaton

Evaluation Metrics

To evaluate model, compare predicted labels to actual labels



Accuracy: proportion of examples where we predicted **correct** label

$$\text{accuracy} = \frac{\# \text{ correct predictions}}{\# \text{ test instances}}$$

Error: proportion of examples where we predicted **incorrect** label

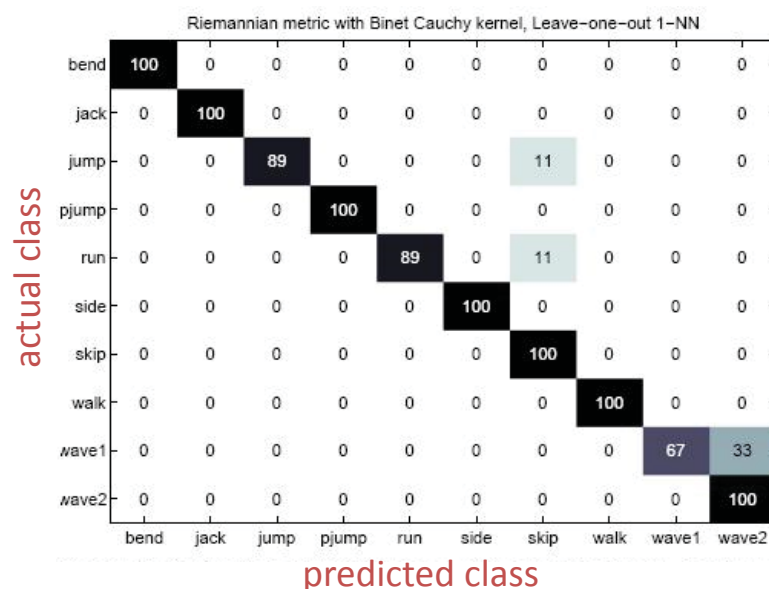
$$\begin{aligned} \text{error} &= 1 - \text{accuracy} \\ &= \frac{\# \text{ incorrect predictions}}{\# \text{ test instances}} \end{aligned}$$

Based on slide by David Kauchak

Confusion Matrices

How can we understand what types of mistakes a classifier makes?

activity recognition from video



Based on slide by David Page
[Image source: jhu.vision.edu]

Confusion Matrix for 2-class problems

- Imagine a classifier that identifies presence of disease

| | | predicted class | |
|--------------|-----|-----------------|----|
| | | Yes | No |
| actual class | Yes | TP | FN |
| | No | FP | TN |

$$\text{accuracy} = \frac{TP + TN}{P + N}$$

TP = person tests positive and really has disease

TN = person tests negative and really does not have disease

FP = person tests positive and does not have disease

FN = person tests negative and has disease

P = actual class is positive = TP + FN

N = actual class is negative = TN + FP

Based on slide by Eric Eaton

Is Accuracy an Adequate Measure?



Confusion Matrix

- Given dataset of P positive instances and N negative instances:

| | predicted class | |
|--------------|-----------------|-------|
| | Yes | No |
| actual class | Yes | TP FN |
| | No | FP TN |

$$\text{accuracy} = \frac{TP + TN}{P + N}$$

- Imagine a classifier that identifies presence of disease

$$\text{sensitivity} = \frac{TP}{TP + FN}$$

(true positive rate) = probability of positive test
given person has disease

$$\text{specificity} = \frac{TN}{TN + FP}$$

(true negative rate) = probability of negative test
given person does not have disease

Based on slide by Eric Eaton

Confusion Matrix: Cancer Dataset

| | screen test | |
|-------------------------|-------------|----------|
| | Yes | No |
| patients with cancer | Yes | 20 10 |
| | No | 180 1820 |

Compute accuracy,
sensitivity, and specificity

Based on slide by Eric Eaton



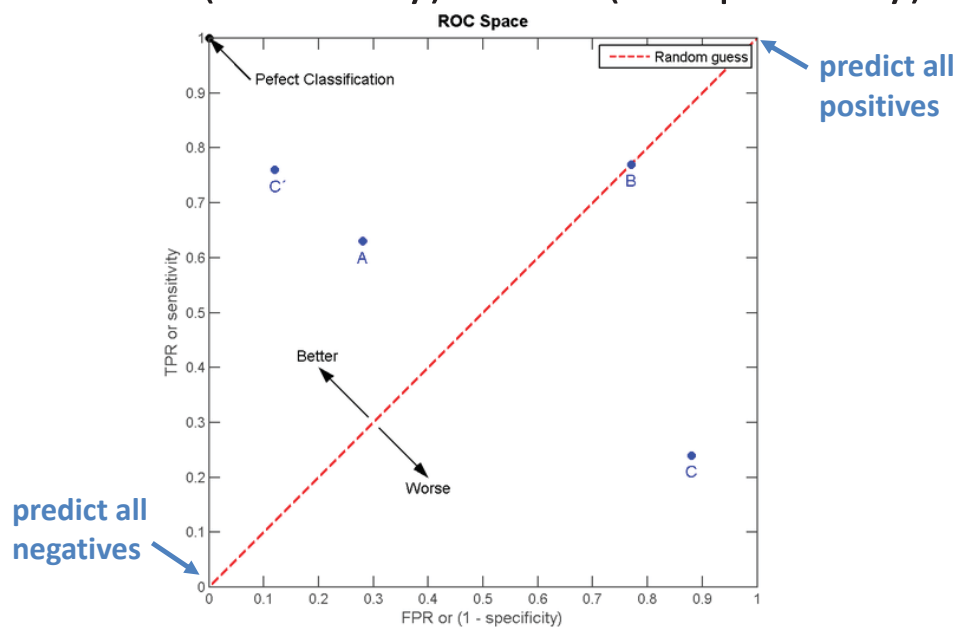
Limitations of Sensitivity / Specificity

- How can you maximize sensitivity [= $TP / (TP + FN)$]?
- How can you maximize specificity [= $TN / (TN + FP)$]?
- What does this mean?



Receiver Operating Characteristic

- Plots TPR (sensitivity) vs FPR (1 – specificity)



[Source: Wikipedia]