Classification:
Issues, Features, Text Categorization

Classification: Recall the Definition

- Given a collection of examples (*training set*)
  - Each example is represented by a set of *features*, sometimes called *attributes*
  - Each example is to be given a label or class
- Find a *model* for the label as a function of the values of features.
- Goal: previously unseen examples should be assigned a label as accurately as possible.
  - A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.

Confusion Matrix

- Confusion Matrix for a binary classifier (two labels) on test set:

	PREDICTED CLASS		
		Class=Yes	Class=No
ACTUAL CLASS	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive)

b: FN (false negative)

c: FP (false positive)

d: TN (true negative)

Classifier Evaluation Measures

- Another widely-used metric: Accuracy of a classifier M is the percentage of test set that are correctly classified by the model M

$$\text{Accuracy} = \frac{a+d}{a+b+c+d} = \frac{TP+TN}{TP+TN+FP+FN}$$

	Yes - C_1	No - C_2
Yes - C_1	a: True positive	b: False negative
No - C_2	c: False positive	d: True negative

Precision = TP/(TP+ FP),

percent correct out of all predicted Yes

Recall = TP/(TP + FN),

percent correct out of all actual Yes

F-Measure = 2 * (Recall * Precision) / (Recall + Precision)

Multi-Class Classification

- Most classification algorithms solve binary classification tasks, while many tasks are naturally multi-class, i.e. there are more than 2 labels
- Multi-Class problems are solved by training a number of binary classifiers and combining them to get a multi-class result
- Confusion matrix is extended to the multi-class case
- Accuracy definition is naturally extended to the multi-class case
- Precision and recall are defined for the binary classifiers trained for each label

Issues with imbalanced classes

- Consider a 2-class problem with labels Yes and No
  - Number of No examples = 990
  - Number of Yes examples = 10

- If model predicts everything to be No, accuracy is 990/1000 = 99 %
  - Accuracy is misleading because model does not detect any Yes example
  - **Precision and recall will be better measures** if you are training a classifier to find rare examples.

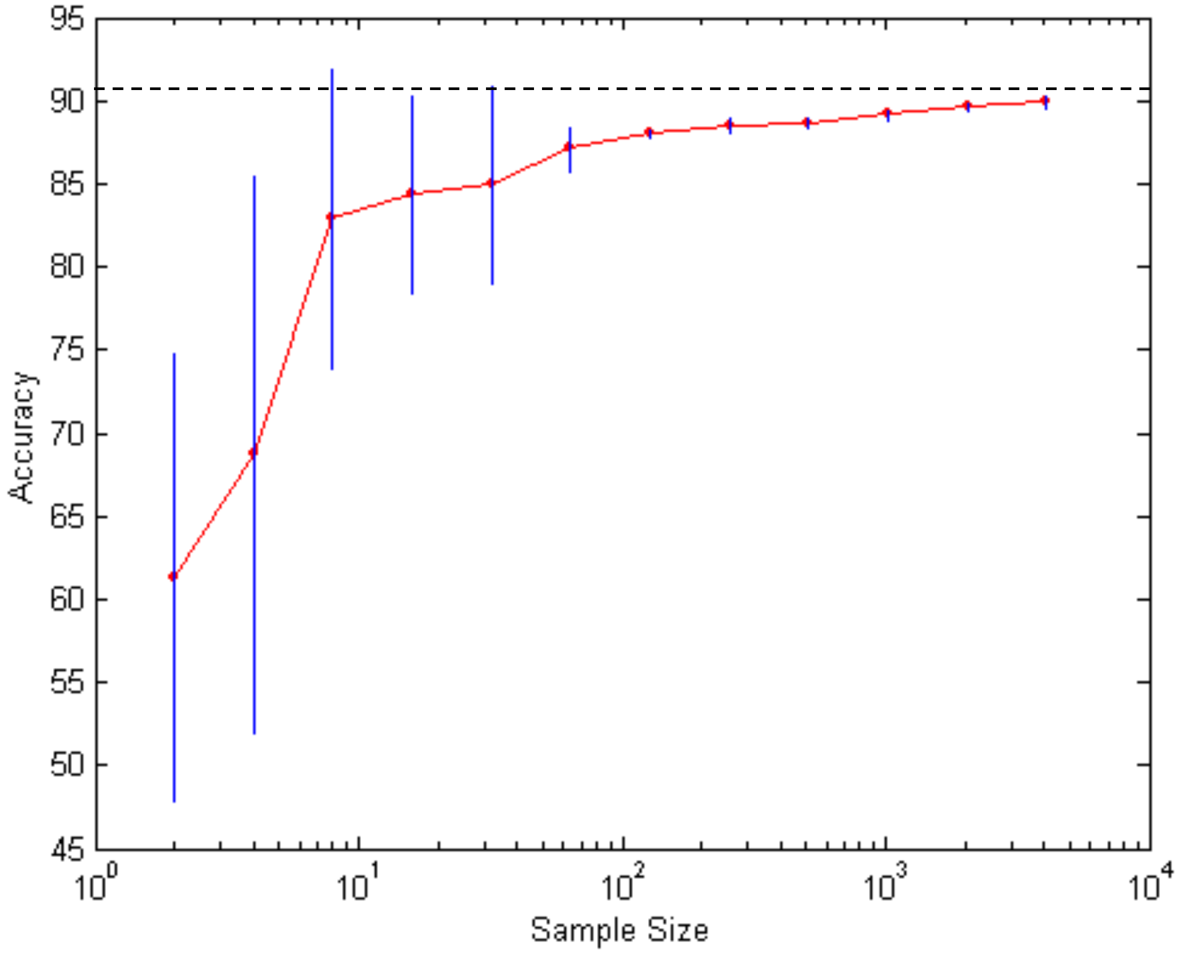
Evaluating the Accuracy of a Classifier

- Holdout method
  - Given data is randomly partitioned into two independent sets
    - Training set (e.g., 2/3) for model construction
    - Test set (e.g., 1/3) for accuracy estimation
- Cross-validation (*k*-fold, where k = 10 is most popular)
  - Randomly partition the data into *k mutually exclusive* subsets, each approximately equal size
  - At *i*-th iteration, use D_i as test set and others as training set

1:	test	train	train	train	train
2:	train	test	train	train	train

. . .

Evaluating the Model - Learning Curve



- Learning curve shows how accuracy changes with varying sample size
- Requires a sampling schedule for creating learning curve

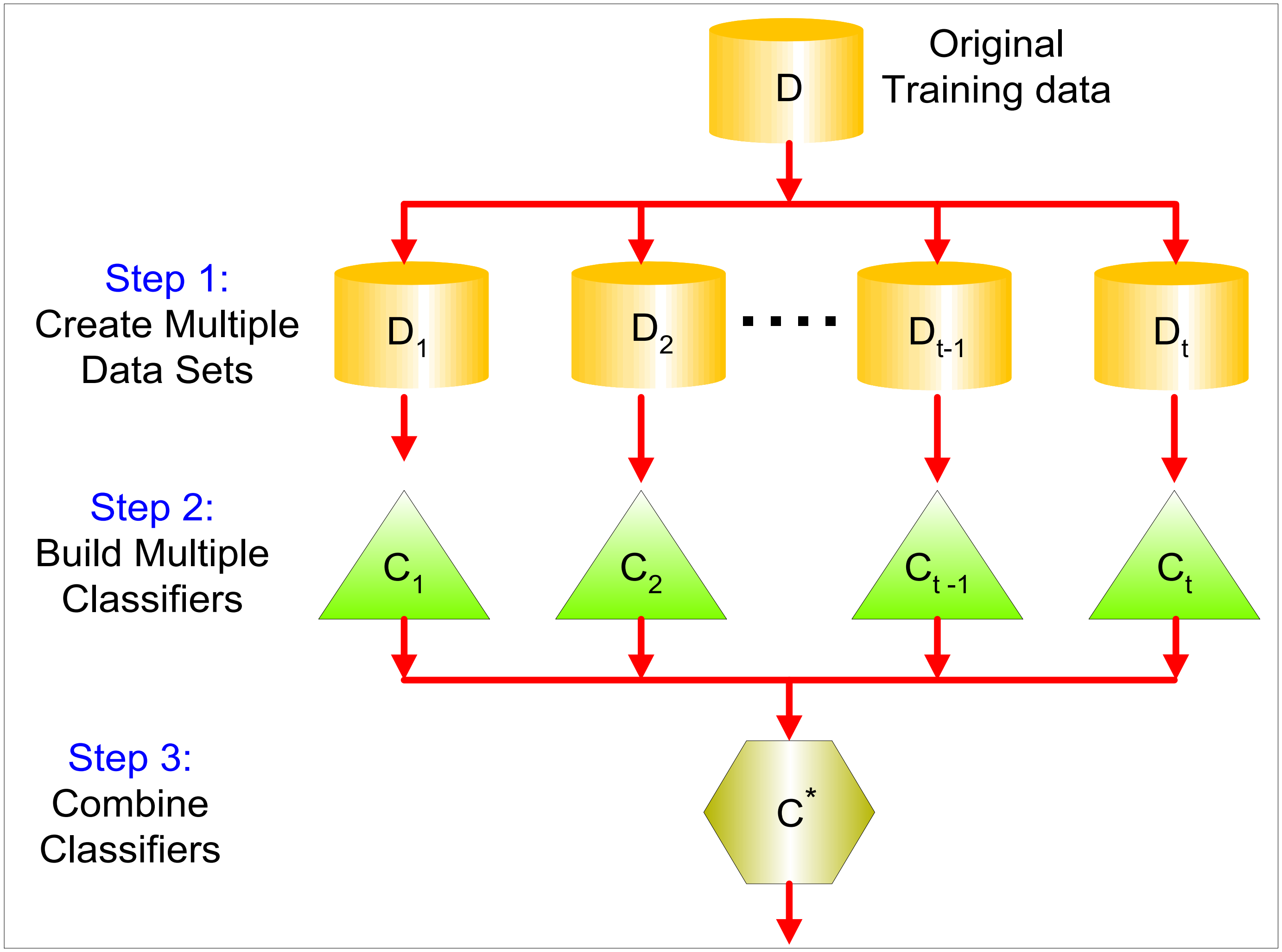
Classifier Performance: Feature Selection

- Too long a training or testing is a performance issue for classification of problems with large numbers of attributes or nominal attributes with large numbers of values
- Feature selection techniques aim to reduce the number of features by finding a smaller or minimal set that can accurately classify the problem
  - reduce the training and prediction time by eliminating noisy or redundant features
- Two main types of techniques
  - Filtering methods apply a statistical or other information measure to the attribute values without running any training and testing
  - Wrapper methods try different combinations of attributes, run cross-validation evaluations and compare the results

Classifier Performance: Ensemble Methods

- Construct a set of classifiers from the training data
- Predict class label of previously unseen records by aggregating predictions made by multiple classifiers
- Examples of ensemble methods
  - Bagging
  - Boosting
  - Heterogeneous classifiers trained on different feature subsets
    - sometimes called mixture of experts

General Idea



Examples of Classification Problems

- Some NLP problems are widely investigated as supervised classification problems, and use a variety of problem instances
  - Text categorization: assigning topic labels to documents
  - Word Sense Disambiguation: assigning a sense to a word, as it occurs in a document
  - Semantic Role Labeling: assigning semantic roles to phrases in a sentence
- From the NLTK book, chapter 6:
  - Classify first names according to gender
  - Document classification (text categorization)
  - Part-Of-Speech tagging
  - Sentence Segmentation
  - Identifying Dialog Act types
  - Recognizing Textual Entailment

Text Categorization

- Represent each document by the words/tokens/terms it contains
  - Sometimes called unigrams, sometimes bag-of-words
- Identify terms from the document text
  - Remove symbols with little meaning
  - Remove words with little meaning – the stop words
  - Stem the meaningful words
    - Remove endings to get root of the word
      - From *enchanted, enchants, enchantment, enchanting*, get the root word *enchant*
  - Group together words into phrases (optional)
    - Proper names or other words that are likely to have a different meaning as a phrase than the individual words
  - After grouping, may also want to lowercase the terms

Document Features

- Use a **feature vector to represent all the words in a document** – one position **for each word in the collection**, representing the weights (often frequency) of words
  - *“Water, water everywhere, and not a drop to drink!”*

$$\begin{array}{ccccccc} \text{water} & \text{everywhere} & \text{not} & \text{drop} & \text{drink} & & \\ (\,2, & 1, & 1, & 1, & 1, & 0, & \ldots\,) \end{array}$$

(shown with frequency weights)

- Another document with the word drink:
  - *“drink …”*

$$\begin{array}{ccccccc} \text{water} & \text{everywhere} & \text{not} & \text{drop} & \text{drink} & & \\ (\,0, & 0, & 0, & 0, & 1, & 0, & \ldots\,) \end{array}$$

- Feature vectors may have thousands of words and are often restricted by a threshold frequency of 5 or more

- Weka demonstration to observe feature vectors
  - Compare
    - Traditional data mining problem
    - Text mining problem