Naïve Bayes Classifiers Christina Wallin, Period 3 Computer Systems Research Lab 2008-2009

<u>Abstract</u>

One part of computational linguistics is the classification and comparison of texts into classes. This comparison could be author classification, spam filtering, or in the case of this project, the classification of texts from different genres of news stories. The goal of the project is to be able to classify a text as belonging to one of two classes based on the actual words in the text. This method of classification is called a naive Bayes classifier. In this age of huge amounts of data available online, a classifier which could discriminate between two types of news could be increasingly useful.

Background

The naive Bayes classification is a relatively simple method for classifying texts based on the false assumption that all of the variables, in this case words in the documents, are independent of each other. Even though this assumption is false, this project is done to achieve fundamental understanding concerning the effectiveness of the naive Bayes as compared to other methods, and to find a way of improving upon the performance of this classifier. However, it is also done to try to provide a way for news stories from different **Results** A working naïve Bayes classifier with both a multivariate and multinomial method of testing has been created. Two different experiments have been doing, to determine whether or not using the Porter stemmer to stem words improves the percentage of files classified correctly, and to see whether the multivariate or the multinomial works better. I found that it in fact it does not help to stem words, and was in fact about a percentage point less effective. For example, with the stemmer, 98.63% correctly classified with vs 97.86% without in alt. atheism and talk.misc.religion. The multinomial and multivariate methods have approximately the same accuracy, with the multivariate more accurate with two test cases and the multinomial more accurate in two others, though only by a small margin in all cases.

<u>Methodology</u>

The programming language used for these manipulations is Python. The database which I will be using to classify texts is the 20 Newsgroups database. There are 20 different genres of news stories, and it is divided into training and testing sets. The training and testing sets are separated in time by a little, and so it is more realistic.

The first step in classifying a document is to read and parse the file using the file.py program, removing all punctuation and case and making a dictionary with the words occurring and their frequencies. In this step, it is possible to use a Porter stemmer to stem words to their roots—for example, "running" and "runs" would both go to "run."

Next, for each class/genre, train.py trains the program as to what characteristics are most prevalent. It does this with the words themselves, creating an array containing the PFX, or probability that each word occurs in the class. As the program goes through in turn all of the files in a class, making a dictionary for each one, the PFX is calculated as the number of texts in a class which contain at least one instance of a word over the total number of texts in a class.

There are two different ways to calculate the PFX, with multnomial and multivariate methods. The multinomial method takes into account the frequency of the words in the texts, whereas th multivariate methods depend upon the number of files in which a particular word is in. Then with this probability vector for each class, I can calculate the probability that a text is of a specific class in test.py by generating the probability vector for that specific text and comparing it to the PFX for each class. For this, each variable (i.e. the occurrence or non-occurrence of each word) has to be calculated in order to form the probability that it is in a particular class. Then, the probabilities of each word are multiplied in order to determine what the probability that the file is in a specific class is. The program has been tested by using small data sets and checking manually whether or not the frequencies were correct, and using my testing program. I also tested the program by making sample data sets based on a programmed-in probability for each word. With this perfect data, I was able to check my PFX vector and found that it figured out the same probability as was programmed in. Thus, the probability calculation is correct. I was also able to check whether the testing part classified the perfect data correctly, which it did.



Program Methodology