# CSE 6363 Project Report 2 :

# Naïve Bayesian learning for classifying news text articles

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# Abstract

Given the goal of training a Naïve bayes classifier, we must use the appropriate methods to train and test the model. This paper will explain my thought process in how I selected what kind of model I decided on, how I implemented it in Python and the experiments.

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Data:

Naïve Bayes classifiers are one among the most successful known algorithms for learning to classify text documents. The dataset contains 20,000 newsgroup messages drawn from the 20 newsgroups. The dataset contains 1000 documents from each of the 20 newsgroups.

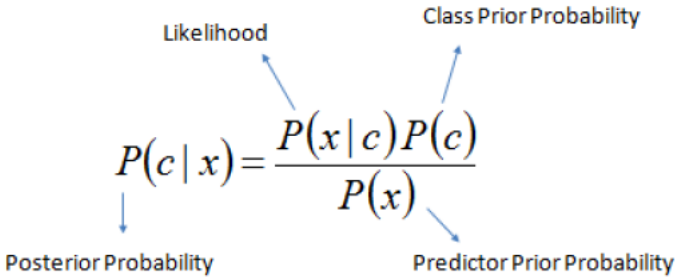
The 20 news groups:

```
alt.atheism                    rec.sport.hockey
comp.graphics                  sci.crypt
comp.os.ms-windows.misc        sci.electronics
comp.sys.ibm.pc.hardware       sci.med
comp.sys.mac.hardware          sci.space
comp.windows.x                 soc.religion.christian
misc.forsale                   talk.politics.guns
rec.autos                      talk.politics.mideast
rec.motorcycles                talk.politics.misc
rec.sport.baseball              talk.religion.misc
```

Requirements:

1. Training a model using Naïve Bayes's theorem to classify news text articles.

   The dataset '20newsgroup' is made up of 20 sub-folders of different fields of news articles. The files are of an unknown extension and various encoding types were tried before 'Latin-1' was successful in opening all the files successfully.
   Each newsgroup or sub-folder is made up of approximately 1000 files.
   The NB classifier – Posterior probability is given by:




2. Using the trained model to do the classification

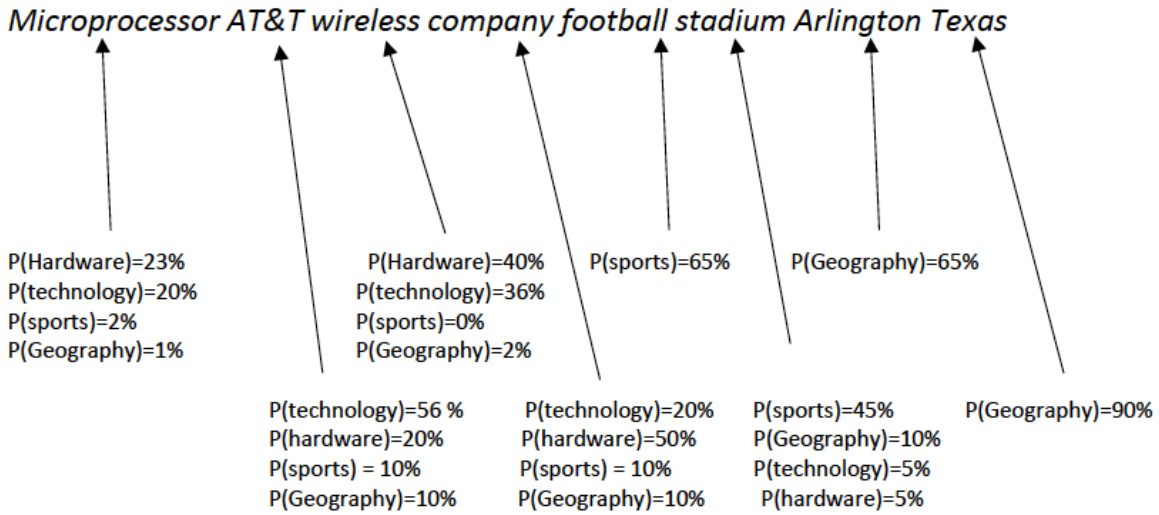
   Coming down to the question, how exactly are we using Bayes to predict the newsgroup of a given file.
   We can illustrate that, with the help of a small example.

   "*The microprocessor was made by AT&T, the wireless company that also has a big football stadium in Arlington, Texas"*

Now, this sentence is the raw form of the text file given. We need to remove certain common words (they are called stop words) that are too generic and just unnecessarily increase the processing time and skew the results.
These stop words are removed from each file and the model is trained. So, the above sentence after data cleaning looks like this.

"*Microprocessor AT&T wireless company football stadium Arlington Texas*"

Now, let's assume the model has been trained and we have a frequency count of the trained words.
The above example sentence will be classified something like this.




So, essentially the words of a sentence are given a probability score, and the sentence is classified as a particular group according to the max probability score.

Now, this is done over larger sets(files) rather than single sentences.
Coming down to, how the probability of each word is calculated, we iterate through each word in each file. Check, if that particular word was encountered before in the present newsgroup or class. If yes, then we increase the frequency count and if no, then we start counting.

For example, if we encountered the word "onomatopoeia" 75 times in the atheism newsgroup (which has 1000 words), the probability that a word that we encounter is "onomatopoeia" and belongs to the "atheism" newsgroup is 75/1000,
Or in short P(onomatopoeia|atheism) = 0.075
And to find if the probability of the class, if the word is "onomatopoeia" is given by:

P(atheism| onomatopoeia)= P(onomatopoeia|atheism) x P(class) P(onomatopoeia)

Where P(class) is the probability of the class and P(onomatopoeia) is the probability of all instances of the word.

Now, to avoid completely jagged results (because of the absence of certain words), Laplacian smoothening is done when we encounter a new word with zero frequency.

3. Experiments and Results

| Stop Word | Dataset % | Laplacian | Time taken in secs | Accuracy in percent |
|---|---|---|---|---|
| Eliminated | 50 | 0.000001 | 77 | 86.8941294530858 |
| Eliminated | 50 | 0.00001 | 78 | 87.21525338685399 |
| Eliminated | 50 | 0.0001 | 74 | 87.46613146011039 |
| Eliminated | 50 | 0.001 | 80 | 87.61665830406422 |
| Eliminated | 50 | 0.01 | 78 | 87.60662318113397 |
| Eliminated | 50 | 0.1 | 78 | 86.97441043652785 |
| Not Eliminated | 50 | 0.001 | 65 | 87.18514801806322 |
| Eliminated | 100 | 0.001 | 131 | 93.0636127225445 |

```
Prediction accuracy =  87.61665830406422 %
Time elapsed:  80 secs
```

At optimum efficiency( 50% dataset, 0.001 Laplacian smoothening and stop words being eliminated) my model has an accuracy of **87.61665830406422%**

```
 98 % tested
 Prediction accuracy =  86.97441043652785 %
```

At 50% test, 0.1 Laplacian Smoothening and stop words being eliminated my model has an accuracy of **86.97441043652785%**

```
Prediction accuracy =  87.60662318113397 %
Time elapsed:  78 secs
```

At 50% test, 0.01 Laplacian Smoothening and stop words being eliminated my model has an accuracy of **87.60662318113397%**

```
Prediction accuracy =  87.46613146011039 %
Time elapsed:  74 secs
```

At 50% test, 0.0001 Laplacian Smoothening and stop words being eliminated my model has an accuracy of **87.46613146011039%**

```
Prediction accuracy =  87.21525338685399 %
Time elapsed:  78 secs
```

At 50% test, 0.00001 Laplacian Smoothening and stop words being eliminated my model has an accuracy of **87.21525338685399%**

```
Prediction accuracy =  86.8941294530858 %
Time elapsed:  77 secs
```

At 50% test, 0.000001 Laplacian Smoothening and stop words being eliminated my model has an accuracy of **86.8941294530858%**

```
98 % tested
Prediction accuracy =  87.18514801806322 %
Time elapsed:  65 secs
```

At 50% test, 0.001 Laplacian Smoothening and stop words **not** being eliminated my model has an accuracy of **87.18514801806322%**

```
Prediction accuracy =  93.0636127225445 %
Time elapsed:  131 secs
```

At 100% test, 0.001 Laplacian Smoothening and stop words being eliminated my model has an accuracy of **87.18514801806322%**

**Methods:**

There are 8 methods in the python file.

1. **def stop_words_calc()**: The stop_words_calc function is used to read the stopwords from a given .txt file and put them in a list. This list is then stored in a stop_words variable to be used later.
   **parameters returned:** text ( a list of single-spaced stop words)

2. **def load_test_files(sub_folders)**: The load_test_files function is used to select a sequentially news group and then sequentially select a file from the newsgroup. The selected file is then removed from the newsgroup's list and the file name is returned.
   **parameters accepted**: subfolders( the list of all newsgroups in the dataset)
   **parameters returned**: text( file name of the randomly selected file)

3. **def preprocessing (text,stop_words):** This function is used to clean the data of all the stop words, spaces, next line and punctuation marks and symbols.
   **parameters accepted**: text( the data in a particular file) , stop_words( the list of stop words)
   **parameters returned**: text( the cleaned data of that particular file)

4. **def calculate(_file_,dictionary,sun_folder_list):** This function is used to calculate the posterior probability of a particular file. We are doing Laplacian smoothening for new words with 0 count frequency. The smoothening peaks at 0.001.
   **parameters accepted**: _file_(the data of a file) , dictionary(the word and frequency count of a particular group) , folder_list( list of all newsgroups in the dataset)
   **parameters returned**: probability( the posterior probabilities)

5. **def open_file(file_location):** This function opens the unknown extension files of the dataset. This was required because, the file couldn't be opened in UTF-8 encoding and needed Latin-1 encoding.

**parameters accepted**: file_location(path of the file)
**parameters returned**: text( opened file)

6. **def train_model(sub_folder_list, stop_words):** This function is used to train the model. It trains the model on 50% + 1 file of the dataset and then removes those files from the main list, for the testing model. This iterates over the first 50% of the dataset, keeps a count of the words encountered and the newsgroups they were encountered in.

**parameters accepted**: sub_folder_list(list of all the newsgroups in the dataset) , stop_words( list of all the stopwords)

7. **def test_model(sub_folder_list, stop_words):** This function is used to test the model on last 50% of the dataset . It creates a confusion matrix for the tested sentence and selects the highest probability for the sentence. If the predicted posterior probability is equal to the actual classification, it is considered a success.

**parameters accepted**: sub_folder_list(list of all the newsgroups in the dataset) , stop_words( list of all the stopwords)
**parameters returned**: prediction(number of successes) , loop-1(total number of tries)

8. **def pathcheck(path, supporting_file_name):** This function is used to check if the supporting files are present in the current directory. If not, it exits the program

**parameters accepted**: path(path of the supporting files) , supporting_file_name( name of the file)