Naïve Bayes Classifier.

Group Members:

Bharat Raghunathan (2015AAPS0263H)
V Thejas (2015A7PS0142H)
Nitish Ravishankar (2015A7PS0152H)

Introduction:

This assignment was an attempt to build a Classifier to perform Sentiment Analysis/ Opinion Mining (i.e. to determine whether a given review has a positive/negative tone) using a Naive Bayes Classifier with the **“naive”** assumption being that “every pair of features are independent to each other” which is of course, an oversimplified assumption, but is nonetheless faster than other more sophisticated methods.

The dataset given was a corpus of movie reviews split into training and test set files respectively, in which the training test files were used only for the purposes of calculating all the required **prior** probabilities as well as the **likelihood** functions (i.e. to pre-calculate $P(a_i|v_j)$), since the Bayesian approach to classifying the new instance aims to assign the most probable target value, v_{MAP}.

$$v_{MAP} = \underset{v_j \in V}{\operatorname{argmax}} P(v_j|a_1, a_2 \ldots a_n)$$

Using Bayes Theorem, we get

$$\begin{aligned} v_{MAP} &= \underset{v_j \in V}{\operatorname{argmax}} \frac{P(a_1, a_2 \ldots a_n|v_j)P(v_j)}{P(a_1, a_2 \ldots a_n)} \\ &= \underset{v_j \in V}{\operatorname{argmax}} P(a_1, a_2 \ldots a_n|v_j)P(v_j) \end{aligned}$$

Now since $P(a_1, a_2 \ldots a_n|v_j) = \prod_i P(a_i|v_j).$ due to the naive assumption,

the Naive Bayes Classifier outputs

$$v_{NB} = \underset{v_j \in V}{\operatorname{argmax}} P(v_j) \prod_i P(a_i|v_j)$$

wherein there are only two v_j (true or false).

In this case, a small optimization can be made by considering each word in the corpus to have simply occurred or not occurred (i.e. we **“binarize”** the occurrences of the words as occurred/not occurred) since the occurrence of the word conveys whether there is a positive sentiment or not, rather than the frequency.

Also, there were some words with high frequency which appeared in almost all documents (movie reviews) which doesn’t help much in predicting the overall sentiment of a review.

These are called **stopwords** and removing them before processing led to slightly better results.

Results:

Some metrics used for evaluating the classifiers in our classification problem.
Accuracy: Number of correct classifications/Total number of classifications.

Positive Precision: Number of True Positives divided by the number of True Positives and False Positives. Putting it another way, it is the number of positive predictions divided by the total number of positive class values predicted. It is also called the Positive Predictive Value (PPV).

Positive Recall: Recall is the number of True Positives divided by the number of True Positives and the number of False Negatives. Putting it another way, it is the number of positive predictions divided by the number of positive class values in the test data. It is also called Sensitivity or the True Positive Rate.

Negative Precision: Number of True Negatives divided by the number of True Negatives and False Negatives. Putting it another way, it is the number of Negative predictions divided by the total number of Negative class values predicted.

Negative Recall: Recall is the number of True Negatives divided by the number of True Negatives and the number of False Positives. Putting it another way, it is the number of Negative predictions divided by the number of Negative class values in the test data.

F-Measure: (referred to as F-Score or F_1-score) = (2*precision*recall)/(precision+recall).

1. **Positive Sentiment** (Results in %)

		No Stopwords	**Short Stopwords**	**Long Stopwords**
Naive Bayes	Accuracy	81.36	82.64	82.29
	Precision	85.90	86.56	86.15
	Recall	75.03	77.26	76.96
	F-Score	80.10	81.65	81.29
Binary Naive Bayes	Accuracy	82.99	83.79	83.35
	Precision	87.23	87.23	86.53
	Recall	77.30	79.18	79.01
	F-Score	81.97	83.01	82.59

2. Negative Sentiment (Results in %)

		No Stopwords	**Short Stopwords**	**Long Stopwords**
Naive Bayes	Accuracy	81.36	82.64	82.29
	Precision	77.84	79.47	79.18
	Recall	87.69	88.01	87.62
	F-Score	82.47	83.52	83.19
Binary Naive Bayes	Accuracy	82.99	83.79	83.35
	Precision	79.62	80.94	80.69
	Recall	88.68	88.41	87.70
	F-Score	83.91	84.51	84.05

Understanding of Results:

It is observed that: -

- Accuracy is the same for both positive and negative sentiments
- Binarizing the Occurrence of words slightly improves the performance of the classifier
- Removing few Stopwords (Short Stopwords) slightly optimizes the performance of the classifier as compared to not removing Stopwords at all.
- However, removing more Stopwords (Long Stopwords) again starts to reduce the performance of the classifier as compared to removing just a few Stopwords.

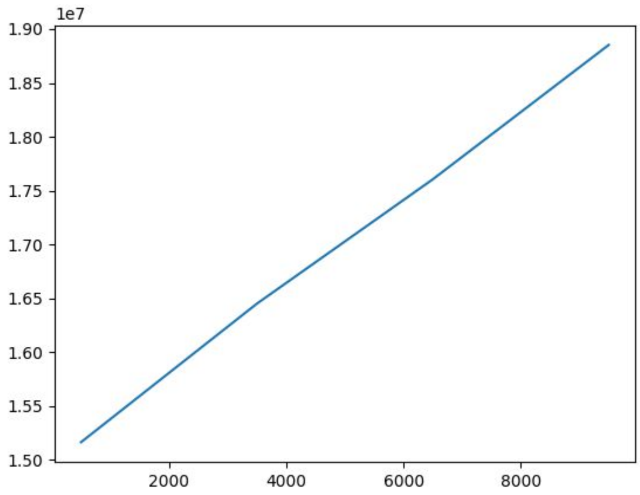
Interpretation & Reasoning Of Results:

- The Accuracy is expected to be the same since it is simply the ratio of the total number of correct classifications (true positives as well as true negatives) to the total number of samples which would not matter whether the sample was a true positive/negative, as long as it is correctly classified.
- Binarizing the occurrence of the words seems to work better since ***more importance is given to whether the words appear or not, rather than its frequencies.*** Moreover, in case ***several occurrences*** of the words are taken into consideration, this ***tends to inflate the probability*** towards positive or negative classification based on the documents in which the word occurs, thus giving biased results.
- Removing a few Stopwords actually helped in ***removing some highly occurring redundant words which probably did not help in determining the sentiment*** of the document.

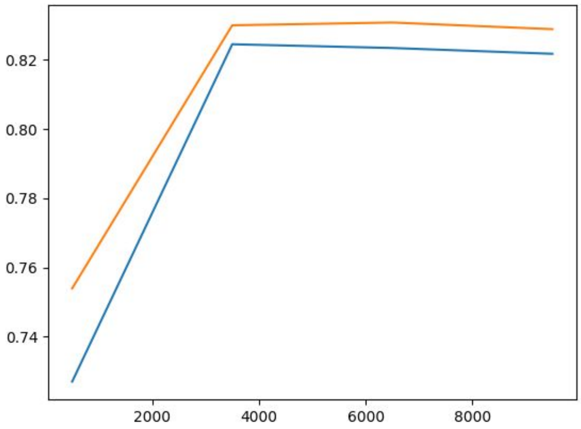
- However, removing more Stopwords could have probably resulted in some ***important words/ informative words having been removed from the document (movie review), thus skewing the prior probability distribution wrongly*** and hence, leading to slightly lower performance.

Analysis of running time and accuracy:

Our program calculated the running time and accuracy for varying input sizes and records the results along with its corresponding input size. This data is plotted in the following figures.



Time in microseconds vs size of input. Shows that our algorithm is asymptotically linear in input size **O(n).**



Accuracy vs size of input. From this graph, we can conclude that beyond certain threshold limit, there is no significant change in the accuracy of the predictions.

Conclusion

The naive Bayes algorithm was implemented and the binary NB and stopwords removal optimizations were performed. From the results, we conclude that by applying these above optimizations, we can achieve better performance in terms of evaluation metrics such as precision, recall, accuracy and F-Measure.

References

1. Machine Learning, Tom Mitchell, McGraw Hill Education (India) Private Limited.