

# Assignment 1 – NaiveBayesClassifier Report

Candidates: 143 Candidate: 128 Candidate: 76 Candidate: 144 Candidate: 46

## How it works

The code for the classifier should be fairly well commented and the purpose of each function and variable. There is also a decent amount of print() messages that should give an indication of what is going on.

## Evaluation Results

### In Total..

**25000** reviews were **scanned in total**.

Of these, **6** reviews were **discarded** because of class probabilities returned were inf or 0.0

This means **24994** reviews were **actually tested**

**20753** of them were **predicted correctly**.

**4241** of them were **predicted incorrectly**.

The scores have been calculated by collecting four different types of predictions: True Positive, False Positive, True Negative and False Negative (e.g True Positive means we were corrected about predicting the individual file to be a positive review).

**Total positive precision** was: 87 percent

**Total negative precision** was: 79 percent

**Total positive recall** was: 77 percent

**Total negative recall** was: 88 percent

**Positive F-measure** was: 81 percent

**Negative F-measure** was: 83 percent

**Overall prediction Accuracy** was: 83 percent.

These test results can be displayed by running the test\_all\_reviews() function in our classifier.

Currently the model does not implement log-likelihoods. We tried to implement this in the class\_probabilities function, but for whatever reason the log-likelihoods reduced our accuracy to about 50 percent on all the different tests. As an alternative we have divided certain variables used in the class probability by 10000 to avoid having the returned probabilities being either too small or too big (inf, or 0.0) (This can be seen in the initialize(function)).

The classifier seems to perform fairly well given the background and the test-data. We think that the F-measure is the best indicator of our performance. Interestingly, its positive precision is significantly higher than the negative one, which would indicate that it is easier for it to recognize positive reviews. The reason for this, we are unsure about at the moment. There is still, however, room for improvement. Using other Natural Language Processing methods, we would probably be able to achieve that. We have brought upon ourselves the addition of stopwords in order to cut down issues/time of processing the data. Though it seems the stopwords have little bearing on the test results, which is not unexpected. We could for instance combine words with the same meaning(synonyms) or similar words into segmented groups. Another step could be to look at the order, and sequences of words in the context of the sentence they are used in. For instance, our classifier doesn't know the meaning of phrase «not good». It just looks at words individually and therefore is susceptible to miss out on valuable semantic information. Hence, why it is «naive».

The performance rate of the classifier is also high: It requires little amount of work/time to run through thousands of reviews. We were able to scan through and make predictions for 25000 reviews in less than 2 minutes on a 5 year old laptop, and in about 30 seconds on a more recent and powerful computer.