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Homework 2 Report- Naive Bayes

For this homework, I attempted to run a Naive Bayes classifier written by scratch on the same movie review dataset used before. My method for implementing it previously was not very inaccurate for not using a machine learning algorithm, but it could have been better. This time, I was hoping to see better results now that I used an algorithm designed for the purpose of classification, however, it did not deliver as high of an accuracy as I hoped. My training and validation sets are in lines while my training sets were fed into the model word by word. This is so the classifier can categorize an entire review rather than just a single word. My classifier outputs results from both the validation set and test set as well as reports each calculation in a separate text file. The results of the best run I achieved are as shown in the following table:

|  |  |  |  |
| --- | --- | --- | --- |
| Set | Correct lines | Incorrect lines | Overall Accuracy |
| Validation | 784 / 1600 | 816 / 1600 | 49.00% |
| Test | 767/ 1599 | 832 / 1599 | 47.97% |

For the most part, reruns of the classifier yield models that perform fairly similar for the most part. Accuracies will hover around 45%. I also excluded common stop words in hopes of increasing accuracy and speed. Running the program takes roughly two minutes.

As for particular samples, they can range from very certain to having very close probabilities. The following are examples of uncertain samples:

|  |
| --- |
| bright seems alternately amused and disgusted with this material and he can't help throwing in a few of his own touches  | 3.7694226452693323e-56 | 1.9343689865763349e-56 | Winning prob: 1.9343689865763349e-56, positive reviews, actual:negative reviews |
| tackles the difficult subject of grief and loss with such lifeembracing spirit that the theme doesn't drag an audience down  | 1.9723432932049933e-53 | 1.1385464553979264e-53 | Winning prob: 1.1385464553979264e-53, positive reviews, actual:negative reviews |
| the kind of trifle that date nights were invented for  | 3.936841472609176e-24 | 1.8009939821070318e-27 | Winning prob: 1.8009939821070318e-27, positive reviews, actual:negative reviews |

and the following of very certain samples:

|  |
| --- |
| béart and berling are both superb while huppert is magnificent  | 1.6224238429058814e-31 | 6.951881234259088e-19 | Winning prob: 6.951881234259088e-19, positive reviews, actual:positive reviews |
| implicitly acknowledges and celebrates the glorious chicanery and selfdelusion of this most american of businesses and for that reason it may be the most oddly honest hollywood document of all  | 6.689435963869557e-65 | 5.843791253213858e-58 | Winning prob: 5.843791253213858e-58, positive reviews, actual:positive reviews |
| the film's snags and stumblings are more than compensated for by its wryly subversive tone  | 1.468491150531588e-34 | 6.173118089178653e-26 | Winning prob: 6.173118089178653e-26, positive reviews, actual:positive reviews |

Based on the difference between the uncertain lines and certain lines, it seems that the more certain samples include more adjectives that make the tone of the sentence very clear while also including words that I would expect to see often in a positive review, whereas the uncertain samples read more neutral or include words that could be commonly seen in both types of reviews.

Since my dataset only included two classes, the most useful features are words that are most often used in positive contexts (good, amazing, beautiful) and words most often used in negative contexts (bad, awful, disgusting).