Instructions: Replace all bracketed text with text for your project. Feel free to add. Leave the document structure in place. Delete these instructions.

[Hadi Baajour, 96316680] CIS4930 Individual Coding Assignment Spring 2023

1. Problem Statement

One of the most fundamental aspects of a human being is the ability to disseminate information to other human beings through a specific language. As technology advances, humans are finding ways to use technological devices in order to capture, store, and use human language for every day tasks. One of the most important machine learning technologies that has increased in popularity and necessity for understanding languages in a deeper level is natural language processing (NLP). Many of the different dialog systems used today are built of the architecture and design discovered through studies in NLP. As dialog systems advance, people need to find a way for these devices to properly understand human spoken languages and figure out whether the speech is positive or negative in connotation. This problem needs to be solved in order train machines to better understand people so that it can assist them with their daily needs. To solve this problem, we must create and train a model that will be able to determine the connotation and intention of textual speech (which has been generated by automatic speech recognition systems) in order to determine and produce an appropriate response.

2. Data Preparation

The textual data provided was prepared in a number of different ways. First, the training and testing data (which were both stored in csv files) were read by the machine and turned into data frames in order to make it easier to filter through the document. The data frames were then checked for their contents using the .head() function and all missing values were removed from the data frames to avoid the machine conflicting with data that is not even present.

After this is done, the text preprocessing stage commences. This is where the textual data is "cleaned" so that it is easier for the machine to interpret the data without having unnecessary text that won't be used by the model. The program will make all the letters lower case, remove all sorts of numerical values, expand all contraction words, remove all special characters, and remove all stop words.

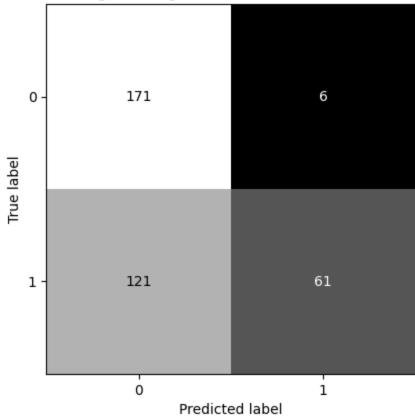
For feature extractions, I used Bag of Words and TF*IDF which were bother used in my classification models. I also used Word2Vec, however this was not added in my classification models.

3. Model Development

- Model Training
 - [Describe the training phrase, which may include what models did you select, how you split training/validation/test sets, training epochs, and any other parameters.]
 - For the training phase, I selected five different models to use with my feature extraction algorithms. Those five models were logistic regression, k-neighbors classification, support vector classification, gaussian naïve bayes, and random forest classifier. The two features used in these models were the bag of words and tf*idf. Each of the data from both these feature extraction methods were fit and transformed in order to be places in the ML models. In this assignment, there was no need to split the testing and training data because they were already given in two different csv files and made into two separate data frames prior to using the models.
- Model Evaluation
 Bag of Words
 - Logistic Regression

| precision | recall | f1-score | support |
|-----------|----------------------|-------------------------------------|--|
| 0.59 | 0.97 | 0.73 | 177 |
| 0.91 | 0.34 | 0.49 | 182 |
| | | 0.65 | 359 |
| 0.75 | 0.65 | 0.61 | 359 |
| 0.75 | 0.65 | 0.61 | 359 |
| | 0.59 0.91 0.75 | 0.59 0.97 0.91 0.34 0.75 0.65 | 0.59 0.97 0.73 0.91 0.34 0.49 0.65 0.75 0.65 0.61 |

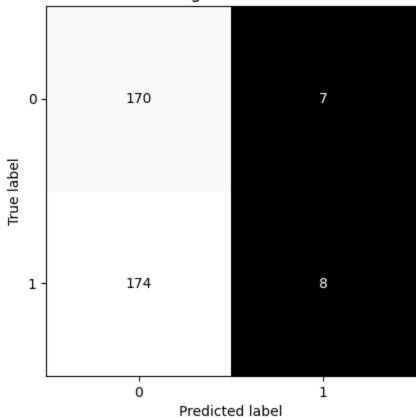
Logistic Regression Confusion Matrix



K Nearest Confusion Matrix

| | precision | recall | f1-score | support |
|--------------|--------------|--------------|--------------|------------|
| 0 1 | 0.49 0.53 | 0.96 0.04 | 0.65 0.08 | 177 182 |
| accuracy | | | 0.50 | 359 |
| macro avg | 0.51 | 0.50 | 0.37 | 359 |
| weighted avg | 0.51 | 0.50 | 0.36 | 359 |

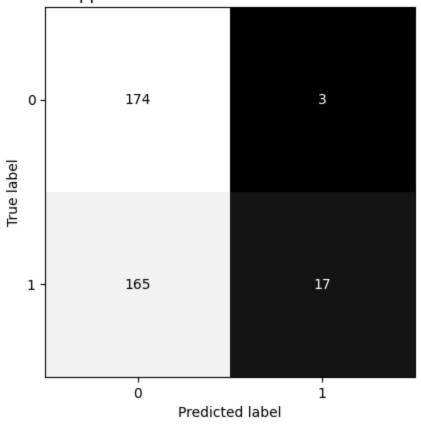
K Nearest Neighbor Confusion Matrix



Support Vector Machine

| | | precision | recall | f1-score | support |
|----------|--------|--------------|--------------|--------------|------------|
| | 0 1 | 0.51 0.85 | 0.98 0.09 | 0.67 0.17 | 177 182 |
| accur | | | | 0.53 | 359 |
| macro | avg | 0.68 | 0.54 | 0.42 | 359 |
| weighted | avg | 0.68 | 0. 53 | 0.42 | 359 |

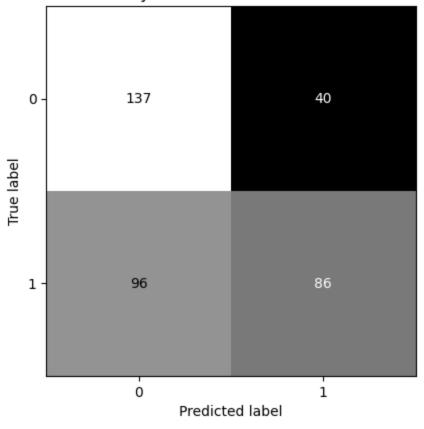
Support Vector Machine Confusion Matrix



Naive Bayes Classifier

| | precision | recall | f1-score | support | |
|-----------------------|-----------|--------|--------------|------------|--|
| lle | 0.59 | 0.77 | 0.67 | 177 | |
| | | 0.47 | 0.56 | 182 | |
| 255117251 | | | 0.63 | 750 | |
| accuracy macro avg | | 0.62 | 0.62 0.61 | 359 359 | |
| ghted ave | | 0.62 | 0.61 | 359 | |
| | | | | | |

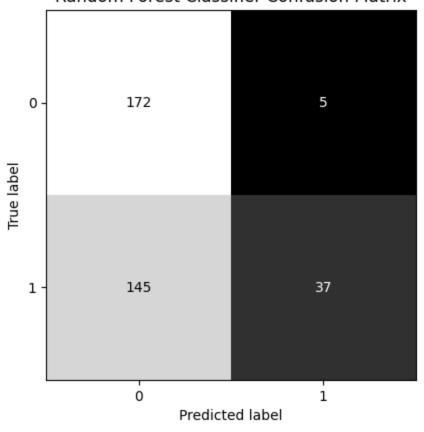
Naive Bayes Classifier Confusion Matrix



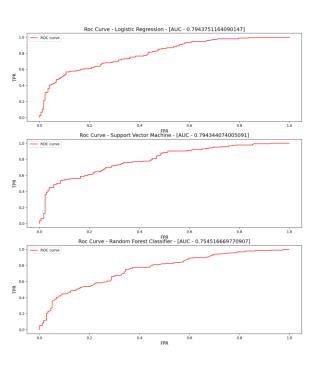
Random Forest Classifier

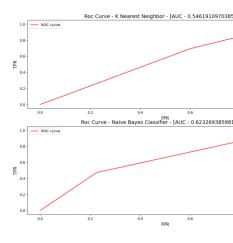
| | | | precision | recall | f1-score | support |
|-----|-------|-----|-----------|--------|----------|---------|
| | | 0 | 0.54 | 0.97 | 0.70 | 177 |
| | | 8 | | | | |
| | | 1 | 0.88 | 0.20 | 0.33 | 182 |
| | | | | | | |
| | accur | acy | | | 0.58 | 359 |
| | macro | avg | 0.71 | 0.59 | 0.51 | 359 |
| wei | ghted | avg | 0.71 | 0.58 | 0.51 | 359 |
| | | | | | | |

Random Forest Classifier Confusion Matrix



ROC Curves



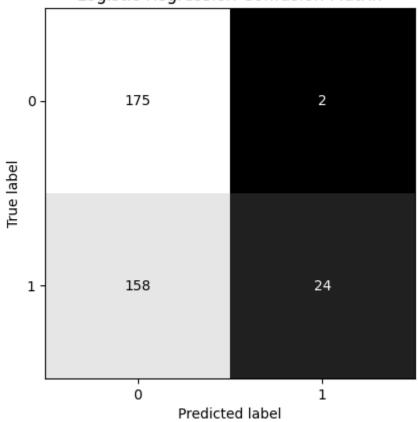


TF*IDF

o Logistic Regression

| | | precision | recall | f1-score | support |
|--------|--------|-----------|--------|----------|---------|
| | | | | | |
| | 0 | 0.53 | 0.99 | 0.69 | 177 |
| | 1 | 0.92 | 0.13 | 0.23 | 182 |
| | | | | | |
| ace | curacy | | | 0.55 | 359 |
| macı | ro avg | 0.72 | 0.56 | 0.46 | 359 |
| weight | ed avg | 0.73 | 0.55 | 0.46 | 359 |

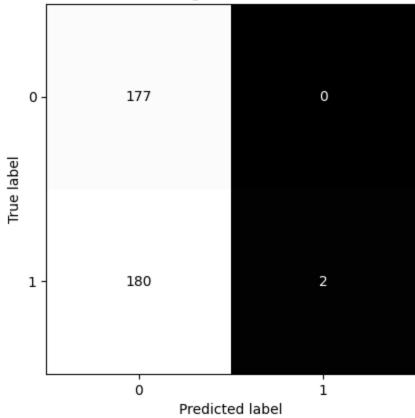
Logistic Regression Confusion Matrix



K Nearest Confusion Matrix

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.50 | 1.00 | 0.66 | 177 |
| 1 | 1.00 | 0.01 | 0.02 | 182 |
| accuracy | | | 0.50 | 359 |
| macro avg | 0.75 | 0.51 | 0.34 | 359 |
| weighted avg | 0.75 | 0.50 | 0.34 | 359 |
| | | | | |

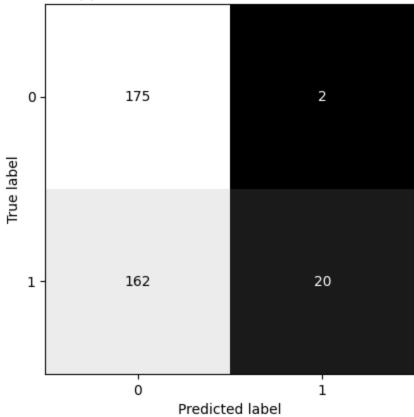
K Nearest Neighbor Confusion Matrix



Support Vector Machine

| | | precision | recall | f1-score | support | |
|----------|-----|-----------|--------|----------|---------|--|
| | 0 | 0.52 | 0.99 | 0.68 | 177 | |
| | 1 | 0.91 | 0.11 | 0.20 | 182 | |
| accur | acv | | | 0.54 | 359 | |
| macro | | 0.71 | 0.55 | 0.44 | 359 | |
| weighted | avg | 0.72 | 0.54 | 0.44 | 359 | |

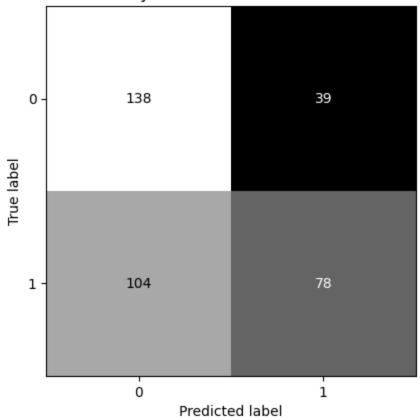
Support Vector Machine Confusion Matrix



Naive Bayes Classifier

| | | | precision | recall | f1-score | support |
|-------|--------|------|-----------|--------|----------|---------|
| | | 0 | 0.57 | 0.78 | 0.66 | 177 |
| | | 1 | 0.67 | 0.43 | 0.52 | 182 |
| | accui | racy | | | 0.60 | 359 |
| | macro | _ | 0.62 | 0.60 | 0.59 | 359 |
| / wei | ighted | avg | 0.62 | 0.60 | 0.59 | 359 |

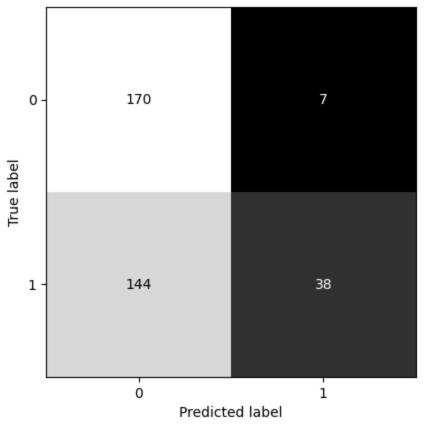
Naive Bayes Classifier Confusion Matrix



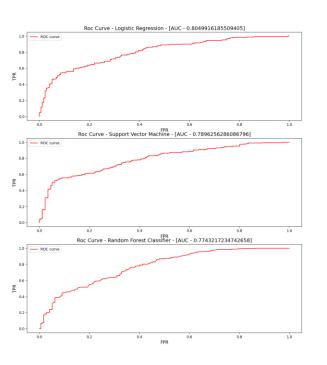
Random Forest Classifier

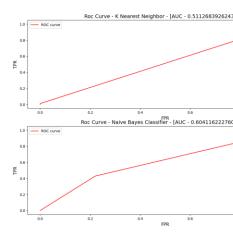
| | | | precision | recall | f1-score | support |
|-----|-------|-----|-----------|--------|----------|---------|
| | | | 0.54 | 0.06 | 0.60 | 477 |
| | | 0 | 0.54 | 0.96 | 0.69 | 177 |
| | | 1 | 0.84 | 0.21 | 0.33 | 182 |
| | | | | | | |
| | accur | acy | | | 0.58 | 359 |
| | macro | avg | 0.69 | 0.58 | 0.51 | 359 |
| wei | ghted | avg | 0.70 | 0.58 | 0.51 | 359 |
| | | | | | | |

Random Forest Classifier Confusion Matrix



ROC Curves





4. Discussion

- For the BOW and TF*IDF data, the SVM model was the one with the highest recall for finding negative text. The logistic regression model had the highest precision for positive textual data. The rain forest and naïve data both performed similarly in terms of their accuracy, f1, precision and recall. The k nearest didn't do so well compared to the rest of the models used. Overall, I believe the model did pretty well for the amount of data given to it. If it were to be given all million textual data lines as input then I believe that it would preform exceptionally well.
- One challenge I met was that the program was running very slow when the program began running the training models. This was because the training csv data had over a million lines of textual data, which is the most I have ever worked with. Due to this issue, I resorted to having the program randomly select 5000 lines of data to use by using the .sample() function on my training data frame.
- This assignment was a very good learning experience. I got to understand what natural learning processing (NLP) is, how it is used, and its importance in the real world. It also helped me understand how to capture textual data and how to clean it up in order for the machine to better understand it. I also learned how to use feature extractions so that the machine can better understand the depth of the language it receives. The information I learned in this project will definitely help me with the final project and how my group and I will go about cleaning and processing textual styled data.

5. Appendix

https://github.com/hadiplays/Assignment-2