Week 5 - Build your own sentiment analysis model

```
In [1]: import pandas as pd
        from textblob import TextBlob
        import numpy as np
        import string
        import warnings
        warnings.filterwarnings('ignore')
        import re
```

1. Get the stemmed data using the same process you did in Week 3.

```
In [2]: labeled train data df = pd.read csv('labeledTrainData.tsv', sep='\t')
          print(labeled train data df.shape)
          labeled train data df.head()
          (25000, 3)
                 id sentiment
                                                                     review
Out[2]:
          0 5814 8
                                 With all this stuff going down at the moment w...
                             1
          1 2381 9
                             1
                                 \The Classic War of the Worlds\" by Timothy Hi...
          2 7759 3
                             0
                                   The film starts with a manager (Nicholas Bell)...
                                 It must be assumed that those who praised this...
          3 3630 4
          4 9495_8
                             1 Superbly trashy and wondrously unpretentious 8...
In [3]: labeled train data df = pd.DataFrame(labeled train data df[['sentiment','review']])
          labeled train data df.head()
             sentiment
Out[3]:
                                                             review
          0
                         With all this stuff going down at the moment w...
          1
                         \The Classic War of the Worlds\" by Timothy Hi...
          2
                     0
                           The film starts with a manager (Nicholas Bell)...
          3
                         It must be assumed that those who praised this...
```

```
In [4]: # Function to remove special characters and spaces
        def clean data(text):
           text=text.lower() #makes text lowercase
           text=re.sub('\\d|\\W+| ',' ',text) #removes extra white space
           text=re.sub('[^a-zA-Z0-9]'," ", text) #removes any non-alphanumeric characters
            return text
```

1 Superbly trashy and wondrously unpretentious 8...

4

```
# Function to remove stop words (and tokenize)
In [5]:
        def Tokenize and RemoveStopWords(txt):
            from nltk import word tokenize
            from nltk.corpus import stopwords
            txt token = word tokenize(txt)
            stop words = stopwords.words('english')
```

```
# Apply NLTK's PorterStemmer
In [6]:
          def stem text(word list):
               from nltk.stem.porter import PorterStemmer
               porter = PorterStemmer()
               return [porter.stem(word) for word in word list]
          #creating new columns in the data frame for each preprocessing step
In [7]:
          labeled train data df['review clean'] = labeled train data df.review.apply(clean data)
          print(labeled train data df.shape)
          #applying tokenizing and remove stop words
          labeled train data df['review tokenized'] = labeled train data df.review clean.apply(Tok
          print(labeled train data df.shape)
          #applying PorterStemmer
          labeled train data df['review stemmed'] = labeled train data df.review tokenized.apply(s
          print(labeled train data df.shape)
          #putting the text back together
          labeled train data df['review final'] = labeled train data df.review stemmed.apply(lambd
          print(labeled train data df.shape)
          labeled train data df.head()
          (25000, 3)
          (25000, 4)
          (25000, 5)
          (25000, 6)
Out[7]:
             sentiment
                                    review
                                                  review_clean
                                                                review_tokenized
                                                                                   review_stemmed
                                                                                                           review_final
                           With all this stuff
                                               with all this stuff
                                                                     [stuff, going,
                                                                                          [stuff, go,
                                                                                                     stuff go moment mj
          0
                     1
                                                                                                       start listen music
                          going down at the
                                              going down at the
                                                                     moment, mj,
                                                                                   moment, mj, start,
                               moment w...
                                                   moment w...
                                                                started, listening,...
                                                                                      listen, music, ...
                                                                                                             watch od...
                          \The Classic War of
                                               the classic war of
                                                                      [classic, war,
                                                                                  [classic, war, world,
                                                                                                        classic war world
                     1
                                                                                       timothi, hine,
                                                                                                           timothi hine
                            the Worlds\" by
                                                 the worlds by
                                                                  worlds, timothy,
                               Timothy Hi...
                                                 timothy hine...
                                                                   hines, enterta...
                                                                                         entertain...
                                                                                                        entertain film ...
                          The film starts with
                                             the film starts with
                                                                      [film, starts,
                                                                                  [film, start, manag,
                                                                                                        film start manag
          2
                     0 a manager (Nicholas
                                             a manager nicholas
                                                                manager, nicholas,
                                                                                   nichola, bell, give,
                                                                                                        nichola bell give
                                     Bell)...
                                                                                             welc...
                                                                                                          welcom inve...
                                                       bell g...
                                                                     bell, giving...
                                                                                       [must, assum,
                         It must be assumed
                                            it must be assumed
                                                                  [must, assumed,
                                                                                                       must assum prais
                                                                                          prais, film,
                     0
          3
                             that those who
                                                that those who
                                                                     praised, film,
                                                                                                       film greatest film
                                                                                       greatest, film,
                               praised this...
                                                  praised this...
                                                                  greatest, filme...
                                                                                                           opera ever...
                                                                                              ope...
                                                                                     [superbl, trashi,
                                                                                                          superbl trashi
                         Superbly trashy and
                                            superbly trashy and
                                                                  [superbly, trashy,
                                                                                         wondrous,
                                                                                                             wondrous
                     1
                                                   wondrously
                                wondrously
                                                                      wondrously,
                                                                                         unpretenti,
                                                                                                       unpretenti exploit
                           unpretentious 8...
                                               unpretentious ...
                                                                  unpretentious, ...
                                                                                            exploi...
                                                                                                                 hoo...
          # column types of each column
In [8]:
          labeled train data df.dtypes
          sentiment
                                    int64
Out[8]:
```

txt no stopwords = [word for word in txt token if word not in stop words]

return txt no stopwords

review

review clean

review tokenized

review stemmed

object

object

object

object

```
review_final object dtype: object
```

2. Split this into a training and test set.

```
In [9]: from sklearn.model selection import train test split
         x = labeled train data df['review final']
         #x = labeled train data df.drop('review final',axis=1)
         y = labeled train data df['sentiment']
         #80% for Training and 20% for Test
         x train, x test, y train, y test = train test split(x, y, test size=0.2)
In [10]: print('x train : ',x train.shape)
         print('x test : ',x_test.shape)
         print('y train : ',y train.shape)
         print('y test : ',y test.shape)
         ## Display number of sentiments in training and test sets
         print(y train.value counts())
         print(y test.value counts())
        x train : (20000,)
         x \text{ test} : (5000,)
        y train : (20000,)
        y test : (5000,)
           10010
             9990
        Name: sentiment, dtype: int64
            2510
            2490
        Name: sentiment, dtype: int64
In [11]: # Frequency of the word in a document using term frequency-inverse document frequency
         from sklearn.feature extraction.text import TfidfVectorizer
         tfidf = TfidfVectorizer()
         tfidf matrix train = tfidf.fit transform(x train)
         # Check the shape to validate tf-idf vectorization
         tfidf matrix train.shape
         (20000, 45326)
Out[11]:
In [12]: tfidf_matrix_test = tfidf.transform(x test)
         # Check the shape to validate
         tfidf matrix test.shape
         (5000, 45326)
Out[12]:
```

3. Fit and apply the tf-idf vectorization to the training set.

```
In [13]: # Create the tf-idf feature matrix for training data
    from sklearn.feature_extraction.text import TfidfVectorizer

tfidfs = TfidfVectorizer()
    x_train_tdif = tfidfs.fit_transform(x_train)

x_train_tdif.shape
```

4. Apply but DO NOT FIT the tf-idf vectorization to the test set (Why?).

```
In [14]: # Create the tf-idf feature matrix for test data
    x_test_tdif = tfidf.transform(x_test)

# Check the shape to validate
    x_test_tdif.shape

Out[14]: (5000, 45326)
```

We expect maximum accuracy from the training set. We do not fit the tf-idf to test set because doing so would cause test data to leak into the training set. Surprisingly high accuracy score could indicate that test data leaked into the training set.

5. Train a logistic regression using the training data.

6. Find the model accuracy on test set.

```
In [16]: from sklearn.metrics import accuracy_score

score = accuracy_score(y_test, pred)
print('Logistic Regression Accuracy score:',score)
#The model has a 88.3% accuracy score
```

Logistic Regression Accuracy score: 0.893

[[2190 300] [235 2275]]

7. Create a confusion matrix for the test set predictions.

```
In [17]: import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

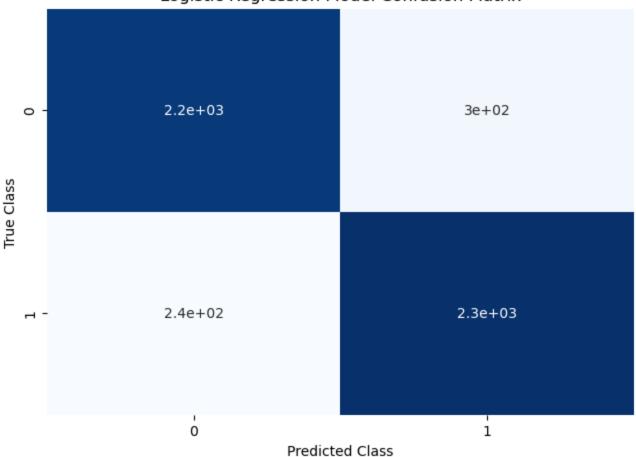
matrix = confusion_matrix(y_test, pred, labels=[1,0])

matrix = confusion_matrix(y_test, pred)
print(matrix)

# Create pandas dataframe
df = pd.DataFrame(matrix)

# Create a heatmap
sns.heatmap(df, annot=True, cbar=None, cmap="Blues")
plt.title("Logistic Regression Model Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```

Logistic Regression Model Confusion Matrix



8. Get the precision, recall, and F1-score for the test set predictions.

```
In [18]: from sklearn.metrics import precision_score, recall_score, f1_score

# Calculate Precision
p = "{:.0%}".format(precision_score(y_test, pred))

# Calculate Recall
r = "{:.0%}".format(recall_score(y_test, pred))

# Calculate F1-score
f1 = "{:.0%}".format(f1_score(y_test, pred))

# Print results
print("Precision:",p)
print("Recall:",r)
print("F1-score:",f1)
Precision: 88%
```

Recall: 91% F1-score: 89%

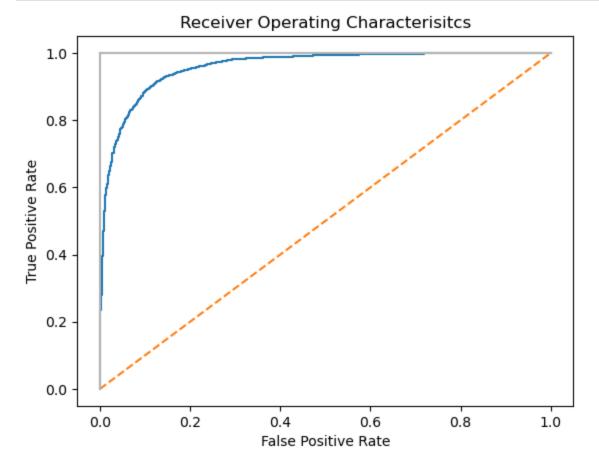
9. Create a ROC curve for the test set.

```
In [19]: # Load libraries
    from sklearn.metrics import roc_curve, roc_auc_score

# Get predicted probabilities
    target_probabilities = logistic_model.predict_proba(x_test_tdif)[:,1]

# Create true and false positive rates
    false_positive_rate, true_positive_rate, threshold = roc_curve(y_test, target_probabilit)
```

```
# Plot ROC curve
plt.title("Receiver Operating Characterisitcs")
plt.plot(false_positive_rate, true_positive_rate)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0], c=".7"), plt.plot([1, 1], c=".7")
plt.ylabel("True Positive Rate")
plt.xlabel("False Positive Rate")
plt.show()
```



10. Pick another classification model you learned about this week and repeat steps (5) – (9).

10.5. Train a logistic regression using the training data.

```
In [20]: from sklearn.neighbors import KNeighborsClassifier

# Train a KNN classifier with 5 neighbors
knnmodel = KNeighborsClassifier()
prediction = knnmodel.fit(x_train_tdif, y_train).predict(x_test_tdif)
prediction
Out[20]: array([1, 0, 0, ..., 0, 0, 1], dtype=int64)
```

10.6. Find the model accuracy on test set.

```
In [21]: score = accuracy_score(y_test, prediction)
    print('Knn Model Accuracy score:',score)
```

Knn Model Accuracy score: 0.7854

10.7. Create a confusion matrix for the test set predictions.

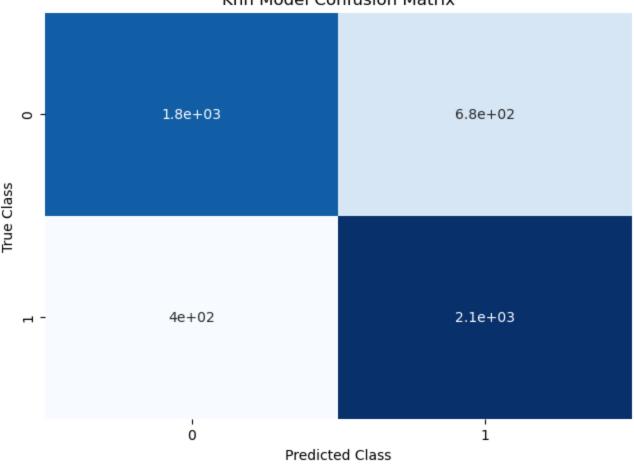
```
In [22]: matrix = confusion_matrix(y_test, prediction, labels=[1,0])
    matrix = confusion_matrix(y_test, prediction)
```

```
print(matrix)
# Create pandas dataframe
df = pd.DataFrame(matrix)

# Create a heatmap
sns.heatmap(df, annot=True, cbar=None, cmap="Blues")
plt.title("Knn Model Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```

[395 2115]]
Knn Model Confusion Matrix

[[1812 678]



10.8 Get the precision, recall, and F1-score for the test set predictions.

```
In [23]: # Calculate Precision
    p = "{:.0%}".format(precision_score(y_test, prediction))

# Calculate Recall
    r = "{:.0%}".format(recall_score(y_test, prediction))

# Calculate F1-score
    f1 = "{:.0%}".format(f1_score(y_test, prediction))

# Print results
    print("Precision:",p)
    print("Recall:",r)
    print("F1-score:",f1)
Precision: 76%
```

10.9 Create a ROC curve for the test set.

Recall: 84% F1-score: 80%

```
In [24]: target_probabilities = knnmodel.predict_proba(x_test_tdif)[:,1]

# Create true and false positive rates
false_positive_rate, true_positive_rate, threshold = roc_curve(y_test, target_probabilit

# Plot ROC curve
plt.title("Receiver Operating Characterisitcs")
plt.plot(false_positive_rate, true_positive_rate)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0], c=".7"), plt.plot([1, 1], c=".7")
plt.ylabel("True Positive Rate")
plt.xlabel("False Positive Rate")
plt.show()
```



