Naive Bayes

August 18, 2018

1 Objective :

Find the best the model with hghest accuracy for Naive Bayes and also find precision, recall, f1 score and confusion matrix of each model.

1.1 Workflow:

1. Sort data based on time.
2. Split data into train and test.
3. Convert reviews of "Amazon Fine Food Review" dataset into vectors using :-
   - Bag of words.
   - TF-IDF
4. Perform feature selection on every model.
5. Find best hyperparameter by Naive Bayes cross validation.
6. Apply Naive Bayes model on the train data.
7. Find accuracy, precision, recall and f1 score of the model.
8. Print confusion matrix and plot error plots for every model.

In [0]:
```
%matplotlib inline

import sqlite3
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
import re, gensim
import string
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import TruncatedSVD
```

```python
from sklearn.cross_validation import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.feature_selection import chi2
```

1.2 Importing data

In [0]:
```python
"""
Reading data from .sqlite file,
choosing only positive and negative reviews not neutral reviews.
"""
# using the SQLite Table to read data.
con = sqlite3.connect('drive/datasets/database.sqlite')

#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query("SELECT * FROM Reviews WHERE Score != 3", con)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
```

1.3 Cleansing data

In [0]:
```python
"""
Below code snippet removes duplicate data from dataset that are repeatedly mentioned.
"""
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True,\
                                      inplace=False, kind='quicksort',\
                                      na_position='last')
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},\
                                  keep='first', inplace=False)
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
# final.shape
```

In [47]:
```python
"""
Sorting data on the basis of TIME
"""
final = final.sort_values(by=['Time'], axis=0)
final.shape
```

Out[47]:
```
(364171, 10)
```

1.4 Text preprocessing

In [20]:
```python
"""
This code snippet does text preprocessing
"""
nltk.download('stopwords')
def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special ch
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer
final_text = []
for index in range(len(final['Text'])):
    filtered_sentence=[]
    sent=cleanhtml(final['Text'].iloc[index]) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():# clean punctuation marks from word
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):# verifying word m
                cleaned_words = cleaned_words.lower()
                if(cleaned_words not in stop):# blocks stopwords
                    s=(sno.stem(cleaned_words))# stemming in process
                    filtered_sentence.append(s)
                else:
                    continue
            else:
                continue
    str1 = " ".join(filtered_sentence) #final cleaned string of words
    final_text.append(str1)
```

```
[nltk_data] Downloading package stopwords to /content/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [21]:
```python
amazon_data_text = pd.Series(final_text)
amazon_data_label = pd.Series(final['Score'])
```

```
print(amazon_data_text.shape)
print(amazon_data_label.shape)
```

```
(364171,)
(364171,)
```

```
In [0]: """
        Spliting sample data into train_data and test_data (75:25)
        """
        x_train, x_test, y_train, y_test = cross_validation.train_test_split(\
                                                                      amazon_data_text,\
                                                                      amazon_data_label
                                                                      test_size = 0.25,\
                                                                      random_state=0)
```

```
In [45]: print("Train data : \n",y_train.value_counts())
```

```
Train data :
 positive    230354
negative     42774
Name: Score, dtype: int64
```

```
In [46]: print("Test data : \n",y_test.value_counts())
```

```
Test data :
 positive    76707
negative    14336
Name: Score, dtype: int64
```

1.4.1 Bag of words.

```
In [24]: """
         This code snippet converts train data from text to vectors by BOW.
         """
         count_vect = CountVectorizer(analyzer='word') #in scikit-learn
         bow_text_train_vector = count_vect.fit_transform(x_train)
         bow_text_train_vector = bow_text_train_vector
         bow_text_train_vector.shape
```

```
Out[24]: (273128, 61712)
```

```
In [25]: """
         This code snippet shows feature selection
         """
         a = chi2(bow_text_train_vector, y_train)
         print("chi2's statistics : ",a[0])
         print("feature probabilities : ",a[1])
```

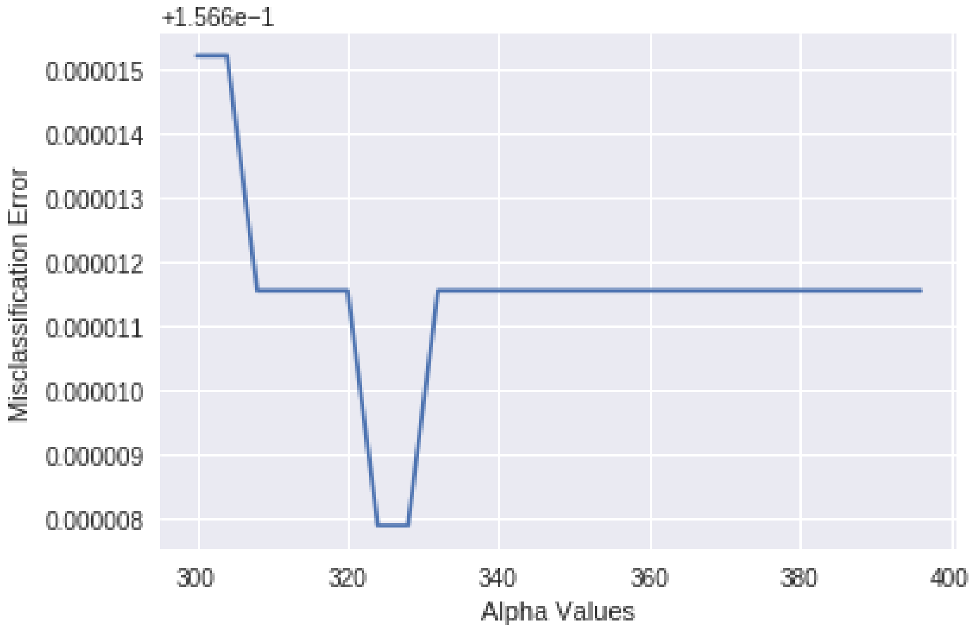
```
chi2's statistics :  [0.37137623 2.92261259 0.18568811 ... 0.18568811 0.18568811 0.18568811]
feature probabilities :  [0.54225506 0.08734634 0.66652986 ... 0.66652986 0.66652986 0.6665298
```

In [26]:
```
"""
This code snippet converts test data from text to vectors by BOW.
"""
bow_text_test_vector = count_vect.transform(x_test)
bow_text_test_vector = bow_text_test_vector
print(bow_text_test_vector.shape)
```

```
(91043, 61712)
```

In [27]:
```
"""
This code snippet helps to find lamda for BernoulliNB and plot error
"""
# empty list that will hold cv scores
cv_scores = []
alpha_values = list(range(300,400,4))
# perform 10-fold cross validation
for al in alpha_values:
    nb = BernoulliNB(alpha = al)
    scores = cross_val_score(nb, bow_text_train_vector,
                             y_train, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())
# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best alpha
bow_optimal_alpha = alpha_values[MSE.index(min(MSE))]
print('The optimal value of alpha is %d.' % bow_optimal_alpha)

# plot misclassification error vs alpha
plt.plot(alpha_values, MSE)

for xy in zip(alpha_values, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Alpha Values')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each alpha value is : ", np.round(MSE,3))
```

```
The optimal value of alpha is 324.
```

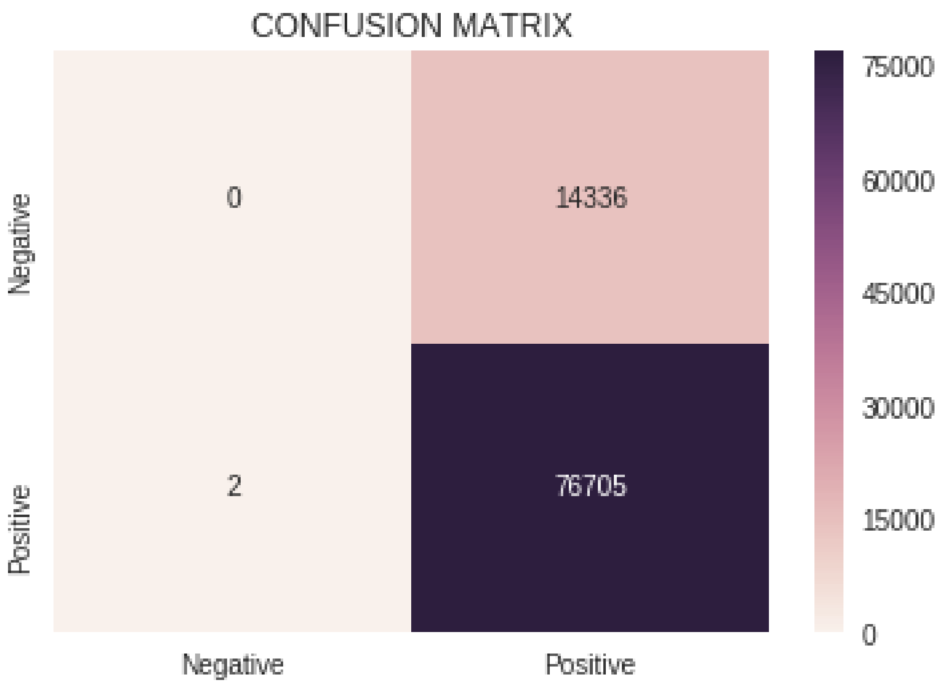



```
the misclassification error for each alpha value is :  [0.157 0.157 0.157 0.157 0.157 0.157 0.1
 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157
 0.157]
```

```
In [28]: """
         This code snippet apply BernoulliNB for above lambda value
         """
         # Instantiate learning model
         nb = BernoulliNB(alpha = bow_optimal_alpha)
         # fitting the model
         nb.fit(bow_text_train_vector, y_train)
         # response prediction
         pred = nb.predict(bow_text_test_vector)
         # evaluate accuracy
         acc = accuracy_score(y_test, pred)*100
         print('\nThe accuracy of the Naive Bayes classifier for alpha = %d is %f%%' % (bow_op
         conf_matrix = confusion_matrix(y_test, pred)
         confusion_matrix_df = pd.DataFrame(conf_matrix,
                                            ["Negative", "Positive"],\
                                            ["Negative", "Positive"],\
                                            dtype=int)
         sns.heatmap(confusion_matrix_df, annot=True, fmt="d")
         plt.title("CONFUSION MATRIX")
```

```
The accuracy of the Naive Bayes classifier for alpha = 324 is 84.251398%
```

Out[28]: Text(0.5,1,'CONFUSION MATRIX')



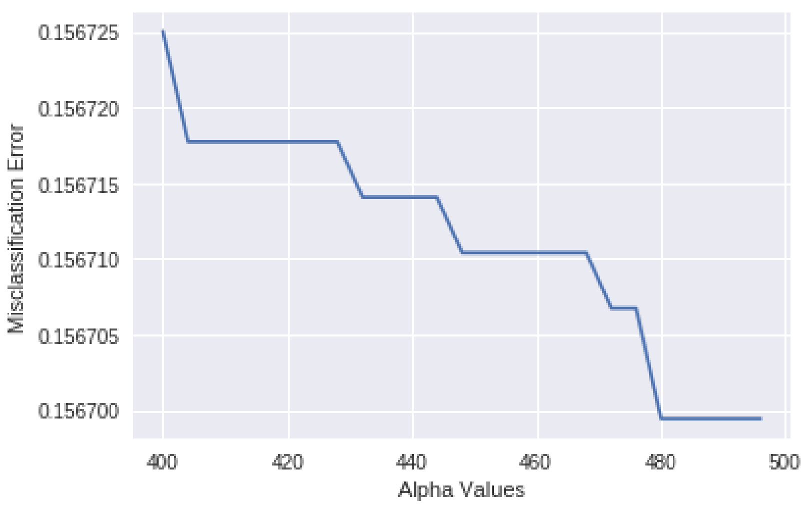
In [29]:
```python
"""
This code snippet shows precision, recall, f1 and support scores for BernoulliNB
"""
print(classification_report(y_test, pred, target_names = np.unique(y_test)))
```

```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00     14336
   positive       0.84      1.00      0.91     76707

avg / total       0.71      0.84      0.77     91043
```

In [30]:
```python
"""
This code snippet helps to find lamda for MultinomialNB and plot error
"""
# empty list that will hold cv scores
cv_scores = []
alpha_values = list(range(400,500,4))
```

```python
# perform 10-fold cross validation
for al in alpha_values:
    nb = MultinomialNB(alpha = al)
    scores = cross_val_score(nb, bow_text_train_vector,
                             y_train, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())
# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best alpha
bow_optimal_alpha = alpha_values[MSE.index(min(MSE))]
print('The optimal value of alpha is %d.' % bow_optimal_alpha)

# plot misclassification error vs alpha
plt.plot(alpha_values, MSE)

for xy in zip(alpha_values, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Alpha Values')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each alpha value is : ", np.round(MSE,3))
```

```
The optimal value of alpha is 480.
```



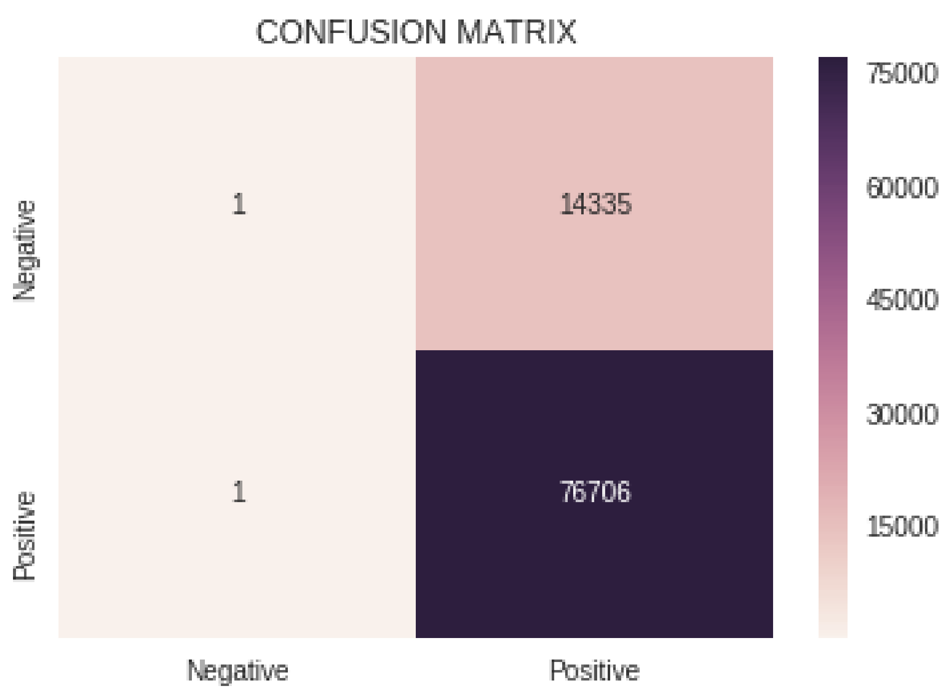

```
the misclassification error for each alpha value is :  [0.157 0.157 0.157 0.157 0.157 0.157 0.1
 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157 0.157
```

0.157]

In [31]:
```
"""
This code snippet apply MultinomialNB for above lambda value
"""
# Instantiate learning model
nb = MultinomialNB(alpha = bow_optimal_alpha)
# fitting the model
nb.fit(bow_text_train_vector, y_train)
# response prediction
pred = nb.predict(bow_text_test_vector)
# evaluate accuracy
acc = accuracy_score(y_test, pred)*100
print('\nThe accuracy of the Naive Bayes classifier for alpha = %d is %f%%' % (bow_op
conf_matrix = confusion_matrix(y_test, pred)
confusion_matrix_df = pd.DataFrame(conf_matrix,
                                   ["Negative", "Positive"],\
                                   ["Negative", "Positive"],\
                                   dtype=int)
sns.heatmap(confusion_matrix_df, annot=True, fmt="d")
plt.title("CONFUSION MATRIX")
```

```
The accuracy of the Naive Bayes classifier for alpha = 480 is 84.253594%
```

Out[31]: Text(0.5,1,'CONFUSION MATRIX')



In [32]:
```
"""
This code snippet shows precision, recall, f1 and support scores for MultinomialNB
"""
print(classification_report(y_test, pred, target_names = np.unique(y_test)))
```

```
             precision    recall  f1-score   support

   negative       0.50      0.00      0.00     14336
   positive       0.84      1.00      0.91     76707

avg / total       0.79      0.84      0.77     91043
```

Observation :

- Here we have applied Bag of words to convert text to vector.
- We got best hyperparameter for the BernoulliNB model is 324 with accuracy 84.251398% .
- We got best hyperparameter for the MultinomialNB model is 480 with accuracy 84.253594% .

1.4.2 TF IDF.

In [33]:
```
"""
This code snippet converts train data from text to vectors by TF_IDF.
"""
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
final_tf_idf_train = tf_idf_vect.fit_transform(x_train)
final_tf_idf_train.shape
```

Out[33]:
```
(273128, 2436312)
```

In [34]:
```
"""
This code snippet converts test data from text to vectors by TF_IDF.
"""
final_tf_idf_test = tf_idf_vect.transform(x_test)
final_tf_idf_test.shape
```

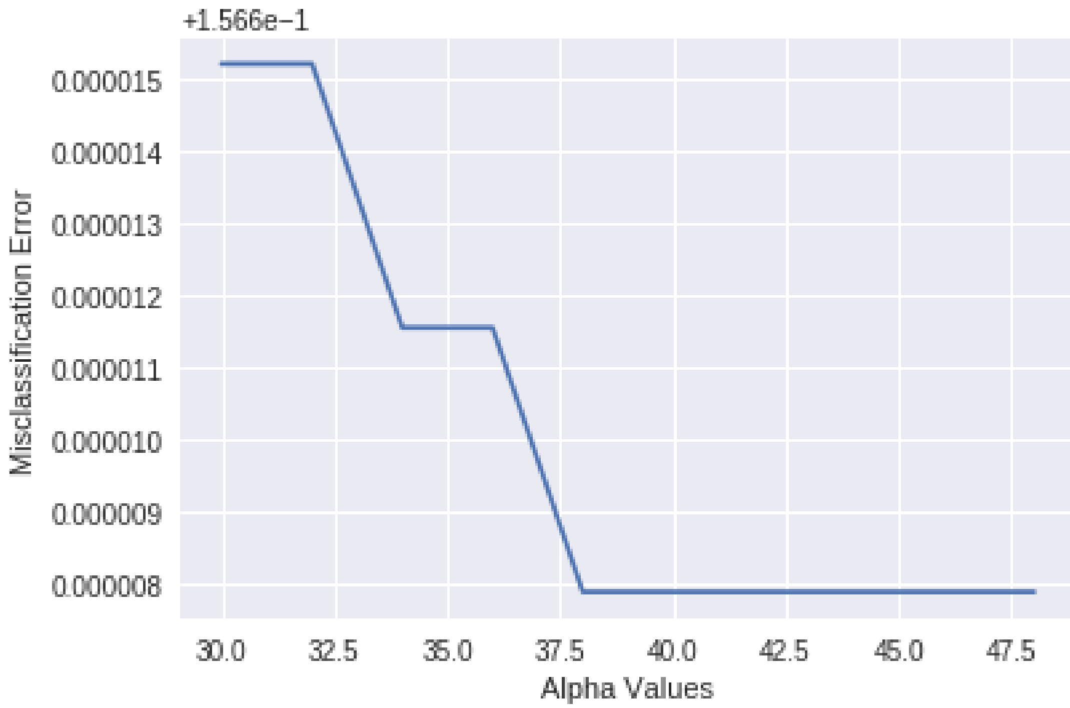
Out[34]:
```
(91043, 2436312)
```

In [35]:
```
"""
This code snippet shows feature selection
"""
a = chi2(final_tf_idf_train, y_train)
print("chi2's statistics : ",a[0])
print("feature probabilities : ",a[1])
```

```
chi2's statistics :  [0.03995276 0.03601368 0.00524348 ... 0.02876846 0.04075579 0.04075579]
feature probabilities :  [0.84157297 0.84948724 0.94227415 ... 0.86531476 0.84001003 0.8400100
```

```
In [36]: """
         This code snippet helps to find lamda for BernoulliNB and plot error
         """
         # empty list that will hold cv scores
         cv_scores = []
         alpha_values = list(range(30,50,2))
         # perform 10-fold cross validation
         for al in alpha_values:
             nb = BernoulliNB(alpha = al)
             scores = cross_val_score(nb, final_tf_idf_train,
                                      y_train, cv=10,
                                      scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x for x in cv_scores]

         # determining best alpha
         optimal_alpha = alpha_values[MSE.index(min(MSE))]
         print('The optimal value of alpha is %d.' % optimal_alpha)

         # plot misclassification error vs alpha
         plt.plot(alpha_values, MSE)

         for xy in zip(alpha_values, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

         plt.xlabel('Alpha Values')
         plt.ylabel('Misclassification Error')
         plt.show()

         print("the misclassification error for each alpha value is : ", np.round(MSE,3))
```

```
The optimal value of alpha is 38.
```

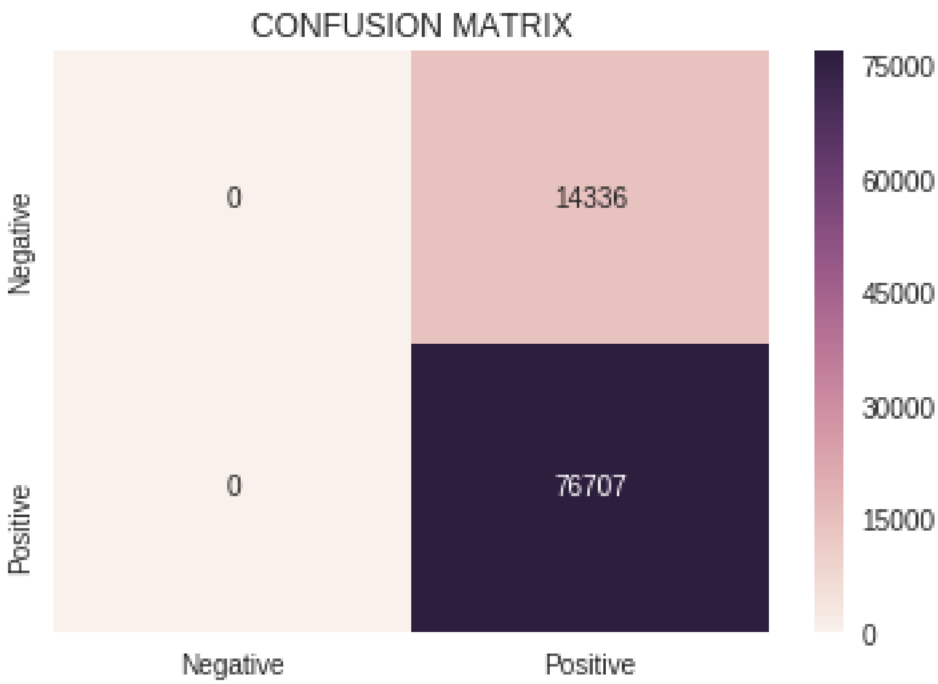



```
the misclassification error for each alpha value is :  [0.157 0.157 0.157 0.157 0.157 0.157 0.1
```

In [37]:
```
"""
This code snippet apply BernoulliNB for above lambda value
"""
# Instantiate learning model
nb = BernoulliNB(alpha = optimal_alpha)
# fitting the model
nb.fit(final_tf_idf_train, y_train)
# response prediction
pred = nb.predict(final_tf_idf_test)
# evaluate accuracy
acc = accuracy_score(y_test, pred)*100
print('\nThe accuracy of the Naive Bayes classifier for alpha = %d is %f%%' % (optima
conf_matrix = confusion_matrix(y_test, pred)
confusion_matrix_df = pd.DataFrame(conf_matrix,
                                   ["Negative", "Positive"],\
                                   ["Negative", "Positive"],\
                                   dtype=int)
sns.heatmap(confusion_matrix_df, annot=True, fmt="d")
plt.title("CONFUSION MATRIX")
```

```
The accuracy of the Naive Bayes classifier for alpha = 38 is 84.253594%
```

Out[37]: Text(0.5,1,'CONFUSION MATRIX')



In [38]:
```
"""
This code snippet shows precision, recall, f1 and support scores for BernoulliNB
"""
print(classification_report(y_test, pred, target_names = np.unique(y_test)))
```

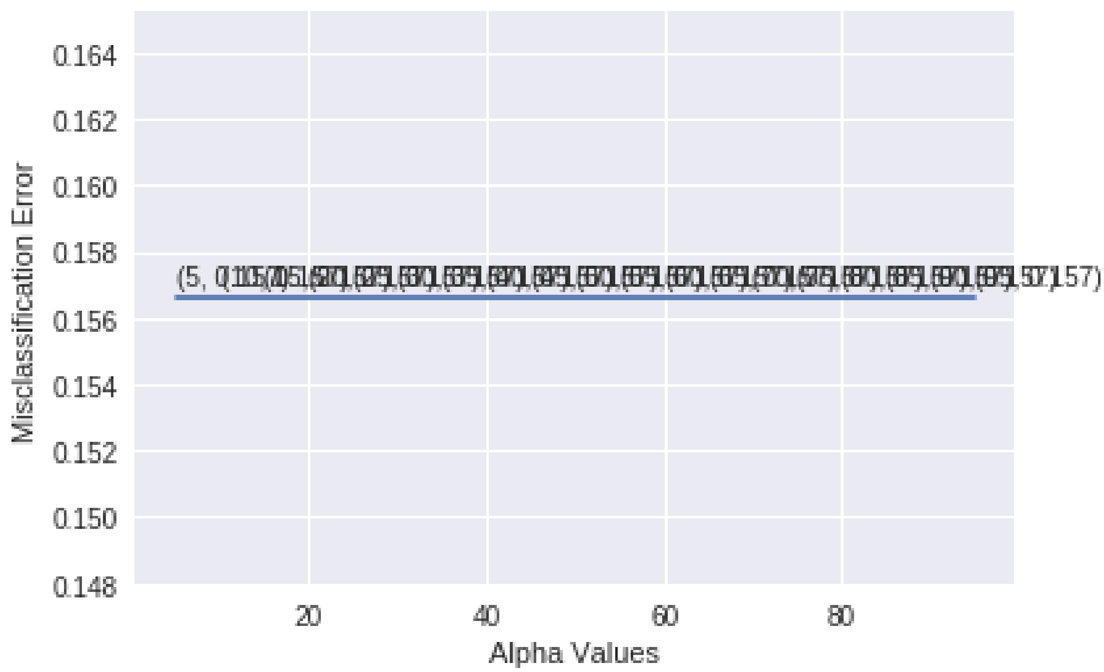
```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00     14336
   positive       0.84      1.00      0.91     76707

avg / total       0.71      0.84      0.77     91043
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

In [39]:
```
"""
This code snippet helps to find lamda for MultinomialNB and plot error
```

```python
"""
# empty list that will hold cv scores
cv_scores = []
alpha_values = list(range(5,100,5))
# perform 10-fold cross validation
for al in alpha_values:
    nb = MultinomialNB(alpha = al)
    scores = cross_val_score(nb, final_tf_idf_train,
                             y_train, cv=10,
                             scoring='accuracy')
    cv_scores.append(scores.mean())
# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best alpha
optimal_alpha = alpha_values[MSE.index(min(MSE))]
print('The optimal value of alpha is %d.' % optimal_alpha)

# plot misclassification error vs alpha
plt.plot(alpha_values, MSE)

for xy in zip(alpha_values, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Alpha Values')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each alpha value is : ", np.round(MSE,3))
```

```
The optimal value of alpha is 5.
```

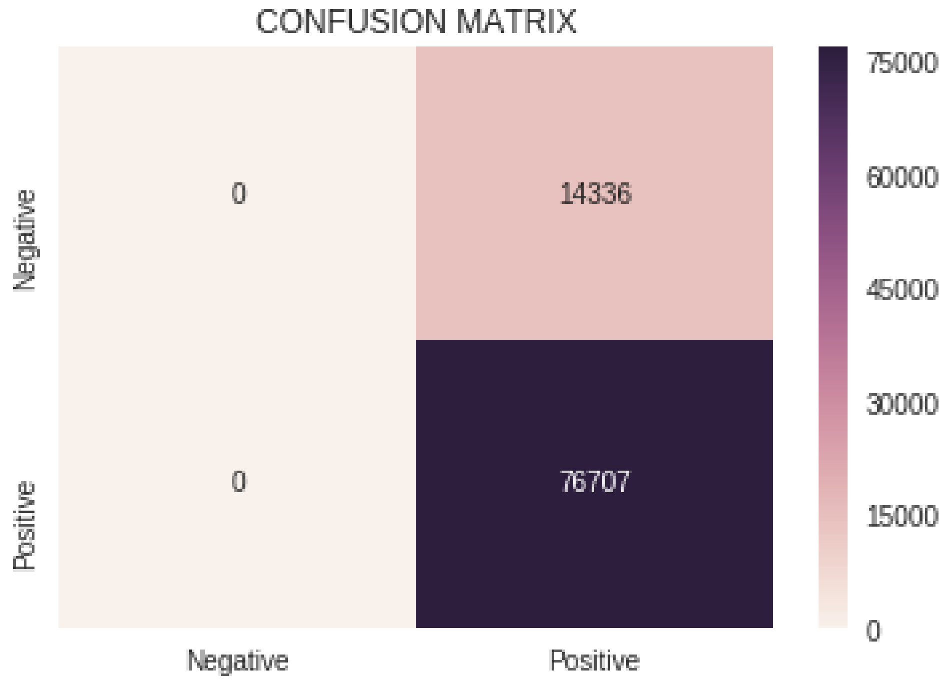



```
the misclassification error for each alpha value is :  [0.157 0.157 0.157 0.157 0.157 0.157 0.1
 0.157 0.157 0.157 0.157 0.157 0.157 0.157]
```

```
In [40]: """
         This code snippet apply MultinomialNB for above lambda value
         """
         # Instantiate learning model
         nb = MultinomialNB(alpha = optimal_alpha)
         # fitting the model
         nb.fit(final_tf_idf_train, y_train)
         # response prediction
         pred = nb.predict(final_tf_idf_test)
         # evaluate accuracy
         acc = accuracy_score(y_test, pred)*100
         print('\nThe accuracy of the Naive Bayes classifier for alpha = %d is %f%%' % (optimal
         conf_matrix = confusion_matrix(y_test, pred)
         confusion_matrix_df = pd.DataFrame(conf_matrix,
                                            ["Negative", "Positive"],\
                                            ["Negative", "Positive"],\
                                            dtype=int)
         sns.heatmap(confusion_matrix_df, annot=True, fmt="d")
         plt.title("CONFUSION MATRIX")
```

```
The accuracy of the Naive Bayes classifier for alpha = 5 is 84.253594%
```

Out[40]: Text(0.5,1,'CONFUSION MATRIX')



In [41]:
```
"""
This code snippet shows precision, recall, f1 and support scores for MultinomialNB
"""
print(classification_report(y_test, pred, target_names = np.unique(y_test)))
```

```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00     14336
   positive       0.84      1.00      0.91     76707

avg / total       0.71      0.84      0.77     91043
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

Observation :

- Here we have applied TF_IDF to convert text to vector.
- We got best hyperparameter for the BernoulliNB model is 38 with accuracy 84.253594%% .
- We got best hyperparameter for the MultinomialNB model is 5 with accuracy 84.253594% .
- MultinomialNB model for TF_IDF is underfitting .

1.4.3 Conclusion :

From the above excercise I got to know that

- BernoulliNB deals with binary classifications and MultinomialNB deals with multiclass classifications.
- Through feature selection we can choose the important feature for our model to train on.
- Naive Bayes is a performance benchmark for all advanced text classification techniques.