Apply_Naive_Bayes_to_Amazon_reviews_[M]

May 27, 2018

```
In [0]: !pip install -U -q PyDrive
```

```
In [0]: from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials

        # 1. Authenticate and create the PyDrive client.
        auth.authenticate_user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get_application_default()
        drive = GoogleDrive(gauth)
```

```
In [3]: file_list = drive.ListFile({'q': "'1pbLvjcsi6UtFm3sPciCJGbCG4NK3uyuS' in parents and tra
        for file1 in file_list:
          print('title: %s, id: %s' % (file1['title'], file1['id']))
```

```
title: Apply Naive Bayes to Amazon reviews [M].ipynb, id: 1qPxAZeYQUM-eqaKnOSM5ubK2IPIVmdyo
title: clean_final.sqlite, id: 1TOHyUqaVFyD8HfIQEM6WN8jF8SpEOsAo
title: KNN on Credit Card fraud detection.ipynb, id: 1CkA-RBfXqvubKkQrpnjbYUKVsC7VHlTl
title: creditcard.csv, id: 1VpeqlSOlPVrlzlMIqvQTzc3Pno_Cj4SV
title: creditcard.csv, id: 1bnZktEq3N_5wjoCH85oIXHxNwXUW_jx-
title: Untitled, id: 1KOwwkizWx3WO8d-zw-YewWIUrPdINYmp
title: final.sqlite, id: 1OzLc3k6-T55I-XRMq47ERyCbQbVw4caF
title: HeavyComputations.ipynb, id: 1aBORe3gqeFY-iNhzMtr-TIkzEyEvFxcG
```

```
In [0]: sql = drive.CreateFile({'id': '1OzLc3k6-T55I-XRMq47ERyCbQbVw4caF'})
        sql.GetContentFile('final.sqlite')
```

```
In [0]: %matplotlib inline
        import pandas as pd
        from sklearn.feature_extraction.text import TfidfVectorizer
        import numpy as np
        import matplotlib.pyplot as plt
        import sqlite3
```

```
In [0]: con = sqlite3.connect('final.sqlite') # this is cleaned dataset
        final = pd.read_sql_query("""
```

```
        SELECT Score, Text_not_included
        FROM reviews
        """, con)
```

```
In [65]: len(final)
```

```
Out[65]: 23953
```

```
In [0]: for i, seq in enumerate(final['Text_not_included']):
          final['Text_not_included'][i]=final['Text_not_included'][i].decode('UTF-8')
```

```
In [0]: from sklearn.model_selection import train_test_split
```

```
In [0]: X_train, X_test, y_train , y_test = train_test_split(final['Text_not_included'], final['
```

```
In [0]: X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.25, shuf
```

```
In [80]: type(y_train)
```

```
Out[80]: pandas.core.series.Series
```

```
In [12]: !pip install imblearn
```

```
Collecting imblearn
  Downloading https://files.pythonhosted.org/packages/81/a7/4179e6ebfd654bd0eac0b9c06125b8b4c96a
Collecting imbalanced-learn (from imblearn)
  Downloading https://files.pythonhosted.org/packages/80/a4/900463a3c0af082aed9c5a43f4ec317a9469
    100% || 153kB 7.2MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from imbalanced-
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from imbalanced-
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from imba
Installing collected packages: imbalanced-learn, imblearn
Successfully installed imbalanced-learn-0.3.3 imblearn-0.0
```

```
In [0]: from sklearn.feature_extraction.text import CountVectorizer
```

```
In [100]: bbow = CountVectorizer(ngram_range = (1,2))
          bbow.fit(X_train)
```

```
Out[100]: CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                  dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                  lowercase=True, max_df=1.0, max_features=None, min_df=1,
                  ngram_range=(1, 2), preprocessor=None, stop_words=None,
                  strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                  tokenizer=None, vocabulary=None)
```

```
In [0]: text_vectors = bbow.transform(X_train)
```

```
In [0]: # Oversampling train set
        import imblearn
        over_sampler=imblearn.over_sampling.SMOTE(ratio='minority')
        X_train_resampled, y_train_resampled = over_sampler.fit_sample(text_vectors, y_train)
```

```
In [103]: X_train_resampled.get_shape()[0]==y_train_resampled.shape[0]
```

```
Out[103]: True
```

```
In [104]: len(y_train_resampled[np.where(y_train_resampled=='positive')])==len(y_train_resampled
```

```
Out[104]: True
```

```
In [105]: X_train_resampled.getrow(5).todense()
```

```
Out[105]: matrix([[0., 0., 0., ..., 0., 0., 0.]])
```

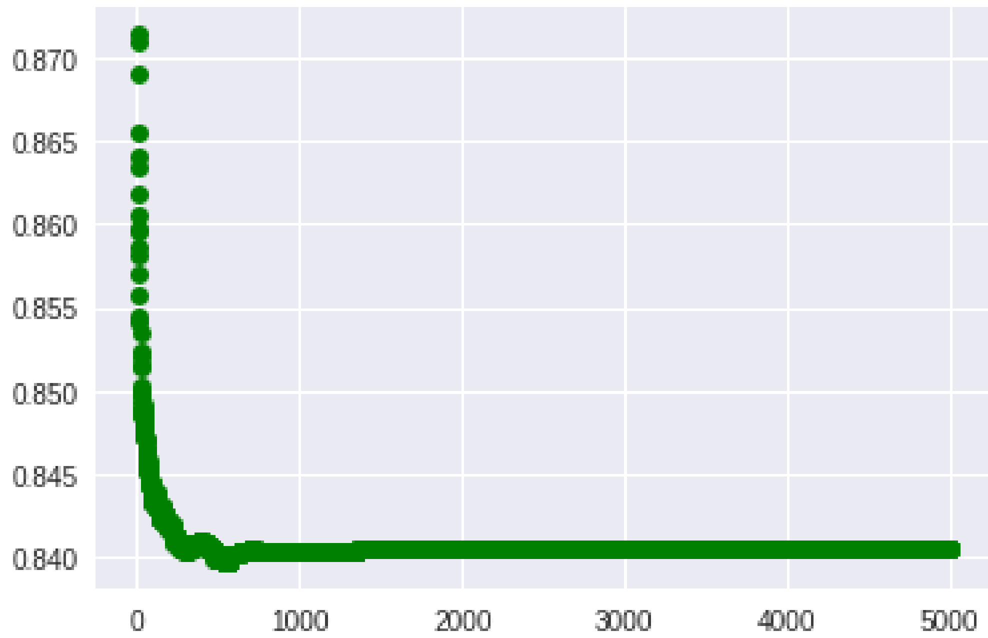
```
In [0]: text_vectors_val=bbow.transform(X_val)
```

```
In [0]: from sklearn.naive_bayes import BernoulliNB
        from sklearn.cross_validation import cross_val_score
        from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

```
In [114]: x=[]
          y=[]
          for alpha in range(1,5001,1):
            nb_clf = BernoulliNB(alpha=alpha, class_prior=[1,1])
            nb_clf.fit(X_train_resampled, y_train_resampled)
            predictions = nb_clf.predict(text_vectors_val)
            accuracy = accuracy_score(y_val, predictions)
            x.append(alpha)
            y.append(accuracy)

          plt.plot(x, y, 'go')
          print('max accuracy {} at alpha = {}'.format(np.max(y), x[np.argmax(y)]))
```

```
max accuracy 0.8714255896472552 at alpha = 2
```




```
In [115]: print('max accuracy {} at alpha = {}'.format(np.max(y), x[np.argmax(y)]))

max accuracy 0.8714255896472552 at alpha = 2

In [0]: test_vectors=bbow.transform(X_test)

In [0]: nb_clf = BernoulliNB(alpha=2, class_prior=[1,1])
        nb_clf.fit(X_train_resampled, y_train_resampled)
        predictions = nb_clf.predict(test_vectors)
        accuracy = accuracy_score(y_test, predictions)

In [118]: accuracy

Out[118]: 0.8668336464203715

In [119]: print(classification_report(y_test, predictions))

             precision    recall  f1-score   support

   negative       0.71      0.22      0.34       733
   positive       0.88      0.98      0.93      4058

avg / total       0.85      0.87      0.84      4791
```

In [120]: print(confusion_matrix(y_test, predictions).T)

```
[[ 163   68]
 [ 570 3990]]
```

In [135]: nb_clf.classes_

Out[135]: array(['negative', 'positive'], dtype='<U8')

In [134]: X_train_resampled.shape

Out[134]: (23972, 303207)

In [138]: len(nb_clf.feature_count_[0])

Out[138]: 303207

In [0]: p_wi_given_y_negative = np.array(np.reshape(nb_clf.feature_log_prob_[0], [-1]))

In [0]: p_wi_given_y_positive = np.array(np.reshape(nb_clf.feature_log_prob_[1], [-1]))

In [0]:
```
feat_indices_negative=np.argsort(-p_wi_given_y_negative)
feat_indices_positive=np.argsort(-p_wi_given_y_positive)
```

In [154]: type(bbow.get_feature_names())

Out[154]: list

In [0]:
```
important_features_negative = np.array(bbow.get_feature_names())[feat_indices_negative]
important_features_positive = np.array(bbow.get_feature_names())[feat_indices_positive]
```

In [164]: important_features_negative[0:100]

Out[164]:
```
array(['not', 'like', 'product', 'tast', 'would', 'buy', 'tri', 'get',
       'one', 'price', 'good', 'flavor', 'dont', 'use', 'review', 'way',
       'purchas', 'made', 'food', 'even', 'store', 'great', 'time',
       'order', 'eat', 'dog', 'box', 'make', 'would not', 'much',
       'bought', 'look', 'love', 'bag', 'think', 'amazon', 'first',
       'realli', 'disappoint', 'could', 'better', 'also', 'didnt',
       'foster', 'price foster', 'smith', 'foster smith', 'want', 'say',
       'bad', 'littl', 'chip', 'okay', 'packag', 'know', 'give', 'well',
       'expens', 'thought', 'got', 'never', 'differ', 'found', 'brand',
       'thing', 'someth', 'not way', 'two', 'okay would', 'way buy',
       'treat', 'ive', 'local', 'howev', 'away', 'quit', 'find', 'day',
       'money', 'open', 'still', 'receiv', 'back', 'tast like', 'ingredi',
       'recommend', 'year', 'sugar', 'product made', 'item', 'drink',
       'old', 'mix', 'mani', 'great review', 'enjoy', 'contain',
       'review product', 'per', 'lot'], dtype='<U33')
```

In [165]: important_features_positive[0:100]

```
Out[165]: array(['not', 'like', 'love', 'good', 'tast', 'great', 'flavor', 'one',
                 'tri', 'use', 'product', 'get', 'make', 'food', 'buy', 'would',
                 'time', 'eat', 'best', 'realli', 'amazon', 'also', 'much', 'find',
                 'price', 'dont', 'well', 'littl', 'recommend', 'order', 'store',
                 'dog', 'even', 'better', 'ive', 'year', 'bag', 'high', 'tea',
                 'day', 'give', 'mix', 'treat', 'sweet', 'look', 'first', 'want',
                 'found', 'favorit', 'chip', 'enjoy', 'drink', 'delici', 'think',
                 'way', 'keep', 'work', 'thing', 'bit', 'brand', 'need', 'made',
                 'lot', 'sinc', 'nice', 'know', 'sugar', 'purchas', 'pack',
                 'bought', 'coffe', 'come', 'snack', 'say', 'could', 'perfect',
                 'still', 'two', 'packag', 'add', 'everi', 'mani', 'alway',
                 'without', 'never', 'healthi', 'differ', 'cant', 'take', 'seem',
                 'local', 'box', 'easi', 'wonder', 'ever', 'water', 'right', 'got',
                 'put', 'fresh'], dtype='<U33')
```

0.1 Results

Optimal alpha = 2 Top 100 features found most commonly in negative and positive reviews are enumerated above Accuracy on test set = 86.68% TPR (recall wrt positive class) = 98% TNR (recall wrt negative class)= 22% FPR = 78% FNR = 2% Precision wrt positive class = 0.88 Precision wrt negative class = 0.71 F1 score wrt positive class = 0.93 F1 score wrt negative class = 0.34

0.1.1 Conclusion

Even after resampling of minority class using SMOTE we observe that Naive Bayes classifier fails miserably in distinguishing negative class from positive class. The ill effects of majority class (positive reviews) dominance are clearly visible in TNR above. More than 50% of negative reviews are being classified as positive. This clearly shows that the 'naive' approximation although giving satifactory results in spam filters, is failing in this case and hence this classifier is not appropriate for text classifications in general.