Naive-Bayes

October 14, 2018

```
In [1]: # ============================== loading libraries =====================================
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn.cross_validation import train_test_split
        from sklearn.neighbors import KNeighborsClassifier
        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 import datasets, neighbors
        from sklearn.model_selection import TimeSeriesSplit
        import pickle
        import scipy
        import time
        # ======================================================================================
```

```
C:\Users\avinash\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [2]: #Function to pickle in an object.
        def openPickleFile(name): #name = the pickle file name, this should be passed as a str
            global temp
            temp = pickle.load(open(name + ".pickle","rb"))
            return temp
```

```
In [3]: openPickleFile("y_train")
        y_train = temp
        print(y_train.shape)
        print(y_train.dtype)
```

```
(33334,)
object
```

In [4]:
```
y_train[y_train == 'positive'] = 1
y_train[y_train == 'negative'] = 0
y_train = y_train.astype(float)
print(y_train.dtype)
```

```
float64
```

In [5]:
```
openPickleFile("y_test")
y_test = temp
print(y_test.shape)
print(y_test.dtype)
```

```
(16666,)
object
```

In [6]:
```
y_test[y_test == 'positive'] = 1
y_test[y_test == 'negative'] = 0
y_test = y_test.astype(float)
print(y_test.dtype)
```

```
float64
```

In [7]:
```
#Function to count no. of unique values in variable of any datatype.
def unique_count(a):
    unique, inverse = np.unique(a, return_inverse=True)
    count = np.zeros(len(unique), np.int)
    np.add.at(count, inverse, 1)
    return np.vstack(( unique, count)).T

unique_count(y_train)
```

Out[7]:
```
array([[0.0000e+00, 4.9490e+03],
       [1.0000e+00, 2.8385e+04]])
```

1 CV using Bernouli Naive-bayes algorithm.

2 1. CV on Standardized data for Unigrams

2.0.1 Simple Cross Validation

In [8]:
```
openPickleFile("X_train_BOW_unigram")
X_train = temp
print(X_train.shape)
print(X_train.dtype)
```

```
(33334, 50)
float64
```

```
In [9]: openPickleFile("X_test_BOW_unigram")
        X_test = temp
        print(X_test.shape)
        print(X_test.dtype)
```

```
(16666, 50)
float64
```

```
In [10]: # split the train data set into cross validation train and cross validation test
         time_start = time.time()
         from sklearn.naive_bayes import *
         from sklearn.naive_bayes import BernoulliNB

         X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_train, y_train, test_size
         alpha = [10**i for i in range(-3,6)]

         for i in alpha:
             # instantiate learning model (alpha = 30)
             clf = BernoulliNB(alpha=i,binarize=0.0,fit_prior=True,class_prior=None)

             #clf = BernoulliNB(alpha=i,binarize=0.1)

             # fitting the model on crossvalidation train
             clf.fit(X_tr, y_tr)

             # predict the response on the crossvalidation train
             pred = clf.predict(X_cv)

             # evaluate CV accuracy
             acc = accuracy_score(y_cv, pred, normalize=True) * float(100)
             print('\nCV accuracy for alpha = %f is %f%%' % (i, acc))

         clf = BernoulliNB(alpha=0.001,binarize=0.1)
         clf.fit(X_tr,y_tr)
         pred = clf.predict(X_test)
         acc = accuracy_score(y_test, pred, normalize=True) * float(100)
         print('\n****Test accuracy for alpha = 0.001 is %f%%' % (acc))

         print ('CV for alpha in range(10e-3, 10e+6) done! Time elapsed: {} seconds'.format(ti
```

```
CV accuracy for alpha = 0.001000 is 85.137715%

CV accuracy for alpha = 0.010000 is 85.137715%
```

```
CV accuracy for alpha = 0.100000 is 85.137715%

CV accuracy for alpha = 1.000000 is 85.137715%

CV accuracy for alpha = 10.000000 is 85.110445%

CV accuracy for alpha = 100.000000 is 85.101354%

CV accuracy for alpha = 1000.000000 is 85.355877%

CV accuracy for alpha = 10000.000000 is 85.183165%

CV accuracy for alpha = 100000.000000 is 85.183165%

****Test accuracy for alpha = 0.001 is 80.709228%
CV for alpha in range(10e-3, 10e+6) done! Time elapsed: 0.5864310264587402 seconds
```

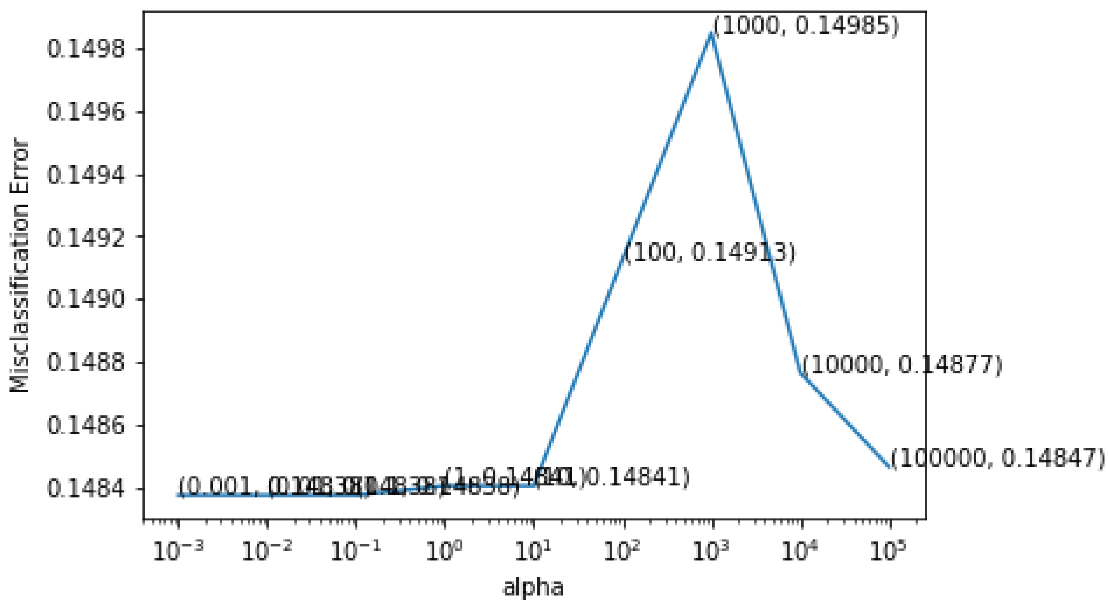
```
In [11]: clf = BernoulliNB(alpha=1e-10)
         clf.fit(X_tr,y_tr)
         clf.predict_proba(X_tr)

Out[11]: array([[0.05066693, 0.94933307],
                [0.09840797, 0.90159203],
                [0.18023902, 0.81976098],
                ...,
                [0.26654398, 0.73345602],
                [0.07889542, 0.92110458],
                [0.09025971, 0.90974029]])
```

2.0.2 10 fold cross validation

```
In [12]: time_start = time.time()

         # creating odd list of K for KNN
         #myList = list(np.arrange(1,2,0.01))
         #alpha = list(filter(lambda x: x % 2 != 0, myList))
         #alpha = list(np.arange(0.1,10,0.1)) #alpha varies the most in this range.
         alpha = [10**i for i in range(-3,6)]

         # empty list that will hold cv scores
         cv_scores = []

         # perform 10-fold cross validation
         for i in alpha:
             clf = BernoulliNB(alpha=i,binarize=0.1)
             scores = cross_val_score(clf, X_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[MSE.index(min(MSE))]
print('\nThe optimal optimal_alpha is %f.' % optimal_alpha)

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

for xy in zip(alpha, np.round(MSE,5)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.xscale('log')
plt.xlabel('alpha')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each alpha value is : ", np.round(MSE,5))

print ('10 fold CV for alpha in range(10e-3, 10e+6) done! Time elapsed: {} seconds'.fo
```

```
The optimal optimal_alpha is 0.001000.
```



```
the misclassification error for each alpha value is :  [0.14838 0.14838 0.14838 0.14841 0.1484
10 fold CV for alpha in range(10e-3, 10e+6) done! Time elapsed: 6.293203830718994 seconds
```

```
In [13]: # =============================== KNN with k = optimal_k ===============================
         # instantiate learning model k = optimal_k
         alpha_optimal = BernoulliNB(alpha=optimal_alpha,binarize=0.1)

         # fitting the model
         alpha_optimal.fit(X_train, y_train)

         # predict the response
         pred = alpha_optimal.predict(X_test)

         # evaluate accuracy
         acc = accuracy_score(y_test, pred) * 100
         print('\nThe accuracy of the Bernoulli for alpha = %f is %f%%' % (optimal_alpha, acc))
```

```
The accuracy of the Bernoulli for alpha = 0.001000 is 80.739230%
```

2.1 Precision, recall, F1 score.

```
In [14]: from sklearn.metrics import precision_recall_fscore_support as score

         precision, recall, fscore, support = score(y_test, pred)

         print('precision: {}'.format(precision))
         print('recall: {}'.format(recall))
         print('fscore: {}'.format(fscore))
         print('support: {}'.format(support))
```

```
precision: [0.06963788 0.82363402]
recall: [0.00861772 0.97573556]
fscore: [0.01533742 0.89325619]
support: [ 2901 13765]
```

```
In [15]: from sklearn.metrics import classification_report

         target_names = ['class 0', 'class 1']
         print(classification_report(y_test, pred, target_names=target_names))
```

```
             precision    recall  f1-score   support

    class 0       0.07      0.01      0.02      2901
    class 1       0.82      0.98      0.89     13765
```

```
avg / total       0.69      0.81      0.74     16666
```

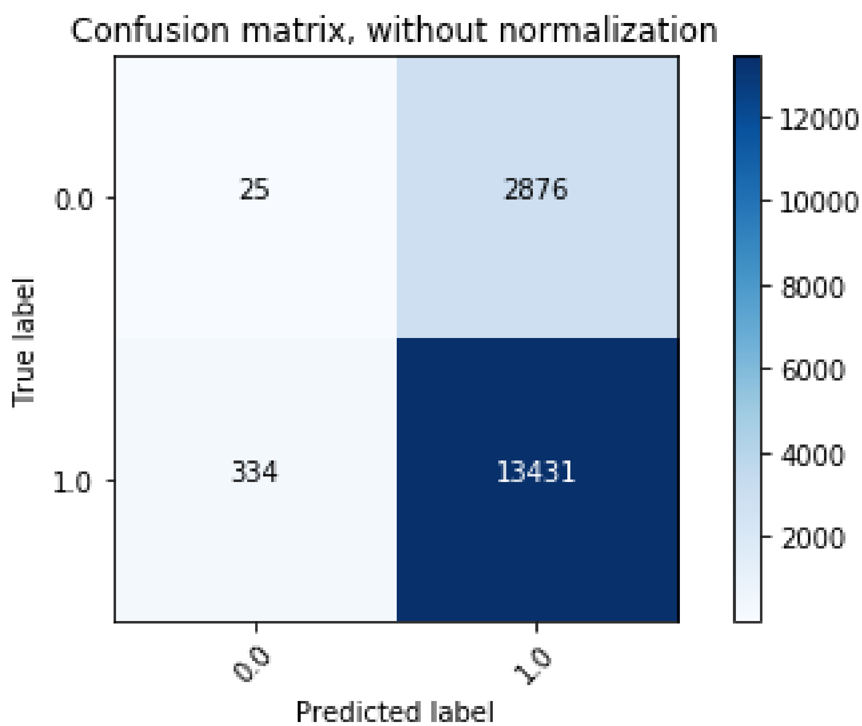
2.2 Confusion Matrix

```
In [16]: #Source: http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_
         print(__doc__)

         import itertools
         from sklearn.metrics import confusion_matrix

         def plot_confusion_matrix(cm, classes,
                                   normalize=False,
                                   title='Confusion matrix',
                                   cmap=plt.cm.Blues):
             """
             This function prints and plots the confusion matrix.
             Normalization can be applied by setting `normalize=True`.
             """
             if normalize:
                 cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                 print("Normalized confusion matrix")
             else:
                 print('Confusion matrix, without normalization')

             print(cm)

             plt.imshow(cm, interpolation='nearest', cmap=cmap)
             plt.title(title)
             plt.colorbar()
             tick_marks = np.arange(len(classes))
             plt.xticks(tick_marks, classes, rotation=45)
             plt.yticks(tick_marks, classes)

             fmt = '.2f' if normalize else 'd'
             thresh = cm.max() / 2.
             for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                 plt.text(j, i, format(cm[i, j], fmt),
                          horizontalalignment="center",
                          color="white" if cm[i, j] > thresh else "black")

             plt.ylabel('True label')
             plt.xlabel('Predicted label')
             plt.tight_layout()
```

```
Automatically created module for IPython interactive environment
```

In [17]:
```
#Source: http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, pred)
np.set_printoptions(precision=2)

class_names=np.unique(y_test)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
#plt.figure()
#plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
#                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[   25  2876]
 [  334 13431]]
```



3 2. CV on Standardized data of Bigrams

```
In [18]: openPickleFile("X_train_BOW_bigrams")
         X_train = temp
         print(X_train.shape)
         print(X_train.dtype)
```

```
(33334, 50)
float64
```

```
In [19]: openPickleFile("X_test_BOW_bigrams")
         X_test = temp
         print(X_test.shape)
         print(X_test.dtype)
```

```
(16666, 50)
float64
```

```
In [20]: unique_count(y_train)
```

```
Out[20]: array([[0.00e+00, 4.95e+03],
                [1.00e+00, 2.84e+04]])
```

```
In [21]: def unique(a):
             unique, counts = np.unique(a, return_counts=True)
             return np.asarray((unique, counts)).T

         unique(y_test)
```

```
Out[21]: array([[0.00e+00, 2.90e+03],
                [1.00e+00, 1.38e+04]])
```

```
In [22]: # split the train data set into cross validation train and cross validation test
         time_start = time.time()
         from sklearn.naive_bayes import *
         from sklearn.naive_bayes import BernoulliNB

         X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_train, y_train, test_size
         alpha = [10**i for i in range(-3,6)]

         for i in alpha:
             # instantiate learning model (alpha = 30)
             clf = BernoulliNB(alpha=i,binarize=0.0,fit_prior=True,class_prior=None)

             #clf = BernoulliNB(alpha=i,binarize=0.1)

             # fitting the model on crossvalidation train
```

```
            clf.fit(X_tr, y_tr)

            # predict the response on the crossvalidation train
            pred = clf.predict(X_cv)

            # evaluate CV accuracy
            acc = accuracy_score(y_cv, pred, normalize=True) * float(100)
            print('\nCV accuracy for alpha = %f is %f%%' % (i, acc))

        clf = BernoulliNB(alpha=0.001,binarize=0.1)
        clf.fit(X_tr,y_tr)
        pred = clf.predict(X_test)
        acc = accuracy_score(y_test, pred, normalize=True) * float(100)
        print('\n****Test accuracy for alpha = 0.001 is %f%%' % (acc))

        print ('CV for alpha in range(10e-3, 10e+6) done! Time elapsed: {} seconds'.format(ti
```

```
CV accuracy for alpha = 0.001000 is 85.474048%

CV accuracy for alpha = 0.010000 is 85.474048%

CV accuracy for alpha = 0.100000 is 85.474048%

CV accuracy for alpha = 1.000000 is 85.474048%

CV accuracy for alpha = 10.000000 is 85.483138%

CV accuracy for alpha = 100.000000 is 85.574039%

CV accuracy for alpha = 1000.000000 is 85.419507%

CV accuracy for alpha = 10000.000000 is 85.419507%

CV accuracy for alpha = 100000.000000 is 85.419507%

****Test accuracy for alpha = 0.001 is 80.421217%
CV for alpha in range(10e-3, 10e+6) done! Time elapsed: 0.6263058185577393 seconds
```

In [23]:
```
clf = BernoulliNB(alpha=1e+2)
clf.fit(X_tr,y_tr)
clf.predict_proba(X_tr)
```

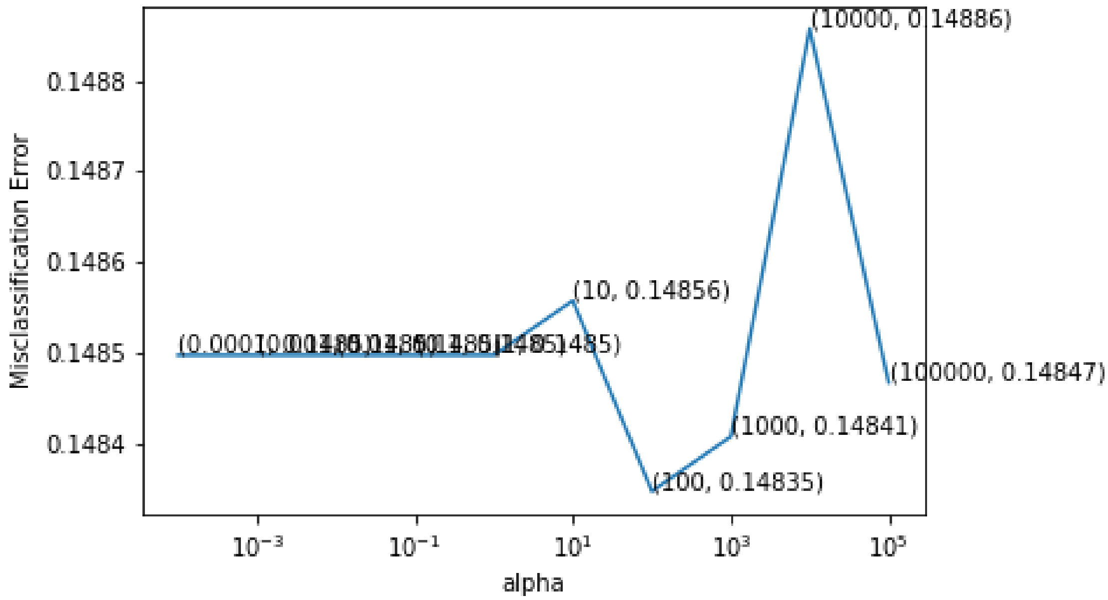
Out[23]:
```
array([[0.1 , 0.9 ],
       [0.39, 0.61],
       [0.08, 0.92],
       ...,
```

```
        [0.06, 0.94],
        [0.07, 0.93],
        [0.06, 0.94]])
```

3.0.1 10 fold cross validation

```
In [24]: time_start = time.time()

         # creating odd list of K for KNN
         #myList = list(np.arrange(1,2,0.01))
         #alpha = list(filter(lambda x: x % 2 != 0, myList))
         #alpha = list(np.arange(0.1,10,0.1)) #alpha varies the most in this range.
         alpha = [10**i for i in range(-4,6)]

         # empty list that will hold cv scores
         cv_scores = []

         # perform 10-fold cross validation
         for i in alpha:
             clf = BernoulliNB(alpha=i,binarize=0.1)
             scores = cross_val_score(clf, X_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[MSE.index(min(MSE))]
         print('\nThe optimal optimal_alpha is %f.' % optimal_alpha)

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

         for xy in zip(alpha, np.round(MSE,5)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xscale('log')
         plt.xlabel('alpha')
         plt.ylabel('Misclassification Error')
         plt.show()

         print("the misclassification error for each alpha value is : ", np.round(MSE,5))

         print ('10 fold CV for alpha in range(10e-4, 10e+6) done! Time elapsed: {} seconds'.fo
```

```
The optimal optimal_alpha is 100.000000.
```




```
the misclassification error for each alpha value is :  [0.15 0.15 0.15 0.15 0.15 0.15 0.15 0.15
10 fold CV for alpha in range(10e-4, 10e+6) done! Time elapsed: 6.854174852371216 seconds
```

```
In [25]: # ============================== KNN with k = optimal_k ===============================
         # instantiate learning model k = optimal_k
         alpha_optimal = BernoulliNB(alpha=optimal_alpha,binarize=0.1)

         # fitting the model
         alpha_optimal.fit(X_train, y_train)

         # predict the response
         pred = alpha_optimal.predict(X_test)

         # evaluate accuracy
         acc = accuracy_score(y_test, pred) * 100
         print('\nThe accuracy of the Bernoulli for alpha = %f is %f%%' % (optimal_alpha, acc))
```

```
The accuracy of the Bernoulli for alpha = 100.000000 is 80.283211%
```

```
In [26]: from sklearn.metrics import precision_recall_fscore_support as score

         precision, recall, fscore, support = score(y_test, pred)

         print('precision: {}'.format(precision))
```

```
        print('recall: {}'.format(recall))
        print('fscore: {}'.format(fscore))
        print('support: {}'.format(support))
```

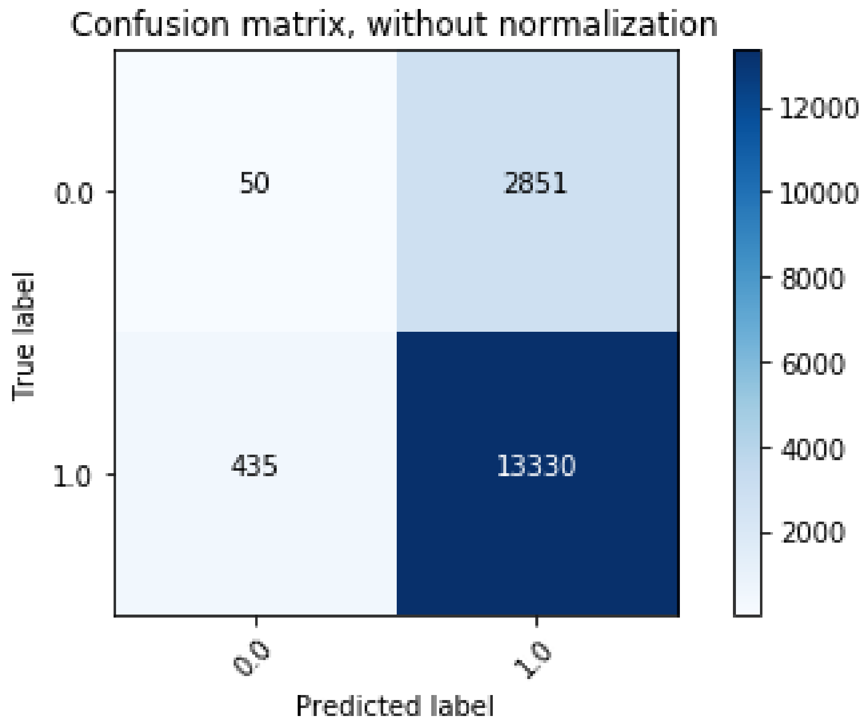
```
precision: [0.1  0.82]
recall: [0.02 0.97]
fscore: [0.03 0.89]
support: [ 2901 13765]
```

```
In [27]: from sklearn.metrics import classification_report

         target_names = ['class 0', 'class 1']
         print(classification_report(y_test, pred, target_names=target_names))
```

```
             precision    recall  f1-score   support

    class 0       0.10      0.02      0.03      2901
    class 1       0.82      0.97      0.89     13765

avg / total       0.70      0.80      0.74     16666
```

```
In [28]: # Compute confusion matrix
         cnf_matrix = confusion_matrix(y_test, pred)
         np.set_printoptions(precision=2)

         class_names=np.unique(y_test)

         # Plot non-normalized confusion matrix
         plt.figure()
         plot_confusion_matrix(cnf_matrix, classes=class_names,
                               title='Confusion matrix, without normalization')

         # Plot normalized confusion matrix
         #plt.figure()
         #plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
         #                      title='Normalized confusion matrix')

         plt.show()
```

```
Confusion matrix, without normalization
[[   50  2851]
 [  435 13330]]
```



4 3. CV on Standardized data for TF-IDF

```
In [29]: openPickleFile("X_train_tf_idf")
         X_train = temp
         print(X_train.shape)
         print(X_train.dtype)
```

```
(33334, 50)
float64
```

```
In [30]: openPickleFile("X_test_tf_idf")
         X_test = temp
         print(X_test.shape)
         print(X_test.dtype)
```

```
(16666, 50)
float64
```

```
In [31]: unique_count(y_train)
```

```
Out[31]: array([[0.00e+00, 4.95e+03],
                [1.00e+00, 2.84e+04]])
```

In [32]:
```
# split the train data set into cross validation train and cross validation test
time_start = time.time()
from sklearn.naive_bayes import *
from sklearn.naive_bayes import BernoulliNB

X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_train, y_train, test_size
alpha = [10**i for i in range(-3,6)]

for i in alpha:
    # instantiate learning model (alpha = 30)
    clf = BernoulliNB(alpha=i,binarize=0.0,fit_prior=True,class_prior=None)

    #clf = BernoulliNB(alpha=i,binarize=0.1)

    # fitting the model on crossvalidation train
    clf.fit(X_tr, y_tr)

    # predict the response on the crossvalidation train
    pred = clf.predict(X_cv)

    # evaluate CV accuracy
    acc = accuracy_score(y_cv, pred, normalize=True) * float(100)
    print('\nCV accuracy for alpha = %f is %f%%' % (i, acc))

clf = BernoulliNB(alpha=0.001,binarize=0.1)
clf.fit(X_tr,y_tr)
pred = clf.predict(X_test)
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for alpha = 0.001 is %f%%' % (acc))

print ('CV for alpha in range(10e-3, 10e+6) done! Time elapsed: {} seconds'.format(ti
```

```
CV accuracy for alpha = 0.001000 is 86.264885%

CV accuracy for alpha = 0.010000 is 86.264885%

CV accuracy for alpha = 0.100000 is 86.273975%

CV accuracy for alpha = 1.000000 is 86.273975%

CV accuracy for alpha = 10.000000 is 86.264885%

CV accuracy for alpha = 100.000000 is 86.210345%

CV accuracy for alpha = 1000.000000 is 85.764930%

CV accuracy for alpha = 10000.000000 is 85.028634%
```

```
CV accuracy for alpha = 100000.000000 is 85.028634%

****Test accuracy for alpha = 0.001 is 80.805232%
CV for alpha in range(10e-3, 10e+6) done! Time elapsed: 0.685166597366333 seconds
```

```
In [33]: clf = BernoulliNB(alpha=1e-10)
         clf.fit(X_tr,y_tr)
         clf.predict_proba(X_tr)
```

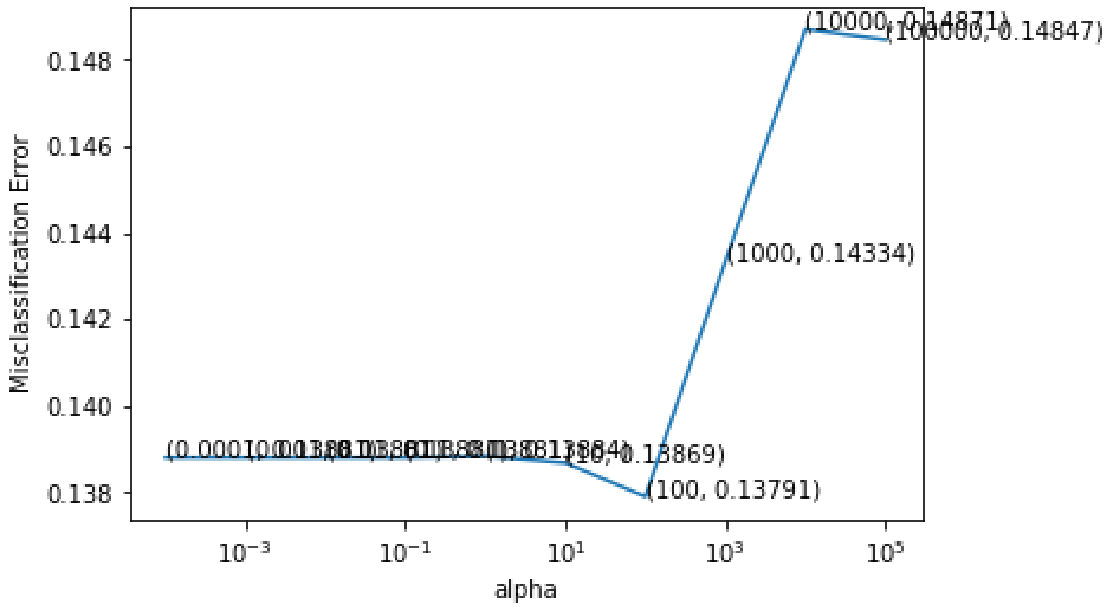
```
Out[33]: array([[0.6 , 0.4 ],
                [0.04, 0.96],
                [0.17, 0.83],
                ...,
                [0.04, 0.96],
                [0.43, 0.57],
                [0.04, 0.96]])
```

4.0.1 10 fold cross validation

```
In [34]: time_start = time.time()

         # creating odd list of K for KNN
         #myList = list(np.arrange(1,2,0.01))
         #alpha = list(filter(lambda x: x % 2 != 0, myList))
         #alpha = list(np.arange(0.1,10,0.1)) #alpha varies the most in this range.
         alpha = [10**i for i in range(-4,6)]

         # empty list that will hold cv scores
         cv_scores = []

         # perform 10-fold cross validation
         for i in alpha:
             clf = BernoulliNB(alpha=i,binarize=0.1)
             scores = cross_val_score(clf, X_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[MSE.index(min(MSE))]
         print('\nThe optimal optimal_alpha is %f.' % optimal_alpha)

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

```
    for xy in zip(alpha, np.round(MSE,5)):
        plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
    plt.xscale('log')
    plt.xlabel('alpha')
    plt.ylabel('Misclassification Error')
    plt.show()

    print("the misclassification error for each alpha value is : ", np.round(MSE,5))

    print ('10 fold CV for alpha in range(10e-4, 10e+6) done! Time elapsed: {} seconds'.fo
```

```
The optimal optimal_alpha is 100.000000.
```




```
the misclassification error for each alpha value is :  [0.14 0.14 0.14 0.14 0.14 0.14 0.14 0.14
10 fold CV for alpha in range(10e-4, 10e+6) done! Time elapsed: 6.795823574066162 seconds
```

```
In [35]: # ============================== KNN with k = optimal_k ==============================
         # instantiate learning model k = optimal_k
         alpha_optimal = BernoulliNB(alpha=optimal_alpha,binarize=0.1)

         # fitting the model
         alpha_optimal.fit(X_train, y_train)

         # predict the response
```

```
pred = alpha_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the Bernoulli for alpha = %f is %f%%' % (optimal_alpha, acc))
```

```
The accuracy of the Bernoulli for alpha = 100.000000 is 80.733229%
```

In [36]:
```
from sklearn.metrics import precision_recall_fscore_support as score

precision, recall, fscore, support = score(y_test, pred)

print('precision: {}'.format(precision))
print('recall: {}'.format(recall))
print('fscore: {}'.format(fscore))
print('support: {}'.format(support))
```

```
precision: [0.22 0.83]
recall: [0.04 0.97]
fscore: [0.07 0.89]
support: [ 2901 13765]
```

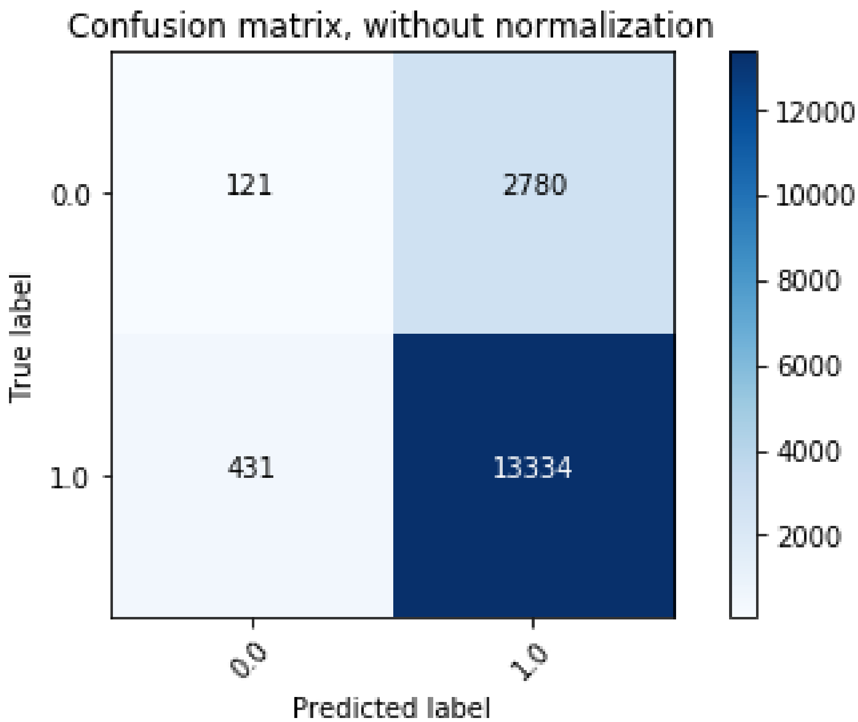
In [37]:
```
from sklearn.metrics import classification_report

target_names = ['class 0', 'class 1']
print(classification_report(y_test, pred, target_names=target_names))
```

```
             precision    recall  f1-score   support

    class 0       0.22      0.04      0.07      2901
    class 1       0.83      0.97      0.89     13765

avg / total       0.72      0.81      0.75     16666
```

In [38]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, pred)
np.set_printoptions(precision=2)

class_names=np.unique(y_test)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')
```

```
# Plot normalized confusion matrix
#plt.figure()
#plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
#                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[   121  2780]
 [   431 13334]]
```



5 4. Feature importance or Top 25 most important words for BOW.

```
In [39]: openPickleFile("X_train")
         X_train = temp
         print(X_train.shape)
         print(X_train.dtype)
```

```
(33334,)
object
```

5.1 Top 25 Bigrams.

```
In [40]: from sklearn.feature_extraction.text import CountVectorizer

         count_vect = CountVectorizer(ngram_range=(1,2))
         count_vect.fit_transform(X_train)

         NB_optimal = BernoulliNB(alpha=1e+2)
         NB_optimal.fit(X_tr, y_tr)
         pred_proba = NB_optimal.predict_proba(X_tr)
         #words = np.take(count_vect.get_feature_names(), pred_proba.argmax(axis=1))

         neg_class_prob_sorted = NB_optimal.feature_log_prob_[0, :].argsort()
         pos_class_prob_sorted = NB_optimal.feature_log_prob_[1, :].argsort()

         print(np.take(count_vect.get_feature_names(), neg_class_prob_sorted[:25]))
         print(np.take(count_vect.get_feature_names(), pos_class_prob_sorted[:25]))
```

```
['aaaaah satisfi' 'aaa spelt' 'aaa tue' 'aad' 'aaaa' 'aaaaaah' 'abandon'
 'aafco' 'aaa' 'aaah inhal' 'aachen printen' 'aauc' 'aafco certifi'
 'abandon one' 'aana' 'aaaaaah melt' 'abalon like' 'aagh' 'abandn pirat'
 'aachen munich' 'aback price' 'aagh yelp' 'aauc shelv' 'aafco profil'
 'aback']
['aaa spelt' 'aaa tue' 'aaaa' 'aaah miss' 'aaaaaah' 'aaaaawsom chump'
 'aaaahhhhhh' 'aaa' 'aana' 'aachen munich' 'aagh yelp' 'aaaahhhhhh must'
 'aaaaawsom' 'aaaaah' 'aaaaaah melt' 'abandon soft' 'abandon hair'
 'aachen printen' 'abandon human' 'aagh' 'aafco larg' 'aad sausag'
 'abandn' 'abalon' 'aback open']
```

6 5. Feature importance or Top 25 most important words for TFIDF.

```
In [41]: from sklearn.feature_extraction.text import TfidfVectorizer

         count_vect = TfidfVectorizer(ngram_range=(1,2))
         count_vect.fit_transform(X_train)

         NB_optimal = BernoulliNB(alpha=1e+2)
         NB_optimal.fit(X_tr, y_tr)
         pred_proba = NB_optimal.predict_proba(X_tr)
         #words = np.take(count_vect.get_feature_names(), pred_proba.argmax(axis=1))

         neg_class_prob_sorted = NB_optimal.feature_log_prob_[0, :].argsort()
         pos_class_prob_sorted = NB_optimal.feature_log_prob_[1, :].argsort()
         np.take
         print(np.take(count_vect.get_feature_names(), neg_class_prob_sorted[:25]))
         print(np.take(count_vect.get_feature_names(), pos_class_prob_sorted[:25]))
```

```
['aaaaah satisfi' 'aaa spelt' 'aaa tue' 'aad' 'aaaa' 'aaaaaah' 'abandon'
 'aafco' 'aaa' 'aaah inhal' 'aachen printen' 'aauc' 'aafco certifi'
 'abandon one' 'aana' 'aaaaaah melt' 'abalon like' 'aagh' 'abandn pirat'
 'aachen munich' 'aback price' 'aagh yelp' 'aauc shelv' 'aafco profil'
 'aback']
['aaa spelt' 'aaa tue' 'aaaa' 'aaah miss' 'aaaaaah' 'aaaaawsom chump'
 'aaaahhhhhh' 'aaa' 'aana' 'aachen munich' 'aagh yelp' 'aaaahhhhhh must'
 'aaaaawsom' 'aaaaah' 'aaaaaah melt' 'abandon soft' 'abandon hair'
 'aachen printen' 'abandon human' 'aagh' 'aafco larg' 'aad sausag'
 'abandn' 'abalon' 'aback open']
```