Objectives:

1. For each Featurization(BOWs, TF-IDF) we need to split the data based on Time Based Slicing and apply Naive Bayes and find test accurcy.
2. Use 10-Fold Cross Validation to determine optimal alpha and apply Naive Bayes with optimal alpha
3. find feature importance (top most words for deciding class labels positive or negative)
4. generate result matrices like accurecy , precision, F1 score, confusion matrix (TPR/FPR/FNR/TNR)

In [1]:
```
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
import re
import gensim
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
```

In [2]:
```
# using the SQLite Table to read data.
con = sqlite3.connect('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 ne
gative rating.
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
```

In [3]:
```
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inp
lace=False, kind='quicksort', na_position='last')
# sort reviews based on ProductId
```

In [4]:
```
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"
}, keep='first', inplace=False)
final.shape
# Remove duplicate reviews
```

Out[4]:
```
(364173, 10)
```

In [5]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of entrie
s left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(364171, 10)
```

Out[5]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [6]:
```
# find sentences containing HTML tags
i=0;
for sent in final['Text'].values:
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
    i += 1;
```

```
6
I set aside at least an hour each day to read to my son (3 y/o). At this poin
t, I consider myself a connoisseur of children's books and this is one of the
best. Santa Clause put this under the tree. Since then, we've read it perpetu
ally and he loves it.<br /><br />First, this book taught him the months of th
e year.<br /><br />Second, it's a pleasure to read. Well suited to 1.5 y/o ol
d to 4+.<br /><br />Very few children's books are worth owning. Most should b
e borrowed from the library. This book, however, deserves a permanent spot on
your shelf. Sendak's best.
```

In [7]:
```
#stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

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 spe
cial characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [8]:
```
#Code for implementing step-by-step the checks mentioned in the pre-processing
 phase
# this code takes a while to run as it needs to run on 500k sentences.
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent) # remove HTML tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                s=(sno.stem(cleaned_words.lower())).encode('utf8')
                filtered_sentence.append(s)
                if (final['Score'].values)[i] == 'positive':
                    all_positive_words.append(s) #list of all words used to de
scribe positive reviews
                if(final['Score'].values)[i] == 'negative':
                    all_negative_words.append(s) #list of all words used to de
scribe negative reviews reviews
            else:
                continue
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    final_string.append(str1)
    i+=1
```

In [9]:
```
final['CleanedText']=final_string
```

In [10]:
```
final = final.sort_values(['Time'], ascending=[True])
final.head()
```

Out[10]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	H
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2
417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0
346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2
417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0

In [11]:
```
positive_50000=final.loc[final['Score'] == "positive"].tail(50000)
negative_50000=final.loc[final['Score'] == "negative"].tail(50000)
pos_neg_1l = pd.concat([positive_50000, negative_50000], axis=0)
labels = pos_neg_1l['Score']
```

Sort the sample values based on time

In [12]:
```
pos_neg_1l = pos_neg_1l.sort_values(['Time'], ascending=[True])
pos_neg_1l.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
288768	312780	B000FPFC4O	A77EO8HXDT3II	Sawyer "book lover"	1
192576	208809	B00004RAMV	A1RVL257CTT821	Carrie Armstrong	1
177947	192959	B000ILA4KW	AQ5JDBXICB18J	R. Culp	0
78622	85503	B002DHTWNO	A4UP3MT4NWCSS	A. Tabachnik "IDF"	9
114848	124563	B000UZLQG2	AQ5JDBXICB18J	R. Culp	1

In [13]:
```
# dict = {"positive" : '1', "negative" : '0'}
# pos_neg_60k['Score1'] = pos_neg_1l['Score'].map(dict)
X = pos_neg_1l['CleanedText']
y = pos_neg_1l['Score']
```

In [14]:
```
from sklearn.model_selection import train_test_split
# Split arrays or matrices into random train and test subsets
# test_size=0.3 means out of 10k 3k will be test set and 7k train set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=0)
```

BOW with NB

In [15]:
```
# BoW: A bag-of-words model, or BoW for short, is a way of extracting features
 from
#      text for use in modeling, such as with machine learning algorithms.
#      It is called a “bag” of words, because any information about the order
 or structure of words
#      in the document is discarded. The model is only concerned with whether
 known words occur in the document,
#      not where in the document.

# https://machinelearningmastery.com/gentle-introduction-bag-words-model/

# CountVectorizer: Convert a collection of text documents to a matrix of token
 counts.
#                  This implementation produces a sparse representation of the
 counts using scipy.sparse.csr_matrix.

###### CODE ######
count_vect = CountVectorizer()
X_train = count_vect.fit_transform(X_train)
X_test = count_vect.transform(X_test)
```

In [16]:
```
# StandardScaler: Transforming data so that mean becomes 0 and std-dev becomes
 1(so that to follow Gaussian Distribution)
# The StandardScaler applies the transformation  fnew=(f−f¯)/σf  to each dimen
sion,
# where  f¯  is the mean and  σf  the standard deviation for that dimension.
# This will result in each dimension having a mean of 0 and a standard deviati
on of 1.
# Please note that when our data is stored in a sparse matrix, for instance wh
en
# we have a DictVectorizer or a CountVectorizer, the StandardScaler will be cr
eated with
# the option with_mean=False. This means that we don't subtract  f¯ . The reas
on is
# that we want to keep the matrix sparse: if an entry was zero before the tran
sformation,
# we'd like it to be zero after the transformation also.

# the call fit_transform consists of a call to fit and then to transform.
# In this case, fit will compute the mean and standard deviation, and then tra
nsform will apply the formula mentioned above.

###### CODE ######
from sklearn.preprocessing import StandardScaler
# prepare the scaler with train data
scaler = StandardScaler(with_mean=False).fit(X_train)
# transform both train and test data
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

```
/home/abhisek1651990/anaconda3/lib/python3.6/site-packages/sklearn/utils/vali
dation.py:475: DataConversionWarning: Data with input dtype int64 was convert
ed to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

In [17]:
```
# The multinomial Naive Bayes classifier is suitable for classification with d
iscrete features
# (e.g., word counts for text classification). The multinomial distribution no
rmally requires integer feature counts.
# However, in practice, fractional counts such as tf-idf may also work.
```

In [18]:
```
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB()
clf.fit(X_train, y_train)
```

Out[18]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

In [19]:
```
y_pred = clf.predict(X_test)
```

In [20]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 77%
```

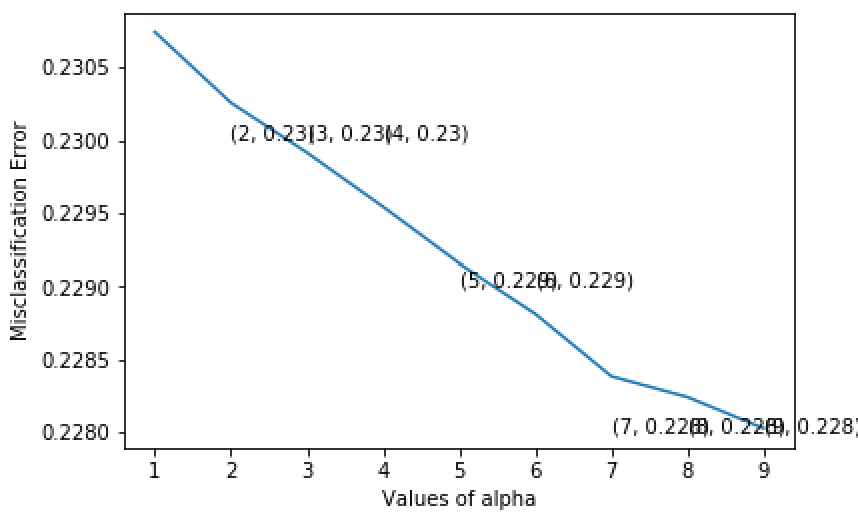
10-Fold Cross Validation to find alpha

In [21]:
```
from sklearn.cross_validation import cross_val_score
from sklearn.naive_bayes import MultinomialNB
# creating odd list of K for KNN
myList = list(range(1,10))

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

# perform 10-fold cross validation
for a in myList:
    mnb = MultinomialNB(alpha=a)
    scores = cross_val_score(mnb, X_train.toarray(), y_train, cv=10, scoring=
'accuracy')
    print(scores)
    cv_scores.append(scores.mean())

MSE = [1 - x for x in cv_scores]

# determining best k
optimal_alpha = myList[MSE.index(min(MSE))]
print('\nThe optimal value of alpha is %d.' % optimal_alpha)

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

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

plt.xlabel('Values of alpha')
plt.ylabel('Misclassification Error')
plt.show()

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

```
/home/abhisek1651990/anaconda3/lib/python3.6/site-packages/sklearn/cross_vali
dation.py:41: DeprecationWarning: This module was deprecated in version 0.18
in favor of the model_selection module into which all the refactored classes
and functions are moved. Also note that the interface of the new CV iterators
are different from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
[ 0.76846165  0.762034    0.76860449  0.78131695  0.76317669  0.76668095
  0.76325189  0.77539649  0.77182455  0.77182455]
[ 0.769033    0.76274818  0.76960434  0.78117412  0.76403371  0.76725246
  0.76396628  0.77553936  0.7721103   0.77196742]
[ 0.76931867  0.76346236  0.76946151  0.78131695  0.76460506  0.76725246
  0.76439491  0.77553936  0.77268181  0.77282469]
[ 0.76960434  0.76389087  0.76974718  0.78174546  0.76474789  0.76739534
  0.76468067  0.77639663  0.77311044  0.77325332]
[ 0.76989002  0.76417655  0.77046136  0.78160263  0.76503357  0.76796685
  0.76482355  0.77696814  0.77411059  0.7733962 ]
[ 0.7706042   0.76446222  0.77103271  0.78160263  0.76531924  0.76839549
  0.76482355  0.77725389  0.77439634  0.77396771]
[ 0.77074704  0.76503357  0.77146122  0.78203114  0.76574775  0.76853836
  0.76525218  0.7778254   0.7746821   0.77482497]
[ 0.77074704  0.7651764   0.77203257  0.78231681  0.76574775  0.76868124
  0.76525218  0.77796828  0.77453922  0.77511073]
[ 0.77103271  0.76546208  0.77231824  0.78217398  0.76589059  0.76910987
  0.76568081  0.77796828  0.7746821   0.77539649]
```

```
The optimal value of alpha is 9.
```




```
the misclassification error for each alpha value is :  [ 0.231  0.23   0.23
0.23   0.229  0.229  0.228  0.228  0.228]
```

In [23]:
```
# dump cv-score in a file
import pickle
pickle_out = open("cv_scores_nb.pickle","wb")
pickle.dump(cv_scores, pickle_out)
pickle_out.close()
```

In [24]:
```
mnb = MultinomialNB(alpha = optimal_alpha)
mnb.fit(X_train, y_train)
```

Out[24]:
```
MultinomialNB(alpha=9, class_prior=None, fit_prior=True)
```

In [25]:
```
y_pred = mnb.predict(X_test)
```

In [26]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 9 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 77%
```

In [27]:
```
# Models like logistic regression, or Naive Bayes algorithm, predict the proba
bilities of observing some outcomes.
# In standard binary regression scenario the models give you probability of ob
serving the "success" category.
# In multinomial case, the models return probabilities of observing each of th
e outcomes.
# Log probabilities are simply natural logarithms of the predicted probabiliti
es.
# Empirical log probability of features given a class, P(x_i|y).
mnb.feature_log_prob_
```

Out[27]:
```
array([[-11.02885423, -11.02885423, -14.44321285, ..., -11.02885423,
        -14.44321285, -14.44321285],
       [-14.30010865, -14.30010865, -10.88575003, ..., -14.30010865,
        -10.88575003, -10.88575003]])
```

In [28]:
```
sorted(mnb.feature_count_[0])[-10:]
```

Out[28]:
```
[22195.611549675465,
 22651.679810131642,
 23369.83532074777,
 24316.557637544312,
 25857.62109103343,
 27283.425931007972,
 30322.198890403124,
 31484.058535013995,
 33347.253087793913,
 33422.712302017244]
```

In [29]:
```
sorted(mnb.feature_count_[1])[-10:]
```

Out[29]:
```
[20091.865024666091,
 20782.685547414825,
 21482.826836358243,
 21946.178277279731,
 22106.548418216498,
 22979.230979129312,
 25344.269109398596,
 26028.280559340383,
 28447.774153617658,
 31865.442119707044]
```

In [30]:
```
# Number of samples encountered for each class during fitting. This value is w
eighted by the sample weight when provided.
mnb.class_count_
```

Out[30]:
```
array([ 35055.,  34945.])
```

In [31]:
```
# Number of samples encountered for each (class, feature) during fitting.
# This value is weighted by the sample weight when provided.
mnb.feature_count_[0]
```

Out[31]:
```
array([ 264.57702095,  264.57702095,    0.        , ...,  264.57702095,
          0.        ,    0.        ])
```

Find Most Important Features

In [35]:
```
def most_important_features(vectorizer, classifier, classlabel, n=20):
    labelid = list(classifier.classes_).index(classlabel)
    feature_names = vectorizer.get_feature_names()
    topn = sorted(zip(classifier.feature_log_prob_[labelid], feature_names))[-
n:]
    for coef, feat in topn:
        if feat not in stop:
            print(classlabel, feat, coef)
        else:
            continue
```

In [36]:
```
# Not considering stopwords while getting important words

stop = set(stopwords.words('english'))
```

In [37]:
```
most_important_features(count_vect, mnb, 'positive')
```

```
positive tri -6.84400788223
positive tast -6.83694219049
positive veri -6.80150380789
positive use -6.7897610457
positive like -6.70488150079
positive good -6.58881509383
positive love -6.49329703454
positive great -6.45459555561
```

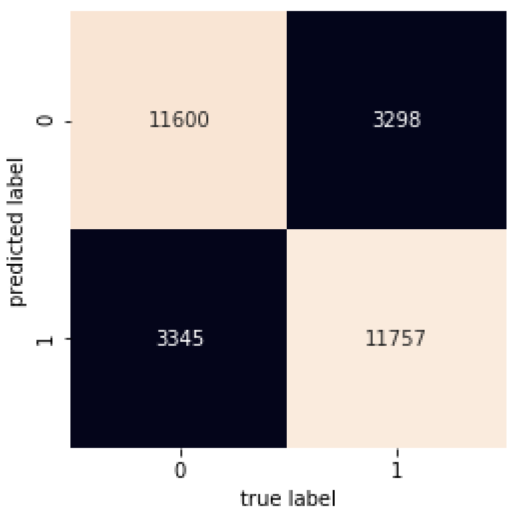
In [38]:
```
most_important_features(count_vect, mnb, 'negative')
```

```
negative one -6.84270659598
negative would -6.80145595237
negative product -6.73907008184
negative like -6.6323821487
negative tast -6.58085100386
```

In [39]:
```
from sklearn.metrics import classification_report
y_pred = mnb.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
             precision    recall  f1-score   support

   negative       0.78      0.78      0.78     14945
   positive       0.78      0.78      0.78     15055

avg / total       0.78      0.78      0.78     30000
```

In [41]:
```
from sklearn.metrics import confusion_matrix
%matplotlib inline
import seaborn as sns
mat = confusion_matrix(y_test, y_pred)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False)
plt.xlabel('true label')
plt.ylabel('predicted label');
```



TF-IDF with NB

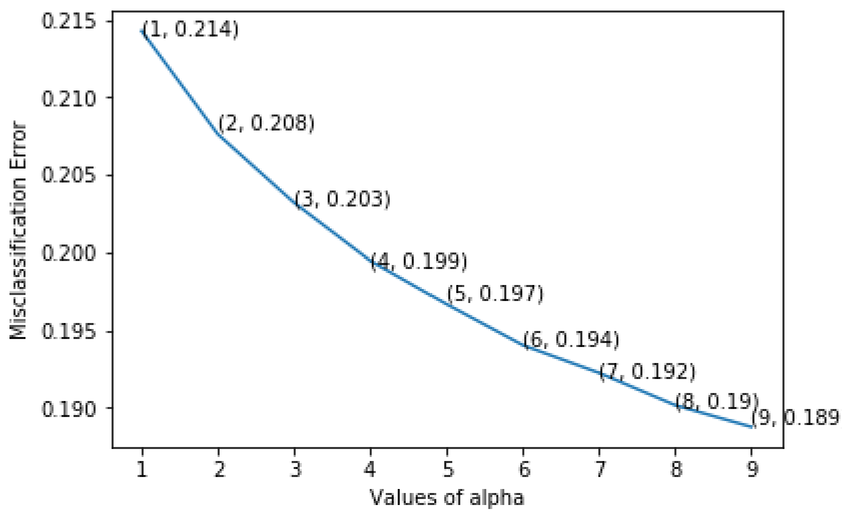
In [42]:
```
from sklearn.model_selection import train_test_split
# Split arrays or matrices into random train and test subsets
# test_size=0.3 means out of 10k 3k will be test set and 7k train set
X_train_tfidf, X_test_tfidf, y_train_tfidf, y_test_tfidf = train_test_split(X,
 y, test_size=0.3, random_state=0)
```

In [43]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
final_tf_idf_train = tf_idf_vect.fit_transform(X_train_tfidf)
final_tf_idf_test = tf_idf_vect.transform(X_test_tfidf)
```

In [44]:
```
from sklearn.preprocessing import StandardScaler
# prepare the scaler with train data
scaler = StandardScaler(with_mean=False).fit(final_tf_idf_train)
# transform both train and test data
final_tf_idf_train = scaler.transform(final_tf_idf_train)
final_tf_idf_test = scaler.transform(final_tf_idf_test)
```

In [55]:
```
from sklearn.cross_validation import cross_val_score
from sklearn.naive_bayes import MultinomialNB
# creating odd list of K for KNN
myList = list(range(1,10))

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

# perform 10-fold cross validation
for a in myList:
    mnb = MultinomialNB(alpha=a)
    scores = cross_val_score(mnb, final_tf_idf_train, y_train_tfidf, cv=10, sc
oring='accuracy')
    print(scores)
    cv_scores.append(scores.mean())

MSE = [1 - x for x in cv_scores]

# determining best k
optimal_alpha = myList[MSE.index(min(MSE))]
print('\nThe optimal value of alpha is %d.' % optimal_alpha)

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

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

plt.xlabel('Values of alpha')
plt.ylabel('Misclassification Error')
plt.show()

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

```
[ 0.78160263  0.78217398  0.78403085  0.78374518  0.78903014  0.78882698
  0.79297042  0.78425489  0.79039863  0.78025432]
[ 0.78803028  0.79088702  0.78988716  0.79131553  0.79474361  0.79597085
  0.79782826  0.79168453  0.79582798  0.78768395]
[ 0.79174404  0.79488644  0.79488644  0.79645765  0.79845736  0.80125732
  0.80154308  0.79611373  0.80040006  0.79225604]
[ 0.79602914  0.79845736  0.79802885  0.80102842  0.80202828  0.80525789
  0.80525789  0.79954279  0.80411487  0.79554222]
[ 0.79888587  0.80145693  0.80117126  0.80431367  0.80531353  0.80782969
  0.80754393  0.80197171  0.8058294   0.79897128]
[ 0.8013141   0.80545636  0.80374232  0.80745608  0.80917012  0.80911559
  0.81068724  0.80468638  0.80797257  0.8001143 ]
[ 0.80388516  0.80645622  0.80588487  0.80874161  0.81116983  0.81054436
  0.81240177  0.80611516  0.80925847  0.80311473]
[ 0.80459934  0.80674189  0.80802742  0.81131267  0.81331238  0.81397342
  0.81525932  0.80868696  0.81140163  0.80511502]
[ 0.80502785  0.80802742  0.80917012  0.81274104  0.81431224  0.81454493
  0.81654522  0.81011573  0.81397342  0.80797257]

The optimal value of alpha is 9.
```




```
the misclassification error for each alpha value is :  [ 0.214  0.208  0.203
0.199  0.197  0.194  0.192  0.19   0.189]
```

In [56]:
```
mnb = MultinomialNB(alpha = optimal_alpha)
mnb.fit(final_tf_idf_train, y_train_tfidf)
```

Out[56]:
```
MultinomialNB(alpha=9, class_prior=None, fit_prior=True)
```

In [57]:
```
# Predicting the Test set results
y_pred = mnb.predict(final_tf_idf_test)
```

In [58]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_tfidf, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 9 is %d%%' % (acc))
```

```
****Test accuracy for k = 9 is 74%
```

In [50]:
```
most_important_features(tf_idf_vect, mnb, 'positive')
```

```
positive veri -9.2882680974
positive tast -9.26373367382
positive use -9.17713029225
positive like -9.15713971073
positive good -9.05719579168
positive great -8.97286239284
positive love -8.95351724708
```

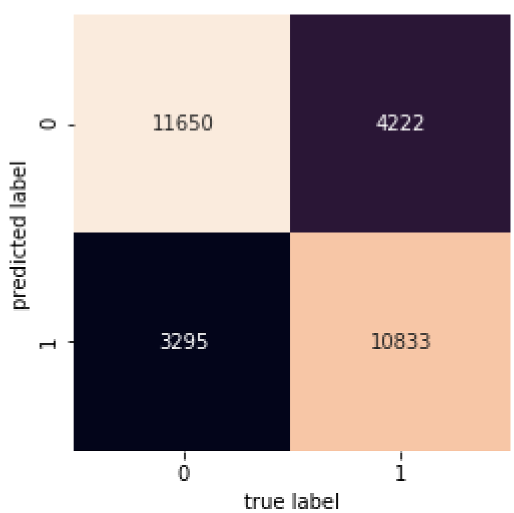
In [51]:
```
most_important_features(tf_idf_vect, mnb, 'negative')
```

```
negative one -9.32587306646
negative would -9.28560015586
negative product -9.19950858645
negative like -9.0816987971
negative tast -9.02859104997
```

In [52]:
```
from sklearn.metrics import classification_report
y_pred = mnb.predict(final_tf_idf_test)
print(classification_report(y_test_tfidf, y_pred))
```

```
             precision    recall  f1-score   support

   negative       0.73      0.78      0.76     14945
   positive       0.77      0.72      0.74     15055

avg / total       0.75      0.75      0.75     30000
```

In [53]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
mat = confusion_matrix(y_test_tfidf, y_pred)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False)
plt.xlabel('true label')
plt.ylabel('predicted label');
```



Conclusion:

In [1]:
```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["Model", "hyper parameter- alpha", "train error", "test erro
r"]
x.add_row(["NB-BOW", 9, "", "23%"])
x.add_row(["NB-TFIDF", 9, "", "26%"])
print("Featurization With Naive Bayes:")
print(x)
```

```
Featurization With Naive Bayes:
+----------+------------------------+-------------+------------+
|  Model   | hyper parameter- alpha | train error | test error |
+----------+------------------------+-------------+------------+
|  NB-BOW  |           9            |             |    23%     |
| NB-TFIDF |           9            |             |    26%     |
+----------+------------------------+-------------+------------+
```

In Naive Bayes our assumption is that each word is independent of each other. we have used two featurization BOW and TFIDF to convert text to vector. Applying Naive Bayes we could see 77% accuracy for BOW and 74% accuracy for TFIDF.