Objectives:

For each Featurization(BOWs, TF-IDF, AVG-W2V, TF-IDF W2V) we need to split the data based on Time Based Slicing and apply KNN and find test accurcy.

Use 10-Fold Cross Validation to determine optimal k and find test accuracy.

Try the same with KD-Tree and Brute Force algo and compare the results.

Loading Libraries

In [2]:
```
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 [71]:
```
# 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 [72]:
```
filtered_data.shape
```

Out[72]: (525814, 10)

In [73]:
```
filtered_data.head()
```

Out[73]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulne
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0

In [74]:
```
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 [75]:
```
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"
}, keep='first', inplace=False)
final.shape
# Remove duplicate reviews
```

Out[75]:
```
(364173, 10)
```

In [76]:
```
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[76]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [77]:
```
# 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 [78]:
```
#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 [79]:
```
#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 [80]:
```
final['CleanedText']=final_string
```

Sort The Data Based On Time

In [81]:
```
final = final.sort_values(['Time'], ascending=[True])
final.head()
```

Out[81]:

	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 [15]:
```
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 [16]:
```
pos_neg_1l = pos_neg_1l.sort_values(['Time'], ascending=[True])
pos_neg_1l.head()
```

Out[16]:

	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 [17]:
```
X = pos_neg_1l['CleanedText']
y = pos_neg_1l['Score']
```

In [18]:
```
# to store these objects in a file

# import pickle
# pickle_out = open("X.pickle","wb")
# pickle.dump(X, pickle_out)
# pickle_out.close()
# pickle_out = open("y.pickle","wb")
# pickle.dump(y, pickle_out)
# pickle_out.close()
```

In [3]:
```
# to get load X and y from pickle objects

# import pickle
# pickle_in = open("X.pickle","rb")
# X = pickle.load(pickle_in)
# pickle_in = open("y.pickle","rb")
# y = pickle.load(pickle_in)
```

In [4]:
```
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)
```

In [21]:
```
# 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.
```

In [5]:
```
# code for Bag Of Words calculation
count_vect = CountVectorizer()
# calculate BOW of trainning data
X_train = count_vect.fit_transform(X_train)
# transform test data
X_test = count_vect.transform(X_test)
```

In [23]:
```
# 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.
```

In [6]:
```
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 [7]:
```
# fit trainning data to the classifiers
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2
)
classifier.fit(X_train, y_train)
```

Out[7]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [ ]:
```
# test score
classifier.score(X_test, y_test)
```

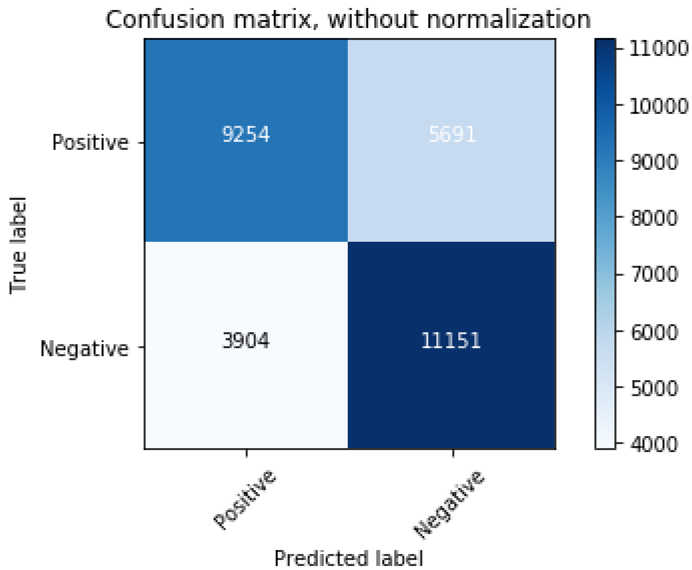
Out[ ]:
```
0.6801666666666667
```

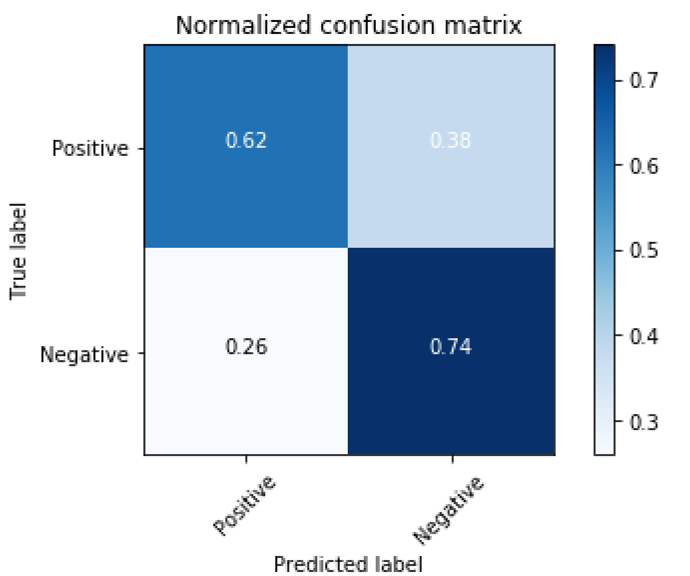
In [ ]:
```
# train score
classifier.score(X_train , y_train)
```

In [9]:
```
y_pred = classifier.predict(X_test)
```

In [10]:
```
# The higher the diagonal values of the confusion matrix the better, indicatin
g many correct predictions.
import itertools

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

# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[ 9254  5691]
 [ 3904 11151]]
Normalized confusion matrix
[[ 0.62  0.38]
 [ 0.26  0.74]]
```





Observation:

The diagonal elements represent the number of points for which the predicted label is equal to the true label,

while off-diagonal elements are those that are mislabeled by the classifier. The higher the diagonal values of

the confusion matrix the better, indicating many correct predictions.

without normalization: Total (9254 + 11151) Points out of 30000(Test Points) are predicted correct. so the accurecy is pretty low (68%) with k = 5

Apply KNN with KD-TREE

In [11]:
```
# we have used a parameter called algorithm as 'kd_tree'
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'kd_tree',  p = 2)
classifier.fit(X_train, y_train)
```

```
/home/abhisek1651990/anaconda3/lib/python3.6/site-packages/sklearn/neighbors/
base.py:212: UserWarning: cannot use tree with sparse input: using brute forc
e
  warnings.warn("cannot use tree with sparse input: "
```

Out[11]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

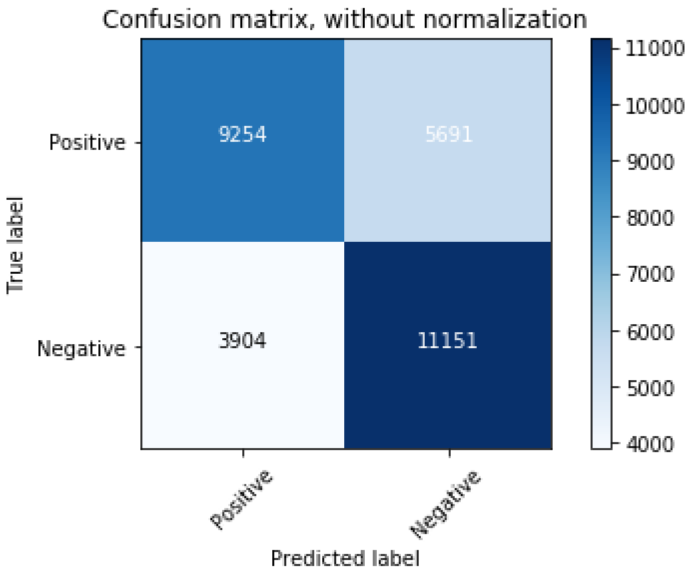
In [12]:
```
# Predicting the Test set results
y_pred = classifier.predict(X_test)
```

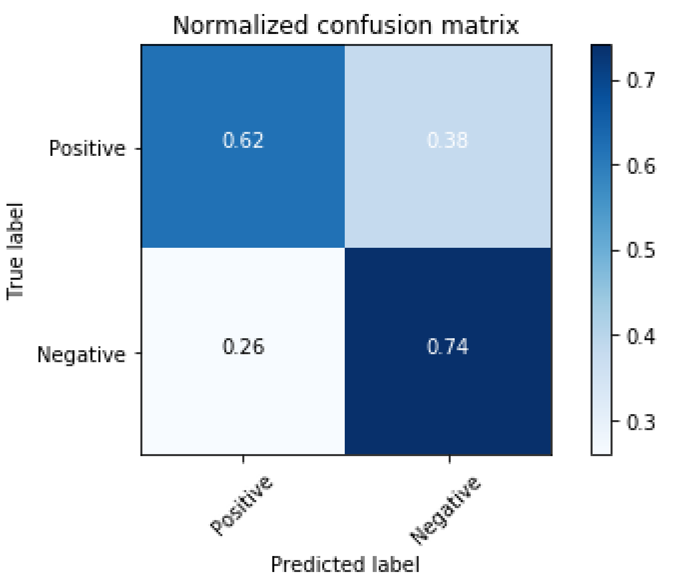
In [13]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 68%
```

In [14]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[ 9254  5691]
 [ 3904 11151]]
Normalized confusion matrix
[[ 0.62  0.38]
 [ 0.26  0.74]]
```





Observations:

Kd-Tree and Auto gives same accurecy.

Apply KNN with BruteForce Algorithm:

In [15]:
```
# we have used a parameter called algorithm as 'brute'. which will use a brute
-force search.
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'brute',  p = 2)
classifier.fit(X_train, y_train)
```

Out[15]:
```
KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

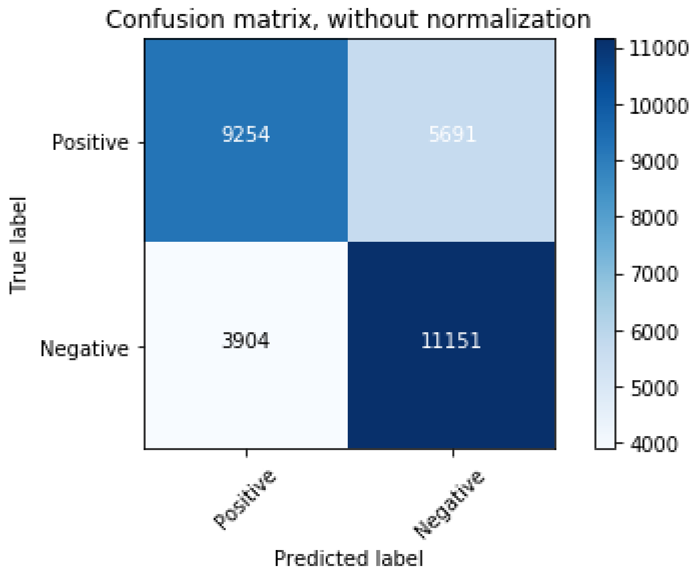
In [16]:
```
# Predicting the Test set results
y_pred = classifier.predict(X_test)
```

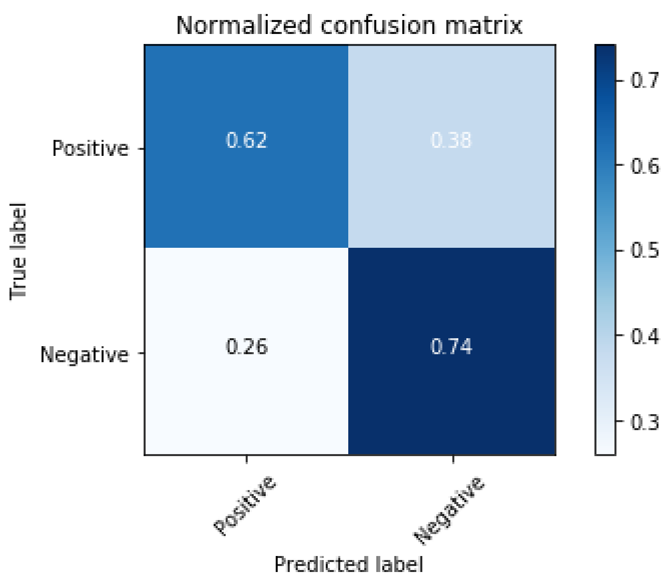
In [17]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 68%
```

In [18]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

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

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

plt.show()
```

```
Confusion matrix, without normalization
[[ 9254  5691]
 [ 3904 11151]]
Normalized confusion matrix
[[ 0.62  0.38]
 [ 0.26  0.74]]
```





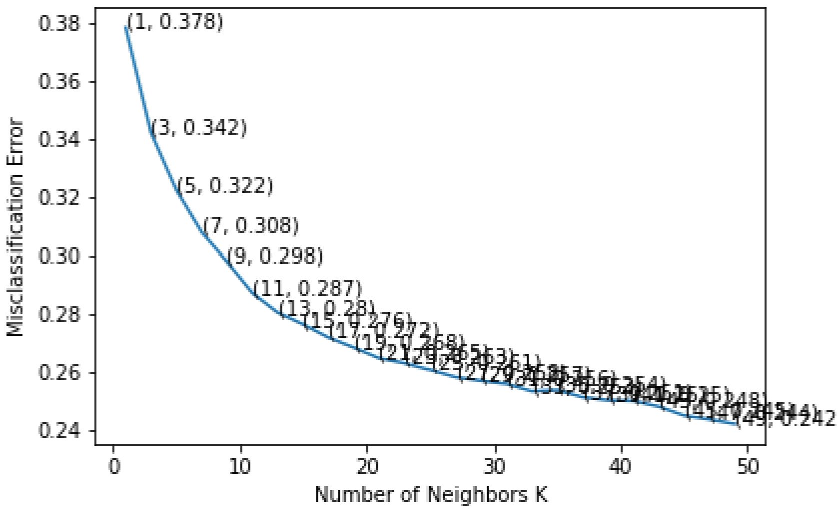
10 fold cross validation BOW

In [19]:
```
# load precomputed cv_score

# import pickle
# pickle_in = open("cvscore.pickle","rb")
# cv_scores = pickle.load(pickle_in)
```

In [20]:

```
# from sklearn.cross_validation import cross_val_score
# # creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

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

# # perform 10-fold cross validation
# for k in neighbors:
#     knn = KNeighborsClassifier(n_neighbors=k)
#     scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accurac
y')
#     cv_scores.append(scores.mean())

# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)

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

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

plt.xlabel('Number of Neighbors K')
plt.ylabel('Misclassification Error')
plt.show()

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

```
The optimal number of neighbors is 49.
```




```
the misclassification error for each k value is :  [ 0.38  0.34  0.32  0.31
0.3   0.29  0.28  0.28  0.27  0.27  0.27  0.26
  0.26  0.26  0.26  0.26  0.25  0.25  0.25  0.25  0.25  0.25  0.24  0.24
  0.24]
```

In [21]:
```
# pickle cv_score in a file

# pickle_out = open("cvscore.pickle","wb")
# pickle.dump(cv_scores, pickle_out)
# pickle_out.close()
```

Observation:

here we have used 10-fold cross validation to get optimal value of k.

with k=49 we will have better accurecy.

In [22]:
```
# ============================== KNN with k = optimal_k ======================
========================
# instantiate learning model k = optimal_k
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

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

# predict the response
y_pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, y_pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k,
acc))
```

```
The accuracy of the knn classifier for k = 49 is 75.993333%
```

In [23]:
```
# test score

knn_optimal.score(X_test, y_test)
```

Out[23]:
```
0.7599333333333335
```

In [ ]:
```
# train score

knn_optimal.score(X_train , y_train)
```

Observation:

it's a resonable gain from 68% to 76% with optimal k of 49.

TFIDF with KNN:

In [24]:
```
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 [25]:
```
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 [26]:
```
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 [27]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2
)
classifier.fit(final_tf_idf_train, y_train_tfidf)
```

Out[27]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

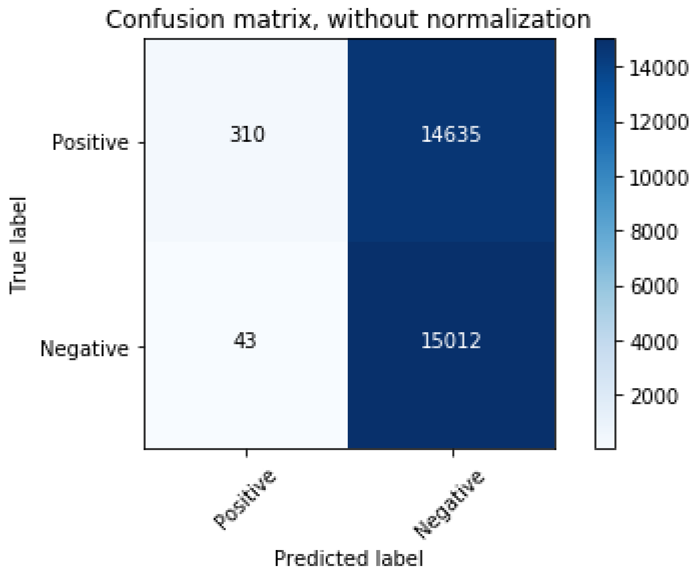
In [28]:
```
# Predicting the Test set results
y_pred = classifier.predict(final_tf_idf_test)
```

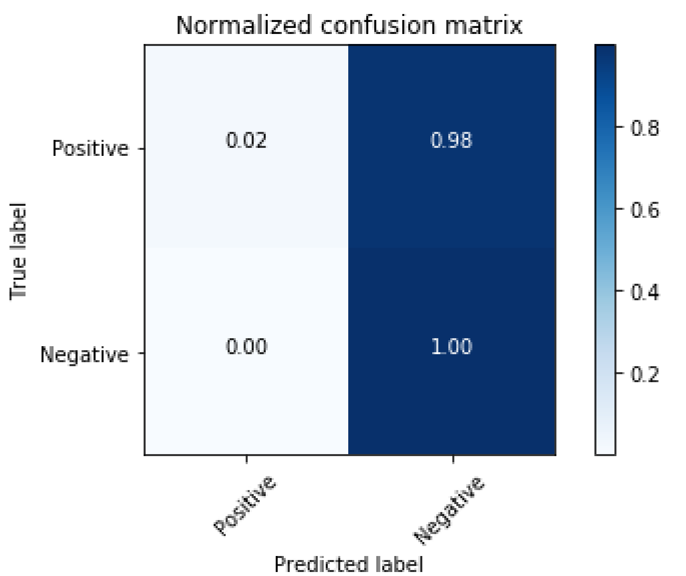
In [29]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_tfidf, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 51%
```

In [30]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_tfidf, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[  310 14635]
 [   43 15012]]
Normalized confusion matrix
[[ 0.02  0.98]
 [ 0.    1.  ]]
```





Observations:

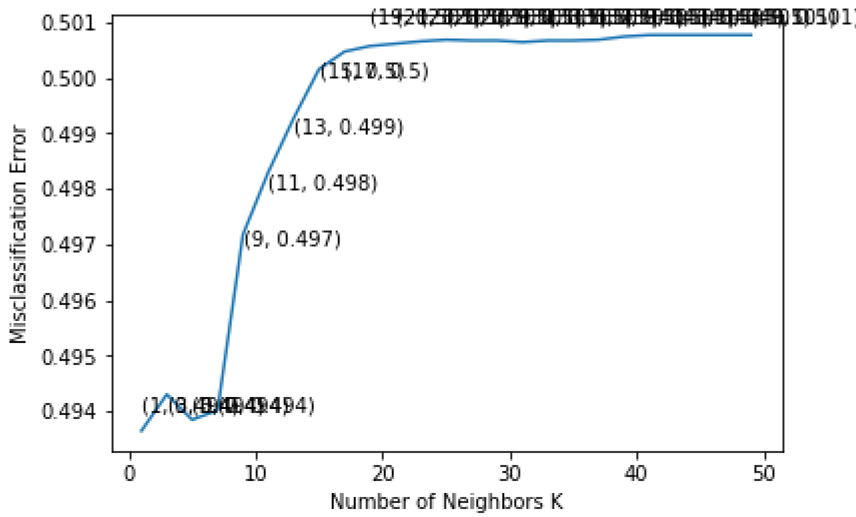
applying KNN with TF-IDF reduced the accurecy to 51%. Lets try to find optimal k with 10-fold cv.

10 fold cross validation TF-IDF

In [31]:
```
# get cvscore

# import pickle
# pickle_in = open("cvscore_tfidf.pickle","rb")
# cv_scores_tfidf = pickle.load(pickle_in)
```

In [32]:
```
from sklearn.cross_validation import cross_val_score
# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

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

# # perform 10-fold cross validation
# for k in neighbors:
#     knn = KNeighborsClassifier(n_neighbors=k)
#     scores = cross_val_score(knn, X_train_tfidf, y_train_tfidf, cv=10, scori
ng='accuracy')
#     cv_scores.append(scores.mean())

# changing to misclassification error
MSE = [1 - x for x in cv_scores_tfidf]

# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)

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

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

plt.xlabel('Number of Neighbors K')
plt.ylabel('Misclassification Error')
plt.show()

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

```
The optimal number of neighbors is 1.

/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)
```




```
the misclassification error for each k value is :  [ 0.49  0.49  0.49  0.49
0.5   0.5   0.5   0.5   0.5   0.5   0.5   0.5
  0.5   0.5   0.5   0.5   0.5   0.5   0.5   0.5   0.5   0.5   0.5   0.5
  0.5 ]
```

In [33]:
```
# dump cv-score in a file

# pickle_out = open("cvscore_tfidf.pickle","wb")
# pickle.dump(cv_scores, pickle_out)
# pickle_out.close()
```

In [34]:
```
# ============================== KNN with k = optimal_k =====================
=========================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(final_tf_idf_train, y_train_tfidf)

# predict the response
y_pred = knn_optimal.predict(final_tf_idf_test)

# evaluate accuracy
acc = accuracy_score(y_test_tfidf, y_pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k,
acc))
```

```
The accuracy of the knn classifier for k = 1 is 50.546667%
```

Observations:

It seems there is no optimal k. it's same for all k. lets try with KD-Tree.

Apply KNN with KD-TREE - TF-IDF

In [37]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'kd_tree', p = 2)
classifier.fit(final_tf_idf_train, y_train_tfidf)
```

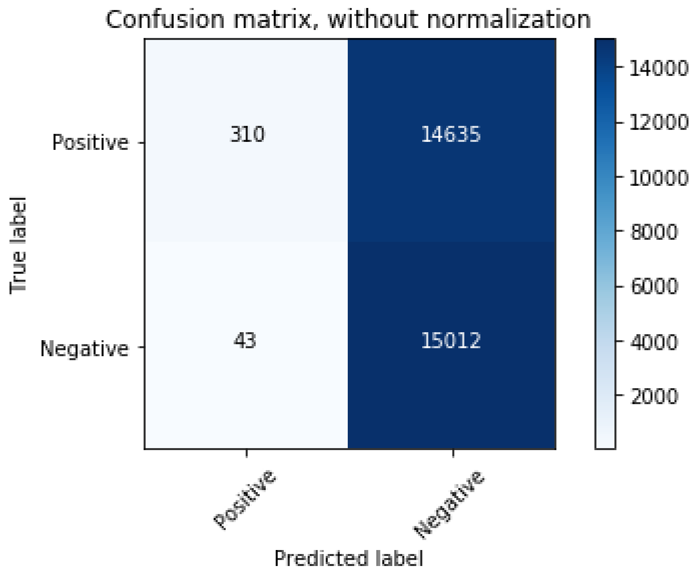
```
/home/abhisek1651990/anaconda3/lib/python3.6/site-packages/sklearn/neighbors/
base.py:212: UserWarning: cannot use tree with sparse input: using brute forc
e
  warnings.warn("cannot use tree with sparse input: "
```

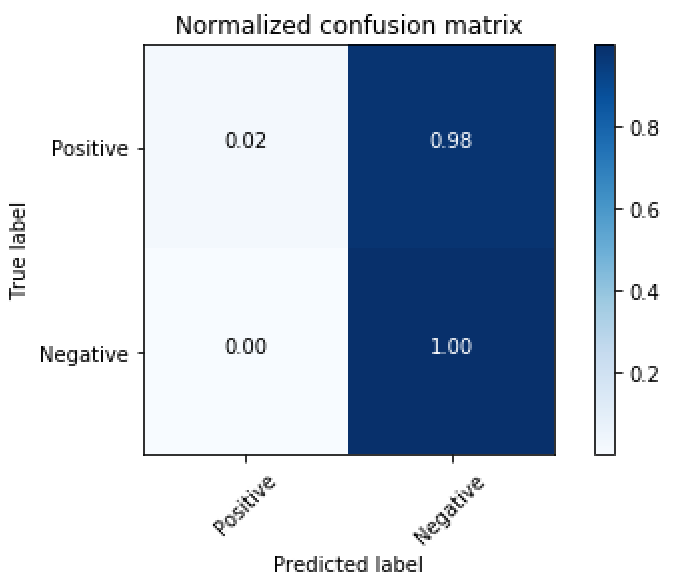
Out[37]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [38]:
```
# Predicting the Test set results
y_pred = classifier.predict(final_tf_idf_test)
```

In [39]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_tfidf, y_pred)
np.set_printoptions(precision=2)

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

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

plt.show()
```

```
Confusion matrix, without normalization
[[  310 14635]
 [   43 15012]]
Normalized confusion matrix
[[ 0.02  0.98]
 [ 0.    1.  ]]
```





Apply KNN with BruteForce Algorithm TF-IDF:

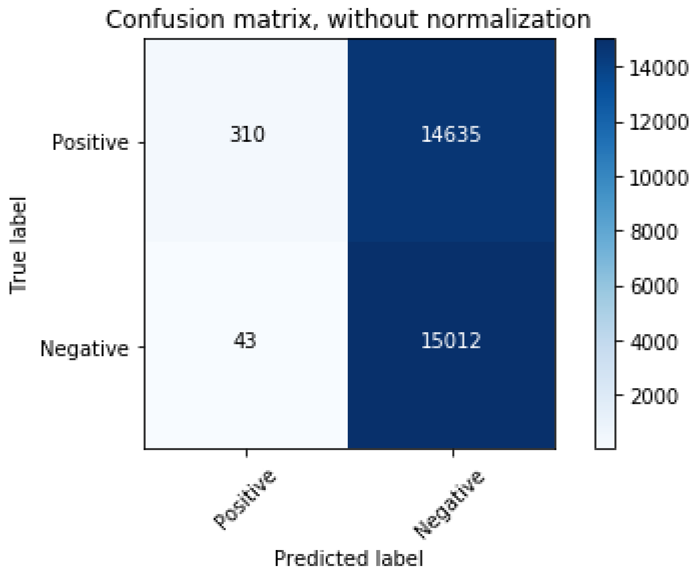
In [41]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'brute', p = 2)
classifier.fit(final_tf_idf_train, y_train_tfidf)
```

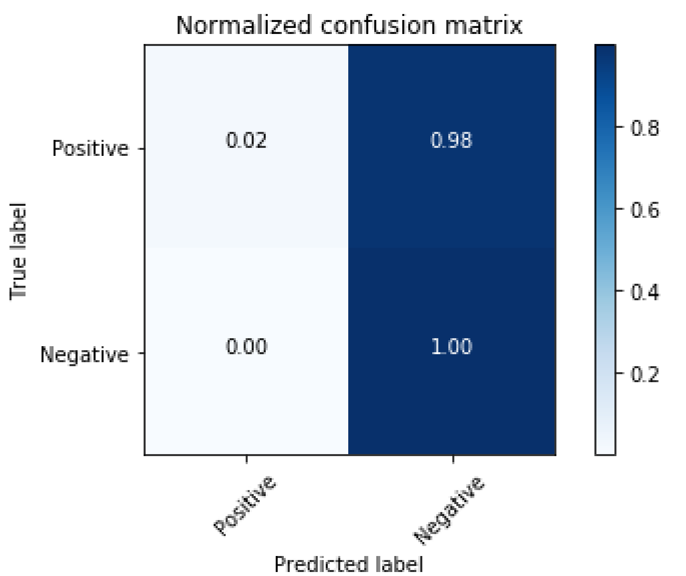
Out[41]:
```
KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [42]:
```
# Predicting the Test set results
y_pred = classifier.predict(final_tf_idf_test)
```

In [43]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_tfidf, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[  310 14635]
 [   43 15012]]
Normalized confusion matrix
[[ 0.02  0.98]
 [ 0.    1.  ]]
```





Avg W2V with KNN:

In [44]:
```
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_avgw2v, X_test_avgw2v, y_train_avgw2v, y_test_avgw2v = train_test_spli
t(X, y, test_size=0.3, random_state=0)
```

In [47]:
```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent=[]
for sent in X_train_avgw2v.values:
    filtered_sentence=[]
    sent=cleanhtml(sent.decode('utf-8'))
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent.append(filtered_sentence)
```

In [48]:
```
w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [49]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
st
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review

    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
70000
50
```

In [50]:
```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent_test=[]
for sent in X_test_avgw2v.values:
    filtered_sentence=[]
    sent=cleanhtml(sent.decode('utf-8'))
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent_test.append(filtered_sentence)
```

In [51]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in th
is list
for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review

    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
/home/abhisek1651990/anaconda3/lib/python3.6/site-packages/ipykernel_launche
r.py:15: RuntimeWarning: invalid value encountered in true_divide
  from ipykernel import kernelapp as app
```

```
30000
50
```

In [52]:
```
df_train = pd.DataFrame(sent_vectors)
df_train = df_train.fillna(df_train.mean())
df_test = pd.DataFrame(sent_vectors_test)
df_test = df_test.fillna(df_test.mean())
from sklearn.preprocessing import StandardScaler
# prepare the scaler with train data
scaler = StandardScaler(with_mean=False).fit(df_train)
# transform both train and test data
standardized_data_train_avgw2v = scaler.transform(df_train)
standardized_data_test_avgw2v = scaler.transform(df_test)
```

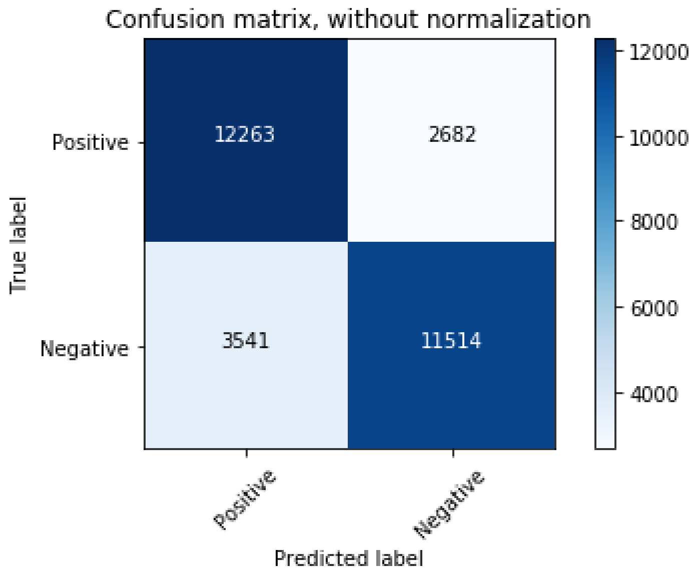
In [53]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2
)
classifier.fit(standardized_data_train_avgw2v, y_train_avgw2v)
```

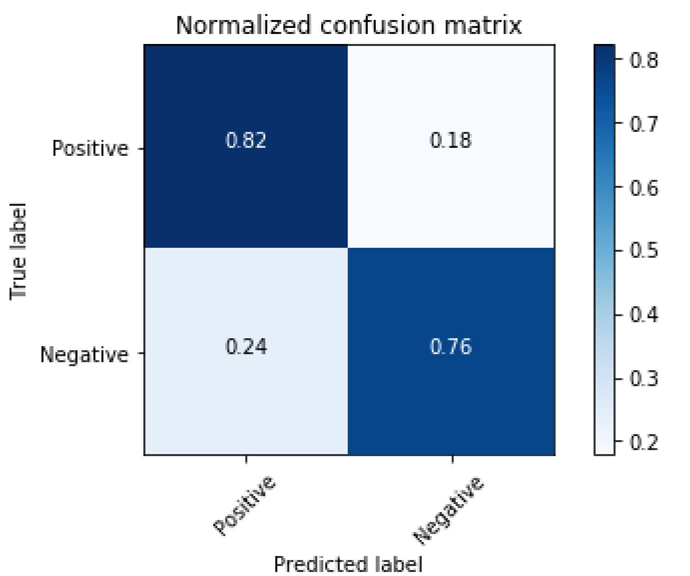
Out[53]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [54]:
```
# Predicting the Test set results
y_pred = classifier.predict(standardized_data_test_avgw2v)
```

In [55]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_avgw2v, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[12263  2682]
 [ 3541 11514]]
Normalized confusion matrix
[[ 0.82  0.18]
 [ 0.24  0.76]]
```





In [56]:
```
classifier.score(standardized_data_test_avgw2v, y_test_avgw2v)
```

Out[56]: 0.79256666666666664

In [57]:
```
classifier.score(standardized_data_train_avgw2v , y_train_avgw2v)
```

Out[57]: 0.86251428571428568

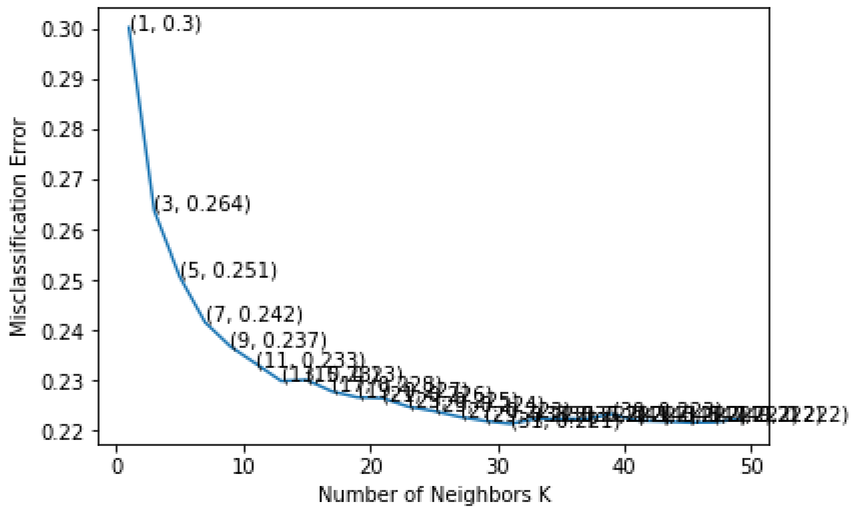
Observation:

its a huge gain since BOW and TF-IDF. Accurecy reached to 79%.

10 fold cross validation- Avg W2V

In [58]:
```
from sklearn.cross_validation import cross_val_score
# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

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

# # perform 10-fold cross validation
# for k in neighbors:
#     knn = KNeighborsClassifier(n_neighbors=k)
#     scores = cross_val_score(knn, standardized_data_train_avgw2v, y_train_av
gw2v, cv=10, scoring='accuracy')
#     cv_scores.append(scores.mean())
import pickle
pickle_in = open("cvscore_avgw2v.pickle","rb")
cv_scores = pickle.load(pickle_in)

# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)

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

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

plt.xlabel('Number of Neighbors K')
plt.ylabel('Misclassification Error')
plt.show()

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

```
The optimal number of neighbors is 31.
```




```
the misclassification error for each k value is :  [ 0.3   0.26  0.25  0.24
0.24  0.23  0.23  0.23  0.23  0.23  0.23  0.23
  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22
  0.22]
```

In [59]:
```
# ============================== KNN with k = optimal_k =====================
=========================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(standardized_data_train_avgw2v, y_train_avgw2v)

# predict the response
pred = knn_optimal.predict(standardized_data_test_avgw2v)

# evaluate accuracy
acc = accuracy_score(y_test_avgw2v, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k,
acc))
```

```
The accuracy of the knn classifier for k = 31 is 81.953333%
```

Observation:

With Optimal K = 31 we have accurecy ~82%. which was 3% higher than default k = 5.

Avg W2V with KNN - KD-Tree:

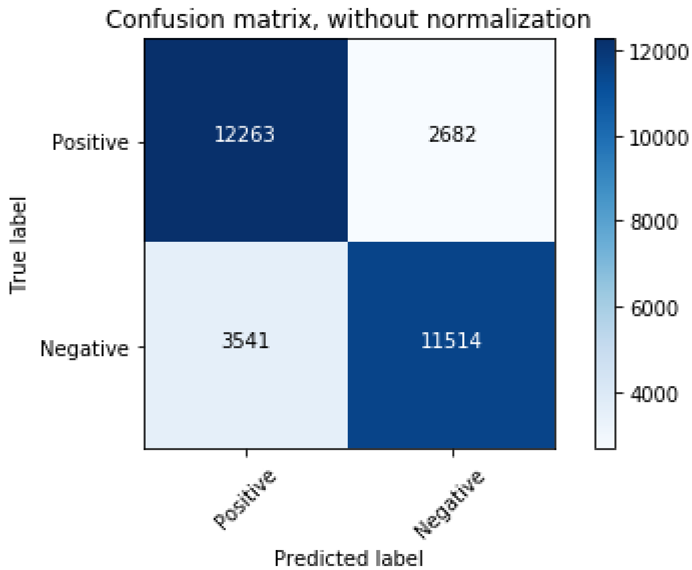
In [60]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'kd_tree', p = 2)
classifier.fit(standardized_data_train_avgw2v, y_train_avgw2v)
```

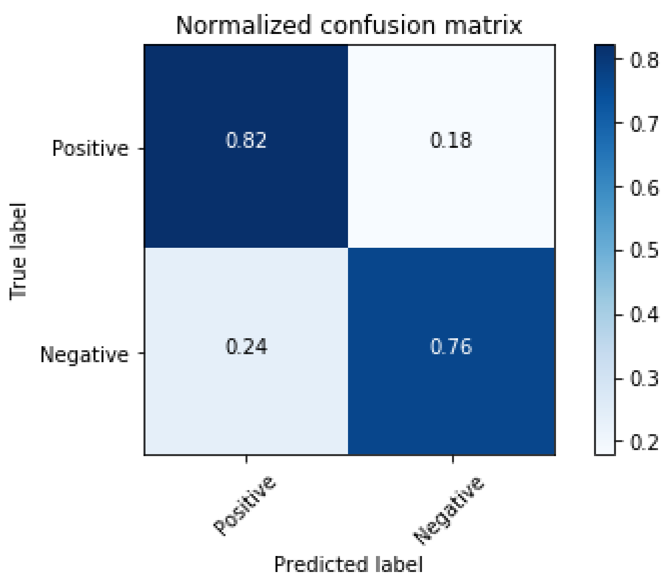
Out[60]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [61]:
```
# Predicting the Test set results
y_pred = classifier.predict(standardized_data_test_avgw2v)
```

In [62]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_avgw2v, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[12263  2682]
 [ 3541 11514]]
Normalized confusion matrix
[[ 0.82  0.18]
 [ 0.24  0.76]]
```





In [63]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_avgw2v, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 79%
```

In [64]:
```
# ============================== KNN with k = optimal_k ======================
========================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(standardized_data_train_avgw2v, y_train_avgw2v)

# predict the response
pred = knn_optimal.predict(standardized_data_test_avgw2v)

# evaluate accuracy
acc = accuracy_score(y_test_avgw2v, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k,
acc))
```

```
The accuracy of the knn classifier for k = 31 is 81.953333%
```

In [ ]:
```
classifier.score(standardized_data_train_avgw2v , y_train_avgw2v)
```

Avg W2V with KNN - Brute Force Algorithm:

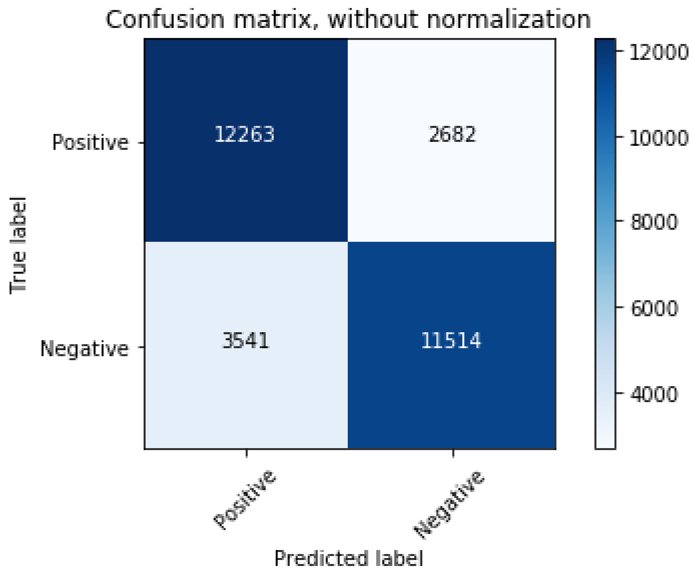
In [65]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'brute', p = 2)
classifier.fit(standardized_data_train_avgw2v, y_train_avgw2v)
```

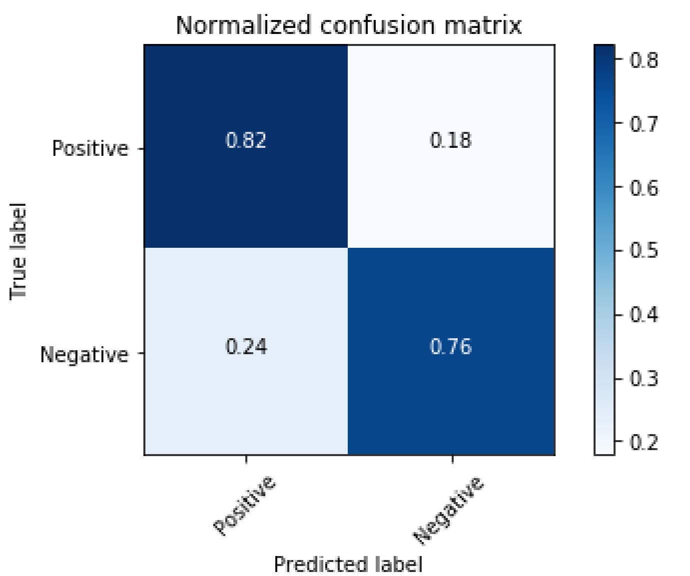
Out[65]:
```
KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [66]:
```
# Predicting the Test set results
y_pred = classifier.predict(standardized_data_test_avgw2v)
```

In [67]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_avgw2v, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[12263  2682]
 [ 3541 11514]]
Normalized confusion matrix
[[ 0.82  0.18]
 [ 0.24  0.76]]
```





In [68]:
```python
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_avgw2v, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 79%
```

In [69]:
```
# ============================== KNN with k = optimal_k =====================
========================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(standardized_data_train_avgw2v, y_train_avgw2v)

# predict the response
pred = knn_optimal.predict(standardized_data_test_avgw2v)

# evaluate accuracy
acc = accuracy_score(y_test_avgw2v, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k,
acc))
```

```
The accuracy of the knn classifier for k = 31 is 81.953333%
```

For TFIDF-W2V taking 40K data

calculating W2V for 40K

In [82]:
```
positive_20000=final.loc[final['Score'] == "positive"].tail(20000)
negative_20000=final.loc[final['Score'] == "negative"].tail(20000)
pos_neg_40k = pd.concat([positive_20000, negative_20000], axis=0)
labels = pos_neg_40k['Score']
```

In [83]:
```
pos_neg_40k = pos_neg_40k.sort_values(['Time'], ascending=[True])
pos_neg_40k.head()
```

Out[83]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
261899	283904	B00455GM9E	A1FBLR62DJ46L3	MaryAnne	0
454702	491596	B001M1Z1EQ	A6KCWLEG41R4J	Ms Sensitive	0
205284	222415	B004E4CCSQ	A2SZLNSI5KOQJT	Carrie, "Formerly "Sister Carrie""	0
326016	352840	B001SAY7BO	A6L0WHWTB31OC	A. M. Smith "morg999"	2
86027	93669	B004IJMVQA	A4OD6YMH5FLV5	S. Montane	1

In [84]:
```
X = pos_neg_40k['CleanedText']
y = pos_neg_40k['Score']
```

In [85]:
```
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_avgw2v, X_test_avgw2v, y_train_avgw2v, y_test_avgw2v = train_test_spli
t(X, y, test_size=0.3, random_state=0)
```

In [86]:
```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent=[]
for sent in X_train_avgw2v.values:
    filtered_sentence=[]
    sent=cleanhtml(sent.decode('utf-8'))
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent.append(filtered_sentence)
```

In [87]:
```
w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [88]:
```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent_test=[]
for sent in X_test_avgw2v.values:
    filtered_sentence=[]
    sent=cleanhtml(sent.decode('utf-8'))
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent_test.append(filtered_sentence)
```

TFIDF-W2V with KNN:

In [89]:
```
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_tfidfw2v, X_test_tfidfw2v, y_train_tfidfw2v, y_test_tfidfw2v = train_t
est_split(X, y, test_size=0.3, random_state=0)
```

In [90]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
final_tf_idf = tf_idf_vect.fit_transform(X_train_tfidfw2v)
```

calculate TF-IDF weighted Word2Vec for train data

In [ ]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
 this list
row=0;
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
                                     #obtain the tf_idfidf of a word in a sent
ence/review
            tf_idf = final_tf_idf[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1
```

In [ ]:
```
# import pickle
# pickle_out = open("train_w2vtfidf.pickle","wb")
# pickle.dump(tfidf_sent_vectors, pickle_out)
# pickle_out.close()
```

In [91]:
```
import pickle
pickle_in = open("train_w2vtfidf.pickle","rb")
tfidf_sent_vectors = pickle.load(pickle_in)
```

calculate TF-IDF weighted Word2Vec for test data

In [ ]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stor
ed in this list
row=0;
for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
                                    #obtain the tf_idfidf of a word in a sent
ence/review
            tf_idf = final_tf_idf[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

In [ ]:
```
# pickle_out = open("test_w2vtfidf.pickle","wb")
# pickle.dump(tfidf_sent_vectors_test, pickle_out)
# pickle_out.close()
```

In [92]:
```
pickle_in = open("test_w2vtfidf.pickle","rb")
tfidf_sent_vectors_test = pickle.load(pickle_in)
```

Do standadization for train and test vectors

In [93]:
```
df_train = pd.DataFrame(tfidf_sent_vectors)
df_train = df_train.fillna(df_train.mean())
df_test = pd.DataFrame(tfidf_sent_vectors_test)
df_test = df_test.fillna(df_test.mean())

from sklearn.preprocessing import StandardScaler
# prepare the scaler with train data
scaler = StandardScaler(with_mean=False).fit(df_train)
# transform both train and test data
standardized_data_tf_idfw2v_train = scaler.transform(df_train)
standardized_data_tf_idfw2v_test = scaler.transform(df_test)
```

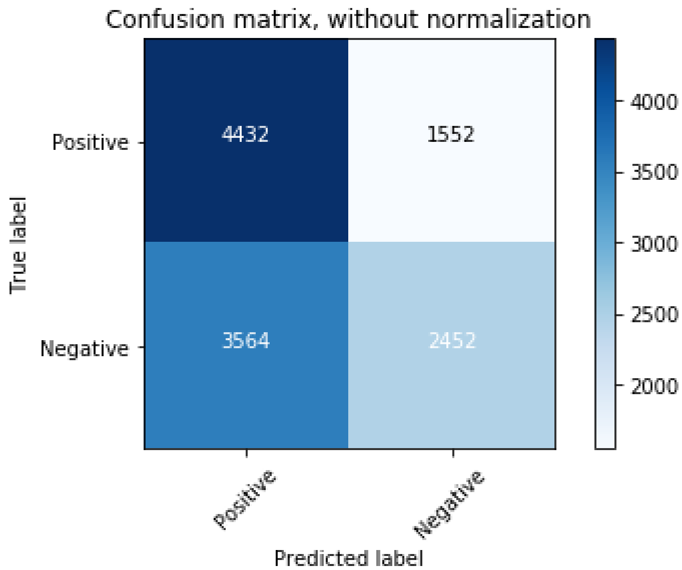
In [94]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2
)
classifier.fit(standardized_data_tf_idfw2v_train, y_train_tfidfw2v)
```

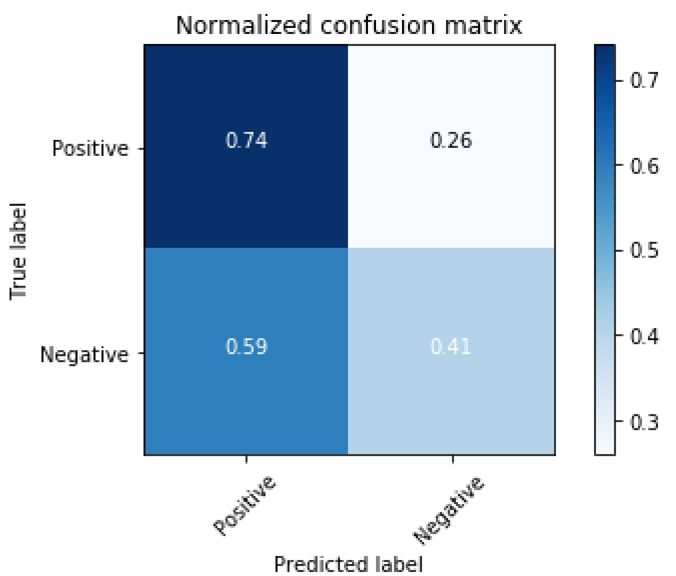
Out[94]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [95]:
```
# Predicting the Test set results
y_pred = classifier.predict(standardized_data_tf_idfw2v_test)
```

In [96]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_tfidfw2v, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[4432 1552]
 [3564 2452]]
Normalized confusion matrix
[[ 0.74  0.26]
 [ 0.59  0.41]]
```





In [97]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_tfidfw2v, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

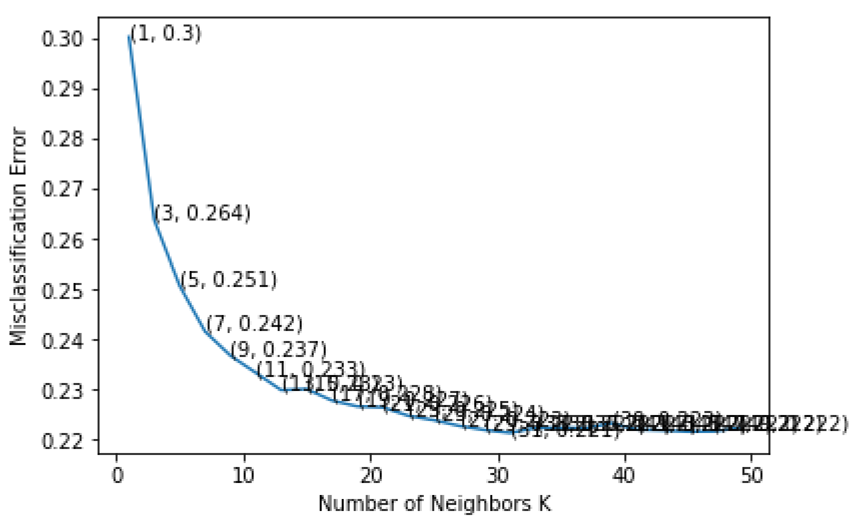
```
****Test accuracy for k = 5 is 57%
```

10 fold cross validation- TF-IDF W2V KNN:

In [98]:
```
# pickle_out = open("cvscore_w2vtfidf.pickle","wb")
# pickle.dump(cv_scores, pickle_out)
# pickle_out.close()

pickle_in = open("cvscore_w2vtfidf.pickle","rb")
cv_scores = pickle.load(pickle_in)
```

In [99]:
```
from sklearn.cross_validation import cross_val_score
# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

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

# # perform 10-fold cross validation
# for k in neighbors:
#     knn = KNeighborsClassifier(n_neighbors=k)
#     scores = cross_val_score(knn, standardized_data_tf_idfw2v_train, y_train
_tfidfw2v, cv=10, scoring='accuracy')
#     cv_scores.append(scores.mean())

# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)

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

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

plt.xlabel('Number of Neighbors K')
plt.ylabel('Misclassification Error')
plt.show()

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

```
The optimal number of neighbors is 31.
```




```
the misclassification error for each k value is :  [ 0.3   0.26  0.25  0.24
0.24  0.23  0.23  0.23  0.23  0.23  0.23  0.23
  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22  0.22
  0.22]
```

In [100]:
```
# ============================== KNN with k = optimal_k =====================
=========================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(standardized_data_tf_idfw2v_train, y_train_tfidfw2v)

# predict the response
pred = knn_optimal.predict(standardized_data_tf_idfw2v_test)

# evaluate accuracy
acc = accuracy_score(y_test_tfidfw2v, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k,
acc))
```

```
The accuracy of the knn classifier for k = 31 is 58.483333%
```

In [107]:
```
knn_optimal.score(standardized_data_tf_idfw2v_train, y_train_tfidfw2v)
```

Out[107]:
```
0.79889285714285718
```

TFIDF-W2V with KNN-KD-Tree:

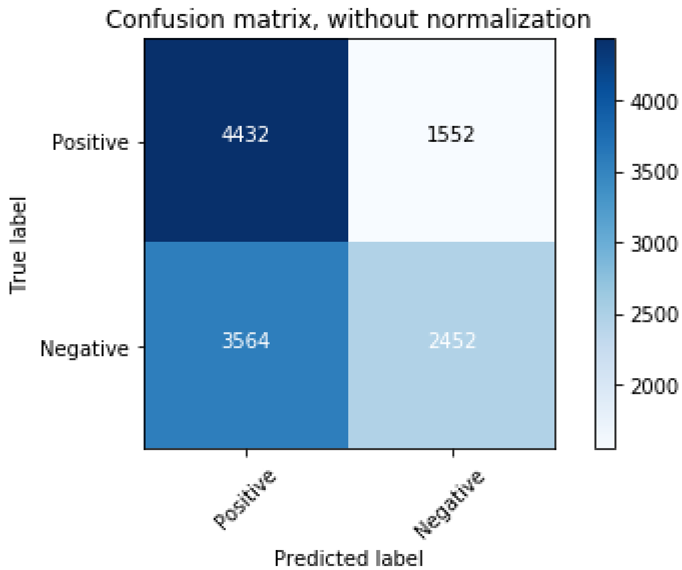
In [102]:
```
# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', algor
ithm = 'kd_tree', p = 2)
classifier.fit(standardized_data_tf_idfw2v_train, y_train_tfidfw2v)
```

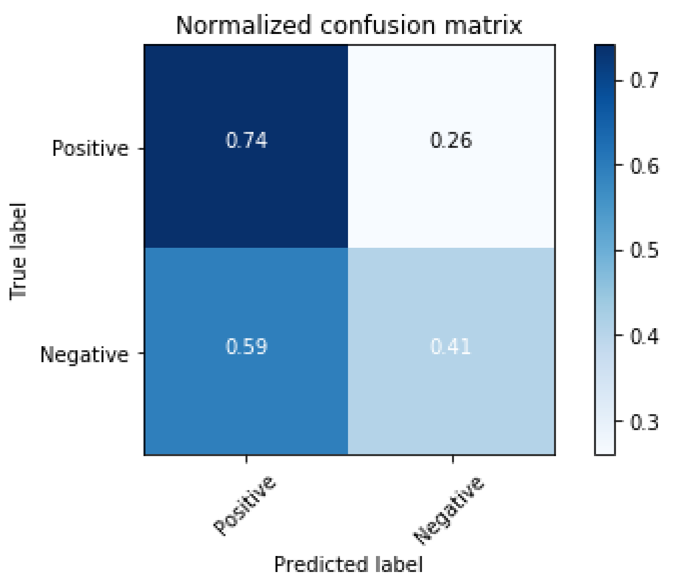
Out[102]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [103]:
```
# Predicting the Test set results
y_pred = classifier.predict(standardized_data_tf_idfw2v_test)
```

In [104]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test_tfidfw2v, y_pred)
np.set_printoptions(precision=2)

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

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Positive','Negative'], normalize=T
rue,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[4432 1552]
 [3564 2452]]
Normalized confusion matrix
[[ 0.74  0.26]
 [ 0.59  0.41]]
```





In [105]:
```
from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_tfidfw2v, y_pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 5 is %d%%' % (acc))
```

```
****Test accuracy for k = 5 is 57%
```

Conclusion:

After performing KNN with each featurization(BOW,TF-IDF,AVG w2V, TF-IDF W2V) we could see KNN with AVG W2V gives better accuracy(~82%) with optimal k. here we have applied 10-Fold cross validation to determine Opimal k and apply it then accuracy increases because we are using cross validation set also as a training set. More data we have more information and hence increases prediction probability.

In [108]:
```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["Model", "hyper parameter- K", "train error", "test error"]
x.add_row(["K-NN-BOW", 49, "", "25%"])
x.add_row(["K-NN-TFIDF", 1, "", "49%"])
x.add_row(["K-NN-AVGW2V", 31, "16%", "18%"])
x.add_row(["K-NN-TFIDFAVGW2V", 31, "21%", "42%"])
print("Featurization With KNN:")
print(x)
```

```
Featurization With KNN:
+------------------+--------------------+-------------+------------+
|      Model       | hyper parameter- K | train error | test error |
+------------------+--------------------+-------------+------------+
|     K-NN-BOW     |         49         |             |    25%     |
|    K-NN-TFIDF    |         1          |             |    49%     |
|   K-NN-AVGW2V    |         31         |     16%     |    18%     |
| K-NN-TFIDFAVGW2V |         31         |     21%     |    42%     |
+------------------+--------------------+-------------+------------+
```