In [1]:

```
#database final.sqlite is created after cleaning the amazon food reviews data

import warnings
warnings.filterwarnings("ignore")
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,f1_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score,make_scorer
from sklearn.metrics import classification_report
from sklearn import cross_validation
import sqlite3
from sklearn.decomposition import TruncatedSVD
import seaborn as sns

from sklearn.metrics import confusion_matrix
from prettytable import PrettyTable

x = PrettyTable()

con=sqlite3.connect("final.sqlite")

# time based sorting
clean_reviews=pd.read_sql_query(""" Select * from Reviews Order By Time""" , con)
clean_reviews=clean_reviews[:100000]
cleaned_text=clean_reviews['CleanedText'].values
score=clean_reviews['Score']
score.value_counts()
```

```
C:\Users\Anvesh Pandey\Anaconda3\lib\site-packages\sklearn\cross_validation.
py:41: DeprecationWarning: This module was deprecated in version 0.18 in fav
or of the model_selection module into which all the refactored classes and f
unctions 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)
```

Out[1]:

```
positive    87729
negative    12271
Name: Score, dtype: int64
```

This is an unbalanced dataset

In [2]:

```
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Vectorization", "Model", "k", "f1 score", "Accuracy"]
```

#Featurization using Bag of Words and model using kNN for classification of review

In [3]:

```
#Featurization using BoW

from sklearn.feature_extraction.text import CountVectorizer
count_vect=CountVectorizer()#max_features=300)
final_counts=count_vect.fit_transform(cleaned_text)

svd = TruncatedSVD(n_components=3000, n_iter=7, random_state=42)
s=svd.fit_transform(final_counts)
#svd.explained_variance_ratio_
#svd.explained_variance_
#count_vect.get_feature_names()
#np.shape(s)
#final_counts=final_counts.toarray()
```

checking for first 3000 features: lets see how much variance does this cover

In [4]:

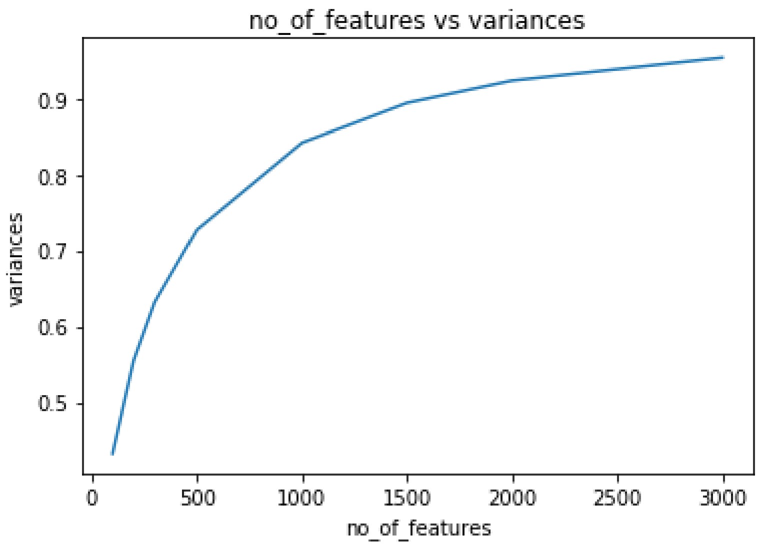
```
svd = TruncatedSVD(n_components=3000, n_iter=7, random_state=42)
s=svd.fit_transform(final_counts)
no_of_features=np.array([100,200,300,500,1000,1500,2000,3000])
variances=[]
for i in no_of_features:
    variances.append(np.sum(svd.explained_variance_ratio_[:i]))
```

In [5]:

```
plt.plot(no_of_features,variances)
plt.xlabel("no_of_features")
plt.ylabel("variances")
plt.title("no_of_features vs variances")
```

Out[5]:

```
Text(0.5,1,'no_of_features vs variances')
```



The plot shows that 80% of variance is covered with 1000 features

In [6]:

```
#variance with 300 features
np.sum(svd.explained_variance_ratio_[:300])
```

Out[6]:

```
0.6319196553731413
```

300 features give us decent amount of information: 63.2% information for 300 features

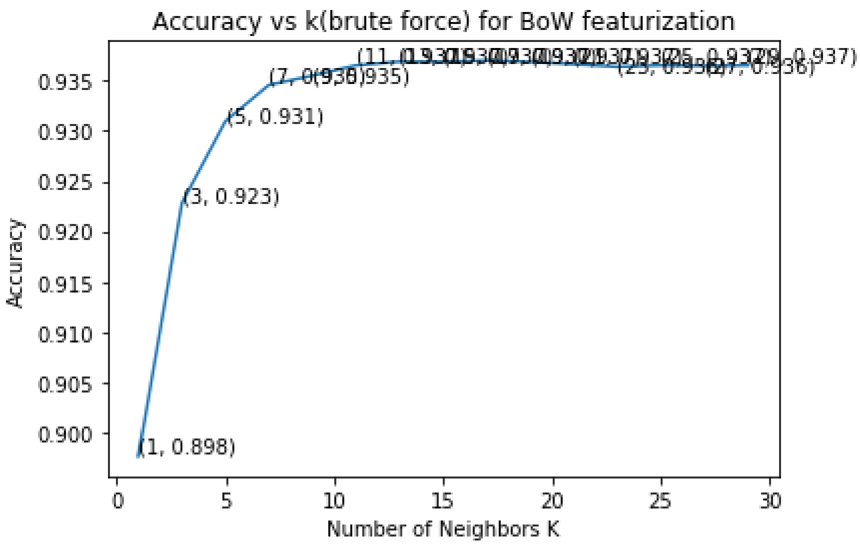
This is good amount of information : not much data is lost Therefore taking 300 feAtures for this exercise

In [7]:

```
svd = TruncatedSVD(n_components=300, n_iter=7, random_state=42)
final_counts=svd.fit_transform(final_counts)
```

In [8]:

```
#kNN brute with 3 fold CV
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts,score,test_size=
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")
for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="brute")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(brute force) for BoW featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)

print ("Optimal_k for BoW featurizatin and knn(brute force) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```




```
Optimal_k for BoW featurizatin and knn(brute force) is  17
Accuracy is  88.09
```

```
Performance becomes somewhat stable at k=17
```

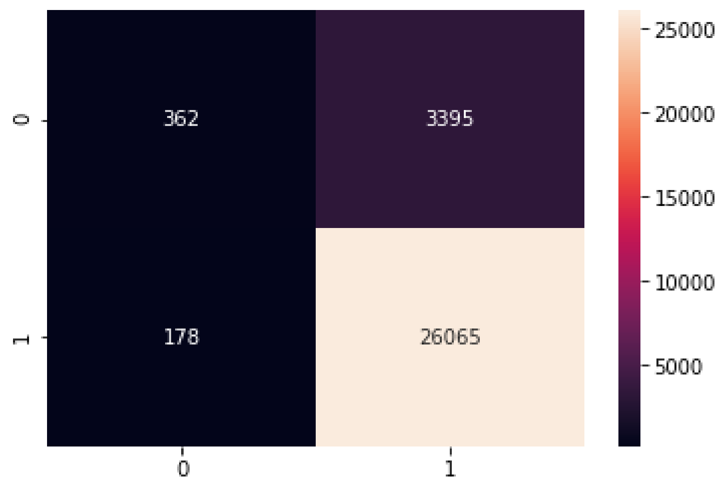
In [9]:

```
y_test=np.asarray(y_test)
```

In [10]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8397563611393886
[[  362  3395]
 [  178 26065]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.67      0.10      0.17      3757
   positive       0.88      0.99      0.94     26243

avg / total       0.86      0.88      0.84     30000
```




```
f1 score is also decent for k=17: It shows 84% f1-score which is good
```

In [11]:

```
x.add_row(["BoW","kNN Brute force",optimal_k,f1,acc])
```

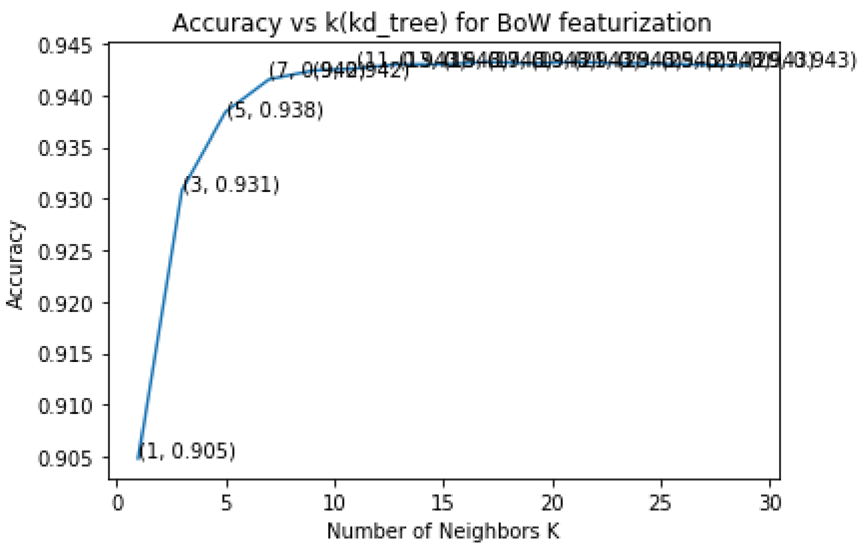
Reducing the number of reviews to 30k for kd tree

In [12]:

```
#kNN kd tree
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts[:30000],score[:3
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="kd_tree")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())
optimal_k=k_values[cv_scores.index(max(cv_scores))]
```

In [13]:

```
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(kd_tree) for BoW featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for BoW featurizatin and knn(kd tree) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```




```
Optimal_k for BoW featurizatin and knn(kd tree) is  17
Accuracy is  89.61
```

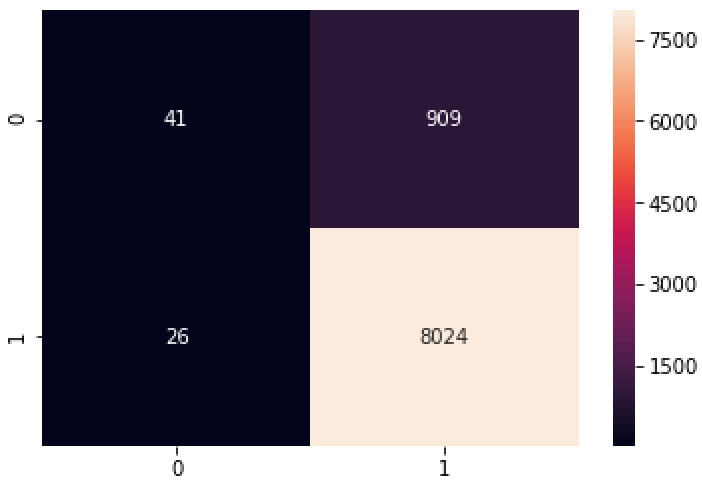
```
The y label in the graph says accuracy but it is actually plotted against f1-score
```

```
good performance is evident with k=17
```

In [14]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.853711627064626
[[  41  909]
 [  26 8024]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.61      0.04      0.08       950
   positive       0.90      1.00      0.94      8050

avg / total       0.87      0.90      0.85      9000
```




```
f1 score of 85.37% gives a lot of confidence on the model
```

In [15]:

```
x.add_row(["BoW","kNN kd_tree",optimal_k,f1,acc])
```

In [16]:

```
#Featurization using Tfidf and model using kNN for classification of review
```

In [17]:

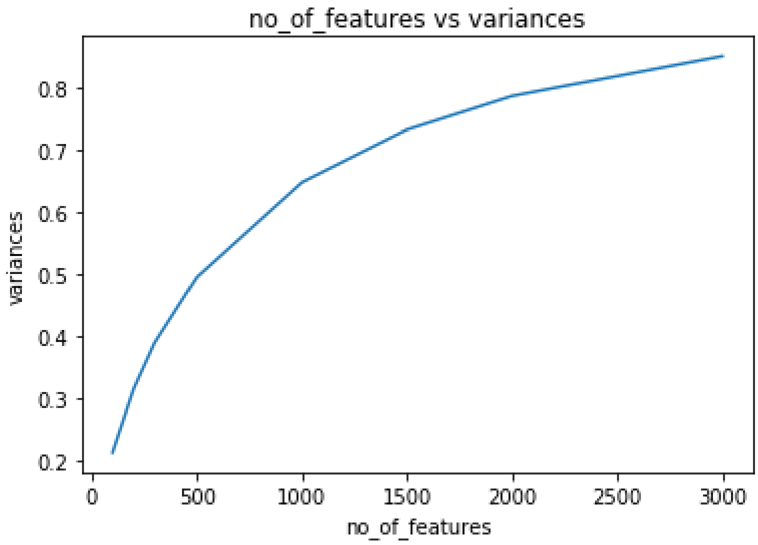
```
#Tfidf
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer()
final_counts= tf_idf_vect.fit_transform(clean_reviews['CleanedText'].values)
final_counts=final_counts.toarray()
```

In [18]:

```
svd = TruncatedSVD(n_components=3000, n_iter=7, random_state=42)
s=svd.fit_transform(final_counts)
no_of_features=np.array([100,200,300,500,1000,1500,2000,3000])
variances=[]
for i in no_of_features:
    variances.append(np.sum(svd.explained_variance_ratio_[:i]))

plt.plot(no_of_features,variances)
plt.xlabel("no_of_features")
plt.ylabel("variances")
plt.title("no_of_features vs variances")

#variance with 300 features
np.sum(svd.explained_variance_ratio_[:300])
```

Out[18]:

0.3891801669102287



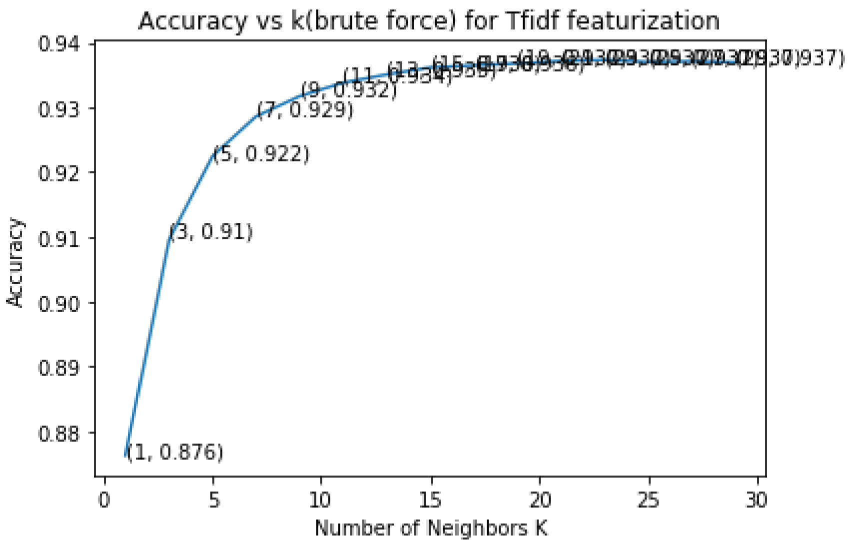
TFIDF covers around 80% of the information with 3000 features. With 300 features around 39% of the information is retained.

In [19]:

```
svd = TruncatedSVD(n_components=300, n_iter=7, random_state=42)
final_counts=svd.fit_transform(final_counts)
```

In [20]:

```
#kNN brute
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts,score,test_size=
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="brute")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(brute force) for Tfidf featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for Tfidf featurizatin and knn(brute force) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```




```
Optimal_k for Tfidf featurizatin and knn(brute force) is  23
Accuracy is  88.1
```

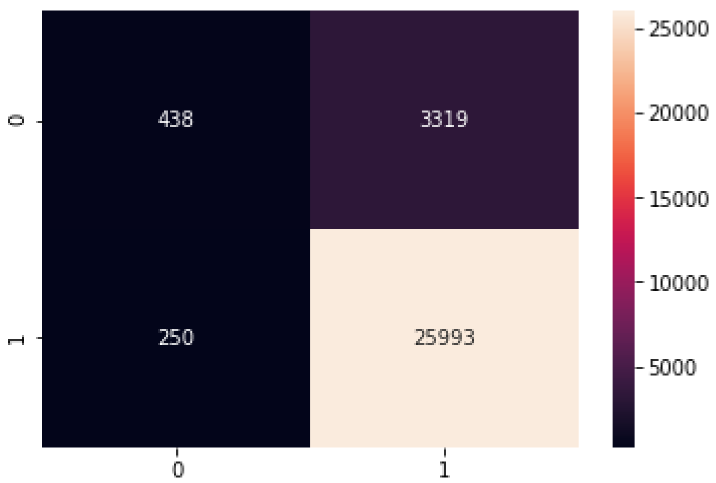
The y label in the graph says accuracy but it is actually plotted against f1-score

```
k=23 gives decent performance (84.32%) with tfidf and knn(brute force)
```

In [21]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f1 score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8432497494428263
[[  438  3319]
 [  250 25993]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.64      0.12      0.20      3757
   positive       0.89      0.99      0.94     26243

avg / total       0.86      0.88      0.84     30000
```



f1 score of 85% infuses confidence in the model

In [22]:

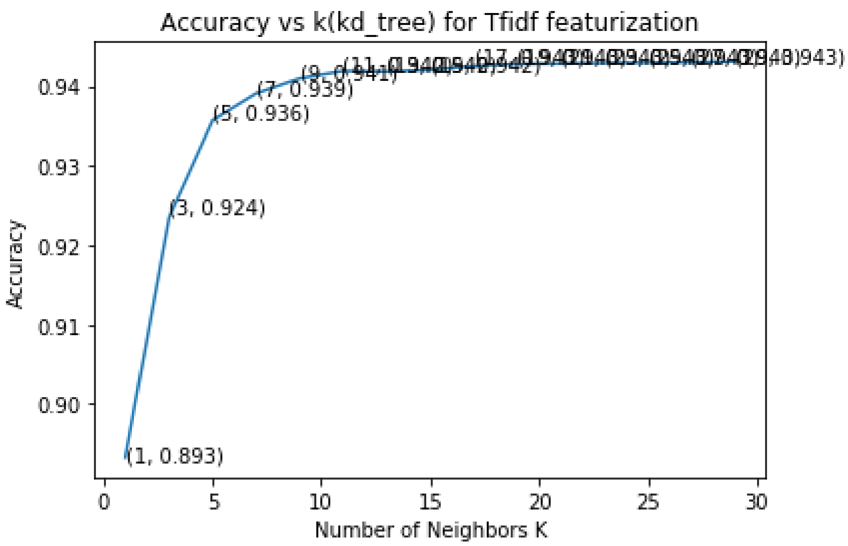
```
x.add_row(["tfIdf","kNN Brute force",optimal_k,f1,acc])
```

In [23]:

```
#kNN kd tree
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts[:30000],score[:3
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="kd_tree")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
```

In [24]:

```
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(kd_tree) for Tfidf featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for Tfidf featurizatin and knn(kd tree) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```




```
Optimal_k for Tfidf featurizatin and knn(kd tree) is  29
Accuracy is  89.61
```

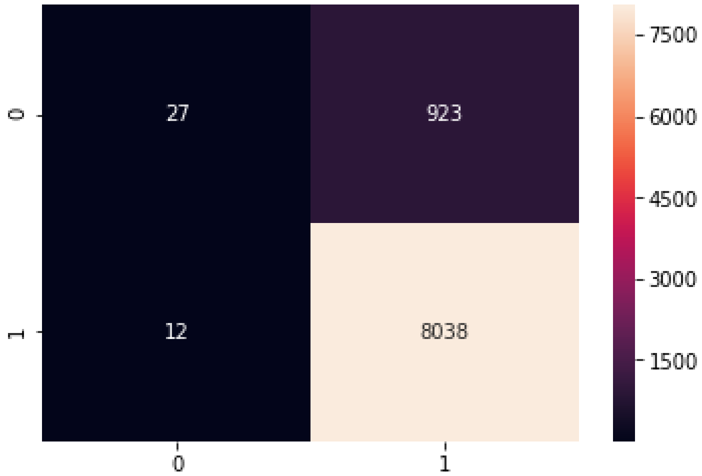
The y label in the graph says accuracy but it is actually plotted against f1-score

f1_score at around 85% for k=29 is goood enough

In [25]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f1 score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8510452084867651
[[  27  923]
 [  12 8038]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.69      0.03      0.05       950
   positive       0.90      1.00      0.95      8050

avg / total       0.88      0.90      0.85      9000
```



86.2% f1 score is good enough for the model

In [26]:

```
x.add_row(["tfIdf","kNN kd_tree",optimal_k,f1,acc])
```

#Featurization using avgWord2Vec and model using kNN for classification of review

In [27]:

```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sent=[]
for sent in clean_reviews['CleanedText'].values:
    list_of_sent.append(sent.split())
```

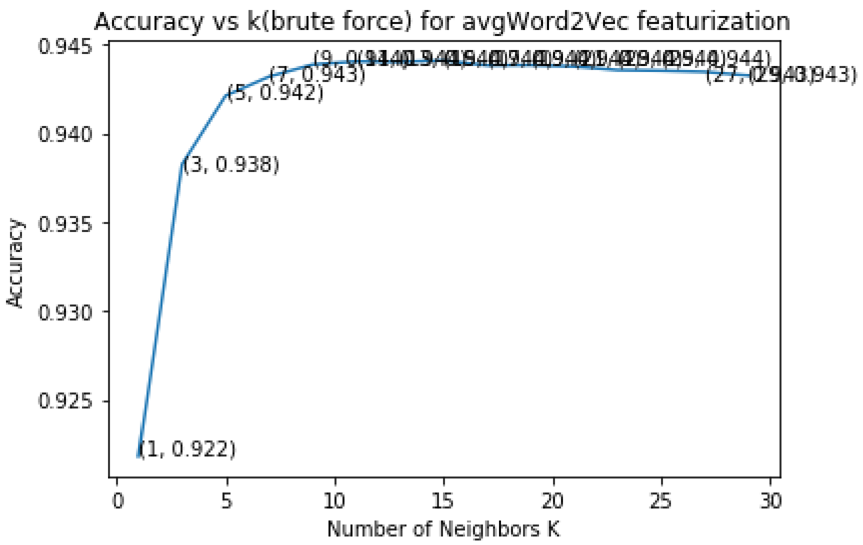
In [28]:

```
import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
sent_vectors = [];
for sent in list_of_sent:
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)

final_counts=sent_vectors
```

```
C:\Users\Anvesh Pandey\Anaconda3\lib\site-packages\gensim\utils.py:1197: Use
rWarning: detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [29]:

```
#kNN brute
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts,score,test_size=
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="brute")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(brute force) for avgWord2Vec featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for avgWord2Vec featurization and knn(brute force) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```




```
Optimal_k for avgWord2Vec featurization and knn(brute force) is  15
Accuracy is  89.47
```

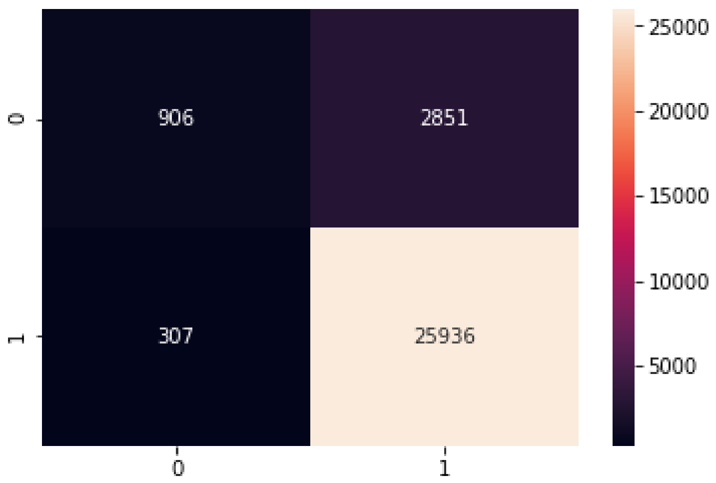
In [ ]:

```
The y label in the graph says accuracy but it is actually plotted against f1-score
```

In [30]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f1 score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8702250481068007
[[  906  2851]
 [  307 25936]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.75      0.24      0.36      3757
   positive       0.90      0.99      0.94     26243

avg / total       0.88      0.89      0.87     30000
```



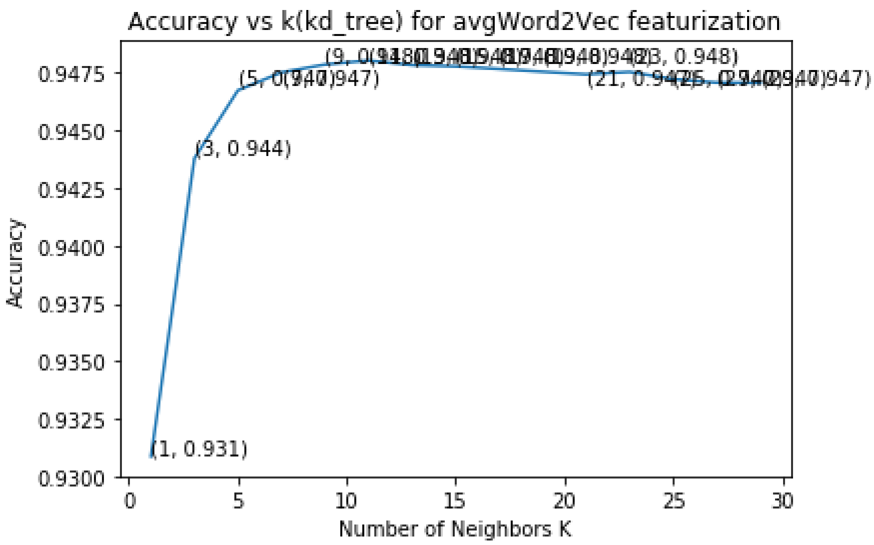
good f1 score - 87.5% is achieved with avgWord2Vec

In [31]:

```
x.add_row(["avgWord2Vec","kNN Brute force",optimal_k,f1,acc])
```

In [32]:

```
#kNN kd tree
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts[:30000],score[:3
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="kd_tree")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(kd_tree) for avgWord2Vec featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for avgWord2Vec featurizatin and knn(kd tree) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```



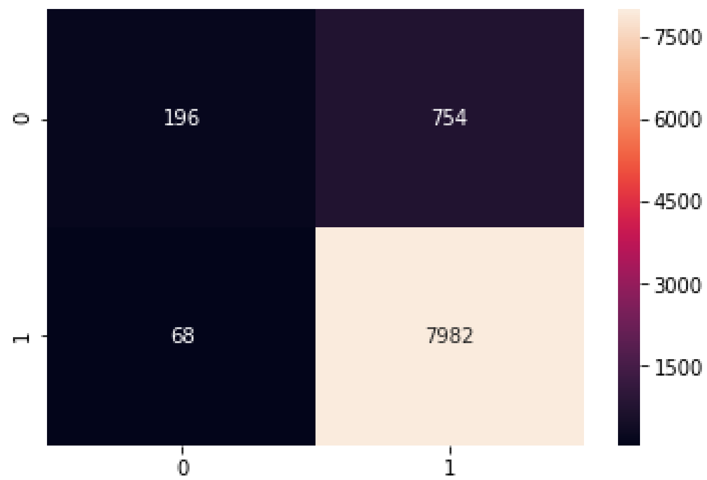

```
Optimal_k for avgWord2Vec featurizatin and knn(kd tree) is  11
Accuracy is  90.87
```

The y label in the graph says accuracy but it is actually plotted against f1-score

In [33]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8847278919509622
[[ 196  754]
 [  68 7982]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.74      0.21      0.32       950
   positive       0.91      0.99      0.95      8050

avg / total       0.90      0.91      0.88      9000
```



With kdtree we have imporved f1 score (88.3%) , that is reasonable

In [34]:

```
x.add_row(["avgWord2Vec","kNN kd_tree",optimal_k,f1,acc])
```

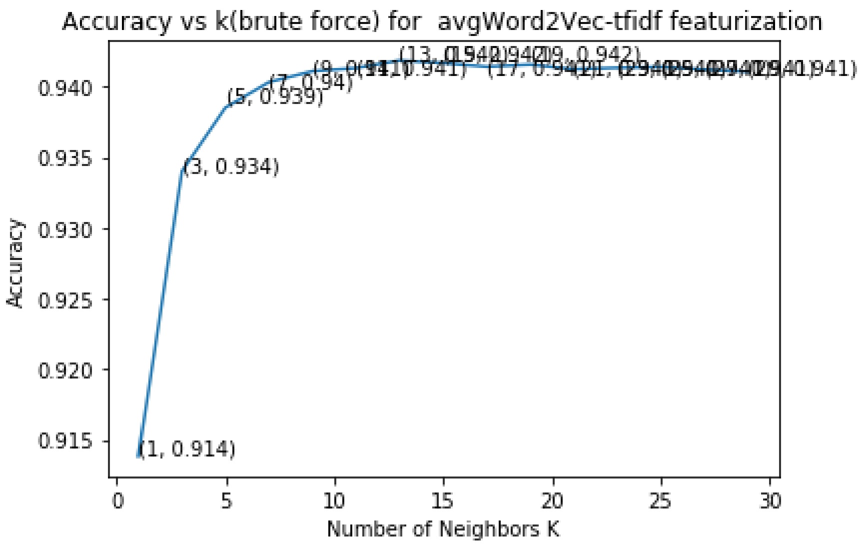
#Featurization using avgWord2Vec-tfidf and model using kNN for classification of review

In [35]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names()
final_tf_idf = tf_idf_vect.fit_transform(clean_reviews['CleanedText'].values)
tfidf_sent_vectors = [];
row=0;
for sent in list_of_sent:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            tf_idf =final_tf_idf[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1

final_counts=tfidf_sent_vectors
```

In [36]:

```
#kNN brute
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts,score,test_size=
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="brute")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(brute force) for  avgWord2Vec-tfidf featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for  avgWord2Vec-tfidf featurizatin and knn(brute force) is ",optimal_k
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```



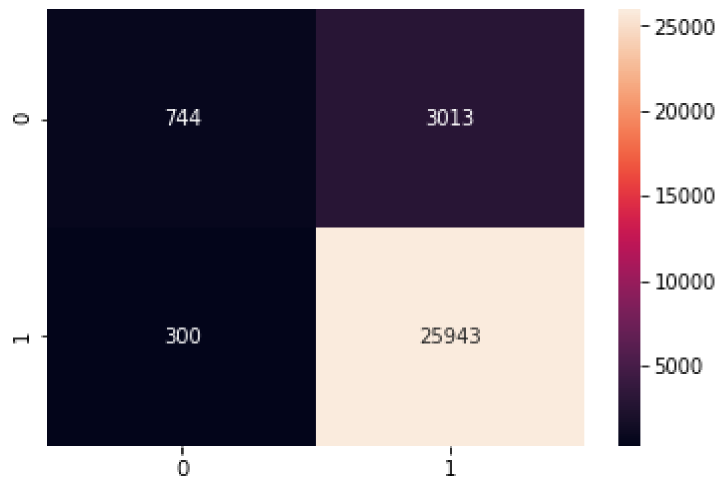

```
Optimal_k for  avgWord2Vec-tfidf featurizatin and knn(brute force) is  13
Accuracy is  88.96
```

The y label in the graph says accuracy but it is actually plotted against f1-score

In [37]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8610781153386613
[[  744  3013]
 [  300 25943]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.71      0.20      0.31      3757
   positive       0.90      0.99      0.94     26243

avg / total       0.87      0.89      0.86     30000
```

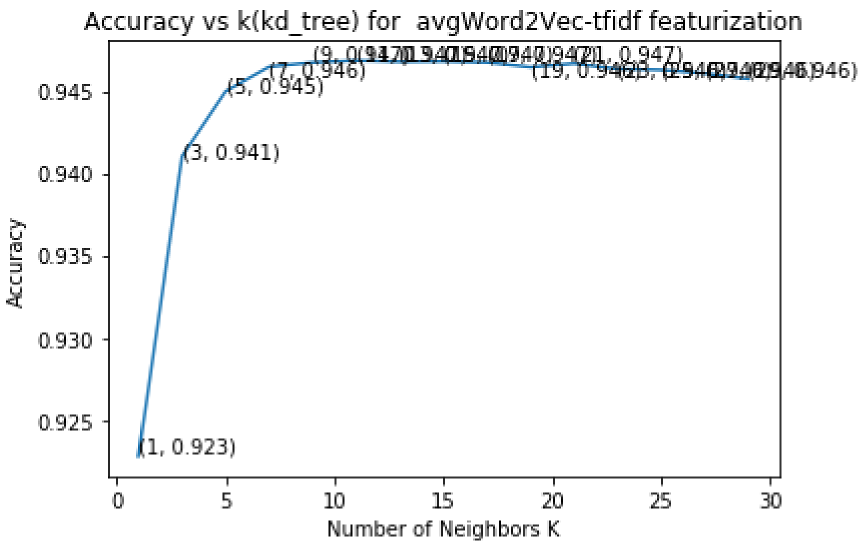


In [38]:

```
x.add_row(["tfidf-avgWord2Vec","kNN Brute force",optimal_k,f1,acc])
```

In [39]:

```
#kNN kd tree
x_tr,x_test,y_tr,y_test = cross_validation.train_test_split(final_counts[:30000],score[:3
k_values=np.arange(1,30,2)
cv_scores=[]
custom_scorer=make_scorer(f1_score,pos_label="positive")

for k in k_values:
    knn=KNeighborsClassifier(n_neighbors=k,weights="distance",algorithm="kd_tree")
    scores=cross_val_score(knn,x_tr,y_tr,cv=3,scoring=custom_scorer)
    cv_scores.append(scores.mean())

optimal_k=k_values[cv_scores.index(max(cv_scores))]
plt.plot(k_values,cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('f1_score')
plt.title("f1_score vs k(kd_tree) for  avgWord2Vec-tfidf featurization")
for xy in zip(k_values, np.round(cv_scores,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
knn_optimal=KNeighborsClassifier(n_neighbors=optimal_k,weights="distance",algorithm="brut
knn_optimal.fit(x_tr,y_tr)
pred=knn_optimal.predict(x_test)
acc=accuracy_score(y_test,pred)
print ("Optimal_k for  avgWord2Vec-tfidf featurizatin and knn(kd tree) is ",optimal_k)
np.round(acc*100,2)
print ("Accuracy is ",np.round(acc*100,2))
```




```
Optimal_k for  avgWord2Vec-tfidf featurizatin and knn(kd tree) is  11
Accuracy is  90.52
```

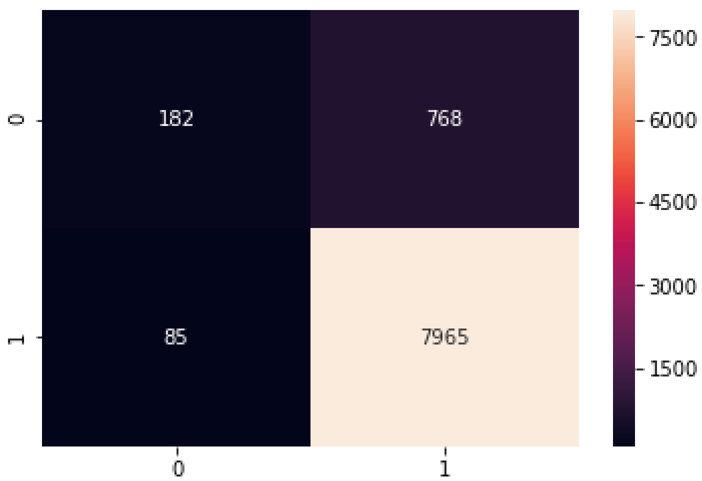
In [ ]:

```
The y label in the graph says accuracy but it is actually plotted against f1-score
```

In [40]:

```
f1=f1_score(y_test,pred,average='weighted')
print ("f1 score is ", f1)
c_matrix=confusion_matrix(y_test, pred)
print (c_matrix)
print (sns.heatmap(c_matrix,annot=True,fmt="d"))
print (classification_report(y_test, pred))
```

```
f score is  0.8805553500603039
[[ 182  768]
 [  85 7965]]
AxesSubplot(0.125,0.125;0.62x0.755)
             precision    recall  f1-score   support

   negative       0.68      0.19      0.30       950
   positive       0.91      0.99      0.95      8050

avg / total       0.89      0.91      0.88      9000
```



In [41]:

```
x.add_row(["tfidf-avgWord2Vec","kNN kd_tree",optimal_k,f1,acc])
```

In [42]:

```
print (x)
```

Vectorization	Model	k	f1 score	Accuracy
BoW	kNN Brute force	17	0.8397563611393886	0.8809
BoW	kNN kd_tree	17	0.853711627064626	0.8961111111111111
tfIdf	kNN Brute force	23	0.8432497494428263	0.8810333333333333
tfIdf	kNN kd_tree	29	0.8510452084867651	0.8961111111111111
avgWord2Vec	kNN Brute force	15	0.8702250481068007	0.8947333333333334
avgWord2Vec	kNN kd_tree	11	0.8847278919509622	0.9086666666666666
tfidf-avgWord2Vec	kNN Brute force	13	0.8610781153386613	0.8895666666666666
tfidf-avgWord2Vec	kNN kd_tree	11	0.8805553500603039	0.9052222222222223

```
Conclusion - From the table it is evident that max f1 score of 88.47% is achieved
using avgWord2Vec and KNN with kd_tree algo. Accuracy is also highest for the same
model.Eleven nearest neighbors gives us the best model. We checked k in range till 30.
29 being the maximum value.
  Therefore we will go with avgWord2Vec and KNN with kd_tree algo to design our model.
```

In [ ]:

```

```