AMAZON ASSIGNMENT

OBJECTIVE:

- TO FIND THE OPTIMAL VALUE OF 'K'(No. of nearest neighbours)
- TO FIND THE ACCURACY SCORE OF OUR PREDICTION ON TEST DATASET.

NOTE:

- Dataset is preprocessed and time-based splitted(Train , Test , Cross-Validate).
- SAMPLE_SIZE: 100000 Reviews (70K-TRAIN , 15K-CROSS_VALIDATE , 15K-TEST).

IMPORTING LIBRARIES AND OUR DATASET

In [0]:

```
import numpy as np
import pandas as pd
import seaborn as sn
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
from tqdm import tqdm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
import sqlite3
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.externals import joblib
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import classification_report
from prettytable import PrettyTable
```

IMPORTING THE PREPROCESSED AND TIME_BASED SPLITTED DATASET

In [0]:
```
Train=joblib.load('TRAIN.joblib')
CrossVal=joblib.load('CROSS_VALIDATE.joblib')
Test=joblib.load('TEST.joblib')
```

In [0]:
```
Train_x=Train['Text'].values
CrossVal_x=CrossVal['Text'].values
Test_x=Test['Text'].values
Train_y=Train['Score'].values
CrossVal_y=CrossVal['Score'].values
Test_y=Test['Score'].values
```

1. BAG OF WORDS

1.1 BRUTE-FORCE METHOD

In [0]:
```
count= CountVectorizer()
```

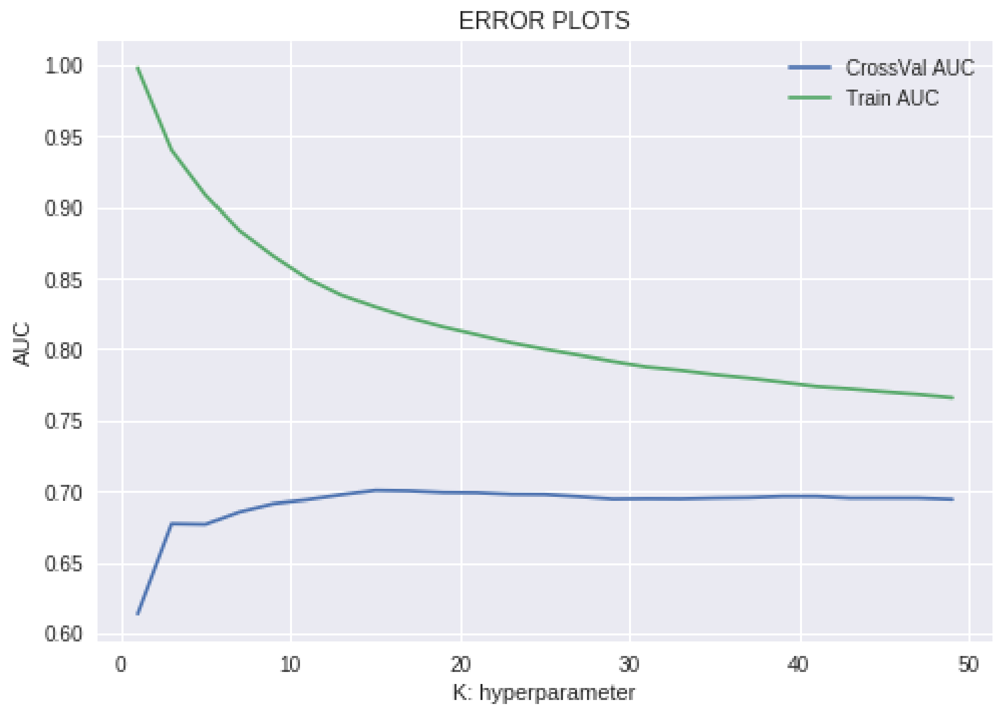
In [0]:
```
count.fit(Train_x)
Train_BOW = count.transform(Train_x)
CrossVal_BOW = count.transform(CrossVal_x)
Test_BOW= count.transform(Test_x)
```

Hyperparameter(K) tuning .

In [0]:
```
Mylist=list(range(50))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_BOW = []
CrossVal_AUC_BOW = []
for i in neighbour:
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='brute')
  neigh.fit(Train_BOW, Train_y)
  Train_y_pred =  neigh.predict_proba(Train_BOW)[:,1]
  Train_AUC_BOW.append(roc_auc_score(Train_y,Train_y_pred))
```

```
    CrossVal_y_pred =  neigh.predict_proba(CrossVal_BOW)[:,1]
    CrossVal_AUC_BOW.append(roc_auc_score(CrossVal_y,CrossVal_y_pred))
```

In [0]:
```
plt.plot(neighbour, CrossVal_AUC_BOW, label='CrossVal AUC')
plt.plot(neighbour, Train_AUC_BOW, label='Train AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



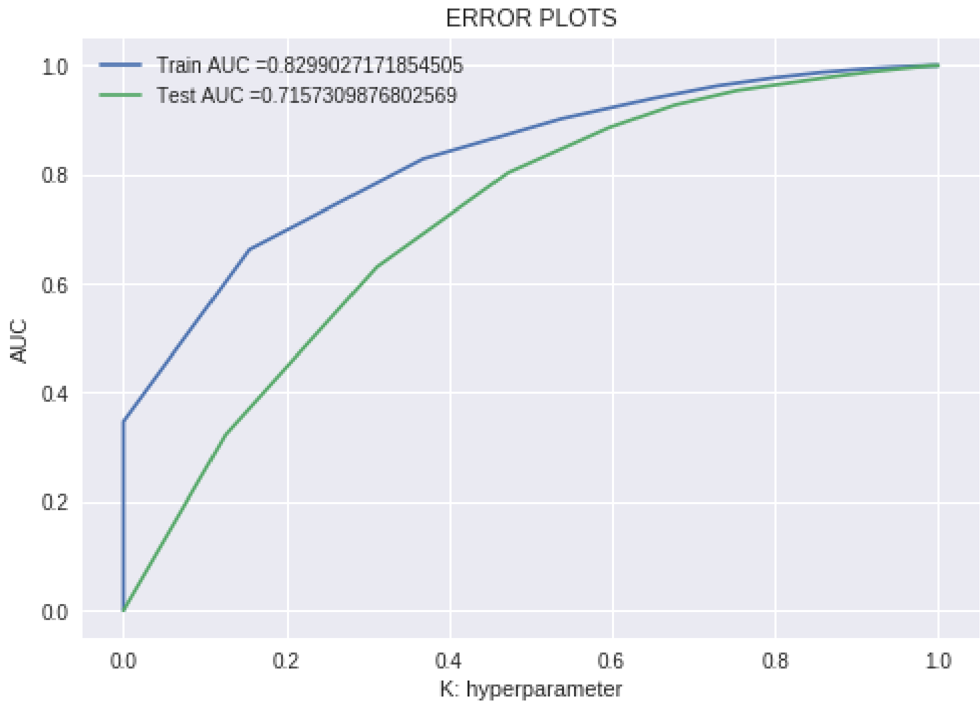
In [0]:
```
optimal_k=neighbour[CrossVal_AUC_BOW.index(max(CrossVal_AUC_BOW))]
print(optimal_k)
```

15

The optimal value of 'K' obtained is 15.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='brut
e')
Classifier.fit(Train_BOW, Train_y)
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y, Classifier.predic
t_proba(Train_BOW)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Test_y, Classifier.predict_p
roba(Test_BOW)[:,1])
```

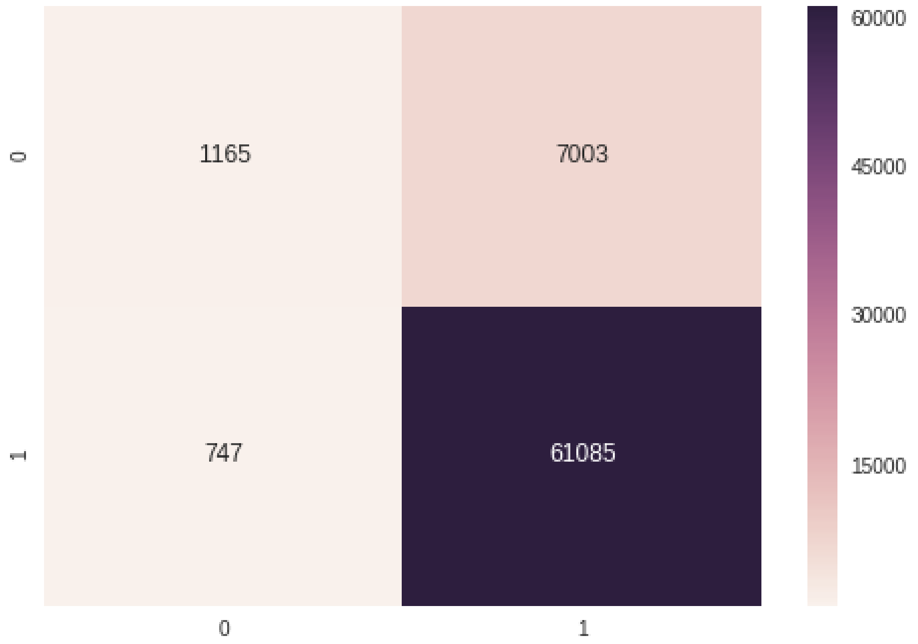
In [0]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
rain_TPR)))
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [0]:
```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y,Classifier.predict(Train_BOW))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [
i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Train Data
```

Out[0]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6cf4fc65f8>
```



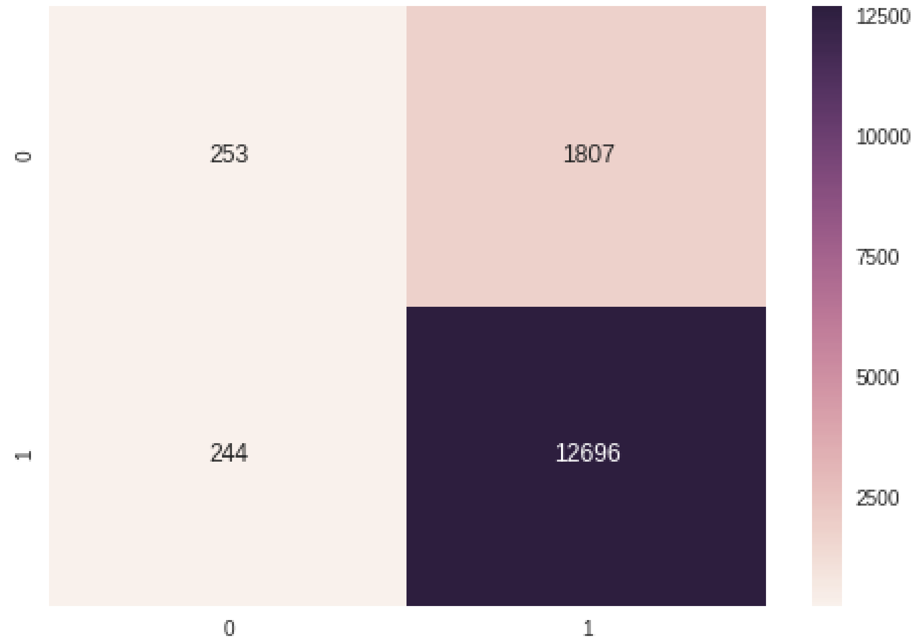
In [0]:

```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Test_y,Classifier.predict(Test_BOW))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Test Data
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6cf539f5c0>
```



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=15 on Test Dataset is 12949(86.32%).
2. The Area Under Curve value for Test Dataset is 0.71573(approx).
3. The brute-force method takes little less time for computation.

1.2 K-D TREE METHOD

Note : We are using 20K data points (14K-TRAIN , 3K-CROSS_VALIDATE , 3K-TEST) for this model .

In [0]:
```
count= CountVectorizer(max_features=500,min_df=10)
```

In [0]:
```
count.fit(Train_x[:14000])
```

```
Train_BOW = count.transform(Train_x[:14000])
CrossVal_BOW = count.transform(Train_x[14000:17000])
Test_BOW= count.transform(Train_x[17000:20000])
```

In [0]:
```
Train_BOW_den=Train_BOW.toarray()
CrossVal_BOW_den=CrossVal_BOW.toarray()
Test_BOW_den=Test_BOW.toarray()
```

In [0]:
```
standardized_vec = StandardScaler(with_mean=False)
standardized_vec.fit(Train_BOW_den)
```

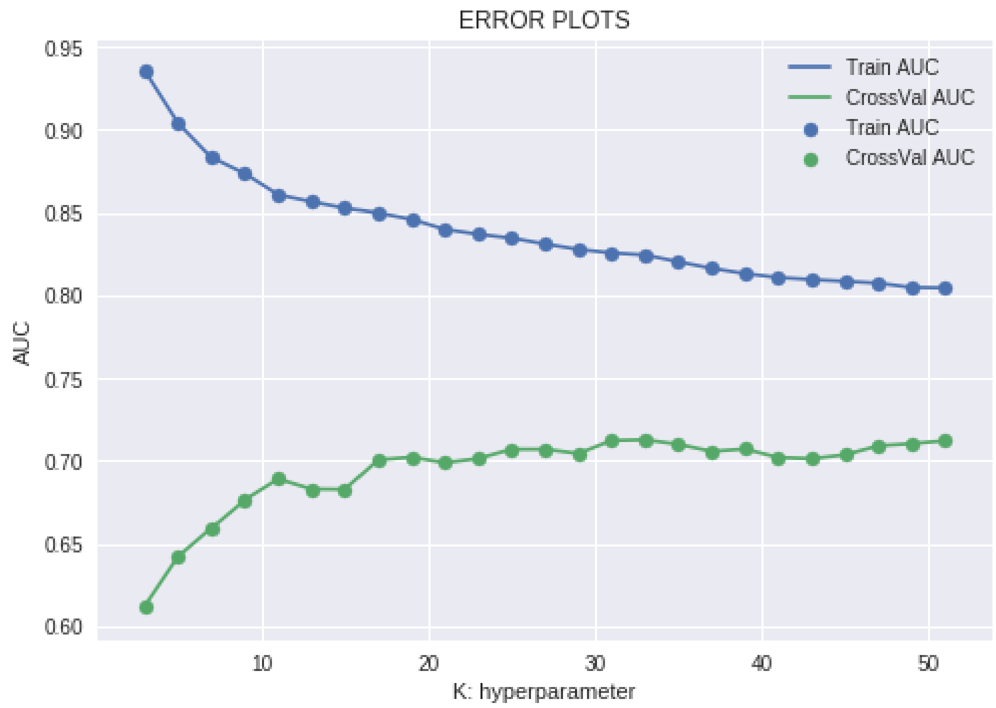
In [0]:
```
Train_BOW_std=standardized_vec.transform(Train_BOW_den)
CrossVal_BOW_std=standardized_vec.transform(CrossVal_BOW_den)
Test_BOW_std=standardized_vec.transform(Test_BOW_den)
```

Hyperparameter(K) tuning .

In [0]:
```
Mylist=list(range(3,52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_BOW = []
CrossVal_AUC_BOW = []
for i in neighbour:
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')
  neigh.fit(Train_BOW_std, Train_y[:14000])
  Train_y_pred =  neigh.predict_proba(Train_BOW_std)[:,1]
  Train_AUC_BOW.append(roc_auc_score(Train_y[:14000],Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(CrossVal_BOW_std)[:,1]
  CrossVal_AUC_BOW.append(roc_auc_score(Train_y[14000:17000],CrossVal_y
_pred))
```

In [0]:
```
plt.plot(neighbour, Train_AUC_BOW, label='Train AUC')
plt.scatter(neighbour, Train_AUC_BOW, label='Train AUC')
plt.plot(neighbour, CrossVal_AUC_BOW, label='CrossVal AUC')
plt.scatter(neighbour,CrossVal_AUC_BOW, label='CrossVal AUC')
plt.legend()
plt.xlabel("K: hyperparameter")
```

```
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [0]:
```
optimal_k=neighbour[CrossVal_AUC_BOW.index(max(CrossVal_AUC_BOW))]
print(optimal_k)
```

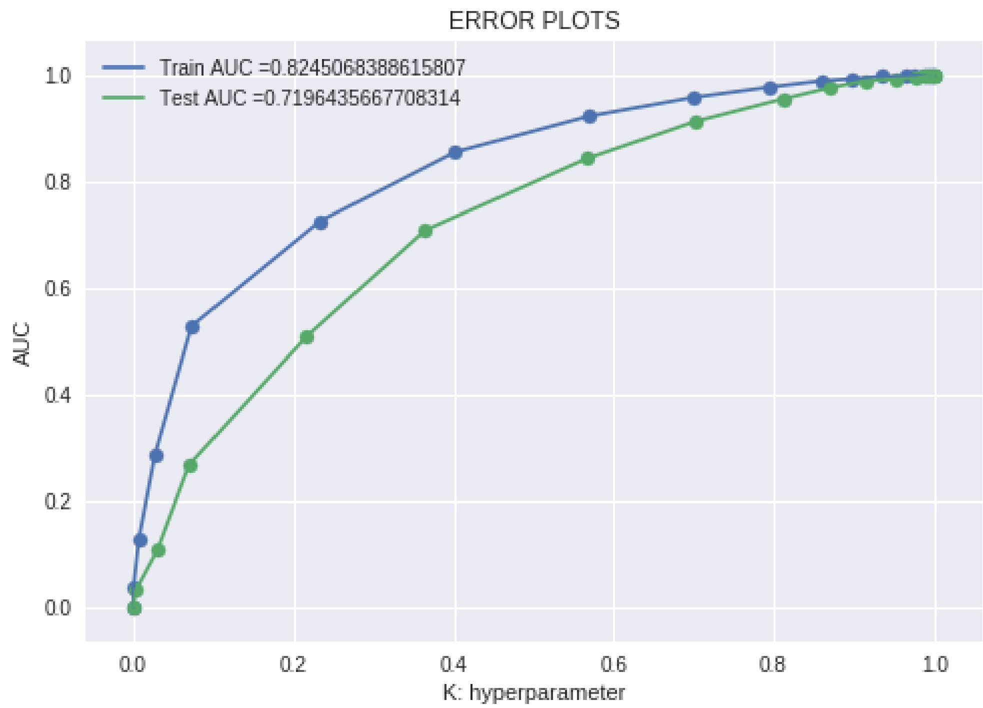
```
33
```

The optimal value of 'K' obtained is 33.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='kd_t
ree')
Classifier.fit(Train_BOW_std, Train_y[:14000])
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y[:14000], Classifie
r.predict_proba(Train_BOW_std)[:,1])
```

```
Test_FPR, Test_TPR, Thresholds = roc_curve(Train_y[17000:20000], Classi
fier.predict_proba(Test_BOW_std)[:,1])
```

In [0]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
rain_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

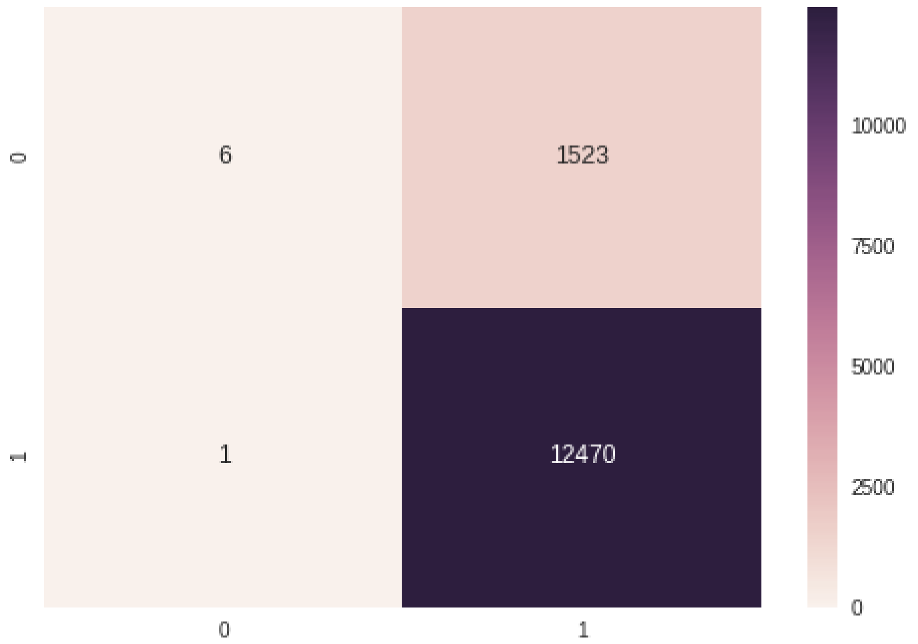


In [0]:
```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y[:14000],Classifier.predict(Train_BOW
```

```
_std))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [
i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Train Data
```

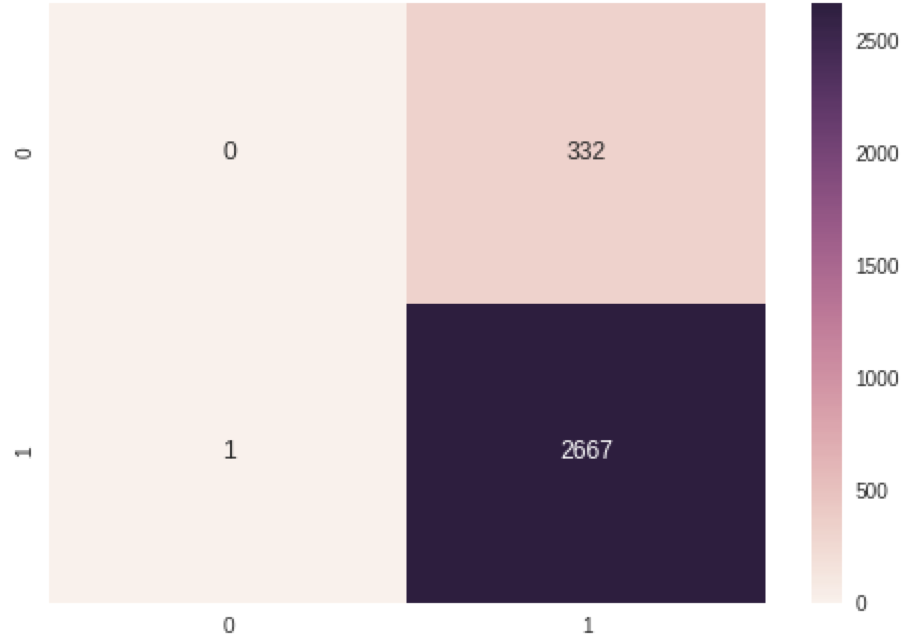
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f50238266a0>



In [0]:
```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Train_y[17000:20000],Classifier.predict(Test_
BOW_std))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Test Data
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5023bd7cf8>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=33 on Test Dataset is 2667(88.9%) little more than brute-force method case .
2. The Area Under Curve value for Test Dataset is 0.719643(approx) a little more than brute-force method case.
3. The kd-tree method takes more time for computation.

2. TF-IDF

2.1 BRUTE-FORCE METHOD

In [0]:
```
tf_idf=TfidfVectorizer()
```

In [0]:
```
tf_idf.fit(Train_x)
```

```
Train_TFIDF = tf_idf.transform(Train_x)
CrossVal_TFIDF = tf_idf.transform(CrossVal_x)
Test_TFIDF= tf_idf.transform(Test_x)
```

Hyperparameter(K) tuning .

In [0]:

```
Mylist=list(range(3,52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_TFIDF = []
CrossVal_AUC_TFIDF = []
for i in neighbour:
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='brute')
  neigh.fit(Train_TFIDF, Train_y)
  Train_y_pred =  neigh.predict_proba(Train_TFIDF)[:,1]
  Train_AUC_TFIDF.append(roc_auc_score(Train_y,Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(CrossVal_TFIDF)[:,1]
  CrossVal_AUC_TFIDF.append(roc_auc_score(CrossVal_y,CrossVal_y_pred))
```

In [0]:

```
plt.plot(neighbour, Train_AUC_TFIDF, label='Train AUC TFIDF')
plt.scatter(neighbour, Train_AUC_TFIDF)
plt.plot(neighbour, CrossVal_AUC_TFIDF, label='CrossVal AUC TFIDF')
plt.scatter(neighbour, CrossVal_AUC_TFIDF)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

In [0]:
```
optimal_k=neighbour[CrossVal_AUC_TFIDF.index(max(CrossVal_AUC_TFIDF))]
print(optimal_k)
```

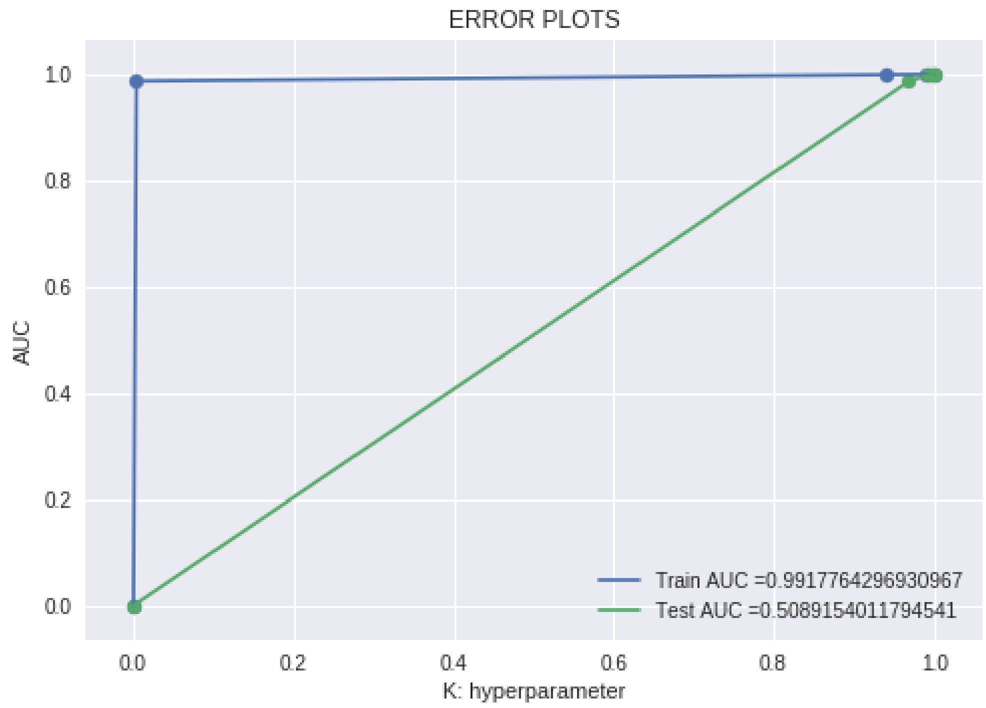
3

The optimal value of 'K' obtained is 3.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='brut
e')
Classifier.fit(Train_TFIDF, Train_y)
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y, Classifier.predic
t_proba(Train_TFIDF)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Test_y, Classifier.predict_p
roba(Test_TFIDF)[:,1])
```

In [0]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
```

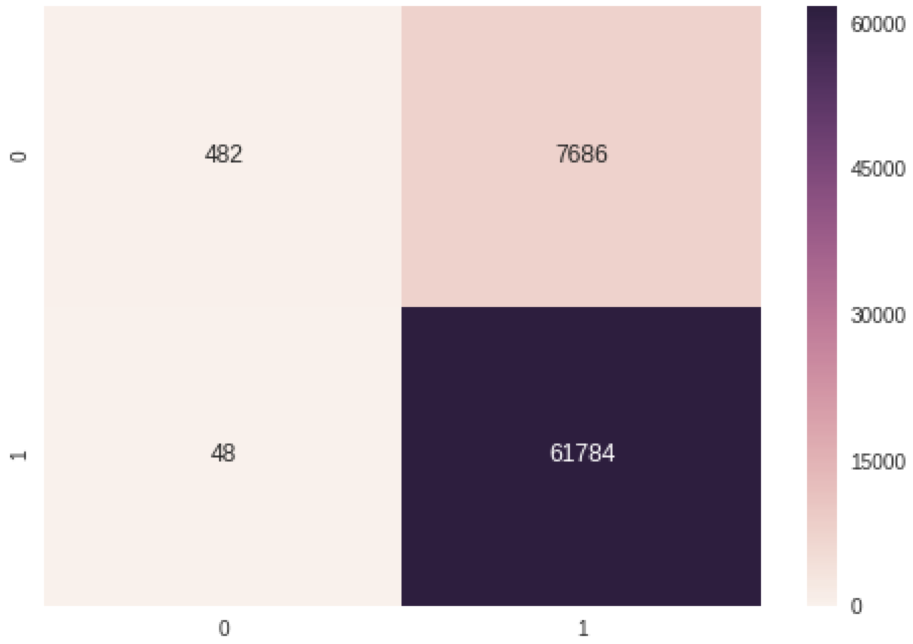
```
rain_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [0]:
```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y,Classifier.predict(Train_TFIDF))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [
i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Train Data
```

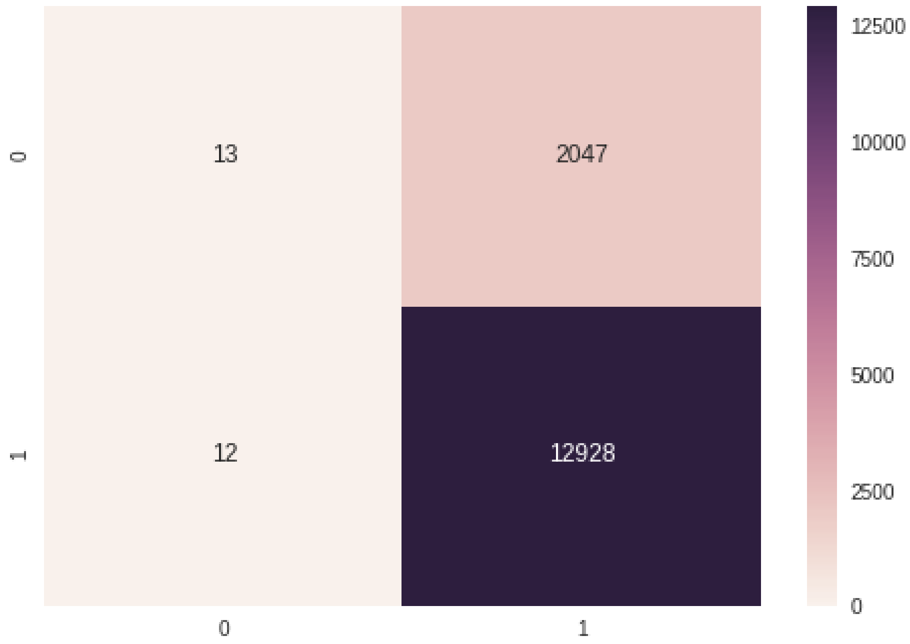
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f50239a9e10>



In [0]:
```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Test_y,Classifier.predict(Test_TFIDF))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Test Data
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f502266c0b8>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=3 on Test Dataset is 12941(86.27%).
2. The Area Under Curve value for Test Dataset is 0.50891(approx).
3. The brute-force method takes little less time for computation.
4. The Area Under Curve value is low with respect to other methods.

2.2 K-D TREE METHOD

Note : We are using 20K data points (14K-TRAIN , 3K-CROSS_VALIDATE , 3K-TEST) for this model .

In [0]:
```
tf_idf=TfidfVectorizer(max_features=500,min_df=10)
```

In [0]:
```
tf_idf.fit(Train_x[:14000])
Train_TFIDF = tf_idf.transform(Train_x[:14000])
CrossVal_TFIDF = tf_idf.transform(Train_x[14000:17000])
Test_TFIDF= tf_idf.transform(Train_x[17000:20000])
```

In [0]:
```
Train_TFIDF_den=Train_TFIDF.toarray()
CrossVal_TFIDF_den=CrossVal_TFIDF.toarray()
Test_TFIDF_den=Test_TFIDF.toarray()
```

In [0]:
```
standardized_vec = StandardScaler(with_mean=False)
standardized_vec.fit(Train_TFIDF_den)
```

In [0]:
```
Train_TFIDF_std=standardized_vec.transform(Train_TFIDF_den)
CrossVal_TFIDF_std=standardized_vec.transform(CrossVal_TFIDF_den)
Test_TFIDF_std=standardized_vec.transform(Test_TFIDF_den)
```

Hyperparameter(K) tuning .

In [0]:
```
Mylist=list(range(52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_TFIDF = []
CrossVal_AUC_TFIDF = []
for i in neighbour:
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')
  neigh.fit(Train_TFIDF_std, Train_y[:14000])
  Train_y_pred =  neigh.predict_proba(Train_TFIDF_std)[:,1]
  Train_AUC_TFIDF.append(roc_auc_score(Train_y[:14000],Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(CrossVal_TFIDF_std)[:,1]
  CrossVal_AUC_TFIDF.append(roc_auc_score(Train_y[14000:17000],CrossVal
_y_pred))
```

In [0]:
```
plt.plot(neighbour, Train_AUC_TFIDF, label='Train AUC TFIDF')
plt.scatter(neighbour, Train_AUC_TFIDF)
plt.plot(neighbour, CrossVal_AUC_TFIDF, label='CrossVal AUC TFIDF')
plt.scatter(neighbour, CrossVal_AUC_TFIDF)
plt.legend()
```

```
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

In [0]:
```
optimal_k=neighbour[CrossVal_AUC_TFIDF.index(max(CrossVal_AUC_TFIDF))]
print(optimal_k)
```

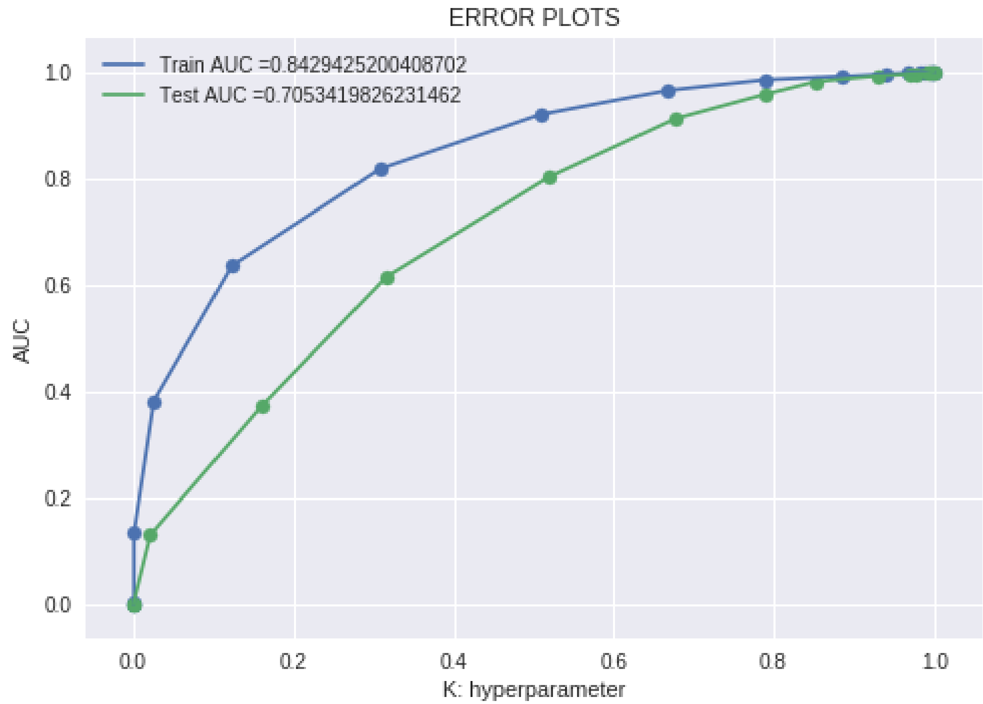
45

The optimal value of 'K' obtained is 45.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='kd_t
ree')
Classifier.fit(Train_TFIDF_std, Train_y[:14000])
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y[:14000], Classifie
```

```
r.predict_proba(Train_TFIDF_std)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Train_y[17000:20000], Classi
fier.predict_proba(Test_TFIDF_std)[:,1])
```

In [0]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
rain_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

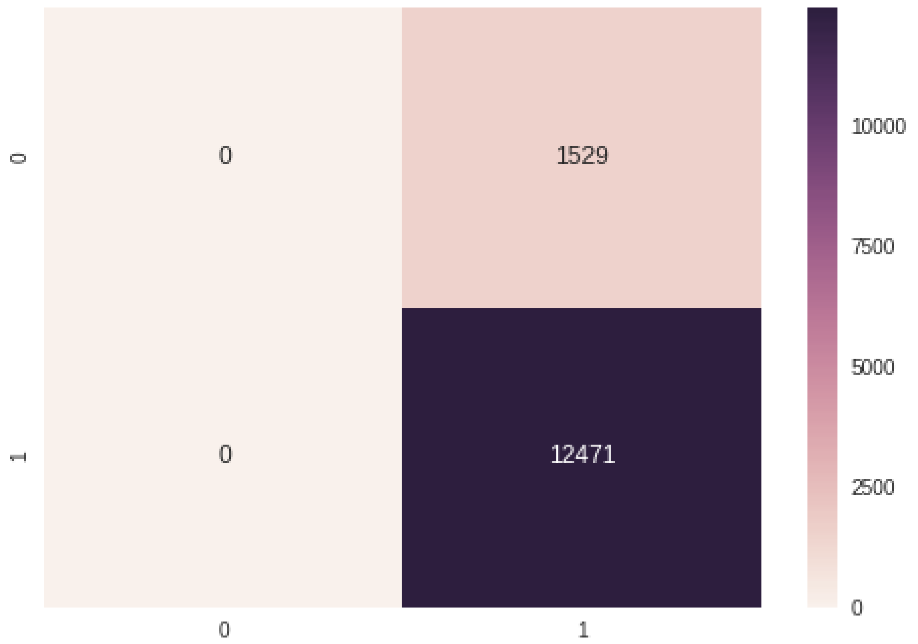


In [0]:
```
print('Confusion Matrix of Train Data')
```

```
Train_mat=confusion_matrix(Train_y[:14000],Classifier.predict(Train_TFIDF_std))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Train Data
```

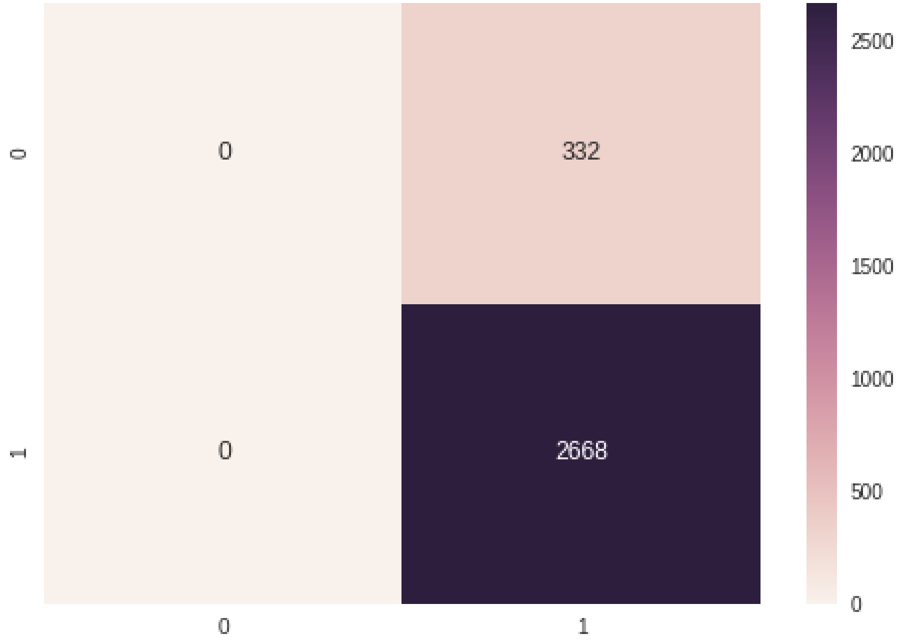
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc8b755ac88>



In [0]:
```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Train_y[17000:20000],Classifier.predict(Test_TFIDF_std))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Test Data
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc8b5b96a20>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=45 on Test Dataset is 2668(88.9%) slightly more than brute-force method.
2. The Area Under Curve value for Test Dataset is 0.70534(approx) , more than brute-force method case.
3. The kd-tree method takes more time for computation.

W0RD2VEC

Converting the words of train data into vectors.

In [0]:
```
i=0
list_of_sentance_train=[]
for sentance in Train_x:
    list_of_sentance_train.append(sentance.split())
```

In [0]:
```
w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50,workers=4
)
w2v_words = list(w2v_model.wv.vocab)
```

3. AVERAGE WORD TO VECTOR.

Computing average word2vec for each review of Train Data .

In [0]:
```
sent_vectors_train = [];
for sent in tqdm(list_of_sentance_train):
  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_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
```

Computing average word2vec for each review of CrossValidate Data .

In [0]:
```
i=0
list_of_sentance_cv=[]
for sentance in CrossVal_x:
    list_of_sentance_cv.append(sentance.split())
```

In [0]:
```
sent_vectors_cv = [];
for sent in tqdm(list_of_sentance_cv):
  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_cv.append(sent_vec)
sent_vectors_cv = np.array(sent_vectors_cv)
```

Computing average word2vec for each review of Test Data

In [0]:
```
i=0
list_of_sentance_test=[]
for sentance in Test_x:
    list_of_sentance_test.append(sentance.split())
```

In [0]:
```
sent_vectors_test = [];
for sent in tqdm(list_of_sentance_test):
  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_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
```

3.1 BRUTE-FORCE METHOD

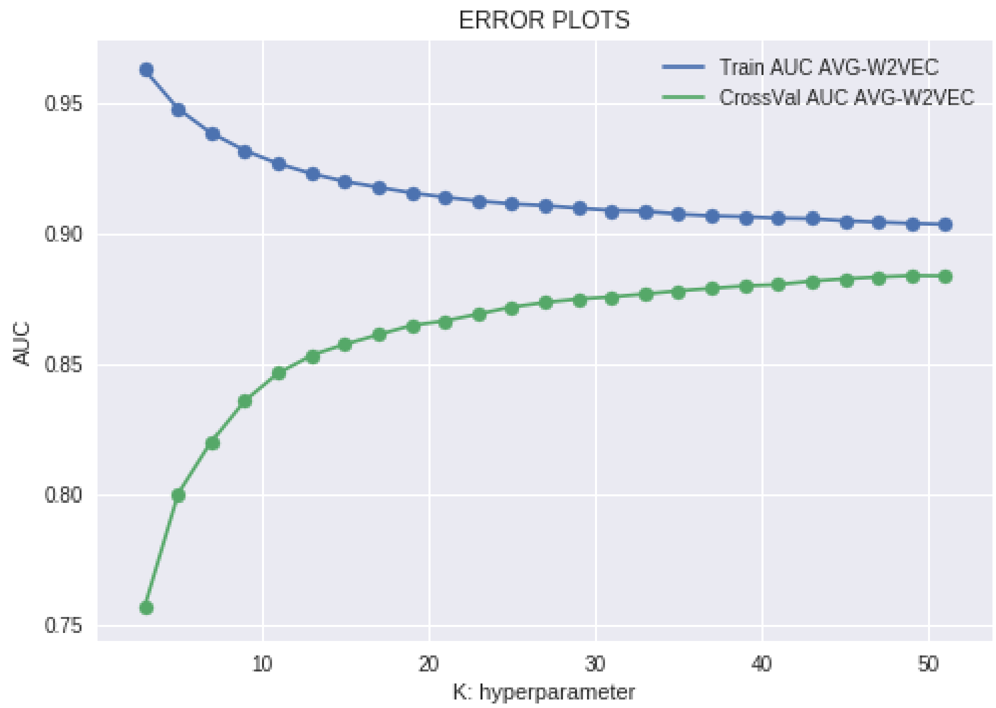
Hyperparameter(K) tuning .

In [0]:
```
Mylist=list(range(3,52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_W2VEC = []
```

```python
CrossVal_AUC_W2VEC = []
for i in neighbour:
  print(i)
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='brute')
  neigh.fit(sent_vectors_train, Train_y)
  Train_y_pred =  neigh.predict_proba(sent_vectors_train)[:,1]
  Train_AUC_W2VEC.append(roc_auc_score(Train_y,Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(sent_vectors_cv)[:,1]
  CrossVal_AUC_W2VEC.append(roc_auc_score(CrossVal_y,CrossVal_y_pred))
```

In [0]:

```python
plt.plot(neighbour, Train_AUC_W2VEC, label='Train AUC AVG-W2VEC')
plt.scatter(neighbour, Train_AUC_W2VEC)
plt.plot(neighbour, CrossVal_AUC_W2VEC, label='CrossVal AUC AVG-W2VEC')
plt.scatter(neighbour, CrossVal_AUC_W2VEC)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [0]:
```
optimal_k=neighbour[CrossVal_AUC_W2VEC.index(max(CrossVal_AUC_W2VEC))]
print(optimal_k)
```

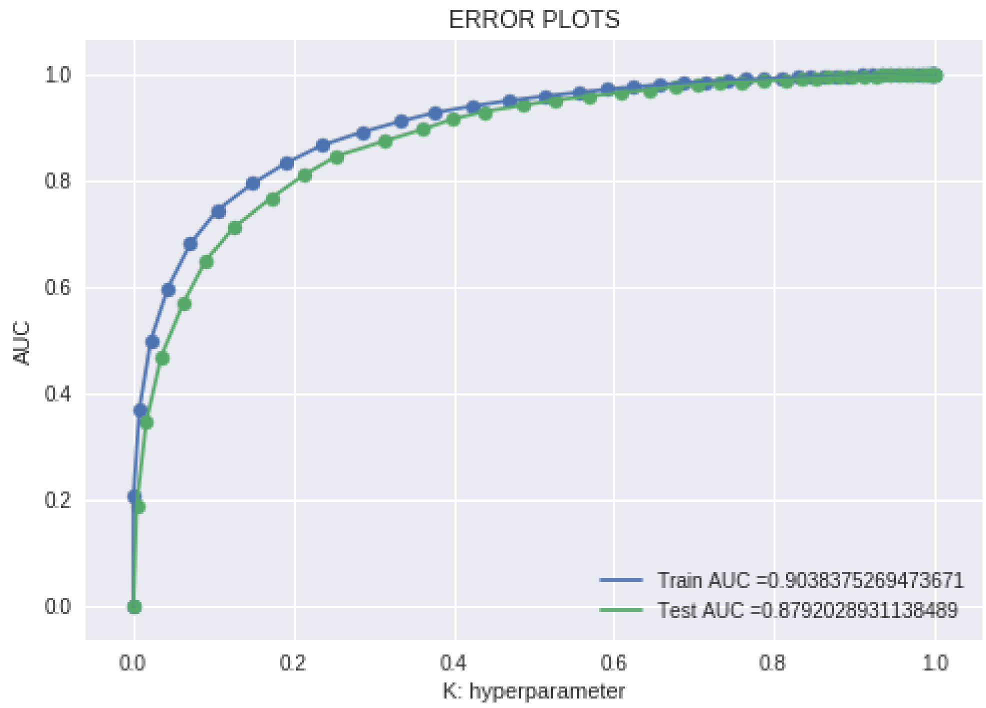
49

The optimal value of 'K' obtained is 49.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='brut
e')
Classifier.fit(sent_vectors_train, Train_y)
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y, Classifier.predic
t_proba(sent_vectors_train)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Test_y, Classifier.predict_p
roba(sent_vectors_test)[:,1])
```

In [0]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
```

```
rain_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

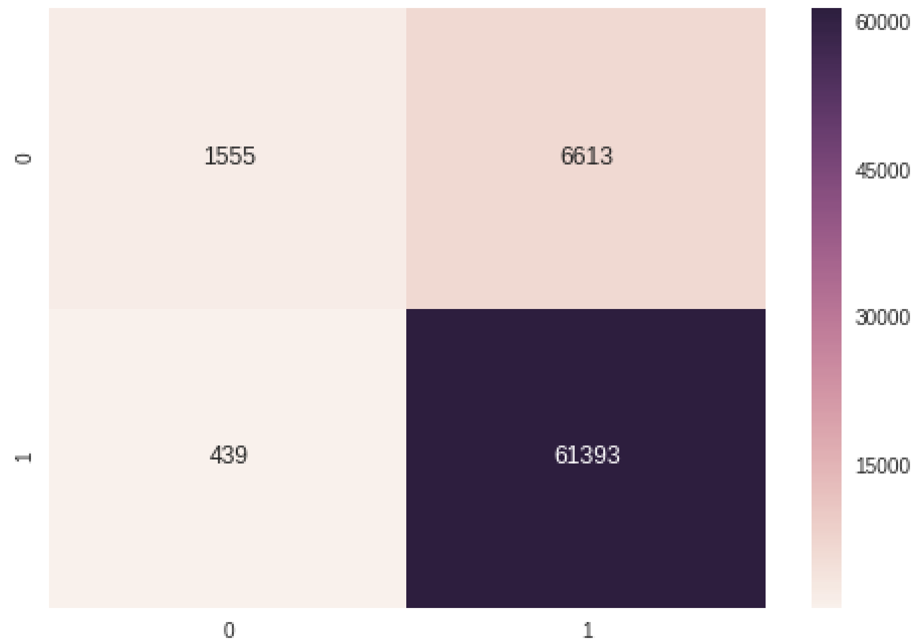


In [0]:

```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y,Classifier.predict(sent_vectors_trai
n))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [
i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Train Data
```

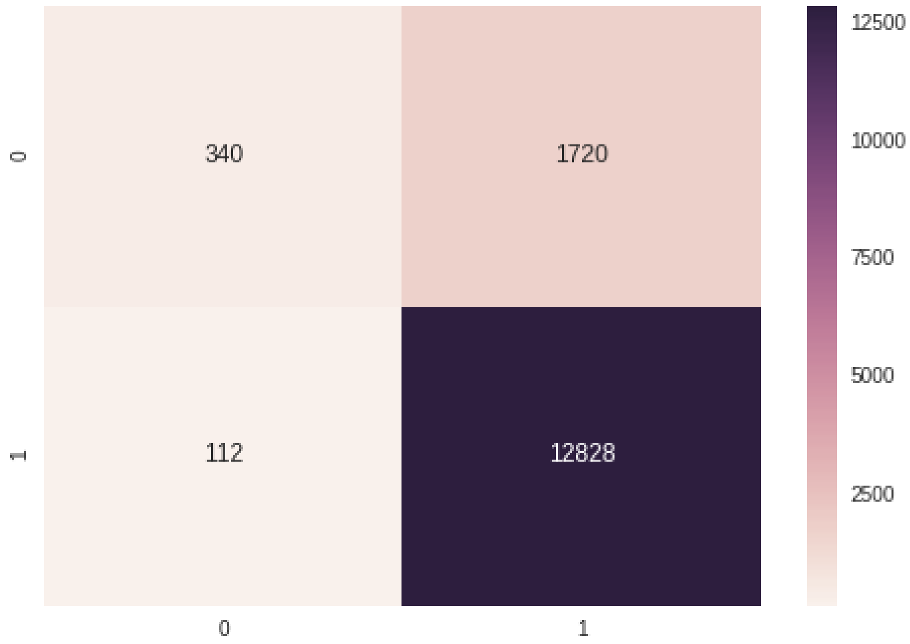
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd56eebfeb8>



In [0]:
```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Test_y,Classifier.predict(sent_vectors_test))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Test Data
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd56edc5da0>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=49 on Test Dataset is 13168(87.78%).
2. The Area Under Curve value for Test Dataset is 0.87920(approx) .
3. The brute-force method takes little less time for computation.
4. The Area Under Curve value is very high with respect to other methods.

3.2 K-D TREE METHOD

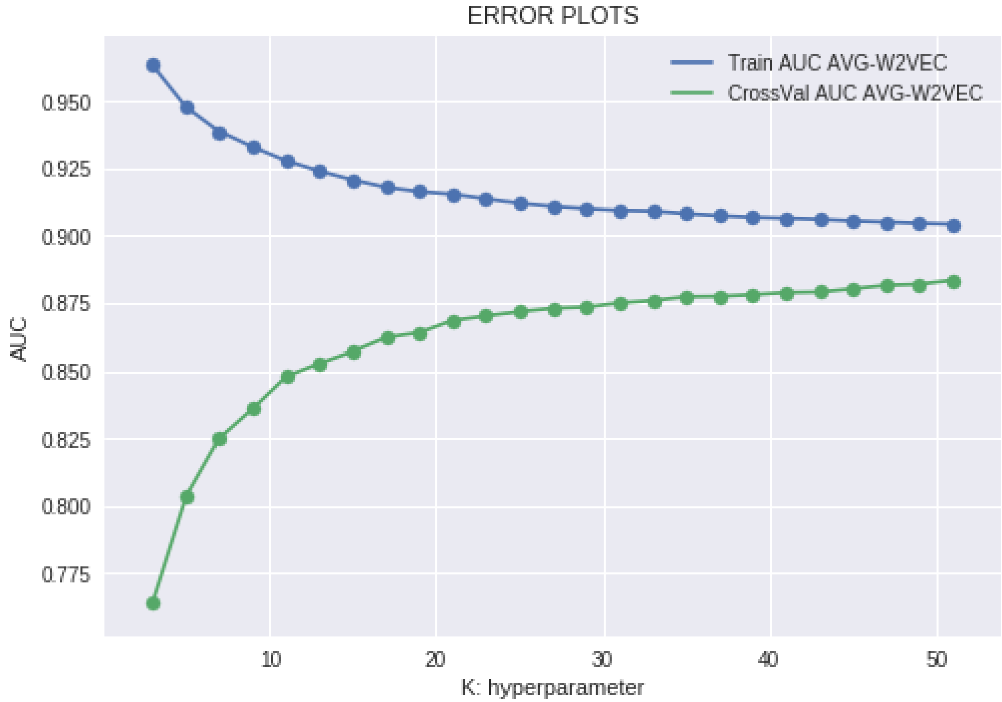
Hyperparameter(K) tuning .

In [0]:
```
Mylist=list(range(3,52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_W2VEC = []
CrossVal_AUC_W2VEC = []
```

```
for i in neighbour:
  print(i)
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')
  neigh.fit(sent_vectors_train, Train_y)
  Train_y_pred =  neigh.predict_proba(sent_vectors_train)[:,1]
  Train_AUC_W2VEC.append(roc_auc_score(Train_y,Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(sent_vectors_cv)[:,1]
  CrossVal_AUC_W2VEC.append(roc_auc_score(CrossVal_y,CrossVal_y_pred))
```

In [0]:

```
plt.plot(neighbour, Train_AUC_W2VEC, label='Train AUC AVG-W2VEC')
plt.scatter(neighbour, Train_AUC_W2VEC)
plt.plot(neighbour, CrossVal_AUC_W2VEC, label='CrossVal AUC AVG-W2VEC')
plt.scatter(neighbour, CrossVal_AUC_W2VEC)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [0]:
```
optimal_k=neighbour[CrossVal_AUC_W2VEC.index(max(CrossVal_AUC_W2VEC))]
print(optimal_k)
```

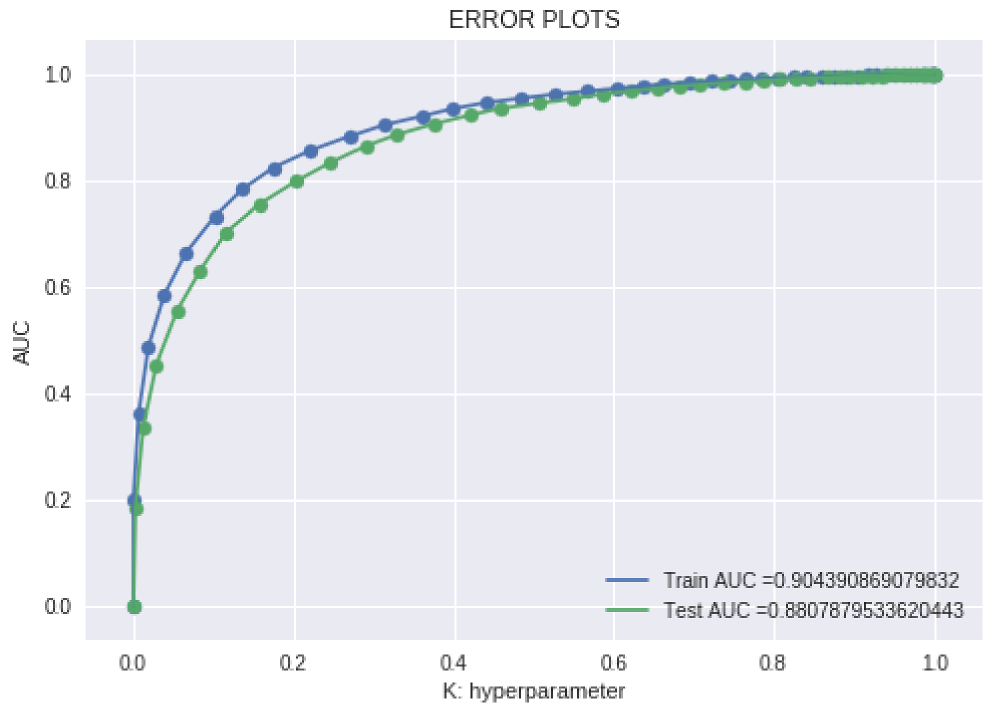
51

The optimal value of 'K' obtained is 51.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='kd_t
ree')
Classifier.fit(sent_vectors_train, Train_y)
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y, Classifier.predic
t_proba(sent_vectors_train)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Test_y, Classifier.predict_p
roba(sent_vectors_test)[:,1])
```

In [0]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
```

```
rain_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```

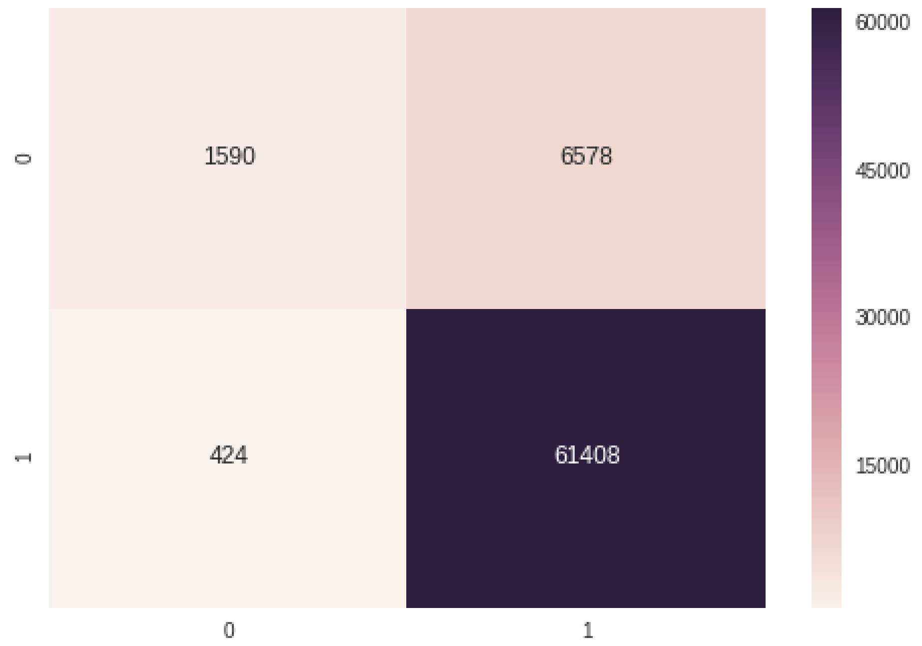


In [0]:

```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y,Classifier.predict(sent_vectors_trai
n))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [
i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

Confusion Matrix of Train Data

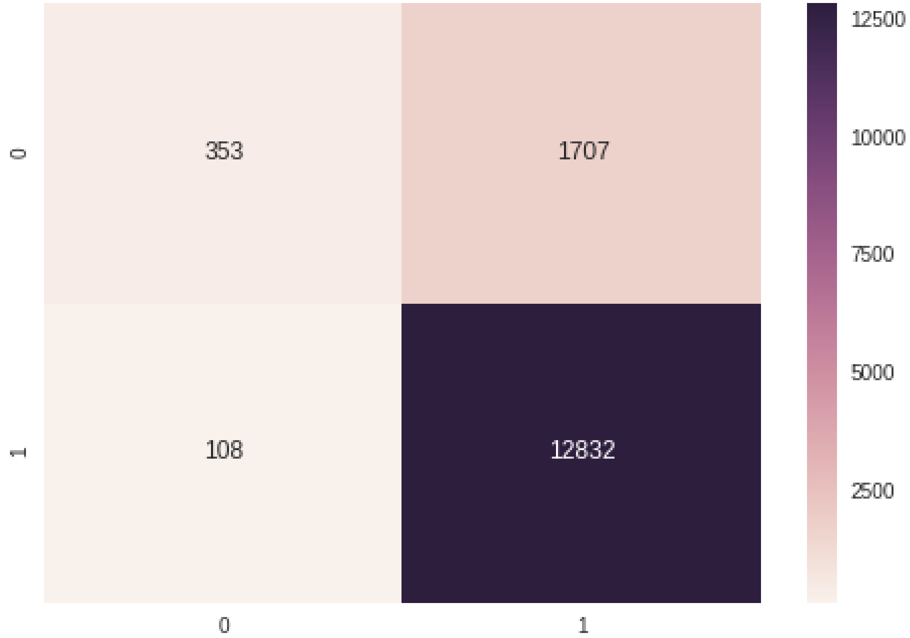
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4efe09fe48>



In [0]:
```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Test_y,Classifier.predict(sent_vectors_test))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

Confusion Matrix of Test Data

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4efde128d0>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=51 on Test Dataset is 13185(87.9%) which is same as brute force method .
2. The Area Under Curve value for Test Dataset is 0.88078(approx) .
3. The kd-tree method takes more time for computation.
4. The Area Under Curve value is high with respect to other methods.

4. TFIDF AVERAGE W2VEC.

Computing tfidf average word2vec for each review of Train dataset.

In [0]:
```
tfidf_feat = tf_idf.get_feature_names()
AVG_TFIDF = []
row=0;
for sent in tqdm(list_of_sentance_train):
```

```
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if((word in w2v_words)&(word in tfidf_feat)):
            vec = w2v_model.wv[word]
            TF_IDF = Train_TFIDF[row , tfidf_feat.index(word)]
            sent_vec += (vec * TF_IDF)
            weight_sum += TF_IDF
    if weight_sum != 0:
        sent_vec /= weight_sum
    AVG_TFIDF.append(sent_vec)
    row+=1;
```

```
100%|██████████| 70000/70000 [56:04<00:00, 20.81it/s]
```

Computing tfidf average word2vec for each review of CrossValidate Data .

In [0]:

```
i=0
list_of_sentance_cv=[]
for sentance in CrossVal_x:
    list_of_sentance_cv.append(sentance.split())
```

In [14]:

```
tfidf_feat = tf_idf.get_feature_names()
AVG_TFIDF_cv = []
row=0;
for sent in tqdm(list_of_sentance_cv):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if((word in w2v_words)&(word in tfidf_feat)):
            vec = w2v_model.wv[word]
            TF_IDF = Train_TFIDF[row , tfidf_feat.index(word)]
            sent_vec += (vec * TF_IDF)
            weight_sum += TF_IDF
    if weight_sum != 0:
        sent_vec /= weight_sum
```

```
    AVG_TFIDF_cv.append(sent_vec)
    row+=1;
```

```
100%|██████████| 15000/15000 [11:47<00:00, 13.16it/s]
```

Computing tfidf average word2vec for each review of Test Data .

In [0]:

```
i=0
list_of_sentance_test=[]
for sentance in Test_x:
    list_of_sentance_test.append(sentance.split())
```

In [16]:

```
tfidf_feat = tf_idf.get_feature_names()
AVG_TFIDF_test = []
row=0;
for sent in tqdm(list_of_sentance_test):
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if((word in w2v_words)&(word in tfidf_feat)):
            vec = w2v_model.wv[word]
            TF_IDF = Train_TFIDF[row , tfidf_feat.index(word)]
            sent_vec += (vec * TF_IDF)
            weight_sum += TF_IDF
    if weight_sum != 0:
        sent_vec /= weight_sum
    AVG_TFIDF_test.append(sent_vec)
    row+=1;
```

```
100%|██████████| 15000/15000 [11:52<00:00, 21.06it/s]
```

4.1 BRUTE-FORCE METHOD

Hyperparameter(K) tuning .

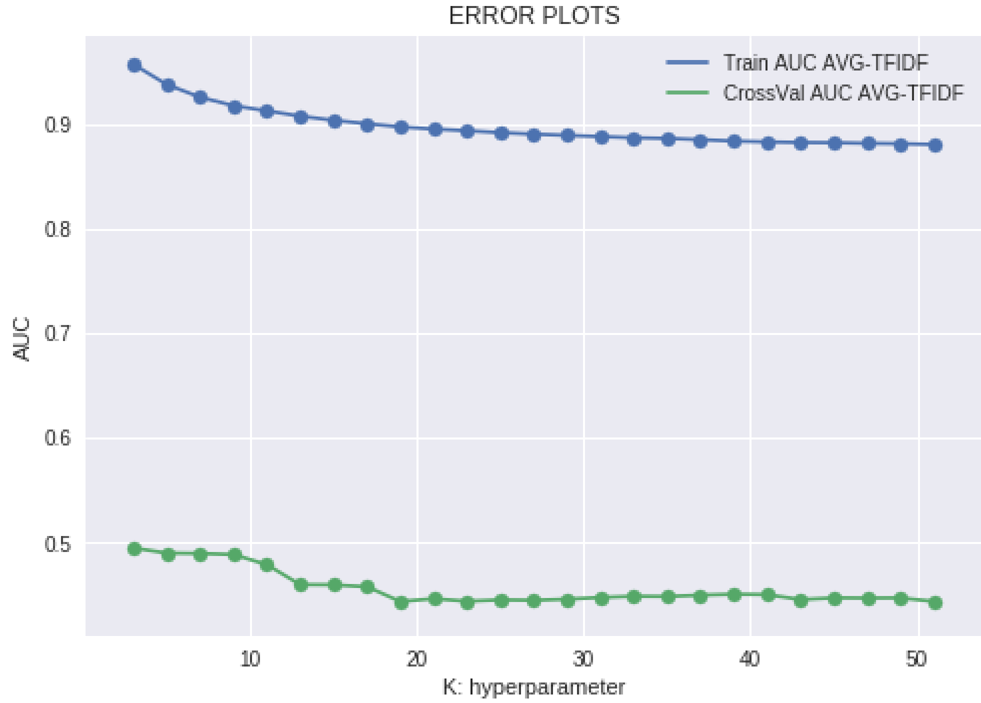
In [0]:

```
Mylist=list(range(3,52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
```

```
Train_AUC_AVGTFIDF = []
CrossVal_AUC_AVGTFIDF = []
for i in neighbour:
  print(i)
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='brute')
  neigh.fit(AVG_TFIDF, Train_y)
  Train_y_pred =  neigh.predict_proba(AVG_TFIDF)[:,1]
  Train_AUC_AVGTFIDF.append(roc_auc_score(Train_y,Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(AVG_TFIDF_cv)[:,1]
  CrossVal_AUC_AVGTFIDF.append(roc_auc_score(CrossVal_y,CrossVal_y_pred
))
```

In [18]:

```
plt.plot(neighbour, Train_AUC_AVGTFIDF, label='Train AUC AVG-TFIDF')
plt.scatter(neighbour, Train_AUC_AVGTFIDF)
plt.plot(neighbour, CrossVal_AUC_AVGTFIDF, label='CrossVal AUC AVG-TFID
F')
plt.scatter(neighbour, CrossVal_AUC_AVGTFIDF)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



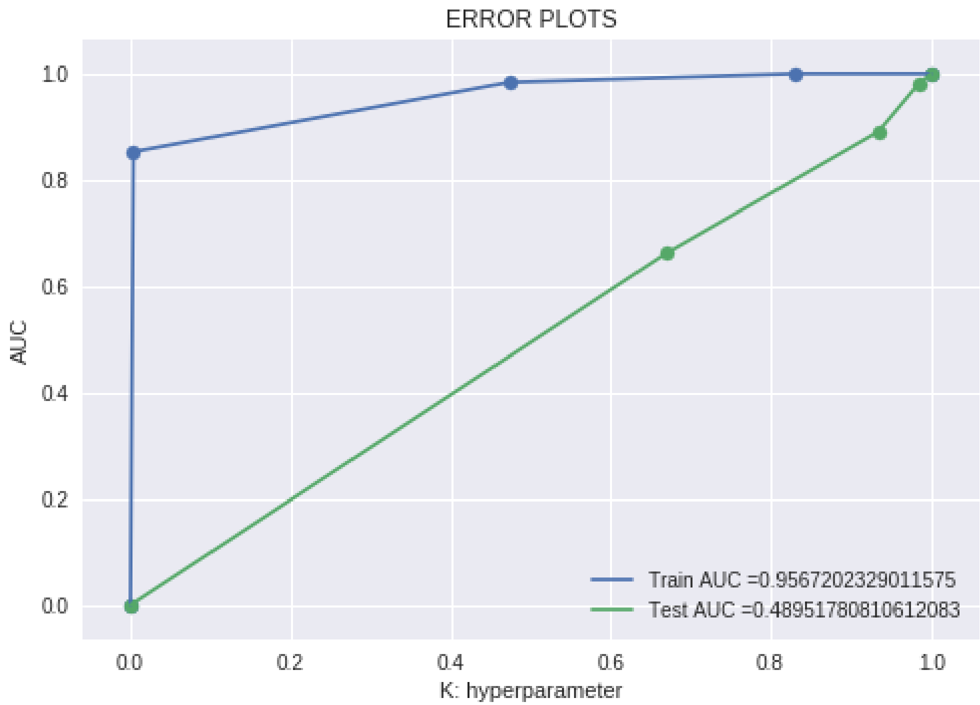
In [19]:
```
optimal_k=neighbour[CrossVal_AUC_AVGTFIDF.index(max(CrossVal_AUC_AVGTFI
DF))]
print(optimal_k)
```

3

The optimal value of 'K' obtained is 3.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='brut
e')
Classifier.fit(AVG_TFIDF, Train_y)
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y, Classifier.predic
t_proba(AVG_TFIDF)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Test_y, Classifier.predict_p
roba(AVG_TFIDF_test)[:,1])
```

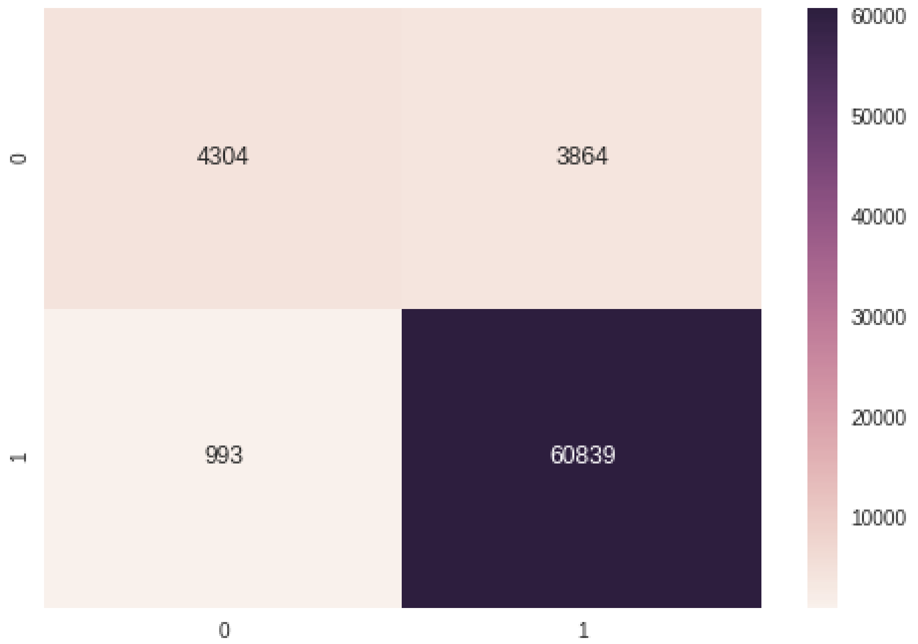
In [22]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, T
rain_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_
TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [23]:
```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y,Classifier.predict(AVG_TFIDF))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [
i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

Confusion Matrix of Train Data

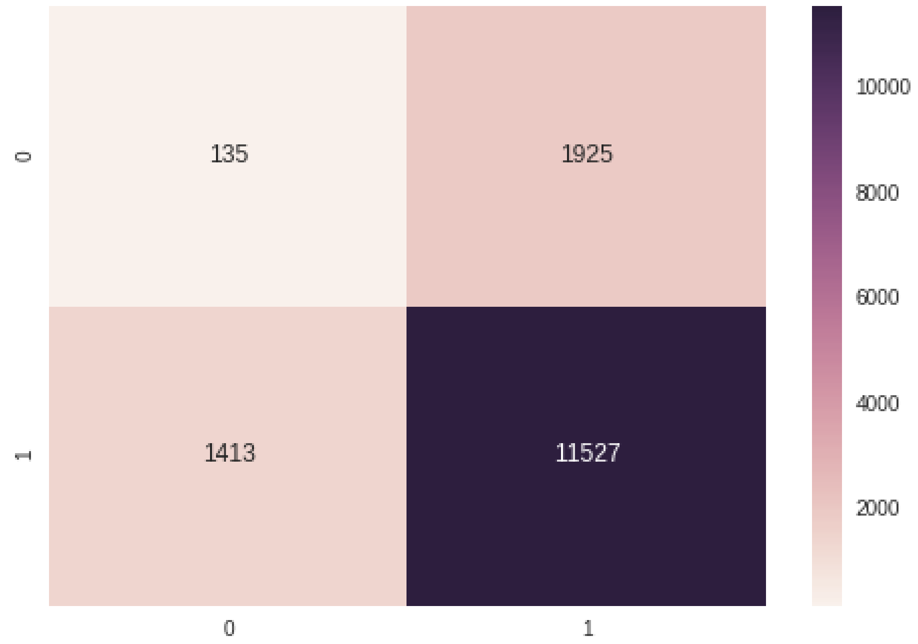
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6b21344198>



In [24]:
```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Test_y,Classifier.predict(AVG_TFIDF_test))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

Confusion Matrix of Test Data

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6b1a110c18>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=3 on Test Dataset is 11662(77.74%).
2. The Area Under Curve value for Test Dataset is 0.48951(approx) .
3. The brute-force method takes little less time for computation.
4. The Area Under Curve value is very low with respect to other methods.

4.2 K-D TREE METHOD

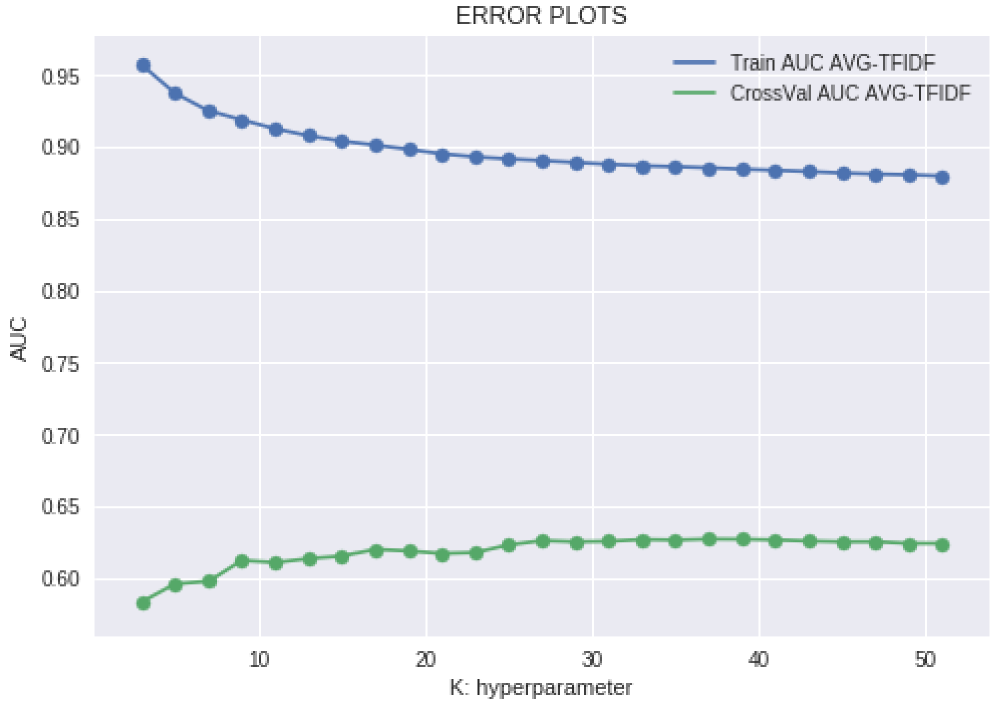
Hyperparameter(K) tuning .

In [0]:
```
Mylist=list(range(3,52))
neighbour=list(filter(lambda x: x%2 != 0 , Mylist))
Train_AUC_AVGTFIDF = []
CrossVal_AUC_AVGTFIDF = []
```

```
for i in neighbour:
  print(i)
  neigh = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')
  neigh.fit(AVG_TFIDF, Train_y)
  Train_y_pred =  neigh.predict_proba(AVG_TFIDF)[:,1]
  Train_AUC_AVGTFIDF.append(roc_auc_score(Train_y,Train_y_pred))
  CrossVal_y_pred =  neigh.predict_proba(AVG_TFIDF_cv)[:,1]
  CrossVal_AUC_AVGTFIDF.append(roc_auc_score(CrossVal_y,CrossVal_y_pred
))
```

In [0]:

```
plt.plot(neighbour, Train_AUC_AVGTFIDF, label='Train AUC AVG-TFIDF')
plt.scatter(neighbour, Train_AUC_AVGTFIDF)
plt.plot(neighbour, CrossVal_AUC_AVGTFIDF, label='CrossVal AUC AVG-TFID
F')
plt.scatter(neighbour, CrossVal_AUC_AVGTFIDF)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



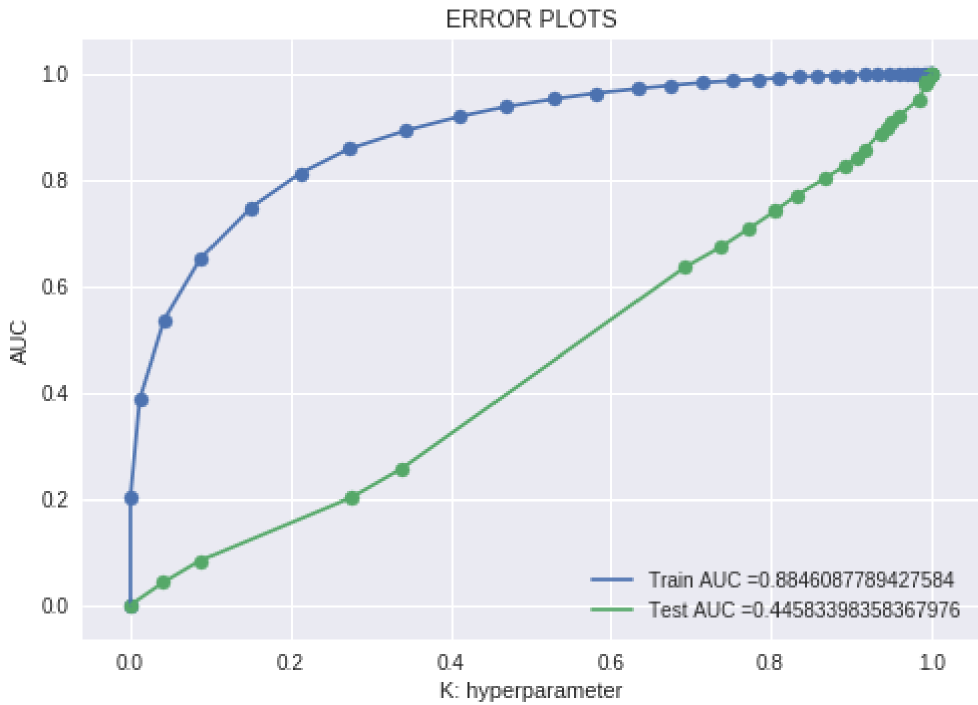
In [0]:
```
optimal_k=neighbour[CrossVal_AUC_AVGTFIDF.index(max(CrossVal_AUC_AVGTFI
DF))]
print(optimal_k)
```

37

The optimal value of 'K' obtained is 37.

In [0]:
```
Classifier = KNeighborsClassifier(n_neighbors=optimal_k,algorithm='kd_t
ree')
Classifier.fit(AVG_TFIDF, Train_y)
Train_FPR, Train_TPR, Thresholds = roc_curve(Train_y, Classifier.predic
t_proba(AVG_TFIDF)[:,1])
Test_FPR, Test_TPR, Thresholds = roc_curve(Test_y, Classifier.predict_p
roba(AVG_TFIDF_test)[:,1])
```

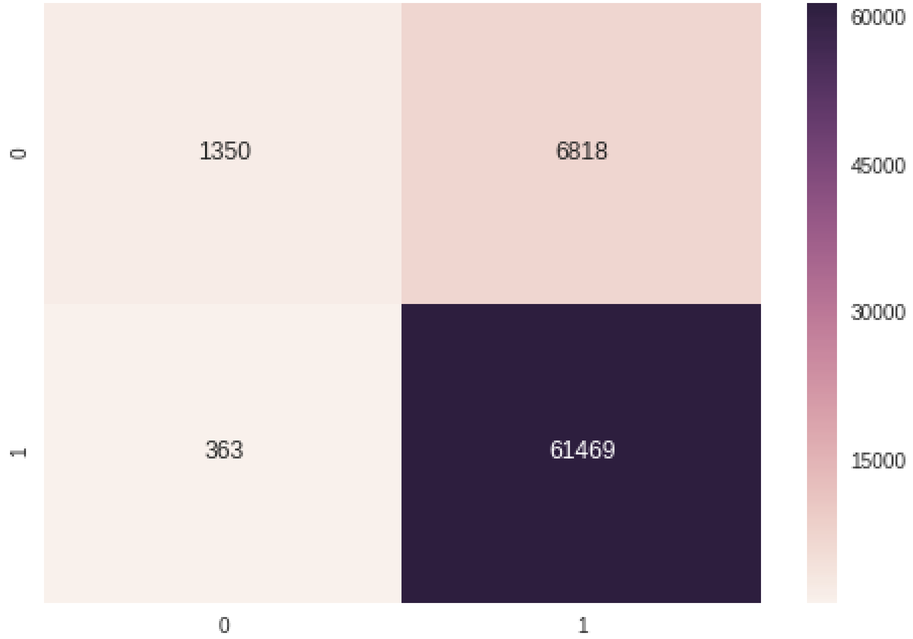
In [30]:
```
plt.plot(Train_FPR, Train_TPR, label="Train AUC ="+str(auc(Train_FPR, Train_TPR)))
plt.scatter(Train_FPR, Train_TPR)
plt.plot(Test_FPR, Test_TPR, label="Test AUC ="+str(auc(Test_FPR, Test_TPR)))
plt.scatter(Test_FPR, Test_TPR)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



In [31]:
```
print('Confusion Matrix of Train Data')
Train_mat=confusion_matrix(Train_y,Classifier.predict(AVG_TFIDF))
Train_cm = pd.DataFrame(Train_mat,index = [i for i in "01"],columns = [i for i in "01"])
sn.heatmap(Train_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Train Data
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6b19d58550>

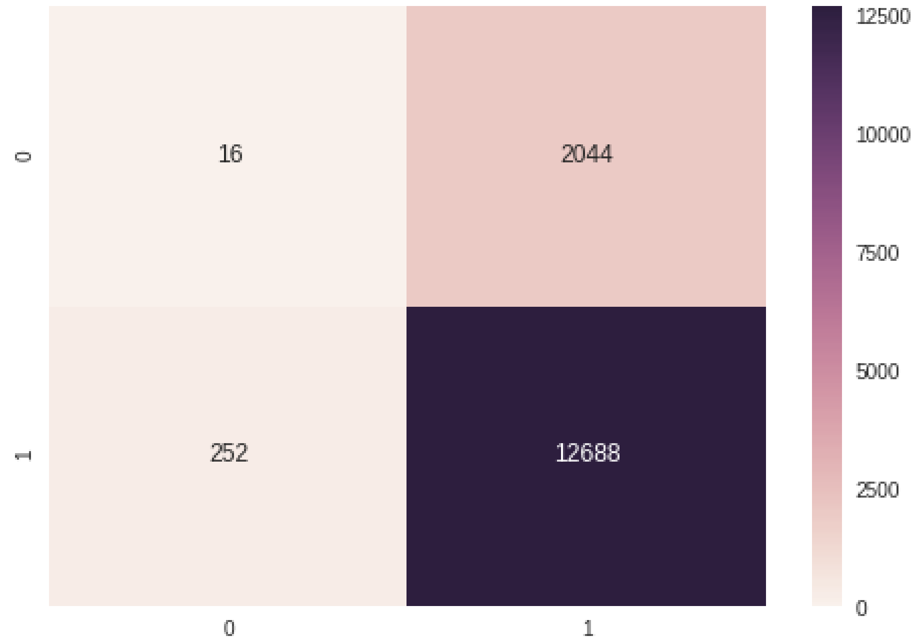


In [32]:

```
print('Confusion Matrix of Test Data')
Test_mat=confusion_matrix(Test_y,Classifier.predict(AVG_TFIDF_test))
Test_cm = pd.DataFrame(Test_mat,index = [i for i in "01"],columns = [i
for i in "01"])
sn.heatmap(Test_cm, annot=True,fmt="d")
```

```
Confusion Matrix of Test Data
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6b19ccecc0>



OBSERVATION.

1. The correct prediction (TP+TN) of our model with K=37 on Test Dataset is 12704(84.69%) .
2. The Area Under Curve value for Test Dataset is 0.44583(approx) .
3. The kd-tree method takes more time for computation.
4. The Area Under Curve value is lowest with respect to other methods.

FINAL TABLE

In [35]:
```
x = PrettyTable()

x.field_names = ["VECTORIZER", "MODEL", "HYPER PARAMETER", "AREA UNDER
 CURVE"]

x.add_row(["BOW","BRUTE",15,0.71573])
```

```
x.add_row(["BOW","KD-TREE",33,0.71964])
x.add_row(["TFIDF","BRUTE",3,0.50891])
x.add_row(["TFIDF","KD-TREE",45,0.70534])
x.add_row(["AVG-W2VEC","BRUTE",49,0.87921])
x.add_row(["AVG-W2VEC","KD-TREE",51,0.88078])
x.add_row(["TFIDF-AVG W2VEC","BRUTE",3,0.48951])
x.add_row(["TFIDF-AVG W2VEC","KD-TREE",37,0.44583])
print(x)
```

```
+-----------------+---------+------------------+-------------------+
|    VECTORIZER   |  MODEL  | HYPER PARAMETER  | AREA UNDER CURVE  |
+-----------------+---------+------------------+-------------------+
|       BOW       |  BRUTE  |        15        |      0.71573      |
|       BOW       | KD-TREE |        33        |      0.71964      |
|      TFIDF      |  BRUTE  |        3         |      0.50891      |
|      TFIDF      | KD-TREE |        45        |      0.70534      |
|    AVG-W2VEC    |  BRUTE  |        49        |      0.87921      |
|    AVG-W2VEC    | KD-TREE |        51        |      0.88078      |
| TFIDF-AVG W2VEC |  BRUTE  |        3         |      0.48951      |
| TFIDF-AVG W2VEC | KD-TREE |        37        |      0.44583      |
+-----------------+---------+------------------+-------------------+
```

POINTS

- AVG-W2VEC KD-TREE model is the best model with AUC value 0.88
- TFIDF-AVG W2VEC KD-TREE model has the lowest value of AUC(0.44583) among all the models.

...END.........