Information about data:

```
                    ->We have the amazon reviews dataset from kaggle

                    ->Reviews are given for the product

                    ->The features of the data were:

                          Id

                          ProductId- unique identifier for the product

                          UserId- unqiue identifier for the user

                          ProfileName

                          HelpfullnessNumerator- number of users who fou
nd the review helpful

                          HelpfulnessDenominator- number of users who in
dicated whether they
                          found the reiew helpful or not

                          Score-rating between 1 and 5

                          Time-timestamp for the review

                          Summary- brief summary of the review

                          Text- text of the review

                    -> Based on the score of the review we review we cla
ssify them into positive
                       and negative

                    Number of reviews: 568,454
```

Objective:

```
-> Classification of test and train data should be based on time

-> Applying NAIVE BAYES model on the amazon food review dataset

-> Finding the Laplace Smoothing parameter(alpha) by performing cros
s validation

-> Important features for the class labels in the dataset
```

```
-> Performance measure using:

                    -> Accuracy

                    -> Precision

                    -> Recall

                    -> F-1 Score

                    -> Confusion Matrix :

                                   -> TPR

                                   -> TNR

                                   -> FPR

                                   -> FNR
```

Importing the required libraries

In [1]:

```
import sqlite3
import numpy as np
import pandas as pd
import matplotlib.pyplot as mp
from sklearn.feature_extraction.text import
TfidfTransformer,TfidfVectorizer,CountVectorizer
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precis
ion_score,recall_score
```

Using the sqlite3 to load data

In [2]:

```
con = sqlite3.connect("database.sqlite")
```

Filtering the reviews with positive and negative based on the score

In [3]:

```

filtereddata = pd.read_sql_query("SELECT * FROM Reviews WHERE Score !=3",co
n)
```

Information about the data:

```
->The shape of data

->dimensionality of data
```

->Number of features

->Sample data

In [4]:

```
print(filtereddata.shape)
print(filtereddata.ndim)
print(filtereddata.columns)
print(filtereddata.head(5))
```

```
(525814, 10)
2
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      5  1303862400
1                     0                       0      1  1346976000
2                     1                       1      4  1219017600
3                     3                       3      2  1307923200
4                     0                       0      5  1350777600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...

1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...

3         Cough Medicine  If you are looking for the secret ingredient i...

4            Great taffy  Great taffy at a great price.  There was a wid...
```

->function to classify reviews into positive and negative based on rating.

->Here we are considering that reviews with a rating more than 3 are as positive and reviews with rating

->less than 3 as negative. So considering 3 as the neutral rating, so neglecting the reviews which are given

with rating of 3

In [5]:

```
def classify(x):
    if x>3:
```

```
        return 'positive'
    return 'negative'

rating = filtereddata['Score']
rating = rating.map(classify)
filtereddata['Score'] = rating
```

In [6]:

```
print(filtereddata.head(5))
```

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

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  positive  1303862400   
1                     0                       0  negative  1346976000   
2                     1                       1  positive  1219017600   
3                     3                       3  negative  1307923200   
4                     0                       0  positive  1350777600   

                 Summary                                               Text  
0  Good Quality Dog Food  I have bought several of the Vitality canned d...  

1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...  
2  "Delight" says it all  This is a confection that has been around a fe...  

3         Cough Medicine  If you are looking for the secret ingredient i...  

4            Great taffy  Great taffy at a great price.  There was a wid...  
```

Exploratory data analysis

Deduplication:removing duplicates

In [7]:

```
dup = pd.read_sql_query("""SELECT * FROM REVIEWS WHERE Score !=3 AND UserId
="AR5J8UI46CURR" ORDER BY ProductId """,con)
dup
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
				Geetha		

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
1	138317	B000HDOPYC	AR5J8UI46CURR	Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

->It shows that same user have 5 reviews at the same time which is not possible

->This is because if we review on product it is applied to different flavors in the product

->In order to remove the product we have to sort them and drop the duplicates

In [8]:

```
sorteddata = filtereddata.sort_values("ProductId",axis=0,ascending=True,inp
lace=False,kind='quicksort',na_position='last')
```

In [9]:

```
finaldata = sorteddata.drop_duplicates(subset=('Time','Text','ProfileName',
'UserId'),keep='first',inplace=False)
```

In [10]:

```
finaldata.shape
```

Out[10]:

```
(364173, 10)
```

->One more observation is that for a product the useful review(helpfullnessnumerator) is greater that the Total number of reviews on the product(helpfullnessdenominator) which is not possible

In [11]:

```
numden = pd.read_sql_query("""SELECT * FROM Reviews WHERE Score !=3 AND Id=
44737 OR Id = 64422 ORDER BY ProductId""",con)
```

In [12]:

```
numden
```

```
finaldata
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [13]:

```
finaldata = finaldata[finaldata.HelpfulnessNumerator<=finaldata.Helpfulness
Denominator]
finaldata
```

Out[13]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1
138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg "(Kate)"	1
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138693	150511	0006641040	A1C9K534BCI9GO	Laura Purdie Salas	0
138694	150512	0006641040	A1DJXZA5V5FFVA	A. Conway	0
138695	150513	0006641040	ASH0DZQQF6AIZ	tessarat	0
138696	150514	0006641040	A2ONB6ZA292PA	Rosalind Matzner	0
138697	150515	0006641040	A2RTT81R6Y3R7X	Lindylu	0
138687	150505	0006641040	A2PTSM496CF40Z	Jason A. Teeple "Nobody made a greater mistak...	1
138698	150516	0006641040	A3OI7ZGH6WZJ5G	Mary Jane Rogers "Maedchen"	0
138700	150518	0006641040	AK1L4EJBA23JF	L. M. Kraus	0
138701	150519	0006641040	A12HY5OZ2QNK4N	Elizabeth H. Roessner	0
138702	150520	0006641040	ADBFSA9KTQANE	James L. Hammock "Pucks Buddy"	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138703	150521	0006641040	A3RMCRB2NDTDYP	Carol Carruthers	0
138704	150522	0006641040	A1S3C5OFU508P3	Charles Ashbacher	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11
138709	150529	0006641040	A25ACLV5KPB4W	Matt Hetling "Matt"	0
138699	150517	0006641040	ABW4IC5G5G8B5	kevin clark	0
138686	150504	0006641040	AQEYF1AXARWJZ	Les Sinclair "book maven"	1
138692	150510	0006641040	AM1MNZMYMS7D8	Dr. Joshua Grossman	0
138680	150498	0006641040	A3SJWISOCP31TR	R. J. Wells	2

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
138677	150494	0006641040	AYZ0PR5QZROD1	Mother of 3 girls	3
138678	150496	0006641040	A3KKR87BJ0C595	Gretchen Goodfellow "Lover of children's lit"	3
138685	150503	0006641040	A3R5XMPFU8YZ4D	Her Royal Motherliness "Nana"	1
138684	150502	0006641040	AVFMJ50HNO21J	Jane Doe	1
138679	150497	0006641040	A1HKYQOFC8ZZCH	Maria Apolloni "lanarossa"	2
...	...	...	...	...	...
35419	38512	B009O7B1I0	A2YWHBF45M64S2	EcyMom	0
195185	211594	B009O7DGEW	A2UAKIEWZLQCUE	Cindy S.	0
494393	534495	B009OY38SY	A1H1OCLG2B4AEQ	base64	0
134853	146374	B009P4KMZA	A217L3D5UK74I6	george karlin	0
430102	465120	B009PCDDO4	A2II09GQGWOMTQ	Brian Nallick "METALMANMN"	1

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
264734	286941	B009PFJUF2	A2UAKIEWZLQCUE	Cindy S.	1
264735	286942	B009PFJUF2	A16HJRHRHNSUZ6	Danielle Tietz	1
241028	261429	B009PG8MVO	A2UAKIEWZLQCUE	Cindy S.	0
269822	292509	B009PIAFTE	A00489763J7YUCSN6CP7K	Andrea Llyod	0
343072	371148	B009PICJTS	A09229701Z8W88AD38877	Kristi Greene	0
427660	462501	B009PIEW3O	A0849196AFU725N8S7RS	Brady Gibson	0
184728	200383	B009RE0Y5G	A3M2YJ76LOMNBK	turbo418	0
178140	193169	B009RSR8HO	A3M3S2NCVZ8UXF	Stephanie	0
178139	193168	B009RSR8HO	A1L130V9KINC45	mildred rosa	0
178138	193167	B009RSR8HO	A5F9OUO3F2N7C	Jan	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
178135	193164	B009RSR8HO	A2IZG2VYD476QH	CSTreviso	1
178136	193165	B009RSR8HO	A1I08MP3H92U6R	Thomas	1
178134	193163	B009RSR8HO	A1QX7TAALGCUKM	H.B. "H.B."	2
178137	193166	B009RSR8HO	AD0V42PRKCDBM	Rachelle	0
178142	193171	B009RSR8HO	AH2FVNP7Z6PZH	Marty Campbell	0
178141	193170	B009RSR8HO	A1TNEJA68OD7ZH	morgan	0
178143	193172	B009RSR8HO	A3JJTHP8T7A8LY	Joanne Eklund "Joanne"	0
178147	193176	B009RSR8HO	A76WHW051R3KV	Shawn "Shawn"	0
178146	193175	B009RSR8HO	A1A0PMN417S4V9	mamaelle "mamaelle"	0
178144	193173	B009RSR8HO	A34TVEXPHSSPBV	Beth	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNum
178145	193174	B009RSR8HO	A4P6AN2L435PV	romano	0
173675	188389	B009SF0TN6	A1L0GWGRK4BYPT	Bety Robinson	0
204727	221795	B009SR4OQ2	A32A6X5KCP7ARG	sicamar	1
5259	5703	B009WSNWC4	AMP7K1O84DH1T	ESTY	0
302474	327601	B009WVB40S	A3ME78KVX31T21	K'la	0

364171 rows × 10 columns

In [14]:

```
print(finaldata.shape)
print(finaldata.head(5))
```

```
(364171, 10)
            Id   ProductId          UserId                      ProfileName  \
138706  150524  0006641040   ACITT7DI6IDDL                  shari zychinski
138688  150506  0006641040  A2IW4PEEKO2R0U                            Tracy
138689  150507  0006641040  A1S4A3IQ2MU7V4            sally sue "sally sue"
138690  150508  0006641040   AZGXZ2UUK6X  Catherine Hallberg "(Kate)"
138691  150509  0006641040  A3CMRKGE0P909G                           Teresa

        HelpfulnessNumerator  HelpfulnessDenominator     Score        Time
\
138706                     0                       0  positive   939340800
138688                     1                       1  positive  1194739200
138689                     1                       1  positive  1191456000
138690                     1                       1  positive  1076025600
138691                     3                       4  positive  1018396800

                                          Summary  \
138706                       EVERY book is educational
138688  Love the book, miss the hard cover version
138689                 chicken soup with rice months
138690        a good swingy rhythm for reading aloud
138691                    A great way to learn the months

                                                             Text
```

```
138706  this witty little book makes my son laugh at l...
138688  I grew up reading these Sendak books, and watc...
138689  This is a fun way for children to learn their ...
138690  This is a great little book to read aloud- it ...
138691  This is a book of poetry about the months of t...
```

BAG OF WORDS:

    -> Applying BOW to convert the text to vectors

    -> Applying BERNOULI NAVIE BAYES to determine alpha value by using c
    ross validation

    -> Examining the accurancy measures

TIME BASED SPLITTING

In [15]:

```
count_vector_data = finaldata.sort_values("Time",axis=0,ascending=True,kind
='quicksort',na_position='last')
```

In [16]:

```
print(count_vector_data.shape)
print(count_vector_data.head(5))
```

```
(364171, 10)
            Id   ProductId          UserId              ProfileName  \
138706  150524  0006641040   ACITT7DI6IDDL          shari zychinski
138683  150501  0006641040   AJ46FKXOVC7NR       Nicholas A Mesiano
417839  451856  B00004CXX9   AIUWLEQ1ADEG5         Elizabeth Medina
346055  374359  B00004CI84  A344SMIA5JECGM          Vincent P. Ross
417838  451855  B00004CXX9   AJH6LUC1UT1ON  The Phantom of the Opera

        HelpfulnessNumerator  HelpfulnessDenominator     Score       Time  \
138706                     0                       0  positive  939340800
138683                     2                       2  positive  940809600
417839                     0                       0  positive  944092800
346055                     1                       2  positive  944438400
417838                     0                       0  positive  946857600

                                                  Summary  \
138706                          EVERY book is educational
138683  This whole series is great way to spend time w...
417839                               Entertainingl Funny!
346055                            A modern day fairy tale
417838                                         FANTASTIC!

                                                     Text
138706  this witty little book makes my son laugh at l...
138683  I can remember seeing the show when it aired o...
417839  Beetlejuice is a well written movie ..... ever...
346055  A twist of rumplestiskin captured on film, sta...
417838  Beetlejuice is an excellent and funny movie. K...
```

In [17]:

```
count_vect = CountVectorizer()
final_count = count_vect.fit_transform(count_vector_data['Text'].values)
```

In [18]:

```
print(type(final_count))
final_count.shape
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

Out[18]:

```
(364171, 115281)
```

In [19]:

```
a = count_vect.inverse_transform(final_count[9])
print(a)
print(final_count[9])
```

```
[array(['tks', 'tell', 'please', 'could', 'vhs', 'today', 'impossible',
       'really', 'video', 'french', 'beatlejuice', 'getting', 'looking',
       'find', 'crazy', 'version', 'not', 'film', 'for', 'something',
       'me', 'to', 'is', 'of', 'about', 'the', 'it', 'this'],
      dtype='<U124')]
  (0, 104497)	1
  (0, 102790)	1
  (0, 80806)	1
  (0, 32479)	1
  (0, 110031)	1
  (0, 104615)	1
  (0, 56957)	1
  (0, 85950)	1
  (0, 110118)	1
  (0, 47622)	2
  (0, 19534)	1
  (0, 49514)	1
  (0, 64959)	1
  (0, 45603)	1
  (0, 32984)	1
  (0, 109908)	2
  (0, 73670)	1
  (0, 45534)	1
  (0, 46897)	1
  (0, 96426)	1
  (0, 67842)	1
  (0, 104542)	1
  (0, 59142)	1
  (0, 74846)	1
  (0, 5150)	1
  (0, 103373)	1
  (0, 59284)	2
  (0, 103749)	1
```

In [20]:

```
score = count_vector_data['Score']
```

In [21]:

In [21]:

```
score.shape
```

Out[21]:

```
(364171,)
```

-> Splitting the data, 70 percent to training and 30 percent to testing

In [22]:

```
x_train = final_count[0:254919]
x_test = final_count[254919:]
y_train = score[0:254919]
y_test = score[254919:]
```

In [23]:

```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(254919, 115281)
(109252, 115281)
(254919,)
(109252,)
```

In [24]:

```
from sklearn.naive_bayes import BernoulliNB
```

In [25]:

```
lst  = list(np.arange(1,30,2))
print(lst)
```

```
[1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29]
```

In [26]:

```
from sklearn.cross_validation import cross_val_score
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\cross_validation.py:41: DeprecationWarning: This module wa
s deprecated in version 0.18 in favor of the model_selection module into wh
ich 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. T
his module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [27]:

```
cross_validation_score = []
for a in lst:
    clasifier = BernoulliNB(alpha=a)
    scores = cross_val_score(clasifier,x_train,y_train,cv=10,scoring='accur
acy')
    cross_validation_score.append(scores.mean())
```

In [28]:

```
cross_validation_score
```

Out[28]:

```
[0.8765921749991934,
 0.8662045645705694,
 0.8576802839678888,
 0.853243581020891б,
 0.8506702142093108,
 0.8497208946219365,
 0.8491834691159585,
 0.8492383898451885,
 0.8492423123367189,
 0.8492776156838302,
 0.8494109917836937,
 0.8496345919598985,
 0.8498032724841004,
 0.8499288022158968,
 0.8499876443594301]
```

In [29]:

```
error = [1 - x for x in cross_validation_score]
print(error)
```

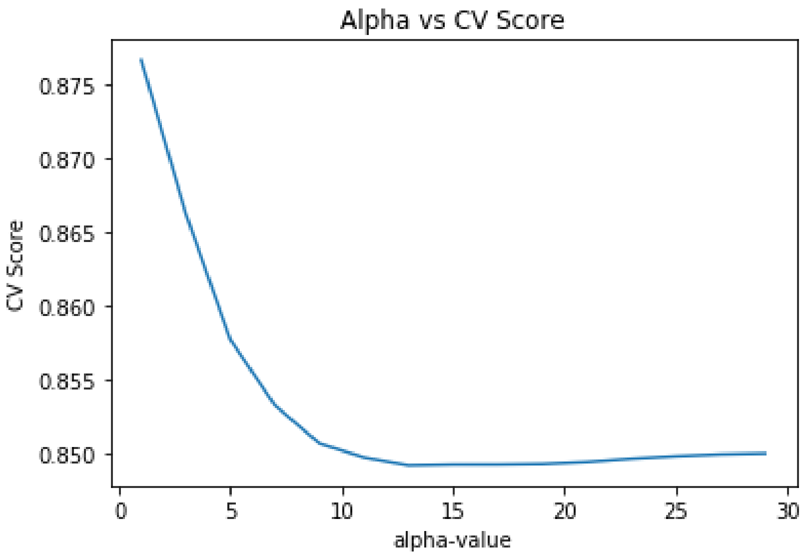
```
[0.1234078250008066, 0.13379543542943062, 0.14231971603211124,
0.1467564189791084, 0.14932978579068923, 0.15027910537806355,
0.15081653088404146, 0.150761610154811б, 0.15075768766328113,
0.1507223843161698, 0.15058900821630627, 0.15036540804010146,
0.15019672751589963, 0.15007119778410316, 0.15001235564056992]
```

In [30]:

```
mp.plot(lst,cross_validation_score)
mp.xlabel('alpha-value')
mp.ylabel("CV Score")
mp.title("Alpha vs CV Score")
```

Out[30]:

```
Text(0.5,1,'Alpha vs CV Score')
```

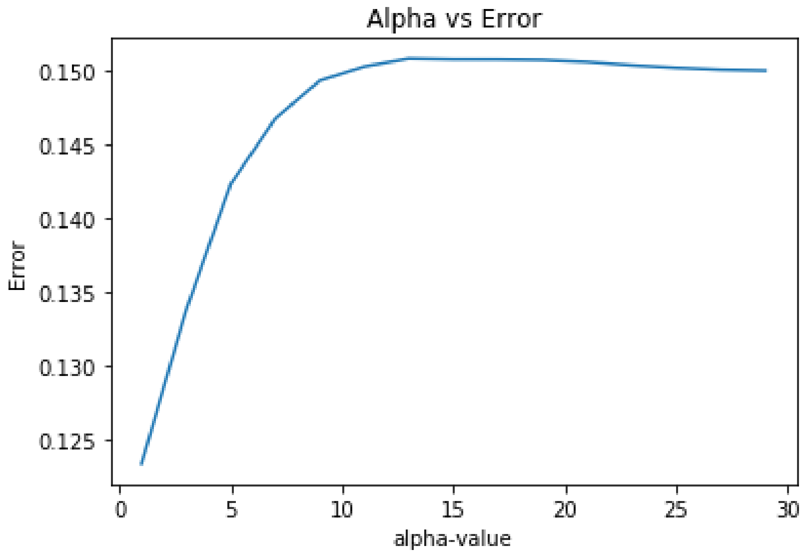


In [31]:

```
mp.plot(lst,error)
mp.xlabel('alpha-value')
mp.ylabel("Error")
mp.title("Alpha vs Error")
```

Out[31]:

```
Text(0.5,1,'Alpha vs Error')
```



In [32]:

```
best_a = lst[error.index(min(error))]
```

In [33]:

```
best_a
```

Out[33]:

```
1
```

Observation:

```
-> The highest accurancy and lowest error is occured when alpha = 1

-> Using alpha = 1 to design the classifier
```

In [34]:

```
bnb = BernoulliNB(alpha=1)
bnb.fit(x_train,y_train)
prdct = bnb.predict(x_test)
```

In [35]:

```
type(bnb)
```

Out[35]:

```
sklearn.naive_bayes.BernoulliNB
```

Calculating Performance measure using:

```
-> Accuracy

-> Precision

-> Recall

-> F-1 Score

-> Confusion Matrix :

        -> TPR

        -> TNR

        -> FPR

        -> FNR
```

ACCURACY SCORE

In [37]:

```
acc = accuracy_score(y_test,prdct)
print(acc)
```

```
0.8615494453190788
```

PRECISION SCORE:

```
        This is the ratio of true positives to sum of true
    positives and false positives
```

In [38]:

```
print(prdct.shape)
print(y_test.shape)
```

```
(109252,)
(109252,)
```

In [39]:

```
prcs = precision_score(y_test,prdct, average =
'binary',pos_label='positive')
```

In [40]:

```
prcs
```

Out[40]:

```
0.9138130686517784
```

RECALL SCORE:

```
This is the ratio of true positives to the sum of true positives and
flase negatives
```

In [41]:

```
rs = recall_score(y_test,prdct,average='binary',pos_label='positive')
```

In [42]:

```
rs
```

Out[42]:

```
0.9189207173037894
```

F-1 SCORE:

```
This is the weighted avergae of precision and recall scores
```

In [43]:

```
f_scr = f1_score(y_test,prdct,pos_label='positive')
```

In [44]:

```
f_scr
```

Out[44]:

```
0.916359775720779
```

CONFUSION-MATRIX:

```
This evaluates the accurancy of a classification
```

In [45]:

```
cm = confusion_matrix(y_test,prdct)
cm
```

Out[45]:

```
array([[11266,  7815],
       [ 7311, 82860]], dtype=int64)
```

In [46]:

```
cmr  = cm.ravel()
cmr
```

Out[46]:

```
array([11266,  7815,  7311, 82860], dtype=int64)
```

In [47]:

```
tn,fp,fn,tp = cmr
```

In [48]:

```
tn
```

Out[48]:

```
11266
```

In [49]:

```
tp
```

Out[49]:

```
82860
```

In [50]:

```
fp
```

Out[50]:

```
7815
```

In [51]:

```
fn
```

Out[51]:

```
7311
```

Note:

```
-> TRUE POSITIVE RATE IS THE RATIO OF TRUE POSITIVES TO TOTAL POSITI
VE

-> TRUE NEGATIVE RATE IS THE RATIO OF TRUE NEGATIVES TO TOTAL NEGATI
VE

-> FALSE POSITIVE RATE IS THE RATIO OF FALSE POSITIVES TO TOTAL POSI
TIVE

-> FALSE NEGATIVE RATE IS THE RATIO OF FALSE NEGATIVES TO TOTAL NEGA
TIVES
```

In [52]:

```
true_positive_rate = tp/(fn+tp)
true_negative_rate = tn/(tn+fp)
false_positive_rate = fp/(fn+tp)
false_negative_rate = fn/(tn+fp)
print("true positive rate is {}".format(true_positive_rate))
print("true_negative_rate is {}".format(true_negative_rate))
print("false positive rate is {}".format(false_positive_rate))
print("false_negative_rate is {}".format(false_negative_rate))
```

```
true positive rate is 0.9189207173037894
true_negative_rate is 0.5904302709501599
false positive rate is 0.08666866287387298
false negative rate is 0.3831560190765683
```

TFIDF:

```
-> Applying TFIDF to convert the text to vectors

-> Applying BERNOULI NAVIE BAYES to determine alpha value by using c
ross validation

-> Examining the accurancy measures
```

Time Based Splitting:

```
Sorting the data based on the time
```

In [53]:

```
tfidf_data = finaldata.sort_values("Time",axis=0,ascending=True,kind='quick
sort',na_position='last')
```

In [54]:

```
print(tfidf_data.shape)
print(tfidf_data.ndim)
print(tfidf_data.columns)
print(tfidf_data.head(5))
```

```
(364171, 10)
2
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
            Id   ProductId          UserId                 ProfileName  \
138706  150524  0006641040   ACITT7DI6IDDL             shari zychinski
138683  150501  0006641040   AJ46FKXOVC7NR          Nicholas A Mesiano
417839  451856  B00004CXX9   AIUWLEQ1ADEG5            Elizabeth Medina
346055  374359  B00004CI84  A344SMIA5JECGM             Vincent P. Ross
417838  451855  B00004CXX9   AJH6LUC1UT1ON  The Phantom of the Opera

        HelpfulnessNumerator  HelpfulnessDenominator     Score       Time  \
138706                     0                       0  positive  939340800
138683                     2                       2  positive  940809600
417839                     0                       0  positive  944092800
346055                     1                       2  positive  944438400
417838                     0                       0  positive  946857600

                                                  Summary  \
138706                          EVERY book is educational
138683  This whole series is great way to spend time w...
417839                              Entertainingl Funny!
346055                           A modern day fairy tale
417838                                        FANTASTIC!

                                                     Text
138706  this witty little book makes my son laugh at l...
138683  I can remember seeing the show when it aired o...
417839  Beetlejuice is a well written movie ..... ever...
```

```
346055  A twist of rumplestiskin captured on film, sta...
417838  Beetlejuice is an excellent and funny movie. K...
```

In [55]:

```
tfid = TfidfVectorizer(ngram_range=(1,2))
```

In [56]:

```
tfid_vect = tfid.fit_transform(tfidf_data['Text'].values)
```

In [57]:

```
print(tfid_vect.shape)
print(type(tfid_vect))
```

```
(364171, 2910192)
<class 'scipy.sparse.csr.csr_matrix'>
```

Splitting first 70 percent of data as training data and rest 30 percent data as test data set

In [58]:

```
x_train1 = tfid_vect[0:254919]
x_test1 = tfid_vect[254919:]
y_train1 = score[0:254919]
y_test1 = score[254919:]
```

In [59]:

```
print(x_train1.shape)
print(x_test1.shape)
print(y_train1.shape)
print(y_test1.shape)
```

```
(254919, 2910192)
(109252, 2910192)
(254919,)
(109252,)
```

In [60]:

```
from sklearn.cross_validation import cross_val_score
```

In [61]:

```
print(lst)
```

```
[1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29]
```

In [62]:

```
cross_validation_score = []
for a in lst:
    clasifier = BernoulliNB(alpha=a)
    scores = cross_val_score(clasifier,x_train1,y_train1,cv=10,scoring='acc
uracy')
    cross_validation_score.append(scores.mean())
```

In [63]:

```
cross_validation_score
```

Out[63]:

```
[0.8519765096110845,
 0.8479320913656231,
 0.8495600569263413,
 0.8502347813314926,
 0.850446612955879,
 0.8505407602931985,
 0.8506898271286316,
 0.8507055180180908,
 0.8507486689643858,
 0.8507604375162041,
 0.8507761288673322,
 0.8507839744659513,
 0.8507761288673322,
 0.8507957430177695,
 0.8508035886163888]
```

In [64]:

```
error = [1 - x for x in cross_validation_score]
```

In [65]:

```
error
```

Out[65]:

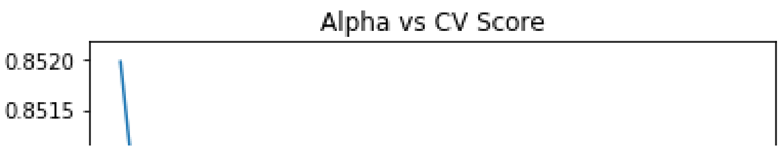
```
[0.1480234903889155,
 0.1520679086343769,
 0.1504399430736587,
 0.14976521866850745,
 0.14955338704412102,
 0.14945923970680153,
 0.14931017287136839,
 0.1492944819819092,
 0.14925133103561417,
 0.14923956248379588,
 0.14922387113266777,
 0.14921602553404867,
 0.14922387113266777,
 0.1492042569822305,
 0.14919641138361117]
```

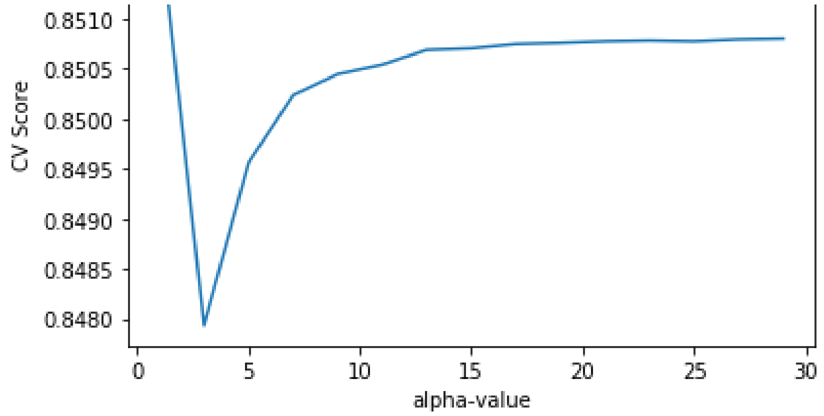
In [66]:

```
mp.plot(lst,cross_validation_score)
mp.xlabel('alpha-value')
mp.ylabel("CV Score")
mp.title("Alpha vs CV Score")
```

Out[66]:

```
Text(0.5,1,'Alpha vs CV Score')
```



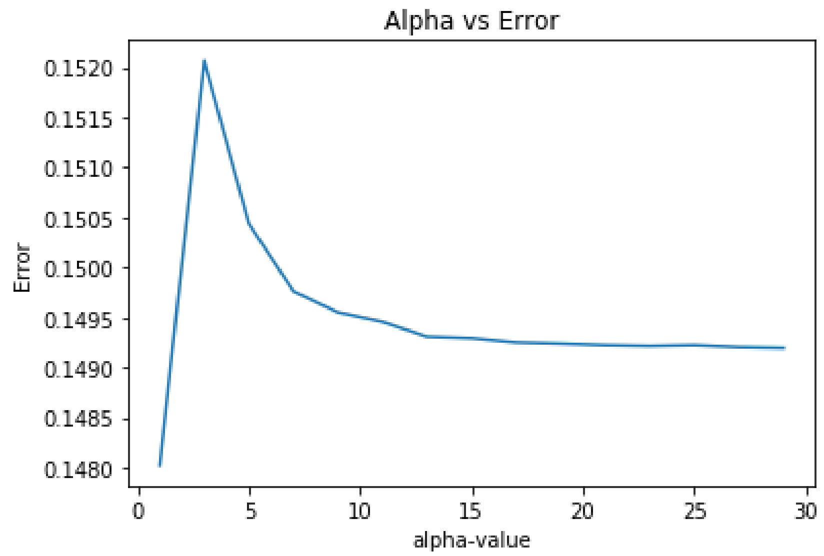


In [67]:

```
mp.plot(lst,error)
mp.xlabel('alpha-value')
mp.ylabel("Error")
mp.title("Alpha vs Error")
```

Out[67]:

```
Text(0.5,1,'Alpha vs Error')
```



In [68]:

```
best_a1 = lst[error.index(min(error))]
print(best_a1)
```

```
1
```

Observation:

    -> The highest accurancy and lowest error is occured when alpha = 1

    -> Using alpha = 1 to design the classifier

In [69]:

```
bernoulinb = BernoulliNB(alpha=1)
bernoulinb.fit(x_train1,y_train1)
prdct1 = bernoulinb.predict(x_test1)
```

Calculating Performance measure using:

```
-> Accuracy

-> Precision

-> Recall

-> F-1 Score

-> Confusion Matrix :

            -> TPR

            -> TNR

            -> FPR

            -> FNR
```

ACCURACY SCORE:

```
TELLS US HOW ACCURATE THE MODEL IS IN PREDICTING
```

In [70]:

```
acc1 = accuracy_score(y_test1,prdct1)
print(acc1)
```

```
0.8321403727162889
```

PRECISION SCORE:

```
     This is the ratio of true positives to sum of true positives an
d false positives
```

In [71]:

```
prcs1 = precision_score(y_test,prdct, average =
'binary',pos_label='positive')
print(prcs1)
```

```
0.9138130686517784
```

RECALL SCORE:

```
This is the ratio of true positives to the sum of true positives and
flase negatives
```

In [72]:

```
rs1 = recall_score(y_test1,prdct1,average='binary',pos_label='positive')
print(rs1)
```

```
0.9563163323019596
```

F-1 SCORE:

```
This is the weighted avergae of precision and recall scores
```

In [73]:

```
f_scr1 = f1_score(y_test1,prdct1,pos_label='positive')

print(f_scr1)
```

```
0.90388515903838
```

CONFUSION-MATRIX:

```
This evaluates the accurancy of a classification
```

In [74]:

```
cmr1 = confusion_matrix(y_test1,prdct1)
print(cmr1)
```

```
[[ 4681 14400]
 [ 3939 86232]]
```

In [75]:

```
tn1,fp1,fn1,tp1 = cmr1.ravel()
```

In [76]:

```
tp1
```

Out[76]:

```
86232
```

In [77]:

```
tn1
```

Out[77]:

```
4681
```

In [78]:

```
fp1
```

Out[78]:

```
14400
```

In [79]:

```
fn1
```

Out[79]:

```
3939
```

Note:

-> TRUE POSITIVE RATE IS THE RATIO OF TRUE POSITIVES TO TOTAL POSITIVE

-> TRUE NEGATIVE RATE IS THE RATIO OF TRUE NEGATIVES TO TOTAL NEGATIVE

-> FALSE POSITIVE RATE IS THE RATIO OF FALSE POSITIVES TO TOTAL POSITIVE

-> FALSE NEGATIVE RATE IS THE RATIO OF FALSE NEGATIVES TO TOTAL NEGATIVES

In [80]:

```
true_positive_rate1 = tp1/(fn1+tp1)

true_negative_rate1 = tn1/(tn1+fp1)

false_positive_rate1 = fp1/(fn1+tp1)

false_negative_rate1 = fn1/(tn1+fp1)

print("true positive rate is {}".format(true_positive_rate1))

print("true_negative_rate is {}".format(true_negative_rate1))

print("false positive rate is {}".format(false_positive_rate1))

print("false_negative_rate is {}".format(false_negative_rate1))
```

```
true positive rate is 0.9563163323019596
true_negative_rate is 0.2453225721922331
false positive rate is 0.15969657650464117
false_negative_rate is 0.20643572139824956
```

NOTE:

```
COMPARISON OF PERFORMANCE RESULTS OCCURED IN BOTH THE MODELS
```

In [81]:

```
d = {'Accurancy Score':[acc,acc1],'Precision Score':[prcs,prcs1],'Recall Sc
ore':[rs,rs1],'F-1 Score':[f_scr,f_scr1],'tn':[tn,tn1],'tp':[tp,tp1],
    'fp':[fp,fp1],'fn':[fn,fn1],'tnr':
[true_negative_rate,true_negative_rate1],
     'tpr':[true_positive_rate,true_negative_rate1],"fpr":
[false_positive_rate,false_negative_rate1],
     'fnr':[false_negative_rate,false_negative_rate1],'Technique':['BOW','T
FIDF']}
```

In [82]:

```
from collections import OrderedDict
```

In [83]:

```
df = pd.DataFrame(data=d,index=['BOW','TFIDF'])
print(df)
```

```
       Accurancy Score  F-1 Score  Precision Score  Recall Score Technique  \
BOW           0.861549   0.916360         0.913813      0.918921       BOW   

TFIDF         0.832140   0.903885         0.913813      0.956316     TFIDF   


         fn       fnr     fp       fpr     tn       tnr     tp       tpr  
BOW    7311  0.383156   7815  0.086669  11266  0.590430  82860  0.918921  
TFIDF  3939  0.206436  14400  0.206436   4681  0.245323  86232  0.245323  
```

WORD2VEC:

```
Constructing the word2vec model vector representation of each word i
n the corpus
```

In [84]:

```
import gensim
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-packages\gensim\utils.py:1197: Us
erWarning: detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [85]:

```
from gensim.models import word2vec
```

->Removing stop words

->Stemming the words

In [86]:

```
import re
def cleanhtml(sentence):
    clean = re.compile("<.*?>")
    cleantext = re.sub(clean," ",sentence)
    return cleantext
def cleanpunct(sentence):
    cleaned = re.sub(r'[?|!|\|#|"]',r' ',sentence)
    cleaned = re.sub(r'[<|,|)|(|>|<]',r' ',cleaned)
    return cleaned
```

Sorting the data based on time to do time based analysis

In [87]:

```
finaldata1 = finaldata.sort_values("Time",axis=0,ascending=True,kind='quick
sort',na_position='last')
```

In [88]:

```
finaldata1.shape
```

Out[88]:

```
(364171, 10)
```

In [89]:

```
i=0
listofsent=[]
for sent in finaldata1['Text'].values:
    filtered_sentences = []
    sent = cleanhtml(sent)
    for w in sent.split():
        for cleanedwordws in cleanpunct(w).split():
            if(cleanedwordws.isalpha()):
                filtered_sentences.append(cleanedwordws.lower())
    listofsent.append(filtered_sentences)
```

In [90]:

```
print(type(listofsent))
print(len(listofsent))
print(finaldata['Text'].values[99])
print(listofsent[99])
```

```
<class 'list'>
364171
My dog loves these treats. He's really picking with his treats so it says a
lot that he loves these. I had been buying him bags of the freeze dried tre
ats at petco, etc. and it was costing a fortune, not to mention they were s
mashed. These are great quality. You get tons!! in the 14 ounce bucket and
my little dog is in love.
['i', 'have', 'baked', 'with', 'this', 'organic', 'vanilla', 'in', 'the', '
past', 'and', 'realized', 'that', 'it', 'is', 'not', 'a', 'vanilla', 'i', '
found', 'this', 'product', 'very', 'misleading', 'even', 'though', 'categor
ized', 'has', 'an', 'organic']
```

Constructing word2vec model with cleaned data with vector representation of each word in 100 dimensions

In [91]:

```
w2vmodel = gensim.models.Word2Vec(listofsent,min_count=5,size=100,workers=4
)
```

In [92]:

```
w2vmodel.most_similar('good')
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-packages\ipykernel_launcher.py:1:
DeprecationWarning: Call to deprecated `most_similar` (Method will be remov
ed in 4.0.0, use self.wv.most_similar() instead).
  """Entry point for launching an IPython kernel.
```

Out[92]:

```
[('great', 0.7910346984863281),
 ('decent', 0.7419871091842651),
 ('terrific', 0.6892297267913818),
 ('fantastic', 0.686516284942627),
 ('nice', 0.6577026844024658),
 ('bad', 0.6547868251800537),
```

```
 ('fine', 0.6223894953727722),
 ('tasty', 0.6080605983734131),
 ('awesome', 0.6049265265464783),
 ('yummy', 0.6035927534103394)]
```

In [93]:

```
w2vmodel.similarity('tasty','bad')
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-packages\ipykernel_launcher.py:1:
DeprecationWarning: Call to deprecated `similarity` (Method will be removed
in 4.0.0, use self.wv.similarity() instead).
  """Entry point for launching an IPython kernel.
```

Out[93]:

```
0.1585759640761753
```

In [94]:

```
w2vmodel.similarity('good','bad')
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-packages\ipykernel_launcher.py:1:
DeprecationWarning: Call to deprecated `similarity` (Method will be removed
in 4.0.0, use self.wv.similarity() instead).
  """Entry point for launching an IPython kernel.
```

Out[94]:

```
0.6547867707189339
```

In [95]:

```
w2vmodel.vector_size
```

Out[95]:

```
100
```

AVERAGE WORD2VEC:

```
By using the vector representation of each word trained by the word2
vec and using them to

construct vector representation of each sentence
```

In [96]:

```
cnt=0
sent_vectors = []
for sent in listofsent:
    sent_vec = np.zeros(100)
    cnt_words =0;
    for word in sent:
        try:
            vec = w2vmodel.wv[word]
            sent_vec += vec
            cnt += 1
        except:
            pass
    sent_vec /= cnt
```

```
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[99999]))
```

```
364171
100
```

In [97]:

```
print(len(sent_vectors))
print(sent_vectors[2])
```

```
364171
[ 0.11377362 -0.12137225  0.04100957  0.11239191 -0.00531377  0.04085946
  0.0476009  -0.09648934 -0.0010986  -0.08091155 -0.06770232 -0.01261855
  0.01557359 -0.0201358  -0.00406908 -0.00294631 -0.06391854 -0.05851824
  0.07370616 -0.10075934  0.01020004  0.17083765  0.09960079 -0.06806491
 -0.07289264  0.0326768   0.03578665  0.03273706  0.04975915  0.12016261
  0.13349243  0.03924221  0.00150166  0.04242722 -0.03049197  0.04398392
 -0.09251195 -0.10949207 -0.10690167 -0.07376308 -0.15553156 -0.09606712
 -0.01030108 -0.10004253 -0.09286605 -0.03293687  0.09037566  0.0018135
 -0.0549786  -0.04505215  0.01651171 -0.08129116  0.11047236 -0.01776721
 -0.00912226  0.06250814  0.00375688 -0.05799512 -0.03087119  0.08339526
 -0.00542605  0.01242891  0.08467643 -0.0678173  -0.10334902  0.12021792
 -0.04506014  0.01100322  0.0178055   0.0526397   0.10796456  0.10078472
 -0.07161491 -0.06737346 -0.04179112 -0.00507344  0.03336954 -0.07394222
 -0.02807944 -0.02381356  0.05421009 -0.06156241  0.14499568 -0.00368346
  0.11554297 -0.06626187  0.09045177  0.02773743 -0.05235551 -0.1141327
  0.02570999  0.14225777 -0.09261952 -0.01611218 -0.04294083 -0.09478964
  0.00405511 -0.04913444  0.00129716 -0.03861467]
```

In [98]:

```
print(type(sent_vectors))
```

```
<class 'list'>
```

In [99]:

```
np.isnan(sent_vectors).any()
```

Out[99]:

```
False
```

In [100]:

```
sent_vectors = np.nan_to_num(sent_vectors)
```

In [101]:

```
sent_vectors.shape
```

Out[101]:

```
(364171, 100)
```

In [102]:

```
xtrain2 = sent_vectors[0:250000]
xtest2 = sent_vectors[250001:]
ytrain2 = finaldata1['Score'][0:250000]
ytest2 = finaldata1['Score'][250001:]
```

In [103]:

```
print(xtrain2.shape)
print(ytrain2.shape)
print(xtest2.shape)
print(ytest2.shape)
```

```
(250000, 100)
(250000,)
(114170, 100)
(114170,)
```

In [104]:

```
from sklearn.cross_validation import cross_val_score
```

In [105]:

```
print(lst)
```

```
[1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29]
```

In [106]:

```
cross_validation_score = []
for a in lst:
    clasifier = BernoulliNB(alpha=a)
    scores = cross_val_score(clasifier,xtrain2,ytrain2,cv=10,scoring='accur
acy')
    cross_validation_score.append(scores.mean())
```

In [107]:

```
error  = [1 - x for x in cross_validation_score]
print(cross_validation_score)
print(error)
```

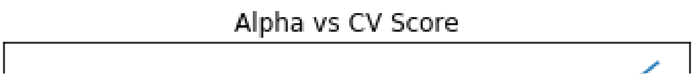
```
[0.825979747778822, 0.826031747298854, 0.8260757477788989,
0.8261197474589501, 0.8261037469789052, 0.8261637471389628,
0.8261597482589564, 0.8261877484190012, 0.8262357495390715,
0.826255750019078, 0.8263357498591868, 0.8263357496991676,
0.8263597496991931, 0.8264197506592955, 0.826459751299334]
[0.174020252221178, 0.17396825270114602, 0.17392425222110108,
0.17388025254104988, 0.1738962530210948, 0.1738362528610372,
0.17384025174104356, 0.17381225158099878, 0.17376425046092847,
0.17374424998092197, 0.17366425014081321, 0.17366425030083243,
0.17364025030080688, 0.17358024934070448, 0.17354024870066598]
```

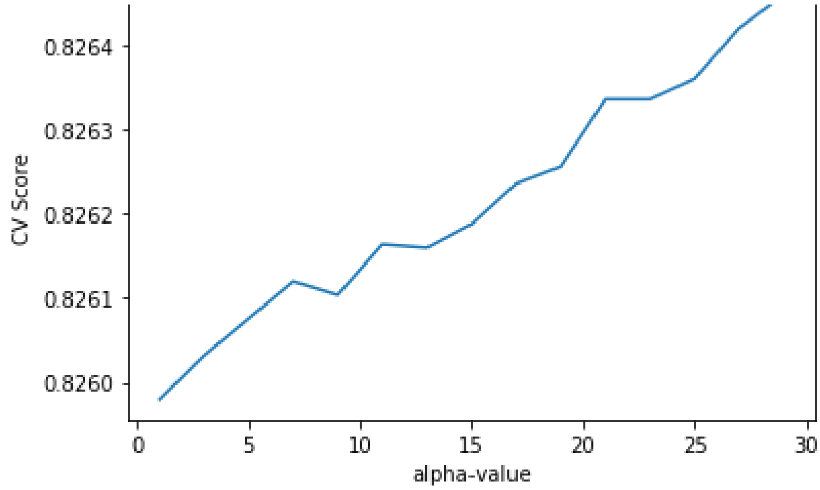
In [108]:

```
mp.plot(lst,cross_validation_score)
mp.xlabel('alpha-value')
mp.ylabel("CV Score")
mp.title("Alpha vs CV Score")
```

Out[108]:

```
Text(0.5,1,'Alpha vs CV Score')
```



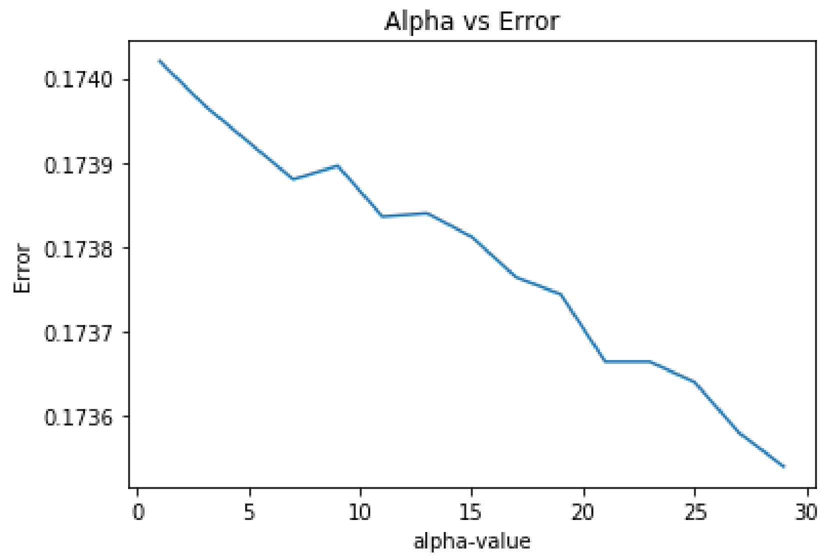


In [109]:

```
mp.plot(lst,error)
mp.xlabel('alpha-value')
mp.ylabel("Error")
mp.title("Alpha vs Error")
```

Out[109]:

```
Text(0.5,1,'Alpha vs Error')
```



In [110]:

```
best_a2 = lst[error.index(min(error))]
print(best_a2)
```

```
29
```

Observation:

    -> The highest accurancy and lowest error is occured when alpha = 29

    -> Using alpha = 1 to design the classifier

In [111]:

```
bernoulinb = BernoulliNB(alpha=29)
```

```
bernoulinb.fit(xtrain2,ytrain2)
prdct2 = bernoulinb.predict(xtest2)
```

In [112]:

```
prdct2.shape
```

Out[112]:

```
(114170,)
```

Calculating Performance measure using:

```
-> Accuracy

-> Precision

-> Recall

-> F-1 Score

-> Confusion Matrix :

        -> TPR

        -> TNR

        -> FPR

        -> FNR
```

ACCURACY SCORE:

```
TELLS US HOW ACCURATE THE MODEL IS IN PREDICTING
```

In [113]:

```
acc2 = accuracy_score(ytest2,prdct2)
print(acc2)
```

```
0.8111938337566786
```

PRECISION SCORE:

```
     This is the ratio of true positives to sum of true positives an
d false positives
```

In [114]:

```
prcs2 = precision_score(ytest2,prdct2, average =
'binary',pos_label='positive')
print(prcs2)
```

```
0.90257540192214
```

RECALL SCORE:

    This is the ratio of true positives to the sum of true positives and
    flase negatives

In [115]:

```
rs2 = recall_score(ytest2,prdct2,average='binary',pos_label='positive')
print(rs2)
```

```
0.8646816725714407
```

F-1 SCORE:

    This is the weighted avergae of precision and recall scores

In [116]:

```
f_scr2 = f1_score(ytest2,prdct2,pos_label='positive')

print(f_scr2)
```

```
0.8832222763963378
```

CONFUSION-MATRIX:

    This evaluates the accurancy of a classification

In [117]:

```
cmr2 = confusion_matrix(ytest2,prdct2)
print(cmr2)
```

```
[[11097  8799]
 [12757 81517]]
```

In [118]:

```
tn2,fp2,fn2,tp2 = cmr2.ravel()
```

In [119]:

```
tn2
```

Out[119]:

```
11097
```

In [120]:

```
fp2
```

Out[120]:

```
8799
```

In [121]:

```
fn2
```

Out[121]:

```
12757
```

In [122]:

```
tp2
```

Out[122]:

```
81517
```

Note:

-> TRUE POSITIVE RATE IS THE RATIO OF TRUE POSITIVES TO TOTAL POSITIVE

-> TRUE NEGATIVE RATE IS THE RATIO OF TRUE NEGATIVES TO TOTAL NEGATIVE

-> FALSE POSITIVE RATE IS THE RATIO OF FALSE POSITIVES TO TOTAL POSITIVE

-> FALSE NEGATIVE RATE IS THE RATIO OF FALSE NEGATIVES TO TOTAL NEGATIVES

In [123]:

```
true_positive_rate2 = tp2/(fn2+tp2)

true_negative_rate2 = tn2/(tn2+fp2)

false_positive_rate2 = fp2/(fn2+tp2)

false_negative_rate2 = fn2/(tn2+fp2)

print("true positive rate is {}".format(true_positive_rate2))

print("true_negative_rate is {}".format(true_negative_rate2))

print("false positive rate is {}".format(false_positive_rate2))

print("false_negative_rate is {}".format(false_negative_rate2))
```

```
true positive rate is 0.8646816725714407
true_negative_rate is 0.5577503015681544
false positive rate is 0.09333432335532596
false_negative_rate is 0.641184157619622
```

TFIDF-WORD2VEC

In [125]:

```
tfid_feat = tfid.get_feature_names()
```

In [126]:

```
len(tfid_feat)
```

Out[126]:

```
2910192
```

In [128]:

```
print(tfid_vect[0,tfid_feat.index('the')])
print(w2vmodel.wv['the'])
a = tfid_vect[0,tfid_feat.index('the')]
b = w2vmodel.wv['the']
c = a*b
print(c)
```

```
0.046955975029953l4
[-0.38087898 -2.564279    0.13754313  1.1316134   0.2925029  -1.3993564
 -2.0217445  -1.2632195  -0.62616086 -1.6356932  -1.3170269   0.7359891
  0.9645069  -0.6551743  -0.6494612  -0.3786263  -0.11755598 -0.14274636
  0.08644295 -0.06626914 -1.7037593   0.52516824 -0.17293733  0.96153486
 -0.32190636  0.7483486   0.48500887 -0.05756575 -1.36634    -0.03375257
  2.14156     0.66630673  0.0186592   0.72309476 -0.993174   -0.87290084
  1.7744738   0.53748536 -1.5149844   0.23560542 -1.4937731  -1.5358757
 -0.6739717  -1.7489989  -0.461739   -0.22216024  0.98151046 -0.47540733
  0.04611142 -0.38541836  2.8489265  -0.3393505   0.6562042   1.1125615
  0.7095221   1.9302902  -0.03608303 -1.567516   -1.91152     1.8805034
  0.34371632 -1.0052359   3.5201755  -2.0378213  -1.0841085   0.3771327
  0.6397638   0.40897596 -0.1265416  -0.4769168   1.3705907  -0.33438414
 -2.2358694  -1.1718905  -0.25857767  1.0542301   0.07859272  1.8086038
 -0.01172563 -0.5436469   0.11463425 -1.1162572   0.84114146  0.7087234
  1.0757393   2.0619328   3.3006823   2.4896271   0.18878168  0.04748195
  1.2467595   2.022931   -1.1726696  -0.7767393  -0.75482285 -1.5867083
  0.03085511  0.10260322  0.4291923  -0.1357655 ]
[-0.01788455 -0.12040823  0.00645847  0.05313601  0.01373476 -0.06570815
 -0.09493299 -0.0593157  -0.029402   -0.07680557 -0.06184228  0.03455909
  0.04528936 -0.03076435 -0.03049609 -0.01777877 -0.00551996 -0.00670279
  0.00405901 -0.00311173 -0.08000168  0.02465979 -0.00812044  0.04514981
 -0.01511543  0.03513944  0.02277406 -0.00270306 -0.06415783 -0.00158488
  0.10055905  0.03128709  0.00087616  0.03395362 -0.04663546 -0.04098791
  0.08332215  0.02523815 -0.07113757  0.01106308 -0.07014158 -0.07211854
 -0.031647   -0.08212595 -0.02168141 -0.01043175  0.04608778 -0.02232322
  0.00216521 -0.01809769  0.13377413 -0.01593453  0.03081271  0.05224141
  0.0333163   0.09063866 -0.00169431 -0.07360424 -0.08975729  0.08830088
  0.01613954 -0.04720183  0.16529328 -0.09568789 -0.05090537  0.01770863
  0.03004073  0.01920387 -0.00594188 -0.02239409  0.06435742 -0.01570133
 -0.10498744 -0.05502726 -0.01214177  0.0495024   0.0036904   0.08492476
 -0.00055059 -0.02552747  0.00538276 -0.05241495  0.03949662  0.0332788
  0.05051239  0.09682007  0.15498675  0.11690287  0.00886443  0.00222956
  0.05854281  0.0949887  -0.05506385 -0.03647255 -0.03544344 -0.07450544
  0.00144883  0.00481783  0.02015314 -0.006375  ]
```

Observation:

```
-> In tfidf-word2vec it calculates the word2vec representation of ea
ch word by using the
      word2vec model

-> It will get the tfidf value of the word from tfidf vectorizer

-> It will product the words with tfidf and words with word2vec in a
sentence and divides
   with total tfidf value of the sentence
```

In [129]:

```
tfid_feat = ttfidf.get_feature_names()
tfidf_sent_vectors = [];
row=0;
for sent in listofsent1:
    sent_vec = np.zeros(100)
    weight_sum =0;
    for word in sent:
        try:
            vec = w2vmodel1.wv[word]

            tfidf = tfid_data[row, tfid_feat.index(word)]
            sent_vec += (vec * tfidf)
            weight_sum += tfidf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1
    print(len(tfidf_sent))
```

Out[129]:

```
364171
```

In [132]:

```
print(tfid_vect[0,tfid_feat.index('in')])
print(w2vmodel.wv['in'])
a = tfid_vect[0,tfid_feat.index('in')]
b = w2vmodel.wv['in']
c = a*b
print(c)
```

```
0.03277183177760655
[ 0.24630567  0.10614999 -0.91066444  1.2145983  -1.3224634  -0.8773522
  0.05536528  0.6256457  -0.90123504  0.35664916  1.3785762   0.12856239
 -0.45661962  0.24288727 -0.8409622   0.5991392  -1.3775203  -1.9029506
 -2.4726315  -0.19539623 -2.1715653   0.7816189  -2.3939776  -0.8510448
 -0.28530917 -0.9710841  -1.8238499  -1.3172127  -0.5602136   1.1191514
  1.9451154  -0.1035039  -0.79132956 -0.45516166  0.02743903 -1.8780525
  1.4846488   0.8606082   2.7319293   2.8509173   0.29704288 -1.5353148
 -1.470713   -0.8125868   0.23036313 -0.5552995  -0.66175985  0.57335806
 -0.2581336  -0.26689422  1.3680589  -0.60551685  0.76724     1.6149808
 -1.8948125  -0.13565017 -1.9780403  -2.407124   -0.9476449   1.509016
  1.628181    0.03786704  1.1902485  -0.1954579  -1.4768878  -0.7792222
  0.78329873  0.45370498 -1.147596    0.60345346 -0.4214382  -0.8726381
 -0.54492754  3.0747972  -1.501521   -2.873879   -2.6592264   1.0230767
  2.6888936   2.9574816   1.4790492   1.7502983  -0.66892487 -0.17983612
 -0.23141876 -1.4595065   3.0802276  -2.001591    0.6550356   0.14405705
 -1.1459281   1.20468    -2.5332794  -1.0205263   1.2336763  -0.9381407
 -0.92940015 -2.9004877  -0.4522038   1.0706956 ]
[ 0.00807189  0.00347873 -0.02984414  0.03980461 -0.04333955 -0.02875244
  0.00181442  0.02050356 -0.02953512  0.01168805  0.04517847  0.00421323
 -0.01496426  0.00795986 -0.02755987  0.01963489 -0.04514387 -0.06236318
 -0.08103266 -0.00640349 -0.07116617  0.02561508 -0.07845504 -0.0278903
 -0.0093501  -0.03182421 -0.0597709  -0.04316748 -0.01835923  0.03667664
  0.063745   -0.00339201 -0.02593332 -0.01491648  0.00089923 -0.06154722
```

```
  0.04865466  0.02820371  0.08953033  0.09342979  0.00973464 -0.05031508
 -0.04819796 -0.02662996  0.00754942 -0.01819818 -0.02168708  0.01879
 -0.00845951 -0.00874661  0.0448338  -0.0198439   0.02514386  0.05292588
 -0.06209648 -0.0044455  -0.06482401 -0.07888587 -0.03105606  0.04945322
  0.05335848  0.00124097  0.03900662 -0.00640551 -0.04840032 -0.02553654
  0.02567014  0.01486874 -0.03760882  0.01977628 -0.0138113  -0.02859795
 -0.01785827  0.10076674 -0.04920759 -0.09418228 -0.08714773  0.0335281
  0.08811997  0.09692209  0.04847115  0.05736048 -0.02192189 -0.00589356
 -0.00758402 -0.0478307   0.10094471 -0.06559581  0.02146672  0.00472101
 -0.03755417  0.03947957 -0.08302021 -0.03344452  0.04042983 -0.03074459
 -0.03045815 -0.0950543  -0.01481955  0.03508866]
```

In [ ]:

```
Note:

    -> It works in such a way that it constructs word2vec for each word in
a sentence and will get the tf-idf value
        of the same word from tf-idf vectorizer

    -> It will do the product of both the values and to that value it will
do average with total tf-idf values of that sentence
```

In [134]:

```
xtrain3 = tfidf_sent[0:250000]
xtest3 = tfidf_sent[250001:]
ytrain3 = finaldata1['Score'][0:250000]
ytest3 = finaldata1['Score'][250001:]
```

In [135]:

```
print(xtrain3.shape)
print(ytrain3.shape)
print(xtest3.shape)
print(ytest3.shape)
```

```
(250000, 100)
(250000,)
(114170, 100)
(114170,)
```

In [137]:

```
from sklearn.cross_validation import cross_val_score
```

In [139]:

```
llst = np.arange(1,50,2)
print(llst)
```

```
[ 1  3  5  7  9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47
 49]
```

In [141]:

```
from sklearn.naive_bayes import BernoulliNB
```

In [149]:

```
cross_validation_score = []
for a in llst:
    classifier = BernoulliNB(alpha=a)
    scores = cross_val_score(classifier,xtrain3,ytrain3,cv=10,scoring='accu
racy')
    cross_validation_score.append(scores.mean())
```

In [150]:

```
error = [1 - x for x in cross_validation_score]
print(cross_validation_score)
print(error)
```

```
[0.825979747778822, 0.826031747298854, 0.8260757477788989,
0.8261197474589501, 0.8261037469789052, 0.8261637471389628,
0.8261597482589564, 0.8261877484190012, 0.8262357495390715,
0.826255750019078, 0.8263357498591868, 0.8263357496991676,
0.8263597496991931, 0.8264197506592955, 0.826459751299334,
0.8265117503394237, 0.8265557493794748, 0.8265637493794749,
0.8265677504994813, 0.8265717495394812, 0.8265717506595003,
0.8266037503395258, 0.8266237504995579, 0.8266517511395837,
0.8267157500196539]
[0.174020252221178, 0.17396825270114602, 0.17392425222110108,
0.17388025254104988, 0.1738962530210948, 0.1738362528610372,
0.17384025174104356, 0.17381225158099878, 0.17376425046092847,
0.17374424998092197, 0.17366425014081321, 0.17366425030083243,
0.17364025030080688, 0.17358024934070448, 0.17354024870066598,
0.1734882496605763, 0.17344425062052515, 0.17343625062052515,
0.17343224950051872, 0.1734282504605188, 0.17342824934049972,
0.17339624966047418, 0.17337624950044206, 0.17334824886041633,
0.17328424998034608]
```

In [151]:

```
print(len(cross_validation_score))
print(len(error))
```

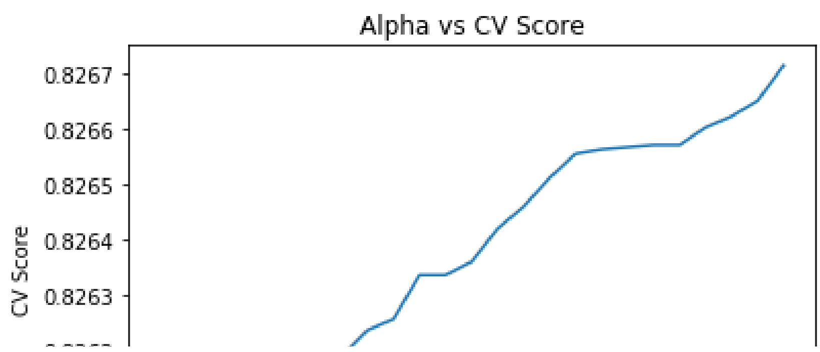
```
25
25
```

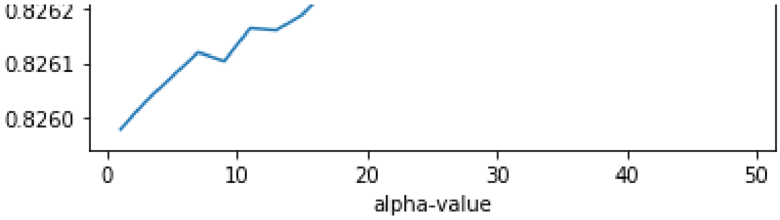
In [152]:

```
mp.plot(llst,cross_validation_score)
mp.xlabel('alpha-value')
mp.ylabel("CV Score")
mp.title("Alpha vs CV Score")
```

Out[152]:

```
Text(0.5,1,'Alpha vs CV Score')
```



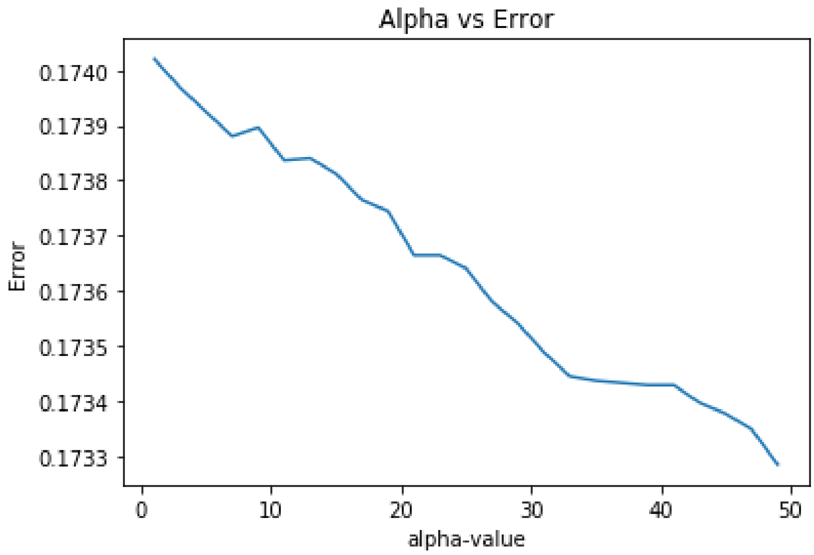


In [153]:

```
mp.plot(llst,error)
mp.xlabel('alpha-value')
mp.ylabel("Error")
mp.title("Alpha vs Error")
```

Out[153]:

```
Text(0.5,1,'Alpha vs Error')
```



In [155]:

```
best_a3 = llst[error.index(min(error))]
print(best_a3)
```

```
49
```

Observation:

```
-> The highest accurancy and lowest error is occured when alpha = 49

-> Using alpha = 1 to design the classifier
```

In [157]:

```
bernoulinb = BernoulliNB(alpha=49)
bernoulinb.fit(xtrain3,ytrain3)
prdct3 = bernoulinb.predict(xtest3)
```

In [158]:

```
prdct3.shape
```

Out[158]:

```
(114170,)
```

Calculating Performance measure using:

```
            -> Accuracy

            -> Precision

            -> Recall

            -> F-1 Score

            -> Confusion Matrix :

                        -> TPR

                        -> TNR

                        -> FPR

                        -> FNR
```

ACCURACY SCORE:

```
TELLS US HOW ACCURATE THE MODEL IS IN PREDICTING
```

In [160]:

```
acc3 = accuracy_score(ytest3,prdct3)
print(acc3)
```

```
0.8116142594376806
```

PRECISION SCORE:

```
     This is the ratio of true positives to sum of true positives an
d false positives
```

In [161]:

```
prcs3 = precision_score(ytest3,prdct3, average =
'binary',pos_label='positive')
print(prcs3)
```

```
0.9025113397499723
```

RECALL SCORE:

```
This is the ratio of true positives to the sum of true positives and
flase negatives
```

In [162]:

```
rs3 = recall_score(ytest3,prdct3,average='binary',pos_label='positive')
print(rs3)
```

0.8653287226594819

F-1 SCORE:

```
This is the weighted avergae of precision and recall scores
```

In [163]:

```
f_scr3 = f1_score(ytest3,prdct3,pos_label='positive')

print(f_scr3)
```

0.8835290040289392

CONFUSION-MATRIX:

```
This evaluates the accurancy of a classification
```

In [164]:

```
cmr3 = confusion_matrix(ytest3,prdct3)
print(cmr3)
```

```
[[11084  8812]
 [12696 81578]]
```

In [165]:

```
tn3,fp3,fn3,tp3 = cmr3.ravel()
```

In [166]:

```
tn3
```

Out[166]:

11084

In [167]:

```
fp3
```

Out[167]:

8812

In [168]:

```
fn3
```

Out[168]:

12696

In [169]:

```
tp3
```

Out[169]:

```
81578
```

Note:

-> TRUE POSITIVE RATE IS THE RATIO OF TRUE POSITIVES TO TOTAL POSITIVE

-> TRUE NEGATIVE RATE IS THE RATIO OF TRUE NEGATIVES TO TOTAL NEGATIVE

-> FALSE POSITIVE RATE IS THE RATIO OF FALSE POSITIVES TO TOTAL POSITIVE

-> FALSE NEGATIVE RATE IS THE RATIO OF FALSE NEGATIVES TO TOTAL NEGATIVES

In [170]:

```
true_positive_rate3 = tp3/(fn3+tp3)

true_negative_rate3 = tn3/(tn3+fp3)

false_positive_rate3 = fp3/(fn3+tp)

false_negative_rate3 = fn3/(tn3+fp3)

print("true positive rate is {}".format(true_positive_rate3))

print("true_negative_rate is {}".format(true_negative_rate3))

print("false positive rate is {}".format(false_positive_rate3))

print("false_negative_rate is {}".format(false_negative_rate3))
```

```
true positive rate is 0.8653287226594819
true_negative_rate is 0.5570969039002814
false positive rate is 0.09221817572941521
false_negative_rate is 0.638118214716526
```

In [171]:

```
d = {'Accurancy Score':[acc,acc1,acc2,acc3],'Precision Score':[prcs,prcs1,p
rcs2,prcs3],'Recall Score':[rs,rs1,rs2,rs3],
     'F-1 Score':[f_scr,f_scr1,f_scr2,f_scr3],'tn':[tn,tn1,tn2,tn3],'tp':
[tp,tp1,tp2,tp3],
    'fp':[fp,fp1,fp2,fp3],'fn':[fn,fn1,fn2,fn3],'tnr':[true_negative_rate,t
rue_negative_rate1,true_negative_rate2,true_negative_rate3],
     'tpr':[true_positive_rate,true_positive_rate1,true_positive_rate2,true
_positive_rate3],
     "fpr":[false_positive_rate,false_positive_rate1,false_positive_rate2,f
alse_positive_rate3],
     'fnr':[false_negative_rate,false_negative_rate1,false_negative_rate2,f
alse_positive_rate3],
     'Technique':['BOW','TFIDF','Average-word2vec','TFIDF-WORD2VEC']}
```

In [173]:

```
df = pd.DataFrame(data =d,index=["BOW",'TFIDF','AVERAGE
WORD2VEC','TFIDF_WORD2VEC'])
print(df)
```

	Accurancy Score	F-1 Score	Precision Score	Recall Score
BOW	0.861549	0.916360	0.913813	0.918921
TFIDF	0.832140	0.903885	0.913813	0.956316
AVERAGE WORD2VEC	0.811194	0.883222	0.902575	0.864682
TFIDF_WORD2VEC	0.811614	0.883529	0.902511	0.865329

	Technique	fn	fnr	fp	fpr	tn	tnr	tp	tpr
BOW	BOW	7311	0.383156	7815	0.086669	11266	0.590430	82860	0.918921
TFIDF	TFIDF	3939	0.206436	14400	0.159697	4681	0.245323	86232	0.956316
AVERAGE WORD2VEC	Average-word2vec	12757	0.641184	8799	0.093334	11097	0.557750	81517	0.864682
TFIDF_WORD2VEC	TFIDF-WORD2VEC	12696	0.092218	8812	0.092218	11084	0.557097	81578	0.865329

CONCLUSION:

```
-> Bow, Tfidf, Average word2vec, Tfidf Word2vec are used to convert
the text to vectors

-> Since it is a two class classification of positive and negative B
ernouli Navie Bayes
   is applied

-> For each technique all the measurements like Accuracy, Precision,
Recall,
    F-1 Score, Confusion Matrix were calculated

-> From confusion matrix,  true negatives, true positives, false neg
atives, false positives,
    true negative rate,true positive rate, false negative rate, fals
e positive rate
    were calculated
```