[5] Assignment 4: Apply Naive Bayes

1. **Apply Multinomial NaiveBayes on these feature sets**
    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

2. **The hyper paramter tuning(find best Alpha)**
    - Find the best hyper parameter which will give the maximum AUC value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Feature importance**
    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using values of `feature_log_prob_` parameter of MultinomialNB and print their corresponding feature names

4. **Feature engineering**
    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

5. **Representation of results**
    - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure. Here on X-axis you will have alpha values, since they have a wide range, just to represent those alpha values on the graph, apply log function on those alpha values.
    - Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
    - Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

6. **Conclusion**
    - You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this link.

Applying Multinomial Naive Bayes

In [3]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
```

```
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
from nltk.stem import PorterStemmer
from nltk.stem.snowball import SnowballStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

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

from tqdm import tqdm
import os
con = sqlite3.connect(r"D:\AppliedAI\AAIC_Course_handouts\11_Amazon Fine Food Reviews\amazon-fine-
food-reviews\database.sqlite")
data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3""",con)

# Change Score with 1 n 2 as -ve and 4 n 5 as +ve

def chng_to_0_or_1 (Score):
    if Score ==4 or Score ==5:
        return 1
    elif Score ==1 or Score ==2:
        return 0
    else:# Thus in case by some mistake any data is their with rating 6 or 7 etc due to some error
is removed
        pass
currentScore = data["Score"]
new_Score = currentScore.map(chng_to_0_or_1)
data["Score"] = new_Score
print ("Number of data points available")
print (data.shape)#Gives original number of data points available


#2 Data Cleaning a.) Getting rid of duplicates and b.) if helpnessdenominator <
helpfulnessnumerator


data = data.drop_duplicates(subset =
["UserId","ProfileName","HelpfulnessNumerator","HelpfulnessDenominator","Score","Time","Summary","
Text"], keep='first', inplace=False)
print ("Number of data points after removing duplicates")
print (data.shape)#Gives data points are deduplication

# Reference: Copied from above cell
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
data=data[data.HelpfulnessNumerator<=data.HelpfulnessDenominator]
print ("Number of data points after removing where HelpfulnessNumerator is more than
HelpfulnessDenominator ")
print (data.shape)

#3 Preprocessing begins

#Convert to lower case,convert shortcut words to proper words, remove Special Character

#i) Convert to lower case:
data["Text"] =  (data["Text"].str.lower())
data["Summary"] =  (data["Summary"].str.lower())

#ii) Convert Shortcuts words to proper words
#List of Words are:https://en.wikipedia.org/wiki/Wikipedia:List_of_English_contractions
#Reference:https://stackoverflow.com/questions/39602824/pandas-replace-string-with-another-string
data['Text'] = data['Text'].replace({"ain't":"am not","amn't":"am not","aren't":"are not", \
```

```
data['Text'] = data['Text'].replace({"ain't":"am not","amn't":"am not","aren't":"are not", \
"can't":"cannot","cause":"because","could've":"could have","couldn't":"could not","couldn't've":"could not have", \
"daren't":"dare not","daresn't":"dare not","dasn't":"dare not","didn't":"did not","doesn't":"does not", \
"don't":"do not","e'er":"ever","everyone's":"everyone is","finna":"fixing to","gimme":"give me", \
"gonna":"going to","gon't":"go not","gotta":"got to","hadn't":"had not","hasn't":"has not","haven't":"have not",\
"he'd":"he had","he'll":"he shall","he's":"he has","he've":"he have","how'd":"how did","how'll":"how will",\
"how're":"how are","how's":"how has","I'd":"I had","I'll":"I shall","I'm":"I am","I'm'a":"I am about to",\
"I'm'o":"I am going to","I've":"I have","isn't":"is not","it'd":"it would","it'll":"it shall","it's":"it has",\
"let's":"let us","mayn't":"may not","may've":"may have","mightn't":"might not","might've":"might have",\
"mustn't":"must not","mustn't've":"must not have","must've":"must have","needn't":"need not","ne'er":"never",\
"o'clock":"of the clock","o'er":"","ol'":"old","oughtn't":"ought not","shalln't":"shall not","shan't":"shall not",\
"she'd":"she had","she'll":"she shall","she's":"she is","should've":"should have","shouldn't":"should not",\
"shouldn't've":"should not have","somebody's":"somebody has","someone's":"someone has","something's":"something has",\
"that'll":"that will","that're":"that are","that's":"that is","that'd":"that would","there'd":"there had",\
"there'll":"there shall","there're":"there are","there's":"there is","these're":"hese are","they'd":"they had",\
"they'll":"they will","they're":"they are","they've":"they have","this's":"","those're":"those are","tis":"it is",\
"twas":"it was","wasn't":"was not","we'd":"we had","we'd've":"we would have","we'll":"we will","we're":"we are",\
"we've":"we have","weren't":"were not","what'd":"what did","what'll":"what will","what're":"what are","what's":"what is",\
"what've":"what have","when's":"when is","where'd":"where did","where're":"where are","where've":"where have",\
"which's":"which has","who'd":"who would","who'd've":"who would have","who'll":"who shall","who're":"who are",\
"who's":"who has","who've":"who have","why'd":"why did","why're":"why are","why's":"why has","won't":"will not",\
"would've":"would have","wouldn't":"would not","y'all":"you all","you'd":"you had","you'll":"you shall","you're":"you are",\
"you've":"you have"})
#############Lets do the same for summary Text##################################
data['Summary'] = data['Summary'].replace({"ain't":"am not","amn't":"am not","aren't":"are not", \
"can't":"cannot","cause":"because","could've":"could have","couldn't":"could not","couldn't've":"could not have", \
"daren't":"dare not","daresn't":"dare not","dasn't":"dare not","didn't":"did not","doesn't":"does not", \
"don't":"do not","e'er":"ever","everyone's":"everyone is","finna":"fixing to","gimme":"give me", \
"gonna":"going to","gon't":"go not","gotta":"got to","hadn't":"had not","hasn't":"has not","haven't":"have not",\
"he'd":"he had","he'll":"he shall","he's":"he has","he've":"he have","how'd":"how did","how'll":"how will",\
"how're":"how are","how's":"how has","I'd":"I had","I'll":"I shall","I'm":"I am","I'm'a":"I am about to",\
"I'm'o":"I am going to","I've":"I have","isn't":"is not","it'd":"it would","it'll":"it shall","it's":"it has",\
"let's":"let us","mayn't":"may not","may've":"may have","mightn't":"might not","might've":"might have",\
"mustn't":"must not","mustn't've":"must not have","must've":"must have","needn't":"need not","ne'er":"never",\
"o'clock":"of the clock","o'er":"","ol'":"old","oughtn't":"ought not","shalln't":"shall not","shan't":"shall not",\
"she'd":"she had","she'll":"she shall","she's":"she is","should've":"should have","shouldn't":"should not",\
"shouldn't've":"should not have","somebody's":"somebody has","someone's":"someone has","something's":"something has",\
"that'll":"that will","that're":"that are","that's":"that is","that'd":"that would","there'd":"there had",\
"there'll":"there shall","there're":"there are","there's":"there is","these're":"hese are","they'd":"they had",\
"they'll":"they will","they're":"they are","they've":"they have","this's":"","those're":"those are","tis":"it is",\
"twas":"it was","wasn't":"was not","we'd":"we had","we'd've":"we would have","we'll":"we will","we're":"we are",\
"we've":"we have","weren't":"were not","what'd":"what did","what'll":"what will","what're":"what are","what's":"what is",\
```

```
re","what's":"what is",\
"what've":"what have","when's":"when is","where'd":"where did","where're":"where are","where've":"
where have",\
"which's":"which has","who'd":"who would","who'd've":"who would have","who'll":"who
shall","who're":"who are",\
"who's":"who has","who've":"who have","why'd":"why did","why're":"why are","why's":"why has","won'
t":"will not",\
"would've":"would have","wouldn't":"would not","y'all":"you all","you'd":"you had","you'll":"you s
hall","you're":"you are",\
"you've":"you have"})
########################################################################################
# iii) Remove Special Characters except alpahbets and numbers
#The reason i dont want to remove number people might write got five eggs as 5 eggs or vice versa
and dont want to lose
#that information which could be useful
#Ref:https://stackoverflow.com/questions/33257344/how-to-remove-special-characers-from-a-column-of
-dataframe-using-module-re
data["Text"]=data["Text"].map(lambda x: re.sub(r'[^a-zA-Z_0-9 -]', '', x))
data["Summary_copy"]=data["Summary"].map(lambda x: re.sub(r'[^a-zA-Z_0-9 -]', '', x))

#The Summary are usually so small if we remove few stopwords the meaning itself would be complely
lost or chamge
# So let us see what all stopwords we have
#Ref::::::::https://stackoverflow.com/questions/5511708/adding-words-to-nltk-stoplist
#https://chrisalbon.com/machine_learning/preprocessing_text/remove_stop_words/

stopwords = nltk.corpus.stopwords.words('english')
newStopWords = ['would','could','br','<br>','<','>']
notstopwords = ['not','no','nor']
stopwords.extend(newStopWords)
stopwords = [word for word in stopwords if word not in notstopwords]

#  iv) For now let us just go with flow will use default stopwords as creating our own stop words
is very time consuming
#Rather will use n-gram stratergy to get rid of problem of stopwords removal changing the meaning
of sentences
#Ref:https://stackoverflow.com/questions/43184364/python-remove-stop-words-from-pandas-dataframe-g
ive-wrong-output
data["New_Text"]= data['Text'].apply(lambda x: [item for item in str.split(x) if item not in stopwo
rds])
data["Summary"]= data['Summary_copy'].apply(lambda x: [item for item in str.split(x) if item not in
stopwords])

#Ref:https://stackoverflow.com/questions/37347725/converting-a-panda-df-list-into-a-
string/37347837
#we are creating new column New_summary so in case in future we need summary it is intact
data["New_Text"]=data["New_Text"].apply(' '.join)
data["Summary"]=data["Summary"].apply(' '.join)

# v) Now lets do Stemming
#https://stackoverflow.com/questions/48617589/beginner-stemming-in-pandas-produces-letters-not-ste
ms
english_stemmer=SnowballStemmer('english', ignore_stopwords=True)
data["New_Text"] = data["New_Text"].apply(english_stemmer.stem)
data["Summary"] = data["Summary"].apply(english_stemmer.stem)
data["New_Text"] = data["New_Text"].astype(str)
data["Summary"] = data["Summary"].astype(str)

#vi) stemming without removing stop words
english_stemmer=SnowballStemmer('english', ignore_stopwords=True)
#https://stackoverflow.com/questions/34724246/attributeerror-float-object-has-no-attribute-lower
data["Text_with_stop"]=data["Text"].astype(str)
data["Summary"]=data["Summary"].astype(str)
data["Text_with_stop"]=data["Text_with_stop"].str.lower().map(english_stemmer.stem)
data["Summary"]=data["Summary"].str.lower().map(english_stemmer.stem)
data["Text_with_stop"]=data["Text_with_stop"].apply(''.join)
data["Summary"]=data["Summary"].apply(''.join)
data["Text_with_stop"] = data["Text_with_stop"].astype(str)
data["Summary"] = data["Summary"].astype(str)
print(data["Score"].value_counts())
print ("Thus we see there are 85% and 15% positive and negative reviews,thus a unbalanced dataset.
So to create a balanced \
dataset we first copy negative dataset 6 times than we sample with same number of times as positiv
e")
# Let include another feature which is the length of the text
data_neg = data[data["Score"] == 0]
data_pos = data[data["Score"] == 1]
data = pd.concat([data_pos,data_neg])
```

```
data = pd.concat([data_pos,data_neg])
#https://stackoverflow.com/questions/46429033/how-do-i-count-the-total-number-of-words-in-a-pandas
-dataframe-cell-and-add-thos
data["Text_length"]= (data["New_Text"].str.count(' ') + 1)
data["Summary_length"]= (data["Summary"].str.count(' ') + 1)
data["Time_formatted"]= pd.to_datetime(data["Time"])
data.sort_values(by=['Time_formatted'], inplace=True)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\gensim\utils.py:1212: UserWarning: detected Windows; al
iasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

```
Number of data points available
(525814, 10)
Number of data points after removing duplicates
(366392, 10)
Number of data points after removing where HelpfulnessNumerator is more than
HelpfulnessDenominator
(366390, 10)
1    308679
0     57711
Name: Score, dtype: int64
Thus we see there are 85% and 15% positive and negative reviews,thus a unbalanced dataset.So to cr
eate a balanced dataset we first copy negative dataset 6 times than we sample with same number of
times as positive
```

In [4]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html
from sklearn.model_selection import train_test_split

Y = data['Score'].values
X_no_stop = data['New_Text'].values
X_summary = data ['Summary'].values

X_no_stop_train, X_no_stop_test, y_train, y_test = train_test_split(X_no_stop, Y, test_size=0.33, s
huffle=False)
X_no_stop_train, X_no_stop_CV, y_train, y_CV = train_test_split(X_no_stop_train, y_train,
test_size=0.33, shuffle=False)

print ("The shape without stopwords of X Train, X CV, X Test, Y Train, Y CV and Y Test respectivel
y are")
print(X_no_stop_train.shape,
X_no_stop_CV.shape,X_no_stop_test.shape,y_train.shape,y_CV.shape,y_test.shape)
```

```
The shape without stopwords of X Train, X CV, X Test, Y Train, Y CV and Y Test respectively are
(164472,) (81009,) (120909,) (164472,) (81009,) (120909,)
```

In [5]:

```
X_summary_train,X_summary_test, y_summary_train, y_summary_test = train_test_split(X_summary, Y, te
st_size=0.33, shuffle=False)
X_summary_train,X_summary_CV, y_summary_train, y_summary_CV =
train_test_split(X_summary_train,y_summary_train, test_size=0.33, shuffle=False)
```

[5.1] Applying Naive Bayes on BOW, SET 1

In [6]:

```
from sklearn.feature_extraction.text import CountVectorizer
import math

vectorizer = CountVectorizer()
bow_X_train_no_stop = vectorizer.fit_transform(X_no_stop_train)
bow_X_test_no_stop = vectorizer.transform(X_no_stop_test)
bow_X_CV_no_stop = vectorizer.transform(X_no_stop_CV)
##################     Summary     ######################################
bow_X_summary_train = vectorizer.fit_transform(X_summary_train)
bow_X_summary_test = vectorizer.transform(X_summary_test)
bow_X_summary_CV = vectorizer.transform(X_summary_CV)
####################################
```

```python
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
from sklearn.naive_bayes import MultinomialNB

# creating odd list of alpha for BOW Naive bays
def tothepower(y):
    return (10**y)
alpha_NB_BOW = list(map(tothepower, list(range(-4, 5))))
print (alpha_NB_BOW)
alpha_NB_BOW_log = [math.log(x) for x in alpha_NB_BOW]
print (alpha_NB_BOW_log)
```

```
[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850929940455, 0.0,
2.302585092994046, 4.605170185988092, 6.907755278982137, 9.210340371976184]
```

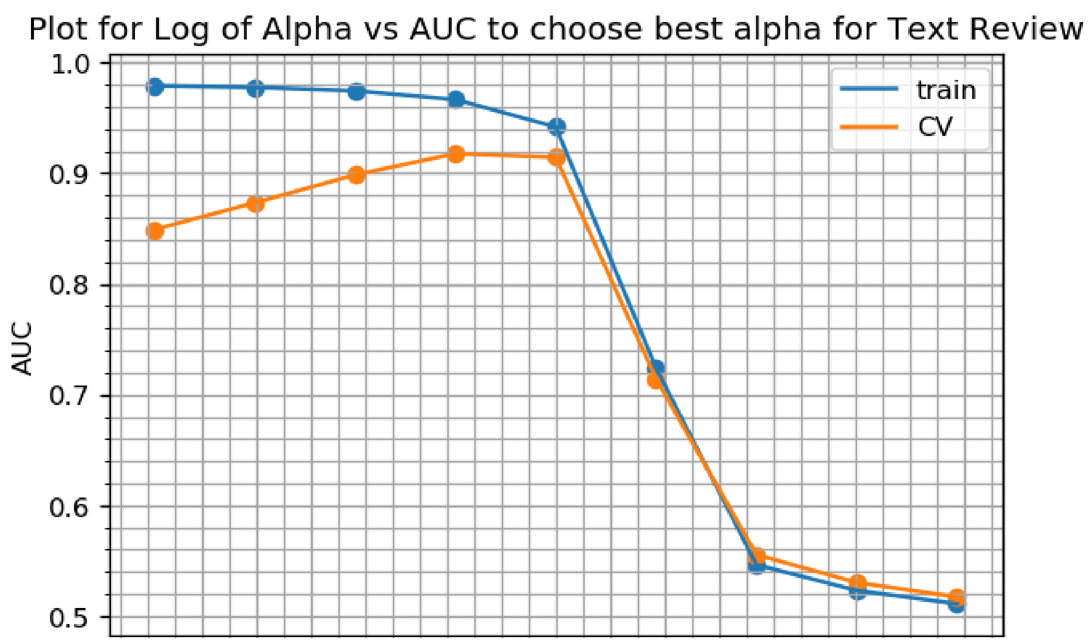
In [7]:

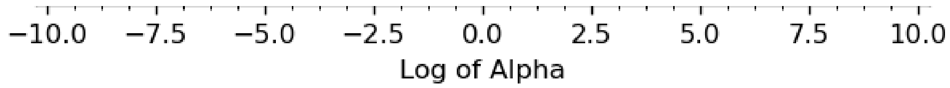
```python
auc_cv_no_stop = []
auc_train_no_stop=[]

for alpha in tqdm(alpha_NB_BOW):
    NB_BOW_no_stop = MultinomialNB(alpha=alpha)
    NB_BOW_no_stop.fit(bow_X_train_no_stop, y_train)
    proba_pred_train_BOW_no_stop=(NB_BOW_no_stop.predict_proba(bow_X_train_no_stop)[:,1])
    proba_pred_cv_BOW_no_stop=(NB_BOW_no_stop.predict_proba(bow_X_CV_no_stop)[:,1])
    auc_train_no_stop.append(roc_auc_score(y_train,proba_pred_train_BOW_no_stop))
    auc_cv_no_stop.append(roc_auc_score(y_CV,proba_pred_cv_BOW_no_stop))
```

```
100%|██████████████████████████████████████████████████████████████████████████| 9/9 [00
:02<00:00,  4.13it/s]
```

In [8]:

```python
default_dpi = plt.rcParamsDefault['figure.dpi']
plt.rcParams['figure.dpi'] = default_dpi*1.2
plt.plot(alpha_NB_BOW_log, auc_train_no_stop)
plt.scatter(alpha_NB_BOW_log, auc_train_no_stop)
plt.plot(alpha_NB_BOW_log, auc_cv_no_stop)
plt.scatter(alpha_NB_BOW_log, auc_cv_no_stop)
plt.xlabel('Log of Alpha')
plt.ylabel('AUC')
plt.title("Plot for Log of Alpha vs AUC to choose best alpha for Text Review")
plt.legend(['train', 'CV'], loc='upper right')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
plt.show()
```





We are performing the same on summary text review

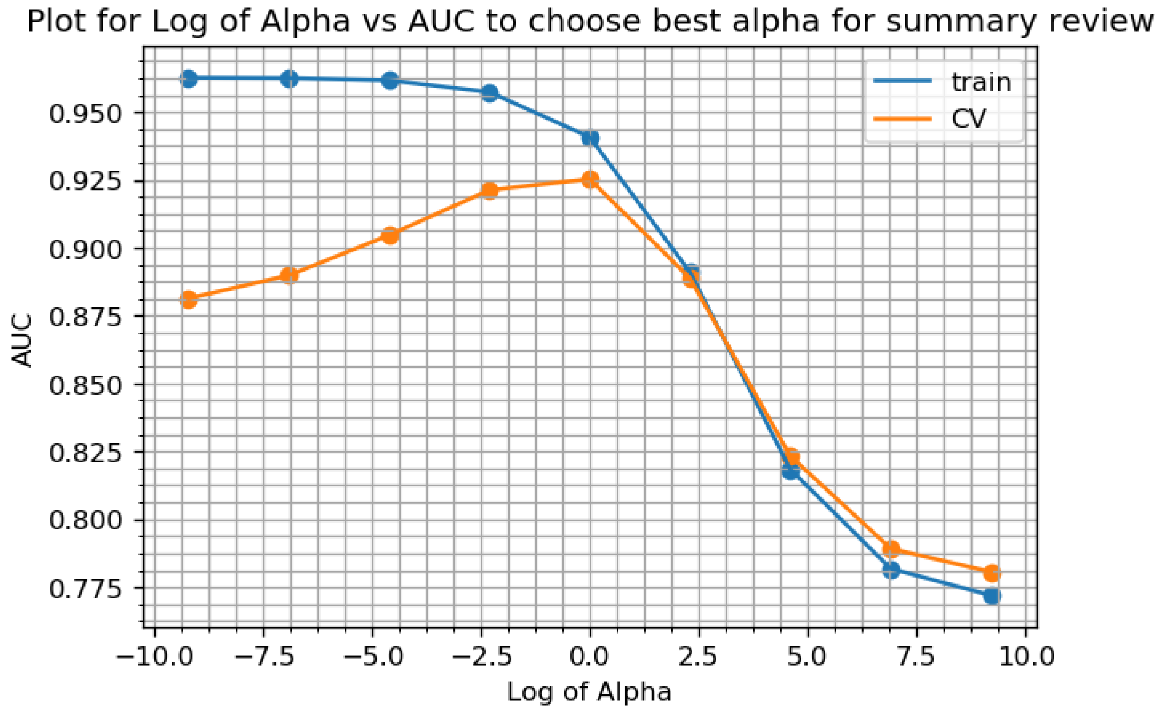
In [9]:

```
auc_cv_summary = []
auc_train_summary=[]

for alpha in tqdm(alpha_NB_BOW):
    NB_BOW_summary = MultinomialNB(alpha=alpha)
    NB_BOW_summary.fit(bow_X_summary_train, y_summary_train)
    proba_pred_train_BOW_summary=(NB_BOW_summary.predict_proba(bow_X_summary_train)[:,1])
    proba_pred_cv_BOW_summary=(NB_BOW_summary.predict_proba(bow_X_summary_CV)[:,1])
    auc_train_summary.append(roc_auc_score(y_summary_train,proba_pred_train_BOW_summary))
    auc_cv_summary.append(roc_auc_score(y_summary_CV,proba_pred_cv_BOW_summary))
```

```
100%|██████████████████████████████████████████████████████████████████████████| 9/9 [00
:01<00:00,  8.46it/s]
```

In [10]:

```
default_dpi = plt.rcParamsDefault['figure.dpi']
plt.rcParams['figure.dpi'] = default_dpi*1.2
plt.plot(alpha_NB_BOW_log, auc_train_summary)
plt.scatter(alpha_NB_BOW_log, auc_train_summary)
plt.plot(alpha_NB_BOW_log, auc_cv_summary)
plt.scatter(alpha_NB_BOW_log, auc_cv_summary)
plt.xlabel('Log of Alpha')
plt.ylabel('AUC')
plt.title("Plot for Log of Alpha vs AUC to choose best alpha for summary review")
plt.legend(['train', 'CV'], loc='upper right')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
plt.show()
```



So we can clearly observe best log of alpha lied somewhere between log of alpha of between -2.5 to 2.5 or alpha of .01 to 10. So let us now narrow down our search for best alpha between .01 to 10

In [11]:

```python
import numpy as np
lis = np.arange (.01, 10, .25)
print (lis)
```

```
[0.01 0.26 0.51 0.76 1.01 1.26 1.51 1.76 2.01 2.26 2.51 2.76 3.01 3.26
 3.51 3.76 4.01 4.26 4.51 4.76 5.01 5.26 5.51 5.76 6.01 6.26 6.51 6.76
 7.01 7.26 7.51 7.76 8.01 8.26 8.51 8.76 9.01 9.26 9.51 9.76]
```

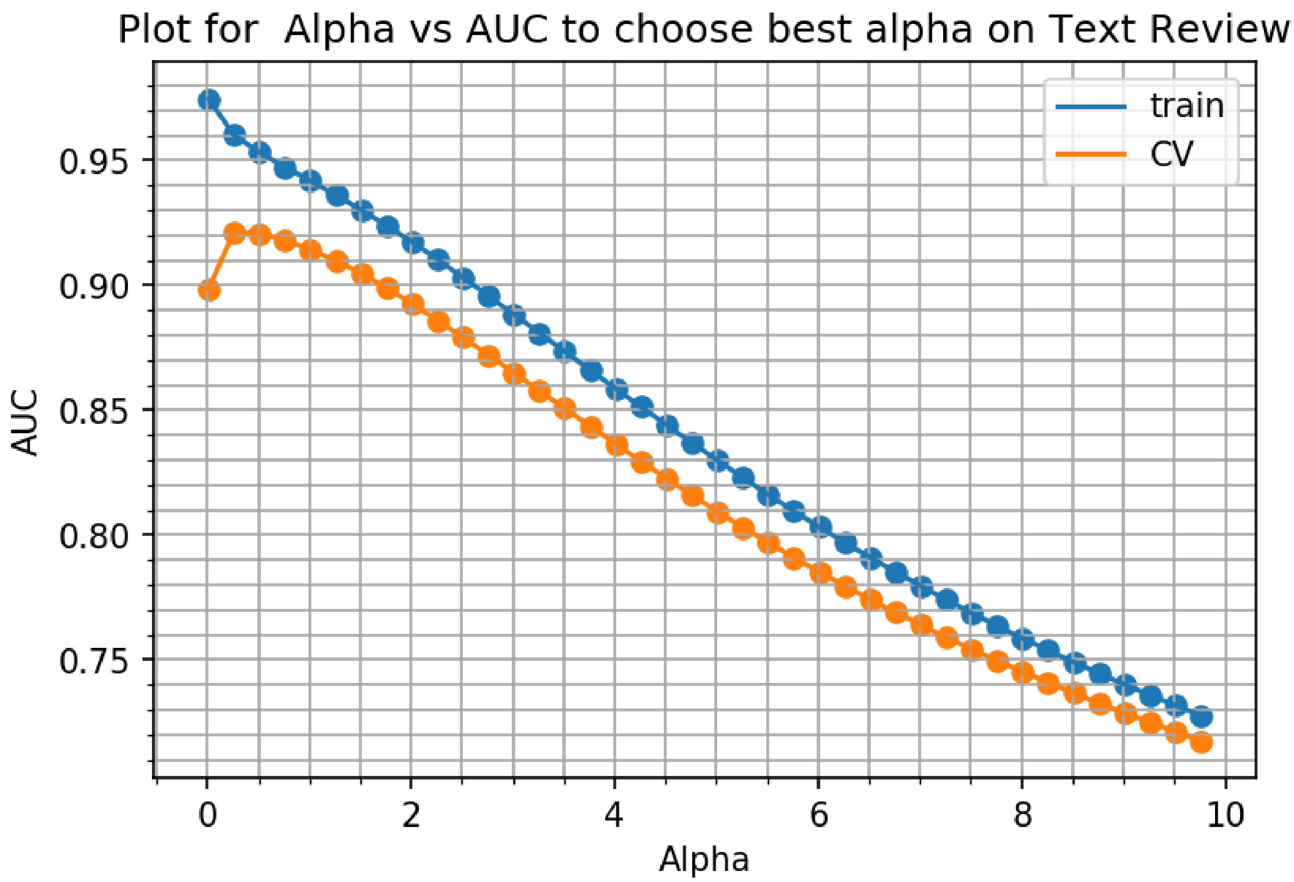
In [12]:

```python
cv_auc = []
train_auc=[]

for alpha in tqdm(lis):
    NB_BOW = MultinomialNB(alpha=alpha)
    NB_BOW.fit(bow_X_train_no_stop, y_train)
    proba_pred_train_BOW=(NB_BOW.predict_proba(bow_X_train_no_stop)[:,1])
    proba_pred_cv_BOW=(NB_BOW.predict_proba(bow_X_CV_no_stop)[:,1])
    train_auc.append(roc_auc_score(y_train,proba_pred_train_BOW))
    cv_auc.append(roc_auc_score(y_CV,proba_pred_cv_BOW))
```

```
100%|██████████████████████████████████████████████████| 40/40
[00:09<00:00,  4.41it/s]
```

In [53]:

```python
default_dpi = plt.rcParamsDefault['figure.dpi']
plt.rcParams['figure.dpi'] = default_dpi*1.5
plt.plot(lis, train_auc)
plt.scatter(lis, train_auc)
plt.plot(lis, cv_auc )
plt.scatter(lis, cv_auc )
plt.xlabel('Alpha')
plt.ylabel('AUC')
plt.title("Plot for  Alpha vs AUC to choose best alpha on Text Review")
plt.legend(['train', 'CV'], loc='upper right')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
plt.show()
```



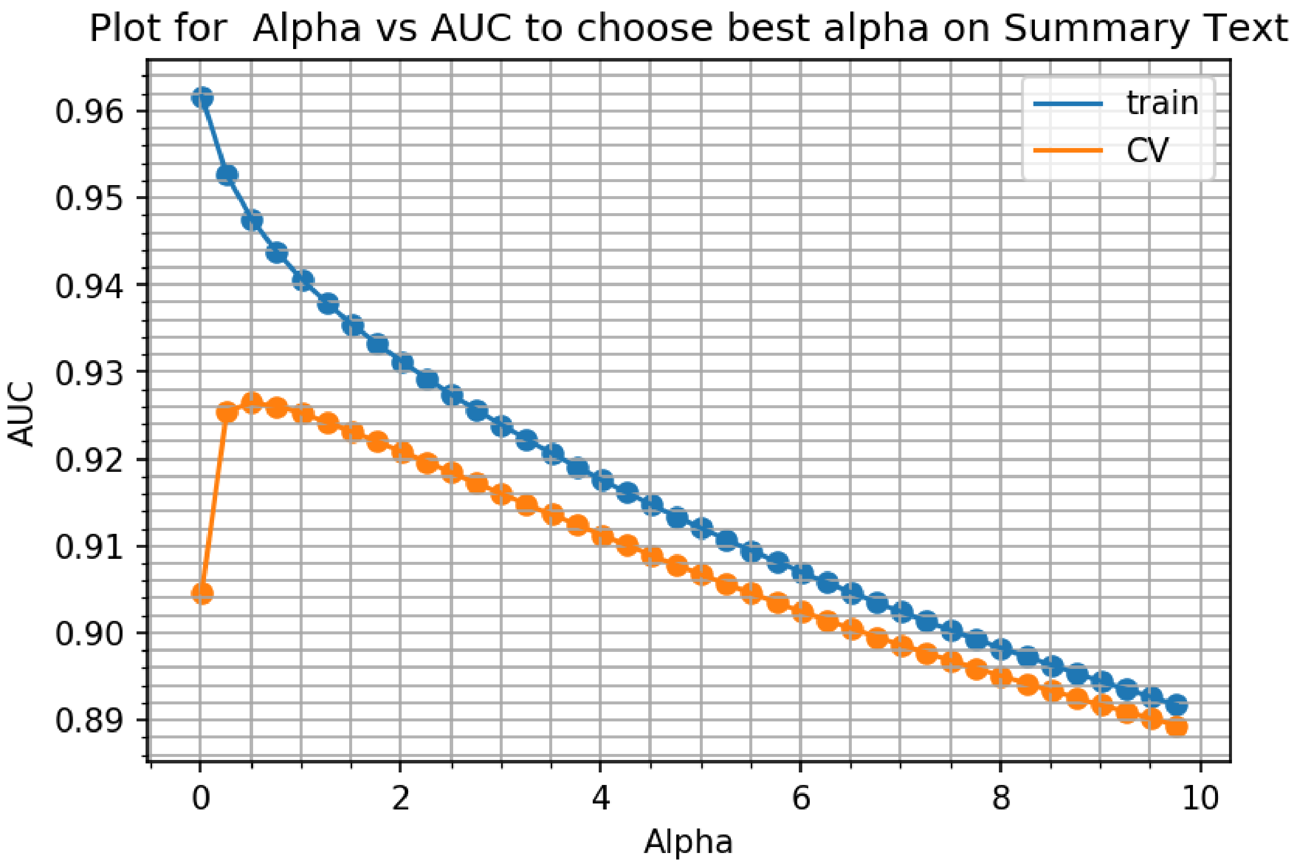
In [14]:

```
cv_auc_sum = []
train_auc_sum=[]

for alpha in tqdm(lis):
    NB_BOW_summary = MultinomialNB(alpha=alpha)
    NB_BOW_summary.fit(bow_X_summary_train, y_summary_train)
    proba_pred_train_BOW_summary=(NB_BOW_summary.predict_proba(bow_X_summary_train)[:,1])
    proba_pred_cv_BOW_summary=(NB_BOW_summary.predict_proba(bow_X_summary_CV)[:,1])
    train_auc_sum.append(roc_auc_score(y_summary_train,proba_pred_train_BOW_summary))
    cv_auc_sum.append(roc_auc_score(y_summary_CV,proba_pred_cv_BOW_summary))
```

```
100%|████████████████████████████████████████| 40/40
[00:04<00:00,  8.60it/s]
```

In [15]:

```
default_dpi = plt.rcParamsDefault['figure.dpi']
plt.rcParams['figure.dpi'] = default_dpi*1.5
plt.plot(lis, train_auc_sum)
plt.scatter(lis, train_auc_sum)
plt.plot(lis, cv_auc_sum )
plt.scatter(lis, cv_auc_sum )
plt.xlabel('Alpha')
plt.ylabel('AUC')
plt.title("Plot for  Alpha vs AUC to choose best alpha on Summary Text")
plt.legend(['train', 'CV'], loc='upper right')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
plt.show()
```



So Best alpha both for Text and Summary is around ".3"

In [16]:

```
bestNB_BOW = MultinomialNB(alpha=.3)
bestNB_BOW.fit(bow_X_train_no_stop, y_train)
```

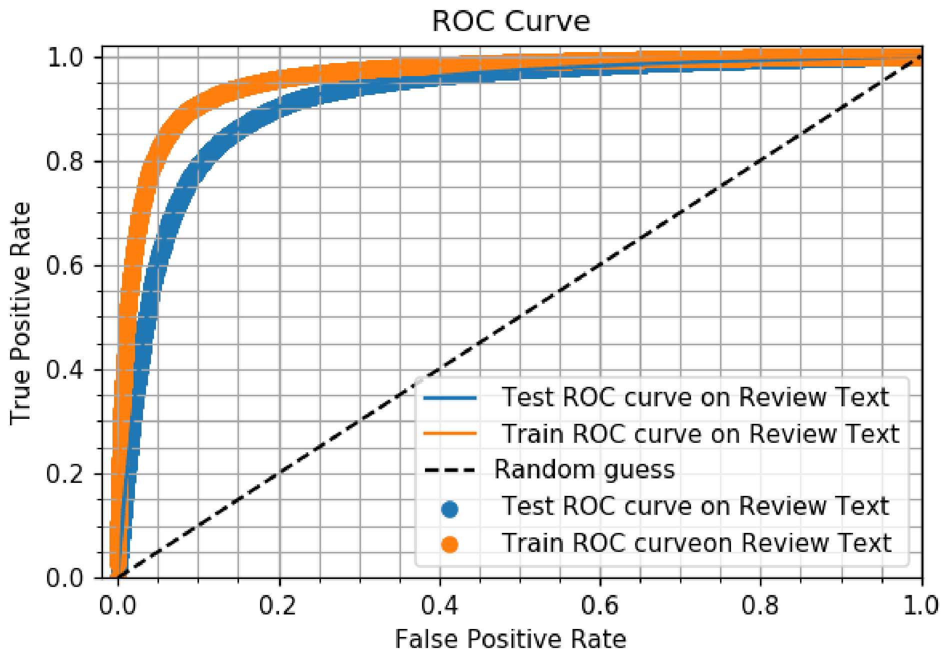
```
bestNB_proba_pred_train_BOW=(bestNB_BOW.predict_proba(bow_X_train_no_stop)[:,1])
bestNB_proba_pred_test_BOW=(bestNB_BOW.predict_proba(bow_X_test_no_stop)[:,1])
```

In [83]:

```
auc_test_BOW  = (roc_auc_score(y_test,bestNB_proba_pred_test_BOW))
auc_train_BOW  = (roc_auc_score(y_train,bestNB_proba_pred_train_BOW))
```

In [54]:

```
from sklearn.metrics import roc_curve
import matplotlib.pyplot as plt
%matplotlib inline

fpr_test_NB_bow_NS, tpr_test_NB_bow_NS, thresholds = roc_curve(y_test, bestNB_proba_pred_test_BOW)
fpr_train_NB_bow_NS, tpr_train_NB_bow_NS, thresholds = roc_curve(y_train,
bestNB_proba_pred_train_BOW)
# create plot
plt.rcParams['figure.dpi'] = default_dpi*1.1
plt.plot(fpr_test_NB_bow_NS, tpr_test_NB_bow_NS, label=' Test ROC curve on Review Text')
plt.scatter(fpr_test_NB_bow_NS, tpr_test_NB_bow_NS, label=' Test ROC curve on Review Text')
plt.plot(fpr_train_NB_bow_NS, tpr_train_NB_bow_NS, label=' Train ROC curve on Review Text')
plt.scatter(fpr_train_NB_bow_NS, tpr_train_NB_bow_NS, label=' Train ROC curveon Review Text')
plt.plot([0, 1], [0, 1], 'k--', label='Random guess')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
_ = plt.xlabel('False Positive Rate')
_ = plt.ylabel('True Positive Rate')
_ = plt.title('ROC Curve')
_ = plt.xlim([-0.02, 1])
_ = plt.ylim([0, 1.02])
_ = plt.legend(loc="lower right")
```



In [55]:

```
bestNB_BOW = MultinomialNB(alpha=.3)
bestNB_BOW.fit(bow_X_train_no_stop, y_train)
bestNB_pred_train_BOW=bestNB_BOW.predict(bow_X_train_no_stop)
bestNB_pred_test_BOW=bestNB_BOW.predict(bow_X_test_no_stop)
```

In [56]:

```
from sklearn.metrics import classification_report

print ("###########################################################")
print ("The classification report on Test dataset on Review Text")
print ("###########################################################")
```

```
print(classification_report(y_test, bestNB_pred_test_BOW))


print ("#########################################################")
print ("The classification report on Training dataset Review Text")
print ("#########################################################")
print(classification_report(y_train, bestNB_pred_train_BOW))
```

```
#########################################################
The classification report on Test dataset on Review Text
#########################################################
             precision    recall  f1-score   support

          0       0.72      0.70      0.71     21261
          1       0.94      0.94      0.94     99648

avg / total       0.90      0.90      0.90    120909

#########################################################
The classification report on Training dataset Review Text
#########################################################
             precision    recall  f1-score   support

          0       0.75      0.79      0.77     22681
          1       0.97      0.96      0.96    141791

avg / total       0.94      0.94      0.94    164472
```

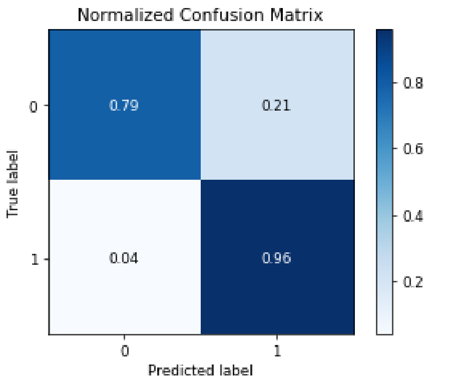
In [57]:

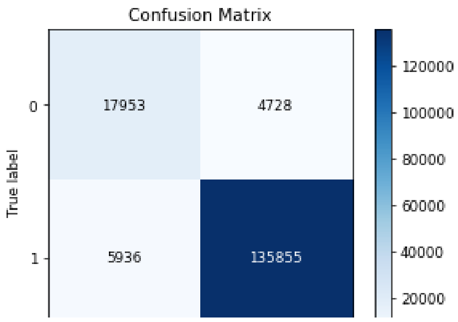
```
from sklearn.metrics import confusion_matrix
import scikitplot.metrics as skplt

plt.rcParams['figure.dpi'] = default_dpi*.63

skplt.plot_confusion_matrix(y_train,bestNB_pred_train_BOW,normalize=True)
print ("IN NOT NORMALIZED FORMAT BELOW")

skplt.plot_confusion_matrix(y_train,bestNB_pred_train_BOW)
```

IN NOT NORMALIZED FORMAT BELOW

Out[57]:

<matplotlib.axes._subplots.AxesSubplot at 0x24e3ea19128>





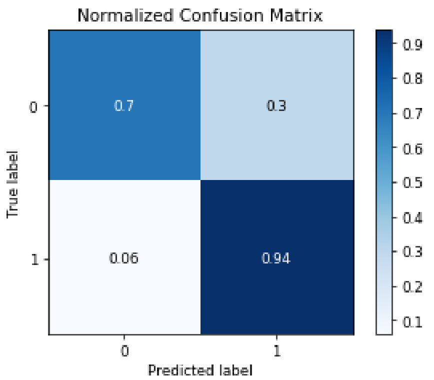
In [21]:

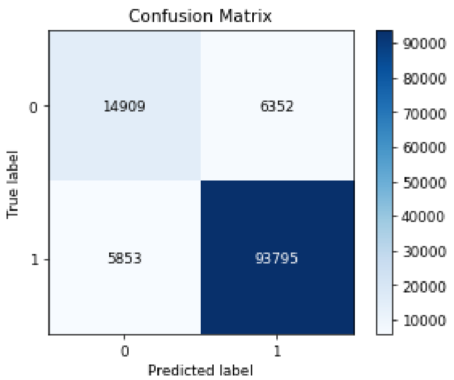
```
from sklearn.metrics import confusion_matrix
import scikitplot.metrics as skplt
plt.rcParams['figure.dpi'] = default_dpi*.63

skplt.plot_confusion_matrix(y_test, bestNB_pred_test_BOW,normalize=True)
print ("IN NOT NORMALIZED FORMAT BELOW")
skplt.plot_confusion_matrix(y_test, bestNB_pred_test_BOW)
```

```
IN NOT NORMALIZED FORMAT BELOW
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24e40581be0>
```





Reference:https://www.kaggle.com/premvardhan/amazon-fine-food-reviews-analysis-naive-bayes

Below is on for Summary Text

In [22]:

```
bestNB_BOW_sum = MultinomialNB(alpha=.3)
bestNB_BOW_sum.fit(bow_X_summary_train, y_summary_train)
bestNB_proba_pred_train_BOW_sum=(bestNB_BOW_sum.predict_proba(bow_X_summary_train)[:,1])
bestNB_proba_pred_test_BOW_sum=(bestNB_BOW_sum.predict_proba(bow_X_summary_test)[:,1])
```

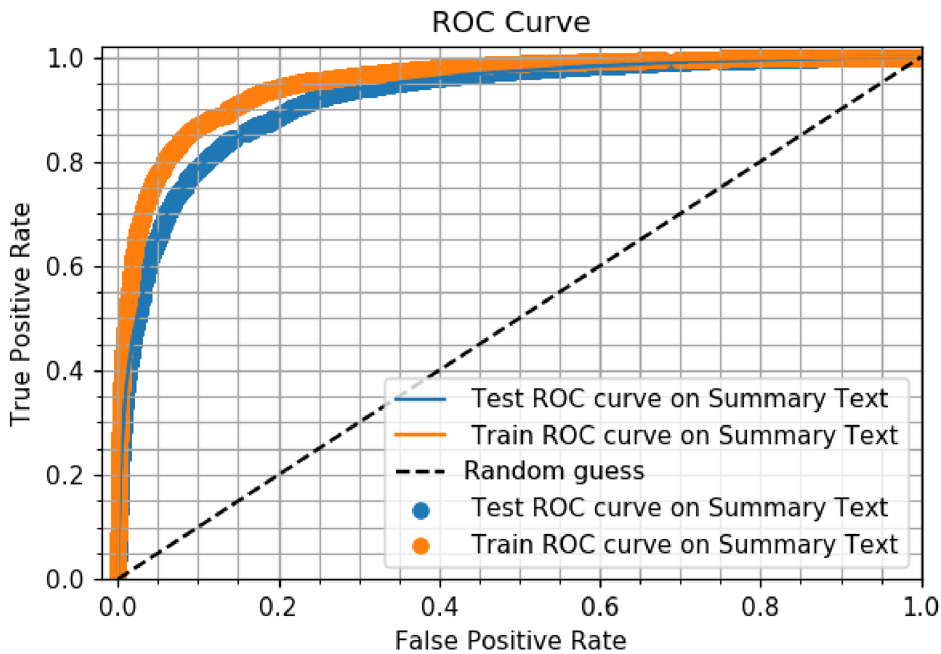
In [84]:

```
auc_train_bow_sum = (roc_auc_score(y_summary_train,bestNB_proba_pred_train_BOW_sum))
auc_test_bow_sum = (roc_auc_score(y_summary_test,bestNB_proba_pred_test_BOW_sum))
```

In [23]:

```
from sklearn.metrics import roc_curve
import matplotlib.pyplot as plt
```

```
%matplotlib inline

fpr_test_NB_bow_NS_sum, tpr_test_NB_bow_NS_sum, thresholds = roc_curve(y_summary_test,
bestNB_proba_pred_test_BOW_sum)
fpr_train_NB_bow_NS_sum, tpr_train_NB_bow_NS_sum, thresholds = roc_curve(y_summary_train,
bestNB_proba_pred_train_BOW_sum)
# create plot
plt.rcParams['figure.dpi'] = default_dpi*1.1
plt.plot(fpr_test_NB_bow_NS_sum, tpr_test_NB_bow_NS_sum, label=' Test ROC curve on Summary Text')
plt.scatter(fpr_test_NB_bow_NS_sum, tpr_test_NB_bow_NS_sum, label=' Test ROC curve on Summary
Text')
plt.plot(fpr_train_NB_bow_NS_sum, tpr_train_NB_bow_NS_sum, label=' Train ROC curve on Summary
Text')
plt.scatter(fpr_train_NB_bow_NS_sum, tpr_train_NB_bow_NS_sum, label=' Train ROC curve on Summary
Text')
plt.plot([0, 1], [0, 1], 'k--', label='Random guess')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
_ = plt.xlabel('False Positive Rate')
_ = plt.ylabel('True Positive Rate')
_ = plt.title('ROC Curve')
_ = plt.xlim([-0.02, 1])
_ = plt.ylim([0, 1.02])
_ = plt.legend(loc="lower right")
```



In [24]:

```
bestNB_BOW_sum = MultinomialNB(alpha=.3)
bestNB_BOW_sum.fit(bow_X_summary_train, y_summary_train)
bestNB_pred_train_BOW_sum=bestNB_BOW_sum.predict(bow_X_summary_train)
bestNB_pred_test_BOW_sum=bestNB_BOW_sum.predict(bow_X_summary_test)
```

In [58]:

```
from sklearn.metrics import classification_report

print ("#############################################################")
print ("The classification report on Test dataset for Summary Text")
print ("#############################################################")

print(classification_report(y_summary_test, bestNB_pred_test_BOW_sum))


print ("#############################################################")
print ("The classification report on Training dataset For Summary Text")
print ("#############################################################")
print(classification_report(y_summary_train, bestNB_pred_train_BOW_sum))
```

```
#############################################################
```

```
The classification report on Test dataset for Summary Text
#######################################################
              precision    recall  f1-score   support

          0       0.76      0.60      0.67     21261
          1       0.92      0.96      0.94     99648

avg / total       0.89      0.90      0.89    120909

#######################################################
The classification report on Training dataset For Summary Text
#######################################################
              precision    recall  f1-score   support

          0       0.78      0.67      0.72     22681
          1       0.95      0.97      0.96    141791

avg / total       0.93      0.93      0.93    164472
```

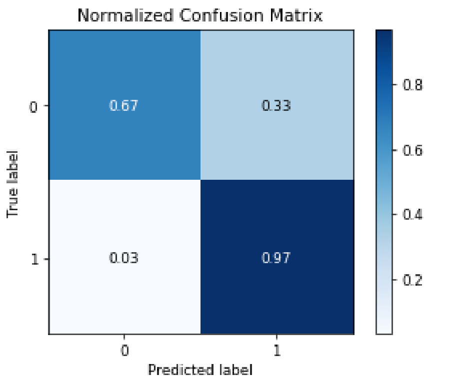
In [26]:

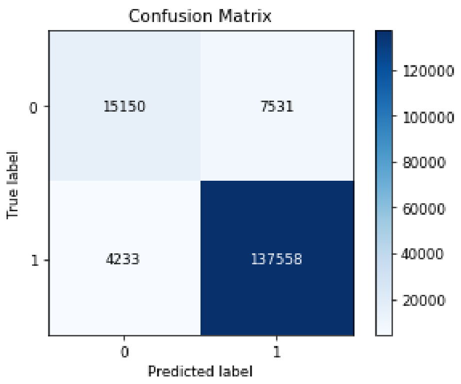
```
from sklearn.metrics import confusion_matrix
import scikitplot.metrics as skplt

plt.rcParams['figure.dpi'] = default_dpi*.63

skplt.plot_confusion_matrix(y_summary_train, bestNB_pred_train_BOW_sum,normalize=True)
print ("IN NOT NORMALIZED FORMAT BELOW")

skplt.plot_confusion_matrix(y_summary_train, bestNB_pred_train_BOW_sum)
```

```
IN NOT NORMALIZED FORMAT BELOW
```

Out[26]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x24e36610668&gt;
```





In [27]:

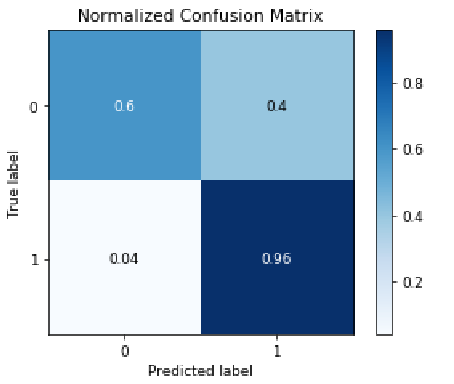
```
from sklearn.metrics import confusion_matrix
import scikitplot.metrics as skplt

plt.rcParams['figure.dpi'] = default_dpi*.63
```

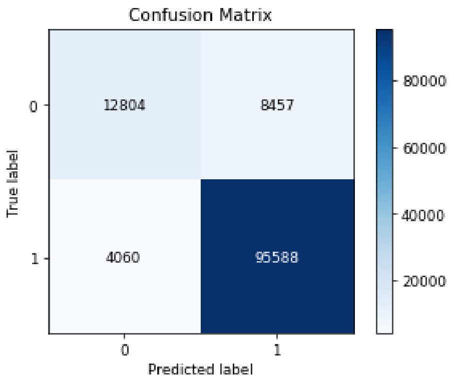
```
skplt.plot_confusion_matrix(y_summary_test, bestNB_pred_test_BOW_sum,normalize=True)
print ("IN NOT NORMALIZED FORMAT BELOW")

skplt.plot_confusion_matrix(y_summary_test, bestNB_pred_test_BOW_sum)
```

```
IN NOT NORMALIZED FORMAT BELOW
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24e4bd5b390>
```





[5.1.1] Top 10 important features of positive class from SET 1

In [28]:

```
bestNB_BOW_sum = MultinomialNB(alpha=.5)
bestNB_BOW_sum.fit(bow_X_summary_train, y_summary_train)
feature_log_prob_ =bestNB_BOW_sum.feature_log_prob_
bow_features_name = vectorizer.get_feature_names()
feature_prob = pd.DataFrame(feature_log_prob_, columns = bow_features_name)
feature_prob_tr = feature_prob.T
feature_count =bestNB_BOW_sum.feature_count_
count = pd.DataFrame(feature_count, columns = bow_features_name)
count_tr = count.T
```

In [29]:

```
print("\n\n Top 10 positive features:-\n",feature_prob_tr[1].sort_values(ascending = False)[0:10])
print ("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!"
)
print ("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!"
)
print ("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!"
)

print ("The count for number of times top most 100 words was used for positive reviews")
print (count_tr[1].sort_values(ascending = False)[0:100])
```

```
 Top 10 positive features:-
 great        -2.983125
good         -3.474666
```

```
best        -3.584458
tea         -4.084955
love        -4.316402
product     -4.401193
excellent   -4.732411
coff        -4.884914
flavor      -4.895109
delici      -4.904781
Name: 1, dtype: float64
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
The count for number of times top most 100 words was used for positive reviews
great        21791.0
good         13329.0
best         11943.0
tea           7240.0
love          5744.0
product       5277.0
excellent     3789.0
coff          3253.0
flavor        3220.0
delici        3189.0
not           3083.0
lov           3043.0
delicious     2764.0
food          2651.0
dog           2568.0
ev            2563.0
stuff         2528.0
snack         2436.0
coffee        2311.0
like          2183.0
treat         2125.0
taste         2043.0
tasty         2040.0
free          2037.0
favorite      2028.0
tast          2017.0
yummi         1941.0
pr            1863.0
yum           1737.0
perfect       1725.0
              ...
low            774.0
awesom         762.0
way            749.0
get            721.0
cats           718.0
fantastic      707.0
chip           705.0
chocol         699.0
oil            692.0
fresh          689.0
pretty         684.0
ever           679.0
amazing        678.0
valu           674.0
breakfast      647.0
cant           636.0
review         633.0
eat            632.0
go             629.0
sauc           629.0
addict         615.0
wow            614.0
salt           605.0
candi          598.0
amazon         591.0
hard           589.0
high           588.0
quick          588.0
work           588.0
loves          584.0
Name: 1, Length: 100, dtype: float64
```

[5.1.2] Top 10 important features of negative class from SET 1

In [30]:

```
print("Top 10 negative features:-\n",feature_prob_tr[0].sort_values(ascending = False)[0:10])
print ("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!"
)
print ("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!"
)
print ("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!"
)
print ("The count for number of times top most 100 words was used for negative reviews")
print (count_tr[0].sort_values(ascending = False)[0:100])
```

```
Top 10 negative features:-
 not           -2.943071
good          -4.290391
like          -4.584330
product       -4.712191
flavor        -4.842844
taste         -4.871808
disappoint    -4.875079
no            -4.888269
bad           -4.922028
great         -4.923746
Name: 0, dtype: float64
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
The count for number of times top most 100 words was used for negative reviews
not           4214.0
good          1095.0
like           816.0
product        718.0
flavor         630.0
taste          612.0
disappoint     610.0
no             602.0
bad            582.0
great          581.0
tast           579.0
dont           541.0
buy            451.0
tastes         427.0
tea            412.0
yuck           309.0
much           308.0
poor           294.0
food           293.0
sweet          286.0
money          276.0
dog            274.0
worst          262.0
coff           262.0
coffee         259.0
made           235.0
way            229.0
really         226.0
sugar          226.0
doesnt         217.0
               ...
little         123.0
expen          123.0
never          121.0
gluten         120.0
shipping       119.0
rip            116.0
packag         115.0
box            115.0
bewar          114.0
overpr         114.0
us             112.0
nothing        112.0
review         111.0
strong         110.0
```

```
contains       110.0
new            110.0
bett           109.0
free           108.0
real           108.0
ship           105.0
wont           105.0
mix            101.0
dogs           101.0
adverti        100.0
bar             99.0
ord             98.0
even            97.0
salti           96.0
low             95.0
cats            94.0
Name: 0, Length: 100, dtype: float64
```

Examples Feature Engineering.

1) The above experiment that we did on text can we do it on summary i.e which word/feature is used most for positive or negative review summary. The reason being in long text we tend to write general works like "product","taste","flavour" which is most used words both for positive and negative review (asked in homework/assignment)

2) Length of text (asked in homework/assignment)

3) Product with highest helpfullness are they sold more compared to lower helpfullness product

4) Does length of text anything to do with helpfullness

5) Does length of text anything to do amount of product sold (score as we dont have data on amount of data sold so lets just take product sold more should have been given good rating)

6) Has number of reviews either good or bad anything to do with amount of product sold

7) UserID who has purchased maximum product do they write summary

8) UserID who has purchased maximum product do they mark text as helpful or not

9) UserID who has purchased maximum product do they read lengthy reviews or shorter reviews

In this assignment lets take up 1) 2) 3) 4) and 5

In [31]:

```
# 1)  The above experiment that we did on text can we do it on summary i.e which word/feature is u
sed most
#for positive or negative review summary. The reason being in long text we tend to write general w
orks
#like "product","taste","flavour" which is most used words both for positive and negative
#review (asked in homework/assignment)
```

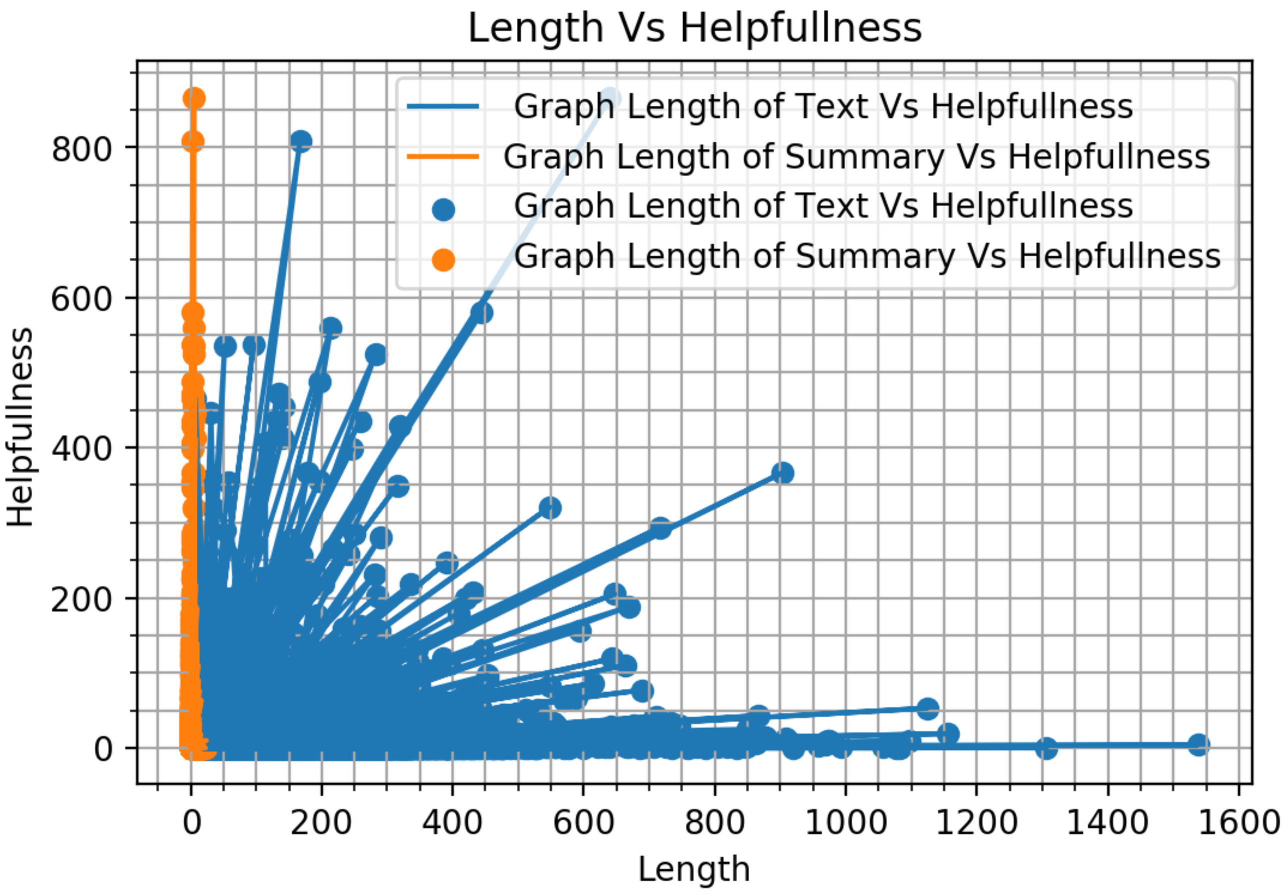
In [32]:

```
# 2) and  4) Any Relation b/w length of Text/Summary and Helpfullness?

import matplotlib.pyplot as plt
%matplotlib inline
#print (data)
lst_len_txt =data["Text_length"].tolist()
lst_len_sum =data["Summary_length"].tolist()
lst_helpfulness = data["HelpfulnessNumerator"].tolist()
```

In [33]:

```
# create plot
plt.rcParams['figure.dpi'] = default_dpi*2
plt.plot(lst_len_txt, lst_helpfulness, label=' Graph Length of Text Vs Helpfullness')
plt.scatter(lst_len_txt, lst_helpfulness, label=' Graph Length of Text Vs Helpfullness')
plt.plot(lst_len_sum, lst_helpfulness, label='Graph Length of Summary Vs Helpfullness')
```

```
plt.scatter(lst_len_sum, lst_helpfulness, label=' Graph Length of Summary Vs Helpfullness')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
_ = plt.xlabel('Length')
_ = plt.ylabel('Helpfullness')
_ = plt.title('Length Vs Helpfullness')
_ = plt.legend(loc="upper right")
```

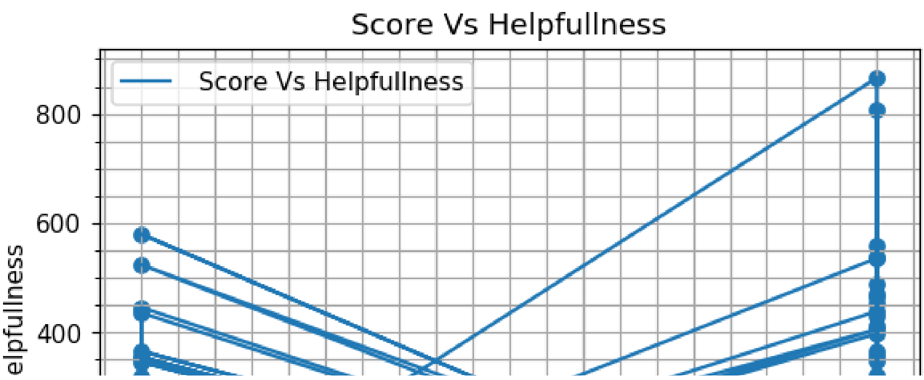


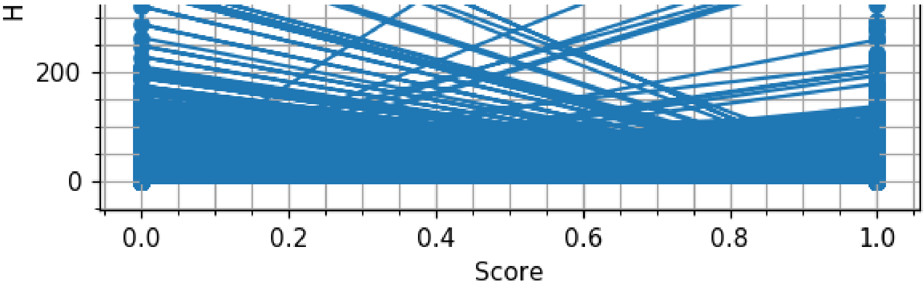
In [34]:

```
# Any relationship b/w Product with higher helpfullness and number of items sold (rating score)
```

In [43]:

```
# create plot
lst_score = data["Score"].tolist()
plt.rcParams['figure.dpi'] = default_dpi*1.1
plt.plot(lst_score, lst_helpfulness, label=' Score Vs Helpfullness')
plt.scatter(lst_score, lst_helpfulness)
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
_ = plt.xlabel('Score')
_ = plt.ylabel('Helpfullness')
_ = plt.title('Score Vs Helpfullness')
_ = plt.legend(loc="upper left")
```





[5.2] Applying Naive Bayes on TFIDF, SET 2

In [59]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer(ngram_range=(1,5))
tfidf_X_train = tf_idf_vect.fit_transform(X_no_stop_train)
tfidf_X_test = tf_idf_vect.transform(X_no_stop_test)
tfidf_X_CV = tf_idf_vect.transform(X_no_stop_CV)

from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
```

In [60]:

```
# creating odd list of alpha for  Naive bays
def tothepower(y):
    return (10**y)
alpha_NB = list(map(tothepower, list(range(-4, 5))))
print (alpha_NB)
alpha_NB_log = [math.log(x) for x in alpha_NB]
print (alpha_NB_log)
```

```
[0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850929940455, 0.0,
2.302585092994046, 4.605170185988092, 6.907755278982137, 9.210340371976184]
```

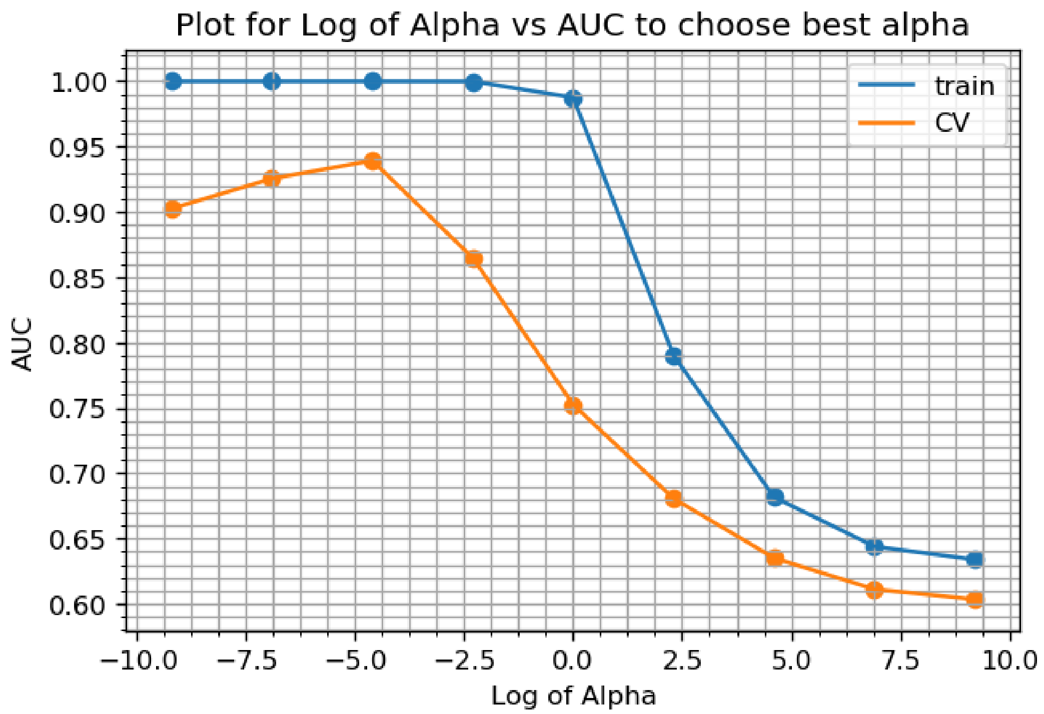
In [61]:

```
auc_cv_tfidf = []
auc_train_tfidf=[]

for alpha in tqdm(alpha_NB):
    NB_tfidf  = MultinomialNB(alpha=alpha)
    NB_tfidf.fit(tfidf_X_train, y_train)
    proba_pred_train_tfidf=(NB_tfidf.predict_proba(tfidf_X_train)[:,1])
    proba_pred_cv_tfidf=(NB_tfidf.predict_proba(tfidf_X_CV)[:,1])
    auc_train_tfidf.append(roc_auc_score(y_train,proba_pred_train_tfidf))
    auc_cv_tfidf.append(roc_auc_score(y_CV,proba_pred_cv_tfidf))
```

```
100%|██████████████████████████████████████████████████████████████| 9/9 [00
:21<00:00,  2.38s/it]
```

In [62]:

```
default_dpi = plt.rcParamsDefault['figure.dpi']
plt.rcParams['figure.dpi'] = default_dpi*1.2
plt.plot(alpha_NB_log, auc_train_tfidf)
plt.scatter(alpha_NB_log, auc_train_tfidf)
plt.plot(alpha_NB_log, auc_cv_tfidf)
plt.scatter(alpha_NB_log, auc_cv_tfidf)
plt.xlabel('Log of Alpha')
plt.ylabel('AUC')
plt.title("Plot for Log of Alpha vs AUC to choose best alpha")
plt.legend(['train', 'CV'], loc='upper right')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
plt.show()
```



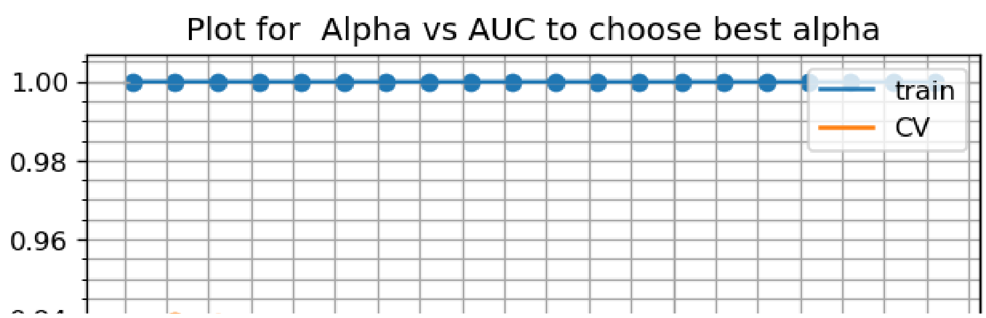
In [65]:

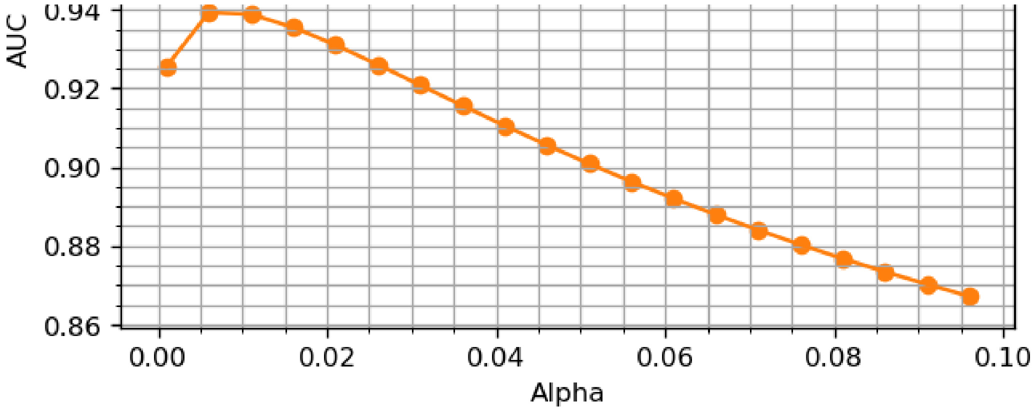
```
import numpy as np
lis_n = np.arange (.001, .1, .005)
auc_cv_tfidf = []
auc_train_tfidf=[]

for alpha in tqdm(lis_n):
    NB_tfidf = MultinomialNB(alpha=alpha)
    NB_tfidf.fit(tfidf_X_train, y_train)
    proba_pred_train_tfidf=(NB_tfidf.predict_proba(tfidf_X_train)[:,1])
    proba_pred_cv_tfidf=(NB_tfidf.predict_proba(tfidf_X_CV)[:,1])
    auc_train_tfidf.append(roc_auc_score(y_train,proba_pred_train_tfidf))
    auc_cv_tfidf.append(roc_auc_score(y_CV,proba_pred_cv_tfidf))
```

```
100%|████████████████████████████████████████████████████████████████| 20/20
[00:46<00:00,  2.30s/it]
```

In [66]:

```
default_dpi = plt.rcParamsDefault['figure.dpi']
plt.rcParams['figure.dpi'] = default_dpi*1.2
plt.plot(lis_n, auc_train_tfidf)
plt.scatter(lis_n, auc_train_tfidf)
plt.plot(lis_n, auc_cv_tfidf)
plt.scatter(lis_n, auc_cv_tfidf)
plt.xlabel('Alpha')
plt.ylabel('AUC')
plt.title("Plot for  Alpha vs AUC to choose best alpha")
plt.legend(['train', 'CV'], loc='upper right')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
plt.show()
```





In [68]:

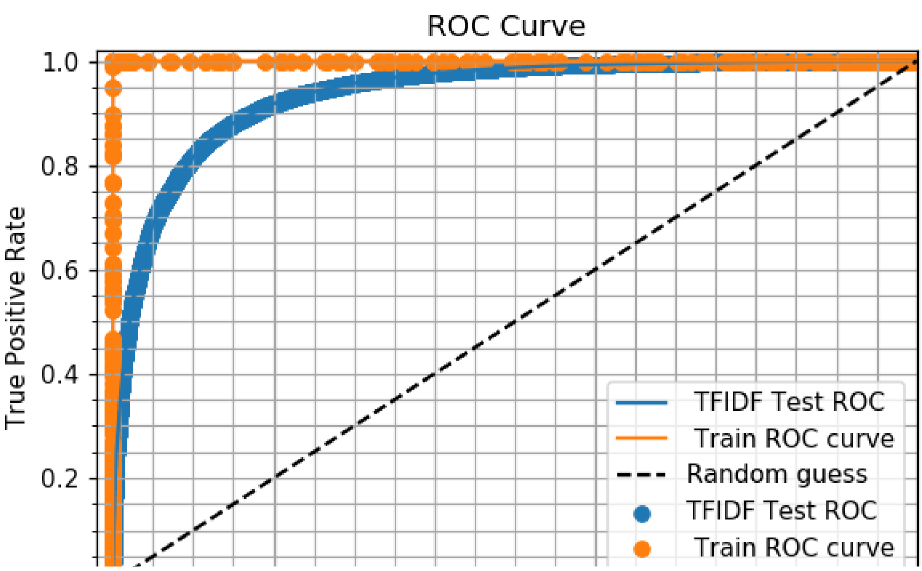
```
bestNB_tfidf = MultinomialNB(alpha=.01)
bestNB_tfidf.fit(tfidf_X_train, y_train)
bestNB_proba_pred_train_tfidf=(bestNB_tfidf.predict_proba(tfidf_X_train)[:,1])
bestNB_proba_pred_test_tfidf=(bestNB_tfidf.predict_proba(tfidf_X_test)[:,1])
```

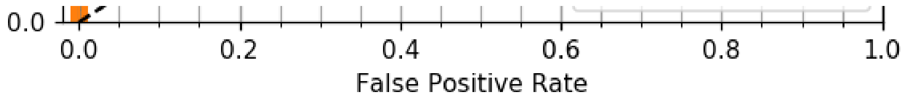
In [85]:

```
auc_test_BOW_tfidf  = (roc_auc_score(y_test,bestNB_proba_pred_test_tfidf))
auc_train_BOW_tfidf  = (roc_auc_score(y_train,bestNB_proba_pred_train_tfidf))
```

In [69]:

```
from sklearn.metrics import roc_curve
import matplotlib.pyplot as plt
%matplotlib inline

fpr_test_NB_tfidf, tpr_test_NB_tfidf, thresholds = roc_curve(y_test, bestNB_proba_pred_test_tfidf)
fpr_train_NB_tfidf, tpr_train_NB_tfidf, thresholds = roc_curve(y_train,
bestNB_proba_pred_train_tfidf)
# create plot
plt.rcParams['figure.dpi'] = default_dpi*1.1
plt.plot(fpr_test_NB_tfidf, tpr_test_NB_tfidf, label=' TFIDF Test ROC ')
plt.scatter(fpr_test_NB_tfidf, tpr_test_NB_tfidf, label='TFIDF Test ROC ')
plt.plot(fpr_train_NB_tfidf, tpr_train_NB_tfidf, label=' Train ROC curve')
plt.scatter(fpr_train_NB_tfidf, tpr_train_NB_tfidf, label=' Train ROC curve')
plt.plot([0, 1], [0, 1], 'k--', label='Random guess')
plt.minorticks_on()
plt.grid(b=True, which='both', color='0.65', linestyle='-')
_ = plt.xlabel('False Positive Rate')
_ = plt.ylabel('True Positive Rate')
_ = plt.title('ROC Curve')
_ = plt.xlim([-0.02, 1])
_ = plt.ylim([0, 1.02])
_ = plt.legend(loc="lower right")
```





In [70]:

```
bestNB_tfidf = MultinomialNB(alpha=.01)
bestNB_tfidf.fit(tfidf_X_train, y_train)
bestNB_pred_train_tfidf=bestNB_tfidf.predict(tfidf_X_train)
bestNB_pred_test_tfidf=bestNB_tfidf.predict(tfidf_X_test)
```

In [71]:

```
from sklearn.metrics import classification_report

print ("#######################################################")
print ("The classification report on Test dataset")
print ("#######################################################")

print(classification_report(y_test, bestNB_pred_test_tfidf))


print ("#######################################################")
print ("The classification report on Training dataset")
print ("#######################################################")
print(classification_report(y_train, bestNB_pred_train_tfidf))
```

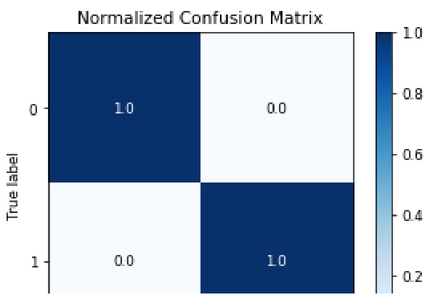
```
#######################################################
The classification report on Test dataset
#######################################################
             precision    recall  f1-score   support

          0       0.95      0.29      0.44     21261
          1       0.87      1.00      0.93     99648

avg / total       0.88      0.87      0.84    120909

#######################################################
The classification report on Training dataset
#######################################################
             precision    recall  f1-score   support

          0       1.00      1.00      1.00     22681
          1       1.00      1.00      1.00    141791

avg / total       1.00      1.00      1.00    164472
```

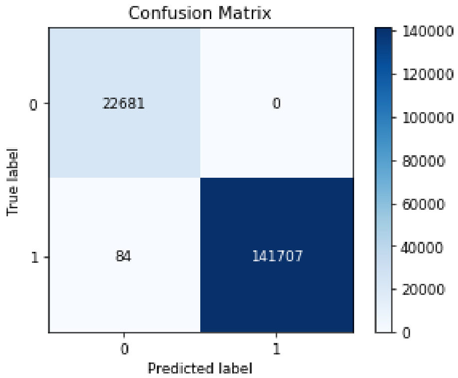
In [72]:

```
from sklearn.metrics import confusion_matrix
import scikitplot.metrics as skplt

plt.rcParams['figure.dpi'] = default_dpi*.63

skplt.plot_confusion_matrix(y_train,bestNB_pred_train_tfidf,normalize=True)
skplt.plot_confusion_matrix(y_train,bestNB_pred_train_tfidf)
```

Out[72]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24e4926c8d0>
```



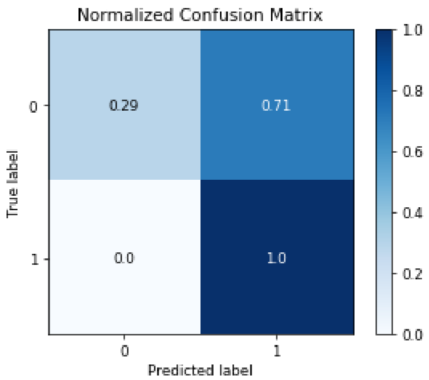


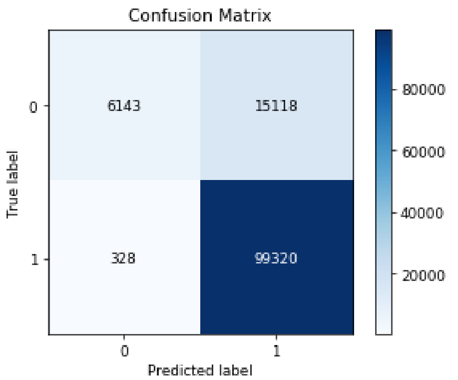
In [73]:

```
from sklearn.metrics import confusion_matrix
import scikitplot.metrics as skplt

plt.rcParams['figure.dpi'] = default_dpi*.63

skplt.plot_confusion_matrix(y_test,bestNB_pred_test_tfidf,normalize=True)
skplt.plot_confusion_matrix(y_test,bestNB_pred_test_tfidf)
```

Out[73]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24f70d60e80>
```





[5.2.1] Top 10 important features of positive class from SET 2

Reference::https://www.kaggle.com/premvardhan/amazon-fine-food-reviews-analysis-naive-bayes

In [74]:

```
bestNB_tfidf_NS = MultinomialNB(alpha=.01)
bestNB_tfidf_NS.fit(tfidf_X_train, y_train)
feature_log_prob_ =bestNB_tfidf_NS.feature_log_prob_  #https://www.kaggle.com/premvardhan/amazon-fi
```

```
ne-food-reviews-analysis-naive-bayes
features_name_tfidf = tf_idf_vect.get_feature_names() #https://www.kaggle.com/premvardhan/amazon-f
ine-food-reviews-analysis-naive-bayes
feature_prob = pd.DataFrame(feature_log_prob_, columns = features_name_tfidf)
#https://www.kaggle.com/premvardhan/amazon-fine-food-reviews-analysis-naive-bayes
feature_prob_tr = feature_prob.T
```

In [75]:

```
print("\n\n Top 10 positive features:-\n",feature_prob_tr[1].sort_values(ascending = False)[0:10])
```

```
 Top 10 positive features:-
 great     -7.607158
tea        -7.673285
good       -7.681102
not        -7.695874
like       -7.756590
coffee     -7.879960
love       -7.916423
product    -7.950869
taste      -7.997868
flavor     -7.998985
Name: 1, dtype: float64
```

[5.2.2] Top 10 important features of negative class from SET 2

In [76]:

```
print("\n\n Top 10 Negative features:-\n",feature_prob_tr[0].sort_values(ascending = False)[0:10])
```

```
 Top 10 Negative features:-
 not       -7.426898
like       -7.958729
product    -8.037271
taste      -8.097037
one        -8.367449
coffee     -8.379036
no         -8.473495
flavor     -8.485542
buy        -8.562469
tea        -8.565086
Name: 0, dtype: float64
```

Feature Engineering

In [78]:

```
# Count of top 100 Words for both positive and negative reviews
feature_count =bestNB_tfidf_NS.feature_count_
count = pd.DataFrame(feature_count, columns = features_name_tfidf)
count_tr = count.T
print ("Count of Words for negative reviews")
print (count_tr[0].sort_values(ascending = False)[0:100])
print ("Count of Words for Positive reviews")
print (count_tr[1].sort_values(ascending = False)[0:100])
```

```
Count of Words for negative reviews
not                284.137962
like               166.934784
product            154.324459
taste              145.370604
one                110.924961
coffee             109.646939
no                  99.763024
flavor              98.568221
buy                 91.269224
tea                 91.030678
```

```
good             90.236301
dont             90.057372
even             80.988011
get              76.511419
much             75.046505
box              74.830627
bad              73.871990
food             73.570499
bought           72.451484
amazon           71.545461
really           68.556866
didnt            63.280645
chocolate        63.262264
tried            63.109487
money            62.651015
im               62.283978
ordered          61.061429
disappointed     59.357593
thought          59.029021
tastes           57.305854
                   ...
still            40.384549
reviews          39.987852
want             39.694172
doesnt           39.588886
find             39.070916
give             38.836775
found            38.481925
cant             38.435621
great            38.410730
sweet            38.293013
package          37.832820
waste            37.796763
nothing          37.309519
maybe            37.308036
drink            37.218839
bags             36.854529
company          36.606153
ingredients      36.539468
store            36.440691
shipping         36.130379
say              35.807589
smell            35.747860
hard             35.667695
pack             35.093514
almost           34.793655
another          34.633925
many             34.408343
different        34.335994
not buy          34.010320
terrible         33.763597
Name: 0, Length: 100, dtype: float64
Count of Words for Positive reviews
great        931.044850
tea          871.468432
good         864.682957
not          852.002864
like         801.811817
coffee       708.749417
love         683.371543
product      660.232153
taste        629.919682
flavor       629.216449
one          623.335626
best         554.395992
find         483.343598
really       475.761534
get          474.848760
use          456.744457
no           449.569144
amazon       447.239510
food         427.302940
price        423.767233
buy          418.640760
little       417.345826
much         416.051020
also         399.525688
make         396.668484
```

```
make          396.668484
time          394.644893
ive           394.266358
chocolate     390.085782
dont          386.545732
tried         377.368390
                 ...
ever          250.122256
many          249.109667
since         248.469441
every         246.555602
box           246.528715
excellent     245.997462
wonderful     245.245455
fresh         244.737704
water         240.862181
bit           240.071227
without       238.326839
stuff         237.765445
healthy       233.460176
think         232.123432
two           230.197483
gluten        229.721572
enjoy         229.040780
organic       228.011061
right         226.500857
tasty         220.861627
hard          220.688534
highly        220.391216
still         219.989719
keep          219.886142
never         219.367616
local         215.324689
quality       213.465080
got           213.311972
stores        211.190253
know          210.942943
Name: 1, Length: 100, dtype: float64
```

[6] Conclusions

In [87]:

```
# Prettytable for alpha,AUC,Precision,recall and Accuracy

from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Algorithm","Parameter alpha","AUC"]

x.add_row(["BOW Naive Bayes Review Text Train Data", .3, auc_train_BOW])
x.add_row(["BOW Naive Bayes Review Text Test Data", .3, auc_test_BOW])
x.add_row(["BOW Naive Bayes Summary Text Train Data", .3, auc_train_bow_sum])
x.add_row(["BOW Naive Bayes Summary Text Test Data", .3, auc_test_bow_sum])
x.add_row(["TFIDF Naive Bayes Review Text Train Data", .01, auc_train_BOW_tfidf])
x.add_row(["TFIDF Naive Bayes Review Text Test Data", .01, auc_test_BOW_tfidf])
print(x)
```

```
+-------------------------------------------+-----------------+--------------------+
|                 Algorithm                 | Parameter alpha |        AUC         |
+-------------------------------------------+-----------------+--------------------+
|   BOW Naive Bayes Review Text Train Data  |       0.3       | 0.9588422862145487 |
|   BOW Naive Bayes Review Text Test Data   |       0.3       | 0.9178479285606571 |
|  BOW Naive Bayes Summary Text Train Data  |       0.3       | 0.951624035695791  |
|   BOW Naive Bayes Summary Text Test Data  |       0.3       | 0.9234990787816754 |
|  TFIDF Naive Bayes Review Text Train Data |       0.01      | 0.9999905009750969 |
|  TFIDF Naive Bayes Review Text Test Data  |       0.01      | 0.9371502082230916 |
+-------------------------------------------+-----------------+--------------------+
```

So we observe for both the algorithms Naive bayes performs lot better compared to KNN and takes lotlesser time as well.

Out of these two (i.e BOW and TFIDF using Naive Bayes we see BOW performs much better as recall value for TFIDF is poor)