## Part 8 - Random Forests & XGBoost

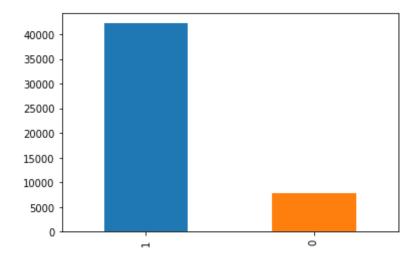
### By Aziz Presswala

```
In [1]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from tqdm import tqdm
        from prettytable import PrettyTable
        from wordcloud import WordCloud
        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.metrics import roc curve, auc, roc auc score
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.model selection import GridSearchCV, RandomizedSearchCV
        from sklearn import model selection
        from sklearn import metrics
        from xgboost import XGBClassifier
        from gensim.models import Word2Vec
```

## [1.0] Splitting the Dataset into Train & Test

In [2]: # Using the CleanedText column saved in final.sqlite db

```
con = sqlite3.connect('final.sqlite')
        filtered_data = pd.read_sql_query("SELECT * FROM Reviews", con)
        filtered data.shape
Out[2]: (364171, 12)
In [3]: # replacing all the 'positive' values of the Score attribute with 1
        filtered data['Score']=filtered data['Score'].replace('positive',1)
In [4]: # replacing all the 'neagtive' values of the Score attribute with 0
        filtered data['Score']=filtered data['Score'].replace('negative',0)
In [5]: #randomly selecting 50k points from the dataset
        df=filtered data.sample(50000)
In [6]: #sort the dataset by timestamp
        df = df.sort values('Time')
        #splitting the dataset into train(70%) & test(30%)
        train data = df[0:35000]
        test data = df[35000:50000]
In [7]: # distribution of output variable
        df['Score'].value counts().plot.bar()
Out[7]: <matplotlib.axes. subplots.AxesSubplot at 0x17a5df551d0>
```



# [2.0] Featurization

### **BAG OF WORDS**

### **TF-IDF**

```
In [11]: #applying fit transform on train datasset
         tf idf vect = TfidfVectorizer(min df=10)
         x train tfidf = tf idf vect.fit transform(train data['CleanedText'].val
         ues)
         x_train_tfidf.shape
Out[11]: (35000, 5251)
In [12]: #applying transform on test dataset
         x test tfidf = tf idf vect.transform(test data['CleanedText'].values)
         x test tfidf.shape
Out[12]: (15000, 5251)
In [13]: y train tfidf = train data['Score']
         y test tfidf = test data['Score']
         Avg. Word2Vec
In [33]: #training Word2Vec Model for train dataset
         i=0
         list of sent=[]
         for sent in train data['CleanedText'].values:
             list of sent.append(sent.split())
In [34]: w2v model=Word2Vec(list of sent,min count=5,size=50, workers=4)
In [35]: X = w2v model[w2v model.wv.vocab]
In [36]: #computing Avg Word2Vec for train dataset
         w2v words = list(w2v model.wv.vocab)
```

```
sent vectors = []; # the avg-w2v for each sentence/review is stored in
          this list
         for sent in tqdm(list of sent): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             cnt words =0; # num of words with a valid vector in the sentence/re
         view
             for word in sent: # for each word in a review/sentence
                 if word in w2v words:
                     vec = w2v model.wv[word]
                     sent vec += vec
                     cnt words += 1
             if cnt words != 0:
                 sent vec /= cnt words
             sent vectors.append(sent vec)
         print(len(sent vectors))
         print(len(sent vectors[0]))
         100%
                    35000/35000 [00:55<00:00, 634.85it/s]
         35000
         50
In [37]: x train w2v = np.array(sent vectors)
         y_train_w2v = train_data['Score']
         x train w2v.shape
Out[37]: (35000, 50)
In [38]: #training Word2Vec Model for test dataset
         i=0
         list of sent1=[]
         for sent in test data['CleanedText'].values:
             list of sent1.append(sent.split())
In [39]: #computing Avg Word2Vec for test dataset
         w2v words = list(w2v model.wv.vocab)
         sent vectors = []; # the avg-w2v for each sentence/review is stored in
          this list
```

```
for sent in tqdm(list of sent1): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             cnt words =0; # num of words with a valid vector in the sentence/re
         view
             for word in sent: # for each word in a review/sentence
                 if word in w2v words:
                     vec = w2v model.wv[word]
                     sent vec += vec
                     cnt words += 1
             if cnt words != 0:
                 sent vec /= cnt words
             sent vectors.append(sent vec)
         print(len(sent vectors))
         print(len(sent_vectors[0]))
         100%|
                    15000/15000 [00:31<00:00, 477.84it/s]
         15000
         50
In [40]: x test w2v = np.array(sent vectors)
         y test w2v = test data['Score']
         x test w2v.shape
Out[40]: (15000, 50)
         TFIDF - Word2Vec
In [51]: # training model for training data
         model = TfidfVectorizer()
         tf idf matrix = model.fit transform(train data['CleanedText'].values)
         # we are converting a dictionary with word as a key, and the idf as a v
         alue
         dictionary = dict(zip(model.get feature names(), list(model.idf )))
In [52]: # TF-IDF weighted Word2Vec
```

```
tfidf feat = model.get feature names() # tfidf words/col-names
         # final tf idf is the sparse matrix with row= sentence, col=word and ce
         ll val = tfidf
         tfidf sent vectors = []; # the tfidf-w2v for each sentence/review is st
         ored in this list
         row=0;
         for sent in tqdm(list of sent): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             weight sum =0; # num of words with a valid vector in the sentence/r
         eview
             for word in sent: # for each word in a review/sentence
                 if word in w2v words:
                     vec = w2v model.wv[word]
                     # tf idf = tf idf matrix[row, tfidf feat.index(word)]
                     # to reduce the computation we are
                     # dictionary[word] = idf value of word in whole courpus
                     # sent.count(word) = tf valeus of word in this review
                     tf idf = dictionary[word]*(sent.count(word)/len(sent))
                     sent vec += (vec * tf idf)
                     weight sum += tf idf
             if weight sum != 0:
                 sent vec /= weight sum
             tfidf sent vectors.append(sent vec)
             row += 1
         100%
                    35000/35000 [01:10<00:00, 493.94it/s]
In [53]: x train tfw2v = np.array(tfidf sent vectors)
         y train tfw2v = train data['Score']
         x train tfw2v.shape
Out[53]: (35000, 50)
In [54]: # training model for test dataset
         tf idf matrix = model.fit transform(test data['CleanedText'].values)
         # we are converting a dictionary with word as a key, and the idf as a v
```

```
alue
         dictionary = dict(zip(model.get feature names(), list(model.idf )))
In [55]: # TF-IDF weighted Word2Vec
         tfidf feat = model.get feature names() # tfidf words/col-names
         # final tf idf is the sparse matrix with row= sentence, col=word and ce
         ll\ val = tfidf
         tfidf sent vectors = []; # the tfidf-w2v for each sentence/review is st
         ored in this list
         row=0:
         for sent in tqdm(list of sent1): # for each review/sentence
             sent vec = np.zeros(50) # as word vectors are of zero length
             weight sum =0; # num of words with a valid vector in the sentence/r
         eview
             for word in sent: # for each word in a review/sentence
                 if word in w2v words:
                     vec = w2v model.wv[word]
                     # tf idf = tf idf matrix[row, tfidf feat.index(word)]
                     # to reduce the computation we are
                     # dictionary[word] = idf value of word in whole courpus
                     # sent.count(word) = tf valeus of word in this review
                     tf idf = dictionary[word]*(sent.count(word)/len(sent))
                     sent vec += (vec * tf idf)
                     weight sum += tf idf
             if weight sum != 0:
                 sent vec /= weight sum
             tfidf sent vectors.append(sent vec)
             row += 1
         100%
                   | 15000/15000 [00:40<00:00, 370.20it/s]
In [56]: x test tfw2v = np.array(tfidf sent vectors)
         y test tfw2v = test data['Score']
         x test tfw2v.shape
Out[56]: (15000, 50)
```

# [3.1] Applying RF

## [3.1.1] Applying Random Forests on BOW, SET 1

```
In [21]: # initializing RandomForestClassifier model
         RFC = RandomForestClassifier(class weight='balanced')
         # hyperparameter values we need to try on classifier
         \max depth = [10, 30, 50, 70, 90, 100]
         n = [50, 100, 200, 300, 400, 500]
         param grid = {'max depth': max depth,
                       'n estimators': n estimators}
         # using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 3 fold CV
         gscv = GridSearchCV(RFC, param grid, scoring='roc auc', cv=3, n jobs=-1
         , return_train score=True)
         gscv.fit(x train bow, y train bow)
         print("Best Max Depth Value:",gscv.best_params_['max_depth'])
         print("Best No. of Estimators:", gscv.best params ['n estimators'])
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 100
         Best No. of Estimators: 500
         Best ROC AUC Score: 0.91873
In [22]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         RFC clf = RandomForestClassifier(max depth=optimal depth, n estimators=
         optimal estimators)
         RFC_clf.fit(x train bow,y train bow)
```

```
#predicting the class label using test data
y_pred = RFC_clf.predict_proba(x_test_bow)[:,1]

#determining the Test roc_auc_score for optimal hyperparameters
auc_score = roc_auc_score(y_test_bow, y_pred)
print('\n**** Test roc_auc_score is %f *****' % (auc_score))

**** Test roc auc score is 0.901450 ****
```

### 1030 100\_000\_30010 13 01301130

### **Seaborn Heatmap on Train Data**

```
In [25]: A = np.array(gscv.cv_results_['mean_train_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

10	0.935843	0.944313	0.949313	0.950013	0.950726	0.951053	- 0.990
30	0.989635	0.991565	0.991993	0.992563	0.992627	0.992584	0.000
20	0.998427	0.998717	0.998917	0.998888	0.998994	0.998938	- 0.975
70	0.999786	0.999839	0.999891	0.999882	0.999883	0.999898	- 0.960
06	0.999978	0.999988	0.99999	0.999992	0.999992	0.999993	
100	0.999993	0.999995	0.999997	0.999998	0.999998	0.999998	- 0.945
	50	100	200	300	400	500	<u> </u>

### **Seaborn Heatmap on Test Data**

```
In [26]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
```

```
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri
dis')
plt.show()
```

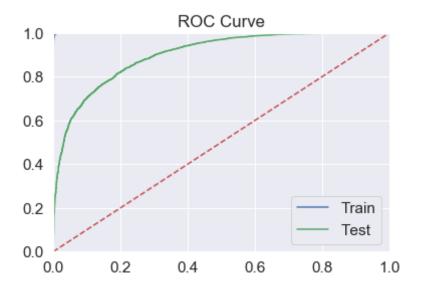
10	0.888192	0.900539	0.905473	0.907507	0.908137	0.908416	- 0.918
30	0.883798	0.887966	0.893023	0.89421	0.893987	0.893553	- 0.912
20	0.884405	0.892815	0.895701	0.89756	0.898563	0.898306	- 0.906
20	0.896994	0.903157	0.906029	0.907857	0.908991	0.909367	- 0.900
8	0.901046	0.909388	0.914891	0.915382	0.916086	0.916489	- 0.894
100	0.905889	0.911586	0.916198	0.918115	0.918121	0.918734	- 0.888
	50	100	200	300	400	500	_

### **ROC Curve**

```
In [27]: # Plotting roc curve on Train Data
    pred_train = RFC_clf.predict_proba(x_train_bow)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_bow, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
    pred_test = RFC_clf.predict_proba(x_test_bow)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_bow, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

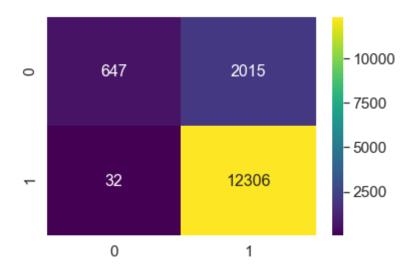
plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```



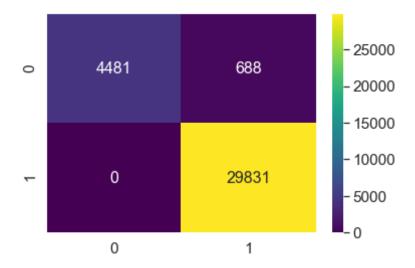
### **Confusion Matrix on Test Data**

```
In [23]: # plotting confusion matrix as heatmap
y_predict = RFC_clf.predict(x_test_bow)
cm = confusion_matrix(y_test_bow, y_predict)
print(cm)
df_cm = pd.DataFrame(cm, range(2), range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g',cmap='vir idis')

[[ 647  2015]
        [ 32  12306]]
Out[23]: <matplotlib.axes. subplots.AxesSubplot at 0x22c62e0d358>
```



### **Confusion Matrix on Train Data**

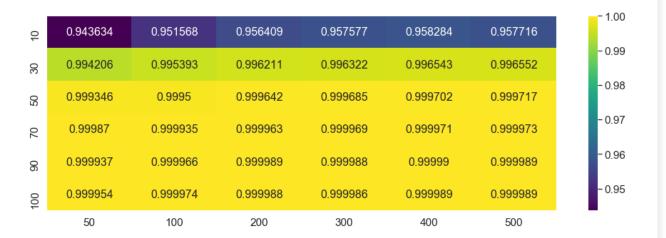


## [3.1.2] Wordcloud of top 20 important features from SET 1

```
threw' disappoint' terribl unfortun' Wastlike' thought love 'horribl' aw' tastgood' great' edici' descript' disgust' eturn worst best'
```

## [3.1.3] Applying Random Forests on TFIDF, SET 2

```
gscv.fit(x train tfidf,y train tfidf)
         print("Best Max Depth Value:",gscv.best params ['max depth'])
         print("Best No. of Estimators:", gscv.best params ['n estimators'])
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 100
         Best No. of Estimators: 400
         Best ROC AUC Score: 0.91914
In [33]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         RFC clf = RandomForestClassifier(max depth=optimal depth, n estimators=
         optimal estimators)
         RFC clf.fit(x train tfidf,y train tfidf)
         #predicting the class label using test data
         y pred = RFC clf.predict proba(x test tfidf)[:,1]
         #determining the Test roc auc score for optimal hyperparameters
         auc score = roc auc score(y test tfidf, y pred)
         print('\n**** Test roc auc score is %f ****' % (auc score))
         **** Test roc auc score is 0.913212 ****
         Seaborn Heatmap on Train Data
In [37]: A = np.array(gscv.cv results ['mean train score'])
         B = np.reshape(A, (6,6))
         df = pd.DataFrame(B, index=max depth, columns=n estimators)
         plt.figure(figsize = (16,5))
         sns.heatmap(df, annot=True, annot kws={"size": 16}, fmt="g", cmap='viri
         dis')
         plt.show()
```



### **Seaborn Heatmap on Test Data**

```
In [38]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viridis')
plt.show()
```

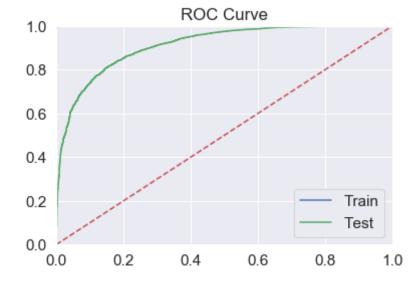
10	0.889141	0.898859	0.904945	0.90714	0.909341	0.908701	-0
30	0.893187	0.902825	0.906959	0.908094	0.910055	0.910546	- 0
20	0.898243	0.903546	0.907565	0.908553	0.909428	0.909753	- 0
20	0.902694	0.908941	0.912828	0.913749	0.914356	0.914318	- 0
06	0.906014	0.912272	0.915785	0.916984	0.9179	0.918179	- 0
100	0.9056	0.913539	0.91723	0.917467	0.919139	0.918656	- c
	50	100	200	300	400	500	

### **ROC Curve**

```
In [36]: # Plotting roc curve on Train Data
    pred_train = RFC_clf.predict_proba(x_train_tfidf)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_tfidf, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

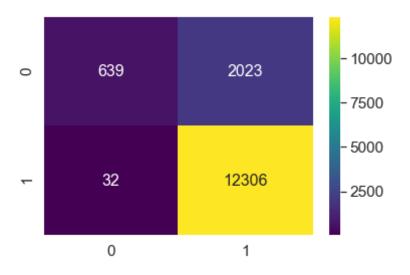
# Plotting roc curve on Test Data
    pred_test = RFC_clf.predict_proba(x_test_tfidf)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_tfidf, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```



**Confusion Matrix on Test Data** 

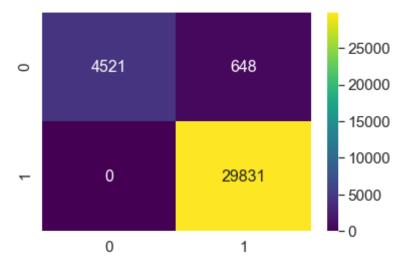
## Out[34]: <matplotlib.axes.\_subplots.AxesSubplot at 0x22c61cda3c8>



#### **Confusion Matrix on Train Data**

```
In [35]: # plotting confusion matrix as heatmap
y_predict = RFC_clf.predict(x_train_tfidf)
cm = confusion_matrix(y_train_tfidf, y_predict)
print(cm)
df_cm = pd.DataFrame(cm, range(2), range(2))
sns.set(font_scale=1.4)
```

Out[35]: <matplotlib.axes.\_subplots.AxesSubplot at 0x22c62767470>



## [3.1.4] Wordcloud of top 20 important features from SET 2

```
In [39]: # Calculate feature importances from decision trees
importances = RFC_clf.feature_importances_

# Sort feature importances in descending order and get their indices
indices = np.argsort(importances)[::-1][:30]

# Get the feature names from the vectorizer
names = tf_idf_vect.get_feature_names()
names = np.array(names)
words = names[indices]
```

```
Out[39]: array(['disappoint', 'great', 'love', 'return', 'wast', 'worst', 'mone
         у',
                'aw', 'horribl', 'terribl', 'would', 'tast', 'bad', 'best',
                'thought', 'good', 'didnt', 'threw', 'refund', 'like', 'disgus
         t',
                'away', 'descript', 'product', 'delici', 'receiv', 'stale',
                'review', 'unfortun', 'mayb'], dtype='<U14')
In [40]: wordcloud = WordCloud(background color='white',
                               max font size=40,
                               scale=3.
                               random state=1).generate(str(words))
         plt.imshow(wordcloud)
         plt.axis("off")
         plt.show()
                        hest' away'unfortun' thought'
```

## [3.1.5] Applying Random Forests on AVG W2V, SET 3

```
In [50]: # initializing RandomForestClassifier model
RFC = RandomForestClassifier(class_weight='balanced')
# hyperparameter values we need to try on classifier
max_depth = [10, 30, 50, 70, 90, 100]
n_estimators = [50, 100, 200, 300, 400, 500]
```

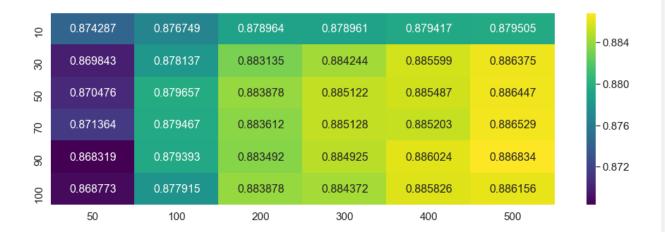
```
param grid = {'max depth':max depth,
                       'n estimators':n estimators}
         # using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 3 fold CV
         gscv = GridSearchCV(RFC, param grid, scoring='roc auc', cv=3, n jobs=-1
         , return train score=True)
         gscv.fit(x train w2v,y train w2v)
         print("Best Max Depth Value:", qscv.best params ['max depth'])
         print("Best No. of Estimators:",gscv.best params ['n estimators'])
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 90
         Best No. of Estimators: 500
         Best ROC AUC Score: 0.88683
In [51]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal_estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         RFC clf = RandomForestClassifier(max depth=optimal depth, n estimators=
         optimal estimators)
         RFC clf.fit(x train w2v,y train w2v)
         #predicting the class label using test data
         y pred = RFC clf.predict proba(x test w2v)[:,1]
         #determining the Test roc auc score for optimal hyperparameters
         auc score = roc auc score(y test w2v, y pred)
         print('\n**** Test roc auc score is %f ****' % (auc score))
         **** Test roc auc score is 0.883588 ****
         Seaborn Heatmap on Train Data
In [57]: A = np.array(gscv.cv results ['mean train score'])
```

```
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri
dis')
plt.show()
```

10	0.976738	0.977798	0.978452	0.978917	0.979075	0.979046
30	1	1	1	1	1	1
20	1	1	1	1	1	1
20	1	1	1	1	1	1
06	1	1	1	1	1	1
100	1	1	1	1	1	1
	50	100	200	300	400	500

### **Seaborn Heatmap on Test Data**

```
In [56]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

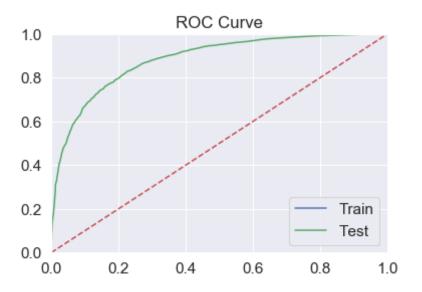


#### **ROC Curve**

```
In [54]: # Plotting roc curve on Train Data
    pred_train = RFC_clf.predict_proba(x_train_w2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_w2v, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
    pred_test = RFC_clf.predict_proba(x_test_w2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_w2v, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

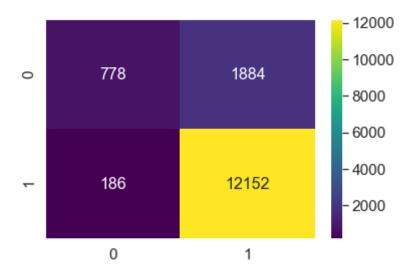
plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```



### **Confusion Matrix on Test Data**

```
In [52]: # plotting confusion matrix as heatmap
y_predict = RFC_clf.predict(x_test_w2v)
cm = confusion_matrix(y_test_w2v, y_predict)
print(cm)
df_cm = pd.DataFrame(cm, range(2), range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='vir idis')

[[ 778    1884]
       [ 186    12152]]
Out[52]: <matplotlib.axes. subplots.AxesSubplot at 0x22c34d808d0>
```

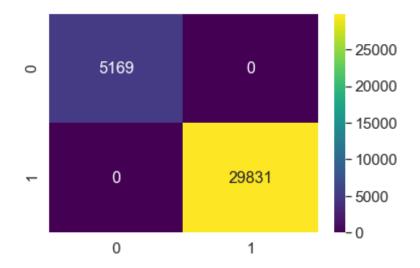


### **Confusion Matrix on Train Data**

```
In [53]: # plotting confusion matrix as heatmap
    y_predict = RFC_clf.predict(x_train_w2v)
    cm = confusion_matrix(y_train_w2v, y_predict)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='vir idis')

[[ 5169     0]
    [ 0 29831]]

Out[53]: <matplotlib.axes. subplots.AxesSubplot at 0x22c34c31208>
```



## [3.1.6] Applying Random Forests on TFIDF W2V, SET 4

```
Best No. of Estimators: 400
Best ROC AUC Score: 0.85953

In [29]: # determining optimal depth and base learners
    optimal_depth = gscv.best_params_['max_depth']
    optimal_estimators = gscv.best_params_['n_estimators']

#training the model using the optimal hyperparameters
RFC_clf = RandomForestClassifier(max_depth=optimal_depth, n_estimators=
    optimal_estimators)
RFC_clf.fit(x_train_tfw2v,y_train_tfw2v)

#predicting the class label using test data
y_pred = RFC_clf.predict_proba(x_test_tfw2v)[:,1]

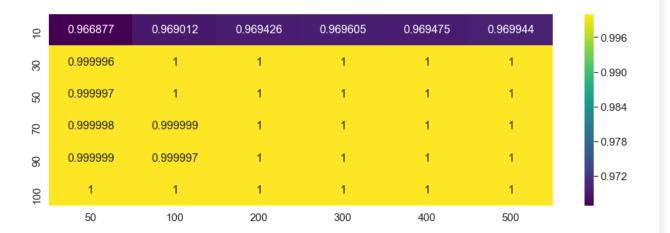
#determining the Test roc_auc_score for optimal hyperparameters
auc_score = roc_auc_score(y_test_tfw2v, y_pred)
print('\n**** Test roc_auc_score is %f *****' % (auc_score))

**** Test roc auc score is 0.849953 ****
```

### **Seaborn Heatmap on Train Data**

Best Max Depth Value: 50

```
In [34]: A = np.array(gscv.cv_results_['mean_train_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viridis')
plt.show()
```



### **Seaborn Heatmap on Test Data**

```
In [33]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

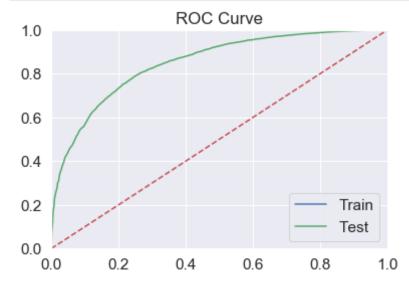
10	0.845309	0.84889	0.84935	0.849532	0.849913	0.850484	
30	0.84093	0.851147	0.855023	0.858087	0.857718	0.858895	- 0.8
20	0.839778	0.847842	0.855578	0.857301	0.859529	0.858924	- 0.8
02	0.841745	0.8501	0.855896	0.857358	0.857989	0.859299	- 0.8
06	0.842132	0.851451	0.855679	0.856814	0.857838	0.858427	- 0.8
100	0.841959	0.849781	0.855955	0.856852	0.857589	0.858879	- 0.8
	50	100	200	300	400	500	0.6

#### **ROC Curve**

```
In [32]: # Plotting roc curve on Train Data
    pred_train = RFC_clf.predict_proba(x_train_tfw2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_tfw2v, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

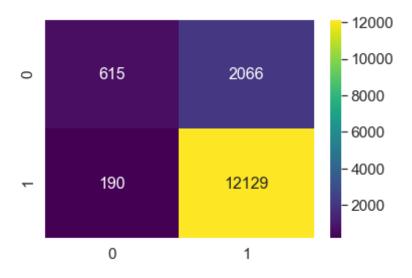
# Plotting roc curve on Test Data
    pred_test = RFC_clf.predict_proba(x_test_tfw2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_tfw2v, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```



**Confusion Matrix on Test Data** 

## Out[30]: <matplotlib.axes.\_subplots.AxesSubplot at 0x18a1c15fb70>



#### **Confusion Matrix on Train Data**

```
In [31]: # plotting confusion matrix as heatmap
y_predict = RFC_clf.predict(x_train_tfw2v)
cm = confusion_matrix(y_train_tfw2v, y_predict)
print(cm)
df_cm = pd.DataFrame(cm, range(2), range(2))
sns.set(font_scale=1.4)
```

```
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',cmap='vir
idis')
[[ 5272     1]
    [     0 29727]]
```

Out[31]: <matplotlib.axes.\_subplots.AxesSubplot at 0x18a1c1fa400>



# [4.0] Applying GBDT using XGBOOST

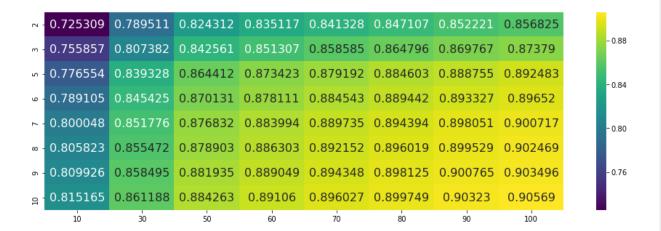
## [4.1.1] Applying XGBOOST on BOW, SET 1

```
# using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 3 fold CV
         gscv = GridSearchCV(XGBC, param grid, scoring='roc auc', cv=3, n jobs=-
         1, return train score=True)
         gscv.fit(x train bow,y train bow)
         print("Best Max Depth Value:", gscv.best params ['max depth'])
         print("Best No. of Estimators:", gscv.best params ['n estimators'])
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 10
         Best No. of Estimators: 100
         Best ROC AUC Score: 0.90569
In [15]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         XGBC clf = XGBClassifier(n estimators=optimal estimators, max depth=opt
         imal depth)
         XGBC clf.fit(x train bow, y train bow)
         #predicting the class label using test data
         y pred = XGBC clf.predict proba(x test bow)[:,1]
         #determining the Test roc auc score for optimal hyperparameters
         auc score = roc auc score(y test bow, y pred)
         print('\n**** Test roc auc score is %f ****' % (auc score))
         **** Test roc auc score is 0.913507 ****
         Seaborn Heatmap on Train Data
In [16]: A = np.array(gscv.cv results ['mean train score'])
         B = np.reshape(A, (8,8))
         df = pd.DataFrame(B, index=max depth, columns=n estimators)
```

```
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot kws={"size": 16}, fmt="g", cmap='viri
dis')
plt.show()
~-0.728121 0.795526 0.831596 0.843945 0.850705 0.856848 0.863324 0.869386
                                                                          -0.95
m 0.760755 0.819603 0.859413 0.869267 0.878427 0.885688 0.891922 0.897472
- 0.90
   0.8112 0.882861 0.915593 0.926482 0.934276 0.940669 0.945521 0.949827
                                                                          - 0.85
   0.8309 0.898648 0.930731 0.940191 0.946674 0.952538 0.957349 0.961161
\infty - 0.84374 | 0.910321 | 0.941263 | 0.949968 | 0.957167 | 0.961545 | 0.966052 | 0.969228
                                                                          - 0.80
o. 0.855346 0.922567 0.951082 0.959244 0.965127 0.969537 0.973131 0.97599
                                                                          - 0.75
  0.865722 0.932314 0.959072 0.966325 0.971349 0.975403 0.978617 0.98114
     10
                                                                100
```

### **Seaborn Heatmap on Test Data**

```
In [17]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (8,8))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

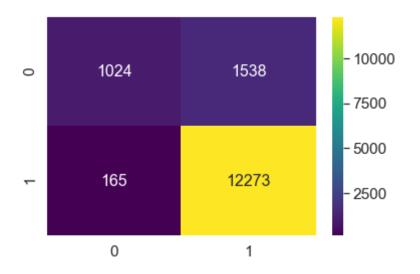


#### **Confusion Matrix on Test Data**

```
In [18]: # plotting confusion matrix as heatmap
    predicted_y = XGBC_clf.predict(x_test_bow)
    cm = confusion_matrix(y_test_bow, predicted_y)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='viridis')

[[ 1024    1538]
    [ 165    12273]]

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x17a4d0d9780>
```

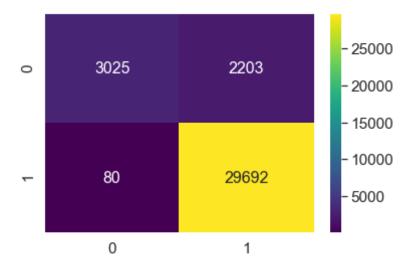


### **Confusion Matrix on Train Data**

```
In [19]: # plotting confusion matrix as heatmap
    predicted_y = XGBC_clf.predict(x_train_bow)
    cm = confusion_matrix(y_train_bow, predicted_y)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='viridis')

[[ 3025     2203]
    [ 80     29692]]

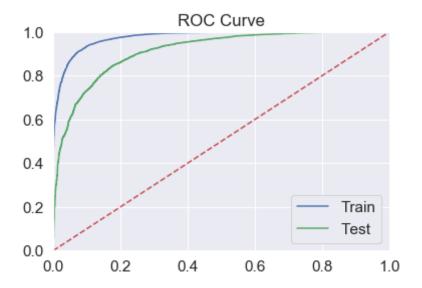
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x17a50f06630>
```



```
In [20]: # Plotting roc curve on Train Data
    pred_train = XGBC_clf.predict_proba(x_train_bow)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_bow, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
    pred_test = XGBC_clf.predict_proba(x_test_bow)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_bow, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```



### **Wordcloud of top 20 important features**

```
threw disappoint delici smooth great worst trash perfect descript return best yummi tasteless disgust refund
```

## [4.1.2] Applying XGBOOST on TFIDF, SET 2

```
print("Best Max Depth Value:",qscv.best params ['max depth'])
         print("Best No. of Estimators:", gscv.best params ['n estimators'])
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 10
         Best No. of Estimators: 100
         Best ROC AUC Score: 0.90605
In [24]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         XGBC clf = XGBClassifier(n estimators=optimal estimators, max depth=opt
         imal depth)
         XGBC clf.fit(x train tfidf, y train tfidf)
         #predicting the class label using test data
         y pred = XGBC clf.predict proba(x test tfidf)[:,1]
         #determining the Test roc auc score for optimal hyperparameters
         auc score = roc auc score(y test tfidf, y pred)
         print('\n**** Test roc auc score is %f ****' % (auc score))
         **** Test roc auc score is 0.913676 ****
         Seaborn Heatmap on Train Data
In [25]: A = np.array(gscv.cv results ['mean train score'])
         B = np.reshape(A, (8,8))
         df = pd.DataFrame(B, index=max depth, columns=n estimators)
         plt.figure(figsize = (16,5))
         sns.heatmap(df, annot=True, annot kws={"size": 16}, fmt="g", cmap='viri
         dis')
         plt.show()
```



#### **Seaborn Heatmap on Test Data**

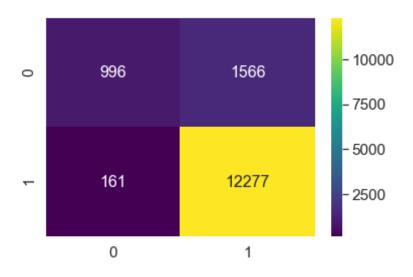
```
In [26]:
            A = np.array(gscv.cv results ['mean test score'])
            B = np.reshape(A, (8,8))
            df = pd.DataFrame(B, index=max depth, columns=n estimators)
            plt.figure(figsize = (16,5))
            sns.heatmap(df, annot=True, annot kws={"size": 16}, fmt="g", cmap='viri
            dis')
            plt.show()
                 0.723091
                                    0.825696
                                                        0.844157
                                                                  0.850184
                                                                            0.855368
                                                                                      0.860063
                           0.79263
                                                                                                     - 0.88
                 0.755598
                           0.815293
                                    0.845119
                                               0.8532
                                                        0.860199
                                                                  0.866112
                                                                             0.8716
                                                                                      0.875695
                 0.779264
                          0.841888
                                              0.873356
                                                        0.880007
                                                                  0.885242
                                                                             0.88931
                                    0.865644
                                                                                      0.892893
             2
                                                                                                     -0.84
                 0.792268
                          0.846858
                                    0.871418
                                              0.878772
                                                        0.885001
                                                                  0.889645
                                                                            0.893864
                                                                                      0.897609
                 0.803386
                                                                            0.897873
                                                                                      0.900982
                                    0.876562
                                              0.883852
                                                        0.889978
                                                                   0.89461
                                                                                                     - 0.80
                 0.812071
                                                                            0.900105
                          0.856479
                                    0.879671
                                              0.887003
                                                        0.892738
                                                                  0.896851
                                                                                      0.902696
                                                                                                     - 0.76
                 0.812808
                          0.858647
                                    0.880879
                                              0.888214
                                                        0.893606
                                                                  0.897961
                                                                            0.900985
                                                                                      0.903681
                 0.817901
                           0.863806
                                    0.885325
                                              0.892547
                                                        0.897513
                                                                  0.900921
                                                                             0.90379
                                                                                      0.906052
             9
                   10
                             30
                                       50
                                                 60
                                                           70
                                                                     80
                                                                               90
                                                                                        100
```

#### **Confusion Matrix on Test Data**

```
In [27]: # plotting confusion matrix as heatmap
    predicted_y = XGBC_clf.predict(x_test_tfidf)
    cm = confusion_matrix(y_test_tfidf, predicted_y)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='vir
    idis')

[[ 996  1566]
    [ 161  12277]]
```

Out[27]: <matplotlib.axes.\_subplots.AxesSubplot at 0x17a4d847ba8>



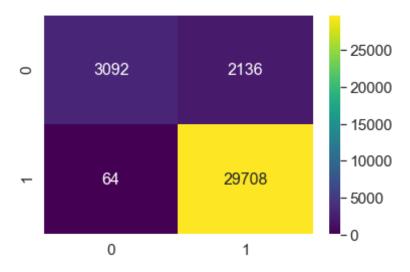
#### **Confusion Matrix in Train Data**

```
In [28]: # plotting confusion matrix as heatmap
predicted_y = XGBC_clf.predict(x_train_tfidf)
cm = confusion_matrix(y_train_tfidf, predicted_y)
```

```
print(cm)
df_cm = pd.DataFrame(cm, range(2), range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='vir
idis')

[[ 3092 2136]
        [ 64 29708]]
```

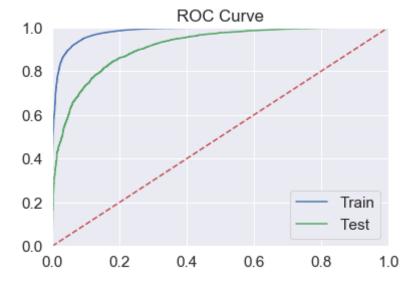
### Out[28]: <matplotlib.axes.\_subplots.AxesSubplot at 0x17a55b24a20>



```
In [30]: # Plotting roc curve on Train Data
    pred_train = XGBC_clf.predict_proba(x_train_tfidf)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_tfidf, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
    pred_test = XGBC_clf.predict_proba(x_test_tfidf)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_tfidf, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')
```

```
plt.title('ROC Curve')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.legend(loc='lower right')
plt.show()
```



# **Wordcloud of top 20 important features**

```
In [31]: # Calculate feature importances from decision trees
importances = XGBC_clf.feature_importances_

# Sort feature importances in descending order and get their indices
indices = np.argsort(importances)[::-1][:30]

# Get the feature names from the vectorizer
names = tf_idf_vect.get_feature_names()
names = np.array(names)
words = names[indices]
```

```
Out[31]: array(['worst', 'return', 'wast', 'descript', 'disappoint', 'wors',
                'delici', 'perfect', 'horribl', 'easi', 'excel', 'favorit',
                'pictur', 'mislead', 'awesom', 'great', 'threw', 'aw', 'best',
                'refund', 'china', 'disgust', 'satisfi', 'tasti', 'label', 'yuc
         k',
                'smooth', 'addict', 'list', 'stuck'], dtype='<U14')
In [32]: wordcloud = WordCloud(background color='white',
                               max font size=40,
                               scale=3.
                               random state=1).generate(str(words))
         plt.imshow(wordcloud)
         plt.axis("off")
         plt.show()
               refund'awesom'stuck'horribl
```

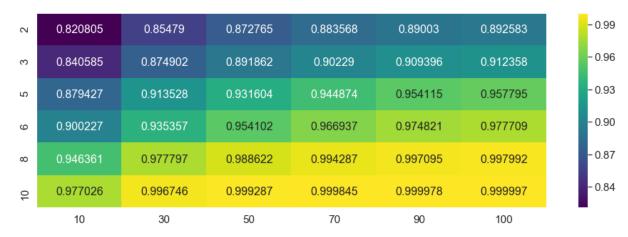
# [4.1.3] Applying XGBOOST on AVG W2V, SET 3

```
In [41]: # initializing XGBClassifier model
   XGBC = XGBClassifier()

# hyperparameter values we need to try on classifier
   max_depth = [2, 3, 5, 6, 8, 10]
   n_estimators = [10, 30, 50, 70, 90, 100]
   param_grid = {'max_depth':max_depth,}
```

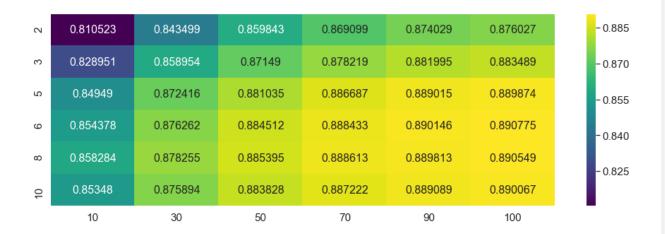
```
'n estimators':n estimators}
         # using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 3 fold CV
         gscv = GridSearchCV(XGBC, param grid, scoring='roc auc', cv=3, n jobs=-
         1, return train score=True)
         gscv.fit(x train w2v,y train w2v)
         print("Best Max Depth Value:",gscv.best params ['max depth'])
         print("Best No. of Estimators:",gscv.best params ['n estimators'])
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 6
         Best No. of Estimators: 100
         Best ROC AUC Score: 0.89078
In [42]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         XGBC clf = XGBClassifier(n estimators=optimal estimators, max depth=opt
         imal depth)
         XGBC clf.fit(x train w2v, y train w2v)
         #predicting the class label using test data
         y pred = XGBC clf.predict proba(x test w2v)[:,1]
         #determining the Test roc auc score for optimal hyperparameters
         auc score = roc auc score(y test w2v, y pred)
         print('\n**** Test roc auc score is %f ****' % (auc score))
         **** Test roc auc score is 0.889072 ****
         Seaborn Heatmap on Train Data
In [43]: A = np.array(gscv.cv results ['mean train score'])
         B = np.reshape(A, (6,6))
```

```
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri
dis')
plt.show()
```



### **Seaborn Heatmap on Test Data**

```
In [44]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

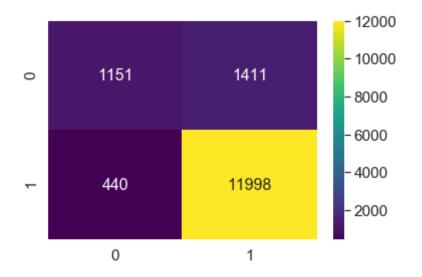


#### **Confusion Matrix on Test Data**

```
In [47]: # plotting confusion matrix as heatmap
    predicted_y = XGBC_clf.predict(x_test_w2v)
    cm = confusion_matrix(y_test_w2v, predicted_y)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='viridis')

[[ 1151    1411]
    [ 440    11998]]

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x17a66ce2a58>
```

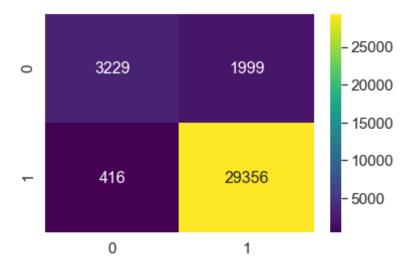


#### **Confusion Matrix on Train Data**

```
In [49]: # plotting confusion matrix as heatmap
    predicted_y = XGBC_clf.predict(x_train_w2v)
    cm = confusion_matrix(y_train_w2v, predicted_y)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g', cmap='vir idis')

[[ 3229    1999]
    [ 416    29356]]

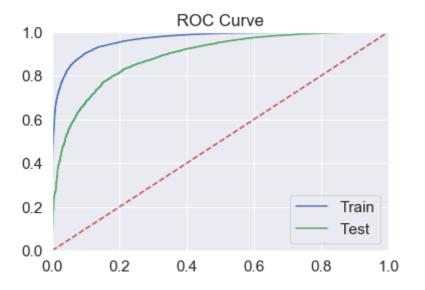
Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x17a67031898>
```



```
In [50]: # Plotting roc curve on Train Data
    pred_train = XGBC_clf.predict_proba(x_train_w2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_tfidf, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
    pred_test = XGBC_clf.predict_proba(x_test_w2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_tfidf, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```

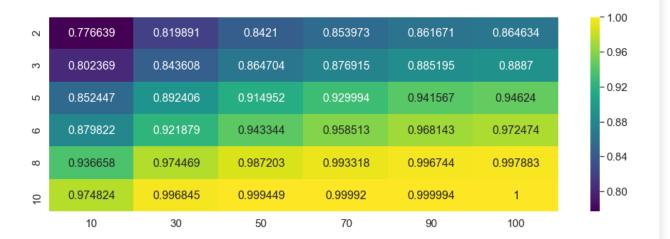


### [4.1.4] Applying XGBOOST on TFIDF W2V, SET 4

```
Best Max Depth Value: 6
         Best No. of Estimators: 100
         Best ROC AUC Score: 0.86542
In [58]: # determining optimal depth and base learners
         optimal depth = gscv.best params ['max depth']
         optimal estimators = gscv.best params ['n estimators']
         #training the model using the optimal hyperparameters
         XGBC clf = XGBClassifier(n estimators=optimal estimators, max depth=opt
         imal depth)
         XGBC clf.fit(x train_tfw2v, y_train_tfw2v)
         #predicting the class label using test data
         y pred = XGBC clf.predict proba(x test tfw2v)[:,1]
         #determining the Test roc auc score for optimal hyperparameters
         auc score = roc auc score(y test tfw2v, y pred)
         print('\n**** Test roc auc score is %f ****' % (auc score))
         **** Test roc auc score is 0.863633 ****
```

### Seaborn Heatmap on Train Data

```
In [59]: A = np.array(gscv.cv_results_['mean_train_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```



#### **Seaborn Heatmap on Test Data**

```
In [60]: A = np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=n_estimators)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

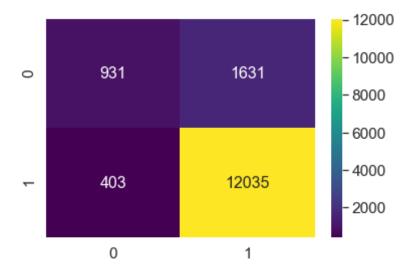
2	0.766167	0.806476	0.826274	0.835804	0.842578	0.844875	-
က	0.786971	0.823629	0.84001	0.848328	0.852686	0.854201	-
2	0.813759	0.841293	0.852735	0.858801	0.862096	0.863205	-
9	0.823374	0.847695	0.857131	0.861883	0.864505	0.865423	_
ø	0.827032	0.849618	0.85762	0.86045	0.862066	0.86269	
10	0.821892	0.84809	0.856055	0.859887	0.862312	0.863236	
	10	30	50	70	90	100	_

#### **Confusion Matrix on Test Data**

```
In [61]: # plotting confusion matrix as heatmap
    predicted_y = XGBC_clf.predict(x_test_tfw2v)
    cm = confusion_matrix(y_test_tfidf, predicted_y)
    print(cm)
    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale=1.4)
    sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',cmap='viridis')

[[ 931  1631]
    [ 403  12035]]
```

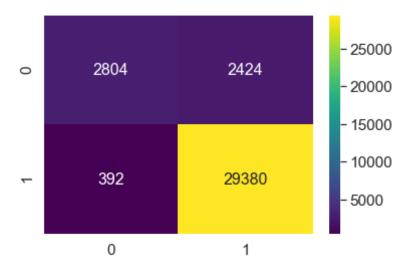
Out[61]: <matplotlib.axes. subplots.AxesSubplot at 0x17a52a44be0>



#### **Confusion Matrix on Train Data**

```
In [62]: # plotting confusion matrix as heatmap
predicted_y = XGBC_clf.predict(x_train_tfw2v)
cm = confusion_matrix(y_train_tfidf, predicted_y)
```

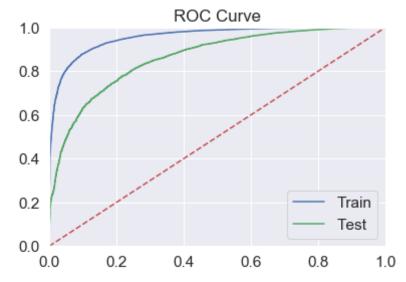
### Out[62]: <matplotlib.axes.\_subplots.AxesSubplot at 0x17a66f3f1d0>



```
In [63]: # Plotting roc curve on Train Data
    pred_train = XGBC_clf.predict_proba(x_train_tfw2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_train_tfidf, pred_train)
    plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
    pred_test = XGBC_clf.predict_proba(x_test_tfw2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_tfidf, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')
```

```
plt.title('ROC Curve')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.legend(loc='lower right')
plt.show()
```



# [5.0] Conclusion

```
vectorizer | max_deptn | n_estimators | Irain AUL | Iest AUL |
              B0W
                           100
                                        500
                                                    0.91873
                                                              0.90145
             TFIDF
                           100
                                        400
                                                   0.91914
                                                            0.91321
                                       500
           Avg W2V
                           90
                                                   0.88683 | 0.88358
                            50
                                       400
                                                   0.85953
           TFIDF-W2V
                                                              0.84995
In [65]: t=PrettyTable()
         t.field names = ['Vectorizer', 'max depth', 'n estimators', 'Train AUC'
         , 'Test AUC'1
         t.add row(['BOW', '10', '100', '0.90569', '0.91350'])
         t.add row(['TFIDF', '10', '100', '0.90605', '0.91367'])
         t.add row(['Avg W2V', '6', '100', '0.89078', '0.88907'])
         t.add row(['TFIDF-W2V', '6', '100', '0.86542', '0.86363'])
         print('***** XGBoost *****')
         print(t)
         ***** XGBoost *****
         +----+
           Vectorizer | max_depth | n_estimators | Train AUC | Test AUC
             BOW
                            10
                                       100
                                                   0.90569
                                                            | 0.91350
             TFIDF
                            10
                                        100
                                                   0.90605
                                                           | 0.91367
                                       100
                                                   0.89078
           Avg W2V
                            6
                                                              0.88907
                                                   0.86542
           TFIDF-W2V
                                        100
                                                            0.86363
```