Part 7 - Decision Trees

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```
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 graphviz import Source
        from IPython.display import SVG
        from tqdm import tqdm
        from prettytable import PrettyTable
        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.model selection import GridSearchCV
        from sklearn import model selection
        from sklearn import metrics
        from sklearn import tree
        from sklearn.tree import DecisionTreeClassifier
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
```

[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 100k points from the dataset
        df=filtered data.sample(100000)
In [6]: #sort the dataset by timestamp
        df = df.sort values('Time')
        #splitting the dataset into train(70%) & test(30%)
        train data = df[0:70000]
        test data = df[70000:100000]
        [2.0] Featurization
        [2.1] BAG OF WORDS
In [7]: #applying fit transform on train datasset
        count vect = CountVectorizer(min df=10)
        x train bow = count vect.fit transform(train data['CleanedText'].values
        x_train_bow.shape
```

Out[7]: (70000 7213)

```
VUCL11: (10000, 1410)
In [8]: #applying transform on test dataset
         x_test_bow = count_vect.transform(test_data['CleanedText'].values)
         x test bow.shape
Out[8]: (30000, 7213)
In [9]: y train bow = train data['Score']
         y test bow = test data['Score']
         [2.2] TF-IDF
In [22]: #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[22]: (70000, 7213)
In [23]: #applying transform on test dataset
         x test tfidf = tf idf vect.transform(test data['CleanedText'].values)
         x test tfidf.shape
Out[23]: (30000, 7213)
In [24]: y train tfidf = train data['Score']
         y test tfidf = test data['Score']
         [2.3] Avg. Word2Vec
In [34]: #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 [35]: w2v model=Word2Vec(list of sent,min count=5,size=50, workers=4)
In [36]: X = w2v \mod [w2v \mod .wv.vocab]
In [37]: #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%|
                    70000/70000 [03:09<00:00, 368.44it/s]
         70000
         50
In [38]: x train w2v = np.array(sent vectors)
         y train w2v = train data['Score']
         x train w2v.shape
Out[38]: (70000, 50)
```

```
In [39]: #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 [40]: #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%
                   30000/30000 [01:18<00:00, 382.73it/s]
         30000
         50
In [41]: x test w2v = np.array(sent vectors)
         y test w2v = test data['Score']
         x test_w2v.shape
Out[41]: (30000, 50)
         [2.4] TFIDF - Word2Vec
```

```
In [49]: # 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 [50]: # 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%
                    70000/70000 [03:51<00:00, 302.89it/s]
```

```
In [51]: x train tfw2v = np.array(tfidf sent vectors)
         y train tfw2v = train data['Score']
         x train tfw2v.shape
Out[51]: (70000, 50)
In [52]: # training model for test dataset
         model = TfidfVectorizer()
         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 [53]: # 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
```

[3.0] Applying Decision Trees

[3.1] Applying Decision Trees on BOW, SET 1

```
In [10]: # initializing DecisionTreeClassifier model
         dtc = DecisionTreeClassifier()
         # hyperparameter values we need to try on classifier
         \max depth = [1, 10, 25, 50, 100, 500]
         min samples split = [5, 10, 25, 50, 100, 500]
         param grid = \{\text{'max depth'}: [1, 10, 25, 50, 100, 500],
                        'min samples split':[5, 10, 25, 50, 100, 500]}
         # using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 5 fold CV
         gscv = GridSearchCV(dtc,param grid,scoring='roc auc',cv=5,n jobs=-1,ret
         urn train score=True)
         gscv.fit(x train bow,y train bow)
         print("Best Max Depth Value:",qscv.best params ['max depth'])
         print("Best Min Sample Split Value:",qscv.best params ['min samples spl
         it'1)
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 50
         Best Min Sample Split Value: 500
         Best ROC AUC Score: 0.82853
```

```
In [11]: # determining optimal depth and sample split values
    optimal_depth = gscv.best_params_['max_depth']
    optimal_sample_split = gscv.best_params_['min_samples_split']

#training the model using the optimal hyperparameters
    dtc_clf = DecisionTreeClassifier(max_depth=optimal_depth, min_samples_s
    plit=optimal_sample_split)
    dtc_clf.fit(x_train_bow,y_train_bow)

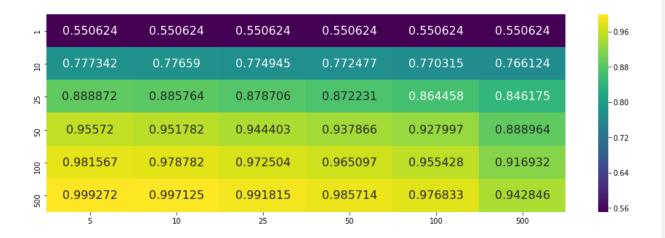
#predicting the class label using test data
    y_pred = dtc_clf.predict_proba(x_test_bow)[:,1]

#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 0.831107 ****
```

Seaborn Heatmap on Train Data

```
In [12]: A=np.array(gscv.cv_results_['mean_train_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=min_samples_split)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```



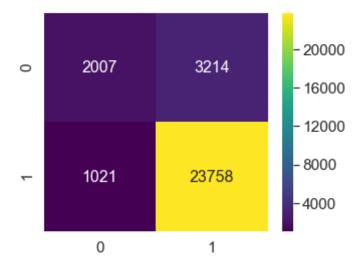
Seaborn Heatmap on Test Data

```
In [13]: A=np.array(gscv.cv_results_['mean_test_score'])
B = np.reshape(A, (6,6))
df = pd.DataFrame(B, index=max_depth, columns=min_samples_split)
plt.figure(figsize = (16,5))
sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viri dis')
plt.show()
```

- 1	0.550624	0.550624	0.550624	0.550624	0.550624	0.550624
요 -	0.744708	0.746541	0.750801	0.755759	0.757397	0.758947
82 -	0.744056	0.755909	0.776381	0.789633	0.803713	0.815216
og -	0.682923	0.703685	0.733304	0.757015	0.780734	0.828533
100	0.648783	0.668609	0.706893	0.73649	0.763611	0.82058
200	0.695281	0.709751	0.731155	0.748767	0.770662	0.809245
	5	10	25	50	100	500

Confusion Matrix on Test Data

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1ee655c5da0>

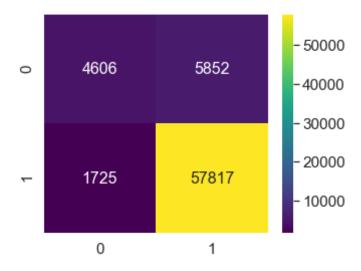


Confusion Matrix on Train Data

```
In [15]: # plotting confusion matrix as heatmap
y_predict = dtc_clf.predict(x_train_bow)
cm = confusion_matrix(y_train_bow, y_predict)
```

```
print(cm)
plt.figure(figsize = (5,4))
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')
[[ 4606    5852]
    [ 1725    57817]]
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1ee685c4860>

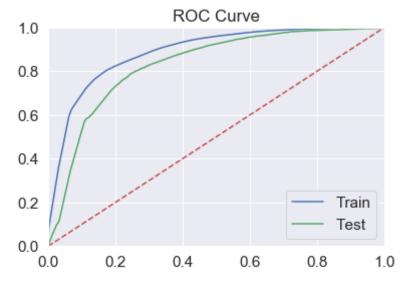


ROC Curve

```
In [16]: # Plotting roc curve on Train Data
    pred_train = dtc_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 = dtc_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()
```



Top 20 important features from SET 1

```
In [17]: # Calculate feature importances from decision trees
importances = dtc_clf.feature_importances_

# Sort feature importances in descending order and get their indices
indices = np.argsort(importances)[::-1][:20]

# Get the feature names from the vectorizer
names = count_vect.get_feature_names()

sns.set(rc={'figure.figsize':(11.7,8.27)})
```

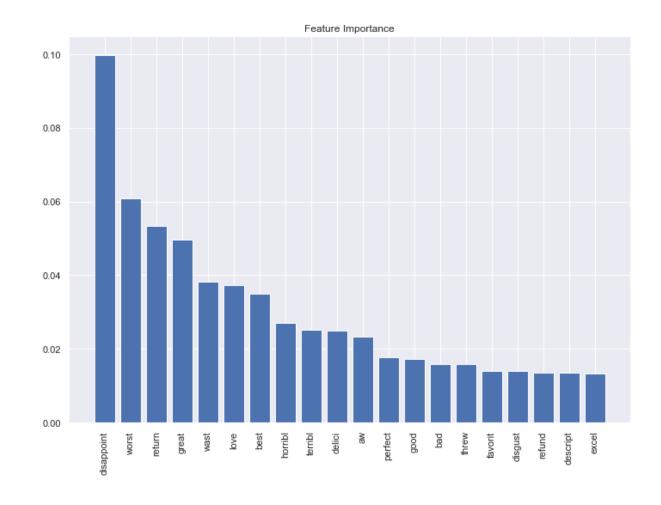
```
# Create plot
plt.figure()

# Create plot title
plt.title("Feature Importance")

# Add bars
plt.bar(range(20), importances[indices])

# Add feature names as x-axis labels
names = np.array(names)
plt.xticks(range(20), names[indices], rotation=90)

# Show plot
plt.show()
```



Graphviz visualization of Decision Tree on BOW, SET 1

```
Out[21]:
         'Source.gv.pdf'
         [3.2] Applying Decision Trees on TFIDF, SET 2
In [25]: # initializing DecisionTreeClassifier model
         dtc = DecisionTreeClassifier()
         # hyperparameter values we need to try on classifier
         \max depth = [1, 10, 25, 50, 100, 500]
         min samples split = [5, 10, 25, 50, 100, 500]
         param grid = \{\text{'max depth'}: [1, 10, 25, 50, 100, 500],
                        'min samples split':[5, 10, 25, 50, 100, 500]}
         # using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 5 fold CV
         gscv = GridSearchCV(dtc,param grid,scoring='roc auc',cv=5,n jobs=-1,ret
         urn train score=True)
         gscv.fit(x train tfidf,y train tfidf)
         print("Best Max Depth Value:",gscv.best params ['max depth'])
         print("Best Min Sample Split Value:",gscv.best params ['min samples spl
         it'1)
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 50
         Best Min Sample Split Value: 500
         Best ROC AUC Score: 0.81669
In [26]: # determining optimal depth and sample split values
         optimal depth = gscv.best params ['max depth']
         optimal sample split = qscv.best params ['min samples split']
         #training the model using the optimal hyperparameters
         dtc clf = DecisionTreeClassifier(max depth=optimal depth, min samples s
         plit=optimal sample split)
         dtc clf.fit(x train tfidf,y_train_tfidf)
```

```
#predicting the class label using test data
y_pred = dtc_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 0.821965 ****

Seaborn Heatmap on Train Data

```
In [27]: A=np.array(gscv.cv_results_['mean_train_score'])
    B = np.reshape(A, (6,6))
    df = pd.DataFrame(B, index=max_depth, columns=min_samples_split)
    plt.figure(figsize = (16,5))
    sns.heatmap(df, annot=True, annot_kws={"size": 16}, fmt="g", cmap='viridis')
    plt.show()
```

-	0.550591	0.550591	0.550591	0.550591	0.550591	0.550591
10	0.774845	0.774234	0.772558	0.770555	0.768775	0.76394
52	0.89161	0.889217	0.884076	0.878401	0.872247	0.855416
22	0.95902	0.956025	0.949753	0.943136	0.935656	0.906584
100	0.98622	0.984142	0.979492	0.973755	0.966519	0.939624
200	0.999706	0.998564	0.995359	0.991086	0.985692	0.964292
	5	10	25	50	100	500

Seaborn Heatmap on Test Data

```
In [28]: A=np.array(gscv.cv_results_['mean_test_score'])
```

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

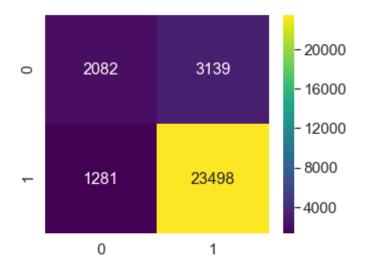
-	0.550193	0.550193	0.550193	0.550193	0.550193	0.550193
9	0.739319	0.739756	0.743157	0.747257	0.748029	0.752068
52	0.748356	0.75819	0.771226	0.784942	0.793058	0.811907
82	0.694764	0.710562	0.741959	0.759686	0.776553	0.816694
100	0.660061	0.680534	0.707538	0.732289	0.756414	0.808202
200	0.691478	0.702486	0.720417	0.737536	0.7481	0.780506
	5	10	25	50	100	500

Confusion Matrix on Test Data

```
In [29]: # plotting confusion matrix as heatmap
    y_predict = dtc_clf.predict(x_test_tfidf)
    cm = confusion_matrix(y_test_tfidf, y_predict)
    print(cm)
    plt.figure(figsize = (5,4))
    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')

[[ 2082    3139]
    [ 1281    23498]]

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0xlee02dd6d30>
```

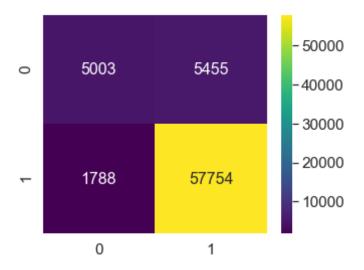


Confusion Matrix on Train Data

```
In [30]: # plotting confusion matrix as heatmap
    y_predict = dtc_clf.predict(x_train_tfidf)
    cm = confusion_matrix(y_train_tfidf, y_predict)
    print(cm)
    plt.figure(figsize = (5,4))
    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')

[[ 5003  5455]
    [ 1788  57754]]

Out[30]: <matplotlib.axes. subplots.AxesSubplot at 0xlee7f719940>
```

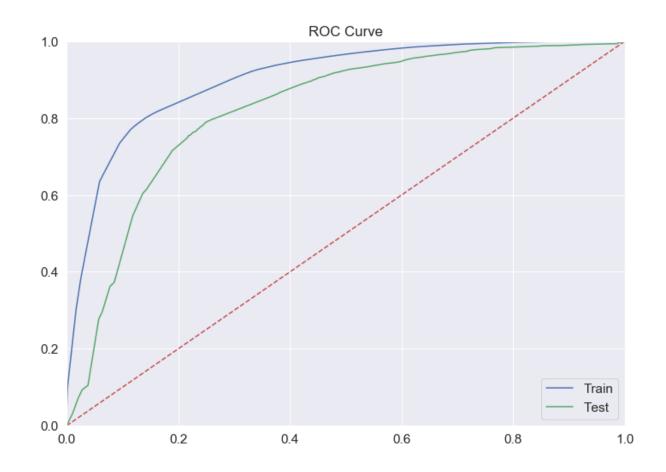


ROC Curve

```
In [31]: # Plotting roc curve on Train Data
    pred_train = dtc_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 = dtc_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()
```



Top 20 important features from SET 2

```
In [32]: # Calculate feature importances from decision trees
importances = dtc_clf.feature_importances_

# Sort feature importances in descending order and get their indices
indices = np.argsort(importances)[::-1][:20]

# Get the feature names from the vectorizer
names = tf_idf_vect.get_feature_names()
```

```
sns.set(rc={'figure.figsize':(11.7,8.27)})

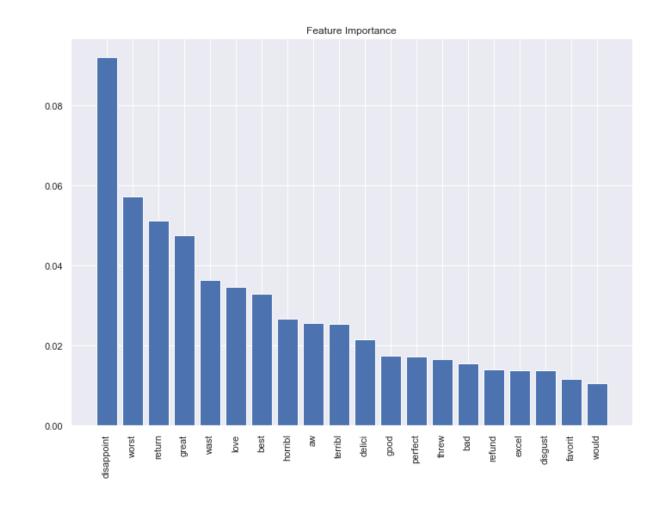
# Create plot
plt.figure()

# Create plot title
plt.title("Feature Importance")

# Add bars
plt.bar(range(20), importances[indices])

# Add feature names as x-axis labels
names = np.array(names)
plt.xticks(range(20), names[indices], rotation=90)

# Show plot
plt.show()
```



Graphviz visualization of Decision Tree on TFIDF, SET 2

```
Out[33]: 'Source.gv.pdf'
         [3.3] Applying Decision Trees on AVG W2V, SET 3
In [42]: # initializing DecisionTreeClassifier model
         dtc = DecisionTreeClassifier()
         # hyperparameter values we need to try on classifier
         \max depth = [1, 10, 25, 50, 100, 500]
         min samples split = [10, 25, 50, 100, 500, 1000]
         param grid = \{\text{'max depth'}: [1, 10, 25, 50, 100, 500],
                        'min samples split':[10, 25, 50, 100, 500, 1000]}
         # using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 5 fold CV
         gscv = GridSearchCV(dtc,param grid,scoring='roc auc',cv=5,n jobs=-1,ret
         urn train score=True)
         gscv.fit(x train w2v,y train w2v)
         print("Best Max Depth Value:",gscv.best params ['max depth'])
         print("Best Min Sample Split Value:", gscv.best params ['min samples spl
         it'1)
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 10
         Best Min Sample Split Value: 500
         Best ROC AUC Score: 0.81900
In [43]: # determining optimal depth and sample split values
         optimal depth = gscv.best params ['max depth']
         optimal sample split = gscv.best params ['min samples split']
         #training the model using the optimal hyperparameters
         dtc clf = DecisionTreeClassifier(max depth=optimal depth, min samples s
         plit=optimal sample split)
         dtc clf.fit(x train w2v,y train w2v)
```

```
#predicting the class label using test data
y_pred = dtc_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 0.823780 ****

Seaborn Heatmap on Train Data

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

-	0.617132	0.617132	0.617132	0.617132	0.617132	0.617132
10	0.902313	0.898246	0.893082	0.886269	0.859092	0.841624
22	0.996237	0.982846	0.964124	0.939949	0.876376	0.849082
22	0.99665	0.983439	0.964613	0.940377	0.876506	0.849097
100	0.996649	0.983385	0.964696	0.940467	0.876519	0.849096
200	0.996645	0.983397	0.964556	0.94049	0.876517	0.849096
	10	25	50	100	500	1000

Seaborn Heatmap on Test Data

```
In [45]: A=np.array(gscv.cv_results_['mean_test_score'])
```

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

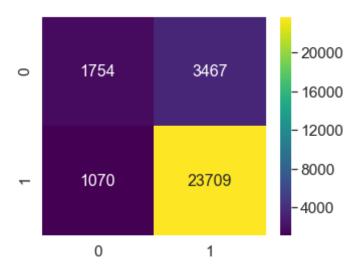
-	0.610287	0.610287	0.610287	0.610287	0.610287	0.610287
9	0.786254	0.797287	0.806326	0.812467	0.819001	0.815199
22	0.674799	0.719025	0.753754	0.785591	0.816449	0.81416
23	0.683198	0.724594	0.756599	0.786442	0.816602	0.813994
100	0.685276	0.724899	0.755307	0.786631	0.816597	0.814081
200	0.685715	0.725726	0.756506	0.785476	0.816301	0.814055
	10	25	50	100	500	1000

Confusion Matrix on Test Data

```
In [46]: # plotting confusion matrix as heatmap
    y_predict = dtc_clf.predict(x_test_w2v)
    cm = confusion_matrix(y_test_w2v, y_predict)
    print(cm)
    plt.figure(figsize = (5,4))
    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')

[[ 1754     3467]
    [ 1070     23709]]

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0xlee176658d0>
```

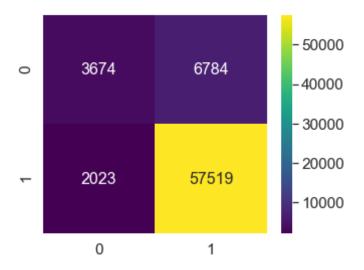


Confusion Matrix on Train Data

```
In [47]: # plotting confusion matrix as heatmap
    y_predict = dtc_clf.predict(x_train_w2v)
    cm = confusion_matrix(y_train_w2v, y_predict)
    print(cm)
    plt.figure(figsize = (5,4))
    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')

[[ 3674 6784]
    [ 2023 57519]]

Out[47]: <matplotlib.axes. subplots.AxesSubplot at 0xlee176bda20>
```

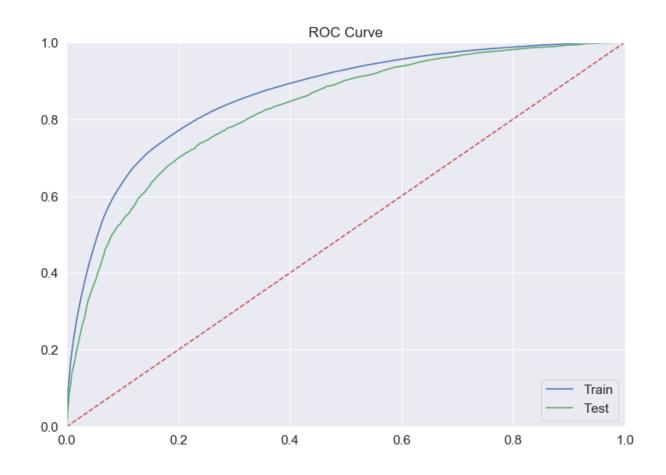


ROC Curve

```
In [48]: # Plotting roc curve on Train Data
    pred_train = dtc_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 = dtc_clf.predict_proba(x_test_w2v)[:,1]
    fpr, tpr, threshold = roc_curve(y_test_w2v, pred_test)
    plt.plot(fpr, tpr, 'g', label='Test')

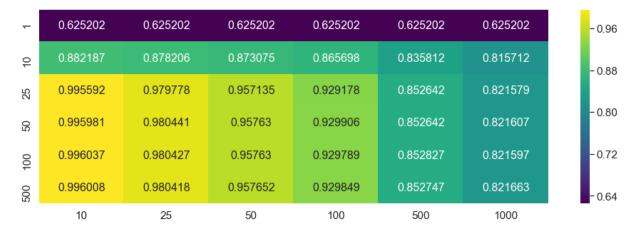
plt.title('ROC Curve')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.legend(loc='lower right')
    plt.show()
```



[3.4] Applying Decision Trees on TFIDF W2V, SET 4

```
# using GridSearchCV to find the optimal value of hyperparameters
         # using roc auc as the scoring parameter & applying 5 fold CV
         gscv = GridSearchCV(dtc,param grid,scoring='roc auc',cv=5,n jobs=-1,ret
         urn train score=True)
         gscv.fit(x train tfw2v,y train tfw2v)
         print("Best Max Depth Value:",gscv.best params ['max depth'])
         print("Best Min Sample Split Value:", gscv.best params ['min samples spl
         it'1)
         print("Best ROC AUC Score: %.5f"%(gscv.best score ))
         Best Max Depth Value: 10
         Best Min Sample Split Value: 500
         Best ROC AUC Score: 0.78579
In [56]: # determining optimal depth and sample split values
         optimal depth = gscv.best params ['max depth']
         optimal sample split = gscv.best params ['min samples split']
         #training the model using the optimal hyperparameters
         dtc clf = DecisionTreeClassifier(max depth=optimal depth, min samples s
         plit=optimal sample split)
         dtc clf.fit(x train tfw2v,y train tfw2v)
         #predicting the class label using test data
         y pred = dtc 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 0.784230 ****
         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=min samples split)
```

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

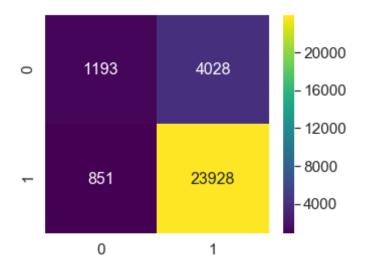


Confusion Matrix on Test Data

```
In [59]: # plotting confusion matrix as heatmap
y_predict = dtc_clf.predict(x_test_tfw2v)
cm = confusion_matrix(y_test_tfw2v, y_predict)
print(cm)
plt.figure(figsize = (5,4))
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')

[[ 1193     4028]
        [ 851     23928]]

Out[59]: <matplotlib.axes. subplots.AxesSubplot at 0xlee17602208>
```

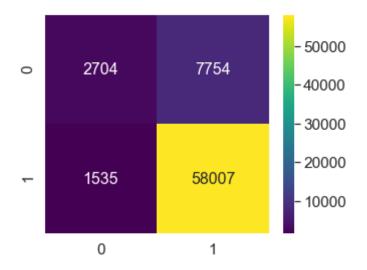


Confusion Matrix on Train Data

```
In [60]: # plotting confusion matrix as heatmap
    y_predict = dtc_clf.predict(x_train_tfw2v)
    cm = confusion_matrix(y_train_tfw2v, y_predict)
    print(cm)
    plt.figure(figsize = (5,4))
    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')

[[ 2704  7754]
    [ 1535  58007]]

Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0xlee188e7668>
```

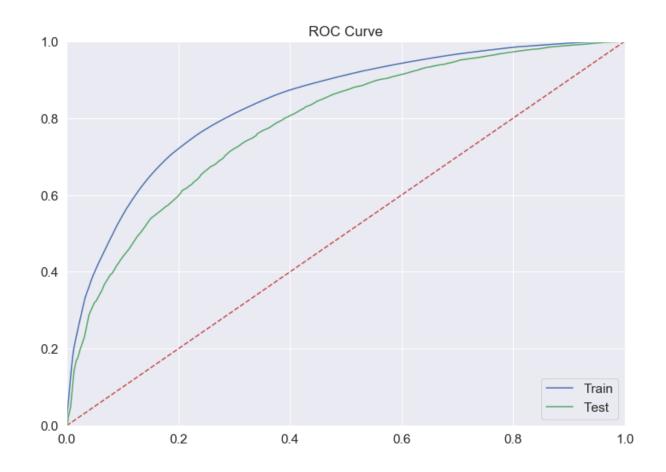


ROC Curve

```
In [61]: # Plotting roc curve on Train Data
    pred_train = dtc_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 = dtc_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()
```



[4.0] Conclusion

+	+		+
BOW	50	500	0.831107
TFIDF	50	500	0.821965
Avg W2V	10	500	0.823780
TFIDF-W2V	10	500	0.784230
+	+		++