08_Amazon_Food_Reviews_DT

April 16, 2019

1 Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective: Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative? [Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 Decision Trees

```
<li><strong>Apply Decision Trees on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
```

```
    </ul>
</li>
<br>
<li><strong>The hyper paramter tuning (best `depth` in range [1, 5, 10, 50, 100, 500, 100], and
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicour
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data</
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this tas
    </ul>
</li>
<br>
<li><strong>Graphviz</strong>
    <ul>
<li>Visualize your decision tree with Graphviz. It helps you to understand how a decision is bei
<li>Since feature names are not obtained from word2vec related models, visualize only BOW & TFID
<li>Make sure to print the words in each node of the decision tree instead of printing its index
<li>Just for visualization purpose, limit max_depth to 2 or 3 and either embed the generated ima
    </ul>
</li>
<br>
<li><strong>Feature importance</strong>
    <ul>
<li>Find the top 20 important features from both feature sets <font color='red'>Set 1</font> and
    </ul>
</li>
<br>
<li><strong>Feature engineering</strong>
    <ul>
<li>To increase the performance of your model, you can also experiment with with feature enginee
        <ul>
        <li>Taking length of reviews as another feature.</li>
        <li>Considering some features from review summary as well.</li>
    </ul>
    </ul>
</li>
<br>
<li><strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for e
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fin
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.co
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
```

```
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table form
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

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.

3 Applying Decision Trees

4 Import Required Packages

In [1]:
```python
import os
from datetime import datetime
import pandas as pd
import numpy as np

# visualization related packages
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

# data prerocessing related
from sklearn.preprocessing import StandardScaler

# import model related packages & its visualization
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
import graphviz

# import model selection packages
from sklearn.model_selection import StratifiedKFold

# import model evaluation related packages
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import auc, roc_curve
from scipy import interp

# calibration related package
```

```
from sklearn.calibration import CalibratedClassifierCV

# visualization related packages
from wordcloud import WordCloud
from prettytable import PrettyTable

# for forming grid
from itertools import product
```

5 UTILS Function

5.1 Data Preprocessing related Functions

```
In [2]: def preprocess_data(config_dict, scaling=True, dim_reduction=False):
            """
            This function does preprocessing of data such as column standardization and
            dimensionality reduction using Truncated SVD
            """

            # Read train, test data frames & truncate it as needed
            train_df = pd.read_csv(config_dict['train_csv_path'], index_col=False)
            train_df = train_df.iloc[0:config_dict['train_size']]
            test_df = pd.read_csv(config_dict['test_csv_path'], index_col=False)
            test_df = test_df.iloc[0:config_dict['test_size']]

            # print the statisics of train, test df
            print('Train df shape',train_df.shape)
            print('Class label distribution in train df:\n', train_df['Label'].value_counts())
            print('Test df shape',test_df.shape)
            print('Class label distribution in test df:\n', test_df['Label'].value_counts())

            # separate features and labels
            train_features = train_df.drop(['Label', 'Id'], axis=1)
            train_labels = train_df['Label']
            test_features = test_df.drop(['Label', 'Id'], axis=1)
            test_labels = test_df['Label']

            # set feature names
            feature_name_list = train_features.columns.values.tolist()

            # If Scaling is opted scale the train, test data
            if scaling:
                standard_scaler = StandardScaler()
                standard_scaler.fit(train_features)

                train_features = pd.DataFrame(standard_scaler.transform(train_features),
                                              columns=feature_name_list)
```

```
        test_features = pd.DataFrame(standard_scaler.transform(test_features),
                                     columns=feature_name_list)

    print('Shape of ->  train features :%d,%d, test features: %d,%d'%(train_features.sha
                                                                      test_features.shap
    print('Shape of -> train labels :%d, test labels: %d'%(train_labels.shape[0],
                                                           test_labels.shape[0],))

    # if dim reduction is opted, reduce the dimension
    if dim_reduction:
        # create an SVD object
        truc_svd = TruncatedSVD(n_components=train_features.shape[1]-1, n_iter=8, algori

        # fit to data
        truc_svd.fit(train_features)

        # get explained variance ratio of each component
        explained_var_ratios = truc_svd.explained_variance_ratio_

        # get cummulative ratio list for selecting the number of components
        cumulative_ratios = np.cumsum(explained_var_ratios)

        # plot the #components vs captured variance in the data
        plt.title('SVD Decomposition')
        plt.xlabel('Number of components')
        plt.ylabel('Cumulative Percentage Ratio')
        plt.plot(range(1, len(cumulative_ratios) + 1), cumulative_ratios)
        plt.show()

        # set a threshold for stopping selection of components.
        svd_thesh = 0.001
        # select the number of components as the first component for which the differenc
        #  very less (less than svd thresh) compared with the very next component
        selected_dim = list(filter(lambda x : x[1] < svd_thesh, enumerate(np.diff(cumula
        print('Num dimensions selected by SVD', selected_dim)
        print('Total variance captured:%f'%(cumulative_ratios[selected_dim]))

        # create an object for selecting the components
        truc_svd = TruncatedSVD(n_components=selected_dim, n_iter=8, algorithm='randomiz
        # refit with the desired number of components
        truc_svd.fit(train_features)

        # reduce the number of dimensions to selected number of components
        train_features = pd.DataFrame(truc_svd.transform(train_features))
        test_features = pd.DataFrame(truc_svd.transform(test_features))

        # get the shape of final data frame and print it
        size_tuple = train_features.shape + test_features.shape
```

```
        print('Shape of train df:(%d,%d), Test DF:(%d,%d)'%size_tuple)


    return (train_features, train_labels, test_features, test_labels,)
```

5.2 Model training and Evaluation related Functions

```
In [3]: def get_confusion_matrix(actual_list, predicted_list, cm_title):
            """
            This function plots the confusion matrix given ground truth and predicted
            """

            conf_matrix = confusion_matrix(actual_list, predicted_list)
            col_names = ['Negative', 'Positive']
            conf_df = pd.DataFrame(conf_matrix,columns=col_names)
            conf_df.index = col_names

            plt.figure(figsize = (5,5))

            plt.title(cm_title)
            sns.set(font_scale=1.4)#for label size


            ax= plt.subplot()
            sns.heatmap(conf_df, annot=True, annot_kws={"size": 16}, fmt='g')
            ax.set_xlabel('Predicted labels');
            ax.set_ylabel('True labels');
            ax.xaxis.set_ticklabels(['Negative', 'Positive']);
            ax.yaxis.set_ticklabels(['Negative', 'Positive']);

            plt.show()
```

```
In [4]: def compute_auc_scores(actual_predicted_list):
            """
            This function computes the auc scores of a prediction
            """

            # separate actual and predicted values
            actual_probs = actual_predicted_list[0]
            predicted_probs = actual_predicted_list[1]

            # compute ROC curve and get the AUC value for this fold
            fpr, tpr, thresholds = roc_curve(actual_probs, predicted_probs)
            # compute AUC score
            auc_score = auc(fpr, tpr)

            return fpr, tpr, thresholds, auc_score
```

```
In [5]: def plot_roc_curves_pair(train_fold_prediction_list, inference_fold_prediction_list, plo
```

```
"""
This function helps to plot the ROC curve for a set of predictions for train and tes
"""

# set figure size
if plot:
    plt.figure(figsize=(10,10))

# reference points for X axis
ref_points = np.linspace(0.0, 1.0, 100)


# -------------------- 1 FOR TRAIN --------------------------------------------
# two lists for auc values and tpr rates
auc_scores_list = list()
tpr_list = list()

# plot ROC curve for each fold
for index, actual_predicted_tuple in enumerate(train_fold_prediction_list):

    # get roc info list
    fpr, tpr, thresholds, auc_score = compute_auc_scores(actual_predicted_tuple)

    # interpolation to approximate the curve
    tp_rates = interp(ref_points, fpr, tpr)
    tp_rates[0] = 0.0 # for setting the bottom left point

    # for plotting the individual fold and finding the average
    auc_scores_list.append(auc_score)
    tpr_list.append(tp_rates)

    # plot this fold info into a fig
    if plot:
        plt.plot(fpr, tpr, alpha=0.6, lw=2, color='b',
                 label='Train AUC for fold %d : %f'%(index+1, auc_score))

    # assign as mean auc
    train_mean_auc = auc_score


# if more than one curve is present plot the mean curve
if len(train_fold_prediction_list) > 1:

    # Plot the mean performance
    mean_tpr = np.mean(tpr_list, axis=0)
    std_tprs = np.std(tpr_list, axis=0)

    # mean value of AUC and its standard deviation
```

```
        mean_auc = auc(ref_points, mean_tpr)
        std_auc = np.std(auc_scores_list)

        # train mean auc
        train_mean_auc = mean_auc

        if plot:
            plt.plot(ref_points, mean_tpr, linestyle='-', color='b', lw=3,
                     alpha=0.8, label='Train Mean AUC %f $\pm$ %f'%(mean_auc,std_auc))


            # Find upper and lower bounds for shading the region around TPRs
            tprs_lower_region = np.maximum(mean_tpr - std_tprs, 0)
            tprs_upper_region = np.minimum(mean_tpr + std_tprs, 1)

            # Fill the region between upper and lower in gray color
            plt.fill_between(ref_points, tprs_lower_region, tprs_upper_region, color='b'
                             label='Train Around the mean TPRs')


    # -------------------- 1 FOR VALIDATION -----------------------------------------
    # two lists for auc values and tpr rates
    auc_scores_list = list()
    tpr_list = list()

    # plot ROC curve for each fold
    for index, actual_predicted_tuple in enumerate(inference_fold_prediction_list):

        # get roc info list
        fpr, tpr, thresholds, auc_score = compute_auc_scores(actual_predicted_tuple)

        # interpolation to approximate the curve
        tp_rates = interp(ref_points, fpr, tpr)
        tp_rates[0] = 0.0 # for setting the bottom left point

        # for plotting the individual fold and finding the average
        auc_scores_list.append(auc_score)
        tpr_list.append(tp_rates)

        # plot this fold info into a fig
        if plot:
            plt.plot(fpr, tpr, alpha=0.6, lw=2, color='g',
                     label= plot_against +' AUC for fold %d : %f'%(index+1, auc_score))

        # assign as mean auc
        val_mean_auc = auc_score
```

```
        if len(inference_fold_prediction_list) > 1:

            # Plot the mean performance
            mean_tpr = np.mean(tpr_list, axis=0)
            std_tprs = np.std(tpr_list, axis=0)

            # mean value of AUC and its standard deviation
            mean_auc = auc(ref_points, mean_tpr)
            std_auc = np.std(auc_scores_list)

            # val mean auc
            val_mean_auc = mean_auc

            if plot:
                plt.plot(ref_points, mean_tpr, linestyle='-', color='g', lw=3,
                         alpha=0.8, label= plot_against + ' Mean AUC %f $\pm$ %f'%(mean_auc,


                # Find upper and lower bounds for shading the region around TPRs
                tprs_lower_region = np.maximum(mean_tpr - std_tprs, 0)
                tprs_upper_region = np.minimum(mean_tpr + std_tprs, 1)

                # Fill the region between upper and lower in gray color
                plt.fill_between(ref_points, tprs_lower_region, tprs_upper_region, color='g'
                                 label= plot_against + ' Around the mean TPRs')

        # Plot the random classifier
        if plot:
            plt.plot([0,1],[0,1], alpha=0.8, linestyle='--', color='red', label='Random Gues
            # arange the plot
            plt.xlim([-0.05, 1.05])
            plt.ylim([-0.05, 1.05])
            plt.xlabel('False Positive Rates')
            plt.ylabel('True Positive Rates')
            plt.title('ROC - Train V/S ' + plot_against)
            plt.legend(loc='lower right')
            plt.show()

        return (train_mean_auc, val_mean_auc)
```

```
In [6]: def create_hyperparam_heatmap(hyper_param_score_list, hamp_title):
        """
        This function accepts a list containing the hyper parameters ('max_depth', 'min_spli
        the corresponding score value, such as AUC, FScore etc and plot the heatmap.
        """

        hyp_score_list = [item[1] for item in hyper_param_score_list]
        coord_list = [item[0] for item in hyper_param_score_list]
```

```
    hyp_df = pd.DataFrame(coord_list, columns=['max_depth', 'min_splits'])
    hyp_df['AUC'] = hyp_score_list

    # pivot the table for heatmap representation
    pivoted_hyp = pd.pivot_table(hyp_df, index='max_depth', columns='min_splits',
                                 values='AUC', fill_value=0)
    sns.heatmap(data=pivoted_hyp, annot=True)
    plt.title(hamp_title)
    plt.show()
```

```
In [7]: def find_best_hyperparameter(config_dict, train_features, train_labels):
    """
    This function helps to find the best hyper parameter (alpha) for MultinomialNB algor
    All set of hyper param values using which the model to be evaluated can be passed to
    list hyperparam_list.
    """

    print('='*100)

    stratified_partition = StratifiedKFold(n_splits=3)

    # read some config settings
    hyperparam_list = config_dict['hyperparam_list']

    hyper_param_scores_list = list()

    for hyp_val in hyperparam_list:

        # declare three lists for holding prediction informations

        # for train set performance
        train_actual_labels_list = list()
        train_predicted_probs_list = list()
        train_predicted_labels_list = list()

        # for validation set performance
        val_actual_labels_list = list()
        val_predicted_probs_list = list()
        val_predicted_labels_list = list()



        # Model defined here
        dt_classifier = DecisionTreeClassifier(max_depth=hyp_val[0], min_samples_split=h

        # Declare a calibrated classifer
        calib_classifier = CalibratedClassifierCV(base_estimator=dt_classifier,
                                                  method='isotonic',
```

```
                                                 cv='prefit')

# Train the model and evaluate it on the current fold data
for train_indices, val_indices in stratified_partition.split(train_features, tra

    # A) train the model suing StratifiedKFold method

    # get the train features, train labels for this fold
    train_feat_data = train_features.iloc[train_indices, :]
    train_label_data = train_labels[train_indices]

    # train the classifier
    dt_classifier.fit(train_feat_data, train_label_data)
    calib_classifier.fit(train_feat_data, train_label_data)

    # estimate the training metrics on (train fold)
    train_eval_y_probs = calib_classifier.predict_proba(train_feat_data)[:, 1]
    train_eval_y_value = dt_classifier.predict(train_feat_data)

    # save the results for ROC plot
    train_actual_labels_list.append(train_label_data)
    train_predicted_probs_list.append(train_eval_y_probs)
    train_predicted_labels_list.append(train_eval_y_value)


    # B) predict the labels and probability for this fold (validation fold)

    # get the validation features, validation labels for this fold
    validation_feat_data = train_features.iloc[val_indices, :]
    validation_label_data = train_labels[val_indices]

    # evaluate the classifier on validation set
    val_actual_labels_list.append(validation_label_data)
    val_eval_y_probs = calib_classifier.predict_proba(validation_feat_data)[:, 1
    val_eval_y_value = dt_classifier.predict(validation_feat_data)

    # save the results for ROC plot
    val_predicted_probs_list.append(val_eval_y_probs)
    val_predicted_labels_list.append(val_eval_y_value)


# plot the results to select best hyper params
# ==============================================================================
# get input data for plotting train and validation
train_fold_prediction_list = list(zip(train_actual_labels_list, train_predicted_
val_fold_prediction_list = list(zip(val_actual_labels_list, val_predicted_probs_

# compute mean AUCs with or without plotting ROC curve
```

```python
    mean_auc_train, mean_auc_val = plot_roc_curves_pair(train_fold_prediction_list,
                                                         val_fold_prediction_list, 'Vali
                                                         plot=False)

    # update the list with the scores for this hyperparam for both tain, validation
    hyper_param_scores_list.append((hyp_val, mean_auc_train, mean_auc_val))

# plot hyper param vs AUC score
hyp_value_list_1 = [item[0][0] for item in hyper_param_scores_list]
hyp_value_list_2 = [item[0][1] for item in hyper_param_scores_list]
tr_auc_list = [item[1] for item in hyper_param_scores_list]
val_auc_list = [item[2] for item in hyper_param_scores_list]

# print k vs auc
print('\n\n max_depth vs AUC score plot')
plt.plot(hyp_value_list_1, tr_auc_list, label='Train AUC')
plt.plot(hyp_value_list_1, val_auc_list, label='Validation AUC')
plt.xlabel('max_depth')
plt.ylabel('AUC Scores')
plt.title('max_depth vs AUC')
plt.legend()
plt.show()


# print k vs auc
print('\n\n min_split vs AUC score plot')
plt.plot(hyp_value_list_2, tr_auc_list, label='Train AUC')
plt.plot(hyp_value_list_2, val_auc_list, label='Validation AUC')
plt.xlabel('min_split')
plt.ylabel('AUC Scores')
plt.title('min_split vs AUC')
plt.legend()
plt.show()

# heatmap plot for selecting the best hyper params
hyper_param_scores_list_train = [(item[0], item[1]) for item in hyper_param_scores_l
hyper_param_scores_list_validation = [(item[0], item[2]) for item in hyper_param_sco

# plot heatmap for train and validation
create_hyperparam_heatmap(hyper_param_scores_list_train, 'Hyper param Heatmap DT-Tra
create_hyperparam_heatmap(hyper_param_scores_list_validation, 'Hyper param Heatmap D

# find the best hyperparameter based on AUC score of validation data and the
# difference between auc validation and auc train scores
#Set the best Hyper param based on above plots
#print('Hyper info\n', hyper_param_scores_list)
best_hyper_param = min(hyper_param_scores_list, key=lambda x: abs(x[1] - x[2]) + (1
print('\n\nBest hyperparam value: ', best_hyper_param)
```

```
        return best_hyper_param
```

```
In [8]: def train_model(config_dict, train_features, train_labels):
            """
            This function train a model, validate it using cross validation and return the best
            obtained during cross validation.
            """

            # get best hyperparam value
            best_hyper_param = find_best_hyperparameter(config_dict, train_features, train_label

            # Final Model defined here
            dt_classifier = DecisionTreeClassifier(max_depth=best_hyper_param[0],
                                                   min_samples_split=best_hyper_param[1])

            # Declare a calibrated classifer
            calib_classifier = CalibratedClassifierCV(base_estimator=dt_classifier,
                                                      method='isotonic',
                                                      cv='prefit')

            # train the classifier
            dt_classifier.fit(train_features, train_labels)
            calib_classifier.fit(train_features, train_labels)


            # return the final model
            return (dt_classifier, calib_classifier,)
```

```
In [9]: def evaluate_model(model, features, labels, tag_name):
            """
            This function test and evaluate the performance on unseen data.
            """

            # separate out models
            dt_classifier = model[0]
            calib_classifier = model[1]

            # estimate the training metrics on (train fold)
            eval_y_probs = calib_classifier.predict_proba(features)[:, 1]
            eval_y_value = dt_classifier.predict(features)

            # print the confusion matrix
            get_confusion_matrix(labels, eval_y_value, tag_name + ' Confusion Matrix')

            # compute precision and other matric
            all_metrics = precision_recall_fscore_support(labels, eval_y_value)
            all_metrics_df = pd.DataFrame(list(all_metrics), columns=['Negative', 'Positive'])
```

```
    all_metrics_df.index = ['Precision', 'Recall', 'Fscore', 'Support']

    # convert fscore to percentage
    #fscores = all_metrics[2] * 100.0

    print(tag_name + ' Evaluation Metrics : \n', all_metrics_df)

    return (eval_y_probs, eval_y_value, all_metrics_df,)
```

In [10]:
```
def get_table_entry(model, auc_score, all_metrics_df):
    """
    This function prepares a table entry for inserting into pretty table
    """
    # round off to 4 decimal places
    fscore_pos = '{0:.4f}'.format(all_metrics_df.loc['Fscore', 'Positive'] * 100.0)
    fscore_neg = '{0:.4f}'.format(all_metrics_df.loc['Fscore', 'Negative'] * 100.0)
    auc_score = '{0:.4f}'.format(auc_score)

    ptabe_entry = [str((model[0].max_depth, model[0].min_samples_split)),
                   auc_score, fscore_neg, fscore_pos]

    print('Results Summary: \n', list(zip(['Hyper Param', 'AUC', 'f-score(-ve)', 'f-sco
                                          ptabe_entry)))

    return ptabe_entry
```

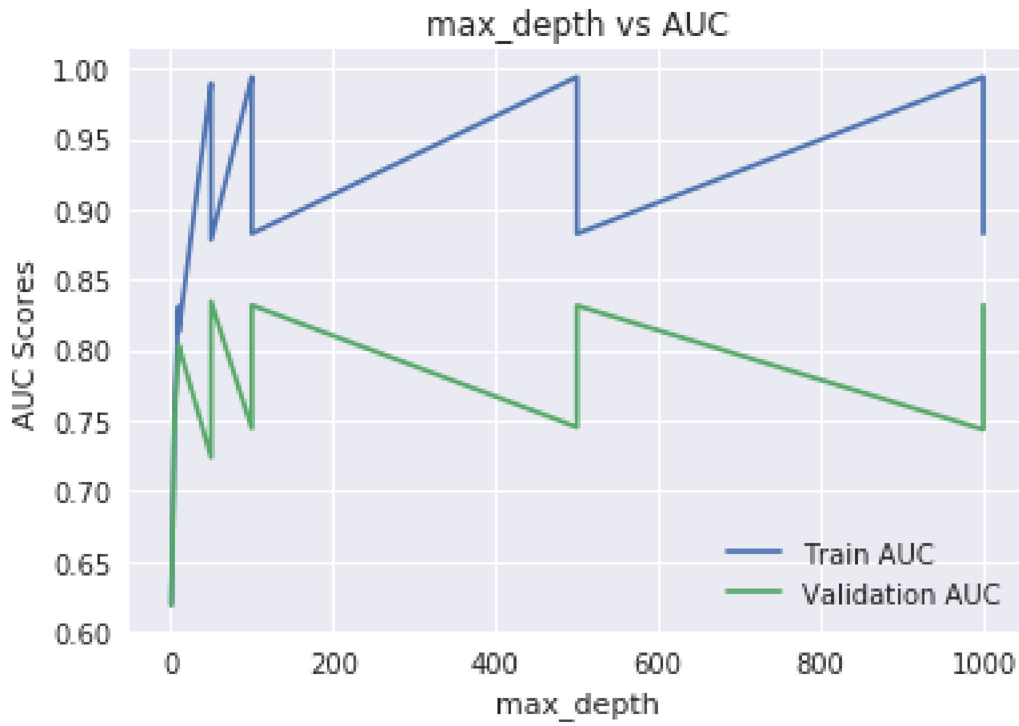
5.3 [A] Applying Decision Trees on BOW, SET 1

In [11]:
```
# form two lists
depth_list = [1, 5, 10, 50, 100, 500, 1000] # depends on size of dataset
min_split_list = [5, 10, 100, 500] # depends on size of dataset

# create a configuartion dictionary
config_dict = {
    'train_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/BOW/tr
    'test_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/BOW/tes
    'train_size' : 70000,
    'test_size' : 30000,
    'hyperparam_list' : product(depth_list, min_split_list)
}
```

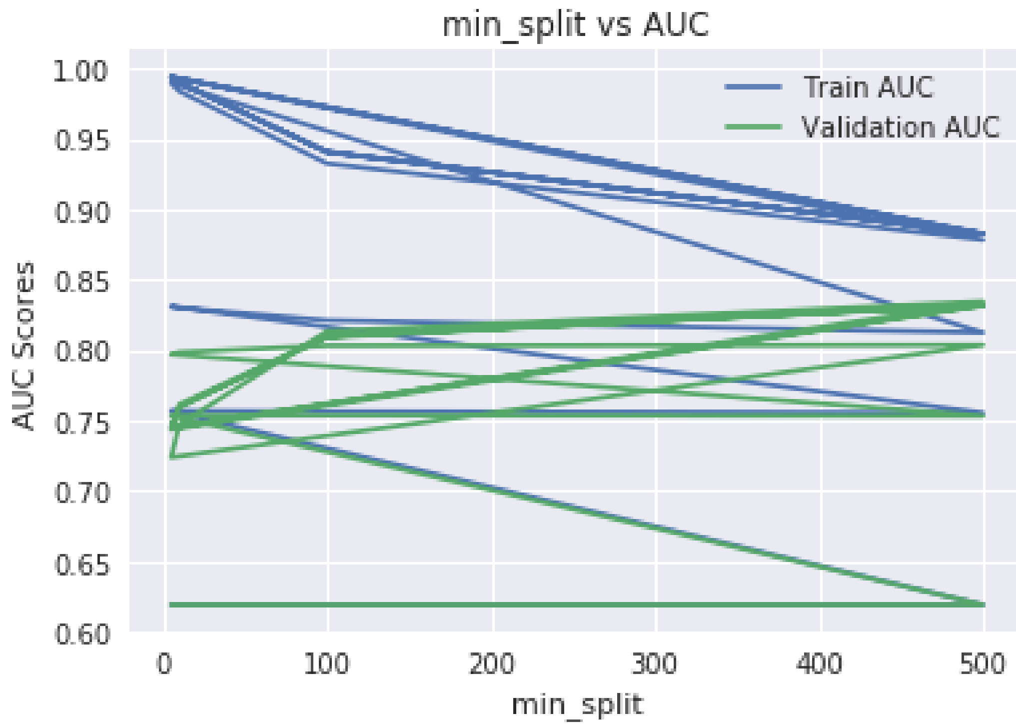
In [12]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                            scaling=True
                                                                            dim_reductio

# get name of all features in a list
feature_name_list = train_features.columns.values.tolist()
```

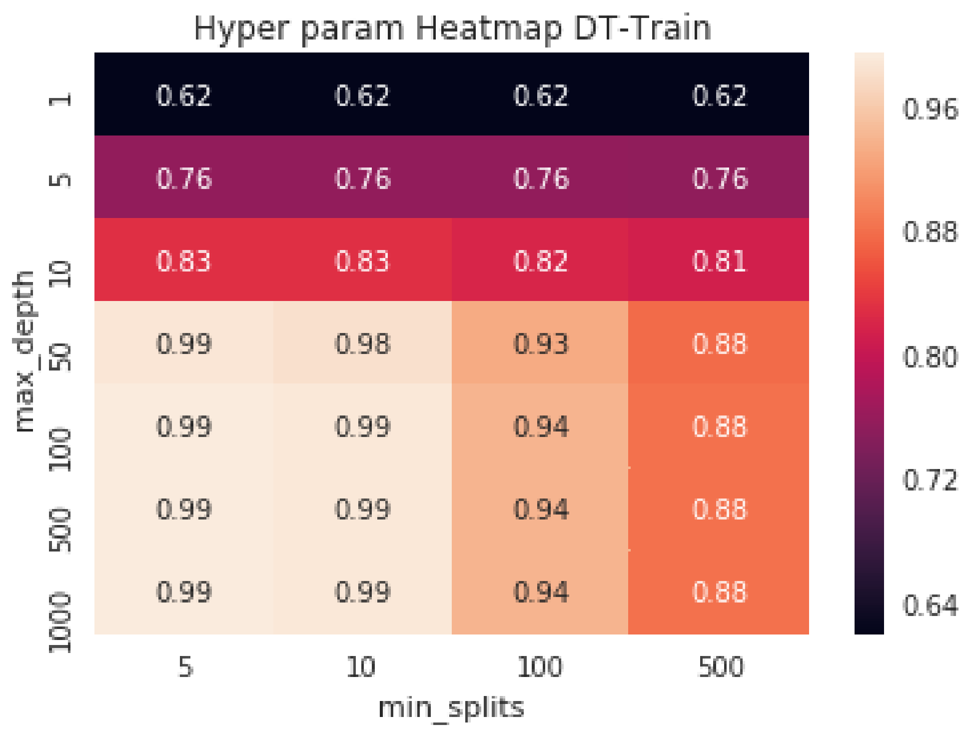
```
        # train the model
        model = train_model(config_dict, train_features, train_labels)

        # evaluate trained model on train data
        tr_eval_y_probs, tr_eval_y_value, tr_all_metrics_df = evaluate_model(model, train_featu

        # evaluate trained model on test data
        ts_eval_y_probs, ts_eval_y_value, ts_all_metrics_df = evaluate_model(model, test_featur

        #  plotting performace of final model on train and test
        tr_fold_prediction_list = list(zip([train_labels], [tr_eval_y_probs]))
        ts_fold_prediction_list = list(zip([test_labels], [ts_eval_y_probs]))
        auc_train, auc_ts = plot_roc_curves_pair(tr_fold_prediction_list,
                                                 ts_fold_prediction_list, 'Test',
                                                 plot=True)

        # get entry for pretty table
        ptabe_entry_a = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

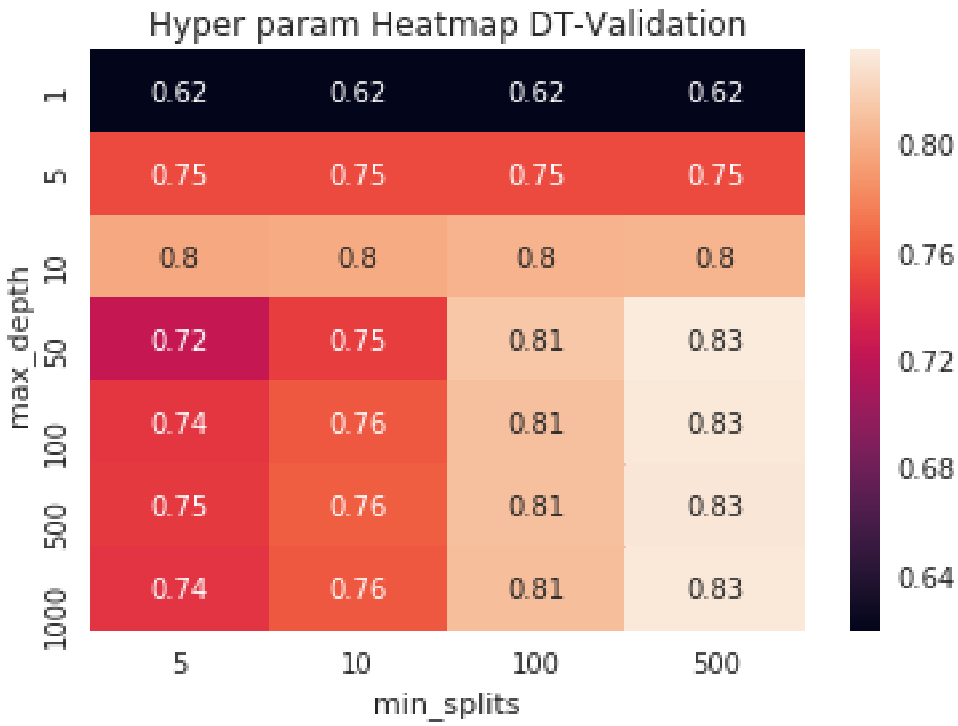
```
Train df shape (69997, 503)
Class label distribution in train df:
 1    35000
0    34997
Name: Label, dtype: int64
Test df shape (30000, 503)
Class label distribution in test df:
 1    24754
0     5246
Name: Label, dtype: int64
Shape of ->  train features :69997,501, test features: 30000,501
Shape of -> train labels :69997, test labels: 30000
==================================================================================================


 max_depth vs AUC score plot
```



`min_split vs AUC score plot`

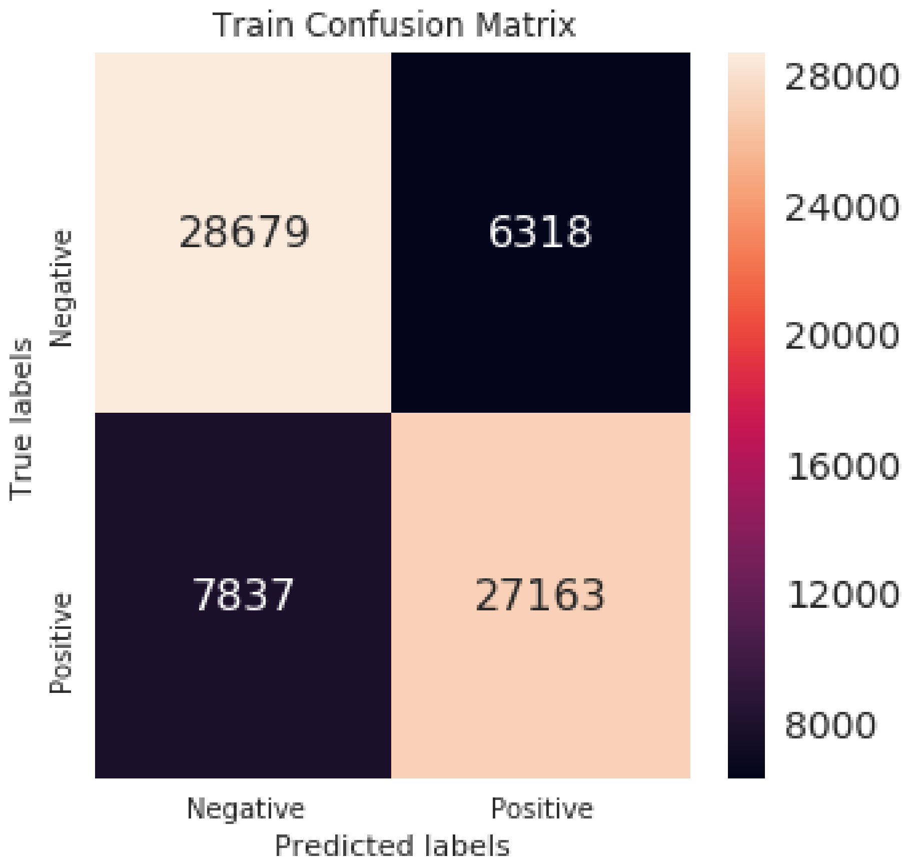

min_split vs AUC
Train AUC
Validation AUC
AUC Scores
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0
100
200
300
400
500
min_split


Hyper param Heatmap DT-Train
max_depth
1
5
10
50
100
500
1000
0.62 0.62 0.62 0.62
0.76 0.76 0.76 0.76
0.83 0.83 0.82 0.81
0.99 0.98 0.93 0.88
0.99 0.99 0.94 0.88
0.99 0.99 0.94 0.88
0.99 0.99 0.94 0.88
5
10
100
500
min_splits
0.96
0.88
0.80
0.72
0.64



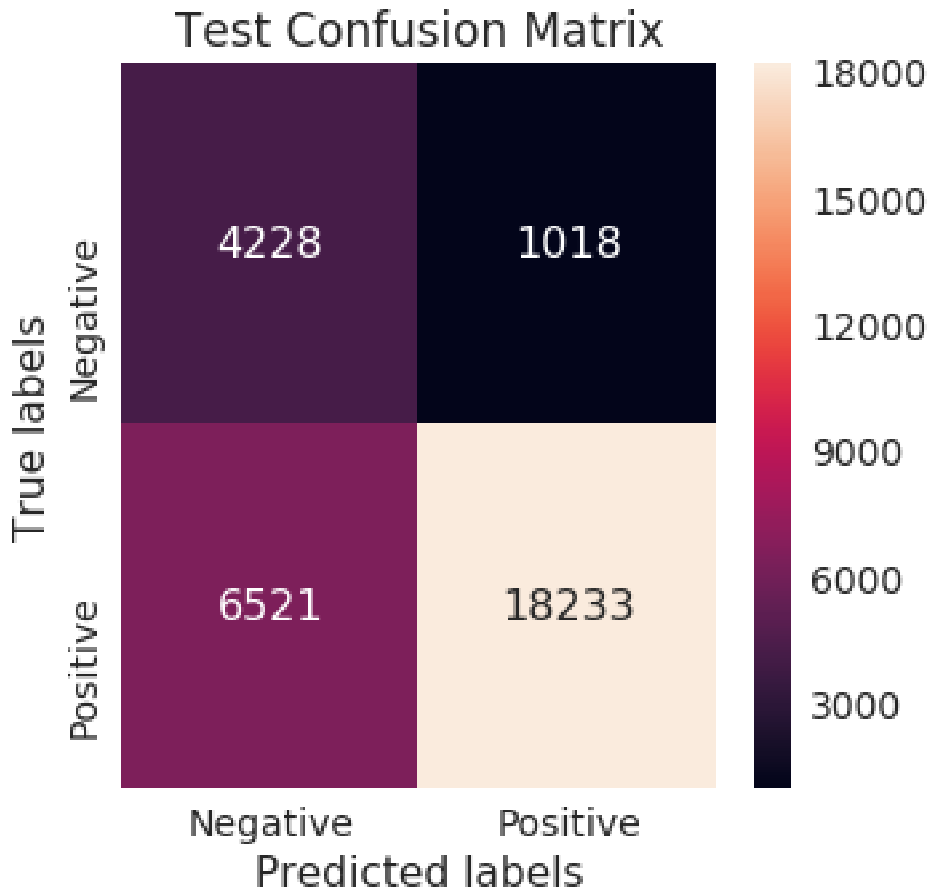

```
Best hyperparam value:  (50, 500)
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```



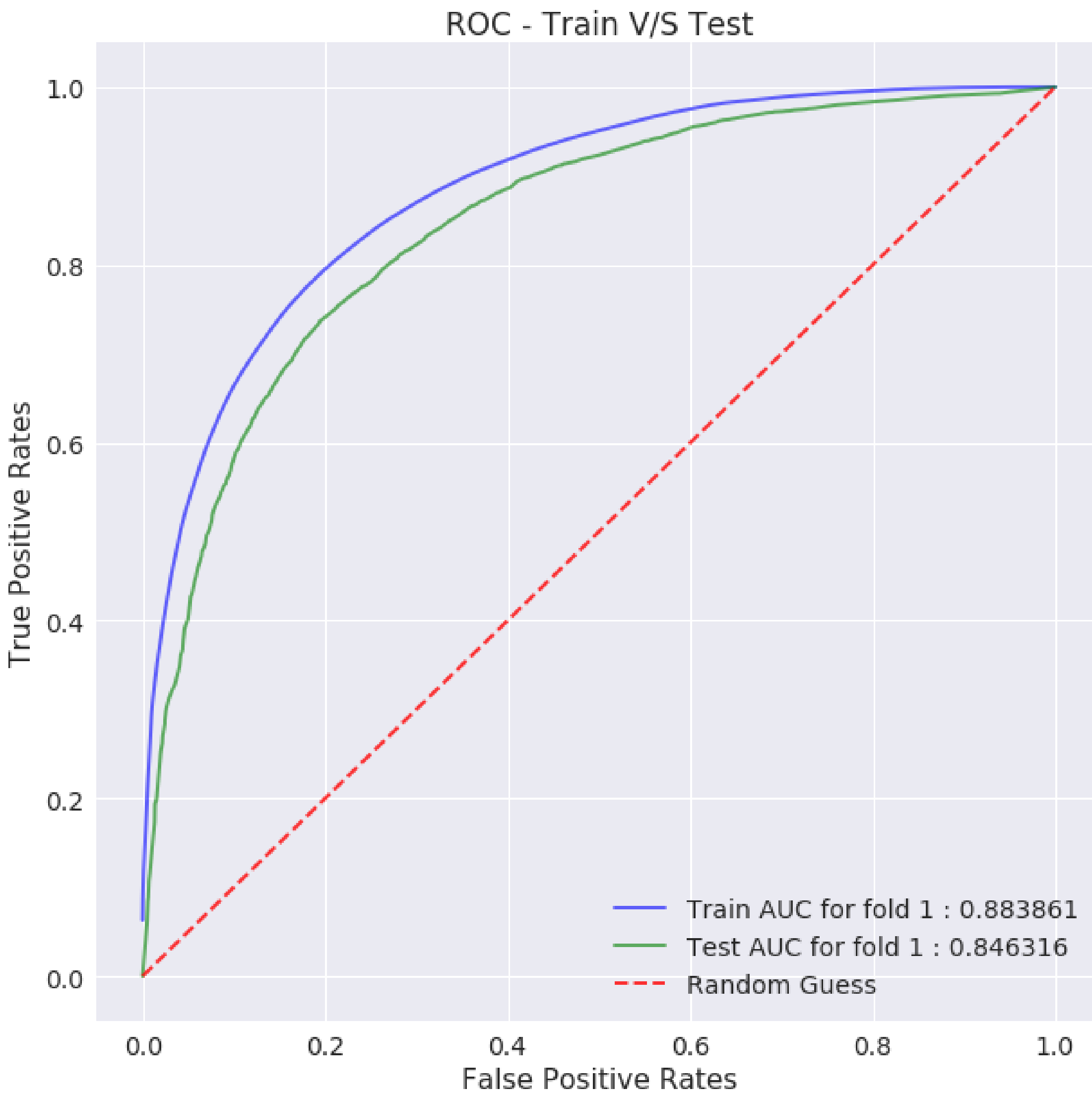

```
Train Evaluation Metrics :
                Negative      Positive
Precision       0.785382      0.811296
Recall          0.819470      0.776086
Fscore          0.802064      0.793300
Support     34997.000000  35000.000000
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```



Test Evaluation Metrics :

	Negative	Positive
Precision	0.393339	0.947120
Recall	0.805947	0.736568
Fscore	0.528665	0.828679
Support	5246.000000	24754.000000




```
Results Summary:
 [('Hyper Param', '(50, 500)'), ('AUC', '0.8463'), ('f-score(-ve)', '52.8665'), ('f-score(+ve)',
```

5.4 Observation

From depth vs AUC curves, as the depth of the tree increases very large, the auc score showed increase for train and validation auc showd decreases (overfit)

The best value of hyper param are (max_depth:50, min_samples_split:500)

5.4.1 [A.1] Top 20 important features from SET 1

```
In [13]: # get feature and its importance as tuple
         feature_imp_info = list(zip(feature_name_list, model[0].feature_importances_))
```

```python
# filter only those features which have a value greater than zero
feature_imp_dict = dict(list(filter(lambda x: x[1] > 0.0, feature_imp_info)))

# create word cloud object for displaying the output
wc = WordCloud(background_color='white', width=800, height=800)
wc_output = wc.generate_from_frequencies(feature_imp_dict)
```

In [14]:
```python
plt.figure(figsize=(8,8))
plt.imshow(wc_output)
plt.axis('off')
plt.tight_layout(pad=0.0)
plt.title('DT Feature Importances')
plt.show()
```

5.5 Observations

The important feature identified include a bigram 'high recommend'
The important features identified include unigram features such as 'great', 'disappoint' etc.

5.5.1 [A.2] Graphviz visualization of Decision Tree on BOW, SET 1

```
In [15]: graph_data = export_graphviz(model[0], out_file=None, filled=True, rounded=True, specia
                                      max_depth=3, class_names = ['NO', 'YES'], feature_names = f
```

```
In [16]: out_file = graphviz.Source(graph_data)
         out_file.render('graph_viz_a2')
```

```
Out[16]: 'graph_viz_a2.pdf'
```

5.6 Observation

From the tree visualization the decisions are made by following the path 'not -> disappoint', 'not -> great' etc.

```
<li> The decision node contains some bigram features such as 'veri disappoint'</li>
```

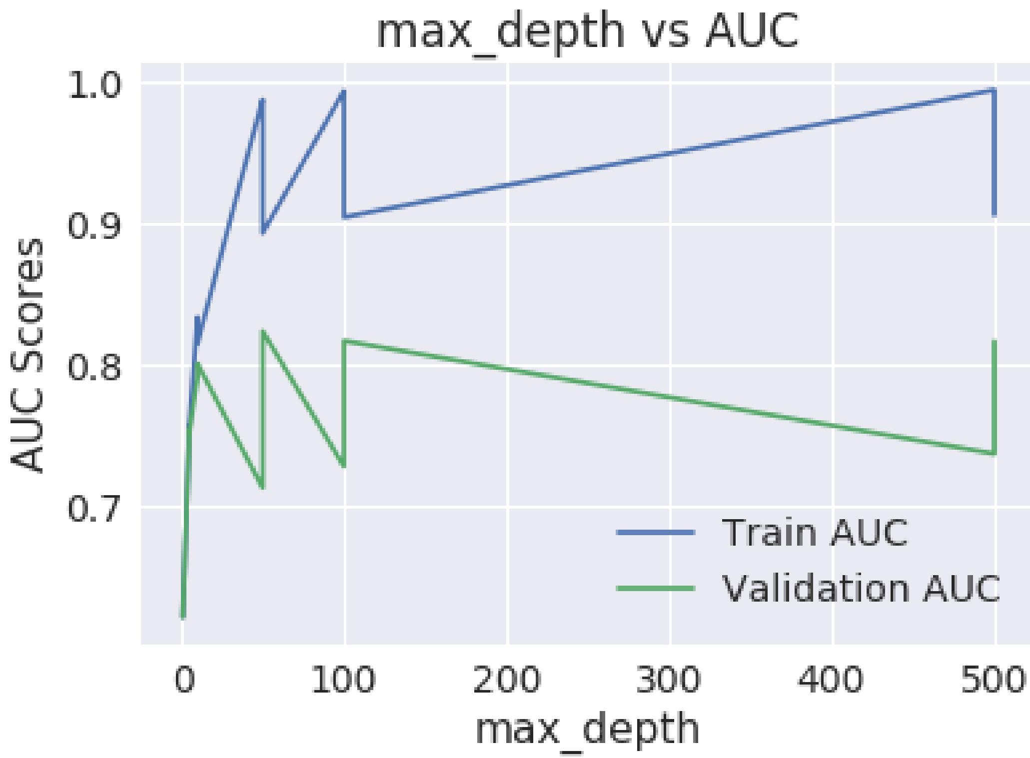
5.7 [B] Applying Decision Trees on TFIDF, SET 2

```
In [17]: # form two lists
         depth_list = [1, 5, 10, 50, 100, 500] # depends on size of dataset
         min_split_list = [5, 10,100, 500] # depends on size of dataset

         config_dict = {
             'train_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF/
             'test_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF/t
             'train_size' : 70000,
             'test_size' : 30000,
             'hyperparam_list' : product(depth_list, min_split_list)
         }
```

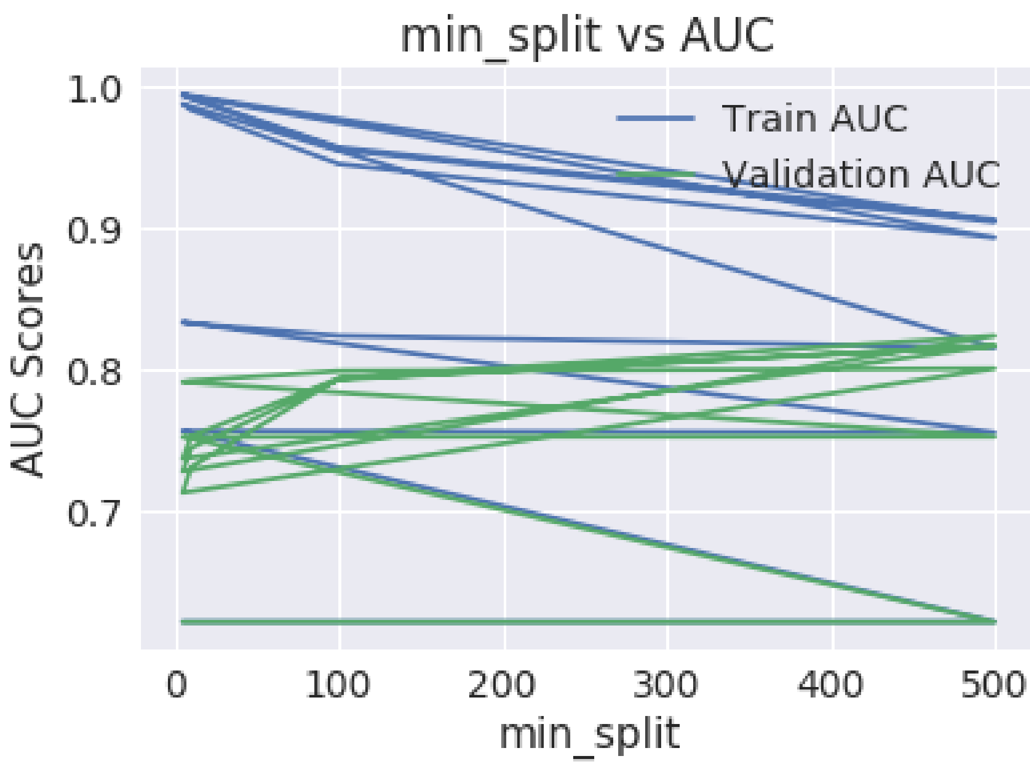
```
In [18]: # read the train, test data and preprocess it
         train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                                   scaling=True
                                                                                   dim_reductio

         # get name of all features in a list
         feature_name_list = train_features.columns.values.tolist()

         # train the model
         model = train_model(config_dict, train_features, train_labels)

         # evaluate trained model on train data
         tr_eval_y_probs, tr_eval_y_value, tr_all_metrics_df = evaluate_model(model, train_featu
```

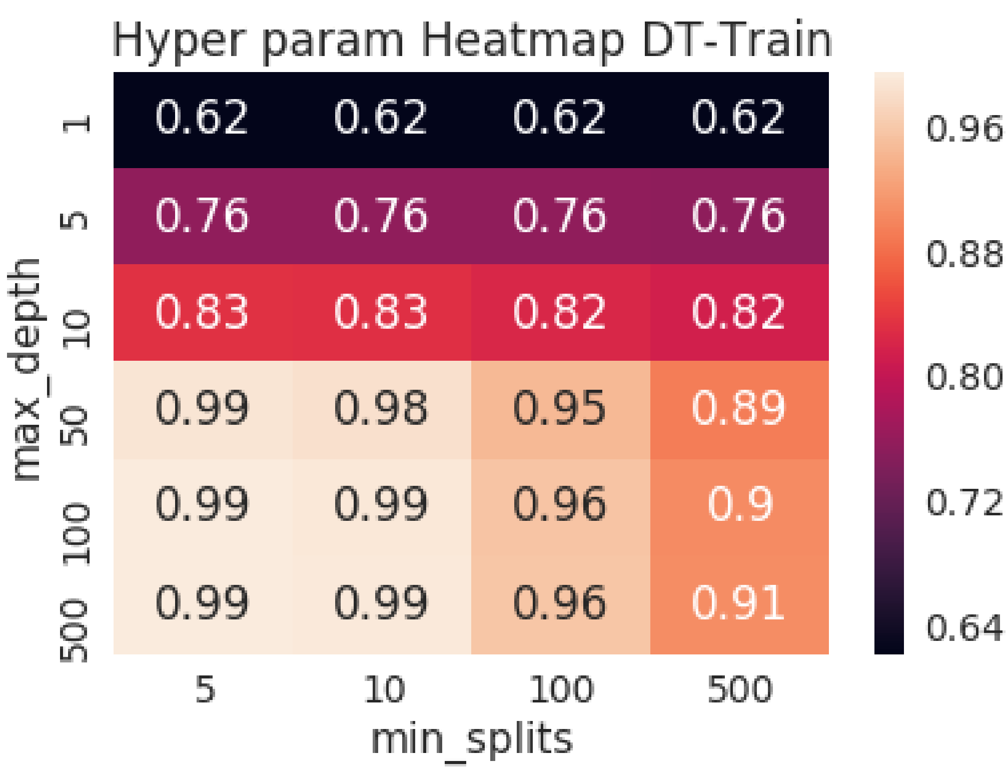
```python
    # evaluate trained model on test data
    ts_eval_y_probs, ts_eval_y_value, ts_all_metrics_df = evaluate_model(model, test_featur

    #  plotting performace of final model on train and test
    tr_fold_prediction_list = list(zip([train_labels], [tr_eval_y_probs]))
    ts_fold_prediction_list = list(zip([test_labels], [ts_eval_y_probs]))
    auc_train, auc_ts = plot_roc_curves_pair(tr_fold_prediction_list,
                                              ts_fold_prediction_list, 'Test',
                                              plot=True)

    # get entry for pretty table
    ptabe_entry_b = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

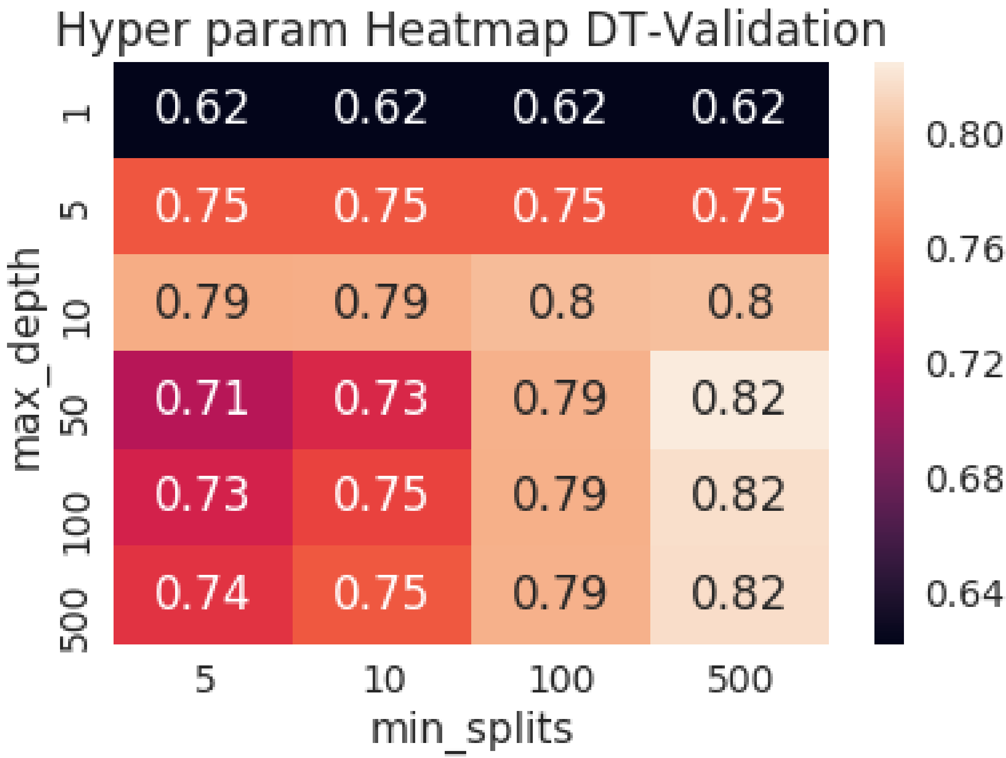
```
Train df shape (69997, 503)
Class label distribution in train df:
 1    35000
0    34997
Name: Label, dtype: int64
Test df shape (30000, 503)
Class label distribution in test df:
 1    24754
0     5246
Name: Label, dtype: int64
Shape of ->  train features :69997,501, test features: 30000,501
Shape of -> train labels :69997, test labels: 30000
====================================================================================================


 max_depth vs AUC score plot
```



min_split vs AUC score plot

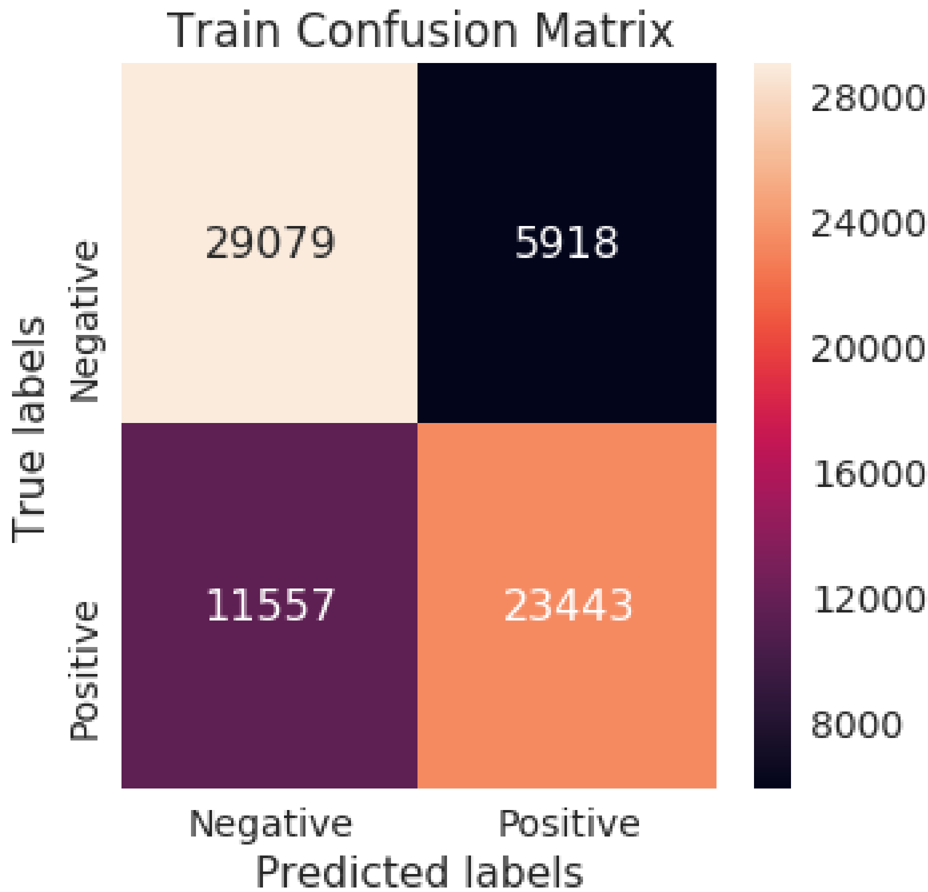

min_split vs AUC
Train AUC
Validation AUC
AUC Scores
1.0
0.9
0.8
0.7
0
100
200
300
400
500
min_split


Hyper param Heatmap DT-Train
max_depth
1
5
10
50
100
500
0.62 0.62 0.62 0.62
0.76 0.76 0.76 0.76
0.83 0.83 0.82 0.82
0.99 0.98 0.95 0.89
0.99 0.99 0.96 0.9
0.99 0.99 0.96 0.91
5
10
100
500
min_splits
0.96
0.88
0.80
0.72
0.64



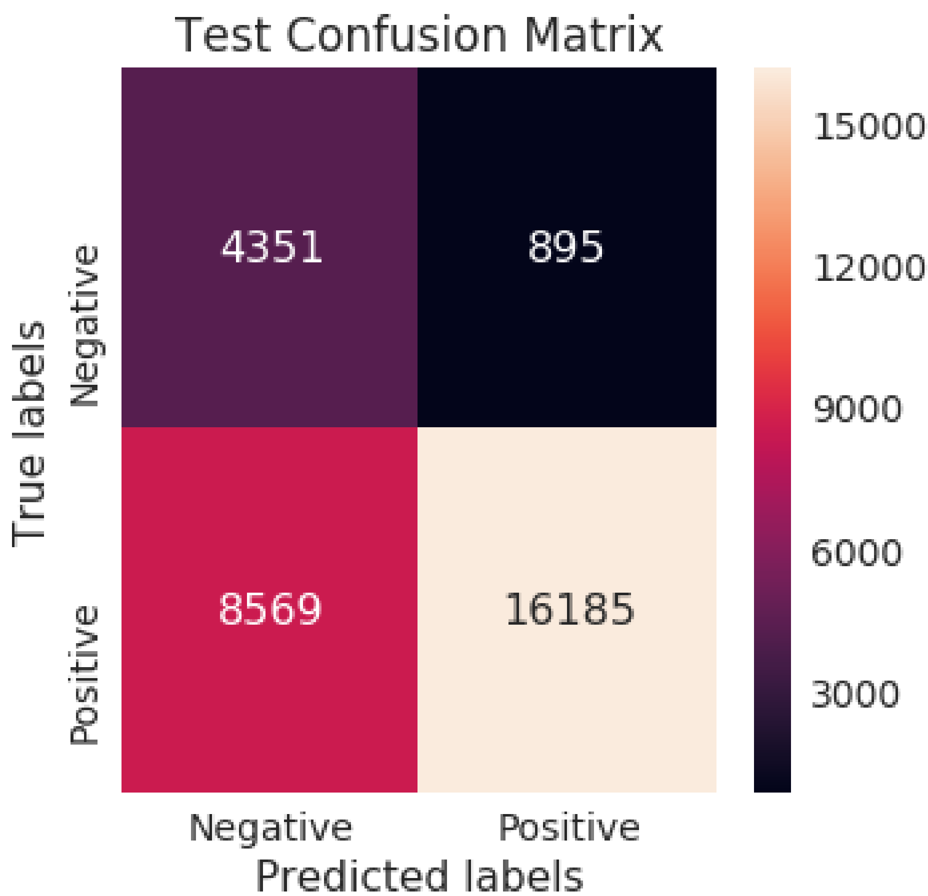

```
Best hyperparam value:  (10, 500)
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```

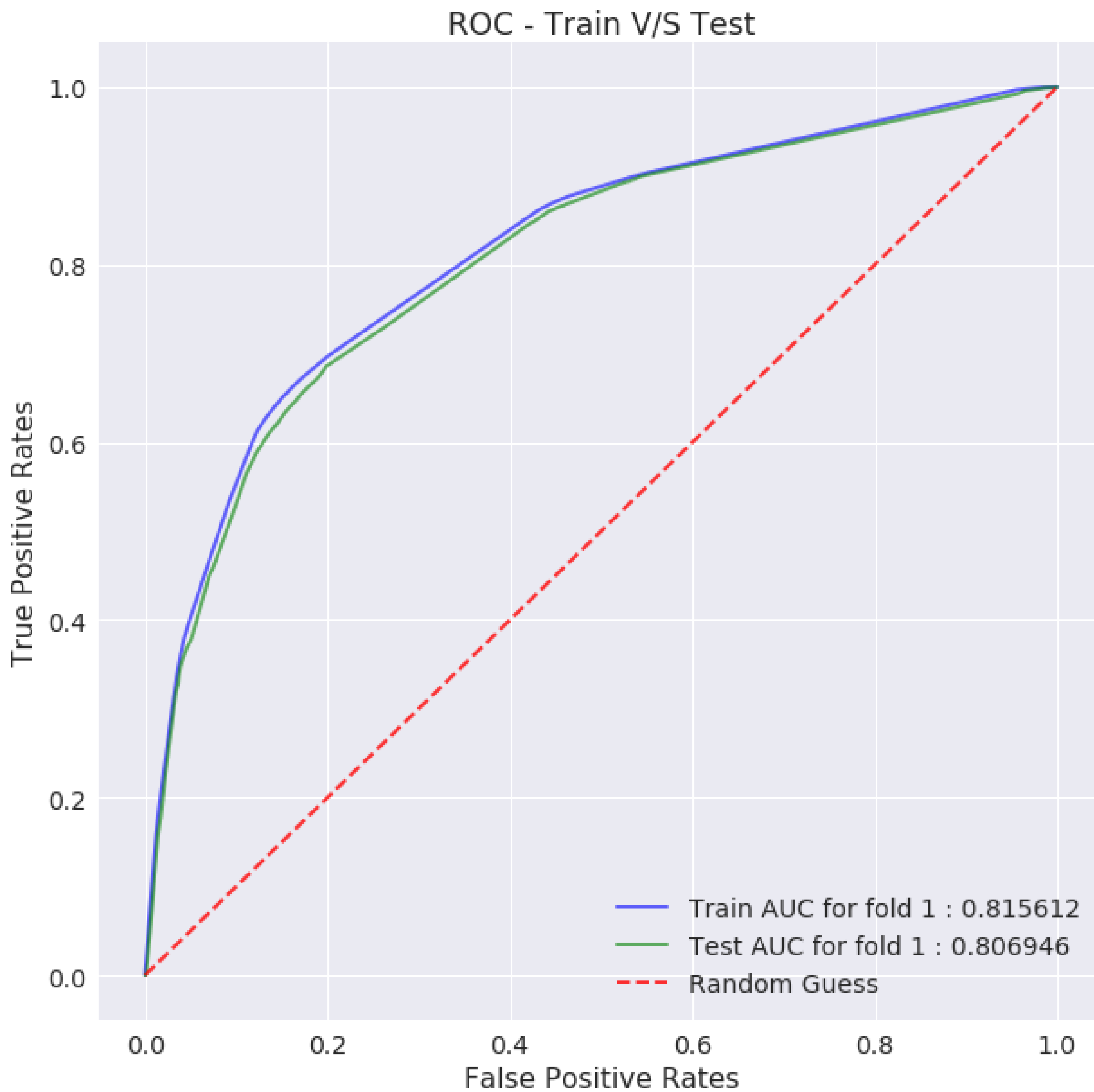



```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```

```
Train Evaluation Metrics :
                Negative       Positive
Precision       0.715597       0.798440
Recall          0.830900       0.669800
Fscore          0.768950       0.728485
Support     34997.000000   35000.000000
```




```
Test Evaluation Metrics :
               Negative       Positive
Precision      0.336765       0.947600
Recall         0.829394       0.653834
Fscore         0.479027       0.773773
Support     5246.000000   24754.000000
```




```
Results Summary:
 [('Hyper Param', '(10, 500)'), ('AUC', '0.8069'), ('f-score(-ve)', '47.9027'), ('f-score(+ve)',
```

The precision for -ve class is less (0.33)
There are 8569 positive data points which got misclassiified
From the hyper param vs auc curve, as the depth of tree increases very large model showed a tendancy to overfit

5.7.1 [B.1] Top 20 important features from SET 2

```
In [19]: # get feature and its importance as tuple
         feature_imp_info = list(zip(feature_name_list, model[0].feature_importances_))
```

```python
# filter only those features which have a value greater than zero
feature_imp_dict = dict(list(filter(lambda x: x[1] > 0.0, feature_imp_info)))

# create word cloud object for displaying the output
wc = WordCloud(background_color='white', width=800, height=800)
wc_output = wc.generate_from_frequencies(feature_imp_dict)
```

In [20]:
```python
plt.figure(figsize=(8,8))
plt.imshow(wc_output)
plt.axis('off')
plt.tight_layout(pad=0.0)
plt.title('DT Feature Importances')
plt.show()
```

5.7.2 [B.2] Graphviz visualization of Decision Tree on TFIDF, SET 2

In [21]:
```
graph_data = export_graphviz(model[0], out_file=None, filled=True, rounded=True, specia
                             max_depth=3, class_names = ['NO', 'YES'], feature_names =
```

In [22]:
```
out_file = graphviz.Source(graph_data)
out_file.render('graph_viz_b2')
```

Out[22]:
```
'graph_viz_b2.pdf'
```

5.8 Observations

Observations are similar to the Bow case

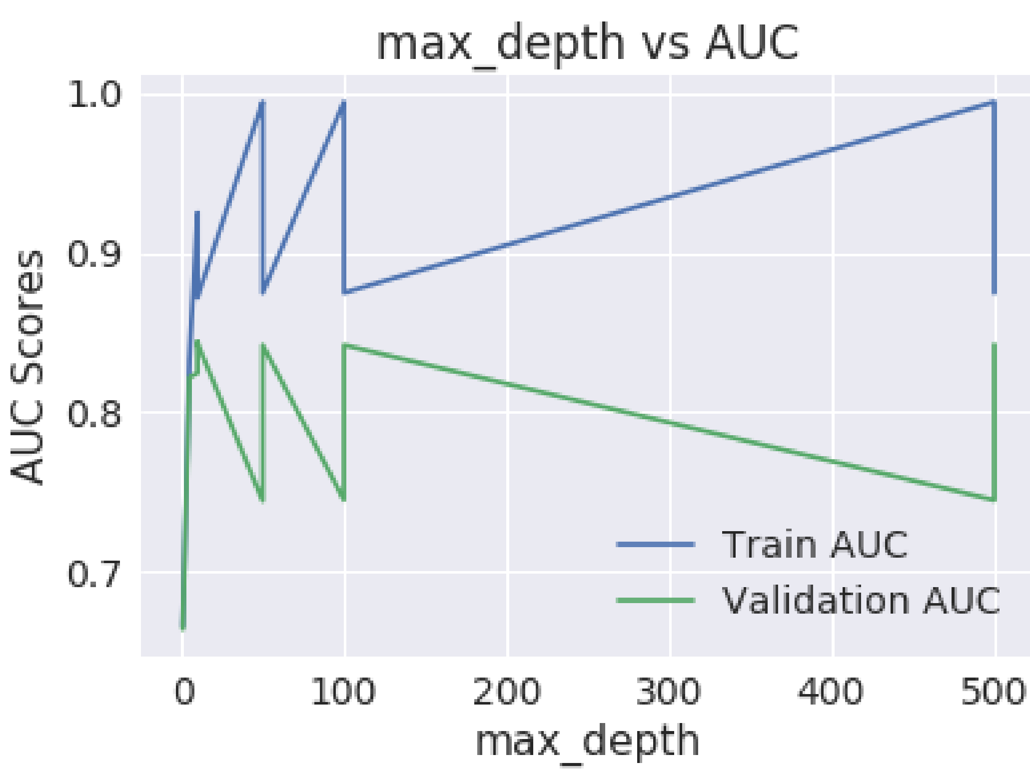
5.9 [C] Applying Decision Trees on AVG W2V, SET 3

In [23]:
```
# form two lists
depth_list = [1, 5, 10, 50, 100, 500] # depends on size of dataset
min_split_list = [5, 10,100, 500] # depends on size of dataset

config_dict = {
    'train_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/AVG_W2
    'test_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/AVG_W2V
    'train_size' : 70000,
    'test_size' : 30000,
    'hyperparam_list' : product(depth_list, min_split_list)
}
```

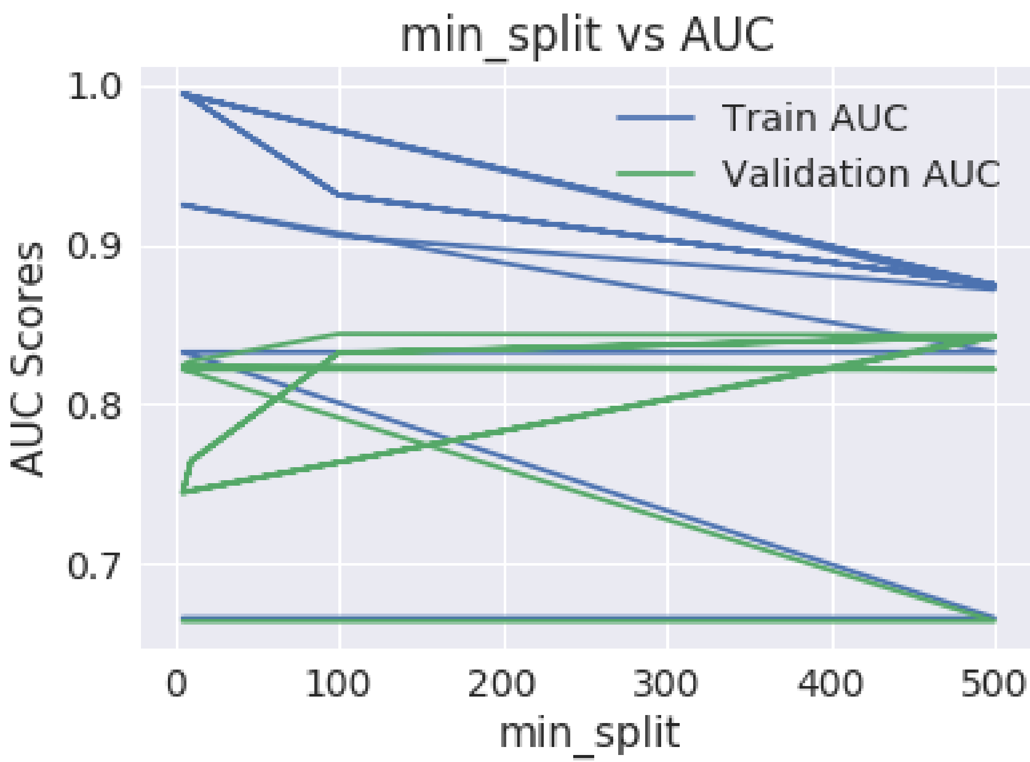
In [24]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                            scaling=True
                                                                            dim_reductio

# get name of all features in a list
feature_name_list = train_features.columns.values.tolist()

# train the model
model = train_model(config_dict, train_features, train_labels)

# evaluate trained model on train data
tr_eval_y_probs, tr_eval_y_value, tr_all_metrics_df = evaluate_model(model, train_featu

# evaluate trained model on test data
ts_eval_y_probs, ts_eval_y_value, ts_all_metrics_df = evaluate_model(model, test_featur

#  plotting performace of final model on train and test
tr_fold_prediction_list = list(zip([train_labels], [tr_eval_y_probs]))
ts_fold_prediction_list = list(zip([test_labels], [ts_eval_y_probs]))
auc_train, auc_ts = plot_roc_curves_pair(tr_fold_prediction_list,
```

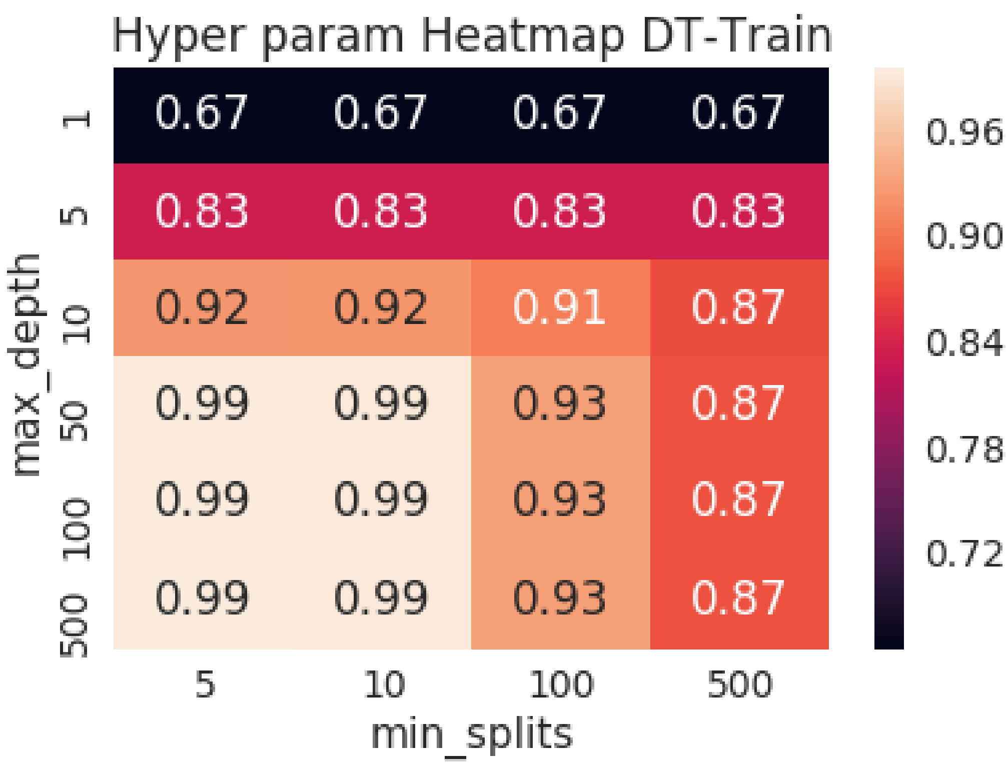
```
                                                     ts_fold_prediction_list, 'Test',
                                                     plot=True)

        # get entry for pretty table
        ptabe_entry_c = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

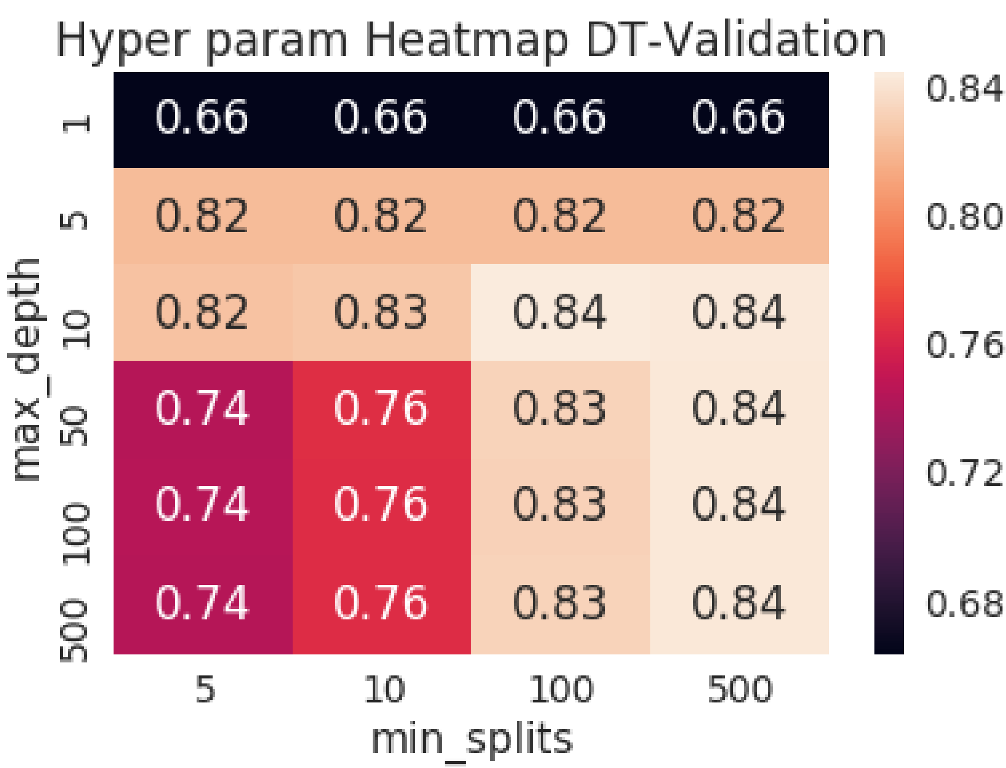
```
Train df shape (69997, 52)
Class label distribution in train df:
 1    35000
0    34997
Name: Label, dtype: int64
Test df shape (30000, 52)
Class label distribution in test df:
 1    24754
0     5246
Name: Label, dtype: int64
Shape of ->  train features :69997,50, test features: 30000,50
Shape of -> train labels :69997, test labels: 30000
===================================================================================================


 max_depth vs AUC score plot
```



min_split vs AUC score plot

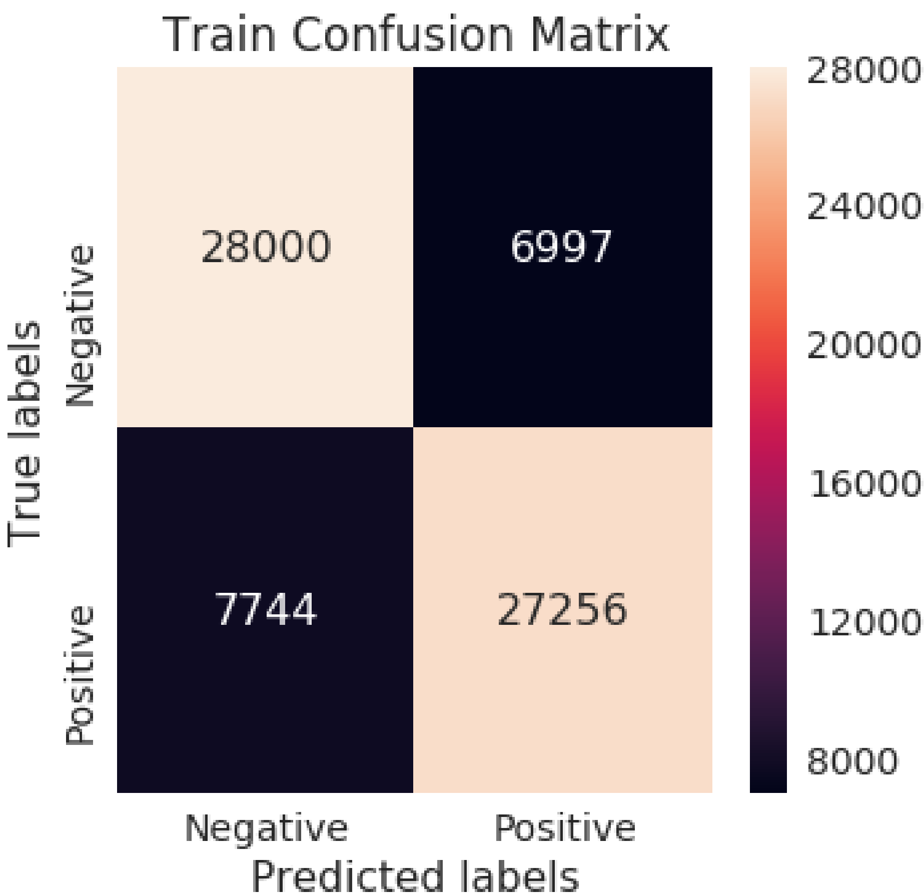



Hyper param Heatmap DT-Train
0.67 0.67 0.67 0.67
0.83 0.83 0.83 0.83
0.92 0.92 0.91 0.87
0.99 0.99 0.93 0.87
0.99 0.99 0.93 0.87
0.99 0.99 0.93 0.87
max_depth
1
5
10
50
100
500
min_splits
5
10
100
500
0.96
0.90
0.84
0.78
0.72


Hyper param Heatmap DT-Validation
0.66 0.66 0.66 0.66
0.82 0.82 0.82 0.82
0.82 0.83 0.84 0.84
0.74 0.76 0.83 0.84
0.74 0.76 0.83 0.84
0.74 0.76 0.83 0.84
max_depth
1
5
10
50
100
500
min_splits
5
10
100
500
0.84
0.80
0.76
0.72
0.68

```
Best hyperparam value:  (10, 500)
```

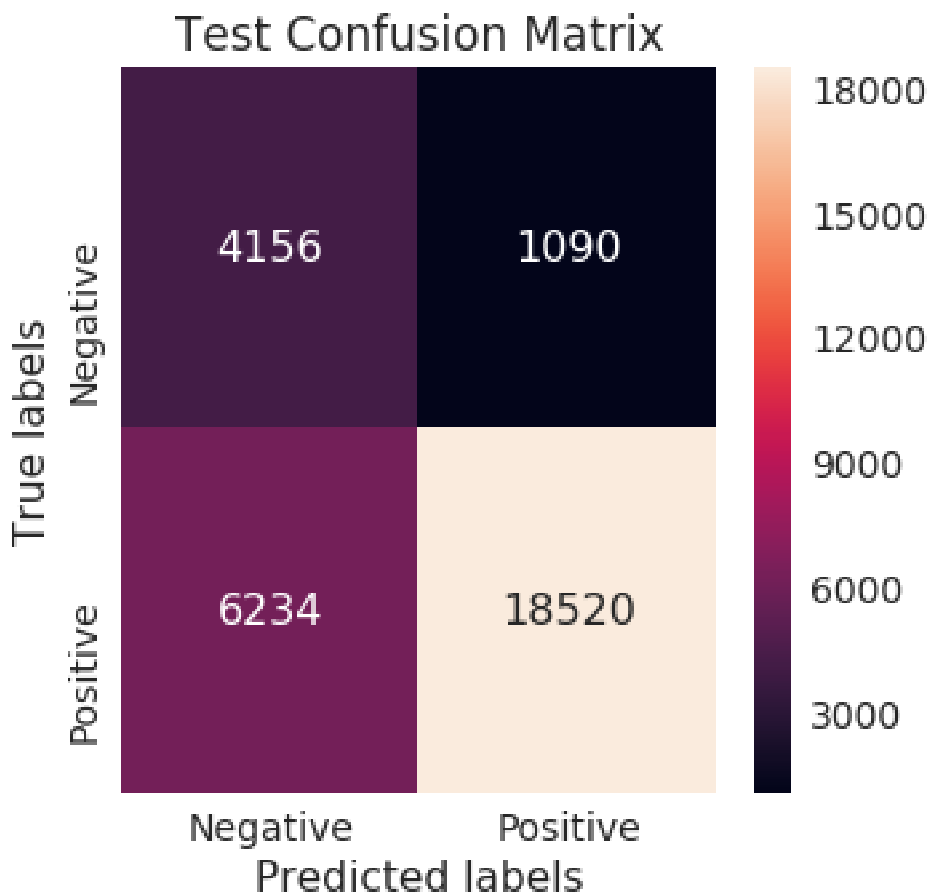
```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```




```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```

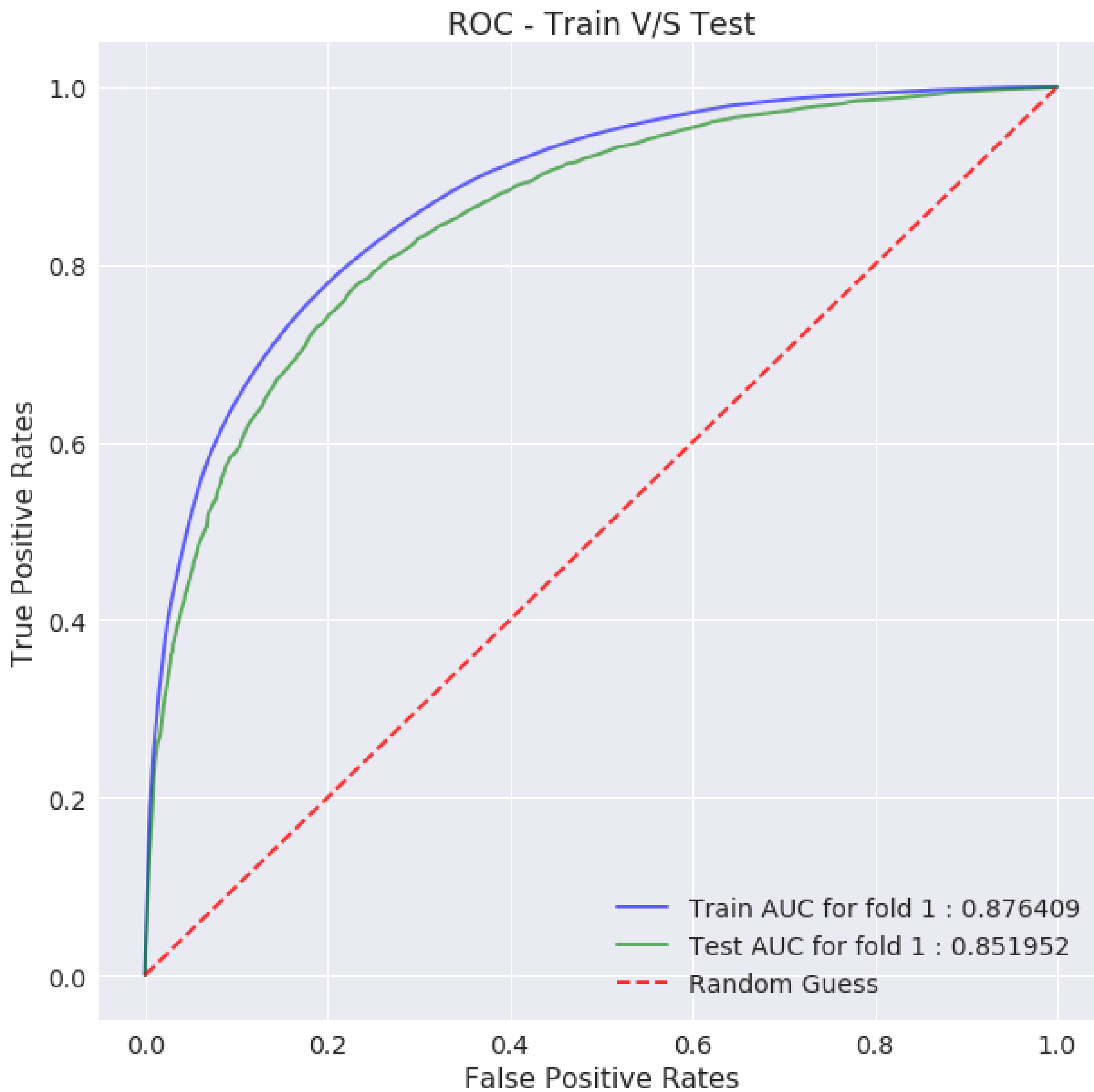
```
Train Evaluation Metrics :
                Negative      Positive
Precision      0.783348      0.795726
```

Recall	0.800069	0.778743
Fscore	0.791620	0.787143
Support	34997.000000	35000.000000



Test Evaluation Metrics :

	Negative	Positive
Precision	0.400000	0.944416
Recall	0.792223	0.748162
Fscore	0.531594	0.834911
Support	5246.000000	24754.000000




```
Results Summary:
 [('Hyper Param', '(10, 500)'), ('AUC', '0.8520'), ('f-score(-ve)', '53.1594'), ('f-score(+ve)',
```

The precision for -ve class is less (0.40)
There are 6234 positive data points which got misclassiified
As the depth increases the model showed a tendancy to overfit

5.10 [D] Applying Decision Trees on TFIDF W2V, SET 4

```
In [25]: # form two lists
         depth_list = [1, 5, 10, 50, 100, 500] # depends on size of dataset
         min_split_list = [5, 10,100, 500] # depends on size of dataset
```

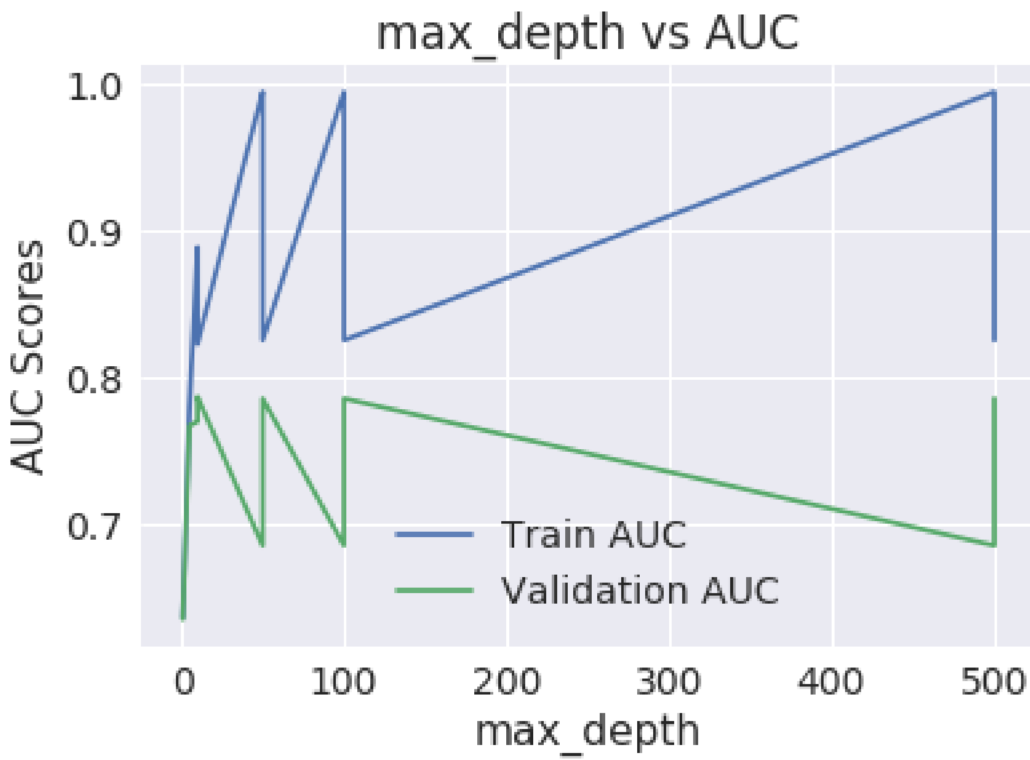
```
config_dict = {
    'train_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF_
    'test_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF_W
    'train_size' : 70000,
    'test_size' : 30000,
    'hyperparam_list' : product(depth_list, min_split_list)
}
```

In [26]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                           scaling=True
                                                                           dim_reductio

# get name of all features in a list
feature_name_list = train_features.columns.values.tolist()

# train the model
model = train_model(config_dict, train_features, train_labels)

# evaluate trained model on train data
tr_eval_y_probs, tr_eval_y_value, tr_all_metrics_df = evaluate_model(model, train_featu

# evaluate trained model on test data
ts_eval_y_probs, ts_eval_y_value, ts_all_metrics_df = evaluate_model(model, test_featur

#  plotting performace of final model on train and test
tr_fold_prediction_list = list(zip([train_labels], [tr_eval_y_probs]))
ts_fold_prediction_list = list(zip([test_labels], [ts_eval_y_probs]))
auc_train, auc_ts = plot_roc_curves_pair(tr_fold_prediction_list,
                                         ts_fold_prediction_list, 'Test',
                                         plot=True)

# get entry for pretty table
ptabe_entry_d = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

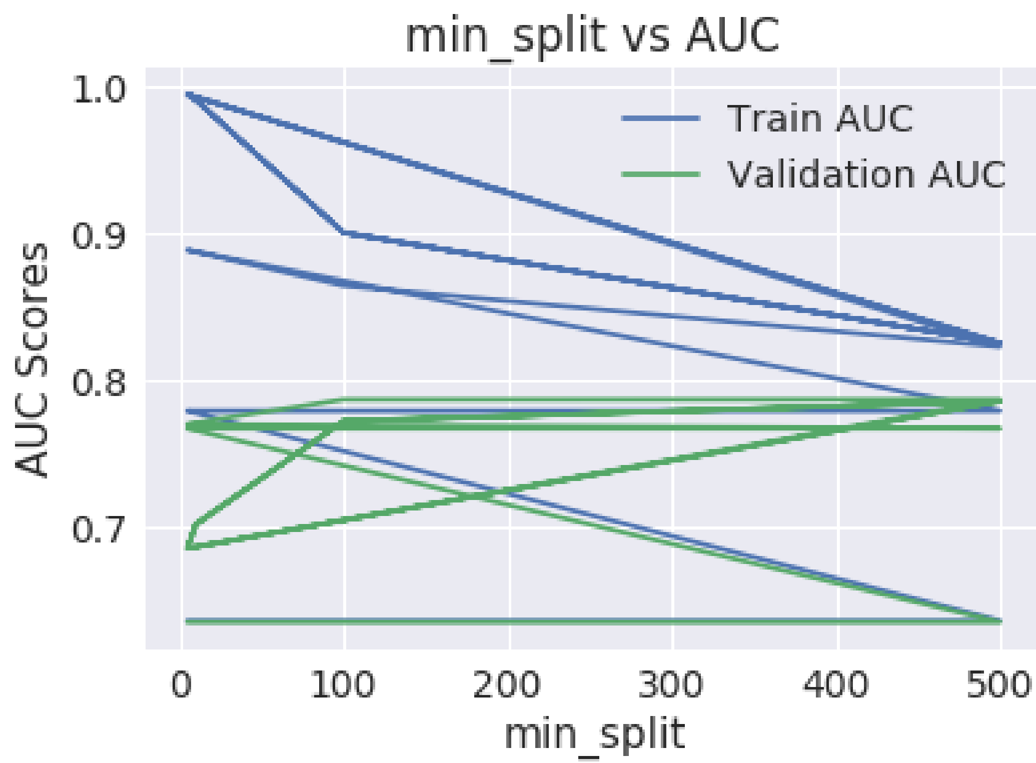
```
Train df shape (69997, 52)
Class label distribution in train df:
 1    35000
0    34997
Name: Label, dtype: int64
Test df shape (30000, 52)
Class label distribution in test df:
 1    24754
0     5246
Name: Label, dtype: int64
Shape of ->  train features :69997,50, test features: 30000,50
Shape of -> train labels :69997, test labels: 30000
```

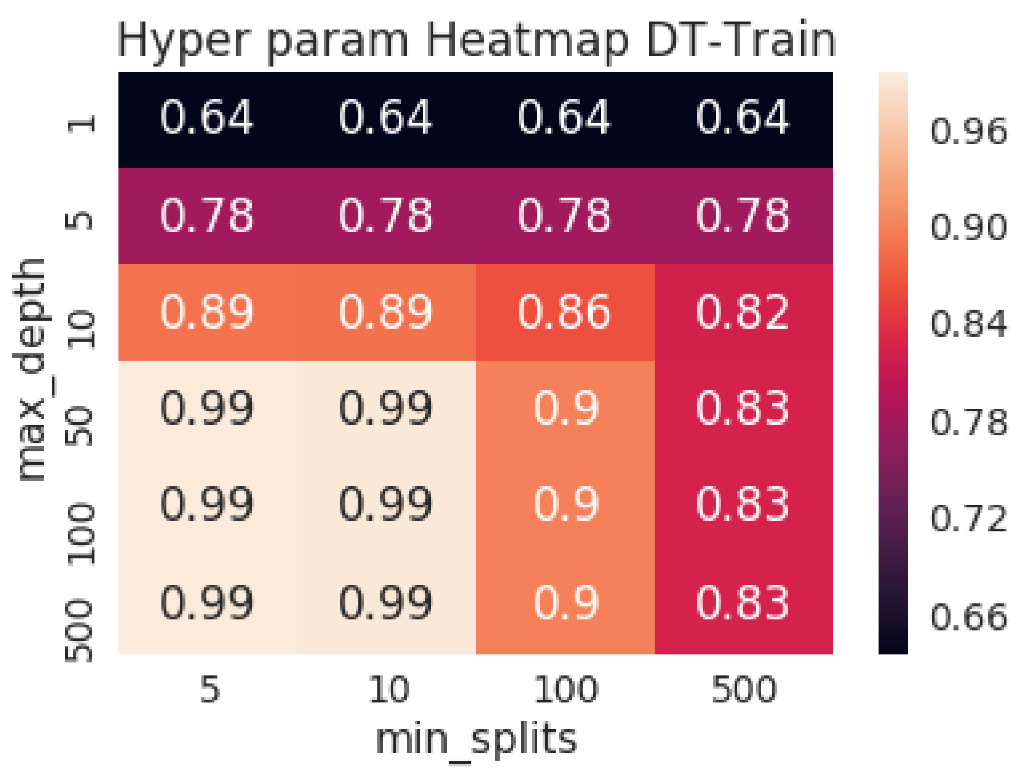
==

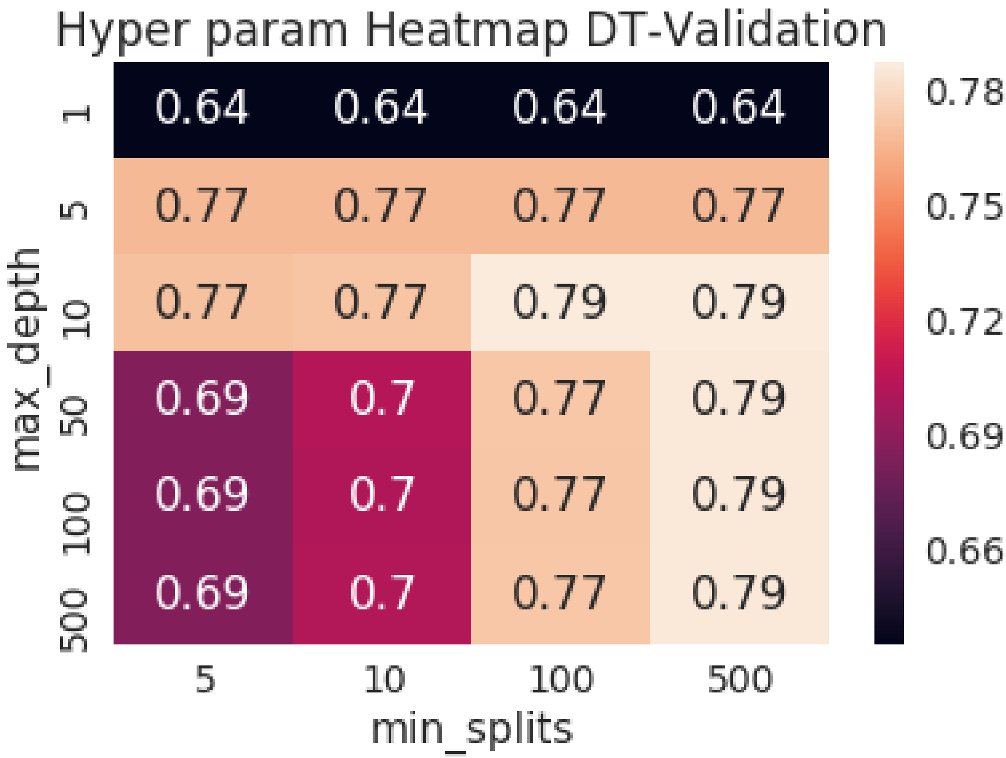
max_depth vs AUC score plot



min_split vs AUC score plot

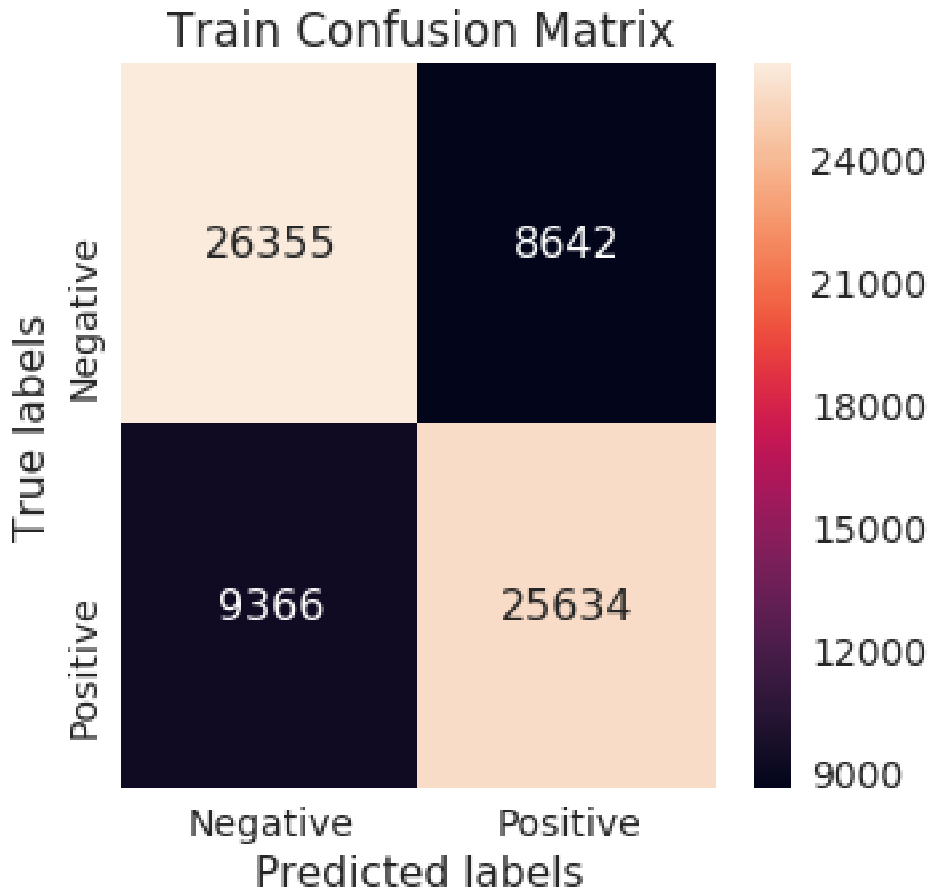

min_split vs AUC
Train AUC
Validation AUC
AUC Scores
min_split
1.0
0.9
0.8
0.7
0
100
200
300
400
500


Hyper param Heatmap DT-Train
max_depth
min_splits
1
5
10
50
100
500
5
10
100
500
0.64 0.64 0.64 0.64
0.78 0.78 0.78 0.78
0.89 0.89 0.86 0.82
0.99 0.99 0.9 0.83
0.99 0.99 0.9 0.83
0.99 0.99 0.9 0.83
0.96
0.90
0.84
0.78
0.72
0.66



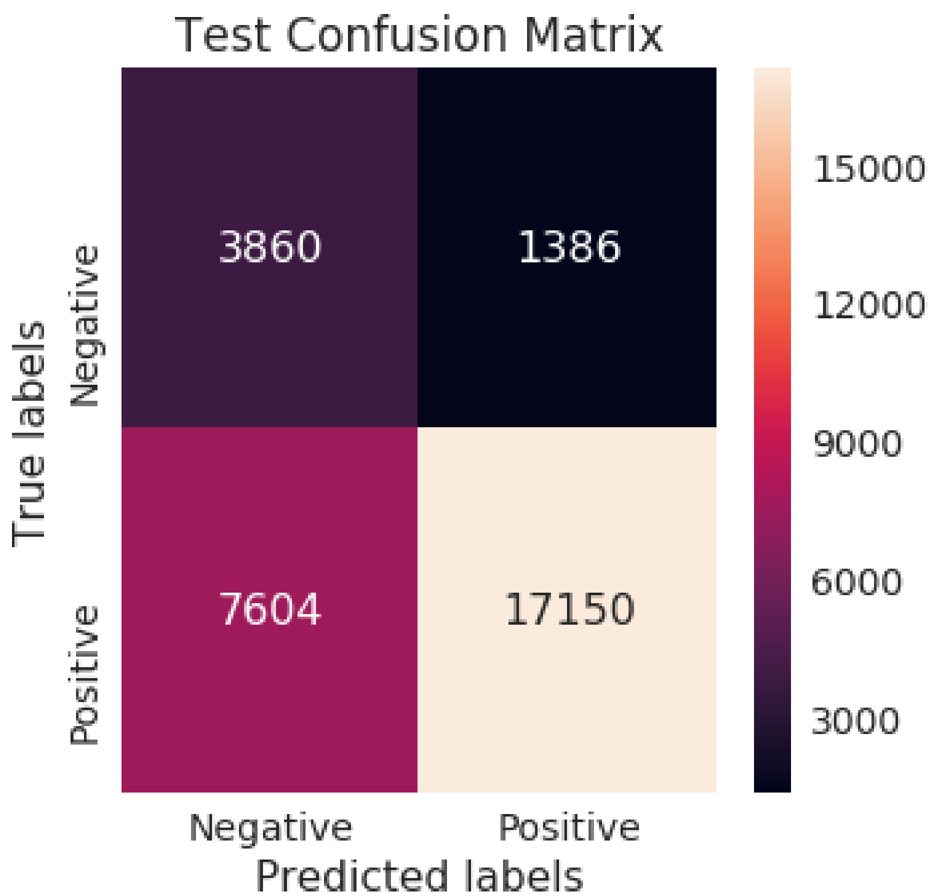

```
Best hyperparam value:  (10, 500)
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```



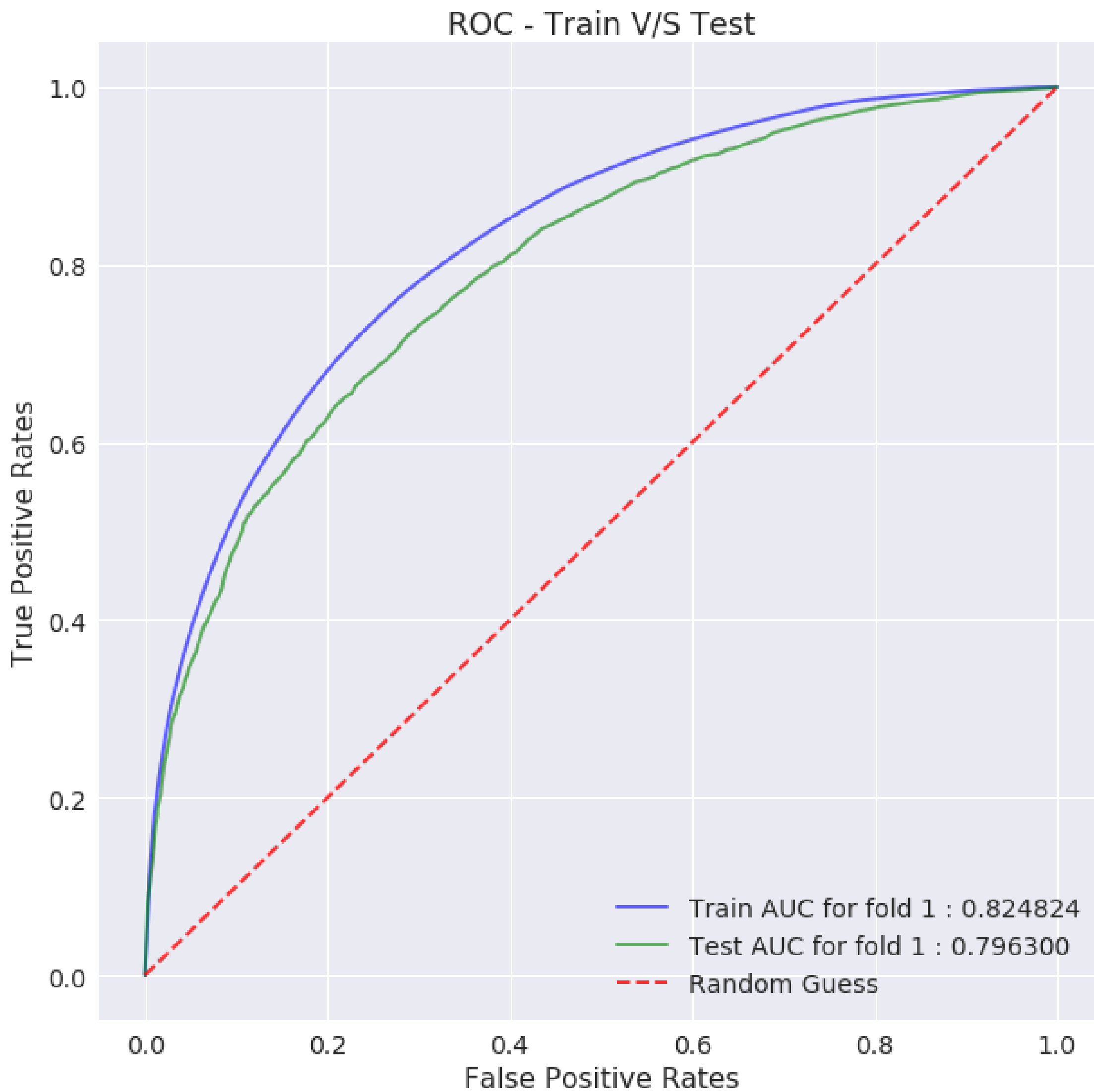

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```

```
Train Evaluation Metrics :
                Negative      Positive
Precision       0.737801      0.747870
Recall          0.753065      0.732400
Fscore          0.745355      0.740054
Support     34997.000000  35000.000000
```



Test Evaluation Metrics :

	Negative	Positive
Precision	0.336706	0.925227
Recall	0.735799	0.692817
Fscore	0.461999	0.792331
Support	5246.000000	24754.000000




```
Results Summary:
 [('Hyper Param', '(10, 500)'), ('AUC', '0.7963'), ('f-score(-ve)', '46.1999'), ('f-score(+ve)',
```

The precision for -ve class is less (0.33)
There are 7604 positive data points which got misclassiified
As the depth increases the model shows a tendancy to overfit

5.11 Observation

As the depth of the tree increases very large, generally the model showed overfit

6 Procedure Summary

Train the Decision tree model with different hyper parameter settings
Select the best model based on the AUC score on validation data set
Idenify the important features and represent it in a wordcloud
Visualize the tree using graphviz, this helps to understand how decision tree performs classification by looking into the attribute values

7 Results Summary

In [27]:
```
Pret_table = PrettyTable()
Pret_table.field_names = ['Vectorizer', '(depth, min_split)', 'AUC', 'Fscore (-ve)', 'F
Pret_table.title = 'DT Results Summary'
```

In [28]:
```
# Decision Tree Results Summary
Pret_table.add_row(['BoW'] + ptabe_entry_a)
Pret_table.add_row(['TF-IDF'] + ptabe_entry_b)
Pret_table.add_row(['Avg W2V'] + ptabe_entry_c)
Pret_table.add_row(['TF-IDF W2V'] + ptabe_entry_d)
```

In [29]:
```
print(Pret_table)
```

```
+-------------------------------------------------------------------------+
|                           DT Results Summary                            |
+------------+--------------------+--------+--------------+--------------+
| Vectorizer | (depth, min_split) |  AUC   | Fscore (-ve) | Fscore (+ve) |
+------------+--------------------+--------+--------------+--------------+
|    BoW     |      (50, 500)     | 0.8463 |   52.8665    |   82.8679    |
|   TF-IDF   |      (10, 500)     | 0.8069 |   47.9027    |   77.3773    |
|  Avg W2V   |      (10, 500)     | 0.8520 |   53.1594    |   83.4911    |
| TF-IDF W2V |      (10, 500)     | 0.7963 |   46.1999    |   79.2331    |
+------------+--------------------+--------+--------------+--------------+
```

8 Conclusions

Comparing with other models Average W2V model showed good performace in terms of f1score on both +ve and -ve class

The models performance on +ve class is good (77% & above fscore) where as the negative class performance is not that good (53% best fscore)

More complicated models can be tried to improve the scores