03_Amazon_Food_Reviews_KNN

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 KNN Algorithm

```
<li><strong>Apply Knn(brute force version) 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>Apply Knn(kd tree version) on these feature sets</strong>
    <br><font color='red'>NOTE: </font>sklearn implementation of kd-tree accepts only dense matr
    <ul>
        <li><font color='red'>SET 5:</font>Review text, preprocessed one converted into vectors
        <pre>
        count_vect = CountVectorizer(min_df=10, max_features=500)
        count_vect.fit(preprocessed_reviews)
        </pre>
        </li>
        <li><font color='red'>SET 6:</font>Review text, preprocessed one converted into vectors
        <pre>
            tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
            tf_idf_vect.fit(preprocessed_reviews)
        </pre>
        </li>
        <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(find best K)</strong>
    <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>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>
```


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 Import Required Packages

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

# import model evaluation and metric related packages
from sklearn.metrics import confusion_matrix, precision_recall_fscore_support
from sklearn.metrics import roc_curve, auc

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

# import model related packages
from sklearn.neighbors import KNeighborsClassifier

# package for model selection
from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import StandardScaler

# package for evaluation
from scipy import interp # for ROC curve
from sklearn.metrics import auc, roc_curve, roc_auc_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support

# for dim reduction
from sklearn.decomposition import TruncatedSVD

# for summarising the results
from prettytable import PrettyTable
```

4 UTIL functions

4.1 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,)
```

4.2 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
```

```python
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 find_best_hyperparameter(config_dict, train_features, train_labels):

            """
            This function helps to find the best hyper parameter (k) for KNN algorithm. eThe par
            this function can be configured to work with brute force method or kd-tree method.
            All set of hyper param values using which the model to be evaluated can be passed to
            list hyperparam_list.
            """

            # get the configuarations
            hyperparam_list = config_dict['hyperparam_list']
            algo_type = config_dict['algo_type']

            print('='*100)

            stratified_partition = StratifiedKFold(n_splits=2)
```

```
# decalre a list to hold the cross validation score for each hyper parameter
hyper_param_scores_list = list()

# do it for all values of k
for k 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
    knn_classifier = KNeighborsClassifier(n_neighbors=k, n_jobs=-1, algorithm=algo_t

    # 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
        knn_classifier.fit(train_feat_data, train_label_data)

        # estimate the training metrics on (train fold)
        train_eval_y_probs = knn_classifier.predict_proba(train_feat_data)[:, 1]
        train_eval_y_value = knn_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 = knn_classifier.predict_proba(validation_feat_data)[:, 1]
                val_eval_y_value = knn_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)

            # 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
            mean_auc_train, mean_auc_val = plot_roc_curves_pair(train_fold_prediction_list,
                                                                val_fold_prediction_list, '
                                                                plot=False)


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


        # plot hyper param vs AUC score
        hyp_value_list = [item[0] 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 The k vs AUC score plot')
        plt.plot(hyp_value_list, tr_auc_list, label='Train AUC')
        plt.plot(hyp_value_list, val_auc_list, label='Validation AUC')
        plt.xlabel('K Values')
        plt.ylabel('AUC Scores')
        plt.title('K vs AUC')
        plt.legend()
        plt.show()

        # 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 [7]: 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 the required fields from the dictionary
    algo_type = config_dict['algo_type']

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

    # Final Model defined here
    knn_classifier = KNeighborsClassifier(n_neighbors=best_hyper_param, n_jobs=-1,
                                          algorithm=algo_type)

    # train the classifier
    knn_classifier.fit(train_features, train_labels)

    # return the trained model
    return knn_classifier
```

In [8]:
```
def evaluate_model(model, features, labels, tag_name):
    """
    This function evaluates models performace on various metrics given
    a evaluation data (either train or test)
    """

    # estimate the training metrics on (train fold)
    eval_y_probs = model.predict_proba(features)[:, 1]
    eval_y_value = model.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 [9]:
```
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.n_neighbors), auc_score, fscore_neg, fscore_pos]

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

    return ptabe_entry
```

4.3 [A] Applying KNN brute force

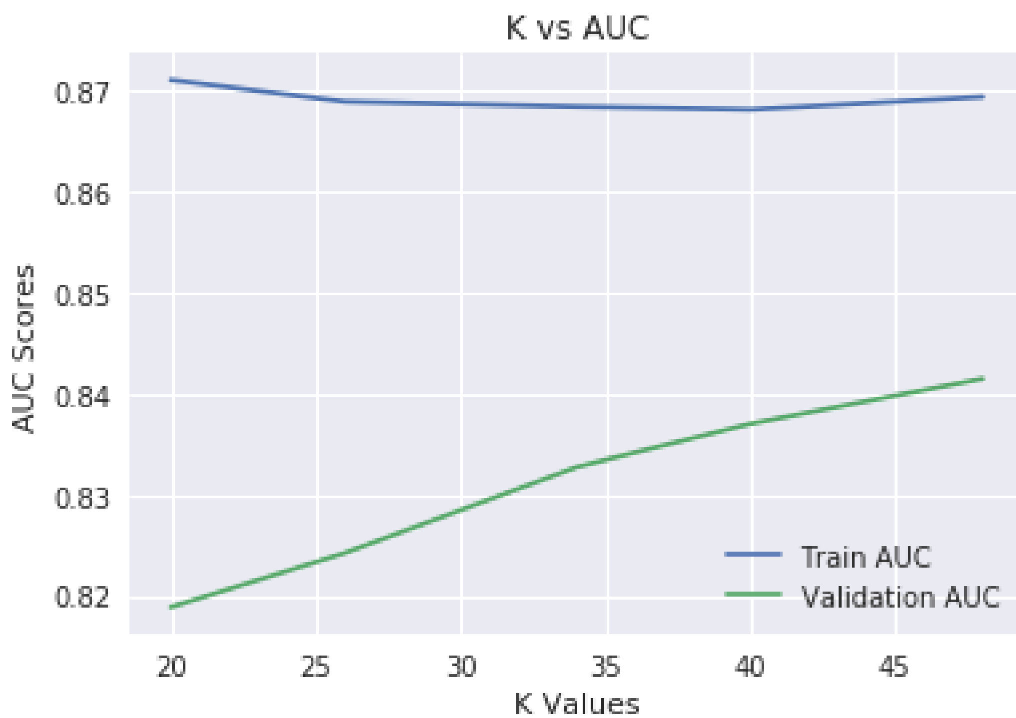
4.3.1 [A.1] Applying KNN brute force on BOW, SET 1

```
In [10]: 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' : 25000,
             'test_size' : 10000,
             'hyperparam_list' : [20, 26, 34, 40, 48],
             'algo_type' : 'brute', # 'brute', 'kd_tree',
         }
```

```
In [11]: # read the train, test data and preprocess it
         train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                                    scaling=Tru
                                                                                    dim_reducti
         # 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_a1 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 503)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 503)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,501, test features: 10000,501
Shape of -> train labels :25000, test labels: 10000
===============================================================================================
```

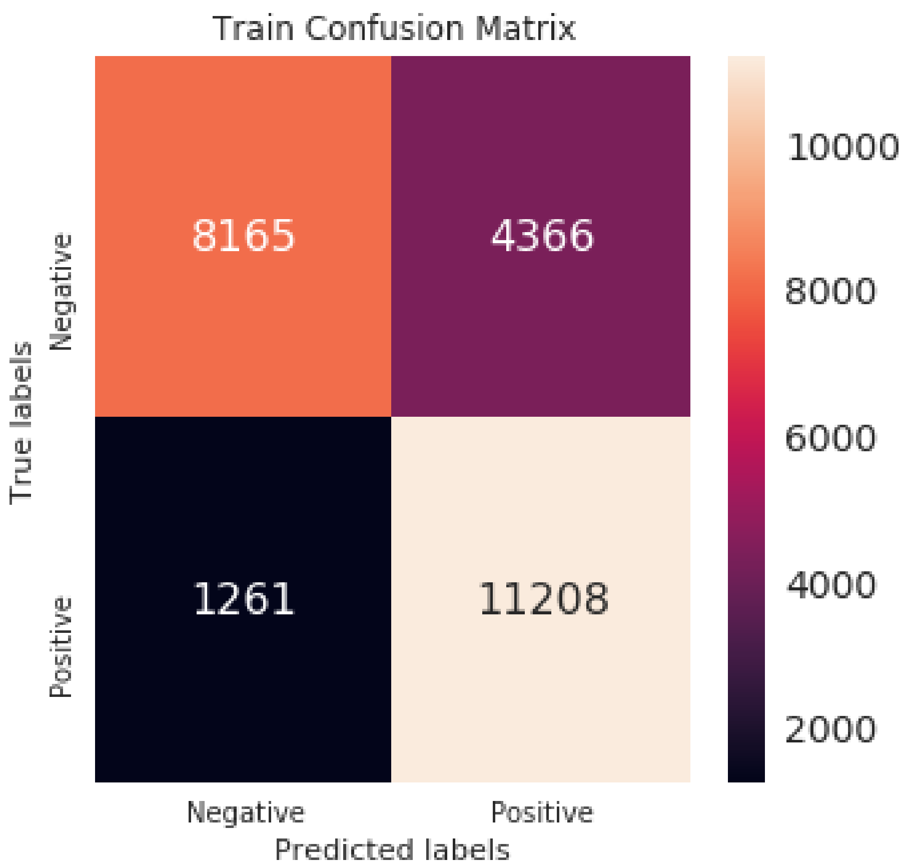
```
 The k vs AUC score plot
```




```
Best hyperparam value:  48
```

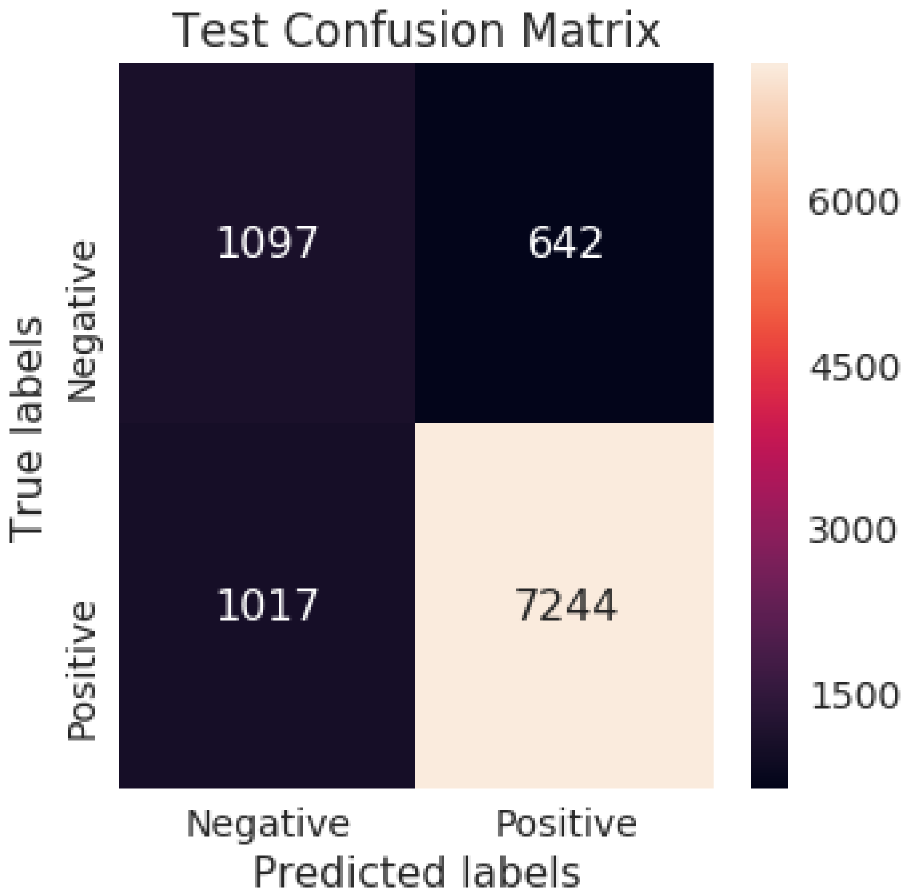
```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
```

```
  warnings.warn(message, mplDeprecation, stacklevel=1)
```



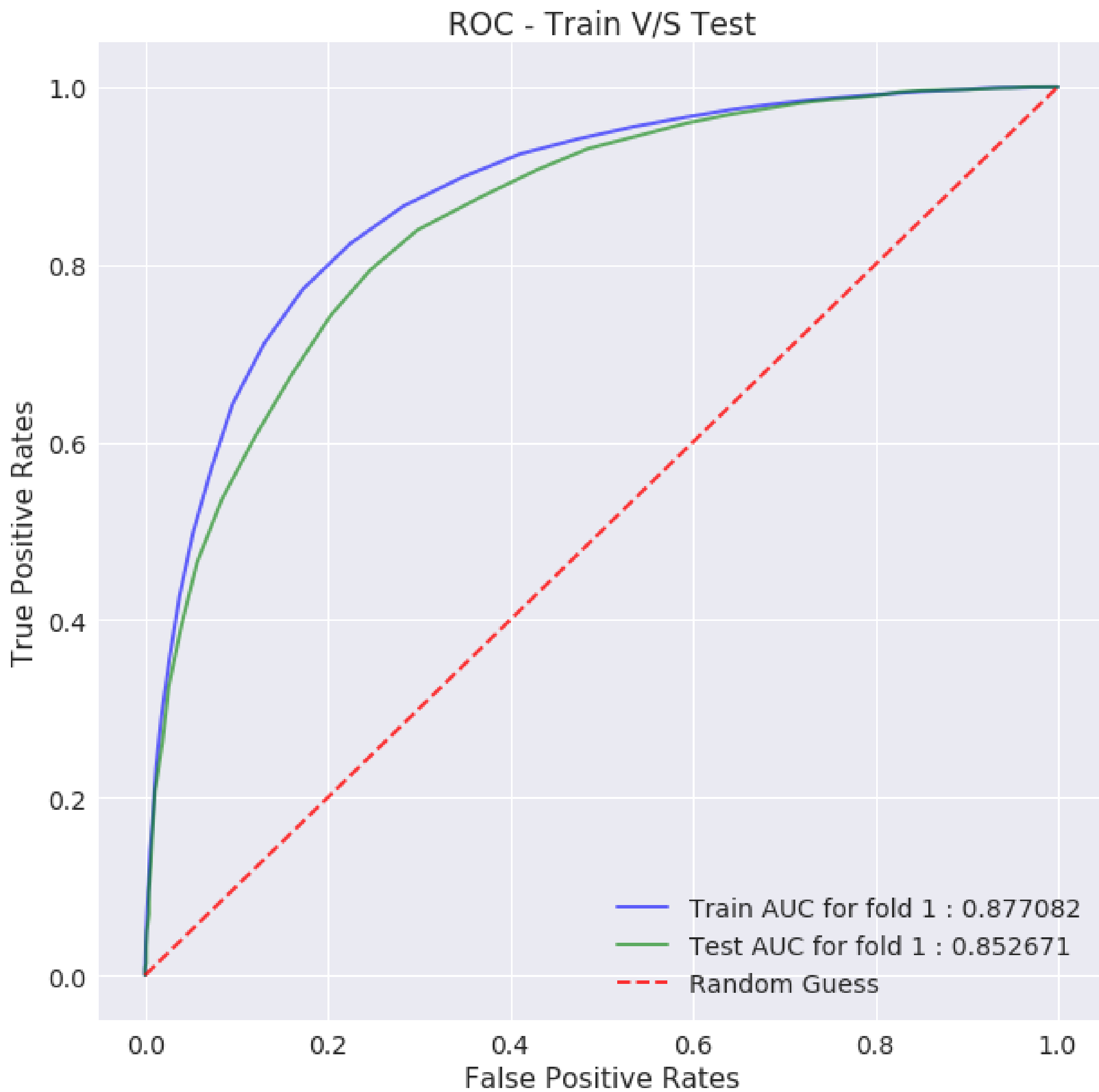

```
Train Evaluation Metrics :
                Negative       Positive
Precision      0.866221      0.719661
Recall         0.651584      0.898869
Fscore         0.743726      0.799344
Support    12531.000000  12469.000000
```

```
/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	0.518921	0.918590
Recall	0.630822	0.876891
Fscore	0.569426	0.897256
Support	1739.000000	8261.000000




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.8527'), ('f-score(-ve)', '56.9426'), ('f-score(+ve)', '89.72
```

As the value of K increases there is slight increase in test auc and slight decrease in train auc. The best K value selected is 48

Performance on +ve class is good(89% f-score) but negative class (56%)

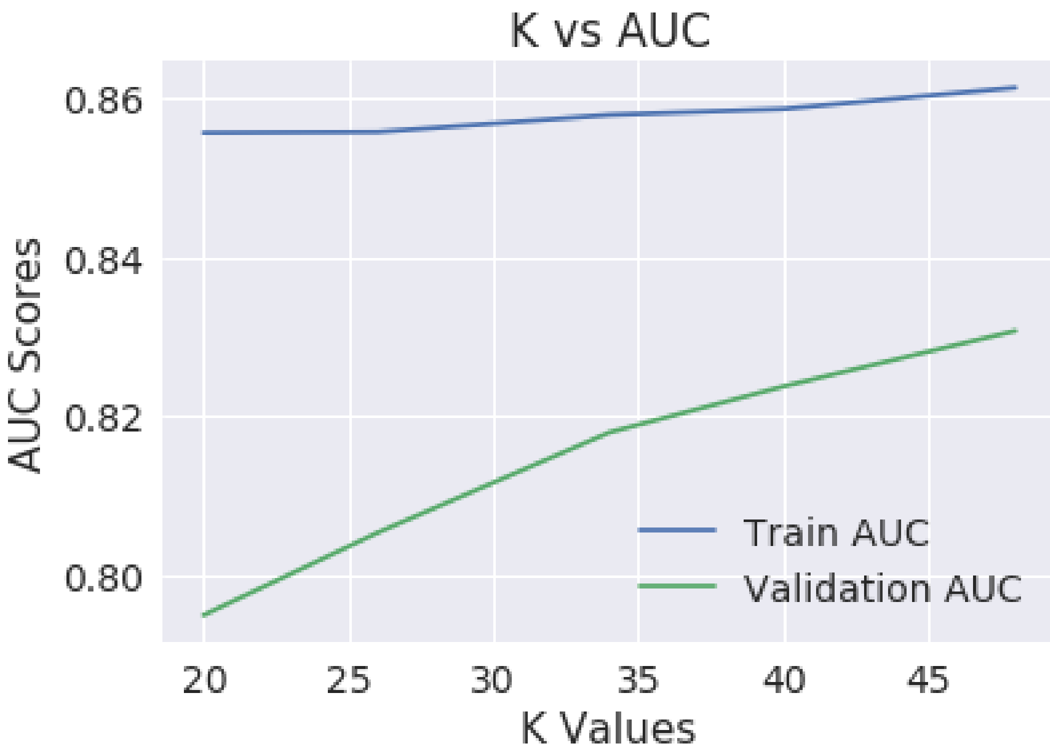
4.3.2 [A.2] Applying KNN brute force on TFIDF, SET 2

```
In [12]: 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' : 25000,
            'test_size' : 10000,
            'hyperparam_list' : [20, 26, 34, 40, 48],
            'algo_type' : 'brute', # 'brute', 'kd_tree',
        }
```

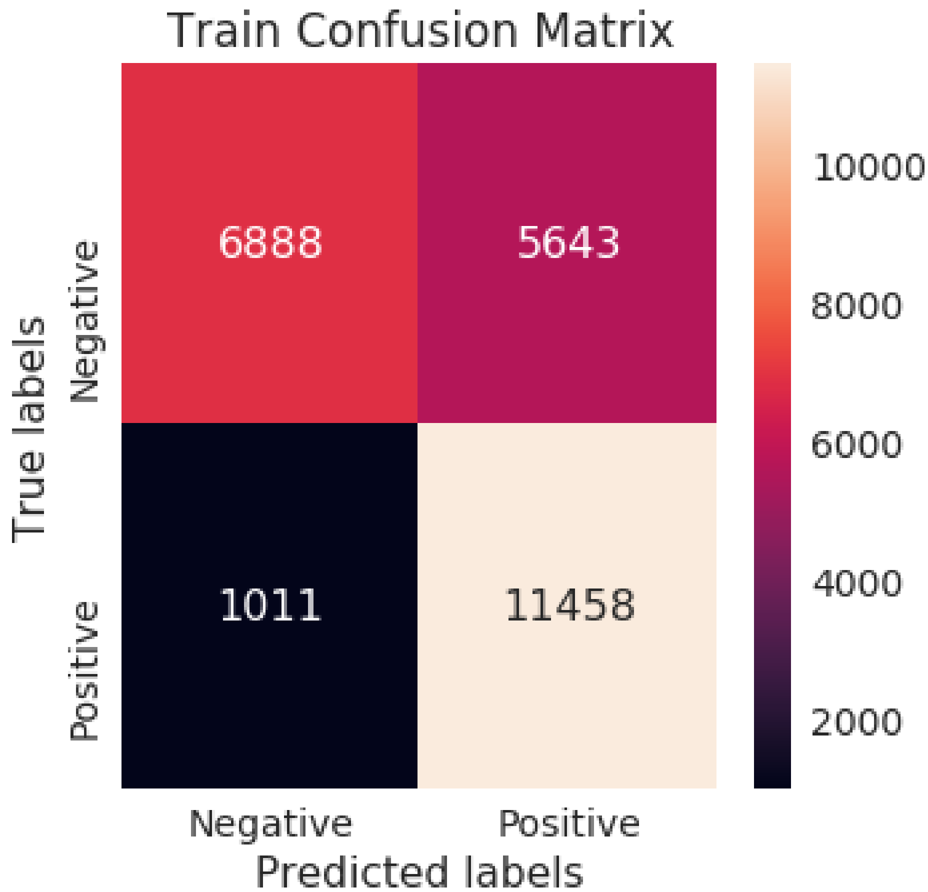
In [13]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                            scaling=Tru
                                                                            dim_reducti

# 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_a2 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 503)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 503)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,501, test features: 10000,501
Shape of -> train labels :25000, test labels: 10000
===============================================================================================


 The k vs AUC score plot
```



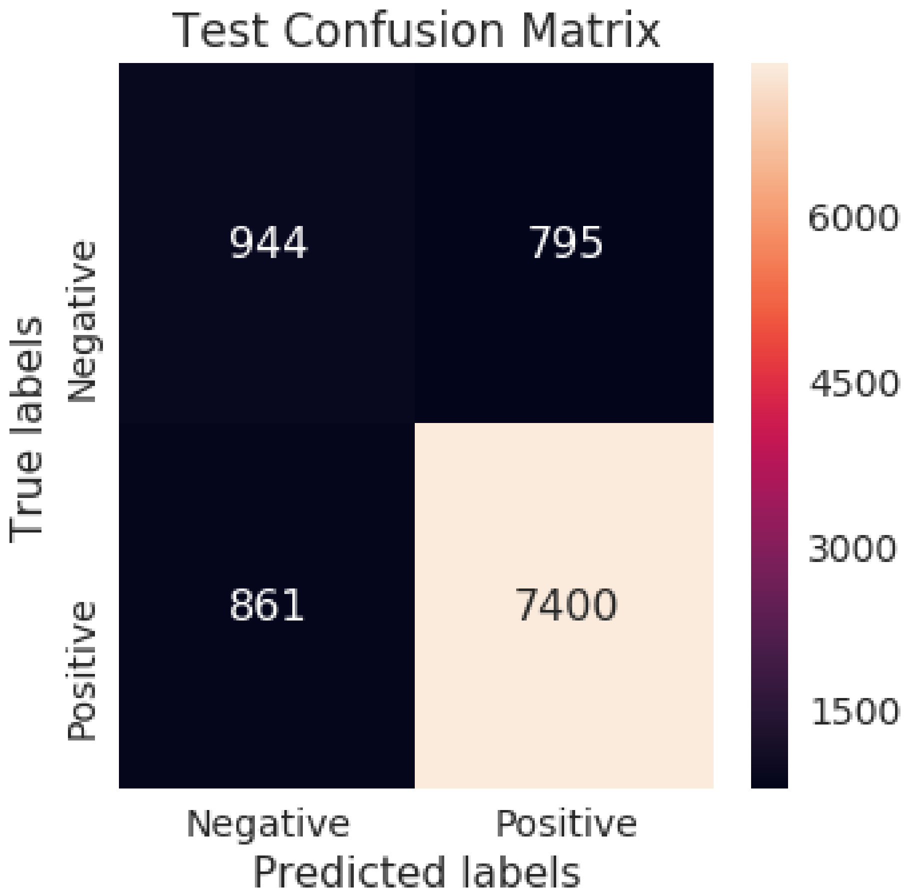

```
Best hyperparam value:  48
```

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



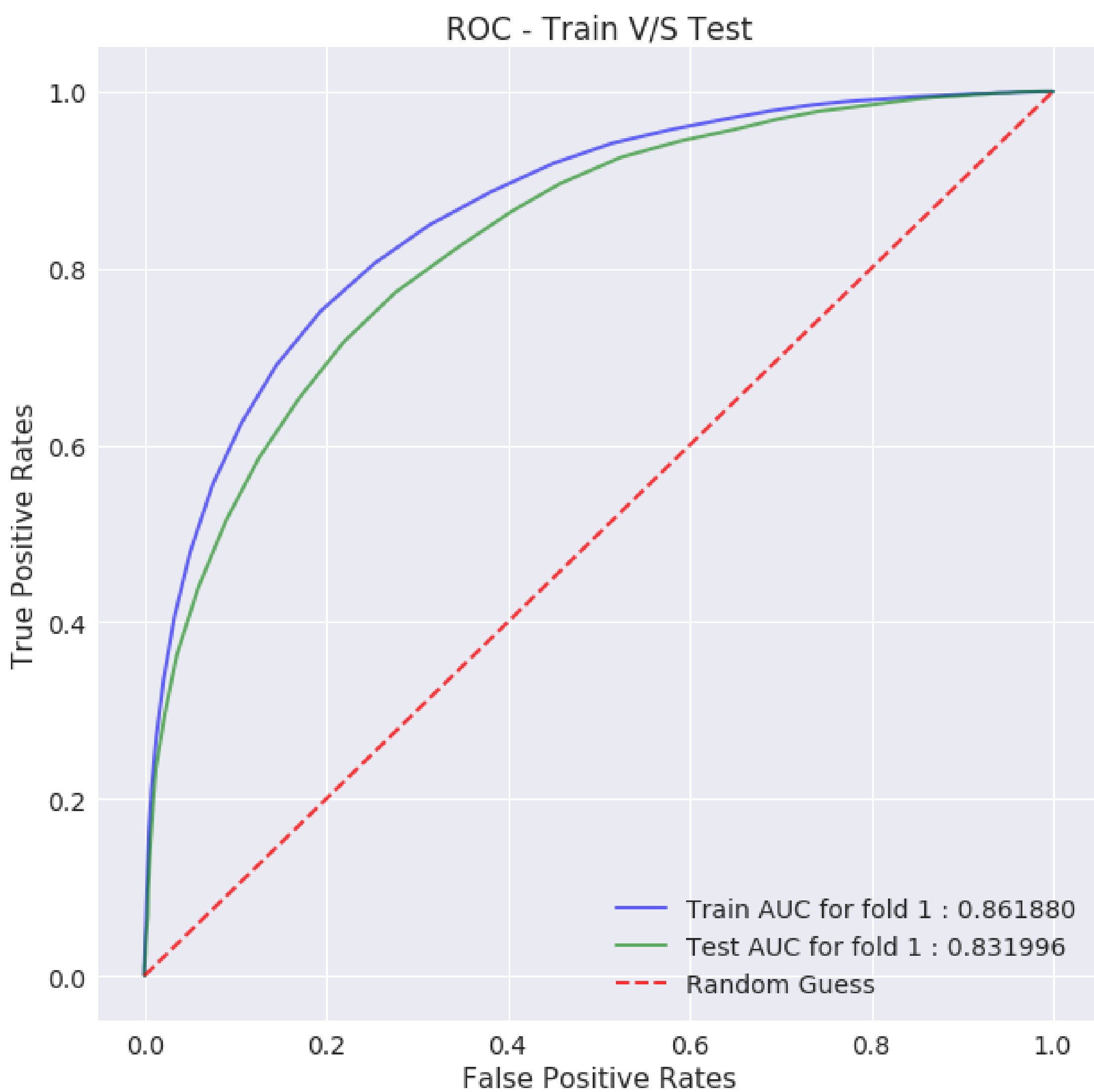

```
Train Evaluation Metrics :
                Negative       Positive
Precision       0.872009       0.670019
Recall          0.549677       0.918919
Fscore          0.674302       0.774975
Support     12531.000000   12469.000000
```

```
/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	0.522992	0.902990
Recall	0.542841	0.895775
Fscore	0.532731	0.899368
Support	1739.000000	8261.000000




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.8320'), ('f-score(-ve)', '53.2731'), ('f-score(+ve)', '89.93
```

As the value of K increases there is slight increase in test auc and train auc. The best K value selected is 48

Performance on +ve class is good(89% f-score) but negative class (53%)

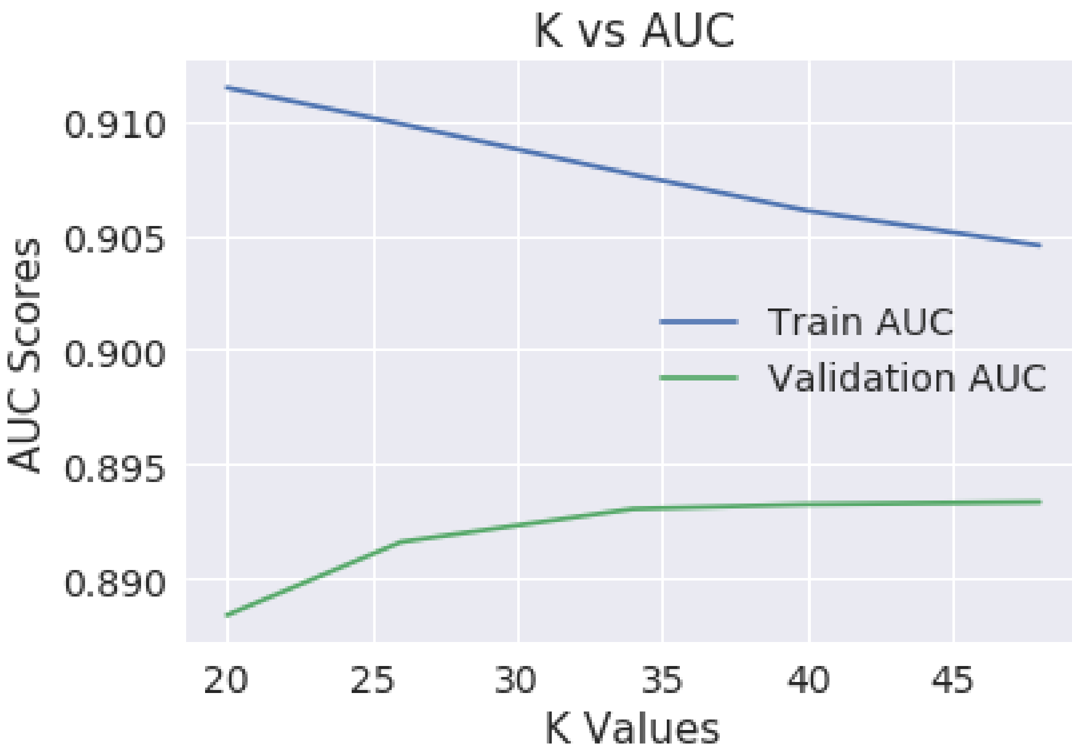
4.3.3 [A.3] Applying KNN brute force on AVG W2V, SET 3

```
In [14]: 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' : 25000,
            'test_size' : 10000,
            'hyperparam_list' : [20, 26, 34, 40, 48],
            'algo_type' : 'brute', # 'brute', 'kd_tree',
        }
```

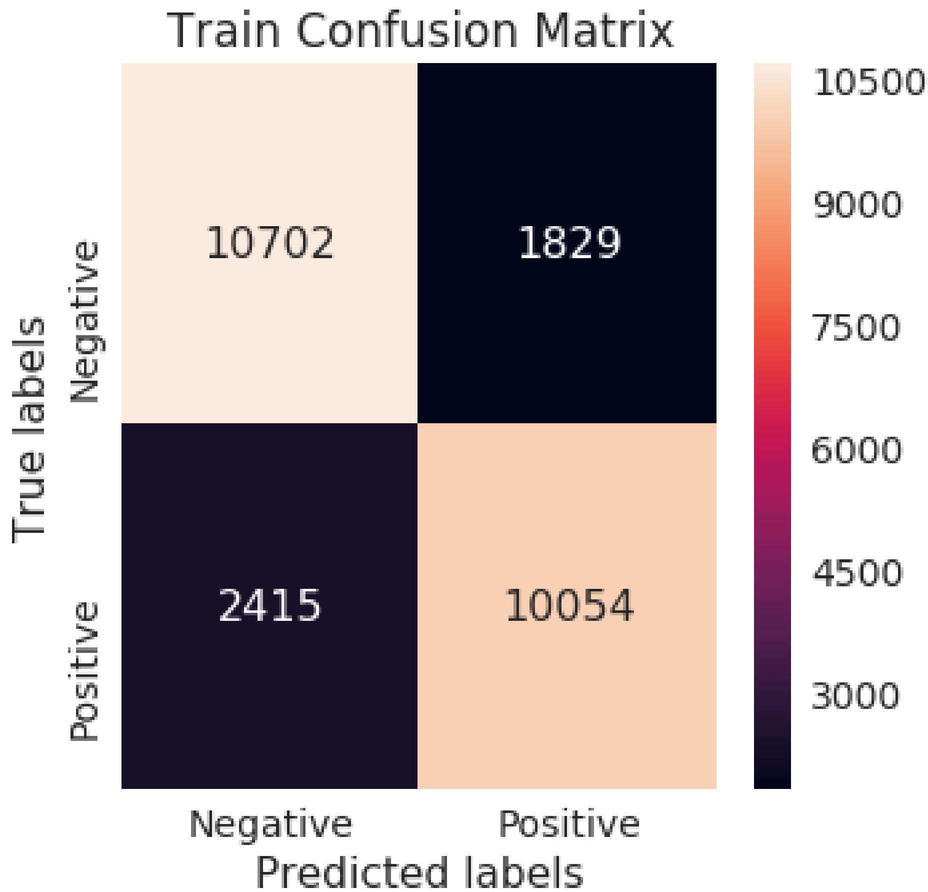
In [15]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                           scaling=Tru
                                                                           dim_reducti


# 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_a3 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 52)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 52)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,50, test features: 10000,50
Shape of -> train labels :25000, test labels: 10000
================================================================================================


 The k vs AUC score plot
```

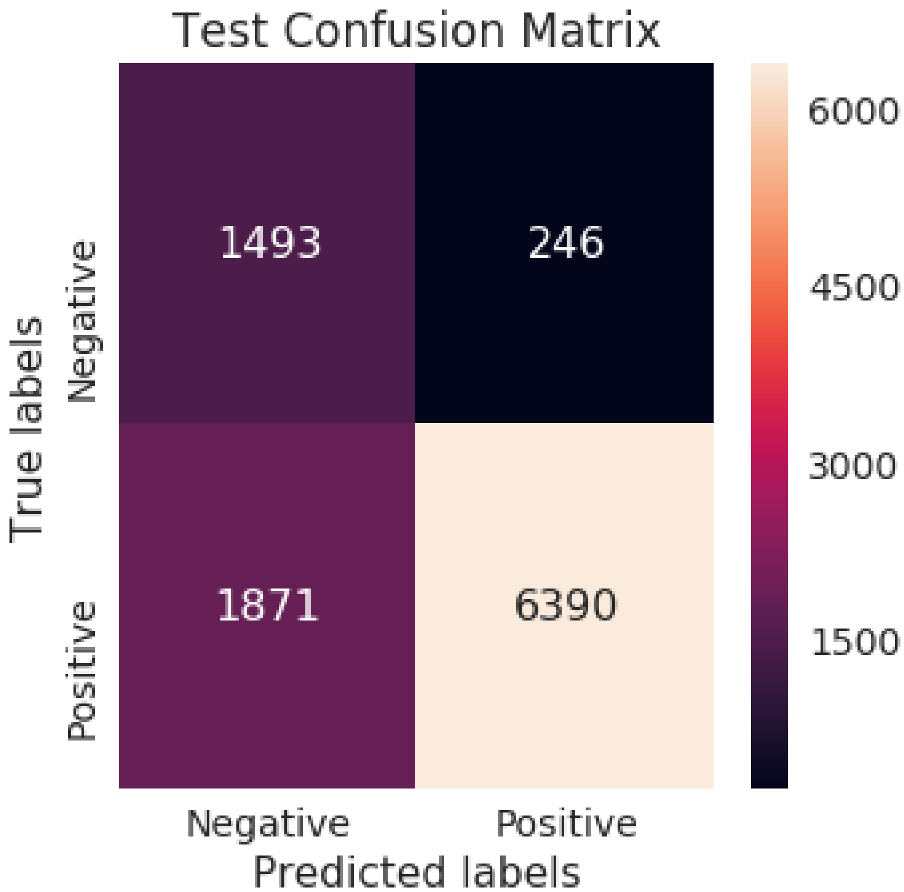



```
Best hyperparam value:  48
```

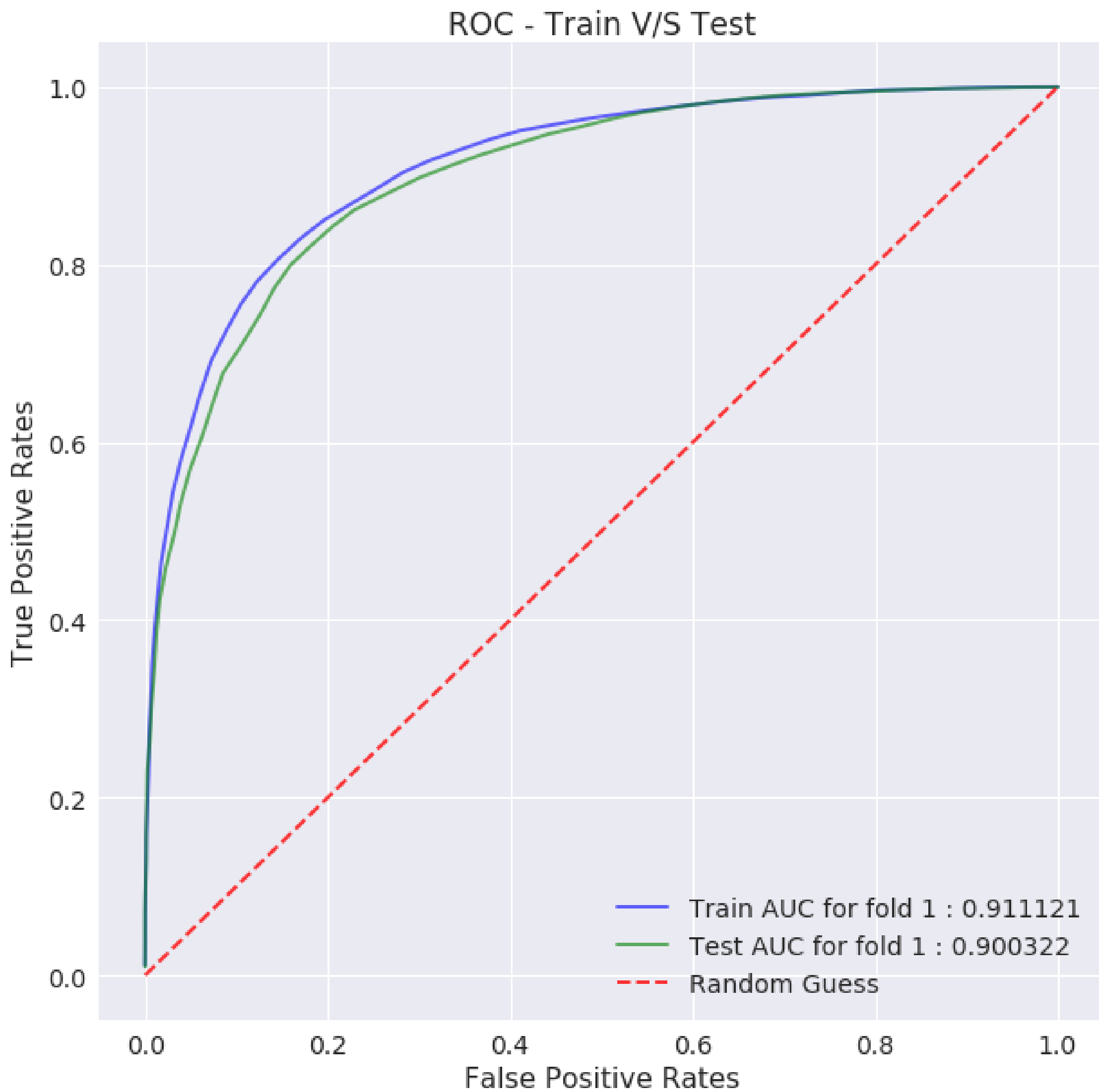
```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:107: Matplotli
  warnings.warn(message, mplDeprecation, stacklevel=1)
```




```
Train Evaluation Metrics :
                Negative       Positive
Precision       0.815888       0.846083
Recall          0.854042       0.806320
Fscore          0.834529       0.825723
Support     12531.000000   12469.000000


/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       0.443817       0.962929
Recall          0.858539       0.773514
Fscore          0.585146       0.857891
Support      1739.000000    8261.000000
```




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.9003'), ('f-score(-ve)', '58.5146'), ('f-score(+ve)', '85.78
```

The hyper param K is selected in such a way that the deviation between train and validation curve is less and the validation AUC score is high

As the value of K increases there is slight increase in test auc and slight decrease in train auc. The best K value selected is 48

F-score value for +ve is really good (85.78) but negative class (58.51)

ROC curves oerlap well and performance of model looks good

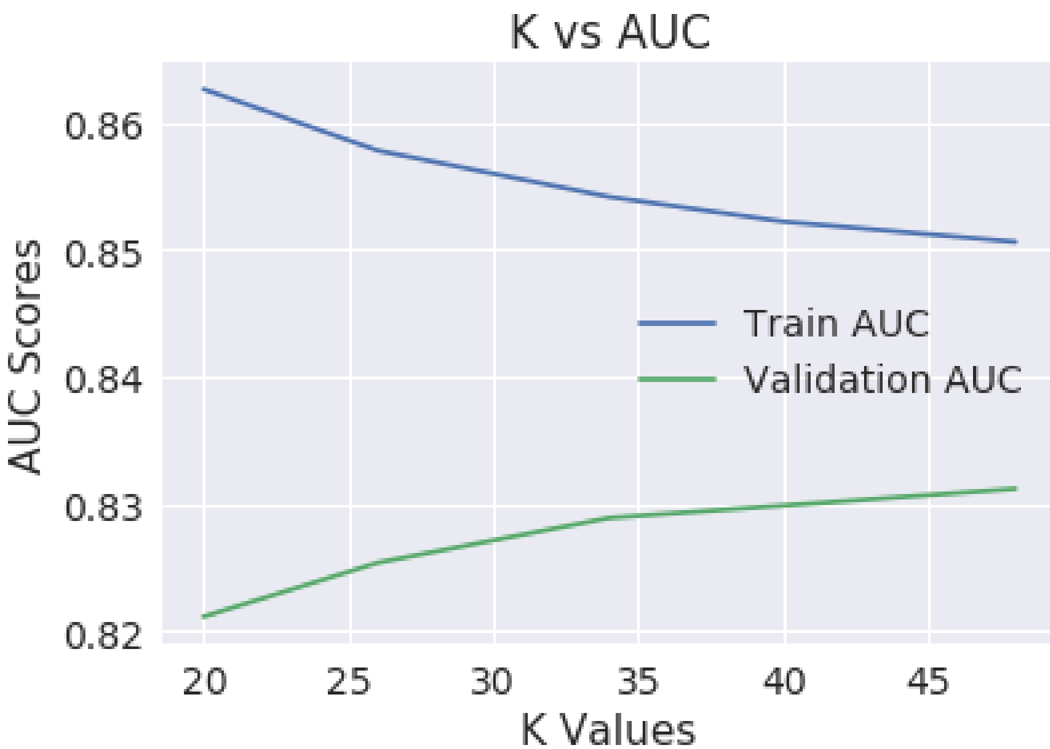
4.3.4 [A.4] Applying KNN brute force on TFIDF W2V, SET 4

```
In [16]: 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' : 25000,
             'test_size' : 10000,
             'hyperparam_list' : [20, 26, 34, 40, 48],
             'algo_type' : 'brute', # 'brute', 'kd_tree',
         }
```

```
In [17]: # read the train, test data and preprocess it
         train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                                     scaling=Tru
                                                                                     dim_reducti


         # 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_a4 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

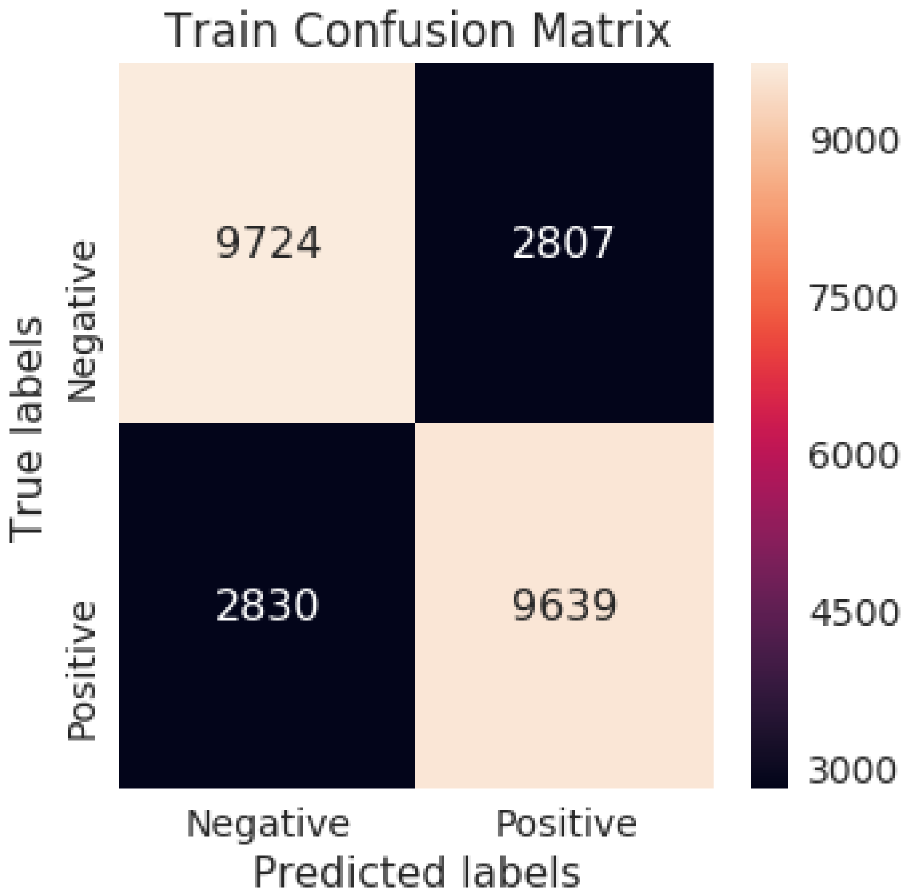
```
Train df shape (25000, 52)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 52)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,50, test features: 10000,50
Shape of -> train labels :25000, test labels: 10000
===================================================================================================
```

The k vs AUC score plot



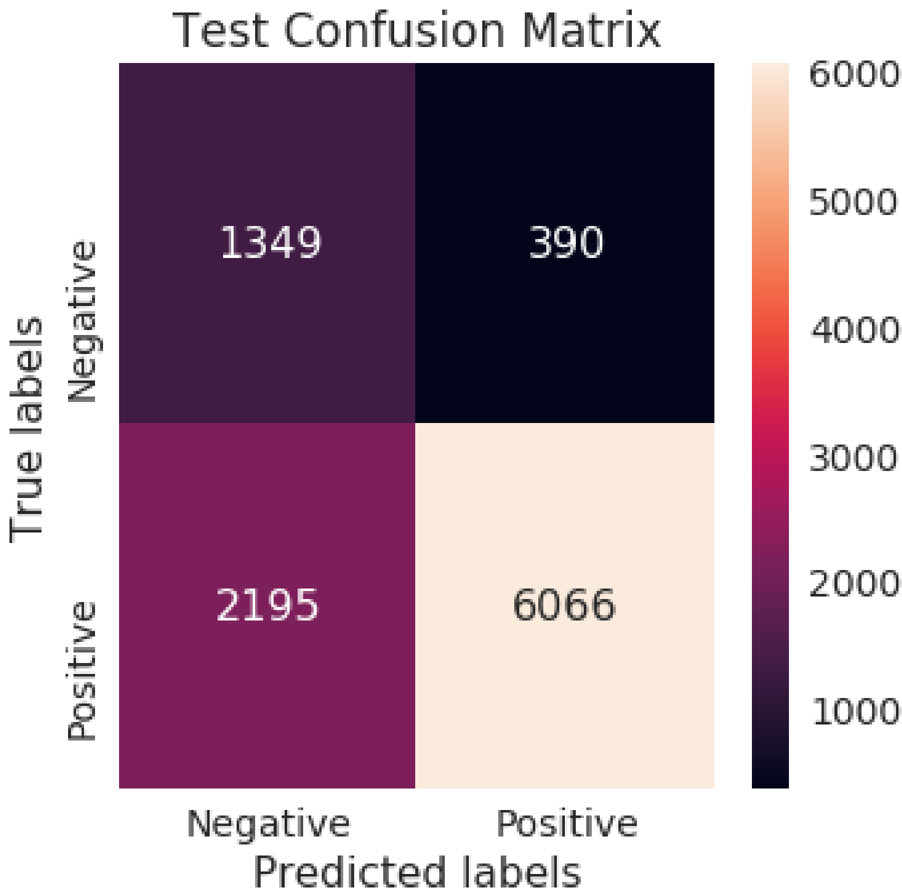

```
Best hyperparam value:  48
```

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



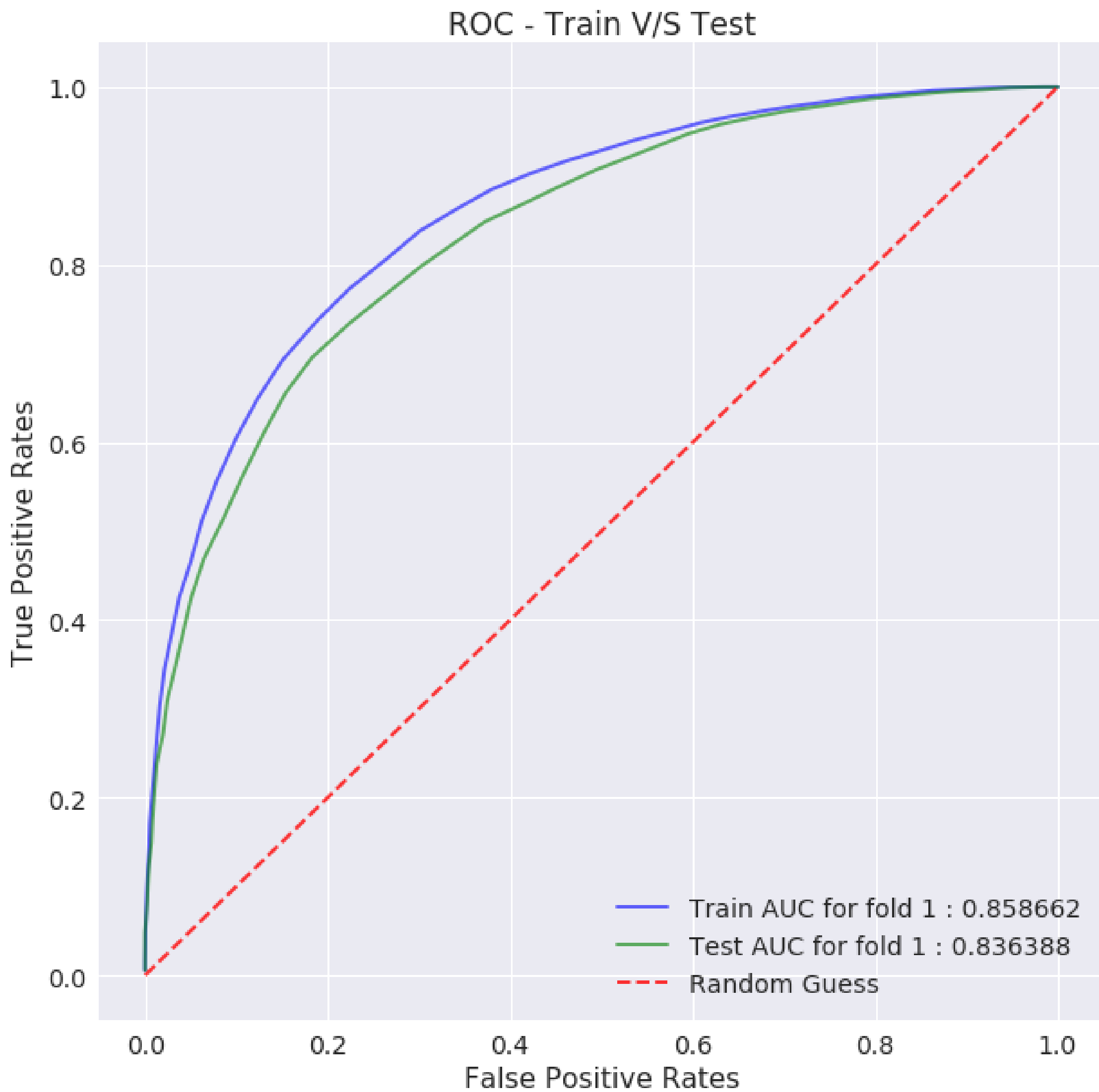

```
Train Evaluation Metrics :
                Negative      Positive
Precision       0.774574      0.774466
Recall          0.775996      0.773037
Fscore          0.775284      0.773751
Support     12531.000000  12469.000000
```

```
/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	0.380643	0.939591
Recall	0.775733	0.734294
Fscore	0.510695	0.824353
Support	1739.000000	8261.000000




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.8364'), ('f-score(-ve)', '51.0695'), ('f-score(+ve)', '82.43
```

Precision for -ve class is low (0.38)
There are many positive data points which are misscalssified (2195)

4.4 [B] Applying KNN kd-tree

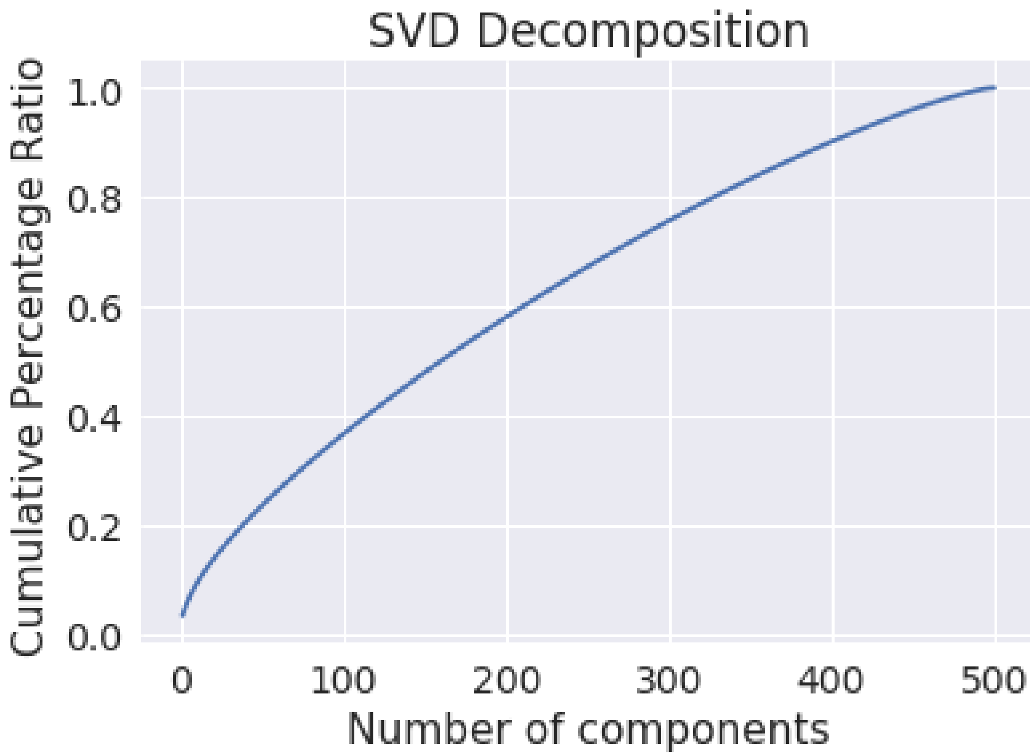
4.4.1 [B.1] Applying KNN kd-tree on BOW, SET 5

```
In [18]: 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' : 25000,
    'test_size' : 10000,
    'hyperparam_list' : [20, 26, 34, 40, 48],
    'algo_type' : 'kd_tree', # 'brute', 'kd_tree',
}
```

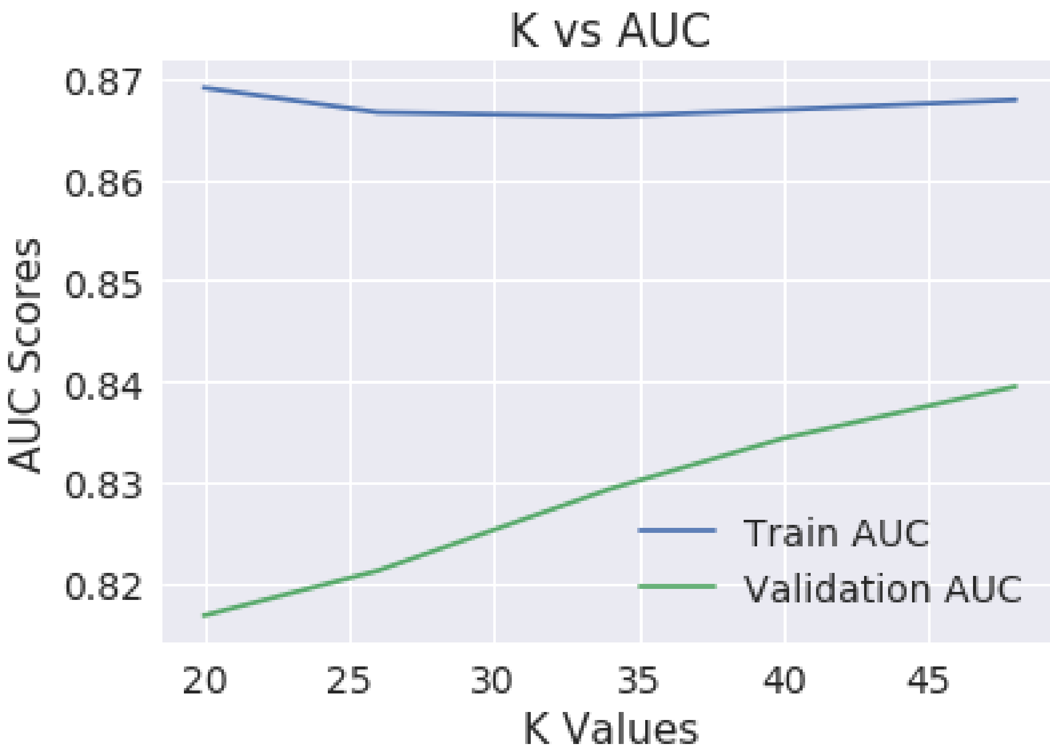
In [19]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                           scaling=Tru
                                                                           dim_reducti

# 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_b1 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 503)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 503)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,501, test features: 10000,501
Shape of -> train labels :25000, test labels: 10000
```



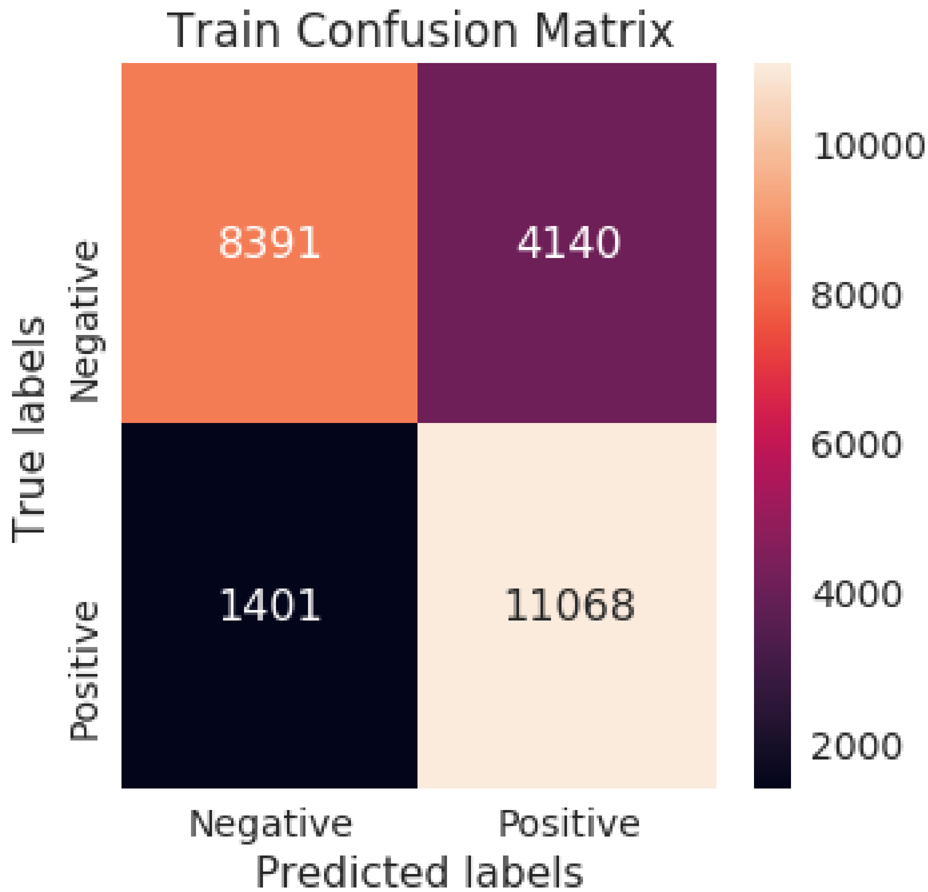

```
Num dimensions selected by SVD 456
Total variance captured:0.967530
Shape of train df:(25000,456), Test DF:(10000,456)
================================================================================================
```

The k vs AUC score plot

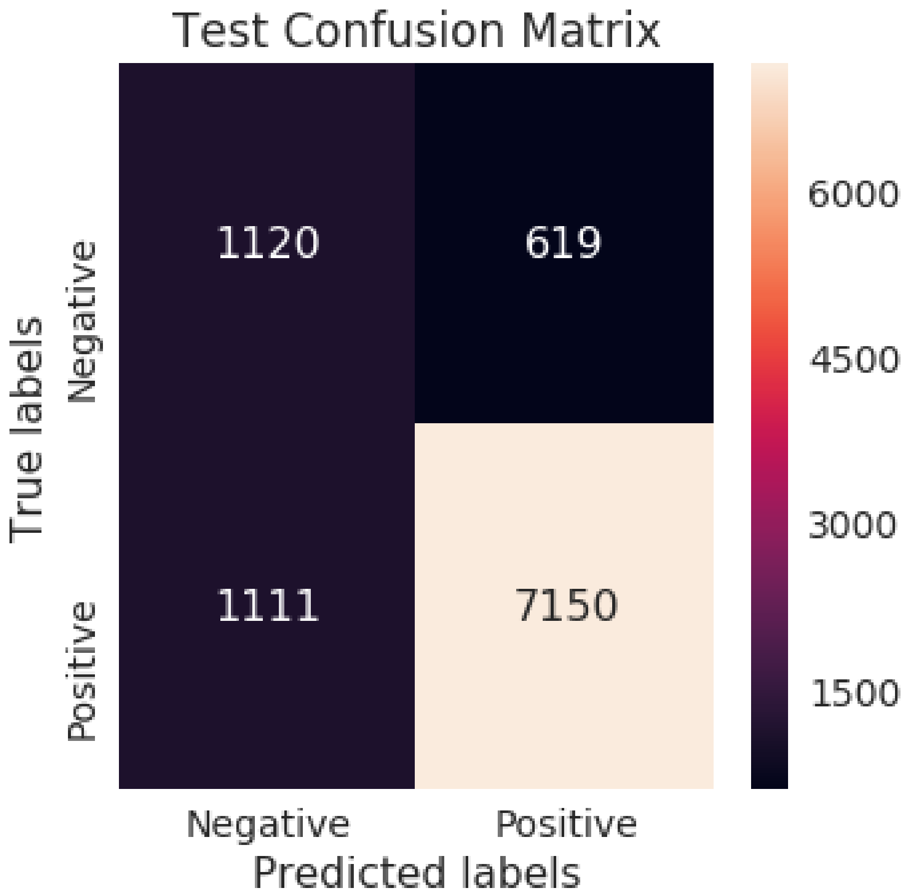



```
Best hyperparam value:  48
```

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

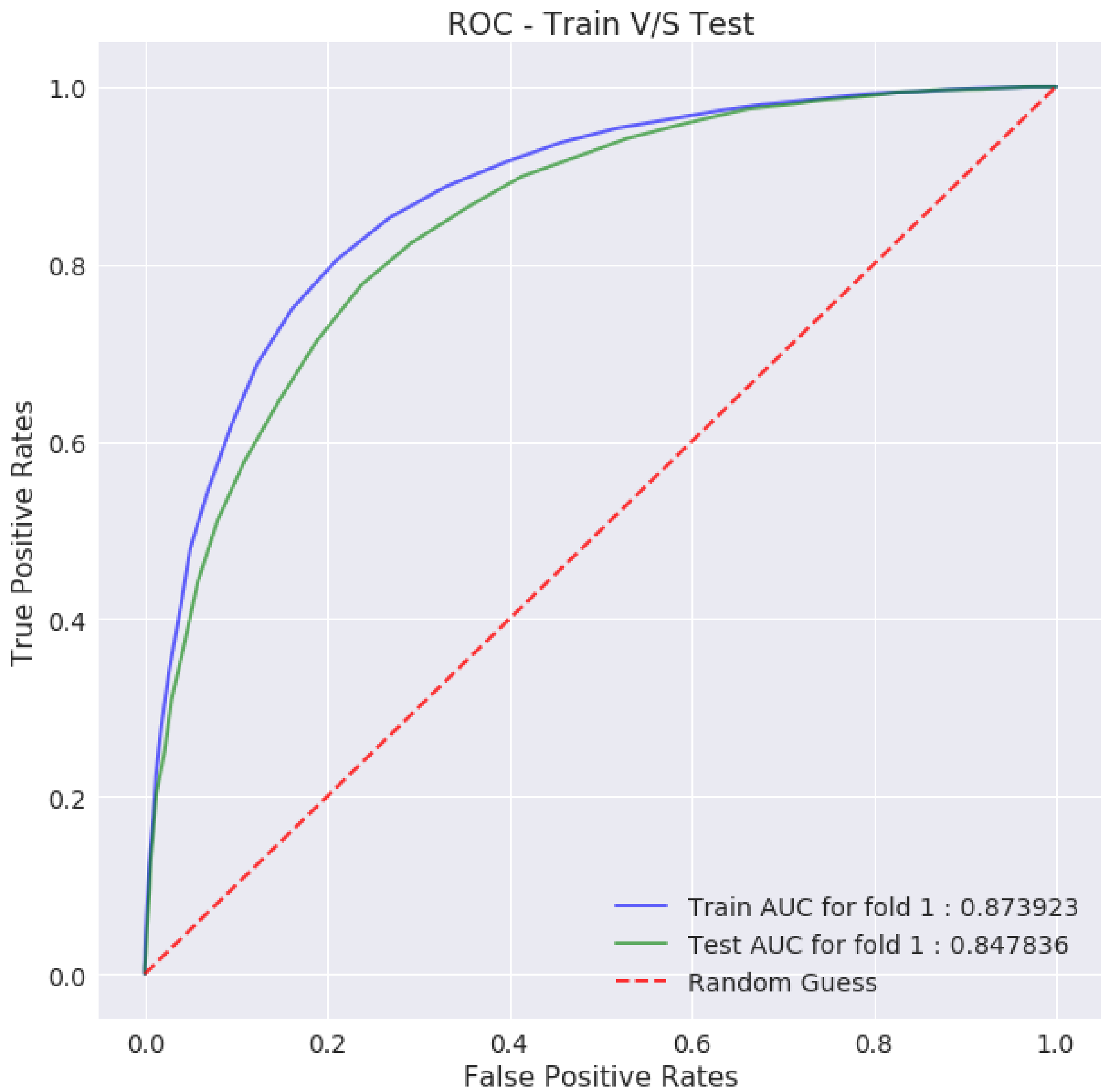



```
Train Evaluation Metrics :
                Negative       Positive
Precision       0.856924       0.727775
Recall          0.669619       0.887641
Fscore          0.751781       0.799798
Support     12531.000000   12469.000000


/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	0.502017	0.920324
Recall	0.644048	0.865513
Fscore	0.564232	0.892077
Support	1739.000000	8261.000000




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.8478'), ('f-score(-ve)', '56.4232'), ('f-score(+ve)', '89.20
```

4.5 Observation

The number of components got reduced to 456 by SVD decomposition
The total variance captured is 96.75 %

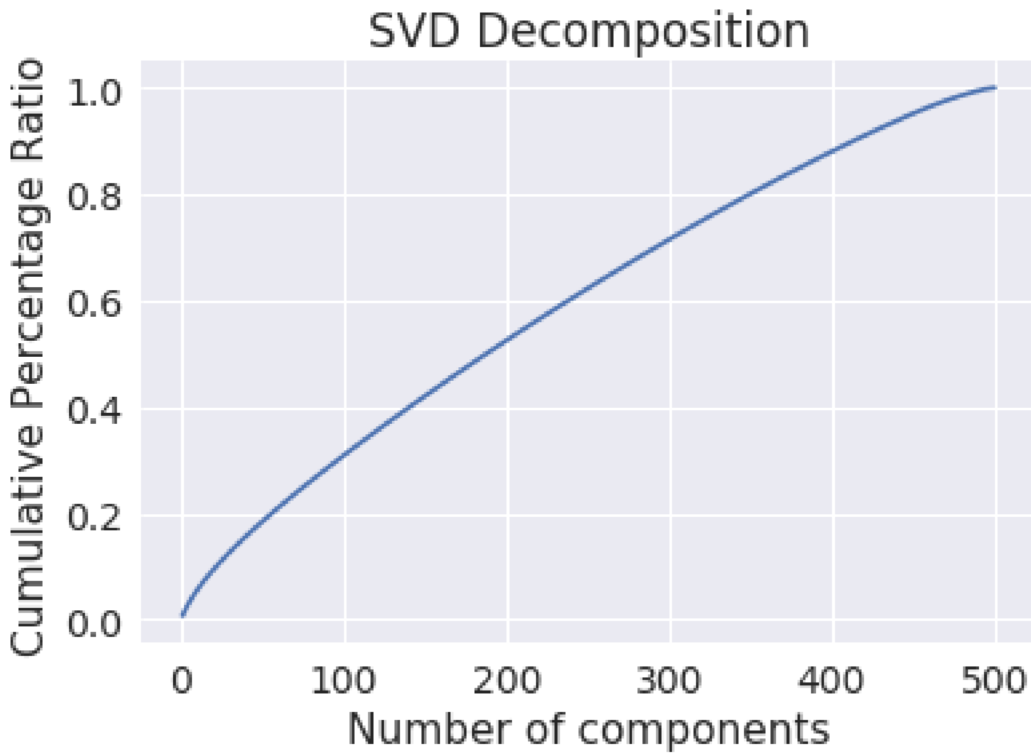
4.5.1 [B.2] Applying KNN kd-tree on TFIDF, SET 6

```
In [20]: 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' : 25000,
            'test_size' : 10000,
            'hyperparam_list' : [20, 26, 34, 40, 48],
            'algo_type' : 'kd_tree', # 'brute', 'kd_tree',
        }
```

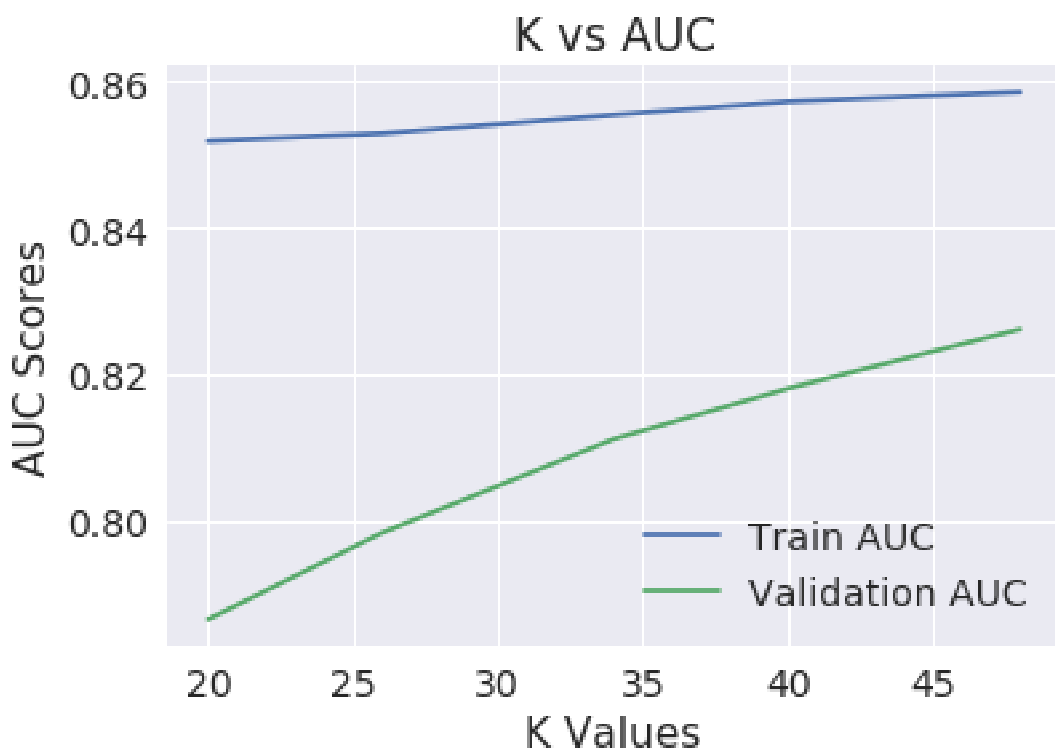
In [21]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                            scaling=Tru
                                                                            dim_reducti

# 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_b2 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 503)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 503)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,501, test features: 10000,501
Shape of -> train labels :25000, test labels: 10000
```



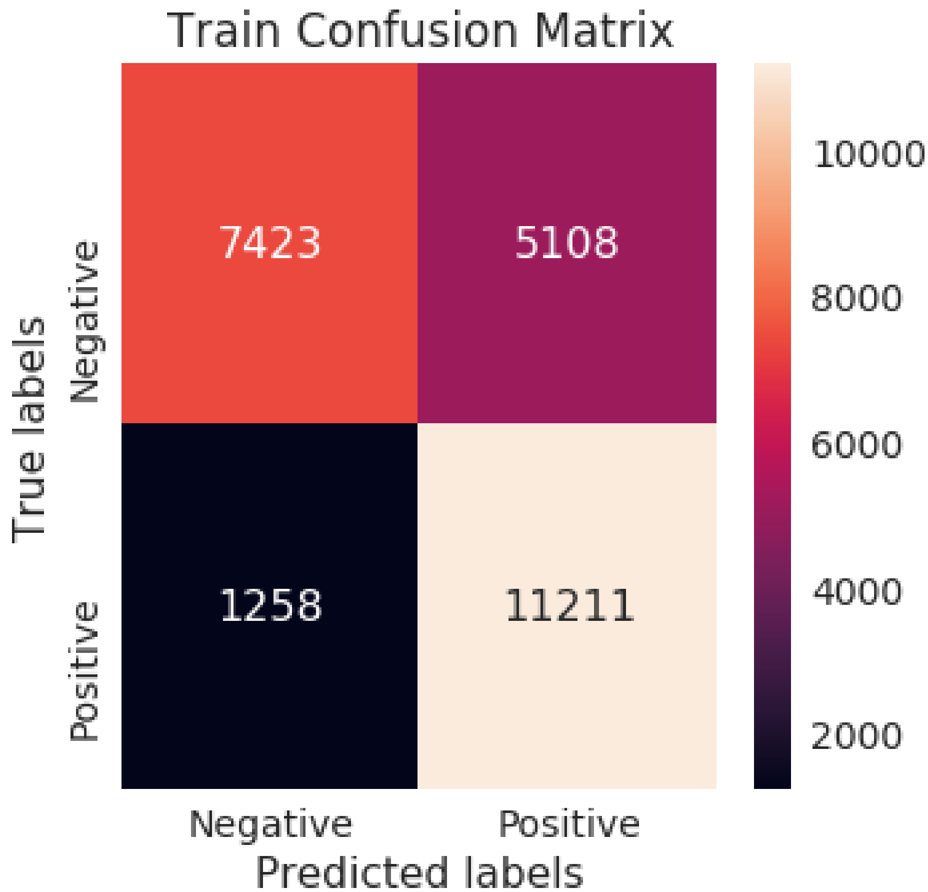

```
Num dimensions selected by SVD 474
Total variance captured:0.980770
Shape of train df:(25000,474), Test DF:(10000,474)
================================================================================================
```

```
 The k vs AUC score plot
```



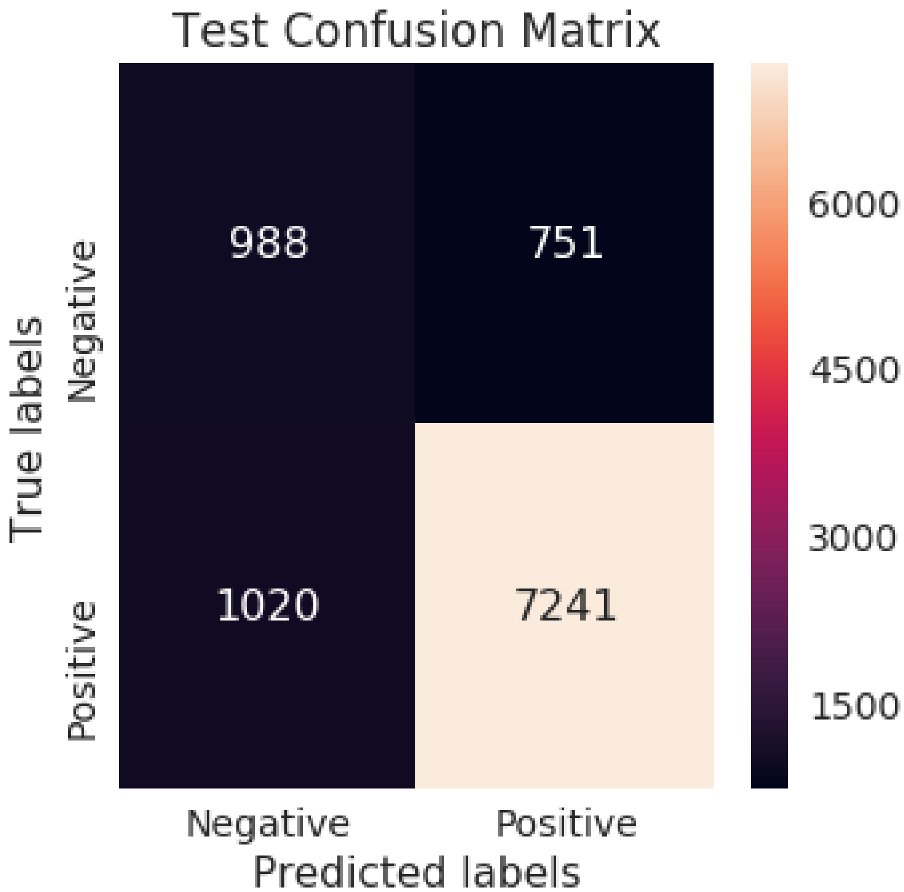

```
Best hyperparam value:  48
```

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

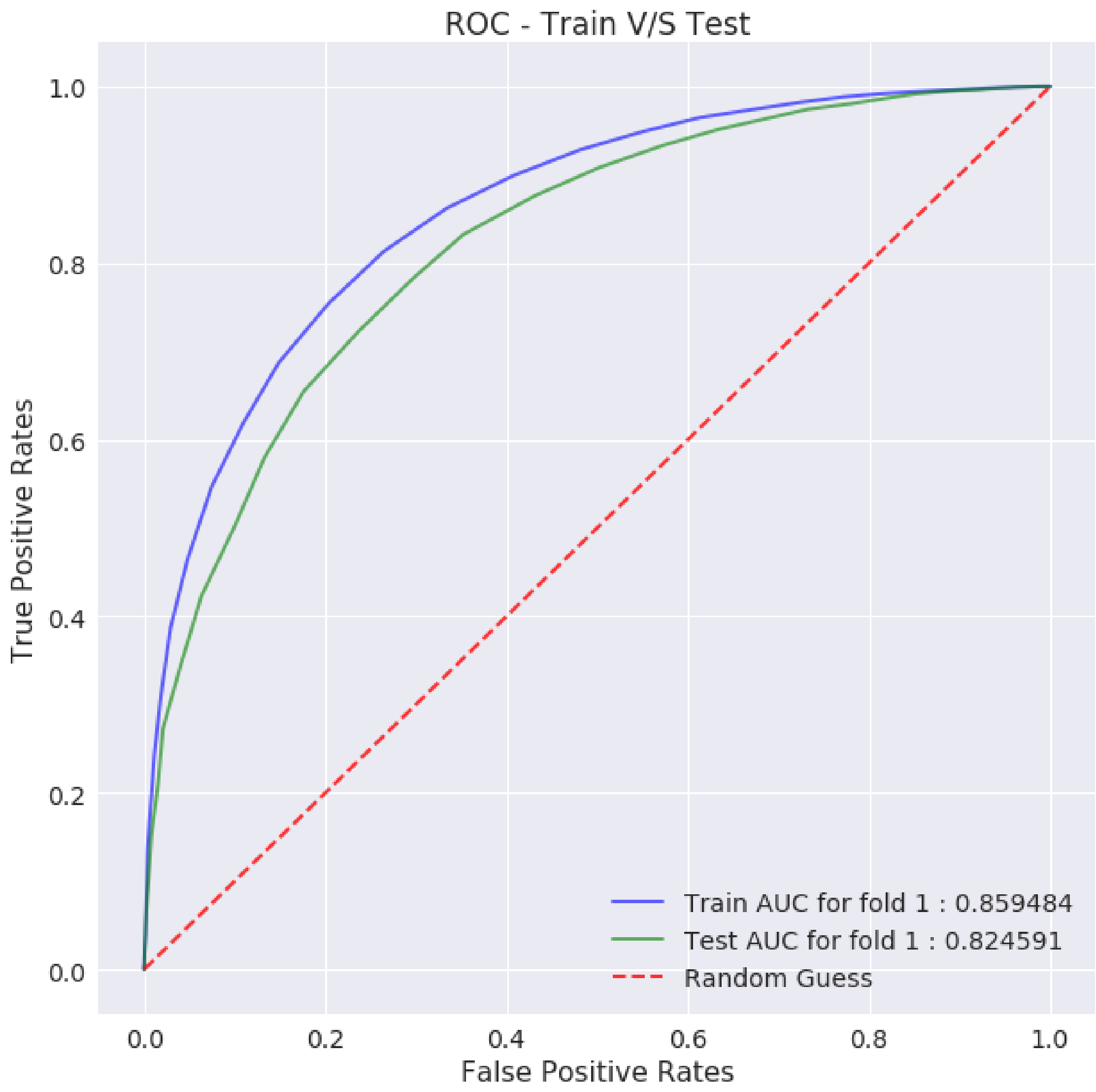



```
Train Evaluation Metrics :
                Negative       Positive
Precision       0.855086       0.686991
Recall          0.592371       0.899110
Fscore          0.699887       0.778866
Support     12531.000000   12469.000000
```

```
/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     0.492032     0.906031
Recall        0.568143     0.876528
Fscore        0.527355     0.891036
Support    1739.000000  8261.000000
```




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.8246'), ('f-score(-ve)', '52.7355'), ('f-score(+ve)', '89.10
```

4.6 Observation

The SVD method reduced dimension of dataset to 471, covering 98% variances
k=48 is the best hyperparameter selected
Recall(0.56) and Precision (0.49) for -ve class is low

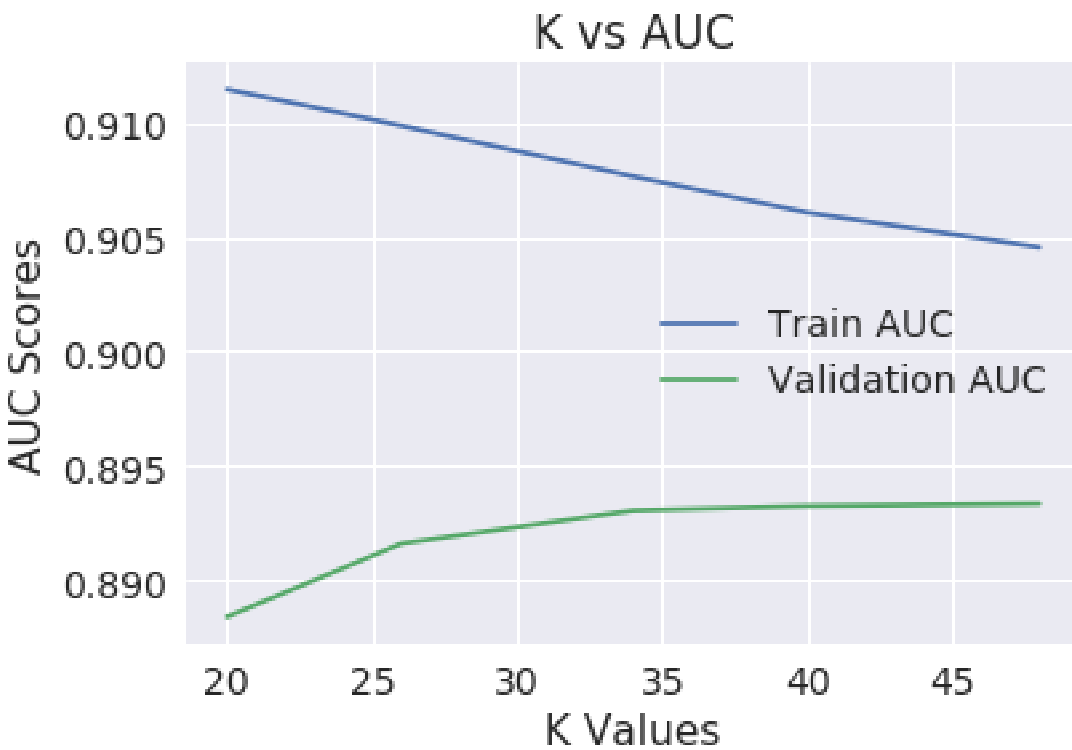
4.6.1 [B.3] Applying KNN kd-tree on AVG W2V, SET 3

```
In [22]: 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' : 25000,
            'test_size' : 10000,
            'hyperparam_list' : [20, 26, 34, 40, 48],
            'algo_type' : 'kd_tree', # 'brute', 'kd_tree',
        }
```

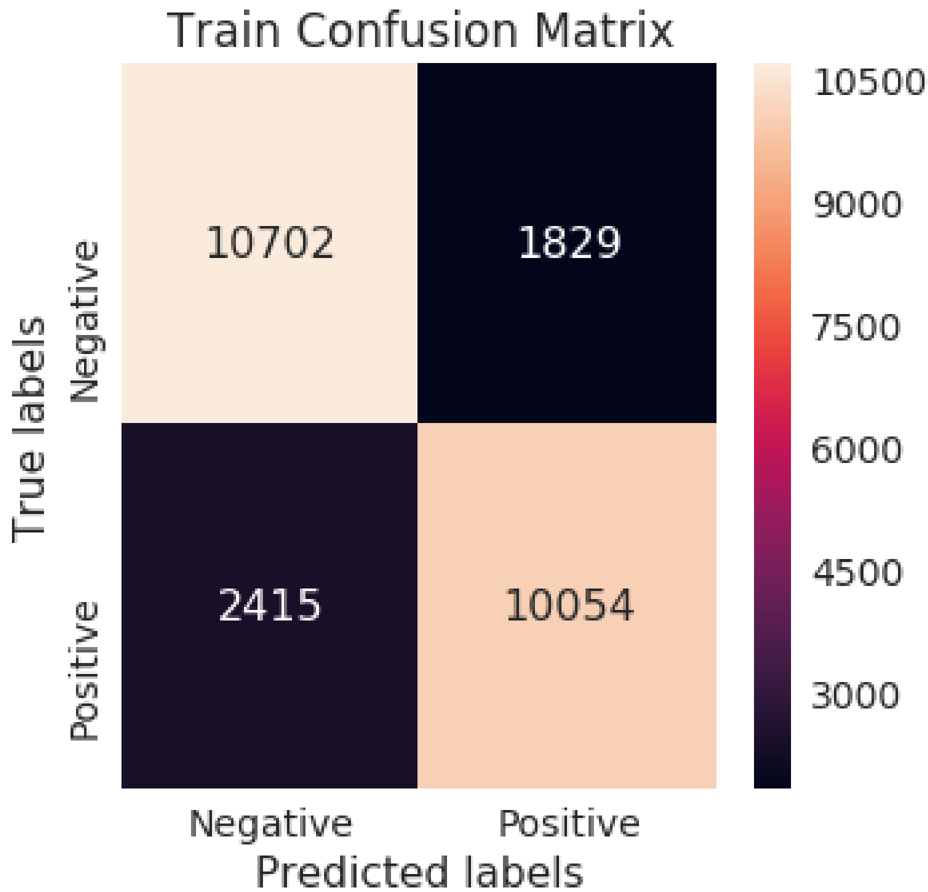
```
In [23]: # read the train, test data and preprocess it
        train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                                 scaling=Tru
                                                                                 dim_reducti

        # 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_b3 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 52)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 52)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,50, test features: 10000,50
Shape of -> train labels :25000, test labels: 10000
=================================================================================================


 The k vs AUC score plot
```



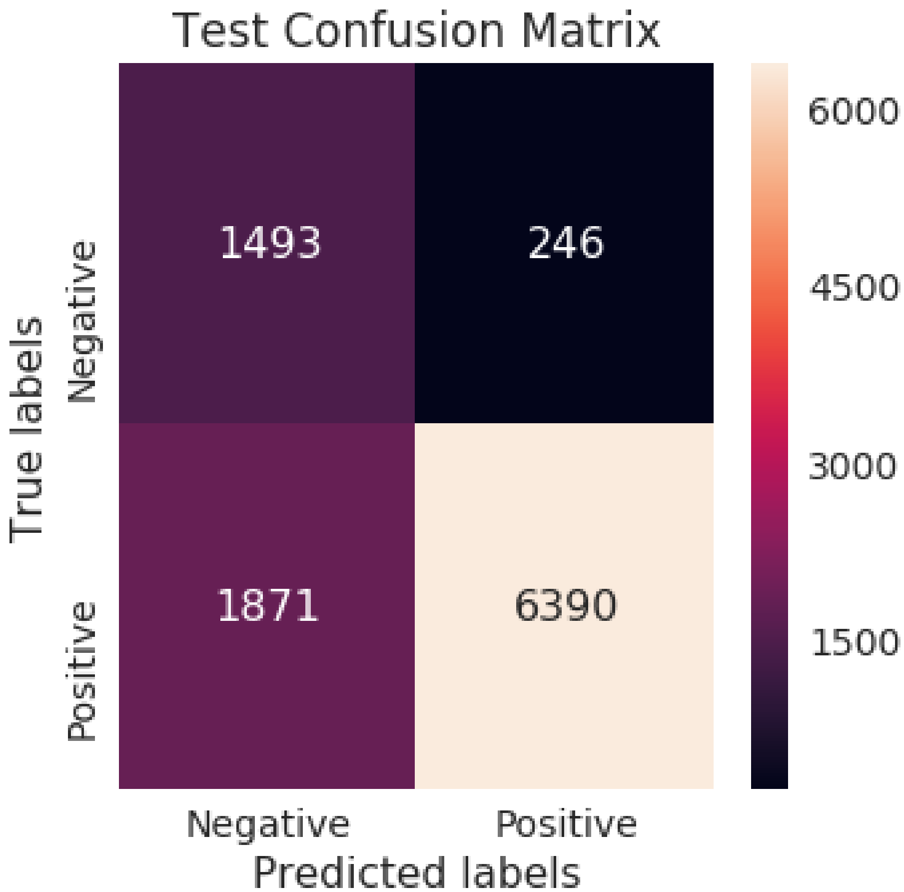

```
Best hyperparam value:  48
```

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

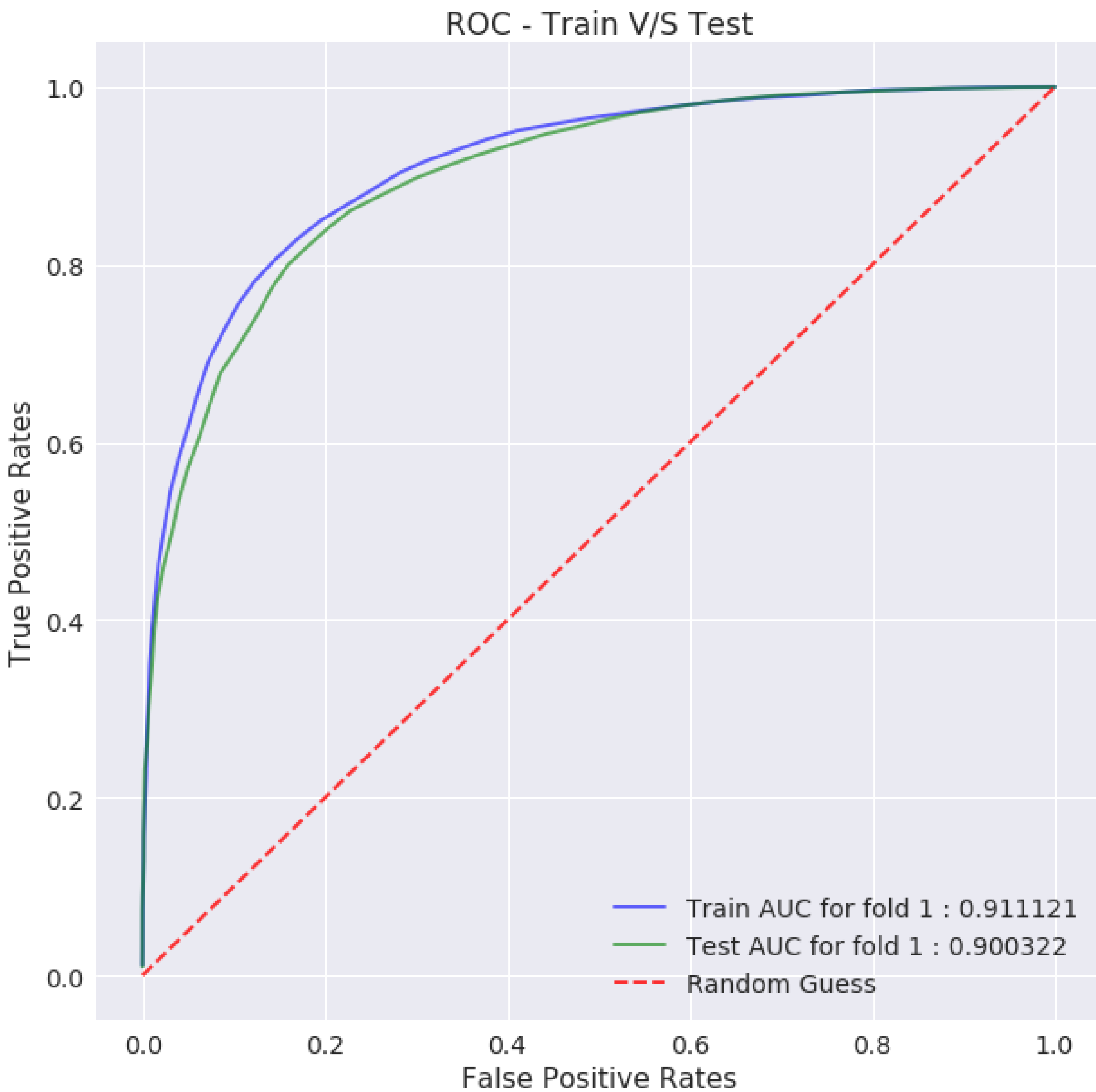



```
Train Evaluation Metrics :
                Negative      Positive
Precision       0.815888      0.846083
Recall          0.854042      0.806320
Fscore          0.834529      0.825723
Support     12531.000000  12469.000000
```

```
/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      0.443817      0.962929
Recall         0.858539      0.773514
Fscore         0.585146      0.857891
Support     1739.000000   8261.000000
```




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.9003'), ('f-score(-ve)', '58.5146'), ('f-score(+ve)', '85.78
```

Precision for -ve class is low (0.43)
There are many positive data points which are misscalssified (1871)
As value of K increases test auc increases slightly and train auc decreases slightly

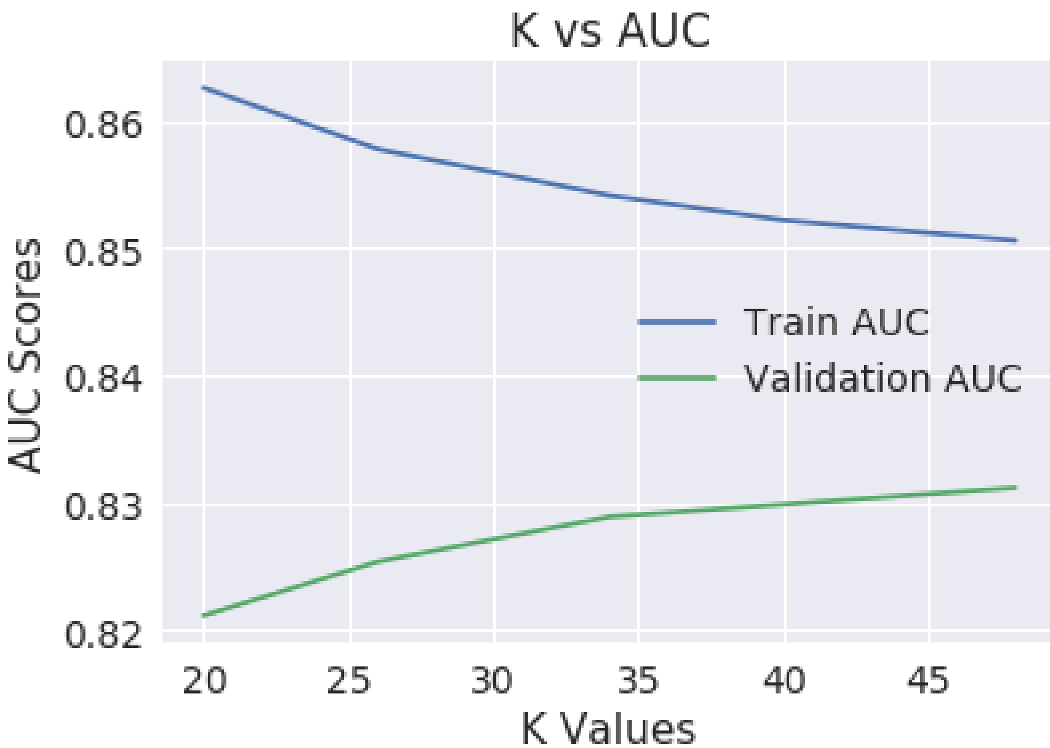
4.6.2 [B.4] Applying KNN kd-tree on TFIDF W2V, SET 4

```
In [24]: 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' : 25000,
            'test_size' : 10000,
            'hyperparam_list' : [20, 26, 34, 40, 48],
            'algo_type' : 'kd_tree', # 'brute', 'kd_tree',
        }
```

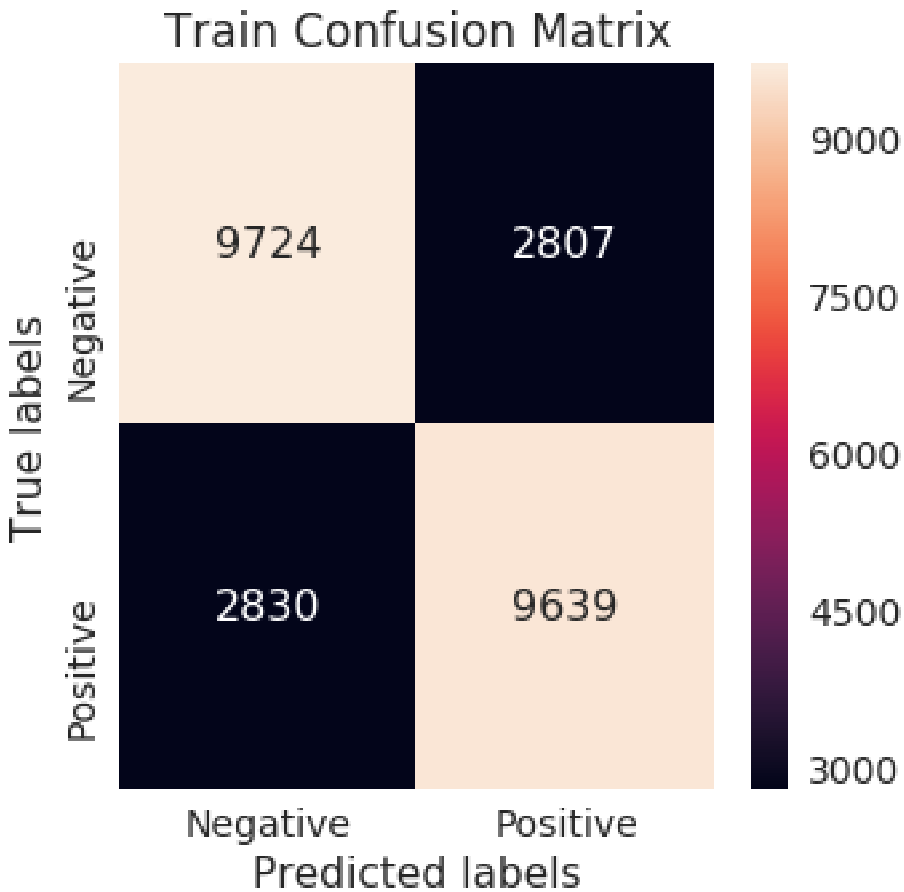
In [25]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                           scaling=Tru
                                                                           dim_reducti

# 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_b4 = get_table_entry(model, auc_ts, ts_all_metrics_df)
```

```
Train df shape (25000, 52)
Class label distribution in train df:
 0    12531
1    12469
Name: Label, dtype: int64
Test df shape (10000, 52)
Class label distribution in test df:
 1    8261
0    1739
Name: Label, dtype: int64
Shape of ->  train features :25000,50, test features: 10000,50
Shape of -> train labels :25000, test labels: 10000
==========================================================================================


 The k vs AUC score plot
```



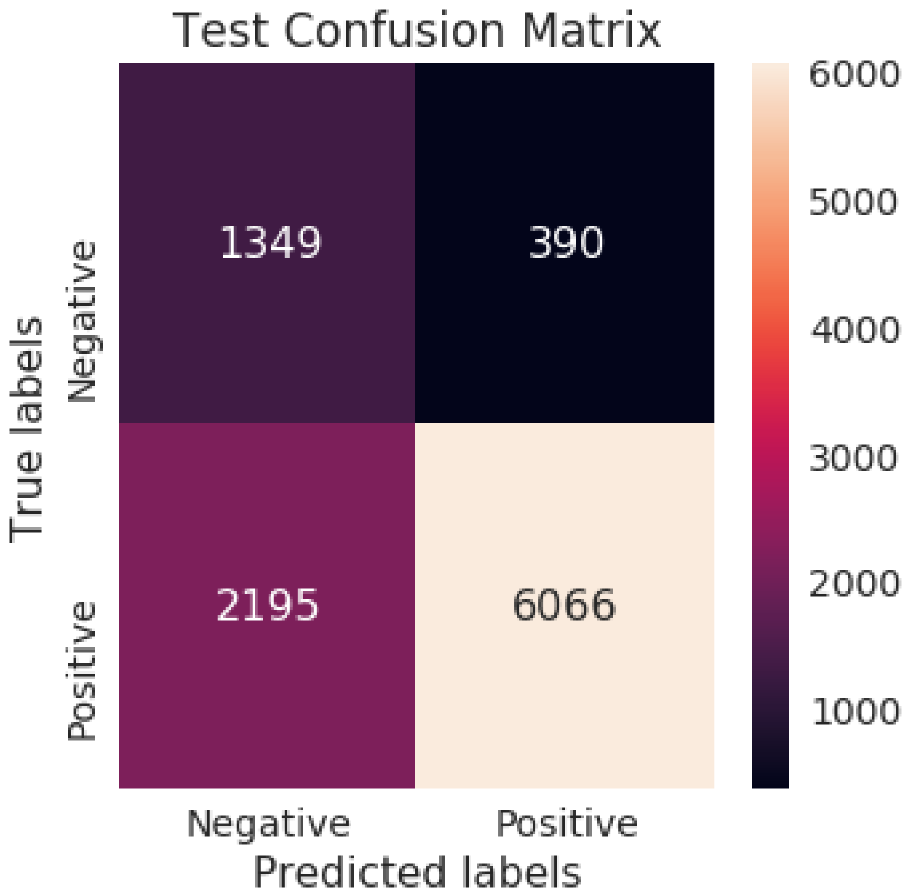

```
Best hyperparam value:  48
```

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

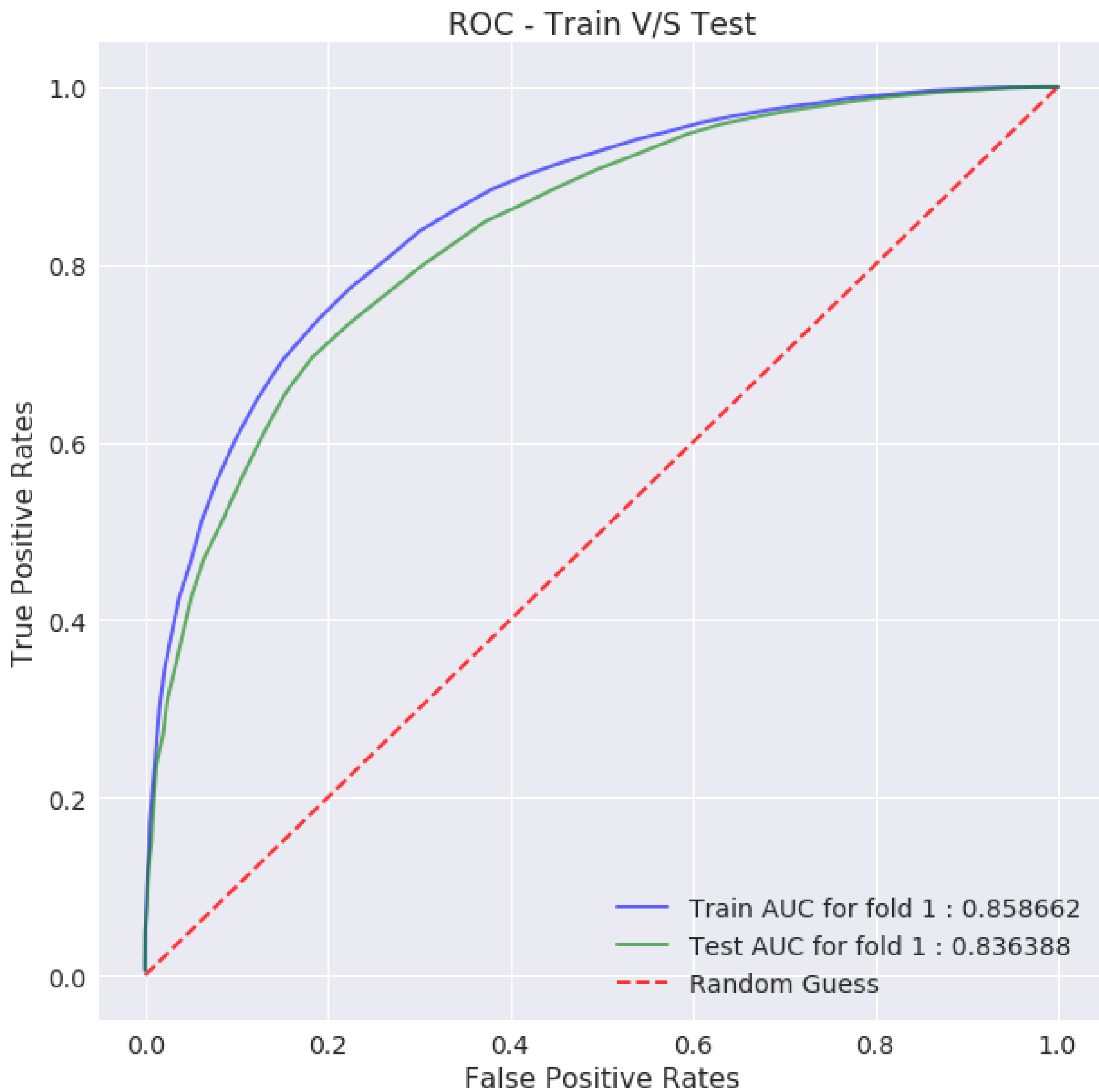



```
Train Evaluation Metrics :
                Negative      Positive
Precision      0.774574      0.774466
Recall         0.775996      0.773037
Fscore         0.775284      0.773751
Support    12531.000000  12469.000000
```

```
/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     0.380643     0.939591
Recall        0.775733     0.734294
Fscore        0.510695     0.824353
Support    1739.000000  8261.000000
```




```
Results Summary:
 [('Hyper Param', '48'), ('AUC', '0.8364'), ('f-score(-ve)', '51.0695'), ('f-score(+ve)', '82.43
```

Precision for -ve class is low (0.38)
There are many positive data points which are misscalssified (2195)

5 Procedure Summary

All data sets are preprocessed using standard scaler, for KD-Tree version the dimension is reduced by applying TruncatedSVD algorithm

Two versio of KNN classifier is tried on all four datasets. Version 1: Brute force & Version 2: KD-Tree version

Trained all models usig all the four different data datasets with different hyper parameter (K) values.

The best hyperparameter is selected using the cross validation method

The performance of each model is visualized by using ROC curve & confusion matrix heatmaps

6 Results Summary

In [26]:
```
Pret_table = PrettyTable()
Pret_table.field_names = ['Vectorizer', 'Method', 'Hyper-Param (K)', 'AUC', 'Fscore (-v
Pret_table.title = 'KNN Results Summary'
```

In [27]:
```
# Brute Force
Pret_table.add_row(['BoW', 'Brute Force'] + ptabe_entry_a1)
Pret_table.add_row(['TF-IDF', 'Brute Force'] + ptabe_entry_a2)
Pret_table.add_row(['Avg W2V', 'Brute Force'] + ptabe_entry_a3)
Pret_table.add_row(['TF-IDF W2V', 'Brute Force'] + ptabe_entry_a4)
# KD Tree
Pret_table.add_row(['BoW Truncated SVD', 'KD-Tree'] + ptabe_entry_b1)
Pret_table.add_row(['TF-IDF Truncated SVD', 'KD-Tree'] + ptabe_entry_b2)
Pret_table.add_row(['Avg W2V', 'KD-Tree'] + ptabe_entry_b3)
Pret_table.add_row(['TF-IDF W2V', 'KD-Tree'] + ptabe_entry_b4)
```

In [28]:
```
print(Pret_table)
```

```
+----------------------------------------------------------------------------------------------+
|                                     KNN Results Summary                                      |
+----------------------+-------------+-----------------+--------+--------------+--------------+
|      Vectorizer      |    Method   | Hyper-Param (K) |  AUC   | Fscore (-ve) | Fscore (+ve) |
+----------------------+-------------+-----------------+--------+--------------+--------------+
|         BoW          | Brute Force |        48       | 0.8527 |   56.9426    |   89.7256    |
|        TF-IDF        | Brute Force |        48       | 0.8320 |   53.2731    |   89.9368    |
|       Avg W2V        | Brute Force |        48       | 0.9003 |   58.5146    |   85.7891    |
|      TF-IDF W2V      | Brute Force |        48       | 0.8364 |   51.0695    |   82.4353    |
|  BoW Truncated SVD   |   KD-Tree   |        48       | 0.8478 |   56.4232    |   89.2077    |
| TF-IDF Truncated SVD |   KD-Tree   |        48       | 0.8246 |   52.7355    |   89.1036    |
|       Avg W2V        |   KD-Tree   |        48       | 0.9003 |   58.5146    |   85.7891    |
|      TF-IDF W2V      |   KD-Tree   |        48       | 0.8364 |   51.0695    |   82.4353    |
+----------------------+-------------+-----------------+--------+--------------+--------------+
```

7 Conclusions

The results otained are same for avg-w2v & tf-idf w2v vec models for both brute-force & KD-Tree version

The performance of the model on +ve class is really good (fscore for +ve is 82% above for any model) and the performance on -ve class is not that good as the fscore for -ve class is below 59% for all model

Considering fscores of +ve & -ve class the best model is BoW Brure Force
More complicated model can be tried to improve the performance