04_Amazon_Food_Reviews_NaiveBayes

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 Naive Bayes Algorithm

```
<li><strong>Apply Multinomial NaiveBayes 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
    </ul>
```

```
</li>
<br>
<li><strong>The hyper paramter tuning(find best Alpha)</strong>
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicour
<li>Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001</li
<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>Feature importance</strong>
    <ul>
<li>Find the top 10 features of positive class and top 10 features of negative class for both fe
    </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 Import Required Packages

4 Applying Multinomial Naive Bayes

In [1]:
```
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
from sklearn.naive_bayes import MultinomialNB

# 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
```

5 UTIL functions

5.1 Data Preprocessing Related Functions

In [2]:
```
def preprocess_data(config_dict, scaling=True, dim_reduction=False):
    """
```

```python
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 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)

    # get list of hyper parameters
    hyperparam_list = config_dict['hyperparam_list']

    stratified_partition = StratifiedKFold(n_splits=5)

    hyper_param_scores_list = list()

    # do for each hyper parameter
    for alpha_val in hyperparam_list:

        # declare three lists for holding prediction informations

        # for train set performance
        train_actual_labels_list = list()
```

```python
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
mnb_classifier = MultinomialNB(alpha=alpha_val)
# Declare a calibrated classifer
calib_classifier = CalibratedClassifierCV(base_estimator=mnb_classifier, method=
                                          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
    mnb_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 = mnb_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 = mnb_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
            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((alpha_val, 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 Log Alpha vs AUC score plot')
        plt.plot(np.log10(hyp_value_list), tr_auc_list, label='Train AUC')
        plt.plot(np.log10(hyp_value_list), val_auc_list, label='Validation AUC')
        plt.xlabel('Log Alpha Values')
        plt.ylabel('AUC Scores')
        plt.title('Log Alpha 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
        hyperparam_list = config_dict['hyperparam_list']

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

        # Final Model defined here
        mnb_classifier = MultinomialNB(alpha=best_hyper_param)
        calib_classifier = CalibratedClassifierCV(base_estimator=mnb_classifier, method='iso

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

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

```
In [8]: def evaluate_model(model, features, labels, tag_name):
            """
            This function test and evaluate the performance on unseen data.
            """
            mnb_classifier, calib_classifier = model

            # estimate the training metrics on (train fold)
            eval_y_probs = calib_classifier.predict_proba(features)[:, 1]
            eval_y_value = mnb_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 [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[0].alpha), 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
```

6 Note

Since the features are count based / frequency based, we need to use Multinomial NaiveBayes Algorithm

6.1 [A] Applying Naive Bayes 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' : 70000,
    'test_size' : 30000,
    'hyperparam_list' : [0.00001, 0.0001, 0.001, 0.01, 0.1, 1.0, 10, 100]
}
```

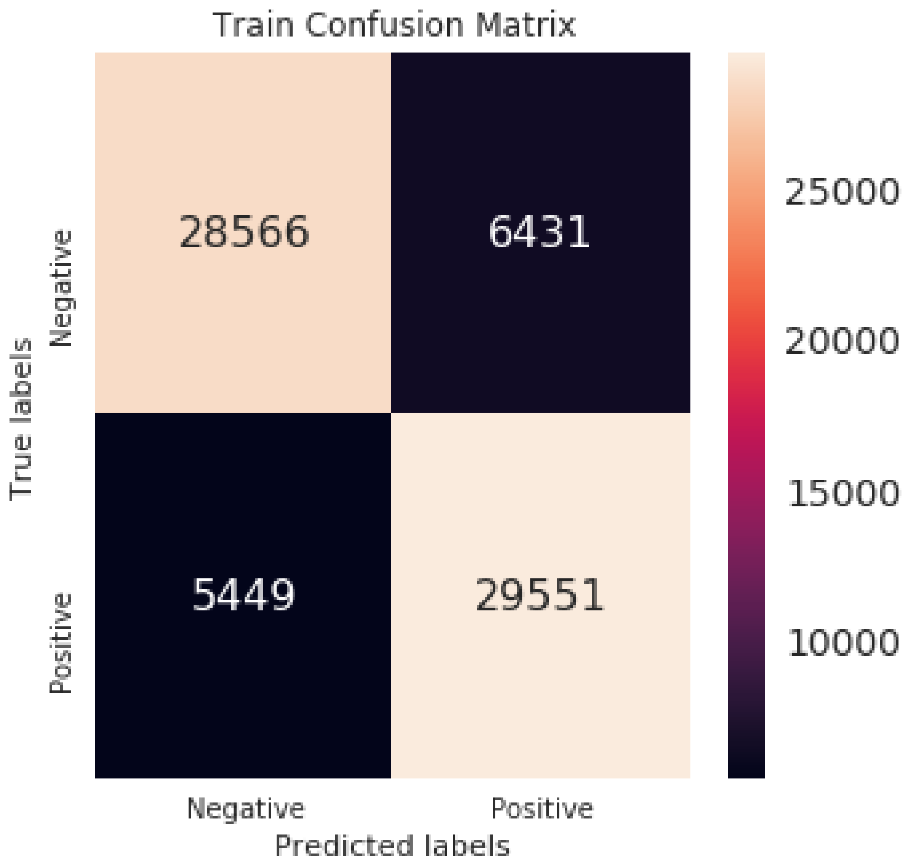
In [11]:
```
# read the train, test data and preprocess it
train_features, train_labels, test_features, test_labels = preprocess_data(config_dict,
                                                                           scaling=Fals
                                                                           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
==================================================================================================


 The Log Alpha vs AUC score plot
```

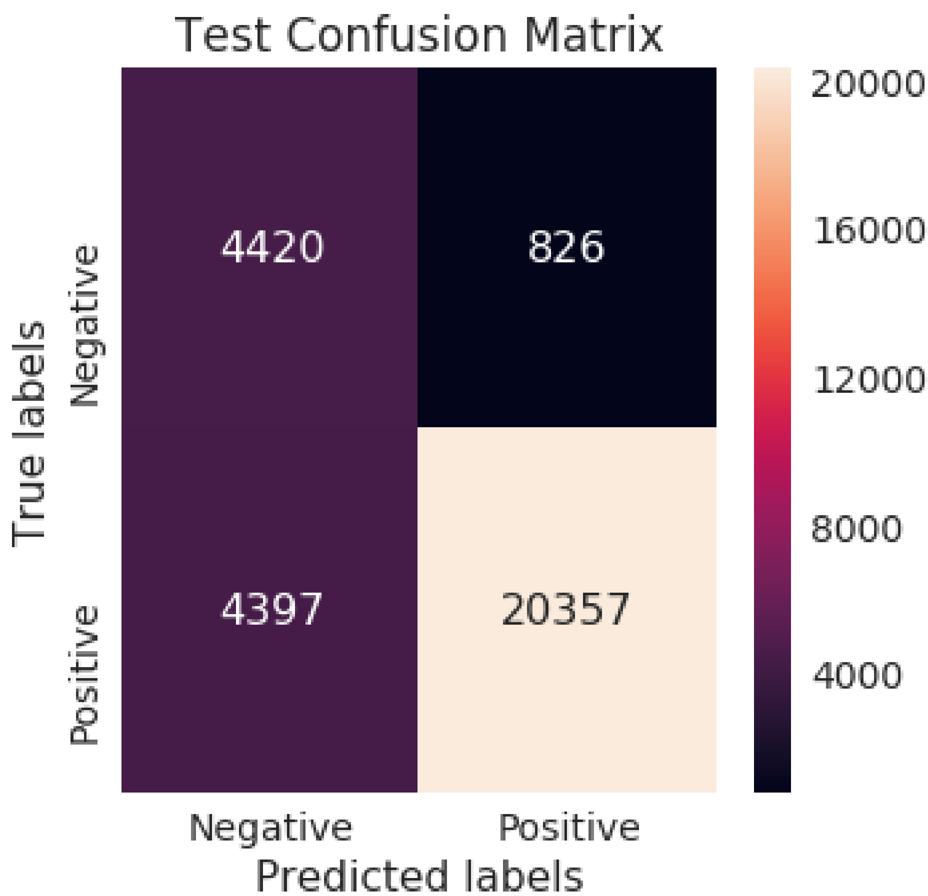
```
Best hyperparam value:  1e-05
```

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



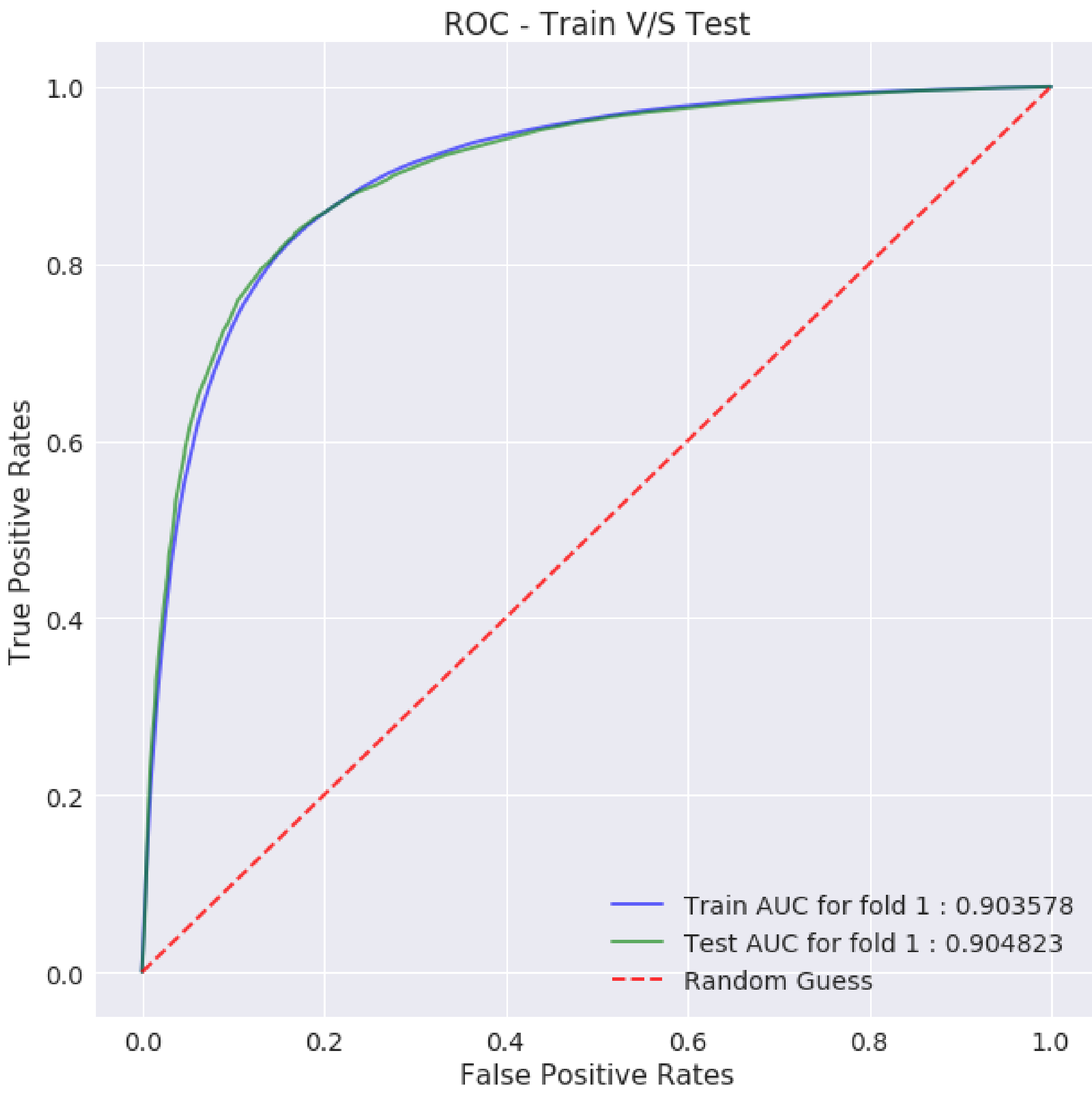

```
Train Evaluation Metrics :
                 Negative       Positive
Precision       0.839806       0.821272
Recall          0.816241       0.844314
Fscore          0.827856       0.832634
Support     34997.000000   35000.000000
```

```
/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	0.501304	0.961006
Recall	0.842547	0.822372
Fscore	0.628600	0.886301
Support	5246.000000	24754.000000




```
Results Summary:
 [('Hyper Param', '1e-05'), ('AUC', '0.9048'), ('f-score(-ve)', '62.8600'), ('f-score(+ve)', '88
```

The model is performing well on positve class as the fscore for +ve class is 88%
The model is not performing well on negative class as the fscore for -ve class is 62%
The ROC curves of train, test are overlapping well

In [12]:
```
# word cloud object for displaying feature importances
wc = WordCloud(background_color='white', width=800, height=800)

# form a feature importance data frame
feat_imp_df = pd.DataFrame({'Feature' : feature_name_list,
```

```
                                    'Importance (+ve)' : model[0].feature_log_prob_[1],
                                    'Importance (-ve)' : model[0].feature_log_prob_[0]},
                                    index=range(len(feature_name_list)))
feat_imp_df.head()
```

Out[12]:

	Feature	Importance (+ve)	Importance (-ve)
0	abl	-7.538247	-8.015246
1	absolut	-7.610099	-8.005688
2	acid	-8.271333	-8.017650
3	actual	-7.199098	-6.982801
4	ad	-7.086040	-7.262110

6.1.1 [A.1] Top 10 important features of positive class from SET 1

In [13]:

```
# annotate with feature names (words)
feat_imp_df_positive =  feat_imp_df[['Feature', 'Importance (+ve)']]
feat_imp_df_positive = feat_imp_df_positive.sort_values(['Importance (+ve)'],
                                                        ascending=False)

# create word cloud
abs_values = abs(feat_imp_df_positive['Importance (+ve)'])
imp_weights = max(abs_values) - abs_values
wc_output = wc.generate_from_frequencies(dict(zip(feat_imp_df_positive['Feature'],
                                                  imp_weights)))
plt.figure(figsize=(8, 8))
plt.imshow(wc_output)
plt.axis('off')
plt.tight_layout(pad=0.0)
plt.title('Important Features of +ve Class')
plt.show()
```

In [14]: # get top 10 important features for +ve class

```python
print('Top 10 important features for +ve class : \n')
feat_imp_df_positive.head(n=10)
```

Top 10 important features for +ve class :

Out[14]:

	Feature	Importance (+ve)
500	Review_Length	-0.519179
283	not	-4.244497
240	like	-4.991022
437	tast	-5.036223
185	good	-5.187882

```
165         flavor        -5.220926
250           love        -5.248881
188          great        -5.273904
468            use        -5.290568
303            one        -5.320925
```

6.1.2 [A.2] Top 10 important features of negative class from SET 1

In [15]:
```
# annotate with feature names (words)
feat_imp_df_negative =  feat_imp_df[['Feature', 'Importance (-ve)']]
feat_imp_df_negative = feat_imp_df_negative.sort_values(['Importance (-ve)'], ascending

# create word cloud
abs_values = abs(feat_imp_df_negative['Importance (-ve)'])
imp_weights = max(abs_values) - abs_values
wc_output = wc.generate_from_frequencies(dict(zip(feat_imp_df_negative['Feature'], imp_
plt.figure(figsize=(8, 8))
plt.imshow(wc_output)
plt.axis('off')
plt.tight_layout(pad=0.0)
plt.title('Important Features of -ve Class')
plt.show()
```


```
In [16]: # get top 10 important features for -ve class
         print('Top 10 important features for -ve class :\n')
         feat_imp_df_negative.head(n=10)
```

Top 10 important features for -ve class :

Out[16]:

	Feature	Importance (-ve)
500	Review_Length	-0.520892
283	not	-3.793111
437	tast	-4.754107
240	like	-4.839897
345	product	-5.001313

```
495          would     -5.175136
303            one     -5.277004
165         flavor     -5.329532
463            tri     -5.449927
472           veri     -5.479246
```

6.2 Observation

The word 'Review_Length' is found almost equally good in deciding label as + ve and -ve

The engineered feature 'review_length' is also helpful in deciding the clasess

Words like 'Review_Length', 'not', 'tast', 'like' are found in both +ve & -ve class

The word 'good' can be seen as a dominant feature in + ve class and 'product' as a dominat one in -ve class. These two words seems very useful in distinguishing between + ve , -ve class

6.3 [B] Applying Naive Bayes on TFIDF, SET 2

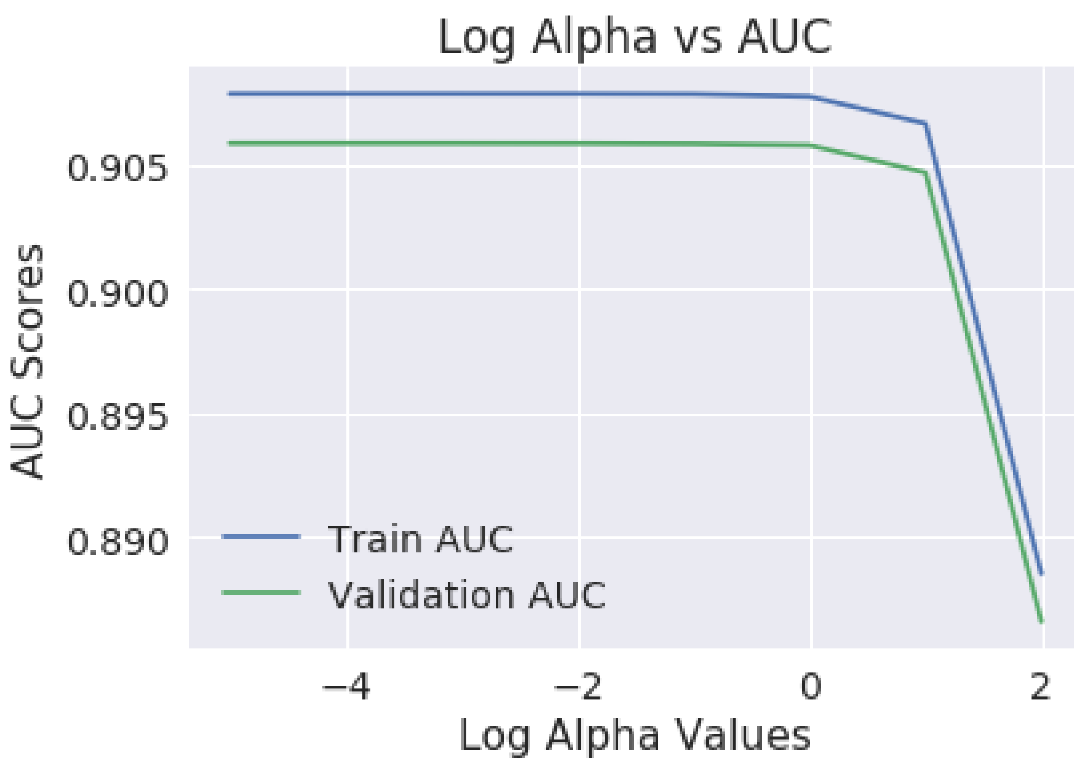
In [17]:
```
config_dict = {
    'train_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF/
    'test_csv_path' : '/home/amd_3/AAIC/ASM_REPO/Processed_data/AMZN_FOOD_REVIW/TFIDF/t
    'train_size' : 70000,
    'test_size' : 30000,
    'hyperparam_list' : [0.00001, 0.0001, 0.001, 0.01, 0.1, 1.0, 10, 100]
}
```

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


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

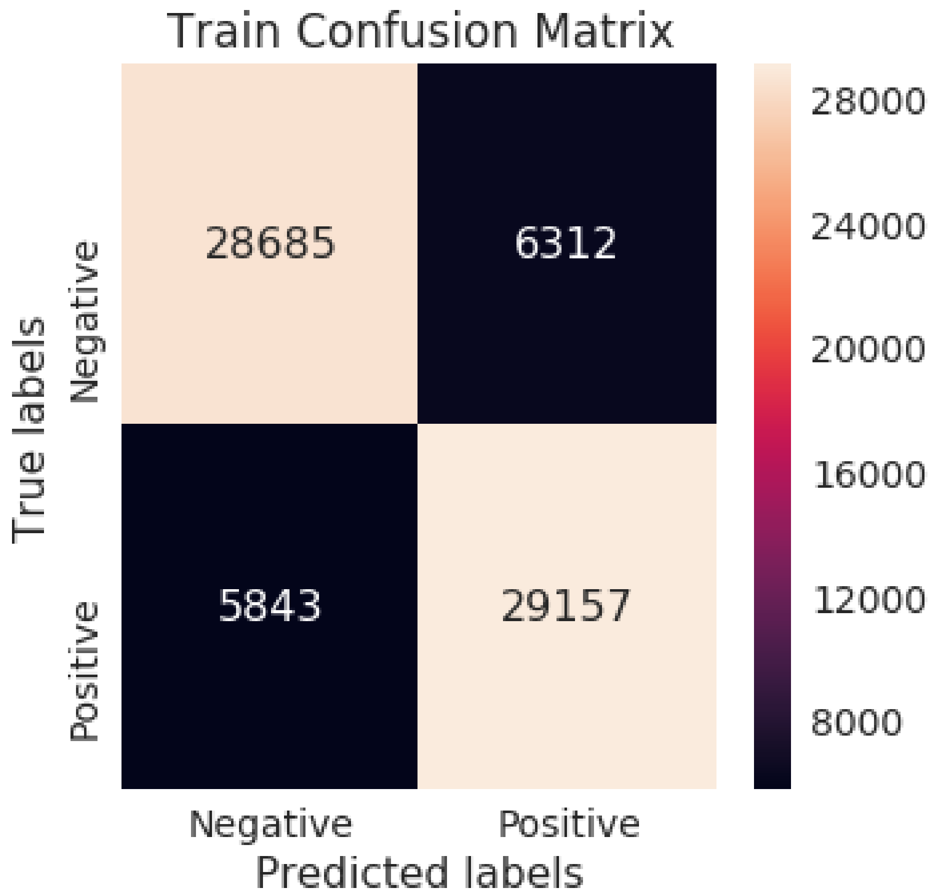
```
Train df shape (69997, 503)
Class label distribution in train df:
 1    35000
0    34997
Name: Label, dtype: int64
Test df shape (30000, 503)
Class label distribution in test df:
 1    24754
0     5246
Name: Label, dtype: int64
Shape of ->  train features :69997,501, test features: 30000,501
Shape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

```
 The Log Alpha vs AUC score plot
```



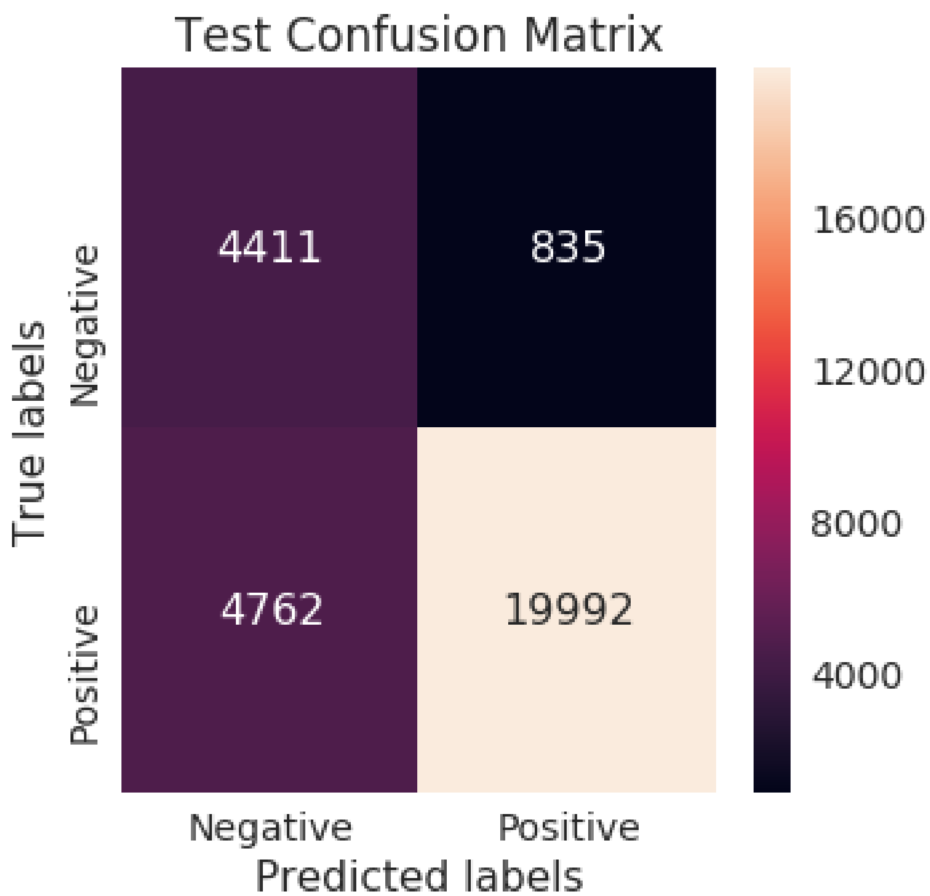
```
Best hyperparam value:  1e-05
```

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



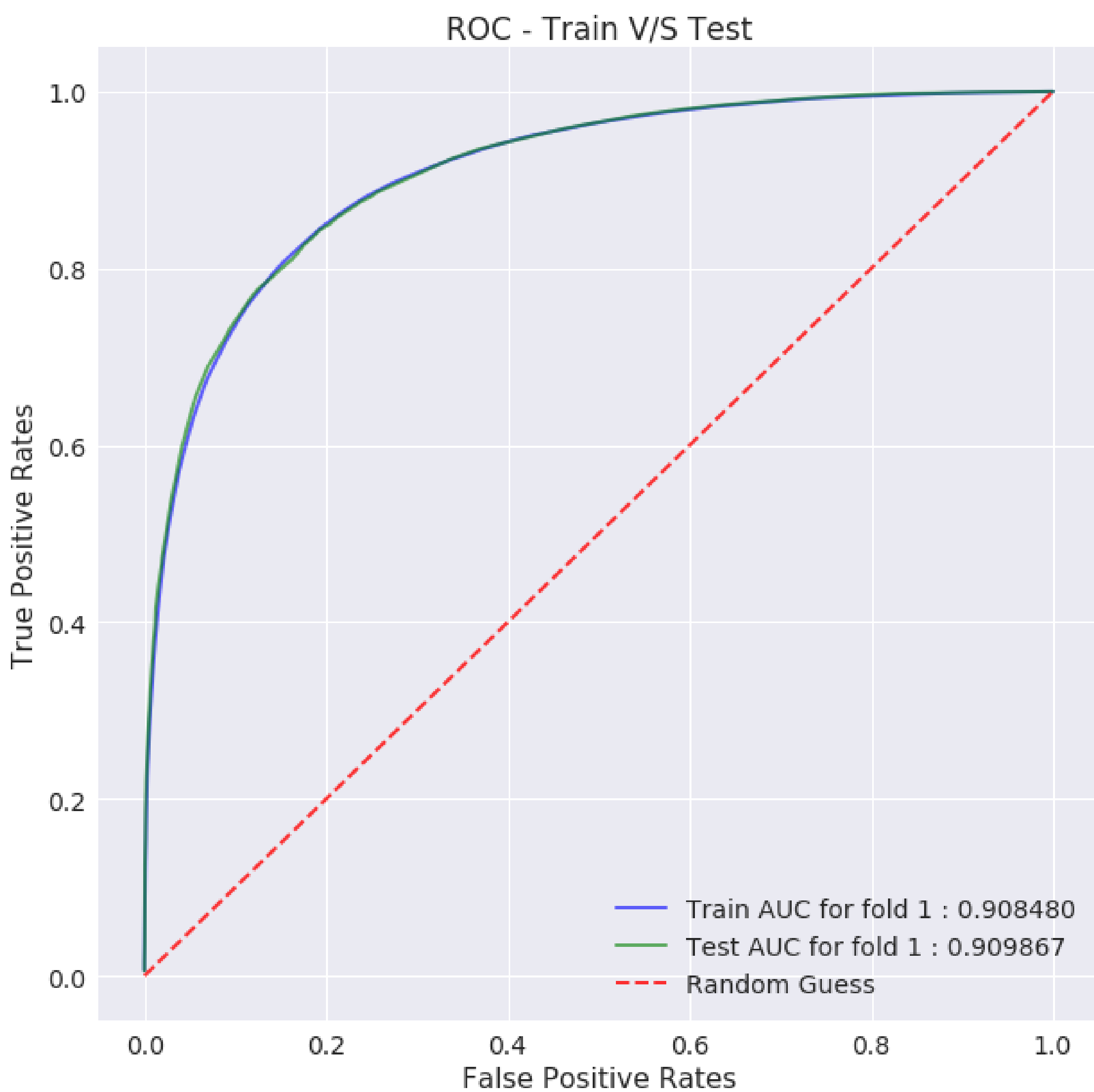

```
Train Evaluation Metrics :
                Negative      Positive
Precision      0.830775      0.822042
Recall         0.819642      0.833057
Fscore         0.825171      0.827513
Support    34997.000000  35000.000000
```

```
/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	0.480868	0.959908
Recall	0.840831	0.807627
Fscore	0.611832	0.877208
Support	5246.000000	24754.000000




```
Results Summary:
 [('Hyper Param', '1e-05'), ('AUC', '0.9099'), ('f-score(-ve)', '61.1832'), ('f-score(+ve)', '87
```

The train, test ROC curves are well overlapping

In [19]:
```
# word cloud object for displaying feature importances
wc = WordCloud(background_color='white', width=800, height=800)

# form a feature importance data frame
feat_imp_df = pd.DataFrame({'Feature' : feature_name_list,
                            'Importance (+ve)' : model[0].feature_log_prob_[1],
                            'Importance (-ve)' : model[0].feature_log_prob_[0]},
```

```
                            index=range(len(feature_name_list)))
feat_imp_df.head()
```

Out[19]:

	Feature	Importance (+ve)	Importance (-ve)
0	abl	-8.742422	-9.378704
1	absolut	-8.725371	-9.242838
2	acid	-9.630804	-9.518430
3	actual	-8.730117	-8.514691
4	ad	-8.582567	-8.817066

6.3.1 [B.1] Top 10 important features of positive class from SET 2

In [20]:
```
# annotate with feature names (words)
feat_imp_df_positive =  feat_imp_df[['Feature', 'Importance (+ve)']]
feat_imp_df_positive = feat_imp_df_positive.sort_values(['Importance (+ve)'], ascending

# create word cloud
abs_values = abs(feat_imp_df_positive['Importance (+ve)'])
imp_weights = max(abs_values) - abs_values
wc_output = wc.generate_from_frequencies(dict(zip(feat_imp_df_positive['Feature'],
                                                  imp_weights)))
plt.figure(figsize=(8, 8))
plt.imshow(wc_output)
plt.axis('off')
plt.tight_layout(pad=0.0)
plt.title('Important Features of +ve Class')
plt.show()
```

Important Features of +ve Class

In [21]:
```python
# get top 10 important features for +ve class
print('Top 10 important features for +ve class : \n')
feat_imp_df_positive.head(n=10)
```

Top 10 important features for +ve class :

Out[21]:

	Feature	Importance (+ve)
500	Review_Length	-0.096354
283	not	-6.677516
188	great	-6.812285
250	love	-6.826352
185	good	-6.958208

```
443            tea       -7.018903
437           tast       -7.023548
240           like       -7.029118
165         flavor       -7.053729
468            use       -7.094215
```

6.3.2 [B.2] Top 10 important features of negative class from SET 2

In [22]:
```python
# annotate with feature names (words)
feat_imp_df_negative =  feat_imp_df[['Feature', 'Importance (-ve)']]
feat_imp_df_negative = feat_imp_df_negative.sort_values(['Importance (-ve)'], ascending

# create word cloud
abs_values = abs(feat_imp_df_negative['Importance (-ve)'])
imp_weights = max(abs_values) - abs_values
wc_output = wc.generate_from_frequencies(dict(zip(feat_imp_df_negative['Feature'],
                                                  imp_weights)))
plt.figure(figsize=(8, 8))
plt.imshow(wc_output)
plt.axis('off')
plt.tight_layout(pad=0.0)
plt.title('Important Features of -ve Class')
plt.show()
```


```
In [23]: # get top 10 important features for -ve class
         print('Top 10 important features for -ve class :\n')
         feat_imp_df_negative.head(n=10)
```

Top 10 important features for -ve class :

Out[23]:

	Feature	Importance (-ve)
500	Review_Length	-0.090754
283	not	-6.171847
437	tast	-6.759895
240	like	-6.884143
345	product	-6.910533

```
495          would       -7.100481
165         flavor       -7.201804
303            one       -7.223312
88           coffe       -7.271277
472           veri       -7.294378
```

The words 'great', 'love', 'good' are found very useful in deciding + ve class
The words 'would', 'product' are found very useful in deciding - ve class
Words like 'Review_Length', 'not', 'tast', 'like' are found in both +ve & -ve class

7 Procedure Summary

Train the multinomial naive bayes algorithm with bow & tf-idf dataset
Fine tune the hyper parameter using cross validation method
Use calibration model to approximate the probaility as the NaiveBayes model doesn't provide true probability value
Choose the best (hyper parameter) alpha value based on the auc score
Train and evaluate the final model using the best hyper param we got
Identify the most important features for both + ve, -ve class and represent the important ones using the wordcloud

8 Results Summary

In [24]:
```python
Pret_table = PrettyTable()
Pret_table.field_names = ['Vectorizer', 'Hyper-Param (alpha)', 'AUC', 'Fscore (-ve)', '
Pret_table.title = 'Multinomial NaiveBayes Results Summary'
```

In [25]:
```python
# Brute Force
Pret_table.add_row(['BoW'] + ptabe_entry_a)
Pret_table.add_row(['TF-IDF'] + ptabe_entry_b)
```

In [26]:
```python
print(Pret_table)
```

```
+---------------------------------------------------------------------+
|                 Multinomial NaiveBayes Results Summary                |
+------------+---------------------+--------+--------------+--------------+
| Vectorizer | Hyper-Param (alpha) |  AUC   | Fscore (-ve) | Fscore (+ve) |
+------------+---------------------+--------+--------------+--------------+
|    BoW     |        1e-05        | 0.9048 |   62.8600    |   88.6301    |
|   TF-IDF   |        1e-05        | 0.9099 |   61.1832    |   87.7208    |
+------------+---------------------+--------+--------------+--------------+
```

9 Conclusions

The performance on +ve class is really good (above 87% f1-score)
The performance on -ve class is not really good as the f1-score is less than 63%

For this particular classification problem low alpha value showed good performance

Naive Bayes model being very simple and makes naive assumption about features may not give good results when features depends to some extend. Need to try more complex model to improve the results