In [1]:
```
#import warnings
#warnings.filterwarnings('ignore')

#sklearn models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, \
        GradientBoostingClassifier, StackingClassifier, BaggingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import LinearSVC, SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.neighbors import KNeighborsClassifier

#sklearn metrics
from sklearn.metrics import roc_curve, auc, average_precision_score, precision_recall_curve
#DOES NOT WORK: , plot_precision_recall_curve
from sklearn.metrics import fbeta_score, make_scorer
from sklearn.metrics import balanced_accuracy_score, precision_score, recall_score, f1_score, roc_auc_
score

#sklearn model selection
from sklearn.model_selection import cross_val_score, cross_validate, train_test_split, cross_val_predi
ct

#scikit-plot
from scikitplot.metrics import plot_precision_recall, plot_roc, plot_confusion_matrix
from scikitplot.estimators import plot_learning_curve

#mlxtend
from mlxtend.plotting import plot_learning_curves, plot_decision_regions


#hyperparameter tuning

#miscellaneous
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

#some "global" variables defined here
random_state_num = 0
cv_num = 10
classes_num = 2 #there are two classes, non-negative (0) and negative (1)
fig_size_tuple = (15,7)
title_fontsize_num = 15
label_fontsize_num = 12
```

Read Trained Word2Vec Embedding Vectors and Engineered Features

We read in the engineered features dataset as a dataframe.

In [2]:
```
#read the csv of engineered features
#then split the columns into
df_gensim_word2vec_features = pd.read_csv('..\data\gensim_word2vec_trained_with_engineered_features.cs
v')
X = df_gensim_word2vec_features.loc[:, df_gensim_word2vec_features.columns != 'binary_response_variabl
e']
Y= df_gensim_word2vec_features.loc[:, df_gensim_word2vec_features.columns == 'binary_response_variabl
e']
```

Split into Train and Test dataset

The dataset is then split into a train and test dataset.

In [3]:
```
#Split into training set, and test set
# we do not need a validation set because we will be doing k-fold cross validation

#split into 0.7 training, and 0.3 testing set
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state = random_state_n
um)

#convert Y_train and Y_test into 1-d array so we don't get stupid warnings about needing a 1d array fo
r Y, in cross_validate function
Y_train_1d = Y_train.values.ravel()
Y_test_1d = Y_test.values.ravel()

#convert Y_train and Y_test into numpy array
Y_train_np_array = Y_train.to_numpy()
Y_test_np_array = Y_test.to_numpy()
```

Models

Here we define a set of "basic" models we use as benchmarks to see which model algorithm is better than the others.

In [4]:
```
stacking_base_learners = [
    ('sbl_1', LogisticRegression(random_state = random_state_num, max_iter = 500, C=1, \
                                               class_weight={1: 0.4, 0: 0.6}, penalty='l1', solver='lib
linear', )),
    ('sbl_2', KNeighborsClassifier(n_neighbors=3, )),
    ('sbl_3', DecisionTreeClassifier()),
    ('sbl_4', GaussianNB())
]

models = [
# Hyperparameter tuned GBM model
#     GradientBoostingClassifier(random_state = random_state_num, min_samples_split=140, min_samples_l
eaf=14, \
#                               subsample=0.9, n_estimators=10, max_features='sqrt', max_depth=8, \
#                               loss='deviance', learning_rate=0.15000000000000002, criterion='friedm
an_mse')

    KNeighborsClassifier(n_neighbors=3, ),
    DecisionTreeClassifier(),
    SVC(C = 1000000, gamma = 'auto', kernel = 'rbf', probability=True),
    GaussianNB(),
    #increased max_iter because it failed to converge at 100
    LogisticRegression(random_state = random_state_num, max_iter = 500, C=1, class_weight={1: 0.4, 0:
0.6}, \
                       penalty='l1', solver='liblinear'),
    AdaBoostClassifier(random_state = random_state_num),
    RandomForestClassifier(random_state = random_state_num),
    GradientBoostingClassifier(random_state = random_state_num),
    BaggingClassifier(base_estimator=LogisticRegression(random_state = random_state_num, max_iter = 50
0, C=1, \
                                                        class_weight={1: 0.4, 0: 0.6}, penalty='l1', s
olver='liblinear')),
    StackingClassifier(estimators=stacking_base_learners, final_estimator=LogisticRegression())
]
```

Hyperparameter Tuning

Hyperparameter tuning is the adjustment of various pre-execution parameters passed to our Machine Learning models that affect their training/execution. Here we use two automated methods of choosing from a wide set of specified parameters - Grid Search (which exhaustively tries all combinations of specified parameters) and Random Search (which tries randomly sampled combinations of parameters).

Grid Search

Grid Search (exhaustive) hyperparameter tuning.

In [ ]:
```
%%script false --no-raise-error
# ^ disables this cell in jupyter notebook

from sklearn.model_selection import GridSearchCV

for model in models:
    model_name = model.__class__.__name__

    #----Logistic Regression Hyperparameter Tuning----

    if model_name == 'LogisticRegression':

        penalty = ['l1', 'l2']
        C = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
        class_weight = [{1:0.5, 0:0.5}, {1:0.4, 0:0.6}, {1:0.6, 0:0.4}, {1:0.7, 0:0.3}]
        solver = ['liblinear', 'saga']

        param_grid = dict(penalty=penalty,
                          C=C,
                          class_weight=class_weight,
                          solver=solver)

        grid = GridSearchCV(estimator=model,
                            param_grid=param_grid,
                            scoring='roc_auc',
                            verbose=1,
                            n_jobs=-1)
        grid_result = grid.fit(X_train, Y_train)
        print('Model Name: ', model_name)
        print('Best Score: ', grid_result.best_score_)
        print('Best Params: ', grid_result.best_params_)

        #----Gradient Boosting Hyperparameter Tuning----

    if model_name == 'GradientBoostingClassifier':

        learning_rate = [0.15,0.1,0.05,0.01,0.005,0.001]
        n_estimators = [100,250,500,750,1000,1250,1500,1750]
        max_depth = [2,3,4,5,6,7]

        param_grid = dict(learning_rate=learning_rate,
                          n_estimators=n_estimators,
                          max_depth=max_depth,)

        grid = GridSearchCV(estimator=model,
                            param_grid=param_grid,
                            scoring='roc_auc',
                            verbose=1,
                            n_jobs=-1)
        grid_result = grid.fit(X_train, Y_train)
        print('Model Name: ', model_name)
        print('Best Score: ', grid_result.best_score_)
        print('Best Params: ', grid_result.best_params_)
```

Random Search

Random Search hyperparameter tuning.

In [ ]:
```
%%script false --no-raise-error
# ^ disables this cell in jupyter notebook

#exploration of specifying a range of values using numpy's logspace function.
#Used to specify range of C values in logistic regression.

import numpy as np

np.set_printoptions(precision=10)
np.set_printoptions(suppress=True)

np.logspace(0, 4, num=10)
```

In [ ]:

```
%%script false --no-raise-error
# ^ disables this cell in jupyter notebook

from sklearn.model_selection import RandomizedSearchCV

for model in models:
    model_name = model.__class__.__name__

    print(model)
    if model_name == 'LogisticRegression':

        penalty = ['l1', 'l2']
        C = np.logspace(0, 4, num=10)
        class_weight = [{1:0.5, 0:0.5}, {1:0.4, 0:0.6}, {1:0.6, 0:0.4}, {1:0.7, 0:0.3}]
        solver = ['liblinear', 'saga']

        param_distributions = dict(penalty=penalty,
                                   C=C,
                                   class_weight=class_weight,
                                   solver=solver)

        random = RandomizedSearchCV(estimator=model,
                                    param_distributions=param_distributions,
                                    scoring='roc_auc',
                                    verbose=1, n_jobs=-1,
                                    n_iter=100)
        random_result = random.fit(X_train, Y_train)

        print('Model Name: ', model_name)
        print('Best Score: ', random_result.best_score_)
        print('Best Params: ', random_result.best_params_)

    if model_name == 'GradientBoostingClassifier':

        loss=["deviance"]
        learning_rate=np.linspace(0.05, 0.2, num=4)
        max_depth=[3,5,8]
        max_features=["log2","sqrt"]
        criterion=["friedman_mse",  "mae"]
        subsample=[0.5, 0.618, 0.8, 0.85, 0.9, 0.95, 1.0]
        n_estimators=[10]

        param_distributions = dict(loss=loss,
                                   learning_rate=learning_rate,
                                #  min_samples_split=min_samples_split,
                                #  min_samples_leaf=min_samples_leaf,
                                   max_depth=max_depth,
                                   max_features=max_features,
                                   criterion=criterion,
                                   subsample=subsample,
                                   n_estimators=n_estimators)

        random = RandomizedSearchCV(estimator=model,
                                    param_distributions=param_distributions,
                                    cv=3,
                                    scoring='roc_auc',
                                    verbose=1,
                                    n_jobs=-1,
                                    n_iter=100)
        random_result = random.fit(X_train, Y_train)

        print('Model Name: ', model_name)
        print('Best Score: ', random_result.best_score_)
        print('Best Params: ', random_result.best_params_)
```

Model Benchmarks using various metrics

Here we use different metrics to becnhmark the models we have defined above. Such metrics include balanced accuracy, precision, recall, F1, F2, and ROC-AUC.

F2 is different than F1 because it places heavier emphasis on recall, rather than precision. This is useful in our case because according to our business problem, there is more value to be gained from correctly identifying tweets of negative sentiment (i.e. the positive cases, or "1s"). Therefore, the opposite holds true as well: there is a heavier cost from misclassifying tweets of negative sentiment as positive sentiment (i.e. we misclassify true positives as false negatives); in real life, this could mean a potential PR disaster. On the other hand, misclassifying tweets of positive sentiment as negative sentiment isn't as costly (i.e. we misclassify true negatives as false positives); in real life, this just means the HR department may have to look at more false positives than a ML algorithm that places equal emphasis on both precision and recall.

In [5]:

```
#custom f2 score
#this places higher value on recall than precision
#i.e. a false negative has higher cost than a false positive
#(this makes sense: a negative tweet we don't catch classify us more than a positive tweet we don't cl
assify)
f2_scorer = make_scorer(fbeta_score, beta=2)

#for the other scorers, we need to create scorers from scratch since we want to use a dictionary for f
2_scorer under 'scoring'
balanced_accuracy_scorer = make_scorer(balanced_accuracy_score)
precision_scorer = make_scorer(precision_score)
recall_scorer = make_scorer(recall_score)
f1_scorer = make_scorer(f1_score)
roc_auc_scorer = make_scorer(roc_auc_score)
```

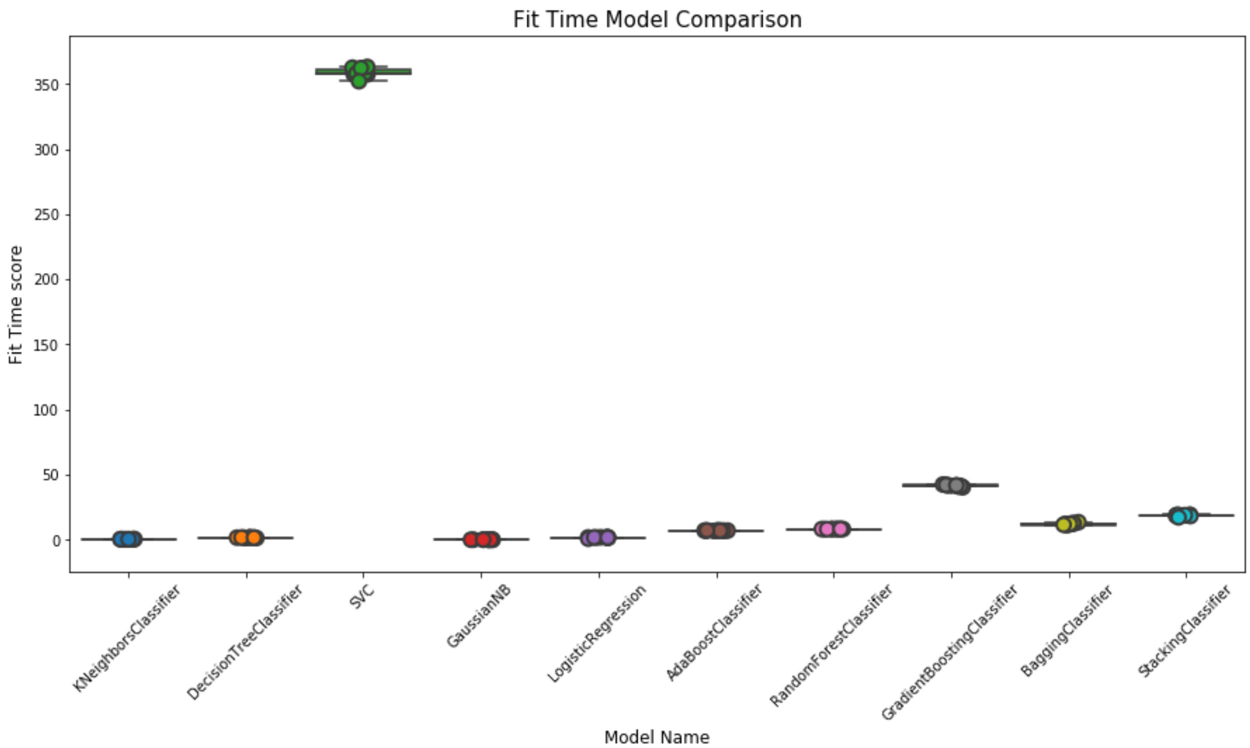
In [6]:
```
cv_result_entries = []

for model in models:
    model_name = model.__class__.__name__


    metrics_dict = cross_validate(
        model,
        X_train,
        Y_train_1d,
        #scoring = ['balanced_accuracy', 'precision', 'recall', 'f1', 'roc_auc'],
        scoring = {
            'balanced_accuracy': balanced_accuracy_scorer,
            'precision': precision_scorer,
            'recall': recall_scorer,
            'f1': f1_scorer,
            'f2': f2_scorer,
            'roc_auc': roc_auc_scorer
        },
        cv = cv_num,
        n_jobs=-1
    )

#REMOVED grid search hyperparam tuning code
#     penalty = ['l1', 'l2']
#     C = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
#     class_weight = [{1:0.5, 0:0.5}, {1:0.4, 0:0.6}, {1:0.6, 0:0.4}, {1:0.7, 0:0.3}]
#     solver = ['liblinear', 'saga']

#     param_grid = dict(penalty=penalty,
#                       C=C,
#                       class_weight=class_weight,
#                       solver=solver)

#     grid = GridSearchCV(estimator=model,
#                         param_grid=param_grid,
#                         scoring='roc_auc',
#                         verbose=1,
#                         n_jobs=-1)
#     grid_result = grid.fit(X_train, Y_train)

#     print('Best Score: ', grid_result.best_score_)
#     print('Best Params: ', grid_result.best_params_)

    for metric_key in metrics_dict.keys():
        for fold_index, metric_score in enumerate(metrics_dict[metric_key]):
            cv_result_entries.append((model_name, fold_index, metric_key, metric_score))

#convert entries into a dataframe
df_cross_validate_results = pd.DataFrame(cv_result_entries, columns =['model_name', 'fold_index', 'met
ric_key', 'metric_score'])
```

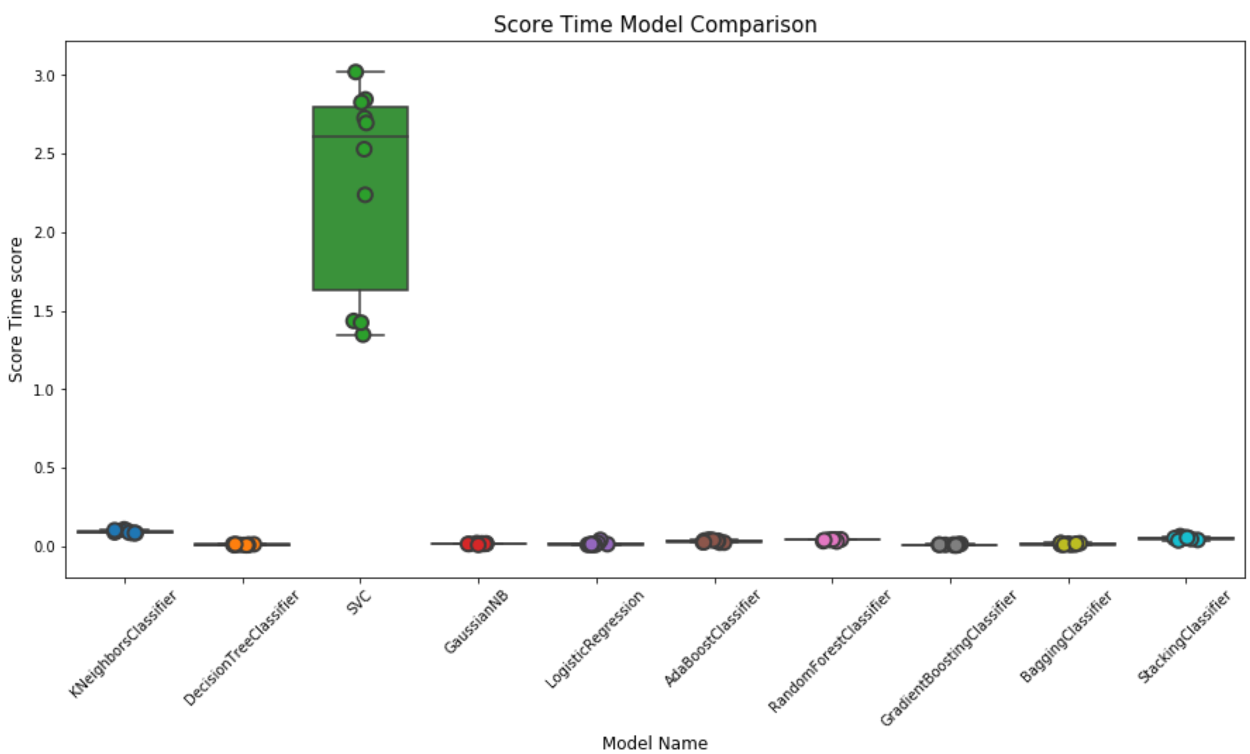
In [7]:
```
#save all results to CSV for reference
df_cross_validate_results.to_csv('df_cross_validate_results.csv')
```

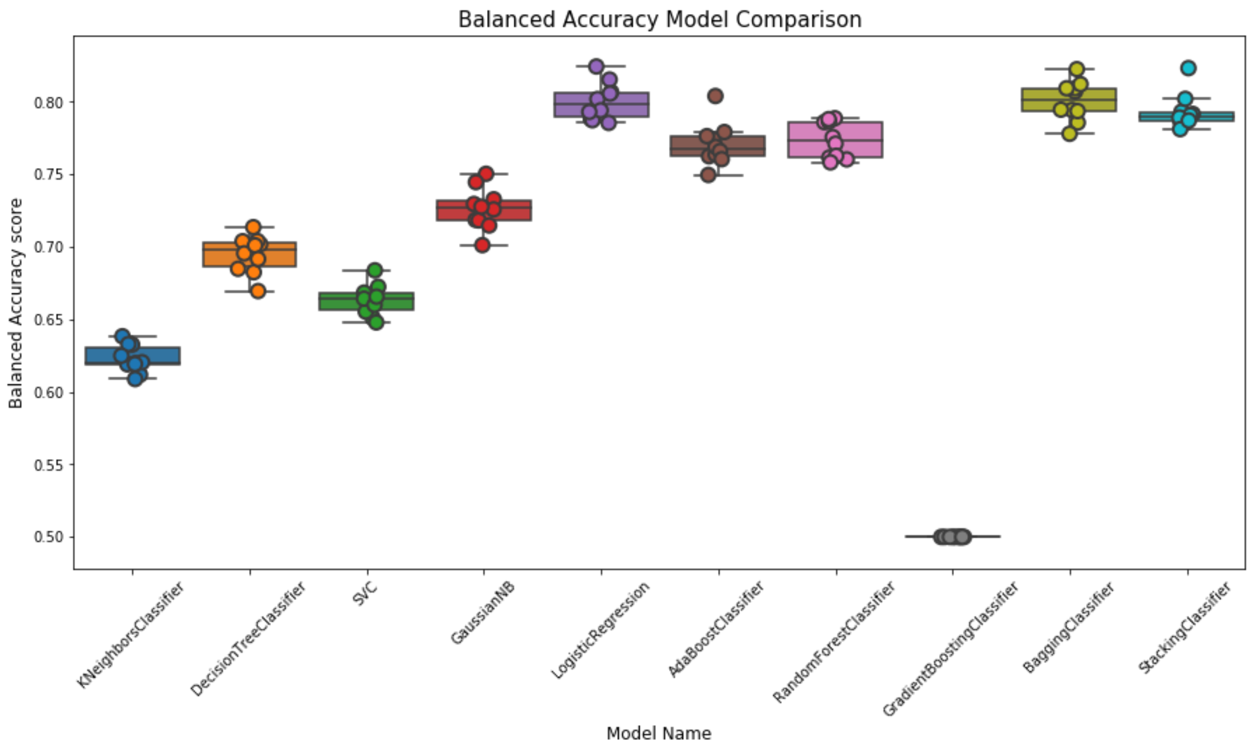
Plotting

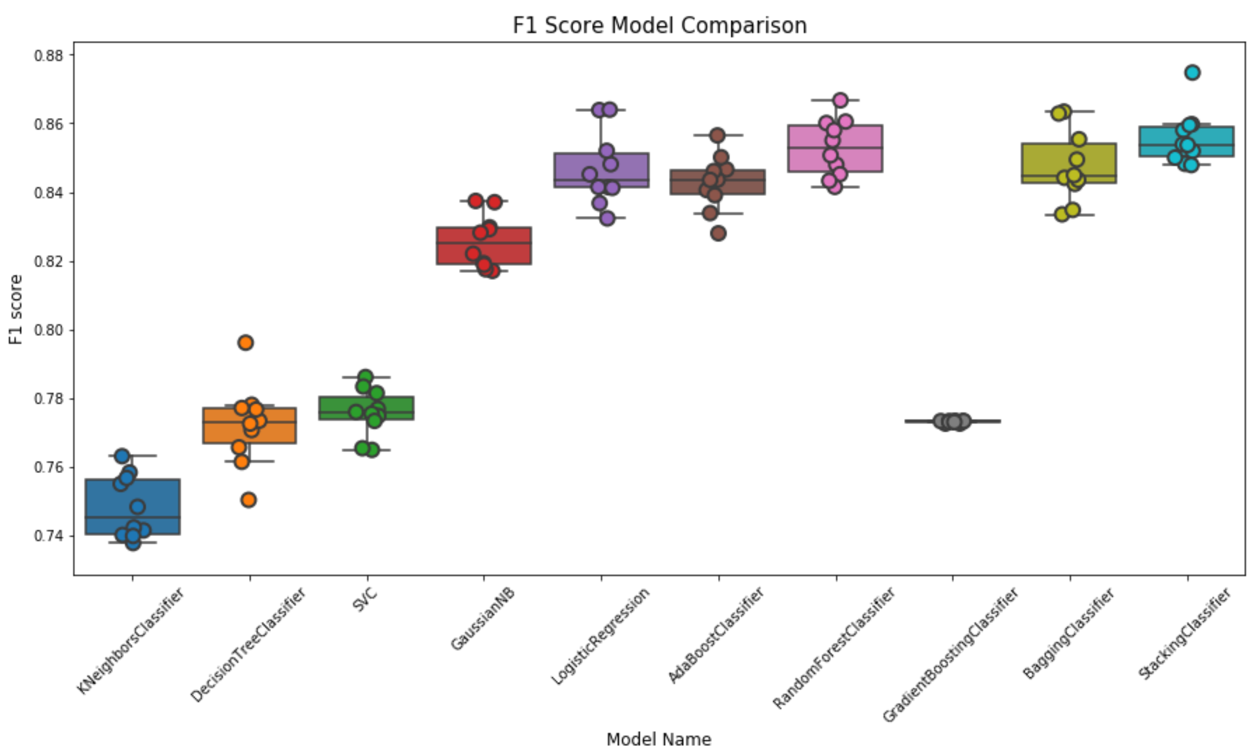
In [8]:
```
df_cv_results_fit_time = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'fit_ti
me']
df_cv_results_score_time = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'scor
e_time']
df_cv_results_balanced_acc = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'te
st_balanced_accuracy']
df_cv_results_precision = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'test_
precision']
df_cv_results_recall = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'test_rec
all']
df_cv_results_f1 = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'test_f1']
df_cv_results_f2 = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'test_f2']
df_cv_results_roc_auc = df_cross_validate_results.loc[df_cross_validate_results.metric_key == 'test_ro
c_auc']


plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_fit_time)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_fit_time, size=10, linewidth=2)
plt.title('Fit Time Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('Fit Time score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_score_time)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_score_time, size=10, linewidth=2)
plt.title('Score Time Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('Score Time score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_balanced_acc)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_balanced_acc, size=10, linewidth=
2)
plt.title('Balanced Accuracy Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('Balanced Accuracy score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_f1)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_f1, size=10, linewidth=2)
plt.title('F1 Score Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('F1 score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_f2)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_f2, size=10, linewidth=2)
plt.title('F2 Score Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('F2 score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_precision)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_precision, size=10, linewidth=2)
plt.title('Precision Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('Precision score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()
```

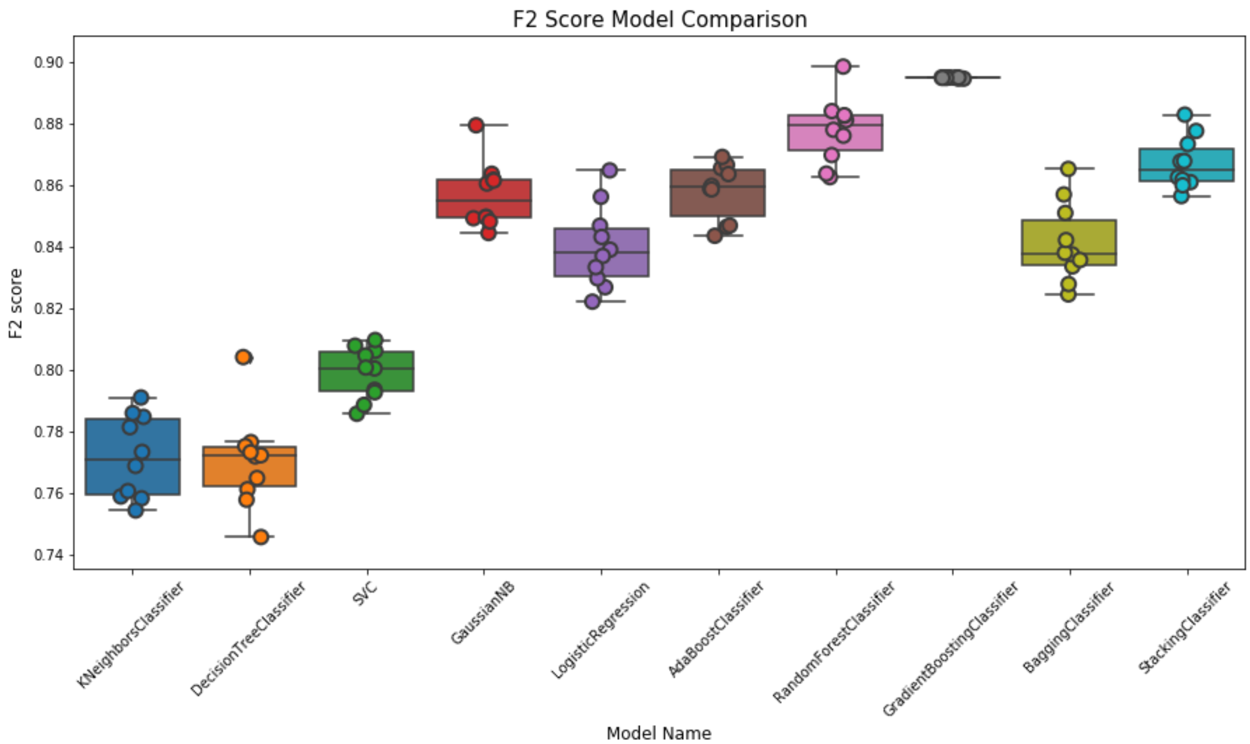
```
plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_recall)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_recall, size=10, linewidth=2)
plt.title('Recall Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('Recall score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=fig_size_tuple)
sns.boxplot(x='model_name', y='metric_score', data = df_cv_results_roc_auc)
sns.stripplot(x='model_name', y='metric_score', data = df_cv_results_roc_auc, size=10, linewidth=2)
plt.title('ROC-AUC Score Model Comparison', fontsize=title_fontsize_num)
plt.xlabel('Model Name', fontsize=label_fontsize_num)
plt.ylabel('ROC-AUC score', fontsize=label_fontsize_num)
plt.xticks(rotation=45)
plt.show()
```

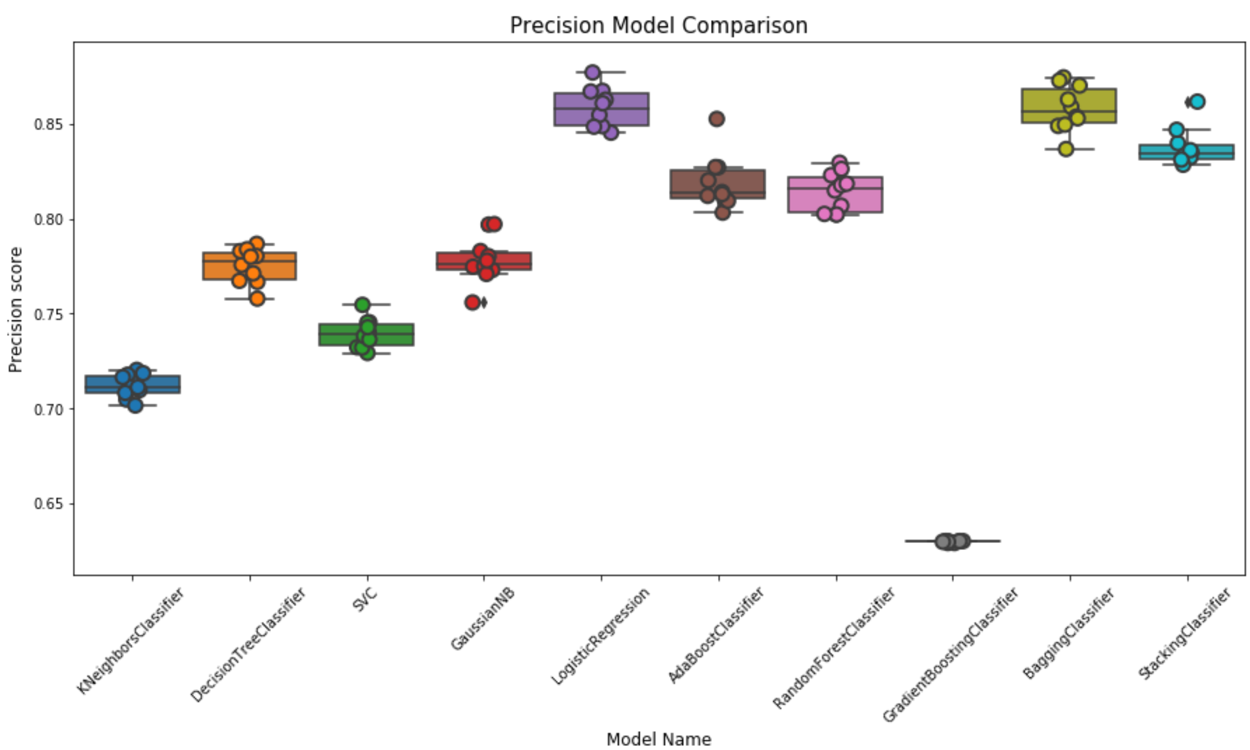

Fit Time Model Comparison
Fit Time score
350
300
250
200
150
100
50
0
KNeighborsClassifier
DecisionTreeClassifier
SVC
GaussianNB
LogisticRegression
AdaBoostClassifier
RandomForestClassifier
GradientBoostingClassifier
BaggingClassifier
StackingClassifier
Model Name

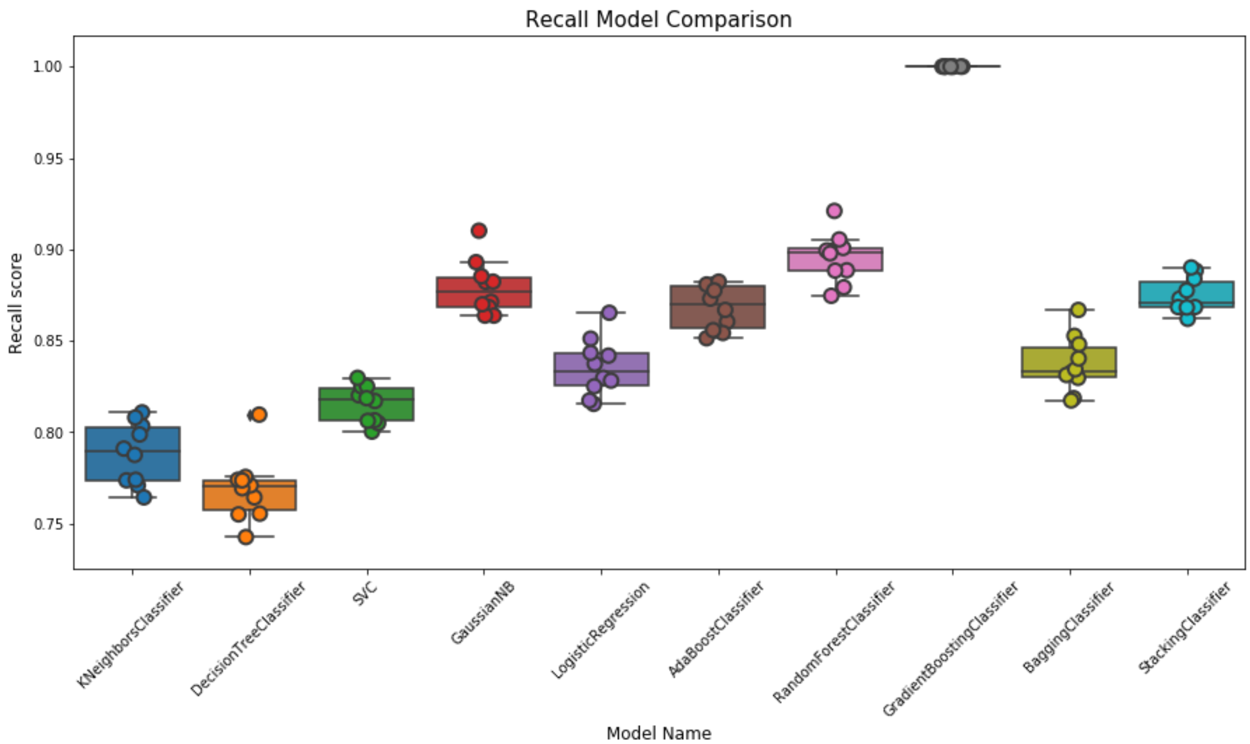

Score Time Model Comparison
Score Time score
3.0
2.5
2.0
1.5
1.0
0.5
0.0
KNeighborsClassifier
DecisionTreeClassifier
SVC
GaussianNB
LogisticRegression
AdaBoostClassifier
RandomForestClassifier
GradientBoostingClassifier
BaggingClassifier
StackingClassifier
Model Name

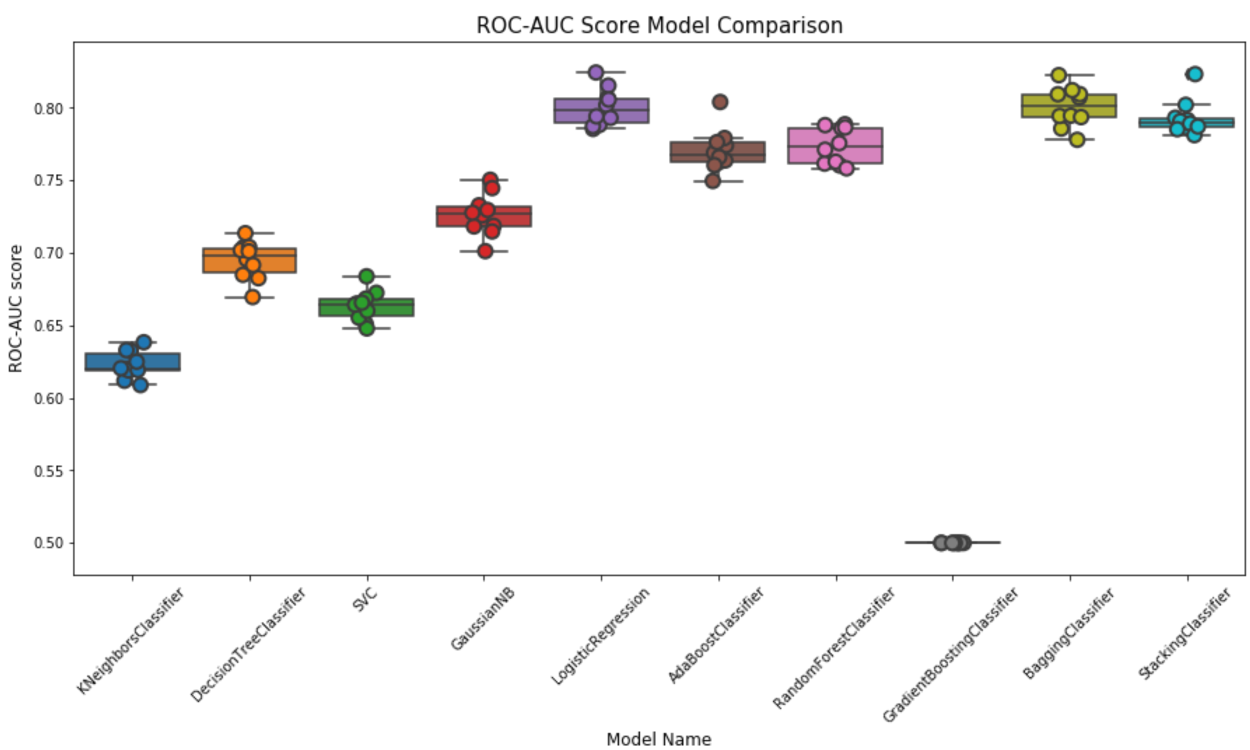

Balanced Accuracy Model Comparison
Balanced Accuracy score
0.80
0.75
0.70
0.65
0.60
0.55
0.50
KNeighborsClassifier
DecisionTreeClassifier
SVC
GaussianNB
LogisticRegression
AdaBoostClassifier
RandomForestClassifier
GradientBoostingClassifier
BaggingClassifier
StackingClassifier
Model Name


F1 Score Model Comparison
F1 score
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
KNeighborsClassifier
DecisionTreeClassifier
SVC
GaussianNB
LogisticRegression
AdaBoostClassifier
RandomForestClassifier
GradientBoostingClassifier
BaggingClassifier
StackingClassifier
Model Name


F2 Score Model Comparison
F2 score
0.90
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
KNeighborsClassifier
DecisionTreeClassifier
SVC
GaussianNB
LogisticRegression
AdaBoostClassifier
RandomForestClassifier
GradientBoostingClassifier
BaggingClassifier
StackingClassifier
Model Name


Precision Model Comparison
Precision score
0.85
0.80
0.75
0.70
0.65
KNeighborsClassifier
DecisionTreeClassifier
SVC
GaussianNB
LogisticRegression
AdaBoostClassifier
RandomForestClassifier
GradientBoostingClassifier
BaggingClassifier
StackingClassifier
Model Name





Receiver Operating Characteristic (ROC) Curves ,Precision-Recall Curves, Learning Curves, and Confusion Matrices

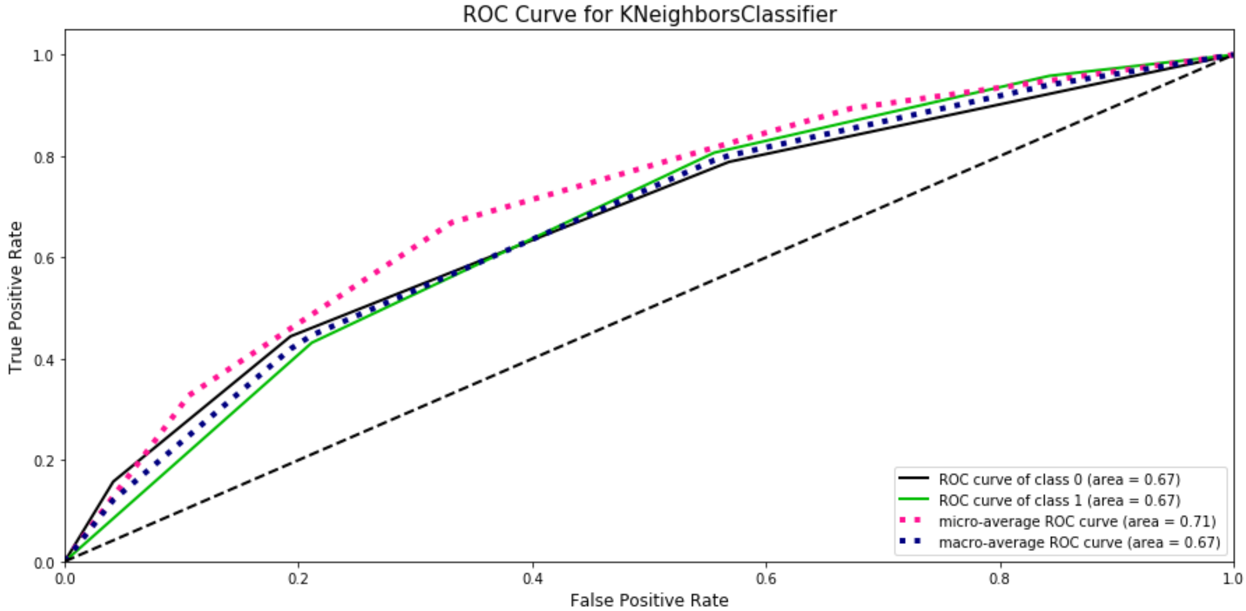
Below are generated ROC curves for the basic models, trained using training data (with 5-fold Cross Validation), and tested with testing data. The ROC curves for both training and testing data are generated onto the same plot for each model.

Also generated are Precision-Recall curves for the basic models as well. Similarly, the Precision-Recall curves for both training and testing data are generated onto the same plot for each model.

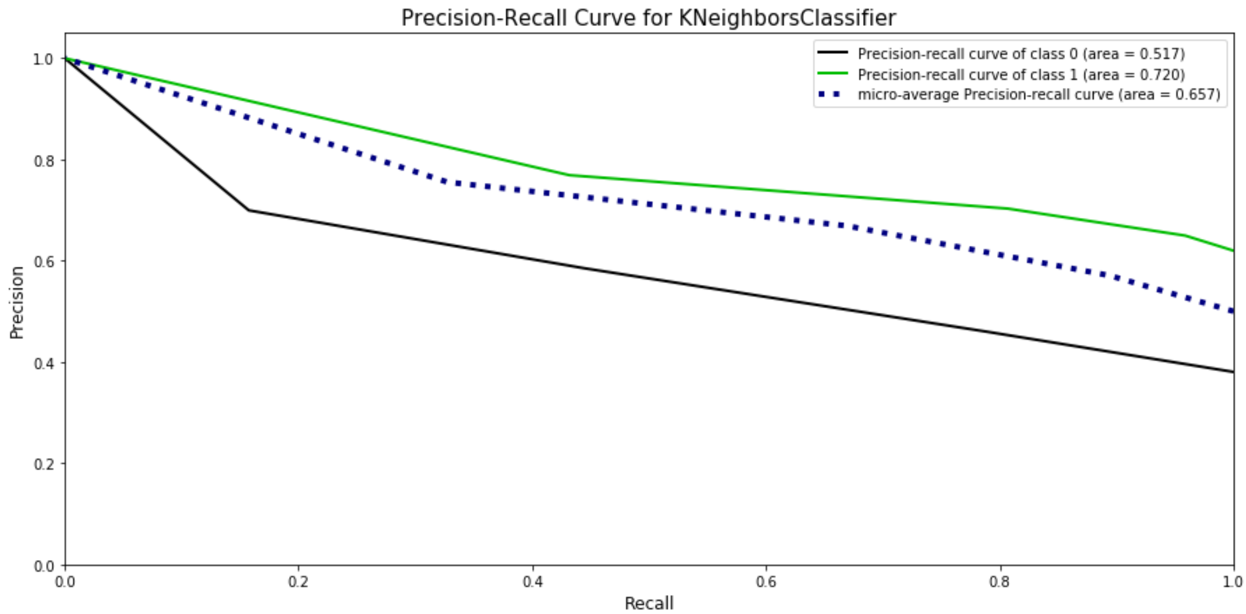
In [9]:
```
#predictions_entries = []

for model in models:
    model_name = model.__class__.__name__

    Y_train_predictions = cross_val_predict(
        model,
        X_train,
        Y_train_1d,
        cv = cv_num,
        method = 'predict_proba',
        n_jobs=-1
    )

    trained_model = model.fit(X_train, Y_train_1d)
    Y_test_predictions = trained_model.predict_proba(X_test)
    Y_test_binary_predictions = trained_model.predict(X_test)

    #ROC
    #train
    # Compute ROC curve and ROC area for each class
    fpr_train = dict()
    tpr_train = dict()
    roc_auc_train = dict()

    for i in range(classes_num):
        fpr_train[i], tpr_train[i], _ = roc_curve(Y_train_np_array[:, 0], Y_train_predictions[:, i])
        roc_auc_train[i] = auc(fpr_train[i], tpr_train[i])

    # Compute micro-average ROC curve and ROC area
    #we only need to provide probability estaimates of the positive class (i.e. Y_train_predictions[:,
1])
    fpr_train["micro"], tpr_train["micro"], _ = roc_curve(Y_train_np_array.ravel(), Y_train_prediction
s[:, 1].ravel())
    roc_auc_train["micro"] = auc(fpr_train["micro"], tpr_train["micro"])

    #test
    # Compute ROC curve and ROC area for each class
    fpr_test = dict()
    tpr_test = dict()
    roc_auc_test = dict()

    for i in range(classes_num):
        fpr_test[i], tpr_test[i], _ = roc_curve(Y_test_np_array[:, 0], Y_test_predictions[:, i])
        roc_auc_test[i] = auc(fpr_test[i], tpr_test[i])

    # Compute micro-average ROC curve and ROC area
    #we only need to provide probability estaimates of the positive class (i.e. Y_train_predictions[:,
1])
    fpr_test["micro"], tpr_test["micro"], _ = roc_curve(Y_test_np_array.ravel(), Y_test_predictions[:,
1].ravel())
    roc_auc_test["micro"] = auc(fpr_test["micro"], tpr_test["micro"])

    #plot roc curve
    #this manually plots roc curve train vs. test
    #line_weight_num = 2.5

    #plt.figure(figsize=fig_size_tuple)
    #plt.plot(fpr_test[1], tpr_test[1], color='red',
    #         lw = line_weight_num, label='ROC curve - Test (area = %0.3f)' % roc_auc_test[1])
    #plt.plot(fpr_train[1], tpr_train[1], color='darkorange',
    #         lw = line_weight_num, label='ROC curve - Train (area = %0.3f)' % roc_auc_train[1])
    #plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    #plt.xlim([0.0, 1.0])
    #plt.ylim([0.0, 1.05])
    #plt.xlabel('False Positive Rate', fontsize=label_fontsize_num)
    #plt.ylabel('True Positive Rate', fontsize=label_fontsize_num)
    #plt.title('Receiver operating characteristic for ' + model_name, fontsize=title_fontsize_num)
    #plt.legend(loc="lower right")
    #plt.show()
```

```
    #uses scikit-plot instead of plotting manually
    plot_roc(Y_test, Y_test_predictions,
            figsize=fig_size_tuple, title_fontsize=title_fontsize_num, text_fontsize=10, title='ROC Cu
rve for ' + model_name)
    plt.xlabel('False Positive Rate', fontsize=label_fontsize_num)
    plt.ylabel('True Positive Rate', fontsize=label_fontsize_num)
    plt.show()


    #Precision-Recall
    #average precision-recall score
    average_precision_train = average_precision_score(Y_train, Y_train_predictions[:, 1])
    average_precision_test = average_precision_score(Y_test, Y_test_predictions[:, 1])

    #rint('Average train precision-recall score: {0:0.3f}'.format(average_precision_train))
    #rint('Average test precision-recall score: {0:0.3f}'.format(average_precision_test))

    #calculate precision recall curve
    precision_train = {}
    precision_test = {}
    recall_train = {}
    recall_test = {}

    precision_train, recall_train, _ = precision_recall_curve(Y_train_np_array.ravel(), Y_train_predic
tions[:, 1].ravel())
    precision_test, recall_test, _ = precision_recall_curve(Y_test_np_array.ravel(), Y_test_prediction
s[:, 1].ravel())

    #plot preciision-recall curve
    #this manually plots precision-recall curve train vs. test
    #plt.figure(figsize=fig_size_tuple)
    #plt.step(recall_train, precision_train, where='post', color='darkblue',
    #         label='Precision-Recall Curve - Train (score = %0.3f)' % average_precision_train)
    #plt.step(recall_test, precision_test, where='post', color='lightblue',
    #         label='Precision-Recall Curve - Test (score = %0.3f)' % average_precision_test)
    #plt.xlabel('Recall', fontsize=label_fontsize_num)
    #plt.ylabel('Precision', fontsize=label_fontsize_num)
    #plt.ylim([0.0, 1.05])
    #plt.xlim([0.0, 1.0])
    #plt.title(
    #    'Precision-Recall Curve for' + model_name, fontsize=title_fontsize_num)
    #plt.legend(loc="lower right")
    #plt.show()

    #this plots a shitty precision recall curve that can't really be modified visually
    #so don't use it unless if you have to
    #disp = plot_precision_recall_curve(model, X_test, Y_test)
    #disp.ax_.set_title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision_test))

    #uses scikit-plot instead of plotting manually
    plot_precision_recall(Y_test, Y_test_predictions,
                          figsize=fig_size_tuple, title_fontsize=title_fontsize_num, text_fontsize=10,
title='Precision-Recall Curve for ' + model_name)
    plt.xlabel('Recall', fontsize=label_fontsize_num)
    plt.ylabel('Precision', fontsize=label_fontsize_num)
    plt.show()

    #plot learning curve
    #this one uses scikitplot to plot a usable learning curve
    #unfortunately we can't really choose a misclassification error for the scoring, so we use F2 inst
ead...not ideal but oh well
    #plot_learning_curve(model, X_test, Y_test_1d, cv = cv_num, random_state = random_state_num,
    #                     scoring = f2_scorer,
    #                     figsize=fig_size_tuple, title_fontsize=title_fontsize_num, text_fontsize=10,
 title='Learning Curve for ' + model_name)
    #plt.show()

    #this one uses mlxtend to plot a better learning curve
    #this is better because it offers misclassification error for the scoring, so more useful
    plt.figure(figsize=fig_size_tuple)
    plot_learning_curves(X_train, Y_train_1d, X_test, Y_test_1d, model)
    plt.title('Learning Curve for ' + model_name, fontsize=title_fontsize_num)
```

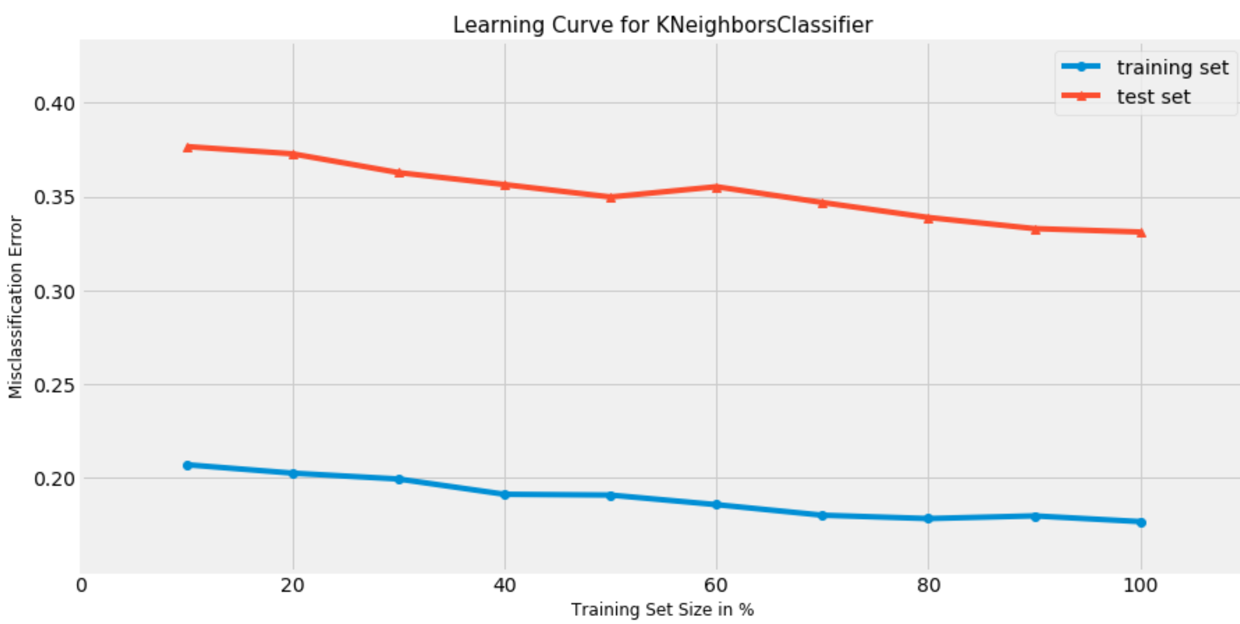
```
    plt.xlabel('Training Set Size in %', fontsize=label_fontsize_num)
    plt.ylabel('Misclassification Error', fontsize=label_fontsize_num)
    plt.show()


    #confusion matrices
    plot_confusion_matrix(Y_test, Y_test_binary_predictions,
                         figsize=fig_size_tuple, title_fontsize=title_fontsize_num, text_fontsize=10,
title='Confusion Matrix for ' + model_name)
    plt.xlabel('Predicted Label', fontsize=label_fontsize_num)
    plt.ylabel('True Label', fontsize=label_fontsize_num)
    plt.show()


    #decision regions
    #not needed at this time, we need to reduce dimensions somehow in order to use decision trees in a
useful manner
```



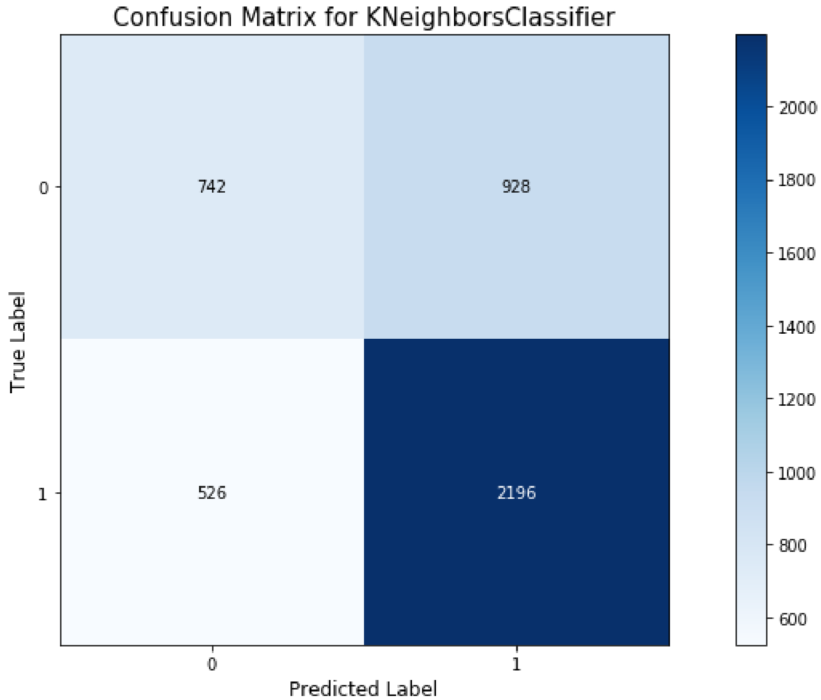
ROC Curve for KNeighborsClassifier
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.67)
ROC curve of class 1 (area = 0.67)
micro-average ROC curve (area = 0.71)
macro-average ROC curve (area = 0.67)



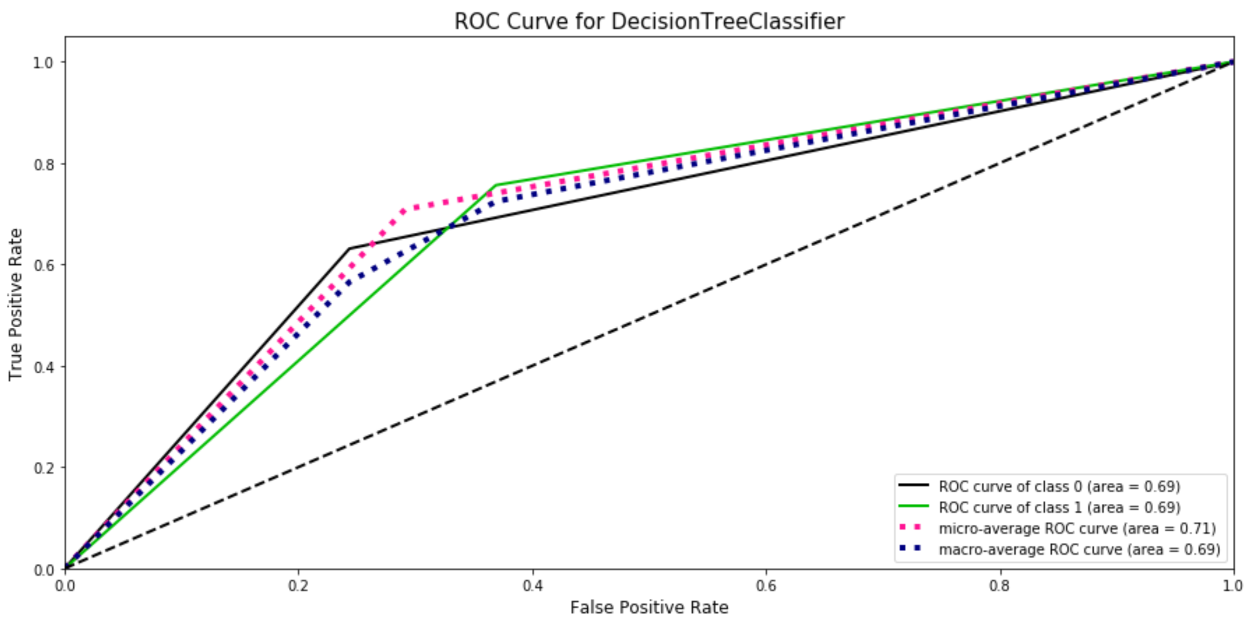
Precision-Recall Curve for KNeighborsClassifier
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 0 (area = 0.517)
Precision-recall curve of class 1 (area = 0.720)
micro-average Precision-recall curve (area = 0.657)



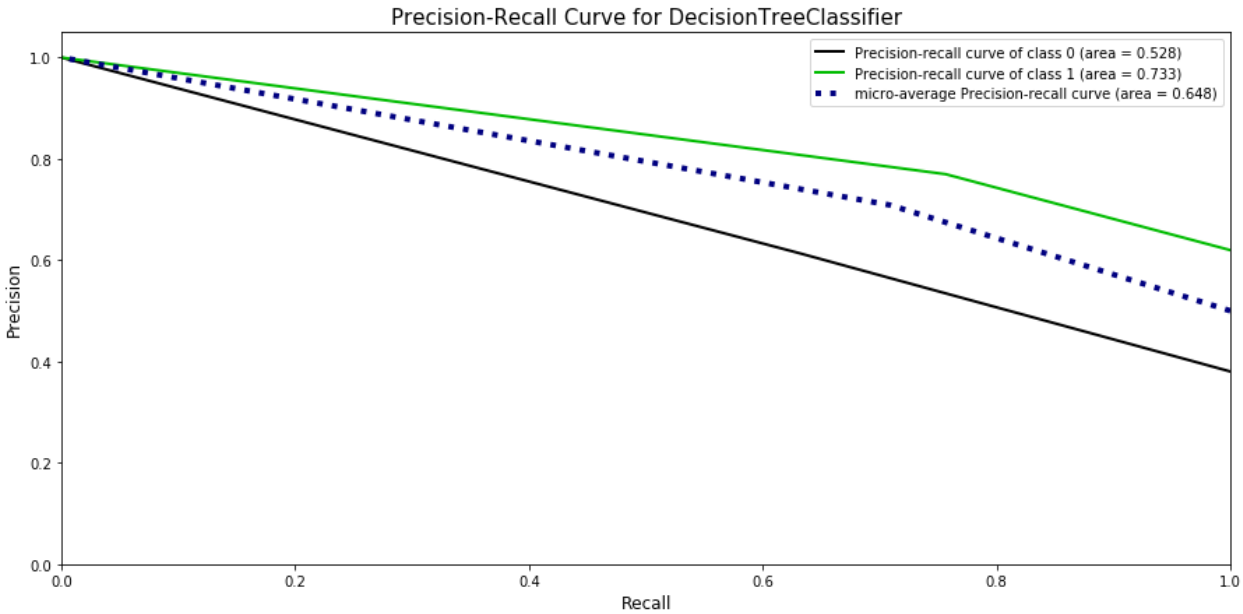
Learning Curve for KNeighborsClassifier
Misclassification Error
Training Set Size in %
0.20
0.25
0.30
0.35
0.40
0
20
40
60
80
100
training set
test set



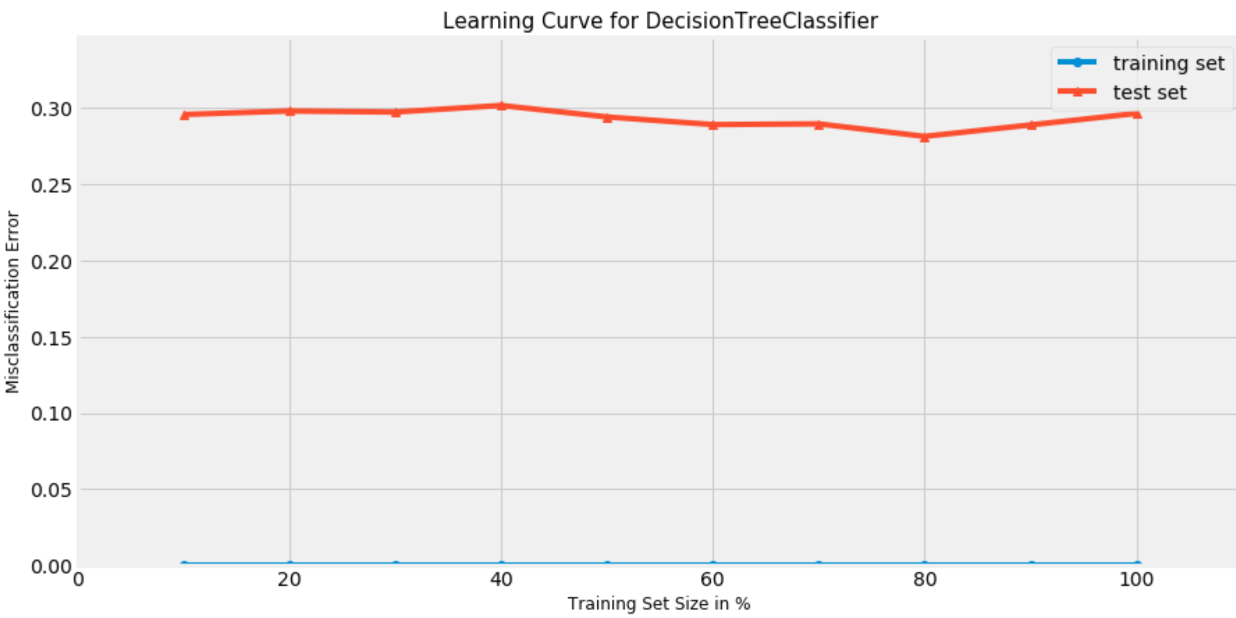
Confusion Matrix for KNeighborsClassifier
742
928
526
2196
True Label
Predicted Label
0
1
2000
1800
1600
1400
1200
1000
800
600



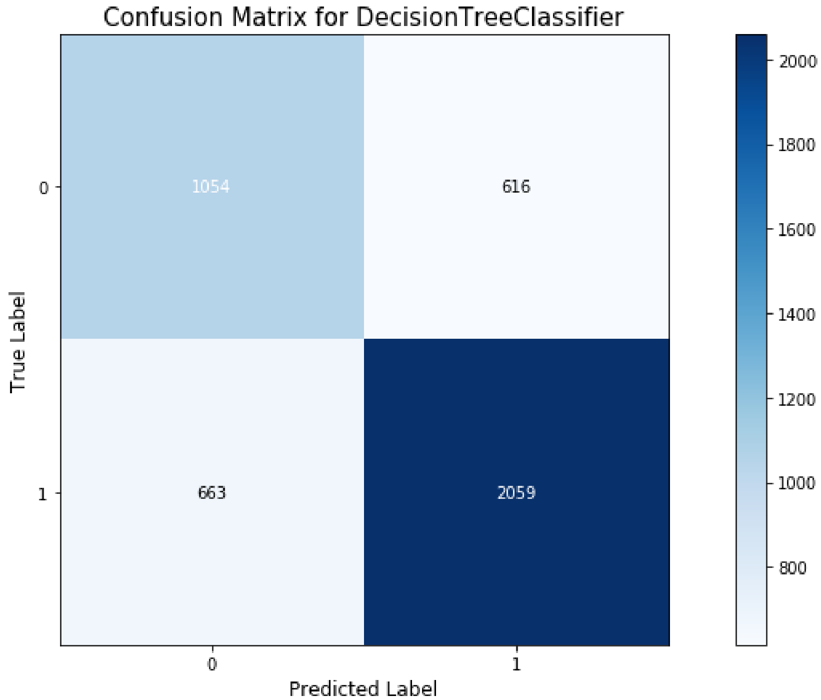
ROC Curve for DecisionTreeClassifier
True Positive Rate
False Positive Rate
ROC curve of class 0 (area = 0.69)
ROC curve of class 1 (area = 0.69)
micro-average ROC curve (area = 0.71)
macro-average ROC curve (area = 0.69)

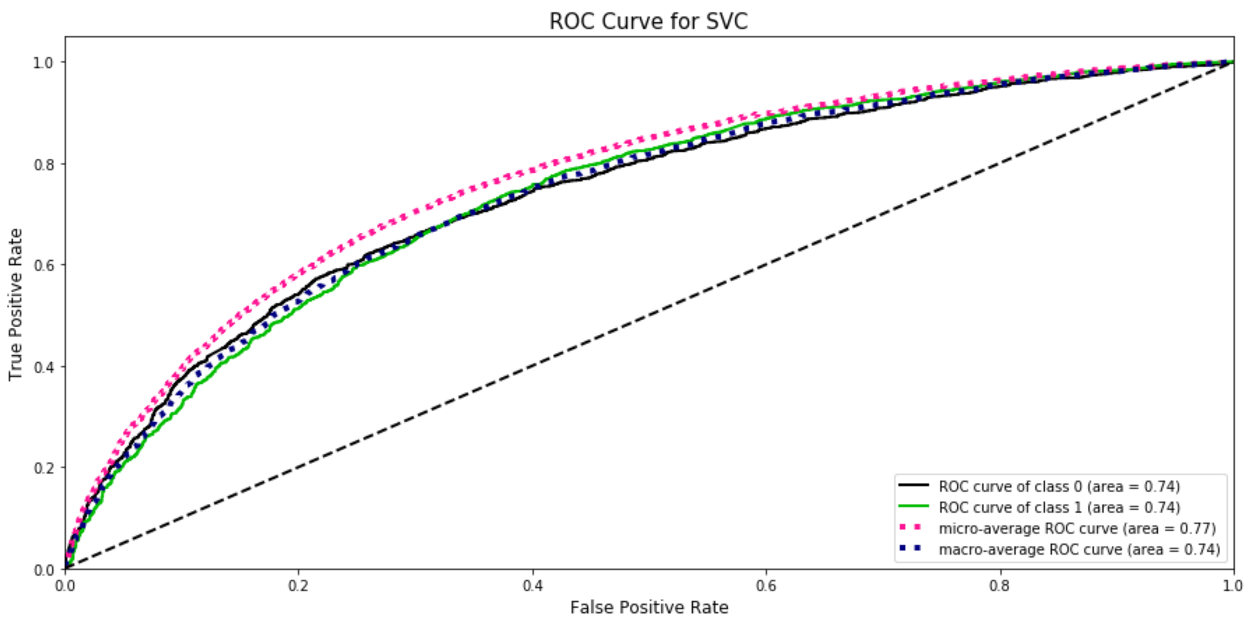


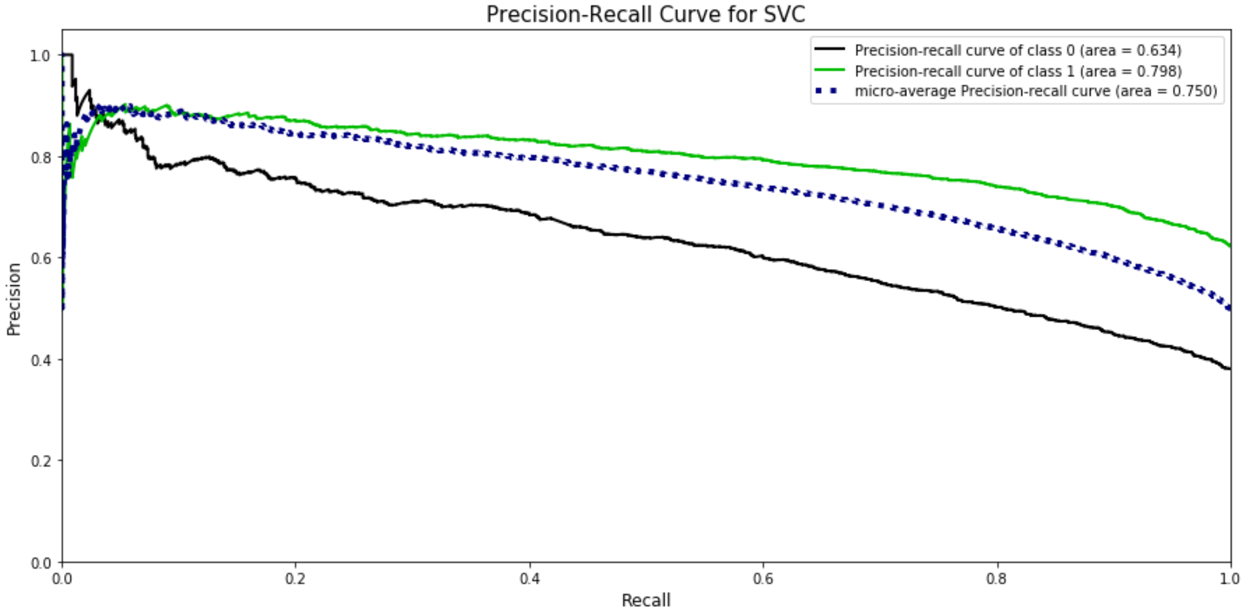
Precision-Recall Curve for DecisionTreeClassifier
Precision-recall curve of class 0 (area = 0.528)
Precision-recall curve of class 1 (area = 0.733)
micro-average Precision-recall curve (area = 0.648)
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

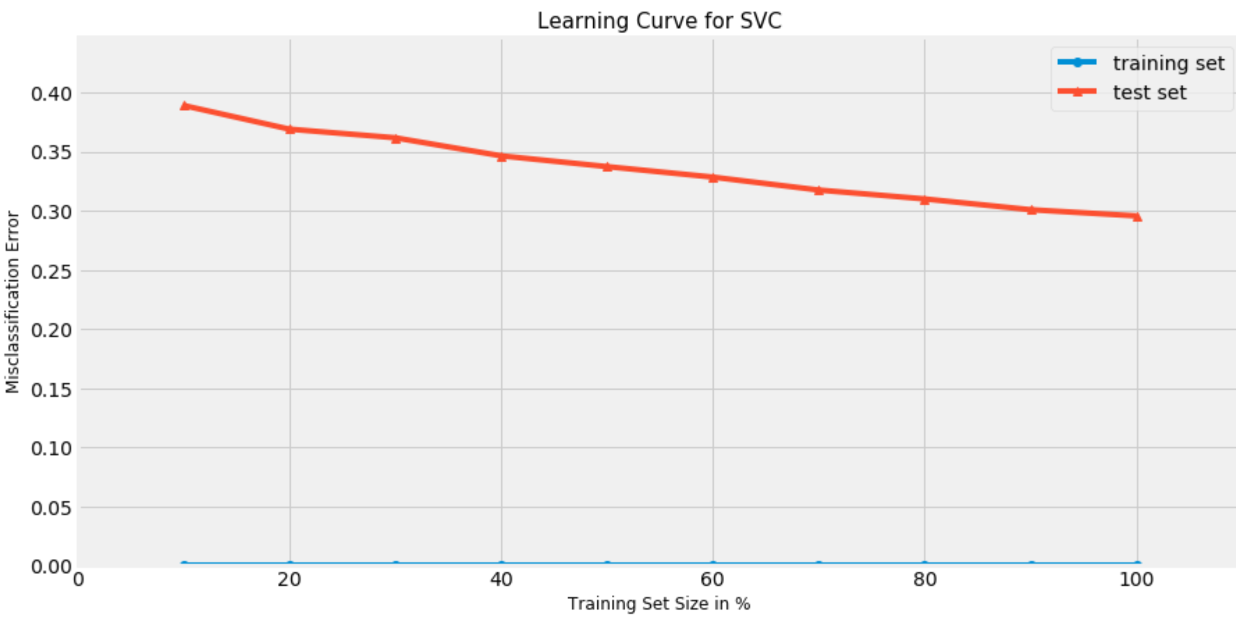


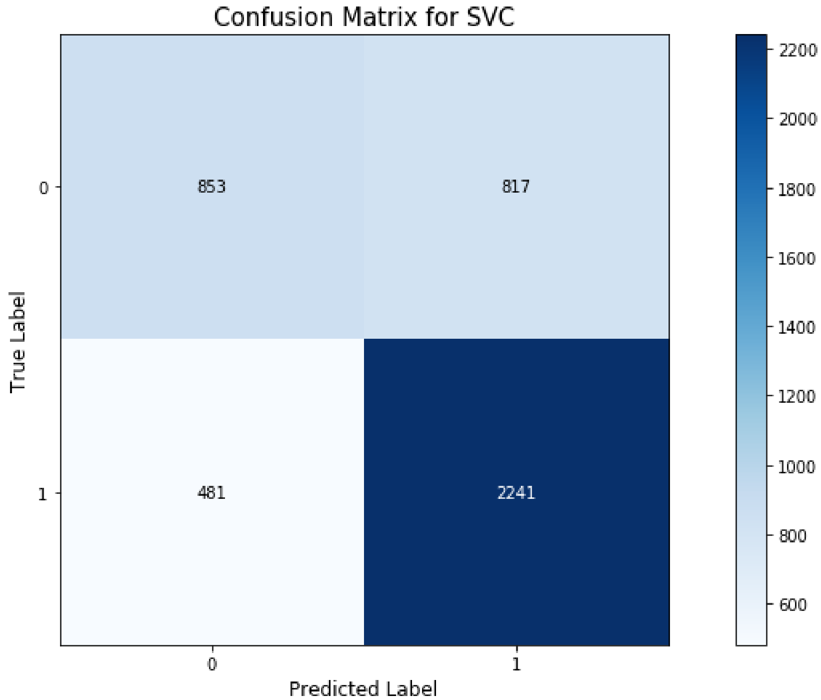
Learning Curve for DecisionTreeClassifier
training set
test set
Misclassification Error
Training Set Size in %
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
20
40
60
80
100


Confusion Matrix for DecisionTreeClassifier
True Label
Predicted Label
0
1
1054
616
663
2059
2000
1800
1600
1400
1200
1000
800

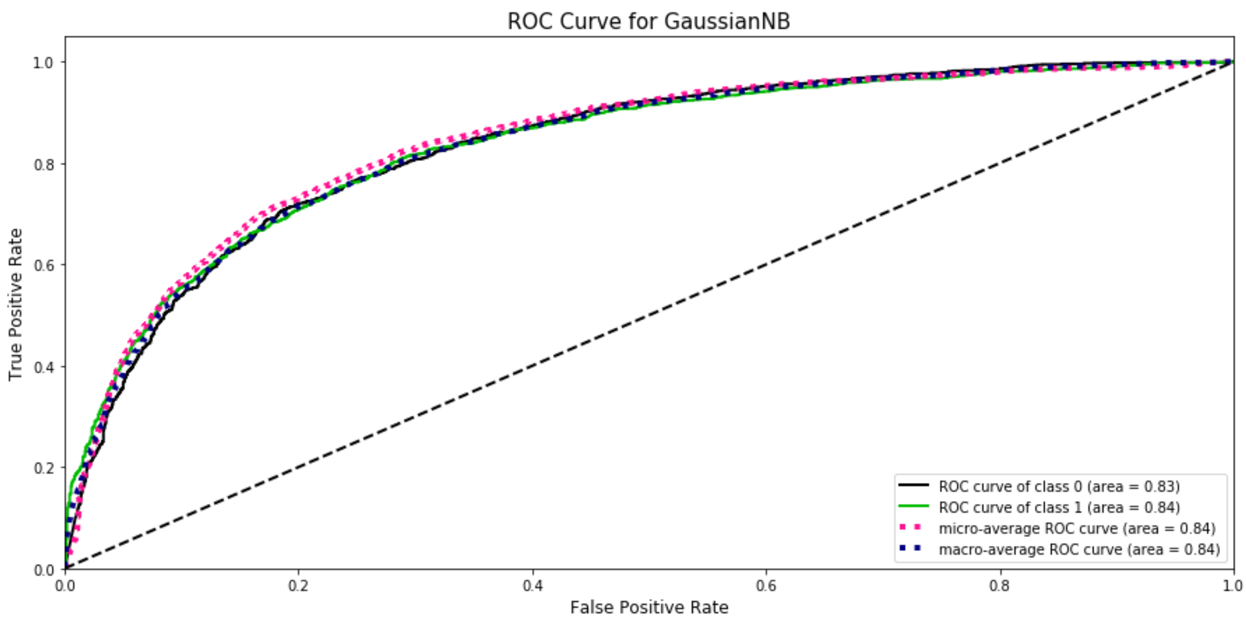

ROC Curve for SVC
True Positive Rate
False Positive Rate
ROC curve of class 0 (area = 0.74)
ROC curve of class 1 (area = 0.74)
micro-average ROC curve (area = 0.77)
macro-average ROC curve (area = 0.74)


Precision-Recall Curve for SVC
Precision-recall curve of class 0 (area = 0.634)
Precision-recall curve of class 1 (area = 0.798)
micro-average Precision-recall curve (area = 0.750)
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

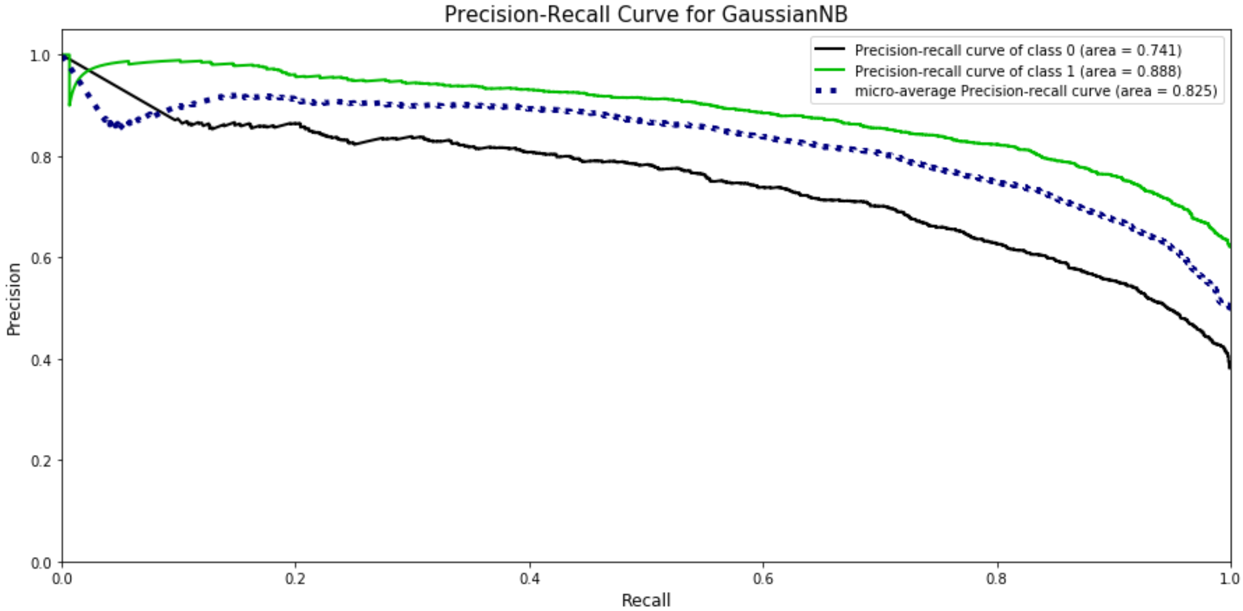

Learning Curve for SVC
training set
test set
Misclassification Error
Training Set Size in %
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0
20
40
60
80
100

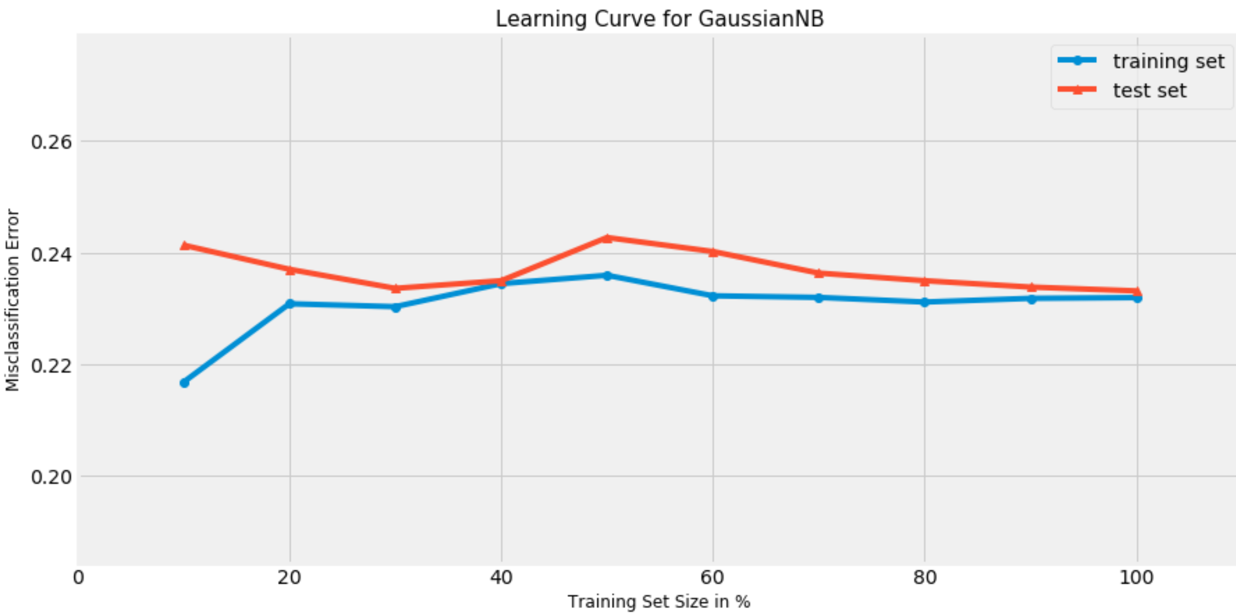


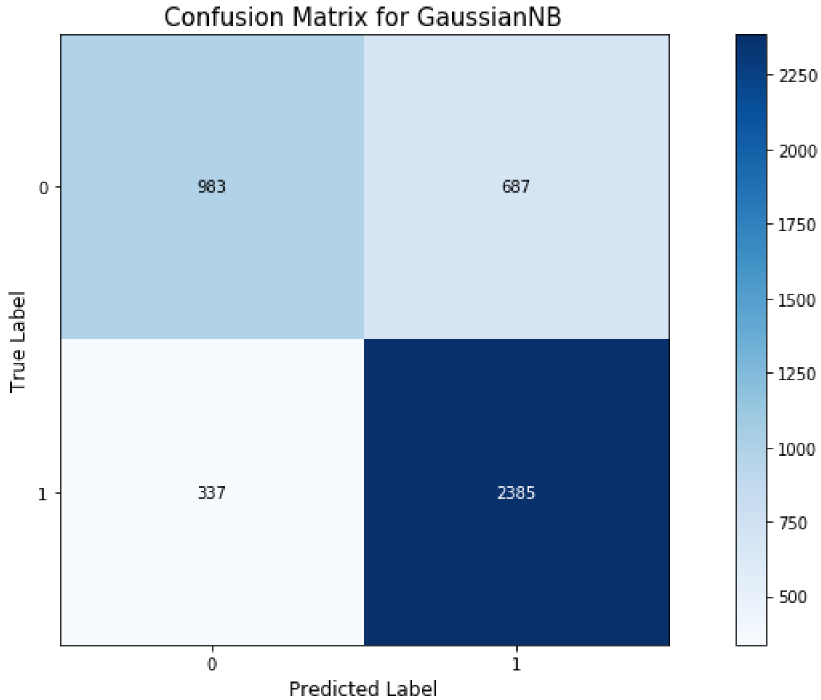
Confusion Matrix for SVC
True Label
Predicted Label
853
817
481
2241
0
1
0
1
2200
2000
1800
1600
1400
1200
1000
800
600



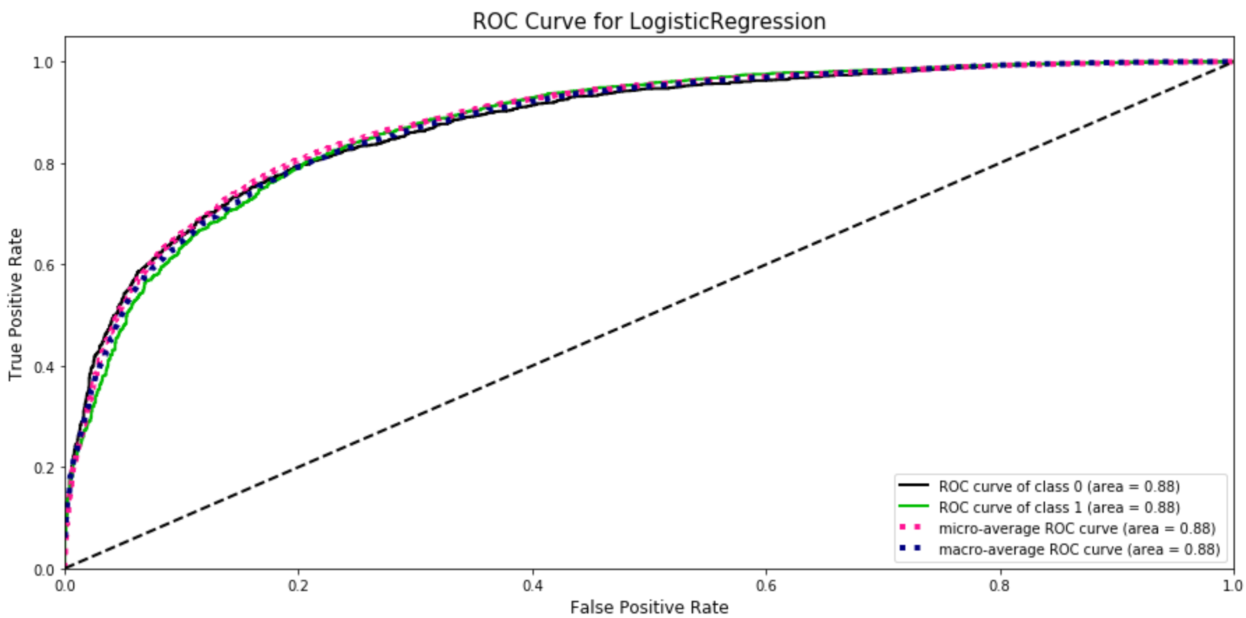
ROC Curve for GaussianNB
True Positive Rate
False Positive Rate
ROC curve of class 0 (area = 0.83)
ROC curve of class 1 (area = 0.84)
micro-average ROC curve (area = 0.84)
macro-average ROC curve (area = 0.84)
0.0
0.2
0.4
0.6
0.8
1.0


Precision-Recall Curve for GaussianNB
Precision-recall curve of class 0 (area = 0.741)
Precision-recall curve of class 1 (area = 0.888)
micro-average Precision-recall curve (area = 0.825)
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

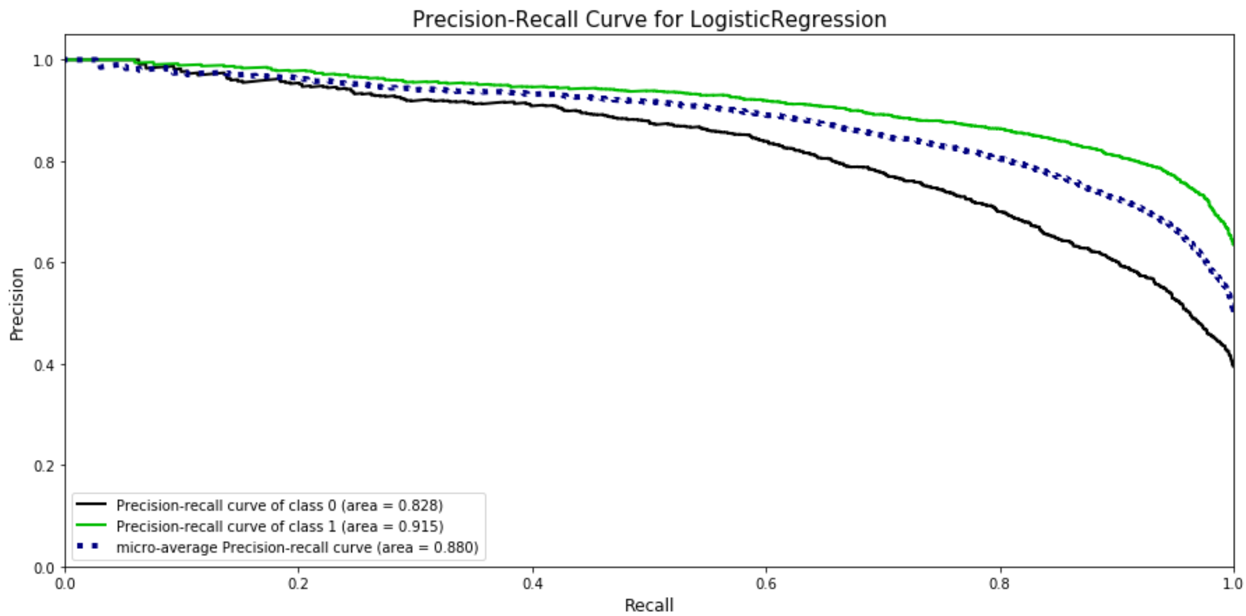

Learning Curve for GaussianNB
training set
test set
Misclassification Error
0.20
0.22
0.24
0.26
Training Set Size in %
0
20
40
60
80
100



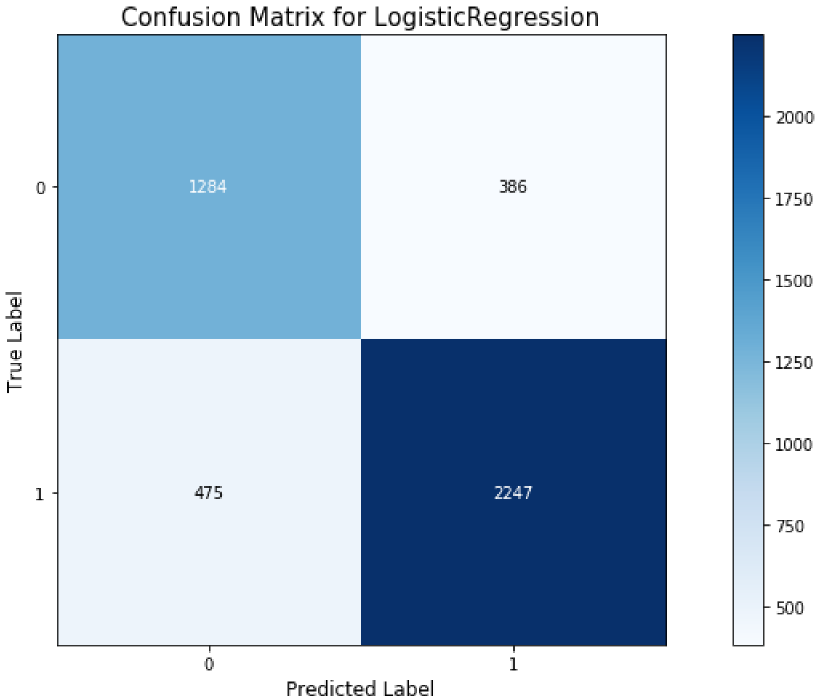
Confusion Matrix for GaussianNB
True Label
Predicted Label
0
1
983
687
337
2385
2250
2000
1750
1500
1250
1000
750
500

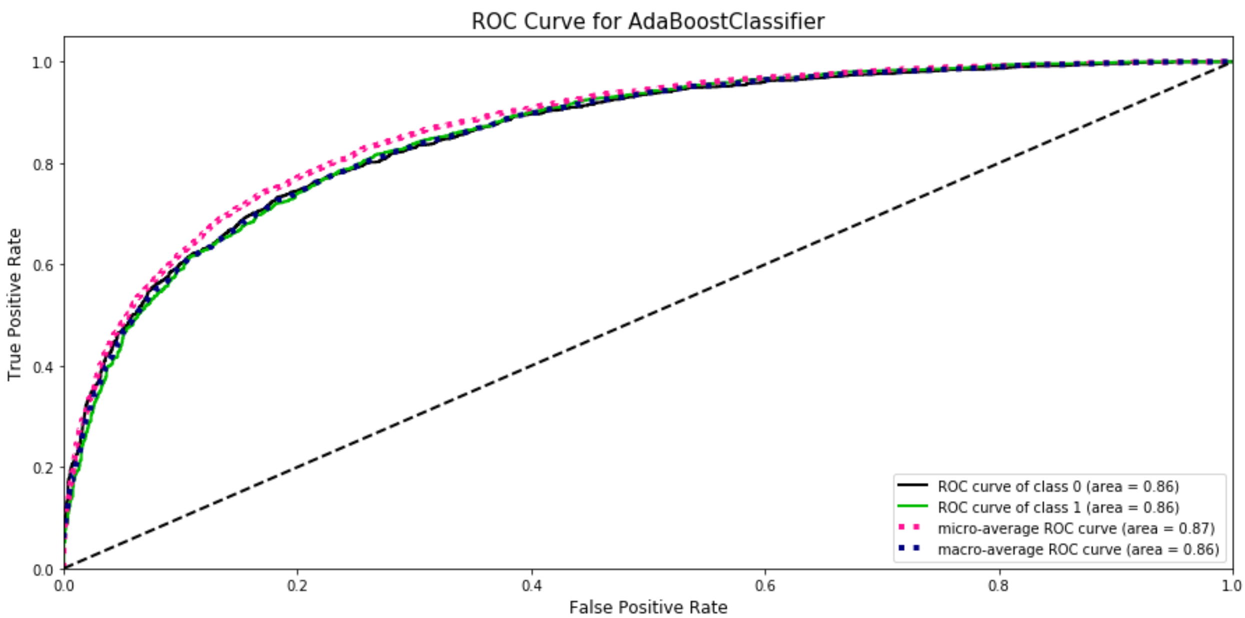


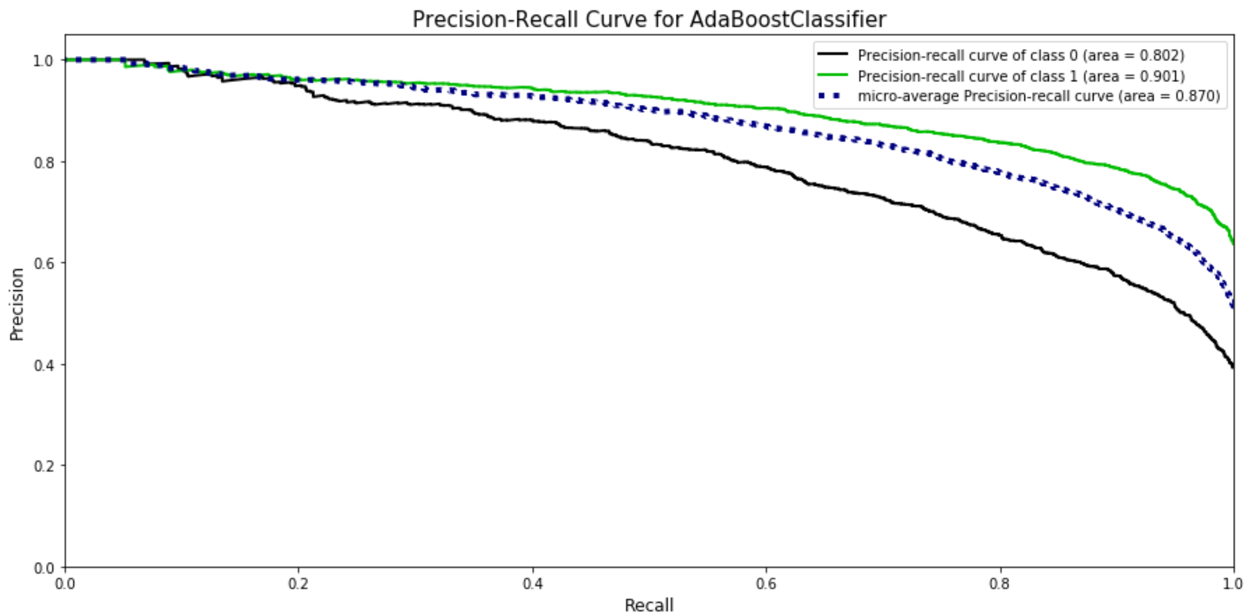
ROC Curve for LogisticRegression
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.88)
ROC curve of class 1 (area = 0.88)
micro-average ROC curve (area = 0.88)
macro-average ROC curve (area = 0.88)

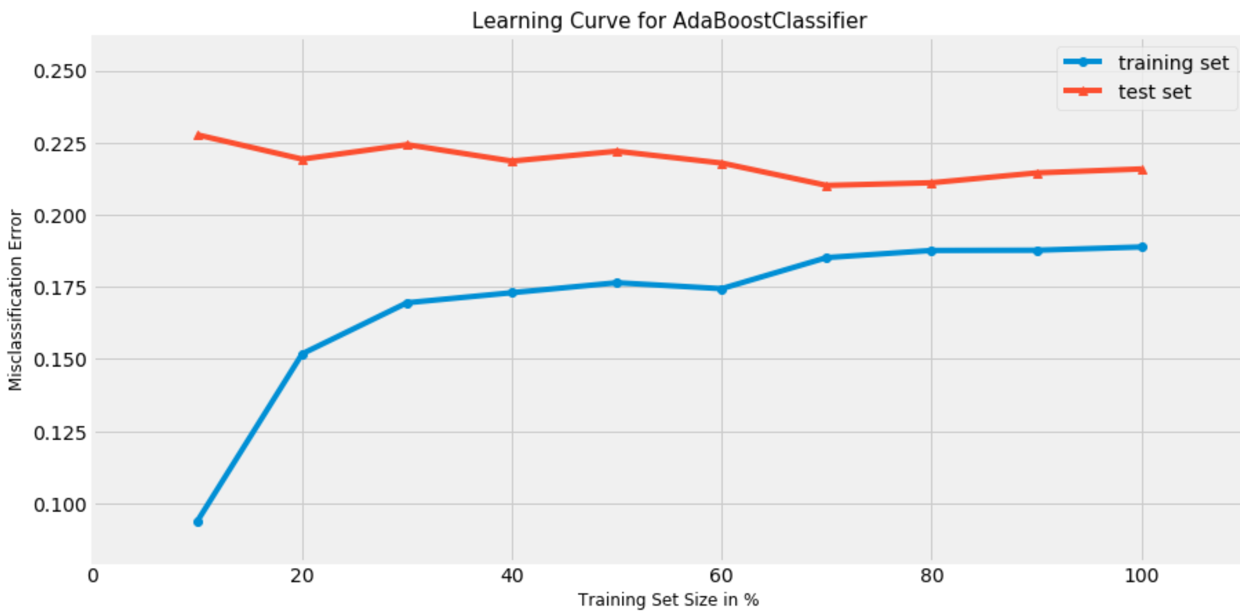

Precision-Recall Curve for LogisticRegression
Precision
Recall
Precision-recall curve of class 0 (area = 0.828)
Precision-recall curve of class 1 (area = 0.915)
micro-average Precision-recall curve (area = 0.880)
0.0
0.2
0.4
0.6
0.8
1.0

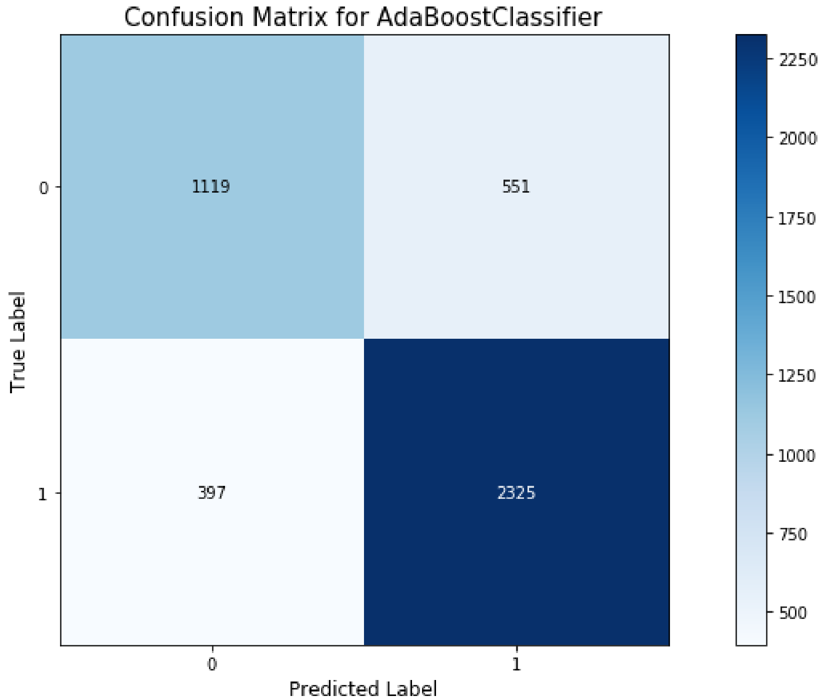

Learning Curve for LogisticRegression
training set
test set
Misclassification Error
Training Set Size in %
0.14
0.16
0.18
0.20
0.22
0.24
0
20
40
60
80
100

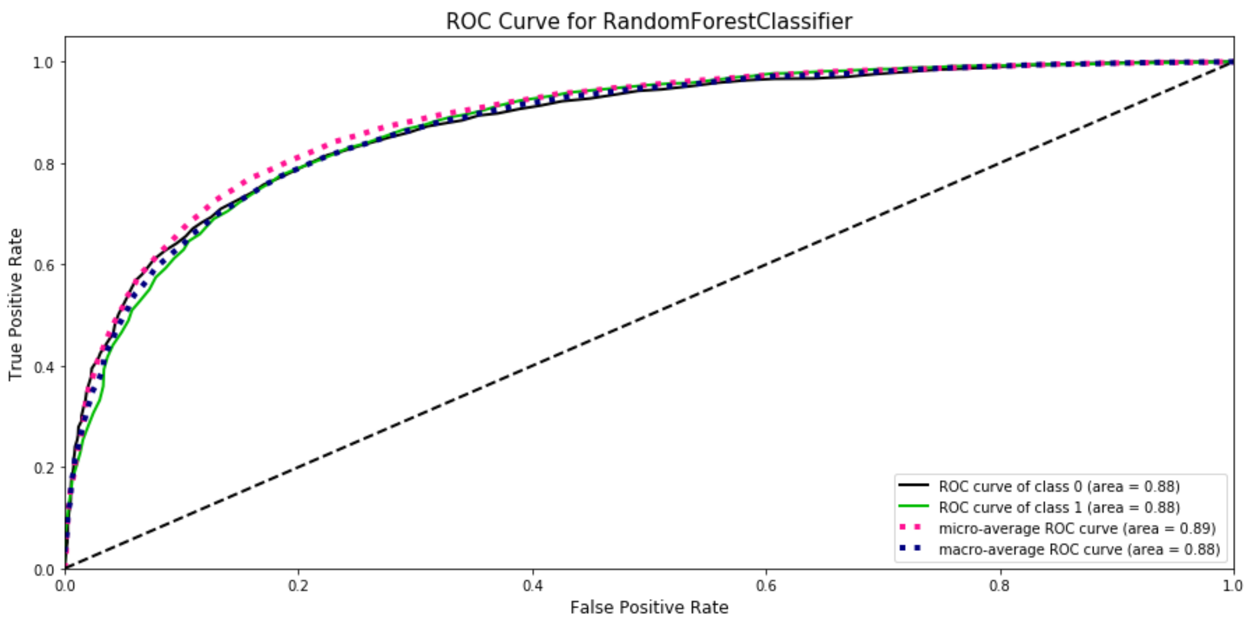

Confusion Matrix for LogisticRegression
True Label
Predicted Label
0
1
1284
386
475
2247
2000
1750
1500
1250
1000
750
500

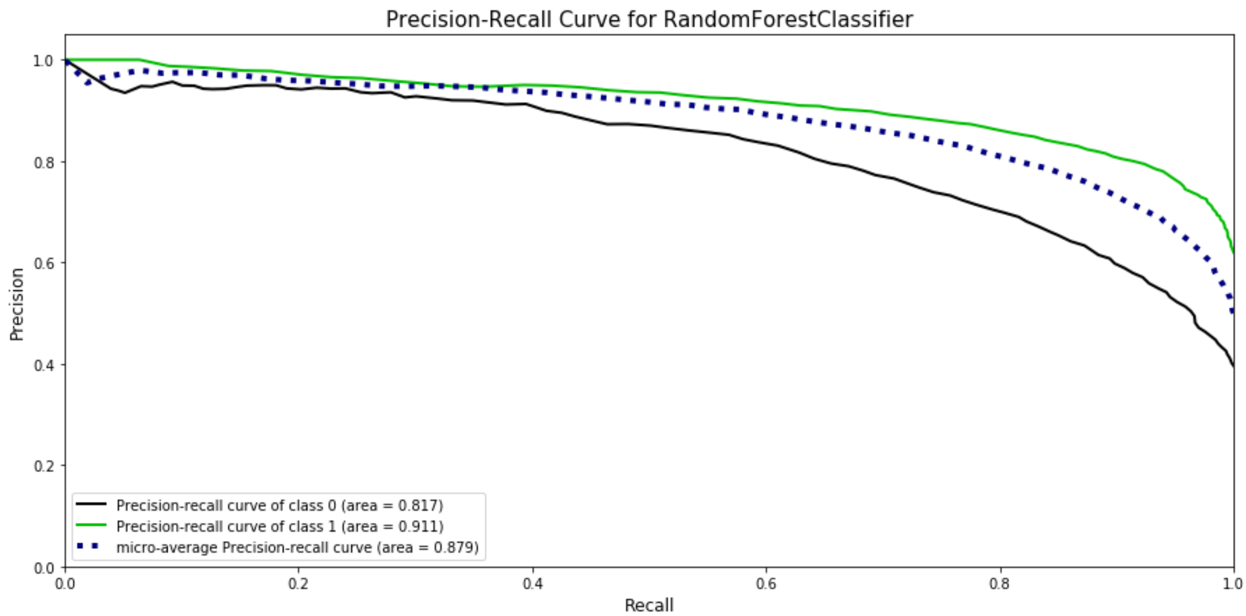

ROC Curve for AdaBoostClassifier
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.86)
ROC curve of class 1 (area = 0.86)
micro-average ROC curve (area = 0.87)
macro-average ROC curve (area = 0.86)

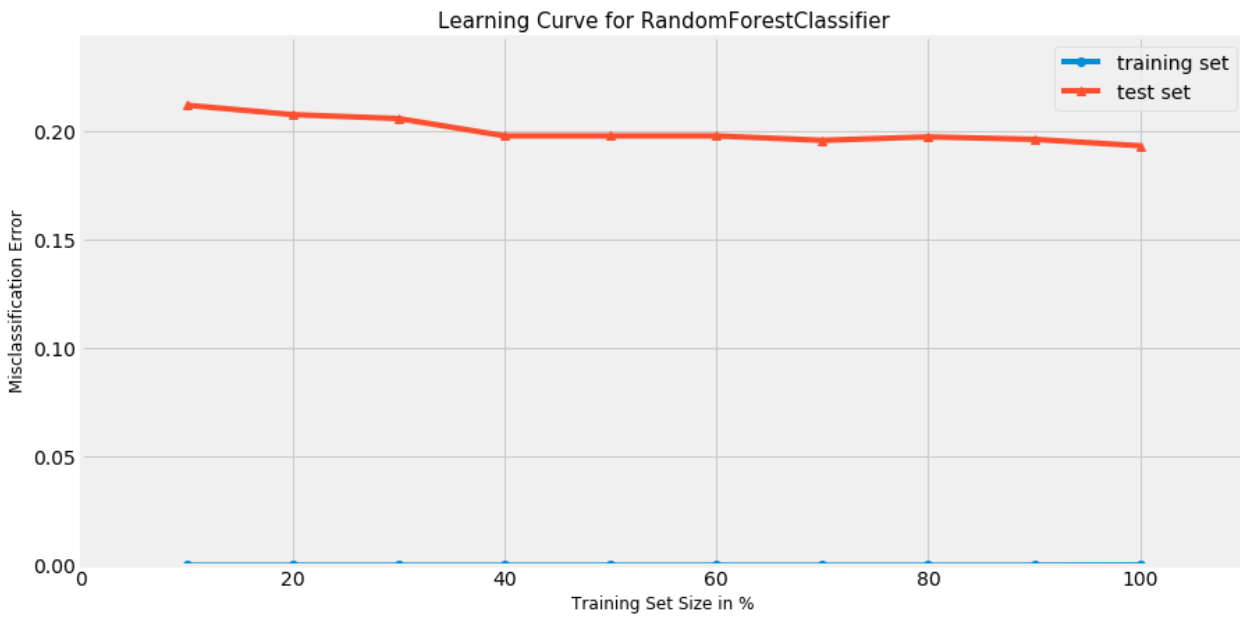

Precision-Recall Curve for AdaBoostClassifier
Precision-recall curve of class 0 (area = 0.802)
Precision-recall curve of class 1 (area = 0.901)
micro-average Precision-recall curve (area = 0.870)
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

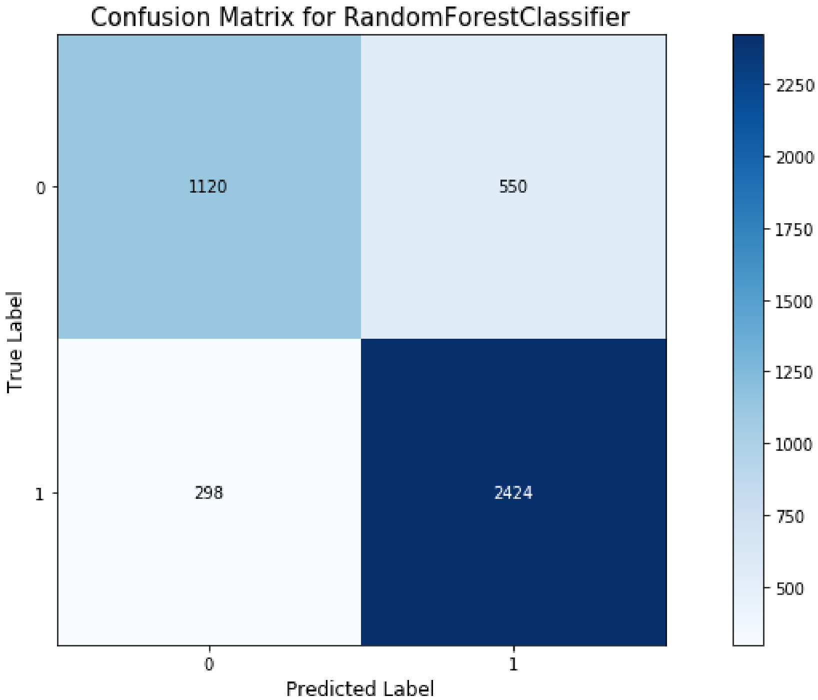

Learning Curve for AdaBoostClassifier
training set
test set
Misclassification Error
Training Set Size in %
0.100
0.125
0.150
0.175
0.200
0.225
0.250
0
20
40
60
80
100


Confusion Matrix for AdaBoostClassifier
1119
551
397
2325
0
1
True Label
0
1
Predicted Label
2250
2000
1750
1500
1250
1000
750
500

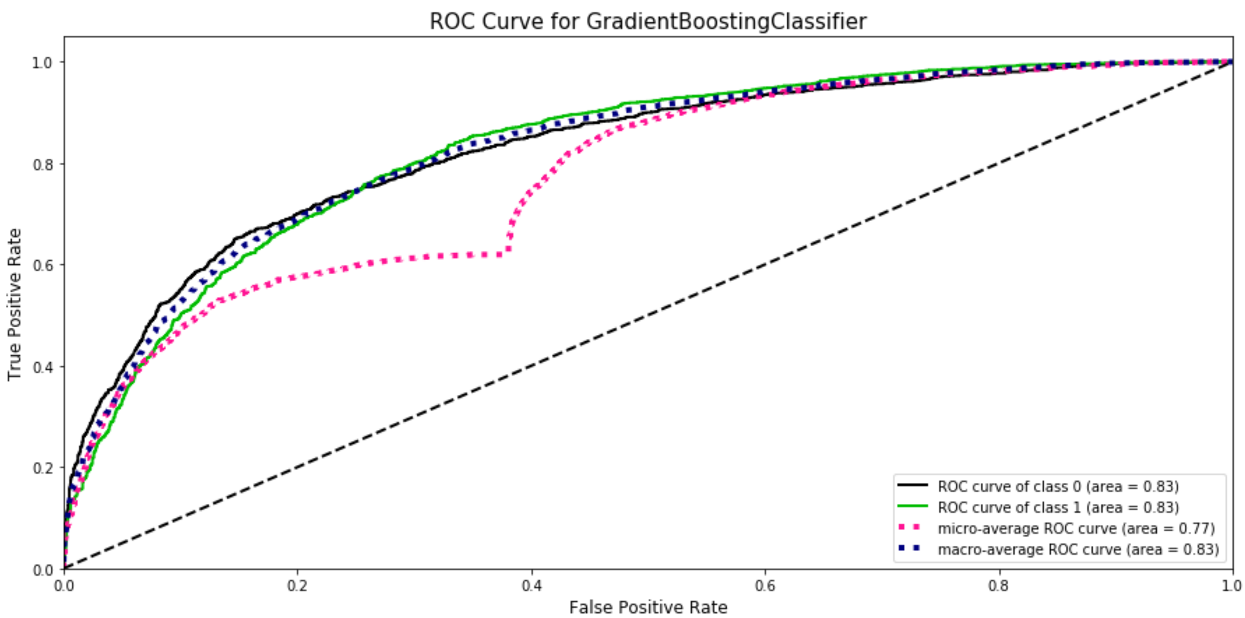

ROC Curve for RandomForestClassifier
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.88)
ROC curve of class 1 (area = 0.88)
micro-average ROC curve (area = 0.89)
macro-average ROC curve (area = 0.88)


Precision-Recall Curve for RandomForestClassifier
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 0 (area = 0.817)
Precision-recall curve of class 1 (area = 0.911)
micro-average Precision-recall curve (area = 0.879)

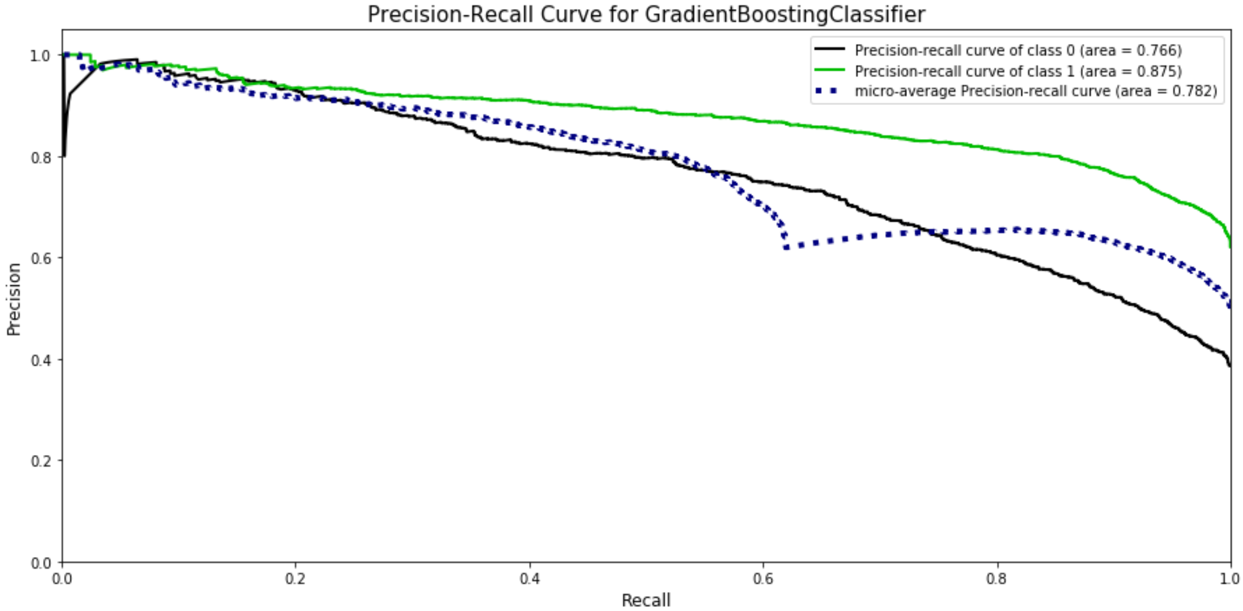

Learning Curve for RandomForestClassifier
training set
test set
0.00
0.05
0.10
0.15
0.20
Misclassification Error
0
20
40
60
80
100
Training Set Size in %

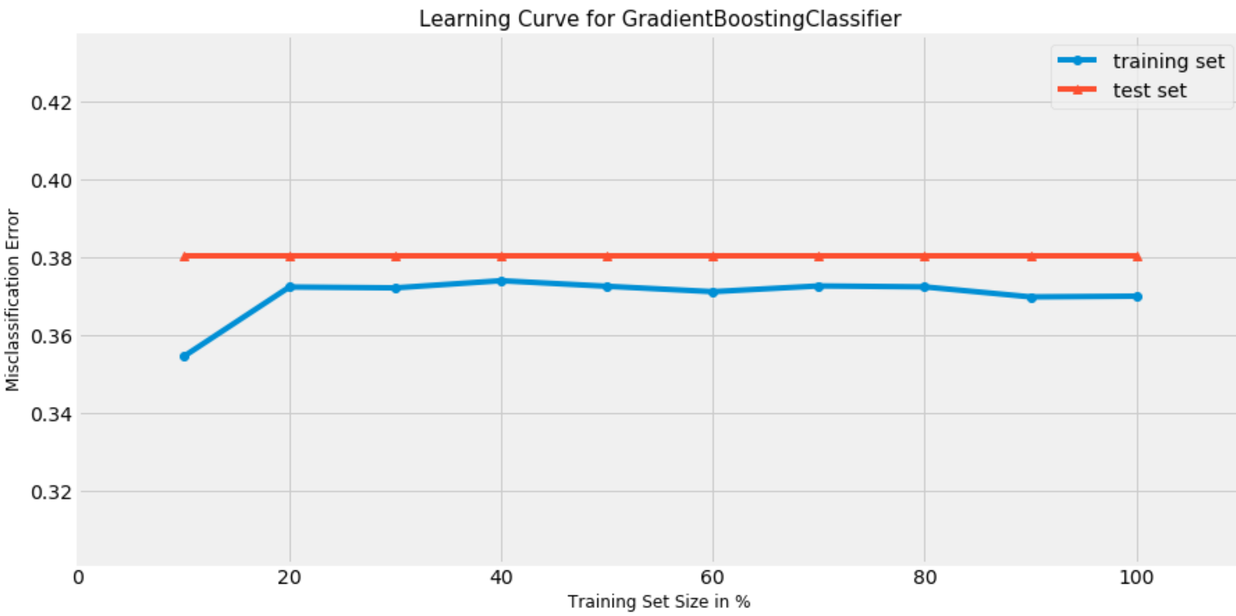


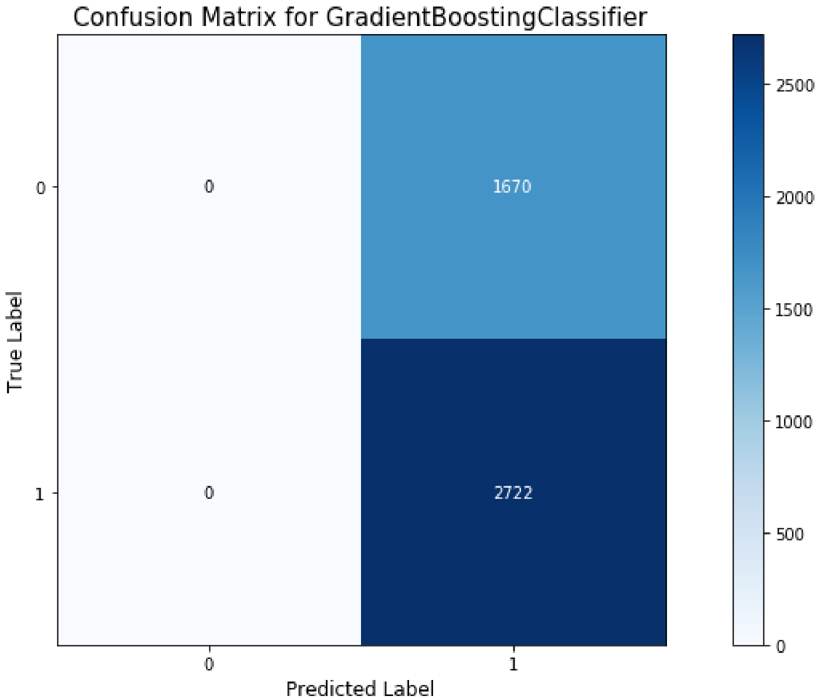
Confusion Matrix for RandomForestClassifier
True Label
Predicted Label
1120
550
298
2424
0
1
2250
2000
1750
1500
1250
1000
750
500

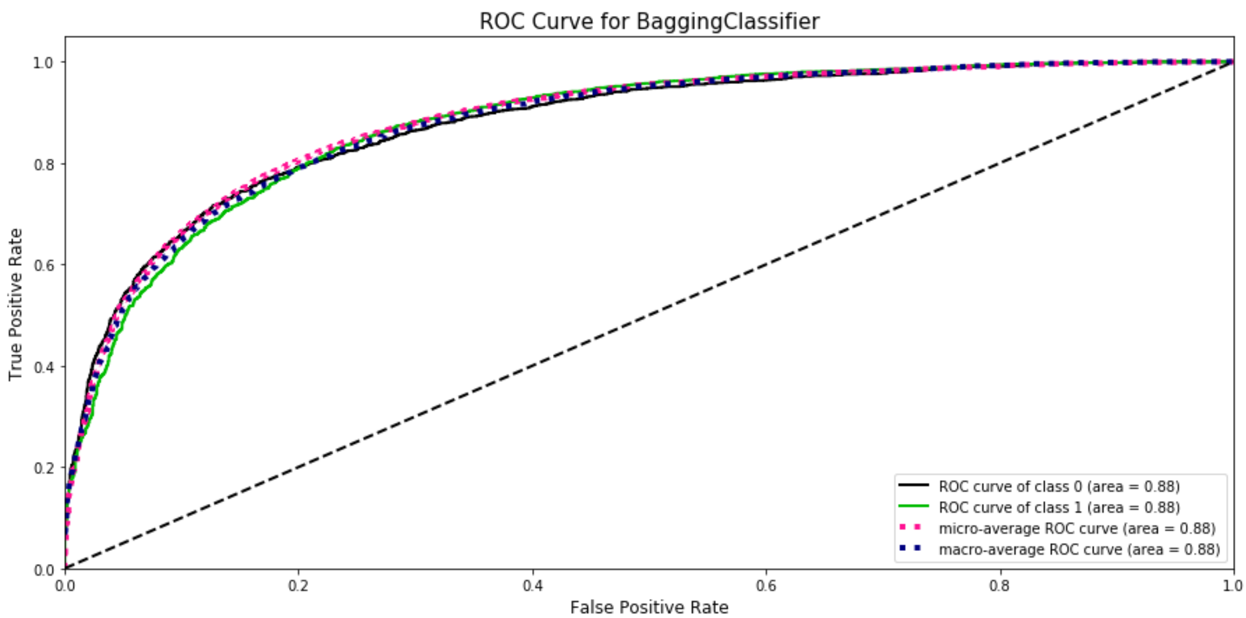


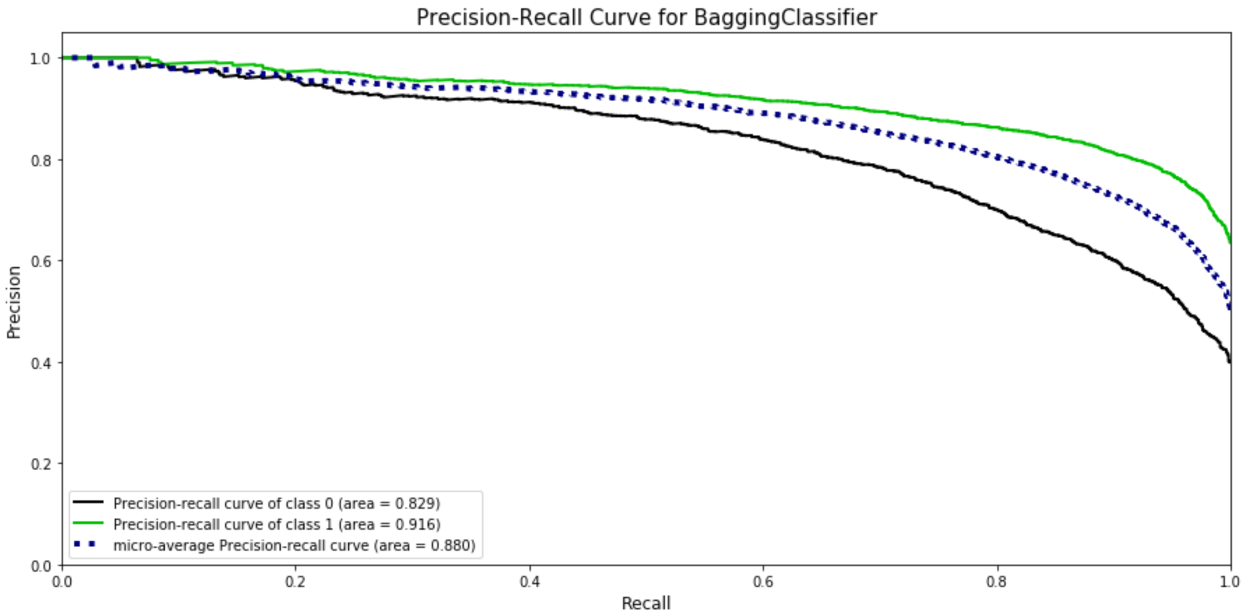
ROC Curve for GradientBoostingClassifier
True Positive Rate
False Positive Rate
ROC curve of class 0 (area = 0.83)
ROC curve of class 1 (area = 0.83)
micro-average ROC curve (area = 0.77)
macro-average ROC curve (area = 0.83)
0.0
0.2
0.4
0.6
0.8
1.0


Precision-Recall Curve for GradientBoostingClassifier
Precision-recall curve of class 0 (area = 0.766)
Precision-recall curve of class 1 (area = 0.875)
micro-average Precision-recall curve (area = 0.782)
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

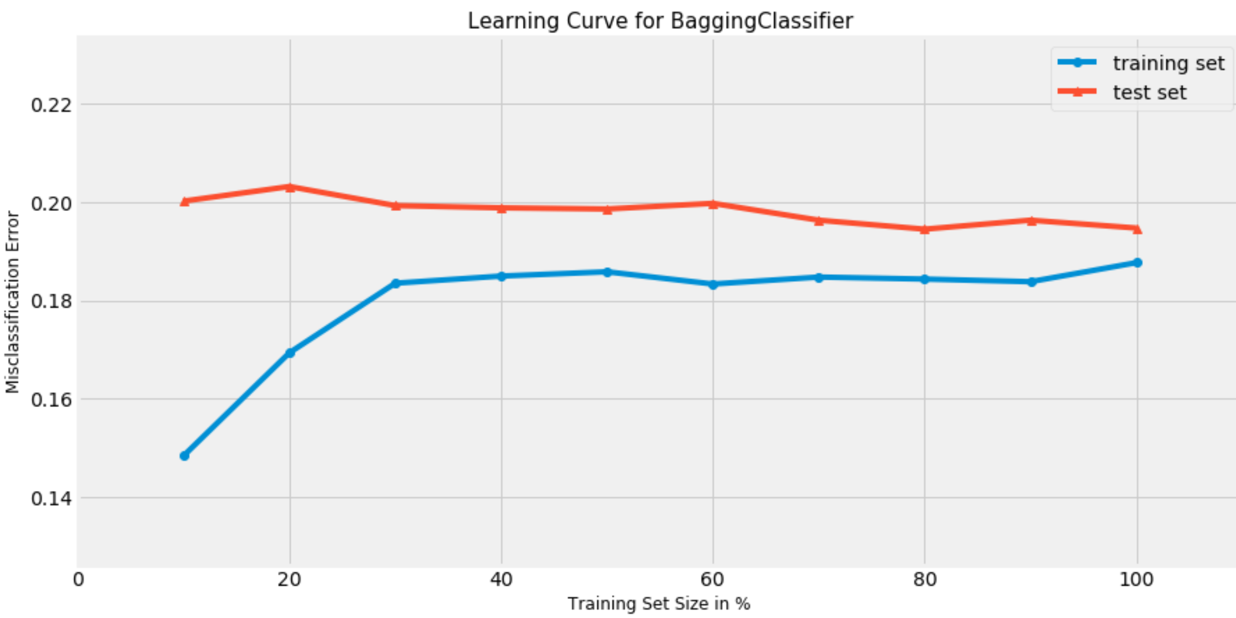

Learning Curve for GradientBoostingClassifier
training set
test set
Misclassification Error
Training Set Size in %
0.42
0.40
0.38
0.36
0.34
0.32
0
20
40
60
80
100


Confusion Matrix for GradientBoostingClassifier
True Label
Predicted Label
0
1
0
1670
0
2722
2500
2000
1500
1000
500
0

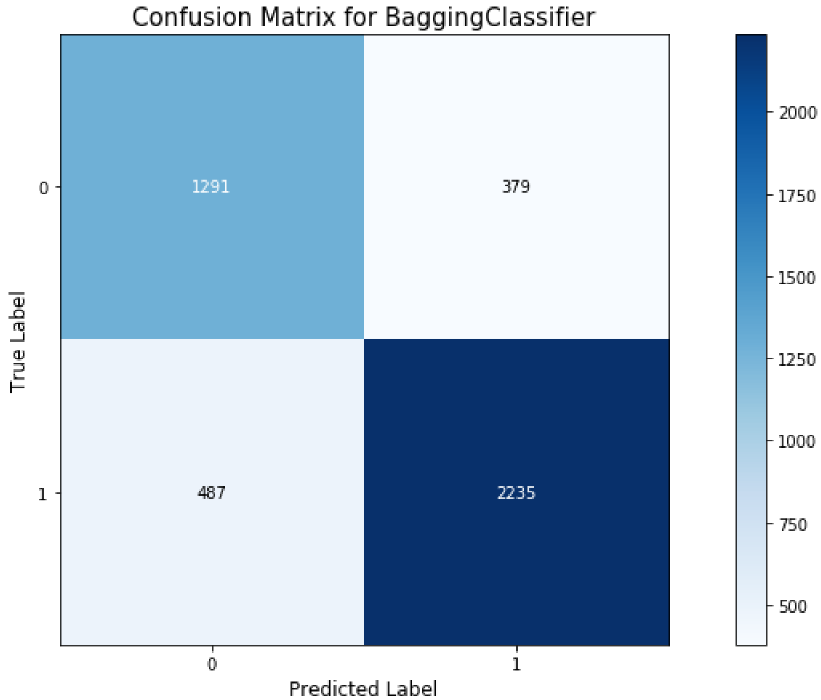

ROC Curve for BaggingClassifier
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.88)
ROC curve of class 1 (area = 0.88)
micro-average ROC curve (area = 0.88)
macro-average ROC curve (area = 0.88)



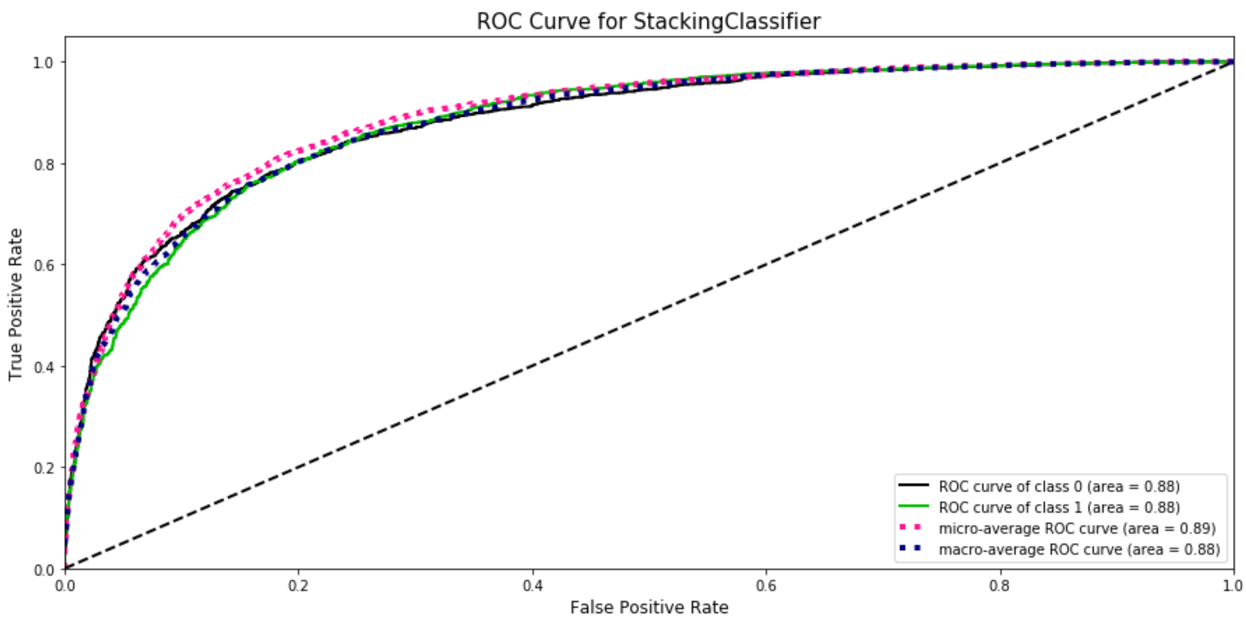
Precision-Recall Curve for BaggingClassifier
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 0 (area = 0.829)
Precision-recall curve of class 1 (area = 0.916)
micro-average Precision-recall curve (area = 0.880)



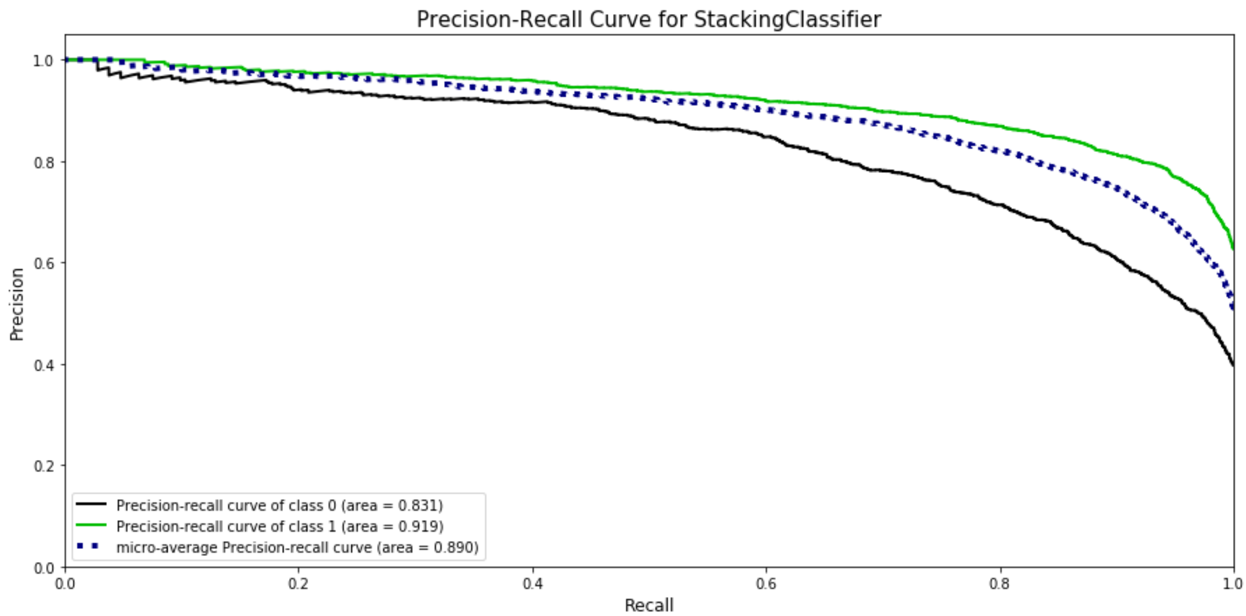
Learning Curve for BaggingClassifier
Misclassification Error
Training Set Size in %
0.22
0.20
0.18
0.16
0.14
0
20
40
60
80
100
training set
test set



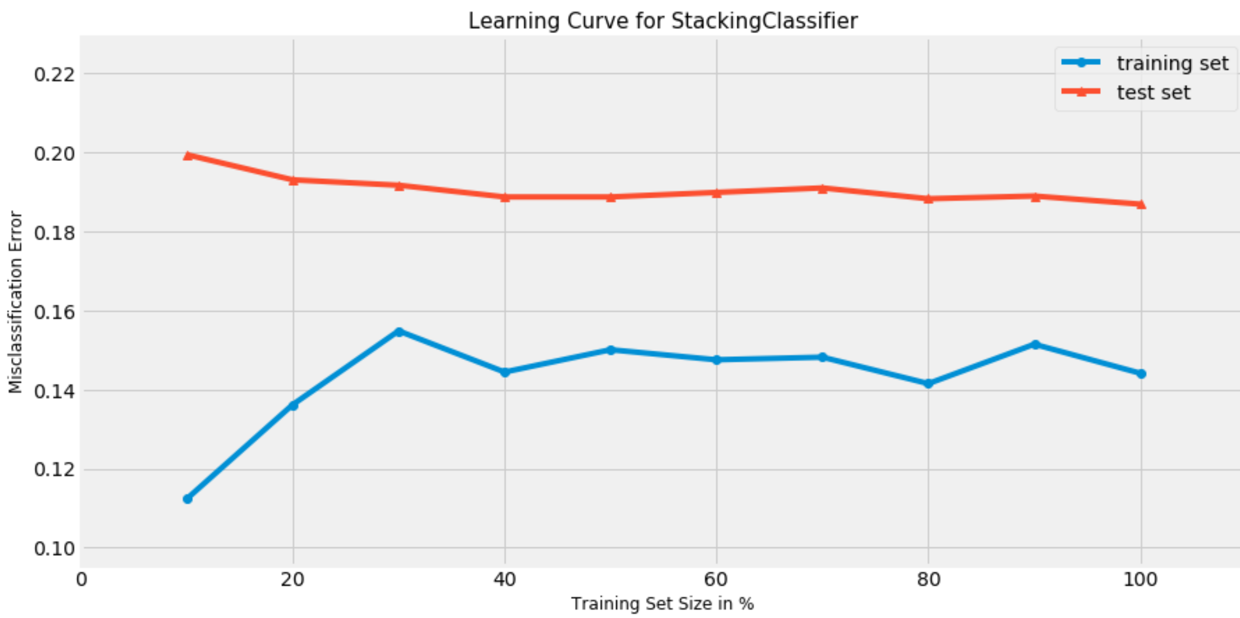
Confusion Matrix for BaggingClassifier
True Label
Predicted Label
0
1
1291
379
487
2235
2000
1750
1500
1250
1000
750
500



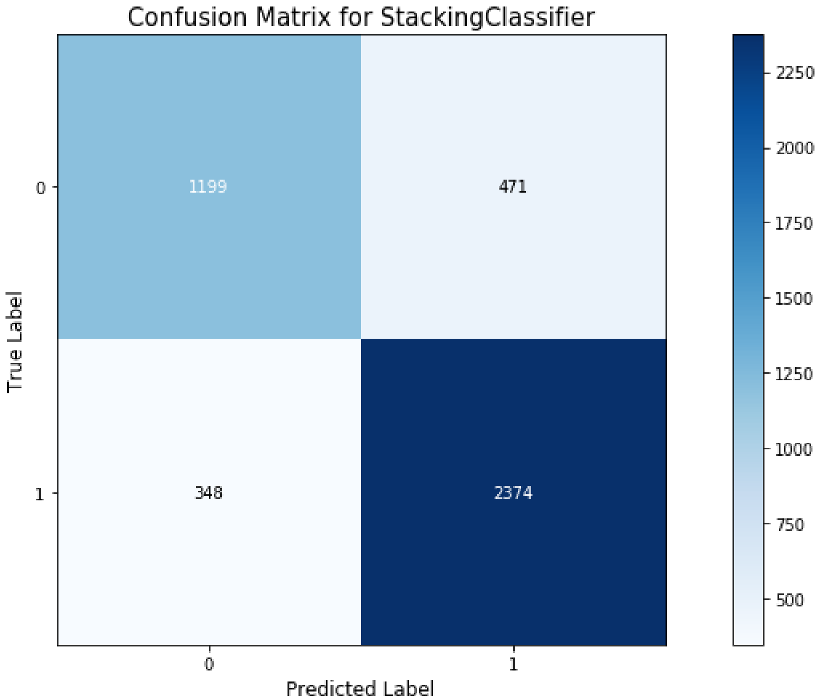
ROC Curve for StackingClassifier
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.88)
ROC curve of class 1 (area = 0.88)
micro-average ROC curve (area = 0.89)
macro-average ROC curve (area = 0.88)



Precision-Recall Curve for StackingClassifier
Precision
Recall
Precision-recall curve of class 0 (area = 0.831)
Precision-recall curve of class 1 (area = 0.919)
micro-average Precision-recall curve (area = 0.890)



Learning Curve for StackingClassifier
training set
test set
Misclassification Error
Training Set Size in %


Confusion Matrix for StackingClassifier
1199
471
348
2374
0
1
True Label
0
1
Predicted Label
2250
2000
1750
1500
1250
1000
750
500

References

Code for this project is either directly from (with some modification), or inspired by, but not limited to the following sources:

- Stacking Ensemble Method: https://towardsdatascience.com/stacking-made-easy-with-sklearn-e27a0793c92b (https://towardsdatascience.com/stacking-made-easy-with-sklearn-e27a0793c92b)
- Model Benchmarking: https://towardsdatascience.com/multi-class-text-classification-with-scikit-learn-12f1e60e0a9f (https://towardsdatascience.com/multi-class-text-classification-with-scikit-learn-12f1e60e0a9f)
- Model Benchmarking (Example Code): https://github.com/susanli2016/Machine-Learning-with-Python/blob/master/Consumer_complaints.ipynb (https://github.com/susanli2016/Machine-Learning-with-Python/blob/master/Consumer_complaints.ipynb)
- SciKit-Learn API Reference: https://scikit-learn.org/stable/modules/classes.html (https://scikit-learn.org/stable/modules/classes.html)
- Ensemble Methods: https://towardsdatascience.com/ensemble-methods-bagging-boosting-and-stacking-c9214a10a205 (https://towardsdatascience.com/ensemble-methods-bagging-boosting-and-stacking-c9214a10a205)
- Respective API Reference for each package used
- Hyperparameter Tuning:
  - https://scikit-learn.org/stable/modules/grid_search.html (https://scikit-learn.org/stable/modules/grid_search.html)
  - https://www.kaggle.com/tboyle10/hyperparameter-tuning (https://www.kaggle.com/tboyle10/hyperparameter-tuning)
  - https://towardsdatascience.com/logistic-regression-model-tuning-with-scikit-learn-part-1-425142e01af5 (https://towardsdatascience.com/logistic-regression-model-tuning-with-scikit-learn-part-1-425142e01af5)
  - https://towardsdatascience.com/hyperparameter-tuning-c5619e7e6624 (https://towardsdatascience.com/hyperparameter-tuning-c5619e7e6624)
  - https://medium.com/@mandava807/cross-validation-and-hyperparameter-tuning-in-python-65cfb80ee485 (https://medium.com/@mandava807/cross-validation-and-hyperparameter-tuning-in-python-65cfb80ee485)
  - http://www.davidsbatista.net/blog/2018/02/23/model_optimization/ (http://www.davidsbatista.net/blog/2018/02/23/model_optimization/)
  - https://www.kaggle.com/willkoehrsen/intro-to-model-tuning-grid-and-random-search (https://www.kaggle.com/willkoehrsen/intro-to-model-tuning-grid-and-random-search)
  - https://chrisalbon.com/machine_learning/model_selection/hyperparameter_tuning_using_grid_search/ (https://chrisalbon.com/machine_learning/model_selection/hyperparameter_tuning_using_grid_search/)
  - https://jakevdp.github.io/PythonDataScienceHandbook/05.03-hyperparameters-and-model-validation.html (https://jakevdp.github.io/PythonDataScienceHandbook/05.03-hyperparameters-and-model-validation.html)
  - https://medium.com/@jackstalfort/hyperparameter-tuning-using-grid-search-and-random-search-f8750a464b35 (https://medium.com/@jackstalfort/hyperparameter-tuning-using-grid-search-and-random-search-f8750a464b35)
  - https://www.kaggle.com/hatone/gradientboostingclassifier-with-gridsearchcv (https://www.kaggle.com/hatone/gradientboostingclassifier-with-gridsearchcv)
  - https://www.datacareer.ch/blog/parameter-tuning-in-gradient-boosting-gbm-with-python/ (https://www.datacareer.ch/blog/parameter-tuning-in-gradient-boosting-gbm-with-python/)
  - https://www.kaggle.com/c/home-credit-default-risk/discussion/60657 (https://www.kaggle.com/c/home-credit-default-risk/discussion/60657)