Modeling Engineering Student Performance

Phase 3 Final Project

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- Scheduled project review date/time: **TBD**
- Instructor name: **James Irving**
- Blog post URL: **TBD**

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2 Introduction

2.1 Business Problem

This project aims to build a predictive classification model of graduating Colombian Engineering students' performance evolution based on their students' socio-economic characteristics and engineering programs they attended.

This information can be helpful for university officials to identify students not fulfilling their potential and providing additional support (financial, etc.) to help them progress in their professional careers. The results of the model also can assist future engineering students in choosing professional programs and universities.

3 Obtain

3.1 Importing Python tools and utilities

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import math
import scipy.stats as stats
import graphviz
import pylab
import joblib
import shap
import lime
import random
from PIL import Image
import os
from IPython.display import HTML

from lime import lime_tabular
from lime import submodular_pick
from yellowbrick.features import Rank2D
from yellowbrick.classifier import ClassificationReport
from matplotlib import style
from graphviz import Source

from sklearn import metrics
from sklearn import set_config
from sklearn import tree

from sklearn.feature_selection import VarianceThreshold
from sklearn.impute import SimpleImputer
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, StackingClassifier

from sklearn.inspection import permutation_importance
from xgboost import XGBRFClassifier,XGBClassifier
from xgboost import plot_importance
from sklearn.model_selection import permutation_test_score
from sklearn.model_selection import StratifiedKFold
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.compose import ColumnTransformer, make_column_transformer


from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import confusion_matrix, plot_confusion_matrix,\
    precision_score, recall_score, accuracy_score, f1_score, log_loss,\
    roc_curve, roc_auc_score, classification_report,plot_roc_curve

from dtreeviz.trees import dtreeviz
from IPython.display import display, Math, Latex
from plotly.subplots import make_subplots


from warnings import filterwarnings
filterwarnings('ignore')

from cf_matrix import make_confusion_matrix

%matplotlib inline
```

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3.2 Functions used

In [2]:

```
def distribution(column):
    """This is a snippet from https://atmamani.github.io/cheatsheets/seaborn/seaborn_cheat_sheet_1/

    Takes in a column of a dataframe and generates a distribution plot of the values in this column
    along with a title that shows mean, standard deviation, skewness and kurtosis.
    No returned values."""
    col_mean = column.mean()
    col_sd = column.std()
    skew_val = stats.skew(column, bias=False)
    kurt_val = stats.kurtosis(column,bias=False)

    ax = sns.distplot(column, kde_kws={"color": "r", "lw": 2, "label": "KDE", "bw_adjust": 3})

    ax.axvline(x=col_mean, color='black', linestyle='dashed')

    ax.axvline(x=col_mean + col_sd, color='red', linestyle='dotted')
    ax.axvline(x=col_mean - col_sd, color='red', linestyle='dotted')

    ax.set_title('$\mu = {}$ | $\sigma = {}$ | Skew = {} | Kurtosis = {}'.
                 format(round(col_mean, 2), round(col_sd, 2), round(skew_val,2), round(kurt_val,2)))

    plt.subplots_adjust(top=0.5)
    plt.tight_layout()


def creating_failing(df, column):
    """A function that creates a new 'FAILING' column in both the training dataframe with target values and
    a df (test target values) dataframe. The function also assigns binary values to this colum in both dataframes
    based on mean value in the training dataframe. 0.0 is assigned to the records that have original values equal
    or more than the mean and 1.0 that are below the mean
    **************************
    Arguments:
    df: test target values dataframe
    column: a source column """

# Identifying a mean of G_SC values for the training set
    mean_=y_train[column].mean()

# Creating a new binary column
    y_train['FAILING'] = [0 if x >= mean_ else 1 for x in (y_train[column])]
    df['FAILING'] = [0 if x >= mean_ else 1 for x in (df[column])]

    y_train_final=y_train.drop([column], axis=1)
    df_final=df.drop([column], axis=1)

    return y_train_final, df_final


def  conf_matrix_pretty(model, X, y, title):
    """This is a function taken from https://github.com/DTrimarchi10/confusion_matrix.
    the code is in cf_matrix.py.
    **************************
    Arguments:
    model: a model to evaluate
    X: a features dataframe
    y: a target dataframe
    the title over a confusion matrix"""

    sns.set_context('talk')
    cm=confusion_matrix(y, model.predict(X))

    labels = ['TN','FP','FN','TP']
    categories = ['Adequate (0)', 'Failing (1)']
    make_confusion_matrix(cm, group_names=labels, categories=categories, cmap='Reds', title=title, figsize=(8,6))


def simple_model_validation(model, set_list, title1, title2):
    """A function generating confusion matrices (train/test) with model metrics and roc curves
    ******************
    Arguments:
    model: a model to evaluate
    set_list: a list of dataframe names [X_train, X_test, y_train, y_test]
    titel1: a title for the training set confusion matrix
    title2: a title for the test set confusion matrix"""

    X_train=set_list[0]
    X_test=set_list[1]
    y_train=set_list[2]
```

```
    y_test=set_list[3]

    y_pred1 = model.predict(X_train)
    y_pred2 = model.predict(X_test)

    print('***************************************')
    print(model)
    print('***************************************\n')


    print('Classification Report for training set')
    print('***************************************')
    print(metrics.classification_report(y_train, y_pred1)+'\n')
    print('Classification Report for test set')
    print('***************************************')
    print(metrics.classification_report(y_test, y_pred2)+'\n')

    print('***************************************')
    diff_acc=round(metrics.accuracy_score(y_pred1, y_train)-metrics.accuracy_score(y_pred2, y_test), 3)
    diff_recall=round(metrics.recall_score(y_pred1, y_train)-metrics.recall_score(y_pred2, y_test), 3)

    print('Differences in Accuracy scores between training and test sets: {}'.
          format(diff_acc))
    print('Differences in Recall scores between training and test sets: {}\n'.
          format(diff_recall))

    conf_matrix_pretty(model, X_train, y_train, title1)
    conf_matrix_pretty(model, X_test, y_test, title2)

    fig,ax = plt.subplots(ncols=2,figsize=(15,7))

    roc_curve1=plot_roc_curve(model, X_train, y_train, ax=ax[0])

    roc_curve1.ax_.plot([0,1],[0,1],ls=':')

    roc_curve2=plot_roc_curve(model, X_test, y_test, ax=ax[1])
    ax[0].set_title('Training set ROC')
    ax[1].set_title('Test set ROC')

    roc_curve2.ax_.plot([0,1],[0,1],ls=':')

    return


def get_importance_logreg_no_plot(model, X):
    """This function is to display feature importances in a regression model, the importance
    is calculated manually for each coefficient. The returned variable is a dataframe with Feature names,
    an importance of the features and a coefficient associated with that feature
    ******************
    Arguments:
    model: a model to evaluate
    X: a dataframe
    """

    feature_names = X.columns
    w0 = model.intercept_[0]
    w = model.coef_[0]

    pd.set_option('display.width', 1000)
    feature_importance = pd.DataFrame(feature_names, columns = ['Feature'])
    feature_importance['Importance'] = pow(math.e, abs(w))
    feature_importance['Coefficient'] = w
    feature_importance = feature_importance.sort_values(by = ["Importance"], ascending=True)

    return feature_importance

def get_importance_logreg(model, X, top_n=30, figsize=(15,15)):
    """Function returns a dataframe with feature importance values and the corresponding coefficient
    in the regression based lodel.It also plots a bar plot of feature importance.
    *************************
    Arguments:
    model: model
    X: a dataframe with the names of the features
    top_n: a number of features to display on a plot (default is 20)
    figure: a tuple with a figure size (default is (15,15))"""

    feature_names = X.columns
    w0 = model.intercept_[0]
    w = model.coef_[0]
```

```
    pd.set_option('display.width', 1000)
    feature_importance = pd.DataFrame(feature_names, columns = ['Feature'])
    feature_importance['Importance'] = pow(math.e, abs(w))
    feature_importance['Coefficient'] = w
    feature_importance = feature_importance.sort_values(by = ["Importance"], ascending=True).tail(top_n)


    ax = feature_importance.plot.barh(x='Feature', y='Importance', figsize=figsize, title='Feature Importance',
                                      ylabel='Feature')
    plt.show()
    return feature_importance

def get_importance_tree(model, X, top_n=30, figsize=(10,10), plot=True):
    """Function returns a dataframe with feature importance values and the corresponding coefficient
    in the decisiontree based model. It also plots a bar plot of feature importance.
    *************************
    Arguments:
    model: model
    X: a dataframe with the names of the features
    top_n: a number of features to display on a plot (default is 20)
    figure: a tuple with a figure size (default is (15,15))"""

    df_importance = pd.Series(model.feature_importances_, index=X.columns)

    if plot:
        df_importance.sort_values(ascending=True).tail(top_n).plot(kind='barh',
                                                                   figsize=figsize, title='Feature Importances',
                                                                   ylabel='Feature')
    else:
        df_importance.sort_values(ascending=True).tail(top_n)

    return df_importance


def adding_to_models_dict(dict_, descr, classifier_name, set_list, model, joblib_file):
    """A function to build a dictionary with all built and evaluated models metrics and information for easy comparison.
    ***************
    Arguments
    dict_: dictionary name
    descr: description of the model ('str')
    classifier_name: the name of the classifier ('str')
    set_list: a list of dataframe names [X_train, X_test, y_train, y_test]
    model: model to add (classifier)
    joblib_file: the name of the file with the saved model ('str')
    """
    X_train=set_list[0]
    X_test=set_list[1]
    y_train=set_list[2]
    y_test=set_list[3]

    y_pred1 = model.predict(X_train)
    y_pred2 = model.predict(X_test)

    acc_score_train=round(metrics.accuracy_score(y_pred1, y_train),3)
    acc_score_test=round(metrics.accuracy_score(y_pred2, y_test),3)

    cm_train=confusion_matrix(y_train, model.predict(X_train))
    cm_test=confusion_matrix(y_test, model.predict(X_test))

    recall_score_train=round(cm_train[1][1]/(cm_train[1,1]+cm_train[1][0]),3)
    recall_score_test=round(cm_test[1][1]/(cm_test[1,1]+cm_test[1][0]),3)
    FN_train=cm_train[1][0]
    FN_test=cm_test[1][0]

    total_records_train=X_train.shape[0]
    total_records_test=X_test.shape[0]

    dict_['Classifier Name'].append(classifier_name)
    dict_['Description'].append(descr)
    dict_['Training or Test'].append('training')
    dict_['Accuracy'].append(acc_score_train)
    dict_['Recall'].append(recall_score_train)
    dict_['FN'].append(FN_train)
    dict_['Total number of records'].append(total_records_train)
    dict_['Saved model'].append(joblib_file)

    dict_['Classifier Name'].append(classifier_name)
    dict_['Description'].append(descr)
```

```
    dict_['Training or Test'].append('test')
    dict_['Accuracy'].append(acc_score_test)
    dict_['Recall'].append(recall_score_test)
    dict_['FN'].append(FN_test)
    dict_['Total number of records'].append(total_records_test)
    dict_['Saved model'].append(joblib_file)

    return dict_


def permutation_of_features_logreg(model, X_train, X_test, y_test):
    """Function returns a dataframe with permutations importance per feature
    along the feature name and the feature importance for a regression model
    **************
    Arguments
    model: logistic regression model
    X_train: training dataset (df)
    X_test: test dataset (df)
    y_test: target values for the test dataset (df)"""

    r_model = permutation_importance(model, X_test, y_test,
                            n_repeats=50, scoring='recall', random_state=123)

    model_perm_importances = pd.Series(r_model['importances_mean'],index=X_train.columns,
                            name = 'Permutation Importance')

    df_perm_model=pd.DataFrame(model_perm_importances)


    df_imp_model=pd.DataFrame(get_importance_logreg_no_plot(model, X_test))
    df_imp_model=df_imp_model.set_index('Feature')
    df_imp_model=df_imp_model.rename(columns={'Importance': 'Feature Importance'})


    model_perm_vs_imp=pd.concat([df_imp_model, df_perm_model], axis=1)

    return model_perm_vs_imp.sort_values('Feature Importance', ascending=False).head(15)


def permutation_of_features_tree(model, X_train, X_test, y_test):
    """Function returns a dataframe with permutations importance per feature
    along the feature name and the feature importance for a decisiontree model
    **************
    Arguments
    model: logistic regression model
    X_train: training dataset (df)
    X_test: test dataset (df)
    y_test: target values for the test dataset (df)"""

    r_model = permutation_importance(model, X_test, y_test,
                            n_repeats=50, scoring='recall', random_state=123)

    model_perm_importances = pd.Series(r_model['importances_mean'],index=X_train.columns,
                            name = 'Permutation Importance')

    df_perm_model=pd.DataFrame(model_perm_importances)


    df_imp_model=pd.DataFrame(get_importance_tree(model, X_test, top_n=50, plot=False))
    df_imp_model=df_imp_model.rename(columns={0: 'Feature_Importance'})


    model_perm_vs_imp=pd.concat([df_imp_model, df_perm_model], axis=1)
    print('Feature Importanve vs Permutation importance for {} model'.format(model))
    return model_perm_vs_imp.sort_values('Feature_Importance', ascending=False).head(15)


def ABS_SHAP(df_shap, df, n=20, figure=(20,20)):
    """The code is taken from https://towardsdatascience.com/explain-your-model-with-the-shap-values-bc36aac4de3d

    Some minor modifications: adjusting figure size and limiting the number of bars to an argument
    output to 10 feature with the highest shapley values. Also added a figuresize as an argument.
    **********************
    Arguments:
    df_shap: shapley values
    df: dataframe to analize (test, train)
    n: number of features to include in the diagram (default=20)
    figure: figure size, default is (20,20)"""

```

```
    # Make a copy of the input data
    shap_v = pd.DataFrame(df_shap)
    feature_list = df.columns
    shap_v.columns = feature_list
    df_v = df.copy().reset_index().drop('index',axis=1)

    # Determine the correlation in order to plot with different colors
    corr_list = list()
    for i in feature_list:
        b = np.corrcoef(shap_v[i],df_v[i])[1][0]
        corr_list.append(b)
    corr_df = pd.concat([pd.Series(feature_list),pd.Series(corr_list)],axis=1).fillna(0)

    # Make a data frame. Column 1 is the feature, and Column 2 is the correlation coefficient
    corr_df.columns  = ['Variable','Corr']
    corr_df['Sign'] = np.where(corr_df['Corr']>0,'red','blue')

    # Plot it
    shap_abs = np.abs(shap_v)
    k=pd.DataFrame(shap_abs.mean()).reset_index()
    k.columns = ['Variable','SHAP_abs']
    k2 = k.merge(corr_df,left_on = 'Variable',right_on='Variable',how='inner')
    k2 = k2.sort_values(by='SHAP_abs',ascending = True).tail(n)
    colorlist = k2['Sign']
    ax = k2.plot.barh(x='Variable',y='SHAP_abs',color = colorlist, figsize=figure,legend=False)
    ax.set_xlabel("SHAP Value (Red = Positive Impact)")

def show_random_observation(model1, model2, X, y, exlainer):
    """This functions displays Lime model explanation for a random observation
    and predicted values from two models.
    **********************
    Arguments
    model1: predictive model #1
    model2: predictive model #2
    X: test set data (dataframe)
    y: test set target (dataframe)
    explainer: lime_tabular.LimeTabularExplainer"""

    idx = random.randint(1, len(X))

    if model1.predict(X)[idx]==0:
        prediction1='Adequate'
    else:
        prediction1='Failing'

    if model2.predict(X)[idx]==0:
        prediction2='Adequate'
    else:
        prediction2='Failing'

    if y.iloc[idx, 0]==0:
        actual='Adequate'
    else:
        actual='Failing'

    print('Prediction from the first model : {}'.format(prediction1))
    print('Prediction from the second model : {}'.format(prediction2))
    print('Actual :   {} '.format(actual))

    exp1 = explainer.explain_instance(X.values[idx], model1.predict_proba, num_features=6)
    exp2 = explainer.explain_instance(X.values[idx], model2.predict_proba, num_features=6)

    exp1.save_to_file('exp1.html')
    exp2.save_to_file('exp2.html')
    exp1.show_in_notebook()
    exp1.as_pyplot_figure();
    exp2.show_in_notebook()
    exp2.as_pyplot_figure();
```

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3.3 Data Understanding

The dataset used in this project has been downloaded from the Mendeley Data Repository (https://data.mendeley.com/datasets/83tcx8psxv). The dataset

has been published in ScienceDirect Elsevier publication "Data in Brief," Volume 30, June 2020, 105537. (https://www.sciencedirect.com/science/article/pii/S2352340920304315)

> **Quote from the paper summary:**
> *"This data article presents data on the results in national assessments for secondary and university education in engineering students. The data contains academic, social, economic information for 12,411 students. The data were obtained by orderly crossing the databases of the Colombian Institute for the Evaluation of Education (ICFES). The structure of the data allows us to observe the influence of social variables and the evolution of students' learning skills."*

The dataset has 44 dependent and independent variables; each row represents a student. The variables correspond to the student's personal information (categorical) and the result obtained in the assessments (numerical). The academic evaluation is recorded at two moments of the student's life. First, the national standardized test scores at the final year of the high school (Saber 11), 2012-2014 years. The second moment of academic assessment is in the final year of their professional training in Engineering, recorded on the national standardized test for higher education (SABER PRO), 2018 year.

3.4 Importing data

In [3]:
```
# Importing raw data
df=pd.read_csv('data/data_academic_performance.csv', encoding='latin1')
pd.set_option('display.width', 1000)
df.head()
```

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Out[3]:

	COD_S11	GENDER	EDU_FATHER	EDU_MOTHER	OCC_FATHER	OCC_MOTHER	STRATUM	SISBEN	PEOPLE_HOUSE	Unnai
0	SB11201210000129	F	Incomplete Professional Education	Complete technique or technology	Technical or professional level employee	Home	Stratum 4	It is not classified by the SISBEN	Three	
1	SB11201210000137	F	Complete Secundary	Complete professional education	Entrepreneur	Independent professional	Stratum 5	It is not classified by the SISBEN	Three	
2	SB11201210005154	M	Not sure	Not sure	Independent	Home	Stratum 2	Level 2	Five	
3	SB11201210007504	F	Not sure	Not sure	Other occupation	Independent	Stratum 2	It is not classified by the SISBEN	Three	
4	SB11201210007548	M	Complete professional education	Complete professional education	Executive	Home	Stratum 4	It is not classified by the SISBEN	One	

5 rows × 45 columns

In [4]:

```
1 df.info()
```

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```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12411 entries, 0 to 12410
Data columns (total 45 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   COD_S11           12411 non-null  object 
 1   GENDER            12411 non-null  object 
 2   EDU_FATHER        12411 non-null  object 
 3   EDU_MOTHER        12411 non-null  object 
 4   OCC_FATHER        12411 non-null  object 
 5   OCC_MOTHER        12411 non-null  object 
 6   STRATUM           12411 non-null  object 
 7   SISBEN            12411 non-null  object 
 8   PEOPLE_HOUSE      12411 non-null  object 
 9   Unnamed: 9        0 non-null      float64
 10  INTERNET          12411 non-null  object 
 11  TV                12411 non-null  object 
 12  COMPUTER          12411 non-null  object 
 13  WASHING_MCH       12411 non-null  object 
 14  MIC_OVEN          12411 non-null  object 
 15  CAR               12411 non-null  object 
 16  DVD               12411 non-null  object 
 17  FRESH             12411 non-null  object 
 18  PHONE             12411 non-null  object 
 19  MOBILE            12411 non-null  object 
 20  REVENUE           12411 non-null  object 
 21  JOB               12411 non-null  object 
 22  SCHOOL_NAME       12411 non-null  object 
 23  SCHOOL_NAT        12411 non-null  object 
 24  SCHOOL_TYPE       12411 non-null  object 
 25  MAT_S11           12411 non-null  int64  
 26  CR_S11            12411 non-null  int64  
 27  CC_S11            12411 non-null  int64  
 28  BIO_S11           12411 non-null  int64  
 29  ENG_S11           12411 non-null  int64  
 30  Cod_SPro          12411 non-null  object 
 31  UNIVERSITY        12411 non-null  object 
 32  ACADEMIC_PROGRAM  12411 non-null  object 
 33  QR_PRO            12411 non-null  int64  
 34  CR_PRO            12411 non-null  int64  
 35  CC_PRO            12411 non-null  int64  
 36  ENG_PRO           12411 non-null  int64  
 37  WC_PRO            12411 non-null  int64  
 38  FEP_PRO           12411 non-null  int64  
 39  G_SC              12411 non-null  int64  
 40  PERCENTILE        12411 non-null  int64  
 41  2ND_DECILE        12411 non-null  int64  
 42  QUARTILE          12411 non-null  int64  
 43  SEL               12411 non-null  int64  
 44  SEL_IHE           12411 non-null  int64  
dtypes: float64(1), int64(17), object(27)
memory usage: 4.3+ MB
```

In [5]:
```
#Show numbers of unique values for each column
df.nunique()
```

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Out[5]:
```
COD_S11             12411
GENDER                  2
EDU_FATHER             12
EDU_MOTHER             12
OCC_FATHER             12
OCC_MOTHER             12
STRATUM                 7
SISBEN                  6
PEOPLE_HOUSE           13
Unnamed: 9              0
INTERNET                2
TV                      2
COMPUTER                2
WASHING_MCH             2
MIC_OVEN                2
CAR                     2
DVD                     2
FRESH                   2
PHONE                   2
MOBILE                  2
REVENUE                 8
JOB                     4
SCHOOL_NAME          3735
SCHOOL_NAT              2
SCHOOL_TYPE             4
MAT_S11                69
CR_S11                 71
CC_S11                 68
BIO_S11                72
ENG_S11                63
Cod_SPro            12395
UNIVERSITY            134
ACADEMIC_PROGRAM       21
QR_PRO                100
CR_PRO                100
CC_PRO                100
ENG_PRO               100
WC_PRO                101
FEP_PRO               236
G_SC                  166
PERCENTILE            100
2ND_DECILE              5
QUARTILE                4
SEL                     4
SEL_IHE                 4
dtype: int64
```

3.5 Description of the variables

- The dataset has 12411 unique records with 44 columns. There are no NULL values in any of the columns.

The annotation to the fields and associated data

(link to the partial definition here (https://www.sciencedirect.com/science/article/pii/S2352340920304315#tbl0001))

COD_S11: S11 test student identifier; 12411 unique values, no duplicates
Cod_SPro: SABER_PRO test student identifier; 12395 unique values, 16 duplicates

Categorical variables
GENDER: Student's gender; 2 unique values (F/M)
EDU_FATHER: Level of education of a student's father; 12 unique values
EDU_MOTHER: Level of education of a student's mother; 12 unique values
OCC_FATHER: Occupation of a student's father; 12 unique values
OCC_MOTHER: Occupation of a student's mother; 12 unique values
STRATUM: Colombian socio-economic class indicator; 7 unique values
SISBEN: Levels of Colombian welfare system; 6 unique values
PEOPLE_HOUSE: Number of people in the household; 13 unique values

INTERNET: Does a household have an internet connection; 2 unique values (Yes/No)
TV: Does a household have a TV; 2 unique values (Yes/No)
COMPUTER: Does a household have a computer; 2 unique values (Yes/No)
WASHING_MCH: Does a household have a washing machine; 2 unique values (Yes/No)
MIC_OVEN: Does a household have a microwave oven; 2 unique values (Yes/No)
CAR: Does a household have a car; 2 unique values (Yes/No)
DVD: Does a household have a DVD player; 2 unique values (Yes/No)
FRESH: Does a household have access to freshwater; 2 unique values (Yes/No)
PHONE: Does a household have a landline phone; 2 unique values (Yes/No)
MOBILE: Does a student have a mobile phone; 2 unique values (Yes/No)
REVENUE: Household income category; 8 unique values
JOB: An indicator if a student had a job; 4 unique values
SCHOOL_NAME: High School name, 3735 unique values
SCHOOL_NAT: High school Private or Public, 2 unique values
SCHOOL_TYPE: School Type, 4 unique values
UNIVERSITY: University Name, 134 unique values
ACADEMIC_PROGRAM: Engineering Program; 21 unique values

Numerical variables
SEL: Student's Socio-Economic level; 4 unique values
SEL_IHE: Average Socio-Economic level of the university/program a student attended; 4 unique level

High School academic assessment results
MAT_S11: Mathematics
CR_S11: Critical Reading
CC_S11: Citizen Competencies
BIO_S11: Biology
ENG_S11: English

Engineering School academic assessment results
QR_PRO: Quantitative Reasoning
CR_PRO: Critical Reading
CC_PRO: Citizen Competencies
ENG_PRO: English
WC_PRO: Written Communication
FEP_PRO: Formulation of Engineering Projects
G_SC: Global Score
PERCENTILE: PErcentile
Quartile: Quartile **2ND_DECILE**: Second Decile

4 Scrub and Explore

4.1 Cleaning the dataset

In [6]:
```
# Dropping empty column #9

df=df.drop(df.columns[9], axis=1)
```
executed in 15ms, finished 23:15:55 2021-05-27

- Dropping all other subject test results in Saber_Pro (post-university assessment). Leaving only the G_SC test results (Global score in post-university examination) as the most relevant to student's performance.
- Dropping PERCENTILE, 2ND_DECILE, and QUARTILE variables because there is no clear definition in the original paper.
- Dropping SCHOOL_NAME variable. School names as a factor in student's performance evolution are outside of this project's scope due to the sheer number of the schools.

In [7]:
```
# Dropping the columns outlined above

cols_to_drop=['CR_PRO','CC_PRO','ENG_PRO','WC_PRO','FEP_PRO','QR_PRO',
              'PERCENTILE','2ND_DECILE','QUARTILE','SCHOOL_NAME']
df=df.drop(cols_to_drop, axis=1)
```
executed in 15ms, finished 23:15:55 2021-05-27

In [8]:
```
1 df.info()
```

executed in 30ms, finished 23:15:55 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12411 entries, 0 to 12410
Data columns (total 34 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   COD_S11           12411 non-null  object
 1   GENDER            12411 non-null  object
 2   EDU_FATHER        12411 non-null  object
 3   EDU_MOTHER        12411 non-null  object
 4   OCC_FATHER        12411 non-null  object
 5   OCC_MOTHER        12411 non-null  object
 6   STRATUM           12411 non-null  object
 7   SISBEN            12411 non-null  object
 8   PEOPLE_HOUSE      12411 non-null  object
 9   INTERNET          12411 non-null  object
 10  TV                12411 non-null  object
 11  COMPUTER          12411 non-null  object
 12  WASHING_MCH       12411 non-null  object
 13  MIC_OVEN          12411 non-null  object
 14  CAR               12411 non-null  object
 15  DVD               12411 non-null  object
 16  FRESH             12411 non-null  object
 17  PHONE             12411 non-null  object
 18  MOBILE            12411 non-null  object
 19  REVENUE           12411 non-null  object
 20  JOB               12411 non-null  object
 21  SCHOOL_NAT        12411 non-null  object
 22  SCHOOL_TYPE       12411 non-null  object
 23  MAT_S11           12411 non-null  int64 
 24  CR_S11            12411 non-null  int64 
 25  CC_S11            12411 non-null  int64 
 26  BIO_S11           12411 non-null  int64 
 27  ENG_S11           12411 non-null  int64 
 28  Cod_SPro          12411 non-null  object
 29  UNIVERSITY        12411 non-null  object
 30  ACADEMIC_PROGRAM  12411 non-null  object
 31  G_SC              12411 non-null  int64 
 32  SEL               12411 non-null  int64 
 33  SEL_IHE           12411 non-null  int64 
dtypes: int64(8), object(26)
memory usage: 3.2+ MB
```

Exploring duplicate values in **Cod_SPro** column

In [9]:
```
1 # How many duplicated in Cod_SPro column
2 df.duplicated(subset=['Cod_SPro']).sum()
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[9]: 16

In [10]:

```
# List them
list_pro=list(df.loc[df.duplicated(subset=['Cod_SPro']), :]['Cod_SPro'])
list_pro
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[10]:

```
['EK201830017763',
 'EK201830167945',
 'EK201830204628',
 'EK201830022057',
 'EK201830072676',
 'EK201830052508',
 'EK201830158353',
 'EK201830060977',
 'EK201830012603',
 'EK201830221937',
 'EK201830013197',
 'EK201830030238',
 'EK201830054744',
 'EK201830036216',
 'EK201830191607',
 'EK201830210897']
```

In [11]:

```
# Listing all duplicate Cod_SPro rows, sorted by Cod_SPro
df[df['Cod_SPro'].isin(list_pro)].sort_values('Cod_SPro')
```

executed in 31ms, finished 23:15:55 2021-05-27

Out[11]:

	COD_S11	GENDER	EDU_FATHER	EDU_MOTHER	OCC_FATHER	OCC_MOTHER	STRATUM	SISBEN	PEOPLE_HOUSE	IN
6524	SB11201320110284	M	Incomplete technical or technological	Complete Secundary	Entrepreneur	Small entrepreneur	Stratum 4	It is not classified by the SISBEN	Two	
2259	SB11201220313289	M	0	0	Entrepreneur	0	Stratum 4	It is not classified by the SISBEN	Two	
8035	SB11201320225581	F	Incomplete Professional Education	Incomplete Secundary	Independent	Home	Stratum 2	Level 2	Four	
604	SB11201220043502	F	Postgraduate education	0	0	Home	Stratum 2	Level 2	Four	
2023	SB11201220288842	M	0	0	0	0	Stratum 3	It is not classified by the SISBEN	Three	
4289	SB11201310002204	M	Complete primary	Complete Secundary	0	Independent	Stratum 3	It is not classified by the SISBEN	Three	
4648	SB11201310072215	M	Complete professional education	Complete professional education	0	Home	Stratum 5	It is not classified by the SISBEN	Four	
2659	SB11201220340907	M	Incomplete primary	Incomplete primary	0	Home	Stratum 5	It is not classified by the SISBEN	Four	
2463	SB11201220326795	M	Complete primary	Complete primary	0	0	Stratum 2	It is not classified by the SISBEN	Three	
8250	SB11201320242054	M	Postgraduate education	Postgraduate education	Technical or professional level employee	Technical or professional level employee	Stratum 2	It is not classified by the SISBEN	Three	
1324	SB11201220171353	M	0	0	0	Home	Stratum 2	It is not classified by the SISBEN	Six	
9758	SB11201320398372	M	Complete primary	Incomplete Secundary	Independent	Home	Stratum 3	Level 3	Six	
4127	SB11201220568660	M	Incomplete primary	Incomplete primary	0	0	Stratum 3	It is not classified by the SISBEN	Two	
5611	SB11201320052262	M	Complete professional education	Complete professional education	Independent	Independent professional	Stratum 3	It is not classified by the SISBEN	Two	
9402	SB11201320339442	F	Incomplete Secundary	Complete technique or technology	Independent	Other occupation	Stratum 3	It is not classified by the SISBEN	Five	
1000	SB11201220095809	F	0	0	0	0	Stratum 3	It is not classified by the SISBEN	Five	

	COD_S11	GENDER	EDU_FATHER	EDU_MOTHER	OCC_FATHER	OCC_MOTHER	STRATUM	SISBEN	PEOPLE_HOUSE	IN
5947	SB11201320072949	M	Incomplete Secundary	Complete Secundary	Other occupation	Other occupation	Stratum 3	It is not classified by the SISBEN	Eight	
984	SB11201220094014	M	0	0	0	0	Stratum 3	It is not classified by the SISBEN	Eight	
4673	SB11201310082281	F	Complete primary	Incomplete Secundary	0	Home	Stratum 1	Level 1	Six	
957	SB11201220092732	F	0	0	0	Home	Stratum 1	Level 1	Six	
5880	SB11201320070596	M	Complete professional education	Postgraduate education	Independent professional	Executive	Stratum 4	It is not classified by the SISBEN	Four	
3082	SB11201220391432	M	Complete professional education	Postgraduate education	Independent professional	Executive	Stratum 4	It is not classified by the SISBEN	Four	
4630	SB11201310056691	M	Complete Secundary	Complete technique or technology	0	Home	Stratum 1	Level 2	Five	
4150	SB11201220571555	M	0	0	0	Home	Stratum 1	Level 2	Five	
4424	SB11201310012059	F	Complete technique or technology	Complete technique or technology	0	Home	Stratum 3	It is not classified by the SISBEN	Four	
11053	SB11201320574340	F	Complete technique or technology	Complete technique or technology	Technical or professional level employee	Home	Stratum 3	It is not classified by the SISBEN	Four	
4636	SB11201310057554	F	Complete professional education	Incomplete Professional Education	0	Home	Stratum 5	It is not classified by the SISBEN	Five	
779	SB11201220064144	F	Incomplete primary	Postgraduate education	0	Home	Stratum 3	It is not classified by the SISBEN	Five	
7920	SB11201320215351	F	Complete Secundary	Complete technique or technology	Executive	Home	Stratum 3	It is not classified by the SISBEN	Three	
11438	SB11201410032085	F	Complete Secundary	Complete Secundary	Small entrepreneur	Small entrepreneur	Stratum 2	Level 2	Three	
778	SB11201220064140	F	Incomplete primary	Incomplete primary	0	0	Stratum 4	It is not classified by the SISBEN	Three	
7430	SB11201320182089	F	Complete professional education	Complete professional education	Retired	Retired	Stratum 4	It is not classified by the SISBEN	Three	

32 rows × 34 columns

The records with duplicate **Cod_SPro** test identifiers seem like errors and will be dropped (32 rows).

In [12]:
```
# Deleting all of the rows with duplicate 'Cod_SPro' identifier
df = df[~df['Cod_SPro'].isin(list_pro)]
```

executed in 15ms, finished 23:15:55 2021-05-27

In [13]:
```
df.info()
```

executed in 31ms, finished 23:15:55 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12379 entries, 0 to 12410
Data columns (total 34 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   COD_S11           12379 non-null  object
 1   GENDER            12379 non-null  object
 2   EDU_FATHER        12379 non-null  object
 3   EDU_MOTHER        12379 non-null  object
 4   OCC_FATHER        12379 non-null  object
 5   OCC_MOTHER        12379 non-null  object
 6   STRATUM           12379 non-null  object
 7   SISBEN            12379 non-null  object
 8   PEOPLE_HOUSE      12379 non-null  object
 9   INTERNET          12379 non-null  object
 10  TV                12379 non-null  object
 11  COMPUTER          12379 non-null  object
 12  WASHING_MCH       12379 non-null  object
 13  MIC_OVEN          12379 non-null  object
 14  CAR               12379 non-null  object
 15  DVD               12379 non-null  object
 16  FRESH             12379 non-null  object
 17  PHONE             12379 non-null  object
 18  MOBILE            12379 non-null  object
 19  REVENUE           12379 non-null  object
 20  JOB               12379 non-null  object
 21  SCHOOL_NAT        12379 non-null  object
 22  SCHOOL_TYPE       12379 non-null  object
 23  MAT_S11           12379 non-null  int64 
 24  CR_S11            12379 non-null  int64 
 25  CC_S11            12379 non-null  int64 
 26  BIO_S11           12379 non-null  int64 
 27  ENG_S11           12379 non-null  int64 
 28  Cod_SPro          12379 non-null  object
 29  UNIVERSITY        12379 non-null  object
 30  ACADEMIC_PROGRAM  12379 non-null  object
 31  G_SC              12379 non-null  int64 
 32  SEL               12379 non-null  int64 
 33  SEL_IHE           12379 non-null  int64 
dtypes: int64(8), object(26)
memory usage: 3.3+ MB
```

A combination of an Engineering Program and a University seems like a more logical feature to correlate with a student's progress

In [14]:
```
# Combining a University name and an academic program name; It can be useful
# for identifying what program is the most successful helping the students achieve their potential

df['PROG_UNIV'] = df['ACADEMIC_PROGRAM'] + '_' + df['UNIVERSITY']
```

executed in 15ms, finished 23:15:55 2021-05-27

In [15]:
```
1 df.nunique()
```

executed in 31ms, finished 23:15:55 2021-05-27

Out[15]:
```
COD_S11             12379
GENDER                  2
EDU_FATHER             12
EDU_MOTHER             12
OCC_FATHER             12
OCC_MOTHER             12
STRATUM                 7
SISBEN                  6
PEOPLE_HOUSE           13
INTERNET                2
TV                      2
COMPUTER                2
WASHING_MCH             2
MIC_OVEN                2
CAR                     2
DVD                     2
FRESH                   2
PHONE                   2
MOBILE                  2
REVENUE                 8
JOB                     4
SCHOOL_NAT              2
SCHOOL_TYPE             4
MAT_S11                69
CR_S11                 71
CC_S11                 68
BIO_S11                72
ENG_S11                63
Cod_SPro            12379
UNIVERSITY            134
ACADEMIC_PROGRAM       21
G_SC                  166
SEL                     4
SEL_IHE                 4
PROG_UNIV             283
dtype: int64
```

Exploring inconsistencies in **PEOPLE_HOUSE** unique values and replacing them with numeric values

In [16]:
```
1 pd.value_counts(df.PEOPLE_HOUSE)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[16]:
```
Four              4759
Five              2864
Three             2337
Six               1086
Two                588
Seven              372
Eight              162
Nueve               74
Ten                 52
Twelve or more      32
0                   21
Once                19
One                 13
Name: PEOPLE_HOUSE, dtype: int64
```

In [17]:
```
# Updating PEOPLE_HOUSE values to numeric

dict = {'Four': 4, 'Five': 5,'Three': 3,'Six': 6, 'Two':2,'Seven': 7,
       'Eight': 8, 'Nueve':9,'Ten': 10,'Twelve or more':12,'0':0,'Once':1,'One':1}

df.PEOPLE_HOUSE=df.PEOPLE_HOUSE.map(dict)
pd.value_counts(df.PEOPLE_HOUSE)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[17]:
```
4     4759
5     2864
3     2337
6     1086
2      588
7      372
8      162
9       74
10      52
12      32
1       32
0       21
Name: PEOPLE_HOUSE, dtype: int64
```

Exploring inconsistencies in **EDU_FATHER** unique values and fixing them

In [18]:
```
pd.value_counts(df.EDU_FATHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[18]:
```
Complete professional education          3010
Complete Secundary                       2840
Complete technique or technology         1192
Incomplete Secundary                     1089
Postgraduate education                   1083
Complete primary                          820
Incomplete primary                        731
Incomplete Professional Education         424
Not sure                                  407
0                                         384
Incomplete technical or technological     276
Ninguno                                   123
Name: EDU_FATHER, dtype: int64
```

In [19]:
```
dict_edu = {'Complete professional education':'Complete professional education',
        'Complete Secundary': 'Complete Secondary',
        'Complete technique or technology':'Complete technique or technology',
        'Incomplete Secundary':'Incomplete Secondary',
        'Postgraduate education':'Postgraduate education',
        'Complete primary ':'Complete primary',
        'Incomplete primary ':'Incomplete primary',
        'Incomplete Professional Education':'Incomplete Professional Education',
        'Not sure':'Not sure',
        '0': 'Unknown',
        'Incomplete technical or technological':'Incomplete technical or technological',
        'Ninguno': 'None'}

```

executed in 15ms, finished 23:15:55 2021-05-27

In [20]:
```
# Updating EDU_FATHER values

df.EDU_FATHER=df.EDU_FATHER.map(dict_edu)
pd.value_counts(df.EDU_FATHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[20]:
```
Complete professional education          3010
Complete Secondary                       2840
Complete technique or technology         1192
Incomplete Secondary                     1089
Postgraduate education                   1083
Complete primary                          820
Incomplete primary                        731
Incomplete Professional Education         424
Not sure                                  407
Unknown                                   384
Incomplete technical or technological     276
None                                      123
Name: EDU_FATHER, dtype: int64
```

Exploring inconsistencies in **EDU_MOTHER** unique values and fixing them

In [21]:
```
pd.value_counts(df.EDU_MOTHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[21]:
```
Complete Secundary                       3102
Complete professional education          3056
Complete technique or technology         1490
Incomplete Secundary                     1053
Postgraduate education                    993
Complete primary                          712
Incomplete primary                        538
Incomplete Professional Education         501
0                                         380
Incomplete technical or technological     341
Not sure                                  179
Ninguno                                    34
Name: EDU_MOTHER, dtype: int64
```

In [22]:
```
# Updating EDU_MOTHER values

df.EDU_MOTHER=df.EDU_MOTHER.map(dict_edu)
pd.value_counts(df.EDU_MOTHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[22]:
```
Complete Secondary                       3102
Complete professional education          3056
Complete technique or technology         1490
Incomplete Secondary                     1053
Postgraduate education                    993
Complete primary                          712
Incomplete primary                        538
Incomplete Professional Education         501
Unknown                                   380
Incomplete technical or technological     341
Not sure                                  179
None                                       34
Name: EDU_MOTHER, dtype: int64
```

Exploring inconsistencies in **OCC_FATHER** unique values and fixing them

In [23]:
```
pd.value_counts(df.OCC_FATHER)
```

executed in 13ms, finished 23:15:55 2021-05-27

Out[23]:
```
Independent                                 2903
Technical or professional level employee    1801
Operator                                    1537
Other occupation                            1086
Executive                                   1076
0                                            922
Independent professional                     913
Small entrepreneur                           691
Retired                                      531
Entrepreneur                                 470
Auxiliary or Administrative                  372
Home                                          77
Name: OCC_FATHER, dtype: int64
```

In [24]:
```
dict_occ = {'Independent':'Independent',
        'Technical or professional level employee': 'Technical or professional level employee',
        'Operator':'Operator',
        'Other occupation':'Other occupation',
        'Executive':'Executive',
        '0':'Unknown',
        'Independent professional':'Independent professional',
        'Small entrepreneur ':'Small entrepreneur',
        'Retired':'Retired',
        'Entrepreneur ':'Entrepreneur',
        'Auxiliary or Administrative': 'Auxiliary or Administrative',
        'Home':'Home'}

```

executed in 14ms, finished 23:15:55 2021-05-27

In [25]:
```
# Updating OCC_FATHER values

df.OCC_FATHER=df.OCC_FATHER.map(dict_occ)
pd.value_counts(df.OCC_FATHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[25]:
```
Independent                                 2903
Technical or professional level employee    1801
Operator                                    1537
Other occupation                            1086
Executive                                   1076
Unknown                                      922
Independent professional                     913
Small entrepreneur                           691
Retired                                      531
Entrepreneur                                 470
Auxiliary or Administrative                  372
Home                                          77
Name: OCC_FATHER, dtype: int64
```

Exploring inconsistencies in **OCC_MOTHER** unique values and fixing them

In [26]:
```
pd.value_counts(df.OCC_MOTHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[26]:
```
Home                                        4643
Technical or professional level employee    1794
Independent                                 1106
Auxiliary or Administrative                  846
Executive                                    792
Independent professional                     714
Operator                                     684
Other occupation                             605
Small entrepreneur                           490
0                                            306
Entrepreneur                                 242
Retired                                      157
Name: OCC_MOTHER, dtype: int64
```

In [27]:
```
# Updating OCC_MOTHER values

df.OCC_MOTHER=df.OCC_MOTHER.map(dict_occ)
pd.value_counts(df.OCC_MOTHER)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[27]:
```
Home                                    4643
Technical or professional level employee    1794
Independent                             1106
Auxiliary or Administrative              846
Executive                                792
Independent professional                 714
Operator                                 684
Other occupation                         605
Small entrepreneur                       490
Unknown                                  306
Entrepreneur                             242
Retired                                  157
Name: OCC_MOTHER, dtype: int64
```

Exploring inconsistencies in **STRATUM** unique values and fixing them

In [28]:
```
pd.value_counts(df.STRATUM)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[28]:
```
Stratum 3    4032
Stratum 2    4023
Stratum 1    1705
Stratum 4    1572
Stratum 5     630
Stratum 6     403
0              14
Name: STRATUM, dtype: int64
```

In [29]:
```
# Updating STRATUM values

df.replace({'STRATUM': {'0': 'Unknown'}}, inplace=True)
pd.value_counts(df.STRATUM)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[29]:
```
Stratum 3    4032
Stratum 2    4023
Stratum 1    1705
Stratum 4    1572
Stratum 5     630
Stratum 6     403
Unknown        14
Name: STRATUM, dtype: int64
```

Exploring inconsistencies in **SISBEN** unique values and fixing them

In [30]:
```
pd.value_counts(df.SISBEN)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[30]:
```
It is not classified by the SISBEN          7510
Level 2                                     2115
Level 1                                     2055
Level 3                                      582
Esta clasificada en otro Level del SISBEN     96
0                                             21
Name: SISBEN, dtype: int64
```

In [31]:
```
# Updating SISBEN values

df.replace({'SISBEN': {'0': 'Unknown',
                       'Esta clasificada en otro Level del SISBEN':'It is classified in another Level of the SISBEN'}},
           inplace=True)
pd.value_counts(df.SISBEN)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[31]:
```
It is not classified by the SISBEN               7510
Level 2                                          2115
Level 1                                          2055
Level 3                                           582
It is classified in another Level of the SISBEN    96
Unknown                                            21
Name: SISBEN, dtype: int64
```

Exploring inconsistencies in **REVENUE** unique values and fixing them

In [32]:
```
pd.value_counts(df.REVENUE)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[32]:
```
Between 1 and less than 2 LMMW     3861
Between 2 and less than 3 LMMW     2781
Between 3 and less than 5 LMMW     2231
less than 1 LMMW                   1036
Between 5 and less than 7 LMMW      969
10 or more LMMW                     717
Between 7 and less than 10 LMMW     508
0                                   276
Name: REVENUE, dtype: int64
```

In [33]:
```
# Updating REVENUE values

df.replace({'REVENUE': {'0': 'Unknown'}}, inplace=True)
pd.value_counts(df.REVENUE)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[33]:
```
Between 1 and less than 2 LMMW     3861
Between 2 and less than 3 LMMW     2781
Between 3 and less than 5 LMMW     2231
less than 1 LMMW                   1036
Between 5 and less than 7 LMMW      969
10 or more LMMW                     717
Between 7 and less than 10 LMMW     508
Unknown                             276
Name: REVENUE, dtype: int64
```

Exploring inconsistencies in **JOB** unique values and fixing them

In [34]:
```
pd.value_counts(df.JOB)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[34]:
```
No                                 11886
Yes, less than 20 hours per week     229
Yes, 20 hours or more per week       134
0                                    130
Name: JOB, dtype: int64
```

In [35]:
```
# Updating JOB values

df.replace({'JOB': {'0': 'Unknown'}}, inplace=True)
pd.value_counts(df.JOB)

# There are very few records with values other than 'No', it might have an adverse effect of models
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[35]:
```
No                                11886
Yes, less than 20 hours per week    229
Yes, 20 hours or more per week      134
Unknown                             130
Name: JOB, dtype: int64
```

Exploring inconsistencies in **SCHOOL_TYPE** unique values and fixing them

In [36]:
```
pd.value_counts(df.SCHOOL_TYPE)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[36]:
```
ACADEMIC              7812
TECHNICAL/ACADEMIC    3506
TECHNICAL             1056
Not apply                5
Name: SCHOOL_TYPE, dtype: int64
```

In [37]:
```
# Updating SCHOOL_TYPE values

df.replace({'SCHOOL_TYPE': {'Not apply': 'NA'}}, inplace=True)
pd.value_counts(df.SCHOOL_TYPE)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[37]:
```
ACADEMIC              7812
TECHNICAL/ACADEMIC    3506
TECHNICAL             1056
NA                       5
Name: SCHOOL_TYPE, dtype: int64
```

Exploring frequency of occurrence of unique **PROG_UNIV** values and leaving only those that occur more or equal 75 times. That step aims to reduce the number of unique values in this categorical column from 283 to a more manageable number.

In [38]:
```
pd.value_counts(df.PROG_UNIV)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[38]:
```
INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                                    294
INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA      -CARTAGENA    209
CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.                              203
INDUSTRIAL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.                            183
CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.                              182
                                                                                              ...
TEXTILE ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-MEDELLIN                                  1
ELECTRONIC ENGINEERING_UNIDAD CENTRAL DEL VALLE DEL CAUCA-TULUA                                  1
INDUSTRIAL CONTROL AND AUTOMATION ENGINEERING_UNIVERSIDAD ANTONIO NARIÑO-BOGOTÁ D.C.             1
ELECTROMECHANICAL ENGINEERING_ESCUELA TECNOLOGICA INSTITUTO TECNICO CENTRAL -BOGOTÁ D.C.         1
INDUSTRIAL ENGINEERING_UNIVERSIDAD MANUELA BELTRAN-UMB--BUCARAMANGA                             1
Name: PROG_UNIV, Length: 283, dtype: int64
```

In [39]:

```
# Replacing PROG_UNIV values with lower frequency of occurance with 'Other'

df_univ_prg=pd.DataFrame(pd.value_counts(df.PROG_UNIV))
df_univ_prg.reset_index(inplace=True)
df_univ_prg = df_univ_prg.rename(columns = {'index':'PROG_UNIV','PROG_UNIV': 'Frequency'})

freq_values=df_univ_prg[df_univ_prg['Frequency'] >= 75]
freq_values.to_csv('data/freq_values.csv', encoding='latin1')
list_to_keep=list(freq_values.PROG_UNIV)
df.loc[~df.PROG_UNIV.isin(list_to_keep), 'PROG_UNIV'] = 'Other'
pd.value_counts(df.PROG_UNIV)
```

executed in 15ms, finished 23:15:55 2021-05-27

Out[39]:

```
Other                                                                                  6268
INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                             294
INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA      -CARTAGENA     209
CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.                       203
INDUSTRIAL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.                     183
CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.                       182
CIVIL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.          160
CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.    157
CIVIL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA                        145
CIVIL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                                  139
CIVIL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA                 134
CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-BOGOTÁ D.C.                                   133
INDUSTRIAL ENGINEERING_UNIVERSIDAD DE PAMPLONA-PAMPLONA                                 129
CIVIL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA                       129
INDUSTRIAL ENGINEERING_UNIVERSIDAD TECNOLOGICA DE PEREIRA - ITP-PEREIRA                 128
INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA                               126
INDUSTRIAL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA                  123
INDUSTRIAL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.                     122
CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-TUNJA                                         121
CIVIL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.                          121
INDUSTRIAL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.     121
CIVIL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.                        119
CIVIL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA                       118
INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DEL HUILA-CORHUILA-NEIVA                118
MECHANICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                             114
INDUSTRIAL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA                   112
CHEMICAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA                                      111
INDUSTRIAL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA            108
INDUSTRIAL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.                   107
CHEMICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                               106
INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DE INVESTIGACION Y DESARROLLO -"UDI"-BUCARAMANGA    106
CIVIL ENGINEERING_UNIVERSIDAD LA GRAN COLOMBIA-BOGOTÁ D.C.                              102
INDUSTRIAL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE                                     100
INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL ATLANTICO-BARRANQUILLA                            99
CIVIL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA                                     99
INDUSTRIAL ENGINEERING_UNIVERSIDAD AUTONOMA DEL CARIBE-BARRANQUILLA                      98
INDUSTRIAL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.                   94
INDUSTRIAL ENGINEERING_UNIVERSIDAD ICESI-CALI                                            91
INDUSTRIAL ENGINEERING_UNIVERSIDAD DISTRITAL"FRANCISCO JOSE DE CALDAS"-BOGOTÁ D.C.       91
INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL VALLE-CALI                                        91
CIVIL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE                                           89
INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA MINUTO DE DIOS -UNIMINUTO-BOGOTÁ D.C.   88
INDUSTRIAL ENGINEERING_POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.                            86
MECHANICAL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA                   86
INDUSTRIAL ENGINEERING_UNIVERSIDAD TECNOLOGICA DE BOLIVAR-CARTAGENA                      85
INDUSTRIAL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA                   84
INDUSTRIAL ENGINEERING_UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA                            82
CIVIL ENGINEERING_UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.                           82
CIVIL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.                           79
CATASTRAL ENGINEERING AND GEODESY_UNIVERSIDAD DISTRITAL"FRANCISCO JOSE DE CALDAS"-BOGOTÁ D.C.    78
INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA                                     78
INDUSTRIAL ENGINEERING_UNIVERSIDAD LIBRE-BOGOTÁ D.C.                                     76
CHEMICAL ENGINEERING_UNIVERSIDAD DE CARTAGENA-CARTAGENA                                  75
Name: PROG_UNIV, dtype: int64
```

In [40]:
```
1 df.info()
```

executed in 31ms, finished 23:15:55 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12379 entries, 0 to 12410
Data columns (total 35 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   COD_S11           12379 non-null  object
 1   GENDER            12379 non-null  object
 2   EDU_FATHER        12379 non-null  object
 3   EDU_MOTHER        12379 non-null  object
 4   OCC_FATHER        12379 non-null  object
 5   OCC_MOTHER        12379 non-null  object
 6   STRATUM           12379 non-null  object
 7   SISBEN            12379 non-null  object
 8   PEOPLE_HOUSE      12379 non-null  int64 
 9   INTERNET          12379 non-null  object
 10  TV                12379 non-null  object
 11  COMPUTER          12379 non-null  object
 12  WASHING_MCH       12379 non-null  object
 13  MIC_OVEN          12379 non-null  object
 14  CAR               12379 non-null  object
 15  DVD               12379 non-null  object
 16  FRESH             12379 non-null  object
 17  PHONE             12379 non-null  object
 18  MOBILE            12379 non-null  object
 19  REVENUE           12379 non-null  object
 20  JOB               12379 non-null  object
 21  SCHOOL_NAT        12379 non-null  object
 22  SCHOOL_TYPE       12379 non-null  object
 23  MAT_S11           12379 non-null  int64 
 24  CR_S11            12379 non-null  int64 
 25  CC_S11            12379 non-null  int64 
 26  BIO_S11           12379 non-null  int64 
 27  ENG_S11           12379 non-null  int64 
 28  Cod_SPro          12379 non-null  object
 29  UNIVERSITY        12379 non-null  object
 30  ACADEMIC_PROGRAM  12379 non-null  object
 31  G_SC              12379 non-null  int64 
 32  SEL               12379 non-null  int64 
 33  SEL_IHE           12379 non-null  int64 
 34  PROG_UNIV         12379 non-null  object
dtypes: int64(9), object(26)
memory usage: 3.4+ MB
```

- Dropping **Cod_SPro** and **COD_S11** columns, they are identifiers that are not needed anymore.
- Dropping **UNIVERSITY and 'ACADEMIC_PROGRAM** columns as redundant to **PROG_UNIV** column

In [41]:

```
df.reset_index(inplace = True)

df=df.drop(['Cod_SPro','UNIVERSITY','ACADEMIC_PROGRAM','COD_S11','index'], axis=1)

df.head()
```

executed in 31ms, finished 23:15:55 2021-05-27

Out[41]:

	GENDER	EDU_FATHER	EDU_MOTHER	OCC_FATHER	OCC_MOTHER	STRATUM	SISBEN	PEOPLE_HOUSE	INTERNET	TV	...
0	F	Incomplete Professional Education	Complete technique or technology	Technical or professional level employee	Home	Stratum 4	It is not classified by the SISBEN	3	Yes	Yes	...
1	F	Complete Secondary	Complete professional education	Entrepreneur	Independent professional	Stratum 5	It is not classified by the SISBEN	3	Yes	Yes	...
2	M	Not sure	Not sure	Independent	Home	Stratum 2	Level 2	5	No	No	...
3	F	Not sure	Not sure	Other occupation	Independent	Stratum 2	It is not classified by the SISBEN	3	Yes	Yes	...
4	M	Complete professional education	Complete professional education	Executive	Home	Stratum 4	It is not classified by the SISBEN	1	Yes	Yes	...

5 rows × 31 columns

In [42]:

```
df.nunique()
```

executed in 31ms, finished 23:15:55 2021-05-27

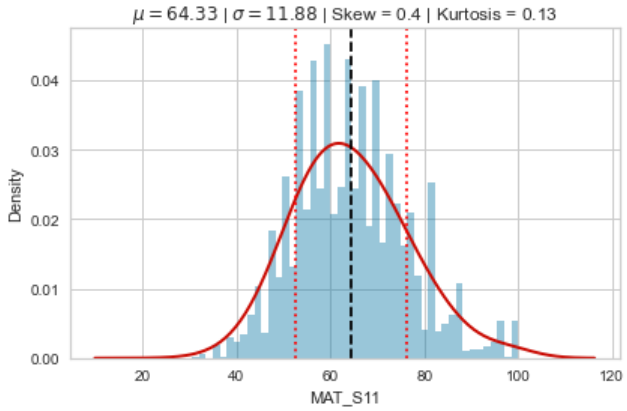
Out[42]:

```
GENDER            2
EDU_FATHER       12
EDU_MOTHER       12
OCC_FATHER       12
OCC_MOTHER       12
STRATUM           7
SISBEN            6
PEOPLE_HOUSE     12
INTERNET          2
TV                2
COMPUTER          2
WASHING_MCH       2
MIC_OVEN          2
CAR               2
DVD               2
FRESH             2
PHONE             2
MOBILE            2
REVENUE           8
JOB               4
SCHOOL_NAT        2
SCHOOL_TYPE       4
MAT_S11          69
CR_S11           71
CC_S11           68
BIO_S11          72
ENG_S11          63
G_SC            166
SEL               4
SEL_IHE           4
PROG_UNIV        53
dtype: int64
```

Exploring distributions of **HS subject scores** and **G_SC** variables

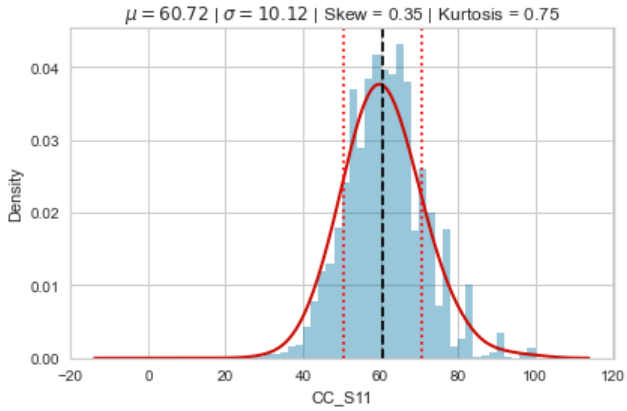
In [43]:
```
1 distribution(df.MAT_S11)
```

executed in 558ms, finished 23:15:56 2021-05-27



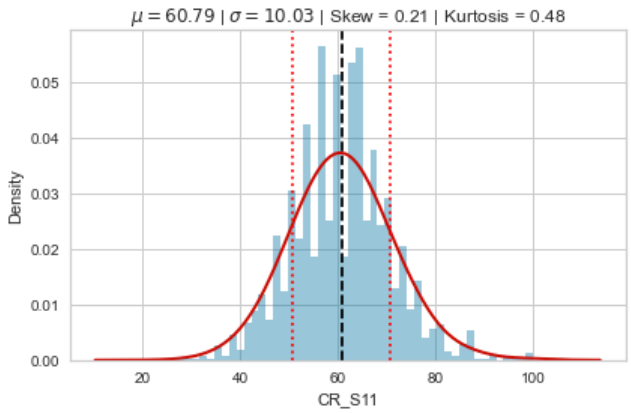
In [44]:
```
1 distribution(df.CC_S11)
```

executed in 254ms, finished 23:15:56 2021-05-27



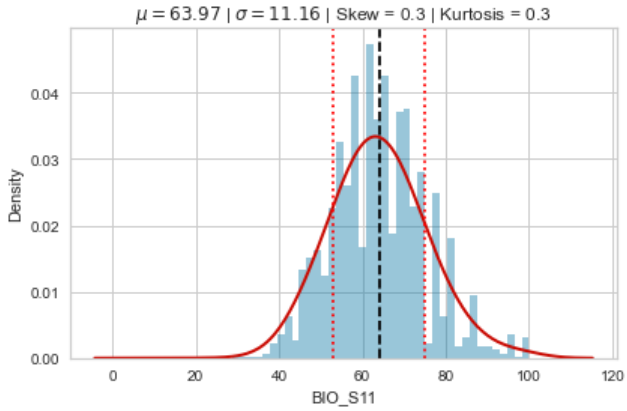
In [45]:
```
1 distribution(df.CR_S11)
```

executed in 239ms, finished 23:15:56 2021-05-27



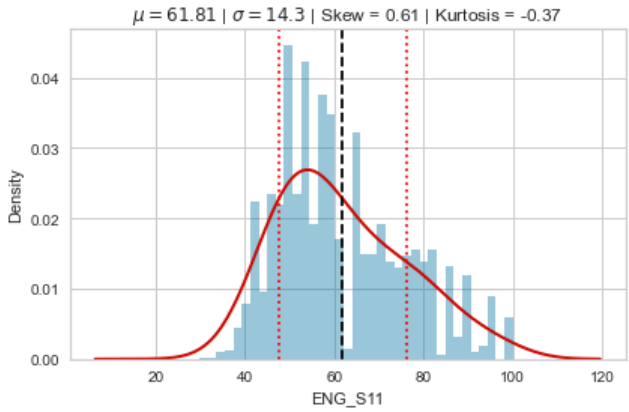
In [46]:
```
1 distribution(df.BIO_S11)
```

executed in 254ms, finished 23:15:57 2021-05-27



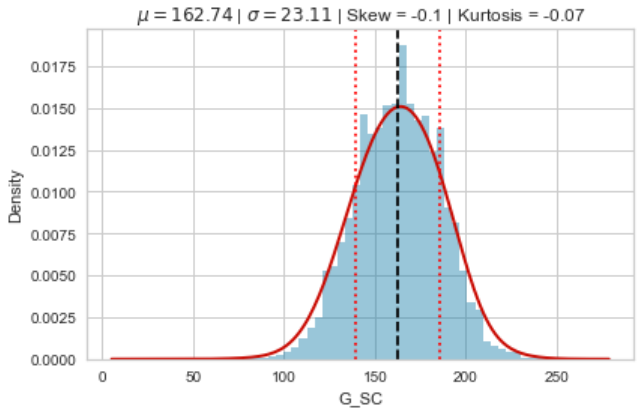
In [47]:
```
1 distribution(df.ENG_S11)
```

executed in 240ms, finished 23:15:57 2021-05-27



In [48]:
```
1 distribution(df.G_SC)
```

executed in 382ms, finished 23:15:57 2021-05-27



All HS scores (except **ENG_S11**, which displays a light skewness to the left) follow close to a normal distribution, **G_PRO** exhibits a normal distribution as well. The **G_SC** variable will be used to set a target class variable: those students whose G_SC scores are below the mean score and those whose scores are equal to or above the mean score.

In [49]:
```
df_clean=df.copy()
```
executed in 15ms, finished 23:15:57 2021-05-27

4.2 Splitting up the dataset into training subset and test subsets

Splitting the cleaned df DataFrame before manipulating **G_SC** to create a final categorical target variable.

In [50]:
```
# Creating dependent and independent variables DataFrames out of df_clean
y = df_clean[['G_SC']].copy()
X = df_clean.drop(columns=['G_SC'], axis=1).copy()
```
executed in 14ms, finished 23:15:57 2021-05-27

In [51]:
```
# Split the data into a training and a test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=123)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```
executed in 15ms, finished 23:15:57 2021-05-27

```
(9284, 30) (9284, 1) (3095, 30) (3095, 1)
```

In [52]:
```
X_train.info()
```
executed in 15ms, finished 23:15:57 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9284 entries, 796 to 3582
Data columns (total 30 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   GENDER        9284 non-null   object
 1   EDU_FATHER    9284 non-null   object
 2   EDU_MOTHER    9284 non-null   object
 3   OCC_FATHER    9284 non-null   object
 4   OCC_MOTHER    9284 non-null   object
 5   STRATUM       9284 non-null   object
 6   SISBEN        9284 non-null   object
 7   PEOPLE_HOUSE  9284 non-null   int64 
 8   INTERNET      9284 non-null   object
 9   TV            9284 non-null   object
 10  COMPUTER      9284 non-null   object
 11  WASHING_MCH   9284 non-null   object
 12  MIC_OVEN      9284 non-null   object
 13  CAR           9284 non-null   object
 14  DVD           9284 non-null   object
 15  FRESH         9284 non-null   object
 16  PHONE         9284 non-null   object
 17  MOBILE        9284 non-null   object
 18  REVENUE       9284 non-null   object
 19  JOB           9284 non-null   object
 20  SCHOOL_NAT    9284 non-null   object
 21  SCHOOL_TYPE   9284 non-null   object
 22  MAT_S11       9284 non-null   int64 
 23  CR_S11        9284 non-null   int64 
 24  CC_S11        9284 non-null   int64 
 25  BIO_S11       9284 non-null   int64 
 26  ENG_S11       9284 non-null   int64 
 27  SEL           9284 non-null   int64 
 28  SEL_IHE       9284 non-null   int64 
 29  PROG_UNIV     9284 non-null   object
dtypes: int64(8), object(22)
memory usage: 2.2+ MB
```

In [53]:
```
1 y_train.head()
```
executed in 15ms, finished 23:15:57 2021-05-27

Out[53]:

	G_SC
796	165
8185	134
6228	162
1116	185
7653	161

In [54]:
```
1 y_test.head()
```
executed in 15ms, finished 23:15:57 2021-05-27

Out[54]:

	G_SC
7911	166
2473	141
5802	132
11893	158
715	157

4.3 Creating a new categorical target variable FAILING.

In [55]:
```
1 G_SC_mean=y_train['G_SC'].mean()
2 print(G_SC_mean)
```
executed in 15ms, finished 23:15:57 2021-05-27

```
162.74224472210255
```

In [56]:
```
1 y_train_final, y_test_final = creating_failing(y_test,'G_SC')
```
executed in 15ms, finished 23:15:57 2021-05-27

In [57]:
```
1 y_train_final
```
executed in 15ms, finished 23:15:57 2021-05-27

Out[57]:

	FAILING
796	0
8185	1
6228	1
1116	0
7653	1
...	...
5218	0
12252	0
1346	1
11646	1
3582	1

9284 rows × 1 columns

In [58]:
```
1 pd.value_counts(y_train_final.FAILING)
```
executed in 15ms, finished 23:15:57 2021-05-27

Out[58]:
```
0    4745
1    4539
Name: FAILING, dtype: int64
```

In [59]:
```
1 pd.value_counts(y_test_final.FAILING)
```
executed in 15ms, finished 23:15:57 2021-05-27

Out[59]:
```
0    1562
1    1533
Name: FAILING, dtype: int64
```

The values are almost equally distributed between the classes

5 Model

5.1 Checking training and test DataFrames

In [60]:
```
1 X_train.head()
```
executed in 30ms, finished 23:15:57 2021-05-27

Out[60]:

	GENDER	EDU_FATHER	EDU_MOTHER	OCC_FATHER	OCC_MOTHER	STRATUM	SISBEN	PEOPLE_HOUSE	INTERNET	TV	...
796	M	Unknown	Unknown	Unknown	Unknown	Stratum 2	It is not classified by the SISBEN	4	Yes	Yes	
8185	M	Complete Secondary	Complete primary	Independent	Home	Stratum 2	It is not classified by the SISBEN	5	Yes	Yes	
6228	M	Complete primary	Incomplete Secondary	Small entrepreneur	Small entrepreneur	Stratum 2	Level 2	4	No	Yes	
1116	M	Incomplete Secondary	Incomplete Secondary	Operator	Home	Stratum 2	Level 1	5	No	Yes	
7653	M	Complete professional education	Complete professional education	Other occupation	Independent professional	Stratum 3	Level 3	3	No	No	

5 rows × 30 columns

In [61]:

```
1 X_train.info()
```

executed in 15ms, finished 23:15:57 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9284 entries, 796 to 3582
Data columns (total 30 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   GENDER        9284 non-null   object
 1   EDU_FATHER    9284 non-null   object
 2   EDU_MOTHER    9284 non-null   object
 3   OCC_FATHER    9284 non-null   object
 4   OCC_MOTHER    9284 non-null   object
 5   STRATUM       9284 non-null   object
 6   SISBEN        9284 non-null   object
 7   PEOPLE_HOUSE  9284 non-null   int64 
 8   INTERNET      9284 non-null   object
 9   TV            9284 non-null   object
 10  COMPUTER      9284 non-null   object
 11  WASHING_MCH   9284 non-null   object
 12  MIC_OVEN      9284 non-null   object
 13  CAR           9284 non-null   object
 14  DVD           9284 non-null   object
 15  FRESH         9284 non-null   object
 16  PHONE         9284 non-null   object
 17  MOBILE        9284 non-null   object
 18  REVENUE       9284 non-null   object
 19  JOB           9284 non-null   object
 20  SCHOOL_NAT    9284 non-null   object
 21  SCHOOL_TYPE   9284 non-null   object
 22  MAT_S11       9284 non-null   int64 
 23  CR_S11        9284 non-null   int64 
 24  CC_S11        9284 non-null   int64 
 25  BIO_S11       9284 non-null   int64 
 26  ENG_S11       9284 non-null   int64 
 27  SEL           9284 non-null   int64 
 28  SEL_IHE       9284 non-null   int64 
 29  PROG_UNIV     9284 non-null   object
dtypes: int64(8), object(22)
memory usage: 2.2+ MB
```

In [62]:
```
1 X_test.info()
```

executed in 15ms, finished 23:15:57 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3095 entries, 7911 to 8324
Data columns (total 30 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   GENDER        3095 non-null   object
 1   EDU_FATHER    3095 non-null   object
 2   EDU_MOTHER    3095 non-null   object
 3   OCC_FATHER    3095 non-null   object
 4   OCC_MOTHER    3095 non-null   object
 5   STRATUM       3095 non-null   object
 6   SISBEN        3095 non-null   object
 7   PEOPLE_HOUSE  3095 non-null   int64
 8   INTERNET      3095 non-null   object
 9   TV            3095 non-null   object
 10  COMPUTER      3095 non-null   object
 11  WASHING_MCH   3095 non-null   object
 12  MIC_OVEN      3095 non-null   object
 13  CAR           3095 non-null   object
 14  DVD           3095 non-null   object
 15  FRESH         3095 non-null   object
 16  PHONE         3095 non-null   object
 17  MOBILE        3095 non-null   object
 18  REVENUE       3095 non-null   object
 19  JOB           3095 non-null   object
 20  SCHOOL_NAT    3095 non-null   object
 21  SCHOOL_TYPE   3095 non-null   object
 22  MAT_S11       3095 non-null   int64
 23  CR_S11        3095 non-null   int64
 24  CC_S11        3095 non-null   int64
 25  BIO_S11       3095 non-null   int64
 26  ENG_S11       3095 non-null   int64
 27  SEL           3095 non-null   int64
 28  SEL_IHE       3095 non-null   int64
 29  PROG_UNIV     3095 non-null   object
dtypes: int64(8), object(22)
memory usage: 749.6+ KB
```

> The preprocessed independent variables training dataset has 9284 records with 30 columns, out of which 22 columns are categorical, and 8 columns are numerical. The test set has 3095 records.

5.2 Building Pipelines and ColumnTransformer and transforming the DateFrame

- Scale numerical columns
- One-hot encode categorical columns

In [63]:
```
1 # Creating a list of numerical columns
2
3 numeric_cols=list(X_train.select_dtypes('int64').columns)
4 print(numeric_cols)
```

executed in 14ms, finished 23:15:58 2021-05-27

```
['PEOPLE_HOUSE', 'MAT_S11', 'CR_S11', 'CC_S11', 'BIO_S11', 'ENG_S11', 'SEL', 'SEL_IHE']
```

In [64]:
```
1 # Creating a list of categorical columns
2
3 categorical_cols=list(X_train.select_dtypes('object').columns)
4 print(categorical_cols)
```

executed in 15ms, finished 23:15:58 2021-05-27

```
['GENDER', 'EDU_FATHER', 'EDU_MOTHER', 'OCC_FATHER', 'OCC_MOTHER', 'STRATUM', 'SISBEN', 'INTERNET', 'TV', 'COMPUTER', 'WASHI
NG_MCH', 'MIC_OVEN', 'CAR', 'DVD', 'FRESH', 'PHONE', 'MOBILE', 'REVENUE', 'JOB', 'SCHOOL_NAT', 'SCHOOL_TYPE', 'PROG_UNIV']
```

In [65]:
```
# Creating a simple one step pipeline for numerical columns standardization

num_pipe = Pipeline([
    ('scaler', MinMaxScaler())])

num_pipe
```

executed in 15ms, finished 23:15:58 2021-05-27

Out[65]:
```
Pipeline(steps=[('scaler', MinMaxScaler())])
```

In [66]:
```
# Creating a simple pipeline to impute the 'Unknown' values in all categorical columns
# with the most frequent value and encode all categorical columns using OneHotEncoder

cat_pipe = Pipeline([('imputer', SimpleImputer(strategy='most_frequent', missing_values='Unknown')),
                     ('encoder', OneHotEncoder(sparse=False, drop='first'))])
cat_pipe
```

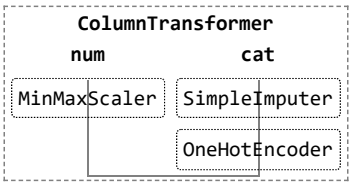
executed in 15ms, finished 23:15:58 2021-05-27

Out[66]:
```
Pipeline(steps=[('imputer',
                 SimpleImputer(missing_values='Unknown',
                               strategy='most_frequent')),
                ('encoder', OneHotEncoder(drop='first', sparse=False))])
```

In [67]:
```
# Creating preprocessing column transformer (for both numeric and categorical columns)

set_config(display='diagram')

preprocessor = ColumnTransformer([
    ('num',num_pipe,numeric_cols),
    ('cat',cat_pipe,categorical_cols)
])

preprocessor
```

executed in 31ms, finished 23:15:58 2021-05-27

Out[67]:



In [68]:
```
# Testing fitting the transformer and transforming the test dataset
X_train_tf = preprocessor.fit_transform(X_train)
X_test_tf = preprocessor.transform(X_test)
X_test_tf
```

executed in 415ms, finished 23:15:58 2021-05-27

Out[68]:
```
array([[0.16666667, 0.41891892, 0.5       , ..., 0.        , 0.        ,
        1.        ],
       [0.25      , 0.43243243, 0.39473684, ..., 0.        , 0.        ,
        1.        ],
       [0.25      , 0.2972973 , 0.25      , ..., 0.        , 0.        ,
        1.        ],
       ...,
       [0.41666667, 0.59459459, 0.47368421, ..., 0.        , 0.        ,
        1.        ],
       [0.25      , 0.58108108, 0.47368421, ..., 0.        , 0.        ,
        0.        ],
       [0.41666667, 0.82432432, 0.67105263, ..., 0.        , 0.        ,
        1.        ]])
```

In [69]:
```
# Creating a list of encoded categorical columns names
cat_features = list(preprocessor.named_transformers_['cat'].named_steps['encoder']\
                            .get_feature_names(categorical_cols))
len(cat_features)
```

executed in 14ms, finished 23:15:58 2021-05-27

Out[69]:
```
124
```

There are 124 categorical columns with binary values (0,1)

In [70]:
```
# Creating a list of all columns
X_cols = numeric_cols+cat_features
len(X_cols)
```

executed in 15ms, finished 23:15:58 2021-05-27

Out[70]: 132

In [71]:
```
# Creating 2 lists of columns, one containing SocioEconomic features and another one only university-program combination f

X_cols_UNVPRG=[c for c in X_cols if 'PROG_' in c]
X_cols_SE=list(set(X_cols)-set(X_cols_UNVPRG))
```

executed in 15ms, finished 23:15:58 2021-05-27

In [72]:
```
#Creating two dataframes out of the arrays generated by preprocessing. Columns are X_cols
X_train_df = pd.DataFrame(preprocessor.transform(X_train),
                          index=X_train.index, columns=X_cols)
X_test_df = pd.DataFrame(preprocessor.transform(X_test),
                          index=X_test.index, columns=X_cols)
```

executed in 79ms, finished 23:15:58 2021-05-27

In [73]:
```
# Spliting the above dataframes with all Features into two: SocioEconomic/HS scores and University/Program names

X_test_df_UNVPRG=X_test_df[X_cols_UNVPRG].copy()
X_test_df_SE=X_test_df[X_cols_SE].copy()


X_train_df_UNVPRG=X_train_df[X_cols_UNVPRG].copy()
X_train_df_SE=X_train_df[X_cols_SE].copy()
```

executed in 15ms, finished 23:15:58 2021-05-27

- X_train_df_UNVPRG and X_test_df_UNVPRG have **52 columns** each
- X_train_df_SE and X_test_df_SE have **80 columns** each

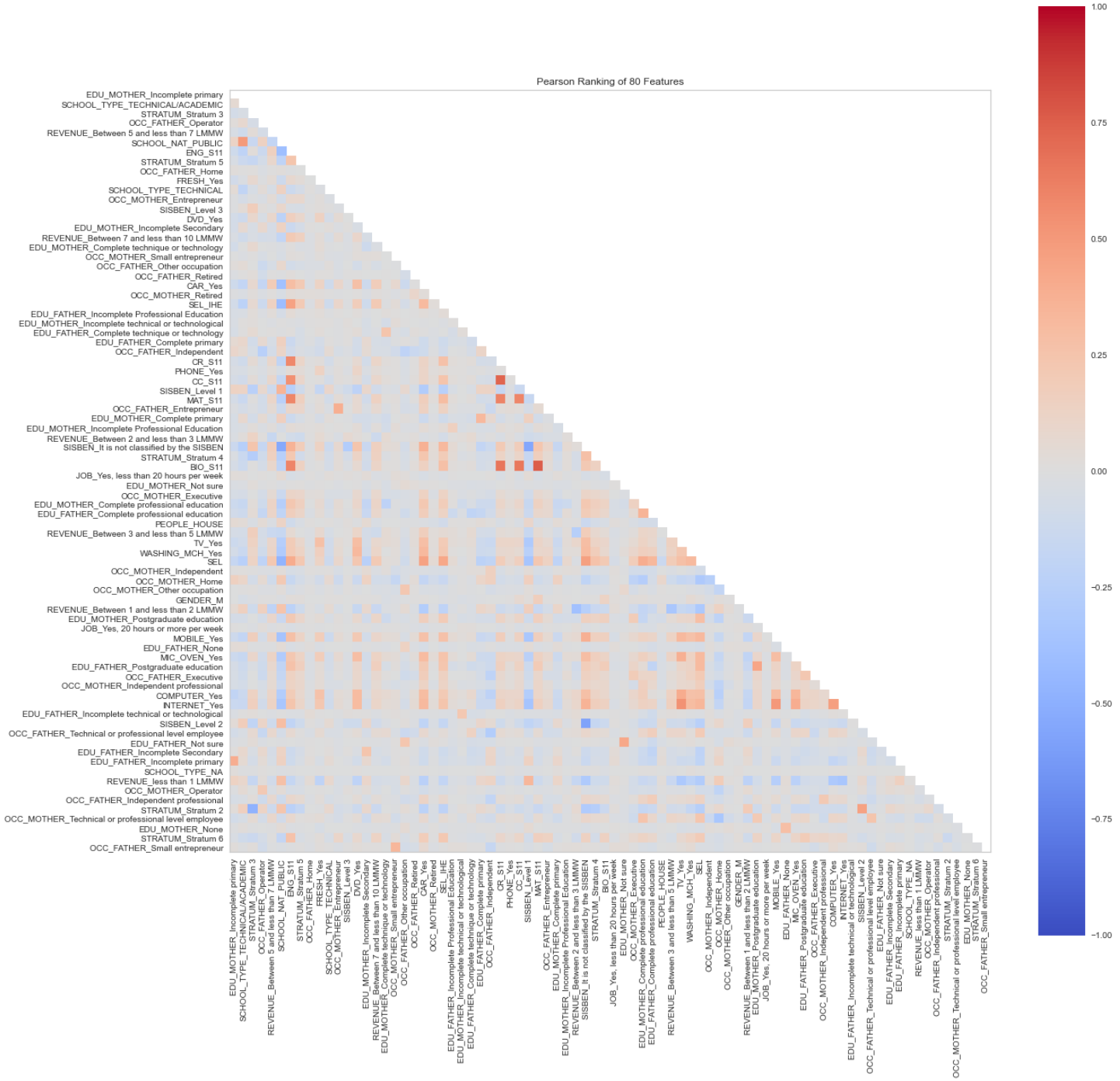
5.3 Building and evaluating simple models

5.3.1 Correlation map of SocioEconomic/HS scores features

In [74]:

```
# Instantiate the visualizer (Yellowbrick) with the Pearson ranking algorithm

fig,ax = plt.subplots(figsize=(20,20))
visualizer = Rank2D(algorithm='pearson', colormap='coolwarm', ax=ax, features=list(X_train_df_SE.columns))

# Fit the data to the visualizer
visualizer.fit(X_train_df_SE, y_train_final)

# Transform the data
visualizer.transform(X_train_df_SE)

visualizer.show()
```

executed in 2.83s, finished 23:16:01 2021-05-27



Out[74]: <AxesSubplot:title={'center':'Pearson Ranking of 80 Features'}>

> There are not very many correlations in the set, though there are some between HS subject scores and socioeconomic indicators like owning a car and SEL value.

5.3.2 Building and evaluating a DummyClassifier model

In [75]:
```
#Building a dummy model with DummyClassifier. I am using the whole dataset (no split between the features)

dummy_num_model_new=DummyClassifier(strategy='most_frequent')
dummy_num_model_new.fit(X_train, y_train_final)
```

executed in 14ms, finished 23:16:01 2021-05-27

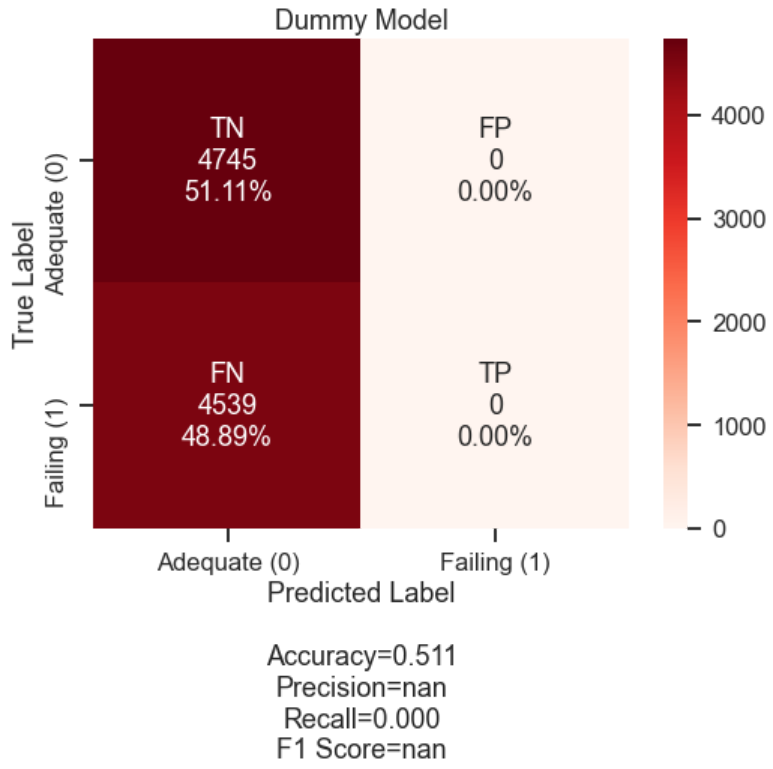
Out[75]:
```
DummyClassifier
DummyClassifier(strategy='most_frequent')
```

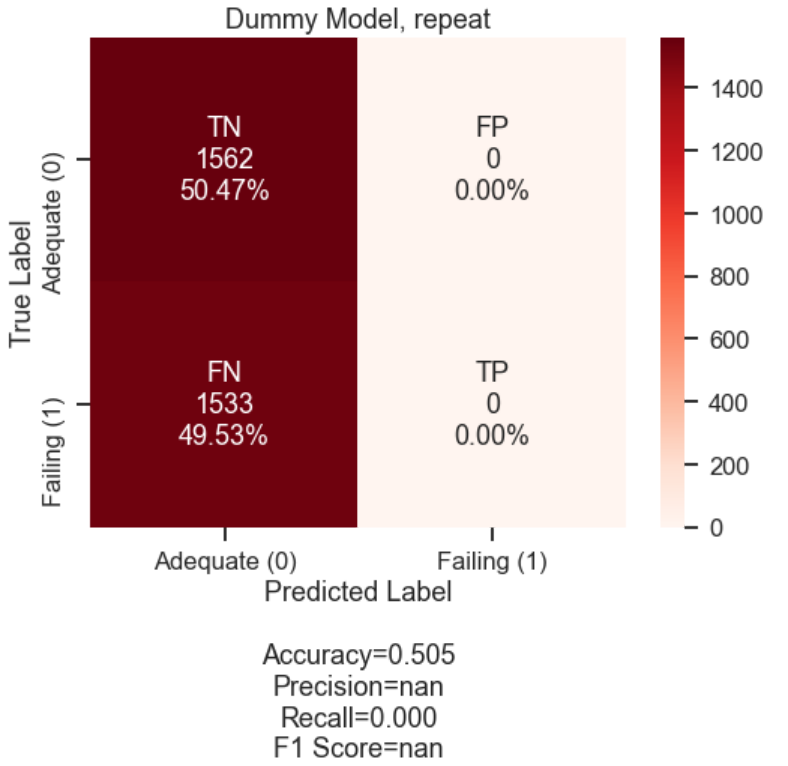
In [76]:

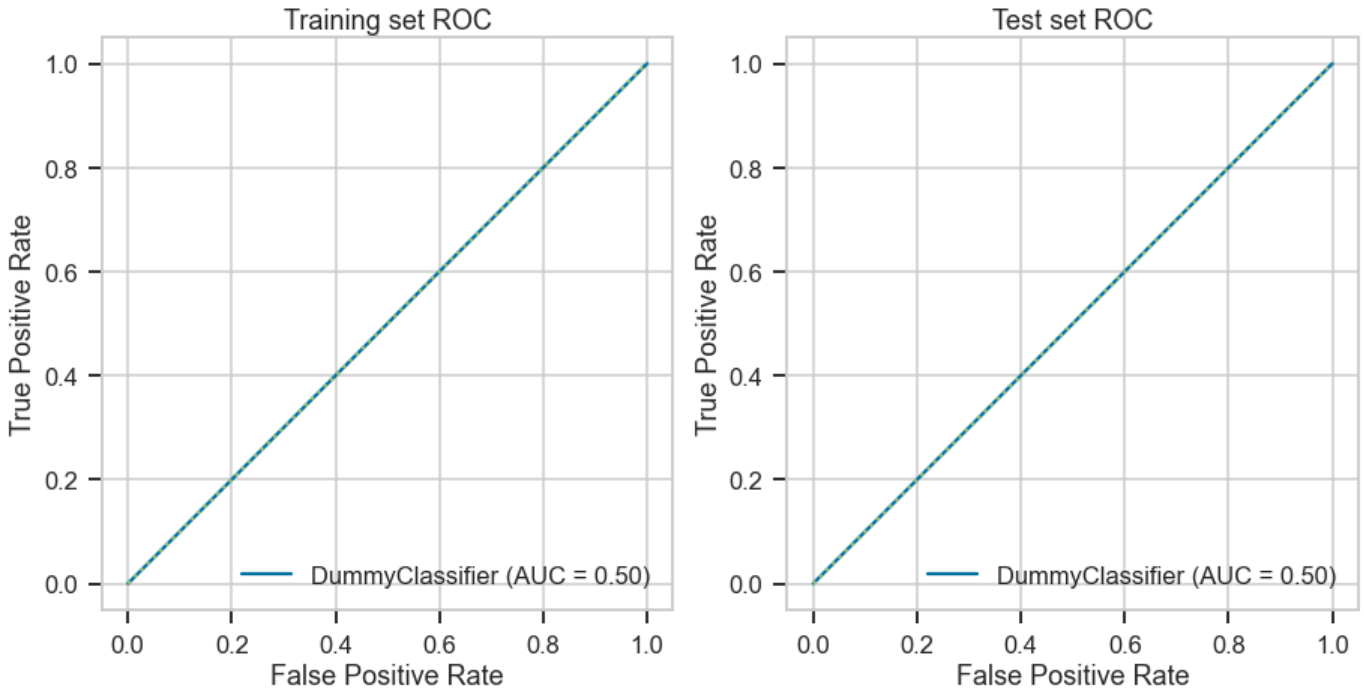
```
# Displaying the metrics and the confusion matrix for the model

set_dummy=[X_train, X_test, y_train_final, y_test_final]
simple_model_validation(dummy_num_model_new, set_dummy,'Dummy Model', 'Dummy Model, repeat')
```

executed in 607ms, finished 23:16:02 2021-05-27

```
**************************************
DummyClassifier(strategy='most_frequent')
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.51      1.00      0.68      4745
           1       0.00      0.00      0.00      4539

    accuracy                           0.51      9284
   macro avg       0.26      0.50      0.34      9284
weighted avg       0.26      0.51      0.35      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.50      1.00      0.67      1562
           1       0.00      0.00      0.00      1533

    accuracy                           0.50      3095
   macro avg       0.25      0.50      0.34      3095
weighted avg       0.25      0.50      0.34      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.006
Differences in Recall scores between training and test sets: 0.0
```







The model predicts the most frequent value (0), accuracy score is about 0.51. It is our Baseline model.

In [77]:

```
# Setting up empty dictionaries to accumulate model info for easier comparison

# For models with SocioEconomic/HS scores features
models_dict_se={'Classifier Name':[], 'Description':[],'Training or Test': [],
             'Accuracy':[],'Recall':[], 'FN':[], 'Total number of records':[], 'Saved model':[]}

# For models with University/Program features
models_dict_up={'Classifier Name':[], 'Description':[],'Training or Test': [],
             'Accuracy':[],'Recall':[], 'FN':[], 'Total number of records':[], 'Saved model':[]}
```

executed in 15ms, finished 23:16:02 2021-05-27

In [78]:
```
# Creating lists with training/test dataframe names to use with models evaluation functions

# SocioEconomic/HS scores features
SE_list=[X_train_df_SE, X_test_df_SE, y_train_final, y_test_final]

# University/Program features
UNVPRG_list=[X_train_df_UNVPRG, X_test_df_UNVPRG, y_train_final, y_test_final]
```

executed in 15ms, finished 23:16:02 2021-05-27

5.3.3 Building Logistic Regression models with SocioEconomic/HS scores features

5.3.3.1 Building and evaluating a Logistic Regression model with default parameters

In [79]:
```
logreg_model1_new=LogisticRegression(random_state=123)
logreg_model1_new.fit(X_train_df_SE, y_train_final)
```

executed in 95ms, finished 23:16:02 2021-05-27

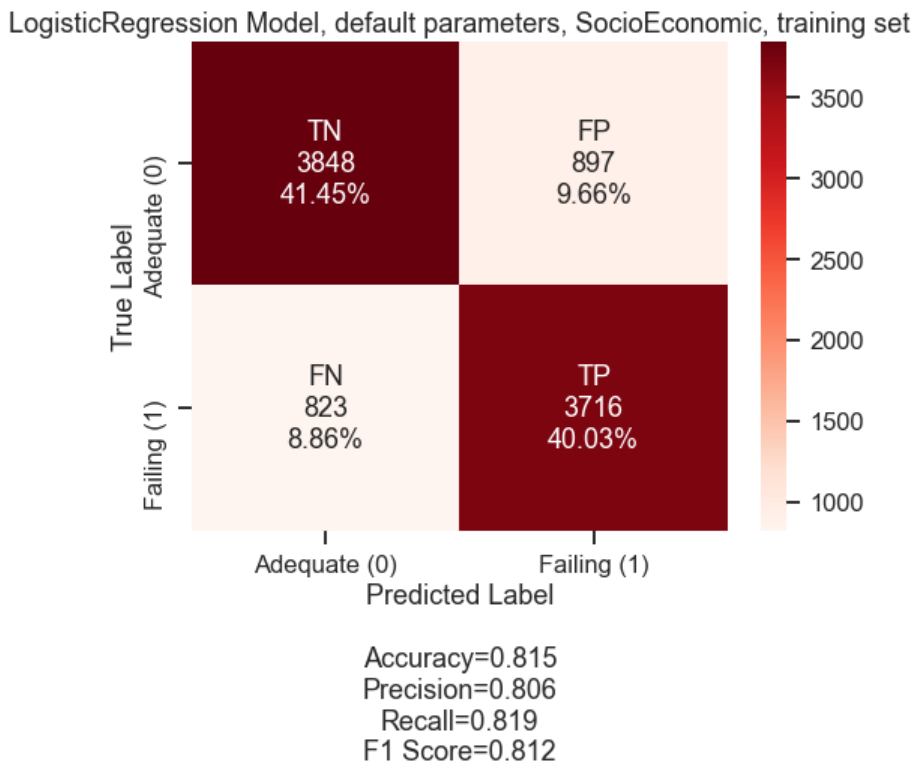
Out[79]:
```
LogisticRegression

LogisticRegression(random_state=123)
```

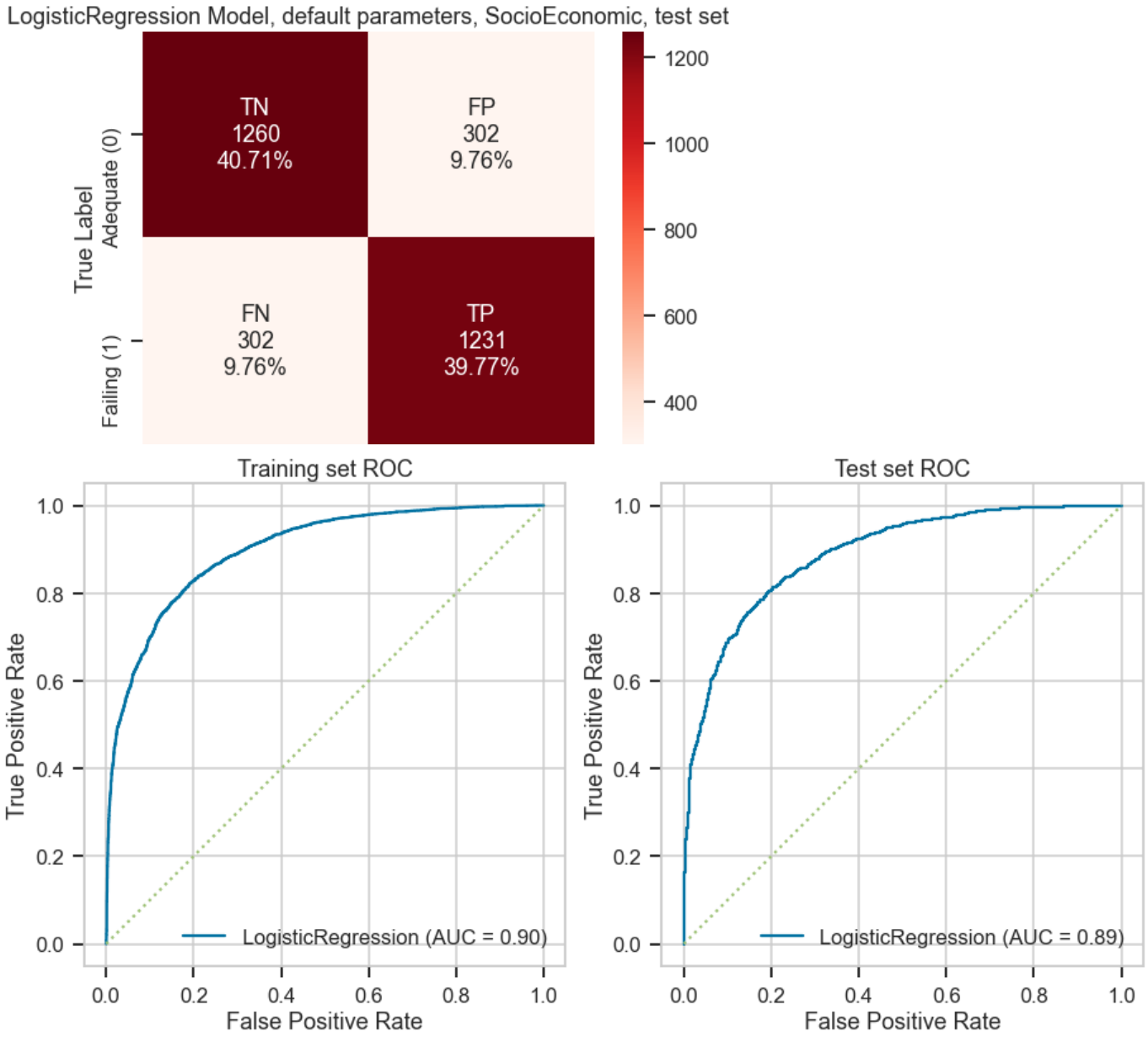
In [80]:

```
simple_model_validation(logreg_model1_new, SE_list,'LogisticRegression Model, default parameters, SocioEconomic, training
                        'LogisticRegression Model, default parameters, SocioEconomic, test set')
```

executed in 591ms, finished 23:16:02 2021-05-27

```
**************************************
LogisticRegression(random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.82      0.81      0.82      4745
           1       0.81      0.82      0.81      4539

    accuracy                           0.81      9284
   macro avg       0.81      0.81      0.81      9284
weighted avg       0.81      0.81      0.81      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.81      0.81      0.81      1562
           1       0.80      0.80      0.80      1533

    accuracy                           0.80      3095
   macro avg       0.80      0.80      0.80      3095
weighted avg       0.80      0.80      0.80      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.01
Differences in Recall scores between training and test sets: 0.003
```





In [81]:

```
se_models_dict=adding_to_models_dict(models_dict_se,'LogisticRegressionClassifier, default params', 'logreg_model1_new',
                                     SE_list, logreg_model1_new, 'not saved')
```

executed in 31ms, finished 23:16:02 2021-05-27

In [82]:
```
SE_df_models=pd.DataFrame(se_models_dict)
SE_df_models
```

executed in 15ms, finished 23:16:02 2021-05-27

Out[82]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model1_new	LogisticRegressionClassifier, default params	training	0.815	0.819	823	9284	not saved
1	logreg_model1_new	LogisticRegressionClassifier, default params	test	0.805	0.803	302	3095	not saved

> The validation metrics of the model are much better than the metrics of the Baseline model. The most important model validation metrics is Recall (Identification of students who are falling behind).

- Training set recall is 0.819
- Test set Recall is 0.803

5.3.3.2 GridSearch best parameters for a Logistic Regression model

In [83]:
```
# params = {'solver':['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
#           'penalty':['l1', 'l2', 'none'],
#            'class_weight': [None,'balanced'],
#           'C': [0.1, 1, 10, 100, 1000],
#           'max_iter':[25,100, 200, 300]}

# ## Instantiate & Fit GridSearchCV
# gridsearch = GridSearchCV(LogisticRegression(random_state=123), params, n_jobs=-1,
#                           cv=5, verbose=2, scoring = 'recall')
# gridsearch.fit(X_train_df_SE, y_train_final)

```

executed in 15ms, finished 23:16:02 2021-05-27

In [84]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:02 2021-05-27

In [85]:
```
# gridsearch.best_estimator_
```

executed in 15ms, finished 23:16:02 2021-05-27

In [86]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/se_progress/LR_best_se_new.joblib')
```

executed in 15ms, finished 23:16:02 2021-05-27

5.3.3.3 Building and evaluating the best parameters Logistic Regression model

In [87]:
```
log_reg_model2_new=joblib.load('models/se_progress/LR_best_se_new.joblib')
```

executed in 13ms, finished 23:16:02 2021-05-27

In [88]:
```
log_reg_model2_new.fit(X_train_df_SE, y_train_final)
```

executed in 221ms, finished 23:16:03 2021-05-27

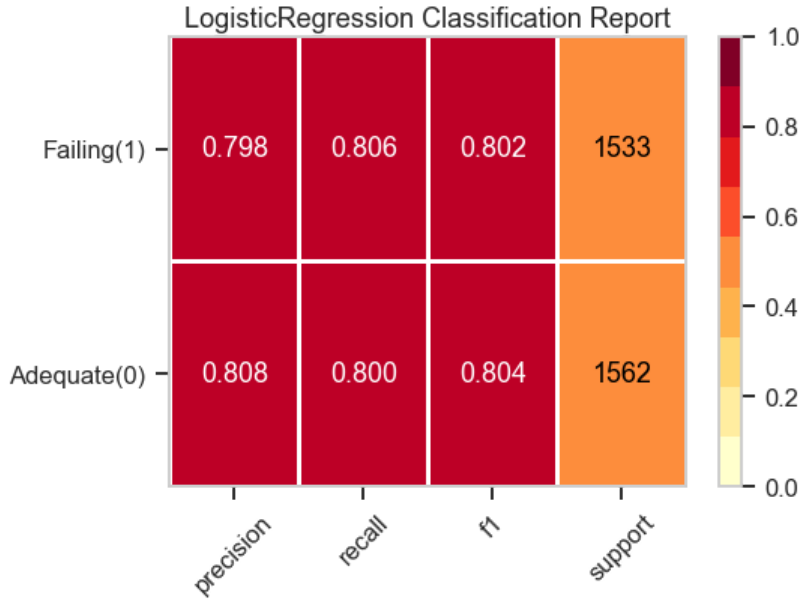
Out[88]:

```
LogisticRegression
LogisticRegression(C=0.1, class_weight='balanced', max_iter=25, penalty='l1',
                   random_state=123, solver='saga')
```

In [89]:

```
viz = ClassificationReport(log_reg_model2_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_SE, y_train_final)

viz.score(X_test_df_SE, y_test_final)

viz.show();
```

executed in 158ms, finished 23:16:03 2021-05-27

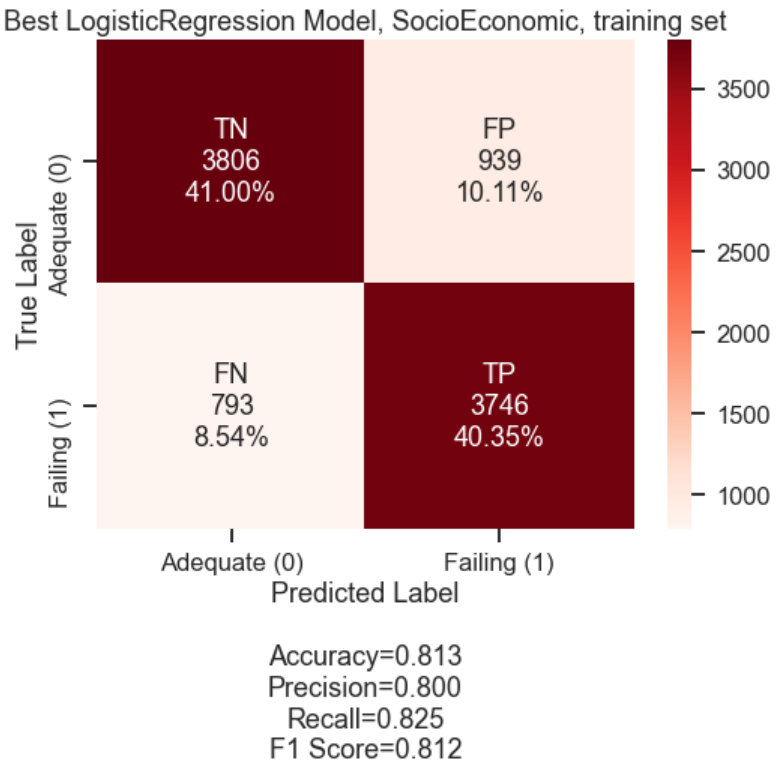


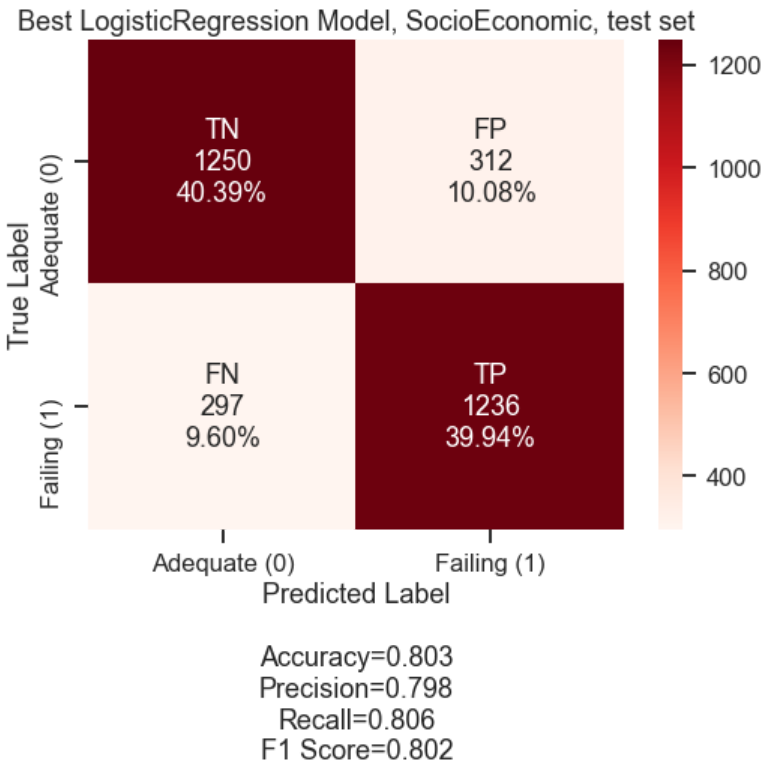
In [90]:

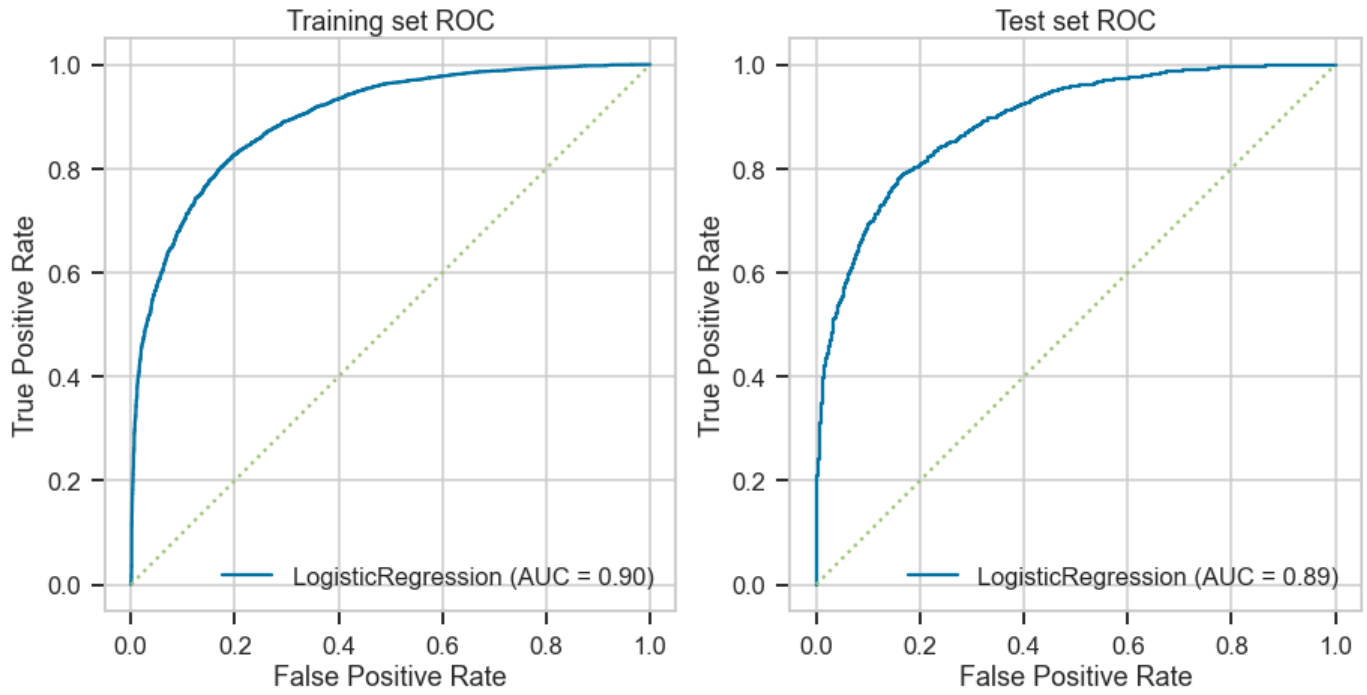
```
simple_model_validation(log_reg_model2_new, SE_list,
                        'Best LogisticRegression Model, SocioEconomic, training set',
                        'Best LogisticRegression Model, SocioEconomic, test set')
```

executed in 591ms, finished 23:16:03 2021-05-27

```
**************************************
LogisticRegression(C=0.1, class_weight='balanced', max_iter=25, penalty='l1',
                   random_state=123, solver='saga')
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.83      0.80      0.81      4745
           1       0.80      0.83      0.81      4539

    accuracy                           0.81      9284
   macro avg       0.81      0.81      0.81      9284
weighted avg       0.81      0.81      0.81      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.81      0.80      0.80      1562
           1       0.80      0.81      0.80      1533

    accuracy                           0.80      3095
   macro avg       0.80      0.80      0.80      3095
weighted avg       0.80      0.80      0.80      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.01
Differences in Recall scores between training and test sets: 0.001
```




Best LogisticRegression Model, SocioEconomic, test set
TN
1250
40.39%
FP
312
10.08%
FN
297
9.60%
TP
1236
39.94%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1200
1000
800
600
400
Accuracy=0.803
Precision=0.798
Recall=0.806
F1 Score=0.802



In [91]:
```
se_models_dict=adding_to_models_dict(models_dict_se,'LogisticRegressionClassifier, best params', 'log_reg_model2_new',
                                     SE_list, log_reg_model2_new,'models/se_progress/LR_best_se_new.joblib')
```

executed in 30ms, finished 23:16:03 2021-05-27

> Best parameters LogisticRegression model shows some improvement over the model with default parameters. The improvement is superficial.

Recall score increased

- Training set: from 0.819 to 0.825
- Test set: from 0.803 to 0.806

5.3.3.4 Gridsearch best parameters for a LogisticRegressionCV model

In [92]:
```
# params = {'solver':['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
#           'penalty':['l1', 'l2'],
#            'scoring':['recall','accuracy','f1'],
#           'class_weight': [None,'balanced'],
#           'max_iter':[25, 100, 200, 300]}

# ## Instantiate & Fit GridSearchCV
# gridsearch = GridSearchCV(LogisticRegressionCV(random_state=123), params, n_jobs=-1,
#                           cv=5, verbose=2, scoring='recall')
# gridsearch.fit(X_train_df_SE, y_train_final)

```

executed in 15ms, finished 23:16:03 2021-05-27

In [93]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:03 2021-05-27

In [94]:
```
# gridsearch.best_estimator_
```

executed in 15ms, finished 23:16:03 2021-05-27

In [95]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/se_progress/LR_best_se_CV_new.joblib')
```

executed in 15ms, finished 23:16:04 2021-05-27

5.3.3.5 Building and evaluating the best parameter LogisticRegressionCV model

In [96]:
```
1 log_reg_model2_CV_new=joblib.load('models/se_progress/LR_best_se_CV_new.joblib')
```

executed in 15ms, finished 23:16:04 2021-05-27

In [97]:
```
1 log_reg_model2_CV_new.fit(X_train_df_SE, y_train_final)
```

executed in 6.61s, finished 23:16:10 2021-05-27

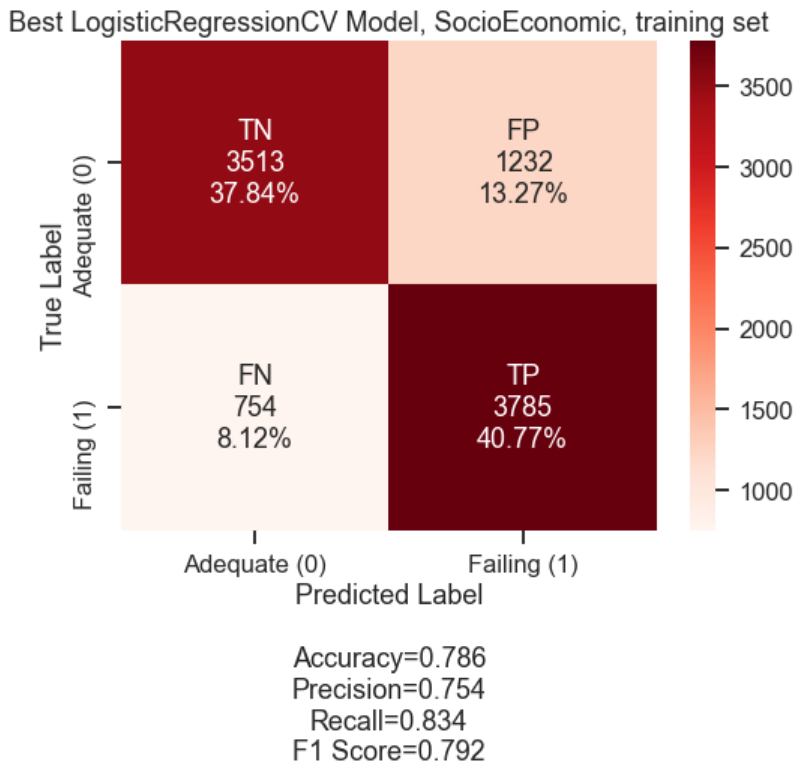
Out[97]:
```
LogisticRegressionCV
LogisticRegressionCV(class_weight='balanced', max_iter=25, penalty='l1',
                     random_state=123, scoring='recall', solver='saga')
```

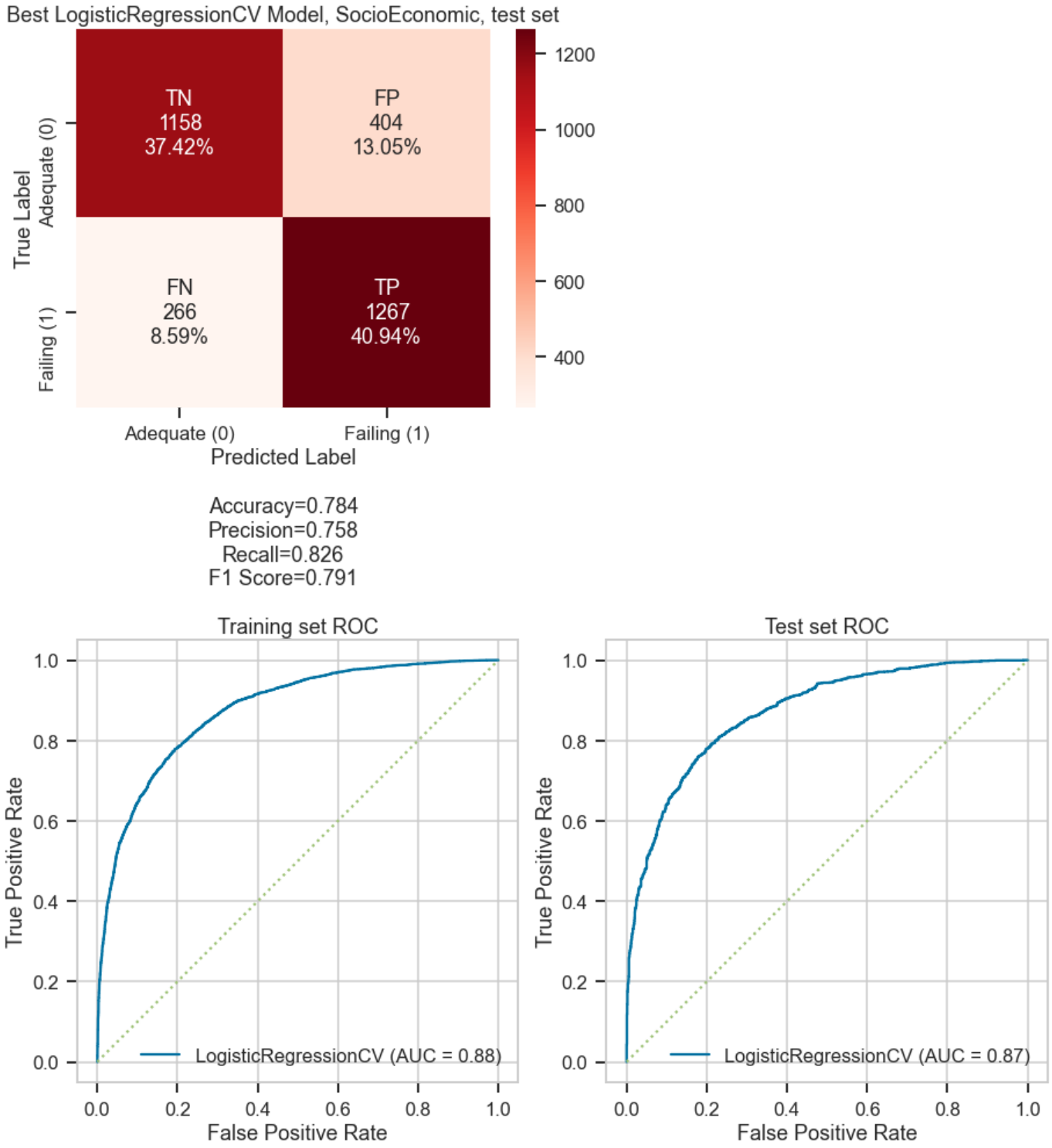
In [98]:

```
simple_model_validation(log_reg_model2_CV_new, SE_list,
                        'Best LogisticRegressionCV Model, SocioEconomic, training set',
                        'Best LogisticRegressionCV Model, SocioEconomic, test set')
```

executed in 606ms, finished 23:16:11 2021-05-27

```
**************************************
LogisticRegressionCV(class_weight='balanced', max_iter=25, penalty='l1',
                     random_state=123, scoring='recall', solver='saga')
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.82      0.74      0.78      4745
           1       0.75      0.83      0.79      4539

    accuracy                           0.79      9284
   macro avg       0.79      0.79      0.79      9284
weighted avg       0.79      0.79      0.79      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.81      0.74      0.78      1562
           1       0.76      0.83      0.79      1533

    accuracy                           0.78      3095
   macro avg       0.79      0.78      0.78      3095
weighted avg       0.79      0.78      0.78      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.003
Differences in Recall scores between training and test sets: -0.004
```





In [99]:

```
se_models_dict=adding_to_models_dict(models_dict_se, 'LogisticRegressionClassifierCV, best params', 'log_reg_model2_CV_ne
                                     SE_list, log_reg_model2_CV_new,'models/se_progress/LR_best_se_CV_new.joblib')
```

executed in 30ms, finished 23:16:11 2021-05-27

In [100]:
```
SE_df_models=pd.DataFrame(se_models_dict)
SE_df_models
```

executed in 15ms, finished 23:16:11 2021-05-27

Out[100]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model1_new	LogisticRegressionClassifier, default params	training	0.815	0.819	823	9284	not saved
1	logreg_model1_new	LogisticRegressionClassifier, default params	test	0.805	0.803	302	3095	not saved
2	log_reg_model2_new	LogisticRegressionClassifier, best params	training	0.813	0.825	793	9284	models/se_progress/LR_best_se_new.joblib
3	log_reg_model2_new	LogisticRegressionClassifier, best params	test	0.803	0.806	297	3095	models/se_progress/LR_best_se_new.joblib
4	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	training	0.786	0.834	754	9284	models/se_progress/LR_best_se_CV_new.joblib
5	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	test	0.784	0.826	266	3095	models/se_progress/LR_best_se_CV_new.joblib

> Best parameters LogisticRegressionCV model shows some improvement over the LogisticRegression model with best parameters.

Recall score increased

- Training set: from 0.825 to 0.834
- Test set: from 0.806 to 0.826

5.3.4 Building Logistic Regression models with Program/University features

5.3.4.1 Building and evaluating a Logistic Regression model with default parameters

In [101]:
```
logreg_model3_new=LogisticRegression(random_state=123)
logreg_model3_new.fit(X_train_df_UNVPRG, y_train_final)
```

executed in 47ms, finished 23:16:11 2021-05-27

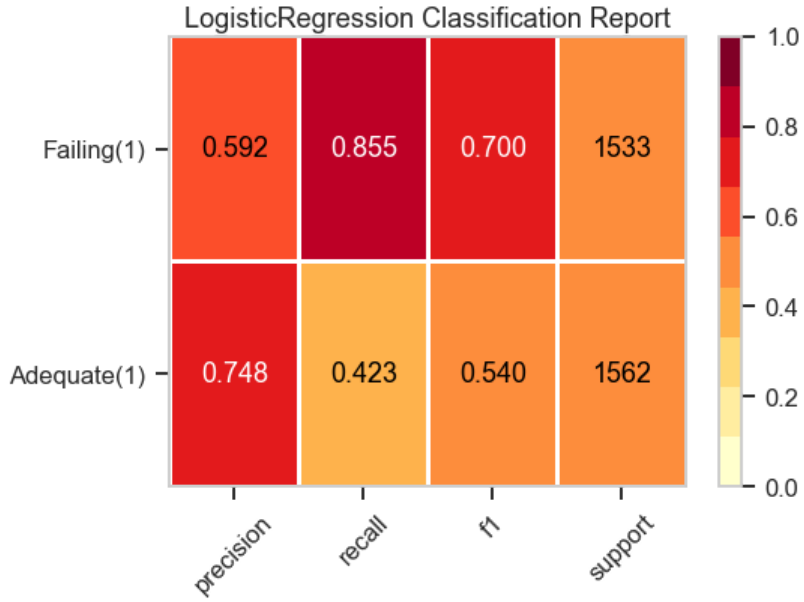
Out[101]:

```
LogisticRegression
LogisticRegression(random_state=123)
```

In [102]:

```
viz = ClassificationReport(logreg_model3_new,
                           classes=['Adequate(1)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_UNVPRG, y_train_final)

viz.score(X_test_df_UNVPRG, y_test_final)

viz.show();
```

executed in 159ms, finished 23:16:11 2021-05-27

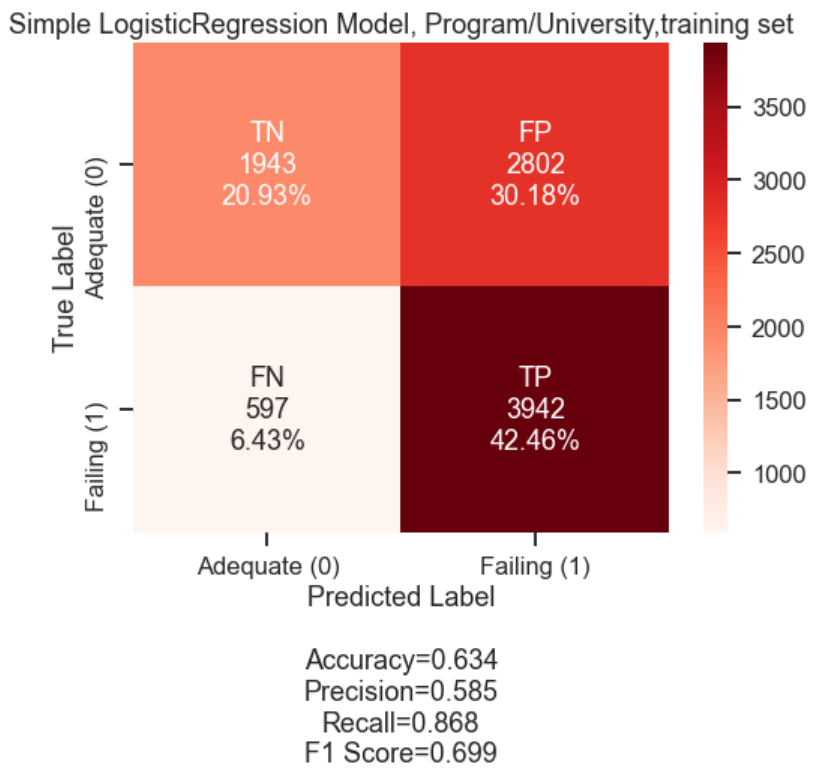


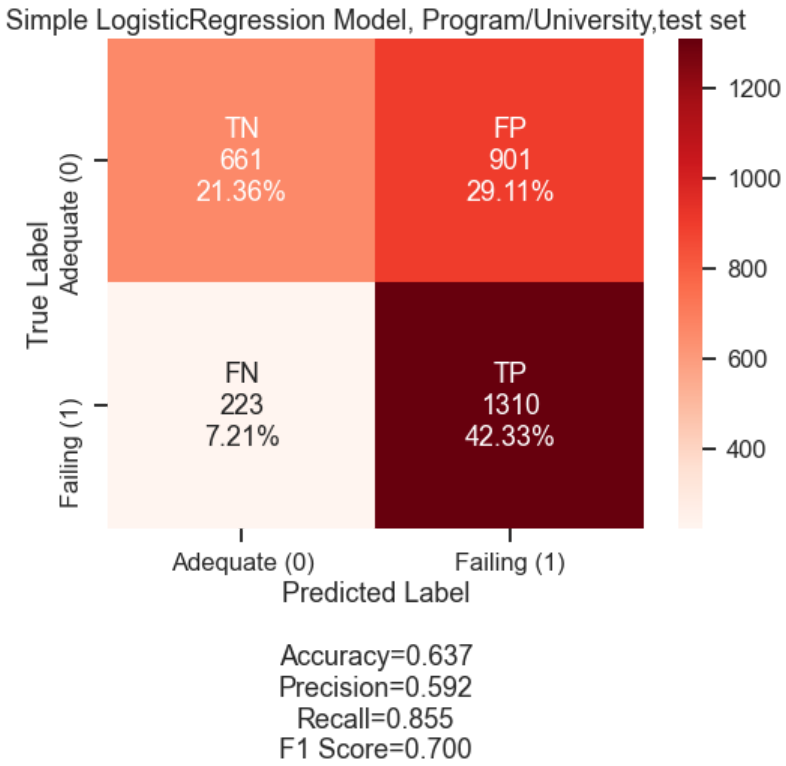
In [103]:

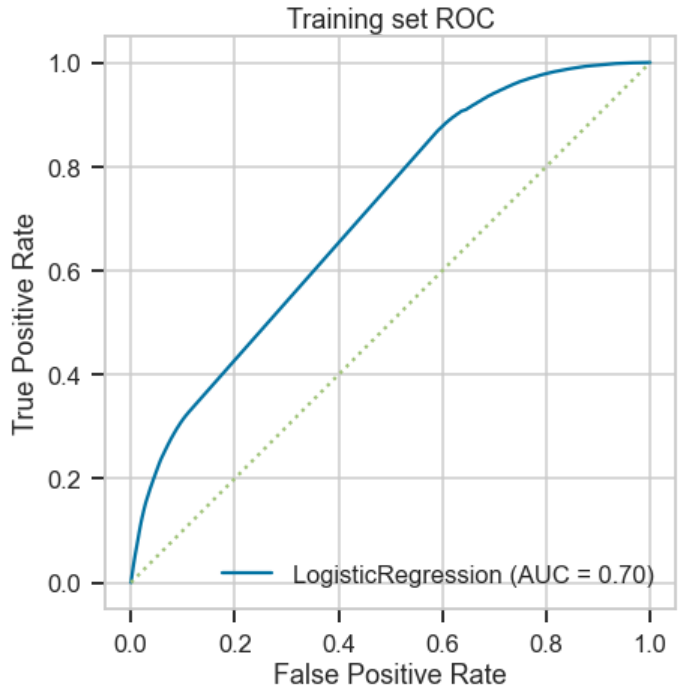
```
simple_model_validation(logreg_model3_new, UNVPRG_list,
                        'Simple LogisticRegression Model, Program/University,training set',
                        'Simple LogisticRegression Model, Program/University,test set')
```

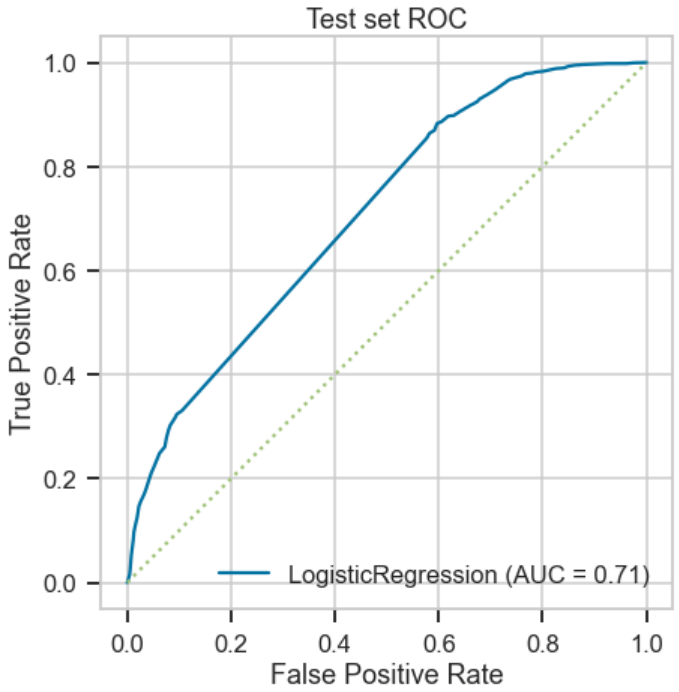
executed in 590ms, finished 23:16:12 2021-05-27

```
**************************************
LogisticRegression(random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.76      0.41      0.53      4745
           1       0.58      0.87      0.70      4539

    accuracy                           0.63      9284
   macro avg       0.67      0.64      0.62      9284
weighted avg       0.68      0.63      0.61      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.75      0.42      0.54      1562
           1       0.59      0.85      0.70      1533

    accuracy                           0.64      3095
   macro avg       0.67      0.64      0.62      3095
weighted avg       0.67      0.64      0.62      3095


**************************************
Differences in Accuracy scores between training and test sets: -0.003
Differences in Recall scores between training and test sets: -0.008
```




Simple LogisticRegression Model, Program/University,test set
TN
661
21.36%
FP
901
29.11%
FN
223
7.21%
TP
1310
42.33%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1200
1000
800
600
400
Accuracy=0.637
Precision=0.592
Recall=0.855
F1 Score=0.700





In [104]:
```
unvprg_models_dict=adding_to_models_dict(models_dict_up,'LogisticRegressionClassifier, default params',
                                         'logreg_model3_new', UNVPRG_list, logreg_model3_new, 'not saved')
```

executed in 31ms, finished 23:16:12 2021-05-27

In [105]:
```
UNVPRG_df_models=pd.DataFrame(unvprg_models_dict)
UNVPRG_df_models
```

executed in 15ms, finished 23:16:12 2021-05-27

Out[105]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model3_new	LogisticRegressionClassifier, default params	training	0.634	0.868	597	9284	not saved
1	logreg_model3_new	LogisticRegressionClassifier, default params	test	0.637	0.855	223	3095	not saved

5.3.4.2 GridSearch best parameters for a Logistic Regression model

In [106]:
```
# params = {'solver':['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
#           'penalty':['l1', 'l2', 'none'],
#            'class_weight': [None,'balanced'],
#           'C': [0.1, 1, 10, 100, 1000],
#           'max_iter':[25, 100, 200, 300]}

# ## Instantiate & Fit GridSearchCV
# gridsearch = GridSearchCV(LogisticRegression(random_state=123), params, n_jobs=-1,
#                           cv=5, verbose=2, scoring = 'accuracy')
# gridsearch.fit(X_train_df_UNVPRG, y_train_final)

```

executed in 15ms, finished 23:16:12 2021-05-27

In [107]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:12 2021-05-27

In [108]:
```
# gridsearch.best_estimator_
```

executed in 15ms, finished 23:16:12 2021-05-27

In [109]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/up_progress/LR_best_up_new.joblib')
```
executed in 15ms, finished 23:16:12 2021-05-27

5.3.4.3 Building the best parameters Logistic Regression model

In [110]:
```
log_reg_model4_new=joblib.load('models/up_progress/LR_best_up_new.joblib')
```
executed in 15ms, finished 23:16:12 2021-05-27

In [111]:
```
log_reg_model4_new.fit(X_train_df_UNVPRG, y_train_final)
```
executed in 63ms, finished 23:16:12 2021-05-27

Out[111]:
```
LogisticRegression
LogisticRegression(C=0.1, max_iter=25, penalty='none', random_state=123,
                   solver='newton-cg')
```

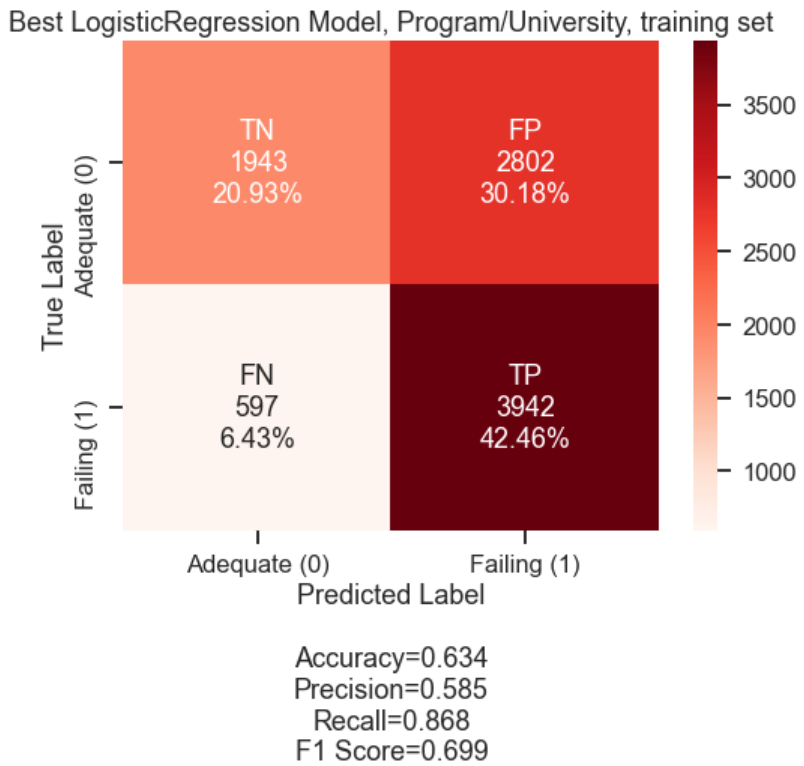
In [112]:
```
viz = ClassificationReport(log_reg_model4_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_UNVPRG, y_train_final)

viz.score(X_test_df_UNVPRG, y_test_final)

viz.show();
```
executed in 302ms, finished 23:16:12 2021-05-27

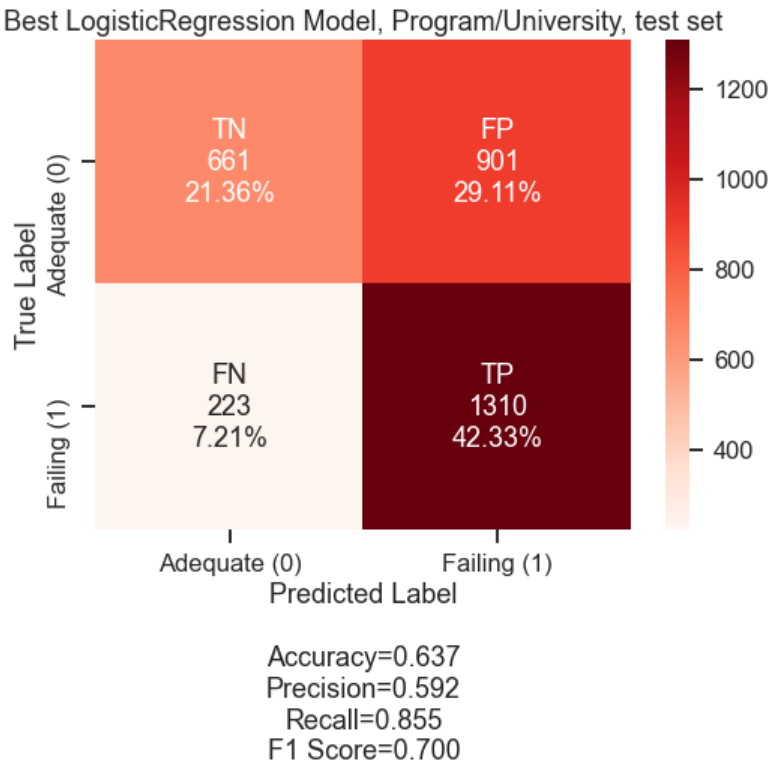
In [113]:

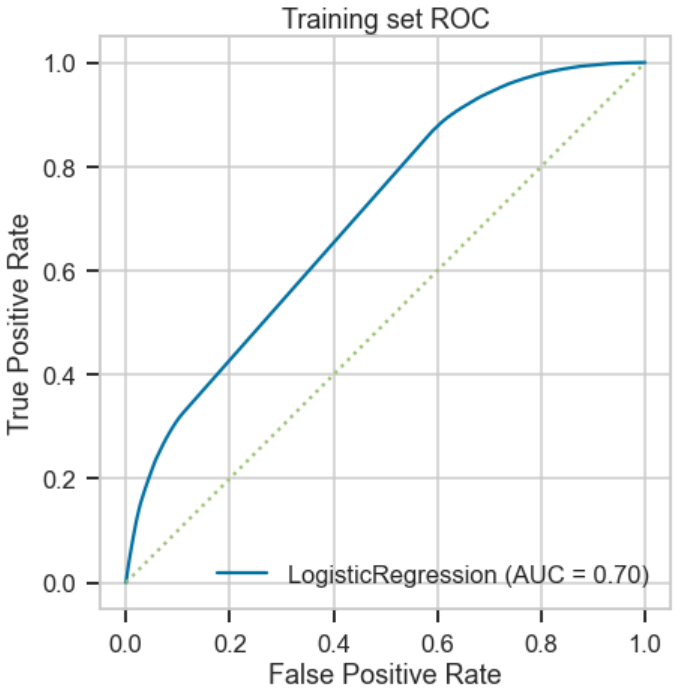
```
simple_model_validation(log_reg_model4_new, UNVPRG_list,
                        'Best LogisticRegression Model, Program/University, training set',
                        'Best LogisticRegression Model, Program/University, test set')
```

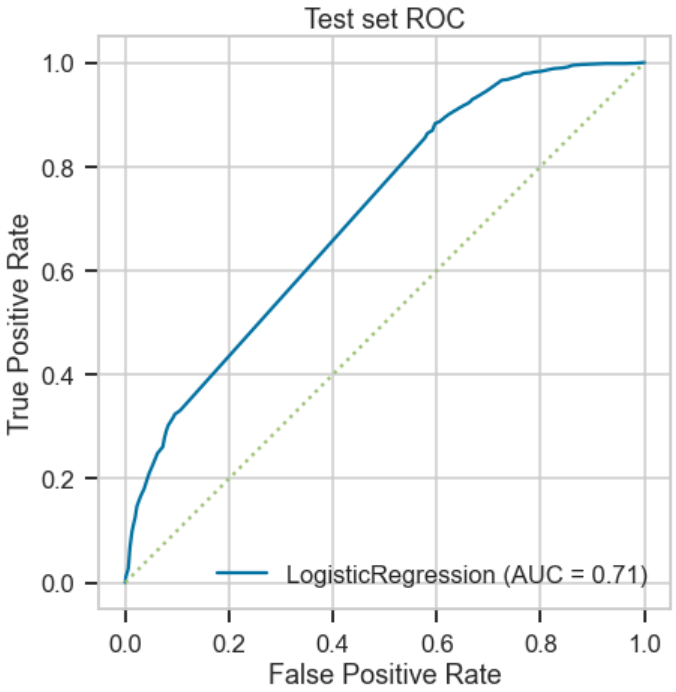
executed in 589ms, finished 23:16:13 2021-05-27

```
**************************************
LogisticRegression(C=0.1, max_iter=25, penalty='none', random_state=123,
                   solver='newton-cg')
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.76      0.41      0.53      4745
           1       0.58      0.87      0.70      4539

    accuracy                           0.63      9284
   macro avg       0.67      0.64      0.62      9284
weighted avg       0.68      0.63      0.61      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.75      0.42      0.54      1562
           1       0.59      0.85      0.70      1533

    accuracy                           0.64      3095
   macro avg       0.67      0.64      0.62      3095
weighted avg       0.67      0.64      0.62      3095


**************************************
Differences in Accuracy scores between training and test sets: -0.003
Differences in Recall scores between training and test sets: -0.008
```




Best LogisticRegression Model, Program/University, test set
TN
661
21.36%
FP
901
29.11%
FN
223
7.21%
TP
1310
42.33%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1200
1000
800
600
400
Accuracy=0.637
Precision=0.592
Recall=0.855
F1 Score=0.700





In [114]:
```
unvprg_models_dict=adding_to_models_dict(models_dict_up,'LogisticRegressionClassifier, best params', 'log_reg_model4_new'
                                         UNVPRG_list, log_reg_model4_new, 'models/up_progress/LR_best_up_new.joblib')
```

executed in 31ms, finished 23:16:13 2021-05-27

> The optimization of the model did not change the scores. Possibly due to the nature of the task, there is no ambiguity which universities provide better education.

5.3.5 Building DecisionTree models with SocioEconomic/HS scores features

5.3.5.1 Building and evaluating a DecisionTree model with default parameters

In [115]:
```
DT_classifier1_new = DecisionTreeClassifier(random_state=123)
DT_classifier1_new.fit(X_train_df_SE, y_train_final)
```

executed in 79ms, finished 23:16:13 2021-05-27

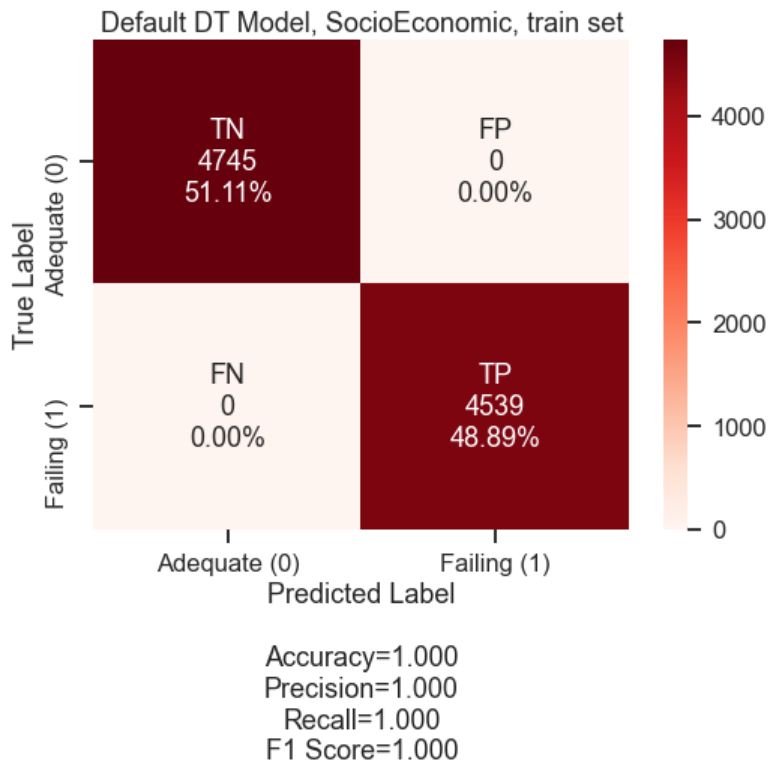
Out[115]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=123)
```

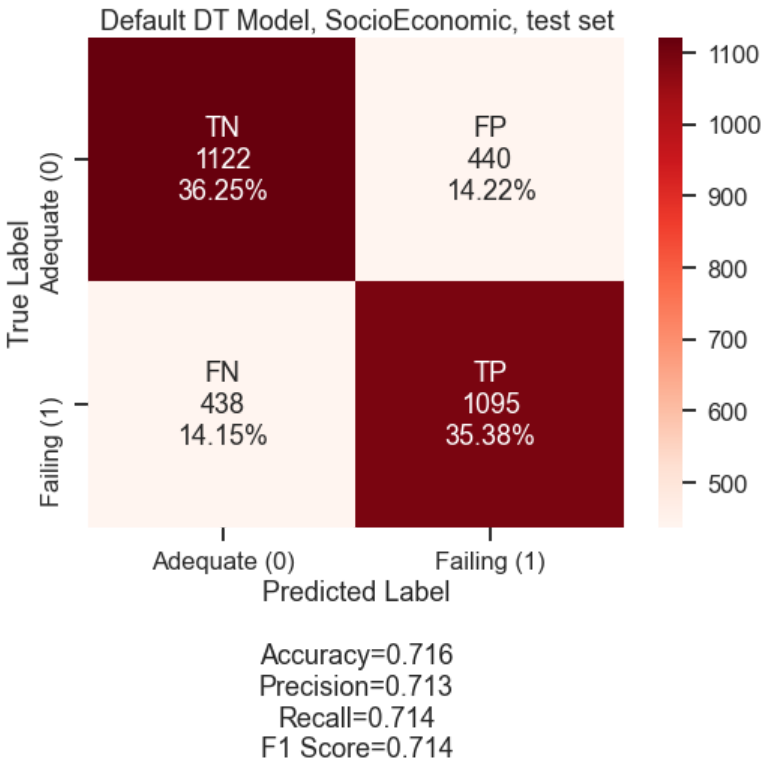
In [116]:

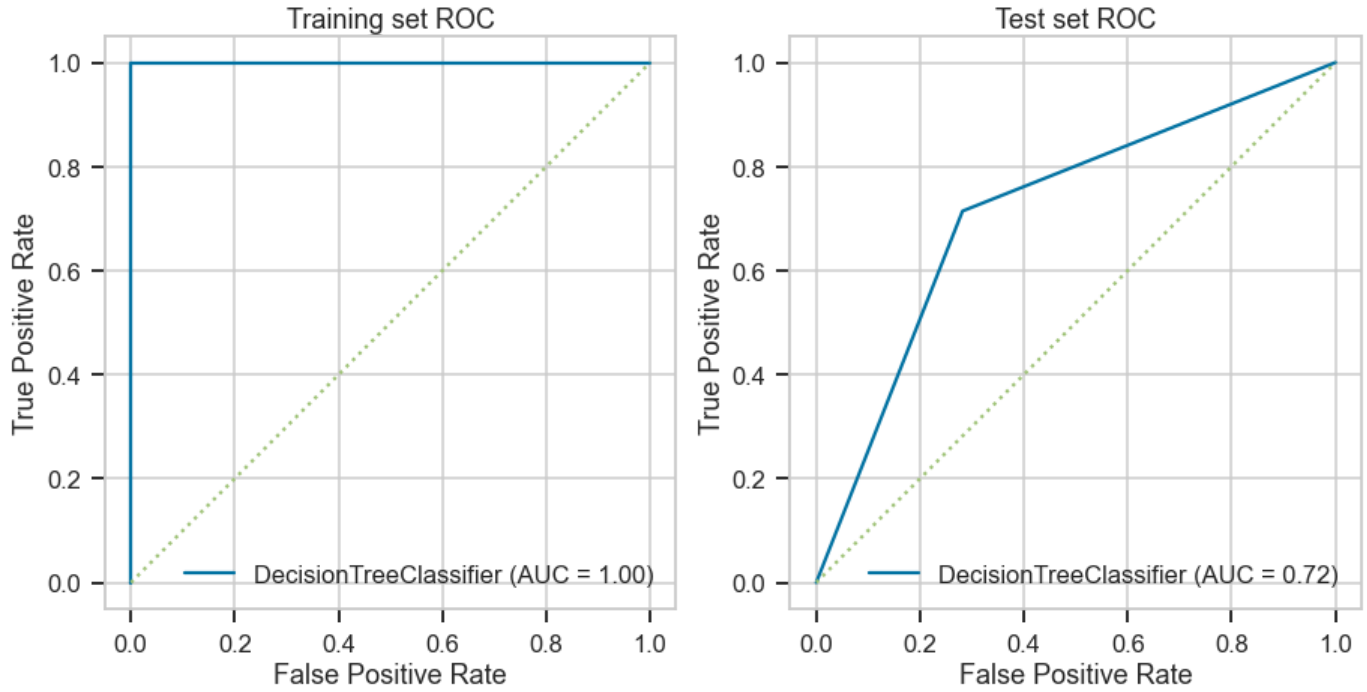
```
simple_model_validation(DT_classifier1_new, SE_list,
                        'Default DT Model, SocioEconomic, train set',
                        'Default DT Model, SocioEconomic, test set')
```

executed in 591ms, finished 23:16:13 2021-05-27

```
**************************************
DecisionTreeClassifier(random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      4745
           1       1.00      1.00      1.00      4539

    accuracy                           1.00      9284
   macro avg       1.00      1.00      1.00      9284
weighted avg       1.00      1.00      1.00      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.72      0.72      0.72      1562
           1       0.71      0.71      0.71      1533

    accuracy                           0.72      3095
   macro avg       0.72      0.72      0.72      3095
weighted avg       0.72      0.72      0.72      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.284
Differences in Recall scores between training and test sets: 0.287
```




Default DT Model, SocioEconomic, test set
TN
1122
36.25%
FP
440
14.22%
FN
438
14.15%
TP
1095
35.38%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1100
1000
900
800
700
600
500
Accuracy=0.716
Precision=0.713
Recall=0.714
F1 Score=0.714



In [117]:
```
se_models_dict=adding_to_models_dict(models_dict_se,'DecisionTreeClassifier, default params',
                                     'DT_classifier1_new', SE_list, DT_classifier1_new, 'not saved')
```

executed in 30ms, finished 23:16:13 2021-05-27

> The over-fitting of the model is very pronounced.

5.3.5.2 GridSearch best parameters for a DecisionTree model

In [118]:
```
# params = {'criterion':['gini', 'entropy'],
#           'splitter':['best', 'random'],
#           'max_depth': [4, 5, 6, 10],
#           'min_samples_leaf': [2,3,5, 10],
#           'class_weight':[None, 'balanced'],
#           'max_features':['auto',10,30,70, None]}

# ## Instantiate & Fit GridSearchCV
# gridsearch = GridSearchCV(DecisionTreeClassifier(random_state=123), params, n_jobs=-1,
#                           cv=5, verbose=2, scoring = 'recall')
# gridsearch.fit(X_train_df_SE, y_train_final)

```

executed in 14ms, finished 23:16:13 2021-05-27

In [119]:
```
# gridsearch.best_estimator_
```

executed in 15ms, finished 23:16:13 2021-05-27

In [120]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:13 2021-05-27

In [121]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/se_progress/DT_best_se_new.joblib')
```

executed in 15ms, finished 23:16:13 2021-05-27

5.3.5.3 Building and evaluating the best parameters DecisionTreen mode

In [122]:
```
DT_classifier2_new = joblib.load('models/se_progress/DT_best_se_new.joblib')
```

executed in 15ms, finished 23:16:13 2021-05-27

In [123]:
```
1 DT_classifier2_new.fit(X_train_df_SE, y_train_final)
```

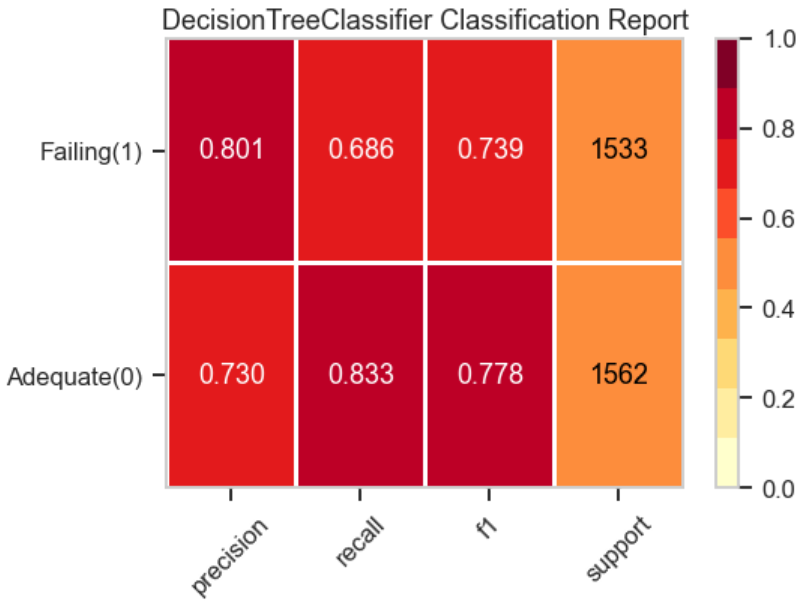
executed in 15ms, finished 23:16:14 2021-05-27

Out[123]:

```
DecisionTreeClassifier

DecisionTreeClassifier(class_weight='balanced', max_depth=5, max_features=10,
                       min_samples_leaf=2, random_state=123, splitter='random')
```

In [124]:
```
1  viz = ClassificationReport(DT_classifier2_new,
2                             classes=['Adequate(0)', 'Failing(1)'],
3                             support=True,
4                             fig=plt.figure(figsize=(8,6)))
5
6  viz.fit(X_train_df_SE, y_train_final)
7
8  viz.score(X_test_df_SE, y_test_final)
9
10 viz.show();
```

executed in 175ms, finished 23:16:14 2021-05-27

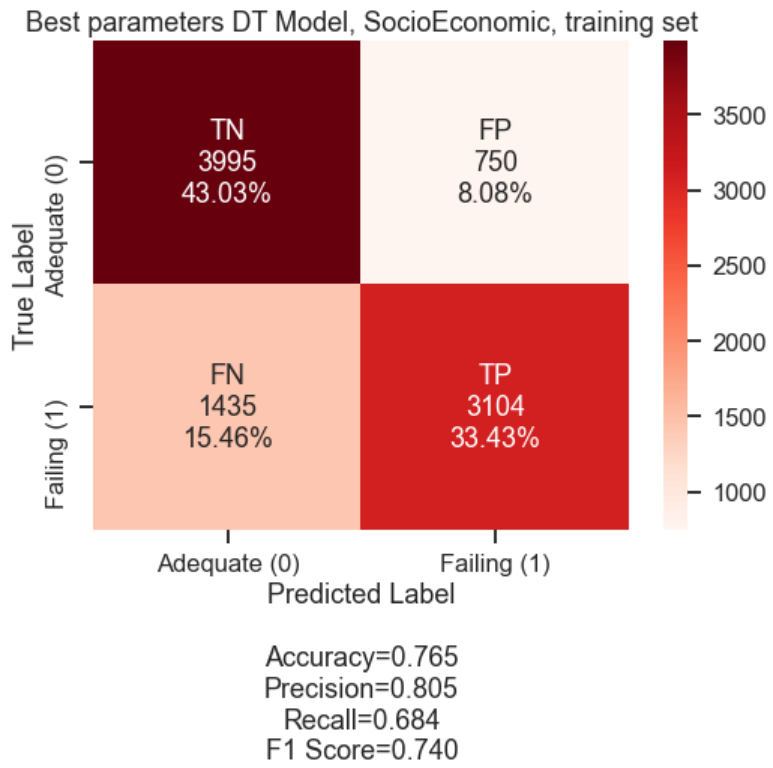


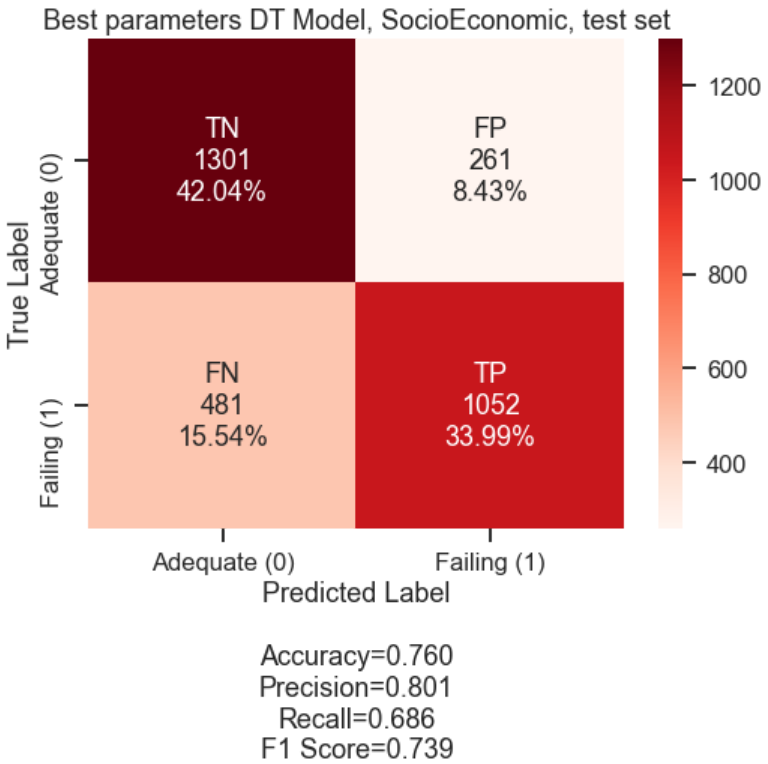
In [125]:

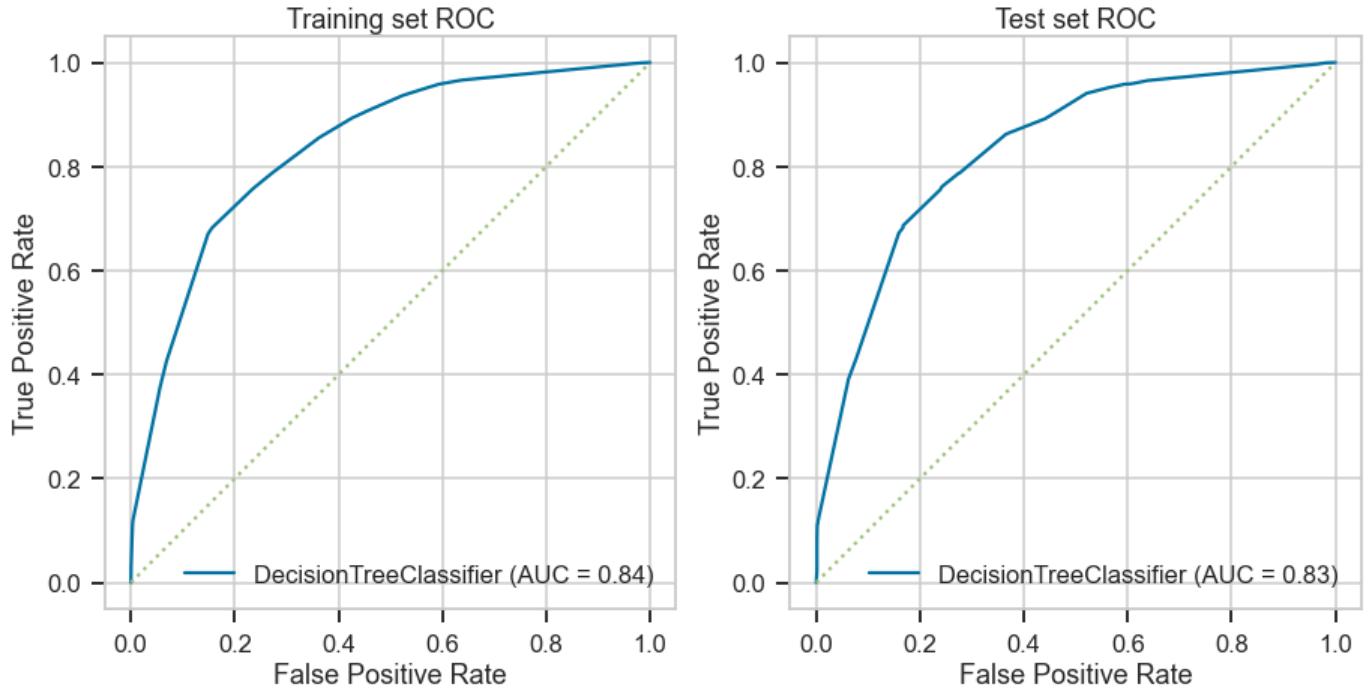
```
simple_model_validation(DT_classifier2_new, SE_list,
                        'Best parameters DT Model, SocioEconomic, training set',
                        'Best parameters DT Model, SocioEconomic, test set')
```

executed in 606ms, finished 23:16:14 2021-05-27

```
**************************************
DecisionTreeClassifier(class_weight='balanced', max_depth=5, max_features=10,
                       min_samples_leaf=2, random_state=123, splitter='random')
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.74      0.84      0.79      4745
           1       0.81      0.68      0.74      4539

    accuracy                           0.76      9284
   macro avg       0.77      0.76      0.76      9284
weighted avg       0.77      0.76      0.76      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.73      0.83      0.78      1562
           1       0.80      0.69      0.74      1533

    accuracy                           0.76      3095
   macro avg       0.77      0.76      0.76      3095
weighted avg       0.77      0.76      0.76      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.004
Differences in Recall scores between training and test sets: 0.004
```




Best parameters DT Model, SocioEconomic, test set
TN
1301
42.04%
FP
261
8.43%
FN
481
15.54%
TP
1052
33.99%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1200
1000
800
600
400
Accuracy=0.760
Precision=0.801
Recall=0.686
F1 Score=0.739



In [126]:
```
se_models_dict=adding_to_models_dict(models_dict_se,'DecisionTreeClassifier, best params','DT_classifier2_new',
                                     SE_list, DT_classifier2_new, 'models/se_progress/DT_best_se_new.joblib')
```

executed in 31ms, finished 23:16:14 2021-05-27

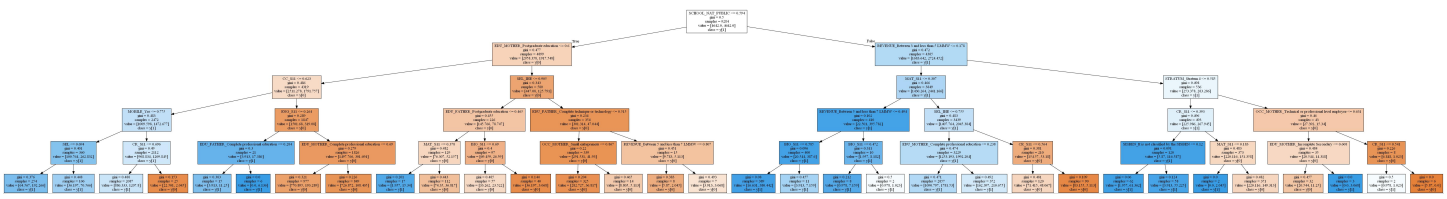
The performance of the DecisionTreeClassifier with best parameters is the best in terms of the Recall score but only slightly

5.3.5.4 Tree visualization

In [127]:
```
dot_data = tree.export_graphviz(DT_classifier2_new, out_file='DT_classifier2_new.dot',
                feature_names=X_train_df_SE.columns,
                class_names=True,
                filled = True)

path = 'DT_classifier2_new.dot'
source_ = Source.from_file(path)
source_.render('DT_classifier2_new', format='jpg', view=True)

#Draw graph
#graph = graphviz.Source(dot_data, format="png")

#graph
```

executed in 1.04s, finished 23:16:15 2021-05-27

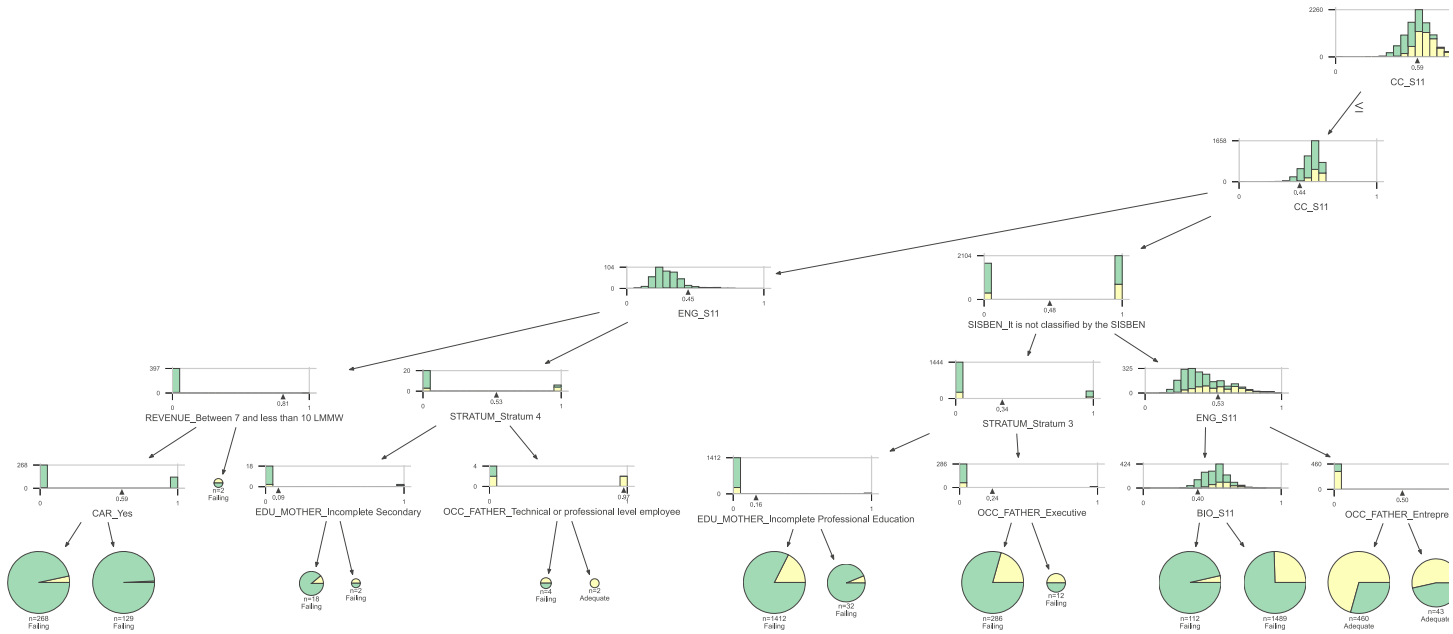
Out[127]: 'DT_classifier2_new.jpg'



In [128]:
```
viz = dtreeviz(DT_classifier2_new,
               X_train_df_SE,
               y_train_final.FAILING,
               target_name='Performance',
               feature_names=X_train_df_SE.columns,
               class_names={1:'Failing',0:'Adequate'},
               show_node_labels = False, scale=0.7)
viz
```

executed in 6.72s, finished 23:16:22 2021-05-27

Out[128]:



5.3.6 Building DecisionTree models with Program/University features

5.3.6.1 Building and evaluating a simple DecisionTree model

In [129]:
```
DT_classifier3_new = DecisionTreeClassifier(random_state=123)
DT_classifier3_new
```

executed in 12ms, finished 23:16:22 2021-05-27

Out[129]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=123)
```

In [130]:
```
DT_classifier3_new.fit(X_train_df_UNVPRG, y_train_final)
```

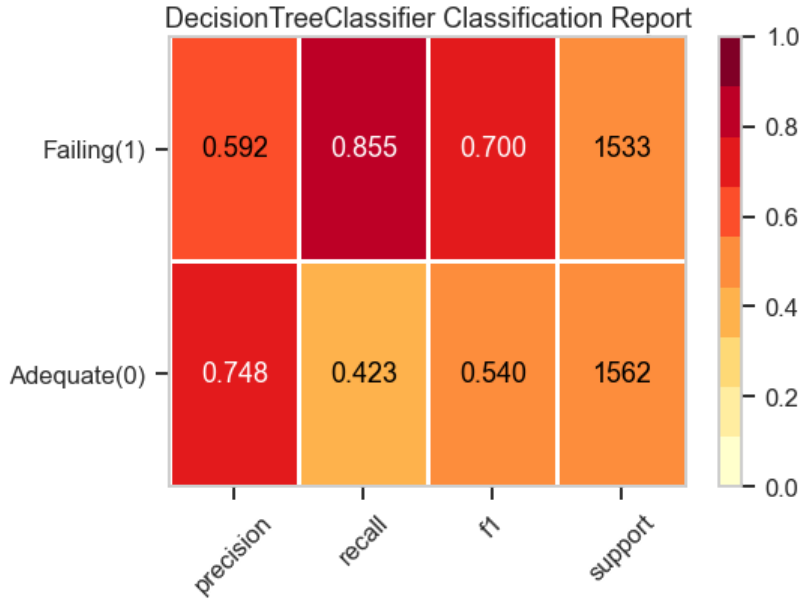
executed in 46ms, finished 23:16:22 2021-05-27

Out[130]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=123)
```

In [131]:

```
viz = ClassificationReport(DT_classifier3_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_UNVPRG, y_train_final)

viz.score(X_test_df_UNVPRG, y_test_final)

viz.show();
```

executed in 159ms, finished 23:16:22 2021-05-27

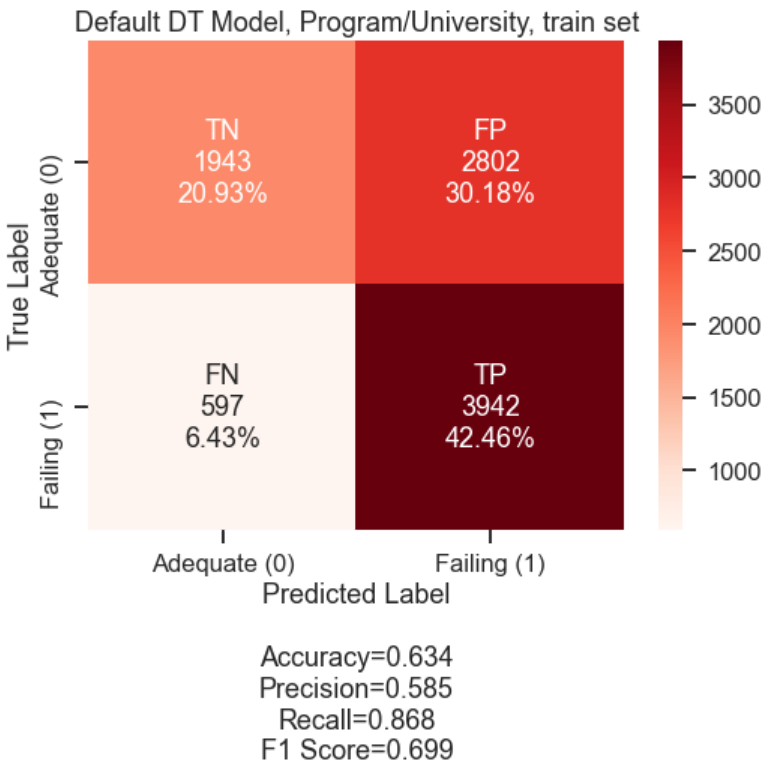


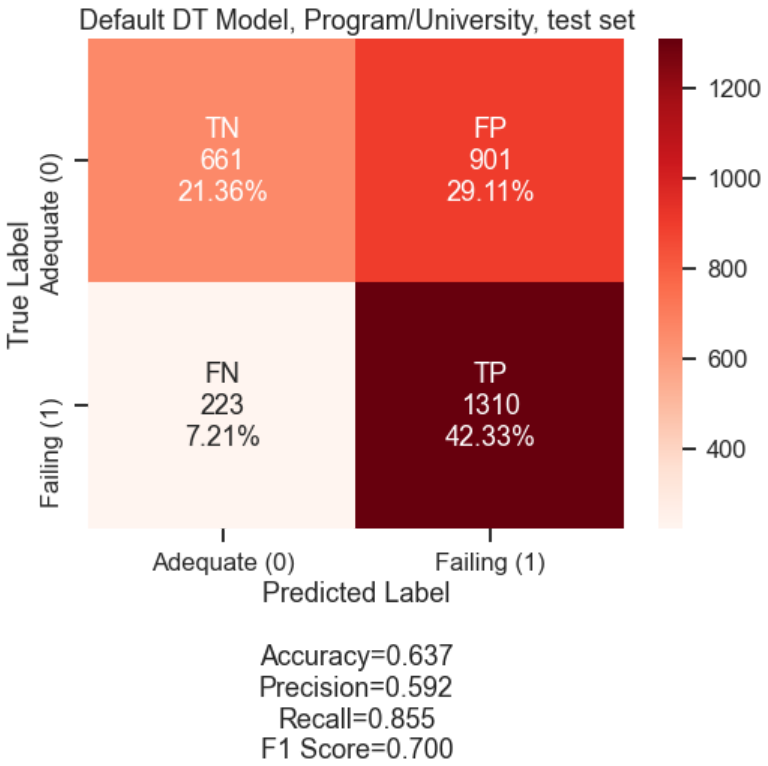
In [132]:

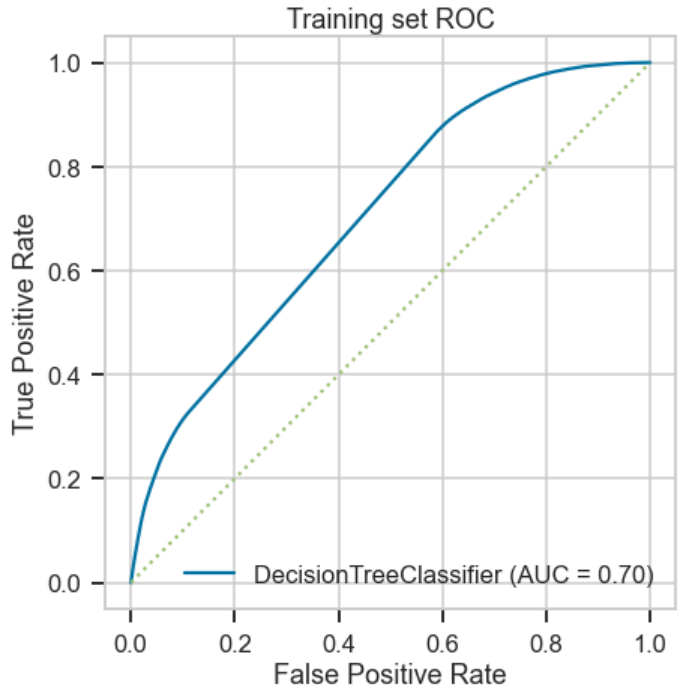
```
simple_model_validation(DT_classifier3_new, UNVPRG_list,
                        'Default DT Model, Program/University, train set',
                        'Default DT Model, Program/University, test set')
```

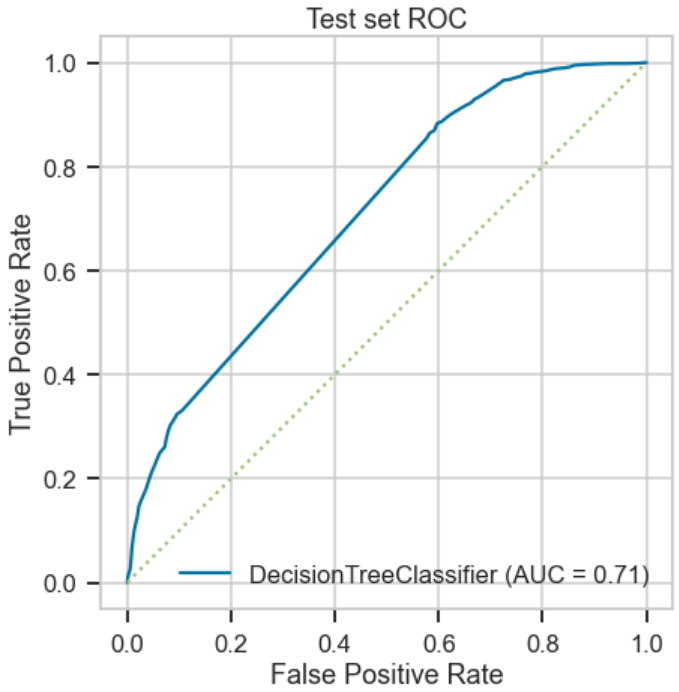
executed in 591ms, finished 23:16:23 2021-05-27

```
**************************************
DecisionTreeClassifier(random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.76      0.41      0.53      4745
           1       0.58      0.87      0.70      4539

    accuracy                           0.63      9284
   macro avg       0.67      0.64      0.62      9284
weighted avg       0.68      0.63      0.61      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.75      0.42      0.54      1562
           1       0.59      0.85      0.70      1533

    accuracy                           0.64      3095
   macro avg       0.67      0.64      0.62      3095
weighted avg       0.67      0.64      0.62      3095


**************************************
Differences in Accuracy scores between training and test sets: -0.003
Differences in Recall scores between training and test sets: -0.008
```




Default DT Model, Program/University, test set
TN
661
21.36%
FP
901
29.11%
FN
223
7.21%
TP
1310
42.33%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1200
1000
800
600
400
Accuracy=0.637
Precision=0.592
Recall=0.855
F1 Score=0.700





DecisionTreeClassifier models with University/Program features are still displaying the same metrics. Not sure of the reason.

5.3.6.2 GridSearch best parameters search for a DecisionTree model

In [133]:
```
# params = {'criterion':['gini', 'entropy'],
#           'splitter':['best', 'random'],
#           'max_depth': [4, 5, 6, 10],
#           'min_samples_leaf': [2,3,5, 10],
#           'class_weight':[None, 'balanced'],
#           'max_features':['auto',10,30,70, None]}


# ## Instantiate & Fit GridSearchCV
# gridsearch = GridSearchCV(DecisionTreeClassifier(random_state=123),params, cv=5, n_jobs=-1, verbose=2, scoring='f1')
# gridsearch.fit(X_train_df_UNVPRG, y_train_final)
```

executed in 14ms, finished 23:16:23 2021-05-27

In [134]:
```
# gridsearch.best_estimator_
```

executed in 15ms, finished 23:16:23 2021-05-27

In [135]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:23 2021-05-27

In [136]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/up_progress/DT_best_up_new.joblib')
```

executed in 15ms, finished 23:16:23 2021-05-27

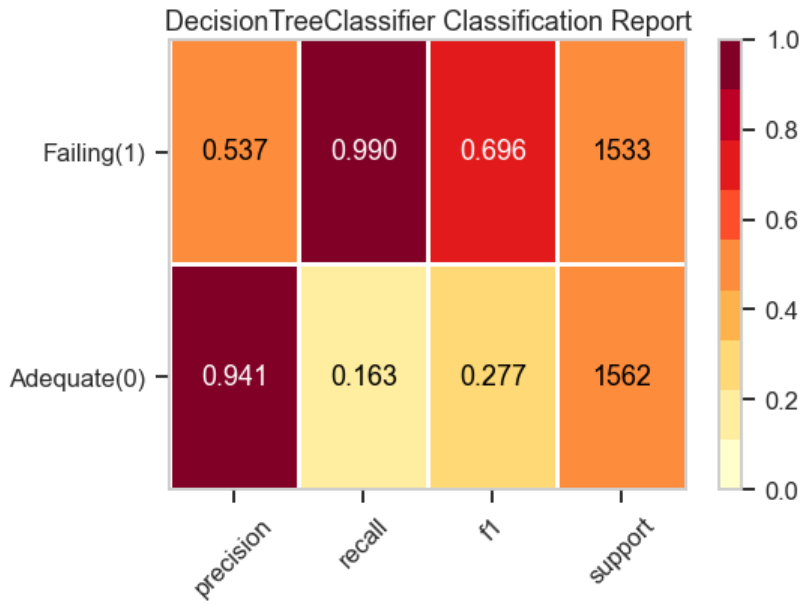
5.3.6.3 Building and evaluating the best parameters Decision Tree model

In [137]:
```
DT_classifier4_new = joblib.load('models/up_progress/DT_best_up_new.joblib')
```
executed in 14ms, finished 23:16:23 2021-05-27

In [138]:
```
DT_classifier4_new.fit(X_train_df_UNVPRG, y_train_final)
```
executed in 31ms, finished 23:16:23 2021-05-27

Out[138]:
```
DecisionTreeClassifier

DecisionTreeClassifier(max_depth=10, min_samples_leaf=2, random_state=123)
```

In [139]:
```
viz = ClassificationReport(DT_classifier4_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_UNVPRG, y_train_final)

viz.score(X_test_df_UNVPRG, y_test_final)

viz.show();
```
executed in 159ms, finished 23:16:23 2021-05-27

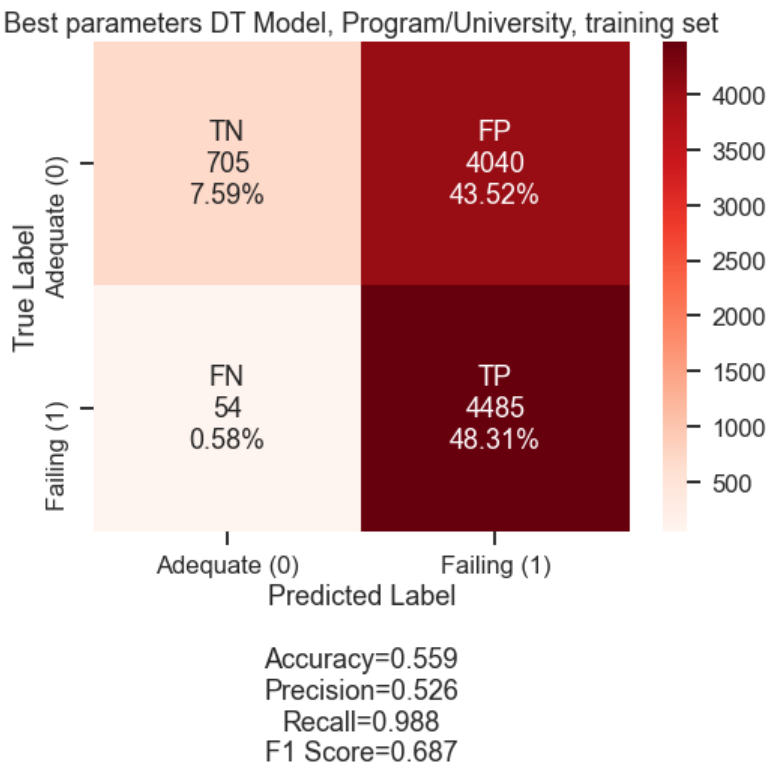


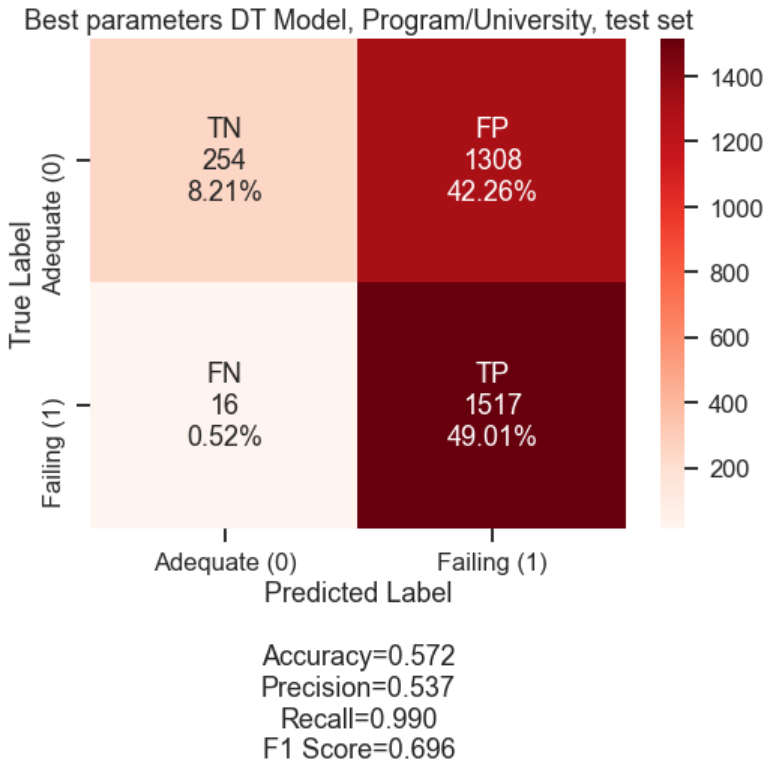
In [140]:

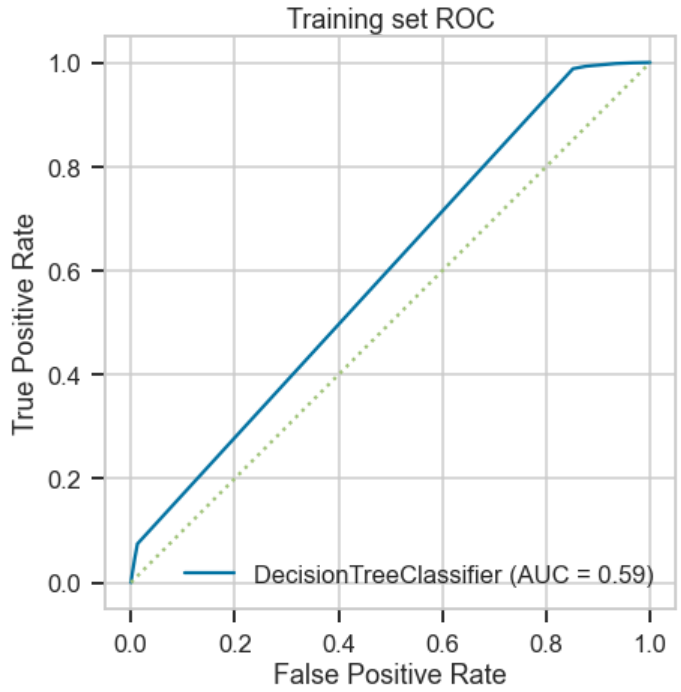
```
simple_model_validation(DT_classifier4_new, UNVPRG_list,
                        'Best parameters DT Model, Program/University, training set',
                        'Best parameters DT Model, Program/University, test set')
```

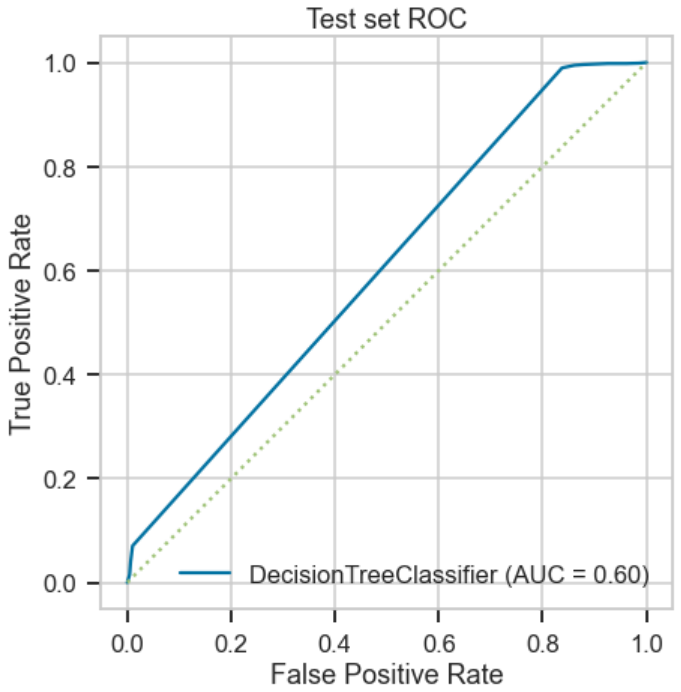
executed in 607ms, finished 23:16:24 2021-05-27

```
**************************************
DecisionTreeClassifier(max_depth=10, min_samples_leaf=2, random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.93      0.15      0.26      4745
           1       0.53      0.99      0.69      4539

    accuracy                           0.56      9284
   macro avg       0.73      0.57      0.47      9284
weighted avg       0.73      0.56      0.47      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.94      0.16      0.28      1562
           1       0.54      0.99      0.70      1533

    accuracy                           0.57      3095
   macro avg       0.74      0.58      0.49      3095
weighted avg       0.74      0.57      0.48      3095


**************************************
Differences in Accuracy scores between training and test sets: -0.013
Differences in Recall scores between training and test sets: -0.011
```




Best parameters DT Model, Program/University, test set
TN
254
8.21%
FP
1308
42.26%
FN
16
0.52%
TP
1517
49.01%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1400
1200
1000
800
600
400
200
Accuracy=0.572
Precision=0.537
Recall=0.990
F1 Score=0.696





In [141]:
```
unvprg_models_dict=adding_to_models_dict(models_dict_up,'DecisionTreeClassifier, best params', 'DT_classifier4_new',
                                         UNVPRG_list, DT_classifier4_new, 'models/up_progress/DT_best_up_new.joblib')
```

executed in 30ms, finished 23:16:24 2021-05-27

> The model shows pretty good recall metrics. However, University/Program models' most important metrics is accuracy or f1, which are not high.

5.3.6.4 Feature selection via VarianceThreshhold

In [142]:
```
# Testing if Feature selection might help with either the performance of the model or make the model more interpretable

selector = VarianceThreshold(threshold=0.0)
selector.fit(X_train_df_UNVPRG)
```

executed in 15ms, finished 23:16:24 2021-05-27

Out[142]:
```
VarianceThreshold

VarianceThreshold()
```

In [143]:
```
keep_features = selector.get_support()
print(keep_features.sum())
keep_features.sum()==len(X_train_df_UNVPRG.columns)
```

executed in 15ms, finished 23:16:24 2021-05-27

```
52
```

Out[143]:
```
True
```

In [144]:
```
selector = VarianceThreshold(threshold=0.01)
selector.fit(X_train_df_UNVPRG)
```

executed in 15ms, finished 23:16:24 2021-05-27

Out[144]:
```
VarianceThreshold

VarianceThreshold(threshold=0.01)
```

In [145]:
```
keep_features = selector.get_support()
print(keep_features.sum())
keep_features.sum()==len(X_train_df_UNVPRG.columns)
```

executed in 15ms, finished 23:16:24 2021-05-27

```
16
```

Out[145]:
```
False
```

> The number of the university/program features decreased dramatically

In [146]:
```
X_train_VT = X_train_df_UNVPRG.loc[:,keep_features]
X_test_VT = X_test_df_UNVPRG.loc[:,keep_features]
X_train_VT
```

executed in 30ms, finished 23:16:24 2021-05-27

Out[146]:

	PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.	PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.	PROG_UNIV_CIVIL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA	PROG_UNIV_CIVIL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.	PROG_UNIV_CIV ENGINEERING_UNIVERSIDA COOPERATIVA I COLOMBIA-BOGOTÁ D.
796	0.0	0.0	0.0	0.0	
8185	0.0	0.0	0.0	0.0	
6228	0.0	0.0	0.0	0.0	
1116	0.0	0.0	0.0	0.0	
7653	0.0	0.0	0.0	0.0	
...	...	...	...	...	
5218	0.0	0.0	0.0	0.0	
12252	0.0	0.0	0.0	0.0	
1346	0.0	0.0	0.0	0.0	
11646	0.0	0.0	0.0	0.0	
3582	0.0	0.0	0.0	0.0	

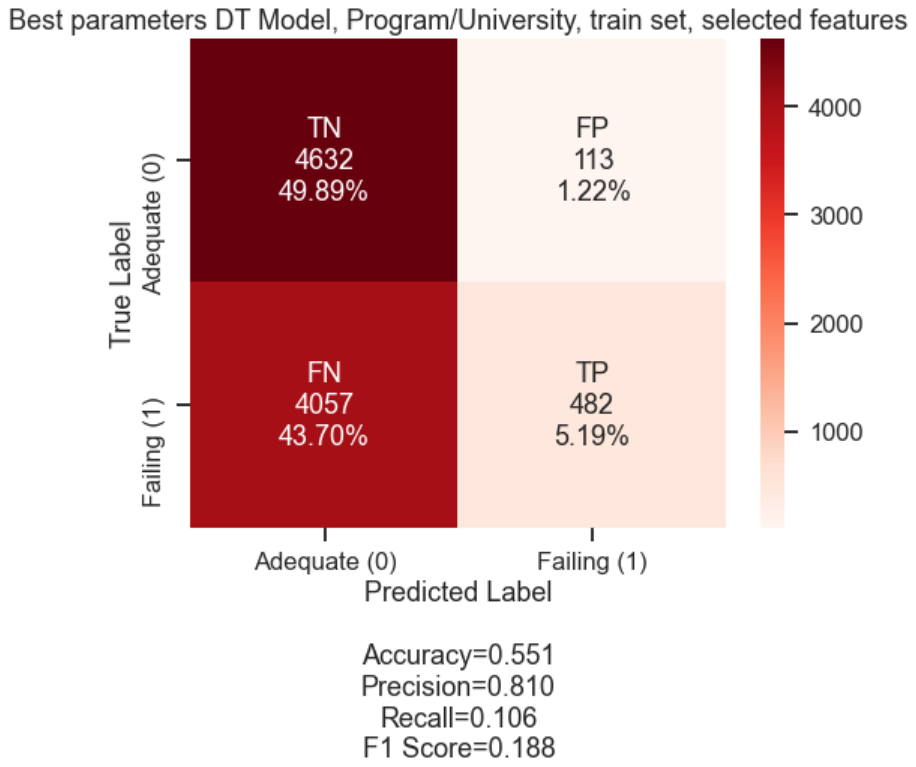
9284 rows × 16 columns

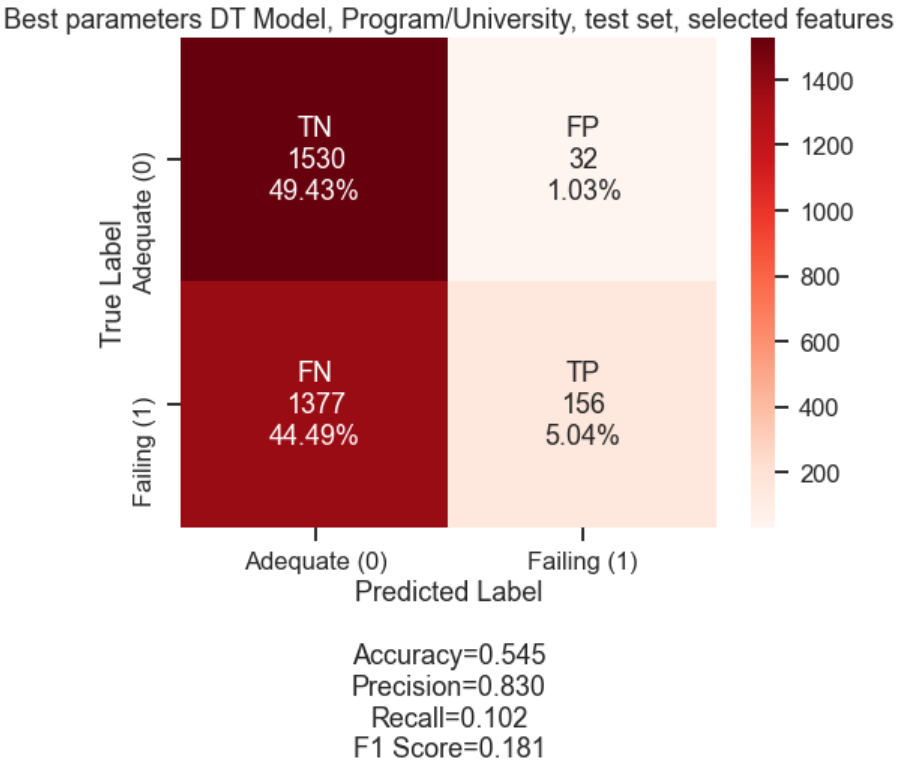
In [147]:

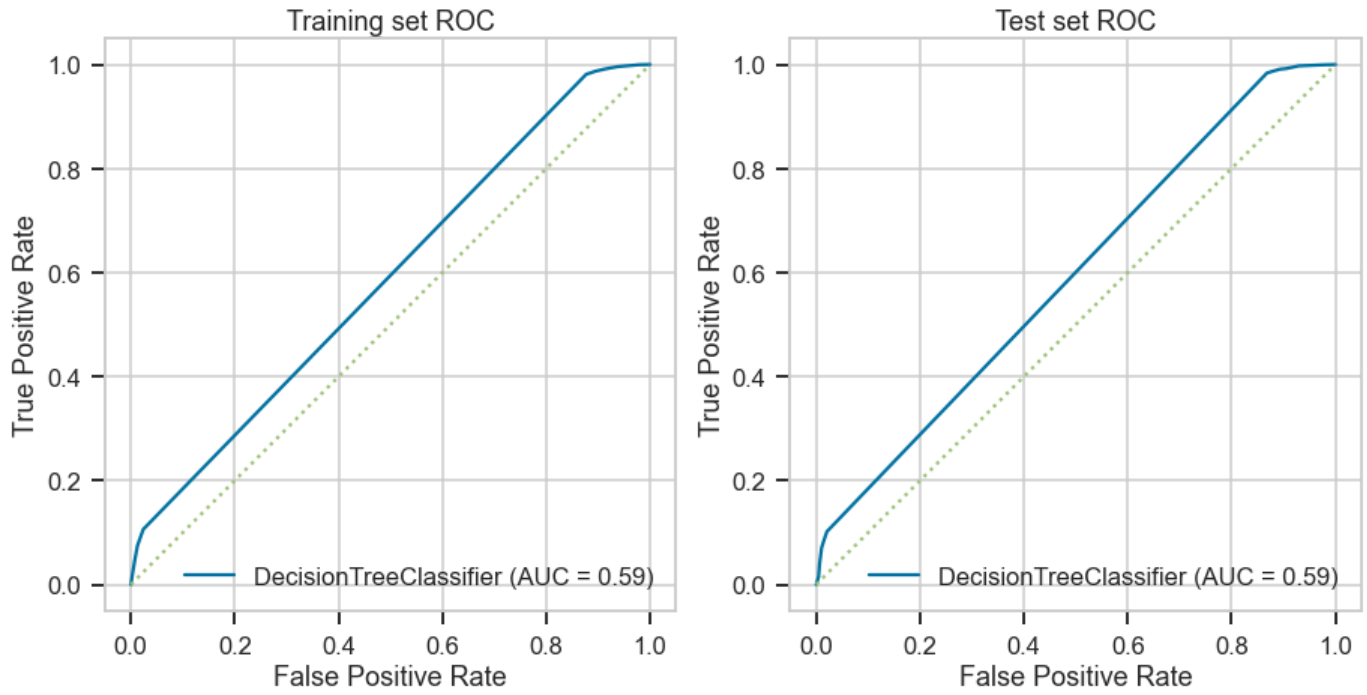
```
DT_classifier5_new = joblib.load('models/up_progress/DT_best_up_new.joblib')
DT_classifier5_new.fit(X_train_VT, y_train_final)

UNVPRG_VT_list=[X_train_VT,  X_test_VT, y_train_final, y_test_final]
simple_model_validation(DT_classifier5_new, UNVPRG_VT_list,
                        'Best parameters DT Model, Program/University, train set, selected features',
                        'Best parameters DT Model, Program/University, test set, selected features')
```

executed in 592ms, finished 23:16:24 2021-05-27

```
**************************************
DecisionTreeClassifier(max_depth=10, min_samples_leaf=2, random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.53      0.98      0.69      4745
           1       0.81      0.11      0.19      4539

    accuracy                           0.55      9284
   macro avg       0.67      0.54      0.44      9284
weighted avg       0.67      0.55      0.44      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.53      0.98      0.68      1562
           1       0.83      0.10      0.18      1533

    accuracy                           0.54      3095
   macro avg       0.68      0.54      0.43      3095
weighted avg       0.68      0.54      0.44      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.006
Differences in Recall scores between training and test sets: -0.02
```




Best parameters DT Model, Program/University, test set, selected features
TN
1530
49.43%
FP
32
1.03%
FN
1377
44.49%
TP
156
5.04%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1400
1200
1000
800
600
400
200
Accuracy=0.545
Precision=0.830
Recall=0.102
F1 Score=0.181

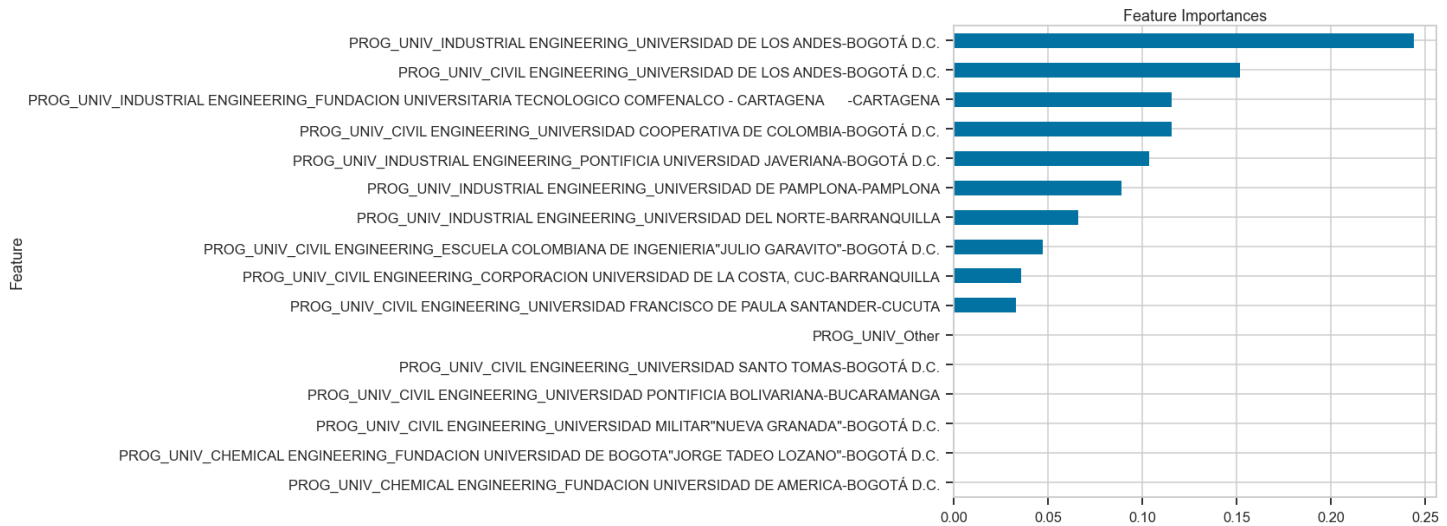


In [148]:
```
1 get_importance_tree(DT_classifier5_new, X_train_VT)
```

executed in 286ms, finished 23:16:25 2021-05-27

Out[148]:

```
PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.                                0.000000
PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.             0.000000
PROG_UNIV_CIVIL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA                          0.035514
PROG_UNIV_CIVIL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.                   0.047016
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.                                0.115337
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                                           0.151516
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA                                0.032894
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.                                 0.000000
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA                                 0.000000
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-BOGOTÁ D.C.                                            0.000000
PROG_UNIV_INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA      -CARTAGENA    0.115589
PROG_UNIV_INDUSTRIAL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.                              0.103567
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.                                      0.243740
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE PAMPLONA-PAMPLONA                                          0.089016
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA                                        0.065812
PROG_UNIV_Other                                                                                            0.000000
dtype: float64
```



In [149]:
```
1 unvprg_models_dict=adding_to_models_dict(models_dict_up,'DecisionTreeClassifier, best params, select features',
2                                          'DT_classifier5_new', UNVPRG_VT_list, DT_classifier5_new, 'not saved')
```

executed in 31ms, finished 23:16:25 2021-05-27

In [150]:
```
UNVPRG_df_models=pd.DataFrame(unvprg_models_dict)
UNVPRG_df_models
```

executed in 15ms, finished 23:16:25 2021-05-27

Out[150]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model3_new	LogisticRegressionClassifier, default params	training	0.634	0.868	597	9284	not saved
1	logreg_model3_new	LogisticRegressionClassifier, default params	test	0.637	0.855	223	3095	not saved
2	log_reg_model4_new	LogisticRegressionClassifier, best params	training	0.634	0.868	597	9284	models/up_progress/LR_best_up_new.joblib
3	log_reg_model4_new	LogisticRegressionClassifier, best params	test	0.637	0.855	223	3095	models/up_progress/LR_best_up_new.joblib
4	DT_classifier4_new	DecisionTreeClassifier, best params	training	0.559	0.988	54	9284	models/up_progress/DT_best_up_new.joblib
5	DT_classifier4_new	DecisionTreeClassifier, best params	test	0.572	0.990	16	3095	models/up_progress/DT_best_up_new.joblib
6	DT_classifier5_new	DecisionTreeClassifier, best params, select fe...	training	0.551	0.106	4057	9284	not saved
7	DT_classifier5_new	DecisionTreeClassifier, best params, select fe...	test	0.545	0.102	1377	3095	not saved

> Feature selection did not improve the accuracy of the previous models. The performance of the model is the worst among all the previous ones.

5.4 Building and Evaluating Ensemble Models

5.4.1 RandomForestClassifier with SocioEconomic/HS scores Features

5.4.1.1 Building and evaluating a RandonForestClassifier model with default parameters

In [151]:
```
rfc1_new = RandomForestClassifier(random_state=123)
```

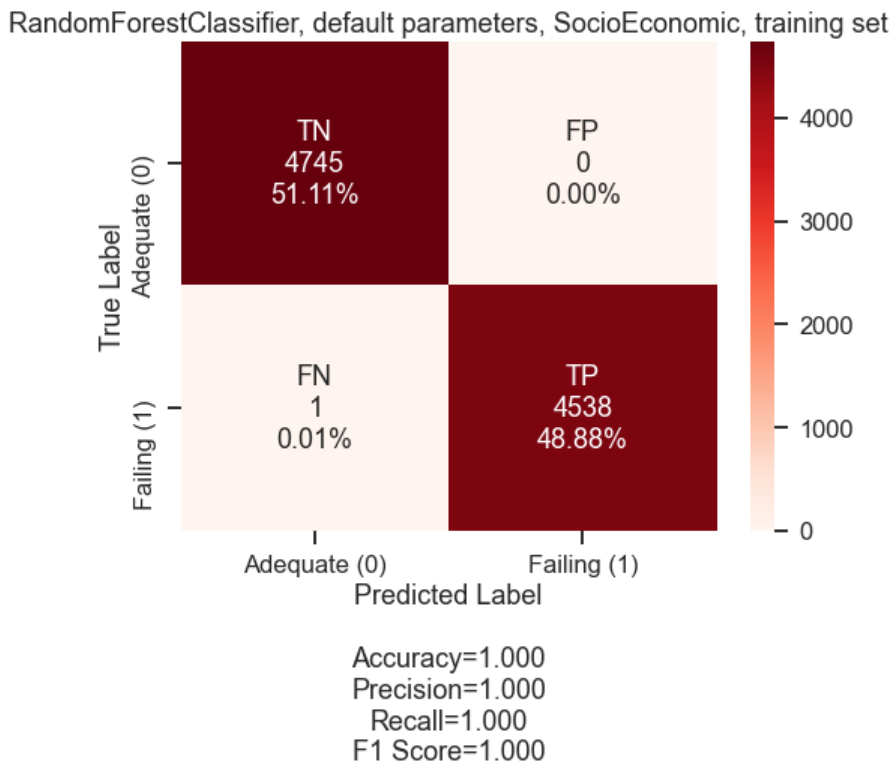
executed in 15ms, finished 23:16:25 2021-05-27

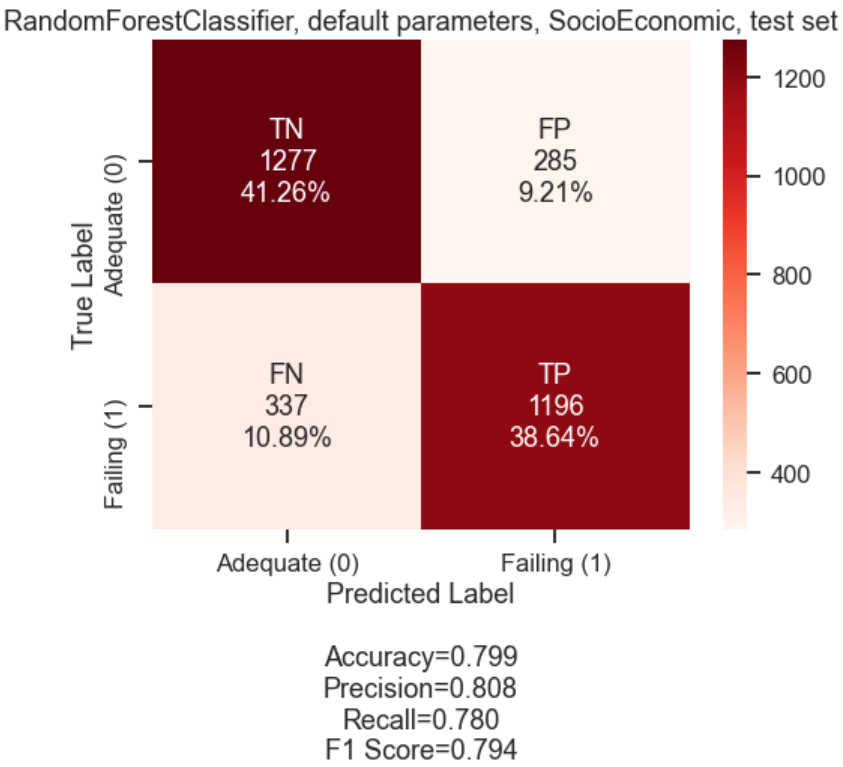
In [152]:

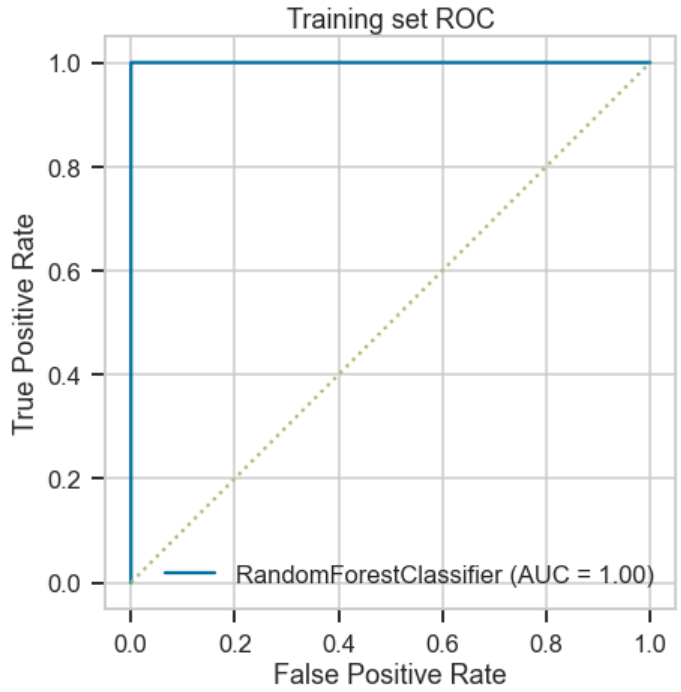
```
rfc1_new.fit(X_train_df_SE, y_train_final)
simple_model_validation(rfc1_new, SE_list,
                        'RandomForestClassifier, default parameters, SocioEconomic, training set',
                        'RandomForestClassifier, default parameters, SocioEconomic, test set')
```

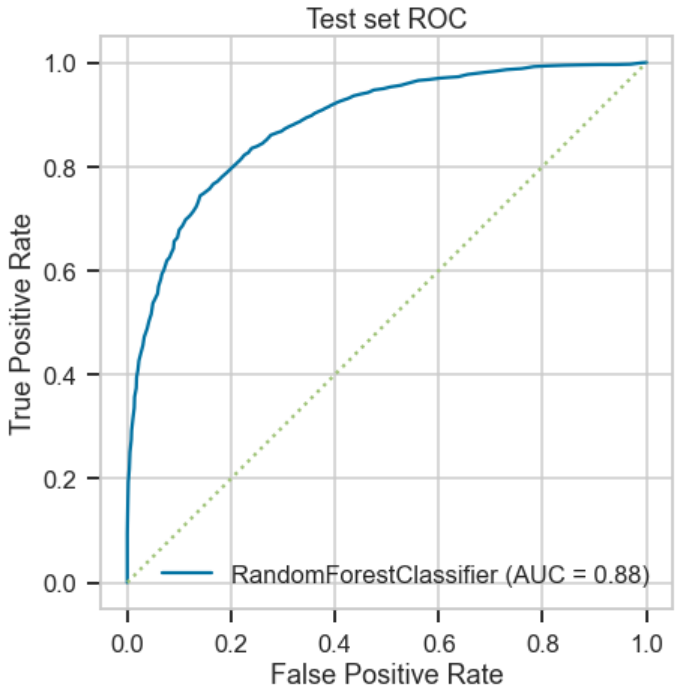
executed in 2.04s, finished 23:16:27 2021-05-27

```
**************************************
RandomForestClassifier(random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      4745
           1       1.00      1.00      1.00      4539

    accuracy                           1.00      9284
   macro avg       1.00      1.00      1.00      9284
weighted avg       1.00      1.00      1.00      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.79      0.82      0.80      1562
           1       0.81      0.78      0.79      1533

    accuracy                           0.80      3095
   macro avg       0.80      0.80      0.80      3095
weighted avg       0.80      0.80      0.80      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.201
Differences in Recall scores between training and test sets: 0.192
```




RandomForestClassifier, default parameters, SocioEconomic, test set
TN
1277
41.26%
FP
285
9.21%
FN
337
10.89%
TP
1196
38.64%
True Label
Adequate (0)
Failing (1)
Adequate (0)
Failing (1)
Predicted Label
1200
1000
800
600
400
Accuracy=0.799
Precision=0.808
Recall=0.780
F1 Score=0.794





In [153]:
```
se_models_dict=adding_to_models_dict(models_dict_se,'RFClassifier, default parameters','rfc1_new',
                                     SE_list, rfc1_new, 'not saved')
```

executed in 413ms, finished 23:16:27 2021-05-27

RandomForestClassifier with default parameters model is overfitted.

5.4.1.2 GridSearch best parameters search for a RandomForestClassifier model

In [154]:
```
RandomForestClassifier().get_params().keys()
```

executed in 15ms, finished 23:16:27 2021-05-27

Out[154]:
```
dict_keys(['bootstrap', 'ccp_alpha', 'class_weight', 'criterion', 'max_depth', 'max_features', 'max_leaf_nodes', 'max_samples', 'min_impurity_decrease', 'min_impurity_split', 'min_samples_leaf', 'min_samples_split', 'min_weight_fraction_leaf', 'n_estimators', 'n_jobs', 'oob_score', 'random_state', 'verbose', 'warm_start'])
```

In [155]:
```
# params= {'criterion':['gini', 'entropy'],
#           'n_estimators': [50, 100, 150, 250],
#           'max_depth': [3, 5, 8, 10],
#           'min_samples_leaf': [2, 5, 10],
#           'class_weight':['balanced_subsample', 'balanced'],
#           'max_features':['auto','sqrt','log2', 25, 50]}

# gridsearch = GridSearchCV(RandomForestClassifier(random_state=123), params, n_jobs=-1,
#                           cv=5, verbose=2, scoring = 'recall')
# gridsearch.fit(X_train_df_SE, y_train_final)
```

executed in 15ms, finished 23:16:27 2021-05-27

In [156]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:27 2021-05-27

In [157]:
```
# gridsearch.best_estimator_
```

executed in 14ms, finished 23:16:27 2021-05-27

In [158]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/se_progress/rfc_best_se_new.joblib')
```

executed in 15ms, finished 23:16:27 2021-05-27

5.4.1.3 Building and evaluating the best parameters RandomForestClassifier model

In [159]:
```
rfc2_new = joblib.load('models/se_progress/rfc_best_se_new.joblib')
```

executed in 31ms, finished 23:16:27 2021-05-27

In [160]:
```
rfc2_new.fit(X_train_df_SE, y_train_final)
```

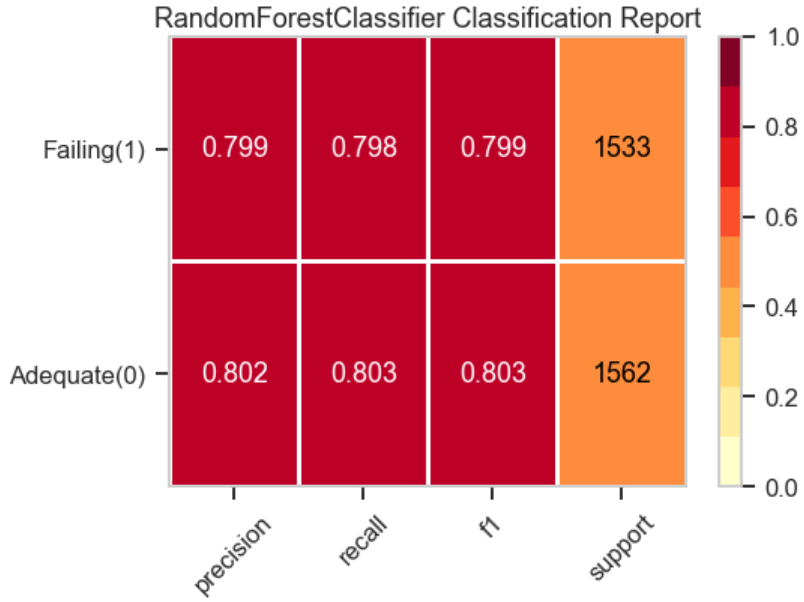
executed in 766ms, finished 23:16:28 2021-05-27

Out[160]:
```
                          RandomForestClassifier
RandomForestClassifier(class_weight='balanced_subsample', max_depth=5,
                       max_features=50, min_samples_leaf=2, n_estimators=50,
                       random_state=123)
```

In [161]:

```
viz = ClassificationReport(rfc2_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_SE, y_train_final)

viz.score(X_test_df_SE, y_test_final)

viz.show();
```

executed in 190ms, finished 23:16:28 2021-05-27

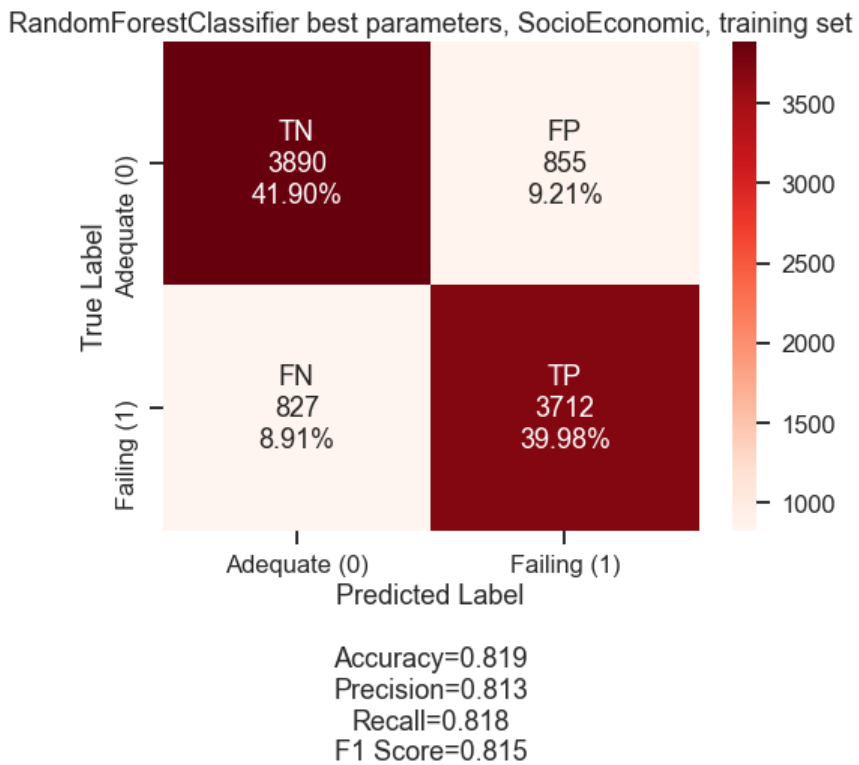


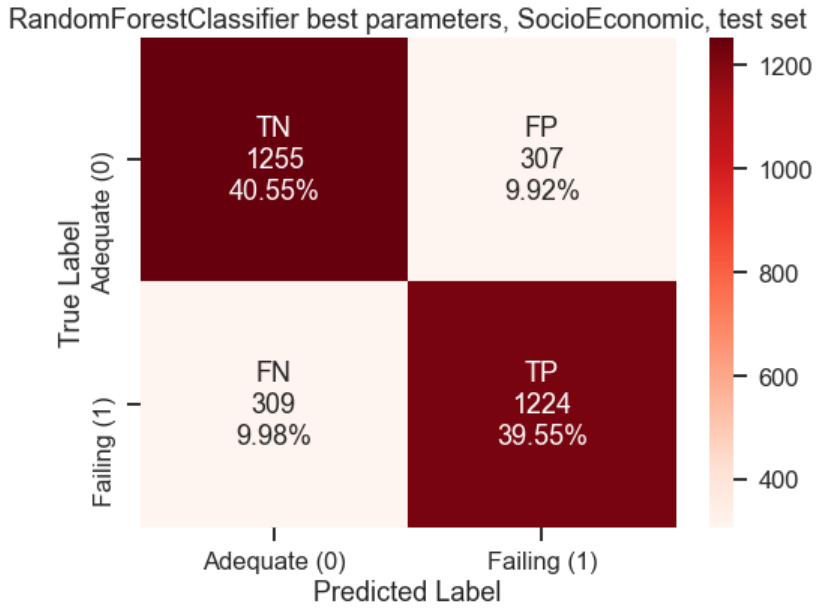
In [162]:

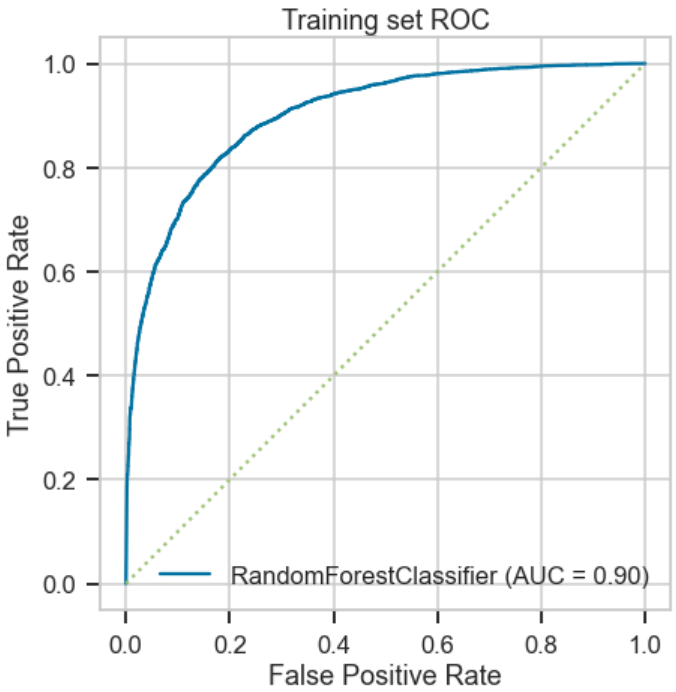
```
simple_model_validation(rfc2_new, SE_list,
                        'RandomForestClassifier best parameters, SocioEconomic, training set',
                        'RandomForestClassifier best parameters, SocioEconomic, test set')
```

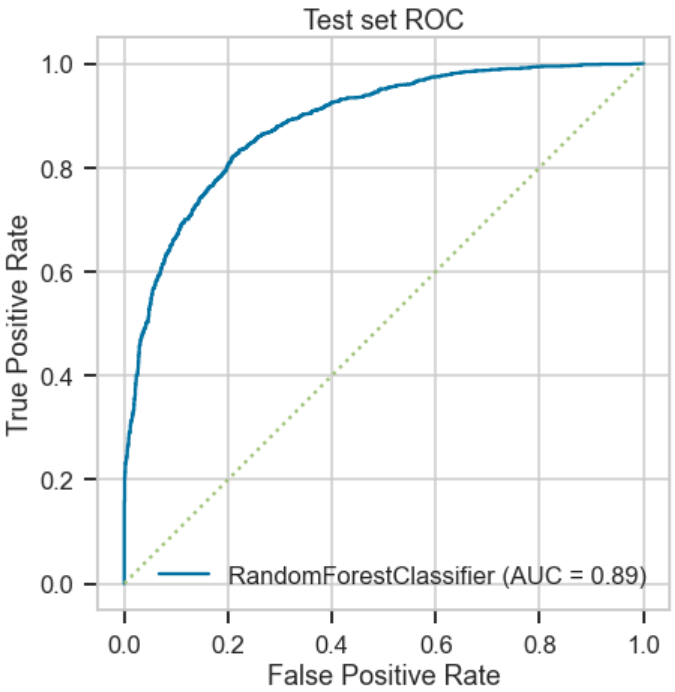
executed in 988ms, finished 23:16:29 2021-05-27

```
**************************************
RandomForestClassifier(class_weight='balanced_subsample', max_depth=5,
                       max_features=50, min_samples_leaf=2, n_estimators=50,
                       random_state=123)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.82      0.82      0.82      4745
           1       0.81      0.82      0.82      4539

    accuracy                           0.82      9284
   macro avg       0.82      0.82      0.82      9284
weighted avg       0.82      0.82      0.82      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.80      0.80      0.80      1562
           1       0.80      0.80      0.80      1533

    accuracy                           0.80      3095
   macro avg       0.80      0.80      0.80      3095
weighted avg       0.80      0.80      0.80      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.018
Differences in Recall scores between training and test sets: 0.013
```









In [163]:

```
se_models_dict=adding_to_models_dict(models_dict_se,'RFClassifier, best parameters','rfc2_new',
                                     SE_list, rfc2_new, 'models/se_progress/rfc_best_se_new.joblib')
```

executed in 111ms, finished 23:16:29 2021-05-27

While the RandomForestClassifier best parameters model performance is good, it is not superior to LogisticRegressionClassifierCV best parameters model.

5.4.2 XGBoostClassifier with SocioEconomic/HS scores features

5.4.2.1 Building and evaluating a XGBoostClassifier model with default parameters

In [164]:
```
1 xgb1_new = XGBClassifier(random_state=123)
```
executed in 15ms, finished 23:16:29 2021-05-27

In [165]:
```
1 xgb1_new.fit(X_train_df_SE, y_train_final)
```
executed in 430ms, finished 23:16:30 2021-05-27

```
[23:16:30] WARNING: ..\src\learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective
'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavio
r.
```

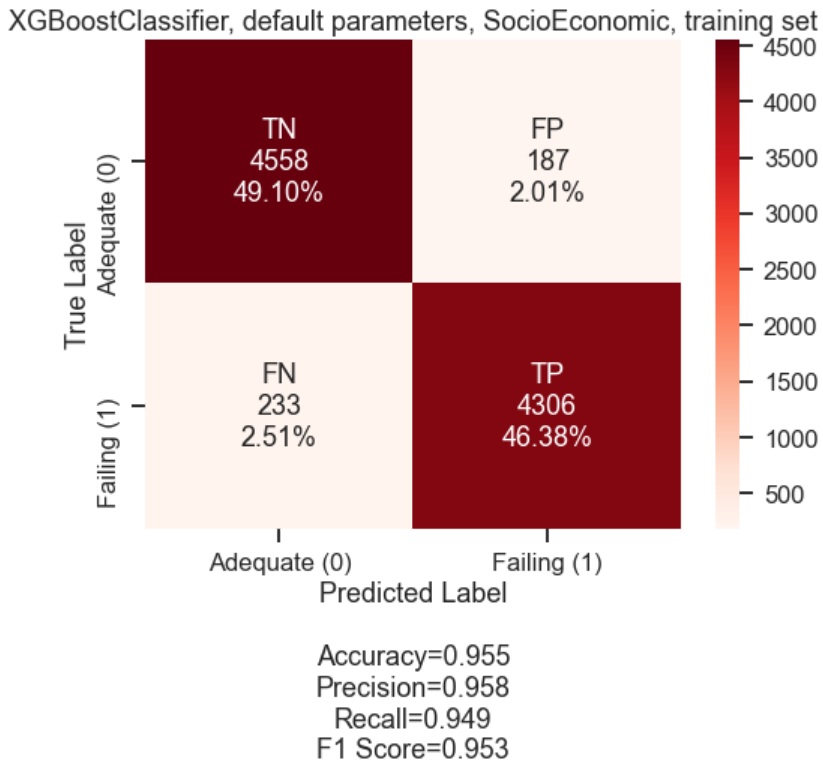
Out[165]:
```
                                  XGBClassifier
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=16, num_parallel_tree=1,
              random_state=123, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

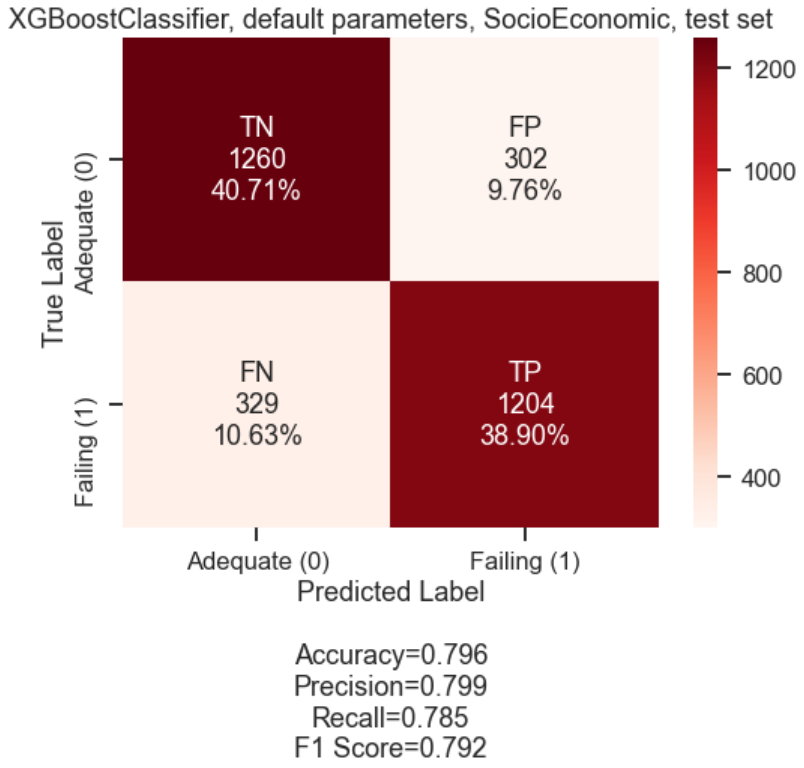
In [166]:

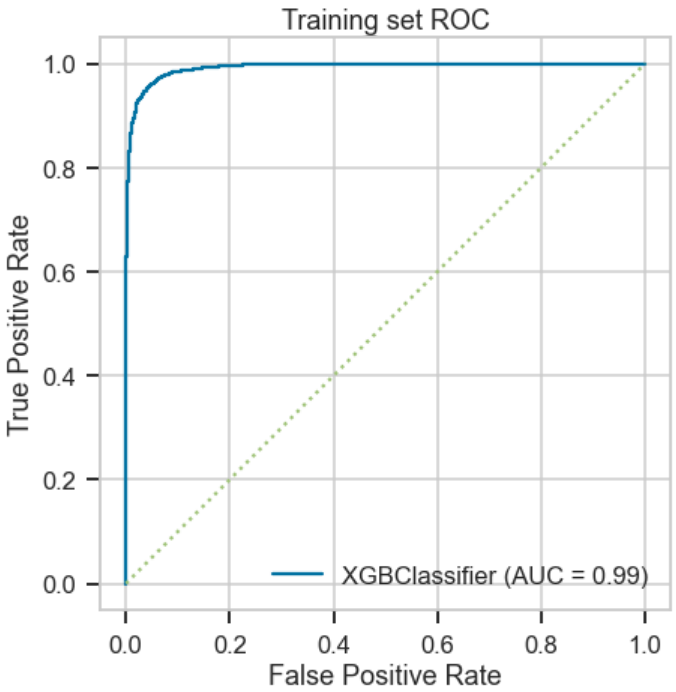
```
simple_model_validation(xgb1_new, SE_list,
                        'XGBoostClassifier, default parameters, SocioEconomic, training set',
                        'XGBoostClassifier, default parameters, SocioEconomic, test set')
```

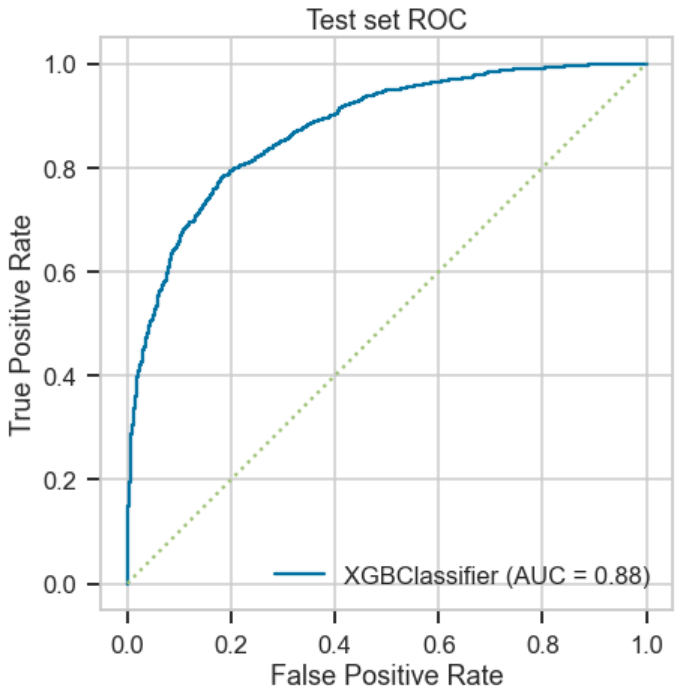
executed in 702ms, finished 23:16:31 2021-05-27

```
**************************************
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=16, num_parallel_tree=1,
              random_state=123, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.95      0.96      0.96      4745
           1       0.96      0.95      0.95      4539

    accuracy                           0.95      9284
   macro avg       0.95      0.95      0.95      9284
weighted avg       0.95      0.95      0.95      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.79      0.81      0.80      1562
           1       0.80      0.79      0.79      1533

    accuracy                           0.80      3095
   macro avg       0.80      0.80      0.80      3095
weighted avg       0.80      0.80      0.80      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.159
Differences in Recall scores between training and test sets: 0.159
```









In [167]:

```
se_models_dict=adding_to_models_dict(models_dict_se,'XGBClassifier, default parameters','xgb1_new',
                                     SE_list, xgb1_new, 'not saved')
```

executed in 47ms, finished 23:16:31 2021-05-27

The XGBClassifier model with default parameters is overfitted. We will continue with GridSearch.

5.4.2.2 GridSearch best parameters search for XGBClassifier model

In [168]:
```
1 XGBClassifier().get_params().keys()
```
executed in 15ms, finished 23:16:31 2021-05-27

Out[168]:
```
dict_keys(['objective', 'use_label_encoder', 'base_score', 'booster', 'colsample_bylevel', 'colsample_bynode', 'colsample_by
tree', 'gamma', 'gpu_id', 'importance_type', 'interaction_constraints', 'learning_rate', 'max_delta_step', 'max_depth', 'min
_child_weight', 'missing', 'monotone_constraints', 'n_estimators', 'n_jobs', 'num_parallel_tree', 'random_state', 'reg_alph
a', 'reg_lambda', 'scale_pos_weight', 'subsample', 'tree_method', 'validate_parameters', 'verbosity'])
```

In [169]:
```
1  # params = {'n_estimators': [50, 100, 150],
2  #           'max_depth': [3, 5, 8],
3  #           'learning_rate': [0.05, 0.1, 0.5],
4  #           'booster':['dart','gblinear'],
5  #           'tree_method':['auto', 'approx', 'hist', 'gpu_hist'],
6  #           'gamma':[0,5,10]}
7
8
9  # gridsearch = GridSearchCV(XGBClassifier(random_state=123), params, n_jobs=-1,
10 #                           cv=5, verbose=2, scoring = 'recall')
11 # gridsearch.fit(X_train_df_SE, y_train_final)
```
executed in 15ms, finished 23:16:31 2021-05-27

In [170]:
```
1 # gridsearch.best_score_
```
executed in 15ms, finished 23:16:31 2021-05-27

In [171]:
```
1 # gridsearch.best_estimator_
```
executed in 15ms, finished 23:16:31 2021-05-27

In [172]:
```
1 # joblib.dump(gridsearch.best_estimator_, 'models/se_progress/xgb_best_se_new.joblib')
```
executed in 15ms, finished 23:16:31 2021-05-27

5.4.2.3 Building and evaluating the best parameters XGBClassifier model

In [173]:
```
1 xgb2_new= joblib.load('models/se_progress/xgb_best_se_new.joblib')
```
executed in 15ms, finished 23:16:31 2021-05-27

In [174]:
```
1 xgb2_new.fit(X_train_df_SE, y_train_final)
```
executed in 143ms, finished 23:16:31 2021-05-27

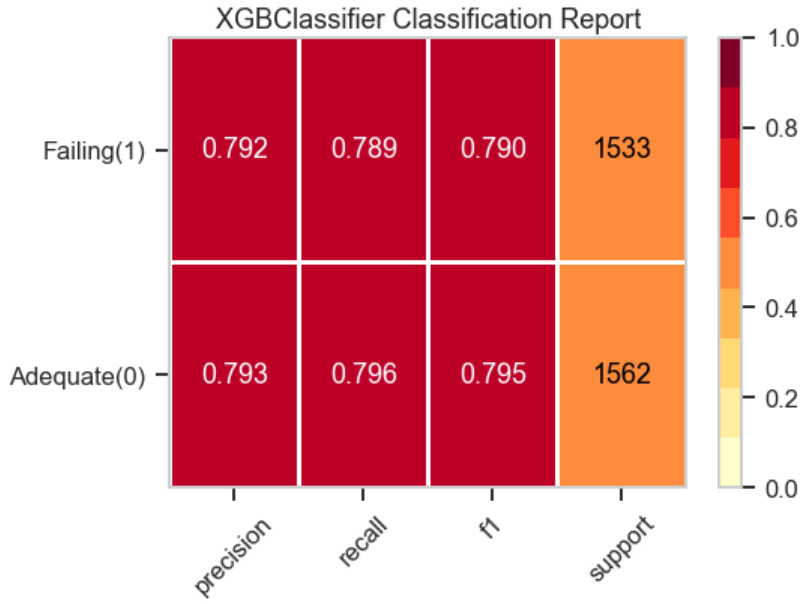
```
[23:16:31] WARNING: ..\src\learner.cc:573:
Parameters: { "gamma", "max_depth", "tree_method" } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[23:16:31] WARNING: ..\src\learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective
'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavio
r.
```

Out[174]:
```
                                  XGBClassifier

XGBClassifier(base_score=0.5, booster='gblinear', colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=10, gpu_id=-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.5, max_delta_step=None, max_depth=3,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=16, num_parallel_tree=None,
              random_state=123, reg_alpha=0, reg_lambda=0, scale_pos_weight=1,
              subsample=None, tree_method='hist', validate_parameters=1,
              verbosity=None)
```

In [175]:

```
viz = ClassificationReport(xgb2_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_SE, y_train_final)

viz.score(X_test_df_SE, y_test_final)

viz.show();
```

executed in 191ms, finished 23:16:31 2021-05-27

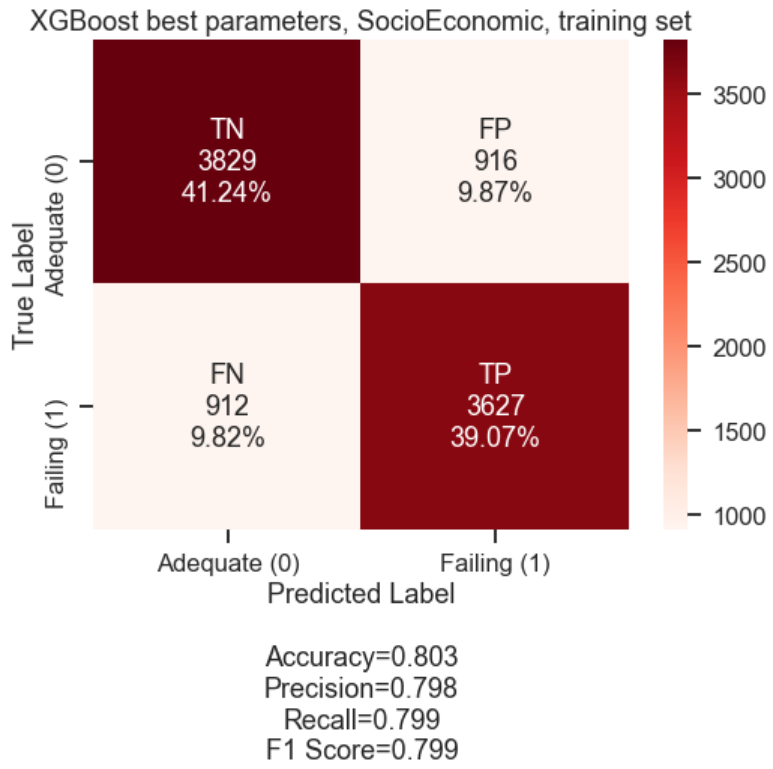


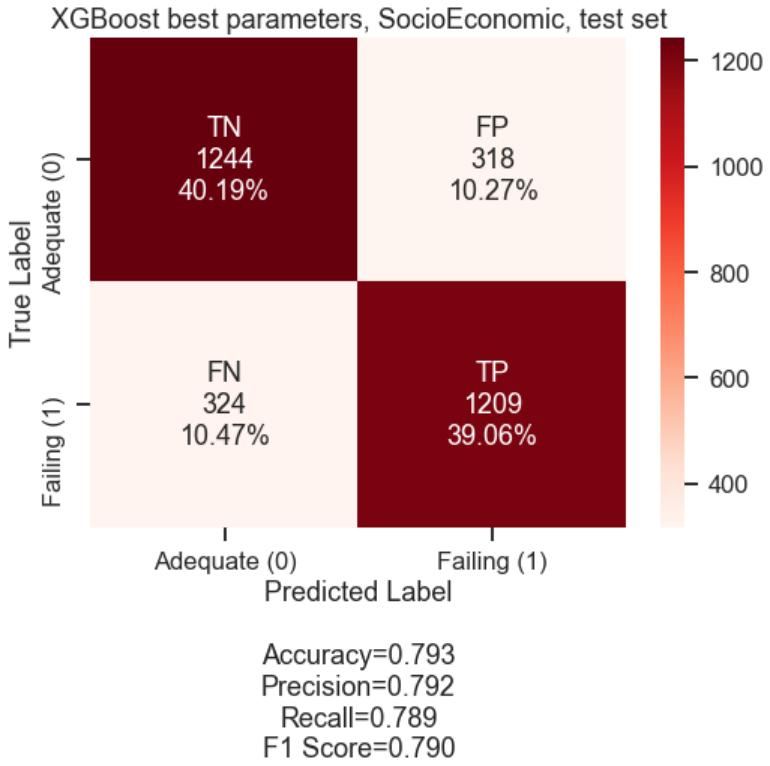
In [176]:

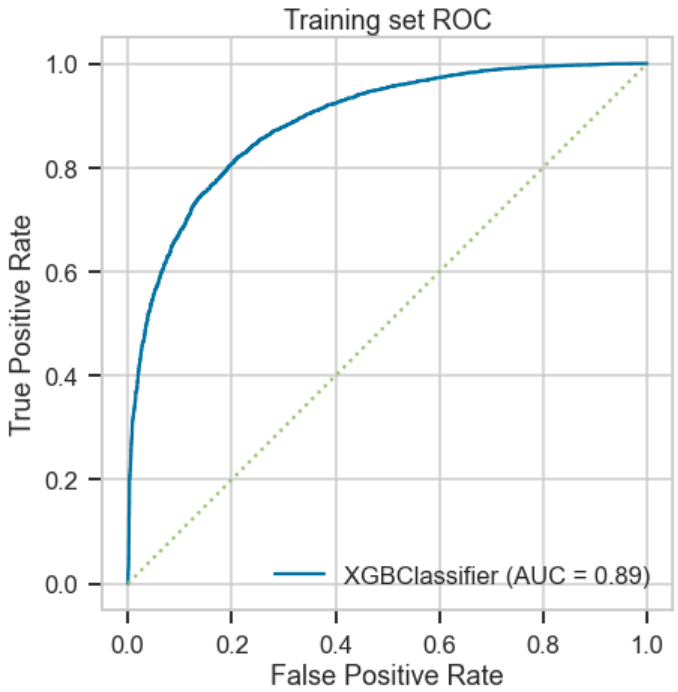
```
simple_model_validation(xgb2_new, SE_list,
                        'XGBoost best parameters, SocioEconomic, training set',
                        'XGBoost best parameters, SocioEconomic, test set')
```

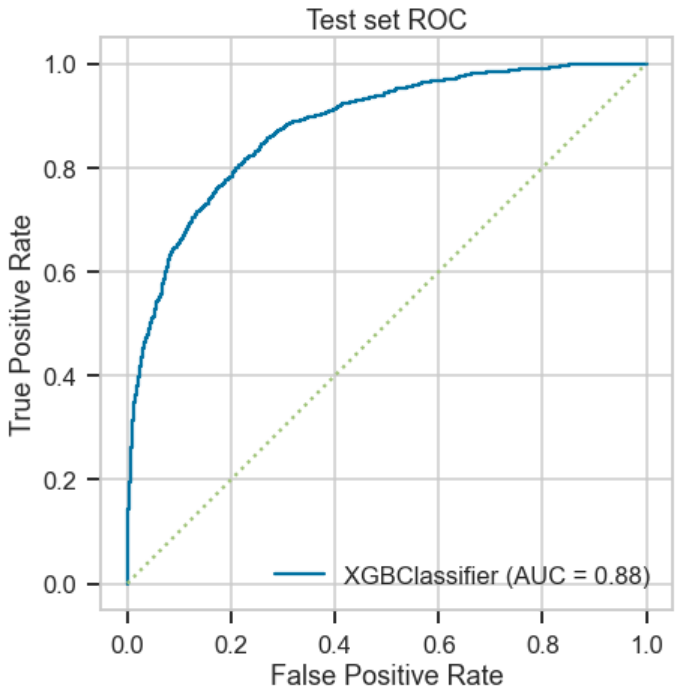
executed in 669ms, finished 23:16:32 2021-05-27

```
**************************************
XGBClassifier(base_score=0.5, booster='gblinear', colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=10, gpu_id=-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.5, max_delta_step=None, max_depth=3,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=16, num_parallel_tree=None,
              random_state=123, reg_alpha=0, reg_lambda=0, scale_pos_weight=1,
              subsample=None, tree_method='hist', validate_parameters=1,
              verbosity=None)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.81      0.81      0.81      4745
           1       0.80      0.80      0.80      4539

    accuracy                           0.80      9284
   macro avg       0.80      0.80      0.80      9284
weighted avg       0.80      0.80      0.80      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.79      0.80      0.79      1562
           1       0.79      0.79      0.79      1533

    accuracy                           0.79      3095
   macro avg       0.79      0.79      0.79      3095
weighted avg       0.79      0.79      0.79      3095


**************************************
Differences in Accuracy scores between training and test sets: 0.011
Differences in Recall scores between training and test sets: 0.007
```









In [177]:

```
se_models_dict=adding_to_models_dict(models_dict_se,'XGBClassifier, best params', 'xgb2_new',
                                     SE_list, xgb2_new, 'models/se_progress/xgb_best_se_new.joblib')
```

executed in 47ms, finished 23:16:32 2021-05-27

5.4.3 XGBoostClassifier with Program/University features

5.4.3.1 Building and evaluating a XGBoostClassifier model with default parameters

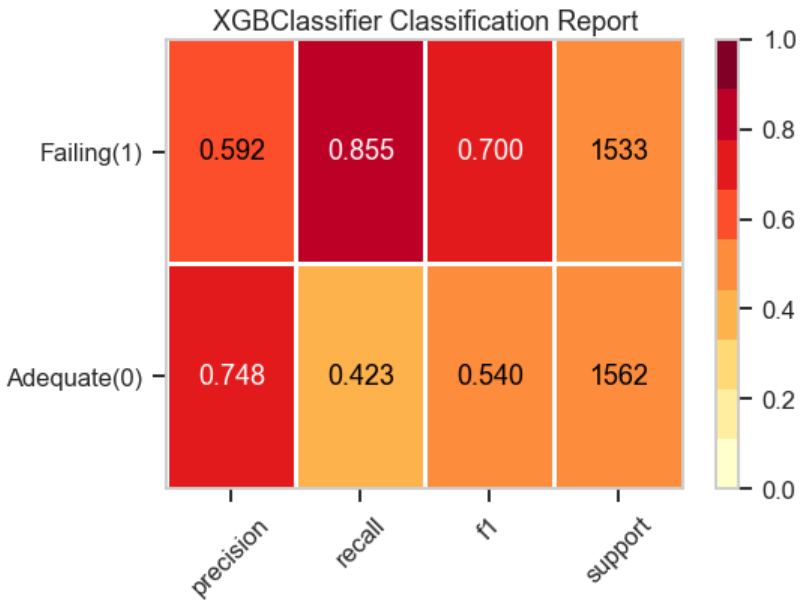
In [178]:
```
1 xgb3_new = XGBClassifier(random_state=123)
```
executed in 15ms, finished 23:16:32 2021-05-27

In [179]:
```
1 xgb3_new.fit(X_train_df_UNVPRG, y_train_final)
```
executed in 286ms, finished 23:16:32 2021-05-27

```
[23:16:32] WARNING: ..\src\learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective
'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavio
r.
```

Out[179]:
```
                                XGBClassifier
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=16, num_parallel_tree=1,
              random_state=123, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

In [180]:
```
1  viz = ClassificationReport(xgb3_new,
2                             classes=['Adequate(0)', 'Failing(1)'],
3                             support=True,
4                             fig=plt.figure(figsize=(8,6)))
5
6  viz.fit(X_train_df_UNVPRG, y_train_final)
7
8  viz.score(X_test_df_UNVPRG, y_test_final)
9
10 viz.show();
```
executed in 191ms, finished 23:16:32 2021-05-27

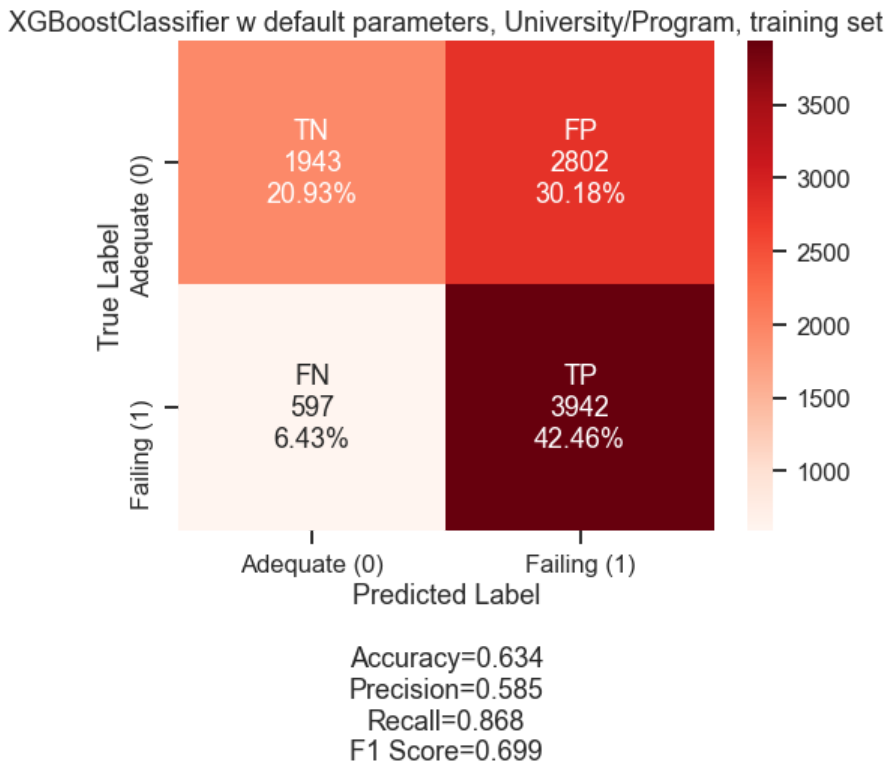


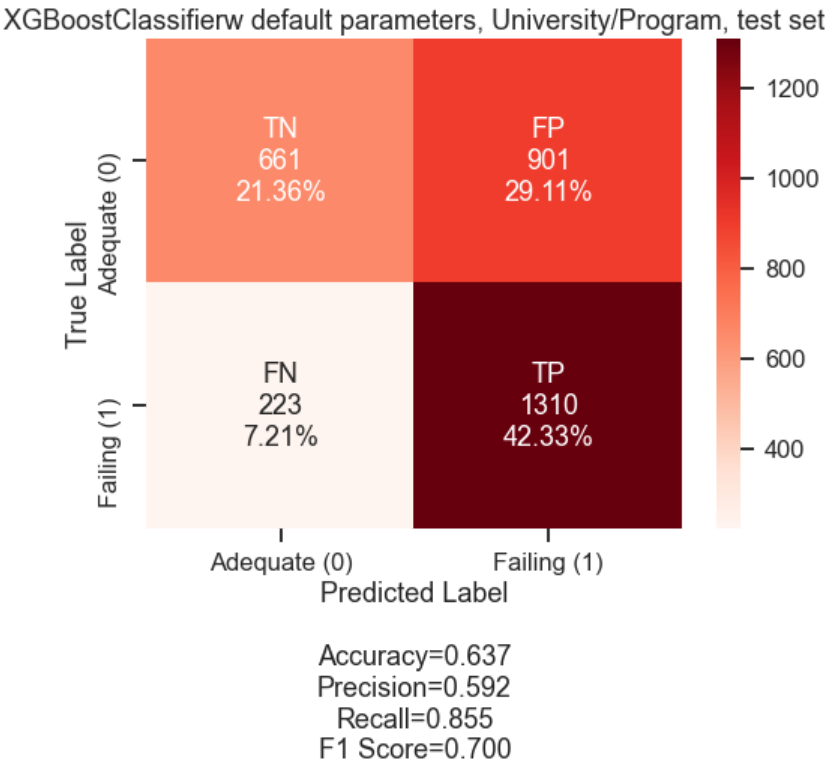
In [181]:

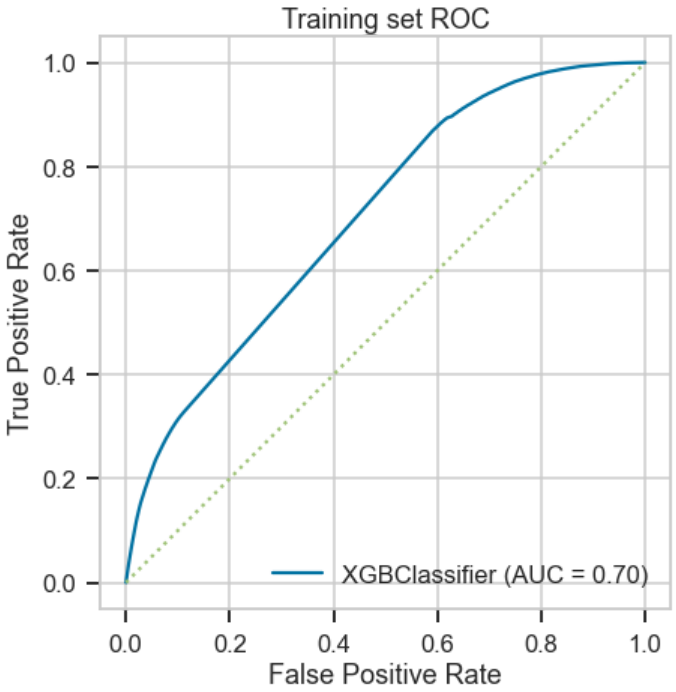
```
simple_model_validation(xgb3_new, UNVPRG_list,
                        'XGBoostClassifier w default parameters, University/Program, training set',
                        'XGBoostClassifierw default parameters, University/Program, test set')
```

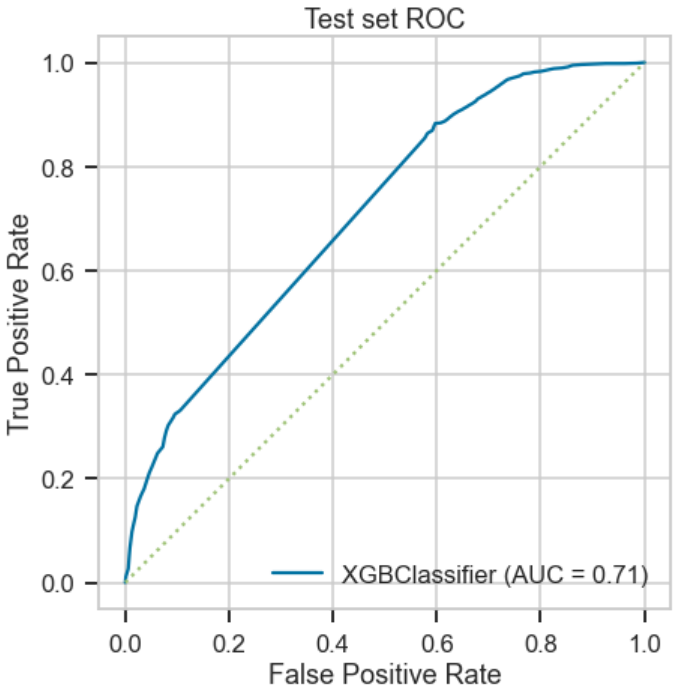
executed in 687ms, finished 23:16:33 2021-05-27

```
**************************************
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=16, num_parallel_tree=1,
              random_state=123, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.76      0.41      0.53      4745
           1       0.58      0.87      0.70      4539

    accuracy                           0.63      9284
   macro avg       0.67      0.64      0.62      9284
weighted avg       0.68      0.63      0.61      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.75      0.42      0.54      1562
           1       0.59      0.85      0.70      1533

    accuracy                           0.64      3095
   macro avg       0.67      0.64      0.62      3095
weighted avg       0.67      0.64      0.62      3095


**************************************
Differences in Accuracy scores between training and test sets: -0.003
Differences in Recall scores between training and test sets: -0.008
```




XGBoostClassifierw default parameters, University/Program, test set
TN
661
21.36%
FP
901
29.11%
FN
223
7.21%
TP
1310
42.33%
True Label
Adequate (0)
Failing (1)
1200
1000
800
600
400
Adequate (0)
Failing (1)
Predicted Label
Accuracy=0.637
Precision=0.592
Recall=0.855
F1 Score=0.700





The model displays the same strange behavior as the previous models with University/Program features.

5.4.3.2 GridSearch best parameters search for XGBClassifier model

In [182]:
```
# params = {'n_estimators': [50, 100, 150],
#           'max_depth': [3, 5, 8],
#           'learning_rate': [0.1, 0.3],
#           'booster':['gblinear','dart'],
#           'tree_method':['auto', 'approx', 'hist', 'gpu_hist']}

# gridsearch = GridSearchCV(XGBClassifier(random_state=123), params, n_jobs=-1,
#                           cv=5, verbose=2, scoring = 'accuracy')

# gridsearch.fit(X_train_df_UNVPRG, y_train_final)
```

executed in 15ms, finished 23:16:33 2021-05-27

In [183]:
```
# gridsearch.best_score_
```

executed in 15ms, finished 23:16:33 2021-05-27

In [184]:
```
# gridsearch.best_estimator_
```

executed in 15ms, finished 23:16:33 2021-05-27

In [185]:
```
# joblib.dump(gridsearch.best_estimator_, 'models/up_progress/xgb_best_up_new.joblib')
```

executed in 15ms, finished 23:16:33 2021-05-27

5.4.3.3 Building and evaluating the best parameters XGBClassifier model

In [186]:
```
xgb3_new=joblib.load('models/up_progress/xgb_best_up_new.joblib')
```

executed in 15ms, finished 23:16:33 2021-05-27

In [187]:
```
1 xgb3_new.fit(X_train_df_UNVPRG, y_train_final)
```

executed in 79ms, finished 23:16:33 2021-05-27

```
[23:16:33] WARNING: ..\src\learner.cc:573:
Parameters: { "max_depth", "tree_method" } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[23:16:33] WARNING: ..\src\learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective
'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavio
r.
```

Out[187]:

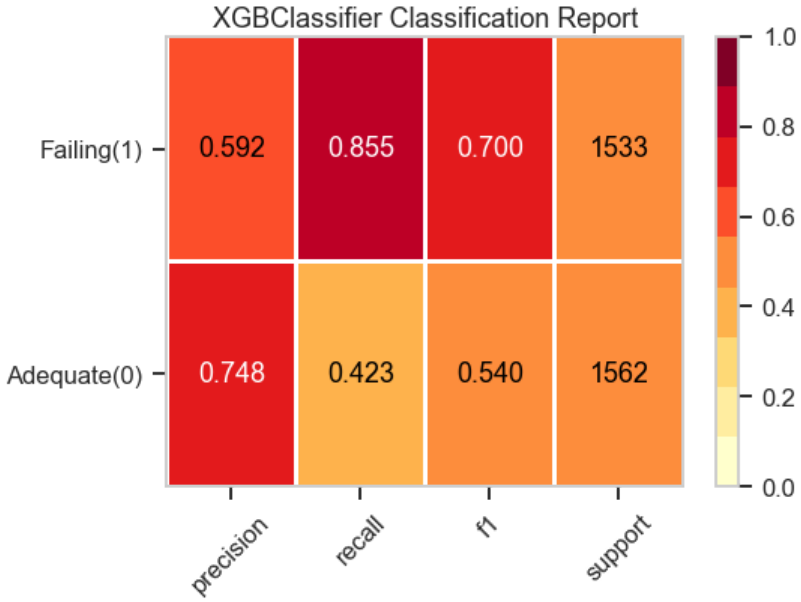
XGBClassifier

```
XGBClassifier(base_score=0.5, booster='gblinear', colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=None,
              gpu_id=-1, importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=None, max_depth=3,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=50, n_jobs=16, num_parallel_tree=None,
              random_state=123, reg_alpha=0, reg_lambda=0, scale_pos_weight=1,
              subsample=None, tree_method='auto', validate_parameters=1,
              verbosity=None)
```

In [188]:

```
viz = ClassificationReport(xgb3_new,
                           classes=['Adequate(0)', 'Failing(1)'],
                           support=True,
                           fig=plt.figure(figsize=(8,6)))

viz.fit(X_train_df_UNVPRG, y_train_final)

viz.score(X_test_df_UNVPRG, y_test_final)

viz.show();
```

executed in 190ms, finished 23:16:33 2021-05-27

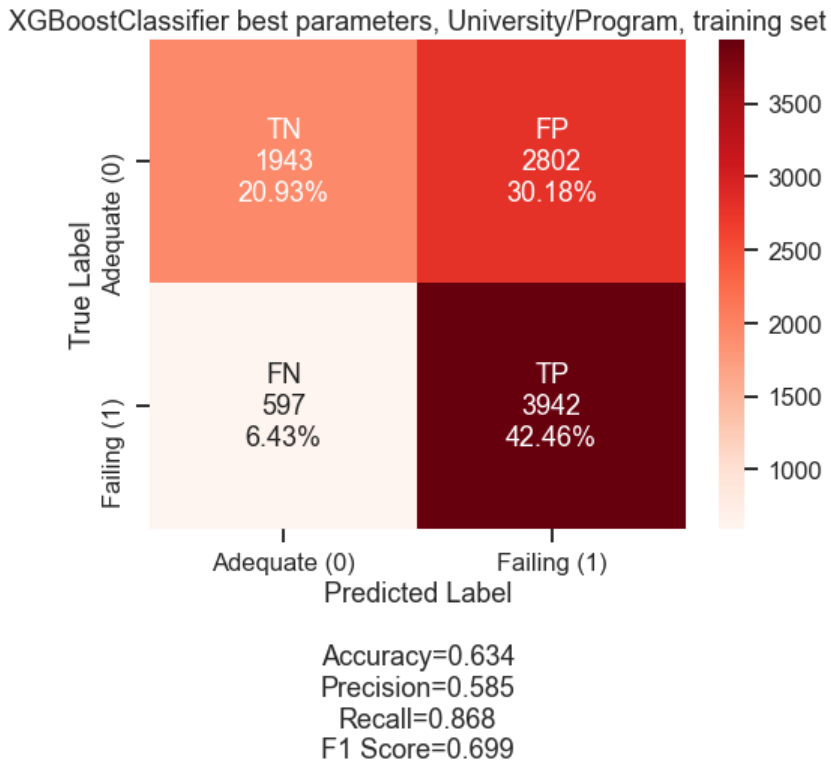


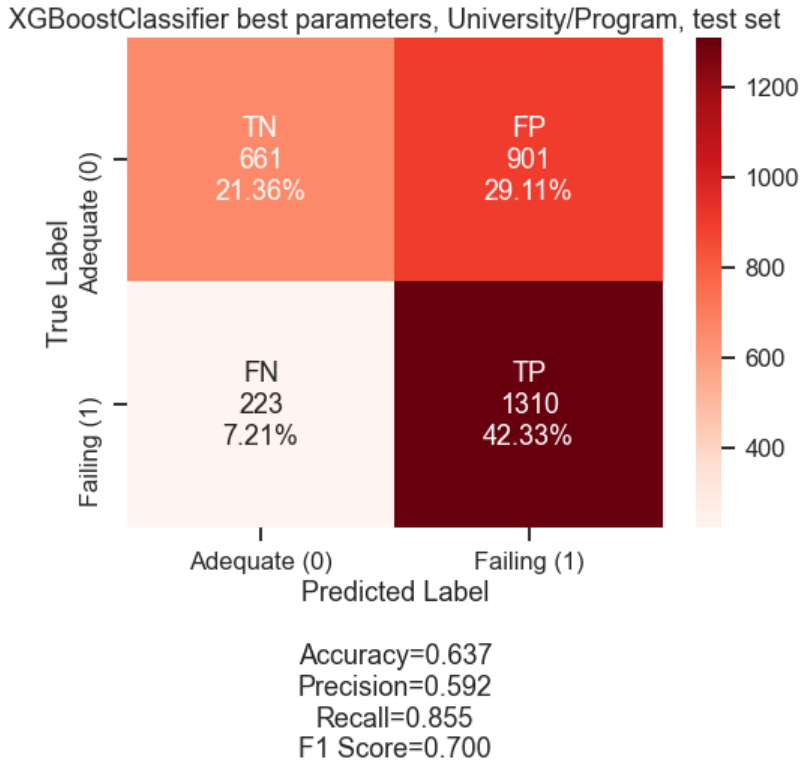
In [189]:

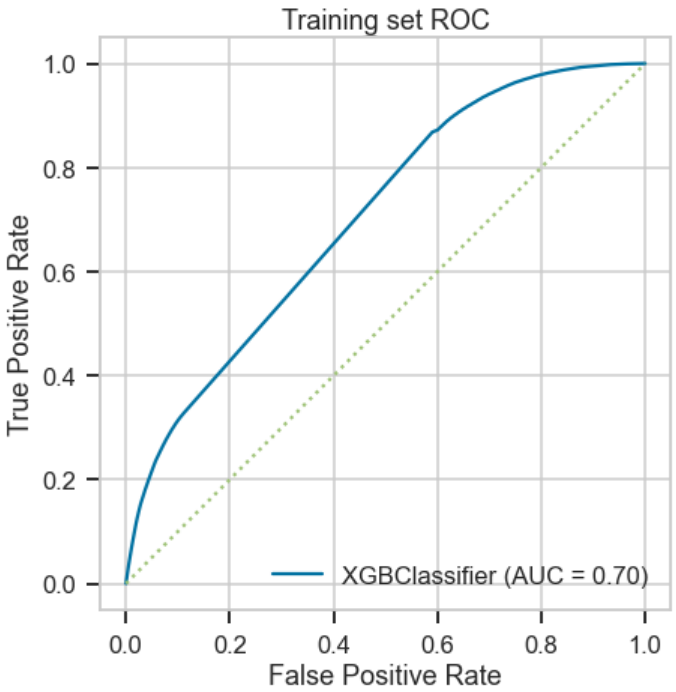
```
simple_model_validation(xgb3_new, UNVPRG_list,
                        'XGBoostClassifier best parameters, University/Program, training set',
                        'XGBoostClassifier best parameters, University/Program, test set')
```

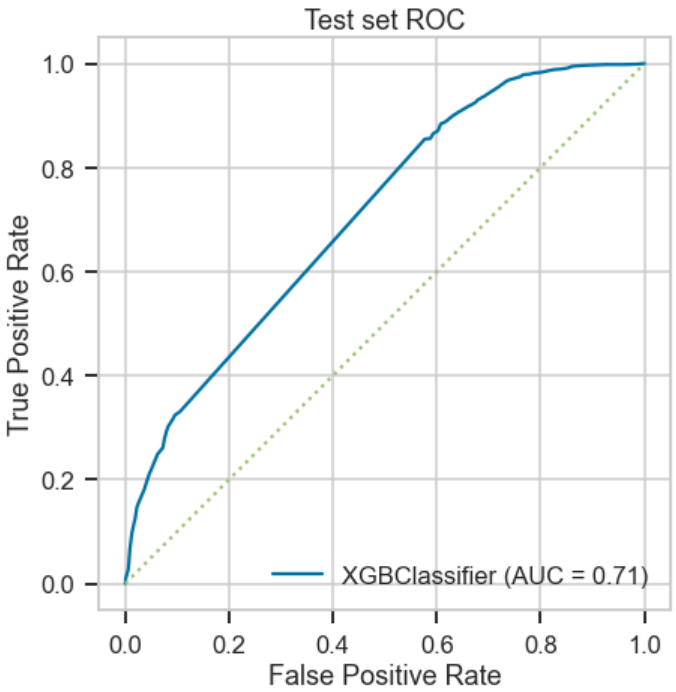
executed in 670ms, finished 23:16:34 2021-05-27

```
**************************************
XGBClassifier(base_score=0.5, booster='gblinear', colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=None,
              gpu_id=-1, importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=None, max_depth=3,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=50, n_jobs=16, num_parallel_tree=None,
              random_state=123, reg_alpha=0, reg_lambda=0, scale_pos_weight=1,
              subsample=None, tree_method='auto', validate_parameters=1,
              verbosity=None)
**************************************

Classification Report for training set
**************************************
              precision    recall  f1-score   support

           0       0.76      0.41      0.53      4745
           1       0.58      0.87      0.70      4539

    accuracy                           0.63      9284
   macro avg       0.67      0.64      0.62      9284
weighted avg       0.68      0.63      0.61      9284


Classification Report for test set
**************************************
              precision    recall  f1-score   support

           0       0.75      0.42      0.54      1562
           1       0.59      0.85      0.70      1533

    accuracy                           0.64      3095
   macro avg       0.67      0.64      0.62      3095
weighted avg       0.67      0.64      0.62      3095


**************************************
Differences in Accuracy scores between training and test sets: -0.003
Differences in Recall scores between training and test sets: -0.008
```









In [190]:
```
unvprg_models_dict=adding_to_models_dict(models_dict_up,'XGBoostClassifier, best params', 'xgb3_new',
                                         UNVPRG_list, xgb3_new, 'models/up_progress/xgb_best_up_new.joblib')
```

executed in 46ms, finished 23:16:34 2021-05-27

5.5 Comparing models

5.5.1 Comparing models with SocioEconomic Features

In [191]:
```
SE_df_models=pd.DataFrame(se_models_dict)
SE_df_models
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[191]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model1_new	LogisticRegressionClassifier, default params	training	0.815	0.819	823	9284	not saved
1	logreg_model1_new	LogisticRegressionClassifier, default params	test	0.805	0.803	302	3095	not saved
2	log_reg_model2_new	LogisticRegressionClassifier, best params	training	0.813	0.825	793	9284	models/se_progress/LR_best_se_new.joblib
3	log_reg_model2_new	LogisticRegressionClassifier, best params	test	0.803	0.806	297	3095	models/se_progress/LR_best_se_new.joblib
4	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	training	0.786	0.834	754	9284	models/se_progress/LR_best_se_CV_new.joblib
5	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	test	0.784	0.826	266	3095	models/se_progress/LR_best_se_CV_new.joblib
6	DT_classifier1_new	DecisionTreeClassifier, default params	training	1.000	1.000	0	9284	not saved
7	DT_classifier1_new	DecisionTreeClassifier, default params	test	0.716	0.714	438	3095	not saved
8	DT_classifier2_new	DecisionTreeClassifier, best params	training	0.765	0.684	1435	9284	models/se_progress/DT_best_se_new.joblib
9	DT_classifier2_new	DecisionTreeClassifier, best params	test	0.760	0.686	481	3095	models/se_progress/DT_best_se_new.joblib
10	rfc1_new	RFClassifier, default parameters	training	1.000	1.000	1	9284	not saved
11	rfc1_new	RFClassifier, default parameters	test	0.799	0.780	337	3095	not saved
12	rfc2_new	RFClassifier, best parameters	training	0.819	0.818	827	9284	models/se_progress/rfc_best_se_new.joblib
13	rfc2_new	RFClassifier, best parameters	test	0.801	0.798	309	3095	models/se_progress/rfc_best_se_new.joblib
14	xgb1_new	XGBClassifier, default parameters	training	0.955	0.949	233	9284	not saved
15	xgb1_new	XGBClassifier, default parameters	test	0.796	0.785	329	3095	not saved
16	xgb2_new	XGBClassifier, best params	training	0.803	0.799	912	9284	models/se_progress/xgb_best_se_new.joblib
17	xgb2_new	XGBClassifier, best params	test	0.793	0.789	324	3095	models/se_progress/xgb_best_se_new.joblib

5.5.2 Comparing models with Program/University Features

In [192]:
```
UNVPRG_df_models=pd.DataFrame(unvprg_models_dict)
UNVPRG_df_models
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[192]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model3_new	LogisticRegressionClassifier, default params	training	0.634	0.868	597	9284	not saved
1	logreg_model3_new	LogisticRegressionClassifier, default params	test	0.637	0.855	223	3095	not saved
2	log_reg_model4_new	LogisticRegressionClassifier, best params	training	0.634	0.868	597	9284	models/up_progress/LR_best_up_new.joblib
3	log_reg_model4_new	LogisticRegressionClassifier, best params	test	0.637	0.855	223	3095	models/up_progress/LR_best_up_new.joblib
4	DT_classifier4_new	DecisionTreeClassifier, best params	training	0.559	0.988	54	9284	models/up_progress/DT_best_up_new.joblib
5	DT_classifier4_new	DecisionTreeClassifier, best params	test	0.572	0.990	16	3095	models/up_progress/DT_best_up_new.joblib
6	DT_classifier5_new	DecisionTreeClassifier, best params, select fe...	training	0.551	0.106	4057	9284	not saved
7	DT_classifier5_new	DecisionTreeClassifier, best params, select fe...	test	0.545	0.102	1377	3095	not saved
8	xgb3_new	XGBoostClassifier, best params	training	0.634	0.868	597	9284	models/up_progress/xgb_best_up_new.joblib
9	xgb3_new	XGBoostClassifier, best params	test	0.637	0.855	223	3095	models/up_progress/xgb_best_up_new.joblib

5.6 The Best Models

5.6.1 SocioEconomic/HS scores models

In [193]:
```
best_df_se=SE_df_models[(SE_df_models['FN'] < 325) & (SE_df_models['Training or Test'] != 'training')]
best_df_se
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[193]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
1	logreg_model1_new	LogisticRegressionClassifier, default params	test	0.805	0.803	302	3095	not saved
3	log_reg_model2_new	LogisticRegressionClassifier, best params	test	0.803	0.806	297	3095	models/se_progress/LR_best_se_new.joblib
5	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	test	0.784	0.826	266	3095	models/se_progress/LR_best_se_CV_new.joblib
13	rfc2_new	RFClassifier, best parameters	test	0.801	0.798	309	3095	models/se_progress/rfc_best_se_new.joblib
17	xgb2_new	XGBClassifier, best params	test	0.793	0.789	324	3095	models/se_progress/xgb_best_se_new.joblib

In [194]:
```
best_df_se_final=SE_df_models[SE_df_models['Classifier Name'].isin(['log_reg_model2_CV_new','rfc2_new'])]
best_df_se_final
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[194]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
4	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	training	0.786	0.834	754	9284	models/se_progress/LR_best_se_CV_new.joblib
5	log_reg_model2_CV_new	LogisticRegressionClassifierCV, best params	test	0.784	0.826	266	3095	models/se_progress/LR_best_se_CV_new.joblib
12	rfc2_new	RFClassifier, best parameters	training	0.819	0.818	827	9284	models/se_progress/rfc_best_se_new.joblib
13	rfc2_new	RFClassifier, best parameters	test	0.801	0.798	309	3095	models/se_progress/rfc_best_se_new.joblib

In [195]:
```
log_reg_model2_CV_new
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[195]:
```
                         LogisticRegressionCV
LogisticRegressionCV(class_weight='balanced', max_iter=25, penalty='l1',
                     random_state=123, scoring='recall', solver='saga')
```

In [196]:
```
rfc2_new
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[196]:
```
                           RandomForestClassifier
RandomForestClassifier(class_weight='balanced_subsample', max_depth=5,
                       max_features=50, min_samples_leaf=2, n_estimators=50,
                       random_state=123)
```

> **Based on the evaluation of the model metrics, the two best models are progressing to the interpretation stage**

- LogisticRegressionCV Classifier with Lasso regularization and 'saga' solver
- RandomForestClassifier with maximum depth=5 and balanced subsample

> The reasoning behind the choice is that while the LogisticRegressionCV model has the best Recall metrics, the RandomForestClassifier has a better balance between the accuracy and the Recall scores. Another reason is that they might provide complementary insight into the solution because of the different nature of these models.

5.6.2 University/Program ranking models

> **4 out of 6 best models with University/Program features have the same model metrics:**

- LogisticRegressionClassifier with default parameters
- LogisticRegressionClassifier with best parameters
- XGBoostClassifier, gbtree booster with best parameters
- XGBoostClassifier, gblinea booster with best parameters

> **The remaining 2 models, both DecisionTree Classifiers have poor accuracy scores. For the goal of correctly ranking Universities/Programs, they are not a good fit:**

- DecisionTreeClassifier with best parameters and a reduced feature set
- DecisionTreeClassifier with best parameters

> **Due to the equal model metrics scores, the choice criteria for the best models is arbitrary. It would be helpful to see if two models from the first list display any differences in feature importance. The choice is**

- LogisticRegressionClassifier with best parameters
- LogisticRegressionClassifier with default parameters

In [197]:
```
1 best_df_up_final=UNVPRG_df_models[UNVPRG_df_models['Classifier Name'].isin(['log_reg_model4_new','logreg_model3_new'])]
2 best_df_up_final
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[197]:

	Classifier Name	Description	Training or Test	Accuracy	Recall	FN	Total number of records	Saved model
0	logreg_model3_new	LogisticRegressionClassifier, default params	training	0.634	0.868	597	9284	not saved
1	logreg_model3_new	LogisticRegressionClassifier, default params	test	0.637	0.855	223	3095	not saved
2	log_reg_model4_new	LogisticRegressionClassifier, best params	training	0.634	0.868	597	9284	models/up_progress/LR_best_up_new.joblib
3	log_reg_model4_new	LogisticRegressionClassifier, best params	test	0.637	0.855	223	3095	models/up_progress/LR_best_up_new.joblib

In [198]:
```
1 log_reg_model4_new
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[198]:

```
LogisticRegression
LogisticRegression(C=0.1, max_iter=25, penalty='none', random_state=123,
                   solver='newton-cg')
```

In [199]:
```
1 logreg_model3_new
```

executed in 15ms, finished 23:16:34 2021-05-27

Out[199]:

```
LogisticRegression
LogisticRegression(random_state=123)
```

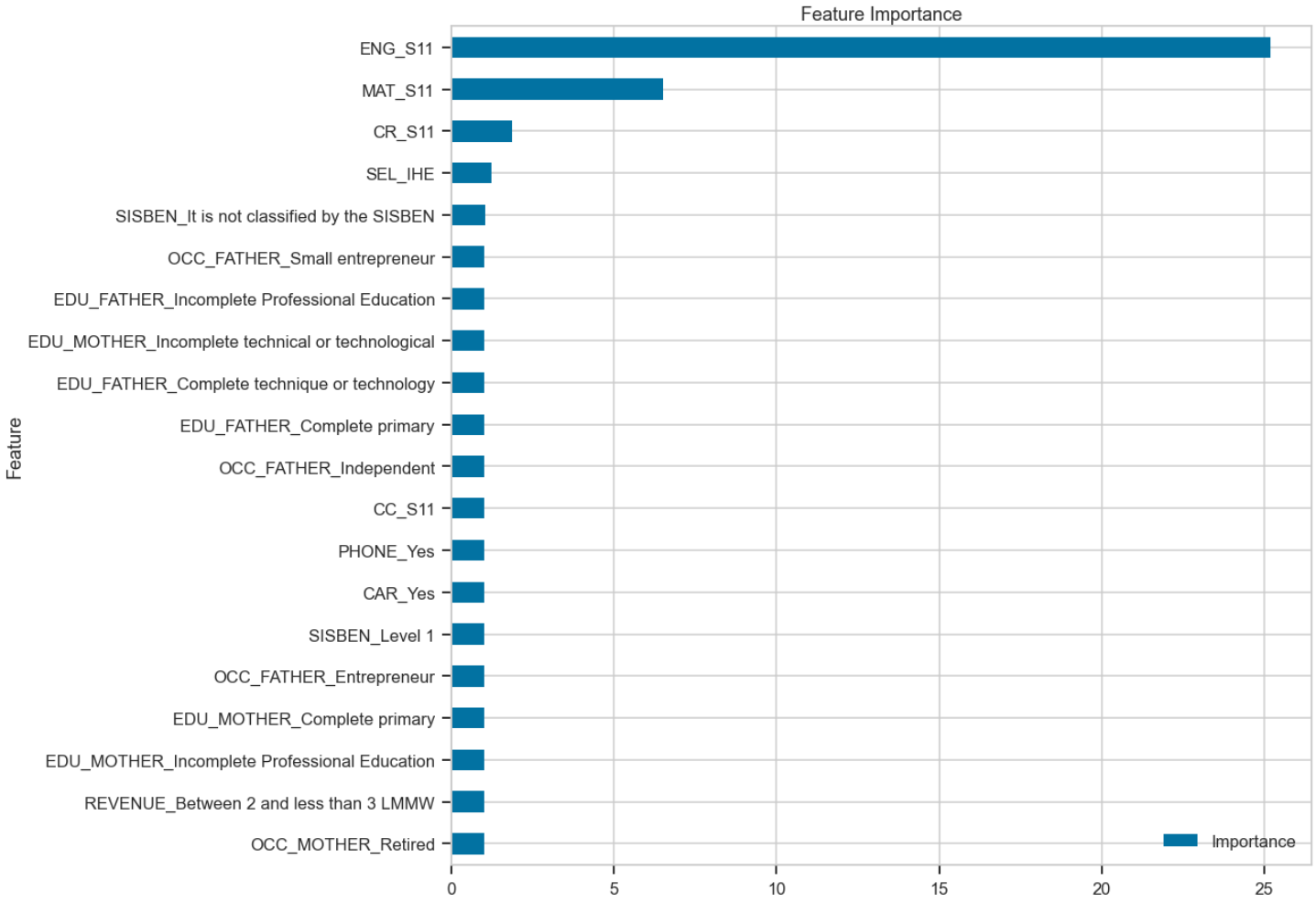
6 iNterpret

6.1 Feature Importance

6.1.1 Feature importance in LogisticRegressionCV best parameters model with SocioEconomic/HS scores features

In [200]:
```
1 get_importance_logreg(log_reg_model2_CV_new, X_train_df_SE,top_n=20)
```

executed in 287ms, finished 23:16:35 2021-05-27



Out[200]:

	Feature	Importance	Coefficient
21	OCC_MOTHER_Retired	1.000000	0.000000
36	REVENUE_Between 2 and less than 3 LMMW	1.000000	0.000000
35	EDU_MOTHER_Incomplete Professional Education	1.000000	0.000000
34	EDU_MOTHER_Complete primary	1.000000	0.000000
33	OCC_FATHER_Entrepreneur	1.000000	0.000000
31	SISBEN_Level 1	1.000000	0.000000
20	CAR_Yes	1.000000	0.000000
29	PHONE_Yes	1.000000	0.000000
30	CC_S11	1.000000	0.000000

	Feature	Importance	Coefficient
27	OCC_FATHER_Independent	1.000000	0.000000
26	EDU_FATHER_Complete primary	1.000000	0.000000
25	EDU_FATHER_Complete technique or technology	1.000000	0.000000
24	EDU_MOTHER_Incomplete technical or technological	1.000000	0.000000
23	EDU_FATHER_Incomplete Professional Education	1.000000	0.000000
79	OCC_FATHER_Small entrepreneur	1.000000	0.000000
37	SISBEN_It is not classified by the SISBEN	1.051295	-0.050023
22	SEL_IHE	1.216819	-0.196240
28	CR_S11	1.853011	-0.616812
32	MAT_S11	6.509079	-1.873198
6	ENG_S11	25.199045	-3.226806

> The feature importance and the coefficients show that 3 HS test scores and 2 SocioEconomic characteristics are the most important predictors of a student's success. They all have negative coefficients: the higher their values, the less chance for a student to fail in the professional school. The five most important ones are listed below in the order of their importance.

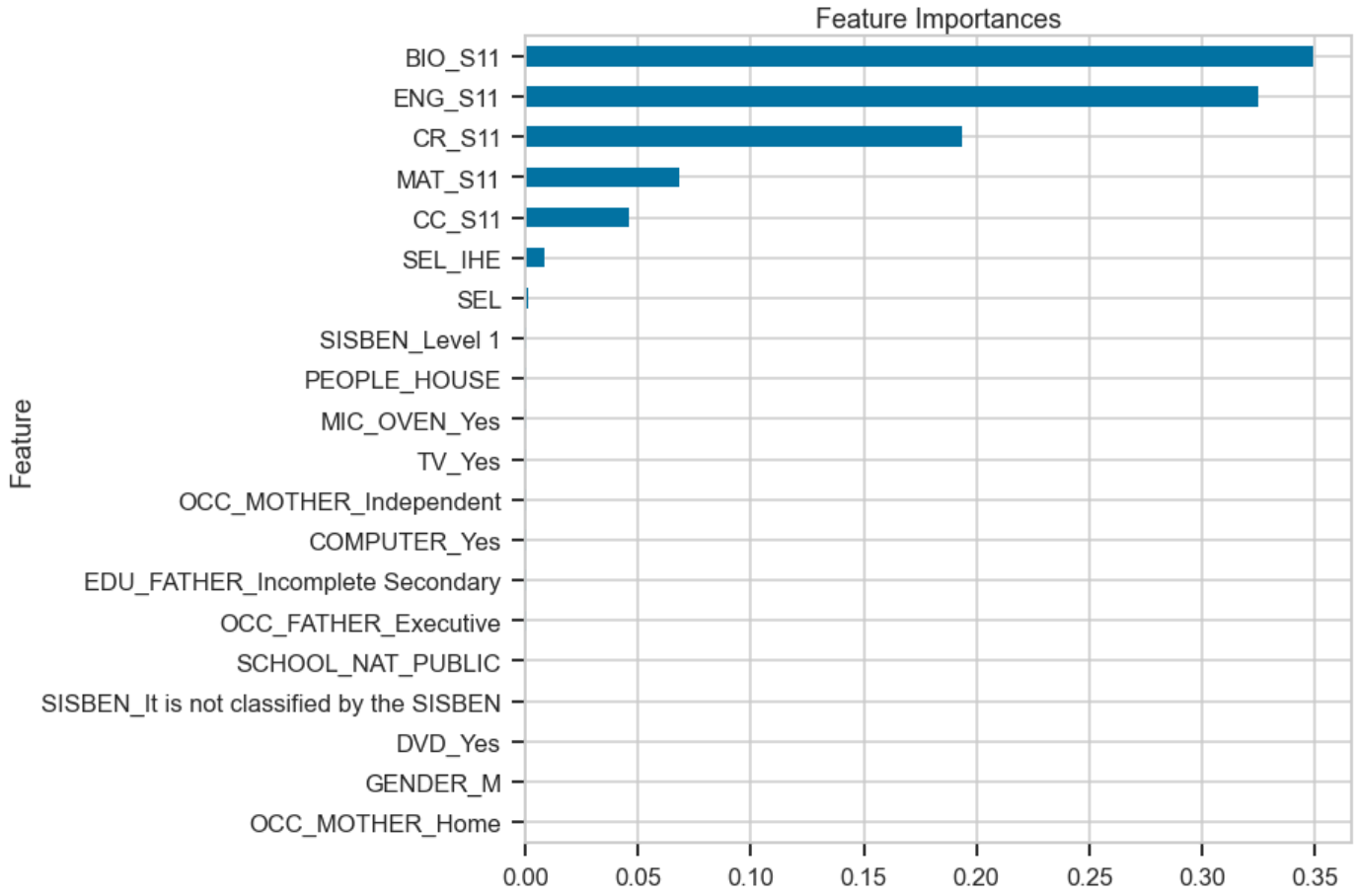
- **ENG_S11**
- **MAT_S11**
- **CR_S11**
- **SEL_IHE**
- **SISBEN_It is not classified by the SISBEN**

6.1.2 Feature importance in RFClassifier best parameters model with SocioEconomic/HS scores features

In [201]:
```
1 get_importance_tree(rfc2_new, X_train_df_SE, top_n=20)
```

executed in 238ms, finished 23:16:35 2021-05-27

Out[201]:
```
EDU_MOTHER_Incomplete primary                          0.000152
SCHOOL_TYPE_TECHNICAL/ACADEMIC                         0.000103
STRATUM_Stratum 3                                      0.000066
OCC_FATHER_Operator                                    0.000000
REVENUE_Between 5 and less than 7 LMMW                 0.000101
                                                         ...
STRATUM_Stratum 2                                      0.000091
OCC_MOTHER_Technical or professional level employee    0.000034
EDU_MOTHER_None                                        0.000000
STRATUM_Stratum 6                                      0.000130
OCC_FATHER_Small entrepreneur                          0.000080
Length: 80, dtype: float64
```



The RandomForestClassifier importance feature analysis also has student's HS test scores as important predictive features as well as

several SocioEconomic features. Seven of them are listed in the order of their importance below:

- **ENG_S11**
- **BIO_S11**
- **CR_S11**
- **CC_S11**
- **MAT_S11**
- **SEL_IHE**

There is apparent overlapping between the most important features of these models. The overlapping features are

- **ENG_S11**
- **MAT_S11**
- **CR_S11**
- **SEL_IHE**

Out of which, the first 3 are indicative of a student's proficiency in mathematics, technology, and critical reasoning. At the same time, the last one is a measure of a socio-economic level.

In [202]:
```
# A dataframe with the most important features from both models combined:
list_corr_=['ENG_S11','BIO_S11','CR_S11','CC_S11','MAT_S11','SEL_IHE']
X_train_df_corr=X_train_df_SE[list_corr_].copy()
X_train_df_corr.info()
```

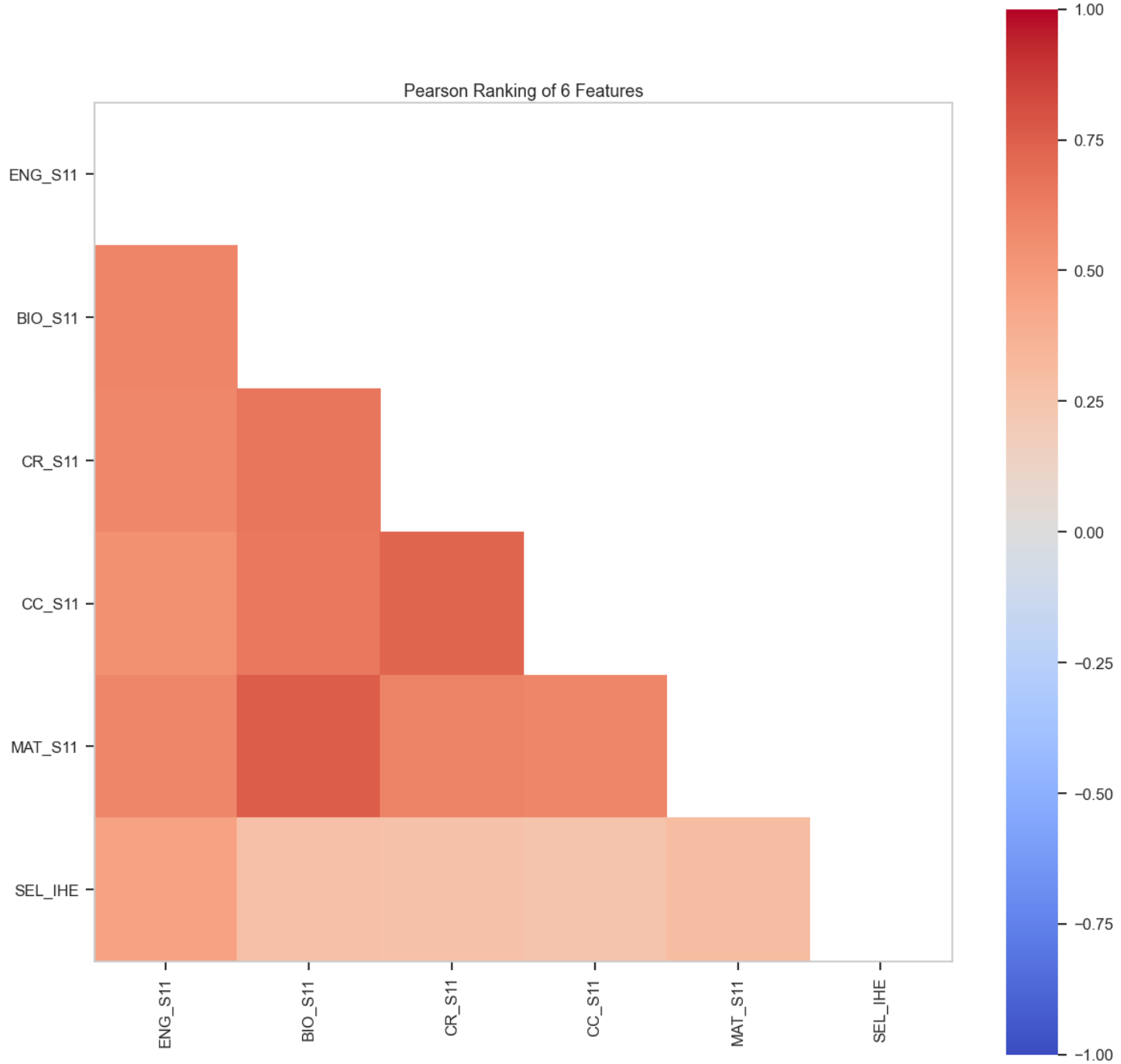
executed in 14ms, finished 23:16:35 2021-05-27

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9284 entries, 796 to 3582
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   ENG_S11  9284 non-null   float64
 1   BIO_S11  9284 non-null   float64
 2   CR_S11   9284 non-null   float64
 3   CC_S11   9284 non-null   float64
 4   MAT_S11  9284 non-null   float64
 5   SEL_IHE  9284 non-null   float64
dtypes: float64(6)
memory usage: 507.7 KB
```

In [203]:

```
fig,ax = plt.subplots(figsize=(20,20))
visualizer = Rank2D(algorithm='pearson', colormap='coolwarm', ax=ax, features=list(X_train_df_corr.columns))

# Fit the data to the visualizer
visualizer.fit(X_train_df_corr, y_train_final)

# Transform the data
visualizer.transform(X_train_df_corr)

visualizer.show()
```

executed in 208ms, finished 23:16:35 2021-05-27



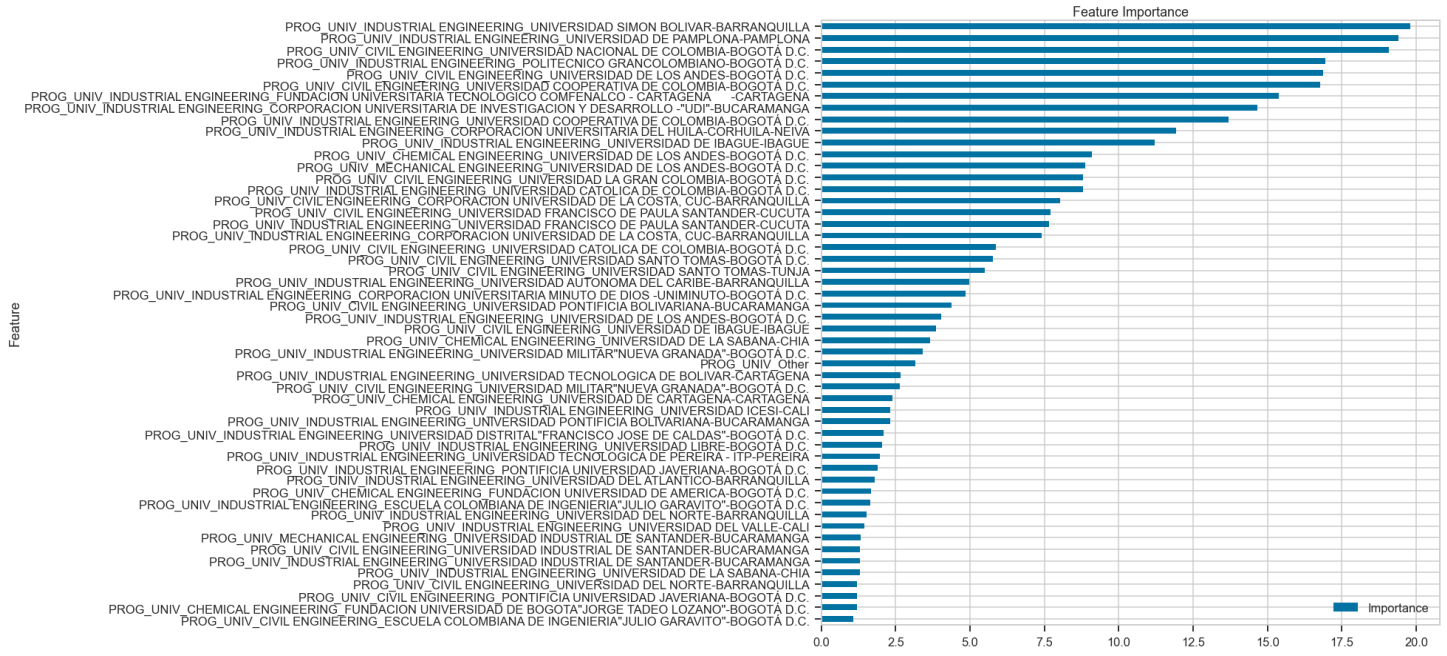
Out[203]: <AxesSubplot:title={'center':'Pearson Ranking of 6 Features'}>

It is obvious the correlation is there, but not much can be done about it.

6.1.3 Feature importance in LogisticRegression best parameters model with Program/University features

In [204]:
```
1 df_ranking_LR4=get_importance_logreg(log_reg_model4_new, X_test_df_UNVPRG, top_n=52)
```

executed in 1.98s, finished 23:16:37 2021-05-27



In [205]:
```
1 a=df_ranking_LR4.sort_values(by='Coefficient').to_html()
2
3 text_file = open('rank_lr4.html', 'w')
4 text_file.write(a)
5 text_file.close()
```

executed in 15ms, finished 23:16:37 2021-05-27

In [206]:
```
1 HTML(filename='rank_lr4.html')
```

executed in 15ms, finished 23:16:37 2021-05-27

Out[206]:

	Feature	Importance	Coefficient
17	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.	19.090912	-2.949212
11	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	16.875082	-2.825838
4	PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	9.090962	-2.207281
49	PROG_UNIV_MECHANICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	8.863693	-2.181963
34	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	4.030777	-1.393959
3	PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA	3.652625	-1.295446
2	PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE CARTAGENA-CARTAGENA	2.386380	-0.869778
41	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD ICESI-CALI	2.310623	-0.837517
39	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DISTRITAL"FRANCISCO JOSE DE CALDAS"-BOGOTÁ D.C.	2.083348	-0.733976
28	PROG_UNIV_INDUSTRIAL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.	1.883130	-0.632935
37	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA	1.525130	-0.422080
33	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA	1.284974	-0.250738
12	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA	1.203217	-0.184999
7	PROG_UNIV_CIVIL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.	1.193191	-0.176631
6	PROG_UNIV_CIVIL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.	1.060614	-0.058848
1	PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.	1.188178	0.172421
42	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA	1.303694	0.265202
14	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA	1.303695	0.265202
50	PROG_UNIV_MECHANICAL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA	1.319991	0.277625
38	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL VALLE-CALI	1.436725	0.362366
25	PROG_UNIV_INDUSTRIAL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.	1.653322	0.502787
0	PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.	1.667357	0.511240
36	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL ATLANTICO-BARRANQUILLA	1.795906	0.585510
48	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD TECNOLOGICA DE PEREIRA - ITP-PEREIRA	1.973319	0.679717
43	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD LIBRE-BOGOTÁ D.C.	2.044430	0.715119
45	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA	2.309204	0.836903
16	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.	2.639982	0.970772
47	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD TECNOLOGICA DE BOLIVAR-CARTAGENA	2.666648	0.980822
51	PROG_UNIV_Other	3.166792	1.152719
44	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.	3.408985	1.226415
10	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE	3.849973	1.348066
18	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA	4.365863	1.473816
24	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA MINUTO DE DIOS -UNIMINUTO-BOGOTÁ D.C.	4.851248	1.579236
29	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD AUTONOMA DEL CARIBE-BARRANQUILLA	4.964068	1.602226
20	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-TUNJA	5.488134	1.702588
19	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-BOGOTÁ D.C.	5.777737	1.754012
8	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.	5.866626	1.769280
21	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA	7.397050	2.001081
40	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA	7.659205	2.035908
13	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA	7.713527	2.042976
5	PROG_UNIV_CIVIL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA	8.039450	2.084361
30	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.	8.799939	2.174745
15	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD LA GRAN COLOMBIA-BOGOTÁ D.C.	8.799941	2.174745
32	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE	11.215605	2.417306
23	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DEL HUILA-CORHUILA-NEIVA	11.916582	2.477931

	Feature	Importance	Coefficient
31	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	13.688790	2.616577
22	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DE INVESTIGACION Y DESARROLLO -"UDI"-BUCARAMANGA	14.666567	2.685571
26	PROG_UNIV_INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA -CARTAGENA	15.370559	2.732454
9	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	16.761787	2.819102
27	PROG_UNIV_INDUSTRIAL ENGINEERING_POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.	16.948023	2.830151
35	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE PAMPLONA-PAMPLONA	19.404994	2.965530
46	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA	19.799856	2.985675

6.1.4 Feature importance in LogisticRegression default parameters model with Program/University features

In [207]:
```
df_ranking_LR3=get_importance_logreg(logreg_model3_new, X_train_df_UNVPRG, top_n=52)
```

executed in 1.85s, finished 23:16:39 2021-05-27

In [208]:
```
b=df_ranking_LR3.sort_values(by='Coefficient').to_html()

text_file = open('rank_lr3.html', 'w')
text_file.write(b)
text_file.close()
```

executed in 15ms, finished 23:16:39 2021-05-27

In [209]:
```
1 HTML(filename='rank_lr3.html')
```

executed in 15ms, finished 23:16:39 2021-05-27

Out[209]:

	Feature	Importance	Coefficient
11	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	13.802187	-2.624827
17	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.	10.578137	-2.358789
4	PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	9.762890	-2.278588
49	PROG_UNIV_MECHANICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	9.551090	-2.256655
34	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	6.967045	-1.941191
3	PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA	5.579093	-1.719026
41	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD ICESI-CALI	3.824514	-1.341431
2	PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE CARTAGENA-CARTAGENA	3.801533	-1.335404
39	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DISTRITAL"FRANCISCO JOSE DE CALDAS"-BOGOTÁ D.C.	3.479286	-1.246827
28	PROG_UNIV_INDUSTRIAL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.	3.423682	-1.230716
37	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA	2.782113	-1.023211
33	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA	2.307255	-0.836059
12	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DEL NORTE-BARRANQUILLA	2.208797	-0.792448
7	PROG_UNIV_CIVIL ENGINEERING_PONTIFICIA UNIVERSIDAD JAVERIANA-BOGOTÁ D.C.	2.164530	-0.772203
6	PROG_UNIV_CIVIL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.	1.995703	-0.690996
1	PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.	1.604127	-0.472580
42	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA	1.463266	-0.380671
14	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA	1.458982	-0.377739
50	PROG_UNIV_MECHANICAL ENGINEERING_UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA	1.432356	-0.359321
38	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL VALLE-CALI	1.330612	-0.285639
25	PROG_UNIV_INDUSTRIAL ENGINEERING_ESCUELA COLOMBIANA DE INGENIERIA"JULIO GARAVITO"-BOGOTÁ D.C.	1.167535	-0.154895
0	PROG_UNIV_CHEMICAL ENGINEERING_FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.	1.162169	-0.150288
36	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DEL ATLANTICO-BARRANQUILLA	1.078813	-0.075862
48	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD TECNOLOGICA DE PEREIRA - ITP-PEREIRA	1.013608	0.013516
43	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD LIBRE-BOGOTÁ D.C.	1.047067	0.045993
45	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA	1.177550	0.163436
16	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.	1.340287	0.292884
47	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD TECNOLOGICA DE BOLIVAR-CARTAGENA	1.345057	0.296437
51	PROG_UNIV_Other	1.627059	0.486774
44	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD MILITAR"NUEVA GRANADA"-BOGOTÁ D.C.	1.705674	0.533960
10	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE	1.909604	0.646896
18	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD PONTIFICIA BOLIVARIANA-BUCARAMANGA	2.177513	0.778183
24	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA MINUTO DE DIOS -UNIMINUTO-BOGOTÁ D.C.	2.365550	0.861010
29	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD AUTONOMA DEL CARIBE-BARRANQUILLA	2.418385	0.883100
20	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-TUNJA	2.686981	0.988418
19	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD SANTO TOMAS-BOGOTÁ D.C.	2.833182	1.041401
8	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.	2.856996	1.049771
21	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA	3.525940	1.260147
40	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA	3.578493	1.274942
13	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD FRANCISCO DE PAULA SANTANDER-CUCUTA	3.711273	1.311375
5	PROG_UNIV_CIVIL ENGINEERING_CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA	3.863702	1.351626
15	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD LA GRAN COLOMBIA-BOGOTÁ D.C.	4.125047	1.417077
30	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.	4.155550	1.424445
32	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE	5.129384	1.634986
23	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DEL HUILA-CORHUILA-NEIVA	5.400467	1.686486

	Feature	Importance	Coefficient
31	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	5.930723	1.780146
22	PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DE INVESTIGACION Y DESARROLLO -"UDI"-BUCARAMANGA	6.408868	1.857683
27	PROG_UNIV_INDUSTRIAL ENGINEERING_POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.	6.907896	1.932665
26	PROG_UNIV_INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA - CARTAGENA	7.213714	1.975984
9	PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	7.719001	2.043685
46	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA	7.798274	2.053902
35	PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE PAMPLONA-PAMPLONA	8.365988	2.124174

Both models have equal Accuracy scores, while the model parameters are slightly different. The ranking of programs is absolutely the same. It is also essential to explore what direction each feature pulls the probability of a predicted value. SHAP technique will be beneficial in that.

6.2 Permutation importance

6.2.1 Permutation importance in LogisticRegressionCV best parameters model with SocioEconomic/HS scores features

In [210]:
```
1 permutation_of_features_logreg(log_reg_model2_new,X_train_df_SE, X_test_df_SE, y_test_final)
```

executed in 13.6s, finished 23:16:52 2021-05-27

Out[210]:

	Feature Importance	Coefficient	Permutation Importance
CR_S11	66.460521	-4.196608	0.012798
ENG_S11	51.313388	-3.937952	0.058787
BIO_S11	34.241189	-3.533429	0.006510
CC_S11	24.418425	-3.195338	0.004997
MAT_S11	14.268481	-2.658053	0.005988
SEL_IHE	2.071732	-0.728385	0.003901
OCC_FATHER_Entrepreneur	1.214932	0.194688	-0.001213
CAR_Yes	1.168274	0.155528	-0.003014
REVENUE_Between 2 and less than 3 LMMW	1.157135	-0.145948	-0.001696
REVENUE_Between 3 and less than 5 LMMW	1.113986	-0.107945	-0.001174
SISBEN_Level 1	1.110200	0.104541	-0.001905
EDU_FATHER_Incomplete Professional Education	1.109338	-0.103764	-0.000313
SEL	1.093798	-0.089656	-0.001853
INTERNET_Yes	1.088699	-0.084984	0.000026
WASHING_MCH_Yes	1.074290	0.071660	-0.001905

6.2.2 Permutation importance in RFClassifier best parameters model with SocioEconomic/HS scores features

In [211]:
```
1 permutation_of_features_tree(rfc2_new, X_train_df_SE, X_test_df_SE, y_test_final)
```

executed in 58.5s, finished 23:17:51 2021-05-27

```
Feature Importanve vs Permutation importance for RandomForestClassifier(class_weight='balanced_subsample', max_depth=5,
                       max_features=50, min_samples_leaf=2, n_estimators=50,
                       random_state=123) model
```

Out[211]:

	Feature_Importance	Permutation Importance
BIO_S11	0.348795	-0.000209
ENG_S11	0.325101	0.056660
CR_S11	0.193624	0.002779
MAT_S11	0.068199	-0.003666
CC_S11	0.045739	0.009237
SEL_IHE	0.008534	0.000183
SEL	0.001098	-0.000404
SISBEN_Level 1	0.000657	0.000535
PEOPLE_HOUSE	0.000604	-0.000261
MIC_OVEN_Yes	0.000526	-0.000509
TV_Yes	0.000435	-0.000417
OCC_MOTHER_Independent	0.000398	0.000705
COMPUTER_Yes	0.000326	-0.000339
EDU_FATHER_Incomplete Secondary	0.000322	-0.000352
OCC_FATHER_Executive	0.000318	0.000052

> Feature permutation importance ranking of both models is congruent with Feature importance analysis results. Each important factor is also ranked high in the predictive value of a feature for these models.

6.2.3 Permutation importance LogisticRegression best parameters model with Program/University features

In [212]:
```
1 permutation_of_features_logreg(log_reg_model4_new, X_train_df_UNVPRG, X_test_df_UNVPRG, y_test_final)
```

executed in 7.49s, finished 23:17:58 2021-05-27

Out[212]:

	Feature Importance	Coefficient	Permutation Importance
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA	19.799856	2.985675	0.010855
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE PAMPLONA-PAMPLONA	19.404994	2.965530	0.013555
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.	19.090912	-2.949212	0.006941
PROG_UNIV_INDUSTRIAL ENGINEERING_POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.	16.948023	2.830151	0.013725
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	16.875082	-2.825838	0.010802
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	16.761787	2.819102	0.022518
PROG_UNIV_INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA -CARTAGENA	15.370559	2.732454	0.027723
PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DE INVESTIGACION Y DESARROLLO -"UDI"-BUCARAMANGA	14.666567	2.685571	0.013568
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	13.688790	2.616577	0.012303
PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DEL HUILA-CORHUILA-NEIVA	11.916582	2.477931	0.018761
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE	11.215605	2.417306	0.007528
PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	9.090962	-2.207281	0.006445
PROG_UNIV_MECHANICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	8.863693	-2.181963	0.009393
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD LA GRAN COLOMBIA-BOGOTÁ D.C.	8.799941	2.174745	0.009524
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD CATOLICA DE COLOMBIA-BOGOTÁ D.C.	8.799939	2.174745	0.013464

6.2.4 Permutation importance in LogisticRegression default parameters model with Program/University features

In [213]:
```
1 permutation_of_features_logreg(logreg_model3_new, X_train_df_UNVPRG, X_test_df_UNVPRG, y_test_final)
```

executed in 7.30s, finished 23:18:06 2021-05-27

Out[213]:

	Feature Importance	Coefficient	Permutation Importance
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	13.802187	-2.624827	0.010802
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.	10.578137	-2.358789	0.006941
PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	9.762890	-2.278588	0.006445
PROG_UNIV_MECHANICAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	9.551090	-2.256655	0.009393
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE PAMPLONA-PAMPLONA	8.365988	2.124174	0.013594
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA	7.798274	2.053902	0.010868
PROG_UNIV_CIVIL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	7.719001	2.043685	0.022531
PROG_UNIV_INDUSTRIAL ENGINEERING_FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA -CARTAGENA	7.213714	1.975984	0.027763
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.	6.967045	-1.941191	0.021096
PROG_UNIV_INDUSTRIAL ENGINEERING_POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.	6.907896	1.932665	0.013751
PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DE INVESTIGACION Y DESARROLLO -"UDI"-BUCARAMANGA	6.408868	1.857683	0.013581
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.	5.930723	1.780146	0.012342
PROG_UNIV_CHEMICAL ENGINEERING_UNIVERSIDAD DE LA SABANA-CHIA	5.579093	-1.719026	0.008076
PROG_UNIV_INDUSTRIAL ENGINEERING_CORPORACION UNIVERSITARIA DEL HUILA-CORHUILA-NEIVA	5.400467	1.686486	0.018865
PROG_UNIV_INDUSTRIAL ENGINEERING_UNIVERSIDAD DE IBAGUE-IBAGUE	5.129384	1.634986	0.007710

The permutation importance analysis does not provide any additional information.

6.3 SHAP and Shapley Values for Model Interpretation

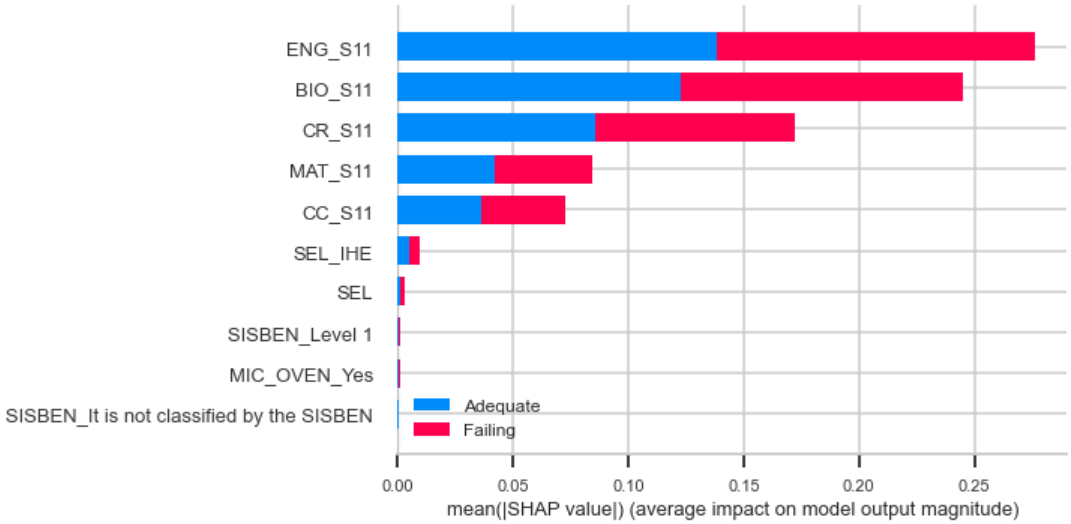
6.3.1 RFClassifier best parameters model with SocioEconomic/HS scores features interpretation with SHAP

In [214]:
```
1 shap.initjs()
```
executed in 15ms, finished 23:18:06 2021-05-27

In [215]:
```
1 shap_values_rfc2 = shap.TreeExplainer(rfc2_new).shap_values(X_train_df_SE)
```
executed in 1.50s, finished 23:18:07 2021-05-27

Shapley values plotting indicates a very

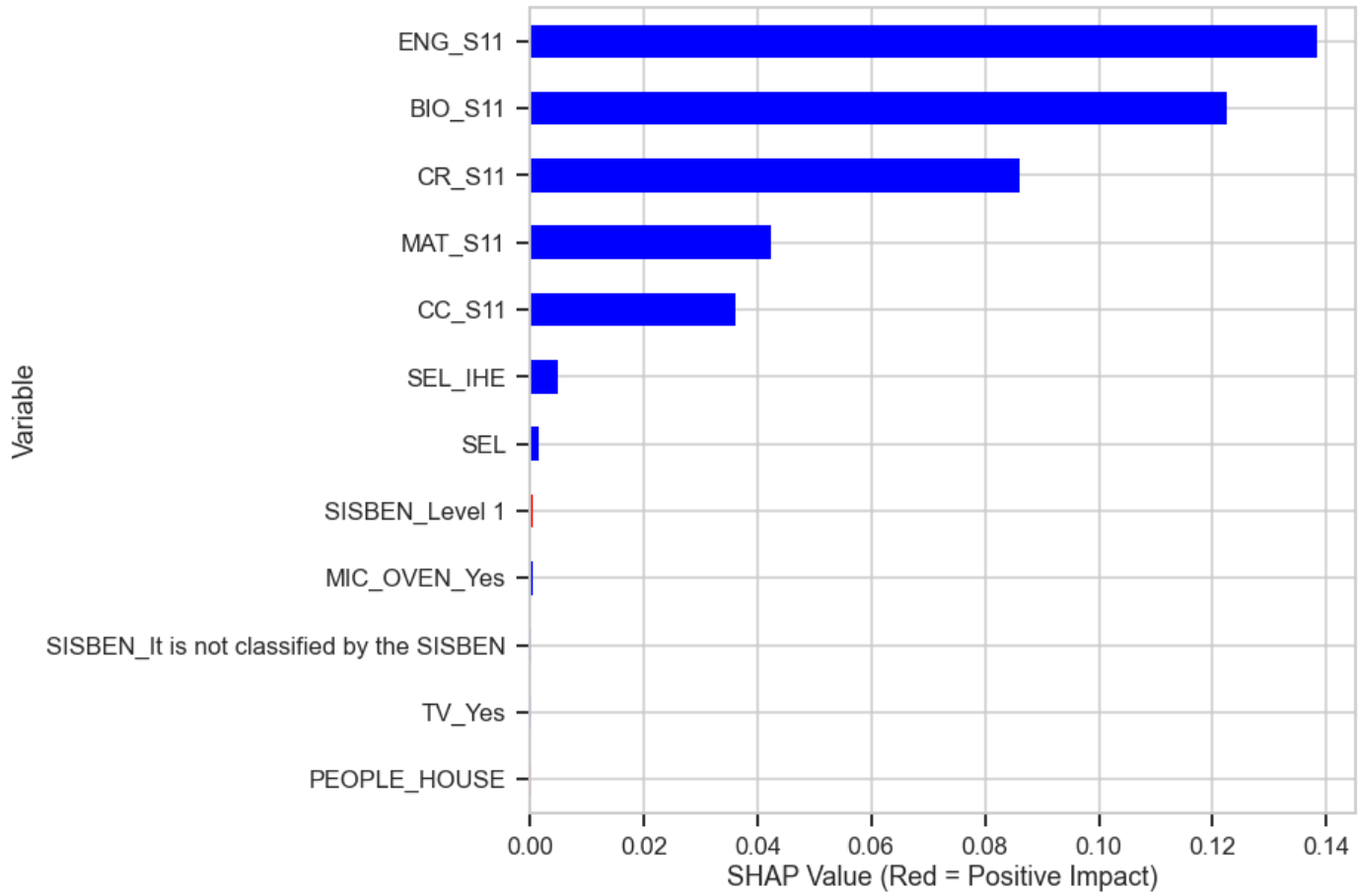
In [216]:
```
1 shap.summary_plot(shap_values_rfc2, X_train_df_SE, plot_type="bar", class_names=['Failing','Adequate'], max_display=10 )
```
executed in 206ms, finished 23:18:08 2021-05-27



SHAP summary plots of decision tree-based algorithms are slightly different from other models. The plot above shows a split between target classes and is indicative of the balanced distribution of feature values between the classes. Such a plot would be more helpful in problem analysis of a multi=class problem.

In [217]:
```
1 ABS_SHAP(shap_values_rfc2[1], X_train_df_SE, n=12, figure=(10,10))
```

executed in 206ms, finished 23:18:08 2021-05-27



ABS_SHAP plot (see function's description) is showing that all important model's features pull a predicted outcome "away" from "Failing." The plot displays mean shapley values for each feature in the model; red features affect the outcome positively, while the blue ones do the opposite.

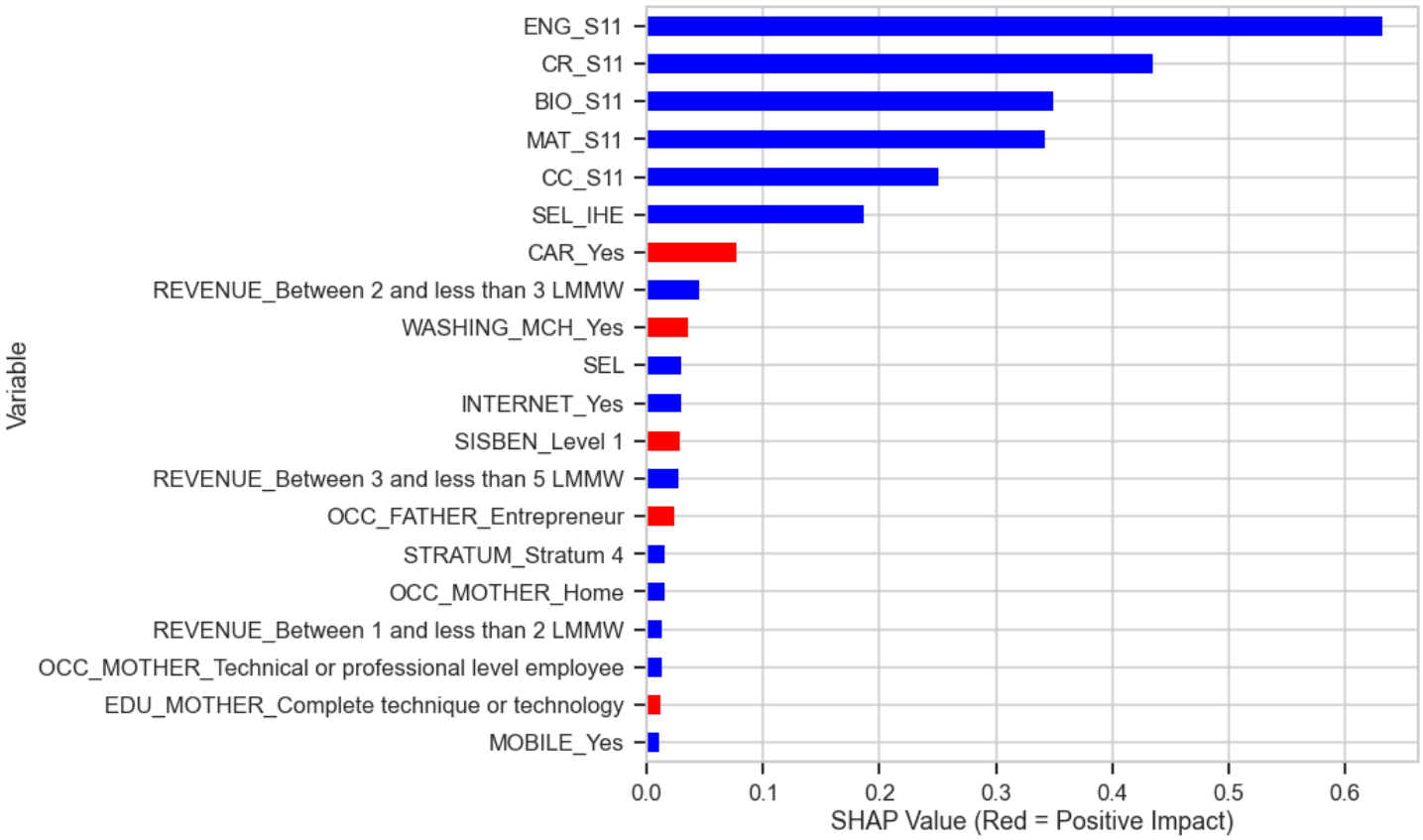
6.3.2 LogisticRegression CV best parametrs model with SocioEconomic/HS scores features interpretation with SHAP

In [218]:
```
1 shap_values_lrcv = shap.LinearExplainer(log_reg_model2_new, X_train_df_SE, feature_dependence="independent").shap_values(
```

executed in 15ms, finished 23:18:08 2021-05-27

In [219]:
```
1 ABS_SHAP(shap_values_lrcv, X_train_df_SE, n=20, figure=(10,10))
```

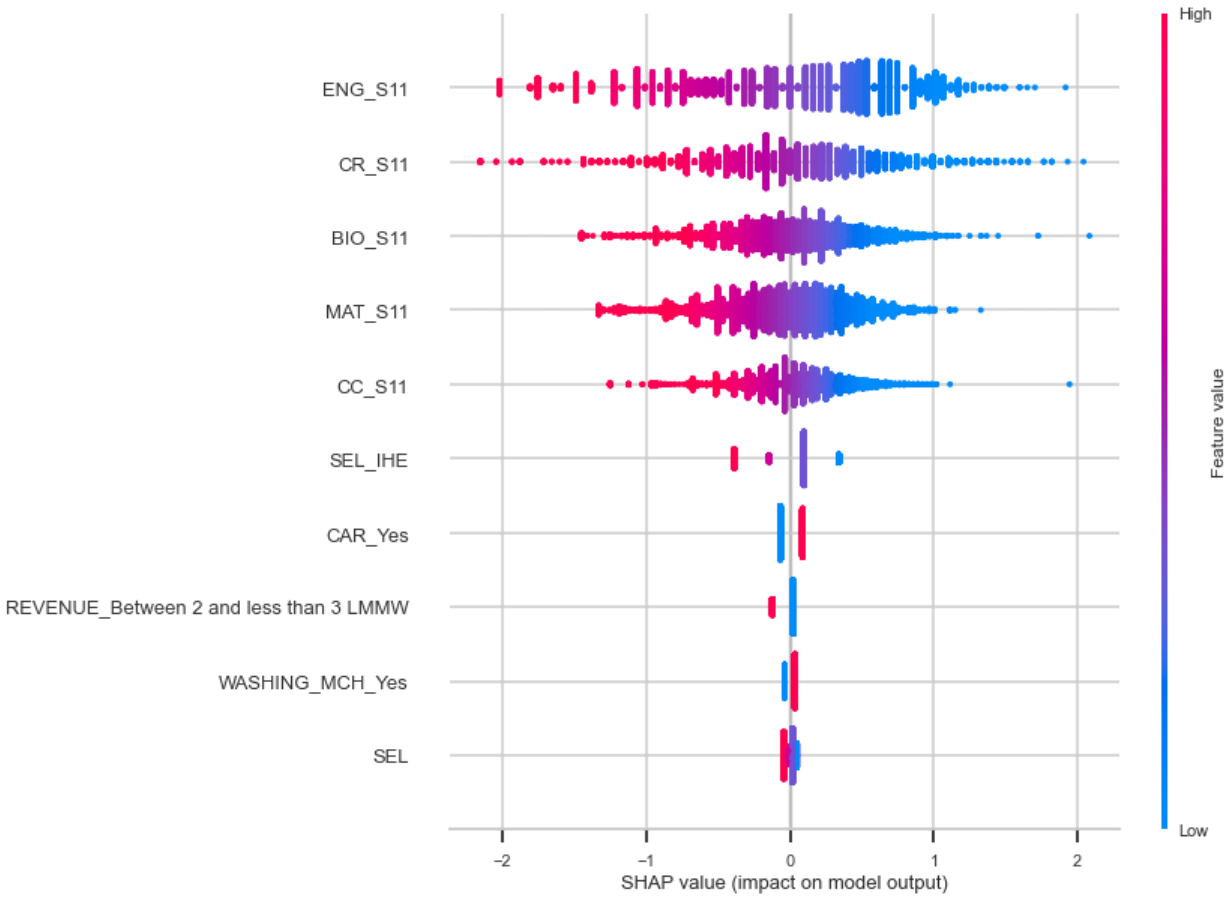
executed in 270ms, finished 23:18:08 2021-05-27



While the results of ABS_SHAP function are somewhat similar to the previous model results, the plot does display some peculiarities. Thus the model has CAR_yes variable in red, which means possession of a car is a factor that might affect the outcome in a positive direction. IT means that a student is slightly more prone to Fail (target=1) if the household has a car. A logical way of looking at that situation is to conclude that possession of a vehicle is a factor that would help students NOT fail. After all, in Colombia, a car is a measure of socio-economic level.

In [220]:
```
1 shap.summary_plot(shap_values_lrcv, X_train_df_SE, plot_size=(10.,10.), max_display=10)
```

executed in 812ms, finished 23:18:09 2021-05-27



- Vertical location shows what features it is depicting
- Color shows whether that feature was high or low for that row of the dataset
- Horizontal location shows whether the effect of that value caused a higher or lower prediction.

6.3.3 LogisticRegression best parametrs model with University/Program features interpretation with

SHAP

In [221]:
```
shap_values_lr4 = shap.LinearExplainer(log_reg_model4_new, X_train_df_UNVPRG,
                                       feature_dependence="independent").shap_values(X_train_df_UNVPRG)
```

executed in 14ms, finished 23:18:09 2021-05-27

In [222]:
```
ABS_SHAP(shap_values_lr4, X_train_df_UNVPRG, n=30, figure=(20,20))
```

executed in 512ms, finished 23:18:09 2021-05-27

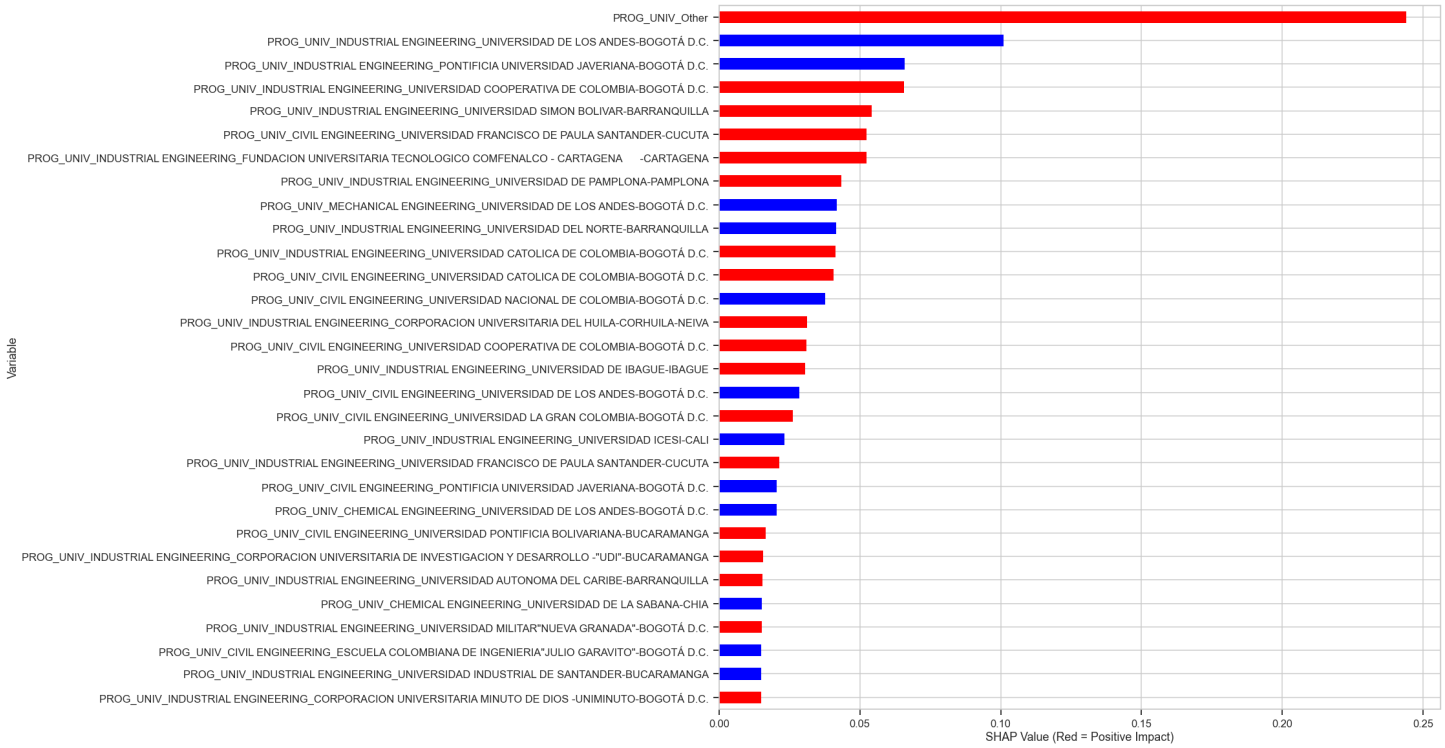
6.3.4 LogisticRegression default parameters model with University/Program features interpretation with SHAP

In [223]:
```
shap_values_lr3 = shap.LinearExplainer(logreg_model3_new, X_train_df_UNVPRG, feature_dependence="independent").shap_values
```

executed in 14ms, finished 23:18:09 2021-05-27

In [224]:
```
1 ABS_SHAP(shap_values_lr3, X_train_df_UNVPRG, n=30, figure=(20,20))
```

executed in 511ms, finished 23:18:10 2021-05-27



> The result of the shapley values plotted is a bit unusual. While the models displayed very similar results in ranking the programs, their shapley values are quite different.

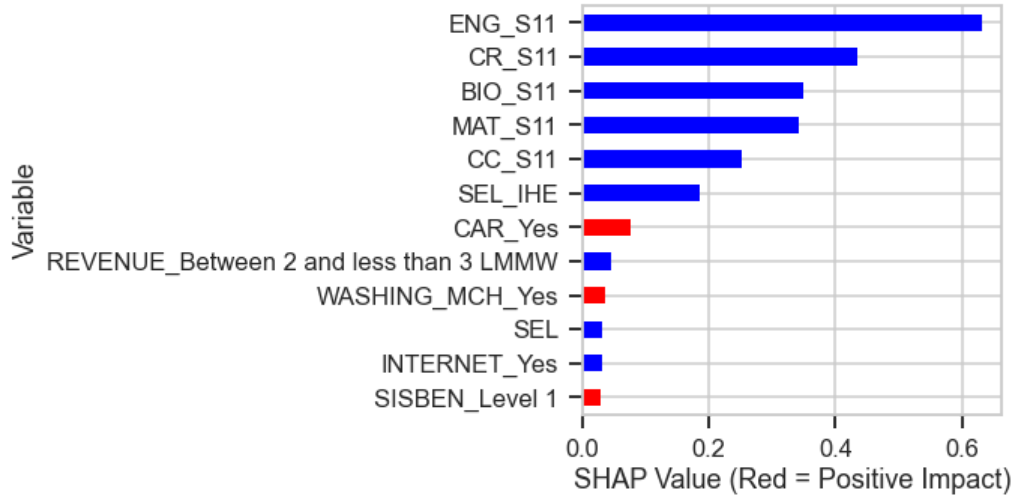
6.3.5 Using LIME to randomly test prediction from models

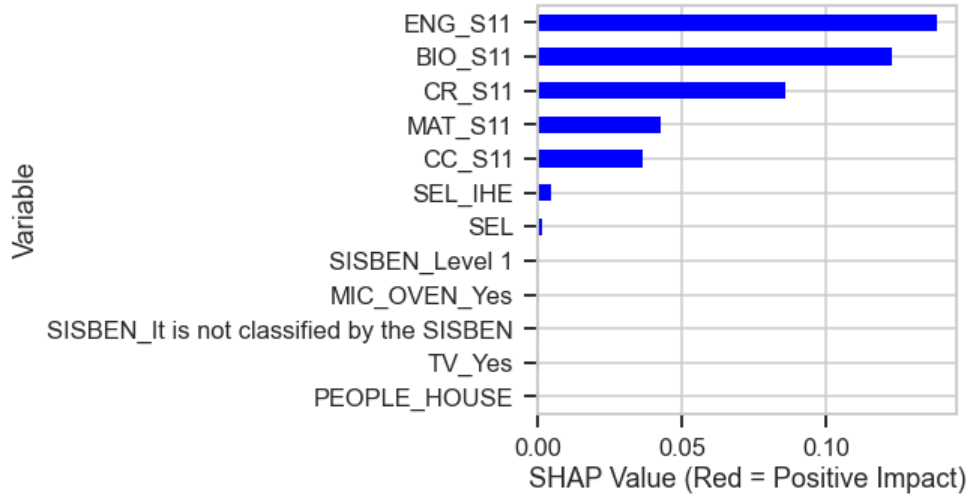
6.3.5.1 Comparing predictions from LogisticRegression and RFClassifier models based on SocioEconomic/HS scores features

- A random observation from the test dataset shows how each model pulls out its' prediction.

In [225]:
```
ABS_SHAP(shap_values_lrcv, X_train_df_SE, n=12, figure=(5,5))
ABS_SHAP(shap_values_rfc2[1], X_train_df_SE, n=12, figure=(5,5))
```

executed in 334ms, finished 23:18:10 2021-05-27





In [226]:
```
#Initalizing a tree explainer
explainer = lime_tabular.LimeTabularExplainer(X_train_df_SE.values, mode="classification",
                                              class_names=['Adequate','Failing'],
                                              feature_names=X_test_df_SE.columns )
```

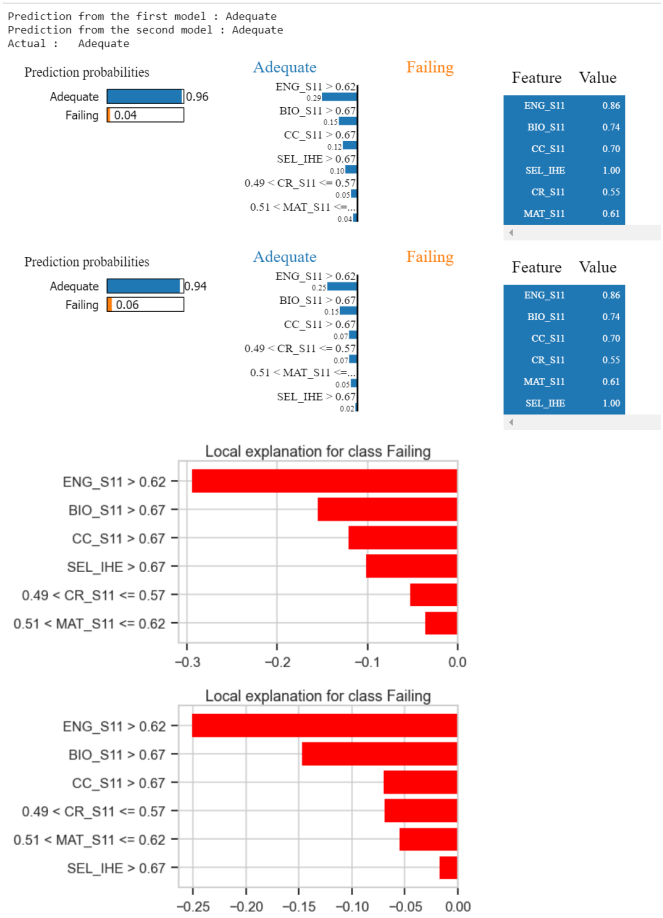
executed in 222ms, finished 23:18:10 2021-05-27

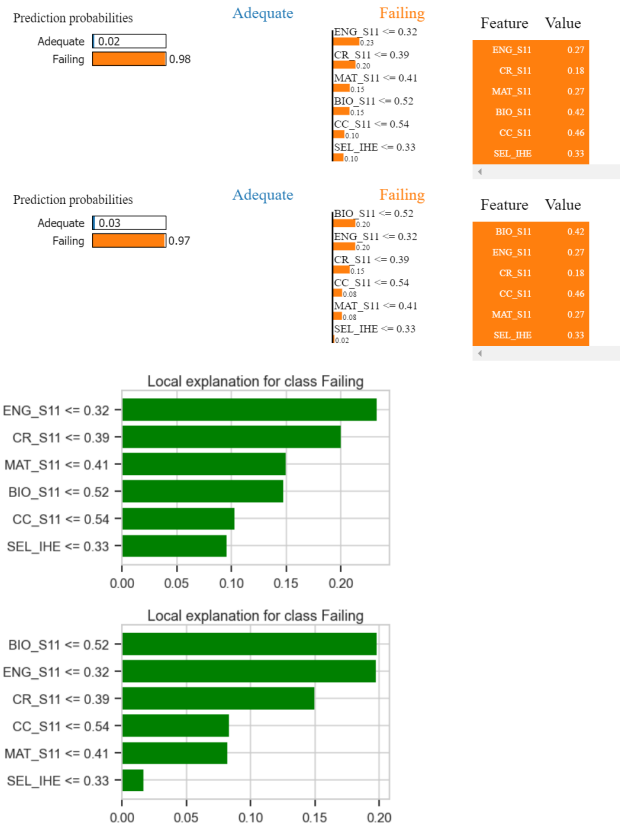
In [*]:
```
# An example of a single observation outcome and its' model prediction
show_random_observation(log_reg_model2_new, rfc2_new, X_test_df_SE, y_test_final, explainer)
```

execution queued 23:16:26 2021-05-27

```
Prediction from the first model : Adequate
Prediction from the second model : Adequate
Actual :   Adequate
```

- To understand how models predict an outcome of each student's class performance we will review several use cases randomly chosen from a test dataset



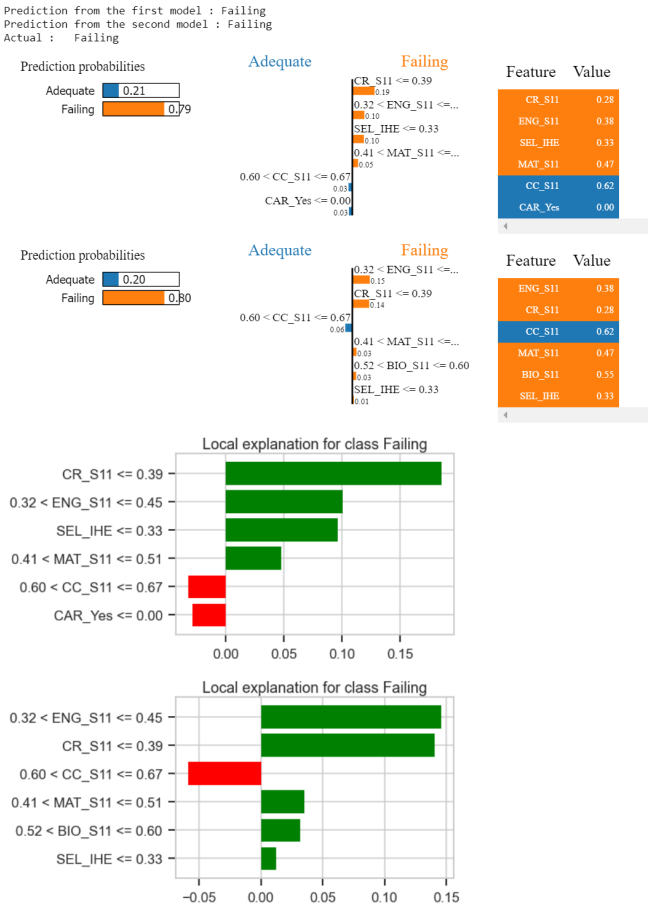


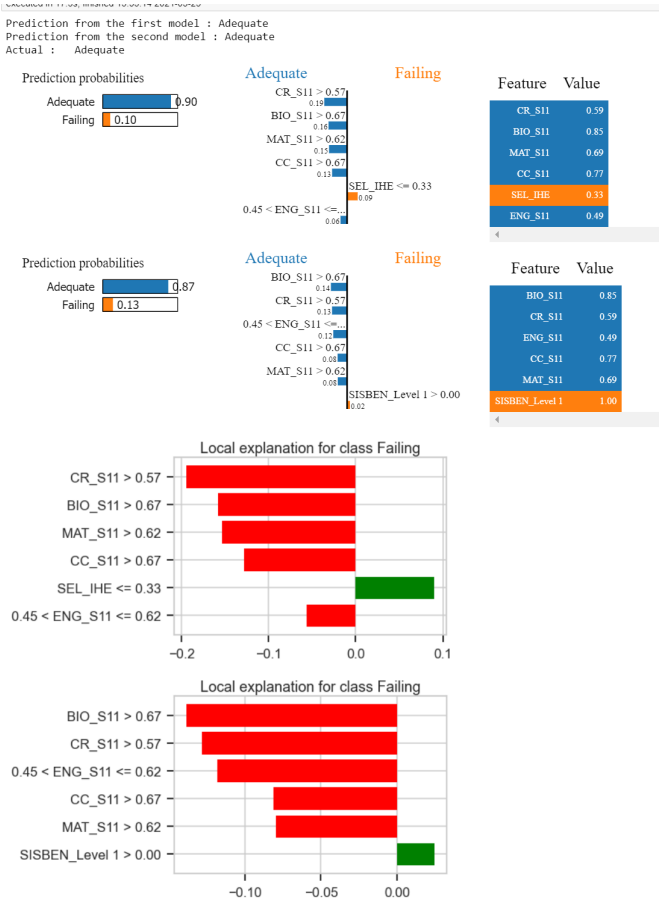
Example 1:

- The first example is a student with outstanding HS test results in an Engineering program at a university with a wealthy student population. The student's performance in the professional program is far from failing. Even from a common-sense point of view, this student has all the factors playing in ze/zir favor.
- The prediction as such makes sense in both models though they sometimes disagree. This use case is not a ground for such disagreement. The predicted probability of such a student failing in a professional program is very low.
- If we look at how the models have come to predicting the probability of the outcome, we can see that the most important factor is the student's HS scores in English and Biology tests. One model gives more importance to biology test results than another; the score was high enough to make it the second decisive factor in both models.

Example 2:

- The second example we have is a student with an opposite situation. The scores in all subject tests are much lower, and the socio-economic level of the students in the Institution of Higher Education is lower too. It means that the student is very likely to fail in the professional tests
- In this case, common sense makes us conclude that such a student will have trouble catching up with the peers across all the programs in the dataset. Especially given the fact that ze/zir school is not the most affluent one.





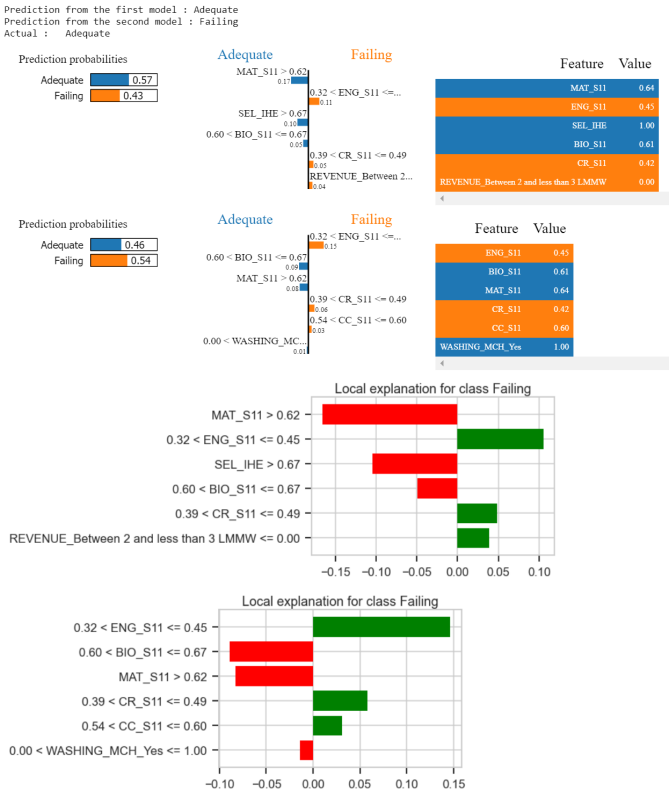
The following two use cases are not that straightforward. Students have some of their HS scores in the lower range while others are in the higher range.

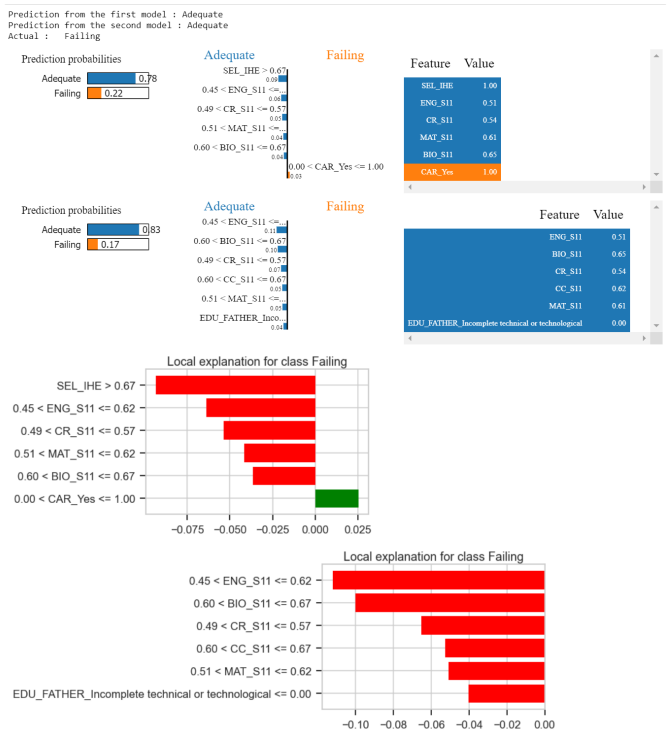
Example 3:

- The first use case is a student with poor HS test results in subjects others than Civics score. Both models were successful in predicting the actual outcome in this case.
- The influence of the Civics score feature was not powerful enough to compensate for the poor performance in other tests.
- Both models were successful in predicting the actual outcome in this case.

Example 4:

- The second use case is a relatively simple case of a student with strong HS scores and at not so affluent university program.
- This case indicates that the socio-economic factors (SEL_IHE and SISBEN are related categories) while being among the most important features, affect professional test scores less than the student's high-school test scores.
- The student succeeded, and both models correctly predicted the outcome.





The subsequent two use cases are the most interesting ones; the models, at least one of them, failed to predict the student's performance correctly.

Example 5:

- In the first use case HS test scores are a mixed bag; also, a student is from a relatively low-income family. The first model predicted his performance correctly, the second one was wrong.
- The importance of the Mathematics HS score in the first model is higher than its importance in the second model (meaning relative importance), especially compared to the English score. At the same time, the second model puts too much emphasis on an English score. Most probably, the prediction of the second model is the result of a combination of both factors.
- More investigation into these factors is needed.
- A combination of both models might be beneficial for the accuracy of prediction.

Example 6:

- The last use case is one of those situations when both models failed to predict the outcome correctly. It is a case all the factors favored the student succeeding, but Ze/zir failed anyway. The HS test scores were high. It is not very clear what ze/zir socio-economic level was. There might have been some factors of personal nature that are impossible to predict. The student possibly had a rough patch in ze/zir life or mental breakdown when taking the professional tests. Anything is possible. There always will be some outliers that are impossible to predict.
- It is essential to understand that no model is perfect. Sometimes they fail to predict the target correctly. But those cases are extremely rare. It took me a while to find an example in the test dataset using the combination of predictions and the actual value as described.

7 Conclusions and Recommendation

Recommendations to university officials looking for a method to identify incoming students at risk of falling behind early:

- Implement a system based on the suggested Machine Learning model that helps in identifying freshmen students that have a higher probability of failing in their professional studies.
- Provide additional help to these students to raise their base knowledge of English, Biology, Critical Reading, and Mathematics. Possibly as tutoring or extra classes.
- While it is not an easily controlled factor, SHE_IHE influence on the outcome suggests that it might be beneficial to find out how this factor affects an engineering educational process.
- Is it correlated with high school scores of students' population? As the higher is overall income-the higher is the overall quality of the schools. Or is it that schools with higher SEL_IHE can pay more to their faculty and staff (tuition is more elevated and less money is spent on providing financial assistance to low-income students)? It is a question to be answered before making any recommendations

Recommendations to potential students:

- Consider Programs/Universities with a higher ranking in the field; it will pay off in your professional results
- Our model list of ranked Programs/Universities might be a starting point.

- Most highly ranked Programs/Universities are located in the capital. Consider moving away from home to have better prospects in your professional life.

Model #1		
Civil Engineering		Civil Engineering
UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.		UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		UNIVERSIDAD LA GRAN COLOMBIA-BOGOTÁ D.C.
UNIVERSIDAD DEL NORTE-BARRANQUILLA		CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA
Industrial Engineering		Industrial Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA
UNIVERSIDAD ICESI-CALI		UNIVERSIDAD DE PAMPLONA-PAMPLONA
UNIVERSIDAD DISTRITAL"FRANCISCO JOSE DE CALDAS"-BOGOTÁ D.C.		POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.
Chemical Engineering		Chemical Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.
UNIVERSIDAD DE LA SABANA-CHIA		FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.
UNIVERSIDAD DE CARTAGENA-CARTAGENA		
Mechanical Engineering		Mechanical Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA

Model #2		
Civil Engineering		Civil Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		UNIVERSIDAD COOPERATIVA DE COLOMBIA-BOGOTÁ D.C.
UNIVERSIDAD NACIONAL DE COLOMBIA-BOGOTÁ D.C.		UNIVERSIDAD LA GRAN COLOMBIA-BOGOTÁ D.C.
UNIVERSIDAD DEL NORTE-BARRANQUILLA		CORPORACION UNIVERSIDAD DE LA COSTA, CUC-BARRANQUILLA
Industrial Engineering		Industrial Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		UNIVERSIDAD DE PAMPLONA-PAMPLONA
UNIVERSIDAD ICESI-CALI		UNIVERSIDAD SIMON BOLIVAR-BARRANQUILLA
UNIVERSIDAD DISTRITAL"FRANCISCO JOSE DE CALDAS"-BOGOTÁ D.C.		**FUNDACION UNIVERSITARIA TECNOLOGICO COMFENALCO - CARTAGENA -CARTAGENA**
		POLITECNICO GRANCOLOMBIANO-BOGOTÁ D.C.
Chemical Engineering		Chemical Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		FUNDACION UNIVERSIDAD DE AMERICA-BOGOTÁ D.C.
UNIVERSIDAD DE LA SABANA-CHIA		FUNDACION UNIVERSIDAD DE BOGOTA"JORGE TADEO LOZANO"-BOGOTÁ D.C.
UNIVERSIDAD DE CARTAGENA-CARTAGENA		
Mechanical Engineering		Mechanical Engineering
UNIVERSIDAD DE LOS ANDES-BOGOTÁ D.C.		UNIVERSIDAD INDUSTRIAL DE SANTANDER-BUCARAMANGA

Limitations of the model:

- The original dataset does not include other essential factors, and therefore the models are biased
- The overall performance of any of the final models is not perfect.
- Some variables in the dataset are correlated with each other, affecting the predictive power of the models.

Suggestion for future improvements:

- Built a regression model instead of a classification one. Classification models are too indiscrete in their predictions.
- Add variables to the original dataset that better describe socio-economic level of a student.
- Consider global score for HS tests to avoid scores correlation
- Update the dataset with more current data.

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