

Imputing missing values with SMOTE Technique

```
##### # Imports
```

```
# Pandas and numpy for data manipulation
```

```
import pandas as pd
```

```
import numpy as np
```

```
# No warnings about setting value on copy of slice
```

```
pd.options.mode.chained_assignment = None
```

```
# Display up to 60 columns of a dataframe
```

```
pd.set_option('display.max_columns', 60)
```

```
# Matplotlib visualization
```

```
import matplotlib.pyplot as plt
```

```
%matplotlib inline
```

```
# Set default font size
```

```
plt.rcParams['font.size'] = 24
```

```
# Internal ipython tool for setting figure size
```

```
from IPython.core.pylabtools import figsize
```

```
# Seaborn for visualization
```

```
import seaborn as sns
```

```
sns.set(font_scale = 2)
```

```
# Splitting data into training and testing
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LogisticRegression, LinearRegression
```

```
# %% [code]
```

```
### Data Cleaning and Formatting
```

```
## Load in the Data and Examine
```

```
# Read in credit into a dataframe
```

```
credit = pd.read_csv('../input/my-dataset/credit_train.csv')
```

```
# Display top of dataframe
```

```
credit.head()
```

```
# %% [code]
```

```
credit.shape
```

```
# %% [markdown]
```

```
## Handling NA vs Changing the type of Fields
```

```
#
```

```
# Always Make sure that ,You should handle Null values in Data on first priority and the typecase them into some categories or in some other form.
```

```
# Lets Find out the Row level Duplicate and Remove them ,Because they are of no Use to us.
```

```
#
```

```
# %% [code]
```

```
#Check for all Row level NULL(It means all column values for that row are null) from Dataframe because they are not carrying any information.
```

```
credit=credit[credit.isna().all(axis=1)==False]
```

```
# %% [code]
```

```
#Check whether Row level NULL are hablded or Not
```

```
credit.shape
```

```
# %% [markdown]
```

As we can see, it looks like some of the credit score are just scaled up by 10. For the ease of our calculation we can consider, scaling them back is accurate.

```
# %% [code]
```

```
credit.describe()
```

```
# %% [code]
```

```
# # Data Types and Missing Values
```

```
# See the column data types and non-missing values
```

```
credit.info()
```

```
# %% [code]
```

```
# Statistics for each column
```

```
credit.describe()
```

```
# %% [code]
```

```
credit.drop(labels=['Loan ID', 'Customer ID'], axis=1, inplace=True)
```

```
# These two features are only for identification.
```

```
# %% [markdown]
```

```
# **hANDLINE CATEGORICAL FEATURES**
```

```
# %% [code]
```

```
credit['Loan Status'] = credit['Loan Status'].map({'Fully Paid':int('0'),'Charged Off':int('1')})
```

```
credit['Term'] = credit['Term'].map({'Short Term':int('0'),'Long Term':int('1')})
```

```
credit['Years in current job'] = credit['Years in current job'].map({'< 1 year':int('0'),'1 year':int('1'),'2 years':int('2'),'3 years':int('3'),'4 years':int('4'),'5 years':int('5'),'6 years':int('6'),'7 years':int('7'),'8 years':int('8'),'9 years':int('9'),'10+ years':int('10')})
```

```
# %% [code]
```

```
del(credit['Months since last delinquent'])
```

```
# %% [code]
```

```
# # Encoding categorical data & Feature Scaling
```

```
# Select the categorical columns
```

```
categorical_subset = credit[['Home Ownership', 'Purpose']]
```

```
# One hot encode
```

```
categorical_subset = pd.get_dummies(categorical_subset)
```

```
# Join the dataframe in credit_train
```

```
# Make sure to use axis = 1 to perform a column bind
```

```
# First I will drop the 'old' categorical datas and after I will join the 'new' one.
```

```
credit.drop(labels=['Home Ownership', 'Purpose'], axis=1, inplace=True)
```

```
credit = pd.concat([credit, categorical_subset], axis = 1)
```

```
# %% [code]
```

```
credit.shape
```

```
# %% [code]
```

```
# # Remove Collinear Features
```

```
def remove_collinear_features(x, threshold):
```

```
    """
```

```
    Objective:
```

```
        Remove collinear features in a dataframe with a correlation coefficient
```

```
        greater than the threshold. Removing collinear features can help a model
```

to generalize and improves the interpretability of the model.

Inputs:

threshold: any features with correlations greater than this value are removed

Output:

dataframe that contains only the non-highly-collinear features

'''

Dont want to remove correlations between Energy Star Score

y = x['Loan Status']

x = x.drop(columns = ['Loan Status'])

Calculate the correlation matrix

corr_matrix = x.corr()

iters = range(len(corr_matrix.columns) - 1)

drop_cols = []

Iterate through the correlation matrix and compare correlations

for i in iters:

for j in range(i):

item = corr_matrix.iloc[j:(j+1), (i+1):(i+2)]

col = item.columns

row = item.index

val = abs(item.values)

If correlation exceeds the threshold

if val >= threshold:

Print the correlated features and the correlation value

print(col.values[0], "|", row.values[0], "|", round(val[0][0], 2))

drop_cols.append(col.values[0])

```
# Drop one of each pair of correlated columns
```

```
drops = set(drop_cols)
```

```
x = x.drop(columns = drops)
```

```
# Add the score back in to the data
```

```
x['Loan Status'] = y
```

```
return x
```

```
# %% [code]
```

```
# Remove the collinear features above a specified correlation coefficient
```

```
credit = remove_collinear_features(credit, 0.6);
```

```
# %% [code]
```

```
credit.shape
```

```
# %% [code]
```

```
# # Missing Values
```

```
# Function to calculate missing values by column
```

```
def missing_values_table(df):
```

```
    # Total missing values
```

```
    mis_val = df.isnull().sum()
```

```
    # Percentage of missing values
```

```
    mis_val_percent = 100 * df.isnull().sum() / len(df)
```

```
    # Make a table with the results
```

```
    mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)
```

Rename the columns

```
mis_val_table_ren_columns = mis_val_table.rename(  
columns = {0 : 'Missing Values', 1 : '% of Total Values'})
```

Sort the table by percentage of missing descending

```
mis_val_table_ren_columns = mis_val_table_ren_columns[  
    mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(  
'% of Total Values', ascending=False).round(1)
```

Print some summary information

```
print ("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"  
      "There are " + str(mis_val_table_ren_columns.shape[0]) +  
      " columns that have missing values.")
```

Return the dataframe with missing information

```
return mis_val_table_ren_columns
```

%% [code]

```
missing_values_table(credit)
```

A curious thing about the table below is the last 10 features have the same number o missing values.

I will go deeper and figure out what is happening.

%% [markdown]

Handling missing value with correlation methods

%% [code]

```
corr = credit.corr()
```

```
corr
```

```
# %% [code]
```

```
sns.heatmap(corr)
```

```
# %% [code]
```

```
corr['Credit Score'][abs(corr['Credit Score']) > 0.1]
```

```
# %% [code]
```

```
corr['Annual Income'][abs(corr['Annual Income']) > 0.1]
```

```
# %% [code]
```

```
corr['Years in current job'][abs(corr['Years in current job']) > 0.1]
```

```
# %% [code]
```

```
corr['Tax Liens'][abs(corr['Tax Liens']) > 0.1]
```

```
# %% [code]
```

```
corr['Maximum Open Credit'][abs(corr['Maximum Open Credit']) > 0.1]
```

```
# %% [code]
```

```
credit_without_mv = credit.dropna()
```

```
# %% [code]
```

```
x1_col = ['Loan Status']
```

```
y1 = credit_without_mv['Credit Score']
```

```
x1 = credit_without_mv['Loan Status']
```

```
# %% [code]
```

```
# %% [code]
```

```
y1 = y1.values.reshape(77427,1)
```



```
x1 = x1.values.reshape(77427,1)
```

```
# %% [code]
```

```
linreg1 = LinearRegression()
```

```
linreg1.fit(x1,y1)
```

```
# %% [code]
```

```
credit['Credit Score'] = credit.apply(lambda x:linreg1.predict(x['Loan Status'].reshape(1,1))[0][0] if  
np.isnan(x['Credit Score']) else x['Credit Score'], axis =1)
```

```
# %% [code]
```

```
credit['Credit Score'].shape
```

```
# %% [code]
```

```
# for Annual income
```

```
x2_col = ['Monthly Debt', 'Years of Credit History', 'Number of Open Accounts', 'Current Credit  
Balance', 'Home Ownership_Home Mortgage', 'Home Ownership_Rent']
```

```
y2 = credit_without_mv['Annual Income']
```

```
x2 = credit_without_mv[x2_col]
```

```
y2 = y2.values.reshape(77427,1)
```

```
x2 = x2.values.reshape(77427,6)
```

```
linreg2 = LinearRegression()
```

```
linreg2.fit(x2,y2)
```

```
credit['Annual Income'] = credit.apply(lambda  
x:linreg2.predict(x[x2_col].values.reshape(1,6))[0][0] if np.isnan(x['Annual Income']) else  
x['Annual Income'], axis =1)
```

```
credit['Annual Income'].shape
```

```
# %% [code]
```

```
# for Years in current job
```

```
x3_col = ['Monthly Debt', 'Years of Credit History', 'Home Ownership_Home Mortgage', 'Home  
Ownership_Rent']
```

```
y3 = credit_without_mv['Years in current job']
```

```
x3 = credit_without_mv[x3_col]
```

```
y3 = y3.values.reshape(77271,1)
```

```
x3 = x3.values.reshape(77271,4)
```

```
linreg3 = LogisticRegression()
```

```
linreg3.fit(x3,y3)
```

```
credit['Years in current job'] = credit.apply(lambda  
x:linreg3.predict(x[x3_col].values.reshape(1,4))[0:4][0] if np.isnan(x['Years in current job']) else  
x['Years in current job'], axis =1)
```

```
credit['Years in current job'].shape
```

```
# %% [code]
```

```
# for Maximum Open Credit
```

```
y4 = credit_without_mv['Maximum Open Credit']
```

```
x4 = credit_without_mv['Current Credit Balance']
```

```
y4 = y4.values.reshape(77271,1)
```

```
x4 = x4.values.reshape(77271,1)
```

```
linreg4 = LinearRegression()
```

```
linreg4.fit(x4,y4)
```

```
credit['Maximum Open Credit'] = credit.apply(lambda x:linreg4.predict(x['Current Credit  
Balance'].reshape(1,1))[0][0] if np.isnan(x['Maximum Open Credit']) else x['Maximum Open  
Credit'], axis =1)
```

```
credit['Maximum Open Credit'].shape
```

```
# %% [code]
```

```
# for Bankruptcies
```

```
x5_col = ['Current Credit Balance', 'Number of Credit Problems']
```

```
y5 = credit_without_mv['Bankruptcies']
```

```
x5 = credit_without_mv[x5_col]
```

```

y5 = y5.values.reshape(77271,1)
x5 = x5.values.reshape(77271,2)
linreg5 = LinearRegression()
linreg5.fit(x5,y5)
credit['Bankruptcies'] = credit.apply(lambda x:linreg5.predict(x[x5_col].values.reshape(1,2))[0][0]
if np.isnan(x['Bankruptcies']) else x['Bankruptcies'], axis =1)
credit['Bankruptcies'].shape

```

```

# %% [code]
# for tax liens

```

```

y6 = credit_without_mv['Tax Liens']
x6 = credit_without_mv['Number of Credit Problems']
y6 = y6.values.reshape(77271,1)
x6 = x6.values.reshape(77271,1)
linreg6 = LinearRegression()
linreg6.fit(x6,y6)
credit['Tax Liens'] = credit.apply(lambda x:linreg6.predict(x['Number of Credit
Problems'].reshape(1,1))[0][0] if np.isnan(x['Tax Liens']) else x['Tax Liens'], axis =1)
credit['Tax Liens'].shape

```

```

# %% [markdown]
# # End hadling missing value using correlation

```

```

# %% [markdown]
# **start SMOTE**

```

```

# %% [code]
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score, roc_auc_score, roc_curve
from sklearn.model_selection import train_test_split

```

```

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import confusion_matrix

import math


def generate_model_report(y_actual, y_predicted):

    conf_mat = confusion_matrix(y_actual, y_predicted)

    true_positive = conf_mat[1,1]

    true_negative = conf_mat[0,0]

    false_positive = conf_mat[0,1]

    false_negative = conf_mat[1,0]

    specificity = (true_negative)/(true_negative + false_positive)

    gm = math.sqrt(specificity * recall_score(y_actual, y_predicted))


    print("Accuracy = " , accuracy_score(y_actual, y_predicted))
    print("Precision = " ,precision_score(y_actual, y_predicted))
    print("Recall/Sensitivity = " ,recall_score(y_actual, y_predicted))
    print("Specificity = " ,specificity)
    print("F1 Score = " ,f1_score(y_actual, y_predicted))
    print("ROC-AUC Score = " ,roc_auc_score(y_actual, y_predicted))
    print("G-Measure = " ,gm)


    sns.heatmap(conf_mat,cmap="coolwarm_r", annot=True,linewidths=0.5,fmt='g')
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted value")
    plt.ylabel("Actual label")
    plt.show()

    pass


def generate_auc_roc_curve(clf, X_test):

    y_pred_proba = clf.predict_proba(X_test)[: , 1]

```

```
fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
auc = roc_auc_score(Y_test, y_pred_proba)
plt.plot(fpr,tpr,label="AUC =" +str(auc))
plt.legend(loc=4)
plt.show()
pass
```

```
# %% [code]
```

```
X = credit.loc[:, credit.columns!='Loan Status']
```

```
Y = credit.loc[:, credit.columns=='Loan Status']
```

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
                                                    test_size=0.2,
                                                    random_state=42)
```

```
# %% [code]
```

```
# # Feature Scaling
```

```
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
```

```
X_train = sc.fit_transform(X_train)
```

```
X_test = sc.transform(X_test)
```

```
# Encoding the Dependent Variable
```

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

```
labelencoder_y_train = LabelEncoder()
```

```
Y_train = labelencoder_y_train.fit_transform(Y_train)
```

```
labelencoder_y_test = LabelEncoder()
```

```
Y_test = labelencoder_y_test.fit_transform(Y_test)
```

```
# %% [code]
```

```
from imblearn.over_sampling import SMOTE
```

```
from imblearn.pipeline import make_pipeline
```

```
sm = SMOTE(random_state=12, ratio = 1.0)
```

```
x_train_res, y_train_res = sm.fit_sample(X_train, Y_train)
```

```
unique, count = np.unique(y_train_res, return_counts=True)
```

```
y_train_smote_value_count = { k:v for (k,v) in zip(unique, count)}
```

```
y_train_smote_value_count
```

```
# %% [code]
```

```
print("logistic regression")
```

```
clf = LogisticRegression().fit(x_train_res, y_train_res)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
print("KNN")
```

```
clf = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2).fit(x_train_res, y_train_res)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
from sklearn import tree
```

```
print("Decision Tree")
```

```
clf = tree.DecisionTreeClassifier(random_state=1).fit(x_train_res, y_train_res)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
print("Naive bayes")
```

```
from sklearn.naive_bayes import GaussianNB
```

```
clf = GaussianNB().fit(x_train_res, y_train_res)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
print("Random forest")
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
clf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy').fit(x_train_res, y_train_res)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
print("XGBoost")
```

```
from xgboost import XGBClassifier
```

```
clf = XGBClassifier().fit(x_train_res, y_train_res)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
### Models to Evaluate
```

```
# We will compare five different machine learning Classification models:
```

```
# 1 - Logistic Regression
```

```
# 2 - K-Nearest Neighbors Classification
```

```
# 3 - Support Vector Machine
```

```
# 4 - Naive Bayes
```

```
# 5 - Random Forest Classification
```

```
# Function to calculate mean absolute error
```

```
def cross_val(X_train, y_train, model):
```

```
    # Applying k-Fold Cross Validation
```

```
    from sklearn.model_selection import cross_val_score
```

```
    accuracies = cross_val_score(estimator = model, X = X_train, y = y_train, cv = 10, verbose = 2)
```

```
    return accuracies.mean()
```

```
def confusion_matrix(X_train, y_train, model):
```

```
    from sklearn.model_selection import cross_val_predict
```

```
    from sklearn.metrics import accuracy_score
```

```
    from sklearn.metrics import precision_score, recall_score
```

```
    from sklearn.metrics import f1_score, roc_auc_score, roc_curve
```

```
    import math
```



```

## confusion metrix

from sklearn.metrics import confusion_matrix

y_pred = cross_val_predict(model, X_train, y_train, cv=3)

conf_mat = confusion_matrix(y_train, y_pred)

true_positive = conf_mat[1,1]

true_negative = conf_mat[0,0]

false_positive = conf_mat[0,1]

false_negative = conf_mat[1,0]

specificity = (true_negative)/(true_negative + false_positive)

gm = math.sqrt(specificity * recall_score(y_train, y_pred))

```

```

print("Accuracy = " , accuracy_score(y_train, y_pred))

print("Precision = " ,precision_score(y_train, y_pred))

print("Recall/ Sensitivity = " ,recall_score(y_train, y_pred))

print("Specificity = " ,specificity)

print("F1 Score = " ,f1_score(y_train, y_pred))

print("ROC-AUC Score = " ,roc_auc_score(y_train, y_pred))

print("G-Measure = " ,gm)

return conf_mat

```

Takes in a model, trains the model, and evaluates the model on the test set

```
def fit_and_evaluate(model):
```

```
    # Train the model
```

```
    #model.fit(X_train, y_train)
```

```
    # Make predictions and evalute
```

```
    #model_pred = model.predict(X_test)
```

```
model_acc_cross = cross_val(x_train_res, y_train_res, model)
print ("print accuracy is ",model_acc_cross)
```

```
con_matrix = confusion_matrix(x_train_res, y_train_res, model)
print ("print confusion matrix is ",con_matrix)
sns.heatmap(con_matrix,cmap="coolwarm_r", annot=True,linewidths=0.5,fmt='g')
plt.title("Confusion Matrix")
plt.xlabel("Predicted value")
plt.ylabel("Actual label")
plt.show()
```

```
# Return the performance metric
return model_acc_cross
```

```
# %% [code]
```

```
# # Logistic Regression
```

```
from sklearn.linear_model import LogisticRegression
```

```
logr = LogisticRegression()
```

```
logr_cross = fit_and_evaluate(logr)
```

```
print('Logistic Regression Performance on the test set: Cross Validation Score = %0.4f' %
logr_cross)
```

```
# %% [code]
```

```
# # K-NN
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
```

```
knn_cross = fit_and_evaluate(knn)
```

```
print('KNN Performance on the test set: Cross Validation Score = %0.4f' % knn_cross)
```

```
# %% [code]

# # Naive Bayes

from sklearn.naive_bayes import GaussianNB

naive = GaussianNB()

naive_cross = fit_and_evaluate(naive)

print('Naive Bayes Performance on the test set: Cross Validation Score = %0.4f' % naive_cross)
```

```
# %% [code]

# Random Forest Classification

from sklearn.ensemble import RandomForestClassifier

random = RandomForestClassifier(n_estimators = 10, criterion = 'entropy')

random_cross = fit_and_evaluate(random)

print('Random Forest Performance on the test set: Cross Validation Score = %0.4f' %
random_cross)
```

```
# %% [code]

# # Gradient Boosting Classification

from xgboost import XGBClassifier

gb = XGBClassifier()

gb_cross = fit_and_evaluate(gb)

print('Gradient Boosting Classification Performance on the test set: Cross Validation Score =
%0.4f' % gb_cross)
```

```
# %% [code]

# # Decision tree

from sklearn import tree

dt = tree.DecisionTreeClassifier(random_state=1)

dt_cross = fit_and_evaluate(dt)
```

```
print('Decision tree Performance on the test set: Cross Validation Score = %0.4f' % dt_cross)
```

Imputing missing values with UndersamplingTechnique

%% [code]

This Python 3 environment comes with many helpful analytics libraries installed

It is defined by the kaggle/python docker image: <https://github.com/kaggle/docker-python>

For example, here's several helpful packages to load in

```
import numpy as np # linear algebra
```

```
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

Input data files are available in the "../input/" directory.

For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

```
import os
```

```
for dirname, _, filenames in os.walk('/kaggle/input'):
```

```
    for filename in filenames:
```

```
        print(os.path.join(dirname, filename))
```

Any results you write to the current directory are saved as output.

%% [code]

Imports

Pandas and numpy for data manipulation

```
import pandas as pd
```

```
import numpy as np
```

No warnings about setting value on copy of slice

```
pd.options.mode.chained_assignment = None
```

Display up to 60 columns of a dataframe

```
pd.set_option('display.max_columns', 60)

# Matplotlib visualization
import matplotlib.pyplot as plt
%matplotlib inline

# Set default font size
plt.rcParams['font.size'] = 24

# Internal ipython tool for setting figure size
from IPython.core.pylabtools import figsize

# Seaborn for visualization
import seaborn as sns
sns.set(font_scale = 2)

# Splitting data into training and testing
from sklearn.model_selection import train_test_split

# %% [code]

# # Data Cleaning and Formatting

# # Load in the Data and Examine

# Read in credit into a dataframe
credit = pd.read_csv('../input/my-dataset/credit_train.csv')

# Display top of dataframe
credit.head()

# %% [code]
```

```
credit.shape
```

```
# %% [code]
```

```
credit.drop(labels=['Loan ID', 'Customer ID'], axis=1, inplace=True)
```

```
# These two features are only for identification.
```

```
# %% [code]
```

```
# # Data Types and Missing Values
```

```
# See the column data types and non-missing values
```

```
credit.info()
```

```
# %% [code]
```

```
# # Missing Values
```

```
# Function to calculate missing values by column
```

```
def missing_values_table(df):
```

```
    # Total missing values
```

```
    mis_val = df.isnull().sum()
```

```
    # Percentage of missing values
```

```
    mis_val_percent = 100 * df.isnull().sum() / len(df)
```

```
    # Make a table with the results
```

```
    mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)
```

```
    # Rename the columns
```

```
    mis_val_table_ren_columns = mis_val_table.rename(
```

```
        columns = {0 : 'Missing Values', 1 : '% of Total Values'})
```

```

# Sort the table by percentage of missing descending
mis_val_table_ren_columns = mis_val_table_ren_columns[
    mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(
'% of Total Values', ascending=False).round(1)

# Print some summary information
print ("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"
      "There are " + str(mis_val_table_ren_columns.shape[0]) +
      " columns that have missing values.")

# Return the dataframe with missing information
return mis_val_table_ren_columns

# %% [code]
missing_values_table(credit)

# %% [code]
credit.drop(credit.tail(514).index, inplace=True) # drop last 514 rows
missing_values_table(credit)

# %% [code]
data_without_ms = credit.dropna()

# %% [code]
data_without_ms.info()

# %% [code]
## categorical data to numerical

data_without_ms['Loan Status'] = data_without_ms['Loan Status'].map({'Fully
Paid':int('0'),'Charged Off':int('1')})

```



```
data_without_ms['Term'] = data_without_ms['Term'].map({'Short Term':int('0'),'Long Term':int('1')})
```

```
data_without_ms['Years in current job'] = data_without_ms['Years in current job'].map({'< 1 year':int('0'),'1 year':int('1'),'2 years':int('2'),'3 years':int('3'),'4 years':int('4'),'5 years':int('5'),'6 years':int('6'),'7 years':int('7'),'8 years':int('8'),'9 years':int('9'),'10+ years':int('10')})
```

```
# %% [code]
```

```
# # Encoding categorical data & Feature Scaling
```

```
# Select the categorical columns
```

```
categorical_subset = data_without_ms[['Home Ownership', 'Purpose']]
```

```
# One hot encode
```

```
categorical_subset = pd.get_dummies(categorical_subset)
```

```
# Join the dataframe in credit_train
```

```
# Make sure to use axis = 1 to perform a column bind
```

```
# First I will drop the 'old' categorical datas and after I will join the 'new' one.
```

```
data_without_ms.drop(labels=['Home Ownership', 'Purpose'], axis=1, inplace=True)
```

```
data_without_ms = pd.concat([data_without_ms, categorical_subset], axis = 1)
```

```
# %% [code]
```

```
data_without_ms.head()
```

```
# %% [code]
```

```
data_without_ms.shape
```

```
# %% [markdown]
```

```
# **Handling under sampling**
```

```

# %% [code]

from sklearn.metrics import accuracy_score

from sklearn.metrics import precision_score, recall_score

from sklearn.metrics import f1_score, roc_auc_score, roc_curve

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import confusion_matrix

import math


def generate_model_report(y_actual, y_predicted):

    conf_mat = confusion_matrix(y_actual, y_predicted)

    true_positive = conf_mat[1,1]

    true_negative = conf_mat[0,0]

    false_positive = conf_mat[0,1]

    false_negative = conf_mat[1,0]

    specificity = (true_negative)/(true_negative + false_positive)

    gm = math.sqrt(specificity * recall_score(y_actual, y_predicted))


    print("Accuracy = " , accuracy_score(y_actual, y_predicted))

    print("Precision = " ,precision_score(y_actual, y_predicted))

    print("Recall/Sensitivity = " ,recall_score(y_actual, y_predicted))

    print("Specificity = " ,specificity)

    print("F1 Score = " ,f1_score(y_actual, y_predicted))

    print("ROC-AUC Score = " ,roc_auc_score(y_actual, y_predicted))

    print("G-Measure = " ,gm)


sns.heatmap(conf_mat,cmap="coolwarm_r", annot=True,linewidths=0.5,fmt='g')

plt.title("Confusion Matrix")

plt.xlabel("Predicted value")

plt.ylabel("Actual label")

```

```
plt.show()
```

```
pass
```

```
minority_class_len = len(data_without_ms[data_without_ms['Loan Status'] == 1])
```

```
print(minority_class_len)
```

```
majority_class_indices = data_without_ms[data_without_ms['Loan Status'] == 0].index
```

```
print(majority_class_indices)
```

```
random_majority_indices = np.random.choice(majority_class_indices,
```

```
        minority_class_len,
```

```
        replace=False)
```

```
print(len(random_majority_indices))
```

```
minority_class_indices = data_without_ms[data_without_ms['Loan Status'] == 1].index
```

```
print(minority_class_indices)
```

```
under_sample_indices = np.concatenate([minority_class_indices,random_majority_indices])
```

```
#under_sample = data_without_ms.loc[under_sample_indices]
```

```
data_without_ms = data_without_ms.loc[under_sample_indices]
```

```
# %% [code]
```

```
def generate_auc_roc_curve(clf, X_test):
```

```
    y_pred_proba = clf.predict_proba(X_test)[:, 1]
```

```
    fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
```

```
    auc = roc_auc_score(Y_test, y_pred_proba)
```

```
    plt.plot(fpr,tpr,label="AUC =" +str(auc))
```

```
    plt.legend(loc=4)
```

```
plt.show()
```

```
pass
```

```
# %% [code]
```

```
print("logistic regression")
```

```
X = data_without_ms.loc[:, data_without_ms.columns!='Loan Status']
```

```
Y = data_without_ms.loc[:, data_without_ms.columns=='Loan Status']
```

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

```
clf = LogisticRegression().fit(X_train, Y_train)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
print("KNN")
```

```
clf = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2).fit(X_train, Y_train)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
from sklearn import tree
```

```
print("Decision Tree")
```

```
clf = tree.DecisionTreeClassifier(random_state=1).fit(X_train, Y_train)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
print("Naive bayes")
```

```
from sklearn.naive_bayes import GaussianNB
```

```
clf = GaussianNB().fit(X_train, Y_train)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
print("Random forest")
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
clf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy').fit(X_train, Y_train)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [code]
```

```
print("XGBoost")
```

```
from xgboost import XGBClassifier
```

```
clf = XGBClassifier().fit(X_train, Y_train)
```

```
Y_Test_Pred = clf.predict(X_test)
```

```
generate_model_report(Y_test, Y_Test_Pred)
```

```
generate_auc_roc_curve(clf, X_test)
```

```
# %% [markdown]
```

```
# # k-fold
```

```
# %% [code]
```

```
# # Split Into Training and Testing Sets
```

```
# Separate out the features and targets
```

```
features = data_without_ms.drop(columns='Loan Status')
```

```
targets = pd.DataFrame(data_without_ms['Loan Status'])
```

```
# Split into 80% training and 20% testing set
```

```
X_train, X_test, y_train, y_test = train_test_split(features, targets, test_size = 0.2, random_state = 16)
```

```
print(X_train.shape)
```

```
print(X_test.shape)
```

```
print(y_train.shape)
```

```
print(y_test.shape)
```

```
# %% [code]
```

```
# # Feature Scaling
```

```
from sklearn.preprocessing import StandardScaler
```

```

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Encoding the Dependent Variable
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
labelencoder_y_train = LabelEncoder()
y_train = labelencoder_y_train.fit_transform(y_train)
labelencoder_y_test = LabelEncoder()
y_test = labelencoder_y_test.fit_transform(y_test)

# %% [code]

# # # Models to Evaluate

# We will compare five different machine learning Classification models:

# 1 - Logistic Regression
# 2 - K-Nearest Neighbors Classification
# 3 - Support Vector Machine
# 4 - Naive Bayes
# 5 - Random Forest Classification

# Function to calculate mean absolute error
def cross_val(X_train, y_train, model):
    # Applying k-Fold Cross Validation
    from sklearn.model_selection import cross_val_score

    accuracies = cross_val_score(estimator = model, X = X_train, y = y_train, cv = 10, verbose = 2)
    return accuracies.mean()

```

```

def confusion_metrix(X_train, y_train, model):

    from sklearn.model_selection import cross_val_predict
    from sklearn.metrics import accuracy_score
    from sklearn.metrics import precision_score, recall_score
    from sklearn.metrics import f1_score, roc_auc_score, roc_curve
    import math

    ## confusion metrix

    from sklearn.metrics import confusion_matrix

    y_pred = cross_val_predict(model, X_train, y_train, cv=3)
    conf_mat = confusion_matrix(y_train, y_pred)
    true_positive = conf_mat[1,1]
    true_negative = conf_mat[0,0]
    false_positive = conf_mat[0,1]
    false_negative = conf_mat[1,0]
    specificity = (true_negative)/(true_negative + false_positive)
    gm = math.sqrt(specificity * recall_score(y_train, y_pred))

    print("Accuracy = " , accuracy_score(y_train, y_pred))
    print("Precision = " ,precision_score(y_train, y_pred))
    print("Recall/ Sensitivity = " ,recall_score(y_train, y_pred))
    print("Specificity = " ,specificity)
    print("F1 Score = " ,f1_score(y_train, y_pred))
    print("ROC-AUC Score = " ,roc_auc_score(y_train, y_pred))
    print("G-Measure = " ,gm)
    return conf_mat

```



```

# Takes in a model, trains the model, and evaluates the model on the test set
def fit_and_evaluate(model):

    # Train the model
    #model.fit(X_train, y_train)

    # Make predictions and evalute
    #model_pred = model.predict(X_test)
    model_acc_cross = cross_val(X_train, y_train, model)
    print ("print accuracy is ",model_acc_cross)

    con_matrix = confusion_metrix(X_train, y_train, model)
    print ("print confusion metrix is ",con_matrix)
    sns.heatmap(con_matrix,cmap="coolwarm_r", annot=True,linewidths=0.5,fmt='g')
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted value")
    plt.ylabel("Actual label")
    plt.show()

    # Return the performance metric
    return model_acc_cross

# %% [code]
# Matplotlib visualization
import matplotlib.pyplot as plt
%matplotlib inline

# Set default font size
plt.rcParams['font.size'] = 24

```

```
# Internal ipython tool for setting figure size
```

```
from IPython.core.pylabtools import figsize
```

```
# Seaborn for visualization
```

```
import seaborn as sns
```

```
sns.set(font_scale = 2)
```

```
# Splitting data into training and testing
```

```
from sklearn.model_selection import train_test_split
```

```
# %% [code]
```

```
# # Decision tree
```

```
from sklearn import tree
```

```
dt = tree.DecisionTreeClassifier(random_state=1)
```

```
dt_cross = fit_and_evaluate(dt)
```

```
print('Decision tree Performance on the test set: Cross Validation Score = %0.4f' % dt_cross)
```

```
# %% [code]
```

```
# # K-NN
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
```

```
knn_cross = fit_and_evaluate(knn)
```

```
print('KNN Performance on the test set: Cross Validation Score = %0.4f' % knn_cross)
```

```
# %% [code]
```

```
# # K-NN
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier(n_neighbors = 1, metric = 'minkowski', p = 2)
```

```
knn_cross = fit_and_evaluate(knn)
```

```
print('KNN Performance on the test set: Cross Validation Score = %0.4f' % knn_cross)
```

```
# %% [code]
```

```
# # K-NN
```

```
# used eclbian distance
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier(n_neighbors = 4, metric = 'minkowski', p = 2)
```

```
knn_cross = fit_and_evaluate(knn)
```

```
print('KNN Performance on the test set: Cross Validation Score = %0.4f' % knn_cross)
```

```
# %% [code]
```

```
# # Logistic Regression
```

```
from sklearn.linear_model import LogisticRegression
```

```
logr = LogisticRegression()
```

```
logr_cross = fit_and_evaluate(logr)
```

```
print('Logistic Regression Performance on the test set: Cross Validation Score = %0.4f' %  
logr_cross)
```

```
# %% [code]
```

```
# # Random Forest Classification
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
random = RandomForestClassifier(n_estimators = 10, criterion = 'entropy')
```

```
random_cross = fit_and_evaluate(random)
```

```
print('Random Forest Performance on the test set: Cross Validation Score = %0.4f' %  
random_cross)
```

```
# %% [code]
```

```
# # Gradiante Boosting Classification
```

```
from xgboost import XGBClassifier

gb = XGBClassifier()

gb_cross = fit_and_evaluate(gb)

print('Gradiente Boosting Classification Performance on the test set: Cross Validation Score =
%0.4f' % gb_cross)

# %% [code]

# # Naive Bayes

from sklearn.naive_bayes import GaussianNB

naive = GaussianNB()

naive_cross = fit_and_evaluate(naive)

print('Naive Bayes Performance on the test set: Cross Validation Score = %0.4f' % naive_cross)
```