Final_Project_Code

December 6, 2022

1 Import the Dataset

[1]:
```
import pandas as pd
df=pd.read_csv("https://raw.githubusercontent.com/MaramShriem/
↪-Marketing-Dataset/main/bank-full.csv",sep=';')
df.to_csv(r'TDMaketing.csv', index = False)#to save the dataset as CSV
```

2 EDA

Dataset Description

[ ]:
```
df.describe(include='all')
```

[ ]:
```
                 age          job  marital  education default        balance  \
count   45211.000000        45211    45211      45211   45211   45211.000000
unique           NaN           12        3          4       2            NaN
top              NaN  blue-collar  married  secondary      no            NaN
freq             NaN         9732    27214      23202   44396            NaN
mean       40.936210          NaN      NaN        NaN     NaN    1362.272058
std        10.618762          NaN      NaN        NaN     NaN    3044.765829
min        18.000000          NaN      NaN        NaN     NaN   -8019.000000
25%        33.000000          NaN      NaN        NaN     NaN      72.000000
50%        39.000000          NaN      NaN        NaN     NaN     448.000000
75%        48.000000          NaN      NaN        NaN     NaN    1428.000000
max        95.000000          NaN      NaN        NaN     NaN  102127.000000

       housing   loan   contact           day  month      duration  \
count    45211  45211     45211  45211.000000  45211  45211.000000
unique       2      2         3           NaN     12           NaN
top        yes     no  cellular           NaN    may           NaN
freq     25130  37967     29285           NaN  13766           NaN
mean       NaN    NaN       NaN     15.806419    NaN    258.163080
std        NaN    NaN       NaN      8.322476    NaN    257.527812
min        NaN    NaN       NaN      1.000000    NaN      0.000000
25%        NaN    NaN       NaN      8.000000    NaN    103.000000
```

```
50%      NaN   NaN       NaN    16.000000   NaN    180.000000
75%      NaN   NaN       NaN    21.000000   NaN    319.000000
max      NaN   NaN       NaN    31.000000   NaN   4918.000000

            campaign         pdays      previous poutcome      y
count   45211.000000  45211.000000  45211.000000    45211  45211
unique           NaN           NaN           NaN        4      2
top              NaN           NaN           NaN  unknown     no
freq             NaN           NaN           NaN    36959  39922
mean        2.763841     40.197828      0.580323      NaN    NaN
std         3.098021    100.128746      2.303441      NaN    NaN
min         1.000000     -1.000000      0.000000      NaN    NaN
25%         1.000000     -1.000000      0.000000      NaN    NaN
50%         2.000000     -1.000000      0.000000      NaN    NaN
75%         3.000000     -1.000000      0.000000      NaN    NaN
max        63.000000    871.000000    275.000000      NaN    NaN
```

[ ]:
```
df.shape[1]
```

[ ]:
```
17
```

[ ]:
```
df.head()
```

[ ]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no

   contact  day month  duration  campaign  pdays  previous poutcome   y
0  unknown    5   may       261         1     -1         0  unknown  no
1  unknown    5   may       151         1     -1         0  unknown  no
2  unknown    5   may        76         1     -1         0  unknown  no
3  unknown    5   may        92         1     -1         0  unknown  no
4  unknown    5   may       198         1     -1         0  unknown  no
```

Check the datatypes of the attributes

[ ]:
```
print(df.dtypes)
```

```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
```

```
loan          object
contact       object
day            int64
month         object
duration       int64
campaign       int64
pdays          int64
previous       int64
poutcome      object
y             object
dtype: object
```

Checking the missing values

```
[ ]: df.isnull().sum()
     #the answer is No
```

```
[ ]: age          0
     job          0
     marital      0
     education    0
     default      0
     balance      0
     housing      0
     loan         0
     contact      0
     day          0
     month        0
     duration     0
     campaign     0
     pdays        0
     previous     0
     poutcome     0
     y            0
     dtype: int64
```

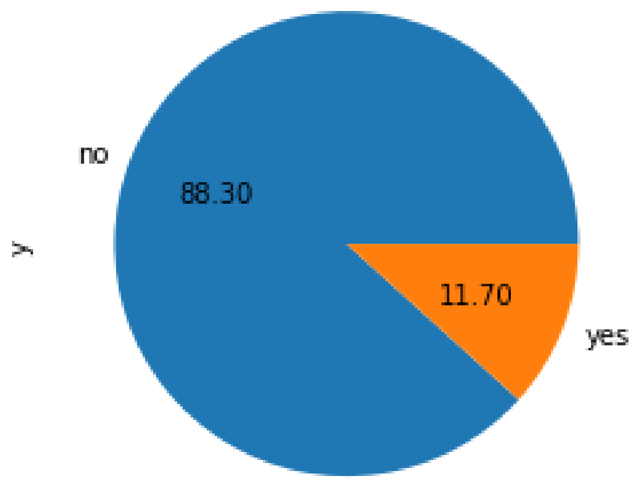
Check if the data is balanced or Imbalanced

```
[ ]: x=df.drop(["y"],axis=1)
     y=df["y"]
     print(y.value_counts())
```

```
no     39922
yes     5289
Name: y, dtype: int64
```

```
[ ]: y.value_counts().plot.pie(autopct="%0.2f")
     #we have only 11.7% of the yes class in the dataset; that means the data in␣
     ↪Imbalanced.
```

[ ]: <AxesSubplot: ylabel='y'>

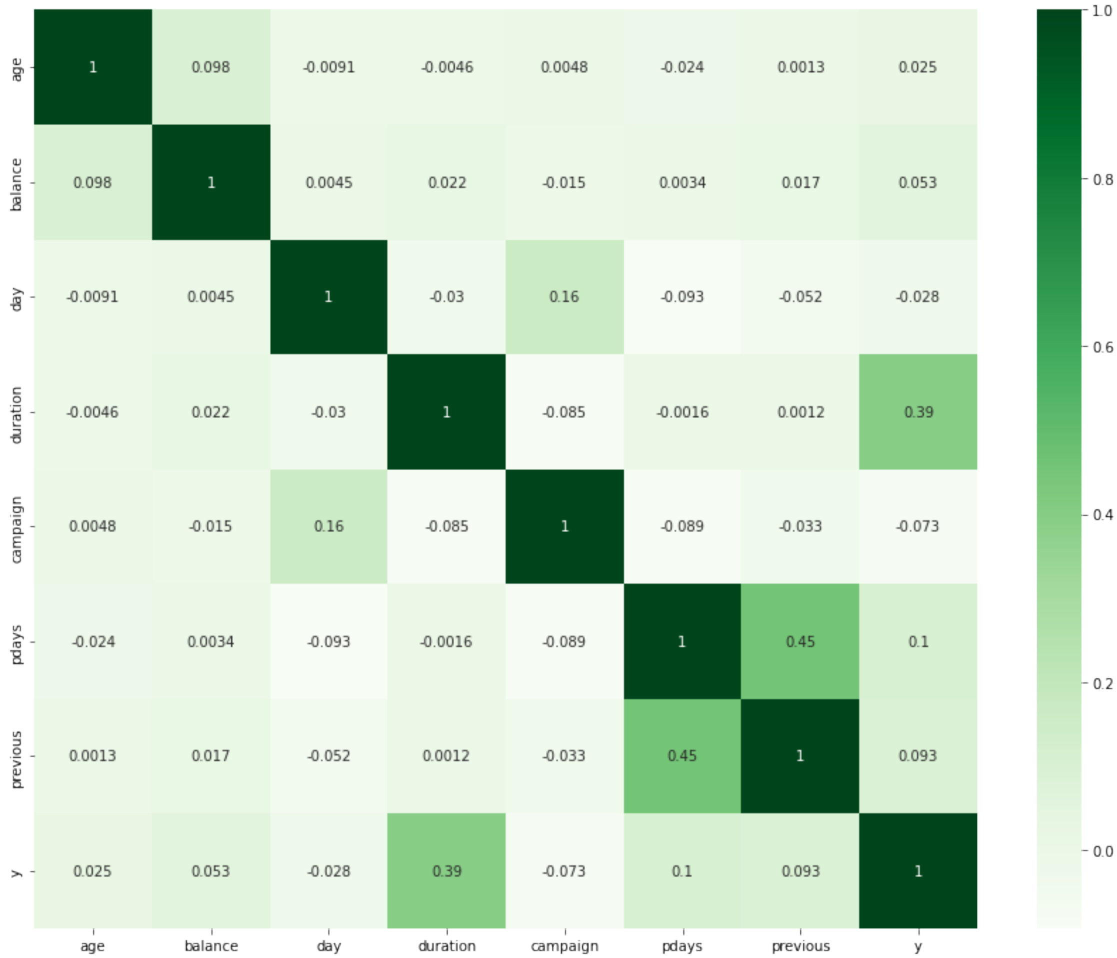


Plot the correlation between numerical variables

[ ]:
```
df['y'].replace({'no':0, 'yes':1}, inplace=True)
df.corr()
```

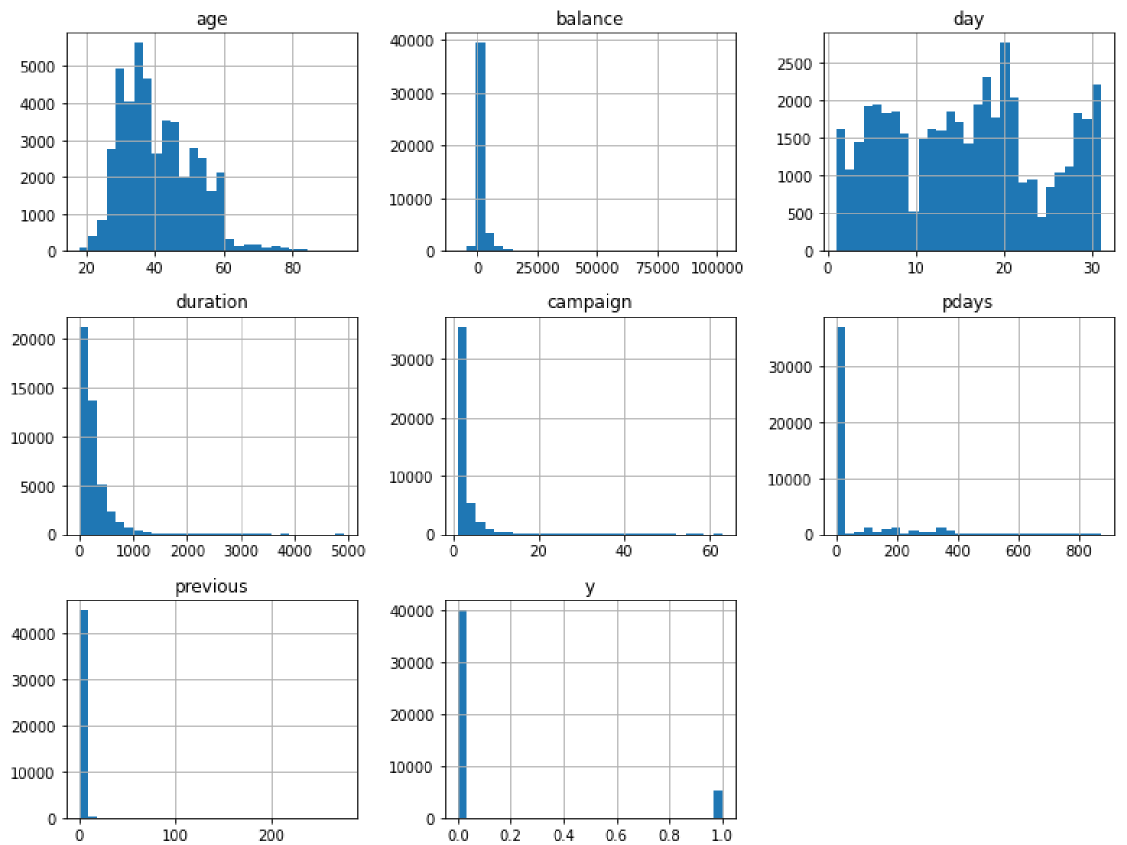
[ ]:
```
               age   balance       day  duration  campaign     pdays  \
age       1.000000  0.097783 -0.009120 -0.004648  0.004760 -0.023758
balance   0.097783  1.000000  0.004503  0.021560 -0.014578  0.003435
day      -0.009120  0.004503  1.000000 -0.030206  0.162490 -0.093044
duration -0.004648  0.021560 -0.030206  1.000000 -0.084570 -0.001565
campaign  0.004760 -0.014578  0.162490 -0.084570  1.000000 -0.088628
pdays    -0.023758  0.003435 -0.093044 -0.001565 -0.088628  1.000000
previous  0.001288  0.016674 -0.051710  0.001203 -0.032855  0.454820
y         0.025155  0.052838 -0.028348  0.394521 -0.073172  0.103621

          previous         y
age       0.001288  0.025155
balance   0.016674  0.052838
day      -0.051710 -0.028348
duration  0.001203  0.394521
campaign -0.032855 -0.073172
pdays     0.454820  0.103621
previous  1.000000  0.093236
y         0.093236  1.000000
```

```
[ ]: import matplotlib.pyplot as plt
     import seaborn as sns
     plt.figure(figsize = (15, 12))
     cor = df.corr()
     sns.heatmap(cor, annot = True, cmap = plt.cm.Greens)
     plt.show()
```



Histograms for numerical variables

```
[ ]: axList = df.hist(bins=29,figsize = (13, 10))
     plt.savefig("Hist.png")
```



Correlation for categorical data

[ ]:
```
!pip install dython
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: dython in /usr/local/lib/python3.8/dist-packages
(0.7.2)
Requirement already satisfied: seaborn>=0.11.0 in /usr/local/lib/python3.8/dist-
packages (from dython) (0.11.2)
Requirement already satisfied: scikit-plot>=0.3.7 in
/usr/local/lib/python3.8/dist-packages (from dython) (0.3.7)
Requirement already satisfied: scipy>=1.7.1 in /usr/local/lib/python3.8/dist-
packages (from dython) (1.7.3)
Requirement already satisfied: psutil>=5.9.1 in /usr/local/lib/python3.8/dist-
packages (from dython) (5.9.4)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.8/dist-
packages (from dython) (1.21.6)
Requirement already satisfied: matplotlib>=3.4.3 in
/usr/local/lib/python3.8/dist-packages (from dython) (3.6.2)
Requirement already satisfied: scikit-learn>=0.24.2 in
```

```
/usr/local/lib/python3.8/dist-packages (from dython) (1.1.3)
Requirement already satisfied: pandas>=1.3.2 in /usr/local/lib/python3.8/dist-
packages (from dython) (1.3.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib>=3.4.3->dython) (21.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (1.4.4)
Requirement already satisfied: pyparsing>=2.2.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (3.0.9)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib>=3.4.3->dython) (7.1.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (1.0.6)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (2.8.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
packages (from matplotlib>=3.4.3->dython) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (4.38.0)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-
packages (from pandas>=1.3.2->dython) (2022.6)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.7->matplotlib>=3.4.3->dython) (1.15.0)
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.8/dist-
packages (from scikit-learn>=0.24.2->dython) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.24.2->dython)
(3.1.0)
```

[ ]:
```
! pip install -U Imbalanced-learn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: Imbalanced-learn in
/usr/local/lib/python3.8/dist-packages (0.9.1)
Requirement already satisfied: scikit-learn>=1.1.0 in
/usr/local/lib/python3.8/dist-packages (from Imbalanced-learn) (1.1.3)
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.8/dist-
packages (from Imbalanced-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from Imbalanced-learn) (3.1.0)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.8/dist-
packages (from Imbalanced-learn) (1.7.3)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.8/dist-
packages (from Imbalanced-learn) (1.21.6)
```

```
[ ]: !pip install matplotlib>=3.4.3
     !pip install dython
     import pandas as pd
     df=pd.read_csv("https://raw.githubusercontent.com/MaramShriem/
      ↪-Marketing-Dataset/main/bank-full.csv",sep=';')
     df.to_csv(r'TDMaketing.csv', index = False)

     from dython.nominal import associations
     selected_column=␣
      ↪df[["job","housing","marital","loan","default","education","contact","month","poutcome","y"
     categorical_df = selected_column.copy()
     categorical_correlation= associations(categorical_df, filename=␣
      ↪'categorical_correlation.png', figsize=(12,12))
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: dython in /usr/local/lib/python3.8/dist-packages
(0.7.2)
Requirement already satisfied: matplotlib>=3.4.3 in
/usr/local/lib/python3.8/dist-packages (from dython) (3.6.2)
Requirement already satisfied: psutil>=5.9.1 in /usr/local/lib/python3.8/dist-
packages (from dython) (5.9.4)
Requirement already satisfied: scikit-learn>=0.24.2 in
/usr/local/lib/python3.8/dist-packages (from dython) (1.1.3)
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packages (from dython) (1.3.5)
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packages (from dython) (0.11.2)
Requirement already satisfied: scipy>=1.7.1 in /usr/local/lib/python3.8/dist-
packages (from dython) (1.7.3)
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/usr/local/lib/python3.8/dist-packages (from dython) (0.3.7)
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packages (from dython) (1.21.6)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib>=3.4.3->dython) (7.1.2)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (4.38.0)
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packages (from matplotlib>=3.4.3->dython) (21.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
packages (from matplotlib>=3.4.3->dython) (0.11.0)
Requirement already satisfied: pyparsing>=2.2.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (3.0.9)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (1.0.6)
Requirement already satisfied: kiwisolver>=1.0.1 in
```
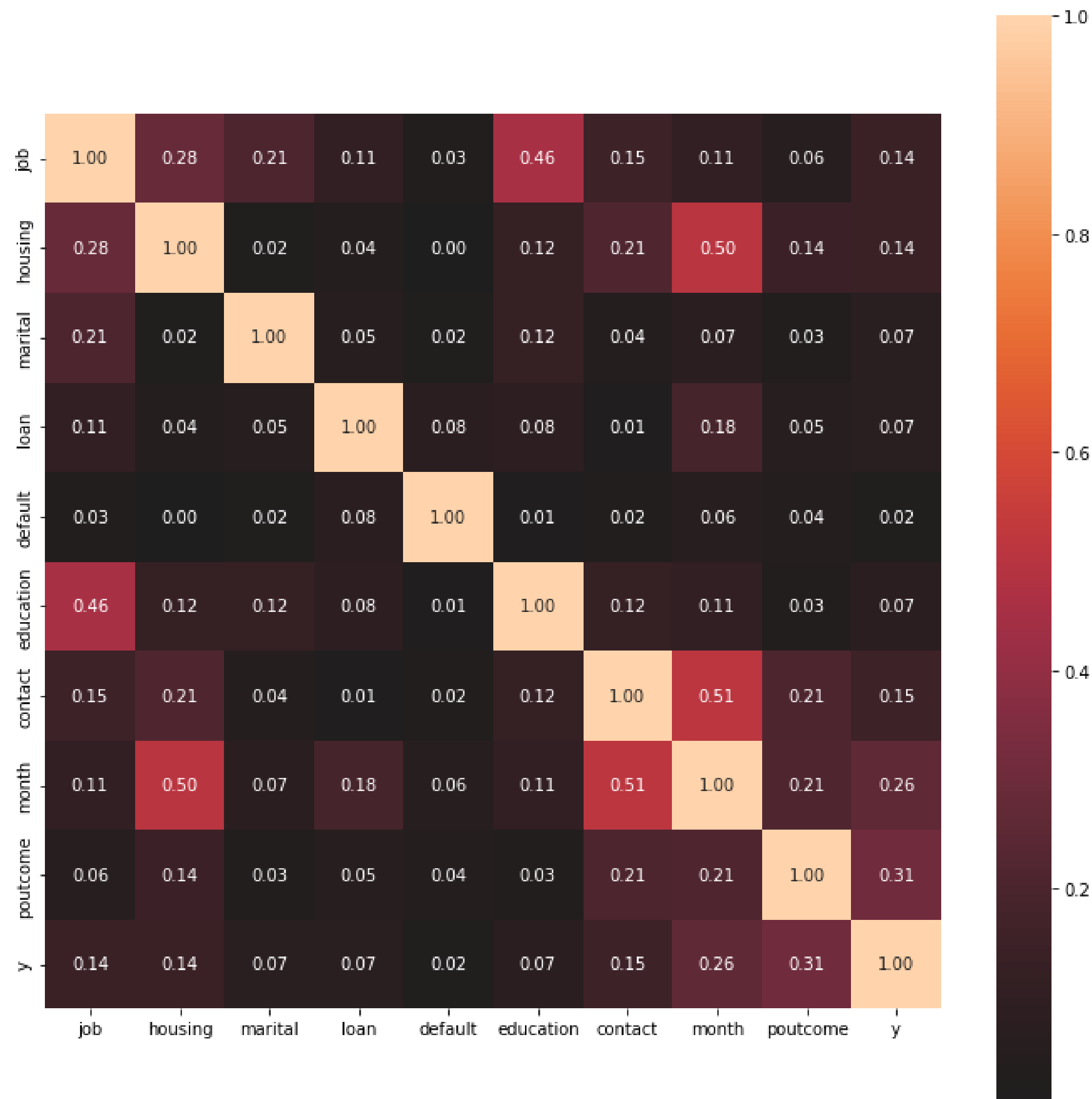

```
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (1.4.4)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.8/dist-packages (from matplotlib>=3.4.3->dython) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-
packages (from pandas>=1.3.2->dython) (2022.6)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.7->matplotlib>=3.4.3->dython) (1.15.0)
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.8/dist-
packages (from scikit-learn>=0.24.2->dython) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.24.2->dython)
(3.1.0)
```



3 Data Preprocessing:

[2]:
```
dff=df.copy()
```

[3]:
```
#Normalize the numeric variables: this is step is important specially when we␣
↪want to build the logistic regression model
#as the numeric variables are not normalliy distriputed and the LG requaired a␣
↪normalized dataset
from sklearn.preprocessing import MinMaxScaler
from sklearn import preprocessing

for column in dff.columns:
    if dff[column].dtype in ['int64', 'float64']:
        X = dff[column].array.reshape(-1,1)
        #build the scaler model
        scaler = MinMaxScaler()

        # fit using the whole dataset
        scaler.fit(X)

        dff[column]=scaler.transform(dff[column].array.reshape(-1, 1)) # Apply␣
↪to to the dataset
display(dff)
```

```
            age            job   marital  education default   balance housing  \
0      0.519481     management   married   tertiary      no  0.092259     yes
1      0.337662     technician    single  secondary      no  0.073067     yes
2      0.194805   entrepreneur   married  secondary      no  0.072822     yes
3      0.376623    blue-collar   married    unknown      no  0.086476     yes
4      0.194805        unknown    single    unknown      no  0.072812      no
...         ...            ...       ...        ...     ...       ...     ...
45206  0.428571     technician   married   tertiary      no  0.080293      no
45207  0.688312        retired  divorced    primary      no  0.088501      no
45208  0.701299        retired   married  secondary      no  0.124689      no
45209  0.506494    blue-collar   married  secondary      no  0.078868      no
45210  0.246753   entrepreneur   married  secondary      no  0.099777      no

      loan   contact       day month  duration  campaign     pdays  previous  \
0       no   unknown  0.133333   may  0.053070  0.000000  0.000000  0.000000
1       no   unknown  0.133333   may  0.030704  0.000000  0.000000  0.000000
2      yes   unknown  0.133333   may  0.015453  0.000000  0.000000  0.000000
3       no   unknown  0.133333   may  0.018707  0.000000  0.000000  0.000000
4       no   unknown  0.133333   may  0.040260  0.000000  0.000000  0.000000
...    ...       ...       ...   ...       ...       ...       ...       ...
45206   no  cellular  0.533333   nov  0.198658  0.032258  0.000000  0.000000
45207   no  cellular  0.533333   nov  0.092721  0.016129  0.000000  0.000000
45208   no  cellular  0.533333   nov  0.229158  0.064516  0.212156  0.010909
```

```
45209   no  telephone  0.533333   nov  0.103294  0.048387  0.000000  0.000000
45210   no   cellular  0.533333   nov  0.073404  0.016129  0.216743  0.040000

      poutcome    y
0      unknown   no
1      unknown   no
2      unknown   no
3      unknown   no
4      unknown   no
...        ...  ...
45206  unknown  yes
45207  unknown  yes
45208  success  yes
45209  unknown   no
45210    other   no

[45211 rows x 17 columns]
```

[4]:
```
#from sklearn import preprocessing
#d = preprocessing.normalize(dff.select_dtypes('int64'))
#names=dff.select_dtypes('int64').columns
#scaled_df = pd.DataFrame(d, columns=names)
#scaled_df
```

label encoder for variable: y

[5]:
```
le = preprocessing.LabelEncoder()
le.fit(dff["y"])
list(le.classes_)
dff["y"]=le.transform(dff["y"])
# we converted the dpendent varaiable to be 0,1 where 0 is for "no" and 1 is␣
↪for "yes" which is the desired output
```

Get dummies

[6]:
```
#get dummies for the rest of categorical variables:
df_cat = dff.select_dtypes('object')
dff = pd.get_dummies(dff, df_cat.columns, drop_first = False)
dff.info()
# we got 52 coulmns (variables)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 52 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  45211 non-null  float64
 1   balance              45211 non-null  float64
```

```
2   day                  45211 non-null  float64
3   duration             45211 non-null  float64
4   campaign             45211 non-null  float64
5   pdays                45211 non-null  float64
6   previous             45211 non-null  float64
7   y                    45211 non-null  int64
8   job_admin.           45211 non-null  uint8
9   job_blue-collar      45211 non-null  uint8
10  job_entrepreneur     45211 non-null  uint8
11  job_housemaid        45211 non-null  uint8
12  job_management       45211 non-null  uint8
13  job_retired          45211 non-null  uint8
14  job_self-employed    45211 non-null  uint8
15  job_services         45211 non-null  uint8
16  job_student          45211 non-null  uint8
17  job_technician       45211 non-null  uint8
18  job_unemployed       45211 non-null  uint8
19  job_unknown          45211 non-null  uint8
20  marital_divorced     45211 non-null  uint8
21  marital_married      45211 non-null  uint8
22  marital_single       45211 non-null  uint8
23  education_primary    45211 non-null  uint8
24  education_secondary  45211 non-null  uint8
25  education_tertiary   45211 non-null  uint8
26  education_unknown    45211 non-null  uint8
27  default_no           45211 non-null  uint8
28  default_yes          45211 non-null  uint8
29  housing_no           45211 non-null  uint8
30  housing_yes          45211 non-null  uint8
31  loan_no              45211 non-null  uint8
32  loan_yes             45211 non-null  uint8
33  contact_cellular     45211 non-null  uint8
34  contact_telephone    45211 non-null  uint8
35  contact_unknown      45211 non-null  uint8
36  month_apr            45211 non-null  uint8
37  month_aug            45211 non-null  uint8
38  month_dec            45211 non-null  uint8
39  month_feb            45211 non-null  uint8
40  month_jan            45211 non-null  uint8
41  month_jul            45211 non-null  uint8
42  month_jun            45211 non-null  uint8
43  month_mar            45211 non-null  uint8
44  month_may            45211 non-null  uint8
45  month_nov            45211 non-null  uint8
46  month_oct            45211 non-null  uint8
47  month_sep            45211 non-null  uint8
48  poutcome_failure     45211 non-null  uint8
49  poutcome_other       45211 non-null  uint8
```

```
 50  poutcome_success     45211 non-null  uint8
 51  poutcome_unknown     45211 non-null  uint8
dtypes: float64(7), int64(1), uint8(44)
memory usage: 4.7 MB
```

4 Split the Data

[12]:
```python
#The split technique that have been chosen  is  holdout split (Test set is 33.
 ↪3% and Training set is 66.7%)
#as this is the most popular way to use, only needs to be run once so has lower␣
 ↪computational costs.
#Many of the researchers on similar topic used this technique and ratio
#Since this method might lead to an overfitting after oversampling technique or␣
 ↪underfitting after undersampling technique.
#The performance will be checked again and average will be taken, after appling␣
 ↪oversampling/undersampling and cross validation

import numpy as np
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test= train_test_split(dff.
 ↪drop(["y"],axis="columns"),dff.y,shuffle=True, random_state=5,test_size=.333)
```

[13]:
```python
len(x_train)#number or rows in train set
```

[13]: 30155

[14]:
```python
len(x_test)#number or rows in test set
```

[14]: 15056

Convert the y variable in the train and test set to flattened array(1D array with all the input-array elements and with the same type as it).

[15]:
```python
y_train = y_train.ravel()
y_test = y_test.ravel()
```

5 Modles Building

The chosen models are Random Forest, Decision Tree, and Logistic Regression. The reason behind choosing these algorithms is that they are the most popular models for a binary classification problem. As what mentioned in the literature review these models were the most common models to solve a binary classification problem on dataset similar/exact to the dataset of this project.

Random forest is the candidate to be the best model perfomance as it was the best in many reviewed related articles.

In addition to that, many studies emphasied that ensemble models perfoms better than other models.

5.1 Imbalanced Data

1. In this stage the models have been built on the Imbalanced dataset, in order to compare the performance results before and after balancing the data. later in this script, an application on over sampling (SMOTE) and undersamping techniques (Random Under Sampling) will be applied and compared.
2. The models have been tuned based on some parameters: A. Random Forest tuned parameters are: Max depth and the n_estimators (number of trees) B. Decision Tree tuned parameters are: Max depth
3. We focused on optimizing F1-Score metric as it was the smallest value in the confusion matrix in the first run time. please note that the tuning process also have been applied to optimize the Accuracy and the AUROC but it didnt improve as expected also it led to a decrease in the MCC while improving the F1-score led to an improvement in MCC.

5.1.1 Random Forest Hyperparameter Tuning (based on max depth, number of trees and F1-Score)

[ ]:
```
'''Grid search (GridSearchCV) is arguably the most basic hyperparameter tuning␣
↪method. With this technique,
we simply build a model for each possible combination of all of the␣
↪hyperparameter values provided,
evaluating each model, and selecting the architecture which produces the best␣
↪results.

For more information about GridSearchCV: https://scikit-learn.org/stable/
↪modules/generated/sklearn.model_selection.GridSearchCV.html'''
```

[ ]:
```
'Grid search (GridSearchCV) is arguably the most basic hyperparameter tuning
method. With this technique, \nwe simply build a model for each possible
combination of all of the hyperparameter values provided, \nevaluating each
model, and selecting the architecture which produces the best results.\n\nFor
more information about GridSearchCV: https://scikit-
learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html'
```

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(random_state=1)
```

[ ]:
```
#This step has been run repeatedly on different ranges of the model parameters␣
↪in order to tune them on the right values.
import numpy as np
from sklearn.model_selection import GridSearchCV
```

```
max_depth_range=np.arange(25,30,1)
n_estimators_range=np.arange(130,180,30)
param_grid=dict(max_depth=max_depth_range,n_estimators=n_estimators_range)
Urfgrid=GridSearchCV(estimator=rf,param_grid=param_grid,scoring="f1",cv=3,n_jobs=-1)
```

[ ]:
```
Urfgrid.fit(x_train,y_train)
```

[ ]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=1), n_jobs=-1,
             param_grid={'max_depth': array([25, 26, 27, 28, 29]),
                         'n_estimators': array([130, 160])},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (Urfgrid.
 ↪best_params_,Urfgrid.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_depth': 29, 'n_estimators': 130} with a score of
0.47
```

[ ]:
```
#data frame of grid search parameters and their F1 Scores scores
import pandas as pd

grid_results = pd.concat([pd.DataFrame(Urfgrid.cv_results_["params"]),
                          pd.DataFrame(Urfgrid.cv_results_["mean_test_score"],␣
 ↪columns=["f1"])],axis=1)
grid_results.head()

#preparing data for making  contour plots
grid_contour = grid_results.groupby(['max_depth','n_estimators']).mean()
grid_contour

#pivot data:
grid_reset=grid_contour.reset_index()
grid_reset.columns=["max_depth","n_estimator","f1"]
grid_pivot=grid_reset.pivot("max_depth","n_estimator")

#assigning the pivoted data into the respective x,y, and z variables
x=grid_pivot.columns.levels[1].values
y=grid_pivot.index.values
z=grid_pivot.values

#2D contour plot
import plotly.graph_objects as go

# X and Y axes labels
```

```
layout = go.Layout(
            xaxis=go.layout.XAxis(
              title=go.layout.xaxis.Title(
              text='n_estimators')
             ),
             yaxis=go.layout.YAxis(
              title=go.layout.yaxis.Title(
              text='max_depth')
            ) )

fig = go.Figure(data = [go.Contour(z=z, x=x, y=y)], layout=layout )

fig.update_layout(title='Imbalanced- Random Forest Hyperparameter tuning',␣
 ↪autosize=False,
                  width=500, height=500,
                  margin=dict(l=65, r=50, b=65, t=90))

fig.show()
```

5.1.2 Decision Tree Hyperparameter Tuning (based on max depth and F1-Score)

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(random_state=1)
```

[ ]:
```
#This step has been run repeatedly on different ranges of the model parameters␣
 ↪in order to tune them on the right values.
import numpy as np
from sklearn.model_selection import GridSearchCV

max_depth_range=np.arange(1,10,1)
param_grid=dict(max_depth=max_depth_range)
Udtgrid=GridSearchCV(estimator=dt,param_grid=param_grid,scoring="f1",cv=10,n_jobs=-1)
```

[ ]:
```
Udtgrid.fit(x_train,y_train)
```

[ ]:
```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random_state=1), n_jobs=-1,
             param_grid={'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (Udtgrid.
 ↪best_params_,Udtgrid.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_depth': 9} with a score of 0.48
```

5.1.3 Logistic Regression Hyperparameter Tuning (based on Max Iteration, Solver and F1-Score)

[ ]:
```
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression(random_state=1,n_jobs=-1)
```

[ ]:
```
#This step has been run repeatedly on different ranges of the model parameters␣
↪in order to tune them on the right values.
import numpy as np
from sklearn.model_selection import GridSearchCV

max_iter=np.arange(100,1000,100)

param_grid=dict(max_iter=max_iter,solver=['liblinear', 'lbfgs'])
Ulgrgrid=GridSearchCV(estimator=lgr,param_grid=param_grid,scoring="f1",cv=3,n_jobs=-1)
# -1 means using all processors. This means that the n_jobs parameter can be␣
↪used to distribute and exploit all the CPUs available in the local computer
```

[ ]:
```
Ulgrgrid.fit(x_train,y_train)
```

[ ]:
```
GridSearchCV(cv=3, estimator=LogisticRegression(n_jobs=-1, random_state=1),
             n_jobs=-1,
             param_grid={'max_iter': array([100, 200, 300, 400, 500, 600, 700,
800, 900]),
                         'solver': ['liblinear', 'lbfgs']},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (Ulgrgrid.
↪best_params_,Ulgrgrid.best_score_))#Mean cross-validated score of the␣
↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_iter': 100, 'solver': 'lbfgs'} with a score of
0.42
```

5.1.4 1. Imbalanced-Train the model and calculate the run time of training the model

[19]:
```
#From the above we can conclude that the best parameters are:

#Random Forest:
U_RF_max_depth= 29 #Is the max depth for each tree in the random forest
U_RF_n_estimators= 130 #Is the number of trees in the random forest

# Decision Tree:
U_DT_max_depth=9  #Is the max depth for the tree
```

```
#Logistic Regression:
U_lgr_max_iter=100 # max_iter is the maximum number of iterations taken for the␣
↪solvers to converge.

U_lgr_solver="lbfgs" #Solver: is the algorithm to use in the optimization␣
↪problem

#These values may differ slightly on each run for tunning.
#Please note that I have saved the parameters values (after tuning) of each␣
↪model in the above variables in order to make the run time shorter everytime␣
↪we need to train the model.
```

[20]:
```
#Random Forest Training
np.random.seed(1)
import time
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=U_RF_n_estimators, max_depth=␣
↪U_RF_max_depth,random_state=1)

startrf=time.time()
rf.fit(x_train,y_train)
endrf=time.time()

#Decision Tree Training
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(max_depth=U_DT_max_depth,random_state=1)

startdt=time.time()
dt.fit(x_train,y_train)
enddt=time.time()

#Linear Regression Training
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression(max_iter=U_lgr_max_iter, solver=U_lgr_solver,n_jobs=-1)
# -1 means using all processors. This means that the n_jobs parameter can be␣
↪used to distribute and exploit all the CPUs available in the local computer
startlgr=time.time()
lgr.fit(x_train,y_train)
endlgr=time.time()

print("RF Training Run Time [s]:",endrf-startrf)
print("DT Training Run Time [s]:",enddt-startdt)
print("LGR Training Run Time [s]:",endlgr-startlgr)

# The results shows the the faster model is the Decision tree, Logistic␣
↪regression, and the Random forest respectively.
```

```
# Random Forest model was the slowest one( which is expected as it is an␣
↪ensemble model)
```

```
RF Training Run Time [s]: 4.76113748550415
DT Training Run Time [s]: 0.1609477996826172
LGR Training Run Time [s]: 0.8442420959472656
```

5.1.5 2. Imbalanced- Run Time for prediction

[21]:
```
# The run time to predict the test set in each model is:
np.random.seed(2)
#Random Forest
startrf=time.time()
y_predictedrf=rf.predict(x_test)
endrf=time.time()

#Decision Tree
startdt=time.time()
y_predicteddt=dt.predict(x_test)
enddt=time.time()

#Logistic Regression
startlgr=time.time()
y_predictedlgr=lgr.predict(x_test)
endlgr=time.time()

print("RF Run Time to Predict the testset [s]:",endrf-startrf)
print("DT Run Time to Predict the testset [s]:",enddt-startdt)
print("LGR Run Time to Predict the testset [s]:",endlgr-startlgr)

# The results shows the the faster model is the Logistic regression,Decision␣
↪tree, and the Random forest respectively.
# Random Forest model was the slowest one( which is expected as it is an␣
↪ensemble model)
```

```
RF Run Time to Predict the testset [s]: 0.3759195804595947
DT Run Time to Predict the testset [s]: 0.003934383392333984
LGR Run Time to Predict the testset [s]: 0.0027048587799072266
```

5.1.6 3. Imbalanced- Confusion Matrix

[22]:
```
from matplotlib import pyplot as plt
from sklearn.metrics import recall_score, make_scorer, confusion_matrix,␣
↪classification_report,ConfusionMatrixDisplay
import matplotlib
```

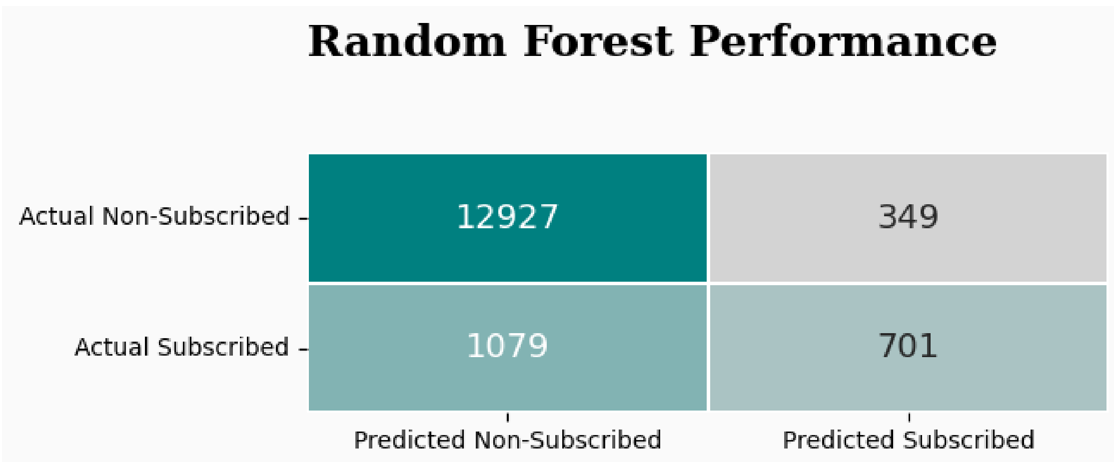
```python
import matplotlib.pyplot as plt
import seaborn as sns
class Colors:
    Gray = "#5d5d5d"
    LightGray = "#fafafa"
    Black = "#000000"
    White = "#FFFFFF"
    Teal = "#008080"
    Aquamarine = "#76c8c8"
    Blue = "#2596be"
    LightCyan = "#badbdb"
    WhiteSmoke = "#dedad2"
    Cream = "#e4bcad"
    PeachPuff = "#df979e"
    HotPink = "#d7658b"
    DeepPink = "#c80064"
    LightSeaGreen = "#20B2AA"
    DarkGray = "#464144"

#Confusion Matrix of Random Forest
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])


cmrf = confusion_matrix(y_test,y_predictedrf)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
 ↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmrf, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
 ↪Subscribed'],annot_kws={"fontsize":14})
print("Random Forest \n",classification_report(y_test, y_predictedrf))
ax0.text(0,-0.75,'Random Forest␣
 ↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')

#Confusion Matrix of Decision Tree
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmdt = confusion_matrix(y_test,y_predicteddt)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
 ↪Teal,Colors.Teal,Colors.Teal]
```

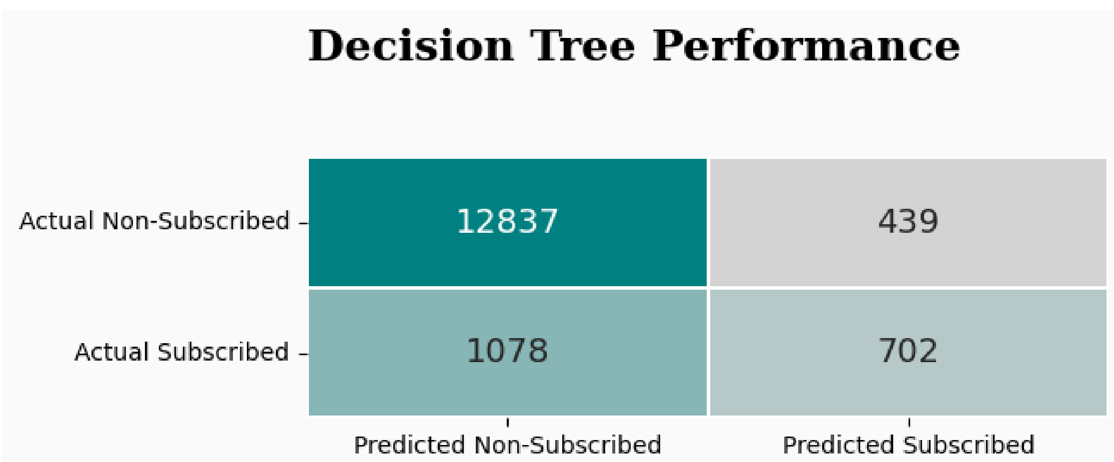
```
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmdt, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
↪Subscribed'],annot_kws={"fontsize":14})
print("Decision Tree\n",classification_report(y_test, y_predicteddt))
ax0.text(0,-0.75,'Decision Tree␣
↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')

#Confusion Matrix of Logistic Regression
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmlgr = confusion_matrix(y_test,y_predictedlgr)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmlgr, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
↪Subscribed'],annot_kws={"fontsize":14})
print("Logistic Regression\n",classification_report(y_test, y_predictedlgr))
ax0.text(0,-0.75,'Logistic Regression␣
↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')
```

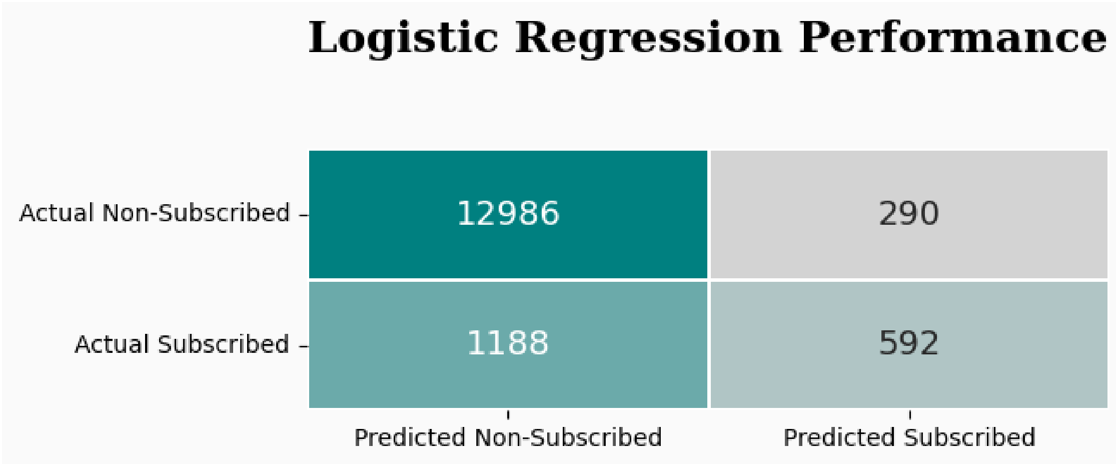
```
Random Forest
               precision    recall  f1-score   support

           0       0.92      0.97      0.95     13276
           1       0.67      0.39      0.50      1780

    accuracy                           0.91     15056
   macro avg       0.80      0.68      0.72     15056
weighted avg       0.89      0.91      0.89     15056

Decision Tree
               precision    recall  f1-score   support

           0       0.92      0.97      0.94     13276
           1       0.62      0.39      0.48      1780

    accuracy                           0.90     15056
   macro avg       0.77      0.68      0.71     15056
weighted avg       0.89      0.90      0.89     15056
```

```
Logistic Regression
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     13276
           1       0.67      0.33      0.44      1780

    accuracy                           0.90     15056
   macro avg       0.79      0.66      0.70     15056
weighted avg       0.89      0.90      0.89     15056
```

[22]: Text(0, -0.75, 'Logistic Regression Performance')







[23]:
```
#checking
tn, fp, fn, tp = cmrf.ravel()
tn, fp, fn, tp
```

[23]: (12927, 349, 1079, 701)

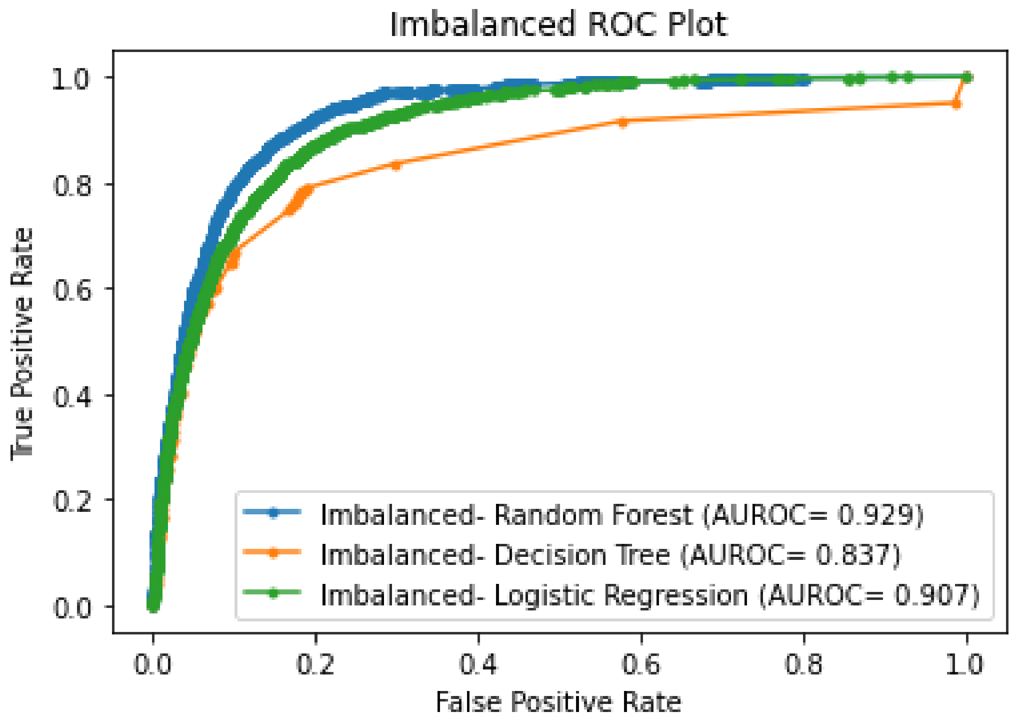
5.1.7 4. Imbalanced- Calculate the AUROC

1. Higher is better
2. Between 0 and 1

[24]:
```
#to get the probabilities of the prediction for each instance in the test set
np.random.seed(1)
rf_probs= rf.predict_proba(x_test)#random forest
dt_probs= dt.predict_proba(x_test)#decision tree
lgr_probs= lgr.predict_proba(x_test)#logistic regression

#to keep the probabilities of positive outcomes

#random forest
rf_probs=rf_probs[:,1]
rf_probs

#decision tree
dt_probs=dt_probs[:,1]
dt_probs

#logistic regression
lgr_probs=lgr_probs[:,1]
lgr_probs
```

```
#Print AUROC score
from sklearn.metrics import roc_curve, roc_auc_score
rf_auc=roc_auc_score(y_test,rf_probs)#random forest
dt_auc=roc_auc_score(y_test,dt_probs)#decision tree
lgr_auc=roc_auc_score(y_test,lgr_probs)#logistic regression

print("Random Forest: AUROC= %.3f" % (rf_auc))#random forest
print("Decision Tree: AUROC= %.3f" % (dt_auc))#decision tree
print("Logistic Regression: AUROC= %.3f" % (lgr_auc))#logistic regression

#Calculate and plot ROC curve
'''roc_curve() returns three arrays, first one is false positive rate(fpr),␣
↪second one is true positive rate(tpr) and the third one is the threshold (_)
#for more information: https://scikit-learn.org/stable/modules/generated/
↪sklearn.metrics.roc_curve.html'''
rf_fpr,rf_tpr,_=roc_curve(y_test,rf_probs)#random forest
dt_fpr,dt_tpr,_=roc_curve(y_test,dt_probs)#decision tree
lgr_fpr,lgr_tpr,_=roc_curve(y_test,lgr_probs)#logistic regression

#plot each model:
import matplotlib.pyplot as plt
plt.plot(rf_fpr,rf_tpr,marker=".",label="Imbalanced- Random Forest (AUROC= %0.
↪3f)" % rf_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.plot(dt_fpr,dt_tpr,marker=".",label="Imbalanced- Decision Tree (AUROC= %0.
↪3f)" % dt_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.plot(lgr_fpr,lgr_tpr,marker=".",label="Imbalanced- Logistic Regression␣
↪(AUROC= %0.3f)" % lgr_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.title("Imbalanced ROC Plot")
plt.legend()
plt.show()

#The results show the best AUROC if for Random forest with 0.93 score followed␣
↪by Logisitic regression and Decision tree respectivily.
```

```
Random Forest: AUROC= 0.929
Decision Tree: AUROC= 0.837
Logistic Regression: AUROC= 0.907
```



5.1.8 5. Imbalanced- Summary (Accuracy, Recall, specificity, AUROC, MCC, Brier_score_loss, Run_time) for the models

[25]:
```
np.random.seed(1)
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,matthews_corrcoef,brier_score_loss,f1_score
from sklearn import tree, linear_model,ensemble
MLA = [tree.DecisionTreeClassifier(max_depth=U_DT_max_depth,random_state=1),
       linear_model.
↪LogisticRegression(max_iter=U_lgr_max_iter,solver=U_lgr_solver,n_jobs=-1),
       ensemble.RandomForestClassifier(n_estimators=U_RF_n_estimators,␣
↪max_depth=U_RF_max_depth,random_state=1)]
import time
name = []
Accuracy = []
Specificity=[]
Sensetivity=[]
alg_auc=[]
Mcc=[]
br_s=[]
f1score=[]
T_time=[]
```

```
P_time=[]
for alg in MLA:
    name.append(alg.__class__.__name__)
    start=time.time()
    alg.fit(x_train,y_train)
    end=time.time()
    startp=time.time()
    y_predicted=alg.predict(x_test)
    endp=time.time()
    Accuracy.append(accuracy_score(y_test,y_predicted))
    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))
    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))
    Mcc.append(matthews_corrcoef(y_test, y_predicted))
    br_s.append(brier_score_loss(y_test, y_predicted))
    f1score.append(f1_score(y_test,y_predicted))
    alg_probs= alg.predict_proba(x_test)
    alg_probs=alg_probs[:,1]
    alg_auc.append(roc_auc_score(y_test,alg_probs))
    T_time.append(end-start)
    P_time.append(endp-startp)


comparison = pd.DataFrame({"name": name, "Accuracy": Accuracy,"Sensetivity":
 ↪Sensetivity,"Specificity":Specificity,"AUC":alg_auc,"MCC":Mcc,"Brier_score":
 ↪br_s,
                           "F1Score":f1score,"TrainingTime_s":␣
 ↪T_time,"Prediction Time [s]": P_time})
display(comparison)

#From the below results we can conclude that the random forest is slightly␣
 ↪better than other models especially
#If we compared them by the Brior_score, Matthew's correlation coefficient␣
 ↪(MCC), Accuracy, and Specificity.
#MCC: Recently alot of researches prove that it is a better measurement␣
 ↪especially for binary classification problems along with the brier score.
```

```
                     name  Accuracy  Sensetivity  Specificity       AUC  \
0  DecisionTreeClassifier  0.899243     0.394382     0.966933  0.837322
1      LogisticRegression  0.901833     0.332584     0.978156  0.907439
2  RandomForestClassifier  0.905154     0.393820     0.973712  0.929200

        MCC  Brier_score   F1Score  TrainingTime_s  Prediction Time [s]
0  0.440803     0.100757  0.480657        0.166441             0.004018
1  0.427229     0.098167  0.444778        1.523420             0.004021
2  0.465894     0.094846  0.495406        4.695622             0.410130
```

5.1.9 6. Imbalanced- Check Over/Underfitting

Brier Score was used to evaluate the model fitting

The reason behind using the Brier score metric is that Brier score measures the mean squared difference between the predicted probability and the actual outcome. The Brier score always takes on a value between zero and one, since this is the largest possible difference between a predicted probability (which must be between zero and one) and the actual outcome (which can take on values of only 0 and 1). It can be decomposed is the sum of refinement loss and calibration loss. The Brier score is appropriate for binary and categorical outcomes that can be structured as true or false, but is inappropriate for ordinal variables which can take on three or more values

Brier score is actually 1-Accuracy

"The Brier score is a strictly proper scoring function that is equivalent to the mean squared error" (Chicco, D., Warrens, M. J., & Jurman, G. (2021)).

*The smaller the Brier score loss, the better, hence the naming with "loss".

1. If the performance of the model on the training set is poor that means the model is underfitting to the test data.
2. If the performance of the model on the test set is poor that means the model is overfitting to the training data.

[ ]:
```
#repeated kfold validation
from numpy import mean
from numpy import std
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,brier_score_loss
from sklearn import tree, linear_model,ensemble
from sklearn.model_selection import validation_curve
from sklearn.model_selection import KFold
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score
import numpy as np
np.random.seed(0)
import matplotlib.pyplot as plt
plt.style.use("ggplot")
```

[ ]:
```
#Decision Tree
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
U_DT_list_training_BrierScore=[]
U_DT_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
```

```
    model=tree.DecisionTreeClassifier(max_depth=U_DT_max_depth,random_state=1)
    model.fit(X_train,Y_train)

    y_train_data_pred=model.predict(X_train)
    y_test_data_pred=model.predict(X_test)

    U_DT_fold_training_BrierScore=brier_score_loss(Y_train,y_train_data_pred)
    U_DT_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

    U_DT_list_training_BrierScore.append(U_DT_fold_training_BrierScore)
    U_DT_list_testing_BrierScore.append(U_DT_fold_testing_BrierScore)
```

[ ]:
```
print("DT_Test_BScore_Mean:", mean(U_DT_list_testing_BrierScore))
print("DT_Train_BScore_Mean:", mean(U_DT_list_training_BrierScore))
```

```
DT_Test_BScore_Mean: 0.09962907548611827
DT_Train_BScore_Mean: 0.07913020226274736
```

[ ]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
 ↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(U_DT_list_training_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Decision Tree \n Training BrierScore across folds")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(U_DT_list_testing_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("Decision Tree \n Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph "Decision Tree␣
 ↪-Training BrierScore across folds" we can see the the models fits really␣
 ↪well as the BrierScore
#is around 0.08.
#in the second graph "Decision Tree -Testing BrierScore across folds"it also␣
 ↪fits well as the BrierScore on the test set is around 0.1.
#That means also that we have a fitted model and stable one.
```

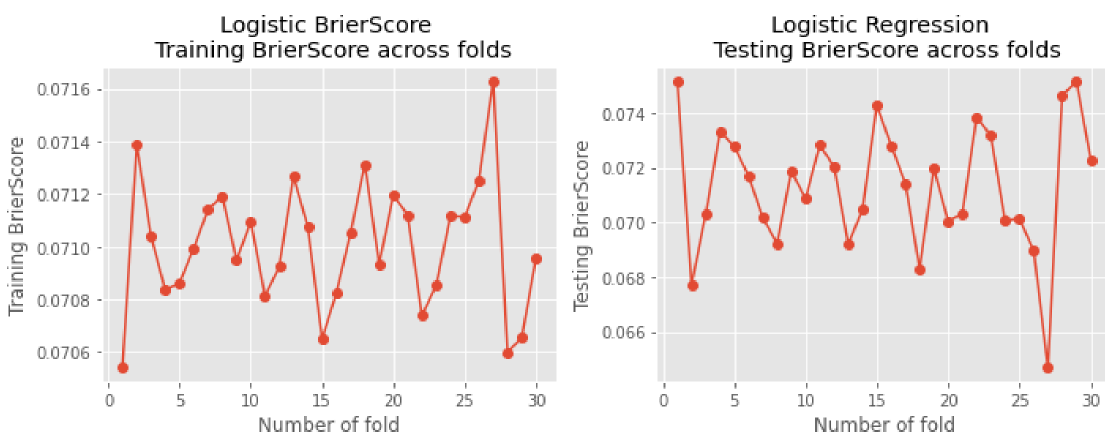
[ ]:
```
#Logistic Regression
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
U_lgr_list_training_BrierScore=[]
U_lgr_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
  model=linear_model.LogisticRegression(max_iter=U_lgr_max_iter,solver=␣
↪U_lgr_solver,random_state=1,n_jobs=-1)
  model.fit(X_train,Y_train)

  y_train_data_pred=(model.predict_proba(X_train))[:,1]
  y_test_data_pred= (model.predict_proba(X_test))[:,1]

  U_lgr_fold_training_BrierScore=brier_score_loss(Y_train,y_train_data_pred)
  U_lgr_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

  U_lgr_list_training_BrierScore.append(U_lgr_fold_training_BrierScore)
  U_lgr_list_testing_BrierScore.append(U_lgr_fold_testing_BrierScore)
```

[ ]:
```
print("LG_Test_BScore_Mean:", mean(U_lgr_list_testing_BrierScore))
print("LG_Train_BScore_Mean:", mean(U_lgr_list_training_BrierScore))
```

```
LG_Test_BScore_Mean: 0.07132303555637362
LG_Train_BScore_Mean: 0.07100383987335479
```

[ ]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
↪phase
plt.figure(figsize = (10, 4))
```

```
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(U_lgr_list_training_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Logistic BrierScore \n Training BrierScore across folds")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(U_lgr_list_testing_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("Logistic Regression \n Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph "Logistic Regression␣
 ↪-Training BrierScore across folds" we can see the the models fits really␣
 ↪well
#as the BrierScore is stable and very small (about 0.07).
#In the second graph "Logistic Regression -Testing BrierScore across folds"it␣
 ↪also fits well as the BrierScore on the test set is also around 0.07.
#That means also that we have a fitted model and stable one.
```



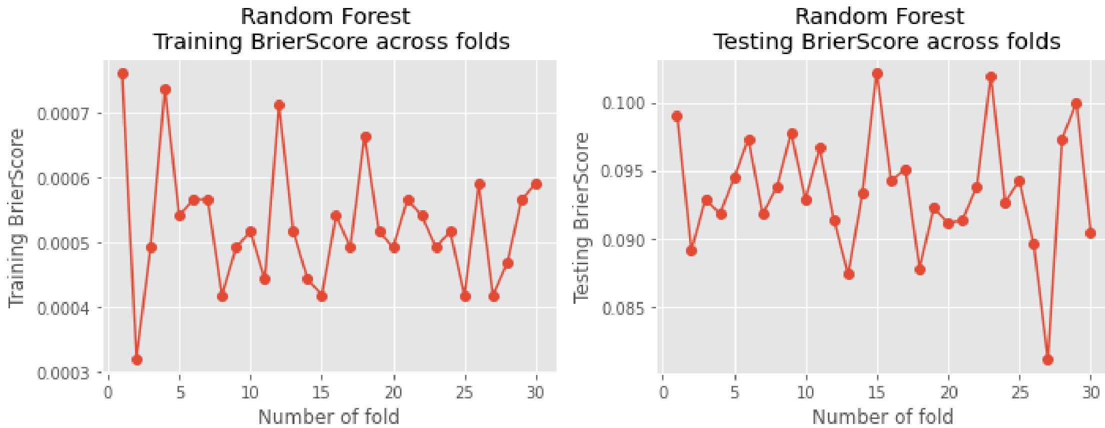
[ ]:
```
#Random Forest
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
U_RF_list_training_BrierScore=[]
U_RF_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
```

```
    X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
    Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
    model=ensemble.RandomForestClassifier(n_estimators=U_RF_n_estimators,␣
↪max_depth=U_RF_max_depth,random_state=1)
    model.fit(X_train,Y_train)

    y_train_data_pred=model.predict(X_train)
    y_test_data_pred=model.predict(X_test)

    U_RF_fold_training_BrierScore=brier_score_loss(Y_train,y_train_data_pred)
    U_RF_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

    U_RF_list_training_BrierScore.append(U_RF_fold_training_BrierScore)
    U_RF_list_testing_BrierScore.append(U_RF_fold_testing_BrierScore)
```

[ ]:
```
print("RF_Test_BScore_Mean:", mean(U_RF_list_testing_BrierScore))
print("RF_Train_BScore_Mean:", mean(U_RF_list_training_BrierScore))
```

```
RF_Test_BScore_Mean: 0.09349489758068094
RF_Train_BScore_Mean: 0.0005267483980666975
```

[ ]:
```
#plot the BrierScore of the training phase and the accuBrierScoreracy of the␣
↪testing phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(U_RF_list_training_BrierScore).
↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Random Forest \n Training BrierScore across folds")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(U_RF_list_testing_BrierScore).
↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("Random Forest \n Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph "Random␣
↪Forest-Training BrierScore across folds" we can see the the models fits␣
↪really well as the BrierScore is almost 0
#in the second graph "Random Forest -Testing BrierScore across folds"it also␣
↪fits well as the BrierScore on the test set is around 0.1.
#That means also that we have a fitted model and stable one.
```



5.2 SMOTE

1. In this stage the models have been built on balanced dataset using SMOTE (Oversampling technique).
2. Sampling stategy parameter in SMOTE function has been tuned for each model in order to optimize the F1 Score.
3. The models have been tuned based on some parameters: A. Random Forest tuned parameters are: Max depth and the n_estimators (number of trees) . B. Decision Tree tuned parameters are: Max depth. C. Logistic Regression tuned parameters are : Max iteration and Solver.
4. We focused on optimizing F1-Score metric as it was the smallest value in the confusion matrix in the first run

5.2.1 1. SMOTE- Hyperparameter Tuning (based on Sampling strategy and F1-Score)

Please note that the sampling strategy is the desired ratio of the number of samples in the minority class over the number of samples in the majority class after resampling.

[7]:
```
import imblearn
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
```

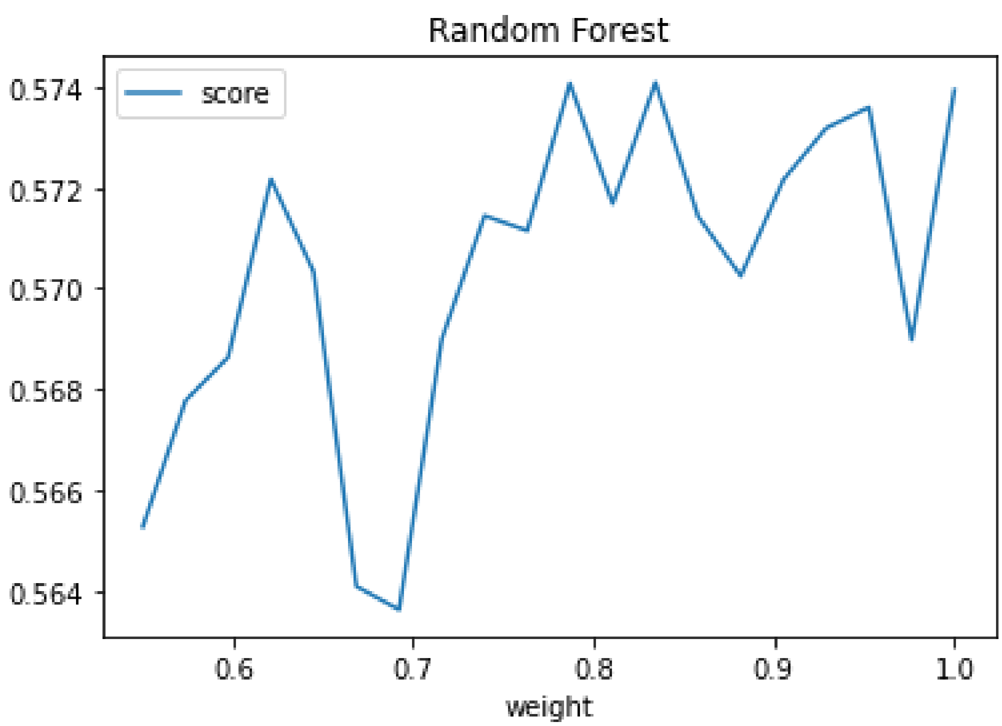
[ ]:
```
#Tuning SMOTE for Random Forest
#This step has been run repeatedly on different ranges of sampling_strategy␣
↪parameter in order to tune it on the right value.
rfweights=np.linspace(0.55,1,20)
pipe=imblearn.pipeline.make_pipeline(SMOTE(),RandomForestClassifier())
```

```
gsc=GridSearchCV(estimator=pipe,param_grid={"smote__sampling_strategy":
↪rfweights},scoring="f1",cv=3,n_jobs=-1)
Srf_grid_result=gsc.fit(x_train,y_train)
```

[ ]:
```
#Random Forest
print("RF-the best parameters are %s with a score of %0.2f" % (Srf_grid_result.
↪best_params_,Srf_grid_result.best_score_))#Mean cross-validated score of the␣
↪best_estimator
weight_roc_auc_score_df=pd.DataFrame({"score":Srf_grid_result.
↪cv_results_["mean_test_score"],"weight":rfweights})
#the score is the average of all cv folds for a single combination of the␣
↪parameters you specify in the tuned_params
weight_roc_auc_score_df.plot(x="weight",title="Random Forest")
```

```
RF-the best parameters are {'smote__sampling_strategy': 0.8342105263157895} with
a score of 0.57
```

[ ]:
```
<AxesSubplot: title={'center': 'Random Forest'}, xlabel='weight'>
```



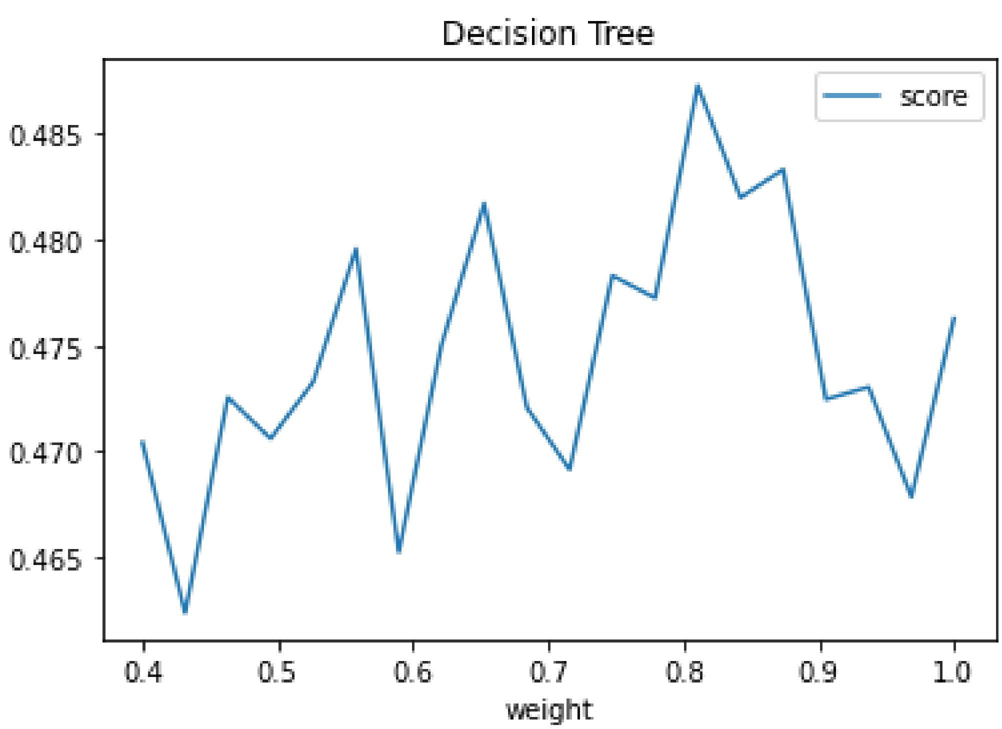
[ ]:
```
#Tuning SMOTE for Decision Tree
#This step has been run repeatedly on different ranges of sampling_strategy␣
↪parameter in order to tune it on the right value.
dtweights=np.linspace(0.4,1,20)
```

```python
pipe=imblearn.pipeline.make_pipeline(SMOTE(),DecisionTreeClassifier())
gsc=GridSearchCV(estimator=pipe,param_grid={"smote__sampling_strategy":
 ↪dtweights},scoring="f1",cv=3,n_jobs=-1)
Sdt_grid_result=gsc.fit(x_train,y_train)
```

[ ]:
```python
#Decision Tree
print("DT-the best parameters are %s with a score of %0.2f" % (Sdt_grid_result.
 ↪best_params_,Sdt_grid_result.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
weight_roc_auc_score_df=pd.DataFrame({"score":Sdt_grid_result.
 ↪cv_results_["mean_test_score"],"weight":dtweights})
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
weight_roc_auc_score_df.plot(x="weight",title="Decision Tree")
```

```
DT-the best parameters are {'smote__sampling_strategy': 0.8105263157894738} with
a score of 0.49
```

[ ]: <AxesSubplot: title={'center': 'Decision Tree'}, xlabel='weight'>



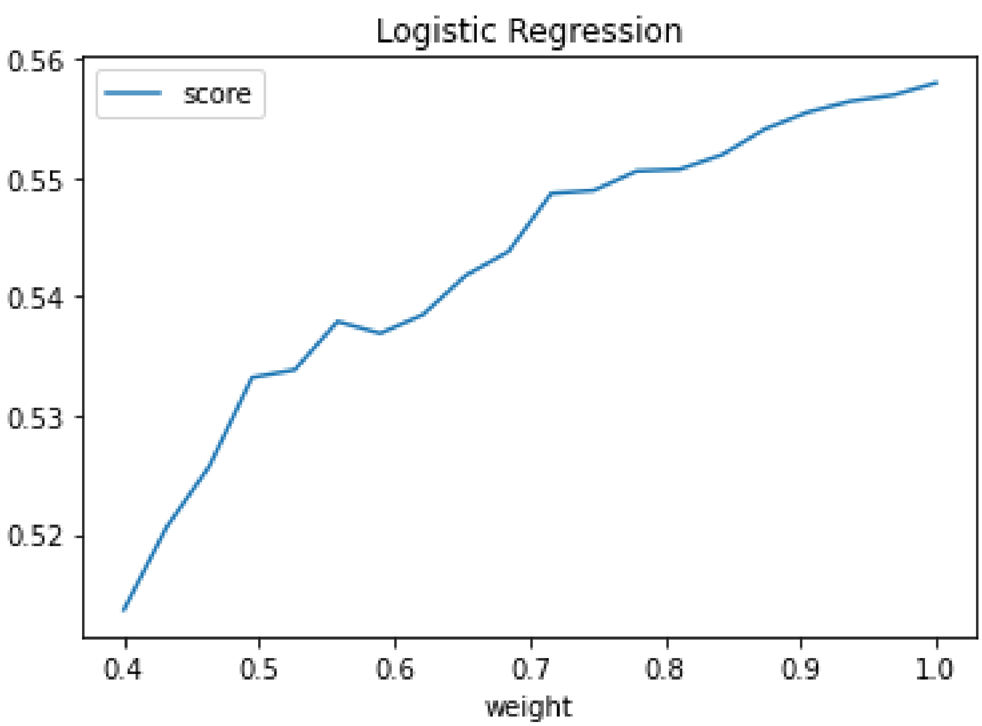
[ ]:
```python
#Tuning SMOTE for Logistic Regression
#This step has been run repeatedly on different ranges of sampling_strategy␣
 ↪parameter in order to tune it on the right value.
```

```python
lgrweights=np.linspace(0.4,1,20)
pipe=imblearn.pipeline.make_pipeline(SMOTE(),LogisticRegression(n_jobs=-1))
gsc=GridSearchCV(estimator=pipe,param_grid={"smote__sampling_strategy":
 ↪lgrweights},scoring="f1",cv=3,n_jobs=-1)
Slgr_grid_result=gsc.fit(x_train,y_train)
```

[ ]:
```python
#Logistic Regression
print("LGR-the best parameters are %s with a score of %0.2f" %␣
 ↪(Slgr_grid_result.best_params_,Slgr_grid_result.best_score_))#Mean␣
 ↪cross-validated score of the best_estimator
weight_roc_auc_score_df=pd.DataFrame({"score":Slgr_grid_result.
 ↪cv_results_["mean_test_score"],"weight":lgrweights})
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
weight_roc_auc_score_df.plot(x="weight",title="Logistic Regression")
```

```
LGR-the best parameters are {'smote__sampling_strategy': 1.0} with a score of
0.56
```

[ ]: <AxesSubplot: title={'center': 'Logistic Regression'}, xlabel='weight'>



5.2.2 *2. Data Balancing: (SMOTE)*

[26]:
```
#from the above we can conclude that the best parameters for smote are:

#Random Forest:
RF_SMT_sampling_strategy=0.8342105263157895

# Decision Tree:
DT_SMT_sampling_strategy=0.8105263157894738

# Logistic Regression:
lgr_SMT_sampling_strategy=1

#These values may differ slightly on each run of the previous tunning.
#Please note that I have saved the smote-sampling strategy values (after␣
↪tuning) for each model in the above variables
#in order to make the run time shorter everytime we need to balance the data.
```

[27]:
```
#The portions for minority and majority before smote
import numpy as np
unique,count=np.unique(y_train,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[27]: {0: 26646, 1: 3509}

[28]:
```
#SMOTE resampling-Decision Tree
from imblearn.over_sampling import SMOTE
smdt=SMOTE(sampling_strategy=DT_SMT_sampling_strategy,random_state=101)
dtx_train_res,dty_train_res=smdt.fit_resample(x_train,y_train)
unique,count=np.unique(dty_train_res,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[28]: {0: 26646, 1: 21597}

[29]:
```
#SMOTE resampling-Random Forest
smrf=SMOTE(sampling_strategy=RF_SMT_sampling_strategy,random_state=12)
rfx_train_res,rfy_train_res=smrf.fit_resample(x_train,y_train)
unique,count=np.unique(rfy_train_res,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[29]: {0: 26646, 1: 22228}

[30]:
```
#SMOTE resampling-Logistic Regression
smtlgr=SMOTE(sampling_strategy=lgr_SMT_sampling_strategy,random_state=13)
```

```
lgrx_train_res,lgry_train_res=smtlgr.fit_resample(x_train,y_train)
unique,count=np.unique(lgry_train_res,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[30]:
```
{0: 26646, 1: 26646}
```

5.2.3 3. SMOTE- Random Forest Hyperparameter Tuning (based on max depth, number of trees and F1-Score)

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(random_state=2)
```

[ ]:
```
import numpy as np
from sklearn.model_selection import GridSearchCV
#This step has been run repeatedly on different ranges of the model parameters␣
↪in order to tune them on the right values.
max_depth_range=np.arange(10,35,1)
n_estimators_range=np.arange(120,200,20)
param_grid=dict(max_depth=max_depth_range,n_estimators=n_estimators_range)
rfgridSmote=GridSearchCV(estimator=rf,param_grid=param_grid,scoring="f1",cv=3,n_jobs=-1)
```

[ ]:
```
rfgridSmote.fit(rfx_train_res,rfy_train_res)
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (rfgridSmote.
↪best_params_,rfgridSmote.best_score_))#Mean cross-validated score of the␣
↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_depth': 32, 'n_estimators': 120} with a score of
0.93
```

[ ]:
```
#data frame of grid search parameters and their accuracy scores
import pandas as pd

grid_results = pd.concat([pd.DataFrame(rfgridSmote.cv_results_["params"]),
                          pd.DataFrame(rfgridSmote.
↪cv_results_["mean_test_score"], columns=["f1"])],axis=1)
grid_results.head()

#preparing data for making  contour plots
grid_contour = grid_results.groupby(['max_depth','n_estimators']).mean()
grid_contour
```

```
#pivot data:
grid_reset=grid_contour.reset_index()
grid_reset.columns=["max_depth","n_estimator","f1"]
grid_pivot=grid_reset.pivot("max_depth","n_estimator")

#assigning the pivoted data into the respective x,y, and z variables
x=grid_pivot.columns.levels[1].values
y=grid_pivot.index.values
z=grid_pivot.values

#2D contour plot
import plotly.graph_objects as go

# X and Y axes labels
layout = go.Layout(
            xaxis=go.layout.XAxis(
              title=go.layout.xaxis.Title(
              text='n_estimators')
             ),
             yaxis=go.layout.YAxis(
              title=go.layout.yaxis.Title(
              text='max_depth')
            ) )

fig = go.Figure(data = [go.Contour(z=z, x=x, y=y)], layout=layout )

fig.update_layout(title='Hyperparameter tuning', autosize=False,
                  width=500, height=500,
                  margin=dict(l=65, r=50, b=65, t=90))

fig.show()
```

5.2.4 4. SMOTE- Decision Tree Hyperparameter Tuning (based on max depth and F1-Score)

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(random_state=2)
```

[ ]:
```
import numpy as np
from sklearn.model_selection import GridSearchCV
#This step has been run repeatedly on different ranges of the model parameters␣
↪in order to tune them on the right values.
max_depth_range=np.arange(1,20,1)
param_grid=dict(max_depth=max_depth_range)
dtgridSmote=GridSearchCV(estimator=dt,param_grid=param_grid,scoring="f1",cv=10,n_jobs=-1)
```

[ ]:
```
dtgridSmote.fit(dtx_train_res,dty_train_res)
```

[ ]:
```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random_state=2), n_jobs=-1,
             param_grid={'max_depth': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9,
10, 11, 12, 13, 14, 15, 16, 17,
       18, 19])},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (dtgridSmote.
 ↪best_params_,dtgridSmote.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_depth': 17} with a score of 0.89
```

5.2.5 3. SMOTE- Logistic Regression Hyperparameter Tuning (based on Max Iteration, Solver and F1-Score)

[ ]:
```
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression(random_state=10)
```

[ ]:
```
#This step has been run repeatedly on different ranges of the model parameters␣
 ↪in order to tune them on the right values.
import numpy as np
from sklearn.model_selection import GridSearchCV

max_iter=np.arange(1000,2100,500)
param_grid=dict(max_iter=max_iter,solver=['liblinear', 'lbfgs'])

lgrgridSmote=GridSearchCV(estimator=lgr,param_grid=param_grid,scoring="f1",cv=3,n_jobs=-1)
```

[ ]:
```
lgrgridSmote.fit(lgrx_train_res,lgry_train_res)
```

[ ]:
```
GridSearchCV(cv=3, estimator=LogisticRegression(random_state=10), n_jobs=-1,
             param_grid={'max_iter': array([1000, 1500, 2000]),
                         'solver': ['liblinear', 'lbfgs']},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (lgrgridSmote.
 ↪best_params_,lgrgridSmote.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params.
#The better Solver after resampling the data using SMOTE is "liblinear".
#after oversamling the data "liblinear" becomes better choice.
```

```
the best parameters are {'max_iter': 1000, 'solver': 'liblinear'} with a score
of 0.89
```

5.2.6 5. SMOTE- Train the model and calculate the run time of training the model

[31]:
```
#from the above we can conclude that the best parameters are:

#Random Forest:
SMT_RF_max_depth= 32
SMT_RF_n_estimators= 120

# Decision Tree:
SMT_DT_max_depth=17

#logistic Regression:
SMT_lgr_max_iter=1000
SMT_lgr_solver="liblinear"

#These values may differ slightly on each run of the previous tunning.
#Please note that I have saved the parameters values (after tuning) of each␣
↪model in the above variables in order
#to make the run time shorter everytime we need to train the model.'''
```

[32]:
```
#RF
import time
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=SMT_RF_n_estimators, max_depth=␣
↪SMT_RF_max_depth,random_state=2)

startrf=time.time()
rf.fit(rfx_train_res,rfy_train_res)
endrf=time.time()

#DT
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(max_depth=SMT_DT_max_depth,random_state=2)

startdt=time.time()
dt.fit(dtx_train_res,dty_train_res)
enddt=time.time()

#LGR
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression(max_iter=SMT_lgr_max_iter,solver=SMT_lgr_solver,random_state=2)

startlgr=time.time()
```

```
lgr.fit(lgrx_train_res,lgry_train_res)
endlgr=time.time()


print("RF Training Run Time [s]:",endrf-startrf)
print("DT Training Run Time [s]:",enddt-startdt)
print("LGR Training Run Time [s]:",endlgr-startlgr)
# The results shows the the faster model is the Logistic Regression,Decision␣
 ↪tree, and Random Forest respectively.
```

```
RF Training Run Time [s]: 8.401374101638794
DT Training Run Time [s]: 0.51639723777771
LGR Training Run Time [s]: 0.4765207767486572
```

5.2.7 6. SMOTE- Run Time for prediction

[33]:
```
# the run time to predict the test set
startrf=time.time()
y_predictedrf=rf.predict(x_test)
endrf=time.time()

startdt=time.time()
y_predicteddt=dt.predict(x_test)
enddt=time.time()

startlgr=time.time()
y_predictedlgr=lgr.predict(x_test)
endlgr=time.time()

print("RF Run Time to Predict the testset [s]:",endrf-startrf)
print("DT Run Time to Predict the testset [s]:",enddt-startdt)
print("LGR Run Time to Predict the testset [s]:",endlgr-startlgr)

# The results shows the the faster model is the Logistic regression, Decision␣
 ↪tree, and the Random forest respectively.
# Random Forest model was the slowest one( which is expected as it is an␣
 ↪ensemble model)
```

```
RF Run Time to Predict the testset [s]: 0.3937664031982422
DT Run Time to Predict the testset [s]: 0.005202531814575195
LGR Run Time to Predict the testset [s]: 0.003000497817993164
```

5.2.8 7. SMOTE- Confusion Matrix

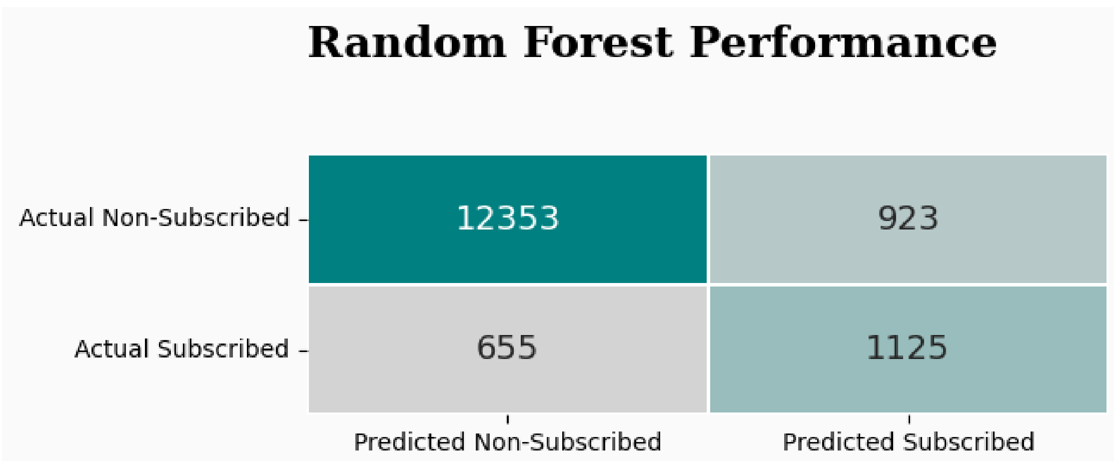
[34]:
```
from sklearn.metrics import recall_score, make_scorer, confusion_matrix,␣
↪classification_report,ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns

class Colors:
    Gray = "#5d5d5d"
    LightGray = "#fafafa"
    Black = "#000000"
    White = "#FFFFFF"
    Teal = "#008080"
    Aquamarine = "#76c8c8"
    Blue = "#2596be"
    LightCyan = "#badbdb"
    WhiteSmoke = "#dedad2"
    Cream = "#e4bcad"
    PeachPuff = "#df979e"
    HotPink = "#d7658b"
    DeepPink = "#c80064"
    LightSeaGreen = "#20B2AA"
    DarkGray = "#464144"

#RF
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmrf = confusion_matrix(y_test,y_predictedrf)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmrf, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
↪Subscribed'],annot_kws={"fontsize":14})
print("Random Forest","\n",classification_report(y_test, y_predictedrf))
ax0.text(0,-0.75,'Random Forest␣
↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')

#DT
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
```

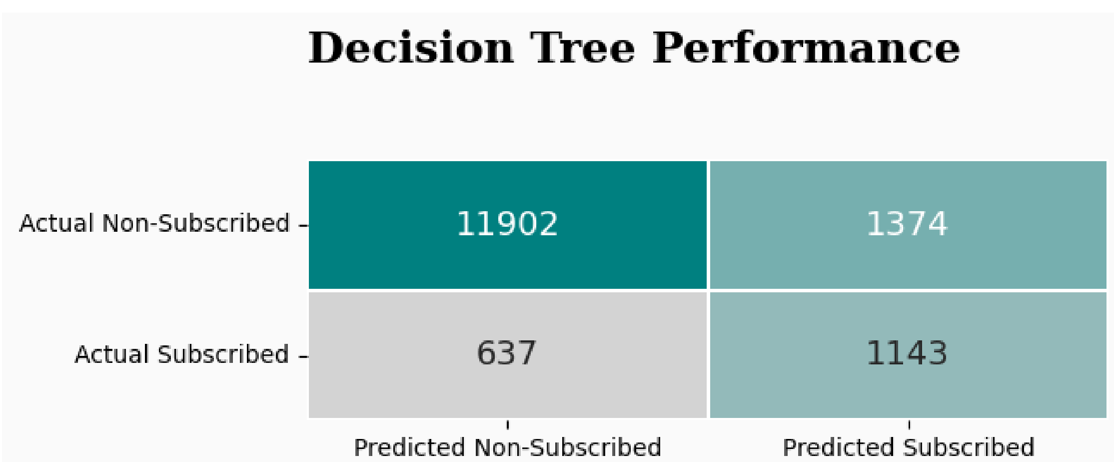
```
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmdt = confusion_matrix(y_test,y_predicteddt)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
 ↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmdt, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
 ↪Subscribed'],annot_kws={"fontsize":14})
print("Decision Tree","\n",classification_report(y_test, y_predicteddt))
ax0.text(0,-0.75,'Decision Tree␣
 ↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')

#logistic regression
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmlgr = confusion_matrix(y_test,y_predictedlgr)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
 ↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmlgr, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
 ↪Subscribed'],annot_kws={"fontsize":14})
print("Logistic Regression","\n",classification_report(y_test, y_predictedlgr))
ax0.text(0,-0.75,'Logistic Regression␣
 ↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')
```

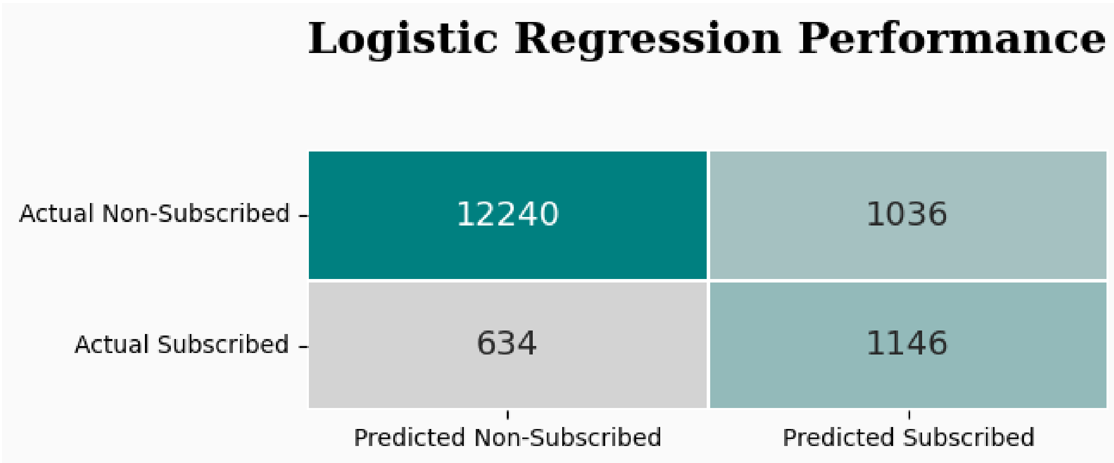
```
Random Forest
              precision    recall  f1-score   support

           0       0.95      0.93      0.94     13276
           1       0.55      0.63      0.59      1780

    accuracy                           0.90     15056
   macro avg       0.75      0.78      0.76     15056
weighted avg       0.90      0.90      0.90     15056

Decision Tree
              precision    recall  f1-score   support

           0       0.95      0.90      0.92     13276
           1       0.45      0.64      0.53      1780
```

```
    accuracy                           0.87     15056
   macro avg       0.70      0.77      0.73     15056
weighted avg       0.89      0.87      0.88     15056

Logistic Regression
              precision    recall  f1-score   support

           0       0.95      0.92      0.94     13276
           1       0.53      0.64      0.58      1780

    accuracy                           0.89     15056
   macro avg       0.74      0.78      0.76     15056
weighted avg       0.90      0.89      0.89     15056
```

[34]: Text(0, -0.75, 'Logistic Regression Performance')







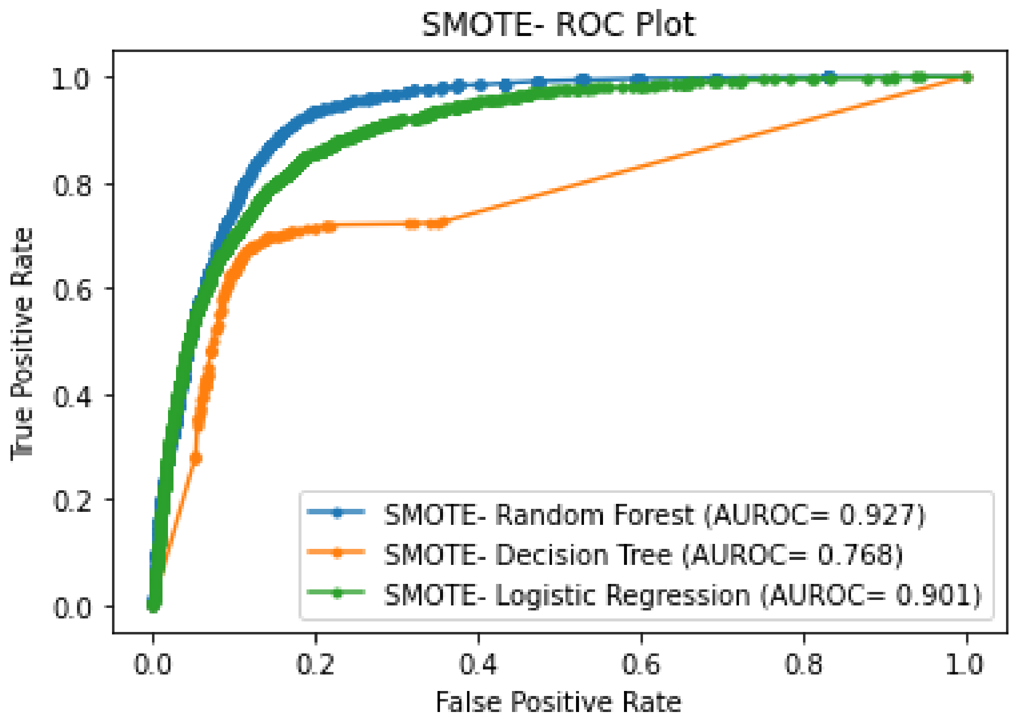
5.2.9 8. SMOTE- Calculate the AUROC

1. Higher is better
2. Between 0 and 1

[35]:
```
#to get the probabilities of the prediction for each instance in the test set
np.random.seed(2)
rf_probs= rf.predict_proba(x_test)
dt_probs= dt.predict_proba(x_test)
lgr_probs= lgr.predict_proba(x_test)

#to keep the probabilities of positive outcomes
rf_probs=rf_probs[:,1]
rf_probs

dt_probs=dt_probs[:,1]
dt_probs

lgr_probs=lgr_probs[:,1]
lgr_probs

#print AUROC score
from sklearn.metrics import roc_curve, roc_auc_score
rf_auc=roc_auc_score(y_test,rf_probs)
dt_auc=roc_auc_score(y_test,dt_probs)
lgr_auc=roc_auc_score(y_test,lgr_probs)

print("Random Forest: AUROC= %.3f" % (rf_auc))
```

```
print("Decision Tree: AUROC= %.3f" % (dt_auc))
print("Logistic Regression: AUROC= %.3f" % (lgr_auc))

#Calculate and plot ROC curve
#roc_curve() returns three arrays, first one is false positive rate(fpr),␣
↪second one is true positive rate(tpr)
#and the third one is the threshold (_).
#For more information: https://scikit-learn.org/stable/modules/generated/
↪sklearn.metrics.roc_curve.html'''
rf_fpr,rf_tpr,_=roc_curve(y_test,rf_probs)
dt_fpr,dt_tpr,_=roc_curve(y_test,dt_probs)
lgr_fpr,lgr_tpr,_=roc_curve(y_test,lgr_probs)

#plot each model:
import matplotlib.pyplot as plt
plt.plot(rf_fpr,rf_tpr,marker=".",label="SMOTE- Random Forest (AUROC= %0.3f)" %␣
↪rf_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.plot(dt_fpr,dt_tpr,marker=".",label="SMOTE- Decision Tree (AUROC= %0.3f)" %␣
↪dt_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.plot(lgr_fpr,lgr_tpr,marker=".",label="SMOTE- Logistic Regression (AUROC=␣
↪%0.3f)" % lgr_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.title("SMOTE- ROC Plot")
plt.legend()
plt.show()
#The results show the best model AUROC is Random forest with 0.93 score␣
↪followed by Logisitic regression and Decision tree respectivily.
#Comparing to the imbalanced section, the AUC has been decreased alittle bit as␣
↪
#logistic regression AUC decreased from 0.90 to 0.89 and Decision tree␣
↪decreased from 0.86 to 0.73.
#Random Forest AUC is stable before and after SMOTE.
```

```
Random Forest: AUROC= 0.927
Decision Tree: AUROC= 0.768
Logistic Regression: AUROC= 0.901
```



5.2.10 9. SMOTE- Summary (ACC,Recall, specificity,AUC,MCC, brier_score_loss,F1 Score, run time) for the models

[36]:
```
np.random.seed(2)
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,brier_score_loss,f1_score,matthews_corrcoef
from sklearn import tree, linear_model,ensemble
SmoteMLA = [tree.
↪DecisionTreeClassifier(max_depth=SMT_DT_max_depth,random_state=2),
       linear_model.
↪LogisticRegression(max_iter=SMT_lgr_max_iter,solver=SMT_lgr_solver,random_state=2),

       ensemble.RandomForestClassifier(n_estimators=SMT_RF_n_estimators,␣
↪max_depth=SMT_RF_max_depth,random_state=2)]
import time
name = []
Accuracy = []
Specificity=[]
Sensetivity=[]
alg_auc=[]
T_time=[]
P_time=[]
```

```
Mcc=[]
br_s=[]
f1score=[]
for alg in SmoteMLA:
    name.append(alg.__class__.__name__)

    if alg.__class__.__name__=="RandomForestClassifier":
      x_Train=rfx_train_res
      y_Train=rfy_train_res
    elif alg.__class__.__name__=="DecisionTreeClassifier":
      x_Train=dtx_train_res
      y_Train=dty_train_res
    elif alg.__class__.__name__=="LogisticRegression":
      x_Train=lgrx_train_res
      y_Train=lgry_train_res


    start=time.time()
    alg.fit(x_Train,y_Train)
    end=time.time()


    startp=time.time()
    y_predicted=alg.predict(x_test)
    endp=time.time()
    Accuracy.append(accuracy_score(y_test,y_predicted))
    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))
    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))
    Mcc.append(matthews_corrcoef(y_test, y_predicted))
    br_s.append(brier_score_loss(y_test, y_predicted))
    f1score.append(f1_score(y_test, y_predicted))
    alg_probs= alg.predict_proba(x_test)
    alg_probs=alg_probs[:,1]
    alg_auc.append(roc_auc_score(y_test,alg_probs))
    T_time.append(end-start)
    P_time.append(endp-startp)


Smotecomparison = pd.DataFrame({"name": name, "Accuracy":␣
 ↪Accuracy,"Sensetivity":Sensetivity,
                                "Specificity":Specificity,"AUC":alg_auc,"MCC":
 ↪Mcc,
                                "Brier_score":br_s,"F1Score":
 ↪f1score,"TrainingTime_s": T_time,
                                "Prediction Time [s]": P_time})
display(Smotecomparison)
```

```
#From the below results we can conclude that the random forest is slightly␣
↪better than other models specially
#if we compared them by the Brior_score, Matthew's correlation coefficient␣
↪(MCC),Accuracy, and Specificity.

#MCC: Recently alot of researches prove that it is a better measurement␣
↪specially
#for binary classification problemns along with the brier score.
#As we tuned the models and SMOTE to improve the F1 score. We can notice a␣
↪slight improvement in MCC, F1 Score, and Sensetivity.
```

```
                     name  Accuracy  Sensetivity  Specificity       AUC  \
0  DecisionTreeClassifier  0.866432     0.642135     0.896505  0.768310
1      LogisticRegression  0.889081     0.643820     0.921964  0.900733
2  RandomForestClassifier  0.895191     0.632022     0.930476  0.926821

        MCC  Brier_score   F1Score  TrainingTime_s  Prediction Time [s]
0  0.466089     0.133568  0.531999        0.521719             0.005543
1  0.518932     0.110919  0.578496        0.462774             0.003030
2  0.529779     0.104809  0.587774        8.230517             0.398217
```

5.2.11 10. SMOTE- Check Over/Underfitting

Brier Score was used to evaluate the model fitting

The reason behind using the Brier score metric is that Brier score measures the mean squared difference between the predicted probability and the actual outcome. The Brier score always takes on a value between zero and one, since this is the largest possible difference between a predicted probability (which must be between zero and one) and the actual outcome (which can take on values of only 0 and 1). It can be decomposed is the sum of refinement loss and calibration loss. The Brier score is appropriate for binary and categorical outcomes that can be structured as true or false, but is inappropriate for ordinal variables which can take on three or more values

Brier score is actually 1-Accuracy

"The Brier score is a strictly proper scoring function that is equivalent to the mean squared error" (Chicco, D., Warrens, M. J., & Jurman, G. (2021)).

*The smaller the Brier score loss, the better, hence the naming with "loss".

1. If the performance of the model on the training set is poor that means the model is underfitting to the test data.
2. If the performance of the model on the test set is poor that means the model is overfitting to the training data.

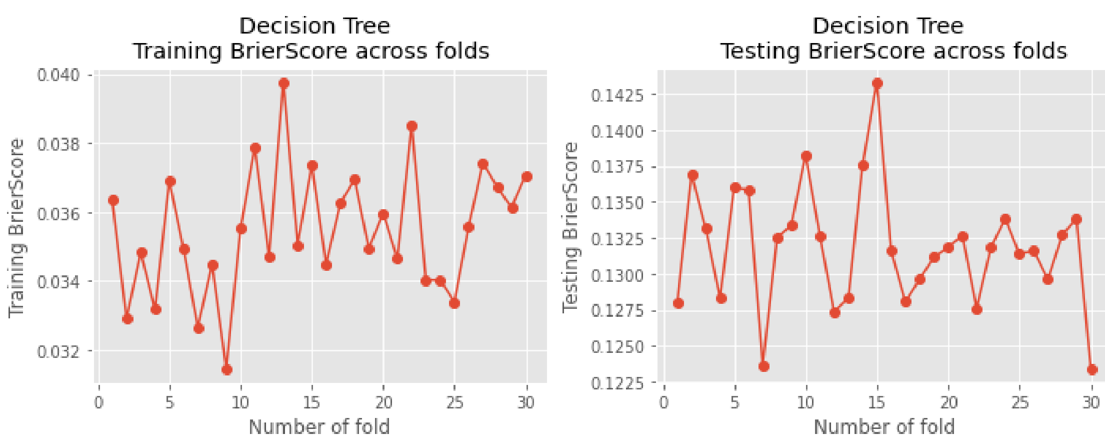
```
[ ]: from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,brier_score_loss
```

```
from sklearn import tree, linear_model,ensemble
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import validation_curve
from sklearn.model_selection import KFold,RepeatedKFold
from sklearn.model_selection import cross_val_score
import numpy as np
np.random.seed(1)
import matplotlib.pyplot as plt
plt.style.use("ggplot")
```

[ ]:
```
#Decision Tree
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
SMT_DT_list_training_BrierScore=[]
SMT_DT_list_testing_BrierScore=[]

X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
  model=tree.DecisionTreeClassifier(max_depth=SMT_DT_max_depth,random_state=2)

# apply the tuned smote to balance the training set:
  smdt=SMOTE(sampling_strategy=DT_SMT_sampling_strategy,random_state=10)
  dtx_train_res,dty_train_res=smdt.fit_resample(X_train,Y_train)

  model.fit(dtx_train_res,dty_train_res)

  y_train_data_pred=model.predict(dtx_train_res)
  y_test_data_pred=model.predict(X_test)

 ␣
 ↪SMT_DT_fold_training_BrierScore=brier_score_loss(dty_train_res,y_train_data_pred)
  SMT_DT_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

  SMT_DT_list_training_BrierScore.append(SMT_DT_fold_training_BrierScore)
  SMT_DT_list_testing_BrierScore.append(SMT_DT_fold_testing_BrierScore)
```

[ ]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
 ↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(SMT_DT_list_training_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
```

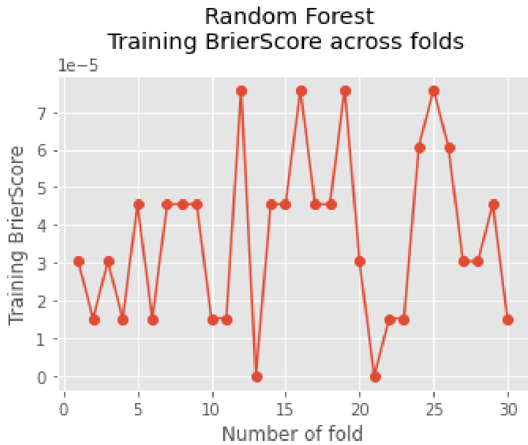
```
plt.title("Decision Tree \n Training BrierScore across folds   ")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(SMT_DT_list_testing_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("  Decision Tree \n   Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph " Decision␣
 ↪Tree-Training BrierScore across folds" we can see that the model
#its really well as the BrierScore is around 0.03.
#In the second graph "Decision Tree -Testing BrierScore across folds"it also␣
 ↪fits well as the BrierScore on the test set is around 0.1 .
#So it fits the training and the test set.
#For sure random forest performs better as we can see that in the random forest␣
 ↪test below.
```

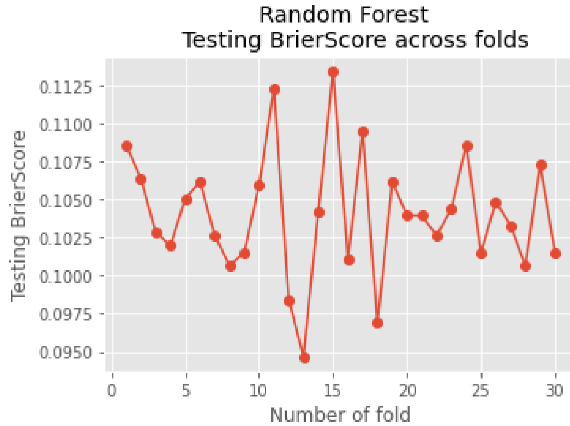


[ ]:
```
#Random Forest
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
SMT_RF_list_training_BrierScore=[]
SMT_RF_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
```

```
    model=ensemble.RandomForestClassifier(n_estimators=SMT_RF_n_estimators,␣
 ↪max_depth=SMT_RF_max_depth,random_state=2)

# apply the tuned smote to balance the training set:
    smrf=SMOTE(sampling_strategy=RF_SMT_sampling_strategy,random_state=10)
    rfx_train_res,rfy_train_res=smrf.fit_resample(X_train,Y_train)

    model.fit(rfx_train_res,rfy_train_res)

    y_train_data_pred=model.predict(rfx_train_res)
    y_test_data_pred=model.predict(X_test)

 ␣
 ↪SMT_RF_fold_training_BrierScore=brier_score_loss(rfy_train_res,y_train_data_pred)
    SMT_RF_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

    SMT_RF_list_training_BrierScore.append(SMT_RF_fold_training_BrierScore)
    SMT_RF_list_testing_BrierScore.append(SMT_RF_fold_testing_BrierScore)
```

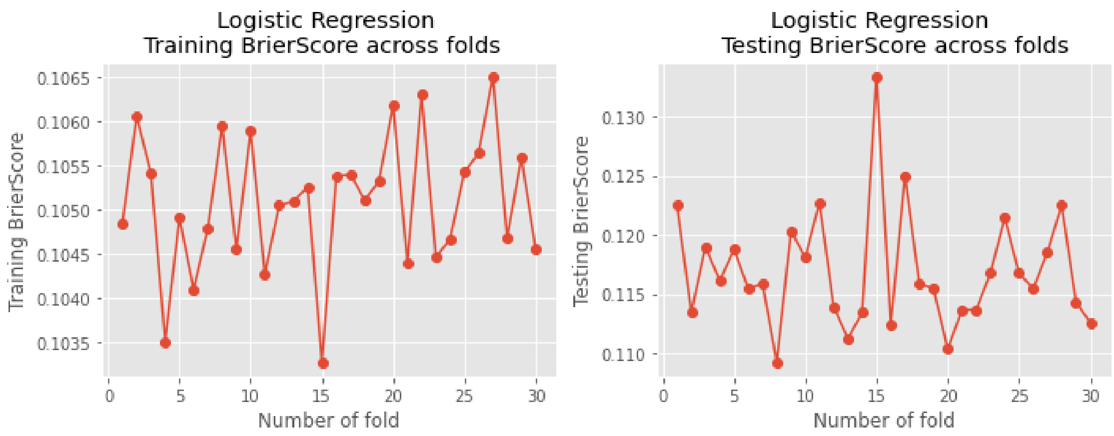
[ ]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
 ↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(SMT_RF_list_training_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Random Forest \n Training BrierScore across folds   ")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(SMT_RF_list_testing_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("  Random Forest \n    Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph "Random␣
 ↪Forest-Training BrierScore across folds"
#we can see the the models fits really well as the BrierScore is almost 0
#In the second graph "Random Forest -Testing BrierScore across folds"it also␣
 ↪fits well as the BrierScore on the test set is around 0.1
```





[ ]:
```
#Logistic Regression
# prepare the cross-validation procedure

cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
SMT_lgr_list_training_BrierScore=[]
SMT_lgr_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
  model=linear_model.
 ↪LogisticRegression(max_iter=SMT_lgr_max_iter,solver=SMT_lgr_solver,random_state=2)

# apply the tuned smote to balance the training set:
  smlgr=SMOTE(sampling_strategy=lgr_SMT_sampling_strategy,random_state=10)
  lgrx_train_res,lgry_train_res=smlgr.fit_resample(X_train,Y_train)

  model.fit(lgrx_train_res,lgry_train_res)

  y_train_data_pred=model.predict(lgrx_train_res)
  y_test_data_pred=model.predict(X_test)

 ␣
 ↪SMT_lgr_fold_training_BrierScore=brier_score_loss(lgry_train_res,y_train_data_pred)
  SMT_lgr_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

  SMT_lgr_list_training_BrierScore.append(SMT_lgr_fold_training_BrierScore)
  SMT_lgr_list_testing_BrierScore.append(SMT_lgr_fold_testing_BrierScore)
```

[ ]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.
↪array(SMT_lgr_list_training_BrierScore).ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Logistic Regression \n Training BrierScore across folds   ")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(SMT_lgr_list_testing_BrierScore).
↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("Logistic Regression \n   Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph " Logistic␣
↪Regression-Training BrierScore across folds" we can see the the models fits␣
↪really well as the BrierScore is around 0.1
#In the second graph "Logistic Regression -Testing BrierScore across folds"it␣
↪also fits well as the BrierScore on the test set is around 0.1 .
#That means that we have a fitted model and stable one.
```



[ ]:
```
display("LG_Test_BScore_Mean:", round(mean(SMT_lgr_list_testing_BrierScore),3))
display("LG_Train_BScore_Mean:",␣
↪round(mean(SMT_lgr_list_training_BrierScore),3))

display("DT_Test_BScore_Mean:", round(mean(SMT_DT_list_testing_BrierScore),3))
```

```
display("DT_Train_BScore_Mean:", round(mean(SMT_DT_list_training_BrierScore),3))

display("RF_Test_BScore_Mean:", round(mean(SMT_RF_list_testing_BrierScore),3))
display("RF_Train_BScore_Mean:", round(mean(SMT_RF_list_training_BrierScore),3))
```

```
'LG_Test_BScore_Mean:'

0.117

'LG_Train_BScore_Mean:'

0.105

'DT_Test_BScore_Mean:'

0.132

'DT_Train_BScore_Mean:'

0.035

'RF_Test_BScore_Mean:'

0.104

'RF_Train_BScore_Mean:'

0.0
```

5.2.12 *11. SMOTE Summary without Tuning*

[ ]:
```
from sklearn.metrics import roc_curve,␣
 ↪roc_auc_score,accuracy_score,recall_score,brier_score_loss,matthews_corrcoef,f1_score
from sklearn import  tree, linear_model,ensemble  #svm, tree, linear_model,␣
 ↪neighbors, naive_bayes, ensemble, discriminant_analysis, gaussian_process
from imblearn.over_sampling import SMOTE

SmoteMLA= [tree.DecisionTreeClassifier(random_state=14),#not tuned
       linear_model.LogisticRegression(random_state=15,n_jobs=-1),#not tuned,
```

```
       ensemble.RandomForestClassifier(random_state=13)]#not tuned]

sm= SMOTE(random_state=101)#SMOTE function without detremining and tuning the
 ↪sampling strategy

import time
name = []
Accuracy = []
Specificity=[]
Sensetivity=[]
alg_auc=[]
T_time=[]
P_time=[]
Mcc=[]
br_s=[]
f1score=[]

for alg in SmoteMLA:
    name.append(alg.__class__.__name__)

    #resambling
    x_Train_res,y_Train_res=sm.fit_resample(x_train,y_train)

    #train the models
    start=time.time()
    alg.fit(x_Train_res,y_Train_res)
    end=time.time()

    #prediting the test set by each model
    startp=time.time()
    y_predicted=alg.predict(x_test)
    endp=time.time()

    #calculating accuracy, specificity, sensetivity, MCC, brier score, F1 score
    Accuracy.append(accuracy_score(y_test,y_predicted))
    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))
    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))
    Mcc.append(matthews_corrcoef(y_test, y_predicted))
    br_s.append(brier_score_loss(y_test, y_predicted))
    f1score.append(f1_score(y_test, y_predicted))

    #computing ROC-AUC
    alg_probs= alg.predict_proba(x_test)
    alg_probs=alg_probs[:,1]
    alg_auc.append(roc_auc_score(y_test,alg_probs))

  #counting the running time of prediting and training mdoel
```

```
    T_time.append(end-start)
    P_time.append(endp-startp)


SMTcomparison_NotTuned = pd.DataFrame({"name": name, "Accuracy":␣
↪Accuracy,"Sensetivity":Sensetivity,
                                       "Specificity":Specificity,"AUC":
↪alg_auc,"Mcc":Mcc,
                                       "brier_score_loss":br_s,"F1Score":
↪f1score,
                                       "Training Time [s]": T_time,"Prediction␣
↪Time [s]": P_time})
display(SMTcomparison_NotTuned)
#If we compared the below result with the results of Smotecomparison,we can␣
↪notice that the tuning didnt show a notable improvement in the results.
```

```
                      name  Accuracy  Sensetivity  Specificity       AUC  \
0   DecisionTreeClassifier  0.860720     0.557303     0.901401  0.729352
1       LogisticRegression  0.890077     0.629213     0.925053  0.899705
2   RandomForestClassifier  0.894660     0.661236     0.925957  0.926318

        Mcc  brier_score_loss   F1Score  Training Time [s]  \
0  0.411602          0.139280  0.486155           0.817559
1  0.515019          0.109923  0.575096           2.168229
2  0.540841          0.105340  0.597462          10.280462

   Prediction Time [s]
0             0.008777
1             0.006218
2             0.477386
```

5.3 *Random Undersampling (RUS)*

1. In this stage the models have been built on balanced dataset using Random Undersampling.
2. Sampling stategy parameter in Undersamping function has been tuned for each model in order to optimize the F1-score.
3. The models have been tuned based on some parameters: A. Random Forest tuned parameters are: Max depth and the n_estimators (number of trees) B. Decision Tree tuned parameters are: Max depth. C. Logistic Regression tuned parameters are : Max iteration and Solver.
4. We focused on optimizing F1-Score metric as it was the smallest value in the confusion matrix in the first run

If the performance is similar or better to SMOTE then using RUS would be chosen as this method would save more time to train models and predict outputs.

5.3.1 1. RUS Hyperparameter Tuning (based on Sampling strategy and F1-Score)

[ ]:
```
#Tuning randomundersampler for Random Forest
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from imblearn.under_sampling import RandomUnderSampler
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
import imblearn
```

[ ]:
```
#Tuning randomundersampler for Random Forest
rfweights=np.linspace(0.3,0.5,50)
pipe=imblearn.pipeline.
 ↪make_pipeline(RandomUnderSampler(),RandomForestClassifier())
gsc=GridSearchCV(estimator=pipe,param_grid={"randomundersampler__sampling_strategy":
 ↪rfweights},scoring="f1",cv=3,n_jobs=-1)
RUSrf_grid_result=gsc.fit(x_train,y_train)

#Tuning randomundersampler for Decision Tree
dtweights=np.linspace(0.8,1,50)
pipe=imblearn.pipeline.
 ↪make_pipeline(RandomUnderSampler(),DecisionTreeClassifier())
gsc=GridSearchCV(estimator=pipe,param_grid={"randomundersampler__sampling_strategy":
 ↪dtweights},scoring="f1",cv=3,n_jobs=-1)
RUSdt_grid_result=gsc.fit(x_train,y_train)

#Tuning randomundersampler for Logistic Regression
lgrweights=np.linspace(0.4,1,20)
pipe=imblearn.pipeline.
 ↪make_pipeline(RandomUnderSampler(),LogisticRegression(solver="liblinear"))
gsc=GridSearchCV(estimator=pipe,param_grid={"randomundersampler__sampling_strategy":
 ↪lgrweights},scoring="f1",cv=3,n_jobs=-1)
RUSlgr_grid_result=gsc.fit(x_train,y_train)
```

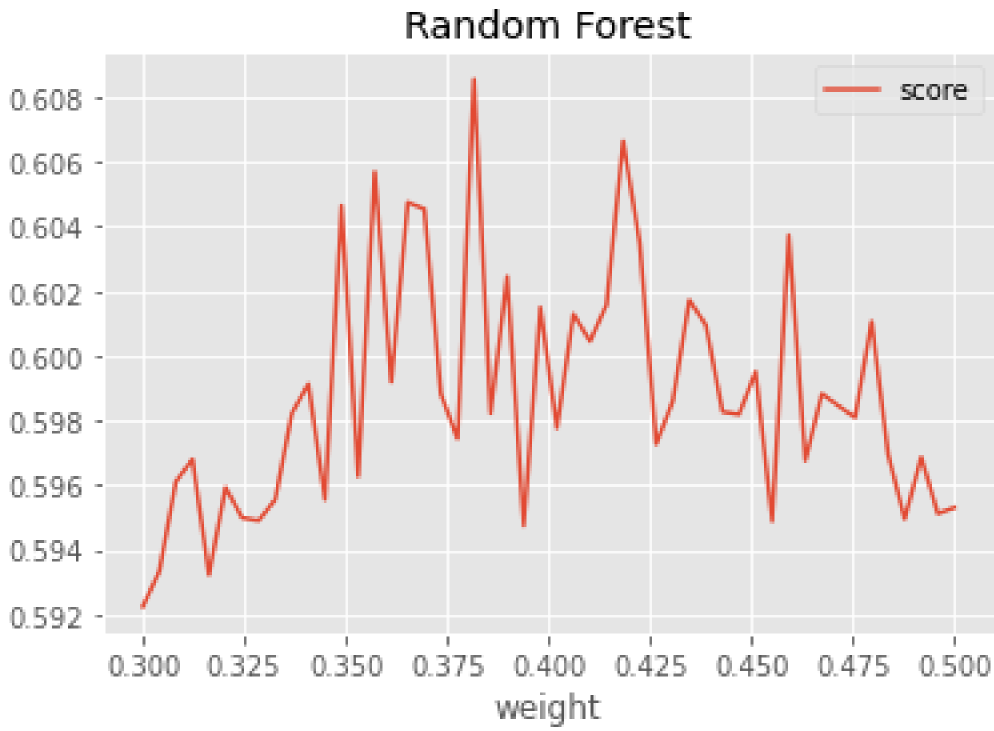
[ ]:
```
#RF
print("RF-the best parameters are %s with a score of %0.2f" %␣
 ↪(RUSrf_grid_result.best_params_,RUSrf_grid_result.best_score_))#Mean␣
 ↪cross-validated score of the best_estimator
weight_roc_auc_score_df=pd.DataFrame({"score":RUSrf_grid_result.
 ↪cv_results_["mean_test_score"],"weight":rfweights})
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
weight_roc_auc_score_df.plot(x="weight",title="Random Forest")

#DT
```

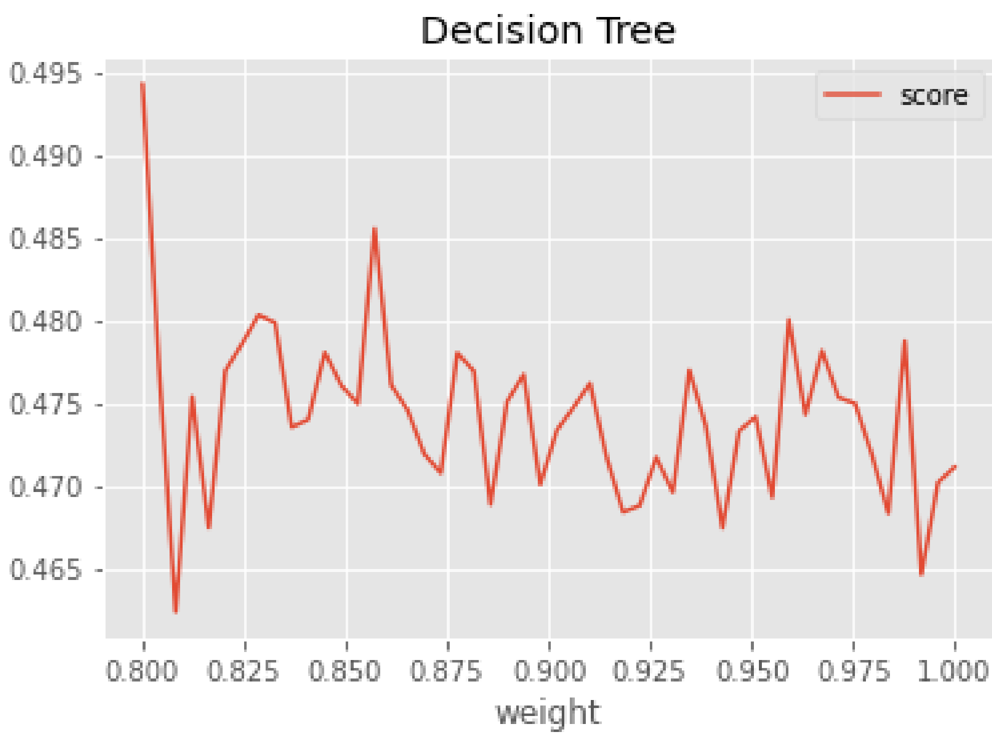
```
print("DT-the best parameters are %s with a score of %0.2f" %␣
↪(RUSdt_grid_result.best_params_,RUSdt_grid_result.best_score_))#Mean␣
↪cross-validated score of the best_estimator
weight_roc_auc_score_df=pd.DataFrame({"score":RUSdt_grid_result.
↪cv_results_["mean_test_score"],"weight":dtweights}) #the score is the␣
↪average of all cv folds for a single combination of the parameters you␣
↪specify in the tuned_params
weight_roc_auc_score_df.plot(x="weight",title="Decision Tree")

#Logistic Regression
print("LGR-the best parameters are %s with a score of %0.2f" %␣
↪(RUSlgr_grid_result.best_params_,RUSlgr_grid_result.best_score_))#Mean␣
↪cross-validated score of the best_estimator
weight_roc_auc_score_df=pd.DataFrame({"score":RUSlgr_grid_result.
↪cv_results_["mean_test_score"],"weight":lgrweights}) #the score is the␣
↪average of all cv folds for a single combination of the parameters you␣
↪specify in the tuned_params
weight_roc_auc_score_df.plot(x="weight",title="Logistic Regression")
```

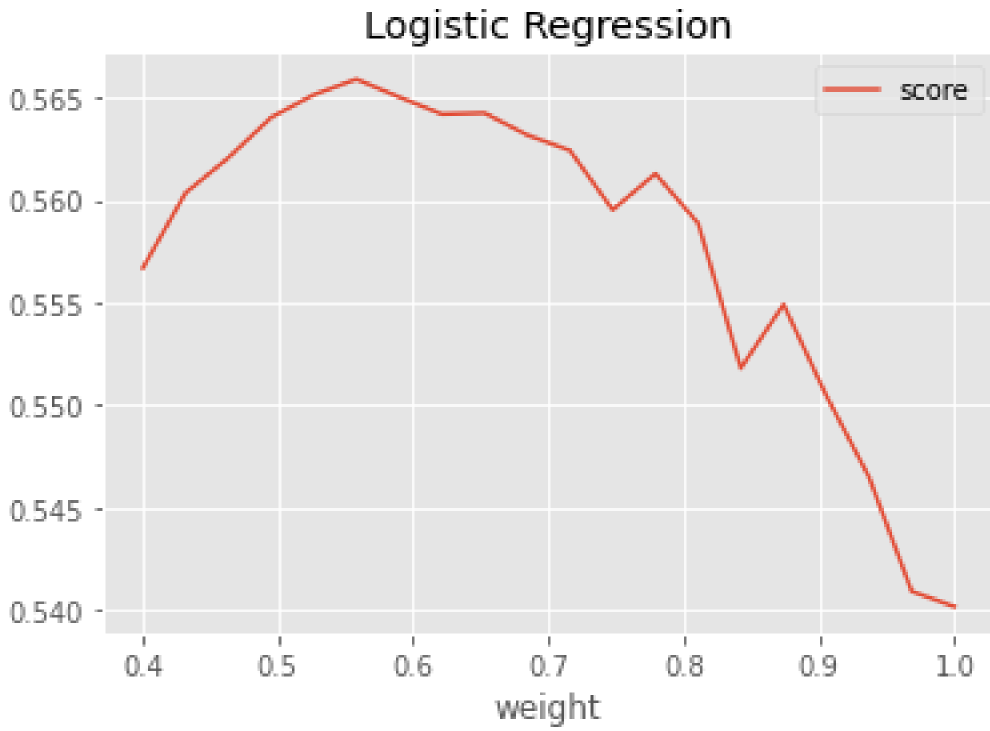
```
RF-the best parameters are {'randomundersampler__sampling_strategy':
0.3816326530612245} with a score of 0.61
DT-the best parameters are {'randomundersampler__sampling_strategy': 0.8} with a
score of 0.49
LGR-the best parameters are {'randomundersampler__sampling_strategy':
0.5578947368421052} with a score of 0.57
```

[ ]:

```
<AxesSubplot: title={'center': 'Logistic Regression'}, xlabel='weight'>
```


Random Forest
score
0.608
0.606
0.604
0.602
0.600
0.598
0.596
0.594
0.592
0.300
0.325
0.350
0.375
0.400
0.425
0.450
0.475
0.500
weight


Decision Tree
score
0.495
0.490
0.485
0.480
0.475
0.470
0.465
0.800
0.825
0.850
0.875
0.900
0.925
0.950
0.975
1.000
weight



5.3.2 *2. Data Balancing: (Random UnderSampling)*

[39]:
```
#Tuning randomundersampler for Random Forest
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from imblearn.under_sampling import RandomUnderSampler
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
import imblearn
```

[40]:
```
#from the above we can conclude that the best parameters for Random␣
↪Undersampling  are:

#Please note that the sampling strategy is the desired ratio of the number of␣
↪samples in the minority
#class over the number of samples in the majority class after resampling.'''

#Random Forest:
RF_RUS_sampling_strategy=0.3816326530612245

# Decision Tree:
DT_RUS_sampling_strategy=0.8
```

```
# Logistic Regression:
lgr_RUS_sampling_strategy=0.5578947368421052

#These values may differ slightly on each run of the previous tunning.
#Please note that I have saved the random undersampling -sampling strategy␣
↪values (after tuning) for each model
#in the above variables in order to make the run time shorter everytime we need␣
↪to balance the data.
```

[41]:
```
#The portions for minority and majority before RUS
import numpy as np
unique,count=np.unique(y_train,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[41]: {0: 26646, 1: 3509}

[42]:
```
#Resample DT
RUSdt=RandomUnderSampler(sampling_strategy=DT_RUS_sampling_strategy,random_state=100)
dtx_train_rus,dty_train_rus=RUSdt.fit_resample(x_train,y_train)
unique,count=np.unique(dty_train_rus,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[42]: {0: 4386, 1: 3509}

[43]:
```
#Resample RF
RUSrf=RandomUnderSampler(sampling_strategy=RF_RUS_sampling_strategy,random_state=11)#
rfx_train_rus,rfy_train_rus=RUSrf.fit_resample(x_train,y_train)
unique,count=np.unique(rfy_train_rus,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[43]: {0: 9194, 1: 3509}

[44]:
```
#Resample logisitic regression
RUSlgr=RandomUnderSampler(sampling_strategy=lgr_RUS_sampling_strategy,random_state=12)
lgrx_train_rus,lgry_train_rus=RUSlgr.fit_resample(x_train,y_train)
unique,count=np.unique(lgry_train_rus,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
y_train_dict_value_count
```

[44]: {0: 6289, 1: 3509}

5.3.3 3.RUS- Random Forest Hyperparameter Tuning (based on max depth, number of trees and F1-Score)

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(random_state=3)
```

[ ]:
```
import numpy as np
from sklearn.model_selection import GridSearchCV

max_depth_range=np.arange(14,20,1)
n_estimators_range=np.arange(10,110,10)
param_grid=dict(max_depth=max_depth_range,n_estimators=n_estimators_range)
rfgridRUS=GridSearchCV(estimator=rf,param_grid=param_grid,scoring="f1",cv=3,n_jobs=-1)
```

[ ]:
```
rfgridRUS.fit(rfx_train_rus,rfy_train_rus)
```

[ ]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=3), n_jobs=-1,
             param_grid={'max_depth': array([14, 15, 16, 17, 18, 19]),
                         'n_estimators': array([ 10,  20,  30,  40,  50,  60,
70,  80,  90, 100])},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (rfgridRUS.
 ↪best_params_,rfgridRUS.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_depth': 17, 'n_estimators': 80} with a score of
0.73
```

[ ]:
```
#data frame of grid search parameters and their accuracy scores
import pandas as pd

grid_results = pd.concat([pd.DataFrame(rfgridRUS.cv_results_["params"]),
                          pd.DataFrame(rfgridRUS.
 ↪cv_results_["mean_test_score"], columns=["f1"])],axis=1)
grid_results.head()

#preparing data for making  contour plots
grid_contour = grid_results.groupby(['max_depth','n_estimators']).mean()
grid_contour

#pivot data:
grid_reset=grid_contour.reset_index()
grid_reset.columns=["max_depth","n_estimator","f1"]
grid_pivot=grid_reset.pivot("max_depth","n_estimator")
```

```
#assigning the pivoted data into the respective x,y, and z variables
x=grid_pivot.columns.levels[1].values
y=grid_pivot.index.values
z=grid_pivot.values

#2D contour plot
import plotly.graph_objects as go

# X and Y axes labels
layout = go.Layout(
            xaxis=go.layout.XAxis(
              title=go.layout.xaxis.Title(
              text='n_estimators')
             ),
             yaxis=go.layout.YAxis(
              title=go.layout.yaxis.Title(
              text='max_depth')
            ) )

fig = go.Figure(data = [go.Contour(z=z, x=x, y=y)], layout=layout )

fig.update_layout(title='Hyperparameter tuning', autosize=False,
                  width=500, height=500,
                  margin=dict(l=65, r=50, b=65, t=90))

fig.show()
```

5.3.4 4. RUS- Decision Tree Hyperparameter Tuning (based on max depth and F1-Score)

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(random_state=3)
```

[ ]:
```
import numpy as np
from sklearn.model_selection import GridSearchCV

max_depth_range=np.arange(1,14,2)
param_grid=dict(max_depth=max_depth_range)
dtgridRUS=GridSearchCV(estimator=dt,param_grid=param_grid,scoring="roc_auc",cv=10,n_jobs=-1)
```

[ ]:
```
np.arange(1,14,2)
```

[ ]:
```
array([ 1,  3,  5,  7,  9, 11, 13])
```

[ ]:
```
dtgridRUS.fit(dtx_train_rus,dty_train_rus)
```

[ ]:
```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random_state=3), n_jobs=-1,
             param_grid={'max_depth': array([ 1,  3,  5,  7,  9, 11, 13])},
             scoring='roc_auc')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (dtgridRUS.
 ↪best_params_,dtgridRUS.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
```

```
the best parameters are {'max_depth': 7} with a score of 0.87
```

5.3.5 3.RUS- Logistic Regression Hyperparameter Tuning (based on max Iteration, Solver, and F1-Score)

[ ]:
```
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression(random_state=3,n_jobs=-1)
```

[ ]:
```
#This step has been run repeatedly on different ranges of the model parameters␣
 ↪in order to tune them on the right values.
import numpy as np
from sklearn.model_selection import GridSearchCV

max_iter=np.arange(60,100,1)
param_grid=dict(max_iter=max_iter,solver=['liblinear', 'lbfgs'])

lgrgridRUS=GridSearchCV(estimator=lgr,param_grid=param_grid,scoring="f1",cv=3,n_jobs=-1)
```

[ ]:
```
lgrgridRUS.fit(rfx_train_rus,rfy_train_rus)
```

[ ]:
```
GridSearchCV(cv=3, estimator=LogisticRegression(n_jobs=-1, random_state=3),
             n_jobs=-1,
             param_grid={'max_iter': array([60, 61, 62, 63, 64, 65, 66, 67, 68,
69, 70, 71, 72, 73, 74, 75, 76,
       77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93,
       94, 95, 96, 97, 98, 99]),
                         'solver': ['liblinear', 'lbfgs']},
             scoring='f1')
```

[ ]:
```
print("the best parameters are %s with a score of %0.2f" % (lgrgridRUS.
 ↪best_params_,lgrgridRUS.best_score_))#Mean cross-validated score of the␣
 ↪best_estimator
#the score is the average of all cv folds for a single combination of the␣
 ↪parameters you specify in the tuned_params
#lbfgs stayed as a better choice.
```

```
the best parameters are {'max_iter': 69, 'solver': 'lbfgs'} with a score of 0.65
```

5.3.6 5. RUS- Train the model and calculate the run time of training the model

[47]:
```
#from the above we can conclude that the best parameters are:

#Random Forest:
RUS_RF_max_depth= 17
RUS_RF_n_estimators= 80

# Decision Tree:

RUS_DT_max_depth=7

#logistic Regression:
RUS_lgr_max_iter=69
RUS_lgr_solver="lbfgs"

#These values may differ slightly on each run of the previous tunning.
#Please note that I have saved the parameters values (after tuning) of each␣
↪model in the above variables
#in order to make the run time shorter everytime we need to train the model.
```

[ ]:
```
#RF
import time
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=RUS_RF_n_estimators, max_depth=␣
↪RUS_RF_max_depth,random_state=3)

startrf=time.time()
rf.fit(rfx_train_rus,rfy_train_rus)
endrf=time.time()

#DT
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(max_depth=RUS_DT_max_depth,random_state=3)
startdt=time.time()
dt.fit(dtx_train_rus,dty_train_rus)
enddt=time.time()

#Logistic Regression
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression(max_iter=RUS_lgr_max_iter,solver=RUS_lgr_solver,n_jobs=-1)
# -1 means using all processors. This means that the n_jobs parameter can be␣
↪used to distribute and exploit all the CPUs available in the local computer
startlgr=time.time()
```

```
lgr.fit(lgrx_train_rus,lgry_train_rus)
endlgr=time.time()


print("RF Training Run Time [s]:",endrf-startrf)
print("DT Training Run Time [s]:",enddt-startdt)
print("LGR Training Run Time [s]:",endlgr-startlgr)
#The results shows the the faster model is the Decision tree,
#Logistic regression, and the Random forest respectively.
#Random Forest model was the slowest one( which is expected as it is an
 ↪ensemble model)
```

```
RF Training Run Time [s]: 1.3602180480957031
DT Training Run Time [s]: 0.043127298355102540
LGR Training Run Time [s]: 1.021684169769287
```

5.3.7 6. RUS- Run Time for prediction

[ ]:
```
# the run time to predict the test set
startrf=time.time()
y_predictedrf=rf.predict(x_test)
endrf=time.time()

startdt=time.time()
y_predicteddt=dt.predict(x_test)
enddt=time.time()

startlgr=time.time()
y_predictedlgr=lgr.predict(x_test)
endlgr=time.time()

print("RF Run Time to Predict the testset [s]:",endrf-startrf)
print("DT Run Time to Predict the testset [s]:",enddt-startdt)
print("LGR Run Time to Predict the testset [s]:",endlgr-startlgr)

# The results shows the the faster model is the Logistic regression,Decision
 ↪tree, and the Random forest respectively.
# Random Forest model was the slowest one( which is expected as it is an
 ↪ensemble model)
```

```
RF Run Time to Predict the testset [s]: 0.2660255432128906
DT Run Time to Predict the testset [s]: 0.006936311721801758
LGR Run Time to Predict the testset [s]: 0.005370140075683594
```

5.3.8 7. RUS- Confusion Matrix

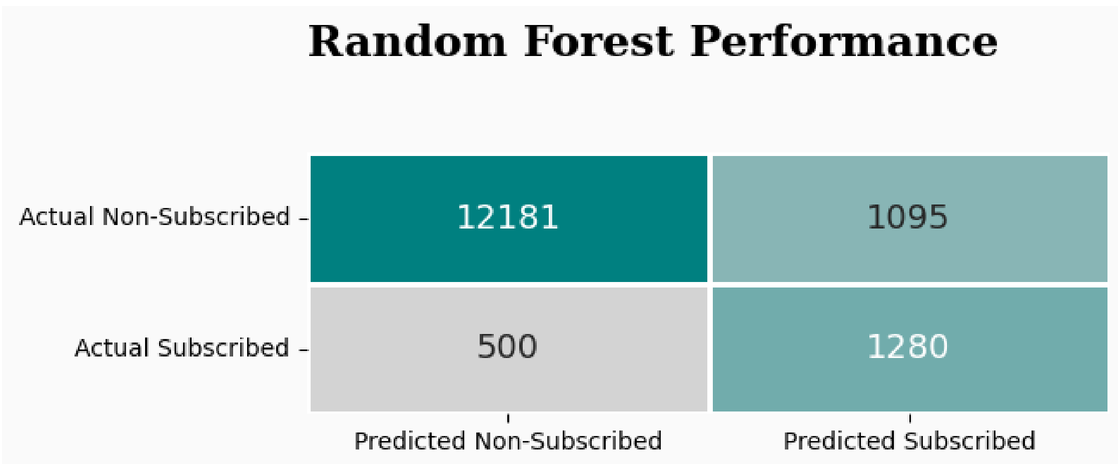
[ ]:
```
from sklearn.metrics import recall_score, make_scorer, confusion_matrix,␣
↪classification_report,ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns

class Colors:
    Gray = "#5d5d5d"
    LightGray = "#fafafa"
    Black = "#000000"
    White = "#FFFFFF"
    Teal = "#008080"
    Aquamarine = "#76c8c8"
    Blue = "#2596be"
    LightCyan = "#badbdb"
    WhiteSmoke = "#dedad2"
    Cream = "#e4bcad"
    PeachPuff = "#df979e"
    HotPink = "#d7658b"
    DeepPink = "#c80064"
    LightSeaGreen = "#20B2AA"
    DarkGray = "#464144"
#RF
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmrf = confusion_matrix(y_test,y_predictedrf)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmrf, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
↪Subscribed'],annot_kws={"fontsize":14})
print("Random Forest","\n",classification_report(y_test, y_predictedrf))
ax0.text(0,-0.75,'Random Forest␣
↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')

#DT
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])
```

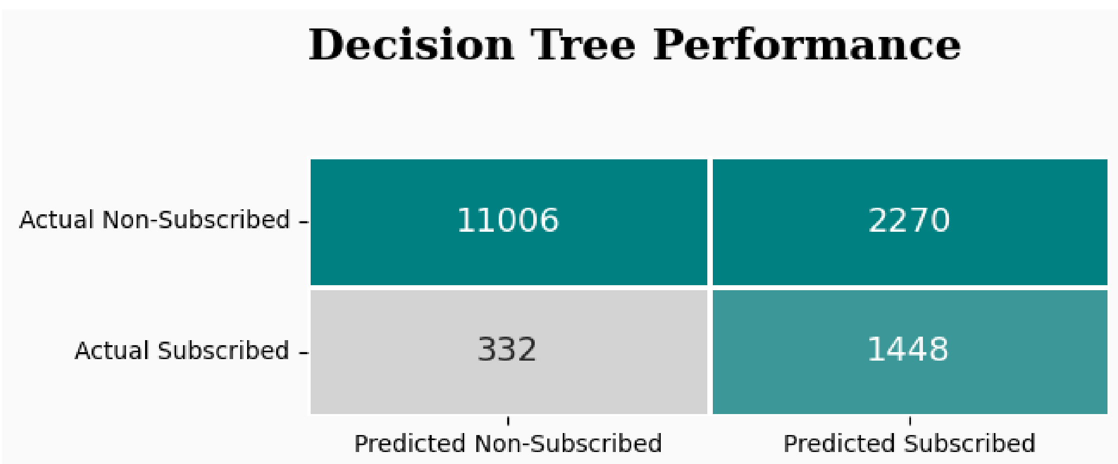
```
cmdt = confusion_matrix(y_test,y_predicteddt)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
 ↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmdt, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
 ↪Subscribed'],annot_kws={"fontsize":14})
print("Decision Tree","\n",classification_report(y_test, y_predicteddt))
ax0.text(0,-0.75,'Decision Tree␣
 ↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')


#logistic regression
fig = plt.figure(figsize=(6, 2), dpi=100, facecolor=Colors.LightGray)
gs = fig.add_gridspec(1, 1)
gs.update(wspace=0.35, hspace=0.27)
ax0 = fig.add_subplot(gs[0:1, 0:1])

cmlgr = confusion_matrix(y_test,y_predictedlgr)
colors = ['lightgray',Colors.Teal,Colors.Teal,Colors.Teal,Colors.Teal,Colors.
 ↪Teal,Colors.Teal,Colors.Teal]
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
sns.heatmap(cmlgr, cmap=colormap,annot=True,fmt="d", linewidths=1,cbar=False,
            yticklabels=['Actual Non-Subscribed','Actual Subscribed'],
            xticklabels=['Predicted Non-Subscribed','Predicted␣
 ↪Subscribed'],annot_kws={"fontsize":14})
print("Logistic Regression","\n",classification_report(y_test, y_predictedlgr))
ax0.text(0,-0.75,'Logistic Regression␣
 ↪Performance',fontsize=18,fontweight='bold',fontfamily='serif')
```

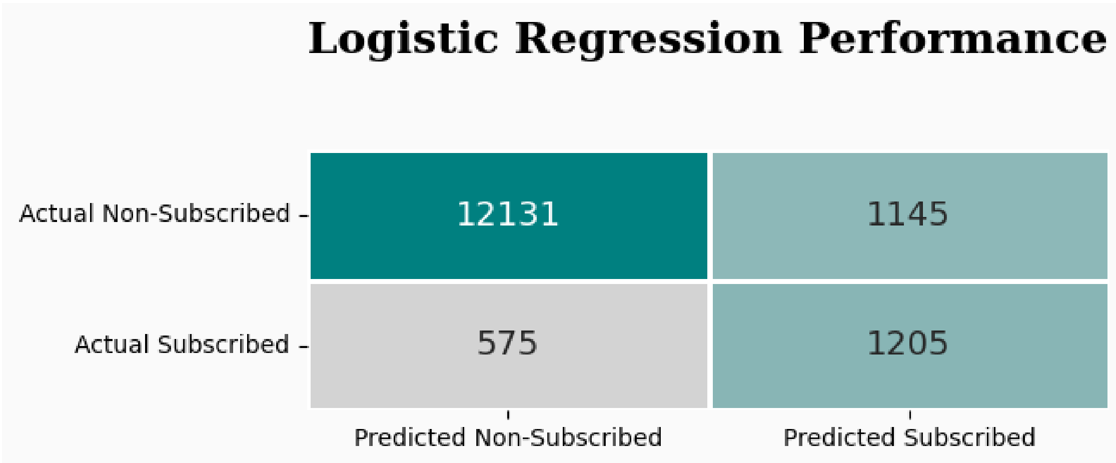
```
Random Forest
              precision    recall  f1-score   support

           0       0.96      0.92      0.94     13276
           1       0.54      0.72      0.62      1780

    accuracy                           0.89     15056
   macro avg       0.75      0.82      0.78     15056
weighted avg       0.91      0.89      0.90     15056

Decision Tree
              precision    recall  f1-score   support

           0       0.97      0.83      0.89     13276
           1       0.39      0.81      0.53      1780
```

```
    accuracy                           0.83     15056
   macro avg       0.68      0.82      0.71     15056
weighted avg       0.90      0.83      0.85     15056

Logistic Regression
              precision    recall  f1-score   support

           0       0.95      0.91      0.93     13276
           1       0.51      0.68      0.58      1780

    accuracy                           0.89     15056
   macro avg       0.73      0.80      0.76     15056
weighted avg       0.90      0.89      0.89     15056
```

[ ]: Text(0, -0.75, 'Logistic Regression Performance')





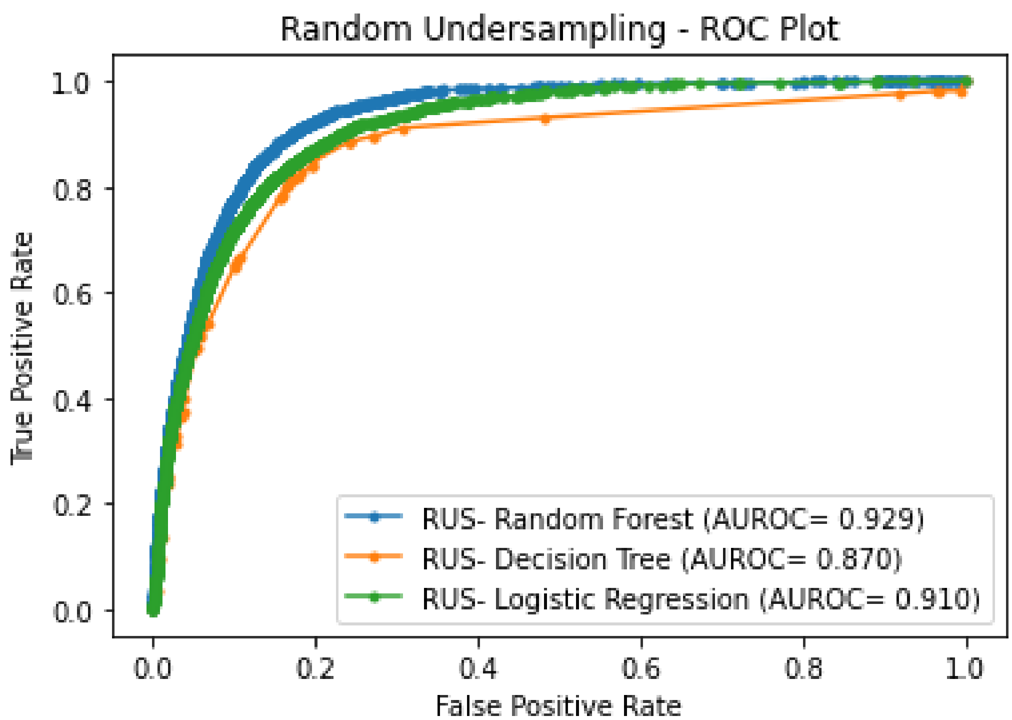


5.3.9 8.RUS- Calculate the AUROC

[ ]:
```
#to get the probabilities of the prediction for each instance in the test set

rf_probs= rf.predict_proba(x_test)
dt_probs= dt.predict_proba(x_test)
lgr_probs= lgr.predict_proba(x_test)

#to keep the probabilities of positive outcomes
rf_probs=rf_probs[:,1]
rf_probs

dt_probs=dt_probs[:,1]
dt_probs

lgr_probs=lgr_probs[:,1]
lgr_probs

#print AUROC score
from sklearn.metrics import roc_curve, roc_auc_score
rf_auc=roc_auc_score(y_test,rf_probs)
dt_auc=roc_auc_score(y_test,dt_probs)
lgr_auc=roc_auc_score(y_test,lgr_probs)

print("Random Forest: AUROC= %.3f" % (rf_auc))
print("Decision Tree: AUROC= %.3f" % (dt_auc))
print("Logistic Regression: AUROC= %.3f" % (lgr_auc))
```

```
#Calculate and plot ROC curve
#roc_curve() returns three arrays, first one is false positive rate(fpr),
#second one is true positive rate(tpr) and the third one is the threshold (_).
#For more information: https://scikit-learn.org/stable/modules/generated/
↪sklearn.metrics.roc_curve.html

rf_fpr,rf_tpr,_=roc_curve(y_test,rf_probs)
dt_fpr,dt_tpr,_=roc_curve(y_test,dt_probs)
lgr_fpr,lgr_tpr,_=roc_curve(y_test,lgr_probs)

import matplotlib.pyplot as plt
plt.plot(rf_fpr,rf_tpr,marker=".",label="RUS- Random Forest (AUROC= %0.3f)" %␣
↪rf_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.plot(dt_fpr,dt_tpr,marker=".",label="RUS- Decision Tree (AUROC= %0.3f)" %␣
↪dt_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.plot(lgr_fpr,lgr_tpr,marker=".",label="RUS- Logistic Regression (AUROC= %0.
↪3f)" % lgr_auc)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')

plt.title("Random Undersampling - ROC Plot")
plt.legend()
plt.show()

#The results show the best model AUROC is Random forest with 0.93 score␣
↪followed by
#Logisitic regression and Decision tree respectivily.
#Comparing to the imbalanced section, the AUC has been increased slightly in␣
↪Decision tree from 0.84 to 0.86.
#Random Forest and logistic regression are stable before and after Random␣
↪UnderSampling.

#Comparing to the SMOTE section, the AUC has been increased slightly as␣
↪logistic regression AUC
# increased from 0.89 to 0.91 and Decision tree increased from 0.77 to 0.87.
#Random Forest is stable before and after Random UnderSampling.
```

```
Random Forest: AUROC= 0.929
Decision Tree: AUROC= 0.870
Logistic Regression: AUROC= 0.910
```



5.3.10 9. RUS- Summary (ACC,Recall, specificity,AUC,MCC, brier_score_loss, F1 Score, run time) for the models

[ ]:
```
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,brier_score_loss,matthews_corrcoef,f1_score
from sklearn import  tree, linear_model,ensemble

RUSMLA = [tree.
↪DecisionTreeClassifier(max_depth=RUS_DT_max_depth,random_state=3),
       linear_model.
↪LogisticRegression(max_iter=RUS_lgr_max_iter,solver=RUS_lgr_solver,random_state=3,n_jobs=-1
       # -1 means using all processors. This means that the n_jobs parameter␣
↪can be used to distribute and exploit all the CPUs available in the local␣
↪computer
       ensemble.RandomForestClassifier(n_estimators=RUS_RF_n_estimators,␣
↪max_depth=RUS_RF_max_depth,random_state=3)
       ]

import time
name = []
Accuracy = []
Specificity=[]
```

```
Sensetivity=[]
alg_auc=[]
T_time=[]
P_time=[]
Mcc=[]
br_s=[]
f1score=[]
for alg in RUSMLA:
    name.append(alg.__class__.__name__)

    if alg.__class__.__name__=="RandomForestClassifier":
      x_Train=rfx_train_rus
      y_Train=rfy_train_rus
    elif alg.__class__.__name__=="DecisionTreeClassifier":
      x_Train=dtx_train_rus
      y_Train=dty_train_rus
    elif alg.__class__.__name__=="LogisticRegression":
      x_Train=lgrx_train_rus
      y_Train=lgry_train_rus



    start=time.time()
    alg.fit(x_Train,y_Train)
    end=time.time()


    startp=time.time()
    y_predicted=alg.predict(x_test)
    endp=time.time()
    Accuracy.append(accuracy_score(y_test,y_predicted))
    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))
    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))
    Mcc.append(matthews_corrcoef(y_test, y_predicted))
    br_s.append(brier_score_loss(y_test, y_predicted))
    f1score.append(f1_score(y_test, y_predicted))
    alg_probs= alg.predict_proba(x_test)
    alg_probs=alg_probs[:,1]
    alg_auc.append(roc_auc_score(y_test,alg_probs))
    T_time.append(end-start)
    P_time.append(endp-startp)


RUScomparison = pd.DataFrame({"name": name, "Accuracy": Accuracy,"Sensetivity":
 ↪Sensetivity,"Specificity":Specificity,
                              "AUC":alg_auc,"Mcc":Mcc,"brier_score_loss":
 ↪br_s,"F1Score":f1score,
```

```
                                "TrainingTime_s": T_time,"Prediction Time [s]":␣
 ↪P_time})
display(RUScomparison)

#From the below results we can conclude that the random forest is slightly␣
 ↪better than other models
#specially if we compared them by the Brior_score,
#Matthew’s correlation coefficient (MCC),Specificity,and AUC.
#Recently alot of researches prove that MCC is a better measurement specially
#for binary classification problems along with the brier score.
# we can notice if we compared the results of this summary with the summary of␣
 ↪SMOTE that the undersampling techniques improves the performance more than␣
 ↪applying SMOTE technique
```

```
                     name  Accuracy  Sensetivity  Specificity       AUC  \
0  DecisionTreeClassifier  0.827179     0.813483     0.829015  0.869632
1      LogisticRegression  0.885760     0.676966     0.913754  0.909707
2  RandomForestClassifier  0.894062     0.719101     0.917520  0.929225

        Mcc  brier_score_loss   F1Score  TrainingTime_s  Prediction Time [s]
0  0.481052          0.172821  0.526737        0.041147             0.007113
1  0.525518          0.114240  0.583535        0.609840             0.005797
2  0.563918          0.105938  0.616125        1.350638             0.287884
```

5.3.11 10. RUS- Check Over/Underfitting

Brier Score was used to evaluate the model fitting

The reason behind using the Brier score metric is that Brier score measures the mean squared difference between the predicted probability and the actual outcome. The Brier score always takes on a value between zero and one, since this is the largest possible difference between a predicted probability (which must be between zero and one) and the actual outcome (which can take on values of only 0 and 1). It can be decomposed is the sum of refinement loss and calibration loss. The Brier score is appropriate for binary and categorical outcomes that can be structured as true or false, but is inappropriate for ordinal variables which can take on three or more values

Brier score is actually 1-Accuracy

”The Brier score is a strictly proper scoring function that is equivalent to the mean squared error” (Chicco, D., Warrens, M. J., & Jurman, G. (2021)).

*The smaller the Brier score loss, the better, hence the naming with “loss”.

If the performance of the model on the training set is poor that means the model is underfitting to the test data.

If the performance of the model on the test set is poor that means the model is overfitting to the training data.

[48]:
```
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,brier_score_loss
from sklearn import tree, linear_model,ensemble
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import validation_curve
from sklearn.model_selection import RepeatedKFold
import numpy as np
np.random.seed(3)
import matplotlib.pyplot as plt
plt.style.use("ggplot")
```

[49]:
```
#Decision Tree
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
RUS_DT_list_training_BrierScore=[]
RUS_DT_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
  model=tree.DecisionTreeClassifier(max_depth=RUS_DT_max_depth,random_state=3)

# apply the tuned Random Undersampling to balance the training set:
 ␣
↪RUSdt=RandomUnderSampler(sampling_strategy=DT_RUS_sampling_strategy,random_state=11)
  dtx_train_rus,dty_train_rus=RUSdt.fit_resample(X_train,Y_train)

  model.fit(dtx_train_rus,dty_train_rus)

  y_train_data_pred=model.predict(dtx_train_rus)
  y_test_data_pred=model.predict(X_test)

 ␣
↪RUS_DT_fold_training_BrierScore=brier_score_loss(dty_train_rus,y_train_data_pred)
  RUS_DT_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

  RUS_DT_list_training_BrierScore.append(RUS_DT_fold_training_BrierScore)
  RUS_DT_list_testing_BrierScore.append(RUS_DT_fold_testing_BrierScore)
```

[50]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(RUS_DT_list_training_BrierScore).
↪ravel(),"o-")
plt.xlabel("Number of fold")
```

```
plt.ylabel("Training BrierScore")
plt.title("Decision Tree \n Training BrierScore across folds    ")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(RUS_DT_list_testing_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("  Decision Tree \n    Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph " Decision␣
 ↪Tree-Training BrierScore across folds",
#we can see the the models fits really well as the BrierScore is around 0.2
#In the second graph "Decision Tree -Testing BrierScore across folds"it also␣
 ↪fits well as the BrierScore on the test set is around 0.2.
#That means also that we have a fitted model and stable one.
```

[51]:
```
#Logistic Regression
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

RUS_lgr_list_training_BrierScore=[]
RUS_lgr_list_testing_BrierScore=[]

X=dff.drop(["y"],axis="columns")
y=dff.y

for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
```

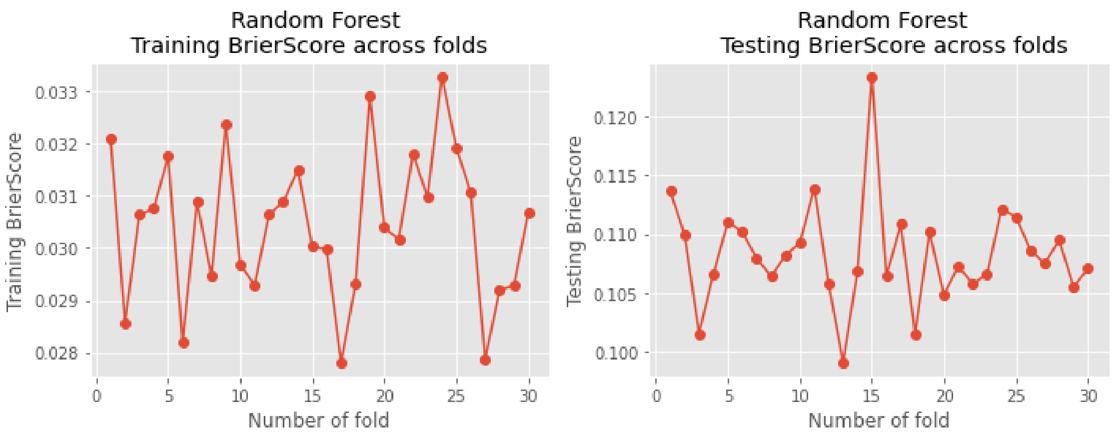
```
    Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
    model=linear_model.
 ↪LogisticRegression(max_iter=RUS_lgr_max_iter,solver=RUS_lgr_solver,random_state=3,n_jobs=-1

# apply the tuned RUS to balance/resample the training set:
 ␣
 ↪RUSlgr=RandomUnderSampler(sampling_strategy=lgr_RUS_sampling_strategy,random_state=11)
    lgrx_train_rus,lgry_train_rus=RUSlgr.fit_resample(X_train,Y_train)

    model.fit(lgrx_train_rus,lgry_train_rus)

    y_train_data_pred=model.predict(lgrx_train_rus)
    y_test_data_pred=model.predict(X_test)

 ␣
 ↪RUS_lgr_fold_training_BrierScore=brier_score_loss(lgry_train_rus,y_train_data_pred)
    RUS_lgr_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

    RUS_lgr_list_training_BrierScore.append(RUS_lgr_fold_training_BrierScore)
    RUS_lgr_list_testing_BrierScore.append(RUS_lgr_fold_testing_BrierScore)
```

[52]:

```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
 ↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.
 ↪array(RUS_lgr_list_training_BrierScore).ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Logistic Regression \n Training BrierScore across folds    ")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(RUS_lgr_list_testing_BrierScore).
 ↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("Logistic Regression \n    Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph "Logistic␣
 ↪Regression-Training BrierScore across folds",
#we can see the the models fits well as the BrierScore is about 0.2
#In the second graph "Logistic Regression -Training BrierScore across folds"
#it also fits well as the BrierScore on the test set is about 0.1. that means␣
 ↪also that we have a fitted model and stable one.
```

[53]:
```
#Random Forest
# prepare the cross-validation procedure
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
RUS_RF_list_training_BrierScore=[]
RUS_RF_list_testing_BrierScore=[]
X=dff.drop(["y"],axis="columns")
y=dff.y
for train_index,test_index in cv.split(dff):
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
  model=ensemble.RandomForestClassifier(n_estimators=RUS_RF_n_estimators,
 ↪max_depth=RUS_RF_max_depth,random_state=3)

# apply the tuned RUS to balance the training set:
 ↪RUSrf=RandomUnderSampler(sampling_strategy=RF_RUS_sampling_strategy,random_state=11)
  rfx_train_rus,rfy_train_rus=RUSrf.fit_resample(X_train,Y_train)

  model.fit(rfx_train_rus,rfy_train_rus)

  y_train_data_pred=model.predict(rfx_train_rus)
  y_test_data_pred=model.predict(X_test)

 ↪RUS_RF_fold_training_BrierScore=brier_score_loss(rfy_train_rus,y_train_data_pred)
  RUS_RF_fold_testing_BrierScore=brier_score_loss(Y_test,y_test_data_pred)

  RUS_RF_list_training_BrierScore.append(RUS_RF_fold_training_BrierScore)
  RUS_RF_list_testing_BrierScore.append(RUS_RF_fold_testing_BrierScore)
```

[54]:
```
#plot the BrierScore of the training phase and the BrierScore of the testing␣
↪phase
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.plot(range(1,cv.get_n_splits()+1),np.array(RUS_RF_list_training_BrierScore).
↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Training BrierScore")
plt.title("Random Forest \n Training BrierScore across folds    ")
plt.tight_layout()
plt.subplot(1,2,2)
plt.plot(range(1,cv.get_n_splits()+1),np.array(RUS_RF_list_testing_BrierScore).
↪ravel(),"o-")
plt.xlabel("Number of fold")
plt.ylabel("Testing BrierScore")
plt.title("  Random Forest \n    Testing BrierScore across folds")
plt.tight_layout()
plt.show()

#From the below graphs if we looked at the the first graph "Random␣
↪Forest-Training BrierScore across folds"
#we can see the the models fits really well as the BrierScore is around 0
#in the second graph "Random Forest -Testing BrierScore across folds"it also␣
↪fits well as the BrierScore on the test set is around 0.1.
#That means also that we have a fitted model and stable one.
```



[56]:
```
from statistics import mean
display("LG_Test_BScore_Mean:", round(mean(RUS_lgr_list_testing_BrierScore),3))
display("LG_Train_BScore_Mean:",␣
↪round(mean(RUS_lgr_list_training_BrierScore),3))
```

```
display("DT_Test_BScore_Mean:", round(mean(RUS_DT_list_testing_BrierScore),3))
display("DT_Train_BScore_Mean:", round(mean(RUS_DT_list_training_BrierScore),3))

display("RF_Test_BScore_Mean:", round(mean(RUS_RF_list_testing_BrierScore),3))
display("RF_Train_BScore_Mean:", round(mean(RUS_RF_list_training_BrierScore),3))
```

```
'LG_Test_BScore_Mean:'

0.117

'LG_Train_BScore_Mean:'

0.174

'DT_Test_BScore_Mean:'

0.177

'DT_Train_BScore_Mean:'

0.161

'RF_Test_BScore_Mean:'

0.108

'RF_Train_BScore_Mean:'

0.03
```

5.3.12 *11. RUS Summary without Tuning*

[ ]:
```
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,brier_score_loss,matthews_corrcoef,f1_score
from sklearn import  tree, linear_model,ensemble

RUSMLA = [tree.DecisionTreeClassifier(random_state=4),#not tuned
       linear_model.LogisticRegression(n_jobs=-1),#not tuned,
       ensemble.RandomForestClassifier(random_state=3)]#not tuned]
```

```python
RUS=RandomUnderSampler(random_state=100)
#random undersampling function without detremining and tuning the sampling strategy

import time
name = []
Accuracy = []
Specificity=[]
Sensetivity=[]
alg_auc=[]
T_time=[]
P_time=[]
Mcc=[]
br_s=[]
f1score=[]
for alg in RUSMLA:
    name.append(alg.__class__.__name__)

    #resambling
    x_Train_rus,y_Train_rus=RUS.fit_resample(x_train,y_train)

    #train the models
    start=time.time()
    alg.fit(x_Train_rus,y_Train_rus)
    end=time.time()

    #prediting the test set by each model
    startp=time.time()
    y_predicted=alg.predict(x_test)
    endp=time.time()

    #calculating accuracy, specificity, sensetivity, MCC, brier score,F1 Score
    Accuracy.append(accuracy_score(y_test,y_predicted))
    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))
    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))
    Mcc.append(matthews_corrcoef(y_test, y_predicted))
    br_s.append(brier_score_loss(y_test, y_predicted))
    f1score.append(f1_score(y_test, y_predicted))

    #computing ROC-AUC
    alg_probs= alg.predict_proba(x_test)
    alg_probs=alg_probs[:,1]
    alg_auc.append(roc_auc_score(y_test,alg_probs))

  #counting the running time of prediting and training mdoel
    T_time.append(end-start)
    P_time.append(endp-startp)
```

```
RUScomparison_NotTuned = pd.DataFrame({"name": name, "Accuracy":␣
↪Accuracy,"Sensetivity":Sensetivity,
                                        "Specificity":Specificity,"AUC":
↪alg_auc,"Mcc":Mcc,"brier_score_loss":br_s,"F1Score":f1score,
                                        "Training Time [s]": T_time,"Prediction␣
↪Time [s]": P_time})
display(RUScomparison_NotTuned)
#If we compared the below result with the results of Smotecomparison,
#we can notice the importance of the tuning as most of these measurements have␣
↪improved.
```

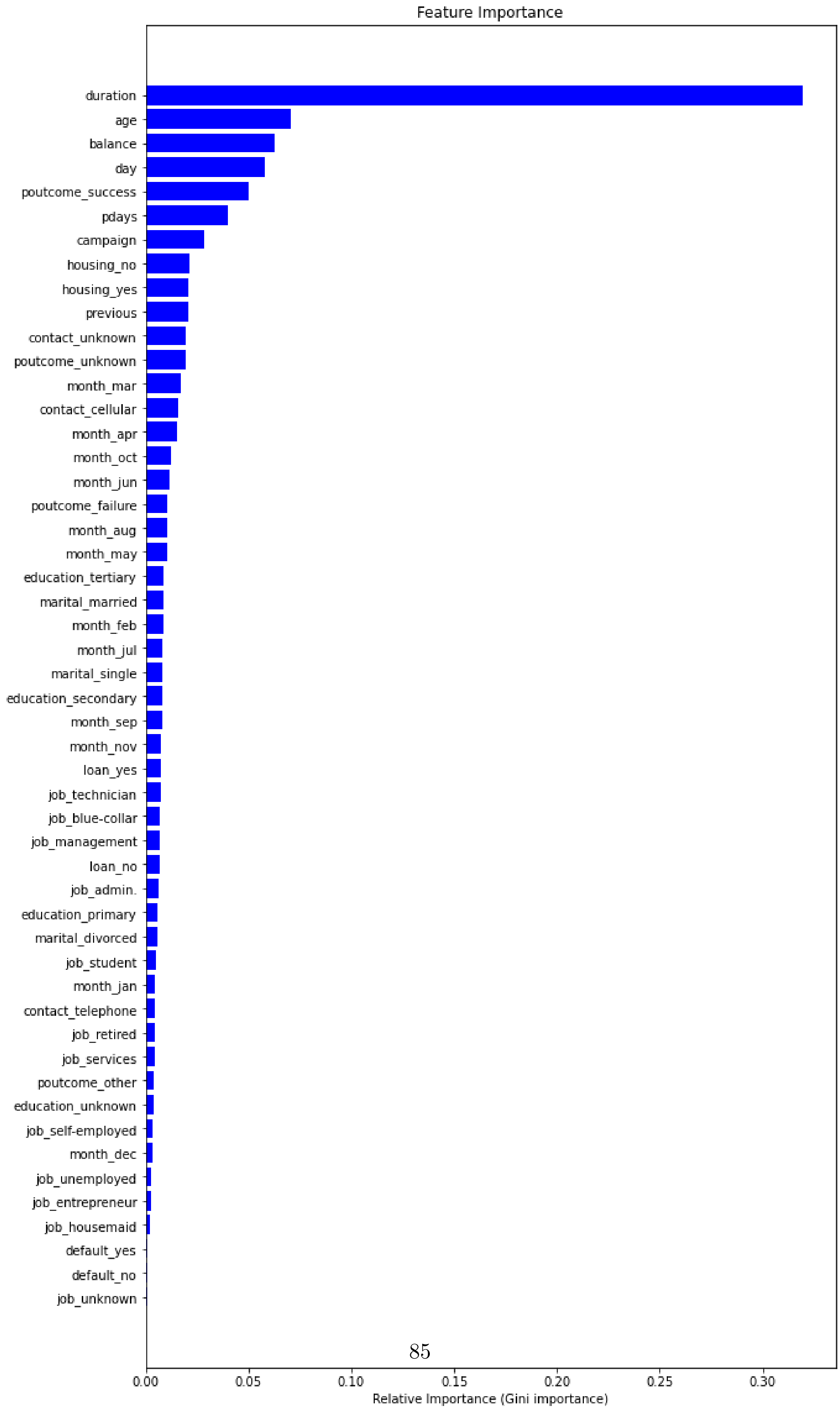
```
                     name  Accuracy  Sensetivity  Specificity       AUC  \
0  DecisionTreeClassifier  0.808050     0.792135     0.810184  0.801159
1      LogisticRegression  0.842853     0.808989     0.847394  0.907632
2  RandomForestClassifier  0.836610     0.890449     0.829391  0.922392

        Mcc  brier_score_loss   F1Score  Training Time [s]  \
0  0.442796          0.191950  0.493870           0.070006
1  0.503436          0.157147  0.548990           1.119425
2  0.532751          0.163390  0.563055           1.056865

   Prediction Time [s]
0             0.007898
1             0.005370
2             0.367377
```

5.4 *Random Forest Feature Importance*

The important features for Random Forest have been extracted based on the best balancing strategy that improved the performance of the Random Forest, which is the random undersampling

[ ]:
```
#important note: The model parameters have been adjusted based on the best␣
↪balancing method.
rf=RandomForestClassifier(n_estimators=RUS_RF_n_estimators,
                          max_depth= RUS_RF_max_depth,random_state=3)
rf.fit(rfx_train_rus,rfy_train_rus)

import matplotlib.pyplot as plt
import seaborn as sns

features=dff.loc[:, dff.columns != 'y'].columns
importances=rf.feature_importances_
indices=np.argsort(importances)
```

```
f = plt.figure()
f.set_figwidth(10)
f.set_figheight(20)
plt.title("Feature Importance")
plt.
↪barh(range(len(indices)),importances[indices],color="b",align="center",height=.
↪8)
plt.yticks(range(len(indices)),[features[i] for i in indices])
plt.xlabel("Relative Importance (Gini importance)")
plt.show()
```


Feature Importance
duration
age
balance
day
poutcome_success
pdays
campaign
housing_no
housing_yes
previous
contact_unknown
poutcome_unknown
month_mar
contact_cellular
month_apr
month_oct
month_jun
poutcome_failure
month_aug
month_may
education_tertiary
marital_married
month_feb
month_jul
marital_single
education_secondary
month_sep
month_nov
loan_yes
job_technician
job_blue-collar
job_management
loan_no
job_admin.
education_primary
marital_divorced
job_student
month_jan
contact_telephone
job_retired
job_services
poutcome_other
education_unknown
job_self-employed
month_dec
job_unemployed
job_entrepreneur
job_housemaid
default_yes
default_no
job_unknown
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Relative Importance (Gini importance)

[ ]:
```
import pandas as pd
df_1=pd.DataFrame({"Feature names":features,"Importances":rf.
↪feature_importances_})
df_1=df_1.sort_values(by="Importances",ascending=False)
df_1
```

[ ]:

	Feature names	Importances
3	duration	0.319455
0	age	0.070855
1	balance	0.062890
2	day	0.057665
49	poutcome_success	0.050000
5	pdays	0.040041
4	campaign	0.028371
28	housing_no	0.021126
29	housing_yes	0.020490
6	previous	0.020401
34	contact_unknown	0.019647
50	poutcome_unknown	0.019590
42	month_mar	0.017013
32	contact_cellular	0.015839
35	month_apr	0.015358
45	month_oct	0.012146
41	month_jun	0.011714
47	poutcome_failure	0.010657
36	month_aug	0.010271
43	month_may	0.010256
24	education_tertiary	0.008878
20	marital_married	0.008740
38	month_feb	0.008499
40	month_jul	0.008367
21	marital_single	0.008220
23	education_secondary	0.008044
46	month_sep	0.007814
44	month_nov	0.007487
31	loan_yes	0.007337
16	job_technician	0.007183
8	job_blue-collar	0.007081
11	job_management	0.007063
30	loan_no	0.006662
7	job_admin.	0.006015
22	education_primary	0.005622
19	marital_divorced	0.005567
15	job_student	0.004826
39	month_jan	0.004659

```
33    contact_telephone     0.004551
12          job_retired     0.004491
14         job_services     0.004293
48        poutcome_other    0.003913
25    education_unknown     0.003635
13    job_self-employed     0.003431
37            month_dec     0.003419
17       job_unemployed     0.002842
9      job_entrepreneur     0.002418
10        job_housemaid     0.002268
27          default_yes     0.001156
26           default_no     0.000992
18          job_unknown     0.000741
```

[ ]:
```
#features with importance more than or equal the mean:
df_1[df_1["Importances"]>=df_1["Importances"].mean()]
```

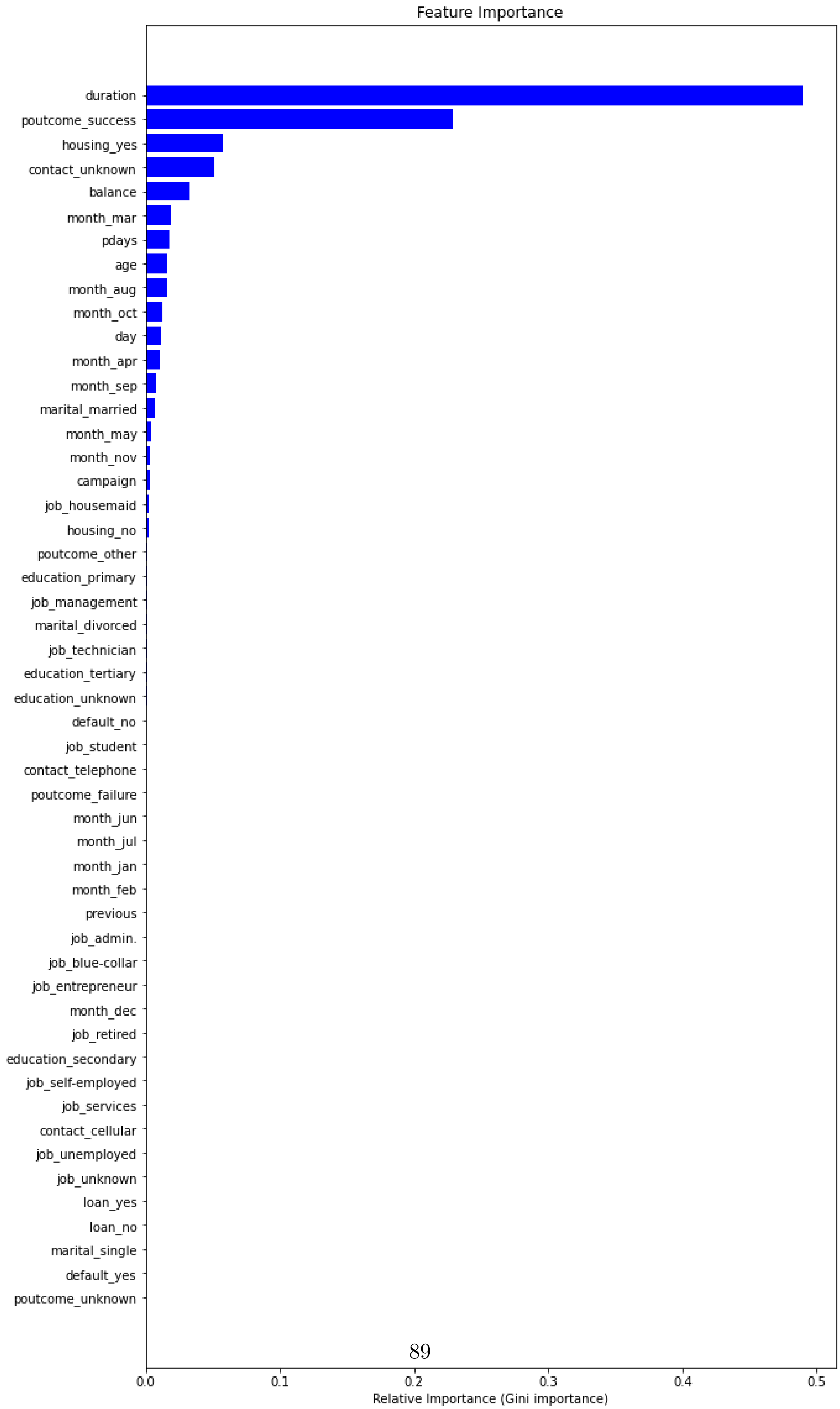
[ ]:
```
          Feature names  Importances
3              duration     0.319455
0                   age     0.070855
1               balance     0.062890
2                   day     0.057665
49     poutcome_success     0.050000
5                 pdays     0.040041
4              campaign     0.028371
28           housing_no     0.021126
29          housing_yes     0.020490
6              previous     0.020401
34      contact_unknown     0.019647
```

[ ]:
```
#or we can just use SelectFromModel to extract the selected features
# SelectFromModel accepts a threshold parameter
#and will select the features whose importance (defined by the coefficients)␣
 ↪are above this threshold.
# the threshold is the mean by default
from sklearn.feature_selection import SelectFromModel
rf=ensemble.RandomForestClassifier(n_estimators=RUS_RF_n_estimators,
                                   max_depth=RUS_RF_max_depth,random_state=3)
rf.fit(rfx_train_rus,rfy_train_rus)

FS = SelectFromModel(rf)
FS.fit(rfx_train_rus, rfy_train_rus)
FS.get_support()
Important_Features= rfx_train_rus.columns[(FS.get_support())]
impresult=pd.DataFrame({"Important_Features": Important_Features})
display(impresult)
```

```
   Important_Features
0                 age
1             balance
2                 day
3            duration
4            campaign
5               pdays
6            previous
7          housing_no
8         housing_yes
9     contact_unknown
10   poutcome_success
```

5.5 *DT Feature Importance*

```
[ ]: #important note: we have to adjust the model parameters based on the best␣
      ↪balancing method.

     dt=DecisionTreeClassifier(max_depth=RUS_DT_max_depth,random_state=3)# rfgridRUS␣
      ↪or rfgridSmote or Urfgrid
     dt.fit(rfx_train_rus,rfy_train_rus) # (rfx_train_rus,rfy_train_rus) or␣
      ↪(rfx_train_res,rfy_train_res) or (x_train,y_train)

     import matplotlib.pyplot as plt
     import seaborn as sns

     features=dff.loc[:, dff.columns != 'y'].columns
     importances=dt.feature_importances_
     indices=np.argsort(importances)

     f = plt.figure()
     f.set_figwidth(10)
     f.set_figheight(20)
     plt.title("Feature Importance")
     plt.
      ↪barh(range(len(indices)),importances[indices],color="b",align="center",height=.
      ↪8)
     plt.yticks(range(len(indices)),[features[i] for i in indices])
     plt.xlabel("Relative Importance (Gini importance)")
     plt.show()
```


Feature Importance
duration
poutcome_success
housing_yes
contact_unknown
balance
month_mar
pdays
age
month_aug
month_oct
day
month_apr
month_sep
marital_married
month_may
month_nov
campaign
job_housemaid
housing_no
poutcome_other
education_primary
job_management
marital_divorced
job_technician
education_tertiary
education_unknown
default_no
job_student
contact_telephone
poutcome_failure
month_jun
month_jul
month_jan
month_feb
previous
job_admin.
job_blue-collar
job_entrepreneur
month_dec
job_retired
education_secondary
job_self-employed
job_services
contact_cellular
job_unemployed
job_unknown
loan_yes
loan_no
marital_single
default_yes
poutcome_unknown
0.0
0.1
0.2
0.3
0.4
0.5
Relative Importance (Gini importance)

```
[ ]: import pandas as pd
     df_1=pd.DataFrame({"Feature names":features,"Importances":dt.
      ↪feature_importances_})
     df_1=df_1.sort_values(by="Importances",ascending=False)
     df_1
```

```
[ ]:          Feature names  Importances
     3             duration     0.489557
     49     poutcome_success     0.229189
     29          housing_yes     0.057850
     34      contact_unknown     0.051323
     1               balance     0.032504
     42            month_mar     0.019111
     5                 pdays     0.017468
     0                   age     0.016224
     36            month_aug     0.016205
     45            month_oct     0.011945
     2                   day     0.011352
     35            month_apr     0.010435
     46            month_sep     0.007474
     20      marital_married     0.006382
     43            month_may     0.003948
     44            month_nov     0.003115
     4              campaign     0.002938
     10        job_housemaid     0.002374
     28           housing_no     0.002042
     48       poutcome_other     0.001320
     22    education_primary     0.001251
     11       job_management     0.001119
     19     marital_divorced     0.001062
     16       job_technician     0.001017
     24   education_tertiary     0.000944
     25    education_unknown     0.000930
     26           default_no     0.000724
     15          job_student     0.000197
     39            month_jan     0.000000
     6              previous     0.000000
     7            job_admin.     0.000000
     47     poutcome_failure     0.000000
     8       job_blue-collar     0.000000
     9      job_entrepreneur     0.000000
     12          job_retired     0.000000
     13    job_self-employed     0.000000
     14         job_services     0.000000
     41            month_jun     0.000000
```

```
40             month_jul     0.000000
38             month_feb     0.000000
27           default_yes     0.000000
37             month_dec     0.000000
17        job_unemployed     0.000000
18           job_unknown     0.000000
33     contact_telephone     0.000000
32      contact_cellular     0.000000
31              loan_yes     0.000000
30               loan_no     0.000000
21        marital_single     0.000000
23   education_secondary     0.000000
50      poutcome_unknown     0.000000
```

[ ]:
```
#features with importance more than or equal the mean:
df_1[df_1["Importances"]>=df_1["Importances"].mean()]
```

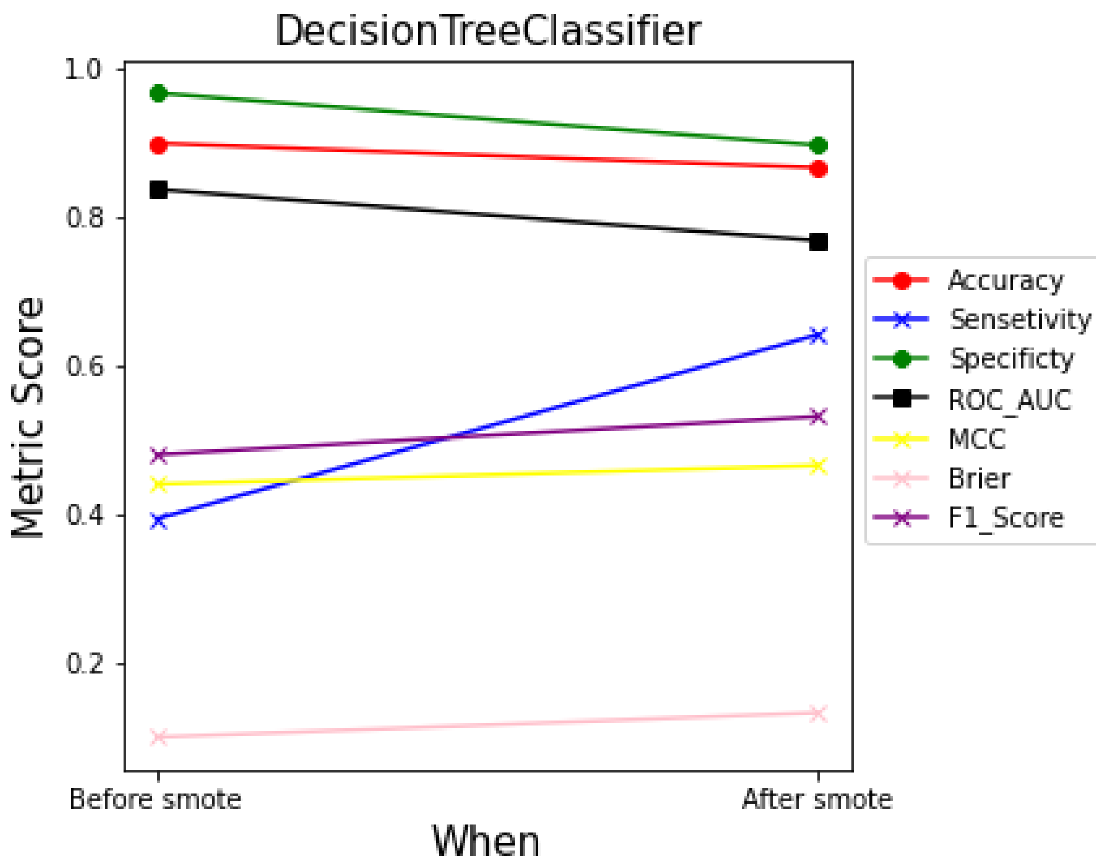
[ ]:
```
        Feature names  Importances
3            duration     0.489557
49   poutcome_success     0.229189
29        housing_yes     0.057850
34    contact_unknown     0.051323
1             balance     0.032504
```

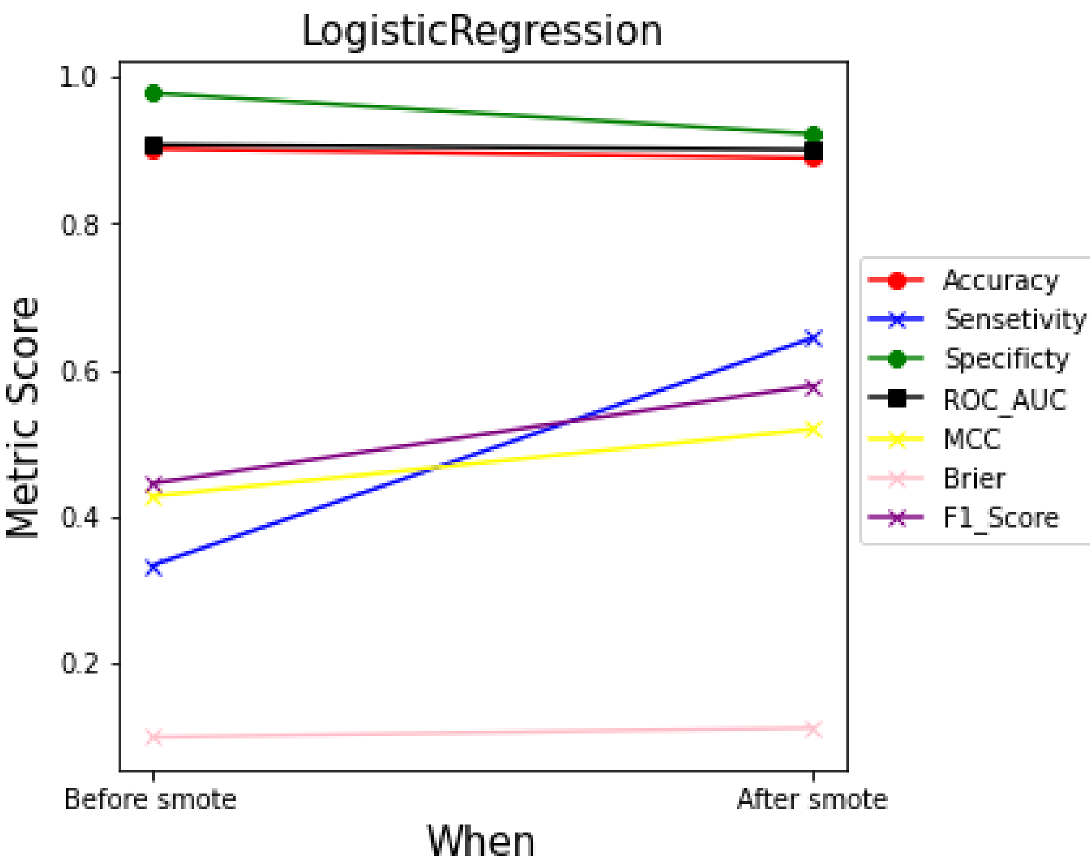
5.6 *Comparisons*

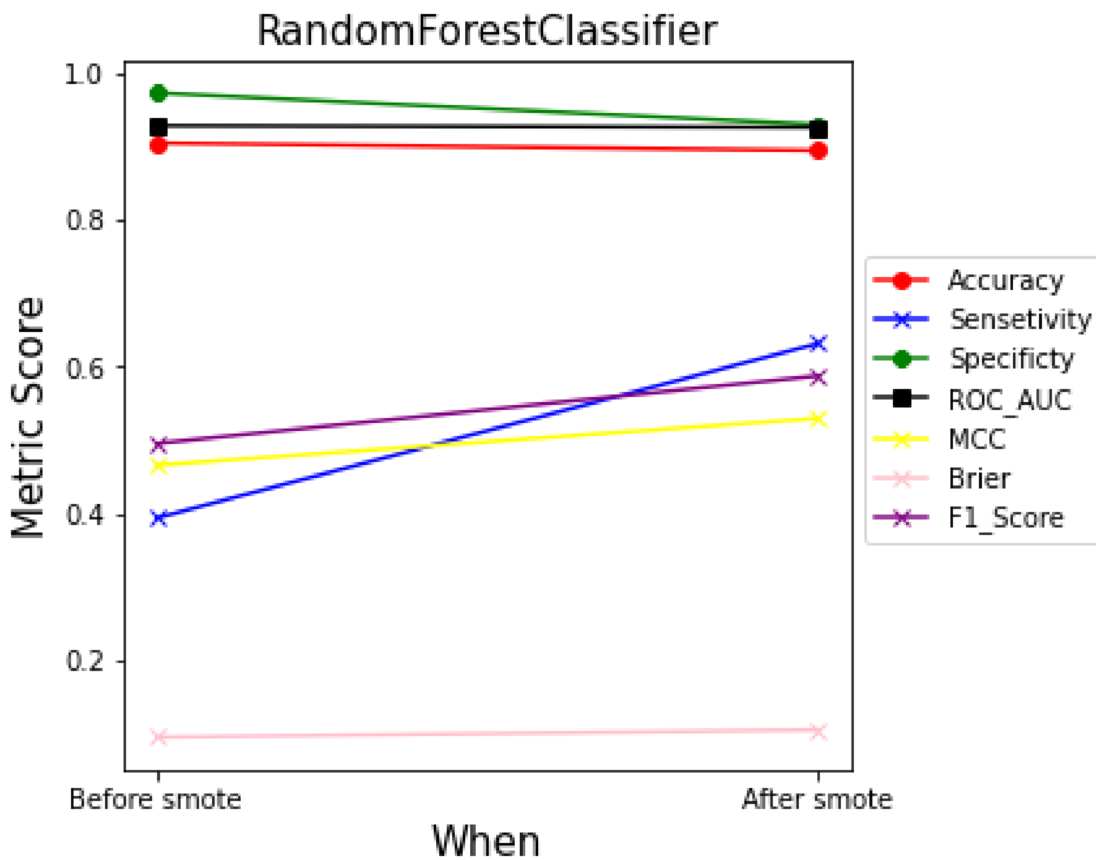
5.6.1 Before SMOTE vs After SMOTE

[ ]:
```
for x in Smotecomparison.name:

  When=["Before smote","After smote"]
  smoteindex=Smotecomparison.loc[Smotecomparison['name'] == x].index.values[0]
  index=comparison.loc[comparison['name'] == x].index.values[0]

  Ac=[comparison.loc[comparison['name'] == x].Accuracy[index],
      Smotecomparison.loc[Smotecomparison['name'] == x].Accuracy[smoteindex]]
  Sen=[comparison.loc[comparison['name'] == x].Sensetivity[index],
       Smotecomparison.loc[Smotecomparison['name'] == x].
↪Sensetivity[smoteindex]]
  SP=[comparison.loc[comparison['name'] == x].Specificity[index],
      Smotecomparison.loc[Smotecomparison['name'] == x].Specificity[smoteindex]]
  ROC_AUC=[comparison.loc[comparison['name'] == x].AUC[index],
           Smotecomparison.loc[Smotecomparison['name'] == x].AUC[smoteindex]]
```

```
MCC2=[comparison.loc[comparison['name'] == x].MCC[index],
         Smotecomparison.loc[Smotecomparison['name'] == x].MCC[smoteindex]]
Brier=[comparison.loc[comparison['name'] == x].Brier_score[index],
         Smotecomparison.loc[Smotecomparison['name'] == x].Brier_score[smoteindex]]
F1=[comparison.loc[comparison['name'] == x].F1Score[index],
         Smotecomparison.loc[Smotecomparison['name'] == x].F1Score[smoteindex]]


plt.figure(figsize=(5, 5))
plt.plot(When, Ac, color='red', marker='o')
plt.plot(When, Sen, color='blue', marker='x')
plt.plot(When, SP, color='green', marker='8')
plt.plot(When, ROC_AUC, color='black', marker='s')
plt.plot(When, MCC2, color='yellow', marker='x')
plt.plot(When, Brier, color='pink', marker='x')
plt.plot(When, F1, color='purple', marker='x')

plt.title(x, fontsize=15)
plt.xlabel('When', fontsize=15)
plt.ylabel('Metric Score', fontsize=15)
plt.legend(['Accuracy', 'Sensetivity','Specificty','ROC_AUC','MCC',"Brier","F1_Score"], fontsize=10,loc='lower left',bbox_to_anchor =(1, .3))

plt.show()
```


DecisionTreeClassifier
1.0
0.8
0.6
0.4
0.2
Metric Score
Before smote
After smote
When
Accuracy
Sensetivity
Specificty
ROC_AUC
MCC
Brier
F1_Score

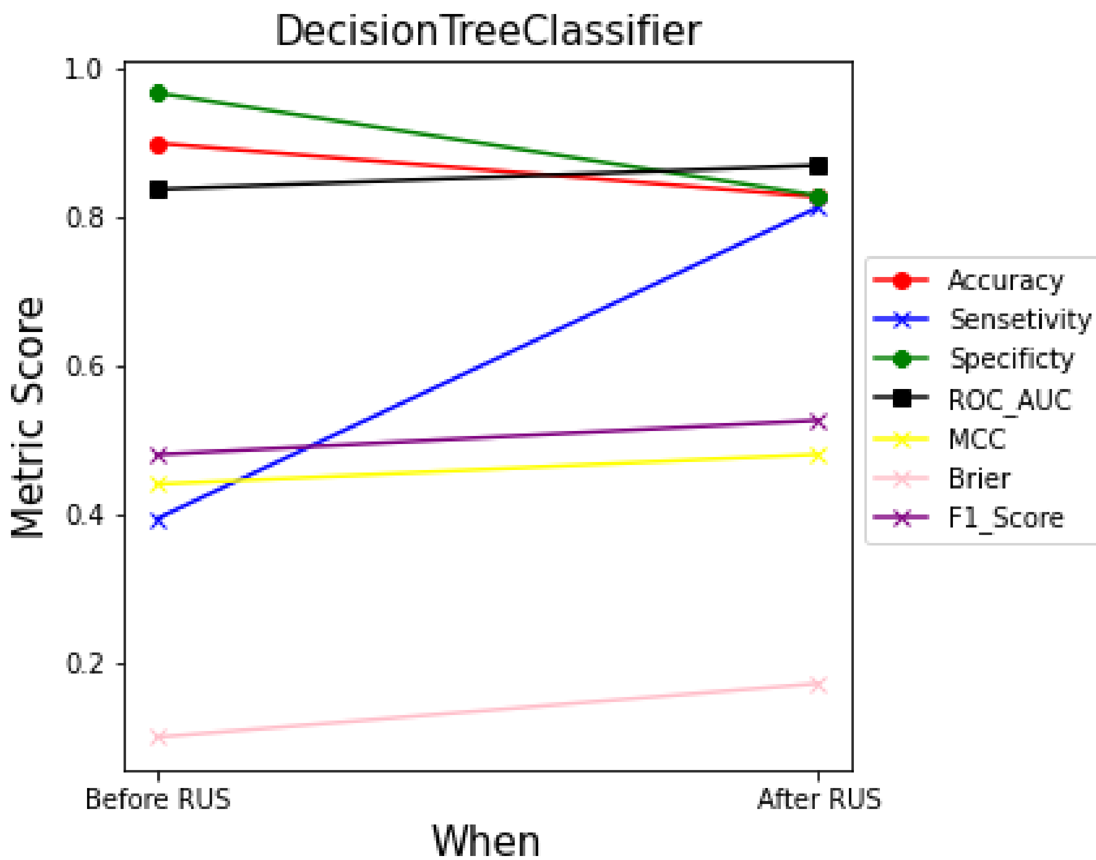

LogisticRegression
1.0
0.8
0.6
0.4
0.2
Metric Score
Before smote
After smote
When
Accuracy
Sensetivity
Specificty
ROC_AUC
MCC
Brier
F1_Score

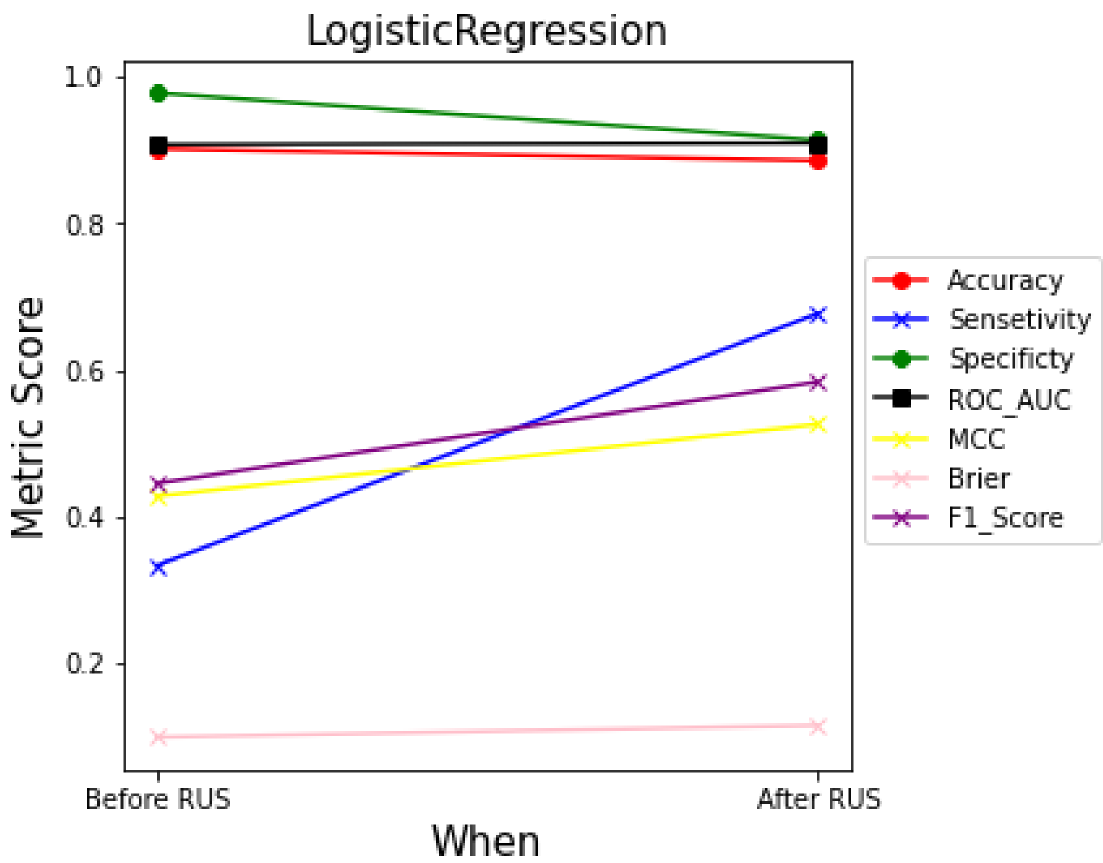


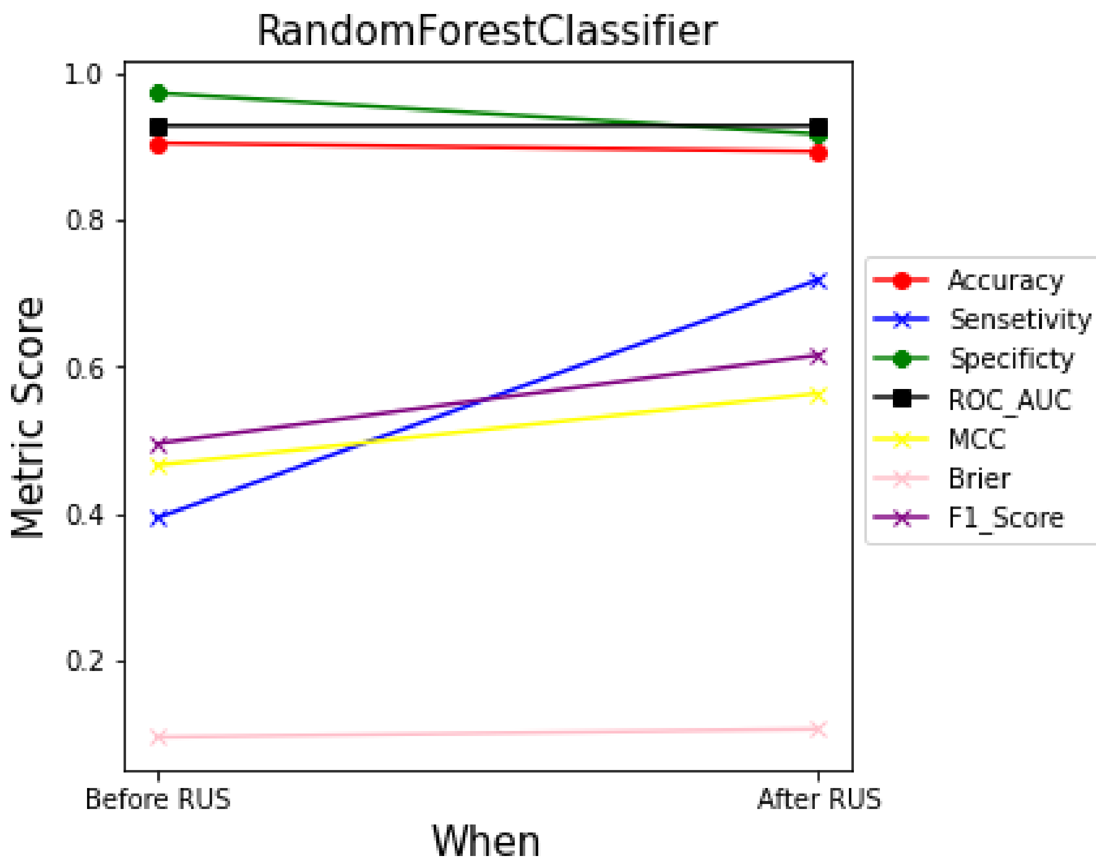
5.6.2 Before RUS vs After RUS

[ ]:
```
for x in RUScomparison.name:

  When=["Before RUS","After RUS"]
  RUSindex=RUScomparison.loc[RUScomparison['name'] == x].index.values[0]
  index=comparison.loc[comparison['name'] == x].index.values[0]

  Ac=[comparison.loc[comparison['name'] == x].Accuracy[index],
      RUScomparison.loc[RUScomparison['name'] == x].Accuracy[RUSindex]]
  Sen=[comparison.loc[comparison['name'] == x].Sensetivity[index],
       RUScomparison.loc[RUScomparison['name'] == x].Sensetivity[RUSindex]]
  SP=[comparison.loc[comparison['name'] == x].Specificity[index],
      RUScomparison.loc[RUScomparison['name'] == x].Specificity[RUSindex]]
  ROC_AUC=[comparison.loc[comparison['name'] == x].AUC[index],
           RUScomparison.loc[RUScomparison['name'] == x].AUC[RUSindex]]
  MCC2=[comparison.loc[comparison['name'] == x].MCC[index],
           RUScomparison.loc[RUScomparison['name'] == x].Mcc[RUSindex]]
```

```
Brier=[comparison.loc[comparison['name'] == x].Brier_score[index],
         RUScomparison.loc[RUScomparison['name'] == x].
↪brier_score_loss[RUSindex]]
F1=[comparison.loc[comparison['name'] == x].F1Score[index],
         RUScomparison.loc[RUScomparison['name'] == x].F1Score[RUSindex]]

plt.figure(figsize=(5, 5))
plt.plot(When, Ac, color='red', marker='o')
plt.plot(When, Sen, color='blue', marker='x')
plt.plot(When, SP, color='green', marker='8')
plt.plot(When, ROC_AUC, color='black', marker='s')
plt.plot(When, MCC2, color='yellow', marker='x')
plt.plot(When, Brier, color='pink', marker='x')
plt.plot(When, F1, color='purple', marker='x')


plt.title(x, fontsize=15)
plt.xlabel('When', fontsize=15)
plt.ylabel('Metric Score', fontsize=15)
plt.legend(['Accuracy',␣
↪'Sensetivity','Specificty','ROC_AUC','MCC',"Brier","F1_Score",],␣
↪fontsize=10,loc='lower left',bbox_to_anchor =(1, .3))

plt.show()
```


DecisionTreeClassifier
1.0
0.8
0.6
0.4
0.2
Metric Score
Before RUS
After RUS
When
Accuracy
Sensetivity
Specificty
ROC_AUC
MCC
Brier
F1_Score

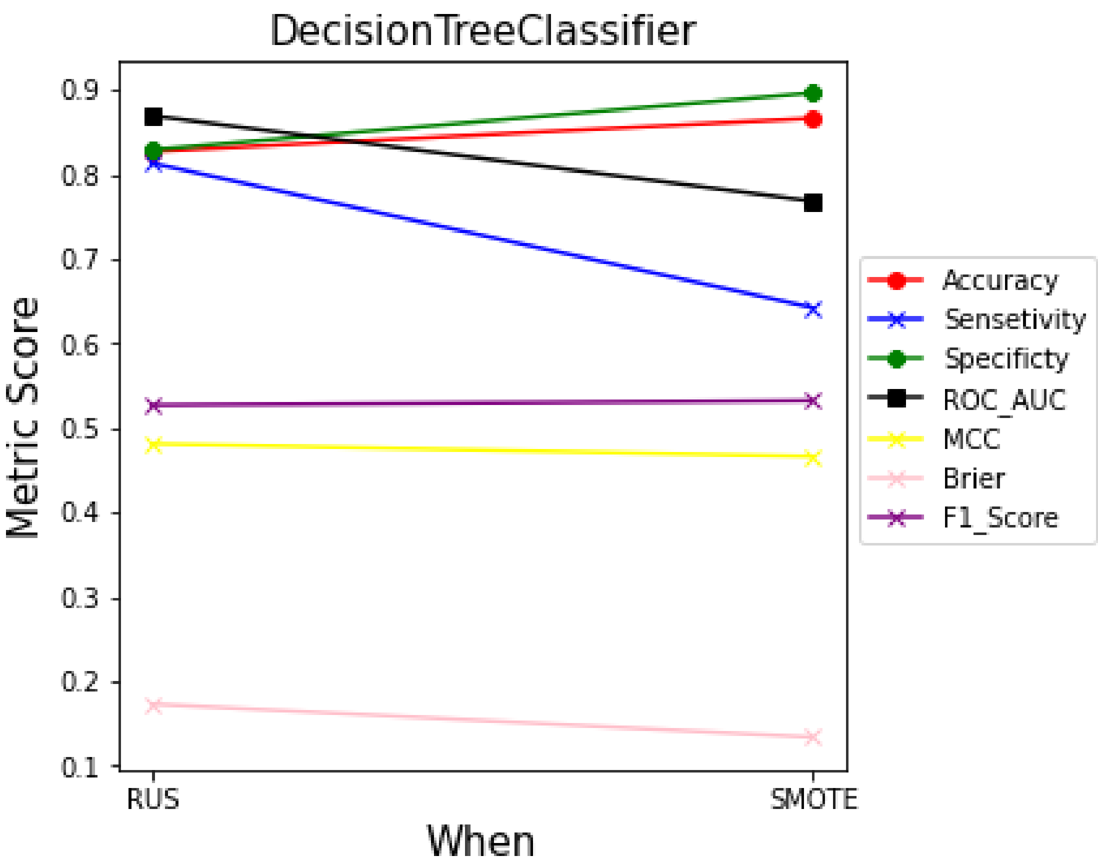

LogisticRegression
1.0
0.8
0.6
0.4
0.2
Metric Score
Before RUS
After RUS
When
Accuracy
Sensetivity
Specificty
ROC_AUC
MCC
Brier
F1_Score

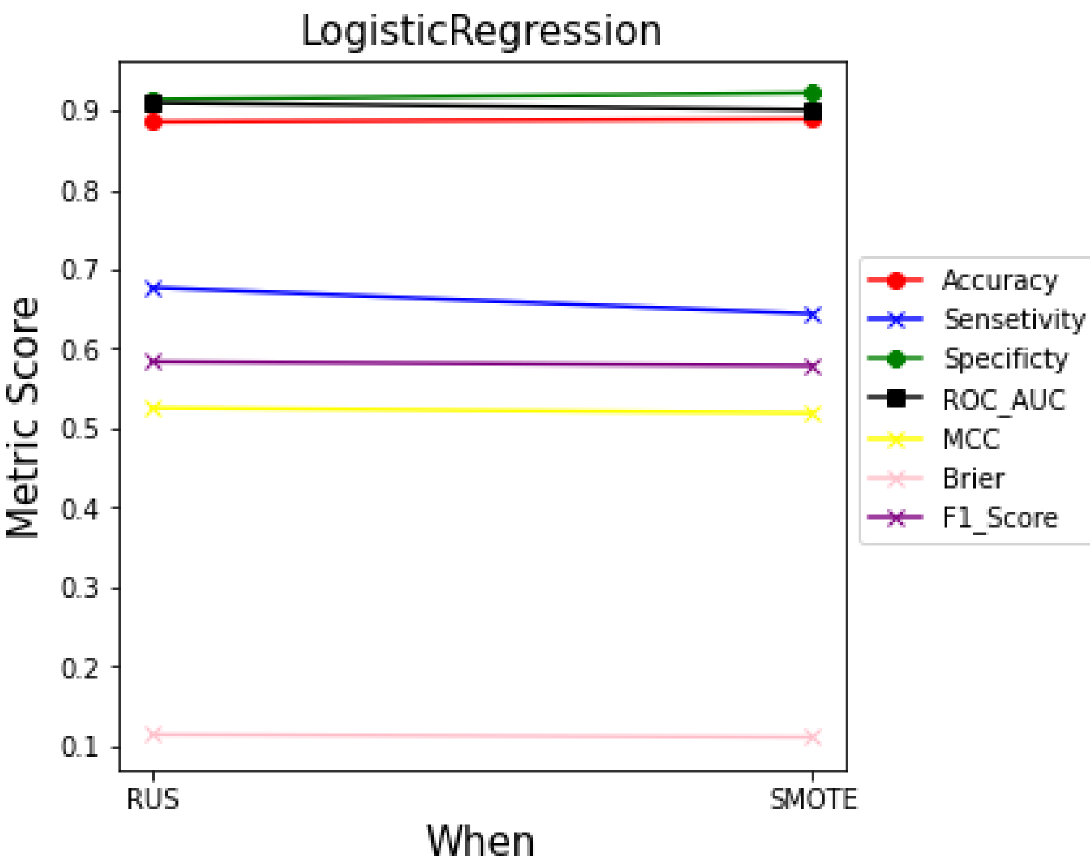


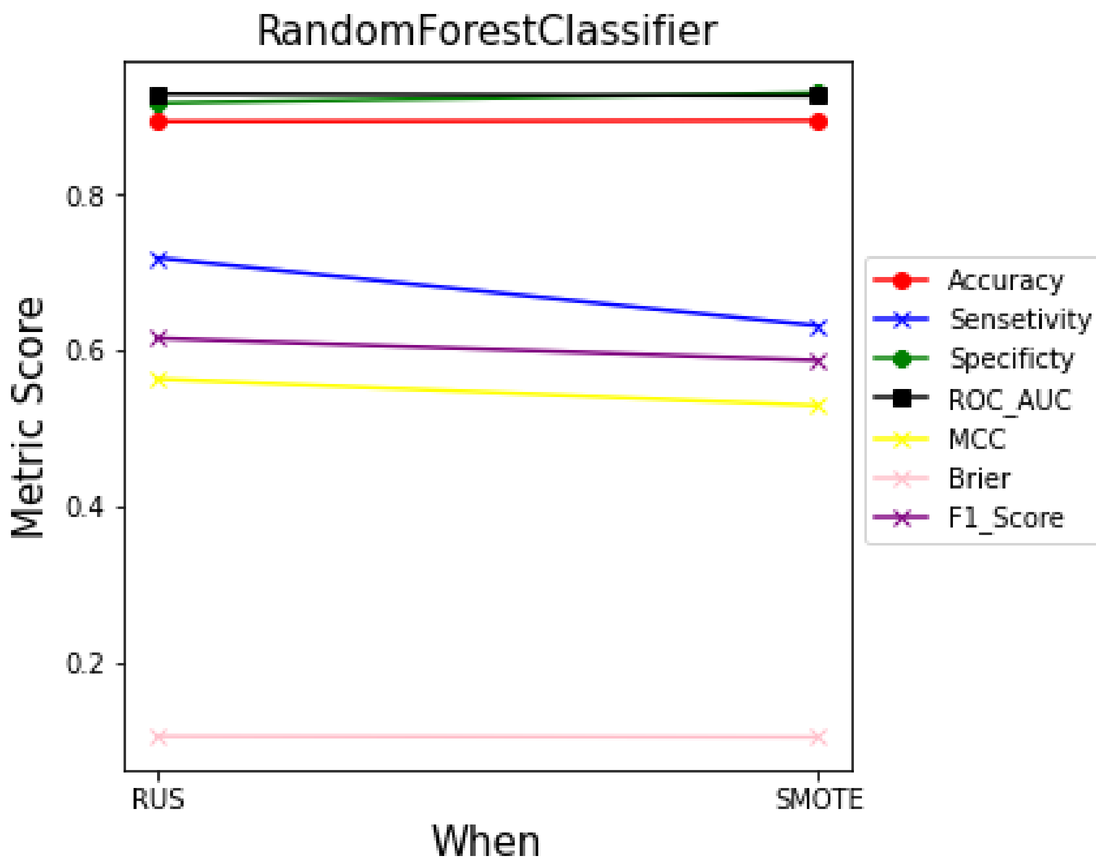
5.6.3 SMOTE VS RUS

[ ]:
```
for x in Smotecomparison.name:

  When=["RUS","SMOTE"]
  smoteindex=Smotecomparison.loc[Smotecomparison['name'] == x].index.values[0]
  RUSindex=RUScomparison.loc[RUScomparison['name'] == x].index.values[0]


  Ac=[RUScomparison.loc[RUScomparison['name'] == x].Accuracy[RUSindex],
      Smotecomparison.loc[Smotecomparison['name'] == x].Accuracy[smoteindex]]
  Sen=[RUScomparison.loc[RUScomparison['name'] == x].Sensetivity[RUSindex],
       Smotecomparison.loc[Smotecomparison['name'] == x].
↪Sensetivity[smoteindex]]
  SP=[RUScomparison.loc[RUScomparison['name'] == x].Specificity[RUSindex],
      Smotecomparison.loc[Smotecomparison['name'] == x].Specificity[smoteindex]]
  ROC_AUC=[RUScomparison.loc[RUScomparison['name'] == x].AUC[RUSindex],
           Smotecomparison.loc[Smotecomparison['name'] == x].AUC[smoteindex]]
```

```
MCC2=[RUScomparison.loc[RUScomparison['name'] == x].Mcc[RUSindex],
         Smotecomparison.loc[Smotecomparison['name'] == x].MCC[smoteindex]]
Brier=[RUScomparison.loc[RUScomparison['name'] == x].
↪brier_score_loss[RUSindex],
         Smotecomparison.loc[Smotecomparison['name'] == x].
↪Brier_score[smoteindex]]
F1=[RUScomparison.loc[RUScomparison['name'] == x].F1Score[RUSindex],
         Smotecomparison.loc[Smotecomparison['name'] == x].
↪F1Score[smoteindex]]


plt.figure(figsize=(5, 5))
plt.plot(When, Ac, color='red', marker='o')
plt.plot(When, Sen, color='blue', marker='x')
plt.plot(When, SP, color='green', marker='8')
plt.plot(When, ROC_AUC, color='black', marker='s')
plt.plot(When, MCC2, color='yellow', marker='x')
plt.plot(When, Brier, color='pink', marker='x')
plt.plot(When, F1, color='purple', marker='x')


plt.title(x, fontsize=15)
plt.xlabel('When', fontsize=15)
plt.ylabel('Metric Score', fontsize=15)
plt.legend(['Accuracy',␣
↪'Sensetivity','Specificty','ROC_AUC','MCC',"Brier","F1_Score"],␣
↪fontsize=10,loc='lower left',bbox_to_anchor =(1, .3))

plt.show()
```


DecisionTreeClassifier
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Metric Score
RUS
SMOTE
When
Accuracy
Sensetivity
Specificty
ROC_AUC
MCC
Brier
F1_Score

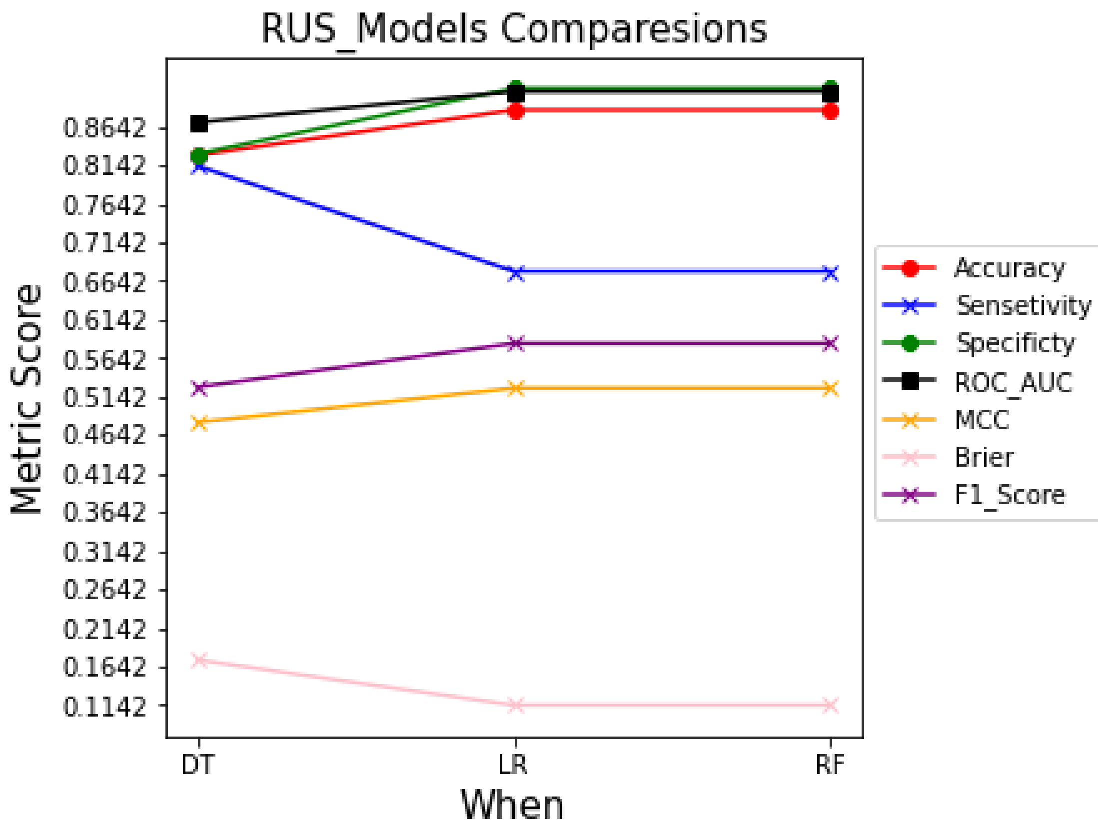

LogisticRegression
Metric Score
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
RUS
SMOTE
When
Accuracy
Sensetivity
Specificty
ROC_AUC
MCC
Brier
F1_Score



5.6.4 RUS_Models Comparesions

```
[ ]: df_T=RUScomparison.T
     df_T

     df_T.drop(index=df_T.index[0],
             axis=0,
             inplace=True)
     df_T=df_T.rename(columns={0: 'DT',1:"LR",2:"RF"})

     for x in df_T.index:

       When=["DT","LR","RF"]
       DTindex=df_T.loc[df_T.index == x]["DT"][0]
       LRindex=df_T.loc[df_T.index == x]["LR"][0]
       RFindex=df_T.loc[df_T.index == x]["LR"][0]

       if x=="Accuracy":
```

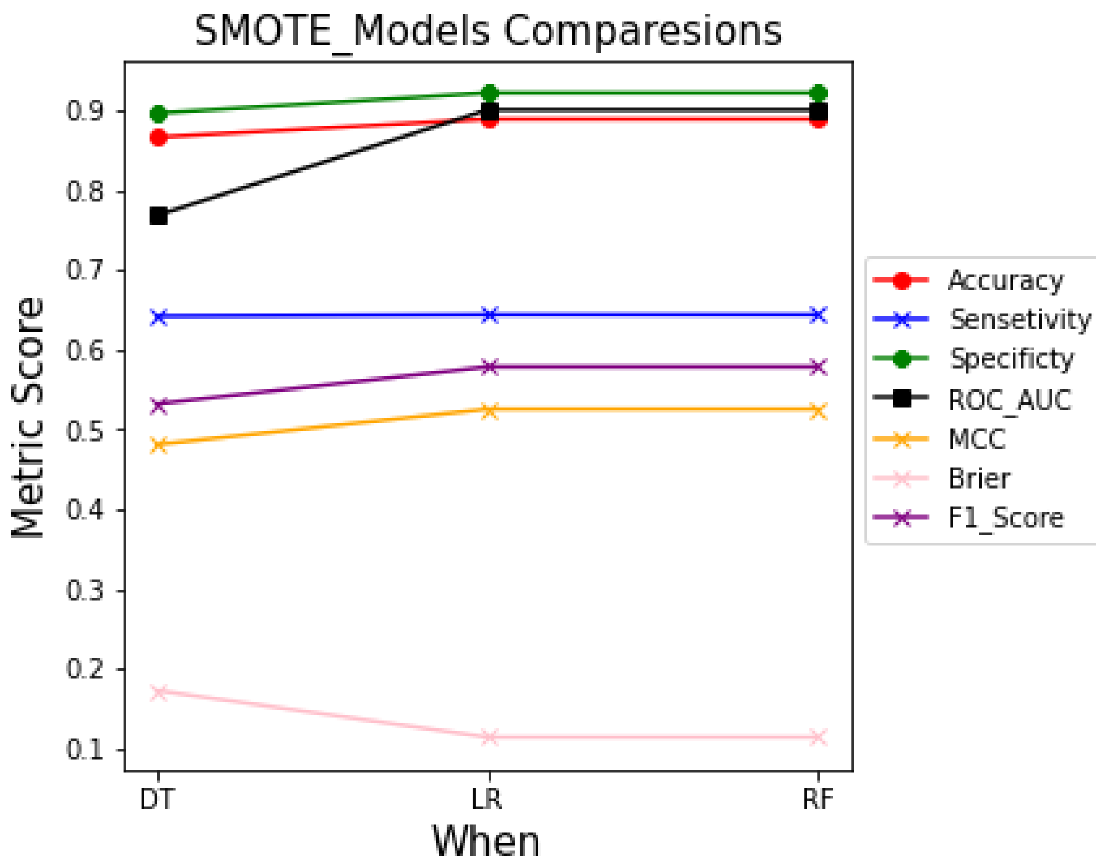
```
    Ac=[DTindex,LRindex,RFindex]

  elif x=="Sensetivity":
    Sen=[DTindex,LRindex,RFindex]

  elif x=="Specificity":
    SP=[DTindex,LRindex,RFindex]

  elif x=="AUC":
    ROC_AUC=[DTindex,LRindex,RFindex]

  if x=="Mcc":
    MCC2=[DTindex,LRindex,RFindex]

  if x=="brier_score_loss":
    Brier=[DTindex,LRindex,RFindex]

  if x=="F1Score":
    F1=[DTindex,LRindex,RFindex]


plt.figure(figsize=(5, 5))
plt.plot(When, Ac, color='red', marker='o')
plt.plot(When, Sen, color='blue', marker='x')
plt.plot(When, SP, color='green', marker='8')
plt.plot(When, ROC_AUC, color='black', marker='s')
plt.plot(When, MCC2, color='orange', marker='x')
plt.plot(When, Brier, color='pink', marker='x')
plt.plot(When, F1, color='purple', marker='x')

plt.yticks(np.arange(min(Brier), max(Ac), 0.05))
plt.title("RUS_Models Comparesions", fontsize=15)
plt.xlabel('When', fontsize=15)
plt.ylabel('Metric Score', fontsize=15)
plt.legend(['Accuracy',␣
 ↪'Sensetivity','Specificty','ROC_AUC','MCC',"Brier","F1_Score"],␣
 ↪fontsize=10,loc='lower left',bbox_to_anchor =(1, .3))

plt.show()
```



5.6.5 SMOTE_Models Comparesions

[ ]:
```
df_T=Smotecomparison.T
df_T

df_T.drop(index=df_T.index[0],
        axis=0,
        inplace=True)
df_T=df_T.rename(columns={0: 'DT',1:"LR",2:"RF"})

for x in df_T.index:

  When=["DT","LR","RF"]
  DTindex=df_T.loc[df_T.index == x]["DT"][0]
  LRindex=df_T.loc[df_T.index == x]["LR"][0]
  RFindex=df_T.loc[df_T.index == x]["LR"][0]

  if x=="Accuracy":
    Ac=[DTindex,LRindex,RFindex]
```

```
  elif x=="Sensetivity":
    Sen=[DTindex,LRindex,RFindex]

  elif x=="Specificity":
    SP=[DTindex,LRindex,RFindex]

  elif x=="AUC":
    ROC_AUC=[DTindex,LRindex,RFindex]

  if x=="Mcc":
    MCC2=[DTindex,LRindex,RFindex]

  if x=="brier_score_loss":
    Brier=[DTindex,LRindex,RFindex]

  if x=="F1Score":
    F1=[DTindex,LRindex,RFindex]


plt.figure(figsize=(5, 5))
plt.plot(When, Ac, color='red', marker='o')
plt.plot(When, Sen, color='blue', marker='x')
plt.plot(When, SP, color='green', marker='8')
plt.plot(When, ROC_AUC, color='black', marker='s')
plt.plot(When, MCC2, color='orange', marker='x')
plt.plot(When, Brier, color='pink', marker='x')
plt.plot(When, F1, color='purple', marker='x')


plt.title("SMOTE_Models Comparesions", fontsize=15)
plt.xlabel('When', fontsize=15)
plt.ylabel('Metric Score', fontsize=15)
plt.legend(['Accuracy',␣
↪'Sensetivity','Specificty','ROC_AUC','MCC',"Brier","F1_Score"],␣
↪fontsize=10,loc='lower left',bbox_to_anchor =(1, .3))

plt.show()
```



6 Friedman Test to know how these models differ and which one is the best:

The Friedman Test is a non-parametric alternative to the Repeated Measures ANOVA. It is used to determine whether or not there is a statistically significant difference between three or more groups in which the same subjects show up in each group.

The procedure involves ranking each row (or block) together, then considering the values of ranks by columns. Applicable to complete block designs, it is thus a special case of the Durbin test.

The reason behind choosing Friendman test is that we want to compare multiple classifiers on multiple datasets (as we will apply the k fold cross validation (1n_splits=10, n_repeats=2).

1. We will first create a data frame that has the result of AUC and MCC for each model on each fold.
2. we will apply the Friedman test to know if the modeles performance are statistically different or not .

-Please note that we already concluded that Random undersampling is the best practice to gain better results and we decided that Random Forest will be the best model as its evaluation results were the best and it was stable on many applied scenarios.

```
[ ]: from sklearn.metrics import roc_curve,␣
     ↪roc_auc_score,accuracy_score,recall_score,brier_score_loss
     from sklearn import tree, linear_model,ensemble
     from sklearn.metrics import mean_absolute_error
     from sklearn.model_selection import validation_curve
     from sklearn.model_selection import RepeatedKFold
     import numpy as np
     np.random.seed(3)
     import matplotlib.pyplot as plt
     plt.style.use("ggplot")
```

6.1 Matthews_corrcoef

```
[ ]: #Matthews_corrcoef
     # prepare the cross-validation procedure
     #Due to the assumption that the test statistic has a chi squared distribution,␣
     ↪the p-value is only reliable for n > 10 and more than 6 repeated samples.
     cv = RepeatedKFold(n_splits=10, n_repeats=2, random_state=111)

     RUS_lgr_list_Test_MCC=[]
     RUS_RF_list_Test_MCC=[]
     RUS_DT_list_Test_MCC=[]

     #RUS_lgr_list_training_MCC=[]
     #RUS_RF_list_training_MCC=[]
     #RUS_DT_list_training_MCC=[]


     X=dff.drop(["y"],axis="columns")
     y=dff.y
     counter=0
     for train_index,test_index in cv.split(dff):
       counter+=1
       X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
       Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]
       log_reg=linear_model.
     ↪LogisticRegression(max_iter=RUS_lgr_max_iter,solver=RUS_lgr_solver,random_state=113,n_jobs=
       DT=tree.DecisionTreeClassifier(max_depth=RUS_DT_max_depth,random_state=113)
       RF=ensemble.RandomForestClassifier(n_estimators=RUS_RF_n_estimators,
                                                                ␣
     ↪max_depth=RUS_RF_max_depth,random_state=113)

     # Apply the tuned RUS to balance/resample the training set:
```

```
#Logistic Regression
 ␣
 ↪RUSlgr=RandomUnderSampler(sampling_strategy=lgr_RUS_sampling_strategy,random_state=11)
  lgrx_train_rus,lgry_train_rus=RUSlgr.fit_resample(X_train,Y_train)
#Decision Tree
 ␣
 ↪RUSdt=RandomUnderSampler(sampling_strategy=DT_RUS_sampling_strategy,random_state=11)
  dtx_train_rus,dty_train_rus=RUSdt.fit_resample(X_train,Y_train)
#Random Forest
 ␣
 ↪RUSrf=RandomUnderSampler(sampling_strategy=RF_RUS_sampling_strategy,random_state=11)
  rfx_train_rus,rfy_train_rus=RUSrf.fit_resample(X_train,Y_train)

#Train the models on the resambles train sets
  log_reg.fit(lgrx_train_rus,lgry_train_rus)#Logistic Regression
  DT.fit(dtx_train_rus,dty_train_rus)#Decision Tree
  RF.fit(rfx_train_rus,rfy_train_rus)#Random Forest

#Predict the test set
  log_reg_y_test_data_pred=log_reg.predict(X_test)
  DT_y_test_data_pred=DT.predict(X_test)
  RF_y_test_data_pred=RF.predict(X_test)

#Calculate MCC for each fold
 ␣
 ↪RUS_lgr_fold_testing_MCC=matthews_corrcoef(Y_test,log_reg_y_test_data_pred)#logistic␣
 ↪Regression
 ␣
 ↪RUS_DT_fold_testing_MCC=matthews_corrcoef(Y_test,DT_y_test_data_pred)#Decision␣
 ↪Tree
  RUS_RF_fold_testing_MCC=matthews_corrcoef(Y_test,RF_y_test_data_pred)#Random␣
 ↪Forest

  RUS_lgr_list_Test_MCC.append(RUS_lgr_fold_testing_MCC)#logistic Regression
  RUS_DT_list_Test_MCC.append(RUS_DT_fold_testing_MCC)#Decision Tree
  RUS_RF_list_Test_MCC.append(RUS_RF_fold_testing_MCC)#Random Forest
```

[ ]:
```
folds=[]
for x in range(counter):
  folds.append(x+1)
Results_MCC= pd.DataFrame({"Fold": folds,"DT":RUS_DT_list_Test_MCC,"LG":
 ↪RUS_lgr_list_Test_MCC,"RF":RUS_RF_list_Test_MCC})
display(Results_MCC)
```

	Fold	DT	LG	RF
0	1	0.488996	0.552656	0.590074
1	2	0.462728	0.522442	0.541534

2	3	0.471281	0.517129	0.571813
3	4	0.491908	0.520569	0.560187
4	5	0.462786	0.491912	0.554265
5	6	0.455930	0.532701	0.569286
6	7	0.477755	0.485883	0.564155
7	8	0.502080	0.502493	0.556888
8	9	0.447865	0.526346	0.554213
9	10	0.466944	0.519891	0.540321
10	11	0.470240	0.520860	0.562804
11	12	0.470980	0.541663	0.576400
12	13	0.488660	0.566835	0.583285
13	14	0.486593	0.504504	0.566506
14	15	0.444202	0.494670	0.548285
15	16	0.452667	0.522086	0.558773
16	17	0.490917	0.496121	0.563371
17	18	0.492884	0.505716	0.567325
18	19	0.488061	0.528497	0.555579
19	20	0.462488	0.476789	0.541600

[ ]:
```
from scipy import stats

#perform Friedman Test
stats.friedmanchisquare(Results_MCC["DT"], Results_MCC["LG"], Results_MCC["RF"])
# The Pvalue is less than 0.05 which means there is a significant difference␣
↪between the three models
```

[ ]:
```
FriedmanchisquareResult(statistic=40.0, pvalue=2.0611536224385566e-09)
```

[ ]:
```
#Interpret the results
#The Friedman Test uses the following null and alternative hypotheses:

#The null hypothesis (H0): There no difference between the models..

#The alternative hypothesis: (Ha): At least one model differs from the rest.

#Since this pvalue=2.0611536224385566e-09 which is less than 0.05, we reject␣
↪the null hypothesis that tsays all the models are similar to each other.
#This returned a statistical difference, but now I would like to find out␣
↪between which models the differences exist.

#The are a number of possibilities to perform posthoc-tests (an extension␣
↪regarding the use of non-parametric tests :
#1  Perform the Nemenyi-test for all pairwise combinations; this is similar to␣
↪the Tukey-test for ANOVA.
#2. Perform the Bonferroni-Dunn-test; in this setting one compares all values␣
↪to a list of control values.
```

6.1.1 Perform the Nemenyi Test

Nemenyi Test: The Friedman Test is used to find whether there exists a significant difference between more than two groups. In such groups, the same subjects show up in each group. If the p-value of the Friedman test turns out to be statistically significant then we can conduct the Nemenyi test to find exactly which groups are different. This test is also known as Nemenyi post-hoc test.

The Friedman Test follows the below hypothesis:

1. The null hypothesis (H0): There no difference between the models.
2. The alternative hypothesis: (Ha): At least one model differs from the rest.

[ ]:
```
pip install scikit-posthocs
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting scikit-posthocs
  Downloading scikit_posthocs-0.7.0-py3-none-any.whl (38 kB)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/dist-
packages (from scikit-posthocs) (3.6.2)
Requirement already satisfied: pandas>=0.20.0 in /usr/local/lib/python3.8/dist-
packages (from scikit-posthocs) (1.3.5)
Requirement already satisfied: seaborn in /usr/local/lib/python3.8/dist-packages
(from scikit-posthocs) (0.11.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages
(from scikit-posthocs) (1.21.6)
Requirement already satisfied: scipy in /usr/local/lib/python3.8/dist-packages
(from scikit-posthocs) (1.7.3)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.8/dist-
packages (from scikit-posthocs) (0.12.2)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.8/dist-packages (from pandas>=0.20.0->scikit-posthocs)
(2.8.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-
packages (from pandas>=0.20.0->scikit-posthocs) (2022.6)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.7.3->pandas>=0.20.0->scikit-posthocs) (1.15.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->scikit-posthocs)
(1.0.6)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib->scikit-posthocs) (7.1.2)
Requirement already satisfied: pyparsing>=2.2.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->scikit-posthocs)
(3.0.9)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib->scikit-posthocs) (21.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->scikit-posthocs)
```

```
(1.4.4)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
packages (from matplotlib->scikit-posthocs) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->scikit-posthocs)
(4.38.0)
Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.8/dist-
packages (from statsmodels->scikit-posthocs) (0.5.3)
Installing collected packages: scikit-posthocs
Successfully installed scikit-posthocs-0.7.0
```

[ ]:
```
# Importing libraries
from scipy import stats
import scikit_posthocs as sp
import numpy as np
```

[ ]:
```
# Conduct the Nemenyi post-hoc test
data = np.array([Results_MCC["DT"], Results_MCC["LG"], Results_MCC["RF"]])
sp.posthoc_nemenyi_friedman(data.T)
```

[ ]:

	0	1	2
0	1.000000	0.004467	0.001000
1	0.004467	1.000000	0.004467
2	0.001000	0.004467	1.000000

[ ]:
```
block=[]
for x in range(len(Results_MCC["Fold"])):
  x+=1
  block.append(x)
FBlock=block+block+block

Results_MCC1=Results_MCC.drop(["Fold"],axis="columns")
longdf=pd.melt(Results_MCC1,var_name="models",value_name="MCC")
longdf["block"]=FBlock
longdf.head()

display(sp.
 ↪posthoc_nemenyi_friedman(longdf,y_col="MCC",group_col="models",block_col="block",melted=Tru
```

	DT	LG	RF
DT	1.000000	0.004467	0.001000
LG	0.004467	1.000000	0.004467
RF	0.001000	0.004467	1.000000

[ ]:
```
#The Nemenyi post-hoc test produces the p-values for each pairwise comparison␣
 ↪of means. These values are:
```

```
# P-value of Decision Tree MCC  vs. Logistic Regression MCC: 0.004467
# P-value of Decision Tree MCC vs. Random Forest MCC: 0.001000
# P-value of Logistic Regression MCC vs. Random Forest MCC:: 0.004467

# so all of them are different from each other
```

6.2 AUROC

[ ]:
```
from sklearn.metrics import roc_curve, roc_auc_score
# prepare the cross-validation procedure
#Due to the assumption that the test statistic has a chi squared distribution,␣
↪the p-value is only reliable for n > 10 and more than 6 repeated samples.
cv = RepeatedKFold(n_splits=10, n_repeats=2, random_state=100)

RUS_lgr_list_Test_AUR=[]
RUS_RF_list_Test_AUR=[]
RUS_DT_list_Test_AUR=[]

X=dff.drop(["y"],axis="columns")
y=dff.y
counter=0
for train_index,test_index in cv.split(dff):
  counter+=1
  X_train,X_test=X.iloc[train_index,:],X.iloc[test_index,:]
  Y_train,Y_test=y.iloc[train_index],y.iloc[test_index]

  log_reg=linear_model.
↪LogisticRegression(max_iter=RUS_lgr_max_iter,solver=RUS_lgr_solver,random_state=113,n_jobs=
  DT=tree.DecisionTreeClassifier(max_depth=RUS_DT_max_depth,random_state=113)
  RF=ensemble.RandomForestClassifier(n_estimators=RUS_RF_n_estimators,
                                                                   ␣
↪max_depth=RUS_RF_max_depth,random_state=113)

# Apply the tuned RUS to balance/resample the training set:
#Logistic Regression
 ␣
↪RUSlgr=RandomUnderSampler(sampling_strategy=lgr_RUS_sampling_strategy,random_state=11)
  lgrx_train_rus,lgry_train_rus=RUSlgr.fit_resample(X_train,Y_train)
#Decision Tree
 ␣
↪RUSdt=RandomUnderSampler(sampling_strategy=DT_RUS_sampling_strategy,random_state=11)
  dtx_train_rus,dty_train_rus=RUSdt.fit_resample(X_train,Y_train)
#Random Forest
 ␣
↪RUSrf=RandomUnderSampler(sampling_strategy=RF_RUS_sampling_strategy,random_state=11)
```

```
  rfx_train_rus,rfy_train_rus=RUSrf.fit_resample(X_train,Y_train)

#Train the models
  log_reg.fit(lgrx_train_rus,lgry_train_rus)#Logistic Regression
  DT.fit(dtx_train_rus,dty_train_rus)#Decision Tree
  RF.fit(rfx_train_rus,rfy_train_rus)#Random Forest

#Predict the test set
  log_reg_y_test_data_pred=log_reg.predict(X_test)
  DT_y_test_data_pred=DT.predict(X_test)
  RF_y_test_data_pred=RF.predict(X_test)

#to get the probabilities of the prediction for each instance in the test set

  rf_probs= RF.predict_proba(X_test)
  dt_probs= DT.predict_proba(X_test)
  lgr_probs= log_reg.predict_proba(X_test)

#to keep the probabilities of positive outcomes
  rf_probs=rf_probs[:,1]
  dt_probs=dt_probs[:,1]
  lgr_probs=lgr_probs[:,1]

#Calculate AUR for each fold

  RUS_RF_fold_testing_AUR=roc_auc_score(Y_test,rf_probs)
  RUS_DT_fold_testing_AUR=roc_auc_score(Y_test,dt_probs)
  RUS_lgr_fold_testing_AUR=roc_auc_score(Y_test,lgr_probs)

  RUS_lgr_list_Test_AUR.append(RUS_lgr_fold_testing_AUR)#logistic Regression
  RUS_DT_list_Test_AUR.append(RUS_DT_fold_testing_AUR)#Decision Tree
  RUS_RF_list_Test_AUR.append(RUS_RF_fold_testing_AUR)#Random Forest
```

[ ]:

```
folds=[]
for x in range(counter):
  folds.append(x+1)
Results_AUR = pd.DataFrame({"Fold": folds,"DT":RUS_DT_list_Test_AUR,"LG":
 ↪RUS_lgr_list_Test_AUR,"RF":RUS_RF_list_Test_AUR})
display(Results_AUR)
```

	Fold	DT	LG	RF
0	1	0.879790	0.899323	0.929742
1	2	0.878971	0.901120	0.922327
2	3	0.883752	0.910998	0.929956
3	4	0.888113	0.909914	0.932232
4	5	0.889347	0.913651	0.937251
5	6	0.881926	0.906999	0.925350

```
6       7  0.877982  0.908436  0.933061
7       8  0.883344  0.904250  0.928707
8       9  0.878467  0.905538  0.924177
9      10  0.884521  0.913012  0.936749
10     11  0.878411  0.905661  0.925791
11     12  0.887769  0.908910  0.928506
12     13  0.869416  0.902577  0.925565
13     14  0.886525  0.910353  0.935359
14     15  0.867020  0.906838  0.930517
15     16  0.881018  0.905133  0.931214
16     17  0.888122  0.905864  0.928019
17     18  0.881229  0.904847  0.929309
18     19  0.896555  0.919044  0.935738
19     20  0.867961  0.907986  0.926515
```

[ ]:
```
from scipy import stats

#perform Friedman Test
stats.friedmanchisquare(Results_AUR["DT"], Results_AUR["LG"], Results_AUR["RF"])
# The Pvalue is less than 0.05 which means there is a significant difference␣
↪between the three models
```

[ ]:
```
FriedmanchisquareResult(statistic=40.0, pvalue=2.0611536224385566e-09)
```

6.2.1 Nemenyi Test

[ ]:
```
# Conduct the Nemenyi post-hoc test
data = np.array([Results_AUR["DT"], Results_AUR["LG"], Results_AUR["RF"]])
sp.posthoc_nemenyi_friedman(data.T)
```

[ ]:
```
          0         1         2
0  1.000000  0.004467  0.001000
1  0.004467  1.000000  0.004467
2  0.001000  0.004467  1.000000
```

[ ]:
```
#The Nemenyi post-hoc test produces the p-values for each pairwise compariso.␣
↪These values are:

# P-value of Decision Tree MCC  vs. Logistic Regression MCC: 0.004467
# P-value of Decision Tree MCC vs. Random Forest MCC: 0.001000
# P-value of Logistic Regression MCC vs. Random Forest MCC:: 0.004467

# So all of them are different from each other
```

7 Export the report

```
[ ]: #convert it to pdf
     !sudo apt-get install texlive-xetex texlive-fonts-recommended␣
      ↪texlive-plain-generic
```

```
[ ]: !jupyter nbconvert --to pdf /content/Final_Project_Code.ipynb
```

```
[NbConvertApp] Converting notebook /content/Final_Project_Code.ipynb to pdf
/usr/local/lib/python3.8/dist-packages/nbconvert/filters/datatypefilter.py:39:
UserWarning: Your element with mimetype(s) dict_keys(['text/html']) is not able
to be represented.
  warn("Your element with mimetype(s) {mimetypes}"
/usr/local/lib/python3.8/dist-packages/nbconvert/filters/datatypefilter.py:39:
UserWarning: Your element with mimetype(s) dict_keys(['text/html']) is not able
to be represented.
  warn("Your element with mimetype(s) {mimetypes}"
/usr/local/lib/python3.8/dist-packages/nbconvert/filters/datatypefilter.py:39:
UserWarning: Your element with mimetype(s) dict_keys(['text/html']) is not able
to be represented.
  warn("Your element with mimetype(s) {mimetypes}"
[NbConvertApp] Support files will be in Final_Project_Code_files/
[NbConvertApp] Making directory ./Final_Project_Code_files
[NbConvertApp] Making directory ./Final_Project_Code_files
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[NbConvertApp] Making directory ./Final_Project_Code_files
[NbConvertApp] Making directory ./Final_Project_Code_files
[NbConvertApp] Making directory ./Final_Project_Code_files
[NbConvertApp] Writing 451286 bytes to ./notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', './notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', './notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 1472480 bytes to /content/Final_Project_Code.pdf
```