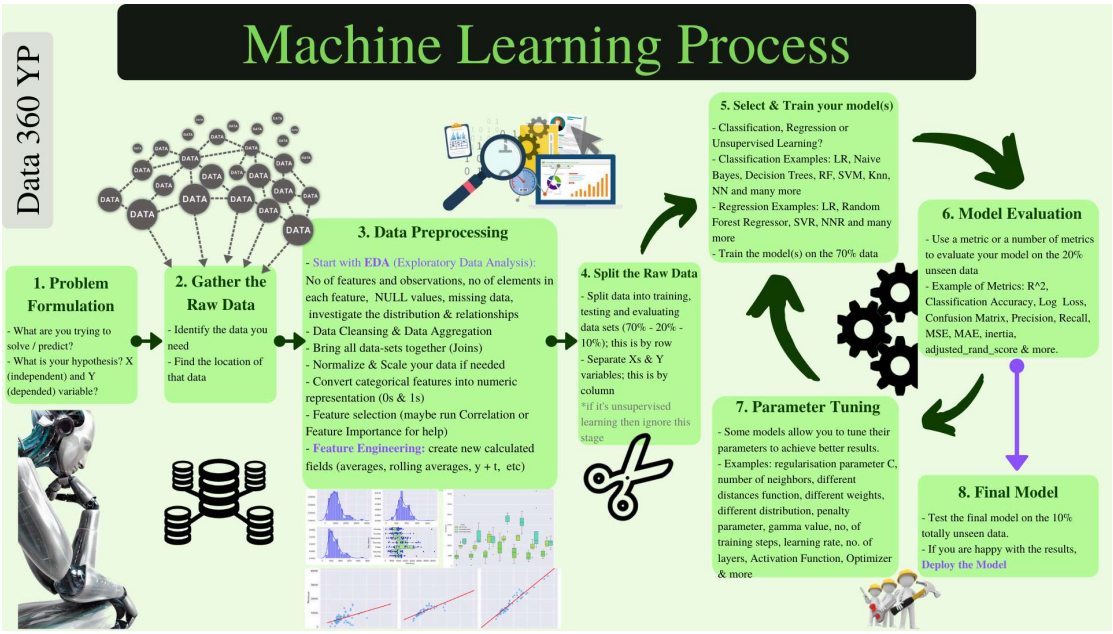
In [50]:

```
### Graphical ML Process

import os
from IPython.display import Image
PATH = r"C:\Users\Araz\Desktop\MUFG\\"
Image(filename = PATH + "MachineLearningProcess.png", width=900, height=9
```

Out[50]:



In [179]:
```
!pip install pandasql
!pip install catboost
```

```
Requirement already satisfied: pandasql in c:\programdata\anaconda3\lib
\site-packages (0.7.3)
Requirement already satisfied: sqlalchemy in c:\programdata\anaconda3\li
b\site-packages (from pandasql) (1.3.9)
Requirement already satisfied: pandas in c:\programdata\anaconda3\lib\si
te-packages (from pandasql) (0.25.1)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\sit
e-packages (from pandasql) (1.16.5)
Requirement already satisfied: python-dateutil>=2.6.1 in c:\programdata
\anaconda3\lib\site-packages (from pandas->pandasql) (2.8.0)
Requirement already satisfied: pytz>=2017.2 in c:\programdata\anaconda3
\lib\site-packages (from pandas->pandasql) (2019.3)
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib
\site-packages (from python-dateutil>=2.6.1->pandas->pandasql) (1.12.0)
Requirement already satisfied: catboost in c:\programdata\anaconda3\lib
\site-packages (1.2.7)
Requirement already satisfied: matplotlib in c:\programdata\anaconda3\li
b\site-packages (from catboost) (3.1.1)
Requirement already satisfied: plotly in c:\programdata\anaconda3\lib\si
te-packages (from catboost) (5.18.0)
Requirement already satisfied: six in c:\programdata\anaconda3\lib\site-
packages (from catboost) (1.12.0)
Requirement already satisfied: graphviz in c:\programdata\anaconda3\lib
\site-packages (from catboost) (0.13.2)
Requirement already satisfied: pandas>=0.24 in c:\programdata\anaconda3
\lib\site-packages (from catboost) (0.25.1)
Requirement already satisfied: numpy<2.0,>=1.16.0 in c:\programdata\anac
onda3\lib\site-packages (from catboost) (1.16.5)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\sit
e-packages (from catboost) (1.3.1)
Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3
\lib\site-packages (from matplotlib->catboost) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anaco
nda3\lib\site-packages (from matplotlib->catboost) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1
in c:\programdata\anaconda3\lib\site-packages (from matplotlib->catboos
t) (2.4.2)
Requirement already satisfied: python-dateutil>=2.1 in c:\programdata\an
aconda3\lib\site-packages (from matplotlib->catboost) (2.8.0)
Requirement already satisfied: packaging in c:\programdata\anaconda3\lib
\site-packages (from plotly->catboost) (19.2)
Requirement already satisfied: tenacity>=6.2.0 in c:\programdata\anacond
a3\lib\site-packages (from plotly->catboost) (8.2.3)
Requirement already satisfied: pytz>=2017.2 in c:\programdata\anaconda3
\lib\site-packages (from pandas>=0.24->catboost) (2019.3)
Requirement already satisfied: setuptools in c:\programdata\anaconda3\li
b\site-packages (from kiwisolver>=1.0.1->matplotlib->catboost) (41.4.0)
```

In [52]:
```
#make function
pysql = lambda q: pdql.sqldf(q, globals())
```

In [53]:
```
import pandas as pd
import pandasql as pdql
```

In [54]:
```
# Packages / libraries
import os #provides functions for interacting with the operating system
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, explained_variance_score, confusior
from math import sqrt

%matplotlib inline

# To install sklearn type "pip install numpy scipy scikit-learn" to the d

# To change scientific numbers to float
np.set_printoptions(formatter={'float_kind':'{:f}'.format})

# Increases the size of sns plots
sns.set(rc={'figure.figsize':(12,10)})

# import sys
# !conda list Check the packages installed
```

In [55]:
```
financial_data = pd.read_csv(r'C:\Users\Araz\Desktop\MUFG\financial_data.

financial_data.drop('Unnamed: 0', axis=1, inplace=True)
financial_data.head(5)
```

Out[55]:

	LOAN_ID	PORTFOLIO	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_RATIO
0	ZZZ0001	C&I	0.113703	0.795355	1156188.606	0.090963
1	ZZZ0002	CRE Permanent	0.622299	0.364232	NaN	0.497840
2	ZZZ0003	CRE Construction	0.609275	0.821238	1046682.630	0.487420
3	ZZZ0004	CRE Construction	0.623379	0.613073	1085325.470	0.498704
4	ZZZ0005	CRE Construction	0.860915	0.709228	1051378.694	0.688732

In [56]:

```
default_data = pd.read_csv(r'C:\Users\Araz\Desktop\MUFG\default_data.csv'
default_data.drop('Unnamed: 0', axis=1, inplace=True)
default_data.head(5)
```

Out[56]:

	loan_number
0	ZZZ00085
1	ZZZ000101
2	ZZZ000108
3	ZZZ000119
4	ZZZ000258

In [57]:

```
#join tables to tag the defaulted loans

data_f = '''
        select
            a.*
            ,case when a.LOAN_ID=b.loan_number then 1 else 0 end as defau
        from financial_data a left join default_data b
        on a.LOAN_ID=b.loan_number
         ;
        '''
pysql(data_f)
```

Out[57]:

	LOAN_ID	PORTFOLIO	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_
0	ZZZ0001	C&I	0.113703	0.795355	1.156189e+06	0.
1	ZZZ0002	CRE Permanent	0.622299	0.364232	NaN	0.
2	ZZZ0003	CRE Construction	0.609275	0.821238	1.046683e+06	0.
3	ZZZ0004	CRE Construction	0.623379	0.613073	1.085325e+06	0.
4	ZZZ0005	CRE Construction	0.860915	0.709228	1.051379e+06	0.
...	...	...	...	...	...	
9995	ZZZ0009996	CRE Construction	0.270278	0.008539	8.850822e+05	0.
9996	ZZZ0009997	CRE Construction	0.475298	0.895215	9.043524e+05	0.
9997	ZZZ0009998	CRE Permanent	0.567873	0.283908	1.148198e+06	0.
9998	ZZZ0009999	CRE Permanent	0.386750	0.022000	9.930722e+05	0.
9999	ZZZ00010000	CRE Permanent	0.989971	10.123400	9.488357e+05	0.

10000 rows × 10 columns

In [58]:

```
#create a dataframe from teh query result
data_c=pysql(data_f)
```

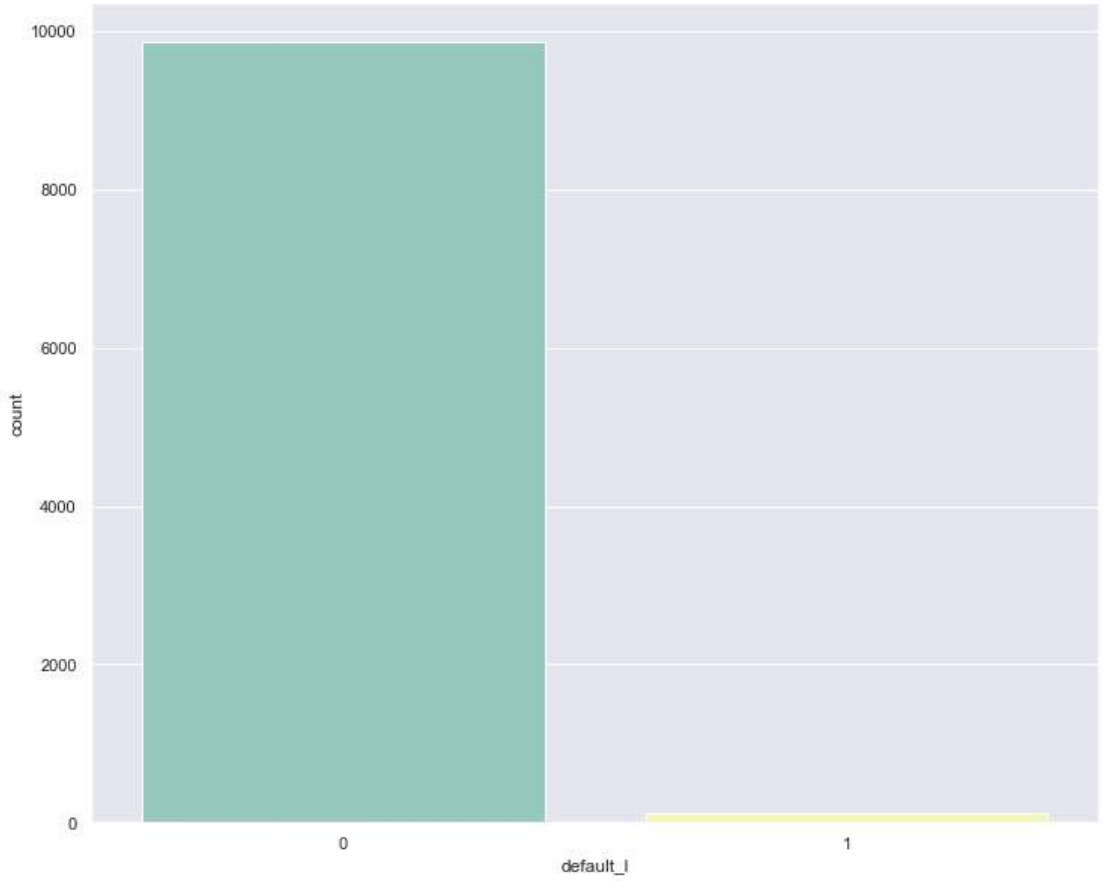
In [59]:
```
data_c.head()
```

Out[59]:

	LOAN_ID	PORTFOLIO	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_RATIO
0	ZZZ0001	C&I	0.113703	0.795355	1156188.606	0.090963
1	ZZZ0002	CRE Permanent	0.622299	0.364232	NaN	0.497840
2	ZZZ0003	CRE Construction	0.609275	0.821238	1046682.630	0.487420
3	ZZZ0004	CRE Construction	0.623379	0.613073	1085325.470	0.498704
4	ZZZ0005	CRE Construction	0.860915	0.709228	1051378.694	0.688732

In [60]:
```
# Investigating the distribution of y

sns.countplot(x = 'default_l', data = data_c, palette = 'Set3')
```

Out[60]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x171900b5d08>
```



In [61]:
```
# Printing the shape
print(data_c.shape)
```

```
(10000, 10)
```

In [62]:
```
#total number of defaults
tot_nr_of_def=data_c['default_1'].sum()
print(tot_nr_of_def)
```

```
129
```

In [63]:
```

# Checking for null values in features

data_c.isnull().sum()
```

Out[63]:
```
LOAN_ID                0
PORTFOLIO              0
DEBT_RATIO          1000
PROFIT_MARGIN          0
TOTAL_ASSETS        1000
QUICK_RATIO            0
CURRENT_RATIO          0
RETURN_ON_EQUITY       0
PD_RISK_RATING         0
default_1              0
dtype: int64
```

In [64]:
```
data_c[data_c['DEBT_RATIO'].isnull()]
```

Out[64]:

	LOAN_ID	PORTFOLIO	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_R
22	ZZZ00023	CRE Permanent	NaN	0.573471	NaN	0.1
29	ZZZ00030	C&I	NaN	0.356815	9.555703e+05	0.0
34	ZZZ00035	CRE Permanent	NaN	0.662805	NaN	0.1
37	ZZZ00038	CRE Permanent	NaN	0.436476	NaN	0.2
40	ZZZ00041	C&I	NaN	0.951417	1.061820e+06	0.4
...	...	...	...	...	...	
9953	ZZZ0009954	CRE Construction	NaN	0.017831	1.000329e+06	0.2
9957	ZZZ0009958	CRE Permanent	NaN	0.135664	8.816934e+05	0.3
9962	ZZZ0009963	C&I	NaN	0.219219	1.003384e+06	0.6
9969	ZZZ0009970	CRE Construction	NaN	0.125559	8.359673e+05	0.3
9976	ZZZ0009977	CRE Permanent	NaN	0.486983	1.122506e+06	0.0

1000 rows × 10 columns

In [66]:
```
data_c[data_c['TOTAL_ASSETS'].isnull()]
```

Out[66]:

	LOAN_ID	PORTFOLIO	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_R
1	ZZZ0002	CRE Permanent	0.622299	0.364232	NaN	0.4
8	ZZZ0009	CRE Construction	0.666084	0.222746	NaN	0.5
9	ZZZ00010	CRE Construction	0.514251	9.987000	NaN	0.4
13	ZZZ00014	CRE Construction	0.923433	0.619878	NaN	0.7
15	ZZZ00016	CRE Permanent	0.837296	0.217779	NaN	0.6
...	...	...	...	...	...	
9922	ZZZ0009923	C&I	0.206959	0.886858	NaN	0.1
9937	ZZZ0009938	CRE Permanent	0.243483	0.384530	NaN	0.1
9939	ZZZ0009940	CRE Construction	0.090892	0.574466	NaN	0.0
9946	ZZZ0009947	CRE Construction	0.413869	0.145694	NaN	0.3
9970	ZZZ0009971	CRE Construction	0.054648	0.686667	NaN	0.0

1000 rows × 10 columns

In [67]:
```
#replace missing data points with mean of total assets

# Deleting the NULL values
#data_c = data_c.dropna(subset = ['TOTAL_ASSETS']) we don't remove to kee
data_c['TOTAL_ASSETS'] = data_c['TOTAL_ASSETS'].fillna((data_c['TOTAL_ASS
# Printing the shape
print(data_c.shape)

# Visualize the NULL observations
data_c.isnull().sum()
```

```
(10000, 10)
```

Out[67]:
```
LOAN_ID               0
PORTFOLIO             0
DEBT_RATIO         1000
PROFIT_MARGIN         0
TOTAL_ASSETS          0
QUICK_RATIO           0
CURRENT_RATIO         0
RETURN_ON_EQUITY      0
PD_RISK_RATING        0
default_1             0
dtype: int64
```

In [68]:
```
#total number of defaults after removing missing

tot_nr_of_def=data_c['default_1'].sum()
print(tot_nr_of_def)
```

```
129
```

In [69]:
```
#replace missing  data points with mean debt ratio

#data_c = data_c.dropna(subset = ['DEBT_RATIO'])
data_c['DEBT_RATIO'] = data_c['DEBT_RATIO'].fillna((data_c['DEBT_RATIO'].
# Printing the shape
print(data_c.shape)

# Visualize the NULL observations
data_c.isnull().sum()
```

```
(10000, 10)
```

Out[69]:
```
LOAN_ID             0
PORTFOLIO           0
DEBT_RATIO          0
PROFIT_MARGIN       0
TOTAL_ASSETS        0
QUICK_RATIO         0
CURRENT_RATIO       0
RETURN_ON_EQUITY    0
PD_RISK_RATING      0
default_1           0
dtype: int64
```

In [70]:
```
# Printing the shape after removing missing
print(data_c.shape)
```

```
(10000, 10)
```

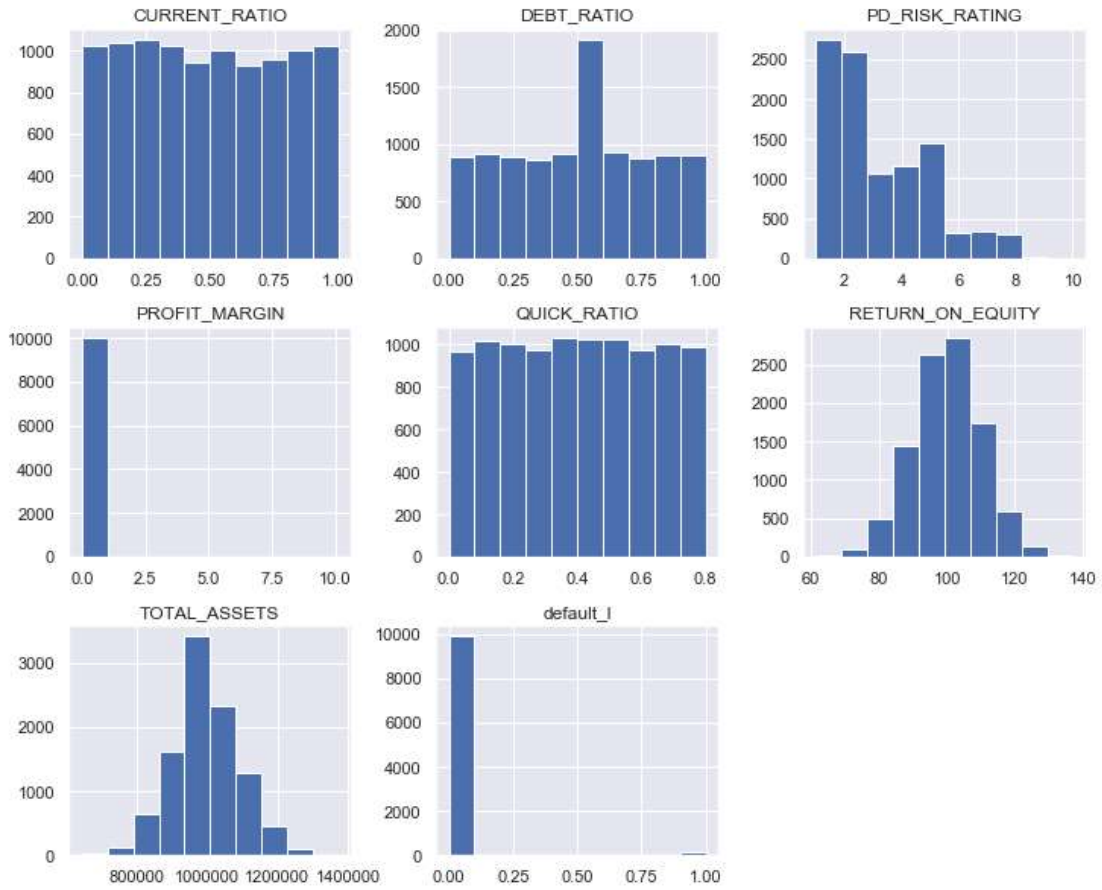
In [71]:
```
#total number of defaults after removing missing
tot_nr_of_def=data_c['default_1'].sum()
print(tot_nr_of_def)
```

```
129
```

In [72]:

```
from pandas.plotting import scatter_matrix
from matplotlib import pyplot

# summarize the shape of the dataset
print(data_c.shape)
# summarize each variable
print(data_c.describe())
# histograms of the variables
data_c.hist()
pyplot.show()
```

```
(10000, 10)
         DEBT_RATIO  PROFIT_MARGIN  TOTAL_ASSETS   QUICK_RATIO  CURRENT_
RATIO  \
count  10000.000000   10000.000000  1.000000e+04  10000.000000   10000.0
00000
mean       0.500821       0.500171  9.990384e+05      0.400250       0.4
95674
std        0.273118       0.334494  9.556056e+04      0.229641       0.2
90899
min        0.000342       0.000148  6.449835e+05      0.000273       0.0
00065
25%        0.278703       0.250202  9.382717e+05      0.201990       0.2
42502
50%        0.500821       0.495737  9.990384e+05      0.401013       0.4
91026
75%        0.722143       0.743321  1.058886e+06      0.597996       0.7
49245
max        0.999594      10.124300  1.372729e+06      0.799675       0.9
99974

       RETURN_ON_EQUITY  PD_RISK_RATING     default_1
count      10000.000000    10000.000000  10000.000000
mean         100.075516        2.989500      0.012900
std           10.095165        1.925035      0.112849
min           61.657742        1.000000      0.000000
25%           93.379452        1.000000      0.000000
50%          100.141522        2.000000      0.000000
75%          106.787248        4.000000      0.000000
max          136.910817       10.000000      1.000000
```



In [73]:

```
# Investigate all the elements whithin each Feature

for column in data_c:
    unique_values = np.unique(data_c[column])
    nr_values = len(unique_values)
    if nr_values <= 10:
        print("The number of values for feature {} is: {} -- {}".format(c
    else:
        print("The number of values for feature {} is: {}".format(column,
```

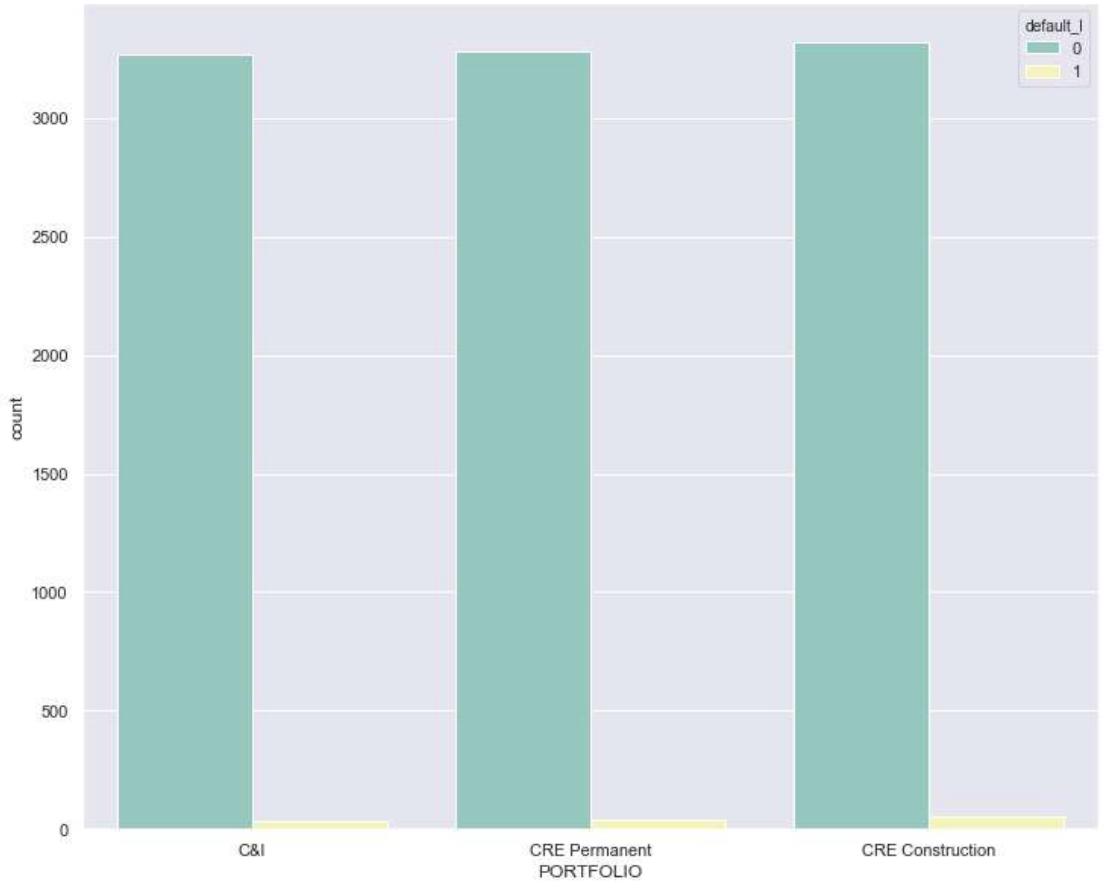
```
The number of values for feature LOAN_ID is: 10000
The number of values for feature PORTFOLIO is: 3 -- ['C&I' 'CRE Construc
tion' 'CRE Permanent']
The number of values for feature DEBT_RATIO is: 9001
The number of values for feature PROFIT_MARGIN is: 10000
The number of values for feature TOTAL_ASSETS is: 9001
The number of values for feature QUICK_RATIO is: 10000
The number of values for feature CURRENT_RATIO is: 10000
The number of values for feature RETURN_ON_EQUITY is: 10000
The number of values for feature PD_RISK_RATING is: 10 -- [ 1  2  3  4
5  6  7  8  9 10]
The number of values for feature default_l is: 2 -- [0 1]
```

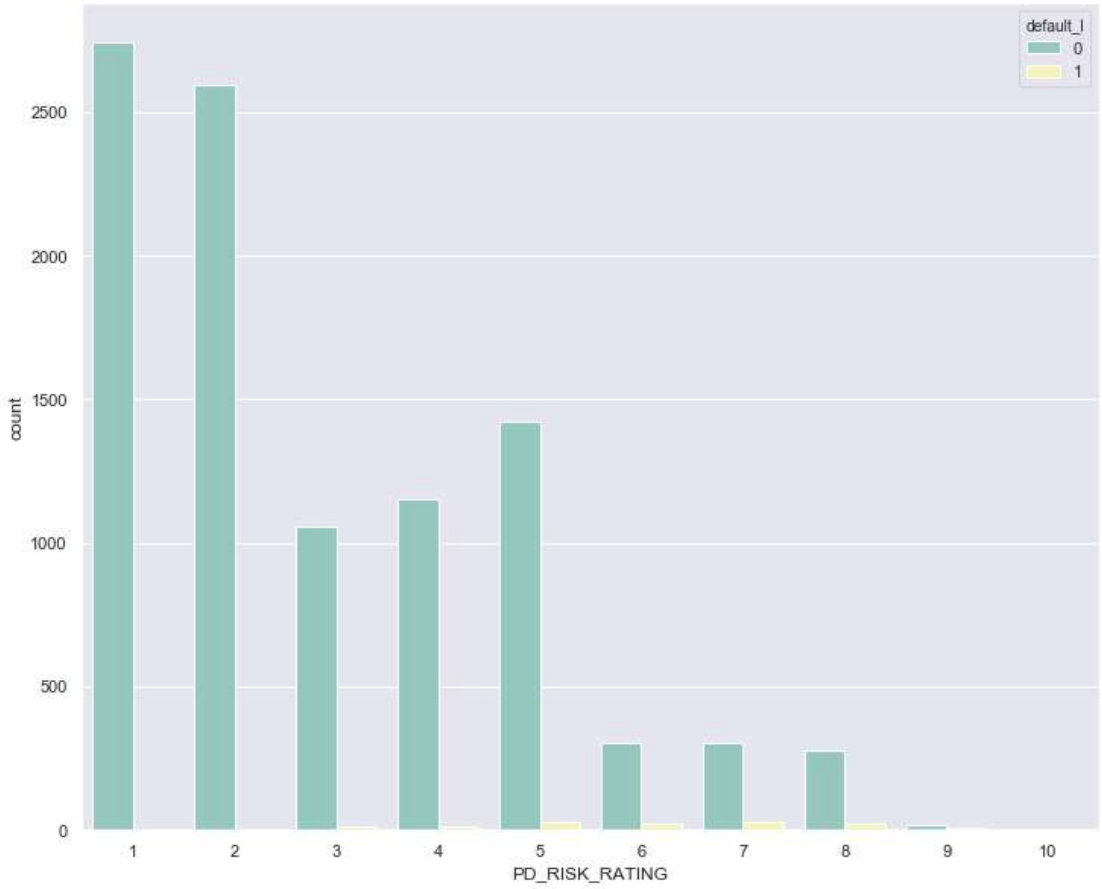
In [74]:
```
data_c.columns
```

Out[74]:
```
Index(['LOAN_ID', 'PORTFOLIO', 'DEBT_RATIO', 'PROFIT_MARGIN', 'TOTAL_ASS
ETS',
       'QUICK_RATIO', 'CURRENT_RATIO', 'RETURN_ON_EQUITY', 'PD_RISK_RATI
NG',
       'default_1'],
      dtype='object')
```

In [75]:

```
# Looping through all the features by our y variable - see if there is re

features = ['PORTFOLIO', 'PD_RISK_RATING']

for f in features:
    sns.countplot(x = f, data = data_c, palette = 'Set3', hue = 'default_
    plt.show()

#It appears that default rate in varies considerably across 3 diffrent po
```




default_l
0
1
2500
2000
1500
1000
500
0
count
1
2
3
4
5
6
7
8
9
10
PD_RISK_RATING

In [76]:

```
# Making categorical variables into numeric representation

new_data_c = pd.get_dummies(data_c, columns = features)

# Notes:
# We can also do this with Label Encoding and OneHotEncoder from the prep

print(data_c.shape)
# print the shape
print(new_data_c.shape)


# Visualizing the data
new_data_c
```

```
(10000, 10)
(10000, 21)
```

Out[76]:

	LOAN_ID	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_RATIO	CURR
0	ZZZ0001	0.113703	0.795355	1.156189e+06	0.090963	
1	ZZZ0002	0.622299	0.364232	9.990384e+05	0.497840	
2	ZZZ0003	0.609275	0.821238	1.046683e+06	0.487420	
3	ZZZ0004	0.623379	0.613073	1.085325e+06	0.498704	
4	ZZZ0005	0.860915	0.709228	1.051379e+06	0.688732	
...	...	...	...	...	...	...
9995	ZZZ0009996	0.270278	0.008539	8.850822e+05	0.216223	
9996	ZZZ0009997	0.475298	0.895215	9.043524e+05	0.380238	
9997	ZZZ0009998	0.567873	0.283908	1.148198e+06	0.454298	
9998	ZZZ0009999	0.386750	0.022000	9.930722e+05	0.309400	
9999	ZZZ00010000	0.989971	10.123400	9.488357e+05	0.791977	

10000 rows × 21 columns

In [78]:
```
#MinMaxScaler Transform

data_c=new_data_c

import pandas as pd
from sklearn.preprocessing import MinMaxScaler

data_c['RETURN_ON_EQUITY'] = data_c['RETURN_ON_EQUITY'].div(100)

scaler = MinMaxScaler()
data_c['TOTAL_ASSETS'] = scaler.fit_transform(data_c[['TOTAL_ASSETS']])
```

In [79]:
```
#verify the distributions after transformatio

# summarize the shape of the dataset
print(data_c.shape)
# summarize each variable
print(data_c.describe())
# histograms of the variables
data_c.hist()
pyplot.show()
```

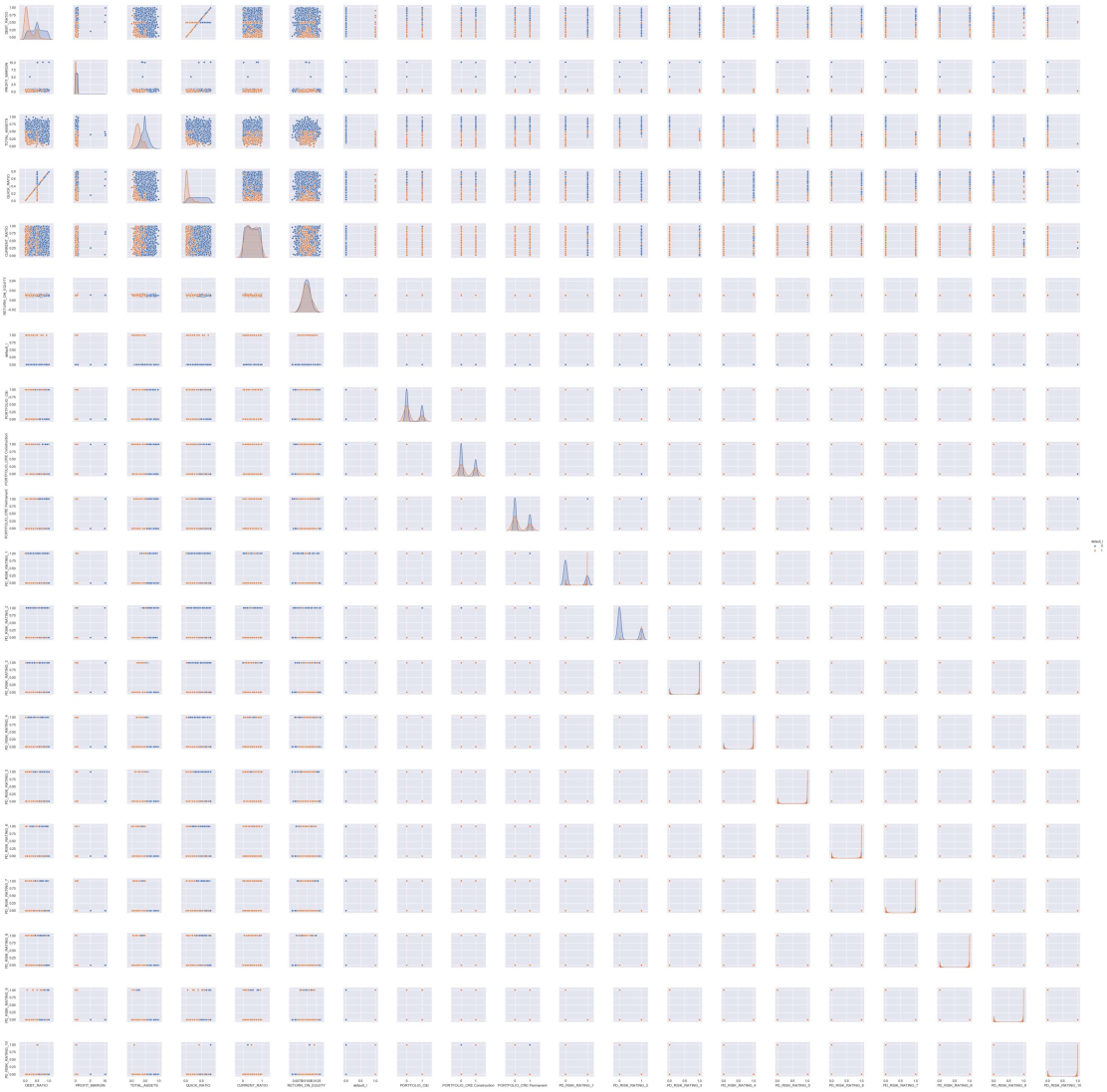
```
(10000, 21)
         DEBT_RATIO  PROFIT_MARGIN  TOTAL_ASSETS   QUICK_RATIO  CURR
ENT_RATIO  \
count  10000.000000   10000.000000  10000.000000  10000.000000   100
00.000000
mean       0.500821       0.500171      0.486509      0.400250
0.495674
std        0.273118       0.334494      0.131310      0.229641
0.290899
min        0.000342       0.000148      0.000000      0.000273
0.000065
25%        0.278703       0.250202      0.403009      0.201990
0.242502
50%        0.500821       0.495737      0.486509      0.401013
0.491026
75%        0.722143       0.743321      0.568747      0.597996
0.749245
max        0.999594      10.124300      1.000000      0.799675
0.999974
```

In [183]:
```
#Adressing Imbalanced Data
```

In [83]:

```
g = sns.pairplot(data_c, hue = 'default_l')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\nonparametric\kd
e.py:487: RuntimeWarning: invalid value encountered in true_divide
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\nonparametric\kde
tools.py:34: RuntimeWarning: invalid value encountered in double_scalars
  FAC1 = 2*(np.pi*bw/RANGE)**2
```



In [189]:

```
# Separate input features and target
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix, r

print(data_c)
#cols = [1]
#data_c.drop(data_c.columns[cols],axis=1,inplace=True)
#print(data_c)

y = data_c.default_l
X = data_c.drop(['LOAN_ID'], axis=1)


# setting up testing and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,

# DummyClassifier to predict only target 0
dummy = DummyClassifier(strategy='most_frequent').fit(X_train, y_train)
dummy_pred = dummy.predict(X_test)

# checking unique labels
print('Unique predicted labels: ', (np.unique(dummy_pred)))

# checking accuracy
print('Test score: ', accuracy_score(y_test, dummy_pred))

#Here we can use the DummyClassifier to always predict “not fraud” just t
```

```
          LOAN_ID  DEBT_RATIO  PROFIT_MARGIN  TOTAL_ASSETS  QUICK_RATIO
\
0         ZZZ0001    0.113703       0.795355      0.702450     0.090963
1         ZZZ0002    0.622299       0.364232      0.486509     0.497840
2         ZZZ0003    0.609275       0.821238      0.551977     0.487420
3         ZZZ0004    0.623379       0.613073      0.605077     0.498704
4         ZZZ0005    0.860915       0.709228      0.558430     0.688732
...           ...         ...            ...           ...          ...
9995   ZZZ0009996    0.270278       0.008539      0.329921     0.216223
9996   ZZZ0009997    0.475298       0.895215      0.356400     0.380238
9997   ZZZ0009998    0.567873       0.283908      0.691470     0.454298
9998   ZZZ0009999    0.386750       0.022000      0.478311     0.309400
9999  ZZZ00010000    0.989971      10.123400      0.417525     0.791977

      CURRENT_RATIO  RETURN_ON_EQUITY  default_l  PORTFOLIO_C&I  \
0          0.963879          0.012061          0              1
1          0.606212          0.010962          0              0
2          0.296746          0.009452          0              0
3          0.641079          0.009493          0              0
4          0.339430          0.010633          0              0
...             ...               ...        ...            ...
9995       0.182243          0.009333          0              0
9996       0.996613          0.011081          0              0
9997       0.030040          0.008719          0              0
9998       0.590155          0.010454          0              0
9999       0.799594          0.009951          0              0

      PORTFOLIO_CRE Construction  ...  PD_RISK_RATING_1  PD_RISK_RATING_
2  \
0                             0  ...                 0
1
1                             0  ...                 0
0
2                             1  ...                 0
1
3                             1  ...                 1
0
4                             1  ...                 0
1
...                         ...  ...               ...
...
9995                          1  ...                 0
0
9996                          1  ...                 0
0
9997                          0  ...                 0
1
9998                          0  ...                 0
0
9999                          0  ...                 0
0

      PD_RISK_RATING_3  PD_RISK_RATING_4  PD_RISK_RATING_5  PD_RISK_RATI
NG_6  \
0                    0                 0                 0
0
1                    0                 1                 0
```

```
0
2                    0                 0                 0
0
3                    0                 0                 0
0
4                    0                 0                 0
0
...                ...               ...               ...
...
9995                 0                 0                 1
0
9996                 1                 0                 0
0
9997                 0                 0                 0
0
9998                 1                 0                 0
0
9999                 1                 0                 0
0

      PD_RISK_RATING_7  PD_RISK_RATING_8  PD_RISK_RATING_9  PD_RISK_RATI
NG_10
0                    0                 0                 0
0
1                    0                 0                 0
0
2                    0                 0                 0
0
3                    0                 0                 0
0
4                    0                 0                 0
0
...                ...               ...               ...
...
9995                 0                 0                 0
0
9996                 0                 0                 0
0
9997                 0                 0                 0
0
9998                 0                 0                 0
0
9999                 0                 0                 0
0

[10000 rows x 21 columns]
Unique predicted labels:  [0]
Test score:  0.986
```

In [84]:
```
# Modeling the data as is
# Train model
lr = LogisticRegression(solver='liblinear').fit(X_train, y_train)

# Predict on training set
lr_pred = lr.predict(X_test)

# Checking accuracy
accuracy_score(y_test, lr_pred)

print(accuracy_score)
# Checking unique values
predictions = pd.DataFrame(lr_pred)
predictions[0].value_counts()

# f1 score
f1_score(y_test, lr_pred)

# recall score
recall_score(y_test, lr_pred)
```

```
<function accuracy_score at 0x00000171854E61F8>
```

Out[84]:
```
1.0
```

In [85]:
```
from sklearn.ensemble import RandomForestClassifier

# train model
rfc = RandomForestClassifier(n_estimators=10).fit(X_train, y_train)

# predict on test set
rfc_pred = rfc.predict(X_test)

accuracy_score(y_test, rfc_pred)

f1_score(y_test, rfc_pred)

recall_score(y_test, rfc_pred)
```

Out[85]:
```
1.0
```

In [101]:

```
from catboost import CatBoostClassifier
# Initialize and train the CatBoost Classifier
# train model
cbc = CatBoostClassifier(n_estimators=10).fit(X_train, y_train)

# predict on test set
cbc_pred = cbc.predict(X_test)

accuracy_score(y_test, cbc_pred)

f1_score(y_test, cbc_pred)

recall_score(y_test, cbc_pred)
```

```
Learning rate set to 0.5
0:      learn: 0.3354897        total: 5.27ms   remaining: 47.4ms
1:      learn: 0.2001766        total: 10.8ms   remaining: 43.1ms
2:      learn: 0.1277116        total: 16.1ms   remaining: 37.5ms
3:      learn: 0.0846967        total: 20.6ms   remaining: 30.8ms
4:      learn: 0.0585930        total: 26.1ms   remaining: 26.1ms
5:      learn: 0.0427677        total: 29.6ms   remaining: 19.7ms
6:      learn: 0.0337755        total: 32.6ms   remaining: 14ms
7:      learn: 0.0265308        total: 35.7ms   remaining: 8.93ms
8:      learn: 0.0235280        total: 39.3ms   remaining: 4.37ms
9:      learn: 0.0194906        total: 43ms     remaining: 0us
```

Out[101]: 0.5714285714285714

In [97]:

```python
from catboost import CatBoostClassifier
from sklearn.model_selection import RandomizedSearchCV

# Initialize CatBoost Classifier
cbc = CatBoostClassifier()

# Setup RandomizedSearchCV
from scipy.stats import randint, uniform

# Parameter distribution
catboost_param_dist = {
    'depth': randint(4, 10),
    'learning_rate': uniform(0.01, 0.3),
    'iterations': randint(10, 1000),
    'l2_leaf_reg': randint(1, 10),
    'border_count': randint(1, 255),
    'bagging_temperature': uniform(0.0, 1.0),
    'random_strength': uniform(0.0, 1.0)
}

random_search_cb = RandomizedSearchCV(estimator=cbc,
                                      param_distributions=catboost_param_
                                      cv=5,
                                      verbose=2,
                                      random_state=42)
# Fit the model
random_search_cb.fit(X_train, y_train)
# Evaluate the model
random_search_cb_score = random_search_cb.score(X_test, y_test)
```

```
650:    learn: 0.0000688        total: 6.09s    remaining: 1.25s
651:    learn: 0.0000688        total: 6.1s     remaining: 1.24s
652:    learn: 0.0000688        total: 6.11s    remaining: 1.23s
653:    learn: 0.0000688        total: 6.11s    remaining: 1.22s
654:    learn: 0.0000688        total: 6.12s    remaining: 1.22s
655:    learn: 0.0000688        total: 6.13s    remaining: 1.21s
656:    learn: 0.0000688        total: 6.14s    remaining: 1.2s
657:    learn: 0.0000688        total: 6.14s    remaining: 1.19s
658:    learn: 0.0000688        total: 6.15s    remaining: 1.18s
659:    learn: 0.0000688        total: 6.16s    remaining: 1.17s
660:    learn: 0.0000688        total: 6.17s    remaining: 1.16s
661:    learn: 0.0000688        total: 6.17s    remaining: 1.15s

662:    learn: 0.0000688        total: 6.18s    remaining: 1.14s
663:    learn: 0.0000688        total: 6.19s    remaining: 1.13s
664:    learn: 0.0000688        total: 6.2s     remaining: 1.12s
665:    learn: 0.0000688        total: 6.2s     remaining: 1.11s
666:    learn: 0.0000688        total: 6.21s    remaining: 1.1s
667:    learn: 0.0000688        total: 6.22s    remaining: 1.09s
668:    learn: 0.0000688        total: 6.23s    remaining: 1.08s
```

In [100]:
```
# predict on test set before oversampling/undersampling
random_search_cb_pred = random_search_cb.predict(X_test)

accuracy_score(y_test, random_search_cb_pred)

f1_score(y_test, random_search_cb_pred)

recall_score(y_test, random_search_cb_pred)

##Accuracy ration on imbalanced data without treatment: 0.685714285714285
```

Out[100]: 0.6857142857142857

In [102]:
```
from xgboost import XGBClassifier
# Initialize and train the CatBoost Classifier
# train model
xgc = XGBClassifier(n_estimators=10).fit(X_train, y_train)

# predict on test set before oversampling/undersampling
xgc_pred = xgc.predict(X_test)

accuracy_score(y_test, xgc_pred)

f1_score(y_test, xgc_pred)

recall_score(y_test, xgc_pred)
#Accuracy ration on imbalanced data without treatment: 0.4
```

Out[102]: 0.4

In [192]:
```
#Trying Naive Bayesian Classifier after Oversampling:
# train model


from sklearn.naive_bayes import GaussianNB
# Initialize and train the Classifier
# train model
gnb = GaussianNB().fit(X_train, y_train)

# predict on test set
gnb_pred = gnb.predict(X_test)

accuracy_score(y_test, gnb_pred)

f1_score(y_test, gnb_pred)

recall_score(y_test, gnb_pred)

#Accuracy  is 1.0
```

Out[192]: 1.0

In [172]:

```
#problem with imbalanced data : problem with Accuracy

#solutions:
#1. Change the performance metric from accuracy to : confusion matrix, pr
#2. Change the algorithm such random forest which works fine with imbalan
#3. Resampling Techniques – Oversample minority class
#4. Resampling techniques – Undersample majority class
#5. Generate synthetic samples (SMOTE)

from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from collections import Counter

# instantiating the random over sampler
ros = RandomOverSampler()
# resampling X, y
X_ros, y_ros = ros.fit_resample(X, y)
# new class distribution
print(Counter(y_ros))

#Counter({0: 9871, 1: 9871})
```

```
Counter({0: 9871, 1: 9871})
```

In [106]:

```
data_c2=data_c.drop('LOAN_ID', axis=1)
data_c2
```

Out[106]:

	DEBT_RATIO	PROFIT_MARGIN	TOTAL_ASSETS	QUICK_RATIO	CURRENT_RATIO	F
0	0.113703	0.795355	0.702450	0.090963	0.963879	
1	0.622299	0.364232	0.486509	0.497840	0.606212	
2	0.609275	0.821238	0.551977	0.487420	0.296746	
3	0.623379	0.613073	0.605077	0.498704	0.641079	
4	0.860915	0.709228	0.558430	0.688732	0.339430	
...	...	...	...	...	...	
9995	0.270278	0.008539	0.329921	0.216223	0.182243	
9996	0.475298	0.895215	0.356400	0.380238	0.996613	
9997	0.567873	0.283908	0.691470	0.454298	0.030040	
9998	0.386750	0.022000	0.478311	0.309400	0.590155	
9999	0.989971	10.123400	0.417525	0.791977	0.799594	

10000 rows × 20 columns

In [113]:

```
from sklearn.utils import resample

# Separate input features and target
df = data_c2

y = df.default_l
X = df.drop('default_l', axis=1)

# setting up testing and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,

# concatenate our training data back together
X = pd.concat([X_train, y_train], axis=1)

# separate minority and majority classes
not_default = X[X.default_l==0]
default = X[X.default_l==1]

# upsample minority
default_upsampled = resample(default,
                             replace=True, # sample with replacement
                             n_samples=len(not_default), # match number in m
                             random_state=27) # reproducible results

# combine majority and upsampled minority
upsampled = pd.concat([not_default, default_upsampled])

# check new class counts
upsampled.default_l.value_counts()

#1    7406
#0    7406
```

Out[113]:

```
1    7406
0    7406
Name: default_l, dtype: int64
```

In [114]:

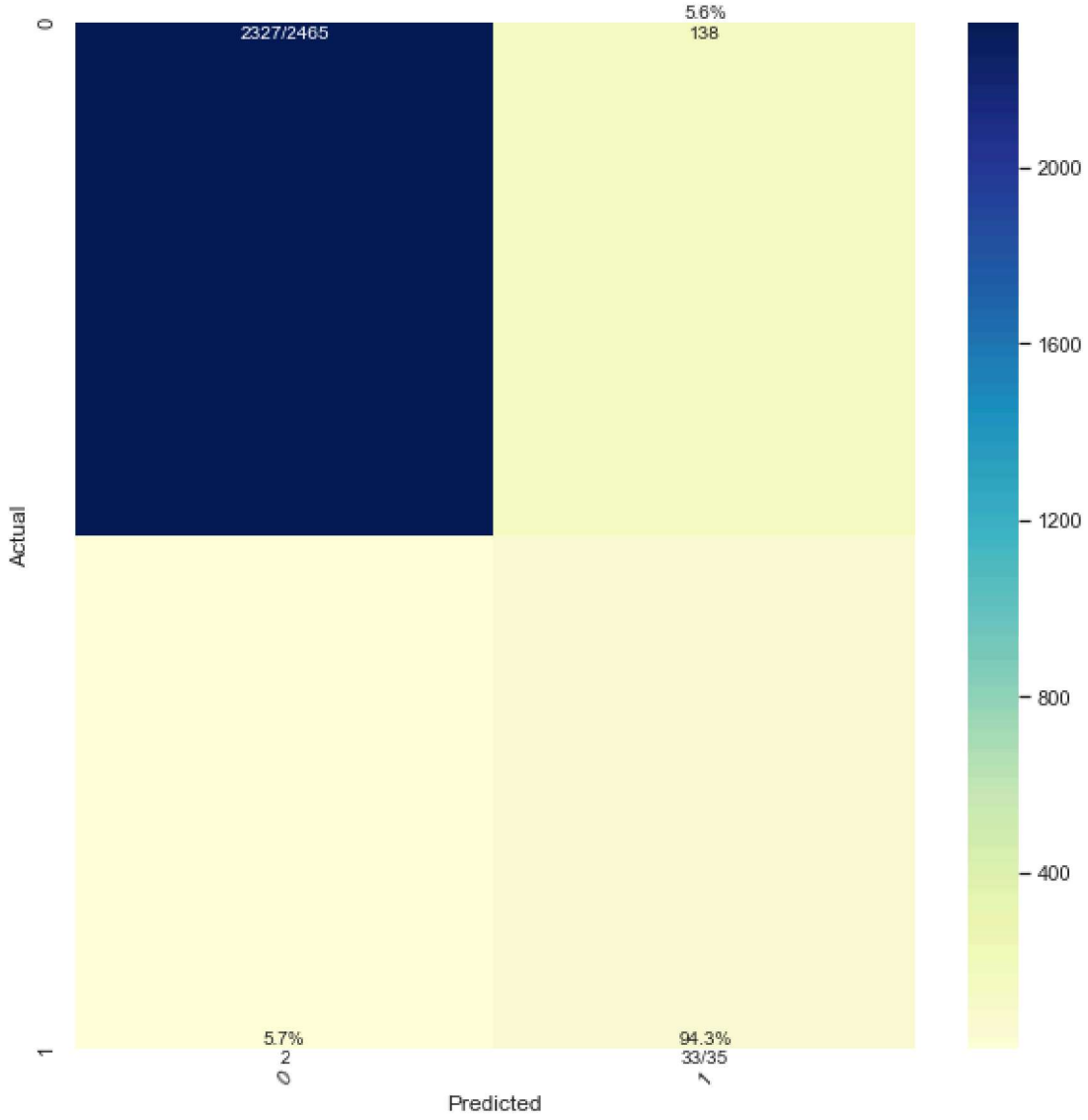
```
# trying logistic regression again with the balanced dataset

y_train = upsampled.default_1
X_train = upsampled.drop('default_1', axis=1)


upsampled = LogisticRegression(solver='liblinear').fit(X_train, y_train)

upsampled_pred = upsampled.predict(X_test)

# Checking accuracy
accuracy_score(y_test, upsampled_pred)

# f1 score
f1_score(y_test, upsampled_pred)

#recall
recall_score(y_test, upsampled_pred)

#0.9428571428571428
```

Out[114]:

```
0.9428571428571428
```

In [115]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_cm(y_true, y_pred, figsize=(10,10)):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_tr
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    fig, ax = plt.subplots(figsize=figsize)
    plt.xticks(rotation=45)
    sns.heatmap(cm, cmap= "YlGnBu", annot=annot, fmt='', ax=ax)


y_pred = upsampled_pred
y_true =y_test

plot_cm(y_true, y_pred)
```


5.6%
2327/2465
138
5.7%
2
94.3%
33/35
0
1
Actual
Predicted
2000
1600
1200
800
400

In [125]:

```
#4. Resampling techniques – Undersample majority class
# still using our separated classes default and not_default from above

# downsample majority
not_default_downsampled = resample(not_default,
                                   replace = False, # sample without replace
                                   n_samples = len(default), # match minorit
                                   random_state = 27) # reproducible results

# combine minority and downsampled majority
downsampled = pd.concat([not_default_downsampled, default])

# checking counts
downsampled.default_1.value_counts()

#1    94
#0    94
```

Out[125]:

```
1    94
0    94
Name: default_1, dtype: int64
```

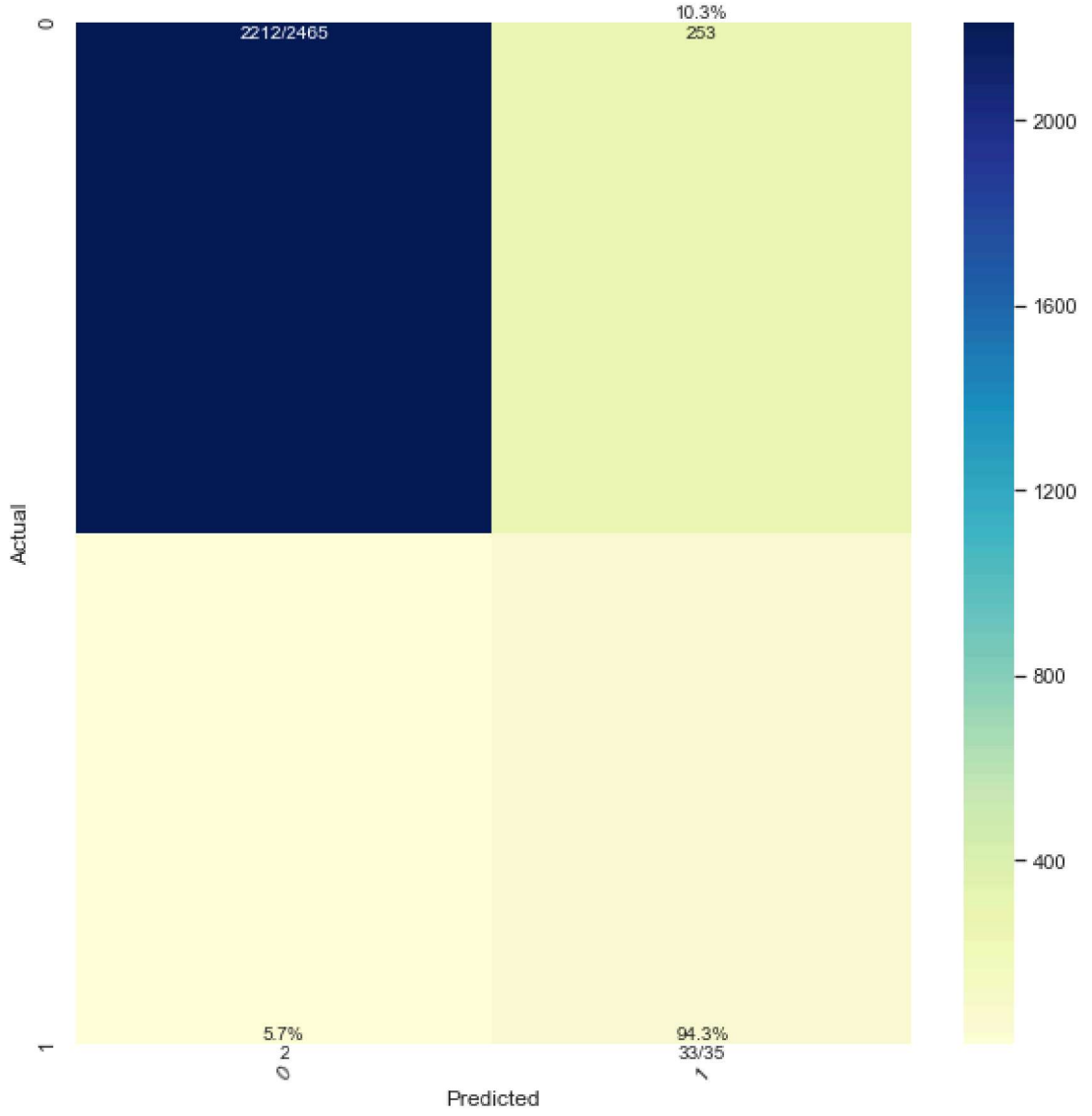
In [126]:

```
# trying logistic regression again with the undersampled dataset

y_train = downsampled.default_1
X_train = downsampled.drop('default_1', axis=1)

undersampled = LogisticRegression(solver='liblinear').fit(X_train, y_trai

undersampled_pred = undersampled.predict(X_test)

# Checking accuracy
accuracy_score(y_test, undersampled_pred)

#0.9

# f1 score
f1_score(y_test, undersampled_pred)

#0.21


recall_score(y_test, undersampled_pred)
#1.0 ?

#import seaborn as sn
#import pandas as pd
#import matplotlib.pyplot as plt

# confusion matrix
#pd.DataFrame(confusion_matrix(y_test, undersampled_pred))
#df_cm=pd.DataFrame(confusion_matrix(y_test, undersampled_pred))

#sn.heatmap(df_cm, annot=True, annot_kws={"size": 8}) # font size




#

#    0      1
#0  2215   250

#1   0     35
```

Out[126]: 0.9428571428571428

In [127]:

```
# confusion matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_cm(y_true, y_pred, figsize=(10,10)):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_tr
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    fig, ax = plt.subplots(figsize=figsize)
    plt.xticks(rotation=45)
    sns.heatmap(cm, cmap= "YlGnBu", annot=annot, fmt='', ax=ax)


y_pred = undersampled_pred
y_true =y_test

plot_cm(y_true, y_pred)
```



In [128]:

```
#5. Generate synthetic samples
from imblearn.over_sampling import SMOTE

# Separate input features and target
y = df.default_1
X = df.drop('default_1', axis=1)

# setting up testing and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,

sm = SMOTE(sampling_strategy=0.5, random_state=27)
X_train, y_train = sm.fit_sample(X_train, y_train)
```

In [152]:

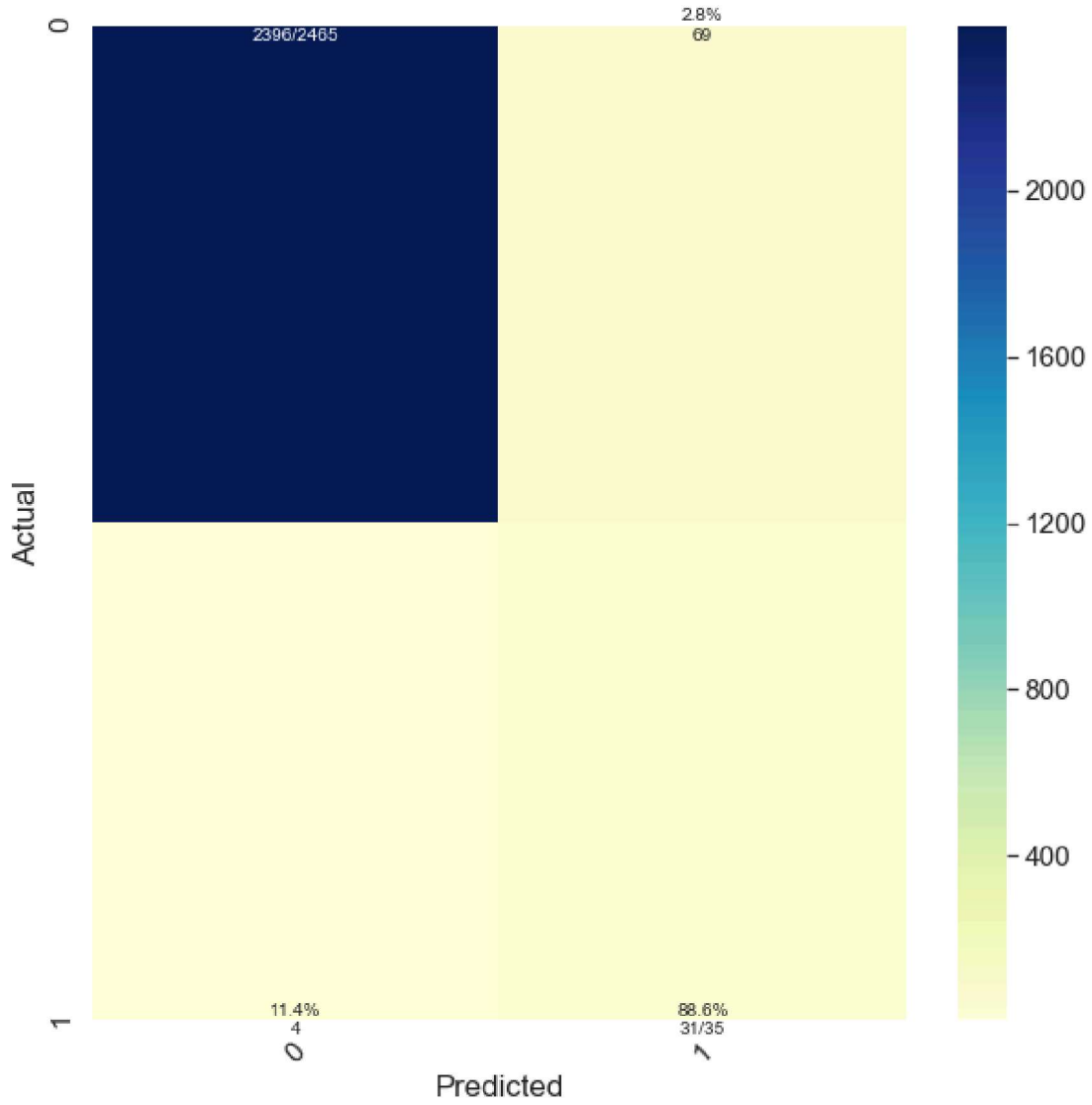
```
smote = LogisticRegression(solver='liblinear').fit(X_train, y_train)

smote_pred = smote.predict(X_test)

# Checking accuracy
accuracy_score(y_test, smote_pred)
#0.972

# f1 score
f1_score(y_test, smote_pred)
#0.459

recall_score(y_test, smote_pred)
#0.88
```

Out[152]:

```
0.45925925925925926
```

In [98]:

```
# confusion matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_cm(y_true, y_pred, figsize=(10,10)):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_tr
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    fig, ax = plt.subplots(figsize=figsize)
    plt.xticks(rotation=45)
    sns.heatmap(cm, cmap= "YlGnBu", annot=annot, fmt='', ax=ax)


y_pred = smote_pred
y_true =y_test

plot_cm(y_true, y_pred)
```



In [130]:

```
#5.3. Feature Selection¶
#Steps of Running Feature Importance
#Split the data into X & y
#Run a Tree-based estimators (i.e. decision trees & random forests)
#Run Feature Importance
```

In [131]:
```
# Run a Tree-based estimators (i.e. decision trees & random forests)

dt = DecisionTreeClassifier(random_state=15, criterion = 'entropy', max_d
dt.fit(X,y)
```

Out[131]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entr
opy',
                       max_depth=10, max_features=None, max_leaf_nodes=N
one,
                       min_impurity_decrease=0.0, min_impurity_split=Non
e,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecate
d',
                       random_state=15, splitter='best')
```

In [134]:
```
# Running Feature Importance

fi_col = []
fi = []

for i,column in enumerate(data_c2.drop('default_1', axis = 1)):
    print('The feature importance for {} is : {}'.format(column, dt.featu

    fi_col.append(column)
    fi.append(dt.feature_importances_[i])
```

```
The feature importance for DEBT_RATIO is : 0.05381108478574461
The feature importance for PROFIT_MARGIN is : 0.09862961048219732
The feature importance for TOTAL_ASSETS is : 0.46116292942094744
The feature importance for QUICK_RATIO is : 0.3060123403494916
The feature importance for CURRENT_RATIO is : 0.018661330977590946
The feature importance for RETURN_ON_EQUITY is : 0.02706631815173732
The feature importance for PORTFOLIO_C&I is : 0.0
The feature importance for PORTFOLIO_CRE Construction is : 0.0
The feature importance for PORTFOLIO_CRE Permanent is : 0.0
The feature importance for PD_RISK_RATING_1 is : 0.0
The feature importance for PD_RISK_RATING_2 is : 0.0
The feature importance for PD_RISK_RATING_3 is : 0.004444051570262035
The feature importance for PD_RISK_RATING_4 is : 0.0
The feature importance for PD_RISK_RATING_5 is : 0.004669885517607448
The feature importance for PD_RISK_RATING_6 is : 0.006956179549254984
The feature importance for PD_RISK_RATING_7 is : 0.008296273275558928
The feature importance for PD_RISK_RATING_8 is : 0.010289995919607275
The feature importance for PD_RISK_RATING_9 is : 0.0
The feature importance for PD_RISK_RATING_10 is : 0.0
```

In [135]:

```
# Creating a Dataframe
fi_col
fi

fi_df = zip(fi_col, fi)
fi_df = pd.DataFrame(fi_df, columns = ['Feature','Feature Importance'])
fi_df


# Ordering the data
fi_df = fi_df.sort_values('Feature Importance', ascending = False).reset_

# Creating columns to keep
columns_to_keep = fi_df['Feature'][0:40]

fi_df
```

Out[135]:

	index	Feature	Feature Importance
0	2	TOTAL_ASSETS	0.461163
1	3	QUICK_RATIO	0.306012
2	1	PROFIT_MARGIN	0.098630
3	0	DEBT_RATIO	0.053811
4	5	RETURN_ON_EQUITY	0.027066
5	4	CURRENT_RATIO	0.018661
6	16	PD_RISK_RATING_8	0.010290
7	15	PD_RISK_RATING_7	0.008296
8	14	PD_RISK_RATING_6	0.006956
9	13	PD_RISK_RATING_5	0.004670
10	11	PD_RISK_RATING_3	0.004444
11	17	PD_RISK_RATING_9	0.000000
12	9	PD_RISK_RATING_1	0.000000
13	12	PD_RISK_RATING_4	0.000000
14	10	PD_RISK_RATING_2	0.000000
15	8	PORTFOLIO_CRE Permanent	0.000000
16	7	PORTFOLIO_CRE Construction	0.000000
17	6	PORTFOLIO_C&I	0.000000
18	18	PD_RISK_RATING_10	0.000000

In [ ]:

```
#using random forest for feature importance
```

In [136]:
```
import pandas as pd

from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
```

In [137]:
```
sel = SelectFromModel(RandomForestClassifier(n_estimators = 100))
sel.fit(X_train, y_train)
```

Out[137]:
```
SelectFromModel(estimator=RandomForestClassifier(bootstrap=True, ccp_alp
ha=0.0,
                                                 class_weight=None,
                                                 criterion='gini',
                                                 max_depth=None,
                                                 max_features='auto',
                                                 max_leaf_nodes=None,
                                                 max_samples=None,
                                                 min_impurity_decrease=
0.0,
                                                 min_impurity_split=Non
e,
                                                 min_samples_leaf=1,
                                                 min_samples_split=2,
                                                 min_weight_fraction_lea
f=0.0,
                                                 n_estimators=100, n_job
s=None,
                                                 oob_score=False,
                                                 random_state=None, verb
ose=0,
                                                 warm_start=False),
                max_features=None, norm_order=1, prefit=False, threshold
=None)
```

In [138]:
```
sel.get_support()
selected_feat= X_train.columns[(sel.get_support())]
len(selected_feat)
```

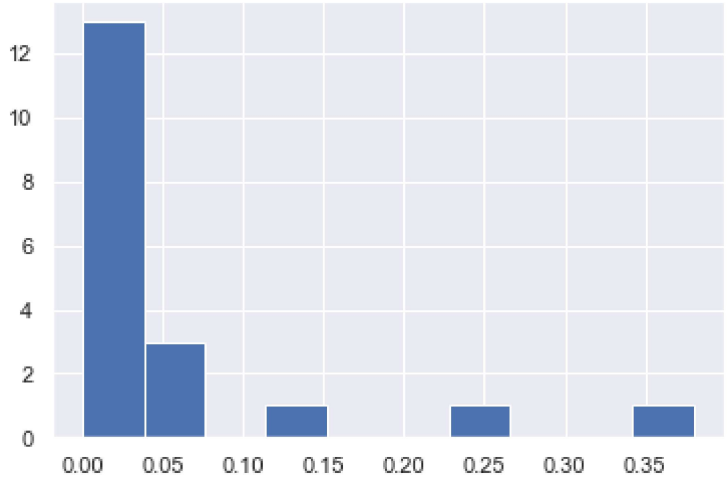
Out[138]:
```
4
```

In [139]:
```
print(selected_feat)
```

```
Index(['DEBT_RATIO', 'PROFIT_MARGIN', 'TOTAL_ASSETS', 'QUICK_RATIO'], dt
ype='object')
```

In [140]:
```
pd.Series(sel.estimator_.feature_importances_.ravel()).hist()
```

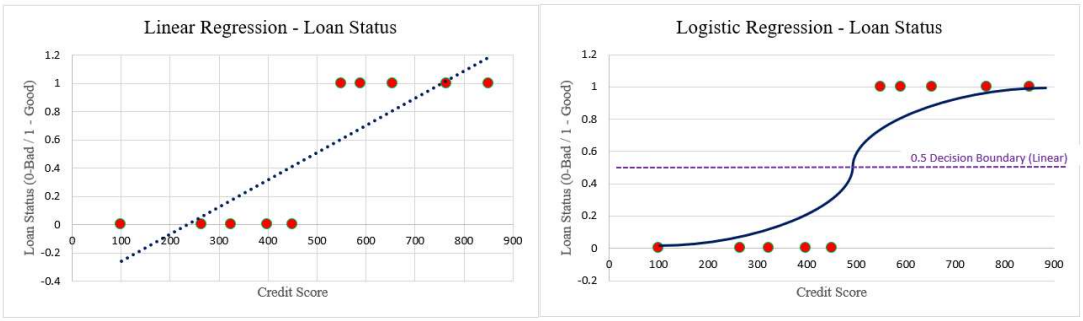
Out[140]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x171b974ad88>
```



In [ ]:
```
#What is Logistic Regression
```

In [141]:
```
PATH = r"C:\Users\Araz\Desktop\MUFG\\"
Image(filename = PATH + "logisticRegression.png", width=900, height=900)
```

Out[141]:

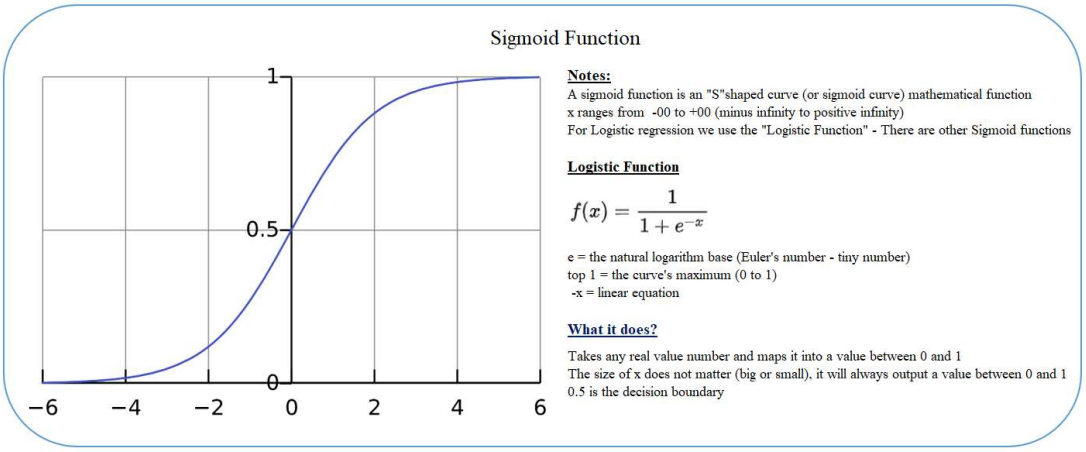


Linear Regression Formula	Logistic Regression Formula
Constant / Intercept, Coefficient $y = b0 + b1x1 + b2x2 + ...bnxn$ Dependent Variable, Independent Variable	the natural logarithm base $p = 1/1 + e^{-(\beta 0+\beta 1X1+\beta 2X2.....\beta nXn)}$ Probability / Log Odds, Linear Regression Formula
Notes	**Notes**
Predicts Continues Numbers Uses the **Least Square Method** to find the best fit	Predicts classes (Yes / No) Uses the **Maximum Likelihood Estimation** to find the best fit

In [56]:

```
### Graphical

PATH = r"C:\Users\Araz\Desktop\MUFG\\"
Image(filename = PATH + "SigmuidFunction.png", width=900, height=900)
```

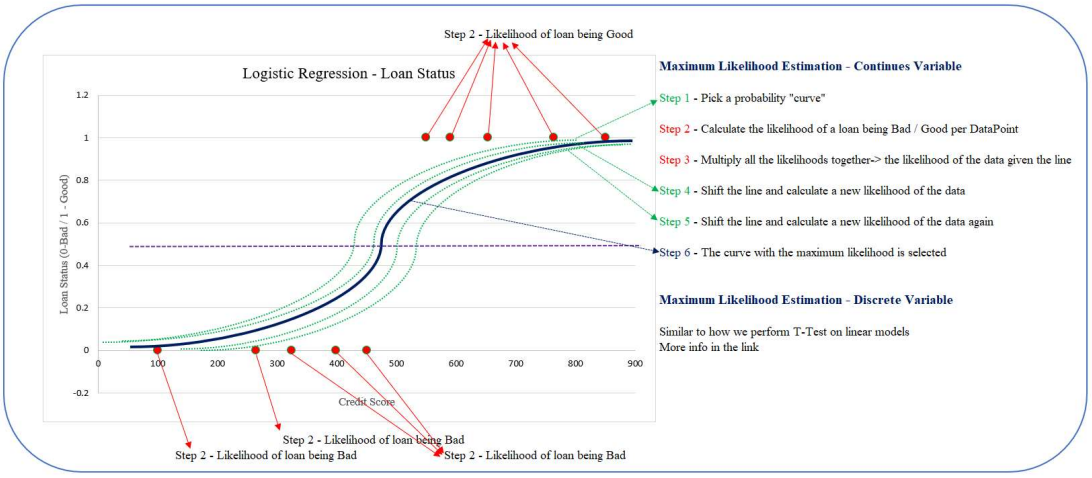
Out[56]:



In [142]:

```
#How Maximum Likelihood works ?
### Graphical

PATH = r"C:\Users\Araz\Desktop\MUFG\\"
Image(filename = PATH + "MaxLikelihood.png", width=900, height=900)
```

Out[142]:

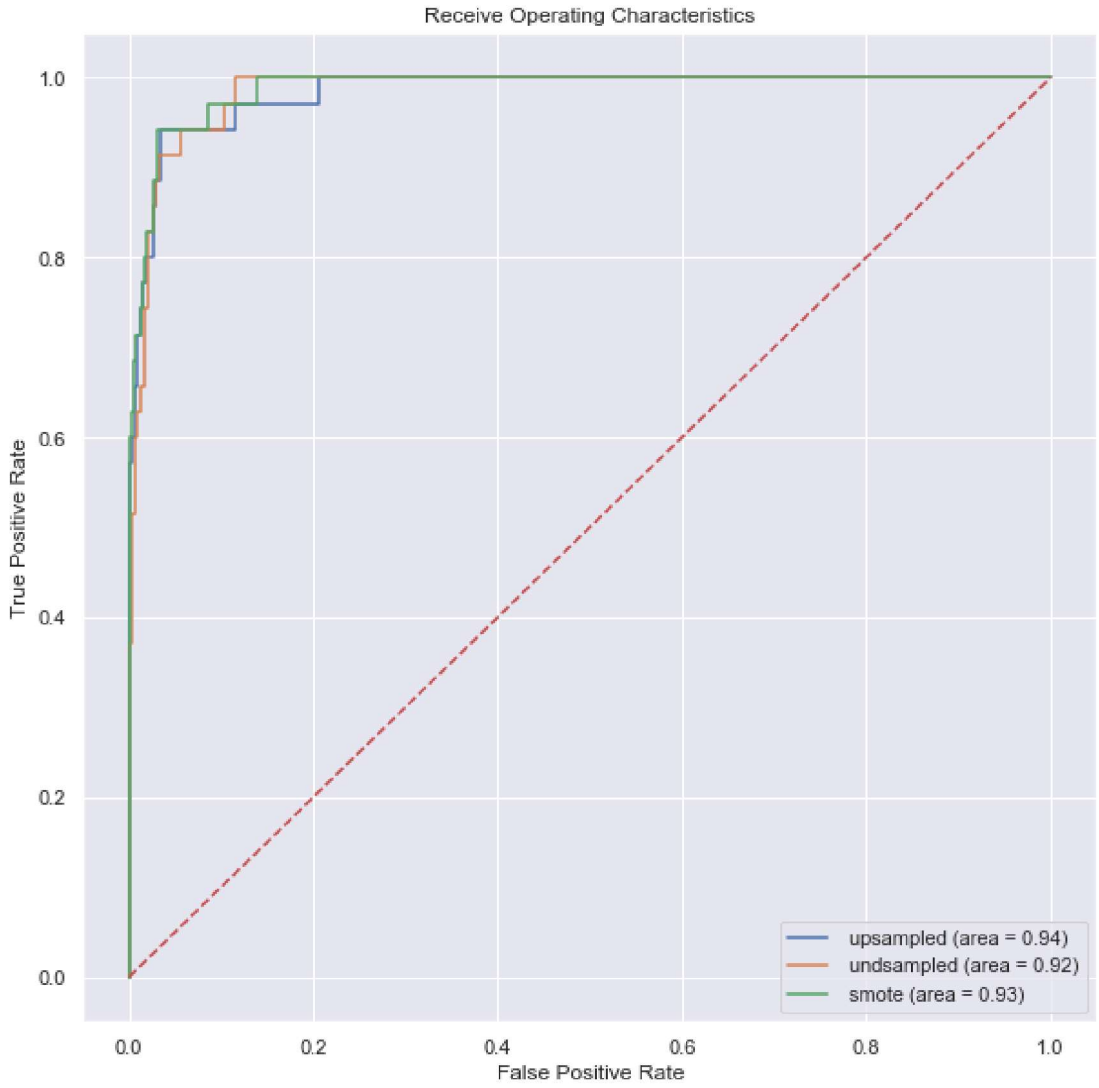


In [164]:

```
#X_train, X_test, y_train, y_test

from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
#Log_roc_auc=roc_auc_score(yValid,smote.predic(xValid))
#fpr,tpr, threshold=roc_curve(yValid,smote.predic(xValid)[:,1])

Log_roc_auc=roc_auc_score(y_test,upsampled.predict(X_test))
fpr,tpr, thresholds=roc_curve(y_test,upsampled.predict_proba(X_test)[:,1]

Log_roc_auc2=roc_auc_score(y_test,undersampled.predict(X_test))
fpr2,tpr2, thresholds=roc_curve(y_test,undersampled.predict_proba(X_test)

Log_roc_auc3=roc_auc_score(y_test,smote.predict(X_test))
fpr3,tpr3, thresholds3=roc_curve(y_test,smote.predict_proba(X_test)[:,1])
```

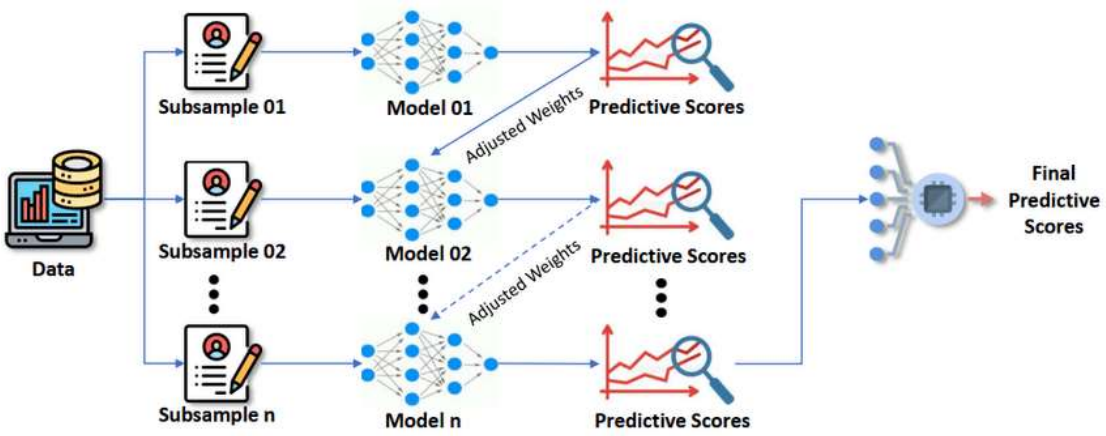
In [165]:

```
plt.figure(figsize=(10,10))
plt.plot(fpr,tpr, Label=" upsampled (area = %0.2f)" % Log_roc_auc)
plt.plot(fpr2,tpr2, Label=" undsampled (area = %0.2f)" % Log_roc_auc2)
plt.plot(fpr3,tpr3, Label=" smote (area = %0.2f)" % Log_roc_auc3)
plt.plot([0, 1], [0, 1],"r--")
plt.xlim(-0.05,1.05)
plt.ylim(-0.05,1.05)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receive Operating Characteristics")
plt.savefig("Log_ROC")
plt.legend(loc="lower right")
plt.show()
```



In [167]:
```
#How Boosting Algorithms works ?
### Graphical

PATH = r"C:\Users\Araz\Desktop\MUFG\\"
Image(filename = PATH + "XGBoost.png", width=900, height=900)
```

Out[167]:

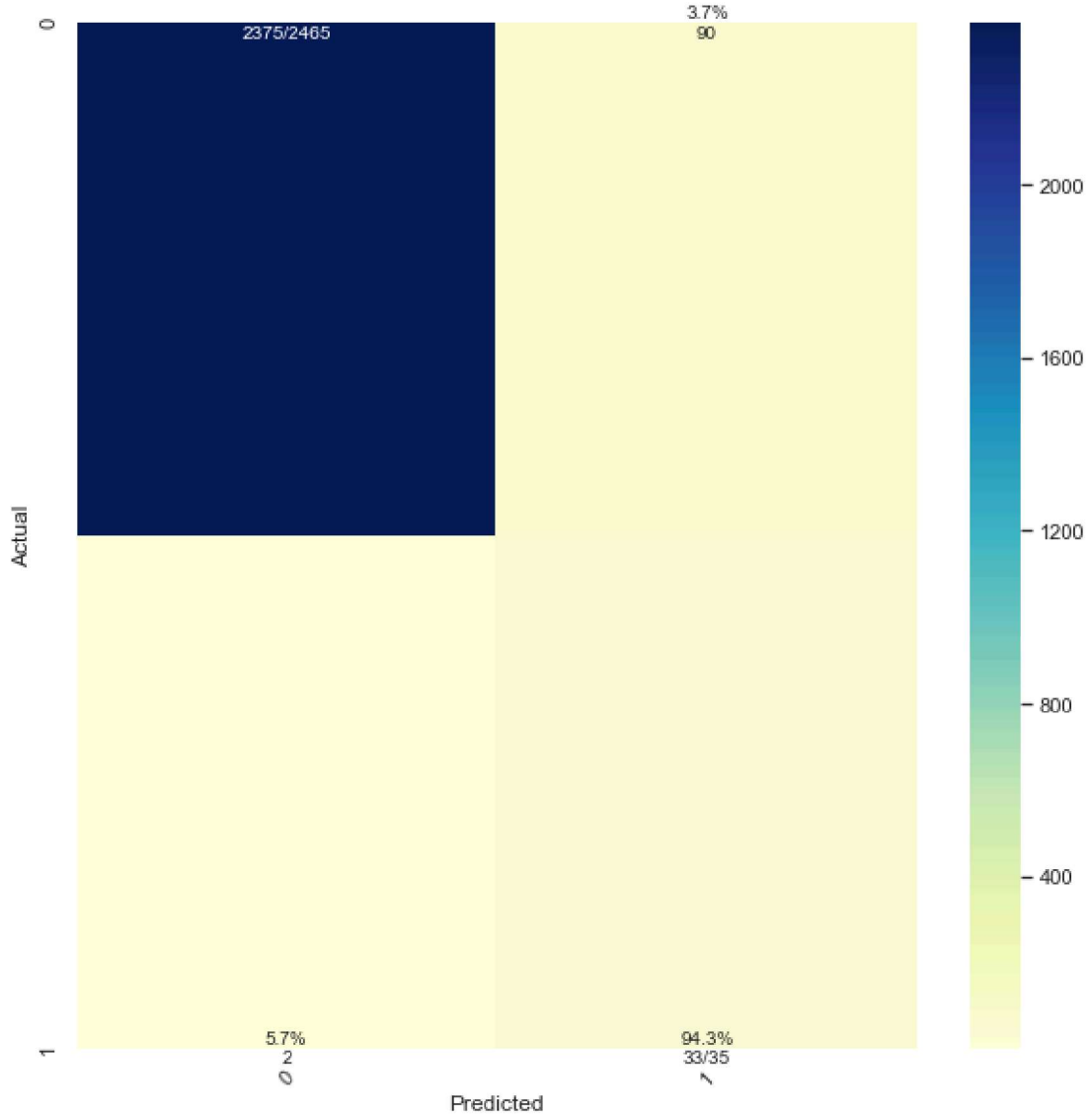


In [123]:
```
#Trying XGboost after Oversampling:
# train model

#y_train = upsampled.default_l
#X_train = upsampled.drop('default_l', axis=1)

from xgboost import XGBClassifier
# Initialize and train the XGBoost Classifier
# train model
xgc = XGBClassifier(n_estimators=10).fit(X_train, y_train)

# predict on test set
xgc_pred = xgc.predict(X_test)

accuracy_score(y_test, xgc_pred)

f1_score(y_test, xgc_pred)

recall_score(y_test, xgc_pred)

#Accuracy increase to 0.9428571428571428 from 0.6857142857142857
```

Out[123]:
```
0.9428571428571428
```

In [173]:

```
# confusion matrix for XGBoost on Upsampled Data

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_cm(y_true, y_pred, figsize=(10,10)):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_tr
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    fig, ax = plt.subplots(figsize=figsize)
    plt.xticks(rotation=45)
    sns.heatmap(cm, cmap= "YlGnBu", annot=annot, fmt='', ax=ax)


y_pred = xgc_pred
y_true =y_test

plot_cm(y_true, y_pred)
```


3.7%
90
2375/2465
5.7%
2
94.3%
33/35
0
1
Actual
0
1
Predicted
2000
1600
1200
800
400

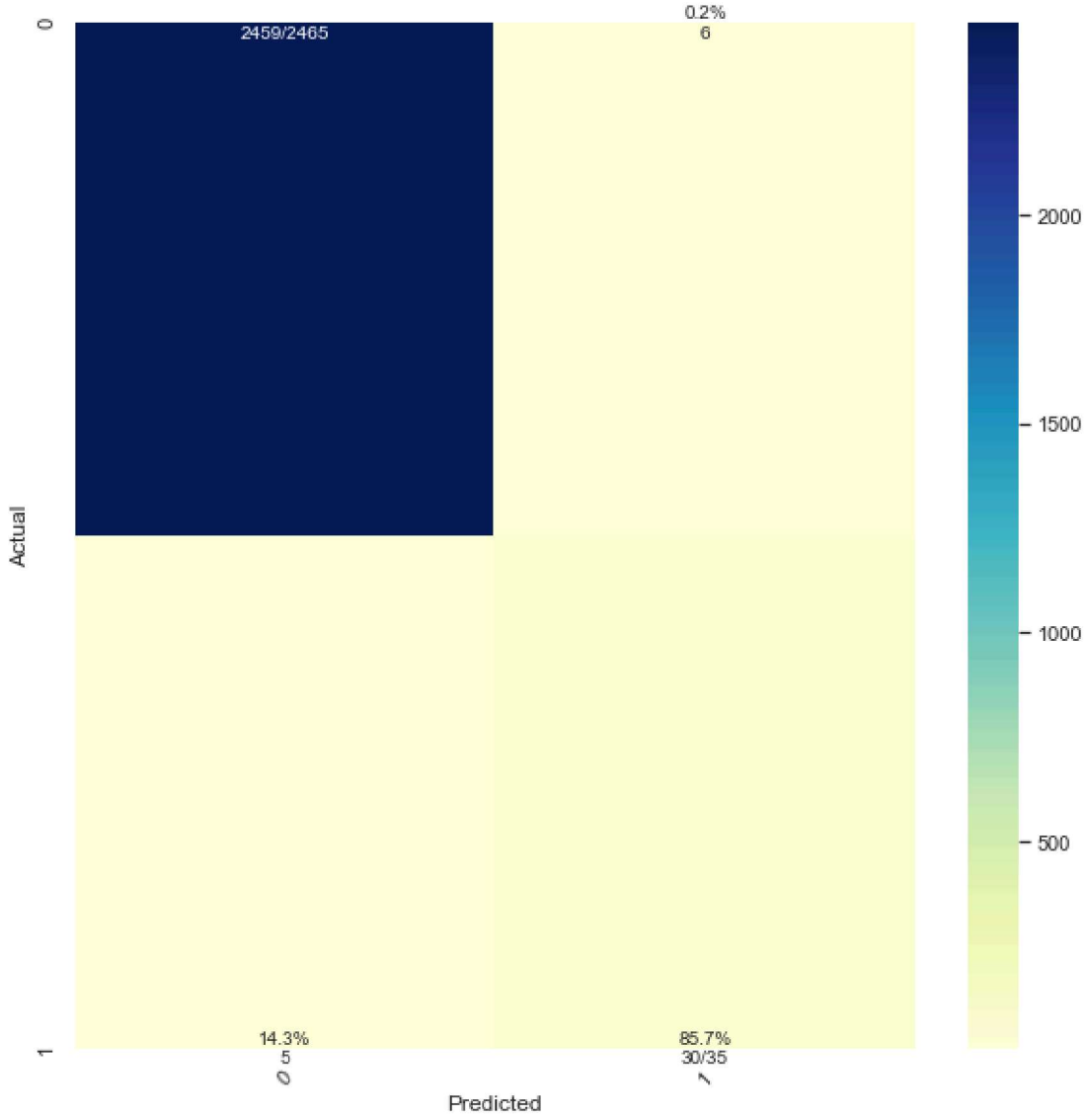
In [122]:

```
#Trying Catboost after Oversampling:
# train model

#y_train = upsampled.default_l
#X_train = upsampled.drop('default_l', axis=1)
from catboost import CatBoostClassifier
from sklearn.model_selection import RandomizedSearchCV

# Initialize CatBoost Classifier
cbc = CatBoostClassifier()

# Setup RandomizedSearchCV
from scipy.stats import randint, uniform

# Parameter distribution
catboost_param_dist = {
    'depth': randint(4, 10),
    'learning_rate': uniform(0.01, 0.3),
    'iterations': randint(10, 1000),
    'l2_leaf_reg': randint(1, 10),
    'border_count': randint(1, 255),
    'bagging_temperature': uniform(0.0, 1.0),
    'random_strength': uniform(0.0, 1.0)
}

random_search_cb = RandomizedSearchCV(estimator=cbc,
                                      param_distributions=catboost_param_
                                      cv=5,
                                      verbose=2,
                                      random_state=42)
# Fit the model on upsampled data
#y_train = upsampled.default_l
#X_train = upsampled.drop('default_l', axis=1)

random_search_cb.fit(X_train, y_train)
# Evaluate the model
random_search_cb_score = random_search_cb.score(X_test, y_test)
# predict on test set
random_search_cb_pred = random_search_cb.predict(X_test)

accuracy_score(y_test, random_search_cb_pred)

f1_score(y_test, random_search_cb_pred)

recall_score(y_test, random_search_cb_pred)
#accuracy improves to 0.8571428571428571 from 0.4
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] bagging_temperature=0.3745401188473625, border_count=93, depth=
6, iterations=81, l2_leaf_reg=5, learning_rate=0.05680559213273095,
random_strength=0.15599452033620265
0:      learn: 0.6461100        total: 4.81ms   remaining: 385ms
1:      learn: 0.6031368        total: 9.6ms    remaining: 379ms
2:      learn: 0.5651710        total: 14ms     remaining: 364ms
3:      learn: 0.5299274        total: 17.8ms   remaining: 342ms
4:      learn: 0.4987736        total: 21.1ms   remaining: 320ms
5:      learn: 0.4699454        total: 25.1ms   remaining: 313ms
6:      learn: 0.4422676        total: 28.4ms   remaining: 300ms
7:      learn: 0.4176183        total: 31.5ms   remaining: 287ms
8:      learn: 0.3942919        total: 34.6ms   remaining: 277ms
9:      learn: 0.3728424        total: 37.9ms   remaining: 269ms
10:     learn: 0.3528308        total: 41.3ms   remaining: 263ms
11:     learn: 0.3347308        total: 44.4ms   remaining: 255ms
12:     learn: 0.3177965        total: 47.9ms   remaining: 250ms
13:     learn: 0.3019135        total: 51ms     remaining: 244ms
14:     learn: 0.2872823        total: 54.4ms   remaining: 239ms
```

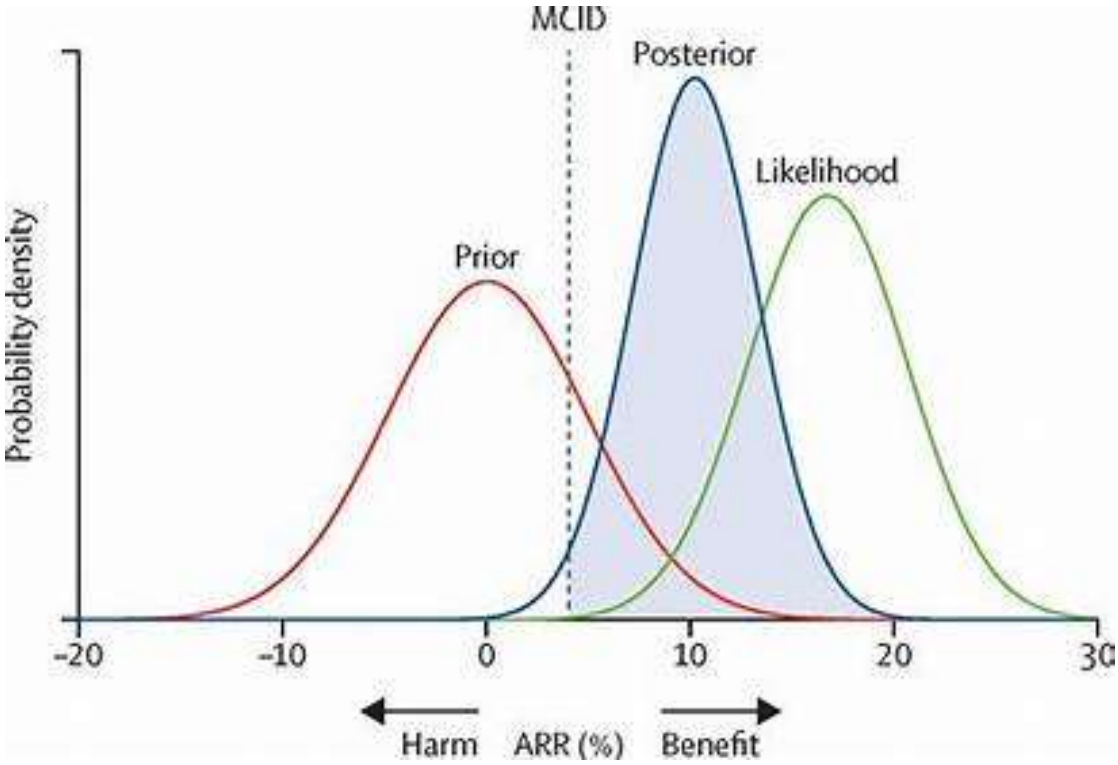
In [174]:

```
# confusion matrix for CatBoost (with Randomized Search for Cross-Validat

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_cm(y_true, y_pred, figsize=(10,10)):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_tr
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    fig, ax = plt.subplots(figsize=figsize)
    plt.xticks(rotation=45)
    sns.heatmap(cm, cmap= "YlGnBu", annot=annot, fmt='', ax=ax)


y_pred = random_search_cb_pred
y_true =y_test

plot_cm(y_true, y_pred)
```


0.2%
2459/2465
6
14.3%
5
85.7%
30/35
0
1
Actual
Predicted
2000
1500
1000
500

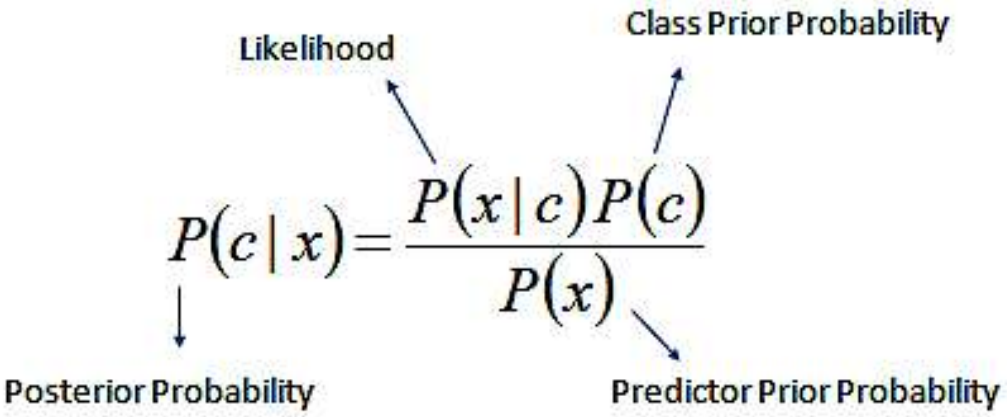
In [201]:
```
#How Naive Bayesian Algorithms works ?
### Graphical

PATH = r"C:\Users\Araz\Desktop\MUFG\\"
Image(filename = PATH + "Bayes.jpg", width=900, height=900)
```

Out[201]:



In [200]:
```
Image(filename = PATH + "Bayes3.png", width=900, height=900)
```

Out[200]:



$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

In [188]:

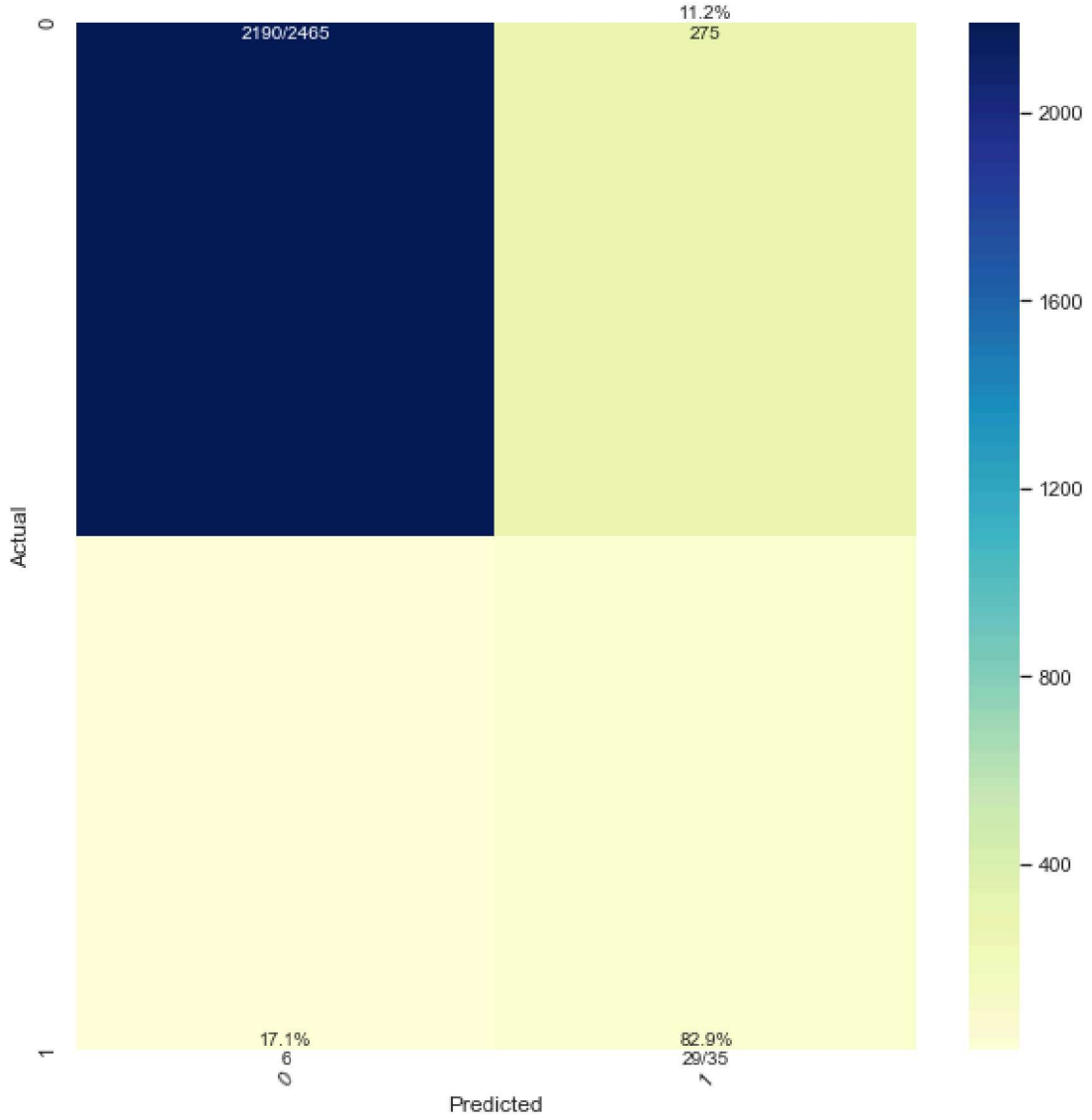
```
#Trying Naive Bayesian Classifier after Oversampling:
# train model

#y_train = upsampled.default_1
#X_train = upsampled.drop('default_1', axis=1)

from sklearn.naive_bayes import GaussianNB
# Initialize and train the Classifier
# train model
gnb = GaussianNB().fit(X_train, y_train)

# predict on test set
gnb_pred = gnb.predict(X_test)

accuracy_score(y_test, gnb_pred)

f1_score(y_test, gnb_pred)

recall_score(y_test, gnb_pred)

#Accuracy ratio on upsampled data  is 0.8876
```

Out[188]:

```
0.8876
```

In [181]:

```
# confusion matrix for Gaussian Naive Bayesian Classifier on Upsampled Da

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

def plot_cm(y_true, y_pred, figsize=(10,10)):
    cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
    cm_sum = np.sum(cm, axis=1, keepdims=True)
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c == 0:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=np.unique(y_true), columns=np.unique(y_tr
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    fig, ax = plt.subplots(figsize=figsize)
    plt.xticks(rotation=45)
    sns.heatmap(cm, cmap= "YlGnBu", annot=annot, fmt='', ax=ax)


y_pred = gnb_pred
y_true =y_test

plot_cm(y_true, y_pred)
```



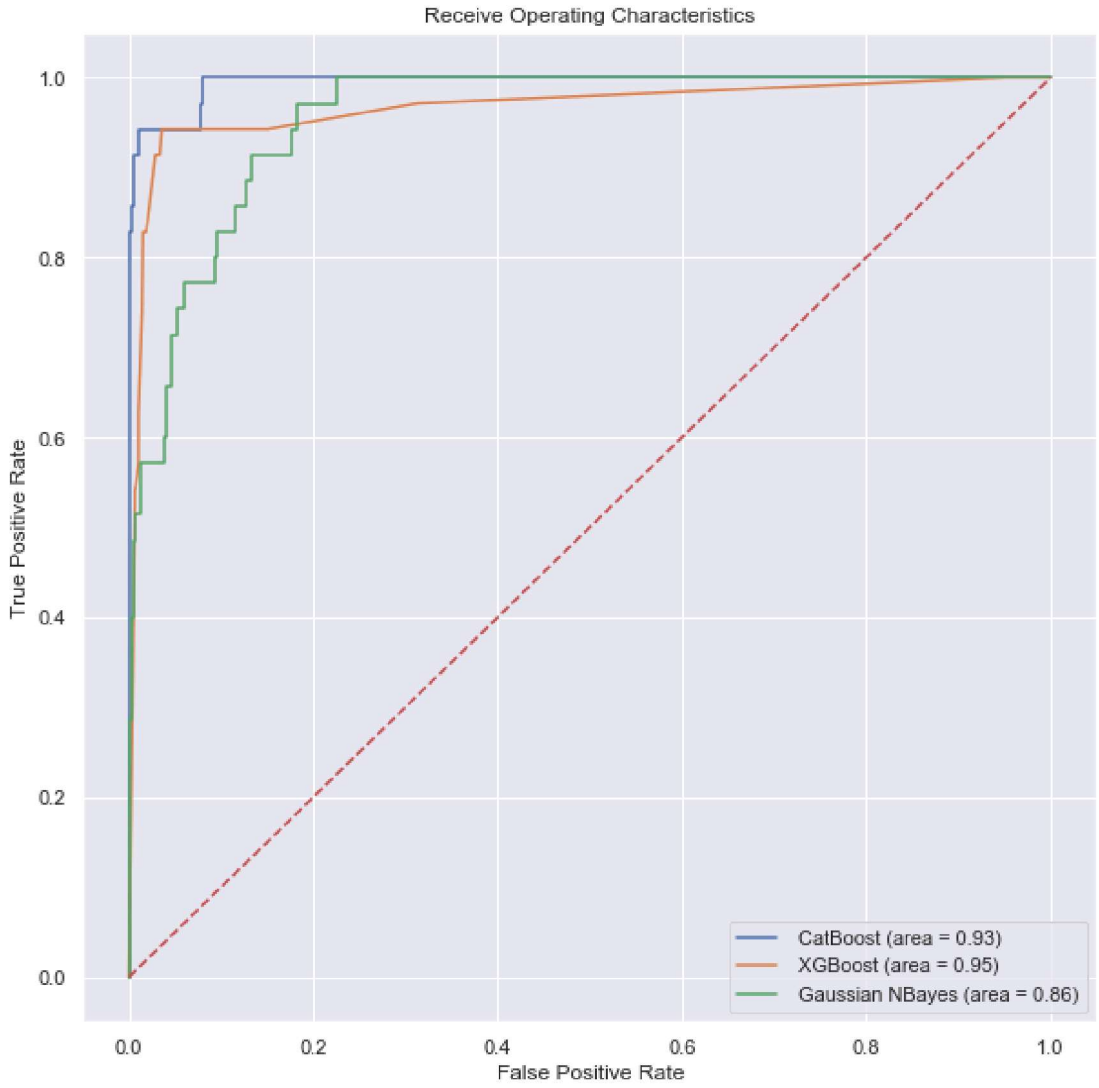
In [168]:
```
Log_roc_auc4=roc_auc_score(y_test,random_search_cb.predict(X_test)) #CatB
fpr4,tpr4, thresholds4=roc_curve(y_test,random_search_cb.predict_proba(X_
```

In [169]:
```
Log_roc_auc5=roc_auc_score(y_test,xgc.predict(X_test)) #XGBosst
fpr5,tpr5, thresholds5=roc_curve(y_test,xgc.predict_proba(X_test)[:,1])
```

In [182]:
```
Log_roc_auc6=roc_auc_score(y_test,gnb.predict(X_test)) #XGBosst
fpr6,tpr6, thresholds6=roc_curve(y_test,gnb.predict_proba(X_test)[:,1])
```

In [194]:

```
plt.figure(figsize=(10,10))

plt.plot(fpr4,tpr4, Label=" CatBoost (area = %0.2f)" % Log_roc_auc4)
plt.plot(fpr5,tpr5, Label=" XGBoost (area = %0.2f)" % Log_roc_auc5)
plt.plot(fpr6,tpr6, Label=" Gaussian NBayes (area = %0.2f)" % Log_roc_auc

plt.plot([0, 1], [0, 1],"r--")
plt.xlim(-0.05,1.05)
plt.ylim(-0.05,1.05)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receive Operating Characteristics")
plt.savefig("Log_ROC")
plt.legend(loc="lower right")
plt.show()
```



In [193]:

```
plt.figure(figsize=(10,10))
plt.plot(fpr,tpr, Label=" upsampled (area = %0.2f)" % Log_roc_auc)
#plt.plot(fpr2,tpr2, Label=" undsampled (area = %0.2f)" % Log_roc_auc2)
#plt.plot(fpr3,tpr3, Label=" smote (area = %0.2f)" % Log_roc_auc3)
plt.plot(fpr4,tpr4, Label=" CatBoost (area = %0.2f)" % Log_roc_auc4)
plt.plot(fpr5,tpr5, Label=" XGB (area = %0.2f)" % Log_roc_auc5)
plt.plot(fpr6,tpr6, Label=" Gaussian NBayes (area = %0.2f)" % Log_roc_auc

plt.plot([0, 1], [0, 1],"r--")
plt.xlim(-0.05,1.05)
plt.ylim(-0.05,1.05)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receive Operating Characteristics")
plt.savefig("Log_ROC")
plt.legend(loc="lower right")
plt.show()
```