In [ ]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import numpy as np
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn import tree
from sklearn.datasets import make_classification
from imblearn.over_sampling import RandomOverSampler
from imblearn.over_sampling import SMOTE
from collections import Counter
from sklearn.model_selection import KFold
```

In [ ]:
```
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
import seaborn as sns
from sklearn.metrics import roc_curve
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
```

In [ ]:
```
### import the dataset
data = pd.read_excel ('hmeq.xlsx')
print (data.shape)
print (data.columns.values)
```

```
(5960, 14)
['CustomerID' 'BAD' 'LOAN' 'MORTDUE' 'VALUE' 'REASON' 'JOB' 'YOJ' 'DEROG'
 'DELINQ' 'CLAGE' 'NINQ' 'CLNO' 'DEBTINC']
```

In [ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5960 entries, 0 to 5959
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   CustomerID  5960 non-null   int64  
 1   BAD         5960 non-null   int64  
 2   LOAN        5960 non-null   int64  
 3   MORTDUE     5442 non-null   float64
 4   VALUE       5848 non-null   float64
 5   REASON      5708 non-null   object 
 6   JOB         5681 non-null   object 
 7   YOJ         5445 non-null   float64
 8   DEROG       5252 non-null   float64
 9   DELINQ      5380 non-null   float64
 10  CLAGE       5652 non-null   float64
 11  NINQ        5450 non-null   float64
 12  CLNO        5738 non-null   float64
 13  DEBTINC     4693 non-null   float64
dtypes: float64(9), int64(3), object(2)
memory usage: 652.0+ KB
```

In [ ]:
```
# Find out the sum of null value in each column
print(data.isnull().sum())
```

```
CustomerID       0
BAD              0
LOAN             0
MORTDUE        518
VALUE          112
REASON         252
JOB            279
YOJ            515
DEROG          708
DELINQ         580
CLAGE          308
NINQ           510
CLNO           222
DEBTINC       1267
dtype: int64
```

In [ ]:
```
# Summary of Missing data percentage
percent_of_missing_value = data.isnull().sum()/len(data)
percent_of_missing_value
```

Out[ ]:
```
CustomerID    0.000000
BAD           0.000000
LOAN          0.000000
MORTDUE       0.086913
VALUE         0.018792
REASON        0.042282
JOB           0.046812
YOJ           0.086409
DEROG         0.118792
DELINQ        0.097315
CLAGE         0.051678
NINQ          0.085570
CLNO          0.037248
DEBTINC       0.212584
dtype: float64
```

Description of each column

Loan: Amount of the loan request

MORTDUE: Amount due on existing mortgage

VALUE: Value of current property

REASON: DebtCon = debt consolidation; HomeImp = home improvement

JOB: Occupational categories (job categories)

YOJ: Years at present job

DEROG: Number of major derogatory reports

DELINQ: Number of delinquent credit lines

CLAGE: Age of oldest credit line in months

NINQ: Number of recent credit inquiries

CLNO: Number of credit lines

DEBTINC: Debt-to-income ratio

In [ ]:
```
data.describe(include= 'all').T
```

Out[ ]:

	count	unique	top	freq	mean	std	min	25%	50%	75%
CustomerID	5960.0	NaN	NaN	NaN	2980.5	1720.648134	1.0	1490.75	2980.5	4470.25
BAD	5960.0	NaN	NaN	NaN	0.199497	0.399656	0.0	0.0	0.0	0.0
LOAN	5960.0	NaN	NaN	NaN	18607.969799	11207.480417	1100.0	11100.0	16300.0	23300.0
MORTDUE	5442.0	NaN	NaN	NaN	73760.8172	44457.609458	2063.0	46276.0	65019.0	91488.0
VALUE	5848.0	NaN	NaN	NaN	101776.048741	57385.775334	8000.0	66075.5	89235.5	119824.25
REASON	5708	2	DebtCon	3928	NaN	NaN	NaN	NaN	NaN	NaN
JOB	5681	6	Other	2388	NaN	NaN	NaN	NaN	NaN	NaN
YOJ	5445.0	NaN	NaN	NaN	8.922268	7.573982	0.0	3.0	7.0	13.0
DEROG	5252.0	NaN	NaN	NaN	0.25457	0.846047	0.0	0.0	0.0	0.0
DELINQ	5380.0	NaN	NaN	NaN	0.449442	1.127266	0.0	0.0	0.0	0.0
CLAGE	5652.0	NaN	NaN	NaN	179.766275	85.810092	0.0	115.116702	173.466667	231.562278
NINQ	5450.0	NaN	NaN	NaN	1.186055	1.728675	0.0	0.0	1.0	2.0
CLNO	5738.0	NaN	NaN	NaN	21.296096	10.138933	0.0	15.0	20.0	26.0
DEBTINC	4693.0	NaN	NaN	NaN	33.779915	8.601746	0.524499	29.140031	34.818262	39.003141

Data Cleaning

In [ ]:
```
# drop N/A in Debt to income variable
data1 = data.drop(data[data.DEBTINC.isna()].index)
data1.shape
```

Out[ ]:
```
(4693, 14)
```

In [ ]:
```
# Impute 0 to N/A to the variables "NINQ" and "DEROG"

data1[['NINQ','DEROG','VALUE','MORTDUE','YOJ']] = data1[['NINQ','DEROG','VALUE','MORTDUE','YOJ']].fillna(0
```

In [ ]:
```
# Impute mean value to the variables: CLNO, DELINQ, CLAGE
data1[['DELINQ','CLNO','CLAGE']]= data1[['DELINQ','CLNO','CLAGE']].fillna(data1[['DELINQ','CLNO','CLAGE']]
```

In [ ]:
```
categorical = [var for var in data1.columns if data1[var].dtype=='O']

print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :\n\n', categorical)
```

```
There are 2 categorical variables

The categorical variables are :

 ['REASON', 'JOB']
```

In [ ]:
```
data1[['REASON', 'JOB']] = data1[['REASON', 'JOB']].fillna('Other')
```

In [ ]:
```
# Impute categorical variables with mode
# data1['REASON'].fillna(data1['REASON'].mode()[0],inplace = True)
```

In [ ]:
```
# Impute job with mode (Categorical variable) because the names of jobs did not be listed, so filling with
data1['JOB'].fillna(data1['JOB'].mode()[0],inplace = True)
```

In [ ]:
```
data1['REASON'].value_counts()
```

Out[ ]:
```
REASON
DebtCon    3128
HomeImp    1369
Other       196
Name: count, dtype: int64
```

In [ ]:
```
data1['JOB'].value_counts()
```

Out[ ]:
```
JOB
Other      2073
ProfExe    1024
Office      789
Mgr         586
Self        142
Sales        79
Name: count, dtype: int64
```

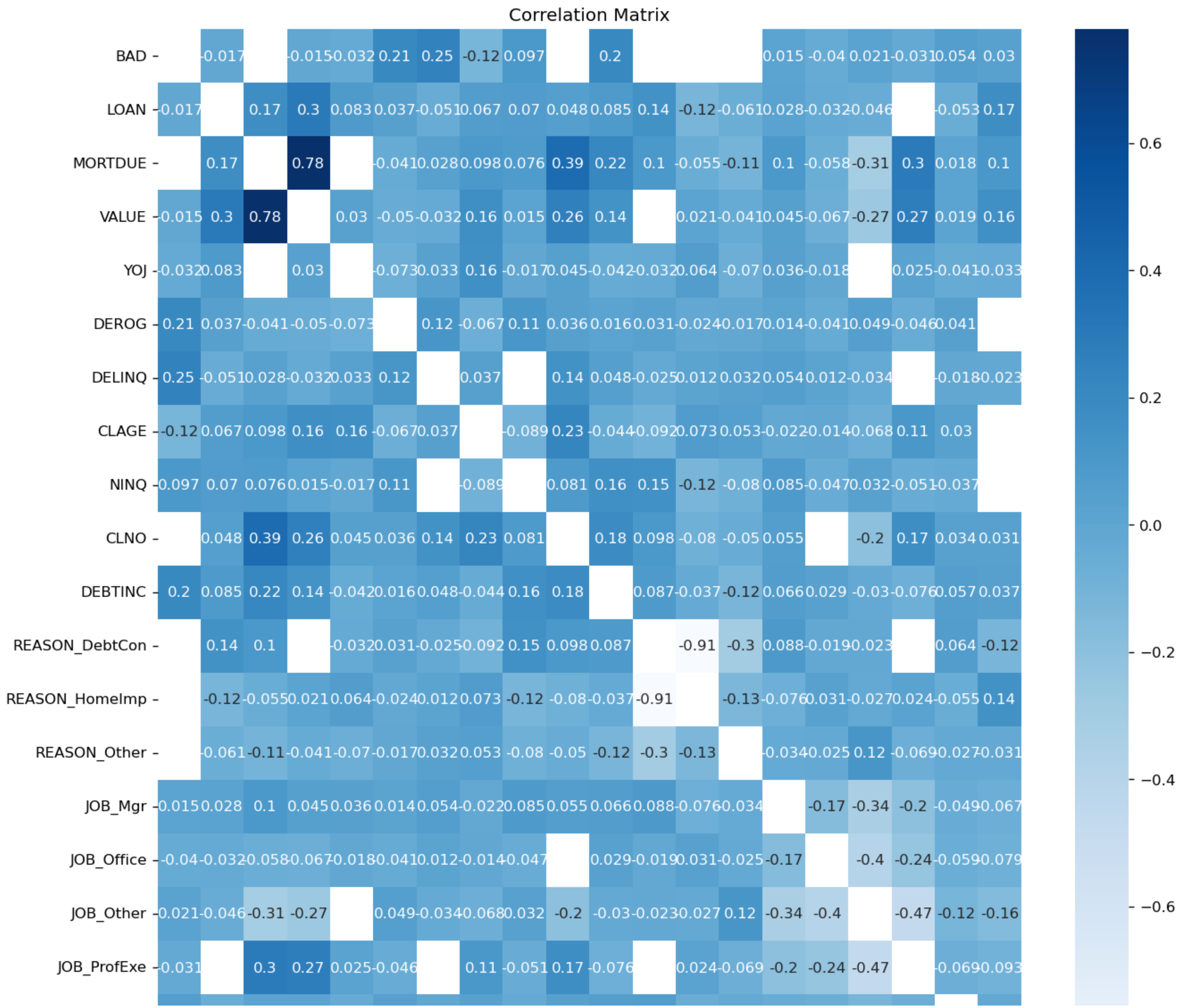
In [ ]:
```
# Convert categorical variables into dummy variables
data2 = pd.get_dummies(data1,columns=['REASON','JOB'],dtype= float)
data2.isna().sum()
```

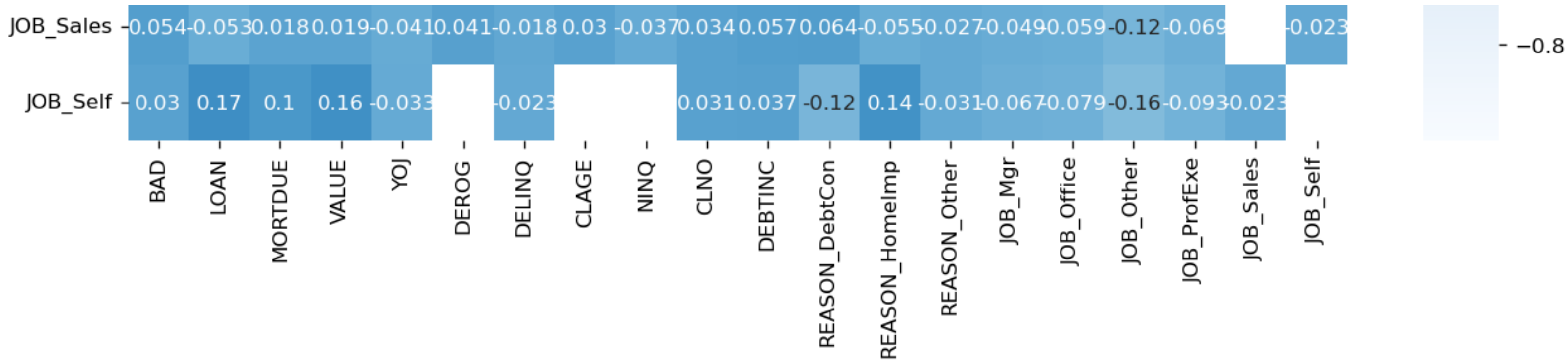
Out[ ]:
```
CustomerID        0
BAD               0
LOAN              0
MORTDUE           0
VALUE             0
YOJ               0
DEROG             0
DELINQ            0
CLAGE             0
NINQ              0
CLNO              0
DEBTINC           0
REASON_DebtCon    0
REASON_HomeImp    0
REASON_Other      0
JOB_Mgr           0
JOB_Office        0
JOB_Other         0
JOB_ProfExe       0
JOB_Sales         0
JOB_Self          0
dtype: int64
```

Create a new data set -- Correlation Matrix

In [ ]:
```python
data3 = data2.loc[:, data2.columns != 'CustomerID']
dfCorr = pd.DataFrame(data3).corr()
filteredDf = dfCorr[((dfCorr >= .01) | (dfCorr <= -.01)) & (dfCorr != 1.000)]
plt.figure(figsize= (13,13))
sns.heatmap(filteredDf, annot = True, cmap = 'Blues')
plt.title('Correlation Matrix')
plt.show
```

Out[ ]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```

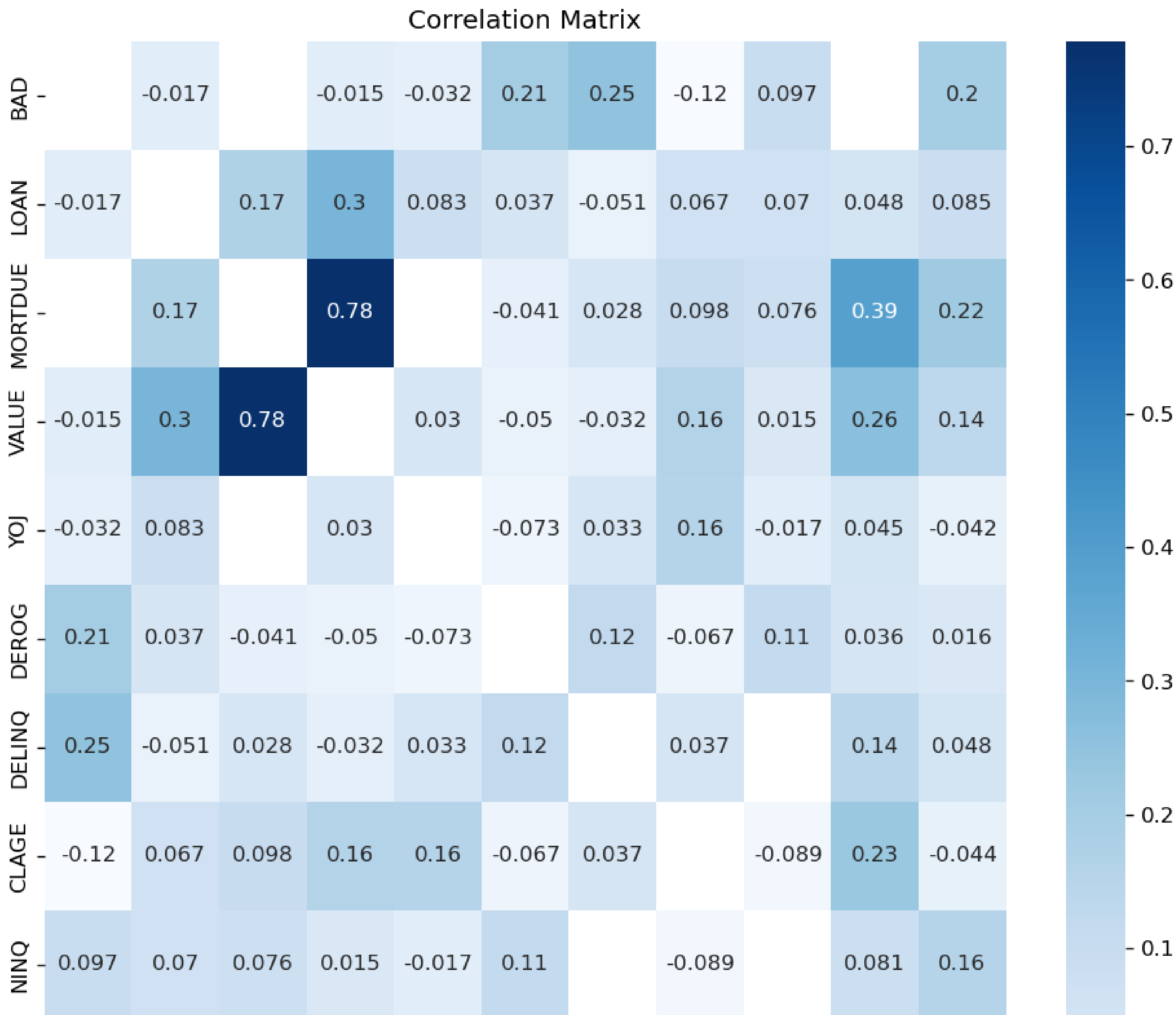

Correlation Matrix
BAD
LOAN
MORTDUE
VALUE
YOJ
DEROG
DELINQ
CLAGE
NINQ
CLNO
DEBTINC
REASON_DebtCon
REASON_HomeImp
REASON_Other
JOB_Mgr
JOB_Office
JOB_Other
JOB_ProfExe
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

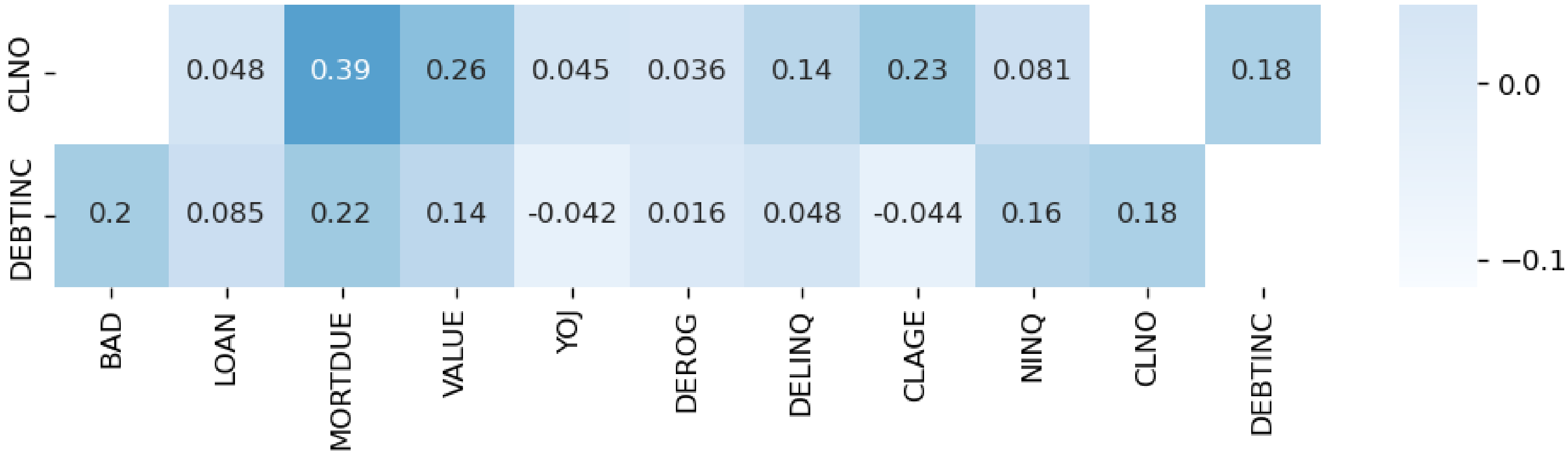


In [ ]:
```
data4 = data1[['BAD', 'LOAN', 'MORTDUE', 'VALUE', 'YOJ', 'DEROG', 'DELINQ',
 'CLAGE', 'NINQ', 'CLNO', 'DEBTINC' ]]
```

In [ ]:
```
## heatmap of correlations - only show if greater than 1% (or threshold can be changed)
dfCorr = pd.DataFrame(data4).corr()
filteredDf = dfCorr[((dfCorr >= .01) | (dfCorr <= -.01)) & (dfCorr != 1.000)]
plt.figure(figsize= (10,10))
sns.heatmap(filteredDf, annot = True, cmap = 'Blues')
plt.title('Correlation Matrix')
plt.show
```

Out[ ]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```


Correlation Matrix
BAD
LOAN
MORTDUE
VALUE
YOJ
DEROG
DELINQ
CLAGE
NINQ
-0.017 -0.015 -0.032 0.21 0.25 -0.12 0.097 0.2
-0.017 0.17 0.3 0.083 0.037 -0.051 0.067 0.07 0.048 0.085
0.17 0.78 -0.041 0.028 0.098 0.076 0.39 0.22
-0.015 0.3 0.78 0.03 -0.05 -0.032 0.16 0.015 0.26 0.14
-0.032 0.083 0.03 -0.073 0.033 0.16 -0.017 0.045 -0.042
0.21 0.037 -0.041 -0.05 -0.073 0.12 -0.067 0.11 0.036 0.016
0.25 -0.051 0.028 -0.032 0.033 0.12 0.037 0.14 0.048
-0.12 0.067 0.098 0.16 0.16 -0.067 0.037 -0.089 0.23 -0.044
0.097 0.07 0.076 0.015 -0.017 0.11 -0.089 0.081 0.16
0.7
0.6
0.5
0.4
0.3
0.2
0.1



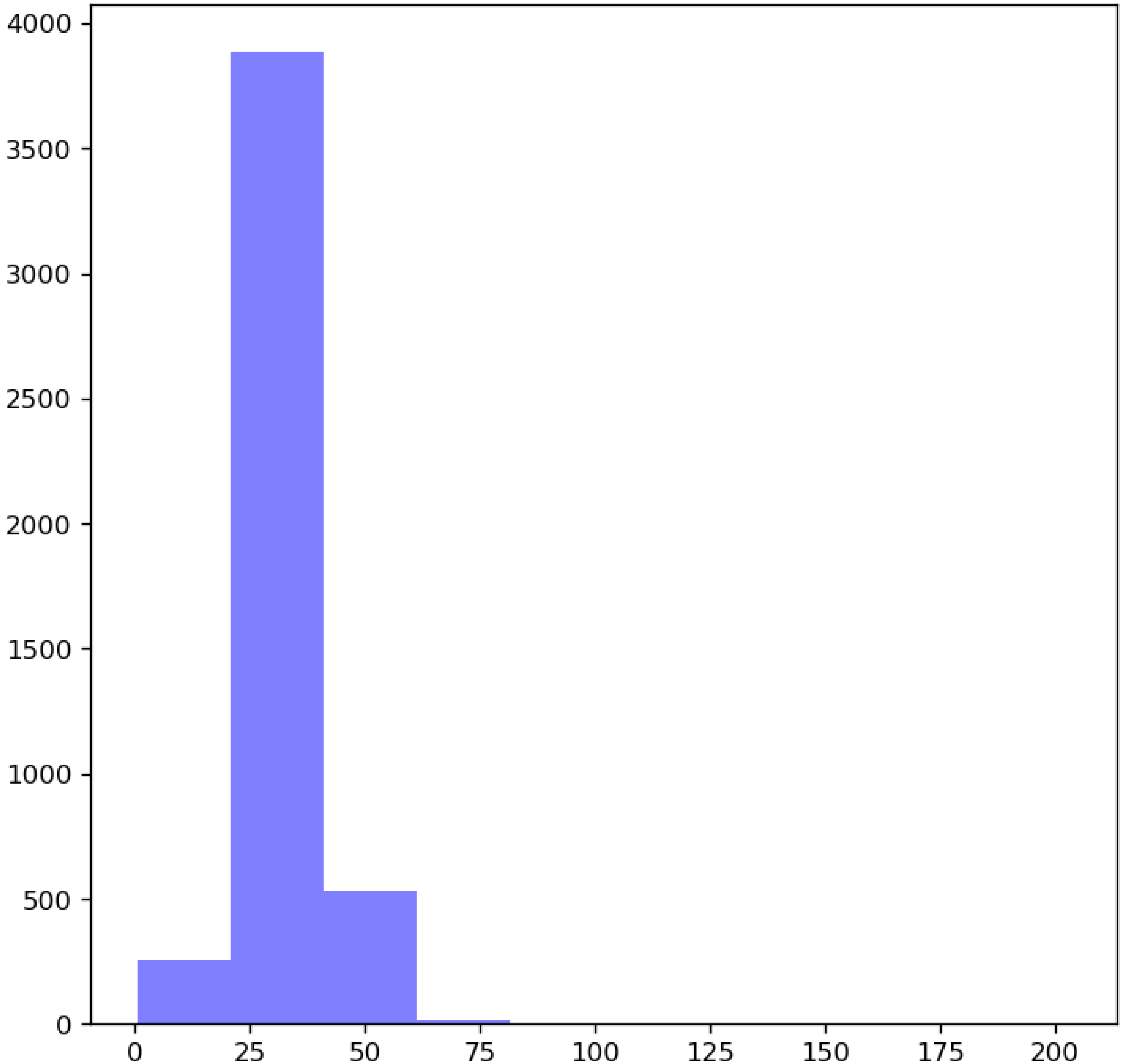
Descriptive stats and histograms for 5 variables

In [ ]:
```
print (data2['DEBTINC'].describe().round(decimals=2))
```

```
count    4693.00
mean       33.78
std         8.60
min         0.52
25%        29.14
50%        34.82
75%        39.00
max       203.31
Name: DEBTINC, dtype: float64
```

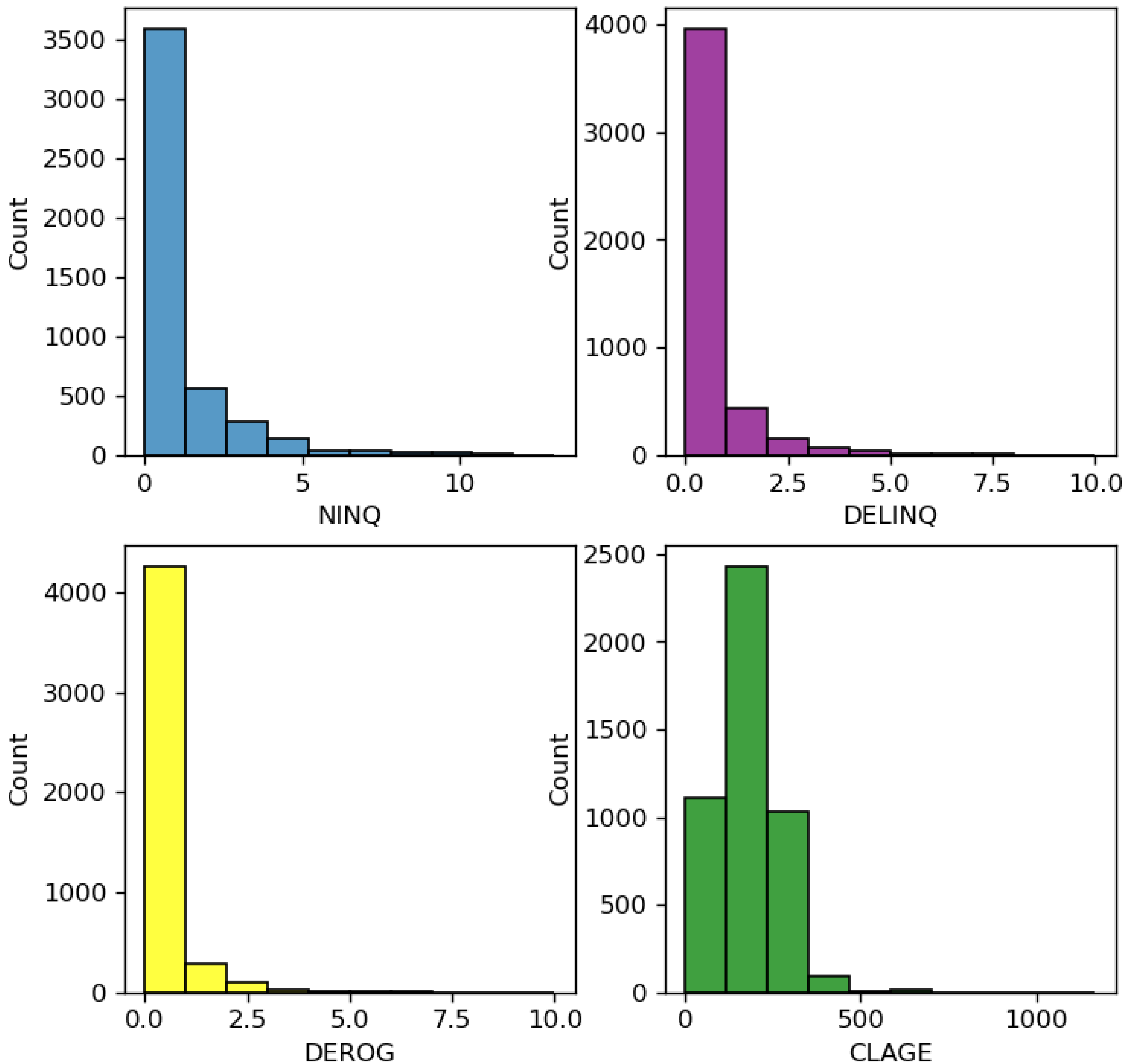
In [ ]:
```
# Descriptive stats and histogram for Debt-to-income variable
import matplotlib.mlab as mlab
x = data2['DEBTINC']
num_bins = 10
n,bins, patches = plt.hist(x, num_bins, facecolor = 'blue', alpha =0.5)
plt.show
```

Out[ ]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```


4000
3500
3000
2500
2000
1500
1000
500
0
0
25
50
75
100
125
150
175
200

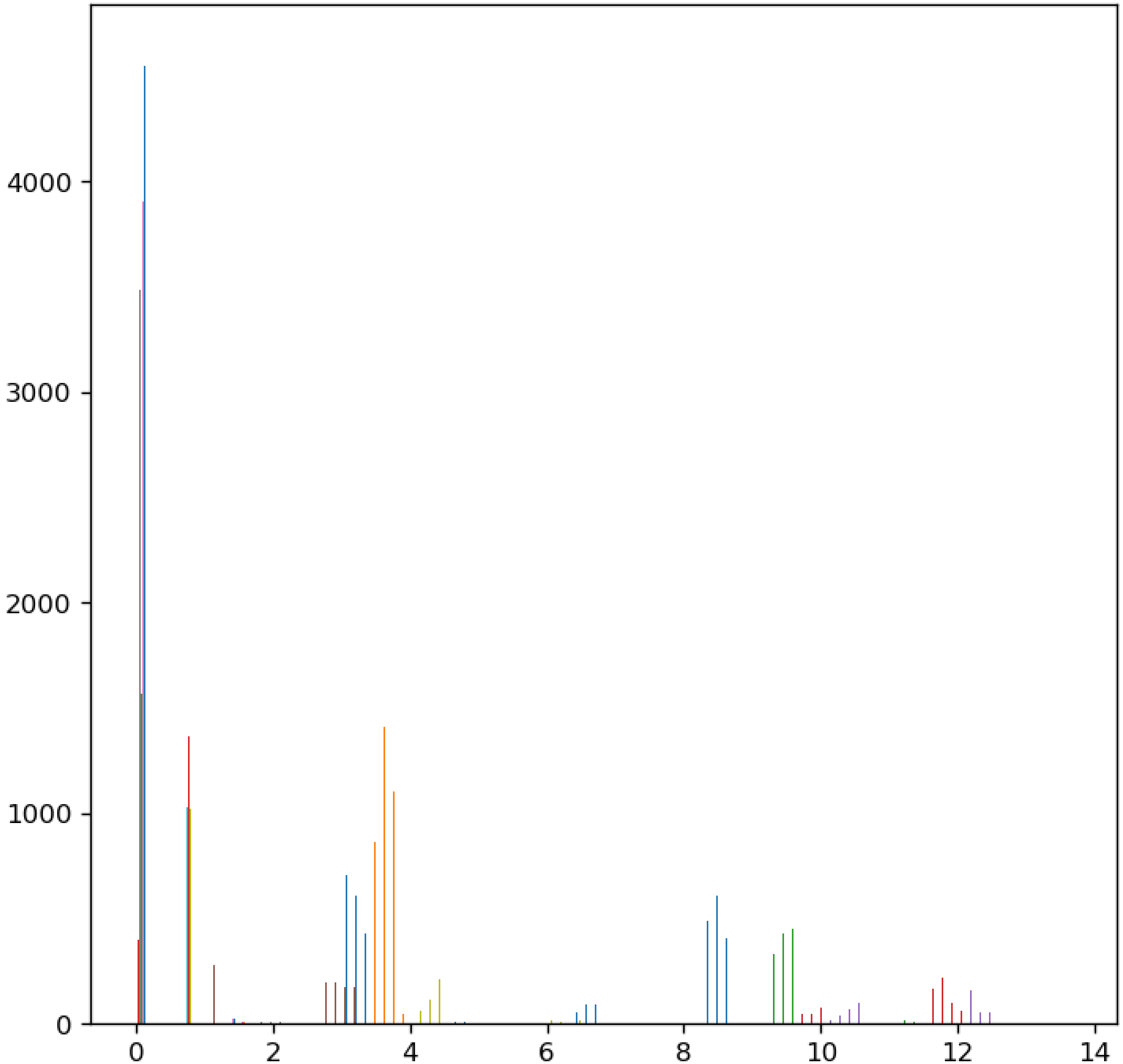
In [ ]:
```
import seaborn as sns

plt.rcParams.update({'figure.figsize':(7,7), 'figure.dpi':120})

fig,ax = plt.subplots(2,2)
sns.histplot(data = data2['NINQ'], bins = 10,ax = ax[0,0])
sns.histplot(data = data2['DELINQ'], bins = 10,ax = ax[0,1],color= 'purple')
sns.histplot(data = data2['DEROG'], bins = 10,ax = ax[1,0],color='yellow')
sns.histplot(data = data2['CLAGE'], bins = 10,ax = ax[1,1],color= 'green')
```

Out[ ]:
```
<Axes: xlabel='CLAGE', ylabel='Count'>
```


Count
NINQ
Count
DELINQ
Count
DEROG
Count
CLAGE

In [ ]:
```
# Applying logarithmic scaling to reduce skewness in data distributions.
# Apply Log Transformation to the data
Log_data = np.log1p(data2)
plt.hist(Log_data,bins = 100, label = 'Log Transformation Data')
```

Out[ ]:
```
(array([[   0.,    0.,    0., ...,    0.,    0.,    0.],
        [4290.,    0.,    0., ...,    0.,    0.,    0.],
        [   0.,    0.,    0., ...,    0.,    0.,    0.],
        ...,
        [3669.,    0.,    0., ...,    0.,    0.,    0.],
        [4614.,    0.,    0., ...,    0.,    0.,    0.],
        [4551.,    0.,    0., ...,    0.,    0.,    0.]]),
 array([ 0.        ,  0.13659921,  0.27319841,  0.40979762,  0.54639682,
         0.68299603,  0.81959523,  0.95619444,  1.09279364,  1.22939285,
         1.36599205,  1.50259126,  1.63919046,  1.77578967,  1.91238887,
         2.04898808,  2.18558728,  2.32218649,  2.45878569,  2.5953849 ,
         2.7319841 ,  2.86858331,  3.00518251,  3.14178172,  3.27838092,
         3.41498013,  3.55157933,  3.68817854,  3.82477774,  3.96137695,
         4.09797615,  4.23457536,  4.37117456,  4.50777377,  4.64437297,
         4.78097218,  4.91757138,  5.05417059,  5.19076979,  5.327369  ,
         5.4639682 ,  5.60056741,  5.73716661,  5.87376582,  6.01036502,
         6.14696423,  6.28356343,  6.42016264,  6.55676184,  6.69336105,
         6.82996025,  6.96655946,  7.10315866,  7.23975787,  7.37635708,
         7.51295628,  7.64955549,  7.78615469,  7.9227539 ,  8.0593531 ,
         8.19595231,  8.33255151,  8.46915072,  8.60574992,  8.74234913,
         8.87894833,  9.01554754,  9.15214674,  9.28874595,  9.42534515,
         9.56194436,  9.69854356,  9.83514277,  9.97174197, 10.10834118,
        10.24494038, 10.38153959, 10.51813879, 10.654738  , 10.7913372 ,
        10.92793641, 11.06453561, 11.20113482, 11.33773402, 11.47433323,
        11.61093243, 11.74753164, 11.88413084, 12.02073005, 12.15732925,
        12.29392846, 12.43052766, 12.56712687, 12.70372607, 12.84032528,
        12.97692448, 13.11352369, 13.25012289, 13.3867221 , 13.5233213 ,
        13.65992051]),
 <a list of 21 BarContainer objects>)
```


4000
3000
2000
1000
0
0
2
4
6
8
10
12
14

Linear Regression -> OLS -> LOGISTIC

```
In [ ]: data_ols = smf.ols(formula = 'BAD ~ DEBTINC + DEROG + DELINQ + NINQ + CLAGE' , data=data2).fit()
        print(data_ols.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    BAD   R-squared:                       0.141
Model:                            OLS   Adj. R-squared:                  0.140
Method:                 Least Squares   F-statistic:                     154.4
Date:                Fri, 12 Jan 2024   Prob (F-statistic):          3.26e-152
Time:                        15:40:51   Log-Likelihood:                -330.30
No. Observations:                4693   AIC:                             672.6
Df Residuals:                    4687   BIC:                             711.3
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.0876      0.018     -4.898      0.000      -0.123      -0.053
DEBTINC        0.0057      0.000     12.793      0.000       0.005       0.007
DEROG          0.0755      0.006     11.964      0.000       0.063       0.088
DELINQ         0.0794      0.005     16.569      0.000       0.070       0.089
NINQ           0.0073      0.002      2.932      0.003       0.002       0.012
CLAGE         -0.0003   4.58e-05     -7.422      0.000      -0.000      -0.000
==============================================================================
Omnibus:                     2514.137   Durbin-Watson:                   1.944
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13926.811
Skew:                           2.647   Prob(JB):                         0.00
Kurtosis:                       9.572   Cond. No.                         963.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

UniVARIATE LOGISTIC MODEL & OOS predictions

out of sample testing and ROC curve

In [ ]:
```
# Pursue intial analysis for gauging the strength and the direction of relationships between each predicto
# Help in identifying which variables might be worth including in more complex models
x = pd.DataFrame(data1['CLAGE']).copy()
y = pd.DataFrame(data1['BAD']).copy()
print(y.value_counts())
```

```
BAD
0      4290
1       403
Name: count, dtype: int64
```

In [ ]:
```
# Apply Oversampling to solve the problem of imbalance data
ros = RandomOverSampler()
x_ros1, y_ros_1 = ros.fit_resample(x,y)
```

In [ ]:
```
x_train,x_test,y_train,y_test = train_test_split(x_ros1,y_ros_1,test_size=0.3,random_state = 0)
```

In [ ]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(6006, 1)
(2574, 1)
(6006, 1)
(2574, 1)
```

In [ ]:
```
x_train = x_train.values.reshape(-1,1)
y_train = y_train.values.reshape(-1)
x_test = x_test.values.reshape(-1,1)
y_test = y_test.values.reshape(-1)
```

In [ ]:
```
lr = LogisticRegression()
lr.fit(x_train, y_train)
y_pred  = lr.predict(x_test)
```

In [ ]:
```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

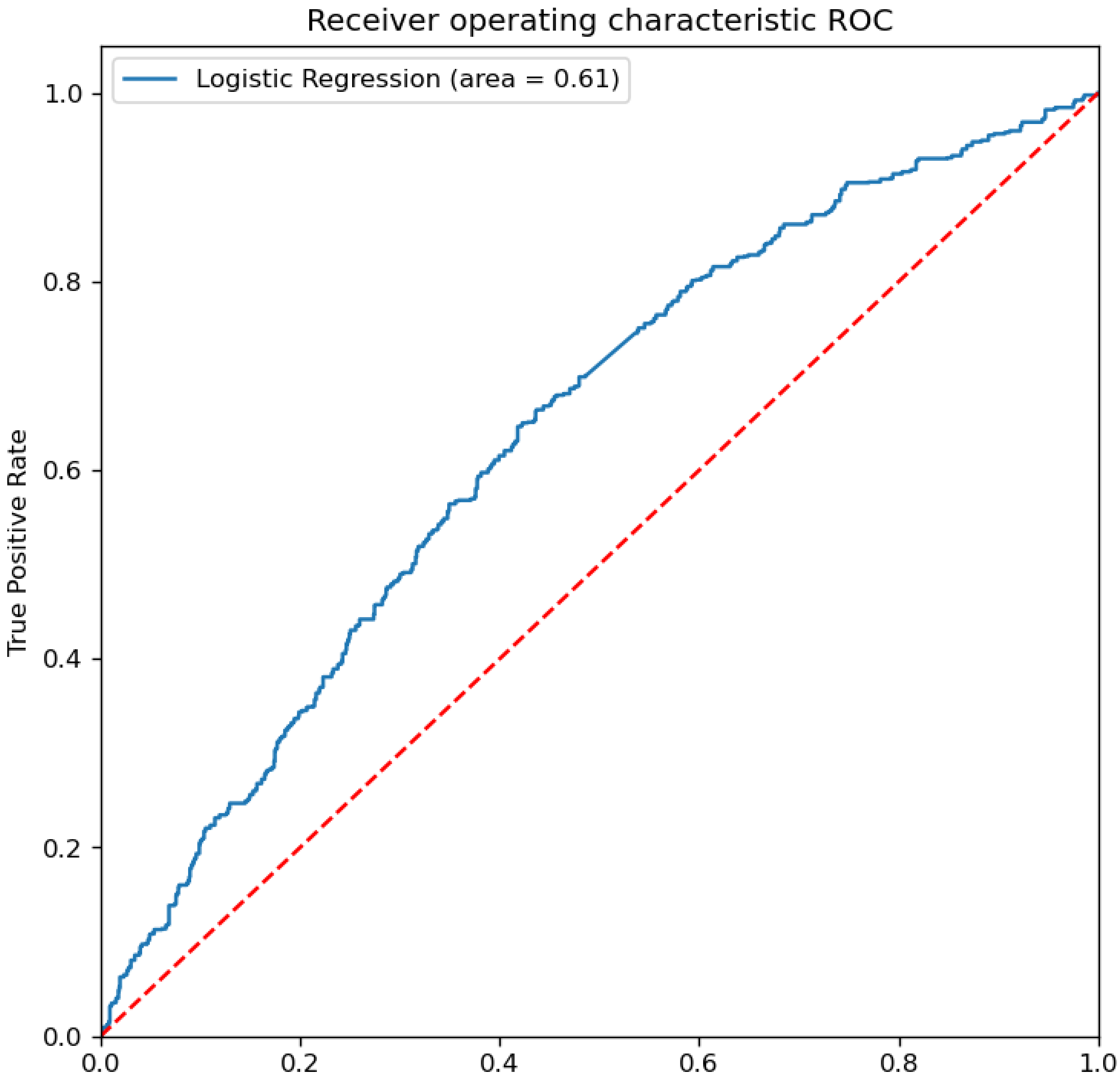
```
[[764 518]
 [497 795]]
```

In [ ]:
```
logit_roc_auc = roc_auc_score(y_test, lr.predict(x_test))
fpr, tpr, thresholds = roc_curve(y_test, lr.predict_proba(x_test)[:,1])
plt.figure()
```

Out[ ]:
```
<Figure size 840x840 with 0 Axes>
<Figure size 840x840 with 0 Axes>
```

In [ ]:
```
plt.plot(fpr, tpr, label = 'Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0,1],[0,1], 'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic ROC')
plt.legend(loc="upper left")
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x2912e5250>
```


Receiver operating characteristic ROC
Logistic Regression (area = 0.61)
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0

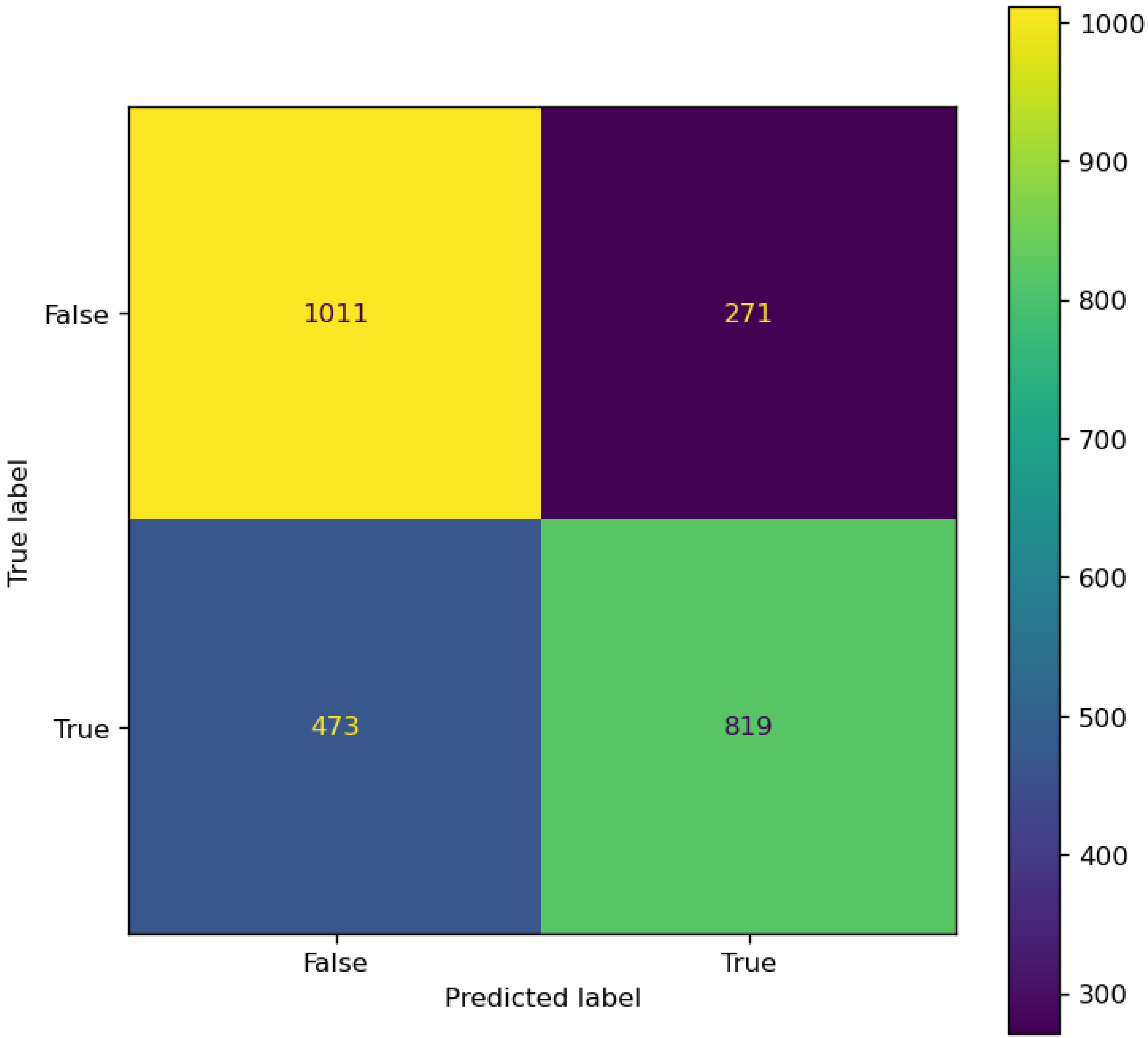
False Positive Rate

Logistic model with 5 variables

In [ ]:
```
#define the predictor variables and the response variable
x = data1[['DEBTINC', 'DEROG', 'DELINQ','NINQ','CLAGE']].copy()
y = data1['BAD'].copy()

# Apply Oversampling to solve the problem of imbalance data
counter = Counter(y)
ros = SMOTE(random_state = 42)
x,y = ros.fit_resample(x,y)
counter1 = Counter(y)

#Split the dataset into 70% training data and 30% test data
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3, random_state= 0)
print('Before :',counter)
print('After :', counter1)


# Fit the model using the train data
log_regression = LogisticRegression()
log_regression.fit(x_train, y_train)

# Confusion matrix
y_pred = log_regression.predict(x_test)
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
print(confusion_matrix)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels = [False,Tr
cm_display.plot()
plt.show()

# Model performances
Accuracy = metrics.accuracy_score(y_test,y_pred)
Precision = metrics.precision_score(y_test,y_pred)
Sensitivity_recall = metrics.recall_score(y_test,y_pred)
Specificity = metrics.recall_score(y_test,y_pred, pos_label=0)
F1_score = metrics.f1_score(y_test,y_pred)
print({"Accuracy":Accuracy,"Precision":Precision,"Sensitivity_recall":Sensitivity_recall,"Specificity":Spe
```

```python
# define metrics
y_pred_proba = log_regression.predict_proba(x_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
print(f'AUC for logitstic regression is: {auc*100:5.2f}%')
```

```
Before : Counter({0: 4290, 1: 403})
After : Counter({1: 4290, 0: 4290})
[[1011  271]
 [ 473  819]]
```


1011
271
473
819
False
True
True label
False
True
Predicted label
1000
900
800
700
600
500
400
300

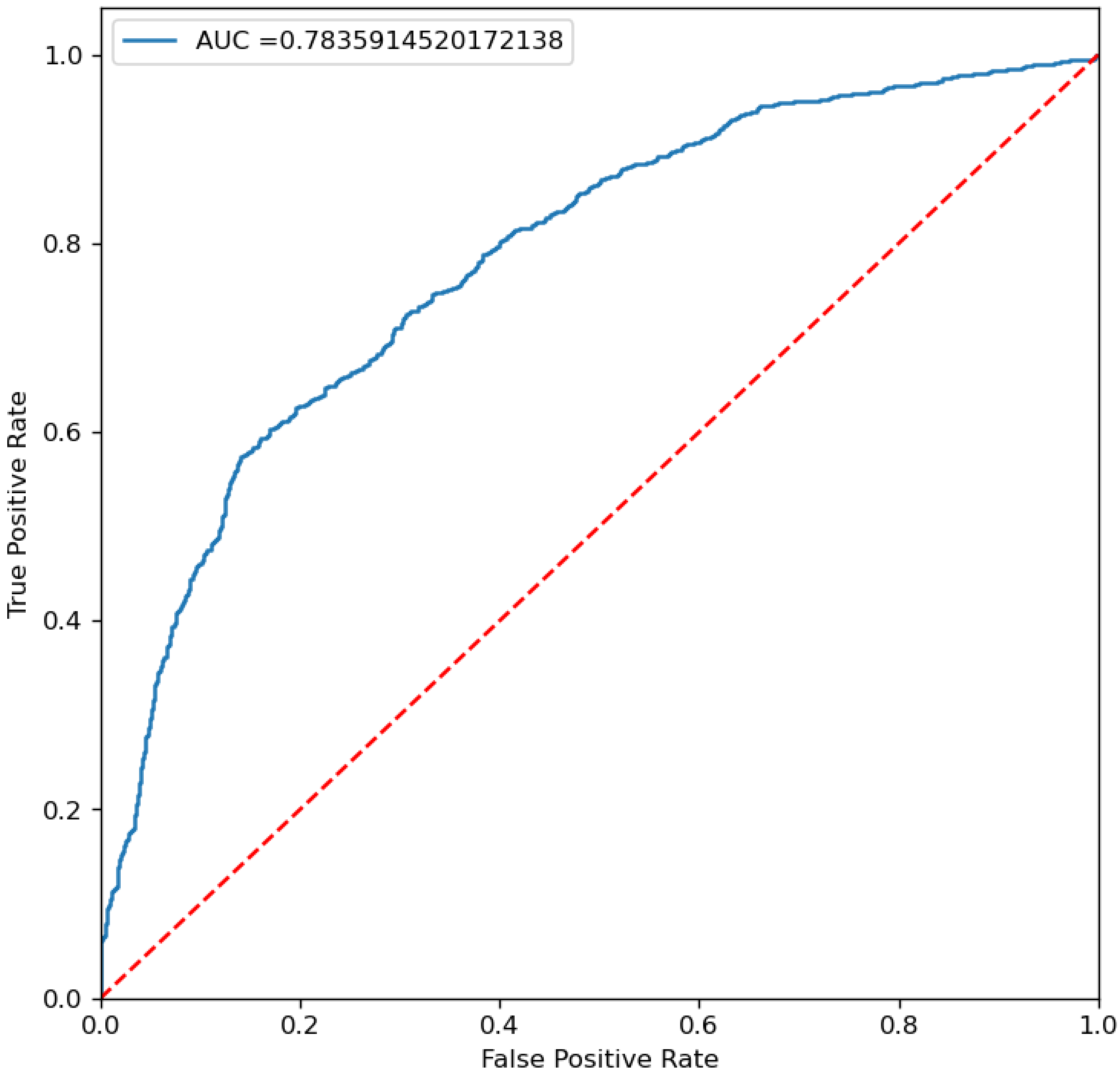
```
{'Accuracy': 0.710955710955711, 'Precision': 0.7513761467889908, 'Sensitivity_recall': 0.6339009287925697,
'Specificity': 0.7886115444617785, 'F1_score': 0.6876574307304786}
AUC for logitstic regression is: 78.36%
```

In [ ]:

```
#create ROC curve
plt.plot(fpr,tpr, label = "AUC ="+ str(auc))
plt.plot([0,1],[0,1], 'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0, 1.05])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend(loc = 2)
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x2913bc090>
```


AUC =0.7835914520172138
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate

In [ ]:
```
##MULTIVARIATE logit MODEL & predictions
model_lr2 = smf.glm('BAD ~ DEBTINC + DEROG + DELINQ + NINQ + CLNO', family = sm.families.Binomial(), data =
print(model_lr2.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                    BAD   No. Observations:                 4693
Model:                            GLM   Df Residuals:                     4687
Model Family:                Binomial   Df Model:                            5
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -1144.2
Date:                Fri, 12 Jan 2024   Deviance:                       2288.5
Time:                        15:40:52   Pearson chi2:                 5.72e+03
No. Iterations:                     6   Pseudo R-squ. (CS):            0.09347
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -5.5301      0.317    -17.450      0.000      -6.151      -4.909
DEBTINC        0.0892      0.008     10.824      0.000       0.073       0.105
DEROG          0.5786      0.065      8.934      0.000       0.452       0.705
DELINQ         0.6584      0.052     12.599      0.000       0.556       0.761
NINQ           0.1139      0.030      3.824      0.000       0.055       0.172
CLNO          -0.0290      0.006     -4.840      0.000      -0.041      -0.017
==============================================================================
```

In [ ]:
```
PD_logit_model = pd.DataFrame(model_lr2.fittedvalues, columns = ['PD_logit_model'])
data5 = pd.concat([data2, PD_logit_model], axis = 1)
data5.head(10)
```

Out[ ]:

	CustomerID	BAD	LOAN	MORTDUE	VALUE	YOJ	DEROG	DELINQ	CLAGE	NINQ	...	REASON_DebtCon	RE
5	6	1	1700	30548.0	40320.0	9.0	0.0	0.00000	101.466002	1.0	...	0.0	
7	8	1	1800	28502.0	43034.0	11.0	0.0	0.00000	88.766030	0.0	...	0.0	
17	18	1	2200	23030.0	0.0	19.0	0.0	0.30543	183.751040	0.0	...	0.0	
19	20	0	2300	102370.0	120953.0	2.0	0.0	0.00000	90.992533	0.0	...	0.0	
25	26	1	2400	34863.0	47471.0	12.0	0.0	0.00000	70.491080	1.0	...	0.0	
26	27	0	2400	98449.0	117195.0	4.0	0.0	0.00000	93.811775	0.0	...	0.0	
34	35	0	2900	103949.0	112505.0	1.0	0.0	0.00000	96.102330	0.0	...	0.0	
35	36	0	2900	104373.0	120702.0	2.0	0.0	0.00000	101.540298	0.0	...	0.0	
36	37	1	2900	7750.0	67996.0	16.0	3.0	0.00000	122.204663	2.0	...	0.0	
37	38	1	2900	61962.0	70915.0	2.0	0.0	0.00000	282.801659	3.0	...	1.0	

10 rows × 22 columns

Decision Tree Model

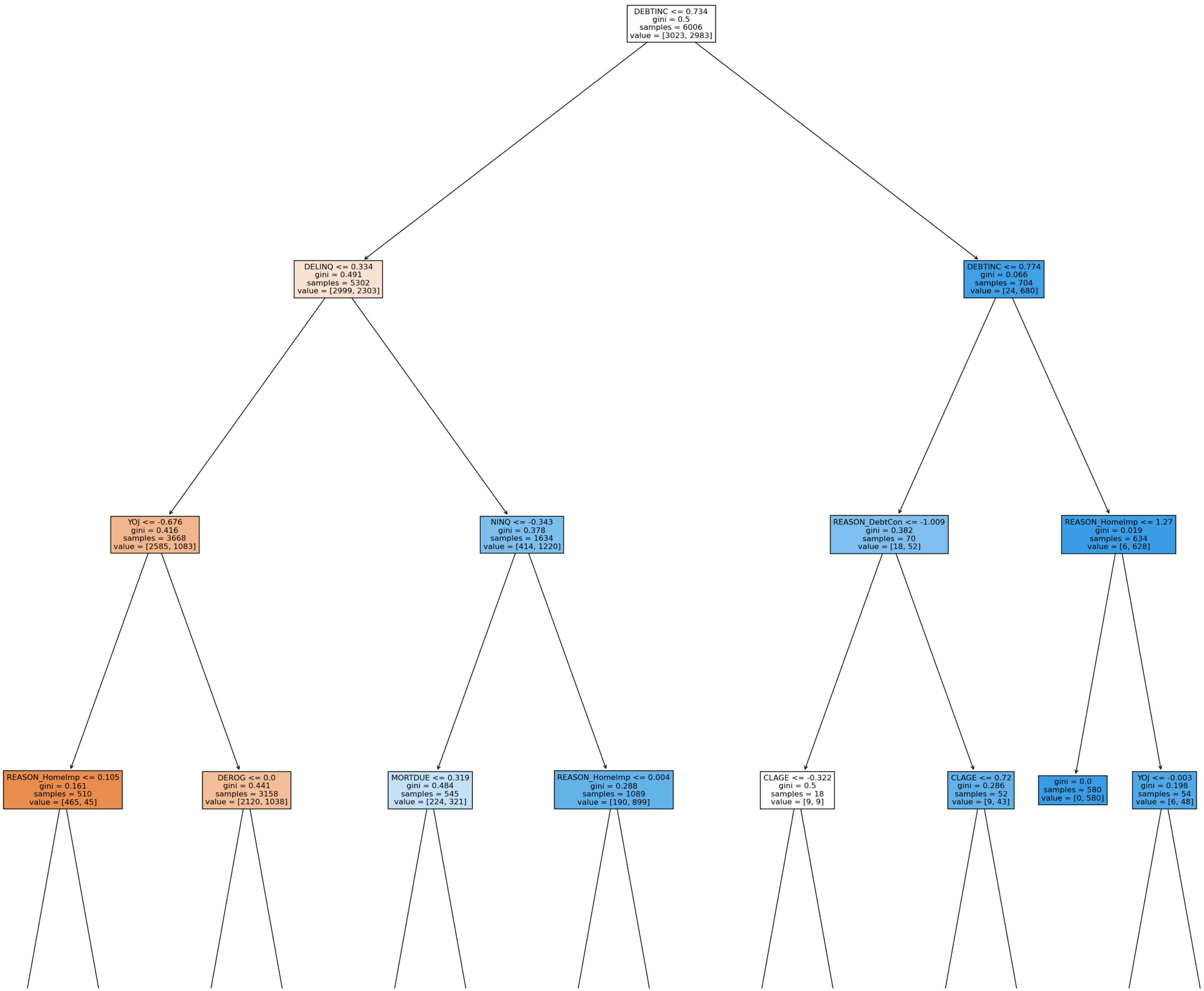
In [ ]:

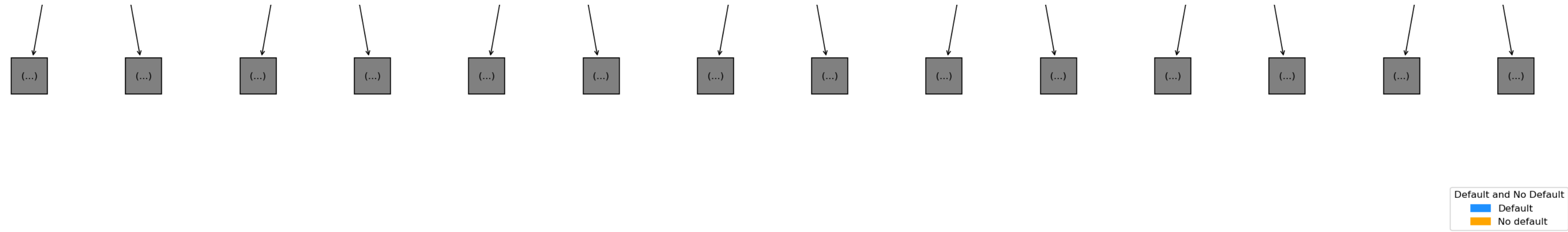
```
x = data3.drop('BAD',axis = 1).copy()
y = data3['BAD'].copy()

# Apply Oversampling to solve the problem of imbalance data
counter = Counter(y)
ros = SMOTE(random_state = 42)
x,y = ros.fit_resample(x,y)
counter1 = Counter(y)
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3, random_state= 42)

# Feature scaling
cols = x_train.columns
```

```
# Transform data to decrease the impact from outliers by suing the median and interquartile range for scal
from sklearn.preprocessing import RobustScaler
scaler = RobustScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)

# Promote hyperparameter tuning to find the optimal parameters for the model
dt = DecisionTreeClassifier(
                           random_state=42)
hyperparameter_space = {'max_depth':[None,3,4,5,6,7,8,9],
                        'min_samples_leaf':[1,2,3,4,5,6],
                        'max_features':['sqrt','log2']}

gs = GridSearchCV(dt, param_grid=hyperparameter_space ,
                  scoring="roc_auc",
                  n_jobs=2, cv=5, return_train_score=True)

gs.fit(x_train, y_train)
print("Optimal hyperparameter combination: ", gs.best_params_)
print("Mean cross-validated AUC of the best_estimator: ",
       gs.best_score_)

best_gs = gs.best_estimator_
# y_pred_proba_tree = best_gs.predict_proba(x_test)[:,1]
# fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba_tree)
# auc = metrics.roc_auc_score(y_test, y_pred_proba_tree)
# print('AUC score in Decision Tree Model is :',auc)

# Calculate the confusion matrix
test_prediction = best_gs.predict(x_test)
metrics.confusion_matrix(y_test,test_prediction,labels = [0,1])

# Measure the model performances
Accuracy_of_tree = accuracy_score(y_test,test_prediction)*100
Precision = metrics.precision_score(y_test,test_prediction)*100
Sensitivity_recall = metrics.recall_score(y_test,test_prediction)*100
Specificity = metrics.recall_score(y_test,test_prediction, pos_label=0)*100
F1_score = metrics.f1_score(y_test,test_prediction)*100
print({"Accuracy":Accuracy_of_tree,"Precision":Precision,"Sensitivity_recall":Sensitivity_recall,"Specific

#Calculate AUCROC
fpr, tpr, _ = metrics.roc_curve(y_test, test_prediction)
```

```
auc = metrics.roc_auc_score(y_test, test_prediction)
print('AUC score in Decision Tree Model is :',auc)

# Visualize the tree
feature_names=x.columns
best_gs.feature_importances_
fig = plt.figure(figsize=(30, 30))
tree.plot_tree(best_gs,feature_names=feature_names, filled=True, fontsize=10, max_depth= 3)

# Example of adding a legend
class_names = ['Default', 'No default']
colors = ['dodgerblue', 'orange']

# Create legend handles and labels
legend_handles = [plt.Rectangle((0, 0), 1, 1, color=color) for color in colors]
legend_labels = class_names

# Add legend to the figure
plt.legend(legend_handles, legend_labels, loc='lower right', title='Default and No Default')

plt.show()
```

```
Optimal hyperparameter combination:  {'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 4}
Mean cross-validated AUC of the best_estimator:  0.95575830711121
{'Accuracy': 93.66744366744368, 'Precision': 95.03937007874016, 'Sensitivity_recall': 92.34889058913542, 'S
pecificity': 95.02762430939227, 'F1_score': 93.67481567714397}
AUC score in Decision Tree Model is : 0.9368825744926385
```


DEBTINC <= 0.734
gini = 0.5
samples = 6006
value = [3023, 2983]
DELINQ <= 0.334
gini = 0.491
samples = 5302
value = [2999, 2303]
DEBTINC <= 0.774
gini = 0.066
samples = 704
value = [24, 680]
YOJ <= -0.676
gini = 0.416
samples = 3668
value = [2585, 1083]
NINQ <= -0.343
gini = 0.378
samples = 1634
value = [414, 1220]
REASON_DebtCon <= -1.009
gini = 0.382
samples = 70
value = [18, 52]
REASON_HomeImp <= 1.27
gini = 0.019
samples = 634
value = [6, 628]
REASON_HomeImp <= 0.105
gini = 0.161
samples = 510
value = [465, 45]
DEROG <= 0.0
gini = 0.441
samples = 3158
value = [2120, 1038]
MORTDUE <= 0.319
gini = 0.484
samples = 545
value = [224, 321]
REASON_HomeImp <= 0.004
gini = 0.288
samples = 1089
value = [190, 899]
CLAGE <= -0.322
gini = 0.5
samples = 18
value = [9, 9]
CLAGE <= 0.72
gini = 0.286
samples = 52
value = [9, 43]
gini = 0.0
samples = 580
value = [0, 580]
YOJ <= -0.003
gini = 0.198
samples = 54
value = [6, 48]



Random Forest Model

In [ ]:
```
x = data3.drop('BAD',axis = 1).copy()
y = data3['BAD'].copy()

# Apply Oversampling to solve the problem of imbalance data
counter = Counter(y)
ros = SMOTE(random_state = 42)
x,y = ros.fit_resample(x,y)
counter1 = Counter(y)
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3, random_state= 42)

n_estimators = [int(x) for x in np.linspace(start = 1, stop = 100, num = 10)]
# Number of features to consider at every split
max_features = ['log2', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(1, 10, num = 1)]
# max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 8, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [2, 4, 6,8]
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
```

```
print(random_grid)

# Use the random grid to search for best hyperparameters to narrow down the range for each hyperparameter
# First create the base model to tune
rf = RandomForestClassifier(random_state = 42)
# Random search of parameters, using 3 fold cross validation,
# search across different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 10, cv = 3, verl
# Fit the random search model
rf_random.fit(x_train, y_train)
# pred_rf= rf_random.predict(x_test)
rf_random.best_params_
```

```
{'n_estimators': [1, 12, 23, 34, 45, 56, 67, 78, 89, 100], 'max_features': ['log2', 'sqrt'], 'max_depth':
[1], 'min_samples_split': [2, 5, 8, 10], 'min_samples_leaf': [2, 4, 6, 8], 'bootstrap': [True, False]}
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=5, n_estima
tors=1; total time=   0.0s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=5, n_estima
tors=1; total time=   0.0s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=5, n_estima
tors=1; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=8, min_samples_split=5, n_estimat
ors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=8, min_samples_split=5, n_estimat
ors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=8, n_estimat
ors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=8, n_estimat
ors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=8, min_samples_split=5, n_estimat
ors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=8, n_estimat
ors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimat
ors=45; total time=   0.1s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estim
ators=78; total time=   0.1s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estim
ators=78; total time=   0.1s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estim
ators=78; total time=   0.2s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimat
ors=45; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimat
ors=45; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=2, n_estimat
ors=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=2, n_estimat
ors=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=2, n_estimat
ors=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=8, min_samples_split=10, n_estima
tors=89; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=8, min_samples_split=10, n_estima
```

```
tors=89; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=4, min_samples_split=8, n_estimat
ors=100; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n_estima
tors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n_estima
tors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n_estima
tors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=8, min_samples_split=10, n_estima
tors=89; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=4, min_samples_split=8, n_estimat
ors=100; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estima
tors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estima
tors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estima
tors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=4, min_samples_split=8, n_estimat
ors=100; total time=   0.1s
```

Out[ ]:

```
{'n_estimators': 78,
 'min_samples_split': 2,
 'min_samples_leaf': 6,
 'max_features': 'sqrt',
 'max_depth': 1,
 'bootstrap': True}
```

In [ ]:

```
# Create the parameter grid based on the results of random search
param_grid = {
    'bootstrap': [False],
    'max_depth': [2, 4, 6],
    'max_features': [2, 3],
    'min_samples_leaf': [1, 2, 3],
    'min_samples_split': [2, 4, 6],
    'n_estimators': [35, 45, 55, 67]
}
# Create a based model
rf = RandomForestClassifier(random_state = 42)
# Instantiate the grid search model
# Now that we know where to concentrate our search, we can explicitly specify every combination of setting:
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid,
```

```
                            cv = 3, n_jobs = -1, verbose = 0)
grid_search.fit(x_train, y_train)
print(grid_search.best_params_)
best_grid = grid_search.best_estimator_

pred_rf= best_grid.predict(x_test)

from sklearn.metrics import classification_report
print("The accuracy of Random Forest model is:", accuracy_score(y_test, pred_rf))
print(classification_report(y_test,pred_rf, target_names= ['Non Default','Default'],digits= 5))
# y_pred_proba_rf = best_grid.predict_proba(x_test)[:,1]
# fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba_rf)
# auc = metrics.roc_auc_score(y_test, y_pred_proba_rf)

auc = metrics.roc_auc_score(y_test, pred_rf)
print('AUC score in Random Forest Model is :',auc)
```

```
{'bootstrap': False, 'max_depth': 6, 'max_features': 3, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_e
stimators': 45}
The accuracy of Random Forest model is: 0.9168609168609169
              precision    recall  f1-score   support

 Non Default    0.87367   0.97159   0.92003      1267
     Default    0.96910   0.86381   0.91343      1307

    accuracy                        0.91686      2574
   macro avg    0.92138   0.91770   0.91673      2574
weighted avg    0.92213   0.91686   0.91668      2574

AUC score in Random Forest Model is : 0.9176983385558547
```

In [ ]:

```
# Use the random grid to search for best hyperparameters to narrow down the range for each hyperparameter
# First create the base model to tune
rf = RandomForestClassifier(random_state = 42)
# Random search of parameters, using 3 fold cross validation,
# search across different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 10, cv = 3, verl
# Fit the random search model
rf_random.fit(x_train, y_train)
# pred_rf= rf_random.predict(x_test)
rf_random.best_params_
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=5, n_estima
tors=1; total time=   0.0s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=5, n_estima
tors=1; total time=   0.0s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=5, n_estima
tors=1; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=8, min_samples_split=5, n_estimat
ors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=8, min_samples_split=5, n_estimat
ors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=8, min_samples_split=5, n_estimat
ors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=8, n_estimat
ors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=8, n_estimat
ors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=8, n_estimat
ors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimat
ors=45; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimat
ors=45; total time=   0.1s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estim
ators=78; total time=   0.1s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estim
ators=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimat
ors=45; total time=   0.1s
[CV] END bootstrap=False, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estim
ators=78; total time=   0.2s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=2, n_estimat
ors=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=2, n_estimat
ors=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n_estima
tors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=2, n_estimat
ors=78; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=8, min_samples_split=10, n_estima
tors=89; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n_estima
```

```
tors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=2, min_samples_split=10, n_estima
tors=12; total time=   0.0s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=8, min_samples_split=10, n_estima
tors=89; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=8, min_samples_split=10, n_estima
tors=89; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estima
tors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estima
tors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=4, min_samples_split=8, n_estimat
ors=100; total time=   0.2s
[CV] END bootstrap=True, max_depth=1, max_features=sqrt, min_samples_leaf=6, min_samples_split=10, n_estima
tors=56; total time=   0.1s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=4, min_samples_split=8, n_estimat
ors=100; total time=   0.2s
[CV] END bootstrap=True, max_depth=1, max_features=log2, min_samples_leaf=4, min_samples_split=8, n_estimat
ors=100; total time=   0.2s
```

Out[ ]:

```
{'n_estimators': 78,
 'min_samples_split': 2,
 'min_samples_leaf': 6,
 'max_features': 'sqrt',
 'max_depth': 1,
 'bootstrap': True}
```

In [ ]:

```
# Create the parameter grid based on the results of random search
param_grid = {
    'bootstrap': [False],
    'max_depth': [2, 4, 6],
    'max_features': [2, 3],
    'min_samples_leaf': [1, 2, 3],
    'min_samples_split': [2, 4, 6],
    'n_estimators': [35, 45, 55, 67]
}
# Instantiate the grid search model
# Now that we know where to concentrate our search, we can explicitly specify every combination of settings
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid,
                           cv = 3, n_jobs = -1, verbose = 0)
grid_search.fit(x_train, y_train)
```

```
print(grid_search.best_params_)
best_grid = grid_search.best_estimator_
```

```
{'bootstrap': False, 'max_depth': 6, 'max_features': 3, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_e
stimators': 45}
```

In [ ]:

```
pred_rf1= best_grid.predict(x_test)

from sklearn.metrics import classification_report
print("The accuracy of Random Forest model is:", accuracy_score(y_test, pred_rf1))
print(classification_report(y_test,pred_rf, target_names= ['Non Default','Default'],digits= 5))
# y_pred_proba_rf = best_grid.predict_proba(x_test)[:,1]
# fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba_rf)
auc = metrics.roc_auc_score(y_test, pred_rf1)
print('AUC score in Random Forest Model is :',auc)
```

```
The accuracy of Random Forest model is: 0.9168609168609169
              precision    recall  f1-score   support

 Non Default    0.87367   0.97159   0.92003      1267
     Default    0.96910   0.86381   0.91343      1307

    accuracy                        0.91686      2574
   macro avg    0.92138   0.91770   0.91673      2574
weighted avg    0.92213   0.91686   0.91668      2574

AUC score in Random Forest Model is : 0.9176983385558547
```

Important features with Random Forest Model

In [ ]:

```
rf_100 = RandomForestClassifier(n_estimators= 100, random_state= 42)
rf_100.fit(x_train, y_train)

feature_scores = pd.Series(rf_100.feature_importances_, index = x_train.columns).sort_values(ascending = Tr
print(feature_scores)
```

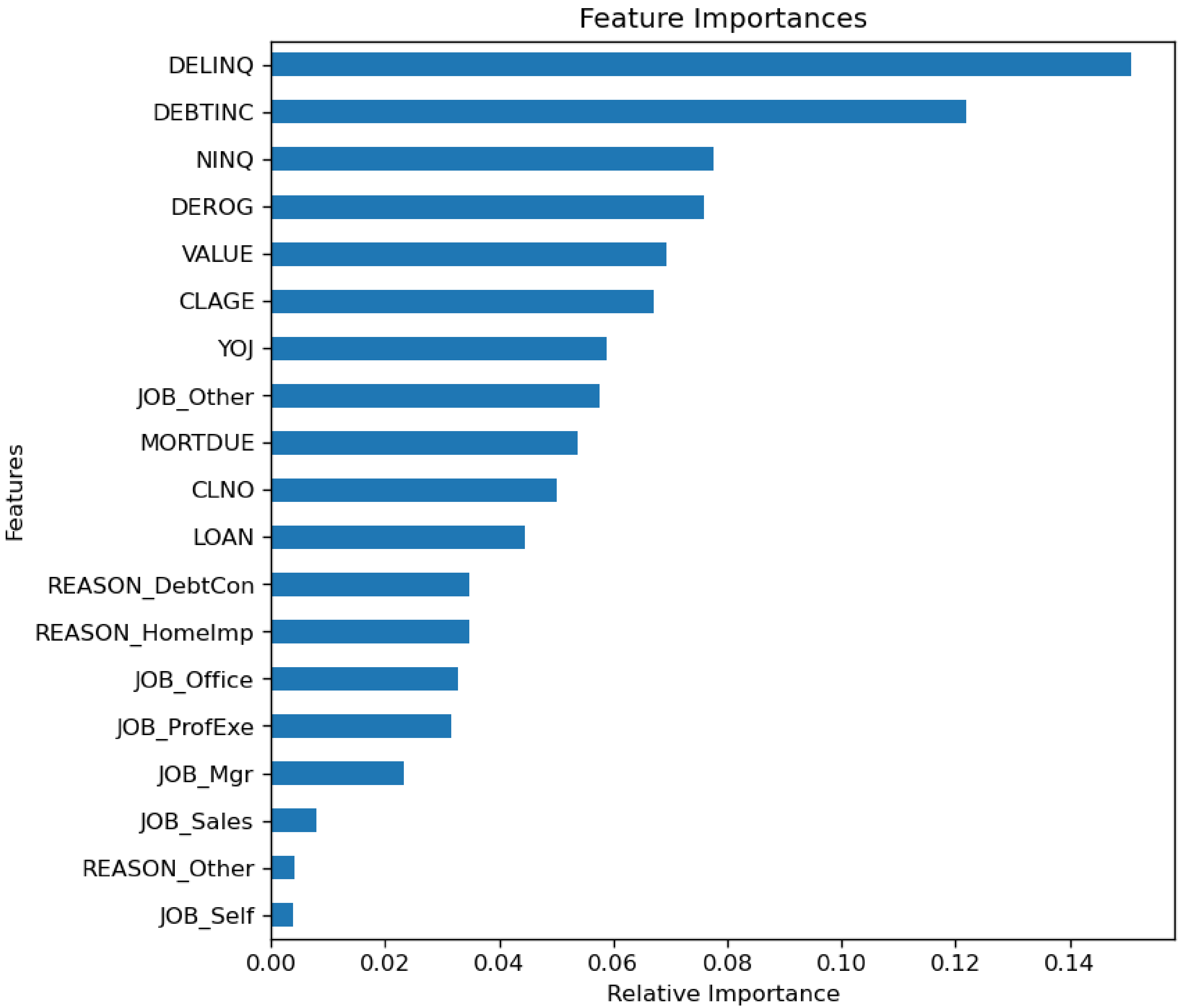
```
JOB_Self          0.003774
REASON_Other      0.004138
JOB_Sales         0.007947
JOB_Mgr           0.023193
JOB_ProfExe       0.031562
JOB_Office        0.032689
REASON_HomeImp    0.034764
REASON_DebtCon    0.034793
LOAN              0.044444
CLNO              0.050142
MORTDUE           0.053698
JOB_Other         0.057701
YOJ               0.058781
CLAGE             0.067136
VALUE             0.069204
DEROG             0.075857
NINQ              0.077573
DEBTINC           0.121762
DELINQ            0.150843
dtype: float64
```

In [ ]:

```
feature_scores.plot(kind = 'barh')
plt.ylabel('Features')
plt.xlabel('Relative Importance')
plt.title('Feature Importances')
```

Out[ ]:

```
Text(0.5, 1.0, 'Feature Importances')
```


Feature Importances
DELINQ
DEBTINC
NINQ
DEROG
VALUE
CLAGE
YOJ
JOB_Other
MORTDUE
CLNO
LOAN
REASON_DebtCon
REASON_HomeImp
JOB_Office
JOB_ProfExe
JOB_Mgr
JOB_Sales
REASON_Other
JOB_Self
Features
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Relative Importance

When considering the factors contributing to the probability of default, DELINQ, DEBTINC, NINQ, DEROG, and VALUE emerge as the most significant predictors. DEBTINC, or the debt-to-income ratio, underscoring the importance of a customer's financial burden in evaluating credit risk. DELINQ (number of delinquent credit lines), NINQ (number of recent credit inquiries), NINQ (number of recent credit inquiries), and DEROG (number of major derogatory reports) exhibit a positive correlation with default probability. These factors are indicative of recent financial stress or mismanagement, which can signal a higher risk of default. However, 'VALUE' of an asset has a negative correlation with default probability. This is because a higher property value can provide a financial safety net, enabling borrowers to access equity in tough times instead of defaulting. It also suggests that the borrower may have greater financial stability and more to lose by defaulting, thereby providing a strong incentive to maintain their loan payments. However, this relationship can be influenced by market conditions and the borrower's overall financial health, underscoring the importance of a multifaceted risk assessment.

Conclusion

1. Logistic Regression has the lowest performance across all metrics compared to the other two models. It has particularly low recall and F1 scores, indicating that it may not be the best at capturing all the default cases.

2. Decision Tree Model shows very high recall and precision. It has the highest F1 score, which is a harmonic mean of precision and recall, suggesting a good balance between the two. Additionally, its AUC is the highest, showing a strong capability in distinguishing between classes.

3. Random Forest has a high precision, indicating that when it predicts a default, it is very likely to be correct. It has a slightly lower recall than the Decision Tree, suggesting it doesn't capture as many of the true default cases. However, it does have a higher accuracy and the AUC score is very close to that of the Decision Tree.

Choosing the Final Model:

The choice of the final model should be guided by the specific business objectives and the costs associated with false positives (incorrectly predicting default when there is none) versus false negatives (failing to predict a default that does occur).

- If the cost of missing a default is very high (a false negative is very costly), the Decision Tree Model may be the best option due to its highest recall and F1 score.

- If the goal is to ensure that the cases identified as defaults are indeed defaults (minimizing false positives), the Random Forest model would be preferable because of its high precision.
- If overall accuracy and the balance between true positive and true negative rates are the priority, then the Random Forest model may be the most suitable as it has the highest accuracy and a very competitive AUC score.

Given the metrics, the Decision Tree Model stands out for its ability to correctly identify default cases (high recall) while maintaining a high precision, and it has the highest AUC score. However, the Random Forest model, with its slightly better accuracy and competitive AUC, could be more appealing if the problem requires a more balanced overall performance.

In this instance, the Decision Tree model's superior performance metrics make it the preferred choice, provided the model's robustness has been validated through appropriate cross-validation techniques and that it has been tested on an independent validation set to confirm these results.