Loan Default Data

The Data is from Kaggle

Business Problem

Banks earn a major revenue from lending loans. But it is often associated with risk. The borrower's may default on the loan. To mitigate this issue, the banks have decided to use Machine Learning to overcome this issue. They have collected past data on the loan borrowers & would like you to develop a strong ML Model to classify if any new borrower is likely to default or not.

The dataset is enormous & consists of multiple deteministic factors like borrowe's income, gender, loan pupose etc. The dataset is subject to strong multicollinearity & empty values. Can you overcome these factors & build a strong classifier to predict defaulters?

Data Dictionary

The features for the dataset is as follwing:

ID:ID number of loan applicants

Year: Year that the applicants applied for the loan

Loan Limits: cf and ncf

Gender: Male, Female, Joint, or Sex Not Available

Approv_in_adv: nopre, pre

Loan_type: type1, 2, 3

Loan_purpose: p1, 2, 3, 4

Credit_worthiness: L1, L2

Open_credit: no nopen credit, open credit

Business_or_commercial: not b/c, b/c

Loan_amount: money loaned to applicants

Rate_of_interest: interest rate of loans

Interest_rate_spread: IRS

Upfront_charges: Charges

term: loan term in days

Neg_ammortization(paying less than interest): not_neg, neg_amm

Interest_Only: not_int, int_only

lump_sum_payment: not_lpsm, lpsm

property_value: property value

construction_type: sb

occupancy_type: pr, sr

secured_by: home

total_units: 1U, 2U, 3U, 4U

income: income of applicants

Credit_type: EQUI, EXP, CRIF, CIB

Credit_score: credit scores of applicants

Co-applicant_credit_type: CIB, EXP

Age: age range

submission_of_application: to_inst, not_inst

LTV: LTV

Region: south, north, central

Security_type: direct, indirect

Status: 1 for default, 0 for no-default

dtir1: integer value

Import Library

```
# Basic Libraries
import pandas as pd
import seaborn as sns

import numpy as np
from numpy import mean
from numpy import std

import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from scipy.stats.mstats import winsorize
import scipy.stats as ss
import math
import seaborn as sns
from datetime import datetime


# Scikit learn
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Perceptron
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import make_pipeline
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import log_loss
from sklearn.metrics import balanced_accuracy_score
from sklearn.metrics import f1_score
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import learning_curve
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor, StackingRegressor
from sklearn.model_selection import cross_val_score
from sklearn.inspection import partial_dependence
from sklearn.inspection import PartialDependenceDisplay
from sklearn.inspection import permutation_importance

from xgboost import XGBClassifier


#!pip install lightgbm
from lightgbm import LGBMClassifier
```

```
!pip install psynlig
from psynlig import pca_explained_variance_bar
```

```
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Building wheels for collected packages: adjustText, sphinx-gallery
  Building wheel for adjustText (setup.py) ... done
  Created wheel for adjustText: filename=adjustText-0.7.3-py3-none-any.whl size=7097 sha256=af30703d9b673398ba4cb875c0d25934f58af1ac2e776
  Stored in directory: /root/.cache/pip/wheels/2f/98/32/afbf902d8f040fadfdf0a44357e4ab750afe165d873bf5893d
  Building wheel for sphinx-gallery (setup.py) ... done
  Created wheel for sphinx-gallery: filename=sphinx_gallery-0.10.1-py3-none-any.whl size=132569 sha256=89146073f3e43286179edb22deab7d0373
```

```
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as imbpipeline
from sklearn.pipeline import Pipeline
```

```
!pip install shap
import shap
```

```
Collecting shap
  Downloading shap-0.40.0-cp37-cp37m-manylinux2010_x86_64.whl (564 kB)
     |████████████████████████████████| 564 kB 11.9 MB/s
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from shap) (1.4.1)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.7/dist-packages (from shap) (21.3)
Requirement already satisfied: numba in /usr/local/lib/python3.7/dist-packages (from shap) (0.51.2)
Collecting slicer==0.0.7
  Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from shap) (1.21.6)
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Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->shap) (1.1.0)
Installing collected packages: slicer, shap
Successfully installed shap-0.40.0 slicer-0.0.7
```

```
!pip install pdpbox
from pdpbox import pdp, get_dataset, info_plots
```

```
Collecting pdpbox
  Downloading PDPbox-0.2.1.tar.gz (34.0 MB)
     |████████████████████████████████| 34.0 MB 1
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: psutil in /usr/local/lib/python3.7/dist-packages (
Collecting matplotlib==3.1.1
  Downloading matplotlib-3.1.1-cp37-cp37m-manylinux1_x86_64.whl (13.1 MB)
```

Read Data

```
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/d
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# Read
file_ = "/content/drive/MyDrive/Colab Notebooks/WOW/Loan_Default.csv"     # adapt this as needed to the file structure on your Goog
df = pd.read_csv(file_)  # read in csv file
df = df.drop(['ID','year'],axis =1)
```

EDA

```
# Shape of df
print("Shape", df.shape)

# Check data types
print(df.info())
```

```
Shape (148670, 32)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 32 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   loan_limit                 145326 non-null  object
 1   Gender                     148670 non-null  object
 2   approv_in_adv              147762 non-null  object
 3   loan_type                  148670 non-null  object
 4   loan_purpose               148536 non-null  object
 5   Credit_Worthiness          148670 non-null  object
 6   open_credit                148670 non-null  object
 7   business_or_commercial     148670 non-null  object
 8   loan_amount                148670 non-null  int64
 9   rate_of_interest           112231 non-null  float64
 10  Interest_rate_spread       112031 non-null  float64
 11  Upfront_charges            109028 non-null  float64
 12  term                       148629 non-null  float64
 13  Neg_ammortization          148549 non-null  object
 14  interest_only              148670 non-null  object
 15  lump_sum_payment           148670 non-null  object
 16  property_value             133572 non-null  float64
 17  construction_type          148670 non-null  object
 18  occupancy_type             148670 non-null  object
 19  Secured_by                 148670 non-null  object
 20  total_units                148670 non-null  object
 21  income                     139520 non-null  float64
 22  credit_type                148670 non-null  object
 23  Credit_Score               148670 non-null  int64
 24  co-applicant_credit_type   148670 non-null  object
 25  age                        148470 non-null  object
 26  submission_of_application  148470 non-null  object
 27  LTV                        133572 non-null  float64
 28  Region                     148670 non-null  object
 29  Security_Type              148670 non-null  object
 30  Status                     148670 non-null  int64
 31  dtir1                      124549 non-null  float64
dtypes: float64(8), int64(3), object(21)
memory usage: 36.3+ MB
None
```

```
# Missing Values
print('Number of missing Values by Feature\n',df.isnull().sum())
columns_with_NaNs = []
for col in df.columns:
    if df[col].isnull().sum() > 0:
        columns_with_NaNs.append(col)
print('Columns with NaNs:',columns_with_NaNs)
# Missing value heatmap
plt.figure(figsize=(10,6))
sns.heatmap(df.isna().transpose(),
                        cmap="YlGnBu",
                        cbar_kws={'label': 'Missing Data Heatmap'})
plt.show()
#impute median missing value
```

```
Number of missing Values by Feature
 loan_limit                    3344
Gender                           0
approv_in_adv                  908
loan_type                        0
loan_purpose                   134
Credit_Worthiness                0
open_credit                      0
business_or_commercial           0
loan_amount                      0
rate_of_interest             36439
Interest_rate_spread         36639
Upfront_charges              39642
term                            41
Neg_ammortization              121
interest_only                    0
lump_sum_payment                 0
property_value               15098
construction_type                0
occupancy_type                   0
Secured_by                       0
total_units                      0
income                        9150
credit_type                      0
Credit_Score                     0
co-applicant_credit_type         0
age                            200
submission_of_application      200
LTV                          15098
Region                           0
Security_Type                    0
Status                           0
dtir1                        24121
dtype: int64
```

```
# Duplicates
duplicates_count = df.duplicated().sum()
print('No. of dups:',duplicates_count)
```

```
duplicates_rows = df[df.duplicated(keep = 'last')] # Note that the last one is kept.
print('Instances that are  duplicates:\n ',duplicates_rows)
```

```
No. of dups: 0
Instances that are  duplicates:
  Empty DataFrame
Columns: [loan_limit, Gender, approv_in_adv, loan_type, loan_purpose, Credit_Worthiness, open_credit, business_or_commercial, loan_amount, 
Index: []

[0 rows x 32 columns]
```

```
# Compute the number of unique values in each feature (includes NaNs)
df.nunique()
```

```
loan_limit                    2
Gender                        4
approv_in_adv                 2
loan_type                     3
loan_purpose                  4
Credit_Worthiness             2
open_credit                   2
business_or_commercial        2
loan_amount                 211
rate_of_interest            131
Interest_rate_spread      22516
Upfront_charges           58271
term                         26
Neg_ammortization             2
interest_only                 2
lump_sum_payment              2
property_value              385
construction_type             2
occupancy_type                3
Secured_by                    2
total_units                   4
income                     1001
credit_type                   4
```

```
Credit_Score                  401
co-applicant_credit_type        2
age                             7
submission_of_application       2
LTV                          8484
Region                          4
Security_Type                   2
Status                          2
dtir1                          57
dtype: int64
```

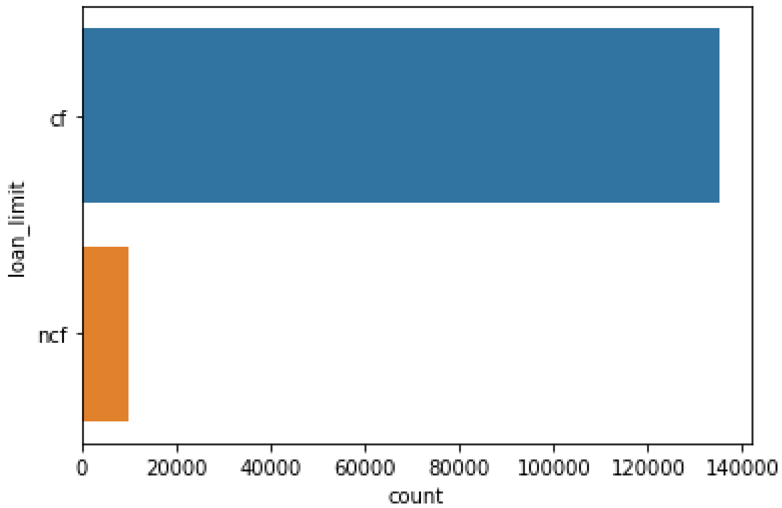
```
# Separate categoricals and quants
# Note: features that would otherwise be categrical, but have more than five categories, will be label encoded and handled as
quants = ['loan_amount','rate_of_interest','Interest_rate_spread','Upfront_charges','property_value','income','Credit_Score','LTV']
dummies = ['loan_limit', 'Gender', 'approv_in_adv', 'loan_type', 'loan_purpose','Credit_Worthiness', 'open_credit', 'business_or_commercia
labels = ['credit_type','co-applicant_credit_type','term']
target = ['Status']

print('Target feature',target)
print('Quant features: ',quants)
print('Features for dummy encoding ',dummies)
print('Features for labels encoding ',labels)
```

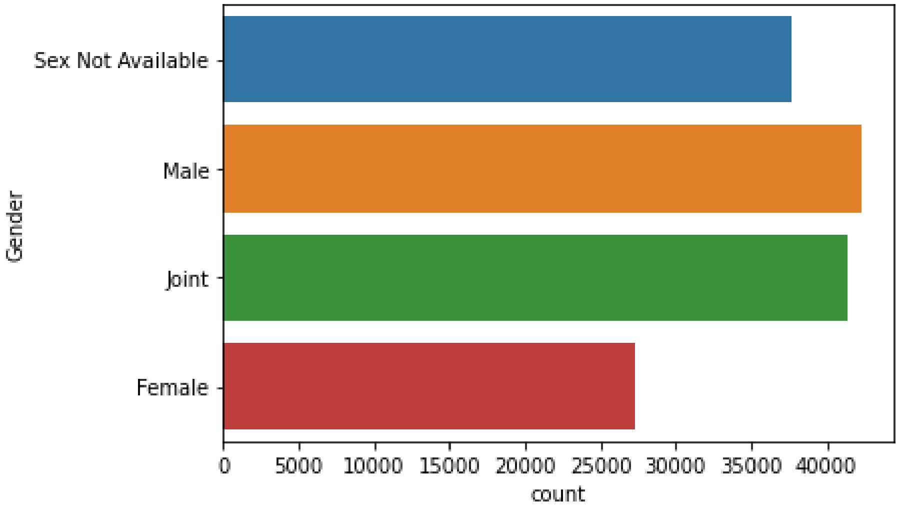
```
Target feature ['Status']
Quant features: ['loan_amount', 'rate_of_interest', 'Interest_rate_spread', 'Upfront_charges', 'property_value', 'income', 'Credit_Score',
Features for dummy encoding ['loan_limit', 'Gender', 'approv_in_adv', 'loan_type', 'loan_purpose', 'Credit_Worthiness', 'open_credit', 'bu
Features for labels encoding ['credit_type', 'co-applicant_credit_type', 'term']
```

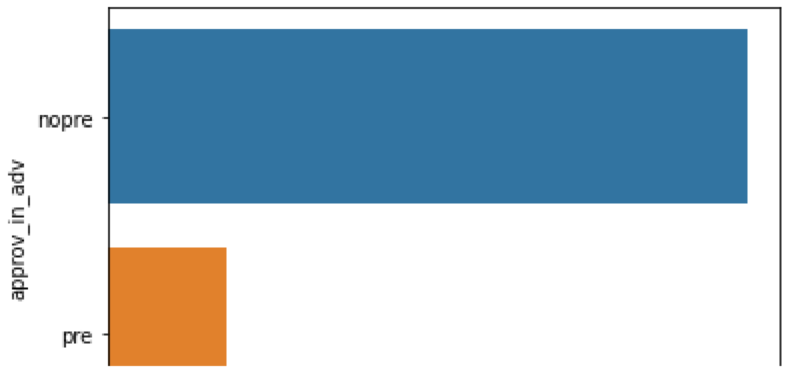
```
# Assess skewness of quants
df[quants].skew()
skew_cols = []
for col in quants:
    if (df[col].skew() > 1.0) or (df[col].skew() < -1):
        skew_cols.append(col)
print("Features requiring skewness correction: ",skew_cols)
```

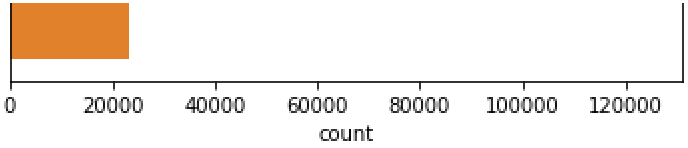
```
Features requiring skewness correction: ['loan_amount', 'Upfront_charges', 'property_value', 'income', 'LTV']
```

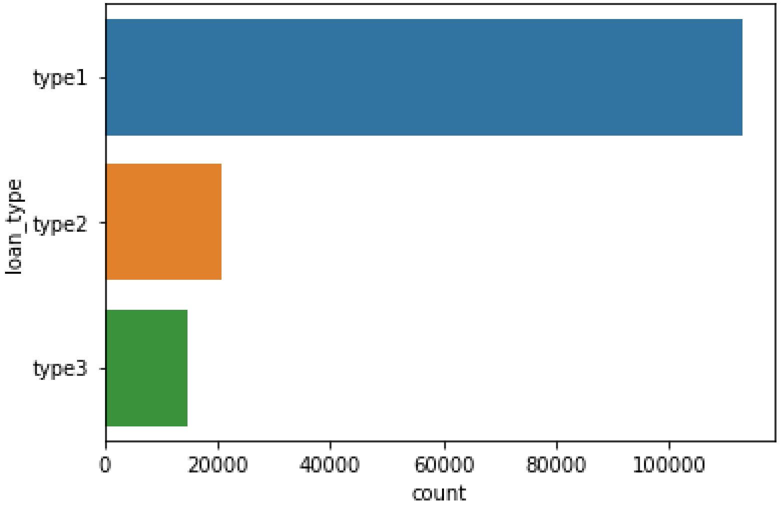
```
# Bar chart dummies
for col in dummies:
    sns.countplot(data=df,y=col)
    plt.show()
# Bar chart labels
for col in labels:
    sns.countplot(data=df,y=col)
```

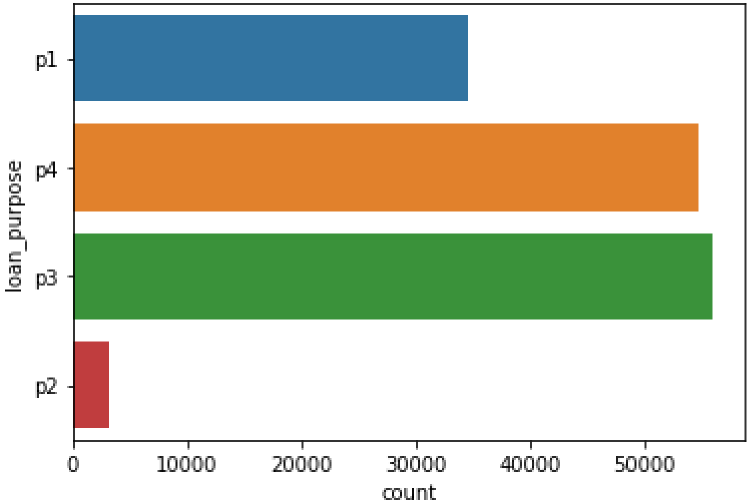

cf
ncf
loan_limit
0
20000
40000
60000
80000
100000
120000
140000
count


Sex Not Available
Male
Joint
Female
Gender
0
5000
10000
15000
20000
25000
30000
35000
40000
count

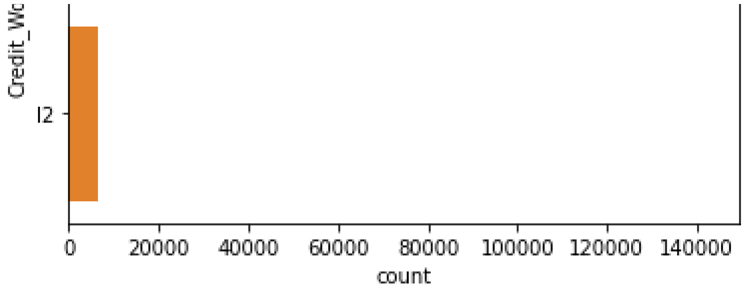

nopre
pre
approv_in_adv

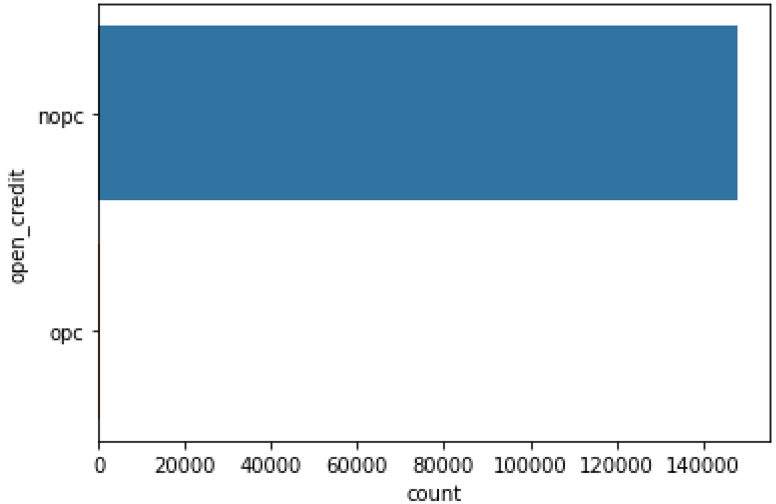

0
20000
40000
60000
80000
100000
120000
count

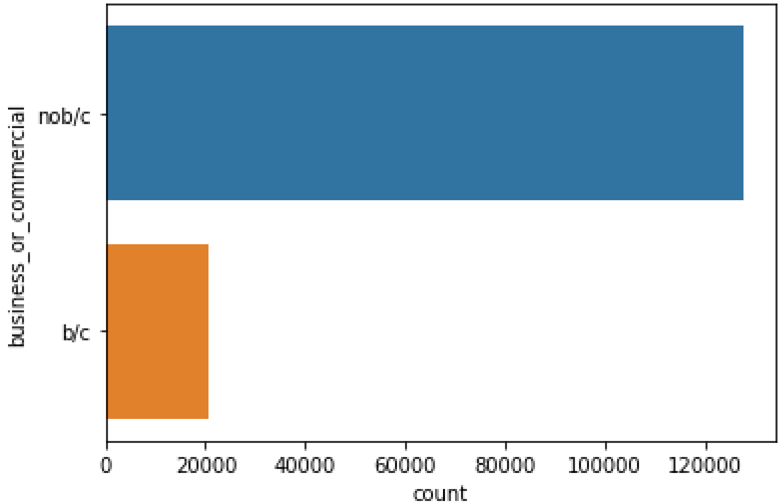

loan_type
type1
type2
type3
0
20000
40000
60000
80000
100000
count

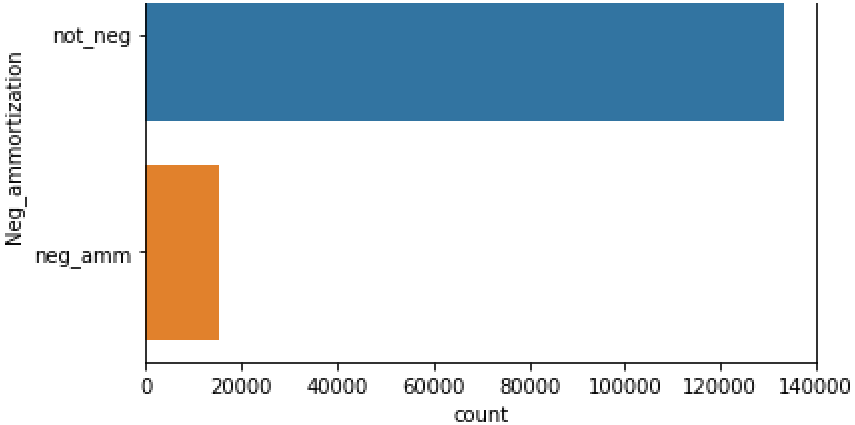

loan_purpose
p1
p4
p3
p2
0
10000
20000
30000
40000
50000
count


l1

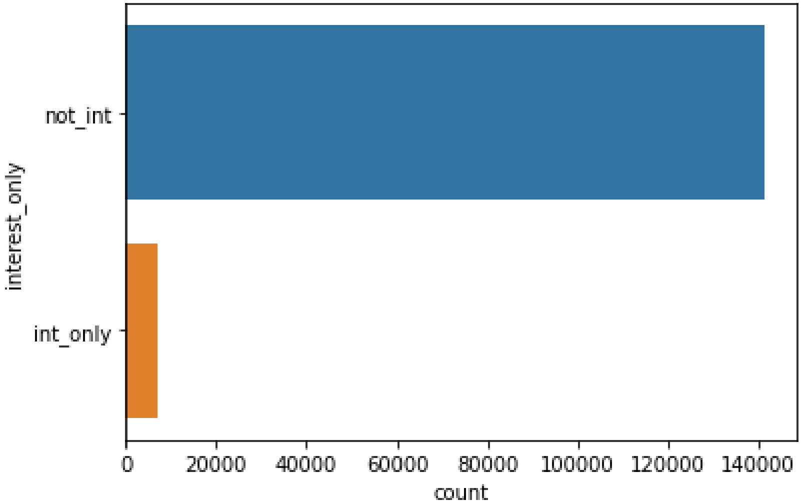

Credit_Wo
l2
0
20000
40000
60000
80000
100000
120000
140000
count


open_credit
nopc
opc
0
20000
40000
60000
80000
100000
120000
140000
count

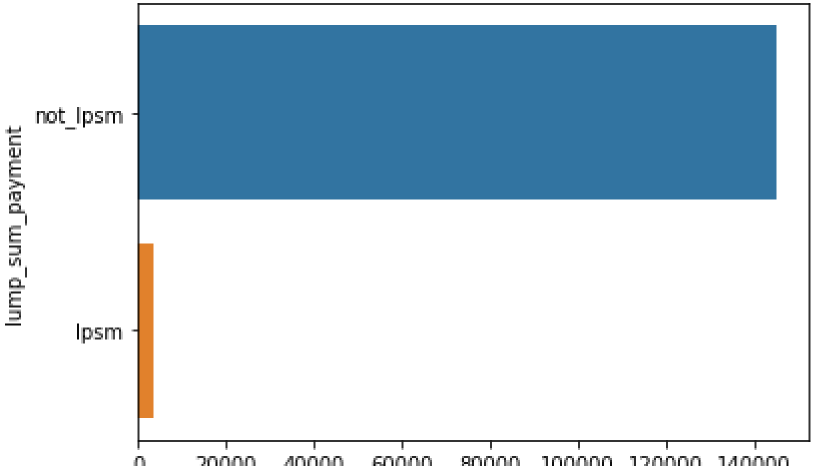

business_or_commercial
nob/c
b/c
0
20000
40000
60000
80000
100000
120000
count



Neg_ammortization
not_neg
neg_amm
0
20000
40000
60000
80000
100000
120000
140000
count

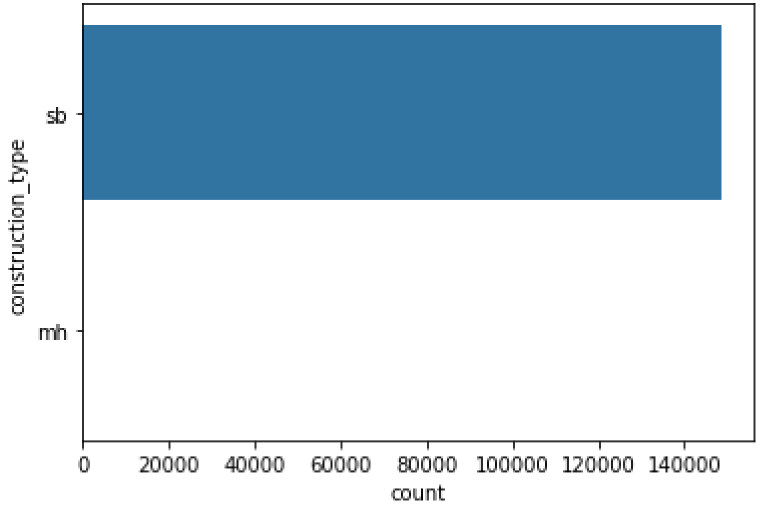


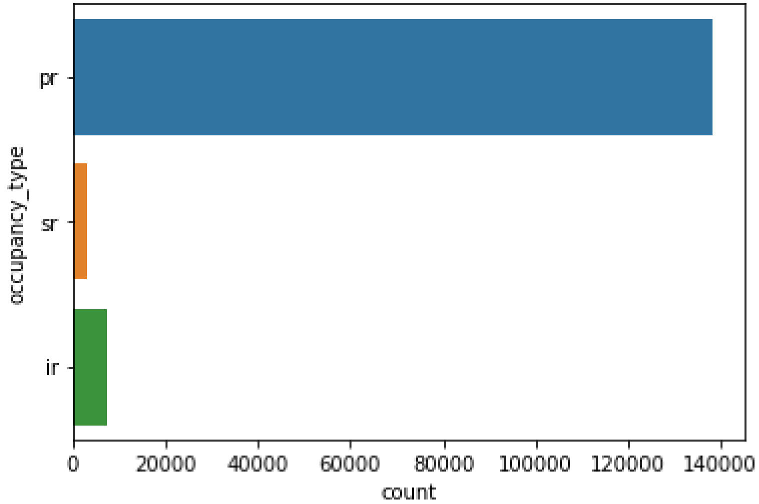
interest_only
not_int
int_only
0
20000
40000
60000
80000
100000
120000
140000
count

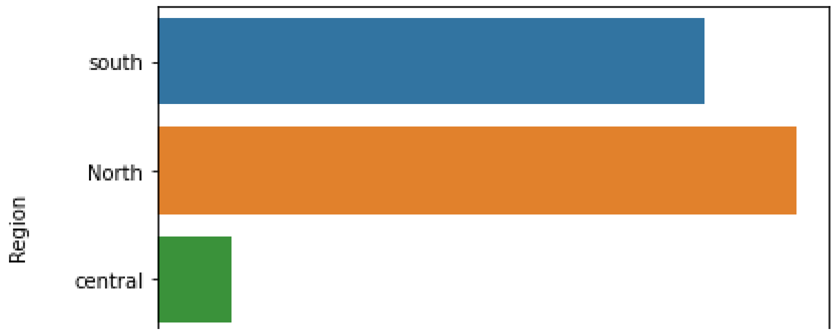


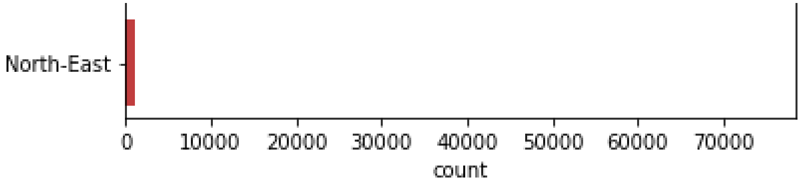
lump_sum_payment
not_lpsm
lpsm

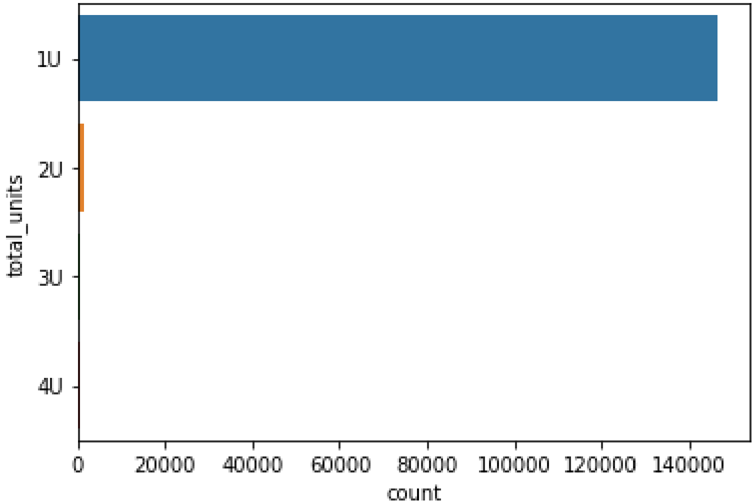

count

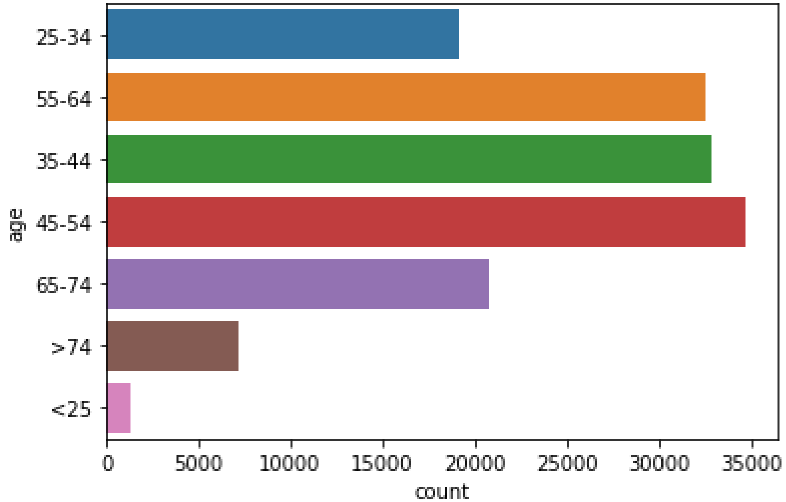

construction_type
sb
mh
0 20000 40000 60000 80000 100000 120000 140000
count


occupancy_type
pr
sr
ir
0 20000 40000 60000 80000 100000 120000 140000
count

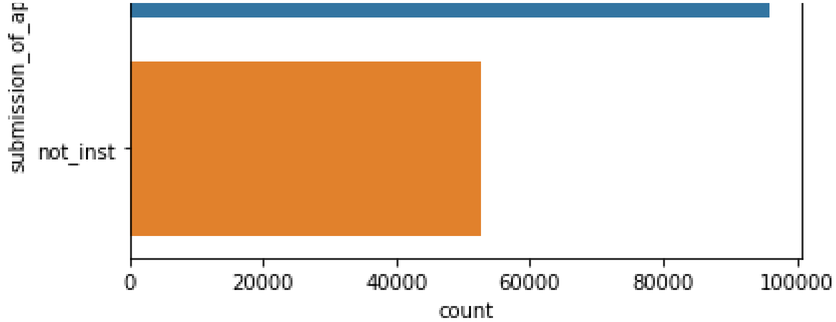

Region
south
North
central


North-East
0
10000
20000
30000
40000
50000
60000
70000
count

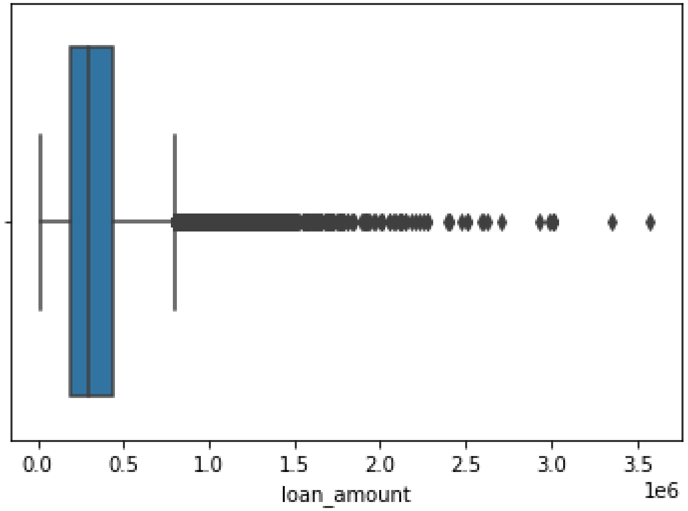

1U
2U
3U
4U
total_units
0
20000
40000
60000
80000
100000
120000
140000
count

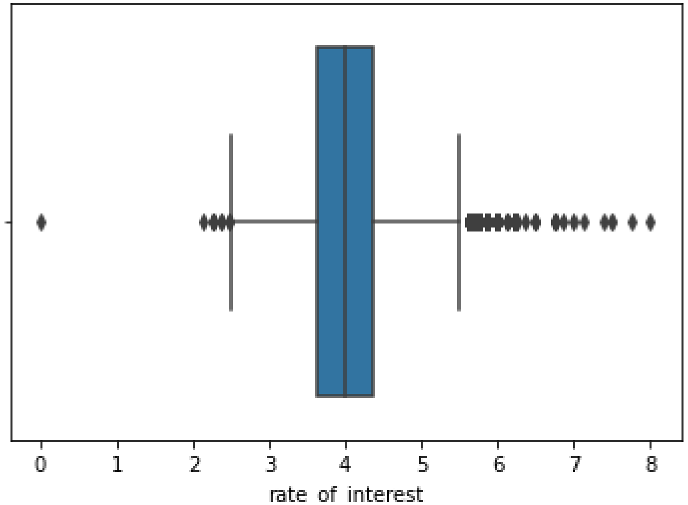

25-34
55-64
35-44
45-54
65-74
>74
<25
age
0
5000
10000
15000
20000
25000
30000
35000
count

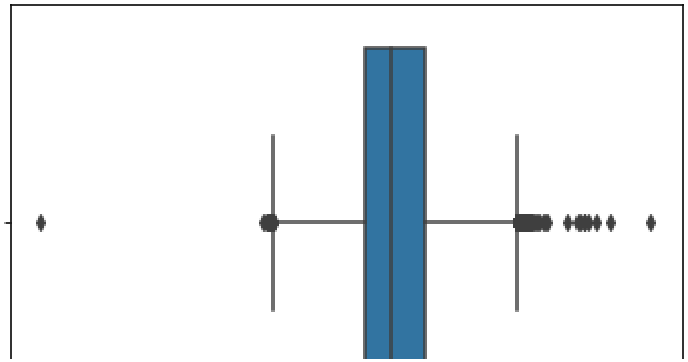

to_inst
plication

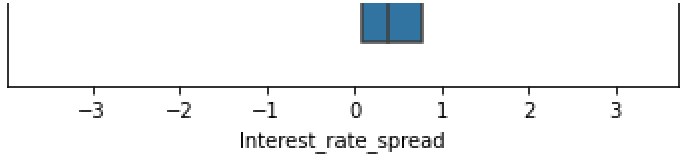


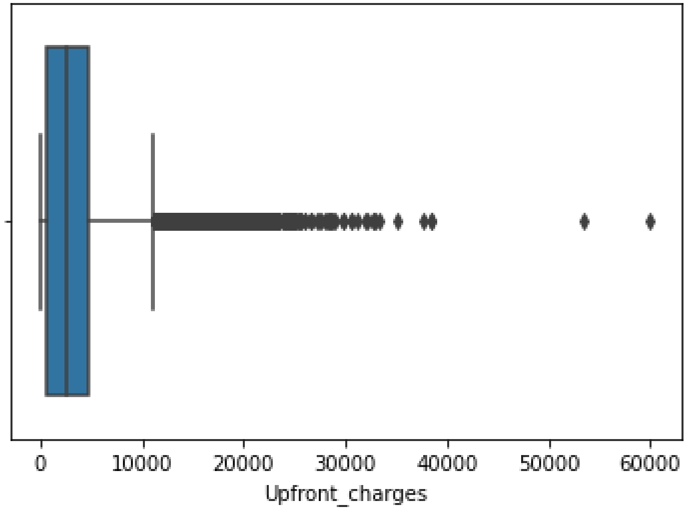

```
# Boxplot the quants to detect outliers
for col in quants:
        sns.boxplot(data=df,x=col)
        plt.show()
```

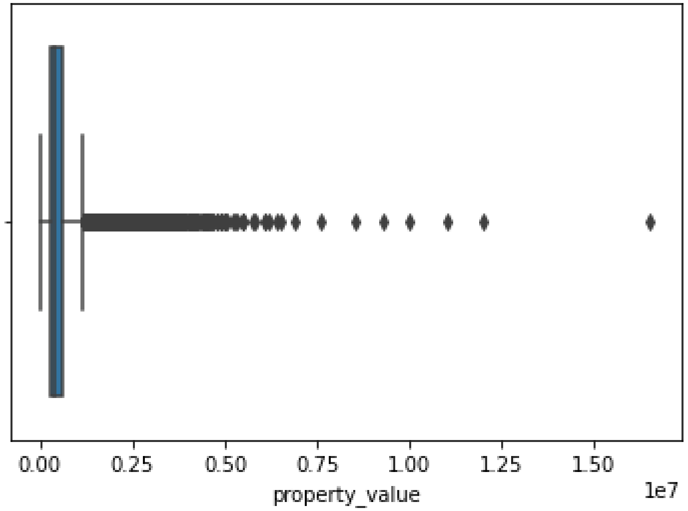

0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
loan_amount
1e6

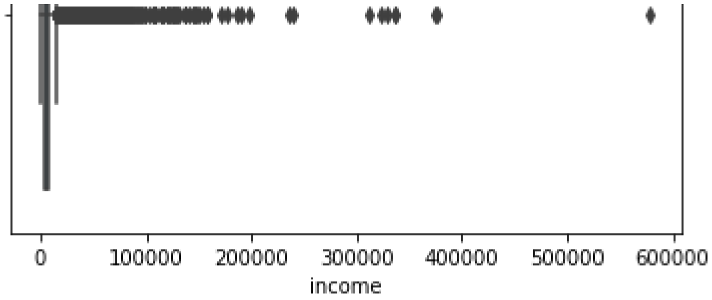

0
1
2
3
4
5
6
7
8
rate_of_interest

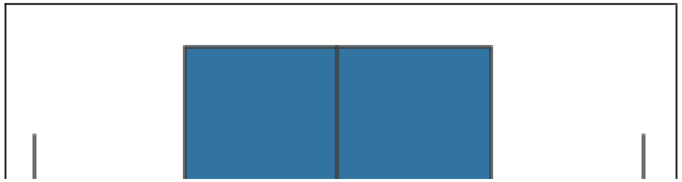



−3
−2
−1
0
1
2
3
Interest_rate_spread


0
10000
20000
30000
40000
50000
60000
Upfront_charges


0.00
0.25
0.50
0.75
1.00
1.25
1.50
property_value
1e7

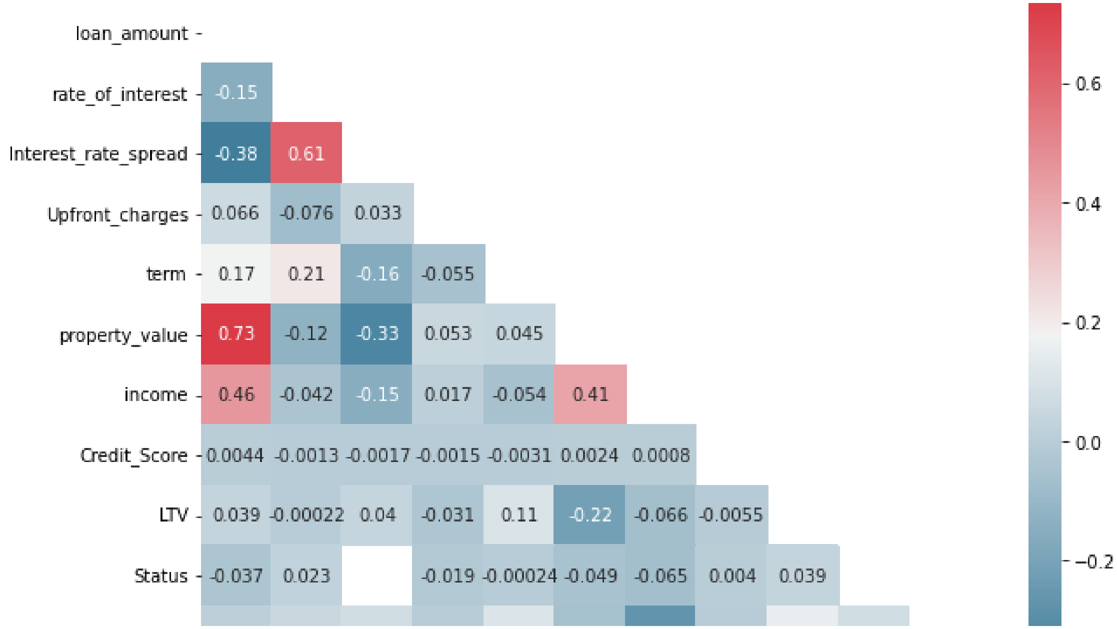




```
# Pairplot the quants
# if len(quants) > 0:
#       sns.pairplot(df[quants])
# else:
#       print("No quant variables")
```

```
#Correlation heatmap
corr = df.corr()
f, ax = plt.subplots(figsize=(10, 7))
mask = np.triu(np.ones_like(corr, dtype=bool))
cmap = sns.diverging_palette(230, 10, as_cmap=True)
sns.heatmap(corr, annot=True, mask = mask, cmap=cmap)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f07f463a650>
```




```
#Summary
print('SUMMARY\n')
print('1. Columns with NaNs:',columns_with_NaNs)
print('2. Instances that are  duplicates:\n ',duplicates_rows)
print('3. Quantitative features: ',quants)
print('4. Target feaure',target)
print('5. Original fetatures that are dummy encoded ',dummies)
print('6. Original features that are label encoded ',labels)
print("7. Quant features requiring skewness correction: ",skew_cols)
print('8. Review boxplots for possible outliers in quant features')
```

```
SUMMARY

1. Columns with NaNs: ['loan_limit', 'approv_in_adv', 'loan_purpose', 'rate_of_interest', 'Interest_rate_spread', 'Upfront_charges', 'term',
2. Instances that are  duplicates:
  Empty DataFrame
Columns: [loan_limit, Gender, approv_in_adv, loan_type, loan_purpose, Credit_Worthiness, open_credit, business_or_commercial, loan_amount,
Index: []
```

```
[0 rows x 32 columns]
3. Quantitative features:  ['loan_amount', 'rate_of_interest', 'Interest_rate_spread', 'Upfront_charges', 'property_value', 'income', 'Cred
4. Target feaure ['Status']
5. Original fetatures that are dummy encoded  ['loan_limit', 'Gender', 'approv_in_adv', 'loan_type', 'loan_purpose', 'Credit_Worthiness', '
6. Original features that are label encoded  ['credit_type', 'co-applicant_credit_type', 'term']
7. Quant features requiring skewness correction:  ['loan_amount', 'Upfront_charges', 'property_value', 'income', 'LTV']
8. Review boxplots for possible outliers in quant features
```

Pre-Processing

```
# replacing missing values

df['rate_of_interest'] = df['rate_of_interest'].fillna(df['rate_of_interest'].median())
df['Interest_rate_spread'] = df['Interest_rate_spread'].fillna(df['Interest_rate_spread'].median())
df['Upfront_charges'] = df['Upfront_charges'].fillna(df['Upfront_charges'].median())
df['term'] = df['term'].fillna(df['term'].median())
df['property_value'] = df['property_value'].fillna(df['property_value'].median())
df['income'] = df['income'].fillna(df['income'].median())
df['LTV'] = df['LTV'].fillna(df['LTV'].median())
df['dtir1'] = df['dtir1'].fillna(df['dtir1'].median())

df.isnull().sum()
```

```
loan_limit                 3344
Gender                        0
approv_in_adv               908
loan_type                     0
loan_purpose                134
Credit_Worthiness             0
open_credit                   0
business_or_commercial        0
loan_amount                   0
rate_of_interest              0
Interest_rate_spread          0
Upfront_charges               0
```

```
term                           0
Neg_ammortization            121
interest_only                  0
lump_sum_payment               0
property_value                 0
construction_type              0
occupancy_type                 0
Secured_by                     0
total_units                    0
income                         0
credit_type                    0
Credit_Score                   0
co-applicant_credit_type       0
age                          200
submission_of_application    200
LTV                            0
Region                         0
Security_Type                  0
Status                         0
dtir1                          0
dtype: int64
```

```
df.dropna(how='any',inplace=True)
df.isnull().sum()
```

```
loan_limit                   0
Gender                       0
approv_in_adv                0
loan_type                    0
loan_purpose                 0
Credit_Worthiness            0
open_credit                  0
business_or_commercial       0
loan_amount                  0
rate_of_interest             0
Interest_rate_spread         0
Upfront_charges              0
term                         0
Neg_ammortization            0
interest_only                0
```

```
lump_sum_payment             0
property_value               0
construction_type            0
occupancy_type               0
Secured_by                   0
total_units                  0
income                       0
credit_type                  0
Credit_Score                 0
co-applicant_credit_type     0
age                          0
submission_of_application    0
LTV                          0
Region                       0
Security_Type                0
Status                       0
dtir1                        0
dtype: int64
```

```
#dummy encoding
df = pd.get_dummies(data = df, columns = ['loan_limit', 'Gender', 'approv_in_adv', 'loan_type', 'loan_purpose','Credit_Worthiness', 'c


#label encoding
from sklearn import preprocessing
print(df.head(5),'\n\n\n')
print(df.info)

label_encoder = preprocessing.LabelEncoder()
for i in ['credit_type','co-applicant_credit_type','term']:
    df[i]= label_encoder.fit_transform(df[i])
    df[i].unique()
df.head(5)
```

```
   loan_amount  rate_of_interest  Interest_rate_spread  Upfront_charges  \
0       116500              3.99                0.3904          2596.45
1       206500              3.99                0.3904          2596.45
2       406500              4.56                0.2000           595.00
3       456500              4.25                0.6810          2596.45
4       696500              4.00                0.3042             0.00

   term  property_value   income credit_type  Credit_Score  \
0  360.0        118000.0   1740.0         EXP           758
1  360.0        418000.0   4980.0        EQUI           552
2  360.0        508000.0   9480.0         EXP           834
3  360.0        658000.0  11880.0         EXP           587
4  360.0        758000.0  10440.0        CRIF           602

  co-applicant_credit_type  ...  total_units_4U  age_35-44  age_45-54  \
0                      CIB  ...               0          0          0
1                      EXP  ...               0          0          0
2                      CIB  ...               0          1          0
3                      CIB  ...               0          0          1
4                      EXP  ...               0          0          0

   age_55-64  age_65-74  age_<25  age_>74  submission_of_application_to_inst  \
0          0          0        0        0                                  1
1          1          0        0        0                                  1
2          0          0        0        0                                  1
3          0          0        0        0                                  0
4          0          0        0        0                                  0

   Security_Type_direct  Secured_by_land
0                     1                0
1                     1                0
2                     1                0
3                     1                0
4                     1                0

[5 rows x 47 columns]
```

```
<bound method DataFrame.info of         loan_amount  rate_of_interest  Interest_r
0            116500             3.990              0.3904          2596.45
1            206500             3.990              0.3904          2596.45
2            406500             4.560              0.2000           595.00
3            456500             4.250              0.6810          2596.45
4            696500             4.000              0.3042             0.00
...             ...               ...                 ...               ...
148665       436500             3.125              0.2571          9960.00
148666       586500             5.190              0.8544             0.00
148667       446500             3.125              0.0816          1226.64
148668       196500             3.500              0.5824          4323.33
148669       406500             4.375              1.3871          6000.00

         term  property_value   income credit_type  Credit_Score  \
0       360.0        118000.0   1740.0         EXP           758
1       360.0        418000.0   4980.0        EQUI           552
2       360.0        508000.0   9480.0         EXP           834
3       360.0        658000.0  11880.0         EXP           587
4       360.0        758000.0  10440.0        CRIF           602
...       ...             ...      ...         ...           ...
148665  180.0        608000.0   7860.0         CIB           659
148666  360.0        788000.0   7140.0         CIB           569
148667  180.0        728000.0   6900.0         CIB           702
148668  180.0        278000.0   7140.0         EXP           737
148669  240.0        558000.0   7260.0         CIB           830

       co-applicant_credit_type  ...  total_units_4U  age_35-44  age_45-54  \
0                           CIB  ...               0          0          0
1                           EXP  ...               0          0          0
2                           CIB  ...               0          1          0
3                           CIB  ...               0          0          1
4                           EXP  ...               0          0          0
...                         ...  ...             ...        ...        ...
148665                      EXP  ...               0          0          0
148666                      CIB  ...               1          0          0
148667                      EXP  ...               0          0          1
148668                      EXP  ...               0          0          0
148669                      CIB  ...               0          0          1
```

```
        age_55-64  age_65-74  age_<25  age_>74  \
0               0          0        0        0
1               1          0        0        0
2               0          0        0        0
3               0          0        0        0
4               0          0        0        0
...           ...        ...      ...      ...
148665          1          0        0        0
148666          0          0        0        0
148667          0          0        0        0
148668          1          0        0        0
148669          0          0        0        0

        submission_of_application_to_inst  Security_Type_direct  \
0                                       1                     1
1                                       1                     1
2                                       1                     1
3                                       0                     1
4                                       0                     1
...                                   ...                   ...
148665                                  1                     1
148666                                  0                     1
148667                                  0                     1
148668                                  1                     1
148669                                  0                     1

        Secured_by_land
0                     0
1                     0
2                     0
3                     0
4                     0
...                 ...
148665                0
```

```
df
```

	loan_amount	rate_of_interest	Interest_rate_spread	Upfront_cl
0	116500	3.990	0.3904	2
1	206500	3.990	0.3904	2
2	406500	4.560	0.2000	
3	456500	4.250	0.6810	2
4	696500	4.000	0.3042	
...	...	...	...	
148665	436500	3.125	0.2571	9
148666	586500	5.190	0.8544	
148667	446500	3.125	0.0816	1
148668	196500	3.500	0.5824	4
148669	406500	4.375	1.3871	6

Skewness Correction

```
df.skew()
```

```
loan_amount                        1.677463
rate_of_interest                   0.531245
Interest_rate_spread               0.401238
Upfront_charges                    2.194068
term                              -2.157635
property_value                     4.896602
income                            18.143188
credit_type                        0.314882
Credit_Score                       0.005893
co-applicant_credit_type           0.001792
LTV                              126.471061
Status                             1.186073
dtir1                             -0.662068
loan_limit_ncf                     3.439015
Gender_Joint                       0.984395
Gender_Male                        0.954088
Gender_Sex Not Available           1.138237
approv_in_adv_pre                  1.861391
loan_type_type2                    2.095348
loan_type_type3                    2.669823
loan_purpose_p2                    6.536983
loan_purpose_p3                    0.513088
loan_purpose_p4                    0.530107
Credit_Worthiness_l2               4.456148
open_credit_opc                   16.252358
business_or_commercial_nob/c      -2.095348
Neg_ammortization_not_neg         -2.668277
interest_only_not_int             -4.259515
lump_sum_payment_not_lpsm         -6.290712
construction_type_sb             -66.031904
occupancy_type_pr                 -3.370392
occupancy_type_sr                  6.677473
Region_North-East                 10.784287
Region_central                     3.766542
Region_south                       0.281978
total_units_2U                     9.877189
total_units_3U                    19.624091
total_units_4U                    21.730241
age_35-44                          1.345056
age_45-54                          1.256775
```

```
    age_55-64                              1.358048
    age_65-74                              2.075411
    age_<25                               10.401688
    age_>74                                4.202218
    submission_of_application_to_inst     -0.607476
    Security_Type_direct                 -66.031904
    Secured_by_land                       66.031904
    dtype: float64
```

```
# Code for skewness correction (see source below)
# Depending upon the characteritics of a feature (column), a log, Box-Cox or power transform is applied to normalize the dist

# -*- coding: utf-8 -*-
"""
Created on Sat Feb 23 14:42:46 2019
@author: DATAmadness
"""

##################################################
# A function that will accept a pandas dataframe
# and auto-transforms columns that exceeds threshold value
#  -  Offers choice between boxcox or log / exponential transformation
#  -  Automatically handles negative values
#  -  Auto recognizes positive /negative skewness

# Further documentation available here:
# https://datamadness.github.io/Skewness_Auto_Transform

def skew_autotransform(DF, include = None, exclude = None, plot = False, threshold = 1, exp = False):

    #Get list of column names that should be processed based on input parameters
    if include is None and exclude is None:
        colnames = DF.columns.values
    elif include is not None:
        colnames = include
    elif exclude is not None:
        colnames = [item for item in list(DF.columns.values) if item not in exclude]
```

```
    else:
        print('No columns to process!')

    #Helper function that checks if all values are positive
    def make_positive(series):
        minimum = np.amin(series)
        #If minimum is negative, offset all values by a constant to move all values to positive teritory
        if minimum <= 0:
            series = series + abs(minimum) + 0.01
        return series


    #Go through desired columns in DataFrame
    for col in colnames:
        #Get column skewness
        skew = DF[col].skew()
        transformed = True

        if plot:
            #Prep the plot of original data
            sns.set_style("darkgrid")
            sns.set_palette("Blues_r")
            fig, axes = plt.subplots(1, 2, figsize=(10, 5))
            #ax1 = sns.distplot(DF[col], ax=axes[0])
            ax1 = sns.histplot(DF[col], ax=axes[0], color="blue", label="100% Equities", kde=True, stat="density", linewidth=
            ax1.set(xlabel='Original ' + str(col))

        #If skewness is larger than threshold and positively skewed; If yes, apply appropriate transformation
        if abs(skew) > threshold and skew > 0:
            skewType = 'positive'
            #Make sure all values are positive
            DF[col] = make_positive(DF[col])

            if exp:
                #Apply log transformation
                DF[col] = DF[col].apply(math.log)
            else:
```

```
                #Apply boxcox transformation
                DF[col] = ss.boxcox(DF[col])[0]
            skew_new = DF[col].skew()

        elif abs(skew) > threshold and skew < 0:
            skewType = 'negative'
            #Make sure all values are positive
            DF[col] = make_positive(DF[col])

            if exp:
                #Apply exp transformation
                DF[col] = DF[col].pow(10)
            else:
                #Apply boxcox transformation
                DF[col] = ss.boxcox(DF[col])[0]
            skew_new = DF[col].skew()

        else:
            #Flag if no transformation was performed
            transformed = False
            skew_new = skew

        #Compare before and after if plot is True
        if plot:
            print('\n ------------------------------------------------------')
            if transformed:
                print('\n %r had %r skewness of %2.2f' %(col, skewType, skew))
                print('\n Transformation yielded skewness of %2.2f' %(skew_new))
                sns.set_palette("Paired")
                #ax2 = sns.distplot(DF[col], ax=axes[1], color = 'r')
                ax2 = sns.histplot(DF[col], ax=axes[1], color="red", label="100% Equities", kde=True, stat="density", lin
                ax2.set(xlabel='Transformed ' + str(col))
                plt.show()
            else:
                print('\n NO TRANSFORMATION APPLIED FOR %r . Skewness = %2.2f' %(col, skew))
                #ax2 = sns.distplot(DF[col], ax=axes[1])
                ax2 = sns.histplot(DF[col], ax=axes[1], color="blue", label="100% Equities", kde=True, stat="density", li
```

```
                        ax2.set(xlabel='NO TRANSFORM ' + str(col))
                        plt.show()


        return DF

df = skew_autotransform(df.copy(deep=True), include=['loan_amount', 'Upfront_charges', 'property_value', 'income', 'LTV'], plot = False,
```

Tukey

```
# X = df.drop(['Status'],axis=1)
# y = df['Status']
cols = X.columns
def tukey_rule(data, col):
        Q1 = data[col].quantile(0.25)
        Q3 = data[col].quantile(0.75)
        IQR = Q3 - Q1
        upper_lim = data[col].quantile(0.5) + 2 * IQR
        lower_lim = data[col].quantile(0.5) - 2 * IQR
        outliers = []
        for index, x in enumerate(data[col]):
                if x < lower_lim or x >= upper_lim:
                        outliers.append(index)
        return outliers

# Identify outliers
for i in cols:
    outliers_Tukey = tukey_rule(X,i)
    print("Column ",i,": ",outliers_Tukey)

# Windsorize X and check the results
print("Descriptive Statistics Before", X.describe())
X_winsorized = X.copy(deep=True)
for i in cols:
```

```
        X_winsorized[i] = winsorize(X[i], limits=(0.05, 0.05))
    print("Descriptive Statistics After", X_winsorized.describe())
    for i in cols:
        print("Column ",i)
        ax = sns.boxplot(data=X_winsorized[i], orient="h", palette="Set2")
        plt.show()
```

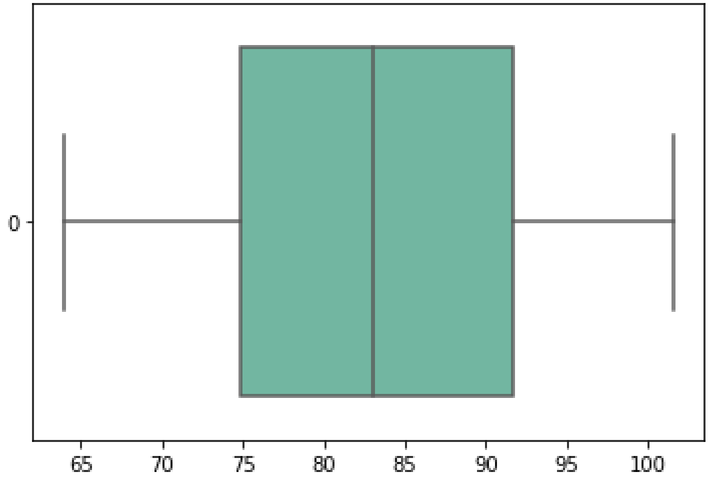
```
Column  loan_amount :  [132, 196, 254, 316, 319, 691, 1487, 1650, 1656, 2162, 225
Column  rate_of_interest :  [25, 32, 37, 45, 126, 142, 143, 197, 198, 254, 272, 2
Column  Interest_rate_spread :  [28, 29, 32, 45, 60, 91, 94, 111, 128, 129, 142,
Column  Upfront_charges :  [4, 12, 23, 28, 31, 51, 57, 58, 59, 60, 71, 76, 77, 83
Column  term :  [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18
Column  property_value :  [85, 87, 91, 165, 196, 254, 264, 294, 316, 319, 342, 41
Column  income :  [39, 51, 132, 138, 139, 157, 178, 199, 282, 288, 316, 319, 329,
Column  credit_type :  []
Column  Credit_Score :  []
Column  co-applicant_credit_type :  []
Column  LTV :  [48, 52, 65, 76, 85, 87, 100, 102, 107, 123, 131, 142, 167, 173, 1
Column  dtir1 :  [19, 53, 100, 114, 121, 132, 157, 161, 185, 199, 208, 299, 307,
Column  loan_limit_ncf :  [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,
Column  Gender_Joint :  []
Column  Gender_Male :  []
IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)

Column  Region_south :  []
Column  total_units_2U :  [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,
Column  total_units_3U :  IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)

Descriptive Statistics Before          loan_amount  rate_of_interest  Interest_ra
count  143983.000000      143983.000000           143983.000000     143983.000000
```

```
count  143983.000000    143983.000000          143983.000000   143983.000000
mean       83.061267         4.027587               0.426660       35.342695
std        11.825135         0.489740               0.446424       18.389425
min        39.213260         0.000000              -3.638000       -2.332919
25%        74.818454         3.750000               0.178100       30.055841
50%        83.084645         3.990000               0.390400       39.321796
75%        91.643321         4.250000               0.617100       45.564845
max       155.220305         8.000000               3.357000      119.412162

                term  property_value         income    credit_type  \
count  143983.000000   143983.000000  143983.000000  143983.000000
mean       21.755846       15.575086      56.295697       1.333532
std         5.247942        0.837380      14.140876       1.195069
min         0.000000       10.212400      -2.294624       0.000000
25%        24.000000       15.053105      47.935553       0.000000
50%        24.000000       15.584606      55.636864       1.000000
75%        24.000000       16.100771      63.514736       3.000000
max        24.000000       21.136277     288.230991       3.000000

        Credit_Score  co-applicant_credit_type  ...  total_units_4U  \
count  143983.000000             143983.000000  ...   143983.000000
mean      699.692672                  0.499552  ...        0.002104
std       115.891056                  0.500002  ...        0.045826
min       500.000000                  0.000000  ...        0.000000
25%       599.000000                  0.000000  ...        0.000000
50%       699.000000                  0.000000  ...        0.000000
75%       800.000000                  1.000000  ...        0.000000
max       900.000000                  1.000000  ...        1.000000

           age_35-44      age_45-54      age_55-64      age_65-74  \
count  143983.000000  143983.000000  143983.000000  143983.000000
mean        0.220971       0.233972       0.219123       0.139968
std         0.414902       0.423356       0.413654       0.346955
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

             age_<25        age_>74  submission_of_application_to_inst  \
```

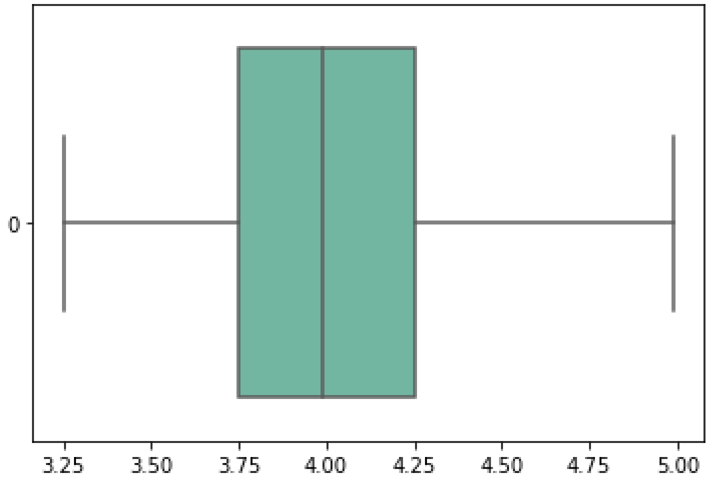
```
            age_<25        age_>74  submission_of_application_to_inst  \
count  143983.000000  143983.000000                      143983.000000
mean        0.008994       0.048527                           0.645312
std         0.094410       0.214877                           0.478420
min         0.000000       0.000000                           0.000000
25%         0.000000       0.000000                           0.000000
50%         0.000000       0.000000                           1.000000
75%         0.000000       0.000000                           1.000000
max         1.000000       1.000000                           1.000000

       Security_Type_direct  Secured_by_land
count         143983.000000    143983.000000
mean               0.999771         0.000229
std                0.015137         0.015137
min                0.000000         0.000000
25%                1.000000         0.000000
50%                1.000000         0.000000
75%                1.000000         0.000000
max                1.000000         1.000000

[8 rows x 46 columns]
Descriptive Statistics After          loan_amount  rate_of_interest  Interest_rat
count  143983.000000    143983.000000     143983.000000    143983.000000
mean       83.066978         4.027034          0.429421        35.016669
std        10.846304         0.437784          0.403301        17.837151
min        63.939746         3.250000         -0.251900        -2.332919
25%        74.818454         3.750000          0.178100        30.055841
50%        83.084645         3.990000          0.390400        39.321796
75%        91.643321         4.250000          0.617100        45.564845
max       101.587897         4.990000          1.313200        59.889538

                term  property_value         income    credit_type  \
count  143983.000000   143983.000000  143983.000000  143983.000000
mean       21.802761       15.570750      56.228515       1.333532
std         5.096575        0.729760      11.130680       1.195069
min         8.000000       14.208047      37.473771       0.000000
25%        24.000000       15.053105      47.935553       0.000000
50%        24.000000       15.584606      55.636864       1.000000
75%        24.000000       16.100771      63.514736       3.000000
max        24.000000       16.862642      78.882121       3.000000
```

```
        Credit_Score  co-applicant_credit_type  ...  total_units_4U  \
count  143983.000000             143983.000000  ...        143983.0
mean      699.694631                  0.499552  ...             0.0
std       114.330662                  0.500002  ...             0.0
min       519.000000                  0.000000  ...             0.0
25%       599.000000                  0.000000  ...             0.0
50%       699.000000                  0.000000  ...             0.0
75%       800.000000                  1.000000  ...             0.0
max       881.000000                  1.000000  ...             0.0

           age_35-44      age_45-54      age_55-64      age_65-74  age_<25  \
count  143983.000000  143983.000000  143983.000000  143983.000000 143983.0
mean        0.220971       0.233972       0.219123       0.139968      0.0
std         0.414902       0.423356       0.413654       0.346955      0.0
min         0.000000       0.000000       0.000000       0.000000      0.0
25%         0.000000       0.000000       0.000000       0.000000      0.0
50%         0.000000       0.000000       0.000000       0.000000      0.0
75%         0.000000       0.000000       0.000000       0.000000      0.0
max         1.000000       1.000000       1.000000       1.000000      0.0

       age_>74  submission_of_application_to_inst  Security_Type_direct  \
count 143983.0                      143983.000000              143983.0
mean       0.0                           0.645312                   1.0
std        0.0                           0.478420                   0.0
min        0.0                           0.000000                   1.0
25%        0.0                           0.000000                   1.0
50%        0.0                           1.000000                   1.0
75%        0.0                           1.000000                   1.0
max        0.0                           1.000000                   1.0

       Secured_by_land
count         143983.0
mean               0.0
std                0.0
min                0.0
25%                0.0
50%                0.0
75%                0.0
```

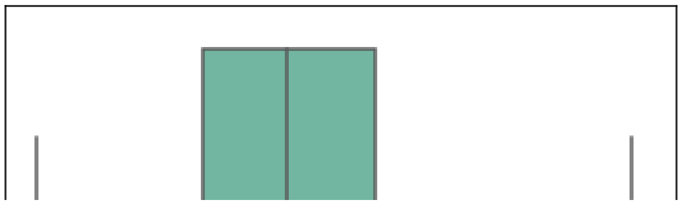
```
75%                 0.0
max                 0.0

[8 rows x 46 columns]
Column  loan_amount
```

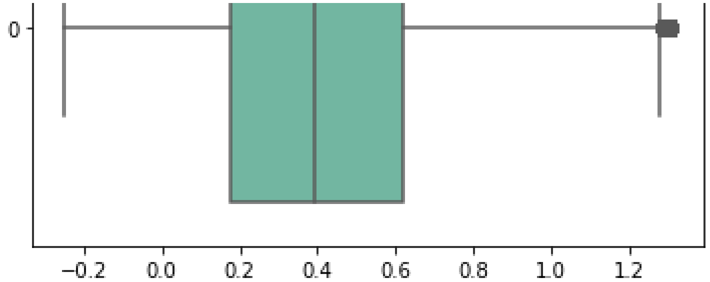



```
Column  rate_of_interest
```

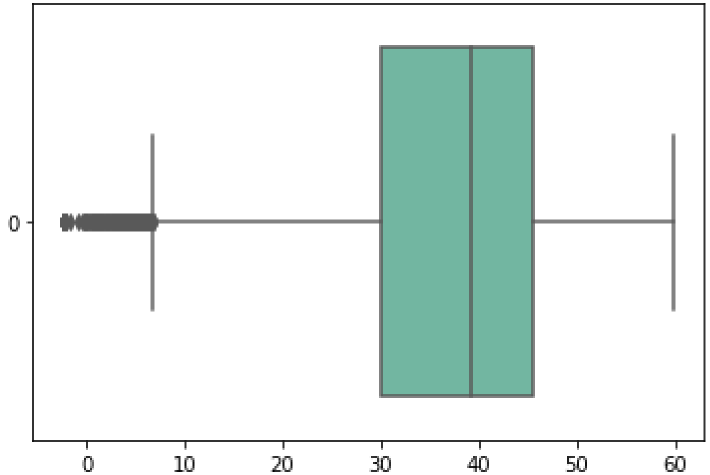



```
Column  Interest_rate_spread
```

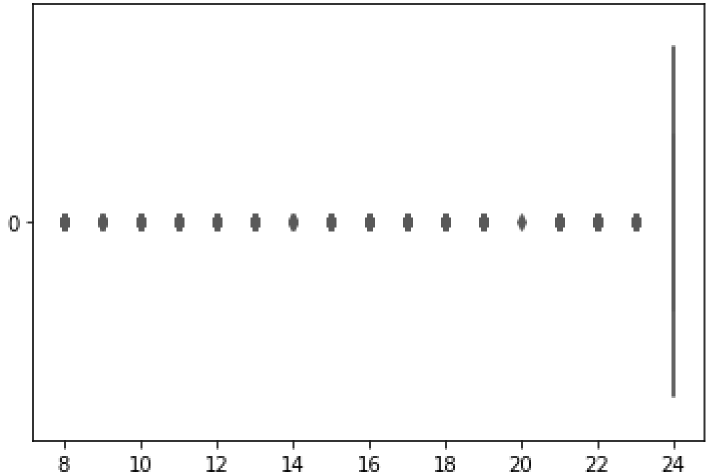




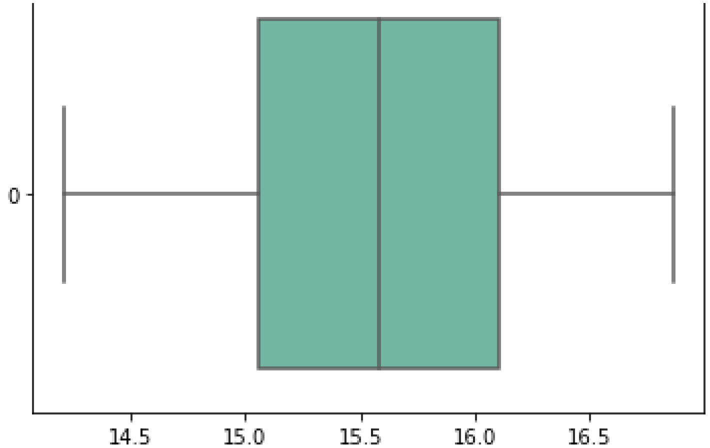
Column Upfront_charges



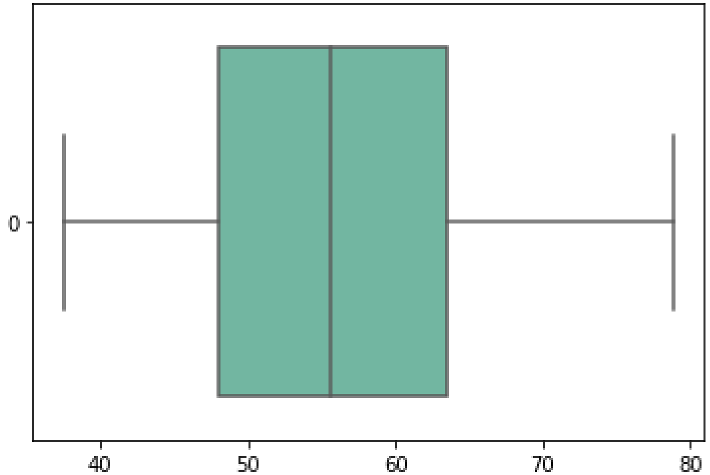
Column term



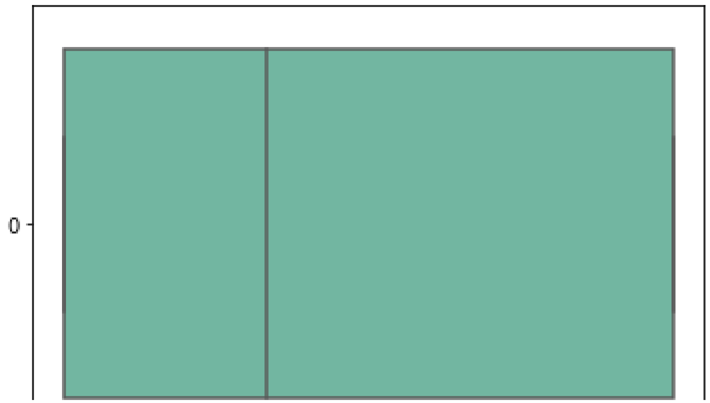
Column property_value

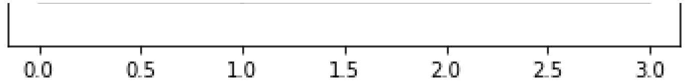


Column income

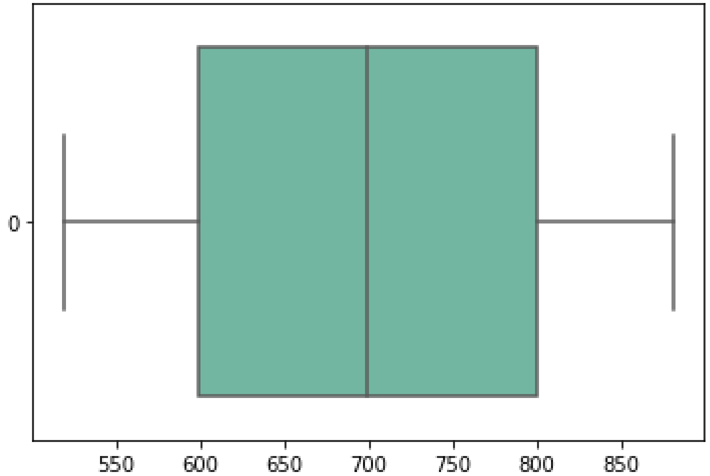


Column credit_type

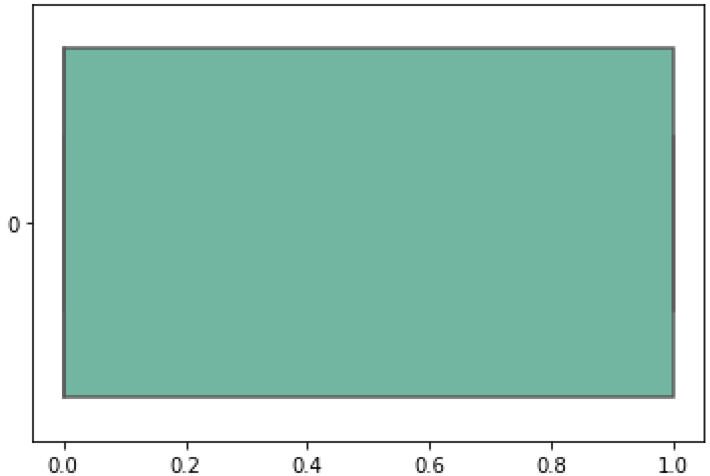




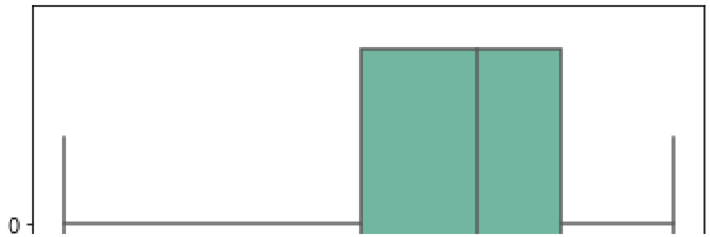
Column Credit_Score

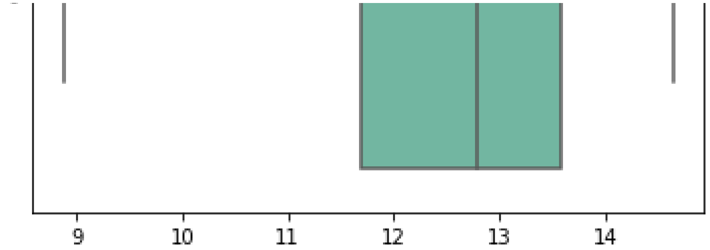


Column co-applicant_credit_type

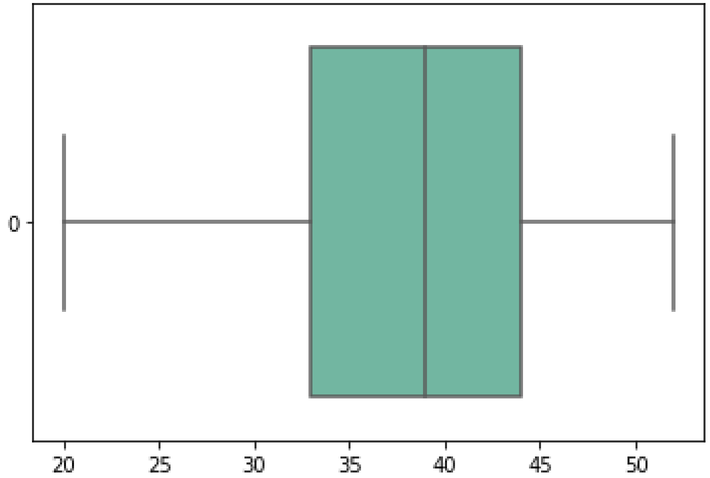


Column LTV

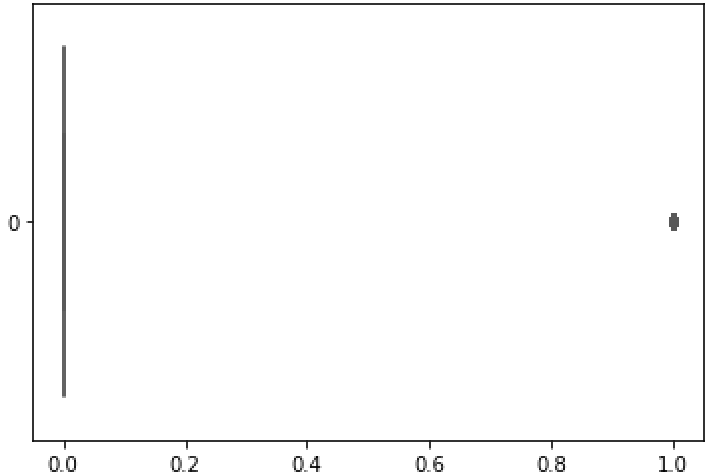




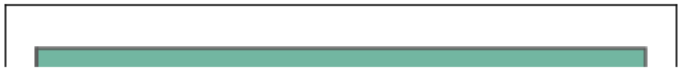
Column dtir1

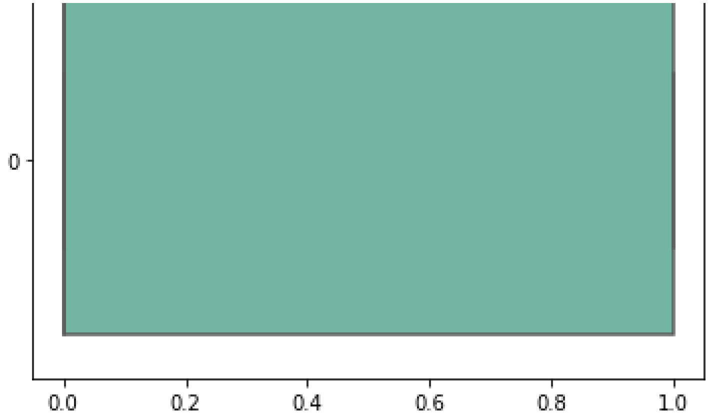


Column loan_limit_ncf

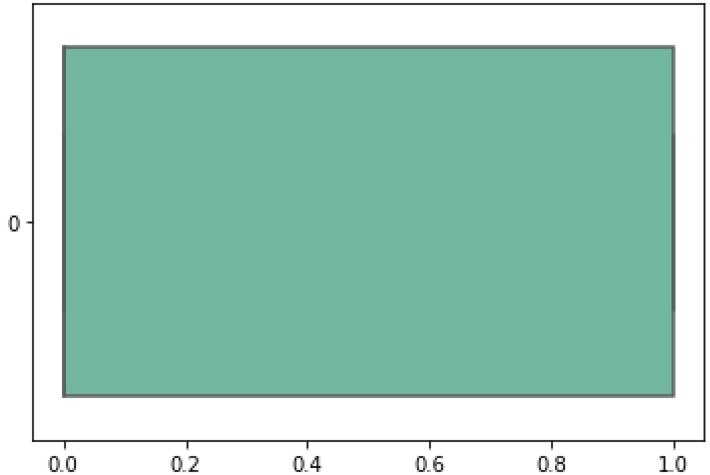


Column Gender_Joint



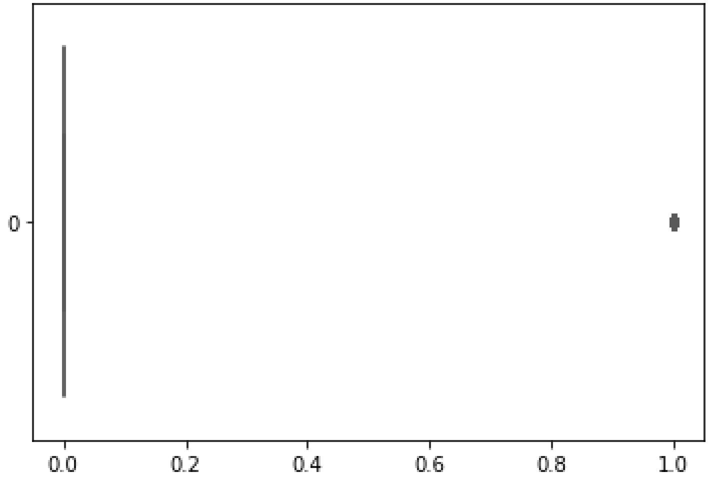


Column Gender_Male

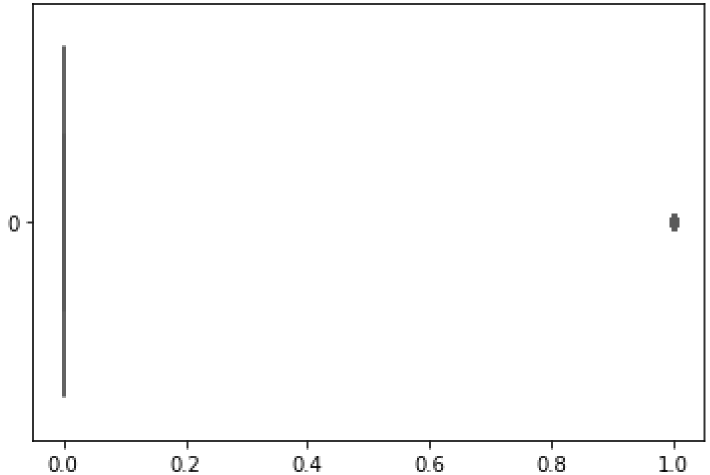


Column Gender_Sex Not Available

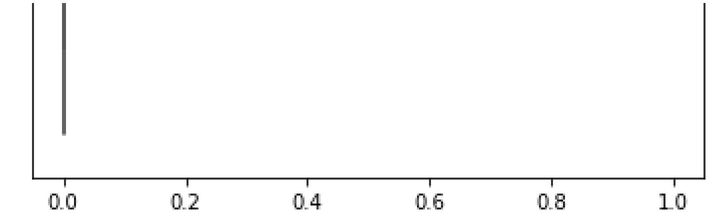
Column approv_in_adv_pre



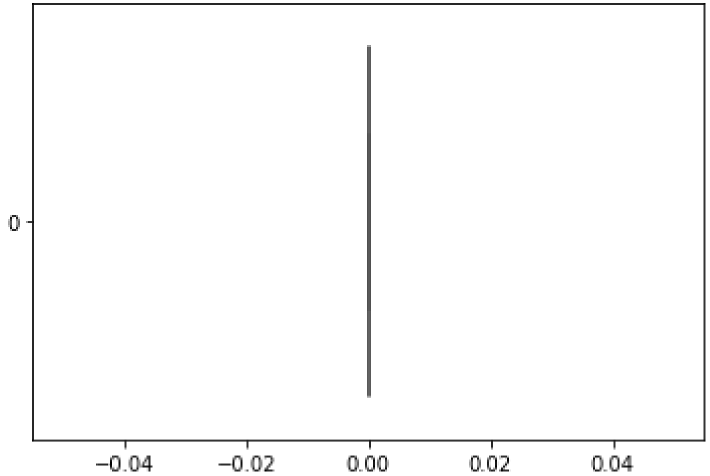
Column loan_type_type2



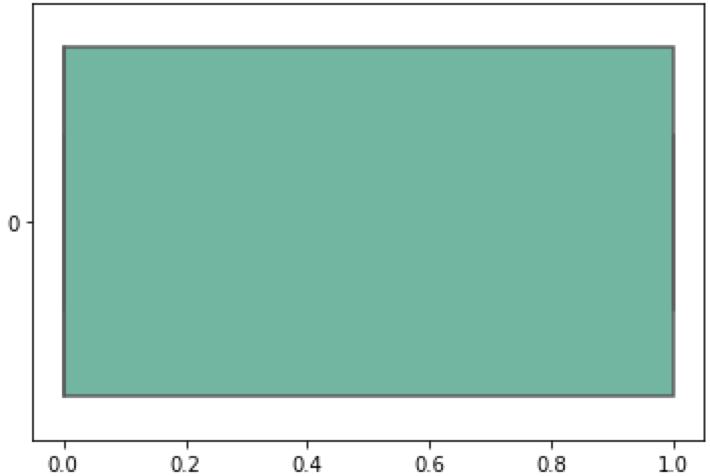
Column loan_type_type3



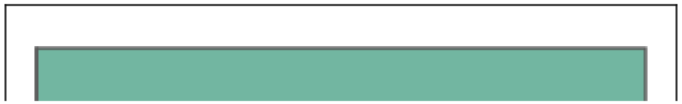
Column loan_purpose_p2

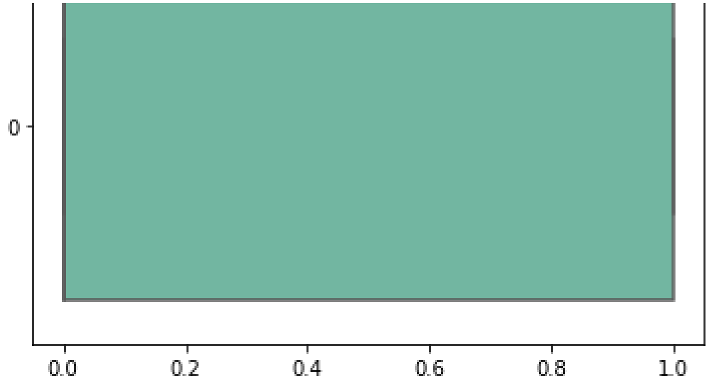


Column loan_purpose_p3

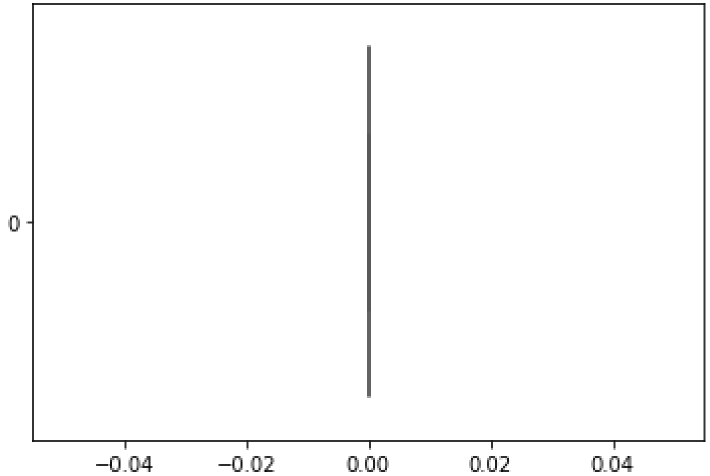


Column loan_purpose_p4

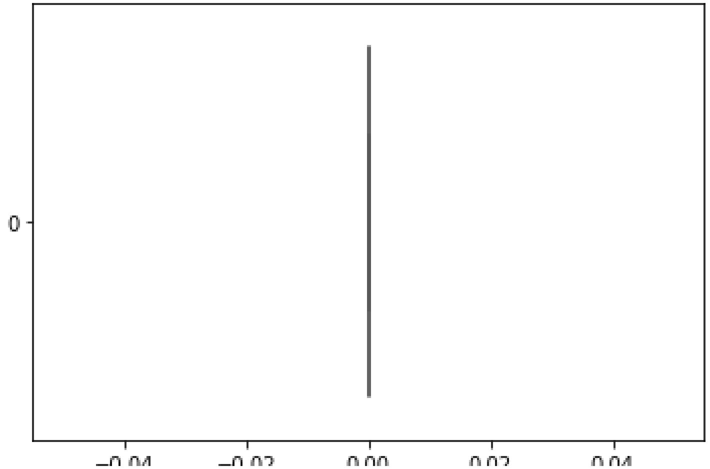




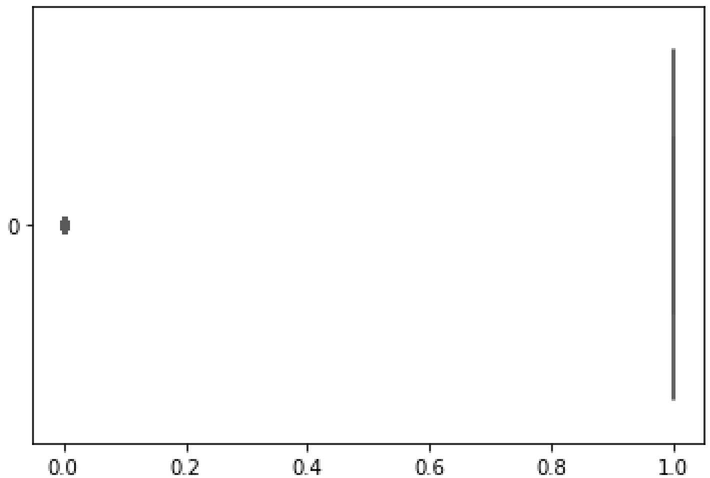
Column Credit_Worthiness_l2



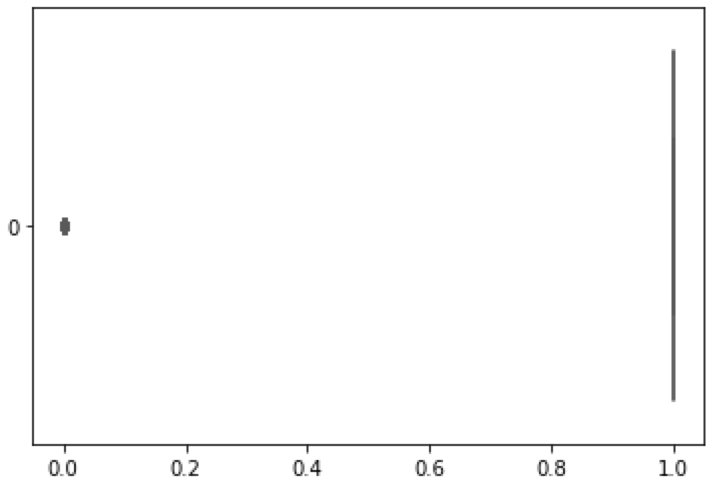
Column open_credit_opc



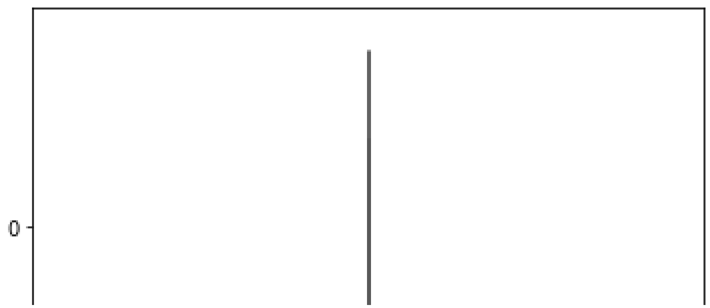
Column business_or_commercial_nob/c

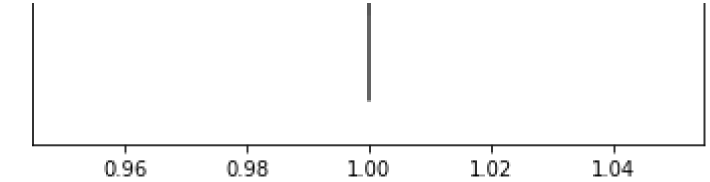


Column Neg_ammortization_not_neg

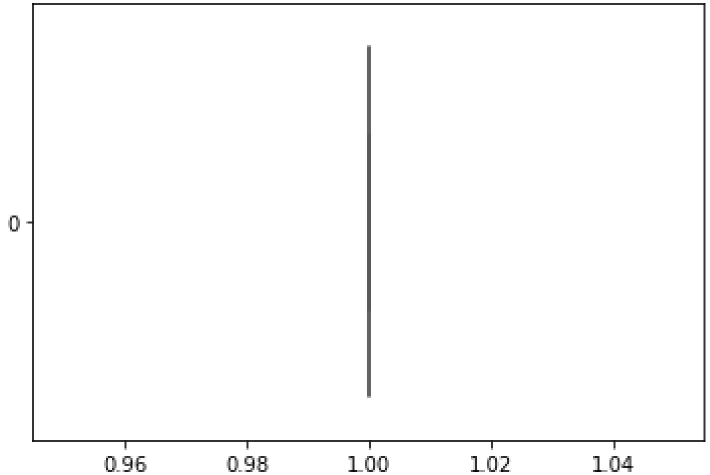


Column interest_only_not_int

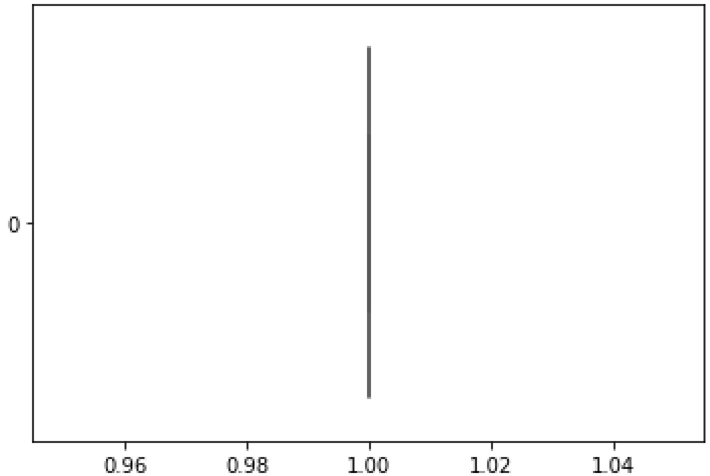




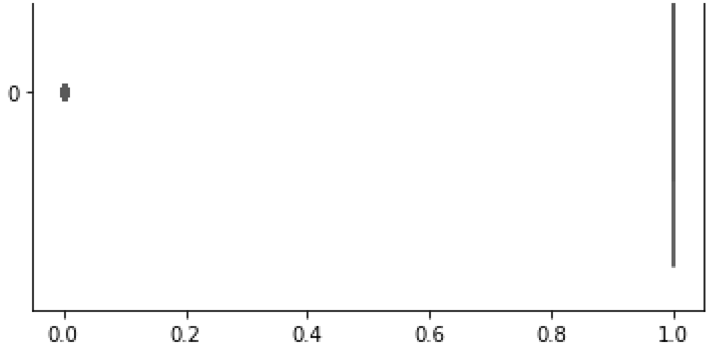
Column lump_sum_payment_not_lpsm



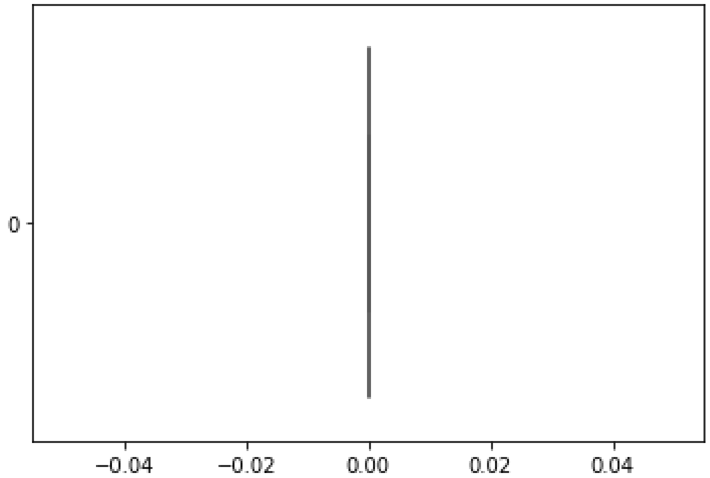
Column construction_type_sb



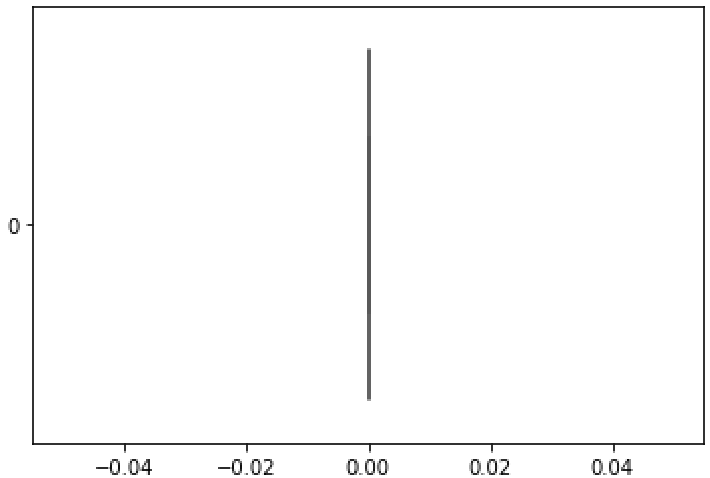
Column occupancy_type_pr



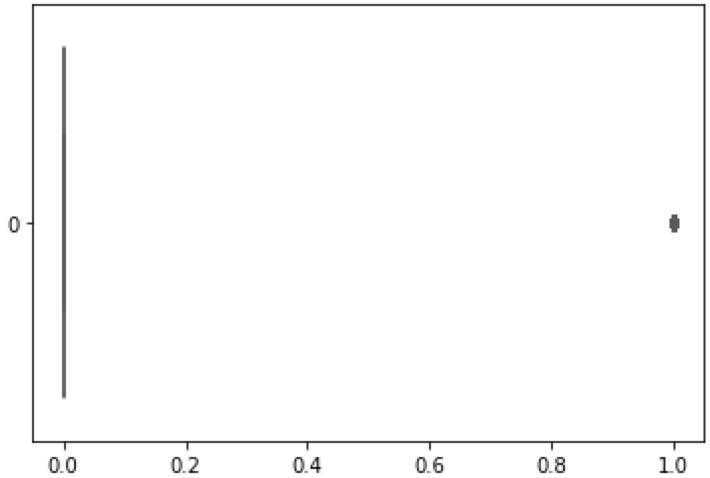
Column occupancy_type_sr



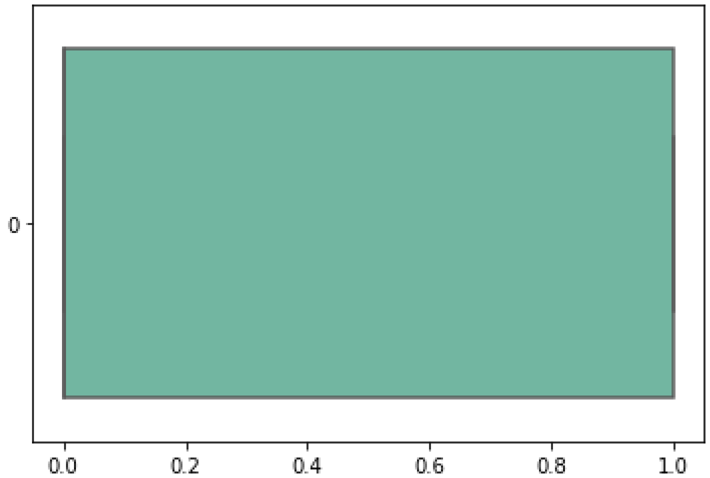
Column Region_North-East



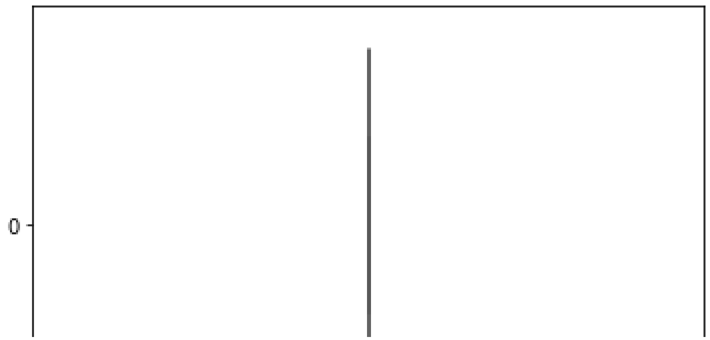
Column Region_central

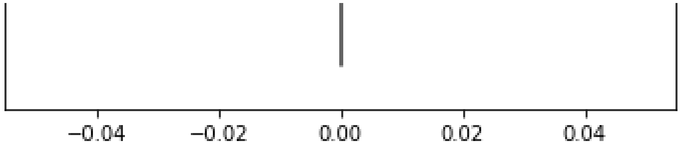


Column Region_south

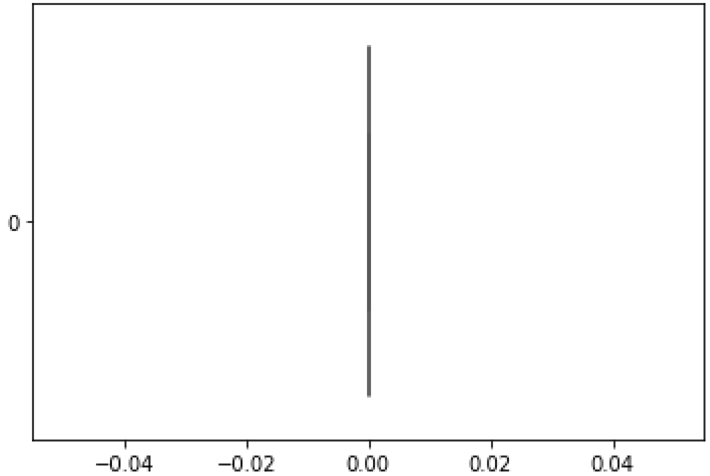


Column total_units_2U

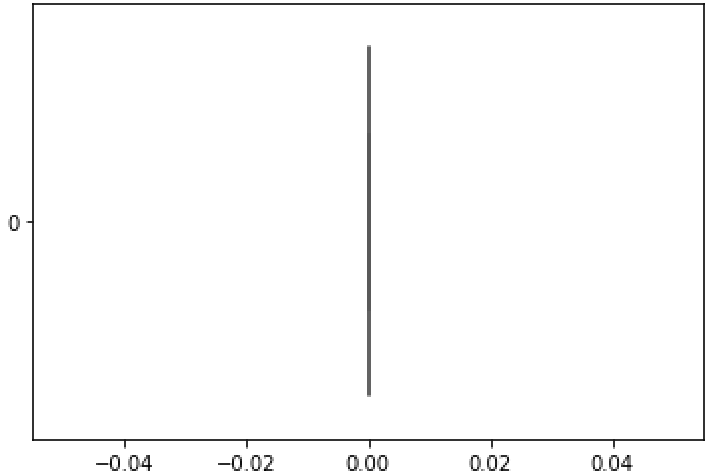




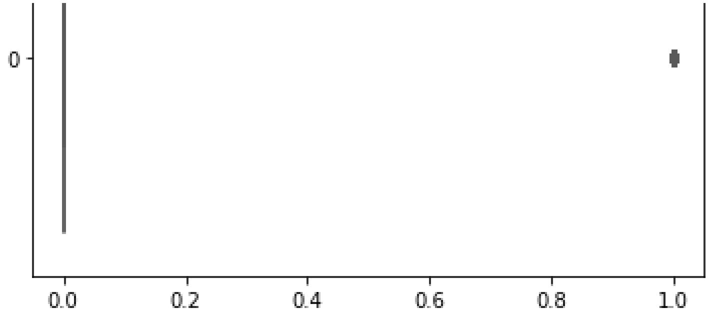
Column total_units_3U



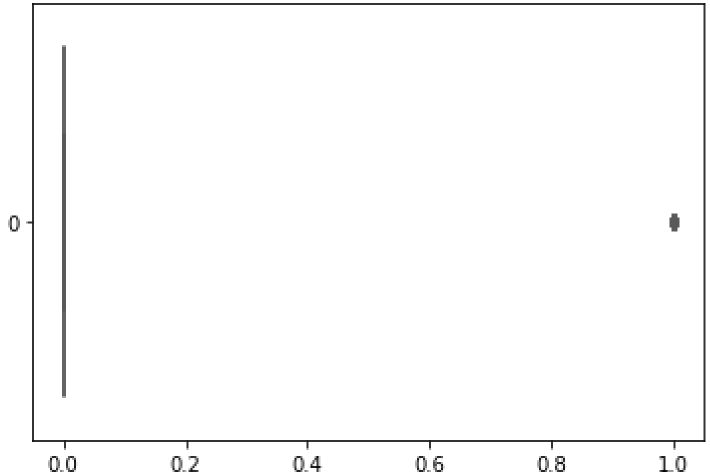
Column total_units_4U



Column age_35-44



Column age_45-54



Column age_55-64

Split Data

```
X = df.drop(['Status'],axis=1)
y = df['Status']
df.head()
```

	loan_amount	rate_of_interest	Interest_rate_spread	Upfront_charges
0	65.434636	3.99	0.3904	39.321796
1	75.772745	3.99	0.3904	39.321796
2	90.006788	4.56	0.2000	22.722094
3	92.687543	4.25	0.6810	39.321796
4	103.112263	4.00	0.3042	-2.332919

5 rows × 47 columns

```
X = X[['Upfront_charges','Interest_rate_spread','rate_of_interest']]
```

```
X.columns
```

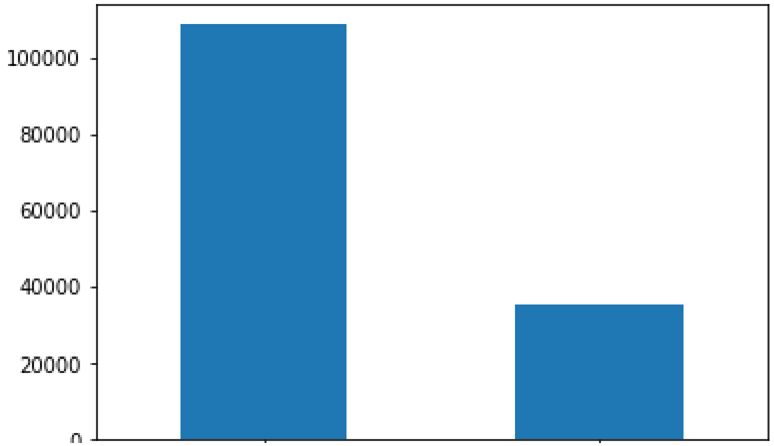
```
Index(['Upfront_charges', 'Interest_rate_spread', 'rate_of_interest'], dtype='object')
```

```
X.describe()
```

	Upfront_charges	Interest_rate_spread	rate_of_interest
count	143983.000000	143983.000000	143983.000000
mean	35.342695	0.426660	4.027587
std	18.389425	0.446424	0.489740
min	-2.332919	-3.638000	0.000000
25%	30.055841	0.178100	3.750000
50%	39.321796	0.390400	3.990000
75%	45.564845	0.617100	4.250000

```
y.describe()
df['Status'].value_counts().plot.bar()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f07f472cb90>




```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =1)
```

```
print('Training  Data  Predictors\n',X_train.head(),  '\nTraining  Data  Target\n',y_train.head(),'\n')
print('Test  Data  Predictors\n',X_test.head(),  '\nTest  Data  Target\n',y_test.head())
```

```
Training Data Predictors
         Upfront_charges  Interest_rate_spread  rate_of_interest
16920          40.637827                0.0051             3.125
104287         39.321796                0.3904             3.990
81593          39.321796                0.3904             3.990
77471          14.799260               -0.2220             3.000
119640         51.965231                0.0268             3.990
Training Data Target
 16920     0
104287    1
81593     1
77471     0
119640    0
Name: Status, dtype: int64

Test Data Predictors
         Upfront_charges  Interest_rate_spread  rate_of_interest
102317         54.935290               -0.1194             3.990
24399          48.637134                0.0528             2.990
125556         47.109717                0.3916             4.250
23750          -2.332919               -0.2148             4.180
72800          49.039783                0.3278             3.875
Test Data Target
 102317    0
24399     0
125556    0
23750     0
72800     0
Name: Status, dtype: int64
```

SMOTE

```
#  SMOTE  (oversampling)
```

```
import numpy as np
from numpy import mean
from numpy import std
import imblearn                                                         # Import the imblea
from imblearn.over_sampling import SMOTE                            # Import SMOTE

sm = SMOTE(random_state=12346)                                       # Create an instance of SMOTE
X_train_SMOTE, y_train_SMOTE = sm.fit_resample(X_train, y_train)     # Apply the SNOTE intance to the training data

print("Shape before SMOTE: ", X_train.shape, y_train.shape)          # Verify the shape has changed and is now balanced.
print("Shape after SMOTE: ", X_train_SMOTE.shape, y_train_SMOTE.shape)
print("Mean of target: ",mean(y_train_SMOTE))
```

```
Shape before SMOTE:  (115186, 3) (115186,)
Shape after SMOTE:  (174008, 3) (174008,)
Mean of target:  0.5
```

Standardization

```
# Standardize
mmsc = StandardScaler()                                              # Create an instance of MinMaxScaler
X_train_SMOTE_std = mmsc.fit_transform(X_train_SMOTE)    # Uses .fit_transform to compute the mean and standard deviaton of trainin
X_test_std = mmsc.transform(X_test)                      # Uses .transform to apply the training set transformation
                                                         # no information from the tes
```

LGBM Feature Importance

```
# Feature Importance
# Code adapted from this source: https://machinelearningmastery.com/calculate-feature-importance-with-python/
# Let's try to weed out the really poor predictors
from matplotlib import pyplot                            # Import pyplot (to be able generate the barchart
model = LGBMClassifier()                                 # Create an instance of a RandomForestClassifier
```

```
# fit the model
model.fit(X_train_SMOTE_std, y_train_SMOTE)                                # Fit the RandomForest instance using the traiing data
# get importance
importance = model.feature_importances_                                # The RandomForestClassifier instance computes feature importar
# summarize feature importance
col_names = X.columns
fig = plt.figure(figsize = (10,10))
plt.barh(col_names, model.feature_importances_)
```

```
<BarContainer object of 3 artists>
```

Model Creation

```
# X = X[['Upfront_charges','Interest_rate_spread','rate_of_interest','property_value','credit_type','dtir1','LTV','Neg_ammortization_not_neg','
```

```
# X = X[['Upfront_charges','Interest_rate_spread','rate_of_interest']]
```

```
X.columns
```

```
Index(['Upfront_charges', 'Interest_rate_spread', 'rate_of_interest'], dtype='object')
```

```
gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
    print('Not connected to a GPU')
else:
    print(gpu_info)
```

```
Sun May 15 23:12:21 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 460.32.03    Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0 |
| N/A   37C    P0    26W / 250W |      0MiB / 16280MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
```

```
+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

```
from sklearn.svm import SVC
from sklearn.datasets import load_digits
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

def plot_learning_curve(
        estimator,
        title,
        X,
        y,
        axes=None,
        ylim=None,
        cv=None,
        n_jobs=None,
        scoring = 'roc_auc_score',
        train_sizes=np.linspace(0.1, 1.0, 5),
):
        """
        Generate 3 plots: the test and training learning curve, the training
        samples vs fit times curve, the fit times vs score curve.

        Parameters
        ----------
        estimator : estimator instance
                An estimator instance implementing `fit` and `predict` methods which
                will be cloned for each validation.

        title : str
                Title for the chart.
```

```
X : array-like of shape (n_samples, n_features)
    Training vector, where ``n_samples`` is the number of samples and
    ``n_features`` is the number of features.

y : array-like of shape (n_samples) or (n_samples, n_features)
    Target relative to ``X`` for classification or regression;
    None for unsupervised learning.

axes : array-like of shape (3,), default=None
    Axes to use for plotting the curves.

ylim : tuple of shape (2,), default=None
    Defines minimum and maximum y-values plotted, e.g. (ymin, ymax).

cv : int, cross-validation generator or an iterable, default=None
    Determines the cross-validation splitting strategy.
    Possible inputs for cv are:

      - None, to use the default 5-fold cross-validation,
      - integer, to specify the number of folds.
      - :term:`CV splitter`,
      - An iterable yielding (train, test) splits as arrays of indices.

    For integer/None inputs, if ``y`` is binary or multiclass,
    :class:`StratifiedKFold` used. If the estimator is not a classifier
    or if ``y`` is neither binary nor multiclass, :class:`KFold` is used.

    Refer :ref:`User Guide <cross_validation>` for the various
    cross-validators that can be used here.

n_jobs : int or None, default=None
    Number of jobs to run in parallel.
    ``None`` means 1 unless in a :obj:`joblib.parallel_backend` context.
    ``-1`` means using all processors. See :term:`Glossary <n_jobs>`
    for more details.
```

```
    train_sizes : array-like of shape (n_ticks,)
        Relative or absolute numbers of training examples that will be used to
        generate the learning curve. If the ``dtype`` is float, it is regarded
        as a fraction of the maximum size of the training set (that is
        determined by the selected validation method), i.e. it has to be within
        (0, 1]. Otherwise it is interpreted as absolute sizes of the training
        sets. Note that for classification the number of samples usually have
        to be big enough to contain at least one sample from each class.
        (default: np.linspace(0.1, 1.0, 5))
    """
    if axes is None:
        _, axes = plt.subplots(1, 3, figsize=(20, 5))

    axes[0].set_title(title)
    if ylim is not None:
        axes[0].set_ylim(*ylim)
    axes[0].set_xlabel("Training examples")
    axes[0].set_ylabel("Score")

    train_sizes, train_scores, test_scores, fit_times, _ = learning_curve(
        estimator,
        X,
        y,
        cv=cv,
        n_jobs=n_jobs,
        train_sizes=train_sizes,
        return_times=True,
    )
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    fit_times_mean = np.mean(fit_times, axis=1)
    fit_times_std = np.std(fit_times, axis=1)
    print('Scores:',test_scores_mean,test_scores_std)

    # Plot learning curve
```

```
    axes[0].grid()
    axes[0].fill_between(
        train_sizes,
        train_scores_mean - train_scores_std,
        train_scores_mean + train_scores_std,
        alpha=0.1,
        color="r",
    )
    axes[0].fill_between(
        train_sizes,
        test_scores_mean - test_scores_std,
        test_scores_mean + test_scores_std,
        alpha=0.1,
        color="g",
    )
    axes[0].plot(
        train_sizes, train_scores_mean, "o-", color="r", label="Training score"
    )
    axes[0].plot(
        train_sizes, test_scores_mean, "o-", color="g", label="Cross-validation score"
    )
    axes[0].legend(loc="best")

    # Plot n_samples vs fit_times
    axes[1].grid()
    axes[1].plot(train_sizes, fit_times_mean, "o-")
    axes[1].fill_between(
        train_sizes,
        fit_times_mean - fit_times_std,
        fit_times_mean + fit_times_std,
        alpha=0.1,
    )
    axes[1].set_xlabel("Training examples")
    axes[1].set_ylabel("fit_times")
    axes[1].set_title("Scalability of the model")

    # Plot fit_time vs score
```

```
        fit_time_argsort = fit_times_mean.argsort()
        fit_time_sorted = fit_times_mean[fit_time_argsort]
        test_scores_mean_sorted = test_scores_mean[fit_time_argsort]
        test_scores_std_sorted = test_scores_std[fit_time_argsort]
        axes[2].grid()
        axes[2].plot(fit_time_sorted, test_scores_mean_sorted, "o-")
        axes[2].fill_between(
                fit_time_sorted,
                test_scores_mean_sorted - test_scores_std_sorted,
                test_scores_mean_sorted + test_scores_std_sorted,
                alpha=0.1,
        )
        axes[2].set_xlabel("fit_times")
        axes[2].set_ylabel("Score")
        axes[2].set_title("Performance of the model")

        return plt


fig, axes = plt.subplots(3, 3, figsize=(20, 20))

title = "Learning Curves (Logistic Regression (Logit))"
# Cross validation with 50 iterations to get smoother mean test and train
# score curves, each time with 20% data randomly selected as a validation set.
cv = ShuffleSplit(n_splits=3, test_size=0.2, random_state=0)
# estimator = kNeighborsClassifier()
estimator = imbpipeline(steps = [['smote', SMOTE(random_state=11)],
                                  ['scaler', StandardScaler()],
                                  ['classifier', LogisticRegression(random_state=11,
                                                                     max_iter=1000)
plot_learning_curve(
        estimator, title, X, y, axes=axes[:, 0], ylim=(0.5, 1.01), cv=cv, n_jobs=4
)


title = "Learning Curves (Decision Tree)"
cv = ShuffleSplit(n_splits=3, test_size=0.2, random_state=0)
```

```
estimator = imbpipeline(steps = [['smote', SMOTE(random_state=11)],
                                 ['scaler', StandardScaler()],
                                 ['classifier', DecisionTreeClassifier()]])
plot_learning_curve(
        estimator, title, X, y, axes=axes[:, 1], ylim=(0.5, 1.01), cv=cv, n_jobs=4
)


title = "Learning Curves (Support Vector Machine)"
cv = ShuffleSplit(n_splits=3, test_size=0.2, random_state=0)
estimator = imbpipeline(steps = [['smote', SMOTE(random_state=11)],
                                 ['scaler', StandardScaler()],
                                 ['classifier', SVC()]])
plot_learning_curve(
        estimator, title, X, y, axes=axes[:, 2], ylim=(0.5, 1.01), cv=cv, n_jobs=4
)

plt.show()

fig, axes = plt.subplots(3, 3, figsize=(20, 20))

title = "Learning Curves (XGBoost)"
# Cross validation with 50 iterations to get smoother mean test and train
# score curves, each time with 20% data randomly selected as a validation set.
cv = ShuffleSplit(n_splits=3, test_size=0.2, random_state=0)
estimator = imbpipeline(steps = [['smote', SMOTE(random_state=11)],
                                 ['scaler', StandardScaler()],
                                 ['classifier', XGBClassifier(random_state=11)]])
plot_learning_curve(
        estimator, title, X, y, axes=axes[:, 0], ylim=(0.5, 1.01), cv=cv, n_jobs=4
)


title = "Learning Curves (Random Forest)"
cv = ShuffleSplit(n_splits=3, test_size=0.2, random_state=0)
#estimator = RandomForestClassifier()
estimator = imbpipeline(steps = [['smote', SMOTE(random_state=11)],
```

```
                                                                 ['scaler', StandardScaler()],
                                                                 ['classifier', RandomForestClassifier()]])
plot_learning_curve(
        estimator, title, X, y, axes=axes[:, 1], ylim=(0.5, 1.01), cv=cv, n_jobs=4
)


title = "Learning Curves (LightGBM)"
cv = ShuffleSplit(n_splits=3, test_size=0.2, random_state=0)
# estimator = LGBMClassifier()
estimator = imbpipeline(steps = [['smote', SMOTE(random_state=11)],
                                                                 ['scaler', StandardScaler()],
                                                                 ['classifier', LGBMClassifier()]])
plot_learning_curve(
        estimator, title, X, y, axes=axes[:, 2], ylim=(0.5, 1.01), cv=cv, n_jobs=4
)

plt.show()
```

Grid Search for DT

```
# Build DT classifer on dataset
from sklearn.metrics import confusion_matrix                                                        # Import confusion_matrix methoc
from sklearn import metrics                                                                                    # Import metrics
DTmodel = DecisionTreeClassifier()                                                                          # Create a LGBMClas
model.fit(X_train_SMOTE_std,y_train_SMOTE)                                                         # Fit the revised training data
y_pred = model.predict(X_test_std)                                                                           # Use model to predict
print('Confusion matrix: \n',confusion_matrix(y_test, y_pred))                          # print confusion matrix using sklearn
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred, pos_label=1)            # Compute true positive rate and false positive r
print('AUC: ', metrics.auc(fpr, tpr))                                                                        # Compute and print the
```

```
Confusion matrix:
 [[21708     1]
 [    0  7088]]
AUC:  0.9999769680777557
```

Grid Search for LGBM

```
# Create an LGBM pipeline with SMOTE and StandardScaler and then gridsearch it using five cross-validation folds
lgbmmodel = imbpipeline([
            ('sample', SMOTE(random_state=123)),
            ('std', StandardScaler()),
            ('clf', LGBMClassifier(boosting_type='gbdt', objective='binary', learning_rate=0.1, bagging_fraction=0.9))])

param_grid = {'clf__learning_rate':[.05,.1,.15],
                    'clf__bagging_fraction':[.1,.3,.5,.7,.9],
                    }
grid = GridSearchCV(estimator=model, param_grid=param_grid, cv = 5, scoring = 'roc_auc')
grid.fit(X, y)
print(grid.best_params_)
print(grid.best_estimator_)
```

```
# Build Random Forest classifer on revised dataset
from sklearn.metrics import confusion_matrix                                    # Import confusion_matrix methoc
from sklearn import metrics                                                                # Import metrics
lgbmmodel = LGBMClassifier()                                                            # Create a LGBMClassifier
lgbmmodel.fit(X_train_SMOTE_std,y_train_SMOTE)                                    # Fit the revised training
y_pred = lgbmmodel.predict(X_test_std)                                                  # Use model to pre
print('Confusion matrix: \n',confusion_matrix(y_test, y_pred))                # print confusion matrix using sklearn
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred, pos_label=1)      # Compute true positive rate and false positive r
print('AUC: ', metrics.auc(fpr, tpr))                                                   # Compute and print the
```

```
Confusion matrix:
 [[21708     1]
 [    0  7088]]
AUC:  0.9999769680777557
```

Propensities

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix

# Get started with LGBM classifier
clm = LGBMClassifier(bagging_fraction = 0.1, learning_rate =0.05)

clm.fit(X_train_SMOTE_std, np.ravel(y_train_SMOTE))                    # Fit model using training data. Ravel converts a column vec
y_pred = clm.predict(X_test_std)                                                  # Apply model to test data
print('Logit: AUC = ', roc_auc_score(y_test,y_pred), ' recall =', recall_score(y_test, y_pred),' accuracy = ', accuracy_score(y_test,
print(confusion_matrix(y_true=y_test,y_pred=y_pred))                                          # Confusion matrix
# print("Logit Model Coefficients",list(clm.coef_))                           # Logistic coefficients (can be used to assess which
```

```
Logit: AUC =  0.9999769680777557  recall = 1.0  accuracy =  0.9999652741605028
[[21708     1]
 [    0  7088]]
```

```
# Examine propensities of logit model
lgbm_propensities = pd.DataFrame(clm.predict_proba(X_test_std))

# Create a dataframe showing actuals, predicted, and propensities
y_pred = pd.DataFrame(y_pred)
y_pred.reset_index(drop = True , inplace = True)
y_test.reset_index(drop = True , inplace = True)
results = pd.concat([y_test, y_pred, lgbm_propensities[1]], axis=1)
results.columns= ['Actual','Predicted','Propensity']

#Compute percentage of instances with propensities in [lower_limit,upper_limit]
upper_limit = 0.7
lower_limit = 0.3
count = 0
for i in range(0,len(lgbm_propensities[1])):
    if((lgbm_propensities.loc[i,1] >= lower_limit) & (lgbm_propensities.loc[i,1] <= upper_limit)):
        count = count + 1
print('Percentage of test instances with propensity in [%1.2f, %1.2f]: %3.2f' % (lower_limit,upper_limit,100 * count/len(lgbm_propens
```

```
# Show instances where predicted and actual differ
print('Instances for which actual and predicted differ:')
discrepancies = results.loc[results['Actual'] != results['Predicted']]
discrepancies
```

```
Percentage of test instances with propensity in [0.30, 0.70]: 0.00
Instances for which actual and predicted differ:
```

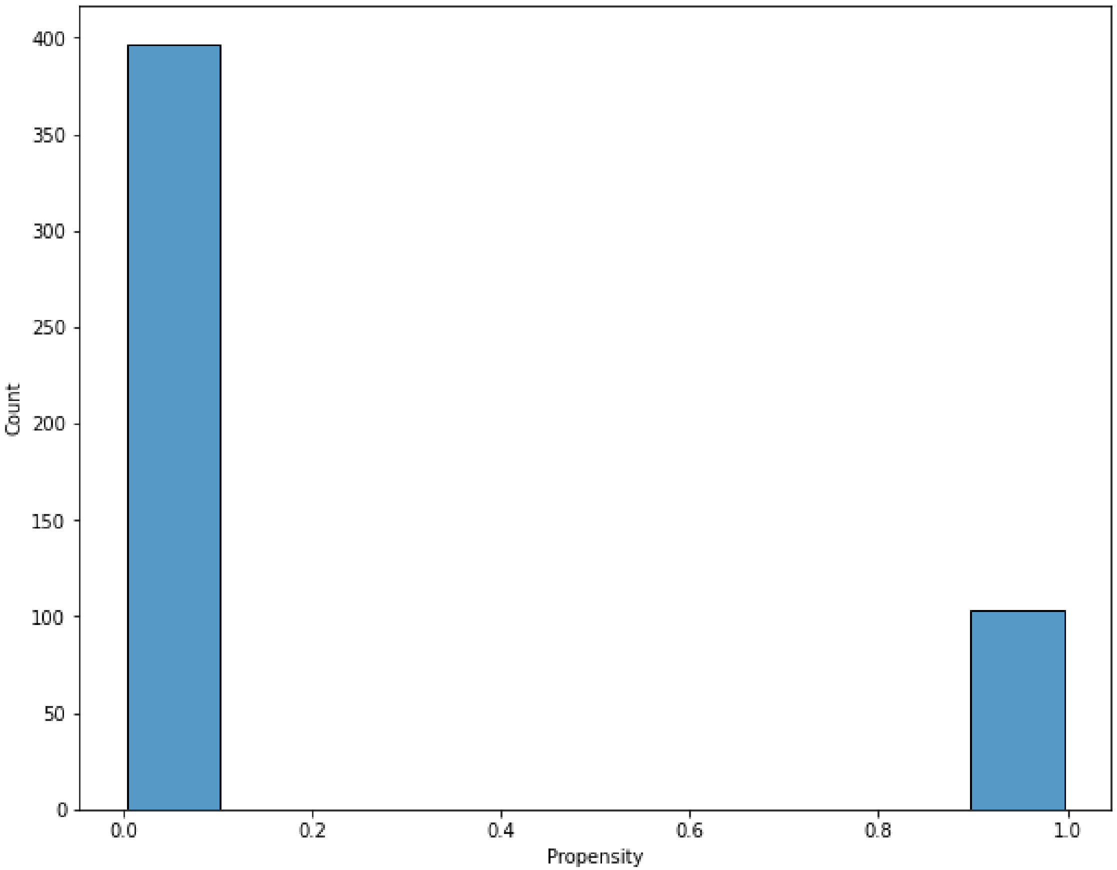
	Actual	Predicted	Propensity
25276	0	1	0.99669

```
results
```

	Actual	Predicted	Propensity
0	0	0	0.00331
1	0	0	0.00331
2	0	0	0.00331
3	0	0	0.00331
4	0	0	0.00331
...	...	...	...
28792	0	0	0.00331
28793	0	0	0.00331
28794	0	0	0.00331
28795	0	0	0.00331
28796	0	0	0.00331

```
sns.histplot(results['Propensity'].sample(500))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f07efb13d90>
```



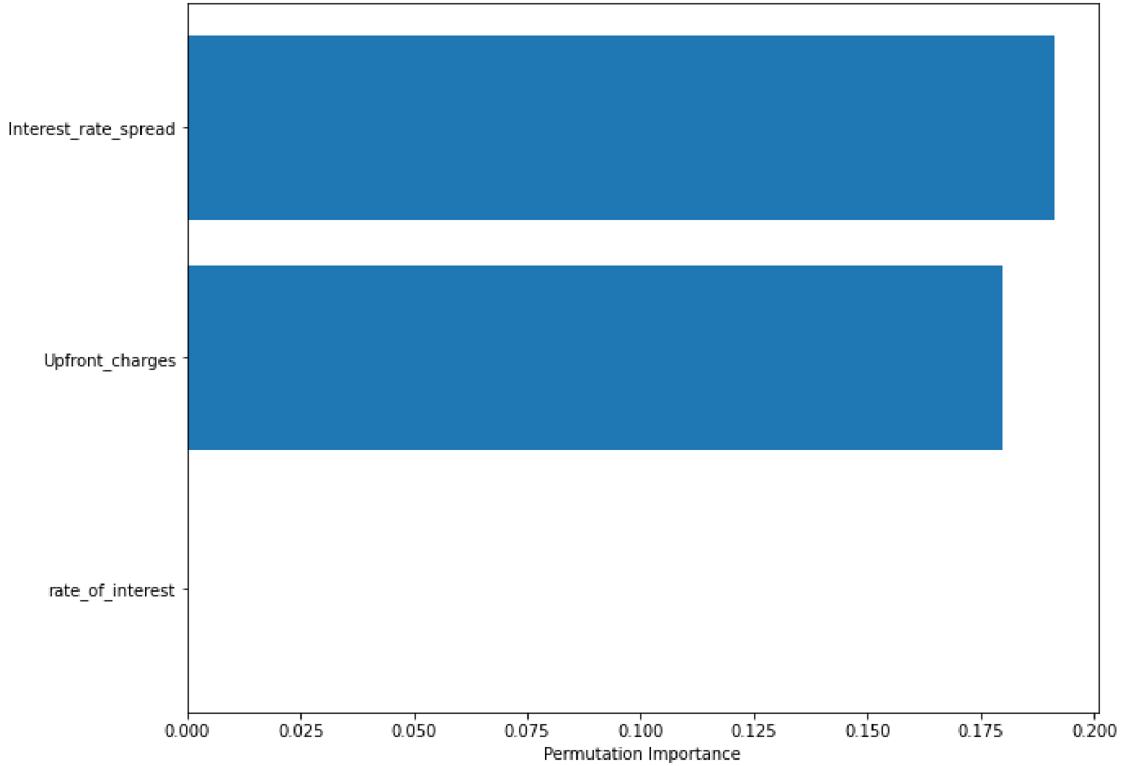
Permutation Feature Importance

```
Xcols = X.columns
col_names = X.columns
```

```
# Assess features important for predictions in the wild
```

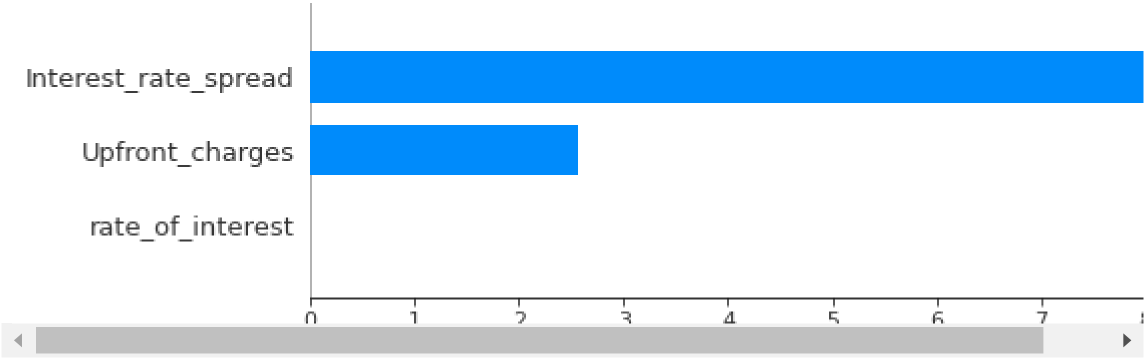
```
from sklearn.inspection import permutation_importance
plt.rcParams["figure.figsize"] = (10,8)
perm_importance = permutation_importance(lgbmmodel, X_test_std, y_test)
sorted_idx = perm_importance.importances_mean.argsort()
plt.barh(Xcols[sorted_idx], perm_importance.importances_mean[sorted_idx])
plt.xlabel("Permutation Importance")
```

```
Text(0.5, 0, 'Permutation Importance')
```



Shapley Values

```
explainer = shap.TreeExplainer(lgbmmodel)
shap_values = explainer.shap_values(X_train_SMOTE_std)
shap.summary_plot(shap_values[1], X_train_SMOTE_std, plot_type='bar',feature_names=col_names)
```

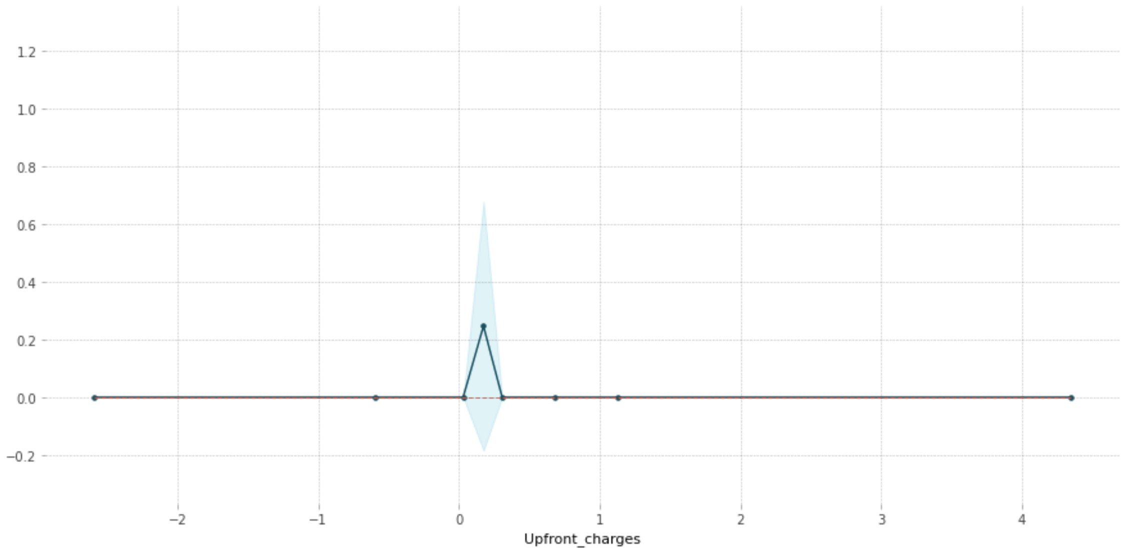


PDP Plots

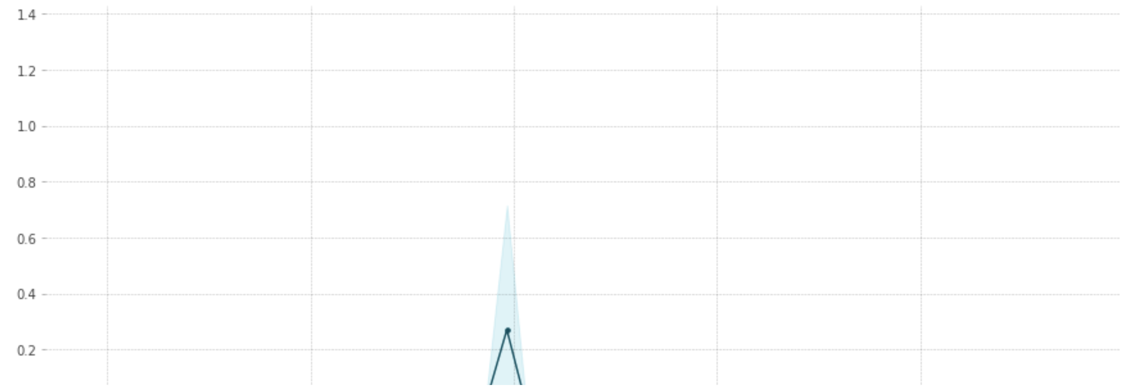
```
# Univariate Partial Dependence Plot
X_test_std=pd.DataFrame(X_test_std)
X_test_std.columns=col_names
for i in col_names:
    pdp_ = pdp.pdp_isolate(model = model, dataset = X_test_std, model_features=col_names, feature = i)
    pdp.pdp_plot(pdp_, str(i))
    plt.show()
```

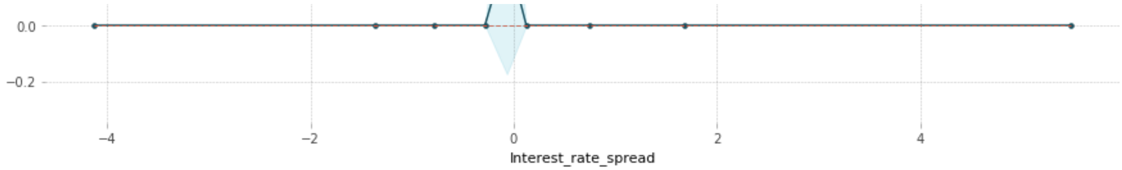
```
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
```

PDP for feature "Upfront_charges"
Number of unique grid points: 8



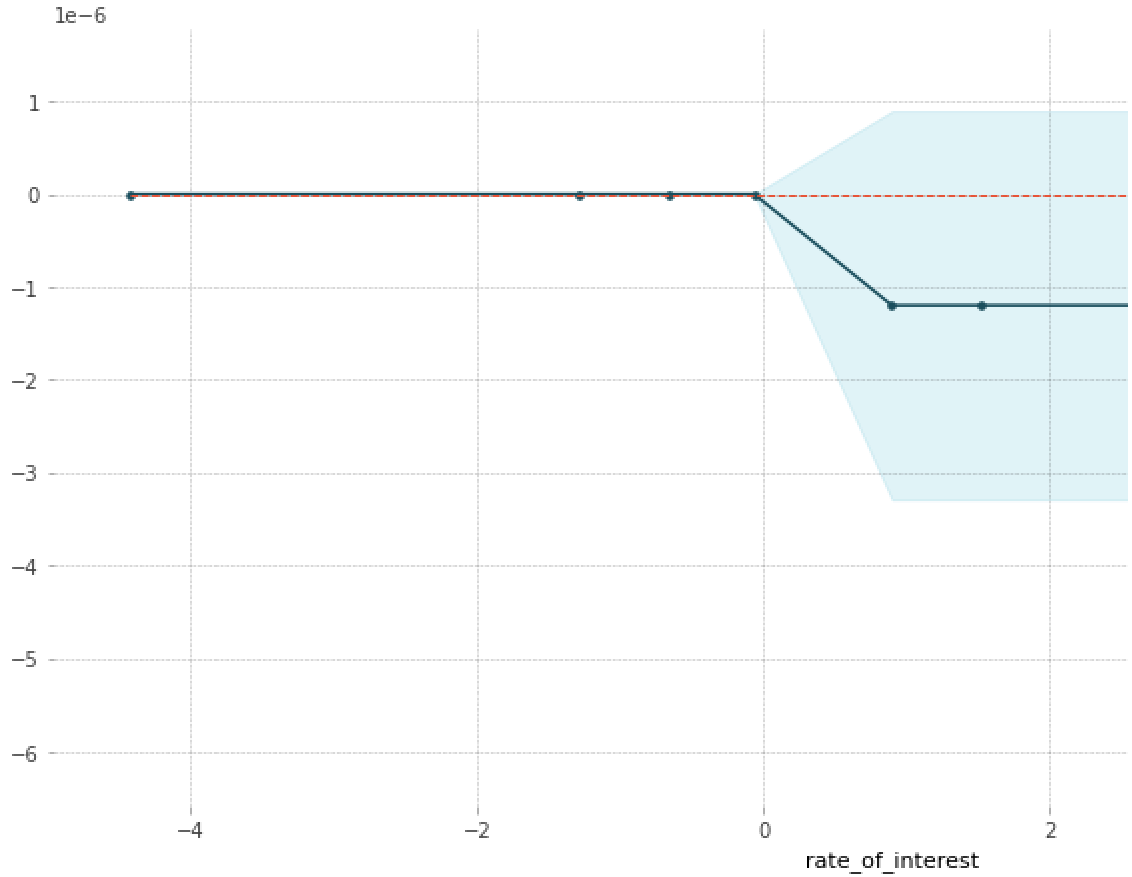
PDP for feature "Interest_rate_spread"
Number of unique grid points: 9





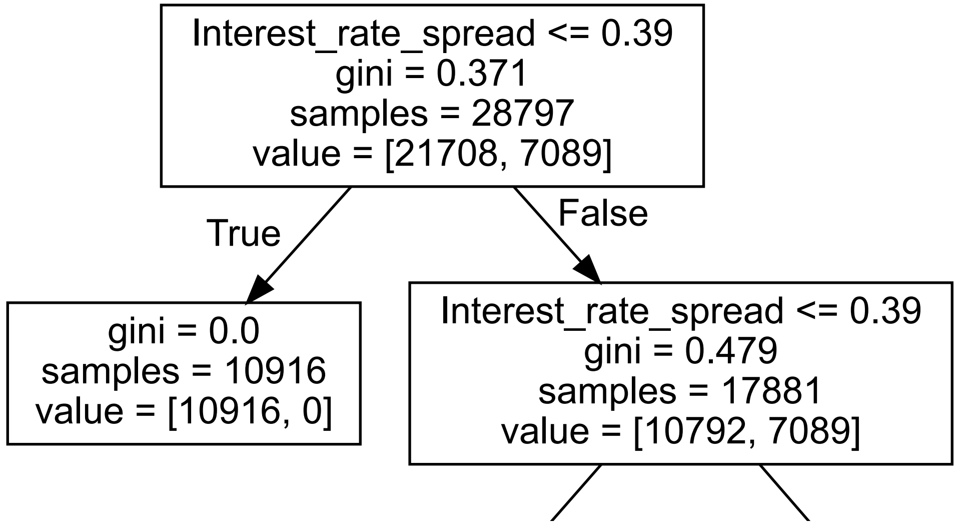
PDP for feature "rate_of_interest"

Number of unique grid points: 7



Surrogate Model

```
# Decision Tree surrogate model of Random Forest model
# Mimics the beahvior of the black box model on data from the wild (i.e., the test set)
from sklearn import tree
import graphviz

proxy = DecisionTreeClassifier(random_state = 20850,max_depth=3)      # Control the depth of the proxy tree here
proxy.fit(X_test,y_pred)

tree_graph = tree.export_graphviz(proxy, out_file = None, feature_names = col_names)
graphviz.Source(tree_graph)
```




```
# How good is this surrogate decision tree model?
# Let's find out by computing the correlation between the predictions of the original model and the surrogate model
y_proxy = proxy.predict(X_test) # Use the decision tree to make predictions
y_proxy = pd.DataFrame(y_proxy)
print('Correlation coefficient of RF predictions and Surrogate Model predictions: ',y_pred.corrwith(y_proxy,axis=0))
```

```
Correlation coefficient of RF predictions and Surrogate Model predictions:  0    1.0
dtype: float64
```


```
clm
```

```
LGBMClassifier(bagging_fraction=0.1, learning_rate=0.05)
```

correlation of surrogate model and LGBM