Home Credit Default Risk (HCDR)

The course project is based on the Home Credit Default Risk (HCDR) Kaggle Competition. The goal of this project is to predict whether or not a client will repay a loan. In order to make sure that people who struggle to get loans due to insufficient or non-existent credit histories have a positive loan experience, Home Credit makes use of a variety of alternative data--including telco and transactional information--to predict their clients' repayment abilities.

Some of the challenges

1. Dataset size
   - (688 meg compressed) with millions of rows of data
   - 2.71 Gig of data uncompressed
- Dealing with missing data
- Imbalanced datasets
- Summarizing transaction data

Kaggle API setup

Kaggle is a Data Science Competition Platform which shares a lot of datasets. In the past, it was troublesome to submit your result as your have to go through the console in your browser and drag your files there. Now you can interact with Kaggle via the command line. E.g.,

```
! kaggle competitions files home-credit-default-risk
```

It is quite easy to setup, it takes me less than 15 minutes to finish a submission.

1. Install library
- Create a API Token (edit your profile on Kaggle.com); this produces `kaggle.json` file
- Put your JSON `kaggle.json` in the right place
- Access competition files; make submissions via the command (see examples below)
- Submit result

For more detailed information on setting the Kaggle API see here and here.

```
!pip install kaggle
```

```
Requirement already satisfied: kaggle in
/usr/local/lib/python3.9/site-packages (1.5.12)
Requirement already satisfied: requests in
/usr/local/lib/python3.9/site-packages (from kaggle) (2.26.0)
Requirement already satisfied: python-slugify in
/usr/local/lib/python3.9/site-packages (from kaggle) (5.0.2)
Requirement already satisfied: python-dateutil in
```

```
/usr/local/lib/python3.9/site-packages (from kaggle) (2.8.2)
Requirement already satisfied: six>=1.10 in
/usr/local/lib/python3.9/site-packages (from kaggle) (1.15.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/site-
packages (from kaggle) (4.62.3)
Requirement already satisfied: certifi in
/usr/local/lib/python3.9/site-packages (from kaggle) (2021.10.8)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.9/site-packages (from kaggle) (1.26.7)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.9/site-packages (from python-slugify->kaggle)
(1.3)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.9/site-packages (from requests->kaggle) (3.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in
/usr/local/lib/python3.9/site-packages (from requests->kaggle) (2.0.4)
WARNING: Running pip as the 'root' user can result in broken
permissions and conflicting behaviour with the system package manager.
It is recommended to use a virtual environment instead:
https://pip.pypa.io/warnings/venv
WARNING: You are using pip version 21.3.1; however, version 24.0 is
available.
You should consider upgrading via the '/usr/local/bin/python -m pip
install --upgrade pip' command.
```

```
!pwd
```

```
/root/shared/Courses/I526_AML_Student/Assignments/Unit-Project-Home-
Credit-Default-Risk/Phase2
```

```
!ls -l  ~/.kaggle/kaggle.json
```

```
ls: cannot access '/root/.kaggle/kaggle.json': No such file or
directory
```

```
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json
```

```
mkdir: cannot create directory ‘/root/.kaggle’: File exists
cp: cannot stat 'kaggle.json': No such file or directory
chmod: cannot access '/root/.kaggle/kaggle.json': No such file or
directory
```

```
! kaggle competitions files home-credit-default-risk
```

```
Traceback (most recent call last):
  File "/usr/local/bin/kaggle", line 5, in <module>
    from kaggle.cli import main
  File "/usr/local/lib/python3.9/site-packages/kaggle/__init__.py",
line 23, in <module>
```

```
    api.authenticate()
  File
"/usr/local/lib/python3.9/site-packages/kaggle/api/kaggle_api_extended
.py", line 164, in authenticate
    raise IOError('Could not find {}. Make sure it\'s located in'
OSError: Could not find kaggle.json. Make sure it's located in
/root/.kaggle. Or use the environment method.
```

Dataset and how to download

Back ground Home Credit Group

Many people struggle to get loans due to insufficient or non-existent credit histories. And, unfortunately, this population is often taken advantage of by untrustworthy lenders.

Home Credit Group

Home Credit strives to broaden financial inclusion for the unbanked population by providing a positive and safe borrowing experience. In order to make sure this underserved population has a positive loan experience, Home Credit makes use of a variety of alternative data--including telco and transactional information--to predict their clients' repayment abilities.

While Home Credit is currently using various statistical and machine learning methods to make these predictions, they're challenging Kagglers to help them unlock the full potential of their data. Doing so will ensure that clients capable of repayment are not rejected and that loans are given with a principal, maturity, and repayment calendar that will empower their clients to be successful.

Background on the dataset

Home Credit is a non-banking financial institution, founded in 1997 in the Czech Republic.

The company operates in 14 countries (including United States, Russia, Kazahstan, Belarus, China, India) and focuses on lending primarily to people with little or no credit history which will either not obtain loans or became victims of untrustworthly lenders.

Home Credit group has over 29 million customers, total assests of 21 billions Euro, over 160 millions loans, with the majority in Asia and and almost half of them in China (as of 19-05-2018).

While Home Credit is currently using various statistical and machine learning methods to make these predictions, they're challenging Kagglers to help them unlock the full potential of their data. Doing so will ensure that clients capable of repayment are not rejected and that loans are given with a principal, maturity, and repayment calendar that will empower their clients to be successful.

Data files overview

The `HomeCredit_columns_description.csv` acts as a data dictioanry.

There are 7 different sources of data:

- **application_train/application_test (307k rows, and 48k rows):** the main training and testing data with information about each loan application at Home Credit. Every loan has its own row and is identified by the feature SK_ID_CURR. The training application data comes with the TARGET indicating **0: the loan was repaid** or **1: the loan was not repaid**. The target variable defines if the client had payment difficulties meaning he/she had late payment more than X days on at least one of the first Y installments of the loan. Such case is marked as 1 while other all other cases as 0.
- **bureau (1.7 Million rows):** data concerning client's previous credits from other financial institutions. Each previous credit has its own row in bureau, but one loan in the application data can have multiple previous credits.
- **bureau_balance (27 Million rows):** monthly data about the previous credits in bureau. Each row is one month of a previous credit, and a single previous credit can have multiple rows, one for each month of the credit length.
- **previous_application (1.6 Million rows):** previous applications for loans at Home Credit of clients who have loans in the application data. Each current loan in the application data can have multiple previous loans. Each previous application has one row and is identified by the feature SK_ID_PREV.
- **POS_CASH_BALANCE (10 Million rows):** monthly data about previous point of sale or cash loans clients have had with Home Credit. Each row is one month of a previous point of sale or cash loan, and a single previous loan can have many rows.
- credit_card_balance: monthly data about previous credit cards clients have had with Home Credit. Each row is one month of a credit card balance, and a single credit card can have many rows.
- **installments_payment (13.6 Million rows):** payment history for previous loans at Home Credit. There is one row for every made payment and one row for every missed payment.

Table sizes

```
name                           [   rows cols]     MegaBytes
-----------------------     ------------------    -------
application_train         : [   307,511, 122]:   158MB
application_test          : [    48,744, 121]:   25MB
bureau                    : [ 1,716,428, 17]    162MB
bureau_balance            : [ 27,299,925, 3]:   358MB
credit_card_balance       : [  3,840,312, 23]   405MB
installments_payments     : [ 13,605,401, 8]    690MB
previous_application      : [  1,670,214, 37]   386MB
POS_CASH_balance          : [ 10,001,358, 8]    375MB
```

image.png

Downloading the files via Kaggle API

Create a base directory:

```
DATA_DIR = "../../../Data/home-credit-default-risk"   #same level as course repo in the data directory
```

Please download the project data files and data dictionary and unzip them using either of the following approaches:

1. Click on the `Download` button on the following Data Webpage and unzip the zip file to the `BASE_DIR`
2. If you plan to use the Kaggle API, please use the following steps.

```
DATA_DIR = "../../../Data/home-credit-default-risk"  #same level as course repo in the data directory
#DATA_DIR = os.path.join('./ddddd/')
!mkdir DATA_DIR

!ls -l DATA_DIR

total 0

! kaggle competitions download home-credit-default-risk -p $DATA_DIR

Traceback (most recent call last):
  File "/usr/local/bin/kaggle", line 5, in <module>
    from kaggle.cli import main
  File "/usr/local/lib/python3.9/site-packages/kaggle/__init__.py", line 23, in <module>
    api.authenticate()
  File "/usr/local/lib/python3.9/site-packages/kaggle/api/kaggle_api_extended.py", line 164, in authenticate
    raise IOError('Could not find {}. Make sure it\'s located in'
OSError: Could not find kaggle.json. Make sure it's located in /root/.kaggle. Or use the environment method.

!pwd

/root/shared/Courses/I526_AML_Student/Assignments/Unit-Project-Home-Credit-Default-Risk/Phase2

!ls -l $DATA_DIR

ls: cannot access '../../../Data/home-credit-default-risk': No such file or directory

!rm -r  DATA_DIR
```

Imports

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import os
import zipfile
from sklearn.base import BaseEstimator, TransformerMixin
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline, FeatureUnion
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import warnings
warnings.filterwarnings('ignore')

# unzippingReq = True #True
# if unzippingReq: #please modify this code
#     zip_ref = zipfile.ZipFile(f'{DATA_DIR}/home-credit-default-
risk.zip', 'r')
#     # extractall():  Extract all members from the archive to the
current working directory. path specifies a different directory to
extract to
#     zip_ref.extractall('{DATA_DIR}')
#     zip_ref.close()
```

Data files overview

Data Dictionary

As part of the data download comes a Data Dictionary. It named `HomeCredit_columns_description.csv`

image.png

Application train

```
#ls -l
../../../Users/woojeongkin/Desktop/24Spring/P556/Final_Project/applica
tion_train.csv
```

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import os
import zipfile
from sklearn.base import BaseEstimator, TransformerMixin
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline, FeatureUnion
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import warnings
warnings.filterwarnings('ignore')

def load_data(in_path, name):
    df = pd.read_csv(in_path)
    print(f"{name}: shape is {df.shape}")
    print(df.info())
    display(df.head(5))
    return df

datasets = {}  # lets store the datasets in a dictionary so we can
keep track of them easily
ds_name = 'application_train'
#DATA_DIR=f"{DATA_DIR}/home-credit-default-risk/"
datasets[ds_name] = load_data(f'{ds_name}.csv', ds_name)

datasets['application_train'].shape
```

```
application_train: shape is (307511, 122)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
None

   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
```

```
4      100007       0         Cash loans          M             N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT
AMT_ANNUITY  \
0               Y             0          202500.0    406597.5
24700.5
1               N             0          270000.0   1293502.5
35698.5
2               Y             0           67500.0    135000.0
6750.0
3               Y             0          135000.0    312682.5
29686.5
4               Y             0          121500.0    513000.0
21865.5

   ...  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
0  ...                 0                0                0
0
1  ...                 0                0                0
0
2  ...                 0                0                0
0
3  ...                 0                0                0
0
4  ...                 0                0                0
0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                       0.0
1                        0.0                       0.0
2                        0.0                       0.0
3                        NaN                       NaN
4                        0.0                       0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]
```

```
(307511, 122)

# DATA_DIR
```

Application test

- **application_train/application_test:** the main training and testing data with information about each loan application at Home Credit. Every loan has its own row and is identified by the feature SK_ID_CURR. The training application data comes with the TARGET indicating **0: the loan was repaid** or **1: the loan was not repaid**. The target variable defines if the client had payment difficulties meaning he/she had late payment more than X days on at least one of the first Y installments of the loan. Such case is marked as 1 while other all other cases as 0.

```
ds_name = 'application_test'
datasets[ds_name] = load_data(f'{ds_name}.csv', ds_name)

application_test: shape is (48744, 121)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48744 entries, 0 to 48743
Columns: 121 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(40), object(16)
memory usage: 45.0+ MB
None

   SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR
FLAG_OWN_REALTY  \
0      100001         Cash loans           F            N
Y
1      100005         Cash loans           M            N
Y
2      100013         Cash loans           M            Y
Y
3      100028         Cash loans           F            N
Y
4      100038         Cash loans           M            Y
N

   CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY
AMT_GOODS_PRICE  \
0             0          135000.0    568800.0      20560.5
450000.0
1             0           99000.0    222768.0      17370.0
180000.0
2             0          202500.0    663264.0      69777.0
630000.0
3             2          315000.0   1575000.0      49018.5
1575000.0
4             1          180000.0    625500.0      32067.0
625500.0
```

```
   ... FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
0  ...                0                 0                 0
0
1  ...                0                 0                 0
0
2  ...                0                 0                 0
0
3  ...                0                 0                 0
0
4  ...                0                 0                 0
0

  AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                        0.0
1                        0.0                        0.0
2                        0.0                        0.0
3                        0.0                        0.0
4                        NaN                        NaN

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         0.0                        0.0
4                         NaN                        NaN

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         0.0
1                        0.0                         3.0
2                        1.0                         4.0
3                        0.0                         3.0
4                        NaN                         NaN

[5 rows x 121 columns]
```

The application dataset has the most information about the client: Gender, income, family status, education ...

The Other datasets

- **bureau:** data concerning client's previous credits from other financial institutions. Each previous credit has its own row in bureau, but one loan in the application data can have multiple previous credits.
- **bureau_balance:** monthly data about the previous credits in bureau. Each row is one month of a previous credit, and a single previous credit can have multiple rows, one for each month of the credit length.
- **previous_application:** previous applications for loans at Home Credit of clients who have loans in the application data. Each current loan in the application data can have multiple

previous loans. Each previous application has one row and is identified by the feature SK_ID_PREV.

- **POS_CASH_BALANCE:** monthly data about previous point of sale or cash loans clients have had with Home Credit. Each row is one month of a previous point of sale or cash loan, and a single previous loan can have many rows.
- credit_card_balance: monthly data about previous credit cards clients have had with Home Credit. Each row is one month of a credit card balance, and a single credit card can have many rows.
- **installments_payment:** payment history for previous loans at Home Credit. There is one row for every made payment and one row for every missed payment.

```
%%time
ds_names = ("application_train", "application_test",
"bureau","bureau_balance","credit_card_balance","installments_payments
",
            "previous_application","POS_CASH_balance")

for ds_name in ds_names:
    datasets[ds_name] = load_data(f'{ds_name}.csv', ds_name)
```

```
application_train: shape is (307511, 122)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
None

   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT
AMT_ANNUITY  \
0               Y             0          202500.0    406597.5
24700.5
1               N             0          270000.0   1293502.5
35698.5
2               Y             0           67500.0    135000.0
6750.0
3               Y             0          135000.0    312682.5
29686.5
4               Y             0          121500.0    513000.0
21865.5

   ...  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
```

```
0  ...                   0                 0                 0
0
1  ...                   0                 0                 0
0
2  ...                   0                 0                 0
0
3  ...                   0                 0                 0
0
4  ...                   0                 0                 0
0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                       0.0
1                        0.0                       0.0
2                        0.0                       0.0
3                        NaN                       NaN
4                        0.0                       0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]

application_test: shape is (48744, 121)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48744 entries, 0 to 48743
Columns: 121 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(40), object(16)
memory usage: 45.0+ MB
None

   SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR
FLAG_OWN_REALTY  \
0      100001         Cash loans           F            N
Y
1      100005         Cash loans           M            N
Y
2      100013         Cash loans           M            Y
Y
```

```
3      100028         Cash loans           F            N
Y
4      100038         Cash loans           M            Y
N

   CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY
AMT_GOODS_PRICE  \
0             0          135000.0    568800.0      20560.5
450000.0
1             0           99000.0    222768.0      17370.0
180000.0
2             0          202500.0    663264.0      69777.0
630000.0
3             2          315000.0   1575000.0      49018.5
1575000.0
4             1          180000.0    625500.0      32067.0
625500.0

   ... FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
0  ...                0                0                0
0
1  ...                0                0                0
0
2  ...                0                0                0
0
3  ...                0                0                0
0
4  ...                0                0                0
0

  AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                        0.0
1                        0.0                        0.0
2                        0.0                        0.0
3                        0.0                        0.0
4                        NaN                        NaN

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         0.0                        0.0
4                         NaN                        NaN

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         0.0
1                        0.0                         3.0
2                        1.0                         4.0
3                        0.0                         3.0
```

```
4                        NaN                        NaN

[5 rows x 121 columns]

bureau: shape is (1716428, 17)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1716428 entries, 0 to 1716427
Data columns (total 17 columns):
 #   Column                  Dtype  
---  ------                  -----  
 0   SK_ID_CURR              int64  
 1   SK_ID_BUREAU            int64  
 2   CREDIT_ACTIVE           object 
 3   CREDIT_CURRENCY         object 
 4   DAYS_CREDIT             int64  
 5   CREDIT_DAY_OVERDUE      int64  
 6   DAYS_CREDIT_ENDDATE     float64
 7   DAYS_ENDDATE_FACT       float64
 8   AMT_CREDIT_MAX_OVERDUE  float64
 9   CNT_CREDIT_PROLONG      int64  
 10  AMT_CREDIT_SUM          float64
 11  AMT_CREDIT_SUM_DEBT     float64
 12  AMT_CREDIT_SUM_LIMIT    float64
 13  AMT_CREDIT_SUM_OVERDUE  float64
 14  CREDIT_TYPE             object 
 15  DAYS_CREDIT_UPDATE      int64  
 16  AMT_ANNUITY             float64
dtypes: float64(8), int64(6), object(3)
memory usage: 222.6+ MB
None

   SK_ID_CURR  SK_ID_BUREAU CREDIT_ACTIVE CREDIT_CURRENCY  DAYS_CREDIT
\
0      215354       5714462        Closed      currency 1         -497

1      215354       5714463        Active      currency 1         -208

2      215354       5714464        Active      currency 1         -203

3      215354       5714465        Active      currency 1         -203

4      215354       5714466        Active      currency 1         -629


   CREDIT_DAY_OVERDUE  DAYS_CREDIT_ENDDATE  DAYS_ENDDATE_FACT  \
0                   0               -153.0             -153.0
1                   0               1075.0                NaN
2                   0                528.0                NaN
3                   0                  NaN                NaN
4                   0               1197.0                NaN
```

```
   AMT_CREDIT_MAX_OVERDUE  CNT_CREDIT_PROLONG  AMT_CREDIT_SUM  \
0                     NaN                   0         91323.0
1                     NaN                   0        225000.0
2                     NaN                   0        464323.5
3                     NaN                   0         90000.0
4                 77674.5                   0       2700000.0

   AMT_CREDIT_SUM_DEBT  AMT_CREDIT_SUM_LIMIT
AMT_CREDIT_SUM_OVERDUE  \
0                  0.0                   NaN                     0.0

1             171342.0                   NaN                     0.0

2                  NaN                   NaN                     0.0

3                  NaN                   NaN                     0.0

4                  NaN                   NaN                     0.0


       CREDIT_TYPE  DAYS_CREDIT_UPDATE  AMT_ANNUITY
0  Consumer credit                -131          NaN
1      Credit card                 -20          NaN
2  Consumer credit                 -16          NaN
3      Credit card                 -16          NaN
4  Consumer credit                 -21          NaN

bureau_balance: shape is (27299925, 3)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27299925 entries, 0 to 27299924
Data columns (total 3 columns):
 #   Column          Dtype
---  ------          -----
 0   SK_ID_BUREAU    int64
 1   MONTHS_BALANCE  int64
 2   STATUS          object
dtypes: int64(2), object(1)
memory usage: 624.8+ MB
None

   SK_ID_BUREAU  MONTHS_BALANCE STATUS
0       5715448               0      C
1       5715448              -1      C
2       5715448              -2      C
3       5715448              -3      C
4       5715448              -4      C

credit_card_balance: shape is (3840312, 23)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3840312 entries, 0 to 3840311
```

```
Data columns (total 23 columns):
 #   Column                      Dtype
---  ------                      -----
 0   SK_ID_PREV                  int64
 1   SK_ID_CURR                  int64
 2   MONTHS_BALANCE              int64
 3   AMT_BALANCE                 float64
 4   AMT_CREDIT_LIMIT_ACTUAL     int64
 5   AMT_DRAWINGS_ATM_CURRENT    float64
 6   AMT_DRAWINGS_CURRENT        float64
 7   AMT_DRAWINGS_OTHER_CURRENT  float64
 8   AMT_DRAWINGS_POS_CURRENT    float64
 9   AMT_INST_MIN_REGULARITY     float64
 10  AMT_PAYMENT_CURRENT         float64
 11  AMT_PAYMENT_TOTAL_CURRENT   float64
 12  AMT_RECEIVABLE_PRINCIPAL    float64
 13  AMT_RECIVABLE               float64
 14  AMT_TOTAL_RECEIVABLE        float64
 15  CNT_DRAWINGS_ATM_CURRENT    float64
 16  CNT_DRAWINGS_CURRENT        int64
 17  CNT_DRAWINGS_OTHER_CURRENT  float64
 18  CNT_DRAWINGS_POS_CURRENT    float64
 19  CNT_INSTALMENT_MATURE_CUM   float64
 20  NAME_CONTRACT_STATUS        object
 21  SK_DPD                      int64
 22  SK_DPD_DEF                  int64
dtypes: float64(15), int64(7), object(1)
memory usage: 673.9+ MB
None

   SK_ID_PREV  SK_ID_CURR  MONTHS_BALANCE  AMT_BALANCE  \
0     2562384      378907              -6       56.970
1     2582071      363914              -1    63975.555
2     1740877      371185              -7    31815.225
3     1389973      337855              -4   236572.110
4     1891521      126868              -1   453919.455

   AMT_CREDIT_LIMIT_ACTUAL  AMT_DRAWINGS_ATM_CURRENT
AMT_DRAWINGS_CURRENT  \
0                   135000                       0.0
877.5
1                    45000                    2250.0
2250.0
2                   450000                       0.0
0.0
3                   225000                    2250.0
2250.0
4                   450000                       0.0
11547.0
```

```
   AMT_DRAWINGS_OTHER_CURRENT  AMT_DRAWINGS_POS_CURRENT  \
0                         0.0                     877.5
1                         0.0                       0.0
2                         0.0                       0.0
3                         0.0                       0.0
4                         0.0                   11547.0

   AMT_INST_MIN_REGULARITY  ...  AMT_RECIVABLE
AMT_TOTAL_RECEIVABLE  \
0                 1700.325  ...          0.000                     0.000

1                 2250.000  ...      64875.555                 64875.555

2                 2250.000  ...      31460.085                 31460.085

3                11795.760  ...     233048.970                233048.970

4                22924.890  ...     453919.455                453919.455


   CNT_DRAWINGS_ATM_CURRENT  CNT_DRAWINGS_CURRENT
CNT_DRAWINGS_OTHER_CURRENT  \
0                       0.0                     1
0.0
1                       1.0                     1
0.0
2                       0.0                     0
0.0
3                       1.0                     1
0.0
4                       0.0                     1
0.0

   CNT_DRAWINGS_POS_CURRENT  CNT_INSTALMENT_MATURE_CUM
NAME_CONTRACT_STATUS  \
0                       1.0                       35.0
Active
1                       0.0                       69.0
Active
2                       0.0                       30.0
Active
3                       0.0                       10.0
Active
4                       1.0                      101.0
Active

   SK_DPD  SK_DPD_DEF
0       0           0
1       0           0
2       0           0
```

```
3       0           0
4       0           0

[5 rows x 23 columns]

installments_payments: shape is (13605401, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13605401 entries, 0 to 13605400
Data columns (total 8 columns):
 #   Column                  Dtype
---  ------                  -----
 0   SK_ID_PREV              int64
 1   SK_ID_CURR              int64
 2   NUM_INSTALMENT_VERSION  float64
 3   NUM_INSTALMENT_NUMBER   int64
 4   DAYS_INSTALMENT         float64
 5   DAYS_ENTRY_PAYMENT      float64
 6   AMT_INSTALMENT          float64
 7   AMT_PAYMENT             float64
dtypes: float64(5), int64(3)
memory usage: 830.4 MB
None

   SK_ID_PREV  SK_ID_CURR  NUM_INSTALMENT_VERSION
NUM_INSTALMENT_NUMBER  \
0     1054186      161674                     1.0
6
1     1330831      151639                     0.0
34
2     2085231      193053                     2.0
1
3     2452527      199697                     1.0
3
4     2714724      167756                     1.0
2

   DAYS_INSTALMENT  DAYS_ENTRY_PAYMENT  AMT_INSTALMENT  AMT_PAYMENT
0          -1180.0             -1187.0        6948.360     6948.360
1          -2156.0             -2156.0        1716.525     1716.525
2            -63.0               -63.0       25425.000    25425.000
3          -2418.0             -2426.0       24350.130    24350.130
4          -1383.0             -1366.0        2165.040     2160.585

previous_application: shape is (1670214, 37)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):
 #   Column                       Non-Null Count    Dtype
---  ------                       --------------    -----
 0   SK_ID_PREV                   1670214 non-null  int64
```

```
 1   SK_ID_CURR                   1670214 non-null  int64
 2   NAME_CONTRACT_TYPE           1670214 non-null  object
 3   AMT_ANNUITY                  1297979 non-null  float64
 4   AMT_APPLICATION              1670214 non-null  float64
 5   AMT_CREDIT                   1670213 non-null  float64
 6   AMT_DOWN_PAYMENT             774370 non-null   float64
 7   AMT_GOODS_PRICE              1284699 non-null  float64
 8   WEEKDAY_APPR_PROCESS_START   1670214 non-null  object
 9   HOUR_APPR_PROCESS_START      1670214 non-null  int64
 10  FLAG_LAST_APPL_PER_CONTRACT  1670214 non-null  object
 11  NFLAG_LAST_APPL_IN_DAY       1670214 non-null  int64
 12  RATE_DOWN_PAYMENT            774370 non-null   float64
 13  RATE_INTEREST_PRIMARY        5951 non-null     float64
 14  RATE_INTEREST_PRIVILEGED     5951 non-null     float64
 15  NAME_CASH_LOAN_PURPOSE       1670214 non-null  object
 16  NAME_CONTRACT_STATUS         1670214 non-null  object
 17  DAYS_DECISION                1670214 non-null  int64
 18  NAME_PAYMENT_TYPE            1670214 non-null  object
 19  CODE_REJECT_REASON           1670214 non-null  object
 20  NAME_TYPE_SUITE              849809 non-null   object
 21  NAME_CLIENT_TYPE             1670214 non-null  object
 22  NAME_GOODS_CATEGORY          1670214 non-null  object
 23  NAME_PORTFOLIO               1670214 non-null  object
 24  NAME_PRODUCT_TYPE            1670214 non-null  object
 25  CHANNEL_TYPE                 1670214 non-null  object
 26  SELLERPLACE_AREA             1670214 non-null  int64
 27  NAME_SELLER_INDUSTRY         1670214 non-null  object
 28  CNT_PAYMENT                  1297984 non-null  float64
 29  NAME_YIELD_GROUP             1670214 non-null  object
 30  PRODUCT_COMBINATION          1669868 non-null  object
 31  DAYS_FIRST_DRAWING           997149 non-null   float64
 32  DAYS_FIRST_DUE               997149 non-null   float64
 33  DAYS_LAST_DUE_1ST_VERSION    997149 non-null   float64
 34  DAYS_LAST_DUE                997149 non-null   float64
 35  DAYS_TERMINATION             997149 non-null   float64
 36  NFLAG_INSURED_ON_APPROVAL    997149 non-null   float64
dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB
None

   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY
AMT_APPLICATION  \
0     2030495      271877     Consumer loans     1730.430
17145.0
1     2802425      108129         Cash loans    25188.615
607500.0
2     2523466      122040         Cash loans    15060.735
112500.0
3     2819243      176158         Cash loans    47041.335
450000.0
```

```
4     1784265       202054         Cash loans    31924.395
337500.0

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE
WEEKDAY_APPR_PROCESS_START  \
0     17145.0               0.0          17145.0
SATURDAY
1    679671.0               NaN         607500.0
THURSDAY
2    136444.5               NaN         112500.0
TUESDAY
3    470790.0               NaN         450000.0
MONDAY
4    404055.0               NaN         337500.0
THURSDAY

   HOUR_APPR_PROCESS_START  ... NAME_SELLER_INDUSTRY  CNT_PAYMENT  \
0                       15  ...         Connectivity         12.0
1                       11  ...                  XNA         36.0
2                       11  ...                  XNA         12.0
3                        7  ...                  XNA         12.0
4                        9  ...                  XNA         24.0

   NAME_YIELD_GROUP       PRODUCT_COMBINATION  DAYS_FIRST_DRAWING  \
0            middle  POS mobile with interest            365243.0
1        low_action          Cash X-Sell: low            365243.0
2              high         Cash X-Sell: high            365243.0
3            middle       Cash X-Sell: middle            365243.0
4              high         Cash Street: high                 NaN

  DAYS_FIRST_DUE DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE
DAYS_TERMINATION  \
0          -42.0                     300.0          -42.0            -
37.0
1         -134.0                     916.0       365243.0
365243.0
2         -271.0                      59.0       365243.0
365243.0
3         -482.0                    -152.0         -182.0           -
177.0
4            NaN                       NaN            NaN
NaN

  NFLAG_INSURED_ON_APPROVAL
0                       0.0
1                       1.0
2                       1.0
3                       1.0
4                       NaN
```

```
[5 rows x 37 columns]

POS_CASH_balance: shape is (10001358, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10001358 entries, 0 to 10001357
Data columns (total 8 columns):
 #   Column                 Dtype
---  ------                 -----
 0   SK_ID_PREV             int64
 1   SK_ID_CURR             int64
 2   MONTHS_BALANCE         int64
 3   CNT_INSTALMENT         float64
 4   CNT_INSTALMENT_FUTURE  float64
 5   NAME_CONTRACT_STATUS   object
 6   SK_DPD                 int64
 7   SK_DPD_DEF             int64
dtypes: float64(2), int64(5), object(1)
memory usage: 610.4+ MB
None

   SK_ID_PREV  SK_ID_CURR  MONTHS_BALANCE  CNT_INSTALMENT  \
0     1803195      182943             -31            48.0
1     1715348      367990             -33            36.0
2     1784872      397406             -32            12.0
3     1903291      269225             -35            48.0
4     2341044      334279             -35            36.0

   CNT_INSTALMENT_FUTURE NAME_CONTRACT_STATUS  SK_DPD  SK_DPD_DEF
0                   45.0               Active       0           0
1                   35.0               Active       0           0
2                    9.0               Active       0           0
3                   42.0               Active       0           0
4                   35.0               Active       0           0

CPU times: user 18.9 s, sys: 3.02 s, total: 21.9 s
Wall time: 33.4 s
```

```
for ds_name in datasets.keys():
    print(f'dataset {ds_name:24}: [ {datasets[ds_name].shape[0]:10,},
{datasets[ds_name].shape[1]}]')
```

```
dataset application_train       : [    307,511, 122]
dataset application_test        : [     48,744, 121]
dataset bureau                  : [  1,716,428, 17]
dataset bureau_balance          : [ 27,299,925, 3]
dataset credit_card_balance     : [  3,840,312, 23]
dataset installments_payments   : [ 13,605,401, 8]
dataset previous_application    : [  1,670,214, 37]
dataset POS_CASH_balance        : [ 10,001,358, 8]
```

Exploratory Data Analysis

Summary of Application train and Application test

Summary of Application train

```
datasets["application_train"].shape
```

```
(307511, 122)
```

- There are a total of 3,07,511 rows in "application training" dataset and 122 features, including the "Target" column.

```
datasets["application_train"].info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 122 columns):
 #    Column                         Dtype
---   ------                         -----
 0    SK_ID_CURR                     int64
 1    TARGET                         int64
 2    NAME_CONTRACT_TYPE             object
 3    CODE_GENDER                    object
 4    FLAG_OWN_CAR                   object
 5    FLAG_OWN_REALTY                object
 6    CNT_CHILDREN                   int64
 7    AMT_INCOME_TOTAL               float64
 8    AMT_CREDIT                     float64
 9    AMT_ANNUITY                    float64
 10   AMT_GOODS_PRICE                float64
 11   NAME_TYPE_SUITE                object
 12   NAME_INCOME_TYPE               object
 13   NAME_EDUCATION_TYPE            object
 14   NAME_FAMILY_STATUS             object
 15   NAME_HOUSING_TYPE              object
 16   REGION_POPULATION_RELATIVE     float64
 17   DAYS_BIRTH                     int64
 18   DAYS_EMPLOYED                  int64
 19   DAYS_REGISTRATION              float64
 20   DAYS_ID_PUBLISH                int64
 21   OWN_CAR_AGE                    float64
 22   FLAG_MOBIL                     int64
 23   FLAG_EMP_PHONE                 int64
 24   FLAG_WORK_PHONE                int64
 25   FLAG_CONT_MOBILE               int64
 26   FLAG_PHONE                     int64
 27   FLAG_EMAIL                     int64
 28   OCCUPATION_TYPE                object
```

```
 29   CNT_FAM_MEMBERS              float64
 30   REGION_RATING_CLIENT         int64
 31   REGION_RATING_CLIENT_W_CITY  int64
 32   WEEKDAY_APPR_PROCESS_START   object
 33   HOUR_APPR_PROCESS_START      int64
 34   REG_REGION_NOT_LIVE_REGION   int64
 35   REG_REGION_NOT_WORK_REGION   int64
 36   LIVE_REGION_NOT_WORK_REGION  int64
 37   REG_CITY_NOT_LIVE_CITY       int64
 38   REG_CITY_NOT_WORK_CITY       int64
 39   LIVE_CITY_NOT_WORK_CITY      int64
 40   ORGANIZATION_TYPE            object
 41   EXT_SOURCE_1                 float64
 42   EXT_SOURCE_2                 float64
 43   EXT_SOURCE_3                 float64
 44   APARTMENTS_AVG               float64
 45   BASEMENTAREA_AVG             float64
 46   YEARS_BEGINEXPLUATATION_AVG  float64
 47   YEARS_BUILD_AVG              float64
 48   COMMONAREA_AVG               float64
 49   ELEVATORS_AVG                float64
 50   ENTRANCES_AVG                float64
 51   FLOORSMAX_AVG                float64
 52   FLOORSMIN_AVG                float64
 53   LANDAREA_AVG                 float64
 54   LIVINGAPARTMENTS_AVG         float64
 55   LIVINGAREA_AVG               float64
 56   NONLIVINGAPARTMENTS_AVG      float64
 57   NONLIVINGAREA_AVG            float64
 58   APARTMENTS_MODE              float64
 59   BASEMENTAREA_MODE            float64
 60   YEARS_BEGINEXPLUATATION_MODE  float64
 61   YEARS_BUILD_MODE             float64
 62   COMMONAREA_MODE              float64
 63   ELEVATORS_MODE               float64
 64   ENTRANCES_MODE               float64
 65   FLOORSMAX_MODE               float64
 66   FLOORSMIN_MODE               float64
 67   LANDAREA_MODE                float64
 68   LIVINGAPARTMENTS_MODE        float64
 69   LIVINGAREA_MODE              float64
 70   NONLIVINGAPARTMENTS_MODE     float64
 71   NONLIVINGAREA_MODE           float64
 72   APARTMENTS_MEDI              float64
 73   BASEMENTAREA_MEDI            float64
 74   YEARS_BEGINEXPLUATATION_MEDI  float64
 75   YEARS_BUILD_MEDI             float64
 76   COMMONAREA_MEDI              float64
 77   ELEVATORS_MEDI               float64
```

```
 78   ENTRANCES_MEDI                  float64
 79   FLOORSMAX_MEDI                  float64
 80   FLOORSMIN_MEDI                  float64
 81   LANDAREA_MEDI                   float64
 82   LIVINGAPARTMENTS_MEDI           float64
 83   LIVINGAREA_MEDI                 float64
 84   NONLIVINGAPARTMENTS_MEDI        float64
 85   NONLIVINGAREA_MEDI              float64
 86   FONDKAPREMONT_MODE              object
 87   HOUSETYPE_MODE                  object
 88   TOTALAREA_MODE                  float64
 89   WALLSMATERIAL_MODE              object
 90   EMERGENCYSTATE_MODE             object
 91   OBS_30_CNT_SOCIAL_CIRCLE        float64
 92   DEF_30_CNT_SOCIAL_CIRCLE        float64
 93   OBS_60_CNT_SOCIAL_CIRCLE        float64
 94   DEF_60_CNT_SOCIAL_CIRCLE        float64
 95   DAYS_LAST_PHONE_CHANGE          float64
 96   FLAG_DOCUMENT_2                 int64
 97   FLAG_DOCUMENT_3                 int64
 98   FLAG_DOCUMENT_4                 int64
 99   FLAG_DOCUMENT_5                 int64
 100  FLAG_DOCUMENT_6                 int64
 101  FLAG_DOCUMENT_7                 int64
 102  FLAG_DOCUMENT_8                 int64
 103  FLAG_DOCUMENT_9                 int64
 104  FLAG_DOCUMENT_10                int64
 105  FLAG_DOCUMENT_11                int64
 106  FLAG_DOCUMENT_12                int64
 107  FLAG_DOCUMENT_13                int64
 108  FLAG_DOCUMENT_14                int64
 109  FLAG_DOCUMENT_15                int64
 110  FLAG_DOCUMENT_16                int64
 111  FLAG_DOCUMENT_17                int64
 112  FLAG_DOCUMENT_18                int64
 113  FLAG_DOCUMENT_19                int64
 114  FLAG_DOCUMENT_20                int64
 115  FLAG_DOCUMENT_21                int64
 116  AMT_REQ_CREDIT_BUREAU_HOUR      float64
 117  AMT_REQ_CREDIT_BUREAU_DAY       float64
 118  AMT_REQ_CREDIT_BUREAU_WEEK      float64
 119  AMT_REQ_CREDIT_BUREAU_MON       float64
 120  AMT_REQ_CREDIT_BUREAU_QRT       float64
 121  AMT_REQ_CREDIT_BUREAU_YEAR      float64
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB

datasets["application_train"].describe() #numerical only features
```

```
          SK_ID_CURR         TARGET   CNT_CHILDREN
AMT_INCOME_TOTAL  \
count  307511.000000  307511.000000  307511.000000      3.075110e+05

mean   278180.518577       0.080729       0.417052      1.687979e+05

std    102790.175348       0.272419       0.722121      2.371231e+05

min    100002.000000       0.000000       0.000000      2.565000e+04

25%    189145.500000       0.000000       0.000000      1.125000e+05

50%    278202.000000       0.000000       0.000000      1.471500e+05

75%    367142.500000       0.000000       1.000000      2.025000e+05

max    456255.000000       1.000000      19.000000      1.170000e+08


         AMT_CREDIT    AMT_ANNUITY  AMT_GOODS_PRICE  \
count  3.075110e+05  307499.000000     3.072330e+05
mean   5.990260e+05   27108.573909     5.383962e+05
std    4.024908e+05   14493.737315     3.694465e+05
min    4.500000e+04    1615.500000     4.050000e+04
25%    2.700000e+05   16524.000000     2.385000e+05
50%    5.135310e+05   24903.000000     4.500000e+05
75%    8.086500e+05   34596.000000     6.795000e+05
max    4.050000e+06  258025.500000     4.050000e+06

       REGION_POPULATION_RELATIVE     DAYS_BIRTH
DAYS_EMPLOYED  ...  \
count                307511.000000  307511.000000  307511.000000  ...

mean                      0.020868  -16036.995067   63815.045904  ...

std                       0.013831    4363.988632  141275.766519  ...

min                       0.000290  -25229.000000  -17912.000000  ...

25%                       0.010006  -19682.000000   -2760.000000  ...

50%                       0.018850  -15750.000000   -1213.000000  ...

75%                       0.028663  -12413.000000    -289.000000  ...

max                       0.072508   -7489.000000  365243.000000  ...


       FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
count     307511.000000     307511.000000     307511.000000
```

```
307511.000000
mean            0.008130          0.000595          0.000507
0.000335
std             0.089798          0.024387          0.022518
0.018299
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

       AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
count               265992.000000              265992.000000
mean                     0.006402                   0.007000
std                      0.083849                   0.110757
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      4.000000                   9.000000

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
count               265992.000000              265992.000000
mean                     0.034362                   0.267395
std                      0.204685                   0.916002
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      8.000000                  27.000000

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
count              265992.000000               265992.000000
mean                    0.265474                    1.899974
std                     0.794056                    1.869295
min                     0.000000                    0.000000
25%                     0.000000                    0.000000
50%                     0.000000                    1.000000
75%                     0.000000                    3.000000
max                   261.000000                   25.000000

[8 rows x 106 columns]

datasets["application_train"].describe(include='all') #look at all
categorical and numerical
```

```
           SK_ID_CURR         TARGET NAME_CONTRACT_TYPE CODE_GENDER  \
count   307511.000000  307511.000000             307511      307511
unique            NaN            NaN                  2           3
top               NaN            NaN         Cash loans           F
freq              NaN            NaN             278232      202448
mean    278180.518577       0.080729                NaN         NaN
std     102790.175348       0.272419                NaN         NaN
min     100002.000000       0.000000                NaN         NaN
25%     189145.500000       0.000000                NaN         NaN
50%     278202.000000       0.000000                NaN         NaN
75%     367142.500000       0.000000                NaN         NaN
max     456255.000000       1.000000                NaN         NaN

       FLAG_OWN_CAR FLAG_OWN_REALTY   CNT_CHILDREN
AMT_INCOME_TOTAL  \
count        307511          307511  307511.000000      3.075110e+05

unique            2               2            NaN               NaN

top               N               Y            NaN               NaN

freq         202924          213312            NaN               NaN

mean            NaN             NaN       0.417052      1.687979e+05

std             NaN             NaN       0.722121      2.371231e+05

min             NaN             NaN       0.000000      2.565000e+04

25%             NaN             NaN       0.000000      1.125000e+05

50%             NaN             NaN       0.000000      1.471500e+05

75%             NaN             NaN       1.000000      2.025000e+05

max             NaN             NaN      19.000000      1.170000e+08


          AMT_CREDIT    AMT_ANNUITY  ...  FLAG_DOCUMENT_18
FLAG_DOCUMENT_19  \
count   3.075110e+05  307499.000000  ...     307511.000000
307511.000000
unique           NaN            NaN  ...               NaN
NaN
top              NaN            NaN  ...               NaN
NaN
freq             NaN            NaN  ...               NaN
NaN
mean    5.990260e+05   27108.573909  ...          0.008130
0.000595
std     4.024908e+05   14493.737315  ...          0.089798
```

```
0.024387
min     4.500000e+04    1615.500000  ...         0.000000
0.000000
25%     2.700000e+05   16524.000000  ...         0.000000
0.000000
50%     5.135310e+05   24903.000000  ...         0.000000
0.000000
75%     8.086500e+05   34596.000000  ...         0.000000
0.000000
max     4.050000e+06  258025.500000  ...         1.000000
1.000000

       FLAG_DOCUMENT_20 FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR  \
count     307511.000000    307511.000000              265992.000000
unique              NaN              NaN                        NaN
top                 NaN              NaN                        NaN
freq                NaN              NaN                        NaN
mean           0.000507         0.000335                   0.006402
std            0.022518         0.018299                   0.083849
min            0.000000         0.000000                   0.000000
25%            0.000000         0.000000                   0.000000
50%            0.000000         0.000000                   0.000000
75%            0.000000         0.000000                   0.000000
max            1.000000         1.000000                   4.000000

       AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
count              265992.000000               265992.000000
unique                       NaN                         NaN
top                          NaN                         NaN
freq                         NaN                         NaN
mean                    0.007000                    0.034362
std                     0.110757                    0.204685
min                     0.000000                    0.000000
25%                     0.000000                    0.000000
50%                     0.000000                    0.000000
75%                     0.000000                    0.000000
max                     9.000000                    8.000000

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
count              265992.000000              265992.000000
unique                       NaN                        NaN
top                          NaN                        NaN
freq                         NaN                        NaN
mean                    0.267395                   0.265474
std                     0.916002                   0.794056
min                     0.000000                   0.000000
25%                     0.000000                   0.000000
50%                     0.000000                   0.000000
75%                     0.000000                   0.000000
max                    27.000000                 261.000000
```

```
        AMT_REQ_CREDIT_BUREAU_YEAR
count                265992.000000
unique                         NaN
top                            NaN
freq                           NaN
mean                      1.899974
std                       1.869295
min                       0.000000
25%                       0.000000
50%                       1.000000
75%                       3.000000
max                      25.000000

[11 rows x 122 columns]
```

```
# Define function to List the categorical and Numerical features in
the dataframe

def datatypes_groups(df, df_name):
    print(f"Description of the {df_name} dataset:\n")
    print("-----"*15)
    print("Data type value counts: \n",df.dtypes.value_counts())

    df_dtypes = df.columns.to_series().groupby(df.dtypes).groups
    print("-----"*15)
    print(f"Categorical and Numerical(int + float) features  of
{df_name}.")
    print("-----"*15)
    print()
    for k, v in df_dtypes.items():
        print({k.name: v})
        print("---"*10)
    print("\n \n")

datatypes_groups(datasets['application_train'], 'application_train')
```

```
Description of the application_train dataset:

----------------------------------------------------------------------
-----
Data type value counts:
 float64    65
int64      41
object     16
dtype: int64
----------------------------------------------------------------------
-----
Categorical and Numerical(int + float) features  of application_train.
----------------------------------------------------------------------
```

```
-----

{'int64': Index(['SK_ID_CURR', 'TARGET', 'CNT_CHILDREN', 'DAYS_BIRTH',
'DAYS_EMPLOYED',
       'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'FLAG_EMP_PHONE',
'FLAG_WORK_PHONE',
       'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL',
'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START',
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY',
'FLAG_DOCUMENT_2',
       'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5',
       'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8',
       'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11',
       'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14',
       'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21'],
      dtype='object')}
------------------------------
{'float64': Index(['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY',
'AMT_GOODS_PRICE',
       'REGION_POPULATION_RELATIVE', 'DAYS_REGISTRATION',
'OWN_CAR_AGE',
       'CNT_FAM_MEMBERS', 'EXT_SOURCE_1', 'EXT_SOURCE_2',
'EXT_SOURCE_3',
       'APARTMENTS_AVG', 'BASEMENTAREA_AVG',
'YEARS_BEGINEXPLUATATION_AVG',
       'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG',
'ENTRANCES_AVG',
       'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG',
       'LIVINGAPARTMENTS_AVG', 'LIVINGAREA_AVG',
'NONLIVINGAPARTMENTS_AVG',
       'NONLIVINGAREA_AVG', 'APARTMENTS_MODE', 'BASEMENTAREA_MODE',
       'YEARS_BEGINEXPLUATATION_MODE', 'YEARS_BUILD_MODE',
'COMMONAREA_MODE',
       'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMAX_MODE',
'FLOORSMIN_MODE',
       'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'LIVINGAREA_MODE',
       'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE',
'APARTMENTS_MEDI',
       'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI',
'YEARS_BUILD_MEDI',
       'COMMONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI',
'FLOORSMAX_MEDI',
       'FLOORSMIN_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI',
       'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI',
```

```
'NONLIVINGAREA_MEDI',
       'TOTALAREA_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE',
       'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE',
       'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE',
       'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
       'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
       'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')}
------------------------------
{'object': Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY',
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE',
'FONDKAPREMONT_MODE',
       'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'],
      dtype='object')}
------------------------------
```

- Explaination
- There are 16 Categorical features and 106 Numerical(int + float) features in the "application_train" dataset.

Summary of Application test

```
datasets["application_test"].shape

(48744, 121)
```

- There are a total of 487,44 rows in "application test" dataset and 122 features, including the "Target" column.

```
datasets["application_test"].info(verbose=True)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48744 entries, 0 to 48743
Data columns (total 121 columns):
 #    Column                        Dtype
---   ------                        -----
 0    SK_ID_CURR                    int64
 1    NAME_CONTRACT_TYPE            object
 2    CODE_GENDER                   object
 3    FLAG_OWN_CAR                  object
 4    FLAG_OWN_REALTY               object
 5    CNT_CHILDREN                  int64
 6    AMT_INCOME_TOTAL              float64
 7    AMT_CREDIT                    float64
```

```
8    AMT_ANNUITY                    float64
9    AMT_GOODS_PRICE                float64
10   NAME_TYPE_SUITE                object
11   NAME_INCOME_TYPE               object
12   NAME_EDUCATION_TYPE            object
13   NAME_FAMILY_STATUS             object
14   NAME_HOUSING_TYPE              object
15   REGION_POPULATION_RELATIVE     float64
16   DAYS_BIRTH                     int64
17   DAYS_EMPLOYED                  int64
18   DAYS_REGISTRATION              float64
19   DAYS_ID_PUBLISH                int64
20   OWN_CAR_AGE                    float64
21   FLAG_MOBIL                     int64
22   FLAG_EMP_PHONE                 int64
23   FLAG_WORK_PHONE                int64
24   FLAG_CONT_MOBILE               int64
25   FLAG_PHONE                     int64
26   FLAG_EMAIL                     int64
27   OCCUPATION_TYPE                object
28   CNT_FAM_MEMBERS                float64
29   REGION_RATING_CLIENT           int64
30   REGION_RATING_CLIENT_W_CITY    int64
31   WEEKDAY_APPR_PROCESS_START     object
32   HOUR_APPR_PROCESS_START        int64
33   REG_REGION_NOT_LIVE_REGION     int64
34   REG_REGION_NOT_WORK_REGION     int64
35   LIVE_REGION_NOT_WORK_REGION    int64
36   REG_CITY_NOT_LIVE_CITY         int64
37   REG_CITY_NOT_WORK_CITY         int64
38   LIVE_CITY_NOT_WORK_CITY        int64
39   ORGANIZATION_TYPE              object
40   EXT_SOURCE_1                   float64
41   EXT_SOURCE_2                   float64
42   EXT_SOURCE_3                   float64
43   APARTMENTS_AVG                 float64
44   BASEMENTAREA_AVG               float64
45   YEARS_BEGINEXPLUATATION_AVG    float64
46   YEARS_BUILD_AVG                float64
47   COMMONAREA_AVG                 float64
48   ELEVATORS_AVG                  float64
49   ENTRANCES_AVG                  float64
50   FLOORSMAX_AVG                  float64
51   FLOORSMIN_AVG                  float64
52   LANDAREA_AVG                   float64
53   LIVINGAPARTMENTS_AVG           float64
54   LIVINGAREA_AVG                 float64
55   NONLIVINGAPARTMENTS_AVG        float64
56   NONLIVINGAREA_AVG              float64
```

```
 57   APARTMENTS_MODE               float64
 58   BASEMENTAREA_MODE             float64
 59   YEARS_BEGINEXPLUATATION_MODE  float64
 60   YEARS_BUILD_MODE              float64
 61   COMMONAREA_MODE               float64
 62   ELEVATORS_MODE                float64
 63   ENTRANCES_MODE                float64
 64   FLOORSMAX_MODE                float64
 65   FLOORSMIN_MODE                float64
 66   LANDAREA_MODE                 float64
 67   LIVINGAPARTMENTS_MODE         float64
 68   LIVINGAREA_MODE               float64
 69   NONLIVINGAPARTMENTS_MODE      float64
 70   NONLIVINGAREA_MODE            float64
 71   APARTMENTS_MEDI               float64
 72   BASEMENTAREA_MEDI             float64
 73   YEARS_BEGINEXPLUATATION_MEDI  float64
 74   YEARS_BUILD_MEDI              float64
 75   COMMONAREA_MEDI               float64
 76   ELEVATORS_MEDI                float64
 77   ENTRANCES_MEDI                float64
 78   FLOORSMAX_MEDI                float64
 79   FLOORSMIN_MEDI                float64
 80   LANDAREA_MEDI                 float64
 81   LIVINGAPARTMENTS_MEDI         float64
 82   LIVINGAREA_MEDI               float64
 83   NONLIVINGAPARTMENTS_MEDI      float64
 84   NONLIVINGAREA_MEDI            float64
 85   FONDKAPREMONT_MODE            object
 86   HOUSETYPE_MODE                object
 87   TOTALAREA_MODE                float64
 88   WALLSMATERIAL_MODE            object
 89   EMERGENCYSTATE_MODE           object
 90   OBS_30_CNT_SOCIAL_CIRCLE      float64
 91   DEF_30_CNT_SOCIAL_CIRCLE      float64
 92   OBS_60_CNT_SOCIAL_CIRCLE      float64
 93   DEF_60_CNT_SOCIAL_CIRCLE      float64
 94   DAYS_LAST_PHONE_CHANGE        float64
 95   FLAG_DOCUMENT_2               int64
 96   FLAG_DOCUMENT_3               int64
 97   FLAG_DOCUMENT_4               int64
 98   FLAG_DOCUMENT_5               int64
 99   FLAG_DOCUMENT_6               int64
 100  FLAG_DOCUMENT_7               int64
 101  FLAG_DOCUMENT_8               int64
 102  FLAG_DOCUMENT_9               int64
 103  FLAG_DOCUMENT_10              int64
 104  FLAG_DOCUMENT_11              int64
 105  FLAG_DOCUMENT_12              int64
```

```
 106  FLAG_DOCUMENT_13              int64
 107  FLAG_DOCUMENT_14              int64
 108  FLAG_DOCUMENT_15              int64
 109  FLAG_DOCUMENT_16              int64
 110  FLAG_DOCUMENT_17              int64
 111  FLAG_DOCUMENT_18              int64
 112  FLAG_DOCUMENT_19              int64
 113  FLAG_DOCUMENT_20              int64
 114  FLAG_DOCUMENT_21              int64
 115  AMT_REQ_CREDIT_BUREAU_HOUR    float64
 116  AMT_REQ_CREDIT_BUREAU_DAY     float64
 117  AMT_REQ_CREDIT_BUREAU_WEEK    float64
 118  AMT_REQ_CREDIT_BUREAU_MON     float64
 119  AMT_REQ_CREDIT_BUREAU_QRT     float64
 120  AMT_REQ_CREDIT_BUREAU_YEAR    float64
dtypes: float64(65), int64(40), object(16)
memory usage: 45.0+ MB
```

```
datasets["application_test"].describe() #numerical only features
```

```
          SK_ID_CURR  CNT_CHILDREN  AMT_INCOME_TOTAL    AMT_CREDIT  \
count   48744.000000  48744.000000      4.874400e+04  4.874400e+04
mean   277796.676350      0.397054      1.784318e+05  5.167404e+05
std    103169.547296      0.709047      1.015226e+05  3.653970e+05
min    100001.000000      0.000000      2.694150e+04  4.500000e+04
25%    188557.750000      0.000000      1.125000e+05  2.606400e+05
50%    277549.000000      0.000000      1.575000e+05  4.500000e+05
75%    367555.500000      1.000000      2.250000e+05  6.750000e+05
max    456250.000000     20.000000      4.410000e+06  2.245500e+06

         AMT_ANNUITY  AMT_GOODS_PRICE  REGION_POPULATION_RELATIVE  \
count   48720.000000     4.874400e+04                48744.000000
mean    29426.240209     4.626188e+05                    0.021226
std     16016.368315     3.367102e+05                    0.014428
min      2295.000000     4.500000e+04                    0.000253
25%     17973.000000     2.250000e+05                    0.010006
50%     26199.000000     3.960000e+05                    0.018850
75%     37390.500000     6.300000e+05                    0.028663
max    180576.000000     2.245500e+06                    0.072508

         DAYS_BIRTH  DAYS_EMPLOYED  DAYS_REGISTRATION  ...
FLAG_DOCUMENT_18  \
count  48744.000000   48744.000000       48744.000000  ...
48744.000000
mean  -16068.084605   67485.366322       -4967.652716  ...
0.001559
std     4325.900393  144348.507136        3552.612035  ...
0.039456
min   -25195.000000  -17463.000000      -23722.000000  ...
0.000000
```

```
25%   -19637.000000   -2910.000000       -7459.250000  ...
0.000000
50%   -15785.000000   -1293.000000       -4490.000000  ...
0.000000
75%   -12496.000000    -296.000000       -1901.000000  ...
0.000000
max    -7338.000000  365243.000000          0.000000  ...
1.000000

       FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  \
count           48744.0           48744.0           48744.0
mean                0.0               0.0               0.0
std                 0.0               0.0               0.0
min                 0.0               0.0               0.0
25%                 0.0               0.0               0.0
50%                 0.0               0.0               0.0
75%                 0.0               0.0               0.0
max                 0.0               0.0               0.0

       AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
count                42695.000000               42695.000000
mean                     0.002108                   0.001803
std                      0.046373                   0.046132
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      2.000000                   2.000000

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
count                42695.000000               42695.000000
mean                     0.002787                   0.009299
std                      0.054037                   0.110924
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      2.000000                   6.000000

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
count               42695.000000                42695.000000
mean                    0.546902                    1.983769
std                     0.693305                    1.838873
min                     0.000000                    0.000000
25%                     0.000000                    0.000000
50%                     0.000000                    2.000000
75%                     1.000000                    3.000000
max                     7.000000                   17.000000

[8 rows x 105 columns]
```

```python
datasets["application_test"].describe(include='all') #look at all categorical and numerical
```

```
              SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
count    48744.000000              48744       48744        48744
unique            NaN                  2           2            2
top               NaN         Cash loans           F            N
freq              NaN              48305       32678        32311
mean    277796.676350                NaN         NaN          NaN
std     103169.547296                NaN         NaN          NaN
min     100001.000000                NaN         NaN          NaN
25%     188557.750000                NaN         NaN          NaN
50%     277549.000000                NaN         NaN          NaN
75%     367555.500000                NaN         NaN          NaN
max     456250.000000                NaN         NaN          NaN

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL
AMT_CREDIT  \
count            48744  48744.000000      4.874400e+04  4.874400e+04

unique               2           NaN               NaN           NaN

top                  Y           NaN               NaN           NaN

freq             33658           NaN               NaN           NaN

mean               NaN      0.397054      1.784318e+05  5.167404e+05

std                NaN      0.709047      1.015226e+05  3.653970e+05

min                NaN      0.000000      2.694150e+04  4.500000e+04

25%                NaN      0.000000      1.125000e+05  2.606400e+05

50%                NaN      0.000000      1.575000e+05  4.500000e+05

75%                NaN      1.000000      2.250000e+05  6.750000e+05

max                NaN     20.000000      4.410000e+06  2.245500e+06


          AMT_ANNUITY  AMT_GOODS_PRICE  ... FLAG_DOCUMENT_18
FLAG_DOCUMENT_19  \
count    48720.000000     4.874400e+04  ...     48744.000000
48744.0
unique            NaN              NaN  ...              NaN
NaN
top               NaN              NaN  ...              NaN
NaN
freq              NaN              NaN  ...              NaN
NaN
```

```
mean     29426.240209     4.626188e+05  ...         0.001559
0.0
std      16016.368315     3.367102e+05  ...         0.039456
0.0
min       2295.000000     4.500000e+04  ...         0.000000
0.0
25%      17973.000000     2.250000e+05  ...         0.000000
0.0
50%      26199.000000     3.960000e+05  ...         0.000000
0.0
75%      37390.500000     6.300000e+05  ...         0.000000
0.0
max     180576.000000     2.245500e+06  ...         1.000000
0.0

       FLAG_DOCUMENT_20 FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR  \
count           48744.0          48744.0               42695.000000
unique              NaN              NaN                        NaN
top                 NaN              NaN                        NaN
freq                NaN              NaN                        NaN
mean                0.0              0.0                   0.002108
std                 0.0              0.0                   0.046373
min                 0.0              0.0                   0.000000
25%                 0.0              0.0                   0.000000
50%                 0.0              0.0                   0.000000
75%                 0.0              0.0                   0.000000
max                 0.0              0.0                   2.000000

        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
count                42695.000000                42695.000000
unique                        NaN                         NaN
top                           NaN                         NaN
freq                          NaN                         NaN
mean                     0.001803                    0.002787
std                      0.046132                    0.054037
min                      0.000000                    0.000000
25%                      0.000000                    0.000000
50%                      0.000000                    0.000000
75%                      0.000000                    0.000000
max                      2.000000                    2.000000

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
count                42695.000000               42695.000000
unique                        NaN                        NaN
top                           NaN                        NaN
freq                          NaN                        NaN
mean                     0.009299                   0.546902
std                      0.110924                   0.693305
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
```

```
50%                         0.000000                   0.000000
75%                         0.000000                   1.000000
max                         6.000000                   7.000000

        AMT_REQ_CREDIT_BUREAU_YEAR
count                 42695.000000
unique                         NaN
top                            NaN
freq                           NaN
mean                      1.983769
std                       1.838873
min                       0.000000
25%                       0.000000
50%                       2.000000
75%                       3.000000
max                      17.000000

[11 rows x 121 columns]
```

```
datatypes_groups(datasets['application_test'], 'application_test')
```

```
Description of the application_test dataset:

----------------------------------------------------------------------
-----
Data type value counts:
 float64    65
int64      40
object     16
dtype: int64
----------------------------------------------------------------------
-----
Categorical and Numerical(int + float) features  of application_test.
----------------------------------------------------------------------
-----

{'int64': Index(['SK_ID_CURR', 'CNT_CHILDREN', 'DAYS_BIRTH',
'DAYS_EMPLOYED',
       'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'FLAG_EMP_PHONE',
'FLAG_WORK_PHONE',
       'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL',
'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START',
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY',
'FLAG_DOCUMENT_2',
       'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5',
       'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8',
       'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11',
```

```
       'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14',
       'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21'],
      dtype='object')}
------------------------------
{'float64': Index(['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY',
'AMT_GOODS_PRICE',
       'REGION_POPULATION_RELATIVE', 'DAYS_REGISTRATION',
'OWN_CAR_AGE',
       'CNT_FAM_MEMBERS', 'EXT_SOURCE_1', 'EXT_SOURCE_2',
'EXT_SOURCE_3',
       'APARTMENTS_AVG', 'BASEMENTAREA_AVG',
'YEARS_BEGINEXPLUATATION_AVG',
       'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG',
'ENTRANCES_AVG',
       'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG',
       'LIVINGAPARTMENTS_AVG', 'LIVINGAREA_AVG',
'NONLIVINGAPARTMENTS_AVG',
       'NONLIVINGAREA_AVG', 'APARTMENTS_MODE', 'BASEMENTAREA_MODE',
       'YEARS_BEGINEXPLUATATION_MODE', 'YEARS_BUILD_MODE',
'COMMONAREA_MODE',
       'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMAX_MODE',
'FLOORSMIN_MODE',
       'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'LIVINGAREA_MODE',
       'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE',
'APARTMENTS_MEDI',
       'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI',
'YEARS_BUILD_MEDI',
       'COMMONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI',
'FLOORSMAX_MEDI',
       'FLOORSMIN_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI',
       'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI',
'NONLIVINGAREA_MEDI',
       'TOTALAREA_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE',
       'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE',
       'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE',
       'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
       'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
       'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')}
------------------------------
{'object': Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY',
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE',
'FONDKAPREMONT_MODE',
       'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'],
```

```
      dtype='object')}
------------------------------
```

- Explaination
- There are 16 Categorical features and 105 Numerical(int + float) features in the "application_test" dataset.

Missing data for application train and test

Missing data for application train

```
# !pip install missingno

import missingno as msno
import matplotlib.pyplot as plt

percent =
(datasets["application_train"].isnull().sum()/datasets["application_tr
ain"].isnull().count()*100).sort_values(ascending = False).round(2)
sum_missing =
datasets["application_train"].isna().sum().sort_values(ascending =
False)
missing_application_train_data  = pd.concat([percent, sum_missing],
axis=1, keys=['Percent', "Train Missing Count"])
missing_application_train_data.head(20)
```

	Percent	Train Missing Count
COMMONAREA_MEDI	69.87	214865
COMMONAREA_AVG	69.87	214865
COMMONAREA_MODE	69.87	214865
NONLIVINGAPARTMENTS_MODE	69.43	213514
NONLIVINGAPARTMENTS_AVG	69.43	213514
NONLIVINGAPARTMENTS_MEDI	69.43	213514
FONDKAPREMONT_MODE	68.39	210295
LIVINGAPARTMENTS_MODE	68.35	210199
LIVINGAPARTMENTS_AVG	68.35	210199
LIVINGAPARTMENTS_MEDI	68.35	210199
FLOORSMIN_AVG	67.85	208642
FLOORSMIN_MODE	67.85	208642
FLOORSMIN_MEDI	67.85	208642
YEARS_BUILD_MEDI	66.50	204488
YEARS_BUILD_MODE	66.50	204488
YEARS_BUILD_AVG	66.50	204488
OWN_CAR_AGE	65.99	202929
LANDAREA_MEDI	59.38	182590
LANDAREA_MODE	59.38	182590
LANDAREA_AVG	59.38	182590

```python
# msno.bar(datasets['application_train'])

# msno.matrix(datasets['application_train'])
```

Missing data for application test

```python
percent =
(datasets["application_test"].isnull().sum()/datasets["application_tes
t"].isnull().count()*100).sort_values(ascending = False).round(2)
sum_missing =
datasets["application_test"].isna().sum().sort_values(ascending =
False)
missing_application_train_data  = pd.concat([percent, sum_missing],
axis=1, keys=['Percent', "Test Missing Count"])
missing_application_train_data.head(20)
```

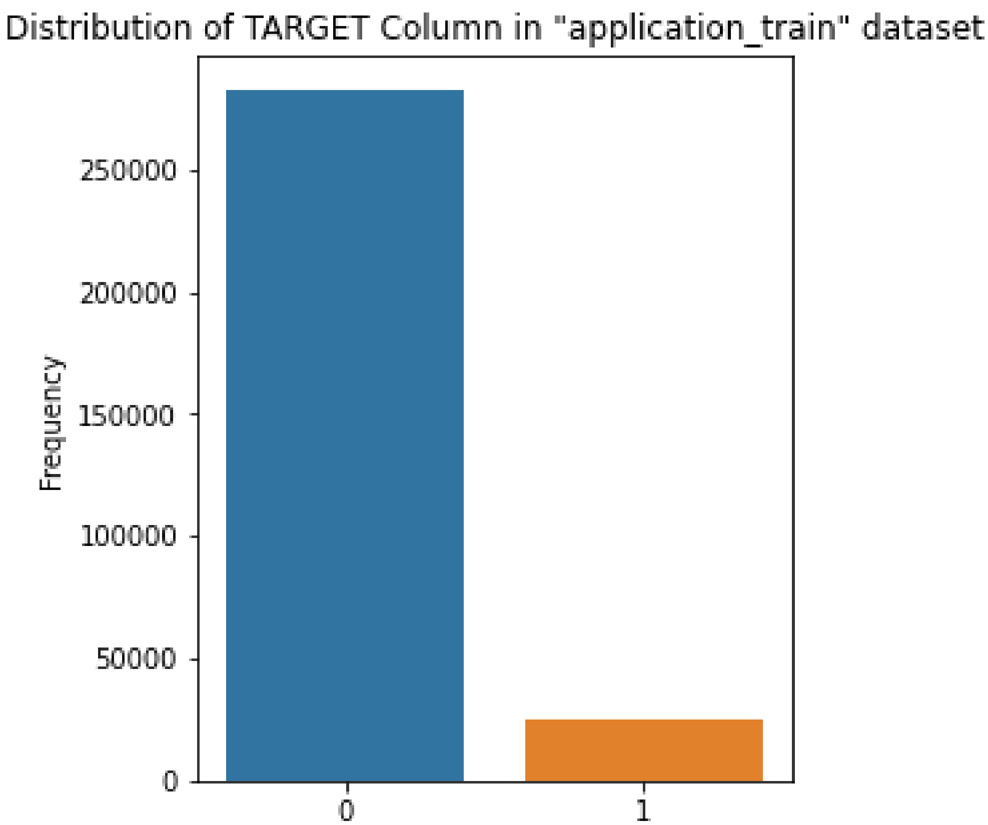
	Percent	Test Missing Count
COMMONAREA_AVG	68.72	33495
COMMONAREA_MODE	68.72	33495
COMMONAREA_MEDI	68.72	33495
NONLIVINGAPARTMENTS_AVG	68.41	33347
NONLIVINGAPARTMENTS_MODE	68.41	33347
NONLIVINGAPARTMENTS_MEDI	68.41	33347
FONDKAPREMONT_MODE	67.28	32797
LIVINGAPARTMENTS_AVG	67.25	32780
LIVINGAPARTMENTS_MODE	67.25	32780
LIVINGAPARTMENTS_MEDI	67.25	32780
FLOORSMIN_MEDI	66.61	32466
FLOORSMIN_AVG	66.61	32466
FLOORSMIN_MODE	66.61	32466
OWN_CAR_AGE	66.29	32312
YEARS_BUILD_AVG	65.28	31818
YEARS_BUILD_MEDI	65.28	31818
YEARS_BUILD_MODE	65.28	31818
LANDAREA_MEDI	57.96	28254
LANDAREA_AVG	57.96	28254
LANDAREA_MODE	57.96	28254

```python
# msno.bar(datasets['application_test'])

# msno.matrix(datasets['application_test'])
```

Distribution of the target column

```python
# Print the value counts of the 'TARGET' column in "application_train"
dataset

print(datasets["application_train"]['TARGET'].value_counts())
```

```
0    282686
1     24825
Name: TARGET, dtype: int64

# Plot the distribution of the values of 'TARGET' column in
"application_train" dataset

import matplotlib.pyplot as plt
import seaborn as sns

target_distribution = datasets["application_train"]
['TARGET'].value_counts()

plt.figure(figsize=(4, 5))

sns.barplot(x=target_distribution.index, y=target_distribution.values)

plt.title('Distribution of TARGET Column in "application_train"
dataset')  # Set the title for your plot
plt.ylabel('Frequency')

plt.show()
```

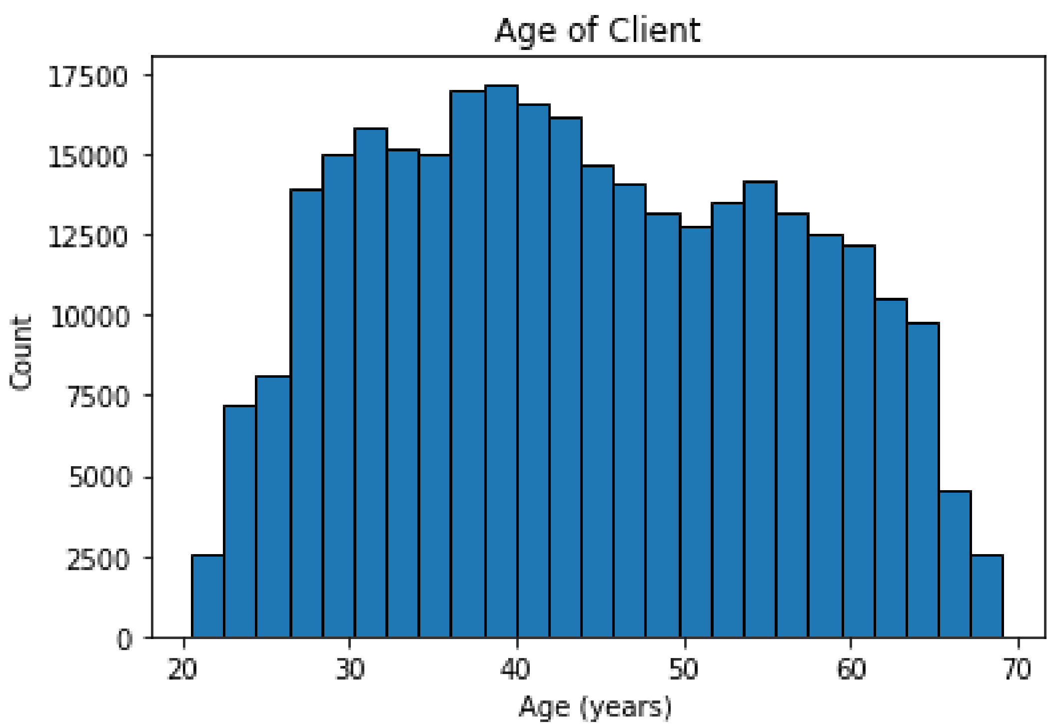


- Explaination

- As shown above, an imbalanced class issue was found in the "application_train" dataset. Class Imbalance is a common problem in machine learning, especially in classification tasks. This problem can negatively impact the performance and accuracy of machine models. Therefore, we need to handle the class imbalance problem before performing machine learning using combining Undersampling and Oversampling' techniques.
- Explaination
- The correlation results with the TARGET column from the application_train dataset showed that the variables most positively correlated with the target variable was DAYS_BIRTH (0.078239), whereas, the variables most negatively correlated with the target variable was EXT_SOURCE_3 (-0.178919).

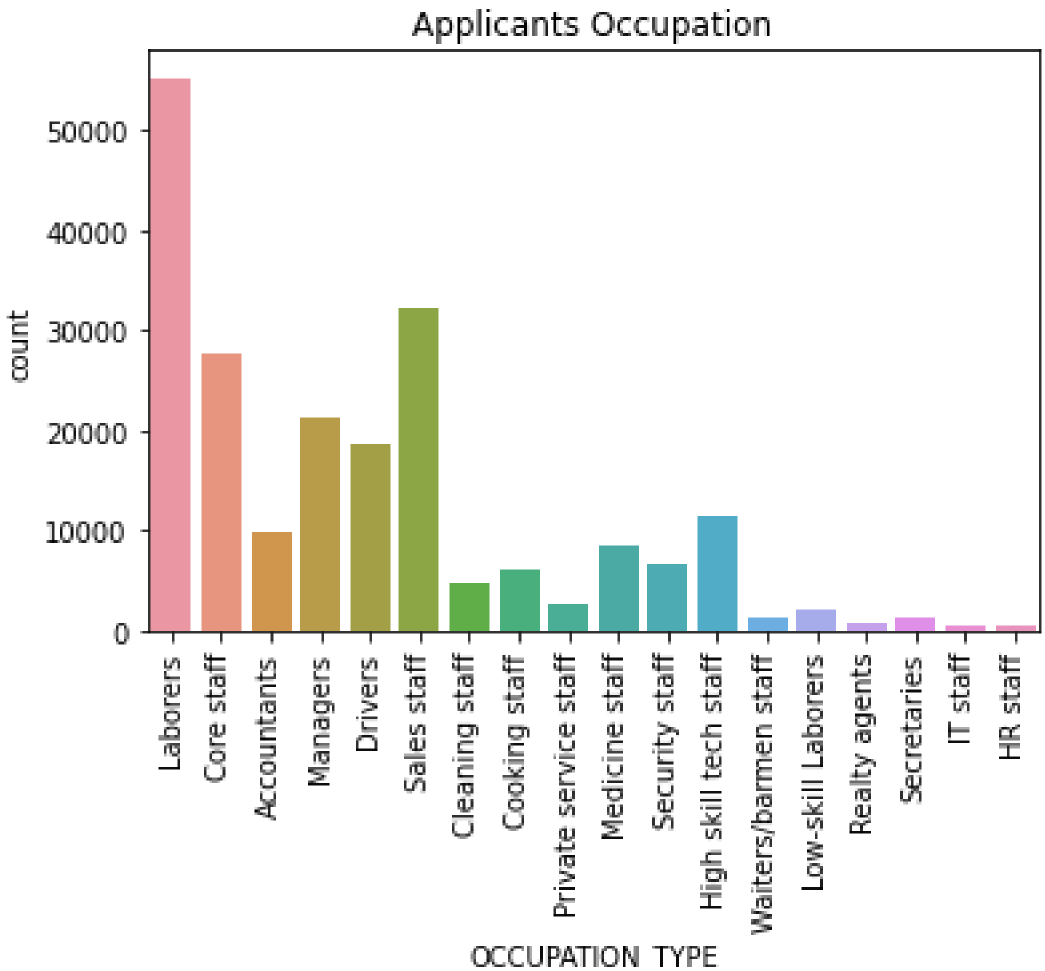
Applicants Age

```
plt.hist(datasets["application_train"]['DAYS_BIRTH'] / -365, edgecolor
= 'k', bins = 25)
plt.title('Age of Client'); plt.xlabel('Age (years)');
plt.ylabel('Count');
```



Applicants occupations

```
sns.countplot(x='OCCUPATION_TYPE',
data=datasets["application_train"]);
plt.title('Applicants Occupation');
plt.xticks(rotation=90);
```



Dataset questions

Unique record for each SK_ID_CURR

```
list(datasets.keys())
```

```
['application_train',
 'application_test',
 'bureau',
 'bureau_balance',
 'credit_card_balance',
 'installments_payments',
 'previous_application',
 'POS_CASH_balance']
```

```
len(datasets["application_train"]["SK_ID_CURR"].unique()) ==
datasets["application_train"].shape[0]
```

```
True
```

```
# is there an overlap between the test and train customers
np.intersect1d(datasets["application_train"]["SK_ID_CURR"],
datasets["application_test"]["SK_ID_CURR"])
```

```
array([], dtype=int64)
```

```
#
datasets["application_test"].shape
```

```
(48744, 121)
```

```
datasets["application_train"].shape
```

```
(307511, 122)
```

previous applications for the submission file

The persons in the kaggle submission file have had previous applications in the `previous_application.csv`. 47,800 out 48,744 people have had previous appications.

```
appsDF = datasets["previous_application"]
display(appsDF.head())
print(f"{appsDF.shape[0]:,} rows, {appsDF.shape[1]:,} columns")
```

```
   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY
AMT_APPLICATION  \
0     2030495      271877     Consumer loans     1730.430
17145.0
1     2802425      108129         Cash loans    25188.615
607500.0
2     2523466      122040         Cash loans    15060.735
112500.0
3     2819243      176158         Cash loans    47041.335
450000.0
4     1784265      202054         Cash loans    31924.395
337500.0

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE
WEEKDAY_APPR_PROCESS_START  \
0     17145.0               0.0          17145.0
SATURDAY
1    679671.0               NaN         607500.0
THURSDAY
2    136444.5               NaN         112500.0
TUESDAY
```

```
3    470790.0               NaN         450000.0
MONDAY
4    404055.0               NaN         337500.0
THURSDAY

   HOUR_APPR_PROCESS_START  ... NAME_SELLER_INDUSTRY  CNT_PAYMENT  \
0                       15  ...         Connectivity         12.0
1                       11  ...                  XNA         36.0
2                       11  ...                  XNA         12.0
3                        7  ...                  XNA         12.0
4                        9  ...                  XNA         24.0

   NAME_YIELD_GROUP       PRODUCT_COMBINATION  DAYS_FIRST_DRAWING  \
0            middle  POS mobile with interest            365243.0
1        low_action          Cash X-Sell: low            365243.0
2              high         Cash X-Sell: high            365243.0
3            middle       Cash X-Sell: middle            365243.0
4              high         Cash Street: high                 NaN

  DAYS_FIRST_DUE DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE
DAYS_TERMINATION  \
0          -42.0                     300.0          -42.0            -
37.0
1         -134.0                     916.0       365243.0
365243.0
2         -271.0                      59.0       365243.0
365243.0
3         -482.0                    -152.0         -182.0           -
177.0
4            NaN                       NaN            NaN
NaN

  NFLAG_INSURED_ON_APPROVAL
0                       0.0
1                       1.0
2                       1.0
3                       1.0
4                       NaN

[5 rows x 37 columns]

1,670,214 rows, 37 columns
```

```python
print(f"There are  {appsDF.shape[0]:,} previous applications")
```

```
There are  1,670,214 previous applications
```

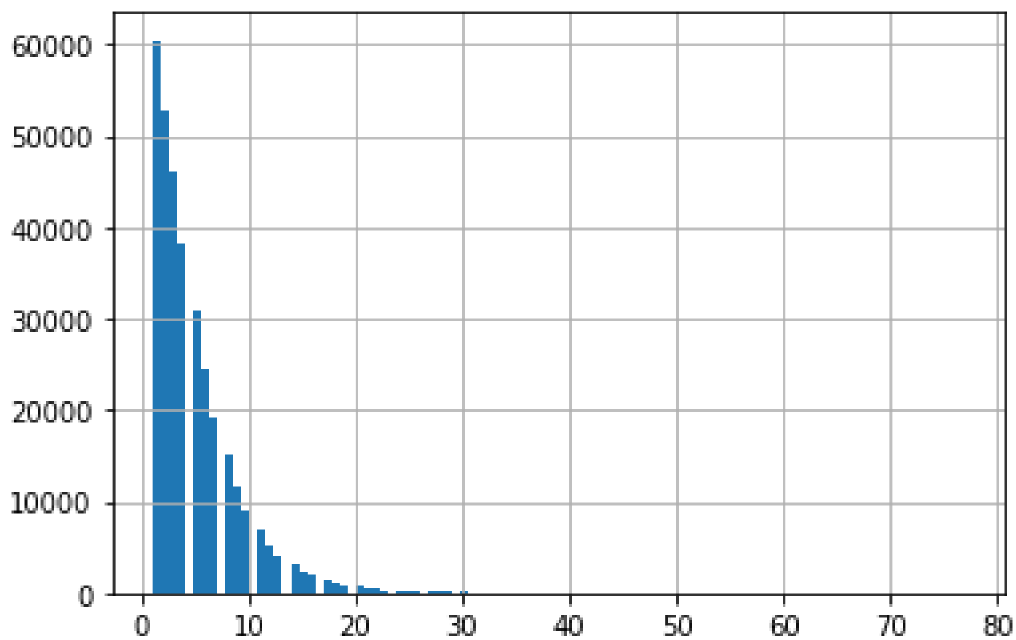
```python
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is
{len(np.intersect1d(datasets["previous_application"]["SK_ID_CURR"],
datasets["application_train"]["SK_ID_CURR"])):,}')
```

```
Number of train applicants with previous applications is 291,057
```

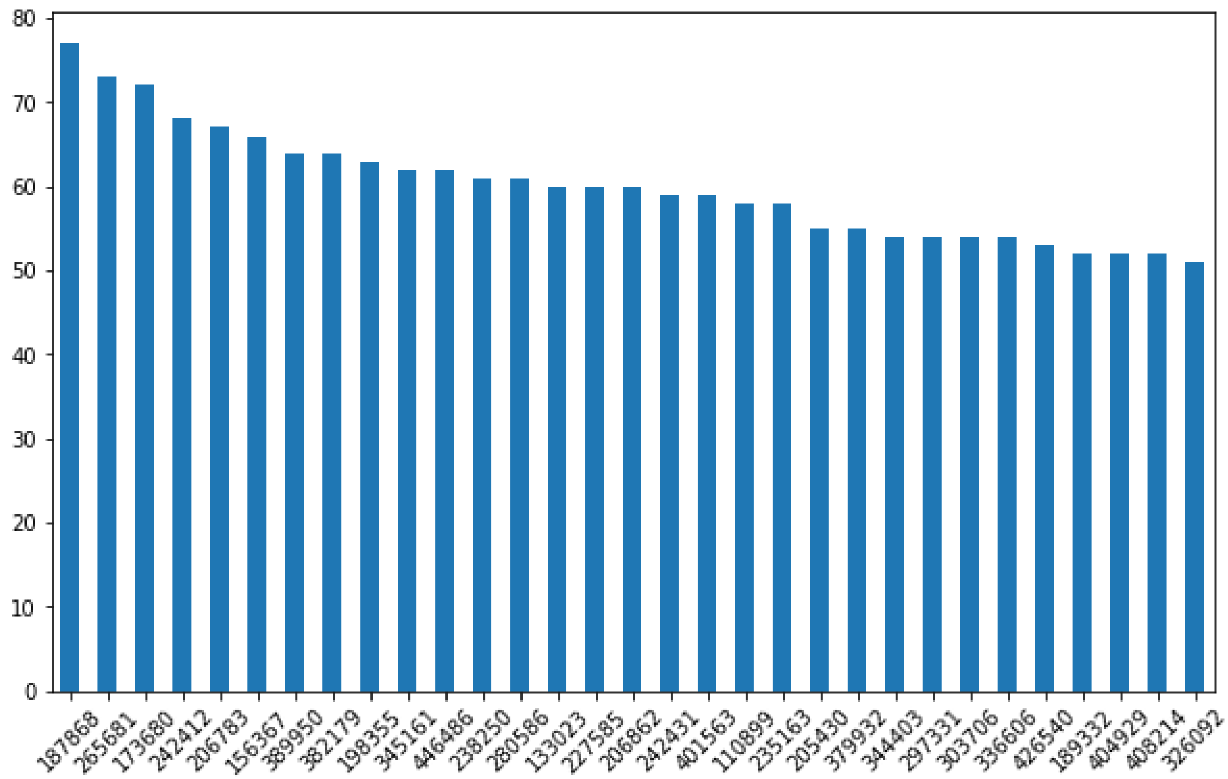
```
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is
{len(np.intersect1d(datasets["previous_application"]["SK_ID_CURR"],
datasets["application_test"]["SK_ID_CURR"])):,}')
```

```
Number of train applicants with previous applications is 47,800
```

```
# How many previous applciations  per applicant in the
previous_application
prevAppCounts = appsDF['SK_ID_CURR'].value_counts(dropna=False)
len(prevAppCounts[prevAppCounts >40])  #more that 40 previous
applications
plt.hist(prevAppCounts[prevAppCounts>=0], bins=100)
plt.grid()
```




```
# Display the applicants with more than 50 applications in the
dataset.

plt.figure(figsize=(10, 6))
prevAppCounts[prevAppCounts >50].plot(kind='bar')
plt.xticks(rotation = 45)
plt.show()
```

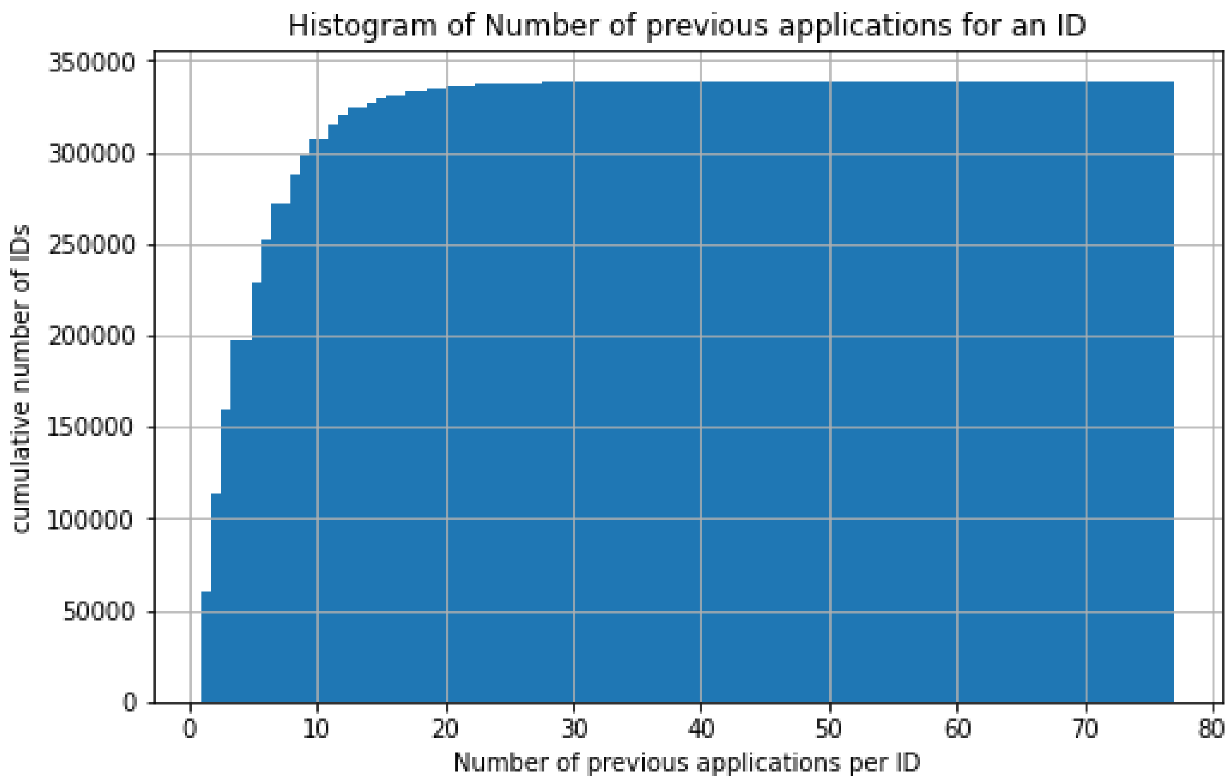


Histogram of Number of previous applications for an ID

```
sum(appsDF['SK_ID_CURR'].value_counts()==1)
```

```
60458
```

```
plt.figure(figsize=(8, 5))
plt.hist(appsDF['SK_ID_CURR'].value_counts(), cumulative =True, bins =
100);
plt.grid()
plt.ylabel('cumulative number of IDs')
plt.xlabel('Number of previous applications per ID')
plt.title('Histogram of Number of previous applications for an ID')
plt.show()
```



Can we differentiate applications by low, medium and high previous apps?

```
* Low = <5 claims (22%)
* Medium = 10 to 39 claims (58%)
* High = 40 or more claims (20%)

apps_all = appsDF['SK_ID_CURR'].nunique()
apps_5plus = appsDF['SK_ID_CURR'].value_counts()>=5
apps_40plus = appsDF['SK_ID_CURR'].value_counts()>=40
print('Percentage with 10 or more previous apps:',
np.round(100.*(sum(apps_5plus)/apps_all),5))
print('Percentage with 40 or more previous apps:',
np.round(100.*(sum(apps_40plus)/apps_all),5))

Percentage with 10 or more previous apps: 41.76895
Percentage with 40 or more previous apps: 0.03453
```

Joining secondary tables with the primary table

In the case of the HCDR competition (and many other machine learning problems that involve multiple tables in 3NF or not) we need to join these datasets (denormalize) when using a machine learning pipeline. Joining the secondary tables with the primary table will lead to lots of new features about each loan application; these features will tend to be aggregate type features or meta data about the loan or its application. How can we do this when using Machine Learning Pipelines?

Joining `previous_application` with `application_x`

We refer to the `application_train` data (and also `application_test` data also) as the **primary table** and the other files as the **secondary tables** (e.g., `previous_application` dataset). All tables can be joined using the primary key `SK_ID_PREV`.

Let's assume we wish to generate a feature based on previous application attempts. In this case, possible features here could be:

- A simple feature could be the number of previous applications.
- Other summary features of original features such as `AMT_APPLICATION`, `AMT_CREDIT` could be based on average, min, max, median, etc.

To build such features, we need to join the `application_train` data (and also `application_test` data also) with the 'previous_application' dataset (and the other available datasets).

When joining this data in the context of pipelines, different strategies come to mind with various tradeoffs:

1. Preprocess each of the non-application data sets, thereby generating many new (derived) features, and then joining (aka merge) the results with the `application_train` data (the labeled dataset) and with the `application_test` data (the unlabeled submission dataset) prior to processing the data (in a train, valid, test partition) via your machine learning pipeline. [This approach is recommended for this HCDR competition. WHY?]

- Do the joins as part of the transformation steps. [Not recommended here. WHY?]. How can this be done? Will it work?
  - This would be necessary if we had dataset wide features such as IDF (inverse document frequency) which depend on the entire subset of data as opposed to a single loan application (e.g., a feature about the relative amount applied for such as the percentile of the loan amount being applied for).

I want you to think about this section and build on this.

Roadmap for secondary table processing

1. Transform all the secondary tables to features that can be joined into the main table the application table (labeled and unlabeled)
   - 'bureau', 'bureau_balance', 'credit_card_balance', 'installments_payments',
   - 'previous_application', 'POS_CASH_balance'

- Merge the transformed secondary tables with the primary tables (i.e., the `application_train` data (the labeled dataset) and with the `application_test` data (the unlabeled submission dataset)), thereby leading to X_train, y_train, X_valid, etc.
- Proceed with the learning pipeline using X_train, y_train, X_valid, etc.
- Generate a submission file using the learnt model

agg detour

Aggregate using one or more operations over the specified axis.

For more details see agg

```
DataFrame.agg(func, axis=0, *args, **kwargs**)
```

Aggregate using one or more operations over the specified axis.

```
df = pd.DataFrame([[1, 2, 3],
                    [4, 5, 6],
                   [7, 8, 9],
                   [np.nan, np.nan, np.nan]],
                   columns=['A', 'B', 'C'])
display(df)
```

	A	B	C
0	1.0	2.0	3.0
1	4.0	5.0	6.0
2	7.0	8.0	9.0
3	NaN	NaN	NaN

```
df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
#        A    B
#max   NaN  8.0
#min   1.0  2.0
#sum  12.0  NaN
```

	A	B
sum	12.0	NaN
min	1.0	2.0
max	NaN	8.0

```
df = pd.DataFrame({'A': [1, 1, 2, 2],
                    'B': [1, 2, 3, 4],
                    'C': np.random.randn(4)})
display(df)
```

	A	B	C
0	1	1	0.981926
1	1	2	-0.647712
2	2	3	0.142058
3	2	4	-1.266687

```
# group by column A:
df.groupby('A').agg({'B': ['min', 'max'], 'C': 'sum'})
#    B             C
#  min max       sum
#A
```

```
#1   1   2  0.590716
#2   3   4  0.704907
```

```
    B             C
  min max       sum
A
1   1   2  0.334214
2   3   4 -1.124629
```

```
appsDF.columns
```

```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE',
'AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT',
'AMT_GOODS_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE',
'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION',
'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')
```

```
funcs = ["a","b","c"]
{f:f"{f}_max" for f in funcs}
```

```
{'a': 'a_max', 'b': 'b_max', 'c': 'c_max'}
```

Multiple condition expressions in Pandas

So far, both our boolean selections have involved a single condition. You can, of course, have as many conditions as you would like. To do so, you will need to combine your boolean expressions using the three logical operators and, or and not.

Use &, | , ~ Although Python uses the syntax and, or, and not, these will not work when testing multiple conditions with pandas. The details of why are explained here.

You must use the following operators with pandas:

- & for and
- | for or
- ~ for not

```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]
```

```
   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY
AMT_APPLICATION  \
6     2315218      175704         Cash loans          NaN
0.0

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE
WEEKDAY_APPR_PROCESS_START  \
6         0.0               NaN              NaN
TUESDAY

   HOUR_APPR_PROCESS_START  ... NAME_SELLER_INDUSTRY  CNT_PAYMENT  \
6                       11  ...                  XNA          NaN

   NAME_YIELD_GROUP  PRODUCT_COMBINATION  DAYS_FIRST_DRAWING
DAYS_FIRST_DUE  \
6               XNA                 Cash                NaN
NaN

  DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE DAYS_TERMINATION  \
6                       NaN            NaN              NaN

  NFLAG_INSURED_ON_APPROVAL
6                       NaN

[1 rows x 37 columns]
```

```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]["AMT_CREDIT"]
```

```
6    0.0
Name: AMT_CREDIT, dtype: float64
```

```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704) &
~(appsDF["AMT_CREDIT"]==1.0)]
```

```
   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY
AMT_APPLICATION  \
6     2315218      175704         Cash loans          NaN
0.0

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE
WEEKDAY_APPR_PROCESS_START  \
6         0.0               NaN              NaN
TUESDAY

   HOUR_APPR_PROCESS_START  ... NAME_SELLER_INDUSTRY  CNT_PAYMENT  \
6                       11  ...                  XNA          NaN

   NAME_YIELD_GROUP  PRODUCT_COMBINATION  DAYS_FIRST_DRAWING
DAYS_FIRST_DUE  \
```

```
6                XNA                    Cash                    NaN
NaN

  DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE DAYS_TERMINATION  \
6                        NaN            NaN              NaN

  NFLAG_INSURED_ON_APPROVAL
6                       NaN

[1 rows x 37 columns]
```

Missing values in prevApps

```
appsDF.isna().sum()
```

```
SK_ID_PREV                           0
SK_ID_CURR                           0
NAME_CONTRACT_TYPE                   0
AMT_ANNUITY                     372235
AMT_APPLICATION                      0
AMT_CREDIT                           1
AMT_DOWN_PAYMENT                895844
AMT_GOODS_PRICE                 385515
WEEKDAY_APPR_PROCESS_START           0
HOUR_APPR_PROCESS_START              0
FLAG_LAST_APPL_PER_CONTRACT          0
NFLAG_LAST_APPL_IN_DAY               0
RATE_DOWN_PAYMENT               895844
RATE_INTEREST_PRIMARY          1664263
RATE_INTEREST_PRIVILEGED       1664263
NAME_CASH_LOAN_PURPOSE               0
NAME_CONTRACT_STATUS                 0
DAYS_DECISION                        0
NAME_PAYMENT_TYPE                    0
CODE_REJECT_REASON                   0
NAME_TYPE_SUITE                 820405
NAME_CLIENT_TYPE                     0
NAME_GOODS_CATEGORY                  0
NAME_PORTFOLIO                       0
NAME_PRODUCT_TYPE                    0
CHANNEL_TYPE                         0
SELLERPLACE_AREA                     0
NAME_SELLER_INDUSTRY                 0
CNT_PAYMENT                     372230
NAME_YIELD_GROUP                     0
PRODUCT_COMBINATION                346
DAYS_FIRST_DRAWING              673065
DAYS_FIRST_DUE                  673065
DAYS_LAST_DUE_1ST_VERSION       673065
DAYS_LAST_DUE                   673065
```

```
DAYS_TERMINATION                673065
NFLAG_INSURED_ON_APPROVAL       673065
dtype: int64

appsDF.columns

Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE',
'AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT',
'AMT_GOODS_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE',
'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION',
'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')
```

feature engineering for prevApp table

The groupby output will have an index or multi-index on rows corresponding to your chosen grouping variables. To avoid setting this index, pass “as_index=False” to the groupby operation.

```
import pandas as pd
import dateutil

# Load data from csv file
data = pd.DataFrame.from_csv('phone_data.csv')
# Convert date from string to date times
data['date'] = data['date'].apply(dateutil.parser.parse,
dayfirst=True)

data.groupby('month', as_index=False).agg({"duration": "sum"})
```

Pandas `reset_index()` to convert Multi-Index to Columns We can simplify the multi-index dataframe using reset_index() function in Pandas. By default, Pandas reset_index() converts the indices to columns.

Fixing Column names after Pandas agg() function to summarize grouped data

Since we have both the variable name and the operation performed in two rows in the Multi-Index dataframe, we can use that and name our new columns correctly.

For more details unstacking groupby results and examples please see here

For more details and examples please see here

feature transformer for prevApp table

```
# Create aggregate features (via pipeline)
class prevAppsFeaturesAggregater(BaseEstimator, TransformerMixin):
    def __init__(self, features=None): # no *args or **kargs
        self.features = features
        self.agg_op_features = {}
        for f in features:
#             self.agg_op_features[f] = {f"{f}_{func}":func for func
in ["min", "max", "mean"]}
            self.agg_op_features[f] =  ["min", "max", "mean"]

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        #from IPython.core.debugger import Pdb as pdb;
pdb().set_trace() #breakpoint; dont forget to quit
        result = X.groupby(["SK_ID_CURR"]).agg(self.agg_op_features)
#         result.columns = result.columns.droplevel()
        result.columns = ["_".join(x) for x in result.columns.ravel()]

        result = result.reset_index(level=["SK_ID_CURR"])
        result['range_AMT_APPLICATION'] =
result['AMT_APPLICATION_max'] - result['AMT_APPLICATION_min']
        return result # return dataframe with the join key
"SK_ID_CURR"


from sklearn.pipeline import make_pipeline
def test_driver_prevAppsFeaturesAggregater(df, features):
    print(f"df.shape: {df.shape}\n")
    print(f"df[{features}][0:5]: \n{df[features][0:5]}")
    test_pipeline =
make_pipeline(prevAppsFeaturesAggregater(features))
    return(test_pipeline.fit_transform(df))

features = ['AMT_ANNUITY', 'AMT_APPLICATION']
features = ['AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT',
'AMT_GOODS_PRICE',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'DAYS_DECISION',
'NAME_PAYMENT_TYPE',
       'CNT_PAYMENT',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE',
'DAYS_LAST_DUE_1ST_VERSION',
```

```
        'DAYS_LAST_DUE', 'DAYS_TERMINATION']
features = ['AMT_ANNUITY', 'AMT_APPLICATION']
res = test_driver_prevAppsFeaturesAggregater(appsDF, features)
print(f"HELLO")
print(f"Test driver: \n{res[0:10]}")
print(f"input[features][0:10]: \n{appsDF[0:10]}")


# QUESTION, should we lower case df['OCCUPATION_TYPE'] as Sales
staff != 'Sales Staff'? (hint: YES)
```

```
df.shape: (1670214, 37)

df[['AMT_ANNUITY', 'AMT_APPLICATION']][0:5]:
   AMT_ANNUITY  AMT_APPLICATION
0     1730.430          17145.0
1    25188.615         607500.0
2    15060.735         112500.0
3    47041.335         450000.0
4    31924.395         337500.0
HELLO
Test driver: 
   SK_ID_CURR  AMT_ANNUITY_min  AMT_ANNUITY_max  AMT_ANNUITY_mean  \
0      100001         3951.000         3951.000       3951.000000   
1      100002         9251.775         9251.775       9251.775000   
2      100003         6737.310        98356.995      56553.990000   
3      100004         5357.250         5357.250       5357.250000   
4      100005         4813.200         4813.200       4813.200000   
5      100006         2482.920        39954.510      23651.175000   
6      100007         1834.290        22678.785      12278.805000   
7      100008         8019.090        25309.575      15839.696250   
8      100009         7435.845        17341.605      10051.412143   
9      100010        27463.410        27463.410      27463.410000   

   AMT_APPLICATION_min  AMT_APPLICATION_max  AMT_APPLICATION_mean  \
0              24835.5              24835.5          24835.500000   
1             179055.0             179055.0         179055.000000   
2              68809.5             900000.0         435436.500000   
3              24282.0              24282.0          24282.000000   
4                  0.0              44617.5          22308.750000   
5                  0.0             688500.0         272203.260000   
6              17176.5             247500.0         150530.250000   
7                  0.0             450000.0         155701.800000   
8              40455.0             110160.0          76741.714286   
9             247212.0             247212.0         247212.000000   

   range_AMT_APPLICATION
0                    0.0
1                    0.0
2               831190.5
```

```
3                    0.0
4                44617.5
5               688500.0
6               230323.5
7               450000.0
8                69705.0
9                    0.0
input[features][0:10]:
   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY
AMT_APPLICATION  \
0     2030495      271877     Consumer loans     1730.430
17145.0
1     2802425      108129         Cash loans    25188.615
607500.0
2     2523466      122040         Cash loans    15060.735
112500.0
3     2819243      176158         Cash loans    47041.335
450000.0
4     1784265      202054         Cash loans    31924.395
337500.0
5     1383531      199383         Cash loans    23703.930
315000.0
6     2315218      175704         Cash loans          NaN
0.0
7     1656711      296299         Cash loans          NaN
0.0
8     2367563      342292         Cash loans          NaN
0.0
9     2579447      334349         Cash loans          NaN
0.0

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE
WEEKDAY_APPR_PROCESS_START  \
0     17145.0               0.0          17145.0
SATURDAY
1    679671.0               NaN         607500.0
THURSDAY
2    136444.5               NaN         112500.0
TUESDAY
3    470790.0               NaN         450000.0
MONDAY
4    404055.0               NaN         337500.0
THURSDAY
5    340573.5               NaN         315000.0
SATURDAY
6         0.0               NaN              NaN
TUESDAY
7         0.0               NaN              NaN
MONDAY
```

```
8         0.0              NaN              NaN
MONDAY
9         0.0              NaN              NaN
SATURDAY

   HOUR_APPR_PROCESS_START  ... NAME_SELLER_INDUSTRY  CNT_PAYMENT  \
0                       15  ...         Connectivity         12.0
1                       11  ...                  XNA         36.0
2                       11  ...                  XNA         12.0
3                        7  ...                  XNA         12.0
4                        9  ...                  XNA         24.0
5                        8  ...                  XNA         18.0
6                       11  ...                  XNA          NaN
7                        7  ...                  XNA          NaN
8                       15  ...                  XNA          NaN
9                       15  ...                  XNA          NaN

   NAME_YIELD_GROUP       PRODUCT_COMBINATION  DAYS_FIRST_DRAWING  \
0            middle  POS mobile with interest            365243.0
1        low_action         Cash X-Sell: low            365243.0
2              high        Cash X-Sell: high            365243.0
3            middle      Cash X-Sell: middle            365243.0
4              high        Cash Street: high                 NaN
5        low_normal         Cash X-Sell: low            365243.0
6               XNA                      Cash                 NaN
7               XNA                      Cash                 NaN
8               XNA                      Cash                 NaN
9               XNA                      Cash                 NaN

  DAYS_FIRST_DUE DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE
DAYS_TERMINATION  \
0          -42.0                     300.0          -42.0            -
37.0
1         -134.0                     916.0       365243.0
365243.0
2         -271.0                      59.0       365243.0
365243.0
3         -482.0                    -152.0         -182.0           -
177.0
4            NaN                       NaN            NaN
NaN
5         -654.0                    -144.0         -144.0           -
137.0
6            NaN                       NaN            NaN
NaN
7            NaN                       NaN            NaN
NaN
8            NaN                       NaN            NaN
NaN
9            NaN                       NaN            NaN
```

```
NaN

  NFLAG_INSURED_ON_APPROVAL
0                        0.0
1                        1.0
2                        1.0
3                        1.0
4                        NaN
5                        1.0
6                        NaN
7                        NaN
8                        NaN
9                        NaN

[10 rows x 37 columns]
```

Feature Engineering for Primary & Secondary Tables

```
# Choosing Highly correlated features from all input datasets

def correlation_files_target(df_name):
  A = datasets["application_train"].copy()
  B = datasets[df_name].copy()
  correlation_matrix =  pd.concat([A.TARGET, B],
axis=1).corr().filter(B.columns).filter(A.columns, axis=0)
  return correlation_matrix

agg_funcs = ['min', 'max', 'mean', 'count', 'sum']

prevApps = datasets['previous_application']
prevApps_features = ['AMT_ANNUITY', 'AMT_APPLICATION']

bureau = datasets['bureau']
bureau_features = ['AMT_ANNUITY', 'AMT_CREDIT_SUM']
# bureau_funcs = ['min', 'max', 'mean', 'count', 'sum']

bureau_bal = datasets['bureau_balance']
bureau_bal_features = ['MONTHS_BALANCE']

cc_bal = datasets['credit_card_balance']
cc_bal_features = ['MONTHS_BALANCE', 'AMT_BALANCE',
'CNT_INSTALMENT_MATURE_CUM']

installments_pmnts = datasets['installments_payments']
installments_pmnts_features = ['AMT_INSTALMENT', 'AMT_PAYMENT']

pos_cash_bal = datasets['POS_CASH_balance']
pos_cash_bal_features = ['CNT_INSTALMENT', 'MONTHS_BALANCE' ]
```

Feature Aggregator

- Added a if statement allowing us to transform bureau_balance as it does not have a SK_ID_CURR as it joins with bureau.csv on the SK_ID_BUREAU column. Will have to keep this in mind when joining the tables.

```
# Pipelines
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import make_pipeline, Pipeline, FeatureUnion
from sklearn.preprocessing import MinMaxScaler, StandardScaler,
OneHotEncoder


class FeaturesAggregator(BaseEstimator, TransformerMixin):
    def __init__(self, file_name=None, features=None, funcs=None):
        self.file_name = file_name
        self.features = features
        self.funcs = funcs
        self.agg_op_features = {}
        for f in self.features:
            temp = {f"{file_name}_{f}_{func}":func for func in
self.funcs}
            self.agg_op_features[f]=[(k, v) for k, v in temp.items()]
        print(self.agg_op_features)
    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        if self.file_name != 'bureau_balance' and self.file_name !=
'bureau':
            result =
X.groupby(["SK_ID_CURR"]).agg(self.agg_op_features)
            result.columns = result.columns.droplevel()
            result = result.reset_index(level=["SK_ID_CURR"])
            return result  # return dataframe with the join key
"SK_ID_CURR"

        elif self.file_name == 'bureau':
            result = X.groupby(["SK_ID_CURR",
"SK_ID_BUREAU"]).agg(self.agg_op_features)
            result.columns = result.columns.droplevel()
            result = result.reset_index(level=["SK_ID_CURR",
"SK_ID_BUREAU"])
            return result  # return dataframe with the join keys
"SK_ID_CURR" AND "SK_ID_BUREAU"

        elif self.file_name == 'bureau_balance':
            result =
X.groupby(["SK_ID_BUREAU"]).agg(self.agg_op_features)
```

```
            result.columns = result.columns.droplevel()
            result = result.reset_index(level=["SK_ID_BUREAU"])
            return result  # return dataframe with the join key
"SK_ID_BUREAU"



class engineer_features(BaseEstimator, TransformerMixin):
    def __init__(self, features=None):
        self

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):

# FROM APPLICATION
        # ADD INCOME CREDIT PERCENTAGE
        X['ef_INCOME_CREDIT_PERCENT'] = (
            X.AMT_INCOME_TOTAL / X.AMT_CREDIT).replace(np.inf, 0)

        # ADD INCOME PER FAMILY MEMBER
        X['ef_FAM_MEMBER_INCOME'] = (
            X.AMT_INCOME_TOTAL / X.CNT_FAM_MEMBERS).replace(np.inf, 0)

        # ADD ANNUITY AS PERCENTAGE OF ANNUAL INCOME
        X['ef_ANN_INCOME_PERCENT'] = (
            X.AMT_ANNUITY / X.AMT_INCOME_TOTAL).replace(np.inf, 0)
```

- Added the pos_cash_pal feature pipeline instead of the application_train feature engineering pipeline because we don't need it as our goal is to do feature aggregation on each of the secondary tables then join them to application train and test

```
from sklearn.pipeline import make_pipeline, Pipeline, FeatureUnion

prevApps_feature_pipeline = Pipeline([
    ('prevApps_aggregator', FeaturesAggregator('prevApps',
prevApps_features, agg_funcs)),
    ])

bureau_feature_pipeline = Pipeline([
    ('bureau_aggregator', FeaturesAggregator('bureau',
bureau_features, agg_funcs)),
    ])

bureau_bal_features_pipeline = Pipeline([
    ('bureau_bal_aggregator', FeaturesAggregator('bureau_balance',
bureau_bal_features , agg_funcs)),
    ])

cc_bal_features_pipeline = Pipeline([
```

```
    ('cc_bal_aggregator', FeaturesAggregator('credit_card_balance',
cc_bal_features , agg_funcs)),
    ])

installments_pmnts_features_pipeline = Pipeline([
    ('installments_pmnts_features_aggregator',
FeaturesAggregator('credit_card_balance',
installments_pmnts_features , agg_funcs)),
    ])

pos_cash_bal_feature_pipeline = Pipeline([
    ('pos_cash_bal_aggregator',FeaturesAggregator('pos_cash_bal',
pos_cash_bal_features , agg_funcs)),  # add some new features
    ])
```

```
{'AMT_ANNUITY': [('prevApps_AMT_ANNUITY_min', 'min'),
('prevApps_AMT_ANNUITY_max', 'max'), ('prevApps_AMT_ANNUITY_mean',
'mean'), ('prevApps_AMT_ANNUITY_count', 'count'),
('prevApps_AMT_ANNUITY_sum', 'sum')], 'AMT_APPLICATION':
[('prevApps_AMT_APPLICATION_min', 'min'),
('prevApps_AMT_APPLICATION_max', 'max'),
('prevApps_AMT_APPLICATION_mean', 'mean'),
('prevApps_AMT_APPLICATION_count', 'count'),
('prevApps_AMT_APPLICATION_sum', 'sum')]}
{'AMT_ANNUITY': [('bureau_AMT_ANNUITY_min', 'min'),
('bureau_AMT_ANNUITY_max', 'max'), ('bureau_AMT_ANNUITY_mean',
'mean'), ('bureau_AMT_ANNUITY_count', 'count'),
('bureau_AMT_ANNUITY_sum', 'sum')], 'AMT_CREDIT_SUM':
[('bureau_AMT_CREDIT_SUM_min', 'min'), ('bureau_AMT_CREDIT_SUM_max',
'max'), ('bureau_AMT_CREDIT_SUM_mean', 'mean'),
('bureau_AMT_CREDIT_SUM_count', 'count'),
('bureau_AMT_CREDIT_SUM_sum', 'sum')]}
{'MONTHS_BALANCE': [('bureau_balance_MONTHS_BALANCE_min', 'min'),
('bureau_balance_MONTHS_BALANCE_max', 'max'),
('bureau_balance_MONTHS_BALANCE_mean', 'mean'),
('bureau_balance_MONTHS_BALANCE_count', 'count'),
('bureau_balance_MONTHS_BALANCE_sum', 'sum')]}
{'MONTHS_BALANCE': [('credit_card_balance_MONTHS_BALANCE_min', 'min'),
('credit_card_balance_MONTHS_BALANCE_max', 'max'),
('credit_card_balance_MONTHS_BALANCE_mean', 'mean'),
('credit_card_balance_MONTHS_BALANCE_count', 'count'),
('credit_card_balance_MONTHS_BALANCE_sum', 'sum')], 'AMT_BALANCE':
[('credit_card_balance_AMT_BALANCE_min', 'min'),
('credit_card_balance_AMT_BALANCE_max', 'max'),
('credit_card_balance_AMT_BALANCE_mean', 'mean'),
('credit_card_balance_AMT_BALANCE_count', 'count'),
('credit_card_balance_AMT_BALANCE_sum', 'sum')],
'CNT_INSTALMENT_MATURE_CUM':
[('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_min', 'min'),
('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_max', 'max'),
```

```
('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_mean', 'mean'),
('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_count', 'count'),
('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_sum', 'sum')]}
{'AMT_INSTALMENT': [('credit_card_balance_AMT_INSTALMENT_min', 'min'),
('credit_card_balance_AMT_INSTALMENT_max', 'max'),
('credit_card_balance_AMT_INSTALMENT_mean', 'mean'),
('credit_card_balance_AMT_INSTALMENT_count', 'count'),
('credit_card_balance_AMT_INSTALMENT_sum', 'sum')], 'AMT_PAYMENT':
[('credit_card_balance_AMT_PAYMENT_min', 'min'),
('credit_card_balance_AMT_PAYMENT_max', 'max'),
('credit_card_balance_AMT_PAYMENT_mean', 'mean'),
('credit_card_balance_AMT_PAYMENT_count', 'count'),
('credit_card_balance_AMT_PAYMENT_sum', 'sum')]}
{'CNT_INSTALMENT': [('pos_cash_bal_CNT_INSTALMENT_min', 'min'),
('pos_cash_bal_CNT_INSTALMENT_max', 'max'),
('pos_cash_bal_CNT_INSTALMENT_mean', 'mean'),
('pos_cash_bal_CNT_INSTALMENT_count', 'count'),
('pos_cash_bal_CNT_INSTALMENT_sum', 'sum')], 'MONTHS_BALANCE':
[('pos_cash_bal_MONTHS_BALANCE_min', 'min'),
('pos_cash_bal_MONTHS_BALANCE_max', 'max'),
('pos_cash_bal_MONTHS_BALANCE_mean', 'mean'),
('pos_cash_bal_MONTHS_BALANCE_count', 'count'),
('pos_cash_bal_MONTHS_BALANCE_sum', 'sum')]}
```

Prepare Datasets

- Added poscashbalDF

```
poscashbalDF = datasets['POS_CASH_balance']

X_train = datasets['application_train']
prevAppsDF = datasets["previous_application"] #prev app
bureauDF = datasets["bureau"] #bureau app
bureaubalDF = datasets['bureau_balance']
ccbalDF = datasets["credit_card_balance"] #prev app
installmentspaymentsDF = datasets["installments_payments"] #bureau app
```

Fit Feature Engineering Pipeline

- Removed the applin pipeline and added the pos_cash_bal_aggregated

```
pos_cash_bal_aggregated =
pos_cash_bal_feature_pipeline.fit_transform(poscashbalDF)
prevApps_aggregated =
prevApps_feature_pipeline.fit_transform(prevAppsDF)
bureau_aggregated = bureau_feature_pipeline.fit_transform(bureauDF)

bureaubal_aggregated =
bureau_bal_features_pipeline.fit_transform(bureaubalDF)
ccblance_aggregated = cc_bal_features_pipeline.fit_transform(ccbalDF)
```

```
installments_pmnts_aggregated =
installments_pmnts_features_pipeline.fit_transform(installmentspayment
sDF)

installments_pmnts_aggregated.head()
```

```
   SK_ID_CURR  credit_card_balance_AMT_INSTALMENT_min  \
0      100001                                3951.000
1      100002                                9251.775
2      100003                                6662.970
3      100004                                5357.250
4      100005                                4813.200

   credit_card_balance_AMT_INSTALMENT_max  \
0                               17397.900
1                               53093.745
2                              560835.360
3                               10573.965
4                               17656.245

   credit_card_balance_AMT_INSTALMENT_mean  \
0                              5885.132143
1                             11559.247105
2                             64754.586000
3                              7096.155000
4                              6240.205000

   credit_card_balance_AMT_INSTALMENT_count  \
0                                         7
1                                        19
2                                        25
3                                         3
4                                         9

   credit_card_balance_AMT_INSTALMENT_sum  \
0                               41195.925
1                              219625.695
2                             1618864.650
3                               21288.465
4                               56161.845

   credit_card_balance_AMT_PAYMENT_min
credit_card_balance_AMT_PAYMENT_max  \
0                             3951.000
17397.900
1                             9251.775
53093.745
2                             6662.970
560835.360
3                             5357.250
```

```
10573.965
4                                 4813.200
17656.245

   credit_card_balance_AMT_PAYMENT_mean  \
0                              5885.132143
1                             11559.247105
2                             64754.586000
3                              7096.155000
4                              6240.205000

   credit_card_balance_AMT_PAYMENT_count
credit_card_balance_AMT_PAYMENT_sum
0                                        7
41195.925
1                                       19
219625.695
2                                       25
1618864.650
3                                        3
21288.465
4                                        9
56161.845
```

```
bureau_aggregated.head()
```

```
   SK_ID_CURR  SK_ID_BUREAU  bureau_AMT_ANNUITY_min
bureau_AMT_ANNUITY_max  \
0      100001       5896630                     0.0
0.0
1      100001       5896631                     0.0
0.0
2      100001       5896632                     0.0
0.0
3      100001       5896633                     0.0
0.0
4      100001       5896634                  4630.5
4630.5

   bureau_AMT_ANNUITY_mean  bureau_AMT_ANNUITY_count
bureau_AMT_ANNUITY_sum  \
0                      0.0                          1
0.0
1                      0.0                          1
0.0
2                      0.0                          1
0.0
3                      0.0                          1
0.0
4                   4630.5                          1
```

```
4630.5

   bureau_AMT_CREDIT_SUM_min  bureau_AMT_CREDIT_SUM_max  \
0                   112500.0                   112500.0
1                   279720.0                   279720.0
2                    91620.0                    91620.0
3                    85500.0                    85500.0
4                   337680.0                   337680.0

   bureau_AMT_CREDIT_SUM_mean  bureau_AMT_CREDIT_SUM_count  \
0                    112500.0                            1
1                    279720.0                            1
2                     91620.0                            1
3                     85500.0                            1
4                    337680.0                            1

   bureau_AMT_CREDIT_SUM_sum
0                   112500.0
1                   279720.0
2                    91620.0
3                    85500.0
4                   337680.0
```

```
bureaubal_aggregated.head()
```

```
   SK_ID_BUREAU  bureau_balance_MONTHS_BALANCE_min  \
0       5001709                                -96
1       5001710                                -82
2       5001711                                 -3
3       5001712                                -18
4       5001713                                -21

   bureau_balance_MONTHS_BALANCE_max
bureau_balance_MONTHS_BALANCE_mean  \
0                                  0                                -
48.0
1                                  0                                -
41.0
2                                  0                                 -
1.5
3                                  0                                 -
9.0
4                                  0                                -
10.5

   bureau_balance_MONTHS_BALANCE_count
bureau_balance_MONTHS_BALANCE_sum
0                                   97                               -
4656
1                                   83                               -
```

```
3403
2                                   4
-6
3                                  19                              -
171
4                                  22                              -
231
```

Join the labeled dataset

```
datasets.keys()
```

```
dict_keys(['application_train', 'application_test', 'bureau',
'bureau_balance', 'credit_card_balance', 'installments_payments',
'previous_application', 'POS_CASH_balance'])
```

```
merge_all_data = True

if merge_all_data:
    prevApps_aggregated = prevApps_feature_pipeline.transform(appsDF)

# merge primary table and secondary tables using features based on
meta data and  aggregage stats
if merge_all_data:
    ### Merging bureau and bureau balancce
    bureau_aggregated = bureau_aggregated.merge(bureaubal_aggregated,
how = 'left', on = "SK_ID_BUREAU")
    ### Train DF
    X_train = X_train.merge(prevApps_aggregated, how = 'left', on =
'SK_ID_CURR')
    X_train = X_train.merge(bureau_aggregated, how = 'left', on =
"SK_ID_CURR")
    X_train = X_train.merge(ccblance_aggregated, how = 'left', on =
"SK_ID_CURR")
    X_train = X_train.merge(installments_pmnts_aggregated, how =
'left', on = "SK_ID_CURR")
    X_train = X_train.merge(pos_cash_bal_aggregated, how = 'left', on
= "SK_ID_CURR")
```

Join the unlabeled dataset (i.e., the submission file)

```
X_kaggle_test= datasets["application_test"]
merge_all_data = True
if merge_all_data:
    X_kaggle_test = X_kaggle_test.merge(prevApps_aggregated, how
='left', on = 'SK_ID_CURR')

    X_kaggle_test = X_kaggle_test.merge(bureau_aggregated, how
='left', on = "SK_ID_CURR")
```

```
    X_kaggle_test = X_kaggle_test.merge(ccblance_aggregated, how
='left', on = "SK_ID_CURR")

    X_kaggle_test = X_kaggle_test.merge(installments_pmnts_aggregated,
how ='left', on="SK_ID_CURR")

    X_kaggle_test = X_kaggle_test.merge(pos_cash_bal_aggregated, how =
'left', on = "SK_ID_CURR")

# approval rate 'NFLAG_INSURED_ON_APPROVAL'

# Convert categorical features to numerical approximations (via
pipeline)
class ClaimAttributesAdder(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self
    def transform(self, X, y=None):
        charlson_idx_dt = {'0': 0, '1-2': 2, '3-4': 4, '5+': 6}
        los_dt = {'1 day': 1, '2 days': 2, '3 days': 3, '4 days': 4,
'5 days': 5, '6 days': 6,
          '1- 2 weeks': 11, '2- 4 weeks': 21, '4- 8 weeks': 42, '26+
weeks': 180}
        X['PayDelay'] = X['PayDelay'].apply(lambda x: int(x) if x !=
'162+' else int(162))
        X['DSFS'] = X['DSFS'].apply(lambda x: None if pd.isnull(x)
else int(x[0]) + 1)
        X['CharlsonIndex'] = X['CharlsonIndex'].apply(lambda x:
charlson_idx_dt[x])
        X['LengthOfStay'] = X['LengthOfStay'].apply(lambda x: None if
pd.isnull(x) else los_dt[x])
        return X
```

Processing pipeline

OHE when previously unseen unique values in the test/validation set

Train, validation and Test sets (and the leakage problem we have mentioned previously):

Let's look at a small usecase to tell us how to deal with this:

- The OneHotEncoder is fitted to the training set, which means that for each unique value present in the training set, for each feature, a new column is created. Let's say we have 39 columns after the encoding up from 30 (before preprocessing).
- The output is a numpy array (when the option sparse=False is used), which has the disadvantage of losing all the information about the original column names and values.
- When we try to transform the test set, after having fitted the encoder to the training set, we obtain a `ValueError`. This is because the there are new, previously unseen unique values in the test set and the encoder doesn’t know how to handle these values. In order

to use both the transformed training and test sets in machine learning algorithms, we need them to have the same number of columns.

This last problem can be solved by using the option handle_unknown='ignore'of the OneHotEncoder, which, as the name suggests, will ignore previously unseen values when transforming the test set.

Here is a example that in action:

```
# Identify the categorical features we wish to consider.
cat_attribs = ['CODE_GENDER',
'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE',

'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']

# Notice handle_unknown="ignore" in OHE which ignore values from the
validation/test that
# do NOT occur in the training set
cat_pipeline = Pipeline([
        ('selector', DataFrameSelector(cat_attribs)),
        ('imputer', SimpleImputer(strategy='most_frequent')),
        ('ohe', OneHotEncoder(sparse=False, handle_unknown="ignore"))
    ])

# # load data
# df = pd.read_csv('chronic_kidney_disease.csv', header="infer")
# # names=['age', ‘bp’, ‘sg’, ‘al’, ‘su’, ‘rbc’, ‘pc’, ‘pcc’, ‘ba’,
‘bgr’, ‘bu’, ‘sc’, ‘sod’, ‘pot’,
# # ‘hemo’, ‘pcv’, ‘wc’, ‘rc’, ‘htn’, ‘dm’, ‘cad’, ‘appet’, ‘pe’,
‘ane’, ‘class’])
# # head of df
# df.head(10)

# # Categorical boolean mask
# categorical_feature_mask = df.dtypes==object
# categorical_feature_mask

# # filter categorical columns using mask and turn it into a list
# categorical_cols = X.columns[categorical_feature_mask].tolist()
# categorical_cols

# from sklearn.preprocessing import OneHotEncoder
# import pandas as pd
# categorical_feature_mask = [True, False]
# # instantiate OneHotEncoder
# enc = OneHotEncoder(categorical_features =
categorical_feature_mask,sparse = False, handle_unknown='ignore')
# # categorical_features = boolean mask for categorical columns
# # sparse = False output an array not sparse matrix
# X_train = pd.DataFrame([['small', 1], ['small', 3], ['medium', 3],
['large', 2]])
```

```
# X_test = [['small', 1.2],  ['medium', 4], ['EXTRA-large', 2]]
# print(f"X_train:\n{X_train}")
# print(f"enc.fit_transform(X_train):\n{enc.fit_transform(X_train)}")
# print(f"enc.transform(X_test):\n{enc.transform(X_test)}")

# print(f"enc.get_feature_names():\n{enc.get_feature_names()}")

# print(f"enc.categories_{enc.categories_}")

# print(f"enc.categories_{enc.categories_}")
# enc.transform([['Female', 1], ['Male', 4]]).toarray()


# enc.inverse_transform([[0, 1, 1, 0, 0], [0, 0, 0, 1, 0]])


# enc.get_feature_names()
```

OHE case study: The breast cancer wisconsin dataset (classification)

```
# from sklearn.datasets import load_breast_cancer
# data = load_breast_cancer(return_X_y=False)
# X, y = load_breast_cancer(return_X_y=True)
# print(y[[10, 50, 85]])
# #([0, 1, 0])
# list(data.target_names)
# #['malignant', 'benign']
# X.shape

# data.feature_names
```

Please this blog for more details of OHE when the validation/test have previously unseen unique values.

HCDR preprocessing

```
# Split the provided training data into training and validationa and
test
# The kaggle evaluation test set has no labels
#
from sklearn.model_selection import train_test_split

use_application_data_ONLY = False #use joined data
if use_application_data_ONLY:
    # just selected a few features for a baseline experiment
    selected_features = ['AMT_INCOME_TOTAL',
'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_SOURCE_1',
        'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER',
'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE',
```

```
'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']
    X_train = datasets["application_train"][selected_features]
    y_train = datasets["application_train"]['TARGET']
    X_train, X_valid, y_train, y_valid = train_test_split(X_train,
y_train, test_size=0.15, random_state=42)
    X_train, X_test, y_train, y_test = train_test_split(X_train,
y_train, test_size=0.15, random_state=42)
    X_kaggle_test= datasets["application_test"][selected_features]
    # y_test = datasets["application_test"]['TARGET']   #why no
TARGET?!! (hint: kaggle competition)



selected_features = ['AMT_INCOME_TOTAL',
'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_SOURCE_1',
        'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER',
'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE',

'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']
y_train = X_train['TARGET']
X_train = X_train[selected_features]
X_train, X_valid, y_train, y_valid = train_test_split(X_train,
y_train, test_size=0.15, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train,
test_size=0.15, random_state=42)
X_kaggle_test= X_kaggle_test[selected_features]
# y_test = datasets["application_test"]['TARGET']   #why no  TARGET?!!
(hint: kaggle competition)


print(f"X train           shape: {X_train.shape}")
print(f"X validation      shape: {X_valid.shape}")
print(f"X test            shape: {X_test.shape}")
print(f"X X_kaggle_test   shape: {X_kaggle_test.shape}")
```

```
X train           shape: (1090501, 14)
X validation      shape: (226402, 14)
X test            shape: (192442, 14)
X X_kaggle_test   shape: (257527, 14)
```

```
from sklearn.base import BaseEstimator, TransformerMixin
import re

# Creates the following date features
# But could do so much more with these features
#    E.g.,
#      extract the domain address of the homepage and OneHotEncode it
#
# ['release_month','release_day','release_year',
'release_dayofweek','release_quarter']
```

```
class prep_OCCUPATION_TYPE(BaseEstimator, TransformerMixin):
    def __init__(self, features="OCCUPATION_TYPE"): # no *args or
**kargs
        self.features = features
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        df = pd.DataFrame(X, columns=self.features)
        #from IPython.core.debugger import Pdb as pdb;
pdb().set_trace() #breakpoint; dont forget to quit
        df['OCCUPATION_TYPE'] = df['OCCUPATION_TYPE'].apply(lambda x:
1. if x in ['Core Staff', 'Accountants', 'Managers', 'Sales Staff',
'Medicine Staff', 'High Skill Tech Staff', 'Realty Agents', 'IT
Staff', 'HR Staff'] else 0.)
        #df.drop(self.features, axis=1, inplace=True)
        return np.array(df.values)  #return a Numpy Array to observe
the pipeline protocol


from sklearn.pipeline import make_pipeline
features = ["OCCUPATION_TYPE"]
def test_driver_prep_OCCUPATION_TYPE():
    print(f"X_train.shape: {X_train.shape}\n")
    print(f"X_train['name'][0:5]: \n{X_train[features][0:5]}")
    test_pipeline = make_pipeline(prep_OCCUPATION_TYPE(features))
    return(test_pipeline.fit_transform(X_train))

x = test_driver_prep_OCCUPATION_TYPE()
print(f"Test driver: \n{test_driver_prep_OCCUPATION_TYPE()[0:10, :]}")
print(f"X_train['name'][0:10]: \n{X_train[features][0:10]}")


# QUESTION, should we lower case df['OCCUPATION_TYPE'] as Sales
staff != 'Sales Staff'? (hint: YES)
```

```
X_train.shape: (1090501, 14)

X_train['name'][0:5]:
        OCCUPATION_TYPE
899239         Laborers
1333889     Sales staff
597650   Medicine staff
209947       Core staff
451114              NaN
X_train.shape: (1090501, 14)

X_train['name'][0:5]:
        OCCUPATION_TYPE
899239         Laborers
1333889     Sales staff
```

```
597650   Medicine staff
209947       Core staff
451114              NaN
Test driver:
[[0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]]
X_train['name'][0:10]:
               OCCUPATION_TYPE
899239               Laborers
1333889           Sales staff
597650         Medicine staff
209947             Core staff
451114                    NaN
1372880  High skill tech staff
486230                    NaN
1127205           Sales staff
1134196        Cleaning staff
1108233                   NaN

# Create a class to select numerical or categorical columns
# since Scikit-Learn doesn't handle DataFrames yet
class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X[self.attribute_names].values

# Identify the numeric features we wish to consider.
num_attribs = [
    'AMT_INCOME_TOTAL',
'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_SOURCE_1',
    'EXT_SOURCE_2','EXT_SOURCE_3']

num_pipeline = Pipeline([
        ('selector', DataFrameSelector(num_attribs)),
        ('imputer', SimpleImputer(strategy='mean')),
        ('std_scaler', StandardScaler()),
    ])
# Identify the categorical features we wish to consider.
cat_attribs = ['CODE_GENDER',
```

```python
'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE',

'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']

# Notice handle_unknown="ignore" in OHE which ignore values from the
validation/test that
# do NOT occur in the training set
cat_pipeline = Pipeline([
        ('selector', DataFrameSelector(cat_attribs)),
        #('imputer', SimpleImputer(strategy='most_frequent')),
        ('imputer', SimpleImputer(strategy='constant',
fill_value='missing')),
        ('ohe', OneHotEncoder(handle_unknown="ignore"))
    ])
#Removed sparse from (sparse=False, 'ohe',
OneHotEncoder(handle_unknown="ignore"))
data_prep_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
        ("cat_pipeline", cat_pipeline),
    ])
```

```python
list(datasets["application_train"].columns)
```

```
['SK_ID_CURR',
 'TARGET',
 'NAME_CONTRACT_TYPE',
 'CODE_GENDER',
 'FLAG_OWN_CAR',
 'FLAG_OWN_REALTY',
 'CNT_CHILDREN',
 'AMT_INCOME_TOTAL',
 'AMT_CREDIT',
 'AMT_ANNUITY',
 'AMT_GOODS_PRICE',
 'NAME_TYPE_SUITE',
 'NAME_INCOME_TYPE',
 'NAME_EDUCATION_TYPE',
 'NAME_FAMILY_STATUS',
 'NAME_HOUSING_TYPE',
 'REGION_POPULATION_RELATIVE',
 'DAYS_BIRTH',
 'DAYS_EMPLOYED',
 'DAYS_REGISTRATION',
 'DAYS_ID_PUBLISH',
 'OWN_CAR_AGE',
 'FLAG_MOBIL',
 'FLAG_EMP_PHONE',
 'FLAG_WORK_PHONE',
 'FLAG_CONT_MOBILE',
 'FLAG_PHONE',
```

```
 'FLAG_EMAIL',
 'OCCUPATION_TYPE',
 'CNT_FAM_MEMBERS',
 'REGION_RATING_CLIENT',
 'REGION_RATING_CLIENT_W_CITY',
 'WEEKDAY_APPR_PROCESS_START',
 'HOUR_APPR_PROCESS_START',
 'REG_REGION_NOT_LIVE_REGION',
 'REG_REGION_NOT_WORK_REGION',
 'LIVE_REGION_NOT_WORK_REGION',
 'REG_CITY_NOT_LIVE_CITY',
 'REG_CITY_NOT_WORK_CITY',
 'LIVE_CITY_NOT_WORK_CITY',
 'ORGANIZATION_TYPE',
 'EXT_SOURCE_1',
 'EXT_SOURCE_2',
 'EXT_SOURCE_3',
 'APARTMENTS_AVG',
 'BASEMENTAREA_AVG',
 'YEARS_BEGINEXPLUATATION_AVG',
 'YEARS_BUILD_AVG',
 'COMMONAREA_AVG',
 'ELEVATORS_AVG',
 'ENTRANCES_AVG',
 'FLOORSMAX_AVG',
 'FLOORSMIN_AVG',
 'LANDAREA_AVG',
 'LIVINGAPARTMENTS_AVG',
 'LIVINGAREA_AVG',
 'NONLIVINGAPARTMENTS_AVG',
 'NONLIVINGAREA_AVG',
 'APARTMENTS_MODE',
 'BASEMENTAREA_MODE',
 'YEARS_BEGINEXPLUATATION_MODE',
 'YEARS_BUILD_MODE',
 'COMMONAREA_MODE',
 'ELEVATORS_MODE',
 'ENTRANCES_MODE',
 'FLOORSMAX_MODE',
 'FLOORSMIN_MODE',
 'LANDAREA_MODE',
 'LIVINGAPARTMENTS_MODE',
 'LIVINGAREA_MODE',
 'NONLIVINGAPARTMENTS_MODE',
 'NONLIVINGAREA_MODE',
 'APARTMENTS_MEDI',
 'BASEMENTAREA_MEDI',
 'YEARS_BEGINEXPLUATATION_MEDI',
 'YEARS_BUILD_MEDI',
```

```
'COMMONAREA_MEDI',
'ELEVATORS_MEDI',
'ENTRANCES_MEDI',
'FLOORSMAX_MEDI',
'FLOORSMIN_MEDI',
'LANDAREA_MEDI',
'LIVINGAPARTMENTS_MEDI',
'LIVINGAREA_MEDI',
'NONLIVINGAPARTMENTS_MEDI',
'NONLIVINGAREA_MEDI',
'FONDKAPREMONT_MODE',
'HOUSETYPE_MODE',
'TOTALAREA_MODE',
'WALLSMATERIAL_MODE',
'EMERGENCYSTATE_MODE',
'OBS_30_CNT_SOCIAL_CIRCLE',
'DEF_30_CNT_SOCIAL_CIRCLE',
'OBS_60_CNT_SOCIAL_CIRCLE',
'DEF_60_CNT_SOCIAL_CIRCLE',
'DAYS_LAST_PHONE_CHANGE',
'FLAG_DOCUMENT_2',
'FLAG_DOCUMENT_3',
'FLAG_DOCUMENT_4',
'FLAG_DOCUMENT_5',
'FLAG_DOCUMENT_6',
'FLAG_DOCUMENT_7',
'FLAG_DOCUMENT_8',
'FLAG_DOCUMENT_9',
'FLAG_DOCUMENT_10',
'FLAG_DOCUMENT_11',
'FLAG_DOCUMENT_12',
'FLAG_DOCUMENT_13',
'FLAG_DOCUMENT_14',
'FLAG_DOCUMENT_15',
'FLAG_DOCUMENT_16',
'FLAG_DOCUMENT_17',
'FLAG_DOCUMENT_18',
'FLAG_DOCUMENT_19',
'FLAG_DOCUMENT_20',
'FLAG_DOCUMENT_21',
'AMT_REQ_CREDIT_BUREAU_HOUR',
'AMT_REQ_CREDIT_BUREAU_DAY',
'AMT_REQ_CREDIT_BUREAU_WEEK',
'AMT_REQ_CREDIT_BUREAU_MON',
'AMT_REQ_CREDIT_BUREAU_QRT',
'AMT_REQ_CREDIT_BUREAU_YEAR']
```

Baseline Model

To get a baseline, we will use some of the features after being preprocessed through the pipeline. The baseline model is a logistic regression model

```
def pct(x):
    return round(100*x,3)

try:
    expLog
except NameError:
    expLog = pd.DataFrame(columns=["exp_name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train AUC",
                                   "Valid AUC",
                                   "Test  AUC",
                                   "Train F1 Score",
                                   "Test F1 Score"
                                  ])
```

%%time np.random.seed(42) full_pipeline_with_predictor = Pipeline([("preparation", data_prep_pipeline), ("linear", LogisticRegression())]) model = full_pipeline_with_predictor.fit(X_train, y_train)

Evaluation metrics

- In the present final project, several evaluation meterics for Classification task were used to evaluate model peroformacnce, including Accuracy, Confusion Matrix, Precision, Recall, F1 Score, AUC-ROC curve.

Accuracy

Accuracy simply measures how often the classifier correctly predicts. We can define accuracy as the ratio of the number of correct predictions and the total number of predictions.

1_R6jP_uvlkcxtQSa264N3Sw.png

Precision

Precision for a label is defined as the number of true positives divided by the number of predicted positives.

0_p1t9CzwpaOXxsx4l.png

Recall

Recall for a label is defined as the total number of true positives divided by the total number of actual positives.

0_XgGoMQLlGGDgpzYa.png

F1 Score

F1 Score is the harmonic mean of precision and recall.

0_tu5x_GEgs-iRpJ9H.png

Confusion Matrix

Confusion Matrix is a performance measurement for the machine learning classification problems where the output can be two or more classes. It is a table with combinations of predicted and actual values.

- True Positive: We predicted positive and it’s true.
- True Negative: We predicted negative and it’s true.
- False Positive (Type 1 Error): We predicted positive and it’s false.
- False Negative (Type 2 Error): We predicted negative and it’s false.

1__JY_jxfndH8oBI3clamifA.png

AUC-ROC

The Receiver Operator Characteristic (ROC) is a probability curve that plots the TPR(True Positive Rate) against the FPR(False Positive Rate) at various threshold values and separates the ‘signal’ from the ‘noise’.

```
from sklearn.metrics import accuracy_score, classification_report

full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("linear", LogisticRegression())
    ])

model = full_pipeline_with_predictor.fit(X_train, y_train)

np.round(accuracy_score(y_train, model.predict(X_train)), 3)

0.921
```

Calculate accuracy, and Classification report of baseline model on testing data

```
# Calculate accuracy, and Classification report of baseline model on
testing data

accuracy_test_baseline = accuracy_score(y_test, model.predict(X_test))
* 100
report_test_baseline = classification_report(y_test,
model.predict(X_test))
```

```
print("Accuracy of Logistic Regression: {:.2f}
%".format(accuracy_test_baseline))
print("...................................................................
..........")
print("Classification report: Logistic Regression")
print()
print(report_test_baseline)
```

```
Accuracy of Logistic Regression: 92.18%
......................................................................
...
Classification report: Logistic Regression

              precision    recall  f1-score   support

           0       0.92      1.00      0.96    177375
           1       0.52      0.01      0.02     15067

    accuracy                           0.92    192442
   macro avg       0.72      0.50      0.49    192442
weighted avg       0.89      0.92      0.89    192442
```

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_train, model.predict_proba(X_train)[:, 1])
```

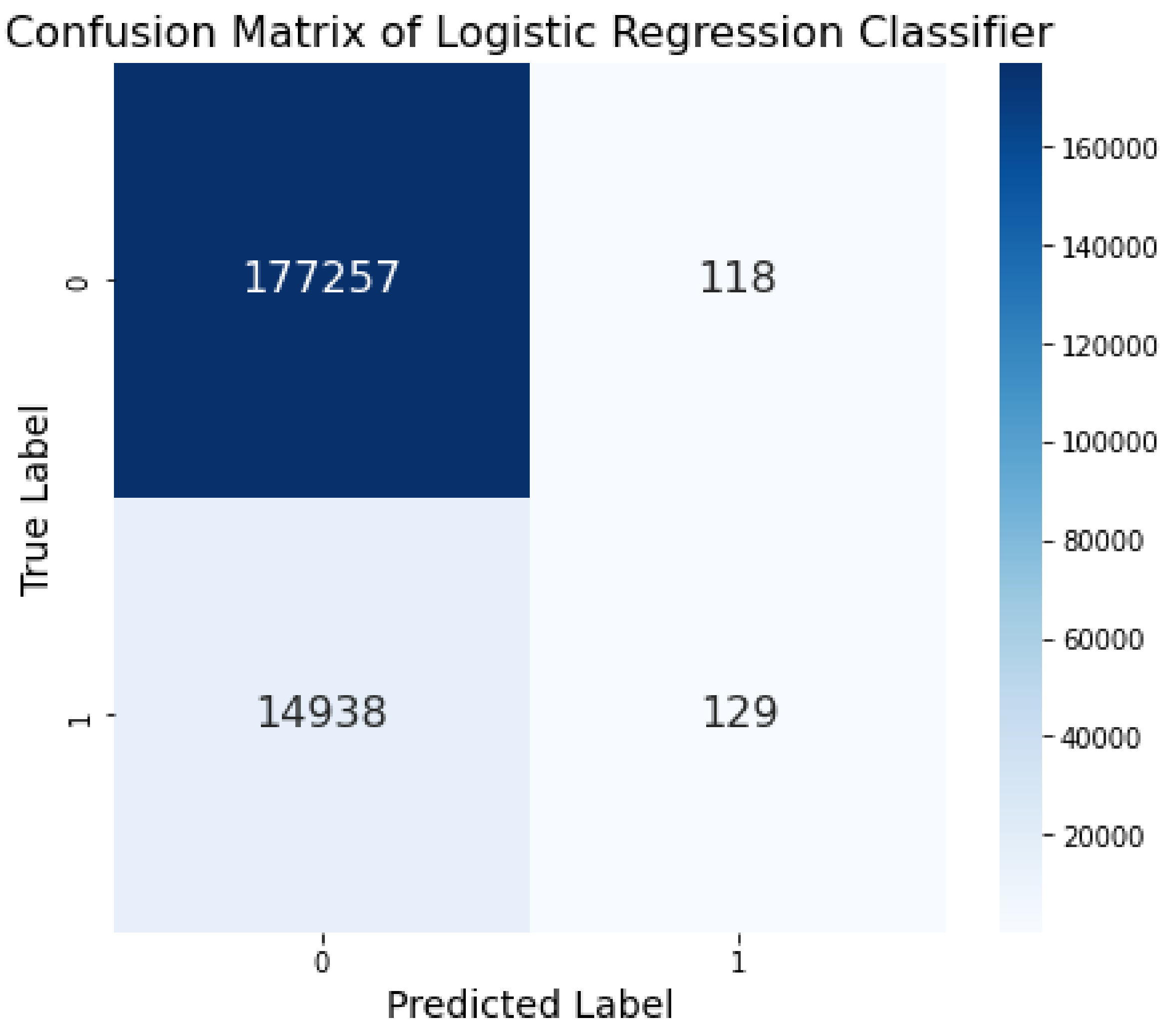
```
0.7411204703455814
```

```
from sklearn.metrics import f1_score
exp_name = f"Baseline_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model.predict(X_train)),
                accuracy_score(y_valid, model.predict(X_valid)),
                accuracy_score(y_test, model.predict(X_test)),
                roc_auc_score(y_train, model.predict_proba(X_train)[:,
1]),
                roc_auc_score(y_valid, model.predict_proba(X_valid)[:,
1]),
                roc_auc_score(y_test, model.predict_proba(X_test)[:,
1]),
                f1_score(y_train, model.predict(X_train)),
                f1_score(y_test, model.predict(X_test))],
    4))
expLog
```

```
               exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC  \
0  Baseline_14_features     0.9211     0.9214     0.9218     0.7411

   Valid AUC  Test  AUC  Train F1 Score  Test F1 Score
0     0.7406     0.7413          0.0174         0.0168
```

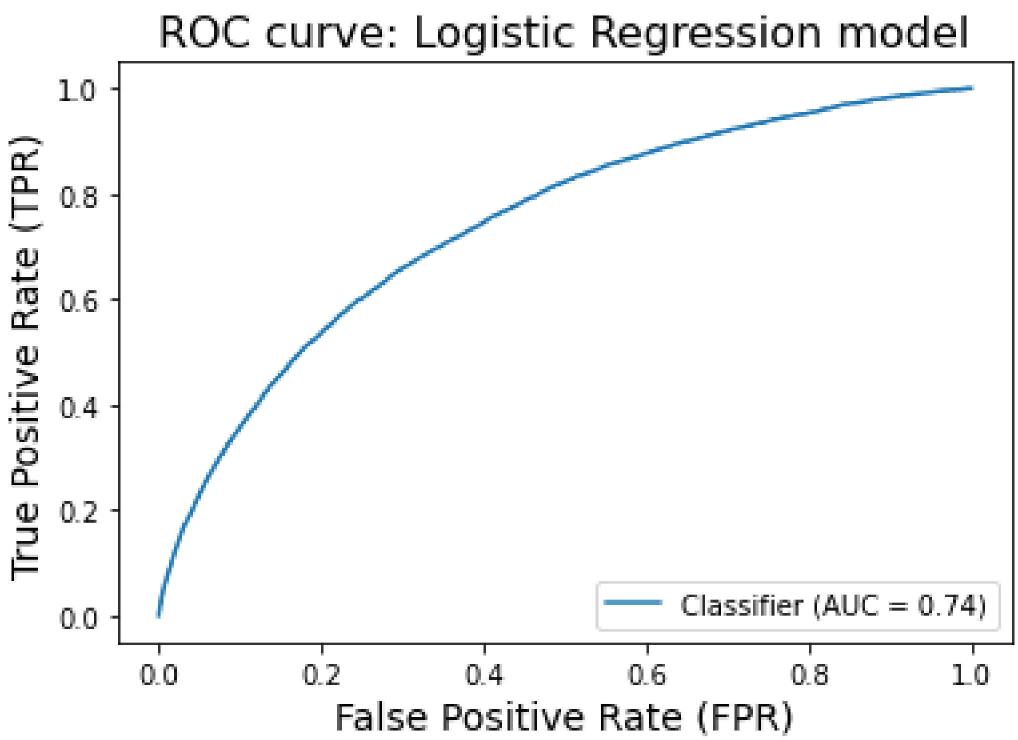
Confusion matrix for baseline model

```
# Create confusion matrix for baseline model

from sklearn.metrics import RocCurveDisplay, confusion_matrix

cm_lr = confusion_matrix(y_test, model.predict(X_test))

plt.figure(figsize = (7, 6))
sns.heatmap(cm_lr, annot = True, fmt = "d", cmap = "Blues",
annot_kws={"fontsize": 16})  # Adjust fontsize here
plt.title("Confusion Matrix of Logistic Regression Classifier",
fontsize = 16)
plt.xlabel("Predicted Label", fontsize = 14)
plt.ylabel("True Label", fontsize = 14)
plt.show()
```



ROC curve for baseline model

```
#Plot the ROC curve for baseline model

y_score = model.predict_proba(X_test)[:, 1]

roc_display = RocCurveDisplay.from_predictions(y_test, y_score)
plt.title("ROC curve: Logistic Regression model", fontsize = 16)  # 
Adjust the title to reflect your model
plt.xlabel("False Positive Rate (FPR)", fontsize = 14)
plt.ylabel("True Positive Rate (TPR)", fontsize = 14)
plt.show()
```



Hyperparameter Tuning of Basline model with grid search CV

```
params_grid = {'linear__penalty': ['l1', 'l2'],
            'linear__tol': [0.0001, 0.00001, 0.0000001],
            'linear__C': [10, 1, 0.1, 0.01]}

# Initialize GridSearchCV with the pipeline and the parameter grid
gs = GridSearchCV(full_pipeline_with_predictor, params_grid, cv=5, 
n_jobs=-1, verbose=2, refit=True)

### Creating a subset as the full file is just too big and crashes my 
kernal
```

```
random_index = X_train.sample(n=100000, random_state=42).index
X_train_subset = X_train.loc[random_index]
y_train_subset = y_train.loc[random_index]
print(X_train_subset.shape)
print(y_train_subset.shape)

gs.fit(X_train_subset, y_train_subset)
```

```
(100000, 14)
(100000,)
Fitting 5 folds for each of 24 candidates, totalling 120 fits
```

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preparation',

FeatureUnion(transformer_list=[('num_pipeline',

Pipeline(steps=[('selector',

DataFrameSelector(attribute_names=['AMT_INCOME_TOTAL',

'AMT_CREDIT',

'DAYS_EMPLOYED',

'DAYS_BIRTH',

'EXT_SOURCE_1',

'EXT_SOURCE_2',

'EXT_SOURCE_3'])),

('imputer',

SimpleImputer()),

('std_scaler',

StandardScaler())])),

('cat_pip...

'NAME_CONTRACT_TYPE',

'NAME_EDUCATION_TYPE',

'OCCUPATION_TYPE',

'NAME_INCOME_TYPE'])),
```

```
('imputer',

SimpleImputer(fill_value='missing',

strategy='constant')),

('ohe',

OneHotEncoder(handle_unknown='ignore'))]))])),
                                       ('linear',
LogisticRegression())]),
             n_jobs=-1,
             param_grid={'linear__C': [10, 1, 0.1, 0.01],
                         'linear__penalty': ['l1', 'l2'],
                         'linear__tol': [0.0001, 1e-05, 1e-07]},
             verbose=2)

best_model = gs.best_estimator_
best_params = gs.best_params_


# Evaluate the best model on the test set
y_pred = best_model.predict(X_test)

best_accuracy = accuracy_score(y_test, y_pred) * 100

print("Best model hyperparameters:", best_params)
print("Accuracy of best model:", best_accuracy)

Best model hyperparameters: {'linear__C': 1, 'linear__penalty': 'l2',
'linear__tol': 0.0001}
Accuracy of best model: 92.17790295257792
```

Calculate accuracy, and Classification report of baseline model on testing data

```
# Calculate accuracy, and Classification report of baseline model on
testing data

accuracy_test_gs = accuracy_score(y_test, best_model.predict(X_test))*
100
report_test_gs = classification_report(y_test,
best_model.predict(X_test))

print("Accuracy of Logistic Regression with hyperparameter tuning:
{:.2f}%".format(accuracy_test_gs))
print("...............................................................
..........")
print("Classification report: Logistic Regression with hyperparameter
```

```
tuning")
print()
print(report_test_gs)
```

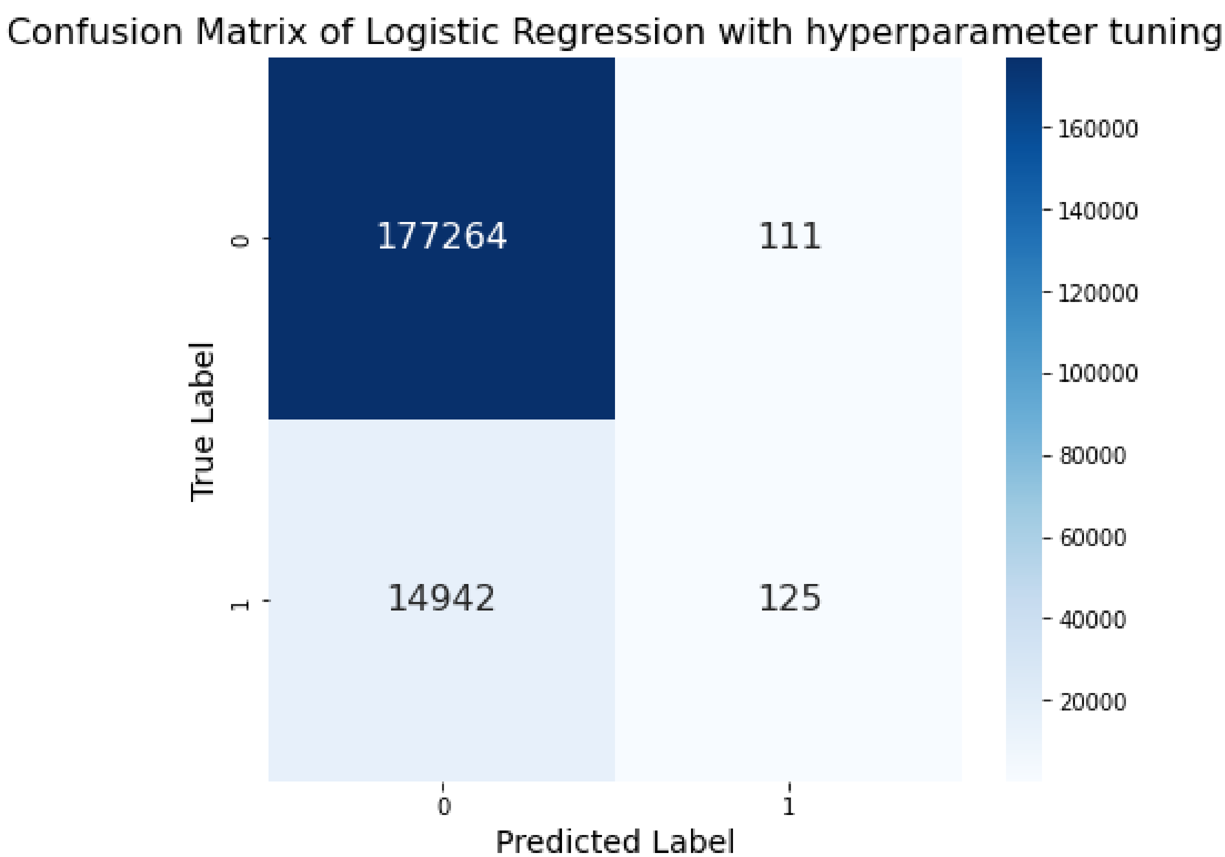
```
Accuracy of Logistic Regression with hyperparameter tuning: 92.18%
......................................................................
...
Classification report: Logistic Regression with hyperparameter tuning

              precision    recall  f1-score   support

           0       0.92      1.00      0.96    177375
           1       0.53      0.01      0.02     15067

    accuracy                           0.92    192442
   macro avg       0.73      0.50      0.49    192442
weighted avg       0.89      0.92      0.89    192442
```

```
exp_name = "GridSearchCV Logistic Regression"

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, best_model.predict(X_train)),
                accuracy_score(y_valid, best_model.predict(X_valid)),
                accuracy_score(y_test, best_model.predict(X_test)),
                roc_auc_score(y_train,
best_model.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid,
best_model.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, best_model.predict_proba(X_test)
[:, 1]),
                f1_score(y_train, best_model.predict(X_train)),
                f1_score(y_test, best_model.predict(X_test))],
    4))
expLog
```

```
                           exp_name  Train Acc  Valid Acc  Test
Acc  \
0               Baseline_14_features     0.9211     0.9214     0.9218

1  GridSearchCV Logistic Regression     0.9211     0.9214     0.9218


   Train AUC  Valid AUC  Test  AUC  Train F1 Score  Test F1 Score
0     0.7411     0.7406     0.7413          0.0174         0.0168
1     0.7399     0.7397     0.7403          0.0163         0.0163
```

Create confusion matrix for Logistic Regression with hyperparameter tuning

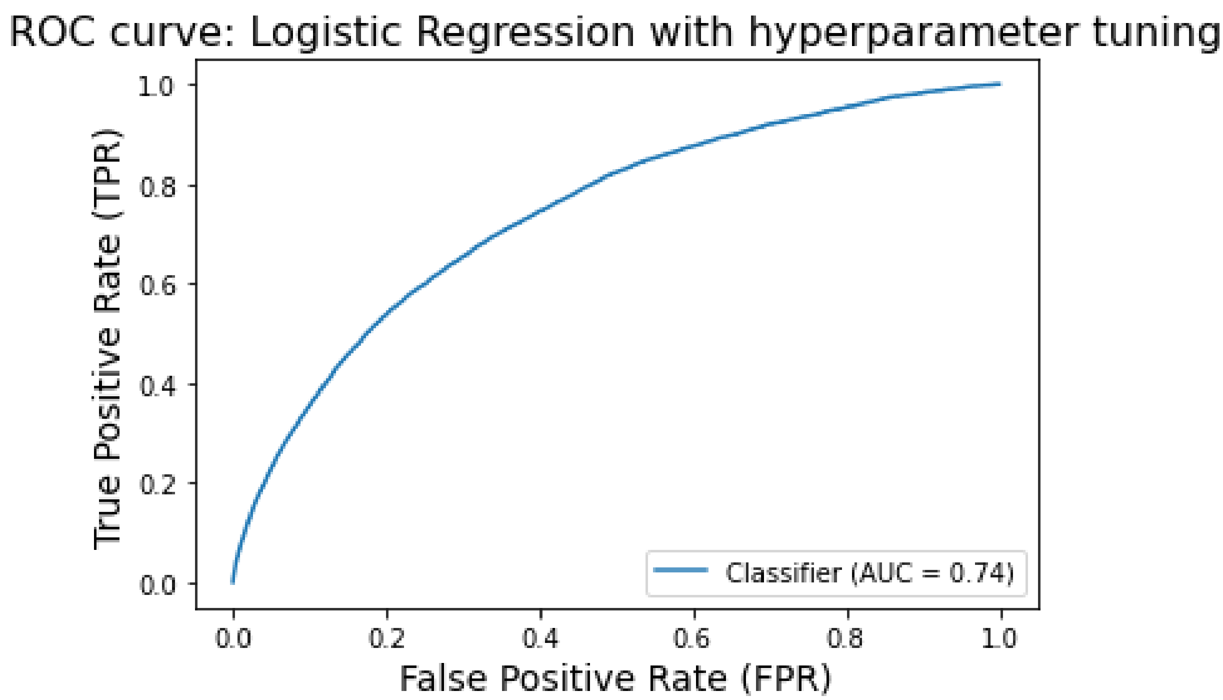
```
# Create confusion matrix for Logistic Regression with hyperparameter
tuning

cm_lr_gs = confusion_matrix(y_test, best_model.predict(X_test))

plt.figure(figsize = (7, 6))
sns.heatmap(cm_lr_gs, annot = True, fmt = "d", cmap = "Blues",
annot_kws={"fontsize": 16})  # Adjust fontsize here
plt.title("Confusion Matrix of Logistic Regression with hyperparameter
tuning", fontsize = 16)
plt.xlabel("Predicted Label", fontsize = 14)
plt.ylabel("True Label", fontsize = 14)
plt.show()
```



Plot the ROC curve for Logistic Regression with hyperparameter tuning

```
#Plot the ROC curve for Logistic Regression with hyperparameter tuning

y_score = best_model.predict_proba(X_test)[:, 1]
```

```
roc_display = RocCurveDisplay.from_predictions(y_test, y_score)
plt.title("ROC curve: Logistic Regression with hyperparameter tuning",
fontsize = 16)  # Adjust the title to reflect your model
plt.xlabel("False Positive Rate (FPR)", fontsize = 14)
plt.ylabel("True Positive Rate (TPR)", fontsize = 14)
plt.show()
```



Submission File Prep

For each SK_ID_CURR in the test set, you must predict a probability for the TARGET variable. The file should contain a header and have the following format:

```
SK_ID_CURR,TARGET
100001,0.1
100005,0.9
100013,0.2
etc.

test_class_scores =
model.predict_proba(X_kaggle_test.drop_duplicates())[:, 1]

test_class_scores[0:10]

array([0.05803146, 0.18384931, 0.02918184, 0.0633911 , 0.11813195,
       0.05099085, 0.01717747, 0.07965406, 0.01475007, 0.18479504])
```

```
# Submission dataframe
submit_df = datasets["application_test"][['SK_ID_CURR']]
submit_df['TARGET'] = test_class_scores

submit_df.head()
```

	SK_ID_CURR	TARGET
0	100001	0.058031
1	100005	0.183849
2	100013	0.029182
3	100028	0.063391
4	100038	0.118132

```
submit_df.to_csv("submission.csv",index=False)
```

Kaggle submission via the command line API

```
# ! kaggle competitions submit -c home-credit-default-risk -f
submission.csv -m "baseline submission"
```

report submission

Click on this link

image.png

Write-up

In this section, we will summarize the work done for phase 2.

Project title:

Predicting credit default risk using machine learning

Team and phase leader plan:

This week, our phase leader is Wunchana Seubwai. Our phase schedule is below

Phase	Phase leader
Phase 1	Evie Mahsem
Phase 2	Wunchana Seubwai
Phase 3	Woojeong Kim
Phase 4	Alaina Barca

Credit assignment plan for phase 2:

Group member	Tasks completed
Evie Mahsem	Did EDA, built baseline pipelines, visualized EDA, contributed to slides
Wunchana Seubwai	Did EDA, built baseline pipelines, visualized EDA, created PPT template and contributed to slides
Woojeong Kim	Led development of PPT slides
Alaina Barca	Wrote report and developed presentation video

Abstract

The aim of this final project on the Home Credit Default Risk dataset is to develop a predictive model that accurately predicts whether a client will default on a loan. For phase 2 of the final project, we implemented several EDA and feature engineering techniques before constructing logistic regression models with and without hyperparameter tuning to identify potential loan defaulters among Home Credit's clientele. Various evaluation metrics, including accuracy score, precision, recall, F-1 score, confusion matrix, and ROC-AUC curve, were used to evaluate model performance. The results demonstrated that both models exhibited similar accuracy across the training, validation, and test datasets, with accuracy scores of around 92% and AUC scores of approximately 0.74. However, we aim to improve our model's performance by addressing class imbalance issues in the dataset. In addition, more machine learning models for classification tasks will be explored in the final project's phase 3.

Introduction

A consumer's ability to access a line of credit is often highly dependent on their credit history, leaving many potentially credit-worthy consumers without traditional loan options simply due to insufficient data. In this project, we will explore data from Home Credit, a lender striving to lend to consumers with insufficient credit histories using alternative lending data, to improve their methods for predicting loan repayment. We will use consumer transaction and payment data to develop pipelines for various machine learning algorithms – including logistic regressions, classification methods, and deep learning models – to predict consumers' likelihood of default. We will evaluate each method's predictive power using the ROC curve and produce a report summarizing the methods tested and the strongest performing predictor of consumer default. We will follow the project schedule for intermediate steps, which includes developing EDA and baseline pipeline in week 14, feature engineering and hyperparameter tuning in week 15, and implementing neural networks, advanced models, and finalizing the project in week 16.

For this phase (week 14), we review the dataset, conduct EDA, basic feature engineering and transformers, develop pipelines for our baseline model, and discuss our initial experimental results. We conclude with next steps for phase 3.

Dataset

The dataset from Home Credit is comprised of seven different sources of data. The first, **application_train/application_test (307k rows, and 48k rows)** is our main training and testing data. Six other datasets supplement the main train and test data. The dataset **bureau (1.7 Million rows)** contains client credit history, **bureau_balance (27 Million rows)** includes monthly credit history, **previous_application (1.6 Million rows)** contains previous applications, **POS_CASH_BALANCE (10 Million rows)** provides monthly data on spending, **credit_card_balance** gives us monthly credit card information, and **installments_payment (13.6 Million rows)** contains previous loan payments with Home Credit, if any.

EDA

From our EDA, we find that there are 16 categorical features and 106 numeric features in the application_train dataset. There are 48,744 rows and 122 features, including the "target" column (which represents whether a loan was repaid, with 0 for no and 1 for yes). There is quite a bit of missing data, with as much as 68.72 percent of some variables' observations missing. There is also quite a bit of class imbalance for our target variable -- 92 percent of the loans in our data are paid (0) and 8 percent are unpaid (1). So, we will need to address this in our analysis. The variable most positive correlated with the target variable is DAYS_BIRTH (0.078), while the variable most negatively correlated with the target variable is EXT_SOURCE_3 (-0.179).

The distribution of applicant age is fairly flat between the ages of 20 and 70, though there are a few spikes around the ages of 30, 40, and 55. More than any other occupation, applicants are laborers, followed by occupations of sales staff and core staff. There are 1.7 million previous credit applications in our data. 291,057 of our 307,511 unique training set applicants have submitted a previous application. This is similar to the rate we see in the test data, with 47,800 out of 48,744 test set applicants submitting a previous application. About 22 percent of applicants have submitted a small number of applications ever (less than 5). 58 percent have submitted a moderate amount of applications (10 to 39), and 20 percent have submitted a large amount of applications (40 or more).

Feature Engineering and transformers

We conduct feature engineering for the prevApp table to address missing values, as well as creating feature transformer via pipeline for the prevApp table. We also construct a feature aggregator for the primary and secondary tables via pipeline. After fitting the feature engineering pipeline, we joined the primary and secondary datasets using features based on metadata and aggregated statistics. We then convert categorical features to numerical approximations via pipeline. We also prepare the data for our baseline model via pipeline, in which we split the provided training data into training and test sets, and identify the numeric features we wish to consider in our analysis.

Pipelines

As described above, we constructed pipelines for the feature engineering and transformer steps in this phase of the project. We also describe the baseline model pipeline below.

Screenshot%20%281315%29.png

Experimental results

In Phase 2 of the final project, We developed our baseline logistic model pipeline, which we evaluate via accuracy, confusion matrix, precision, recall, F1 score, and AUC-ROC curve. We conducted hyperparameter tuning of the baseline model with grid search CV, and also evaluated model performance across the same tests.

As shown in Figure 1, Figure 2, and Table 1, Our baseline logistic model had train dataset accuracy of 0.921, a .741 AUC and a 0.017 F1 score. The test dataset had an accuracy of 0.922, a 0.741 AUC, and a 0.017 F1 score. The confusion matrix reveals we had 92.1% true negatives, 7.8% false negatives, 0.1% true positives, and 0.1% false positives. The small proportion of any positives is indicative of our imbalanced target class, and may mean we need to do more to address our imbalance issue.

We then conduct hyperparameter tuning via grid search CV. We experienced memory issues at this stage and were forced to run on a random subset of the data. According to our grid search results, the best model is a ridge regression with a tolerance of 0.0001 and a relatively strict regularization strength of 1. With this model, we see a training dataset accuracy of 0.921, a .740 AUC and a 0.016 F1 score. The test dataset had an accuracy of 0.922, a 0.740 AUC, and a 0.016 F1 score. Although the numbers shifted slightly in our confusion matrix, the percentages were the same as those presented for the baseline model above.

Figure%201_FP%20Phase%202_Group%202.png

Figure%202_FP%20Phase%202_Group%202-2.png

Table%201_FP%20Phase%202_Group%202.png

Discussion

All models (Logistic Regression with and without hyperparameter tuning) performed well with comparable results in terms of accuracy, ROC curve, evaluation metrics, and confusion matrix for 'Class 0'. However, the machine learning models failed to accurately predict of 'Class 1'.

Based on Class '1' results, the logistic regression models with and without hyperparameter tuning performed similarly with very low precision, recall, and F1-scores. This data indicated that models failed to predict 'Class 1' accurately. A significant class imbalance could significantly impact the learning process of the machine learning models. The machine learning models may have been trained with a bias toward the majority class ('Class 0'). Consequently, the models may overfit with the majority class ('Class 0') and have difficulty accurately predicting the rare instances of 'Class 1'.

Class Imbalance is a common problem in machine learning, especially in classification tasks. This problem can negatively impact the performance and accuracy of machine models. Therefore, We would like to improve our model performance through the implementation the technique to handle class imbalance issues in the dataset, such as the Synthetic Minority Over-sampling Technique (SMOTE). In addition, more machine learning model for classification task such as random forest, SVM, ANN will be used in the final project phase 3.

Conclusion

In this study, we performed EDA, feature engineering, and baseline model using logistic regression models, with and without hyperparameter tuning, to identify potential loan defaulters within the Home Credit Default Risk dataset. Both logistic regression models achieved high accuracy levels of approximately 92% and ROC-AUC scores around 0.74. However, the models failed to predict 'Class 1'(loan defaulters) accurately, as indicated by the low precision, recall, and F1-scores for this class. These results suggest a significant class imbalance within the dataset, which negatively impacted the model's predictive performance for the minority class. Next, we would like to handle class imbalance issue and used another machine learning model that work well with classimblance dataset to enhance model performance.

Kaggle Submission

download%20%2812%29.png

References

Some of the material in this notebook has been adopted from here

- https://www.kaggle.com/competitions/home-credit-default-risk/overview
- https://medium.com/analytics-vidhya/home-credit-default-risk-part-1-business-understanding-data-cleaning-and-eda-1203913e979c
- https://medium.com/@dhruvnarayanan20/home-credit-default-risk-part-2-feature-engineering-and-modelling-i-be9385ad77fd
- https://medium.com/@soohyunniekimm/logistic-regression-with-columntransformer-pipeline-and-gridsearchcv-d2e3a781422f
- https://www.analyticsvidhya.com/blog/2021/07/metrics-to-evaluate-your-classification-model-to-take-the-right-decisions/
- https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/
- https://medium.com/@okanyenigun/handling-class-imbalance-in-machine-learning-cb1473e825ce

TODO: Predicting Loan Repayment with Automated Feature Engineering in Featuretools

Read the following:

- feature engineering via Featuretools library:
  - https://github.com/Featuretools/predict-loan-repayment/blob/master/Automated%20Loan%20Repayment.ipynb

- https://www.analyticsvidhya.com/blog/2018/08/guide-automated-feature-engineering-featuretools-python/
- feature engineering paper: https://dai.lids.mit.edu/wp-content/uploads/2017/10/DSAA_DSM_2015.pdf
- https://www.analyticsvidhya.com/blog/2017/08/catboost-automated-categorical-data/

Phase 3 Start

Once we've established a baseline logistic regression model, the next steps typically involve iteratively improving our model's performance through various means such as feature engineering, trying different algorithms, hyperparameter tuning, and ensembling methods. Here's a breakdown of what we can explore next:

step1. **Feature Engineering**:

This step involves creating new features or modifying existing ones to better capture the underlying patterns in our data. we can try techniques like one-hot encoding for categorical variables in the previous section, binning numeric variables, creating interaction terms, or applying transformations like logarithms or square roots. Additionally, we can derive features from domain knowledge or various data sources if available and relevant.

step2. **Algorithm Selection**:

Logistic regression is one of many algorithms we can try. We can explore tree-based models like decision trees, random forests, or gradient boosting machines (GBMs = Gradient-Boosting Machine). Neural networks, support vector machines (SVMs), and k-nearest neighbors (KNN) are other options to consider. Each algorithm has its own strengths and weaknesses, and different algorithms may perform better on different datasets.

step3. **Hyperparameter Tuning**:

Once we've chosen an algorithm, we can optimize its performance by tuning its hyperparameters. Grid search, random search, or more advanced optimization techniques like Bayesian optimization can be used to find the best combination of hyperparameters. Hyperparameters control aspects of the model such as its complexity, regularization strength, and learning rate.

step4. **Model Evaluation**:

Use appropriate evaluation metrics to assess the performance of our models. For binary classification problems like credit default prediction, metrics include accuracy, precision, recall, F1 score, p-value and area under the ROC curve (AUC-ROC). It's essential to evaluate models on a separate validation dataset to ensure their generalization ability.

step5. **Ensembling**:

Ensembling involves combining predictions from multiple models to improve performance. Techniques like bagging (e.g., random forests), boosting (e.g., AdaBoost, gradient boosting), and stacking can be used to create robust ensembles. Ensembling can help mitigate the weaknesses of individual models and leads to better overall performance.

step6. **Model Interpretation and selection**:

Understanding why our model makes certain predictions is crucial, especially in sensitive applications like credit risk assessment. Techniques like feature importance analysis, partial dependence plots, and SHAP (SHapley Additive exPlanations) values can help interpret complex models.

step7. **Handling Imbalance**:

For the dataset having imbalanced problem(e.g., significantly more non-defaulters than defaulters), techniques like oversampling, undersampling, or using algorithms specifically designed for imbalanced data (e.g., SMOTE) may be necessary to improve model performance. By systematically exploring these avenues, we can incrementally enhance the performance of our model beyond the baseline logistic regression.

0. Preparation for Feature Engineering

```
from sklearn.model_selection import ShuffleSplit
import gc

cvSplits = ShuffleSplit(n_splits=3, test_size=0.3, random_state=0)
gc.collect()
```

```
22192
```

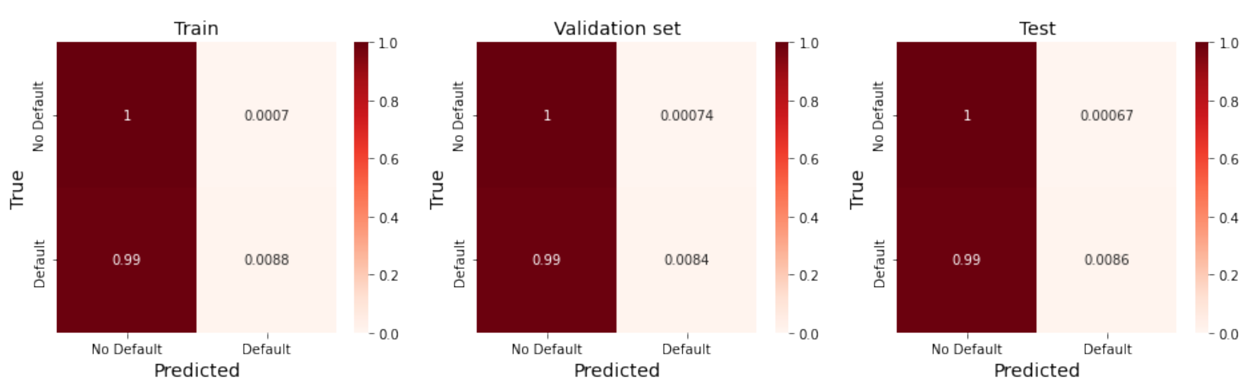
```
from time import time
from sklearn.model_selection import cross_validate
import sklearn.metrics as metrics
from sklearn.metrics import (accuracy_score, confusion_matrix,
f1_score, log_loss,
                             classification_report, roc_auc_score,
make_scorer,
                             roc_curve, ConfusionMatrixDisplay,
precision_recall_curve,
                             explained_variance_score,
RocCurveDisplay, PrecisionRecallDisplay)

start_time = time()
np.random.seed(42)

model = full_pipeline_with_predictor.fit(X_train, y_train)

# Define scores of cross-validation
scoring_metrics = {
    'accuracy': make_scorer(accuracy_score),
    'roc_auc': 'roc_auc',
    'f1': make_scorer(f1_score),
    'log_loss': make_scorer(log_loss)
}

logit_scores = cross_validate(model, X_train, y_train, cv=cvSplits,
scoring=scoring_metrics,
```

```
                              return_train_score=True, n_jobs=-1)
train_time = round(time() - start_time, 4)

# Time and score valid predictions
start_time = time()
logit_score_valid = full_pipeline_with_predictor.score(X_valid,
y_valid)
valid_time = round(time() - start_time, 4)

# Time and score test predictions
start_time = time()
logit_score_test = full_pipeline_with_predictor.score(X_test, y_test)
test_time = round(time() - start_time, 4)
```

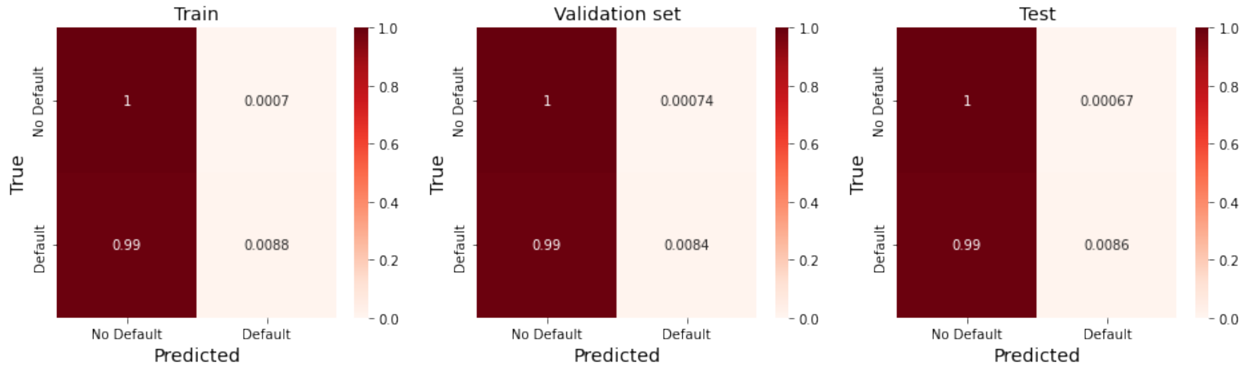
Setting Matircs and confusion matrix

```
# Create confusion matrix for the best model
# roc curve, precision recall curve for each model
class_labels = ["No Default","Default"]

fprs, tprs, precisions, recalls, names, scores, cvscores, pvalues,
accuracy, cnfmatrix = list(), list(), list(), list(), list(), list(),
list(), list(), list(), list()
features_list, final_best_clf,results = {}, {},[]



def plot_confusion_matrices(model, X_train_data, y_train_data,
X_test_data, y_test_data, X_valid_data, y_valid_data, cnfmatrix):
    # Predictions
    preds_test = model.predict(X_test_data)
    preds_train = model.predict(X_train_data)
    preds_valid = model.predict(X_valid_data)

    # Calculate confusion matrices
    train_confusion_matrix = confusion_matrix(y_train_data,
preds_train).astype(np.float32)
    train_confusion_matrix /= train_confusion_matrix.sum(axis=1)[:,
np.newaxis]

    test_confusion_matrix = confusion_matrix(y_test_data,
preds_test).astype(np.float32)
    test_confusion_matrix /= test_confusion_matrix.sum(axis=1)[:,
np.newaxis]

    valid_confusion_matrix = confusion_matrix(y_valid_data,
preds_valid).astype(np.float32)
    valid_confusion_matrix /= valid_confusion_matrix.sum(axis=1)[:,
np.newaxis]
```

```
    # Plot confusion matrices
    plt.figure(figsize=(16, 4))

    plt.subplot(131)
    g = sns.heatmap(train_confusion_matrix, vmin=0, vmax=1,
annot=True, cmap="Reds")
    plt.xlabel("Predicted", fontsize=14)
    plt.ylabel("True", fontsize=14)
    g.set(xticklabels=class_labels, yticklabels=class_labels)
    plt.title("Train", fontsize=14)

    plt.subplot(132)
    g = sns.heatmap(valid_confusion_matrix, vmin=0, vmax=1,
annot=True, cmap="Reds")
    plt.xlabel("Predicted", fontsize=14)
    plt.ylabel("True", fontsize=14)
    g.set(xticklabels=class_labels, yticklabels=class_labels)
    plt.title("Validation set", fontsize=14);

    plt.subplot(133)
    g = sns.heatmap(test_confusion_matrix, vmin=0, vmax=1, annot=True,
cmap="Reds")
    plt.xlabel("Predicted", fontsize=14)
    plt.ylabel("True", fontsize=14)
    g.set(xticklabels=class_labels, yticklabels=class_labels)
    plt.title("Test", fontsize=14)

    # Append confusion matrix of the test set
    cnfmatrix.append(test_confusion_matrix)

    return cnfmatrix


cnfmatrix =
plot_confusion_matrices(model,X_train,y_train,X_test,y_test,X_valid,
y_valid,cnfmatrix)
```



```python
# Confusion matrix for baseline model
_=plot_confusion_matrices(model,X_train,y_train,X_test,y_test,X_valid,
y_valid,cnfmatrix)
```



Function for AUC (Area under ROC curve)

```python
def roc_curve_cust(model, X_train_data, y_train_data, X_test_data,
y_test_data, X_valid_data, y_valid_data, fprs, tprs, name):
    fpr, tpr, threshold = roc_curve(y_test_data,
model.predict_proba(X_test_data)[:, 1])
    fprs.append(fpr)
    tprs.append(tpr)
    train_roc_display = RocCurveDisplay.from_estimator(model,
X_train_data, y_train_data, name="TrainRocAuc")
    test_roc_display = RocCurveDisplay.from_estimator(model,
X_test_data, y_test_data, name="TestRocAuc", ax=train_roc_display.ax_)
    valid_roc_display = RocCurveDisplay.from_estimator(model,
X_valid_data, y_valid_data, name="ValidRocAuc",
ax=test_roc_display.ax_)
    valid_roc_display.ax_.set_title("ROC Curve Comparison - " + name)
    plt.legend(bbox_to_anchor=(1.04,1), loc="upper left",
borderaxespad=0)
    plt.show()
    return fprs, tprs
```

Algorithm and ensemble experiments from hyperparameter tuning (Step2-4)

Now, we will go through the experiments for the following 4 acheivements.

- Algorithm Selection: Explore various algorithms such as decision trees, random forests, GBMs, neural networks, SVMs, and KNN, considering their strengths and weaknesses to find the best fit for your dataset.

- Hyperparameter Tuning: Optimize algorithm performance by adjusting hyperparameters using techniques like grid search, random search, or Bayesian optimization, controlling aspects like model complexity, regularization, and learning rate.
- Model Evaluation: Assess model performance using metrics like accuracy, precision, recall, F1 score, and AUC-ROC, ensuring validation on a separate dataset to gauge generalization ability.
- Ensembling: Combine predictions from multiple models using techniques like bagging, boosting, or stacking to improve overall performance by leveraging the strengths of individual models and mitigating their weaknesses.

Grid Search and RFE from adjusting hyper parameters

```
data_prep_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
        ("cat_pipeline", cat_pipeline),
    ])

# !pip install lightgbm

from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_validate
from sklearn.utils import resample

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.decomposition import PCA
from sklearn.feature_selection import RFE
from sklearn.ensemble import VotingClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import mutual_info_classif

from sklearn.metrics import accuracy_score, confusion_matrix,
f1_score, log_loss, classification_report, roc_auc_score, make_scorer
from scipy import stats
import json
from matplotlib import pyplot
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import (roc_curve, ConfusionMatrixDisplay,
precision_recall_curve,
                             explained_variance_score,
RocCurveDisplay, PrecisionRecallDisplay)
```

Setting the algorithm and ensemble and tuning hyper parameters

```
classifiers = [
        [('Logistic Regression',
LogisticRegression(solver='saga',random_state=42, max_iter =
100),"RFE")],
        [('Support Vector',
SVC(random_state=42,probability=True),"SVM")],
        [('Gradient Boosting',
GradientBoostingClassifier(warm_start=True, random_state=42),"RFE")],
        [('XGBoost', XGBClassifier(random_state=42),"RFE")],
        [('Light Gradient-Boosting Machine',
LGBMClassifier(boosting_type='gbdt', random_state=42),"RFE")],
        [('Random Forest',
RandomForestClassifier(random_state=42),"RFE")]
    ]

# Define grid search parameters for each classifier
params_grid = {
        'Logistic Regression': {
            'penalty': ('l1', 'l2','elasticnet'),
            'tol': (0.01, 0.001),
            'C': (1, 0.01),
        },
    'Gradient Boosting':  {
            'max_depth': [5,10], # Lowering helps with overfitting.
            'max_features': [5,10],
            'validation_fraction': [0.2],
            'n_iter_no_change': [10],
            'tol': [0.1,0.01],
            'n_estimators':[1000],
            'subsample' : [0.8],   #It represents the fraction of
observations to be randomly sampled for each tree.
            'min_samples_leaf' : [3,5],
        },
        'XGBoost':  {
            'max_depth': [3,5], # Lowering max depth helps with
overfitting.
            'n_estimators':[300,500],
            'gamma': [0, 1, 10, 100],
            'eta' : [0.001, 0.01,0.1],
            'colsample_bytree' : [0.2,0.5],
        },
        'Light Gradient-Boosting Machine':  {
```

```
            'n_estimators':[1000],
            'learning_rate': [0.01],
            'boosting_type':['goss','dart'],
            'max_depth': [2],  # Lowering max depth helps with 
overfitting.
            'num_leaves': [5], # = max depth
            'max_bin' : [100],  #Setting max bin to high values has a 
similar effect as increasing the value of num_leaves.
        },

        'Random Forest':  {
            'min_samples_split': [5],
            'min_samples_leaf': [5],
            'n_estimators':[10, 20],
            'max_depth': [5],
            'max_features': [10, 13]
        },
        'Support Vector' : {
            'kernel': ('rbf','poly'),
            'degree': (4, 5),
            'C': ( 0.01, 0.1),   #Allowing for misclassification due 
to low C.
            'gamma':(0.1, 1)  #Low gamma results in high variance and 
low bias.
        }

    }

# Set feature selection settings
feature_selection_steps = 0.5  # Features removed each step
features_used = len(selected_features)  # Number of features used
features_used
```

```
14
```

```
def precision_recall_cust(model,X_train,y_train,X_test,
y_test,X_valid, y_valid,precisions,recalls,name):
    # plot precision_recall Test
    precision, recall, threshold = 
precision_recall_curve(y_test,model.predict_proba(X_test)[:, 1])
    precisions.append(precision)
    recalls.append(recall)

    # plot combined Precision Recall curve for train, valid, test
    show_train_precision = RocCurveDisplay.from_estimator(model, 
X_train, y_train, name="TrainPresRecal")
    show_test_precision = RocCurveDisplay.from_estimator(model, 
X_test, y_test, name="TestPresRecal", ax=show_train_precision.ax_)
    show_valid_precision = RocCurveDisplay.from_estimator(model, 
X_valid, y_valid, name="ValidPresRecal", ax=show_test_precision.ax_)
```

```
    show_valid_precision.ax_.set_title ("Precision Recall Curve
Comparison - " + name)
    plt.legend(bbox_to_anchor=(1.04,1), loc="upper left",
borderaxespad=0)
    plt.show()
    return precisions,recalls

try:
    Log
except NameError:
    Log = pd.DataFrame(columns=["exp_name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train AUC",
                                   "Valid AUC",
                                   "Test  AUC",
                                   "Train F1 Score",
                                   "Valid F1 Score",
                                   "Test F1 Score",
                                   "Train Log Loss",
                                   "Valid Log Loss",
                                   "Test Log Loss",
                                   "P Score"
                                  ])

# roc curve, precision recall curve for each model
pvalues, accuracy, fprs, recalls, names, tprs, precisions, scores,
cvscores, cnfmatrix = list(), list(), list(), list(), list(), list(),
list(), list(), list(), list()
features_list, final_best_clf,results = {}, {},[]

import pickle
metrics = {'accuracy': make_scorer(accuracy_score),
            'roc_auc': 'roc_auc',
            'f1': make_scorer(f1_score),
            'log_loss': make_scorer(log_loss)
          }


# Set up classifier names and initialize empty lists for confusion
matrices, ROC curves, and precision-recall curves
names = ['Baseline LR']


def RunGridResearch(in_classifiers, confusion_matrices, fprs, tprs,
precisions, recalls):
    # Iterate over classifiers and their parameters
    for (name, classifier, ft_sel) in in_classifiers:
            # Print classifier name and its parameters
```

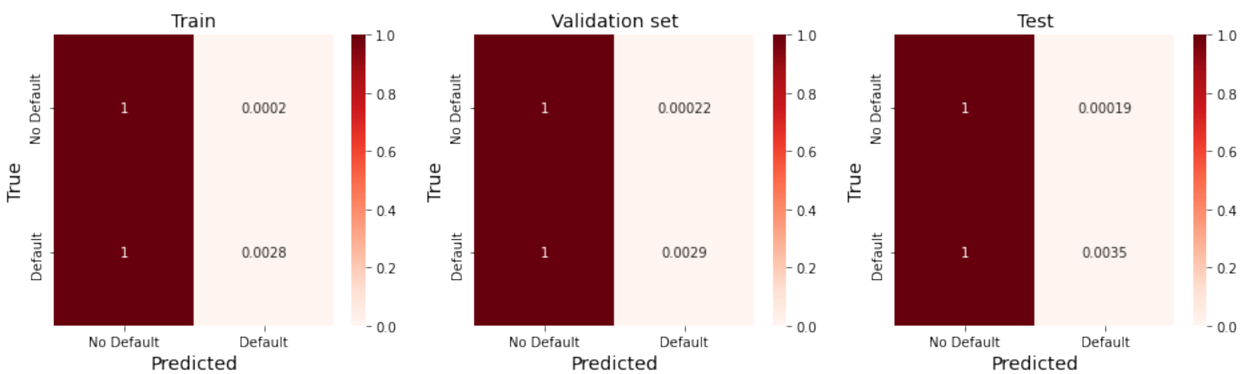
```
            print('---- ', name,' Start----')
            parameters = params_grid[name]
            print("Parameters are :")
            for p in sorted(parameters.keys()):
                print("\t"+str(p)+": "+ str(parameters[p]))

            # Generate pipeline from the feature selection method
            if ft_sel == "SVM":
                full_pipeline_with_predictor = Pipeline([
                ("preparation", data_prep_pipeline),
                ("predictor", classifier)
                ])
            else:
                full_pipeline_with_predictor = Pipeline([
                ("preparation", data_prep_pipeline),
                ('RFE', RFE(estimator=classifier,
n_features_to_select=features_used, step=feature_selection_steps)),
                ("predictor", classifier)
                ])

            # Running grid search
            params = {}
            for p in parameters.keys():
                pipe_key = 'predictor__'+str(p)
                params[pipe_key] = parameters[p]
            grid_search = GridSearchCV(full_pipeline_with_predictor,
params, cv=cvSplits, scoring='roc_auc',
                                       n_jobs=10, verbose=1)
            grid_search.fit(X_train, y_train)

            # Print cross-validation scores with the best estimator
            best_train = pct(grid_search.best_score_)
            print("Cross validation using best estimator")
            best_train_scores =
cross_validate(grid_search.best_estimator_, X_train, y_train,
cv=cvSplits, scoring=metrics,

return_train_score=True, n_jobs=10)

            # Collect training and validation scores
            train_accuracy_best =
np.round(best_train_scores['train_accuracy'].mean(), 4)
            valid_accuracy_best =
np.round(best_train_scores['test_accuracy'].mean(), 4)

            train_f1_best =
np.round(best_train_scores['train_f1'].mean(), 4)
            valid_f1_best =
np.round(best_train_scores['test_f1'].mean(), 4)
```

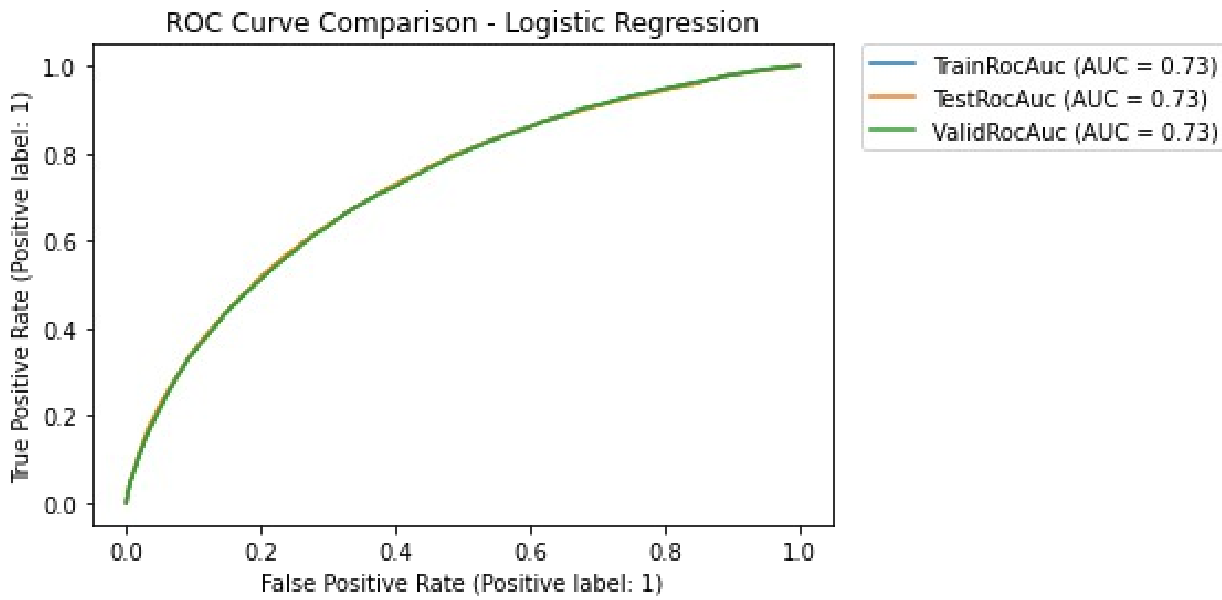
```
            train_logloss_best =
np.round(best_train_scores['train_log_loss'].mean(), 4)
            valid_logloss_best =
np.round(best_train_scores['test_log_loss'].mean(), 4)

            train_roc_auc_best =
np.round(best_train_scores['train_roc_auc'].mean(), 4)
            valid_roc_auc_best =
np.round(best_train_scores['test_roc_auc'].mean(), 4)
            valid_time =
np.round(best_train_scores['score_time'].mean(), 4)


            # Append results
            results.append(best_train_scores['train_accuracy'])
            names.append(name)

            # Conduct t-test with baseline logit and best estimator
            (t_stat, p_value) =
stats.ttest_rel(logit_scores['train_roc_auc'],
best_train_scores['train_roc_auc'])

            # Fit and predict with the best estimator
            print("Fitting and Predicting using the best estimator")
            start = time()
            model = grid_search.best_estimator_.fit(X_train, y_train)
            print('Pickeling the Model')
            pickle.dump(model, open(f"RFE_best_model_{name}.pkl",
"wb"))
            train_time = round(time() - start, 4)

            # Predictions
            start = time()
            y_test_pred = model.predict(X_test)
            test_time = round(time() - start, 4)
            scores.append(roc_auc_score(y_test,
model.predict_proba(X_test)[:, 1]))
            accuracy.append(accuracy_score(y_test, y_test_pred))

            # Create confusion matrix for the best model
            confusion_matrices = plot_confusion_matrices(model,
X_train, y_train, X_test, y_test, X_valid, y_valid,
confusion_matrices)

            # Create AUC ROC curve
            fprs, tprs = roc_curve_cust(model, X_train, y_train,
X_test, y_test, X_valid, y_valid, fprs, tprs, name)

            # Create Precision-Recall curve
            precisions, recalls = precision_recall_cust(model,
```

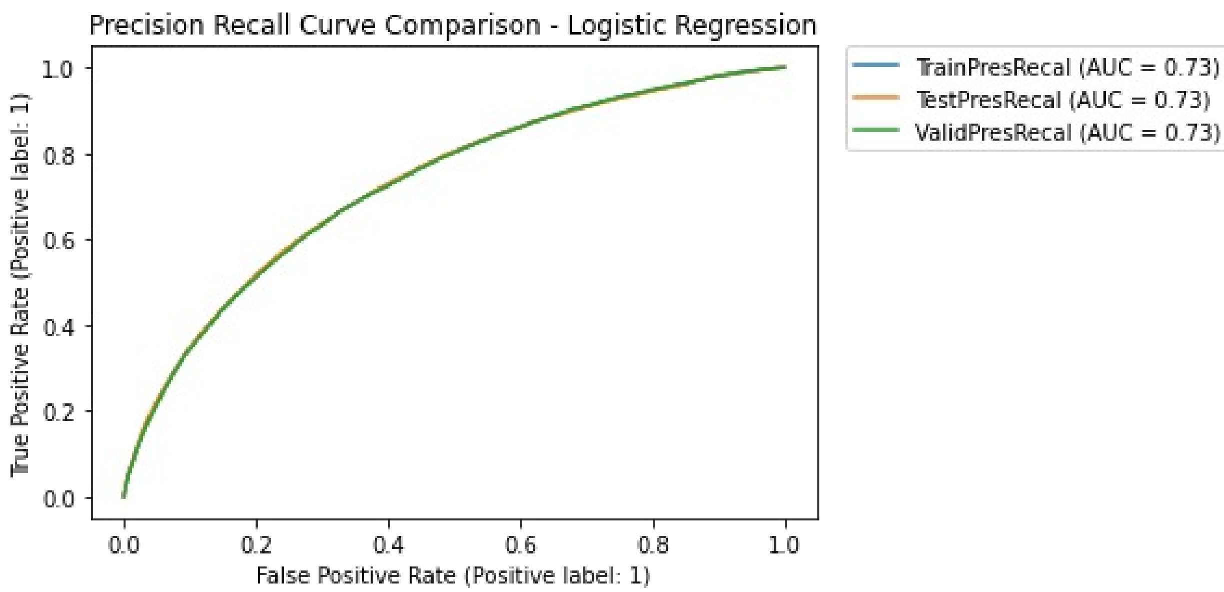
```
X_train, y_train, X_test, y_test, X_valid, y_valid, precisions,
recalls, name)

            # Best Model
            final_best_clf[name] = pd.DataFrame([{'label':
grid_search.best_estimator_.named_steps['predictor'].__class__.__name_
_,
                                              'predictor':
grid_search.best_estimator_.named_steps['predictor']}])


            # Collect the best parameters from the grid search
            print("Best Parameters depicted from our experiments
are:")
            best_parameters = grid_search.best_estimator_.get_params()
            param_dump = []
            for param_name in sorted(params.keys()):
                param_dump.append((param_name,
(best_parameters[param_name])))
                print("\t"+str(param_name)+": " +
str(best_parameters[param_name]))
            print("---- ",name," Finish ---- ")
            print("")

            # Record the results
            exp_name = name
            Log.loc[len(Log)] = [f"{exp_name}"] + list(np.round(
               [train_accuracy_best,
                    valid_accuracy_best,
                    accuracy_score(y_test, y_test_pred),
                    train_roc_auc_best,
                    valid_roc_auc_best,
                    roc_auc_score(y_test, model.predict_proba(X_test)
[:, 1]),
                    train_f1_best,
                    valid_f1_best,
                    f1_score(y_test, y_test_pred),
                    train_logloss_best,
                    valid_logloss_best,
                    log_loss(y_test, y_test_pred),
                    p_value], 4))


def featureAnalysis(picked_model,name):
    # Unpickling the best pipeline
    with open(picked_model, 'rb') as file:
        model = pickle.load(file)
    # Getting the OHE feature names
    cat_attribs = model.named_steps['preparation'].transformer_list[1]
[1].named_steps['ohe'].get_feature_names_out()
```

```
    feature_list = list(num_attribs) + list(cat_attribs)

    rfe = model.named_steps['RFE']
    #names.append(name)
    features_list[name] = pd.DataFrame({'feature_name': feature_list,
                                        'feature_importance':
rfe.ranking_[:200]})
    for i in range(len(feature_list)):
        print(f"Feature {feature_list[i]}: Selected (Rank:
{rfe.ranking_[i]})")

RunGridResearch(classifiers[0],cnfmatrix,fprs,tprs,precisions,recalls)
```

```
----  Logistic Regression  Start----
Parameters are :
     C: (1, 0.01)
     penalty: ('l1', 'l2', 'elasticnet')
     tol: (0.01, 0.001)
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Cross validation using best estimator
Fitting and Predicting using the best estimator
Pickeling the Model
```








```
Best Parameters depicted from our experiments are:
	predictor__C: 1
	predictor__penalty: l2
	predictor__tol: 0.001
----  Logistic Regression  Finish ----


featureAnalysis('RFE_best_model_Logistic Regression.pkl', 'Logistic Regression')

Feature AMT_INCOME_TOTAL: Selected (Rank: 3)
Feature AMT_CREDIT: Selected (Rank: 3)
Feature DAYS_EMPLOYED: Selected (Rank: 3)
```

```
Feature DAYS_BIRTH: Selected (Rank: 3)
Feature EXT_SOURCE_1: Selected (Rank: 2)
Feature EXT_SOURCE_2: Selected (Rank: 1)
Feature EXT_SOURCE_3: Selected (Rank: 1)
Feature x0_F: Selected (Rank: 2)
Feature x0_M: Selected (Rank: 2)
Feature x0_XNA: Selected (Rank: 3)
Feature x1_N: Selected (Rank: 1)
Feature x1_Y: Selected (Rank: 1)
Feature x2_N: Selected (Rank: 1)
Feature x2_Y: Selected (Rank: 1)
Feature x3_Cash loans: Selected (Rank: 1)
Feature x3_Revolving loans: Selected (Rank: 1)
Feature x4_Academic degree: Selected (Rank: 3)
Feature x4_Higher education: Selected (Rank: 1)
Feature x4_Incomplete higher: Selected (Rank: 2)
Feature x4_Lower secondary: Selected (Rank: 3)
Feature x4_Secondary / secondary special: Selected (Rank: 2)
Feature x5_Accountants: Selected (Rank: 2)
Feature x5_Cleaning staff: Selected (Rank: 3)
Feature x5_Cooking staff: Selected (Rank: 3)
Feature x5_Core staff: Selected (Rank: 2)
Feature x5_Drivers: Selected (Rank: 3)
Feature x5_HR staff: Selected (Rank: 3)
Feature x5_High skill tech staff: Selected (Rank: 1)
Feature x5_IT staff: Selected (Rank: 3)
Feature x5_Laborers: Selected (Rank: 3)
Feature x5_Low-skill Laborers: Selected (Rank: 3)
Feature x5_Managers: Selected (Rank: 2)
Feature x5_Medicine staff: Selected (Rank: 2)
Feature x5_Private service staff: Selected (Rank: 3)
Feature x5_Realty agents: Selected (Rank: 3)
Feature x5_Sales staff: Selected (Rank: 3)
Feature x5_Secretaries: Selected (Rank: 3)
Feature x5_Security staff: Selected (Rank: 3)
Feature x5_Waiters/barmen staff: Selected (Rank: 3)
Feature x5_missing: Selected (Rank: 2)
Feature x6_Businessman: Selected (Rank: 3)
Feature x6_Commercial associate: Selected (Rank: 1)
Feature x6_Maternity leave: Selected (Rank: 3)
Feature x6_Pensioner: Selected (Rank: 1)
Feature x6_State servant: Selected (Rank: 1)
Feature x6_Student: Selected (Rank: 3)
Feature x6_Unemployed: Selected (Rank: 3)
Feature x6_Working: Selected (Rank: 1)
```

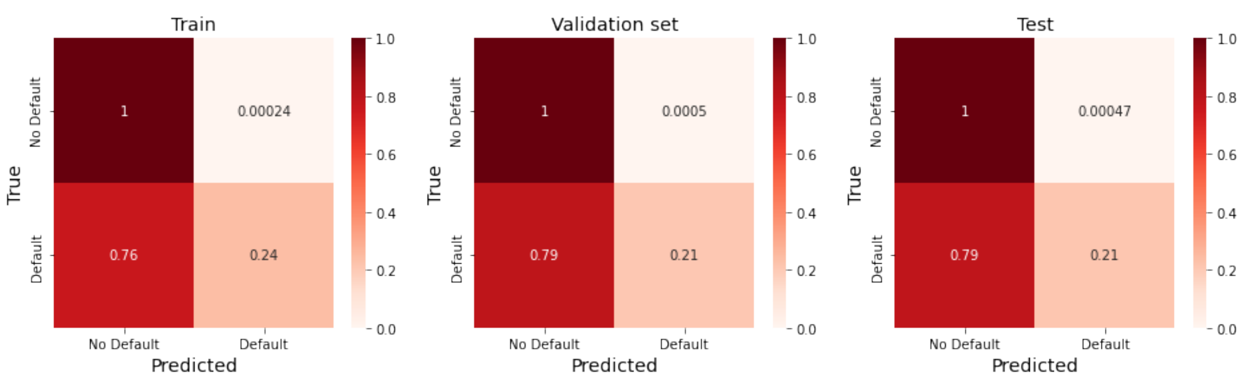
```
gc.collect()
```

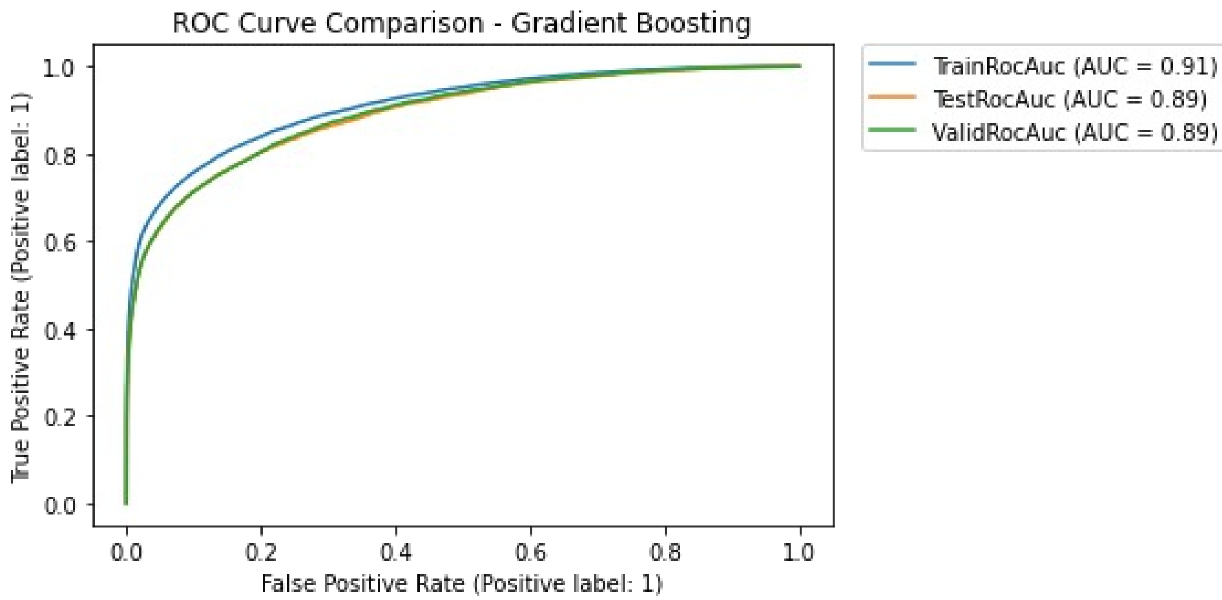
```
21285
```

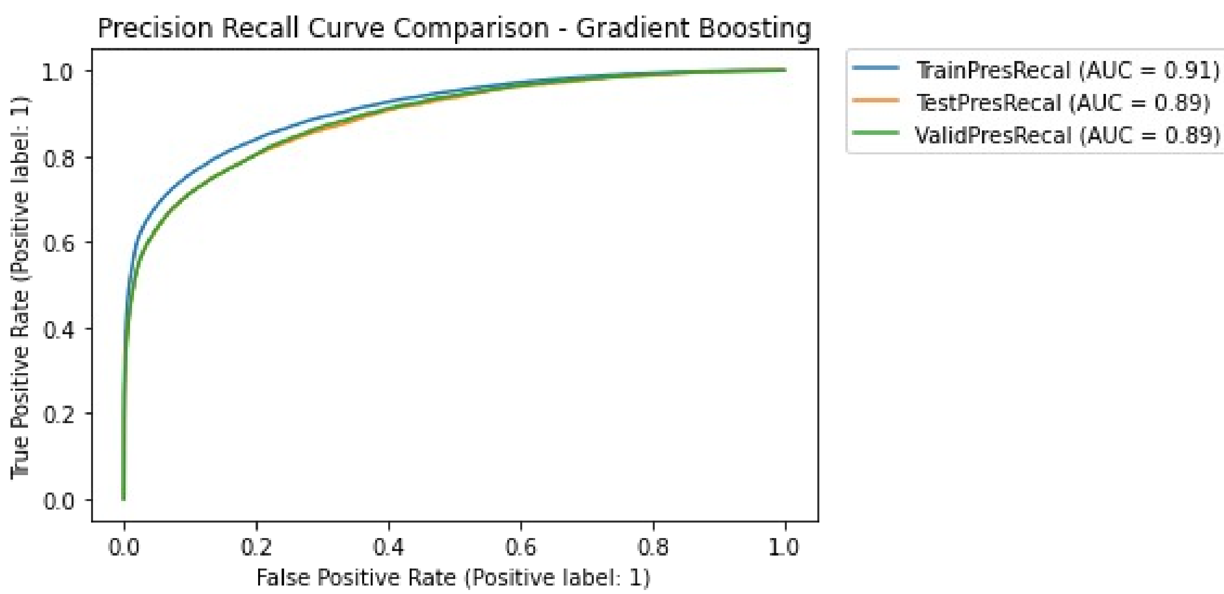
```
Log

                exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284

   Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score  Train Log
Loss  \
0     0.728          0.0058          0.0058         0.0069
2.7304

   Valid Log Loss  Test Log Loss  P Score
0          2.7208         2.7008   0.0017
```

Gradient Boosting

```
RunGridResearch(classifiers[2],cnfmatrix,fprs,tprs,precisions,recalls)

----  Gradient Boosting  Start----
Parameters are :
      max_depth: [5, 10]
      max_features: [5, 10]
      min_samples_leaf: [3, 5]
      n_estimators: [1000]
      n_iter_no_change: [10]
      subsample: [0.8]
      tol: [0.1, 0.01]
      validation_fraction: [0.2]
Fitting 3 folds for each of 16 candidates, totalling 48 fits
Cross validation using best estimator
Fitting and Predicting using the best estimator
Pickeling the Model
```








```
Best Parameters depicted from our experiments are:
     predictor__max_depth: 10
     predictor__max_features: 10
     predictor__min_samples_leaf: 3
     predictor__n_estimators: 1000
     predictor__n_iter_no_change: 10
     predictor__subsample: 0.8
     predictor__tol: 0.01
     predictor__validation_fraction: 0.2
----  Gradient Boosting  Finish ----
```

```python
featureAnalysis('RFE_best_model_Gradient Boosting.pkl','Gradient Boosting')
```

```
Feature AMT_INCOME_TOTAL: Selected (Rank: 1)
Feature AMT_CREDIT: Selected (Rank: 1)
Feature DAYS_EMPLOYED: Selected (Rank: 1)
Feature DAYS_BIRTH: Selected (Rank: 1)
Feature EXT_SOURCE_1: Selected (Rank: 1)
Feature EXT_SOURCE_2: Selected (Rank: 1)
Feature EXT_SOURCE_3: Selected (Rank: 1)
Feature x0_F: Selected (Rank: 2)
Feature x0_M: Selected (Rank: 1)
Feature x0_XNA: Selected (Rank: 3)
Feature x1_N: Selected (Rank: 3)
Feature x1_Y: Selected (Rank: 3)
Feature x2_N: Selected (Rank: 1)
Feature x2_Y: Selected (Rank: 1)
Feature x3_Cash loans: Selected (Rank: 1)
Feature x3_Revolving loans: Selected (Rank: 2)
Feature x4_Academic degree: Selected (Rank: 3)
Feature x4_Higher education: Selected (Rank: 1)
Feature x4_Incomplete higher: Selected (Rank: 3)
Feature x4_Lower secondary: Selected (Rank: 3)
Feature x4_Secondary / secondary special: Selected (Rank: 1)
Feature x5_Accountants: Selected (Rank: 3)
Feature x5_Cleaning staff: Selected (Rank: 3)
Feature x5_Cooking staff: Selected (Rank: 3)
Feature x5_Core staff: Selected (Rank: 2)
Feature x5_Drivers: Selected (Rank: 2)
Feature x5_HR staff: Selected (Rank: 3)
Feature x5_High skill tech staff: Selected (Rank: 3)
Feature x5_IT staff: Selected (Rank: 3)
Feature x5_Laborers: Selected (Rank: 2)
Feature x5_Low-skill Laborers: Selected (Rank: 2)
Feature x5_Managers: Selected (Rank: 3)
Feature x5_Medicine staff: Selected (Rank: 3)
Feature x5_Private service staff: Selected (Rank: 2)
Feature x5_Realty agents: Selected (Rank: 3)
Feature x5_Sales staff: Selected (Rank: 2)
Feature x5_Secretaries: Selected (Rank: 3)
Feature x5_Security staff: Selected (Rank: 2)
Feature x5_Waiters/barmen staff: Selected (Rank: 3)
Feature x5_missing: Selected (Rank: 3)
Feature x6_Businessman: Selected (Rank: 3)
Feature x6_Commercial associate: Selected (Rank: 3)
Feature x6_Maternity leave: Selected (Rank: 3)
Feature x6_Pensioner: Selected (Rank: 3)
Feature x6_State servant: Selected (Rank: 2)
Feature x6_Student: Selected (Rank: 3)
```

```
Feature x6_Unemployed: Selected (Rank: 3)
Feature x6_Working: Selected (Rank: 1)
```

```
gc.collect()
```

```
21765
```

Log

```
              exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284
1    Gradient Boosting     0.9332     0.9312     0.9379     0.8804
0.8585

   Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score  Train Log
Loss  \
0     0.7280          0.0058          0.0058         0.0069
2.7304
1     0.8904          0.2729          0.2351         0.3486
2.3087

   Valid Log Loss  Test Log Loss  P Score
0          2.7208         2.7008   0.0017
1          2.3765         2.1453   0.0003
```

XGBoost

```
#
RunGridResearch(classifiers[3],cnfmatrix,fprs,tprs,precisions,recalls)
```

```
----  XGBoost  Start----
Parameters are :
     colsample_bytree: [0.2, 0.5]
     eta: [0.001, 0.01, 0.1]
     gamma: [0, 1, 10, 100]
     max_depth: [3, 5]
     n_estimators: [300, 500]
Fitting 3 folds for each of 96 candidates, totalling 288 fits

----------------------------------------------------------------------
-----
KeyboardInterrupt                         Traceback (most recent call
last)
<ipython-input-315-d856158cb356> in <module>
----> 1
RunGridResearch(classifiers[3],cnfmatrix,fprs,tprs,precisions,recalls)

<ipython-input-138-dae3e6a4d279> in RunGridResearch(in_classifiers,
confusion_matrices, fprs, tprs, precisions, recalls)
```

```
     41             grid_search =
GridSearchCV(full_pipeline_with_predictor, params, cv=cvSplits,
scoring='roc_auc',
     42                                            n_jobs=10, verbose=1)
---> 43             grid_search.fit(X_train, y_train)
     44
     45             # Print cross-validation scores with the best
estimator

/usr/local/lib/python3.9/site-packages/sklearn/model_selection/_search
.py in fit(self, X, y, groups, **fit_params)
    889                 return results
    890
--> 891             self._run_search(evaluate_candidates)
    892
    893             # multimetric is determined here because in the
case of a callable

/usr/local/lib/python3.9/site-packages/sklearn/model_selection/_search
.py in _run_search(self, evaluate_candidates)
   1390     def _run_search(self, evaluate_candidates):
   1391         """Search all candidates in param_grid"""
-> 1392         evaluate_candidates(ParameterGrid(self.param_grid))
   1393
   1394

/usr/local/lib/python3.9/site-packages/sklearn/model_selection/_search
.py in evaluate_candidates(candidate_params, cv, more_results)
    836                     )
    837
--> 838                 out = parallel(
    839                     delayed(_fit_and_score)(
    840                         clone(base_estimator),

/usr/local/lib/python3.9/site-packages/joblib/parallel.py in
__call__(self, iterable)
   2005         next(output)
   2006
-> 2007         return output if self.return_generator else
list(output)
   2008
   2009     def __repr__(self):

/usr/local/lib/python3.9/site-packages/joblib/parallel.py in
_get_outputs(self, iterator, pre_dispatch)
   1648
   1649             with self._backend.retrieval_context():
-> 1650                 yield from self._retrieve()
   1651
   1652         except GeneratorExit:
```

```
/usr/local/lib/python3.9/site-packages/joblib/parallel.py in
_retrieve(self)
   1760                     (self._jobs[0].get_status(
   1761                         timeout=self.timeout) == TASK_PENDING)):
-> 1762                     time.sleep(0.01)
   1763                     continue
   1764

KeyboardInterrupt:

# featureAnalysis('RFE_best_model_XGBoost.pkl')

# Log
```

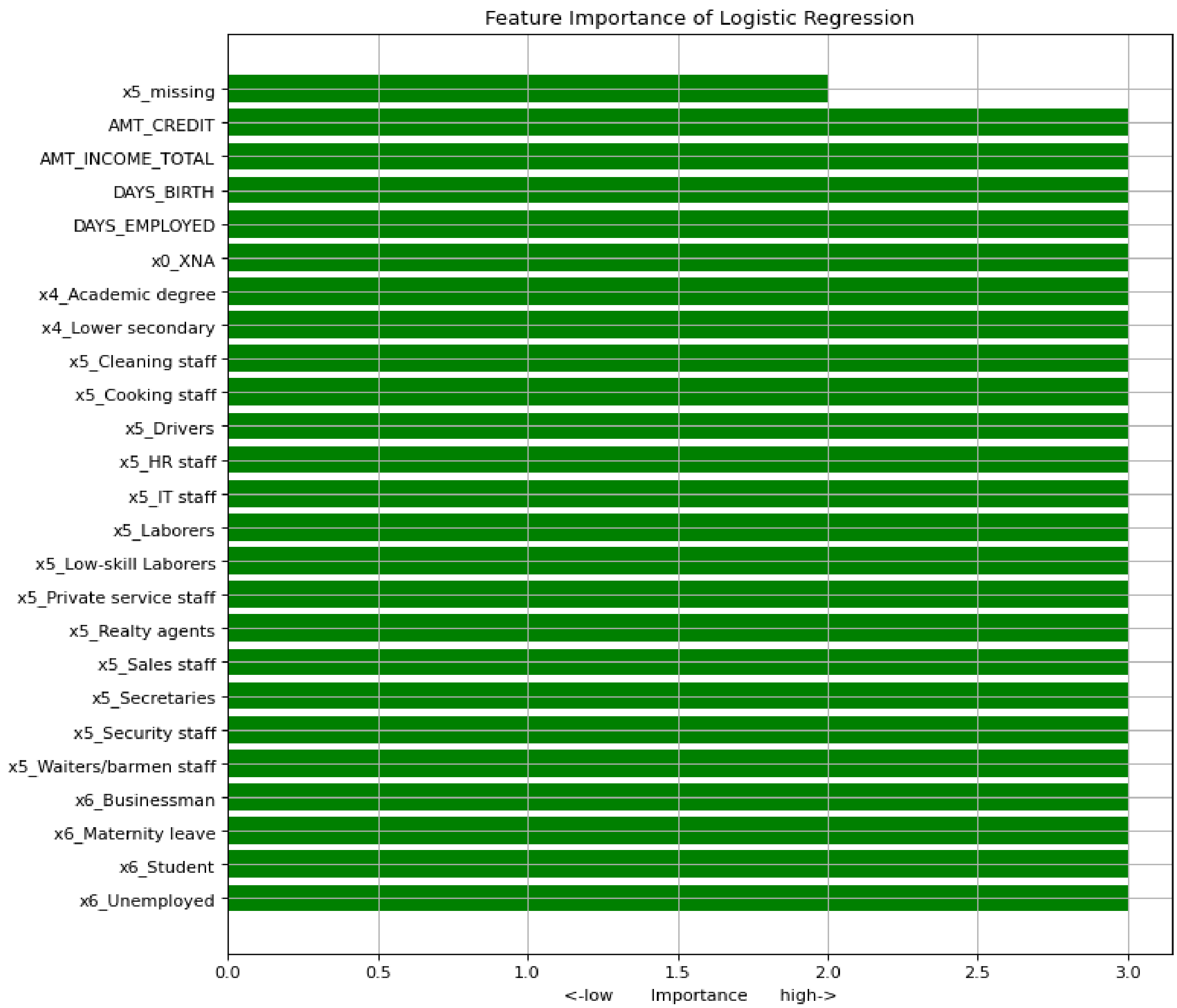
Random Forest

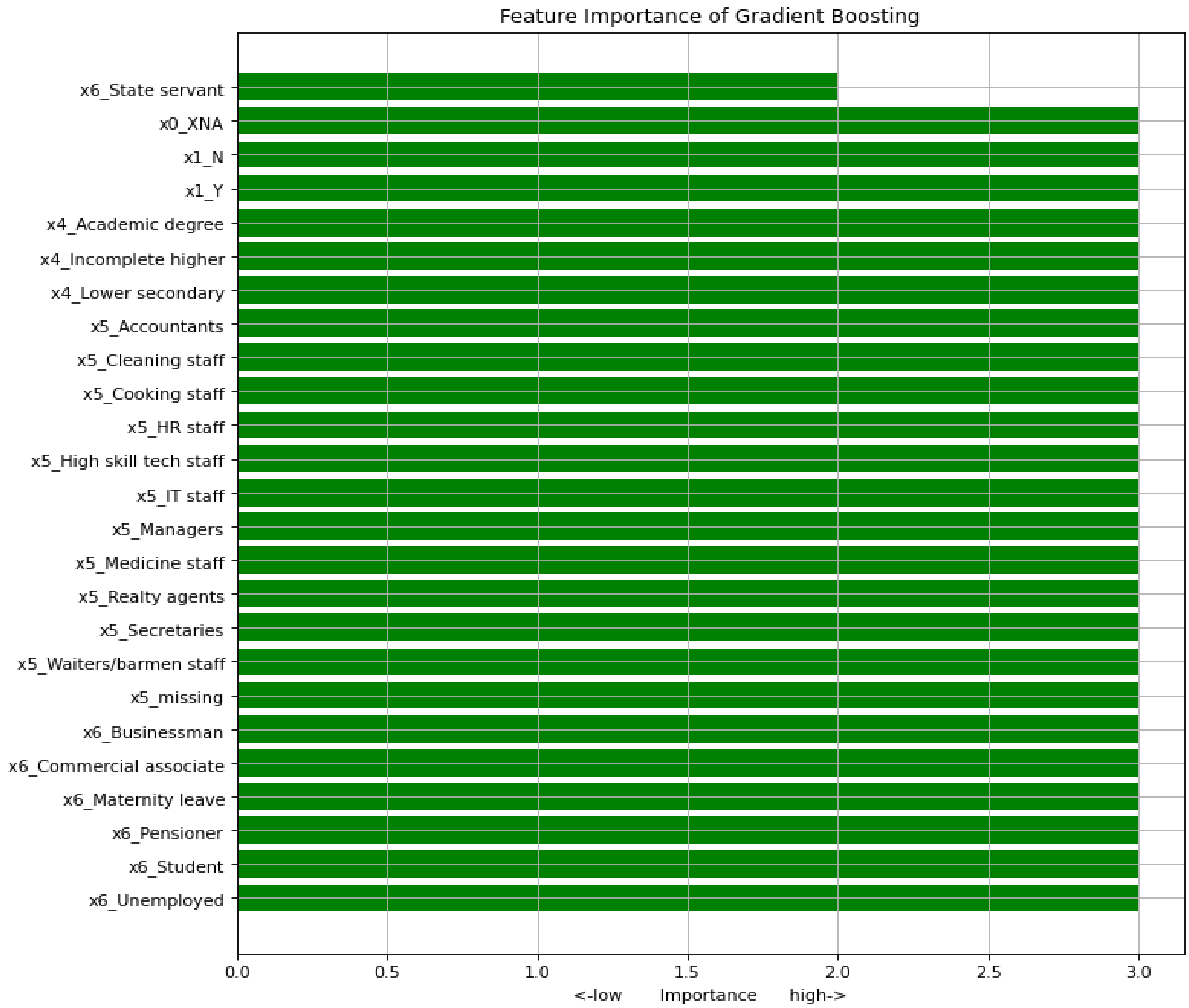
```
#
RunGridResearch(classifiers[5],cnfmatrix,fprs,tprs,precisions,recalls)

----  Random Forest  Start----
Parameters are :
     max_depth: [5]
     max_features: [10, 13]
     min_samples_leaf: [5]
     min_samples_split: [5]
     n_estimators: [10, 20]
Fitting 3 folds for each of 4 candidates, totalling 12 fits

# featureAnalysis('RFE_best_model_Random Forest.pkl')

# Log
```

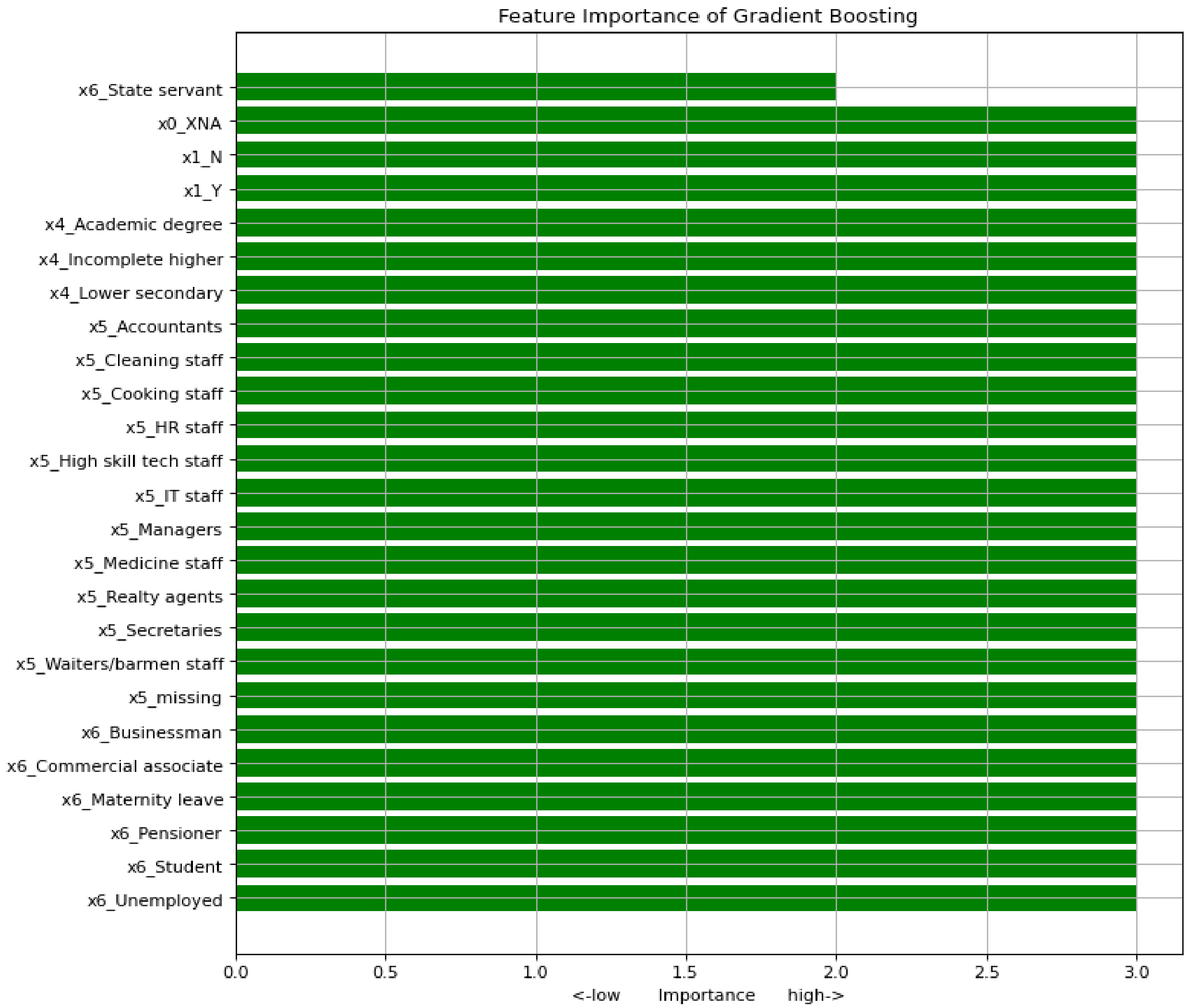
Model Validation (Step5)

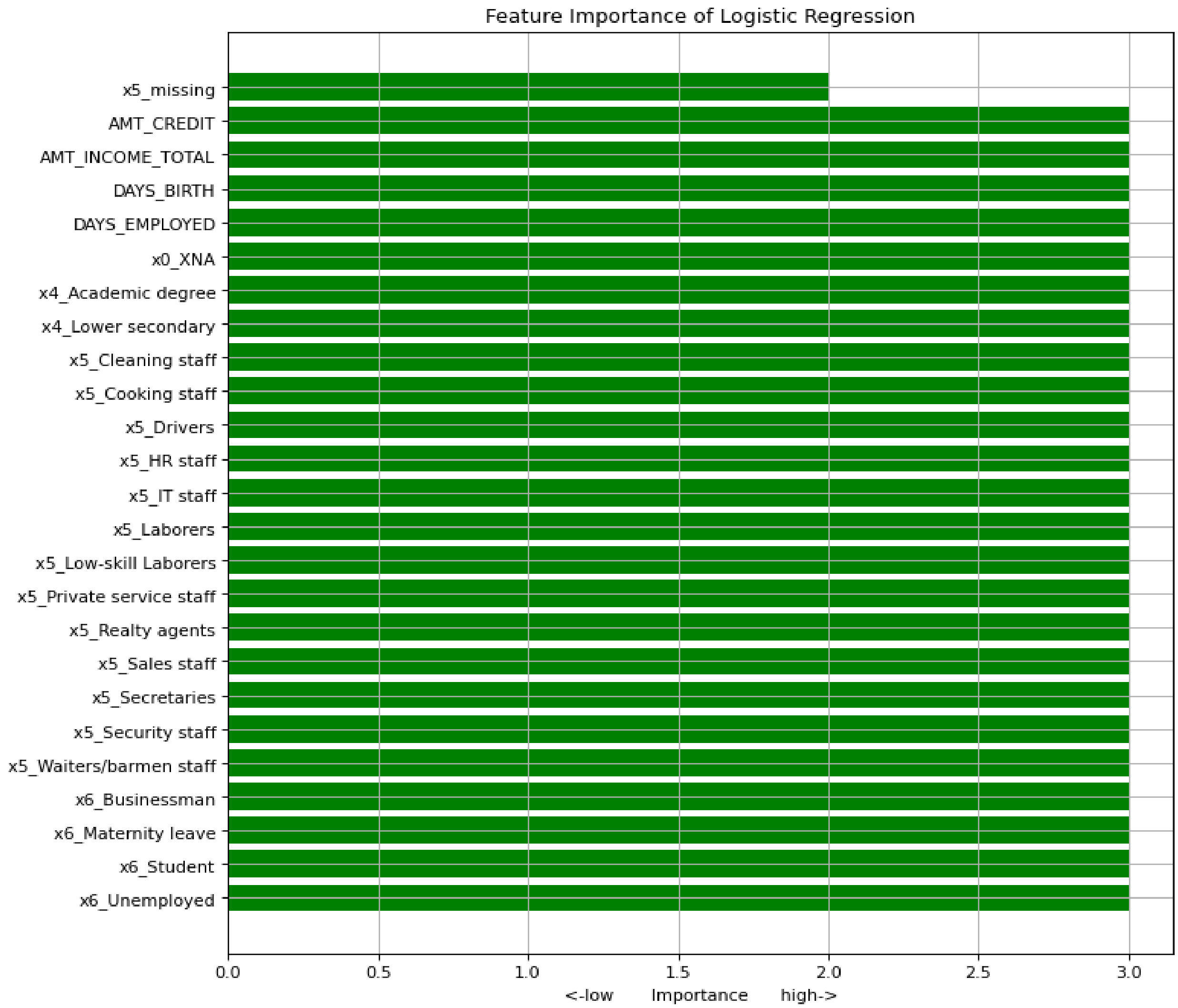
```
for name in names[1:-1]:
    plt.figure(figsize=(10, 10), dpi=80)
    features_df =
features_list[name].sort_values(by=['feature_importance',
'feature_name'], ascending=[False, False])
    orderednames = np.array(features_df.head(25)['feature_name'])
    Importancesinorder = np.array(features_df.head(25)
['feature_importance'])

    #Setting option for visulizing the graphs.
    plt.barh(range(len(orderednames)), Importancesinorder, color='g',
align='center')
    plt.xlabel('<-low       Importance      high->')
    plt.yticks(range(len(orderednames)), orderednames)
```

```
#Explain each axis
plt.title(f'Feature Importance of {name}')
plt.grid()
plt.show()
```



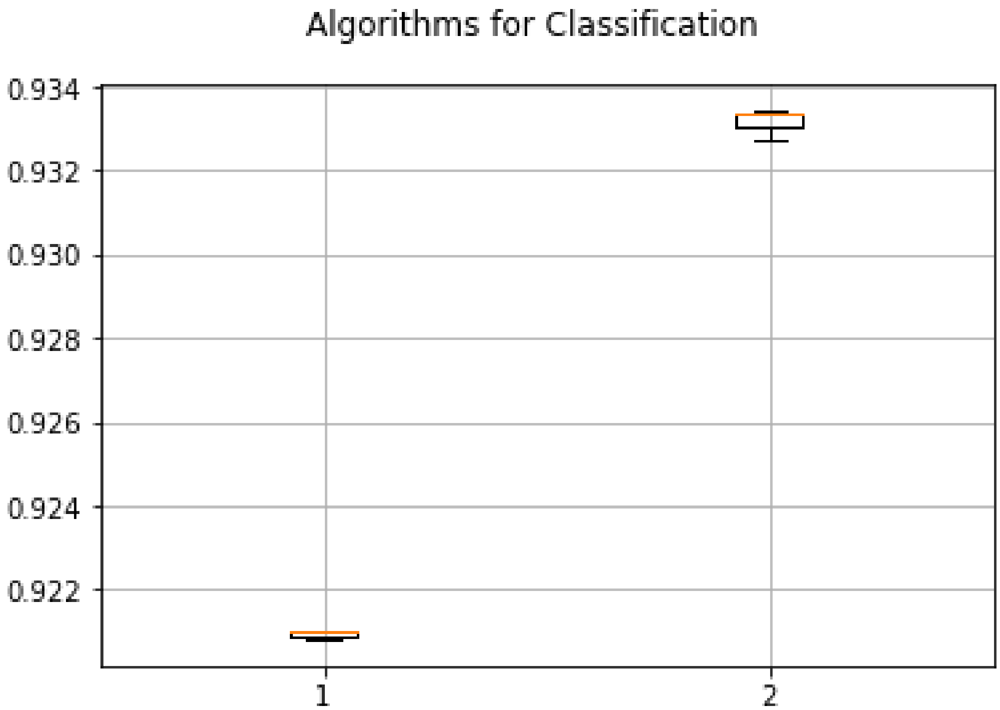

Feature Importance of Gradient Boosting
x6_State servant
x0_XNA
x1_N
x1_Y
x4_Academic degree
x4_Incomplete higher
x4_Lower secondary
x5_Accountants
x5_Cleaning staff
x5_Cooking staff
x5_HR staff
x5_High skill tech staff
x5_IT staff
x5_Managers
x5_Medicine staff
x5_Realty agents
x5_Secretaries
x5_Waiters/barmen staff
x5_missing
x6_Businessman
x6_Commercial associate
x6_Maternity leave
x6_Pensioner
x6_Student
x6_Unemployed
0.0
0.5
1.0
1.5
2.0
2.5
3.0
<-low Importance high->


Feature Importance of Gradient Boosting
x6_State servant
x0_XNA
x1_N
x1_Y
x4_Academic degree
x4_Incomplete higher
x4_Lower secondary
x5_Accountants
x5_Cleaning staff
x5_Cooking staff
x5_HR staff
x5_High skill tech staff
x5_IT staff
x5_Managers
x5_Medicine staff
x5_Realty agents
x5_Secretaries
x5_Waiters/barmen staff
x5_missing
x6_Businessman
x6_Commercial associate
x6_Maternity leave
x6_Pensioner
x6_Student
x6_Unemployed
0.0
0.5
1.0
1.5
2.0
2.5
3.0
<-low Importance high->



Boxplot Comparison with Cross Validation Results

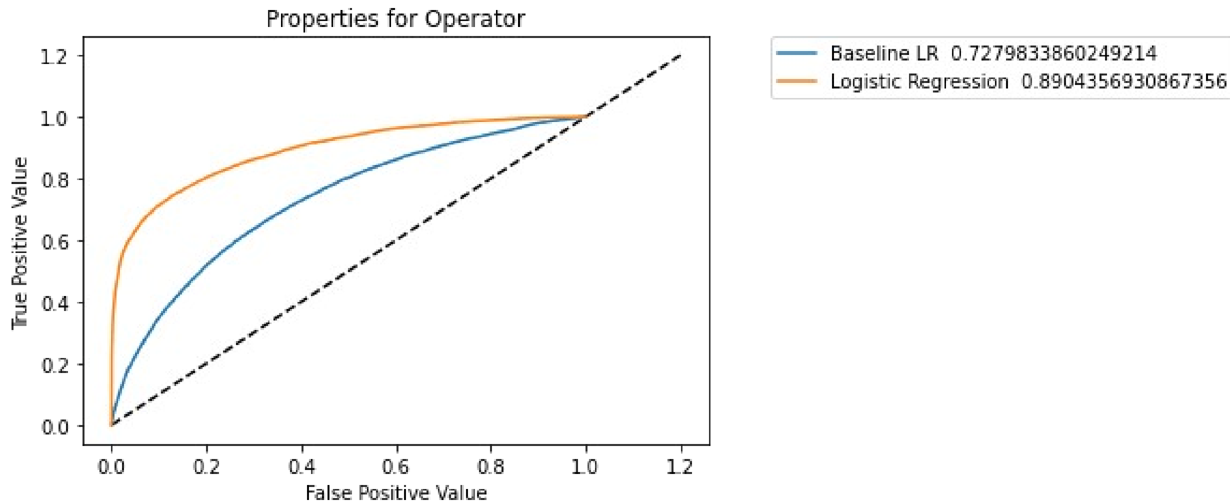
```
# Boxplots for the previous feature engineering
fig = pyplot.figure()
fig.suptitle('Algorithms for Classification')

# Setting the subplots
subax = fig.add_subplot(111)
pyplot.boxplot(results)
#subax.set_xticklabels(names)
pyplot.grid()
pyplot.show()
```



AUC : Area Under the ROC Curve

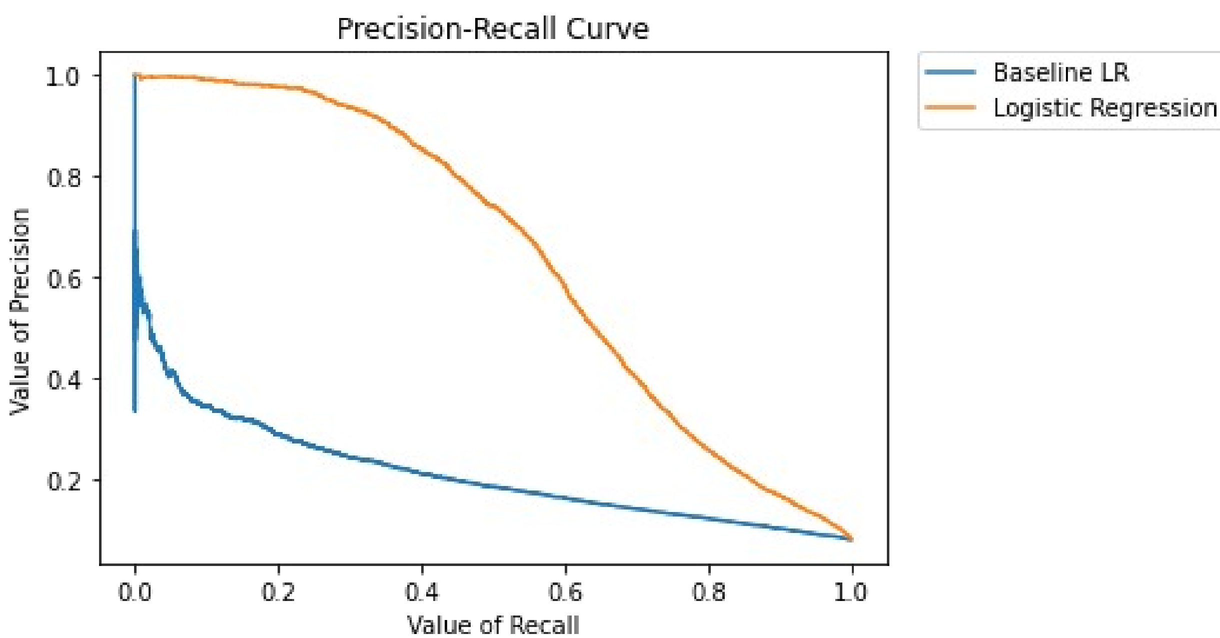
```
print(names)
# ROC fore each classifier
plt.plot([0,1.2],[0,1.2], 'k--')
for i in range(len(names)-1):
    plt.plot(fprs[i],tprs[i],label = names[i] + '  ' + str(scores[i]))

#Making the description by option for visulization
plt.legend(bbox_to_anchor=(1.1,1), loc="upper left", borderaxespad=0)
plt.xlabel("False Positive Value")
plt.ylabel("True Positive Value")
plt.title('Properties for Operator')
plt.show()
```

```
['Baseline LR', 'Logistic Regression', 'Gradient Boosting']
```



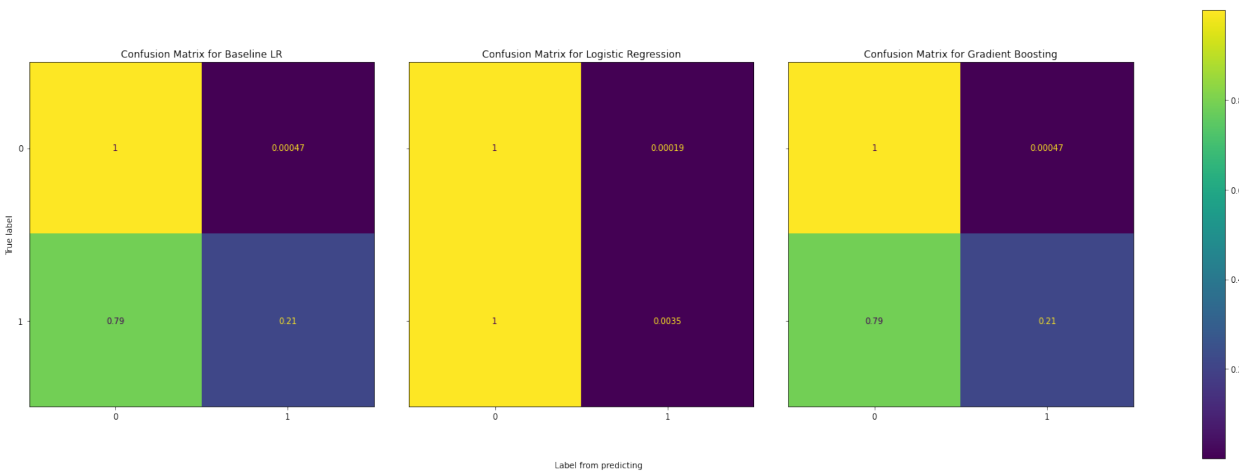
Precision Recall Curve

```
# Precision recall curve for each of the classifier
for i in range(len(names)-1):
    plt.plot(recalls[i],precisions[i],label = names[i])
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left", borderaxespad=0)

#Making the description by option for visulization
plt.xlabel("Value of Recall")
plt.ylabel("Value of Precision")
plt.title('Precision-Recall Curve')
plt.show()
```



Confusion Matrix

```
# Setting confusion matrix for each of the classifier
f, axes = plt.subplots(1, len(names), figsize=(30, 10), sharey='row')
for i in range(len(names)):
    #Labeling
    disp = ConfusionMatrixDisplay(cnfmatrix[i-1], display_labels=['0',
'1'])

    #Plotting
    disp.plot(ax=axes[i], xticks_rotation=0)

    #Visualization
    disp.ax_.set_title("Confusion Matrix for " + names[i])
    disp.ax_.set_xlabel('')
    disp.im_.colorbar.remove()
    if i!=0:
        disp.ax_.set_ylabel('')

# Text
f.text(0.42, 0.11, 'Label from predicting', ha='left')
plt.subplots_adjust(wspace=0.10, hspace=0.1)

#Add color
f.colorbar(disp.im_, ax=axes)
plt.show()
```



Reuslts for the best classification method

```
pd.set_option('display.max_colwidth', None)
Log

                  exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284
```

```
1    Gradient Boosting     0.9332     0.9312     0.9379     0.8804
0.8585

   Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score  Train Log
Loss  \
0     0.7280          0.0058          0.0058         0.0069
2.7304
1     0.8904          0.2729          0.2351         0.3486
2.3087

   Valid Log Loss  Test Log Loss  P Score
0          2.7208         2.7008   0.0017
1          2.3765         2.1453   0.0003

final_best_clf
model_selection = ['Logistic Regression','Gradient Boosting']
```

Model selection from selecting the best k value-Adjusting baseline model(Step 6)

To find the best model, algorithm of classification(SelectkBest module of sk-learning) is employed.

We will use Cross fold Accuracy, p-value, ROC_AUC_Score, F1_Score and LogLoss with Confusion matrix.

```
# Initialize Arrays we used

del fprs[1:]
del accuracy[1:]
del cnfmatrix[1:]
del precisions[1:]
del recalls[1:]
del names[1:]
del scores[1:]
del cvscores[1:]
del tprs[1:]
del pvalues[1:]
del results[1:]

#Define empty objects
final_best_clf,results = {}, {}


print(names)

['Baseline LR']
```

Preparation for Pipeline

```
classifiers = [
        [('Logistic Regression',
LogisticRegression(solver='saga',random_state=42),"SelectKbest")],
        [('Gradient Boosting',
GradientBoostingClassifier(warm_start=True,
random_state=42),"SelectKbest")],
        [('Random Forest',
RandomForestClassifier(random_state=42),"SelectKbest")]
    ]
```

Models and hyper parameter palettee

```
# Arrange grid search parameters for each classifier
params_grid = {
        'Logistic Regression': {
            'penalty': ('l1', 'l2','elasticnet'),
            'tol': (0.0001, 0.00001),
            'C': (10, 1, 0.1, 0.01),
        },
    'Gradient Boosting':  {
            'max_depth': [5,10], # Lowering helps with overfitting.
            'max_features': [5,10],
            'validation_fraction': [0.2],
            'n_iter_no_change': [10],
            'tol': [0.1,0.01],
            'n_estimators':[1000],
            'subsample' : [0.8],   #It represents the fraction of
observations to be randomly sampled for each tree.
            'min_samples_leaf' : [3,5],
        },
#         'Random Forest':  {
#             'min_samples_split': [5],
#             'min_samples_leaf': [5],
#             'n_estimators':[10, 20],
#             'max_depth': [5],
#             'max_features': [10, 13]
    }
```

Process The Grid Search

```
results = []
results.append(logit_scores['train_accuracy'])
def
RunGridResearch(in_classifiers,cnfmatrix,fprs,tprs,precisions,recalls)
:
    for (name, classifier,ft_sel) in in_classifiers:
            # Print classifier name and its parameters
            print('---- ', name,' Start----')
```

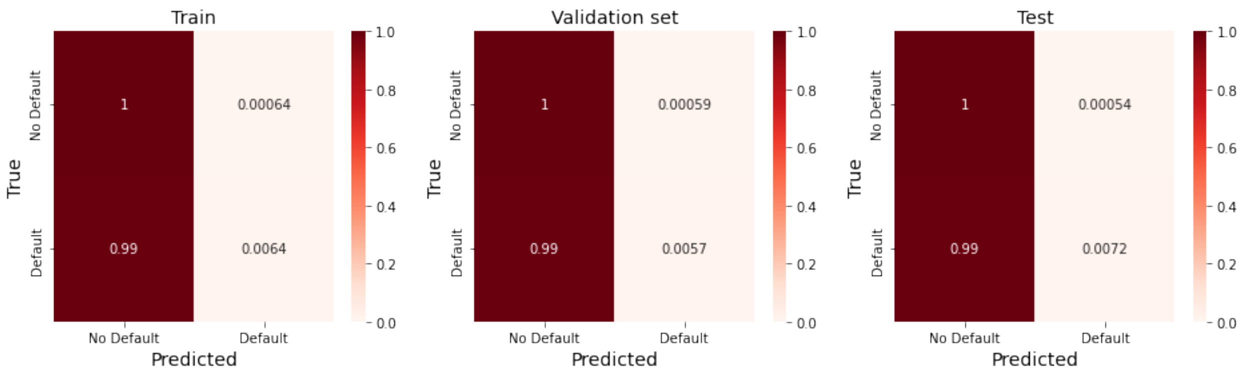
```
            parameters = params_grid[name]
            print("Parameters are :")
            for p in sorted(parameters.keys()):
                print("\t"+str(p)+": "+ str(parameters[p]))

            # Generate pipeline from the feature selection method
            full_pipeline_with_predictor = Pipeline([
                ("preparation", data_prep_pipeline),

('SelectKbest',SelectKBest(score_func=mutual_info_classif,
k=features_used)),
                ("predictor", classifier)
                ])

            # Running grid search
            params = {}
            for p in parameters.keys():
                pipe_key = 'predictor__'+str(p)
                params[pipe_key] = parameters[p]
            grid_search = GridSearchCV(full_pipeline_with_predictor,
params, cv=cvSplits, scoring='roc_auc',
                                       n_jobs=10,verbose=1)
            grid_search.fit(X_train, y_train)


            best_train = pct(grid_search.best_score_)

            # Print cross-validation scores with the best estimator
            print("Best Parameters depicted from our experiments
are:")
            best_train_scores =
cross_validate(grid_search.best_estimator_, X_train,
y_train,cv=cvSplits,scoring=metrics,

return_train_score=True, n_jobs=10)

            # Collect training and validation scores
            train_accuracy_best =
np.round(best_train_scores['train_accuracy'].mean(), 4)
            valid_accuracy_best =
np.round(best_train_scores['test_accuracy'].mean(), 4)

            train_f1_best =
np.round(best_train_scores['train_f1'].mean(), 4)
            valid_f1_best =
np.round(best_train_scores['test_f1'].mean(), 4)

            train_logloss_best =
np.round(best_train_scores['train_log_loss'].mean(), 4)
            valid_logloss_best =
```

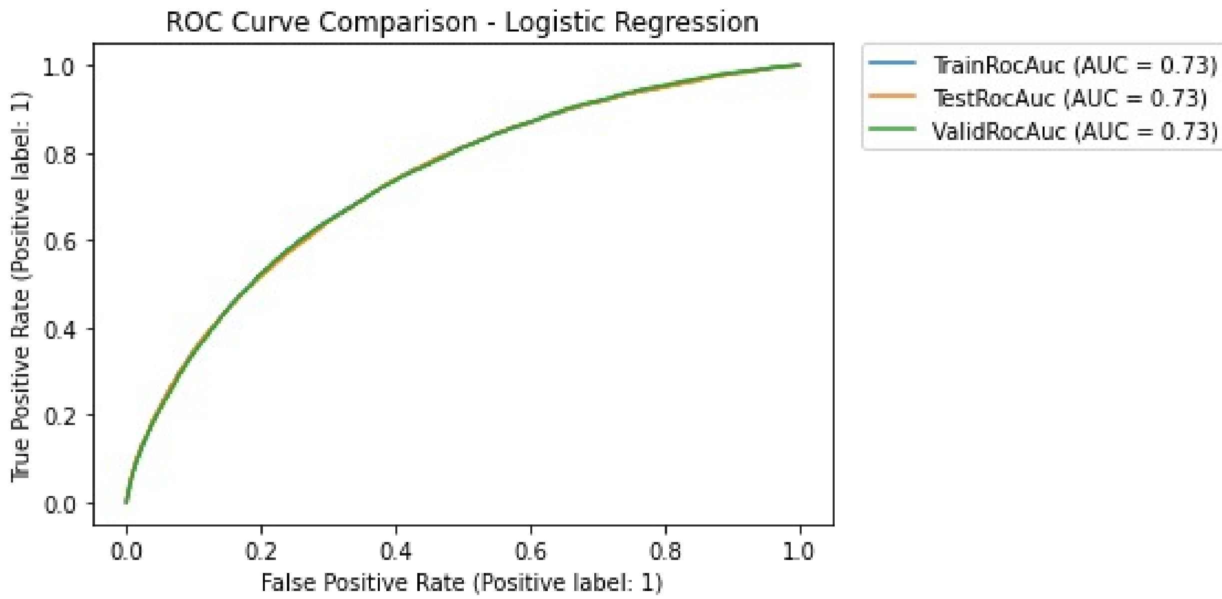
```
np.round(best_train_scores['test_log_loss'].mean(), 4)

            train_roc_auc_best =
np.round(best_train_scores['train_roc_auc'].mean(), 4)
            valid_roc_auc_best =
np.round(best_train_scores['test_roc_auc'].mean(), 4)
            valid_time =
np.round(best_train_scores['score_time'].mean(), 4)

            # Append results
            results.append(best_train_scores['train_accuracy'])
            names.append(name)

            # t-test with best estimator
            (t_stat, p_value) =
stats.ttest_rel(logit_scores['train_roc_auc'],
best_train_scores['train_roc_auc'])

            # Fit and predict with the best estimator
            print("Fitting and Predicting using the best estimator")
            start = time()
            model = grid_search.best_estimator_.fit(X_train, y_train)
            print('Pickeling the Model')
            pickle.dump(model,
open(f"SelectKbest_best_model_{name}.pkl", "wb"))
            train_time = round(time() - start, 4)

            # Best estimator prediction time
            start = time()
            y_test_pred = model.predict(X_test)
            test_time = round(time() - start, 4)
            scores.append(roc_auc_score(y_test,
model.predict_proba(X_test)[:, 1]))
            accuracy.append(accuracy_score(y_test, y_test_pred))

            # Confusion matrix of the best model
            cnfmatrix =
plot_confusion_matrices(model,X_train,y_train,X_test,y_test,X_valid,
y_valid,cnfmatrix)

            # AUC ROC curve
            fprs,tprs = roc_curve_cust(model,X_train,y_train,X_test,
y_test,X_valid, y_valid,fprs,tprs,name)

            # Precision recall curve
            precisions,recalls =
precision_recall_cust(model,X_train,y_train,X_test, y_test,X_valid,
y_valid,precisions,recalls,name)

            #Best Model
```

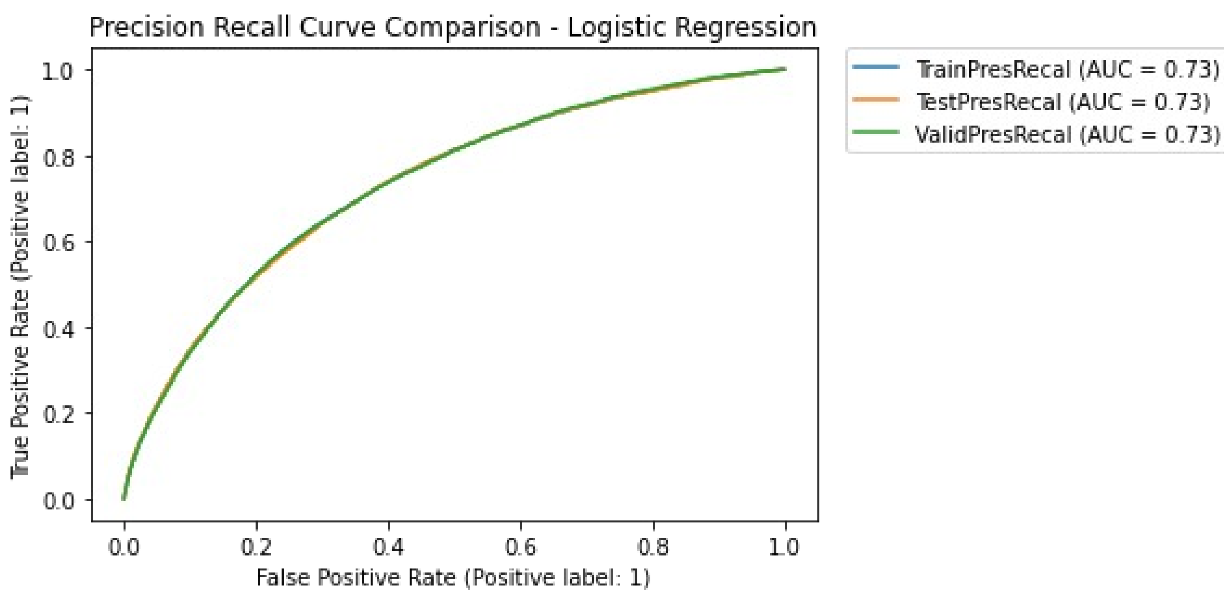
```
            final_best_clf[name]=pd.DataFrame([{'label':
grid_search.best_estimator_.named_steps['predictor'].__class__.__name_
_,
                                           'predictor':
grid_search.best_estimator_.named_steps['predictor']}])

            # Collect the best parameters from the grid search
            print("Best Parameters:")
            best_parameters = grid_search.best_estimator_.get_params()
            paramdump = []
            for param_name in sorted(params.keys()):
                paramdump.append((param_name,
(best_parameters[param_name])))
                print("\t"+str(param_name)+": " +
str(best_parameters[param_name]))
            print("---- ",name," Finish ---- ")
            print("")

            # Record the results
            exp_name = name
            Log.loc[len(Log)] = [f"{exp_name}"] + list(np.round(
               [train_accuracy_best,
                    valid_accuracy_best,
                    accuracy_score(y_test, y_test_pred),
                    train_roc_auc_best,
                    valid_roc_auc_best,
                    roc_auc_score(y_test, model.predict_proba(X_test)
[:, 1]),
                    train_f1_best,
                    valid_f1_best,
                    f1_score(y_test, y_test_pred),
                    train_logloss_best,
                    valid_logloss_best,
                    log_loss(y_test, y_test_pred),
                    p_value], 4))
```

Logistic Regression

```
RunGridResearch(classifiers[0],cnfmatrix,fprs,tprs,precisions,recalls)

----  Logistic Regression  Start----
Parameters are :
     C: (10, 1, 0.1, 0.01)
     penalty: ('l1', 'l2', 'elasticnet')
     tol: (0.0001, 1e-05)
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best Parameters depicted from our experiments are:
Fitting and Predicting using the best estimator
Pickeling the Model
```


Train
Validation set
Test
True
No Default
Default
Predicted
1
0.00064
0.99
0.0064
0.00059
0.0057
0.00054
0.0072
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve Comparison - Logistic Regression
TrainRocAuc (AUC = 0.73)
TestRocAuc (AUC = 0.73)
ValidRocAuc (AUC = 0.73)
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
0.0
0.2
0.4
0.6
0.8
1.0


Precision Recall Curve Comparison - Logistic Regression
TrainPresRecal (AUC = 0.73)
TestPresRecal (AUC = 0.73)
ValidPresRecal (AUC = 0.73)
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
0.0
0.2
0.4
0.6
0.8
1.0

```
Best Parameters:
      predictor__C: 10
      predictor__penalty: l1
      predictor__tol: 0.0001
----  Logistic Regression  Finish ----


Log

              exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284
1    Gradient Boosting     0.9332     0.9312     0.9379     0.8804
0.8585
2  Logistic Regression     0.9207     0.9211     0.9218     0.7313
0.7314

   Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score  Train Log
Loss  \
0     0.7280          0.0058          0.0058         0.0069
2.7304
1     0.8904          0.2729          0.2351         0.3486
2.3087
2     0.7322          0.0127          0.0143         0.0143
2.7375

   Valid Log Loss  Test Log Loss  P Score
0          2.7208         2.7008   0.0017
1          2.3765         2.1453   0.0003
2          2.7263         2.7018   0.0065
```

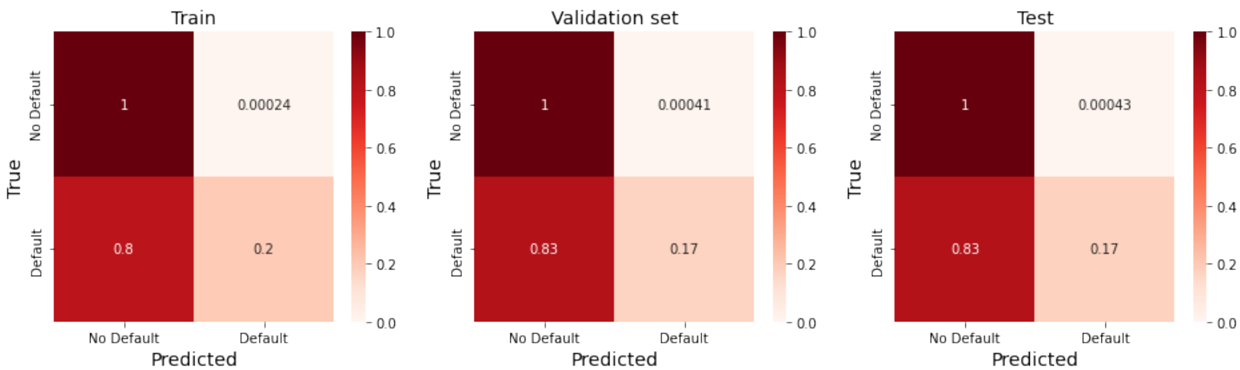
Random Forest

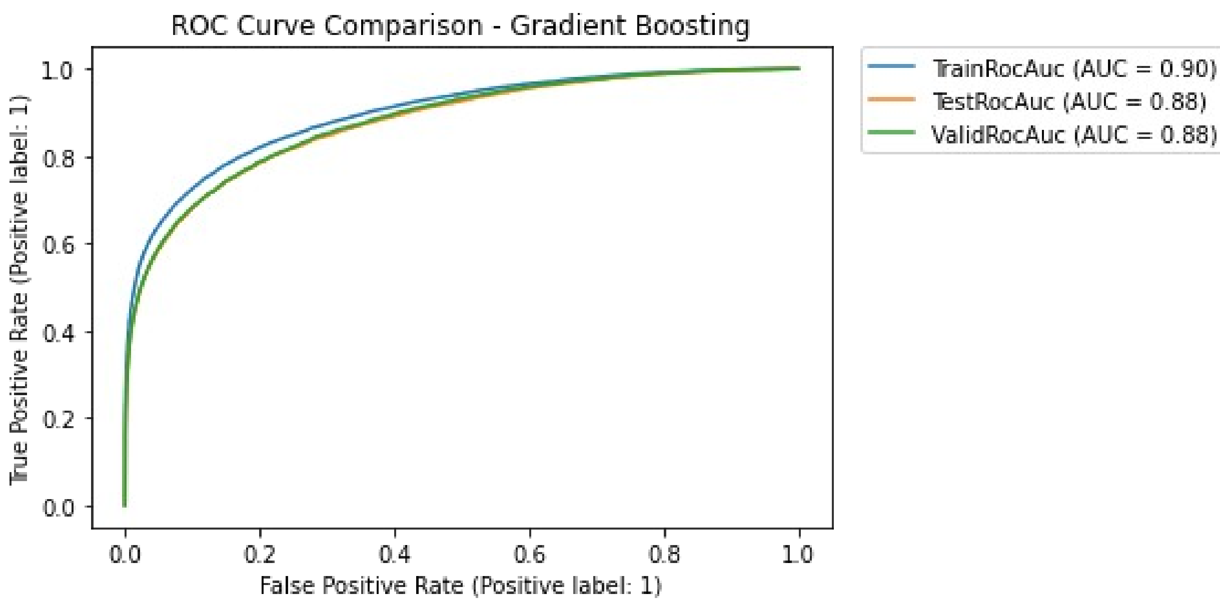
```
#
RunGridResearch(classifiers[3],cnfmatrix,fprs,tprs,precisions,recalls)

# Log
```

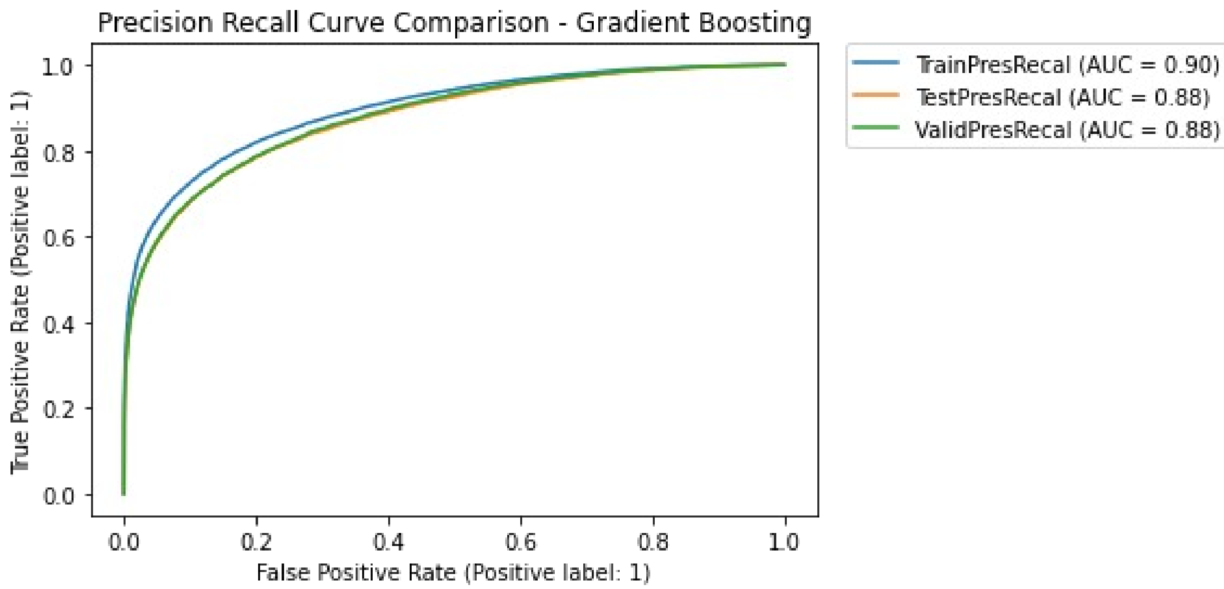
Gradient Boosting

```
RunGridResearch(classifiers[1],cnfmatrix,fprs,tprs,precisions,recalls)

----  Gradient Boosting  Start----
Parameters are :
      max_depth: [5, 10]
      max_features: [5, 10]
      min_samples_leaf: [3, 5]
      n_estimators: [1000]
      n_iter_no_change: [10]
      subsample: [0.8]
```

```
     tol: [0.1, 0.01]
     validation_fraction: [0.2]
Fitting 3 folds for each of 16 candidates, totalling 48 fits
Best Parameters depicted from our experiments are:
Fitting and Predicting using the best estimator
Pickeling the Model
```







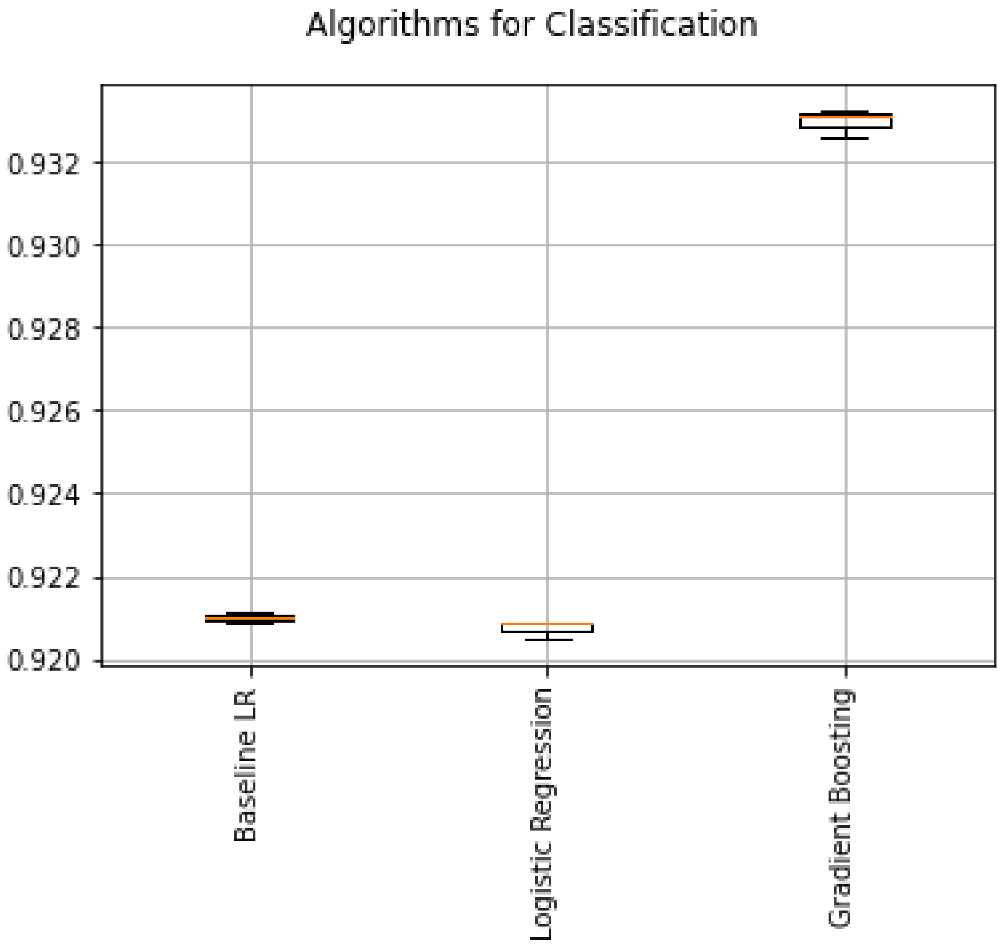

```
Best Parameters:
      predictor__max_depth: 10
      predictor__max_features: 10
      predictor__min_samples_leaf: 5
      predictor__n_estimators: 1000
      predictor__n_iter_no_change: 10
      predictor__subsample: 0.8
      predictor__tol: 0.01
      predictor__validation_fraction: 0.2
----  Gradient Boosting  Finish ----


Log

             exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284
1    Gradient Boosting     0.9332     0.9312     0.9379     0.8804
0.8585
2  Logistic Regression     0.9207     0.9211     0.9218     0.7313
0.7314
3    Gradient Boosting     0.9330     0.9311     0.9348     0.8754
0.8535

   Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score  Train Log
Loss  \
0     0.7280          0.0058          0.0058          0.0069
2.7304
1     0.8904          0.2729          0.2351          0.3486
2.3087
2     0.7322          0.0127          0.0143          0.0143
```

```
2.7375
3     0.8773          0.2693          0.2337          0.2926
2.3145

   Valid Log Loss  Test Log Loss  P Score
0          2.7208         2.7008   0.0017
1          2.3765         2.1453   0.0003
2          2.7263         2.7018   0.0065
3          2.3781         2.2521   0.0002
```

Model Validation

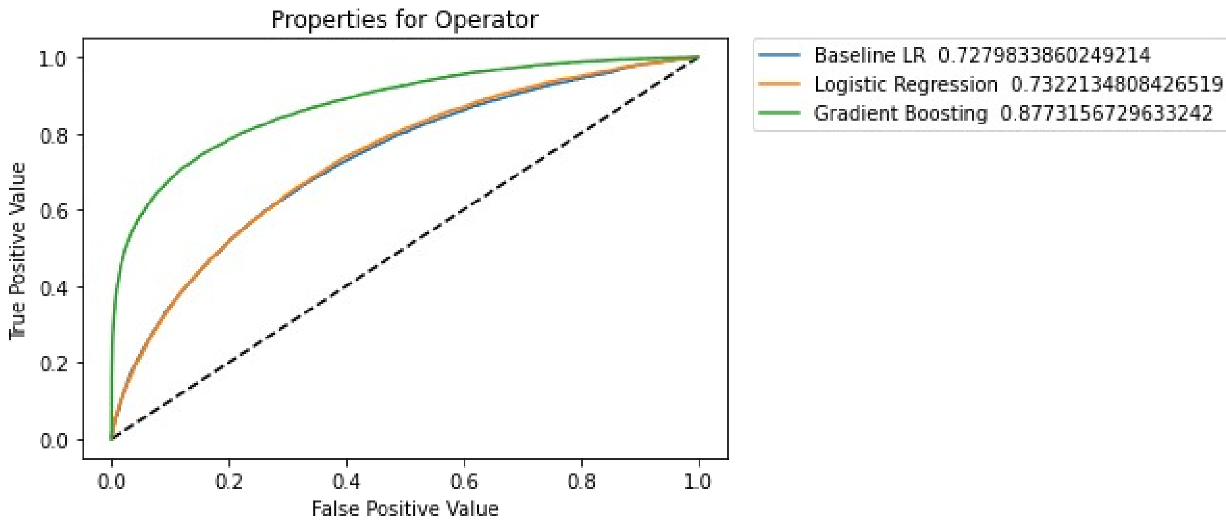
Boxplot Comparison with Cross Validation Results

```
# Boxplots for the previous feature engineering
fig = pyplot.figure()
fig.suptitle('Algorithms for Classification')

# Setting the subplots
subax = fig.add_subplot(111)
pyplot.boxplot(results)
subax.set_xticklabels(names,rotation=90)
pyplot.grid()
pyplot.show()
```



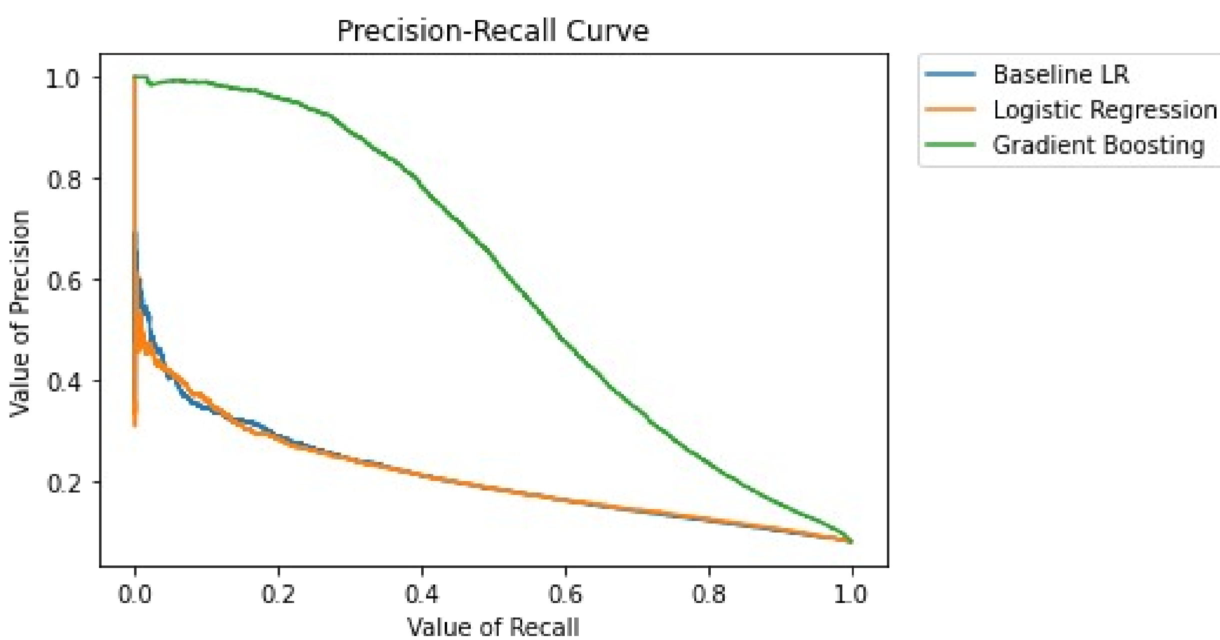
AUC : Area Under the ROC Curve

```
# roc curve fpr, tpr  for all classifiers
plt.plot([0,1],[0,1], 'k--')
for i in range(len(names)):
    plt.plot(fprs[i],tprs[i],label = names[i] + '   ' + str(scores[i]))

#Making the description by option for visulization
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left", borderaxespad=0)
plt.xlabel("False Positive Value")
plt.ylabel("True Positive Value")
plt.title('Properties for Operator')
plt.show()
```



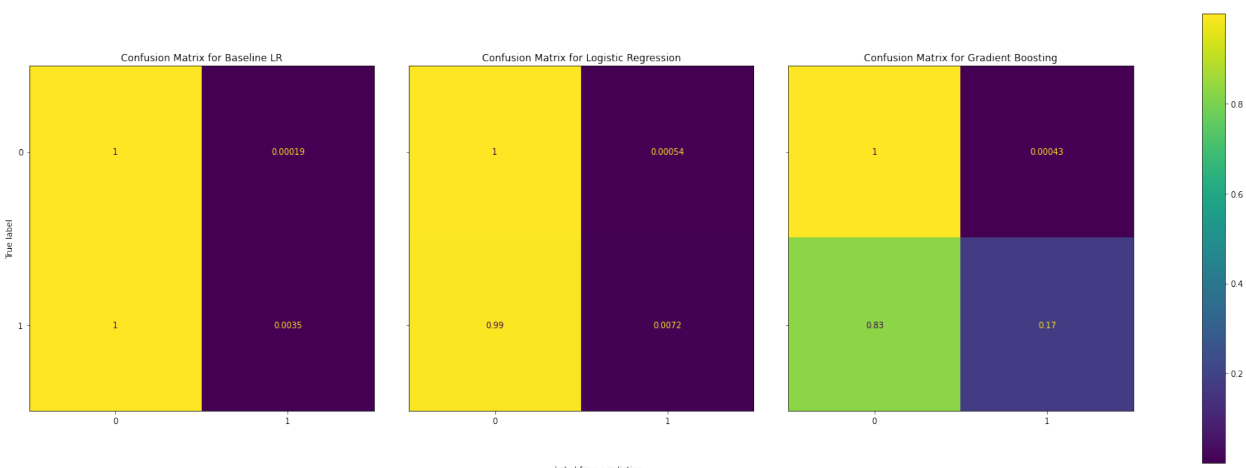
Precision Recall Curve

```
# precision recall curve  for all classifiers
for i in range(len(names)):
    plt.plot(recalls[i],precisions[i],label = names[i])
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left", borderaxespad=0)

#Making the description by option for visulization
plt.xlabel("Value of Recall")
plt.ylabel("Value of Precision")
plt.title('Precision-Recall Curve')
plt.show()
```



Confusion Matrix

```
# Setting confusion matrix for each of the classifier
f, axes = plt.subplots(1, len(names), figsize=(30, 10), sharey='row')
for i in range(len(names)):
    #Labeling
    disp = ConfusionMatrixDisplay(cnfmatrix[i], display_labels=['0',
'1'])

    #Plotting
    disp.plot(ax=axes[i], xticks_rotation=0)

    #Visualization
    disp.ax_.set_title("Confusion Matrix for " + names[i])
    disp.ax_.set_xlabel('')
    disp.im_.colorbar.remove()
    if i!=0:
        disp.ax_.set_ylabel('')

# Text
f.text(0.42, 0.11, 'Label from predicting', ha='left')
plt.subplots_adjust(wspace=0.10, hspace=0.1)

#Add color
f.colorbar(disp.im_, ax=axes)
plt.show()
```



Results from Model Selection

```
pd.set_option('display.max_colwidth', None)
Log
```

```
              exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284
```

```
1    Gradient Boosting     0.9332     0.9312     0.9379     0.8804
0.8585
2  Logistic Regression     0.9207     0.9211     0.9218     0.7313
0.7314
3    Gradient Boosting     0.9330     0.9311     0.9348     0.8754
0.8535

   Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score  Train Log
Loss  \
0     0.7280          0.0058          0.0058         0.0069
2.7304
1     0.8904          0.2729          0.2351         0.3486
2.3087
2     0.7322          0.0127          0.0143         0.0143
2.7375
3     0.8773          0.2693          0.2337         0.2926
2.3145

   Valid Log Loss  Test Log Loss  P Score
0          2.7208         2.7008   0.0017
1          2.3765         2.1453   0.0003
2          2.7263         2.7018   0.0065
3          2.3781         2.2521   0.0002
```

SMOTE(Step 7)

To solve the probleme of imbalance, we will experiment model by using the SMOTE.

```
classifiers = [
        [('Logistic Regression SMOTE',
LogisticRegression(solver='saga',random_state=42),"SMOTE")],
        [('Gradient Boosting SMOTE',
GradientBoostingClassifier(random_state=42),"SMOTE")]]

params_grid = {
        'Logistic Regression SMOTE':  {
            'penalty': ('l1', 'l2','elasticnet'),
            'tol': (0.0001, 0.00001),
            'C': (10, 1, 0.1, 0.01),
        },
        'Gradient Boosting SMOTE':  {
            'max_depth': [5,10], # Lowering helps with overfitting.
            'max_features': [5,10],
            'validation_fraction': [0.2],
            'n_iter_no_change': [10],
            'tol': [0.1,0.01],
            'n_estimators':[1000],
            'subsample' : [0.8],   #It represents the fraction of
```

```
observations to be randomly sampled for each tree.
            'min_samples_leaf' : [3,5],
    }
}

# !pip install imblearn

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
results=[]

def
RunGridResearchSMOTE(in_classifiers,cnfmatrix,fprs,tprs,precisions,rec
alls):
    for (name, classifier,ft_sel) in in_classifiers:
            # Print classifier name and its parameters
            print('---- ', name,' Start----')
            parameters = params_grid[name]
            print("Parameters are :")
            for p in sorted(parameters.keys()):
                print("\t"+str(p)+": "+ str(parameters[p]))

            # generate the pipeline from feature selection method
            full_pipeline_with_predictor = Pipeline([
                ("preparation", data_prep_pipeline),
                ('SMOTE', SMOTE(random_state=42,
sampling_strategy=0.25, k_neighbors=3)),
                ("predictor", classifier)
                ])

            # Running grid search
            params = {}
            for p in parameters.keys():
                pipe_key = 'predictor__'+str(p)
                params[pipe_key] = parameters[p]
            grid_search = GridSearchCV(full_pipeline_with_predictor,
params, cv=cvSplits, scoring='roc_auc',
                                       n_jobs=1,verbose=1)
            grid_search.fit(X_train, y_train)


            best_train = pct(grid_search.best_score_)


            print("Cross validation using best estimator")
            best_train_scores =
cross_validate(grid_search.best_estimator_, X_train,
y_train,cv=cvSplits,scoring=metrics,

return_train_score=True, n_jobs=10)
```

```
            # Collect training and validation scores
            train_accuracy_best =
np.round(best_train_scores['train_accuracy'].mean(), 4)
            valid_accuracy_best =
np.round(best_train_scores['test_accuracy'].mean(), 4)

            train_f1_best =
np.round(best_train_scores['train_f1'].mean(), 4)
            valid_f1_best =
np.round(best_train_scores['test_f1'].mean(), 4)

            train_logloss_best =
np.round(best_train_scores['train_log_loss'].mean(), 4)
            valid_logloss_best =
np.round(best_train_scores['test_log_loss'].mean(), 4)

            train_roc_auc_best =
np.round(best_train_scores['train_roc_auc'].mean(), 4)
            valid_roc_auc_best =
np.round(best_train_scores['test_roc_auc'].mean(), 4)
            valid_time =
np.round(best_train_scores['score_time'].mean(), 4)

            # Append all results
            results.append(best_train_scores['train_accuracy'])
            names.append(name)

            # t-test with best estimator
            (t_stat, p_value) =
stats.ttest_rel(logit_scores['train_roc_auc'],
best_train_scores['train_roc_auc'])


            # Fit and predict with the best estimator
            print("Fitting and Predicting using the best estimator")

            model = grid_search.best_estimator_.fit(X_train, y_train)
            print('Pickeling the Model')
            pickle.dump(model, open(f"SMOTE_best_model_{name}.pkl",
"wb"))
            start = time()
            train_time = round(time() - start, 4)



            y_test_pred = model.predict(X_test)
            start = time()
            test_time = round(time() - start, 4)
            scores.append(roc_auc_score(y_test,
model.predict_proba(X_test)[:, 1]))
```

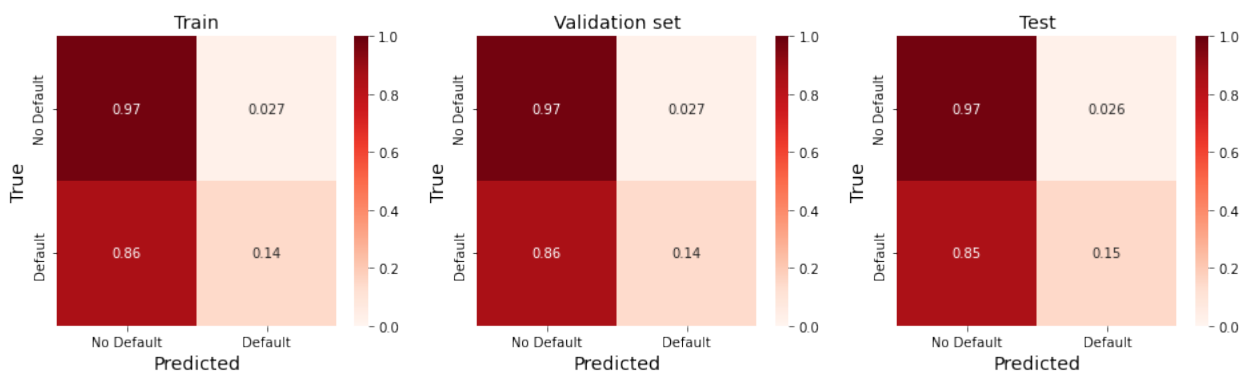
```
            accuracy.append(accuracy_score(y_test, y_test_pred))

            # Cnfusion matrix for the best model
            cnfmatrix =
plot_confusion_matrices(model,X_train,y_train,X_test,y_test,X_valid,
y_valid,cnfmatrix)

            # AUC ROC curve
            fprs,tprs = roc_curve_cust(model,X_train,y_train,X_test,
y_test,X_valid, y_valid,fprs,tprs,name)

            # Precision recall curve
            precisions,recalls =
precision_recall_cust(model,X_train,y_train,X_test, y_test,X_valid,
y_valid,precisions,recalls,name)

            # Finding Best Mode
            final_best_clf[name]=pd.DataFrame([{'label':
grid_search.best_estimator_.named_steps['predictor'].__class__.__name_
_,
                                               'predictor':
grid_search.best_estimator_.named_steps['predictor']}])
            # Collect the best parameters from the grid search
            print("Best Parameters:")
            best_parameters = grid_search.best_estimator_.get_params()
            paramdump = []
            for param_name in sorted(params.keys()):
                paramdump.append((param_name,
(best_parameters[param_name])))
                print("\t"+str(param_name)+": " +
str(best_parameters[param_name]))
            print("---- ",name," Finish ---- ")
            print("")

            # Record the results
            exp_name = name
            Log.loc[len(Log)] = [f"{exp_name}"] + list(np.round(
               [train_accuracy_best,
                    valid_accuracy_best,
                    accuracy_score(y_test, y_test_pred),
                    train_roc_auc_best,
                    valid_roc_auc_best,
                    roc_auc_score(y_test, model.predict_proba(X_test)
[:, 1]),
                    train_f1_best,
                    valid_f1_best,
                    f1_score(y_test, y_test_pred),
                    train_logloss_best,
                    valid_logloss_best,
```

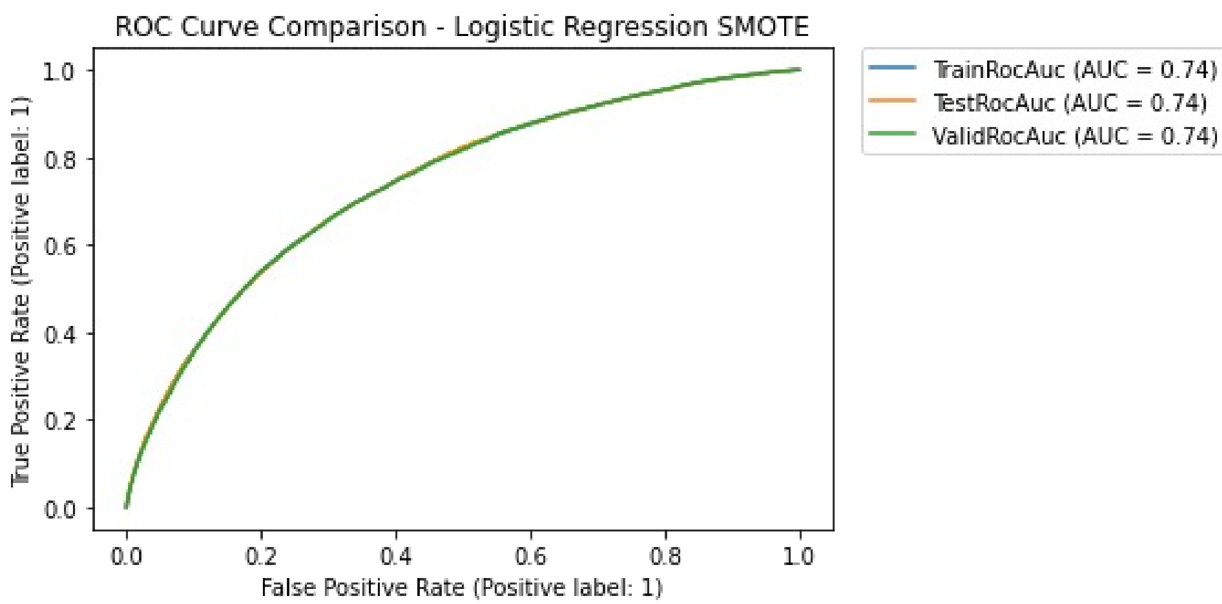
```
                    log_loss(y_test, y_test_pred),
                    p_value], 4))
```

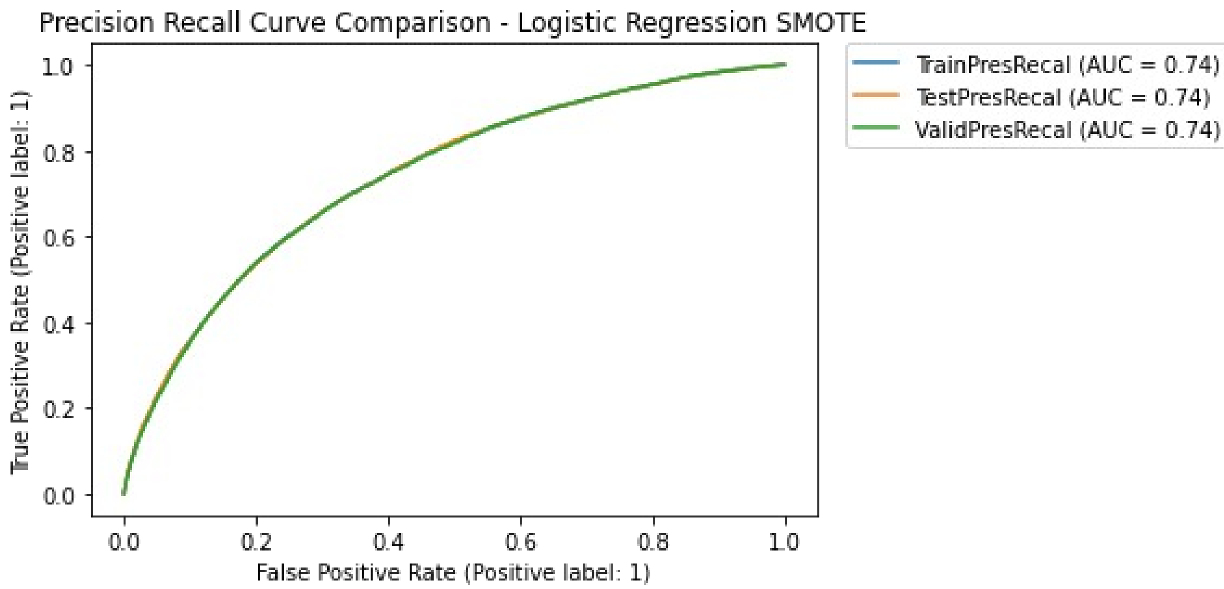
Logistic Regression

```
RunGridResearchSMOTE(classifiers[0],cnfmatrix,fprs,tprs,precisions,rec
alls)
```

```
----  Logistic Regression SMOTE  Start----
Parameters are :
     C: (10, 1, 0.1, 0.01)
     penalty: ('l1', 'l2', 'elasticnet')
     tol: (0.0001, 1e-05)
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Cross validation using best estimator
Fitting and Predicting using the best estimator
Pickeling the Model
```








```
Best Parameters:
      predictor__C: 0.01
      predictor__penalty: l2
      predictor__tol: 0.0001
----  Logistic Regression SMOTE  Finish ----


Log

                    exp_name  Train Acc  Valid Acc  Test  Acc  Train
AUC  \
0  Logistic Regression SMOTE     0.9079     0.9081     0.9094
0.7402

   Valid AUC  Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score
\
0     0.7405     0.7405          0.1985          0.1964         0.2049


   Train Log Loss  Valid Log Loss  Test Log Loss  P Score
0          3.1823           3.174         3.1292   0.0019
```

Gradient Boosting

RunGridResearchSMOTE(classifiers[1],cnfmatrix,fprs,tprs,precisions,recalls)

```
Log

                    exp_name  Train Acc  Valid Acc  Test  Acc  Train
AUC  \
0  Logistic Regression SMOTE     0.9079     0.9081     0.9094
0.7402
```

```
1    Gradient Boosting SMOTE     0.9401     0.9353     0.9316
0.8993

   Valid AUC  Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score
\
0     0.7405     0.7405          0.1985          0.1964         0.2049

1     0.8733     0.8601          0.5029          0.4509         0.4155


   Train Log Loss  Valid Log Loss  Test Log Loss  P Score
0          3.1823          3.1740         3.1292   0.0019
1          2.0694          2.2354         2.3619   0.0030
```

Results for the SMOTE

```
pd.set_option('display.max_colwidth', None)
Log

                    exp_name  Train Acc  Valid Acc  Test  Acc  Train
AUC  \
0  Logistic Regression SMOTE     0.9079     0.9081     0.9094
0.7402
1    Gradient Boosting SMOTE     0.9401     0.9353     0.9316
0.8993

   Valid AUC  Test  AUC  Train F1 Score  Valid F1 Score  Test F1 Score
\
0     0.7405     0.7405          0.1985          0.1964         0.2049

1     0.8733     0.8601          0.5029          0.4509         0.4155


   Train Log Loss  Valid Log Loss  Test Log Loss  P Score
0          3.1823          3.1740         3.1292   0.0019
1          2.0694          2.2354         2.3619   0.0030
```

Write-up

In this section, we will summarize the work done for phase 3.

Project title:

Predicting credit default risk using machine learning

Team and phase leader plan:

This week, our phase leader is Woojeong Kim. Our phase schedule is below

Phase	Phase leader
Phase 1	Evie Mahsem
Phase 2	Wunchana Seubwai
Phase 3	Woojeong Kim
Phase 4	Alaina Barca

Credit assignment plan for phase 3:

Group member	Tasks completed
Evie Mahsem	Did feature engineering, hyperparameter tuning, additional feature selection, ensemble methods.
Wunchana Seubwai	Wrote report
Woojeong Kim	Did feature engineering, hyperparameter tuning, additional feature selection, ensemble methods.
Alaina Barca	Developed slides and presentation video

Abstract

The aim of this final project on the Home Credit Default Risk dataset is to develop a predictive model that accurately predicts whether a client will default on a loan. For phase 3 of the final project, our classification model performance to identify potential loan defaulters among Home Credit's clientele have been improved by implementing several methods, including adding more feature engineering techniques, using more machine learning algorithm (Logistic regression and gradient boosting machines), hyperparameter tuning, handle class imbalance issue using Synthetic Minority Over-sampling TEchnique (SMOTE). Several evaluation metrics, including accuracy score, precision, recall, F-1 score, confusion matrix, and ROC-AUC curve, were used to evaluate model performance. Without SMOTE, Gradient Boosting outperformed Logistic Regression in terms of accuracy, AUC, and F1 score across training, validation, and test sets. With SMOTE, there was an overall improvement in the performance metrics, particularly the F1 score, indicating that SMOTE effectively mitigated class imbalance. Specifically, Gradient Boosting with SMOTE demonstrated a marked increase in the F1 score, rising from approximately 0.27 to 0.50 on the training set, and from 0.23 to 0.45 on the validation set, despite a marginal decrease in accuracy and AUC compared to the model without SMOTE. In the final project phase 4, a neural network, advanced model architectures, and loss functions will be implemented to improve classification performance for Home Credit Default Risk dataset.

Introduction

A consumer's ability to access a line of credit is often highly dependent on their credit history, leaving many potentially credit-worthy consumers without traditional loan options simply due to insufficient data. In this project, we will explore data from Home Credit, a lender striving to lend to consumers with insufficient credit histories using alternative lending data, to improve their methods for predicting loan repayment. We will use consumer transaction and payment data to develop pipelines for various machine learning algorithms – including logistic regressions, classification methods, and deep learning models – to predict consumers' likelihood of default. We will evaluate each method's predictive power using the ROC curve and produce a report summarizing the methods tested and the strongest performing predictor of consumer default. We will follow the project schedule for intermediate steps, which includes developing EDA and baseline pipeline in week 14, feature engineering and hyperparameter tuning in week 15, and implementing neural networks, advanced models, and finalizing the project in week 16.

For this phase (week 15), several methods, including additional feature engineering techniques, using more machine learning algorithm (Logistic regression and gradient boosting machines), hyperparameter tuning, Synthetic Minority Over-sampling TEchnique (SMOTE), have been implemented. The result from phase 2 and phase 3 was discussed. We conclude with next steps for phase 4.

Dataset

The dataset from Home Credit is comprised of seven different sources of data. The first, **application_train/application_test (307k rows, and 48k rows)** is our main training and testing data. Six other datasets supplement the main train and test data. The dataset **bureau (1.7 Million rows)** contains client credit history, **bureau_balance (27 Million rows)** includes monthly credit history, **previous_application (1.6 Million rows)** contains previous applications, **POS_CASH_BALANCE (10 Million rows)** provides monthly data on spending, **credit_card_balance** gives us monthly credit card information, and **installments_payment (13.6 Million rows)** contains previous loan payments with Home Credit, if any.

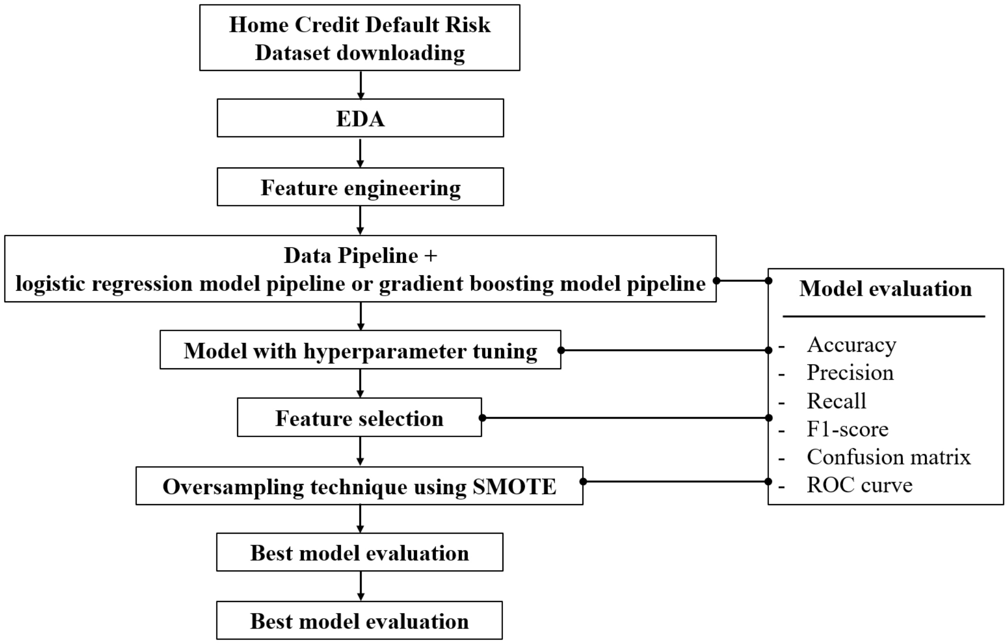
Feature Engineering

In final project phase 3, several feature engineering have been used to improve model performance, including

- Numerical Features Processing (num_pipeline): num_pipeline involves a pipeline that processes numerical features.
- Categorical Features Processing (cat_pipeline): this pipeline is probably responsible for handling categorical variables.
- Feature selection by SelectKBest which selects the top k features based on a scoring function (in this case, mutual_info_classif which measures the dependency between variables).
- SMOTE (Synthetic Minority Over-sampling Technique) is also included in the pipeline, which is a technique to address class imbalance by oversampling the minority class in the dataset.

Modeling Pipelines

The data analysis pipeline of the final project phase 3 was shown below.



Experimental results

In Phase 3 of the final project, We implemented additional techniques, including feature engineering, hyperparameter tuning, feature selection, ensemble methods, and addressing class imbalance, into our machine learning model to identify potential loan defaulters within the Home Credit Default Risk dataset. The classification performance of each machine learning models were evaluated via accuracy, confusion matrix, precision, recall, F1 score, and AUC-ROC curve.

As shown in Figure 1 and Figure 2, the confusion matrix indicated that Gradient Boosting model outperforms Logistic Regression model in distinguishing between defaulters and non-defaulters on the Home Credit Default Risk dataset across training, validation, and test sets. However, despite hyperparameter tuning and feature selection, there is no marked improvement in the classification performance of either the Gradient Boosting or Logistic Regression models, particularly for the defaulter class.

In comparision with baseline Logistic Regression model, Gradient Boosting models with hyperparameter tuning and feature selection exhibit higher overall accuracy score (Figure 3A) and AUC score (Figure 3B), Precision-Recall curve (Figure 3C), and confusion matrix (Figure 4) than baseline Logistic Regression model as well as Logistic Regression models with hyperparameter tuning and feature selection.

To address the imbalance issue identified in the Home Credit Default Risk dataset during phase 2, Synthetic Minority Over-sampling TEchnique (SMOTE) was used in the present study. As shown in Figure 6, The logistic regression and gradient boosting models, after hyperparameter tuning, feature selection, and SMOTE, both show high accuracy for 'No Default' predictions across training, validation, and test sets. The inclusion of SMOTE has improved the 'Default' prediction capabilities of both models compared to those without SMOTE. The classification performance of six experimental models were shown in Table 1. Models 1 and 2 were Logistic

Regression (LR) and Gradient Boosting (GB) with hyperparameter tuning, respectively. Both models exhibited comparable accuracy, with Model 2 showing a marginally higher Test Accuracy (0.9379) and Test AUC (0.8904). Models 3 (LR) and 4 (GB) improved upon Models 1 and 2 by incorporating feature selection alongside hyperparameter tuning, leading to slightly improved Test AUC scores. Models 5 (LR) and 6 (GB), which applied hyperparameter tuning, feature selection, and SMOTE, showed a substantial improvement in F1 scores on the Test set, with Model 6 achieving the highest Test F1 Score (0.4155) and Test AUC (0.8601) among all models.

These information indicated that among the six models evaluated, Gradient Boosting with hyperparameter tuning, feature selection, and SMOTE achieved the highest classification performance.

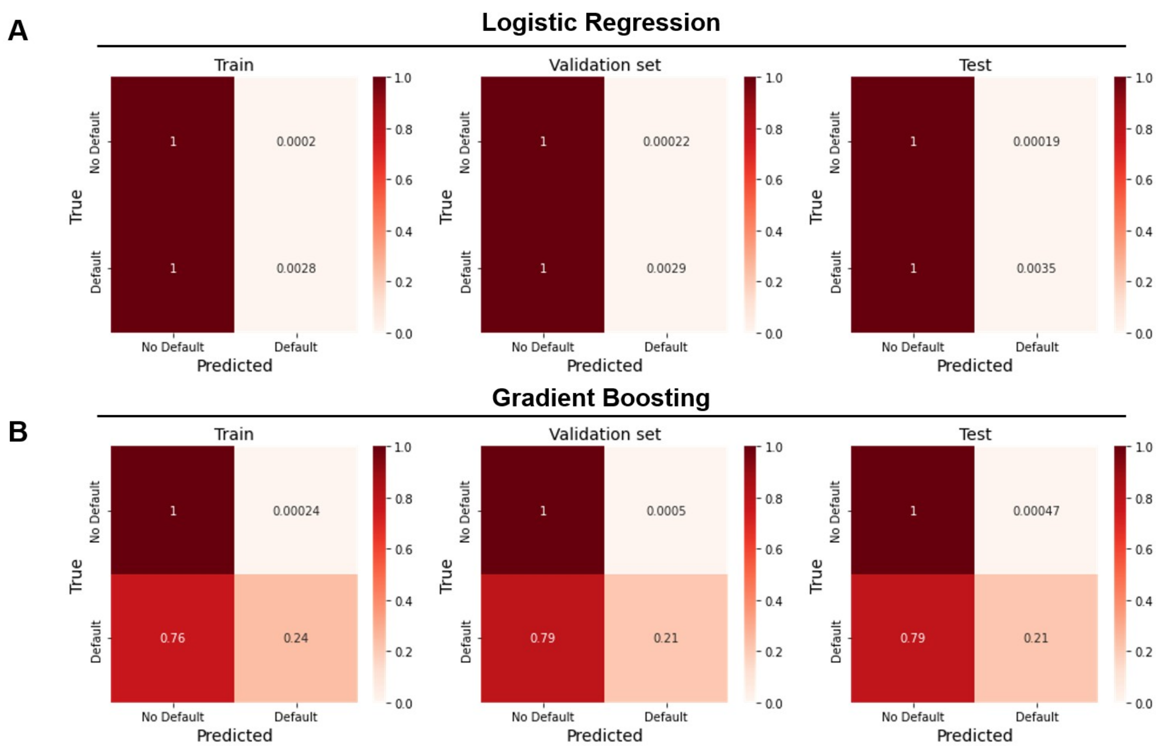


Figure 1 Confusion matrix of LR and GB models with hyperparameter tuning
(A) Logistic regression model, (B) Gradient boosting model.

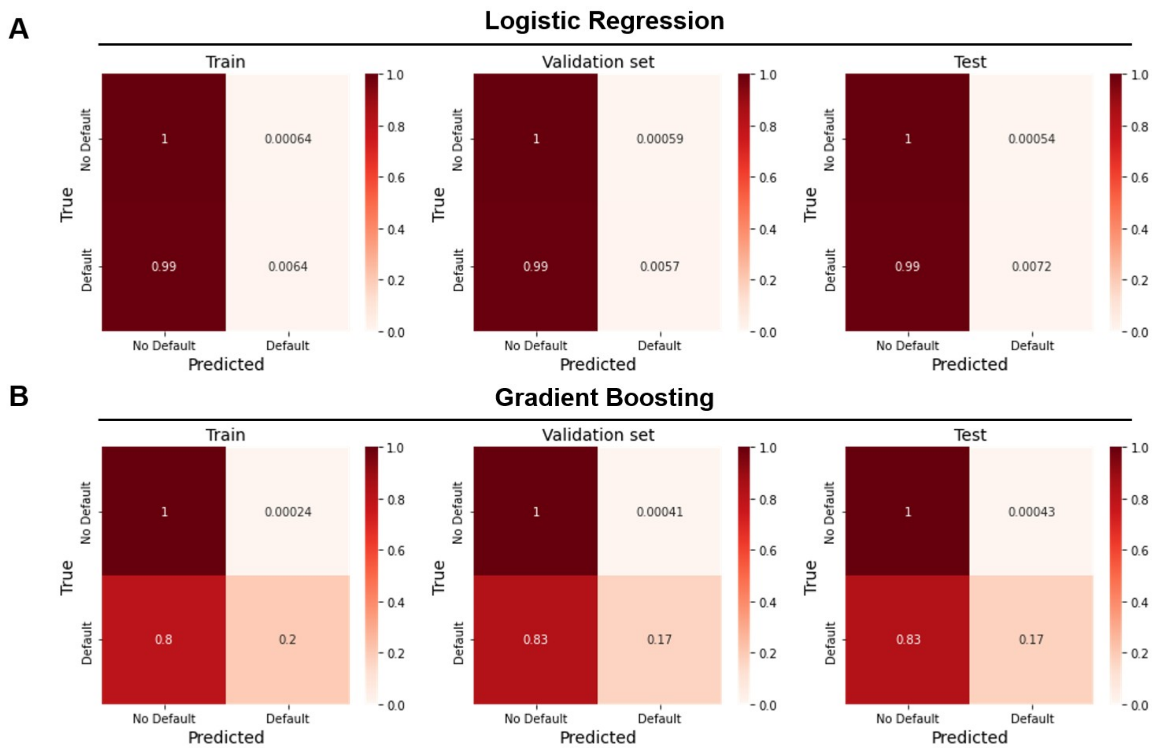


Figure 2 Confusion matrix of LR and GB models with hyperparameter tuning and feature selection
(A) Logistic regression model, (B) Gradient boosting model.

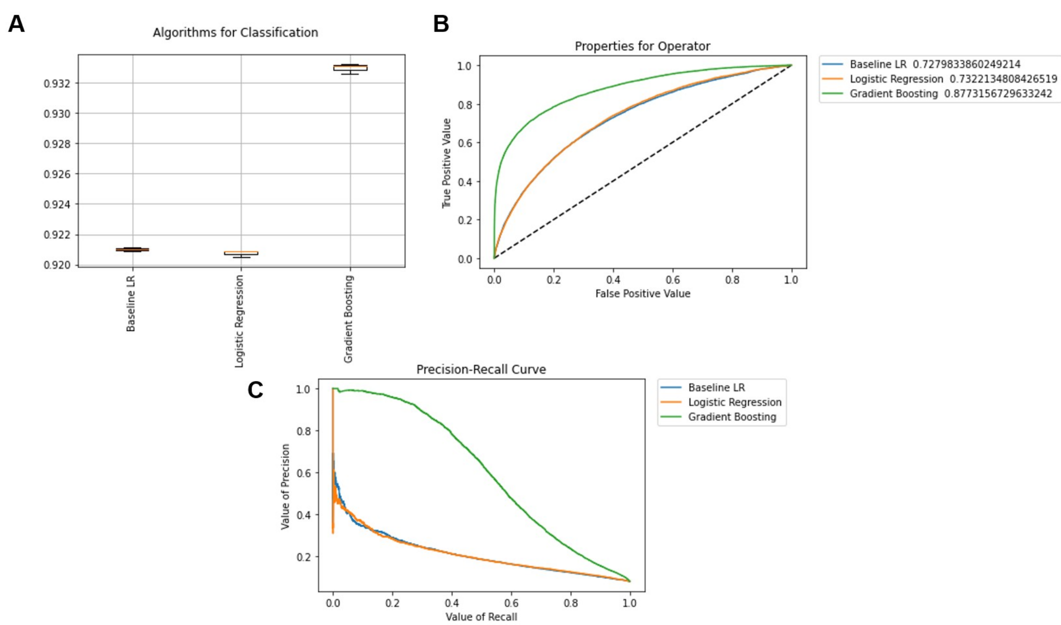


Figure 3 Classification performance of LR and GB models with hyperparameter tuning and feature selection.
(A) Accuracy, (B) ROC curve, (C) Precision Recall curve.

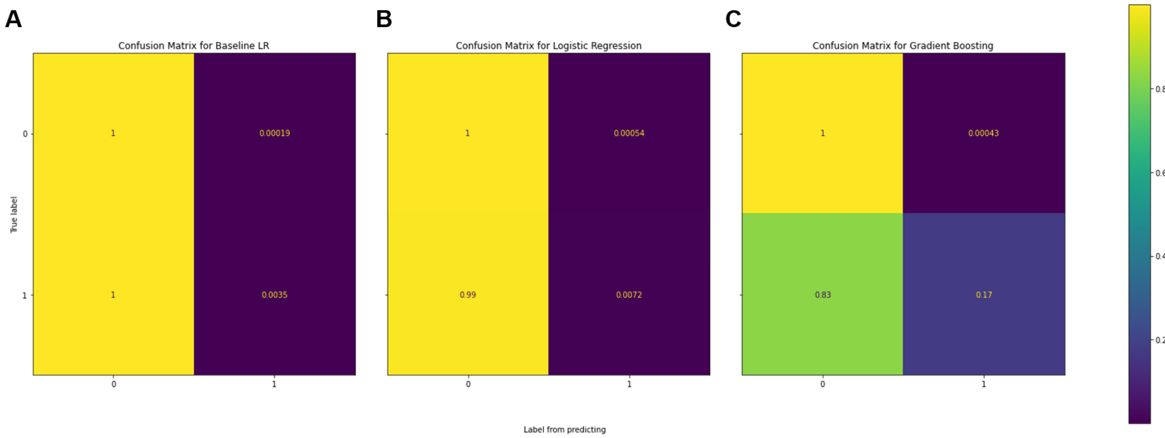


Figure 4 Confusion matrix of LR and GB models with hyperparameter tuning and feature selection.
(A) Baseline Logistic regression model, (B) Logistic regression model, (B) Gradient boosting model

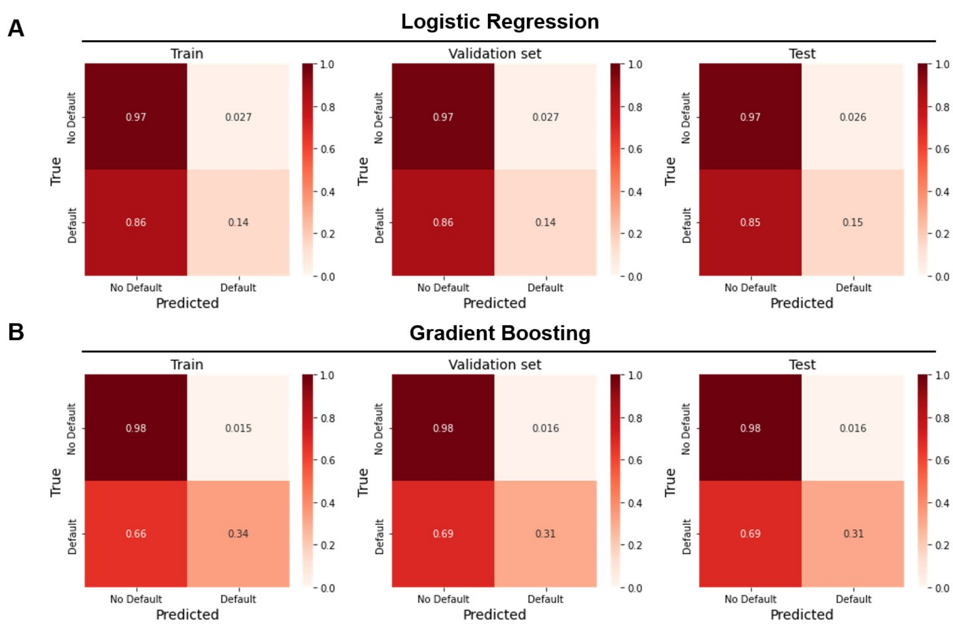


Figure 5 Confusion matrix of LR and GB models with hyperparameter tuning, feature selection, and SMOTE
(A) Logistic regression model, (B) Gradient boosting model.

Table 1. The results of the various experiments.

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1 Score	Valid F1 Score	Test F1 Score	Train Log Loss	Valid Log Loss	Test Log Loss	P Score
Model 1	Logistic Regression	0.9209	0.9212	0.9218	0.7279	0.7284	0.7280	0.0058	0.0058	0.0069	2.7304	2.7208	2.7008	0.0017
Model 2	Gradient Boosting	0.9332	0.9312	0.9379	0.8804	0.8585	0.8904	0.2729	0.2351	0.3486	2.3087	2.3765	2.1453	0.0003
Model 3	Logistic Regression	0.9207	0.9211	0.9218	0.7313	0.7314	0.7322	0.0127	0.0143	0.0143	2.7375	2.7263	2.7018	0.0065
Model 4	Gradient Boosting	0.9330	0.9311	0.9348	0.8754	0.8535	0.8773	0.2693	0.2337	0.2926	2.3145	2.3781	2.2521	0.0002

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1 Score	Valid F1 Score	Test F1 Score	Train Log Loss	Valid Log Loss	Test Log Loss	P Score
Model 5	Logistic Regression SMOTE	0.9079	0.9081	0.9094	0.7402	0.7405	0.7405	0.1985	0.1964	0.2049	3.1823	3.1740	3.1292	0.0019
Model 6	Gradient Boosting SMOTE	0.9401	0.9353	0.9316	0.8993	0.8733	0.8601	0.5029	0.4509	0.4155	2.0694	2.2354	2.3619	0.0030

Remark:
Model 1 and 2: LR and GB models with hyperparameter tuning
Model 3 and 4: LR and GB models with hyperparameter tuning + feature selection
Model 5 and 6: LR and GB models with hyperparameter tuning + feature selection + SMOTE

Discussion

Gradient Boosting, a machine learning ensemble technique, with SMOTE technique performed better classification performance than Gradient Boosting without SMOTE and logistic regression models (with and without SMOTE technique) in terms of accuracy, ROC curve, evaluation metrics, and confusion matrix for 'Class 0' and 'Class 1'.

Gradient Boosting combined with SMOTE significantly enhances classification performance on the Home Credit Default Risk dataset by effectively addressing class imbalance, improving the model's sensitivity and specificity, and enabling more robust learning of complex patterns, leading to superior results in accuracy, AUC score, the confusion matrix and F-1 score.

The main problem in final project phase 3 was the large sample size of the Home Credit Default Risk dataset, which led to extensive computational times and required high-performance computing resources. Initially, our team planned to use several machine learning models, including decision trees, random forests, gradient boosting, neural networks, support vector machines (SVMs), and k-nearest neighbors (KNN). However, running all these models exceeded a computational time of 24 hours. Therefore, we ultimately narrowed our focus to two models: logistic regression and gradient boosting. It would be beneficial if the instructor could provide access to cloud computing resources for each group.

Conclusion

In this final project phase 3, we implemented additional techniques into our machine learning model to identify potential loan defaulters within the Home Credit Default Risk dataset. These techniques included feature engineering, hyperparameter tuning, feature selection, ensemble methods, and addressing class imbalance.

Without SMOTE, Gradient Boosting outperformed Logistic Regression in terms of accuracy, AUC, and F1 score. With SMOTE, there was an overall improvement in the performance metrics, particularly the F1 score, indicating that SMOTE effectively mitigated class imbalance. Specifically, Gradient Boosting with SMOTE demonstrated a marked increase in the F1 score, rising from approximately 0.27 to 0.50 on the training set, and from 0.23 to 0.45 on the validation set, despite a marginal decrease in accuracy and AUC compared to the model without SMOTE.

Compared to the baseline models in phase 2, our classification model with SMOTE technique in phase 3 performed higher accuracy score, AUC score, and also F1-score, especially in Gradient Boosting model. This improvement suggests that Gradient Boosting with the application of SMOTE seems to be the most effective model for Home Credit Default Risk dataset, providing a good balance of accuracy, AUC, and F1 score, which are crucial for evaluating performance in credit risk prediction.

Next, we plan to apply a Neural Network, Advanced model architectures, and loss functions to further improve model performance.

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Kaggle submission