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
```

```python
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 (194129, 122)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194129 entries, 0 to 194128
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(103), int64(3), object(16)
memory usage: 180.7+ MB
None
```

{"type":"dataframe"}

```
(194129, 122)
```

```python
# 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
```

{"type":"dataframe"}

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 (194129, 122)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194129 entries, 0 to 194128
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(103), int64(3), object(16)
memory usage: 180.7+ MB
None
```

{"type":"dataframe"}

```
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
```

{"type":"dataframe"}

```
bureau: shape is (1068746, 17)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1068746 entries, 0 to 1068745
Data columns (total 17 columns):
 #   Column                  Non-Null Count    Dtype
---  ------                  --------------    -----
 0   SK_ID_CURR              1068746 non-null  int64
 1   SK_ID_BUREAU            1068746 non-null  int64
 2   CREDIT_ACTIVE           1068746 non-null  object
 3   CREDIT_CURRENCY         1068746 non-null  object
 4   DAYS_CREDIT             1068746 non-null  int64
 5   CREDIT_DAY_OVERDUE      1068745 non-null  float64
 6   DAYS_CREDIT_ENDDATE     1002301 non-null  float64
 7   DAYS_ENDDATE_FACT       671713 non-null   float64
 8   AMT_CREDIT_MAX_OVERDUE  364579 non-null   float64
 9   CNT_CREDIT_PROLONG      1068745 non-null  float64
 10  AMT_CREDIT_SUM          1068737 non-null  float64
 11  AMT_CREDIT_SUM_DEBT     908323 non-null   float64
 12  AMT_CREDIT_SUM_LIMIT    696486 non-null   float64
 13  AMT_CREDIT_SUM_OVERDUE  1068745 non-null  float64
 14  CREDIT_TYPE             1068745 non-null  object
 15  DAYS_CREDIT_UPDATE      1068745 non-null  float64
 16  AMT_ANNUITY             324524 non-null   float64
dtypes: float64(11), int64(3), object(3)
```

```
memory usage: 138.6+ MB
None
```

{"summary":"{\n \"name\": \"get_ipython()\",\n \"rows\": 5,\n \"fields\": [\n   {\n   \"column\": \"SK_ID_CURR\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0,\n   \"min\": 215354,\n   \"max\": 215354,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   215354\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"SK_ID_BUREAU\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 1,\n   \"min\": 5714462,\n   \"max\": 5714466,\n   \"num_unique_values\": 5,\n   \"samples\": [\n   5714463\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"CREDIT_ACTIVE\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 2,\n   \"samples\": [\n   \"Active\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"CREDIT_CURRENCY\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 1,\n   \"samples\": [\n   \"currency 1\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_CREDIT\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 201,\n   \"min\": -629,\n   \"max\": -203,\n   \"num_unique_values\": 4,\n   \"samples\": [\n   -208\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"CREDIT_DAY_OVERDUE\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.0,\n   \"min\": 0.0,\n   \"max\": 0.0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   0.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_CREDIT_ENDDATE\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 616.164142092024,\n   \"min\": -153.0,\n   \"max\": 1197.0,\n   \"num_unique_values\": 4,\n   \"samples\": [\n   1075.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_ENDDATE_FACT\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": null,\n   \"min\": -153.0,\n   \"max\": -153.0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   -153.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"AMT_CREDIT_MAX_OVERDUE\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": null,\n   \"min\": 77674.5,\n   \"max\": 77674.5,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   77674.5\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"CNT_CREDIT_PROLONG\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\":

```
0.0,\n        \"min\": 0.0,\n        \"max\": 0.0,\n
\"num_unique_values\": 1,\n        \"samples\": [\n          0.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"AMT_CREDIT_SUM\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1120575.5125591492,\n        \"min\": 90000.0,\n        \"max\":
2700000.0,\n        \"num_unique_values\": 5,\n        \"samples\": [\
n          225000.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"AMT_CREDIT_SUM_DEBT\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 121157.09010206543,\n        \"min\":
0.0,\n        \"max\": 171342.0,\n        \"num_unique_values\": 2,\n
\"samples\": [\n          171342.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"AMT_CREDIT_SUM_LIMIT\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
null,\n        \"min\": null,\n        \"max\": null,\n
\"num_unique_values\": 0,\n        \"samples\": [],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"AMT_CREDIT_SUM_OVERDUE\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.0,\n        \"min\": 0.0,\n        \"max\": 0.0,\n
\"num_unique_values\": 1,\n        \"samples\": [],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"CREDIT_TYPE\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 2,\n        \"samples\": [],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"DAYS_CREDIT_UPDATE\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
50.474746160827785,\n        \"min\": -131.0,\n        \"max\": -
16.0,\n        \"num_unique_values\": 4,\n        \"samples\": [],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"AMT_ANNUITY\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
null,\n        \"min\": null,\n        \"max\": null,\n
\"num_unique_values\": 0,\n        \"samples\": [],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe"}
```


```
bureau_balance: shape is (7624903, 3)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7624903 entries, 0 to 7624902
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: 174.5+ MB
None
```

{"summary":"{\n \"name\": \"get_ipython()\",\n \"rows\": 5,\n \"fields\": [\n   {\n   \"column\": \"SK_ID_BUREAU\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0,\n   \"min\": 5715448,\n   \"max\": 5715448,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   5715448\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"MONTHS_BALANCE\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 1,\n   \"min\": -4,\n   \"max\": 0,\n   \"num_unique_values\": 5,\n   \"samples\": [\n   -1\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"STATUS\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 1,\n   \"samples\": [\n   \"C\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

```
credit_card_balance: shape is (945811, 23)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 945811 entries, 0 to 945810
Data columns (total 23 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   SK_ID_PREV                  945811 non-null  int64
 1   SK_ID_CURR                  945811 non-null  int64
 2   MONTHS_BALANCE              945810 non-null  float64
 3   AMT_BALANCE                 945810 non-null  float64
 4   AMT_CREDIT_LIMIT_ACTUAL     945810 non-null  float64
 5   AMT_DRAWINGS_ATM_CURRENT    751119 non-null  float64
 6   AMT_DRAWINGS_CURRENT        945810 non-null  float64
 7   AMT_DRAWINGS_OTHER_CURRENT  751119 non-null  float64
 8   AMT_DRAWINGS_POS_CURRENT    751119 non-null  float64
 9   AMT_INST_MIN_REGULARITY     876087 non-null  float64
 10  AMT_PAYMENT_CURRENT         747988 non-null  float64
 11  AMT_PAYMENT_TOTAL_CURRENT   945810 non-null  float64
 12  AMT_RECEIVABLE_PRINCIPAL    945810 non-null  float64
 13  AMT_RECIVABLE               945810 non-null  float64
 14  AMT_TOTAL_RECEIVABLE        945810 non-null  float64
 15  CNT_DRAWINGS_ATM_CURRENT    751119 non-null  float64
 16  CNT_DRAWINGS_CURRENT        945810 non-null  float64
 17  CNT_DRAWINGS_OTHER_CURRENT  751119 non-null  float64
 18  CNT_DRAWINGS_POS_CURRENT    751119 non-null  float64
 19  CNT_INSTALMENT_MATURE_CUM   876087 non-null  float64
 20  NAME_CONTRACT_STATUS        945810 non-null  object
 21  SK_DPD                      945810 non-null  float64
 22  SK_DPD_DEF                  945810 non-null  float64
dtypes: float64(20), int64(2), object(1)
```

```
memory usage: 166.0+ MB
None
```

{"type":"dataframe"}

```
installments_payments: shape is (1913651, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1913651 entries, 0 to 1913650
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   float64
 4   DAYS_INSTALMENT         float64
 5   DAYS_ENTRY_PAYMENT      float64
 6   AMT_INSTALMENT          float64
 7   AMT_PAYMENT             float64
dtypes: float64(6), int64(2)
memory usage: 116.8 MB
None
```

{"summary":"{\n \"name\": \"get_ipython()\",\n \"rows\": 5,\n \"fields\": [\n   {\n   \"column\": \"SK_ID_PREV\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 713958,\n   \"min\": 1054186,\n   \"max\": 2714724,\n   \"num_unique_values\": 5,\n   \"samples\": [\n   1330831,\n   2714724,\n   2085231\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"SK_ID_CURR\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 20684,\n   \"min\": 151639,\n   \"max\": 199697,\n   \"num_unique_values\": 5,\n   \"samples\": [\n   151639,\n   167756,\n   193053\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"NUM_INSTALMENT_VERSION\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.7071067811865476,\n   \"min\": 0.0,\n   \"max\": 2.0,\n   \"num_unique_values\": 3,\n   \"samples\": [\n   1.0,\n   0.0,\n   2.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"NUM_INSTALMENT_NUMBER\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 13.989281611290838,\n   \"min\": 1.0,\n   \"max\": 34.0,\n   \"num_unique_values\": 5,\n   \"samples\": [\n   34.0,\n   2.0,\n   1.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_INSTALMENT\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 926.8384433114544,\n   \"min\": -

2418.0,\n   \"max\": -63.0,\n   \"num_unique_values\": 5,\n
\"samples\": [\n   -2156.0,\n   -1383.0,\n   -
63.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_ENTRY_PAYMENT\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 928.7713927549664,\n   \"min\": -
2426.0,\n   \"max\": -63.0,\n   \"num_unique_values\": 5,\n
\"samples\": [\n   -2156.0,\n   -1366.0,\n   -
63.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"AMT_INSTALMENT\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 11839.325156793355,\n   \"min\":
1716.525,\n   \"max\": 25425.0,\n   \"num_unique_values\":
5,\n   \"samples\": [\n   1716.525,\n   2165.04,\n
25425.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"AMT_PAYMENT\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 11840.261866322362,\n   \"min\":
1716.525,\n   \"max\": 25425.0,\n   \"num_unique_values\":
5,\n   \"samples\": [\n   1716.525,\n   2160.585,\n
25425.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}


```
previous_application: shape is (435637, 37)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 435637 entries, 0 to 435636
Data columns (total 37 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   SK_ID_PREV                   435637 non-null  int64
 1   SK_ID_CURR                   435637 non-null  int64
 2   NAME_CONTRACT_TYPE           435637 non-null  object
 3   AMT_ANNUITY                  339497 non-null  float64
 4   AMT_APPLICATION              435637 non-null  float64
 5   AMT_CREDIT                   435637 non-null  float64
 6   AMT_DOWN_PAYMENT             205185 non-null  float64
 7   AMT_GOODS_PRICE              336366 non-null  float64
 8   WEEKDAY_APPR_PROCESS_START   435637 non-null  object
 9   HOUR_APPR_PROCESS_START      435637 non-null  int64
 10  FLAG_LAST_APPL_PER_CONTRACT  435637 non-null  object
 11  NFLAG_LAST_APPL_IN_DAY       435637 non-null  int64
 12  RATE_DOWN_PAYMENT            205185 non-null  float64
 13  RATE_INTEREST_PRIMARY        1560 non-null    float64
 14  RATE_INTEREST_PRIVILEGED     1560 non-null    float64
 15  NAME_CASH_LOAN_PURPOSE       435637 non-null  object
 16  NAME_CONTRACT_STATUS         435637 non-null  object
 17  DAYS_DECISION                435637 non-null  int64
 18  NAME_PAYMENT_TYPE            435637 non-null  object
 19  CODE_REJECT_REASON           435637 non-null  object
 20  NAME_TYPE_SUITE              221847 non-null  object
```

```
 21  NAME_CLIENT_TYPE               435637 non-null  object
 22  NAME_GOODS_CATEGORY            435637 non-null  object
 23  NAME_PORTFOLIO                 435637 non-null  object
 24  NAME_PRODUCT_TYPE              435637 non-null  object
 25  CHANNEL_TYPE                   435637 non-null  object
 26  SELLERPLACE_AREA               435637 non-null  int64
 27  NAME_SELLER_INDUSTRY           435637 non-null  object
 28  CNT_PAYMENT                    339498 non-null  float64
 29  NAME_YIELD_GROUP               435637 non-null  object
 30  PRODUCT_COMBINATION            435552 non-null  object
 31  DAYS_FIRST_DRAWING             261808 non-null  float64
 32  DAYS_FIRST_DUE                 261808 non-null  float64
 33  DAYS_LAST_DUE_1ST_VERSION      261808 non-null  float64
 34  DAYS_LAST_DUE                  261808 non-null  float64
 35  DAYS_TERMINATION               261808 non-null  float64
 36  NFLAG_INSURED_ON_APPROVAL      261808 non-null  float64
dtypes: float64(15), int64(6), object(16)
memory usage: 123.0+ MB
None
```

{"type":"dataframe"}

```
POS_CASH_balance: shape is (2667626, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2667626 entries, 0 to 2667625
Data columns (total 8 columns):
 #   Column                 Dtype
---  ------                 -----
 0   SK_ID_PREV             int64
 1   SK_ID_CURR             float64
 2   MONTHS_BALANCE         float64
 3   CNT_INSTALMENT         float64
 4   CNT_INSTALMENT_FUTURE  float64
 5   NAME_CONTRACT_STATUS   object
 6   SK_DPD                 float64
 7   SK_DPD_DEF             float64
dtypes: float64(6), int64(1), object(1)
memory usage: 162.8+ MB
None
```

{"summary":"{\n \"name\": \"get_ipython()\",\n \"rows\": 5,\n
\"fields\": [\n   {\n   \"column\": \"SK_ID_PREV\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
250398,\n   \"min\": 1715348,\n   \"max\": 2341044,\n
\"num_unique_values\": 5,\n   \"samples\": [\n   1715348,\
n   2341044,\n   1784872\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"SK_ID_CURR\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
85728.52693415419,\n   \"min\": 182943.0,\n   \"max\":

397406.0,\n   \"num_unique_values\": 5,\n   \"samples\": [\n 367990.0,\n   334279.0,\n   397406.0\n   ],\n \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"MONTHS_BALANCE\",\n \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 1.7888543819998317,\n   \"min\": -35.0,\n   \"max\": -31.0,\n   \"num_unique_values\": 4,\n   \"samples\": [\n -33.0,\n   -35.0,\n   -31.0\n   ],\n \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"CNT_INSTALMENT\",\n \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 14.696938456699069,\n   \"min\": 12.0,\n   \"max\": 48.0,\n \"num_unique_values\": 3,\n   \"samples\": [\n   48.0,\n 36.0,\n   12.0\n   ],\n   \"semantic_type\": \"\",\n \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"CNT_INSTALMENT_FUTURE\",\n   \"properties\": {\n \"dtype\": \"number\",\n   \"std\": 14.219704638282751,\n \"min\": 9.0,\n   \"max\": 45.0,\n   \"num_unique_values\": 4,\n   \"samples\": [\n   35.0,\n   42.0,\n 45.0\n   ],\n   \"semantic_type\": \"\",\n \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"NAME_CONTRACT_STATUS\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 1,\n   \"samples\": [\n   \"Active\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n \"column\": \"SK_DPD\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.0,\n   \"min\": 0.0,\n \"max\": 0.0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   0.0\n   ],\n   \"semantic_type\": \"\",\n \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"SK_DPD_DEF\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.0,\n   \"min\": 0.0,\n \"max\": 0.0,\n   \"num_unique_values\": 1,\n   \"samples\": [\n   0.0\n   ],\n   \"semantic_type\": \"\",\n \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

```
CPU times: user 18.5 s, sys: 2.12 s, total: 20.6 s
Wall time: 21.8 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       : [    194,129, 122]
dataset application_test        : [     48,744, 121]
dataset bureau                  : [  1,068,746, 17]
dataset bureau_balance          : [  7,624,903, 3]
dataset credit_card_balance     : [    945,811, 23]
dataset installments_payments   : [  1,913,651, 8]
```

```
dataset previous_application      : [    435,637, 37]
dataset POS_CASH_balance          : [  2,667,626, 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
```

```python
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'])
```

```python
# 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'])
```

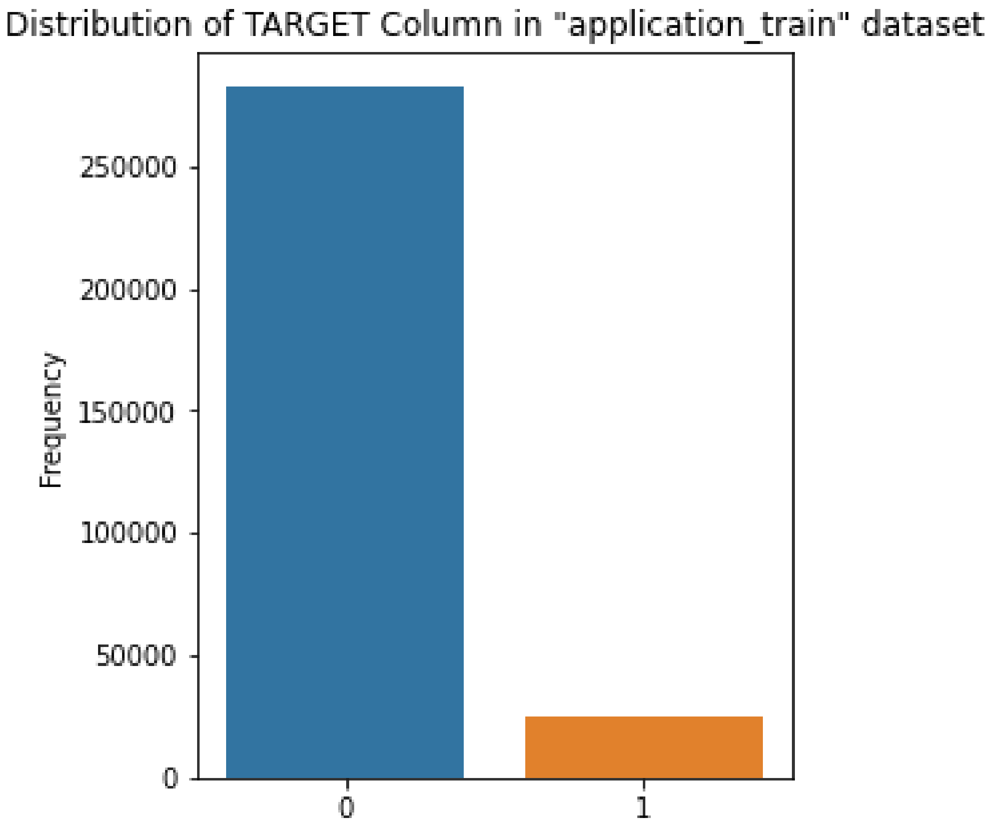
```python
# msno.matrix(datasets['application_test'])
```

Distribution of the target column

```
# 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
```

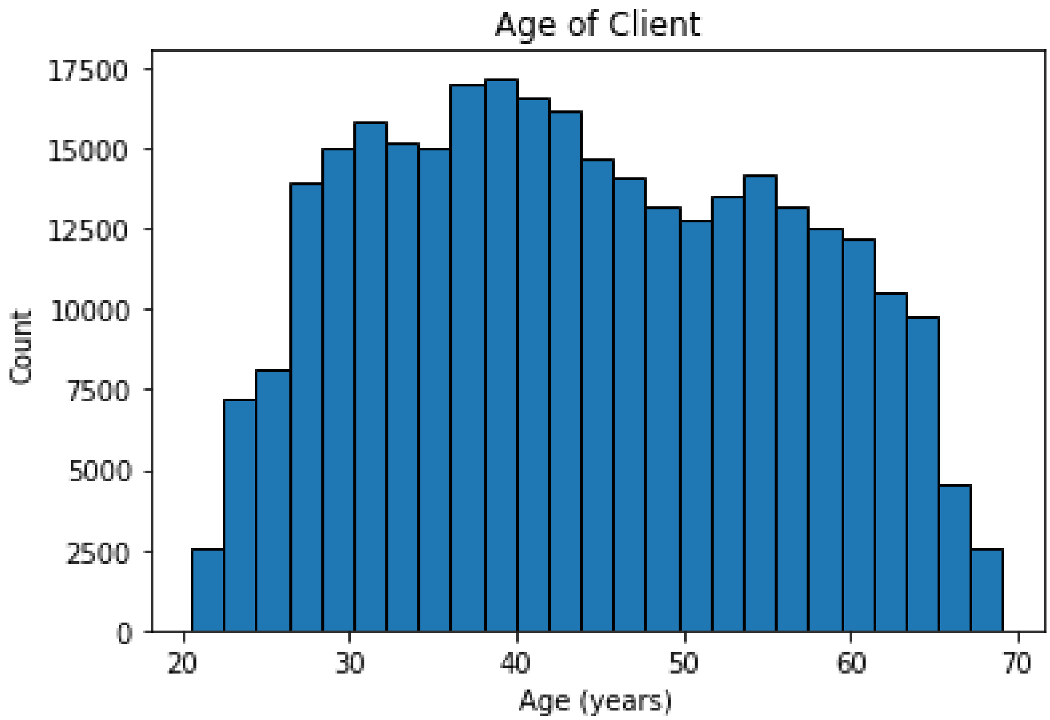
```
# Plot the distribution of the values of 'TARGET' column in
"application_train" dataset

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).

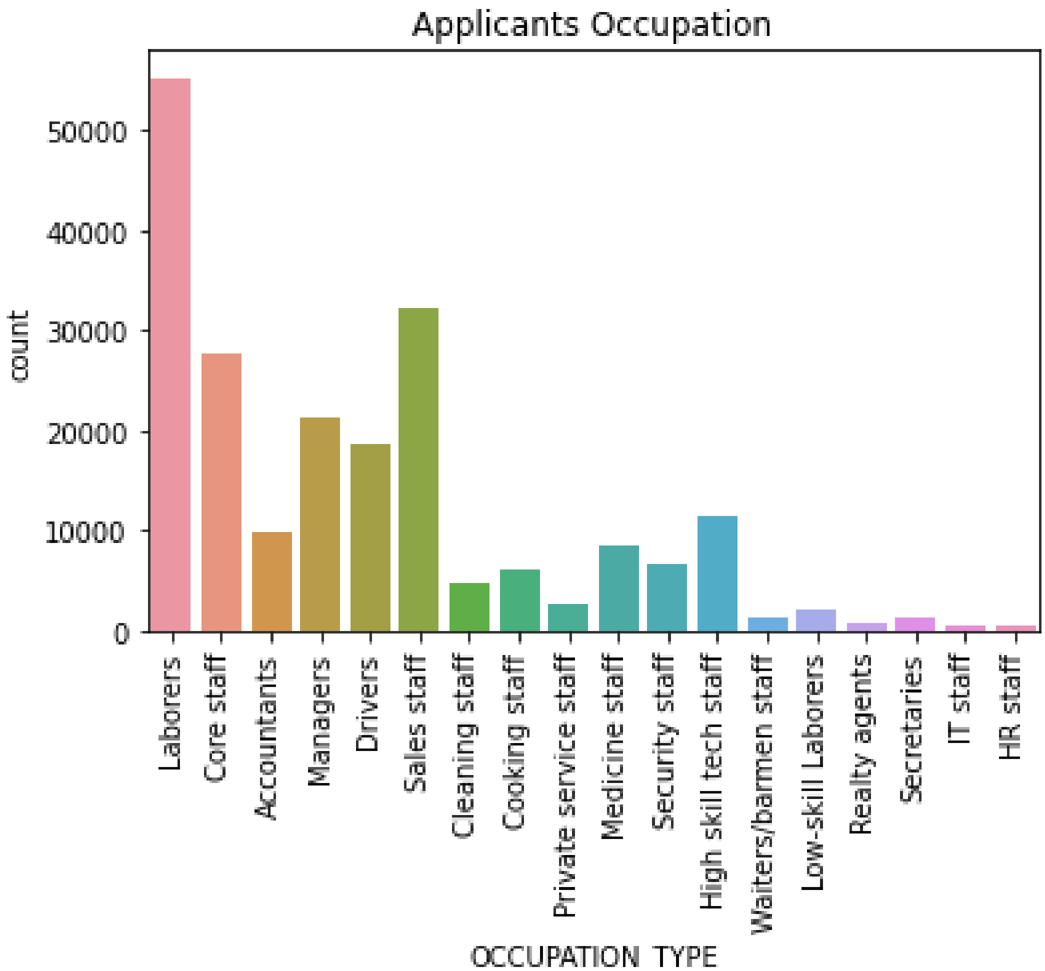
Applicants Age

```
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")
```

{"type":"dataframe"}

```
435,637 rows, 37 columns
```

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

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

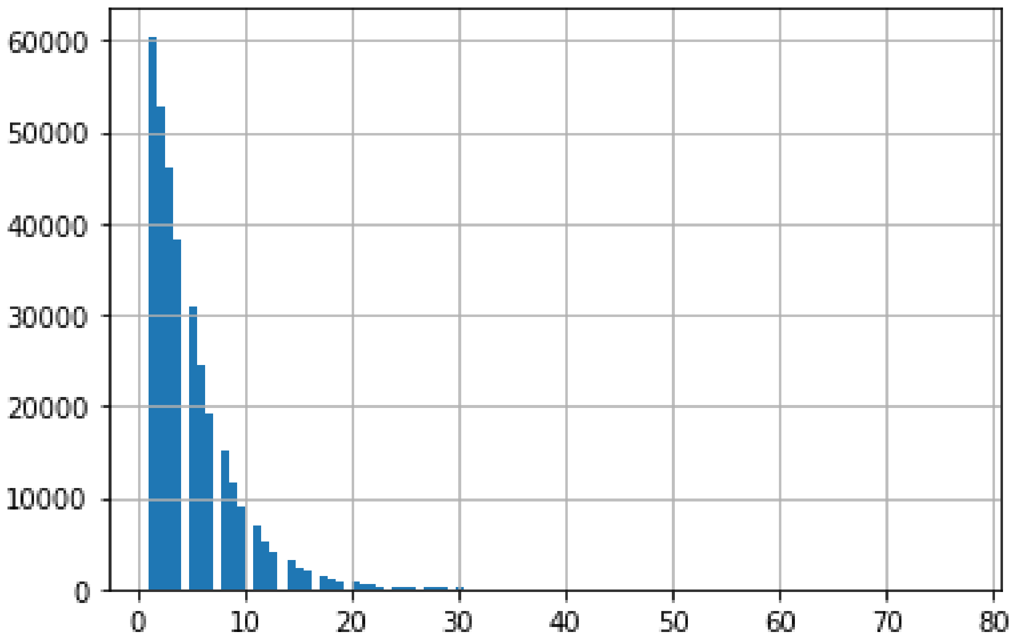
```
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is
{len(np.intersect1d(datasets["previous_application"]["SK_ID_CURR"],
datasets["application_train"]["SK_ID_CURR"])):,}')
```

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

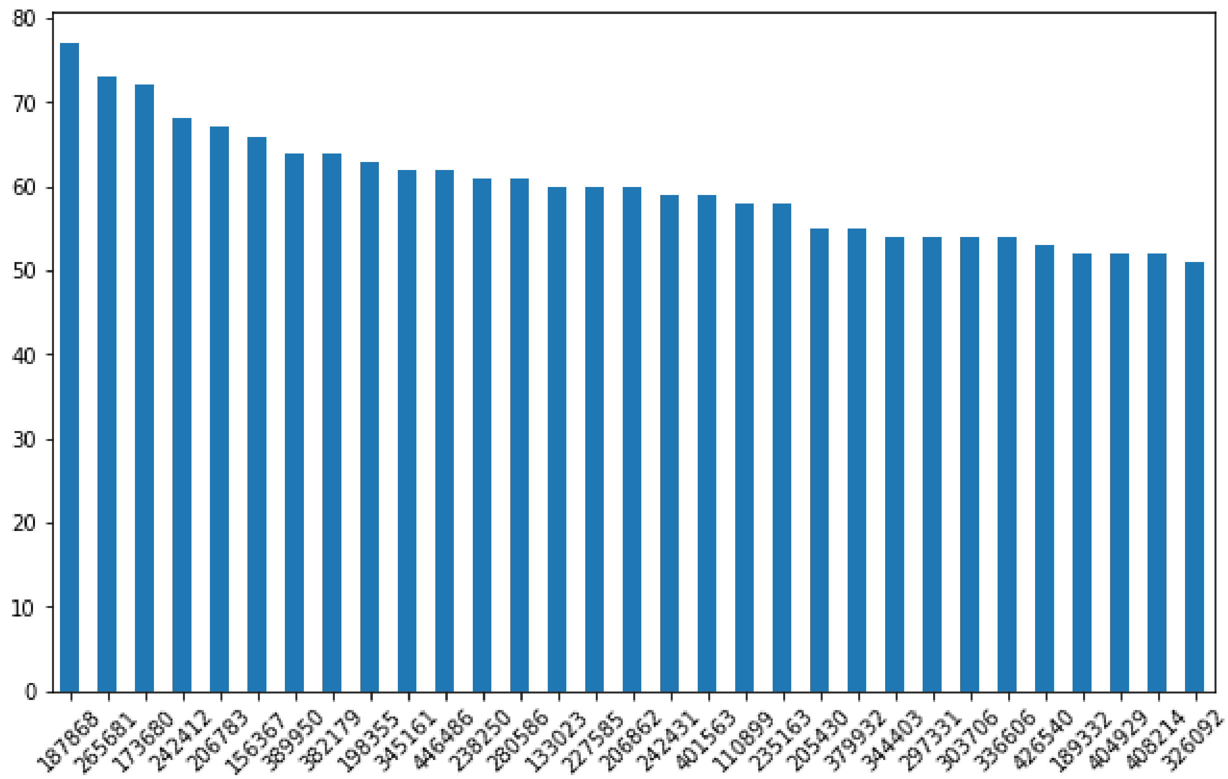
```
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is
{len(np.intersect1d(datasets["previous_application"]["SK_ID_CURR"],
datasets["application_test"]["SK_ID_CURR"])):,}')
```

```
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()
```

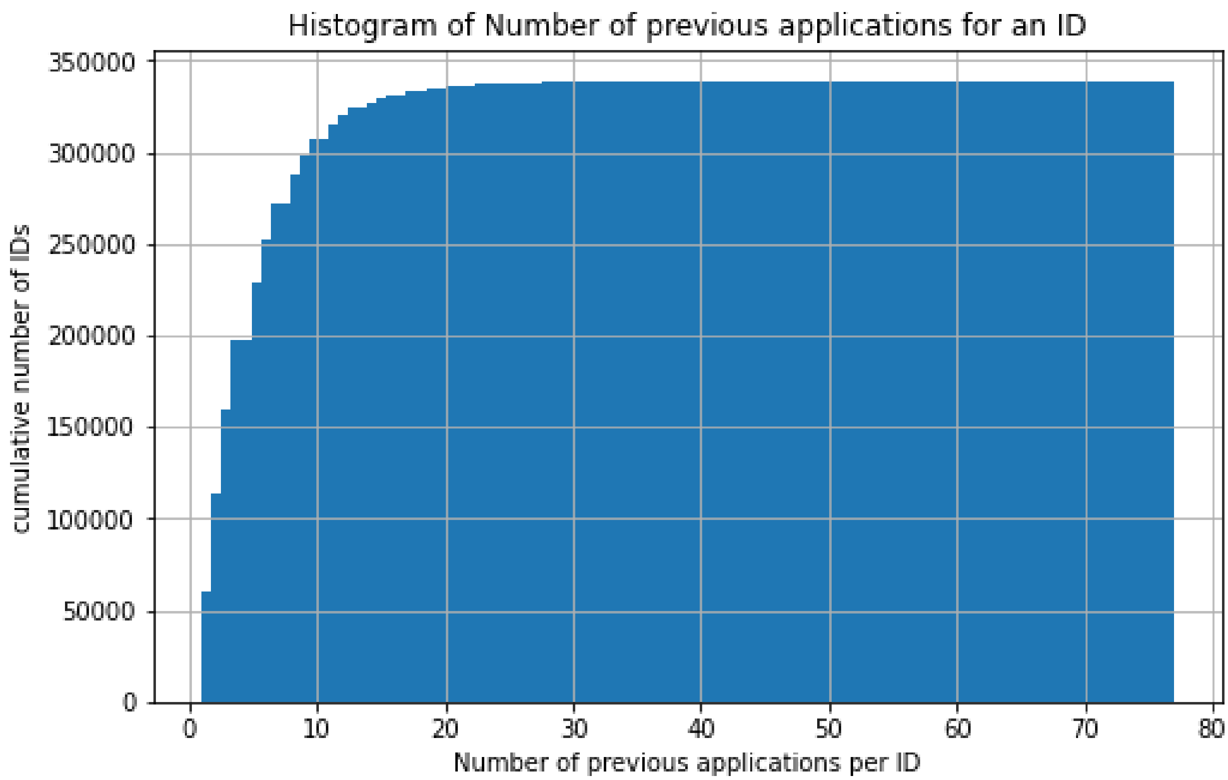


Histogram of Number of previous applications for an ID

```
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)
```

{"summary":"{\n \"name\": \"df\",\n \"rows\": 4,\n \"fields\": [\n   {\n   \"column\": \"A\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 3.0,\n   \"min\": 1.0,\n   \"max\": 7.0,\n   \"num_unique_values\": 3,\n   \"samples\": [\n   1.0,\n   4.0,\n   7.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"B\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 3.0,\n   \"min\": 2.0,\n   \"max\": 8.0,\n   \"num_unique_values\": 3,\n   \"samples\": [\n   2.0,\n   5.0,\n   8.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"C\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 3.0,\n   \"min\": 3.0,\n   \"max\": 9.0,\n   \"num_unique_values\": 3,\n   \"samples\": [\n   3.0,\n   6.0,\n   9.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe","variable_name":"df"}

```
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
```

```python
# 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
```

```python
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')
```

```python
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_GOOGS_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: (435637, 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         3951.0000
1      100006        24246.000        24246.000        24246.0000
2      100007        13010.985        16509.600        14760.2925
3      100008        17885.835        17885.835        17885.8350
4      100009         8996.760         8996.760         8996.7600
5      100011              NaN              NaN              NaN
6      100012         3012.075         3012.075         3012.0750
7      100013         6538.185        23153.985        14846.0850
8      100016         6725.205         6725.205         6725.2050
9      100017        16967.295        16967.295        16967.2950
```

```
   AMT_APPLICATION_min  AMT_APPLICATION_max  AMT_APPLICATION_mean  \
0              24835.5              24835.5               24835.5   
1             675000.0             675000.0              675000.0   
2             180000.0             225000.0              202500.0   
3             162598.5             162598.5              162598.5   
4              98239.5              98239.5               98239.5   
5                  0.0                  0.0                   0.0   
6              18720.0              18720.0               18720.0   
7                  0.0             450000.0              167010.0   
8              47115.0              47115.0               47115.0   
9             158040.0             158040.0              158040.0   

   range_AMT_APPLICATION  
0                    0.0  
1                    0.0  
2                45000.0  
3                    0.0  
4                    0.0  
5                    0.0  
6                    0.0  
7               450000.0  
8                    0.0  
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']
```

```python
# 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.

```python
# 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: (465193, 14)
X validation      shape: (96580, 14)
X test            shape: (82093, 14)
X X_kaggle_test   shape: (182319, 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: (465193, 14)

X_train['name'][0:5]:
       OCCUPATION_TYPE
631162      Core staff
130282        Managers
116972        Laborers
83830              NaN
509179      Core staff
X_train.shape: (465193, 14)

X_train['name'][0:5]:
       OCCUPATION_TYPE
631162      Core staff
130282        Managers
116972        Laborers
83830              NaN
509179      Core staff
Test driver:
[[0.]
 [1.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [1.]
 [0.]]
X_train['name'][0:10]:
       OCCUPATION_TYPE
631162      Core staff
130282        Managers
116972        Laborers
83830              NaN
509179      Core staff
288953     Sales staff
583711         Drivers
280108             NaN
542529        Managers
457086             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',
'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),
    ])

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 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
```

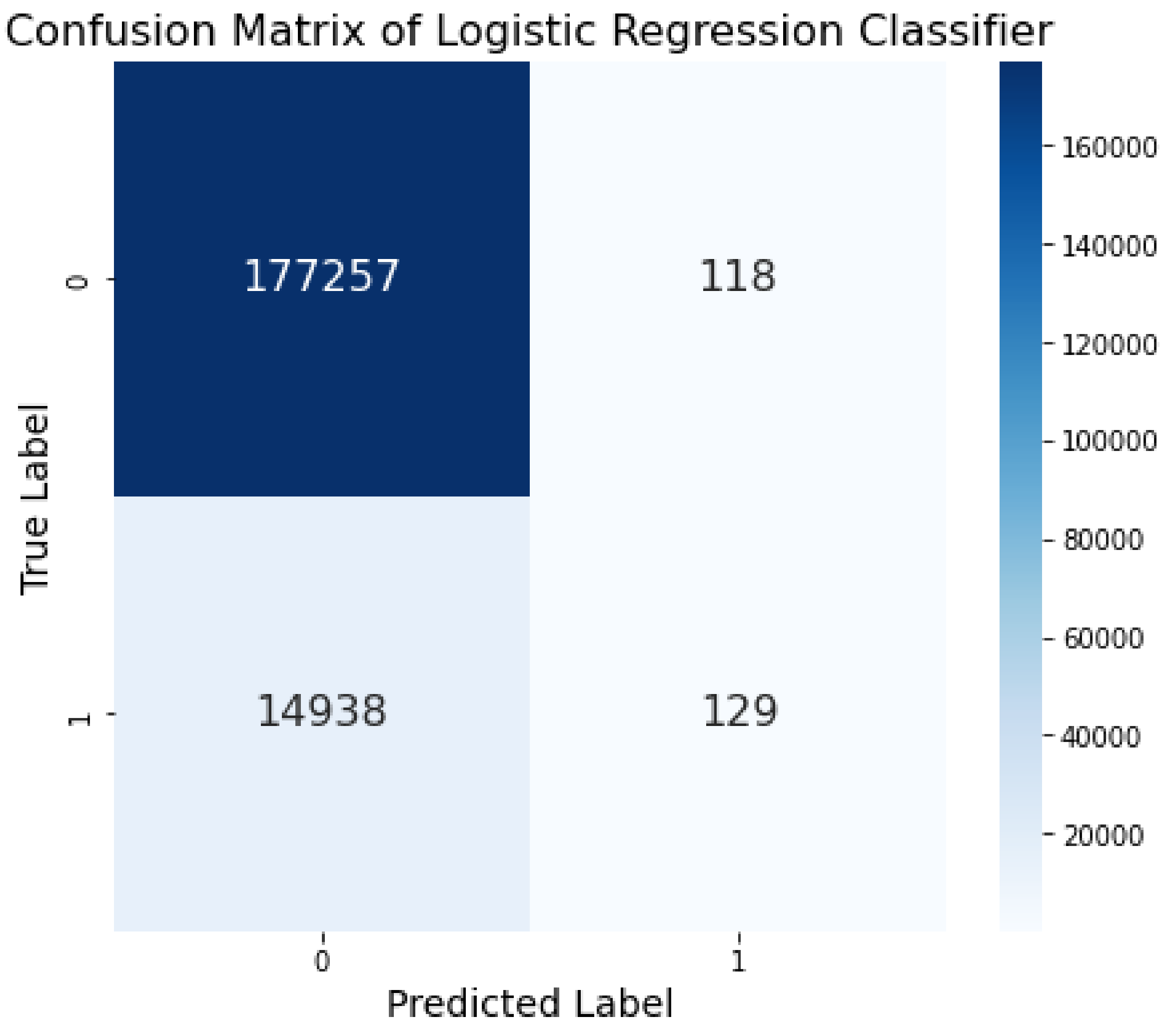
```
from sklearn.metrics import f1_score
exp_name = f"Baseline_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model.predict(X_train)),
```

```
                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
```

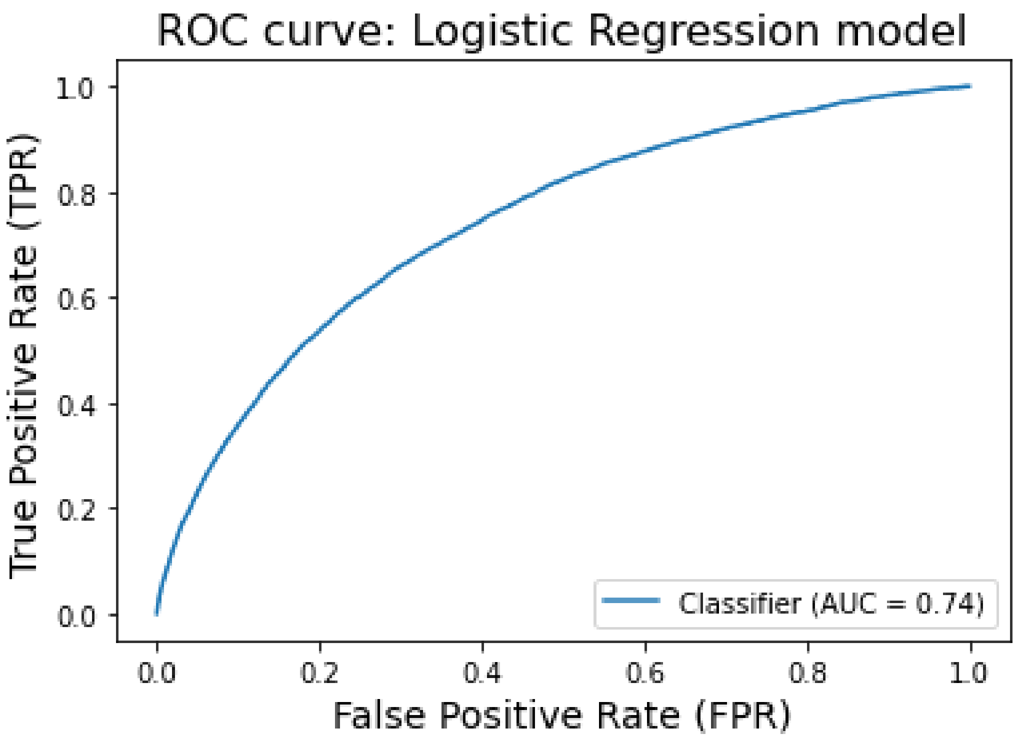
Confusion matrix for baseline model

```
# 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
```

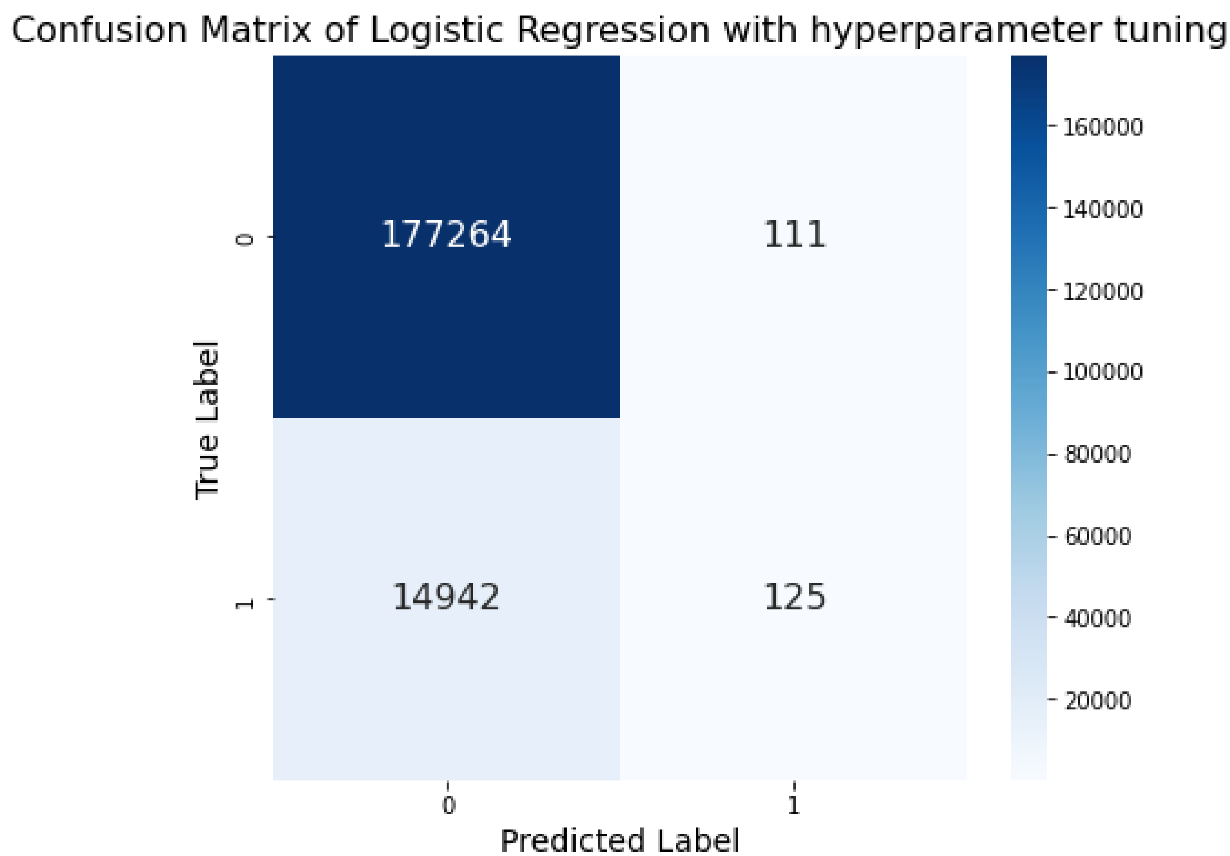
```
    accuracy                           0.92    192442
   macro avg       0.73      0.50      0.49    192442
weighted avg       0.89      0.92      0.89    192442
```

```
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
```

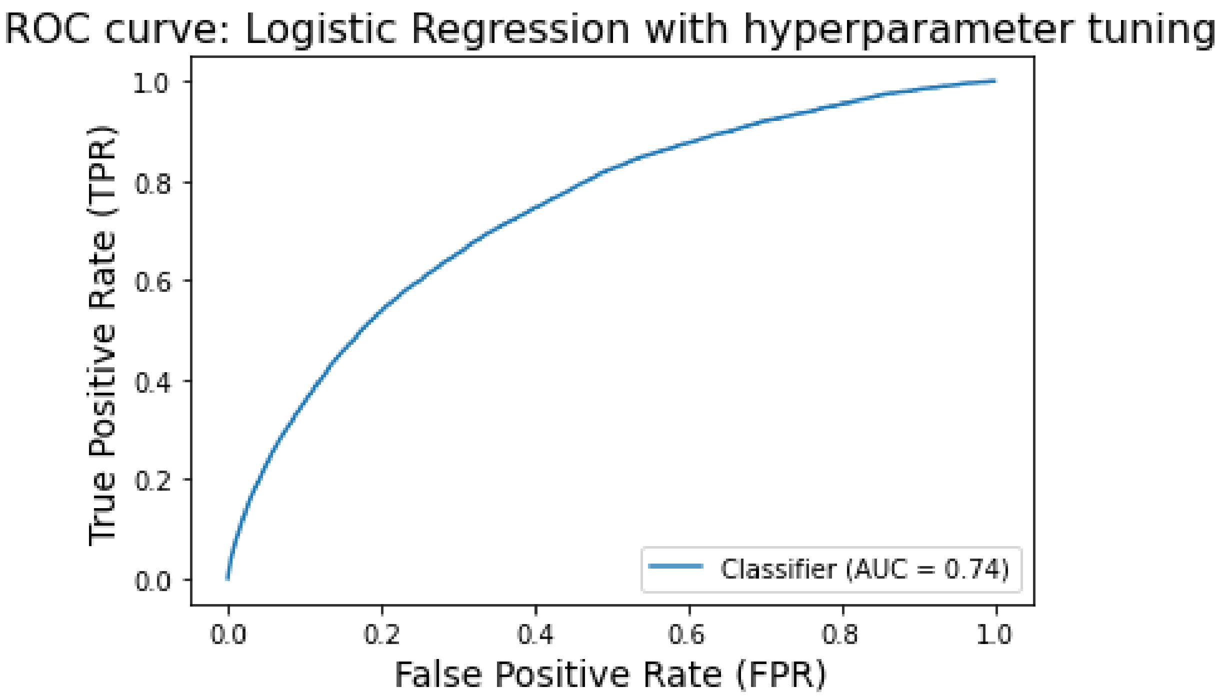
Create confusion matrix for Logistic Regression with hyperparameter tuning

```
# 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

Group member	Tasks completed
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
```

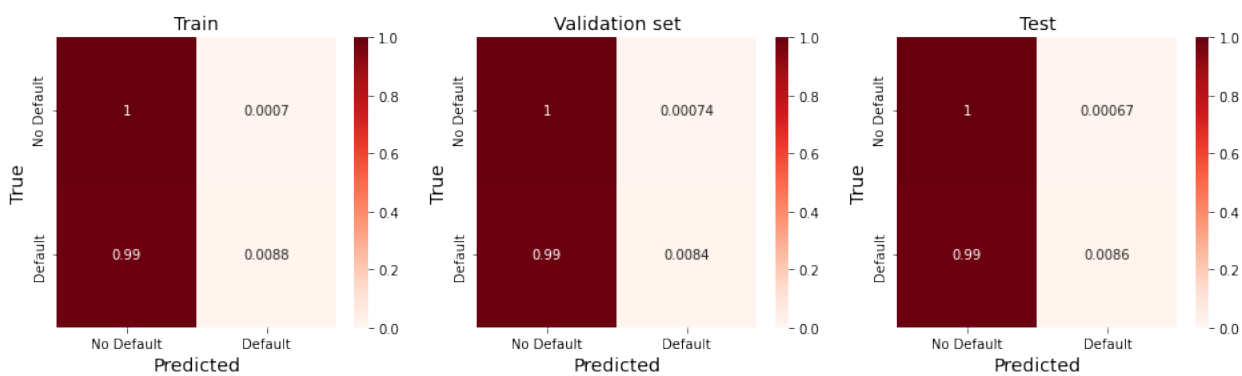
```
from time import time
from sklearn.model_selection import cross_validate
import sklearn.metrics as metrics
from sklearn.metrics import (accuracy_score, confusion_matrix,
f1_score, log_loss,
                             classification_report, roc_auc_score,
make_scorer,
                             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)
```

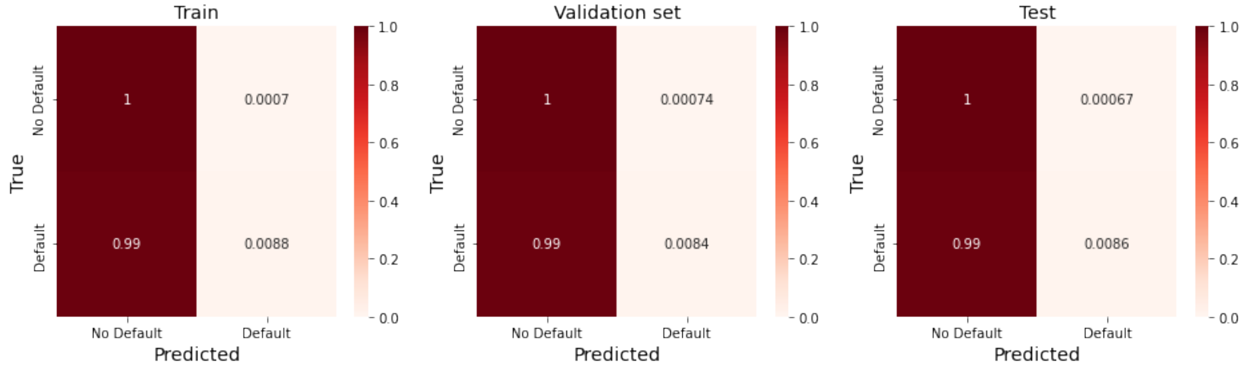
Setting Matircs and confusion matrix

```
# 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")
```

```python
    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)

```
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
```

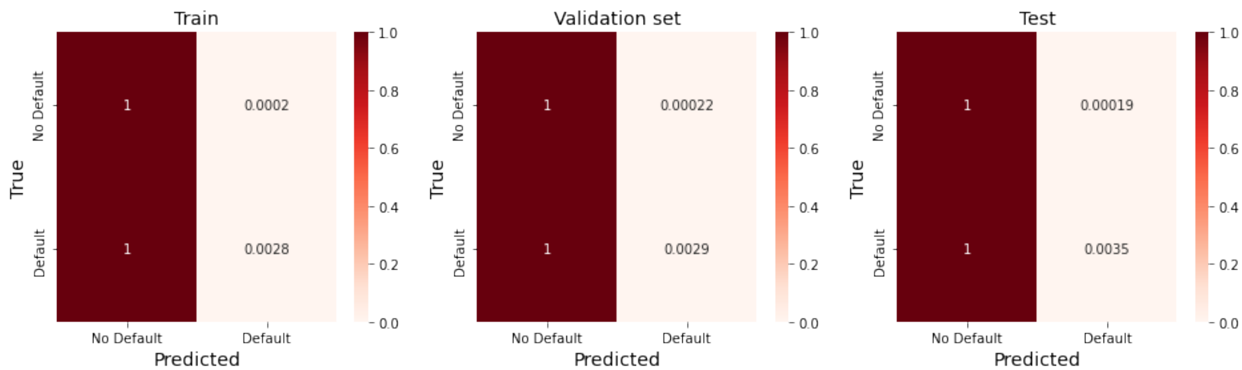
```
try:
    Log
except NameError:
    Log = pd.DataFrame(columns=["exp_name",
                                  "Train Acc",
                                  "Valid Acc",
                                  "Test  Acc",
                                  "Train AUC",
                                  "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
```

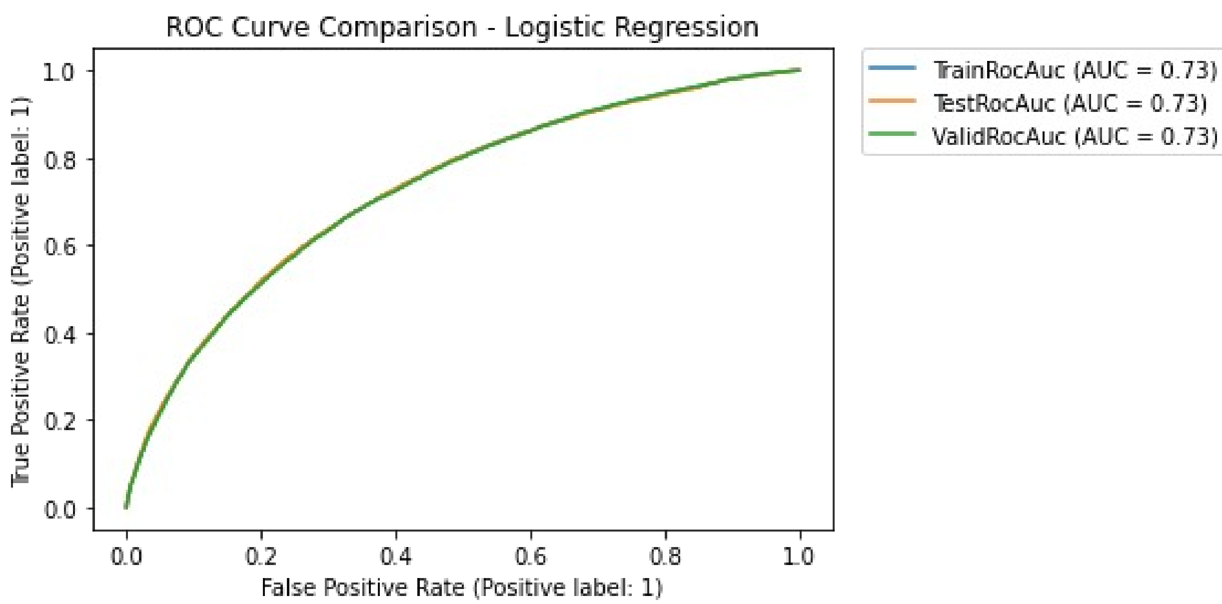
```
            if ft_sel == "SVM":
                full_pipeline_with_predictor = Pipeline([
                ("preparation", data_prep_pipeline),
                ("predictor", classifier)
                ])
            else:
                full_pipeline_with_predictor = Pipeline([
                ("preparation", 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)
```

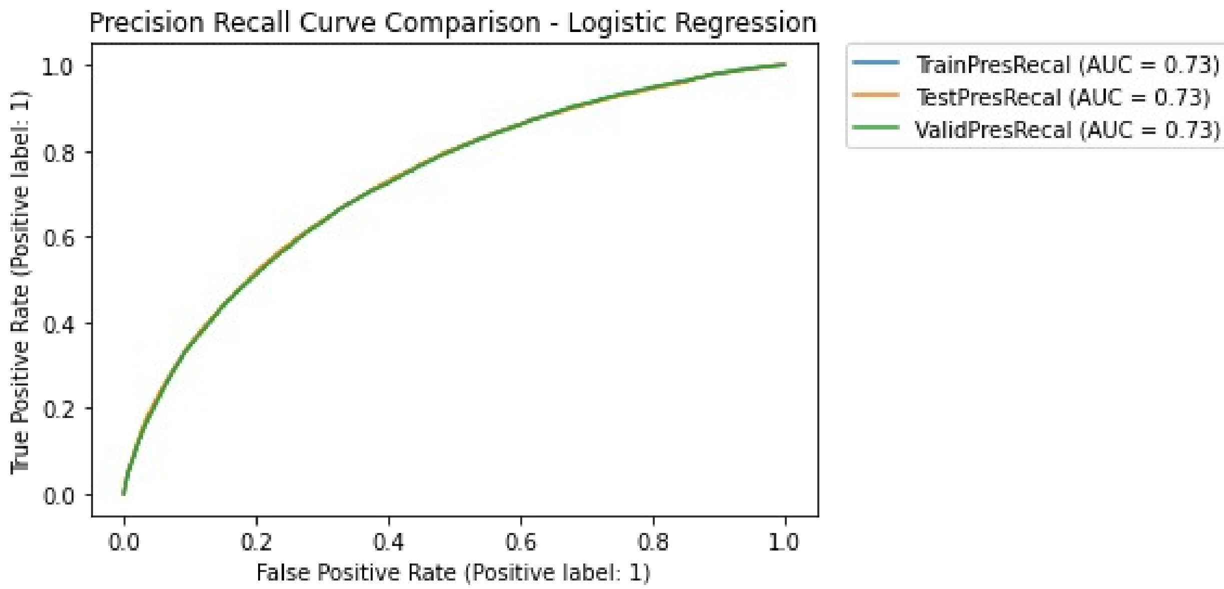
```
            valid_roc_auc_best =
np.round(best_train_scores['test_roc_auc'].mean(), 4)
            valid_time =
np.round(best_train_scores['score_time'].mean(), 4)


            # 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
```

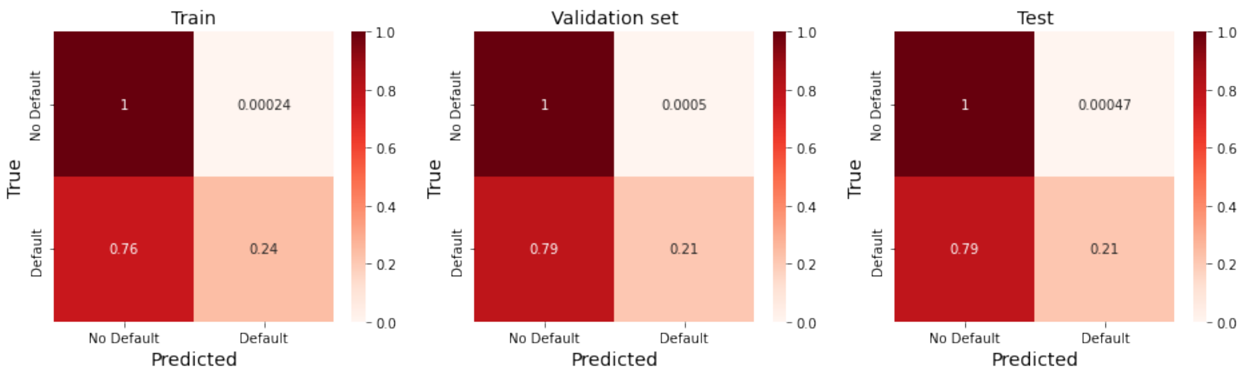
```
Log
```

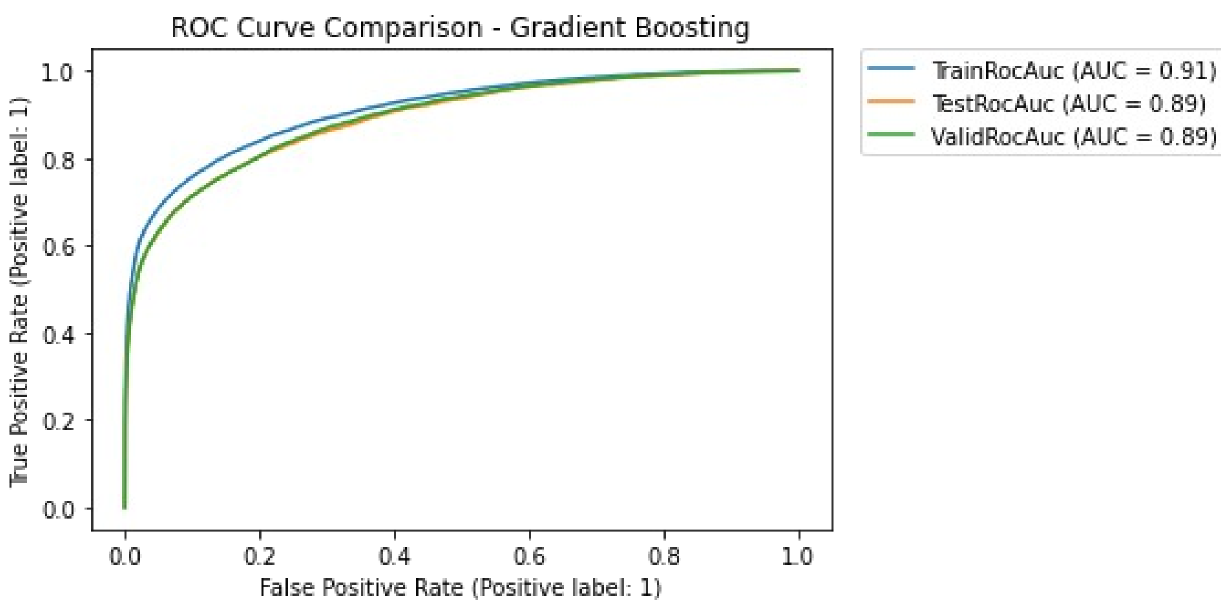
```
              exp_name  Train Acc  Valid Acc  Test  Acc  Train AUC
Valid AUC  \
0  Logistic Regression     0.9209     0.9212     0.9218     0.7279
0.7284

   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
```

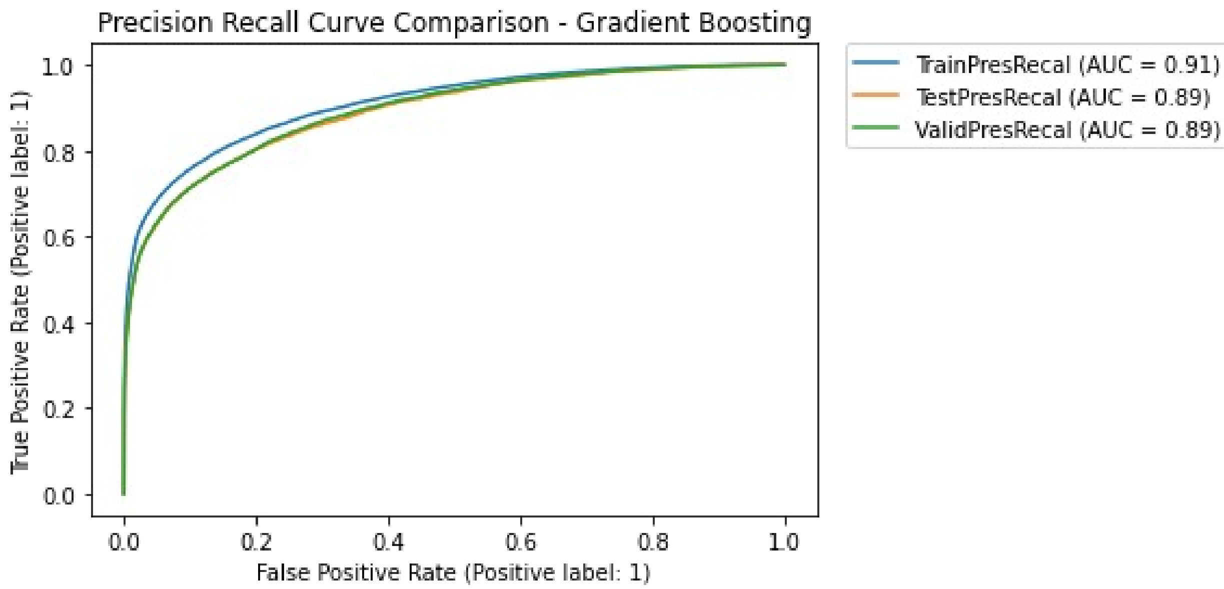
Gradient Boosting

```
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 ----
```

```
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

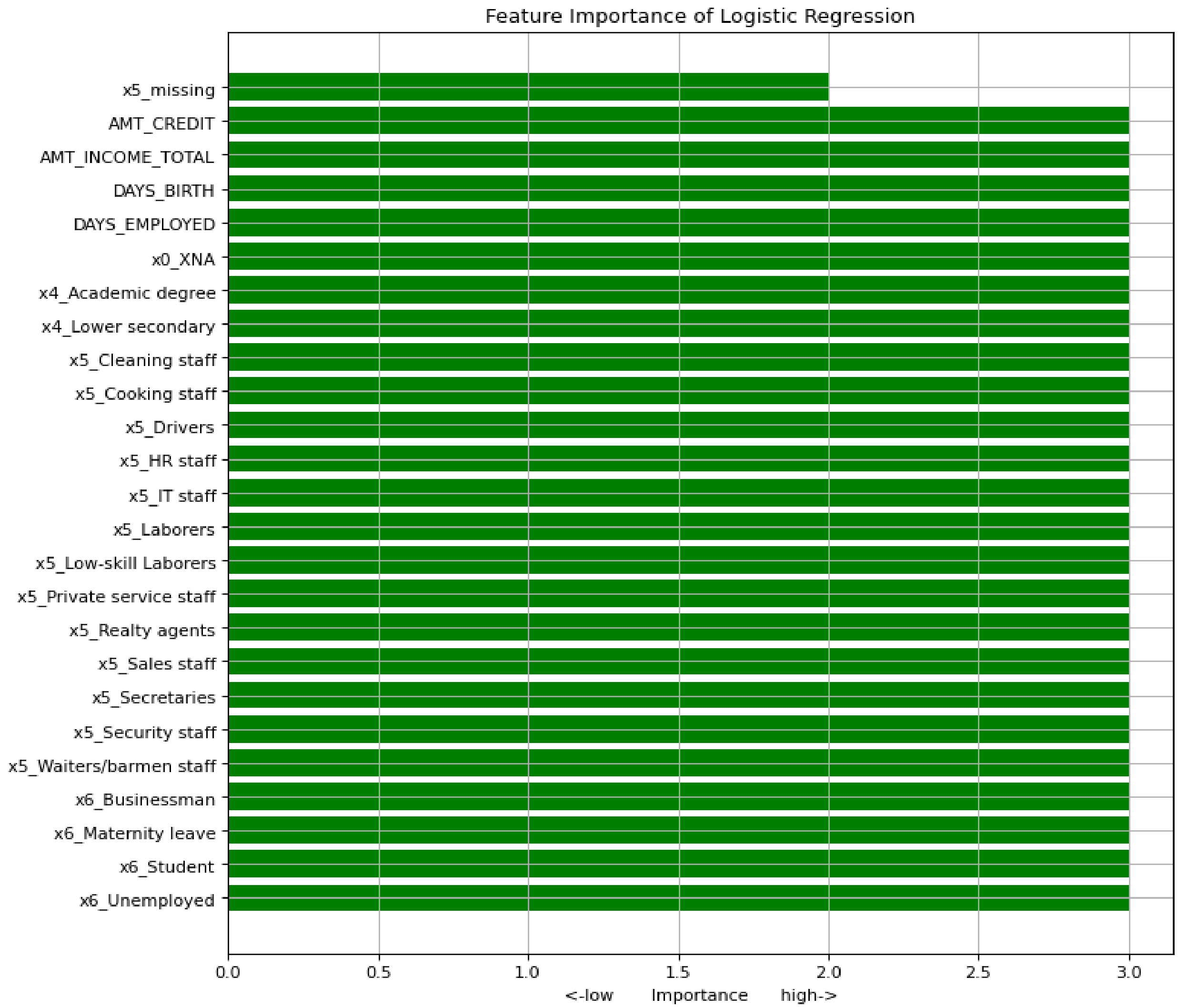
```
#
RunGridResearch(classifiers[5],cnfmatrix,fprs,tprs,precisions,recalls)
```

```
----  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
```

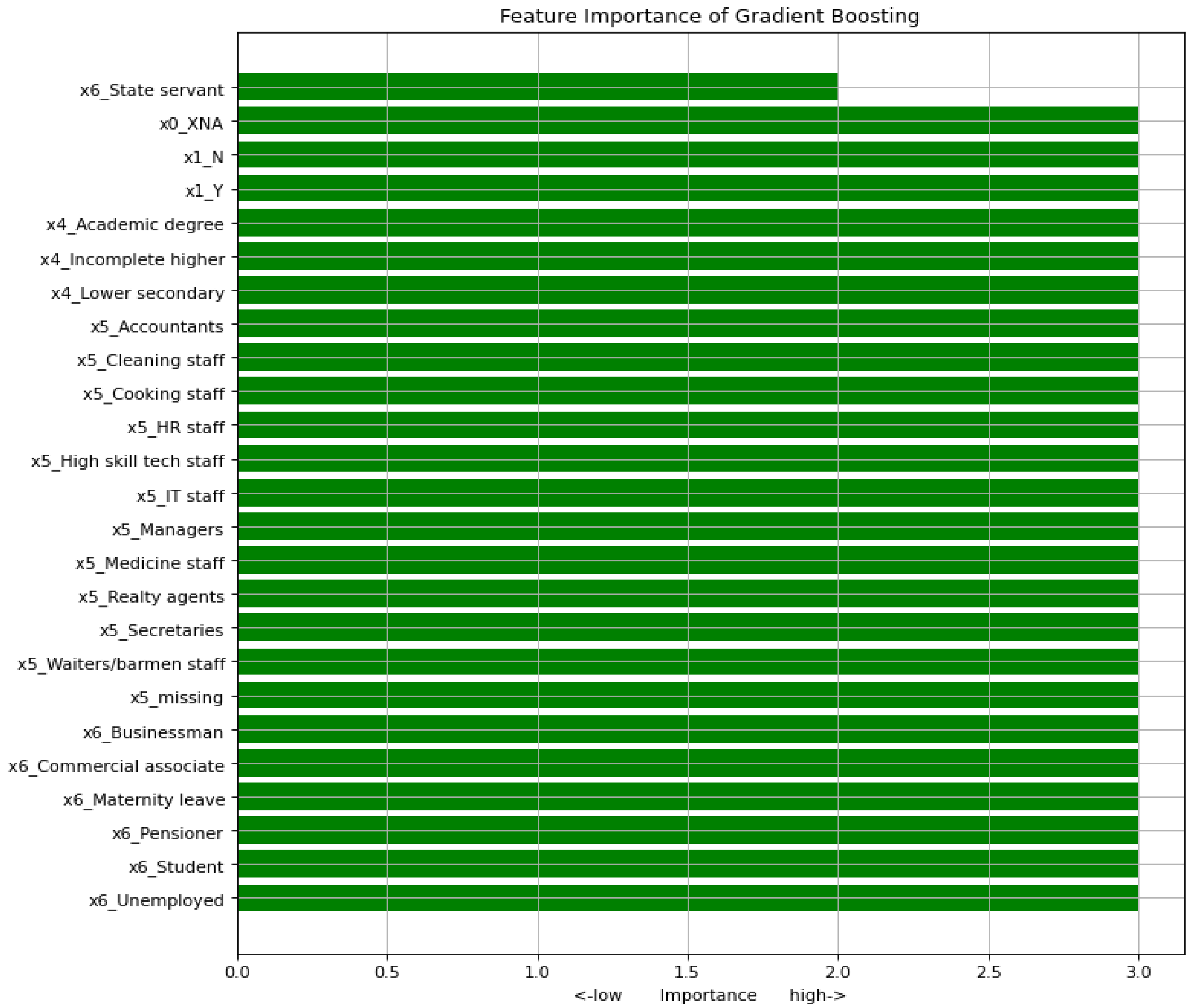
```
# featureAnalysis('RFE_best_model_Random Forest.pkl')

# Log
```

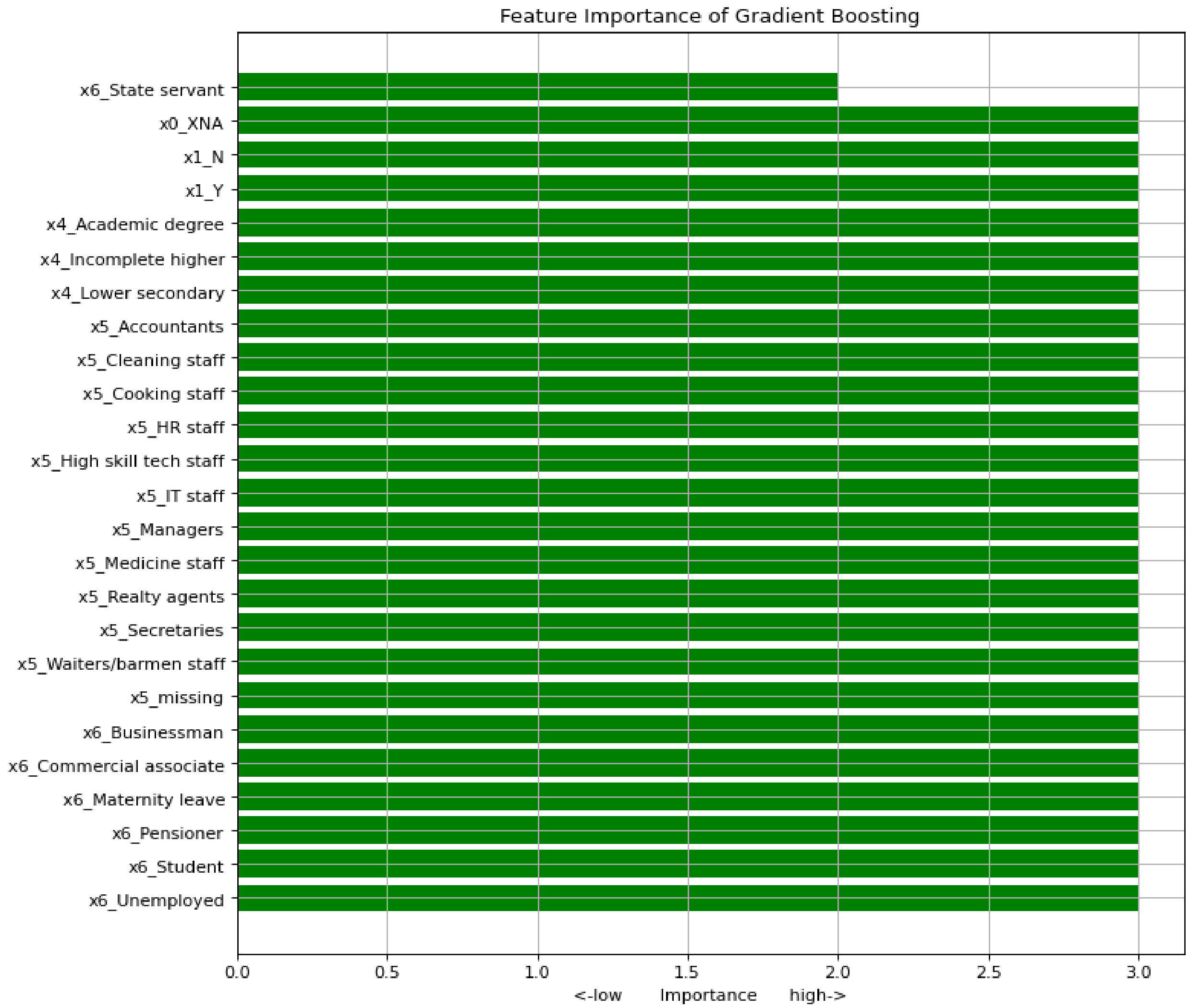
Model Validation (Step5)

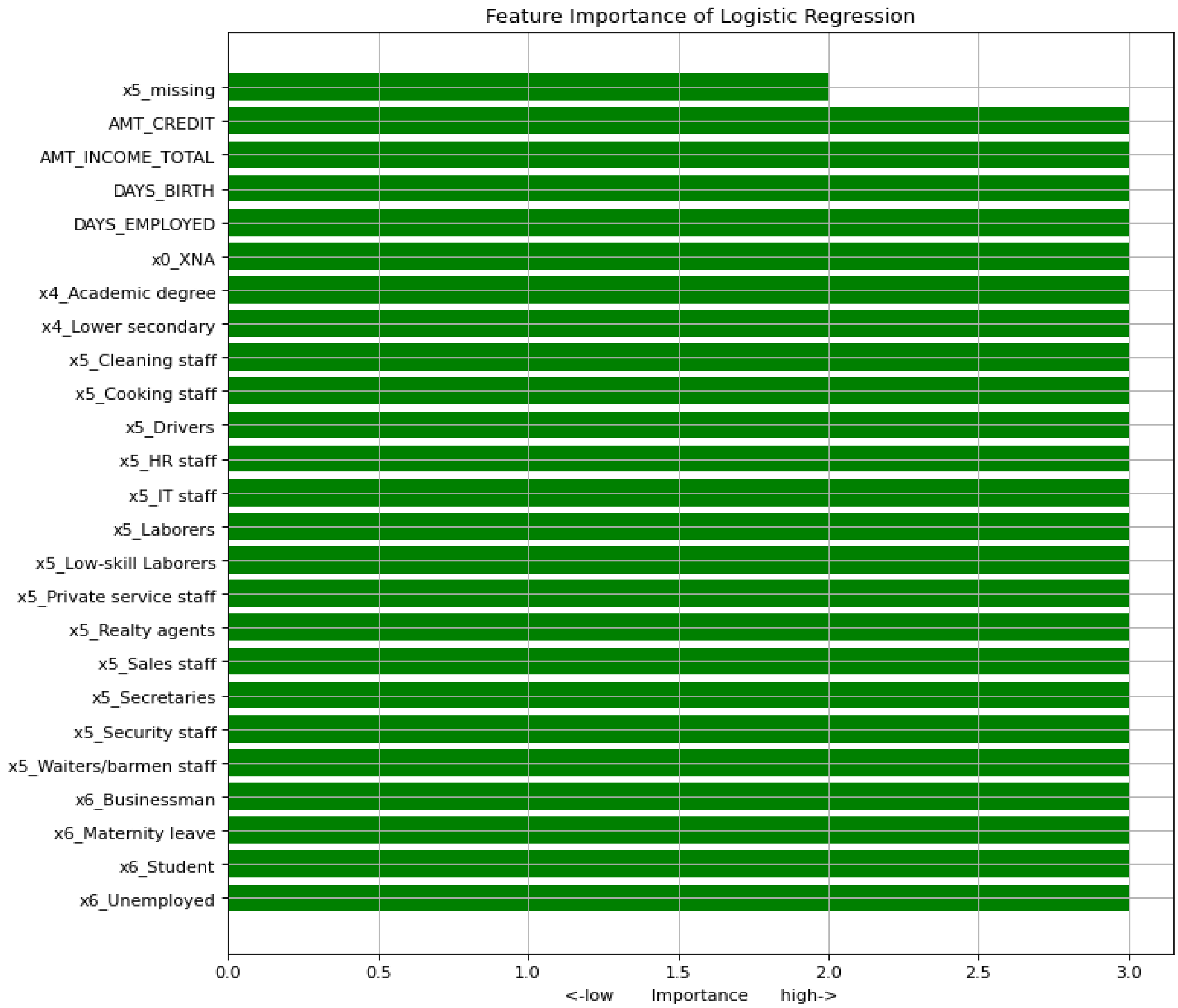
```
for name in names[1:-1]:
    plt.figure(figsize=(10, 10), dpi=80)
    features_df = 
features_list[name].sort_values(by=['feature_importance', 
'feature_name'], ascending=[False, False])
    orderednames = np.array(features_df.head(25)['feature_name'])
    Importancesinorder = np.array(features_df.head(25)
['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 Logistic Regression
x5_missing
AMT_CREDIT
AMT_INCOME_TOTAL
DAYS_BIRTH
DAYS_EMPLOYED
x0_XNA
x4_Academic degree
x4_Lower secondary
x5_Cleaning staff
x5_Cooking staff
x5_Drivers
x5_HR staff
x5_IT staff
x5_Laborers
x5_Low-skill Laborers
x5_Private service staff
x5_Realty agents
x5_Sales staff
x5_Secretaries
x5_Security staff
x5_Waiters/barmen staff
x6_Businessman
x6_Maternity leave
x6_Student
x6_Unemployed
0.0
0.5
1.0
1.5
2.0
2.5
3.0
<-low Importance high->

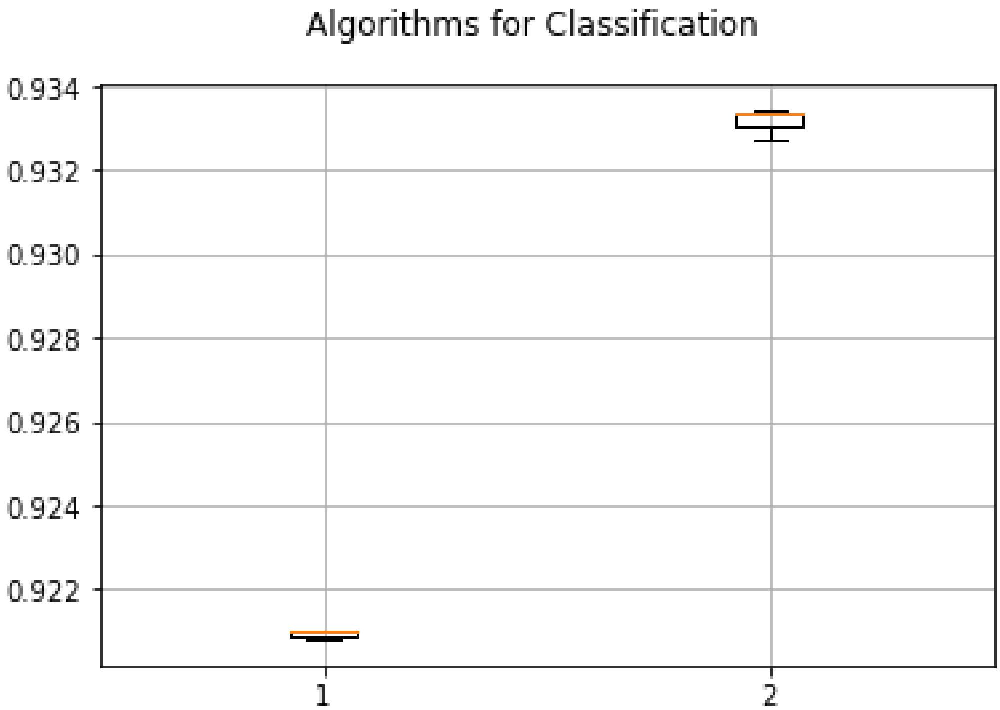

Feature Importance of Gradient Boosting
x6_State servant
x0_XNA
x1_N
x1_Y
x4_Academic degree
x4_Incomplete higher
x4_Lower secondary
x5_Accountants
x5_Cleaning staff
x5_Cooking staff
x5_HR staff
x5_High skill tech staff
x5_IT staff
x5_Managers
x5_Medicine staff
x5_Realty agents
x5_Secretaries
x5_Waiters/barmen 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->


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

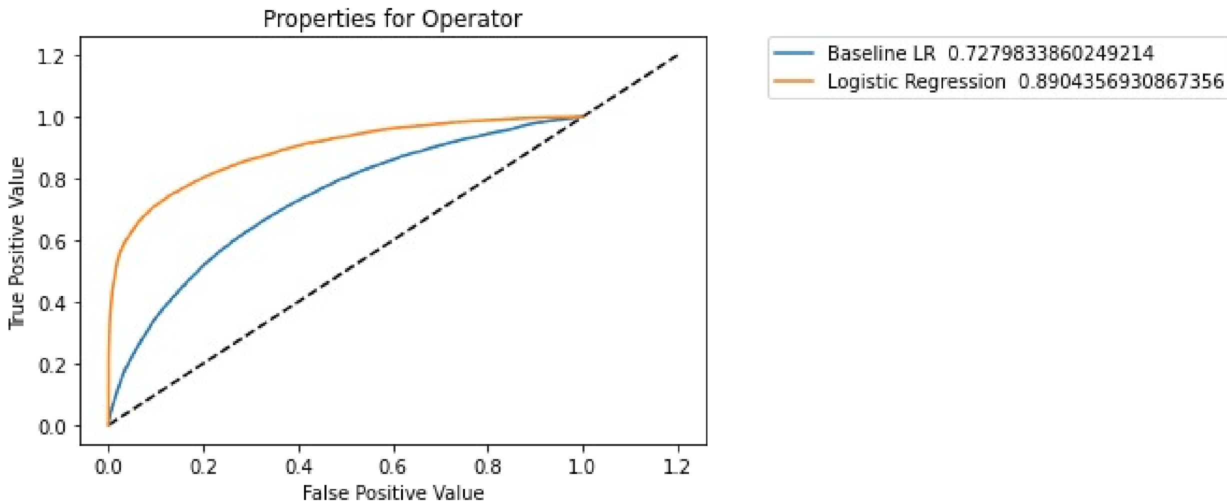
```
# Boxplots for the previous feature engineering
fig = pyplot.figure()
fig.suptitle('Algorithms for Classification')

# 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

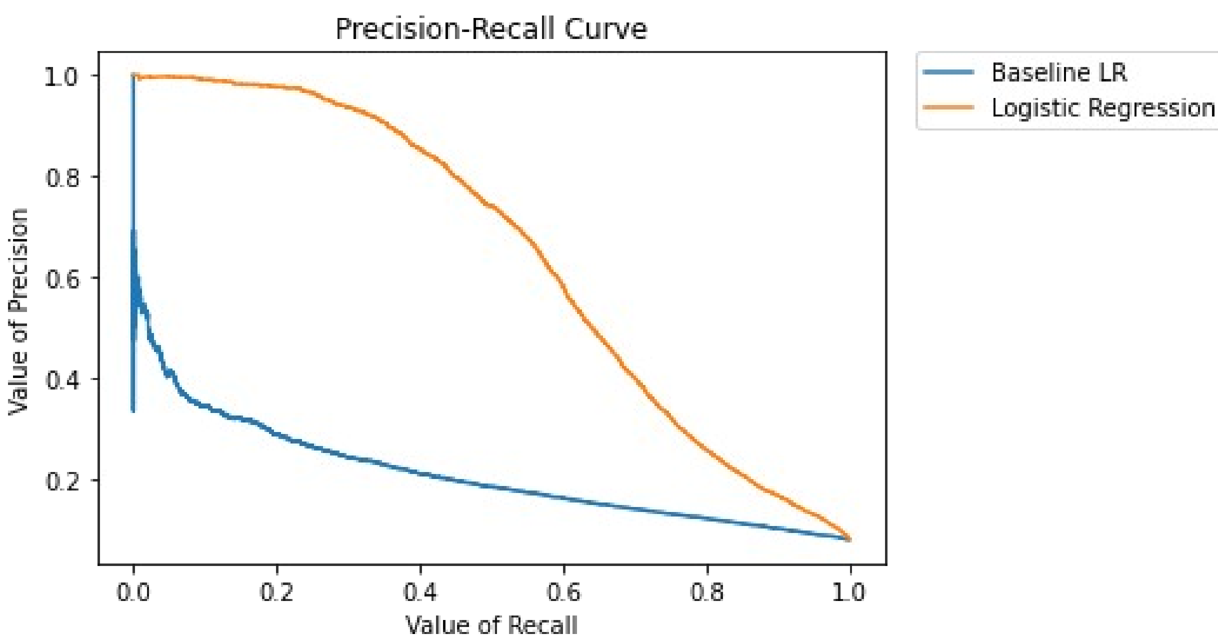
```
print(names)
# ROC fore each classifier
plt.plot([0,1.2],[0,1.2], 'k--')
for i in range(len(names)-1):
    plt.plot(fprs[i],tprs[i],label = names[i] + '   ' + str(scores[i]))

#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']
```



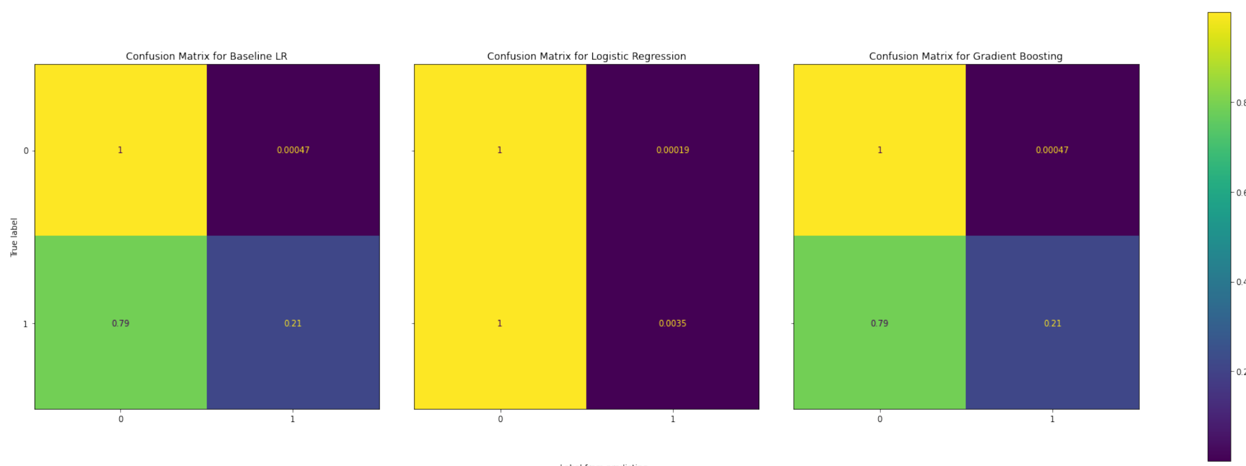
Precision Recall Curve

```
# 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 =
```

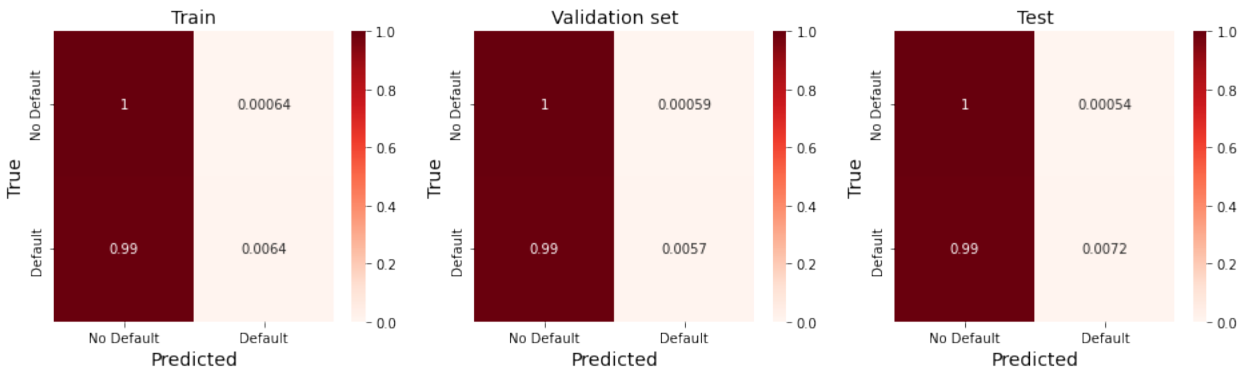
```
np.round(best_train_scores['test_log_loss'].mean(), 4)

            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
```

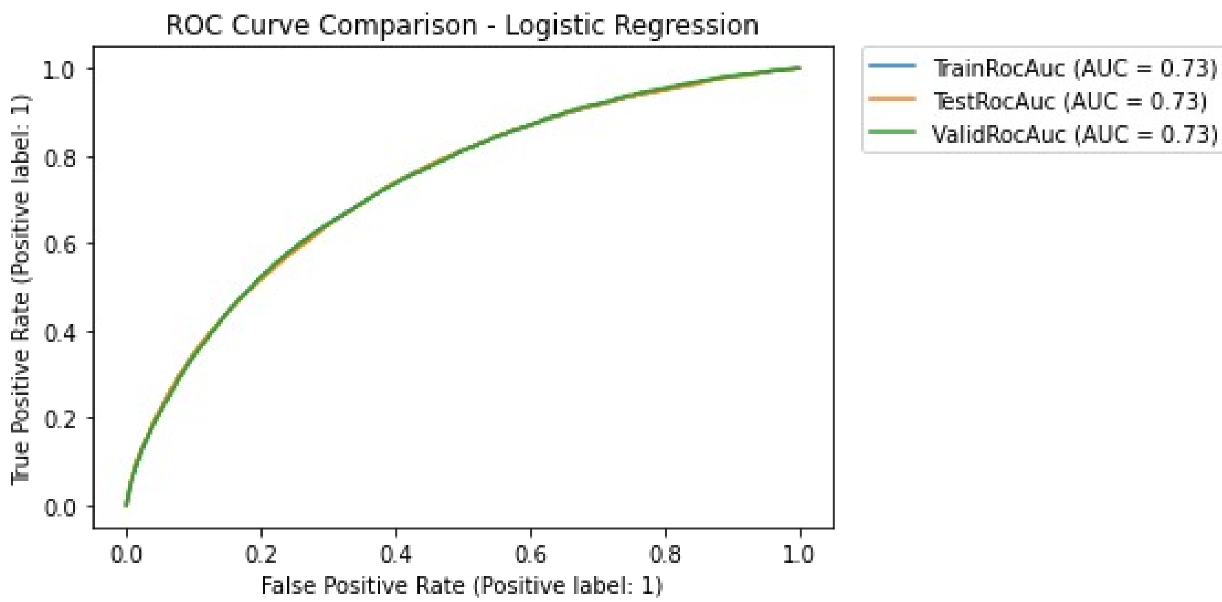
```
            final_best_clf[name]=pd.DataFrame([{'label':
grid_search.best_estimator_.named_steps['predictor'].__class__.__name_
_,
                                            'predictor':
grid_search.best_estimator_.named_steps['predictor']}])

            # 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))
```

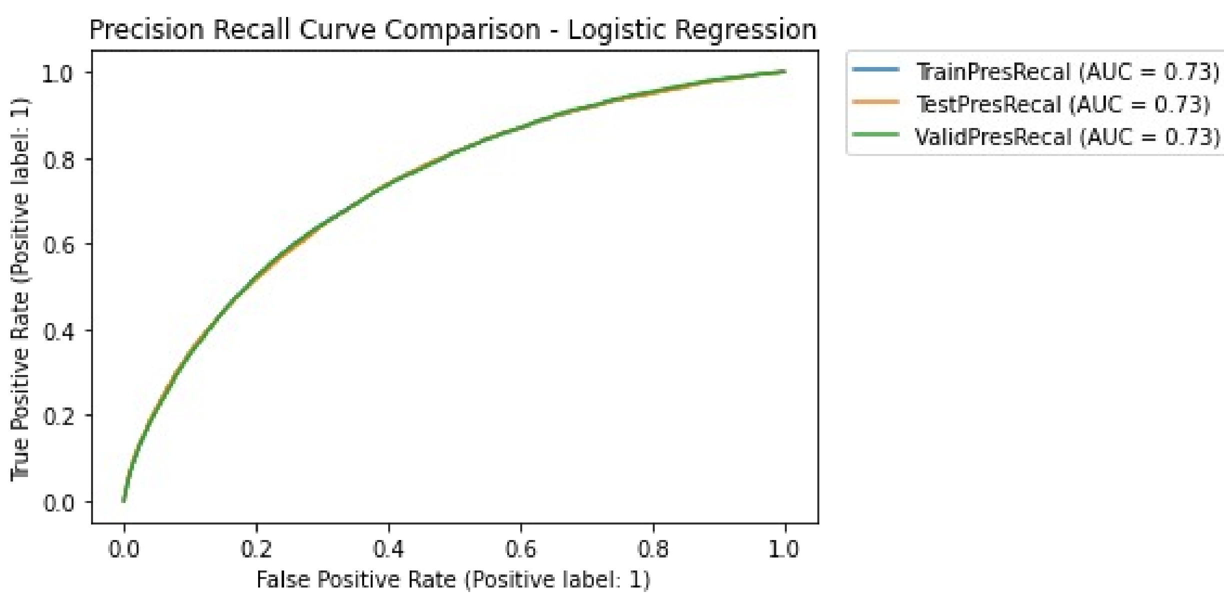
Logistic Regression

```
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
No Default
Default
1
0.00064
0.99
0.0064
1
0.00059
0.99
0.0057
1
0.00054
0.99
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
```

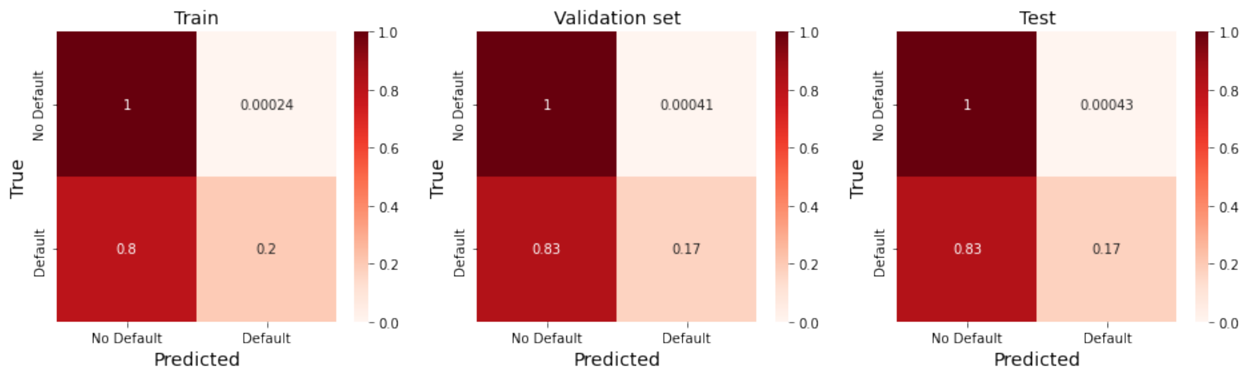
Random Forest

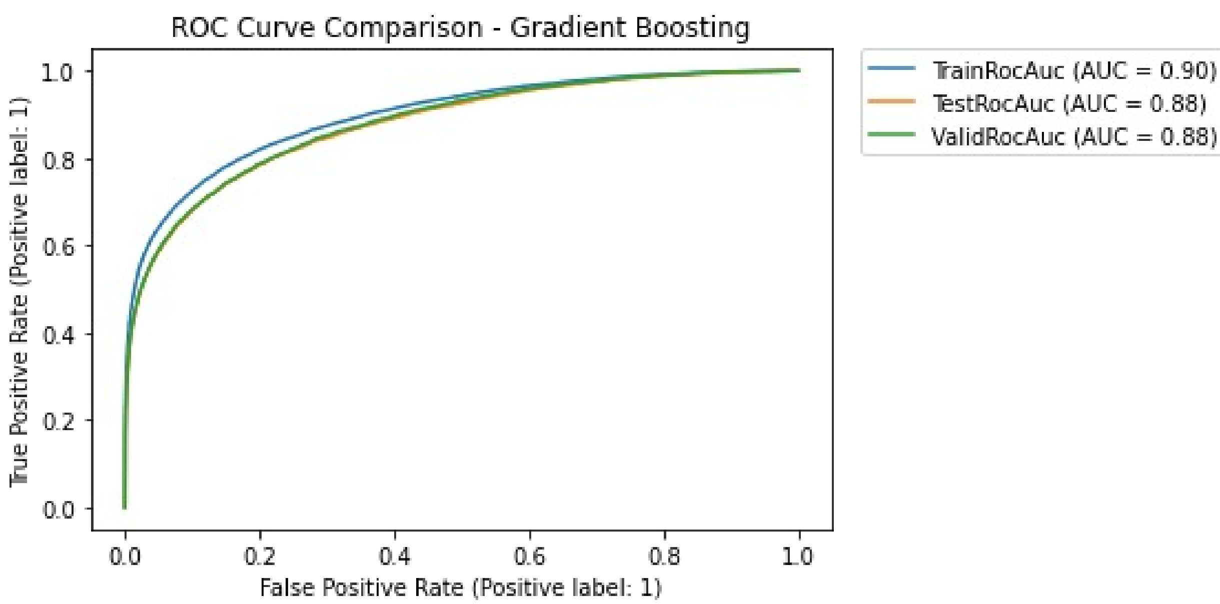
```
#
RunGridResearch(classifiers[3],cnfmatrix,fprs,tprs,precisions,recalls)

# Log
```

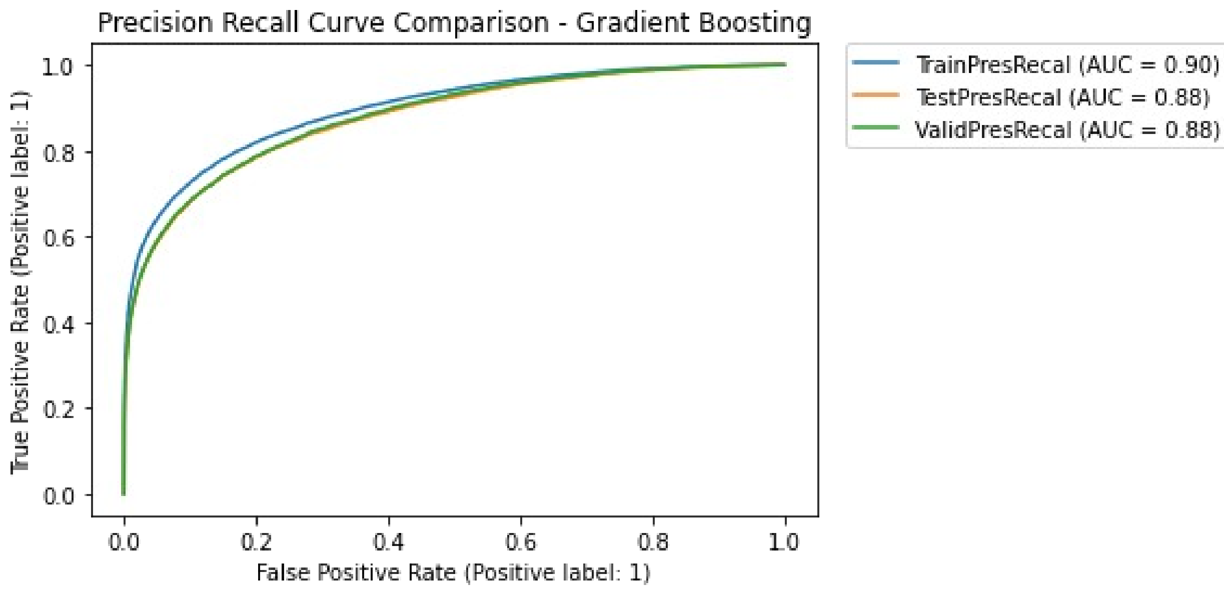
Gradient Boosting

```
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
```







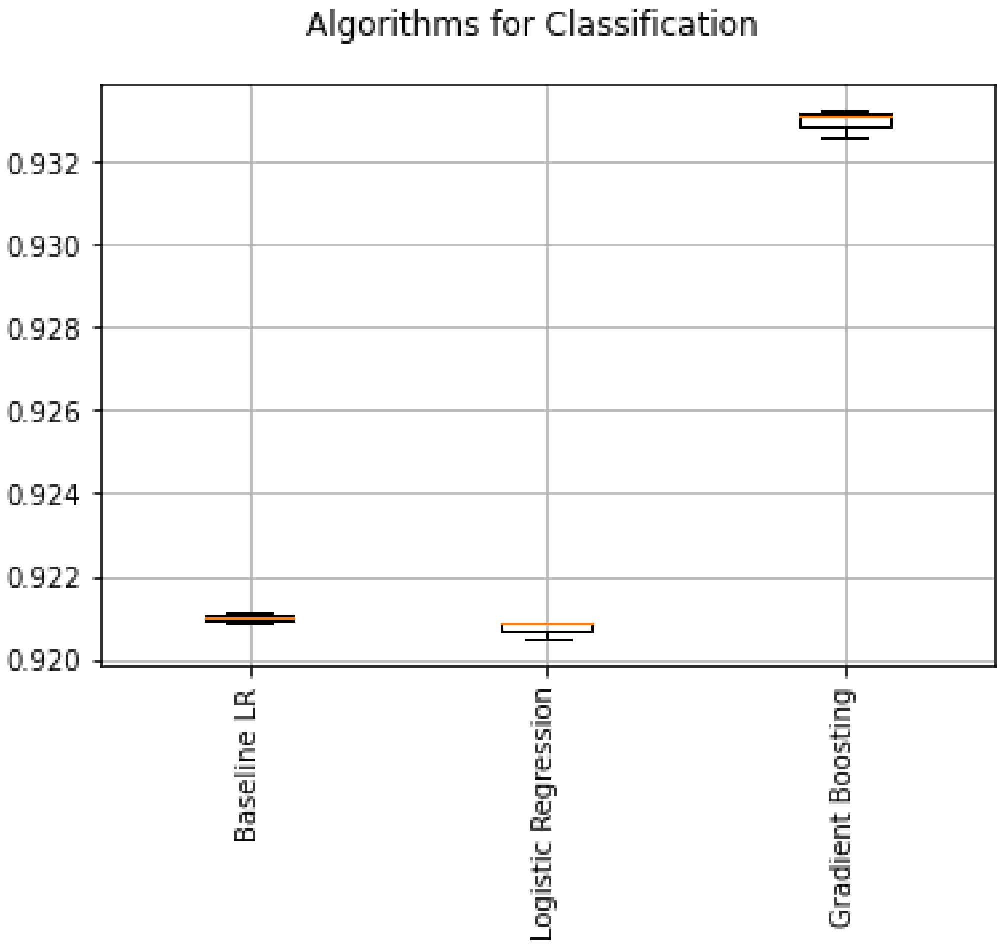

```
Best Parameters:
	predictor__max_depth: 10
	predictor__max_features: 10
	predictor__min_samples_leaf: 5
	predictor__n_estimators: 1000
	predictor__n_iter_no_change: 10
	predictor__subsample: 0.8
	predictor__tol: 0.01
	predictor__validation_fraction: 0.2
----  Gradient Boosting  Finish ----


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

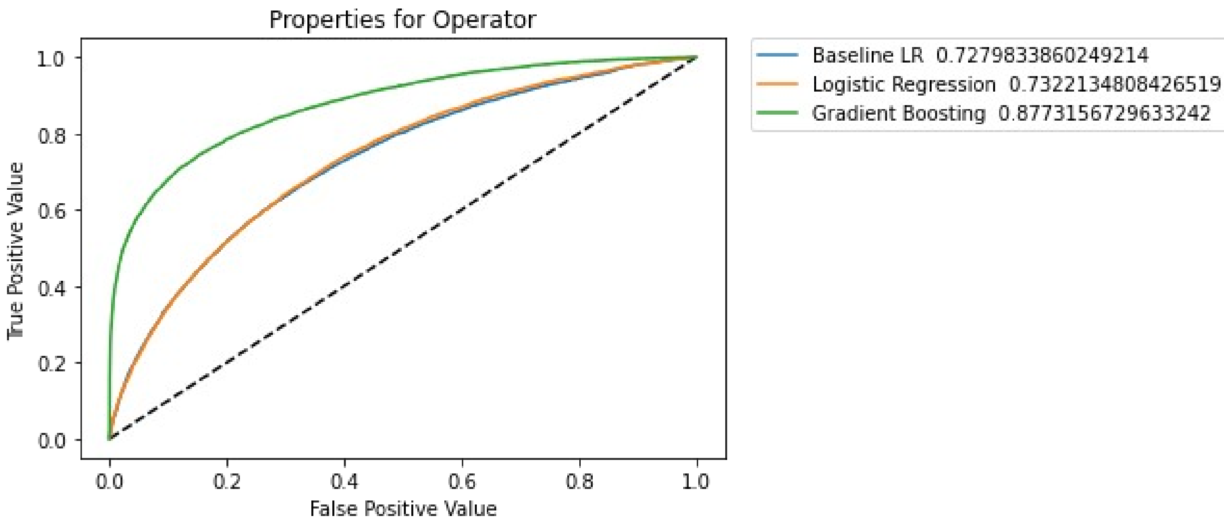
Boxplot Comparison with Cross Validation Results

```
# 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()
```



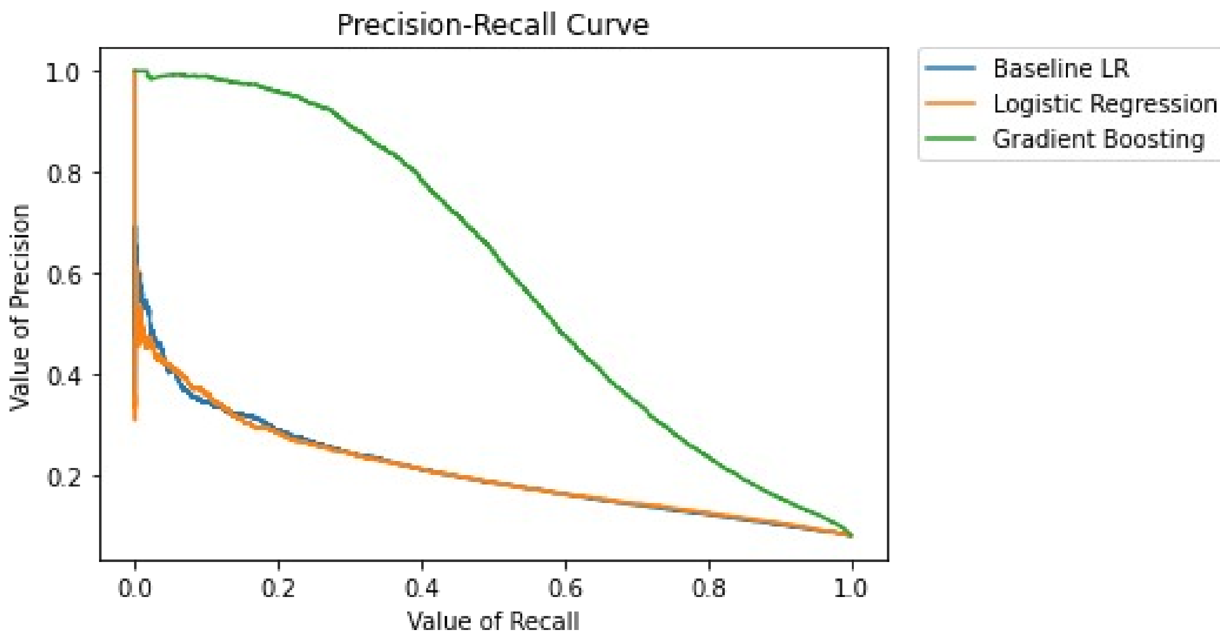
AUC : Area Under the ROC Curve

```
# 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()
```



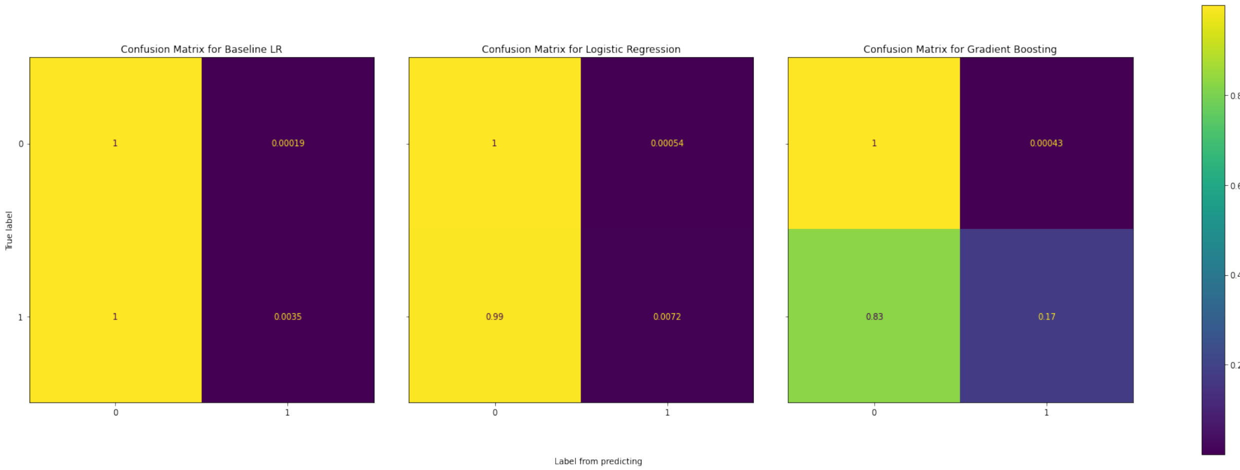
Precision Recall Curve

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

# 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'])
```

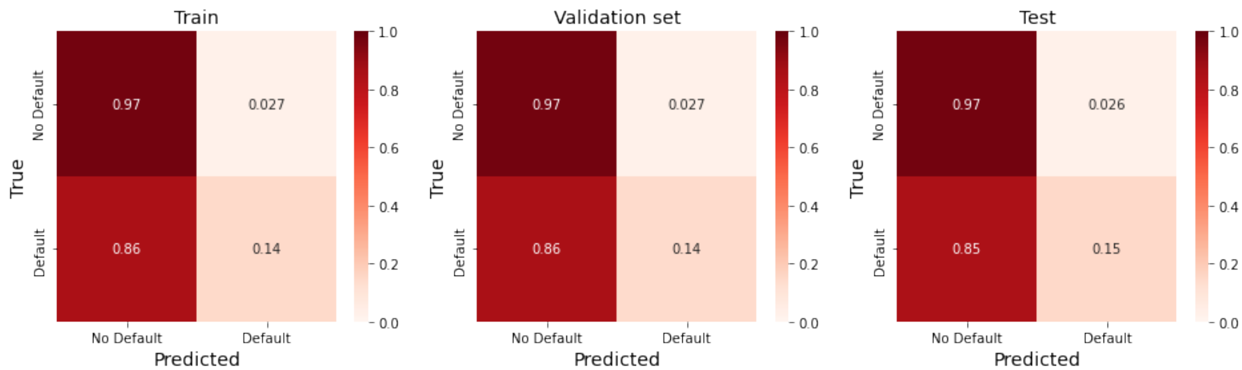
```
            names.append(name)

            # 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))
```

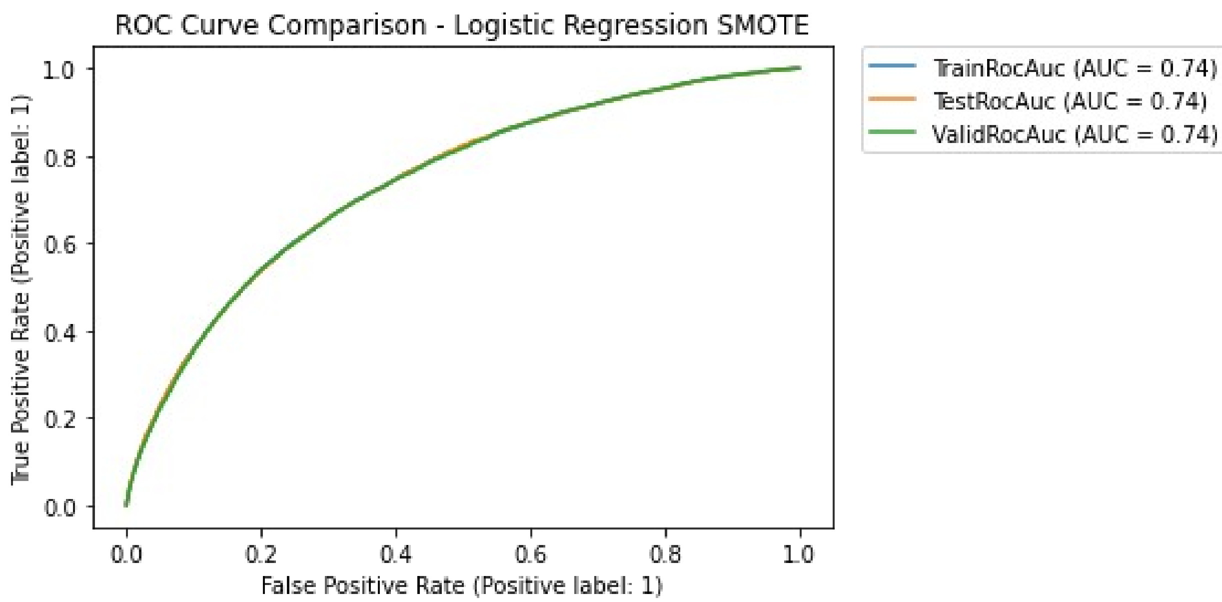
Logistic Regression

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

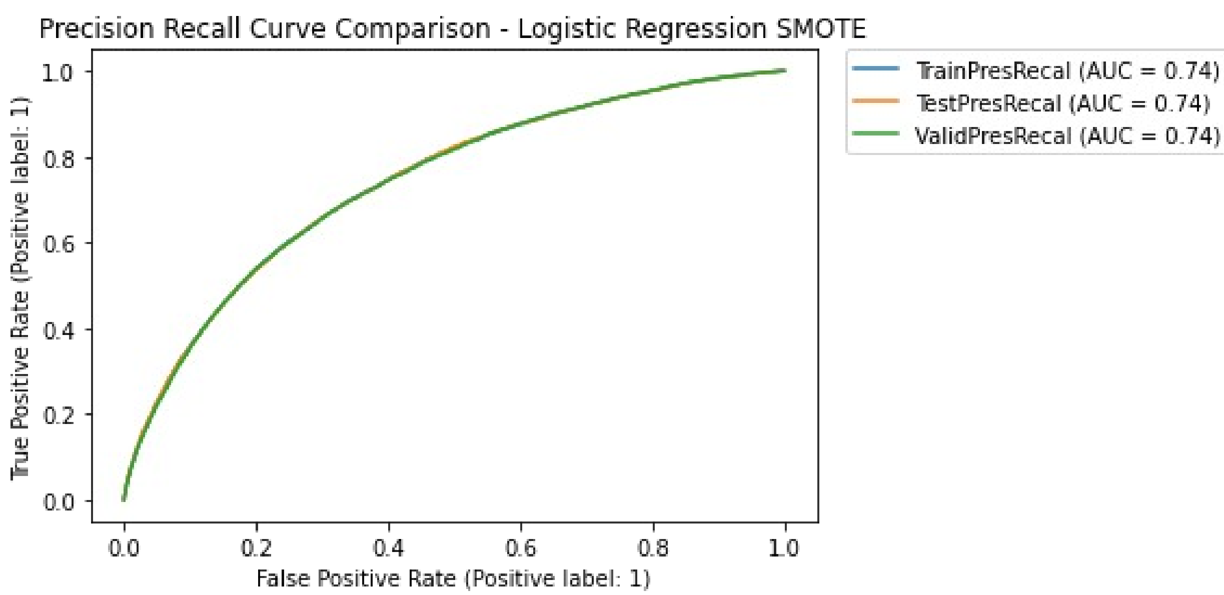
```
----  Logistic Regression SMOTE  Start----
Parameters are :
     C: (10, 1, 0.1, 0.01)
     penalty: ('l1', 'l2', 'elasticnet')
     tol: (0.0001, 1e-05)
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Cross validation using best estimator
Fitting and Predicting using the best estimator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



Train
Validation set
Test
True
No Default
Default
Predicted
0.97
0.027
0.86
0.14
0.026
0.85
0.15



ROC Curve Comparison - Logistic Regression SMOTE
TrainRocAuc (AUC = 0.74)
TestRocAuc (AUC = 0.74)
ValidRocAuc (AUC = 0.74)
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)



Precision Recall Curve Comparison - Logistic Regression SMOTE
TrainPresRecal (AUC = 0.74)
TestPresRecal (AUC = 0.74)
ValidPresRecal (AUC = 0.74)
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)

```
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

Group member	Tasks completed
	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.

Phase%203_Analysis%20Work%20Flow.png

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.

Phase%203_Figure%201_LR%20and%20GB%20models%20with%20hyperparameter%20tuning.png

Phase%203_Figure%202_models%20with%20hyperparameter%20tuning_selection.png

Phase%203_Figure%203_models%20with%20hyperparameter%20tuning_selection.png

Phase%203_Figure%204_models%20with%20hyperparameter%20tuning_selection.png

Phase%203_Figure%205_models%20with%20hyperparameter,selection,%20smote.png

Phase%203_Table%201.png

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.

References

- https://www.analyticsvidhya.com/blog/2021/08/conceptual-understanding-of-logistic-regression-for-data-science-beginners/
- https://www.analyticsvidhya.com/blog/2021/09/gradient-boosting-algorithm-a-complete-guide-for-beginners/#:~:text=What%20is%20Gradient%20Boosting%3F,%2C%20typically%20decision%20trees%2C%20sequentially.
- https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/
- https://www.analyticsvidhya.com/blog/2018/06/comprehensive-guide-for-ensemble-models/

Kaggle submission

%E1%84%89%E1%85%B3%E1%84%8F
%E1%85%B3%E1%84%85%E1%85%B5%E1%86%AB

%E1%84%89%E1%85%A3%E1%86%BA%202024-04-15%20%E1%84%8B
%E1%85%A9%E1%84%92%E1%85%AE%209.10.51.png

```
%%shell
jupyter nbconvert --to html
/Users/woojeongkin/Desktop/24Spring/P556/Final_Project/Phase_3/Group2_
Phase3_Ver9_notebook.ipynb
```

```
[NbConvertApp] WARNING | pattern
'/Users/woojeongkin/Desktop/24Spring/P556/Final_Project/Phase_3/Group2
_Phase3_Ver9_notebook.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE
RELEASES.

Options
=======
The options below are convenience aliases to configurable class-
options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an
error and include the error message in the cell output (the default
behaviour is to abort conversion). This flag is only relevant if '--
execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
```

```
    read a single notebook file from stdin. Write the resulting
notebook with default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False --
NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False --
NbConvertApp.export_format=notebook --FilesWriter.build_directory= --
ClearOutputPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True --
TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True --
TemplateExporter.exclude_input=True --
TemplateExporter.exclude_input_prompt=True]
--allow-chromium-download
    Whether to allow downloading chromium if no suitable version is
found on the system.
    Equivalent to: [--WebPDFExporter.allow_chromium_download=True]
--disable-chromium-sandbox
    Disable chromium security sandbox when converting to PDF..
    Equivalent to: [--WebPDFExporter.disable_sandbox=True]
--show-input
    Shows code input. This flag is only useful for dejavu users.
    Equivalent to: [--TemplateExporter.exclude_input=False]
--embed-images
    Embed the images as base64 dataurls in the output. This flag is
only useful for the HTML/WebPDF/Slides exports.
    Equivalent to: [--HTMLExporter.embed_images=True]
--sanitize-html
    Whether the HTML in Markdown cells and cell outputs should be
sanitized..
    Equivalent to: [--HTMLExporter.sanitize_html=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN',
'ERROR', 'CRITICAL']
```

```
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides', 'webpdf']
            or a dotted object name that represents the import path
for an
            ``Exporter`` class
    Default: ''
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_name]
--template-file=<Unicode>
    Name of the template file to use
    Default: None
    Equivalent to: [--TemplateExporter.template_file]
--theme=<Unicode>
    Template specific theme(e.g. the name of a JupyterLab CSS theme
distributed
    as prebuilt extension for the lab template)
    Default: 'light'
    Equivalent to: [--HTMLExporter.theme]
--sanitize_html=<Bool>
    Whether the HTML in Markdown cells and cell outputs should be
sanitized.This
    should be set to True by nbviewer or similar tools.
    Default: False
    Equivalent to: [--HTMLExporter.sanitize_html]
--writer=<DottedObjectName>
    Writer class used to write the
                                        results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                        results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    overwrite base name use for output files.
                can only be used when converting one notebook at a
time.
```

```
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each
notebook. To recover
                                  previous default behaviour
(outputting to the current
                                  working directory) use . as the flag
value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url
pointing to a copy
            of reveal.js.
            For speaker notes to work, this must be a relative path to
a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of
the
            current directory (from which the server is run).
            See the usage documentation

(https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-html-
slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb --to html

            Options include ['asciidoc', 'custom', 'html', 'latex',
'markdown', 'notebook', 'pdf', 'python', 'rst', 'script', 'slides',
'webpdf'].

            > jupyter nbconvert --to latex mynotebook.ipynb
```

```
            Both HTML and LaTeX support multiple output templates.
LaTeX includes
            'base', 'article' and 'report'.  HTML includes 'basic',
'lab' and
            'classic'. You can specify the flavor of the format used.

            > jupyter nbconvert --to html --template lab
mynotebook.ipynb

            You can also pipe the output to stdout, rather than a file

            > jupyter nbconvert mynotebook.ipynb --stdout

            PDF is generated via latex

            > jupyter nbconvert mynotebook.ipynb --to pdf

            You can get (and serve) a Reveal.js-powered slideshow

            > jupyter nbconvert myslides.ipynb --to slides --post
serve

            Multiple notebooks can be given at the command line in a
couple of
            different ways:

            > jupyter nbconvert notebook*.ipynb
            > jupyter nbconvert notebook1.ipynb notebook2.ipynb

            or you can specify the notebooks list in a config file,
containing::

                c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

            > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.


----------------------------------------------------------------------
-----
CalledProcessError                        Traceback (most recent call
last)
<ipython-input-2-0bb64444a457> in <cell line: 1>()
----> 1 get_ipython().run_cell_magic('shell', '', 'jupyter nbconvert
--to html
/Users/woojeongkin/Desktop/24Spring/P556/Final_Project/Phase_3/Group2_
Phase3_Ver9_notebook.ipynb\n')

/usr/local/lib/python3.10/dist-packages/google/colab/_shell.py in
run_cell_magic(self, magic_name, line, cell)
```

```
    332     if line and not cell:
    333       cell = ' '
--> 334     return super().run_cell_magic(magic_name, line, cell)
    335
    336

/usr/local/lib/python3.10/dist-packages/IPython/core/interactiveshell.
py in run_cell_magic(self, magic_name, line, cell)
   2471             with self.builtin_trap:
   2472                 args = (magic_arg_s, cell)
-> 2473                 result = fn(*args, **kwargs)
   2474             return result
   2475

/usr/local/lib/python3.10/dist-packages/google/colab/_system_commands.
py in _shell_cell_magic(args, cmd)
    110   result = _run_command(cmd, clear_streamed_output=False)
    111   if not parsed_args.ignore_errors:
--> 112     result.check_returncode()
    113   return result
    114

/usr/local/lib/python3.10/dist-packages/google/colab/_system_commands.
py in check_returncode(self)
    135   def check_returncode(self):
    136     if self.returncode:
--> 137       raise subprocess.CalledProcessError(
    138           returncode=self.returncode, cmd=self.args,
output=self.output
    139       )

CalledProcessError: Command 'jupyter nbconvert --to html
/Users/woojeongkin/Desktop/24Spring/P556/Final_Project/Phase_3/Group2_
Phase3_Ver9_notebook.ipynb
' returned non-zero exit status 255.
```

#Phase 4

```
!pip install -q pytorch-lightning

━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 801.9/801.9 kB 2.3 MB/s eta
0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 841.5/841.5 kB 28.1 MB/s eta
0:00:00

import torch
import torch.utils.data
import torch.nn as nn
```

```
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
import pytorch_lightning as pl
from torchmetrics import Accuracy
from pytorch_lightning.callbacks import ModelCheckpoint
from pytorch_lightning.loggers import TensorBoardLogger
from torch.utils.tensorboard import SummaryWriter
```

Develop neural network using PyTorch

Prep data

```
torch.manual_seed(0)
device = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")

# load data
hcdr_application = pd.read_csv("/application_train.csv")
X = hcdr_application.drop('TARGET', axis = 1)
y = hcdr_application.TARGET
print("Shapes:", X.shape, y.shape)

# train test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.15, random_state=42, shuffle = True)
X_train, X_validation, y_train, y_validation =
train_test_split(X_train, y_train, test_size=0.15, random_state=42,
shuffle=True)

## Scaling
numerical_features = X.select_dtypes(include =
['int64','float64']).columns
numerical_features = numerical_features.tolist()

num_pipeline =Pipeline([('std',StandardScaler()),
        ('imputer', SimpleImputer(strategy='mean'))
])
```

```
categorical_features = X.select_dtypes(include = ['object']).columns
categorical_features = categorical_features.tolist()


cat_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='most_frequent')),
        ('ohe', OneHotEncoder(sparse=False, handle_unknown="ignore"))
    ])

features = numerical_features + categorical_features

data_pipeline = ColumnTransformer([
       ("num_pipeline", num_pipeline, numerical_features),
       ("cat_pipeline", cat_pipeline, categorical_features)],
        remainder='drop',
        n_jobs=-1
    )


X_train = data_pipeline.fit_transform(X_train)
X_validation = data_pipeline.transform(X_validation) #Transform
validation set with the same constants
X_test = data_pipeline.transform(X_test) #Transform test set with the
same constants


y_train = y_train.to_numpy()
y_validation = y_validation.to_numpy()
y_test = y_test.to_numpy()

# convert numpy arrays to tensors
X_train_tensor = torch.from_numpy(X_train)
X_valid_tensor = torch.from_numpy(X_validation)
X_test_tensor = torch.from_numpy(X_test)
y_train_tensor = torch.from_numpy(y_train)
y_valid_tensor = torch.from_numpy(y_validation)
y_test_tensor = torch.from_numpy(y_test)

# create TensorDataset in PyTorch
hcdr_train = torch.utils.data.TensorDataset(X_train_tensor,
y_train_tensor)
hcdr_valid = torch.utils.data.TensorDataset(X_valid_tensor,
y_valid_tensor)
hcdr_test = torch.utils.data.TensorDataset(X_test_tensor,
y_test_tensor)

# print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
# create dataloader
# DataLoader is implemented in PyTorch, which will return an iterator
to iterate training data by batch.
```

```
train_batch_size = 96
valid_test_batch_size = 64
trainloader_hcdr = torch.utils.data.DataLoader(hcdr_train,
batch_size=train_batch_size, shuffle=True, num_workers=2)
validloader_hcdr = torch.utils.data.DataLoader(hcdr_valid,
batch_size=valid_test_batch_size, shuffle=True, num_workers=2)
testloader_hcdr = torch.utils.data.DataLoader(hcdr_test,
batch_size=valid_test_batch_size, shuffle=True, num_workers=2)
```

```
Shapes: (307511, 121) (307511,)
```

```
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/
backend/fork_exec.py:38: RuntimeWarning: os.fork() was called.
os.fork() is incompatible with multithreaded code, and JAX is
multithreaded, so this will likely lead to a deadlock.
  pid = os.fork()
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/backend/
fork_exec.py:38: RuntimeWarning: os.fork() was called. os.fork() is
incompatible with multithreaded code, and JAX is multithreaded, so
this will likely lead to a deadlock.
  pid = os.fork()
```

Define deep neural network

```
# Method to create, define and run a deep neural network model

def run_hcdr_model(
    hidden_layer_neurons=[32, 16, 8],
    opt=optim.SGD,
    epochs=5,
    learning_rate=1e-3
):

    writer = SummaryWriter()

    D_in = X_test.shape[1]  # Input layer neurons depend on the input
dataset shape
    D_out = 2  # Output layer neurons - depend on what you're trying
to predict, here, 2 classes: 0 and 1

    str_neurons = [str(h) for h in hidden_layer_neurons]
    arch_string = f"{D_in}-{'-'.join(str_neurons)}-{D_out}"

    layers = [
        torch.nn.Linear(D_in, hidden_layer_neurons[0]),  #
X.matmul(W1)
        nn.ReLU(),  # ReLU( X.matmul(W1))
    ]

    # Add hidden layers
    for i in range(1, len(hidden_layer_neurons)):
```

```
        prev, curr = hidden_layer_neurons[i - 1],
hidden_layer_neurons[i]
        layers.append(torch.nn.Linear(prev, curr))
        layers.append(nn.ReLU())


    # Add final layer
    layers.append(nn.Linear(hidden_layer_neurons[-1], D_out)) #
Relu( X.matmul(W1)).matmul(W2))

    # Use the nn package to define our model and loss function.
    # use the sequential API makes things simple
    model = torch.nn.Sequential(*layers)

    model.to(device)

    # use Cross Entropy and SGD optimizer.
    loss_fn = nn.CrossEntropyLoss()  #for classfication
    optimizer = opt(model.parameters(), lr=learning_rate)

    #summary(model, (4, 20))
    print('-'*50)
    print('Model:')
    print(model)
    print('-'*50)

    '''
    Training Process:
        Load a batch of data.
        Zero the grad.
        Predict the batch of the data through net i.e forward pass.
        Calculate the loss value by predict value and true value.
        Backprop i.e get the gradient with respect to parameters
        Update optimizer i.e gradient update
    '''

    loss_history = []
    acc_history = []
    def train_epoch(epoch, model, loss_fn, opt, train_loader):
        running_loss = 0.0
        count = 0
        y_pred = []
        epoch_target = []
        # dataset API gives us pythonic batching
        for batch_id, data in enumerate(train_loader):
            inputs, target = data[0].to(device), data[1].to(device)
            # 1:zero the grad, 2:forward pass, 3:calculate loss,  and
4:backprop!
            opt.zero_grad()
            preds = model(inputs.float()) #prediction over the input
```

```
data

            # compute loss and gradients
            loss = loss_fn(preds, target)    #mean loss for this batch

            loss.backward() #calculate nabla_w
            loss_history.append(loss.item())
            opt.step()  #update W
            y_pred.extend(torch.argmax(preds, dim=1).tolist())
            epoch_target.extend(target.tolist())
            #from IPython.core.debugger import Pdb as pdb;
pdb().set_trace() #breakpoint; dont forget to quit

            running_loss += loss.item()
            count += 1

        loss = np.round(running_loss/count, 3)

        #accuracy
        correct = (np.array(y_pred) == np.array(epoch_target))
        accuracy = correct.sum() / correct.size
        accuracy = np.round(accuracy, 3)
        return loss, accuracy



    #from IPython.core.debugger import Pdb as pdb;
pdb().set_trace() #breakpoint; dont forget to quit
    def evaluate_model(epoch, model, loss_fn, opt, data_loader, tag =
"Test"):
        overall_loss = 0.0
        count = 0
        y_pred = []
        epoch_target = []
        for i,data in enumerate(data_loader):
            inputs, target = data[0].to(device), data[1].to(device)
            preds = model(inputs.float())

            loss = loss_fn(preds, target)           # compute loss
value

            overall_loss += (loss.item())  # compute total loss to
save to logs
            y_pred.extend(torch.argmax(preds, dim=1).tolist())
            epoch_target.extend(target.tolist())
            count += 1

        # compute mean loss
        loss = np.round(overall_loss/count, 3)
        #accuracy
```

```
        correct = (np.array(y_pred) == np.array(epoch_target))
        accuracy = correct.sum() / correct.size
        accuracy = np.round(accuracy, 3)
        return loss, accuracy



    for epoch in range(epochs):
        # print(f"Epoch {epoch+1}")
        train_loss, train_accuracy = train_epoch(epoch, model,
loss_fn, optimizer, trainloader_hcdr)
        valid_loss, valid_accuracy = evaluate_model(epoch, model,
loss_fn, optimizer, validloader_hcdr, tag = "Validation")
        print(f"Epoch {epoch+1}: Train Accuracy: {train_accuracy}\t
Validation Accuracy: {valid_accuracy}")
    print("-"*50)
    test_loss, test_accuracy = evaluate_model(epoch, model, loss_fn,
opt, testloader_hcdr, tag="Test")

    for epoch in range(epochs):
      model.train()
      train_loss = 0.0
      correct = 0
      total = 0
      for inputs, targets in trainloader_hcdr:
          optimizer.zero_grad()
          outputs = model(inputs.float())
          loss = loss_fn(outputs, targets)
          loss.backward()
          optimizer.step()

          train_loss += loss.item()
          _, predicted = torch.max(outputs, 1)
          total += targets.size(0)
          correct += (predicted == targets).sum().item()

      train_accuracy = correct / total
      train_loss /= len(trainloader_hcdr)

      # Log training loss and accuracy
      writer.add_scalar('Loss/train', train_loss, epoch)
      writer.add_scalar('Accuracy/train', train_accuracy, epoch)

      # Validate the model
      model.eval()
      val_loss = 0.0
      correct = 0
      total = 0
      with torch.no_grad():
          for inputs, targets in validloader_hcdr:
```

```
            outputs = model(inputs.float())
            loss = loss_fn(outputs, targets)
            val_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            total += targets.size(0)
            correct += (predicted == targets).sum().item()

    val_accuracy = correct / total
    val_loss /= len(validloader_hcdr)

    # Log validation loss and accuracy
    writer.add_scalar('Loss/validation', val_loss, epoch)
    writer.add_scalar('Accuracy/validation', val_accuracy, epoch)

  # Close the TensorBoard writer
  writer.close()

  return arch_string, train_accuracy, valid_accuracy, test_accuracy
```

Run deep neural network and log to tensorboard for viz

```
torch.manual_seed(0)

hidden_layer_neurons = [64, 32, 16]
opt = optim.Adam
epochs = 10
learning_rate = 0.001

arch_string, train_accuracy, valid_accuracy, test_accuracy =
run_hcdr_model(
    hidden_layer_neurons,
    opt,
    epochs,
    learning_rate
)


try: hcdrLog
except : hcdrLog = pd.DataFrame(
    columns=[
        "Architecture string",
        "Optimizer",
        "Epochs",
        "Train accuracy",
        "Valid accuracy",
        "Test accuracy",
    ]
)

hcdrLog.loc[len(hcdrLog)] = [
```

```
    arch_string,
    f"{opt}",
    f"{epochs}",
    f"{train_accuracy * 100}%",
    f"{valid_accuracy * 100}%",
    f"{test_accuracy * 100}%",
]

hcdrLog
```

```
--------------------------------------------------
Model:
Sequential(
  (0): Linear(in_features=245, out_features=64, bias=True)
  (1): ReLU()
  (2): Linear(in_features=64, out_features=32, bias=True)
  (3): ReLU()
  (4): Linear(in_features=32, out_features=16, bias=True)
  (5): ReLU()
  (6): Linear(in_features=16, out_features=2, bias=True)
)
--------------------------------------------------

/usr/lib/python3.10/multiprocessing/popen_fork.py:66: RuntimeWarning:
os.fork() was called. os.fork() is incompatible with multithreaded
code, and JAX is multithreaded, so this will likely lead to a
deadlock.
  self.pid = os.fork()
/usr/lib/python3.10/multiprocessing/popen_fork.py:66: RuntimeWarning:
os.fork() was called. os.fork() is incompatible with multithreaded
code, and JAX is multithreaded, so this will likely lead to a
deadlock.
  self.pid = os.fork()

Epoch 1: Train Accuracy: 0.918    Validation Accuracy: 0.916
Epoch 2: Train Accuracy: 0.92     Validation Accuracy: 0.916
Epoch 3: Train Accuracy: 0.92     Validation Accuracy: 0.916
Epoch 4: Train Accuracy: 0.92     Validation Accuracy: 0.916
Epoch 5: Train Accuracy: 0.92     Validation Accuracy: 0.916
Epoch 6: Train Accuracy: 0.921    Validation Accuracy: 0.915
Epoch 7: Train Accuracy: 0.921    Validation Accuracy: 0.916
Epoch 8: Train Accuracy: 0.921    Validation Accuracy: 0.915
Epoch 9: Train Accuracy: 0.921    Validation Accuracy: 0.915
Epoch 10: Train Accuracy: 0.922   Validation Accuracy: 0.915
--------------------------------------------------
```


```
{"summary":"{\n  \"name\": \"hcdrLog\",\n  \"rows\": 1,\n  \"fields\":
[\n    {\n      \"column\": \"Architecture string\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 1,\n        \"samples\": [\n          \"245-64-
```

```
32-16-2\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Optimizer\",\n      \"properties\": {\n        \"dtype\":
\"string\",\n        \"num_unique_values\": 1,\n        \"samples\":
[\n          \"<class 'torch.optim.adam.Adam'>\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Epochs\",\n      \"properties\":
{\n        \"dtype\": \"string\",\n        \"num_unique_values\": 1,\n
\"samples\": [\n          \"10\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Train accuracy\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 1,\n        \"samples\": [\n
\"92.67202578136252%\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Valid accuracy\",\n      \"properties\": {\n        \"dtype\":
\"string\",\n        \"num_unique_values\": 1,\n        \"samples\":
[\n          \"91.5%\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Test accuracy\",\n      \"properties\": {\n        \"dtype\":
\"string\",\n        \"num_unique_values\": 1,\n        \"samples\":
[\n          \"91.8%\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"hcdrLog"}
```


Evaluating the neural network using TensorBoard

```
%reload_ext tensorboard
%tensorboard --logdir=runs
```

```
<IPython.core.display.Javascript object>
```

##Multitask Loss Function

Prepare data

```
# Set random seed and device
torch.manual_seed(0)
device = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")

# Load data
hcdr_application = pd.read_csv("/application_train.csv")
X = hcdr_application.drop('TARGET', axis=1)
y = hcdr_application['TARGET']
print("Shapes:", X.shape, y.shape)

# Data Cleaning and Preprocessing
numerical_features = X.select_dtypes(include=['int64',
'float64']).columns.tolist()
```

```
categorical_features =
X.select_dtypes(include=['object']).columns.tolist()

# Pipeline for numerical features
num_pipeline = Pipeline([
    ('std', StandardScaler()),
    ('imputer', SimpleImputer(strategy='mean'))
])

# Pipeline for categorical features
cat_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('ohe', OneHotEncoder(sparse=False, handle_unknown="ignore"))
])

# Combine pipelines
data_pipeline = ColumnTransformer([
    ("num_pipeline", num_pipeline, numerical_features),
    ("cat_pipeline", cat_pipeline, categorical_features)],
    remainder='drop',
    n_jobs=-1
)

# Apply the data pipeline
X_transformed = data_pipeline.fit_transform(X)

# Split the data into training, validation, and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_transformed, y,
test_size=0.15, random_state=42, shuffle=True)
X_train, X_validation, y_train, y_validation =
train_test_split(X_train, y_train, test_size=0.15, random_state=42,
shuffle=True)

# Convert numpy arrays to tensors
X_train_tensor = torch.from_numpy(X_train).float()
X_validation_tensor = torch.from_numpy(X_validation).float()
X_test_tensor = torch.from_numpy(X_test).float()
y_train_tensor = torch.from_numpy(y_train.values).long()  #
Classification target
y_validation_tensor = torch.from_numpy(y_validation.values).long()
y_test_tensor = torch.from_numpy(y_test.values).long()

# Create PyTorch datasets
train_dataset = torch.utils.data.TensorDataset(X_train_tensor,
y_train_tensor)
validation_dataset =
torch.utils.data.TensorDataset(X_validation_tensor,
y_validation_tensor)
test_dataset = torch.utils.data.TensorDataset(X_test_tensor,
y_test_tensor)
```

```
# Create PyTorch dataloaders
train_loader = torch.utils.data.DataLoader(train_dataset,
batch_size=96, shuffle=True, num_workers=2)
validation_loader = torch.utils.data.DataLoader(validation_dataset,
batch_size=64, shuffle=False, num_workers=2)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=64,
shuffle=False, num_workers=2)
```

```
Shapes: (307511, 121) (307511,)
```

```
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/
backend/fork_exec.py:38: RuntimeWarning: os.fork() was called.
os.fork() is incompatible with multithreaded code, and JAX is
multithreaded, so this will likely lead to a deadlock.
  pid = os.fork()
```

Define model, loss function, and train

```
# Define the model architecture
class MLPClassifier(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super(MLPClassifier, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        out = self.fc1(x)
        out = self.relu(out)
        out = self.fc2(out)
        return out

# Define the loss function
class CustomLoss(nn.Module):
    def __init__(self, alpha):
        super(CustomLoss, self).__init__()
        self.alpha = alpha
        self.classification_loss = nn.CrossEntropyLoss()
        self.regression_loss = nn.MSELoss()

    def forward(self, output_classification, target_classification,
output_regression=None, target_regression=None):
        classification_loss =
self.classification_loss(output_classification, target_classification)
        if output_regression is not None and target_regression is not
None:
            regression_loss = self.regression_loss(output_regression,
target_regression)
```

```
            loss = classification_loss + self.alpha * regression_loss
        else:
            loss = classification_loss
        return loss

# Define the training function
def train(model, criterion, optimizer, train_loader,
validation_loader, epochs, log_dir):
    writer = SummaryWriter(log_dir=log_dir)
    model.train()
    for epoch in range(epochs):
        running_loss = 0.0
        for i, data in enumerate(train_loader, 0):
            inputs, labels = data
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
        train_loss = running_loss / len(train_loader)

        # Validation loss
        model.eval()
        val_running_loss = 0.0
        with torch.no_grad():
            for i, data in enumerate(validation_loader, 0):
                inputs, labels = data
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = model(inputs)
                val_loss = criterion(outputs, labels)
                val_running_loss += val_loss.item()
        val_loss = val_running_loss / len(validation_loader)

        # Log training and validation loss
        writer.add_scalar('Loss/train', train_loss, epoch)
        writer.add_scalar('Loss/validation', val_loss, epoch)
        print(f'Epoch [{epoch+1}/{epochs}], Train Loss:
{train_loss:.4f}, Validation Loss: {val_loss:.4f}')
    writer.close()

# Initialize the model, loss function, and optimizer
model = MLPClassifier(input_size=X_train_tensor.shape[1],
hidden_size=64, num_classes=2).to(device)
criterion = CustomLoss(alpha=0.5).to(device)
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

```
# Run the training
train(model, criterion, optimizer, train_loader, validation_loader,
epochs=10, log_dir='logs')
```

```
Epoch [1/10], Train Loss: 0.2556, Validation Loss: 0.2575
Epoch [2/10], Train Loss: 0.2499, Validation Loss: 0.2576
Epoch [3/10], Train Loss: 0.2487, Validation Loss: 0.2573
Epoch [4/10], Train Loss: 0.2475, Validation Loss: 0.2586
Epoch [5/10], Train Loss: 0.2463, Validation Loss: 0.2612
Epoch [6/10], Train Loss: 0.2450, Validation Loss: 0.2620
Epoch [7/10], Train Loss: 0.2439, Validation Loss: 0.2637
Epoch [8/10], Train Loss: 0.2428, Validation Loss: 0.2677
Epoch [9/10], Train Loss: 0.2419, Validation Loss: 0.2694
Epoch [10/10], Train Loss: 0.2409, Validation Loss: 0.2693
```

Run model on test, log results to tensorboard

```
# Evaluate the model on the test set
model.eval()
correct = 0
total = 0
with torch.no_grad():
    for inputs, labels in test_loader:
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = model(inputs)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
accuracy = 100 * correct / total
print(f'Test Accuracy: {accuracy:.2f}%')
```

```
Test Accuracy: 91.89%
```

Evaluate multitask loss function using TensorBoard

```
# Note we logged to tensorboard differently here -- using "logs"
instead of "runs"
%reload_ext tensorboard
%tensorboard --logdir='logs'
```

```
<IPython.core.display.Javascript object>
```

Phase 4 Report Write-up

In the final phase of our project, we implemented advanced techniques to improve the performance of our machine learning model for identifying potential loan defaulters in the Home Credit Default Risk dataset. Techniques such as feature engineering, hyperparameter tuning, feature selection, ensemble methods, and class imbalance mitigation through SMOTE were employed. Initially, Gradient Boosting outperformed Logistic Regression in accuracy, AUC, and F1 score. However, upon integrating SMOTE to address class imbalance, there was a substantial improvement in performance metrics, particularly in the F1 score, indicating effective mitigation of class imbalance. Notably, the Gradient Boosting model with SMOTE exhibited a marked increase in the F1 score, indicating enhanced performance on both training and validation sets compared to the model without SMOTE.

Furthermore, compared to the baseline models from the previous phase, our model incorporating SMOTE in Phase 3 demonstrated significant improvements in accuracy, AUC score, and F1-score, with the most notable enhancement observed in the Gradient Boosting model. This suggests that Gradient Boosting with SMOTE is the most effective model for the Home Credit Default Risk dataset, offering a balanced performance across key metrics crucial for evaluating credit risk prediction.

In the Phase4, our next steps involve leveraging advanced techniques such as Neural Networks, advanced model architectures, and customized loss functions to further elevate the performance of our model, aiming to achieve even higher accuracy and predictive power in credit risk assessment.

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	Wrote report
Wunchana Seubwai	Developed slides and presentation video
Woojeong Kim	Wrote report
Alaina Barca	Did Neural Network Coding work

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 4 of the final project, we implented a neural network and test that said network with a muilttask loss function.

Our hope is that this neural network will result in us getting a better prediction when compared to our previous phases 2 and 3 where we just did feature engineering, hyperparameter tuning and used SMOTE to get the most out of our logistic and gradient boosting models. We can see that our test accuary is 91.89% within this DNN when compaired to our gradient boosting test accuary of 93.16%. This will be the final model as there is no phase 5.

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 16), we implented a neural network and test that said network with a muilttask loss function and have finalized our models.

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 4, much like phases 2/3, 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.

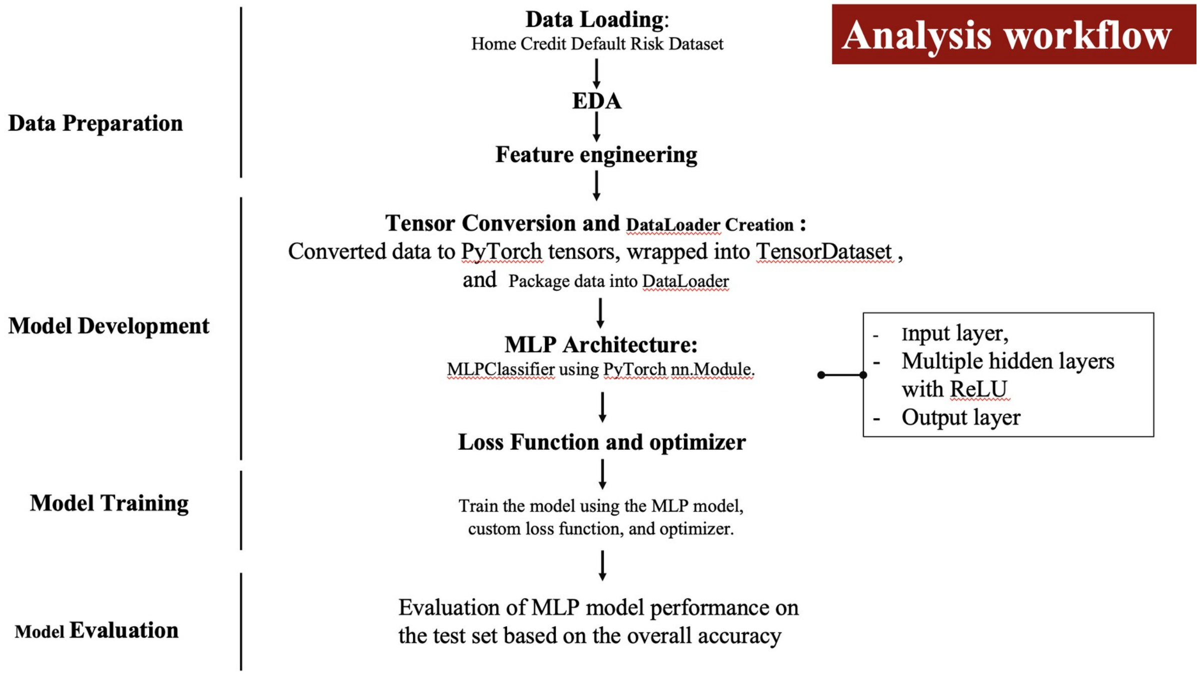
Neural Network Strategy

In final project phase 4, Neural Network have been used to improve model performance. This include the following components to predict 0 or 1 of 'TARGET' column.

- Epoch: This column indicates the epoch number, representing each complete pass of the training dataset through the neural network during the training process.
- Train Accuracy: This column shows the accuracy achieved on the training dataset at each epoch. It represents the proportion of correctly classified examples in the training set.
- Validation Accuracy: This column displays the accuracy achieved on the validation dataset at each epoch. It represents the proportion of correctly classified examples in the validation set, which is used to monitor the model's performance on unseen data and to prevent overfitting.
- Train Loss: This column indicates the loss (or error) computed on the training dataset at each epoch. The loss is a measure of how well the model is performing, with lower values indicating better performance.
- Validation Loss: This column shows the loss computed on the validation dataset at each epoch. Similar to training loss, it measures the performance of the model on unseen data. An increase in validation loss compared to training loss can indicate overfitting.

Modeling Pipelines

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



Experimental results

In Phase 4 of the final project, building upon our phases 2 and 3, we implemented a deep neural network using the Python package pytorch. We then evaluated it using a multitask loss function and plotted it using a tensor board.

When it comes to our phase 4 model (DNN) we find that it had a test accuracy of 91.89% which is less than our best performance from phase 3. This model was our gradient boosting model that was SMOTED (Test Score of 93.16%). That being said, our DNN is slightly better than our logistic regression which was SMOTED (Test Score of 90.94%).

When we compare this against our best models from phase 2 we had a logistic regression model (Test Score of 92.2%); however, this model had a lot of imbalance issues which we solved in phase 3.

From the below Epoch 1 -10 results table, we can draw the following analysis.

1. Accuracy: Both training and validation accuracies are quite high, hovering around 91-92%. This suggests that the model is performing well in terms of correctly classifying examples from both the training and validation sets. However, there doesn't seem to be much improvement in accuracy across epochs, indicating that the model may have already reached a plateau in performance.

2. Loss: Both training and validation losses are decreasing initially but start to increase slightly towards the later epochs. This could indicate that the model is starting to overfit the training data, as evidenced by the increasing validation loss despite stable or decreasing training loss.

-> Overall, while the model seems to be performing reasonably well in terms of accuracy, it might benefit from techniques to address overfitting, such as regularization or adjusting model complexity. Additionally, further analysis, such as examining learning curves or using different evaluation metrics, could provide more insights into the model's performance.

Epoch	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss
Epoch 1	Train Accuracy: 0.918	Validation Accuracy: 0.916	Train Loss: 0.2556	Validation Loss: 0.2575
Epoch 2	Train Accuracy: 0.92	Validation Accuracy: 0.916	Train Loss: 0.2499	Validation Loss: 0.2576
Epoch 3	Train Accuracy: 0.92	Validation Accuracy: 0.916	Train Loss: 0.2487	Validation Loss: 0.2573
Epoch 4	Train Accuracy: 0.92	Validation Accuracy: 0.916	Train Loss: 0.2475	Validation Loss: 0.2586
Epoch 5	Train Accuracy: 0.92	Validation Accuracy: 0.916	Train Loss: 0.2463	Validation Loss: 0.2612
Epoch 6	Train Accuracy: 0.921	Validation Accuracy: 0.915	Train Loss: 0.2450	Validation Loss: 0.2620
Epoch 7	Train Accuracy: 0.921	Validation Accuracy: 0.916	Train Loss: 0.2439	Validation Loss: 0.2637
Epoch 8	Train Accuracy: 0.921	Validation Accuracy: 0.915	Train Loss: 0.2428	Validation Loss: 0.2677
Epoch 9	Train Accuracy: 0.921	Validation Accuracy: 0.915	Train Loss: 0.2419	Validation Loss: 0.2694
Epoch 10	Train Accuracy: 0.922	Validation Accuracy: 0.915	Train Loss: 0.2409	Validation Loss: 0.2693

Epoch	Train Accuracy	Validation Accuracy	Test Accuracy	Train Loss	Validation Loss
Epoch 10	0.922	0.915	0.918	Train Loss: 0.2409	Validation Loss: 0.2693

Discussion

Now, we consider deeper into the analysis of the Epoch10 results table as above, considering both the merits and demerits of the neural network (NN) method, and suggesting further steps to improve its performance:

- Merits of MLP on our data(successes and surprises):

(1) High Accuracy: The MLP achieves high accuracy, with both training and validation accuracies consistently above 91%. This indicates that the model effectively captures patterns in the data and makes accurate predictions.

(2) Flexibility in Learning Complex Patterns: MLPs are known for their ability to learn complex non-linear relationships in data. The consistent accuracy across epochs suggests that the MLP is successfully learning the underlying patterns in the Home Credit Default Risk dataset.

(3) Scalability: MLPs can be scaled up to handle large datasets and high-dimensional input spaces. This scalability allows for effective learning from extensive data sources, which is evident in the consistent performance of the MLP across epochs.

- Demerits of MLP on our data:

(1) Potential Overfitting: While the accuracy remains high, the increasing gap between training and validation losses suggests potential overfitting. Overfitting occurs when the model memorizes noise in the training data, leading to reduced generalization performance on unseen data. Regularization techniques, such as dropout or L2 regularization, may help mitigate overfitting.

(2) Training Complexity: Training MLPs can be computationally intensive, particularly for deep architectures or large datasets. The need for optimization and tuning of hyperparameters adds to the computational complexity. Efficient training strategies and computational resources are required to train MLPs effectively.

(3) Hyperparameter Sensitivity: MLPs have several hyperparameters that need to be tuned, including the number of hidden layers, neurons per layer, learning rate, and regularization strength. Finding the optimal set of hyperparameters can be challenging and may require extensive experimentation.

Conclusion

In this final project phase 4, we implemented a DNN model that built upon our phases 2 and 3 to identify potential loan defaulters within the Home Credit Default Risk dataset.

From the experimental results that our SMOTED gradient boosting model (Score of 93.16%) outperformed every model we have so far. There could be many reason as to why our DNN did not perform to the standard we believed. Thsi could be anything from not getting the most optimial hyper-parameters for our DNN to an error in the implmention. It is quite hard to tell and if we had another week to work on this we would defentily look into the reason by running a more indepth hyper-parameter tuning and checked our pipelines again for any errors.

From the second table with 'test accuracy' and 'validation loss', we can derive the following conclusion. The Multilayer Perceptron (MLP) demonstrates high accuracy across various datasets, with training, validation, and test accuracies reaching 92.2%, 91.5%, and 91.8% respectively. This suggests the model adeptly captures intricate patterns within the data, facilitating precise predictions. MLPs exhibit notable flexibility in learning complex non-linear relationships inherent in the Home Credit Default Risk dataset, as evidenced by their consistent high accuracy on both training and validation sets. Additionally, their scalability enables efficient processing of large datasets and high-dimensional input spaces, further enhancing their ability to extract meaningful insights from extensive data sources and contribute to the model's exceptional accuracy.

However, despite its strengths, the MLP method faces challenges, including the risk of overfitting. The widening gap between training and validation losses indicates a potential for overfitting, where the model memorizes noise in the training data, compromising its generalization performance on unseen data. To mitigate this, implementing regularization techniques such as dropout or L2 regularization is recommended. Moreover, the computational intensity of training MLPs, especially for deep architectures or large datasets, necessitates efficient optimization and tuning of hyperparameters. Strategies to manage training complexity and judicious allocation of computational resources are crucial for effectively training MLPs and maximizing their predictive performance.

Further steps to address the above demerits:

- Regularization: Implement regularization techniques such as dropout or L2 regularization to prevent overfitting and improve generalization performance.
- Hyperparameter Tuning: Conduct thorough hyperparameter tuning to optimize the model's architecture and parameters for improved performance. This includes tuning the number of hidden layers, neurons per layer, learning rate, and regularization strength.
- Model Evaluation: Assess the model's performance using additional metrics beyond accuracy, such as precision, recall, and F1-score, to gain a comprehensive

understanding of its effectiveness. This can help identify areas of improvement and guide further optimization efforts.

- Interpretability Techniques: Explore techniques for enhancing the interpretability of the MLP model, such as feature importance analysis or model-agnostic interpretability methods like SHAP (SHapley Additive exPlanations) values. Understanding the factors driving the model's predictions can provide valuable insights for decision-making.

->By addressing the challenges associated with MLPs and leveraging their strengths, we can enhance the performance and interpretability of the model for the Home Credit Default Risk prediction task.

Gap Analysis

Gap analysis serves as a strategic planning method utilized to evaluate the difference, or "gap," between current performance and desired objectives. It entails assessing the existing state of affairs within an organization or project against the envisioned future state, pinpointing any disparities, and formulating strategies to effectively bridge those gaps.

Group	Submission date and time	Phase number	Phase number	Use this column for sorting Kaggle submission AUC score (public)	Test AUC score	Training Time	Machine Learning alg	Uses GPU	Architecture for deep learning Or number of decision trees	number of features	Number of features selected	5 most important features	NN Architecture - Example- 173-100(ReLU) -2(CXE)	Major ahha /surprise
Group 6 HCDR	4/21/2024	4		0.509	0.92	5 minutes	Neural Network w/PyTorch		64/32/16	357	357	DAYS_BIRTH, EXT_SOURCE3	357-64-32-16-2	Neural network did not perform well at all! Very surprised
Group2_HCDR	4/21/2024 7:15 PM	4		0.7441	0.7357	2 min	Multitask Loss F	No	Classification and reg	245	245	N/A	245-64-2	MLP performed better than logistic regression with SMOTE but not better than our gradient boosting model with SMOTE.
Group1_HCDR	4/21/2024 11:44 PM	4		0.7255	0.734793		NN	No	NA	124	124	DAYS_BIRTH, EXT_SOURCE3, REGION_RATING, DAYS_LAST_PHONE_CHANC DAYS_EMPLOYED	245-16-2	Baseline model of logistic regression performed slightly better than any nn architectures we consideres.

Gap analysis involves comparing the performance of different groups or entities to identify areas of improvement or advantage. In our case, let's analyze the performance gaps between our group (Group2) and the other two groups (Group1 and Group6) based on the Kaggle submission AUC scores(Group 2 got 0.7441 on this) as above figure.

1. **Gap with Group1 (AUC Score: 0.7255)**:
   - Advantages of Group2:
     - Higher AUC Score: Our group achieved a significantly higher AUC score compared to Group1, indicating that our model is better at distinguishing between default and non-default cases.
     - Potential Feature Engineering: Our group might have employed better feature engineering techniques or model optimization strategies to achieve this higher AUC score.
   - Areas for Improvement:
     - Model Complexity: Since both groups used MLP, there might be room to further optimize the architecture or hyperparameters of our neural network to improve performance.
     - Data Preprocessing: Investigate if there are any additional preprocessing steps that could enhance the model's performance.
2. **Gap with Group6 (AUC Score: 0.509)**:
   - Advantages of Group2:

    - Significantly Higher AUC Score: Our group's model vastly outperformed Group6's model in terms of AUC score.
    - Model Effectiveness: Our MLP architecture seems to be more effective in this context compared to the one used by Group6.
  - Areas for Improvement:
    - Knowledge Sharing: Since our model significantly outperformed Group6's model, consider sharing insights or techniques with them that could potentially help improve their performance.
    - Further Experimentation: Explore if there are additional model architectures or techniques that could be more suitable for the dataset, beyond just MLP.

In summary, while our group (Group2) has performed well compared to both Group1 and Group6, there are still opportunities for improvement, particularly in fine-tuning the model architecture, optimizing hyperparameters, and potentially exploring alternative algorithms or techniques. Sharing knowledge and collaborating with the other groups could also lead to mutual improvements in performance.