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 uncompressed) 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.

In [1]:
```
!pip install kaggle
```

```
Collecting kaggle
  Downloading kaggle-1.5.12.tar.gz (58 kB)
     |████████████████████████████████| 58 kB 1.7 MB/s eta 0:00:01
Requirement already satisfied: six>=1.10 in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages (from
kaggle) (1.15.0)
Requirement already satisfied: certifi in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages (from ka
ggle) (2020.12.5)
Requirement already satisfied: python-dateutil in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages
(from kaggle) (2.8.1)
Requirement already satisfied: requests in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages (from k
aggle) (2.25.1)
Requirement already satisfied: tqdm in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages (from kaggl
e) (4.59.0)
Collecting python-slugify
  Downloading python_slugify-6.1.1-py2.py3-none-any.whl (9.1 kB)
Requirement already satisfied: urllib3 in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages (from ka
ggle) (1.26.4)
Collecting text-unidecode>=1.3
  Downloading text_unidecode-1.3-py2.py3-none-any.whl (78 kB)
     |████████████████████████████████| 78 kB 6.4 MB/s eta 0:00:011
Requirement already satisfied: chardet<5,>=3.0.2 in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-package
s (from requests->kaggle) (4.0.0)
Requirement already satisfied: idna<3,>=2.5 in /Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages (fr
om requests->kaggle) (2.10)
Building wheels for collected packages: kaggle
  Building wheel for kaggle (setup.py) ... done
  Created wheel for kaggle: filename=kaggle-1.5.12-py3-none-any.whl size=73053 sha256=86bc61f6ed907a7524d7849576e
9b984a6a5bb8454c317b9d4b88b2e1b87a6a5
  Stored in directory: /Users/nidhisaduvala/Library/Caches/pip/wheels/29/da/11/144cc25aebdaeb4931b231e25fd34b394e
6a5725cbb2f50106
Successfully built kaggle
Installing collected packages: text-unidecode, python-slugify, kaggle
Successfully installed kaggle-1.5.12 python-slugify-6.1.1 text-unidecode-1.3
```

In [2]:
```
!pwd
```

```
/Users/nidhisaduvala/Desktop/Spring/Courses/AML526/I526_AML_Student/Assignments/Unit-Project-Home-Credit-Default-Risk/HCDR_Phase_1_baseline_submission
```

In [3]:
```
!mkdir ~/.kaggle
!cp /root/shared/Downloads/kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json
```

```
cp: /root/shared/Downloads/kaggle.json: No such file or directory
chmod: /Users/nidhisaduvala/.kaggle/kaggle.json: No such file or directory
```

In [4]:
```
! kaggle competitions files home-credit-default-risk
```

```
Traceback (most recent call last):
  File "/Users/nidhisaduvala/opt/anaconda3/bin/kaggle", line 5, in <module>
    from kaggle.cli import main
  File "/Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages/kaggle/__init__.py", line 23, in <module>
    api.authenticate()
  File "/Users/nidhisaduvala/opt/anaconda3/lib/python3.8/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 /Users/nidhisaduvala/.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

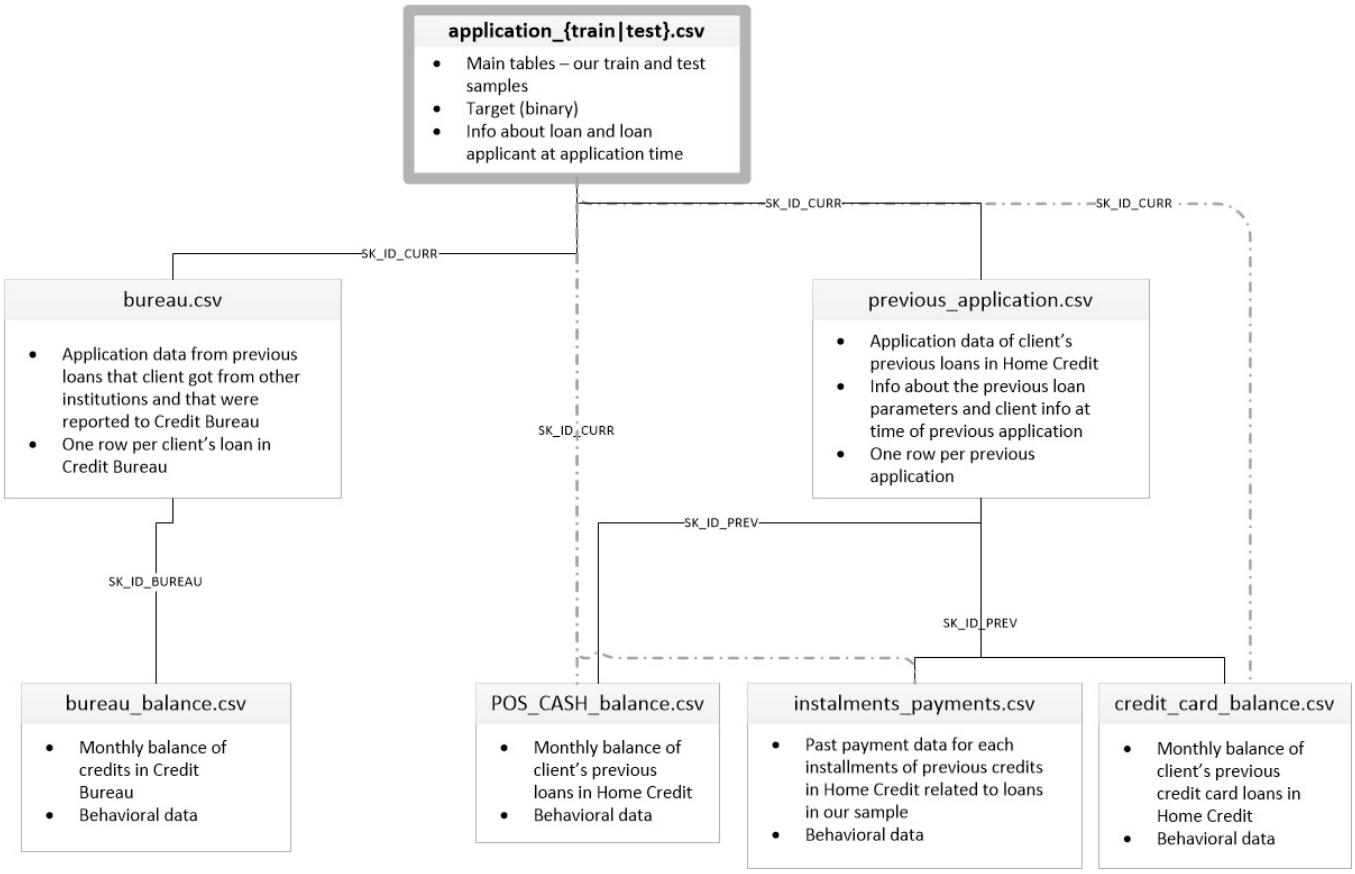
There are 7 different sources of data:

- **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.

- **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.

In [5]:
```
# ![alt](home_credit.png "Home credit")
```



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.

In [6]:
```
DATA_DIR = "/Users/nidhisaduvala/Desktop/Spring/AML/home-credit-default-risk"   #same level as course repo in the
#DATA_DIR = os.path.join('./ddddd/')
!mkdir $DATA_DIR
```

```
mkdir: /Users/nidhisaduvala/Desktop/Spring/AML/home-credit-default-risk: File exists
```

In [7]:
```
!ls -l $DATA_DIR
```

```
total 5242728
```

```
-rw-rw-r--@ 1 nidhisaduvala  staff      37383 Dec 11  2019 HomeCredit_columns_description.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  392703158 Dec 11  2019 POS_CASH_balance.csv
-rw-rw-r--@ 1 nidhisaduvala  staff   26567651 Dec 11  2019 application_test.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  166133370 Dec 11  2019 application_train.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  170016717 Dec 11  2019 bureau.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  375592889 Dec 11  2019 bureau_balance.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  424582605 Dec 11  2019 credit_card_balance.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  723118349 Dec 11  2019 installments_payments.csv
-rw-rw-r--@ 1 nidhisaduvala  staff  404973293 Dec 11  2019 previous_application.csv
-rw-rw-r--@ 1 nidhisaduvala  staff     536202 Dec 11  2019 sample_submission.csv
```

In [8]:

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

```
Traceback (most recent call last):
  File "/Users/nidhisaduvala/opt/anaconda3/bin/kaggle", line 5, in <module>
    from kaggle.cli import main
  File "/Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages/kaggle/__init__.py", line 23, in <module>
    api.authenticate()
  File "/Users/nidhisaduvala/opt/anaconda3/lib/python3.8/site-packages/kaggle/api/kaggle_api_extended.py", line 1
64, 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 /Users/nidhisaduvala/.kaggle. Or use the environme
nt method.
```

Imports

In [9]:

```
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')
```

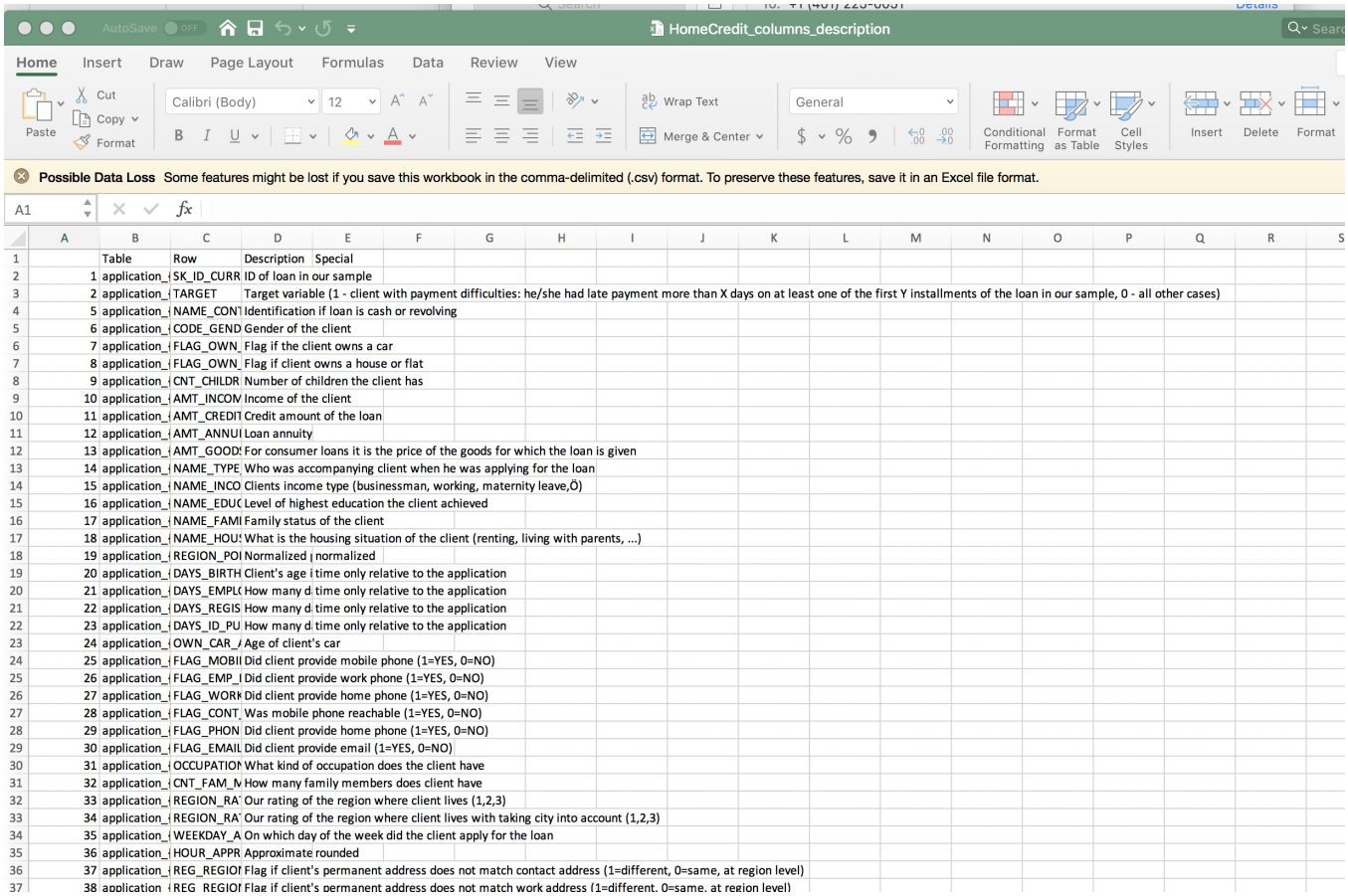
In [10]:

```
unzippingReq = False
if unzippingReq: #please modify this code
    zip_ref = zipfile.ZipFile('application_train.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('application_test.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('bureau_balance.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('bureau.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('credit_card_balance.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('installments_payments.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('POS_CASH_balance.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
    zip_ref = zipfile.ZipFile('previous_application.csv.zip', 'r')
    zip_ref.extractall('datasets')
    zip_ref.close()
```

Data files overview

Data Dictionary

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



HomeCredit_columns_description

Possible Data Loss Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in an Excel file format.

	Table	Row	Description	Special
1	application_{	SK_ID_CURR	ID of loan in our sample	
2	application_{	TARGET	Target variable (1 - client with payment difficulties: he/she had late payment more than X days on at least one of the first Y installments of the loan in our sample, 0 - all other cases)	
5	application_{	NAME_CONT	Identification if loan is cash or revolving	
6	application_{	CODE_GEND	Gender of the client	
7	application_{	FLAG_OWN_	Flag if the client owns a car	
8	application_{	FLAG_OWN_	Flag if client owns a house or flat	
9	application_{	CNT_CHILDR	Number of children the client has	
10	application_{	AMT_INCOM	Income of the client	
11	application_{	AMT_CREDIT	Credit amount of the loan	
12	application_{	AMT_ANNUI	Loan annuity	
13	application_{	AMT_GOODS	For consumer loans it is the price of the goods for which the loan is given	
14	application_{	NAME_TYPE	Who was accompanying client when he was applying for the loan	
15	application_{	NAME_INCO	Clients income type (businessman, working, maternity leave,Ö)	
16	application_{	NAME_EDUC	Level of highest education the client achieved	
17	application_{	NAME_FAMI	Family status of the client	
18	application_{	NAME_HOUS	What is the housing situation of the client (renting, living with parents, ...)	
19	application_{	REGION_POI	Normalized p	normalized
20	application_{	DAYS_BIRTH	Client's age i	time only relative to the application
21	application_{	DAYS_EMPL	How many d	time only relative to the application
22	application_{	DAYS_REGIS	How many d	time only relative to the application
23	application_{	DAYS_ID_PU	How many d	time only relative to the application
24	application_{	OWN_CAR_A	Age of client's car	
25	application_{	FLAG_MOBIL	Did client provide mobile phone (1=YES, 0=NO)	
26	application_{	FLAG_EMP_P	Did client provide work phone (1=YES, 0=NO)	
27	application_{	FLAG_WORK	Did client provide home phone (1=YES, 0=NO)	
28	application_{	FLAG_CONT	Was mobile phone reachable (1=YES, 0=NO)	
29	application_{	FLAG_PHON	Did client provide home phone (1=YES, 0=NO)	
30	application_{	FLAG_EMAIL	Did client provide email (1=YES, 0=NO)	
31	application_{	OCCUPATION	What kind of occupation does the client have	
32	application_{	CNT_FAM_M	How many family members does client have	
33	application_{	REGION_RA	Our rating of the region where client lives (1,2,3)	
34	application_{	REGION_RA	Our rating of the region where client lives with taking city into account (1,2,3)	
35	application_{	WEEKDAY_A	On which day of the week did the client apply for the loan	
36	application_{	HOUR_APPR	Approximate rounded	
37	application_{	REG_REGION	Flag if client's permanent address does not match contact address (1=different, 0=same, at region level)	
38	application_{	REG_REGION	Flag if client's permanent address does not match work address (1=different, 0=same, at region level)	

Application train

In [11]:

```
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'
datasets[ds_name] = load_data(os.path.join(DATA_DIR, f'{ds_name}.csv'), ds_name)

datasets['application_train'].shape
```

```
application_train: shape is (307511, 122)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

None

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TC
0	100002	1	Cash loans	M	N	Y	0	202
1	100003	0	Cash loans	F	N	N	0	270
2	100004	0	Revolving loans	M	Y	Y	0	67
3	100006	0	Cash loans	F	N	Y	0	135
4	100007	0	Cash loans	M	N	Y	0	121

5 rows × 122 columns

Out[11]: (307511, 122)

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.

In [12]:
```
ds_name = 'application_test'
datasets[ds_name] = load_data(os.path.join(DATA_DIR, f'{ds_name}.csv'), ds_name)
```

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

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AM
0	100001	Cash loans	F	N	Y	0	135000.0	
1	100005	Cash loans	M	N	Y	0	99000.0	
2	100013	Cash loans	M	Y	Y	0	202500.0	
3	100028	Cash loans	F	N	Y	2	315000.0	
4	100038	Cash loans	M	Y	N	1	180000.0	

5 rows × 121 columns

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

The Other datasets

- **bureau:** data concerning client's previous credits from other financial institutions. Each previous credit has its own row in bureau, but one loan in the application data can have multiple previous credits.
- **bureau_balance:** monthly data about the previous credits in bureau. Each row is one month of a previous credit, and a single previous credit can have multiple rows, one for each month of the credit length.
- **previous_application:** previous applications for loans at Home Credit of clients who have loans in the application data. Each current loan in the application data can have multiple previous loans. Each previous application has one row and is identified by the feature SK_ID_PREV.
- **POS_CASH_BALANCE:** monthly data about previous point of sale or cash loans clients have had with Home Credit. Each row is one month of a previous point of sale or cash loan, and a single previous loan can have many rows.
- credit_card_balance: monthly data about previous credit cards clients have had with Home Credit. Each row is one month of a credit card balance, and a single credit card can have many rows.
- **installments_payment:** payment history for previous loans at Home Credit. There is one row for every made payment and one row for every missed payment.

In [13]:
```
%%time
ds_names = ("application_train", "application_test", "bureau","bureau_balance","credit_card_balance","installment
```

```
            "previous_application","POS_CASH_balance")

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

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

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TC
0	100002	1	Cash loans	M	N	Y	0	202
1	100003	0	Cash loans	F	N	N	0	270
2	100004	0	Revolving loans	M	Y	Y	0	67
3	100006	0	Cash loans	F	N	Y	0	135
4	100007	0	Cash loans	M	N	Y	0	121

5 rows × 122 columns

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

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AM
0	100001	Cash loans	F	N	Y	0	135000.0	
1	100005	Cash loans	M	N	Y	0	99000.0	
2	100013	Cash loans	M	Y	Y	0	202500.0	
3	100028	Cash loans	F	N	Y	2	315000.0	
4	100038	Cash loans	M	Y	N	1	180000.0	

5 rows × 121 columns

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

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	CREDIT_DAY_OVERDUE	DAYS_CREDIT_ENDDATE	DAY
0	215354	5714462	Closed	currency 1	-497	0	-153.0	
1	215354	5714463	Active	currency 1	-208	0	1075.0	
2	215354	5714464	Active	currency 1	-203	0	528.0	
3	215354	5714465	Active	currency 1	-203	0	NaN	
4	215354	5714466	Active	currency 1	-629	0	1197.0	

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

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

```
credit_card_balance: shape is (3840312, 23)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3840312 entries, 0 to 3840311
Data columns (total 23 columns):
 #   Column                       Dtype
---  ------                       -----
 0   SK_ID_PREV                   int64
 1   SK_ID_CURR                   int64
 2   MONTHS_BALANCE               int64
 3   AMT_BALANCE                  float64
 4   AMT_CREDIT_LIMIT_ACTUAL      int64
 5   AMT_DRAWINGS_ATM_CURRENT     float64
 6   AMT_DRAWINGS_CURRENT         float64
 7   AMT_DRAWINGS_OTHER_CURRENT   float64
 8   AMT_DRAWINGS_POS_CURRENT     float64
 9   AMT_INST_MIN_REGULARITY      float64
 10  AMT_PAYMENT_CURRENT          float64
 11  AMT_PAYMENT_TOTAL_CURRENT    float64
 12  AMT_RECEIVABLE_PRINCIPAL     float64
 13  AMT_RECIVABLE                float64
 14  AMT_TOTAL_RECEIVABLE         float64
 15  CNT_DRAWINGS_ATM_CURRENT     float64
 16  CNT_DRAWINGS_CURRENT         int64
 17  CNT_DRAWINGS_OTHER_CURRENT   float64
 18  CNT_DRAWINGS_POS_CURRENT     float64
 19  CNT_INSTALMENT_MATURE_CUM    float64
 20  NAME_CONTRACT_STATUS         object
 21  SK_DPD                       int64
 22  SK_DPD_DEF                   int64
dtypes: float64(15), int64(7), object(1)
memory usage: 673.9+ MB
None
```

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	AMT_BALANCE	AMT_CREDIT_LIMIT_ACTUAL	AMT_DRAWINGS_ATM_CURRENT	AMT_DRAW
0	2562384	378907	-6	56.970	135000	0.0	
1	2582071	363914	-1	63975.555	45000	2250.0	
2	1740877	371185	-7	31815.225	450000	0.0	
3	1389973	337855	-4	236572.110	225000	2250.0	
4	1891521	126868	-1	453919.455	450000	0.0	

5 rows × 23 columns

```
installments_payments: shape is (13605401, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13605401 entries, 0 to 13605400
Data columns (total 8 columns):
 #   Column                  Dtype
---  ------                  -----
 0   SK_ID_PREV              int64
 1   SK_ID_CURR              int64
 2   NUM_INSTALMENT_VERSION  float64
 3   NUM_INSTALMENT_NUMBER   int64
 4   DAYS_INSTALMENT         float64
 5   DAYS_ENTRY_PAYMENT      float64
 6   AMT_INSTALMENT          float64
 7   AMT_PAYMENT             float64
dtypes: float64(5), int64(3)
```

```
memory usage: 830.4 MB
None
```

	SK_ID_PREV	SK_ID_CURR	NUM_INSTALMENT_VERSION	NUM_INSTALMENT_NUMBER	DAYS_INSTALMENT	DAYS_ENTRY_PAYMENT	AMT_I
0	1054186	161674	1.0	6	-1180.0	-1187.0	
1	1330831	151639	0.0	34	-2156.0	-2156.0	
2	2085231	193053	2.0	1	-63.0	-63.0	
3	2452527	199697	1.0	3	-2418.0	-2426.0	
4	2714724	167756	1.0	2	-1383.0	-1366.0	

```
previous_application: shape is (1670214, 37)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):
 #   Column                       Non-Null Count    Dtype
---  ------                       --------------    -----
 0   SK_ID_PREV                   1670214 non-null  int64
 1   SK_ID_CURR                   1670214 non-null  int64
 2   NAME_CONTRACT_TYPE           1670214 non-null  object
 3   AMT_ANNUITY                  1297979 non-null  float64
 4   AMT_APPLICATION              1670214 non-null  float64
 5   AMT_CREDIT                   1670213 non-null  float64
 6   AMT_DOWN_PAYMENT             774370 non-null   float64
 7   AMT_GOODS_PRICE              1284699 non-null  float64
 8   WEEKDAY_APPR_PROCESS_START   1670214 non-null  object
 9   HOUR_APPR_PROCESS_START      1670214 non-null  int64
 10  FLAG_LAST_APPL_PER_CONTRACT  1670214 non-null  object
 11  NFLAG_LAST_APPL_IN_DAY       1670214 non-null  int64
 12  RATE_DOWN_PAYMENT            774370 non-null   float64
 13  RATE_INTEREST_PRIMARY        5951 non-null     float64
 14  RATE_INTEREST_PRIVILEGED     5951 non-null     float64
 15  NAME_CASH_LOAN_PURPOSE       1670214 non-null  object
 16  NAME_CONTRACT_STATUS         1670214 non-null  object
 17  DAYS_DECISION                1670214 non-null  int64
 18  NAME_PAYMENT_TYPE            1670214 non-null  object
 19  CODE_REJECT_REASON           1670214 non-null  object
 20  NAME_TYPE_SUITE              849809 non-null   object
 21  NAME_CLIENT_TYPE             1670214 non-null  object
 22  NAME_GOODS_CATEGORY          1670214 non-null  object
 23  NAME_PORTFOLIO               1670214 non-null  object
 24  NAME_PRODUCT_TYPE            1670214 non-null  object
 25  CHANNEL_TYPE                 1670214 non-null  object
 26  SELLERPLACE_AREA             1670214 non-null  int64
 27  NAME_SELLER_INDUSTRY         1670214 non-null  object
 28  CNT_PAYMENT                  1297984 non-null  float64
 29  NAME_YIELD_GROUP             1670214 non-null  object
 30  PRODUCT_COMBINATION          1669868 non-null  object
 31  DAYS_FIRST_DRAWING           997149 non-null   float64
 32  DAYS_FIRST_DUE               997149 non-null   float64
 33  DAYS_LAST_DUE_1ST_VERSION    997149 non-null   float64
 34  DAYS_LAST_DUE                997149 non-null   float64
 35  DAYS_TERMINATION             997149 non-null   float64
 36  NFLAG_INSURED_ON_APPROVAL    997149 non-null   float64
dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB
None
```

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS
0	2030495	271877	Consumer loans	1730.430	17145.0	17145.0	0.0	
1	2802425	108129	Cash loans	25188.615	607500.0	679671.0	NaN	
2	2523466	122040	Cash loans	15060.735	112500.0	136444.5	NaN	
3	2819243	176158	Cash loans	47041.335	450000.0	470790.0	NaN	
4	1784265	202054	Cash loans	31924.395	337500.0	404055.0	NaN	

5 rows × 37 columns

```
POS_CASH_balance: shape is (10001358, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10001358 entries, 0 to 10001357
Data columns (total 8 columns):
 #   Column                 Dtype
---  ------                 -----
 0   SK_ID_PREV             int64
 1   SK_ID_CURR             int64
 2   MONTHS_BALANCE         int64
 3   CNT_INSTALMENT         float64
 4   CNT_INSTALMENT_FUTURE  float64
 5   NAME_CONTRACT_STATUS   object
```

```
 6   SK_DPD                  int64
 7   SK_DPD_DEF              int64
dtypes: float64(2), int64(5), object(1)
memory usage: 610.4+ MB
None
```

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	CNT_INSTALMENT	CNT_INSTALMENT_FUTURE	NAME_CONTRACT_STATUS	SK_DPD	SK_D
0	1803195	182943	-31	48.0	45.0	Active	0	
1	1715348	367990	-33	36.0	35.0	Active	0	
2	1784872	397406	-32	12.0	9.0	Active	0	
3	1903291	269225	-35	48.0	42.0	Active	0	
4	2341044	334279	-35	36.0	35.0	Active	0	

```
CPU times: user 22.9 s, sys: 3.08 s, total: 26 s
Wall time: 26.9 s
```

In [14]:
```
for ds_name in datasets.keys():
    print(f'dataset {ds_name:24}: [ {datasets[ds_name].shape[0]:10,}, {datasets[ds_name].shape[1]}]')
```

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

Exploratory Data Analysis Phase -1

Descriptive statistics

● A data dictionary of the raw features.

● Pandas profiling in jupyter notebook.

● We did descriptive analysis on the dataset such as data type of each feature, dataset size (rows and columns = 307511, 122), and summary statistics such as the number of observations, mean, standard deviation, maximum, minimum, and quartiles for all features and split of data is as follows Train: 70%, Test 20%, Validation 10%.

● We generated charts on descriptive statistics of the target dataset.

Summary of Application train

In [28]:
```
application_test = pd.read_csv('/Users/nidhisaduvala/Desktop/Spring/AML/home-credit-default-risk/application_test
application_train = pd.read_csv('/Users/nidhisaduvala/Desktop/Spring/AML/home-credit-default-risk/application_tra
```

In [29]:
```
def EDA(df,df_name):
    print("Test description; data type: {}".format(df_name))
    print(df.dtypes)
    print("\n#############################################################\n")
    print(" Dataset size (rows columns): {}".format(df_name))
    print(df.shape)
    print("\n#############################################################\n")
    print("Summary statistics: {}".format(df_name))
    print(df.describe())
    print("\n#############################################################\n")
    print("Correlation analysis: {}".format(df_name))
    print(df.corr())
    print("\n#############################################################\n")
```

```
    print("Other Analysis: {}".format(df_name))
    print("1. Checking for Null values: {}".format(df_name))
    print(df.isna().sum())
    print("\n2. Info")
    print(df.info())
```

In [33]:

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

```
Test description; data type: application_train
SK_ID_CURR                     int64
TARGET                         int64
NAME_CONTRACT_TYPE            object
CODE_GENDER                   object
FLAG_OWN_CAR                  object
                               ...
AMT_REQ_CREDIT_BUREAU_DAY     float64
AMT_REQ_CREDIT_BUREAU_WEEK    float64
AMT_REQ_CREDIT_BUREAU_MON     float64
AMT_REQ_CREDIT_BUREAU_QRT     float64
AMT_REQ_CREDIT_BUREAU_YEAR    float64
Length: 122, dtype: object

############################################################

 Dataset size (rows columns): application_train
(307511, 122)

############################################################

Summary statistics: application_train
          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]

############################################################

Correlation analysis: application_train
                            SK_ID_CURR    TARGET  CNT_CHILDREN  \
SK_ID_CURR                    1.000000 -0.002108     -0.001129
TARGET                       -0.002108  1.000000      0.019187
CNT_CHILDREN                 -0.001129  0.019187      1.000000
AMT_INCOME_TOTAL             -0.001820 -0.003982      0.012882
AMT_CREDIT                   -0.000343 -0.030369      0.002145
...                                ...       ...           ...
AMT_REQ_CREDIT_BUREAU_DAY    -0.002193  0.002704     -0.000366
AMT_REQ_CREDIT_BUREAU_WEEK    0.002099  0.000788     -0.002436
AMT_REQ_CREDIT_BUREAU_MON     0.000485 -0.012462     -0.010808
AMT_REQ_CREDIT_BUREAU_QRT     0.001025 -0.002022     -0.007836
AMT_REQ_CREDIT_BUREAU_YEAR    0.004659  0.019930     -0.041550

                            AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
SK_ID_CURR                         -0.001820   -0.000343    -0.000433
TARGET                             -0.003982   -0.030369    -0.012817
CNT_CHILDREN                        0.012882    0.002145     0.021374
AMT_INCOME_TOTAL                    1.000000    0.156870     0.191657
AMT_CREDIT                          0.156870    1.000000     0.770138
...                                      ...         ...          ...
AMT_REQ_CREDIT_BUREAU_DAY           0.002944    0.004238     0.002185
AMT_REQ_CREDIT_BUREAU_WEEK          0.002387   -0.001275     0.013881
AMT_REQ_CREDIT_BUREAU_MON           0.024700    0.054451     0.039148
AMT_REQ_CREDIT_BUREAU_QRT           0.004859    0.015925     0.010124
AMT_REQ_CREDIT_BUREAU_YEAR          0.011690   -0.048448    -0.011320

                            AMT_GOODS_PRICE  REGION_POPULATION_RELATIVE  \
SK_ID_CURR                        -0.000232                    0.000849
TARGET                            -0.039645                   -0.037227
CNT_CHILDREN                      -0.001827                   -0.025573
AMT_INCOME_TOTAL                   0.159610                    0.074796
AMT_CREDIT                         0.986968                    0.099738
...                                     ...                         ...
AMT_REQ_CREDIT_BUREAU_DAY          0.004677                    0.001399
AMT_REQ_CREDIT_BUREAU_WEEK        -0.001007                   -0.002149
AMT_REQ_CREDIT_BUREAU_MON          0.056422                    0.078607
AMT_REQ_CREDIT_BUREAU_QRT          0.016432                   -0.001279
AMT_REQ_CREDIT_BUREAU_YEAR        -0.050998                    0.001003

                            DAYS_BIRTH  DAYS_EMPLOYED  ...  FLAG_DOCUMENT_18  \
SK_ID_CURR                   -0.001500       0.001366  ...          0.000509
TARGET                        0.078239      -0.044932  ...         -0.007952
CNT_CHILDREN                  0.330938      -0.239818  ...          0.004031
AMT_INCOME_TOTAL              0.027261      -0.064223  ...          0.003130
AMT_CREDIT                   -0.055436      -0.066838  ...          0.034329
...                                ...            ...  ...               ...
AMT_REQ_CREDIT_BUREAU_DAY     0.002255       0.000472  ...          0.013281
AMT_REQ_CREDIT_BUREAU_WEEK   -0.001336       0.003072  ...         -0.004640
AMT_REQ_CREDIT_BUREAU_MON     0.001372      -0.034457  ...         -0.001565
AMT_REQ_CREDIT_BUREAU_QRT    -0.011799       0.015345  ...         -0.005125
AMT_REQ_CREDIT_BUREAU_YEAR   -0.071983       0.049988  ...         -0.047432

                            FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  \
SK_ID_CURR                          0.000167          0.001073
TARGET                             -0.001358          0.000215
CNT_CHILDREN                        0.000864          0.000988
AMT_INCOME_TOTAL                    0.002408          0.000242
AMT_CREDIT                          0.021082          0.031023
...                                      ...               ...
AMT_REQ_CREDIT_BUREAU_DAY           0.001126         -0.000120
```

AMT_REQ_CREDIT_BUREAU_WEEK	-0.001275	-0.001770
AMT_REQ_CREDIT_BUREAU_MON	-0.002729	0.001285
AMT_REQ_CREDIT_BUREAU_QRT	-0.001575	-0.001010
AMT_REQ_CREDIT_BUREAU_YEAR	-0.007009	-0.012126

	FLAG_DOCUMENT_21	AMT_REQ_CREDIT_BUREAU_HOUR
SK_ID_CURR	0.000282	-0.002672
TARGET	0.003709	0.000930
CNT_CHILDREN	-0.002450	-0.000410
AMT_INCOME_TOTAL	-0.000589	0.000709
AMT_CREDIT	-0.016148	-0.003906
...	...	...
AMT_REQ_CREDIT_BUREAU_DAY	-0.001130	0.230374
AMT_REQ_CREDIT_BUREAU_WEEK	0.000081	0.004706
AMT_REQ_CREDIT_BUREAU_MON	-0.003612	-0.000018
AMT_REQ_CREDIT_BUREAU_QRT	-0.002004	-0.002716
AMT_REQ_CREDIT_BUREAU_YEAR	-0.005457	-0.004597

	AMT_REQ_CREDIT_BUREAU_DAY
SK_ID_CURR	-0.002193
TARGET	0.002704
CNT_CHILDREN	-0.000366
AMT_INCOME_TOTAL	0.002944
AMT_CREDIT	0.004238
...	...
AMT_REQ_CREDIT_BUREAU_DAY	1.000000
AMT_REQ_CREDIT_BUREAU_WEEK	0.217412
AMT_REQ_CREDIT_BUREAU_MON	-0.005258
AMT_REQ_CREDIT_BUREAU_QRT	-0.004416
AMT_REQ_CREDIT_BUREAU_YEAR	-0.003355

	AMT_REQ_CREDIT_BUREAU_WEEK
SK_ID_CURR	0.002099
TARGET	0.000788
CNT_CHILDREN	-0.002436
AMT_INCOME_TOTAL	0.002387
AMT_CREDIT	-0.001275
...	...
AMT_REQ_CREDIT_BUREAU_DAY	0.217412
AMT_REQ_CREDIT_BUREAU_WEEK	1.000000
AMT_REQ_CREDIT_BUREAU_MON	-0.014096
AMT_REQ_CREDIT_BUREAU_QRT	-0.015115
AMT_REQ_CREDIT_BUREAU_YEAR	0.018917

	AMT_REQ_CREDIT_BUREAU_MON
SK_ID_CURR	0.000485
TARGET	-0.012462
CNT_CHILDREN	-0.010808
AMT_INCOME_TOTAL	0.024700
AMT_CREDIT	0.054451
...	...
AMT_REQ_CREDIT_BUREAU_DAY	-0.005258
AMT_REQ_CREDIT_BUREAU_WEEK	-0.014096
AMT_REQ_CREDIT_BUREAU_MON	1.000000
AMT_REQ_CREDIT_BUREAU_QRT	-0.007789
AMT_REQ_CREDIT_BUREAU_YEAR	-0.004975

	AMT_REQ_CREDIT_BUREAU_QRT
SK_ID_CURR	0.001025
TARGET	-0.002022
CNT_CHILDREN	-0.007836
AMT_INCOME_TOTAL	0.004859
AMT_CREDIT	0.015925
...	...
AMT_REQ_CREDIT_BUREAU_DAY	-0.004416
AMT_REQ_CREDIT_BUREAU_WEEK	-0.015115
AMT_REQ_CREDIT_BUREAU_MON	-0.007789
AMT_REQ_CREDIT_BUREAU_QRT	1.000000
AMT_REQ_CREDIT_BUREAU_YEAR	0.076208

	AMT_REQ_CREDIT_BUREAU_YEAR
SK_ID_CURR	0.004659
TARGET	0.019930
CNT_CHILDREN	-0.041550
AMT_INCOME_TOTAL	0.011690
AMT_CREDIT	-0.048448
...	...
AMT_REQ_CREDIT_BUREAU_DAY	-0.003355
AMT_REQ_CREDIT_BUREAU_WEEK	0.018917
AMT_REQ_CREDIT_BUREAU_MON	-0.004975
AMT_REQ_CREDIT_BUREAU_QRT	0.076208
AMT_REQ_CREDIT_BUREAU_YEAR	1.000000

```
[106 rows x 106 columns]

############################################################

Other Analysis: application_train
1. Checking for Null values: application_train
SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                                 ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 122, dtype: int64

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

In [15]:
```
datasets["application_train"].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

In [16]:
```
datasets["application_train"].describe() #numerical only features
```

Out[16]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPU
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	307499.000000	3.072330e+05	
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	27108.573909	5.383962e+05	
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	14493.737315	3.694465e+05	
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.500000	4.050000e+04	
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16524.000000	2.385000e+05	
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	24903.000000	4.500000e+05	
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596.000000	6.795000e+05	
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	258025.500000	4.050000e+06	

8 rows × 106 columns

In [17]:
```
datasets["application_test"].describe() #numerical only features
```

Out[17]:

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_RELATI
count	48744.000000	48744.000000	4.874400e+04	4.874400e+04	48720.000000	4.874400e+04	48744.0000
mean	277796.676350	0.397054	1.784318e+05	5.167404e+05	29426.240209	4.626188e+05	0.0212
std	103169.547296	0.709047	1.015226e+05	3.653970e+05	16016.368315	3.367102e+05	0.0144
min	100001.000000	0.000000	2.694150e+04	4.500000e+04	2295.000000	4.500000e+04	0.0002
25%	188557.750000	0.000000	1.125000e+05	2.606400e+05	17973.000000	2.250000e+05	0.0100
50%	277549.000000	0.000000	1.575000e+05	4.500000e+05	26199.000000	3.960000e+05	0.0188
75%	367555.500000	1.000000	2.250000e+05	6.750000e+05	37390.500000	6.300000e+05	0.0286
max	456250.000000	20.000000	4.410000e+06	2.245500e+06	180576.000000	2.245500e+06	0.0725

8 rows × 105 columns

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

In [ ]:
```

```

Missing data for application train

In [18]:
```
percent = (datasets["application_train"].isnull().sum()/datasets["application_train"].isnull().count()*100).sort_
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)
```

Out[18]:

	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

In [19]:
```
percent = (datasets["application_test"].isnull().sum()/datasets["application_test"].isnull().count()*100).sort_va
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)
```

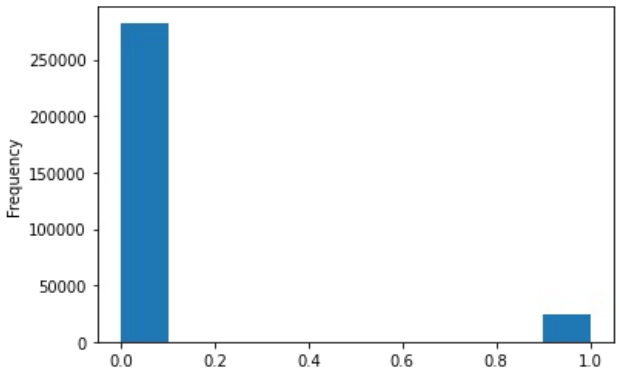
Out[19]:

	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

Distribution of the target column

In [20]:
```
datasets["application_train"]['TARGET'].astype(int).plot.hist();
```



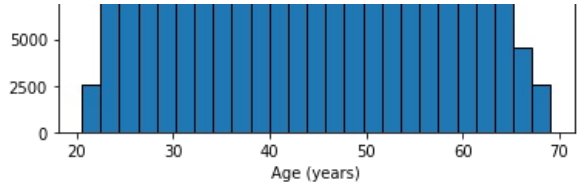
Correlation with the target column

In [21]:
```
correlations = datasets["application_train"].corr()['TARGET'].sort_values()
print('Most Positive Correlations:\n', correlations.tail(10))
print('\nMost Negative Correlations:\n', correlations.head(10))
```

```
Most Positive Correlations:
 FLAG_DOCUMENT_3                0.044346
REG_CITY_NOT_LIVE_CITY          0.044395
FLAG_EMP_PHONE                  0.045982
REG_CITY_NOT_WORK_CITY          0.050994
DAYS_ID_PUBLISH                 0.051457
DAYS_LAST_PHONE_CHANGE          0.055218
REGION_RATING_CLIENT            0.058899
REGION_RATING_CLIENT_W_CITY     0.060893
DAYS_BIRTH                      0.078239
TARGET                          1.000000
Name: TARGET, dtype: float64

Most Negative Correlations:
 EXT_SOURCE_3                 -0.178919
EXT_SOURCE_2                 -0.160472
EXT_SOURCE_1                 -0.155317
DAYS_EMPLOYED                -0.044932
FLOORSMAX_AVG                -0.044003
FLOORSMAX_MEDI               -0.043768
FLOORSMAX_MODE               -0.043226
AMT_GOODS_PRICE              -0.039645
REGION_POPULATION_RELATIVE   -0.037227
ELEVATORS_AVG                -0.034199
Name: TARGET, dtype: float64
```

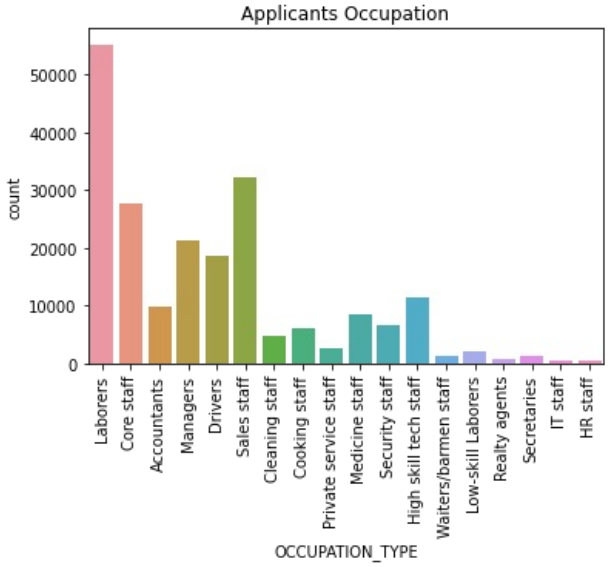
Applicants Age

In [22]:
```
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

In [23]:
```
sns.countplot(x='OCCUPATION_TYPE', data=datasets["application_train"]);
plt.title('Applicants Occupation');
plt.xticks(rotation=90);
```



Target Vs borrowers based on gender

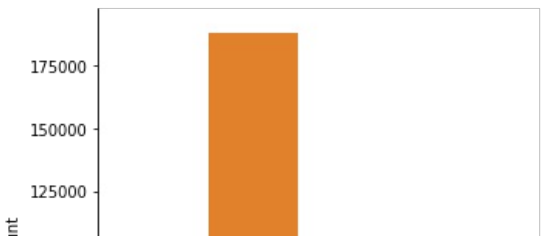
In [34]:
```
male_data = application_train[application_train['CODE_GENDER']=='M']['TARGET'].value_counts().reset_index().renam
male_data['count_percent'] = male_data['user_count']/male_data['user_count'].sum()*100
male_data['CODE_GENDER'] = 'M'
female_data = application_train[application_train['CODE_GENDER']=='F']['TARGET'].value_counts().reset_index().rer
female_data['count_percent'] = female_data['user_count']/female_data['user_count'].sum()*100
female_data['CODE_GENDER'] = 'F'
gender_data = male_data.append(female_data, ignore_index=True,sort=False)
gender_data
```

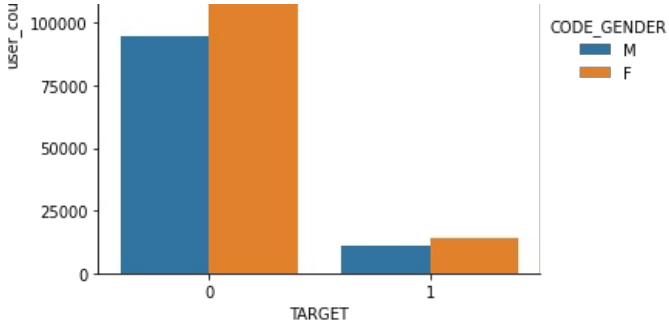
Out[34]:

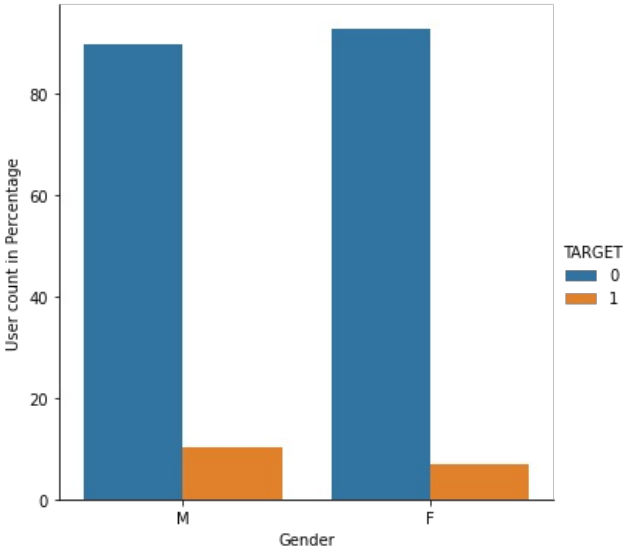
	TARGET	user_count	count_percent	CODE_GENDER
0	0	94404	89.858080	M
1	1	10655	10.141920	M
2	0	188278	93.000672	F
3	1	14170	6.999328	F

In [35]:
```
sns.catplot(data=gender_data, kind="bar", x="TARGET", y="user_count", hue="CODE_GENDER")
sns.catplot(data=gender_data, kind="bar", x="CODE_GENDER", y="count_percent", hue="TARGET")
plt.xlabel("Gender")
plt.ylabel('User count in Percentage')
```

Out[35]:
```
Text(10.772152777777777, 0.5, 'User count in Percentage')
```





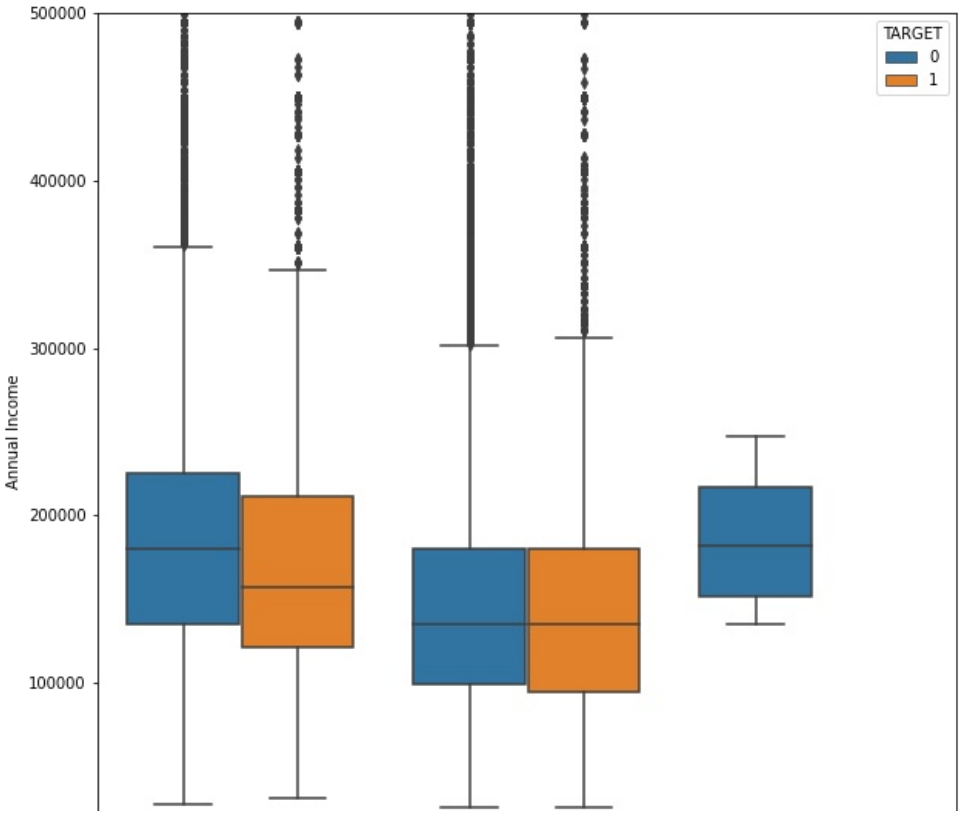


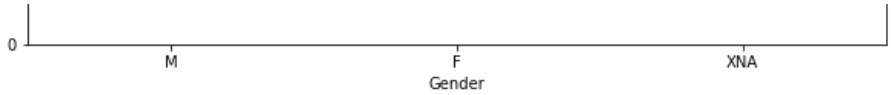
Male most likely to default than Female based on percentage of defaulter_count(Second Graph)

Gender Vs Income based on Target

In [36]:
```
fig,ax = plt.subplots(figsize = (10,10))
sns.boxplot(x='CODE_GENDER',hue = 'TARGET',y='AMT_INCOME_TOTAL', data=application_train)
plt.ylim(0, 500000)
plt.xlabel("Gender")
plt.ylabel('Annual Income')
```

Out[36]:
```
Text(0, 0.5, 'Annual Income')
```





Own House count based Target

In [37]:

```
own_house_data = application_train[application_train['FLAG_OWN_REALTY']=='Y']['TARGET'].value_counts().reset_inde
own_house_data['OWN_HOUSE'] = 'Y'
own_house_data['count_percent'] = own_house_data['user_count']/own_house_data['user_count'].sum()*100
not_own_house_data = application_train[application_train['FLAG_OWN_REALTY']=='N']['TARGET'].value_counts().reset_
not_own_house_data['OWN_HOUSE'] = 'N'
not_own_house_data['count_percent'] = not_own_house_data['user_count']/not_own_house_data['user_count'].sum()*100
own_house_data = own_house_data.append(not_own_house_data,ignore_index=True,sort=False)
own_house_data
```

Out[37]:

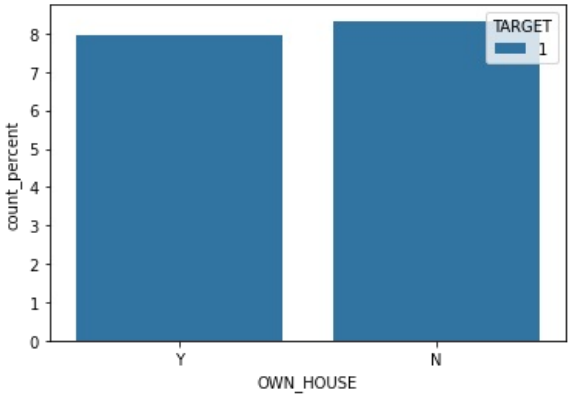
	TARGET	user_count	OWN_HOUSE	count_percent
0	0	196329	Y	92.038423
1	1	16983	Y	7.961577
2	0	86357	N	91.675071
3	1	7842	N	8.324929

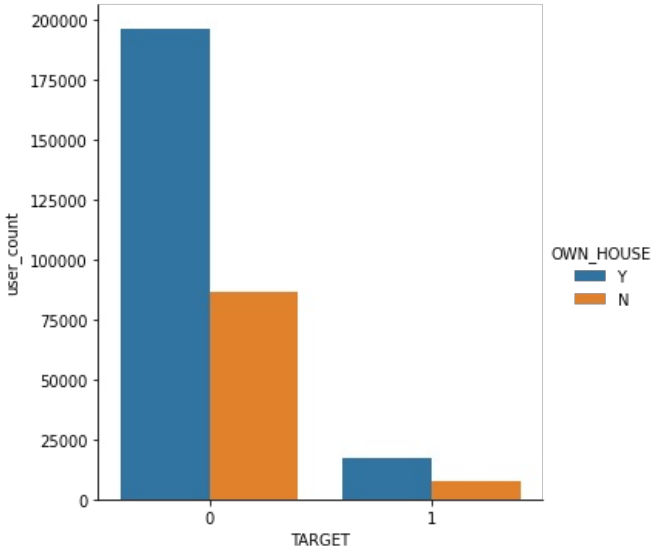
In [38]:

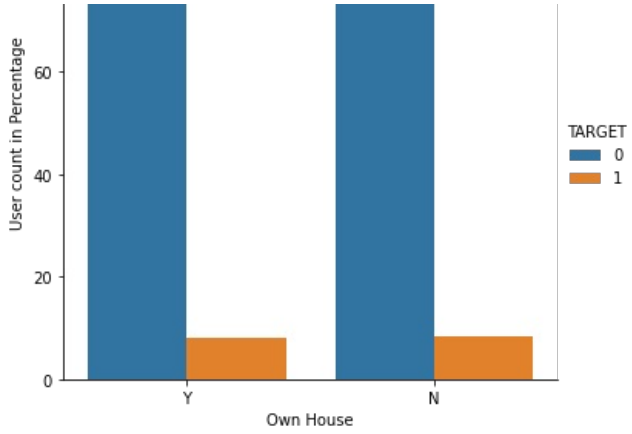
```
sns.barplot(x='OWN_HOUSE',y='count_percent',hue = 'TARGET',data=own_house_data[own_house_data['TARGET']==1])

sns.catplot(data=own_house_data, kind="bar", x="TARGET", y="user_count", hue="OWN_HOUSE")

sns.catplot(data=own_house_data, kind="bar", x="OWN_HOUSE", y="count_percent", hue="TARGET")
plt.xlabel("Own House")
plt.ylabel('User count in Percentage')
```

Out[38]:

```
Text(10.772152777777777, 0.5, 'User count in Percentage')
```







Not a significant difference, but borrowers who own a house are more likely to pay

Own car count based Target

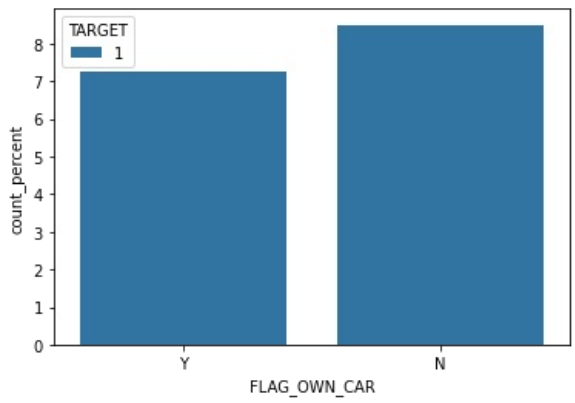
In [39]:
```
own_car_data = application_train[application_train['FLAG_OWN_CAR']=='Y']['TARGET'].value_counts().reset_index().r
own_car_data['FLAG_OWN_CAR'] = 'Y'
own_car_data['count_percent'] = own_car_data['user_count']/own_car_data['user_count'].sum()*100
not_own_car_data = application_train[application_train['FLAG_OWN_CAR']=='N']['TARGET'].value_counts().reset_index
not_own_car_data['FLAG_OWN_CAR'] = 'N'
not_own_car_data['count_percent'] = not_own_car_data['user_count']/not_own_car_data['user_count'].sum()*100
own_car_data = own_car_data.append(not_own_car_data,ignore_index=True,sort=False)
own_car_data
```

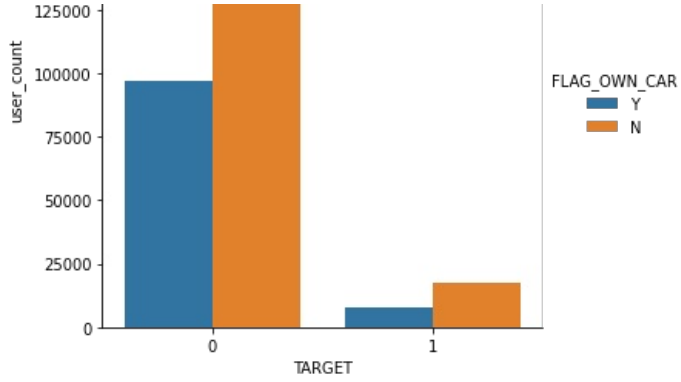
Out[39]:

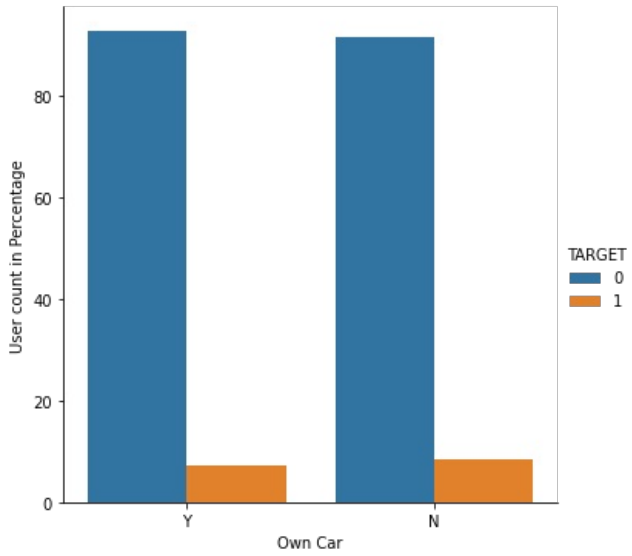
	TARGET	user_count	FLAG_OWN_CAR	count_percent
0	0	97011	Y	92.756270
1	1	7576	Y	7.243730
2	0	185675	N	91.499773
3	1	17249	N	8.500227

In [40]:
```
sns.barplot(x='FLAG_OWN_CAR',y='count_percent',hue = 'TARGET',data=own_car_data[own_car_data['TARGET']==1])

sns.catplot(data=own_car_data, kind="bar", x="TARGET", y="user_count", hue="FLAG_OWN_CAR")

sns.catplot(data=own_car_data, kind="bar", x="FLAG_OWN_CAR", y="count_percent", hue="TARGET")
plt.xlabel("Own Car")
plt.ylabel('User count in Percentage')
```

Out[40]:
```
Text(10.772152777777777, 0.5, 'User count in Percentage')
```





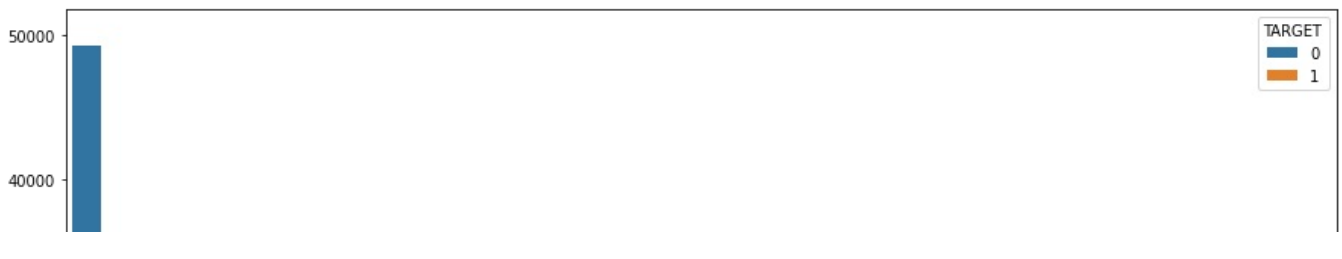


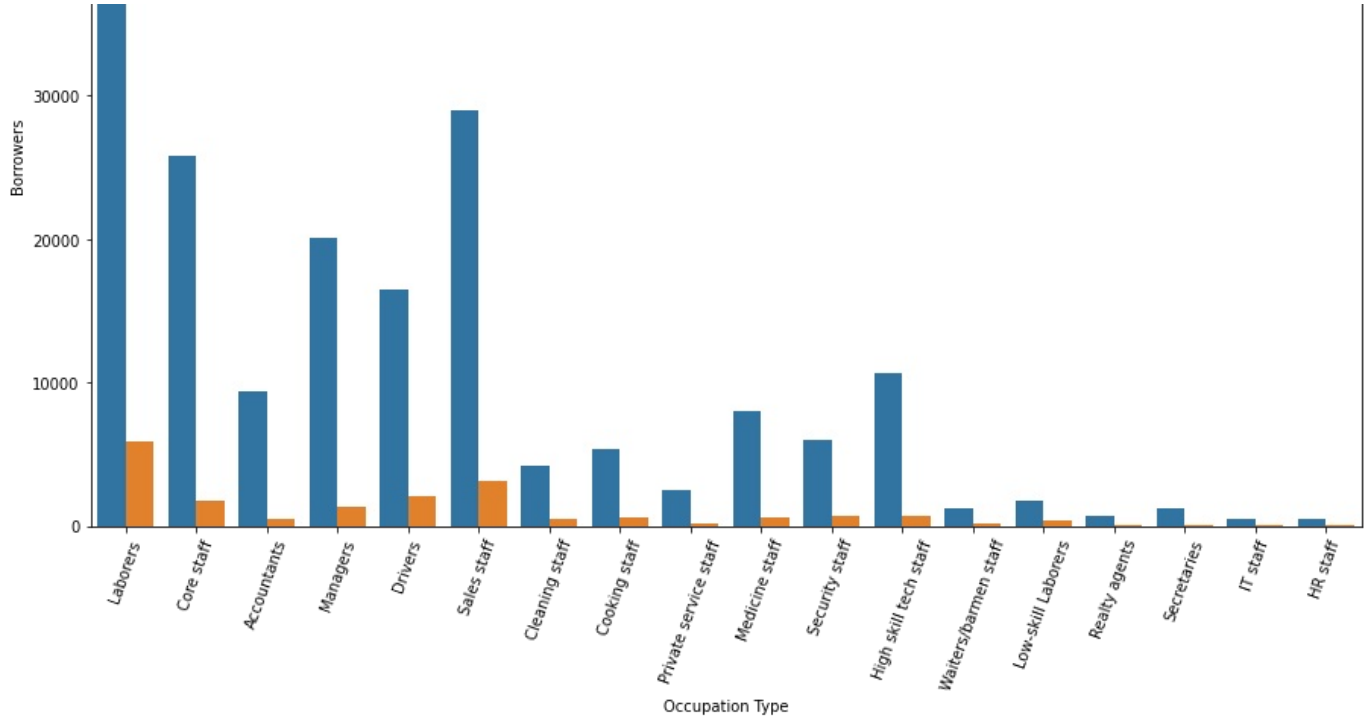
Borrowers owning a car are more likely to pay on time

Occupation type count based on Target

In [41]:
```
fig, ax = plt.subplots(figsize=(15,9))
sns.countplot(x='OCCUPATION_TYPE', hue = 'TARGET',data=application_train)
plt.xlabel("Occupation Type")
plt.ylabel('Borrowers')
plt.xticks(rotation=70)
```

Out[41]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17]),
 [Text(0, 0, 'Laborers'),
  Text(1, 0, 'Core staff'),
  Text(2, 0, 'Accountants'),
  Text(3, 0, 'Managers'),
  Text(4, 0, 'Drivers'),
  Text(5, 0, 'Sales staff'),
  Text(6, 0, 'Cleaning staff'),
  Text(7, 0, 'Cooking staff'),
  Text(8, 0, 'Private service staff'),
  Text(9, 0, 'Medicine staff'),
  Text(10, 0, 'Security staff'),
  Text(11, 0, 'High skill tech staff'),
  Text(12, 0, 'Waiters/barmen staff'),
  Text(13, 0, 'Low-skill Laborers'),
  Text(14, 0, 'Realty agents'),
  Text(15, 0, 'Secretaries'),
  Text(16, 0, 'IT staff'),
  Text(17, 0, 'HR staff')])
```

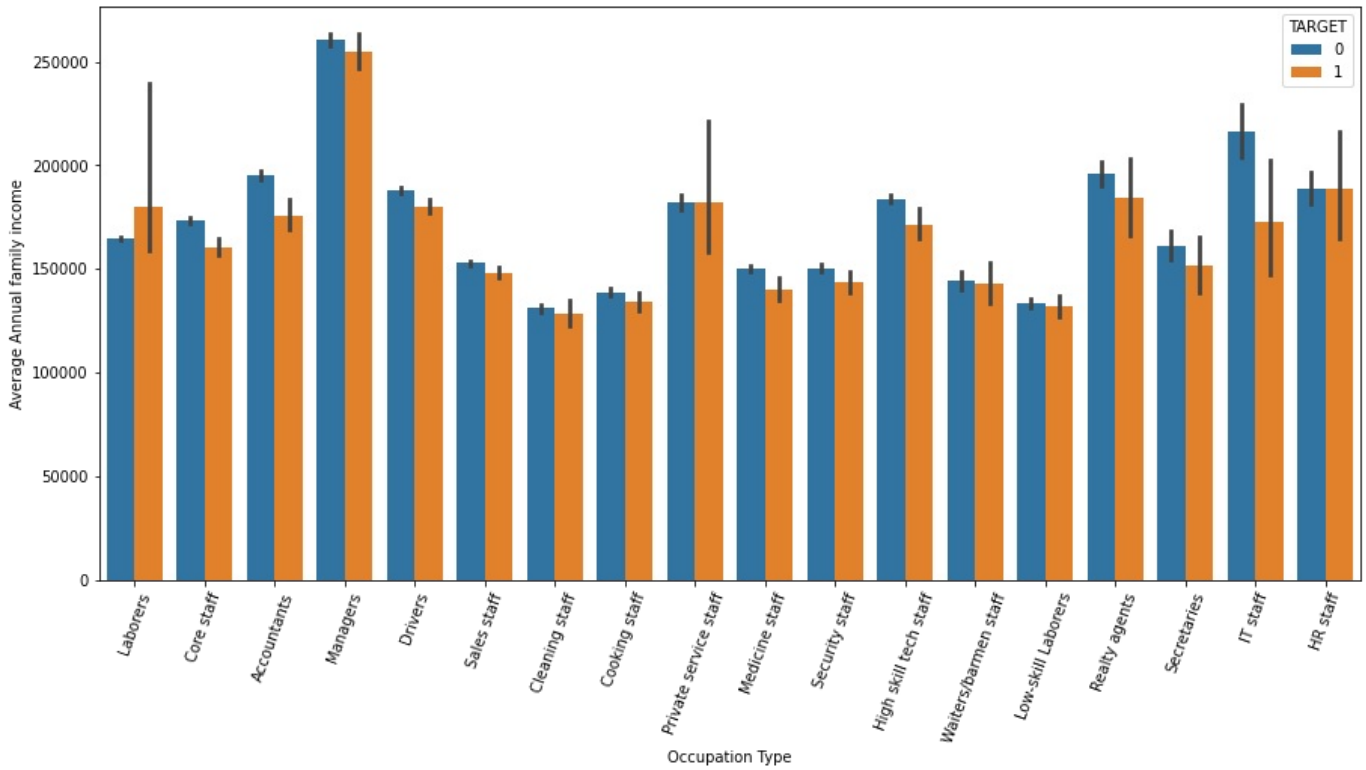




Occupation type vs income based on Target

In [42]:
```
fig, ax = plt.subplots(figsize=(15,7))
sns.barplot(x='OCCUPATION_TYPE',y='AMT_INCOME_TOTAL',hue = 'TARGET',data=application_train)
plt.xticks(rotation=70)
plt.xlabel("Occupation Type")
plt.ylabel("Average Annual family income")
```

Out[42]:
```
Text(0, 0.5, 'Average Annual family income')
```



In [43]:
```
income_credit_ratio_data = application_train[['AMT_INCOME_TOTAL','AMT_CREDIT','TARGET']]
income_credit_ratio_data['IC_ratio'] = income_credit_ratio_data['AMT_INCOME_TOTAL']/income_credit_ratio_data['AMT
income_credit_ratio_data['quantile'] = pd.qcut(income_credit_ratio_data['IC_ratio'],q = 10, labels = False)
income_credit_ratio_data
```

Out[43]:

	AMT_INCOME_TOTAL	AMT_CREDIT	TARGET	IC_ratio	quantile

0	202500.0	406597.5	1	0.498036	7
1	270000.0	1293502.5	0	0.208736	2
2	67500.0	135000.0	0	0.500000	7
3	135000.0	312682.5	0	0.431748	6
4	121500.0	513000.0	0	0.236842	3
...	...	...	...	...	...
307506	157500.0	254700.0	0	0.618375	8
307507	72000.0	269550.0	0	0.267112	4
307508	153000.0	677664.0	0	0.225776	3
307509	171000.0	370107.0	1	0.462029	7
307510	157500.0	675000.0	0	0.233333	3

307511 rows × 5 columns

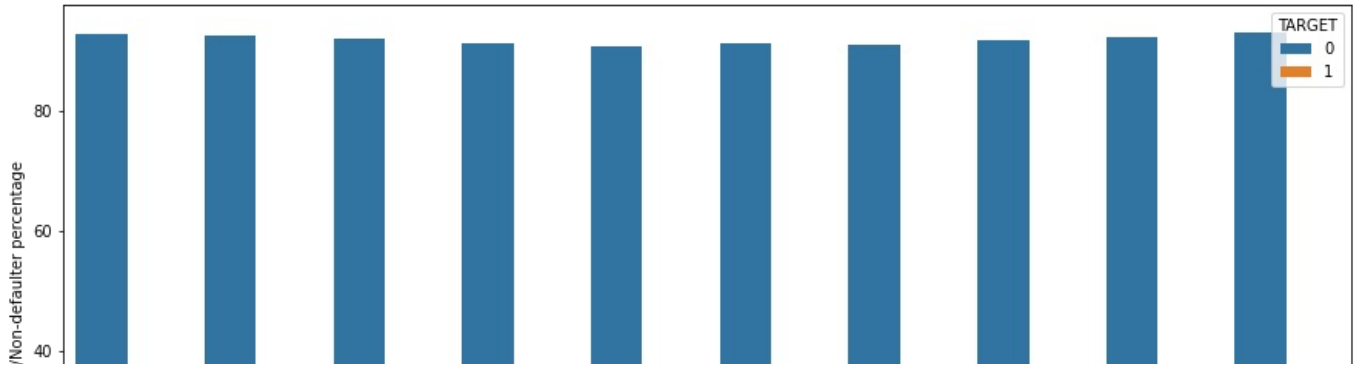
In [44]:
```
income_credit_ratio_data = income_credit_ratio_data.groupby(['quantile','TARGET'])['AMT_INCOME_TOTAL'].count().re
income_credit_ratio_data['count_percent'] = income_credit_ratio_data.apply(lambda x: x['user_count']/income_credi
income_credit_ratio_data
```

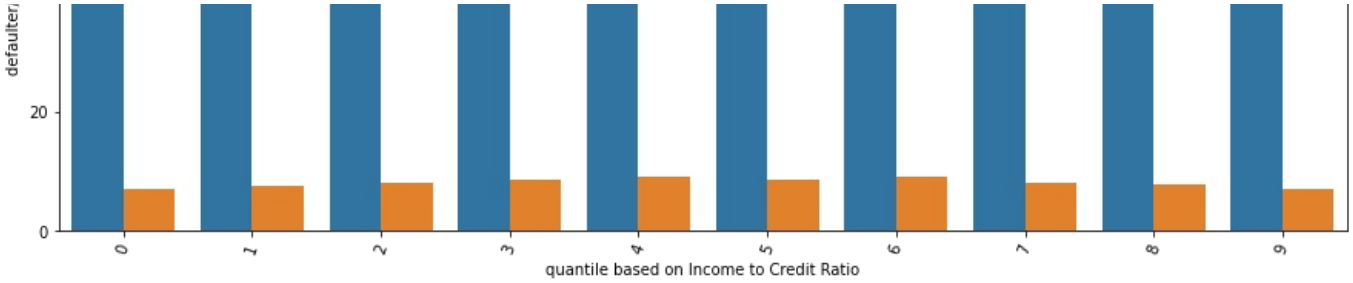
Out[44]:

	quantile	TARGET	user_count	count_percent
0	0	0	28613	92.929523
1	0	1	2177	7.070477
2	1	0	28499	92.577313
3	1	1	2285	7.422687
4	2	0	28241	92.035196
5	2	1	2444	7.964804
6	3	0	28128	91.375110
7	3	1	2655	8.624890
8	4	0	27899	90.805234
9	4	1	2825	9.194766
10	5	0	28298	91.307434
11	5	1	2694	8.692566
12	6	0	27764	91.023539
13	6	1	2738	8.976461
14	7	0	28498	91.863839
15	7	1	2524	8.136161
16	8	0	28126	92.264795
17	8	1	2358	7.735205
18	9	0	28620	93.088307
19	9	1	2125	6.911693

In [45]:
```
fig, ax = plt.subplots(figsize=(15,7))
sns.barplot(x='quantile',y='count_percent',hue = 'TARGET',data=income_credit_ratio_data)
plt.xticks(rotation=70)
plt.xlabel("quantile based on Income to Credit Ratio")
plt.ylabel("defaulter/Non-defaulter percentage")
```

Out[45]: Text(0, 0.5, 'defaulter/Non-defaulter percentage')

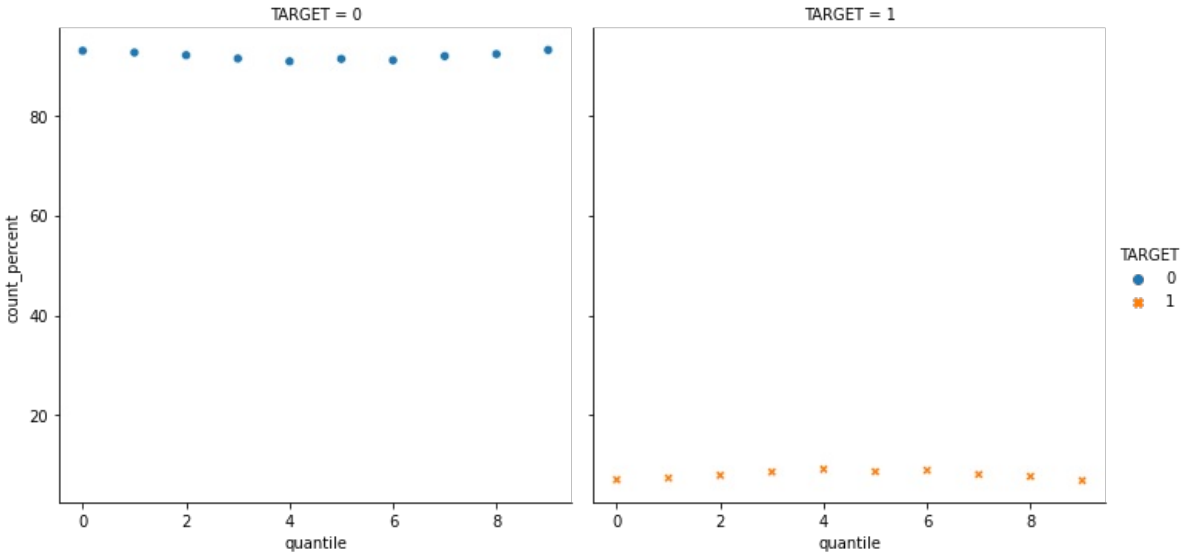




In [46]:

```
sns.relplot(
    data=income_credit_ratio_data, x="quantile", y="count_percent",
    col="TARGET", hue="TARGET", style="TARGET",
    kind="scatter"
)
```

Out[46]: <seaborn.axisgrid.FacetGrid at 0x7fae439c0640>



Defaulters percentage is less when IC_ratio is either Low or High

Repayers to Applicants Ratio

In [47]:

```
occ_data = pd.DataFrame(data=application_train.groupby(['OCCUPATION_TYPE','TARGET']).count()['SK_ID_CURR'])
occ_data = occ_data.reset_index()
value_counts = occ_data['SK_ID_CURR'].values
def repayers_to_applicants_ratio(values):
    flag = 1
    ratios = []
    for count in range(len(values)):
        if flag == 1:
            current_number = values[count]
            next_number = values[count+1]
            ratios.append(current_number/(current_number+next_number))
            ratios.append(current_number/(current_number+next_number))
        flag=flag*-1
    return ratios
occ_data['Ratio R/A'] = repayers_to_applicants_ratio(value_counts)
occ_ratio = occ_data.groupby(['OCCUPATION_TYPE','Ratio R/A']).count().drop(['TARGET', 'SK_ID_CURR'],axis=1)
occ_ratio = occ_ratio.reset_index()
occ_ratio = occ_ratio.sort_values(['Ratio R/A'],ascending=False)
occ_ratio
```

Out[47]:

	OCCUPATION_TYPE	Ratio R/A
0	Accountants	0.951697
6	High skill tech staff	0.938401
10	Managers	0.937860
3	Core staff	0.936960
5	HR staff	0.936057

7	IT staff	0.935361
12	Private service staff	0.934012
11	Medicine staff	0.932998
15	Secretaries	0.929502
13	Realty agents	0.921438
1	Cleaning staff	0.903933
14	Sales staff	0.903682
2	Cooking staff	0.895560
8	Laborers	0.894212
16	Security staff	0.892576
17	Waiters/barmen staff	0.887240
4	Drivers	0.886739
9	Low-skill Laborers	0.828476

Correlation of the positive days since birth and target

In [48]:
```
# Find the correlation of the positive days since birth and target
application_train['DAYS_BIRTH'] = abs(application_train['DAYS_BIRTH'])
-1*(application_train['DAYS_BIRTH'].corr(application_train['TARGET']))
```

Out[48]: 0.07823930830982737

Correlation of the positive days since employement and target

In [49]:
```
application_train['DAYS_EMPLOYED'] = abs(application_train['DAYS_EMPLOYED'])
-1*(application_train['DAYS_EMPLOYED'].corr(application_train['TARGET']))
```

Out[49]: 0.04704582521599308

Fetching important releavant features

In [50]:
```
imp_features = ['FLOORSMAX_MEDI', 'ELEVATORS_MEDI', 'AMT_GOODS_PRICE', 'EMERGENCYSTATE_MODE', 'NAME_TYPE_SUITE',
imp_features = ['CODE_GENDER','FLAG_OWN_REALTY','FLAG_OWN_CAR','AMT_CREDIT','AMT_ANNUITY','DAYS_EMPLOYED','OWN_CA
imp_features = list(set(imp_features))
```

Pandas profiling (contains correlation graphs between features)

In [52]:
```
from pandas_profiling import ProfileReport
profile = ProfileReport(application_train[imp_features], title='HomeCredit Dataset Pandas Profiling Report', expl
```

In [53]:
```
profile
```

Overview

Dataset statistics

Variable types

Number of variables	30
Number of observations	307511
Missing cells	2447652
Missing cells (%)	26.5%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	168.5 MiB
Average record size in memory	574.6 B

Numeric	19
Boolean	3
Categorical	8

Alerts

`ELEVATORS_MEDI` is highly correlated with `APARTMENTS_MODE` and 1 other fields (APARTMENTS_MODE, FLOORSMAX_MEDI)	**High correlation**
`APARTMENTS_MODE` is highly correlated with `ELEVATORS_MEDI` and 4 other fields (ELEVATORS_MEDI, BASEMENTAREA_MEDI, ENTRANCES_MEDI, FLOORSMAX_MEDI, BASEMENTAREA_MODE)	**High correlation**
`BASEMENTAREA_MEDI` is highly correlated with `APARTMENTS_MODE` and 2 other fields (APARTMENTS_MODE, ENTRANCES_MEDI, BASEMENTAREA_MODE)	**High correlation**
`AMT_GOODS_PRICE` is highly correlated with `AMT_CREDIT` and 1 other fields (AMT_CREDIT, AMT_ANNUITY)	**High correlation**

Out[53]:

In [ ]:

Dataset questions

Unique record for each SK_ID_CURR

In [54]:
```
datasets.keys()
```

Out[54]:
```
dict_keys(['application_train', 'application_test', 'bureau', 'bureau_balance', 'credit_card_balance', 'installments_payments', 'previous_application', 'POS_CASH_balance'])
```

In [55]:
```
len(datasets["application_train"]["SK_ID_CURR"].unique()) == datasets["application_train"].shape[0]
```

Out[55]:
```
True
```

In [56]:
```
np.intersect1d(datasets["application_train"]["SK_ID_CURR"], datasets["application_test"]["SK_ID_CURR"])
```

Out[56]:
```
array([], dtype=int64)
```

In [57]:
```
datasets["application_test"].shape
```

Out[57]:
```
(48744, 121)
```

In [58]:
```
datasets["application_train"].shape
```

Out[58]:
```
(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.

In [64]:
```
#appsDF.shape()
```

In [65]:
```
appsDF = datasets["previous_application"]
```

In [66]:
```
len(np.intersect1d(datasets["previous_application"]["SK_ID_CURR"], datasets["application_test"]["SK_ID_CURR"]))
```

Out[66]: 47800

In [67]:
```
print(f"There are  {appsDF.shape[0]:,} previous applications")
```

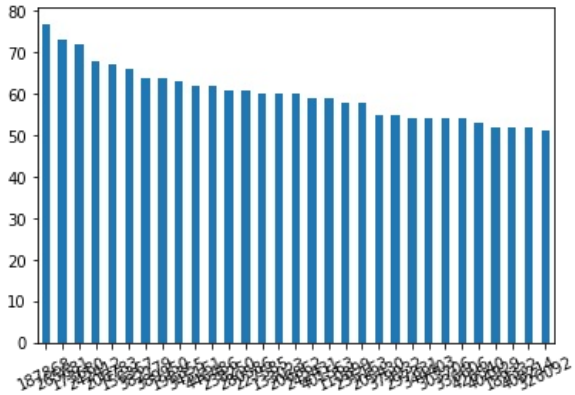
```
There are  1,670,214 previous applications
```

In [68]:
```
# How many entries are there for each month?
prevAppCounts = appsDF['SK_ID_CURR'].value_counts(dropna=False)
```

In [69]:
```
len(prevAppCounts[prevAppCounts >40])  #more that 40 previous applications
```

Out[69]: 101

In [70]:
```
prevAppCounts[prevAppCounts >50].plot(kind='bar')
plt.xticks(rotation=25)
plt.show()
```



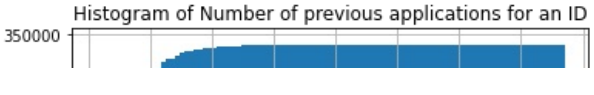
Histogram of Number of previous applications for an ID

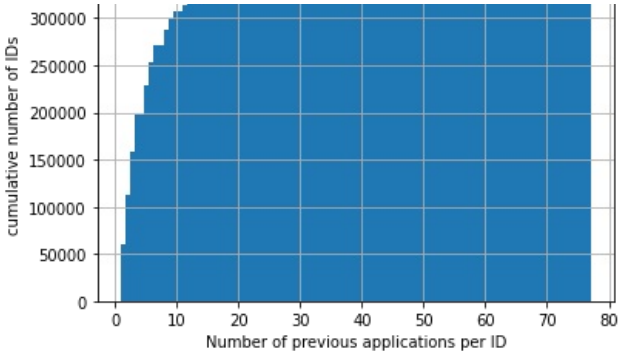
In [71]:
```
sum(appsDF['SK_ID_CURR'].value_counts()==1)
```

Out[71]: 60458

In [72]:
```
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')
```

Out[72]: Text(0.5, 1.0, 'Histogram of Number of previous applications for an ID')





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%)

In [73]:

```
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.

In [74]:
```
df = pd.DataFrame([[1, 2, 3],
                   [4, 5, 6],
                  [7, 8, 9],
                  [np.nan, np.nan, np.nan]],
                  columns=['A', 'B', 'C'])
```

In [75]:
```
df
```

Out[75]:

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

In [76]:
```
df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
#         A    B
#max    NaN  8.0
#min    1.0  2.0
#sum   12.0  NaN
```

Out[76]:

	A	B
sum	12.0	NaN
min	1.0	2.0
max	NaN	8.0

In [77]:
```
df = pd.DataFrame({'A': [1, 1, 2, 2],
                   'B': [1, 2, 3, 4],
                   'C': np.random.randn(4)})
df
```

Out[77]:

	A	B	C
0	1	1	-1.003927
1	1	2	0.031532
2	2	3	-0.846962
3	2	4	0.481881

In [78]:
```
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
```

Out[78]:

Out[78]:

	B		C
	min	max	sum
A			
1	1	2	-0.972395
2	3	4	-0.365081

In [79]:
```
appsDF.columns
```

Out[79]:
```
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')
```

In [ ]:
```
```

In [80]:
```
funcs = ["a","b","c"]
{f:f"{f}_max" for f in funcs}
```

Out[80]:
```
{'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

In [81]:
```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]
```

Out[81]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS
6	2315218	175704	Cash loans	NaN	0.0	0.0	NaN	

1 rows × 37 columns

In [82]:
```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704) & ~(appsDF["AMT_CREDIT"]==1.0)]
```

Out[82]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS
6	2315218	175704	Cash loans	NaN	0.0	0.0	NaN	

1 rows × 37 columns

Missing values in prevApps

In [83]:
```
appsDF.isna().sum()
```

Out[83]:
```
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
```

In [84]:
```
appsDF.columns
```

Out[84]:
```
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

In [87]:
```
#agg_op_features
```

feature transformer for prevApp table

Join the labeled dataset

In [96]:
```
~3==3
```

Out[96]:
```
False
```

In [97]:
```
datasets.keys()
```

Out[97]:
```
dict_keys(['application_train', 'application_test', 'bureau', 'bureau_balance', 'credit_card_balance', 'installments_payments', 'previous_application', 'POS_CASH_balance'])
```

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

In [100…
```
# approval rate 'NFLAG_INSURED_ON_APPROVAL'
```

In [101…
```
# 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"))
    ])
```

In [103…
```
# Categorical boolean mask
categorical_feature_mask = df.dtypes==object
categorical_feature_mask
```

Out[103…
```
A    False
B    False
C    False
dtype: bool
```

In [ ]:

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

In [107…
```
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
```

```
[0 1 0]
```

Out[107… (569, 30)

In [108…
```
data.feature_names
```

Out[108…
```
array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean smoothness', 'mean compactness', 'mean concavity',
       'mean concave points', 'mean symmetry', 'mean fractal dimension',
       'radius error', 'texture error', 'perimeter error', 'area error',
       'smoothness error', 'compactness error', 'concavity error',
       'concave points error', 'symmetry error',
       'fractal dimension error', 'worst radius', 'worst texture',
       'worst perimeter', 'worst area', 'worst smoothness',
       'worst compactness', 'worst concavity', 'worst concave points',
       'worst symmetry', 'worst fractal dimension'], dtype='<U23')
```

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

HCDR preprocessing

In [111…
```
# 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
```

In [112…
```
# 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(sparse=False, handle_unknown="ignore"))
    ])

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

```
    ])
```

In [113…
```
list(datasets["application_train"].columns)
```

Out[113…
```
['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']
```

Our 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

In [123…

```
# imports
import warnings
warnings.simplefilter('ignore')

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import re
from time import time
from scipy import stats
import json

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder

from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

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.pipeline import Pipeline, FeatureUnion
from sklearn.metrics import make_scorer, roc_auc_score, log_loss, accuracy_score
from sklearn.preprocessing import LabelEncoder

from sklearn.metrics import confusion_matrix

from IPython.display import display, Math, Latex
```

In [124…

```
df = application_train
df.head()
```

Out[124…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TC
0	100002	1	Cash loans	M	N	Y	0	202
1	100003	0	Cash loans	F	N	N	0	270
2	100004	0	Revolving loans	M	Y	Y	0	67
3	100006	0	Cash loans	F	N	Y	0	135
4	100007	0	Cash loans	M	N	Y	0	121

5 rows × 122 columns

In [125…

```
y = df['TARGET']
x = df.drop(columns='TARGET')
```

Building Logistic Regression baseline pipeline

In [126…

```
results = pd.DataFrame(columns=["ExpID", "Cross fold train accuracy", "Test Accuracy", "Validation Accuracy", "AU

def pct(x):
    return round(100*x,1)


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


def returnModel(x,y,results,description_text):
    num_attribs = []
    cat_attribs = []

    for col in x.columns.tolist():
        if x[col].dtype in (['int','float']):
            num_attribs.append(col)
        else:
            cat_attribs.append(col)

    le_dict = {}
    for col in x.columns.tolist():
        if df[col].dtype == 'object':
            le = LabelEncoder()
            x[col] = x[col].fillna("NULL")
            x[col] = le.fit_transform(x[col])
            le_dict['le_{}'.format(col)] = le

    num_pipeline =Pipeline([('selector',DataFrameSelector(num_attribs)),
                            ('scaler', StandardScaler()),
                           ('imputer', SimpleImputer(strategy = 'median'))
                            ])


    cat_pipeline = Pipeline([
        ('selector', DataFrameSelector(cat_attribs)),
        ('imputer', SimpleImputer(strategy='most_frequent'))
    ])


    full_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
```

```
        ("cat_pipeline", cat_pipeline),
    ])

    np.random.seed(42)
    full_pipeline_with_predictor = Pipeline([
            ("preparation", num_pipeline),
            ("linear", LogisticRegression(random_state=42))
        ])

    # split 20% test data with random seed set to 42 for correct results
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=42)
    x_train, x_valid, y_train, y_valid = train_test_split(x_train, y_train, test_size=0.2, random_state=42)
    print("train data set: ")
    print(x_train.shape,y_train.shape)
    print("test data set: ")
    print(x_test.shape,y_test.shape)
    print("validation data set: ")
    print(x_valid.shape,y_valid.shape)


    start = time()
    full_pipeline_with_predictor.fit(x_train, y_train)
    np.random.seed(42)

    cv30Splits = ShuffleSplit(n_splits = 30, test_size = 0.3, random_state = 0)
    logit_scores = cross_val_score(full_pipeline_with_predictor, x_train, y_train, cv = cv30Splits)
    logit_score_train = logit_scores.mean()
    train_time = np.round(time() - start, 4)

    # Time and score test predictions
    start = time()
    logit_score_test  = full_pipeline_with_predictor.score(x_test, y_test)
    test_time = np.round(time() - start, 4)

    start = time()
    logit_score_valid  = full_pipeline_with_predictor.score(x_valid, y_valid)
    valid_time = np.round(time() - start, 4)

    AUC = roc_auc_score(y_test,full_pipeline_with_predictor.predict(x_test))
    print("AUC is {}".format(AUC))
    print("\n............\n")
    print("Confusion Matrix: {}".format(confusion_matrix(y_test, full_pipeline_with_predictor.predict(x_test))))

    no_of_inputs = x.shape[1]

    temp_df = pd.DataFrame()
    temp_df = temp_df.append(pd.Series(["Baseline with {} inputs".format(no_of_inputs), pct(logit_score_train), p
                AUC, train_time, test_time, valid_time, "{} - Untuned LogisticRegression".format(description_te
    temp_df.columns = results.columns

    results = results.append(temp_df,ignore_index=True)

    return le_dict, full_pipeline_with_predictor, results
```

Loss function used (data loss and regularization parts) in latex

In [127…

```
display(Math(r'[L_\varepsilon(y,f(x,w))=\max\{0, |y-f(x,w)|-\varepsilon\}]'))
```

$$[L_{\varepsilon}(y,f(x,w)) = \max\{0, |y-f(x,w)| - \varepsilon\}]$$

In [128…

```
le_dict, full_pipeline_with_predictor, results = returnModel(x,y,results,"Unbalanced Dataset")
```

```
train data set:
(196806, 121) (196806,)
test data set:
(61503, 121) (61503,)
validation data set:
(49202, 121) (49202,)
AUC is 0.5034324684759044

............

Confusion Matrix: [[56508    46]
 [ 4911    38]]
```

In [129…

```
results
```

Out[129…

	ExpID	Cross fold train	Test	Validation	AUC	Train	Test	Validation

		accuracy	Accuracy	Accuracy		Time(s)	Time(s)	Time(s)	Experiment description
0	Baseline with 121 inputs	92.0	91.9	91.8	0.503432	77.6094	0.1369	0.1191	Unbalanced Dataset - Untuned LogisticRegression

Submission 1

In [131…
```
test_data_set = application_test
test_data_set.head()
```

Out[131…

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT
0	100001	Cash loans	F	N	Y	0	135000.0	
1	100005	Cash loans	M	N	Y	0	99000.0	
2	100013	Cash loans	M	Y	Y	0	202500.0	
3	100028	Cash loans	F	N	Y	2	315000.0	
4	100038	Cash loans	M	Y	N	1	180000.0	

5 rows × 121 columns

In [132…
```
for col in test_data_set.columns.tolist():
    for le in le_dict:
        if col in le:
            test_data_set[col] = le_dict[le].fit_transform(test_data_set[col])
```

In [133…
```
output_data = test_data_set[['SK_ID_CURR']]
output_data['TARGET'] = pd.Series(full_pipeline_with_predictor.predict(test_data_set).tolist())
```

In [134…
```
output_data['TARGET'].value_counts()
```

Out[134…
```
0    48695
1       49
Name: TARGET, dtype: int64
```

In [136…
```
output_data.to_csv('./outputphase1.csv', index=False)
```

Improving the AUC

In [137…
```
df['TARGET'].value_counts()
```

Out[137…
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

In [138…
```
final_data = df[df['TARGET']==1]
final_data = final_data.append(df[df['TARGET']==0].reset_index(drop=True).sample(n = 50000))
print(final_data.shape)
final_data.head()
```

```
(74825, 122)
```

Out[138…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_T
0	100002	1	Cash loans	M	N	Y	0	202
26	100031	1	Cash loans	F	N	Y	0	112
40	100047	1	Cash loans	M	N	Y	0	202
42	100049	1	Cash loans	F	N	N	0	135
81	100096	1	Cash loans	F	N	Y	0	81

5 rows × 122 columns

In [139…
```
x = final_data.drop(columns='TARGET')
y = final_data['TARGET']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.2, shuffle=True, random_state=42)
print(x_train.shape,y_train.shape)
```

```
(59860, 121) (59860,)
```

In [140…
```
le_dict, full_pipeline_with_predictor, results = returnModel(x,y,results,"50000 non-defaulters Balanced Dataset")
```

```
train data set:
(47888, 121) (47888,)
test data set:
(14965, 121) (14965,)
validation data set:
(11972, 121) (11972,)
AUC is 0.6286824253693222

............

Confusion Matrix: [[8907 1144]
 [3090 1824]]
```

In [141…
```
results
```

Out[141…

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Validation Time(s)	Experiment description
0	Baseline with 121 inputs	92.0	91.9	91.8	0.503432	77.6094	0.1369	0.1191	Unbalanced Dataset - Untuned LogisticRegression
1	Baseline with 121 inputs	71.6	71.7	72.0	0.628682	20.8099	0.0237	0.0211	50000 non-defaulters Balanced Dataset - Untune...

Submission 2

In [142…
```
#checking across the test dataset

output_data = test_data_set[['SK_ID_CURR']]
output_data['TARGET'] = pd.Series(full_pipeline_with_predictor.predict(test_data_set).tolist())
```

In [143…
```
output_data['TARGET'].value_counts()
```

Out[143…
```
0    43723
1     5021
Name: TARGET, dtype: int64
```

In [144…
```
output_data.to_csv('./output_submission_1_phase1.csv', index=False)
```

Approach 2

In [145…
```
final_data = df[df['TARGET']==1]
final_data = final_data.append(df[df['TARGET']==0].reset_index(drop=True).sample(n = 75000))
print(final_data.shape)
final_data.head()
```

```
(99825, 122)
```

Out[145…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_T
0	100002	1	Cash loans	M	N	Y	0	202
26	100031	1	Cash loans	F	N	Y	0	112
40	100047	1	Cash loans	M	N	Y	0	202

42	100049	1	Cash loans	F	N	N	0	13
81	100096	1	Cash loans	F	N	Y	0	8

5 rows × 122 columns

In [146…
```
x = final_data.drop(columns='TARGET')
y = final_data['TARGET']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.2, shuffle=True, random_state=42)
print(x_train.shape,y_train.shape)
```

```
(79860, 121) (79860,)
```

In [147…
```
le_dict, full_pipeline_with_predictor, results = returnModel(x,y,results,"75000 non-defaulters Balanced Dataset")
```

```
train data set:
(63888, 121) (63888,)
test data set:
(19965, 121) (19965,)
validation data set:
(15972, 121) (15972,)
AUC is 0.5772520859994552

............

Confusion Matrix: [[14204   772]
 [ 3961  1028]]
```

In [148…
```
results
```

Out[148…

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Validation Time(s)	Experiment description
0	Baseline with 121 inputs	92.0	91.9	91.8	0.503432	77.6094	0.1369	0.1191	Unbalanced Dataset - Untuned LogisticRegression
1	Baseline with 121 inputs	71.6	71.7	72.0	0.628682	20.8099	0.0237	0.0211	50000 non-defaulters Balanced Dataset - Untune...
2	Baseline with 121 inputs	77.0	76.3	76.8	0.577252	26.7786	0.0390	0.0257	75000 non-defaulters Balanced Dataset - Untune...

Submission 3

In [149…
```
#checking for test dataset
```

In [150…
```
output_data = test_data_set[['SK_ID_CURR']]
output_data['TARGET'] = pd.Series(full_pipeline_with_predictor.predict(test_data_set).tolist())
```

In [151…
```
output_data['TARGET'].value_counts()
```

Out[151…
```
0    45856
1     2888
Name: TARGET, dtype: int64
```

Phase-2

Feature Engineering

In [79]:
```
import warnings
warnings.simplefilter('ignore')
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import re
from time import time
from scipy import stats
import json

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder

from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

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.pipeline import Pipeline, FeatureUnion
from sklearn.metrics import make_scorer, roc_auc_score, log_loss, accuracy_score
from sklearn.preprocessing import LabelEncoder

from sklearn.metrics import confusion_matrix
from IPython.display import display, Math, Latex


from sklearn.linear_model import Lasso,Ridge,LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb

# Read data from application_train dataset.
data = pd.read_csv('/Users/nidhisaduvala/Desktop/Spring/AML/home-credit-default-risk/application_train.csv')
data.head()
```

Out[79]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TC
0	100002	1	Cash loans	M	N	Y	0	202
1	100003	0	Cash loans	F	N	N	0	270
2	100004	0	Revolving loans	M	Y	Y	0	67
3	100006	0	Cash loans	F	N	Y	0	135
4	100007	0	Cash loans	M	N	Y	0	121

5 rows × 122 columns

In [80]:

```
y = data['TARGET']
X = data.drop(['SK_ID_CURR','TARGET'], axis = 1)
```

In [81]:

```
experimentLog = pd.DataFrame(columns=["ExpID", "Cross fold train accuracy", "Test Accuracy", "Validation Accuracy

def pct(x):
    return round(100*x,1)


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


def returnModel(x,y,experimentLog,description_text):
    num_attribs = []
    cat_attribs = []
```

```
    for col in x.columns.tolist():
        if x[col].dtype in (['int','float']):
            num_attribs.append(col)
        else:
            cat_attribs.append(col)

    le_dict = {}
    for col in x.columns.tolist():
        if X[col].dtype == 'object':
            le = LabelEncoder()
            x[col] = x[col].fillna("NULL")
            x[col] = le.fit_transform(x[col])
            le_dict['le_{}'.format(col)] = le

    num_pipeline =Pipeline([('selector',DataFrameSelector(num_attribs)),
                            ('scaler', StandardScaler()),
                           ('imputer', SimpleImputer(strategy = 'median'))
                            ])


    cat_pipeline = Pipeline([
        ('selector', DataFrameSelector(cat_attribs)),
        ('imputer', SimpleImputer(strategy='most_frequent'))
    ])


    full_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
        ("cat_pipeline", cat_pipeline),
    ])

    np.random.seed(42)
    full_pipeline_with_predictor = Pipeline([
            ("preparation", num_pipeline),
            ("linear", LogisticRegression(random_state=42))
        ])

    # split 20% test data with random seed set to 42 for correct experimentLog
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=42)
    x_train, x_valid, y_train, y_valid = train_test_split(x_train, y_train, test_size=0.2, random_state=42)
    print("train data set: ")
    print(x_train.shape,y_train.shape)
    print("test data set: ")
    print(x_test.shape,y_test.shape)
    print("validation data set: ")
    print(x_valid.shape,y_valid.shape)


    start = time()
    full_pipeline_with_predictor.fit(x_train, y_train)
    np.random.seed(42)

    cv30Splits = ShuffleSplit(n_splits = 30, test_size = 0.3, random_state = 0)
    logit_scores = cross_val_score(full_pipeline_with_predictor, x_train, y_train, cv = cv30Splits)
    logit_score_train = logit_scores.mean()
    train_time = np.round(time() - start, 4)

    # Time and score test predictions
    start = time()
    logit_score_test  = full_pipeline_with_predictor.score(x_test, y_test)
    test_time = np.round(time() - start, 4)

    start = time()
    logit_score_valid  = full_pipeline_with_predictor.score(x_valid, y_valid)
    valid_time = np.round(time() - start, 4)

    AUC = roc_auc_score(y_test,full_pipeline_with_predictor.predict(x_test))
    print("AUC is {}".format(AUC))
    print("\n.............\n")
    print("Confusion Matrix: {}".format(confusion_matrix(y_test, full_pipeline_with_predictor.predict(x_test))))

    no_of_inputs = x.shape[1]

    temp_df = pd.DataFrame()
    temp_df = temp_df.append(pd.Series(["Baseline with {} inputs".format(no_of_inputs), pct(logit_score_train), p
                AUC, train_time, test_time, "{} - Baseline LogisticRegression".format(description_text)]),ignor
    temp_df.columns = experimentLog.columns

    experimentLog = experimentLog.append(temp_df,ignore_index=True)

    return le_dict, full_pipeline_with_predictor, experimentLog
```

In [82]:

```
le_dict, full_pipeline_with_predictor, experimentLog = returnModel(X,y,experimentLog,"All features Dataset")
```

```
train data set:
(196806, 120) (196806,)
```

```
test data set:
(61503, 120) (61503,)
validation data set:
(49202, 120) (49202,)
AUC is 0.5043329019692199

............

Confusion Matrix: [[56507    47]
 [ 4902    47]]
```

In [83]:
```
experimentLog
```

Out[83]:

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	78.5206	0.1277	All features Dataset - Baseline LogisticRegres...

Additional EDA

Discarding features with null values more than 30%

In [88]:
```
null_data = X.isna().sum().reset_index().rename(columns={'index':'col_name',0:'null_count'})
null_data['count_%'] = null_data['null_count']/len(X)*100
null_data = null_data[null_data['count_%'] <= 30]
null_data
```

Out[88]:

	col_name	null_count	count_%
0	NAME_CONTRACT_TYPE	0	0.000000
1	CODE_GENDER	0	0.000000
2	FLAG_OWN_CAR	0	0.000000
3	FLAG_OWN_REALTY	0	0.000000
4	CNT_CHILDREN	0	0.000000
...	...	...	...
115	AMT_REQ_CREDIT_BUREAU_DAY	41519	13.501631
116	AMT_REQ_CREDIT_BUREAU_WEEK	41519	13.501631
117	AMT_REQ_CREDIT_BUREAU_MON	41519	13.501631
118	AMT_REQ_CREDIT_BUREAU_QRT	41519	13.501631
119	AMT_REQ_CREDIT_BUREAU_YEAR	41519	13.501631

75 rows × 3 columns

In [89]:
```
selected_columns = null_data['col_name'].tolist() + ['TARGET']
print(selected_columns)
```

```
['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_F
AMILY_STATUS', 'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATI
ON', 'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLA
G_EMAIL', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_A
PPR_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', 'ORGANIZA
TION_TYPE', 'EXT_SOURCE_2', 'EXT_SOURCE_3', 'FONDKAPREMONT_MODE', 'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGE
NCYSTATE_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_S
OCIAL_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_DOCUMEN
T_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_BUR
EAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDI
T_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR', 'TARGET']
```

In [90]:
```
null_data['col_type'] = null_data['col_name'].apply(lambda x: X[x].dtype)
null_data[null_data['count_%'] > 0]
```

Out[90]:

	col_name	null_count	count_%	col_type
7	AMT_ANNUITY	12	0.003902	float64
8	AMT_GOODS_PRICE	278	0.090403	float64
27	CNT_FAM_MEMBERS	2	0.000650	float64
40	EXT_SOURCE_2	660	0.214626	float64
41	EXT_SOURCE_3	60965	19.825307	float64
89	OBS_30_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
90	DEF_30_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
91	OBS_60_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
92	DEF_60_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
93	DAYS_LAST_PHONE_CHANGE	1	0.000325	float64
114	AMT_REQ_CREDIT_BUREAU_HOUR	41519	13.501631	float64
115	AMT_REQ_CREDIT_BUREAU_DAY	41519	13.501631	float64
116	AMT_REQ_CREDIT_BUREAU_WEEK	41519	13.501631	float64
117	AMT_REQ_CREDIT_BUREAU_MON	41519	13.501631	float64
118	AMT_REQ_CREDIT_BUREAU_QRT	41519	13.501631	float64
119	AMT_REQ_CREDIT_BUREAU_YEAR	41519	13.501631	float64

Filling null values in NAME_TYPE_SUITE column with "Other_C"

In [91]:

```
X_feature = data[selected_columns]
X_feature['NAME_TYPE_SUITE'].fillna('Other_C', inplace=True)
X_feature.head()
```

Out[91]:

	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AM
0	Cash loans	M	N	Y	0	202500.0	406597.5	
1	Cash loans	F	N	N	0	270000.0	1293502.5	
2	Revolving loans	M	Y	Y	0	67500.0	135000.0	
3	Cash loans	F	N	Y	0	135000.0	312682.5	
4	Cash loans	M	N	Y	0	121500.0	513000.0	

5 rows × 76 columns

Filling null values in the columns containing keyword AMT_REQ_CREDIT column with 0

In [92]:

```
temp_col_reqd = null_data[null_data['null_count'] != 0].reset_index(drop=True)['col_name'].tolist()
for col in temp_col_reqd:
    if 'AMT_REQ_CREDIT' in col:
        print("columns to be filled with 0 is: {}".format(col))
        X_feature[col].fillna(0,inplace=True)
```

```
columns to be filled with 0 is: AMT_REQ_CREDIT_BUREAU_HOUR
columns to be filled with 0 is: AMT_REQ_CREDIT_BUREAU_DAY
columns to be filled with 0 is: AMT_REQ_CREDIT_BUREAU_WEEK
columns to be filled with 0 is: AMT_REQ_CREDIT_BUREAU_MON
columns to be filled with 0 is: AMT_REQ_CREDIT_BUREAU_QRT
columns to be filled with 0 is: AMT_REQ_CREDIT_BUREAU_YEAR
```

Filling null values in the column containing keyword CNT_SOCIAL_CIRCLE with 0¶

In [93]:

```
for col in temp_col_reqd:
    if 'CNT_SOCIAL_CIRCLE' in col:
        print("columns to be filled with 0 is: {}".format(col))
        X_feature[col].fillna(0,inplace=True)
```

```
columns to be filled with 0 is: OBS_30_CNT_SOCIAL_CIRCLE
columns to be filled with 0 is: DEF_30_CNT_SOCIAL_CIRCLE
columns to be filled with 0 is: OBS_60_CNT_SOCIAL_CIRCLE
```

```
columns to be filled with 0 is: DEF_60_CNT_SOCIAL_CIRCLE
```

Filling null values in the column CNT_FAM_MEMBERS with median

In [94]:
```
for col in temp_col_reqd:
    if 'CNT_FAM_MEMBERS' in col:
        print("columns to be filled with median is: {}".format(col))
        X_feature[col].fillna(X_feature[col].median(),inplace=True)
```

```
columns to be filled with median is: CNT_FAM_MEMBERS
```

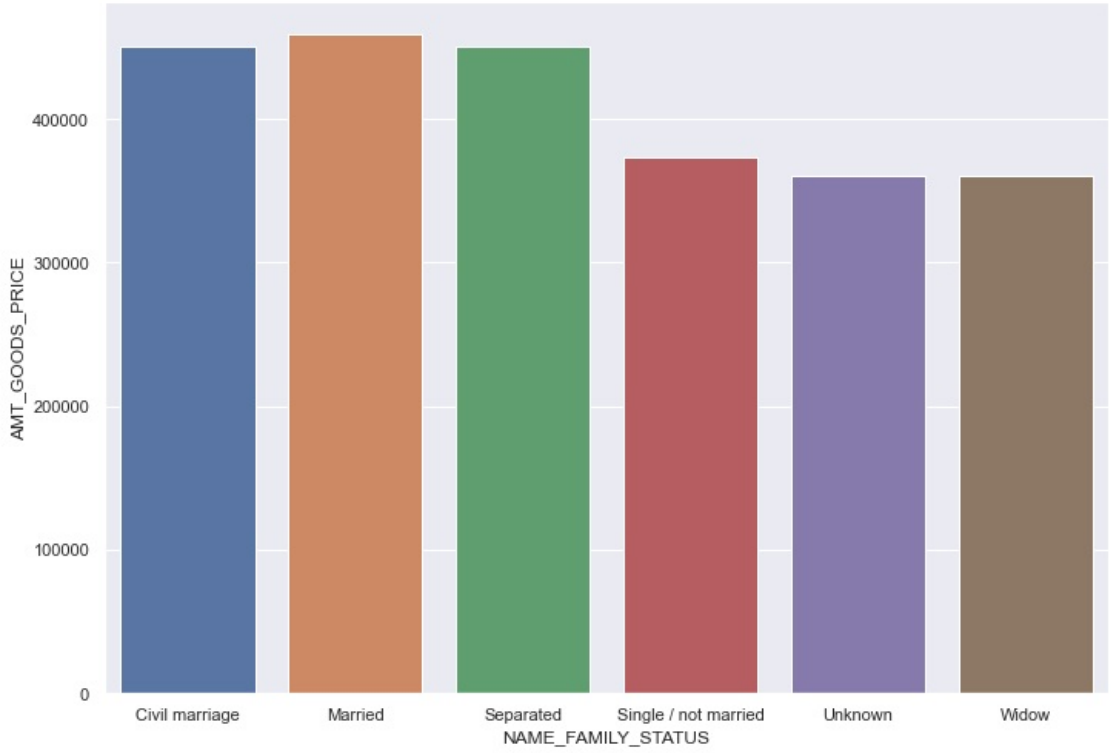
Filling null values in the column AMT_GOODS_PRICE with median fopr the respective category

In [95]:
```
temp_plt_data = X_feature[['AMT_GOODS_PRICE','NAME_FAMILY_STATUS']]
temp_plt_data = temp_plt_data.groupby('NAME_FAMILY_STATUS')['AMT_GOODS_PRICE'].median().reset_index()
temp_plt_data['AMT_GOODS_PRICE'] = temp_plt_data['AMT_GOODS_PRICE'].fillna(temp_plt_data['AMT_GOODS_PRICE'].min()
temp_plt_data.head()
```

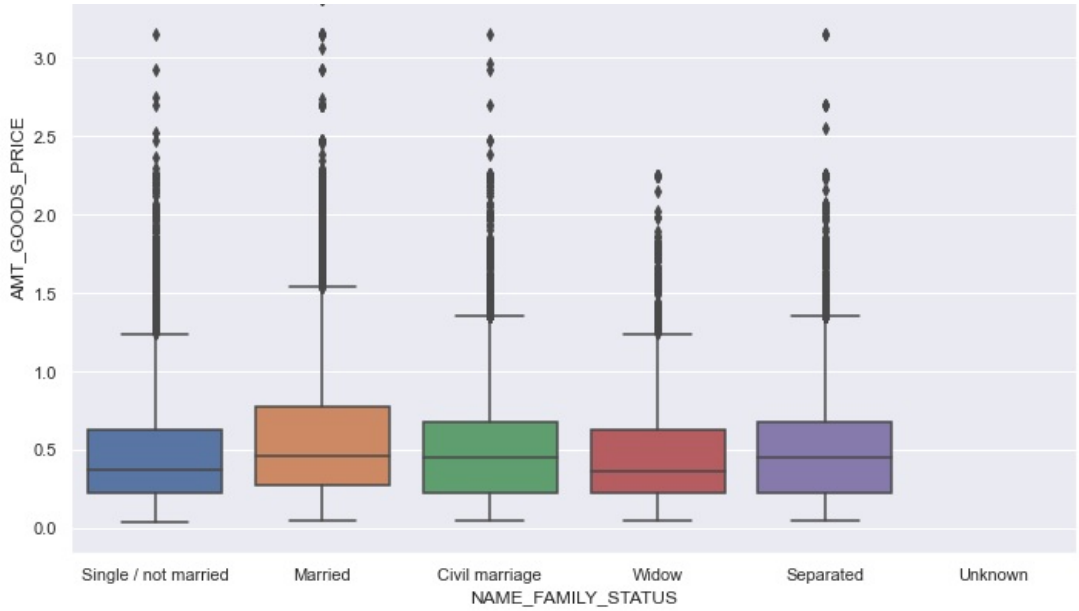
Out[95]:

	NAME_FAMILY_STATUS	AMT_GOODS_PRICE
0	Civil marriage	450000.0
1	Married	459000.0
2	Separated	450000.0
3	Single / not married	373500.0
4	Unknown	360000.0

In [96]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
ax = sns.barplot(x="NAME_FAMILY_STATUS", y="AMT_GOODS_PRICE", data=temp_plt_data)
```



In [97]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
ax = sns.boxplot(x="NAME_FAMILY_STATUS", y="AMT_GOODS_PRICE", data=X_feature)
```



In [98]:
```
def fill_category_value(a):
    if a['AMT_GOODS_PRICE'] == np.inf:
        return temp_plt_data[temp_plt_data['NAME_FAMILY_STATUS']==a['NAME_FAMILY_STATUS']]['AMT_GOODS_PRICE'].val
    else:
        return a['AMT_GOODS_PRICE']

for col in temp_col_reqd:
    X_feature['AMT_GOODS_PRICE'] = X_feature['AMT_GOODS_PRICE'].fillna(np.inf)
    if 'AMT_GOODS_PRICE' in col:
        print("columns to be filled with category median is: {}".format(col))
        X_feature['AMT_GOODS_PRICE'] = X_feature.apply(lambda a: fill_category_value(a),axis=1)
```

```
columns to be filled with category median is: AMT_GOODS_PRICE
```

Dropping one single row with column DAYS_LAST_PHONE_CHANGE as null

In [99]:
```
X_feature.dropna(subset=['DAYS_LAST_PHONE_CHANGE'], inplace=True)
```

Dropping 12 rows with column AMT_ANNUITY as null

In [100…
```
X_feature.dropna(subset=['AMT_ANNUITY'], inplace=True)
X_feature = X_feature.reset_index(drop=True)
```

Checking highest correlated features with External Source to replace the null values with

In [101…
```
### Check for EXT_SOURCE_2
```

In [102…
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

temp_corr_df = pd.DataFrame()

for col in X_feature.columns.tolist():
    if X_feature[col].dtype == 'int':
        l = [col, X_feature['EXT_SOURCE_2'].corr(X_feature[col])]
    else:
        l = [col, X_feature['EXT_SOURCE_2'].corr(pd.DataFrame(LabelEncoder().fit_transform(X_feature[[col]]))[0])]
    temp_corr_df = temp_corr_df.append(pd.Series(l),ignore_index=True)
temp_corr_df = temp_corr_df.rename(columns={0:'col_name',1:'correlation_with_EXT_2'})
temp_corr_df['correlation_with_EXT_2'] = abs(temp_corr_df['correlation_with_EXT_2'])
temp_corr_df.sort_values(by='correlation_with_EXT_2',ascending=False).head(6).tail(5)
```

Out[102…

	col_name	correlation_with_EXT_2
27	REGION_RATING_CLIENT	0.292903
28	REGION_RATING_CLIENT_W_CITY	0.288306

48	DAYS_LAST_PHONE_CHANGE	0.195766
5	AMT_INCOME_TOTAL	0.170547
75	TARGET	0.160471

In [103…
```
#REGION_RATING_CLIENT : Our rating of the region where our client lives
```

In [104…
```
region_rating_grouped = X_feature.groupby('REGION_RATING_CLIENT')['EXT_SOURCE_2'].median().reset_index()


def fill_external_source2(a):
    if a['EXT_SOURCE_2'] == np.inf:
        return region_rating_grouped[region_rating_grouped['REGION_RATING_CLIENT']==a['REGION_RATING_CLIENT']]['E
    else:
        return a['EXT_SOURCE_2']

X_feature['EXT_SOURCE_2'] = X_feature['EXT_SOURCE_2'].fillna(np.inf)
X_feature['EXT_SOURCE_2'] = X_feature.apply(lambda a: fill_external_source2(a),axis=1)
```

In [105…
```
#Check for EXT_SOURCE_3
```

In [106…
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

temp_corr_df = pd.DataFrame()

for col in X_feature.columns.tolist():
    if X_feature[col].dtype == 'int':
        l = [col, X_feature['EXT_SOURCE_3'].corr(X_feature[col])]
    else:
        l = [col, X_feature['EXT_SOURCE_3'].corr(pd.DataFrame(LabelEncoder().fit_transform(X_feature[[col]]))[0])]
    temp_corr_df = temp_corr_df.append(pd.Series(l),ignore_index=True)
temp_corr_df = temp_corr_df.rename(columns={0:'col_name',1:'correlation_with_EXT_3'})
temp_corr_df['correlation_with_EXT_3'] = abs(temp_corr_df['correlation_with_EXT_3'])
temp_corr_df = temp_corr_df.sort_values(by='correlation_with_EXT_3',ascending=False).head(10).tail(9)
temp_corr_df
```

Out[106…

	col_name	correlation_with_EXT_3
15	DAYS_BIRTH	0.205474
75	TARGET	0.178929
18	DAYS_ID_PUBLISH	0.131598
20	FLAG_EMP_PHONE	0.115284
16	DAYS_EMPLOYED	0.113426
38	EXT_SOURCE_2	0.109728
17	DAYS_REGISTRATION	0.107570
5	AMT_INCOME_TOTAL	0.088906
37	ORGANIZATION_TYPE	0.087994

In [107…
```
ext_source_data = X_feature[temp_corr_df['col_name'].tolist()+['EXT_SOURCE_3']]

for col in ext_source_data.columns.tolist():
    if col != 'EXT_SOURCE_3':
        ext_source_data[col] = LabelEncoder().fit_transform(X_feature[[col]])

ext_source3_train = ext_source_data[ext_source_data['EXT_SOURCE_3'].notnull()]
ext_source3_test = ext_source_data[ext_source_data['EXT_SOURCE_3'].isnull()]
ext_source3_train.shape, ext_source3_test.shape
```

Out[107… ((246535, 10), (60963, 10))

In [108…
```
exs3_y_train = ext_source3_train[['EXT_SOURCE_3']]
exs3_X_train = ext_source3_train.drop(columns=['EXT_SOURCE_3'])

exs3_X_test = ext_source3_test.drop(columns=['EXT_SOURCE_3'])
```

In [109…
```
from sklearn.linear_model import LinearRegression
```

```
model = LinearRegression().fit(exs3_X_train, exs3_y_train)
y_pred_exs3 = model.predict(exs3_X_test)

exs3_output = exs3_X_test
exs3_output['exs3_y'] = y_pred_exs3
exs3_output
```

Out[109…

	DAYS_BIRTH	TARGET	DAYS_ID_PUBLISH	FLAG_EMP_PHONE	DAYS_EMPLOYED	EXT_SOURCE_2	DAYS_REGISTRATION	AMT_INCOI
1	8382	0	5876	1	11384	85079	14501	
3	6142	0	3730	1	9533	90559	5854	
4	5215	0	2709	1	9534	36021	11376	
9	10676	0	2175	1	10553	110724	1373	
14	10562	0	4111	1	12369	89028	15072	
...	...	...	...	...	...	...	...	
307471	12298	0	6132	1	12244	109216	13156	
307488	12184	0	2387	1	11526	76369	14289	
307491	8442	0	5908	1	5318	68374	5889	
307493	15818	0	4185	1	12336	96856	7231	
307494	4372	0	2077	0	12573	11578	11299	

60963 rows × 10 columns

In [110…

```
exs3_output = exs3_output.reset_index().rename(columns={'index':'index_to_be_updated'})
for i in exs3_output['index_to_be_updated'].tolist():
    X_feature['EXT_SOURCE_3'].iloc[i] = exs3_output[exs3_output['index_to_be_updated']==i]['exs3_y'].values[0]
```

Checking the null values in the Train dataset

In [111…

```
new_null_data = X_feature.isna().sum().reset_index().rename(columns={'index':'col_name',0:'null_count'})
new_null_data['count_%'] = new_null_data['null_count']/len(X_feature)*100
new_null_data = new_null_data[new_null_data['count_%'] <= 30]
new_null_data['col_type'] = new_null_data['col_name'].apply(lambda x: X_feature[x].dtype)
new_null_data[new_null_data['count_%'] > 0]
```

Out[111…

	col_name	null_count	count_%	col_type

In [112…

```
X_feature.isna().sum()
```

Out[112…

```
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
FLAG_OWN_REALTY               0
CNT_CHILDREN                  0
                             ..
AMT_REQ_CREDIT_BUREAU_WEEK    0
AMT_REQ_CREDIT_BUREAU_MON     0
AMT_REQ_CREDIT_BUREAU_QRT     0
AMT_REQ_CREDIT_BUREAU_YEAR    0
TARGET                        0
Length: 76, dtype: int64
```

Training and testing with the selected columns

Adding Additional relevant features felt

In [113…

```
X_feature['AMT_CREDIT_TO_ANNUITY_RATIO'] = X_feature['AMT_CREDIT'] / X_feature['AMT_ANNUITY']
X_feature['Tot_EXTERNAL_SOURCE'] = X_feature['EXT_SOURCE_2'] + X_feature['EXT_SOURCE_3']
X_feature['Salary_to_credit'] = X_feature['AMT_INCOME_TOTAL']/X_feature['AMT_CREDIT']
X_feature['Annuity_to_salary_ratio'] = X_feature['AMT_ANNUITY']/X_feature['AMT_INCOME_TOTAL']
```

In [114…

```
y = X_feature[['TARGET']]
```

```
X = X_feature.drop(['TARGET'], axis = 1)
```

In [115…
```
le_dict, full_pipeline_with_predictor, experimentLog = returnModel(X,y,experimentLog,"Selected features Dataset")
```

```
train data set:
(196798, 79) (196798, 1)
test data set:
(61500, 79) (61500, 1)
validation data set:
(49200, 79) (49200, 1)
AUC is 0.5055379338757116

............

Confusion Matrix: [[56484    58]
 [ 4898    60]]
```

In [116…
```
experimentLog
```

Out[116…

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	78.5206	0.1277	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505538	47.0562	0.0612	Selected features Dataset - Baseline LogisticR...

In [ ]:

In [ ]:

In [ ]:

Hyperparameter tuning(Grid Search)

In [117…
```
train = X_feature
train.shape
```

Out[117… (307498, 80)

In [118…
```
features = train.columns.tolist()
features.remove('TARGET')
len(features)
```

Out[118… 79

In [119…
```
le_dict = {}

for col in features:
    if train[col].dtype == 'object':
        le = LabelEncoder()
        train[col] = le.fit_transform(train[col])
        le_dict['le_{}'.format(col)] = le
X = train[features]
y = train['TARGET']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=42)
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=0.2, random_state=42)
```

Decision Making Tree

In [120…
```
DMT_pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('regressor', DecisionTreeClassifier(random_state=100))
```

```
])

param_grid = [{
    'regressor__max_depth': [2, 3],
    'regressor__min_samples_split': [2, 3],
}]

start = time()
dmt_search = GridSearchCV(estimator=DMT_pipe, param_grid=param_grid, cv=2)
dmt_search.fit(X_train, y_train)
train_time = np.round(time() - start, 4)

trainAcc  = dmt_search.score(X_train, y_train)
validAcc  = dmt_search.score(X_valid, y_valid)
start = time()
testAcc  = dmt_search.score(X_test, y_test)
test_time = np.round(time() - start, 4)

number_of_inputs = X_train.shape[1]
AUC = roc_auc_score(y_test,dmt_search.predict(X_test))

try: experimentLog
except : experimentLog = pd.DataFrame(columns=["ExpID", "Cross fold train accuracy", "Test Accuracy", "Validation
                                               "AUC", "Train Time(s)", "Test Time(s)","Experiment description"])
experimentLog.loc[len(experimentLog)] =[f"Gridsearch Decision Making Tree with {number_of_inputs} inputs",
                                        f"{trainAcc*100:8.2f}%", f"{testAcc*100:8.2f}%", f"{validAcc*100:8.2f}%",
                                        train_time, test_time,
                                        "Decision Making Tree GridSearch with selected features from Lasso/Ridge"
```

In [121…

```
experimentLog
```

Out[121…

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	78.5206	0.1277	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505538	47.0562	0.0612	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	91.91%	91.98%	91.96%	0.500000	5.2731	0.0123	Decision Making Tree GridSearch with selected ...

In [122…

```
test_data=pd.read_csv('/Users/nidhisaduvala/Desktop/Spring/AML/home-credit-default-risk/application_test.csv')
```

In [ ]:

Lasso Regression

In [125…

```
lasso_pipeline = Pipeline([
                    ('scaler',StandardScaler()),
                    ('model',Lasso())
])


lasso_pipeline = GridSearchCV(lasso_pipeline,
                     {'model__alpha':[0.0001,0.001,0.01,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,2,3,4,5,6,7,8,9,10
                     cv = 5, scoring="neg_mean_squared_error",verbose=3
                     )

start = time()
lasso_pipeline.fit(X_train, y_train)
train_time = np.round(time() - start, 4)

trainAcc  = lasso_pipeline.score(X_train, y_train)
validAcc  = lasso_pipeline.score(X_valid, y_valid)
start = time()
testAcc  = lasso_pipeline.score(X_test, y_test)
test_time = np.round(time() - start, 4)

AUC = roc_auc_score(y_test,lasso_pipeline.predict(X_test))
number_of_inputs = X_train.shape[1]

#del experimentLog
try: experimentLog
except : experimentLog = pd.DataFrame(columns=["ExpID", "Cross fold train accuracy", "Test Accuracy", "Validation
                                               "AUC", "Train Time(s)", "Test Time(s)","Experiment description"])
experimentLog.loc[len(experimentLog)] =[f"Lasso Reg with {number_of_inputs} inputs",
                                        f"{trainAcc*100:8.2f}%", f"{testAcc*100:8.2f}%", f"{validAcc*100:8.2f}%",
                                        train_time, test_time,
```

```
                                    "Lasso Regression for feature selection"]
```

```
Fitting 5 folds for each of 22 candidates, totalling 110 fits
[CV 1/5] END ..........................model__alpha=0.0001; total time=   8.1s
[CV 2/5] END ..........................model__alpha=0.0001; total time=   6.4s
[CV 3/5] END ..........................model__alpha=0.0001; total time=   6.1s
[CV 4/5] END ..........................model__alpha=0.0001; total time=   9.0s
[CV 5/5] END ..........................model__alpha=0.0001; total time=   7.5s
[CV 1/5] END ...........................model__alpha=0.001; total time=   1.1s
[CV 2/5] END ...........................model__alpha=0.001; total time=   1.0s
[CV 3/5] END ...........................model__alpha=0.001; total time=   1.6s
[CV 4/5] END ...........................model__alpha=0.001; total time=   1.7s
[CV 5/5] END ...........................model__alpha=0.001; total time=   1.0s
[CV 1/5] END ............................model__alpha=0.01; total time=   0.3s
[CV 2/5] END ............................model__alpha=0.01; total time=   0.3s
[CV 3/5] END ............................model__alpha=0.01; total time=   0.3s
[CV 4/5] END ............................model__alpha=0.01; total time=   0.3s
[CV 5/5] END ............................model__alpha=0.01; total time=   0.4s
[CV 1/5] END .............................model__alpha=0.1; total time=   0.3s
[CV 2/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.1; total time=   0.2s
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[CV 3/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.2; total time=   0.2s
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[CV 2/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.4; total time=   0.2s
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[CV 2/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.5; total time=   0.2s
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[CV 2/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.7; total time=   0.2s
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[CV 3/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.8; total time=   0.3s
[CV 5/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.9; total time=   0.2s
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[CV 2/5] END ...............................model__alpha=1; total time=   0.2s
[CV 3/5] END ...............................model__alpha=1; total time=   0.2s
[CV 4/5] END ...............................model__alpha=1; total time=   0.2s
[CV 5/5] END ...............................model__alpha=1; total time=   0.2s
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[CV 2/5] END ...............................model__alpha=2; total time=   0.2s
[CV 3/5] END ...............................model__alpha=2; total time=   0.2s
[CV 4/5] END ...............................model__alpha=2; total time=   0.2s
[CV 5/5] END ...............................model__alpha=2; total time=   0.2s
[CV 1/5] END ...............................model__alpha=3; total time=   0.2s
[CV 2/5] END ...............................model__alpha=3; total time=   0.2s
[CV 3/5] END ...............................model__alpha=3; total time=   0.2s
[CV 4/5] END ...............................model__alpha=3; total time=   0.2s
[CV 5/5] END ...............................model__alpha=3; total time=   0.2s
[CV 1/5] END ...............................model__alpha=4; total time=   0.2s
[CV 2/5] END ...............................model__alpha=4; total time=   0.2s
[CV 3/5] END ...............................model__alpha=4; total time=   0.2s
[CV 4/5] END ...............................model__alpha=4; total time=   0.2s
[CV 5/5] END ...............................model__alpha=4; total time=   0.2s
```

```
[CV 1/5] END ..............................model__alpha=5; total time=   0.2s
[CV 2/5] END ..............................model__alpha=5; total time=   0.2s
[CV 3/5] END ..............................model__alpha=5; total time=   0.2s
[CV 4/5] END ..............................model__alpha=5; total time=   0.2s
[CV 5/5] END ..............................model__alpha=5; total time=   0.2s
[CV 1/5] END ..............................model__alpha=6; total time=   0.2s
[CV 2/5] END ..............................model__alpha=6; total time=   0.2s
[CV 3/5] END ..............................model__alpha=6; total time=   0.2s
[CV 4/5] END ..............................model__alpha=6; total time=   0.2s
[CV 5/5] END ..............................model__alpha=6; total time=   0.2s
[CV 1/5] END ..............................model__alpha=7; total time=   0.2s
[CV 2/5] END ..............................model__alpha=7; total time=   0.2s
[CV 3/5] END ..............................model__alpha=7; total time=   0.2s
[CV 4/5] END ..............................model__alpha=7; total time=   0.2s
[CV 5/5] END ..............................model__alpha=7; total time=   0.2s
[CV 1/5] END ..............................model__alpha=8; total time=   0.2s
[CV 2/5] END ..............................model__alpha=8; total time=   0.2s
[CV 3/5] END ..............................model__alpha=8; total time=   0.2s
[CV 4/5] END ..............................model__alpha=8; total time=   0.2s
[CV 5/5] END ..............................model__alpha=8; total time=   0.2s
[CV 1/5] END ..............................model__alpha=9; total time=   0.2s
[CV 2/5] END ..............................model__alpha=9; total time=   0.2s
[CV 3/5] END ..............................model__alpha=9; total time=   0.2s
[CV 4/5] END ..............................model__alpha=9; total time=   0.2s
[CV 5/5] END ..............................model__alpha=9; total time=   0.2s
[CV 1/5] END .............................model__alpha=10; total time=   0.2s
[CV 2/5] END .............................model__alpha=10; total time=   0.2s
[CV 3/5] END .............................model__alpha=10; total time=   0.2s
[CV 4/5] END .............................model__alpha=10; total time=   0.2s
[CV 5/5] END .............................model__alpha=10; total time=   0.2s
```

In [127…

```
experimentLog
```

Out[127…

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	78.5206	0.1277	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505538	47.0562	0.0612	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	91.91%	91.98%	91.96%	0.500000	5.2731	0.0123	Decision Making Tree GridSearch with selected ...
3	Lasso Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.755827	71.5090	0.0438	Lasso Regression for feature selection

In [128…

```
print(lasso_pipeline.best_params_)
coefficients = lasso_pipeline.best_estimator_.named_steps['model'].coef_
importance = np.abs(coefficients)
len(np.array(features)[importance > 0])
```

```
{'model__alpha': 0.0001}
```

Out[128… 74

Ridge Regression

In [129…

```
ridge_pipeline = Pipeline([
                    ('scaler',StandardScaler()),
                    ('model',Ridge())
])


ridge_pipeline = GridSearchCV(ridge_pipeline,
                     {'model__alpha':[0.0001,0.001,0.01,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,2,3,4,5,6,7,8,9,10
                     cv = 5, scoring="neg_mean_squared_error",verbose=3
                     )

start = time()
ridge_pipeline.fit(X_train, y_train)
train_time = np.round(time() - start, 4)

trainAcc  = ridge_pipeline.score(X_train, y_train)
```

```
validAcc  = ridge_pipeline.score(X_valid, y_valid)
start = time()
testAcc  = ridge_pipeline.score(X_test, y_test)
test_time = np.round(time() - start, 4)

AUC = roc_auc_score(y_test,ridge_pipeline.predict(X_test))
number_of_inputs = X_train.shape[1]

try: experimentLog
except : experimentLog = pd.DataFrame(columns=["ExpID", "Cross fold train accuracy", "Test Accuracy", "Validation
                                               "AUC", "Train Time(s)", "Test Time(s)","Experiment description"])
experimentLog.loc[len(experimentLog)] =[f"Ridge Reg with {number_of_inputs} inputs",
                                        f"{trainAcc*100:8.2f}%", f"{testAcc*100:8.2f}%", f"{validAcc*100:8.2f}%",
                                        train_time, test_time,
                                        "Ridge Regression for feature selection"]
```

```
Fitting 5 folds for each of 22 candidates, totalling 110 fits
[CV 1/5] END ..........................model__alpha=0.0001; total time=   0.6s
[CV 2/5] END ..........................model__alpha=0.0001; total time=   0.2s
[CV 3/5] END ..........................model__alpha=0.0001; total time=   0.2s
[CV 4/5] END ..........................model__alpha=0.0001; total time=   0.2s
[CV 5/5] END ..........................model__alpha=0.0001; total time=   0.2s
[CV 1/5] END ...........................model__alpha=0.001; total time=   0.2s
[CV 2/5] END ...........................model__alpha=0.001; total time=   0.2s
[CV 3/5] END ...........................model__alpha=0.001; total time=   0.2s
[CV 4/5] END ...........................model__alpha=0.001; total time=   0.2s
[CV 5/5] END ...........................model__alpha=0.001; total time=   0.2s
[CV 1/5] END ............................model__alpha=0.01; total time=   0.2s
[CV 2/5] END ............................model__alpha=0.01; total time=   0.2s
[CV 3/5] END ............................model__alpha=0.01; total time=   0.2s
[CV 4/5] END ............................model__alpha=0.01; total time=   0.2s
[CV 5/5] END ............................model__alpha=0.01; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.1; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.2; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.3; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.4; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.5; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.6; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.7; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.8; total time=   0.2s
[CV 1/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 2/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 3/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 4/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 5/5] END .............................model__alpha=0.9; total time=   0.2s
[CV 1/5] END ...............................model__alpha=1; total time=   0.2s
[CV 2/5] END ...............................model__alpha=1; total time=   0.2s
[CV 3/5] END ...............................model__alpha=1; total time=   0.2s
[CV 4/5] END ...............................model__alpha=1; total time=   0.2s
[CV 5/5] END ...............................model__alpha=1; total time=   0.2s
[CV 1/5] END ...............................model__alpha=2; total time=   0.2s
[CV 2/5] END ...............................model__alpha=2; total time=   0.2s
```

```
[CV 3/5] END ..............................model__alpha=2; total time=   0.2s
[CV 4/5] END ..............................model__alpha=2; total time=   0.2s
[CV 5/5] END ..............................model__alpha=2; total time=   0.2s
[CV 1/5] END ..............................model__alpha=3; total time=   0.2s
[CV 2/5] END ..............................model__alpha=3; total time=   0.2s
[CV 3/5] END ..............................model__alpha=3; total time=   0.2s
[CV 4/5] END ..............................model__alpha=3; total time=   0.2s
[CV 5/5] END ..............................model__alpha=3; total time=   0.2s
[CV 1/5] END ..............................model__alpha=4; total time=   0.2s
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[CV 3/5] END ..............................model__alpha=4; total time=   0.2s
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[CV 5/5] END ..............................model__alpha=4; total time=   0.2s
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[CV 2/5] END ..............................model__alpha=5; total time=   0.2s
[CV 3/5] END ..............................model__alpha=5; total time=   0.2s
[CV 4/5] END ..............................model__alpha=5; total time=   0.2s
[CV 5/5] END ..............................model__alpha=5; total time=   0.2s
[CV 1/5] END ..............................model__alpha=6; total time=   0.2s
[CV 2/5] END ..............................model__alpha=6; total time=   0.2s
[CV 3/5] END ..............................model__alpha=6; total time=   0.2s
[CV 4/5] END ..............................model__alpha=6; total time=   0.2s
[CV 5/5] END ..............................model__alpha=6; total time=   0.2s
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[CV 2/5] END ..............................model__alpha=7; total time=   0.2s
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[CV 4/5] END ..............................model__alpha=7; total time=   0.2s
[CV 5/5] END ..............................model__alpha=7; total time=   0.2s
[CV 1/5] END ..............................model__alpha=8; total time=   0.2s
[CV 2/5] END ..............................model__alpha=8; total time=   0.2s
[CV 3/5] END ..............................model__alpha=8; total time=   0.2s
[CV 4/5] END ..............................model__alpha=8; total time=   0.2s
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[CV 2/5] END ..............................model__alpha=9; total time=   0.2s
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[CV 4/5] END ..............................model__alpha=9; total time=   0.2s
[CV 5/5] END ..............................model__alpha=9; total time=   0.2s
[CV 1/5] END .............................model__alpha=10; total time=   0.2s
[CV 2/5] END .............................model__alpha=10; total time=   0.2s
[CV 3/5] END .............................model__alpha=10; total time=   0.2s
[CV 4/5] END .............................model__alpha=10; total time=   0.2s
[CV 5/5] END .............................model__alpha=10; total time=   0.2s
```

In [49]:
```
experimentLog
```

Out[49]:

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	75.0335	0.1572	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505538	47.0067	0.0526	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	7.84%	7.56%	7.35%	0.738725	5.1077	0.0321	Decision Making Tree GridSearch with selected ...
3	Lasso Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.755827	67.5748	0.0357	Lasso Regression for feature selection
4	Ridge Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.756776	17.6560	0.0099	Ridge Regression for feature selection

In [130…
```
print(ridge_pipeline.best_params_)
coefficients = ridge_pipeline.best_estimator_.named_steps['model'].coef_
importance = np.abs(coefficients)
len(np.array(features)[importance > 0.005])
```

```
{'model__alpha': 3}
```

Out[130… 22

Logistic Regression

In [131…
```
logistic = LogisticRegression(max_iter=10000, tol=0.1)
```

```
clf_pipe = Pipeline(steps=[("logistic", logistic)])
param_grid = {
    "logistic__C": np.logspace(-4, 4, 10)
}


# Time and score test predictions
start = time()

clf_search = GridSearchCV(clf_pipe, param_grid, n_jobs=-1)
clf_search.fit(X_train, y_train)
train_time = np.round(time() - start, 4)

trainAcc  = clf_search.score(X_train, y_train)
validAcc  = clf_search.score(X_valid, y_valid)
start = time()
testAcc  = clf_search.score(X_test, y_test)
test_time = np.round(time() - start, 4)

number_of_inputs = X_train.shape[1]
AUC = roc_auc_score(y_test,clf_search.predict(X_test))

try: experimentLog
except : experimentLog = pd.DataFrame(columns=["ExpID", "Cross fold train accuracy", "Test Accuracy", "Validation
                                               "AUC", "Train Time(s)", "Test Time(s)","Experiment description"])
experimentLog.loc[len(experimentLog)] =[f"Gridsearch LogReg with {number_of_inputs} inputs",
                                        f"{trainAcc*100:8.2f}%", f"{testAcc*100:8.2f}%", f"{validAcc*100:8.2f}%",
                                        train_time, test_time,
                                        "LogReg GridSearch with selected features"]
```

In [132…

```
experimentLog
```

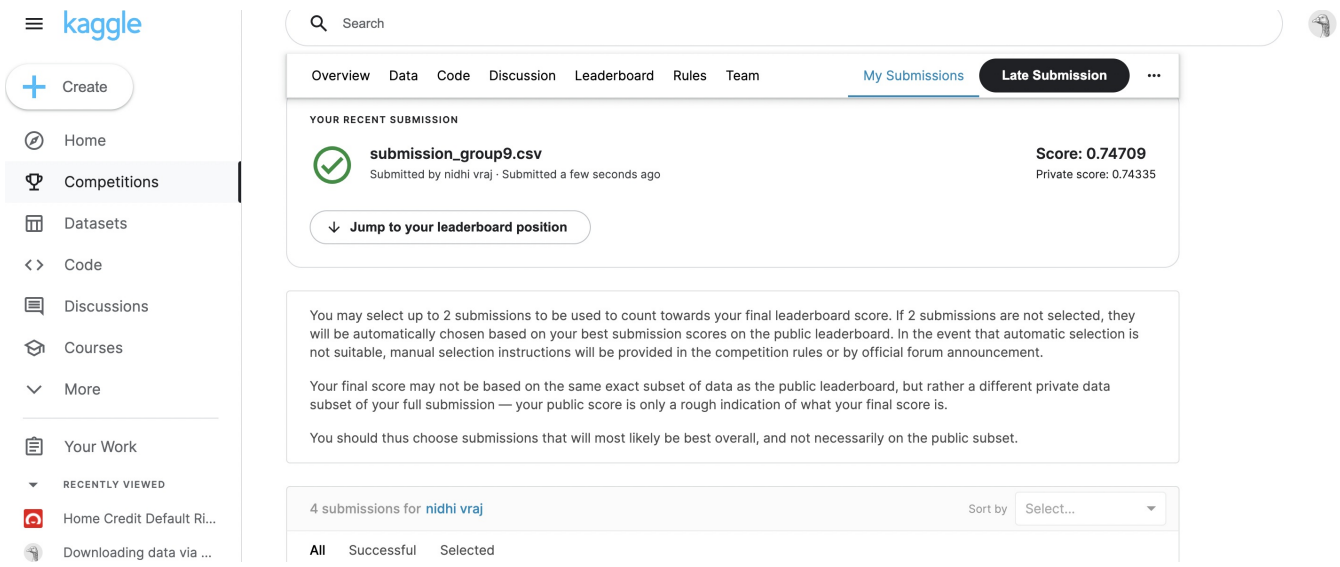
Out[132…

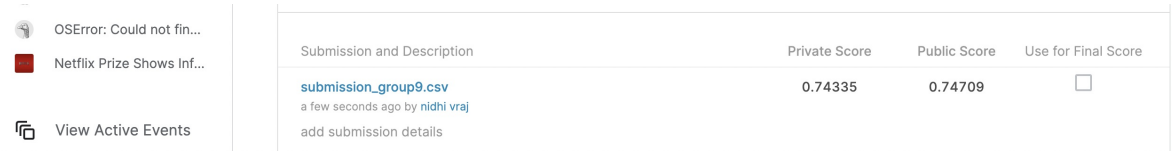
	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	78.5206	0.1277	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505538	47.0562	0.0612	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	91.91%	91.98%	91.96%	0.500000	5.2731	0.0123	Decision Making Tree GridSearch with selected ...
3	Lasso Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.755827	71.5090	0.0438	Lasso Regression for feature selection
4	Ridge Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.756776	18.4472	0.0195	Ridge Regression for feature selection
5	Gridsearch LogReg with 79 inputs	91.91%	91.98%	91.96%	0.500000	73.7680	0.0612	LogReg GridSearch with selected features

In [ ]:

Kaggle submission via the command line API

Screenshot of kaggle submission





report submission

Click on this link

Write-up (Phase -2)

Abstract

HomeCredit uses Machine Learning Modeling to provide unsecured loans based on a user's credit history, repayment patterns, and other data. Credit history is a metric that explains a user's credibility based on factors such as the user's average/minimum/maximum balance, Bureau scores recorded, salary, and repayment patterns. We use kaggle datasets to undertake exploratory data analysis, develop machine learning pipelines, and evaluate models across many evaluation metrics for a model to be deployed as part of this project. We offer feature engineering, hyperparameter tuning, and modeling pipelines in phase 2. We used a regression of baseline inputs and chosen features for Logistic, Decision Making Tree, Lasso, and Ridge Regressions. The baseline pipeline has the highest test accuracy with 92%, followed by Logistic regression with 91.98%, then Decision Making tree, and finally Lasso and Ridge being the least accurate.

Project Description

Data Description

- application_{train|test}.csv
  This is the main table, broken into two files for Train (with TARGET) and Test (without TARGET). Static data for all applications. One row represents one loan in our data sample.

- POS_CASH_balance.csv
  This dataset gives information about previous credits information such as contract status, number of installments left to pay, DPD(days past due), etc. of the current application. Monthly balance snapshots of previous POS (point of sales) and cash loans that the applicant had with Home Credit.

- bureau.csv
  All client's previous credits provided by other financial institutions were reported to the Credit Bureau (for clients who have a loan in our sample). For every loan in our sample, there are as many rows as the number of credits the client had in the Credit Bureau before the application date.

- bureau_balance.csv
  Monthly balances of previous credits in the Credit Bureau. This table has one row for each month of history of every previous credit reported to the Credit Bureau.

- credit_card_balance.csv
  Monthly balance snapshots of previous credit cards that the applicant has with Home Credit.

- previous_application.csv
  All previous applications for Home Credit loans of clients who have loans in our sample. There is one row for each previous application related to loans in our data sample.

- installments_payments.csv
  Repayment history for the previously disbursed credits in Home Credit related to the loans in our sample. There is a) one row for every payment that was made plus b) one row each for missed payment. One row is equivalent to one payment of one installment OR one installment corresponding to one payment of one previous Home Credit credit related to loans in our sample.

1. Train dataset in application.csv

- Shape: (307511, 122)
- First five rows and seven columns look like:

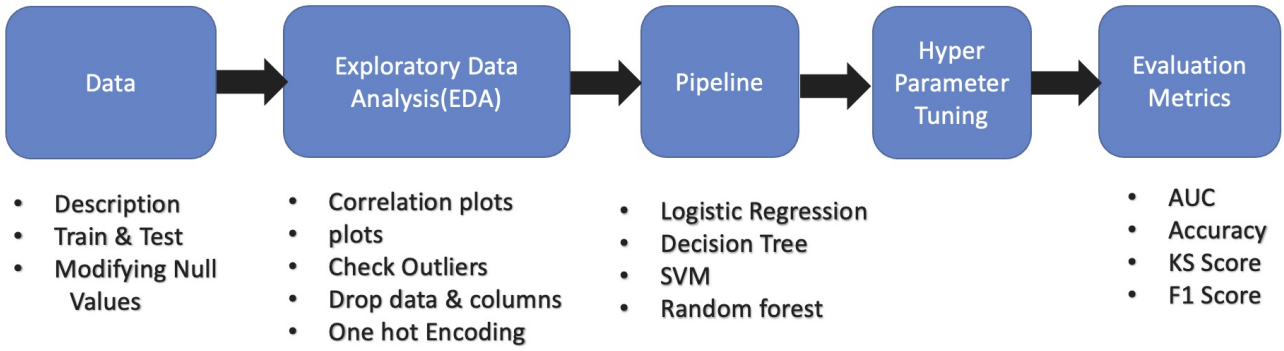
SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN
100002	1	Cash loans	M	N	Y	0
100003	0	Cash loans	F	N	N	0
100004	0	Revolving loans	M	Y	Y	0
100006	0	Cash loans	F	N	Y	0

100007	0	Cash loans	M	N	Y	0

- We discarded features with null values more than 30%. We present null percentage of ten features in the below table as an example.

	col_name	null_count	count_%
0	NAME_CONTRACT_TYPE	0	0.000000
1	CODE_GENDER	0	0.000000
2	FLAG_OWN_CAR	0	0.000000
3	FLAG_OWN_REALTY	0	0.000000
4	CNT_CHILDREN	0	0.000000
...	...	...	...
115	AMT_REQ_CREDIT_BUREAU_DAY	41519	13.501631
116	AMT_REQ_CREDIT_BUREAU_WEEK	41519	13.501631
117	AMT_REQ_CREDIT_BUREAU_MON	41519	13.501631
118	AMT_REQ_CREDIT_BUREAU_QRT	41519	13.501631
119	AMT_REQ_CREDIT_BUREAU_YEAR	41519	13.501631

Workflow



Feature Engineering and transformers

	col_name	null_count	count_%	col_type
7	AMT_ANNUITY	12	0.003902	float64
8	AMT_GOODS_PRICE	278	0.090403	float64
27	CNT_FAM_MEMBERS	2	0.000650	float64
40	EXT_SOURCE_2	660	0.214626	float64
41	EXT_SOURCE_3	60965	19.825307	float64
89	OBS_30_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
90	DEF_30_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
91	OBS_60_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
92	DEF_60_CNT_SOCIAL_CIRCLE	1021	0.332021	float64
93	DAYS_LAST_PHONE_CHANGE	1	0.000325	float64
114	AMT_REQ_CREDIT_BUREAU_HOUR	41519	13.501631	float64
115	AMT_REQ_CREDIT_BUREAU_DAY	41519	13.501631	float64
116	AMT_REQ_CREDIT_BUREAU_WEEK	41519	13.501631	float64
117	AMT_REQ_CREDIT_BUREAU_MON	41519	13.501631	float64
118	AMT_REQ_CREDIT_BUREAU_QRT	41519	13.501631	float64
119	AMT_REQ_CREDIT_BUREAU_YEAR	41519	13.501631	float64

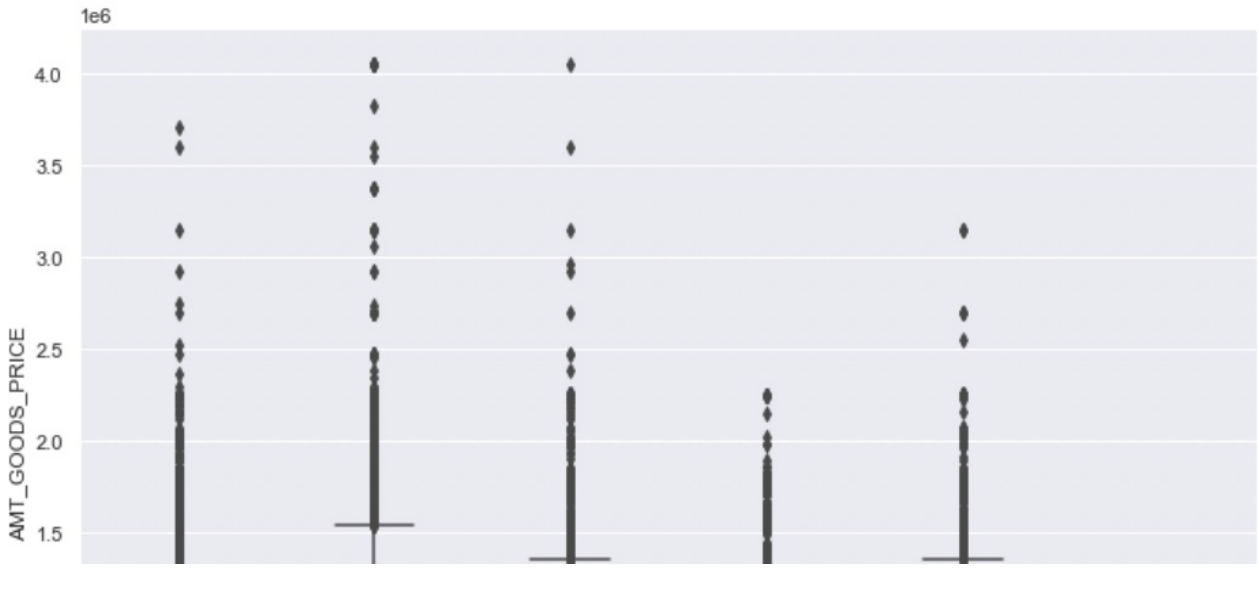
Step 1: - We discarded columns which are having more than 30% of Null Values The above table shows the count of NA values of remaining columns and their percentages

Step 2: - 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 gives the number of enquiries done. As the number is not available, we can assume no enquiries are made. So, we replace NA values with 0

Step 3: - OBS_30_CNT_SOCIAL_CIRCLE, DEF_30_CNT_SOCIAL_CIRCLE, OBS_60_CNT_SOCIAL_CIRCLE, DEF_60_CNT_SOCIAL_CIRCLE gives us number of immediate connections who have a loan in Home Credit. Since we don't have data, we can assume there are no immediate connections. So, we replace NA values with 0.

Step 4: - CNT_FAM_MEMBERS NA values are filled with median

Step 5: - AMT_GOODS_PRICE values are depending on NAME_FAMILY_STATUS categories. So we replaced NA values with medians w.r.t NAME_FAMILY_STATUS. We can see in below figure that AMT_GOODS_PRICE is depends on NAME_FAMILY_STATUS.



Step 6: - Dropped DAYS_LAST_PHONE_CHANGE column because there is only 1 row.

Step 7: - To replace EXT_SOURCE_2 NA values, we found top 5 variables which are highly correlated. REGION_RATING_CLIENT is highly correlated with EXT_SOURCE_2. As REGION_RATING_CLIENT is categorical, we fill NA values with median based on categories.

Step 8: - To replace EXT_SOURCE_3 NA values, we found top 5 variables which are highly correlated. DAYS_BIRTH is highly correlated with EXT_SOURCE_2. As DAYS_BIRTH is numerical, we fill NA values using Linear Regression.

Provide additional features added to training data

- We trained and tested with selected columns.
  - AMT_CREDIT_TO_ANNUITY_RATIO
  - Tot_EXTERNAL_SOURCE
  - Salary_to_credit
  - Annuity_to_salary_ratio
- Additionally we tried several other features like segregated bins based on AMT_ANNUITY, AMT_SALARY based on percentile, but these features were not of help for us either in increasing accuracy or AUC.
- We also tried using one-hot encoding instead of label encoding and performed modelling across Baseline and checked the results, but we found no improvement across AUC or accuracy.

Impact of these new features added to the model

- Then, we ran Logistic regression with these selected features and compared it with the baseline logistic regression model, as presented in the modeling session.
- The addition of these features to the training data have made an impact as presented in the below Table.

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	110.2988	0.0994	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505520	96.4481	0.0506	Selected features Dataset - Baseline LogisticR...

Why we chose the method and approach

- Filling null values across categorical and continuous variables should be handled separately. It won't be feasible to fill all categorical variables with most_repeated or least repeated values and fill with either 0’s or median values across continuous variables.
- Ratios across income/credit requested/credit to be paid per year would be a good measure to judge an individual’s credibility and repayment ability so we considered adding above

Hyperparameter tuning

- After Feature Engineering, we tuned our model to find the optimal parameters. As we will further discuss, we will use Decision Making Tree in addition to baseline and selected Logistic Regression.
- The hyperparameter tuning for grid search was conducted for decision Making Tree, Lasso Regression, Ridge Regression, and Logistic Regression.

Decision Making Tree

Decision Making Tree

- For a Decision Tree model, we used different maximum depths and the number of sample split.

```
DMT_pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('regressor', DecisionTreeClassifier(random_state=100))
])

param_grid = [{
    'regressor__max_depth': [2, 3],
    'regressor__min_samples_split': [2, 3],
}]
```

Lasso Regression

```
lasso_pipeline = Pipeline([
                    ('scaler',StandardScaler()),
                    ('model',Lasso())
])


lasso_pipeline = GridSearchCV(lasso_pipeline,
                     {'model__alpha':[0.0001,0.001,0.01,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,2,3,4,5,6,7,8,9,10]},
                     cv = 5, scoring="neg_mean_squared_error",verbose=3
                     )
```

- For Lasso Regression, we used different alpha parameters and controlled the weighting of the penalty to the loss function.

Ridge Regression

```
ridge_pipeline = Pipeline([
                    ('scaler',StandardScaler()),
                    ('model',Ridge())
])


ridge_pipeline = GridSearchCV(ridge_pipeline,
                     {'model__alpha':[0.0001,0.001,0.01,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,2,3,4,5,6,7,8,9,10]},
                     cv = 5, scoring="neg_mean_squared_error",verbose=3
                     )
```

- For Ridge Regression, we used different alpha parameters and controlled the weighting of the penalty to the loss function.

Logistic Regression

```
logistic = LogisticRegression(max_iter=10000, tol=0.1)
clf_pipe = Pipeline(steps=[("logistic", logistic)])
param_grid = {
    "logistic__C": np.logspace(-4, 4, 10)
}
```

- For Logistic Regression, we used different C parameters and controlled the penalty strength.

Pipelines

The goal here is to predict whether the customer who has reached out to Home Credit for a loan is a defaulter or not. Therefore, this is a supervised classification task, and the output of the target variable is either 1 or 0 where 1 means non-defaulter and 0 means defaulter.

- We are planning to use the following algorithms in our machine learning pipeline.
  1) Logistic Regression
  2) Decision Trees
  4) Ridge Regression
  5) Lasso Regression

Logistic Regression

Logistic Regression can be used as a baseline model along with feature selection techniques like RFE,PCA, SelectKbest.

In statistics, the (binary) logistic model (or logit model) is a statistical model that models the probability of one event (out of two alternatives) taking place by having the log-odds (the logarithm of the odds) for the event be a linear combination of one or more independent variables ("predictors"). In regression analysis, logistic regression[1] (or logit regression) is estimating the parameters of a logistic model (the coefficients in the linear combination). Formally, in binary logistic regression there is a single binary dependent variable, coded by a indicator variable, where the two values are labeled "0" and "1", while the independent variables can each be a binary variable (two classes, coded by an indicator variable) or a continuous variable (any real value). The corresponding probability of the value labeled "1" can vary between 0 (certainly the value "0") and 1 (certainly the value "1"), hence the labeling;[2] the function that converts log-odds to probability is the logistic function, hence the name. The unit of measurement for the log-odds scale is called a logit, from logistic unit, hence the alternative names

loss function:

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1-y_i) \cdot log(1-p(y_i))$$

Binary Cross-Entropy / Log Loss

Decision Trees:

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements.

A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules.

In decision analysis, a decision tree and the closely related influence diagram are used as a visual and analytical decision support tool, where the expected values (or expected utility) of competing alternatives are calculated.

loss function:

Information gain

Information gain $IG(A)$ is the measure of the difference in entropy from before to after the set S is split on an attribute A. In other words, how much uncertainty in S was reduced after splitting set S on attribute A.

$$IG(A, S) = H(S) - \sum_{t \in T} p(t)H(t)$$

Where,

- $H(S)$ – Entropy of set S
- T – The subsets created from splitting set S by attribute A such that $S = \bigcup_{t \in T} t$
- $p(t)$ – The proportion of the number of elements in t to the number of elements in set S
- $H(t)$ – Entropy of subset t

In ID3, information gain can be calculated (instead of entropy) for each remaining attribute. The attribute with the **largest** information gain is used to split the set S on this iteration.

Lasso Regression:

LASSO is a penalized regression approach that estimates the regression coefficients by maximizing the log-likelihood function (or the sum of squared residuals) with the constraint that the sum of the absolute values of the regression coefficients, ∑kj=1||βj||, is less than or equal to a positive constant s. One interesting property of LASSO is that the estimates of the regression coefficients are sparse, which means that many components are exactly 0. That is, LASSO automatically deletes unnecessary covariates.

loss function:

$$L1: \quad J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost(h_\theta(x^{(i)}), y^{(i)}) \quad s.t. \quad ||\theta||_1 <= C$$

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost(h_\theta(x^{(i)}), y^{(i)}) + \frac{\lambda}{m}\sum_{j=1}^{n} |\theta_j|$$

Regularization of Logistic Regression:

Ridge Regression:

Ridge regression is a method of estimating the coefficients of multiple-regression models in scenarios where linearly independent variables are highly correlated.This method performs L2 regularization. When the issue of multicollinearity occurs, least-squares are unbiased, and variances are large, this results in predicted values being far away from the actual values. n ridge regression, the first step is to standardize the variables (both dependent and independent) by subtracting their means and dividing by their standard deviations. This causes a challenge in notation since we must somehow indicate whether the variables in a particular formula are standardized or not. As far as standardization is concerned, all ridge regression calculations are based on standardized variables. When the final regression coefficients are displayed, they are adjusted back into their original scale. However, the ridge trace is on a standardized scale.

loss function:

$$L2: \quad J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost(h_\theta(x^{(i)}), y^{(i)}) \quad s.t. \quad ||\theta||_2^2 <= C^2$$

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost(h_\theta(x^{(i)}), y^{(i)}) + \frac{\lambda}{2m}\sum_{j=1}^{n} \theta_j^2$$

$$m = number\ of\ samples, \quad n = number\ of\ features$$

Machine Learning Pipeline Steps:

1. Data Preprocessing
   a. Gather Kaggle's raw data.
   b. Perform exploratory data analysis on the dataset.
   c. Feature engineering for improving performance of machine learning model.
2. Model Selection
   a. Develop and test various candidate models, such as "Logistic Regression","Decision Making Trees", "Random Forest", and "SVMs.
   b. Based on the evaluation measures, select the best model.
   c. Use various evaluation metrics like "accuracy," "F1 Score," and "AUC."
3. Prediction Generation
   a. Prepare the new data and extract the features as before.
   b. Once the winning model has been chosen, use it to make predictions on the new data.

Results and discussion of results

Logistic Regression

- As we have seen the table for logistic regression, results for baseline and selected logistic regressions have been presented.
- Baseline logistic regression and selected logistic regression have similar test accuracies and AUC. They have similar cross fold train accuracy as well.
- Since baseline logistic regression already has fairly high test accuracy i.e. 92 and decent AUC 0.504, there seems no significant advantage for selecting features.

Decision Making Tree

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	110.2988	0.0994	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505520	96.4481	0.0506	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	7.84%	7.56%	7.35%	0.738725	4.4617	0.0129	Decision Making Tree GridSearch with selected ...

- In the above table, results for the decision tree have been presented.
- Decision tree has low test accuracy i.e. 7.56% and high AUC 0.738.
- Compared to baseline regressions, the decision tree lost test accuracy but gained AUC.
- This loss of test accuracy may be due to the short dept of the decision tree, compared to the number of variables we have used.

Lasso Regression

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	110.2988	0.0994	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505520	96.4481	0.0506	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	7.84%	7.56%	7.35%	0.738725	4.4617	0.0129	Decision Making Tree GridSearch with selected ...
3	Lasso Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.755827	131.6072	0.0224	Lasso Regression for feature selection

- In the above table, results for the lasso regression have been presented.
- Test accuracy has decreased to -6.89%, whereas AUC increased to 0.755.
- Although AUC has increased, since test accuracy has significantly fallen, we should not use Lasso regression.
- We believe that these negative results could be due to score functions in the lasso regression blocks.

Ridge Regression

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description

0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	110.2988	0.0994	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505520	96.4481	0.0506	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	7.84%	7.56%	7.35%	0.738725	4.4617	0.0129	Decision Making Tree GridSearch with selected ...
3	Lasso Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.755827	131.6072	0.0224	Lasso Regression for feature selection
4	Ridge Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.756776	30.4069	0.0134	Ridge Regression for feature selection

- In the above table, results for ridge regression have been presented.
- Test accuracy has decreased to -6.89%, whereas AUC increased to 0.756.
- Although AUC has increased, since test accuracy has significantly fallen, we should not use Ridge regression.
- We believe that these negative results could be due to score functions in the ridge regression blocks.

Logistic Regression GridSearch

	ExpID	Cross fold train accuracy	Test Accuracy	Validation Accuracy	AUC	Train Time(s)	Test Time(s)	Experiment description
0	Baseline with 120 inputs	92.0	92.0	91.8	0.504333	110.2988	0.0994	All features Dataset - Baseline LogisticRegres...
1	Baseline with 79 inputs	91.9	91.9	91.8	0.505520	96.4481	0.0506	Selected features Dataset - Baseline LogisticR...
2	Gridsearch Decision Making Tree with 79 inputs	7.84%	7.56%	7.35%	0.738725	4.4617	0.0129	Decision Making Tree GridSearch with selected ...
3	Lasso Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.755827	131.6072	0.0224	Lasso Regression for feature selection
4	Ridge Reg with 79 inputs	-6.89%	-6.87%	-6.89%	0.756776	30.4069	0.0134	Ridge Regression for feature selection
5	Gridsearch LogReg with 79 inputs	91.91%	91.98%	91.96%	0.500000	55.1705	0.0168	LogReg GridSearch with selected features

- Results for Logistic Regression GridSearch have been presented.
- Test accuracy is as high as 91.98%, but AUC is slightly lower than the baseline regression.
- AUC for logistic regression gridsearch is 0.5, whereas that of baseline is 0.504.
- Since test accuracy and AUC are both higher for baseline regression, we should choose baseline logistic regression instead of gridsearch logistic regression.

Conclusion

The objective of the HCDR project is to predict the repayment ability of the financially under-served population. This project is important because well-established predictions are necessary to both the loaner and borrower. Real-time Homecredit is able to display loan offers to its

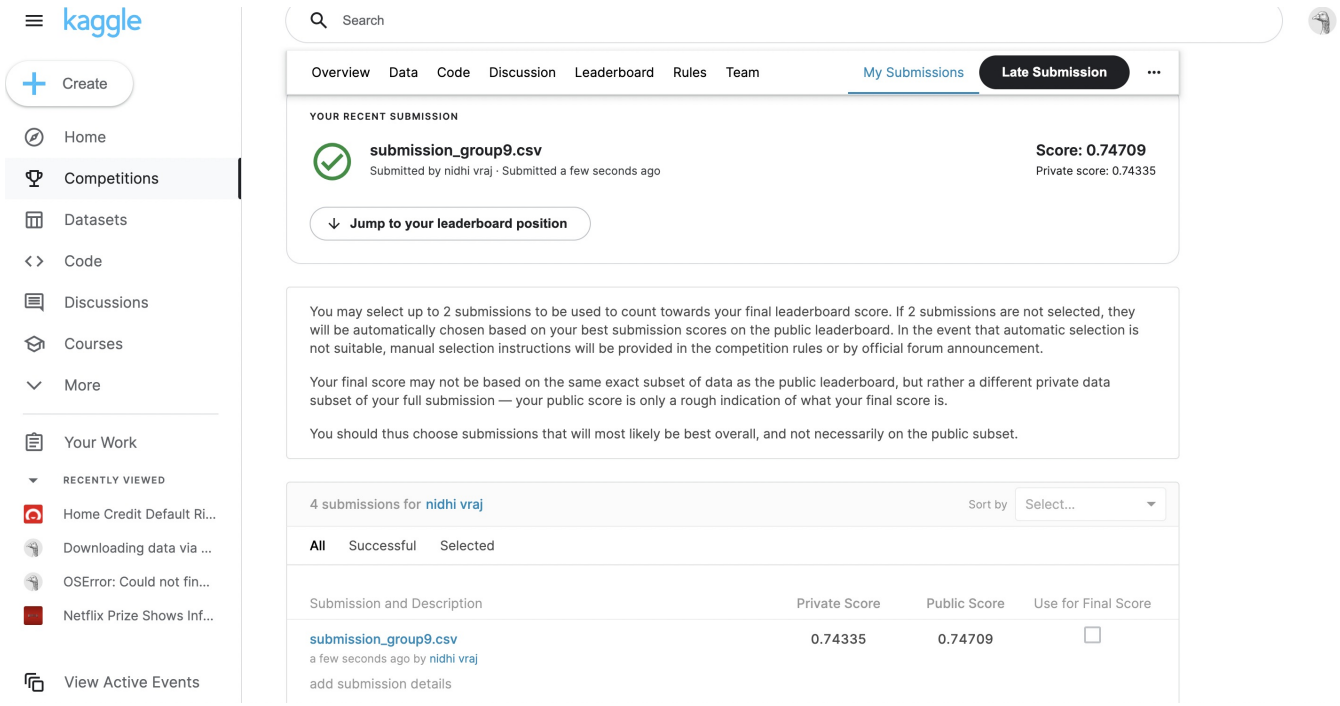
customers with the maximum amount and APR using their ML pipelines where fetching data from the data providers via APIs, performing EDA and fitting it to the model to generate scores occurs in microseconds of time. Hence Risk analysis becomes very critical in this regard where NPA(Non-Performing Asset) expected is less than 5% in order to run a profitable business.

Credit history is a measure explaining the credibility of a user generated using parameters like average/min/max balance maintained by the user, Bureau scores reported, salary etc and repayment patterns could be analysed using the timely defaults/repayments made by the user in the past. Alternate data includes other parameters like geographic data, social media data, calling/SMS data etc. As part of this project we would be using the datasets provided by kaggle to perform exploratory data analysis, build machine learning pipelines and evaluate the models across several evaluation metrics for a model to be deployed.

In phase 2, we estimated several models including both classification and regression models. We did feature selection, data imputation, and hyperparameter tuning. First, we did feature selection and imputation. We filled in the missing values of selected features. Then, we decided to add relevant features based on our prior knowledge. Next, we tuned the hyperparameters with the help of GridSearchCV. To find the best model, we trained and evaluated several models like Logistic Regression, Decision Tree Model, Lasso Regression and Ridge Regression. In phase 2, classification models cannot win the baseline model. Among regression models, the ridge regression model shows the best performance.

In phase 3, we plan to implement a deep learning model and build additional models in PyTorch. The problems that we are currently facing are that with the feature selection and imputation step, we cannot improve the test accuracy or AUC of the baseline model. Unlike regression models, we cannot develop a classification model better than the baseline. So, to address these issues, in phase 3, we plan to build a multilayer model in PyTorch for loan default classification. As a stretch goal, we will develop and implement a new multitask loss function in Pytorch. These will be submitted to Kaggle and we will report our scores.

Kaggle Submission



References

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

https://towardsdatascience.com/building-a-logistic-regression-in-python-step-by-step-becd4d56c9c8

https://online.stat.psu.edu/stat857/node/216/

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/