Team Information

Project Title - 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.

Group Number - 21

Names -

Kumar Saurabh (ksaurabh@iu.edu)

Shubham Thakur (sbmthakur@iu.edu)

Ameya Dalvi (abdalvi@iu.edu)

Vishwa Shrirame (vshriram@iu.edu)

Team Photos

Kumar Saurabh

Shubham Thakur

Ameya Dalvi

Vishwa Shrirame

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
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: kaggle in /usr/local/lib/python3.7/site-package
s (1.5.12)
Requirement already satisfied: requests in /usr/local/lib/python3.7/site-packa
ges (from kaggle) (2.25.1)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/site-packag
es (from kaggle) (2021.5.30)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.7/sit
e-packages (from kaggle) (2.8.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/site-packages
(from kaggle) (4.62.1)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.7/site-pack
ages (from kaggle) (1.15.0)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/site-packag
es (from kaggle) (1.26.6)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.7/site
-packages (from kaggle) (5.0.2)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.
7/site-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/site-p
ackages (from requests->kaggle) (2.10)
Requirement already satisfied: chardet<5,>=3.0.2 in /usr/local/lib/python3.7/s
ite-packages (from requests->kaggle) (4.0.0)
WARNING: You are using pip version 21.2.4; however, version 21.3.1 is availabl
e.
You should consider upgrading via the '/usr/local/bin/python -m pip install --
upgrade pip' command.
```

In [6]:
```
!pwd
```

```
/N/home/u100/vshriram/Carbonate/I526_AML_Student/Assignments/Unit-Project-Home
-Credit-Default-Risk
```

In [10]:
```
!mkdir ~/.kaggle
#!cp /N/u/vshriram/Carbonate/Downloads/kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json
```

```
mkdir: cannot create directory '/N/u/vshriram/Carbonate/.kaggle': File exists
```

In [11]:
```
! kaggle competitions files home-credit-default-risk
```

```
name                                  size  creationDate
------------------------------------  -----  -------------------
credit_card_balance.csv              405MB  2019-12-11 02:55:35
bureau_balance.csv                   358MB  2019-12-11 02:55:35
application_test.csv                  25MB  2019-12-11 02:55:35
POS_CASH_balance.csv                 375MB  2019-12-11 02:55:35
HomeCredit_columns_description.csv    37KB  2019-12-11 02:55:35
bureau.csv                           162MB  2019-12-11 02:55:35
application_train.csv                158MB  2019-12-11 02:55:35
previous_application.csv             386MB  2019-12-11 02:55:35
sample_submission.csv                524KB  2019-12-11 02:55:35
installments_payments.csv            690MB  2019-12-11 02:55:35
```

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.

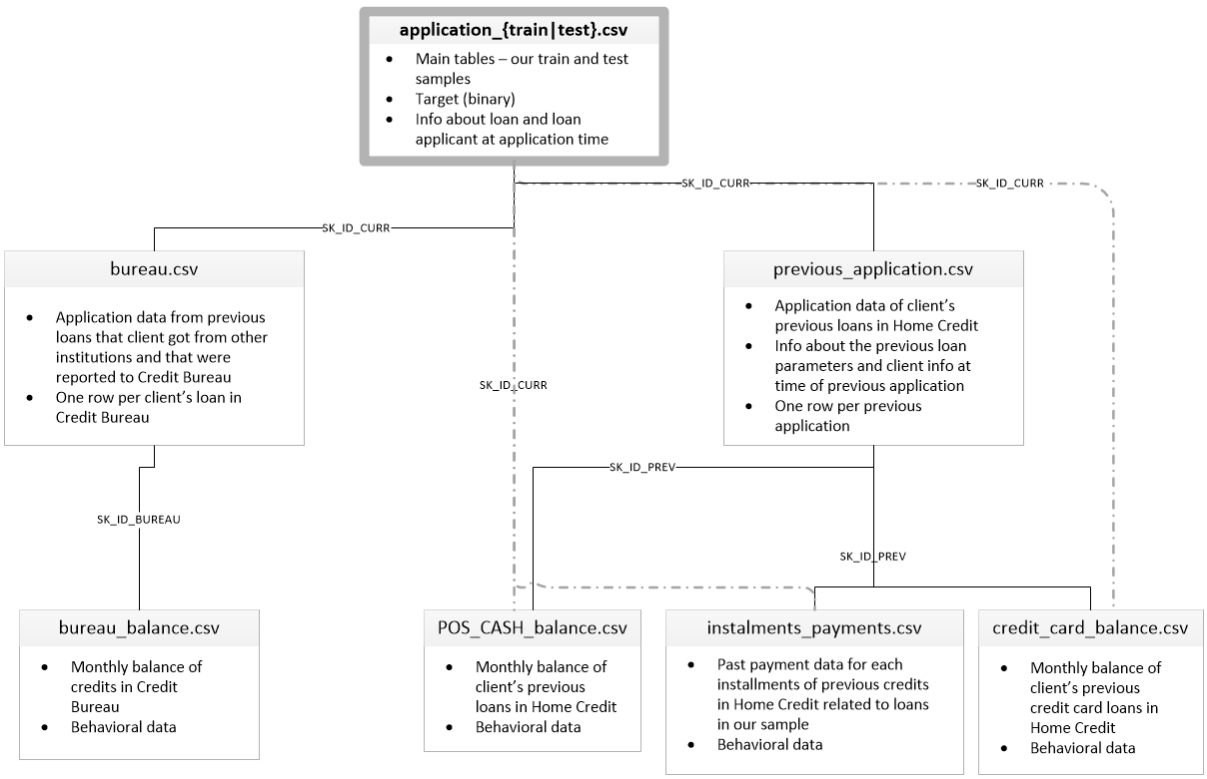
Data files overview

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 [ ]:
```
# ![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 [1]:
```
DATA_DIR = "/N/u/vshriram/Carbonate/I526_AML_Student/Assignments/Unit-Project-
```

```
#DATA_DIR = "/root/shared/I526_AML_Student/Data/home-credit-default-risk"
#DATA_DIR = os.path.join('./ddddd/')
!mkdir $DATA_DIR
```

```
mkdir: cannot create directory '/N/u/vshriram/Carbonate/I526_AML_Student/Assig
nments/Unit-Project-Home-Credit-Default-Risk': File exists
```

In [2]:

```
!ls -l $DATA_DIR
```

```
total 7161760
-rw-rw-r-- 1 vshriram vshriram   11889867 Dec  6 17:22 Group21_Phase1(1)(1).ip
ynb
-rw-rw-r-- 1 vshriram vshriram   11283226 Dec 12 18:19 Group21_Phase2 (2).ipyn
b
-rw-r--r-- 1 vshriram vshriram   20907849 Dec 12 00:34 Group21_Phase2.ipynb
-rw-rw-r-- 1 vshriram vshriram    5428396 Dec  7 17:07 Group23_Phase2_AML.ipyn
b
drwxrwxr-x 3 vshriram vshriram      32768 Nov 29 20:47 HCDR_Phase_1_baseline_s
ubmission
-rw-rw-r-- 1 vshriram vshriram     875737 Dec  7 14:06 HW10_End_to_end_Machine
_Learning_Project (1).html
-rw-rw-r-- 1 vshriram vshriram      37383 Dec 11  2019 HomeCredit_columns_desc
ription.csv
-rw-rw-r-- 1 vshriram vshriram  392703158 Dec 11  2019 POS_CASH_balance.csv
-rw-r--r-- 1 vshriram vshriram      21462 Dec  6 21:37 Untitled.ipynb
-rw-rw-r-- 1 vshriram vshriram   26567651 Dec 11  2019 application_test.csv
-rw-rw-r-- 1 vshriram vshriram  166133370 Dec 11  2019 application_train.csv
-rw-rw-r-- 1 vshriram vshriram  170016717 Dec 11  2019 bureau.csv
-rw-rw-r-- 1 vshriram vshriram  375592889 Dec 11  2019 bureau_balance.csv
-rw-rw-r-- 1 vshriram vshriram  424582605 Dec 11  2019 credit_card_balance.csv
-rw-r--r-- 1 vshriram vshriram  721616255 Dec  4 11:40 home-credit-default-ris
k.zip
-rw-rw-r-- 1 vshriram vshriram  723118349 Dec 11  2019 installments_payments.c
sv
-rw-rw-r-- 1 vshriram vshriram  404973293 Dec 11  2019 previous_application.cs
v
-rw-rw-r-- 1 vshriram vshriram     536202 Dec 11  2019 sample_submission.csv
-rw-r--r-- 1 vshriram vshriram    1325792 Dec  7 20:46 submission.csv
-rw-r--r-- 1 vshriram vshriram 1278347733 Dec  6 21:28 train.pkl
-rw-r--r-- 1 vshriram vshriram 1297567752 Dec  7 19:40 train2.pkl
-rw-r--r-- 1 vshriram vshriram 1298414174 Dec  7 20:02 train3.pkl
```

In [14]:

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

```
Downloading home-credit-default-risk.zip to /N/u/vshriram/Carbonate/I526_AML_S
tudent/Assignments/Unit-Project-Home-Credit-Default-Risk
 99%|████████████████████████████████████▉| 682M/688M [00:06<00:00, 140M
B/s]
100%|████████████████████████████████████▉| 688M/688M [00:06<00:00, 115M
B/s]
```

In [1]:

```
pip install missingno
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: missingno in /N/home/u100/vshriram/Carbonate/.l
ocal/lib/python3.7/site-packages (0.5.0)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/site-packages
(from missingno) (1.6.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/site-packages
(from missingno) (1.19.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/site-pac
kages (from missingno) (3.4.2)
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/site-packag
es (from missingno) (0.11.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.7/site-
packages (from matplotlib->missingno) (8.3.1)
```

```
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/s
ite-packages (from matplotlib->missingno) (1.3.1)
Requirement already satisfied: pyparsing>=2.2.1 in /usr/local/lib/python3.7/si
te-packages (from matplotlib->missingno) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/site-p
ackages (from matplotlib->missingno) (0.10.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.
7/site-packages (from matplotlib->missingno) (2.8.2)
Requirement already satisfied: six in /usr/local/lib/python3.7/site-packages
(from cycler>=0.10->matplotlib->missingno) (1.15.0)
Requirement already satisfied: pandas>=0.23 in /usr/local/lib/python3.7/site-p
ackages (from seaborn->missingno) (1.3.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/site-p
ackages (from pandas>=0.23->seaborn->missingno) (2021.1)
WARNING: You are using pip version 21.2.4; however, version 21.3.1 is availabl
e.
You should consider upgrading via the '/usr/local/bin/python -m pip install --
upgrade pip' command.
Note: you may need to restart the kernel to use updated packages.
```

In [439…

```
pip install tensorboard
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: tensorboard in /usr/local/lib/python3.7/site-pa
ckages (2.6.0)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.7/s
ite-packages (from tensorboard) (2.0.1)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in /usr/l
ocal/lib/python3.7/site-packages (from tensorboard) (0.6.1)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/
lib/python3.7/site-packages (from tensorboard) (0.4.5)
Requirement already satisfied: google-auth<2,>=1.6.3 in /usr/local/lib/python
3.7/site-packages (from tensorboard) (1.35.0)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.7/
site-packages (from tensorboard) (52.0.0.post20210125)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/li
b/python3.7/site-packages (from tensorboard) (1.8.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/sit
e-packages (from tensorboard) (3.3.4)
Requirement already satisfied: absl-py>=0.4 in /usr/local/lib/python3.7/site-p
ackages (from tensorboard) (0.13.0)
Requirement already satisfied: grpcio>=1.24.3 in /usr/local/lib/python3.7/site
-packages (from tensorboard) (1.39.0)
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/python3.7/site-pa
ckages (from tensorboard) (0.37.0)
Requirement already satisfied: protobuf>=3.6.0 in /usr/local/lib/python3.7/sit
e-packages (from tensorboard) (3.17.3)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.
7/site-packages (from tensorboard) (2.25.1)
Requirement already satisfied: numpy>=1.12.0 in /usr/local/lib/python3.7/site-
packages (from tensorboard) (1.19.5)
Requirement already satisfied: six in /usr/local/lib/python3.7/site-packages
(from absl-py>=0.4->tensorboard) (1.15.0)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.7/site-
packages (from google-auth<2,>=1.6.3->tensorboard) (4.7.2)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python
3.7/site-packages (from google-auth<2,>=1.6.3->tensorboard) (4.2.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python
3.7/site-packages (from google-auth<2,>=1.6.3->tensorboard) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/pyth
on3.7/site-packages (from google-auth-oauthlib<0.5,>=0.4.1->tensorboard) (1.3.
0)
Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.7/
site-packages (from markdown>=2.6.8->tensorboard) (3.10.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python3.
7/site-packages (from pyasn1-modules>=0.2.1->google-auth<2,>=1.6.3->tensorboar
d) (0.4.8)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/
```

```
site-packages (from requests<3,>=2.21.0->tensorboard) (2021.5.30)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python
3.7/site-packages (from requests<3,>=2.21.0->tensorboard) (1.26.6)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/site-p
ackages (from requests<3,>=2.21.0->tensorboard) (2.10)
Requirement already satisfied: chardet<5,>=3.0.2 in /usr/local/lib/python3.7/s
ite-packages (from requests<3,>=2.21.0->tensorboard) (4.0.0)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/sit
e-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<0.5,>=0.4.1->t
ensorboard) (3.1.1)
Requirement already satisfied: typing-extensions>=3.6.4 in /usr/local/lib/pyth
on3.7/site-packages (from importlib-metadata->markdown>=2.6.8->tensorboard)
(3.7.4.3)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/site-pack
ages (from importlib-metadata->markdown>=2.6.8->tensorboard) (3.5.0)
WARNING: You are using pip version 21.2.4; however, version 21.3.1 is availabl
e.
You should consider upgrading via the '/usr/local/bin/python -m pip install --
upgrade pip' command.
Note: you may need to restart the kernel to use updated packages.
```

Imports

In [3]:

```
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, make_pipeline
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import missingno as msno
from sklearn.metrics import mean_squared_error
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings('ignore')
```

In [7]:

```
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`

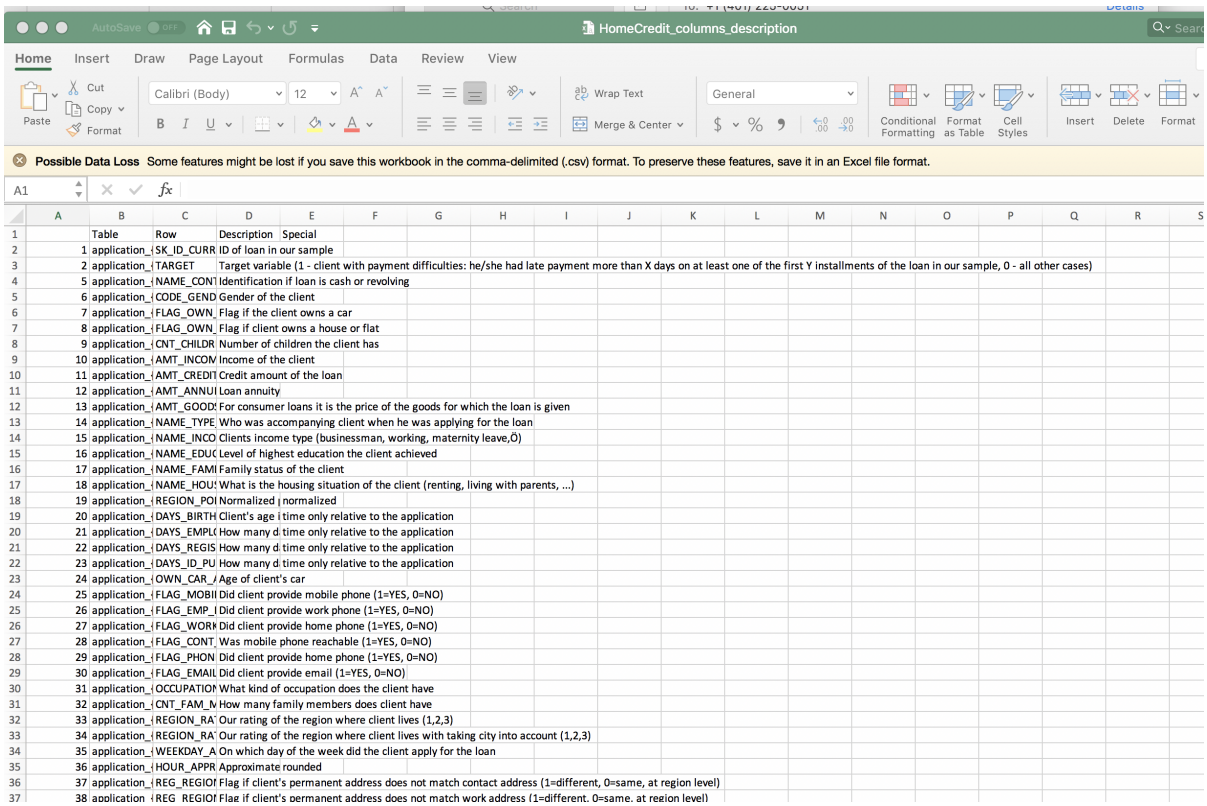


	Table	Row	Description	Special
1	application_{	SK_ID_CURR	ID of loan in our sample	
2	application_{	TARGET	Target variable (1 - client with payment difficulties: he/she had late payment more than X days on at least one of the first Y installments of the loan in our sample, 0 - all other cases)	
3	application_{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

Application train

In [4]:

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

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_OV
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	

5 rows × 122 columns

Out[4]: (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 [5]:

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

```
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_REALT
0	100001	Cash loans	F	N	
1	100005	Cash loans	M	N	
2	100013	Cash loans	M	Y	
3	100028	Cash loans	F	N	
4	100038	Cash loans	M	Y	

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 [6]:

```
%%time
ds_names = ("application_train", "application_test", "bureau","bureau_balance
            "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'), d
```

```
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_OV
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	

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_REALT
0	100001	Cash loans	F	N	
1	100005	Cash loans	M	N	
2	100013	Cash loans	M	Y	
3	100028	Cash loans	F	N	
4	100038	Cash loans	M	Y	

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_
0	215354	5714462	Closed	currency 1	-497	

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	CREDIT_
1	215354	5714463	Active	currency 1	-208	
2	215354	5714464	Active	currency 1	-203	
3	215354	5714465	Active	currency 1	-203	
4	215354	5714466	Active	currency 1	-629	

```
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_ACTUA

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	AMT_BALANCE	AMT_CREDIT_LIMIT_ACTUA
0	2562384	378907	-6	56.970	1350(
1	2582071	363914	-1	63975.555	450(
2	1740877	371185	-7	31815.225	4500(
3	1389973	337855	-4	236572.110	2250(
4	1891521	126868	-1	453919.455	4500(

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

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

5 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_FUTU
0	1803195	182943	-31	48.0	4
1	1715348	367990	-33	36.0	3
2	1784872	397406	-32	12.0	
3	1903291	269225	-35	48.0	4
4	2341044	334279	-35	36.0	3

```
CPU times: user 36.8 s, sys: 4.92 s, total: 41.7 s
Wall time: 41.7 s
```

In [14]:

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

```
dataset application_train       : [    307,511, 122]
```

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

Exploratory Data Analysis

Summary of Application train

In [8]:
```
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 [9]:
```
datasets["application_train"].describe() #numerical only features
```

Out[9]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	A
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	3
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	2

8 rows × 106 columns

In [10]:
```
datasets["application_test"].describe() #numerical only features
```

Out[10]:

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	A
count	48744.000000	48744.000000	4.874400e+04	4.874400e+04	48720.000000	
mean	277796.676350	0.397054	1.784318e+05	5.167404e+05	29426.240209	
std	103169.547296	0.709047	1.015226e+05	3.653970e+05	16016.368315	
min	100001.000000	0.000000	2.694150e+04	4.500000e+04	2295.000000	
25%	188557.750000	0.000000	1.125000e+05	2.606400e+05	17973.000000	
50%	277549.000000	0.000000	1.575000e+05	4.500000e+05	26199.000000	
75%	367555.500000	1.000000	2.250000e+05	6.750000e+05	37390.500000	
max	456250.000000	20.000000	4.410000e+06	2.245500e+06	180576.000000	

8 rows × 105 columns

In [17]:
```
datasets["application_train"].describe(include='all') #look at all categorica
```

Out[17]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_C
count	307511.000000	307511.000000	307511	307511	307
unique	NaN	NaN	2	3	
top	NaN	NaN	Cash loans	F	
freq	NaN	NaN	278232	202448	202
mean	278180.518577	0.080729	NaN	NaN	N
std	102790.175348	0.272419	NaN	NaN	N
min	100002.000000	0.000000	NaN	NaN	N
25%	189145.500000	0.000000	NaN	NaN	N
50%	278202.000000	0.000000	NaN	NaN	N
75%	367142.500000	0.000000	NaN	NaN	N
max	456255.000000	1.000000	NaN	NaN	N

11 rows × 122 columns

In [18]:
```
datasets["application_train"].size
```

Out[18]:
```
37516342
```

In [19]:
```
datasets["application_train"].shape
```

Out[19]:
```
(307511, 122)
```

Dividing the train dataset into train and validation sets

In [20]:
```
X = datasets["application_train"].drop(['TARGET'], axis = 1)
y = datasets["application_train"]["TARGET"]

# Split the provided training data into training and validationa and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ran
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_
print(f"X train           shape: {X_train.shape}")
print(f"X validation      shape: {X_valid.shape}")
print(f"X test            shape: {X_test.shape}")
```

```
X train           shape: (196806, 121)
X validation      shape: (49202, 121)
X test            shape: (61503, 121)
```

Summary Statistics -

In [21]:
```
X_train.info()
X_train.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 196806 entries, 9717 to 255
Columns: 121 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
```

```
dtypes: float64(65), int64(40), object(16)
memory usage: 183.2+ MB
```

Out[21]:

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY
count	196806.000000	196806.000000	1.968060e+05	1.968060e+05	196798.000000
mean	278195.549368	0.416786	1.683316e+05	5.993323e+05	27109.915949
std	102732.472419	0.719989	1.055828e+05	4.029388e+05	14475.618426
min	100003.000000	0.000000	2.565000e+04	4.500000e+04	1993.500000
25%	189184.250000	0.000000	1.125000e+05	2.700000e+05	16524.000000
50%	278235.500000	0.000000	1.440000e+05	5.147775e+05	24907.500000
75%	367111.750000	1.000000	2.025000e+05	8.086500e+05	34609.500000
max	456254.000000	19.000000	1.350000e+07	4.050000e+06	258025.500000

8 rows × 105 columns

In [22]:

```
# Concatenating X_train and y_train
Xy_train = pd.concat([X_train, y_train], axis=1)
Xy_train.head()
```

Out[22]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_
9717	111307	Cash loans	F	N	
203356	335752	Cash loans	F	Y	
81757	194805	Cash loans	F	Y	
84860	198457	Cash loans	F	N	
234668	371838	Cash loans	F	N	

5 rows × 122 columns

Determine the categorical and numerical features

In [23]:

```
numerical_features = X_train.select_dtypes(include = ['int64', 'float64']).co
categorical_features = X_train.select_dtypes(include = ['object', 'bool']).co
print(f"\nNumerical features : {list(numerical_features)}")
print(f"\nCategorical features : {list(categorical_features)}")
```

```
Numerical features : ['SK_ID_CURR', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_C
REDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIVE', 'DAYS_
BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OWN_CAR_AG
E', 'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FL
AG_PHONE', 'FLAG_EMAIL', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RA
TING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION',
'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIV
E_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'EXT_SOURCE_1',
'EXT_SOURCE_2', 'EXT_SOURCE_3', 'APARTMENTS_AVG', 'BASEMENTAREA_AVG', 'YEARS_B
EGINEXPLUATATION_AVG', 'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG',
'ENTRANCES_AVG', 'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG', 'LIVINGAPAR
TMENTS_AVG', 'LIVINGAREA_AVG', 'NONLIVINGAPARTMENTS_AVG', 'NONLIVINGAREA_AVG',
'APARTMENTS_MODE', 'BASEMENTAREA_MODE', 'YEARS_BEGINEXPLUATATION_MODE', 'YEARS
_BUILD_MODE', 'COMMONAREA_MODE', 'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMA
X_MODE', 'FLOORSMIN_MODE', 'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'LIVINGAR
EA_MODE', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE', 'APARTMENTS_MEDI',
'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI', 'YEARS_BUILD_MEDI', 'COMM
ONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI', 'FLOORSMAX_MEDI', 'FLOORSMIN
```

```
_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI', 'LIVINGAREA_MEDI', 'NONLIVIN
GAPARTMENTS_MEDI', 'NONLIVINGAREA_MEDI', 'TOTALAREA_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', 'F
LAG_DOCUMENT_8', 'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'F
LAG_DOCUMENT_12', 'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15',
'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17', 'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_1
9', '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']

Categorical features : ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYP
E', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE', 'WEEKDAY_APP
R_PROCESS_START', 'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE', 'HOUSETYPE_MODE',
'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE']
```

Missing data Analysis

Missing data for application train

In [24]:

```
percent = (datasets["application_train"].isnull().sum()/datasets["application_
sum_missing = datasets["application_train"].isna().sum().sort_values(ascendin
missing_application_train_data  = pd.concat([percent, sum_missing], axis=1, k
missing_application_train_data.head(20)
```

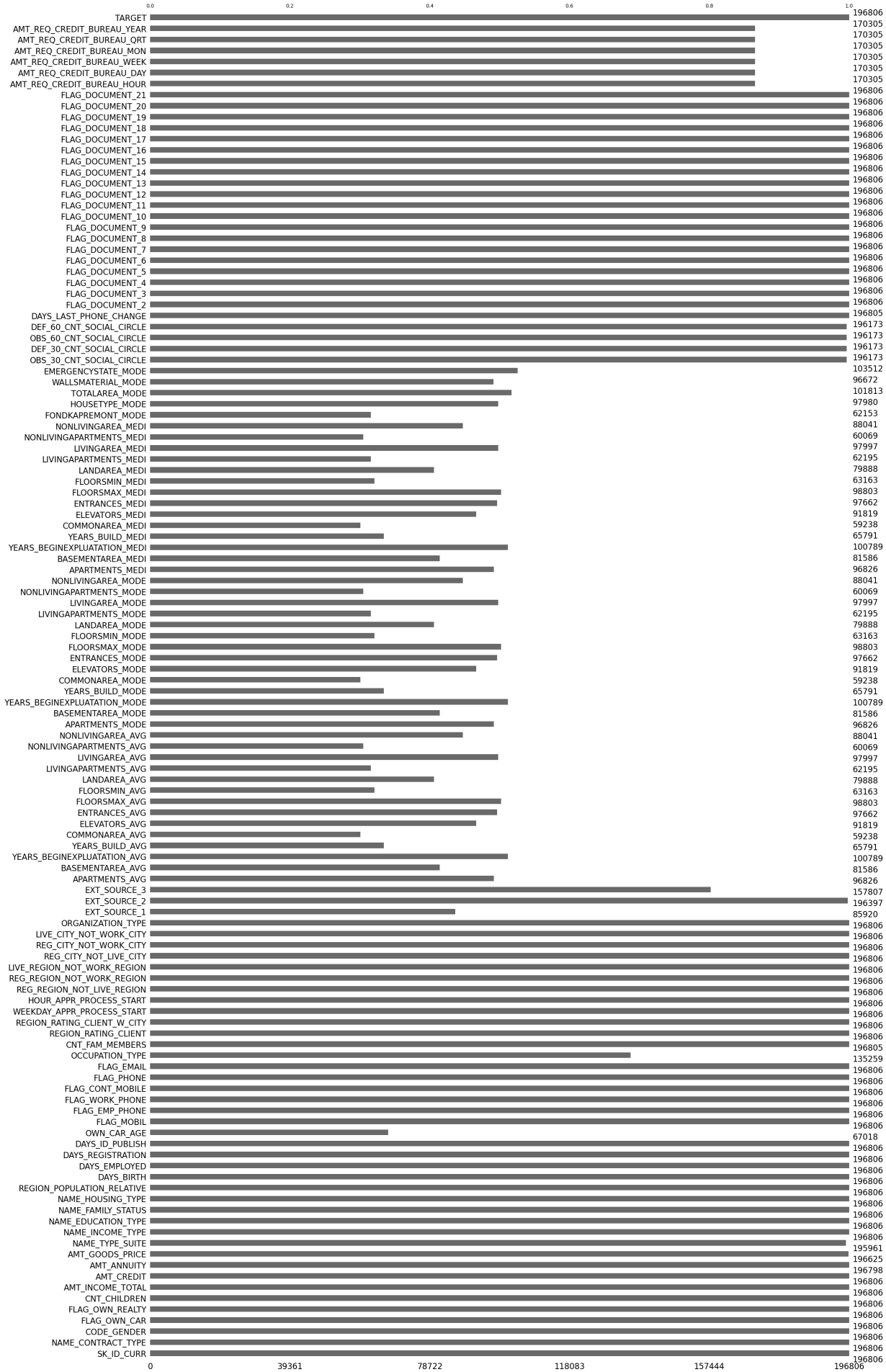
Out[24]:

	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

Bar plot of missing values in each column

In [25]:

```
msno.bar(Xy_train)
plt.show()
```



In [26]:
```
Xy_train.isnull().sum()
```

Out[26]:
```
SK_ID_CURR    0
```

```
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
FLAG_OWN_REALTY                   0
                                 ...
AMT_REQ_CREDIT_BUREAU_WEEK    26501
AMT_REQ_CREDIT_BUREAU_MON     26501
AMT_REQ_CREDIT_BUREAU_QRT     26501
AMT_REQ_CREDIT_BUREAU_YEAR    26501
TARGET                            0
Length: 122, dtype: int64
```

We notice there are a lot of missing values in the dataset

In [27]:
```
missing_application_train_data
```

Out[27]:

	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
...	...	...
NAME_HOUSING_TYPE	0.00	0
NAME_FAMILY_STATUS	0.00	0
NAME_EDUCATION_TYPE	0.00	0
NAME_INCOME_TYPE	0.00	0
SK_ID_CURR	0.00	0

122 rows × 2 columns

In [28]:
```
percent_data = missing_application_train_data.iloc[:,0]
missing_application_train_data['Percent']
percent_data_df = pd.DataFrame(missing_application_train_data['Percent'], col
```

In [29]:
```
percent_data_df = percent_data_df[percent_data_df['Percent'] != 0.0]
percent_data_df
```

Out[29]:

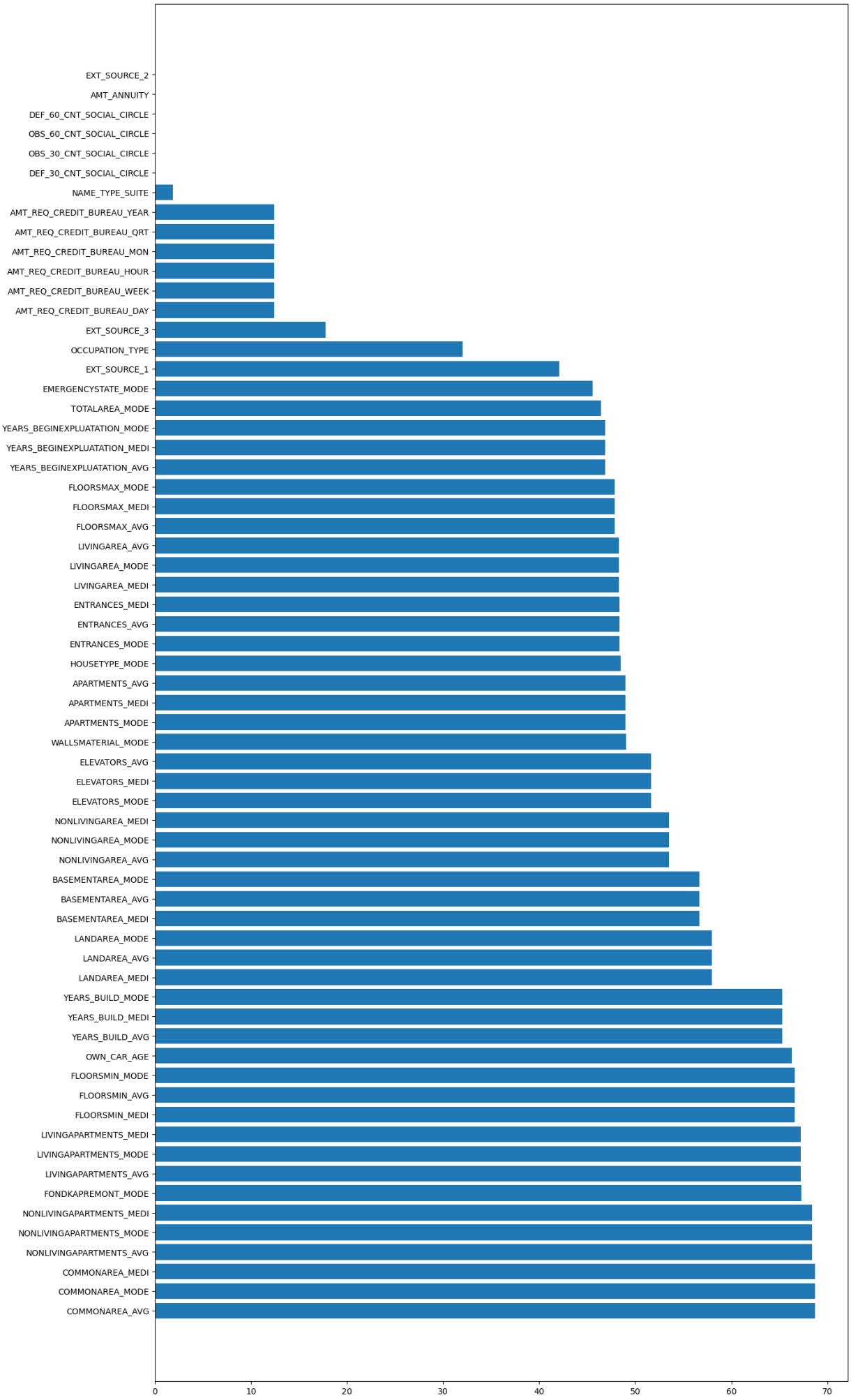
	Percent
COMMONAREA_MEDI	69.87
COMMONAREA_AVG	69.87
COMMONAREA_MODE	69.87
NONLIVINGAPARTMENTS_MODE	69.43
NONLIVINGAPARTMENTS_AVG	69.43
...	...
DEF_30_CNT_SOCIAL_CIRCLE	0.33
OBS_60_CNT_SOCIAL_CIRCLE	0.33

	Percent
DEF_60_CNT_SOCIAL_CIRCLE	0.33
EXT_SOURCE_2	0.21
AMT_GOODS_PRICE	0.09

64 rows × 1 columns

Bar plot of the percentage of missing values in each column

In [23]:
```
plt.figure(figsize = (15,30))
plt.barh(y = percent_data_df.index, width = percent_data_df['Percent'])
plt.show()
```



Imputing Missing data

We will construct the numerical pipeline and categorical pipeline

In [28]:
```
num_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('imputer', SimpleImputer(strategy = 'median'))
])

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

In [29]:
```
data_pipeline = ColumnTransformer([
    ("num_pipeline", num_pipeline, numerical_features),
    ("cat_pipeline", cat_pipeline, categorical_features)], remainder = 'drop'

X_train_transformed = data_pipeline.fit_transform(X_train)

column_names = list(numerical_features)  + \
               list(data_pipeline.transformers_[1][1].named_steps["ohe"].get_

display(pd.DataFrame(X_train_transformed,  columns=column_names).head())
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	-1.624501	-0.578880	-0.528796	1.188441	0.175508	
1	0.560257	0.810033	0.749824	1.304588	1.218472	
2	-0.811727	0.810033	0.110514	-0.452448	-0.310068	
3	-0.776179	-0.578880	0.749824	1.188441	0.529898	
4	0.911520	0.810033	-0.315693	0.559617	-0.197845	

5 rows × 245 columns

In [30]:
```
X_train_transformed_df = pd.DataFrame(X_train_transformed, columns=column_nam
X_train_transformed_df
```

Out[30]:

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	A
0	-1.624501	-0.578880	-0.528796	1.188441	0.175508	
1	0.560257	0.810033	0.749824	1.304588	1.218472	
2	-0.811727	0.810033	0.110514	-0.452448	-0.310068	
3	-0.776179	-0.578880	0.749824	1.188441	0.529898	
4	0.911520	0.810033	-0.315693	0.559617	-0.197845	
...	...	...	...	...	...	
196801	0.105580	2.198946	0.962928	1.748359	0.769578	
196802	-0.647728	-0.578880	0.195756	2.349464	1.072985	
196803	0.569894	0.810033	0.110514	-0.705648	-0.784764	
196804	0.743462	2.198946	-0.315693	-0.640427	-1.242051	

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	A
196805	-1.731692	0.810033	0.536721	1.042029	0.270945	

196806 rows × 245 columns

In [31]:
```
X_train_transformed_df.isnull().sum()
```

Out[31]:
```
SK_ID_CURR                          0
CNT_CHILDREN                        0
AMT_INCOME_TOTAL                    0
AMT_CREDIT                          0
AMT_ANNUITY                         0
                                   ..
WALLSMATERIAL_MODE_Panel            0
WALLSMATERIAL_MODE_Stone, brick     0
WALLSMATERIAL_MODE_Wooden           0
EMERGENCYSTATE_MODE_No              0
EMERGENCYSTATE_MODE_Yes             0
Length: 245, dtype: int64
```

Correlation Analysis

Correlation with the target column

In [32]:
```
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
```

In [33]:
```
correlations = pd.DataFrame(correlations, columns = ['TARGET'])
correlations
```

Out[33]:

	TARGET
EXT_SOURCE_3	-0.178919

	TARGET
EXT_SOURCE_2	-0.160472
EXT_SOURCE_1	-0.155317
DAYS_EMPLOYED	-0.044932
FLOORSMAX_AVG	-0.044003
...	...
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

106 rows × 1 columns

In [34]:
```
# To get top 4 correlated attributes
correlations["abs_Target"] = np.abs(correlations["TARGET"])
display(correlations)
correlations.sort_values("abs_Target", ascending = False, inplace = True)
display(correlations)
correlations
```

	TARGET	abs_Target
EXT_SOURCE_3	-0.178919	0.178919
EXT_SOURCE_2	-0.160472	0.160472
EXT_SOURCE_1	-0.155317	0.155317
DAYS_EMPLOYED	-0.044932	0.044932
FLOORSMAX_AVG	-0.044003	0.044003
...	...	...
DAYS_LAST_PHONE_CHANGE	0.055218	0.055218
REGION_RATING_CLIENT	0.058899	0.058899
REGION_RATING_CLIENT_W_CITY	0.060893	0.060893
DAYS_BIRTH	0.078239	0.078239
TARGET	1.000000	1.000000

106 rows × 2 columns

	TARGET	abs_Target
TARGET	1.000000	1.000000
EXT_SOURCE_3	-0.178919	0.178919
EXT_SOURCE_2	-0.160472	0.160472
EXT_SOURCE_1	-0.155317	0.155317
DAYS_BIRTH	0.078239	0.078239

	TARGET	abs_Target
...	...	...
FLAG_DOCUMENT_12	-0.000756	0.000756
FLAG_MOBIL	0.000534	0.000534
FLAG_CONT_MOBILE	0.000370	0.000370
FLAG_DOCUMENT_5	-0.000316	0.000316
FLAG_DOCUMENT_20	0.000215	0.000215

106 rows × 2 columns

Out[34]:

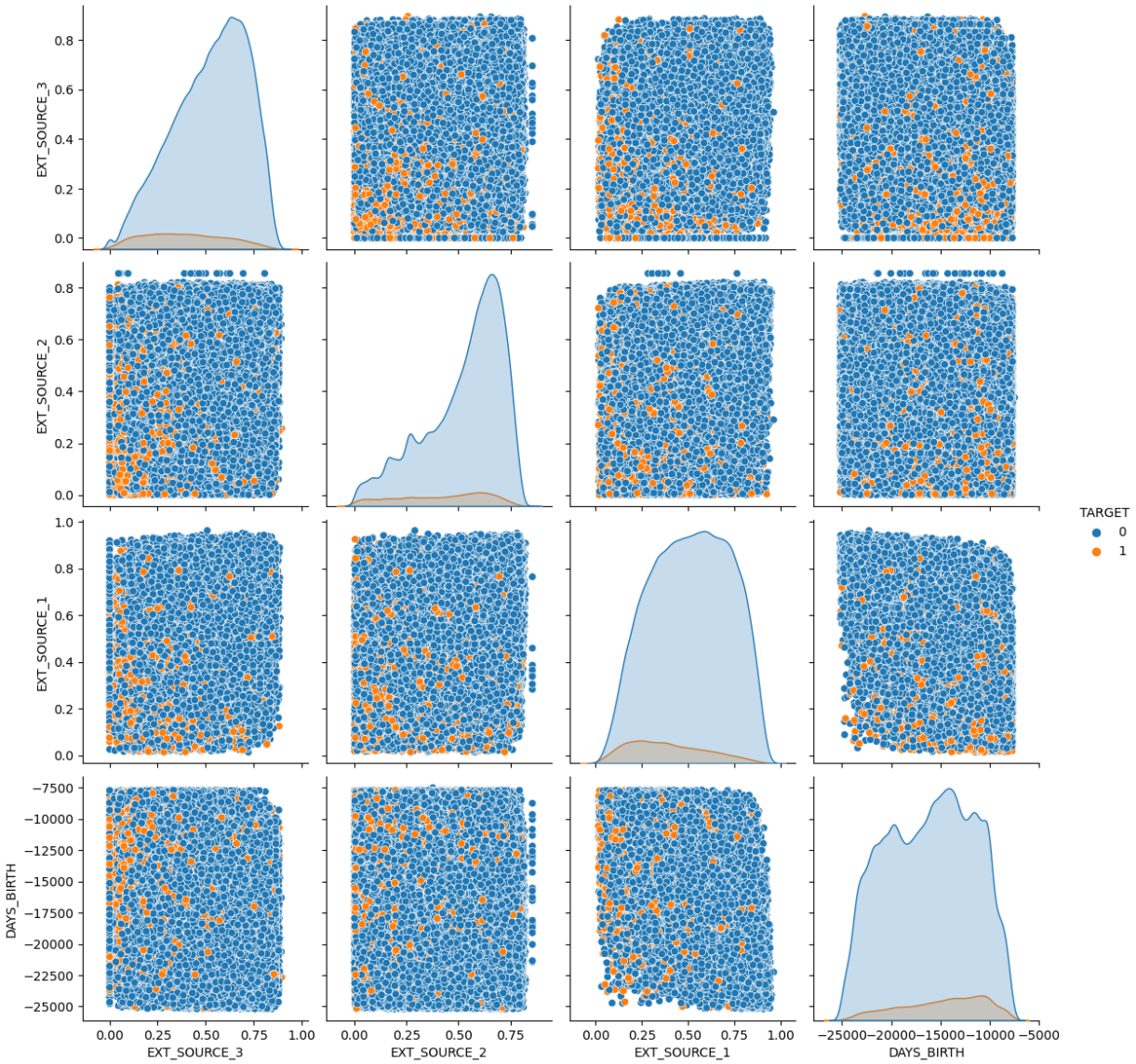
	TARGET	abs_Target
TARGET	1.000000	1.000000
EXT_SOURCE_3	-0.178919	0.178919
EXT_SOURCE_2	-0.160472	0.160472
EXT_SOURCE_1	-0.155317	0.155317
DAYS_BIRTH	0.078239	0.078239
...	...	...
FLAG_DOCUMENT_12	-0.000756	0.000756
FLAG_MOBIL	0.000534	0.000534
FLAG_CONT_MOBILE	0.000370	0.000370
FLAG_DOCUMENT_5	-0.000316	0.000316
FLAG_DOCUMENT_20	0.000215	0.000215

106 rows × 2 columns

Pair plot of the 4 top correlated features

In [31]:

```
attributes = ["EXT_SOURCE_3", "EXT_SOURCE_2", "EXT_SOURCE_1","DAYS_BIRTH"]
sns.pairplot(data = datasets["application_train"], hue="TARGET", vars = attri
plt.show()
```



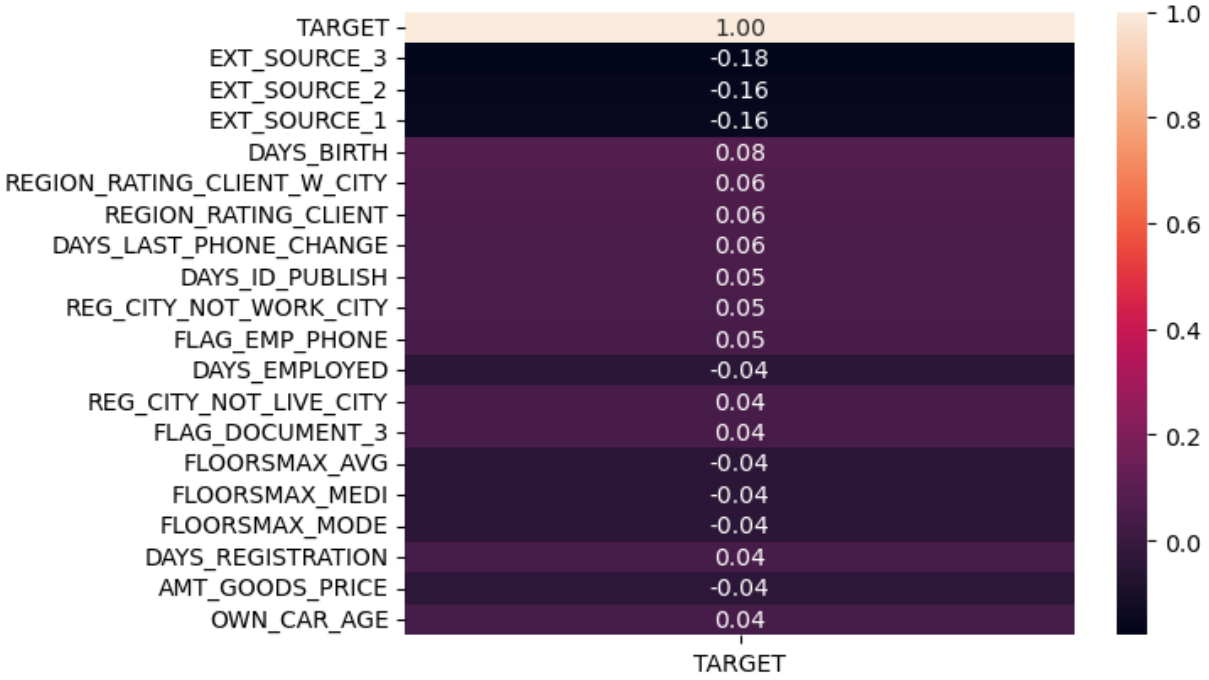
We can see the plot of the top 4 correlated attributes with the Target column. EXT_SOURCE_1 seems to be normally distributed while others are skewed but can be approximated to normal distribution.

In [35]:
```
correlations.isnull().count()
```

Out[35]:
```
TARGET        106
abs_Target    106
dtype: int64
```

Heatmap of correlated attributes

In [50]:
```
corr_target = correlations.drop(['abs_Target'], axis = 1)
corr_target= corr_target[:20].dropna()
sns.heatmap(corr_target, annot=True, fmt='.2f')
plt.show()
```

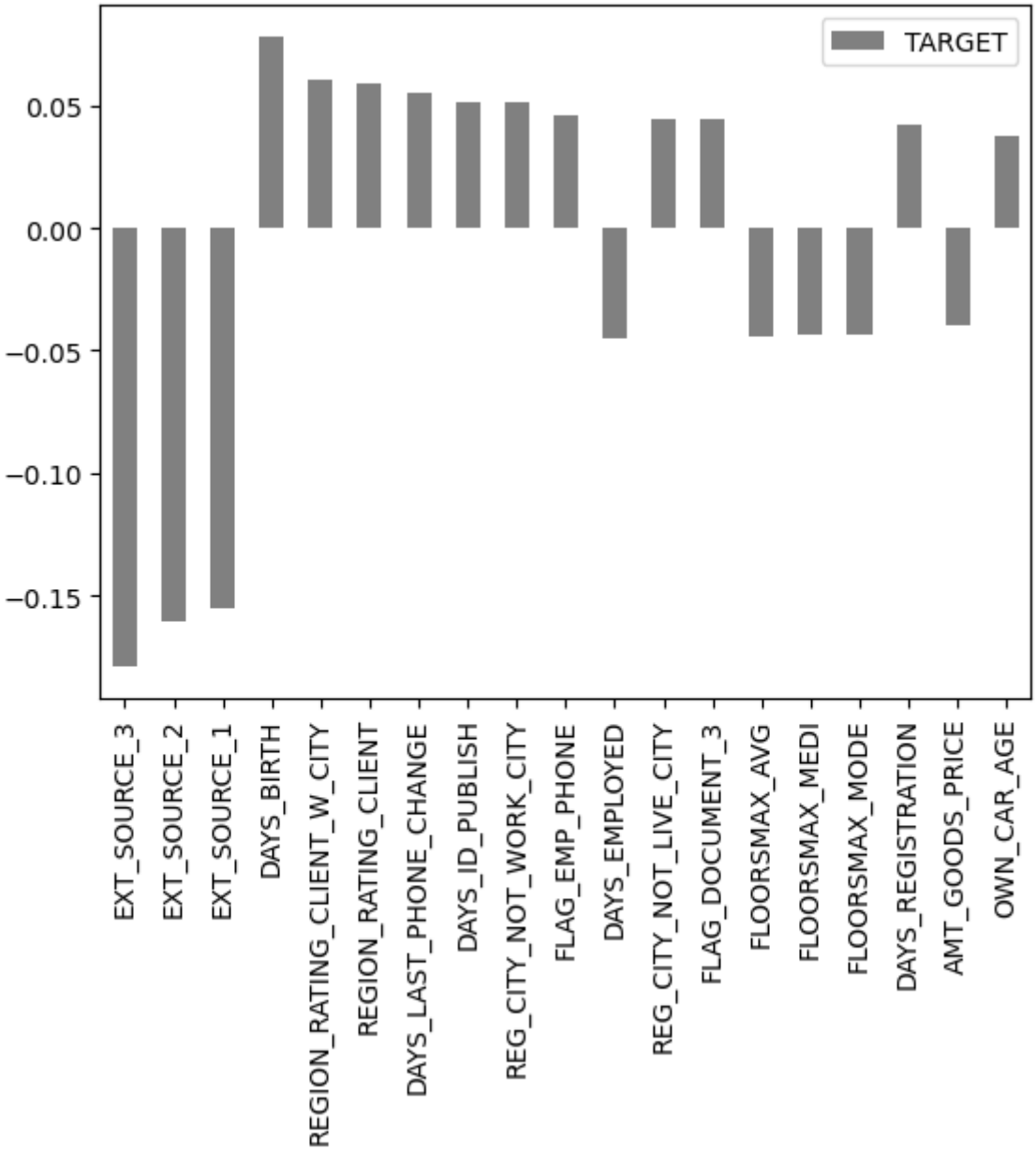


Bar plot of correlated attributes

In [51]:

```
plt.figure(figsize=(15,7))
plot = corr_target[1:].plot(kind = 'bar', color = 'grey')
plt.setp(plot.get_xticklabels(), rotation=90)
plt.show()
```

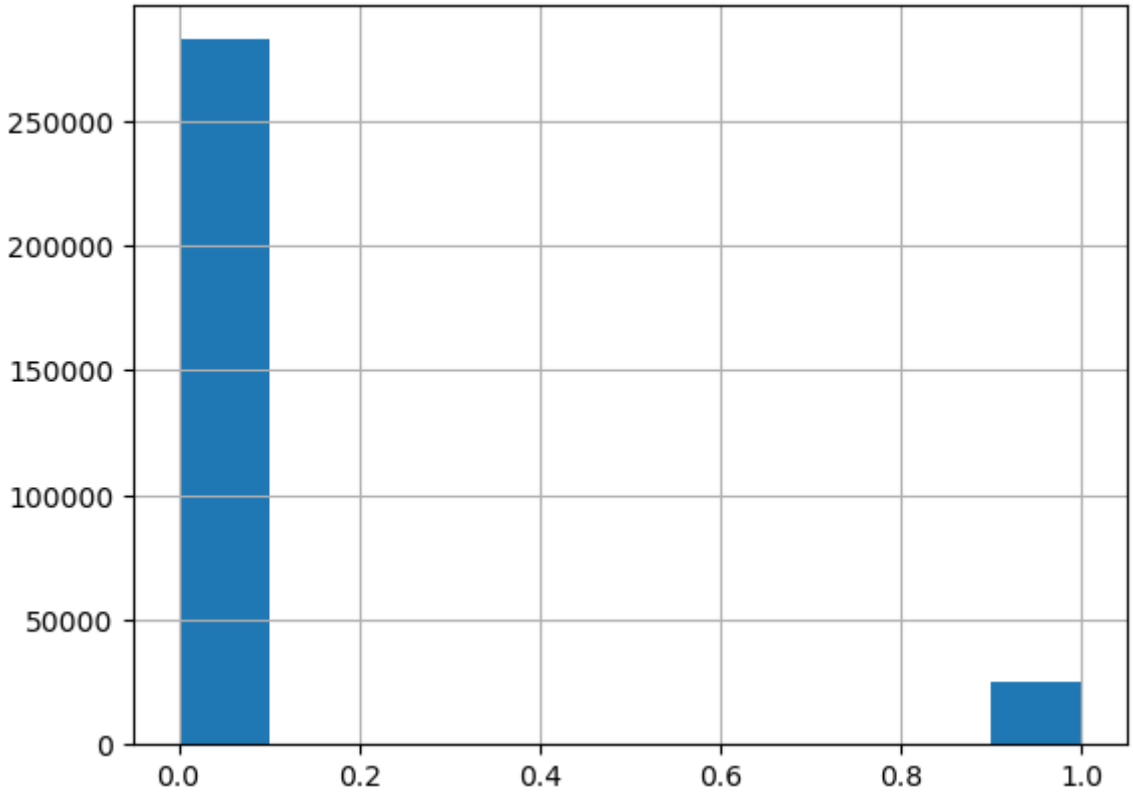
```
<Figure size 1500x700 with 0 Axes>
```



Visual EDA

Distribution of the target column

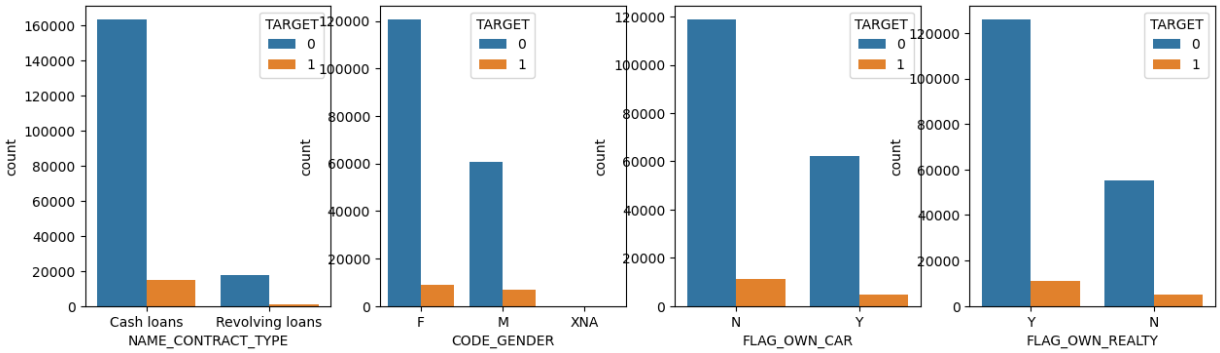
In [52]:
```
datasets["application_train"]['TARGET'].astype(int).hist()
plt.show()
```



Evaluating categorical features with respect to TARGET

TARGET - 0: LOAN WAS REPAID 1: LOAN WAS NOT REPAID

In [55]:
```
cat_vars = list(categorical_features)[:4]
plt.figure(figsize=(15,4))
for idx, cat in enumerate(cat_vars):
    plt.subplot(1, len(cat_vars), idx+1)
    sns.countplot(Xy_train[cat], hue=Xy_train['TARGET'])
plt.show()
```

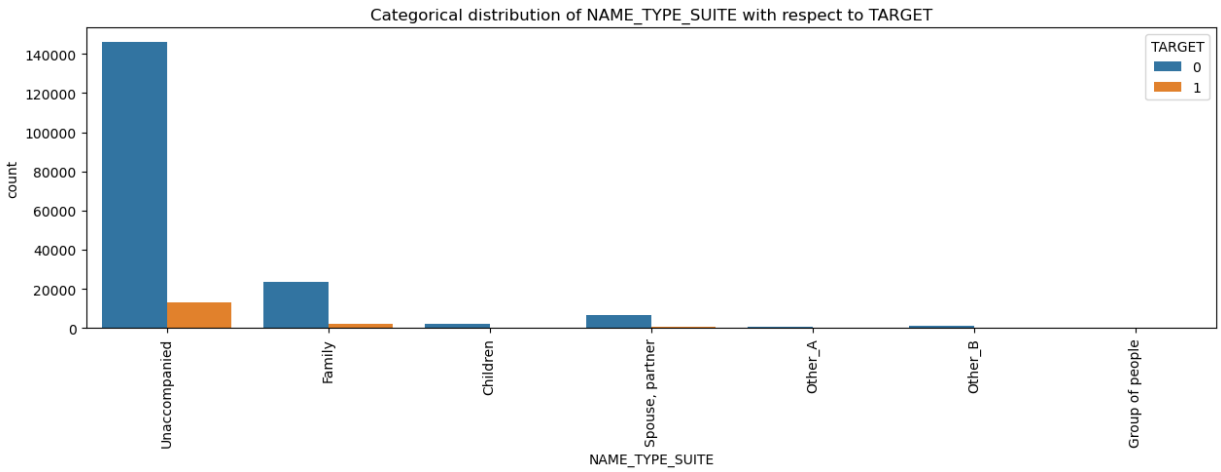


- We notice that Cash loans are beind repaid more than Revolving loans
- More number of female borrowers have repaid loans than male borrowers
- We notice that a client who do not own a car repays loan easily than a client who owns a car
- We notice the same trend for a client who owns a house or flat. Owner of a real estate will repay loans less easily than a person who do not owns any real estate

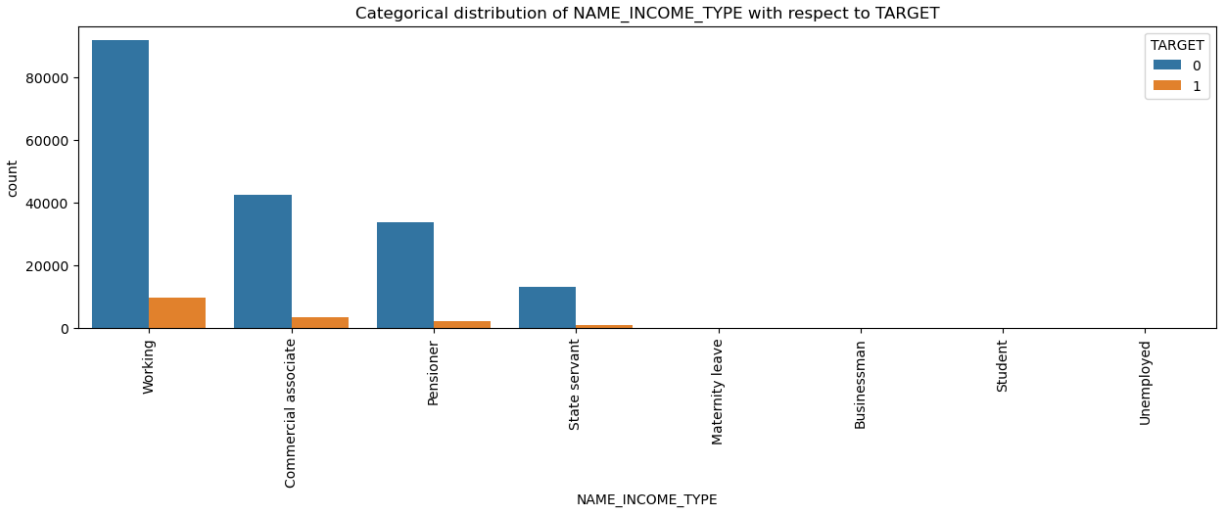
In [144…
```
explainations = ['We can see that people who are not accompanied by anyone th
```

In [145…

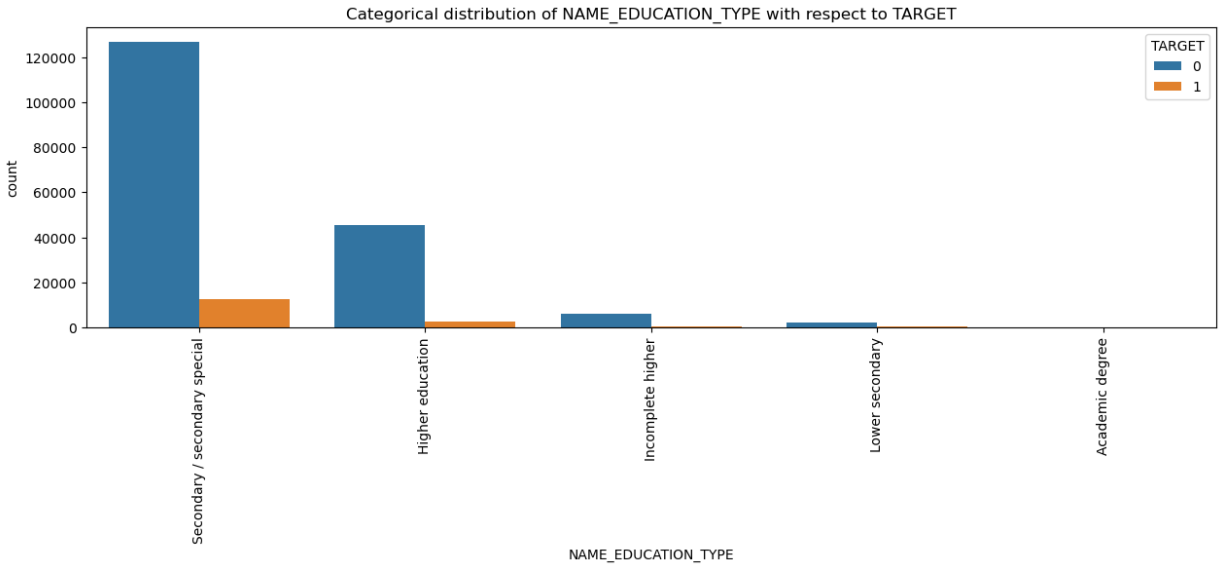
```
i = 0
for cat in list(categorical_features[4:14]):
    plt.figure(figsize=(15,4))
    plot = sns.countplot(x=cat, data=Xy_train, hue = Xy_train['TARGET'])
    plt.setp(plot.get_xticklabels(), rotation=90)
    plt.title(f'Categorical distribution of {cat} with respect to TARGET')
    plt.show()
    print(explainations[i])
    i += 1
```



We can see that people who are not accompanied by anyone that is people having no dependents are able to repay loans easier.

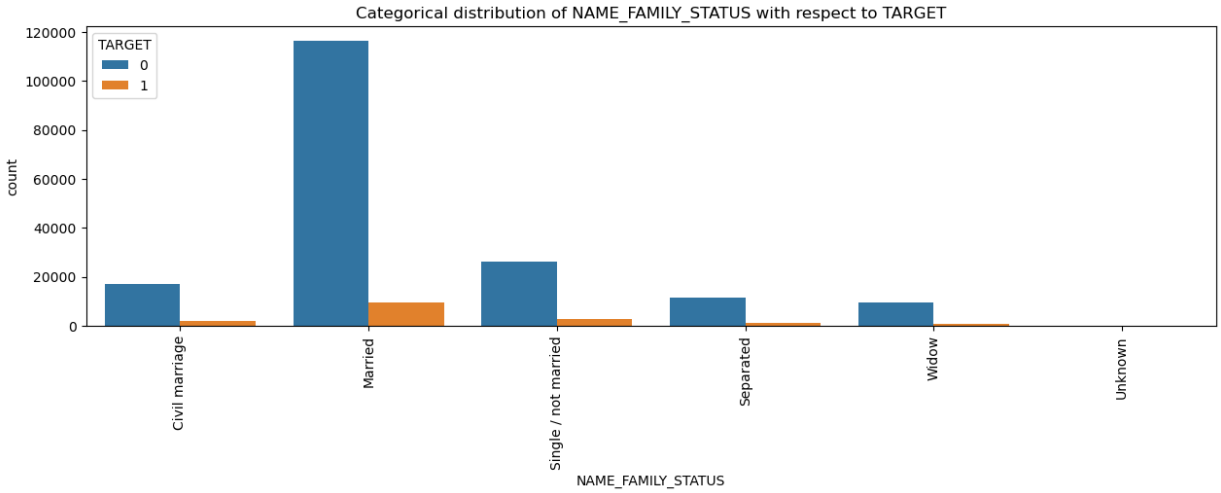


Working class people usually require more loans as compared to other income type people.

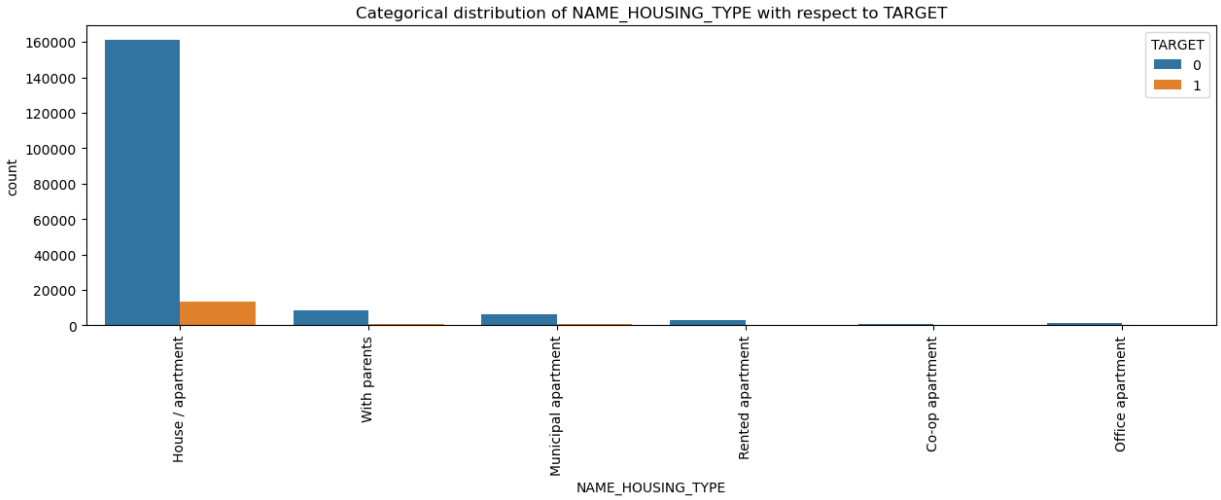


We see that people who have education as Secondary/Secondary special require m

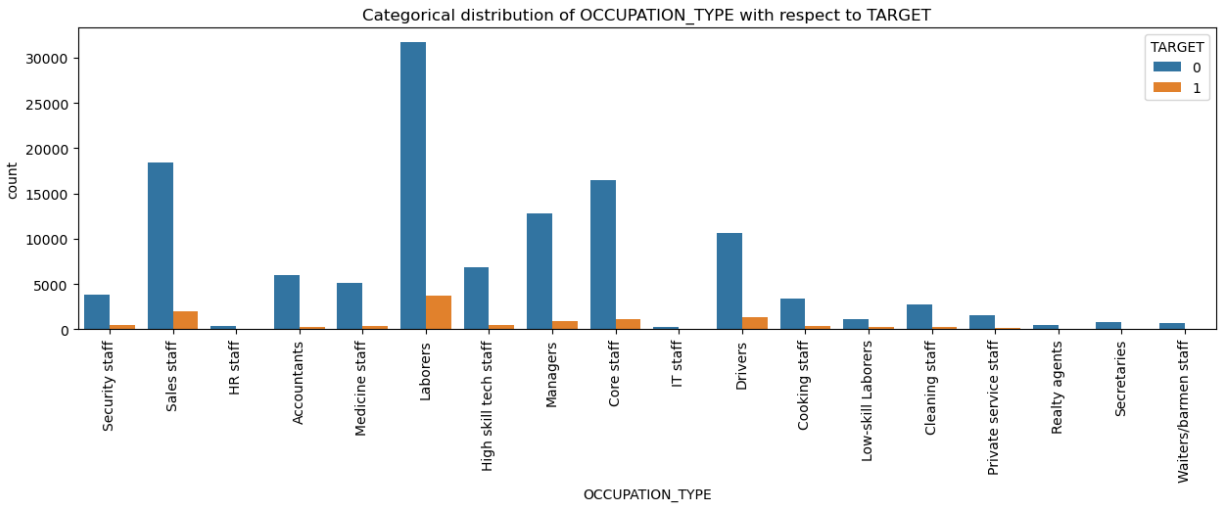
ore loans than people of other education backgrounds.



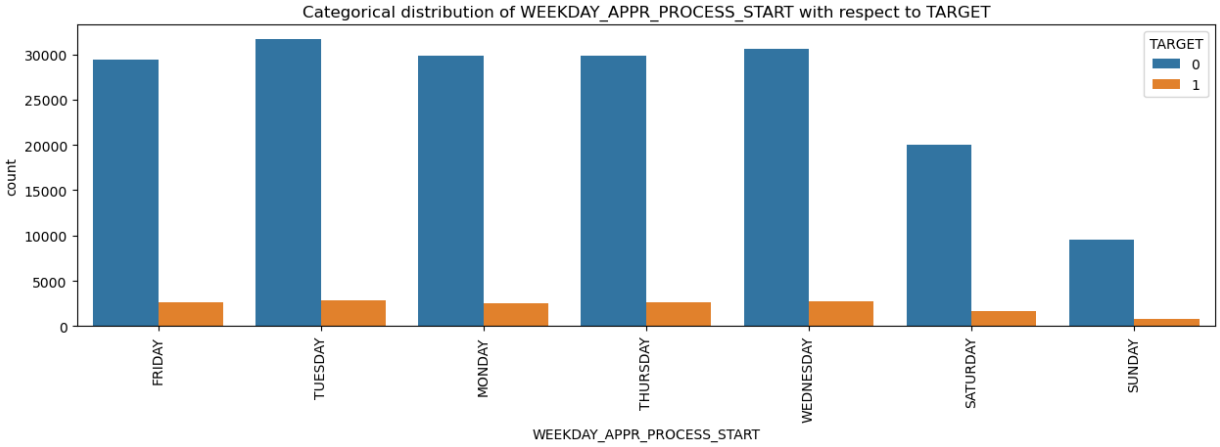
People who are married have taken more loans and repaid them as compared to pe ople having other than marriage family status



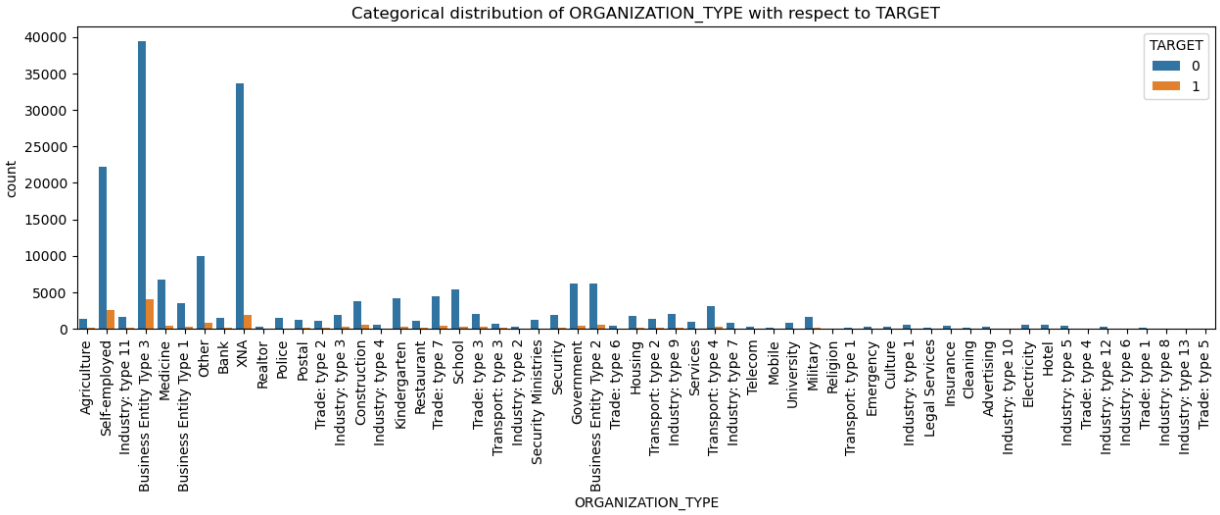
We see that people who live alone and in apartments require more loans than ot her people



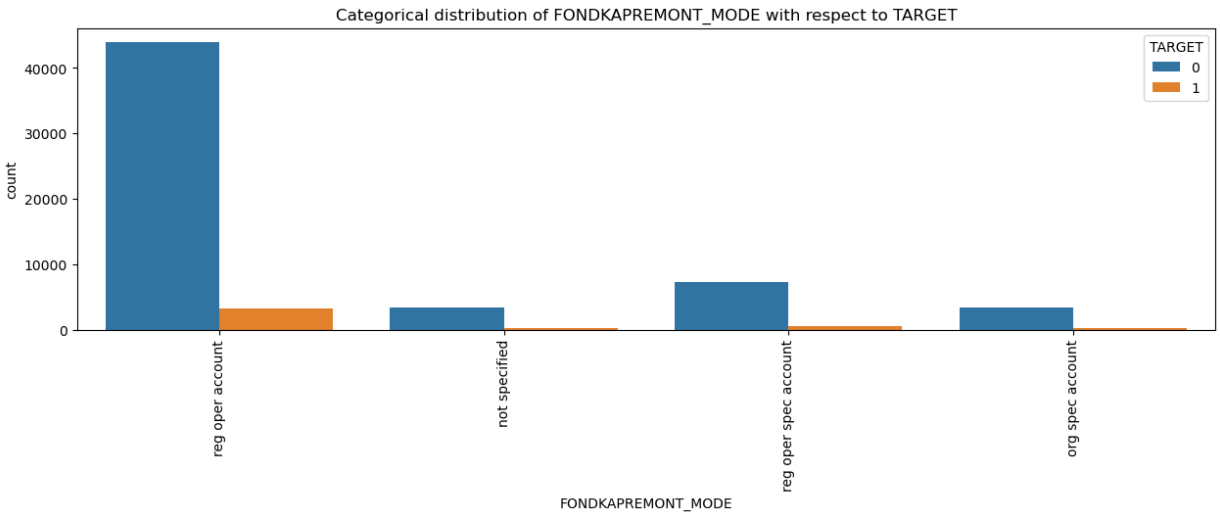
Laborers have repaid more loans than people with other occupations

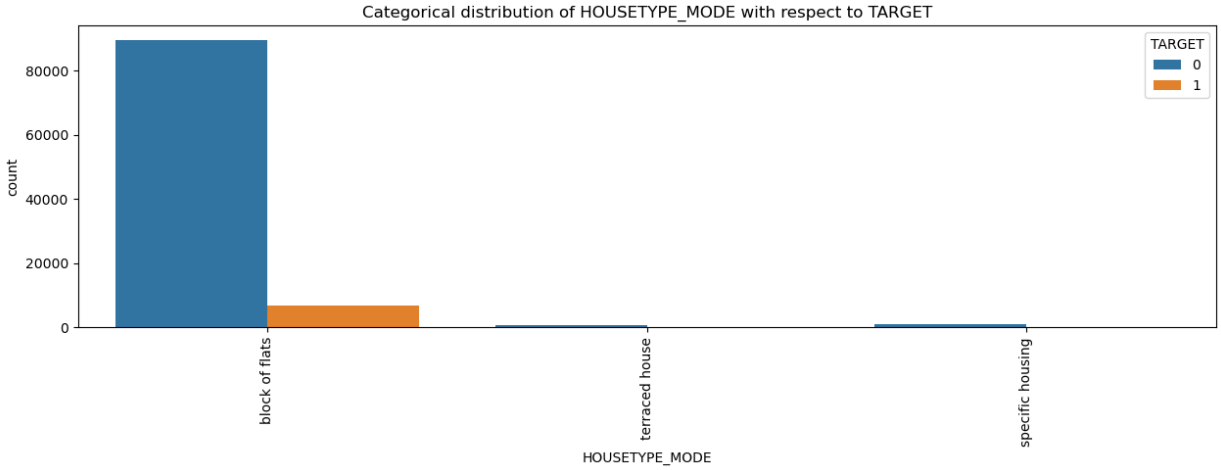


People have repaid more loans on Tuesday than any other day of the week



People belonging to Business organization have repaid more loans than other or ganization types



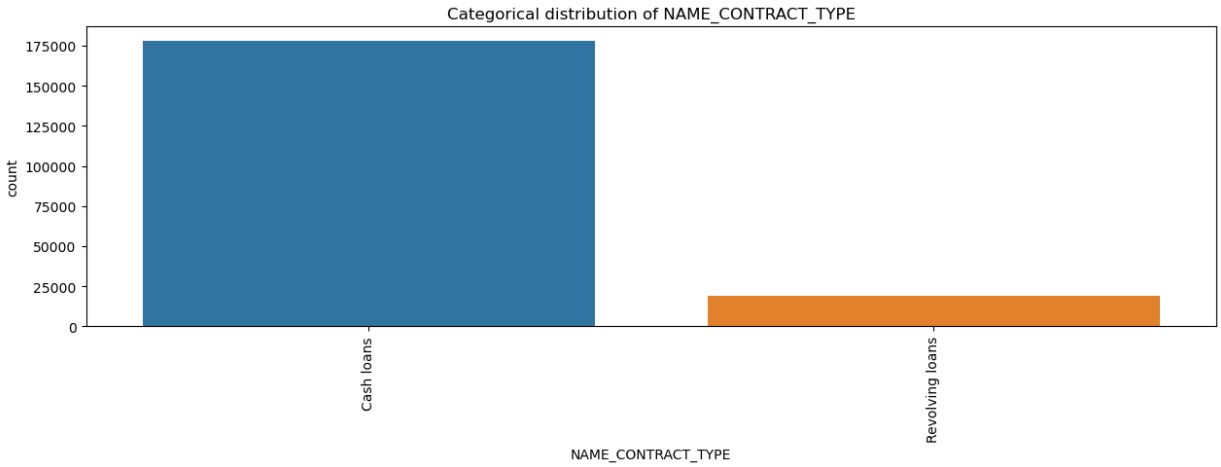


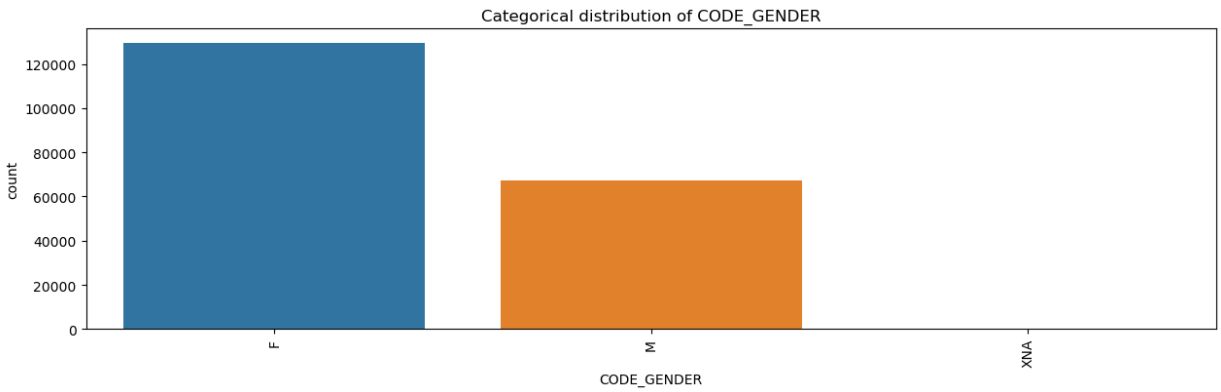
People who live in flats have repaid more loans than people who live in other types of houses

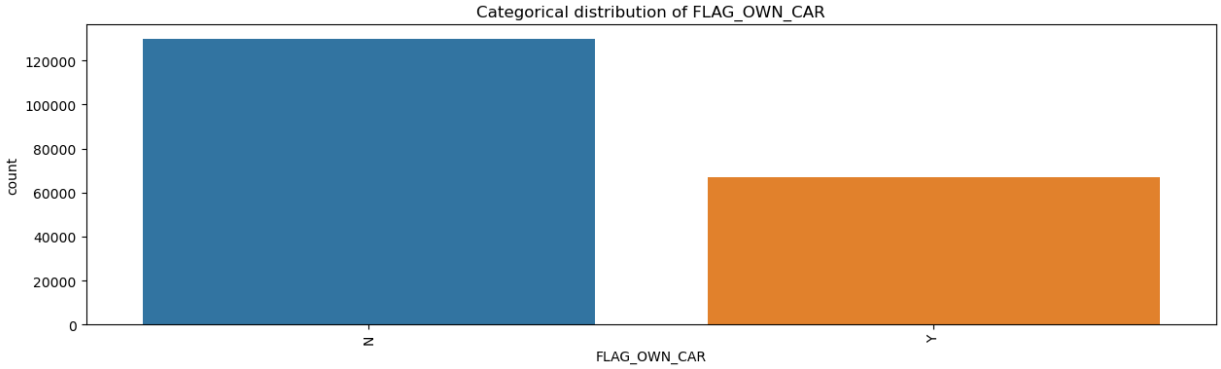
Categorical distribution

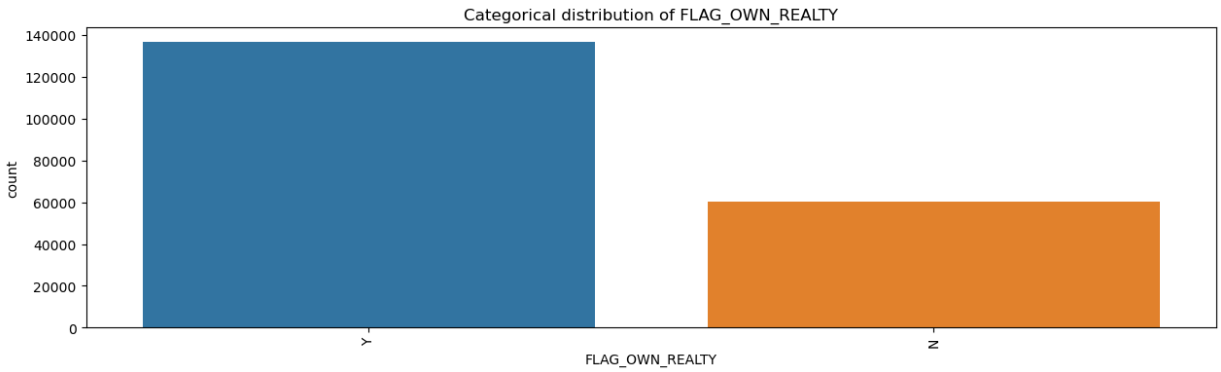
In [149…

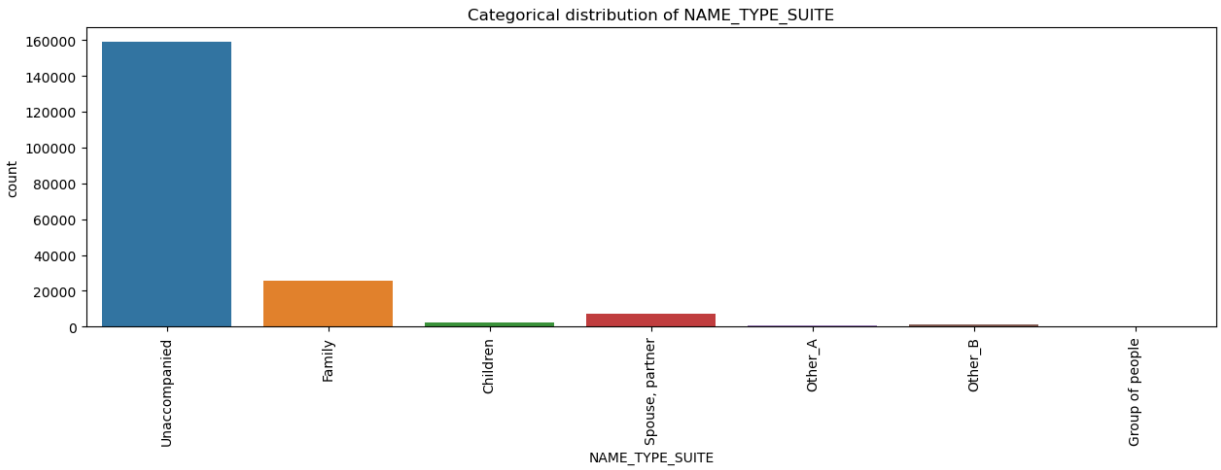
```
for cat in list(categorical_features[:14]):
    plt.figure(figsize=(15,4))
    plot = sns.countplot(x=cat, data=Xy_train)
    plt.setp(plot.get_xticklabels(), rotation=90)
    plt.title(f'Categorical distribution of {cat}')
    plt.show()
```

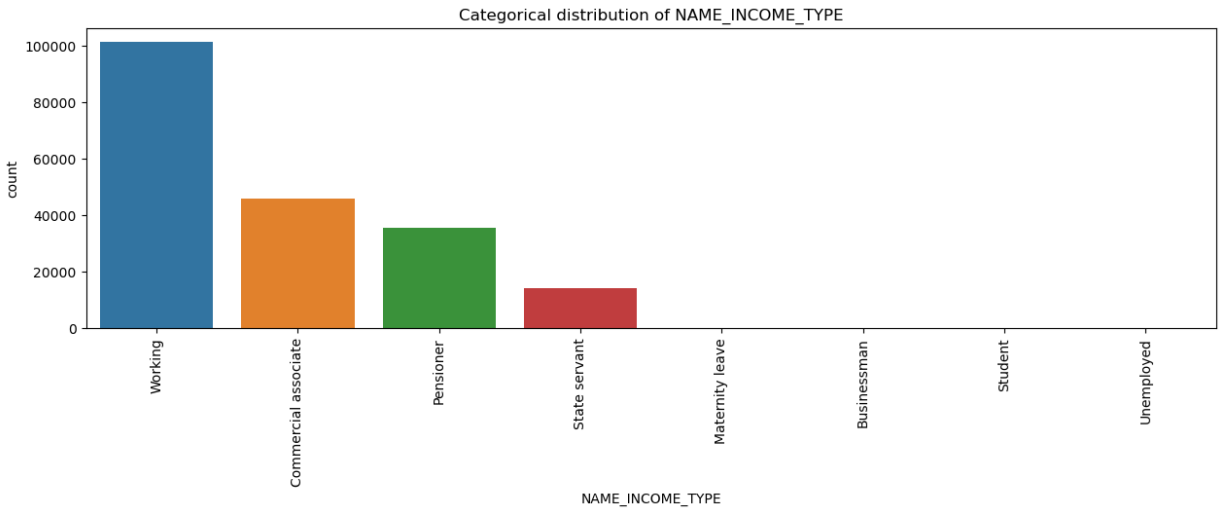


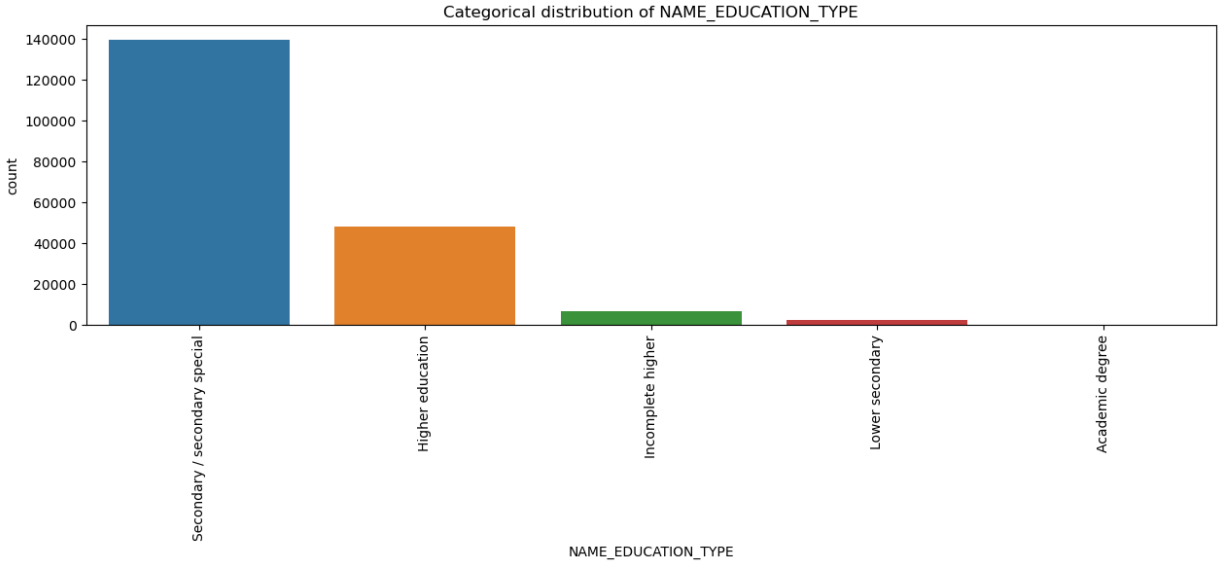


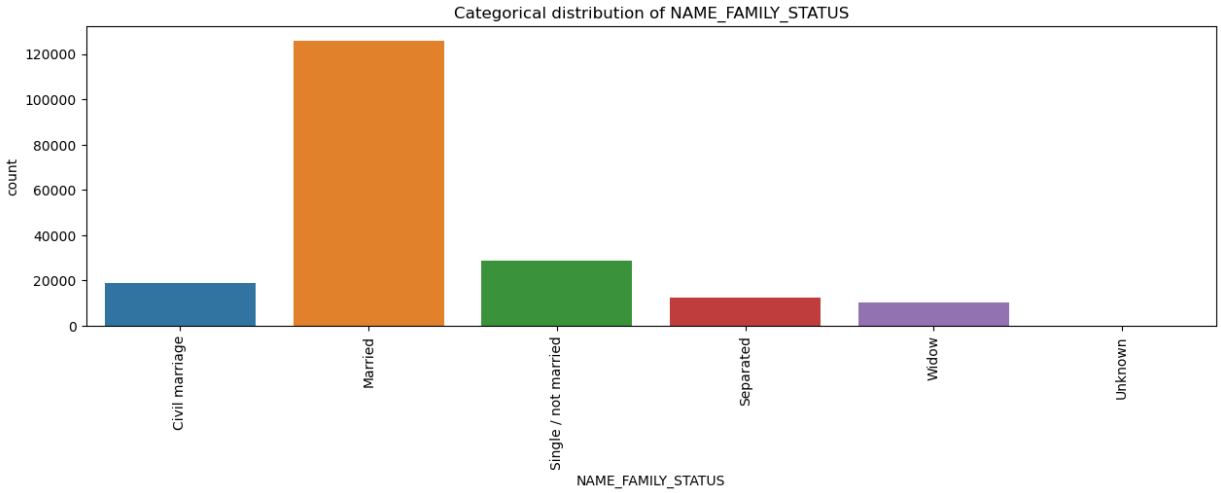

Categorical distribution of FLAG_OWN_CAR
count
0
20000
40000
60000
80000
100000
120000
N
Y
FLAG_OWN_CAR

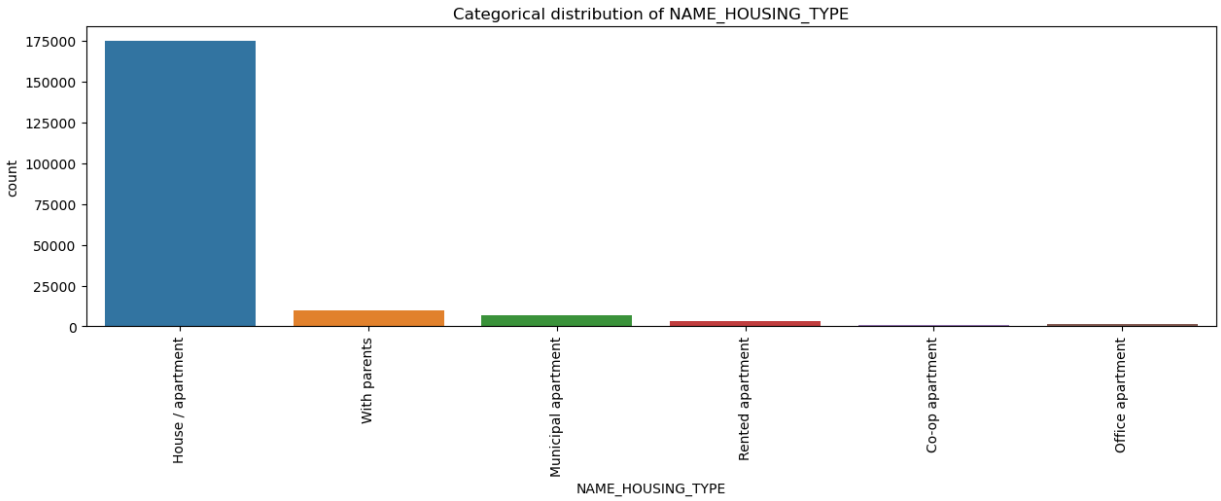

Categorical distribution of FLAG_OWN_REALTY
count
0
20000
40000
60000
80000
100000
120000
140000
Y
N
FLAG_OWN_REALTY

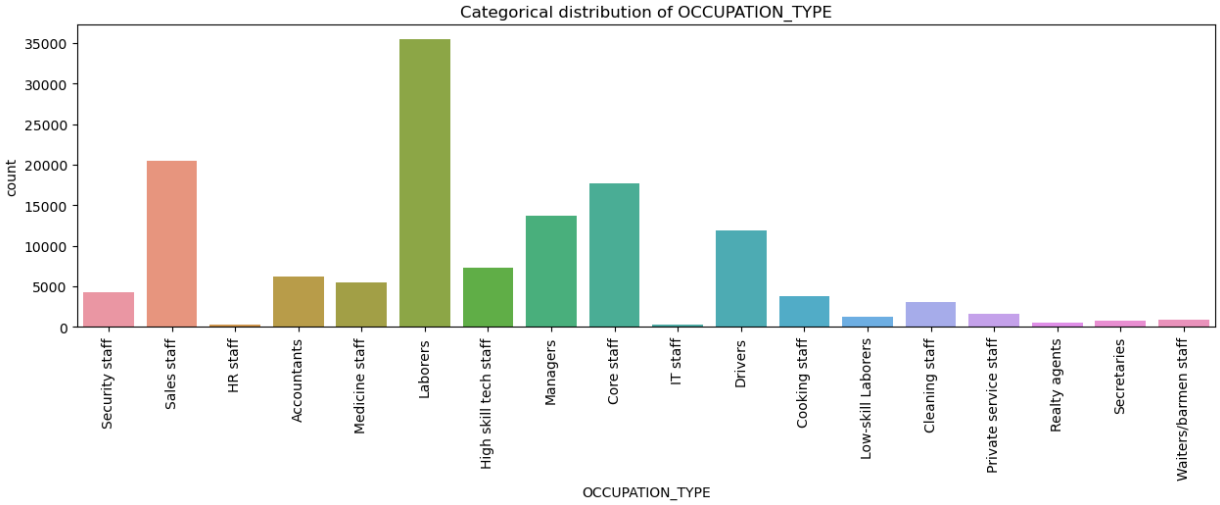

Categorical distribution of NAME_TYPE_SUITE
count
0
20000
40000
60000
80000
100000
120000
140000
160000
Unaccompanied
Family
Children
Spouse, partner
Other_A
Other_B
Group of people
NAME_TYPE_SUITE

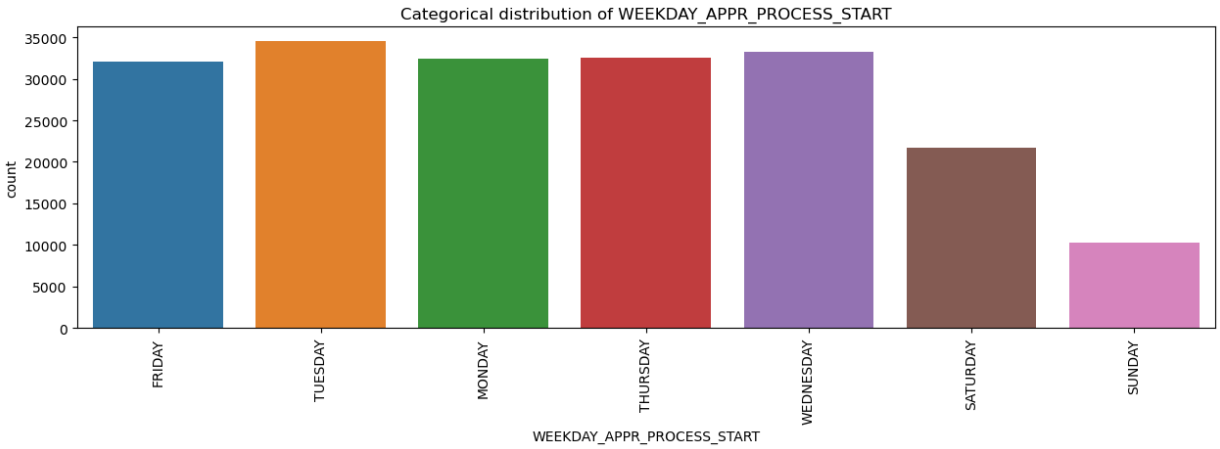

Categorical distribution of NAME_INCOME_TYPE
count
0
20000
40000
60000
80000
100000
Working
Commercial associate
Pensioner
State servant
Maternity leave
Businessman
Student
Unemployed
NAME_INCOME_TYPE

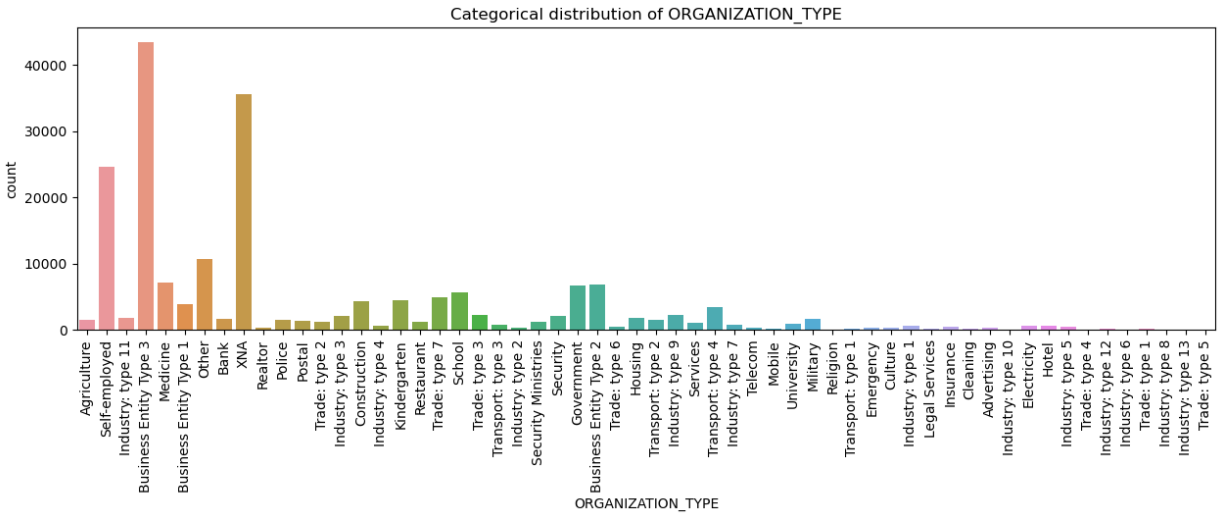

Categorical distribution of NAME_EDUCATION_TYPE
count
0
20000
40000
60000
80000
100000
120000
140000
Secondary / secondary special
Higher education
Incomplete higher
Lower secondary
Academic degree
NAME_EDUCATION_TYPE

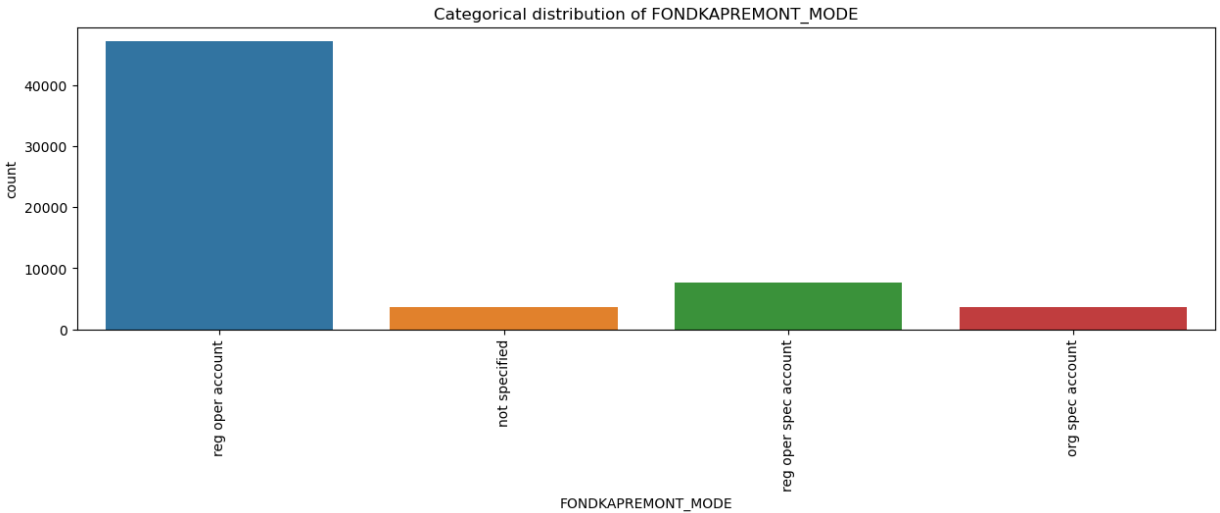

Categorical distribution of NAME_FAMILY_STATUS
count
0
20000
40000
60000
80000
100000
120000
Civil marriage
Married
Single / not married
Separated
Widow
Unknown
NAME_FAMILY_STATUS

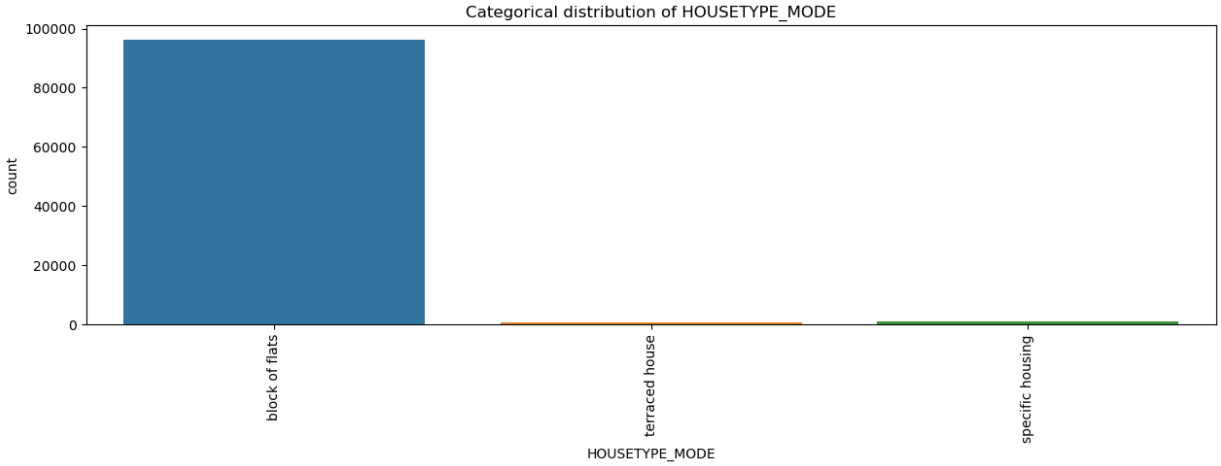

Categorical distribution of NAME_HOUSING_TYPE
count
0
25000
50000
75000
100000
125000
150000
175000
House / apartment
With parents
Municipal apartment
Rented apartment
Co-op apartment
Office apartment
NAME_HOUSING_TYPE


Categorical distribution of OCCUPATION_TYPE
count
0
5000
10000
15000
20000
25000
30000
35000
Security staff
Sales staff
HR staff
Accountants
Medicine staff
Laborers
High skill tech staff
Managers
Core staff
IT staff
Drivers
Cooking staff
Low-skill Laborers
Cleaning staff
Private service staff
Realty agents
Secretaries
Waiters/barmen staff
OCCUPATION_TYPE


Categorical distribution of WEEKDAY_APPR_PROCESS_START
count
0
5000
10000
15000
20000
25000
30000
35000
FRIDAY
TUESDAY
MONDAY
THURSDAY
WEDNESDAY
SATURDAY
SUNDAY
WEEKDAY_APPR_PROCESS_START


Categorical distribution of ORGANIZATION_TYPE
count
0
10000
20000
30000
40000
Agriculture
Self-employed
Industry: type 11
Business Entity Type 3
Medicine
Business Entity Type 1
Other
Bank
XNA
Realtor
Police
Postal
Trade: type 2
Industry: type 3
Construction
Industry: type 4
Kindergarten
Restaurant
Trade: type 7
School
Trade: type 3
Transport: type 3
Industry: type 2
Security Ministries
Security
Government
Business Entity Type 2
Trade: type 6
Housing
Transport: type 2
Industry: type 9
Services
Transport: type 4
Industry: type 7
Telecom
Mobile
University
Military
Religion
Transport: type 1
Emergency
Culture
Industry: type 1
Legal Services
Insurance
Cleaning
Advertising
Industry: type 10
Electricity
Hotel
Industry: type 5
Trade: type 4
Industry: type 12
Industry: type 6
Trade: type 1
Industry: type 8
Industry: type 13
Trade: type 5
ORGANIZATION_TYPE

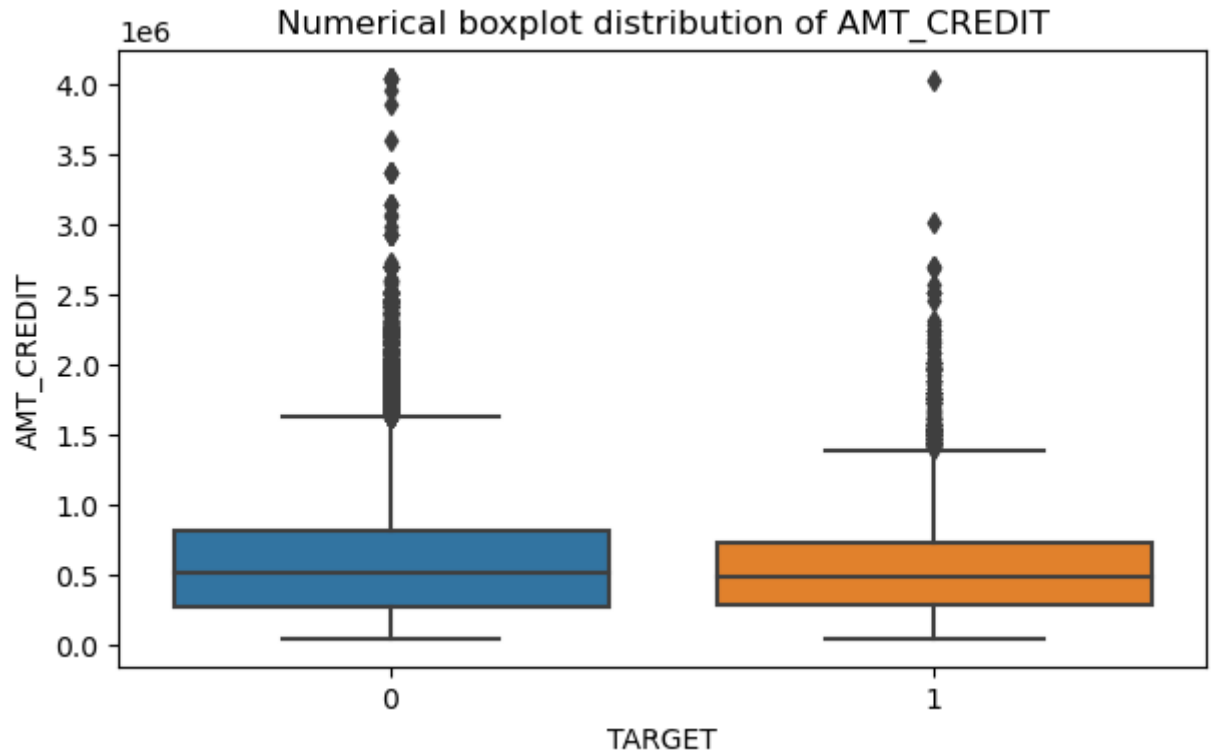

Categorical distribution of FONDKAPREMONT_MODE
count
0
10000
20000
30000
40000
reg oper account
not specified
reg oper spec account
org spec account
FONDKAPREMONT_MODE

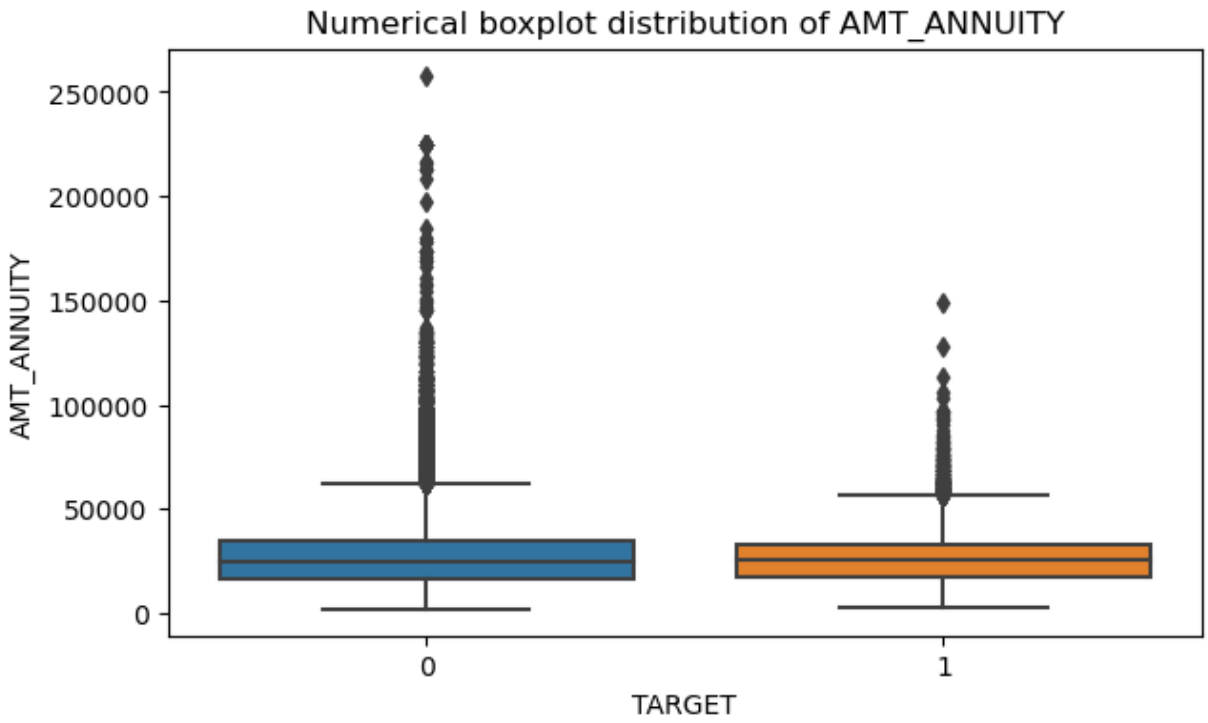


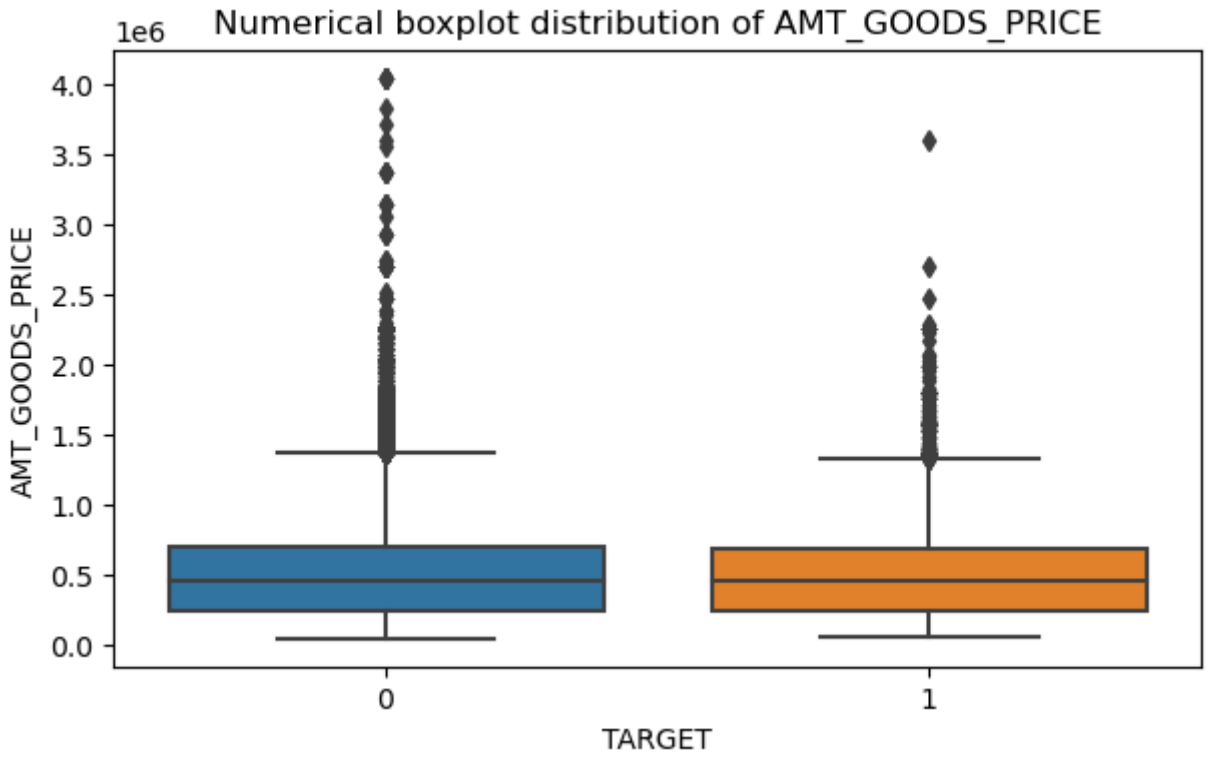
Numerical distribution

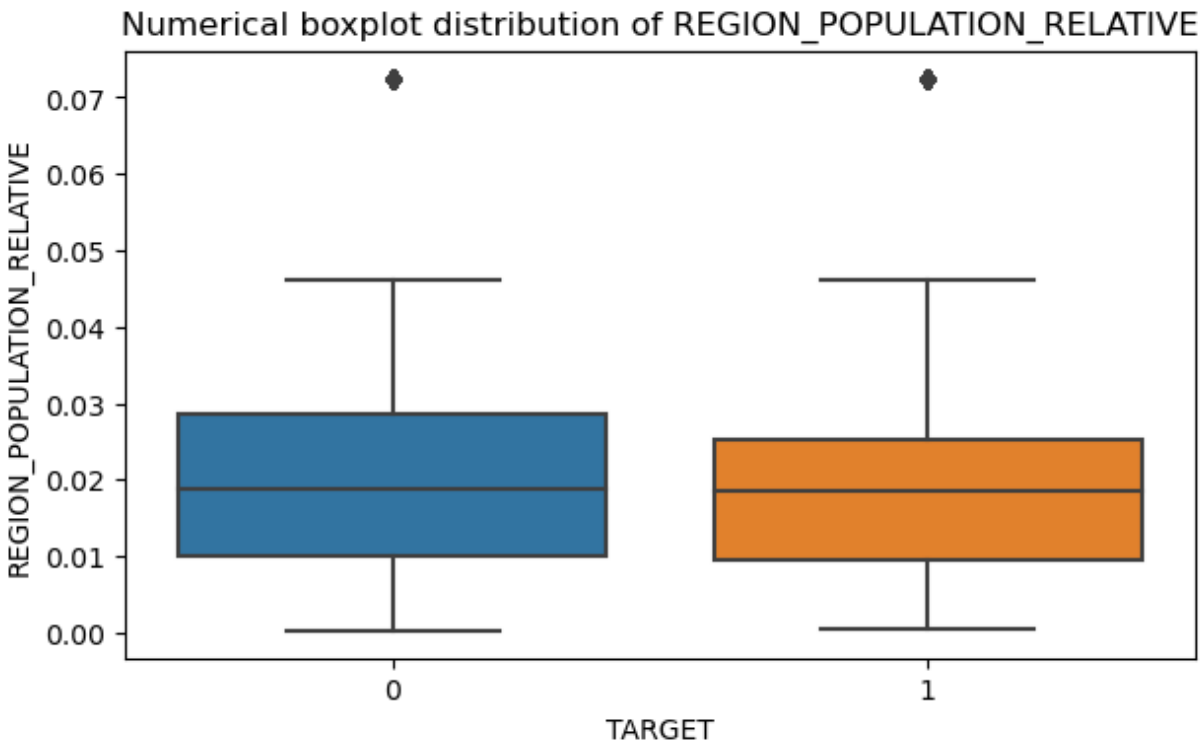
In [150…

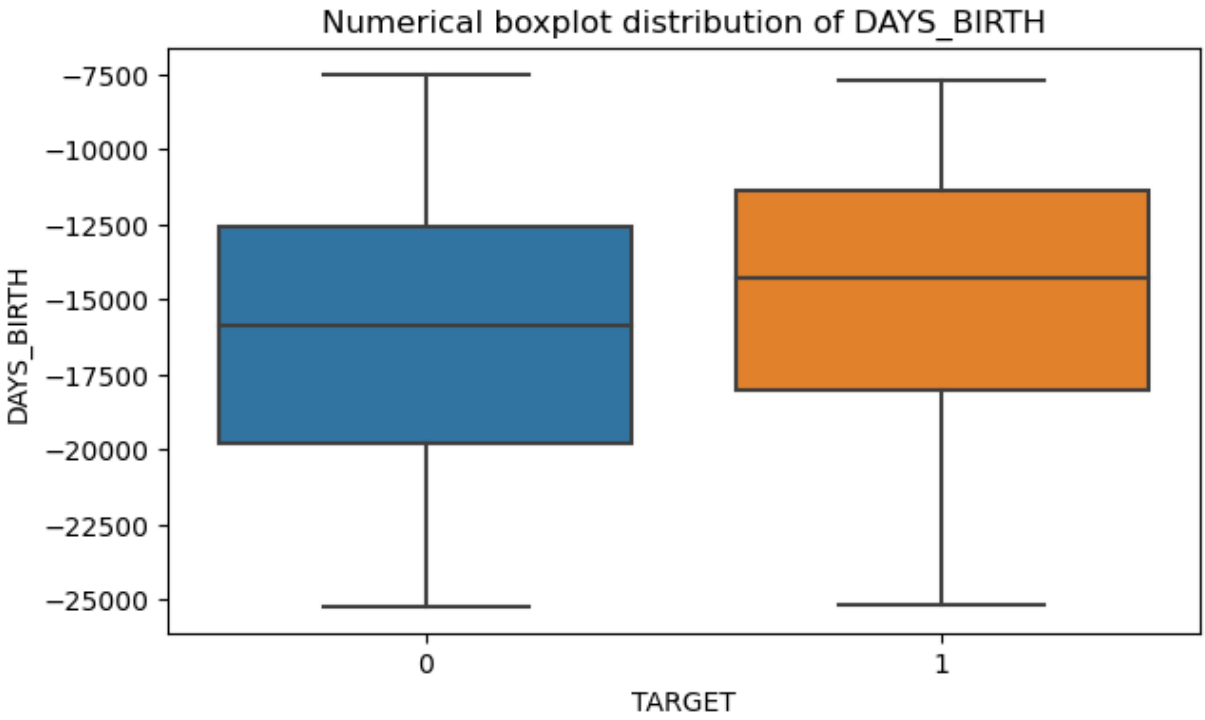
```
for num in list(numerical_features[3:8]):
    plt.figure(figsize=(7, 4))
    sns.boxplot(x = 'TARGET', y = num, data = Xy_train)
    plt.title(f'Numerical boxplot distribution of {num}')
    #plt.setp(plot.get_xticklabels(), rotation=90)
    plt.show()
```




Numerical boxplot distribution of AMT_ANNUITY
AMT_ANNUITY
250000
200000
150000
100000
50000
0
0
1
TARGET


Numerical boxplot distribution of AMT_GOODS_PRICE
1e6
AMT_GOODS_PRICE
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
TARGET

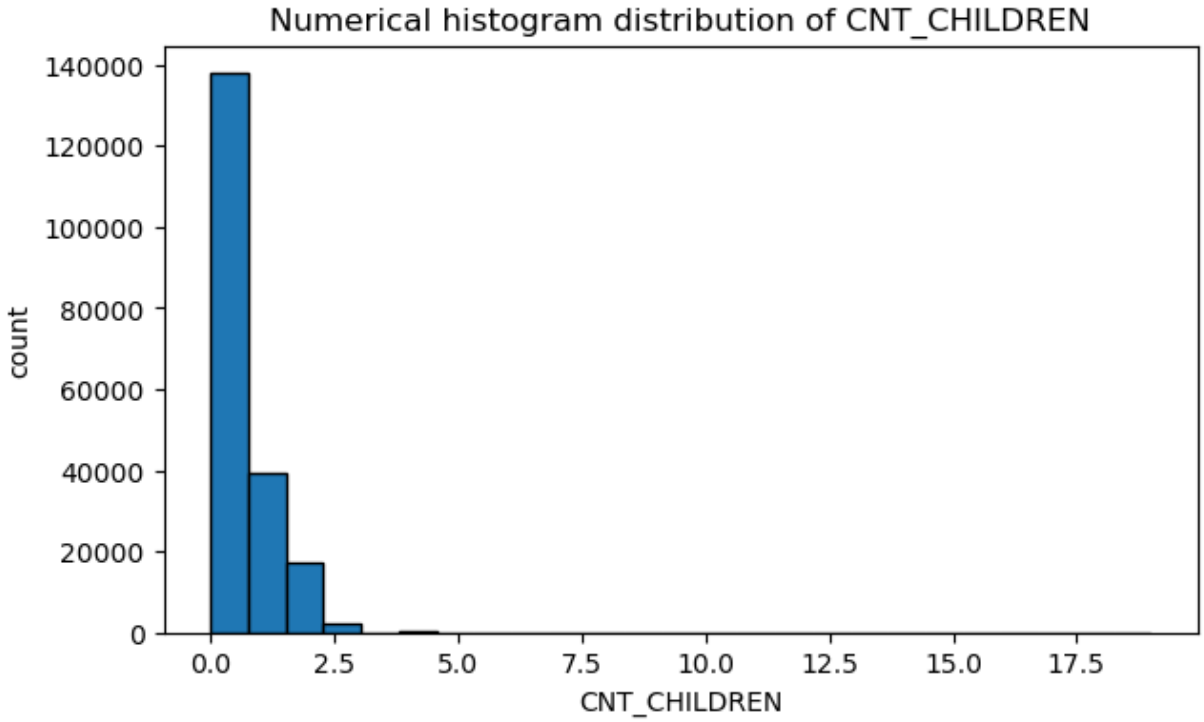


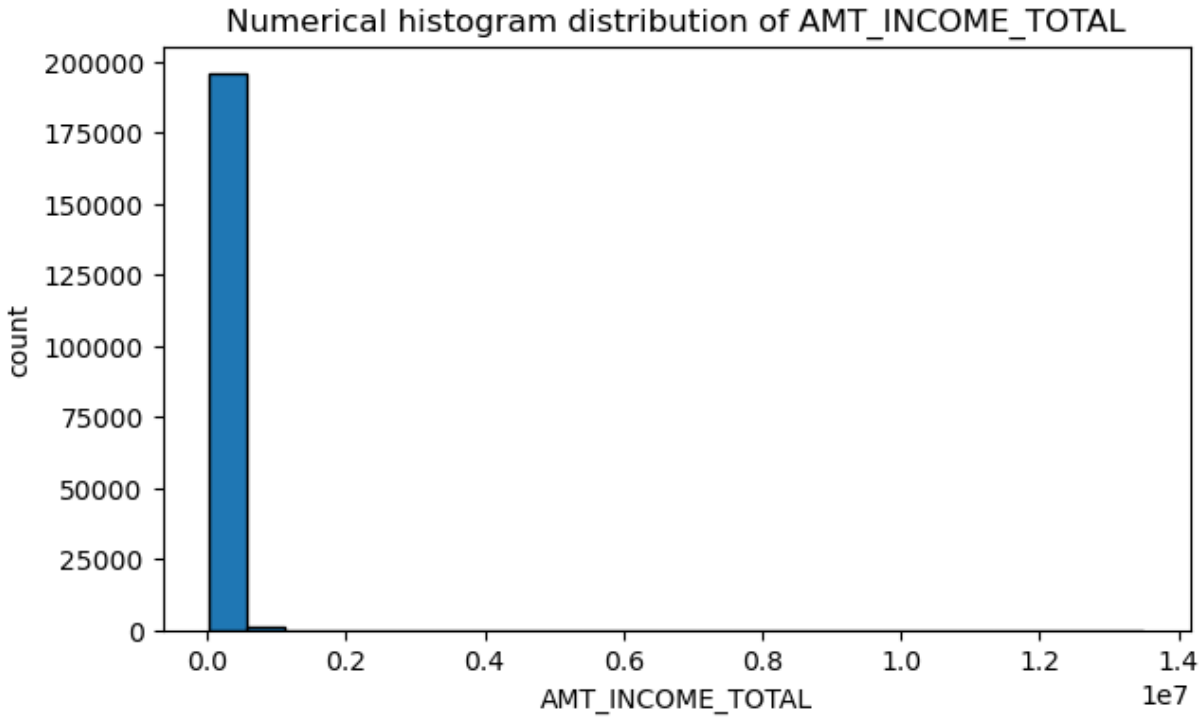


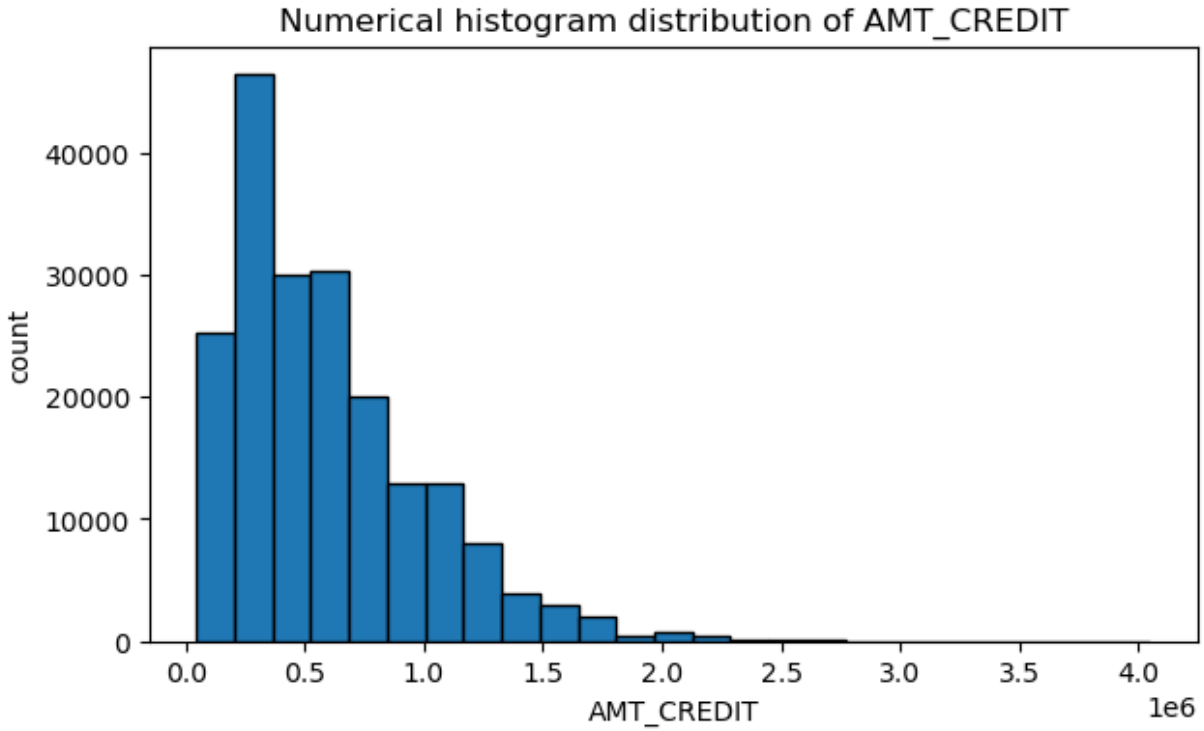
We notice that there are many outliers in the data as seen in the box plot. We can visualize the median and the quantiles of each column data by these box plots.

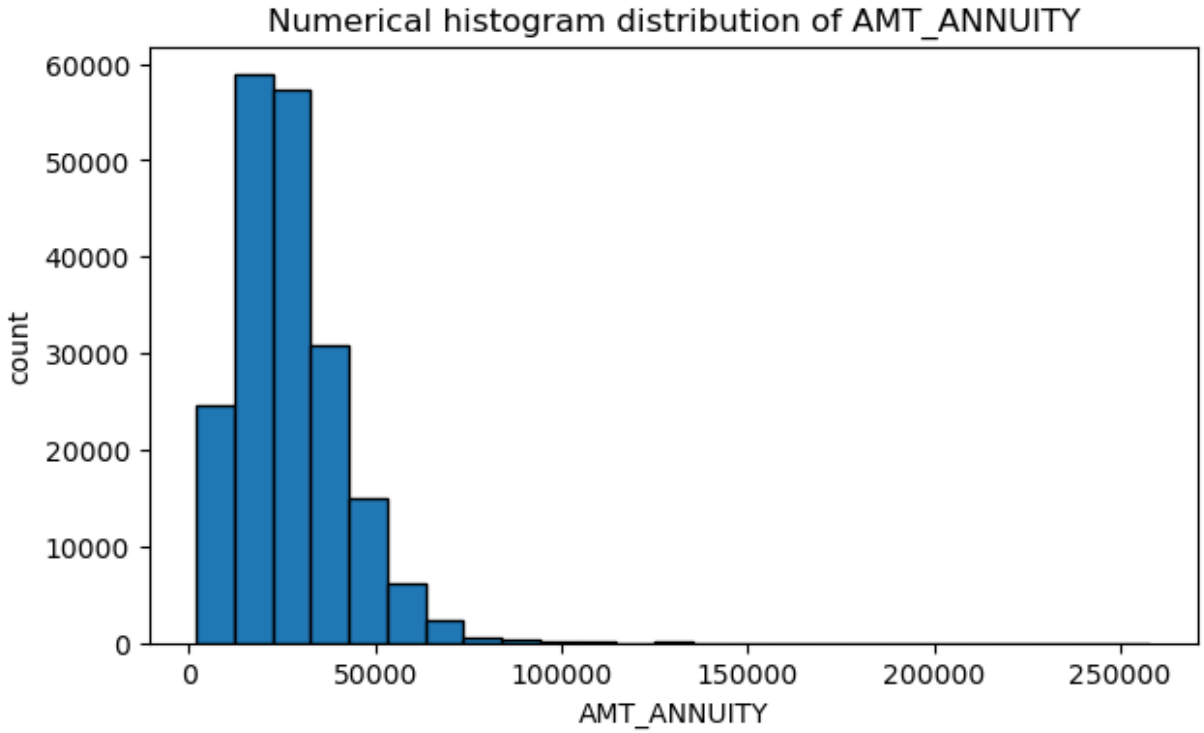
In [151…

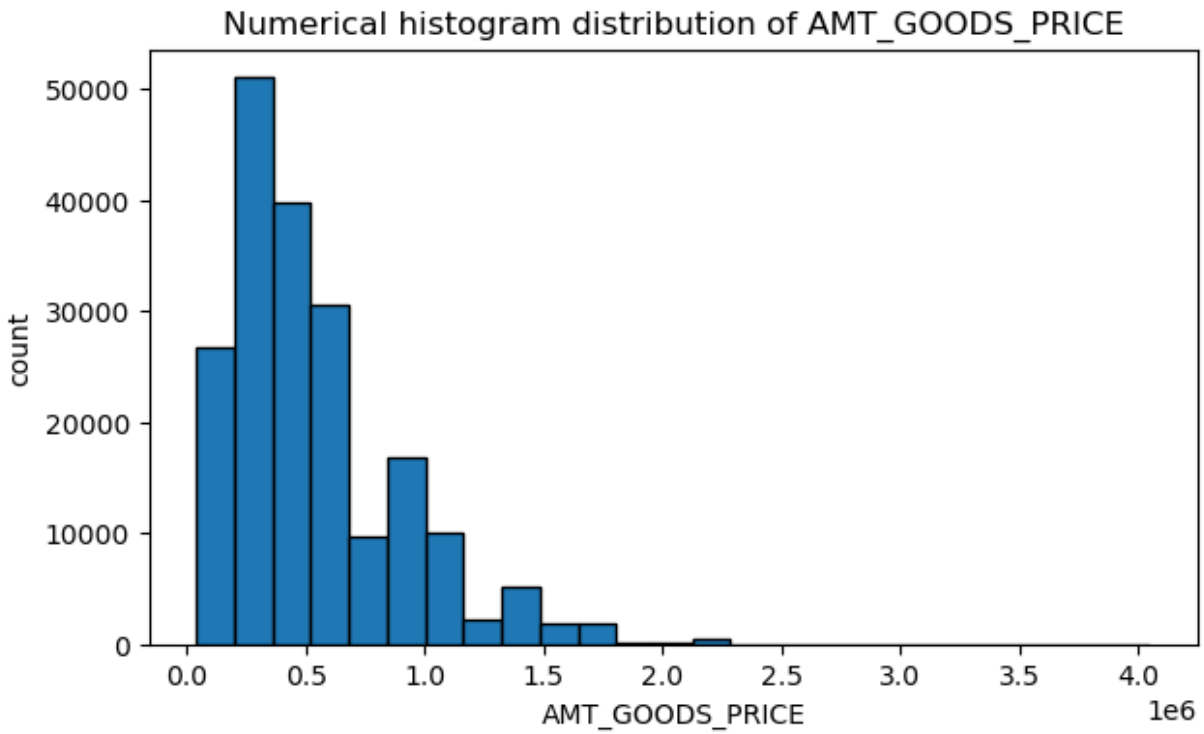
```
for num in list(numerical_features[1:7]):
    plt.figure(figsize=(7, 4))
    plt.hist(Xy_train[num], edgecolor = 'k', bins = 25)
    plt.xlabel(num)
    plt.ylabel('count')
    plt.title(f'Numerical histogram distribution of {num}')
    #plt.setp(plot.get_xticklabels(), rotation=90)
    plt.show()
```

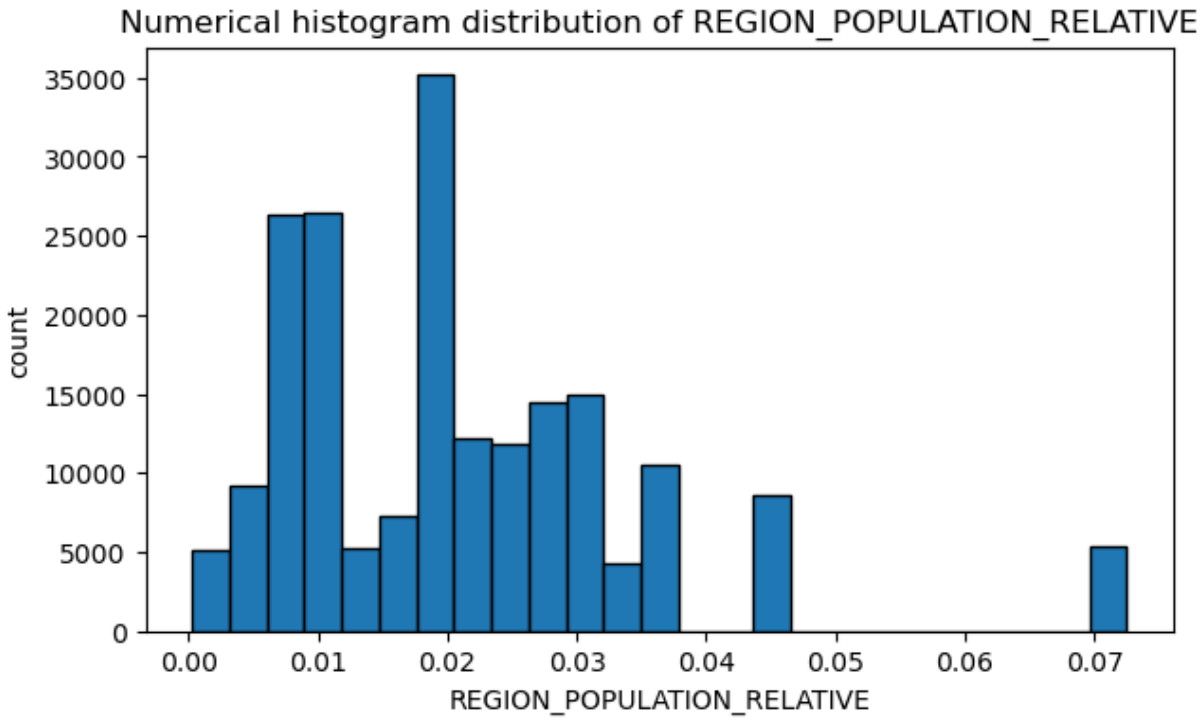

Numerical histogram distribution of CNT_CHILDREN
count
CNT_CHILDREN
0
20000
40000
60000
80000
100000
120000
140000
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Numerical histogram distribution of AMT_INCOME_TOTAL
count
AMT_INCOME_TOTAL
1e7
0
25000
50000
75000
100000
125000
150000
175000
200000
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4


Numerical histogram distribution of AMT_CREDIT
count
40000
30000
20000
10000
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
AMT_CREDIT
1e6


Numerical histogram distribution of AMT_ANNUITY
count
60000
50000
40000
30000
20000
10000
0
0
50000
100000
150000
200000
250000
AMT_ANNUITY

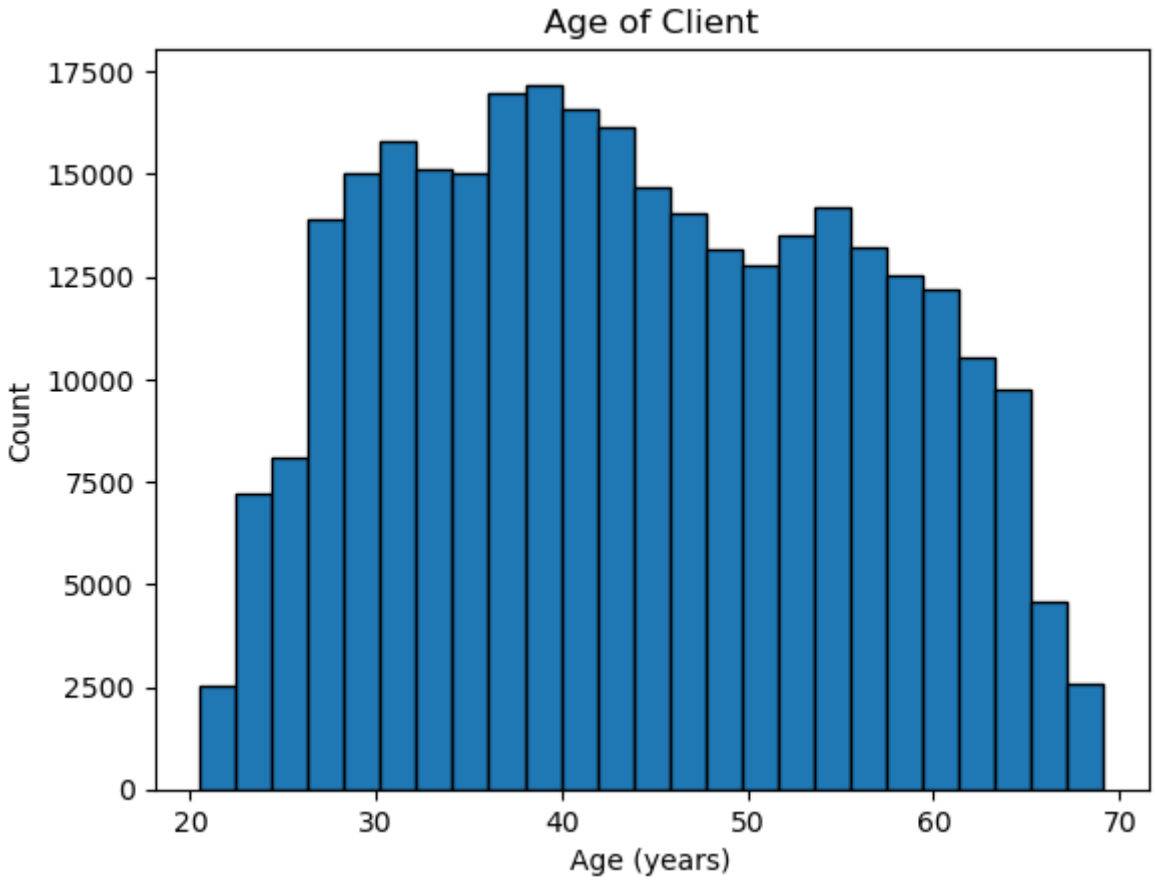




Histogram plot shows the distribution of data over a range. We have visualized each numerical data column's data distribution.

Applicants Age

In [32]:
```
plt.hist(datasets["application_train"]['DAYS_BIRTH'] / -365, edgecolor = 'k',
plt.title('Age of Client')
plt.xlabel('Age (years)')
plt.ylabel('Count')
plt.show()
```

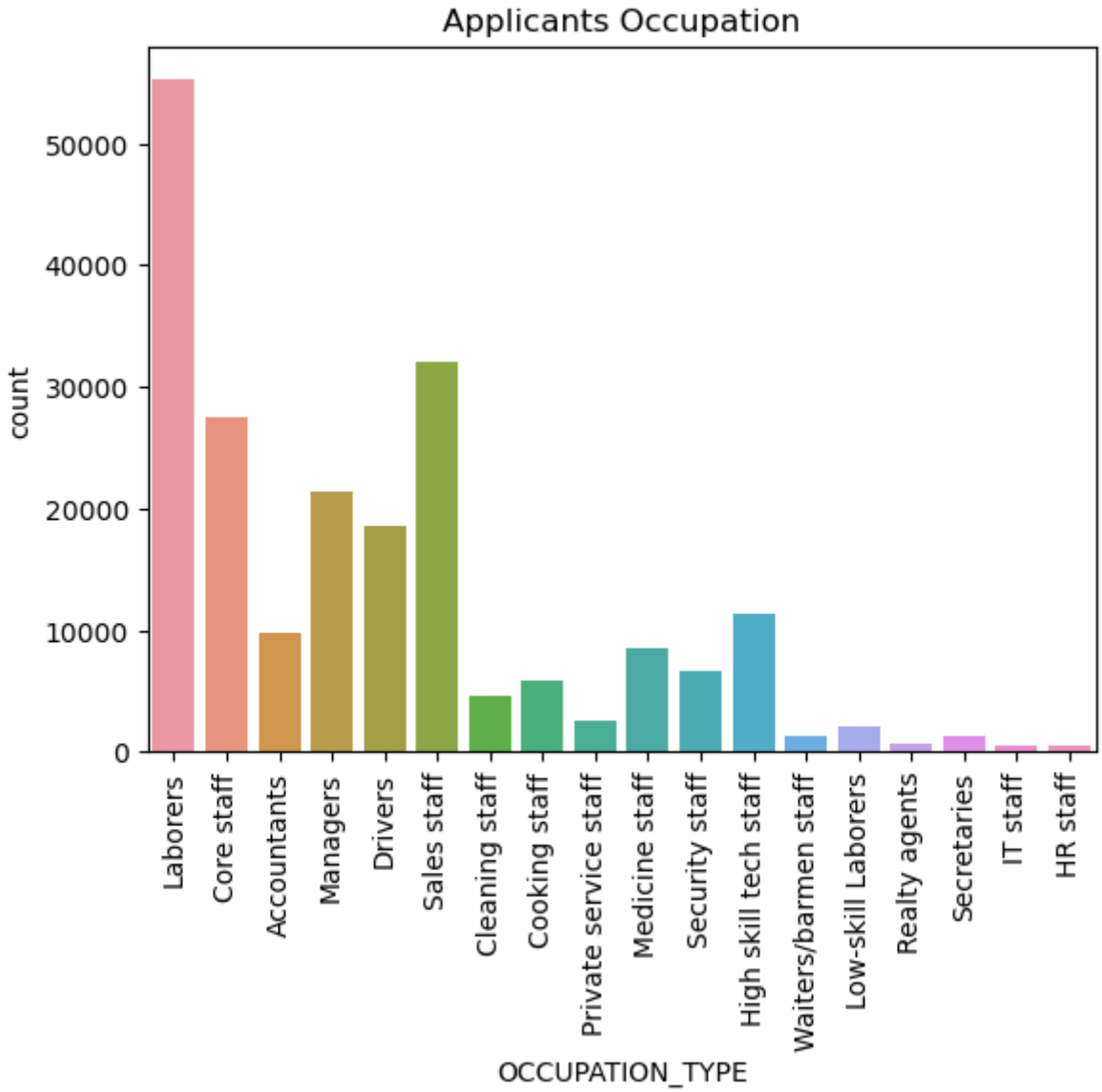


Here we can conclude that people of age 30-50 take more loan applications

Applicants occupations

In [197…

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



Laborers require more loans as compared to other occupation type people

Dataset questions

Unique record for each SK_ID_CURR

In [209…
```
datasets.keys()
```

Out[209…
```
dict_keys(['application_train', 'application_test', 'bureau', 'bureau_balanc
e', 'credit_card_balance', 'installments_payments', 'previous_application', 'P
OS_CASH_balance'])
```

In [210…
```
len(datasets["application_train"]["SK_ID_CURR"].unique()) == datasets["applic
```

Out[210…
```
True
```

In [211…
```
np.intersect1d(datasets["application_train"]["SK_ID_CURR"], datasets["applica
```

Out[211…
```
array([], dtype=int64)
```

In [212…

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

Out[212… (48744, 121)

In [213…
```
datasets["application_train"].shape
```

Out[213… (307511, 122)

Input Features -

In [38]:
```
numerical_features = X_train.select_dtypes(include = ['int64', 'float64']).co
categorical_features = X_train.select_dtypes(include = ['object', 'bool']).co
print(f"\nNumerical features : {list(numerical_features)}")
print(f"\nCategorical features : {list(categorical_features)}")
```

```
Numerical features : ['SK_ID_CURR', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_C
REDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIVE', 'DAYS_
BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OWN_CAR_AG
E', 'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FL
AG_PHONE', 'FLAG_EMAIL', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RA
TING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION',
'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIV
E_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'EXT_SOURCE_1',
'EXT_SOURCE_2', 'EXT_SOURCE_3', 'APARTMENTS_AVG', 'BASEMENTAREA_AVG', 'YEARS_B
EGINEXPLUATATION_AVG', 'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG',
'ENTRANCES_AVG', 'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG', 'LIVINGAPAR
TMENTS_AVG', 'LIVINGAREA_AVG', 'NONLIVINGAPARTMENTS_AVG', 'NONLIVINGAREA_AVG',
'APARTMENTS_MODE', 'BASEMENTAREA_MODE', 'YEARS_BEGINEXPLUATATION_MODE', 'YEARS
_BUILD_MODE', 'COMMONAREA_MODE', 'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMA
X_MODE', 'FLOORSMIN_MODE', 'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'LIVINGAR
EA_MODE', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE', 'APARTMENTS_MEDI',
'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI', 'YEARS_BUILD_MEDI', 'COMM
ONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI', 'FLOORSMAX_MEDI', 'FLOORSMIN
_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI', 'LIVINGAREA_MEDI', 'NONLIVIN
GAPARTMENTS_MEDI', 'NONLIVINGAREA_MEDI', 'TOTALAREA_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', 'F
LAG_DOCUMENT_8', 'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'F
LAG_DOCUMENT_12', 'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15',
'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17', 'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_1
9', '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']

Categorical features : ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYP
E', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE', 'WEEKDAY_APP
R_PROCESS_START', 'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE', 'HOUSETYPE_MODE',
'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE']
```

In [61]:
```
len(list(numerical_features))
```

Out[61]: 105

In [62]:
```
len(list(categorical_features))
```

Out[62]: 16

In [158…
```
total_input_features = len(list(numerical_features)) + len(list(categorical_f
total_input_features
```

Out[158… 121

Modeling

Baseline Logistic Regression -

The objective function for the learning a binomial logistic regression model (log loss) can be stated as follows:

$$\underset{\theta}{\operatorname{argmin}}\left[\mathrm{CXE}\right] = \underset{\theta}{\operatorname{argmin}}\left[-\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}log\left(\hat{p}^{(i)}\right) + (1-y^{(i)})log\left(1-\hat{p}^{(i)}\right)\right]\right]$$

The corresponding gradient function of partial derivatives is as follows (after a little bit of math):

$$\begin{aligned}\nabla_{\mathrm{CXE}}(\theta) &= \begin{pmatrix} \frac{\partial}{\partial\theta_0}\mathrm{CXE}(\theta) \\ \frac{\partial}{\partial\theta_1}\mathrm{CXE}(\theta) \\ \vdots \\ \frac{\partial}{\partial\theta_n}\mathrm{CXE}(\theta) \end{pmatrix} \\ &= \frac{2}{m}\mathbf{X}^T\cdot(\hat{p}_y - \mathbf{y})\end{aligned}$$

For completeness learning a binomial logistic regression model via gradient descent would use the following step iteratively:

$$\theta^{(\text{next step})} = \theta - \eta\nabla_{\mathrm{CXE}}(\theta)$$

In [39]:
```
num_pipeline = Pipeline([
            ('scaler', StandardScaler()),
            ('imputer', SimpleImputer(strategy = 'median'))
    ])

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

In [197…
```
results = pd.DataFrame(columns = ["Pipeline", "Dataset", "TrainAcc", "ValidAc
```

In [198…
```
def model_logreg(X_train):

    data_pipeline = ColumnTransformer([
        ("num_pipeline", num_pipeline, numerical_features),
        ("cat_pipeline", cat_pipeline, categorical_features)], remainder = 'd

    X_train_transformed = data_pipeline.fit_transform(X_train)
```

```
    column_names = list(numerical_features)  + \
                   list(data_pipeline.transformers_[1][1].named_steps["ohe"].

    X_train_transformed_df = pd.DataFrame(X_train_transformed,  columns=colum

    display(X_train_transformed_df.head())

    clf_pipe = make_pipeline(data_pipeline, LogisticRegression())
    clf_pipe.fit(X_train, y_train)

    train_acc = clf_pipe.score(X_train, y_train)
    validAcc  = clf_pipe.score(X_valid, y_valid)
    testAcc   = clf_pipe.score(X_test, y_test)


    ## Plotting AUC / ROC
    ns_probs = [0 for _ in range(len(y_test))]
    lr_probs = clf_pipe.predict_proba(X_test)
    # keep probabilities for the positive outcome only
    lr_probs = lr_probs[:, 1]
    # calculate scores
    ns_auc = roc_auc_score(y_test, ns_probs)
    lr_auc = roc_auc_score(y_test, lr_probs)

    print('No Skill: ROC AUC=%.3f' % (ns_auc))
    print('Logistic: ROC AUC=%.3f' % (lr_auc))
    # calculate roc curves
    ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)
    lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_probs)
    # plot the roc curve for the model
    plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
    plt.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
    # axis labels
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    # show the legend
    plt.legend()
    # show the plot
    plt.show()

    train_roc = roc_auc_score(y_train, clf_pipe.predict_proba(X_train)[:, 1])
    test_roc = roc_auc_score(y_test, clf_pipe.predict_proba(X_test)[:, 1])
    valid_roc = roc_auc_score(y_valid, clf_pipe.predict_proba(X_valid)[:, 1])

    results.loc[len(results)] = ["Baseline Logistic Regression","HCDR",f"{tra
                                 f"{validAcc*100:8.2f}%", f"{testAcc*100:8.2f

    display(results)
    return clf_pipe
```

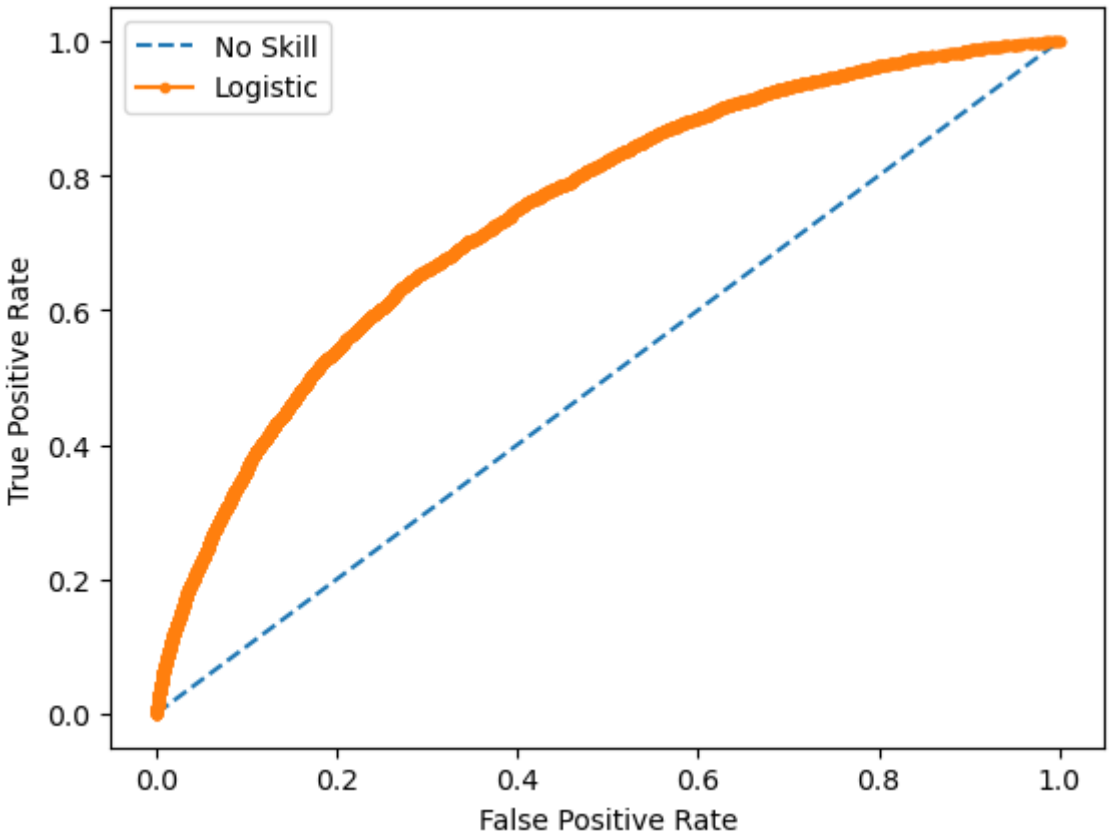
In [199…

```
logreg = model_logreg(X_train)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	-1.624501	-0.578880	-0.528796	1.188441	0.175508	
1	0.560257	0.810033	0.749824	1.304588	1.218472	
2	-0.811727	0.810033	0.110514	-0.452448	-0.310068	
3	-0.776179	-0.578880	0.749824	1.188441	0.529898	
4	0.911520	0.810033	-0.315693	0.559617	-0.197845	

5 rows × 245 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.745
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC
0	Baseline Logistic Regression	HCDR	91.95%	91.77%	91.93%	0.7491	0.7451	0.7407

Baseline Decision Tree Classifier -

Cost functions used for classification and regression.

In both cases the cost functions try to find most homogeneous branches, or branches having groups with similar responses.

Regression : sum(y — prediction)²

Classification : G = sum(pk * (1 — pk))

A Gini score gives an idea of how good a split is by how mixed the response classes are in the groups created by the split. Here, pk is proportion of same class inputs present in a particular group.

DecisionTreeClassifier

The function to measure the quality of a split. Supported criteria are “gini” for the Gini impurity and “entropy” for the information gain. Information gain uses the entropy measure as the impurity measure and splits a node such that it gives the most amount of information gain. Whereas Gini Impurity measures the divergences between the probability distributions

of the target attribute's values and splits a node such that it gives the least amount of impurity.

Gini : $1 - \sum_{i=1}^{m}(P_j^2)$

Entropy : $\sum_{i=1}^{m}\left(P_j \cdot \log\left(P_j\right)\right)$

Feature importance formula

To calculate the importance of each feature, we will mention the decision point itself and its child nodes as well. The following formula covers the calculation of feature importance.

For each decision tree, Scikit-learn calculates a nodes importance using Gini Importance, assuming only two child nodes (binary tree):

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)}$$

Where

ni_j= the importance of node j

w_j = weighted number of samples reaching node j

C_j= the impurity value of node j

left(j) = child node from left split on node j

right(j) = child node from right split on node j

The importance for each feature on a decision tree is then calculated as:

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k\ \epsilon\ all\ nodes} ni_k}$$

fi_i is feature importance for i^{th} feature

These can then be normalized to a value between 0 and 1 by dividing by the sum of all feature importance values:

$$norm fi_i = \frac{fi_i}{\sum_{j\ \epsilon\ all\ features} fi_j}$$

Reference: https://towardsdatascience.com/the-mathematics-of-decision-trees-random-forest-and-feature-importance-in-scikit-learn-and-spark-f2861df67e3#:~:text=Feature%20importance%20is%20calculated%20as,the%20more%20impo

Decision Trees Parameters for classification

- **criterion{"gini", "entropy"}, default="gini"** :The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain.

- **max_depth, default=None** : The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.

- **min_samples_leaf int or float, default=1** : The minimum number of samples required to be at a leaf node. A split point at any depth will only be considered if it leaves at least min_samples_leaf training samples in each of the left and right branches. This may have the effect of smoothing the model, especially in regression.

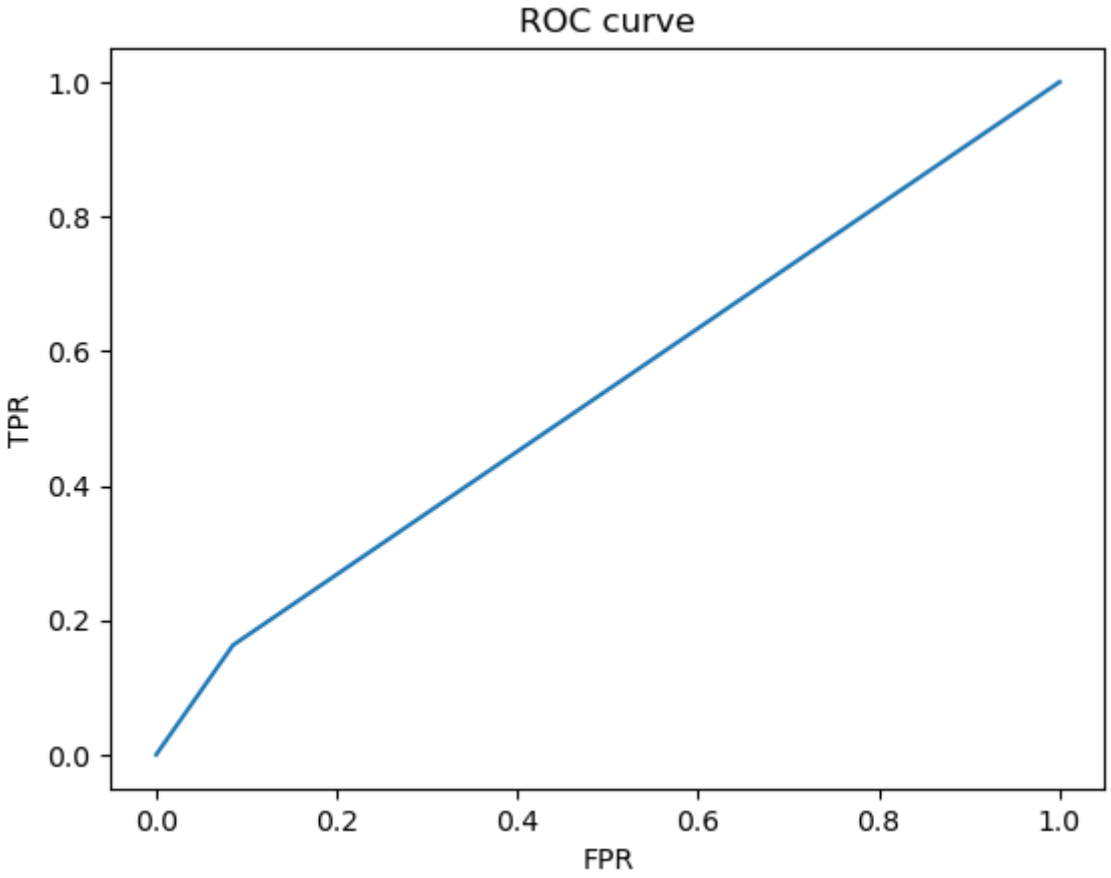
In [200…

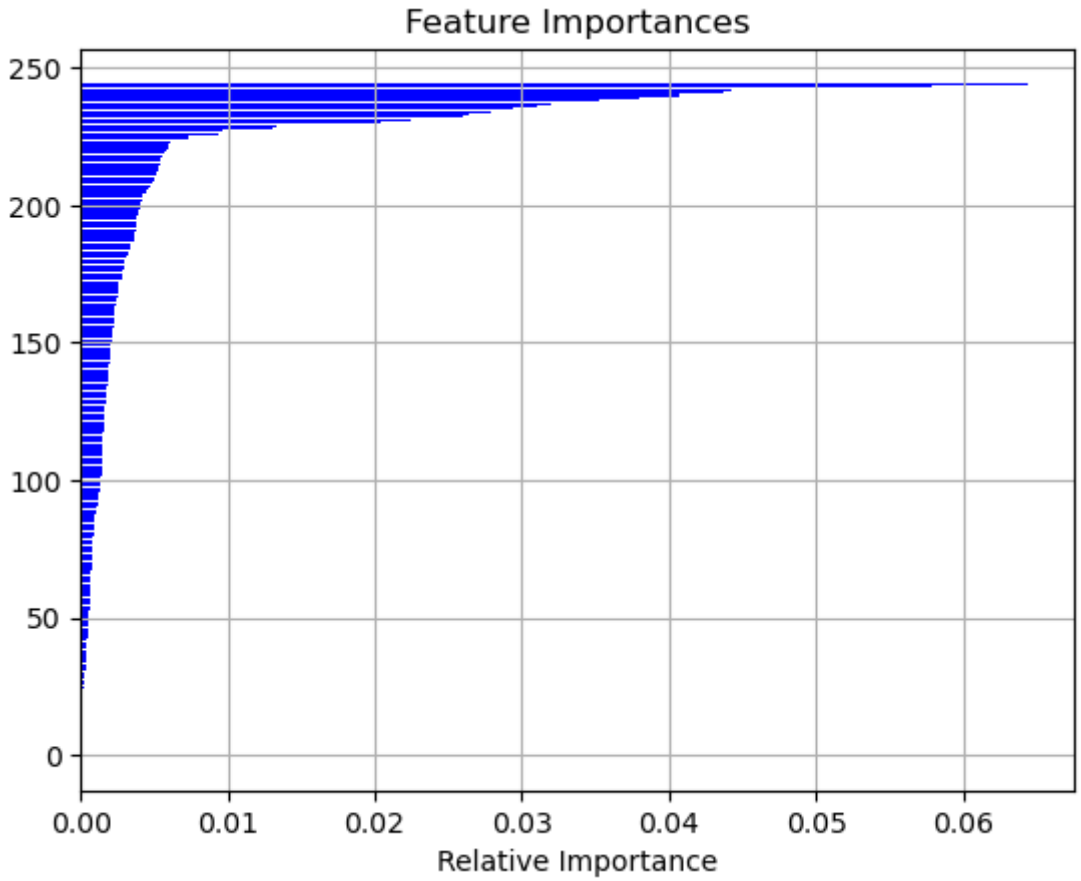
```
def model_dt(X_train):

    tree = DecisionTreeClassifier(criterion='gini', random_state = 42)

    data_pipeline_dt = make_pipeline(data_pipeline, tree)

    data_pipeline_dt.fit(X_train, y_train)

    train_acc = data_pipeline_dt.score(X_train, y_train)
    validAcc  = data_pipeline_dt.score(X_valid, y_valid)
    testAcc   = data_pipeline_dt.score(X_test, y_test)

    predictions = data_pipeline_dt.predict_proba(X_test)
    print ("Score",roc_auc_score(y_test, predictions[:,1]))


    fpr, tpr, _ = roc_curve(y_test, predictions[:,1])

    plt.clf()
    plt.plot(fpr, tpr)
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.title('ROC curve')
    plt.show()

    features = X_train.columns
    importances = tree.feature_importances_
    indices = np.argsort(importances)
    top_feature = indices[0]

    plt.title('Feature Importances')
    plt.barh(range(len(indices)), importances[indices], color='b', align='cen
    #plt.yticks(range(len(indices)), [features[i] for i in indices])
    plt.xlabel('Relative Importance')
    plt.grid()
    plt.show();

    print(f"The feature having highest importance is {features[top_feature]}"

    train_roc = roc_auc_score(y_train, data_pipeline_dt.predict_proba(X_train
    test_roc = roc_auc_score(y_test, data_pipeline_dt.predict_proba(X_test)[:
    valid_roc = roc_auc_score(y_valid, data_pipeline_dt.predict_proba(X_valid

    results.loc[len(results)] = ["Baseline Decision Tree","HCDR",f"{train_acc
                                 f"{validAcc*100:8.2f}%", f"{testAcc*100:8.2f

    display(results)
```

In [201…

```
model_dt(X_train)
```

```
Score 0.5388834038729503
```






```
The feature having highest importance is NAME_EDUCATION_TYPE
```

	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC
0	Baseline Logistic Regression	HCDR	91.95%	91.77%	91.93%	0.7491	0.7451	0.7407

	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC
1	Baseline Decision Tree	HCDR	100.00%	85.08%	85.46%	1.0	0.5389	0.5333

Baseline Random Forest Classifier -

Random Forest Parameters

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

- **n_estimators, default=100** : The number of trees in the forest.
- **max_depthint, default=None** : The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.
- **max_features** : The number of features to consider when looking for the best split.
- **min_impurity_decreasefloat, default=0.0** : Threshold for early stopping in tree growth. A node will be split if this split induces a decrease of the impurity greater than or equal to this value.
- **bootstrapbool, default=True** : Whether bootstrap samples are used when building trees. If False, the whole dataset is used to build each tree.

Feature Importance

Yet another great quality of Random Forests is that they make it easy to measure the relative importance of each feature. Scikit-Learn measures a feature's importance by looking at how much the tree nodes that use that feature reduce impurity on average (across all trees in the forest). More precisely, it is a weighted average, where each node's weight is equal to the number of training samples that are associated with it.

In [202…

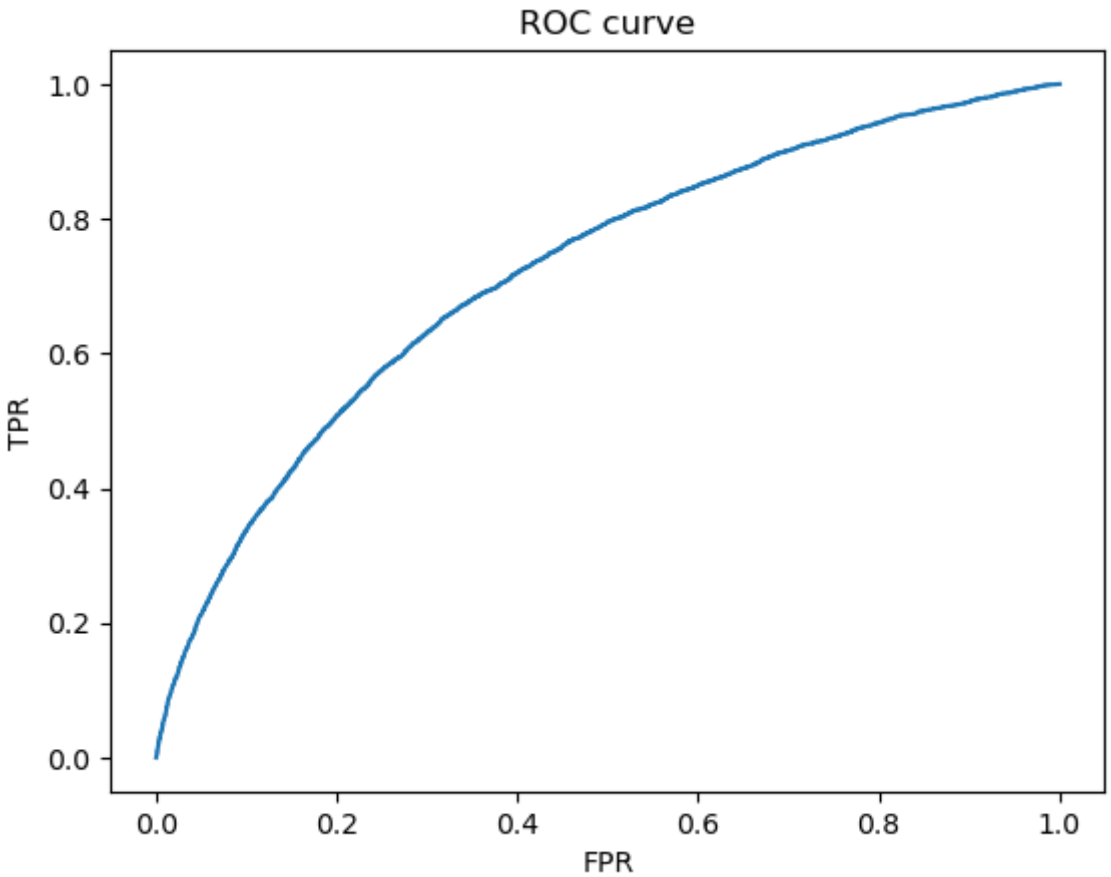
```
def model_rf(X_train):

    RF = RandomForestClassifier(random_state = 42,n_estimators=20, criterion=

    data_pipeline_rf = make_pipeline(data_pipeline, RF)

    data_pipeline_rf.fit(X_train, y_train)

    train_acc = data_pipeline_rf.score(X_train, y_train)
    validAcc  = data_pipeline_rf.score(X_valid, y_valid)
    testAcc   = data_pipeline_rf.score(X_test, y_test)

    predictions = data_pipeline_rf.predict_proba(X_test)
    print ("Score",roc_auc_score(y_test, predictions[:,1]))


    fpr, tpr, _ = roc_curve(y_test, predictions[:,1])

    plt.clf()
```

```
    plt.plot(fpr, tpr)
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.title('ROC curve')
    plt.show()


    train_roc = roc_auc_score(y_train, data_pipeline_rf.predict_proba(X_train
    test_roc = roc_auc_score(y_test, data_pipeline_rf.predict_proba(X_test)[:
    valid_roc = roc_auc_score(y_valid, data_pipeline_rf.predict_proba(X_valid

    results.loc[len(results)] = ["Baseline Random Forest","HCDR",f"{train_acc
                                 f"{validAcc*100:8.2f}%", f"{testAcc*100:8.2f

    display(results)

    return data_pipeline_rf,RF
```

In [203…

```
rf_pipe, RF = model_rf(X_train)
```

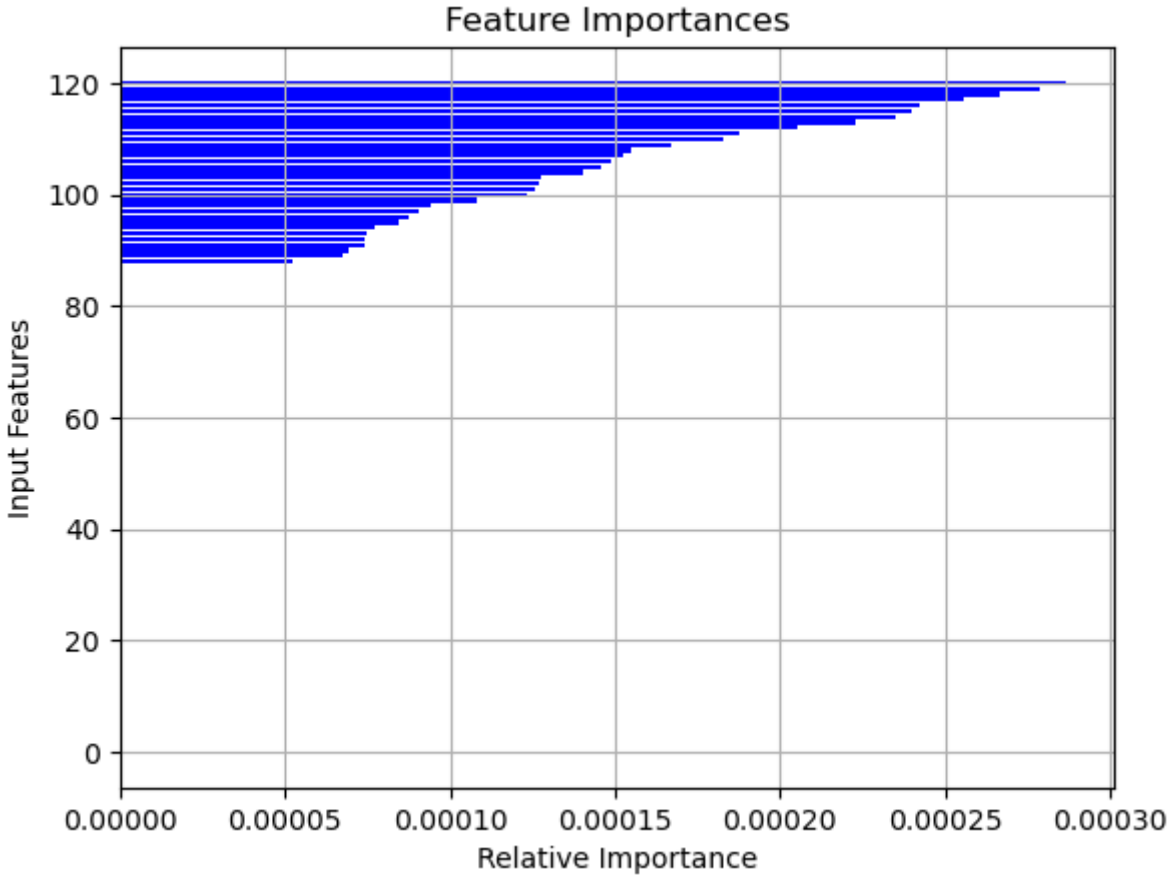
```
Score 0.7202735379743133
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC
0	Baseline Logistic Regression	HCDR	91.95%	91.77%	91.93%	0.7491	0.7451	0.7407
1	Baseline Decision Tree	HCDR	100.00%	85.08%	85.46%	1.0	0.5389	0.5333
2	Baseline Random Forest	HCDR	91.95%	91.78%	91.95%	0.7355	0.7203	0.7146

Feature Importances of Random Forest Classifier

In [205…
```
features = X_train.columns
#print(len(features))
importances = RF.feature_importances_
indices = np.argsort(importances)[:len(features)]
#print(len(indices))

plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center'
#plt.yticks(range(len(indices)), [i for i in features])
plt.xlabel('Relative Importance')
plt.ylabel('Input Features')
plt.grid()
plt.show();
```



Feature Engineering

Bureau table

In [177…
```
bureau_data = datasets['bureau']
```

In [178…
```
bureau_data
```

Out[178…

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	C
0	215354	5714462	Closed	currency 1	-497	
1	215354	5714463	Active	currency 1	-208	
2	215354	5714464	Active	currency 1	-203	

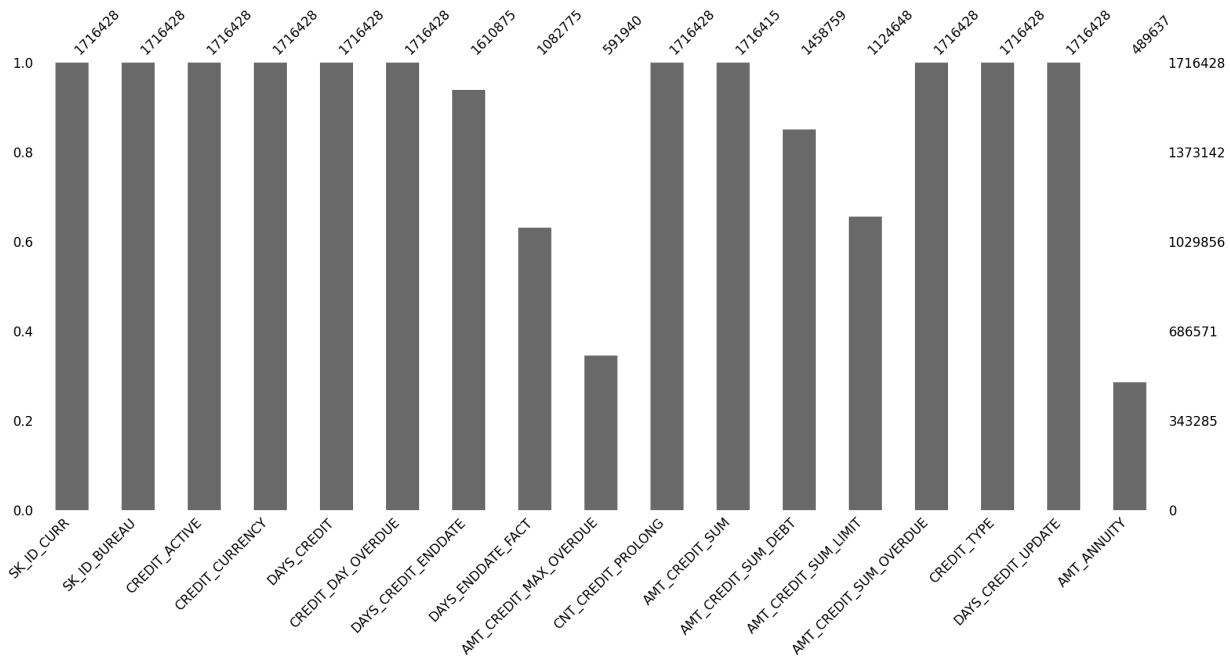
	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	C
3	215354	5714465	Active	currency 1	-203	
4	215354	5714466	Active	currency 1	-629	
...	...	...	...	...	...	
1716423	259355	5057750	Active	currency 1	-44	
1716424	100044	5057754	Closed	currency 1	-2648	
1716425	100044	5057762	Closed	currency 1	-1809	
1716426	246829	5057770	Closed	currency 1	-1878	
1716427	246829	5057778	Closed	currency 1	-463	

1716428 rows × 17 columns

In [179…
```
bureau_data['DAYS_CREDIT'].value_counts()
```

Out[179…
```
-364     1330
-336     1248
-273     1238
-357     1218
-343     1203
         ...
-4        113
-3         74
-2         42
 0         25
-1         17
Name: DAYS_CREDIT, Length: 2923, dtype: int64
```

In [180…
```
msno.bar(bureau_data)
plt.show()
```



In [181…
```
corr = bureau_data.corr()['DAYS_CREDIT'].sort_values(ascending = False)
```

```
print('Most Positive Correlations:\n', corr.head(10))
print('\nMost Negative Correlations:\n', corr.tail(10))
```

```
Most Positive Correlations:
 DAYS_CREDIT              1.000000
DAYS_ENDDATE_FACT        0.875359
DAYS_CREDIT_UPDATE       0.688771
DAYS_CREDIT_ENDDATE      0.225682
AMT_CREDIT_SUM_DEBT      0.135397
AMT_CREDIT_SUM           0.050883
AMT_CREDIT_SUM_LIMIT     0.025140
SK_ID_BUREAU             0.013015
AMT_ANNUITY              0.005676
SK_ID_CURR               0.000266
Name: DAYS_CREDIT, dtype: float64

Most Negative Correlations:
 AMT_CREDIT_SUM_DEBT       0.135397
AMT_CREDIT_SUM            0.050883
AMT_CREDIT_SUM_LIMIT      0.025140
SK_ID_BUREAU              0.013015
AMT_ANNUITY               0.005676
SK_ID_CURR                0.000266
AMT_CREDIT_SUM_OVERDUE   -0.000383
AMT_CREDIT_MAX_OVERDUE   -0.014724
CREDIT_DAY_OVERDUE       -0.027266
CNT_CREDIT_PROLONG       -0.030460
Name: DAYS_CREDIT, dtype: float64
```

In [182…

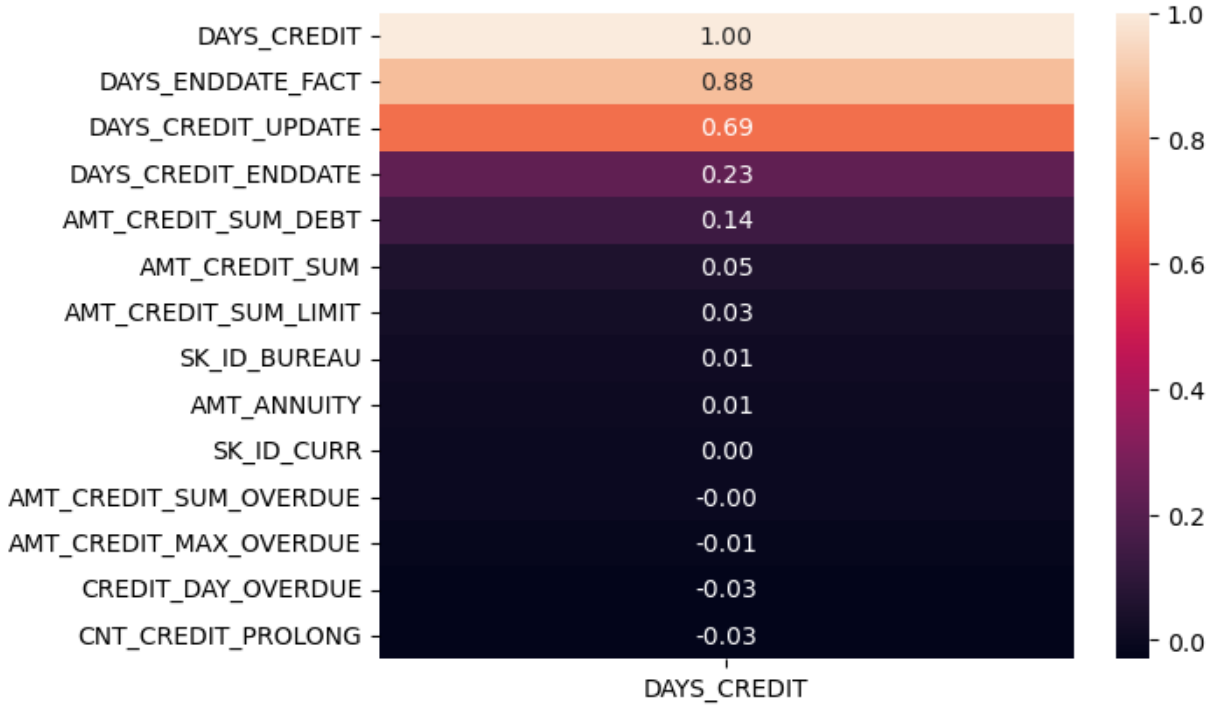
```
bureau_corr = pd.DataFrame(corr, columns = ['DAYS_CREDIT'])
bureau_corr
```

Out[182…

	DAYS_CREDIT
DAYS_CREDIT	1.000000
DAYS_ENDDATE_FACT	0.875359
DAYS_CREDIT_UPDATE	0.688771
DAYS_CREDIT_ENDDATE	0.225682
AMT_CREDIT_SUM_DEBT	0.135397
AMT_CREDIT_SUM	0.050883
AMT_CREDIT_SUM_LIMIT	0.025140
SK_ID_BUREAU	0.013015
AMT_ANNUITY	0.005676
SK_ID_CURR	0.000266
AMT_CREDIT_SUM_OVERDUE	-0.000383
AMT_CREDIT_MAX_OVERDUE	-0.014724
CREDIT_DAY_OVERDUE	-0.027266
CNT_CREDIT_PROLONG	-0.030460

In [183…

```
bureau_corr= bureau_corr[:20].dropna()
sns.heatmap(bureau_corr, annot = True ,fmt='.2f')
plt.show()
```



In [184…
```
bureau_data['CREDIT_TYPE'].value_counts()
```

Out[184…
```
Consumer credit                                 1251615
Credit card                                      402195
Car loan                                          27690
Mortgage                                          18391
Microloan                                         12413
Loan for business development                      1975
Another type of loan                               1017
Unknown type of loan                                555
Loan for working capital replenishment              469
Cash loan (non-earmarked)                            56
Real estate loan                                     27
Loan for the purchase of equipment                   19
Loan for purchase of shares (margin lending)          4
Mobile operator loan                                  1
Interbank credit                                      1
Name: CREDIT_TYPE, dtype: int64
```

In [185…
```
bureau_data['CREDIT_ACTIVE'].value_counts()
```

Out[185…
```
Closed      1079273
Active       630607
Sold           6527
Bad debt         21
Name: CREDIT_ACTIVE, dtype: int64
```

In [186…
```
bureau_data['CREDIT_ACTIVE_CLASSIFY'] = bureau_data['CREDIT_ACTIVE']

def classify(x):
    if x == 'Closed':
        y = 0
    else:
        y = 1
    return y

bureau_data['CREDIT_ACTIVE_CLASSIFY'] = bureau_data.apply(lambda x: classify(
```

In [187…

```
bureau_data['CREDIT_ACTIVE_CLASSIFY'].value_counts()
```

Out[187…
```
0    1079273
1     637155
Name: CREDIT_ACTIVE_CLASSIFY, dtype: int64
```

In [188…
```
active_loan = bureau_data.groupby(by = ['SK_ID_CURR'])['CREDIT_ACTIVE_CLASSIF
active_loan
```

Out[188…

	SK_ID_CURR	ACTIVE_LOANS_PERCENTAGE
0	100001	0.428571
1	100002	0.250000
2	100003	0.250000
3	100004	0.000000
4	100005	0.666667
...	...	...
305806	456249	0.153846
305807	456250	0.666667
305808	456253	0.500000
305809	456254	0.000000
305810	456255	0.454545

305811 rows × 2 columns

In [192…
```
bureau_data = bureau_data.merge(active_loan, on = ['SK_ID_CURR'], how = 'left
bureau_data
```

Out[192…

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	C
0	215354	5714462	Closed	currency 1	-497	
1	215354	5714463	Active	currency 1	-208	
2	215354	5714464	Active	currency 1	-203	
3	215354	5714465	Active	currency 1	-203	
4	215354	5714466	Active	currency 1	-629	
...	...	...	...	...	...	
1716423	259355	5057750	Active	currency 1	-44	
1716424	100044	5057754	Closed	currency 1	-2648	
1716425	100044	5057762	Closed	currency 1	-1809	
1716426	246829	5057770	Closed	currency 1	-1878	
1716427	246829	5057778	Closed	currency 1	-463	

1716428 rows × 19 columns

In [193…
```
bureau_data.drop(['AMT_ANNUITY','DAYS_ENDDATE_FACT','CREDIT_CURRENCY','CREDIT_
```

In [194…
```
bureau_data
```

Out[194…

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	DAYS_CREDIT	CREDIT_DAY_OVERDUI
0	215354	5714462	Closed	-497	
1	215354	5714463	Active	-208	
2	215354	5714464	Active	-203	
3	215354	5714465	Active	-203	
4	215354	5714466	Active	-629	
...	...	...	...	...	...
1716423	259355	5057750	Active	-44	
1716424	100044	5057754	Closed	-2648	
1716425	100044	5057762	Closed	-1809	
1716426	246829	5057770	Closed	-1878	
1716427	246829	5057778	Closed	-463	

1716428 rows × 15 columns

In [151…
```
bureau_data['CNT_CREDIT_PROLONG'].value_counts()
```

Out[151…
```
0    1707314
1       7620
2       1222
3        191
4         54
5         21
9          2
6          2
8          1
7          1
Name: CNT_CREDIT_PROLONG, dtype: int64
```

In [195…
```
bureau_data['AMT_CREDIT_MAX_OVERDUE'].fillna(0, inplace = True)
```

In [196…
```
bureau_data['AMT_CREDIT_SUM_LIMIT'].isnull().value_counts()
```

Out[196…
```
False    1124648
True      591780
Name: AMT_CREDIT_SUM_LIMIT, dtype: int64
```

In [197…
```
bureau_data['AMT_CREDIT_SUM'].fillna(0, inplace = True)
```

```
bureau_data['AMT_CREDIT_SUM_LIMIT'].fillna(0, inplace = True)
```

In [198…

```
bureau_data[['AMT_CREDIT_SUM','AMT_CREDIT_SUM_DEBT','AMT_CREDIT_SUM_LIMIT']]
```

Out[198…

	AMT_CREDIT_SUM	AMT_CREDIT_SUM_DEBT	AMT_CREDIT_SUM_LIMIT
0	91323.00	0.0	0.0
1	225000.00	171342.0	0.0
2	464323.50	NaN	0.0
3	90000.00	NaN	0.0
4	2700000.00	NaN	0.0
…	…	…	…
1716423	11250.00	11250.0	0.0
1716424	38130.84	0.0	0.0
1716425	15570.00	NaN	0.0
1716426	36000.00	0.0	0.0
1716427	22500.00	0.0	0.0

1716428 rows × 3 columns

In [199…

```
bureau_data['AMT_CREDIT_SUM_DEBT'].fillna(bureau_data['AMT_CREDIT_SUM'], inpl
```

In [200…

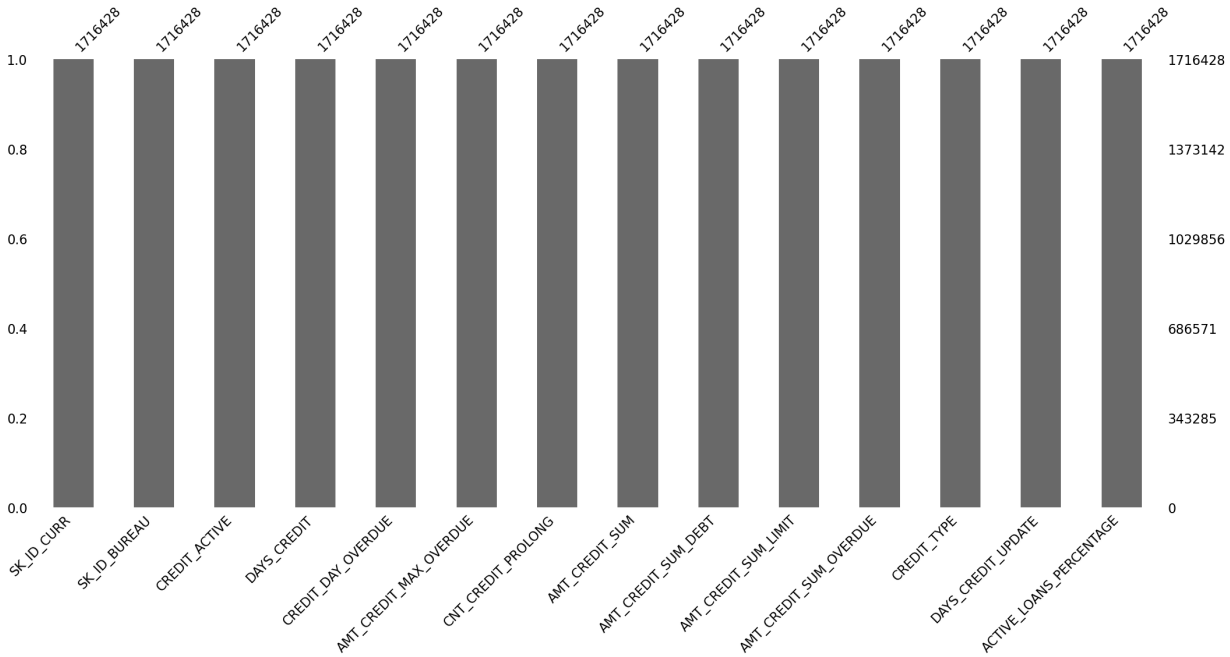
```
difference = bureau_data['AMT_CREDIT_SUM'] - bureau_data['AMT_CREDIT_SUM_DEBT
bureau_data['AMT_CREDIT_SUM_LIMIT'].fillna(difference, inplace = True)
```

In [201…

```
bureau_data.drop('DAYS_CREDIT_ENDDATE', axis = 1, inplace = True)
```

In [202…

```
msno.bar(bureau_data)
plt.show()
```



Our Model Pipeline

In [153…

```
results = pd.DataFrame(columns = ["Pipeline",
                                  "Dataset",
                                  "TrainAcc",
                                  "ValidAcc",
                                  "TestAcc",
                                  "TrainROC",
                                  "TestROC",
                                  "ValidROC",
                                  "Feature Added"])
```

In [154…

```
def model_logreg(train,feature):

    X = train.drop(['TARGET'], axis = 1)
    y = train["TARGET"]

    # Split the provided training data into training and validationa and test
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
    X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, t
    print(f"X train           shape: {X_train.shape}")
    print(f"X validation      shape: {X_valid.shape}")
    print(f"X test            shape: {X_test.shape}")

    numerical_features = X_train.select_dtypes(include = ['int64', 'float64']
    categorical_features = X_train.select_dtypes(include = ['object', 'bool']
    #print(f"\nNumerical features : {list(numerical_features)}")
    #print(f"\nCategorical features : {list(categorical_features)}")

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

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

```
    data_pipeline = ColumnTransformer([
        ("num_pipeline", num_pipeline, numerical_features),
        ("cat_pipeline", cat_pipeline, categorical_features)], remainder = 'd

    X_train_transformed = data_pipeline.fit_transform(X_train)

    column_names = list(numerical_features)  + \
                   list(data_pipeline.transformers_[1][1].named_steps["ohe"].

    X_train_transformed_df = pd.DataFrame(X_train_transformed,  columns=colum

    display(X_train_transformed_df.head())

    clf_pipe = make_pipeline(data_pipeline, LogisticRegression())
    clf_pipe.fit(X_train, y_train)

    train_acc = clf_pipe.score(X_train, y_train)
    validAcc  = clf_pipe.score(X_valid, y_valid)
    testAcc   = clf_pipe.score(X_test, y_test)


    ## Plotting AUC / ROC
    ns_probs = [0 for _ in range(len(y_test))]
    lr_probs = clf_pipe.predict_proba(X_test)
    # keep probabilities for the positive outcome only
    lr_probs = lr_probs[:, 1]
    # calculate scores
    ns_auc = roc_auc_score(y_test, ns_probs)
    lr_auc = roc_auc_score(y_test, lr_probs)

    print('No Skill: ROC AUC=%.3f' % (ns_auc))
    print('Logistic: ROC AUC=%.3f' % (lr_auc))
    # calculate roc curves
    ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)
    lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_probs)
    # plot the roc curve for the model
    plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
    plt.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
    # axis labels
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    # show the legend
    plt.legend()
    # show the plot
    plt.show()

    train_roc = roc_auc_score(y_train, clf_pipe.predict_proba(X_train)[:, 1])
    test_roc = roc_auc_score(y_test, clf_pipe.predict_proba(X_test)[:, 1])
    valid_roc = roc_auc_score(y_valid, clf_pipe.predict_proba(X_valid)[:, 1])

    results.loc[len(results)] = ["Logistic Regression","HCDR",f"{train_acc*10
                                 f"{validAcc*100:8.2f}%", f"{testAcc*100:8.2f

    display(results)

    return clf_pipe
```

Feature 1 : Percentage of Active Loans

In [205…

```
bureau_active_loans = pd.DataFrame(bureau_data[['SK_ID_CURR','ACTIVE_LOANS_PE
```

In [206…
```
bureau_active_loans
```

Out[206…

	SK_ID_CURR	ACTIVE_LOANS_PERCENTAGE
0	215354	0.545455
1	215354	0.545455
2	215354	0.545455
3	215354	0.545455
4	215354	0.545455
...	...	...
1716423	259355	1.000000
1716424	100044	0.545455
1716425	100044	0.545455
1716426	246829	0.258065
1716427	246829	0.258065

1716428 rows × 2 columns

In [203…
```
train = datasets['application_train']
train
```

Out[203…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	
...	...	...	...	...	...	...
307506	456251	0	Cash loans	M	N	
307507	456252	0	Cash loans	F	N	
307508	456253	0	Cash loans	F	N	
307509	456254	1	Cash loans	F	N	
307510	456255	0	Cash loans	F	N	

307511 rows × 117 columns

In [ ]:
```
train.drop(['DAYS_LAST_PHONE_CHANGE','OBS_30_CNT_SOCIAL_CIRCLE','OBS_60_CNT_S
```

In [207…
```
train = train.merge(bureau_active_loans, on = 'SK_ID_CURR', how = 'left')
```

In [208…
```
train
```

Out[208…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 118 columns

In [209…

```
train = train.loc[:, ~train.columns.str.startswith("FLAG_DOCUMENT_")]
train = train.loc[:, ~train.columns.str.endswith("MODE")]
train = train.loc[:, ~train.columns.str.endswith("MEDI")]
train = train.loc[:, ~train.columns.str.endswith("AVG")]
```

In [210…

```
train
```

Out[210…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 51 columns

In [41]:

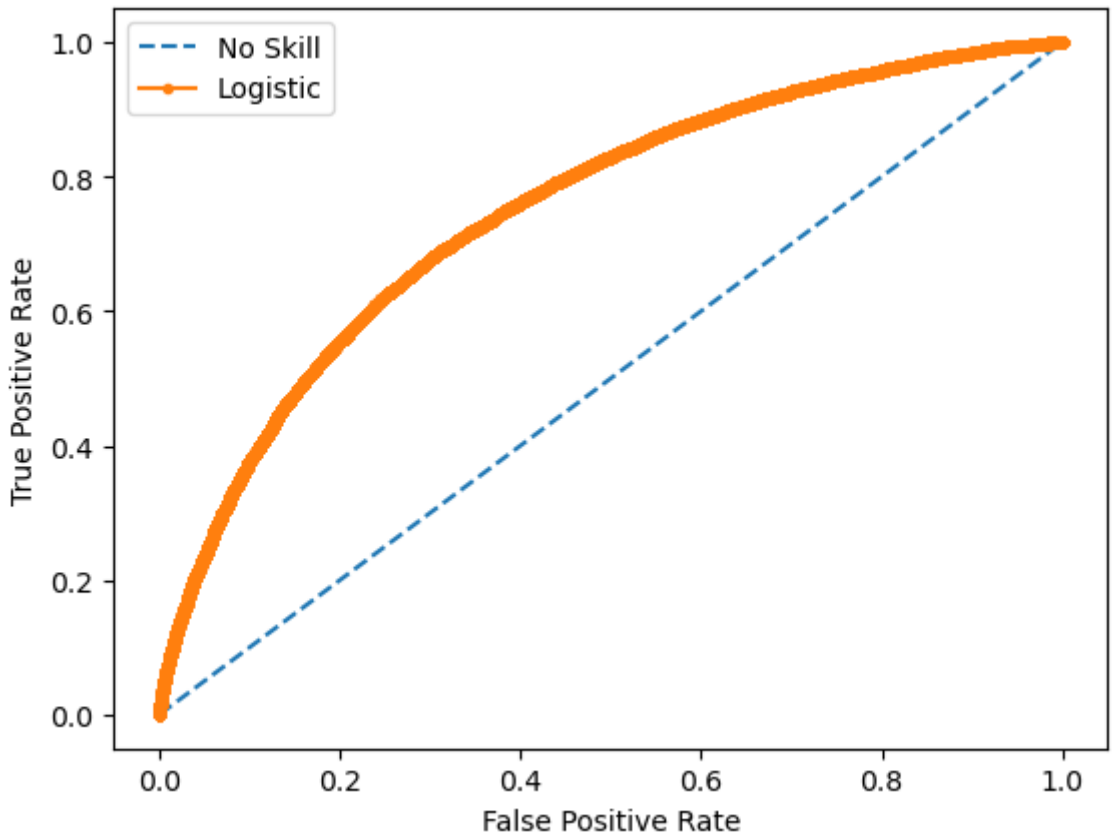
```
active_loan_model = model_logreg(train, 'Active loan Percentage feature')
```

```
X train           shape: (965980, 97)
X validation      shape: (241496, 97)
X test            shape: (301869, 97)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	-0.714681	-0.585812	0.000407	-0.970848	-0.215580	
1	-1.062862	-0.585812	-0.191312	2.262115	1.247094	
2	1.282842	-0.585812	0.057922	-0.187606	-0.483416	
3	-0.163686	-0.585812	-0.287171	1.231743	0.630882	
4	-0.411456	-0.585812	1.150719	3.407022	2.134300	

5 rows × 220 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.751
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Featur Adde
0	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.752	0.7505	0.7496	Active loa Percentag featur

Feature 2: Credit income percentage feature

In [211…

```
amt_income = train['AMT_INCOME_TOTAL']
amt_credit = train['AMT_CREDIT']
credit_income_perc = amt_income/amt_credit
train['CREDIT_INCOME_RATIO'] = credit_income_perc
train['CREDIT_INCOME_RATIO']
```

Out[211…

```
0          0.498036
1          0.498036
2          0.498036
3          0.498036
```

```
4          0.498036
             ...
1509340    0.233333
1509341    0.233333
1509342    0.233333
1509343    0.233333
1509344    0.233333
Name: CREDIT_INCOME_RATIO, Length: 1509345, dtype: float64
```

In [212…

```
train
```

Out[212…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 52 columns

In [44]:

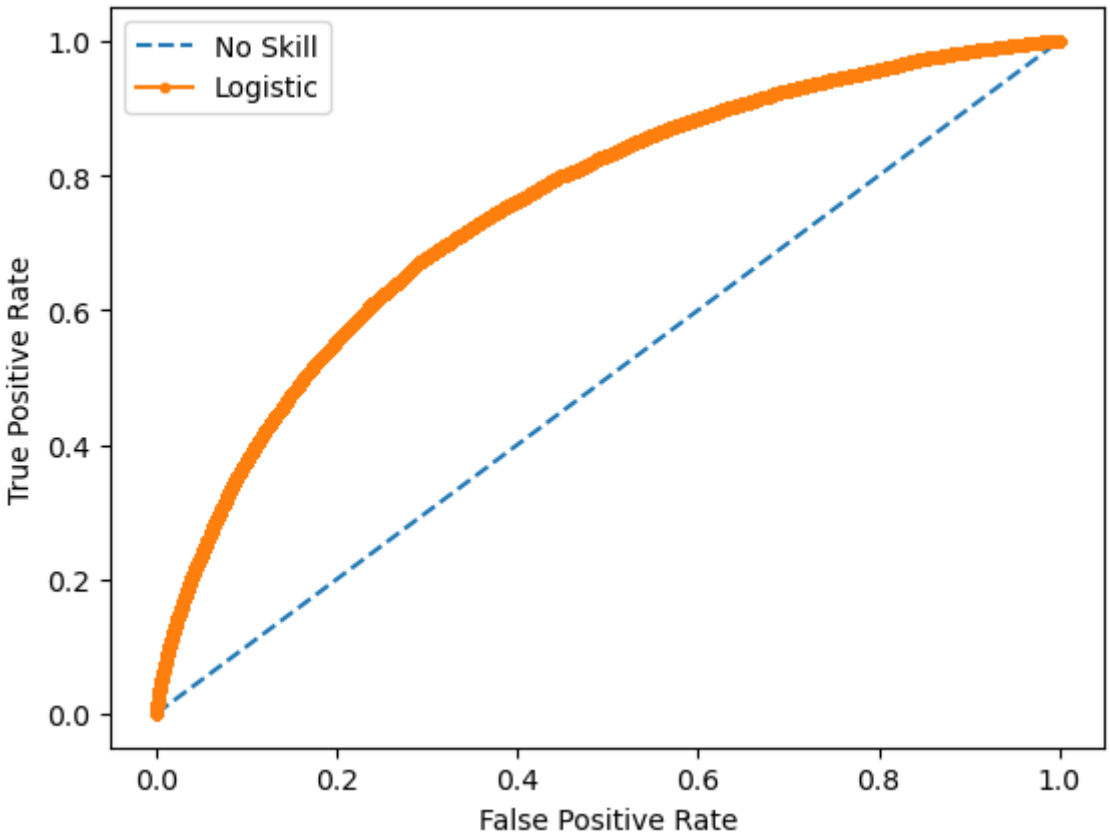
```
credit_income_model = model_logreg(train, 'Credit Income Ratio feature')
```

```
X train           shape: (965980, 98)
X validation      shape: (241496, 98)
X test            shape: (301869, 98)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	-0.714681	-0.585812	0.000407	-0.970848	-0.215580	
1	-1.062862	-0.585812	-0.191312	2.262115	1.247094	
2	1.282842	-0.585812	0.057922	-0.187606	-0.483416	
3	-0.163686	-0.585812	-0.287171	1.231743	0.630882	
4	-0.411456	-0.585812	1.150719	3.407022	2.134300	

5 rows × 221 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.751
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Featur Adde
0	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.752	0.7505	0.7496	Active loa Percentag featur
1	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7526	0.7511	0.7502	Cred Incom Rati featur

Feature 3: Credit Annuity Ratio of the Application

How many years does it take for the borrower to repay the amount he asked for the application -

In [213…
```
train['YEARS_TO_PAY'] = (train['AMT_CREDIT']/train['AMT_ANNUITY']).round()
```

In [214…
```
train[['YEARS_TO_PAY']]
```

Out[214…

	YEARS_TO_PAY
0	16.0
1	16.0
2	16.0
3	16.0
4	16.0
...	...

	YEARS_TO_PAY
1509340	14.0
1509341	14.0
1509342	14.0
1509343	14.0
1509344	14.0

1509345 rows × 1 columns

In [215…
```
np.isinf(train[['YEARS_TO_PAY']]).values.sum()
```

Out[215… 0

In [216…
```
train
```

Out[216…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 53 columns

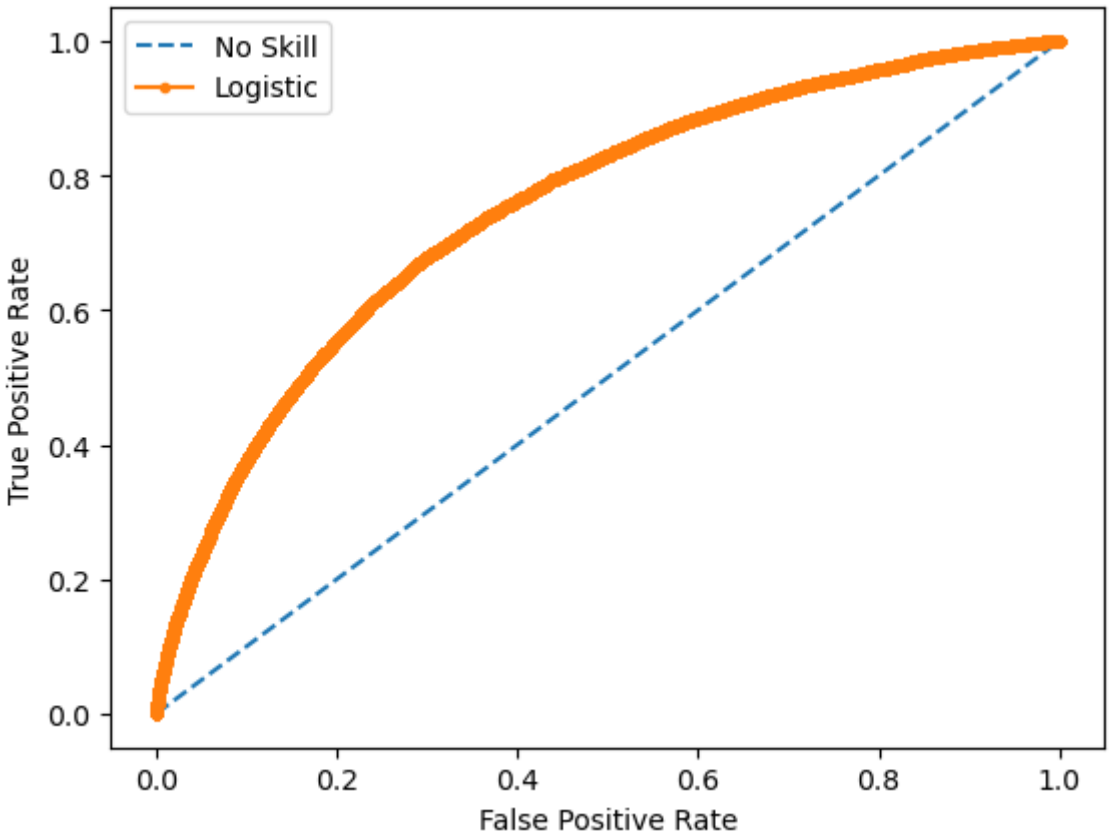
In [49]:
```
years_to_pay_model = model_logreg(train, 'Credit-Annuity Ratio of Current App
```

```
X train           shape: (965980, 99)
X validation      shape: (241496, 99)
X test            shape: (301869, 99)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	-0.714681	-0.585812	0.000407	-0.970848	-0.215580	
1	-1.062862	-0.585812	-0.191312	2.262115	1.247094	
2	1.282842	-0.585812	0.057922	-0.187606	-0.483416	
3	-0.163686	-0.585812	-0.287171	1.231743	0.630882	
4	-0.411456	-0.585812	1.150719	3.407022	2.134300	

5 rows × 222 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.751
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Featur Adde
0	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.752	0.7505	0.7496	Active loa Percentag featur
1	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7526	0.7511	0.7502	Cred Incom Rati featur
2	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7525	0.7511	0.7501	Credit Annuit Ratio c Currer Applicatio Fe.

Feature 4: Income Annuity Ratio of the Application

In [217…
```
train['INCOME_ANNUITY'] = (train['AMT_INCOME_TOTAL']/train['AMT_ANNUITY']).ro
```

In [218…
```
train[['INCOME_ANNUITY']]
```

Out[218…

	INCOME_ANNUITY
0	8.0
1	8.0

	INCOME_ANNUITY
2	8.0
3	8.0
4	8.0
...	...
1509340	3.0
1509341	3.0
1509342	3.0
1509343	3.0
1509344	3.0

1509345 rows × 1 columns

In [219…
```
train
```

Out[219…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 54 columns

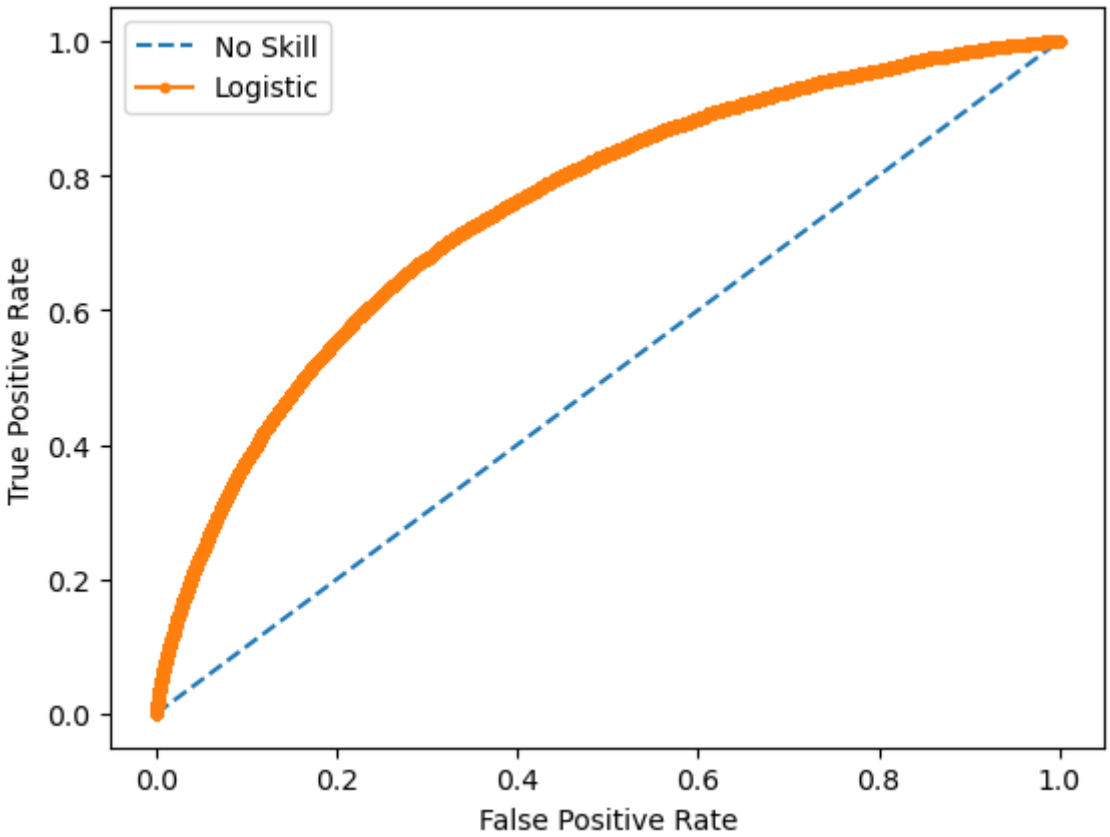
In [53]:
```
income_annuity_model = model_logreg(train, 'Income-Annuity Ratio of Current Ap
```

```
X train           shape: (965980, 100)
X validation      shape: (241496, 100)
X test            shape: (301869, 100)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	-0.714681	-0.585812	0.000407	-0.970848	-0.215580	
1	-1.062862	-0.585812	-0.191312	2.262115	1.247094	
2	1.282842	-0.585812	0.057922	-0.187606	-0.483416	
3	-0.163686	-0.585812	-0.287171	1.231743	0.630882	
4	-0.411456	-0.585812	1.150719	3.407022	2.134300	

5 rows × 223 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.751
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Featur Adde
0	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.752	0.7505	0.7496	Active loa Percentag featur
1	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7526	0.7511	0.7502	Cred Incom Rati featur
2	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7525	0.7511	0.7501	Credit Annuit Ratio c Currer Applicatio Fe.
3	Logistic Regression	HCDR	92.14%	92.15%	92.13%	0.7527	0.7513	0.7504	Income Annuit Ratio c Currer Applicatio Fe.

In [ ]:

Feature 5: Average of "Days past due" per customer

Credit card balance data

In [178…
```
credit_card = datasets['credit_card_balance']
```

In [179…
```
credit_card[['SK_ID_CURR', 'SK_ID_PREV','SK_DPD']]
```

Out[179…

	SK_ID_CURR	SK_ID_PREV	SK_DPD
0	378907	2562384	0
1	363914	2582071	0
2	371185	1740877	0
3	337855	1389973	0
4	126868	1891521	0
…	…	…	…
3840307	328243	1036507	0
3840308	347207	1714892	0
3840309	215757	1302323	0
3840310	430337	1624872	0
3840311	236760	2411345	0

3840312 rows × 3 columns

In [180…
```
credit_card['SK_DPD'].value_counts()
```

Out[180…
```
0       3686957
1         90369
8          2772
32         2340
7          1797
          ...
1520          1
1712          1
195           1
1306          1
446           1
Name: SK_DPD, Length: 917, dtype: int64
```

In [181…
```
credit_avg_grp = credit_card.groupby(by = ['SK_ID_CURR'])['SK_DPD'].mean().re
credit_card = credit_card.merge(credit_avg_grp, on = ['SK_ID_CURR'], how = 'l
```

In [182…
```
credit_card
```

Out[182…

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

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	AMT_BALANCE	AMT_CREDIT_LIMIT
3840307	1036507	328243	-9	0.000	
3840308	1714892	347207	-9	0.000	
3840309	1302323	215757	-9	275784.975	
3840310	1624872	430337	-10	0.000	
3840311	2411345	236760	-10	0.000	

3840312 rows × 24 columns

In [183…
```
credit_card['AVG_DPD'].value_counts()
```

Out[183…
```
0.000000     2264271
0.010417      103968
0.020833       64224
0.031250       43648
0.010526       39615
              ...
28.750000          4
11.000000          4
5.750000           4
6.000000           3
9.000000           2
Name: AVG_DPD, Length: 3945, dtype: int64
```

In [184…
```
credit_card['AVG_DPD'].isnull().sum()
```

Out[184… 0

In [185…
```
credit_avg_dpd = credit_card[['SK_ID_CURR', 'AVG_DPD']]
credit_avg_dpd
```

Out[185…

	SK_ID_CURR	AVG_DPD
0	378907	0.127660
1	363914	0.010417
2	371185	0.000000
3	337855	0.000000
4	126868	0.010417
…	…	…
3840307	328243	0.000000
3840308	347207	0.000000
3840309	215757	0.000000
3840310	430337	0.000000
3840311	236760	0.432432

3840312 rows × 2 columns

In [186…
```
credit_avg_dpd = credit_avg_dpd[:1509345]
```

In [187…
```
train
```

Out[187…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 101 columns

In [188…
```
import gc
gc.collect()
```

Out[188… 20

In [189…
```
train = train.merge(credit_avg_dpd, on = 'SK_ID_CURR', how = 'left')
train
```

Out[189…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
8472905	456255	0	Cash loans	F	N	
8472906	456255	0	Cash loans	F	N	
8472907	456255	0	Cash loans	F	N	
8472908	456255	0	Cash loans	F	N	
8472909	456255	0	Cash loans	F	N	

8472910 rows × 102 columns

In [190…
```
train['AVG_DPD'].isnull().sum()
```

Out[190… 1054730

In [191…
```
train['AVG_DPD'].value_counts()
```

Out[191…
```
0.000000     4209361
0.010417      210565
0.020833      122392
0.010526       87922
0.031250       83724
              ...
1.625000           3
2.923077           2
39.500000          2
9.200000           2
23.200000          1
Name: AVG_DPD, Length: 3603, dtype: int64
```

In [192…
```
train = train[:1700000]
```

In [193…
```
train
```

Out[193…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	172394	1	Cash loans	M	Y	
1699996	172394	1	Cash loans	M	Y	
1699997	172394	1	Cash loans	M	Y	
1699998	172394	1	Cash loans	M	Y	
1699999	172394	1	Cash loans	M	Y	

1700000 rows × 102 columns

In [194…
```
train['AVG_DPD'].isnull().sum()
```

Out[194… 214613

In [195…
```
train['AVG_DPD'].fillna(0, inplace = True)
```

In [196…
```
train['AVG_DPD'].value_counts()
```

Out[196…
```
0.000000    1060899
0.010417      45943
0.020833      24935
0.031250      17953
0.010526      14949
```

```
              ...
1.636364          3
3.111111          3
1.818182          3
3.166667          2
1.666667          2
Name: AVG_DPD, Length: 1216, dtype: int64
```

In [197…

```
train['AVG_DPD'].isnull().sum()
```

Out[197… 0

In [198…

```
train
```

Out[198…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	172394	1	Cash loans	M	Y	
1699996	172394	1	Cash loans	M	Y	
1699997	172394	1	Cash loans	M	Y	
1699998	172394	1	Cash loans	M	Y	
1699999	172394	1	Cash loans	M	Y	

1700000 rows × 102 columns

In [75]:

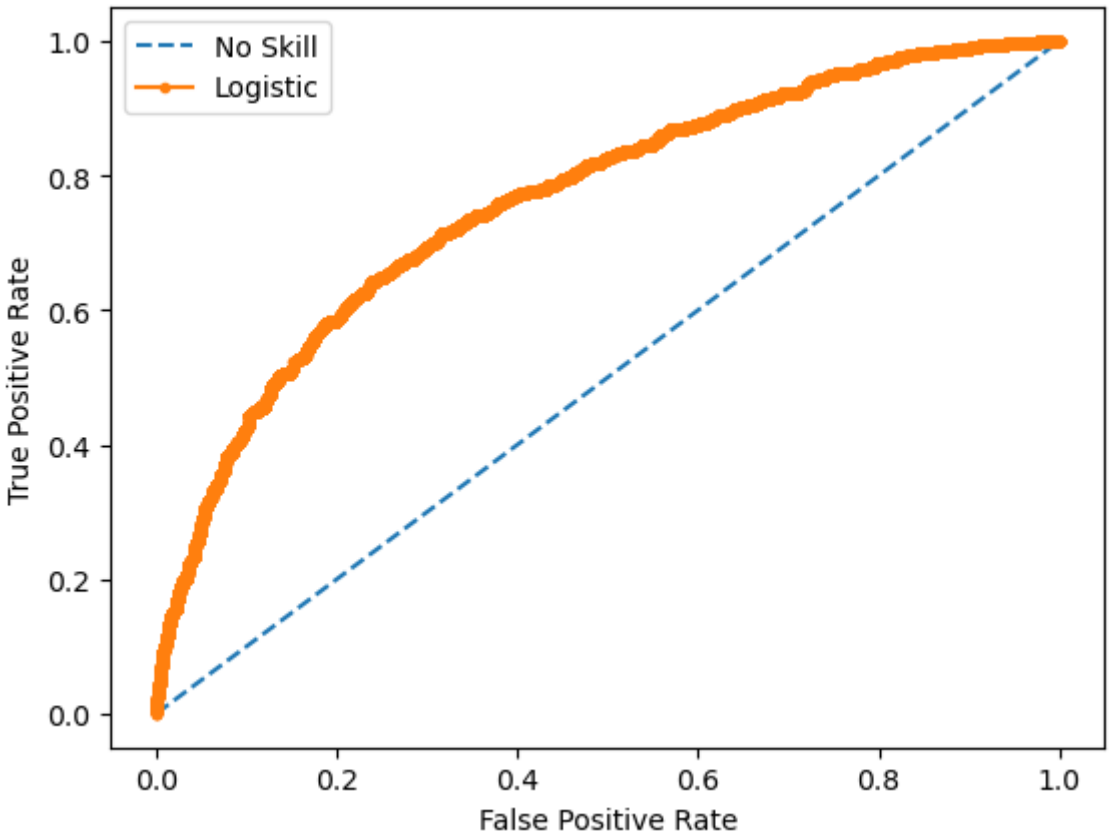
```
avg_dpd_model = model_logreg(train, 'Average DPD Feature')
```

```
X train           shape: (1088000, 101)
X validation      shape: (272000, 101)
X test            shape: (340000, 101)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	1.630563	3.585626	-0.407585	-0.095343	0.075151	
1	1.312255	-0.555794	-0.166599	0.406231	0.618199	
2	0.219138	0.824679	0.194881	-0.552245	0.477013	
3	-1.725651	0.824679	-0.287092	-0.357542	0.265558	
4	-1.193248	-0.555794	-0.166599	0.120300	0.776871	

5 rows × 225 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.763
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Featur Adde
0	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.752	0.7505	0.7496	Active loa Percentag featur
1	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7526	0.7511	0.7502	Cred Incom Rati featur
2	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7525	0.7511	0.7501	Credit Annuit Ratio c Currer Applicatio Fe.
3	Logistic Regression	HCDR	92.14%	92.15%	92.13%	0.7527	0.7513	0.7504	Income Annuit Ratio c Currer Applicatio Fe.
4	Logistic Regression	HCDR	92.10%	92.02%	92.08%	0.7599	0.7628	0.7625	Averag DPI Featur

In [220…

```
train
```

Out[220…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 54 columns

In [221…
```
train_features = train
```

In [144…
```
train_features = train_features.loc[:, ~train_features.columns.str.endswith("
train_features = train_features.loc[:, ~train_features.columns.str.endswith("
train_features = train_features.loc[:, ~train_features.columns.str.endswith("
```

In [222…
```
train_features
```

Out[222…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509340	456255	0	Cash loans	F	N	
1509341	456255	0	Cash loans	F	N	
1509342	456255	0	Cash loans	F	N	
1509343	456255	0	Cash loans	F	N	
1509344	456255	0	Cash loans	F	N	

1509345 rows × 54 columns

In [223…
```
train_features['TARGET'].value_counts()
```

Out[223…
```
0    1390368
1     118977
Name: TARGET, dtype: int64
```

In [224…
```
train_zero_fe = train_features[train_features['TARGET'] == 0][:300000]
```

```
train_zero_fe
```

Out[224…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
8	100003	0	Cash loans	F	N	
9	100003	0	Cash loans	F	N	
10	100003	0	Cash loans	F	N	
11	100003	0	Cash loans	F	N	
12	100004	0	Revolving loans	M	Y	
...	...	...	...	...	...	
326055	177024	0	Cash loans	F	N	
326056	177024	0	Cash loans	F	N	
326057	177025	0	Cash loans	F	Y	
326058	177025	0	Cash loans	F	Y	
326059	177025	0	Cash loans	F	Y	

300000 rows × 54 columns

In [225…

```
train_one_fe = train_features[train_features['TARGET'] == 1]
train_one_fe
```

Out[225…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1509183	456225	1	Cash loans	M	N	
1509184	456225	1	Cash loans	M	N	
1509185	456225	1	Cash loans	M	N	
1509215	456233	1	Cash loans	F	N	
1509333	456254	1	Cash loans	F	N	

118977 rows × 54 columns

In [226…

```
train_features_fe = pd.concat([train_zero_fe, train_one_fe], axis = 0, ignore
train_features_fe
```

Out[226…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
0	100003	0	Cash loans	F	N	
1	100003	0	Cash loans	F	N	
2	100003	0	Cash loans	F	N	

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
3	100003	0	Cash loans	F	N	
4	100004	0	Revolving loans	M	Y	
...	...	...	...	...	...	
418972	456225	1	Cash loans	M	N	
418973	456225	1	Cash loans	M	N	
418974	456225	1	Cash loans	M	N	
418975	456233	1	Cash loans	F	N	
418976	456254	1	Cash loans	F	N	

418977 rows × 54 columns

In [151…
```
train_features_fe.columns
```

Out[151…
```
Index(['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',
       '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',
       'ACTIVE_LOANS_PERCENTAGE', 'CREDIT_INCOME_RATIO', 'YEARS_TO_PAY',
       'INCOME_ANNUITY', 'AVG_DPD'],
      dtype='object')
```

In [150…
```
train_features_fe.drop(['OVERDUE_DEBT_RATIO'], axis = 1, inplace = True)
```

In [227…
```
train_features_fe.drop(['SK_ID_CURR'], axis = 1, inplace = True)
```

In [169…
```
train_features_fe.drop(['AVG_DPD'], axis = 1, inplace = True)
```

In [228…
```
after_balancing_model = model_logreg(train_features_fe, 'After balancing data
```

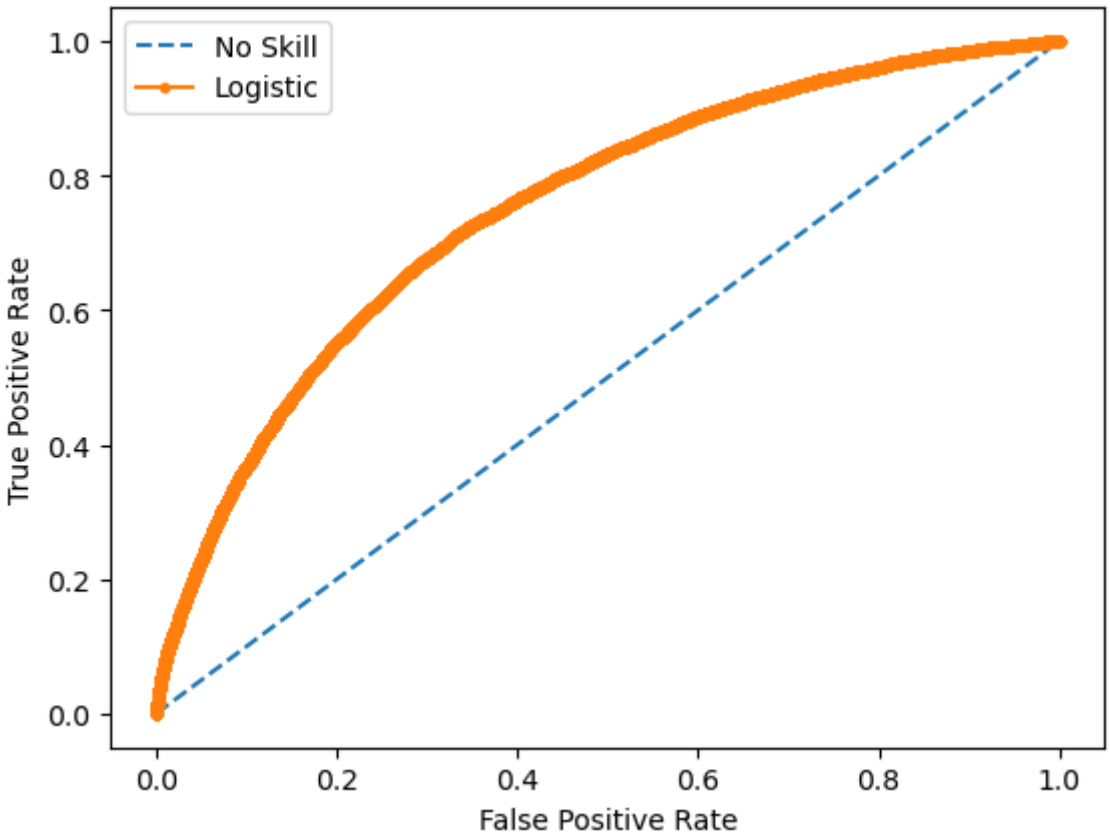
```
X train           shape: (268144, 52)
X validation      shape: (67037, 52)
X test            shape: (83796, 52)
```

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	F
0	0.766147	0.189471	-0.177851	-0.696794	-0.266415	
1	-0.593431	-0.393030	-0.641324	-0.714714	-0.525290	
2	-0.593431	-0.238303	-0.242989	-0.377809	-0.241761	

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	F
3	-0.593431	-0.356624	-1.342220	-1.397321	-1.289585	
4	-0.593431	-0.083576	-0.034710	-0.050353	-0.278743	

5 rows × 164 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.751
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Feature Added
0	Logistic Regression	HCDR	94.18%	94.12%	94.15%	0.9709	0.97	0.9708	After balancing data
1	Logistic Regression	HCDR	93.61%	93.56%	93.55%	0.9689	0.9682	0.9688	After balancing data
2	Logistic Regression	HCDR	75.18%	75.00%	74.95%	0.7525	0.7506	0.752	After balancing data

In [170…

```
avg_dpd_model_1 = model_logreg(train_features_fe, 'After balancing data')
```

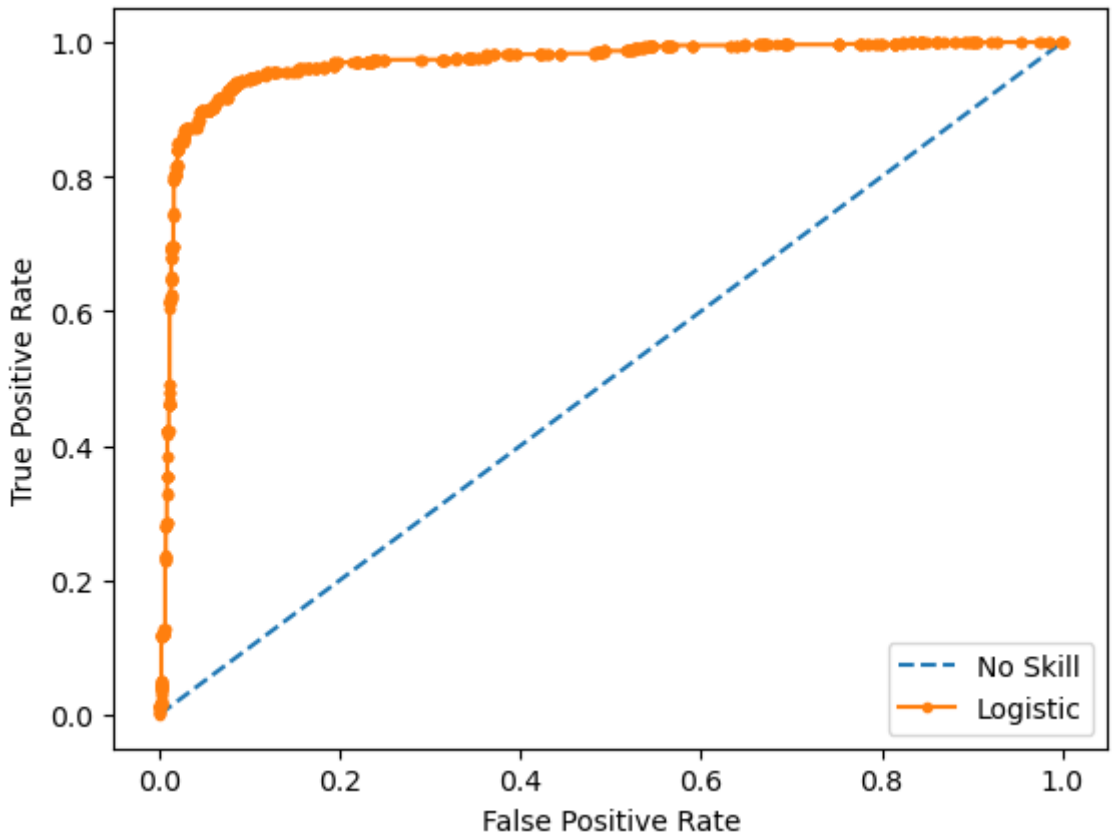
```
X train           shape: (269028, 52)
X validation      shape: (67257, 52)
X test            shape: (84072, 52)
```

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	F
0	2.001085	-0.879924	-0.120733	-0.350369	-0.264956	
1	-0.597219	-0.230093	-0.213129	-0.133947	-0.025806	

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	F
2	0.701933	1.502791	-0.105438	-0.050035	-0.250888	
3	0.701933	-0.533347	0.571544	1.298998	0.677577	
4	-0.597219	0.636349	0.598449	0.283711	0.396224	

5 rows × 152 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.968
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Feature Added
0	Logistic Regression	HCDR	94.18%	94.12%	94.15%	0.9709	0.97	0.9708	After balancing data
1	Logistic Regression	HCDR	93.61%	93.56%	93.55%	0.9689	0.9682	0.9688	After balancing data

In [155…

```
avg_dpd_model_1 = model_logreg(train_features_fe, 'After balancing data')
```

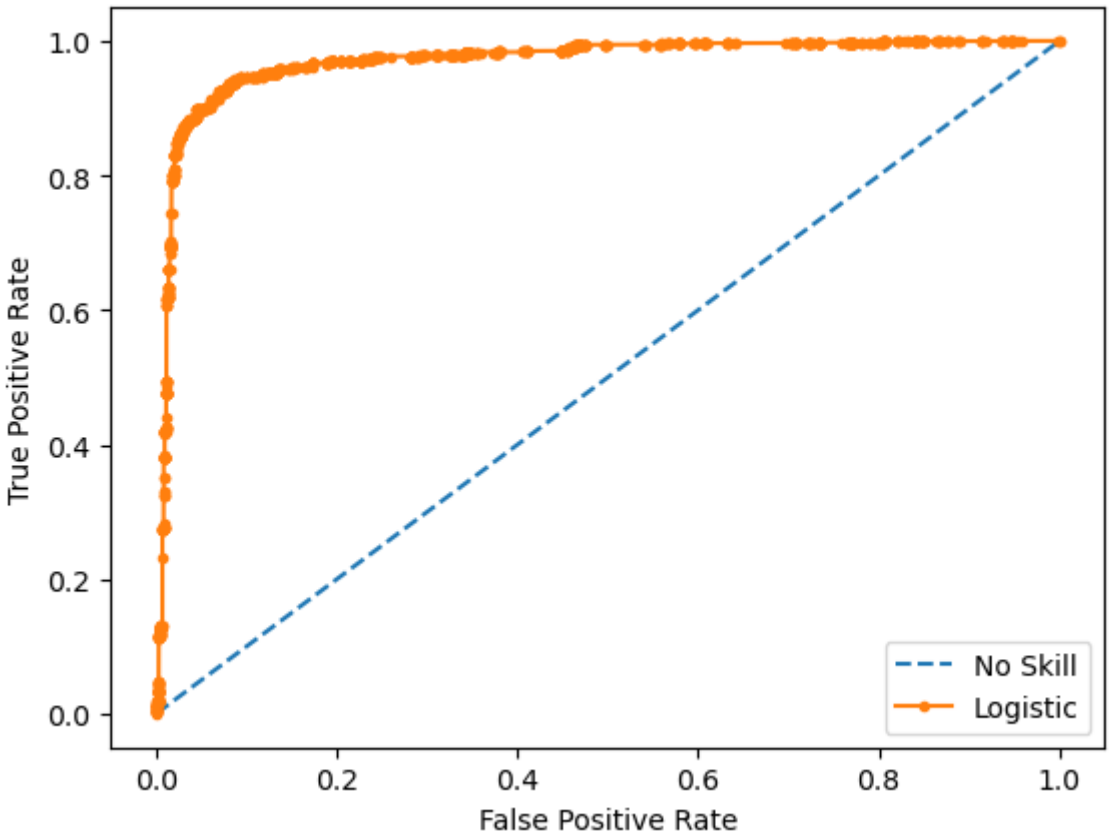
```
X train           shape: (269028, 53)
X validation      shape: (67257, 53)
X test            shape: (84072, 53)
```

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	F
0	2.001085	-0.879924	-0.120733	-0.350369	-0.264956	
1	-0.597219	-0.230093	-0.213129	-0.133947	-0.025806	
2	0.701933	1.502791	-0.105438	-0.050035	-0.250888	

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	F
3	0.701933	-0.533347	0.571544	1.298998	0.677577	
4	-0.597219	0.636349	0.598449	0.283711	0.396224	

5 rows × 153 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.970
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Feature Added
0	Logistic Regression	HCDR	94.18%	94.12%	94.15%	0.9709	0.97	0.9708	After balancing data

Feature 6: Debt Overdue per Customer

In [239…

```
bureau_data
```

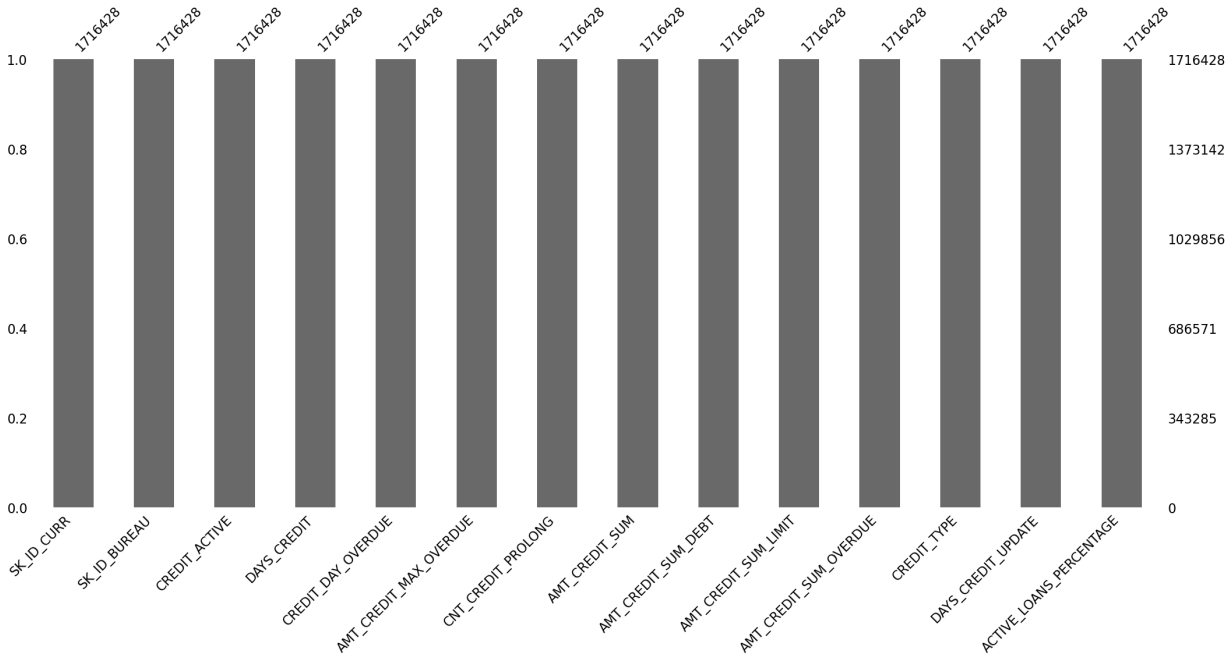
Out[239…

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	DAYS_CREDIT	CREDIT_DAY_OVERDUI
0	215354	5714462	Closed	-497	(
1	215354	5714463	Active	-208	(
2	215354	5714464	Active	-203	(
3	215354	5714465	Active	-203	(
4	215354	5714466	Active	-629	(

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	DAYS_CREDIT	CREDIT_DAY_OVERDUI
...	...	...	...	...	..
1716423	259355	5057750	Active	-44	(
1716424	100044	5057754	Closed	-2648	(
1716425	100044	5057762	Closed	-1809	(
1716426	246829	5057770	Closed	-1878	(
1716427	246829	5057778	Closed	-463	(

1716428 rows × 14 columns

In [82]:
```
msno.bar(bureau_data)
plt.show()
```



In [240…
```
total_debt_grpby = bureau_data[['SK_ID_CURR', 'AMT_CREDIT_SUM_DEBT']].groupby
total_overdue_grpby = bureau_data[['SK_ID_CURR', 'AMT_CREDIT_SUM_OVERDUE']].g
```

In [241…
```
bureau_data = bureau_data.merge(total_debt_grpby, on = ['SK_ID_CURR'], how =
bureau_data = bureau_data.merge(total_overdue_grpby, on = ['SK_ID_CURR'], how
```

In [242…
```
del total_debt_grpby
del total_overdue_grpby
```

In [243…
```
bureau_data[['SK_ID_CURR', 'TOTAL_CUSTOMER_DEBT','TOTAL_CUSTOMER_OVERDUE']]
```

Out[243…

	SK_ID_CURR	TOTAL_CUSTOMER_DEBT	TOTAL_CUSTOMER_OVERDUE
0	215354	4141399.680	0.0
1	215354	4141399.680	0.0

	SK_ID_CURR	TOTAL_CUSTOMER_DEBT	TOTAL_CUSTOMER_OVERDUE
2	215354	4141399.680	0.0
3	215354	4141399.680	0.0
4	215354	4141399.680	0.0
...	...	...	...
1716423	259355	22500.000	0.0
1716424	100044	1523334.600	0.0
1716425	100044	1523334.600	0.0
1716426	246829	237417.525	0.0
1716427	246829	237417.525	0.0

1716428 rows × 3 columns

In [244…
```
bureau_data['TOTAL_CUSTOMER_OVERDUE'].value_counts()
```

Out[244…
```
0.000          1686808
4.500             2152
9.000              755
13.500             642
22.500             498
                  ...
402.165              1
1361214.000          1
1617403.500          1
18920.250            1
20263.500            1
Name: TOTAL_CUSTOMER_OVERDUE, Length: 1369, dtype: int64
```

In [245…
```
bureau_data['TOTAL_CUSTOMER_DEBT'].value_counts()
```

Out[245…
```
0.00           133334
225000.00        2392
450000.00        2009
90000.00         1245
675000.00        1182
                 ...
11614.50            1
87561.00            1
187132.50           1
1871731.62          1
175054.50           1
Name: TOTAL_CUSTOMER_DEBT, Length: 201075, dtype: int64
```

In [246…
```
bureau_data['OVERDUE_DEBT_RATIO'] = bureau_data['TOTAL_CUSTOMER_OVERDUE']/bur
```

In [247…
```
np.isinf(bureau_data[['OVERDUE_DEBT_RATIO']]).values.sum()
```

Out[247…
```
418
```

In [248…
```
index_to_drop = bureau_data.loc[bureau_data['OVERDUE_DEBT_RATIO'] == np.inf]
```

In [249…
```
len(index_to_drop)
```

Out[249… 418

In [250…
```
bureau_data.drop(index_to_drop.index, inplace = True)
```

In [251…
```
np.isinf(bureau_data[['OVERDUE_DEBT_RATIO']]).values.sum()
```

Out[251… 0

In [253…
```
bureau_data['OVERDUE_DEBT_RATIO'].value_counts()
```

Out[253…
```
0.000000    1553892
1.000000        160
0.000030         61
0.014851         51
0.000059         47
             ...
0.000233          1
0.344647          1
0.021647          1
0.080689          1
0.001196          1
Name: OVERDUE_DEBT_RATIO, Length: 3630, dtype: int64
```

In [254…
```
debt_ovd = bureau_data[['SK_ID_CURR','OVERDUE_DEBT_RATIO']]
debt_ovd
```

Out[254…

	SK_ID_CURR	OVERDUE_DEBT_RATIO
0	215354	0.0
1	215354	0.0
2	215354	0.0
3	215354	0.0
4	215354	0.0
...	...	...
1716423	259355	0.0
1716424	100044	0.0
1716425	100044	0.0
1716426	246829	0.0
1716427	246829	0.0

1716010 rows × 2 columns

In [257…
```
train
```

Out[257…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	172394	1	Cash loans	M	Y	
1699996	172394	1	Cash loans	M	Y	
1699997	172394	1	Cash loans	M	Y	
1699998	172394	1	Cash loans	M	Y	
1699999	172394	1	Cash loans	M	Y	

1700000 rows × 102 columns

In [258…
```
debt_ovd = debt_ovd[:1500000]
```

In [259…
```
train = train.merge(debt_ovd, on = 'SK_ID_CURR', how = 'left')
```

In [260…
```
train = train[:1700000]
train
```

Out[260…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	108558	0	Cash loans	F	N	
1699996	108558	0	Cash loans	F	N	
1699997	108558	0	Cash loans	F	N	
1699998	108558	0	Cash loans	F	N	
1699999	108558	0	Cash loans	F	N	

1700000 rows × 103 columns

In [102…
```
train['OVERDUE_DEBT_RATIO'].value_counts()
```

Out[102…
```
0.000000     1579821
0.000188        8064
0.000342        4860
0.000290        3584
0.000137        2400
              ...
0.000027           1
```

```
0.000286            1
91.000000           1
0.013688            1
0.000699            1
Name: OVERDUE_DEBT_RATIO, Length: 79, dtype: int64
```

In [103…

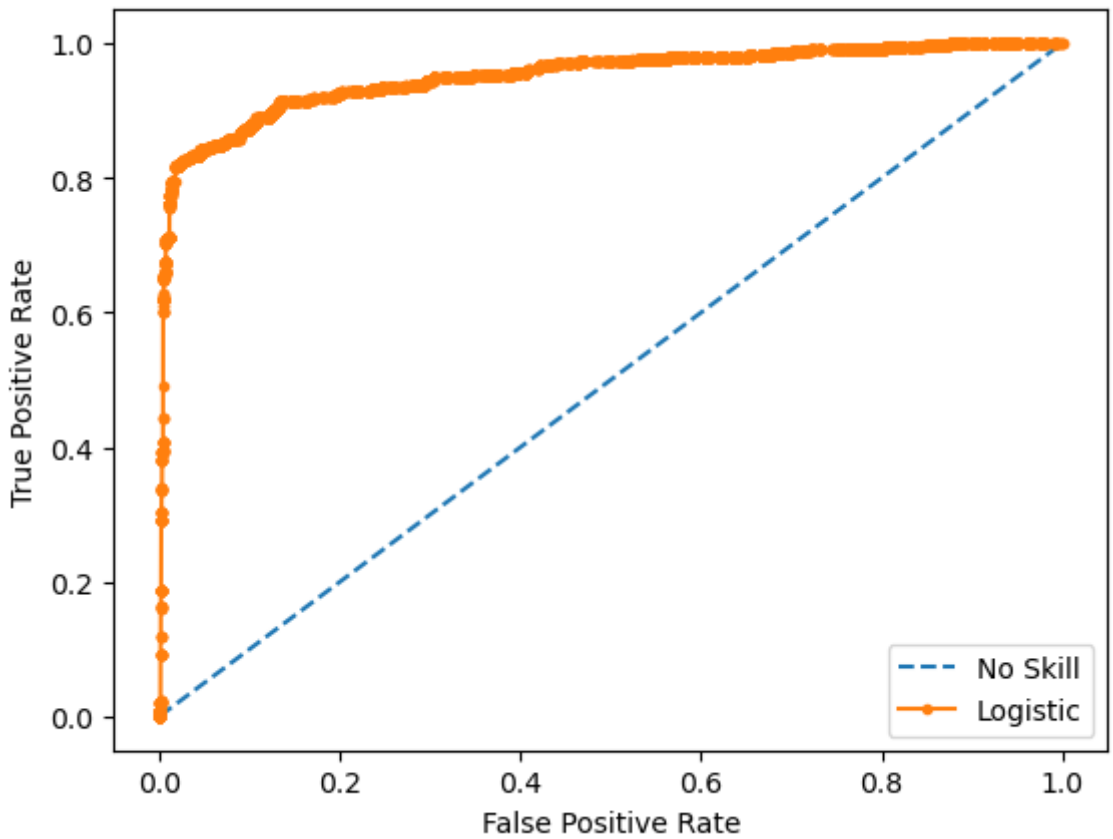
```
debt_ovd_model = model_logreg(train,'Debt Overdue of each Customer Feature')
```

```
X train           shape: (1088000, 102)
X validation      shape: (272000, 102)
X test            shape: (340000, 102)
```

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GC
0	1.634258	0.799427	-0.223311	-0.568658	-0.872830	
1	1.311380	-0.568021	-1.053014	-0.661751	-0.951324	
2	0.228227	0.799427	-0.223311	0.838082	0.035543	
3	-1.667291	2.166875	-0.223311	-0.568658	-0.600944	
4	-1.208422	-0.568021	1.021244	2.088601	0.864284	

5 rows × 221 columns

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.951
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Feature Added
0	Logistic Regression	HCDR	97.04%	97.03%	97.00%	0.9521	0.9505	0.9515	Debt Overdue of each Customer Feature

We believe that this sudden spike of accuracy is due to overfitting and thus we will keep the last test accuracy i.e 92.13% as our result from feature engineering

Random Forest Classifier (Ensemble method)

Feature Importances on ensemble method

In [116…

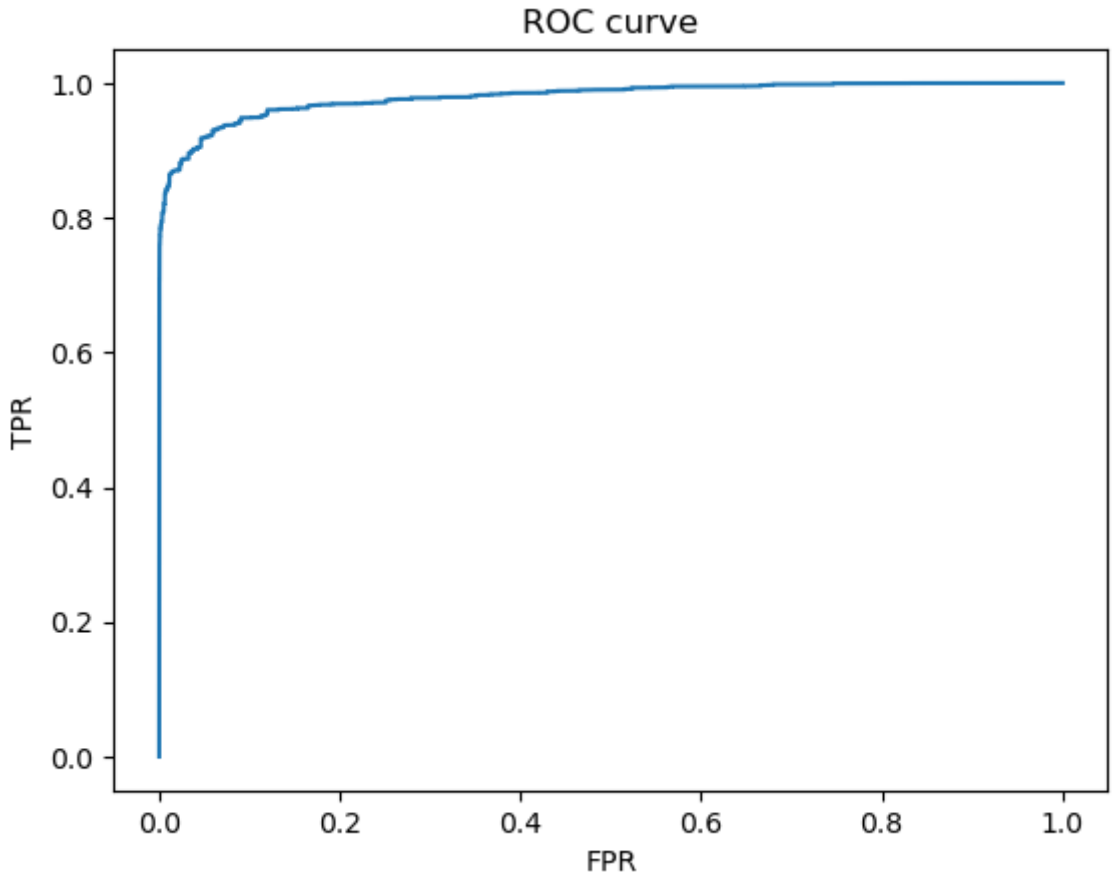
```
def model_rf(train):

    X = train.drop(['TARGET'], axis = 1)
    y = train["TARGET"]

    # Split the provided training data into training and validationa and test
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
    X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, t
    print(f"X train           shape: {X_train.shape}")
    print(f"X validation      shape: {X_valid.shape}")
    print(f"X test            shape: {X_test.shape}")

    numerical_features = X_train.select_dtypes(include = ['int64', 'float64']
    categorical_features = X_train.select_dtypes(include = ['object', 'bool']
    #print(f"\nNumerical features : {list(numerical_features)}")
    #print(f"\nCategorical features : {list(categorical_features)}")

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

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

    data_pipeline = ColumnTransformer([
        ("num_pipeline", num_pipeline, numerical_features),
        ("cat_pipeline", cat_pipeline, categorical_features)], remainder = 'd


    RF = RandomForestClassifier(random_state = 42,n_estimators=20, criterion=

    data_pipeline_rf = make_pipeline(data_pipeline, RF)

    data_pipeline_rf.fit(X_train, y_train)

    train_acc = data_pipeline_rf.score(X_train, y_train)
    validAcc  = data_pipeline_rf.score(X_valid, y_valid)
    testAcc   = data_pipeline_rf.score(X_test, y_test)

    predictions = data_pipeline_rf.predict_proba(X_test)
    print ("Score",roc_auc_score(y_test, predictions[:,1]))


    fpr, tpr, _ = roc_curve(y_test, predictions[:,1])

    plt.clf()
    plt.plot(fpr, tpr)
    plt.xlabel('FPR')
    plt.ylabel('TPR')
```

```
    plt.title('ROC curve')
    plt.show()


    train_roc = roc_auc_score(y_train, data_pipeline_rf.predict_proba(X_train
    test_roc = roc_auc_score(y_test, data_pipeline_rf.predict_proba(X_test)[:
    valid_roc = roc_auc_score(y_valid, data_pipeline_rf.predict_proba(X_valid

    results.loc[len(results)] = ["Random Forest","HCDR",f"{train_acc*100:8.2f
                                 f"{validAcc*100:8.2f}%", f"{testAcc*100:8.2f

    display(results)

    return data_pipeline_rf,RF
```

In [117…

```
debt_ovd_model_pipe, rf = model_rf(train)
```

```
X train           shape: (1088000, 102)
X validation      shape: (272000, 102)
X test            shape: (340000, 102)
Score 0.9796172080754798
```



	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Feature Added
0	Logistic Regression	HCDR	97.04%	97.03%	97.00%	0.9521	0.9505	0.9515	Debt Overdue of each Customer Feature
1	Random Forest	HCDR	96.77%	96.78%	96.76%	0.9803	0.9796	0.9786	Ensemble method

In [162…

```
train
```

Out[162…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	108558	0	Cash loans	F	N	
1699996	108558	0	Cash loans	F	N	
1699997	108558	0	Cash loans	F	N	
1699998	108558	0	Cash loans	F	N	
1699999	108558	0	Cash loans	F	N	

1700000 rows × 103 columns

In [104…

```
train_columns = ['ACTIVE_LOANS_PERCENTAGE','CREDIT_INCOME_RATIO','YEARS_TO_PA
```

In [165…

```
features = train_columns
importances = rf.feature_importances_
indices = np.argsort(importances[-6:])
```

In [163…

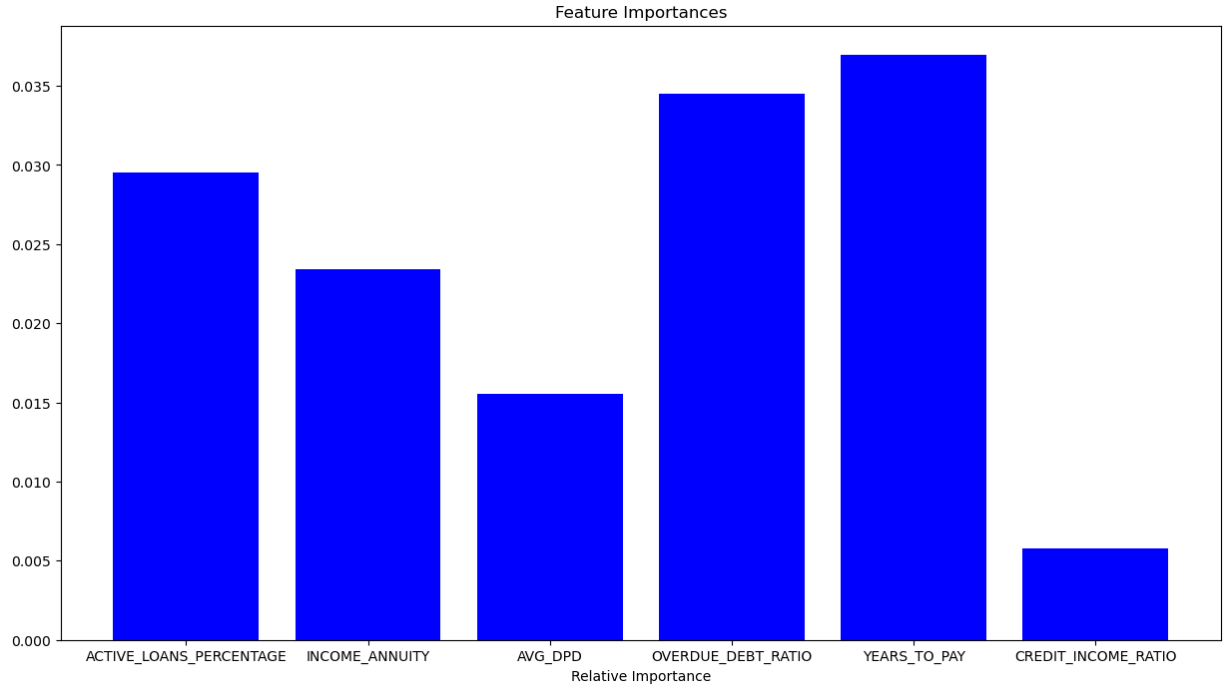
```
importances[-6:]
```

Out[163…

```
array([0.00000000e+00, 2.55603290e-04, 6.82355186e-05, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00])
```

In [176…

```
plt.figure(figsize = (15, 8))
plt.title('Feature Importances')
plt.bar(range(len(indices)), importances[indices], color='b', align='center')
plt.xticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show();
```



As per the Feature Importances plot we conclude that Credit Annuity Ratio of the Application Feature(Feature no 3) is the most important feature

Hyperparameter Tuning

In [299…
```
train = pd.read_pickle('train2.pkl')
```

In [300…
```
train
```

Out[300…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	172394	1	Cash loans	M	Y	
1699996	172394	1	Cash loans	M	Y	
1699997	172394	1	Cash loans	M	Y	
1699998	172394	1	Cash loans	M	Y	
1699999	172394	1	Cash loans	M	Y	

1700000 rows × 102 columns

In [262…
```
train.to_pickle('train3.pkl')
```

In [301…
```
X = train.drop(['TARGET'], axis = 1)
y = train["TARGET"]

# Split the provided training data into training and validationa and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ran
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_
print(f"X train           shape: {X_train.shape}")
print(f"X validation      shape: {X_valid.shape}")
print(f"X test            shape: {X_test.shape}")
```

```
X train           shape: (1088000, 101)
X validation      shape: (272000, 101)
X test            shape: (340000, 101)
```

In [302…
```
numerical_features = X_train.select_dtypes(include = ['int64', 'float64']).co
categorical_features = X_train.select_dtypes(include = ['object', 'bool']).co

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

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

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

In [303…
```
X_train_transformed = data_pipeline.fit_transform(X_train)

column_names = list(numerical_features)  + \
                   list(data_pipeline.transformers_[1][1].named_steps["ohe"].

X_train_transformed_df = pd.DataFrame(X_train_transformed,  columns=column_na
```

In [304…
```
X_train_transformed_df
```

Out[304…

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	A
0	1.630563	3.585626	-0.407585	-0.095343	0.075151	
1	1.312255	-0.555794	-0.166599	0.406231	0.618199	
2	0.219138	0.824679	0.194881	-0.552245	0.477013	
3	-1.725651	0.824679	-0.287092	-0.357542	0.265558	
4	-1.193248	-0.555794	-0.166599	0.120300	0.776871	
…	…	…	…	…	…	
1087995	-0.306728	2.205153	-0.166599	-0.552245	-0.462392	
1087996	1.043074	-0.555794	0.797347	0.096633	0.328379	
1087997	1.186413	-0.555794	0.194881	-0.011405	-0.190059	
1087998	-1.327695	-0.555794	-0.431684	-0.882114	-1.128169	
1087999	1.666854	0.824679	-0.648572	0.096763	-0.566663	

1088000 rows × 225 columns

In [305…
```
X_test_transformed = data_pipeline.fit_transform(X_test)
column_names = list(numerical_features)  + \
                   list(data_pipeline.transformers_[1][1].named_steps["ohe"].

X_test_transformed_df = pd.DataFrame(X_test_transformed,  columns=column_name
```

In [306…
```
X_test_transformed_df
```

Out[306…

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	A
0	-0.447151	-0.556897	0.869128	1.011823	1.281185	
1	-0.391754	-0.556897	-0.030261	-0.676659	0.929630	
2	0.329466	-0.556897	0.434424	1.949191	1.178944	
3	-1.330138	-0.556897	0.239556	-0.012484	0.404555	
4	1.535746	-0.556897	-0.255108	-1.264610	-0.998764	
…	…	…	…	…	…	
339995	0.036900	-0.556897	-0.180159	0.801808	0.337469	
339996	0.655356	-0.556897	0.569332	0.865105	0.106539	
339997	1.709535	-0.556897	-0.434986	-0.558115	-0.428212	
339998	1.169414	-0.556897	-0.434986	-0.210165	0.238130	
339999	1.079105	0.824931	0.569332	1.606087	0.754175	

340000 rows × 222 columns

In [307…
```
set(X_train_transformed_df.columns).difference(set(X_test_transformed_df.colu
```

Out[307…
```
{'NAME_FAMILY_STATUS_Unknown',
 'NAME_INCOME_TYPE_Businessman',
 'NAME_INCOME_TYPE_Maternity leave'}
```

In [308…
```
X_test_transformed_df['NAME_FAMILY_STATUS_Unknown'] = 0
X_test_transformed_df['NAME_INCOME_TYPE_Businessman'] = 0
X_test_transformed_df['NAME_INCOME_TYPE_Maternity leave'] = 0
```

In [309…
```
X_train_transformed_df.shape
```

Out[309…
```
(1088000, 225)
```

In [310…
```
X_test_transformed_df.shape
```

Out[310…
```
(340000, 225)
```

In [311…
```
X_test_transformed = X_test_transformed_df.to_numpy()
```

In [312…
```
X_test_transformed.shape
```

Out[312… (340000, 225)

Hyperparameter tuning for logistic regression

In [313…
```
param_grid_lr = {
    'C': [10**x for x in range(-3,4)],
    'penalty': ['l1','l2']
}
```

In [317…
```
grid_search_lr = GridSearchCV(LogisticRegression(), param_grid = param_grid_l
```

In [318…
```
grid_search_model1 = grid_search_lr.fit(X_train_transformed, y_train)
```

Best parameters for Logistic Regression

In [319…
```
grid_search_lr.best_params_
```

Out[319… {'C': 100, 'penalty': 'l2'}

In [235…
```
grid_search_lr.best_estimator_.fit(X_train_transformed, y_train)
```

Out[235… LogisticRegression(C=100)

In [279…
```
best_train_accuracy = grid_search_lr.best_estimator_.score(X_train_transforme
best_train_accuracy*100
```

Out[279… 97.09981617647058

In [280…
```
best_test_accuracy = grid_search_lr.best_estimator_.score(X_test_transformed,
best_test_accuracy*100
```

Out[280… 92.4614705882353

After performing Hyperparameter tuning for logistic regression we are getting an improved test accuracy of 92.46%.

Hyperparameter tuning for random forest classifier

In [49]:
```
param_grid = {
    'n_estimators': [80, 100,120],
    'max_depth' : [3, 4],
    'criterion' :['gini','entropy']
}
```

In [50]:
```
grid_search = GridSearchCV(RandomForestClassifier(), param_grid = param_grid,
```

In [52]:
```
grid_search.fit(X_train_transformed, y_train)
```

Out[52]:
```
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'criterion': ['gini', 'entropy'], 'max_depth': [3,
4],
                         'n_estimators': [80, 100, 120]},
             scoring='accuracy')
```

Best parameters for Random Forest Classifier

In [53]:
```
grid_search.best_params_
```

Out[53]:
```
{'criterion': 'gini', 'max_depth': 4, 'n_estimators': 80}
```

In [55]:
```
grid_search.best_estimator_.fit(X_train_transformed, y_train)
```

Out[55]:
```
RandomForestClassifier(max_depth=4, n_estimators=80)
```

In [89]:
```
best_train_accuracy = grid_search.best_estimator_.score(X_train_transformed, 
```

In [90]:
```
best_train_accuracy*100
```

Out[90]:
```
94.196875
```

In [100…
```
best_test_accuracy = grid_search.best_estimator_.score(X_test_transformed, y_
```

In [101…
```
best_test_accuracy*100
```

Out[101…
```
92.975
```

After performing Hyperparameter tuning for random forest classifier we are getting an improved test accuracy of 92.975%.

Neural Network Implementation (Phase 3)

In [244…
```
import torch
import torch.nn as nn
import torch.optim
import torch.nn.functional as F
from torch.utils.data import DataLoader
from tensorflow.keras.callbacks import TensorBoard
```

In [448…
```
import torchvision
from torch.utils.tensorboard import SummaryWriter
writer = SummaryWriter("runs/")
```

In [245…
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

In [246…
```
train = datasets['application_train']
```

In [247…
```
train
```

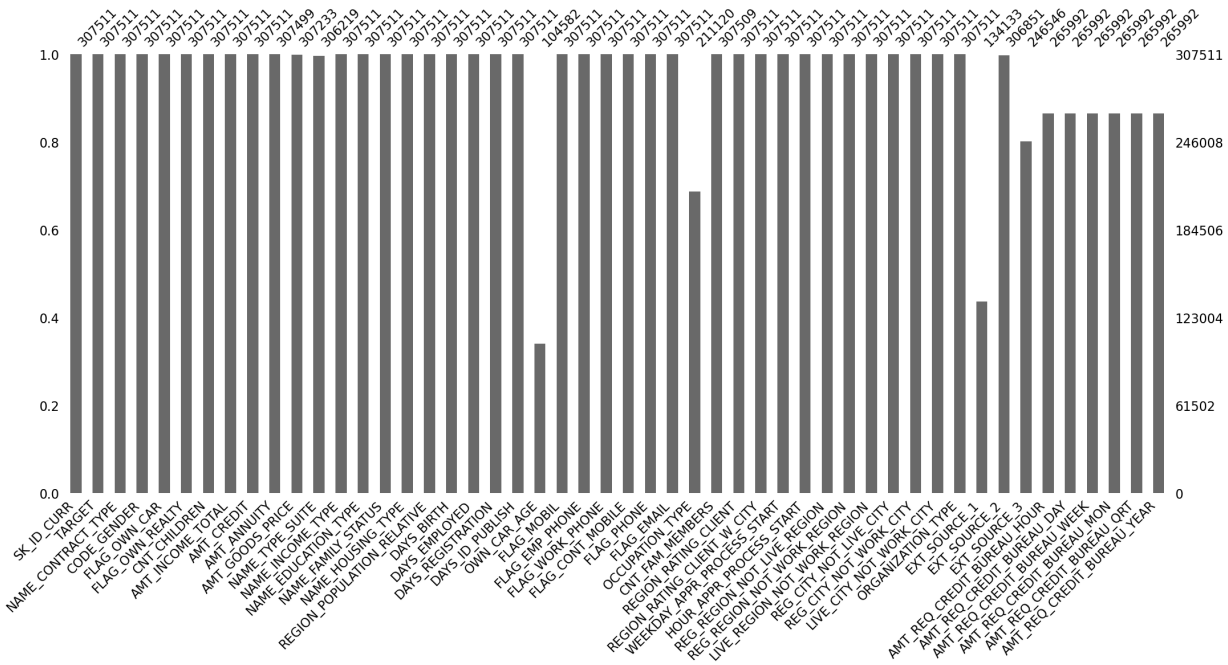
Out[247…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	
...	...	...	...	...	...	
307506	456251	0	Cash loans	M	N	
307507	456252	0	Cash loans	F	N	
307508	456253	0	Cash loans	F	N	
307509	456254	1	Cash loans	F	N	
307510	456255	0	Cash loans	F	N	

307511 rows × 117 columns

In [249…
```
train.drop(['DAYS_LAST_PHONE_CHANGE','OBS_30_CNT_SOCIAL_CIRCLE','OBS_60_CNT_S
train = train.loc[:, ~train.columns.str.startswith("FLAG_DOCUMENT_")]
train = train.loc[:, ~train.columns.str.endswith("MODE")]
train = train.loc[:, ~train.columns.str.endswith("MEDI")]
train = train.loc[:, ~train.columns.str.endswith("AVG")]
```

In [250…
```
import missingno as msno
msno.bar(train)
plt.show()
```



In [251…
```
train
```

Out[251…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	
...	...	...	...	...	...	
307506	456251	0	Cash loans	M	N	
307507	456252	0	Cash loans	F	N	
307508	456253	0	Cash loans	F	N	
307509	456254	1	Cash loans	F	N	
307510	456255	0	Cash loans	F	N	

307511 rows × 50 columns

In [252…

```
numerical_features = train.select_dtypes(include = ['int64', 'float64']).colu
categorical_features = train.select_dtypes(include = ['object', 'bool']).colu
```

In [253…

```
print(f"\nNumerical features : {list(numerical_features)}")
print(f"\nCategorical features : {list(categorical_features)}")
```

```
Numerical features : ['SK_ID_CURR', 'TARGET', 'CNT_CHILDREN', 'AMT_INCOME_TOTA
L', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIV
E', 'DAYS_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OW
N_CAR_AGE', 'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBI
LE', 'FLAG_PHONE', 'FLAG_EMAIL', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'R
EGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_R
EGION', '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', 'EXT_SOU
RCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_3', 'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ
_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MO
N', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR']

Categorical features : ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYP
E', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE', 'WEEKDAY_APP
R_PROCESS_START', 'ORGANIZATION_TYPE']
```

In [254…

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

```
Most Positive Correlations:
 OWN_CAR_AGE                  0.037612
DAYS_REGISTRATION            0.041975
REG_CITY_NOT_LIVE_CITY       0.044395
FLAG_EMP_PHONE               0.045982
REG_CITY_NOT_WORK_CITY       0.050994
DAYS_ID_PUBLISH              0.051457
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
AMT_GOODS_PRICE               -0.039645
REGION_POPULATION_RELATIVE    -0.037227
AMT_CREDIT                    -0.030369
HOUR_APPR_PROCESS_START       -0.024166
FLAG_PHONE                    -0.023806
AMT_ANNUITY                   -0.012817
Name: TARGET, dtype: float64
```

In [255…

```
correlations = pd.DataFrame(correlations, columns = ['TARGET'])
correlations
```

Out[255…

	TARGET
EXT_SOURCE_3	-0.178919
EXT_SOURCE_2	-0.160472
EXT_SOURCE_1	-0.155317
DAYS_EMPLOYED	-0.044932
AMT_GOODS_PRICE	-0.039645
REGION_POPULATION_RELATIVE	-0.037227
AMT_CREDIT	-0.030369
HOUR_APPR_PROCESS_START	-0.024166
FLAG_PHONE	-0.023806
AMT_ANNUITY	-0.012817
AMT_REQ_CREDIT_BUREAU_MON	-0.012462
AMT_INCOME_TOTAL	-0.003982
SK_ID_CURR	-0.002108
AMT_REQ_CREDIT_BUREAU_QRT	-0.002022
FLAG_EMAIL	-0.001758
FLAG_CONT_MOBILE	0.000370
FLAG_MOBIL	0.000534
AMT_REQ_CREDIT_BUREAU_WEEK	0.000788
AMT_REQ_CREDIT_BUREAU_HOUR	0.000930
AMT_REQ_CREDIT_BUREAU_DAY	0.002704
LIVE_REGION_NOT_WORK_REGION	0.002819
REG_REGION_NOT_LIVE_REGION	0.005576
REG_REGION_NOT_WORK_REGION	0.006942
CNT_FAM_MEMBERS	0.009308
CNT_CHILDREN	0.019187
AMT_REQ_CREDIT_BUREAU_YEAR	0.019930
FLAG_WORK_PHONE	0.028524
LIVE_CITY_NOT_WORK_CITY	0.032518

	TARGET
OWN_CAR_AGE	0.037612
DAYS_REGISTRATION	0.041975
REG_CITY_NOT_LIVE_CITY	0.044395
FLAG_EMP_PHONE	0.045982
REG_CITY_NOT_WORK_CITY	0.050994
DAYS_ID_PUBLISH	0.051457
REGION_RATING_CLIENT	0.058899
REGION_RATING_CLIENT_W_CITY	0.060893
DAYS_BIRTH	0.078239
TARGET	1.000000

In [256…

```
correlations["abs_Target"] = np.abs(correlations["TARGET"])
correlations.sort_values("abs_Target", ascending = False, inplace = True)
correlations
```

Out[256…

	TARGET	abs_Target
TARGET	1.000000	1.000000
EXT_SOURCE_3	-0.178919	0.178919
EXT_SOURCE_2	-0.160472	0.160472
EXT_SOURCE_1	-0.155317	0.155317
DAYS_BIRTH	0.078239	0.078239
REGION_RATING_CLIENT_W_CITY	0.060893	0.060893
REGION_RATING_CLIENT	0.058899	0.058899
DAYS_ID_PUBLISH	0.051457	0.051457
REG_CITY_NOT_WORK_CITY	0.050994	0.050994
FLAG_EMP_PHONE	0.045982	0.045982
DAYS_EMPLOYED	-0.044932	0.044932
REG_CITY_NOT_LIVE_CITY	0.044395	0.044395
DAYS_REGISTRATION	0.041975	0.041975
AMT_GOODS_PRICE	-0.039645	0.039645
OWN_CAR_AGE	0.037612	0.037612
REGION_POPULATION_RELATIVE	-0.037227	0.037227
LIVE_CITY_NOT_WORK_CITY	0.032518	0.032518
AMT_CREDIT	-0.030369	0.030369
FLAG_WORK_PHONE	0.028524	0.028524
HOUR_APPR_PROCESS_START	-0.024166	0.024166
FLAG_PHONE	-0.023806	0.023806
AMT_REQ_CREDIT_BUREAU_YEAR	0.019930	0.019930

	TARGET	abs_Target
CNT_CHILDREN	0.019187	0.019187
AMT_ANNUITY	-0.012817	0.012817
AMT_REQ_CREDIT_BUREAU_MON	-0.012462	0.012462
CNT_FAM_MEMBERS	0.009308	0.009308
REG_REGION_NOT_WORK_REGION	0.006942	0.006942
REG_REGION_NOT_LIVE_REGION	0.005576	0.005576
AMT_INCOME_TOTAL	-0.003982	0.003982
LIVE_REGION_NOT_WORK_REGION	0.002819	0.002819
AMT_REQ_CREDIT_BUREAU_DAY	0.002704	0.002704
SK_ID_CURR	-0.002108	0.002108
AMT_REQ_CREDIT_BUREAU_QRT	-0.002022	0.002022
FLAG_EMAIL	-0.001758	0.001758
AMT_REQ_CREDIT_BUREAU_HOUR	0.000930	0.000930
AMT_REQ_CREDIT_BUREAU_WEEK	0.000788	0.000788
FLAG_MOBIL	0.000534	0.000534
FLAG_CONT_MOBILE	0.000370	0.000370

In [257…
```
train_f = train[['TARGET','EXT_SOURCE_3','EXT_SOURCE_2','EXT_SOURCE_1','DAYS_
```

In [258…
```
train_f
```

Out[258…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
0	1	0.139376	0.262949	0.083037	-9461	
1	0	NaN	0.622246	0.311267	-16765	
2	0	0.729567	0.555912	NaN	-19046	
3	0	NaN	0.650442	NaN	-19005	
4	0	NaN	0.322738	NaN	-19932	
...	...	...	...	...	...	
307506	0	NaN	0.681632	0.145570	-9327	
307507	0	NaN	0.115992	NaN	-20775	
307508	0	0.218859	0.535722	0.744026	-14966	
307509	1	0.661024	0.514163	NaN	-11961	
307510	0	0.113922	0.708569	0.734460	-16856	

307511 rows × 11 columns

In [259…
```
train_f['TARGET'].value_counts()
```

Out[259…
```
0    282686
```

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

In [260…
```
train_f['TARGET'].describe()
```

Out[260…
```
count    307511.000000
mean          0.080729
std           0.272419
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max           1.000000
Name: TARGET, dtype: float64
```

In [261…
```
train_features = pd.read_pickle('train3.pkl')
```

In [262…
```
train_features
```

Out[262…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
0	100002	1	Cash loans	M	N	
1	100002	1	Cash loans	M	N	
2	100002	1	Cash loans	M	N	
3	100002	1	Cash loans	M	N	
4	100002	1	Cash loans	M	N	
...	...	...	...	...	...	
1699995	108558	0	Cash loans	F	N	
1699996	108558	0	Cash loans	F	N	
1699997	108558	0	Cash loans	F	N	
1699998	108558	0	Cash loans	F	N	
1699999	108558	0	Cash loans	F	N	

1700000 rows × 103 columns

In [263…
```
train_features['TARGET'].value_counts()
```

Out[263…
```
0    1579643
1     120357
Name: TARGET, dtype: int64
```

In [264…
```
train_zero = train_features[train_features['TARGET'] == 0]
train_zero
```

Out[264…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
64	100003	0	Cash loans	F	N	
65	100003	0	Cash loans	F	N	
66	100003	0	Cash loans	F	N	
67	100003	0	Cash loans	F	N	

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	F
68	100003	0	Cash loans	F	N	
...	...	...	...	...	...	
1699995	108558	0	Cash loans	F	N	
1699996	108558	0	Cash loans	F	N	
1699997	108558	0	Cash loans	F	N	
1699998	108558	0	Cash loans	F	N	
1699999	108558	0	Cash loans	F	N	

1579643 rows × 103 columns

In [265…

```
train_zero = train_zero[:120357]
train_zero
```

Out[265…

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FL
64	100003	0	Cash loans	F	N	
65	100003	0	Cash loans	F	N	
66	100003	0	Cash loans	F	N	
67	100003	0	Cash loans	F	N	
68	100003	0	Cash loans	F	N	
...	...	...	...	...	...	
126015	100504	0	Cash loans	F	N	
126016	100504	0	Cash loans	F	N	
126017	100504	0	Cash loans	F	N	
126018	100504	0	Cash loans	F	N	
126019	100504	0	Cash loans	F	N	

120357 rows × 103 columns

In [266…

```
train_f['ACTIVE_LOANS_PERCENTAGE'] = train_features['ACTIVE_LOANS_PERCENTAGE'
train_f['CREDIT_INCOME_RATIO'] = train_features['CREDIT_INCOME_RATIO'][:30751
train_f['YEARS_TO_PAY'] = train_features['YEARS_TO_PAY'][:307511]
train_f['INCOME_ANNUITY'] = train_features['INCOME_ANNUITY'][:307511]
```

In [267…

```
train_f
```

Out[267…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
0	1	0.139376	0.262949	0.083037	-9461	
1	0	NaN	0.622246	0.311267	-16765	
2	0	0.729567	0.555912	NaN	-19046	
3	0	NaN	0.650442	NaN	-19005	
4	0	NaN	0.322738	NaN	-19932	

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
...	...	...	...	...	...	
307506	0	NaN	0.681632	0.145570	-9327	
307507	0	NaN	0.115992	NaN	-20775	
307508	0	0.218859	0.535722	0.744026	-14966	
307509	1	0.661024	0.514163	NaN	-11961	
307510	0	0.113922	0.708569	0.734460	-16856	

307511 rows × 15 columns

In [268…
```
train_f['TARGET'].value_counts()
```

Out[268…
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

In [269…
```
train_zero = train_f[train_f['TARGET'] == 0]
train_zero
```

Out[269…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
1	0	NaN	0.622246	0.311267	-16765	
2	0	0.729567	0.555912	NaN	-19046	
3	0	NaN	0.650442	NaN	-19005	
4	0	NaN	0.322738	NaN	-19932	
5	0	0.621226	0.354225	NaN	-16941	
...	...	...	...	...	...	
307505	0	0.742182	0.346391	NaN	-24384	
307506	0	NaN	0.681632	0.145570	-9327	
307507	0	NaN	0.115992	NaN	-20775	
307508	0	0.218859	0.535722	0.744026	-14966	
307510	0	0.113922	0.708569	0.734460	-16856	

282686 rows × 15 columns

In [380…
```
train_zero_f = train_zero.sample(n = 125000, random_state=1)
train_zero_f
```

Out[380…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
229005	0	0.713631	0.510759	0.858157	-22456	
14166	0	0.396220	0.652577	0.764642	-19506	
67925	0	0.689479	0.644868	NaN	-10245	
297809	0	NaN	0.218719	0.294392	-9349	
272986	0	0.318596	0.433441	NaN	-13464	

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
...	...	...	...	...	...	
162751	0	0.546023	0.455792	0.650485	-12033	
283535	0	0.767523	0.640635	NaN	-16100	
221483	0	0.749022	0.626840	0.794135	-18112	
11620	0	0.427657	0.229003	NaN	-14814	
225177	0	NaN	0.751044	NaN	-20220	

125000 rows × 15 columns

In [381…

```
train_one = train_f[train_f['TARGET'] == 1]
train_one
```

Out[381…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
0	1	0.139376	0.262949	0.083037	-9461	
26	1	0.190706	0.548477	NaN	-18724	
40	1	0.320163	0.306841	NaN	-17482	
42	1	0.399676	0.674203	0.468208	-13384	
81	1	0.720944	0.023952	NaN	-24794	
...	...	...	...	...	...	
307448	1	0.360613	0.329708	0.073452	-9918	
307475	1	0.424130	0.583214	0.634729	-13416	
307481	1	0.511892	0.713524	NaN	-20644	
307489	1	0.397946	0.615261	NaN	-16471	
307509	1	0.661024	0.514163	NaN	-11961	

24825 rows × 15 columns

In [382…

```
train_f1 = pd.concat([train_zero_f, train_one], axis = 0, ignore_index = True
train_f1
```

Out[382…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
0	0	0.713631	0.510759	0.858157	-22456	
1	0	0.396220	0.652577	0.764642	-19506	
2	0	0.689479	0.644868	NaN	-10245	
3	0	NaN	0.218719	0.294392	-9349	
4	0	0.318596	0.433441	NaN	-13464	
...	...	...	...	...	...	
149820	1	0.360613	0.329708	0.073452	-9918	
149821	1	0.424130	0.583214	0.634729	-13416	
149822	1	0.511892	0.713524	NaN	-20644	

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
149823	1	0.397946	0.615261	NaN	-16471	
149824	1	0.661024	0.514163	NaN	-11961	

149825 rows × 15 columns

In [383…
```
train_f1['TARGET'].value_counts()
```

Out[383…
```
0    125000
1     24825
Name: TARGET, dtype: int64
```

In [384…
```
num_pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('imputer', SimpleImputer(strategy = 'mean'))
])
train_f_nt = train_f1.drop('TARGET', axis = 1)
train_f_transformed = num_pipeline.fit_transform(train_f_nt)
```

In [385…
```
train_f_nt
```

Out[385…

	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RATING_CLI
0	0.713631	0.510759	0.858157	-22456	
1	0.396220	0.652577	0.764642	-19506	
2	0.689479	0.644868	NaN	-10245	
3	NaN	0.218719	0.294392	-9349	
4	0.318596	0.433441	NaN	-13464	
...	...	...	...	...	
149820	0.360613	0.329708	0.073452	-9918	
149821	0.424130	0.583214	0.634729	-13416	
149822	0.511892	0.713524	NaN	-20644	
149823	0.397946	0.615261	NaN	-16471	
149824	0.661024	0.514163	NaN	-11961	

149825 rows × 14 columns

In [386…
```
train_f_transformed
```

Out[386…
```
array([[ 1.07416901e+00,  2.91790754e-02,  1.71950528e+00, ...,
         3.50250579e-01, -1.53231874e+00, -5.89779917e-01],
       [-5.22701628e-01,  7.53242843e-01,  1.28004684e+00, ...,
         2.18019534e-02, -1.66569121e-01,  3.71126751e-01],
       [ 9.52661156e-01,  7.13884723e-01,  4.67519818e-16, ...,
        -7.41588177e-01,  1.44749861e+00, -3.49553250e-01],
       ...,
       [ 5.92350574e-02,  1.06441836e+00,  4.67519818e-16, ...,
         3.72726211e+00, -1.65647779e+00,  1.57226009e+00],
       [-5.14014503e-01,  5.62725792e-01,  4.67519818e-16, ...,
         3.72726211e+00, -1.65647779e+00,  1.57226009e+00],
```

```
       [ 8.09503549e-01,  4.65572525e-02,  4.67519818e-16, ...,
         3.72726211e+00, -1.65647779e+00,  1.57226009e+00]])
```

In [387…
```
column_names = list(train_f_nt.columns)

train_f_transformed_df = pd.DataFrame(train_f_transformed,  columns=column_na
```

In [388…
```
train_f_transformed_df['TARGET'] = train_f1['TARGET']
```

In [389…
```
train_f_transformed_df
```

Out[389…

	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RATING_CLI
0	1.074169e+00	0.029179	1.719505e+00	-1.497423	
1	-5.227016e-01	0.753243	1.280047e+00	-0.820308	
2	9.526612e-01	0.713885	4.675198e-16	1.305372	
3	2.924445e-16	-1.461859	-9.298265e-01	1.511031	
4	-9.132213e-01	-0.365578	4.675198e-16	0.566514	
...	...	...	...	...	
149820	-7.018373e-01	-0.895198	-1.968105e+00	1.380428	
149821	-3.822852e-01	0.399105	6.695401e-01	0.577531	
149822	5.923506e-02	1.064418	4.675198e-16	-1.081514	
149823	-5.140145e-01	0.562726	4.675198e-16	-0.123684	
149824	8.095035e-01	0.046557	4.675198e-16	0.911498	

149825 rows × 15 columns

In [390…
```
train_f_transformed_df['TARGET'].isnull().sum()
```

Out[390… 0

In [391…
```
train_f_transformed_df['TARGET'].value_counts()
```

Out[391…
```
0    125000
1     24825
Name: TARGET, dtype: int64
```

In [438…
```
train_f_transformed_df.to_csv("train_nn.csv")
```

In [392…
```
X = train_f_transformed_df.drop(['TARGET'], axis = 1).values
y = train_f_transformed_df["TARGET"].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ran
```

In [393…
```
len(X_test)
```

Out[393… 29965

In [394…
```
X_train = torch.FloatTensor(X_train)
X_test = torch.FloatTensor(X_test)
y_train = torch.tensor(y_train, dtype=torch.long, device=device)
y_test = torch.tensor(y_test, dtype=torch.long, device=device)
```

Multi-layer perceptron

In [395…
```
class MLP(nn.Module):
    def __init__(self,input_features=14,hidden1=20,hidden2=20,out_features=2)
        super().__init__()
        self.f_connected1 = nn.Linear(input_features,hidden1)
        self.f_connected2 = nn.Linear(hidden1,hidden2)
        self.out = nn.Linear(hidden2,out_features)
    def forward(self,x):
        x = F.leaky_relu(self.f_connected1(x))
        x = F.leaky_relu(self.f_connected2(x))
        x = self.out(x)
        return x
```

Single-layer perceptron

In [466…
```
class SLP(nn.Module):
    def __init__(self,input_features=14,hidden1=20,out_features=2):
        super().__init__()
        self.f_connected1 = nn.Linear(input_features,hidden1)
        self.out = nn.Linear(hidden1,out_features)
    def forward(self,x):
        x = F.leaky_relu(self.f_connected1(x))
        x = self.out(x)
        return x
```

In [396…
```
torch.manual_seed(20)
model= MLP()
```

In [467…
```
torch.manual_seed(20)
model2= SLP()
```

In [397…
```
model.parameters
```

Out[397…
```
<bound method Module.parameters of MLP(
  (f_connected1): Linear(in_features=14, out_features=20, bias=True)
  (f_connected2): Linear(in_features=20, out_features=20, bias=True)
  (out): Linear(in_features=20, out_features=2, bias=True)
)>
```

In [398…
```
loss_function = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(),lr=0.01)
```

Training for Multi-layer perceptron

In [444…
```
size_ = y_train.shape[0]
acc = 0
```

```
epochs = 1000
final_losses = []
for i in range(epochs):
    i += 1
    y_pred = model.forward(X_train)
    loss = loss_function(y_pred,y_train)
    final_losses.append(loss.item())
    _, predicted = torch.max(y_pred, 1)
    acc = (predicted == y_train).sum().item()
    if i%100 == 1:
        print("Epoch Number: {} and the loss: {} accuracy {}".format(i,loss.i
        writer.add_scalar('Training loss', loss.item(), i)
        writer.add_scalar('Accuracy', acc/size_, i)
        acc = 0
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

```
Epoch Number: 1 and the loss: 0.39586523175239563 accuracy 0.8388536626063741
Epoch Number: 101 and the loss: 0.39574986696243286 accuracy 0.83882863340564
Epoch Number: 201 and the loss: 0.39562028646469116 accuracy 0.839003837810779
3
Epoch Number: 301 and the loss: 0.39556336402893066 accuracy 0.838887034874019
7
Epoch Number: 401 and the loss: 0.39552903175354004 accuracy 0.838953779409310
8
Epoch Number: 501 and the loss: 0.3954128921031952 accuracy 0.838978808610045
Epoch Number: 601 and the loss: 0.39543044567108154 accuracy 0.839070582346070
5
Epoch Number: 701 and the loss: 0.39534348249435425 accuracy 0.839020523944602
Epoch Number: 801 and the loss: 0.39528822898864746 accuracy 0.838887034874019
7
Epoch Number: 901 and the loss: 0.3952784836292267 accuracy 0.838895377940931
```

Training for Single-layer perceptron

In [468…

```
size_ = y_train.shape[0]
acc = 0
epochs = 1000
final_losses = []
for i in range(epochs):
    i += 1
    y_pred = model2.forward(X_train)
    loss = loss_function(y_pred,y_train)
    final_losses.append(loss.item())
    _, predicted = torch.max(y_pred, 1)
    acc = (predicted == y_train).sum().item()
    if i%100 == 1:
        print("Epoch Number: {} and the loss: {} accuracy {}".format(i,loss.i
        writer.add_scalar('Training loss', loss.item(), i)
        writer.add_scalar('Accuracy', acc/size_, i)
        acc = 0
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

```
Epoch Number: 1 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 101 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 201 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 301 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 401 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 501 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 601 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 701 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
```

```
Epoch Number: 801 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
Epoch Number: 901 and the loss: 0.5945405960083008 accuracy 0.7735357917570499
```

In [449…
```
writer.add_graph(model, X_train)
writer.close()
```

In [404…
```
predictions = []
with torch.no_grad():
    for i,data in enumerate(X_test):
        y_pred = model(data)
        predictions.append(y_pred.argmax().item())
```

In [296…
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predictions)
cm
```

Out[296…
```
array([[24676,   300],
       [ 4620,   369]])
```

In [406…
```
from sklearn.metrics import accuracy_score
score = accuracy_score(y_test,predictions)
score
```

Out[406…
```
0.8358084431837143
```

In [469…
```
predictions2 = []
with torch.no_grad():
    for i,data in enumerate(X_test):
        y_pred = model2(data)
        predictions2.append(y_pred.argmax().item())
```

In [470…
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predictions)
cm
```

Out[470…
```
array([[24600,   376],
       [ 4559,   430]])
```

In [471…
```
from sklearn.metrics import accuracy_score
score = accuracy_score(y_test,predictions)
score
```

Out[471…
```
0.8353078591690305
```

In [372…
```
len(probabilities)
```

Out[372…
```
49965
```

In [373…
```
len(X_test)
```

Out[373…
```
49965
```

Submission File Prep

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

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

In [409…
```
X_kaggle_test = datasets["application_test"]
```

In [412…
```
X_kaggle_test
```

Out[412…

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_R
0	100001	Cash loans	F	N	
1	100005	Cash loans	M	N	
2	100013	Cash loans	M	Y	
3	100028	Cash loans	F	N	
4	100038	Cash loans	M	Y	
...	...	...	...	...	
48739	456221	Cash loans	F	N	
48740	456222	Cash loans	F	N	
48741	456223	Cash loans	F	Y	
48742	456224	Cash loans	M	N	
48743	456250	Cash loans	F	Y	

48744 rows × 116 columns

Preprocessing for Feature Engineering ML Model

In [414…
```
#X_kaggle_test.drop(['DAYS_LAST_PHONE_CHANGE','OBS_30_CNT_SOCIAL_CIRCLE','OBS_
X_kaggle_test = X_kaggle_test.loc[:, ~X_kaggle_test.columns.str.startswith("F
X_kaggle_test = X_kaggle_test.loc[:, ~X_kaggle_test.columns.str.endswith("MOD
X_kaggle_test = X_kaggle_test.loc[:, ~X_kaggle_test.columns.str.endswith("MED
X_kaggle_test = X_kaggle_test.loc[:, ~X_kaggle_test.columns.str.endswith("AVG
```

In [415…
```
X_kaggle_test.shape
```

Out[415… `(48744, 49)`

In [417…
```
X_kaggle_test['ACTIVE_LOANS_PERCENTAGE'] = train_features_fe['ACTIVE_LOANS_PE
X_kaggle_test['CREDIT_INCOME_RATIO'] = train_features_fe['CREDIT_INCOME_RATIO
X_kaggle_test['YEARS_TO_PAY'] = train_features_fe['YEARS_TO_PAY']
X_kaggle_test['INCOME_ANNUITY'] = train_features_fe['INCOME_ANNUITY']
```

In [418…
```
X_kaggle_test.shape
```

Out[418…
```
(48744, 53)
```

In [419…
```
X_kaggle_test
```

Out[419…

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_R
0	100001	Cash loans	F	N	
1	100005	Cash loans	M	N	
2	100013	Cash loans	M	Y	
3	100028	Cash loans	F	N	
4	100038	Cash loans	M	Y	
...	...	...	...	...	
48739	456221	Cash loans	F	N	
48740	456222	Cash loans	F	N	
48741	456223	Cash loans	F	Y	
48742	456224	Cash loans	M	N	
48743	456250	Cash loans	F	Y	

48744 rows × 53 columns

In [238…
```
X_kaggle_test.drop(['SK_ID_CURR'], axis = 1, inplace = True)
```

In [172…
```
X_kaggle_test.drop(['AVG_DPD'], axis = 1, inplace = True)
```

In [239…
```
test_class_scores = after_balancing_model.predict_proba(X_kaggle_test)[:, 1]
```

In [240…
```
# Submission dataframe
submit_df = datasets["application_test"][['SK_ID_CURR']]
submit_df['TARGET'] = test_class_scores

submit_df.head()
```

Out[240…

	SK_ID_CURR	TARGET
0	100001	0.210149
1	100005	0.443293
2	100013	0.200282
3	100028	0.138116
4	100038	0.358870

Preprocessing for Neural Network model

In [427…
```
X_kaggle_test = datasets["application_test"]
```

In [426…
```
train_f1
```

Out[426…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
0	0	0.713631	0.510759	0.858157	-22456	
1	0	0.396220	0.652577	0.764642	-19506	
2	0	0.689479	0.644868	NaN	-10245	
3	0	NaN	0.218719	0.294392	-9349	
4	0	0.318596	0.433441	NaN	-13464	
...	...	...	...	...	...	
149820	1	0.360613	0.329708	0.073452	-9918	
149821	1	0.424130	0.583214	0.634729	-13416	
149822	1	0.511892	0.713524	NaN	-20644	
149823	1	0.397946	0.615261	NaN	-16471	
149824	1	0.661024	0.514163	NaN	-11961	

149825 rows × 15 columns

In [428…
```
X_kaggle_test_f = X_kaggle_test[['EXT_SOURCE_3','EXT_SOURCE_2','EXT_SOURCE_1'
X_kaggle_test_f['ACTIVE_LOANS_PERCENTAGE'] = train_f1['ACTIVE_LOANS_PERCENTAG
X_kaggle_test_f['CREDIT_INCOME_RATIO'] = train_f1['CREDIT_INCOME_RATIO']
X_kaggle_test_f['YEARS_TO_PAY'] = train_f1['YEARS_TO_PAY']
X_kaggle_test_f['INCOME_ANNUITY'] = train_f1['INCOME_ANNUITY']
```

In [429…
```
X_kaggle_test_f.shape
```

Out[429… `(48744, 14)`

In [430…
```
num_pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('imputer', SimpleImputer(strategy = 'mean'))
])
X_kaggle_test_f_transformed = num_pipeline.fit_transform(X_kaggle_test_f)
```

In [422…
```
column_names = list(numerical_features)

X_kaggle_test_transformed_df = pd.DataFrame(X_kaggle_test_transformed,  colum
```

In [432…
```
X_kaggle_test_nn = torch.FloatTensor(X_kaggle_test_f_transformed)
```

In [433…
```
predictions = []
probabilities = []
with torch.no_grad():
    for i,data in enumerate(X_kaggle_test_nn):
        y_pred = model(data)
        probabilities.append(F.softmax(y_pred)[1].item())
```

```
            predictions.append(y_pred.argmax().item())
#           print(y_pred.argmax().item())
```

In [434…

```
len(probabilities)
```

Out[434… 48744

In [435…

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

submit_df.head()
```

Out[435…

	SK_ID_CURR	TARGET
0	100001	0.106409
1	100005	0.165703
2	100013	0.053740
3	100028	0.104068
4	100038	0.211880

In [436…

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

Preprocessing for Grid Search

In [205…

```
X_kaggle_test = X_kaggle_test.loc[:, ~X_kaggle_test.columns.str.startswith("F
```

In [206…

```
X_kaggle_test.shape
```

Out[206… (48744, 96)

In [207…

```
X_kaggle_test['ACTIVE_LOANS_PERCENTAGE'] = train['ACTIVE_LOANS_PERCENTAGE']
X_kaggle_test['CREDIT_INCOME_RATIO'] = train['CREDIT_INCOME_RATIO']
X_kaggle_test['YEARS_TO_PAY'] = train['YEARS_TO_PAY']
X_kaggle_test['INCOME_ANNUITY'] = train['INCOME_ANNUITY']
X_kaggle_test['AVG_DPD'] = train['AVG_DPD']
```

In [208…

```
X_kaggle_test
```

Out[208…

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

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_R
48739	456221	Cash loans	F	N	
48740	456222	Cash loans	F	N	
48741	456223	Cash loans	F	Y	
48742	456224	Cash loans	M	N	
48743	456250	Cash loans	F	Y	

48744 rows × 101 columns

In [282…
```
numerical_features = X_kaggle_test.select_dtypes(include = ['int64', 'float64
categorical_features = X_kaggle_test.select_dtypes(include = ['object', 'bool

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

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

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

In [283…
```
X_kaggle_test_transformed = data_pipeline.fit_transform(X_kaggle_test)
column_names = list(numerical_features)  + \
                   list(data_pipeline.transformers_[1][1].named_steps["ohe"].
```

In [285…
```
X_kaggle_test_transformed_df = pd.DataFrame(X_kaggle_test_transformed,  colum
```

In [329…
```
X_kaggle_test_transformed_df.shape
```

Out[329… (48744, 225)

In [330…
```
X_train_transformed_df.shape
```

Out[330… (1088000, 225)

In [324…
```
set(X_train_transformed_df.columns).difference(set(X_kaggle_test_transformed_
```

Out[324…
```
{'CODE_GENDER_XNA',
 'NAME_FAMILY_STATUS_Unknown',
 'NAME_INCOME_TYPE_Maternity leave'}
```

In [326…
```
X_kaggle_test_transformed_df['CODE_GENDER_XNA'] = X_train_transformed_df['COD
X_kaggle_test_transformed_df['NAME_FAMILY_STATUS_Unknown'] = X_train_transfor
X_kaggle_test_transformed_df['NAME_INCOME_TYPE_Maternity leave'] = X_train_tr
```

In [331…
```
X_kaggle_test_transformed_4 = X_kaggle_test_transformed_df.to_numpy()
```

In [332…
```
test_class_scores = grid_search_model1.predict_proba(X_kaggle_test_transforme
```

In [333…
```
test_class_scores[0:10]
```

Out[333…
```
array([0.01205682, 0.23306839, 0.11699465, 0.10186553, 0.05286666,
       0.20762748, 0.05490155, 0.07793292, 0.00758586, 0.12317721])
```

In [334…
```
# Submission dataframe
submit_df = datasets["application_test"][['SK_ID_CURR']]
submit_df['TARGET'] = test_class_scores

submit_df.head()
```

Out[334…

	SK_ID_CURR	TARGET
0	100001	0.012057
1	100005	0.233068
2	100013	0.116995
3	100028	0.101866
4	100038	0.052867

In [335…
```
submit_df.to_csv("submission.csv",index=False)
```

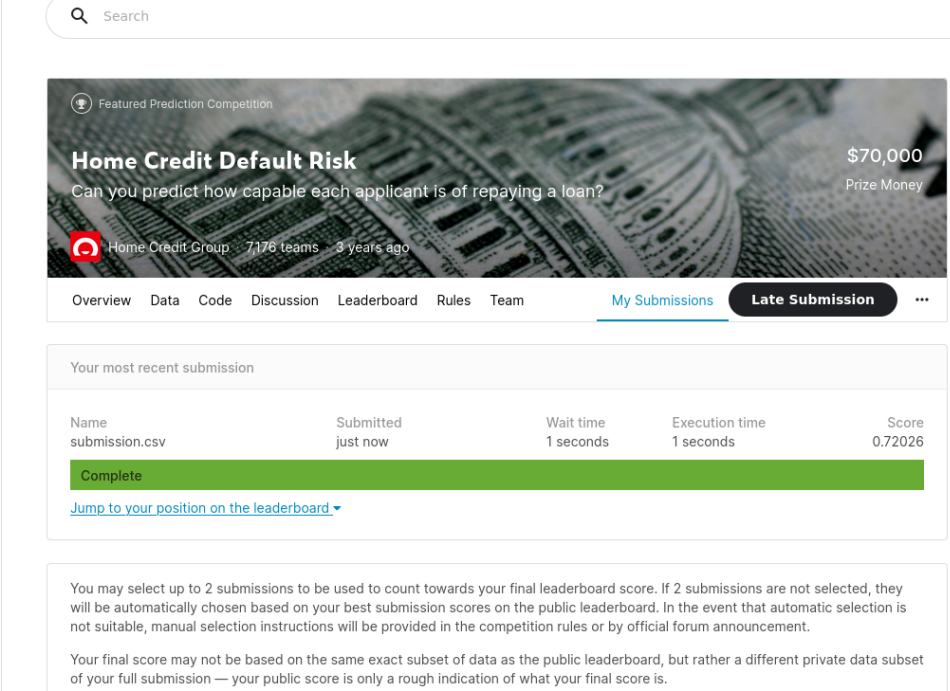
Kaggle submission via the command line API

In [437…
```
! kaggle competitions submit -c home-credit-default-risk -f submission.csv -m
```

```
100%|████████████████████████████████████████| 1.25M/1.25M [00:01<00:00, 1.25M
B/s]
Successfully submitted to Home Credit Default Risk
```

Our Submission

file:///N/u/vshriram/Carbonate/Desktop/kagglePhase3.png



report submission

Click on this link

Abstract

The main goal of this project is to build an optimal ML model which will predict if a loan applicant will be able to repay his/her loan. In Phase 2, we extended our work from Phase 1 and implemented Feature Engineering where we consider potential features from other tables, did feature selection from the derived features, analysis of feature importances and implemented Hyper Parameter Tuning. In feature engineering, we derived 6 additional features and we achieved an improvement over our baseline model however some feature models are leading to over-fitting and thus in our future scope we aim to select the most important features having balanced data to avoid over-fitting. The most important feature relevant to our goal was the Credit Annuity ratio of the current application. We identified this by implementing feature importances on our model. After performing Hyper-parameter tuning on logistic regression(our best pipeline) we achieved the test accuracy of 92.46%. In Phase 3, we extended our work from Phase 2 and we performed a deep learning algorithm which will predict our goal of the project. The Deep Learning Algorithm used was the Multi-Layer Perceptron which is a kind of Artificial Neural network. The main goal of this phase was to implement MLP and visualize the training model on TensorBoard. We also identified Data Leakage in our project and their respective reasons. Another goal of this phase was to improve our results from Phase 2 and we were successful in doing that.

Introduction

Data Description:

- application_{train|test}.csv

The main table is divided into two files: Train (with TARGET) and Test (without TARGET) (without TARGET).

- bureau.csv

All past credit issued to the client by other financial institutions and reported to the Credit Bureau.

- bureau_balance.csv

Monthly balances of previous credits in Credit Bureau.

- POS_CASH_balance.csv

Monthly balance snapshots of the applicant's prior POS (point of sale) and cash loans with Home Credit.

- credit_card_balance.csv

Monthly balance snapshots of the applicant's prior credit cards with Home Credit.

- previous_application.csv

All prior Home Credit loan applications of clients with loans in our sample.

- installments_payments.csv

Payment history in Home Credit for previously disbursed credits related to the loans in our sample.

- HomeCredit_columns_description.csv

The columns in the various data files are described in this file.

The tasks to be tackled are:

- Feature Engineering
- Hyperparameter Tuning
- Analysis of Feature Importance
- Ensemble Methods

In Phase 2, we implemented Feature engineering to identify potential features that could help us get better results. We mainly derived 6 features:

- **Active loan Percentage feature:**
  We take into consideration the number of active-loans feature from the bureau data so as to indicate whether a candidate will be able to handle another loan with his existing set of loans.

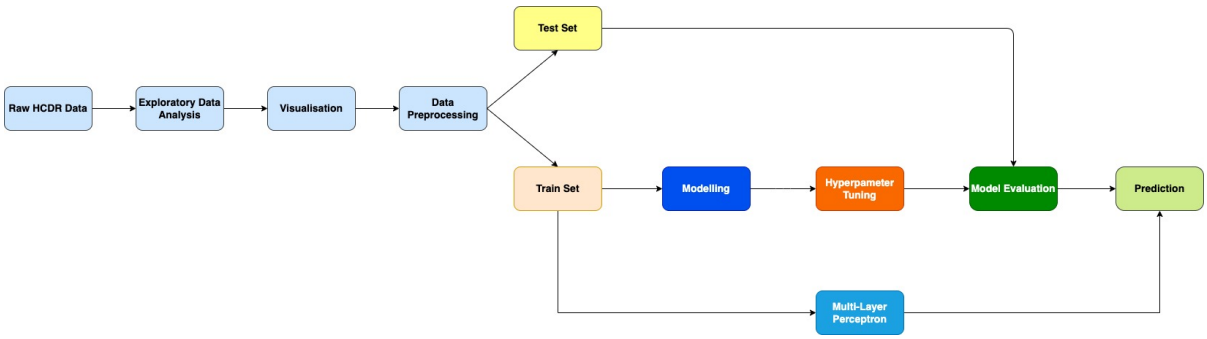
- **Credit Income Ratio feature:** This is the ratio of the candidate's total income to the loan amount requested. A higher value indicates a higher chance of repayment in ideal conditions.

- **Credit Annuity Ratio of the Application:**
  This is the ratio of the loan amount requested to the loan annuity. The number of years does it take for the borrower to repay the amount he requested for the application.

- **Income Annuity Ratio of the Application:**
  This is the ratio of the candidate's total income to the loan annuity. The number of years does it take for the borrower to repay the amount he requested for the application.

- **Average of "Days past due" per customer:**
  The average of all the previous days past due of all previous loan applications of a candidate.

- **Debt Overdue per Customer:**
  The ratio of Amount Overdue on the Loan amount to the total loan amount. Higher the Overdue, will it be considered as against



Pipelines

In [ ]:
```
num_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('imputer', SimpleImputer(strategy = 'median'))
])

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

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

Here we created two different pipelines for numerical and categorical features respectively. Performed standardization and imputation on the numerical features and performed imputations and one-hot encoding on the categorical features. We combined the two pipelines using Column Transformer and passed for modeling.

In [ ]:
```
clf_pipe = make_pipeline(data_pipeline, LogisticRegression())
```

We are passing the combined data pipeline to Logistic Regression model in this pipeline

In [ ]:
```
RF = RandomForestClassifier(random_state = 42,n_estimators=20, criterion='gin

data_pipeline_rf = make_pipeline(data_pipeline, RF)
```

Here we are passing the data pipeline to the Random Forest classifier

Feature Engineering

We derived 6 features in total out of which we selected 5 for our modeling.

1. Active loan Percentage feature
2. Credit Income Ratio feature
3. Credit Annuity Ratio of the Application
4. Income Annuity Ratio of the Application
5. Average of "Days past due" per customer
6. Debt Overdue per Customer

Impact of these features to the model -

1. Active loan Percentage feature
    - We achieved an improved result using this feature over our baseline model.
2. Credit Income Ratio feature
    - We achieved a slight improvement in the testROC using this feature.
3. Credit Annuity Ratio of the Application
    - This feature was identified as the most important using Feature Importances on the model.
4. Income Annuity Ratio of the Application
    - We achieved a slight improvement in the testROC using this feature.
5. Average of "Days past due" per customer
    - We achieved a significant improvement in the testROC using this feature.
6. Debt Overdue per Customer
    - We are receiving a spike in the result using this feature. We think this is because of overfitting.

Neural Network

Multi-Layer Perceptron

- The perceptron can be used as a binary classification model, defining a linear decision boundary. It finds the separating hyperplane that minimizes the distance between misclassified points and the decision boundary.

- To minimize this distance, Perceptron uses Stochastic Gradient Descent as the optimization function. If the data is linearly separable, it is guaranteed that Stochastic Gradient Descent will converge in a finite number of steps.

- The last piece that Perceptron needs is the activation function, the function that determines if the neuron will fire or not. We have used Leaky Relu as the activation function.

- A Multilayer Perceptron has input and output layers, and one or more hidden layers with many neurons stacked together. And while in the Perceptron the neuron must have an

activation function that imposes a threshold, like ReLU or sigmoid, neurons in a Multilayer Perceptron can use any arbitrary activation function.

Loss function used in the Neural Network -

Cross Entropy Loss

Cross Entropy Loss criterion computes the cross entropy loss between input and target.

It is useful when training a classification problem with C classes. If provided, the optional argument weight should be a 1D Tensor assigning weight to each of the classes. This is particularly useful when you have an unbalanced training set.

In our project, we do have a unbalanced training set as we have about 270000 target variables as 0 (i.e people who havent repaid their loan) among 300000 data points.

Equation -

Cross-entropy can be calculated using the probabilities of the events from P and Q, as follows:

```
H(P, Q) = − sum x in X P(x) * log(Q(x))
```

Where P(x) is the probability of the event x in P, Q(x) is the probability of event x in Q and log is the base-2 logarithm

Single Layer Peceptron Model

In [ ]:
```
class SLP(nn.Module):
    def __init__(self,input_features=14,hidden1=20,out_features=2):
        super().__init__()
        self.f_connected1 = nn.Linear(input_features,hidden1)
        self.out = nn.Linear(hidden1,out_features)
    def forward(self,x):
        x = F.leaky_relu(self.f_connected1(x))
        x = self.out(x)
        return x
```

In our Neural network we have used 14 input features and 1 linear hidden layer having 20 neurons and 2 output features.

In the forward propagation we have used leaky_relu as the activation function

Multi Layer Perceptron Model

In [ ]:
```
class MLP(nn.Module):
    def __init__(self,input_features=14,hidden1=20,hidden2=20,out_features=2)
        super().__init__()
        self.f_connected1 = nn.Linear(input_features,hidden1)
        self.f_connected2 = nn.Linear(hidden1,hidden2)
        self.out = nn.Linear(hidden2,out_features)
    def forward(self,x):
        x = F.leaky_relu(self.f_connected1(x))
        x = F.leaky_relu(self.f_connected2(x))
```

```
        x = self.out(x)
        return x
```

In our Neural network we have used 14 input features and 2 linear hidden layers having 20 neurons each and 2 output features.

In the forward propagation we have used leaky_relu as the activation function

In [456…

```
size_ = y_train.shape[0]
acc = 0
epochs = 1000
final_losses = []
for i in range(epochs):
    i += 1
    y_pred = model.forward(X_train)
    loss = loss_function(y_pred,y_train)
    final_losses.append(loss.item())
    _, predicted = torch.max(y_pred, 1)
    acc = (predicted == y_train).sum().item()
    if i%100 == 1:
        print("Epoch Number: {} and the loss: {} accuracy {}".format(i,loss.i
        writer.add_scalar('Training loss', loss.item(), i)
        writer.add_scalar('Accuracy', acc/size_, i)
        acc = 0
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

```
Epoch Number: 1 and the loss: 0.39511343836784363 accuracy 0.8388119472718171
Epoch Number: 101 and the loss: 0.395035058259964 accuracy 0.8389537794093108
Epoch Number: 201 and the loss: 0.3950144350528717 accuracy 0.838895377940931
Epoch Number: 301 and the loss: 0.3949779272079468 accuracy 0.8390372100784248
Epoch Number: 401 and the loss: 0.39475810527801514 accuracy 0.839037210078424
8
Epoch Number: 501 and the loss: 0.3946821391582489 accuracy 0.839020523944602
Epoch Number: 601 and the loss: 0.39463287591934204 accuracy 0.839204071416652
8
Epoch Number: 701 and the loss: 0.39447444677352905 accuracy 0.839287502085766
7
Epoch Number: 801 and the loss: 0.3945179283618927 accuracy 0.8391706991490072
Epoch Number: 901 and the loss: 0.3944171071052551 accuracy 0.8391790422159185
```

In [461…

```
predictions = []
with torch.no_grad():
    for i,data in enumerate(X_test):
        y_pred = model(data)
        predictions.append(y_pred.argmax().item())
```

In [462…

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predictions)
cm
```

Out[462…

```
array([[24600,   376],
       [ 4559,   430]])
```

In [463…

```
from sklearn.metrics import accuracy_score
score = accuracy_score(y_test,predictions)
score
```

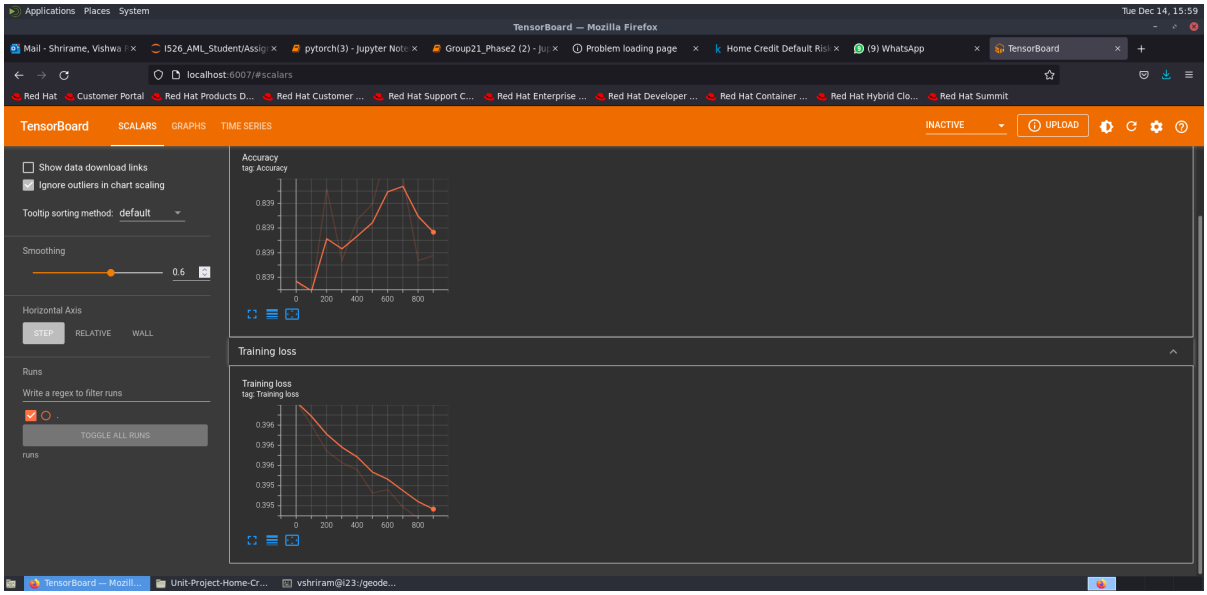
Out[463…

```
0.8353078591690305
```

We received a test accuracy of 83.53% using the Neural network model

Visualization of training model in TensorBoard

file:///N/u/vshriram/Carbonate/Desktop/tensorboard.png



Leakage

There has been some data leakage in our implementation. I'll state these pointwise -

- In the Feature Engineering section of our project, we developed some custom features from the other dataset like bureau.csv, credit_card_balance.csv and after merging them on SK_ID_CURR with the main application train dataset, we were getting many duplicate entries of a specific customer. Because of that when training it on our Pipeline, we were experiencing some variations in the ROC curve as well as a sudden spike in training accuracy . We knew this happened because of overfitting on the data. When we predicted using this model and sent to Kaggle we got a very decreased accuracy of 64%.

- Later in Phase 3, we improved our previous model by removing some redundant features and the features which were causing overfitting and trained the model on our pipeline. This time we received a very improved score of 0.73136 score on Kaggle than our Phase 2 submission score which was 0.6491.

- Also the dataset is very imbalanced and because of that we are experiencing very good accuracy from our ML models. The TARGET feature which basically denotes whether an applicant has repaid loan or not is very imbalanced because out of 300000 entries, 270000 entries havent repaid their loan whereas the remaining entries have repaid loan. When performing feature engineering we experience a huge difference between people who have repaid loan and people who haven't repaid loan. Our model is able to predict most of the entries right because of such imbalance dataset.

- In Phase 3 we balanced the dataset by reducing the number of 0 values in TARGET feature and sent this to our Neural Network model to get a test accuracy of 83.55%. The

kaggle submission score we received was 0.7202 which was an improved score from the Phase 2 score which was 0.6491.

Modeling Pipelines

Families of Input Features -

In [457…

```
numerical_features = train.select_dtypes(include = ['int64', 'float64']).colu
categorical_features = train.select_dtypes(include = ['object', 'bool']).colu

print("\n Numerical Features - {}".format(numerical_features))
print("\n Categorical Features - {}".format(categorical_features))
```

```
 Numerical Features - Index(['SK_ID_CURR', 'TARGET', 'CNT_CHILDREN', 'AMT_INCO
ME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',
       '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', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START',
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'EXT_SOURCE_1',
       'EXT_SOURCE_2', 'EXT_SOURCE_3', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')

 Categorical Features - Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_
CAR', 'FLAG_OWN_REALTY',
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE'],
      dtype='object')
```

In [458…

```
print("Number of Input Features to the Neural network- ")
train_f1
```

```
Number of Input Features to the Neural network-
```

Out[458…

	TARGET	EXT_SOURCE_3	EXT_SOURCE_2	EXT_SOURCE_1	DAYS_BIRTH	REGION_RA
0	0	0.713631	0.510759	0.858157	-22456	
1	0	0.396220	0.652577	0.764642	-19506	
2	0	0.689479	0.644868	NaN	-10245	
3	0	NaN	0.218719	0.294392	-9349	
4	0	0.318596	0.433441	NaN	-13464	
...	...	...	...	...	...	
149820	1	0.360613	0.329708	0.073452	-9918	
149821	1	0.424130	0.583214	0.634729	-13416	
149822	1	0.511892	0.713524	NaN	-20644	
149823	1	0.397946	0.615261	NaN	-16471	
149824	1	0.661024	0.514163	NaN	-11961	

149825 rows × 15 columns

In [459…
```
print("Count of Input Features - ", len(train_f1.columns) - 1)
```

```
Count of Input Features -  14
```

Hyperaparameters considered for Logistic Regression -

In [460…
```
param_grid_lr = {
    'C': [10**x for x in range(-3,4)],
    'penalty': ['l1','l2']
}
```

Loss function used - Cross Entropy Loss

Cross Entropy Loss criterion computes the cross entropy loss between input and target.

It is useful when training a classification problem with C classes. If provided, the optional argument weight should be a 1D Tensor assigning weight to each of the classes. This is particularly useful when you have an unbalanced training set.

In our project, we do have a unbalanced training set as we have about 270000 target variables as 0 (i.e people who havent repaid their loan) among 300000 data points.

Equation -

Cross-entropy can be calculated using the probabilities of the events from P and Q, as follows:

```
H(P, Q) = – sum x in X P(x) * log(Q(x))
```

Where P(x) is the probability of the event x in P, Q(x) is the probability of event x in Q and log is the base-2 logarithm

Experimental results

Before Hyper-Parameter Tuning

	Pipeline	Dataset	TrainAcc	ValidAcc	TestAcc	TrainROC	TestROC	ValidROC	Feature Added
0	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.752	0.7505	0.7496	Active loan Percentage feature
1	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7526	0.7511	0.7502	Credit Income Ratio feature
2	Logistic Regression	HCDR	92.13%	92.15%	92.13%	0.7525	0.7511	0.7501	Credit-Annuity Ratio of Current Application Fe...
3	Logistic Regression	HCDR	92.14%	92.15%	92.13%	0.7527	0.7513	0.7504	Income-Annuity Ratio of Current Application Fe...
4	Logistic Regression	HCDR	92.10%	92.02%	92.08%	0.7599	0.7628	0.7625	Average DPD Feature

After Hyper-Parameter Tuning

```
best_test_accuracy = grid_search_lr.best_estimator_.score(X_test_transformed, y_test)
best_test_accuracy*100
```

```
92.4614705882353
```

After performing Hyperparameter tuning for logistic regression we are getting an improved test accuracy of 92.46%.

Best parameters for Logistic Regression

```
grid_search_lr.best_params_
```

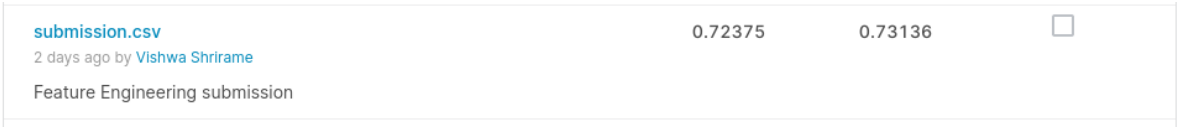
```
{'C': 100, 'penalty': 'l2'}
```

Best parameters for Random Forest Classifier

```
grid_search.best_params_
```

```
{'criterion': 'gini', 'max_depth': 4, 'n_estimators': 80}
```

Improved Kaggle Score of Phase 2



Confusion Matrix of our Neural network model

In [464…

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predictions)
cm
```

Out[464…

```
array([[24600,   376],
       [ 4559,   430]])
```

Test Accuracy Score

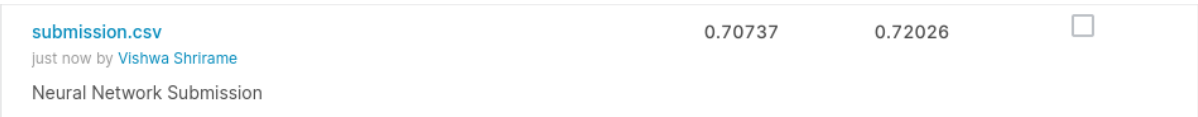
In [465…

```
from sklearn.metrics import accuracy_score
score = accuracy_score(y_test,predictions)
score
```

Out[465…

```
0.8353078591690305
```

Kaggle submission of our Neural network model



Discussion Experimental Results

In Phase 2, we mainly considered Logistic Regression and Random Forest Classifier as our candidate models based on last phases' result.

Additionally, as Feature Engineering was to be done in this particular phase, we derived 6 new candidate features from the given set of datasets out of which we selected **5** for our model training.

Including these Features helped increase the Test accuracy of Logistic Regression from **91.93%** to **92.08%** as it can be seen from the results.

This accuracy was before Hyperparameter Tuning. We then performed Hyperparameter Tuning to further improve our insights on the model.

HyperParameter tuning helped improve the Test Accuracy for Logistic Regression from **92.08%** to **92.46%**

Important Callout: The last feature that we **did not** select for our model training was **Debt Overdue per Customer**. Selecting this feature caused a sudden spike in our test accuracy

from **92.08% to 97.00%**. We believe that this sudden spike of accuracy is due to overfitting and thus we will keep the last test accuracy i.e 92.13% as our result from feature engineering.

Similarly for Random Forest Classifier, we were able to achieve test accuracy of **92.975%**

Phase 3 -

In this Phase 3 we first improved our results from Phase 2 and we achieved a Kaggle submission this time of 0.73136 from our previous score of 0.6491.

We implemented deep learning in this phase and we employed a Multi-Layer Perceptron as our model.

We received the train accuracy of 83.91% after 1000 epochs and a test accuracy of 83.53%.

We then visualized our training model on TensorBoard and generated a plot of loss function and accuracy.

We also implemented a Single Layer perceptron model and achieved a slight less accurracy as compared to multi layer.

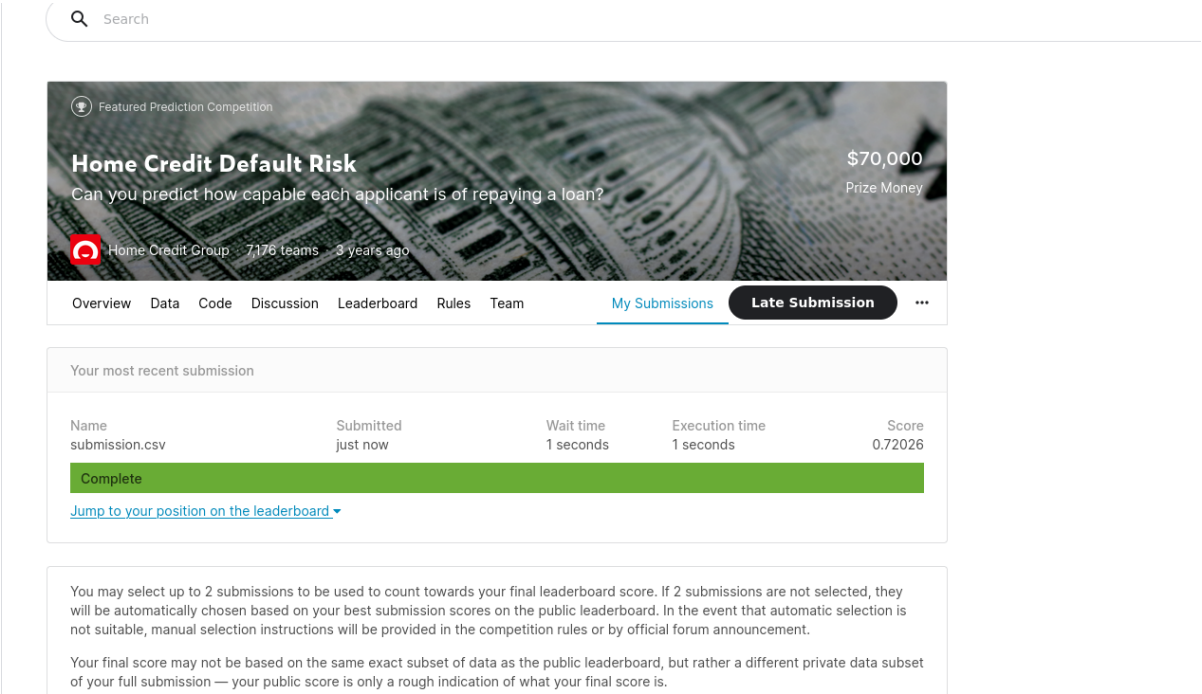
Conclusion

The main purpose of this project is to create a Machine Learning model that can predict whether or not a loan applicant will be able to repay the loan. Many worthy applicants with no credit history or default history are getting without any statistical analysis. The ML model in our work is trained using the HCDR dataset. It will be able to predict whether an applicant will be able to repay his loan or not based on the history of similar applicants in the past. This would help in filtering applicants with a good statistical backing derived from various factors that are taken into consideration. This would help both, a worthy applicant in securing a loan and the bank to grow their business further. We perfomed feature engineering, feature selection and hyperparameter tuning to improve our classification model to accurately predict whether the loan applicant is able to repay his loan or not. We identified that the Credit Annuity Ratio of the Application feature as the most important feature in our implementation. This feature is basically the ratio between the amount of loan credited to the annual annuity of the loan applicant. The result which we got after modeling and fine tuning provides confidence that it will be able to successfully predict applicants' credit worthiness. Their might be some inaccurate feature selections in our work as we got a decreased score on our kaggle submission. We will be analyzing what features are causing this and add or remove some more features to improve our score.

This is the third iteration of our model and we improved the inaccurate feature selections thus also improving the Kaggle submission. We also implemented a deep learning algorithm - Multi-layer Perceptron and generated a classified model to aid our implementation. We made use of TensorBoard to visualize our training model in real-time. We found that by improving feature selection and balancing the data, we are achieving better results. We also found that Multi-layer Perceptron model performs better than Single Layer Perceptron model.

Kaggle Submission

file:///N/u/vshriram/Carbonate/Desktop/kagglePhase3.png



References

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

1. Understanding AUC - ROC Curve
2. Better Heatmaps and Correlation Matrix Plots in Python
3. Bar Plots and Modern Alternatives
4. Data Visualization using Matplotlib
5. sklearn.ensemble.RandomForestClassifier
6. sklearn.ensemble.RandomForestClassifier
7. Feature Engineering
8. https://machinelearningmastery.com/cross-entropy-for-machine-learning/
9. https://towardsdatascience.com/multilayer-perceptron-explained-with-a-real-life-example-and-python-code-sentiment-analysis-cb408ee93141

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/