Home Credit Default Risk (HCDR)

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

Some of the challenges

1. Dataset size
   - (688 meg compressed) with millions of rows of data
   - 2.71 Gig of data uncompressed

- Dealing with missing data
- Imbalanced datasets
- Summarizing transaction data

Kaggle API setup

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

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

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

1. Install library

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

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

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

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.9/site-packages (1.5.12)
Requirement already satisfied: certifi in /usr/local/lib/python3.9/site-packages (from k
aggle) (2021.10.8)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.9/site-packages
(from kaggle) (2.8.2)
Requirement already satisfied: requests in /usr/local/lib/python3.9/site-packages (from
kaggle) (2.26.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/site-packages (from kagg
le) (4.62.3)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.9/site-packages
(from kaggle) (5.0.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.9/site-packages (from k
```

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

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

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

In [3]:
```
!ls -l  ~/.kaggle/kaggle.json
```

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

In [4]:
```
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json
```

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

In [5]:
```
! kaggle competitions files home-credit-default-risk
```

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

Dataset and how to download

Back ground Home Credit Group

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

Home Credit Group

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

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

Background on the dataset

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

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

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

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

Data files overview

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

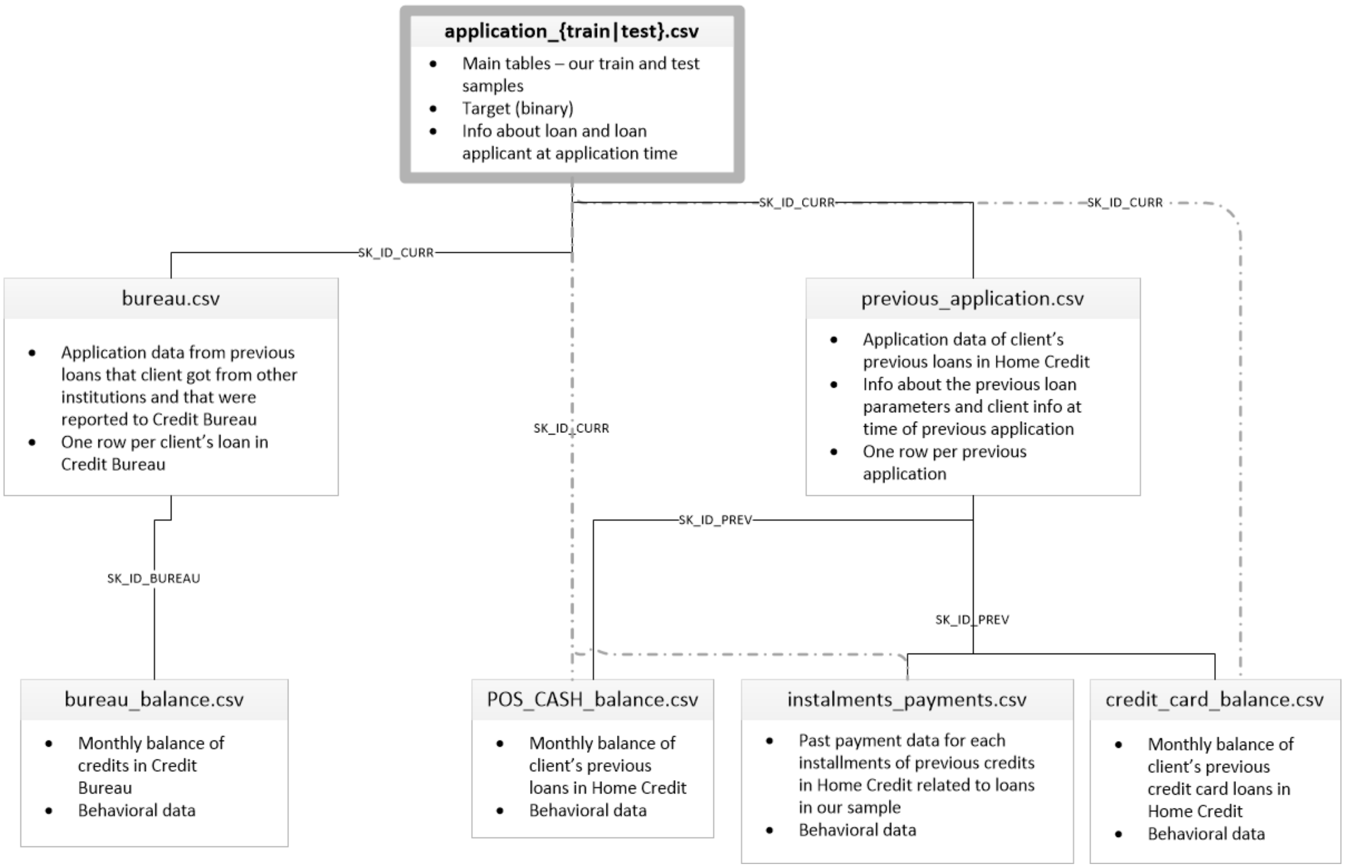
There are 7 different sources of data:

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

Table sizes

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

In [ ]:



Downloading the files via Kaggle API

Create a base directory:

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

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

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

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

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

```
total 0
```

In [8]:
```
! kaggle competitions download home-credit-default-risk -p $DATA_DIR
```

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

In [9]:
```
!pwd
```

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

In [10]:
```
!ls -l $DATA_DIR
```

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

In [11]:
```
!rm -r  DATA_DIR
```

Imports

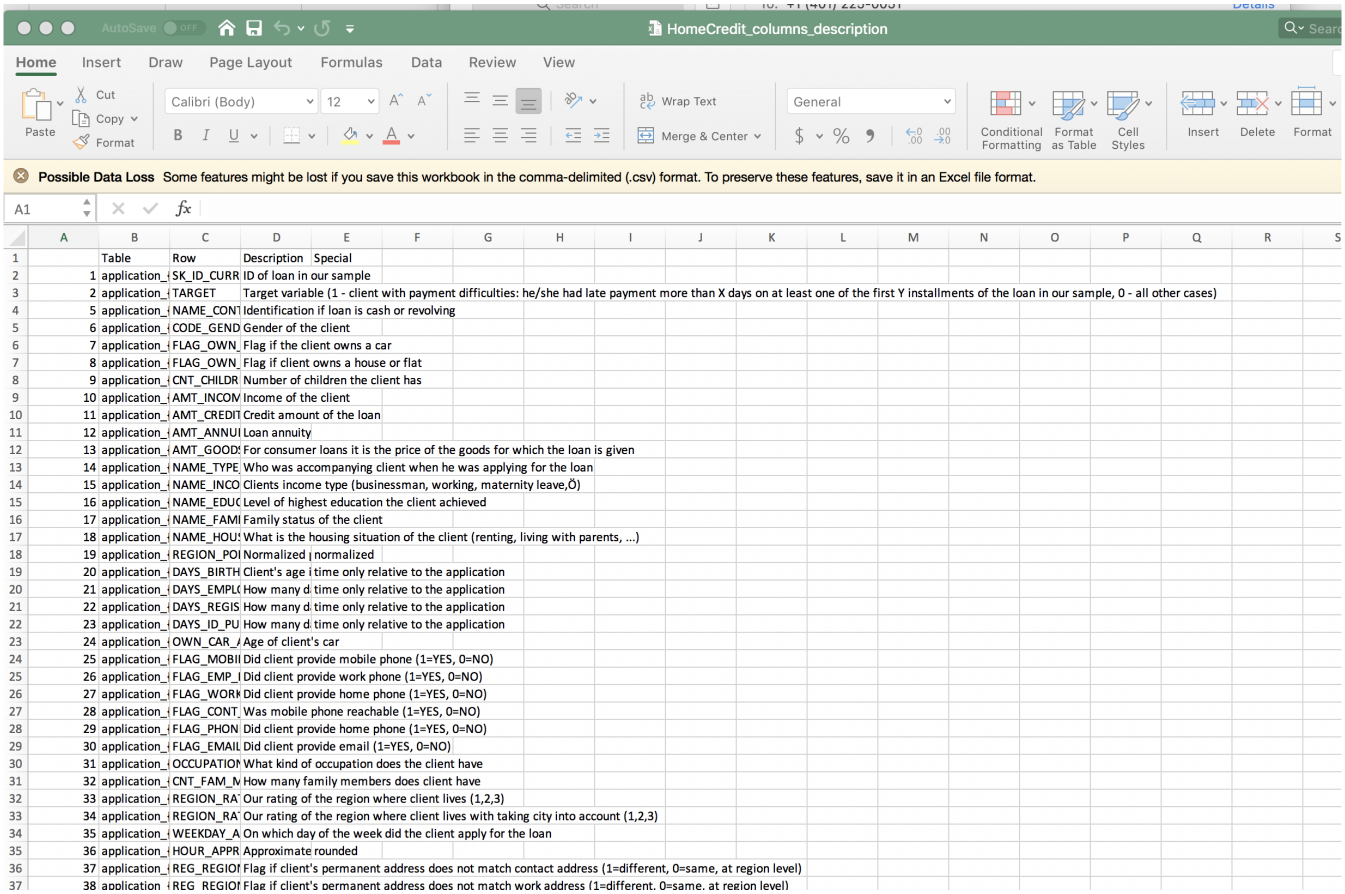
In [12]:
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import os
import zipfile
from sklearn.base import BaseEstimator, TransformerMixin
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline, FeatureUnion
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import warnings
warnings.filterwarnings('ignore')
```

In [13]:
```
# unzippingReq = True #True
# if unzippingReq: #please modify this code
#     zip_ref = zipfile.ZipFile(f'{DATA_DIR}/home-credit-default-risk.zip', 'r')
#     # extractall():  Extract all members from the archive to the current working direc
#     zip_ref.extractall('{DATA_DIR}')
#     zip_ref.close()
```

Data files overview

Data Dictionary

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



	A	B	C	D	E
1		Table	Row	Description	Special
2	1	application_{	SK_ID_CURR	ID of loan in our sample	
3	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)	
4	5	application_{	NAME_CONT	Identification if loan is cash or revolving	
5	6	application_{	CODE_GEND	Gender of the client	
6	7	application_{	FLAG_OWN_	Flag if the client owns a car	
7	8	application_{	FLAG_OWN_	Flag if client owns a house or flat	
8	9	application_{	CNT_CHILDR	Number of children the client has	
9	10	application_{	AMT_INCOM	Income of the client	
10	11	application_{	AMT_CREDIT	Credit amount of the loan	
11	12	application_{	AMT_ANNUI	Loan annuity	
12	13	application_{	AMT_GOODS	For consumer loans it is the price of the goods for which the loan is given	
13	14	application_{	NAME_TYPE_	Who was accompanying client when he was applying for the loan	
14	15	application_{	NAME_INCO	Clients income type (businessman, working, maternity leave,Ö)	
15	16	application_{	NAME_EDUC	Level of highest education the client achieved	
16	17	application_{	NAME_FAMI	Family status of the client	
17	18	application_{	NAME_HOUS	What is the housing situation of the client (renting, living with parents, ...)	
18	19	application_{	REGION_POI	Normalized p	normalized
19	20	application_{	DAYS_BIRTH	Client's age i	time only relative to the application
20	21	application_{	DAYS_EMPLC	How many d	time only relative to the application
21	22	application_{	DAYS_REGIS	How many d	time only relative to the application
22	23	application_{	DAYS_ID_PU	How many d	time only relative to the application
23	24	application_{	OWN_CAR_A	Age of client's car	
24	25	application_{	FLAG_MOBII	Did client provide mobile phone (1=YES, 0=NO)	
25	26	application_{	FLAG_EMP_I	Did client provide work phone (1=YES, 0=NO)	
26	27	application_{	FLAG_WORK	Did client provide home phone (1=YES, 0=NO)	
27	28	application_{	FLAG_CONT_	Was mobile phone reachable (1=YES, 0=NO)	
28	29	application_{	FLAG_PHON	Did client provide home phone (1=YES, 0=NO)	
29	30	application_{	FLAG_EMAIL	Did client provide email (1=YES, 0=NO)	
30	31	application_{	OCCUPATION	What kind of occupation does the client have	
31	32	application_{	CNT_FAM_M	How many family members does client have	
32	33	application_{	REGION_RAT	Our rating of the region where client lives (1,2,3)	
33	34	application_{	REGION_RAT	Our rating of the region where client lives with taking city into account (1,2,3)	
34	35	application_{	WEEKDAY_A	On which day of the week did the client apply for the loan	
35	36	application_{	HOUR_APPR	Approximate	rounded
36	37	application_{	REG_REGION	Flag if client's permanent address does not match contact address (1=different, 0=same, at region level)	
37	38	application_{	REG_REGION	Flag if client's permanent address does not match work address (1=different, 0=same, at region level)	

Application train

In [14]:
```
ls -l ../../../Data/home-credit-default-risk/'{DATA_DIR}'/application_train.csv
```

```
ls: cannot access '../../../Data/home-credit-default-risk/../../../Data/home-credit-defa
ult-risk/application_train.csv': No such file or directory
```

In [15]:
```
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')
```

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

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

datasets['application_train'].shape
```

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

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

5 rows × 122 columns

Out[15]:
```
(307511, 122)
```

In [16]:
```python
DATA_DIR
```

Out[16]:
```
'../../../Data/home-credit-default-risk'
```

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 [17]:
```python
ds_name = 'application_test'
datasets[ds_name] = load_data(os.path.join('{DATA_DIR}', f'{ds_name}.csv'), ds_name)
```

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

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILD
0	100001	Cash loans	F	N	Y	

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

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 [18]:

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

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

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

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

5 rows × 122 columns

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

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

5 rows × 121 columns

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

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	CREDIT_DAY_OVERDUE
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	(

```
bureau_balance: shape is (27299925, 3)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27299925 entries, 0 to 27299924
Data columns (total 3 columns):
 #   Column          Dtype
---  ------          -----
```

```
 0   SK_ID_BUREAU    int64
 1   MONTHS_BALANCE  int64
 2   STATUS          object
dtypes: int64(2), object(1)
memory usage: 624.8+ MB
None
```

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

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

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

5 rows × 23 columns

```
installments_payments: shape is (13605401, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13605401 entries, 0 to 13605400
Data columns (total 8 columns):
```

```
 #   Column                  Dtype  
---  ------                  -----  
 0   SK_ID_PREV              int64  
 1   SK_ID_CURR              int64  
 2   NUM_INSTALMENT_VERSION  float64
 3   NUM_INSTALMENT_NUMBER   int64  
 4   DAYS_INSTALMENT         float64
 5   DAYS_ENTRY_PAYMENT      float64
 6   AMT_INSTALMENT          float64
 7   AMT_PAYMENT             float64
dtypes: float64(5), int64(3)
memory usage: 830.4 MB
None
```

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

```
previous_application: shape is (1670214, 37)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):
 #   Column                       Non-Null Count    Dtype  
---  ------                       --------------    -----  
 0   SK_ID_PREV                   1670214 non-null  int64  
 1   SK_ID_CURR                   1670214 non-null  int64  
 2   NAME_CONTRACT_TYPE           1670214 non-null  object 
 3   AMT_ANNUITY                  1297979 non-null  float64
 4   AMT_APPLICATION              1670214 non-null  float64
 5   AMT_CREDIT                   1670213 non-null  float64
 6   AMT_DOWN_PAYMENT             774370 non-null   float64
 7   AMT_GOODS_PRICE              1284699 non-null  float64
 8   WEEKDAY_APPR_PROCESS_START   1670214 non-null  object 
 9   HOUR_APPR_PROCESS_START      1670214 non-null  int64  
 10  FLAG_LAST_APPL_PER_CONTRACT  1670214 non-null  object 
 11  NFLAG_LAST_APPL_IN_DAY       1670214 non-null  int64  
 12  RATE_DOWN_PAYMENT            774370 non-null   float64
 13  RATE_INTEREST_PRIMARY        5951 non-null     float64
 14  RATE_INTEREST_PRIVILEGED     5951 non-null     float64
 15  NAME_CASH_LOAN_PURPOSE       1670214 non-null  object 
 16  NAME_CONTRACT_STATUS         1670214 non-null  object 
 17  DAYS_DECISION                1670214 non-null  int64  
 18  NAME_PAYMENT_TYPE            1670214 non-null  object 
 19  CODE_REJECT_REASON           1670214 non-null  object 
 20  NAME_TYPE_SUITE              849809 non-null   object 
 21  NAME_CLIENT_TYPE             1670214 non-null  object 
 22  NAME_GOODS_CATEGORY          1670214 non-null  object 
 23  NAME_PORTFOLIO               1670214 non-null  object 
 24  NAME_PRODUCT_TYPE            1670214 non-null  object 
 25  CHANNEL_TYPE                 1670214 non-null  object 
 26  SELLERPLACE_AREA             1670214 non-null  int64  
 27  NAME_SELLER_INDUSTRY         1670214 non-null  object 
 28  CNT_PAYMENT                  1297984 non-null  float64
 29  NAME_YIELD_GROUP             1670214 non-null  object 
 30  PRODUCT_COMBINATION          1669868 non-null  object 
 31  DAYS_FIRST_DRAWING           997149 non-null   float64
 32  DAYS_FIRST_DUE               997149 non-null   float64
 33  DAYS_LAST_DUE_1ST_VERSION    997149 non-null   float64
 34  DAYS_LAST_DUE                997149 non-null   float64
 35  DAYS_TERMINATION             997149 non-null   float64
```

```
 36  NFLAG_INSURED_ON_APPROVAL    997149 non-null   float64
dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB
None
```

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

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_FUTURE	NAME_CON
0	1803195	182943	-31	48.0	45.0	
1	1715348	367990	-33	36.0	35.0	
2	1784872	397406	-32	12.0	9.0	
3	1903291	269225	-35	48.0	42.0	
4	2341044	334279	-35	36.0	35.0	

```
CPU times: user 19.6 s, sys: 3.85 s, total: 23.5 s
Wall time: 33.1 s
```

In [19]:
```
for ds_name in datasets.keys():
    print(f'dataset {ds_name:24}: [ {datasets[ds_name].shape[0]:10,}, {datasets[ds_name]
```

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

Exploratory Data Analysis

Summary of Application train and Application test

Summary of Application train

In [20]:
```
datasets["application_train"].shape
```

Out[20]:
```
(307511, 122)
```

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

In [21]:
```
datasets["application_train"].info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 122 columns):
 #    Column                        Dtype
---   ------                        -----
 0    SK_ID_CURR                    int64
 1    TARGET                        int64
 2    NAME_CONTRACT_TYPE            object
 3    CODE_GENDER                   object
 4    FLAG_OWN_CAR                  object
 5    FLAG_OWN_REALTY               object
 6    CNT_CHILDREN                  int64
 7    AMT_INCOME_TOTAL              float64
 8    AMT_CREDIT                    float64
 9    AMT_ANNUITY                   float64
 10   AMT_GOODS_PRICE               float64
 11   NAME_TYPE_SUITE               object
 12   NAME_INCOME_TYPE              object
 13   NAME_EDUCATION_TYPE           object
 14   NAME_FAMILY_STATUS            object
 15   NAME_HOUSING_TYPE             object
 16   REGION_POPULATION_RELATIVE    float64
 17   DAYS_BIRTH                    int64
 18   DAYS_EMPLOYED                 int64
 19   DAYS_REGISTRATION             float64
 20   DAYS_ID_PUBLISH               int64
 21   OWN_CAR_AGE                   float64
 22   FLAG_MOBIL                    int64
 23   FLAG_EMP_PHONE                int64
 24   FLAG_WORK_PHONE               int64
 25   FLAG_CONT_MOBILE              int64
 26   FLAG_PHONE                    int64
 27   FLAG_EMAIL                    int64
 28   OCCUPATION_TYPE               object
 29   CNT_FAM_MEMBERS               float64
 30   REGION_RATING_CLIENT          int64
 31   REGION_RATING_CLIENT_W_CITY   int64
 32   WEEKDAY_APPR_PROCESS_START    object
 33   HOUR_APPR_PROCESS_START       int64
 34   REG_REGION_NOT_LIVE_REGION    int64
 35   REG_REGION_NOT_WORK_REGION    int64
 36   LIVE_REGION_NOT_WORK_REGION   int64
 37   REG_CITY_NOT_LIVE_CITY        int64
 38   REG_CITY_NOT_WORK_CITY        int64
 39   LIVE_CITY_NOT_WORK_CITY       int64
 40   ORGANIZATION_TYPE             object
 41   EXT_SOURCE_1                  float64
 42   EXT_SOURCE_2                  float64
 43   EXT_SOURCE_3                  float64
 44   APARTMENTS_AVG                float64
```

```
45   BASEMENTAREA_AVG              float64
46   YEARS_BEGINEXPLUATATION_AVG   float64
47   YEARS_BUILD_AVG               float64
48   COMMONAREA_AVG                float64
49   ELEVATORS_AVG                 float64
50   ENTRANCES_AVG                 float64
51   FLOORSMAX_AVG                 float64
52   FLOORSMIN_AVG                 float64
53   LANDAREA_AVG                  float64
54   LIVINGAPARTMENTS_AVG          float64
55   LIVINGAREA_AVG                float64
56   NONLIVINGAPARTMENTS_AVG       float64
57   NONLIVINGAREA_AVG             float64
58   APARTMENTS_MODE               float64
59   BASEMENTAREA_MODE             float64
60   YEARS_BEGINEXPLUATATION_MODE  float64
61   YEARS_BUILD_MODE              float64
62   COMMONAREA_MODE               float64
63   ELEVATORS_MODE                float64
64   ENTRANCES_MODE                float64
65   FLOORSMAX_MODE                float64
66   FLOORSMIN_MODE                float64
67   LANDAREA_MODE                 float64
68   LIVINGAPARTMENTS_MODE         float64
69   LIVINGAREA_MODE               float64
70   NONLIVINGAPARTMENTS_MODE      float64
71   NONLIVINGAREA_MODE            float64
72   APARTMENTS_MEDI               float64
73   BASEMENTAREA_MEDI             float64
74   YEARS_BEGINEXPLUATATION_MEDI  float64
75   YEARS_BUILD_MEDI              float64
76   COMMONAREA_MEDI               float64
77   ELEVATORS_MEDI                float64
78   ENTRANCES_MEDI                float64
79   FLOORSMAX_MEDI                float64
80   FLOORSMIN_MEDI                float64
81   LANDAREA_MEDI                 float64
82   LIVINGAPARTMENTS_MEDI         float64
83   LIVINGAREA_MEDI               float64
84   NONLIVINGAPARTMENTS_MEDI      float64
85   NONLIVINGAREA_MEDI            float64
86   FONDKAPREMONT_MODE            object
87   HOUSETYPE_MODE                object
88   TOTALAREA_MODE                float64
89   WALLSMATERIAL_MODE            object
90   EMERGENCYSTATE_MODE           object
91   OBS_30_CNT_SOCIAL_CIRCLE      float64
92   DEF_30_CNT_SOCIAL_CIRCLE      float64
93   OBS_60_CNT_SOCIAL_CIRCLE      float64
94   DEF_60_CNT_SOCIAL_CIRCLE      float64
95   DAYS_LAST_PHONE_CHANGE        float64
96   FLAG_DOCUMENT_2               int64
97   FLAG_DOCUMENT_3               int64
98   FLAG_DOCUMENT_4               int64
99   FLAG_DOCUMENT_5               int64
100  FLAG_DOCUMENT_6               int64
101  FLAG_DOCUMENT_7               int64
102  FLAG_DOCUMENT_8               int64
103  FLAG_DOCUMENT_9               int64
104  FLAG_DOCUMENT_10              int64
105  FLAG_DOCUMENT_11              int64
106  FLAG_DOCUMENT_12              int64
107  FLAG_DOCUMENT_13              int64
108  FLAG_DOCUMENT_14              int64
109  FLAG_DOCUMENT_15              int64
110  FLAG_DOCUMENT_16              int64
```

```
 111   FLAG_DOCUMENT_17              int64
 112   FLAG_DOCUMENT_18              int64
 113   FLAG_DOCUMENT_19              int64
 114   FLAG_DOCUMENT_20              int64
 115   FLAG_DOCUMENT_21              int64
 116   AMT_REQ_CREDIT_BUREAU_HOUR    float64
 117   AMT_REQ_CREDIT_BUREAU_DAY     float64
 118   AMT_REQ_CREDIT_BUREAU_WEEK    float64
 119   AMT_REQ_CREDIT_BUREAU_MON     float64
 120   AMT_REQ_CREDIT_BUREAU_QRT     float64
 121   AMT_REQ_CREDIT_BUREAU_YEAR    float64
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

In [22]:
```
datasets["application_train"].describe() #numerical only features
```

Out[22]:

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

8 rows × 106 columns

In [23]:
```
datasets["application_train"].describe(include='all') #look at all categorical and numer
```

Out[23]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN
count	307511.000000	307511.000000	307511	307511	307511	
unique	NaN	NaN	2	3	2	
top	NaN	NaN	Cash loans	F	N	
freq	NaN	NaN	278232	202448	202924	
mean	278180.518577	0.080729	NaN	NaN	NaN	
std	102790.175348	0.272419	NaN	NaN	NaN	
min	100002.000000	0.000000	NaN	NaN	NaN	
25%	189145.500000	0.000000	NaN	NaN	NaN	
50%	278202.000000	0.000000	NaN	NaN	NaN	
75%	367142.500000	0.000000	NaN	NaN	NaN	
max	456255.000000	1.000000	NaN	NaN	NaN	

11 rows × 122 columns

In [24]:
```
# Define function to List the categorical and Numerical features in the dataframe

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

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

In [25]:
```
datatypes_groups(datasets['application_train'], 'application_train')
```

```
Description of the application_train dataset:

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

{'int64': Index(['SK_ID_CURR', 'TARGET', 'CNT_CHILDREN', 'DAYS_BIRTH', 'DAYS_EMPLOYED',
       'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',
       'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START',
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'FLAG_DOCUMENT_2',
       'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5',
       'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8',
       'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11',
       'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14',
       'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21'],
      dtype='object')}
------------------------------
{'float64': Index(['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',
       'REGION_POPULATION_RELATIVE', 'DAYS_REGISTRATION', 'OWN_CAR_AGE',
       'CNT_FAM_MEMBERS', 'EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'APARTMENTS_AVG', 'BASEMENTAREA_AVG', 'YEARS_BEGINEXPLUATATION_AVG',
       'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG', 'ENTRANCES_AVG',
       'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG',
       'LIVINGAPARTMENTS_AVG', 'LIVINGAREA_AVG', 'NONLIVINGAPARTMENTS_AVG',
       'NONLIVINGAREA_AVG', 'APARTMENTS_MODE', 'BASEMENTAREA_MODE',
       'YEARS_BEGINEXPLUATATION_MODE', 'YEARS_BUILD_MODE', 'COMMONAREA_MODE',
       'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMAX_MODE', 'FLOORSMIN_MODE',
       'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'LIVINGAREA_MODE',
       'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE', 'APARTMENTS_MEDI',
       'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI', 'YEARS_BUILD_MEDI',
       'COMMONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI', 'FLOORSMAX_MEDI',
       'FLOORSMIN_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI',
       'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI', 'NONLIVINGAREA_MEDI',
       'TOTALAREA_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE',
       'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE',
       'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE',
       'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
       'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
       'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')}
------------------------------
```

```
{'object': Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALT
Y',
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE',
       'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'],
      dtype='object')}
------------------------------
```

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

Summary of Application test

In [26]:
```
datasets["application_test"].shape
```

Out[26]:
```
(48744, 121)
```

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

In [27]:
```
datasets["application_test"].info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48744 entries, 0 to 48743
Data columns (total 121 columns):
 #    Column                        Dtype
---   ------                        -----
 0    SK_ID_CURR                    int64
 1    NAME_CONTRACT_TYPE            object
 2    CODE_GENDER                   object
 3    FLAG_OWN_CAR                  object
 4    FLAG_OWN_REALTY               object
 5    CNT_CHILDREN                  int64
 6    AMT_INCOME_TOTAL              float64
 7    AMT_CREDIT                    float64
 8    AMT_ANNUITY                   float64
 9    AMT_GOODS_PRICE               float64
 10   NAME_TYPE_SUITE               object
 11   NAME_INCOME_TYPE              object
 12   NAME_EDUCATION_TYPE           object
 13   NAME_FAMILY_STATUS            object
 14   NAME_HOUSING_TYPE             object
 15   REGION_POPULATION_RELATIVE    float64
 16   DAYS_BIRTH                    int64
 17   DAYS_EMPLOYED                 int64
 18   DAYS_REGISTRATION             float64
 19   DAYS_ID_PUBLISH               int64
 20   OWN_CAR_AGE                   float64
 21   FLAG_MOBIL                    int64
 22   FLAG_EMP_PHONE                int64
 23   FLAG_WORK_PHONE               int64
 24   FLAG_CONT_MOBILE              int64
 25   FLAG_PHONE                    int64
 26   FLAG_EMAIL                    int64
 27   OCCUPATION_TYPE               object
```

```
28   CNT_FAM_MEMBERS              float64
29   REGION_RATING_CLIENT         int64
30   REGION_RATING_CLIENT_W_CITY  int64
31   WEEKDAY_APPR_PROCESS_START   object
32   HOUR_APPR_PROCESS_START      int64
33   REG_REGION_NOT_LIVE_REGION   int64
34   REG_REGION_NOT_WORK_REGION   int64
35   LIVE_REGION_NOT_WORK_REGION  int64
36   REG_CITY_NOT_LIVE_CITY       int64
37   REG_CITY_NOT_WORK_CITY       int64
38   LIVE_CITY_NOT_WORK_CITY      int64
39   ORGANIZATION_TYPE            object
40   EXT_SOURCE_1                 float64
41   EXT_SOURCE_2                 float64
42   EXT_SOURCE_3                 float64
43   APARTMENTS_AVG               float64
44   BASEMENTAREA_AVG             float64
45   YEARS_BEGINEXPLUATATION_AVG  float64
46   YEARS_BUILD_AVG              float64
47   COMMONAREA_AVG               float64
48   ELEVATORS_AVG                float64
49   ENTRANCES_AVG                float64
50   FLOORSMAX_AVG                float64
51   FLOORSMIN_AVG                float64
52   LANDAREA_AVG                 float64
53   LIVINGAPARTMENTS_AVG         float64
54   LIVINGAREA_AVG               float64
55   NONLIVINGAPARTMENTS_AVG      float64
56   NONLIVINGAREA_AVG            float64
57   APARTMENTS_MODE              float64
58   BASEMENTAREA_MODE            float64
59   YEARS_BEGINEXPLUATATION_MODE float64
60   YEARS_BUILD_MODE             float64
61   COMMONAREA_MODE              float64
62   ELEVATORS_MODE               float64
63   ENTRANCES_MODE               float64
64   FLOORSMAX_MODE               float64
65   FLOORSMIN_MODE               float64
66   LANDAREA_MODE                float64
67   LIVINGAPARTMENTS_MODE        float64
68   LIVINGAREA_MODE              float64
69   NONLIVINGAPARTMENTS_MODE     float64
70   NONLIVINGAREA_MODE           float64
71   APARTMENTS_MEDI              float64
72   BASEMENTAREA_MEDI            float64
73   YEARS_BEGINEXPLUATATION_MEDI float64
74   YEARS_BUILD_MEDI             float64
75   COMMONAREA_MEDI              float64
76   ELEVATORS_MEDI               float64
77   ENTRANCES_MEDI               float64
78   FLOORSMAX_MEDI               float64
79   FLOORSMIN_MEDI               float64
80   LANDAREA_MEDI                float64
81   LIVINGAPARTMENTS_MEDI        float64
82   LIVINGAREA_MEDI              float64
83   NONLIVINGAPARTMENTS_MEDI     float64
84   NONLIVINGAREA_MEDI           float64
85   FONDKAPREMONT_MODE           object
86   HOUSETYPE_MODE               object
87   TOTALAREA_MODE               float64
88   WALLSMATERIAL_MODE           object
89   EMERGENCYSTATE_MODE          object
90   OBS_30_CNT_SOCIAL_CIRCLE     float64
91   DEF_30_CNT_SOCIAL_CIRCLE     float64
92   OBS_60_CNT_SOCIAL_CIRCLE     float64
93   DEF_60_CNT_SOCIAL_CIRCLE     float64
```

```
 94   DAYS_LAST_PHONE_CHANGE         float64
 95   FLAG_DOCUMENT_2                int64
 96   FLAG_DOCUMENT_3                int64
 97   FLAG_DOCUMENT_4                int64
 98   FLAG_DOCUMENT_5                int64
 99   FLAG_DOCUMENT_6                int64
 100  FLAG_DOCUMENT_7                int64
 101  FLAG_DOCUMENT_8                int64
 102  FLAG_DOCUMENT_9                int64
 103  FLAG_DOCUMENT_10               int64
 104  FLAG_DOCUMENT_11               int64
 105  FLAG_DOCUMENT_12               int64
 106  FLAG_DOCUMENT_13               int64
 107  FLAG_DOCUMENT_14               int64
 108  FLAG_DOCUMENT_15               int64
 109  FLAG_DOCUMENT_16               int64
 110  FLAG_DOCUMENT_17               int64
 111  FLAG_DOCUMENT_18               int64
 112  FLAG_DOCUMENT_19               int64
 113  FLAG_DOCUMENT_20               int64
 114  FLAG_DOCUMENT_21               int64
 115  AMT_REQ_CREDIT_BUREAU_HOUR     float64
 116  AMT_REQ_CREDIT_BUREAU_DAY      float64
 117  AMT_REQ_CREDIT_BUREAU_WEEK     float64
 118  AMT_REQ_CREDIT_BUREAU_MON      float64
 119  AMT_REQ_CREDIT_BUREAU_QRT      float64
 120  AMT_REQ_CREDIT_BUREAU_YEAR     float64
dtypes: float64(65), int64(40), object(16)
memory usage: 45.0+ MB
```

In [28]:

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

Out[28]:

	SK_ID_CURR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRIC
count	48744.000000	48744.000000	4.874400e+04	4.874400e+04	48720.000000	4.874400e+0
mean	277796.676350	0.397054	1.784318e+05	5.167404e+05	29426.240209	4.626188e+0
std	103169.547296	0.709047	1.015226e+05	3.653970e+05	16016.368315	3.367102e+0
min	100001.000000	0.000000	2.694150e+04	4.500000e+04	2295.000000	4.500000e+0
25%	188557.750000	0.000000	1.125000e+05	2.606400e+05	17973.000000	2.250000e+0
50%	277549.000000	0.000000	1.575000e+05	4.500000e+05	26199.000000	3.960000e+0
75%	367555.500000	1.000000	2.250000e+05	6.750000e+05	37390.500000	6.300000e+0
max	456250.000000	20.000000	4.410000e+06	2.245500e+06	180576.000000	2.245500e+0

8 rows × 105 columns

In [29]:

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

Out[29]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_
count	48744.000000	48744	48744	48744	48744	4t
unique	NaN	2	2	2	2	
top	NaN	Cash loans	F	N	Y	
freq	NaN	48305	32678	32311	33658	
mean	277796.676350	NaN	NaN	NaN	NaN	
std	103169.547296	NaN	NaN	NaN	NaN	
min	100001.000000	NaN	NaN	NaN	NaN	

25%	188557.750000	NaN	NaN	NaN	NaN
50%	277549.000000	NaN	NaN	NaN	NaN
75%	367555.500000	NaN	NaN	NaN	NaN
max	456250.000000	NaN	NaN	NaN	NaN

11 rows × 121 columns

In [30]:
```
datatypes_groups(datasets['application_test'], 'application_test')
```

```
Description of the application_test dataset:

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

{'int64': Index(['SK_ID_CURR', 'CNT_CHILDREN', 'DAYS_BIRTH', 'DAYS_EMPLOYED',
       'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',
       'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START',
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'FLAG_DOCUMENT_2',
       'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5',
       'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8',
       'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11',
       'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14',
       'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21'],
      dtype='object')}
-------------------------------
{'float64': Index(['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',
       'REGION_POPULATION_RELATIVE', 'DAYS_REGISTRATION', 'OWN_CAR_AGE',
       'CNT_FAM_MEMBERS', 'EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'APARTMENTS_AVG', 'BASEMENTAREA_AVG', 'YEARS_BEGINEXPLUATATION_AVG',
       'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG', 'ENTRANCES_AVG',
       'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG',
       'LIVINGAPARTMENTS_AVG', 'LIVINGAREA_AVG', 'NONLIVINGAPARTMENTS_AVG',
       'NONLIVINGAREA_AVG', 'APARTMENTS_MODE', 'BASEMENTAREA_MODE',
       'YEARS_BEGINEXPLUATATION_MODE', 'YEARS_BUILD_MODE', 'COMMONAREA_MODE',
       'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMAX_MODE', 'FLOORSMIN_MODE',
       'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'LIVINGAREA_MODE',
       'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE', 'APARTMENTS_MEDI',
       'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI', 'YEARS_BUILD_MEDI',
       'COMMONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI', 'FLOORSMAX_MEDI',
       'FLOORSMIN_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI',
       'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI', 'NONLIVINGAREA_MEDI',
       'TOTALAREA_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE',
       'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE',
       'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE',
       'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
       'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
       'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')}
-------------------------------
{'object': Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALT
Y',
```

```
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE',
       'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'],
      dtype='object')}
------------------------------
```

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

Missing data for application train and test

Missing data for application train

In [31]:
```
!pip install missingno
```

```
Requirement already satisfied: missingno in /usr/local/lib/python3.9/site-packages (0.5.
2)
Requirement already satisfied: numpy in /usr/local/lib/python3.9/site-packages (from mis
singno) (1.22.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.9/site-packages (from m
issingno) (0.11.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.9/site-packages (fro
m missingno) (3.4.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.9/site-packages (from mis
singno) (1.7.3)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/site-packag
es (from matplotlib->missingno) (1.3.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.9/site-pac
kages (from matplotlib->missingno) (2.8.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/site-packages
(from matplotlib->missingno) (9.0.0)
Requirement already satisfied: pyparsing>=2.2.1 in /usr/local/lib/python3.9/site-package
s (from matplotlib->missingno) (3.0.6)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/site-packages (f
rom matplotlib->missingno) (0.11.0)
Requirement already satisfied: pandas>=0.23 in /usr/local/lib/python3.9/site-packages (f
rom seaborn->missingno) (1.3.5)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.9/site-packages (f
rom pandas>=0.23->seaborn->missingno) (2021.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/site-packages (from
python-dateutil>=2.7->matplotlib->missingno) (1.15.0)
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting
 behaviour with the system package manager. It is recommended to use a virtual environme
nt instead: https://pip.pypa.io/warnings/venv
WARNING: You are using pip version 21.3.1; however, version 24.0 is available.
You should consider upgrading via the '/usr/local/bin/python -m pip install --upgrade pi
p' command.
```

In [32]:
```
import missingno as msno
import matplotlib.pyplot as plt
```

In [33]:
```
percent = (datasets["application_train"].isnull().sum()/datasets["application_train"].is
sum_missing = datasets["application_train"].isna().sum().sort_values(ascending = False)
missing_application_train_data  = pd.concat([percent, sum_missing], axis=1, keys=['Perce
missing_application_train_data.head(20)
```

Out[33]:

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

In [34]:
```
# msno.bar(datasets['application_train'])
```

In [35]:
```
# msno.matrix(datasets['application_train'])
```

Missing data for application test

In [36]:
```
percent = (datasets["application_test"].isnull().sum()/datasets["application_test"].isnu
sum_missing = datasets["application_test"].isna().sum().sort_values(ascending = False)
missing_application_train_data  = pd.concat([percent, sum_missing], axis=1, keys=['Perce
missing_application_train_data.head(20)
```

Out[36]:

	Percent	Test Missing Count
COMMONAREA_AVG	68.72	33495
COMMONAREA_MODE	68.72	33495
COMMONAREA_MEDI	68.72	33495
NONLIVINGAPARTMENTS_AVG	68.41	33347
NONLIVINGAPARTMENTS_MODE	68.41	33347
NONLIVINGAPARTMENTS_MEDI	68.41	33347
FONDKAPREMONT_MODE	67.28	32797
LIVINGAPARTMENTS_AVG	67.25	32780
LIVINGAPARTMENTS_MODE	67.25	32780
LIVINGAPARTMENTS_MEDI	67.25	32780

FLOORSMIN_MEDI	66.61	32466
FLOORSMIN_AVG	66.61	32466
FLOORSMIN_MODE	66.61	32466
OWN_CAR_AGE	66.29	32312
YEARS_BUILD_AVG	65.28	31818
YEARS_BUILD_MEDI	65.28	31818
YEARS_BUILD_MODE	65.28	31818
LANDAREA_MEDI	57.96	28254
LANDAREA_AVG	57.96	28254
LANDAREA_MODE	57.96	28254

In [37]:
```
# msno.bar(datasets['application_test'])
```

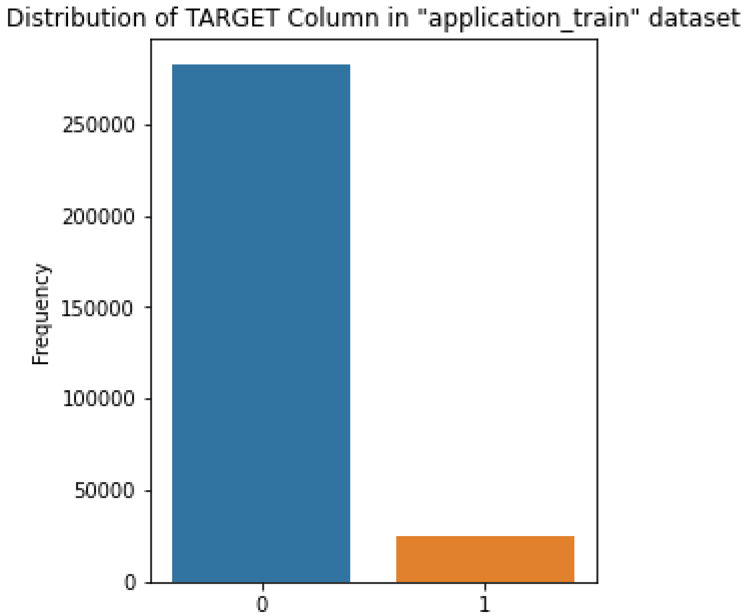
In [38]:
```
# msno.matrix(datasets['application_test'])
```

Distribution of the target column

In [39]:
```
# Print the value counts of the 'TARGET' column in "application_train" dataset

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

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

In [40]:
```
# Plot the distribution of the values of 'TARGET' column in "application_train" dataset

import matplotlib.pyplot as plt
import seaborn as sns

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

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

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

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

plt.show()
```



- Explaination
- As shown above, an imbalanced class issue was found in the "application_train" dataset. Class Imbalance is a common problem in machine learning, especially in classification tasks. This problem can negatively impact the performance and accuracy of machine models. Therefore, we need to handle the class imbalance problem before performing machine learning using combining Undersampling and Oversampling' techniques.

Correlation with the target column

In [41]:
```
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 [42]:
```
# Get the top 10 most positively and negatively correlated features
```

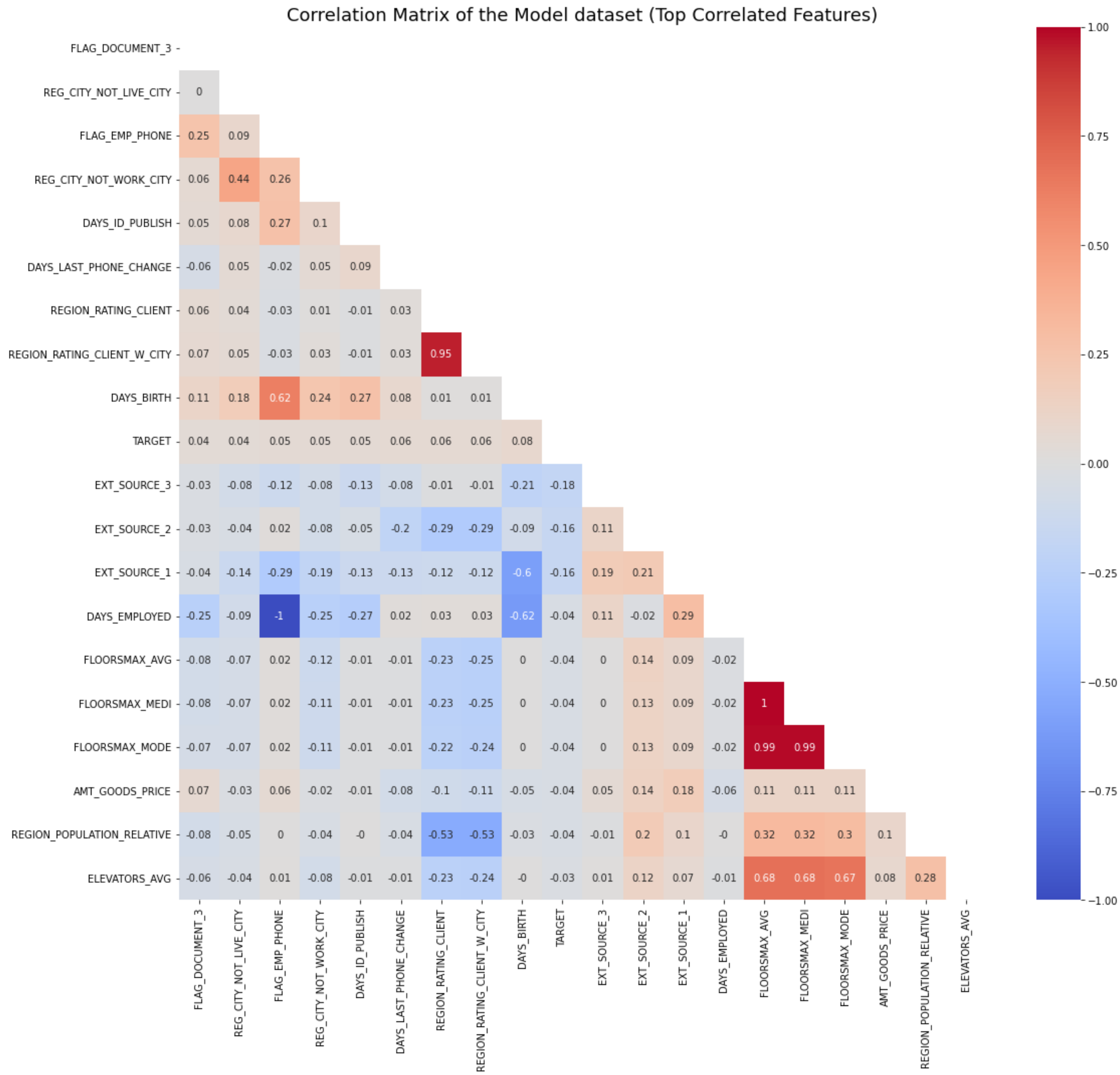
```python
most_positive_correlations = correlations.tail(10).index.tolist() #Positively correlated

most_negative_correlations = correlations.head(10).index.tolist() #Negatively correlated

top_correlated_features = most_positive_correlations + most_negative_correlations
top_correlated_features
```

Out[42]:

```
['FLAG_DOCUMENT_3',
 'REG_CITY_NOT_LIVE_CITY',
 'FLAG_EMP_PHONE',
 'REG_CITY_NOT_WORK_CITY',
 'DAYS_ID_PUBLISH',
 'DAYS_LAST_PHONE_CHANGE',
 'REGION_RATING_CLIENT',
 'REGION_RATING_CLIENT_W_CITY',
 'DAYS_BIRTH',
 'TARGET',
 'EXT_SOURCE_3',
 'EXT_SOURCE_2',
 'EXT_SOURCE_1',
 'DAYS_EMPLOYED',
 'FLOORSMAX_AVG',
 'FLOORSMAX_MEDI',
 'FLOORSMAX_MODE',
 'AMT_GOODS_PRICE',
 'REGION_POPULATION_RELATIVE',
 'ELEVATORS_AVG']
```

In [43]:

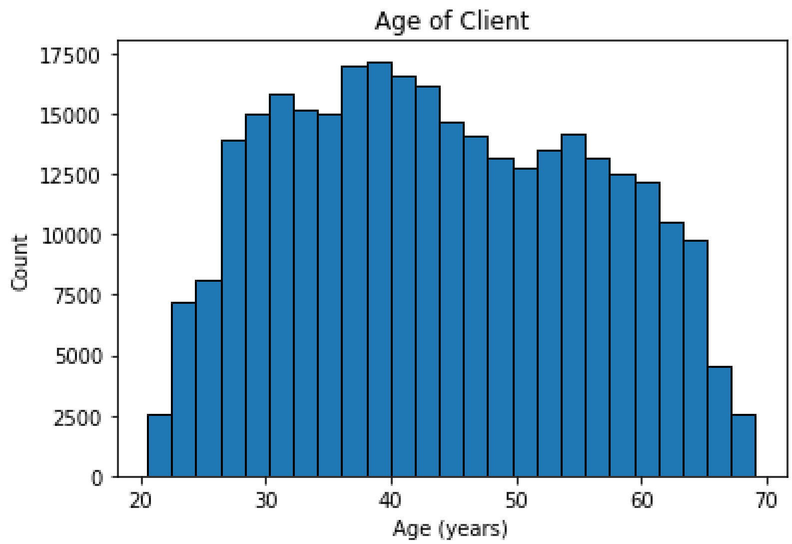
```python
# Subset the 'application_train' dataset to include only the top correlated features
application_train_subset = datasets["application_train"][top_correlated_features]

# Calculate the correlation matrix for the subset of features
matrix_model_subset = application_train_subset.corr().round(2)

# Applying mask
mask = np.triu(np.ones_like(matrix_model_subset, dtype=bool))

# Plotting a triangle correlation heatmap for the subset of features
plt.figure(figsize=(18, 16))
sns.heatmap(matrix_model_subset, annot=True, mask=mask, cmap='coolwarm')
plt.title('Correlation Matrix of the Model dataset (Top Correlated Features)', fontsize=
plt.show()
```



- Explaination
- The correlation results with the TARGET column from the application_train dataset showed that the variables most positively correlated with the target variable was DAYS_BIRTH (0.078239), whereas, the variables most negatively correlated with the target variable was EXT_SOURCE_3 (-0.178919).

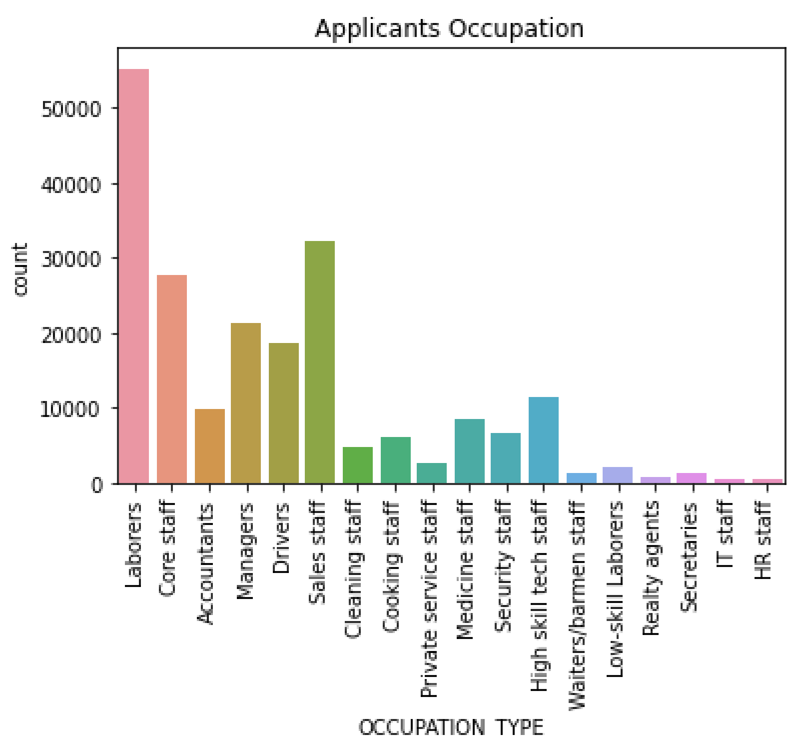
Applicants Age

In [44]:
```
plt.hist(datasets["application_train"]['DAYS_BIRTH'] / -365, edgecolor = 'k', bins = 25)
plt.title('Age of Client'); plt.xlabel('Age (years)'); plt.ylabel('Count');
```



Applicants occupations

In [45]:
```
sns.countplot(x='OCCUPATION_TYPE', data=datasets["application_train"]);
plt.title('Applicants Occupation');
plt.xticks(rotation=90);
```



In [ ]:

In [ ]:

Dataset questions

Unique record for each SK_ID_CURR

In [46]:
```
list(datasets.keys())
```

```
['application_train',
```

Out[46]:
```
 'application_test',
 'bureau',
 'bureau_balance',
 'credit_card_balance',
 'installments_payments',
 'previous_application',
 'POS_CASH_balance']
```

In [47]:
```python
len(datasets["application_train"]["SK_ID_CURR"].unique()) == datasets["application_train
```

Out[47]:
```
True
```

In [48]:
```python
# is there an overlap between the test and train customers
np.intersect1d(datasets["application_train"]["SK_ID_CURR"], datasets["application_test"]
```

Out[48]:
```
array([], dtype=int64)
```

In [49]:
```python
#
datasets["application_test"].shape
```

Out[49]:
```
(48744, 121)
```

In [50]:
```python
datasets["application_train"].shape
```

Out[50]:
```
(307511, 122)
```

previous applications for the submission file

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

In [51]:
```python
appsDF = datasets["previous_application"]
display(appsDF.head())
print(f"{appsDF.shape[0]:,} rows, {appsDF.shape[1]:,} columns")
```

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

5 rows × 37 columns

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

In [52]:
```python
print(f"There are  {appsDF.shape[0]:,} previous applications")
```

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

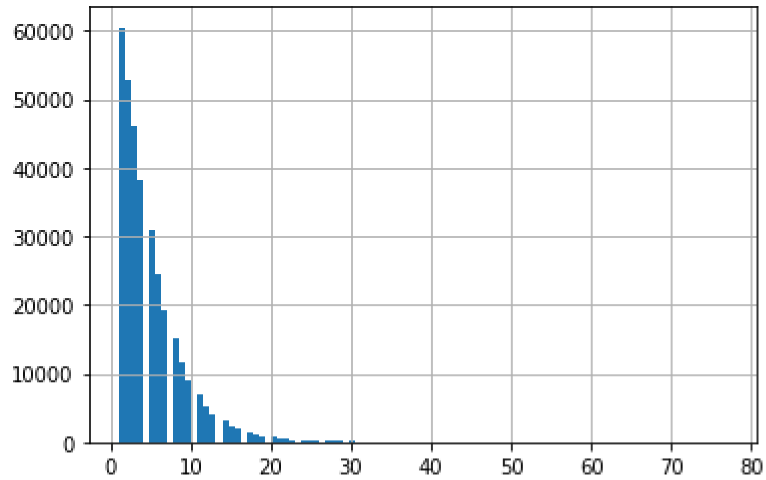
In [53]:
```python
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is {len(np.intersect1d(dat
```

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

In [54]:
```python
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is {len(np.intersect1d(dat
```

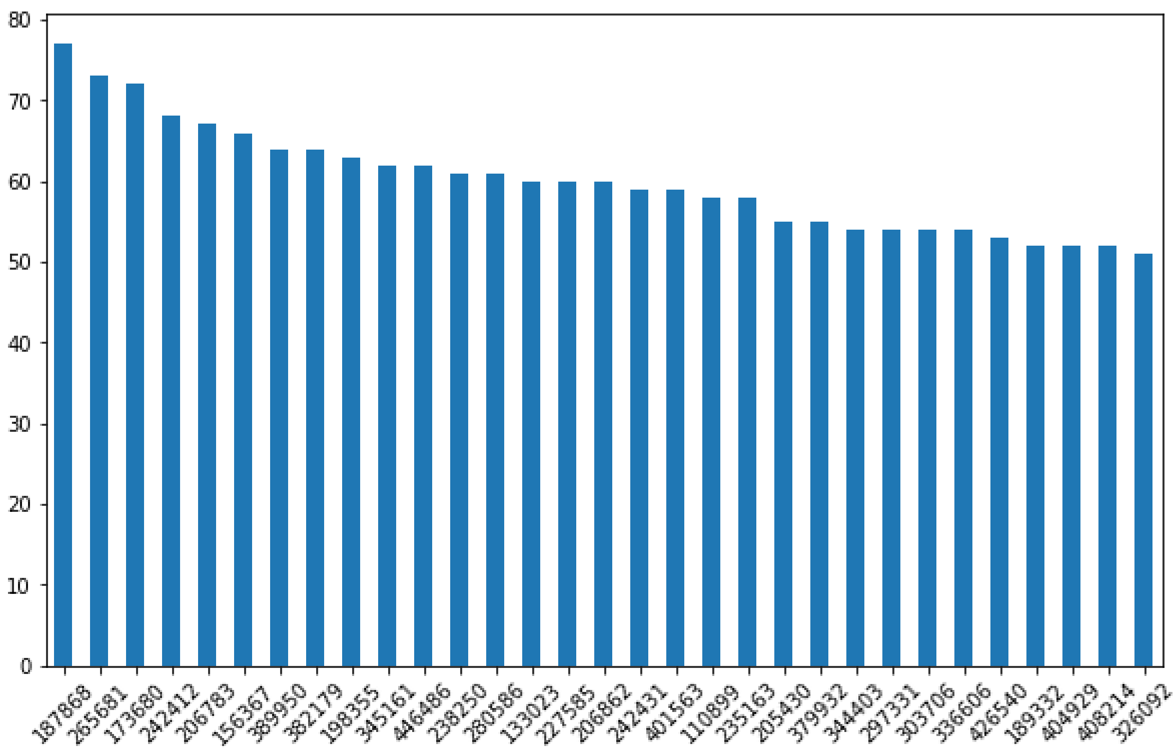
```
Number of train applicants with previous applications is 47,800
```

In [55]:
```python
# How many previous applciations  per applicant in the previous_application
prevAppCounts = appsDF['SK_ID_CURR'].value_counts(dropna=False)
len(prevAppCounts[prevAppCounts >40])  #more that 40 previous applications
plt.hist(prevAppCounts[prevAppCounts>=0], bins=100)
plt.grid()
```



In [ ]:

In [56]:
```python
# Display the applicants with more than 50 applications in the dataset.

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

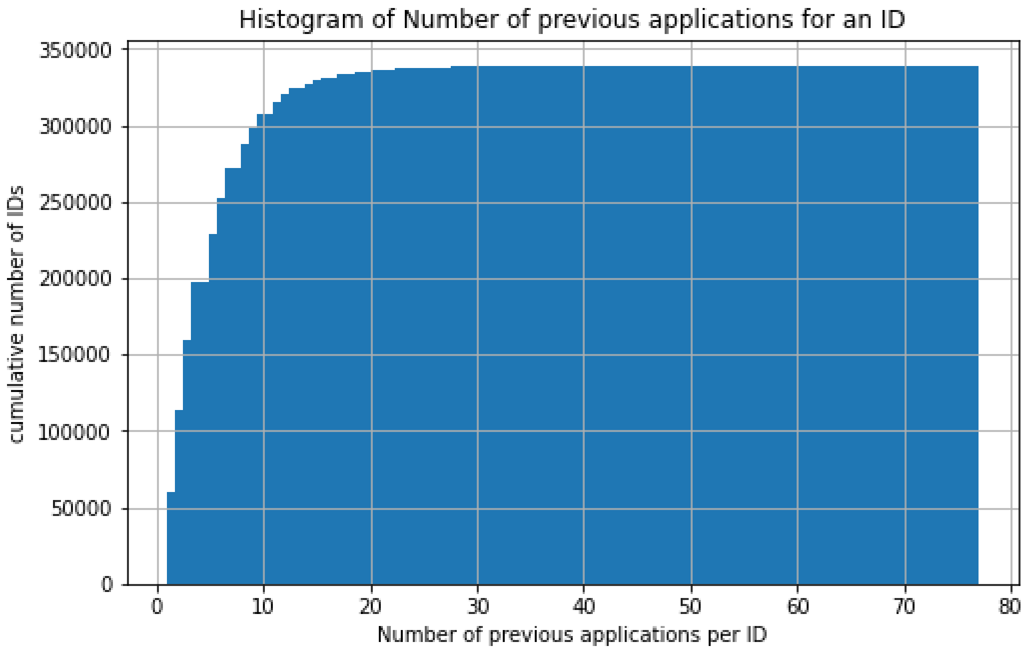


Histogram of Number of previous applications for an ID

In [57]:
```python
sum(appsDF['SK_ID_CURR'].value_counts()==1)
```

Out[57]:
```
60458
```

In [58]:
```
plt.figure(figsize=(8, 5))
plt.hist(appsDF['SK_ID_CURR'].value_counts(), cumulative =True, bins = 100);
plt.grid()
plt.ylabel('cumulative number of IDs')
plt.xlabel('Number of previous applications per ID')
plt.title('Histogram of Number of previous applications for an ID')
plt.show()
```



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

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

In [59]:
```
apps_all = appsDF['SK_ID_CURR'].nunique()
apps_5plus = appsDF['SK_ID_CURR'].value_counts()>=5
apps_40plus = appsDF['SK_ID_CURR'].value_counts()>=40
print('Percentage with 10 or more previous apps:', np.round(100.*(sum(apps_5plus)/apps_a
print('Percentage with 40 or more previous apps:', np.round(100.*(sum(apps_40plus)/apps_
```

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

Joining secondary tables with the primary table

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

Joining `previous_application` with `application_x`

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

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

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

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

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

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

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

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

Roadmap for secondary table processing

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

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

agg detour

Aggregate using one or more operations over the specified axis.

For more details see agg

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

Aggregate using one or more operations over the specified axis.

In [60]:
```python
df = pd.DataFrame([[1, 2, 3],
                    [4, 5, 6],
                   [7, 8, 9],
                   [np.nan, np.nan, np.nan]],
                   columns=['A', 'B', 'C'])
display(df)
```

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

In [61]:
```python
df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
#         A     B
#max    NaN   8.0
#min    1.0   2.0
#sum   12.0   NaN
```

Out[61]:

	A	B
sum	12.0	NaN
min	1.0	2.0
max	NaN	8.0

In [62]:
```python
df = pd.DataFrame({'A': [1, 1, 2, 2],
                    'B': [1, 2, 3, 4],
                    'C': np.random.randn(4)})
display(df)
```

	A	B	C
0	1	1	-1.924206
1	1	2	-0.839642
2	2	3	-1.597312
3	2	4	-0.823235

In [63]:
```python
# group by column A:
df.groupby('A').agg({'B': ['min', 'max'], 'C': 'sum'})
#    B             C
#   min max       sum
#A
#1    1    2   0.590716
#2    3    4   0.704907
```

Out[63]:

	B		C
	min	**max**	**sum**
A			
1	1	2	-2.763848
2	3	4	-2.420547

In [64]:
```python
appsDF.columns
```

```
Out[64]: Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOODS_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION', 'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')
```

In [ ]:

```
In [65]: funcs = ["a","b","c"]
{f:f"{f}_max" for f in funcs}
```

```
Out[65]: {'a': 'a_max', 'b': 'b_max', 'c': 'c_max'}
```

Multiple condition expressions in Pandas

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

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

You must use the following operators with pandas:

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

```
In [66]: appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]
```

Out[66]:

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

1 rows × 37 columns

```
In [67]: appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]["AMT_CREDIT"]
```

```
Out[67]: 6    0.0
Name: AMT_CREDIT, dtype: float64
```

```
In [68]: appsDF[0:50][(appsDF["SK_ID_CURR"]==175704) & ~(appsDF["AMT_CREDIT"]==1.0)]
```

Out[68]:

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

1 rows × 37 columns

Missing values in prevApps

In [69]:
```
appsDF.isna().sum()
```

Out[69]:
```
SK_ID_PREV                           0
SK_ID_CURR                           0
NAME_CONTRACT_TYPE                   0
AMT_ANNUITY                     372235
AMT_APPLICATION                      0
AMT_CREDIT                           1
AMT_DOWN_PAYMENT                895844
AMT_GOODS_PRICE                 385515
WEEKDAY_APPR_PROCESS_START           0
HOUR_APPR_PROCESS_START              0
FLAG_LAST_APPL_PER_CONTRACT          0
NFLAG_LAST_APPL_IN_DAY               0
RATE_DOWN_PAYMENT               895844
RATE_INTEREST_PRIMARY          1664263
RATE_INTEREST_PRIVILEGED       1664263
NAME_CASH_LOAN_PURPOSE               0
NAME_CONTRACT_STATUS                 0
DAYS_DECISION                        0
NAME_PAYMENT_TYPE                    0
CODE_REJECT_REASON                   0
NAME_TYPE_SUITE                 820405
NAME_CLIENT_TYPE                     0
NAME_GOODS_CATEGORY                  0
NAME_PORTFOLIO                       0
NAME_PRODUCT_TYPE                    0
CHANNEL_TYPE                         0
SELLERPLACE_AREA                     0
NAME_SELLER_INDUSTRY                 0
CNT_PAYMENT                     372230
NAME_YIELD_GROUP                     0
PRODUCT_COMBINATION                346
DAYS_FIRST_DRAWING              673065
DAYS_FIRST_DUE                  673065
DAYS_LAST_DUE_1ST_VERSION       673065
DAYS_LAST_DUE                   673065
DAYS_TERMINATION                673065
NFLAG_INSURED_ON_APPROVAL       673065
dtype: int64
```

In [70]:
```
appsDF.columns
```

Out[70]:
```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOODS_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION', 'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')
```

feature engineering for prevApp table

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

```
import pandas as pd
import dateutil

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

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

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

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

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

For more details unstacking groupby results and examples please see here

For more details and examples please see here

In [71]:
```
features = ['AMT_ANNUITY', 'AMT_APPLICATION']
print(f"{appsDF[features].describe()}")
agg_ops = ["min", "max", "mean"]
result = appsDF.groupby(["SK_ID_CURR"], as_index=False).agg("mean") #group by ID
display(result.head())
print("-"*50)
result = appsDF.groupby(["SK_ID_CURR"], as_index=False).agg({'AMT_ANNUITY' : agg_ops, 'A
result.columns = result.columns.map('_'.join)
display(result)
result['range_AMT_APPLICATION'] = result['AMT_APPLICATION_max'] - result['AMT_APPLICATIO
print(f"result.shape: {result.shape}")
result[0:10]
```

```
        AMT_ANNUITY  AMT_APPLICATION
count  1.297979e+06     1.670214e+06
mean   1.595512e+04     1.752339e+05
std    1.478214e+04     2.927798e+05
min    0.000000e+00     0.000000e+00
25%    6.321780e+03     1.872000e+04
50%    1.125000e+04     7.104600e+04
75%    2.065842e+04     1.803600e+05
max    4.180581e+05     6.905160e+06
```

	SK_ID_CURR	SK_ID_PREV	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_
0	100001	1.369693e+06	3951.000	24835.50	23787.00	2520.0	
1	100002	1.038818e+06	9251.775	179055.00	179055.00	0.0	
2	100003	2.281150e+06	56553.990	435436.50	484191.00	3442.5	
3	100004	1.564014e+06	5357.250	24282.00	20106.00	4860.0	
4	100005	2.176837e+06	4813.200	22308.75	20076.75	4464.0	

5 rows × 21 columns

```
--------------------------------------------------
```

	SK_ID_CURR_	AMT_ANNUITY_min	AMT_ANNUITY_max	AMT_ANNUITY_mean	AMT_APPLICATION_min
0	100001	3951.000	3951.000	3951.000000	24835.5

1	100002	9251.775	9251.775	9251.775000	179055.0
2	100003	6737.310	98356.995	56553.990000	68809.5
3	100004	5357.250	5357.250	5357.250000	24282.0
4	100005	4813.200	4813.200	4813.200000	0.0
...	...	...	...	...	...
338852	456251	6605.910	6605.910	6605.910000	40455.0
338853	456252	10074.465	10074.465	10074.465000	57595.5
338854	456253	3973.095	5567.715	4770.405000	19413.0
338855	456254	2296.440	19065.825	10681.132500	18846.0
338856	456255	2250.000	54022.140	20775.391875	45000.0

338857 rows × 7 columns

```
result.shape: (338857, 8)
```

Out[71]:

	SK_ID_CURR_	AMT_ANNUITY_min	AMT_ANNUITY_max	AMT_ANNUITY_mean	AMT_APPLICATION_min	AMT
0	100001	3951.000	3951.000	3951.000000	24835.5	
1	100002	9251.775	9251.775	9251.775000	179055.0	
2	100003	6737.310	98356.995	56553.990000	68809.5	
3	100004	5357.250	5357.250	5357.250000	24282.0	
4	100005	4813.200	4813.200	4813.200000	0.0	
5	100006	2482.920	39954.510	23651.175000	0.0	
6	100007	1834.290	22678.785	12278.805000	17176.5	
7	100008	8019.090	25309.575	15839.696250	0.0	
8	100009	7435.845	17341.605	10051.412143	40455.0	
9	100010	27463.410	27463.410	27463.410000	247212.0	

In [72]:
```
result.isna().sum()
```

Out[72]:
```
SK_ID_CURR_               0
AMT_ANNUITY_min         480
AMT_ANNUITY_max         480
AMT_ANNUITY_mean        480
AMT_APPLICATION_min       0
AMT_APPLICATION_max       0
AMT_APPLICATION_mean      0
range_AMT_APPLICATION     0
dtype: int64
```

feature transformer for prevApp table

In [73]:
```
# Create aggregate features (via pipeline)
class prevAppsFeaturesAggregater(BaseEstimator, TransformerMixin):
    def __init__(self, features=None): # no *args or **kargs
        self.features = features
        self.agg_op_features = {}
        for f in features:
#             self.agg_op_features[f] = {f"{f}_{func}":func for func in ["min", "max", "
            self.agg_op_features[f] =  ["min", "max", "mean"]

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

```
        return self

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

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


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

features = ['AMT_ANNUITY', 'AMT_APPLICATION']
features = ['AMT_ANNUITY',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOODS_PRICE',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CNT_PAYMENT',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION']
features = ['AMT_ANNUITY', 'AMT_APPLICATION']
res = test_driver_prevAppsFeaturesAggregater(appsDF, features)
print(f"HELLO")
print(f"Test driver: \n{res[0:10]}")
print(f"input[features][0:10]: \n{appsDF[0:10]}")


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

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

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

   AMT_APPLICATION_min  AMT_APPLICATION_max  AMT_APPLICATION_mean  \
0              24835.5              24835.5          24835.500000
1             179055.0             179055.0         179055.000000
2              68809.5             900000.0         435436.500000
3              24282.0              24282.0          24282.000000
4                  0.0              44617.5          22308.750000
```

```
5                 0.0             688500.0         272203.260000
6             17176.5             247500.0         150530.250000
7                 0.0             450000.0         155701.800000
8             40455.0             110160.0          76741.714286
9            247212.0             247212.0         247212.000000

   range_AMT_APPLICATION
0                    0.0
1                    0.0
2               831190.5
3                    0.0
4                44617.5
5               688500.0
6               230323.5
7               450000.0
8                69705.0
9                    0.0
input[features][0:10]:
   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY  AMT_APPLICATION  \
0     2030495      271877     Consumer loans     1730.430          17145.0
1     2802425      108129         Cash loans    25188.615         607500.0
2     2523466      122040         Cash loans    15060.735         112500.0
3     2819243      176158         Cash loans    47041.335         450000.0
4     1784265      202054         Cash loans    31924.395         337500.0
5     1383531      199383         Cash loans    23703.930         315000.0
6     2315218      175704         Cash loans          NaN              0.0
7     1656711      296299         Cash loans          NaN              0.0
8     2367563      342292         Cash loans          NaN              0.0
9     2579447      334349         Cash loans          NaN              0.0

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE WEEKDAY_APPR_PROCESS_START  \
0     17145.0               0.0          17145.0                   SATURDAY
1    679671.0               NaN         607500.0                   THURSDAY
2    136444.5               NaN         112500.0                    TUESDAY
3    470790.0               NaN         450000.0                     MONDAY
4    404055.0               NaN         337500.0                   THURSDAY
5    340573.5               NaN         315000.0                   SATURDAY
6         0.0               NaN              NaN                    TUESDAY
7         0.0               NaN              NaN                     MONDAY
8         0.0               NaN              NaN                     MONDAY
9         0.0               NaN              NaN                   SATURDAY

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

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

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

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

[10 rows x 37 columns]
```

Feature Engineering for Primary & Secondary Tables

In [74]:
```
# Choosing Highly correlated features from all input datasets

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

In [75]:
```
df_name = "previous_application"
correlation_matrix = correlation_files_target(df_name)
print(f"Correlation of the {df_name} against the Target is :")
correlation_matrix.T.TARGET.sort_values(ascending= False)
```

Out[75]:
```
Correlation of the previous_application against the Target is :
AMT_DOWN_PAYMENT             0.002496
CNT_PAYMENT                  0.002341
DAYS_LAST_DUE_1ST_VERSION    0.001908
AMT_CREDIT                   0.001833
AMT_APPLICATION              0.001689
AMT_GOODS_PRICE              0.001676
SK_ID_CURR                   0.001107
NFLAG_INSURED_ON_APPROVAL    0.000879
RATE_DOWN_PAYMENT            0.000850
RATE_INTEREST_PRIMARY        0.000542
SK_ID_PREV                   0.000362
DAYS_DECISION               -0.000482
AMT_ANNUITY                 -0.000492
DAYS_FIRST_DUE              -0.000943
SELLERPLACE_AREA            -0.000954
DAYS_TERMINATION            -0.001072
NFLAG_LAST_APPL_IN_DAY      -0.001256
DAYS_FIRST_DRAWING          -0.001293
DAYS_LAST_DUE               -0.001940
HOUR_APPR_PROCESS_START     -0.002285
RATE_INTEREST_PRIVILEGED    -0.026427
Name: TARGET, dtype: float64
```

In [76]:
```
df_name = "bureau"
correlation_matrix = correlation_files_target(df_name)
print(f"Correlation of the {df_name} against the Target is :")
correlation_matrix.T.TARGET.sort_values(ascending= False)
```

Out[76]:
```
Correlation of the bureau against the Target is :
DAYS_CREDIT_UPDATE        0.002159
DAYS_CREDIT_ENDDATE       0.002048
SK_ID_BUREAU              0.001550
DAYS_CREDIT               0.001443
AMT_CREDIT_SUM            0.000218
DAYS_ENDDATE_FACT         0.000203
AMT_ANNUITY               0.000189
AMT_CREDIT_MAX_OVERDUE   -0.000389
CNT_CREDIT_PROLONG       -0.000495
AMT_CREDIT_SUM_LIMIT     -0.000558
AMT_CREDIT_SUM_DEBT      -0.000946
SK_ID_CURR               -0.001070
AMT_CREDIT_SUM_OVERDUE   -0.001464
CREDIT_DAY_OVERDUE       -0.001815
Name: TARGET, dtype: float64
```

In [77]:
```
df_name = "bureau_balance"
correlation_matrix = correlation_files_target(df_name)
print(f"Correlation of the {df_name} against the Target is :")
correlation_matrix.T.TARGET.sort_values(ascending= False)
```

Out[77]:
```
Correlation of the bureau_balance against the Target is :
SK_ID_BUREAU      0.001223
MONTHS_BALANCE   -0.005262
Name: TARGET, dtype: float64
```

In [78]:
```
df_name = "credit_card_balance"
correlation_matrix = correlation_files_target(df_name)
print(f"Correlation of the {df_name} against the Target is :")
correlation_matrix.T.TARGET.sort_values(ascending= False)
```

Out[78]:
```
Correlation of the credit_card_balance against the Target is :
CNT_DRAWINGS_ATM_CURRENT      0.001908
AMT_DRAWINGS_ATM_CURRENT      0.001520
AMT_INST_MIN_REGULARITY       0.001435
SK_ID_CURR                    0.001086
AMT_CREDIT_LIMIT_ACTUAL       0.000515
AMT_BALANCE                   0.000448
SK_ID_PREV                    0.000446
AMT_RECIVABLE                 0.000412
AMT_TOTAL_RECEIVABLE          0.000407
AMT_RECEIVABLE_PRINCIPAL      0.000383
SK_DPD                        0.000092
SK_DPD_DEF                   -0.000201
CNT_INSTALMENT_MATURE_CUM    -0.000342
MONTHS_BALANCE               -0.000768
AMT_PAYMENT_CURRENT          -0.001129
AMT_PAYMENT_TOTAL_CURRENT    -0.001395
AMT_DRAWINGS_CURRENT         -0.001419
CNT_DRAWINGS_CURRENT         -0.001764
CNT_DRAWINGS_OTHER_CURRENT   -0.001833
CNT_DRAWINGS_POS_CURRENT     -0.002387
AMT_DRAWINGS_OTHER_CURRENT   -0.002672
AMT_DRAWINGS_POS_CURRENT     -0.003518
Name: TARGET, dtype: float64
```

In [79]:
```
df_name = "POS_CASH_balance"
correlation_matrix = correlation_files_target(df_name)
print(f"Correlation of the {df_name} against the Target is :")
correlation_matrix.T.TARGET.sort_values(ascending= False)
```

Out[79]:
```
Correlation of the POS_CASH_balance against the Target is :
CNT_INSTALMENT_FUTURE    0.002811
MONTHS_BALANCE           0.002775
SK_ID_PREV               0.002164
CNT_INSTALMENT           0.001434
SK_DPD                   0.000050
SK_ID_CURR              -0.000136
SK_DPD_DEF              -0.001362
Name: TARGET, dtype: float64
```

In [80]:
```
agg_funcs = ['min', 'max', 'mean', 'count', 'sum']

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

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

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

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

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

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

Feature Aggregator

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

In [81]:
```
# Pipelines
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import make_pipeline, Pipeline, FeatureUnion
from sklearn.preprocessing import MinMaxScaler, StandardScaler, OneHotEncoder


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

    def transform(self, X, y=None):
        if self.file_name != 'bureau_balance' and self.file_name != 'bureau':
            result = X.groupby(["SK_ID_CURR"]).agg(self.agg_op_features)
```

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

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

        elif self.file_name == 'bureau_balance':
            result = X.groupby(["SK_ID_BUREAU"]).agg(self.agg_op_features)
            result.columns = result.columns.droplevel()
            result = result.reset_index(level=["SK_ID_BUREAU"])
            return result  # return dataframe with the join key "SK_ID_BUREAU"
```

In [82]:

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

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

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

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

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

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

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

In [83]:

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

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

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

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

cc_bal_features_pipeline = Pipeline([
    ('cc_bal_aggregator', FeaturesAggregator('credit_card_balance', cc_bal_features , ag
    ])

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

```
pos_cash_bal_feature_pipeline = Pipeline([
    ('pos_cash_bal_aggregator',FeaturesAggregator('pos_cash_bal', pos_cash_bal_features
    ])
```

```
{'AMT_ANNUITY': [('prevApps_AMT_ANNUITY_min', 'min'), ('prevApps_AMT_ANNUITY_max', 'ma
x'), ('prevApps_AMT_ANNUITY_mean', 'mean'), ('prevApps_AMT_ANNUITY_count', 'count'), ('p
revApps_AMT_ANNUITY_sum', 'sum')], 'AMT_APPLICATION': [('prevApps_AMT_APPLICATION_min',
'min'), ('prevApps_AMT_APPLICATION_max', 'max'), ('prevApps_AMT_APPLICATION_mean', 'mea
n'), ('prevApps_AMT_APPLICATION_count', 'count'), ('prevApps_AMT_APPLICATION_sum', 'su
m')]}
{'AMT_ANNUITY': [('bureau_AMT_ANNUITY_min', 'min'), ('bureau_AMT_ANNUITY_max', 'max'),
('bureau_AMT_ANNUITY_mean', 'mean'), ('bureau_AMT_ANNUITY_count', 'count'), ('bureau_AMT
_ANNUITY_sum', 'sum')], 'AMT_CREDIT_SUM': [('bureau_AMT_CREDIT_SUM_min', 'min'), ('burea
u_AMT_CREDIT_SUM_max', 'max'), ('bureau_AMT_CREDIT_SUM_mean', 'mean'), ('bureau_AMT_CRED
IT_SUM_count', 'count'), ('bureau_AMT_CREDIT_SUM_sum', 'sum')]}
{'MONTHS_BALANCE': [('bureau_balance_MONTHS_BALANCE_min', 'min'), ('bureau_balance_MONTH
S_BALANCE_max', 'max'), ('bureau_balance_MONTHS_BALANCE_mean', 'mean'), ('bureau_balance
_MONTHS_BALANCE_count', 'count'), ('bureau_balance_MONTHS_BALANCE_sum', 'sum')]}
{'MONTHS_BALANCE': [('credit_card_balance_MONTHS_BALANCE_min', 'min'), ('credit_card_bal
ance_MONTHS_BALANCE_max', 'max'), ('credit_card_balance_MONTHS_BALANCE_mean', 'mean'),
('credit_card_balance_MONTHS_BALANCE_count', 'count'), ('credit_card_balance_MONTHS_BALA
NCE_sum', 'sum')], 'AMT_BALANCE': [('credit_card_balance_AMT_BALANCE_min', 'min'), ('cre
dit_card_balance_AMT_BALANCE_max', 'max'), ('credit_card_balance_AMT_BALANCE_mean', 'mea
n'), ('credit_card_balance_AMT_BALANCE_count', 'count'), ('credit_card_balance_AMT_BALAN
CE_sum', 'sum')], 'CNT_INSTALMENT_MATURE_CUM': [('credit_card_balance_CNT_INSTALMENT_MAT
URE_CUM_min', 'min'), ('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_max', 'max'), ('cr
edit_card_balance_CNT_INSTALMENT_MATURE_CUM_mean', 'mean'), ('credit_card_balance_CNT_IN
STALMENT_MATURE_CUM_count', 'count'), ('credit_card_balance_CNT_INSTALMENT_MATURE_CUM_su
m', 'sum')]}
{'AMT_INSTALMENT': [('credit_card_balance_AMT_INSTALMENT_min', 'min'), ('credit_card_bal
ance_AMT_INSTALMENT_max', 'max'), ('credit_card_balance_AMT_INSTALMENT_mean', 'mean'),
('credit_card_balance_AMT_INSTALMENT_count', 'count'), ('credit_card_balance_AMT_INSTALM
ENT_sum', 'sum')], 'AMT_PAYMENT': [('credit_card_balance_AMT_PAYMENT_min', 'min'), ('cre
dit_card_balance_AMT_PAYMENT_max', 'max'), ('credit_card_balance_AMT_PAYMENT_mean', 'mea
n'), ('credit_card_balance_AMT_PAYMENT_count', 'count'), ('credit_card_balance_AMT_PAYME
NT_sum', 'sum')]}
{'CNT_INSTALMENT': [('pos_cash_bal_CNT_INSTALMENT_min', 'min'), ('pos_cash_bal_CNT_INSTA
LMENT_max', 'max'), ('pos_cash_bal_CNT_INSTALMENT_mean', 'mean'), ('pos_cash_bal_CNT_INS
TALMENT_count', 'count'), ('pos_cash_bal_CNT_INSTALMENT_sum', 'sum')], 'MONTHS_BALANCE':
[('pos_cash_bal_MONTHS_BALANCE_min', 'min'), ('pos_cash_bal_MONTHS_BALANCE_max', 'max'),
('pos_cash_bal_MONTHS_BALANCE_mean', 'mean'), ('pos_cash_bal_MONTHS_BALANCE_count', 'cou
nt'), ('pos_cash_bal_MONTHS_BALANCE_sum', 'sum')]}
```

Prepare Datasets

- Added poscashbalDF

In [84]:

```
poscashbalDF = datasets['POS_CASH_balance']

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

Fit Feature Engineering Pipeline

- Removed the applin pipeline and added the pos_cash_bal_aggregated

In [85]:
```
pos_cash_bal_aggregated = pos_cash_bal_feature_pipeline.fit_transform(poscashbalDF)
prevApps_aggregated = prevApps_feature_pipeline.fit_transform(prevAppsDF)
bureau_aggregated = bureau_feature_pipeline.fit_transform(bureauDF)
```

In [86]:
```
bureaubal_aggregated = bureau_bal_features_pipeline.fit_transform(bureaubalDF)
ccblance_aggregated = cc_bal_features_pipeline.fit_transform(ccbalDF)
installments_pmnts_aggregated = installments_pmnts_features_pipeline.fit_transform(insta
```

In [87]:
```
installments_pmnts_aggregated.head()
```

Out[87]:

	SK_ID_CURR	credit_card_balance_AMT_INSTALMENT_min	credit_card_balance_AMT_INSTALMENT_max	credit
0	100001	3951.000	17397.900	
1	100002	9251.775	53093.745	
2	100003	6662.970	560835.360	
3	100004	5357.250	10573.965	
4	100005	4813.200	17656.245	

In [88]:
```
bureau_aggregated.head()
```

Out[88]:

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

In [89]:
```
bureaubal_aggregated.head()
```

Out[89]:

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

Join the labeled dataset

In [90]:
```
datasets.keys()
```

Out[90]:
```
dict_keys(['application_train', 'application_test', 'bureau', 'bureau_balance', 'credit_
card_balance', 'installments_payments', 'previous_application', 'POS_CASH_balance'])
```

In [91]:
```
merge_all_data = True

if merge_all_data:
    prevApps_aggregated = prevApps_feature_pipeline.transform(appsDF)

# merge primary table and secondary tables using features based on meta data and  aggreg
if merge_all_data:
```

```
    ### Merging bureau and bureau balancce
    bureau_aggregated = bureau_aggregated.merge(bureaubal_aggregated, how = 'left', on =
    ### Train DF
    X_train = X_train.merge(prevApps_aggregated, how = 'left', on = 'SK_ID_CURR')
    X_train = X_train.merge(bureau_aggregated, how = 'left', on = "SK_ID_CURR")
    X_train = X_train.merge(ccblance_aggregated, how = 'left', on = "SK_ID_CURR")
    X_train = X_train.merge(installments_pmnts_aggregated, how = 'left', on = "SK_ID_CUR
    X_train = X_train.merge(pos_cash_bal_aggregated, how = 'left', on = "SK_ID_CURR")
```

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

In [92]:

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

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

    X_kaggle_test = X_kaggle_test.merge(ccblance_aggregated, how ='left', on = "SK_ID_CU

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

    X_kaggle_test = X_kaggle_test.merge(pos_cash_bal_aggregated, how = 'left', on = "SK_
```

In [93]:

```
# approval rate 'NFLAG_INSURED_ON_APPROVAL'
```

In [94]:

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

Processing pipeline

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

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

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

- The OneHotEncoder is fitted to the training set, which means that for each unique value present in the training set, for each feature, a new column is created. Let's say we have 39 columns after the encoding up from 30 (before preprocessing).
- The output is a numpy array (when the option sparse=False is used), which has the disadvantage of losing all the information about the original column names and values.
- When we try to transform the test set, after having fitted the encoder to the training set, we obtain a `ValueError`. This is because the there are new, previously unseen unique values in the test set and

the encoder doesn't know how to handle these values. In order to use both the transformed training and test sets in machine learning algorithms, we need them to have the same number of columns.

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

Here is a example that in action:

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

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

In [95]:
```
# # load data
# df = pd.read_csv('chronic_kidney_disease.csv', header="infer")
# # names=['age', 'bp', 'sg', 'al', 'su', 'rbc', 'pc', 'pcc', 'ba', 'bgr', 'bu', 'sc', '
# # 'hemo', 'pcv', 'wc', 'rc', 'htn', 'dm', 'cad', 'appet', 'pe', 'ane', 'class'])
# # head of df
# df.head(10)
```

In [96]:
```
# # Categorical boolean mask
# categorical_feature_mask = df.dtypes==object
# categorical_feature_mask
```

In [97]:
```
# # filter categorical columns using mask and turn it into a list
# categorical_cols = X.columns[categorical_feature_mask].tolist()
# categorical_cols
```

In [98]:
```
# from sklearn.preprocessing import OneHotEncoder
# import pandas as pd
# categorical_feature_mask = [True, False]
# # instantiate OneHotEncoder
# enc = OneHotEncoder(categorical_features = categorical_feature_mask,sparse = False, ha
# # categorical_features = boolean mask for categorical columns
# # sparse = False output an array not sparse matrix
# X_train = pd.DataFrame([['small', 1], ['small', 3], ['medium', 3], ['large', 2]])
# X_test = [['small', 1.2],  ['medium', 4], ['EXTRA-large', 2]]
# print(f"X_train:\n{X_train}")
# print(f"enc.fit_transform(X_train):\n{enc.fit_transform(X_train)}")
# print(f"enc.transform(X_test):\n{enc.transform(X_test)}")

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

In [99]:
```
# print(f"enc.categories_{enc.categories_}")

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


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

```
# enc.get_feature_names()
```

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

In [100…
```
# from sklearn.datasets import load_breast_cancer
# data = load_breast_cancer(return_X_y=False)
# X, y = load_breast_cancer(return_X_y=True)
# print(y[[10, 50, 85]])
# #([0, 1, 0])
# list(data.target_names)
# #['malignant', 'benign']
# X.shape
```

In [101…
```
# data.feature_names
```

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

HCDR preprocessing

In [102…
```
# Split the provided training data into training and validationa and test
# The kaggle evaluation test set has no labels
#
from sklearn.model_selection import train_test_split

use_application_data_ONLY = False #use joined data
if use_application_data_ONLY:
    # just selected a few features for a baseline experiment
    selected_features = ['AMT_INCOME_TOTAL',  'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH',
        'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER', 'FLAG_OWN_REALTY','FLAG_OWN_CAR','N
                   'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']
    X_train = datasets["application_train"][selected_features]
    y_train = datasets["application_train"]['TARGET']
    X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=0.
    X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_size=0.15
    X_kaggle_test= datasets["application_test"][selected_features]
    # y_test = datasets["application_test"]['TARGET']   #why no  TARGET?!! (hint: kaggle



selected_features = ['AMT_INCOME_TOTAL',  'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_
        'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER', 'FLAG_OWN_REALTY','FLAG_OWN_CAR','N
                   'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']
y_train = X_train['TARGET']
X_train = X_train[selected_features]
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=0.15,
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_size=0.15, ra
X_kaggle_test= X_kaggle_test[selected_features]
# y_test = datasets["application_test"]['TARGET']   #why no  TARGET?!! (hint: kaggle com


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

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

In [103…

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

# Creates the following date features
# But could do so much more with these features
#    E.g.,
#      extract the domain address of the homepage and OneHotEncode it
#
# ['release_month','release_day','release_year', 'release_dayofweek','release_quarter']
class prep_OCCUPATION_TYPE(BaseEstimator, TransformerMixin):
    def __init__(self, features="OCCUPATION_TYPE"): # no *args or **kargs
        self.features = features
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        df = pd.DataFrame(X, columns=self.features)
        #from IPython.core.debugger import Pdb as pdb;    pdb().set_trace() #breakpoint;
        df['OCCUPATION_TYPE'] = df['OCCUPATION_TYPE'].apply(lambda x: 1. if x in ['Core
        #df.drop(self.features, axis=1, inplace=True)
        return np.array(df.values)  #return a Numpy Array to observe the pipeline protoc


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

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


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

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

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

X_train['name'][0:5]:
        OCCUPATION_TYPE
899239         Laborers
1333889     Sales staff
597650   Medicine staff
209947       Core staff
451114              NaN
Test driver:
[[0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]]
```

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

In [104…

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

In [105…

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

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

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

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

In [106…

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

Out[106]:

```
['SK_ID_CURR',
 'TARGET',
 'NAME_CONTRACT_TYPE',
 'CODE_GENDER',
 'FLAG_OWN_CAR',
 'FLAG_OWN_REALTY',
 'CNT_CHILDREN',
 'AMT_INCOME_TOTAL',
 'AMT_CREDIT',
 'AMT_ANNUITY',
 'AMT_GOODS_PRICE',
 'NAME_TYPE_SUITE',
```

```
'NAME_INCOME_TYPE',
'NAME_EDUCATION_TYPE',
'NAME_FAMILY_STATUS',
'NAME_HOUSING_TYPE',
'REGION_POPULATION_RELATIVE',
'DAYS_BIRTH',
'DAYS_EMPLOYED',
'DAYS_REGISTRATION',
'DAYS_ID_PUBLISH',
'OWN_CAR_AGE',
'FLAG_MOBIL',
'FLAG_EMP_PHONE',
'FLAG_WORK_PHONE',
'FLAG_CONT_MOBILE',
'FLAG_PHONE',
'FLAG_EMAIL',
'OCCUPATION_TYPE',
'CNT_FAM_MEMBERS',
'REGION_RATING_CLIENT',
'REGION_RATING_CLIENT_W_CITY',
'WEEKDAY_APPR_PROCESS_START',
'HOUR_APPR_PROCESS_START',
'REG_REGION_NOT_LIVE_REGION',
'REG_REGION_NOT_WORK_REGION',
'LIVE_REGION_NOT_WORK_REGION',
'REG_CITY_NOT_LIVE_CITY',
'REG_CITY_NOT_WORK_CITY',
'LIVE_CITY_NOT_WORK_CITY',
'ORGANIZATION_TYPE',
'EXT_SOURCE_1',
'EXT_SOURCE_2',
'EXT_SOURCE_3',
'APARTMENTS_AVG',
'BASEMENTAREA_AVG',
'YEARS_BEGINEXPLUATATION_AVG',
'YEARS_BUILD_AVG',
'COMMONAREA_AVG',
'ELEVATORS_AVG',
'ENTRANCES_AVG',
'FLOORSMAX_AVG',
'FLOORSMIN_AVG',
'LANDAREA_AVG',
'LIVINGAPARTMENTS_AVG',
'LIVINGAREA_AVG',
'NONLIVINGAPARTMENTS_AVG',
'NONLIVINGAREA_AVG',
'APARTMENTS_MODE',
'BASEMENTAREA_MODE',
'YEARS_BEGINEXPLUATATION_MODE',
'YEARS_BUILD_MODE',
'COMMONAREA_MODE',
'ELEVATORS_MODE',
'ENTRANCES_MODE',
'FLOORSMAX_MODE',
'FLOORSMIN_MODE',
'LANDAREA_MODE',
'LIVINGAPARTMENTS_MODE',
'LIVINGAREA_MODE',
'NONLIVINGAPARTMENTS_MODE',
'NONLIVINGAREA_MODE',
'APARTMENTS_MEDI',
'BASEMENTAREA_MEDI',
'YEARS_BEGINEXPLUATATION_MEDI',
'YEARS_BUILD_MEDI',
'COMMONAREA_MEDI',
'ELEVATORS_MEDI',
```

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

Baseline Model

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

In [107…

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

In [108…

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

```
                                   "Test  AUC",
                                   "Train F1 Score",
                                   "Test F1 Score"
                                  ])
```

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

Evaluation metrics

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

Accuracy

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

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

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

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall

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

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

F1 Score

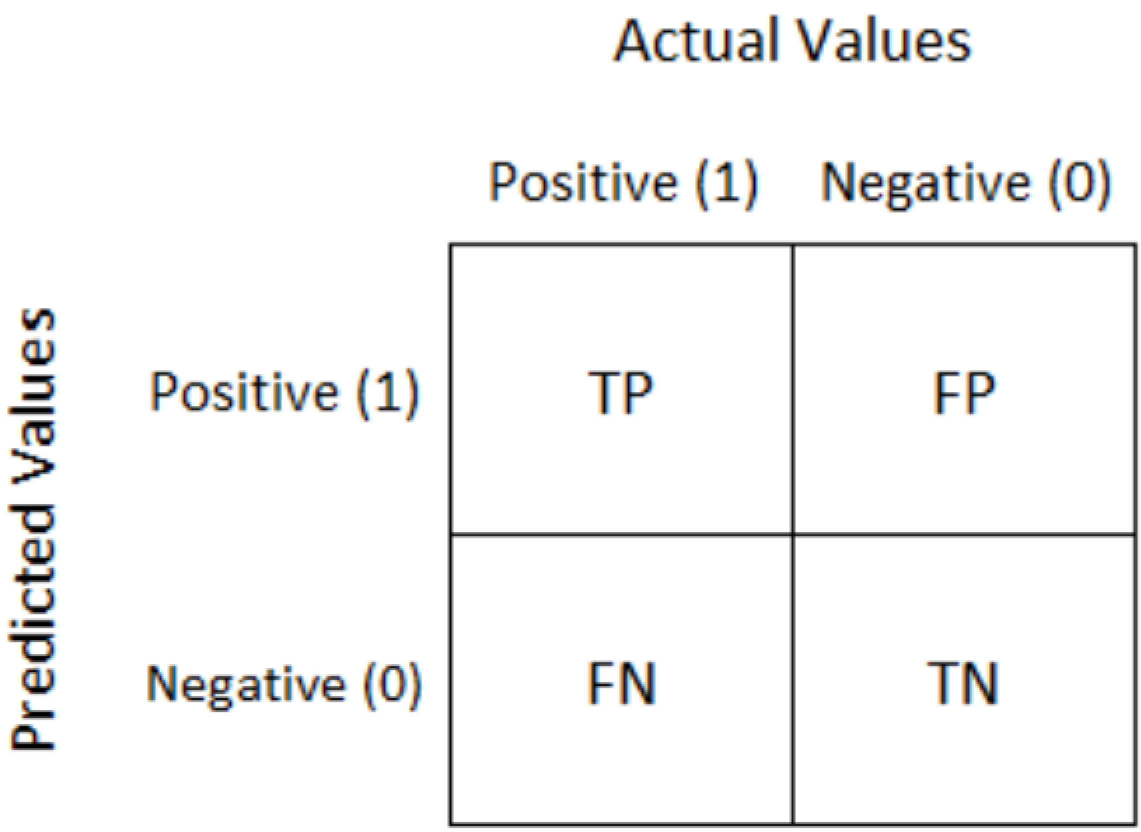
F1 Score is the harmonic mean of precision and recall.

$$F1 = 2.\ \frac{Precision\ \times Recall}{Precision + Recall}$$

Confusion Matrix

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

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



AUC-ROC

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

In [109…

```
from sklearn.metrics import accuracy_score, classification_report

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

```
model = full_pipeline_with_predictor.fit(X_train, y_train)

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

Out[109]:

```
0.921
```

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

In [110…

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

accuracy_test_baseline = accuracy_score(y_test, model.predict(X_test)).round(4) * 100
report_test_baseline = classification_report(y_test, model.predict(X_test))

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

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

              precision    recall  f1-score   support

           0       0.92      1.00      0.96    177375
           1       0.52      0.01      0.02     15067

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

In [111…

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

Out[111]:

```
0.7411204457223629
```

In [112…

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

Out[112]:

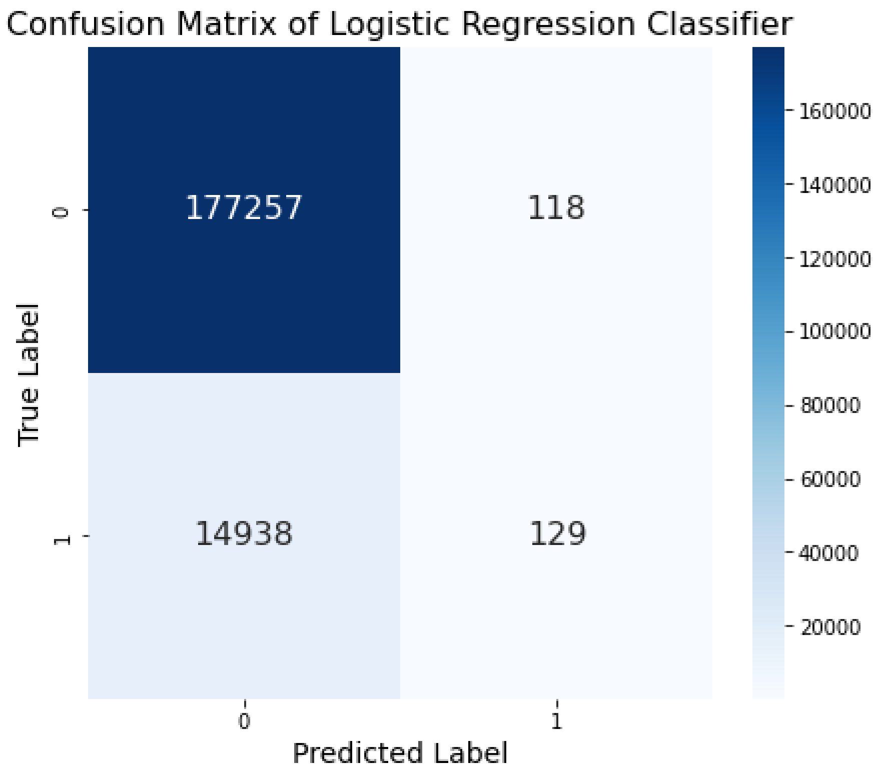
	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1 Score	Test F1 Score
0	Baseline_14_features	0.9211	0.9214	0.9218	0.7411	0.7406	0.7413	0.0174	0.0168

Confusion matrix for baseline model

In [113…

```
# Create confusion matrix for baseline model
```

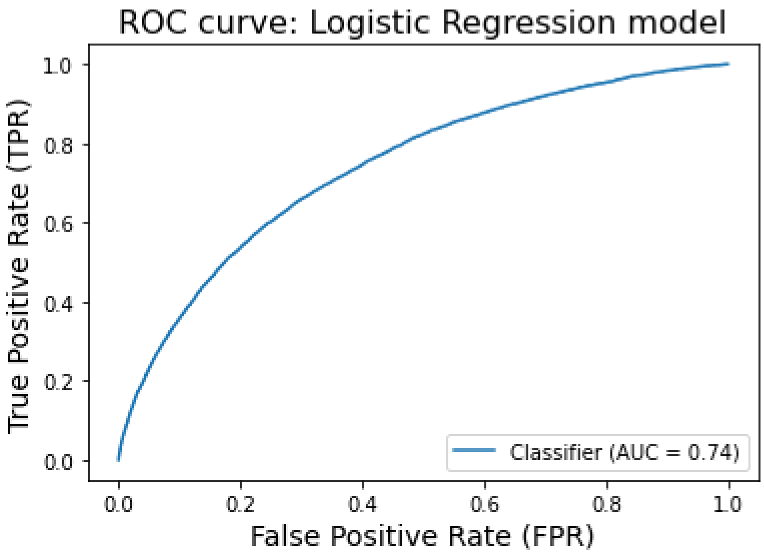
```
from sklearn.metrics import RocCurveDisplay, confusion_matrix

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

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



ROC curve for baseline model

In [115…

```
#Plot the ROC curve for baseline model

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

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



Hyperparameter Tuning of Basline model with grid search CV

In [116…

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

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

### Creating a subset as the full file is just too big and crashes my kernal
random_index = X_train.sample(n=100000, random_state=42).index
X_train_subset = X_train.loc[random_index]
y_train_subset = y_train.loc[random_index]
print(X_train_subset.shape)
print(y_train_subset.shape)

gs.fit(X_train_subset, y_train_subset)
```

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

Out[116]:

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preparation',
                                        FeatureUnion(transformer_list=[('num_pipeline',
                                                                        Pipeline(steps=
[('selector',

  DataFrameSelector(attribute_names=['AMT_INCOME_TOTAL',

                                     'AMT_CREDIT',

                                     'DAYS_EMPLOYED',

                                     'DAYS_BIRTH',

                                     'EXT_SOURCE_1',

                                     'EXT_SOURCE_2',

                                     'EXT_SOURCE_3'])),

('imputer',

  SimpleImputer()),
```

```
 ('std_scaler',

   StandardScaler())])),
                                                                         ('cat_pip...

                                    'NAME_EDUCATION_TYPE',

                                    'OCCUPATION_TYPE',

                                    'NAME_INCOME_TYPE'])),

 ('imputer',

   SimpleImputer(fill_value='missing',

                 strategy='constant')),

 ('ohe',

   OneHotEncoder(handle_unknown='ignore',

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

In [117…

```
best_model = gs.best_estimator_
best_params = gs.best_params_


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

best_accuracy = accuracy_score(y_test, y_pred).round(4) * 100

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

```
Best model hyperparameters: {'linear__C': 1, 'linear__penalty': 'l2', 'linear__tol': 0.0
001}
Accuracy of best model: 92.17999999999999
```

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

In [118…

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

accuracy_test_gs = accuracy_score(y_test, best_model.predict(X_test)).round(4) * 100
report_test_gs = classification_report(y_test, best_model.predict(X_test))

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

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

              precision    recall  f1-score   support
```

```
           0       0.92      1.00      0.96    177375
           1       0.53      0.01      0.02     15067

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

In [119…

```python
exp_name = "GridSearchCV Logistic Regression"

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

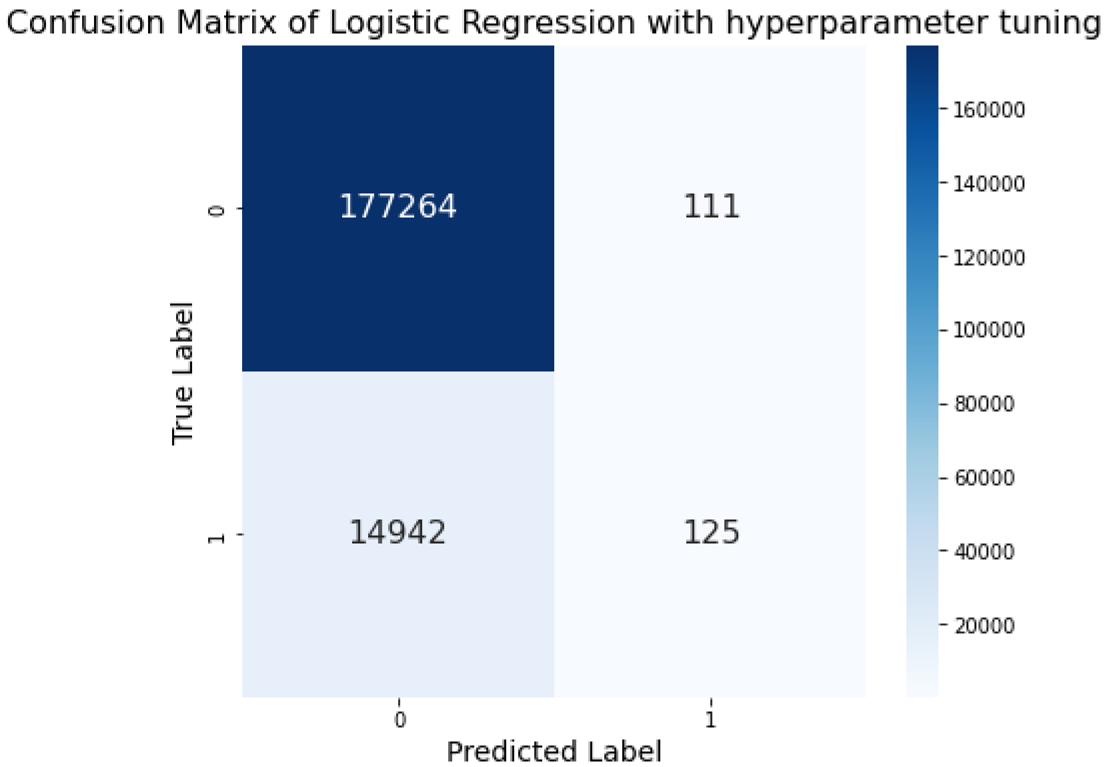
Out[119]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1 Score	Test F1 Score
0	Baseline_14_features	0.9211	0.9214	0.9218	0.7411	0.7406	0.7413	0.0174	0.0168
1	GridSearchCV Logistic Regression	0.9211	0.9214	0.9218	0.7399	0.7397	0.7403	0.0163	0.0163

Create confusion matrix for Logistic Regression with hyperparameter tuning

In [120…

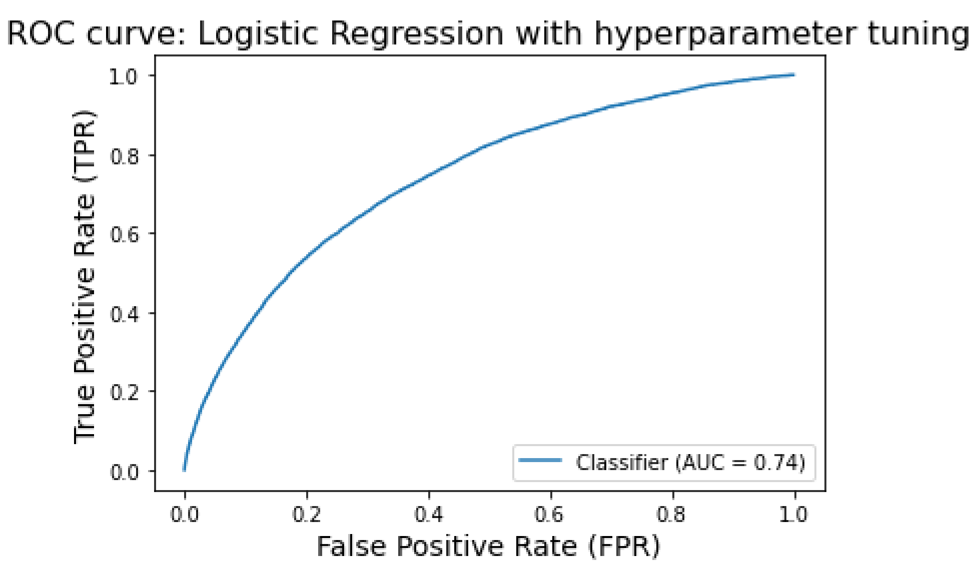
```python
# Create confusion matrix for Logistic Regression with hyperparameter tuning

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

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



Plot the ROC curve for Logistic Regression with hyperparameter tuning

In [121…

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

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

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



Submission File Prep

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

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

In [122…
```
test_class_scores = model.predict_proba(X_kaggle_test.drop_duplicates())[:, 1]
```

In [123…
```
test_class_scores[0:10]
```

Out[123]:
```
array([0.05803207, 0.18385248, 0.02918214, 0.06339177, 0.11813162,
       0.05098996, 0.01717775, 0.07965548, 0.01474992, 0.18479812])
```

In [124…
```
# Submission dataframe
submit_df = datasets["application_test"][['SK_ID_CURR']]
submit_df['TARGET'] = test_class_scores

submit_df.head()
```

Out[124]:

	SK_ID_CURR	TARGET
0	100001	0.058032
1	100005	0.183852
2	100013	0.029182
3	100028	0.063392
4	100038	0.118132

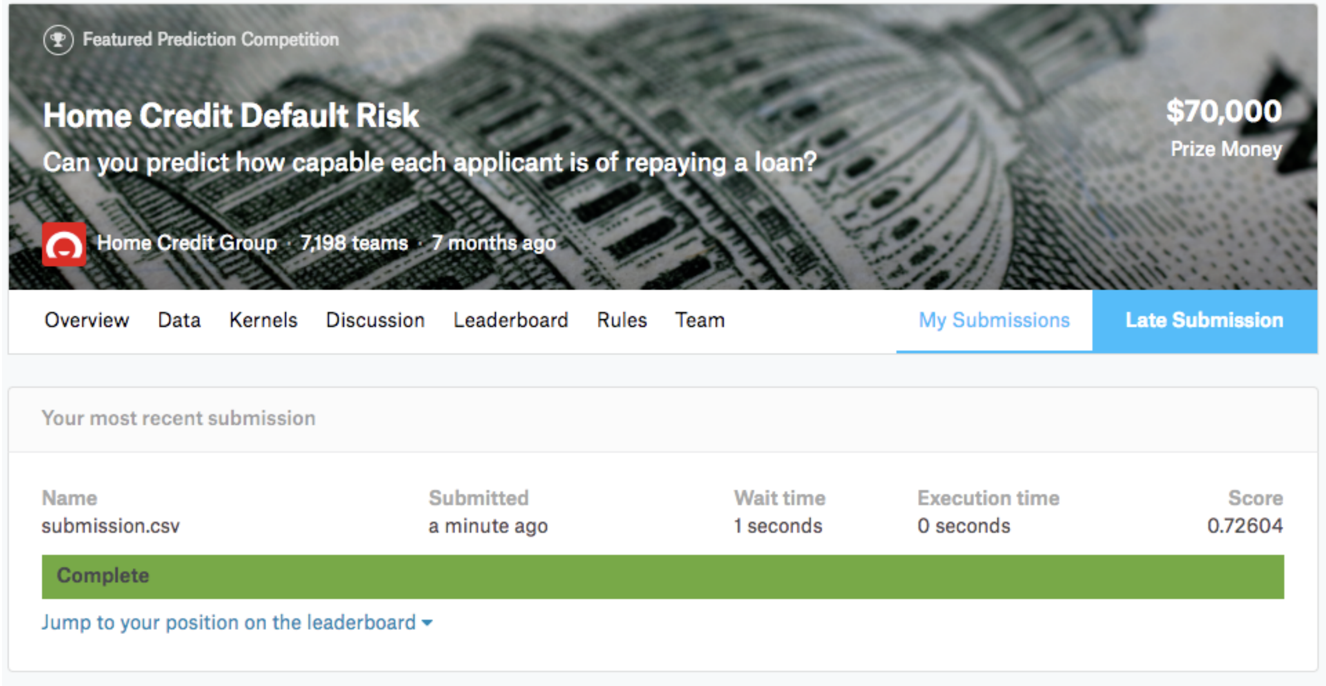
In [125…
```
submit_df.to_csv("submission.csv",index=False)
```

Kaggle submission via the command line API

In [ ]:
```
! kaggle competitions submit -c home-credit-default-risk -f submission.csv -m "baseline
```

report submission

Click on this link



Write-up

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

Project title:

Predicting credit default risk using machine learning

Team and phase leader plan:

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

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

Credit assignment plan for phase 2:

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

Abstract

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

Introduction

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

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

Dataset

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

EDA

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

(1). So, we will need to address this in our analysis. The variable most positive correlated with the target variable is DAYS_BIRTH (0.078), while the variable most negatively correlated with the target variable is EXT_SOURCE_3 (-0.179).

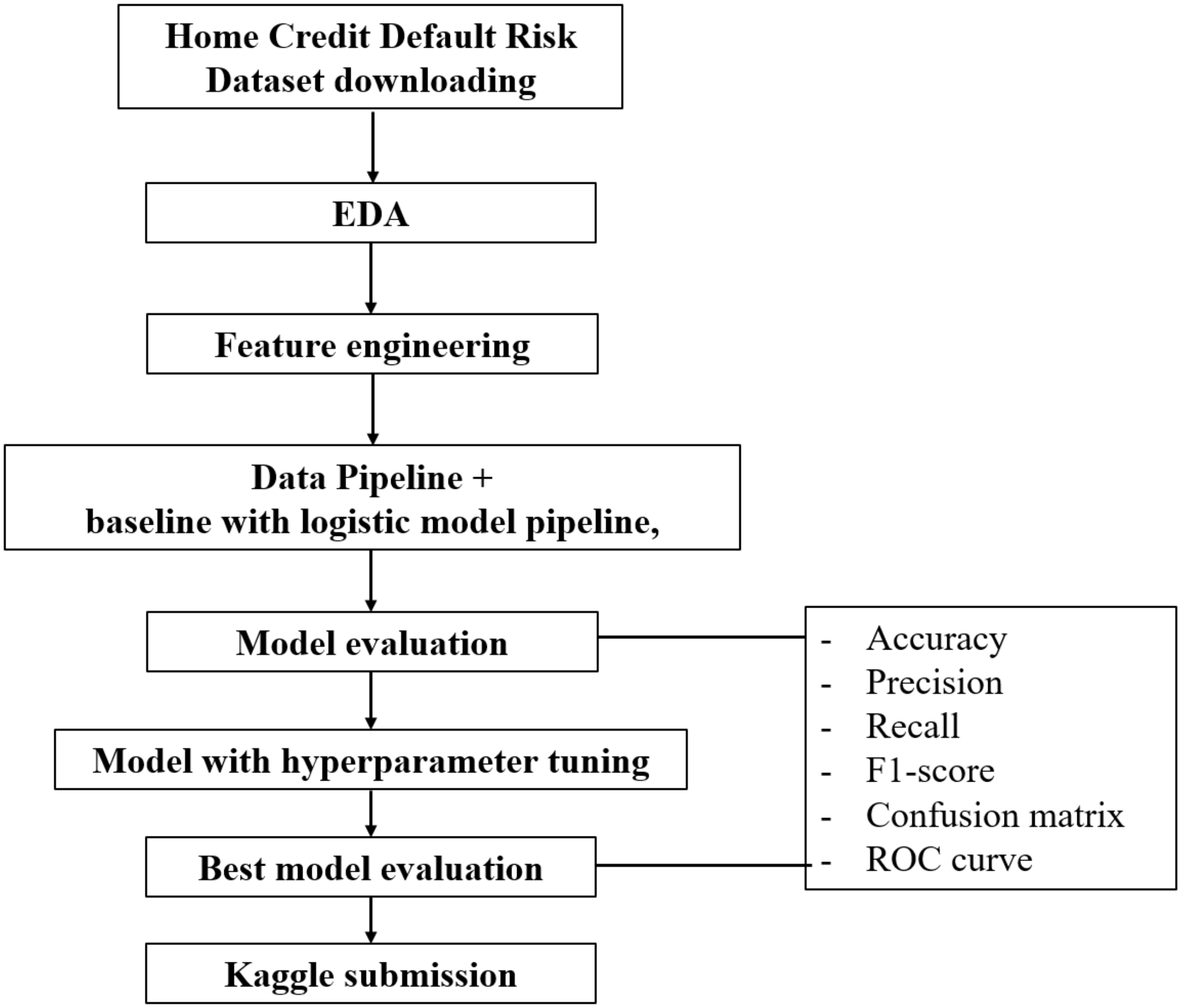
The distribution of applicant age is fairly flat between the ages of 20 and 70, though there are a few spikes around the ages of 30, 40, and 55. More than any other occupation, applicants are laborers, followed by occupations of sales staff and core staff. There are 1.7 million previous credit applications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

Feature Engineering and transformers

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

Pipelines

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



Experimental results

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

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

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

A.

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

              precision    recall  f1-score   support

           0       0.92      1.00      0.96    177375
           1       0.52      0.01      0.02     15067

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

B.

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

              precision    recall  f1-score   support

           0       0.92      1.00      0.96    177375
           1       0.53      0.01      0.02     15067

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

Figure 1 Accuracy score and classification report.
(A) Logistic regression model, (B) Logistic regression model with hyperparameter tuning.

A.

B.

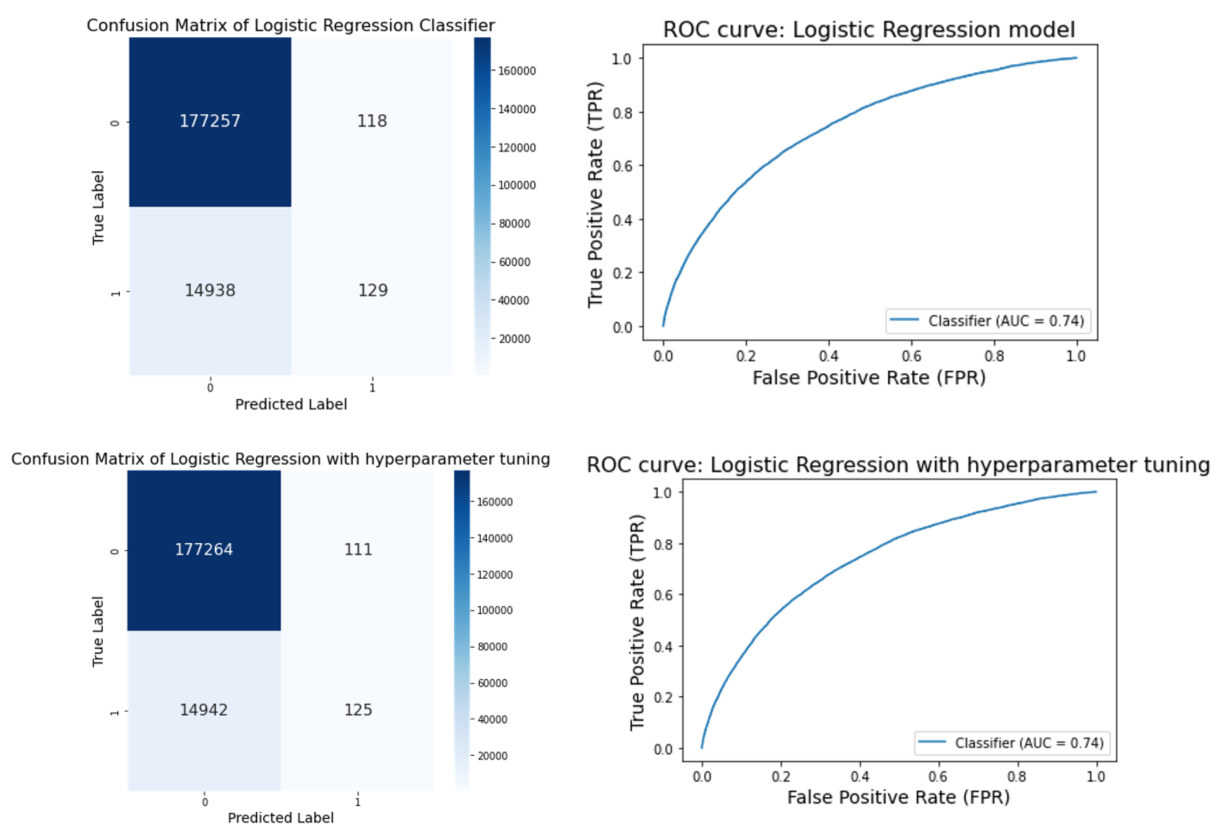


Figure 2 Confusion matrix and ROC curve.
(A) Logistic regression model, (B) Logistic regression model with hyperparameter tuning.

Table 1. The results of the various experiments.

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1 Score	Test F1 Score
0	Baseline_14_features	0.9211	0.9214	0.9218	0.7411	0.7406	0.7413	0.0174	0.0168
1	GridSearchCV Logistic Regression	0.9211	0.9214	0.9218	0.7399	0.7397	0.7403	0.0163	0.0163

Discussion

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

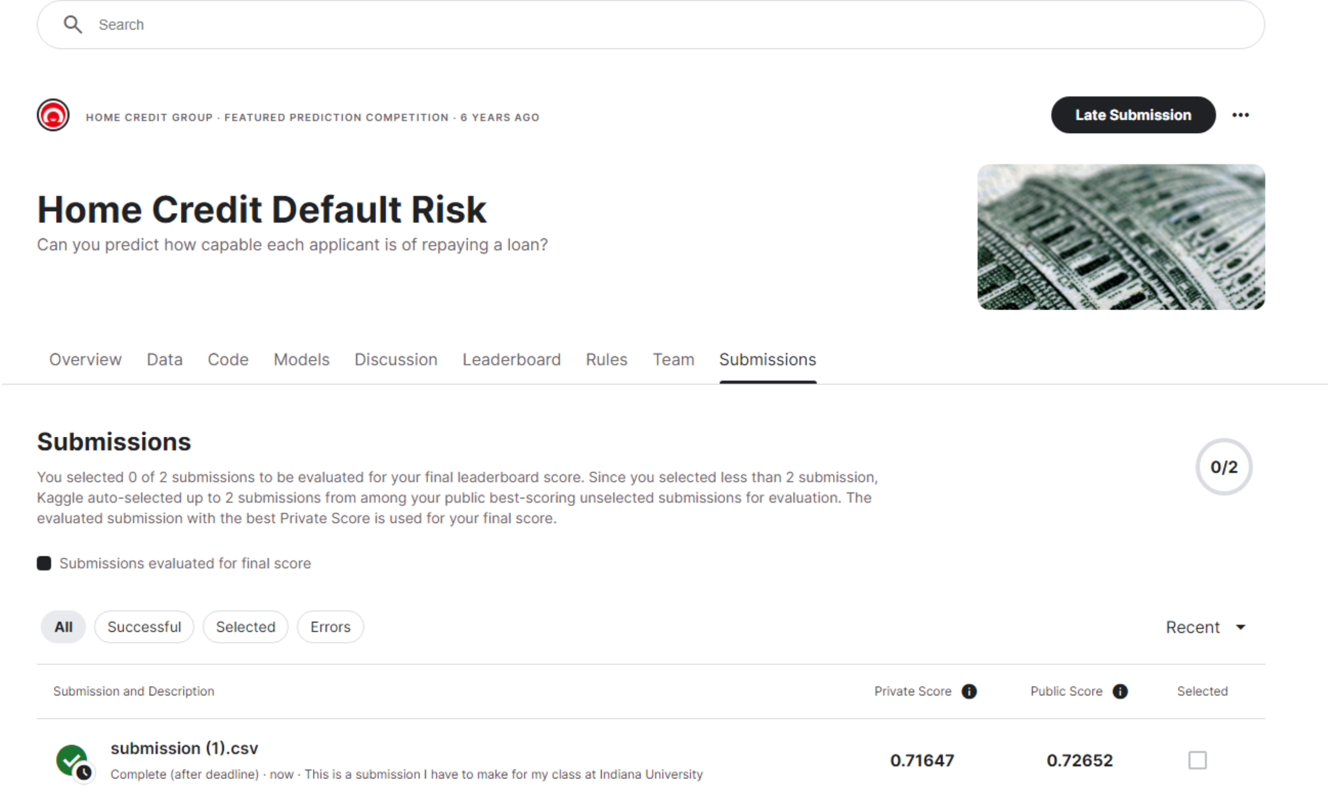
Based on Class '1' results, the logistic regression models with and without hyperparameter tuning performed similarly with very low precision, recall, and F1-scores. This data indicated that models failed to predict 'Class 1' accurately. A significant class imbalance could significantly impact the learning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

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

Conclusion

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

Kaggle Submission



References

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

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

TODO: Predicting Loan Repayment with Automated Feature Engineering in Featuretools

Read the following:

- feature engineering via Featuretools library:

        - https://github.com/Featuretools/predict-loan-repayment/blob/master/Automated%20Loan%20Repayment.ipynb
- https://www.analyticsvidhya.com/blog/2018/08/guide-automated-feature-engineering-featuretools-python/
- feature engineering paper: https://dai.lids.mit.edu/wp-content/uploads/2017/10/DSAA_DSM_2015.pdf
- https://www.analyticsvidhya.com/blog/2017/08/catboost-automated-categorical-data/