Kaggle API setup

In [720…

```
!pip install kaggle
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: kaggle in /usr/local/lib/python3.7/site-packages (1.5.12)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/site-packages (from k
aggle) (1.26.6)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.7/site-packages
(from kaggle) (5.0.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/site-packages (from kagg
le) (4.62.1)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.7/site-packages (from
kaggle) (1.15.0)
Requirement already satisfied: requests in /usr/local/lib/python3.7/site-packages (from
kaggle) (2.25.1)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.7/site-packages
(from kaggle) (2.8.2)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/site-packages (from k
aggle) (2021.5.30)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.7/site-pack
ages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/site-packages (f
rom requests->kaggle) (2.10)
Requirement already satisfied: chardet<5,>=3.0.2 in /usr/local/lib/python3.7/site-packag
es (from requests->kaggle) (4.0.0)
```

In [721…

```
!pip install pandoc
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pandoc in /N/home/u070/raknarne/Carbonate/.local/lib/pyth
on3.7/site-packages (1.1.0)
Requirement already satisfied: ply in /N/home/u070/raknarne/Carbonate/.local/lib/python
3.7/site-packages (from pandoc) (3.11)
Requirement already satisfied: plumbum in /N/home/u070/raknarne/Carbonate/.local/lib/pyt
hon3.7/site-packages (from pandoc) (1.7.1)
```

In [722…

```
!pip install hyperopt
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: hyperopt in /N/home/u070/raknarne/Carbonate/.local/lib/py
thon3.7/site-packages (0.2.7)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.7/site-packages (fr
om hyperopt) (1.6.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/site-packages (from hyp
eropt) (1.19.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/site-packages (from hyp
eropt) (1.6.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/site-packages (from hype
ropt) (4.62.1)
Requirement already satisfied: py4j in /N/home/u070/raknarne/Carbonate/.local/lib/python
3.7/site-packages (from hyperopt) (0.10.9.3)
Requirement already satisfied: networkx>=2.2 in /usr/local/lib/python3.7/site-packages
(from hyperopt) (2.6.2)
Requirement already satisfied: six in /usr/local/lib/python3.7/site-packages (from hyper
```

```
opt) (1.15.0)
Requirement already satisfied: future in /N/home/u070/raknarne/Carbonate/.local/lib/pyth
on3.7/site-packages (from hyperopt) (0.18.2)
```

In [723...

```
!pwd
```

```
/N/home/u070/raknarne/Carbonate/Documents/I526_AML_Student/Assignments/Unit-Project-Home
-Credit-Default-Risk
```

In [724...

```
!mkdir ~/.kaggle
!cp /N/home/u070/raknarne/Carbonate/Downloads/kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json
```

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

In [725...

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

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

Downloading the files via Kaggle API

In [726...

```
DATA_DIR = "/N/home/u070/raknarne/Carbonate/Documents/Data/home-credit-default-risk"
#DATA_DIR = os.path.join('./ddddd/')
!mkdir $DATA_DIR
```

```
mkdir: cannot create directory '/N/home/u070/raknarne/Carbonate/Documents/Data/home-cred
it-default-risk': File exists
```

In [727...

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

```
total 3326848
-rw-rw-r-- 1 raknarne raknarne     37383 Dec 11  2019 HomeCredit_columns_description.csv
-rw-rw-r-- 1 raknarne raknarne 392703158 Dec 11  2019 POS_CASH_balance.csv
-rw-rw-r-- 1 raknarne raknarne  26567651 Dec 11  2019 application_test.csv
-rw-rw-r-- 1 raknarne raknarne 166133370 Dec 11  2019 application_train.csv
-rw-rw-r-- 1 raknarne raknarne 170016717 Dec 11  2019 bureau.csv
-rw-rw-r-- 1 raknarne raknarne 375592889 Dec 11  2019 bureau_balance.csv
-rw-rw-r-- 1 raknarne raknarne 424582605 Dec 11  2019 credit_card_balance.csv
-rw-r--r-- 1 raknarne raknarne 721616255 Nov 29 10:27 home-credit-default-risk.zip
-rw-rw-r-- 1 raknarne raknarne 723118349 Dec 11  2019 installments_payments.csv
-rw-rw-r-- 1 raknarne raknarne 404973293 Dec 11  2019 previous_application.csv
-rw-rw-r-- 1 raknarne raknarne    536202 Dec 11  2019 sample_submission.csv
```

In [728...

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

```
Downloading home-credit-default-risk.zip to /N/home/u070/raknarne/Carbonate/Documents/Da
ta/home-credit-default-risk
 99%|█████████████████████████████████████████▉ | 678M/688M [00:02<00:00, 300MB/s]
100%|██████████████████████████████████████████| 688M/688M [00:02<00:00, 279MB/s]
```

Imports

In [729…

```python
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import os
import zipfile
from sklearn.base import BaseEstimator, TransformerMixin
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline, FeatureUnion
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import warnings
warnings.filterwarnings('ignore')
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
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, ShuffleSplit, cross_val_score
from sklearn.metrics import roc_curve,roc_auc_score,accuracy_score
from scipy import stats
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

Data Loads

Back ground Home Credit Group

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

Home Credit Group

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

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

Background on the dataset

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

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

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

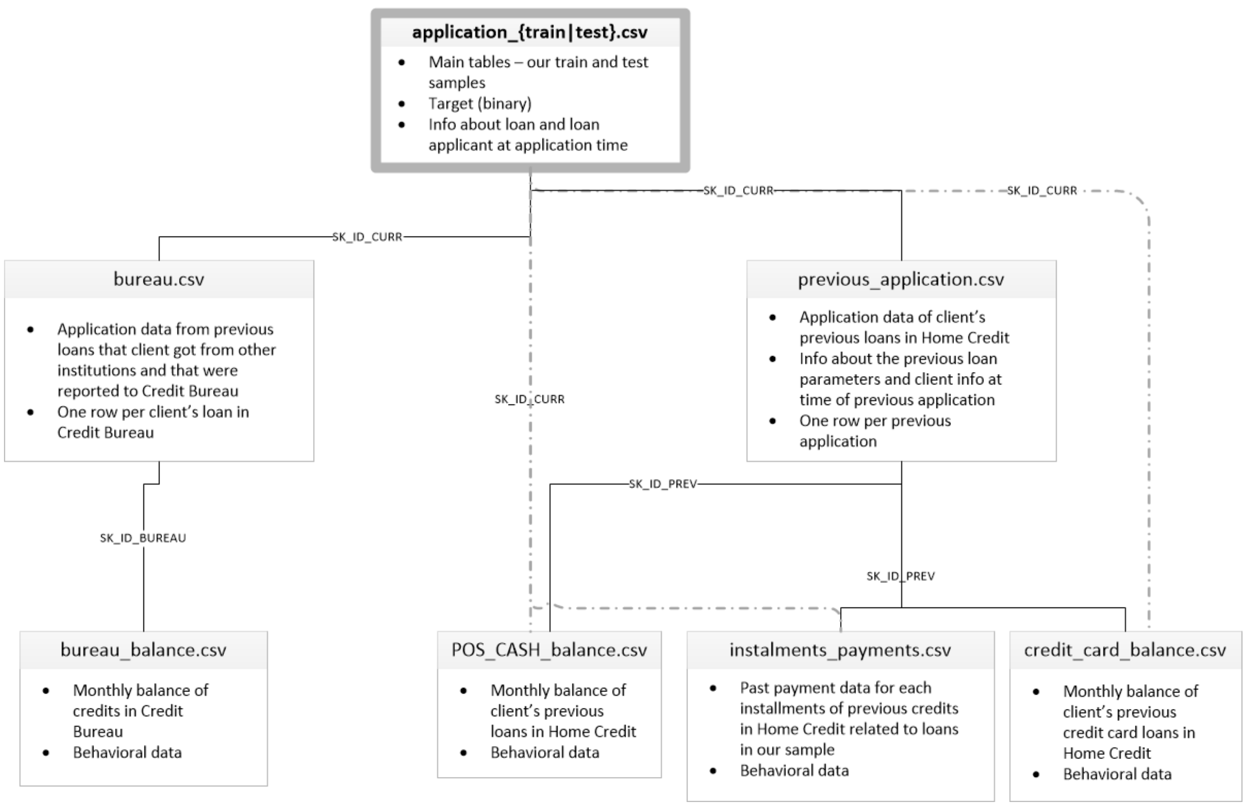
While Home Credit is currently using various statistical and machine learning methods to make these predictions, they're challenging Kagglers to help them unlock the full potential of their data. Doing so will ensure that clients capable of repayment are not rejected and that loans are given with a principal,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

Data files overview

There are 7 different sources of data:

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

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



Application_Train data load

In [730…

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

datasets['application_train'].shape
```

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

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
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[730…

```
(307511, 122)
```

Application_Test data load

In [731…

```
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_CHI
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

Other Datasets load

In [732…

```
%%time
ds_names = ("application_train", "application_test", "bureau","bureau_balance","credit_
            "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_CHI
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_OVERDU
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_DR
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_INSTALMI
0	1054186	161674	1.0	6	-118
1	1330831	151639	0.0	34	-215
2	2085231	193053	2.0	1	-6
3	2452527	199697	1.0	3	-24
4	2714724	167756	1.0	2	-138

```
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
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_
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 42.7 s, sys: 10.9 s, total: 53.6 s
Wall time: 53.6 s
```

EDA

Missing data for application train

In [733…

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

Out[733…

	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

Missing data for application test

In [734…

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

Out[734…

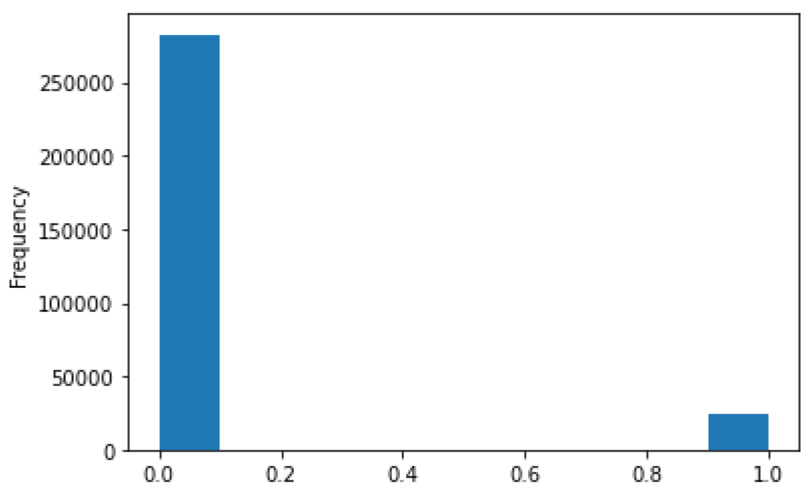
	Percent	Test Missing Count
COMMONAREA_AVG	68.72	33495
COMMONAREA_MODE	68.72	33495
COMMONAREA_MEDI	68.72	33495
NONLIVINGAPARTMENTS_AVG	68.41	33347
NONLIVINGAPARTMENTS_MODE	68.41	33347
NONLIVINGAPARTMENTS_MEDI	68.41	33347

	Percent	Test Missing Count
FONDKAPREMONT_MODE	67.28	32797
LIVINGAPARTMENTS_AVG	67.25	32780
LIVINGAPARTMENTS_MODE	67.25	32780
LIVINGAPARTMENTS_MEDI	67.25	32780
FLOORSMIN_MEDI	66.61	32466
FLOORSMIN_AVG	66.61	32466
FLOORSMIN_MODE	66.61	32466
OWN_CAR_AGE	66.29	32312
YEARS_BUILD_AVG	65.28	31818
YEARS_BUILD_MEDI	65.28	31818
YEARS_BUILD_MODE	65.28	31818
LANDAREA_MEDI	57.96	28254
LANDAREA_AVG	57.96	28254
LANDAREA_MODE	57.96	28254

Distribution of the target column

In [735…

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



Correlation with the target column

In [736…

```
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
```

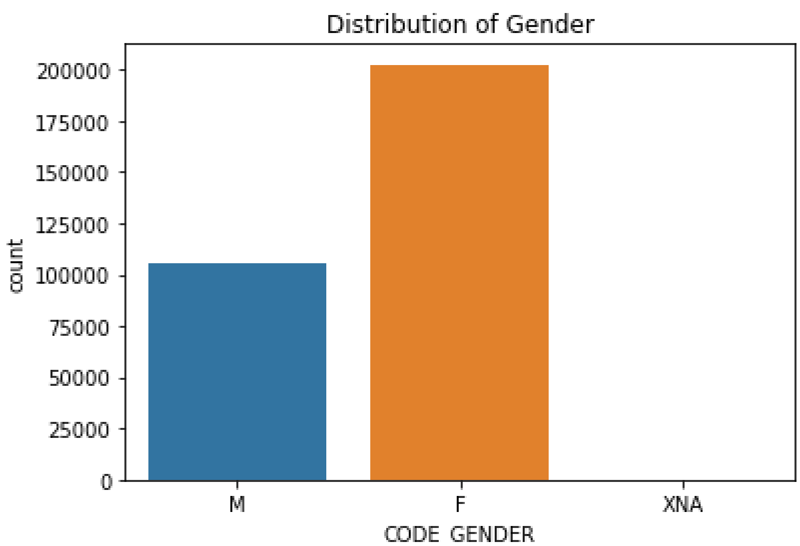
In [737…

```
app_train=datasets["application_train"]
app_test=datasets["application_test"]
```

Distribution of Gender

In [738…

```
sns.countplot(data = app_train, x ='CODE_GENDER')
plt.title('Distribution of Gender')
plt.show()
```



Defaulters by Age group

It looks like we have more female Applicants when compared to male

In [739…

```
age_data = app_train[['TARGET', 'DAYS_BIRTH']]
age_data['YEARS_BIRTH'] = age_data['DAYS_BIRTH'] / -365

#age_data

# Bin the age data
age_data['YEARS_BINNED'] = pd.cut(age_data['YEARS_BIRTH'], bins = np.linspace(20, 70, n
age_data.head(10)
```

Out[739...

	TARGET	DAYS_BIRTH	YEARS_BIRTH	YEARS_BINNED
0	1	-9461	25.920548	(25.0, 30.0]
1	0	-16765	45.931507	(45.0, 50.0]
2	0	-19046	52.180822	(50.0, 55.0]
3	0	-19005	52.068493	(50.0, 55.0]
4	0	-19932	54.608219	(50.0, 55.0]
5	0	-16941	46.413699	(45.0, 50.0]
6	0	-13778	37.747945	(35.0, 40.0]
7	0	-18850	51.643836	(50.0, 55.0]
8	0	-20099	55.065753	(55.0, 60.0]
9	0	-14469	39.641096	(35.0, 40.0]

In [740...

```
# Group by the bin and calculate averages
age_groups  = age_data.groupby('YEARS_BINNED').mean()
age_groups
```

Out[740...

	TARGET	DAYS_BIRTH	YEARS_BIRTH
YEARS_BINNED			
(20.0, 25.0]	0.123036	-8532.795625	23.377522
(25.0, 30.0]	0.111436	-10155.219250	27.822518
(30.0, 35.0]	0.102814	-11854.848377	32.479037
(35.0, 40.0]	0.089414	-13707.908253	37.555913
(40.0, 45.0]	0.078491	-15497.661233	42.459346
(45.0, 50.0]	0.074171	-17323.900441	47.462741
(50.0, 55.0]	0.066968	-19196.494791	52.593136
(55.0, 60.0]	0.055314	-20984.262742	57.491131
(60.0, 65.0]	0.052737	-22780.547460	62.412459
(65.0, 70.0]	0.037270	-24292.614340	66.555108

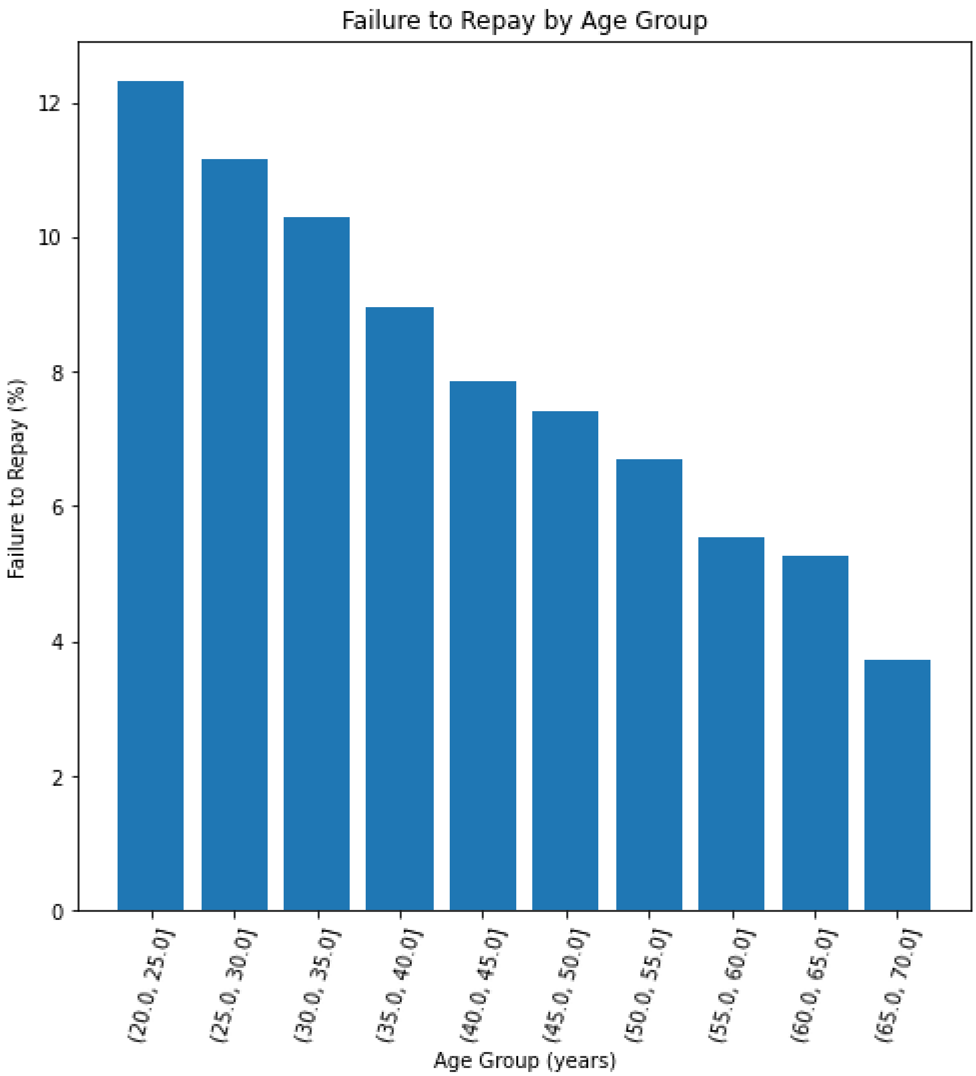
It can be observed that most of the defaulters are approximately 27-40 yrs old.

In [741...

```
%matplotlib inline
plt.figure(figsize = (8, 8))

# Graph the age bins and the average of the target as a bar plot
plt.bar(age_groups.index.astype(str), 100 * age_groups['TARGET'])

# Plot labeling
plt.xticks(rotation = 75); plt.xlabel('Age Group (years)'); plt.ylabel('Failure to Repa
plt.title('Failure to Repay by Age Group');
```



Handling incorrect values of Employment Days

In [742…

```
anom = datasets["application_train"][datasets["application_train"]['DAYS_EMPLOYED'] ==
non_anom = datasets["application_train"][datasets["application_train"]['DAYS_EMPLOYED']
print('The non-anomalies default on %0.2f%% of loans' % (100 * non_anom['TARGET'].mean(
print('The anomalies default on %0.2f%% of loans' % (100 * anom['TARGET'].mean()))
print('There are %d anomalous days of employment' % len(anom))
```

```
The non-anomalies default on 8.66% of loans
The anomalies default on 5.40% of loans
There are 55374 anomalous days of employment
```

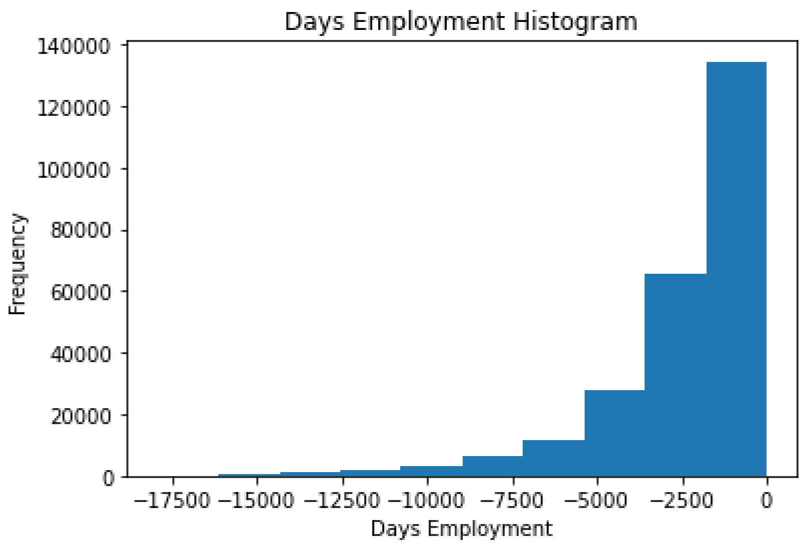
In [743…

```
# Remove the anomalies and review the histogram again
```

```
app_train['DAYS_EMPLOYED_ANOM'] = app_train["DAYS_EMPLOYED"] == 365243

# Replace the anomalous values with nan
app_train['DAYS_EMPLOYED'].replace({365243: np.nan}, inplace = True)

app_train['DAYS_EMPLOYED'].plot.hist(title = 'Days Employment Histogram');
plt.xlabel('Days Employment');
```



In [744…

```
# drop column DAYS_EMPLOYED_ANOM
app_train.drop(['DAYS_EMPLOYED_ANOM'], axis=1, inplace=True)
app_train.head()
```

Out[744…

	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

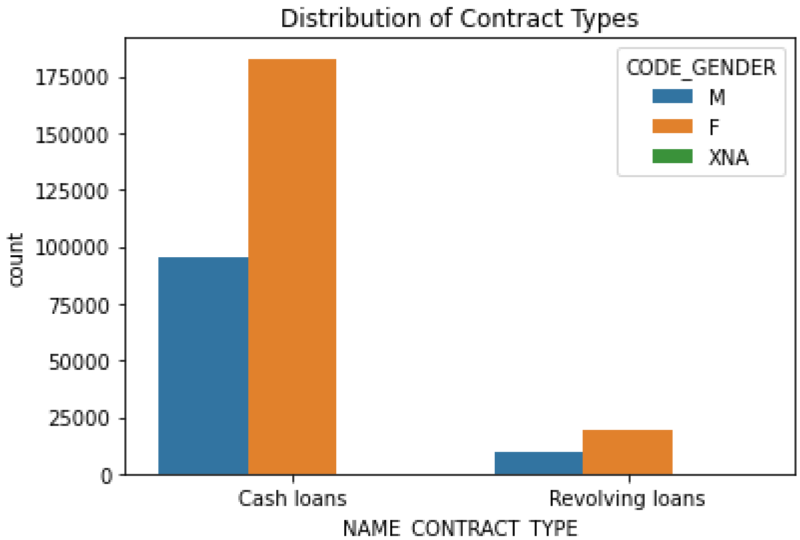
5 rows × 122 columns

Applicants with less than 2 years of employment are less likely to repay the loan.

Distribution of Contrcat types

In [745…

```
sns.countplot(data = app_train, x ='NAME_CONTRACT_TYPE', hue = 'CODE_GENDER')
plt.title('Distribution of Contract Types')
plt.show()
```

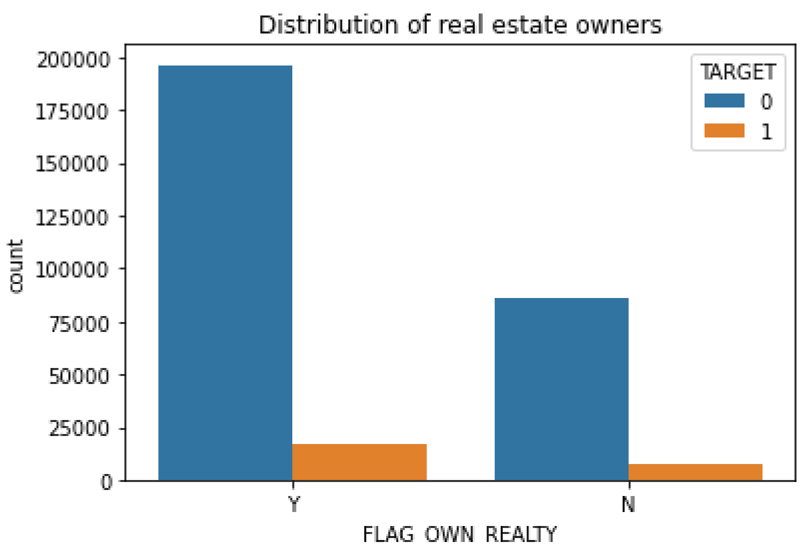


It can be seen that in general people mostly go for Cash loans as compared to revolving loans and both type of contracts are dominated by females.

Distribution of Real estate Owners

In [746…

```
sns.countplot(data = app_train, x ='FLAG_OWN_REALTY', hue = 'TARGET')
plt.title('Distribution of real estate owners')
plt.show()
```

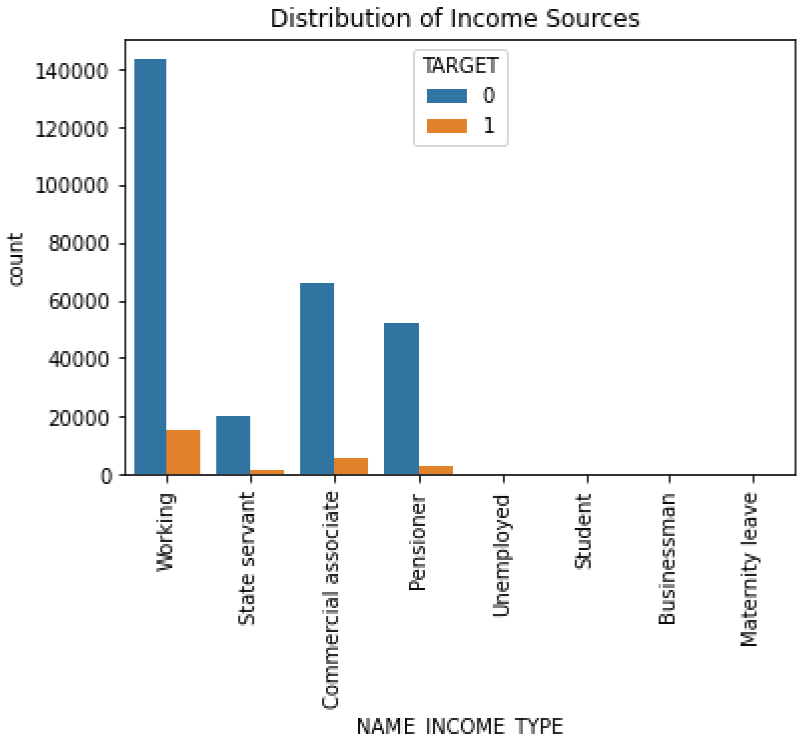


Generally people who own a realty are more likely to go for loans as compared to people who don't own one.

Distribution of Income Sources

In [747…

```
sns.countplot(data = app_train, x ='NAME_INCOME_TYPE', hue = 'TARGET')
plt.title('Distribution of Income Sources ')
plt.xticks(rotation = 90)
plt.show()
```

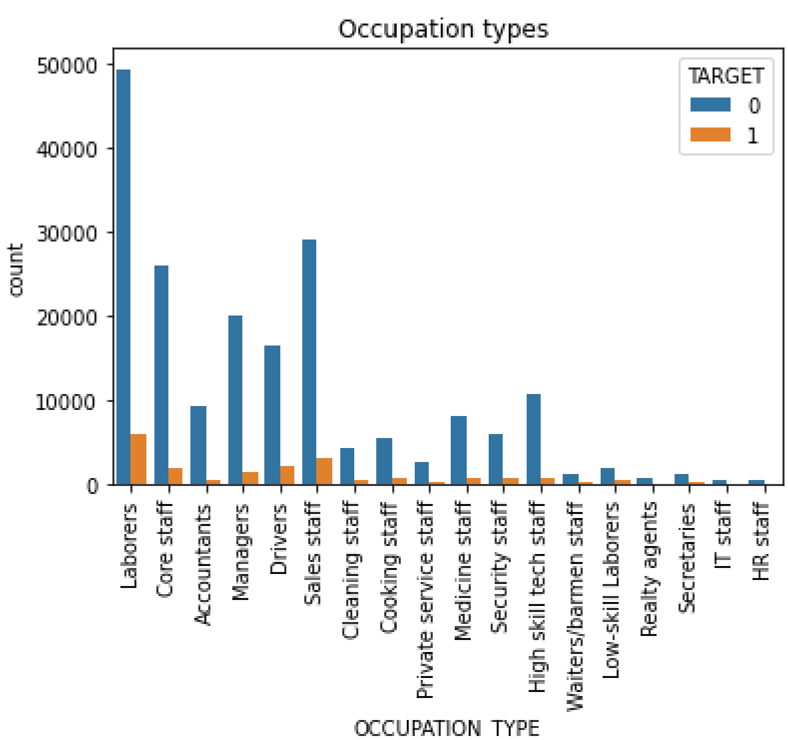


It can be observed that most of the defaulters belong to the working class followed by Commercial associates. A state servant is the least likely to fail repaying the loan amount

Occupation Types

In [748…

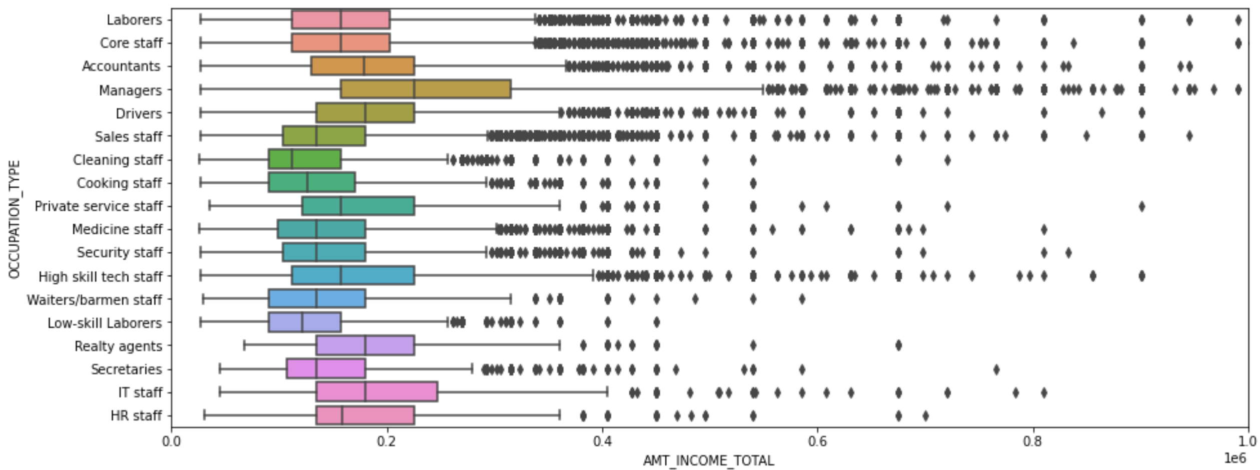
```
sns.countplot(data = app_train, x ='OCCUPATION_TYPE', hue = 'TARGET')
plt.title('Occupation types ')
plt.xticks(rotation = 90)
plt.show()
```



People who do not provide their occupation details and those who are labourers are more likely to fail paying back the loan.

In [749…

```
ig, ax = plt.subplots(figsize=(15, 6))
ax = sns.boxplot(y = "OCCUPATION_TYPE", x = "AMT_INCOME_TOTAL", orient = "h", data = ap
plt.xlim([0, 1e6])
plt.show()
```



Basic EDA of all the data sets

Previous Application Data

In [750…

```
def basic_eda(df, datafile_name="Datafile name"):
    print(f"\n*************************",datafile_name,"******************************
    print(f"Performing basic EDA on {datafile_name} dataset\n")
    print(f"* The dataset has {df.shape[0]} rows and {df.shape[1]} columns.")
    print("\n* First 10 rows of the dataset:\n")
    display(df.head(10))
    print("\n* Describing the dataset statistics:\n", )
    display(df.describe())
    print("\n* Fetching info of the dataset: \n")
    display(df.info())
    print("\n* Check data distribution: ")
    df.hist(figsize=(20,30))


df_prev_app = datasets["previous_application"]
basic_eda(df_prev_app, 'previous_applications')
```

```
************************* previous_applications ******************************

Performing basic EDA on previous_applications dataset

* The dataset has 1670214 rows and 37 columns.

* First 10 rows of the dataset:
```

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT
0	2030495	271877	Consumer loans	1730.430	17145.0	17145.0

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT
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	1383531	199383	Cash loans	23703.930	315000.0	340573.5
6	2315218	175704	Cash loans	NaN	0.0	0.0
7	1656711	296299	Cash loans	NaN	0.0	0.0
8	2367563	342292	Cash loans	NaN	0.0	0.0
9	2579447	334349	Cash loans	NaN	0.0	0.0

10 rows × 37 columns

```
* Describing the dataset statistics:
```

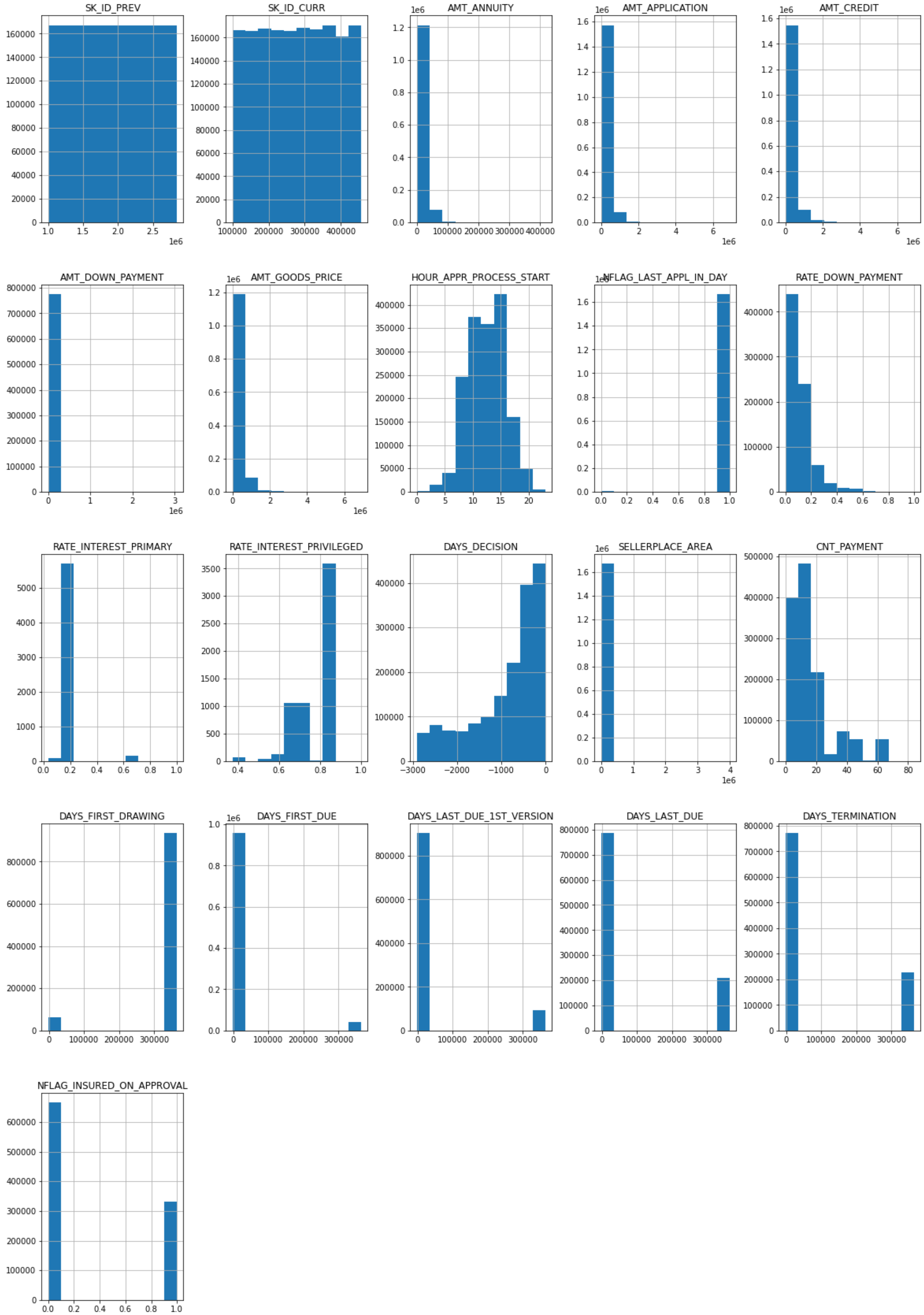
	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAY
count	1.670214e+06	1.670214e+06	1.297979e+06	1.670214e+06	1.670213e+06	7.74370
mean	1.923089e+06	2.783572e+05	1.595512e+04	1.752339e+05	1.961140e+05	6.69740
std	5.325980e+05	1.028148e+05	1.478214e+04	2.927798e+05	3.185746e+05	2.09215
min	1.000001e+06	1.000010e+05	0.000000e+00	0.000000e+00	0.000000e+00	-9.0000(
25%	1.461857e+06	1.893290e+05	6.321780e+03	1.872000e+04	2.416050e+04	0.00000
50%	1.923110e+06	2.787145e+05	1.125000e+04	7.104600e+04	8.054100e+04	1.63800
75%	2.384280e+06	3.675140e+05	2.065842e+04	1.803600e+05	2.164185e+05	7.74000
max	2.845382e+06	4.562550e+05	4.180581e+05	6.905160e+06	6.905160e+06	3.06004

8 rows × 21 columns

```
* Fetching info of the dataset:

<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
* Check data distribution:
```



In [751…

```
# Missing Values in Application Data
```

```
percent = (df_prev_app.isnull().sum()/df_prev_app.isnull().count()*100).sort_values(asc
sum_missing = df_prev_app.isna().sum().sort_values(ascending = False)
missing_application_train_data  = pd.concat([percent, sum_missing], axis=1, keys=['Perc
missing_application_train_data.head(20)
```

Out[751...

	Percent	Train Missing Count
RATE_INTEREST_PRIVILEGED	99.64	1664263
RATE_INTEREST_PRIMARY	99.64	1664263
AMT_DOWN_PAYMENT	53.64	895844
RATE_DOWN_PAYMENT	53.64	895844
NAME_TYPE_SUITE	49.12	820405
NFLAG_INSURED_ON_APPROVAL	40.30	673065
DAYS_TERMINATION	40.30	673065
DAYS_LAST_DUE	40.30	673065
DAYS_LAST_DUE_1ST_VERSION	40.30	673065
DAYS_FIRST_DUE	40.30	673065
DAYS_FIRST_DRAWING	40.30	673065
AMT_GOODS_PRICE	23.08	385515
AMT_ANNUITY	22.29	372235
CNT_PAYMENT	22.29	372230
PRODUCT_COMBINATION	0.02	346
AMT_CREDIT	0.00	1
NAME_YIELD_GROUP	0.00	0
NAME_PORTFOLIO	0.00	0
NAME_SELLER_INDUSTRY	0.00	0
SELLERPLACE_AREA	0.00	0

In [752...

```
# Dropping columns RATE_INTEREST_PRIVILEGED and RATE_INTEREST_PRIMARY as these have mor
df_prev_app.drop(['RATE_INTEREST_PRIVILEGED','RATE_INTEREST_PRIMARY'],axis=1, inplace=T

# Create correlation matrix
corr_matrix = df_prev_app.corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))

# Find index of feature columns with correlation greater than 0.85
to_drop = [column for column in upper.columns if any(upper[column] > 0.85)]
print("Dropping: ", to_drop)
# Drop features
df_prev_app_new = df_prev_app.drop(df_prev_app[to_drop], axis=1)

df_prev_app_new.head()
```

```
Dropping:  ['AMT_CREDIT', 'AMT_GOODS_PRICE', 'DAYS_TERMINATION']
```

Out[752…

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

5 rows × 32 columns

POS_CASH_balance Data

In [753…

```
df_pos_cash = datasets['POS_CASH_balance']
basic_eda(df_pos_cash, 'POS_CASH_balance')
```

```
************************** POS_CASH_balance ******************************

Performing basic EDA on POS_CASH_balance dataset

* The dataset has 10001358 rows and 8 columns.

* First 10 rows of the dataset:
```

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	CNT_INSTALMENT	CNT_INSTALMENT_FUTURE	NAME_
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	
5	2207092	342166	-32	12.0	12.0	
6	1110516	204376	-38	48.0	43.0	
7	1387235	153211	-35	36.0	36.0	
8	1220500	112740	-31	12.0	12.0	
9	2371489	274851	-32	24.0	16.0	

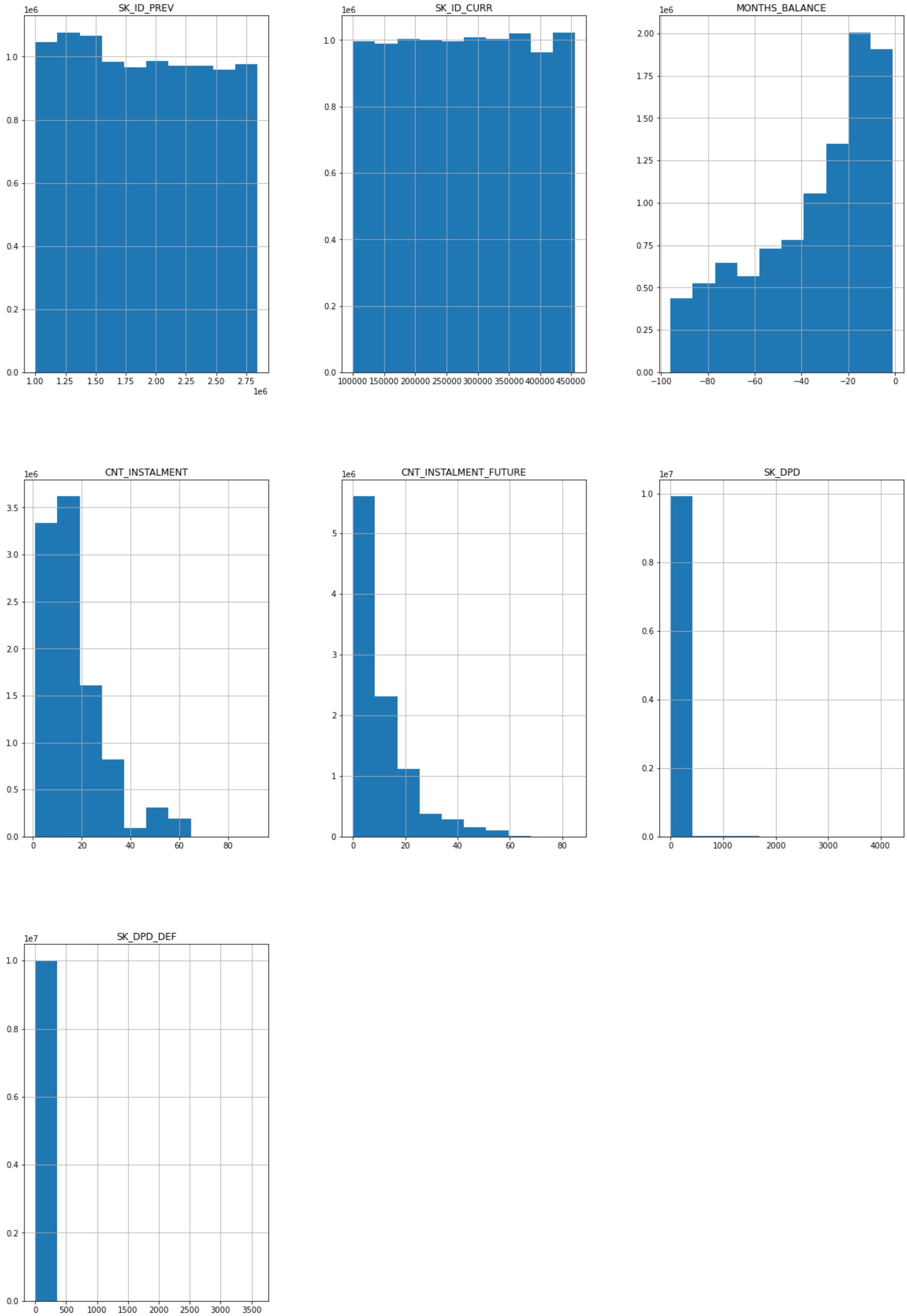
```
* Describing the dataset statistics:
```

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	CNT_INSTALMENT	CNT_INSTALMENT_FUTURE
count	1.000136e+07	1.000136e+07	1.000136e+07	9.975287e+06	9.975271e+06
mean	1.903217e+06	2.784039e+05	-3.501259e+01	1.708965e+01	1.048384e+01

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	CNT_INSTALMENT	CNT_INSTALMENT_FUTURE
std	5.358465e+05	1.027637e+05	2.606657e+01	1.199506e+01	1.110906e+01
min	1.000001e+06	1.000010e+05	-9.600000e+01	1.000000e+00	0.000000e+00
25%	1.434405e+06	1.895500e+05	-5.400000e+01	1.000000e+01	3.000000e+00
50%	1.896565e+06	2.786540e+05	-2.800000e+01	1.200000e+01	7.000000e+00
75%	2.368963e+06	3.674290e+05	-1.300000e+01	2.400000e+01	1.400000e+01
max	2.843499e+06	4.562550e+05	-1.000000e+00	9.200000e+01	8.500000e+01

```
* Fetching info of the dataset:

<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
* Check data distribution:
```



In [754…

```
# This gives us latest record of each loan
```

```
# MONTHS_BALANCE has 0 for current, -1 for previous etc.
# Value of -8 in this field means 8 months back the loan was completed.

df_pos_cash_latest = df_pos_cash.loc[df_pos_cash.groupby(['SK_ID_PREV','SK_ID_CURR'])['

df_pos_cash_latest.head()
```

Out[754…

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	CNT_INSTALMENT	CNT_INSTALMENT_FUTURE
45995	1000001	158271	-8	2.0	0.0
2792302	1000002	101962	-50	4.0	0.0
7085917	1000003	252457	-1	12.0	9.0
4078063	1000004	260094	-22	7.0	0.0
7852623	1000005	176456	-46	10.0	0.0

In [755…

```
df_pos_cash_latest['NAME_CONTRACT_STATUS'].value_counts()
```

Out[755…

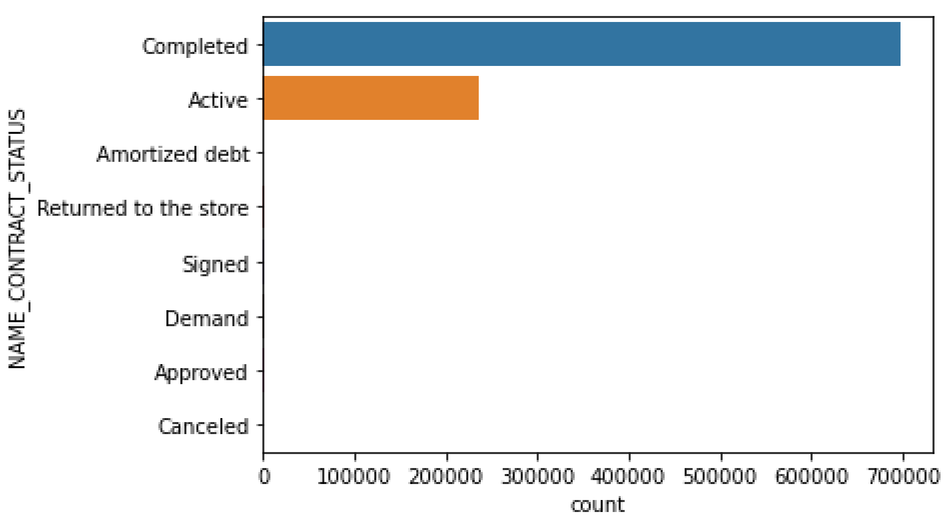
```
Completed                698421
Active                   236149
Signed                     1272
Returned to the store       304
Demand                      102
Approved                     58
Amortized debt               17
Canceled                      2
Name: NAME_CONTRACT_STATUS, dtype: int64
```

In [756…

```
sns.countplot(y='NAME_CONTRACT_STATUS', data=df_pos_cash_latest)
```

Out[756…

```
<AxesSubplot:xlabel='count', ylabel='NAME_CONTRACT_STATUS'>
```



Bureau Data

In [757…

```
bureau_df = datasets['bureau']
basic_eda(bureau_df, 'bureau')
```

```
************************* bureau *****************************

Performing basic EDA on bureau dataset

* The dataset has 1716428 rows and 17 columns.

* First 10 rows of the dataset:
```

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	CREDIT_DAY_OVERDU
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	
5	215354	5714467	Active	currency 1	-273	
6	215354	5714468	Active	currency 1	-43	
7	162297	5714469	Closed	currency 1	-1896	
8	162297	5714470	Closed	currency 1	-1146	
9	162297	5714471	Active	currency 1	-1146	

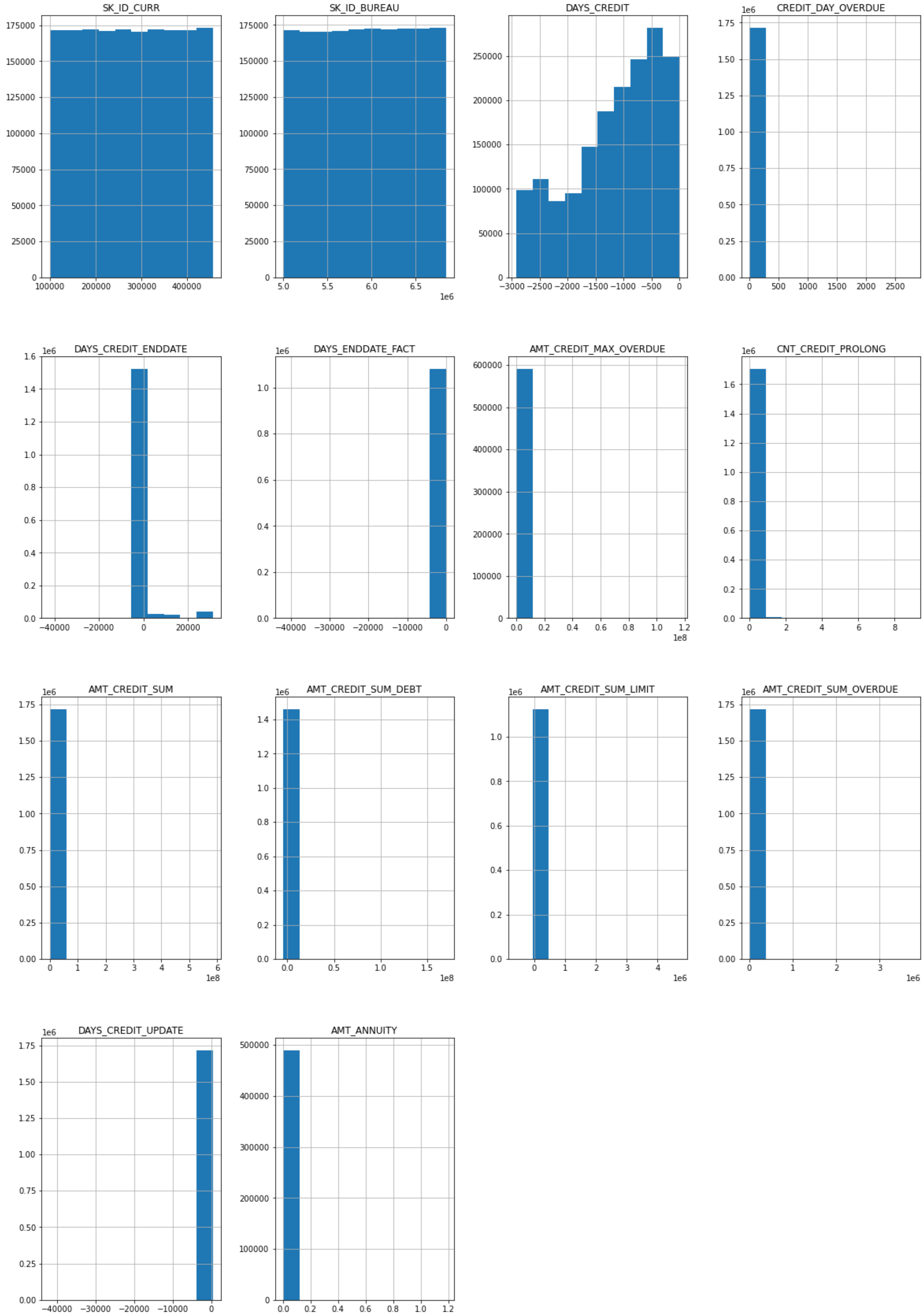
```
* Describing the dataset statistics:
```

	SK_ID_CURR	SK_ID_BUREAU	DAYS_CREDIT	CREDIT_DAY_OVERDUE	DAYS_CREDIT_ENDDATE	DA
count	1.716428e+06	1.716428e+06	1.716428e+06	1.716428e+06	1.610875e+06	
mean	2.782149e+05	5.924434e+06	-1.142108e+03	8.181666e-01	5.105174e+02	
std	1.029386e+05	5.322657e+05	7.951649e+02	3.654443e+01	4.994220e+03	
min	1.000010e+05	5.000000e+06	-2.922000e+03	0.000000e+00	-4.206000e+04	
25%	1.888668e+05	5.463954e+06	-1.666000e+03	0.000000e+00	-1.138000e+03	
50%	2.780550e+05	5.926304e+06	-9.870000e+02	0.000000e+00	-3.300000e+02	
75%	3.674260e+05	6.385681e+06	-4.740000e+02	0.000000e+00	4.740000e+02	
max	4.562550e+05	6.843457e+06	0.000000e+00	2.792000e+03	3.119900e+04	

```
* Fetching info of the dataset:

<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
* Check data distribution:
```



Credit Card Balance Data

In [758…

```
df_credit = datasets['credit_card_balance']
basic_eda(df_credit, 'credit_card_balance')
```

```
************************* credit_card_balance ******************************

Performing basic EDA on credit_card_balance dataset

* The dataset has 3840312 rows and 23 columns.

* First 10 rows of the dataset:
```

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	AMT_BALANCE	AMT_CREDIT_LIMIT_ACTUAL	AMT_DR
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	2646502	380010	-7	82903.815	270000	
6	1079071	171320	-6	353451.645	585000	
7	2095912	118650	-7	47962.125	45000	
8	2181852	367360	-4	291543.075	292500	
9	1235299	203885	-5	201261.195	225000	

10 rows × 23 columns

```
* Describing the dataset statistics:
```

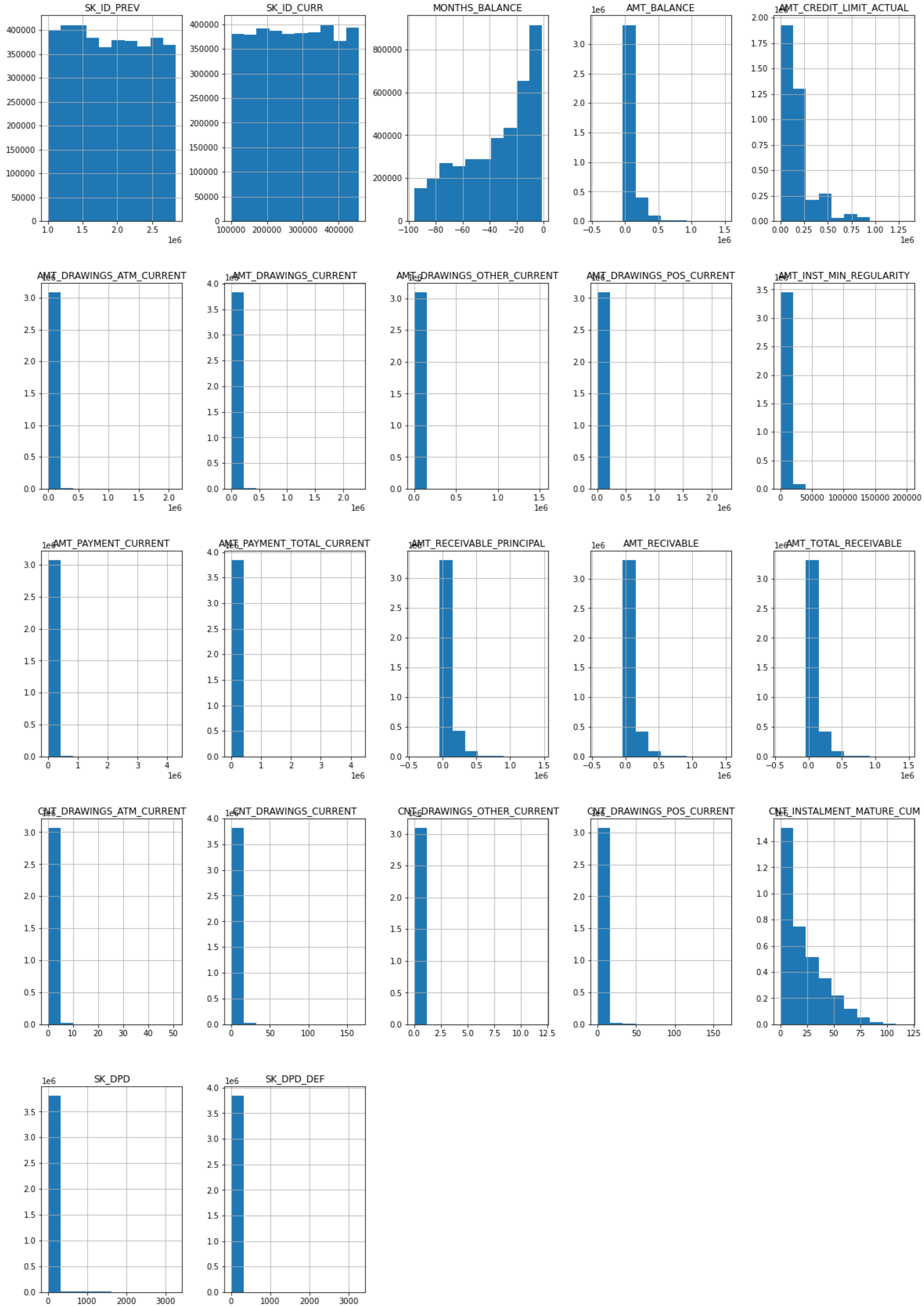
	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	AMT_BALANCE	AMT_CREDIT_LIMIT_ACTUAL	A
count	3.840312e+06	3.840312e+06	3.840312e+06	3.840312e+06	3.840312e+06	
mean	1.904504e+06	2.783242e+05	-3.452192e+01	5.830016e+04	1.538080e+05	
std	5.364695e+05	1.027045e+05	2.666775e+01	1.063070e+05	1.651457e+05	
min	1.000018e+06	1.000060e+05	-9.600000e+01	-4.202502e+05	0.000000e+00	
25%	1.434385e+06	1.895170e+05	-5.500000e+01	0.000000e+00	4.500000e+04	
50%	1.897122e+06	2.783960e+05	-2.800000e+01	0.000000e+00	1.125000e+05	
75%	2.369328e+06	3.675800e+05	-1.100000e+01	8.904669e+04	1.800000e+05	
max	2.843496e+06	4.562500e+05	-1.000000e+00	1.505902e+06	1.350000e+06	

8 rows × 22 columns

```
* Fetching info of the dataset:

<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
* Check data distribution:
```



In [759…

```
len(bureau_df['SK_ID_CURR'].unique())
```

305811

Out[759…

InstallmentPayments Data

In [760…

```
df_installments = datasets['installments_payments']
basic_eda(df_installments, 'installments_payments')
```

```
************************** installments_payments ******************************

Performing basic EDA on installments_payments dataset

* The dataset has 13605401 rows and 8 columns.

* First 10 rows of the dataset:
```

	SK_ID_PREV	SK_ID_CURR	NUM_INSTALMENT_VERSION	NUM_INSTALMENT_NUMBER	DAYS_INSTALMI
0	1054186	161674	1.0	6	-118
1	1330831	151639	0.0	34	-215
2	2085231	193053	2.0	1	-(
3	2452527	199697	1.0	3	-24'
4	2714724	167756	1.0	2	-138
5	1137312	164489	1.0	12	-138
6	2234264	184693	4.0	11	-34
7	1818599	111420	2.0	4	-9(
8	2723183	112102	0.0	14	-1(
9	1413990	109741	1.0	4	-5:

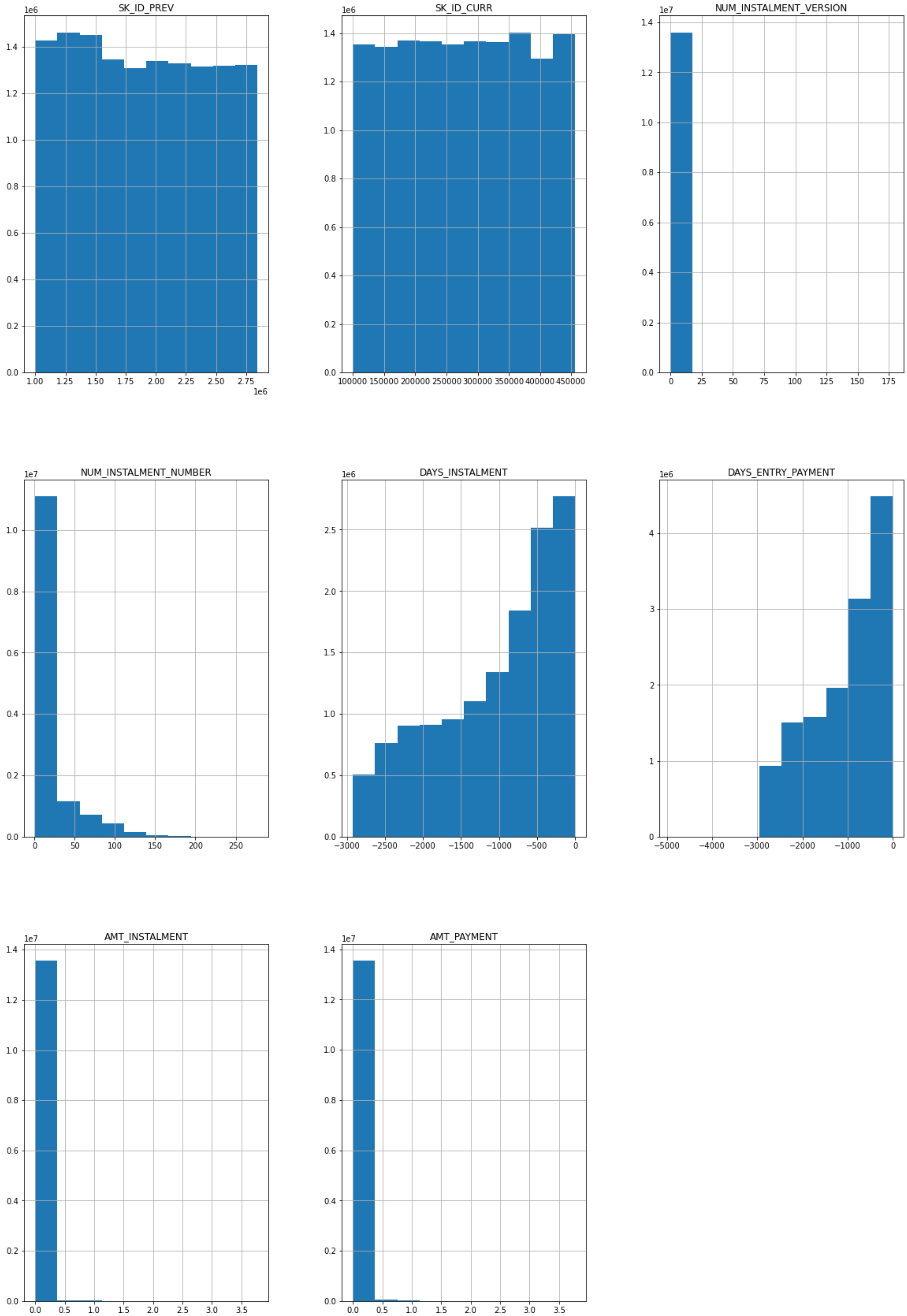
```
* Describing the dataset statistics:
```

	SK_ID_PREV	SK_ID_CURR	NUM_INSTALMENT_VERSION	NUM_INSTALMENT_NUMBER	DAYS_IN
count	1.360540e+07	1.360540e+07	1.360540e+07	1.360540e+07	1.3
mean	1.903365e+06	2.784449e+05	8.566373e-01	1.887090e+01	-1.0
std	5.362029e+05	1.027183e+05	1.035216e+00	2.666407e+01	8.0
min	1.000001e+06	1.000010e+05	0.000000e+00	1.000000e+00	-2.9
25%	1.434191e+06	1.896390e+05	0.000000e+00	4.000000e+00	-1.6
50%	1.896520e+06	2.786850e+05	1.000000e+00	8.000000e+00	-8.1
75%	2.369094e+06	3.675300e+05	1.000000e+00	1.900000e+01	-3.6
max	2.843499e+06	4.562550e+05	1.780000e+02	2.770000e+02	-1.0

```
* Fetching info of the dataset:

<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
* Check data distribution:
```


SK_ID_PREV
SK_ID_CURR
NUM_INSTALMENT_VERSION
NUM_INSTALMENT_NUMBER
DAYS_INSTALMENT
DAYS_ENTRY_PAYMENT
AMT_INSTALMENT
AMT_PAYMENT

Feature Engineering

In [761…

```
# Dictionary of Final Data sets

final_ds_names = ("bureau_final","credit_card_balance_final","installments_payments_fin
            "previous_application_final","POS_CASH_balance_final")

final_ds = dict()
```

Excess Loan Feature

In [762…

```
# Create a feature to see if the loan amount is larger than the value of the underlying

app_train['EXCESS_LOAN'] = app_train['AMT_CREDIT'] - app_train['AMT_GOODS_PRICE']


app_train['EXCESS_LOAN'].mask(app_train['EXCESS_LOAN']<0, 0, inplace=True)
```

Flag Document Counts

In [763…

```
flag_docs = ['SK_ID_CURR']
for cols in app_train.columns:
    if cols[0:8] == 'FLAG_DOC':
        flag_docs.append(cols)

flag_df = app_train[flag_docs]
flag_pivot = flag_df.melt(id_vars = 'SK_ID_CURR', var_name = 'Document', value_name = "
flag_counts = flag_pivot.groupby('SK_ID_CURR').sum()
flag_counts.head()
```

Out[763…

	FLAG_DOCS_SUBMITTED
SK_ID_CURR	
100002	1
100003	1
100004	0
100006	1
100007	1

Income Per Family

In [764…

```
app_train_final = pd.merge(app_train, flag_counts, 'left', 'SK_ID_CURR')
app_train_final['INCOME_PER_FAMILY_MEMBER'] = app_train_final['AMT_INCOME_TOTAL']/app_t


app_train_final['DEBT_TO_INCOME'] = app_train_final['AMT_ANNUITY'] / (app_train_final['
```

In [765…

```
app_train_final.head(15)
```

Out[765…

	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	100008	0	Cash loans	M	N	Y
6	100009	0	Cash loans	F	Y	Y
7	100010	0	Cash loans	M	Y	Y
8	100011	0	Cash loans	F	N	Y
9	100012	0	Revolving loans	M	N	Y
10	100014	0	Cash loans	F	N	Y
11	100015	0	Cash loans	F	N	Y
12	100016	0	Cash loans	F	N	Y
13	100017	0	Cash loans	M	Y	N
14	100018	0	Cash loans	F	N	Y

15 rows × 126 columns

Adding the same above features to the test data

In [766…

```
app_test = datasets['application_test']

app_test['EXCESS_LOAN'] = app_test['AMT_CREDIT'] - app_test['AMT_GOODS_PRICE']
app_test['EXCESS_LOAN'].mask(app_test['EXCESS_LOAN']<0, 0, inplace=True)
app_test.head()
```

Out[766…

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHI
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 × 122 columns

In [767…

```
flag_docs = ['SK_ID_CURR']
for cols in app_test.columns:
    if cols[0:8] == 'FLAG_DOC':
        flag_docs.append(cols)

flag_df = app_test[flag_docs]
flag_pivot = flag_df.melt(id_vars = 'SK_ID_CURR', var_name = 'Document', value_name = "
flag_counts = flag_pivot.groupby('SK_ID_CURR').sum()
flag_counts.head()
```

Out[767…

	FLAG_DOCS_SUBMITTED
SK_ID_CURR	
100001	1
100005	1
100013	1
100028	1
100038	1

In [768…

```
app_test_final = pd.merge(app_test, flag_counts, 'left', 'SK_ID_CURR')


app_test_final['INCOME_PER_FAMILY_MEMBER'] = app_test_final['AMT_INCOME_TOTAL']/app_tes



app_test_final['DEBT_TO_INCOME'] = app_test_final['AMT_ANNUITY'] / (app_test_final['AMT
```

In [769…

```
app_test_final.head(15)
```

Out[769…

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
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	100042	Cash loans	F	Y	Y	
6	100057	Cash loans	M	Y	Y	
7	100065	Cash loans	M	N	Y	
8	100066	Cash loans	F	N	Y	
9	100067	Cash loans	F	Y	Y	
10	100074	Cash loans	F	N	Y	

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
11	100090	Cash loans	F	N	Y	
12	100091	Cash loans	F	N	Y	
13	100092	Cash loans	F	Y	Y	
14	100106	Revolving loans	M	N	Y	

15 rows × 125 columns

OHE on Categorical features

In [770…

```
df_pos_cash_latest_status = df_pos_cash_latest[['SK_ID_PREV','SK_ID_CURR','NAME_CONTRAC
df_pos_cash_latest_status.head()
```

Out[770…

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_STATUS
45995	1000001	158271	Completed
2792302	1000002	101962	Completed
7085917	1000003	252457	Active
4078063	1000004	260094	Completed
7852623	1000005	176456	Completed

In [771…

```
df_dummies = pd.get_dummies(df_pos_cash_latest_status['NAME_CONTRACT_STATUS'])
df_dummies.head()
```

Out[771…

	Active	Amortized debt	Approved	Canceled	Completed	Demand	Returned to the store	Signed
45995	0	0	0	0	1	0	0	0
2792302	0	0	0	0	1	0	0	0
7085917	1	0	0	0	0	0	0	0
4078063	0	0	0	0	1	0	0	0
7852623	0	0	0	0	1	0	0	0

In [772…

```
df_pos_cash_latest_status = pd.concat([df_pos_cash_latest_status,df_dummies] , axis=1,
df_pos_cash_latest_status.head()
```

Out[772…

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_STATUS	Active	Amortized debt	Approved	Canceled
45995	1000001	158271	Completed	0	0	0	0
2792302	1000002	101962	Completed	0	0	0	0

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_STATUS	Active	Amortized debt	Approved	Canceled
7085917	1000003	252457	Active	1	0	0	0
4078063	1000004	260094	Completed	0	0	0	0
7852623	1000005	176456	Completed	0	0	0	0

In [773…

```
d = {
    'SK_ID_PREV':['size'],
    'CNT_INSTALMENT_FUTURE':['min'],
    'CNT_INSTALMENT':['max']

}
df_agg = df_pos_cash.groupby(['SK_ID_CURR', 'SK_ID_PREV']).agg(d)


df_agg.columns = df_agg.columns.droplevel()

df_agg.reset_index(inplace=True)

df_agg.columns=['SK_ID_CURR','SK_ID_PREV','Count','Remaining_repays','Initial_term']
display(df_agg.head())
```

	SK_ID_CURR	SK_ID_PREV	Count	Remaining_repays	Initial_term
0	100001	1369693	5	0.0	4.0
1	100001	1851984	4	0.0	4.0
2	100002	1038818	19	6.0	24.0
3	100003	1810518	8	0.0	12.0
4	100003	2396755	12	1.0	12.0

In [774…

```
df_final = pd.merge(df_agg,df_pos_cash_latest_status,how='left')
```

In [775…

```
df_final.head()
```

Out[775…

	SK_ID_CURR	SK_ID_PREV	Count	Remaining_repays	Initial_term	NAME_CONTRACT_STATUS	Active
0	100001	1369693	5	0.0	4.0	Completed	0
1	100001	1851984	4	0.0	4.0	Completed	0
2	100002	1038818	19	6.0	24.0	Active	1
3	100003	1810518	8	0.0	12.0	Completed	0
4	100003	2396755	12	1.0	12.0	Active	1

In [776…

```
d2 = {
    'SK_ID_PREV':['size'],
    'Remaining_repays':['sum'],
    'Initial_term':  ['min','max'],
    'Active':        ['sum'],
    'Amortized debt':['sum'],
    'Approved':      ['sum'],
    'Canceled':      ['sum'],
    'Completed':     ['sum'],
    'Demand':        ['sum'],
    'Returned to the store':['sum'],
    'Signed':        ['sum']
}
df_out = df_final.groupby('SK_ID_CURR').agg(d2)

# display(df_out.head())

df_out.columns = df_out.columns.droplevel()

df_out.reset_index(inplace=True)

df_out.columns=['SK_ID_CURR','Count','Total_Remaining_repays','Min_Initial_term','Max_I
display(df_out.head())
```

	SK_ID_CURR	Count	Total_Remaining_repays	Min_Initial_term	Max_Initial_term	Active	Amortized debt
0	100001	2	0.0	4.0	4.0	0	0
1	100002	1	6.0	24.0	24.0	1	0
2	100003	3	1.0	6.0	12.0	1	0
3	100004	1	0.0	4.0	4.0	0	0
4	100005	1	0.0	12.0	12.0	0	0

In [777…

```
final_ds['POS_CASH_balance_final'] = df_out
```

In [778…

```
cat_features = ['NAME_CONTRACT_TYPE', 'WEEKDAY_APPR_PROCESS_START','NAME_CONTRACT_STATU
df_prev_app_new_cat = df_prev_app_new[cat_features]

imputed = SimpleImputer(fill_value='missing', strategy='constant').fit_transform(df_pre

ohe = OneHotEncoder().fit(imputed)
cat = pd.DataFrame(ohe.transform(imputed).toarray(
            ), index=df_prev_app_new_cat.index, columns=list(ohe.get_feature_names(cat_

cat.columns=['Cashloans', 'Consumerloans', 'Revolvingloans', 'XNA', 'FRIDAY', 'MONDAY',
cat.head()
```

Out[778…

Cashloans	Consumerloans	Revolvingloans	XNA	FRIDAY	MONDAY	SATURDAY	SUNDAY	THURSD

	Cashloans	Consumerloans	Revolvingloans	XNA	FRIDAY	MONDAY	SATURDAY	SUNDAY	THURSD
0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	(
1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	'
2	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
3	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	(
4	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	'

Aggregation by loan types

In [779...

```
df_prev_app_new= pd.concat([df_prev_app_new,cat], axis=1)

d = {
 'Cashloans'     : ['sum'],
 'Consumerloans' : ['sum'],
 'Revolvingloans': ['sum'],
 'XNA'            : ['sum'],
 'FRIDAY'         : ['sum'],
 'MONDAY'         : ['sum'],
 'SATURDAY'       : ['sum'],
 'SUNDAY'         : ['sum'],
 'THURSDAY'       : ['sum'],
 'TUESDAY'        : ['sum'],
 'WEDNESDAY'      : ['sum'],
 'Approved'       : ['sum'],
 'Canceled'       : ['sum'],
 'Refused'        : ['sum'],
 'Unusedoffer'   : ['sum'],
 'SK_ID_PREV'                  : ['size'],
 'AMT_ANNUITY'                 : ['min','max','mean'],
 'AMT_APPLICATION'             : ['min','max','mean'],
 'DAYS_DECISION'               : ['min','max','mean'],
}


df_out = df_prev_app_new.groupby(by='SK_ID_CURR').agg(d)

df_out.columns = df_out.columns.droplevel()

df_out.reset_index(inplace=True)

df_out.columns= ['SK_ID_CURR','Cash loans', 'Consumer loans', 'Revolvingloans', 'XNA',
display(df_out.head())
```

	SK_ID_CURR	Cash loans	Consumer loans	Revolvingloans	XNA	FRIDAY	MONDAY	SATURDAY	SUNDAY	THU
0	100001	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	
1	100002	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	
2	100003	1.0	2.0	0.0	0.0	1.0	0.0	1.0	1.0	

	SK_ID_CURR	Cash loans	Consumer loans	Revolvingloans	XNA	FRIDAY	MONDAY	SATURDAY	SUNDAY	THU
3	100004	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	
4	100005	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	

5 rows × 26 columns

In [780...

```
final_ds['previous_application_final'] = df_out
```

Late Payments

In [781...

```
# Avg_installment_days_difference and Avg_installment_amount_difference
# Let's start with the bureau balance dataset first

bb_df = datasets['bureau_balance']
```

In [782...

```
## We are going to focus on the number of months that had a late payment

tot_month_counts = bb_df.groupby('SK_ID_BUREAU').count()['STATUS']
late_month_counts = bb_df[(bb_df['STATUS'] != '0') & (bb_df['STATUS'] != 'C') & (bb_df[
status_df = pd.merge(left = tot_month_counts, right = late_month_counts, how = 'left',

status_df.fillna(0, inplace = True)
status_df.head()
```

Out[782...

	STATUS_tot	STATUS_late
SK_ID_BUREAU		
5001709	97	0.0
5001710	83	0.0
5001711	4	0.0
5001712	19	0.0
5001713	22	0.0

In [783...

```
## Now let's work on the bureau dataset

bureau_df = datasets['bureau']
bureau_df.head()
```

Out[783...

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	CREDIT_DAY_OVERDU
0	215354	5714462	Closed	currency 1	-497	
1	215354	5714463	Active	currency 1	-208	

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

In [784…

```
## Pick out just the credit card data

cc_debt_df = bureau_df[bureau_df['CREDIT_TYPE'] == 'Credit card']
cc_debt_df.drop(cc_debt_df.columns.difference(['SK_ID_CURR','CREDIT_TYPE', 'AMT_CREDIT_
cc_debt_df = cc_debt_df.groupby('SK_ID_CURR').sum()
cc_debt_df.rename({'SK_ID_CURR': 'SK_ID_CURR', 'AMT_CREDIT_SUM_DEBT': 'CREDIT_CARD_DEBT
cc_debt_df.head()
```

Out[784…

	CREDIT_CARD_DEBT
SK_ID_CURR	
100002	0.0
100003	0.0
100005	0.0
100009	326628.0
100011	0.0

Active Loans

In [785…

```
## Count how many active loans the applicant has when they are applying for the Home Cr

active_df = bureau_df[bureau_df['CREDIT_ACTIVE'] == 'Active']
active_df.drop(active_df.columns.difference(['SK_ID_CURR','CREDIT_ACTIVE']), 1, inplace
active_df = active_df.groupby('SK_ID_CURR').count()
active_df.rename({'SK_ID_CURR': 'SK_ID_CURR', 'CREDIT_ACTIVE': 'TOTAL_ACTIVE_LOANS'}, a
active_df.head()
```

Out[785…

	TOTAL_ACTIVE_LOANS
SK_ID_CURR	
100001	3
100002	2
100003	1
100005	2
100008	1

In [786…

```
bureau_df.drop(bureau_df.columns.difference(['SK_ID_CURR','AMT_CREDIT_SUM_OVERDUE', 'AM


## combine the bureau dataset with the late payment info from bureau_balance dataset

combined_bureau_df = pd.merge(bureau_df, status_df, 'left','SK_ID_BUREAU')



combined_bureau_df.drop('SK_ID_BUREAU', inplace = True, axis = 1)


combined_bureau_df = combined_bureau_df.groupby('SK_ID_CURR').sum()

bureau_final = pd.merge(combined_bureau_df, active_df, 'left', 'SK_ID_CURR')
bureau_final = pd.merge(bureau_final, cc_debt_df, 'left', 'SK_ID_CURR')
## transform/combine several features into new ones

bureau_final['Percent_Late'] = bureau_final['STATUS_late']/bureau_final['STATUS_tot']
bureau_final['PERCENT_CREDIT_CARD'] = bureau_final['CREDIT_CARD_DEBT']/bureau_final['AM


bureau_final.drop(['STATUS_tot', 'STATUS_late', 'CREDIT_CARD_DEBT'], axis = 1, inplace



## Make the columns headers more descriptive

bureau_final.rename({'AMT_CREDIT_SUM_DEBT': 'TOTAL_DEBT', 'AMT_CREDIT_SUM_OVERDUE': 'TO
bureau_final['PERCENT_CREDIT_CARD'] = bureau_final['PERCENT_CREDIT_CARD'].fillna(0)
bureau_final['TOTAL_NUMBER_OF_ACTIVE_LOANS'] = bureau_final['TOTAL_NUMBER_OF_ACTIVE_LOA
bureau_final.head()
```

Out[786…

	TOTAL_DEBT	TOTAL_DEBT_OVERDUE	TOTAL_NUMBER_OF_ACTIVE_LOANS	PERCENT_LATE	P
SK_ID_CURR					
100001	596686.5	0.0	3.0	0.005814	
100002	245781.0	0.0	2.0	0.245455	
100003	0.0	0.0	1.0	NaN	
100004	0.0	0.0	0.0	NaN	
100005	568408.5	0.0	2.0	0.000000	

In [787…

```
final_ds['bureau_final'] = bureau_final
```

In [788…

```
df_installments['installment_days_difference']=df_installments['DAYS_ENTRY_PAYMENT']-df
df_installments['installment_amount_difference']=df_installments['AMT_PAYMENT']-df_inst
df_installments.head()
```

Out[788…

	SK_ID_PREV	SK_ID_CURR	NUM_INSTALMENT_VERSION	NUM_INSTALMENT_NUMBER	DAYS_INSTALMI
0	1054186	161674	1.0	6	-118

	SK_ID_PREV	SK_ID_CURR	NUM_INSTALMENT_VERSION	NUM_INSTALMENT_NUMBER	DAYS_INSTALMI
1	1330831	151639	0.0	34	-21!
2	2085231	193053	2.0	1	-(
3	2452527	199697	1.0	3	-24'
4	2714724	167756	1.0	2	-13!

In [789…

```
d = {
    'installment_days_difference':['mean'],
    'installment_amount_difference':['mean']

}
df_ins_agg = df_installments.groupby(['SK_ID_CURR', 'SK_ID_PREV']).agg(d)
# display(df_ins_agg.head())

df_ins_agg.columns = df_ins_agg.columns.droplevel()
# display(df_ins_agg.head())
df_ins_agg.reset_index(inplace=True)
# display(df_ins_agg.head())
df_ins_agg.columns=['SK_ID_CURR','SK_ID_PREV','Avg_installment_days_difference', 'Avg_i
display(df_ins_agg.head())
```

	SK_ID_CURR	SK_ID_PREV	Avg_installment_days_difference	Avg_installment_amount_difference
0	100001	1369693	-15.500000	0.0
1	100001	1851984	3.666667	0.0
2	100002	1038818	-20.421053	0.0
3	100003	1810518	-4.428571	0.0
4	100003	2396755	-6.750000	0.0

In [790…

```
d2 = {
    'Avg_installment_days_difference':['mean'],
    'Avg_installment_amount_difference':['mean']
}
df_ins_out = df_ins_agg.groupby('SK_ID_CURR').agg(d2)

# display(df_ins_out.head())

df_ins_out.columns = df_ins_out.columns.droplevel()

df_ins_out.reset_index(inplace=True)

df_ins_out.columns=['SK_ID_CURR','Avg_installment_days_difference', 'Avg_installment_am
display(df_ins_out.head())
```

	SK_ID_CURR	Avg_installment_days_difference	Avg_installment_amount_difference
0	100001	-5.916667	0.0
1	100002	-20.421053	0.0

	SK_ID_CURR	Avg_installment_days_difference	Avg_installment_amount_difference
2	100003	-7.448413	0.0
3	100004	-7.666667	0.0
4	100005	-23.555556	0.0

In [791…

```
final_ds['installments_payments_final'] = df_ins_out
```

Percent of Late Payments

In [792…

```
tot_month_counts = df_credit.groupby('SK_ID_PREV').count()['MONTHS_BALANCE']
late_month_counts = df_credit[(df_credit['SK_DPD'] != 0)].groupby('SK_ID_PREV').count()
df_credit_late = pd.merge(left = tot_month_counts, right = late_month_counts, how = 'le

df_credit_late.fillna(0, inplace = True)
df_credit_late.head()
```

Out[792…

	MONTHS_BALANCE	SK_DPD
SK_ID_PREV		
1000018	5	0.0
1000030	8	0.0
1000031	16	0.0
1000035	5	0.0
1000077	11	0.0

In [793…

```
df_credit_late['Payment_Pass_Due_Perc'] = df_credit_late['SK_DPD']/df_credit_late['MONT
df_credit_late.head()
```

Out[793…

	MONTHS_BALANCE	SK_DPD	Payment_Pass_Due_Perc
SK_ID_PREV			
1000018	5	0.0	0.0
1000030	8	0.0	0.0
1000031	16	0.0	0.0
1000035	5	0.0	0.0
1000077	11	0.0	0.0

In [794…

```
d = {
    'AMT_BALANCE':['mean'],
    'AMT_CREDIT_LIMIT_ACTUAL':['mean'],
    'AMT_PAYMENT_TOTAL_CURRENT':['mean'],
```

```
}
df_credit_agg = df_credit.groupby(['SK_ID_CURR','SK_ID_PREV']).agg(d)


df_credit_agg.columns = df_credit_agg.columns.droplevel()

df_credit_agg.reset_index(inplace=True)

df_credit_agg.columns=['SK_ID_CURR', 'SK_ID_PREV','CC_Average_Monthly_Balance','CC_Aver
display(df_credit_agg.head())
```

	SK_ID_CURR	SK_ID_PREV	CC_Average_Monthly_Balance	CC_Average_Credit_Card_Limit	CC_Average_Mc
0	100006	1489396	0.000000	270000.000000	
1	100011	1843384	54482.111149	164189.189189	
2	100013	2038692	18159.919219	131718.750000	
3	100021	2594025	0.000000	675000.000000	
4	100023	1499902	0.000000	135000.000000	

In [795…

```
combined_credit_df = pd.merge(df_credit_agg, df_credit_late, 'left','SK_ID_PREV')
#combined_credit_df.head()
dropped_credit_df=combined_credit_df.drop(columns=['MONTHS_BALANCE', 'SK_DPD'])
dropped_credit_df.head()
```

Out[795…

	SK_ID_CURR	SK_ID_PREV	CC_Average_Monthly_Balance	CC_Average_Credit_Card_Limit	CC_Average_Mc
0	100006	1489396	0.000000	270000.000000	
1	100011	1843384	54482.111149	164189.189189	
2	100013	2038692	18159.919219	131718.750000	
3	100021	2594025	0.000000	675000.000000	
4	100023	1499902	0.000000	135000.000000	

In [796…

```
d2 = {
    'CC_Average_Monthly_Balance':['sum'],
    'CC_Average_Credit_Card_Limit':['mean'],
    'CC_Average_Monthly_Payments':['sum'],
    'Payment_Pass_Due_Perc': ['mean']

}
df_credit_out = dropped_credit_df.groupby('SK_ID_CURR').agg(d2)

# display(df_out.head())

df_credit_out.columns = df_credit_out.columns.droplevel()

df_credit_out.reset_index(inplace=True)
```

```
df_credit_out.columns=['SK_ID_CURR','CC_Average_Monthly_Balance','CC_Average_Credit_Car
display(df_credit_out.head())
```

	SK_ID_CURR	CC_Average_Monthly_Balance	CC_Average_Credit_Card_Limit	CC_Average_Monthly_Paymer
0	100006	0.000000	270000.000000	0.0000
1	100011	54482.111149	164189.189189	4520.0675
2	100013	18159.919219	131718.750000	6817.1723
3	100021	0.000000	675000.000000	0.0000
4	100023	0.000000	135000.000000	0.0000

Final Data sets after Feature Engineering

In [797…

```
final_ds['credit_card_balance_final'] = df_credit_out
```

In [798…

```
for i in final_ds.keys():
    print(i, " shape: ", final_ds[i].shape)
```

```
POS_CASH_balance_final  shape:  (337252, 13)
previous_application_final  shape:  (338857, 26)
bureau_final  shape:  (305811, 5)
installments_payments_final  shape:  (339587, 3)
credit_card_balance_final  shape:  (103558, 5)
```

In [799…

```
# save files into a pickle file to save running time
import pickle
with open('final_datasets.pickle', 'wb') as f:
    pickle.dump(final_ds, f, protocol=pickle.HIGHEST_PROTOCOL)
```

In [800…

```
# load datasets from a pickle file
import pickle
with open('final_datasets.pickle', 'rb') as f:
    final_ds = pickle.load(f)
```

HCDR Preprocessing

Selecting HIghly corelated features

In [801…

```
correlations = app_train.corr()['TARGET'].sort_values()
num_of_features = 20
```

Selected Features

In [802…

```
# +1 in tail() so that TARGET is not considered in num_of_features
selected_features = list(correlations.tail(num_of_features//2 + 1).index) + list(correl
selected_features.remove('TARGET')

# We don't have any categorical features in the highly correlated features. Hence we se
categoricals = ['CODE_GENDER', 'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE', '

selected_features = selected_features + categoricals
print()
print("Selected features= ", selected_features)
```

```
Selected features=  ['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_CLIEN
T', 'REGION_RATING_CLIENT_W_CITY', 'DAYS_EMPLOYED', 'DAYS_BIRTH', 'EXT_SOURCE_3', 'EXT_S
OURCE_2', 'EXT_SOURCE_1', 'FLOORSMAX_AVG', 'FLOORSMAX_MEDI', 'FLOORSMAX_MODE', 'AMT_GOOD
S_PRICE', 'REGION_POPULATION_RELATIVE', 'ELEVATORS_AVG', 'ELEVATORS_MEDI', 'CODE_GENDE
R', 'FLAG_OWN_REALTY', 'FLAG_OWN_CAR', 'NAME_CONTRACT_TYPE', 'NAME_EDUCATION_TYPE', 'OCC
UPATION_TYPE', 'NAME_INCOME_TYPE']
```

In [803…

```
# Split the provided training data into training and validation. Not creating test data

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','
                   '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=0.1
    X_kaggle_test= datasets["application_test"][selected_features]
else:
    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=0.1
    X_kaggle_test= datasets["application_test"][selected_features]

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

```
X train           shape: (222176, 27)
Y train           shape: (222176,)

X validation      shape: (46127, 27)
Y validation      shape: (46127,)

X test            shape: (39208, 27)
```

```
Y test           shape: (39208,)

X X_kaggle_test   shape: (48744, 27)
```

Pipeline Creation

In [804…

```
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 [805…

```
# seperate the featured into numerical and catagorical for pipelines

num_attribs = [ 'FLAG_DOCUMENT_3', 'REG_CITY_NOT_LIVE_CITY', 'FLAG_EMP_PHONE', 'REG_CIT
               'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE', 'REGION_RATING_CLIENT', 'RE
               'EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_EMPLOYED', 'FLOORS
               'FLOORSMAX_MEDI', 'FLOORSMAX_MODE', 'AMT_GOODS_PRICE' ]

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

cat_attribs = ['CODE_GENDER', 'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE',
               'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']

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 [806…

```
def pct(x):
    return round(100*x,3)
try:
    expLog
except NameError:
    expLog = pd.DataFrame(columns=["exp_name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train AUC",
                                   "Valid AUC",
                                   "Test  AUC",
```

```
                    "Train Time"
                   ])
```

Model 0: Baseline Logistic Model

In [807…

```
from time import time
start = time()

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


model_0 = full_pipeline_with_predictor.fit(X_train, y_train)
train_time = np.round(time() - start, 4)
```

In [808…

```
from sklearn.metrics import accuracy_score

np.round(accuracy_score(y_train, model_0.predict(X_train)), 3)
```

Out[808…

```
0.92
```

In [809…

```
x=len(expLog)
expLog.drop(index=range(0,x),axis=0,inplace=True)
expLog
```

Out[809…

exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time

In [810…

```
from sklearn.metrics import accuracy_score, roc_auc_score

exp_name = f"Baseline_Logistic_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_0.predict(X_train)),
                accuracy_score(y_valid, model_0.predict(X_valid)),
                accuracy_score(y_test, model_0.predict(X_test)),
                roc_auc_score(y_train, model_0.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_0.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_0.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[810…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258

In [811…

```
expLog
```

Out[811...

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258

Merge Additional Data Sets

In [812...

```
# Merge additional datasetswith X_train, y_train, X_val, y_val
print(datasets["application_train"].head())
selected_features = ['SK_ID_CURR','TARGET'] + selected_features
df_train_selected = datasets["application_train"][selected_features]


selected_features.remove('TARGET')
df_test_selected  = datasets["application_test"][selected_features]
df_train_selected.columns
```

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

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

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

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

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

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR  EXCESS_LOAN
0                        0.0                         1.0      55597.5
1                        0.0                         0.0     164002.5
2                        0.0                         0.0          0.0
```

```
3                          NaN                           NaN      15682.5
4                          0.0                           0.0          0.0

[5 rows x 123 columns]
```

Out[812…

```
Index(['SK_ID_CURR', 'TARGET', '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_EMPLOYED', 'DAYS_BIRTH',
       'EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'FLOORSMAX_AVG',
       'FLOORSMAX_MEDI', 'FLOORSMAX_MODE', 'AMT_GOODS_PRICE',
       'REGION_POPULATION_RELATIVE', 'ELEVATORS_AVG', 'ELEVATORS_MEDI',
       'CODE_GENDER', 'FLAG_OWN_REALTY', 'FLAG_OWN_CAR', 'NAME_CONTRACT_TYPE',
       'NAME_EDUCATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYPE'],
      dtype='object')
```

In [813…

```
print(datasets["application_test"].columns)
```

```
Index(['SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
       'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT',
       'AMT_ANNUITY', 'AMT_GOODS_PRICE',
       ...
       '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',
       'EXCESS_LOAN'],
      dtype='object', length=122)
```

In [814…

```
print("Train: ", df_train_selected.shape)
print("Test: ",  df_test_selected.shape)
```

```
Train:  (307511, 29)
Test:  (48744, 28)
```

In [815…

```
# Merge all 6 additional datasets to the training and testing sets

def merge_additional(df):
    df = pd.merge(df, final_ds['POS_CASH_balance_final'][['SK_ID_CURR','Count','Total_R
                        'left', on='SK_ID_CURR')
    print("Merged POS_CASH_balance: ",  df.shape)

    df = pd.merge(df, final_ds['bureau_final'], 'left',  on='SK_ID_CURR')
    print("Merged bureau: ",  df.shape)

    df = pd.merge(df, final_ds['installments_payments_final'], 'left', on='SK_ID_CURR')
    print("Merged installments_payments: ",  df.shape)

    df = pd.merge(df, final_ds['previous_application_final'], 'left', on='SK_ID_CURR')
    print("Merged previous_application_final: ",  df.shape)

    df = pd.merge(df, final_ds['credit_card_balance_final'], 'left', on='SK_ID_CURR')
    print("Merged credit_card_balance_final: ",  df.shape)

    return df
```

In [816…

```
df_train_selected = merge_additional(df_train_selected)
df_test_selected = merge_additional(df_test_selected)
```

```
Merged POS_CASH_balance:  (307511, 32)
Merged bureau:  (307511, 37)
Merged installments_payments:  (307511, 39)
Merged previous_application_final:  (307511, 64)
Merged credit_card_balance_final:  (307511, 68)
Merged POS_CASH_balance:  (48744, 31)
Merged bureau:  (48744, 36)
Merged installments_payments:  (48744, 38)
Merged previous_application_final:  (48744, 63)
Merged credit_card_balance_final:  (48744, 67)
```

In [817…

```
print("Train: ", df_train_selected.shape)
print("Test: ",  df_test_selected.shape)
```

```
Train:  (307511, 68)
Test:  (48744, 67)
```

In [818…

```
selected_features.remove('SK_ID_CURR')
selected_features = selected_features + ['Count',  'Total_Remaining_repays',  'TOTAL_DE
                                          'TOTAL_DEBT_OVERDUE',  'TOTAL_NUMBER_OF_ACTIVE
                                          'PERCENT_CREDIT_CARD',  'Avg_installment_days_
                                          'Cash loans', 'Consumer loans', 'Revolvingloan
                                          'THURSDAY', 'TUESDAY', 'WEDNESDAY', 'Approved'
                                          'Tot_AMT_ANNUITY_min', 'Tot_AMT_ANNUITY_max',
                                          'Tot_AMT_APPLICATION_max', 'Tot_AMT_APPLICATIO
                                          'DAYS_DECISION_mean', 'CC_Average_Monthly_Bala
                                          'CC_Average_percentage_pass_due']
```

In [819…

```
df_train_selected.columns
```

Out[819…

```
Index(['SK_ID_CURR', 'TARGET', '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_EMPLOYED', 'DAYS_BIRTH',
       'EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'FLOORSMAX_AVG',
       'FLOORSMAX_MEDI', 'FLOORSMAX_MODE', 'AMT_GOODS_PRICE',
       'REGION_POPULATION_RELATIVE', 'ELEVATORS_AVG', 'ELEVATORS_MEDI',
       'CODE_GENDER', 'FLAG_OWN_REALTY', 'FLAG_OWN_CAR', 'NAME_CONTRACT_TYPE',
       'NAME_EDUCATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYPE', 'Count',
       'Total_Remaining_repays', 'Max_Initial_term', 'TOTAL_DEBT',
       'TOTAL_DEBT_OVERDUE', 'TOTAL_NUMBER_OF_ACTIVE_LOANS', 'PERCENT_LATE',
       'PERCENT_CREDIT_CARD', 'Avg_installment_days_difference',
       'Avg_installment_amount_difference', 'Cash loans', 'Consumer loans',
       'Revolvingloans', 'XNA', 'FRIDAY', 'MONDAY', 'SATURDAY', 'SUNDAY',
       'THURSDAY', 'TUESDAY', 'WEDNESDAY', 'Approved', 'Canceled', 'Refused',
       'Unusedoffer', 'Total_records', 'Tot_AMT_ANNUITY_min',
       'Tot_AMT_ANNUITY_max', 'Tot_AMT_ANNUITY_mean',
       'Tot_AMT_APPLICATION_min', 'Tot_AMT_APPLICATION_max',
       'Tot_AMT_APPLICATION_mean', 'DAYS_DECISION_min', 'DAYS_DECISION_max',
       'DAYS_DECISION_mean', 'CC_Average_Monthly_Balance',
       'CC_Average_Credit_Card_Limit', 'CC_Average_Monthly_Payments',
       'CC_Average_percentage_pass_due'],
      dtype='object')
```

In [820…

```
X_train = df_train_selected[selected_features]
y_train = df_train_selected['TARGET']
```

```
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, r
X_kaggle_test= df_test_selected[selected_features]

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

```
X train           shape: (222176, 66)
Y train           shape: (222176,)

X validation      shape: (46127, 66)
Y validation      shape: (46127,)

X test            shape: (39208, 66)
Y test            shape: (39208,)

X X_kaggle_test   shape: (48744, 66)
```

In [821…

```
new_cols = list()
for i in final_ds.keys():
#     print(final_ds[i].columns)
    new_cols += list(final_ds[i].columns)
new_cols
```

Out[821…

```
['SK_ID_CURR',
 'Count',
 'Total_Remaining_repays',
 'Min_Initial_term',
 'Max_Initial_term',
 'Active',
 'Amortized debt',
 'Approved',
 'Canceled',
 'Completed',
 'Demand',
 'Returned to the store',
 'Signed',
 'SK_ID_CURR',
 'Cash loans',
 'Consumer loans',
 'Revolvingloans',
 'XNA',
 'FRIDAY',
 'MONDAY',
 'SATURDAY',
 'SUNDAY',
 'THURSDAY',
 'TUESDAY',
 'WEDNESDAY',
 'Approved',
 'Canceled',
```

```
 'Refused',
 'Unusedoffer',
 'Total_records',
 'Tot_AMT_ANNUITY_min',
 'Tot_AMT_ANNUITY_max',
 'Tot_AMT_ANNUITY_mean',
 'Tot_AMT_APPLICATION_min',
 'Tot_AMT_APPLICATION_max',
 'Tot_AMT_APPLICATION_mean',
 'DAYS_DECISION_min',
 'DAYS_DECISION_max',
 'DAYS_DECISION_mean',
 'TOTAL_DEBT',
 'TOTAL_DEBT_OVERDUE',
 'TOTAL_NUMBER_OF_ACTIVE_LOANS',
 'PERCENT_LATE',
 'PERCENT_CREDIT_CARD',
 'SK_ID_CURR',
 'Avg_installment_days_difference',
 'Avg_installment_amount_difference',
 'SK_ID_CURR',
 'CC_Average_Monthly_Balance',
 'CC_Average_Credit_Card_Limit',
 'CC_Average_Monthly_Payments',
 'CC_Average_percentage_pass_due']
```

In [822…

```
X_train.head()
```

Out[822…

	FLAG_DOCUMENT_3	REG_CITY_NOT_LIVE_CITY	FLAG_EMP_PHONE	REG_CITY_NOT_WORK_CITY	I
21614	1	0	1	0	
209797	1	0	1	1	
17976	1	0	0	0	
282543	1	0	1	1	
52206	1	1	0	0	

5 rows × 66 columns

Model 1 : Logistic Regression with Additional Features

In [823…

```
# Logistic regression with our selected 66 features

num_attribs = ['FLAG_DOCUMENT_3', 'REG_CITY_NOT_LIVE_CITY', 'FLAG_EMP_PHONE', 'REG_CITY
               'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE', 'REGION_RATING_CLIENT', 'RE
               'EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_EMPLOYED', 'FLOORS
               'FLOORSMAX_MEDI', 'FLOORSMAX_MODE', 'AMT_GOODS_PRICE',
               'Count',  'Total_Remaining_repays',  'TOTAL_DEBT',  'Max_Initial_term',
               'TOTAL_DEBT_OVERDUE',  'TOTAL_NUMBER_OF_ACTIVE_LOANS',  'PERCENT_LATE',
               'PERCENT_CREDIT_CARD',  'Avg_installment_days_difference',  'Avg_install
               'Cash loans', 'Consumer loans', 'Revolvingloans', 'XNA', 'FRIDAY', 'MOND
```

```
                'TUESDAY', 'WEDNESDAY', 'Approved', 'Canceled', 'Refused', 'Unusedoffer'
                'Tot_AMT_ANNUITY_max', 'Tot_AMT_ANNUITY_mean', 'Tot_AMT_APPLICATION_min'
                'Tot_AMT_APPLICATION_mean', 'DAYS_DECISION_min', 'DAYS_DECISION_max', 'D
                'CC_Average_Credit_Card_Limit','CC_Average_Monthly_Payments','CC_Average
               ]

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

cat_attribs = ['CODE_GENDER', 'FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE',
               'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']

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 [824…

```
from time import time
start = time()

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


model_1 = full_pipeline_with_predictor.fit(X_train, y_train)
train_time = np.round(time() - start, 4)
```

In [825…

```
from sklearn.metrics import accuracy_score, roc_auc_score

exp_name = f"LogisticRegression_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_1.predict(X_train)),
                accuracy_score(y_valid, model_1.predict(X_valid)),
                accuracy_score(y_test, model_1.predict(X_test)),
                roc_auc_score(y_train, model_1.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_1.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_1.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[825…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445

Model 2: Hyperparameter Tuning with Gridsearch CV

In [826…

```
from sklearn.model_selection import GridSearchCV

full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("linear", LogisticRegression(verbose = 1))
    ])

param_grid = {'linear__penalty':['l1','l2', 'elasticnet'],
              'linear__C': [1, 10, 100, 1000, 10000]
             }


start = time()
model_2 = GridSearchCV(full_pipeline_with_predictor, param_grid, cv=10, n_jobs=4)

model_2.fit(X_train,y_train)
train_time = np.round(time() - start, 4)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    6.3s finished
```

In [827…

```
exp_name = f"LogisticRegression_GSCV_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_2.predict(X_train)),
                accuracy_score(y_valid, model_2.predict(X_valid)),
                accuracy_score(y_test, model_2.predict(X_test)),
                roc_auc_score(y_train, model_2.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_2.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_2.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[827…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622

Model 3: RandomForest

In [828…

```
from sklearn.ensemble import RandomForestClassifier
rnd_clf = RandomForestClassifier(n_estimators=500, max_leaf_nodes=20, n_jobs=4, random_

start = time()

# %%time
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("random_forest", rnd_clf)
    ])


model_3 = full_pipeline_with_predictor.fit(X_train, y_train)

train_time = np.round(time() - start, 4)
```

In [829…

```
from sklearn.metrics import accuracy_score, roc_auc_score

exp_name = f"RamdomForest_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_3.predict(X_train)),
                accuracy_score(y_valid, model_3.predict(X_valid)),
                accuracy_score(y_test, model_3.predict(X_test)),
                roc_auc_score(y_train, model_3.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_3.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_3.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[829…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804

Model 4: Random Forest Hyper Parameter Tuning

In [830…

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from tempfile import mkdtemp
from shutil import rmtree

cachedir = mkdtemp()
```

```
start = time()

full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("RandomForest", RandomForestClassifier())  # iterations=100,learning_rate=0.03
    ])


params = {
    'RandomForest__n_estimators': [100],

    'RandomForest__max_depth': [5,10,15,20],
#     'RandomForest__max_features': [5,7,9]
}


rnd_clf = RandomizedSearchCV(full_pipeline_with_predictor, params,
#                            n_iter=15,
                             cv = 10,
                             scoring='roc_auc',
                             verbose=2,
                             n_jobs=4)


cv_fit = rnd_clf.fit(X_train, y_train)
model_4 = cv_fit.best_estimator_
train_time = np.round(time() - start, 4)
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits
```

In [831…

```
exp_name = f"RamdomForestCV_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_4.predict(X_train)),
                accuracy_score(y_valid, model_4.predict(X_valid)),
                accuracy_score(y_test, model_4.predict(X_test)),
                roc_auc_score(y_train, model_4.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_4.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_4.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[831…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470

Model 5 : XgBoost

In [832...

```
import xgboost as xgb
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("xgboost", xgb.XGBClassifier())
    ])

start = time()
model_5 = full_pipeline_with_predictor.fit(X_train, y_train)
train_time = np.round(time() - start, 4)
```

```
[11:10:59] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evalu
ation metric used with the objective 'binary:logistic' was changed from 'error' to 'logl
oss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

In [833...

```
exp_name = f"XGBoost_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_5.predict(X_train)),
                accuracy_score(y_valid, model_5.predict(X_valid)),
                accuracy_score(y_test, model_5.predict(X_test)),
                roc_auc_score(y_train, model_5.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_5.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_5.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[833...

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957

Model 6: Ada Boost

In [834...

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("AdaBoost", AdaBoostClassifier())
    ])

start = time()
model_6 = full_pipeline_with_predictor.fit(X_train, y_train)
train_time = np.round(time() - start, 4)
```

In [835...

```
exp_name = f"AdaBoost_{len(selected_features)}_features"
```

```
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_6.predict(X_train)),
                accuracy_score(y_valid, model_6.predict(X_valid)),
                accuracy_score(y_test, model_6.predict(X_test)),
                roc_auc_score(y_train, model_6.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_6.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_6.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[835…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957
6	AdaBoost_66_features	0.9199	0.9195	0.9156	0.7598	0.7547	0.7582	68.2524

Model 7: Grad Boost

In [836…

```
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("GradBoost", GradientBoostingClassifier())
    ])

start = time()
model_7 = full_pipeline_with_predictor.fit(X_train, y_train)
train_time = np.round(time() - start, 4)
```

In [837…

```
exp_name = f"GradientBoost_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_7.predict(X_train)),
                accuracy_score(y_valid, model_7.predict(X_valid)),
                accuracy_score(y_test, model_7.predict(X_test)),
                roc_auc_score(y_train, model_7.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_7.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_7.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[837…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957
6	AdaBoost_66_features	0.9199	0.9195	0.9156	0.7598	0.7547	0.7582	68.2524
7	GradientBoost_66_features	0.9208	0.9197	0.9164	0.7729	0.7636	0.7626	299.1295

Model 8: Lightgbm

In [838…

```
import lightgbm as lg

params = {
    'n_estimators': 1000, 'learning_rate': 0.1, 'n_jobs': 4
}

full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ('mdl',  lg.LGBMClassifier(**params))
    ])

start = time()
model_8= full_pipeline_with_predictor.fit(X_train, y_train)
train_time = np.round(time() - start, 4)

print("LGBM accuracy score: ", np.round(accuracy_score(y_train, model_8.predict(X_train

print("LGBM roc_auc_score: ", roc_auc_score(y_train, model_8.predict_proba(X_train)[:,
```

```
LGBM accuracy score:  0.939
LGBM roc_auc_score:  0.9599107292047562
```

In [839…

```
exp_name = f"Lightgbm_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_8.predict(X_train)),
                accuracy_score(y_valid, model_8.predict(X_valid)),
                accuracy_score(y_test, model_8.predict(X_test)),
                roc_auc_score(y_train, model_8.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_8.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_8.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[839…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957
6	AdaBoost_66_features	0.9199	0.9195	0.9156	0.7598	0.7547	0.7582	68.2524
7	GradientBoost_66_features	0.9208	0.9197	0.9164	0.7729	0.7636	0.7626	299.1295
8	Lightgbm_66_features	0.9394	0.9190	0.9155	0.9599	0.7647	0.7624	16.3087

In [840…

```
expLog
```

Out[840…

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957
6	AdaBoost_66_features	0.9199	0.9195	0.9156	0.7598	0.7547	0.7582	68.2524
7	GradientBoost_66_features	0.9208	0.9197	0.9164	0.7729	0.7636	0.7626	299.1295
8	Lightgbm_66_features	0.9394	0.9190	0.9155	0.9599	0.7647	0.7624	16.3087

Model 9: Light GBM Tuned

In [841…

```
from hyperopt import STATUS_OK, Trials, fmin, hp, tpe
def objective(params):
    params = {
        'max_depth': int(params['max_depth']),
        'reg_alpha': "{:.3f}".format(params['reg_alpha']),
        'reg_lambda': "{:.3f}".format(params['reg_lambda']),
        'colsample_bytree': '{:.3f}'.format(params['colsample_bytree']),
        'learning_rate': '{:.3f}'.format(params['learning_rate']),
        'min_child_weight': int(params['min_child_weight']),
        'subsample': '{:.3f}'.format(params['subsample']),
    }

    full_pipeline_with_predictor = Pipeline([
```

```
        ("preparation", data_prep_pipeline),
        ('mdl',  lg.LGBMClassifier(**params))
    ])



    gbm_model = full_pipeline_with_predictor.fit(X_train, y_train)


    predictions = gbm_model.predict_proba(X_valid)[:, 1]
    score = roc_auc_score(y_valid, predictions)

    return {'loss': 1-score, 'status': STATUS_OK}


space = {
    'max_depth': hp.quniform('max_depth', 2, 8, 1),
    'colsample_bytree': hp.quniform('colsample_bytree', 0.3, 1.0, 0.1),
    'learning_rate': hp.quniform('learning_rate', 0.025, 0.1, 0.025),
    'min_child_weight': hp.quniform('min_child_weight', 1, 6, 1),
    'subsample': hp.quniform('subsample', 0.5, 1, 0.05),
    'reg_alpha': hp.quniform('reg_alpha', 0.0, 1, 0.1),
    'reg_lambda': hp.quniform('reg_lambda', 0.0, 1, 0.1),

}

best = fmin(fn=objective,
            space=space,
            algo=tpe.suggest,
            max_evals=30)
print(best)
```

```
100%|██████████| 30/30 [02:24<00:00,  4.83s/trial, best loss: 0.22848532621931128]
{'colsample_bytree': 0.30000000000000004, 'learning_rate': 0.1, 'max_depth': 6.0, 'min_c
hild_weight': 1.0, 'reg_alpha': 0.7000000000000001, 'reg_lambda': 0.1, 'subsample': 0.7
5}
```

In [842…

```
best = {'colsample_bytree': 0.30000000000000004
        ,'learning_rate': 0.1
        ,'max_depth': 6
        ,'min_child_weight': 1.0
        ,'reg_alpha': 0.7
        ,'reg_lambda': 0.1
        ,'subsample': 0.75}


best['max_depth'] = int(best['max_depth'])
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ('mdl',  lg.LGBMClassifier(n_estimators=1000, n_jobs = -1, **best))
    ])
model_9 = full_pipeline_with_predictor.fit(X_train, y_train)
```

In [843…

```
exp_name = f"LightgbmTuned_{len(selected_features)}_features"
expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [accuracy_score(y_train, model_9.predict(X_train)),
                accuracy_score(y_valid, model_9.predict(X_valid)),
                accuracy_score(y_test, model_9.predict(X_test)),
```

```
                roc_auc_score(y_train, model_9.predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, model_9.predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, model_9.predict_proba(X_test)[:, 1]),
                train_time
                ],4))

expLog
```

Out[843...

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957
6	AdaBoost_66_features	0.9199	0.9195	0.9156	0.7598	0.7547	0.7582	68.2524
7	GradientBoost_66_features	0.9208	0.9197	0.9164	0.7729	0.7636	0.7626	299.1295
8	Lightgbm_66_features	0.9394	0.9190	0.9155	0.9599	0.7647	0.7624	16.3087
9	LightgbmTuned_66_features	0.9337	0.9193	0.9159	0.9308	0.7663	0.7656	16.3087

Preparing Submission Data

In [844...

```
test_class_scores = model_9.predict_proba(X_kaggle_test)[:, 1]
```

In [845...

```
test_class_scores[0:10]
```

Out[845...

```
array([0.0365777 , 0.07682451, 0.0505086 , 0.06351052, 0.10368943,
       0.02445801, 0.02006455, 0.02240253, 0.00987776, 0.09019442])
```

In [846...

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

submit_df.head()
```

Out[846...

	SK_ID_CURR	TARGET
0	100001	0.036578
1	100005	0.076825
2	100013	0.050509
3	100028	0.063511
4	100038	0.103689

In [847…
```
submit_df.to_csv("submission.csv",index=False)
```

Kaggle Submission

In [597…
```
! kaggle competitions submit -c home-credit-default-risk -f submission.csv -m "Phase2 s
```

```
100%|██████████████████████████████████████| 1.27M/1.27M [00:01<00:00, 1.29MB/s]
Successfully submitted to Home Credit Default Risk
```

Write-up

Abstract

The course project is based on the Home Credit Default Risk (HCDR) Kaggle Competition. Our goal is to create a machine learning model that is well optimized and performs efficiently to asses this risk for lender. There are many factors in a person's life that lenders can use to assess this risk such as previous credit history, occupation, age, location, credit card usage, and others. We will be studying these factors when trying to assess a loan application and provides them with the decision-making guidance they need for a sustainable business operation.

Entire project is being implemented in 3 phases. In Phase 1, We experimented with classification algorithms like Logistic regression and Random Forest as our baseline models with features from 3 out of the 8 available datasets. We have conducted 4 experiments in total in this phase using the above mentioned models and datasets which provides information about client's previous monthly credits, monthly balance of client's previous loan, monthly data about previous credit cards, and payment history, furthermore, we will walk you through the results in coming sections of this presentation. We hope to produce a model that will allow Home Credit to successfully predict the likelihood of repayment so that more people can have access to much needed loans.

Project Description

We have experimented with various classification algorithms in order to determine which produces the most accurate predictions. We have conducted the following experiments so far: Baseline Logistic Regression, Logistic Regression with Additional Features 66, Logistic Regression with GridSearch, Random Forest with Additional Features 66, Random Forest with RandomizedSearchCV, XGBoost without RandomizedSearchCV, GradBoost, Adaboost, LightGBM without RandomizedSearchCV and LightGBM Tuned

We hope to produce a model that will allow Home Credit to successfully predict the likelihood of repayment so that more people can have access to much needed loans.

Back ground Home Credit Group

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

Home Credit Group

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

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

Background on the dataset

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

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

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

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

Data files overview

There are 7 different sources of data:

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

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

Feature Engineering and transformers

Feature engineering is a process that can include both feature creation (adding new features to existing data) and feature selection (identifying only the most significant features or using other dimensionality reduction techniques). We may utilize a variety of ways to both build and pick features. Applied group_by and grouped the data, taking SK_ID_CURR as a key, and aggregated using aggerate functions and using some features from the previous_application data set.

We have performed correlation analysis in section 4.4 and picked up the highly correlated features for the experiments in this phase.

The features being used include the general data about the borrower and the two most common categories of data are categorical and numerical data. Although both data formats contain two subcategories, there are several variances between them. These distinctions endow them with distinct characteristics that are equally helpful in statistical analysis. Numerical data types include numerical data. Total income, credit amount, employment details and history, age, and other numerical or quantitative statistics are examples. Categorical data, on the other hand, are qualitative data types. gender, Real estates owned, Cars owned, type of contract, employment details, and Educational details, and so on are some instances. We have used the following Features

Selected features = ['Count', 'Total_Remaining_repays', 'TOTAL_DEBT', 'Max_Initial_term', 'TOTAL_DEBT_OVERDUE', 'TOTAL_NUMBER_OF_ACTIVE_LOANS', 'PERCENT_LATE', 'PERCENT_CREDIT_CARD', 'Avg_installment_days_difference', 'Avg_installment_amount_difference', 'Cash loans', 'Consumer loans', 'Revolvingloans', 'XNA', 'FRIDAY', 'MONDAY', 'SATURDAY', 'SUNDAY', 'THURSDAY', 'TUESDAY', 'WEDNESDAY', 'Approved', 'Canceled', 'Refused', 'Unusedoffer', 'Total_records', 'Tot_AMT_ANNUITY_min', 'Tot_AMT_ANNUITY_max', 'Tot_AMT_ANNUITY_mean', 'Tot_AMT_APPLICATION_min', 'Tot_AMT_APPLICATION_max', 'Tot_AMT_APPLICATION_mean', 'DAYS_DECISION_min', 'DAYS_DECISION_max', 'DAYS_DECISION_mean', 'CC_Average_Monthly_Balance','CC_Average_Credit_Card_Limit', 'CC_Average_Monthly_Payments', 'CC_Average_percentage_pass_due']

In selected feature we are dealing with the general information such as remaining repays, Debt records, Number of active loans and their types, information about installments, Previous loans approved or canclled, annuity information, Monthly balance and expenditure, Credit card limit .

num_attribs = ['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', 'EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_EMPLOYED', 'FLOORSMAX_AVG', 'FLOORSMAX_MEDI', 'FLOORSMAX_MODE', 'AMT_GOODS_PRICE', 'Count', 'Total_Remaining_repays', 'TOTAL_DEBT', 'Max_Initial_term', 'TOTAL_DEBT_OVERDUE', 'TOTAL_NUMBER_OF_ACTIVE_LOANS', 'PERCENT_LATE', 'PERCENT_CREDIT_CARD', 'Avg_installment_days_difference', 'Avg_installment_amount_difference', 'Cash loans', 'Consumer loans', 'Revolvingloans', 'XNA', 'FRIDAY', 'MONDAY', 'SATURDAY', 'SUNDAY', 'THURSDAY', 'TUESDAY', 'WEDNESDAY', 'Approved', 'Canceled', 'Refused', 'Unusedoffer', 'Total_records', 'Tot_AMT_ANNUITY_min', 'Tot_AMT_ANNUITY_max', 'Tot_AMT_ANNUITY_mean', 'Tot_AMT_APPLICATION_min', 'Tot_AMT_APPLICATION_max', 'Tot_AMT_APPLICATION_mean', 'DAYS_DECISION_min', 'DAYS_DECISION_max', 'DAYS_DECISION_mean','CC_Average_Monthly_Balance', 'CC_Average_Credit_Card_Limit','CC_Average_Monthly_Payments','CC_Average_percentage_pass_due']

In numerical attributes we are dealing with the data obtained in the numerical form such as age, debt information, information about installments, Annuity informations, Monthly payment and balance, credit card limit.

cat_attribs= ['CODE_GENDER','FLAG_OWN_REALTY','FLAG_OWN_CAR','NAME_CONTRACT_TYPE','NAME_EDUCATION

In categorical attributes we are dealing with the data which can be used to categorize an individual based on gender, Real estates owned, Cars owned, type of contract, employment details, and Educational details.

Hyperparameter Tuning

In this Phase, we have done hyperparameter tuning using GridSearchCV and also used Bayesian approach from Hyperopt package to tune the LightGBM model.

Hyper-parameters are parameters that are not directly learnt within estimators. In scikit-learn they are passed as arguments to the constructor of the estimator classes. Typical examples include C, kernel and gamma for Support Vector Classifier, alpha for Lasso, etc.

A machine learning model has multiple parameters that are not trained by the training set. These parameters control the accuracy of the model. Therefore, the hyperparameters are particularly important in a data science project.

GRID SEARCH - Grid search is a tuning technique that attempts to compute the optimum values of hyperparameters. It is an exhaustive search that is performed on the specific parameter values of a model. The model is also known as an estimator.

GridSearchCV: GridSearchCV is a library function that is a member of sklearn's model_selection package. It helps to loop through predefined hyperparameters and fit your estimator (model) on your training set. So, in the end, you can select the best parameters from the listed hyperparameters.

Bayesian Hyperparameter Optimization: Build a probability model of the objective function and use it to select the most promising hyperparameters to evaluate in the true objective function.

HYPEROPT: Hyperopt is a python library for search spaces optimizing. Currently it offers two algorithms in optimization: 1. Random Search and 2. Tree of Parzen Estimators (TPE) which is a Bayesian approach which makes use of P(x|y) instead of P(y|x), based on approximating two different distributions separated by a threshold instead of one in calculating the Expected Improvement

Pipelines

Build Numeric Pipeline

```
Identify the numeric features we wish to consider.

Create a pipeline for the numeric features.

Use DataFrameSelector() to select the desired numeric features

Use SimpleImputer() for missing data: there are quite a few missing
values in the dataset. Missing values will be imputed using the feature
mean.

Use StandardScaler() to standardize the data
```

The numeric pipeline will look like as follows:

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

Build Categorical Pipeline:

```
Identify the categorical features we wish to consider.
```

```
Identify the range of expected values for the categorical features.

Create a pipeline for the categorical features.

Use SimpleImputer() for missing data: there are quite a few missing
values in the dataset. Missing values will be imputed using constant
values.
```

Then use One Hot Encoding

The numeric pipeline will look like as follows:

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

Union numeric pipeline and categorical pipeline:

The codes will looks like as follows:

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

full_pipeline = Pipeline([("preparation", data_prep_pipeline)])

Experimental results

XGBoost and LighGBM are better performing models from our experiments so far.

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train Time
0	Baseline_Logistic_27_features	0.9198	0.9193	0.9162	0.7398	0.7397	0.7417	5.8258
1	LogisticRegression_66_features	0.9199	0.9195	0.9164	0.7550	0.7547	0.7541	7.4445
2	LogisticRegression_GSCV_66_features	0.9199	0.9194	0.9164	0.7550	0.7546	0.7541	144.7622
3	RamdomForest_66_features	0.9198	0.9194	0.9160	0.7479	0.7453	0.7429	56.5804
4	RamdomForestCV_66_features	0.9198	0.9194	0.9160	0.8248	0.7561	0.7528	809.2470
5	XGBoost_66_features	0.9270	0.9191	0.9157	0.8630	0.7649	0.7641	19.9957
6	AdaBoost_66_features	0.9199	0.9195	0.9156	0.7598	0.7547	0.7582	68.2524
7	GradientBoost_66_features	0.9208	0.9197	0.9164	0.7729	0.7636	0.7626	299.1295
8	Lightgbm_66_features	0.9394	0.9190	0.9155	0.9599	0.7647	0.7624	16.3087
9	LightgbmTuned_66_features	0.9337	0.9193	0.9159	0.9308	0.7663	0.7656	16.3087

Discussion

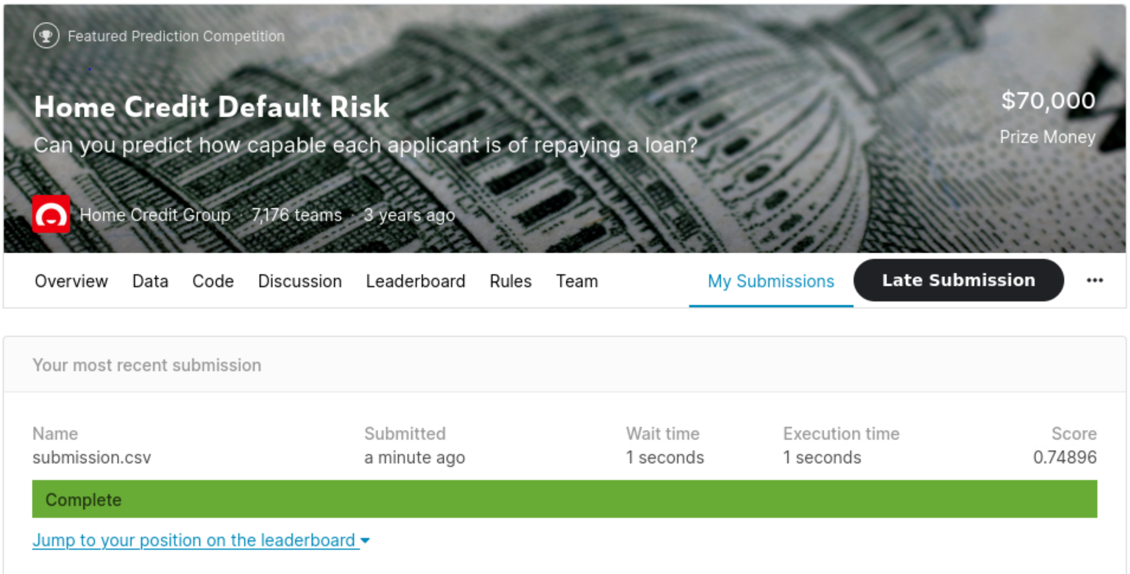
```
We have experimented the following 7 models:
    Baseline Logistic Regression with 27 features
    Logistic Regression with additional features
    Logistic Regression with GridSearchCV
    Random Forest with additional features
    Random Forest with RandomSearchCV
    XGBoost with additional features
    GradBoost with additional features
    LightGBM with additional features
    LightGBM with Hperparameter tuning
```

So far our best model is LightGBM with Hyperparameter Tuning. Our highest Kaggle scores for it are 0.0.75347 on private board and 0.74896 on public board. As we expected, our models did take time to run when we used GridSearch CV or RandomsearchCV techniques. We have opted to use Bayesian Hyperparameter optimization for tuning LightGBM model and we have observed a better performamce interms of run time. We have also observed that XGBoost and LightGBM models have given very similar AUC scores of 0.7641 and 0.7656 respectively. We will continue to focus on Hyper parameter tuning of AdaBoost,GradBoost models, additional featuring engineering and implementation of a deep learning model for Phase 3 and we are hoping to see better scores for our models.

Conclusion

In Phase II of the project, we focused on improving the test accuracy, additional feature engineering, hyperparameter tuning, feature selection, analysis of feature importance, and other ensemble methods. We have seen the test accuracy of 0.76 for XGBOOST, ADA BOOST, and LIGHTBGM with 66 features. Furthermore, LIGHTBGM after tuning has shown slight improvement and got 0.765 AUC. Other observation from the experiments in this phase is that the training times of LIGHTGBM and XGBOOST are much lower when compared to other models. It is very evident that Feature Engineering and Hyperparameter tuning played a crucial role in getting the better results. In the final phase of the project, we will try and do more hyper parameter tuning, implement a neural network model and compare the results from phases I and II.

Kaggle Submission


Featured Prediction Competition
Home Credit Default Risk
Can you predict how capable each applicant is of repaying a loan?
$70,000
Prize Money
Home Credit Group · 7,176 teams · 3 years ago
Overview
Data
Code
Discussion
Leaderboard
Rules
Team
My Submissions
Late Submission
Your most recent submission
Name
submission.csv
Submitted
a minute ago
Wait time
1 seconds
Execution time
1 seconds
Score
0.74896
Complete
Jump to your position on the leaderboard

In [ ]: