Kaggle API setup

In [3]:

```
!pip install kaggle
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.7/site-packages (1.5.12)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.7/site-packages (from
kaggle) (1.15.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/site-packages (from kagg
le) (4.62.1)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.7/site-packages
(from kaggle) (2.8.2)
Requirement already satisfied: requests in /usr/local/lib/python3.7/site-packages (from
kaggle) (2.25.1)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.7/site-packages
(from kaggle) (5.0.2)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/site-packages (from k
aggle) (2021.5.30)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/site-packages (from k
aggle) (1.26.6)
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)
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting
behaviour with the system package manager. It is recommended to use a virtual environmen
t instead: https://pip.pypa.io/warnings/venv
WARNING: You are using pip version 21.2.4; however, version 21.3.1 is available.
You should consider upgrading via the '/usr/local/bin/python -m pip install --upgrade pi
p' command.
```

In [19]:

```
!pip install pandoc
```

```
Collecting pandoc
  Downloading pandoc-1.1.0-py3-none-any.whl (27 kB)
Collecting ply
  Downloading ply-3.11-py2.py3-none-any.whl (49 kB)
     |████████████████████████████████| 49 kB 2.2 MB/s eta 0:00:01
Collecting plumbum
  Downloading plumbum-1.7.0-py2.py3-none-any.whl (116 kB)
     |████████████████████████████████| 116 kB 4.9 MB/s eta 0:00:01
Installing collected packages: ply, plumbum, pandoc
Successfully installed pandoc-1.1.0 plumbum-1.7.0 ply-3.11
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting
behaviour with the system package manager. It is recommended to use a virtual environmen
t instead: https://pip.pypa.io/warnings/venv
WARNING: You are using pip version 21.2.4; however, version 21.3.1 is available.
You should consider upgrading via the '/usr/local/bin/python -m pip install --upgrade pi
p' command.
```

In [4]:

```
!pwd
```

```
/root/shared/Courses/AML526/I526_AML_Student/Assignments/Unit-Project-Home-Credit-Defaul
t-Risk/HCDR_Phase_1_baseline_submission
```

In [5]:
```
!mkdir ~/.kaggle
!cp /root/shared/Downloads/kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json
```

```
mkdir: cannot create directory ‘/root/.kaggle’: File exists
```

In [6]:
```
! kaggle competitions files home-credit-default-risk
```

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

Downloading the files via Kaggle API

In [4]:
```
DATA_DIR = "/root/shared/Data/home-credit-default-risk"   #same level as course repo in
#DATA_DIR = os.path.join('./ddddd/')
!mkdir $DATA_DIR
```

```
mkdir: cannot create directory ‘/root/shared/Data/home-credit-default-risk’: File exists
```

In [8]:
```
!ls -l $DATA_DIR
```

```
total 3326068
-rwxrwxrwx 1 root root     37383 Dec 11  2019 HomeCredit_columns_description.csv
-rwxrwxrwx 1 root root 392703158 Dec 11  2019 POS_CASH_balance.csv
-rwxrwxrwx 1 root root  26567651 Dec 11  2019 application_test.csv
-rwxrwxrwx 1 root root 166133370 Dec 11  2019 application_train.csv
-rwxrwxrwx 1 root root 170016717 Dec 11  2019 bureau.csv
-rwxrwxrwx 1 root root 375592889 Dec 11  2019 bureau_balance.csv
-rwxrwxrwx 1 root root 424582605 Dec 11  2019 credit_card_balance.csv
-rw-r--r-- 1 root root 721616255 Nov 13 03:36 home-credit-default-risk.zip
-rwxrwxrwx 1 root root 723118349 Dec 11  2019 installments_payments.csv
-rwxrwxrwx 1 root root 404973293 Dec 11  2019 previous_application.csv
-rwxrwxrwx 1 root root    536202 Dec 11  2019 sample_submission.csv
```

In [10]:
```
! kaggle competitions download home-credit-default-risk -p $DATA_DIR --force
```

```
Downloading home-credit-default-risk.zip to /root/shared/Data/home-credit-default-risk
100%|████████████████████████████████████████▉| 688M/688M [05:34<00:00, 1.21MB/s]
100%|████████████████████████████████████████| 688M/688M [05:34<00:00, 2.15MB/s]
```

Imports

In [2]:
```
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

Application_Train data load

In [5]:

```
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[5]:
```
(307511, 122)
```

Application_Test data load

In [7]:
```
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 [8]:
```
%%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

	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	-241
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

	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 45.9 s, sys: 7.47 s, total: 53.4 s
Wall time: 1min 30s
```

EDA

Missing data for application train

In [9]:

```
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[9]:

	Percent	Train Missing Count

	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 [10]:

```
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[10]:

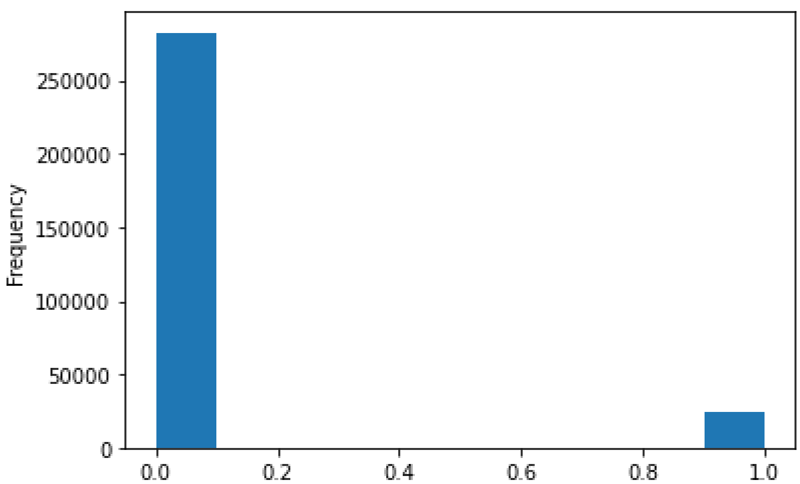
	Percent	Test Missing Count
COMMONAREA_AVG	68.72	33495
COMMONAREA_MODE	68.72	33495
COMMONAREA_MEDI	68.72	33495
NONLIVINGAPARTMENTS_AVG	68.41	33347
NONLIVINGAPARTMENTS_MODE	68.41	33347
NONLIVINGAPARTMENTS_MEDI	68.41	33347

	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 [23]:

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



Correlation with the target column

In [24]:

```
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
```

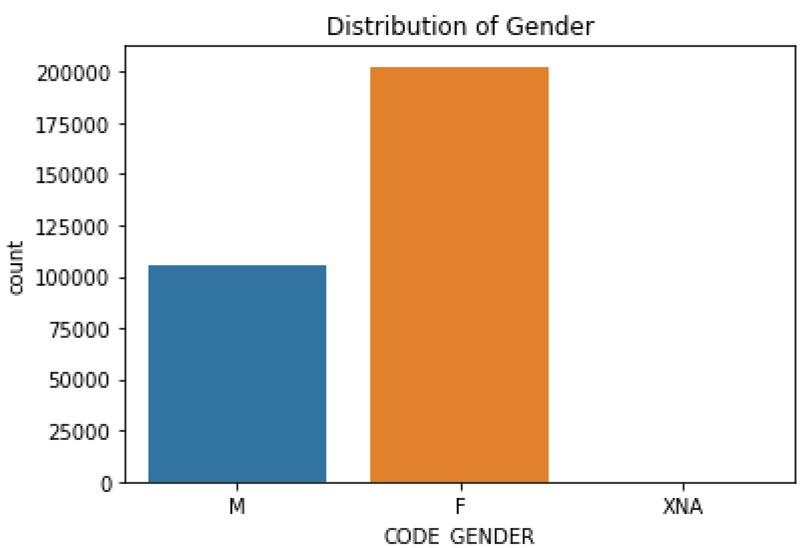
```
FLAG_EMP_PHONE                 0.045982
REG_CITY_NOT_WORK_CITY         0.050994
DAYS_ID_PUBLISH                0.051457
DAYS_LAST_PHONE_CHANGE         0.055218
REGION_RATING_CLIENT           0.058899
REGION_RATING_CLIENT_W_CITY    0.060893
DAYS_BIRTH                     0.078239
TARGET                         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 [12]:

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

In [26]:

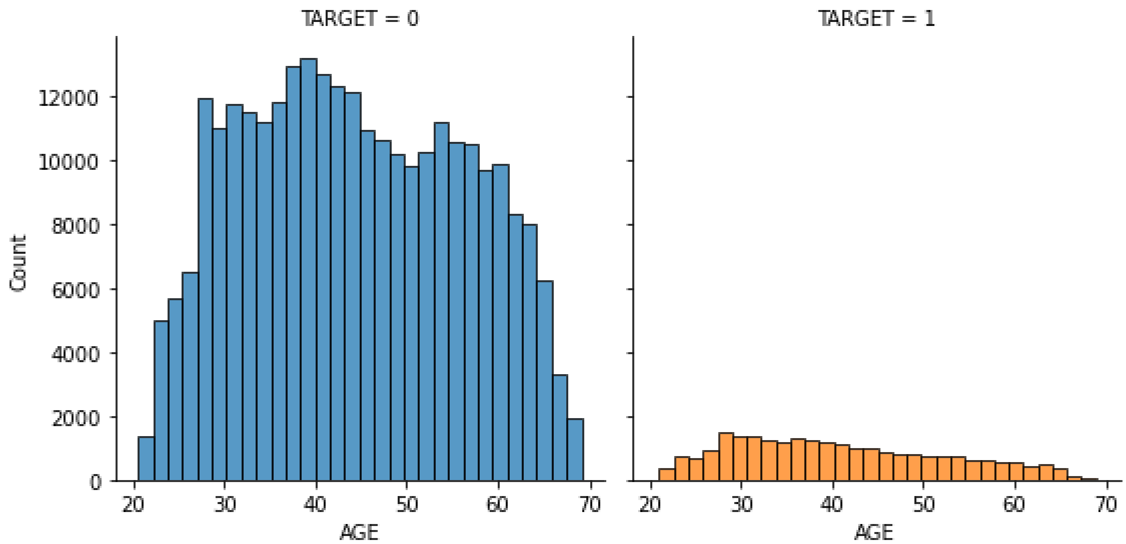
```
sns.countplot(data = app_train, x ='CODE_GENDER')
plt.title('Distribution of Gender')
plt.show()
```



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

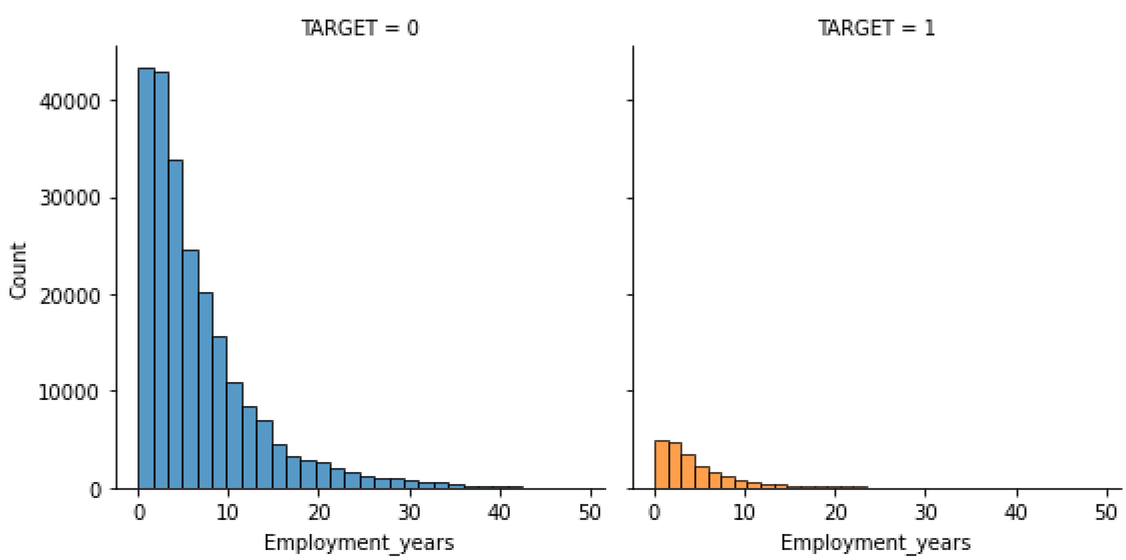
In [29]:

```
app_train['AGE'] = app_train['DAYS_BIRTH']/-365
fig = sns.FacetGrid(app_train, col='TARGET', hue='TARGET', height=4)
fig.map(sns.histplot, 'AGE', bins=30, kde=False)
plt.show()
```



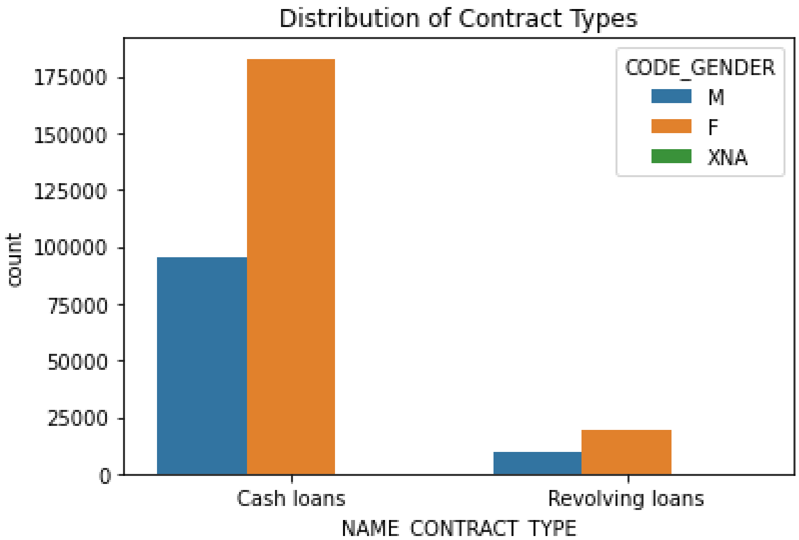
It can be observed that most of the defaulters are approximately 27-40 yrs old.

In [32]:
```
# replace the incorrect values of Days_Employed
import numpy as np

# Create an error flag column
app_train['DAYS_EMPLOYED_ERROR'] = app_train["DAYS_EMPLOYED"] == 365243
app_test['DAYS_EMPLOYED_ERROR'] = app_test["DAYS_EMPLOYED"] == 365243 # do the same for

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

app_train['Employment_years'] = app_train['DAYS_EMPLOYED']/-365
fig = sns.FacetGrid(app_train, col='TARGET', hue='TARGET', height=4)
fig.map(sns.histplot, 'Employment_years', bins=30, kde=False)
plt.show()
```



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

In [34]:
```
sns.countplot(data = app_train, x ='NAME_CONTRACT_TYPE', hue = 'CODE_GENDER')
plt.title('Distribution of Contract Types')
plt.show()
```

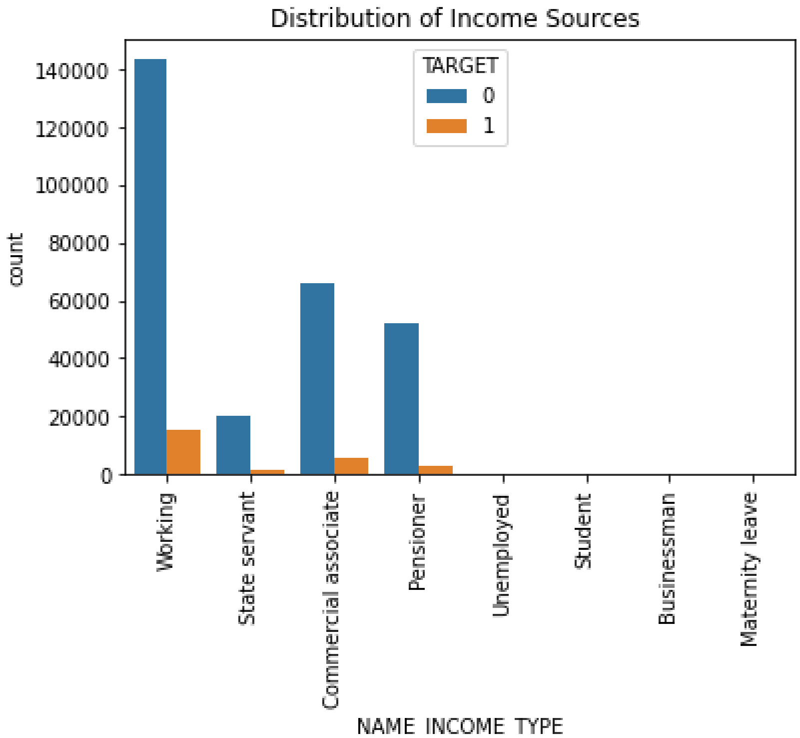


It can be seen that in general people mostly go for Cash loans as compared to revolving loans and both type of contracts are dominated by females.

In [36]:
```
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.

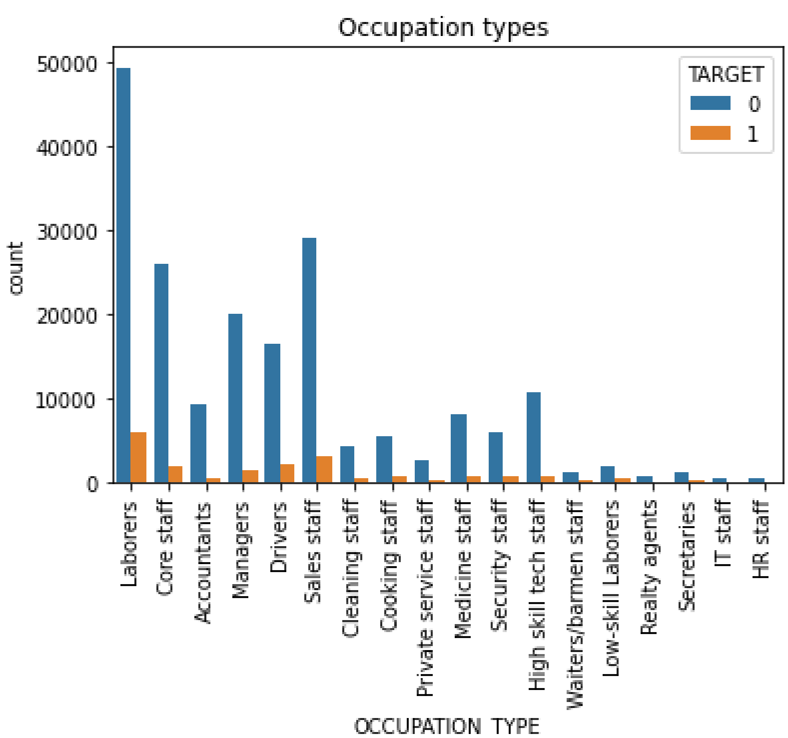
In [13]:
```
sns.countplot(data = app_train, x ='NAME_INCOME_TYPE', hue = 'TARGET')
plt.title('Distribution of Income Sources ')
plt.xticks(rotation = 90)
plt.show()
```



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

In [40]:

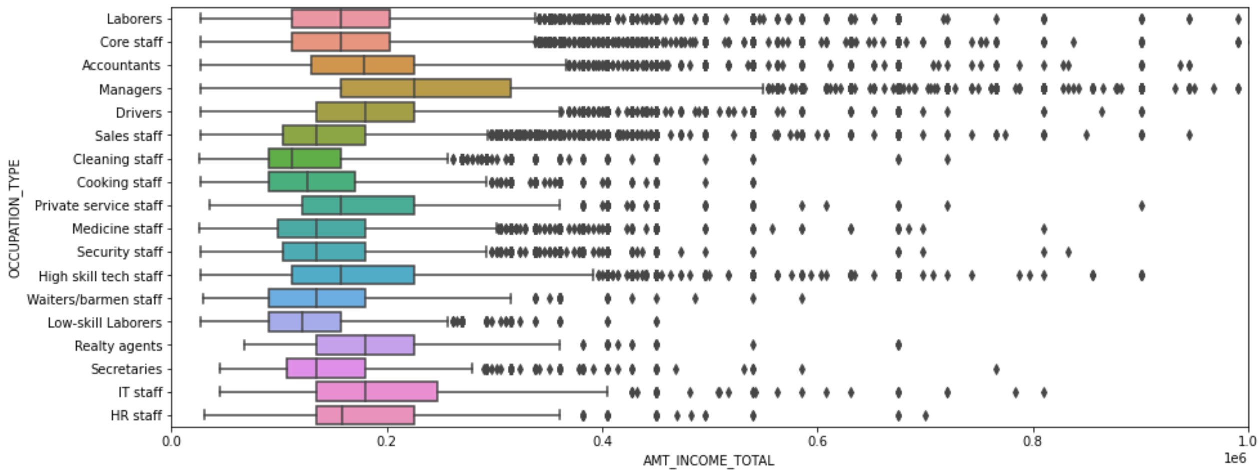
```
sns.countplot(data = app_train, x ='OCCUPATION_TYPE', hue = 'TARGET')
plt.title('Occupation types ')
plt.xticks(rotation = 90)
plt.show()
```



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

In [42]:

```
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()
```



Processing Pipeline

In [64]:

```
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 [71]:

```
def previous_app():
    df_pa = datasets['previous_application']
    #df_pa.drop('SK_ID_PREV', axis = 1, inplace = True)



    numcols = df_pa.select_dtypes(exclude= 'object').columns
    catcols = df_pa.select_dtypes(include= 'object').columns

    num = df_pa[numcols]
    cat = df_pa[catcols]

    num.index = num['SK_ID_CURR']
    cat.index = num['SK_ID_CURR']

    catind = cat.index


    num.drop('SK_ID_CURR', inplace= True, axis = 1)
    num = num.groupby('SK_ID_CURR').agg([np.sum, np.mean,max,min])
    num.columns = num.columns.map('_'.join)
    mdl = StandardScaler().fit(num)
    num = pd.DataFrame(mdl.transform(num),index = num.index, columns = num.columns)
```

```
    cat = SimpleImputer(strategy='constant').fit_transform(cat)
    mdl = OneHotEncoder().fit(cat)

    cat = pd.DataFrame(mdl.transform(cat).toarray(), index = catind, columns = mdl.get_
    cat = cat.groupby('SK_ID_CURR').agg(np.mean)
    final = num.merge(cat, how = 'left', on = 'SK_ID_CURR')
    return final
```

In [66]:

```
def load_train():
    df_train = app_train

    selected_features = ['SK_ID_CURR','AMT_INCOME_TOTAL',  'AMT_CREDIT','DAYS_EMPLOYED'
                'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER', 'FLAG_OWN_REALTY','FLA
                 'NAME_CONTRACT_TYPE','NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME


    df_train['DAYS_EMPLOYED'].replace({365243: np.nan}, inplace = True)
    df_train['DAYS_BIRTH'] = df_train['DAYS_BIRTH']/-365


    X_train= df_train[selected_features]
    y_train = df_train['TARGET']


    X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=0

    X_val_ind = X_valid['SK_ID_CURR']



    X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_size=0.1

    X_train_ind = X_train['SK_ID_CURR']
    X_test_ind = X_test['SK_ID_CURR']


    X_valid.drop('SK_ID_CURR', inplace = True , axis = 1)
    X_train.drop('SK_ID_CURR', inplace = True , axis = 1)
    X_test.drop('SK_ID_CURR', inplace = True , axis = 1)

    return X_train, y_train, X_valid, y_valid, X_test, y_test, X_train_ind, X_val_ind,
```

In [67]:

```
def transform_train(X_train, X_valid, X_test, X_train_ind, X_val_ind, X_test_ind):
    num_attribs = ['AMT_INCOME_TOTAL',  'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_
               'EXT_SOURCE_2','EXT_SOURCE_3']

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


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

    cat_pipeline = Pipeline([
                        ('selector', DataFrameSelector(cat_attribs)),
```

```
                            ('imputer', SimpleImputer(strategy='constant')),
                            ('ohe', OneHotEncoder(sparse=False, handle_unknown="ignore"
                            ])

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

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

    X_train = pd.DataFrame(full_pipeline.fit_transform(X_train), index  = X_train_ind)
    X_valid = pd.DataFrame(full_pipeline.transform(X_valid), index = X_val_ind)
    X_test = pd.DataFrame(full_pipeline.transform(X_test), index= X_test_ind)

    return full_pipeline, X_train, X_valid, X_test
```

Baseline Model

In [48]:

```
def BaselineApproach(fitted_models,expLog, X_train,X_valid, X_test,y_train,y_test,y_val
    models = [LogisticRegression(n_jobs = -1, solver = 'lbfgs')
          ,RandomForestClassifier(n_jobs = -1,n_estimators = 100)]

    models_name = ['Logistic','RandomForest']
    ctr = 0
    p_value = 0
    for model in models:
        cv = ShuffleSplit(n_splits=30, test_size=0.3, random_state=0)
        np.random.seed(42)
        model.fit(X_train, y_train)
        exp_name = f"Model_{models_name[ctr]}_features_{X_train.shape[1]}"
        fitted_models.append(model)
        if ctr   == 0:
            logit_scores = cross_val_score(model, X_train, y_train, cv=cv)
        else:
            best_train_scores = cross_val_score(model, X_train, y_train, cv=cv)
            (t_stat, p_value) = stats.ttest_rel(logit_scores, best_train_scores)

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

Merge data from Previous Application file

In [62]:

```
def merge_df(X_train, X_valid, X_test, df_pv_app):
    X_train = X_train.merge(df_pv_app, how = 'left', on = 'SK_ID_CURR')
    X_valid = X_valid.merge(df_pv_app, how = 'left', on = 'SK_ID_CURR')
    X_test =  X_test.merge(df_pv_app, how = 'left', on = 'SK_ID_CURR')
```

```
    X_train.fillna(0, inplace = True)
    X_valid.fillna(0, inplace = True)
    X_test.fillna(0, inplace = True)

    return X_train, X_valid, X_test
```

Baseline model with Previous Application

In [51]:

```
def BaselinPlusPvApp(logit_scores,fitted_models,expLog, X_train,X_valid, X_test,y_train
    models = [LogisticRegression(n_jobs = -1, solver = 'lbfgs' )
              ,RandomForestClassifier(n_jobs = -1,n_estimators = 100)]
    models_name = ['Logistic_Prev_app','RandomForest_prev_app']
    ctr = 0
    p_value = 0
    for model in models:
        cv = ShuffleSplit(n_splits=30, test_size=0.3, random_state=0)
        np.random.seed(42)
        model.fit(X_train, y_train)
        exp_name = f"Model_{models_name[ctr]}_features_{X_train.shape[1]}"
        fitted_models.append(model)
        best_train_scores = cross_val_score(model, X_train, y_train, cv=cv)
        (t_stat, p_value) = stats.ttest_rel(logit_scores, best_train_scores)

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

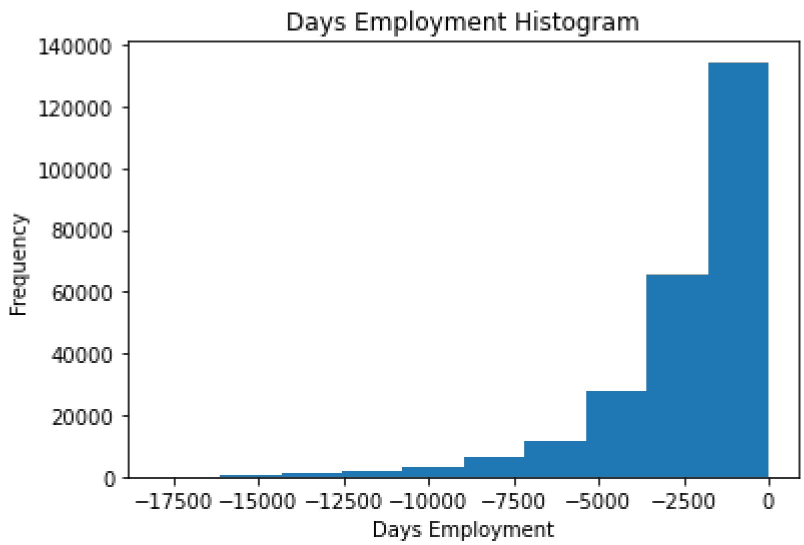
Performance Metrics

In [60]:

```
fitted_models = []
expLog = pd.DataFrame(columns=["exp_name",
                               "Train Acc",
                               "Valid Acc",
                               "Test  Acc",
                               "Train AUC",
                               "Valid AUC",
                               "Test  AUC",
                               "P_Value"
                              ])

#Loading & Transforming Train
X_train, y_train, X_valid, y_valid, X_test, y_test, X_train_ind, X_val_ind, X_test_ind

full_pipeline, X_train, X_valid, X_test = transform_train(X_train, X_valid, X_test, X_t

#BaselIne Model
logit_scores_baseline = BaselineApproach(fitted_models,expLog, X_train,X_valid, X_test,
expLog
```

Out[60]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	Model_Logistic_features_48	0.9191	0.9192	0.9196	0.7357	0.7407	0.7450	0.0000
1	Model_RandomForest_features_48	0.9999	0.9194	0.9194	1.0000	0.7100	0.7169	0.1024



In [72]:

```
df_pv_app = previous_app()
X_train, X_valid, X_test = merge_df(X_train, X_valid, X_test, df_pv_app)
BaselinPlusPvApp(logit_scores_baseline,fitted_models,expLog, X_train,X_valid, X_test,y_
expLog
```

Out[72]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	Model_Logistic_features_48	0.9191	0.9192	0.9196	0.7357	0.7407	0.7450	0.0000
1	Model_RandomForest_features_48	0.9999	0.9194	0.9194	1.0000	0.7100	0.7169	0.1024
2	Model_Logistic_Prev_app_features_269	0.9193	0.9194	0.9196	0.7567	0.7584	0.7601	0.0068
3	Model_RandomForest_prev_app_features_269	1.0000	0.9194	0.9195	1.0000	0.7168	0.7197	0.0000

In [70]:

```
datasets['previous_application'].describe()
```

Out[70]:

	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_G
count	1.670214e+06	1.297979e+06	1.670214e+06	1.670213e+06	7.743700e+05	1
mean	2.783572e+05	1.595512e+04	1.752339e+05	1.961140e+05	6.697402e+03	2
std	1.028148e+05	1.478214e+04	2.927798e+05	3.185746e+05	2.092150e+04	3
min	1.000010e+05	0.000000e+00	0.000000e+00	0.000000e+00	-9.000000e-01	(
25%	1.893290e+05	6.321780e+03	1.872000e+04	2.416050e+04	0.000000e+00	5
50%	2.787145e+05	1.125000e+04	7.104600e+04	8.054100e+04	1.638000e+03	1
75%	3.675140e+05	2.065842e+04	1.803600e+05	2.164185e+05	7.740000e+03	2

	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_G
max	4.562550e+05	4.180581e+05	6.905160e+06	6.905160e+06	3.060045e+06	6

Preparing Submission Data

In [80]:

```
def test_sub(full_pipeline,df_pv_app,fitted_models):
    df_test = app_test

    tst_ind = df_test['SK_ID_CURR']
    test = pd.DataFrame(full_pipeline.transform(df_test), index = tst_ind)
    test = test.merge(df_pv_app, how = 'left', on = 'SK_ID_CURR')
    test.fillna(0,inplace = True)
    pred = fitted_models[3].predict_proba(test)[:,1]
    sub = pd.DataFrame(tst_ind)
    sub['TARGET'] = pred
    sub.to_csv('submission.csv', index = False)
```

In [82]:

```
test_sub(full_pipeline,df_pv_app,fitted_models)
```

Kaggle Submission

In [83]:

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

```
100%|████████████████████| 566k/566k [00:01<00:00, 488kB/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 will be 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 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

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).

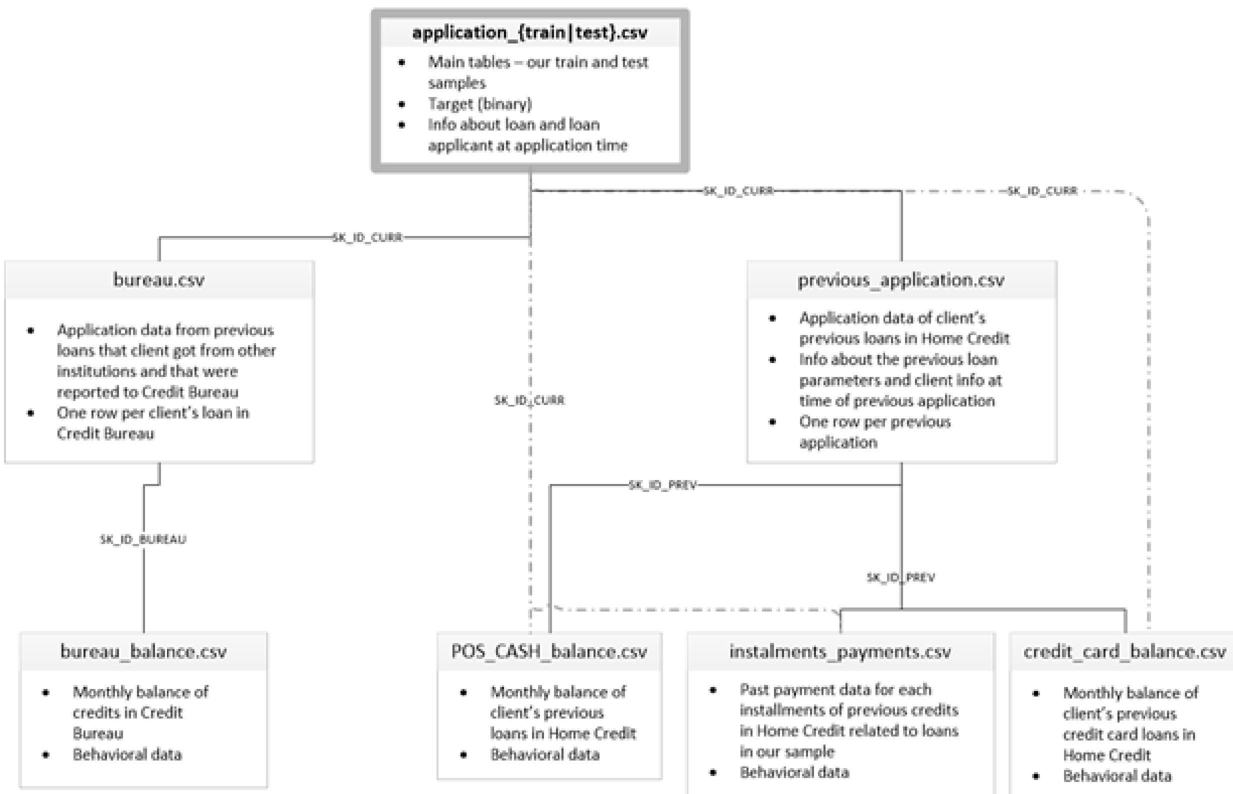
While Home Credit is currently using various statistical and machine learning methods to make these predictions, they're challenging Kagglers to help them unlock the full potential of their data. Doing so will ensure that clients capable of repayment are not rejected and that loans are given with a principal,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



Project Phases and Activities

Completed

Phase 1	Phase 2	Phase 3
Data download	Feature Engineering	Implement Neural network
		Compare the results of the expermients from previous phases
Data Load	Hyperparameter Tuning	
Perform EDA	Additional Feature Selection	Final Report out
Modelling Pipelines	Ensemble Methods	
Baseline Models		
Analyze the results		

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.

We have used the following Features

Selected features = ['SK_ID_CURR','AMT_INCOME_TOTAL', 'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_SOURCE_1', 'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER', 'FLAG_OWN_REALTY','FLAG_OWN_CAR', 'NAME_CONTRACT_TYPE','NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INCOME_TYPE']

num_attribs = ['AMT_INCOME_TOTAL', 'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','EXT_SOURCE_1', 'EXT_SOURCE_2','EXT_SOURCE_3']

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

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

	exp_name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	P_Value
0	Model_Logistic_features_48	0.9191	0.9192	0.9196	0.7357	0.7407	0.7450	0.0000
1	Model_RandomForest_features_48	0.9999	0.9194	0.9194	1.0000	0.7100	0.7169	0.1024
2	Model_Logistic_Prev_app_features_269	0.9193	0.9194	0.9196	0.7567	0.7584	0.7601	0.0068
3	Model_RandomForest_prev_app_features_269	1.0000	0.9194	0.9195	1.0000	0.7168	0.7197	0.0000

Initially, we got the test AUC of 0.74 and 0.71 with Logistic Regression and Random Forest, respectively, and after merging with the previous application_data we could see a small increase in AUC in the Logistic Regression, but it had no effect in the Random Forest Model.

Discussion

We have conducted 4 different experiments in this Phase using Logistic regression and Random Forrest algorithms. We have first conducted the experiment with teh data only from Application Train and Application Test data set with out including supporting datasets. We have observed that we got 74% AUC with logistic regression and 71% with Random forrest. We have then added additional features from Previous application data and observed that AUC for logist regression increased to 76% and haven't seen any improvement with Random forrest.

Conclusion

By adding features from previous application data set , we have seen that accuracy improved from 74% to 76% for our baseline Logistic regression model. We haven't seen the improvement with the Random forest model. This shows the importance of doing EDA on other supporting datasets to find out the right features and use that in our models.

We followed a machine learning project's general outline:

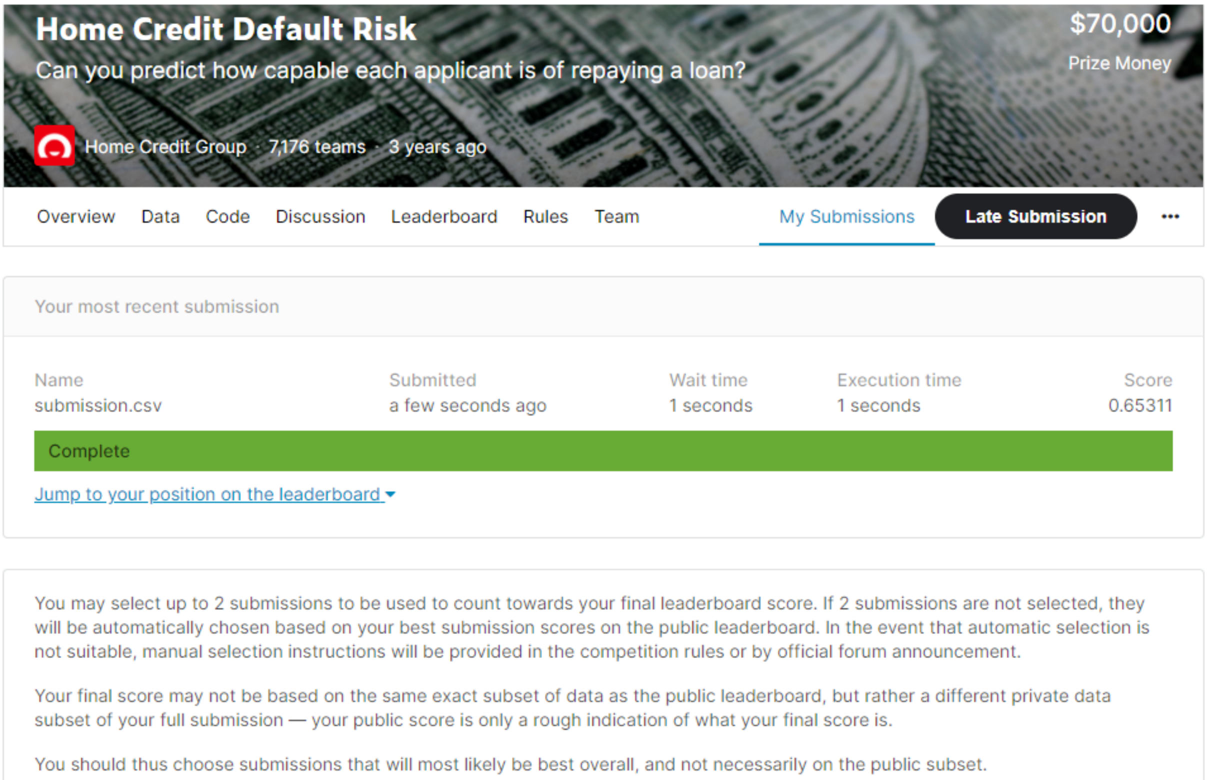
```
•Recognize the issue and the data.
•Cleaning and formatting of data (this was mostly done for us)
•Examine exploratory data
•Model to start with:  Baseline model
•Improved model
•Interpretation of the model (just a little)
```

Our focus in the coming phases will be on

```
Exploring new features

Hyperparameter tuning
```

```
Implement/explore other models like Gradient Boost and AdaBoost
```

Kaggle Submission



In [ ]: